# A Survey on Similarity-based Reasoning

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## 1. Introduction

Similarity-based reasoning is an approach to intelligent system opposite to deductive reasoning. Essentially, this reasoning approach draws conclusions by similarity rather than by chaining generalized rules. The reason for this transition is manifold. Some researchers believe that it conforms to human reasoning. Some use it to simplify problem solving and knowledge representation in domains without well-defined theory while others use it to switch among domains for commonsense reasoning and creativity. Though researchers have distinct standards as to this approach, they observe one principle or assumption: past experiences provide clues for future reasoning. Therefore, in such system, knowledge should contain sources or templates for future reference. By this assumption, many potential problems arise as how to represent, store and retrieve sources as well as how to adapt to and learning from new situation.

Research on these problems falls into two fields: case-based reasoning and analogical reasoning. They differ in their scope of problems studied (Leake 1996). The former one gives more engineering consideration, i.e., how to mechanize the entire process for some purposes (e.g., problem solving) while the latter one focuses primarily on similarity and mapping, most from a psychological perspective to simulate human analogy. Since CBR system has clear goal, it is domain specific while analogical reasoning is more general. Although CBR has more pragmatic consideration, it stems from psychological investigations of the role of memory in human story understanding by R.C. Schank (Schank 1982). Hence, both CBR and analogical reasoning have psychological basis. Characterizing the meaning of similarity and analogy in human reasoning is the most notable one.

In psychology, similarity and analogy are two relevant but separate concepts (Gentner, A. 1997). Similarity concerns storing and retrieving experiences on the basis of similarity to a category/concept representation, whereas analogy is a clever, sophisticated process used in creative discovery. Therefore, similarity provides more general insight of human concept and thinking while analogy constraints to mapping between source and target in some representation.

Since similarity is more general, analogy can be seen as one aspect of similarity. In psychology, there are three types of similarities: *surface similarity*, e.g., a bicycle reminds one of a pair of eyeglasses; *sublime similarity* like the periodic table of elements and one of octaves in music. The most common one, however, is *mundane similarity*: when a bicycle reminds one of another bicycle (Gentner, K. 1991). The representation structures underlying this intuitive categorization of similarity are discussed in (Falkenhainer, Forbus, K. and Gentner, D 1986): mundane similarity essentially concerns concept categories. A surface similarity or a mere-appearance match is primarily the mapping by *object-descriptions*. In analogy or sublime similarity, however, it is the matches of *relational structures* unsupported by surface similarity. *Literal similarity* typically occurs in within-domain comparisons, in which the objects involved look alike as well as act alike. An example of a literal similarity is the comparison "Kool-Aid is like juice". Actually, there is a fourth kind of similarity called shared abstraction originated from Greek philosophers such as Plato and

Aristotle (Shelley 2003). Analogous objects share not only a relation, but also an idea, a pattern, a regularity, an attribute, an effect or a function. However, in D. Gentner's Structure Mapping Theory (Gentner, D., Holyoak, K.J., Kokinov, B. (Eds.) (2001).., 2001), she claims that when it comes to abstraction, few, if any, attributes exist that do not contribute to the base (source)'s relational structure. In other words, similarity between two objects is either surface or relation.

This paper tries to give a thorough survey about studies on these problems. In section 2, we first discuss case-based reasoning. The third section considers models and theories of analogy. Section 4 makes a more substantial discussion about the similarity in concept representation. Memory is critical in similarity-based reasoning, so learning comes in nature with the reasoning process. This will be covered in section 5. The section 6 deals with the integration of other knowledge and reasoning with similarity-based reasoning while the section 7 makes comparisons between several similarity-based models and systems. Finally, in section 8 (a relatively more important section), we (I) discuss how does similarity-based reasoning aids the physical tool use problem.

# 2. Case-based Reasoning

To demonstrate the differences between reasoning based on similarity and that on deductive rules, it is better to start from CBR since it illustrates the entire process of similarity-based reasoning in a pragmatic system. CBR has many applications (Kolodner 1996): in problem solving, CBR can be applied in design or constraints problem, planning and diagnosis. In interpretation, it can facilitate case and concept classification, adversarial reasoning i.e., persuasive arguments such as case-based legal system and projecting effects of a decision or a plan. Finally, CBR supports decision aiding and teaching.

## 2.1. The process of CBR

Aamodt & Plaza's (Aamodt 1994) classic model of the problem solving cycle in CBR includes retrieve, reuse, revise and retain. A case in a case base (or memory) includes a problem description and the associated solution. In retrieval phase, the *similarities* of the current problem to previous problems are measured, and one or more similar cases are retrieved. The solutions of retrieved cases are *reused* and possibly *adapted (revised)* to account for the new problem. Following the application of revised solution, the problem description and its solution can be *retained* as a new case in light of an evaluation of the success.

The model above gives an account of processes in a CBR system, but it provides few insights about human behavior. A human account of CBR typical involves situation assessment, problem solving and learning (Leake 1996). Human case-based problem solving starts from the assessment of the situation, i.e., the process of analyzing a situation and elaborating it such that its description is in the same vocabulary as cases already in the case library (Kolodner 1996). First, situation assessment is usually tricky because there is much unstated fact in a situation and are always innumerable features of new situations that could be elaborated. Problem solving corresponds to retrieval, reuse and revision phases of Aamodt & Plaza's model. Second, as discussed above, problem solving can be seen as exploiting the relationship between similarities in two spaces: problem description space and problem solution space. For example, a new plan is generated by retrieving a prior plan for a similar goal, determining the differences between the old and new goals, and adapting the plan to take the new goals into account. Third, we always learn from experience of a new situation. The experience can be success (success driven learning) as well as failure (failure-driven learning). The success-driven learning simply stores the new problem and solution without repeating the problem solving cycle from scratch. Learning from failure is more complex, which can trigger multiple types of learning. If the task at hand fails, we may repair failed solutions or store failure information. The indexing criteria can also be revised to retrieval better solution. Another kind of failure is *expectation failure* (Schank 1982), i.e., the observed outcomes differ- for better or for worse- from predictions. In this case, how to anticipate similar problem precisely should be learned. Finally, as pointed out in (Kolodner 1996), these steps are in some sense recursive. For example, learning or evaluation may lead to propose re-retrieval or additional adaptation of the solution.

