EVOLUTIONARY ADAPTATION IN CASE-BASED REASONING

AN APPLICATION TO CROSS-DOMAIN ANALOGIES FOR MEDIATION

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Dedicated to my parents

Nihayet Bayraktar & Süleyman Zafer Baydin

for their endless support
and encouragement

ABSTRACT

Analogy plays a fundamental role in problem solving and it lies behind many processes central to human cognitive capacity, to the point that it has been considered "the core of cognition". Analogical reasoning functions through the process of *transfer*, the use of knowledge learned in one situation in another for which it was not targeted. The *case-based reasoning* (CBR) paradigm presents a highly related, but slightly different model of reasoning mainly used in artificial intelligence, different in part because analogical reasoning commonly focuses on cross-domain structural similarity whereas CBR is concerned with transfer of solutions between semantically similar cases within one specific domain.

In this dissertation, we join these interrelated approaches from cognitive science, psychology, and artificial intelligence, in a CBR system where case retrieval and adaptation are accomplished by the Structure Mapping Engine (SME) and are supported by commonsense reasoning integrating information from several knowledge bases. For enabling this, we use a case representation structure that is based on semantic networks. This gives us a CBR model capable of recalling and adapting solutions from seemingly different, but structurally very similar domains, forming one of our contributions in this study.

A traditional weakness of research on CBR systems has always been about adaptation, where most applications settle for a very simple "reuse" of the solution from the retrieved case, mostly through *null adaptation* or *substitutional adaptation*. The difficulty of adaptation is even more obvious for our case of cross-domain CBR using semantic networks. Solving this difficulty paves the way to another contribution of this dissertation, where we introduce a novel *generative adaptation* technique based on evolutionary computation that enables the spontaneous creation or modification of semantic networks according to the needs of CBR adaptation.

For the evaluation of this work, we apply our CBR system to the problem of mediation, an important method in conflict resolution. The mediation problem is non-trivial and presents a very good real world example where we can spot structurally similar problems from domains seemingly as far as international relations, family disputes, and intellectual rights.

RESUM

L'analogia juga un papel fonamental en la resolució de problemes i es troba darrere de molts dels processos centrals de la capacitat cognitiva humana, fins al punt que s'ha considerat " el nucli del coneixement". El raonament analògic funciona a través del procés de *la transferència*, l'ús del coneixement après en una situació en l'altra per a la qual no va ser destinat. El paradigma de *raonament basat en casos* (case-based reasoning, CBR) presenta un model molt relacionat, però lleugerament diferent de raonament utilitzat principalment en la intel·ligència artificial; diferent en part perquè el raonament analògic se centra habitualment en la similitud estructural entre-dominis mentre que CBR té a veure amb la transferència de solucions entre els casos semànticament similars dins d'un domini específic.

En aquesta tesi, ens unim a aquests enfocaments interrelacionats de la ciÃšncia cognitiva, la psicologia i la intel·ligència artificial, en un sistema CBR, on la recuperació i l'adaptació es duen a terme per l'Motor d'Associació Estructural (SME) i són recolzats per el raonament de sentit comú integrant la informació des de diverses bases de coneixement. Per permetre això, utilitzem una estructura de representació de casos que es basa en les xarxes semàntiques. Això ens dóna un model CBR capaç de recuperar i adaptar solucions de dominis que són aparentment diferents però estructuralment molt similars, formant una de les nostres contribucions en aquest estudi.

Una de les principals limitacions de la investigació sobre els sistemes CBR sempre ha estat l'adaptació, on la majoria de les aplicacions es van conformar amb una simple "reutilització" de la solució del cas recuperat, principalment mitjançant una *adaptació null* o *adaptació sustitucional*. La dificultat de l'adaptació és encara més evident per al nostre cas d'inter-domini CBR utilitzant xarxes semàntiques. Resoldre aquesta dificultat aplana el camí per a una contribució igualment important d'aquesta tesi, on s'introdueix una tècnica nova *d'adaptació generativa* basada en la computació evolutiva que permet la creació o modificació espontània de les xarxes semàntiques d'acord a les necessitats d'adaptació CBR.

Per a l'avaluació d'aquest treball, apliquem el nostre sistema CBR al problema de la mediació, un mètode important en la resolució de conflictes. El problema de la mediació no és trivial i representa un molt bon exemple del món real, en el qual podem detectar problemes estructuralment similars de dominis aparentment tan lluny com les relacions internacionals, conflictes familiars i els drets intel·lectuals.

PUBLICATIONS

Some ideas and figures included in this thesis have appeared previously in the following published articles:

A. G. Baydin and R. López de Mántaras. Evolution of ideas: A novel memetic algorithm based on semantic networks. In *Proceedings of the IEEE Congress on Evolutionary Computation, CEC 2012, IEEE World Congress On Computational Intelligence, WCCI 2012, Brisbane, Australia, June 10–15, 2012*, pages 2653–2660. IEEE Press, 2012.

A. G. Baydin, R. López de Mántaras, and S. Ontañón. Automated generation of cross-domain analogies via evolutionary computation. In *Proceedings of the Third International Conference on Computational Creativity, Dublin, Ireland, May 30–June 1, 2012*, pages 25–32, Dublin, Ireland, 2012. University College Dublin.

A. G. Baydin, R. López de Mántaras, S. Simoff, and C. Sierra. CBR with commonsense reasoning and structure mapping: An application to mediation. In A. Ram and N. Wiratunga, editors, *Proceedings of the 19th International Conference on Case Based Reasoning, Greenwich, London, September 12–15, 2011*, Lecture Notes in Artificial Intelligence, pages 378–392, Heidelberg, 2011. Springer.

"I believe our future depends powerfully
on how well we understand this Cosmos
in which we float like a mote of dust in the morning sky."

— Carl Sagan

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Part I

BACKGROUND

In the chapters forming this first part, we start by discussing the power and central role of analogies in human cognition and present the problem of cross-domain case-based reasoning applied to mediation. After summarizing the focus and objectives of the dissertation, we introduce our approach based on evolutionary adaptation and commonsense reasoning and make clear the novel contributions of this research. During our discourse on related work, we provide a comprehensive review of the state of the art in the fields of analogy, case-based reasoning, and conflict resolution.

1

INTRODUCTION

"All perception of truth is the detection of an analogy..."
— Henry David Thoreau (1949)

1.1 FOCUS AND MOTIVATION

Imagine that you are a doctor about to administer radiotherapy to a cancer patient suffering from a malignant tumor. The sickness is fatal and if the tumor is not treated, the patient is going to die. There is a kind of radiation beam at your disposal that is harmless in low intensities, but is able to destroy the tumor if it can be directed to the tumor site with higher intensity.

But there is a setback: the radiation beam with that level of intensity is also going to destroy healthy tissue it is going to pass through before reaching the malignant tumor. The radiation ray is not harmful to tissues at lower intensities. Can you think about a procedure to administer the radiation beam to the malignant tumor without affecting healthy tissues?

The "radiation problem" was introduced by Karl Duncker in 1945.

The case we presented is called "Duncker's radiation problem", and is an example of problem solving in psychology, introduced by Gestalt psychologist Duncker (1945) and continued to be employed by many researchers in the field (Gick and Holyoak, 1980; Keane, 1985).

In this classic example, when test participants are asked to solve the problem, most of them fail to produce a solution. However, when they are told a second story in addition to the radiation problem, their rate of solution increases significantly.

The second story concerns a military general aiming to capture an enemy fortress (Figure 1). The general has an army of enough size to capture the fortress with a full-scale attack, but there is a hindrance. All the roads leading to the fortress are blocked by mines, which allow small groups of fortress-owner's scouts to pass through safely, but get triggered whenever a large group of men try to cross.

The general figures out a strategy: he divides his troops into several small groups that march to the fortress on different roads, but times

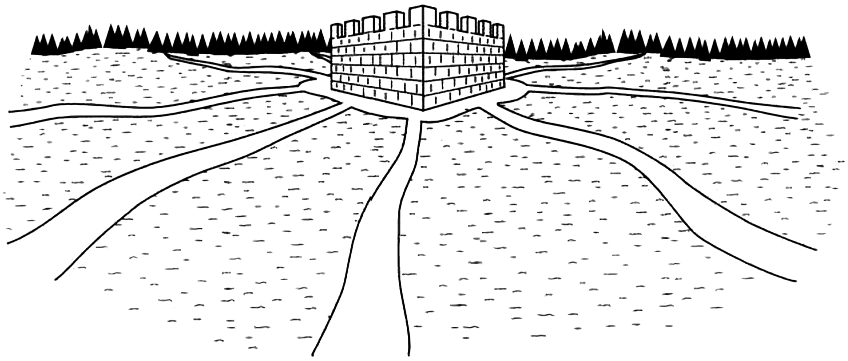


Figure 1: Assault on the fortress in Duncker's example (Davies, 2002).

Table 1: Results from the study of Gick and Holyoak (1980) on Duncker's radiation problem.

Success rate (%)	Increase (%)	Conditions
10%		No base problem, no hint (Control group)
30%	20%	Base problem, no hint
75%	45%	Base problem and hint

this in such a way that they arrive at the fortress at the same time to launch a full-scale attack.

The effect of base problem and hints

When test participants are presented only the original radiation problem, only 10 % are able to solve the it (Gick and Holyoak, 1980). But when the participants are asked to read the story of the general prior to being presented with the radiation problem, there is a three-fold increase in the solution rate, up to 30 %.

Moreover, when the participants who read the story of the general are given an additional hint of using the other story as help, the solution rate dramatically increases to 75 % (Table 1).

What is taking place in these experiments is a direct observation of the potential of a very powerful cognitive process: ***analogy***.

The solution is straightforward: we have to realize that we can treat the intensity of the radiation analogous to the size of an assault group in the general's army. As such, the tumor plays the role of the fortress, the high intensity radiation beam corresponds to a large group of soldiers, and the low intensity radiation beam corresponds to a small group of soldiers. One can split the radiation beam into multiple low intensity and harmless beams, and direct these beams towards the tumor from different angles. In this way, when the beams converge on the aimed site, the accumulated intensity of radiation is able to destroy the tumor, without the individual low intensity beams being harmful to healthy surrounding tissue (Figure 2).

Analogy is fundamental to problem solving and creativity and it has been demonstrated many times over that it lies behind many processes central to human cognitive capacity (Holyoak and Thagard, 1996), even to the point that it has been considered "the core of cognition" (Hofstadter, 2001).

Analogical reasoning functions through the process of *transfer* (Kolodner, 2002; Gentner et al., 2003), the use of knowledge learned in one situation, or domain, in another for which it was not targeted. The known situation from which the transfer is done is called the *base*, or the *source* (the general's story in the case of Duncker's radiation problem), while the situation onto which the transfer is done is called the *target* (the radiotherapy).

According to whether the base and the target belong to identical or distant domains, there are two types of analogy: *intra-domain*, confined to surface similarities within the same domain; and *cross-domain*, using deep structural similarities between semantically distant information.

The ability to make deep, structural analogies forms the basis of problem solving particularly for *ill-defined* problems, i.e. problems that do not have clear goals or solution paths (Schacter, 2009). The results in Table 1 suggest that noticing an analogy and constructing an analogy are separate steps. Noticing structural analogies is often hindered by surface features of the involved concepts.

An instance of this phenomenon, called *functional fixedness*, is defined by (Duncker, 1945) as a "mental block against using an object in a new way that is required to solve a problem". Functional fixedness results from a cognitive bias limiting the use of an object only in the way it is traditionally used.

Functional fixedness is a "mental block against using an object in a new way that is required to solve a problem"

A classic experiment demonstrating functional fixedness is the "candle problem" (Duncker, 1945; Adamson, 1952). In this experiment, participants are given a candle, a box of thumbtacks, and a book of matches. Then they are asked to attach the candle to the wall so that it would not drip onto the table below.

The solution is to empty the box of thumbtacks, put the candle into the box, nail the box to the wall, and lit the candle with a match (Figure 3).

Without noticing a structural analogy of treating the box as a kind of candle-holder, most participants initially try to attach the candle directly to the wall with tacks or glue it to the wall by melting the candle, which are not very useful methods. This is because of the fixation on the box's normal function as a container of thumbtacks.

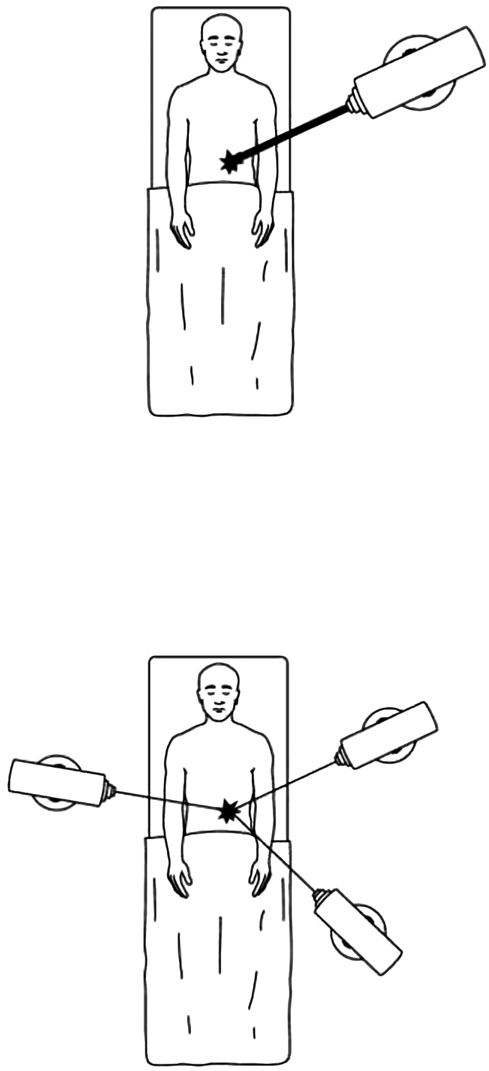


Figure 2: The radiation therapy patient in Duncker's example (Davies, 2002).

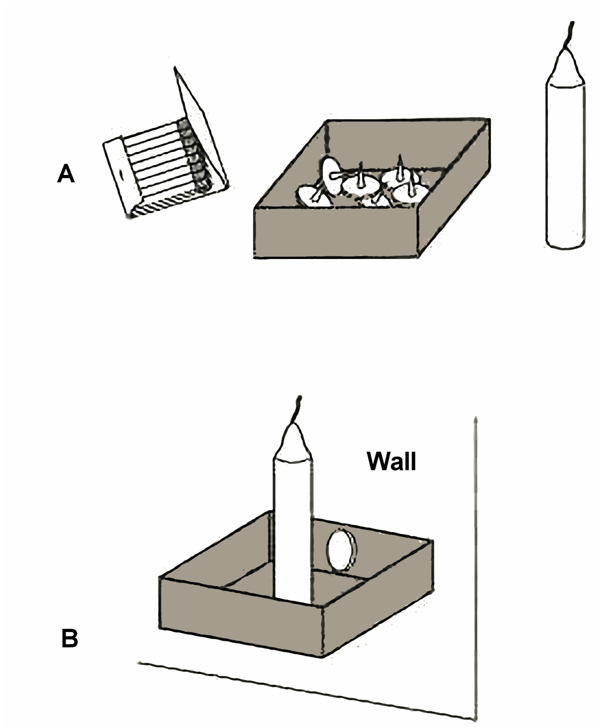


Figure 3: Representation of the cognitive performance test known as *candle problem* (Duncker, 1945).

However, when participants are presented with the thumbtacks *next to* the box, rather than *inside* it, virtually all of them achieve the optimal solution by re-conceptualizing the problem from a structural point of view (Adamson, 1952; Frank and Ramscar, 2003). It has been also noted that this phenomenon occurs not only with physical objects, but also with mental objects or concepts (Duncker, 1945).

While research in psychology and cognitive science have been more concerned with structural and cross-domain analogical studies, many of the actual implementations of analogical reasoning in artificial intelligence (AI) have been restricted to intra-domain transfer.

Using and combining objects or concepts in new ways in order to accomplish an objective is seen as one of the modes of creativity, and within AI, this has been a long-standing goal of achieving human-like *computational creativity* (Boden, 2004, 2009). In order to achieve this, there is a need for models of problem solving where it is possible to use analogies from remote domains to trigger creative insight.

In this dissertation, we are concerned with exactly this kind of insight gained through cross-domain structural analogies. Our approach is formulated as a *case-based reasoning* (CBR) system (Kolodner, 1992; Aamodt and Plaza, 1994).

CBR, in its simplest formulation, is a computational model using prior experience, in the form of cases in a case base, to understand

and solve new problems. It works by a cycle of: retrieval of a case from the case base that is most similar to the new problem; adaptation of the retrieved solution to the new problem; and retaining of the solved new case in the case base, for future reference.

The CBR approach is one of the many algorithmic models formulated within the subfield of analogical reasoning in AI, which is focused more on practical applications. On the theoretical front, the dominant school of research has been advanced by Gentner (Falkenhainer et al., 1989; Gentner and Markman, 1997) and describes analogy as a structural mapping (or, alignment) of elements from a base domain to those in a target domain via systemic structural similarities. This approach, the *structure mapping theory* (SMT), has been cited as the most influential work to date on the modeling of analogy-making (French, 2002).

Alternative approaches in the field include the coherence based view developed by Thagard et al. (1990); Holyoak and Thagard (1996), in which analogy is considered as a constraint satisfaction problem involving structure, semantic similarity, and purpose.

Much like the observations in cognitive science, the origins of CBR research lie in the realization that making analogies based on a collection of successfully solved cases would be useful for addressing open-ended and ill-defined problems. The advantages of this are listed by Kolodner (1993) as:

- allowing the reasoner to propose solutions quickly;
- allowing the reasoner to propose solutions in domains not completely understood by the reasoner; and
- providing the reasoner with a means for evaluating solutions when no algorithmic method is available for evaluation.

However, within AI practice, work within the CBR and analogical reasoning communities have been separated to a degree.

This has been in part because analogical reasoning models have been commonly focusing on cross-domain mappings whereas CBR has been usually limited to transfer of solutions between semantically similar cases within specific single domains (Thagard et al., 1990).

CBR research has been mostly limited to transfer of solutions within a single domain.

In this dissertation, we visit these interrelated approaches from cognitive science, psychology, and artificial intelligence, and formulate a CBR system in which case retrieval and adaptation are accomplished through structure mapping theory, supported by commonsense reasoning integrating information from several knowledge bases. For enabling this, we use a graph-based case representation structure. These give us a CBR model capable of recalling and adapting solutions from seemingly different, but structurally similar domains.

1.2 APPROACH

1.2.1 *Inter-Domain Case-Based Reasoning*

A pivotal part of this research is the integration of the computational *Structure Mapping Engine* (SME) into a CBR framework.

The SME (Falkenhainer et al., 1989; Forbus et al., 1994; Gentner and Markman, 1997) is a very fast analogical matching algorithm firmly based on the psychological *structure mapping theory* of Gentner. It is a very robust algorithm, having been used in many practical applications by a variety of research groups, and it is considered the most influential work on the modeling of analogy-making (French, 2002).

For the representation of cases, we employ semantic networks, which are graphs representing semantic relations between concepts (Sowa, 1991, 2000). In a semantic network, knowledge is expressed in the form of binary relations, represented by edges, and concepts, represented by nodes.

Figure 4 shows a graph representation of a simple semantic network. Adopting the notation of `IsA(bird, animal)` to mean that the concepts `bird` and `animal` are connected by the directed relation `IsA(·,·)`, i.e. "bird is an animal", we also represent semantic networks from time to time in this dissertation as lists of such relations.

Differing from the traditional separation of cases into *case description* and *case solution* parts (Aamodt and Plaza, 1994) in CBR, we make the decision of having the semantic network as the sole representation structure for each case, incorporating elements from both the description and the solution in an interconnected structure.

We use semantic networks to represent, jointly, the case description and solution.

Realizing the robustness of SME in mapping whatever substructures forming the solution in the retrieved semantic network into the network representing the new case, we believe that this design decision gives our approach an elegant and simple representation scheme. It is, though, still possible to retain semantic networks belonging to the unsolved state of a case, together with the adapted state, and inspect the differences between the unsolved and solved states to annotate the parts playing a role in the solution.

Another important advantage of this representation is that it provides a kind of "least common denominator" between the various components of our CBR system and the knowledge bases that we use in several stages of retrieval and adaptation. In short, semantic networks provide a simple, straightforward, yet powerful means to represent our cases.

In its original formulation and implementation, SME is based on a predicate calculus representation and manually constructed inputs given in LISP language.

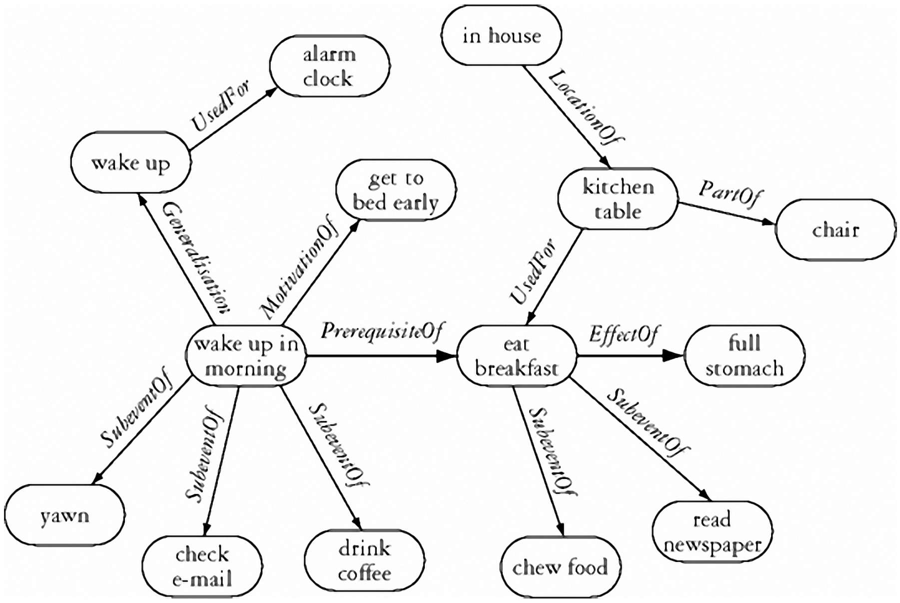


Figure 4: A semantic network with 14 concepts, 13 relations (part of ConceptNet) (Liu et al., 2006).

For the work in this dissertation, we had to develop a new implementation of SME that we adapted to work on semantic networks instead of predicate calculus. This implementation of the SME takes as input the base and target semantic networks, and produces three main types of output:

1. a list of all possible *analogical mappings* between the base and target semantic networks;
2. a list of *correspondences* between the concepts in the base and target semantic networks, for each possible analogical mapping; and
3. a *structural evaluation score* indicating the quality and extent of each possible analogical mapping.

Analogies discovered by SME are used for case retrieval and adaptation.

We use the output of SME for two principal parts of the CBR cycle. Firstly, given a new case without a solution, the algorithm uses the structural evaluation scores of all possible analogies between the new case (the target domain) and each case in the case base (the base domain) for the CBR retrieval stage.

Secondly, when the case with the best structural evaluation score is retrieved, the analogical mapping between the retrieved case and the new case is used in the CBR adaptation stage, by producing inferences from the base domain about the solution in the target domain.

Our approach of combining CBR with SME provides a potent model for problem solution through cross-domain, deep, structural analogies, and has the potential to extend the application of CBR from its conventional territory of single domain expert systems.

The critical role of this kind of structural reasoning in problem solving is supported by ample evidence from the fields of psychology and pedagogy (Chi and Glaser, 1985), where it has been known that the process of transfer is facilitated by abstract structural representations rather than superficial similarities.

Examples include the better solution finding ability of those who classify by abstract structure than those who classify by surface content in mathematical problems (Silver, 1981) and the ability of solving large-scale management problems by structural analogies rather than a superficial mapping (Bearman et al., 2002).

For the evaluation of this work, we apply our CBR system to the problem of mediation, an important method in conflict resolution (Moore, 2003). The mediation problem is non-trivial and presents a very good real world example where we can spot structurally similar problems from domains seemingly as far as international relations, family disputes, and intellectual rights. Even when conflicts from different domains are semantically distant, they can be structurally similar, i.e. they can share a common structure describing the relations between components of the conflict, enabling the transfer of solutions in-between (Simoff et al., 2009).

1.2.2 *Challenges*

The representation based on semantic networks, and the nature of information contained within the cases, prompt the addition of some new components to the conventional CBR cycle.

The fact that any operation altering a semantic network has to produce meaningful relations to be useful (Figure 4) sets constraints on the type of alterations any algorithm can follow on a semantic network.

Simply put, the operations should be constrained by commonsense knowledge to be meaningful: a relation such as `IsA(bird, animal)` is meaningful, while `Causes(bird, table)` is not. For this reason, during the case retrieval and adaptation stages of the algorithm we make use of the emerging field of *commonsense reasoning*.

Commonsense reasoning is the type of reasoning involved in everyday thinking, based on the general knowledge of how the world works (Mueller, 2006). It comprises information such as `HasA(human, brain)`, `IsA(sun, star)`, or `CapableOf(ball, roll)`, which are acquired and taken for granted by any adult human, but which need to be introduced in a particular way to a computational reasoning system.

We use commonsense reasoning and several commonsense knowledge bases.

Knowledge bases such as the ConceptNet project of the MIT Media Lab (Havasi et al., 2007) and Cyc maintained by Cycorp company are set up to assemble and classify commonsense information for the use of AI community. We make use of mainly ConceptNet, and also WordNet, to address the restrictions of processing commonsense knowledge within our CBR algorithm.

During CBR retrieval, information from these databases are used to produce expansions of the semantic networks representing the new case, for assisting the discovery of analogies of larger extent.

This is achieved through an iterative procedure that we call *semantic network expansion*, which enlarges the network by adding new concepts through relations involving concepts already existing in the network.

Through this procedure, our algorithm is able to produce meaningful expansions of a semantic network of any given size, allowing the discovery of analogies more extensive and systemic than what would be possible with the initial network.

During CBR adaptation, we use the analogical mapping provided by SME from the retrieved case (the base domain) into the new case (the target domain) to produce inferences about the concepts and relations that should be present in the semantic network of the new case, to provide a solution. Information from commonsense knowledge bases enables the algorithm to identify, in the target domain of the new case, structures that would correspond to those forming the solution of the retrieved case in the base domain.

Another crucial challenge for this research is encountered when the adaptation based on analogical inference is not sufficient.

In general, the adaptation aspect has been a traditional weakness of research on CBR systems, where most applications settled for a very simple "reuse" of the solution from the retrieved case, mostly through *null adaptation*, meaning no adaptation at all, or *substitutional adaptation*, meaning only minor modifications of the values of some attributes (Wilke and Bergmann, 1998).

Under this scheme, our adaptation method based on analogical inference using SME mappings falls under substitutional adaptation. During our experiments, albeit we observe that this adaptation is effective and straightforward for a multitude of cases, it is not always successful.

For solving this difficulty, we envision a novel *generative adaptation* technique based on evolutionary computation that enables the spontaneous creation or modification of semantic networks under a fitness measure .

We introduce a novel generative adaptation technique based on evolutionary algorithms.

Inspired by the biological process of evolution, evolutionary algorithms (EA) simulate the progression of variation, natural selection,

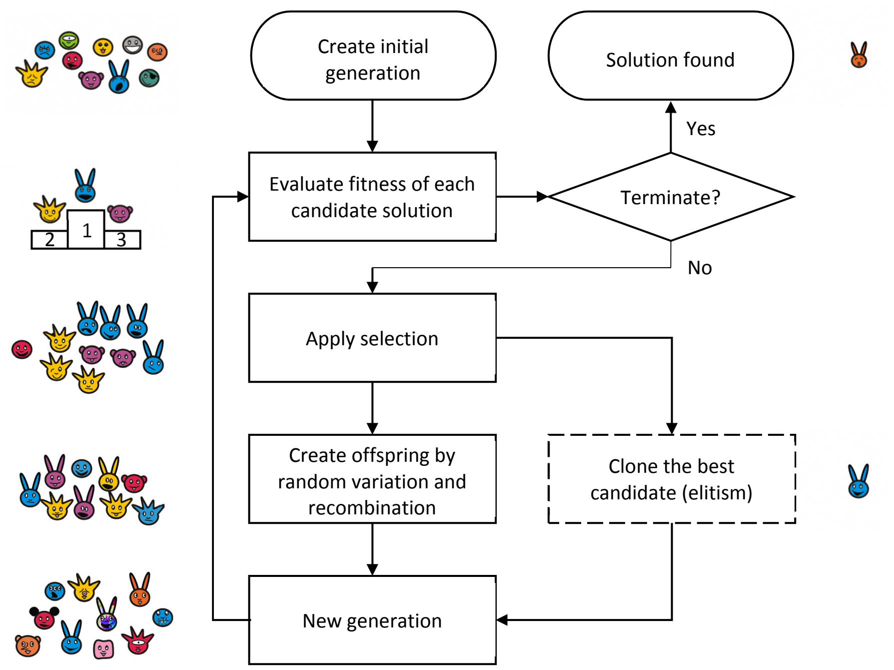


Figure 5: Flowchart of a traditional evolutionary algorithm. Representation of candidate solutions taken from Björnsdotter (2006).

and heredity to find novel solutions to problems in engineering and sciences (Coello et al., 2007) (Figure 5). The technique that we introduce is basically a novel type of graph-based EA with a semantic network-based solution structure. For enabling this, we define new formulations of EA variation operations such as crossover and mutation that we adapt to work on semantic networks and that employ commonsense reasoning to keep the networks meaningful. We posit this algorithm as a novel *memetic algorithm*, in the sense that it constitutes an implementation of the idea of "memetics" from the field of cultural evolution.

Lastly, a third, and very demanding, challenge during this research has been the collection of cases of mediation for forming a sufficiently diverse CBR case base. For doing this, we have reviewed the literature on mediation and international relations, searched through conflict resolution databases and benefited from the contributions of a mediation expert.

1.3 CONTRIBUTIONS

After addressing the challenges posed by our approach, we can summarize the original contributions of this dissertation as follows.

Semantic network-based representation in CBR. Using a semantic network-based representation in CBR, we unify case description and solution in an interconnected structural representation. This representation scheme forms the basis of our approach in evolutionary adaptation and cross-domain CBR, and we discuss it in Chapters 4 and 7.

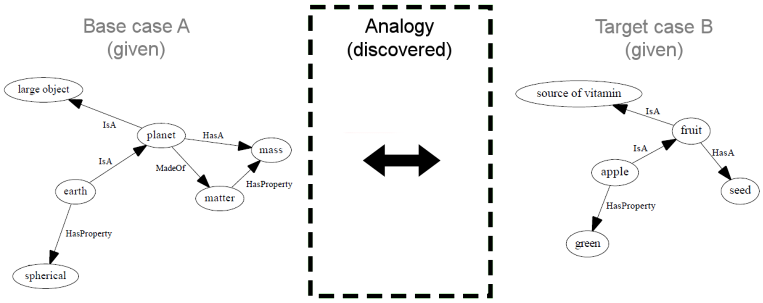
Combining SME with CBR. We introduce a CBR system where case retrieval and adaptation are accomplished through SME. Combining SME with CBR provides a powerful computational model capable of recalling and adapting solutions from seemingly different, but structurally similar domains. We discuss the approach in detail in Chapter 7.

CBR and commonsense reasoning. The retrieval and adaptation stages of the CBR algorithm are supported by commonsense reasoning backed by commonsense knowledge bases, in order to ensure that the operations on the semantic network representation are bound to produce meaningful results. The role of commonsense reasoning in our CBR approach is explained in Chapter 7.

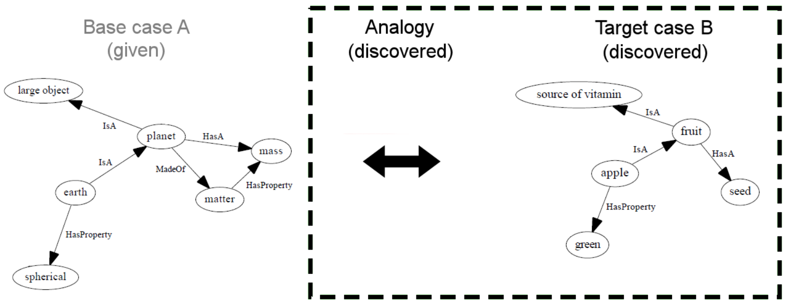
CBR and evolutionary adaptation. We envision an open-ended generative adaptation technique for CBR, based on our novel memetic algorithm for the spontaneous generation of semantic networks. We introduce the technique in Chapter 5 and illustrate it with a working example in Chapter 6.

Automated generation of analogies. One of the key contributions in this dissertation concerns a specific application of our novel memetic algorithm (Chapter 6). Defining the fitness function as the structural evaluation score of the SME mapping between a candidate target network and a given base network, we are able to create structurally analogous networks to any given network. This means that we are able to spontaneously generate analogies, together with analogous networks, to any given network in any domain. Taking into account that algorithms in the analogical reasoning field have been only addressing the mapping problem between two given existing domains (Figure 6), our technique is significant for the fields of analogical reasoning and computational creativity.

Evaluation. We evaluate the cross-domain CBR system with the problem of mediation (Moore, 2003). We present results about the classification of conflicts into structurally equivalent "conflict categories", following the observation that many cases from seemingly far domains have structurally equivalent causes and solutions. We discuss the correspondence of these structural categories to different types of "general principles" of problem solving observed in cognitive science literature. Evaluation is presented in Chapter 8.



(a)



(b)

Figure 6: Contribution to computational analogy-making. (a) Existing work in the field, restricted to finding analogical mappings between a given pair of domains (b) Our novel approach, capable of creating novel analogies as well as the analogous case itself.

Mediation case base. We establish a mediation case base of conflicts from a variety of domains, presented using the unifying semantic network representation. A part of the cases are collected from literature, including both educational examples and real-world instances. We are also given several cases about familial disputes (e.g. divorce, custody) from the Balearic Islands, provided by mediation expert Dr. Josep Redorta. The final case base covers a variety of domains ranging from familial disputes to international conflicts and intellectual property. We discuss the creation of the case base in Chapter 8 and present the full case base in Appendix A.

Implementations. The components including the CBR algorithm forming the backbone of our approach, SME adapted to work on semantic networks, the commonsense reasoning module and its interfaces with knowledge bases, and the evolutionary computation module have been implemented in C# language. The code will be made available online with the hope that it would be useful for researchers in the field.

1.4 OUTLINE

The dissertation is organized into nine chapters arranged under four different headlines.

In the first part, *Background*, after this introductory Chapter 1 about the focus, objective, and contributions of our research, we continue with a detailed review of related literature forming the basis of this study, in Chapter 2. We provide a comprehensive evaluation of the state of the art in the fields of analogy, case-based reasoning, and conflict resolution.

The dissertation then continues with the second part, *Evolutionary Adaptation*, where we introduce the evolutionary adaptation technique forming one of the two major contributions of this study. Following an initial discussion of the foundations and practice of evolutionary computation and graph based methods from a general point of view in Chapter 3, we introduce the representation scheme based on semantic networks that is used throughout the dissertation, in Chapter 4. In the subsequent Chapter 5, we provide a detailed description of the novel algorithm and its implementation, including the commonsense reasoning interface making use of commonsense knowledge bases, the general cycle of selection and reproduction, and a discussion of possible fitness measures. Finally, in Chapter 6, we introduce our approach for the automated generation of analogies and illustrate the functioning of the algorithm by means of examples.

In the part that follows, *Mediation*, we present, firstly, our CBR model integrating SME and commonsense reasoning in Chapter 7, and discuss the analogical reasoning approach we take to address the problem of mediation. Within the rest of this part, in Chapter 8, we present our data forming the mediation case base, consisting of hypothetical cases, real world cases collected from literature, and cases provided by the mediation expert.

The dissertation concludes with the final part, *Summary*, where in Chapter 9 we present an overall review of our approach and a discussion of the lessons learned during this research. Finally, we deliberate on the limitations of our approach and share some insights about future work directions following this study.

Finally, under *Appendices*, we provide a full transcription of our mediation case base in Appendix A with the aim that it will be useful for the CBR community, given that it is the first such case base combining cases from a broad range of conflict domains and using a semantic network based representation.

2

RELATED WORK

"The mind is not a vessel that needs filling,
but wood that needs igniting."

— Lucius Mestrius Plutarchus (c. 100 AD)

2.1 ANALOGIES, METAPHORS, ALLEGORIES

The notion of analogy (from Greek αναλογια, "proportion" (Liddell and Scott, 1940)) has been studied and discussed since the time of classical antiquity. The term, as implied by its meaning, originally meant "proportionality" in a mathematical sense, understood as an identity of relation between two ordered pairs, such as given by the *four-term* representation:

- `swimming : fish :: flying : _____` [1]

Plato and Aristotle considered analogy as a shared abstraction and agreed that analogies could be used as arguments (Shelley, 2003). Analogies were extensively used in the dialectic method of argumentation for making abstractions easier to understand and for resolving disagreement.

A highly influential and important early example of analogy from this period is the "Allegory of the Cave" presented by Plato in his work *The Republic* (Plato, 1935). In the form of a dialogue between Socrates and Plato's brother Glaucon, the analogy illustrates the nature of reality and the material world known to us through our senses.

Plato's Allegory of the Cave

The analogy concerns a group of people who have spent their lives chained inside a cave, their necks fixed to look at a wall

1 A possible answer is "bird".

in front of them (Figure 7). Behind the prisoners there is a large fire and between the prisonsers and the fire people walk carrying things that cast shadows on the wall. The prisoners only see the shadows on the wall, and they do not have any perception of the fire or the people, or the real shape of the objects casting the shadow. Similarly, they only hear the echoes off the wall of the noise produced by the people.

The prisoners would take the shadows to be real things and echoes to be real sounds, since these would be the only things they have ever seen and heard, it would be their reality.

If one of the prisoners is freed from the chains, he would come to understand that the shadows and echoes do not constitute reality at all, as he can now perceive the true form of reality that has been producing these reflections. The prisoner's eyes will be "aching", and he will be inclined to go back and view what he has always seen as the pleasant and painless acceptance of truth. This stage of thinking is noted as "belief".

If the prisoner is further brought out of the cave into full daylight, for a time, he would be in bewilderment, fear, and blindness because of the power of sun's light. After his eyes adjust to sunlight, he would begin to observe items and people in their own existence and recognize that the Sun is the source of all the seasons and the years and this is the real "Form of the Good". This stage of thinking is noted as "understanding".

At this stage the analogy considers the question of whether the prisoner would want to return to the formerly accepted reality of truth to share his experience, or stay in the real world. If he returned, the other prisoners would ridicule the freed prisoner and ironically find him insane for not being able to see the shadows in the way they do. This represents the "leadership" duty of those who have achieved true understanding of the intelligible world to be responsible leaders and to not disdain those who do not yet share their enlightenment.

The Allegory of the Cave is a particularly good example, as it presents, through interconnected powerful analogies on several levels, most of Plato's main philosophical thoughts (Kreis, 2012):

- The world revealed by our senses are not the real one, but only a poor copy of it. The real world can only be apprehended intellectually.
- Knowledge cannot be transferred from teacher to student. Rather, education consists of directing students' minds toward what is real, and letting them apprehend it themselves.

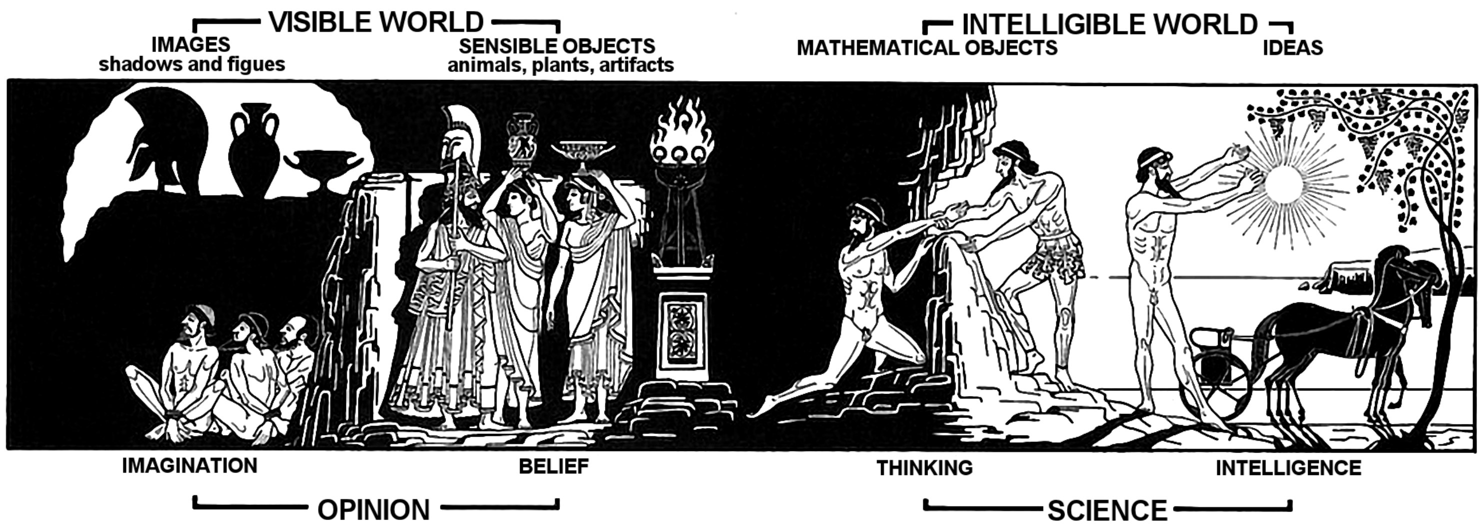


Figure 7: The *Allegory of the Cave* presented by Plato in *The Republic*. Figure translated into English from Gómez (2010).

- Enlightened individuals have an obligation to the rest of society. A good society must be one in which truly wise are the rulers—the Philosopher-King.

Analogies have been highly important in legal systems since the Roman period, through the Medieval period, up until today; in Islamic law introduced in 7th century, analogies were used as the basis of classification of precedents, where a new case was assimilated into one or more previous cases which are most relevant to the current case—in a procedure highly reminiscent of CBR (Sowa and Majumdar, 2003). In Christian theology, analogies were employed in order to explain the interpretation and attributes of God, by scholars such as Thomas Aquinas. Medieval theories of analogy made a distinction between expressions used in *univocal* (always used in the same sense), *equivocal* (used with quite different senses), and *analogical* (used with related senses) ways; analogical terms were deemed particularly useful for metaphysics and theology (Ashworth, 2009).

In modern philosophy, a highly remarkable work on analogies was by Hesse (1966), who explained that models and analogies are integral to understanding scientific practice and advancement. In psychology, early research on analogies focused on simple four-term analogies (Table 2). This type of analogy exercise is still used in psychological testing and education, for applications such as the determination of analogical reasoning abilities of individuals, as in the Miller Analogies Test for graduate school admissions in the United States (Kaplan and Saccuzzo, 2009). Visual analogy exercises (Figure 8) consitute another commonly encountered application, which regularly form an integral part of IQ tests and which are used in the assessment and development of logical thinking ability in educational settings.

When talking about analogies, one has to be aware of distinctions between several related terms explaining the role of a particular analogy in communication and commonsense.

Metaphors (from Greek μεταφορα, "carrying over" (Liddell and Scott, 1940)) are a type of analogy-based figure of speech[2], where one makes an assertion that—from a certain perspective—something is the same as another otherwise unrelated thing (Richards, 1936). Characteristically, metaphors compare two things without using words such as "like" or "as":

- We are all shadows on the wall of time.

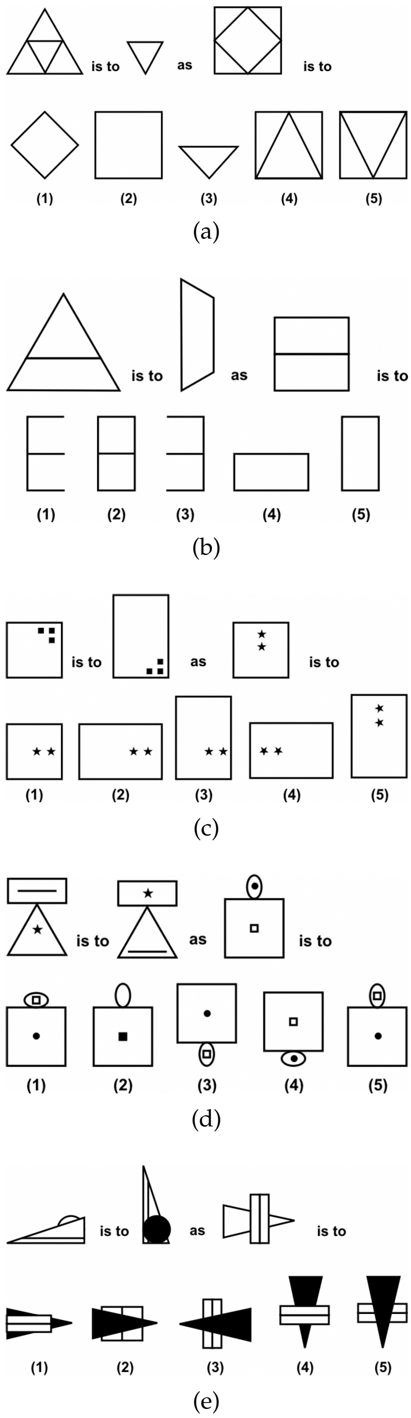
- The test was a walk in the park.

2 A *figure of speech* is the usage of a word or phrase in a different meaning than it seems to say. It forms the basic instrument to express any analogical reasoning in natural language.

Table 2: Verbal analogy exercise. For each item, one selects the word that completes an analogy, where the pairs on the left and right have the same relationship (Spears, 1998).

Analogy exercise	Answer
`arrival : departure :: _____ : death`	a) `life`
	b) `person`
	c) `birth`
	d) `train`
`elbow : arm :: knee : _____`	a) `walking`
	b) `finger`
	c) `leg`
	d) `nose`
`university : institution :: mayor : _____`	a) `official`
	b) `town`
	c) `law`
	d) `councilman`
`book : _____ :: comb : tooth`	a) `title`
	b) `library`
	c) `page`
	d) `knowledge`
`egg : fish :: _____ : plant`	a) `leaf`
	b) `root`
	c) `seed`
	d) `stem`
`violence : activity :: melancholy : _____`	a) `evening`
	b) `cruelty`
	c) `mood`
	d) `silence`
`car : road :: train : _____`	a) `track`
	b) `vehicle`
	c) `fast`
	d) `wheel`

(Answers: c, c, a, c, c, c, a)



(Answers: 1, 5, 3, 5, 5)

Figure 8: Visual analogy exercise. For each item, one identifies the relationship between the first two figures and selects the answer figure bearing the same relationship to the third figure (Public Service Commission of Canada, 2011).

- That burden is my cross to bear.

An *allegory* (from Greek, αλληγορια, "veiled language" (Liddell and Scott, 1940)) is a specialized type of metaphor where a story illustrates an important attribute of the subject. Allegories are metaphors considered from a literary, visual art, or musical perspective, symbolizing ideas and concepts. They have been widely used throughout history to illustrate complex ideas in readily understandable and tangible ways. Allegory is traditionally treated as a literary device[3] and a part of rhetoric (Kennedy, 1999).

Another figure of speech, *simile*, is a comparison of two things through the expression of resemblance by using words such as "like" or "as" (Kennedy and Gioia, 2007):

Similes are analogical comparisons weaker than metaphors.

- She is like a candy so sweet.
- He was as hungry as a lion.
- As busy as a bee.

Even if metaphors and similes are seen as interchangeable, in rhetoric speech, similes are distinguished from metaphors in that a metaphor is stronger and more encompassing. On the contrary, a simile accepts any imperfections or limitations of the comparative relationship expressed by it, therefore granting the using person some form of protection against criticism.

Another related term, *metonymy* (from Greek, μηωνυμια, "a change of name" (Liddell and Scott, 1940)), describes a figure of speech where one thing or concept is not called by its own name, but by the name of one of its characteristics or the name of something associated with it. Examples include the use of "Hollywood" to refer to the United States film industry, or "dish" to refer to an entire plate of food. Thus, a metonymy is not an analogy.

2.1.1 *Cognition and Creativity*

There is evidence that analogical reasoning is at the core of higher-order cognition, and it enters into creative discovery, problem-solving, categorization, and learning (Hofstadter, 2001; Gentner and Smith, 2012).

The term "metaphor", in the fields of cognitive science and psychology, has been used as a technical term within the models of *conceptual metaphor* or *cognitive metaphor*, referring to the understanding of one *conceptual domain* in terms of another (Lakoff, 1993; Lakoff and Johnson, 2003; Kövecses, 2010).

3 A literary device is a standardized means used by authors convey their message.

Metaphors as the basis of human thinking and sense-making.

Table 3 gives a collection of conceptual metaphors, illustrating the fundamental nature and ubiquity of metaphors in human thinking and sense-making. It is also worth noting that the word "metaphor"—with the meaning of "carrying over"—itself is also a metaphor, understanding the *idea* domain in terms of a *spatial* process.

In this line of research, metaphors are not simply devices of language; rather, they are the building blocks of human thinking and sense-making, which is subsequently *revealed* by language. Metaphors are fundamentally conceptual in nature and are grounded in everyday experience, while metaphorical language is a secondary expression of this.

Lakoff and Johnson (2003) state that the deep philosophical debate between objectivism[4] and subjectivism[5] can be reconciled by a third approach which they call "experientialist synthesis".

In this view, metaphors enable a comprehension of some experiences which cannot be fully understood, such as emotional responses, aesthetic appreciation, and religious views. This can bring together the objectivist demand for absolute truth and the subjectivist call for unconstrained imagination, explaining our understanding of the world arising out of our interaction with it.

In a similar vein, researchers such as Pinker (2007) argue that human intellect understands everything except the physical world of falling objects by analogies, and, for this reason, a great proportion of our language is metaphorical. According to Pinker, human intelligence consists of:

- a repertoire of concepts (objects, space, time, causation, intention); and
- a process of metaphorical abstraction, with which conceptual structures are bleached of their content and are applied to new, abstract domains.

Therefore, the process of metaphorical abstraction "allows a species that evolved with rocks and tools and animals to conceptualize mathematics, physics, law and other abstract domains." (Pinker, 2005). Sowa and Majumdar (2003) support that analogical reasoning, via structure mapping, forms the bridge from perception to all forms of reasoning, ranging from the most casual to the most advanced.

Analogy-making ability is extensively linked with creative thought (Hofstadter, 1995; Holyoak and Thagard, 1996; Ward et al., 2001; Bo-

4 *Objectivism*: The view that reality is mind-independent and has a unique description even outside of a subject's individual feelings or interpretations. Dominating Western philosophy since the ancient Greeks.

5 *Subjectivism*: The tenet that our mental activity is the only unquestionable fact of our experience. Also related with existentialism, phenomenology etc.

Table 3: Several examples of conceptual metaphors.

Conceptual metaphor	**Conceptual base and target domains**
Prices are rising	Understanding *quantity* in terms of *directionality*
I attacked every weak point in his argument	Understanding *argumentation* in terms of *war*
Winter is coming	Understanding *time* in terms of *space*
What is the foundation for that idea?	Understanding *idea* in terms of *physical structure*
This is a shaky argument	Understanding *idea* in terms of *physical structure*
I am really attracted to you	Understanding *emotion* as a *force*
I have led a full life	Understanding *life* as a *container*
There is no room for you in my life	Understanding *life* as a *container*

den, 2004) and regularly plays a fundamental role in creativity expressed in arts and sciences. Boden (2009) classifies analogy as a form of *combinational creativity*, noting that it works by producing unfamiliar combinations of familiar ideas.

In addition to literary use of metaphors and allegories in written language that we have already covered, analogies often constitute the basis of composition in all art forms including visual or musical. For example, in classical music, it is highly common to formulate interpretations of a composer's work in terms of tonal allegories (Chafe, 1991).

In visual arts, examples of artistic analogy range from paintings from earlier periods, such as the allegorical composition of Melencolia I by the Renaissance master Albrect Dürer (Figure 9), to modern usage in film, such as the many layers of allegory in Stanley Kubrick's 2001: A Space Odyssey (Pezzotta, 2012).

In science, conceptual metaphors are very often used to convey and understand new theories and models.

Conceptual metaphors are very often used in science to convey new theories.

A key example of analogy-based explanations is Johannes Kepler's explanation of the laws of heliocentric planetary motion with an analogy to light radiating from the Sun Gentner et al. (1997). Kepler argued, in his *Astronomia Nova*, as light can travel undetectably on its way between the source and destination, and yet illuminate the destination, so can motive force be undetectable on its way from the Sun to planet, yet affect planet's motion (Kepler, 1609). Paving the way to a heliocentric understanding of free floating bodies—opposed to celestial objects on concentric rotating spheres—Kepler's work is recognized as one of the most important works in Scientific Revolution.

Another instance is Ernest Rutherford's analogy between the atom and the Solar System (Rutherford, 1911), where the internal structure of the atom is explained by electrons circling the nucleus in orbits like planets around the Sun (Figure 10). This model, which was later improved by Niels Bohr to give rise to the Rutherford-Bohr model, was one of the "planetary models" of the atom, where the electromagnetic force between the positively-charged nucleus and the negatively-charged electrons were presented as being analogous to the gravitational force between the sun and the planets. Earlier models of the atom were, also notably, explained using analogies, including "plum pudding" model of Joseph John Thomson and the "billiard ball" model of John Dalton (Figure 11).

The usage of analogies in scientific practice was analyzed in general by Hesse (1966), who argues that models and analogies are key to scientific advancement, and, in order to understand a new system or phenomenon, we often use models comparing the new phenomenon

Figure 9: The *Melencolia I* engraving by German Renaissance master Albrecht Dürer (1514). Its allegorical meaning has been subject of many interpretations due to the many elements of composition within the piece (e.g. tools of geometry, a magic square, a rhombohedron, hourglass, purse and keys) (Schuster, 1991). One interpretation is that it references the predomination of "imagination" over "mind" or "reason".

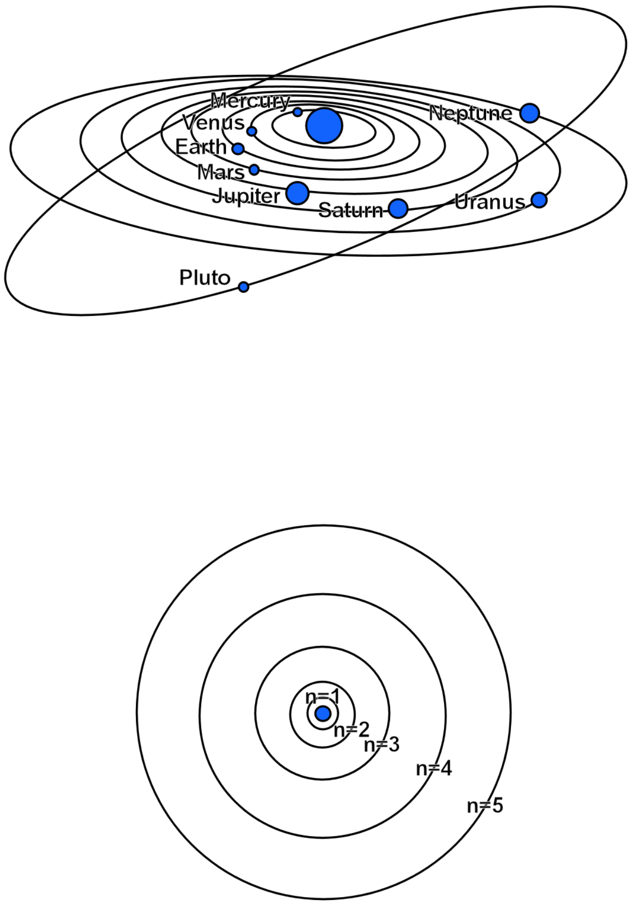


Figure 10: The Rutherford-Bohr model was one of the "planetary models" of the atom (bottom), analogous to the Solar System (top).

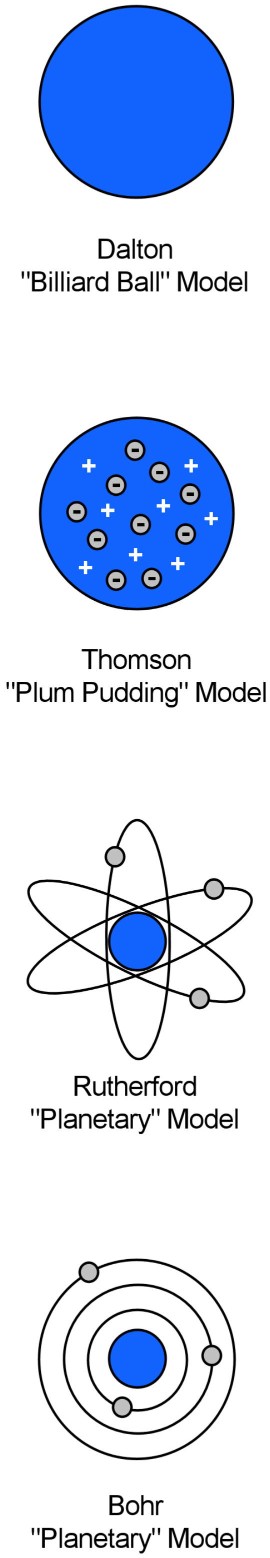


Figure 11: The Dalton (1805), Thomson (1904), Rutherford (1911), and Bohr (1913) models of the atom with their corresponding analogies.

with an existing one that is more familiar. Hesse classifies scientific analogies into three types:

1. Positive analogies, concerning features known to be present in both systems.

2. Negative analogies, concerning features known to be present in one system but absent in the other.

3. Neutral analogies, concerning features whose positive or negative status are uncertain.

New models can start as neutral analogies and gradually converge into a positive or negative type. An example is the initial neutral analogy between the light waves and mechanical (e.g. acoustic or water) waves in late 19th century, giving rise to the question of whether there is a physical medium—called *luminiferous ether*—in space for the propagation of light. Following several conclusive experiments, it is now known that light waves have no physical medium to travel through, and this analogy is a negative one.

2.2 AI AND ANALOGY

In early stages of AI research, several approaches started to address the problem of modeling analogies with complex representations and computational specificity.

(Minsky, 1992) classifies methods and representations within AI according to the number of involved causes and the size of their effects; e.g. a problem with many causes each with a small effect would be suitable for statistical methods or neural networks, while a problem with only a few large-effect causes would be a candidate for applying logical reasoning. Within this classification, analogical reasoning fills an application domain where there are many causes with moderate to large effects (Figure 12).

Models in computational analogy research have been categorized by French (2002) into three categories:

1. *symbolic models*, following the symbolic paradigm in AI and employing symbols, logic, planning, search, and means-ends analysis;

2. *connectionist models*, following the connectionist paradigm with networks, nodes, weights, and activation; and

3. *hybrid models* that combine both.

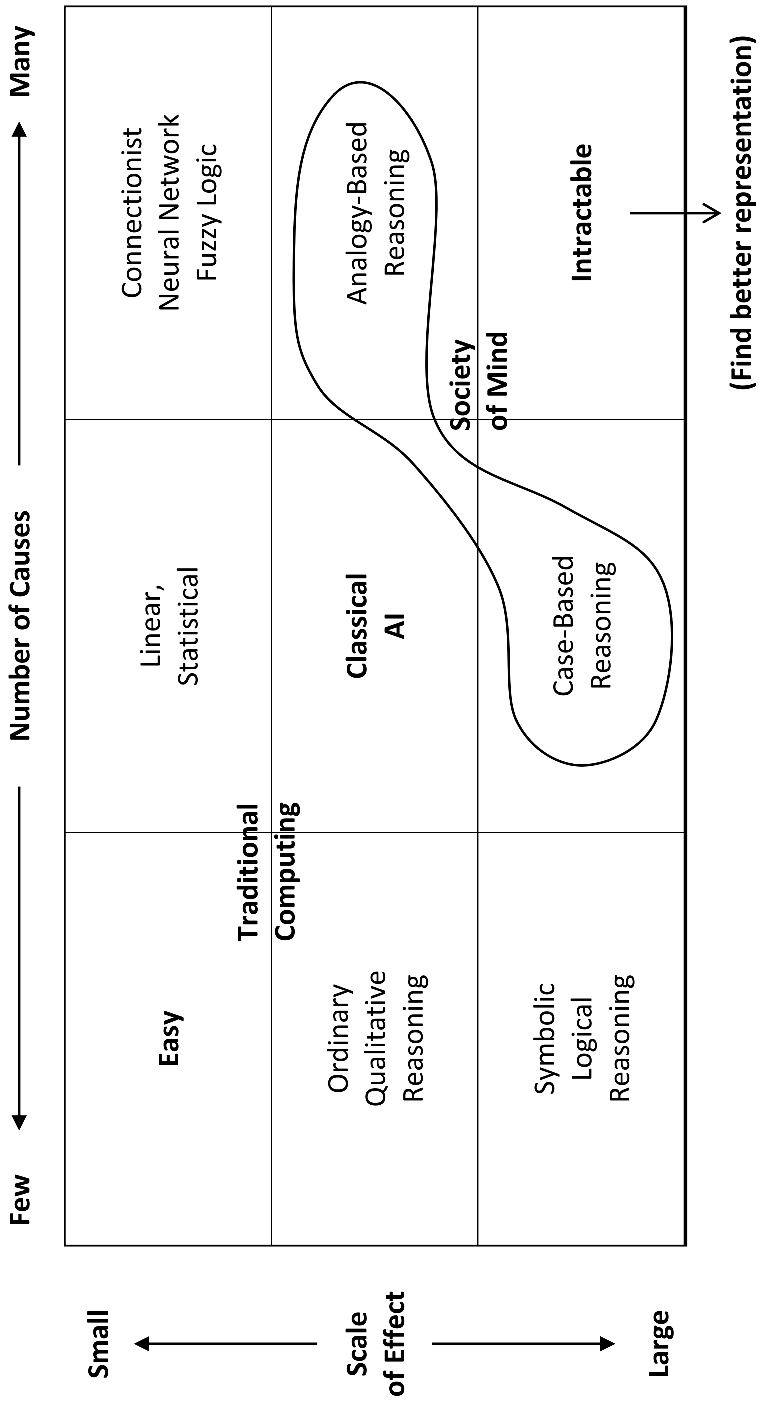


Figure 12: The "casual diversity matrix". Redrawing of the diagram from Minsky (1992).

Within the symbolic tradition, the *Argus* model by Reitman (1965) is cited as the first computer model of analogy-making (French, 2002). The program concerned simple proportional analogies of the type considered in psychology (Table 2), and it could select an answer to a question such as `bear : pig :: chair : _____` from a collection of four choices such as `foot`, `table`, `coffee`, `strawberry`[6].

Another influential early work was the ANALOGY model by Evans (1968), designed to solve geometric analogy intelligence questions of the type we have discussed in Figure 8. The model functioned through the input of low level descriptions of the figures, from which higher level descriptions were drawn.

There were also related models involving formal logic and automated theorem proving. The ZORBA-1 by Kling (1971), for instance, solved new problems by retrieving analogous problems and applying their proofs to the target problem at hand, not unlike the CBR technique to be introduced later.

Approaches from the following period include the work of Winston (1980) on computational matching and inference, and the work of Carbonell (1985) on the transfer of solution methods from one problem to another.

In contemporary models, analogical reasoning is seen through a structural point of view.

Work on computational analogy making in AI eventually inspired psychologists to work out detailed models of how analogies are represented and processed. In contemporary studies, analogical reasoning is mostly seen through a structural point of view, framed by the structure mapping theory based on psychology (Gentner, 1983; Gentner and Markman, 1997; Gentner et al., 2003). In this line of work, Gentner et al. (2003) identifies several phenomena observed in human analogy-making, and asserts that any model of analogy must sufficiently account for these 4.

Influential works within the connectionist approach include the ACME model by Holyoak and Thagard (1989), in which analogy-making emerges as a result of parallel activation within a neural network-like structure. The model functions through getting representations of the target and source domains as an input and building a constraint satisfaction network that contains *hypothesis nodes* corresponding to all possible matches between pairs in the source and the target. Constraints are implemented as excitatory or inhibitory links between these nodes, producing dynamics where contradictory hypotheses compete with and suppress each other. The approach is coupled with the ARC model of retrieval (Thagard et al., 1990), where mapping is dominated by structural similarity and retrieval is dominated by semantic similarity.

6 The answer would be `table`.

Table 4: Basic phenomena of analogy (Gentner and Markman, 1995; Gentner et al., 2003).

	Phenomenon	Description
1	Relational similarity	Analogies involve relational commonalities; object commonalities are optional.
2	Structural consistency	Analogical mapping involves one-to-one correspondence and parallel connectivity.
3	Systematicity	In interpreting analogy, connected systems of relations are preferred over isolated relations.
4	Candidate inferences	Analogical inferences are generated via structural completion.
5	Alignable differences	Differences that are connected to the common system are rendered more salient by a comparison.
6	Interactive mapping	Analogy interpretation depends on both terms. The same term yields different interpretations in different pairings.
7	Multiple interpretations	Analogy allows multiple interpretations of a single comparison.
8	Cross-mapping	Analogies are more difficult to process when there are competing object matches.

Among recent connectionist models are the STAR-1 (Halford et al., 1994) and STAR-2 (Wilson et al., 2000) models of distributed connectionist models based on a tensor product approach; the LISA model relying on a foundation of partially distributed representations of concepts, selective activation, and dynamic binding (Hummel and Holyoak, 1997); and neural network-based approaches such as the model by Jani and Levine (2000) based on Adaptive Resonance Theory.

Other approaches to analogical reasoning within AI include the view of Hofstadter (1995) of analogy as a kind of high-level perception, where one situation is perceived as another one. Veale and Keane (1997) extend the work in analogical reasoning to the more specific case of metaphors, which describe the understanding of one kind of thing in terms of another. A highly related cognitive theory is the *conceptual blending* idea developed by Fauconnier and Mark (2002), which involves connecting several existing concepts to create new meaning, operating below the level of consciousness as a fundamental mechanism of cognition. An implementation of this idea is given by Pereira (2007) as a computational model of abstract thought, creativity, and language.

Analogical reasoning plays a fundamental role in the modeling of generalization and learning in AI, given the fact that the ability to generalize based on singular experiences is central to human learning. Wareham and van Rooij (2011) treat generalizations as abstractions derived by extracting common analogical structure from sets of exemplars, such as a child's forming of categories after encountering pet or farm animals and using these to classify new encounters in the zoo (Figure 13). The understanding of generalizations as abstractions based on analogical structure has support from psychology (Gentner and Namy, 1999; Gentner and Lowenstein, 2002).

2.2.1 *Structure Mapping Theory*

Structure mapping theory (SMT) (Gentner, 1983; Gentner and Markman, 1997; Gentner and Smith, 2012) is based on the observation that an analogy is basically a *mapping* from a base domain into a target domain. An important characteristic of SMT is that it ignores surface features and it can uncover mappings between potentially very distant things, if they have a similar representational structure.

Analogical reasoning within SMT involves three processes: The mapping depends on the alignment of base and target representations, based on a common *relational structure* (Figure 14 (a)). This alignment can be subsequently used for projecting inferences. In SMT, inference happens as a natural outcome of the structural alignment

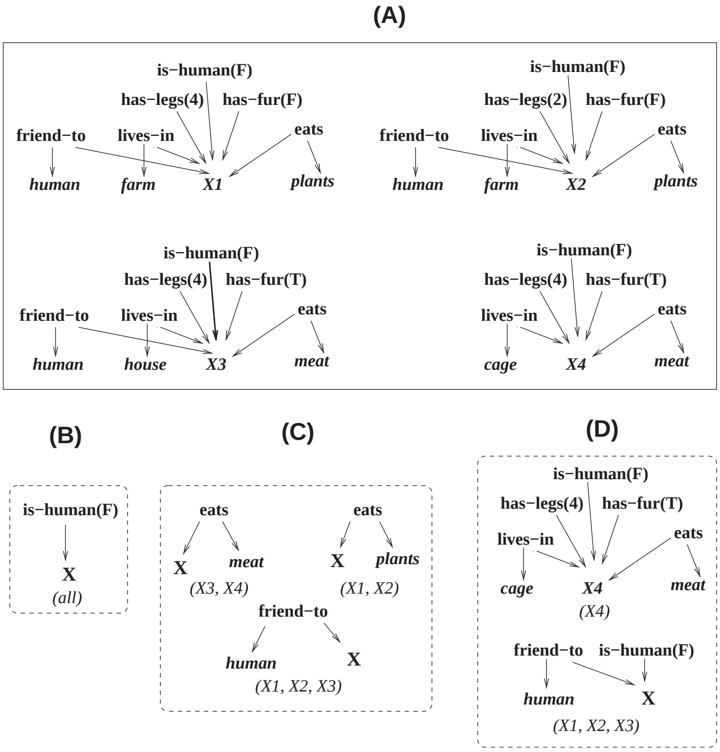


Figure 13: Examples of analogy-based generalization (AbG) given by Wareham and van Rooij (2011). (A) Predicates a child has about four different animals X1, X2, X3, and X4 (B), (C), (D) represent generalizations with different degrees of informativity, distinctness, and compactness.

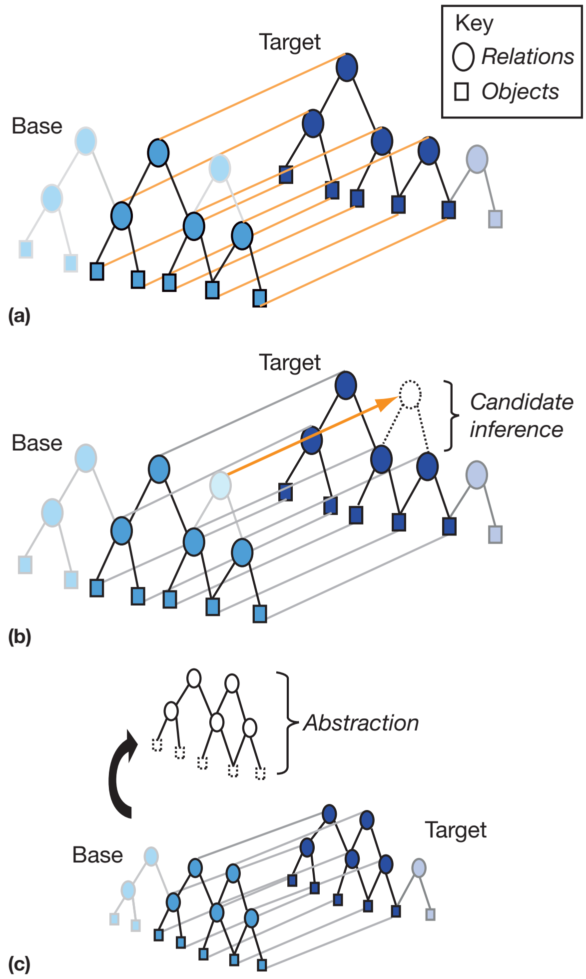


Figure 14: The processes of (a) alignment, (b) inference, and (c) abstraction in the structure mapping process (Gentner and Smith, 2012).

process. Where parts of the base relational pattern have no matching representation in the target, these can be brought over to the target domain as candidate inferences (Figure 14 (b)). Lastly, the mapping can be used for deriving abstractions about the common relational pattern (Figure 14 (c)).

A typical example given for illustrating the idea of mapping within SMT is the analogy between the Rutherford-Bohr atom model and the Solar System, which we have already discussed in Section 2.1.1. Using a predicate calculus representation, Figure 15 illustrates a structural mapping between these domains.

The algorithmic-level account of SMT, and its computational implementation is referred to as the Structure Mapping Engine (SME), first presented by Falkenhainer et al. (1989) and later improved by Forbus et al. (1994). The algorithm works by taking the predicate calculus descriptions of the base and target domains, comprising (1) *entities*

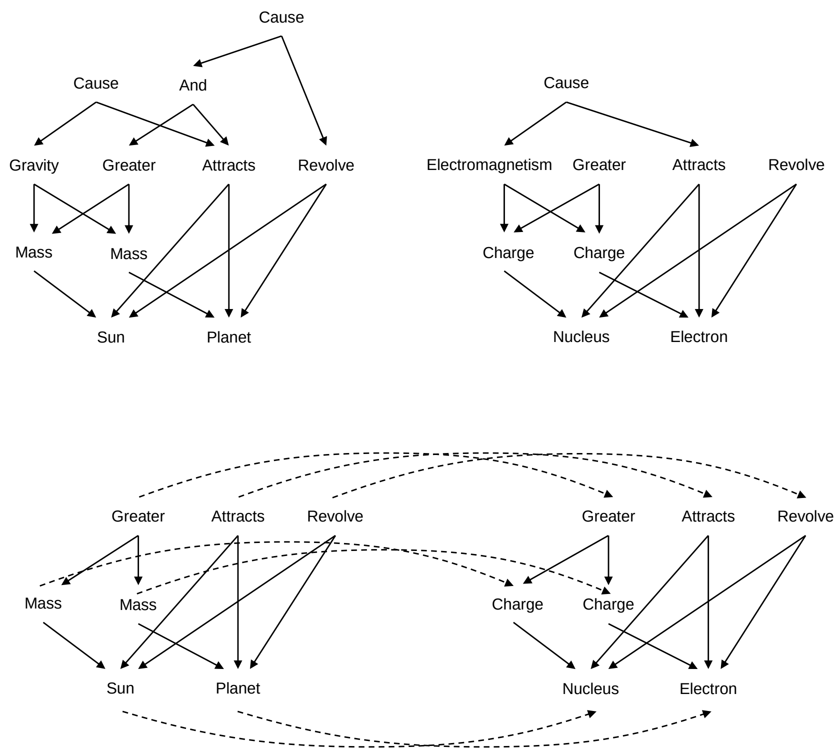


Figure 15: Representation of the Rutherford-Bohr atom model – Solar System analogy (cf. Figure 10) as graphs: predicates about the two domains (top), analogy as a mapping of structure between the two domains (bottom).

Table 5: Basic elements of the predicate calculus representation used by SME (in LISP notation).

- ***Entities*** are logical individuals, e.g. physical objects or abstract concepts, such as `Sun` and `Planet` in Figure 15.
- Predicates refer to any functor in a predicate calculus statement.
  - ***Functions*** map one or more entities into another entity or constant, such as `(Mass Sun)`, "the mass of the Sun", in Figure 15.
  - ***Attributes*** describe some property of an entity, such as `(Yellow Sun)`, "the Sun is yellow". Attributes are logically equivalent to a combination of a function and a constant: `(= (Color Sun) Yellow)`, "the color of the Sun is yellow".
  - ***Relations*** have multiple arguments, which can be either entities or other predicates, such as `(Greater (Mass Sun) (Mass Planet))`, "the mass of the Sun is greater than the mass of the planet", in Figure 15.

and (2) predicates that can be in the form of *relations*, *attributes*, and *functions* (Table 5).

Given the propositional representations of the base and target domains (e.g. Figure 17 and Figure 18, Figure 16), SME functions in four steps (Forbus et al., 1994; Gentner and Markman, 1997):

1. *Local match construction*. For each pair of expressions in the base and target domains with an identical predicate, create a *match hypothesis* (MH). Corresponding arguments of each MH are also matched if (1) their predicates are identical, (2) the predicates are functions, or (3) they are entities.

2. *Kernel construction*, working by taking all MHs which are structurally consistent and which are not the argument of any other MH, and creating a *kernel* from this and every other MH below it.

3. *Structural evaluation*, propagating scores through the network of MHs, resulting in a preference of systematicity. The score of a mapping is the sum of all scores of MHs that constitute the mapping.

4. *Merging*, constructing global interpretations of match by finding structurally consistent combinations of kernels maximizing structural evaluation scores.

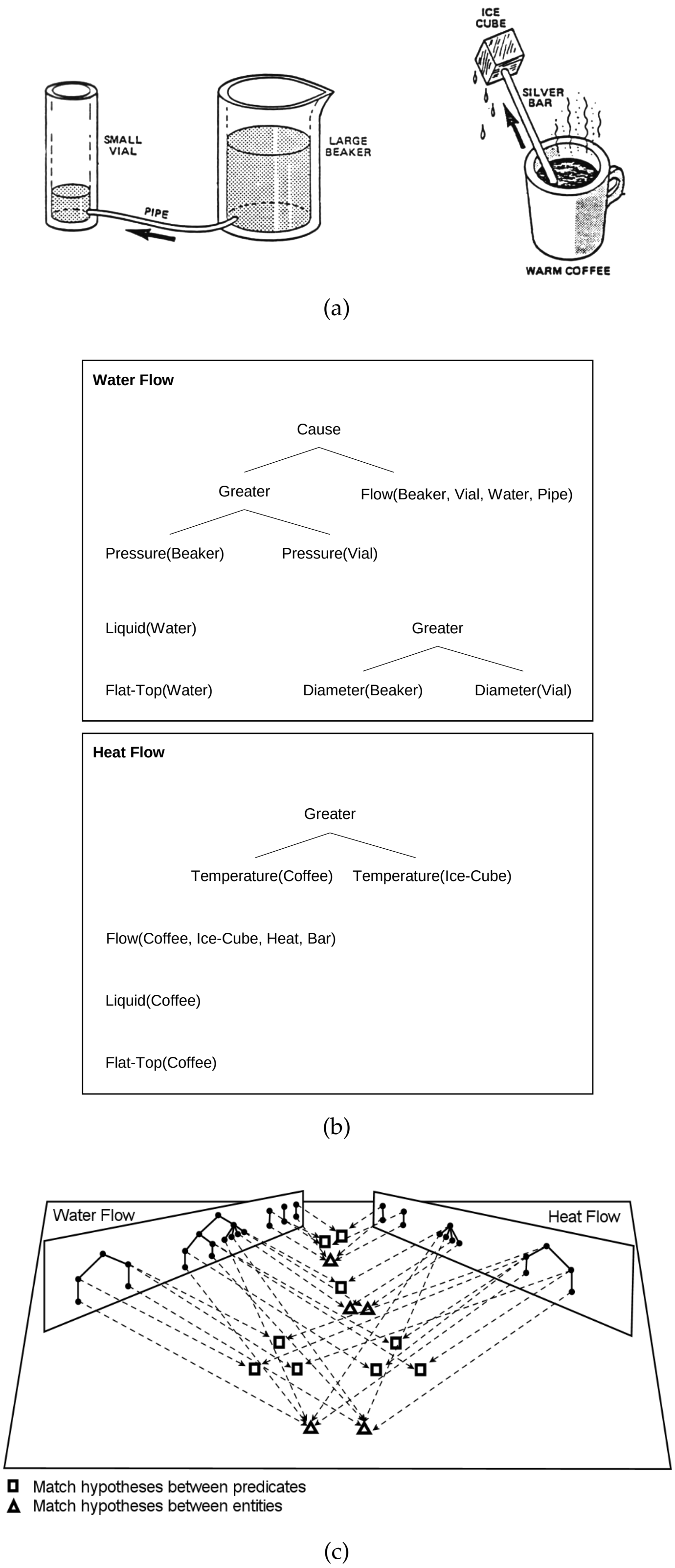


Figure 16: The `Water Flow` and `Heat Flow` domains from Falkenhainer et al. (1989). (a) Depiction of the analogy; (b) Propositional representation of the domains; (c) The process of match construction.

```
(defDescription simple-water-flow
    entities (water beaker vial pipe)
    expressions (((flow beaker vial water pipe) :name wflow)
        ((pressure beaker) :name pressure-beaker)
        ((pressure vial) :name pressure-vial)
        ((greater pressure-beaker pressure-vial) : name >pressure)
        ((greater (diameter beaker) (diameter vial)) :name >diameter)
        ((cause >pressure wflow) :name cause-flow)
        (flat-top water)
        (liquid water)))
```

Figure 17: Description group of the `Water Flow` domain (Falkenhainer et al., 1989).

```
(defDescription simple-heat-flow
    entities (coffee ice-cube bar heat)
    expressions (((flow coffee ice-cube heat bar) :name hflow)
        ((temperature coffee) :name temp-coffee)
        ((temperature ice-cube) :name temp-ice-cube)
        ((greater temp-coffee temp-ice-cube) : name >temperature)
        (flat-top coffee)
        (liquid coffee)))
```

Figure 18: Description group of the `Heat Flow` domain (Falkenhainer et al., 1989).

In this study, we make use of our own implementation of SME based on the original description by (Falkenhainer et al., 1989) and adapt it to the simple concept–relation structure of semantic networks. The details are given in Chapter 4 and Chapter 7.

2.3 CASE-BASED REASONING

Case-based reasoning (CBR) is a problem solving paradigm in AI where specific knowledge of previously solved cases are utilized to address a new problem. The roots of CBR approach can be traced back to the work of Schank (1982) on the modeling of dynamic memory, where he explored the role of the memory of previous situations in problem solving and learning, eventually forming the basis of the earliest CBR systems. This occurred around the same time of Gentner's work on developing a theoretical framework for analogical reasoning, which we have covered in detail up to this point.

A pioneering work in the field was by Kolodner (1983), where she developed the first CBR system called CYRUS, working on cases of the travels and meetings of the ex-US Secretary of State Cyrus Vance. The model set forth by CYRUS was followed by several other early CBR systems, including MEDIATOR by Simpson (1985), CHEF by Hammond (1986), PERSUADER bySycara (1987), CASEY by Koton (1989) and JULIA by Hinrichs (1992). Other notable CBR systems included the HYPO system concerning the role of precedence in legal reasoning by Ashley (1990) and the GREBE system combining CBR with general domain knowledge by Branting (1991). Following the 1990s, the CBR field has proved to be an established field within AI with a rapidly growing number of applications (Aamodt and Plaza, 1994).

From the point of its foundation, CBR research has been inherently related to the research in analogical reasoning. However, there are some fundamental differences between the CBR approach and the work on analogical reasoning in cognitive science. Lopez De Mantaras et al. (2005) cite the most important difference as being related to generality: Analogy research is fundamentally focused on generality, treating the processes of matching and retrieval as broadly general cognitive processes operating over structural mental representations. In contrast to this, CBR systems have been focusing on specific tasks on well defined limited domains, where domain-specific matchers, index-based retrieval systems, and similarity metrics are commonly employed.

There are differences in approach between CBR and the general field of analogical reasoning.

The contrast between these two approaches have been somewhat bridged by the MAC/FAC (for "many are called but few are chosen") model of Forbus et al. (1995), which postulates a two staged retrieval where a non-structural and fast first stage filtering is followed by a structural match in the second stage.

In retrospect, the significance and basis of the CBR approach can be found in very early works such as the observation of Wittgenstein (1953) about natural concepts, where objects such as tables and chairs are polymorphic and cannot be classified by a single set of features but instead can be defined by a set of cases with family resemblances. This work was cited by Aamodt and Plaza (1994) as a philosophical basis for CBR.

In general, as a major advantage, the CBR approach can be applied to problem domains that are only partially understood, and can provide solutions when no algorithmic or rule-based method is available. The main advantages of CBR over rule-based models include the following (Watson and Marir, 1994):

- CBR systems can be built where a model of the problem does not exist;
- Implementation is commonly made easy, as a task of identifying relevant case features;
- CBR systems can be rolled out with only a partial case base, as it will be continually growing due to its cyclic nature;
- CBR systems are highly efficient by avoiding the need to infer answers from first principles each time;
- Retrieved cases can be used to provide satisfactory explanations as to why the given solution is produced; and
- The case-based nature of the learning system makes maintenance easier.

The CBR model has been traditionally presented as a continuous cycle of *retrieval*, *reuse*, *revision*, and *retaining* of cases, noted as the mnemonic of “the four REs” (Aamodt and Plaza, 1994) (Figure 19).

As the CBR system encounters a new problem, it *retrieves* one or more previously encountered cases from its case base; *reuses* the retrieved case to attempt to solve the new problem; *revises* the reused solution if necessary; and *retains* the new solution as a new case in the case base, for future reference. In this dissertation, we prefer the more simplified approach of classifying CBR stages as *retrieval*, *adaptation*, and *retaining*.

2.3.1 *Representation*

Case representation is a major initial consideration of any new CBR system, fundamentally affecting the implementation of the remaining

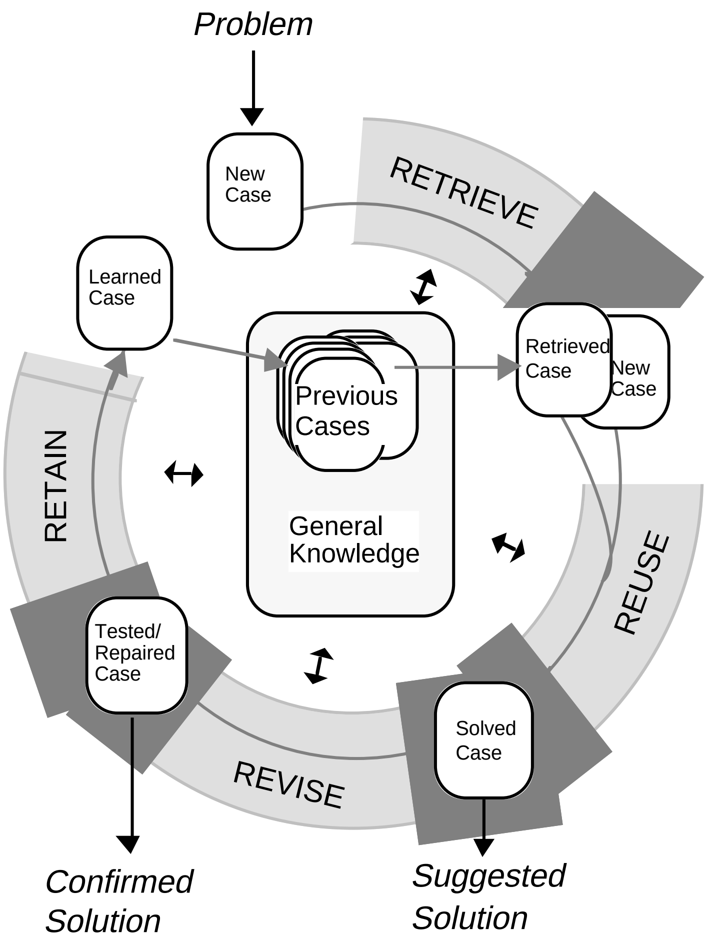


Figure 19: Overview of the traditional case-based reasoning cycle (Aamodt and Plaza, 1994).

aspects of the cycle. A case in CBR comprises knowledge about a lesson learned during a past situation and the context in which this can be used. A typical CBR case contains information about (Watson and Marir, 1994):

- the *problem* describing the state of the world when the case occurred;
- the *solution* describing the derived solution to the problem; and
- the *outcome* describing the state of the world after the case occurred.

One can make different combinations of these three types of information in a case representation scheme: cases comprising problems and solutions can be used to derive solutions to new problems, while cases comprising information about problems and their outcomes can be used to evaluate and make predictions about new problems.

Theoretically, all representational formalisms encountered in AI literature can be used as a basis of CBR case representation, including frames, propositional logic, rule-based systems, and networks. In practice, most CBR systems employ one of three major types of case representation: feature-vector (or *propositional*) representation, structured (or *relational*) representation, or textual (or *semi-structured*) representation (Bergmann et al., 2005).

There are also more advanced, hybrid, approaches to case representation, such as hierarchical representations making use of multiple representations for the same case at different levels of abstraction (Kolodner, 1993) and the use of generalized cases covering a subspace of the representation space, in contrast to single cases representing single experiences (Bergmann and Vollrath, 1999).

Case collection in CBR is an incremental process. That is, due to the cyclic nature of CBR, in which the case base is repeatedly enlarged with new cases as they are encountered, the system can be deployed with only an initial partial case base. However, there are some considerations to take into account as to what kind of cases should be included in the initial case base. Kolodner and Leake (1996) suggests that (1) the cases should cover as much as possible the range of reasoning tasks the system will undertake, and (2) over this range, they should cover already well-known solutions and well-known mistakes.

2.3.2 *Retrieval*

The case retrieval stage concerns the recalling of the most similar cases to the current case at hand, through a retrieval algorithm using an indexing scheme or some kind of similarity metric computed in real time. The planning and implementation of the retrieval stage is crucial for especially large-scale problem domains, where it is very common for CBR systems to handle thousands of cases in one case base (Watson and Marir, 1994).

An issue highly related with case retrieval is the indexing of cases, whereby cases are assigned indices to facilitate their retrieval. There are both manual and automated methods of case indexing. Some common methods of indexing include:

- *indexing by features and dimensions*, where the domain is analyzed for determining the important dimensions and the cases are indexed by their values along these dimensions (e.g. MEDIATOR (Simpson, 1985), indexing along the type and function of disputed objects and the relationship of the parties);
- *difference-based indexing*, where indices differentiate a case from other cases (e.g. CYRUS (Kolodner, 1983), discovering and selecting indices which differentiate cases best);
- *similarity-based indexing*, where, after a process of generalization creating a set of indices describing abstract cases covering a common set of features, the unshared features are used as indices to original cases (Hammond, 1989); and
- *inductive learning based indexing*, where predictive features are identified and used as indices (Goodman, 1989).

Case retrieval in CBR differs from database searches that look for a specific value among a given set of records. Due to the fact that in general there would be no existing case that would exactly match any given new problem, retrieval in CBR typically involves partial matches.

A common method of retrieval widely used in CBR is *nearest neighbor* calculations, where similarity between cases is calculated using a weighted sum of their features. A disadvantage of nearest neighbor approaches is that the retrieval time scales linearly with the number of cases in the case base.

Other retrieval methods are based on *induction*, where features that are most useful for discriminating cases are discovered by a learning algorithm, producing a decision tree structure to parse the case base. The ID3 algorithm by Quinlan (1986) is a prototypical example. The approach can also be improved by manually identifying important relevant case features beforehand.

2.3.3 *Adaptation*

After the retrieval stage, the solution of the matching case from the case base should be adapted to address the new case.

Adaptation in CBR remains somewhat under-addressed and controversial.

While issues such as case representation, similarity computations, and retrieval have been amply addressed in CBR literature, adaptation has been considered the most difficult step and remains somewhat under-addressed and controversial (Cunningham, 1998; Wilke and Bergmann, 1998). In large scale applications, while it is commonly easy to accumulate a sufficient number of cases, the formulation of the required adaptation scheme is often difficult. Therefore, it is not uncommon to use very simplistic adaptation rules, or, bypass adaptation entirely, and to try to make up for this deficiency with a very comprehensive case base ensuring the availability of a similar case for every problem instance (Leake, 1996).

However, it has been also argued that this forms one of the fundamental advantages of CBR (Cunningham, 1998). This is because one may argue that the approach of reusing past cases for addressing new problems, in contrast to problem solving from *first principles*[7], is only advantageous and sensible with minimal adaptation. In fact, the main motivation behind CBR is to avoid first principles reasoning as much as possible and to expect that retrieval and adaptation would be simpler and sufficient (Figure 20).

Adaptation models in CBR can be classified into several categories (Cunningham et al., 1994; Watson and Marir, 1994; Kolodner and Leake, 1996; Wilke and Bergmann, 1998):

- Null adaptation
- Substitutional adaptation
- Transformational adaptation
- Generative adaptation

Null adaptation is a direct simple application of the retrieved solution to the current problem without adapting. It is often suitable for classification tasks, or tasks which involve complex reasoning but a simple solution.

7 A *first principle*, in logic, is a foundational proposition that cannot be deduced from any other proposition. In reasoning, it is used to mean that a problem is addressed without reference to another through analogy and a solution is formulated from scratch.

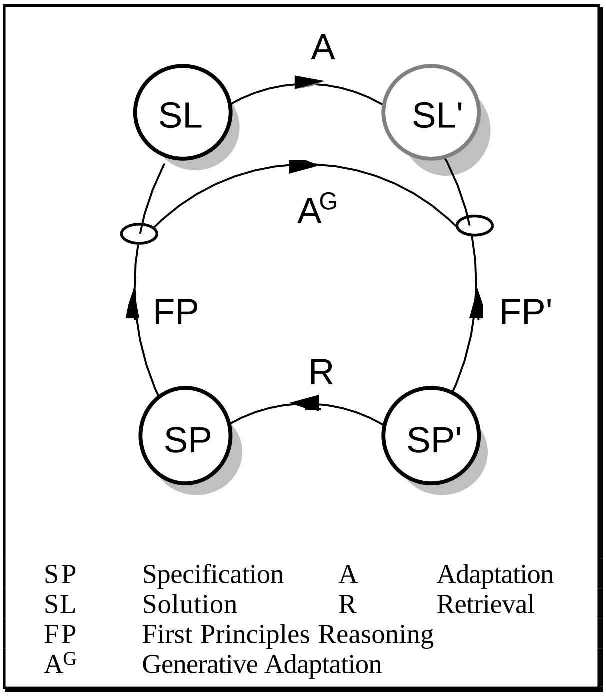


Figure 20: Transformation and mappings involved in case-based reasoning. The pairs SP, SL and SP', SL' represent problem specification and solution for the retrieved and new cases, respectively (Cunningham et al., 1994).

Substitutional adaptation is accomplished by substituting values appropriate for the new case in place of the values of the retrieved case. This type of adaptation involves only changes in the values of some attributes and the structure of the new solution remains unchanged from the retrieved case.

Transformational adaptation involves structural changes to the solution, such as the rearrangement of solution elements, or the modification, addition, or deletion of these elements. Transformational adaptation typically employs a fixed set of adaptation operators or rules, which are defined based on domain knowledge (Kolodner, 1993).

Generative adaptation comprises the most complex adaptation techniques encountered in CBR literature, and involves the reworking of a portion or the whole of the reasoning process that led to the solution of the retrieved case. Generative adaptation has been also referred to as *derivational analogy* (Veloso and Carbonell, 1994).

2.3.4 *Retaining*

In the classical representation of the CBR cycle, retaining is the final step after an acceptable solution to the new case has been produced by the system. The newly solved case is added to the case base of the system for making it available for future retrieval, enabling the CBR system to learn from its problem solving experience. The retaining of new cases enlarges the coverage of problem space represented by the case base.

In addition to the solution to the problem, the steps used in deriving that solution can also be stored as a part of the case. For example, in a CBR system using generative adaptation such as derivational analogy, *derivational traces* describing the decision-making process for solving the problem can be retained for future use (Veloso and Carbonell, 1994).

A related issue is the maintenance of the case base (Smyth, 1998), for preventing uncontrolled growth of case bases and addressing issues related to retrieval efficiency. Depending on the design of the CBR system and the complexity of the used case representation, many approaches are possible. For example, if a newly solved case is found to be highly similar to a case already in the case base, the new case may not be retained at all, or the two cases may be merged.

2.4 CONFLICT RESOLUTION

A conflict is defined as a "disagreement through which the parties involved perceive a threat to their needs, interests or concerns" (Webne-Behrman, 1998). Conflicts are more than simple disagreements in that the parties in conflict perceive a threat to their well-being and act upon the basis of their perceptions of the situation, rather than an objective review of it.

Conflict resolution comprises the methods and processes involved in facilitating peaceful resolution of a conflict. The term "conflict resolution" is used interchangeably with "dispute resolution", the difference being that a dispute is a typically short-term disagreement over a particular issue, whereas conflicts are continual disputes with higher frustration levels. An example for this distinction is the Cold War between the United States and the Soviet Union, where each round of Strategic Arms Limitation Talks, the Cuban Missile Crisis, the Vietnam War, and the invasion of Afghanistan constituted *disputes* within the broader *conflict* of the Cold War (Olympio, 2005).

Conflict resolution is a relatively new field, emerging after World War II.

As an academic field and professional practice, conflict resolution is relatively new, emerging approximately after World War II (Deutsch et al., 2011). Conflicts can range widely in their scale, interpersonal to intergroup to international, involving individuals or larger social structures.

As they are results of human interactions, conflicts arise due to some fundamental psychological processes. Deutsch et al. (2011) identify, among these, the processes of motivation, trust, communication, emotions, self-control, power, and judgmental biases.

When faced with conflict, the parties can employ a number of different strategies or resolution styles to address the problem, depending on their *pro-self* or *pro-social*[8] goals. H. and Robbennolt (2007) categorize these resolution strategies as: *avoidance*, *yielding* or *accommodating*, *competition*, *cooperation*, and *conciliation* or *compromising*.

Beyond private decisions of the parties in conflict, there are also formal frameworks for the resolution of conflicts on different levels. Figure 21 gives an overview of the spectrum of conflict resolution processes, in the order of increasing coercion. At the left end of the spectrum, there are conciliatory and peaceful outcomes of conflict, while on the other side one of the parties relies on coercion and public action to force the other party into submission.

The most common way to reach a mutually acceptable agreement is through *negotiation*, where the parties exchange arguments voluntarily to resolve their differences (Moore, 2003). Where negotiations are hard to initiate or have been stagnant, assistance from a third, impartial, party from outside the dispute can be requested through a *mediation* process. In more difficult situations, the parties can leave the decision making totally in the hands of a third party through processes such as *arbitration* or *judicial decision*.

2.4.1 *Agreement Technologies*

As an outcome of negotiation processes, *agreement* forms one of the crucial social concepts helping individuals to cope with their social environment. It is present in virtually all human interactions and therefore constitutes an interesting phenomenon that should be addressed in models of societies.

Lying in the interdisciplinary boundary between the disciplines of social psychology, social neuroscience, and the multi-agent systems (MAS) subfield of systems science, the newly emerging field of *agreement technologies* models agreement using autonomous agents (Jennings, 2005; Ossowski et al., 2013).

The approach of agreement technologies are highly relevant in large-scale distributed systems where human transactions and interactions are increasingly mediated by computers. It proposes to use MAS methodology for understanding the performance of social systems, and envisions distributed systems where interactions between artificial agents are based on the concept of agreement.

8 A *pro-social* behavior is one that is intended to benefit another, or the society as a whole, related with the concept of altruism.

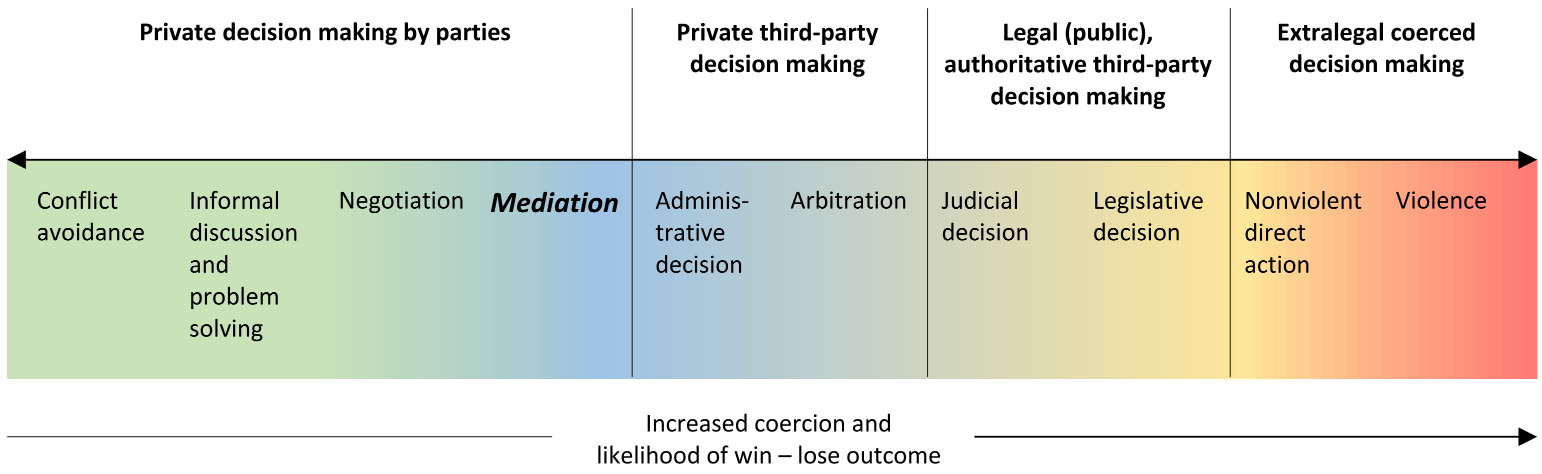


Figure 21: Continuum of conflict management and resolution approaches, highlighting mediation. Based on Moore (2003).

The study presented in the final part of this dissertation, where we apply the techniques we developed to the problem of mediation, forms a part of the Spanish Consolider Project on Agreement Technologies[9] and the larger Agreement Technologies Action of the European Cooperation in Science and Technology (COST)[10].

2.4.2 *AI, Law, and Conflict Resolution*

An interest in applications concerning law and political science has been present since the early days of AI research. The field of *legal reasoning*, in particular, investigates formal and computational theories for analyzing legal problems, creation of arguments, and making decisions (Gardner, 1984; Ashley, 1991).

Case-based legal reasoning models and models of legal argumentation constitute two important approaches within AI and law studies (Hafner, 1998). The pioneering legal CBR model was the HYPO model (Rissland and Ashley, 2005; Ashley, 1990) for analyzing cases and constructing legal arguments in the trade secrets domain. This CBR system used a selection of law-related features as dimensions for indexing the encountered cases for retrieval. An important reason for the compatibility of legal reasoning and CBR is the fact that the practice of law is highly accustomed to the notions of precedence and cases.

Similarly, in an extension of the CBR approach introduced by HYPO, the GREBE system by Branting (1991) investigated the use of cases for identifying portions of relevant existing cases with imperfect matches. The innovation in the GREBE model was the use of general domain knowledge, albeit limited, to address the weakness of CBR in making use of connections of features making up the cases. Our approach of combining commonsense knowledge with a CBR framework in this dissertation can be seen a revisiting and improvement upon the work of Branting, by making use of the newly developing field of commonsense reasoning.

Examples in the legal argumentation front include the logical argumentation framework presented by Prakken (1993), where two conflicting arguments can be compared using ordering principles applied to the legal premises of the arguments, and the discourse-based model of Loui and J. (1995), where they focus on defining categories of rationales used in adversarial legal arguments.

In conflict resolution, there is ongoing research on the discovery of knowledge in international conflict management databases (Fürnkranz et al., 1997). AI techniques have also been considered for developing

9 http://www.agreement-technologies.org/
10 http://www.agreement-technologies.eu/

general theories of conflict and applying previously successful resolution strategies to new cases, as in the case of the case-based MEDIATOR system of Simpson (1985) that we have previously mentioned.

AI techniques have been also used to learn patterns in international events that lead to crises and to use this information for early warning systems (Merritt et al., 1993). They have been also used to detect regularities in collections of conflicts to gain insight into the parameters affecting the escalation of crises (Mallery and Sherman, 1993; Schrodt, 1996).

2.4.3 *Mediation*

Mediation is a process of dispute resolution where an intermediary, called a "mediator", assists two or more negotiating parties to reach an agreement in a dispute, who have failed to do so on their own. It can be seen as an extension of the negotiation process involving the intervention of a third party who has limited authoritative decision making power Moore (2003). The mediator assists the parties to voluntarily reach a mutually acceptable solution through impartial techniques to improve their dialog and perception of the dispute.

Mediation assists parties in conflict to reach a mutually acceptable solution.

In the field of law, mediation is defined as a form of *alternative dispute resolution* (ADR), i.e. a collection of techniques the parties might resort to instead of a judicial process, including, besides mediation, other types such as facilitation[11] and arbitration[12] (Nabatchi and Bingham, 2004) (Figure 21).

Two defining aspects of a mediation process are (Pace University School of Law, 2008):

- that the mediators have special training that allows them to identify issues and explore options for solutions based on their experience, often by drawing parallels with similar past cases; and
- that the mediators handle the discussion with total impartiality, without having a personal stance on the discussed issues, and instead, offering to expand the discussion beyond the original dispute for allowing creative new solutions.

Mediation is commonly resorted to in a wide variety of domains and scales, including interpersonal disputes such as workplace and family disputes, intergroup disputes such as commercial or community disputes, and international disputes involving diplomacy and commerce.

11 The intermediary constructively organizes a discussion.
12 The intermediary has the power to impose a resolution.

International conflicts, in particular, provide interesting examples of how the mediation process is carried out and how powerful mediation can be in terms of the scale of conflicts it can address.

A prototypical example of a large-scale conflict successfully resolved by mediation is the Beagle conflict between Chile and Argentina over the possession of several islands located near Beagle Channel, in the southern tip of South America, and the scope of the maritime jurisdiction associated with these islands (Laudy, 2000).

The conflict began in 1904 with the Argentine claims over the islands. After passing through several stages over a long period, including negotiation, international tribunal, and threats of war, the disagreement was resolved through the mediation of Pope John Paul II in 1980 (Figure 22).

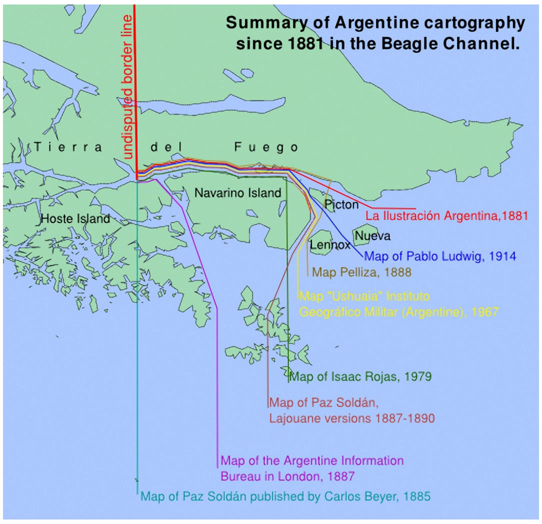
Another highly cited instance of large-scale mediation is the signing of the Camp David Accords between Egypt and Israel under the mediation of the United States President Jimmy Carter, in 1978 (Hinton, 2004).

This mediation concerned the cessation of the state of war that had existed between the parties since the 1948 Arab–Israeli War and the normalization of relations. The agreement reached under the mediation process finally resulted in the 1979 signing of the Egypt–Israel Peace Treaty (Figure 23).

In the second part of this dissertation, we introduce an analogical reasoning approach to the problem of mediation. The basis of our approach will be the observation that, *even if two instances of conflict are from seemingly distant domains and with different scales, their underlying structures can be, more than often, analogous* (Simpson, 1985; Kolodner and Simpson, 1989; Simoff et al., 2008, 2009).

We achieve this through a case-based reasoning system using semantic networks as the representation scheme. We discuss the basis and steps of this approach in detail in7 and Chapter 8.

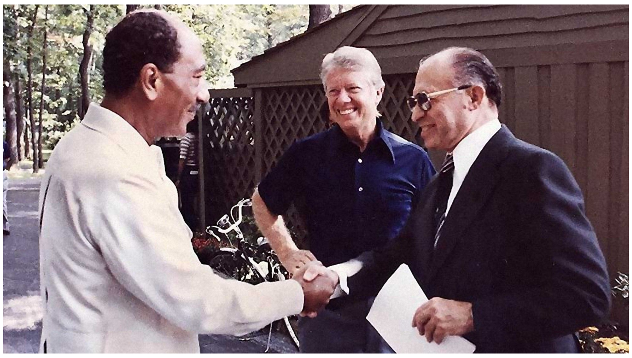
(a)



(b)

(c)

Figure 22: The papal mediation of the Beagle conflict between Chile and Argentina. (a) Pope John Paul II with the delegations of the parties at the beginning of the mediation, May 1979 (Rodríguez Guarachi, 2004). (b) Different interpretations of the boundary treaty of 1881. (c) The mediated solution to the territorial conflict, 1980. (Both maps by Wikimedia Commons user "Createaccount")



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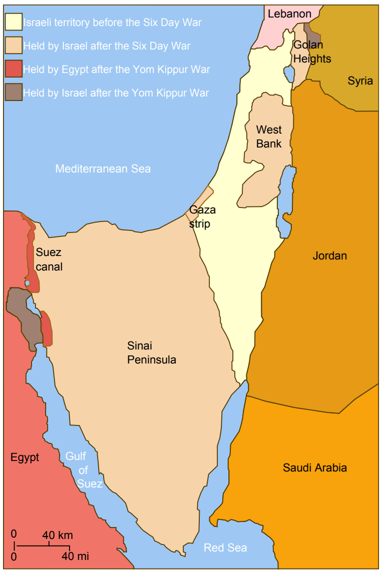

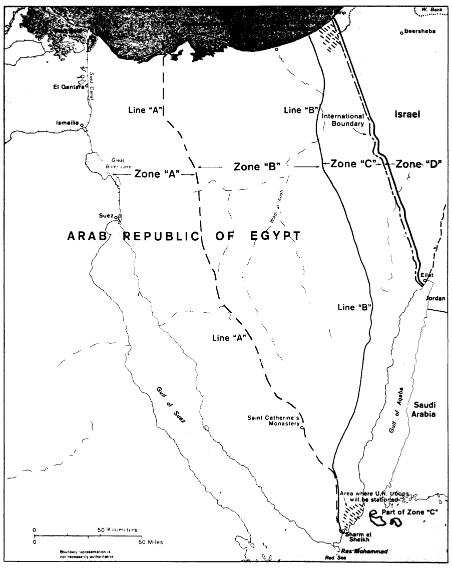

(b)

(c)

Figure 23: The *Camp David Accords* were mediated by United States President Jimmy Carter between Egyptian President Anwar El Sadat and Israeli Prime Minister Menachem Begin. (a) Begin, Carter, and El Sadat at Camp David, 1978 (Karl Schumacher–AFP/Getty Images). (b) Egypt and Israeli territory in Sinai at the end of the Yom Kippur War, 1973. (Map by Wikimedia Commons user "Raul654") (c) Withdrawal stages of Israel after mediation (Israel Ministry of Foreign Affairs, 1979).

Part II

EVOLUTIONARY ADAPTATION

In the following chapters, after a focused discussion of the foundation and practice of evolutionary computation methods, we lay out the evolutionary adaptation technique. This involves the case representation structure based on semantic networks that we use throughout the dissertation, the commonsense reasoning approach working in conjunction with knowledge bases, and a very detailed explanation of the novel algorithm. We also present examples elucidating the working steps of our approach.

3

EVOLUTIONARY COMPUTATION

"... from so simple a beginning,
endless forms most beautiful and most wonderful
have been, and are being, evolved"

— Charles Darwin (1859)

In his book, *On the Origin of Species*, Darwin (1859) said:

> "Owing to this struggle for life, any variation, however slight and from whatever cause proceeding, if it be in any degree profitable to an individual of any species, in its infinitely complex relations to other organic beings and to external nature, will tend to the preservation of that individual, and will generally be inherited by its offspring."

The model of evolution by means of natural selection has proved to be one of the most powerful theories in the history of science, explaining the processes giving rise to diversity encountered at all scales in biology, including species, individual organisms, and molecular level (Hall and Hallgrimsson, 2008). The model explains that heritable variations in organisms cause different rates of survival for individuals, that individuals with higher survival ability will have more chance to live and produce offspring, and that their variations will be passed over to following generations as *adaptations*.

Within the many outcomes of the evolutionary processes in biology, such as speciation, extinction, or co-evolution, adaptation is the most interesting from the perspective of AI and optimization. The process of adaptation is a natural instance of optimization. It is clearly demonstrable in action, through examples such as *homology*, where organisms can show adaptations of form and function of organs in different species, inherited from a common ancestor, causing them to thrive in their natural habitats (Figure 24). It is also evident in cases where a particular form or function does not follow from common ancestry, but due to similar environmental selection pressures, can converge into highly similar outcomes. These cases constitute examples of boilogical *analogy* (Figure 25). It is also interesting to note, in

The biological process of evolution is a natural instance of optimization.

relation with our discussion of analogies in previous chapters, the sense of the word "analogy" here refers to similar traits or organs evolved in two strictly unrelated ways.

The basis of the model of evolution is simple, consisting of just three facts (Lewontin, 1970):

1. more offspring are produced than can possibly survive (competition);

2. traits vary among individuals, leading to different rates of survival and reproduction (variation and "survival of the fittest"); and

3. trait differences are heritable, causing advantageous variations to be preserved (adaptation).

This simplicity eventually led to the idea of using similar algorithmic procedures to harness the power of adaptation in "computer simulations of natural evolution", forming the field of *evolutionary computation*. This field uses differing models of the evolutionary process to address continuous and combinatorial optimization problems (Fogel, 2006).

Evolutionary algorithms (EA) maintain a population of structures with a specific representation, selected for the addressed problem, and, in an iterative procedure, apply variation operators and selection guided by a given fitness function. EA is particularly powerful when one is interested in a "black-box" solution, as the only thing needed by the optimization procedure is a fitness function that can evaluate and assign values to candidate solutions according to how well they perform under some desired category. From a machine learning perspective, EA systems are able to produce solutions with just a description of the desired outcome, without any regard to how the solutions actually work or how they are arrived at.

Algorithm 1 outlines the procedure for a typical EA.

After populating the initial generation with random individuals, the algorithm is a continuous iteration of the cycle of variation and selection under a fitness measure.

The most commonly encountered variation operations in conventional EA are *recombination* (or, *crossover*), modeling the molecular process of genetic exchange, and *mutation*, modeling the process of change in genetic sequence. Thus, in its most basic incarnation, the algorithm has three basic parameters, describing the size of the population $\mathtt{Size}_{\mathtt{p}}\mathtt{op}$; the probability of recombination $\mathtt{Prob}_{\mathtt{rec}}$, and the probability of mutation $\mathtt{Prob}_{\mathtt{mut}}$. It is also supplied with a fitness function to assign fitness values to individuals in the evaluation of each generation, and a stop criterion to end the evolution procedure.

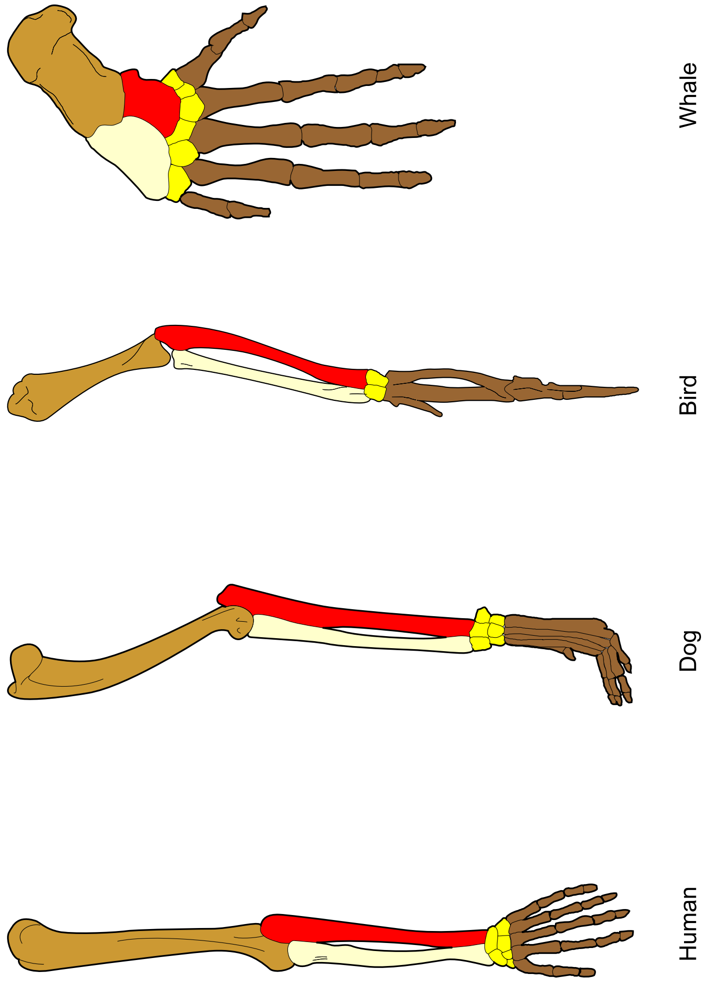

Figure 24: The principle of *homology* in biology. The bones shown by the same color in the forelimbs of four vertebrates (human, dog, bird, and whale) are inherited from their last common ancestor. (Wikimedia Commons user "Vladlen666".)

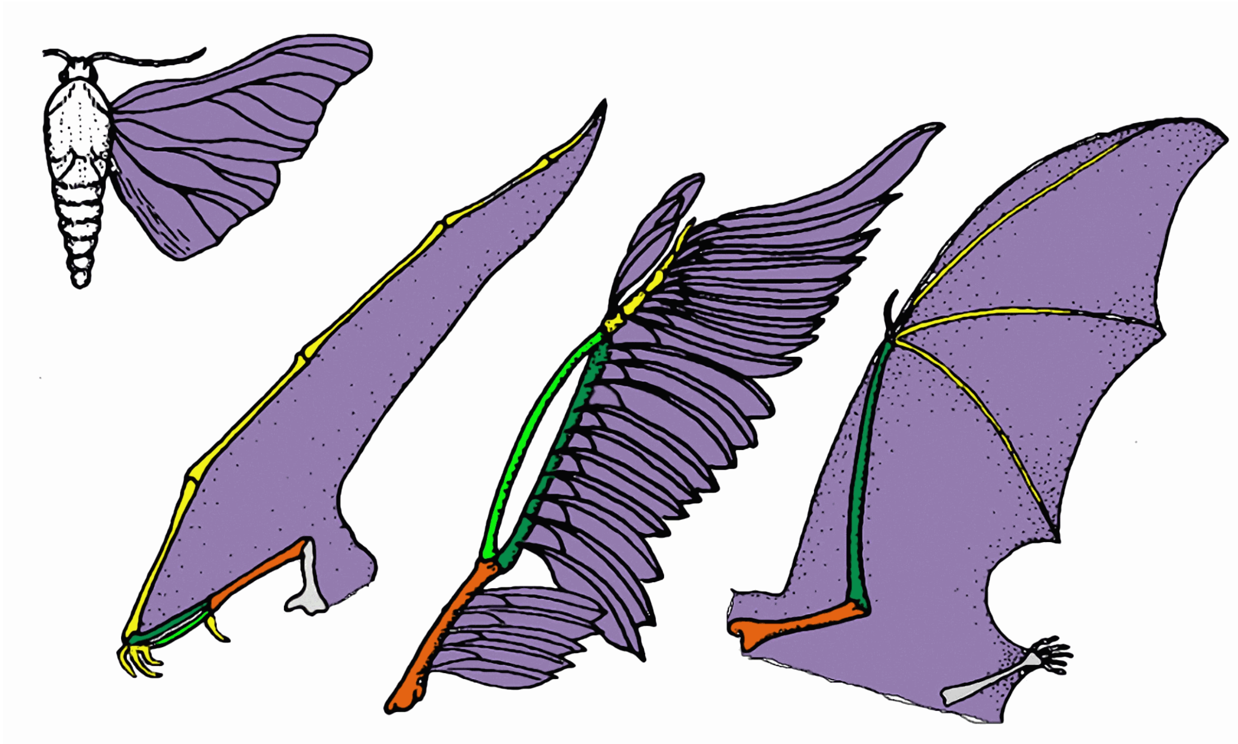

Figure 25: The principle of *analogy* in biology. Flying surfaces of the wings of moth, pterodactyl, bird, and bat evolved independently under similar environments and selection pressures and do not share a common ancestor (Krempels, 2006). (Note, however, that the bones of the three vertebrates are homologous.)

Algorithm 1 Procedure for a typical evolutionary algorithm.

procedure EVOLUTIONARYALGORITHM
  $P(t = 0) \leftarrow$ INITIALIZEPOPULATION($Size_{pop}$)
  repeat
    $\phi(t) \leftarrow$ EVALUATEFITNESSES($P(t)$)
    $S(t) \leftarrow$ SELECTION($P(t), \phi(t)$)
    $R(t) \leftarrow$ RECOMBINE($S(t), Prob_{rec}$)
    $M(t) \leftarrow$ MUTATE($R(t), Prob_{mut}$)
    $P(t+1) \leftarrow M(t)$
    $t \leftarrow t + 1$
  until stop criterion
end procedure

The origins of EA can be traced to three related, but in some respects significantly different, early models introduced in the 1960s and 1970s: "evolutionary programming" by F. et al. (1966), "evolution strategies" by Rechenberg (1973), and "genetic algorithms" by Holland (1975).