## 2.2. Why CBR?

Section 2.1 gives a sketch of the CBR process. In this section, we try to uncover a deeper question: why do we need CBR and what is the philosophy behind this simple process. As mentioned in introduction, CBR is a principle transformation from deductive system. Thus, in this section, we mainly focus on the benefit of CBR, assumptions under CBR and difficulties with CBR

### 2.2.1. What is a case?

The definition given in (Kolodner 1996) is:

> A case is a contextualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoner.

What common to all cases is that they represent an experienced situation. But not all experiences are useful. Only those experiences that are different in some way from what is expected by other cases or by general knowledge are worth to remember. In other words, case should teach some useful lessons. These lessons include (Kolodner 1996):

- How to achieve a goal
- How to achieve several goals in conjunction
- The circumstances of the situation in terms of goal
- How to bring about the state required for achieving goal
- What might go wrong in achieving the goal
- The effects of an action

These lessons actually specify what the content of a case is:

1. *Problem/situation description*: it embraces goals and circumstance
2. *Solution*: answer the “how” question
3. *Outcome*: effects or feedback from the environment for evaluating and analyzing

Since cases are related to specific situations, it is not generalized compared with rules. However, in a cognitive model, both of them can play critical roles. For one thing, general knowledge can give guidance at every phase of case based reasoning. For another thing, the organization of abstractions and cases in a memory changes dynamically over time and with experience. Actually, when it comes to abstraction, the boundary between case and rule is nevertheless blurring. A situation description, to some extent, has to stand on some abstraction level. To separate them, a case can be seen as locate in low level of abstraction hierarchy and can be used more directly by appropriate situation description.

### 2.2.2. The Potential Benefits of CBR

As stated above, a case is stored "as-it" without the need to generalize to rules. In some sense, CBR provides a not perfect but effective solution to real world problems rather than a generative system which needs to account for all possible problems in principle. CBR modifies results of prior reasoning rather than repeating the entire prior efforts, which reduces search space and improves computational efficiency. A case itself implies the context of assessing the problem situation and evaluating the solution, and it is in nature goal-directed. In addition, because CBR saves failed solutions as well as successes, it can warn of potential problems to avoid. These make CBR useful for problems in uncertain, complex and dynamic domain, and with incomplete theory such as common sense problem. It is also claimed that this is the way that human solve problems.

However, few of these benefits come without a price. In the next two sections, the assumption and difficulties behind these benefits are examined.

### 2.2.3. Assumptions

To judge a theory or an approach, it is better to inspect closely to its assumptions. There are several assumptions for CBR.

1. Knowledge representation assumption

CBR knowledge is represented as cases, i.e., past experiences in episodic memory. It assumes that this specialized representation is the basis of human problem solving. Other information can also be implied in CBR system. In the knowledge container view of CBR (Richter 1998), apart from the vocabulary used to describe cases and the case base, the information is also implied in the similarity measurement and adaptation knowledge.

2. Similarity assumption

Similarity is the core of CBR, this assumption states the more similar of two problem descriptions, the more useful of the matched solution to the new problem (Brigitte Bartsch-Sp?rl, Andr¨¦ H¨¹bner 1999). The similar statement is that the retrieval distance R in the problem space is commensurate with distance A in the solution space (Lopez de Mantaras, et al. 2005).

3. Decomposition assumption

In R4 model of CBR, every phase can be seen as a separate task containing a number of alternative techniques. This is known as the task-method decomposition model (Aamodt 1994).

### 2.2.4. Paradoxes

Each assumption above contains some paradoxes which place many potential troubles for CBR.

For knowledge representation assumption, not all domains are natural CBR domains; cases may be unavailable, or may be available but in a hard-to-use form. CBR is expected to solve problems in those domains that have incomplete or few theories, but the success of every phase depends heavily on domain knowledge. For example, determining which aspects of a situation to adapt and how to control the adaptation process relies on a great amount of domain knowledge.

For similarity assumption, the validity of similarity depends on how to represent knowledge. There is no universal measurement for all representations. Moreover, a case can be considered as similar to the current problem, if the solution of that case can be easily reused for the problem. But, in general, this similarity measurement can only be determined by the effect of the solution to the new problem. As for human, we have the insight to which part of the problem description/representation is relevant, and this “insight”, which might in turn be the result of similarity measurement or general knowledge, guiding us to find the similar solution.

By the previous discussion, it is obvious that CBR procedures is inseparable (against task decomposition assumption), a later step may affect the result of a previous step. For example, there is research on adaptation-guided retrieval, which extends the retrieval measurement on similarity to solution utility by adaptation (Lopez de Mantaras, et al, 2005).

## 2.3. A Comparison between Research topics in 1996 and 2005

Since Schank’s (Schank 1982) seminal study on memory in human story understanding, CBR has experienced a progress of more than 20 years. This section gives a summary of this progress by comparing two survey papers (Leake 1996) and (Lopez de Mantaras, McSherry, David, Bridge, Derek, Leake, David, Smyth, Barry, Craw, Susan, Faltings, Boi, Maher, Mary Lou, Cox, Michael, Forbus, Kenneth, Keane, Mark, Aamodt, Agnar, Watson, Ian 2005). In 1996’s survey, the research focused on defining the procedures and techniques within R4 model whereas in 2005, the focus had shifted to two critical problems: retrieval and adaptation as well as the integration of ideas from cognitive science and traditional AI. Some other papers are also referenced when the topics are related.