The origins of EA can be traced to three early models introduced in 1960s and 1970s: "evolutionary programming", "evolution strategies", and "genetic algorithms".

Out of the three, the genetic algorithms (GA) paradigm introduced by (Holland, 1975) has been the most popular, having been applied to optimization problems in almost every imaginable field of science and engineering, including natural sciences, economics, computer aided design, and scheduling (Mitchell and Taylor, 1999). In conventional GA, solutions are represented in the form of fixed or variable length strings, which describe, through some kind of encoding procedure specific to the problem, a full candidate solution. The variation operators in GA are virtually always crossover and mutation.

Evolutionary programming (EP), on the other hand, is similar to GA but the structure of the solutions are fixed and the numerical parameters within this structure are subject to evolution. The EP method was originally used to simulate evolution as a learning process to be utilized in AI (F. et al., 1966). Another distinguishing characteristic of EP is its dependence on mutation as the main variation operation.

In evolutionary strategies (ES), one typically works with a representation based on vectors of real numbers, which are subjected to evolution under self-adaptive mutation rates. Owing to the real number-based representation, mutations are typically performed by adding a normally distributed random value to each vector component.

The idea that a simple progression of variation, natural selection, and heredity can account for the great complexity and apparent design observed in living beings has eventually led to the formulation of *Universal Darwinism*, generalizing the mechanisms and extending the domain of this process to systems outside biology, including economics, psychology, physics, and even culture Dennett (1995); Bickhard and Campbell (2003).

Within this larger framework, the concept of *meme* introduced by Dawkins as an evolving unit of culture—or information, idea, or belief—analogous to a *gene* Dawkins (1989), hosted, altered, and reproduced in individuals' minds, forms the basis of the field of memetics[1].

Within the discipline of evolutionary computation, the recently maturing field of memetic algorithms (MA) has experienced increasing interest as a successful method for solving many hard optimization problems Moscato (1989); Moscato et al. (2004); Krasnogor and Smith (2005). The existing formulation of MA is essentially a hybrid approach, combining classical EA with local search, where the population-based global sampling of EA in each generation is followed by a local search, or learning, performed by each candidate solution (Algorithm 2).

Algorithm 2 Procedure for a typical memetic algorithm.

procedure MEMETICALGORITHM
  $P(t=0) \leftarrow$ INITIALIZEPOPULATION($Size_{pop}$)
  repeat
    $\phi(t) \leftarrow$ EVALUATEFITNESSES($P(t)$)
    $S(t) \leftarrow$ SELECTION($P(t), \phi(t)$)
    $V(t) \leftarrow$ VARIATION($S(t), Prob_{rec}, Prob_{mut}$)
    for all individual i in $V(t)$ **do**
      $i \leftarrow$ LOCALIMPROVEMENT(i)
    end for
    $P(t+1) \leftarrow V(t)$
    $t \leftarrow t+1$
  until stop criterion
end procedure

For this reason, the MA approach has been often referred to under different names besides MA, such as "hybrid EAs" or "Lamarckian EAs". To date, MAs have been successfully applied to a wide variety of problem domains such as NP-hard optimization problems Bui and Moon (1996); Merz (2002), engineering Cotta and Troya (2001), machine learning Abbass (2001); Mignotte et al. (2000), and robotics Chaiyaratana and Zalzala (1999).

1 Quoting Dawkins Dawkins (1989): *"Examples of memes are tunes, ideas, catch-phrases, clothes fashions, ways of making pots or of building arches. Just as genes propagate themselves in the gene pool by leaping from body to body via sperms or eggs, so memes propagate themselves in the meme pool by leaping from brain to brain..."*

3.1 GRAPH BASED METHODS

There are several existing algorithms using graph-based representations for the encoding of candidate solutions in EA Montes and Wyatt (2004). The most notable work among these is genetic programming (GP) Koza et al. (2003), where candidate solutions are pieces of computer program represented in a tree hierarchy, which is actually a specific type of graph structure Montes and Wyatt (2004). The trees are formed by *functions* and *terminals*, where the terminal set consists of variables and constants, and the function set can contain mathematical functions, logical functions, or functions controlling program flow, specific to the target problem.

GP has specialized crossover and mutation operations. In the crossover operation, two candidate solutions are combined to from two new solutions as their offspring. This is accomplished by randomly selecting *crossover fragments* in both parents, deleting the selected fragment of the first parent and inserting the the fragment from the second parent (Figure 26). The second offspring is produced by the same operation in reverse order.

Due to its tree-based structure, one of the important advantages of GP is that it is still possible to create nonidentical offspring even in the case that the same parent is selected to mate with itself in the crossover operation (Figure 27). This is in stark contrast with approaches such as GA, where a crossover operation of identical parents would yield identical offspring due to the linear nature of the representation.

In GP, there are two main types of mutations (Figure 28): the first one involves the random change of the type of a function or terminal at a randomly selected position in the candidate solution; while in the second one an entire subtree of the candidate solution can be replaced by a new randomly created subtree.

In parallel distributed genetic programming (PDGP) Poli (1999), the restrictions of the tree structure of GP is relaxed by allowing multiple outputs from a node, which allows a high degree of parallelism in the evolved programs. In evolutionary graph generation (EGG) Chen et al. (2002) the focus is on evolving graphs with applications in electronic circuit design. Genetic network programming (GNP) Katagiri et al. (2002); Mabu et al. (2007) introduces compact networks with conditional branching and action nodes; and similarly, neural programming (NP) Teller (1998) combines GP with artificial neural networks for the discovery of network structures via evolution.

The use of a graph-based representation makes the design of variation operators specific to graphs necessary. In works such as GNP, this is facilitated by using a string-based encoding of node names, types, and connectivity, permitting operators very close to their coun-

The use of a graph-based representation makes the design of variation operators specific to graphs necessary.

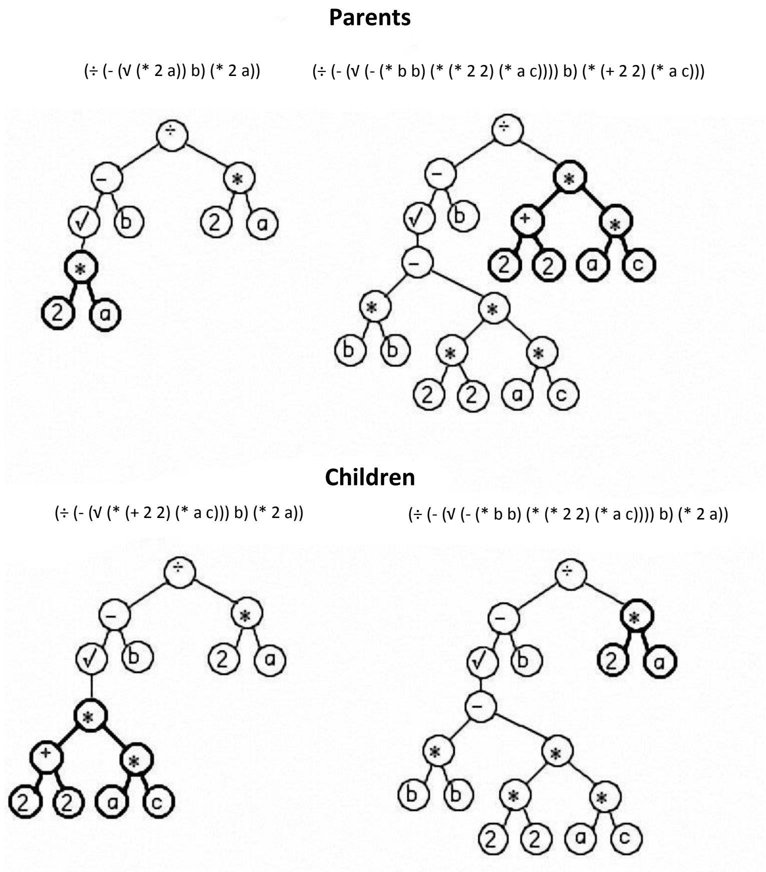

Figure 26: The crossover operation in genetic programming with different parents. The bold sections of both parents are swapped to create the offspring (Fernandez, 2013).

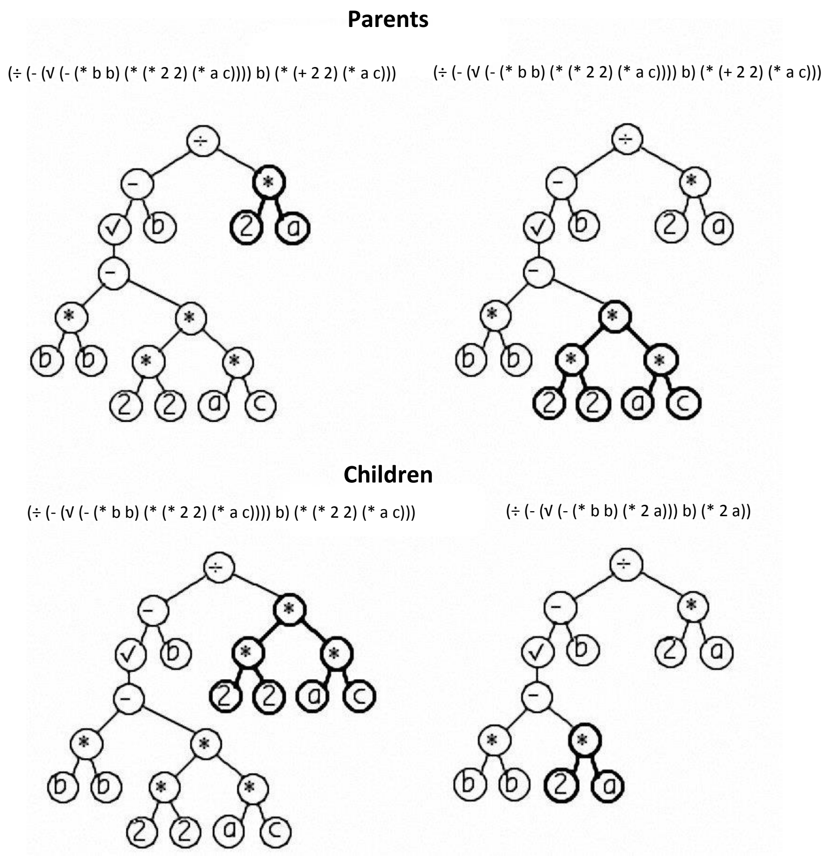

Figure 27: The crossover operation in genetic programming with identical parents. The bold sections are swapped to create the offspring (Fernandez, 2013).

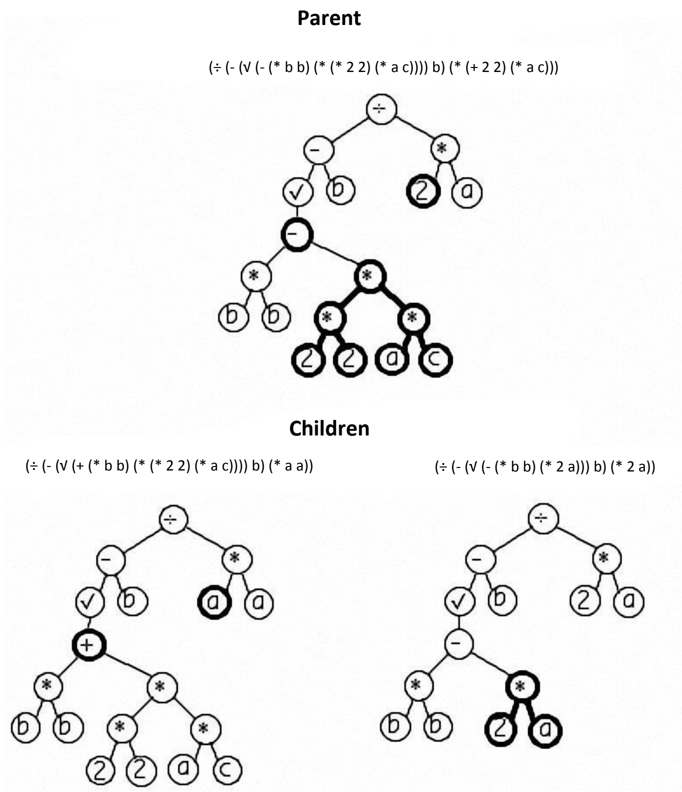

Figure 28: The mutation operation in genetic programming. The mutant on the left illustrates two mutations: change of a single terminal (2) into another (a) and the change of a single function $(-)$ into another $(+)$. The mutant on the right illustrates the replacement of a subtree $(*(*22)(*ac))$ by another subtree $(*2a)$ (Fernandez, 2013).

terparts in conventional EA; and in PDGP, the operations are simplified by making nodes occupy points in a fixed-size two-dimensional grid.

In this part of dissertation, we introduce a novel, graph-based, EA approach based on the concept of memes, where the individuals forming the population represent units of knowledge that are undergoing variation, transmission, and selection. The algorithm we introduce is centered on the use of semantic networks for encoding evolving information.

What is common within GP related algorithms is that the output of each node in the graph can constitute an input to another node. In comparison, for the semantic network-based representation that we use here, the range of connections that can form a graph of a given set of concepts is limited by commonsense knowledge, i.e. the relations have to make sense to be useful. To address this issue, we introduce new crossover and mutation operations for memetic variation, in Chapter 5, making use of commonsense reasoning Mueller (2006); Havasi et al. (2007) and adapted to work on semantic networks.

4

CASE REPRESENTATION

"There are more things in heaven and earth, Horatio,
Than are dreamt of in your philosophy."

Hamlet (1.5.166–7), Hamlet to Horatio

— William Shakespeare (1603)

4.1 KNOWLEDGE REPRESENTATION, ONTOLOGIES, AND GRAPHS

The case representation structure we use in the evolutionary adaptation and case-based reasoning stages of this dissertation is based on the representation framework of *ontologies*. Having the meaning of "the study of existence" in philosophy, an ontology, in the field of information science, is a formal means of representing knowledge as a set of concepts and relations between pairs of concepts (Gruber, 1993; Guarino et al., 2009).

For the sake of clarity, one has to make a distinction between the subject called ontology, which is "the study of categories of things that exist or may exist in some domain" and *an ontology*, which is a product of such a study, "a catalog of the types of things that are assumed to exist in a domain of interest `D` from the perspective of a person who uses a language `L` for the purpose of talking about `D`." (Sowa, 2000). As such, within AI, ontologies allow representations of things and their properties within a given domain that is formalized in a way allowing automatic information processing.

In a highly cited definition, Gruber (1993) describes an ontology as a formal, explicit specification of a shared conceptualization, which is subsequently analyzed by Richter (2003) as having the properties of being:

- *formal*, that is, machine understandable through formal languages;
- *explicitly specified*, containing explicitly defined concepts, properties, relations, functions, constraints, or axioms;

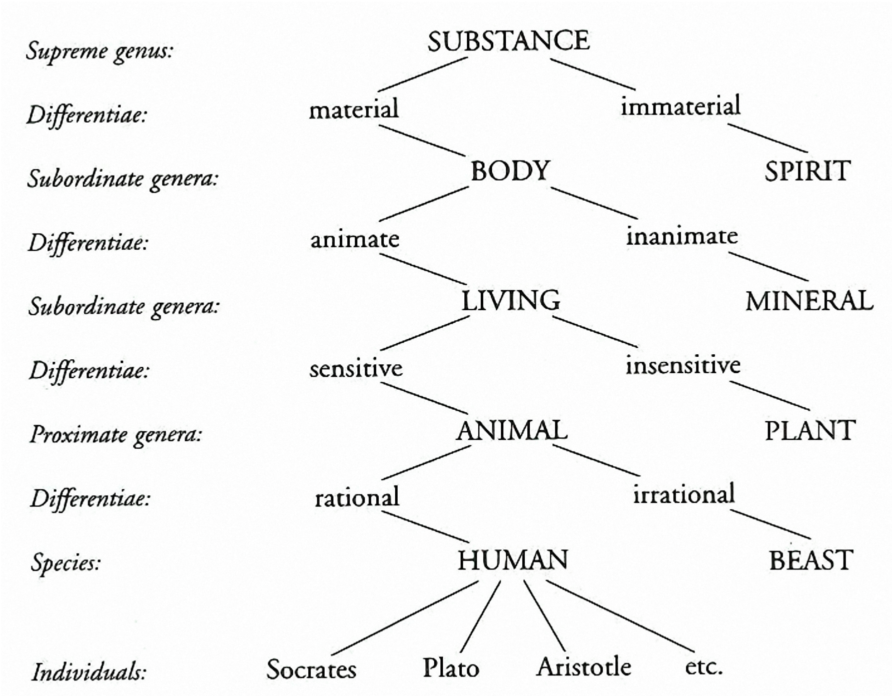

Figure 29: The Tree of Porphyry, as drawn by Peter of Spain (c. 1270) (de Rijk, 1972).

- *shared*, representing consensual knowledge of a community; and
- *conceptualization*, that is, an abstract model of some phenomenon in the world.

Just as the meaning of "ontology", in the sense of studying the nature of existence, comes from metaphysics; the first examples of concretely built ontology instances come from early philosophy.

The most important and influential early ontology is Aristotle's *Categories*, in which he introduces a 10-fold classification of all the possible kinds of things that can be the subject or the predicate of a proposition (Cohen, 2012). The Categories place every object of human understanding under one of the ten categories of

1. *substance* (ουσια, essence or substance);
2. *quantity* (ποσον, how much);
3. *quality* (ποιον, of what kind or quality);
4. *relation* (προστι, toward something);
5. *place* (που, where);
6. *time* (ποτε, when);
7. *situation* (κεισθαι, being in a position);

8. *condition* (εχειν, to have);
9. *action* (ποιειν, to make); and
10. *passion* (πασχειν, to undergo, receive a change from another object).

Owing to their interconnected structure of concepts and relations, ontologies can be readily considered as labeled and directed graphs (Hoser et al., 2006). This has been the case at least since the representation known as the "Tree of Porphyry" (Figure 29) dating from the 3rd century neo-Platonist philosopher Porphyry (de Rijk, 1972). The tree suggested by Porphyry—in only textual discussion by himself, but turned into a diagram by later philosophers—is actually a graph representation of Aristotle's Categories. In another early instance, Catalan philosopher Ramon Llull provided a graph structured representation of nature and logic (Figure 30) (Sowa, 2000).

In modern scholarship, graphs constitute the standard and irreplaceable representation in many fields ranging from information science to biology, such as the extreme example of Figure 31 showing the interconnected major metabolic pathways making up life on Earth.

A comparison of Figure 30 and Figure 31, as much as it concerns two distant instances in medieval philosophy and modern biochemistry, is also interesting from a perspective of thinking about how far we have progressed in terms of the complexity of our understanding and description of the nature of human existence.

In information science, there are efforts to establish general ontologies called *upper ontologies* or *top-level ontologies*, which contain descriptions of very general concepts that are the same across all knowledge domains (Niles and Pease, 2001). For the approach undertaken in this dissertation about evolutionary adaptation and case-based reasoning, we make extensive use of *commonsense reasoning*, which utilizes upper ontologies built for reasoning with commonsense knowledge.

4.2 SEMANTIC NETWORKS

A semantic network is a graphic notation for the representation of knowledge in the form of sets of nodes representing concepts, interconnected by edges representing relations (Fig. 32). This type of graph representation has found use in many subfields of artificial intelligence, including natural language processing, machine translation, and information retrieval. Constructs resembling semantic networks have long been in use also in other fields such as philosophy and linguistics.

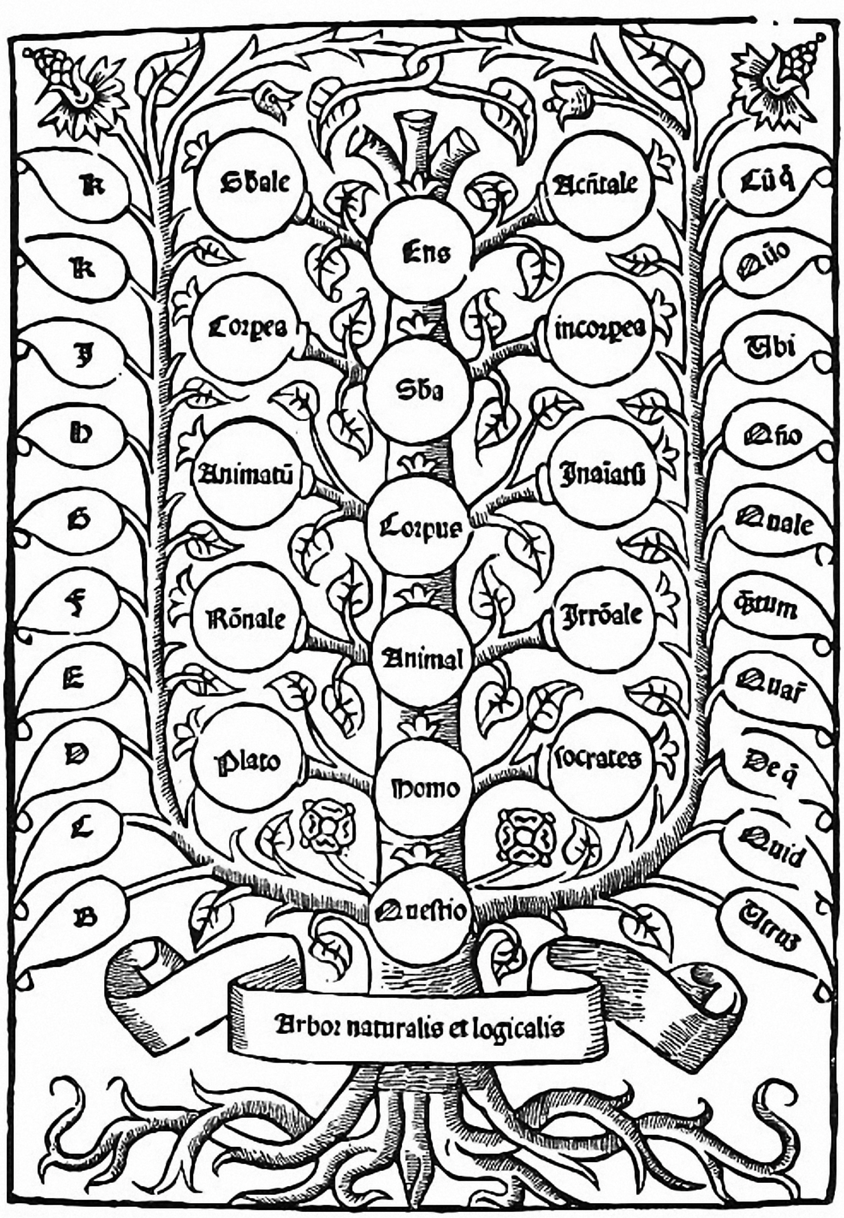

Figure 30: The Tree of Nature and Logic by the Catalan philosopher Ramon Llull (1305). The main trunk represents the Tree of Porphyry (cf. Figure 29), the ten leaves on the right represent ten types of questions, and the ten leaves on the left represent a system of rotating disks for generating answers (Sowa, 2000).

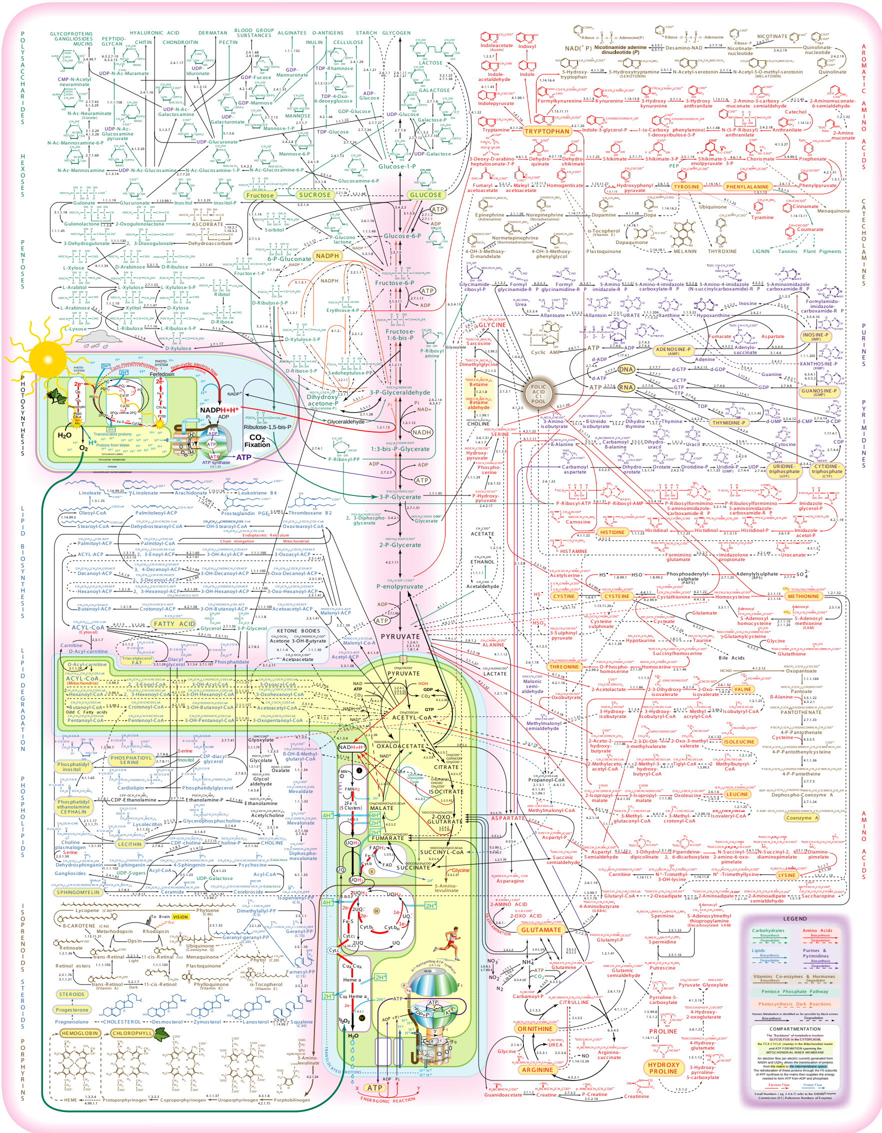

Figure 31: Graph representation of the major biophysical processes constituting life on Earth, including glycolytic pathway, Krebs cycle, respiratory chain, ATP synthesis, and carbohydrate, amino acid, and lipid metabolism (Nicholson, 2003).

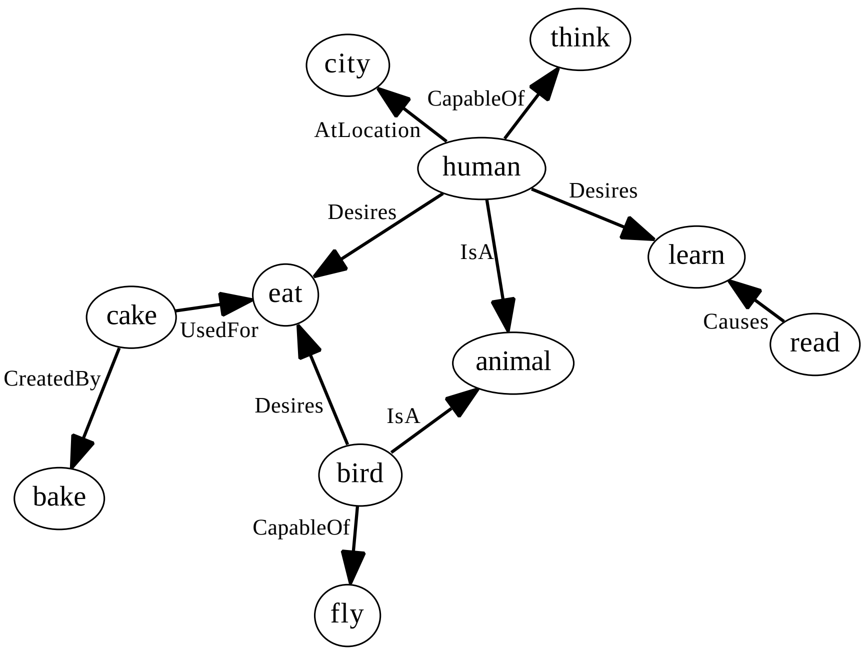

Figure 32: A semantic network with 11 concepts and 11 relations.

An important characteristic of a semantic network is whether it is definitional or assertional: in definitional networks the emphasis is on taxonomic relations (e.g. $\mathsf{IsA(bird, animal)}$[1]) describing a subsumption hierarchy that is true by definition; in assertional networks, the relations describe instantiations and assertions that are contingently true (e.g. $\mathsf{AtLocation(human, city)}$) Sowa (1991, 2000). In this study we combine the two approaches for increased expressivity. As such, semantic networks provide a simple yet powerful means to represent the "memes" of Dawkins as data structures that are algorithmically manipulatable, allowing a procedural implementation of memetic evolution.

Semantic networks constitute the main representation structure that we use, both in this part about evolutionary adaptation and the part concerning case-based mediation.

In several key stages of our approach, we need to employ structure mapping through our SME implementation in conjunction with the semantic network representation. These stages are, for the case-based mediation approach, the computation of SME-based retrieval scores between semantic networks together with the adaptation of networks through SME-based inferences (Chapter 7), and, for the evolutionary generation of analogies, the calculation of fitness scores for candidate solutions through SME (Chapter 6).

1 Here we adopt the notation $\mathsf{IsA(bird, animal)}$ to mean that the concepts bird and animal are connected by the directed relation IsA, i.e. "bird is an animal."

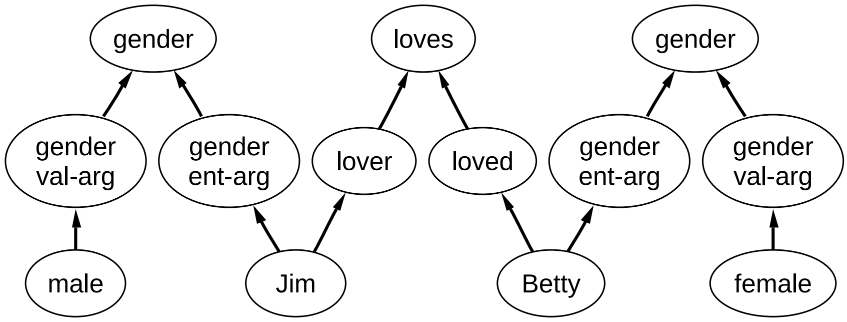

Figure 33: Translation between predicate calculus and semantic networks. The predicate calculus representation of the knowledge "Jim loves Betty", `loves(Jim, Betty)`, `gender(Jim, male)`, `gender(Betty, female)`, is equivalent to the given semantic network (Larkey and Love, 2003).

The use of SME with semantic networks necessitates the introduction of a mapping between the concept and relation based structure of semantic networks and the predicate calculus based representation traditionally used in SME applications (Table 5).

A highly versatile such mapping is given by Larkey and Love (2003). Given an information such as "Jim (a man) loves Betty (a woman)", one can transform the predicate calculus representation of `loves(Jim, Betty)`, `gender(Jim, male)`, `gender(Betty, female)` (Figure 33) into a semantic network representation by (1) converting predicates into nodes such as `gender` and `loves`; (2) creating argument nodes for each argument of a predicate and connecting these to the predicate node, such as `lover` and `loved` denoting the arguments of the `loves` predicate; (3) instantiating entities and values as nodes in the graph and connecting these to the corresponding argument nodes.

This kind of mapping makes it possible, theoretically, to represent arbitrarily complex information within the simple representation framework of semantic networks. As an example, one can represent meta-information such as "John knows that Jim loves Betty".

However, the approach of Larkey and Love (2003) requires the creation of ad hoc "relation nodes" for the representation of relations between concepts and the usage of unlabeled directed edges. On the other hand, the existing structure of the commonsense knowledge bases that we interface extensively, mainly ConceptNet, (Chapter 5) are based on nodes representing concepts and labeled directed edges representing relations (as in Figure 32). In this representation, nodes can have arbitrary names but the names of edges come from a limited set of basic relation names (e.g. the set of relations in Table 8). Because of this, we take another approach for mapping between semantic networks and predicate calculus.

Table 6: The correspondence between SME predicate calculus statements (Falkenhainer et al., 1989) and semantic network structure that we use to apply structure mapping to semantic networks.

Predicate calculus	Semantic networks
Entity	Concept (node)
Relation	Relation (edge)
Attribute	`IsA` or `HasProperty` relation
Function	Not employed

Table 6 gives the list of correspondences we define between the two representation schemes. We treat "entities" as concepts, relations as relations, attributes as `IsA` relations, and we exclude functions. Using these correspondences, we make use of our own implementation of SME, based on the original description by Falkenhainer et al. (1989) but adapted to work on the semantic network structure. The details of implementation are given in Chapter 6.

5

ADAPTATION OF SEMANTIC NETWORKS

"They are in you and me; they created us, body and mind;
and their preservation is the ultimate rationale for our existence.

They have come a long way, those replicators.
*Now they go by the name of **genes**, and we are their survival machines."*

— Richard Dawkins (1976)

In this part, we present a complete, in-depth description of our novel semantic network-based evolutionary algorithm.

The algorithm enables the spontaneous creation of semantic networks optimized under a given quantifiable fitness measure. *It is, to the best of our knowledge, the first instance in literature where semantic networks are created via an evolutionary optimization process, with specially developed structural variation operators respecting the semantics of commonsense relations.* For this reason, our algorithm is by its own accord a significantly novel contribution to the fields of semantic networks and graph-based EA.

We demonstrate our approach via a fitness function that uses analogical similarity as a success measure, in Chapter 6. This particular application is interesting from the perspective of research on analogical reasoning, because it enables the creation of novel analogous target cases to a given base case.

Furthermore, we envision the use of this algorithm as a novel open-ended generative adaptation technique for case-based reasoning, reinforcing the substitutional adaptation based on analogical inference that we use in the next part of the dissertation (Chapter 7).

We use the term "memetic" in a different technical sense from the existing algorithms classified as MA, and with an implication a lot closer to the meaning of the word as introduced by Dawkins.

We pose the algorithm that we develop for the adaptation of semantic networks as a novel type of memetic algorithm (MA). In this designation, we use the term "memetic" in a different technical sense from the existing algorithms classified as MA, and with an implication far more closer to the meaning of the word as introduced by Dawkins (1989) in his original work.

This is due to several reasons.

Within the existing field of MA, the approach is characterized by a synergy of population-based optimization and separate individual learning or local improvement procedures (Moscato, 1989; Moscato et al., 2004). We have already mentioned this in Chapter 3 and presented an algorithm outlining the progress of a typical MA (Algorithm 2).

From a biological perspective, this approach of memetics emphasizes the effect of society, culture, and learning on the survival of individuals on top of their physical traits emerging through genetic evolution. An example would be the use of knowledge and technology by the human species to survive in diverse environments, far beyond the physical capabilities available to them solely by the human body: The anatomic characteristics of the human body have been evolving as a member of the primate order of the mammals, with the *Homo sapiens* species being identifiable since at least approximately 200,000 years (Alemseged et al., 2002)[1], while developments such as writing, technology, and science—achieved through cultural evolution using virtually the same anatomical configuration—are only about 12,000 years old[2].

Similarly, in MA, one treats the effects of cultural evolution as a local refinement process for each individual, running on top of a global optimization that is population based. So, the emphasis is on the local refinement of each individual due to memetic evolutionary factors. In algorithmic terms, this results in a combination of population-based global search with a local search step run for each individual. Thus, *the only connection of the existing work in MA with the idea of "memetics" is using this word as a synonym for "local refinement of candidate solutions".*

In contrast, the emphasis in our approach is directly on the memetic evolution itself, given

1. it is the units of culture, or information (represented as semantic networks) that are undergoing variation, transmission, and selection, exactly in the original sense of memetics as it was introduced by Dawkins (1989);

2. we have variation operators developed specific for this knowledge representation-based approach, respecting the semantics and commonsensical correctness of the evolving structures; and

3. the whole process is guided by a fitness measure that is defined as a function of some selected set of features of the knowledge represented by each individual.

1 Modern *Homo sapiens* first appears in the fossil record in Africa approximately 195,000 years ago (McDougall et al., 2005). This record is corroborated by quantitative models of divergence in molecular biology pointing to a most recent common ancestor about 200,000 years ago (Stoneking and Soodyall, 1996).

2 The beginning of human civilization is generally associated with the Neolithic Revolution at the end of the last Ice Age, around 12,000 years ago (Barker, 2006)

Our algorithm, outlined in Algorithm 3, proceeds similar to conventional EA, with a relatively small set of parameters. The descriptions of initialization, selection, memetic variation, and fitness evaluation steps are presented in detail in the following sections. The parameters affecting each step of the algorithm, along with their explanations, are summarized in Table 7.

Algorithm 3 Procedure for the novel semantic network based memetic algorithm that we introduce. Refer to Table 7 for an overview of involved parameters.

procedure MEMETICALGORITHM
    $P(t = 0) \leftarrow$ INITIALIZEPOPULATION($Size_{pop}$, $Size_{network}$, $Score_{min}$, $Count_{timeout}$)
    repeat
        $\phi(t) \leftarrow$ EVALUATEFITNESSES($P(t)$)
        $N(t) \leftarrow$ NEXTGENERATION($P(t)$, $\phi(t)$, $Size_{pop}$, $Size_{tourn}$, $Prob_{win}$, $Prob_{rec}$, $Prob_{mut}$, $Score_{min}$, $Count_{timeout}$)
        $P(t+1) \leftarrow N(t)$
        $t \leftarrow t+1$
    until stop criterion
end procedure

5.1 COMMONSENSE REASONING

A foundational issue that comes with our approach is the problem of reconciling the intrinsically random nature of evolutionary operations with the requirement that the evolving semantic networks should be meaningful.

A foundational issue that comes with our approach is the problem of reconciling the intrinsically random nature of evolutionary operations with the requirement that the evolving semantic networks should be meaningful.

This is so because of the fact that, unlike existing graph-based EA approaches such as GP or GNP, not every node in a semantic network graph can be connected to an arbitrary other node through an arbitrary type of relation. This issue is relevant in every type of modification operation that needs to be executed during the course of our algorithm.

We address this problem by utilizing the nascent subfield of AI named *commonsense reasoning* (Davis and Morgenstern, 2004; Mueller, 2006; Havasi et al., 2007).

Commonsense reasoning refers to the type of reasoning involved in everyday human thinking, based on *commonsense knowledge* that an ordinary person is expected to know, or “the knowledge of how the world works” (Mueller, 2006).

Within AI, since the pioneering work by McCarthy (1958), commonsense reasoning has been commonly regarded as a key ability that a

Table 7: The typical parameter set used during experiments.

	Parameter	Interval	Explanation
Evolution	$Size_{pop}$	$[1, \infty)$	Number of individuals forming the population
	$Prob_{rec}$	$[0, 1]$	Probability of applying crossover operation
	$Prob_{mut}$	$[0, 1]$	Probability of applying mutation operation
Semantic networks	$Size_{network}$	$[1, \infty)$	Maximum size of randomly created semantic networks in the initial population
	$Score_{min}$	$[-10, 10]$	Minimum quality score of commonsense relations used throughout the algorithm
	$Count_{timeout}$	$[1, \infty)$	Timeout value for the number of trials in commonsense retrieval operations
Tournament selection	$Size_{tourn}$	$[1, Size_{pop}]$	Number of individuals randomly selected from the population for each tournament selection event
	$Prob_{win}$	$[0, 1]$	The probability that the best individual in the ranked list of tournament participants wins the tournament

system must possess in order to be considered truly intelligent (Minsky, 2006).

AI research has a long tradition of collecting and harnessing scientific theories or specialized knowledge in the solution of specific problems. In contrast, McCarthy (1990) gives three reasons for supporting the study of commonsense knowledge in addition to specialized, or scientific, knowledge:

- When developing and conveying a scientific theory, commonsense knowledge is used to decide what phenomena are to be studied and how the formal terms relate to the commonsense world. Commonsense knowledge is required to interpret science.

- Commonsense knowledge is required for solving problems in the real world, most importantly because of its role in identifying what facts are relevant to solving the problem at hand.

- Creating or thinking about meta theories of scientific knowledge requires insight stemming from commonsense knowledge.

Recent advances in commonsense reasoning include work on the connections of commonsense knowledge with natural language processing (Liu and Singh, 2004) and the automation of commonsense reasoning using event calculus (Mueller, 2009). Work is also underway with the creation of generic simulated environments where researchers can test their commonsense reasoner systems (Smith and Morgan, 2010).

There is an active effort to assemble and classify commonsense information involved in everyday human thinking into ontologies and present these to the use of scientific community in the form of commonsense knowledge bases, of which *Cyc*[3] maintained by the Cycorp company and the *ConceptNet* project[4] (Havasi et al., 2007) of Massachusetts Institute of Technology (MIT) Media Lab are the most prominent examples.

5.2 COMMONSENSE KNOWLEDGE BASES

5.2.1 *MIT ConceptNet*

The ConceptNet project is a part of the Open Mind Common Sense (OMCS) initiative of the MIT Media Lab, with a goal of building a large scale commonsense knowledge base through volunteer contributions.

3 http://www.cyc.com
4 http://csc.media.mit.edu/docs/conceptnet/

The OMCS system is based on the input of commonsense knowledge from the general public through several ways, including free-form natural language input that is subsequently parsed and semi-structured fill-in-the-blanks type of forms (Havasi et al., 2007). The data collected through this process are eventually extracted into a large scale semantic network forming the core of ConceptNet.

As of 2013, ConceptNet is in version 5[5] and, in addition to data collected in previous versions through OMCS, it has been extended to include other data sources such as the Wikipedia and Wiktionary projects of the Wikimedia Foundation[6] and the DBPedia project[7] of the University of Leipzig and the Freie Universität Berlin.

Access to the ConceptNet database is provided through a web API based on the JavaScript Object Notation (JSON) text based data interchange standard. The data forming ConceptNet is also available for download in JSON and comma separated value (CSV) formats.

In our implementation, we utilize the previous version of ConceptNet, version 4, due to performance reasons. This is because of the nature of our evolutionary algorithm making tens of thousands of queries to the commonsense knowledge base during the creation of random semantic networks and the application of variation operators. ConceptNet 4 provides the complete dataset in the locally accessible and highly efficient SQLite database format, which enables substantially faster access to the knowledge base compared with the web API or the textual formats of the current version.

ConceptNet version 4 provides us with approximately 566,000 assertions involving 322,000 concepts.

According to the study by Diochnos (2013), which provides a computational analysis of ConceptNet version 4, the knowledge base includes 566,094 assertions and 321,993 concepts. The assertions involving two concepts (such as `HasA(cat, tail)`) are constructed by a limited set of relation types that are specified beforehand (Table 8).

The variety of assertions in ConceptNet, initially contributed by volunteers from the general public, makes it somewhat prone to noise. According to our experience, the noise usually comes from contributions such as charged statements about political issues, biased views about gender issues, or attempts of making fun.

We address this problem by ignoring all assertions with a reliability score (determined by contributors' voting) below a set minimum $\mathtt{Score}_{\mathtt{min}}$ (Table 7). The default reliability score for a statement is 1 (Havasi et al., 2007) and zero or negative reliability scores are a good indication of information that can be considered noise.

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5 http://conceptnet5.media.mit.edu/
6 http://www.wikimedia.org/
7 http://dbpedia.org/

Table 8: The set of relation types used in ConceptNet version 4.

Name of relation	Meaning
IsA	What kind of thing is it?
HasA	What does it possess?
PartOf	What is it part of?
UsedFor	What do you use it for?
AtLocation	Where would you find it?
CapableOf	What can it do?
MadeOf	What is it made of?
CreatedBy	How do you bring it into existence?
HasSubevent	What do you do to accomplish it?
HasFirstSubevent	What do you do first to accomplish it?
HasLastSubevent	What do you do last to accomplish it?
HasPrerequisite	What do you need to do first?
MotivatedByGoal	Why would you do it?
Causes	What does it make happen?
Desires	What does it want?
CausesDesire	What does it make you want to do?
HasProperty	What properties does it have?
ReceivesAction	What can you do to it?
DefinedAs	How do you define it?
SymbolOf	What does it represent?
LocatedNear	What is it typically near?
ObstructedBy	What would prevent it from happening?
ConceptuallyRelatedTo	What is related to it in an unknown way?
InheritsFrom	(not stored, but used in some applications)

5.2.2 *WordNet*

The lexical database WordNet[8] (Fellbaum, 1998) maintained by the Cognitive Science Laboratory at Princeton University also has characteristics of a commonsense knowledge base.

Being one of the most widely used natural language resources (Havasi et al., 2007), the original purpose in the conceiving of WordNet was to produce a combination of a dictionary and thesaurus and to support AI applications involving text analysis. For this reason, WordNet is based on a grouping of words into *synsets* or *synonym rings* which hold together all elements that are considered semantically equivalent[9].

In addition to these synset groupings, WordNet includes *pointers* that are used to represent relations between the words in different synsets. These include semantic pointers that represent relations between word meanings and lexical pointers that represent relations between word forms. The types of available relation information include:

- For noun synsets:
  - *Hypernyms*: Y is a hypernym of X if every X is a kind of Y (*feline* is a hypernym of *cat*)
  - *Hyponyms*: Y is a hyponym of X is every Y is a kind of X (*cat* is a hyponym of *feline*)
  - *Coordinate terms*: Y is a coordinate term of X if they share a hypernym (*cat* and *tiger* are coordinate terms of each other)
  - *Holonyms*: Y is a holonym of X if X is a part of Y (*automobile* is a holonym of *wheel*)
  - *Meronyms*: Y is a meronym of X if Y is a part of X (*wheel* is a meronym of *automobile*)
- For verb synsets:
  - *Hypernym*: The verb Y is a hypernym of the verb X if the activity X is a kind of Y (*to move* is a hypernym of *to fly*)
  - *Troponym*: The verb Y is a troponym of the verb X if the activity Y is a doing X in some manner (*to nibble* is a troponym of *to eat*)
  - *Entailment*: The verb Y is entailed by X if by doing X you must be doing Y (*to sleep* is entailed by *to snore*)

8 http://wordnet.princeton.edu
9 Another definition of *synset* is that it is a set of synonyms that are interchangeable without changing the truth value of any propositions in which they are embedded.

Table 9: The set of correspondences between WordNet and ConceptNet relation types.

WordNet		ConceptNet	
Relation	Example	Relation	Example
Hypernym	*canine* is a hypernym of *dog*	`IsA`	`IsA(dog, canine)`
Holonym	*automobile* is a holonym of *wheel*	`PartOf`	`PartOf(wheel, automobile)`
Meronym	*wheel* is a meronym of *automobile*	`PartOf`	`PartOf(wheel, automobile)`
Attribute	*edible* is an attribute of *pear*	`HasProperty`	`HasProperty(pear, edible)`
Entailment	*to sleep* is entailed by *to snore*	`Causes`	`Causes(sleep, snore)`

  - *Coordinate terms*: Verbs sharing a common hypernym are coordinate terms (*to whisper* and *to shout* are coordinate terms of each other)

- For adjective synsets:
  - *Related nouns*
  - *Similar to*
  - *Participle of verb*
- For adverb synsets:
  - *Root adjectives*

For treating WordNet as a commonsense knowledge base compatible with ConceptNet, we utilize the set of correspondences we outline in Table 9. Similar approaches have also been used by other researchers in the field, such as by Kuo and Hsu (2010).

WordNet version 3 contributes approximately 117,000 synsets.

In the implementation of our algorithm, we answer the various types of queries to commonsense knowledge bases (such as the RandomConcept() call in Algorithm 5) via ConceptNet or WordNet on a random basis. When the query is answered by information retrieved from WordNet, we return the information formatted in ConceptNet structure based on the correspondences outlined in Table 9 and attach the maximum reliability score of 10, since the information in WordNet is provided by domain experts and virtually devoid of noise.

In our implementation we make use of WordNet version 3, contributing definitional relations involving around 117,000 synsets. Another thing to note here is that, in the next version of ConceptNet, version 5, the information in WordNet already constitutes one of the main data sources incorporated automatically into ConceptNet. For our implementation this means that, in case we switch from ConceptNet version 4 to version 5, our approach of accessing WordNet would be obsolete.

5.3 INITIALIZATION

At the start of a run, the population of size $\mathtt{Size}_{\mathtt{pop}}$ is initialized with individuals created by a specialized commonsense-aware algorithm that we developed for this purpose and we call *random semantic network generation* (Algorithm 4).

The random semantic network generation algorithm (Algorithm 5) is capable of assembling semantic networks of any given size, by starting from a network comprising only one concept randomly picked from commonsense knowledge bases and running a semantic network expansion algorithm that

1. randomly picks a concept in the given network (e.g. `human`);
2. compiles a list of relations, from commonsense knowledge bases, that the picked concept can be involved in (e.g. `CapableOf(human, think)`, `Desires(human, eat)`, $\cdots$);
3. appends to the network a relation randomly picked from this list, together with the other involved concept; and
4. repeats this process until a given number of concepts have been appended to the network, or a set timeout $\mathtt{Count}_{\mathtt{timeout}}$ has been reached (as a failsafe for situations where there are not enough relations involving the concepts in the network being created).

Networks generated through our random technique are still totally meaningful, because they are combinations of meaningful pieces of harvested information.

Figure 34 presents an example of a random semantic network created via this procedure. It is very important to note here that *even if it is grown in a random manner, the network itself is totally meaningful, because it is a combination of meaningful pieces of information harvested from commonsense knowledge bases*.

The initialization algorithm depends upon the parameters of $\mathtt{Size}_{\mathtt{network}}$, the intended number of concepts in the randomly created semantic networks, and $\mathtt{Score}_{\mathtt{min}}$, the minimum ConceptNet relation score that should be satisfied by the retrieved relations (Table 7).

Algorithm 4 Procedure for the creation procedure for the initial random population.

```
procedure InitializePopulation(Size_pop, Size_network, Score_min, Count_timeout)
    initialize P                                        ▷ The return array
    for Size_pop times do
        r ← RandomNetwork(Size_network, Score_min, Count_timeout)   ▷ Generate a new random network
        AppendTo(P, r)
    end for
    return P
end procedure
```

Algorithm 5 The random semantic network generation algorithm. The algorithm is presented here in a form simpler than the actual implementation, for the sake of clarity.

```
procedure RandomNetwork(Size_network, Score_min, Count_timeout)
    initialize net                                      ▷ Empty return network
    initialize c                                        ▷ Random initial seed concept
    for Count_timeout times do
        c ← RandomConcept(Score_min)
        rels ← InvolvedRelations(c)
        if Size(rels) ⩾ Size_network then
            AppendTo(net, c)
            break for                ▷ Favor a seed with more than a few relations
        end if
    end for
    t ← 0
    repeat
        c ← RandomConceptIn(net)
        rels ← InvolvedRelations(c)          ▷ The set of relations involving c
        r ← RandomRelationIn(rels)
        if Score(r) ⩾ Score_min then
            AppendTo(net, r)        ▷ Append to the network net the relation r and its involved concepts
        end if
        t ← t + 1
    until Size(net) ⩾ Size_network or t ⩾ Count_timeout
    return net
end procedure
```

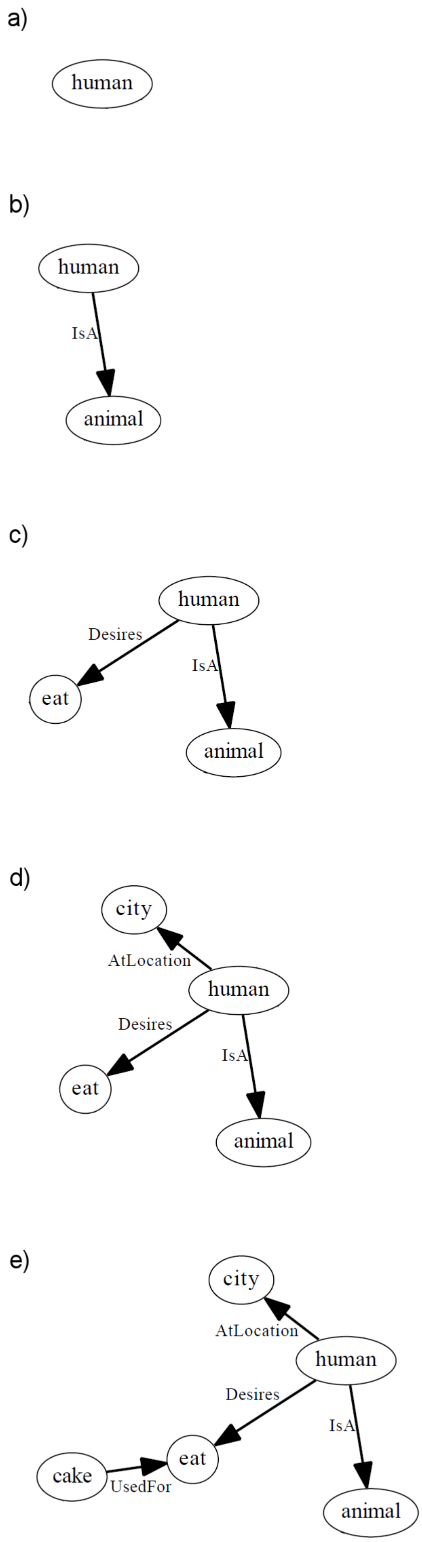


Figure 34: The process of random semantic network generation, starting with a single random concept in (a) and proceeding with (b), (c), (d), (e), adding new random concepts from the set of concepts related to existing ones.

5.4 FITNESS MEASURE

After the initial population of individuals are created by the random semantic network generation algorithm that we outlined in Section 5.3, the algorithm proceeds by assigning fitness values to each individual (Algorithm 6).

Algorithm 6 Procedure for assigning fitness values for every member of the population.

```
procedure EvaluateFitnesses(P(t))
    initialize ϕ                                    ▷ The return array
    for each individual i in P(t) do
        AppendTo(ϕ, Fitness(i))
    end for
    return ϕ
end procedure
```

The fitness measure defines the environment within which candidate solutions "live".

In analogy with the biological process of evolution, in evolutionary computation, the fitness measure basically defines the environment within which the individuals representing candidate solutions "live". Combined with a selection procedure where individuals with higher fitness are preferred over those with lower fitness, this has the effect of putting *evolutionary pressure* towards the solution of the problem at hand.

Since the evolving individuals in our approach represent pieces of knowledge, or memes, the fitness measure for evolutionary selection is defined as a function of the represented knowledge. The fitness measure can be formulated as a combination of any features of a semantic network that can be measured in a quantitative way. These can include graph-theoretical properties of semantic networks, such as the number of nodes or edges, shortest path length, or the clustering coefficient (Steyvers and Tenenbaum, 2005)

Due to the fact that our approach constitutes the first instance of computational implementation focused directly on the evolution of memes themselves, it also falls on us to introduce fitness measures of interest for its validation.

As an example for showcasing our approach, in Chapter 6 we define a fitness measure based on analogical similarity to an existing semantic network given as an input to the system. This, in effect, promotes the spontaneous generation of semantic networks that are in each generation more and more structurally analogous to a given network.

In general terms, a direct and very interesting application of our approach would be to devise computational experiments with realistically formed fitness functions modeling selectionist theories of knowledge, which remain untested until this time.

One such theory is the *evolutionary epistemology* theory of Campbell (Bickhard and Campbell, 2003), which describes the development of human knowledge and creativity through selectionist principles, such as the *blind variation and selective retention* (BVSR) principle.

Another interesting possibility is to make the inclusion of certain concepts in the evolving semantic networks a requirement, allowing the discovery of memes formed around a given set of seed concepts. This can be also achieved through starting the initialization procedure described in Section 5.3 (Algorithm 5) with the given concepts.

After all the individuals in the current generation are assigned fitness values, the algorithm proceeds with the creation of the next generation of individuals, by creating offspring through the application of variation operators (Algorithm 7). But before this, the algorithm has to apply a selection procedure to pick the individuals from the current population that will be "surviving", based on their fitness values, to produce offspring.

Algorithm 7 Procedure for the creation of the next generation of individuals.

procedure NEXTGENERATION($P(t)$, $\phi(t)$, $Size_{pop}$, $Size_{tourn}$, $Prob_{win}$, $Prob_{rec}$, $Prob_{mut}$, $Score_{min}$, $Count_{timeout}$)
  initialize N ▷ The return array
  $c \leftarrow Size_{pop} Prob_{rec}/2$ ▷ Number of crossover events
  $r \leftarrow Size_{pop} - 2c$ ▷ Number of reproduction events
  for c times **do**
    $p1 \leftarrow$ SELECT($P(t)$, $\phi(t)$, $Size_{tourn}$, $Prob_{win}$)
    $p2 \leftarrow$ SELECT($P(t)$, $\phi(t)$, $Size_{tourn}$, $Prob_{win}$)
    $o1, o2 \leftarrow$ CROSSOVER($p1$, $p2$) ▷ Crossover the two parents
    APPENDTO(N, o1) ▷ Two offspring from each crossover
    APPENDTO(N, o2)
  end for
  for $r - 1$ times **do**
    $m \leftarrow$ SELECT($P(t)$, $\phi(t)$, $Size_{tourn}$, $Prob_{win}$)
    $m \leftarrow$ MUTATE(m, $Prob_{mut}$) ▷ Mutate an individual
    APPENDTO(N, m)
  end for
  APPENDTO(N, BESTINDIVIDUAL($P(t)$, $\phi(t)$)) ▷ Elitism
  return N
end procedure

5.5 SELECTION

After the assignment of a fitness value to each individual in the current generation (Section 5.4), all individuals in the population are replaced with offspring generated via variation operators applied on selected parents.

In any evolutionary approach, parents are probabilistically selected from the population according to their fitness. The progression of the evolutionary process under fitness pressure is realized by favoring the survival and reproduction of individuals with higher fitness.

There are various selection schemes employed in conventional EA, including techniques such as rank selection, steady state selection, and Boltzmann selection. A highly used selection scheme is the so called *roulette wheel selection* method, where the individuals are assigned slices of a "roulette wheel" proportional to their share of fitness in the total fitness of the population. A random "spin" of this roulette wheel then gives each individual a chance of being picked in proportion to its fitness value (Blickle and Thiele, 1996).

In our algorithm we employ the tournament selection scheme.

In our algorithm we employ another commonly encountered selection scheme, *tournament selection* (Blickle, 2000). We make this choice because it is better at preserving population diversity[10] and allows the selection pressure to be easily adjusted through simple parameters (Pohlheim, 2006).

Tournament selection involves, for each selection event, running "tournaments" among a group of $\mathrm{Size}_{\mathrm{tourn}}$ individuals randomly selected from the population (Figure 35). The individuals in this tournament pool then challenge each other in groups of two, where the individual with the higher fitness will win with probability $\mathrm{Prob}_{\mathrm{win}}$. This method, in effect, simulates biological mating patterns in which two members of the same sex compete to mate with a third one of a different sex for the recombination of genetic material.

Algorithm 8 gives an overview of the tournament selection procedure that we use in our implementation.

Under this selection scheme, while individuals with higher fitness have better chance of being selected, an individual with low fitness still has a chance, however small, to produce offspring. Adjusting the parameters $\mathrm{Size}_{\mathrm{tourn}}$ and $\mathrm{Prob}_{\mathrm{win}}$ (Table 7) gives one an intuitive and straightforward way to adjust the selection pressure on both strong and weak individuals.

10 *Diversity*, in EA, is a measure of homogeneity of the individuals in the population. A drop in diversity means that there is an increase in the number of identical individuals in the population, which is not desirable for the progress of evolution.