In (Leake 1996), D. Leake proposed several research concerns in terms of R4 model: case representation, retrieval, adaptation, similarity assessment, case evaluation and case base coverage and collection.

As for case representation, apart from above mentioned problem-solution representation, there is solution derivation representation, i.e., store and reuse traces of how those solutions were derived, instead of the actual solutions; This is also called *derivational analogy* which has close relation with introspective reasoning and learning.

Case retrieval is a search strategy based on similarity measurement. Another component is case indexes that combining case’s important descriptors to distinguish it from other cases. Indexing can also hold structures in case library organization. Indexing has two approaches: top-down, i.e., problem description based retrieval, and bottom-up, favoring features that are useful to discriminate between the cases.

Since rule-based adaptation may suffer paradoxes, there are more choices either by improving capabilities, e.g., providing domain independent rules to find domain-specific information, derivational analogy, case-based adaptation rules, supporting adaptation with introspective reasoning, combining rules and cases for adaptation learning, representing case hierarchically, etc, or by decreasing the adaptation need, e.g., alleviating the adaptation burden by refining other components, and adapting the context rather than the case. Kolodner (Kolodner 1993) gives more details by list ten methods for adaptation. However, most approaches are not so good. The most efficient way suggested is still by users.

One issue in similarity assessment is how to determine the right features to compare. This is a paradox for real problem as stated before. Decisions about which features are important are often based on explanations of feature relevance, but the explanations may be imperfect. Another problem is insufficient problem description to determine the similarity. Leake suggested that situation assessment and similarity assessment may need to be combined to solve the paradox. One method is *constructive similarity assessment*, which “builds up a description of the input situation based on prior cases, and evaluates similarity by whether the retrieved case is adaptable to the new situation, rather than following any static criteria”. Another suggestion is domain independent utility similarity criteria, such as dependent on the resulting plan and execution time for case-based planning.

The knowledge paradox exists in every step of CBR. Case evaluation may require considerable domain knowledge and reasoning effort. When facing this paradox, some authors resort to use case itself to replace rule-based knowledge. For case evaluation, some similar cases can be used as benchmark.

A design decision is about which and how many cases are stored. It is important to consider the maximum size of case library meanwhile provide sufficient coverage. As suggested in (Kolodner 1996), the memory update for case may consider the retrieval issue. An analogous process may be carried out and look for a place to insert the case since case library may be organized as some structure according to a certain indexing.

(Lopez de Mantaras, McSherry, David, Bridge, Derek, Leake, David, Smyth, Barry, Craw, Susan, Faltings, Boi, Maher, Mary Lou, Cox, Michael, Forbus, Kenneth, Keane, Mark, Aamodt, Agnar, Watson, Ian 2005) is a survey with collective efforts by almost all experts in CBR community. The focus is on retrieval, reuse and revision, and retention.

The similarity assessment has considered the results in analogical reasoning and cognitive science community. Similarity is divided into surface similarity and structural similarity. The case in surface similarity is typically represented as feature vector and is retrieved by“k nearest neighbor”. With this representation, a local similarity measure is usually defined for each attribute and a global similarity measure is computed as a weighted average of the local similarities. Some strategies permit more flexibility. For example, *fish and shrink strategy* in which cases are linked according to specific aspect similarities assumes that if a case does not fit a query then this will reduce the likely usefulness of its neighbors. Though computationally expensive, retrieval based on structural similarity has the advantage that more relevant cases may be retrieved. K, Forbus et al.’s MAC/FAC model (Forbus, Gentner, D. & Law, K. 1994) combines surface and structural similarity in a two-stage retrieval process to mitigate the extra cost. Others include object-oriented case representation, frame-base representation, and graph structure based case representation to capture both case and general domain knowledge, and *generalized cases* providing solutions to a set of closely related problems. Spreading activation methods using interconnected network of nodes is efficient and flexible enough to handle incomplete case descriptions, but requires spread guiding knowledge. Finally, with so many ways of measuring similarity, some researchers view similarity in a general way, independent of any specific algorithm, and develop general similarity framework.

Several authors have questioned the assumption on which similarity-based retrieval is based, namely that the most similar cases are most useful for solving the target problem. They try to get rid of the limitations of retrieval based purely on similarity. These include *adaptation-guided retrieval*, *diversity-conscious retrieval* combining measures of similarity and diversity of cases, *compromise-driven retrieval* based on a weaker assumption that a given case is more acceptable than another if it is more similar to the user's query and it involves a subset of the compromises that the other case involves, *order-based retrieval* defining and combining ordering relations between cases rather than scoring the cases (the previous three approaches are most often used in CBR recommender systems). A more popular subject is explanation-oriented retrieval. There is a need for a system to explain and justify their reasoning. Different aspects of explanation can serve different goals. More commonly, the goal is to explain how the system reaches its conclusions. Precedent-based explanations which have long been a feature of legal argumentation are questioned by several authors. Precedent-based explanations resemble the knowledge assumption of CBR, namely, past experience provides solution for future cases. One question is that the proposed solution or explanation are often less informative and should be supported by an analysis of the *pros* and *cons* of the proposed solution. Other considerations such as noteworthy distinctions among cases and the existence of counterexamples are equally important. Cases that lie between the target problem and the decision boundary can often be more useful for explanation than the most similar one.

Adaptation occurs as subsequence of case reuse, or as feedback about a proposed solution indicating that a repair is needed. There are two dimensions with respect to adaptation methods: what is changed in the retrieved solution, and how the change is achieved. With regard to these two dimensions, there are three types of adaptation methods: *substitution adaptation*: reinstantiates some part(s) of the retrieved solution, *transformation adaptation*: alters the structure of the solution, and more complex *generative adaptation*: replays the method of deriving the retrieved solution on the new problem. In substitution and transformation, several notable methods involve Déjà Vu, a system with hierarchies of related cases and adoption of a hierarchical model of case retrieval and reuse, *model-based adaptation* in which causal reasoning is integrated with CBR, *evolutionary adaptation* which resembles the adaptation in genetic algorithm and *constraint satisfaction problem adaptation* in design. Generative adaptation may result in substitution or in a transformation since it replays the solution derivation. In *derivational analogy*, an analogy between the new and retrieved problems is used to adapt the method of deriving the solution. *Derivational replay* is a variant of derivational analogy. It recomputes a replacement by replaying the computation for the new problem.

As in Leake's 1996 survey, the difficulty of acquiring adaptation knowledge was identified in early CBR research but, until recently, relatively little effort has been devoted to automating the acquisition of adaptation knowledge. Several systems exploit the knowledge already captured in the cases as a source of adaptation knowledge.

Retention issue in CBR is somewhat overlooked (as in Leake's 1996 survey, this is only a design consideration). Most, for example, simply record the target problem specification and the final solution, with the implicit assumption that the outcome was successful. In fact, retention has two issues, one is still case representation, which is related to what to store, the other is learning, which concerns how to store. Here the focus is on the first one, i.e., what to store. When outcomes are less reliable or when the criteria for success are more complex, case representations must include additional information on the outcome of the solution and fine-grained information on how well the solution addresses many dimensions of the system's goals. What to store may concern the solution itself as well as process that brought about the solution, i.e., derivational traces. The importance of learning is based on the prevailing assumption that learning would occur as a by-product of every problem solving episode. However, this may suffer the *utility problem*, i.e., the performance degradation experienced by speed-up learners as a result of more learned knowledge. For example, overly specific rules that are seldom applicable, or rules with a high match cost, or rules that offer limited speed-up are contributed to performance degradation. Thus, there should be a natural trade-off between the benefits of speed-up knowledge and the cost of its application. As for CBR, it is necessary to retain new cases selectively by a *competence model* to evaluate the contributions of individual cases to problem solving competence or a case-based maintenance system. A more comprehensive discussion of learning with regard to similarity based reasoning will be presented in later section.

The discussion above shows that nearly every possible problem of CBR has undergone a comprehensive investigation. Current research tends to solve more pragmatic problems and pursue integration. These efforts include CBR for Incompletely-Described Cases (Leake 2004), merging of case bases (Sooriamurthi 2003, David B. Leake and Raja Sooriamurthi 2003, Sooriamurthi 2002), and the integration of CBR and probability (Halstead, K. 2005), etc.

# 3. Models and Theories of Analogy

## 3.1. Introduction

In ancient Greek, analogy was understood as *identity of relation* between any two ordered pairs. Kant's Critique of Judgment (Kant 1987) also held to this notion. The example is "analogy question" such as HAND : PALM : : FOOT : ____; (*sole*). This relation is not apparent in some lexical definitions of palm and sole, where the former is defined as the inner surface of the hand, and the latter as the underside of the foot. It is easy to find the answer for any English speaker. But it is more difficult to identify and describe the exact relation. Analogy and abstraction are different cognitive processes, and analogy is often an easier one. As in the introduction of this survey, another view of analogy held by Plato and Aristotle was s*hared abstraction*. Moreover there are some efforts to reduce the analogy to other reasoning processes (though they are not so plausible) such as Bacon's view of *special case of induction* and *Hidden deduction*.

Modern accounts of analogy are extensionally close to shared abstraction, but framed in other theory. One is the *structure mapping theory* by Dedre Gentner, which depends on the mapping of source and target extensively between descriptions of objects, between relations of objects and between relations of relations. Douglas Hofstadter and his team argue that there is no line between perception, including high-level perception (a concept clarified later), and analogical thought (Hofstadter 2001). This argument implies that analogy is the basis of cognitive process. However, it has been argued (Morrison and Dietrich 1995) that Hofstadter's and Gentner's groups do not defend opposite views, but are instead dealing with different aspects of analogy. In fact, Hofstadter's theory concerns more about concept organization from an analogy point of view. Thus the detailed discussion will be postponed to later section. This section concentrates on structure mapping theory along with a brief preview of high-level perception.

## 3.2. Structure Mapping Theory (SMT)

Analogy is a psychological endeavor which discovers the underlying mechanism of human cognition. The computational models are built for testifying the human cognitive theory. Thus, this section is organized as follow: first, several models based on structure mapping theory are discussed. Then, some psychological evidence is presented to support the theory.

### 3.2.1. Models of Structure Mapping

The fundamental principle of SMT is systematicity: people prefer to map systems of predicates that contain higher-order relations, rather than to map isolated predicates. Several models of matching are developed on this principle mainly by Qualitative Reasoning Group led by K. Forbus and D. Gentner at Northwestern University.

The earliest model laying the foundation for computational analogy is Structure Mapping Engine (Falkenhainer, Forbus, K.D., & Gentner, D. 1989). The SME is developed on the basis of one-to-one, structurally consistent mapping with systematicity bias, namely, analogy conveys a system of connected knowledge, not a mere assortment of independent facts. It is the amount of common higher-order relational structure that determines which of several possible matches is preferred. Another design principle is that the *SES* (*Structural Evaluation Score*, A numerical estimate of match quality) reflects the aesthetics of the particular type of comparison, not validity or potential usefulness.

The representation convention of SME contains *entities* (Individuals and constants), *predicates* for functions, attributes, and relations, and *Dgroup* (a frame-like description group is a collection of entities and facts about them, considered as a unit). The algorithm is carried out as graph matching on Dgroup. SME has no other encoded knowledge of either base or target domain. Neither rules of inference nor even logical connectives themselves are built into the algorithm. Instead, match rules specifying what pairwise matches are possible and providing measures of quality are provided as the model input to enable large extends of flexibility.