Algorithm 8 The tournament selection algorithm for the selection of individuals from the current generation.

procedure SELECT($P(t)$, $\phi(t)$, $\mathrm{Size}_{\mathrm{tourn}}$, $\mathrm{Prob}_{\mathrm{win}}$)
  $w \leftarrow$ RANDOMMEMBER($P(t)$) ▷ Current winner
  for $\mathrm{Size}_{\mathrm{tourn}} - 1$ times **do**
    $o \leftarrow$ RANDOMMEMBER($P(t)$) ▷ The next opponent
    if LOOKUPFITNESS($\phi(t)$, o) $\geqslant$ LOOKUPFITNESS($\phi(t)$, w) **then**
      if RANDOMREAL(0, 1) $\leqslant \mathrm{Prob}_{\mathrm{win}}$ **then**
        $w \leftarrow o$ ▷ Opponent defeats current winner
      end if
    end if
  end for
  return w
end procedure

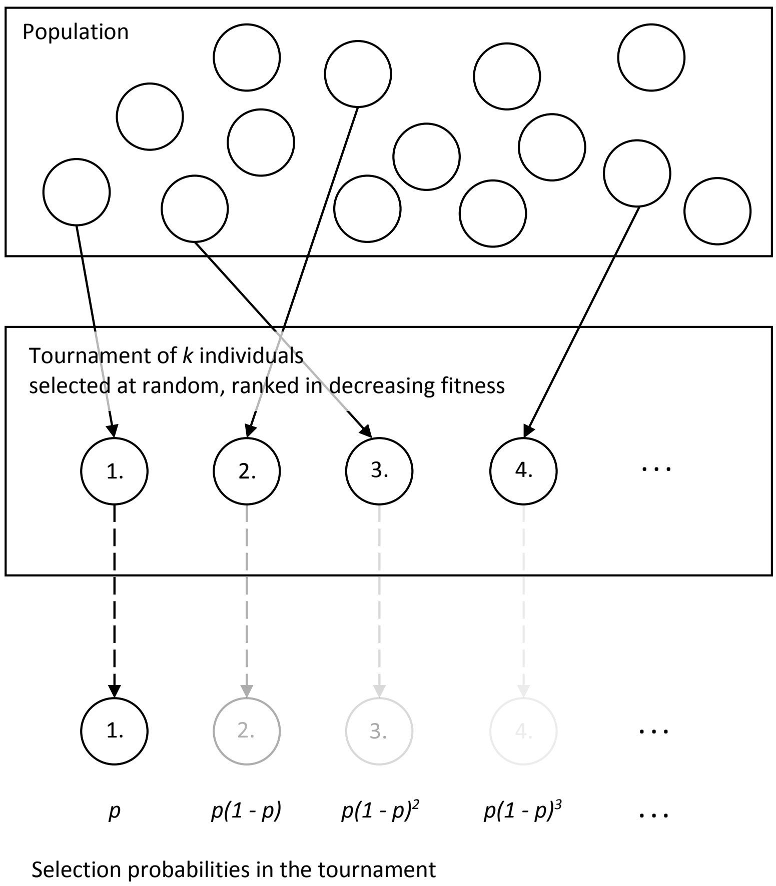


Figure 35: The tournament selection process.

In our implementation, we also allow reselection, meaning that the same individual from a particular generation can be selected more than once to produce offspring in different combinations.

5.6 memetic variation operators

Variation operators form the last step in the cycle of our algorithm by creating the next generation of individuals before going back to the step of fitness evaluation (Algorithm 3).

In contrast with existing graph-based evolutionary approaches such as GP, PDGP, and GNP that we have discussed in Chapter 3, our representation does not permit arbitrary connections between different nodes in the network and requires special variation operators that should respect the commonsense structure of the represented knowledge.

This means that any variation operation on the individuals should:

1. preserve the structure of the modified network within boundaries set by commonsense knowledge; and
2. ensure that even the nodes and edges randomly introduced into a semantic network connect to existing ones through *meaningful* relations.

Here we present the *commonsense crossover* and *commonsense mutation* operators that we set up specific to semantic networks.

Using these variation operators, the next step in the cycle of our algorithm is the creation of the offspring through these operators (Algorithm 7). Crossover is applied to parents selected from the population until $\mathtt{Size}_{\mathtt{pop}} \times \mathtt{Prob}_{\mathtt{rec}}$ offspring are created (Table 7), where each crossover event creates two offspring from two parents.

Following the tradition in the GP field (Koza et al., 2003), we design the variation process such that the offspring created by crossover do not undergo mutation. The mutation operator is applied only to the rest of individuals that are copied, or "reproduced", directly from the previous generation.

For generating the remaining part of the population, we reproduce $\mathtt{Size}_{\mathtt{pop}} \times (1 - \mathtt{Prob}_{\mathtt{rec}}) - 1$ number of individuals selected, and make these subject to mutation. The last individual (hence the remaining -1 in the previous equation) is created by reproducing the individual with the current best fitness, without any modifications. This practice is called "elitism" in EA literature, and makes the best fitness value in each generation a monotonically increasing function of time.

5.6.1 *Commonsense Crossover*

In classical EA, features representing individuals are commonly encoded as linear strings and the crossover operation simulating genetic recombination is simply defined as a cutting and merging of this one dimensional object from two parents; and in graph-based approaches such as GP, subgraphs can be freely exchanged between parent graphs (Pereira et al., 1999; Koza et al., 2003; Montes and Wyatt, 2004).

Here, as mentioned, the requirement that a semantic network has to make sense imposes significant constraints on the nature of recombination.

We introduce two types of commonsense crossover that are tried in sequence.

To address this, we introduce two types of *commonsense crossover* that are tried in sequence by the variation algorithm.

The first type attempts a sub-graph interchange between two selected parents similar to common crossover in standard GP; and where this is not feasible due to the commonsense structure of relations forming the parents, the second type falls back to a combination of both parents into a new offspring.

5.6.1.1 *Type I Crossover (Subgraph Crossover)*

Firstly, a pair of concepts, one from each parent, that are *interchangeable*[11] are selected as *crossover concepts*, picked randomly out of all possible such pairs.

For instance, for the parent networks in Figure 36 and Figure 37, `bird` and `airplane` are interchangeable, since they can replace each other in the relations `CapableOf(·, fly)` and `AtLocation(·, air)`.

In each parent, a subgraph is formed, containing:

1. the crossover concept;
2. the set of all relations, and associated concepts, that are not common with the other crossover concept

   For example, in Figure 36, `HasA(bird, feather)` and `AtLocation(bird, forest)`; and in Figure 37, `HasA(airplane, propeller)`, `MadeOf(airplane, metal)`, and `UsedFor(airplane, travel)`; and
3. the set of all relations and concepts connected to those found in the previous step, excluding the ones that are also one of those common with the other crossover concept.

11 We define two concepts from different semantic networks as *interchangeable* if both can replace the other in all, or part, of the relations the other is involved in, queried from commonsense knowledge bases.

For example, in Figure 36 including `PartOf(feather, wing)` and `PartOf(tree, forest)`; and in Figure 37, including `MadeOf(propeller, metal)`); but excluding the concept `fly` in Figure 36, because of the relation `CapableOf(·, fly)`.

This, in effect, forms a subgraph of information specific to the crossover concept, which is insertable into the other parent. Any relations between the subgraph and the rest of the network not going through the crossover concept are severed (e.g. `UsedFor(wing, fly)` in Figure 36).

The two offspring are formed by exchanging these subgraphs between the parent networks (Figure 38 and Figure 39).

5.6.1.2 *Type II Crossover (Graph Merging Crossover)*

Given two parent networks, such as Figure 40 and Figure 41, where no interchangeable concepts between these two can be located, the system falls back to the simpler type II crossover.

A concept from each parent that is *attachable*[12] to the other parent is selected as a *crossover concept*.

The two parents are merged into an offspring by attaching a concept in one parent to another concept in the other parent, picked randomly out of all possible attachments (`CreatedBy(art, human)` in Figure 42. Another possibility is `Desires(human, joy)`.). The second offspring is formed randomly in the same way. In the case that no attachable concepts are found, the parents are merged as two separate clusters within the same individual.

5.6.2 *Commonsense Mutation*

We introduce several types of commonsense mutation operators employing commonsense knowledge bases.

We introduce several types of *commonsense mutation* operators that modify a parent by means of information from commonsense knowledge bases.

For each mutation to be performed, the type is picked at random with uniform probability. If the selected type of mutation is not feasible due to the commonsense structure of the parent, another type is again picked. In the case that a set timeout of $\mathrm{Count}_{\mathrm{timeout}}$ trials has been reached without any operation, the parent is returned as it is.

12 We define a distinct concept as *attachable* to a semantic network if at least one commonsense relation connecting the concept to any of the concepts in the network can be discovered from commonsense knowledge bases.

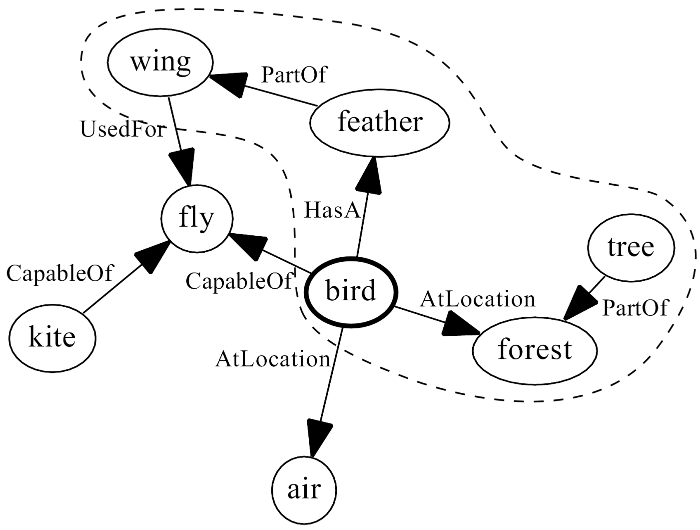


Figure 36: Commonsense crossover type I (subgraph crossover). Parent 1, centered on the concept `bird`.

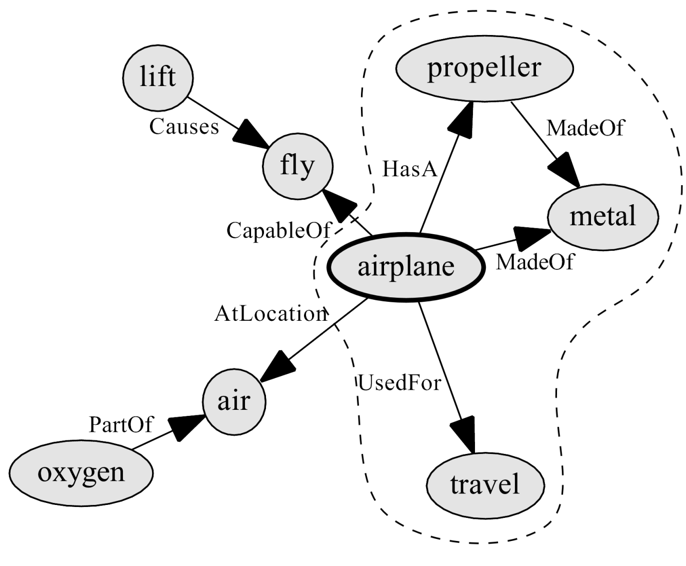


Figure 37: Commonsense crossover type I (subgraph crossover). Parent 2, centered on the concept `airplane`.

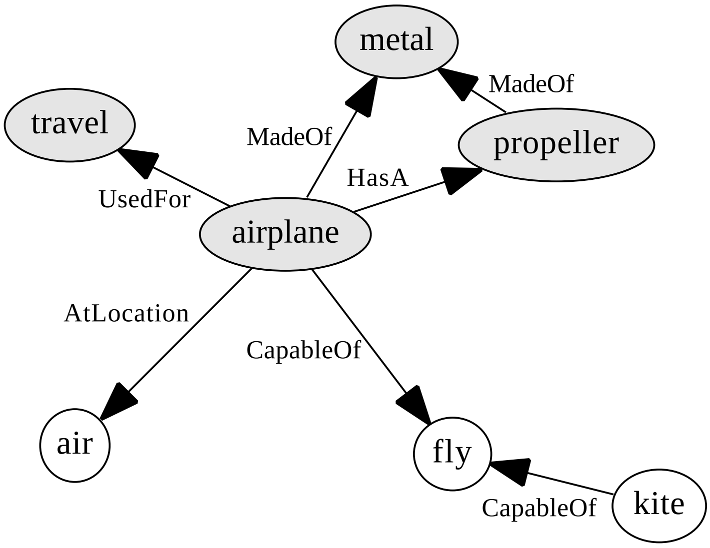


Figure 38: Commonsense crossover type I (subgraph crossover). Offspring 1.

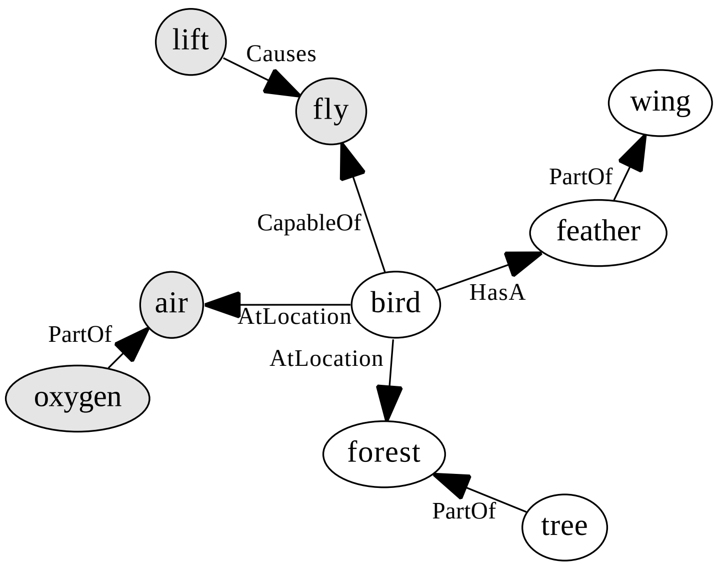


Figure 39: Commonsense crossover type I (subgraph crossover). Offspring 2.

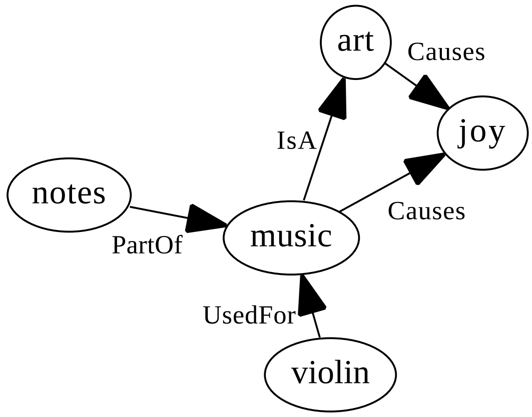


Figure 40: Commonsense crossover type II (graph merging crossover). Parent 1.

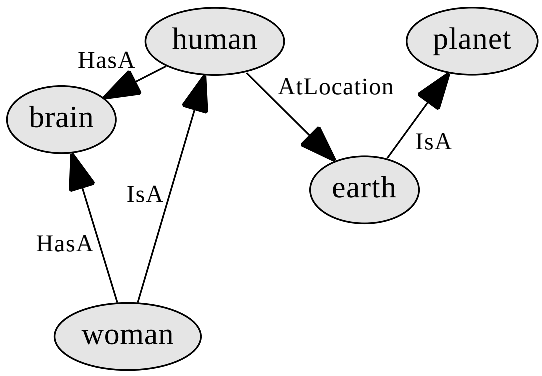


Figure 41: Commonsense crossover type II (graph merging crossover). Parent 2.

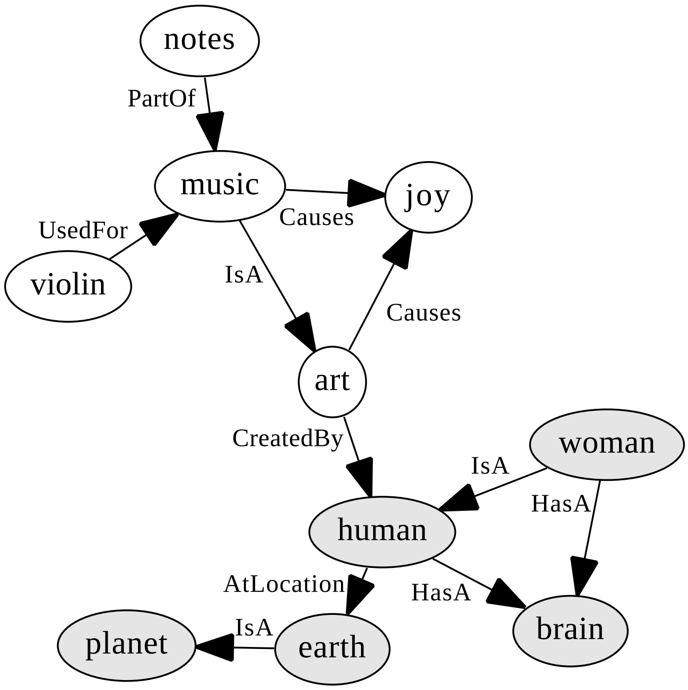


Figure 42: Commonsense crossover type II (graph merging crossover). Offspring, merging by the relation `CreatedBy(art, human)`. If no concepts attachable through commonsense relations are encountered, the offspring is formed by merging the parent networks as two separate clusters within the same semantic network.

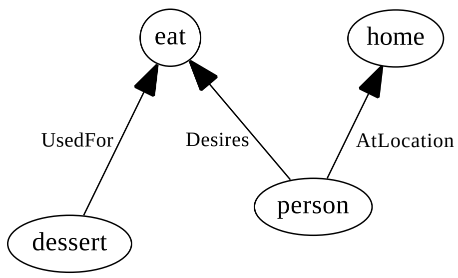


Figure 43: Example illustrating commonsense mutation type I (before).

5.6.2.1 *Type I (Concept Attachment)*

A new concept randomly picked from the set of concepts *attachable* to the parent is attached through a new relation to one of existing concepts (Figure 43 and Figure 44).

5.6.2.2 *Type IIa (Relation Addition)*

A new relation connecting two existing concepts in the parent is added, possibly connecting unconnected clusters within the same network (Figure 45 and Figure 46).

5.6.2.3 *Type IIb (Relation Deletion)*

A randomly picked relation in the parent is deleted, possibly leaving unconnected clusters within the same network (Figure 47 and Figure 48).

5.6.2.4 *Type IIIa (Concept Addition)*

A randomly picked new concept is added to the parent as a new cluster (Figure 49 and Figure 50).

5.6.2.5 *Type IIIb (Concept Deletion)*

A randomly picked concept is deleted with all the relations it is involved in, possibly leaving unconnected clusters within the same network (Figure 51 and Figure 52).

5.6.2.6 *Type IV (Concept Replacement)*

A concept in the parent, randomly picked from the set of those with at least one *interchangeable* concept, is replaced with one of its interchangeable concepts, again randomly picked. Any relations left unsatisfied by the new concept are deleted (Figure 53 and Figure 54).

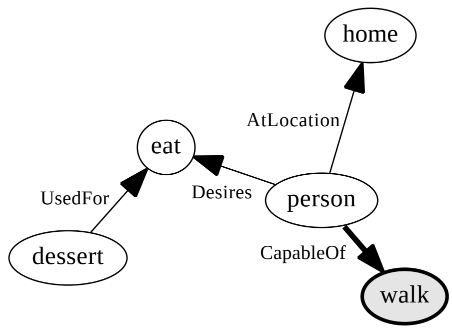


Figure 44: Example illustrating commonsense mutation type I (after).

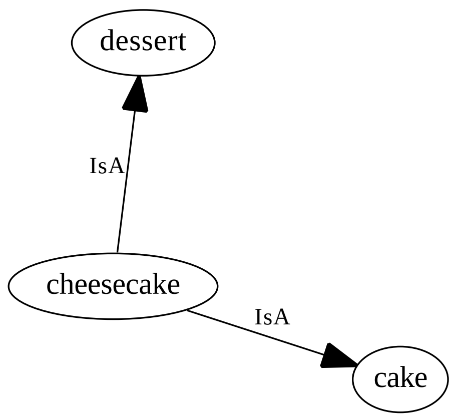


Figure 45: Example illustrating commonsense mutation type IIa (before).

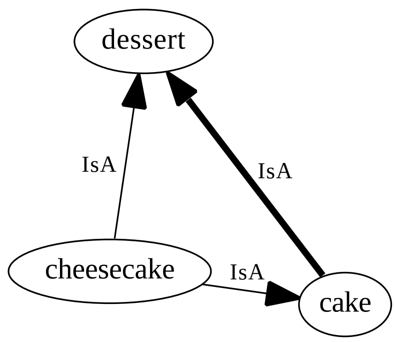


Figure 46: Example illustrating commonsense mutation type IIa (after).

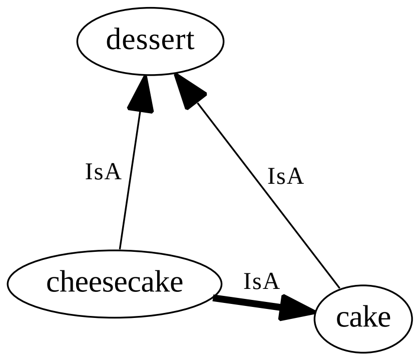


Figure 47: Example illustrating commonsense mutation type IIb (before).

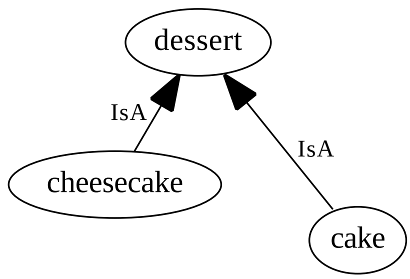


Figure 48: Example illustrating commonsense mutation type IIb (after).

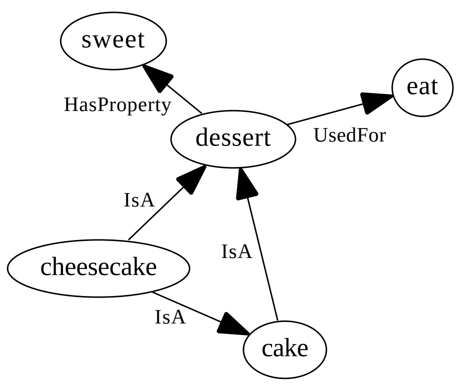


Figure 49: Example illustrating commonsense mutation type IIIa (before).

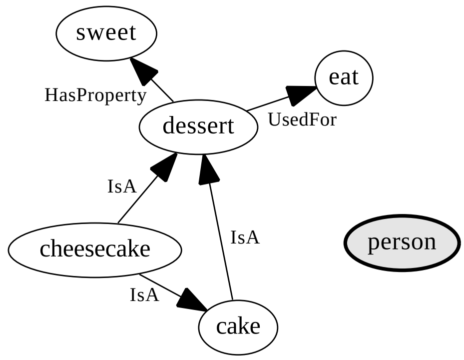


Figure 50: Example illustrating commonsense mutation type IIIa (after).

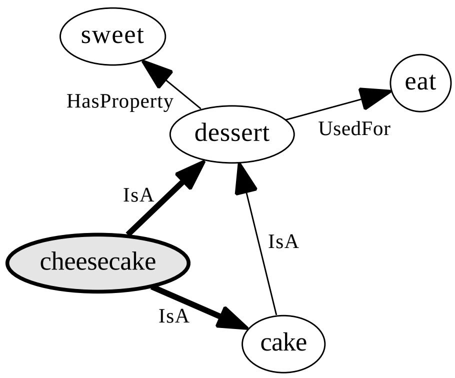


Figure 51: Example illustrating commonsense mutation type IIIb (before).

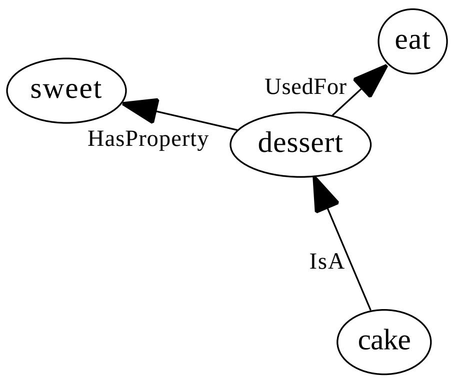


Figure 52: Example illustrating commonsense mutation type IIIb (after).

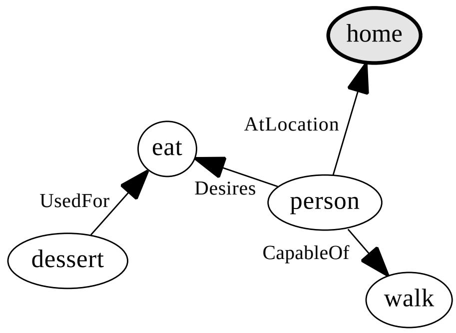


Figure 53: Example illustrating commonsense mutation type IV (before).

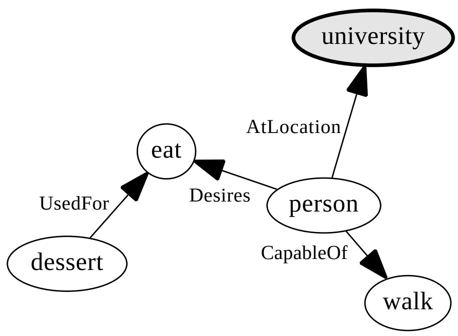


Figure 54: Example illustrating commonsense mutation type IV (after).

6

AUTOMATED GENERATION OF ANALOGIES

"I used to be crustacean
In an underwater nation
And I surf in celebration
Of a billion adaptations"

— Eddie Vedder (2006)

In this chapter we demonstrate our method for the adaptation of semantic networks, with a memetic fitness measure defined based on analogical similarity.

This fitness measure constitutes an interesting and practical choice for evaluating our work, because it not only validates the viability of the novel technique that we introduce, but also produces results highly valuable and interesting for the fields of analogical reasoning and computational creativity. This demonstrates one of the key contributions in this dissertation.

To evaluate our approach, we first introduce the fitness measure based on structure mapping. The rest of the chapter then summarizes our choice of parameters and results from experiments.

6.1 ANALOGY AS A FITNESS MEASURE

Within the field of analogical reasoning, mainly following the interpretation of Gentner (1983, 1989), the analogy-making process is typically analyzed as a combination of several processes.

It has been suggested by Hall (1989) and supported by others such as Novick and Holyoak (1991) that analogical reasoning essentially comprises four main abstract processes:

1. *retrieval*, or recognition of a source, given a target description;
2. *mapping* between the source and target;
3. *elaboration* and evaluation of the mapping; and
4. *consolidation*, or learning, of the outcome.

Other researchers (Chalmers et al., 1992) have suggested that one should also include the process of *representation building* within this list. It has been also demonstrated that these subprocesses do not need to be operating in a linear order, and occur in a dynamic and interconnected nature (Eskridge, 1994).

Returning to the Solar System–atom analogy example (Figure 10) of Chapter 2, presented with the problem of producing a better understanding of the structure of an atom, one might *retrieve* the Solar System model and devise several *mappings* between the Solar System and atom domains. These mappings would then need to be *elaborated upon* and adapted to the current case. If, this process yields a better understanding of the problem at hand, one might *consolidate* the structural similarities uncovered by the mapping as generalized knowledge.

It would be also relevant here to note that this mentioned view of analogy-making, comprising the processes of retrieval, mapping, elaboration, and consolidation, form the basis of the case-based reasoning (CBR) paradigm that we have reviewed in Chapter 2 (Figure 19), corresponding roughly to the stages of *retrieval*, *reusing*, *revision*, and *retaining*.

Computational approaches within the analogical reasoning field have been so far mostly concerned with the mapping problem.

In contrast with the research in CBR that has been focused more on the retrieval part of the process compared with the adaptation part, the computational approaches within the analogical reasoning field have been mostly concerned with the *mapping* problem (French, 2002). Put in a different way, models developed and implemented are focused on constructing mappings between two given source and target domains (Figure 55 (a)). This focus neglects the problem of retrieval or recognition of a new source domain, given a target domain, or the other way round.

By combining our algorithm for the evolution of semantic networks with a fitness measure based on analogical similarity, we can essentially produce a method to address this creativity-related subproblem of analogical reasoning, which has remained, so far, virtually untouched.

We accomplish this by:

1. providing our evolutionary algorithm with a "reference" semantic network that will represent the input to the system; and

2. running the evolutionary process under a fitness function which is basically the *structural evaluation score* from SME, that is, a quantitative measure of analogical similarity to the given "reference" network

This, in effect, creates a "survival of the fittest analogies" process where, starting from a random initial population of semantic networks, one gets semantic networks that get gradually more analogous to the given reference network.

Algorithm 9 The procedure for the computation of SME-based fitness measure.

```
procedure Fitness(i, network_reference)
    initialize totalscore                          ▷ The return value
    base ← net_reference                           ▷ Reference network
    target ← i                                     ▷ Current network
    analogies ← SME(base, target)
    totalscore ← 0
    for each analogy in analogies do
        totalscore ← totalscore+ Score(analogy)
    end for
    return totalscore  ▷ Sum of structural evaluation scores of all possible analogies
end procedure
```

In our implementation, we define the fitness measure to take the reference semantic network as the *base* and the individual whose fitness is just being evaluated as the *target* (Algorithm 9). In other terms, this means that the system produces structurally analogous target networks for a given base network. From a computational creativity perspective, an interpretation for this would be the "imagining", or creation, of a novel case that is analogous to a case at hand.

This designation of the base and target roles for the two networks is an arbitrary choice, and it is straightforward to define the fitness function in the other direction. So, if the system would be set up such that it would produce base networks, given the target network, one can then interpret this as the the classical retrieval process in analogical reasoning, where one is supposed to retrieve a base case that is analogous to the currently encountered case, for using it as a basis for solution.

If one subscribes to the "retrieval of a base case" interpretation, since the ultimate source of all the information underlying the generated networks is the commonsense knowledge bases, one can treat this source of knowledge as a part of the system's memory, and see it as a "generic case base" from which the base cases are retrieved.

On the other hand, if we consider the "imagination of a novel case" interpretation, our system, in fact, replicates a mode of behavior observed in psychology research where an analogy is not always simply "recognized" between an original case and a retrieved analogous case from memory, but the analogous case can sometimes be created together with the analogy (Clement, 1988).

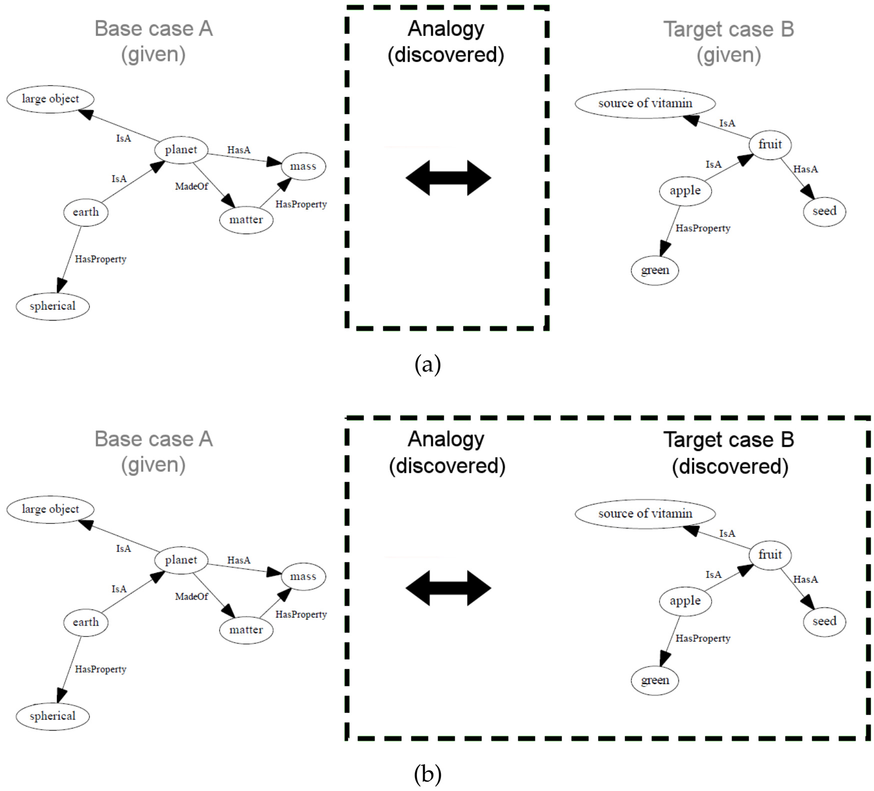


Figure 55: Contribution to computational analogy-making. (a) Existing work in the field, restricted to finding analogical mappings between a given pair of domains (b) Our novel approach, capable of creating novel analogies as well as the analogous case itself.

The approach that we present here is capable of creating, in addition to the analogical mapping, a novel analogous case itself (Figure 55 (b)). Considering the depth of commonsense knowledge sources, this creation process is virtually open-ended; and due to the random nature of the evolutionary optimization algorithm that we employ, it produces different analogous cases in each run of the algorithm.

The capability of open-ended creation of novel analogies makes our approach valuable for analogical reasoning and computational creativity.

This capability of open-ended creation of novel analogous cases is, to our knowledge, the first of its kind and makes our approach highly significant for the analogical reasoning and computational creativity fields.

For the computation of fitness scores, we make use of our own implementation of SME (Chapter 7) based on the original description by Falkenhainer et al. (1989) and adapt it to the concept–relation structure of semantic networks, as already outlined in Chapter 4.

6.2 EXPERIMENTATION WITH EXAMPLE CASES

With the implementation of analogical similarity-based fitness measure that we described so far, we carried out numerous experiments with reference networks representing different domains.

In this part, we present the results from two such experiments that we deem interesting because of the quality of solutions from a structural similarity perspective. These results also demonstrate the inherent ability of the approach to exhibit computational creativity, delivering analogous cases that can be considered inventive and surprising.

Table 7 provides an overview of the parameter values that we used for conducting the experiments we present here, the roles of which in the evolutionary algorithm we had explained in Chapter 5.

The role of crossover and mutation operators and the selection of their probabilities for a particular application are have been a traditional subject of debate in EA literature (Spears, 1992; Srinivas and Patnaik, 1994). This has been due to the fact that the roles of these variation operators have not been proven on a theoretically sound basis, excluding the original effort by Holland (1975) for analyzing genetic algorithms (GA) through the *schema theorem*[1].

Since the foundation of the field, in essence, the debate has been mainly centered on the relative importance of the crossover and mutation operators in the progress of evolution. It has been the case that in the approaches of evolutionary programming (EP) (F. et al., 1966) and evolution strategies (ES) (Rechenberg, 1973) mutation has been considered the key genetic operator and the driving force of the optimization process, while researchers following the GA tradition consider that crossover is the more powerful of the two operators.

For selection of parameters, we follow the established consensus in the graph-based EA field led by GP.

For our approach, we make the decision to follow the somewhat established consensus in the graph-based EA field (Pereira et al., 1999), dominated by genetic programming (GP) and the selection of parameters by the pioneering work of Koza.

Thus, we use a crossover probability of $\mathtt{Prob}_{\mathtt{rec}} = 0.85$, similar to the high crossover probabilities typically $\geqslant 0.9$ encountered in GP literature (Koza et al., 2003).

However, unlike the typical GP mutation value of $\leqslant 0.1$, we employ a somewhat-above-average mutation rate of $\mathtt{Prob}_{\mathtt{mut}} = 0.15$.

Due to the fact that our algorithm is the first attempt at having a graph-based computational simulation of memetics, this mutation rate is somewhat arbitrary and is dependent on our subjective interpretation of the mutation events in memetic processes. Nonetheless,

1 In short, the *schema theorem* is an analytical proof that, during the run of a classical genetic algorithm with a string based representation, low-order schemata with above-average fitness will eventually dominate and increase in successive generations.

Table 10: The parameter set used during experiments. Refer to Table 7 for an explanation of the parameters.

	Parameter	Value
Evolution	$\mathsf{Size}_{\mathsf{pop}}$	200
	$\mathsf{Prob}_{\mathsf{rec}}$	0.85
	$\mathsf{Prob}_{\mathsf{mut}}$	0.15
Semantic networks	$\mathsf{Size}_{\mathsf{network}}$	5
	$\mathsf{Score}_{\mathsf{min}}$	2
	$\mathsf{Count}_{\mathsf{timeout}}$	10
Tournament selection	$\mathsf{Size}_{\mathsf{tourn}}$	8
	$\mathsf{Prob}_{\mathsf{win}}$	0.8

we have certain preliminary support for a high mutation rate from the theory of memetics, where it has been postulated, for example by Gil-White (2008), that memes would have a high tendency of mutation.

We select a population size of $\mathsf{Size}_{\mathsf{pop}} = 200$ individuals, and subject this population to tournament selection with a tournament size of $\mathsf{Size}_{\mathsf{tourn}} = 8$ and a winning probability $\mathsf{Prob}_{\mathsf{win}} = 0.8$.

Using this parameter set, here we present the results from two runs of experiment:

1. analogies generated for a network describing some basic astronomical knowledge, shown in Figure 56; and

2. analogies generated for a network describing familial relations, shown in Figure 58.

For the first reference base network (Figure 56), after a run of the algorithm for 35 generations, the system produced the target network shown in Figure 57.

The produced target network exhibits an almost one-to-one structural correspondence with the reference network, missing only one node (`mass` in the original network) and two relations both pertaining to this missing node (`HasA(planet, mass)` and `HasProperty(matter, mass)`). The discovered analogy is remarkably inventive, and draws a parallel between the Earth and an apple: Just as the Earth is like an apple, planets are like fruits and the solar system is like a tree holding these fruits. Just as the solar system is a part of the universe, a tree is a part of a forest.

It is an intuitive analogy and leaves us with the impression that it is comparable with the classic analogy between the atom and the Solar

System (Figure 10) that we mentioned in Chapter 2. Table 11 gives a full list of all the correspondences.

For the second reference network (Figure 58), in a run after 42 generations, our algorithm produced the network shown in Figure 59.

The produced analogy can be again considered "creative", drawing a parallel between human beings and musical instruments. It considers a mother as a clarinet and a father as a drum; and just as a mother is a woman and a father a man, a clarinet is an instance of wind instrument and a drum is an instance of percussion instrument. The rest of the correspondences also follow in a somewhat intuitive way. Again, Table 12 gives a list of correspondences.

During our experiments, we observed that under the selected parameter set, the evolutionary process approaches equilibrium conditions after approximately 50 generations. This behavior is typical and expected in EA approaches and manifests itself with an initial exponential or logarithmic growth in fitness that asymptotically approaches a fitness plateau, after which fitness increasing events will be sporadic and negligible.

Figure 60 shows the progression of the average fitness of the population and the fitness of the best individual for each passing generation, during the course of one of our experiments with the reference network in Figure 56, which lasted for 50 generations. We observe that the evolution process asymptotically reaches a fitness plateau after about 40 generations.

Coinciding with the progression of fitness values, we observe, in Figure 61, the sizes of individual semantic networks both for the best individual and as a population average. Just as in the fitness values, there is a pronounced stabilization of the network size for the best individual in the population, occurring around the 40th generation. While the value stabilizes for the best individual, the population average for the network size keeps a trend of (gradually slowing) increase.

Our interpretation of this phenomenon is that, once the size of the best network becomes comparable with the size of the given reference network (Figure 56, comprising 10 concepts and 11 relations) and the analogies considered by the SME algorithm have already reached a certain quality, further increases in the network size would not cause substantial improvement on the SME structural evaluation score. This is because the analogical mapping from the reference semantic network to the current best individual is already highly optimized and very close to the ideal case of a structurally one-to-one mapping (cf. Figure 56, 10 concepts, 11 relations, and Figure 57, 9 concepts, 9 relations).

In general, our experiments demonstrate that, combined with the SME-based fitness measure, the algorithm we developed is capable of

Table 11: Experiment 1: Correspondences between the base and target networks, after 35 generations.

Base	Target
Concepts	
`earth`	`apple`
`moon`	`leave`
`planet`	`fruit`
`solar system`	`tree`
`galaxy`	`forest`
`universe`	`forest`
`spherical`	`green`
`matter`	(N/A)
`mass`	`seed`
`large object`	`source of vitamin`
Relations	
`HasA(earth, moon)`	`HasA(apple, leave)`
`HasProperty(earth, spherical)`	`HasProperty(apple, green)`
`HasProperty(moon, spherical)`	`HasProperty(leave, green)`
`IsA(earth, planet)`	`IsA(apple, fruit)`
`IsA(planet, large object)`	`IsA(fruit, source of vitamin)`
`AtLocation(planet, solar system)`	`AtLocation(fruit, tree)`
`AtLocation(solar system, galaxy)`	`AtLocation(tree, mountain)`
`PartOf(solar system, universe)`	`PartOf(tree, forest)`
`MadeOf(planet, matter)`	(N/A)
`HasA(planet, mass)`	`HasA(fruit, seed)`
`HasProperty(matter, mass)`	(N/A)

Table 12: Experiment 2: Correspondences between the base and target networks, after 42 generations.

Base	Target
Concepts	
mother	clarinet
father	drum
woman	wind instrument
man	percussion instrument
human	instrument
home	music hall
care	perform glissando
family	(N/A)
sleep	make music
dream	play instrument
female	member of orchestra
Relations	
IsA(mother, woman)	IsA(clarinet, wind instrument)
IsA(father, man)	IsA(drum, percussion instrument)
IsA(woman, human)	IsA(wind instrument, instrument)
AtLocation(human, home)	AtLocation(instrument, music hall)
IsA(man, human)	IsA(percussion instrument, instrument)
PartOf(mother, family)	(N/A)
PartOf(father, family)	(N/A)
CapableOf(mother, care)	CapableOf(clarinet, perform glissando)
CapableOf(human, sleep)	CapableOf(instrument, make music)
HasSubevent(sleep, dream)	HasSubevent(make music, play instrument)
IsA(woman, female)	IsA(wind instrument, member of orchestra)

spontaneously creating collections of semantic networks analogous to the one given as a reference. In most cases, our implementation was able to reach extensive analogies within 50 generations and reasonable computational resources, where a typical run of experiment took around 45 minutes on a mid-range laptop computer with AMD Athlon II 2.2 GHz processor and 8 GB of RAM.

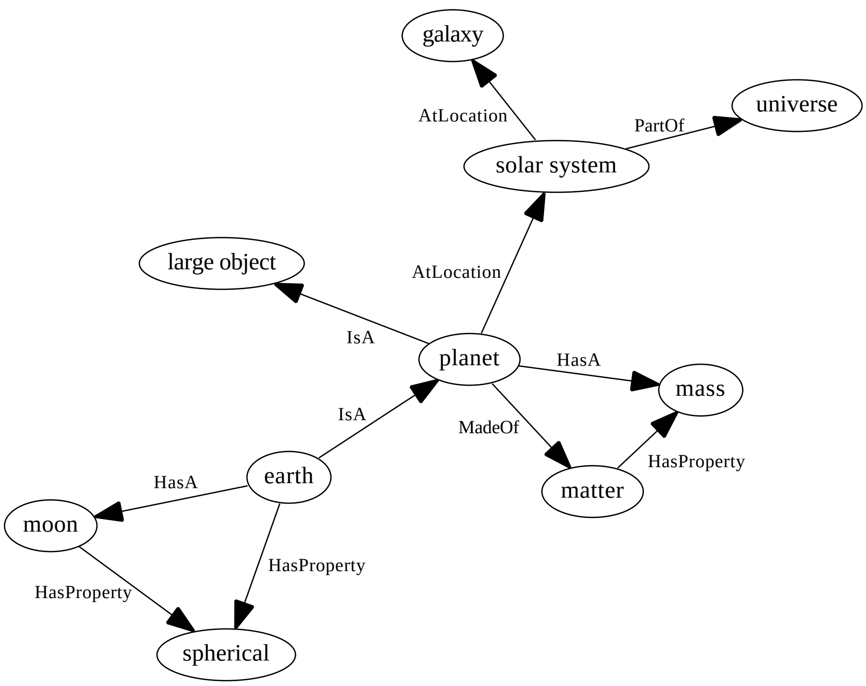


Figure 56: Experiment 1: Given semantic network, 10 concepts, 11 relations (base domain).

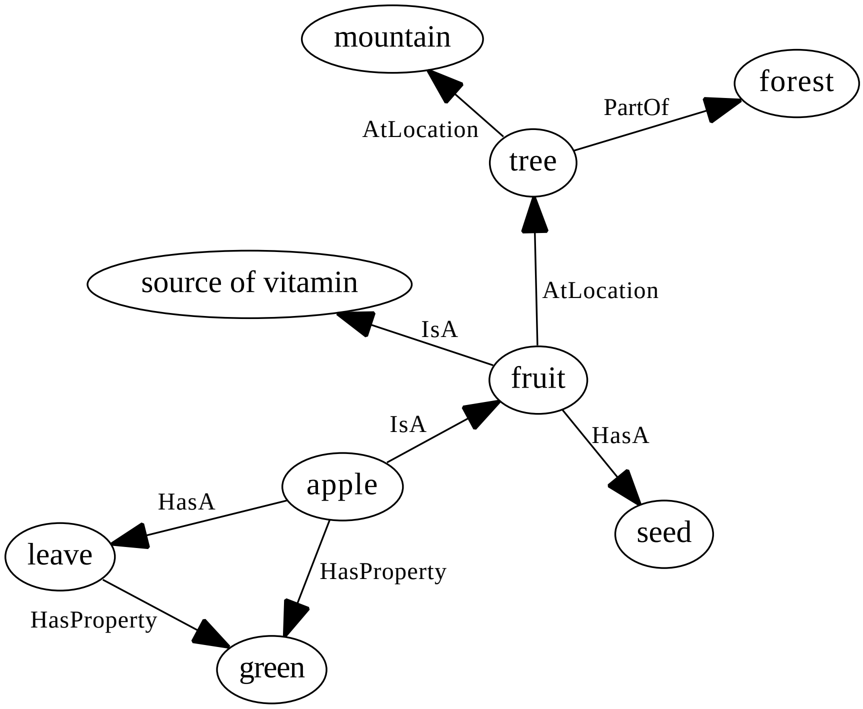


Figure 57: Experiment 1: Evolved individual, 9 concepts, 9 relations (target domain). The evolved individual is encountered after 35 generations, with fitness value 2.8. Concepts and relations of the individual not involved in the analogy are not shown here for clarity.

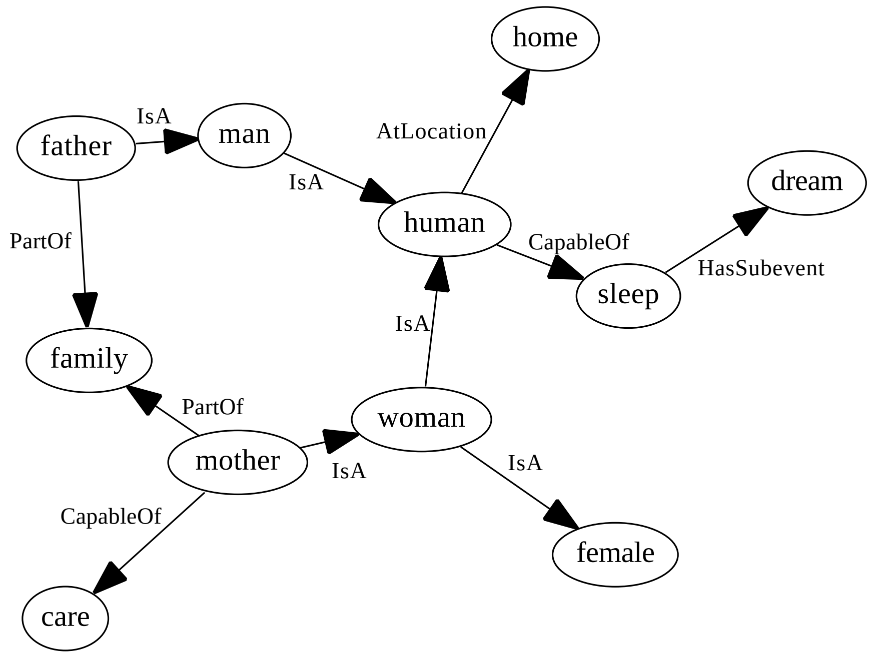


Figure 58: Experiment 2: Given semantic network, 11 concepts, 11 relations (base domain).

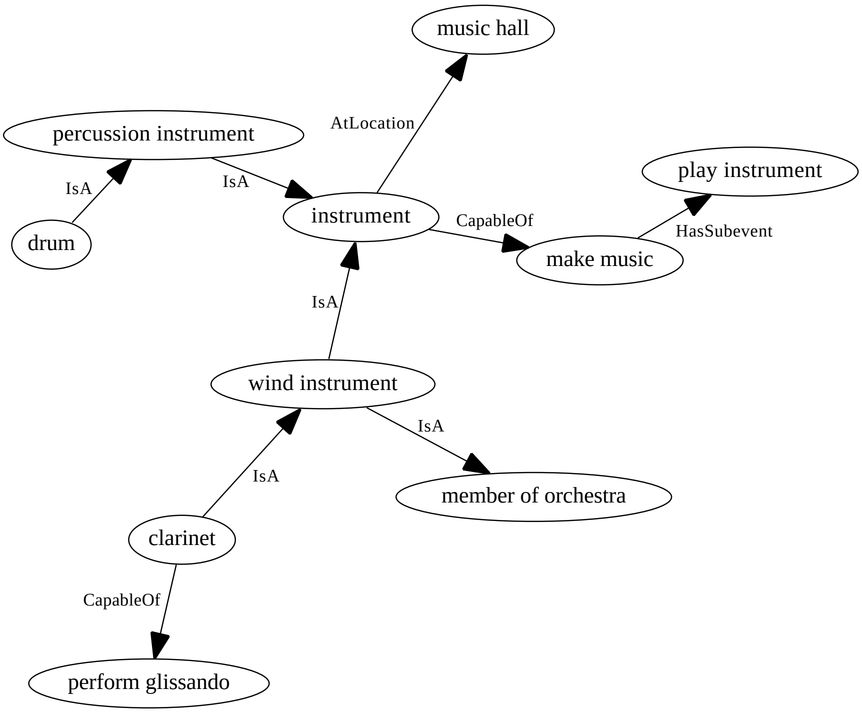


Figure 59: Experiment 1: Evolved individual, 10 concepts, 9 relations (target domain). The evolved individual is encountered after 42 generations, with fitness value 2.7. Concepts and relations of the individual not involved in the analogy are not shown here for clarity.

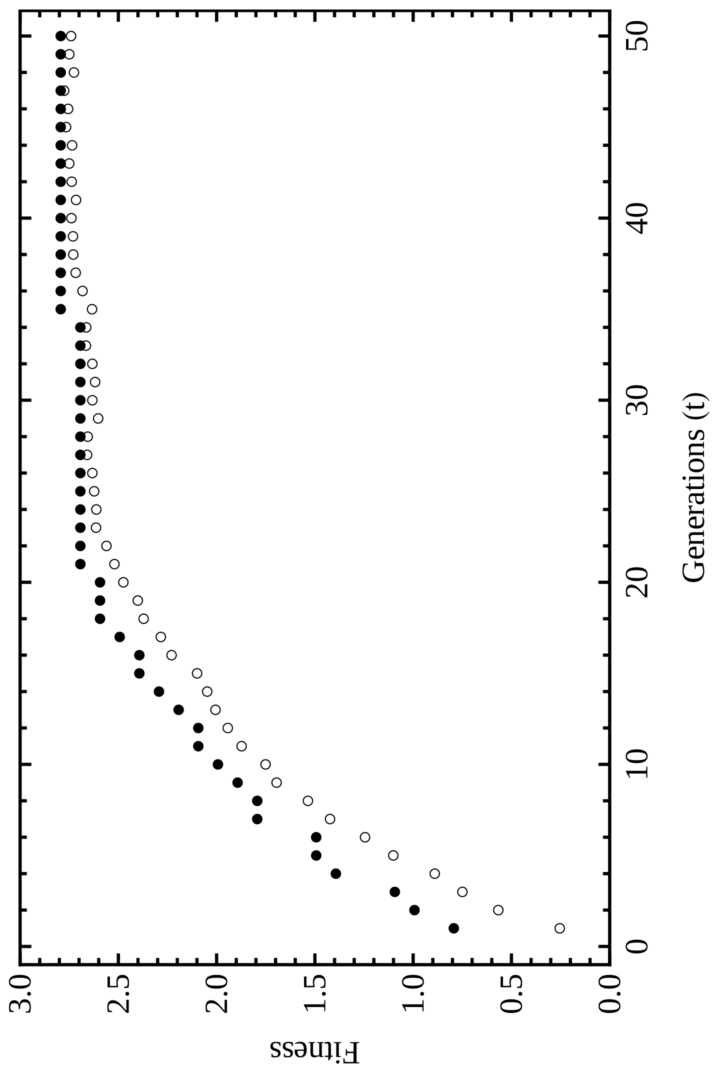


Figure 60: Progress of fitness during a typical run with parameters given in Table 10. Filled circles represent the best individual in a generation, while the empty circles represent population average.

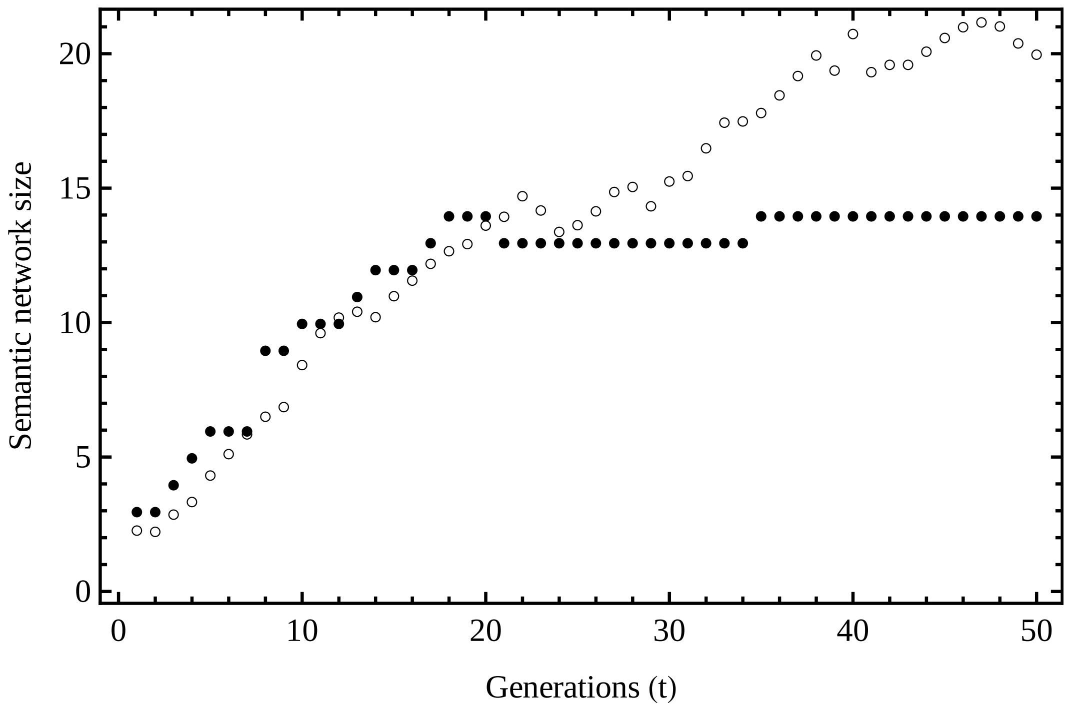


Figure 61: Progress of semantic network size during a typical run with parameters given in Table 10. Filled circles represent the best individual in a generation, while the empty circles represent population average. Network size is taken to be the number of relations (edges) in the semantic network.

Part III

MEDIATION

This part presents, firstly, the analogical reasoning approach we take to address the problem of mediation, discussing the use of structure mapping for case retrieval and adaptation, and the integration of evolutionary adaptation into the case-based reasoning framework. The part then continues with the presentation of our case sources, the final case base, and experiments validating our structural approach. We also present our results of classifying conflicts into categories according to their underlying analogous structures.

7

CASE-BASED MEDIATION

"Man must evolve for all human conflict a method which rejects revenge, aggression and retaliation."

— Martin Luther King, Jr. (1964)

In this chapter we present the details of our case-based reasoning (CBR) approach to the problem of mediation.

One of our contributions is the use of a semantic network-based representation in a CBR system, which we have introduced in Chapter 4 in the previous part about evolutionary adaptation. This representation scheme has the advantage of being simple and flexible, but requires the development of specific retrieval and adaptation procedures.

For addressing the retrieval and adaptation in our semantic network-based CBR, we combine CBR with our implementation of the structure mapping engine (SME) that we adapt to work on semantic networks (Chapter 4).

The SME implementation provides

1. the similarity metric that we use for case retrieval, through structural evaluation scores; and
2. an adaptation mechanism via substitution, through the mapping between the retrieved case as the base domain and the current case as the target domain.

The combination of CBR and SME provides a robust computational model capable of recalling and adapting solutions from seemingly different, but structurally similar, domains.

The combination of CBR and SME provides a model capable of recalling solutions from seemingly different, but structurally similar, domains.

Again, as in the part about the adaptation of semantic networks that we described in Chapter 5, the use of semantic networks and the nature of the information contained within requires the system to take commonsense relations into account. This is to ensure that the operations on the semantic network representation produce meaningful results. Accordingly, we augment the traditional CBR cycle with semantic network-specific algorithms based on commonsense reasoning.

Another key contribution we present is the introduction of an open-ended generative adaptation technique for CBR, based on our novel memetic algorithm for the spontaneous generation of semantic networks (Chapter 5). We pose this option as a "backup" adaptation technique that the system falls back to, in cases where the SME-based adaptation fails.

7.1 THE APPROACH AND ITS ORIGINS

7.1.1 *Mediation and Analogical Reasoning*

As we have already discussed in detail, in Chapter 2, when a person is confronted by a novel problem, drawing analogies to similar problems with known solutions constitutes a powerful way of solution.

Analogical transfer ability is one of the most important factors that make human problem solvers more flexible than expert systems in AI. The way forward from traditional, brittle, and domain-specific AI to systems capable robust intelligence, therefore, lies in modeling and implementing retrieval and use of analogies in different problems.

Mediation, or conflict resolution in general, is a highly interesting problem for experimenting with computational analogy making due to several reasons.

Firstly, mediation problems can be encountered in vastly different domains and scales. These include interpersonal disputes such as workplace and family disputes, intergroup disputes such as commercial or community disputes, and international disputes involving diplomacy and commerce. This offers us a diverse collection of domains to experiment with domain-specific and cross-domain knowledge.

Moreover, similar to the conflicts that are being addressed, the mediating entity itself can belong to vastly different scales. For instance, within international relations, Bercovitch (1992) states that all mediators fall into one of three categories:

1. individuals;
2. states; and
3. institutions and organizations.

The fundamental hypothesis underlying our approach here is that, *even if the instances of mediation problems, and the mediators themselves,* *can be in vastly differing domains and scales, we can still discover cross-domain structural similarities that can allow us to retrieve and reuse analogies with past problems* (Simoff et al., 2008, 2009; Baydin et al., 2011).

Our fundamental hypothesis is the feasibility of discovering cross-domain structural similarities even between vastly differing domains and scales.

For implementing this, we model the mediation process as a cross-domain CBR system, which has access to a collection of past cases from different domains.

Our view is compatible with the reflection by Rubin (1992), stating that "no matter how complex, powerful, or formal the organization responsible for intervention [...], the work of mediation is eventually carried out by *individuals*, who [...] act in a surprisingly similar manner". This observation assists us in our effort to generalize the mediation process and it also forms a basis for combining cases of different domains in one case base.