In structure mapping theory, analogy is comprised of three subprocesses: *access*: retrieves the base analogous or similar to the target, *mapping and inference*: candidate inferences containing correspondence between base and target, and *evaluation and use*: structural and domain-independent evaluation of the match by estimation criteria–the degree of structural similarity involved (structural criteria), validity of the match and the inference and usefulness (relevance). The SME algorithm corresponds to the theory by four steps:

**Step 1: Local match construction**: allowable matches are specified by match constructor rules

**Step 2: Global Match Construction**: *gmaps* consist of maximal, structurally consistent collections of match hypotheses in step 1.

**Step 3: Compute Candidate Inferences**: each gmap represents a set of correspondences that can serve as an interpretation of the match.

**Step 4: Compute Structural Evaluation Scores**: use match evidence rules to assign and manage numerical scores by *belief maintenance system*.

MAC/FAC model (for "many are called but few are chosen") is a similarity-based model to simulate human retrieval and reminding based on SME (Gentner, K. 1991). It tries to simulate three psychological phenomena in human reminding:

(1) People are extremely good at judging similarity and analogy when given items to compare.

(2) Superficial remindings are much more frequent than structural remindings.

(3) People sometimes experience and use purely structural analogical remindings.

These phenomena embrace a paradox: the mapping process is actually very sensitive to structural soundness unsupported by surface similarity, but we often give precedence to literal similarity, based on both structural and superficial commonalities, or superficial similarity, based only on surface commonalities. MAC/FAC resolves this paradox by offering a two-stage model:

- **MAC stage**: cheap but structurally stupid match processes by the dot product of a secondary representation—content vectors.
- **FAC stage:** judging structural soundness on each of the results of the MAC stage by SME in parallel.

There are two notable drawbacks of original SME. The first is that it needs to construct all structurally consistent interpretations of an analogy, which is both psychologically implausible and computationally inefficient. The second is that SME contains no mechanism for focusing on interpretations relevant to an analogizer's goals. For these problems, Falkenhainer developed *contextual structure mapping* (Falkenhainer 1990). In his paper, he presented two forms of context in analogy: first, the context in which the analogy is performed. Second, each statement being compared is done so within the context of each analogue's overall description. In his sense, taking context into consideration is equivalent to assigning each element of an analogue's description an identifiable role. His model is a knowledge-intensive adaptation of structure-mapping theory, which presents analogy elaboration as a mapping and analyzing cycle, in which two situations are placed in correspondence, followed by problem solving and inference production focused on correspondence inadequacies. In fact, his model is a hybrid system combining several knowledge representations and reasoning approaches into a single analogical making system. The detail will be presented in the later section for hybrid approach. Holyoak and Thagard's *ACME* model (Holyoak, P. 1989) blends structural, semantic, and pragmatic considerations into weights in a connectionist network. In addition to biasing preference for correspondences according to relevance, they allow queries to be inserted in the target description as explicit goals. *Pragmatic marking* model (Forbus, D. 1990) focuses the mapping to produce relevant, yet novel, inferences and is consistent with both standard and contextual structure mapping. For pragmatic issue, it uses the greedy merge algorithm for approximating "best" interpretation and alternate interpretation and combining local matches into consistent global interpretations. For goals, it filters what subsets of local matches are considered by whether or not they can support candidate inferences relevant to the analogizer's stated goal.

There are other models that concern a variety of aspects of analogy. *I-SME* (Forbus, Ferguson, R. and Gentner, D. 1994) is a structure mapping model operating incrementally. It can extend its existing interpretations when given new information about base or target. This incremental analogy is based on three observations: (1) metaphor understanding: readers often build up correspondences across several sentences; (2) problem solving: go back and forth, seeking additional ways to interpret the new problem in light of the old; (3) conceptual change: new data can lead to analogies being modified or abandoned. *MAGI* model (Ferguson 1994) uses the SME to flexibly and reliably match a description against itself. The idea is brought about from considerations that how analogy might be used to break the world into comprehensible parts instead of interrelating distinct parts of the world. In particular, this model handles how people use symmetry and regularity to facilitate the encoding task. *SHAKEN* model (Nicholson, K. 2002) uses a cognitive simulation of analogical processing to answer comparison questions such as "How is X like Y?" and "How are X and Y different?", to support domain experts in entering new knowledge. By utilizing SME, the model addresses three key issues in answering comparison questions: 1. Case construction. How should the concept descriptions be automatically generated from the underlying knowledge base? 2. Evaluating candidate inferences. How should the inferences generated from the comparison be tested? 3. Summarization. How should the results of the comparison be used to generate a helpful answer? Finally, Yan, et al. (Yan, Forbus, K., and Gentner, D. 2003) models a theory of rerepresentation in analogical matching for SME. Rerepresentation which re-construes parts of compared situations in order to improve a match appears to be an important technique for achieving flexibility in analogical matching. Their model divides the problem into detecting opportunities for rerepresentation, generating rerepresentation suggestions based on libraries of general methods, and strategies for controlling the rerepresentation process.

#### 3.2.2. Psychological evidence

This sub-section examines psychological evidence for structural mapping theory. The evidence can also characterize the human analogical reasoning process.

Analogy is one of similarity-based reasoning. In mundane life, there are many cognitive processes relevant to similarity (Gentner, A. 1997): storing experiences in categories: similarity to a category representation or to stored exemplars; new problems are solved using procedures taken from prior similar problems; inferences about people are influenced by their similarity to other known individuals; responding affectively to a situation may be based in part on our responses to previous similar situations.

Two major similarity types take part in analogical reasoning: surface similarity and relational similarity. Similar case retrieval is heavily influenced by surface properties more than by deep similarities. Yet when people are given the analogues, they find the comparisons easy. This demonstrates that systematicity is a key element of people's implicit rules for analogical mapping (Falkenhainer, Forbus, K.D., & Gentner, D. 1989). Adults tend to include relations and omit attributes in their interpretations of analogy. Thus, CBR and machine learning systems that use feature vectors are unlikely to be good models of human cognition.

Further research on developmental psychology shows that young children prefer surface information while at older ages, they follow systematic mappings. This shift from surface to systematic mappings is also featured in novice to expert transition (Falkenhainer, Forbus, K.D., & Gentner, D. 1989). Yet there is disagreement as to the nature of this shift (Gentner, Rattermann, M. J., Markman, A. Kotovsky, L. 1995). First, is this an accumulation of relational structure knowledge or the change of the algorithm for analogical mapping? Second, is it maturational or the product of learning? Third, is it an all-or-none shift from object similarity to relational similarity? In (Gentner, Rattermann, M. J., Markman, A. Kotovsky, L. 1995), D. Gentner et al. argue that analogical development is primarily a matter of changes in knowledge, rather than changes in global competence or processing capacity. The second claim is that language learning — specifically, the acquisition of relational terms — is crucial in the development of relational comparison. The third claim is that the process of similarity comparison is instrumental in the development of analogy. These three claims further sustain the conjecture that the acquisition of relational language and the process of relational comparison provide mutual bootstrapping that drives representational change.

Another psychological phenomenon is that when people are required to respond fast, their judgments of similarity are apt to attribute matches while with ample time, relational matches would be preferable. This is so called *Time-Course Effects* in comparison (Lovett, Gentner, D., and Forbus, K 2006). One interpretation of this temporal pattern is that attribute matches enter into the comparison process before relational matches. However, a more favorable explanation is that attributes are encoded before relations. In this case, if the comparison process begins before the encoding is completed, early matches will involve attributes but not relations.

All these psychological arguments try to verify that systematic structure matching is an innate and essential mechanism for analogy.

## 3.3. Introduction to High-level Perception and Fluid Analogies Theory

As in the introduction of section 3, Douglas Hofstadter regards analogy as the basis of cognition rather than an individual cognitive process. In his theory of mind, the (visual) perceptual process can be thought of as the triggering of mental categories — often standard lexical items — by scenes. The sensory input nevertheless may have no direct relation with high-level mental process. He introduces the term *high-level perception* to account that abstract mental process is essentially similar to perception. The initial visual perception activates several mental categories (or concepts). These concepts further activate a host of other interrelated concepts and bring them up to “center stage”. This process iterates to characterize the abstract mental processes. A (visual) perception is a concept projection process while a high-level perception is the same.

Concepts or mental categories are descriptions of particular past situations. Analogy takes part in the triggering of prior mental categories by some kind of input — whether sensory or more abstract. Specifically, this concept triggering is a mapping process between the current situation and the past situation.

By this discussion, it is apparent that Hofstadter's theory is not a competing one of the structure mapping theory. High-level perception theory considers more about mental structure and concept organization without particular attention on mapping itself. SMT, on the contrary, focuses more on the criteria for a good simulation of human mapping. In this sense, high-level perception is a more complete mental theory.

Although analogy takes a central role in high-level perception theory, it is not the only elements. Other critical building blocks includes: mental activity consists of many tiny independent events and the models involve the nondeterministic interaction of these tiny events that take place in simulated parallel (this process is termed *parallel terraced scan*); the mental categories are also quintessentially fluid entities — they adapt to a set of incoming stimuli and try to align themselves with it. This fluidity of the human mind enables mind to establish connections between apparently dissimilar things, which is the "hidden wellsprings of creativity". By this notion, Hofstadter's theory is also termed as *Fluid Analogies Theory*.

There are two full-fledged models in microdomain built under the theory. Copycat is a perception-based, emergent architecture for Mental Fluidity. The emergent means the mental process is a statistical consequence of myriad small computational actions. Mental Fluidity or concept slippages will occur only under specific pressures. The author claims that the model is neither symbolic nor connectionist but situated somewhere in between these extremes. For one thing, the concept is represented by symbolic structure. For the other thing, random concept activation follows a mechanism similar to spread activation of connectionism on concept structure. Metacat's architecture extends Copycat by integrating self-consciousness ability, i.e., the ability of a system to perceive and respond to patterns that arise not only in its immediate perceptions of the world, but also in its own processing of those perceptions. This self-consciousness allows the system compare and contrast answers in an insightful way, and can often recognize when it has fallen into a repetitive cycle of behavior by monitoring its own processing.

Since Hofstadter's theory and the Copycat have more to do with concept organization and representation. They will be further examined in the context of similarity and concept later. Metacat's detail will be shown in Meta-control section for similarity reasoning.

## 3.4. Matching criteria: What counts?

By structural mapping theory, the criteria for sound matching are the degree to which the analogs share systematic relational structure. This view is consolidated in (Forbus, D. 1989) where the authors try to validate that while other criteria (such as factual correctness and relevance to current goals) are also important, they cannot replace structural evaluation.

The criteria of matching can be generalized as constraints involved in mapping. Matching is a process to satisfy multiple (possibly competing) constraints of mapping. However, Hofstadter's theory challenges this view by claiming that when humans make analogies, we not only construct mental mappings according to constraints, we also understand the meaning of the concepts connected by these mapping-structures (Marshall 2006). This is the symbol-grounding problem (Harnad 1990), recast in analogical guise. Some connectionist models of analogy have attempted to address this problem in a holistic fashion (most by spread activation) by moving away from the use of symbolic representations of source and target situations, such as distributed encoding techniques (Plate 1998).

# 4. Concept Theory and Similarity

Research on concept has two interrelated purposes: to categorize and represent knowledge and to find out the basic mechanism of "understanding". Though there is controversy about whether the meaning can be endowed by symbolic structures (this is the problem of symbol grounding), mental category has long been the center of this endeavor because it is obvious that one concept exist as distinguishing between mental categories, i.e., an object is more similar to those in the same concept category than those out of the category. Early concept theory stands around the notion of the "black-white" concept. However, many psychological experiments provide evidence against this view, instead, support the messy view (Lovett, Gentner, D., and Forbus, K 2006) or the fluid view (Hofstadter 2001) of concept organization. These notions perceive similarity between objects of the same or distinct concepts not as all-or-none but as graded and dynamic criteria.