On a different note, analogical reasoning is inherently connected to mediation and legal reasoning, through the role of analogies in argumentation. Analogies allow one to make a case and guide an audience toward a particular framing and set of inferences. For example, Gentner and Smith (2012) notes web discussions using analogical arguments made after the decision of a United States district court in December 2002, which ordered Microsoft to include Sun Microsystems' Java framework with the Windows operating system. Some of the examples she gives are:

- "*Please explain to me why Microsoft should be forced to include third party software in their OS? Every time I buy a six pack of coke, should a can of Pepsi be included?*"
- "*That would be like (my attorney) being forced to refer clients to his competition, since they didn't have as much business as him.*"
- "*If Ford had a monopoly on cars, they certainly would not be allowed to sell their cars with only Ford brand radios and tiers ...*"

Considering the power of analogies in argumentation and in convincing other people to alter a particular viewpoint, a case-based analogical reasoning approach to mediation has a very practical advantage. A CBR system, due to its inherent dependence on previously encountered cases, has the ability to back any of its solutions with supporting explanations, in terms of analogies with prior cases in its case base.

7.1.2 *The MEDIATOR*

The origins of our case-based approach to the problem of mediation can be illustrated by revisiting one of the classical mediation cases that we have mentioned in Chapter 2.

In Figure 23, we have seen an overview of the territorial conflict between Egypt and Israel that was eventually mediated by the Unites States President Jimmy Carter in 1978. The conflict, having its roots in the 1948 Arab–Israeli War, concerned the possession of the Sinai Peninsula territory between the two states. It was successfully resolved through the US-led mediation process known as Camp David Accords in 1978 (Hinton, 2004), finally ending with the signing of the Egypt–Israel Peace Treaty of 1979.

This instance of mediation, which we will hereafter shortly call the "Sinai conflict", was one of the cases used in introducing the CBR system called MEDIATOR (Simpson, 1985; Kolodner and Simpson, 1989). In fact, the MEDIATOR system was the earliest application of the CBR paradigm to analogy-making (French, 2002).

The MEDIATOR system was the earliest application of CBR to analogy-making.

Let us first consider a toy example of mediation also given by Simpson (1985), involving a resource dispute where two sisters want to get hold of the same orange.

```
Desires(Sister 1, orange)
Desires(Sister 2, orange)
```

A mediator first assumes that a simple division of the orange into two halves would solve the dispute, but this is unacceptable for the parties.

After a point in the mediation process, it is revealed that one sister wants the `orange` for the reason of cooking a `cake` and the other for making a `drink` (Figure 62 (a)).

```
Desires(Sister 1, orange)
Desires(Sister 2, orange)
Desires(Sister 1, cake)
Desires(Sister 2, drink)
UsedFor(orange, cake)
UsedFor(orange, drink)
```

Based on general domain knowledge, the mediator knows that for cooking a `cake`, only the `peel` is sufficient, whereas for making the `drink`, only the `pulp` is sufficient.

The solution is then to redefine the disputed resource as an entity composed of a `peel` and a `pulp` and to assign these to the parties (Figure 62 (b)).

```
Desires(Sister 1, orange)
Desires(Sister 2, orange)
```

```
Desires(Sister 1, cake)
Desires(Sister 2, drink)
UsedFor(orange, cake)
UsedFor(orange, drink)
PartOf(peel, orange)
PartOf(pulp, orange)
UsedFor(peel, cake)
UsedFor(pulp, drink)
Gets(Sister 1, peel)
Gets(Sister 2, pulp)
```

This simple toy mediation case embodies the essence of how the Sinai conflict was mediated.

In Sinai conflict, the countries of `Egypt` and `Israel` had a dispute over the control of the `Sinai` peninsula following the Yom Kippur War in 1973 (Figure 23 (b)).

```
Desires(Egypt, Sinai)
Desires(Israel, Sinai)
```

Furthermore, we know that during this conflict, the primary motives for Egypt and Israel were to ensure their `sovereignty` and `security`, respectively (Figure 63 (a)).

Trying to build an analogy with the orange dispute, we can consider a structural correspondence between concept pairs in these domains, e.g. `orange` ↦ `Sinai`[1].

```
Sister 1 ↦ Egypt
Sister 2 ↦ Israel
orange ↦ Sinai
cake ↦ sovereignty
drink ↦ security
Desires(Sister 1, orange) ↦ Desires(Egypt, Sinai)
Desires(Sister 2, orange) ↦ Desires(Israel, Sinai)
Desires(Sister 1, cake) ↦ Desires(Egypt, sovereignty)
Desires(Sister 2, drink) ↦ Desires(Israel, security)
UsedFor(orange, cake) ↦ UsedFor(Sinai, sovereignty)
UsedFor(orange, drink) ↦ UsedFor(Sinai, security)
```

Moreover, by this analogical mapping we can *infer* that, corresponding to `peel` and `pulp` in the base domain, there may exist two more

1 We use the notation `a` ↦ `b` to mean "`a` maps to `b`".

concepts `*concept 1`[2] and `*concept 2` in the target domain that we can base a solution upon.

```
peel ↦ *concept 1
pulp ↦ *concept 2
PartOf(peel, orange) ↦ PartOf(*concept 1, Sinai)
PartOf(pulp, orange) ↦ PartOf(*concept 2, Sinai)
UsedFor(peel, cake) ↦ UsedFor(*concept 1, sovereignty)
UsedFor(pulp, drink) ↦ UsedFor(*concept 2, security)
Gets(Sister 1, peel) ↦ Gets(Egypt, *concept 1)
Gets(Sister 2, pulp) ↦ Gets(Israel, *concept 2)
```

Such a division of the Sinai Peninsula, in fact was possible, and this formed the basis on which the dispute was successfully mediated in 1979. The division involved the civilian and military control of the same territory, which we denote `*concept 1` ≡ **`civilian`** and `*concept 2` ≡ **`military`** (Figure 23 (c) and Figure 63 (b))

```
Desires(Egypt, Sinai)
Desires(Israel, Sinai)
Desires(Egypt, sovereignty)
Desires(Israel, security)
UsedFor(Sinai, sovereignty)
UsedFor(Sinai, security)
PartOf(civilian, Sinai)
PartOf(military, Sinai)
UsedFor(civilian, sovereignty)
UsedFor(military, security)
Gets(Egypt, civilian)
Gets(Israel, military)
```

This solution by "agreeable division of resources based on the real goals of the disputants" can form a basis for solving many future cases of mediation involving resource conflicts.

We can achieve this by using the structure mapping engine (SME) for the retrieval and adaptation of cases. By using structural mapping, this ability is maintained regardless of the actual scale or domain of any considered conflict, because the solutions are reached only through similarities in relational structures of the conflicts.

2 With the symbol "*", we denote a concept in the target domain whose existence is inferred (or postulated) by the structural correspondences between the base and target domains.

The uncovering of these postulated concepts—namely, that the control of a territory has `civilian` and `military` aspects—requires knowledge which can be both possibly domain-specific or general.

In our approach, we address this requirement via commonsense reasoning, producing expansions of the current case network before structure mapping, to maximize the extent of the subgraph that can participate in the mapping. We present the details of the case expansion process further in this chapter.

7.1.3 *General Domain Knowledge and GREBE*

The use of commonsense reasoning in our approach can be interpreted, from a CBR perspective, as a new attempt of *integrating general domain knowledge* into a CBR system, which has been an important focus of CBR research.

The use of commonsense reasoning can be seen as an instance of integrating general domain knowledge into CBR.

Early examples such as the PROTOS system by Bareiss et al. (1988), which aimed at bringing together general domain knowledge with case specific knowledge in a unified representation, show that this has been a fundamental issue since the early days of CBR.

But, it is with another influential CBR system, the GREBE by Branting (1991, 2003, 2010) (Chapter 2), that our approach shares significant similarities in addressing the problem of general knowledge.

GREBE (Generator of Recursive Exemplar-Based Explanations) is a system for legal analysis that uses "a relational representation in the form of ground tuples for the facts of precedents and new cases" (Branting, 2003). Thus, the representation scheme used by GREBE is almost identical to our semantic network representation of cases.

Furthermore, grounded on this relational representation structure, the system uses a similarity assessment based on structure matching, which practically corresponds to our use of SME for case retrieval and adaptation.

Figure 64 gives a portion of the facts comprising the so-called *Jarek's Case* in GREBE. The case basically includes the facts and relational structure involved in the compensation payment of a railroad employee after an injury.

Our approach and GREBE share a similar intuition about the necessity of having a commonsense component in the CBR system. In GREBE, this was achieved by a set of "commonsense rules" that basically attempted to cover everyday information of the type we have dealt with in the previous part of this dissertation (Chapter 5).

However, these commonsense rules in GREBE were hand-coded and very limited in number (numbering about a hundred rules). This was presumably due to the absence of readily available commonsense knowledge bases that we now have access to.

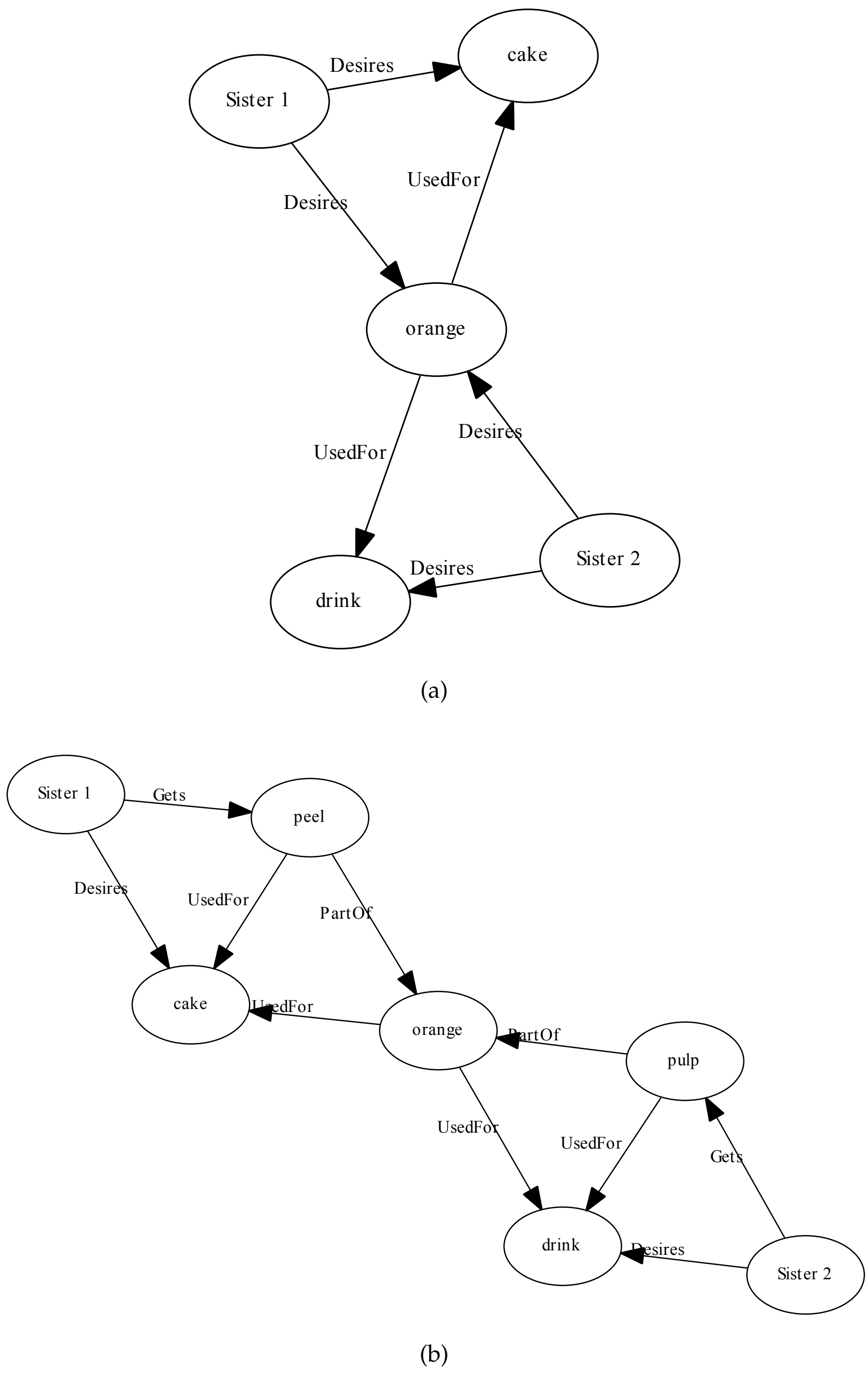
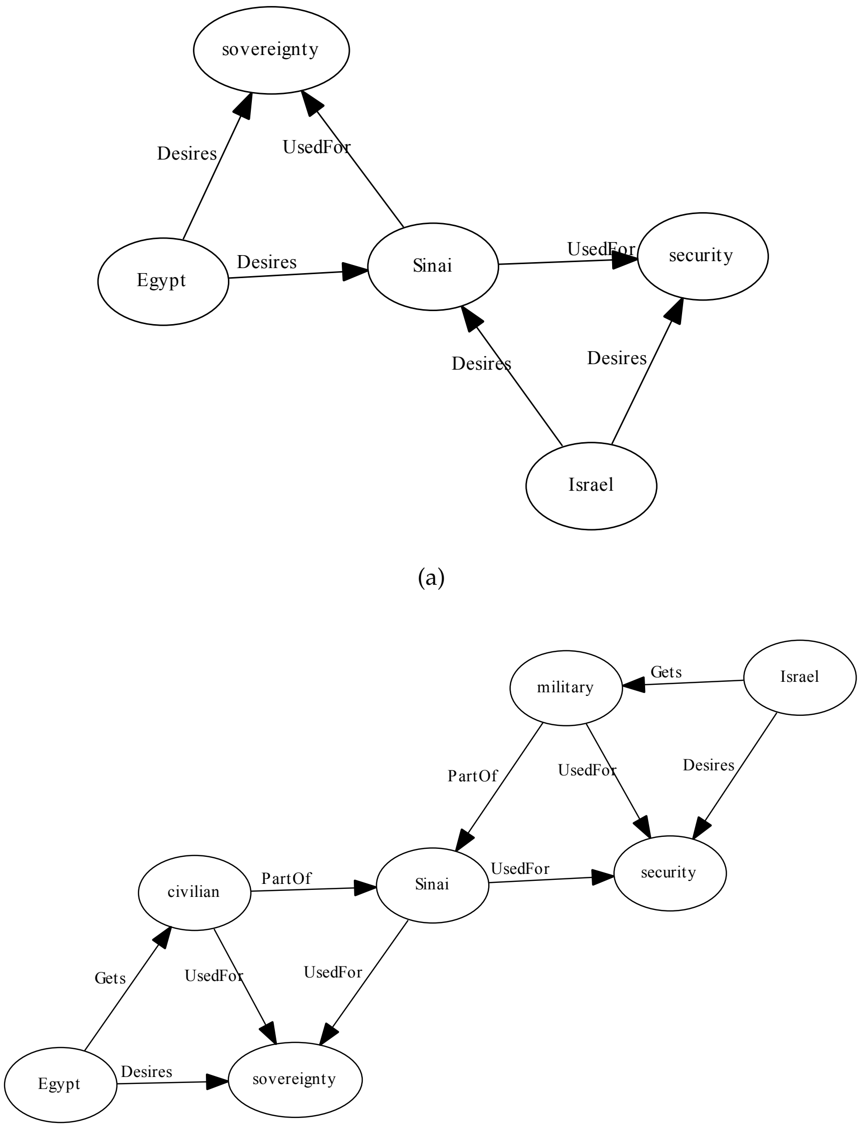


Figure 62: The orange dispute case, semantic network representation. (a) Unsolved case network. (b) Solved case network.



(a)

(b)

Figure 63: The Sinai dispute case, semantic network representation. (a) Unsolved case network. (b) Solved case network.

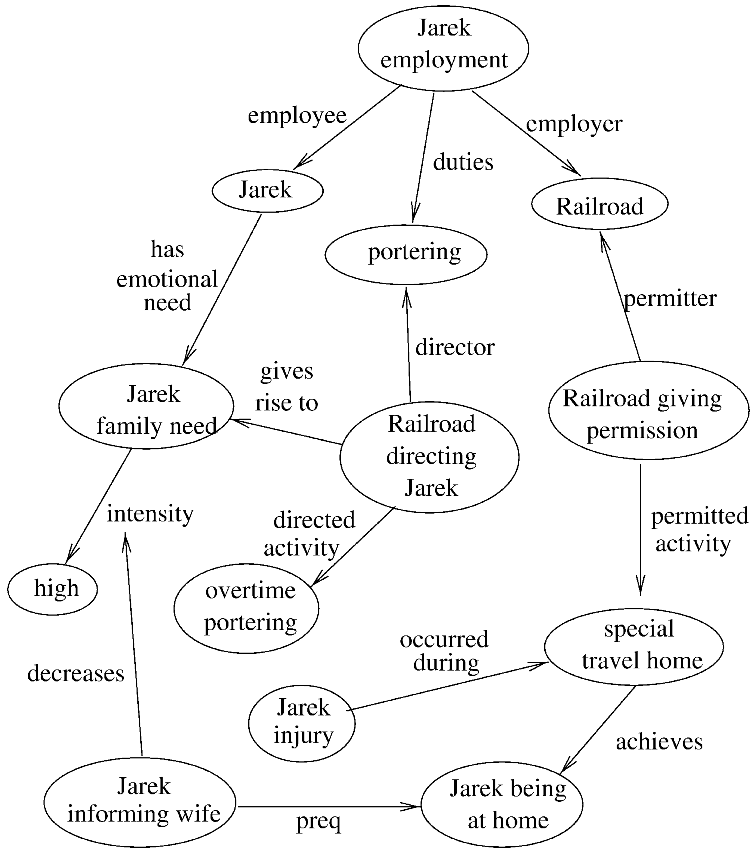


Figure 64: Representation of the facts in *Jarek's Case*, concerning the compensation of an injured railroad employee, in the GREBE system of Branting (2003).

Consequently, our case-based approach to mediation can be considered as a revisiting of two highly influential earlier CBR designs, MEDIATOR and GREBE, now armed with commonsense reasoning, SME, and a semantic network representation.

We produce an actual working implementation of the approach that was introduced by MEDIATOR but has remained a theoretical toy model until this time, at the same time making the idea of GREBE about commonsense rules a working reality.

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7.2 MEDIATION AGENT

Our work on CBR mediation fits into a theoretical framework in which the role of mediation was envisioned to be performed by a mediator agent in a multi-agent system (Simoff et al., 2009). This perspective is, in turn, related with the recent effort in AI for studying negotiation processes using agent based modeling (Beer et al., 1999; Kraus, 2001; Yager, 2007; Jonker et al., 2007) and developing support tools for mediation (Chalamish and Kraus, 2007).

Within this framework, the envisioned system is to act as a mediator in between several negotiating agents in a multi-agent environment, in similar fashion to the "curious negotiator" model by Simoff and Debenham (2002).

The original design (Baydin et al., 2011) calls for a CBR cycle (Figure 65) integrated with analogical and commonsense reasoning components, capable of: (1) creating a middle-ground case representation covering the views of all agents in dispute; (2) using this representation for the retrieval of cases through analogical reasoning from a case base of previous successful mediations in various domains; and (3) adapting a solution for the current case, again by utilizing the middle-ground representation and the retrieved previous case, taking the goals and reservations of the parties into account.

The framework calls for dialog between the mediator agent (denoted μ) and the negotiator agents in dispute (denoted α, β etc.), for getting the initial information to represent the new case and to propose solutions to the negotiator agents. The case base C holds instances of successfully solved past conflicts. Each case c_i in the case base is described by the set

$$c_i = \{o_i, A_i, G_i, R_i, S_i\} \ , \tag{1}$$

denoting respectively the associated network of the dispute, the agents, their goals, their reservations, and the solution.

By definition, the network o_i encompasses all information needed to describe the case, thus A_i, G_i, R_i, and S_i already exist as subgraphs

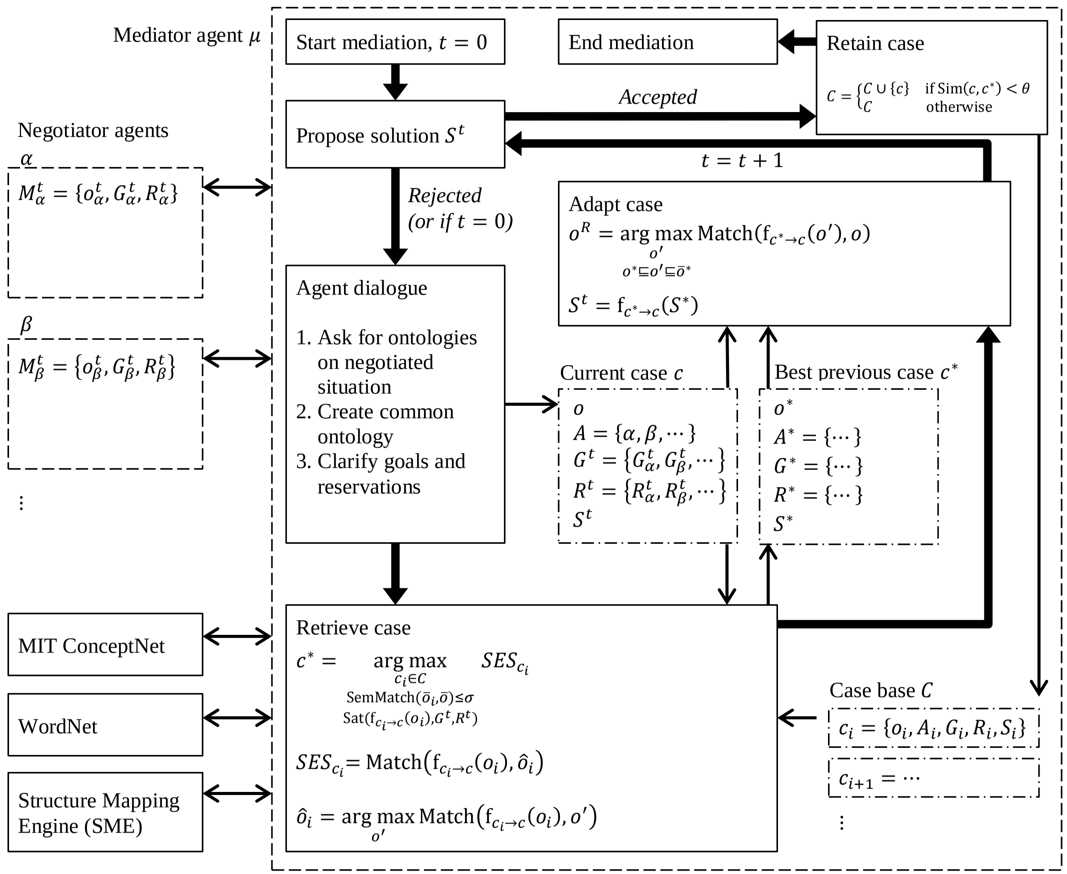


Figure 65: The original CBR mediation cycle envisioned as part of an agent-based mediation framework, including argumentation (Baydin et al., 2011).
C

of concepts and relations embedded into the network. Still, they are also explicitly listed as features of the case c_i for illustrating the concepts and relations corresponding to the agents and their goals and reservations.

In the framework, it is envisioned that the parties can modify their stances

$$M_\alpha^t = \{o_\alpha^t, G_\alpha^t, R_\alpha^t\} \ , \tag{2}$$

after successive solution proposals S^t, where t is the time index of the current CBR iteration.

After the initial dialog, and the representation of the current case c, the algorithm proceeds by case retrieval and adaptation stages.

Before retrieval, for enabling the discovery of extensive analogies between different domains, we treat every given network o as a partial view of a more general network $\bar{o}$, denoted $o \sqsubseteq \bar{o}$, and we produce expansions of a given network

$$o \sqsubseteq o' \sqsubseteq \bar{o}. \tag{3}$$

Retrieval is dependent on SME, addressing the fulfillment of two functions:

1. the computing of a match score between two networks (or, semantic networks), i.e. $\mathrm{Match}(f_{c_i \to c}(o_i), o'))$; and
2. providing the mapping function f between two domains, through which one can infer previously unknown information in the target domain, i.e. $f_{c^* \to c}(S^*)$.

Given two networks in different domains, SME gives a set of all structurally meaningful analogical mappings between these, each with its attached structural evaluation score (SES_{c_i} in Figure 65).

Retrieval from the case base is done by finding the case that maximizes structural similarity with the current case, as described in Algorithm 10.

After the retrieval of the best case c^*, while the algorithm picks the analogy with the highest score to act as our analogical mapping function f, in the implementation of the Match function, we the scores from all possible analogies between the given two networks are summed up as a measure of the susceptibility of these two to analogies.

In principle, the adaptation stage of this model falls under *substitutional adaptation* (Cunningham et al., 1994; Wilke and Bergmann, 1998), where the substitutions are made by the analogical mapping function

Algorithm 10 Procedure for case retrieval through structure mapping.

procedure RETRIEVE(c, C) ▷ Current case c, case base C

$c^* \leftarrow \underset{\substack{c_i \in C \\ \text{SemMatch}(\bar{o}_i, \bar{o}) \leqslant \sigma \\ \text{Sat}(f_{c_i \to c}(o_i), G^t, R^t)}}{\arg\max} \text{SES}(c_i)$

return c^* ▷ Case with best score

end procedure

procedure SES(c_i) ▷ Structural evaluation

$\hat{o}_i \leftarrow \underset{\substack{o' \\ o \sqsubseteq o' \sqsubseteq \bar{o}}}{\arg\max} \text{Match}(f_{c_i \to c}(o_i), o')$ ▷ Expansions $\hat{o}_i$ of network o

$s \leftarrow \text{Match}(f_{c_i \to c}(o_i), \hat{o}_i)$ ▷ Structural evaluation scores

return s

end procedure

f from c^* to c. Hence, we get a candidate solution to the current case by the mapping

$$S^t = f_{c^* \to c}(S^*)) \tag{4}$$

where S^* is the solution of the retrieved case c^*. We use the mapping $f_{c^* \to c}$ corresponding to an analogical match established between o, the network of the current case, and

$$o^R = \underset{\substack{o' \\ o^* \sqsubseteq o' \sqsubseteq \bar{o}^*}}{\arg\max} \text{Match}(f_{c^* \to c}(o'), o) \ , \tag{5}$$

an expanded network of the retrieved case (Figure 65).

At the point in the CBR cycle where the proposed solution is accepted by the parties in conflict, the case base C is updated to include the case c now with an accepted solution S^t. This new solution is retained whenever the newly solved case c is sufficiently different from the retrieved case c^*, compared with a similarity threshold parameter θ, in order to prevent overpopulation of the case base with extremely similar instances.

We focus our attention on CBR retrieval and adaptation and exclude the argumentation process.

7.2.1 *Moving Forward*

Proceeding from the ideas introduced by the previous framework, we focus our attention on the actual implementation of the CBR-related retrieval and adaptation processes, and make the decision of limiting the scope of this current work to exclude the argumentation process.

Figure 66 gives an overview of our final system for CBR mediation.

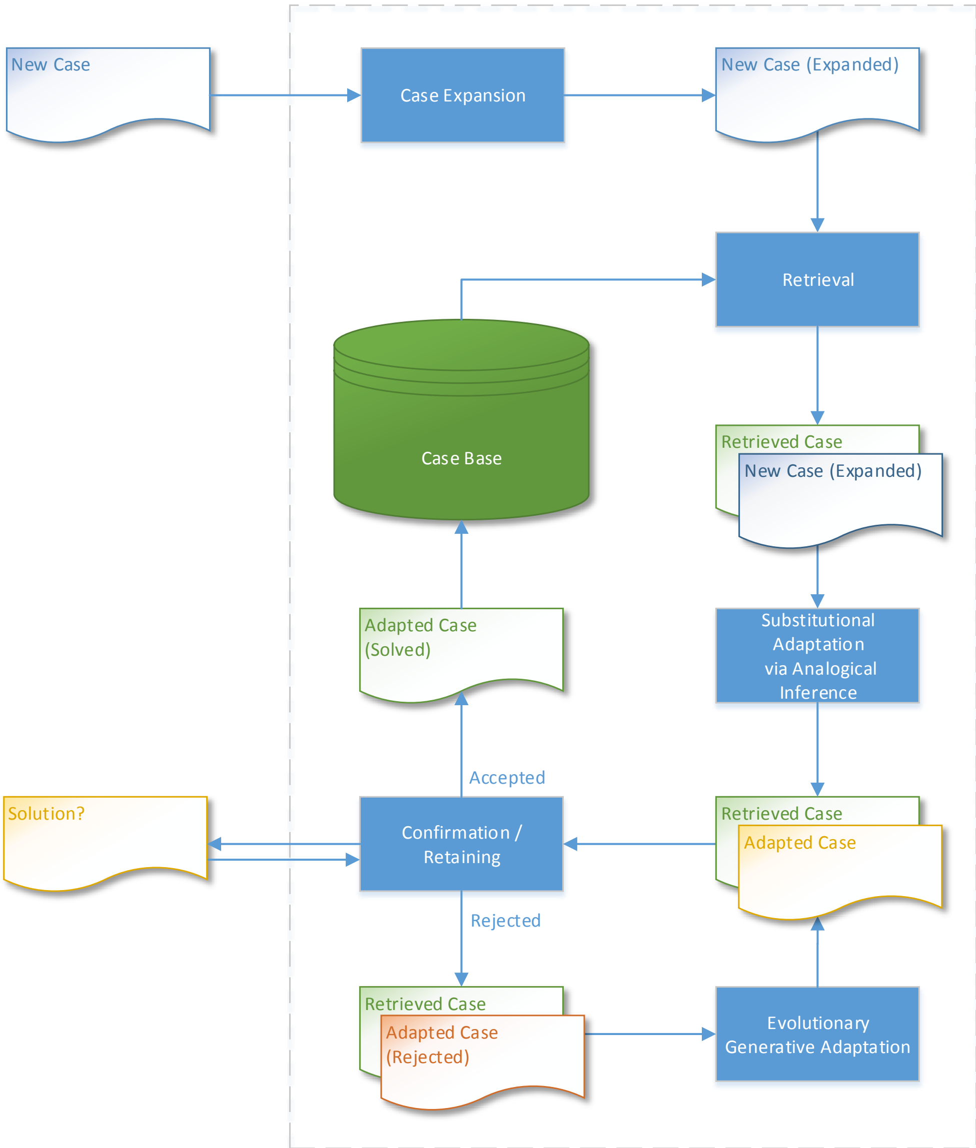


Figure 66: The final flowchart of the CBR mediator model, focused on retrieval and adaptation, and excluding argumentation. Compare with Figure 65.

Presented with a new case, the model basically proceeds by case expansion, retrieval, adaptation, and retaining.

Before retrieval, the new case is altered through a procedure that we call *semantic network expansion*. This procedure is based on commonsense reasoning and is similar to the random semantic network generation method that we employ in the evolutionary adaptation part of our work (Chapter 5). The details of this are given in Section 7.4.2.

The retrieval and adaptation stages work by structure mapping as before and depend upon the SME implementation. That is, cases from the case base are retrieved according to the structural similarity score provided by SME, and, adaptation is performed by mapping the nodes from the retrieved case to the current case, using the mapping function already constructed during the retrieval stage.

Another idea we employ here is the modification of the conventional CBR algorithm to introduce an evolutionary generative adaptation stage to the cycle, which the system would fall back to when the SME-based adaptation fails to produce an acceptable result.

Furthermore, the updated model enables us to use the representation scheme that we will introduce in Section 7.3, based on a straightforward semantic network-only structure.

In other words, because we are not interested in having an automated negotiation component at this stage, we exclude the parts of the representation explicitly identifying the agents and their goals and reservations (e.g. G^t, R^t). Instead, we leave these aspects embedded in case networks, open to human interpretation.

7.3 MEDIATION CASE REPRESENTATION

In simplest terms, a case in CBR is a contextualized piece of knowledge representing an experience (Kolodner, 1993).

A case usually contains a past lesson that is the content of the case and the context in which the lesson can be used. A typical case representation contains (Kolodner, 1993):

1. the problem that describes the state of the world when the case occurred;

2. the solution which states the derived solution to that problem; and

3. the outcome which describes the state of the world after the case occurred.

Here we take a similar but somewhat simpler approach. Our representation structure for mediation cases is based on the same semantic network structure that we have introduced in Chapter 4.

With this representation, in contrast with conventional feature–attribute based CBR representations making a clear distinction between the case "description" and "solution", we can describe all elements that participate in a case all at once, as parts of the same case network. These include the agents involved in a case, their actions, beliefs, or desires, and how these relate to the external world.

We represent all elements participating in the case as parts of the same semantic network.

In addition to its straightforward simplicity, the most important advantage prompting us to make this representation decision is the ease of applying structure mapping, via SME, for both retrieval and adaptation in our approach.

Given a base and a target case network, in one simple step, SME can generate:

1. the structural evaluation score indicating the degree analogical similarity between the two cases, while doing retrieval; and

2. the mapping function that can be used for the transfer of elements forming the solution from the base to the target network, via inference, while doing adaptation.

Figure 67 and Figure 68 show what we call the "fused" representation of the orange and Sinai conflicts given before as "unsolved" and "solved" states in Figure 62 and Figure 63.

The fused representation of a case is produced by the union of the unsolved and solved networks of the case[3].

In the case base, we retain the unsolved, solved, and fused networks for each case (Table 69). The fused representation is used for the internal running of the algorithm, while the unsolved and solved representations provide an intuitive way to study conflict cases and solutions by humans.

Given an unsolved network as the current case, during retrieval, we run SME to assign similarity scores between the unsolved network of the current case (the target) and the fused network of each of the cases (the base) in the case base. During adaptation, we use the mapping that has been already produced by SME to map the solved network of the retrieved case to become the solved network of the current case.

While the unsolved and solved networks of a case are more illustrative for a human observer, having the fused network provides the

3 Note that, for the orange conflict, the `Desires(Sister 1, orange)` relation exists in the unsolved network but not in the solved network; similarly, the `Gets(Sister 1, peel)` relation only exists in the solved network.

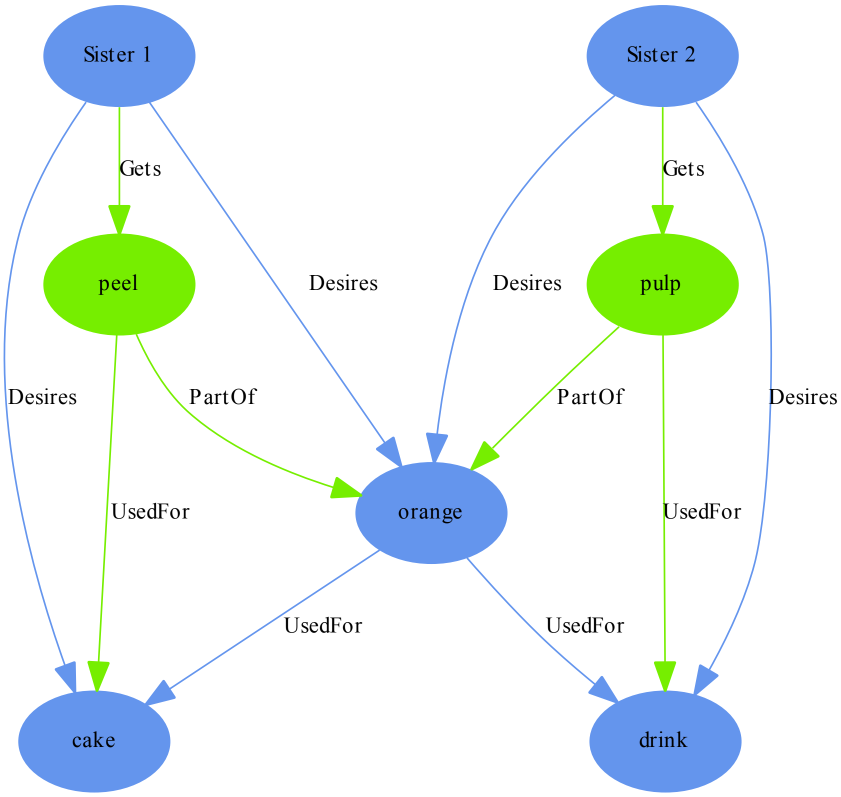


Figure 67: The orange dispute case, fused representation of solved and unsolved case networks. Blue (or dark) color represents the unsolved network, green (or light) color represents the additions/-modifications for solution.

CBR algorithm with an opportunity to catch as many analogical correspondences as possible between a new unsolved case and the solved cases in the case base.

For seeing the advantage of this, consider not having the fused network and running SME between the unsolved current network as the target and the solved networks in the case base: the mapping would miss crucial structural clues that might have disappeared during the solution process of the case in the case base (e.g. the relation `Desires(Sister 1, orange)` disappearing as the conflict is resolved).

There are, in principle, no limits imposed on the available types of relations that we can use for case descriptions, or the language we can use as relation labels. For instance, GREBE forms an instance of the approach where relations are freely labeled in the best way to describe the problem at hand (Figure 64).

We do, however, make the choice of constraining ourselves as much as possible to the limited set of relation types provided by ConceptNet version 4 (Table 8) that we have covered in Chapter 5. This is

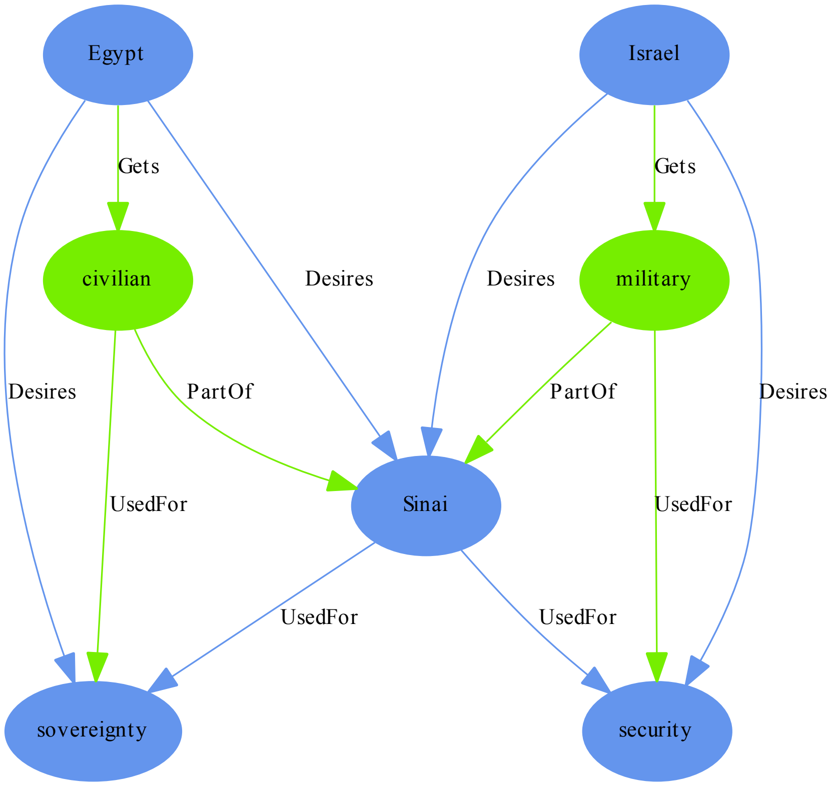


Figure 68: The Sinai dispute case, fused representation of solved and unsolved case networks. Blue (or dark) color represents the unsolved network, green (or light) color represents the additions/-modifications for solution.

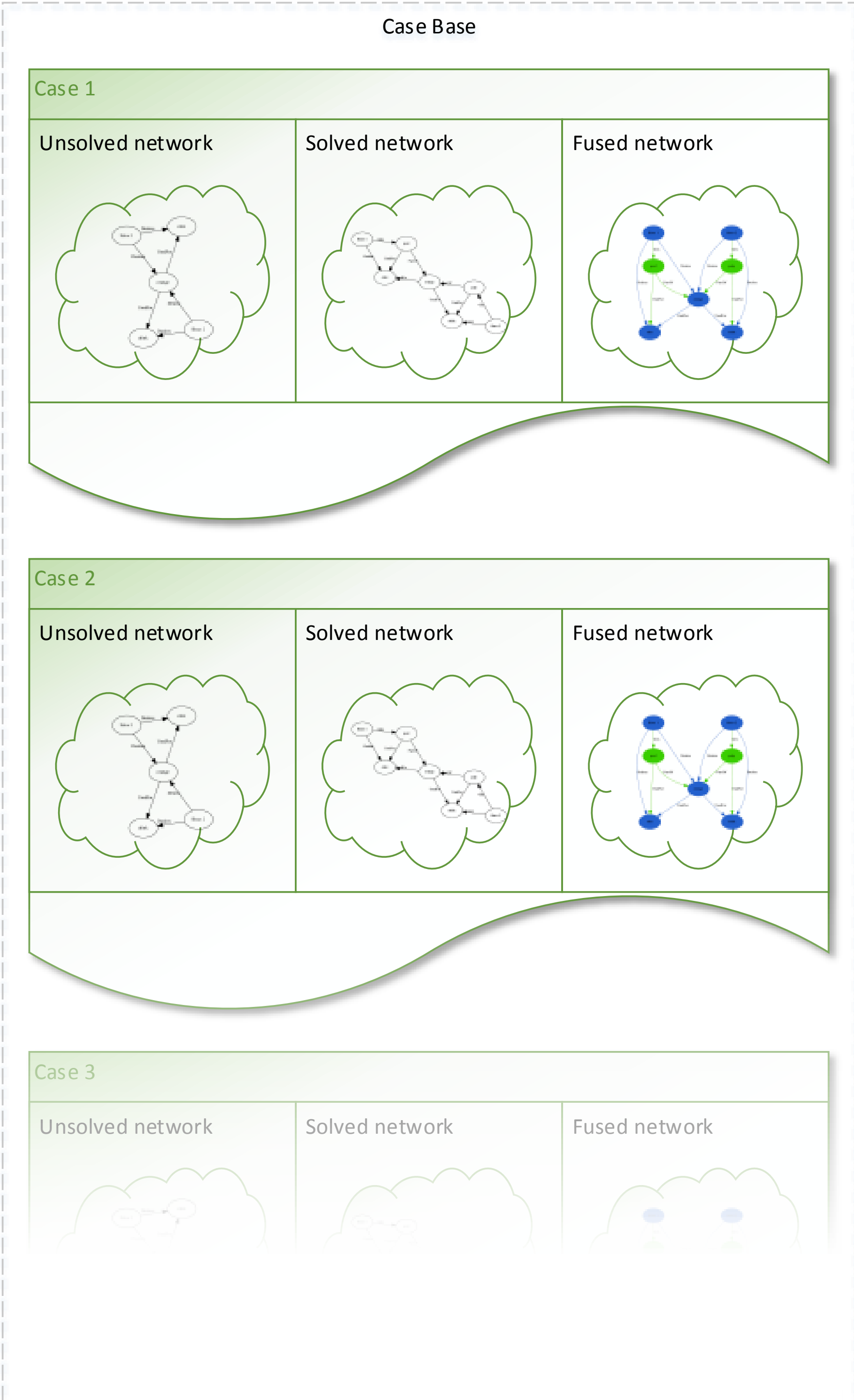


Figure 69: Diagram illustrating the representation structure of the cases within the CBR case base. Each case holds the corresponding unsolved, solved, and fused networks describing the conflict.

due to considerations of compatibility and consistency. ConceptNet forms the backbone of our commonsense reasoning approach and for all commonsense operations, including the evolutionary adaptation technique for the cases, we are dependent on queries to knowledge expressed in ConceptNet using this set of relations.

For helping the representation process of cases, we make use of some rules of thumb introduced by Chen (1976) for the *entity–relationship (ER) model* used in describing databases. These rules of thumb provide a reference for mapping natural language descriptions onto ER diagrams.

Combining the rules of Chen (1976) with the correspondences between predicate calculus statements and semantic network structure that we employ for integrating SME with semantic networks (Table 6) in Chapter 4, we arrive at the list given in Table 13.

7.4 RETRIEVAL

7.4.1 *Structure Mapping Engine*

For the retrieval of cases with the capability of spotting cross-domain structural similarities, we again employ our own implementation of SME that we adapt to work on semantic networks, as described in Chapter 4.

Retrieval process starts by running the SME algorithm between the fused case network of each case in the case base, taking it as the base domain, and the unsolved case network of the new case, taking it as the target domain (Figure 70).

Before starting the procedure, the unsolved case network is altered through the case expansion procedure (Section 7.4.2). The expansion of the unsolved case enlarges the target case with numerous related concepts and relations, and enables the discovery of more extensive analogical mappings.

The expansion of the unsolved case enables the discovery of extensive analogical mappings.

The expanded network also serves a very important role in the adaptation procedure that will follow retrieval. It introduces new concepts and relations into the network with the intention that some of these would become the target of analogical mappings from the solved case network.

Each run of SME produces a collection of all possible analogical mappings between the base and target domains. This usually means that, for cases comparable in size with the one in Figure 67, we produce approximately 10 to 15 structurally consistent analogies.

For the purpose of retrieval, we calculate the overall similarity score between the new case and a case in the case base by summing up the

Table 13: The correspondence between SME predicate calculus statements (Falkenhainer et al., 1989) and semantic network structure that we use to apply structure mapping to semantic networks.

English grammar structure	ER structure	Semantic networks
Common noun	Entity type (entity category)	Concept
Proper noun	Entity (entity instance)	Concept
Transitive verb	Relationship type	Relation
Intransitive verb	Attribute type	`IsA` or `HasProperty` relation
Adjective	Attribute for entity	`IsA` or `HasProperty` relation
Adverb	Attribute for relationship	Not employed

structural evaluation scores (indicating the quality and extent of the mapping) of all possible mappings.

Cases in the case base are ranked according to their overall structural evaluation scores and the case with the highest score is retrieved.

The collection of all computed mappings are also kept for being later used in the adaptation procedure (Section 7.5.1).

SME is very robust and fast with the computation of matching scores between networks in real time. Still, in the event that the case base becomes prohibitively large for the computation of structural evaluation scores for each retrieval phase, a *base filtering* approach for retrieval (Smyth and Cunningham, 1993) can also be employed, in effect running the analogical reasoning process on a smaller subgroup for each retrieval.

7.4.2 *Expansion of Cases via Commonsense Reasoning*

An important contribution we deliver for the retrieval and adaptation stages of the CBR system is the case expansion procedure that is using information from commonsense knowledge bases.

The case expansion algorithm is critical in two main stages of our CBR cycle:

1. for retrieval, the expansion of the unsolved case network for the current case enables the discovery of extensive analogies; and
2. more importantly, for adaptation, introducing the potential building blocks of a solution via analogical inference from the base domain into the target domain.

The former can be seen as a relative improvement of CBR retrieval performance by utilizing commonsense reasoning methods, whereas the latter role, in adaptation, is crucial for the transfer of solutions from the retrieved case to the current case.

The case expansion procedure thus serves as the implementation of the idea of discovering the "postulated" concepts and relations, which we have discussed in detail in Section 7.1.2.

Basically, the procedure (Algorithm 11) works by taking a given network and expanding it via inserting new concepts and relations involving existing concepts, until the total number of concepts equals its previous value multiplied by a given expansion factor $\eta \geqslant 1$.

This procedure works in a similar fashion to our random semantic network generation algorithm that we employ in evolutionary adaptation (Algorithm 5).

In Chapter 8 we will evaluate the case expansion approach with several experiments and discuss its contribution to the CBR cycle.

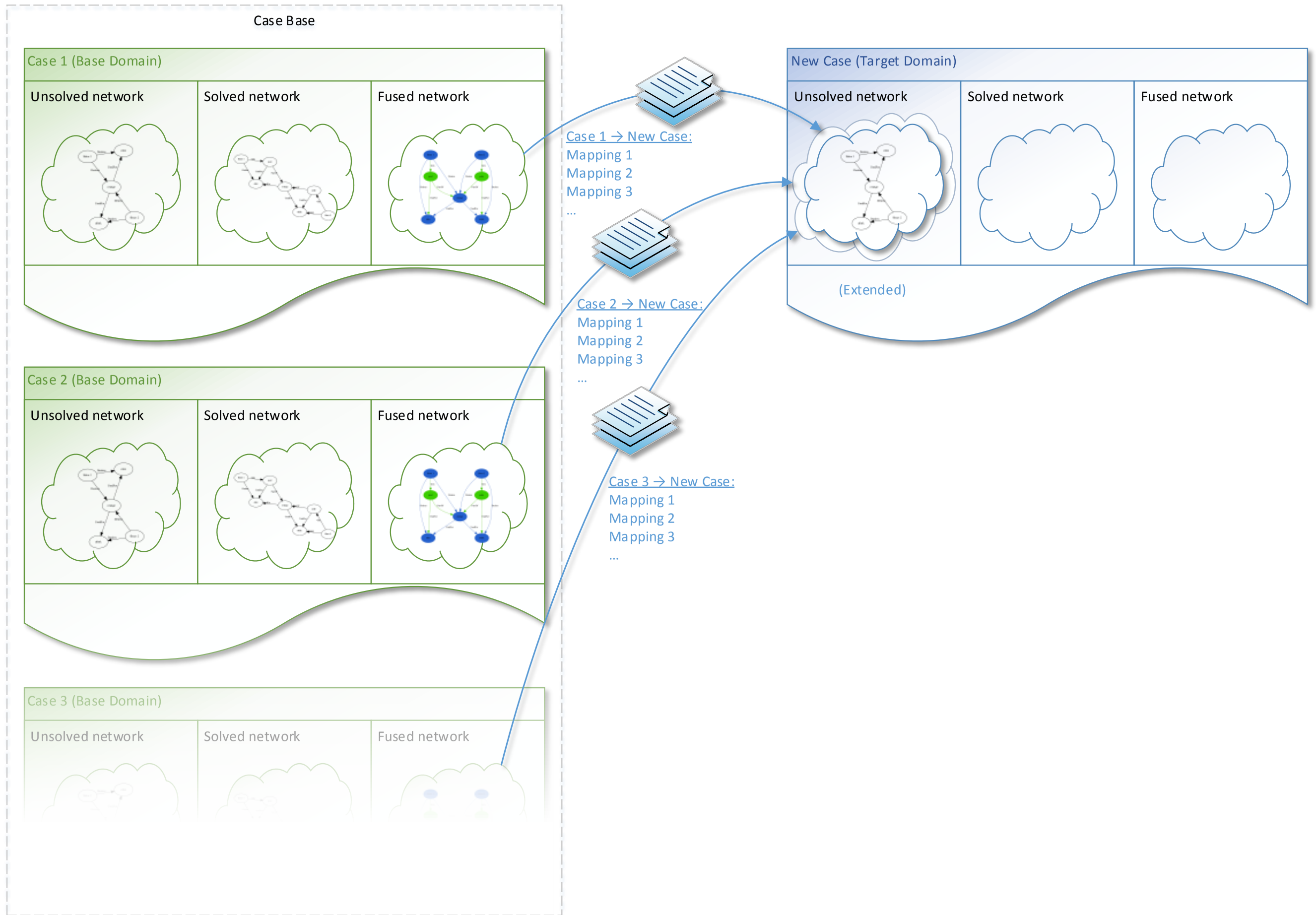


Figure 70: The retrieval process. For every pair, SME gives a list of all possible analogical mappings between the base and target domains. For each case in the case base, retrieval score is calculated by summing up the structural evaluation scores of all possible analogies with the new case.

Algorithm 11 Procedure for case expansion via commonsense reasoning.

```
procedure EXPAND(o, η)                          ▷ Network o, expansion factor η
    c ← ⌊(η − 1) NumConcepts(o)⌋               ▷ Number of new concepts
    while c > 0 do
        con ← RANDOM(o)                         ▷ Random concept in o
        Create network r of all concepts in relation with con
          from commonsense knowledge bases
        if r ≠ ∅ then
            new ← RANDOM(r)                     ▷ Random concept in r
            APPENDTO(o, new)                    ▷ Append new to o with
corresponding relation
            n ← n − 1                           ▷ New concept appended
        end if
    end while
end procedure
```

In the series of figures from Figure 71 through Figure 75, we see an example illustrating the case expansion process, with incremental expansion until 320 % of the original number of nodes in the network.

7.5 ADAPTATION

7.5.1 *Substitutional Adaptation via Inferences*

Our primary means of adaptation in the CBR cycle is to use substitution via an analogical mapping function between the retrieved and new cases.

Figure 76 shows an overview of the adaptation process.

Firstly, as we have already mentioned in Section 7.4.2, we need to modify the unsolved network of the current case through the case expansion process.

Then, the list of all possible analogical mappings between the fused network of the retrieved case (base domain) and the unsolved network of the new case (target domain) should be computed.

After that, the mapping with the highest structural evaluation score is used to map the solved network of the retrieved case into a solved network for the new case.

Lastly, the unsolved and solved case networks for the current case are merged to create the fused network of the current case. This fused network will be used, if the case is accepted as solved and put into the case base, when considering this case for future retrievals.

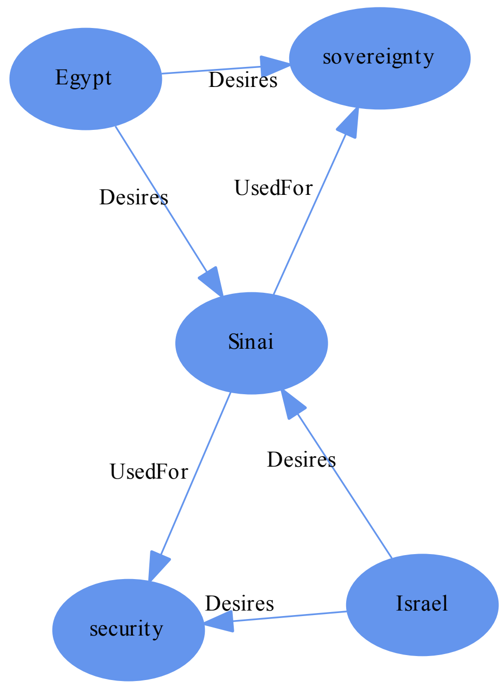


Figure 71: Example expansion process through commonsense reasoning. Sinai conflict unsolved case network, initial stage (5 concepts, 6 relations).

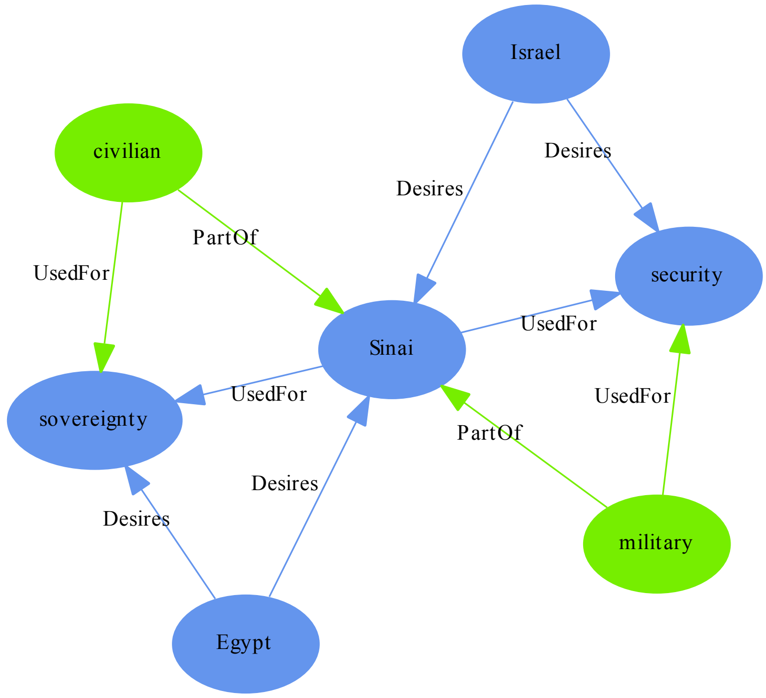


Figure 72: Example expansion process through commonsense reasoning. Sinai conflict unsolved case network, 40% expansion (7 concepts, 10 relations). Green (or light) color represents the newly attached concepts and relations.

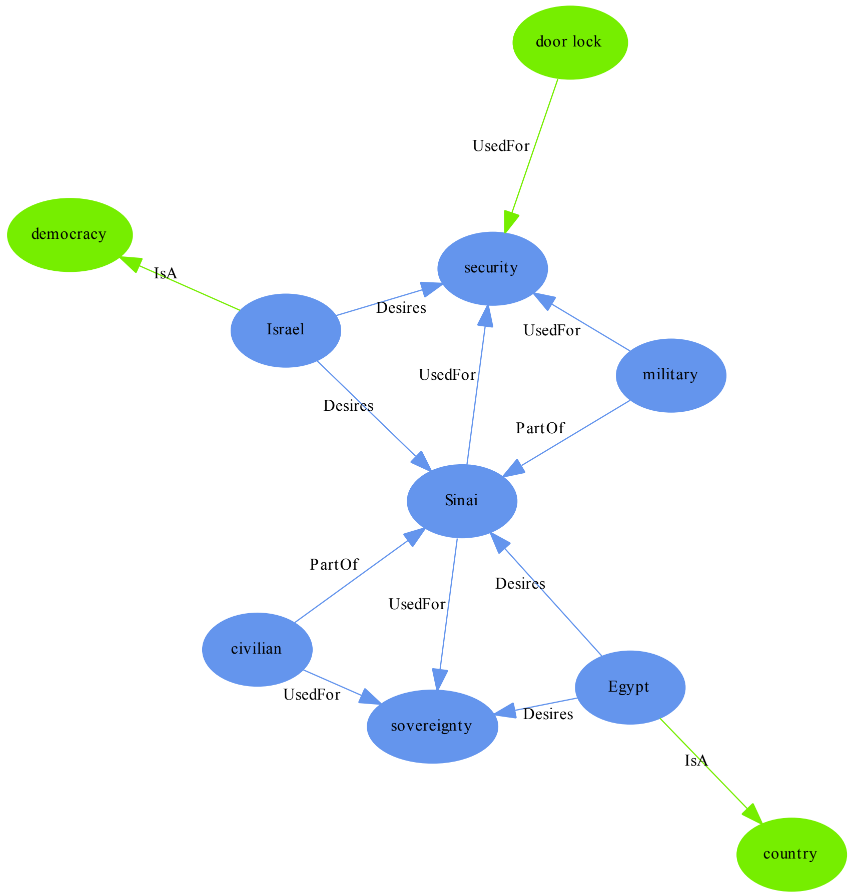


Figure 73: Example expansion process through commonsense reasoning. Sinai conflict unsolved case network, 100% (10 concepts, 13 relations). Green (or light) color represents the newly attached concepts and relations.