## 4.1. Messy concepts

Messy concepts have three characteristics: they have gray areas of interpretation, they change, and they have exceptions. In the penumbra, there are often good reasons to call an instance "in" and equally good ones to call it "out." Psychology has long since abandoned the view that concepts are defined by universally valid, necessary and sufficient features, replacing it with new paradigms — the prototype view, i.e., categories have a graded structure, and knowledge views, i.e., capturing information such as commonsense knowledge about the purposes of the category. The change of representational framework which often occurs with learning, is supposed to take place along with other concept change as well as generalization, rules and prototypes changes.

## 4.2. Hofstadter's Fluid Analogies Theory

### 4.2.1. How are Concepts Represented and Organized?

In section 3.3, we give a brief review of Fluid Analogies Theory. In this theory, perception and "high-level perception" are the mental processes by recursive triggering of mental categories, which is also the analogy making.

Concepts are organized in terms of an inherited notion: chunking. Chunking has long history in memory study raised from research on chess. Chess master has more ability to combine pieces of information into meaningful patterns or chunks. Newell's unified theory of cognition (Newell 1990) organizes the memory for problem solving by chunking. In Fluid Analogies Theory, chunking is a means for concept organization — taking "small" concepts and putting them together into bigger and bigger ones, thus recursively building up a giant repertoire of concepts in the mind. By this structure, grades of labels of categories — simple words, compound words, short phrases and longer phrases — are in concert with chunking of meanings.

An individual concept has a mental lexicon with a vast storehouse of triggerable analogies, which accommodates effortlessly mapping between the phrase's meaning and the situation. On higher level, complex lexical items are still the name of a certain category of situations. Every concept has a core or a prototype. The concept blur, however, is due to the subtleties of mapping situations onto other situations—due, in other words, to the human facility of making analogies. The point is that a concept is a package of analogies both between concept and situation and between individual concepts.

A typical lexical item might be that of a molecule with two, three, or more nuclei that share an irregularly shaped electron cloud. Polysemy, i.e., the possession of multiple meanings and metaphor makes the concept regions nonspherical, complex and idiosyncratic. The simplest shaped concepts are those low frequent, sophisticated adult concepts whereas the most frequently encountered concepts, whose elaborate ramifications and tendrils constitute the highest degree of twistiness.

#### 4.2.2. Mental Processes— The Central Cognitive Loop

Each of the above expressions, then, can be thought of as the name of a particular type of situation. A situation may evoke two or more lexical items at once and fragments of the various evoked competitors wind up getting spliced together. Such a large-scale memory chunk can be thought of as being stored in long-term memory as a "node" — that is, something that can be retrieved as a relatively discrete and separable whole. It is thrown in the "bucket" of short-term memory, where it is available for scrutiny. Scrutiny consists in the act of "unpacking" the node to some degree, which means that inside it are found other nodes linked together by some fabric of relationships, and this process of unpacking can then be continued recursively, given that the contents of unpacked nodes themselves are placed in short-term memory as well, and hence are themselves subject to more detailed scrutiny, if so desired. The scrutiny is a high-level perception process, and thanks to analogy (by somewhat random activation), the high-level perceptual act can activate yet further nodes, which are then in turn accessed, transferred, unpacked, etc. This mental process is called *the central cognitive loop*.

The unpacking process is highly context-dependent (i.e., sensitive to what concepts have been recently activated), and hence will yield a somewhat different filling-up of short-term memory on each occasion that the same high-level node is pulled up out of the ocean of long-term memory. The deeply goal-driven nature of human thought under the randomness of the posited central loop can be seen as the perceptions are continually seeking to cast the world in terms of a set of high-level concepts that they tend to favor. If the current perception of a situation leads one into a state of cognitive dissonance, then one goes back and searches for a new way to perceive it.

Besides perception, this theory can also give a reasonable explanation of language and communication. The usual goal of communication is to set up "the same thought" in the receiver's brain as is currently taking place in the sender's brain. The process is beginning from the compression of the complex symbolic "dance" occurring in the sender's brain into a temporal chain of sounds or a string of visual signs, which are then absorbed by the receiver's brain. Two brains are, however, generally far more unalike than our society is predicated on mutual comprehensibility mediated by language. Thus, all communication is via analogy: there are mental "dances" in two distinct media.

#### 4.2.3. Copycat

Copycat is a realization of Fluid Analogies Theory in a micordomain (the letter-analogy problem domain) (Hofstadter, M. 1994). The architecture simulates mental processes by stochastically selected agents (a.k.a, *Codelets*) performing their own tasks (it's similar to Minsky's Soceity of Mind). There are three major components of the Copycat architecture:

- *Slipnet*: a semantic network of nodes in long-term memory.
- *Workspace:* the location of perceptual activity in short-term memory.
- *Coderack*: "stochastic waiting room", in which small agents who wish to carry out tasks in the Workspace wait to be called.

Codelets look for sameness, successor, or predecessor relationships among letters, possibly chunking them together into groups based on a common relationship. High-level behavior emerges in a *bottom-up* fashion from the collective actions of many codelets working in parallel. Every codelet has an urgency value that reflects the estimated promise of the pathway it is exploring. If a concept structure seems promising enough, it gets built by chains of codelets in Workspace, and acquires a strength value indicating how well it fits into its surrounding context. The structure in Workspace is built in light of the activation of concepts in Slipnet. This activation, which may spread to neighboring concepts, strongly affects the nondeterministic decisions made by codelets, resulting in *top-down* pressure that guides the program in its search for a good interpretation of a problem. Slipnet concepts also serve as the basic building blocks for other structures called rules, which describe how strings change. The overall degree of Workspace organization is measured by a number from 0 to 100 called *Temperature*. This number is a function of the total quality of structures present in the Workspace. Temperature also regulates the amount of randomness used by codelets in making decisions. In other words, temperature plays both a passive and an active role.