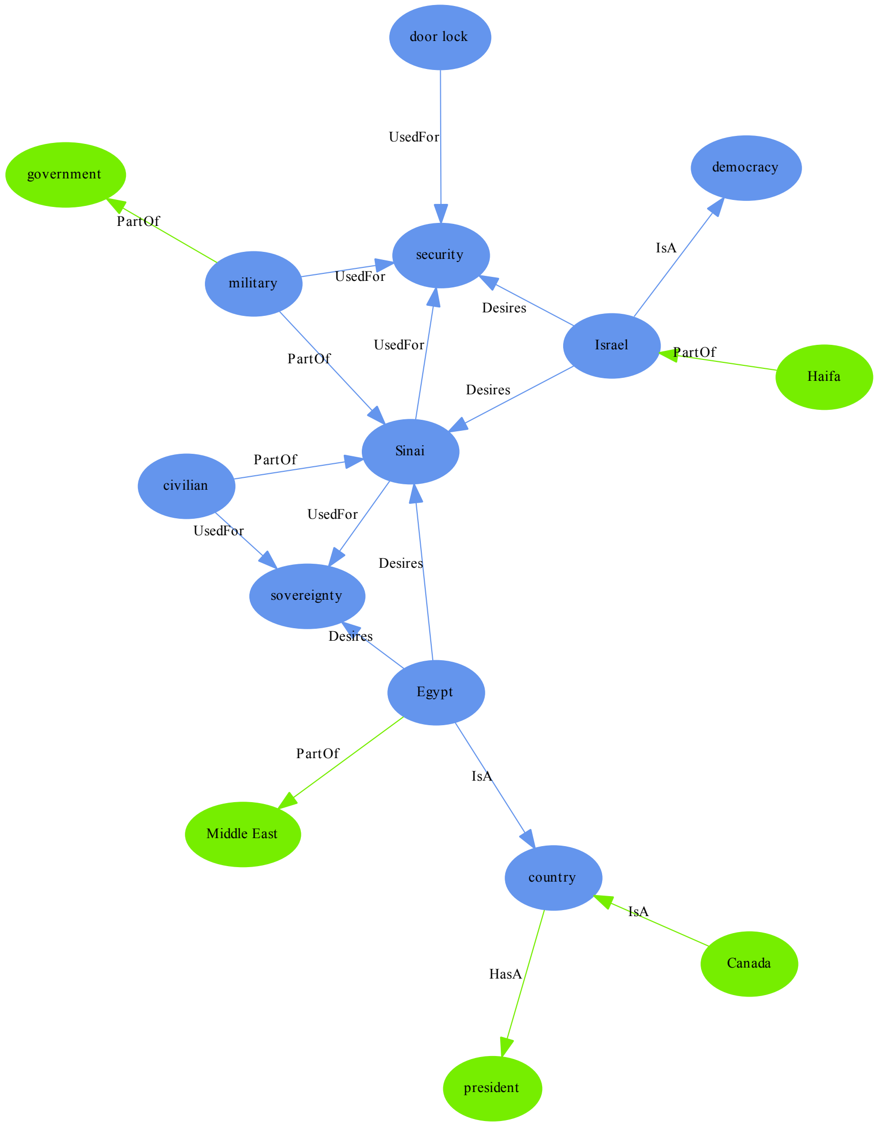


Figure 74: Example expansion process through commonsense reasoning. Sinai conflict unsolved case network, 200% expansion (15 concepts, 18 relations). Green (or light) color represents the newly attached concepts and relations.

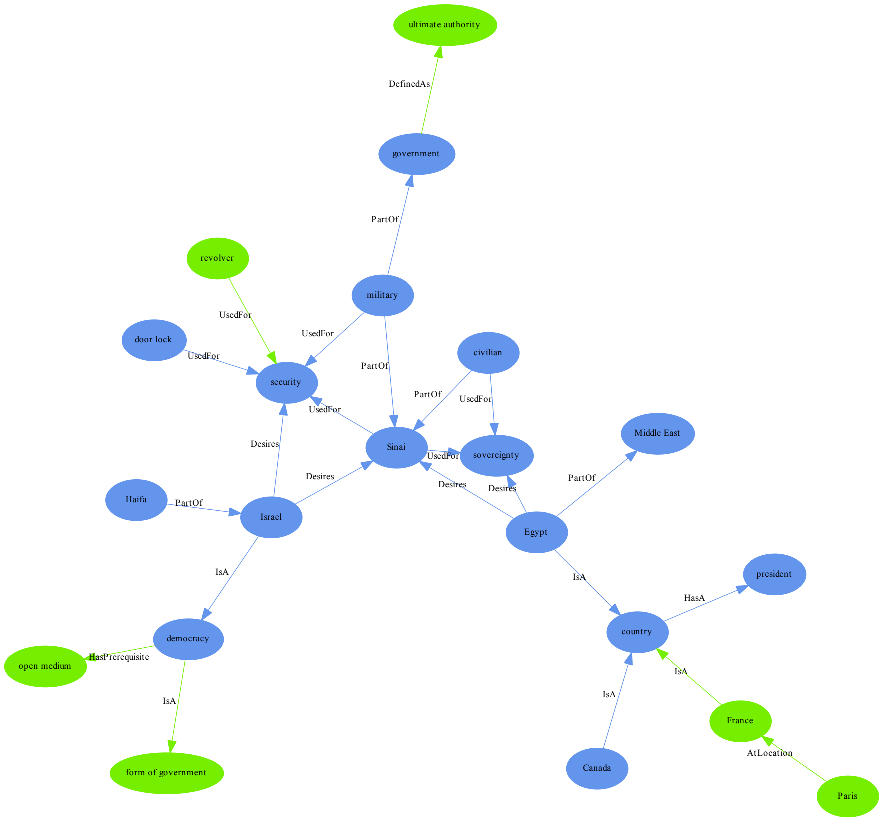


Figure 75: Example expansion process through commonsense reasoning. Sinai conflict unsolved case network, 320% expansion (21 concepts, 24 relations)). Green (or light) color represents the newly attached concepts and relations.

The role of the case expansion procedure in the adaptation process is inherently connected to our discussion of the basic mediation example in Section 7.1.2.

During our adaptation process, there are three possibilities regarding the outcome of the analogical mapping of a concept or relation from the domain of the retrieved case into the domain of the new case. A structure in the domain of the retrieved case can:

1. be mapped into a structure in the domain of the new case, which was already present in the given unsolved network of the new case at the time it was supplied to the CBR cycle;

2. be mapped into a structure in the domain of the *expanded new case* that was introduced via the case expansion procedure; and

3. not be mapped into any existing structure in the target domain, in which case the target of the mapping would be a "postulated" unknown target structure.

For the first possibility, an example would be the mapping of `cake` $\mapsto$ `sovereignty` in the example that we used in Section 7.1.2.

It is theoretically possible that the solution of the new case can be formed entirely of the concepts and relations already present in the unsolved case network. In this case, the adaptation would amount to a "reordering" or "arrangement" of the structure of the conflict to reach a solution.

For the second possibility, the mapping would involve structures in the target network that were introduced through the case expansion procedure. In the same example, the mapping of `peel` $\mapsto$ `civilian` would be such a mapping. In this case, the adaptation would be based on a "novelty" or "innovation" that introduces new ways to structure or perceive the conflict.

Thus, the novelty needed for the solution of the new case is supplied in our CBR adaptation method by a combination of general knowledge accessed through commonsense knowledge bases and the knowledge channeled from the case base through analogical mapping.

The second and third possibilities are basically instances of the process of inference in the structure mapping theory (Figure 14) that we discussed in Chapter 2.

For the third possibility, we will be left with some structures in the solved network of the current case for which we have no labels, such as the mapping of `peel` $\mapsto$ `*concept 1` before the expansion procedure. Even if this occurrence is not desirable, a suggested structure of a proposed solution would still be in place and the unknown concepts

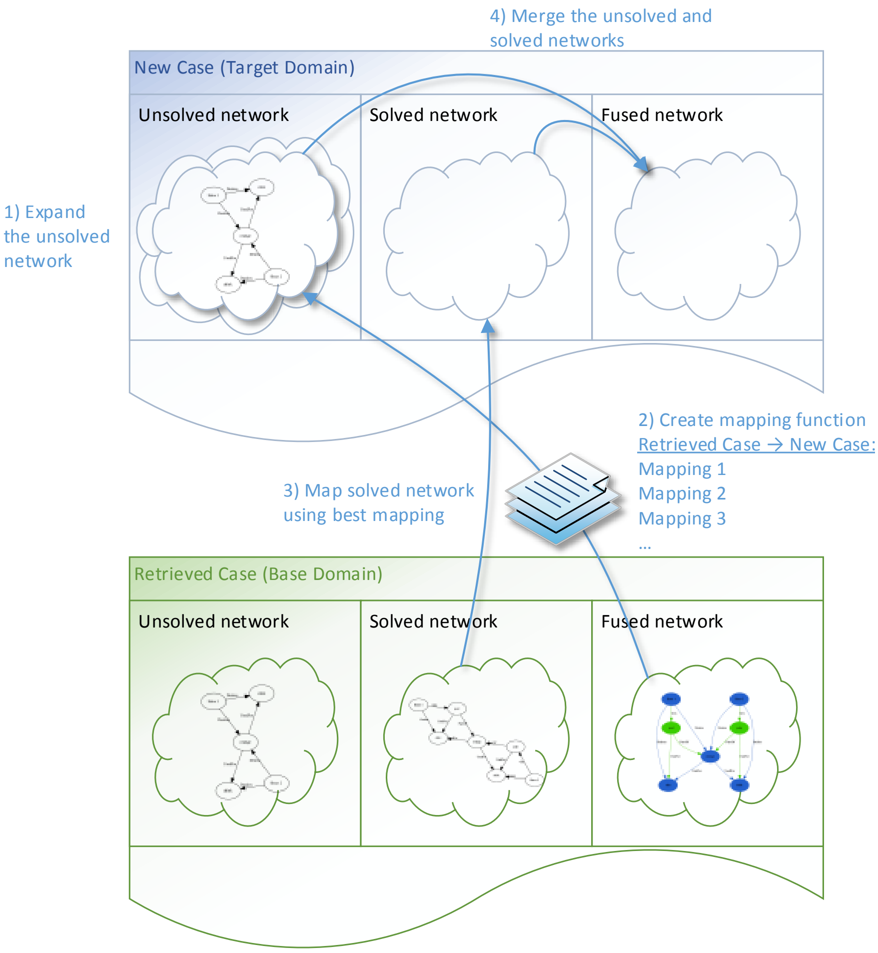


Figure 76: The substitutional adaptation procedure from the retrieved case (base domain) to the new case (target domain). The mapping function is created from the base fused network to the target unsolved network, and subsequently used to map the base solved into the target solved network.

will be open to human interpretation, providing potential insight for a possible solution of the case.

Regarding the implementation, a thing to note is that the expanded unsolved case network and the list of all possible analogical mappings from the retrieved case have been already calculated and kept during retrieval.

This essentially means that virtually all of the computations necessary for the adaptation procedure have already been performed in the retrieval stage, as a side-effect of our design for retrieval. Due to this design, adaptation is comparatively straightforward and computationally efficient.

Most of the computations necessary for the adaptation procedure have already been performed during the retrieval stage.

7.5.2 *Generative Evolutionary Adaptation*

For the cases where the adapted solution provided by the analogical inference based adaptation technique that we introduced in Section 7.5.1 fails to provide acceptable results, the system would fall back to a generative evolutionary adaptation technique (Figure 66).

Recognizing that the adaptation process is an instance of the problem of finding a network—in the domain of the new case—that is structurally analogous to the retrieved case, we again employ the approach we developed for the automated generation of analogies in Chapter 6.

For the adaptation problem, we employ the evolutionary approach developed for the automated generation of analogies.

For this, we embed, into the CBR cycle, the evolutionary adaptation technique based on semantic networks that we introduced in Chapter 5.

Figure 77 provides an overview of the flow of the adaptation algorithm. The algorithm is connected to the rest of the CBR system in Figure 66 via the inputs of the currently *rejected adapted case* and the *retrieved case*, and the output of a *new adapted case*.

The evolutionary algorithm is run in the target domain (i.e. the domain of the new case), with the fitness function measuring the analogical similarity to the retrieved case, calculated by our implementation of SME.

The algorithm proceeds as follows:

1. The initial population of candidate cases are created by variations of the supplied rejected adapted case. This is achieved through the same variation procedure that is defined in Chapter 5, but taking the supplied case as the sole input to the process.

2. The fitness of all the individuals in the population are computed using the SME-based fitness function defined in Chapter 6, taking the retrieved case as the base domain and the individual whose fitness is being evaluated as the target domain.

3. The individuals with known fitness values are then subjected to selection and variation as usual, until a given threshold for the number of generations has been reached. When the evolutionary cycle has been run for this set number of times, the best individual in the current population is given back to the CBR cycle as a new adapted case.

The parameters affecting the adaptation process are same as we introduced in Chapter 5 (Table 7). To the collection of $\mathrm{Size}_{\mathrm{pop}}$, number of individuals; $\mathrm{Prob}_{\mathrm{rec}}$, probability of crossover; $\mathrm{Prob}_{\mathrm{mut}}$, probability of mutation; $\mathrm{Score}_{\mathrm{min}}$, minimum quality score; $\mathrm{Count}_{\mathrm{timeout}}$,

timeout value for commonsense operations; Size_{tourn}, size of tournament; and Prob_{win}, probability of tournament win, we add a threshold value for the number of generations for which the evolutionary cycle will be run, calling it $\mathsf{Threshold}_{gens}$.

We do not use the $\mathsf{Size}_{network}$ parameter that originally denoted the size of the randomly generated semantic networks in the initial population, since we seed the initial population with variations of the rejected adapted network that is supplied in the beginning of the adaptation process.

The technique thus works through a closed cycle of evolutionary improvements that is run for a predetermined amount of generations, presenting the best individual case as the adapted output at the end of these cycles.

In the internal cycle of the evolutionary adaptation, the varying cases are tested using a fitness function measuring their analogical similarity to the retrieved case. The adapted case, in the end, is then evaluated by the "confirmation / retaining" step of the CBR cycle (Figure 66).

An alternative approach would be to turn this adaptation system into an entirely *interactive evolutionary algorithm* type of system, where all fitness evaluations would be delegated to the "confirmation / retaining" step of the CBR cycle (Figure 66).

Interactive evolutionary algorithms (Takagi, 2001; Fukumoto, 2010) are a recently developed technique that use a fitness function outside the algorithm for fitness evaluations. They have been frequently used in problems where the form of the fitness function is not known or cannot be defined, such as *visual appeal* in the field of evolutionary art.

Depending on the implementation of the rest of the actors (i.e. the negotiating agents interfacing with the mediator agent) of the original theoretical framework for mediation (Figure 65), this type of approach would be an applicable alternative.

In the case that the fitness evaluations would be delegated to the CBR "confirmation / retaining" step, one would need to modify the system for getting feedback about the solutions proposed by the CBR system to the outside world.

As with all EA methods, the optimization process would benefit from having a gradual evaluation feedback, for instance in terms of a real number score expressing the quality of the solution, rather than the binary "accepted" or "rejected" confirmation that we currently have in the CBR cycle (Jin, 2005).

In literature, evolutionary methods have been mentioned to be a part of the collection of methods for attacking the adaptation problem in CBR (Lopez De Mantaras et al., 2005). However, this method of

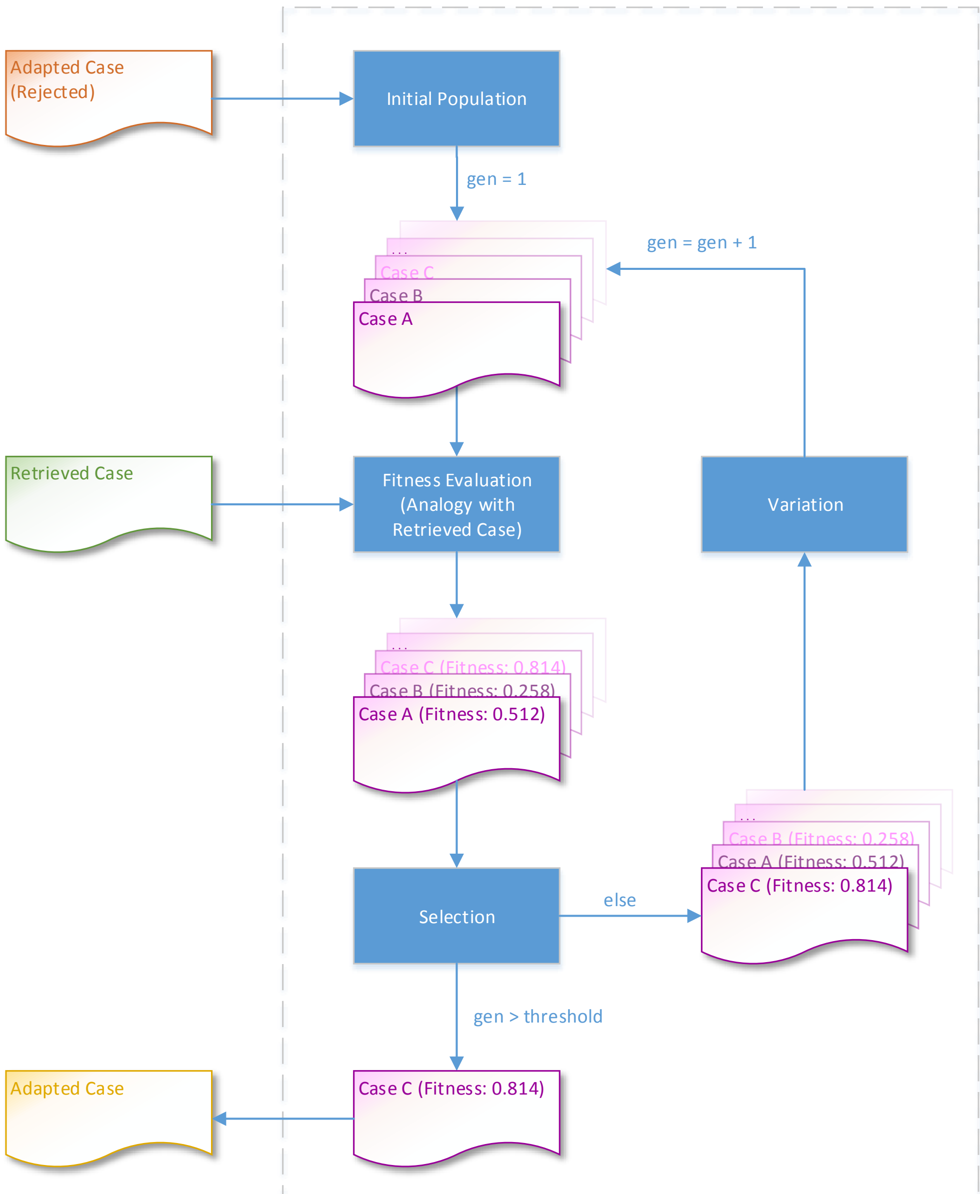


Figure 77: The generative evolutionary adaptation technique in the CBR cycle. The evolutionary cycle runs until a given threshold for the number of generations is reached and then supplies the best individual as the adapted case. See Figure 66 to see how it fits into the overall CBR cycle.

adaptation is still largely unexplored, and is nearly limited to the *case-based design* subfield.

An example from the case-based design field is the work by Gómez de Silva Garza and Maher (2000) where they apply an evolutionary case adaptation technique for a problem involving the layout of floor plans under some aesthetic constraints. Similarly, Rosenman (2000) develops a case-based model for the two dimensional spatial design of houses. In both of these examples, the authors pose an evolutionary technique as a promising way for addressing the "unresolved problem of adaptation" in CBR (Gómez de Silva Garza and Maher, 2000).

Recalling one of the original inspirations for our current work, Kolodner and Simpson (1989) talk about the possibility of having a generative adaptation component for their model of MEDIATOR, supporting the analogical reasoning approach. They envision several approaches that do not rely on past experiences, including plan-instantiation, applying a collection of predetermined "inference rules", and problem reduction.

Our work on evolutionary adaptation can be seen as an implementation of this idea, depending on the semantic network adaptation technique we introduced in the previous parts of this dissertation.

8

EXPERIMENTS AND EVALUATION

"It might be a good idea if the various countries of the world would occasionally swap history books, just to see what other people are doing with the same set of facts."

— William E. Vaughan (1915–1977)

8.1 SOURCES

We create a mediation case base of conflicts from a wide variety of problem domains, using the case representation principles that we introduced in Section 7.3 from Chapter 7.

The cases we collect are based on information from international conflict databases, conflicts from literature, imaginary examples, and conflicts made available by a mediation expert.

The cases we collect are based on information from international conflict databases, conflicts from literature, imaginary examples, and conflicts made available by a mediation expert. In the case base, we strive to represent as many different domains as possible within the boundaries of this study, ranging from familial and intellectual property disputes to international conflicts.

8.1.1 *International Conflict Databases*

An important topic within mediation studies is international conflict resolution, and the international relations field constitutes a very valuable resource for collecting mediation cases. Incorporating international conflicts into our case base is desirable primarily because we would like to experiment, to a certain degree, with non-trivial real world disputes.

We also hope that having cases based on, or inspired by, real world conflicts would render our study interesting for researchers in social sciences and related fields.

There have been numerous attempts over the years at cataloging international conflicts. In general, conflict databases designed with a perspective of conflict resolution and prevention include the following (Fürnkranz et al., 1997):

- The Butterworth dataset (Butterworth and Scranton, 1976)
- CONFMAN database of conflict management attempts (Bercovitch and Langley, 1993)
- Conflict and Peace Data Bank (COPDAB) Project (Azar, 1980)
- Correlates of War Militarized Interstate Disputes dataset (Gochman and Maoz, 1984)
- International Crisis Behavior (ICB) project (Brecher and Wilkenfeld, 2000)
- Event data sets of the KEDS and PANDA projects (Schrodt et al., 1994)
- KOSIMO database of conflicts (Pfetsch and Billing, 1994)
- SHERFACS database (Sherman, 1988)
- Uppsala Conflict Data Program (UCDP) maintained by Uppsala University in Sweden and the International Peace Research Institute (PRIO) in Oslo, Norway (Kreutz, 2010)

The main aim of these datasets is to list and index conflicts according to a chosen set of features.

On the other hand, they do not readily submit to our approach, since the data they represent are virtually always in a feature-vector format that includes neither detailed descriptions nor the solution steps for solved conflicts. Table 78 gives an example of such a dataset, from the UCDP project.

As we are interested in representing the cases in a format covering the structural and conceptual relationships within conflicts and their solutions, this lack of detailed descriptions severely limits the usefulness of these datasets for our approach. However, we do use them as inspiration for searching through literature and collecting information on selected conflicts.

8.1.2 *Cases from Literature*

Due to the absence of databases where conflicts are represented with enough structural detail, we are faced with the problem of formulating cases inspired from mediation and conflict resolution literature to allow us to perform our experiments.

To broaden the scope of our search, we take notice that the design of neither our case representation scheme nor the CBR cycle asks specifically for processes of “mediation”. All we need is a description of a conflict and its solution, regardless of whether this solution

Count	Count2	ConflictID	Ep	ConflEp	Location	SideA	SideB	Incomp	Terr	YEAR (fina	Type2	Years	EpStartDate	EpStartPr	EpEnd	EpEndDate	EpEndPre	Outcome	VicSide	Region	Version
174	20	88	1	88_1	Mozambiqu	Portugal	Frelimo	1	Mozambiqu	1974	1	1964-1974	1964-11-19	1	1	1974-09-07	1	1		4	1-2010
175	21	89	1	89_1	South Yem	United King	FLOSY	1	Aden/Soutl	1967	1	1964-1967	1964-11-25	1	1	1967-11-29	1	6		2	1-2010
176	127	90	1	90_1	Burundi	Burundi	Military fac	2		1965	3	1965	1965-10-18	1	1	1965-10-18	1	4	1	4	1-2010
177	128	90	2	90_2	Burundi	Burundi	Palipehutu	2		1992	3	1991-1992	1991-11-27	2	1	1992-12-31	5	5		4	1-2010
178	129	90	3	90_3	Burundi	Burundi	CNDD, Fro	2		2006	3	1994-2006	1994-10-18	1	1	2006-09-07	1	1		4	1-2010
179	130	90	4	90_4	Burundi	Burundi	Palipehutu	2		2008	3	2008	2008-03-01	1	1	2008-12-04	1	1		4	1-2010
180	131	91	1	91_1	Chad	Chad	Frolinat, Fi	2		1972	3	1966-1972	1966-07-01	4	1	1972-11-24	1	4	1	4	1-2010
181	132	91	2	91_2	Chad	Chad	FAN, FAP,	2		1984	3	1976-1984	1976-02-28	1	1	1984-12-31	5	5		4	1-2010
182	133	91	3	91_3	Chad	Chad	GUNT, CD	2		1987	3	1986-1987	1986-01-01	5	1	1987-11-01	1	4	1	4	1-2010
183	134	91	4	91_4	Chad	Chad	MOSANAT	2		1994	3	1989-1994	1989-03-03	2	1	1994-12-31	5	5		4	1-2010
184	135	91	5	91_5	Chad	Chad	FARF, MDI	2		2002	3	1997-2002	1997-10-30	1	1	2002-12-31	5	5		4	1-2010
185	136	91	6	91_6	Chad	Chad	FUCD, UFI	2		2009	3	2005-2009	2005-12-18	1	0					4	1-2010
186	137	92	1	92_1	Colombia	Colombia	FARC, ELN	2		2009	3	1964-2009	1964-01-01	5	0					5	1-2010
187	138	93	1	93_1	Dominican	Dominican	Military fac	2		1965	3	1965	1965-04-24	1	1	1965-08-31	1	1		5	1-2010
188	139	94	1	94_1	Indonesia	Indonesia	OPM	1	West Papu	1965	3	1965	1965-07-28	2	1	1965-12-31	5	5		3	1-2010
189	140	94	2	94_2	Indonesia	Indonesia	OPM	1	West Papu	1969	3	1967-1969	1967-01-01	5	1	1969-12-31	5	5		3	1-2010
190	141	94	3	94_3	Indonesia	Indonesia	OPM	1	West Papu	1978	3	1976-1978	1976-01-01	5	1	1978-12-31	5	5		3	1-2010
191	142	94	4	94_4	Indonesia	Indonesia	OPM	1	West Papu	1981	3	1981	1981-01-01	5	1	1981-12-31	5	5		3	1-2010
192	143	95	1	95_1	Peru	Peru	MIR, ELN	2		1965	3	1965	1965-08-03	2	1	1965-12-31	2	4	1	5	1-2010
193	144	95	2	95_2	Peru	Peru	Sendero Lu	2		1999	3	1982-1999	1982-08-22	2	1	1999-12-31	5	2		5	1-2010
194	145	95	3	95_3	Peru	Peru	Sendero Lu	2		2009	3	2007-2009	2007-11-14	1	0					5	1-2010
195	29	96	1	96_1	North Vietr	North Vietr	South Vietr	1	South Vietr	1975	2	1965-1975	1965-01-01	5	1	1975-04-30	1	4	2	3	1-2010
196	30	97	1	97_1	Cambodia,	Cambodia	Thailand	1	Common B	1978	2	1977-1978	1977-01-01	5	1	1978-12-31	5	5		3	1-2010
197	146	98	1	98_1	Ghana	Ghana	NLC	2		1966	3	1966	1966-02-24	1	1	1966-02-24	1	4	2	4	1-2010
198	147	98	2	98_2	Ghana	Ghana	Military fac	2		1981	3	1981	1981-12-31	1	1	1981-12-31	1	4	2	4	1-2010
199	148	98	3	98_3	Ghana	Ghana	Military fac	2		1983	3	1983	1983-06-19	1	1	1983-06-19	1	4	1	4	1-2010

Figure 78: A sample portion of the Uppsala Conflict Data Program (UCDP) Conflict Termination Dataset (Kreutz, 2010), version 2010–1–November 2010, maintained by Uppsala University, Sweden.

was reached by a mediation process. Keeping this in mind, almost all successfully solved conflicts can be treated as mediation cases, meaning that they could have been solved by mediation and they can give insight for the resolution of other conflicts.

8.1.2.1 *Beagle Channel*

This is a case inspired by the real world conflict between Chile and Argentina over the possession of several islands in the Beagle Channel, which we have discussed in Chapter 2 (Figure 79).

Unsolved case: Chile has sovereignty over the islands and this is recognized by the international community, but not by Argentina. Argentina has a claim over the possession of the islands.

Solved case: Argentina recognizes the sovereignty of Chile over the islands. Both countries agree to a redefinition of maritime boundaries in the region that will prevent conflicts in the future. Argentina gets increased maritime rights in the region.

8.1.2.2 *Beer Production*

This is a case inspired by the real world purchase of a brewery in Seville, Spain, involving beer companies Cruzcampo and Heineken (Figure 80).

Unsolved case: The brewery is owned by Cruzcampo, but the company is faced with maintenance costs and economic problems. Heineken has a production at the facility, under agreement with Cruzcampo.

Solved case: Heineken gets the factory, and together with it the economic burden of operation. Cruzcampo makes production, under agreement, but loses the dominance in the production and the market to Heineken.

8.1.2.3 *Bookshelf*

This is an imaginary case involving two children and access to a bookshelf (Figure 81). It is intended to be the prototypical example of situations where one party convinces the other to do something in exchange of a benefit or payment.

Unsolved case: One child has a bookshelf and prevents the other child from accessing it.

Solved case: The other child gives a candy, thereby convincing the child to provide access.

8.1.2.4 *Fishing Rights*

This is case inspired by the real world events involving the fishing rights of a maritime region in the Atlantic between the European Union and Morocco (Figure 82).

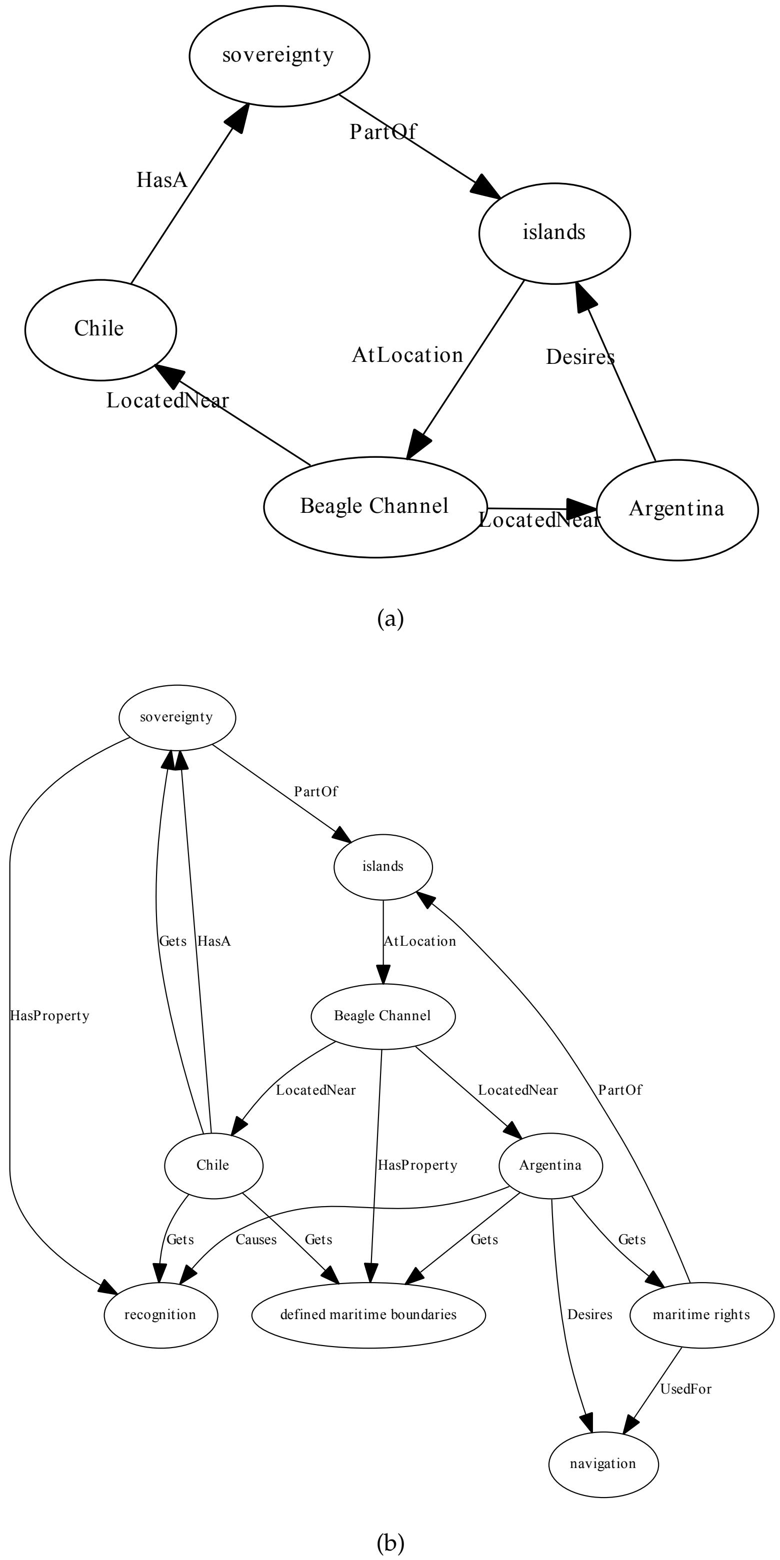
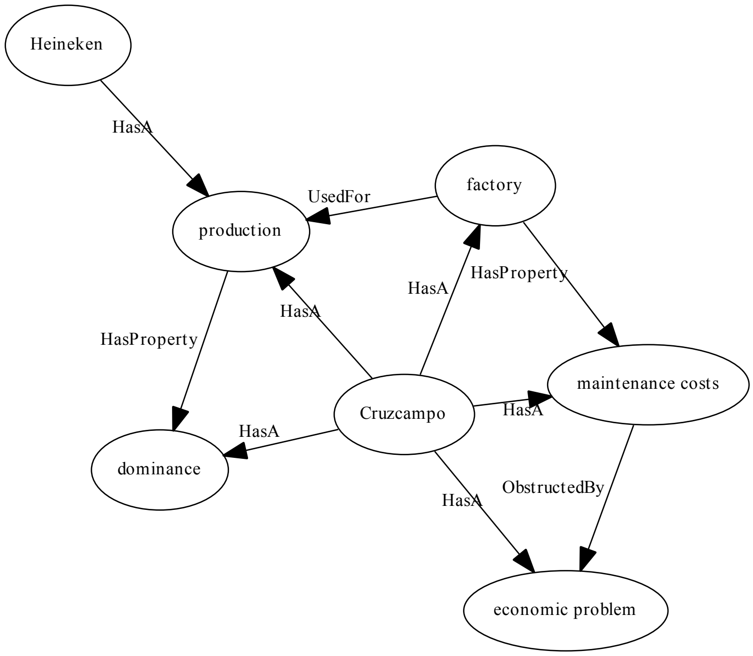
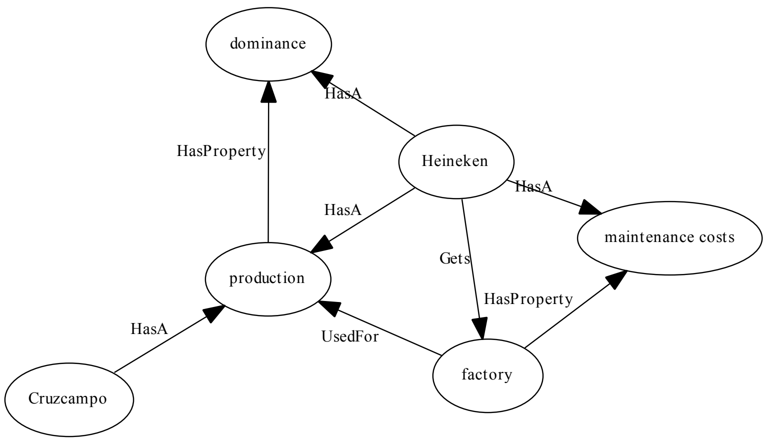


Figure 79: *Beagle Channel* case. (a) Unsolved case network; (b) solved case network.



(a)



(b)

Figure 80: *Beer Production* case. (a) Unsolved case network; (b) solved case network.

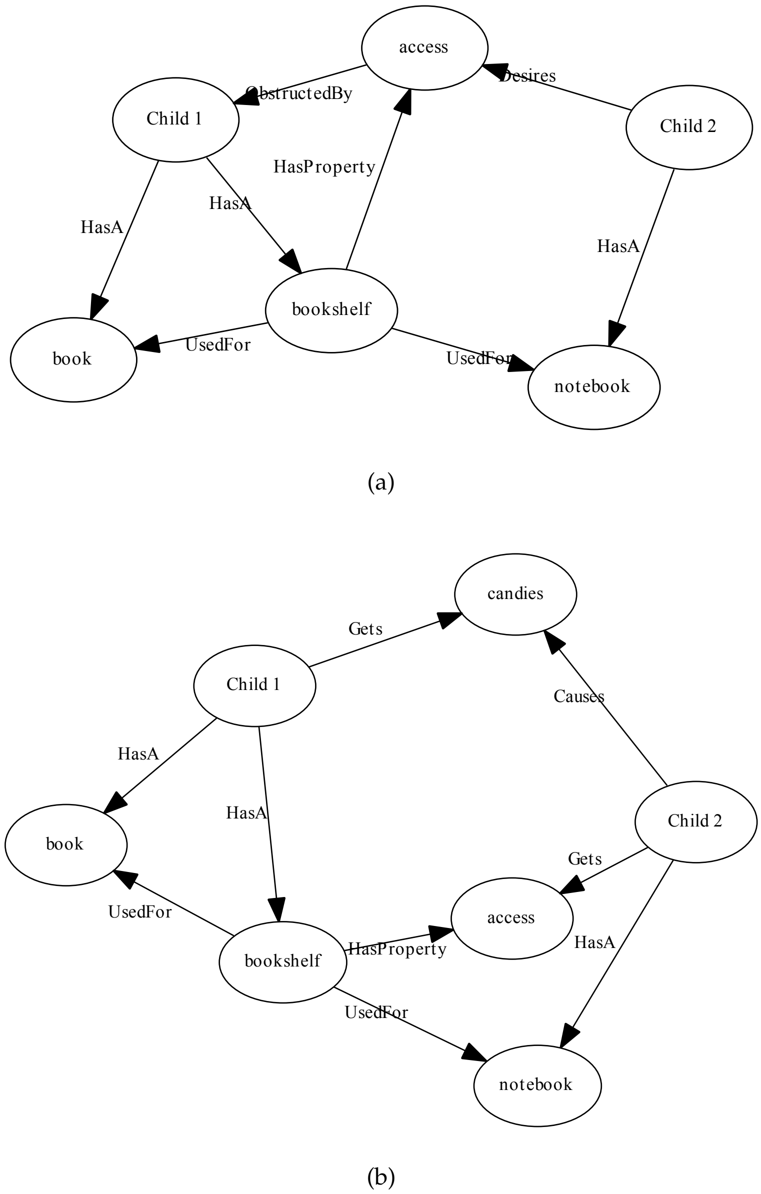


Figure 81: *Bookshelf* case. (a) Unsolved case network; (b) solved case network.

Unsolved case: Morocco has, under its possession, an economically significant fishing region in the Atlantic. The European Union access to this region is hindered by pirate ships allegedly supported by Morocco.

Solved case: Morocco and the European Union agree on a schedule to use the fishing region together. Morocco receives monetary compensation from the European Union.

8.1.2.5 *Fugitive*

This is a case inspired by events in news media involving a fugitive between the United States and Russia (Figure 83).

Unsolved case: A United States citizen escapes from his country where he is wanted for arrest. The fugitive is currently in an airport in Russia. The United States wants the deportation of the person from Russia.

Solved case: Russia agrees with deportation, on the condition that the fugitive gets good treatment by the Unites States authorities.

8.1.2.6 *Indus Waters*

This is a case inspired by the Indus Waters Treaty signed between Pakistan and India in 1960, mediated by the World Bank (Figure 84).

Unsolved case: Pakistan and India have conflict over the possession of the Indus Basin, which is a very important source of water supply for their populations.

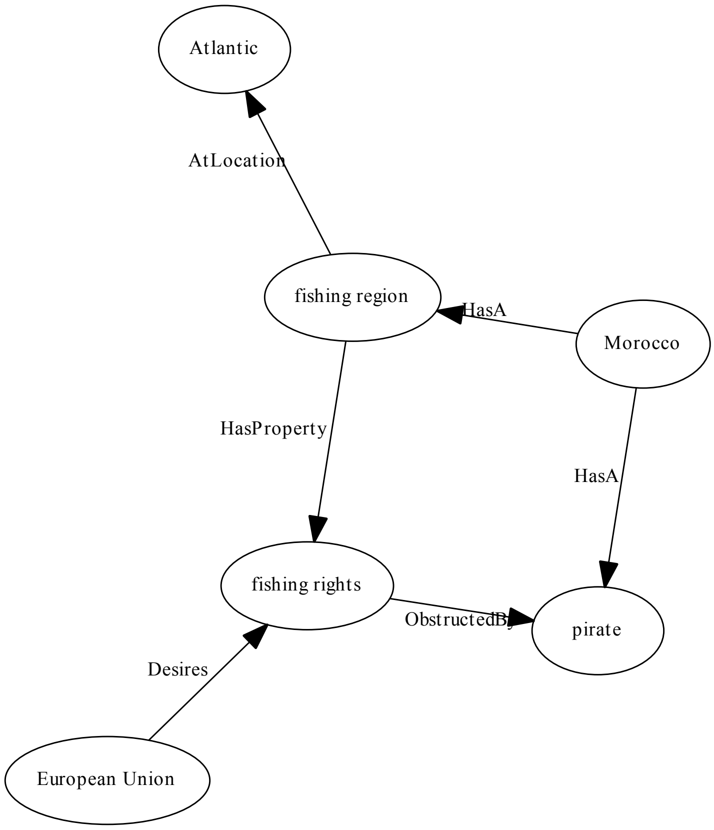
Solved case: The basin is divided into Western and Eastern parts, which are assigned to Pakistan and India, respectively. But do to the fact that the river flows from the East to the West, India gets higher benefit from this arrangement due to increased water supply. The losses of Pakistan are covered by monetary compensation provided by India.

8.1.2.7 *Insurance*

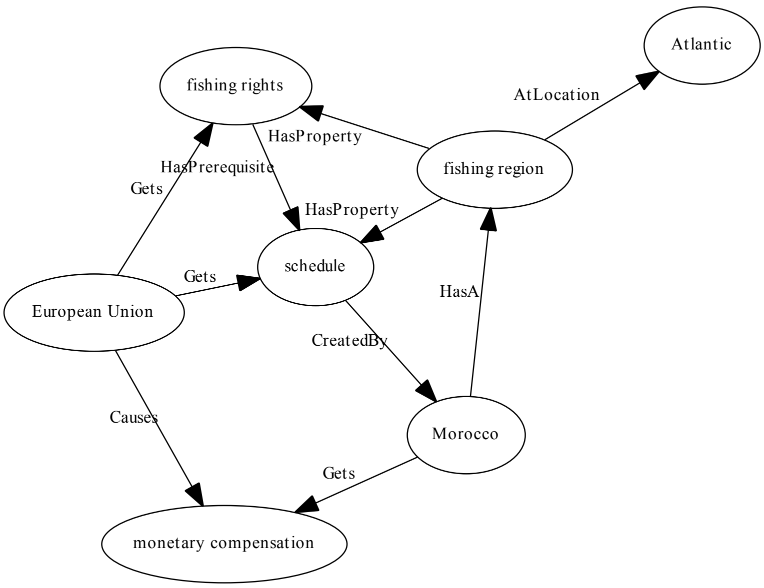
This is an imaginary case about a customer who wants to go to court against a company to get their medical costs covered after an accident (Figure 85).

Unsolved case: The customer has an accident in the shop of the company and this incurs medical bills. The customer wants to bring this case to the court to court, which is bad for the publicity of the company.

Solved case: The customer agrees to drop their case after a monetary compensation by the company.

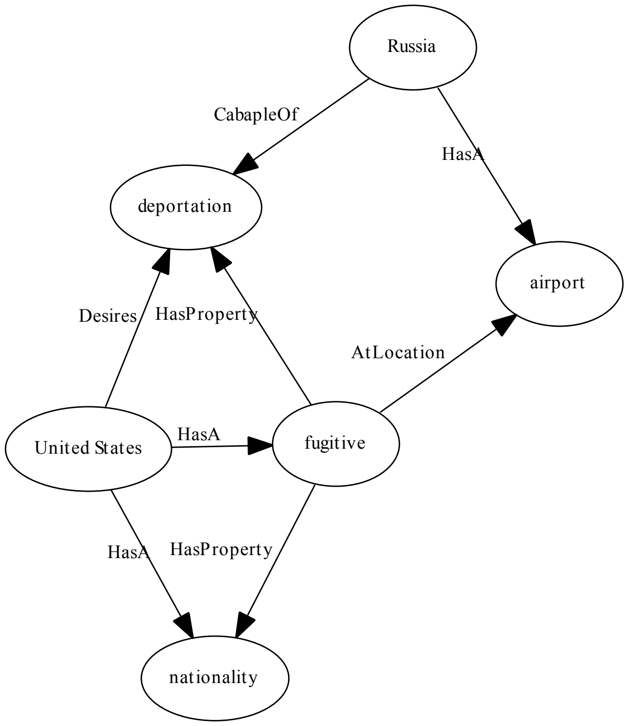


(a)

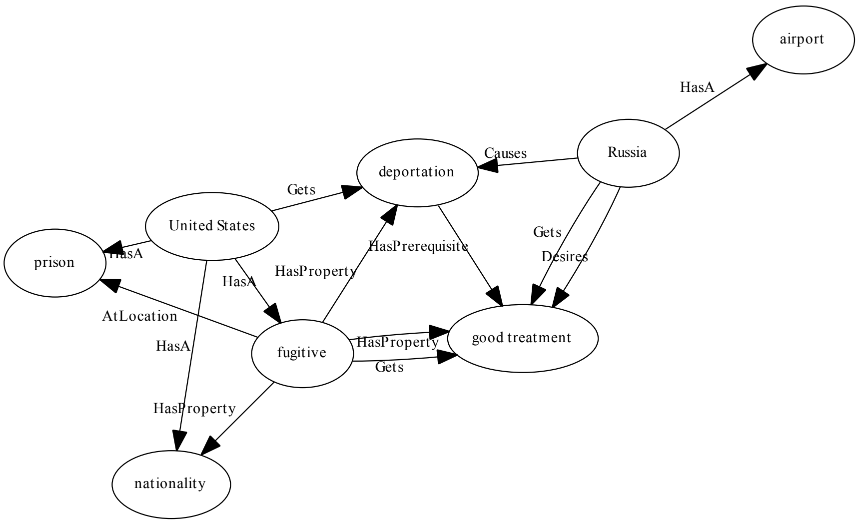


(b)

Figure 82: *Fishing Rights* case. (a) Unsolved case network; (b) solved case network.



(a)



(b)

Figure 83: *Fugitive* case. (a) Unsolved case network; (b) solved case network.

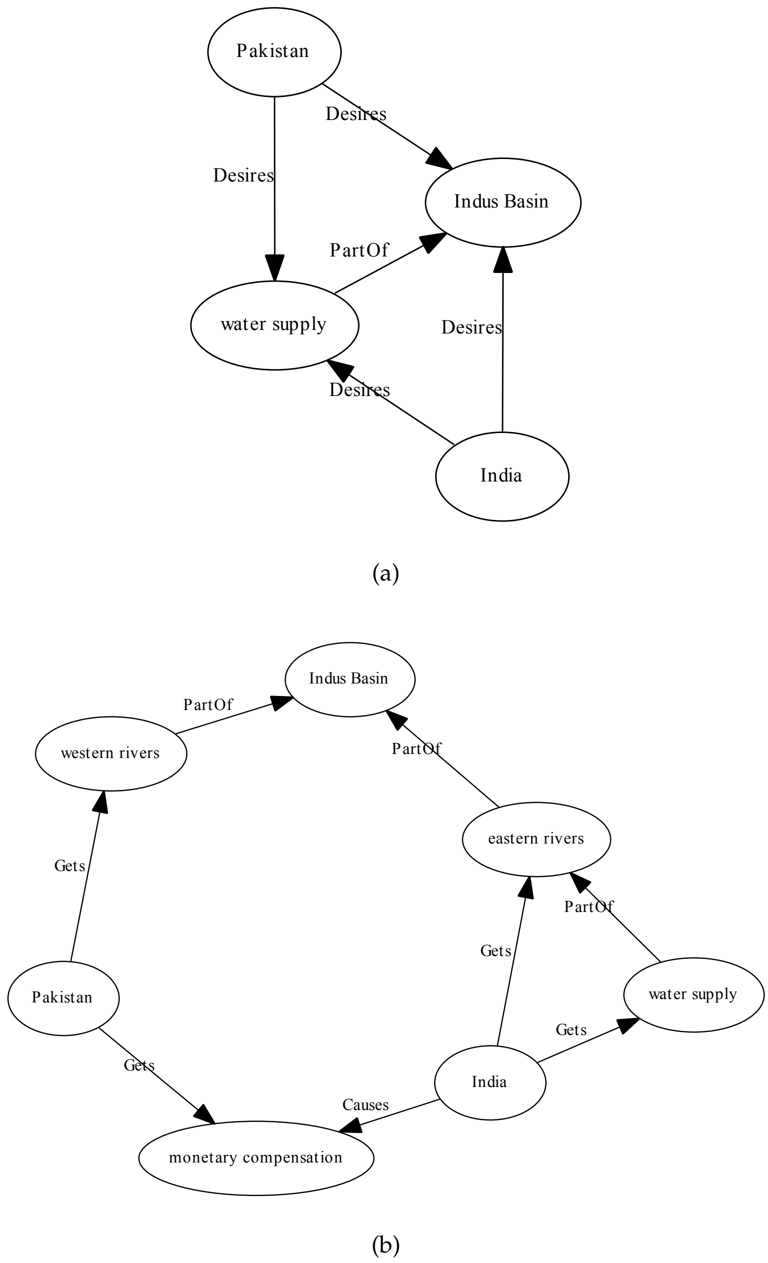


Figure 84: *Indus Waters* case. (a) Unsolved case network; (b) solved case network.

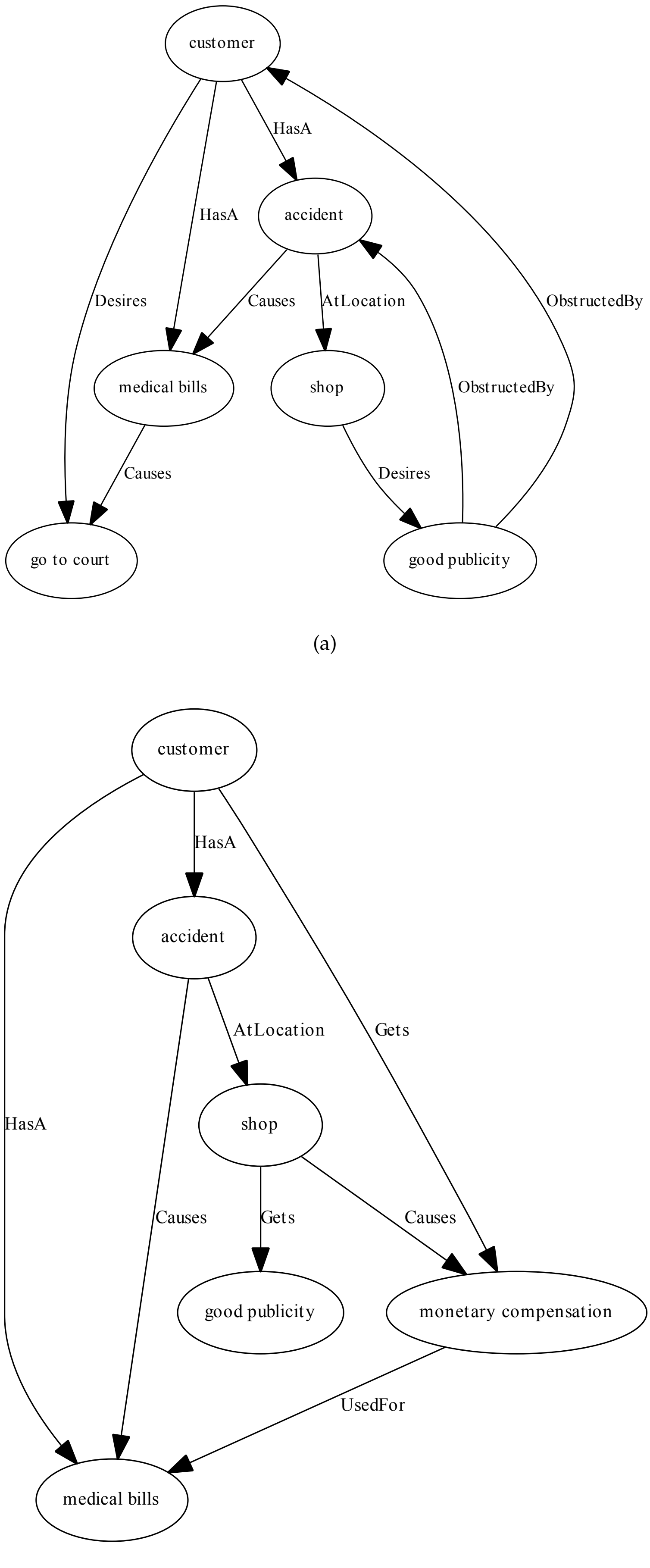


Figure 85: *Insurance* case. (a) Unsolved case network; (b) solved case network.

8.1.2.8 *Iranian Hostage Crisis*

This case is inspired by the real world events surrounding the diplomatic crisis between the United States and Iran in 1979, where the United States embassy in Tehran was occupied with its staff taken as hostages (Figure 86). A solution to the crisis was mediated by Algeria.

Unsolved case: The United States embassy is occupied by Iran, and the staff taken hostage. Iran desires the United States to stop getting involved in Iran's internal affairs and to lift its economic embargo on the country.

Solved case: United States agrees to lift the embargo and assure Iran that its internal affairs will be free of interference. In return, Iran agrees to free the hostages and pay its existing debts to United States institutions.

8.1.2.9 *Market Access*

This is an imaginary case inspired by commerce literature, involving two countries negotiating on market access rights (Figure 87).

Unsolved case: China desires to conduct commercial activity in the Spanish market, but it does not have the necessary permissions and is obstructed by local regulations.

Solved case: Spain gives China access to its local market under some regulations. In return, China gives monetary compensation to Spain.

8.1.2.10 *Music Band*

This is an imaginary case involving intellectual property of a song created together by two members of a band (Figure 88).

Unsolved case: Two members of a music band created a song together. But one of them started a collaboration with another band, and due to this, the other member wants to break up the band. They both claim ownership of their intellectual creation.

Solved case: The musicians agree to the break up. The musician who has a collaboration with another band agrees to forfeit their rights on the intellectual property, in exchange for monetary compensation.

8.1.2.11 *Orange*

This is the one of the cases from Kolodner and Simpson (1989) that we have discussed extensively in Chapter 7 (Figure 89).

8.1.2.12 *Patent*

This case is about the manufacturing rights of an invention, inspired by literature about patenting conflicts (Figure 90).

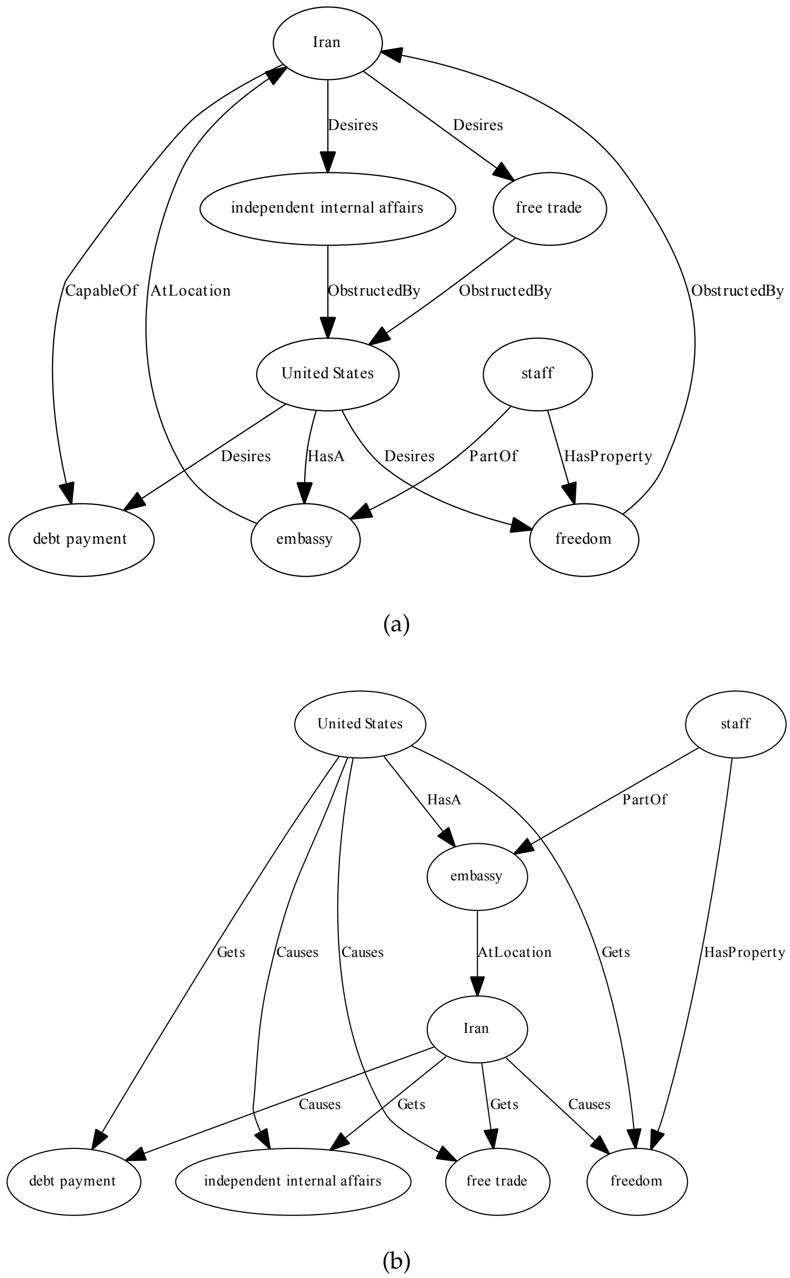


Figure 86: *Iranian Hostage Crisis* case. (a) Unsolved case network; (b) solved case network.

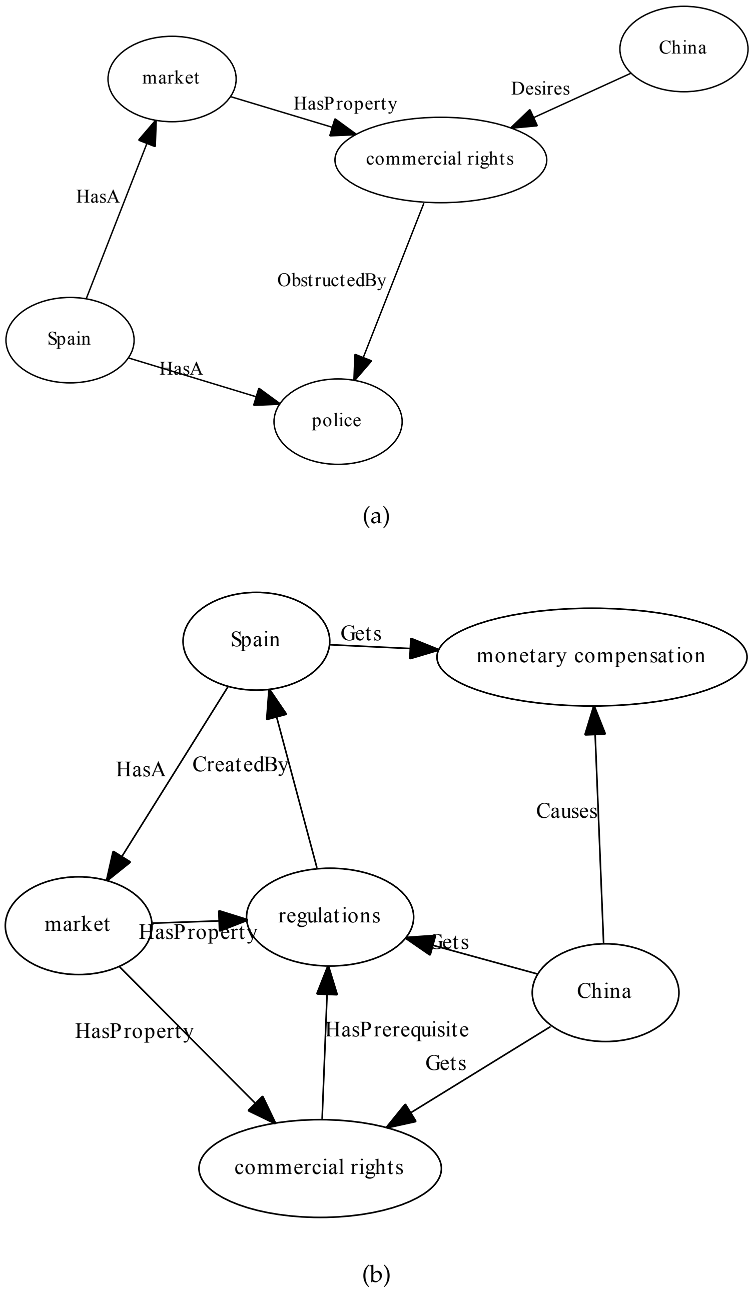


Figure 87: *Market Access* case. (a) Unsolved case network; (b) solved case network.

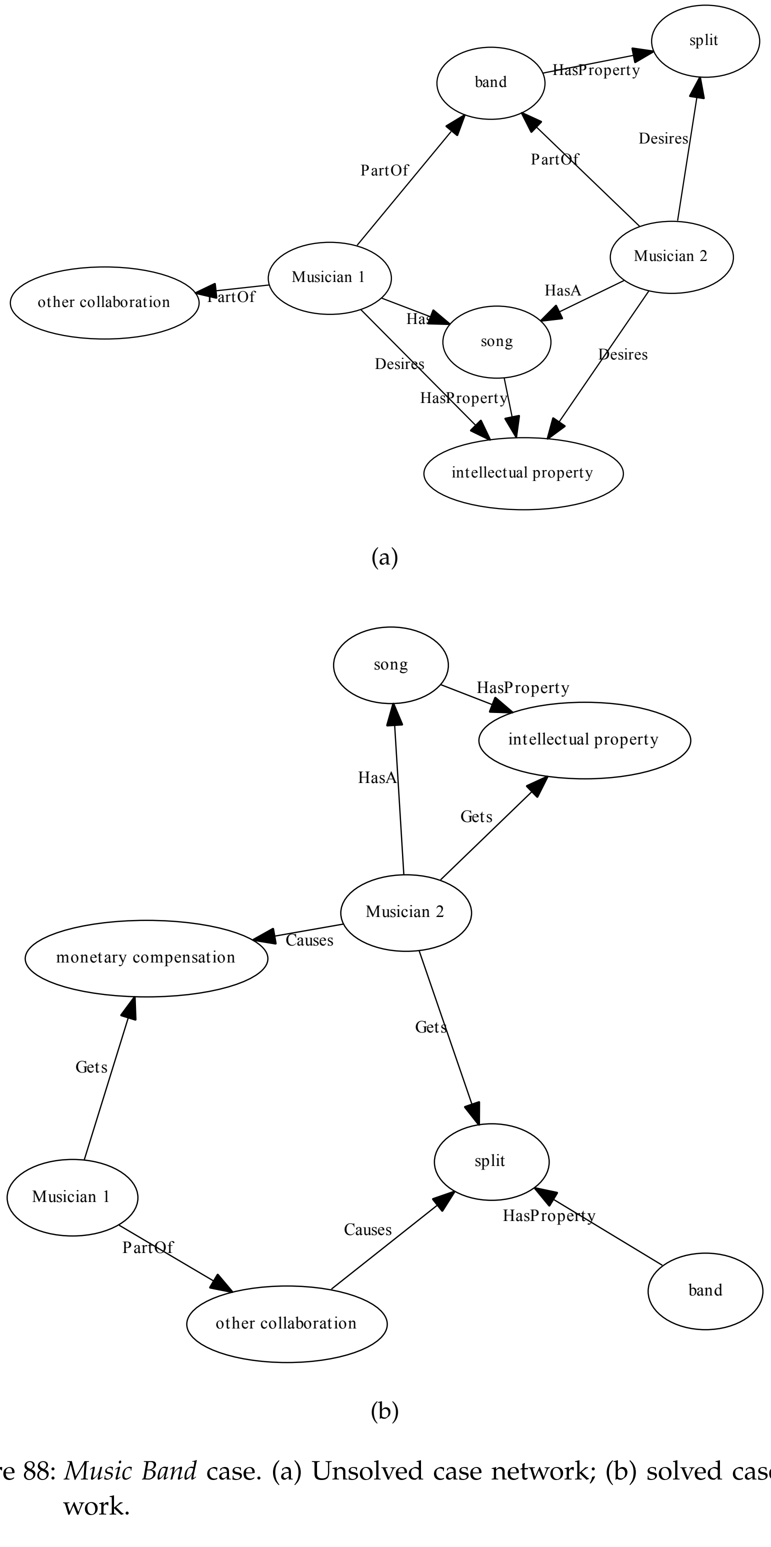


Figure 88: *Music Band* case. (a) Unsolved case network; (b) solved case network.

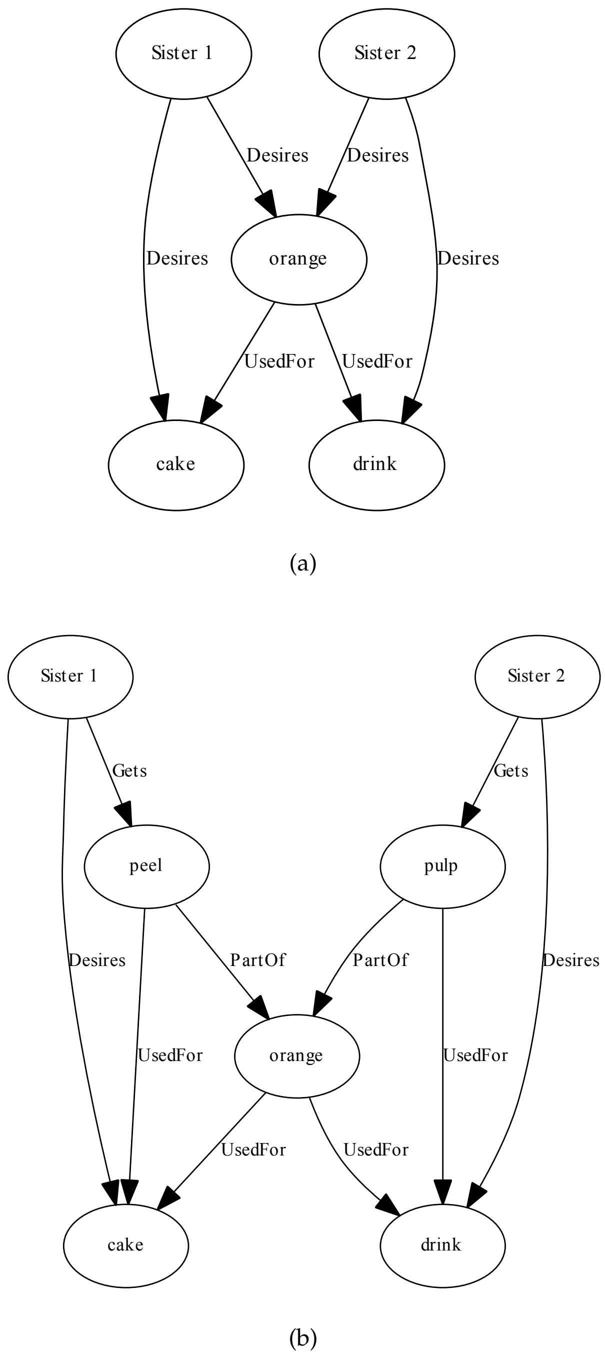


Figure 89: *Orange* case. (a) Unsolved case network; (b) solved case network.

Unsolved case: A company has an invention and holds the manufacturing rights for this invention. It comes to the company's attention that a manufacturer has been manufacturing their invention without permission. The company therefore desires monetary compensation for their losses.

Solved case: The manufacturer agrees to recognize and publicize the ownership of the manufacturing rights of the inventor company. In return for public recognition, the company forgoes any claim about monetary compensation.

8.1.2.13 *Rhodesia Britain*

This case is inspired by the real world negotiations between Rhodesia (later Zimbabwe) and the British Government that brought independence to the British colony in 1979 (Figure 91).

Unsolved case: Rhodesia and the British Government had been parties in an armed conflict and they both want a ceasefire. Rhodesia desires to gain independence and perform a land reform. There is a white minority in the country.

Solved case: Rhodesia is allowed to draft a constitution paving the way to independence and the land reform. British government gets rights for the white minority in the country.

8.1.2.14 *Sinai*

This is the one of the cases from Kolodner and Simpson (1989) that we have discussed extensively in Chapter 7 (Figure 92).

8.1.2.15 *Software Use*

This case is inspired by a scenario provided by the World Intellectual Property Organization[1], involving an airline company using the product of a software company (Figure 93).

Unsolved case: The airline company had purchased a software from a software company, but later terminated their agreement. The airline company maintains that they still have a right for continued use of the software already in their possession. The software company believes that the software should be returned and its use should be ceased.

Solved case: The airline company agrees to get a license allowing the continued use of the existing software. The software company gets a payment for this license.

1 http://wipo.int/amc/en/mediation/case-example.html

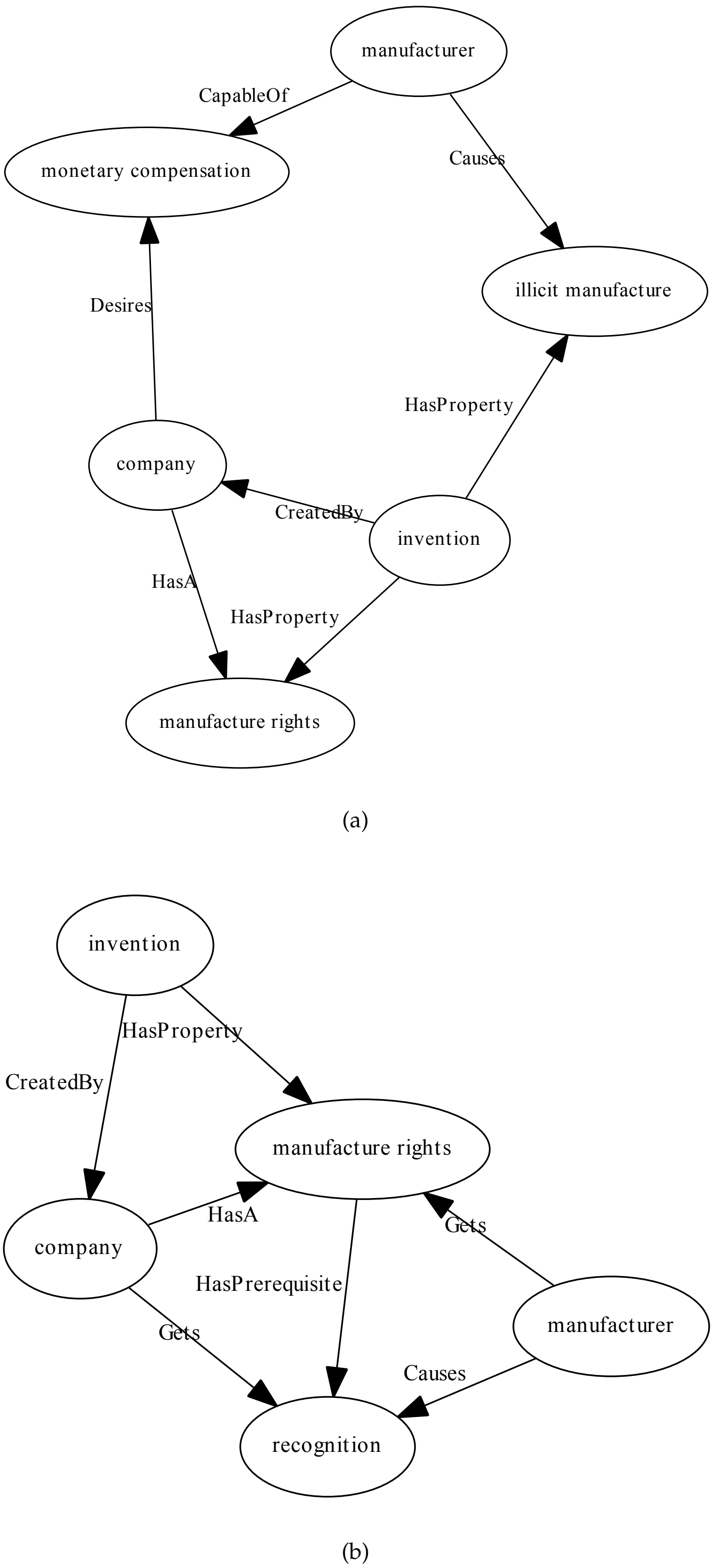


Figure 90: *Patent* case. (a) Unsolved case network; (b) solved case network.

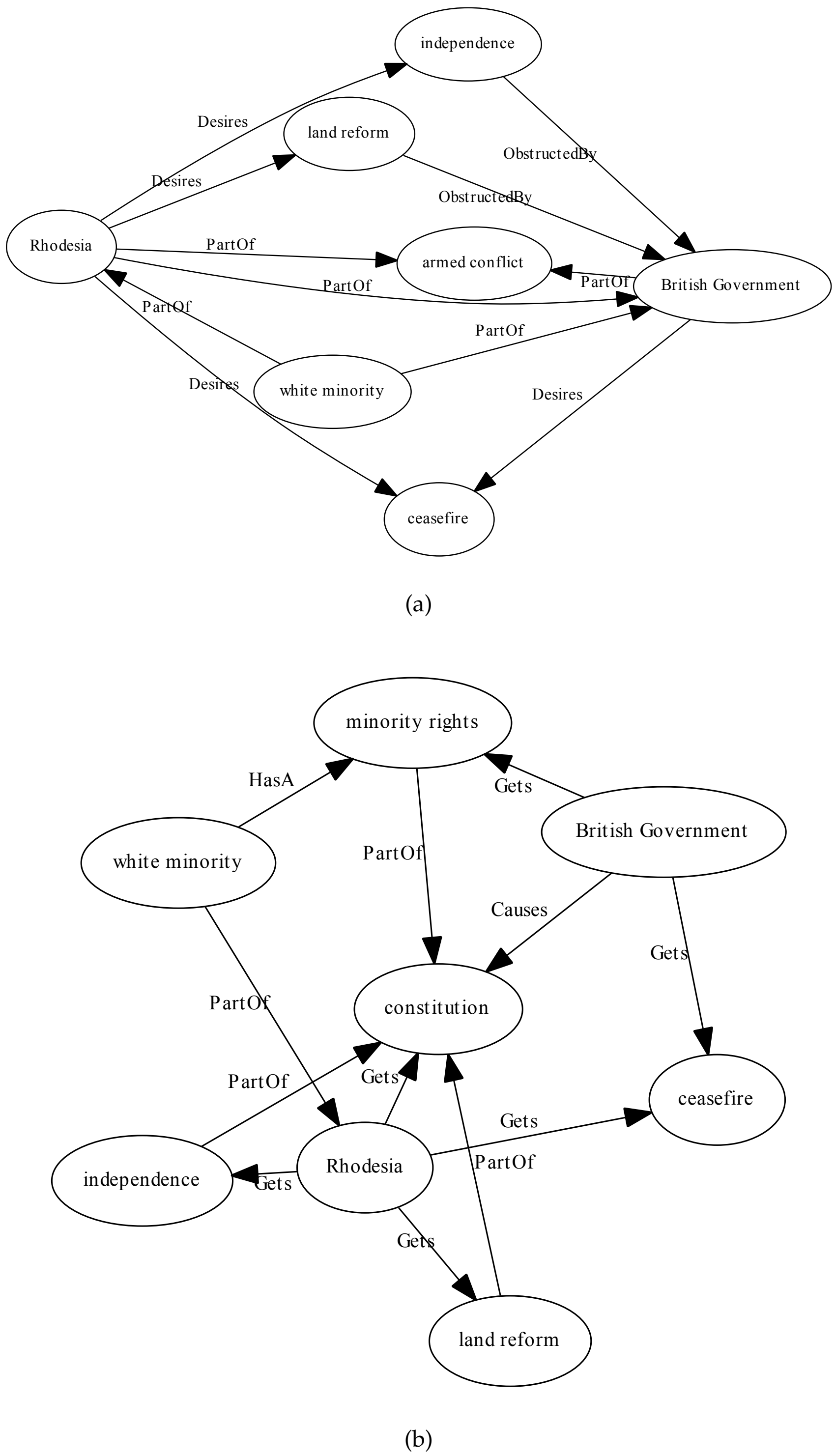


Figure 91: *Rhodesia Britain* case. (a) Unsolved case network; (b) solved case network.

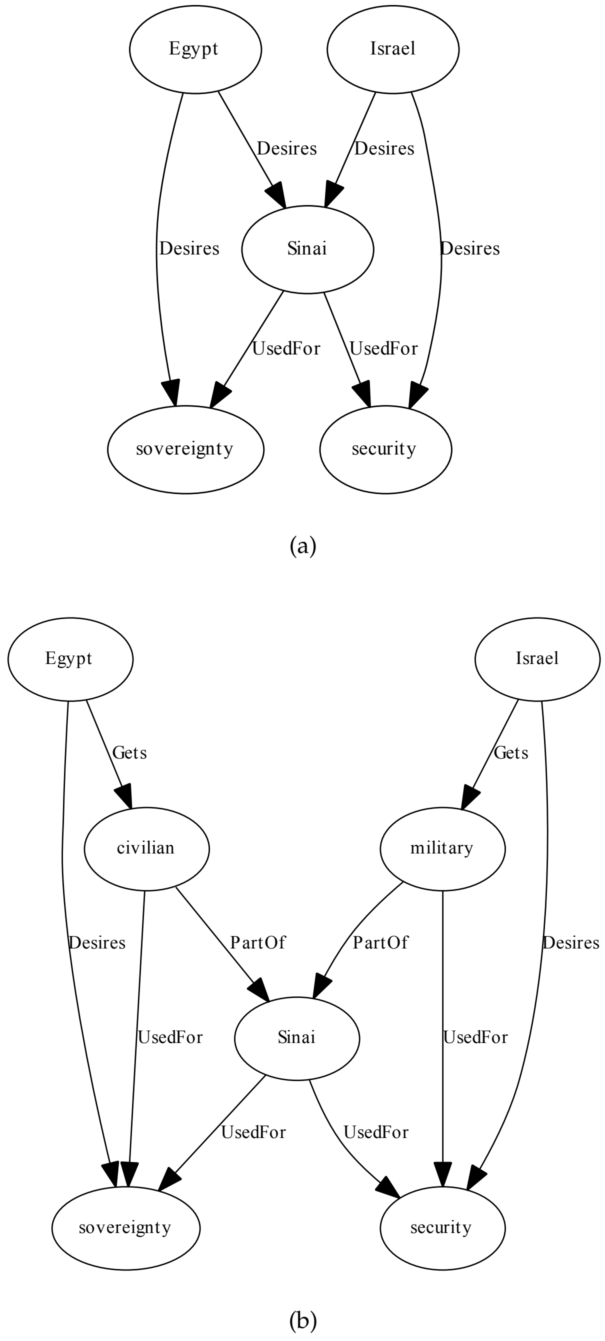


Figure 92: *Sinai* case. (a) Unsolved case network; (b) solved case network.

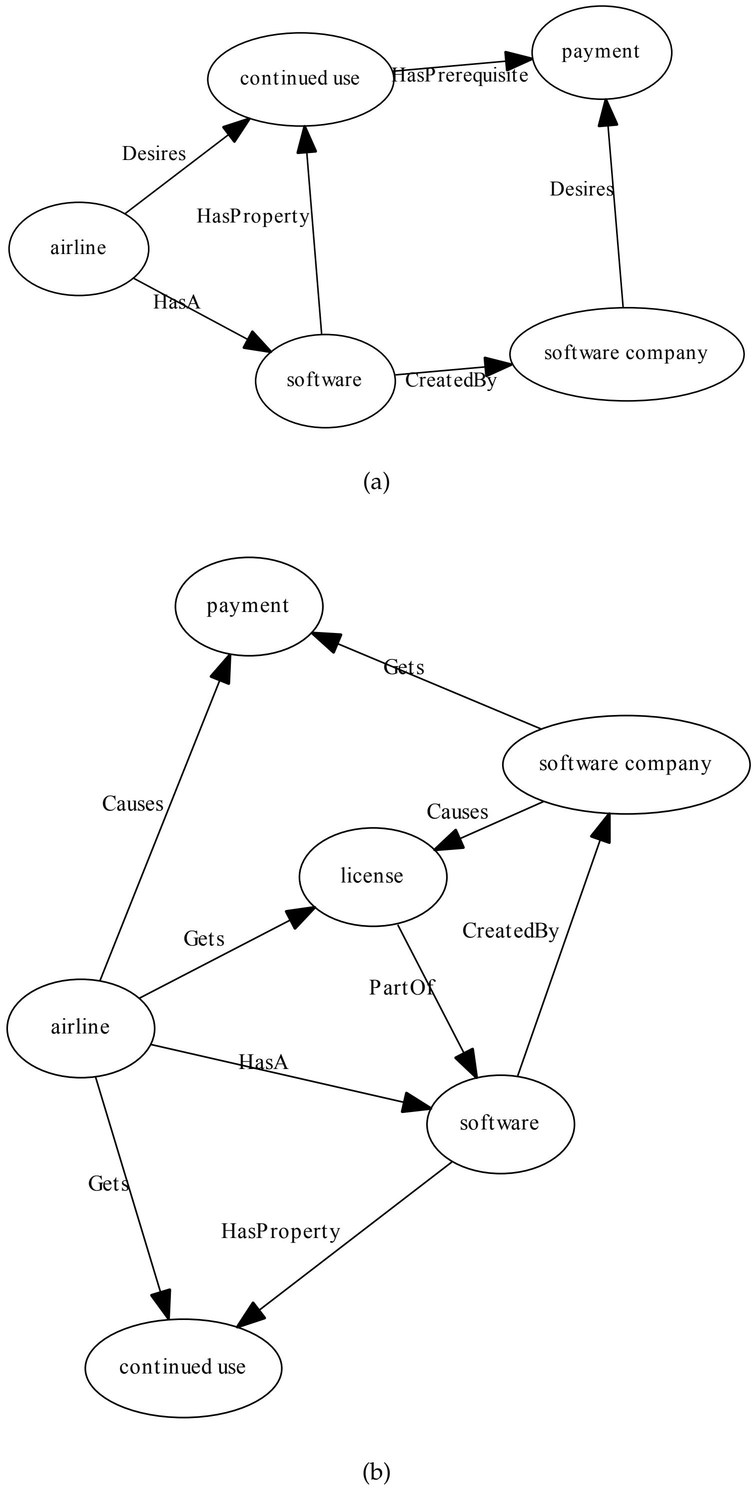


Figure 93: *Software Use* case. (a) Unsolved case network; (b) solved case network.

8.1.2.16 *Sports Teams*

This is an imaginary case involving the change of teams of a sports player (Figure 94).

Unsolved case: A sports team holds the contract of a player. But the player desires to participate in another team. The other team desires to have a contract with this player.

Solved case: The original team agrees to allow the other team to have a contract with the player and gets a monetary compensation for this. The player would play for the new team but the original team would also have access to this player at times.

8.1.3 *Cases Supplied by a Mediation Expert*

We also had the opportunity to access real-world mediation cases provided by mediation expert Dr. Josep Redorta.

In addition to the cases we have covered so far, we also had the opportunity to access some real-world mediation cases provided by mediation expert Dr. Josep Redorta.

Dr. Redorta is a family mediator recognized by the Center of Family Mediation of Catalunya[2], an arbitrator of the Labor Court of Catalunya, and a member of the European Court of Arbitration[3]. He is the author of several reference books in the field (Redorta, 2005a,b, 2007).

The provided cases are a collection of familial disputes, such as divorce and custody, from the Balearic Islands, covering a period between 2005 and 2008.

The cases include the names and personal details of the persons involved, but we leave any identifiable details out of our case representations and descriptions, which are already far more simplified compared with reality.

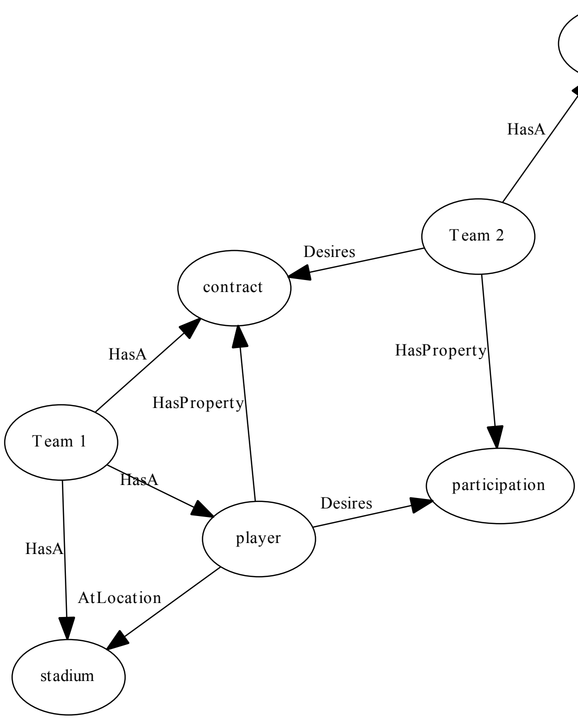
8.1.3.1 *Disability*

This case concerns the property ownership and household arrangements of a married couple after one of them gets disability following an accident (Figure 95).

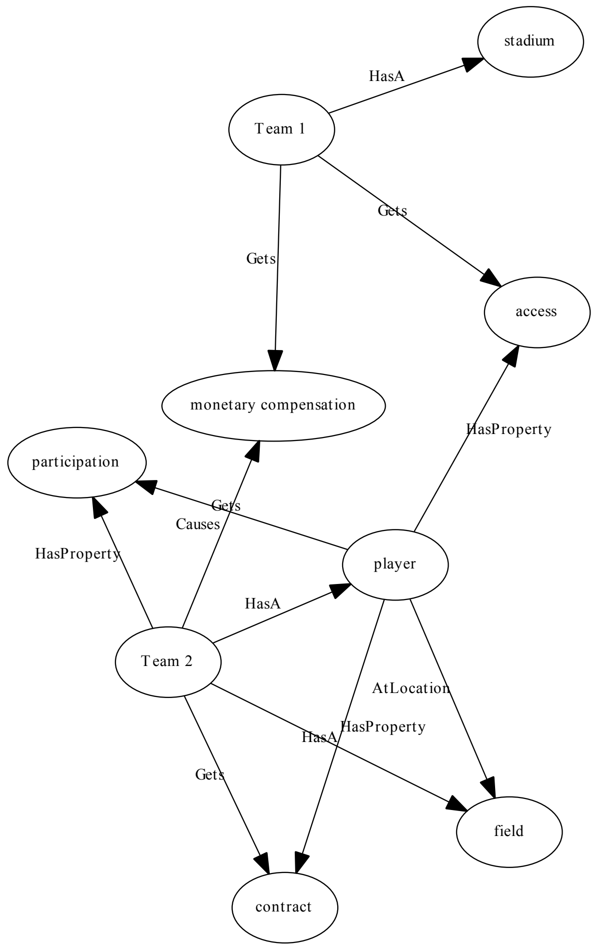
Unsolved case: The husband and wife are living in the same house together with their child. Their child is influenced more by the father due to his role as the provider. After the husband gets disability, he has difficulty in covering the financial costs associated with the running of the household.

Solved case: The wife undertakes the costs of running the household, and in return she gets the ownership of the house. Ass a result, the child is more influenced by the mother.

2 www.gencat.cat/mediacio
3 http://cour-europe-arbitrage.org/

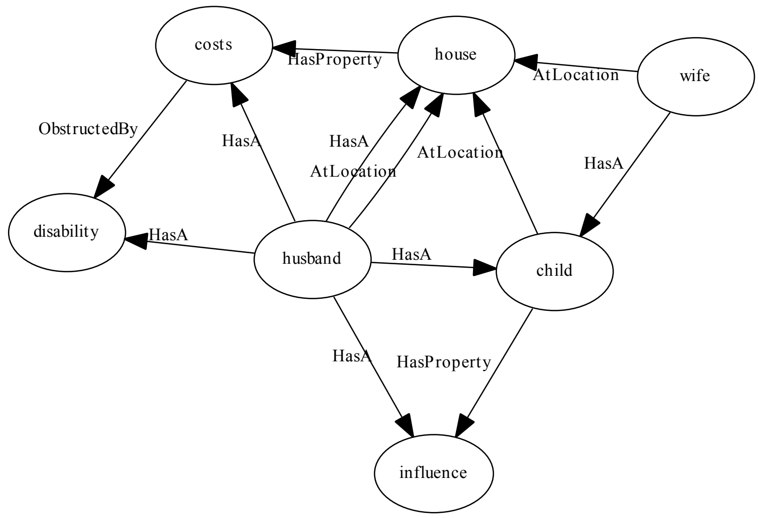


(a)

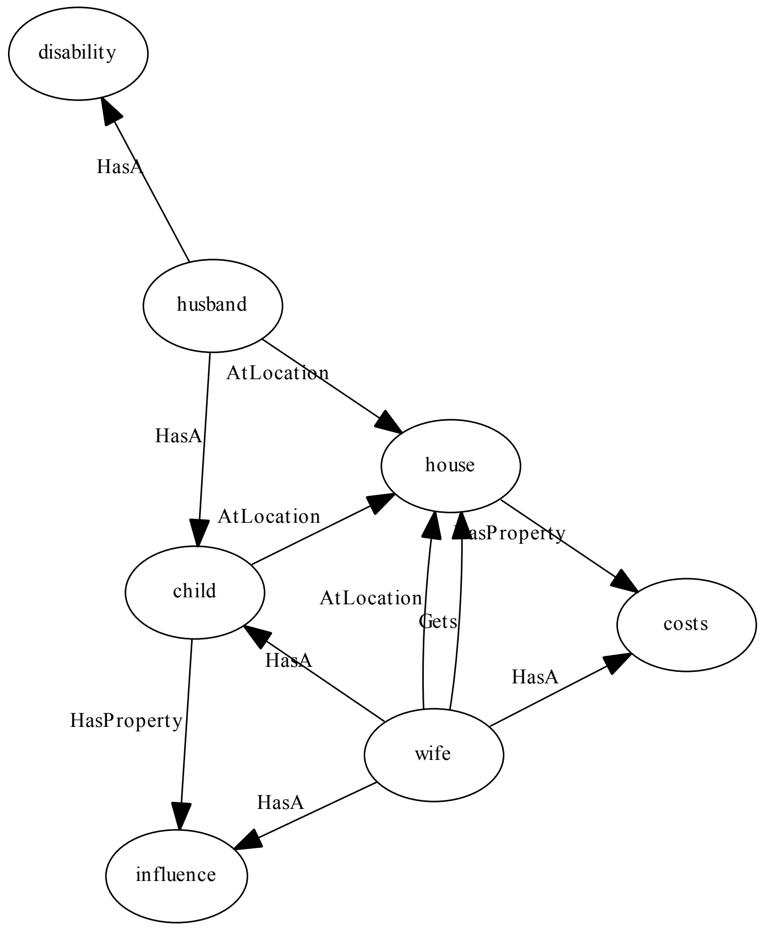


(b)

Figure 94: *Sports Teams* case. (a) Unsolved case network; (b) solved case network.



(a)



(b)

Figure 95: *Disability* case. (a) Unsolved case network; (b) solved case network.

8.1.3.2 *Divorce*

This case concerns the divorce of a husband and wife and the custody of their daughter, after one of the partners had another relationship (Figure 96).

Unsolved case: The husband and wife have a daughter. After the husband had another relationship, they want to arrange a divorce, but they have disagreement over the custody of their daughter.

Solved case: The parties agree to divorce. The wife gets the custody of their daughter. The husband gets a right to visit the daughter.

8.1.3.3 *Runaway Son*

This case concerns the son of a divorced couple, who escaped from his mother to live with his father (Figure 97).

Unsolved case: The couple is divorced and the mother has the custody of their son. But the son experiences some difficulties with his mother and decides to live with his father. The mother demands that the father sends their son back.

Solved case: The father agrees to send their son back to his mother, on the condition that the mother will improve her relation with the son.

8.2 PUTTING TOGETHER THE CASE BASE

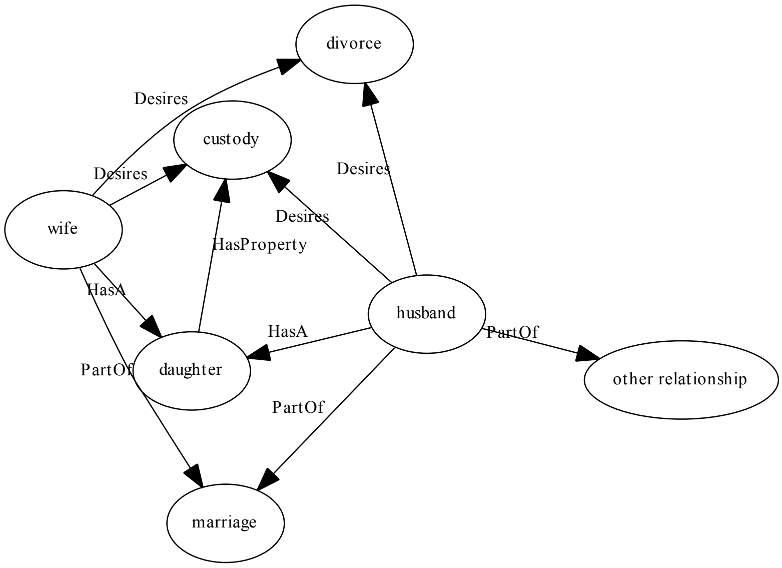
The cases we chose for our case base are represented using the set of relations available in ConceptNet version 4, as given in Table 8. As we have already discussed in Section 7.3, there is no particular reason for doing this except to increase the chances of benefiting from the ConceptNet knowledge base during the commonsense operations.

However, for representing instances where one of the parties in conflict receives or gets access to something, we introduce a relation type that we call "`Gets`".

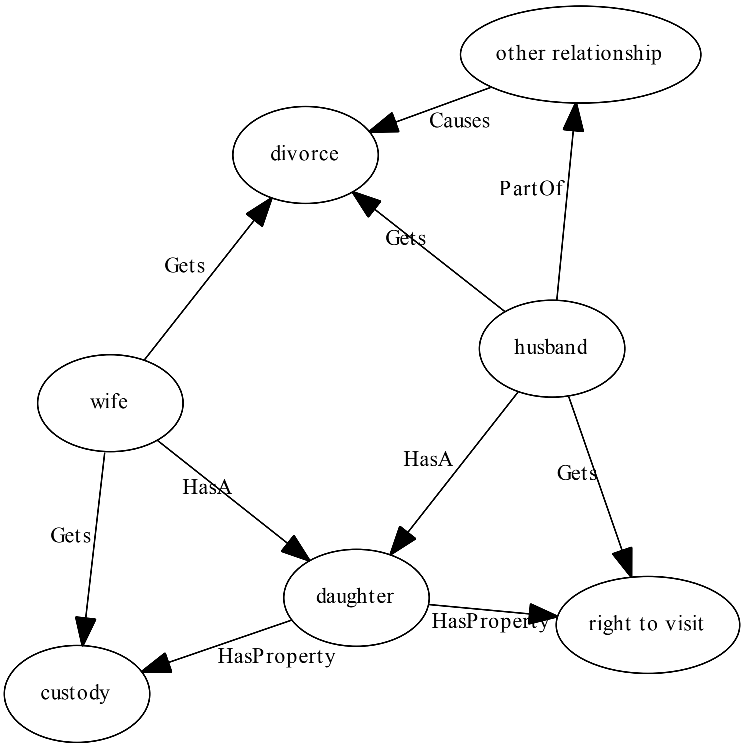
In the end, we create a case base formed by 19 cases, comprising cases from different conflict domains and all possible scales, including individual, group (companies), and international levels.

Figure 98 presents a histogram illustrating the frequency of the type of relations that we use within the case base. One can see that the three most commonly used relations are `Gets`, `HasA`, and `Desires`. This is meaningful given the nature of our cases representing conflicts and their solutions.

In Figure 99 we show the distributions of the number of concepts and relations within the cases in the case base. The average number of concepts per one case is 7.57895, while the average number of relations are 14.5789.



(a)



(b)

Figure 96: *Divorce* case. (a) Unsolved case network; (b) solved case network.

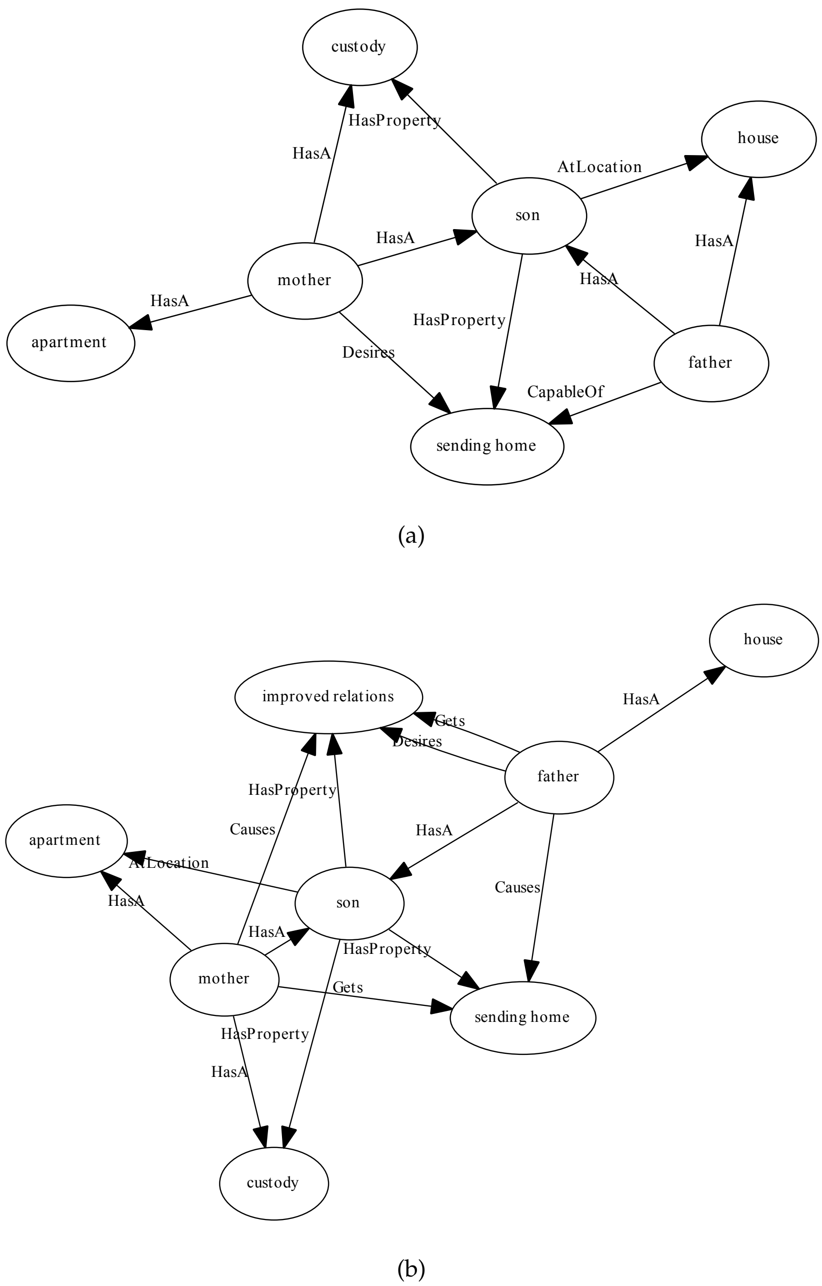


Figure 97: *Runaway Son* case. (a) Unsolved case network; (b) solved case network.

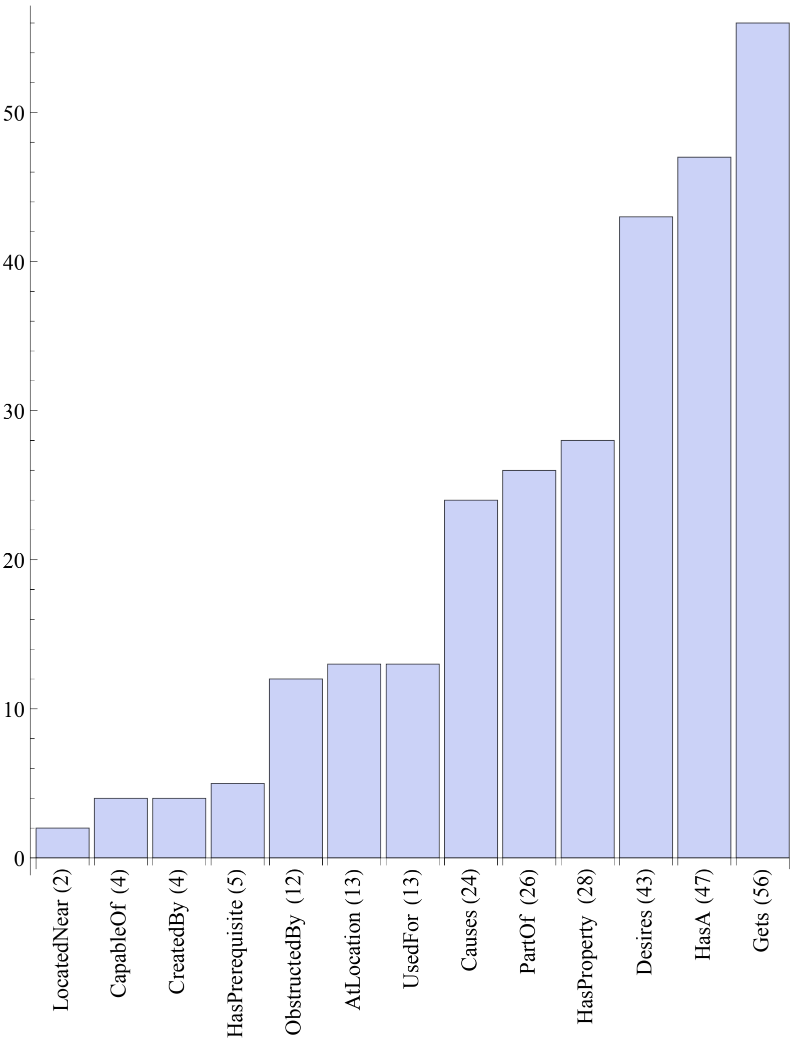


Figure 98: Histogram showing the frequency of relation types used throughout the 19 cases in the case base.

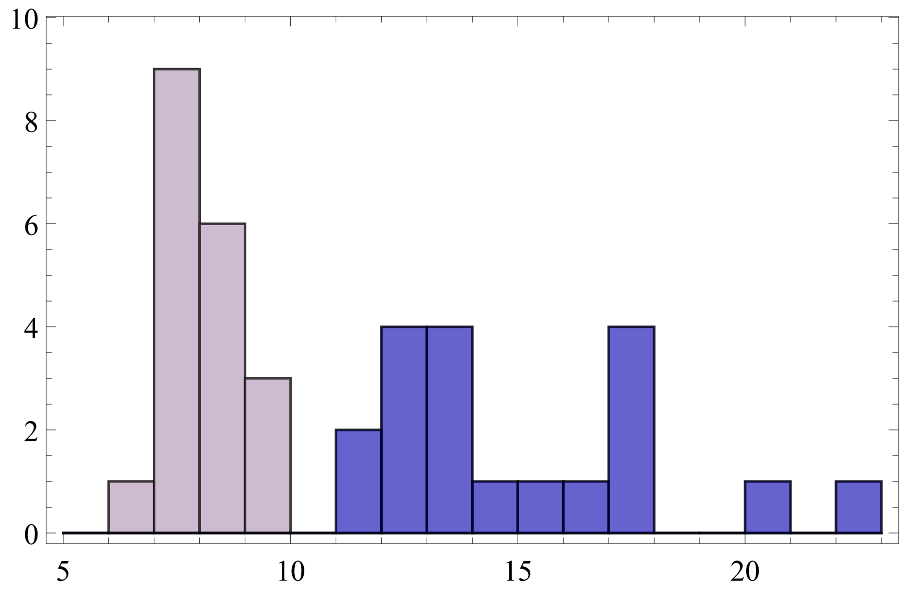


Figure 99: Distribution of the number of concepts (purple, or lighter color) and relations (blue, or darker color) throughout the 19 cases in the case base. Average number of concepts: 7.57895, average number of relations: 14.5789.

8.3 EXPANSION OF CASES

For evaluating the effect of the semantic network expansion algorithm that we discussed in Section 7.4.2, we make a series of experiments between the *Orange* and *Sinai* cases. We take the fused case network of the *Orange* case as the base domain and the unsolved case network of the *Sinai* case as the target domain, representing a retrieval operation for the *Sinai* domain as the new case.

As we have already mentioned, this algorithm is being used for producing an expanded version of the unsolved case network of the current case (Figure 66), for enabling the discovery of larger analogical mappings and for providing the substitutional adaptation method material in the target domain to work upon.

Figure 100 illustrates how the number of discovered analogies and the average and maximum structural evaluation scores are affected by the case expansion factor η. We can clearly identify an increasing trend in the number of possible analogies with increasing number of nodes in the network, as expected (Figure 100 (a)).

However, we observe that while the number of possible analogies keeps increasing, the structural evaluation scores attained by these discovered analogies do not increase beyond a certain boundary, regardless the increase in network size. As exemplified in Figure 100 (b) between the *Orange* and *Sinai* domains, we generally observe that there exists an asymptotic upper bound for the quality of attainable analogies between any two domains.

For understanding this, we reason that, while the number of analogies keeps monotonically increasing with the expansion factor η (Figure 100 (a)), the maximum possible extent of any possible analogies are bound by the size of the base network. That is to say, once a one-to-one mapping from the base network to the expanding target network is established, further improvements are impossible.

For the purpose of adaptation, an already established one-to-one mapping would also mean that all the elements in the domain of the current case, which will correspond to those forming the solution in the retrieved case, are discovered.

Based on this observation, and taking into account the average size of our cases in the case base, we limited the expansion factor η in our implementation by a maximum of $\eta_{max} = 6$ during all our experiments.

8.4 retrieval

In Table 14, we present the results from computing, with our SME implementation, the structural evaluation scores between the fused case networks of all case pairs in the case base. The values given are the sum of the scores of all possible analogical mappings discovered for each pair.

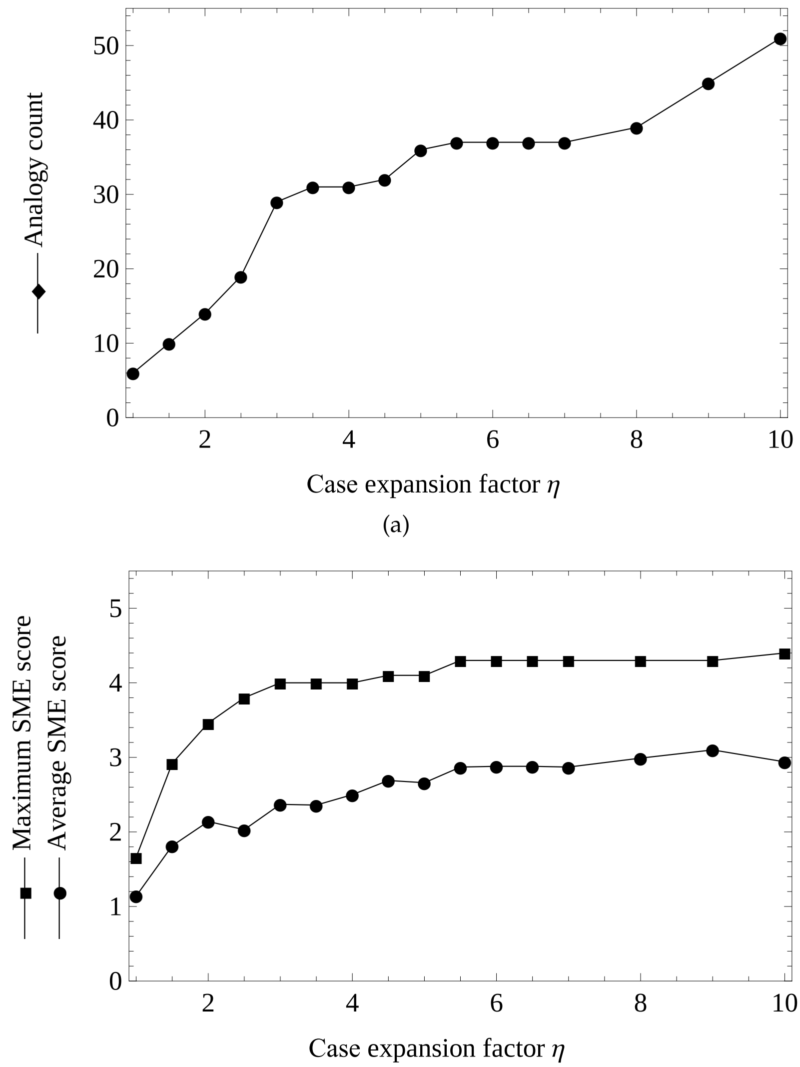
Since these scores are computed using fused case networks, this matrix of total structural evaluation scores indicates the overall presence and quality of structural correspondences between the conflict domains represented in the case base.

During the process of discovery of these analogies, the SME implementation, as we outlined in Section 2.2.1 (Chapter 2), goes through the stages of math hypothesis creation and the collection of these hypotheses into self-consistent match collections.

In Table 15, we see the total number of match hypotheses considered for the discovery of analogies by the SME algorithm, for each case pair.

Lastly, in Table 16, we see the total number of self-consistent analogical mappings between each case pair.

Our CBR mediation approach is dependent on the existence of underlying cross-domain similarities between these cases of conflicts from disparate domains. The widespread structural similarities existing between the cases can already be spotted in the given matrices, and the they will be illustrated further in this chapter. But, a complementary study of semantic similarity should also be performed to en-



(b)

Figure 100: Plots of (a) the number of analogies and (b) the maximum and average SME structural evaluation scores, corresponding to a given case expansion factor η. Computations are performed for the *Orange* case.

Table 14: Matrix of total structural evaluation scores of analogical mappings computed by the SME implementation, between all cases in the case base. Each score is the total of all the possible analogical mappings found by SME between each pair. Scores are computed between the fused case networks for each case.

		Target Domain																		
		Beagle Channel	Beer Production	Bookshelf	Disability	Divorce	Fishing Rights	Fugitive	Indus Waters	Insurance	Iranian Hostage Crisis	Market Access	Music Band	Orange	Patent	Rhodesia Britain	Runaway Son	Sinai	Software Use	Sports Teams
Base Domain	Beagle Channel	33.3	11.7	10.7	12.4	21.4	16.8	19.8	21	10.5	23.7	13.1	16.7	14.7	10.9	28.2	19.3	14.7	13.5	25.8
	Beer Production	8.2	36.8	15	32.4	11.8	9.8	21.7	1.6	9.6	9.6	9.8	11.8	2.2	6.2	8	24.5	2.2	6.7	23.1
	Bookshelf	8.8	22.4	9.3	17	11.2	7.9	17.2	5.8	8.5	10	7.9	10.9	8.8	5.9	10.3	17.3	8.8	5.6	17.1
	Disability	10.3	32.6	14.2	35.9	11.8	11.1	23	1.6	8.6	9.9	9.8	11.9	0.8	5.9	8	23.9	0.8	5.9	25.3
	Divorce	19	9.6	8.7	8.8	25	11.5	14.3	20.6	10	20	11.5	21.9	13	8.7	39.6	15.9	13	12.4	20.9
	Fishing Rights	11.3	13.1	7.6	12.5	11.6	10.6	15.6	7.9	7.5	14.8	10	10.7	5.2	8	14.9	15.8	5.2	6.3	17.2
	Fugitive	17.5	24.4	12.5	22.5	17	13.8	26.6	9.9	10.2	15.3	11.8	15.6	7.2	8.5	15.5	27.2	7.2	9.8	25.3
	Indus Waters	19.9	1.6	5.6	1.6	19.3	7.1	9.4	20.8	8.5	19.4	7.1	18	13.5	7.2	35.7	7.2	13.5	9.8	12.3
	Insurance	11.5	12.5	8.1	10.3	12.1	8.4	12.1	8.5	14.5	19.4	8.4	11.2	8.1	5.5	11.5	14.1	8.1	9	15.1
	Iranian Hostage Crisis	20.4	11.1	9.6	11.2	21.2	11.4	17.4	23.5	17.3	24.2	11.6	19.4	13.9	10.7	28.4	19.5	13.9	14.1	18.3
	Market Access	11.2	13.5	7.3	11.1	11.9	10.2	13.9	7.9	6.9	12.1	10.2	8.8	5.2	7.9	13.2	14.7	5.2	6	17.2
	Music Band	19.2	8.9	8.4	8	17.9	10.3	15.2	18.3	10.4	18.5	10.3	16.8	11.4	8.3	35.7	17.6	11.4	12.3	16.1
	Orange	13.9	2.2	9.2	0.8	15.4	5.6	6.4	17.8	9.7	12.8	5.6	11.8	20.1	4.4	22.7	5.6	20.1	7.9	8
	Patent	9.6	8.2	4.7	7.1	9.6	7.8	9.6	7.6	5.3	12.3	7.8	9.2	4.4	6.7	10.1	10.3	4.4	6.5	11.7
	Rhodesia Britain	28.6	8.3	9.5	7.9	33.5	12.1	15.6	36.9	11.7	28.7	12.1	29.8	20.2	12.7	76.4	11.8	20.2	16.6	18.3
	Runaway Son	14	29.2	16.3	28.9	15.1	13.6	26.2	8.4	12	15.1	12.4	16.5	6	8.9	13.4	32.2	6	10.9	28.2
	Sinai	13.9	2.2	9.2	0.8	15.4	5.6	6.4	17.8	9.7	12.8	5.6	11.8	20.1	4.4	22.7	5.6	20.1	7.9	8
	Software Use	11.3	6.7	6	6	11.7	8.7	12.1	13.1	8	15.9	8.7	11.5	7	6.1	19.8	11.7	7	7.2	13.5
	Sports Teams	18.6	29.8	16.9	28.6	18.6	15.7	26.1	11.2	13.4	17	14.6	16.9	6.8	9.8	18	28.5	6.8	10.9	36.8

Table 15: Matrix of total number of match hypotheses discovered by the SME implementation, between all cases in the case base. The match hypotheses are later grouped into self-consistent sets analogies, given in Table 16. Mappings are computed between the fused case networks for each case.

		Target Domain																	
		Beagle Channel	Beer Production	Bookshelf	Disability	Divorce	Fishing Rights	Fugitive	Indus Waters	Insurance	Iranian Hostage Crisis	Market Access	Music Band	Orange	Patent	Rhodesia Britain	Runaway Son	Sinai	Software Use	Sports Teams
Base Domain	Beagle Channel	135	54	60	57	123	75	96	111	63	114	72	105	78	57	168	87	78	78	114
	Beer Production	54	213	93	186	72	72	123	12	63	51	72	69	18	42	48	144	18	39	150
	Bookshelf	60	93	63	78	63	51	72	39	57	69	51	57	48	36	66	78	48	42	87
	Disability	57	186	78	192	66	75	129	12	63	57	66	63	6	39	45	147	6	36	153
	Divorce	123	72	63	66	150	75	105	135	69	129	75	129	90	60	201	102	90	87	123
	Fishing Rights	75	72	51	75	75	69	87	51	54	84	66	66	30	51	81	84	30	57	99
	Fugitive	96	123	72	129	105	87	135	63	69	99	81	93	42	63	93	135	42	69	150
	Indus Waters	111	12	39	12	135	51	63	147	57	120	51	114	96	42	219	54	96	78	75
	Insurance	63	63	57	63	69	54	69	57	81	111	51	66	48	42	87	78	48	54	81
	Iranian Hostage Crisis	114	51	69	57	129	84	99	120	111	186	81	117	78	72	177	105	78	93	114
	Market Access	72	72	51	66	75	66	81	51	51	81	66	66	30	51	81	78	30	57	93
	Music Band	105	69	57	63	129	66	93	114	66	117	66	117	72	57	174	96	72	78	108
	Orange	78	18	48	6	90	30	42	96	48	78	30	72	120	24	132	36	120	48	48
	Patent	57	42	36	39	60	51	63	42	42	72	51	57	24	51	57	66	24	51	69
	Rhodesia Britain	168	48	66	45	201	81	93	219	87	177	81	174	132	57	366	81	132	111	114
	Runaway Son	87	144	78	147	102	84	135	54	78	105	78	96	36	66	81	153	36	66	156
	Sinai	78	18	48	6	90	30	42	96	48	78	30	72	120	24	132	36	120	48	48
	Software Use	78	39	42	36	87	57	69	78	54	93	57	78	48	51	111	66	48	66	78
	Sports Teams	114	150	87	153	123	99	150	75	81	114	93	108	48	69	114	156	48	78	177

Table 16: Matrix of total number of possible analogical mappings discovered by the SME implementation, between all cases in the case base. Mappings are computed between the fused case networks for each case.

		Target Domain																		
		Beagle Channel	Beer Production	Bookshelf	Disability	Divorce	Fishing Rights	Fugitive	Indus Waters	Insurance	Iranian Hostage Crisis	Market Access	Music Band	Orange	Patent	Rhodesia Britain	Runaway Son	Sinai	Software Use	Sports Teams
Base Domain	Beagle Channel	13	12	12	13	18	15	20	16	13	19	12	15	11	9	27	17	11	13	22
	Beer Production	11	21	13	20	14	10	17	4	11	11	10	11	4	8	13	17	4	9	17
	Bookshelf	9	18	5	14	10	6	11	7	7	7	6	9	9	6	11	9	9	5	14
	Disability	12	19	13	22	14	13	22	4	10	11	11	11	2	7	12	20	2	7	23
	Divorce	17	11	8	11	9	8	12	19	7	14	8	10	14	8	26	11	14	10	16
	Fishing Rights	9	13	7	14	9	6	12	7	7	11	6	7	6	8	14	10	6	5	13
	Fugitive	18	19	9	21	13	10	14	15	10	13	9	14	12	9	17	13	12	8	17
	Indus Waters	16	4	8	4	19	8	11	13	10	18	8	19	13	8	31	8	13	9	12
	Insurance	12	13	7	12	11	8	10	9	10	14	8	9	8	7	10	11	8	9	12
	Iranian Hostage Crisis	14	11	7	13	16	8	13	15	16	6	8	13	12	8	18	11	12	8	13
	Market Access	11	14	6	12	9	6	10	7	7	8	6	6	6	7	13	9	6	5	13
	Music Band	15	11	8	11	9	7	12	17	8	14	7	9	12	8	24	13	12	10	12
	Orange	11	4	9	2	17	6	9	14	9	12	6	14	12	4	22	8	12	9	11
	Patent	9	10	5	9	11	7	9	8	7	11	7	9	4	4	11	9	4	6	12
	Rhodesia Britain	23	12	11	11	27	11	16	30	11	19	11	24	18	12	42	13	18	16	17
	Runaway Son	13	21	10	26	11	8	13	11	10	9	8	11	9	8	14	13	9	7	17
	Sinai	11	4	9	2	17	6	9	14	9	12	6	14	12	4	22	8	12	9	11
	Software Use	11	9	5	8	10	7	9	12	8	9	7	10	8	6	18	7	8	4	10
	Sports Teams	16	24	13	25	16	12	18	11	11	12	11	14	9	10	17	18	9	9	19

able a comparison, in order to really justify our SME-based approach and the somewhat complicated design of our model.

For this, we make use of a *bag-of-words* model (Wu et al., 2010) of text representation, where any collection of textual information can be converted to a vector of integer values for comparison of semantic content, without any regard to structure.

For example, consider the two sentences: *"Over thirty meteorites have been found that came from Mars."* and *"Some meteorites contain evidence that they have been exposed to water when on Mars."*.

From the words that we encounter in both sentences we can build a dictionary with 19 "word dimensions":

> 1: been 2: came 3: contain 4: evidence 5: exposed 6: found 7: from 8: have 9: mars 10: meteorites 11: on 12: over 13: some 14: that 15: they 16: thirty 17: to 18: water 19: when

We can then use this dictionary to express both sentences in the form of vectors in this "word space", giving: [1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0] and [1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1]. These vectors can then be used for calculating the semantic similarity between the two sentences, via a simple Euclidean distance calculation.

For calculating semantic similarity between cases, we convert each case network into a collection of the names of concepts that are present in the network. The cases are then treated as sentences that are given to the bag-of-words calculation.

Table 17 gives the resulting similarity matrix we obtain with the bag-of-words metric. As expected, direct semantic similarities between cases are sparse, resulting from common concepts that can be encountered across related cases, such as `monetary compensation` or `recognition`.

The information contained within similarity matrices presented in Table 14, for structural similarity, and in Table 17, for semantic similarity, can be presented in ways that enable more intuitive comparisons.

One such way that we employ here is to use *phylogenetic trees*, a type of branching diagram that is used in computational biology to illustrate taxonomy of species (Otu and Sayood, 2003). In biology, phylogenetic trees of a group of species are generated by quantitative measures of genetic similarity obtained from molecular DNA sequences.

Phylogenetic trees are usually computed from a square matrix of genetic distances between each pair of species in a collection. Thus, taking our structural and semantic similarity matrices as the input, we can generate family trees illustrating our conflict cases, where

Table 17: The matrix of bag-of-words similarity between each case in the case base. The computation only takes the names of concepts in each case into account, representing semantic similarity.

		Target Domain																		
		Beagle Channel	Beer Production	Bookshelf	Disability	Divorce	Fishing Rights	Fugitive	Indus Waters	Insurance	Iranian Hostage Crisis	Market Access	Music Band	Orange	Patent	Rhodesia Britain	Runaway Son	Sinai	Software Use	Sports Teams
Base Domain	Beagle Channel	1	0	0	0	0	0	0	0	0	0	0	0	0	0.0666	0	0	0.0666	0	0
	Beer Production	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Bookshelf	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0666
	Disability	0	0	0	1	0.1538	0	0	0	0	0	0	0	0	0	0	0.0714	0	0	0
	Divorce	0	0	0	0.1538	1	0	0	0	0	0	0	0	0	0	0	0.0666	0	0	0
	Fishing Rights	0	0	0	0	0	1	0	0.0714	0.0714	0	0.0714	0.0666	0	0.0714	0	0	0	0	0.0625
	Fugitive	0	0	0	0	0	0	1	0	0	0.0666	0	0	0	0	0	0	0	0	0
	Indus Waters	0	0	0	0	0	0.0714	0	1	0.0769	0	0.0769	0.0714	0	0.0769	0	0	0	0	0.0666
	Insurance	0	0	0	0	0	0.0714	0	0.0769	1	0	0.0769	0.0714	0	0.0769	0	0	0	0	0.0666
	Iranian Hostage Crisis	0	0	0	0	0	0	0.0666	0	0	1	0	0	0	0	0	0	0	0	0
	Market Access	0	0	0	0	0	0.0714	0	0.0769	0.0769	0	1	0.0714	0	0.0769	0	0	0	0	0.0666
	Music Band	0	0	0	0	0	0.0666	0	0.0714	0.0714	0	0.0714	1	0	0.0714	0	0	0	0	0.0625
	Orange	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	Patent	0.0666	0	0	0	0	0.0714	0	0.0769	0.0769	0	0.07692	0.0714	0	1	0	0	0	0	0.0666
	Rhodesia Britain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	Runaway Son	0	0	0	0.0714	0.0666	0	0	0	0	0	0	0	0	0	0	1	0	0	0
	Sinai	0.0666	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	Software Use	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	Sports Teams	0	0	0.0666	0	0	0.0625	0	0.0666	0.0666	0	0.0666	0.0625	0	0.0666	0	0	0	0	1

we can identify major categories, and subcategories, of conflict structures.

We generate family trees of our conflict cases, where we identify major categories of conflict structures.

Figure 101 gives the *structure-based phylogenetic tree* of our conflict cases, based on their pairwise structural similarities.

Keeping in mind the descriptions of our cases, in this tree, we can identify several main branches corresponding to different structural "types of conflict".

In the left main branch of the tree, the grouping together of the *Orange* and *Sinai* cases[4] is noticeable, followed by the *Indus Waters* case involving a similar repartitioning of resources in the problem solution. Further up the tree, we find the closely connected branches of *Rhodesia Britain*, *Divorce*, and *Beagle Channel* conflicts, which also involve some part of resource allocation. Following this branch further, we come to a region with *Music Band*, *Software Use*, *Iranian Hostage Crisis*, and *Insurance* conflicts, which involve, in some way or another, arrangements of compensation.

In the right main branch, we spot the grouping of *Bookshelf*, *Disability*, *Beer Production*, *Runaway Son*, *Sports Teams*, and *Fugitive* cases, roughly involving a rearrangement of issues after some change in conditions. Up the branch, the cases of *Patent*, *Market Access*, and *Fishing Rights* are grouped, being similar in the sense of having access rights for a resource.

The structure-based tree is a demonstration that our model is capable of discovering and harnessing cross-domain structural similarities underlying the cases.

In comparison, the *semantics-based phylogenetic tree* that we present in Figure 102 is comparatively shallow. However, we can still notice useful information, such as the grouping of *Runaway Son*, *Divorce*, and *Disability* cases all provided by the mediation expert Josep Redorta, and having similar semantics due to all of them being family conflicts.

Thus, other than evaluating the usefulness of our structure-based approach, these two trees also serve another purpose:

We can use the semantics-based tree to identify different *conflict domains*, whereas the structure-based tree can be used for identifying different *structural conflict categories*. We will talk more about the identification of these categories in Section 8.5.

The total analogical similarity scores we presented in Table 14 were computed between fused case networks to study the overall structural similarities between our cases.

However, it is important to remember that the actual retrieval process is performed for a new case with only the unsolved case net-

4 The *Orange* and *Sinai* cases were in the first place designed to have equivalent structure.

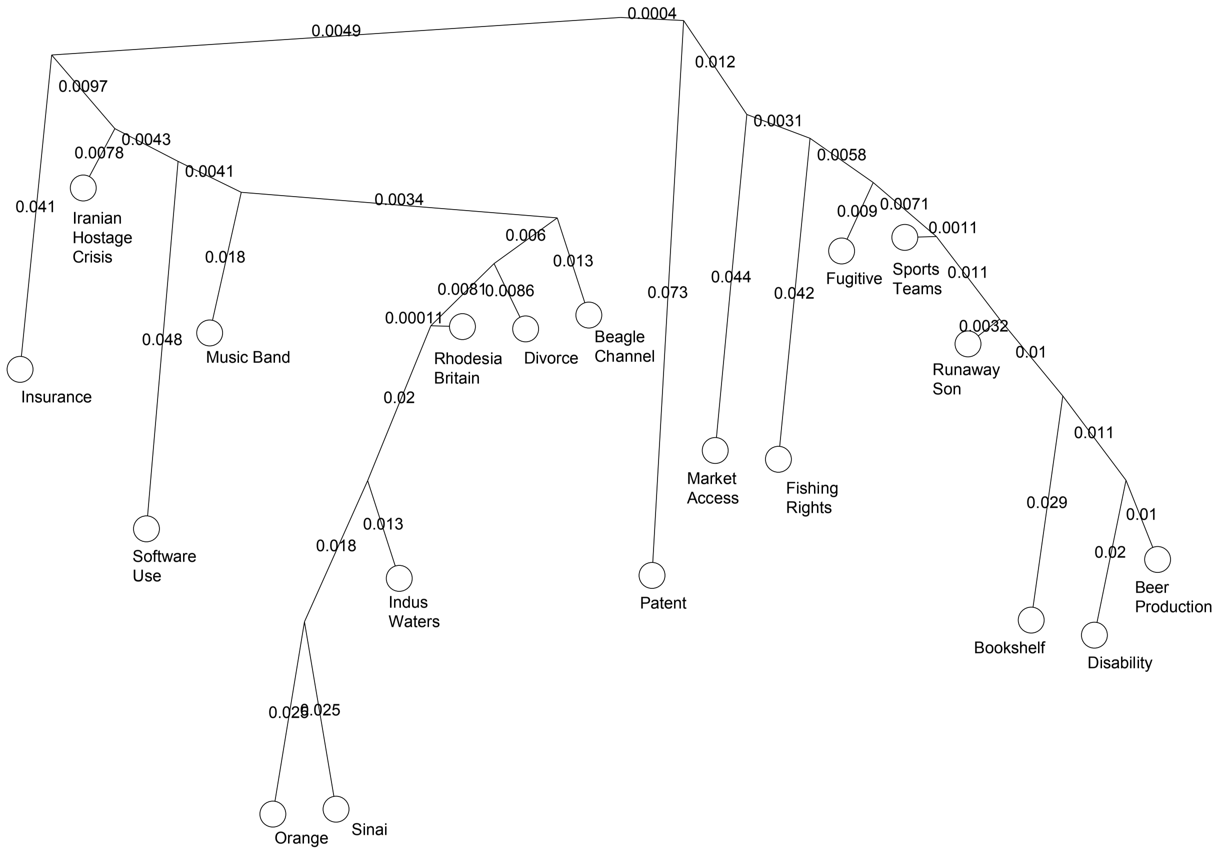


Figure 101: *Structure-based phylogenetic tree* of the cases. Generated by taking the multiplicative inverse of the structural evaluation scores given in Table 14 and feeding the resulting distance matrix to the TreeGen tool (ETH Zürich, 2013) for rooted phylogenetic trees.

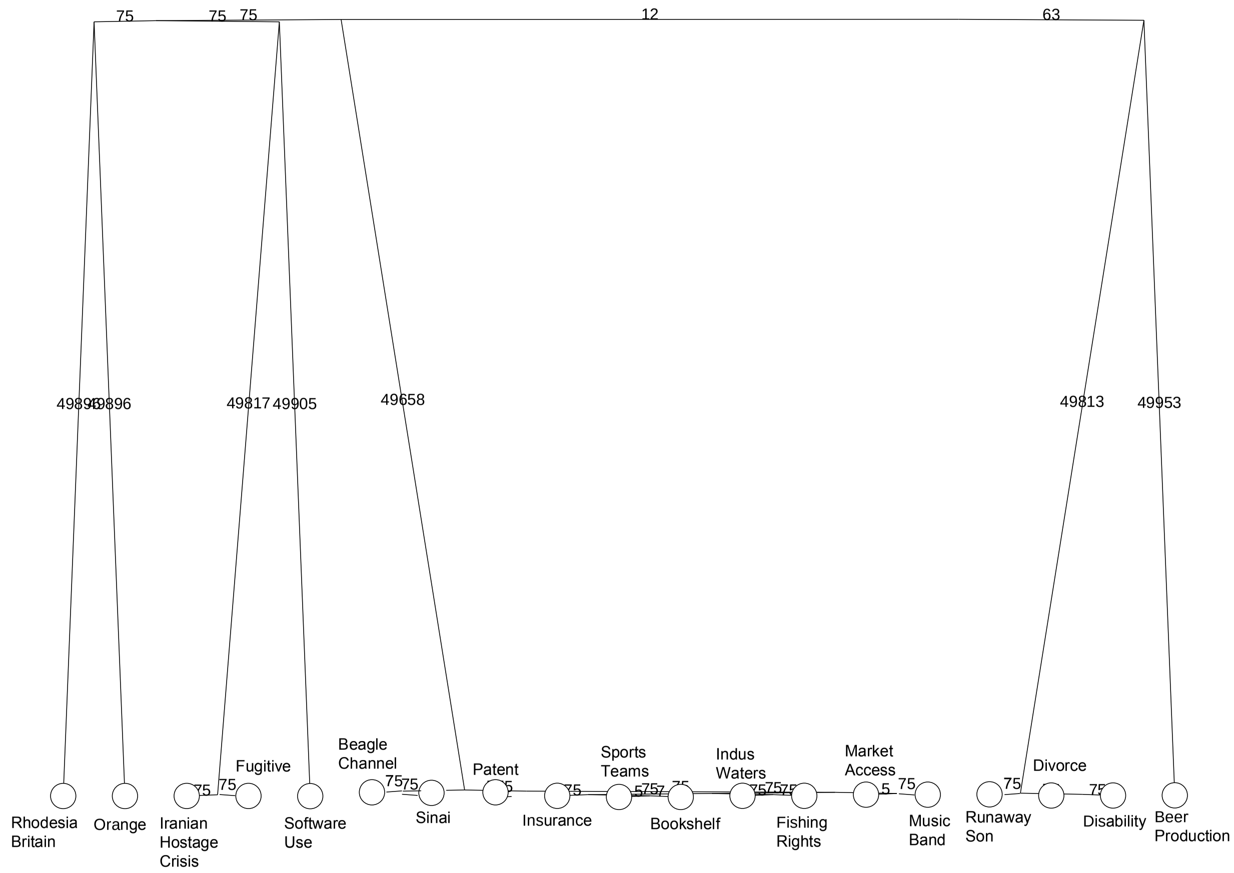


Figure 102: *Semantics-based phylogenetic tree* of the cases. Generated by taking the multiplicative inverse of the bag-of-words similarity matrix given in Table 17 and feeding the resulting distance matrix to the TreeGen tool (ETH Zürich, 2013) for rooted phylogenetic trees.

work of the new case and the fused case networks in the case base (Figure 70).

Table 18 gives the retrieval scores computed using the fused networks as the base domain and the unsolved networks as the target domain. This means that we can use this matrix to see which case would be retrieved for any case given to the CBR algorithm as a new case without solution. Taking any column as the new case without solution, the retrieved case would be the row with the highest score.

8.5 STRUCTURAL CLASSIFICATION OF CONFLICTS

Instances of conflict cited in mediation literature range from familial disputes about inheritance or divorce to workplace disputes between coworkers, and from tenant–landlord disputes about the rent of a property to full-fledged armed conflicts between countries Domenici and Littlejohn (2001).

We have already demonstrated that even if conflicts may seem highly unrelated in terms of their semantics (or domain), they can share deep structural similarities. The idea underlying our approach, indeed, was that there should be a (possibly limited) number of generic structural categories into which conflicts from seemingly different domains can fall.

We consider that these categories would be highly related with the existing discussions of the "problem solving" process in cognitive science literature. Returning to the beginning of this dissertation, the radiation problem of Chapter 1, an example is the "general principle" from the tumor problem of Duncker (Gick and Holyoak, 1983):

> "If you need a large force to accomplish some purpose, but are prevented from applying such a force directly, many smaller forces applied simultaneously from different directions may work just as well."

Another example would be the "resource splitting" way of solution that is used in the work of Kolodner and Simpson (1989), the *Orange* and *Sinai* analogy we have already covered in detail in Chapter 7.

Other "general principles" in the structuring of conflicts should be identifiable. An example discussion of structural reasons underlying conflicts is given by Windle and Warren (2007), where they identify conflict types between individuals in an educational setting:

1. data conflicts, meaning conflicts that can be solved by acquisition of new data;

2. relationship, or in general, communication conflicts;

Table 18: The retrieval matrix. Values indicate the total structural evaluation score computed for every run from the *fused case network* of a case (base domain, given in rows) into the *unsolved case network* of another case (target domain, given in columns).

		Target Domain																		
		Beagle Channel	Beer Production	Bookshelf	Disability	Divorce	Fishing Rights	Fugitive	Indus Waters	Insurance	Iranian Hostage Crisis	Market Access	Music Band	Orange	Patent	Rhodesia Britain	Runaway Son	Sinai	Software Use	Sports Teams
Base Domain	Beagle Channel	3.9	6.1	4.4	7.6	7.4	3.2	3.9	4.2	3.6	6.7	2.8	8.6	3.6	4	7.8	5.4	3.6	2.7	6.4
	Beer Production	3.2	30.6	13.2	29.4	7	6.6	12.5	0	6.5	6.7	6.6	10.2	0.8	5	0.8	19.9	0.8	3.8	18.5
	Bookshelf	2	14.4	6.6	13.8	5.9	4	6.1	1.6	5.2	4.4	4	5.7	3.2	3.1	2.2	9.8	3.2	2.7	9.2
	Disability	5.2	25.7	13	32.3	6.4	8.8	12.5	0	7.5	8.1	7	10.4	0	5	0.8	19.4	0	3.7	17
	Divorce	3.6	6.2	5.5	6.2	13	4.1	6	6	6.3	9.6	4.1	13	6.2	4.4	14	8.6	6.2	4.8	9.8
	Fishing Rights	1.6	9	4	10.7	5	2.9	4.8	1.6	4.5	6.6	2.6	5.3	1.6	3.9	2.2	7.4	1.6	3.6	6.5
	Fugitive	3.6	17.8	9	20.4	10.3	6.8	10.9	3.2	7	8.6	6.3	10.3	3.6	5.5	3.6	16.4	3.6	5.9	13.2
	Indus Waters	3.3	0	1.6	0	10.4	1.6	1.6	6.8	4	10.1	1.6	9.6	6.6	2	14.6	1.6	6.6	3.2	3.2
	Insurance	2.4	9	5.2	8.6	6	3.9	3.6	3.2	7.9	8.4	3.5	4.5	4.4	2.7	4.9	5.6	4.4	2.7	7.2
	Iranian Hostage Crisis	3.1	7.3	4.1	8.5	11.5	4.2	4.4	6	10.1	14.4	3.8	9.9	6.6	5.6	12.3	6.8	6.6	4.9	7.3
	Market Access	1.6	8.2	4.4	8.2	4.4	3	4	1.6	4	5	3	4.7	1.6	3.9	2.2	6.8	1.6	3.3	7.4
	Music Band	3.2	6.7	4.5	6.7	12.4	3.4	5.5	5.2	6.1	9.4	3.4	10.1	5	4.6	11.7	7.6	5	3.6	8
	Orange	2.6	1.6	5.6	0	9	1.6	1.6	7.6	4	7.4	1.6	6.9	8.6	1.6	10.3	1.6	8.6	4	4
	Patent	0.8	5.6	2.3	5.6	3.6	2	2.9	1.6	3.1	4.5	2	4.1	1.6	3.5	1.6	4.7	1.6	2.4	4.3
	Rhodesia Britain	6.4	3.6	3.8	3.6	20.1	3.8	4	9	6.8	15.4	3.8	18.6	6.4	3.6	26.3	4.8	6.4	4	6.8
	Runaway Son	4	23.6	11.3	26.9	9	8.3	12.6	3.2	8.9	9.9	7.1	10.7	3.6	7.1	3.6	18.5	3.6	5.4	16.9
	Sinai	2.6	1.6	5.6	0	9	1.6	1.6	7.6	4	7.4	1.6	6.9	8.6	1.6	10.3	1.6	8.6	4	4
	Software Use	1.6	3.3	2.2	3.3	6.2	1.9	2.9	3.6	4.6	4.9	1.9	5.6	3.6	3.2	6.4	4.6	3.6	2.5	4.1
	Sports Teams	4	21.1	10.9	22.9	9	8	11.8	3.2	8	8.4	7	9.3	3.6	6.1	3.6	16.2	3.6	4.8	16.9

3. value conflicts, involving incompatible beliefs and perceptions;
4. resource conflicts;
5. history conflicts, with origins in past events;
6. "structural" conflicts[5], existing outside the immediate world of individuals concerned; and
7. psychological conflicts, relating to desires of power, autonomy, recognition, etc.

For experimenting with this idea of structural conflict categories, we make use of clustering based on our existing data of analogical similarities within the case base.

Figure 103 gives the result of classifying our 19 cases into three clusters, using using a *k-medoids* algorithm applied to the coordinates of a 2D phylogenetic placement map, derived from the phylogenetic tree we present in Figure 101.

The results are remarkable:

In the three cases of *Patent*, *Market Access*, and *Fishing Rights* (green rectangles), we immediately identify conflicts which have been resolved using a rights-based structure and some form of *compensation*. We assign this conflict structure the name **"access rights conflict"**.

Within the cluster formed by *Insurance*, *Bookshelf*, *Sports Teams*, *Fugitive*, *Runaway Son*, *Beer Production*, and *Disability* (blue diamonds), the dominant theme is the *amendment* of some arrangement in response to a change in some previous condition. We assign this conflict structure the name **"amendment conflict"**.

Lastly, in the cluster formed by *Orange*, *Sinai*, *Indus Waters*, *Beagle Channel*, *Divorce*, *Rhodesia Britain*, *Iranian Hostage Crisis*, *Music Band*, and *Software Use* (red points), we identify a structure which involves conflicts based on *imposed conditions* or solutions based on *partitioning of underlying resources* according to the real desires of the parties. It is particularly significant that most instances of international conflicts that we have in the case base are classified into this cluster. We assign this conflict structure the name **"partitioning conflict"**.

Even if these structural groupings were already evident in the structure-based phylogenetic tree that we presented in Figure 101, clustering provides a straightforward way of identifying the structural categories that we are interested in discovering.

With a larger and more representative case base, we would be able to gain more insight into the structural "general principles" of conflict resolution, further validating our approach.

5 Authors use the word "structural" for referring to external realities affecting a conflict.

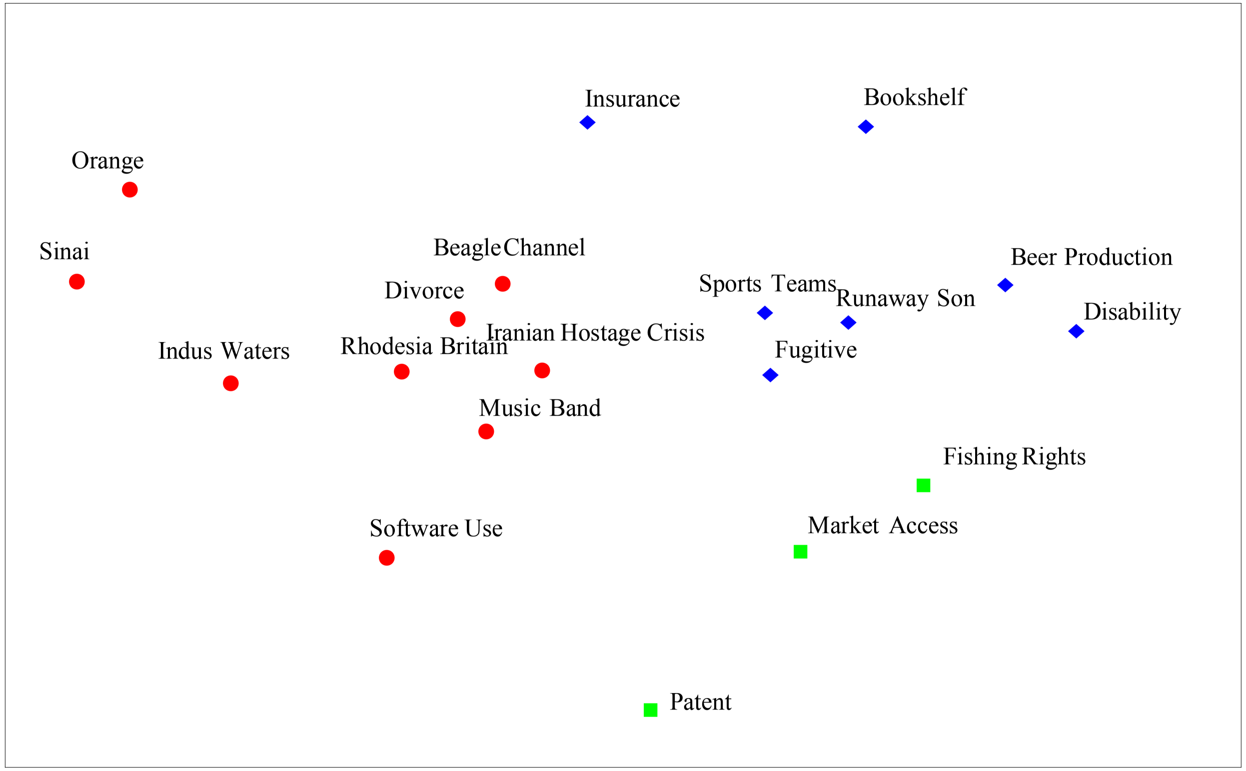


Figure 103: Cluster analysis of the cases in the case base. Three clusters are generated using *k-medoids* algorithm applied to the coordinates of 2D phylogenetic placement map generated by TreeGen tool (ETH Zürich, 2013).

Part IV

SUMMARY

In the final part of the dissertation, we provide an overall review of our approach. Following a discussion of the lessons learned and limitations of the research, we share some insights about future work directions following this study.

9

CONCLUSION

> *"I am turned into a sort of machine for observing facts and grinding out conclusions."*
>
> — Charles Darwin (1880)

9.1 LESSONS LEARNED

This dissertation introduced several original approaches that we can, in principle, classify under two main parts.

The first part concerns the development of a novel graph-based evolutionary algorithm (EA) that employs semantic networks as evolving individuals. This model is in effect an implementation of a long-standing idea, namely, *memetics*, in the field of cultural evolution.

In the second part, we communicate the details of a case-based reasoning (CBR) approach to the problem of mediation, where we discuss several innovations to address conflict resolution in a cross-domain fashion.

Between these two parts, a unifying theme is the use of a semantic network-based case representation.

In EA, the use of semantic networks provides a simple yet powerful means of representing pieces of evolving knowledge, enabling us to deliver the first implementation of the idea of memetics where the evolving data structures truly are fragments of knowledge. Because this work constitutes the first instance of using a semantic network-based EA, it falls upon us to introduce the necessary crossover and mutation variation operators working on semantic networks.

In the part of CBR, we use semantic networks as a universal representation to handle cases from widely different conflict domains. Different from the conventional approach in CBR where case representations have clearly identified parts for case description and solution, we use a "unified" representation where the concepts and relations describing both the problem and its solutions can reside within the same network. This unified representation also enables the use of analogical mapping for both of CBR retrieval and adaptation stages.

The second important overlap between the two parts of dissertation is the use of commonsense reasoning and commonsense knowledge bases. Their use is necessitated by the semantic network-based representation and the logical expectation of having all instances of these with meaningful information content.

We make extensive use of this in the EA part, because essentially all operations during an EA run are modifications of existing semantic networks and therefore have to follow commonsense rules depending on information from commonsense knowledge bases. Put another way, we use a combination of random processes using non-random structured fundamental operations that obey the limits of commonsense knowledge, guided by selection pressure under the defined fitness function.

In the CBR cycle, we make use of commonsense reasoning to consider analogical mappings between expanded versions of the cases, where, through an automated procedure, the system enlarges the networks to include more concepts and relations that involve the existing ones. This enables the CBR method to capture more extensive analogies between different domains and also represents a novel way to address an ongoing problem of including general knowledge into CBR systems.

Finally, the third overlap is due to the use of the Structure Mapping Engine (SME) as a key component for analogical reasoning in both parts of the dissertation.

In EA, we make use of SME as the basis of a fitness function that we use in our experiments. Defining the fitness function as the analogical similarity computed by SME between a given semantic network and the evolving networks forming the population, we create a system that is capable of spontaneous generation of analogous networks to a given network. This system constitutes a first in the analogical reasoning field, because existing systems have been limited to only finding analogies between two existing networks.

SME forms a crucial part of our CBR system as well, where we use it for both case retrieval and case adaptation. This is enabled by our unified representation scheme based on semantic networks. For retrieval, SME provides the similarity score between the new case and the cases in the case base, computed using their structural similarity. The same analogical mapping, whose score is used for retrieval, is also used as a function transferring the solution from the retrieved case (the base domain) to the new case (the target domain).

On top of these overlaps, we also consider two more combinations of the evolutionary approach with our CBR mediation system. First is to consider the semantic network-based EA as a generative adaptation component that the CBR system falls back to in cases where the

SME-based adaptation is not satisfactory. This can, in principle, provide the system with a means to address the adaptation problem by creating solutions in an open-ended way, as we demonstrated within the part of EA.

A second thought for combination is to make use of the generative power of EA to create variations of cases in the case base. This can be considered as another way to address the generative adaptation problem: while, by definition, the generative adaptation component would have to create solutions on-the-fly, this process can be delegated to a "case-base enrichment" procedure where variations of the cases in the case base are generated off-line, which can serve the same purpose of on-the-fly solutions in future instances adaptation.

9.2 LIMITATIONS

From a general perspective, we can argue that our research addresses a fundamental question involving CBR and the related field of analogical reasoning: generality and specificity.

Research within the analogical reasoning field has been traditionally focused on generality, treating the matching and retrieval problems as broadly general cognitive processes operating over structural mental representations.

In contrast, CBR systems have mostly proven their success with focusing on specific tasks on well defined domains, where domain-specific representations and index-based retrieval systems are commonly employed.

To a certain degree, our approach in this dissertation have aspects combining the characteristics of both of these two methods. The most important factor in this is the use of semantic networks as a simple and generic representation scheme that is applicable to almost any problem domain. For the example problem of mediation, this enables us to have conflicts from highly different domains in the same case base and be able to recognize and utilize their underlying structural similarities. In other words, we have a CBR system with the characteristics of an analogical reasoning model designed for generality.

It is important, however, to note that our research has limitations.

The most considerable limitation comes from our choice of using semantic networks instead of a more powerful representation scheme. For example, using SME as the key component of our approach, it would be highly desirable and logical to use predicate calculus to represent our cases. Instead, we limit the representation to semantic networks, and provide our own implementation of SME that we adapt to work on the simple directed graph structure of semantic networks.

This choice of limiting the representation was mainly directed by our dependence on ConceptNet version 4 as the main commonsense knowledge base used in this study, which is dependent on semantic network representation. Furthermore, we also made the choice of preferring the set of relations that were defined by ConceptNet conventions, with the aim of getting the maximum benefit from the use of this system.

In more than a few cases, this limitation has caused considerable difficulty in representing mediation cases in necessary detail or fidelity to the original description in the source material. It should be noted, however, that in the next version of ConceptNet (version 5), the research team has made a decision to move to a "hypergraph" representation, where one can have relations about instances of relation between concepts. This can, in effect, increase the expressivity of the system greatly.

Another weakness in the current study concerns the selection of parameter values in our EA approach. Due to the fact that our algorithm is the first attempt at having a graph-based implementation of memetics, we are faced with selecting mutation and crossover rates without any antecedents. Even in the theoretical field of cultural evolution, discussions of the frequency of variation events are virtually nonexistent. This makes our parameter values rather arbitrary, roughly guided by the general convention in the general EA field.

Lastly, we have not fully addressed a mediation framework that would involve agents functioning in a multi agent system. Specifically, we have not addressed the argumentation part of the problem of mediation, which would involve negotiator agents communicating their views on the conflict to a mediator agent, and stating their acceptance or rejection of the solutions proposed by the system. Given the depth and complexity of the parts we have presented, we had a choice of keeping argumentation outside the scope of this dissertation.

9.3 FUTURE WORK

Possible future work for the continuation of the lines of research that we have presented can be divided into several categories.

For the part regarding EA, it would be interesting to experiment with extensions of the simple SME-based fitness measure that we have used here. As semantic networks are graphs, a straightforward possibility is to take graph-theoretical properties of candidate networks into account, such as the clustering coefficient or shortest path length. With these kinds of constraints, the selection pressure on the network structure in the system can be adjusted in a more controlled way.

Another highly interesting prospect with the EA system would be to consider different types of mutation and crossover operators, and doing the necessary study for grounding the design of such operators on existing theories of cultural transmission and variation. Combined with realistically formed fitness functions, one can use such a system for modeling selectionist theories of knowledge. Performing experiments with such a setup could be considered a "memetic simulation" and comparable to computational simulations of genetic processes performed in computational biology.

For the EA method, a more practical application that we foresee we can achieve in the short-term is computational creativity. Already with the SME-based fitness function that we demonstrated in this dissertation, it would be possible to create systems for tasks such as story generation based on analogies. This would involve giving the system an existing story as an input, and getting an analogous story in another domain as the output. For doing this we would need to define a structural representation scheme of story elements, and, preferably an automated way of turning this structural representation into textual information as the final story.

With such a story generation system implemented, its components can also find use in our original experimentation area of mediation, where the system could generate stories that will provide explanation and support to solutions presented by the system to the parties.

For the CBR system, the way forward would be to address the negotiation and argumentation sides of the problem. This would involve thinking about the process of dialog between agents and the mediator, which should be implemented from an AI argumentation perspective.

Finally, the case base that we used here can be enlarged with more cases from other possible sources. As the case base gets larger, one can also start to consider doing experiments with case-base maintenance.

Part V

APPENDIX

A

MEDIATION CASE BASE

BEAGLE CHANNEL

Unsolved case network

```
Chile
Argentina
sovereignty
islands
Beagle Channel
HasA(Chile, sovereignty)
PartOf(sovereignty, islands)
AtLocation(islands, Beagle Channel)
Desires(Argentina, islands)
LocatedNear(Beagle Channel, Chile)
LocatedNear(Beagle Channel, Argentina)
```

Solved case network

```
sovereignty
navigation
recognition
maritime rights
Beagle Channel
defined maritime boundaries
islands
Argentina
Chile
HasA(Chile, sovereignty)
Gets(Chile, sovereignty)
Gets(Chile, recognition)
Gets(Chile, defined maritime boundaries)
```

```
Causes(Argentina, recognition)
Gets(Argentina, maritime rights)
Desires(Argentina, navigation)
Gets(Argentina, defined maritime boundaries)
PartOf(sovereignty, islands)
AtLocation(islands, Beagle Channel)
LocatedNear(Beagle Channel, Chile)
LocatedNear(Beagle Channel, Argentina)
HasProperty(Beagle Channel, defined maritime boundaries)
HasProperty(sovereignty, recognition)
PartOf(maritime rights, islands)
UsedFor(maritime rights, navigation)
```

Fused case network

```
sovereignty
navigation
recognition
maritime rights
Beagle Channel
defined maritime boundaries
islands
Argentina
Chile
HasA(Chile, sovereignty)
Gets(Chile, sovereignty)
Gets(Chile, recognition)
Gets(Chile, defined maritime boundaries)
Causes(Argentina, recognition)
Gets(Argentina, maritime rights)
Desires(Argentina, navigation)
Gets(Argentina, defined maritime boundaries)
PartOf(sovereignty, islands)
AtLocation(islands, Beagle Channel)
LocatedNear(Beagle Channel, Chile)
LocatedNear(Beagle Channel, Argentina)
HasProperty(Beagle Channel, defined maritime boundaries)
HasProperty(sovereignty, recognition)
PartOf(maritime rights, islands)
UsedFor(maritime rights, navigation)
Desires(Argentina, islands)
```

BEER PRODUCTION

Unsolved case network

```
economic problem
Cruzcampo
Heineken
factory
maintenance costs
production
dominance
HasA(Cruzcampo, economic problem)
HasA(Cruzcampo, factory)
HasA(Cruzcampo, production)
HasA(Cruzcampo, maintenance costs)
ObstructedBy(maintenance costs, economic problem)
HasProperty(factory, maintenance costs)
UsedFor(factory, production)
HasProperty(production, dominance)
HasA(Heineken, production)
HasA(Cruzcampo, dominance)
```

Solved case network

```
Cruzcampo
Heineken
factory
maintenance costs
production
dominance
HasA(Cruzcampo, production)
HasProperty(factory, maintenance costs)
HasA(Heineken, maintenance costs)
HasProperty(production, dominance)
UsedFor(factory, production)
HasA(Heineken, production)
HasA(Heineken, dominance)
Gets(Heineken, factory)
```

Fused case network

```
economic problem
Cruzcampo
Heineken
factory
maintenance costs
production
dominance
HasA(Cruzcampo, economic problem)
HasA(Cruzcampo, factory)
HasA(Cruzcampo, production)
HasA(Cruzcampo, maintenance costs)
ObstructedBy(maintenance costs, economic problem)
HasProperty(factory, maintenance costs)
UsedFor(factory, production)
HasProperty(production, dominance)
HasA(Heineken, production)
HasA(Cruzcampo, dominance)
HasA(Heineken, maintenance costs)
HasA(Heineken, dominance)
Gets(Heineken, factory)
```

BOOKSHELF

Unsolved case network

```
Child 1
Child 2
bookshelf
book
notebook
access
HasA(Child 1, book)
HasA(Child 1, bookshelf)
UsedFor(bookshelf, book)
HasA(Child 2, notebook)
Desires(Child 2, access)
HasProperty(bookshelf, access)
UsedFor(bookshelf, notebook)
ObstructedBy(access, Child 1)
```

Solved case network

```
Child 1
Child 2
bookshelf
book
notebook
access
candies
Gets(Child 1, candies)
Causes(Child 2, candies)
HasA(Child 1, book)
HasA(Child 1, bookshelf)
UsedFor(bookshelf, book)
HasA(Child 2, notebook)
Gets(Child 2, access)
HasProperty(bookshelf, access)
UsedFor(bookshelf, notebook)
```

Fused case network

```
Child 1
Child 2
bookshelf
book
notebook
access
HasA(Child 1, book)
HasA(Child 1, bookshelf)
UsedFor(bookshelf, book)
HasA(Child 2, notebook)
Desires(Child 2, access)
HasProperty(bookshelf, access)
UsedFor(bookshelf, notebook)
ObstructedBy(access, Child 1)
candies
Gets(Child 1, candies)
Causes(Child 2, candies)
Gets(Child 2, access)
```

DISABILITY

Unsolved case network

```
disability
husband
wife
house
costs
child
influence
HasA(husband, disability)
HasA(husband, house)
AtLocation(husband, house)
HasA(husband, costs)
HasA(husband, child)
HasA(husband, influence)
ObstructedBy(costs, disability)
HasProperty(house, costs)
AtLocation(wife, house)
HasA(wife, child)
HasProperty(child, influence)
AtLocation(child, house)
```

Solved case network

```
disability
husband
wife
house
costs
child
influence
HasA(husband, disability)
AtLocation(husband, house)
HasA(husband, child)
HasProperty(house, costs)
AtLocation(wife, house)
HasA(wife, child)
Gets(wife, house)
HasProperty(child, influence)
AtLocation(child, house)
```

```
HasA(wife, influence)
```

Fused case network

```
disability
husband
wife
house
costs
child
influence
HasA(husband, disability)
HasA(husband, house)
AtLocation(husband, house)
HasA(husband, costs)
HasA(husband, child)
HasA(husband, influence)
ObstructedBy(costs, disability)
HasProperty(house, costs)
AtLocation(wife, house)
HasA(wife, child)
HasProperty(child, influence)
AtLocation(child, house)
Gets(wife, house)
HasA(wife, influence)
```

DIVORCE

Unsolved case network

```
marriage
divorce
husband
wife
daughter
custody
other relationship
PartOf(husband, marriage)
PartOf(husband, other relationship)
HasA(husband, daughter)
Desires(husband, custody)
Desires(husband, divorce)
PartOf(wife, marriage)
Desires(wife, divorce)
Desires(wife, custody)
HasA(wife, daughter)
HasProperty(daughter, custody)
```

Solved case network

```
divorce
husband
wife
daughter
custody
other relationship
PartOf(husband, other relationship)
Causes(other relationship, divorce)
Gets(husband, divorce)
Gets(wife, divorce)
HasA(husband, daughter)
Gets(husband, right to visit)
HasProperty(daughter, right to visit)
Gets(wife, custody)
HasA(wife, daughter)
HasProperty(daughter, custody)
```

Fused case network

```
divorce
husband
wife
daughter
custody
other relationship
PartOf(husband, other relationship)
Causes(other relationship, divorce)
Gets(husband, divorce)
Gets(wife, divorce)
HasA(husband, daughter)
Gets(husband, right to visit)
HasProperty(daughter, right to visit)
Gets(wife, custody)
HasA(wife, daughter)
HasProperty(daughter, custody)
marriage
PartOf(husband, marriage)
Desires(husband, custody)
Desires(husband, divorce)
PartOf(wife, marriage)
Desires(wife, divorce)
Desires(wife, custody)
```

FISHING RIGHTS

Unsolved case network

```
Morocco
European Union
pirate
fishing region
fishing rights
Atlantic
Desires(European Union, fishing rights)
HasA(Morocco, pirate)
HasA(Morocco, fishing region)
ObstructedBy(fishing rights, pirate)
HasProperty(fishing region, fishing rights)
AtLocation(fishing region, Atlantic)
```

Solved case network

```
Morocco
European Union
monetary compensation
schedule
fishing region
fishing rights
Atlantic
Gets(Morocco, monetary compensation)
Causes(European Union, monetary compensation)
HasA(Morocco, fishing region)
HasProperty(fishing region, fishing rights)
AtLocation(fishing region, Atlantic)
HasProperty(fishing region, schedule)
HasPrerequisite(fishing rights, schedule)
Gets(European Union, fishing rights)
Gets(European Union, schedule)
CreatedBy(schedule, Morocco)
```

Fused case network

```
Morocco
European Union
pirate
fishing region
fishing rights
Atlantic
Desires(European Union, fishing rights)
HasA(Morocco, pirate)
HasA(Morocco, fishing region)
ObstructedBy(fishing rights, pirate)
HasProperty(fishing region, fishing rights)
AtLocation(fishing region, Atlantic)
monetary compensation
schedule
Gets(Morocco, monetary compensation)
Causes(European Union, monetary compensation)
HasProperty(fishing region, schedule)
HasPrerequisite(fishing rights, schedule)
Gets(European Union, fishing rights)
Gets(European Union, schedule)
CreatedBy(schedule, Morocco)
```

FUGITIVE

Unsolved case network

```
United States
Russia
deportation
nationality
fugitive
airport
Desires(United States, deportation)
HasA(United States, fugitive)
HasA(United States, nationality)
HasProperty(fugitive, nationality)
HasProperty(fugitive, deportation)
AtLocation(fugitive, airport)
HasA(Russia, airport)
CabapleOf(Russia, deportation)
```

Solved case network

```
United States
Russia
deportation
nationality
fugitive
airport
prison
good treatment
Gets(United States, deportation)
HasA(United States, fugitive)
HasA(United States, nationality)
HasA(United States, prison)
HasProperty(fugitive, nationality)
HasProperty(fugitive, deportation)
HasProperty(fugitive, good treatment)
Gets(fugitive, good treatment)
AtLocation(fugitive, prison)
HasA(Russia, airport)
Causes(Russia, deportation)
Desires(Russia, good treatment)
Gets(Russia, good treatment)
```

```
HasPrerequisite(deportation, good treatment)
```

Fused case network

```
United States
Russia
deportation
nationality
fugitive
airport
Desires(United States, deportation)
HasA(United States, fugitive)
HasA(United States, nationality)
HasProperty(fugitive, nationality)
HasProperty(fugitive, deportation)
AtLocation(fugitive, airport)
HasA(Russia, airport)
CabapleOf(Russia, deportation)
prison
good treatment
Gets(United States, deportation)
HasA(United States, prison)
HasProperty(fugitive, good treatment)
Gets(fugitive, good treatment)
AtLocation(fugitive, prison)
Causes(Russia, deportation)
Desires(Russia, good treatment)
Gets(Russia, good treatment)
HasPrerequisite(deportation, good treatment)
```

INDUS WATERS

Unsolved case network

```
Pakistan
India
Indus Basin
water supply
Desires(Pakistan, Indus Basin)
Desires(India, Indus Basin)
PartOf(water supply, Indus Basin)
Desires(Pakistan, water supply)
Desires(India, water supply)
```

Solved case network

```
Pakistan
India
Indus Basin
water supply
monetary compensation
Gets(Pakistan, monetary compensation)
Gets(Pakistan, western rivers)
Causes(India, monetary compensation)
PartOf(western rivers, Indus Basin)
PartOf(eastern rivers, Indus Basin)
Gets(India, eastern rivers)
PartOf(water supply, eastern rivers)
Gets(India, water supply)
```

Fused case network

```
Pakistan
India
Indus Basin
water supply
monetary compensation
Gets(Pakistan, monetary compensation)
Gets(Pakistan, western rivers)
Causes(India, monetary compensation)
```

```
PartOf(western rivers, Indus Basin)
PartOf(eastern rivers, Indus Basin)
Gets(India, eastern rivers)
PartOf(water supply, eastern rivers)
Gets(India, water supply)
Desires(Pakistan, Indus Basin)
Desires(India, Indus Basin)
PartOf(water supply, Indus Basin)
Desires(Pakistan, water supply)
Desires(India, water supply)
```

INSURANCE

Unsolved case network

```
customer
shop
go to court
medical bills
accident
good publicity
shop
Desires(customer, go to court)
HasA(customer, medical bills)
HasA(customer, accident)
ObstructedBy(good publicity, customer)
Desires(shop, good publicity)
AtLocation(accident, shop)
ObstructedBy(good publicity, accident)
Causes(accident, medical bills)
Causes(medical bills, go to court)
```

Solved case network

```
customer
shop
medical bills
accident
good publicity
monetary compensation
shop
Gets(customer, monetary compensation)
HasA(customer, medical bills)
HasA(customer, accident)
Gets(shop, good publicity)
AtLocation(accident, shop)
Causes(accident, medical bills)
UsedFor(monetary compensation, medical bills)
Causes(shop, monetary compensation)
```

Fused case network

```
customer
shop
go to court
medical bills
accident
good publicity
Desires(customer, go to court)
HasA(customer, medical bills)
HasA(customer, accident)
ObstructedBy(good publicity, customer)
Desires(shop, good publicity)
AtLocation(accident, shop)
ObstructedBy(good publicity, accident)
Causes(accident, medical bills)
Causes(medical bills, go to court)
monetary compensation
Gets(customer, monetary compensation)
HasA(customer, accident)
Gets(shop, good publicity)
UsedFor(monetary compensation, medical bills)
Causes(shop, monetary compensation)
```

IRANIAN HOSTAGE CRISIS

Unsolved case network

```
Iran
United States
independent internal affairs
debt payment
free trade
embassy
staff
freedom
Desires(Iran, independent internal affairs)
CapableOf(Iran, debt payment)
Desires(Iran, free trade)
ObstructedBy(independent internal affairs, United States)
Desires(United States, debt payment)
ObstructedBy(free trade, United States)
AtLocation(embassy, Iran)
HasA(United States, embassy)
PartOf(staff, embassy)
HasProperty(staff, freedom)
ObstructedBy(freedom, Iran)
Desires(United States, freedom)
```

Solved case network

```
Iran
United States
debt payment
free trade
independent internal affairs
embassy
staff
freedom
Gets(Iran, independent internal affairs)
Causes(Iran, debt payment)
Gets(Iran, free trade)
Causes(Iran, freedom)
Causes(United States, independent internal affairs)
Gets(United States, debt payment)
Causes(United States, free trade)
```

```
HasA(United States, embassy)
AtLocation(embassy, Iran)
PartOf(staff, embassy)
HasProperty(staff, freedom)
Gets(United States, freedom)
```

Fused case network

```
Iran
United States
independent internal affairs
debt payment
free trade
embassy
staff
freedom
Desires(Iran, independent internal affairs)
CapableOf(Iran, debt payment)
Desires(Iran, free trade)
ObstructedBy(independent internal affairs, United States)
Desires(United States, debt payment)
ObstructedBy(free trade, United States)
AtLocation(embassy, Iran)
HasA(United States, embassy)
PartOf(staff, embassy)
HasProperty(staff, freedom)
ObstructedBy(freedom, Iran)
Desires(United States, freedom)
Gets(Iran, independent internal affairs)
Causes(Iran, debt payment)
Gets(Iran, free trade)
Causes(Iran, freedom)
Causes(United States, independent internal affairs)
Gets(United States, debt payment)
Causes(United States, free trade)
Gets(United States, freedom)
```

MARKET ACCESS

Unsolved case network

```
Spain
China
police
market
commercial rights
HasA(Spain, police)
HasA(Spain, market)
HasProperty(market, commercial rights)
Desires(China, commercial rights)
ObstructedBy(commercial rights, police)
```

Solved case network

```
Spain
China
monetary compensation
regulations
market
commercial rights
Gets(Spain, monetary compensation)
Causes(China, monetary compensation)
Gets(China, commercial rights)
Gets(China, regulations)
HasA(Spain, market)
HasProperty(market, regulations)
HasProperty(market, commercial rights)
HasPrerequisite(commercial rights, regulations)
CreatedBy(regulations, Spain)
```

Fused case network

```
Spain
China
police
market
commercial rights
```

```
HasA(Spain, police)
HasA(Spain, market)
HasProperty(market, commercial rights)
Desires(China, commercial rights)
ObstructedBy(commercial rights, police)
monetary compensation
regulations
Gets(Spain, monetary compensation)
Causes(China, monetary compensation)
Gets(China, commercial rights)
Gets(China, regulations)
HasProperty(market, regulations)
HasPrerequisite(commercial rights, regulations)
CreatedBy(regulations, Spain)
```

MUSIC BAND

Unsolved case network

```
Musician 1
Musician 2
band
split
other collaboration
song
intellectual property
PartOf(Musician 1, other collaboration)
PartOf(Musician 1, band)
PartOf(Musician 2, band)
HasProperty(band, split)
Desires(Musician 2, intellectual property)
Desires(Musician 1, intellectual property)
HasA(Musician 1, song)
HasA(Musician 2, song)
Desires(Musician 2, split)
HasProperty(song, intellectual property)
```

Solved case network

```
Musician 1
Musician 2
band
split
other collaboration
song
intellectual property
monetary compensation
PartOf(Musician 1, other collaboration)
Causes(other collaboration, split)
Gets(Musician 1, monetary compensation)
HasProperty(band, split)
Gets(Musician 2, intellectual property)
HasA(Musician 2, song)
Gets(Musician 2, split)
Causes(Musician 2, monetary compensation)
HasProperty(song, intellectual property)
```

Fused case network

```
Musician 1
Musician 2
band
split
other collaboration
song
intellectual property
monetary compensation
PartOf(Musician 1, other collaboration)
Causes(other collaboration, split)
Gets(Musician 1, monetary compensation)
HasProperty(band, split)
Gets(Musician 2, intellectual property)
HasA(Musician 2, song)
Gets(Musician 2, split)
Causes(Musician 2, monetary compensation)
HasProperty(song, intellectual property)
PartOf(Musician 1, band)
PartOf(Musician 2, band)
Desires(Musician 2, intellectual property)
Desires(Musician 1, intellectual property)
HasA(Musician 1, song)
Desires(Musician 2, split)
```

ORANGE

Unsolved case network
Sister 1 Sister 2 orange cake drink Desires(Sister 1, orange) Desires(Sister 1, cake) UsedFor(orange, cake) Desires(Sister 2, drink) orange(Sister 2, orange) UsedFor(orange, drink)
Solved case network
Sister 1 Sister 2 orange cake drink peel pulp Desires(Sister 1, cake) Gets(Sister 1, peel) UsedFor(peel, cake) PartOf(peel, orange) UsedFor(orange, cake) Desires(Sister 2, drink) Gets(Sister 2, pulp) UsedFor(pulp, drink) PartOf(pulp, orange) UsedFor(orange, drink)
Fused case network
Sister 1 Sister 2

```
orange
cake
drink
Desires(Sister 1, orange)
Desires(Sister 1, cake)
UsedFor(orange, cake)
Desires(Sister 2, drink)
orange(Sister 2, orange)
UsedFor(orange, drink)
peel
pulp
Gets(Sister 1, peel)
UsedFor(peel, cake)
PartOf(peel, orange)
Gets(Sister 2, pulp)
UsedFor(pulp, drink)
PartOf(pulp, orange)
```

PATENT

Unsolved case network

```
company
manufacturer
monetary compensation
manufacture rights
invention
illicit manufacture
Desires(company, monetary compensation)
HasA(company, manufacture rights)
CreatedBy(invention, company)
HasProperty(invention, illicit manufacture)
HasProperty(invention, manufacture rights)
Causes(manufacturer, illicit manufacture)
CapableOf(manufacturer, monetary compensation)
```

Solved case network

```
company
manufacturer
recognition
manufacture rights
invention
Gets(company, recognition)
HasA(company, manufacture rights)
HasPrerequisite(manufacture rights, recognition)
CreatedBy(invention, company)
HasProperty(invention, manufacture rights)
Causes(manufacturer, recognition)
Gets(manufacturer, manufacture rights)
```

Fused case network

```
company
manufacturer
monetary compensation
manufacture rights
invention
```

```
illicit manufacture
Desires(company, monetary compensation)
HasA(company, manufacture rights)
CreatedBy(invention, company)
HasProperty(invention, illicit manufacture)
HasProperty(invention, manufacture rights)
Causes(manufacturer, illicit manufacture)
CapableOf(manufacturer, monetary compensation)
recognition
Gets(company, recognition)
HasPrerequisite(manufacture rights, recognition)
Causes(manufacturer, recognition)
Gets(manufacturer, manufacture rights)
```

RHODESIA BRITAIN

Unsolved case network

```
Rhodesia
British Government
armed conflict
ceasefire
independence
land reform
white minority
PartOf(Rhodesia, armed conflict)
PartOf(British Government, armed conflict)
Desires(Rhodesia, ceasefire)
Desires(British Government, ceasefire)
Desires(Rhodesia, independence)
ObstructedBy(independence, British Government)
PartOf(Rhodesia, British Government)
Desires(Rhodesia, land reform)
ObstructedBy(land reform, British Government)
PartOf(white minority, Rhodesia)
PartOf(white minority, British Government)
```

Solved case network

```
Rhodesia
British Government
ceasefire
independence
land reform
white minority
constitution
Gets(Rhodesia, ceasefire)
Gets(British Government, ceasefire)
Gets(Rhodesia, independence)
Gets(Rhodesia, constitution)
PartOf(independence, constitution)
PartOf(land reform, constitution)
Gets(Rhodesia, land reform)
PartOf(white minority, Rhodesia)
HasA(white minority, minority rights)
PartOf(minority rights, constitution)
```

```
Gets(British Government, minority rights)
Causes(British Government, constitution)
```

Fused case network

```
Rhodesia
British Government
armed conflict
ceasefire
independence
land reform
white minority
PartOf(Rhodesia, armed conflict)
PartOf(British Government, armed conflict)
Desires(Rhodesia, ceasefire)
Desires(British Government, ceasefire)
Desires(Rhodesia, independence)
ObstructedBy(independence, British Government)
PartOf(Rhodesia, British Government)
Desires(Rhodesia, land reform)
ObstructedBy(land reform, British Government)
PartOf(white minority, Rhodesia)
PartOf(white minority, British Government)
constitution
Gets(Rhodesia, ceasefire)
Gets(British Government, ceasefire)
Gets(Rhodesia, independence)
Gets(Rhodesia, constitution)
PartOf(independence, constitution)
PartOf(land reform, constitution)
Gets(Rhodesia, land reform)
HasA(white minority, minority rights)
PartOf(minority rights, constitution)
Gets(British Government, minority rights)
Causes(British Government, constitution)
```

RUNAWAY SON

Unsolved case network

`mother`
`father`
`son`
`custody`
`house`
`apartment`
`sending home`
`HasA(mother, son)`
`HasA(mother, custody)`
`Desires(mother, sending home)`
`HasA(mother, apartment)`
`HasProperty(son, sending home)`
`HasProperty(son, custody)`
`HasA(father, son)`
`HasA(father, house)`
`CapableOf(father, sending home)`
`AtLocation(son, house)`

Solved case network

`mother`
`father`
`son`
`custody`
`house`
`apartment`
`sending home`
`improved relations`
`HasA(mother, son)`
`HasA(mother, custody)`
`Gets(mother, sending home)`
`HasA(mother, apartment)`
`HasProperty(son, sending home)`
`Causes(father, sending home)`
`Causes(mother, improved relations)`
`HasProperty(son, custody)`
`HasA(father, son)`
`HasA(father, house)`

```
AtLocation(son, apartment)
Desires(father, improved relations)
Gets(father, improved relations)
HasProperty(son, improved relations)
```

Fused case network

```
mother
father
son
custody
house
apartment
sending home
HasA(mother, son)
HasA(mother, custody)
Desires(mother, sending home)
HasA(mother, apartment)
HasProperty(son, sending home)
HasProperty(son, custody)
HasA(father, son)
HasA(father, house)
CapableOf(father, sending home)
AtLocation(son, house)
improved relations
Gets(mother, sending home)
Causes(father, sending home)
Causes(mother, improved relations)
AtLocation(son, apartment)
Desires(father, improved relations)
Gets(father, improved relations)
HasProperty(son, improved relations)
```

SINAI

Unsolved case network

```
Egypt
Israel
Sinai
sovereignty
security
Desires(Egypt, Sinai)
Desires(Egypt, sovereignty)
UsedFor(Sinai, sovereignty)
Desires(Israel, security)
Sinai(Israel, Sinai)
UsedFor(Sinai, security)
```

Solved case network

```
Egypt
Israel
Sinai
sovereignty
security
civilian
military
Desires(Egypt, sovereignty)
Gets(Egypt, civilian)
UsedFor(civilian, sovereignty)
PartOf(civilian, Sinai)
UsedFor(Sinai, sovereignty)
Desires(Israel, security)
Gets(Israel, military)
UsedFor(military, security)
PartOf(military, Sinai)
UsedFor(Sinai, security)
```

Fused case network

```
Egypt
Israel
```

```
Sinai
sovereignty
security
Desires(Egypt, Sinai)
Desires(Egypt, sovereignty)
UsedFor(Sinai, sovereignty)
Desires(Israel, security)
Sinai(Israel, Sinai)
UsedFor(Sinai, security)
civilian
military
Gets(Egypt, civilian)
UsedFor(civilian, sovereignty)
PartOf(civilian, Sinai)
Gets(Israel, military)
UsedFor(military, security)
PartOf(military, Sinai)
```

SOFTWARE USE

Unsolved case network

```
airline
software company
payment
continued use
software
HasA(airline, software)
Desires(airline, continued use)
HasProperty(software, continued use)
HasPrerequisite(continued use, payment)
Desires(software company, payment)
CreatedBy(software, software company)
```

Solved case network

```
airline
software company
payment
continued use
software
license
HasA(airline, software)
Gets(airline, continued use)
Causes(airline, payment)
HasProperty(software, continued use)
PartOf(license, software)
Gets(airline, license)
Causes(software company, license)
Gets(software company, payment)
CreatedBy(software, software company)
```

Fused case network

```
airline
software company
payment
continued use
```

```
software
license
HasA(airline, software)
Gets(airline, continued use)
Causes(airline, payment)
HasProperty(software, continued use)
PartOf(license, software)
Gets(airline, license)
Causes(software company, license)
Gets(software company, payment)
CreatedBy(software, software company)
Desires(airline, continued use)
HasPrerequisite(continued use, payment)
Desires(software company, payment)
```

SPORTS TEAMS

Unsolved case network

```
Team 1
Team 2
player
contract
stadium
field
participation
HasA(Team 1, stadium)
HasA(Team 1, player)
AtLocation(player, stadium)
HasA(Team 1, contract)
HasProperty(player, contract)
Desires(Team 2, contract)
HasA(Team 2, field)
HasProperty(Team 2, participation)
Desires(player, participation)
```

Solved case network

```
Team 1
Team 2
player
stadium
field
participation
contract
access
monetary compensation
HasA(Team 1, stadium)
AtLocation(player, field)
HasA(Team 2, field)
HasProperty(Team 2, participation)
HasA(Team 2, player)
Gets(Team 1, access)
HasProperty(player, access)
HasProperty(player, contract)
Gets(Team 2, contract)
Gets(player, participation)
```

```
Gets(Team 1, monetary compensation)
Causes(Team 2, monetary compensation)
```

Fused case network

```
Team 1
Team 2
player
contract
stadium
field
participation
HasA(Team 1, stadium)
HasA(Team 1, player)
AtLocation(player, stadium)
HasA(Team 1, contract)
HasProperty(player, contract)
Desires(Team 2, contract)
HasA(Team 2, field)
HasProperty(Team 2, participation)
Desires(player, participation)
access
monetary compensation
AtLocation(player, field)
HasA(Team 2, player)
Gets(Team 1, access)
HasProperty(player, access)
Gets(Team 2, contract)
Gets(player, participation)
Gets(Team 1, monetary compensation)
Causes(Team 2, monetary compensation)
```

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DECLARATION

I declare that this thesis is entirely the result of my own work under the supervision of Prof. Ram'on López de Mántaras Badia. Where other sources of information have been used, they have been acknowledged.

It is submitted for the doctorate degree in Informatics at the Universitat Autònoma de Barcelona, Barcelona, Spain. It has not been submitted before for any other degree or examination at any other university.

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Atılım Güneş Baydin

colophon

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