The randomness is enabled by *The Parallel Terraced Scan*, i.e., many potential directions being explored; the most attractive of these tend to be the actual directions chosen. This is by the assumption that conscious experience is essentially unitary, although it is an outcome of many parallel unconscious processes. Thus, the purpose of micro-exploration is to efficiently explore the vast, foggy world of possibilities lying ahead without getting bogged down in a combinatorial explosion. In this sense, randomness is equivalent to nonbiasedness. This randomness is also regulated by some mechanism like temperature, pressure, rules and mental bias to give the system a relatively deterministic overall trend. This is most similar to genetic algorithm to find the global optimization by randomly exploring many possibilities.

## 5. Learning and Similarity

In the early work on the role of memory in human story understanding (Schank 1982), R. Schank has recognized the interplay of understanding, learning and memory. In CBR, complementary with the principle of reasoning by remembering is the principle that reasoning is remembered . This means that reasoning and learning are intimately connected. Kolodner (Kolodner 1996) defines learning in CBR as keeping track of what worked and didn't work and why. Therefore, not only we need to retain the successful or failed new solution, but also store the explanation for the success or the failure.

By comparing CBR learning with inductive learning and explanation learning, we will find both pros and cons for all the learning approaches. CBR has no generalization but doesn't discard the example whereas *inductive learning* just keeps the generalized rules. Another view about this difference is that unlike the generalization in training time of inductive learning, CBR actually adopts a “lazy generalization” strategy, i.e., implicit generalization until testing or when it is needed to solve a new problem. This alleged “generalization” always has some purposes. On the contrary, the difficulty for the rule-induction algorithm is in anticipating the different directions in which it should attempt to generalize its training examples. CBR therefore tends to be a good approach for rich, complex domains in which there are myriad ways to generalize a case. However, this generalization suffers a theoretical problem: the generalization where data is too scarce for statistical relevance is inherently based on *anecdotal evidence*. In other words, the generalization direction is not statistically guaranteed. Substantially, this is a restatement of the insufficient assumption of CBR: prior cases can provide solution for future similar cases. Human selectively adopt this strategy for problem solving under the guidance of general knowledge which, in some sense, is the result of social statistics. *Explanation-based learning* can also allow single-case learning and generalization, but it is different from CBR in that EBL uses rules to explain example and then guide generalization. However, CBR’s adaptation can be more flexible than EBL by integrating knowledge guidance and other operations other than generalization, such as specialization and substitution.

The scope of learning studies in analogical reasoning community is more extensive. The efforts are made primarily in psychological study of how analogical mapping can impact human learning mechanism. Analogy takes its role in concept change, which can be seen as the subject convergence of structure mapping theory and fluid analogies theory. D. Gentner et al. (Gentner. D, Brem, S. et al) summarize four ways in which analogical reasoning facilitates change of knowledge/concepts:

(a) Highlighting, the process of alignment causes the matching aspects of the domains to become more salient, highlighting of common information can influence category formation.
(b) Projection of candidate inferences. These projected inferences, if accepted, add to the knowledge in the target domain.
(c) Rerepresentation, the representation of either or both domains is changed to improve the match. Typically, this involves a kind of tinkering in order that two initially mismatching predicates can be adjusted to match.
(d) Restructuring, Restructuring is the process of large-scale rearrangement of elements of the target domain to form a new coherent explanation.

Similarity-based accounts for categorization have been criticized on the grounds that they fail to capture the role of theory-based knowledge in category formation. However, in (Kuehne, Forbus, K., Gentner, D. and Quinn, B. 2000), the authors claims that similarity, when understood as the result of an alignment process, is capable of incorporating theory-based knowledge and higher order relations into the process of category learning. They also develop a similarity-based category learning model SEQL where categories are represented via structured descriptions and formed by a process of progressive abstraction, through successive comparison with incoming exemplars (Kuehne, Gentner, D. and Forbus, K. 2000). If the new exemplar and the category are sufficiently similar, the category description is modified to be their intersection -- i.e., the commonalities computed via structural alignment by SME by a generalization algorithm. If the new exemplar is not sufficiently similar, it is stored separately and may later be used as the seed of a new category. A recent research (Lovett, Lockwood, K., Dehghani, M., & Forbus, K 2007) reconsider categories learning from fewer than ten examples.

# 6. Hybrid Approaches

As mentioned before, CBR and analogical reasoning is only a part of human cognitive processes. To build a more robust and flexible system, it is desirable to combine several approaches together. When it comes to construct cognitive architecture, more comprehensive reasoning and knowledge representation methods will be unified. There are also many integration stands with regards to the problem at hand.

When we discussed CBR systems at section 2, we mentioned the "knowledge containers" for task-decomposable problem (Richter 1998), i.e., each phase of CBR can be seen as a container of varieties of knowledge such as the case-base, case adaptation knowledge and similarity criteria. In this notion, the knowledge containers may need to be updated over time in order to maintain or improve performance in response to changes in the system's knowledge, task, environment, or user base. This needs us develop background maintenance system for the practicing system (David B. Leake, Qiang Yang, and David C. Wilson 2001). Knowledge containers can be extended to not just for task decomposition but for the system separated into individual parts. For example, for messy concept representation (Rissland 2006), we can use rules, prototypes, or models for the core and cases or examples for the penumbra.

The integration of reasoning methods is as popular a research spotlight as knowledge integration. These reasoning methods include rule-based deductive reasoning, case-based reasoning, analogical reasoning, abduction, and hypothetical reasoning. There are two styles of reasoning integration. One is that different reasoning methods take equivalent roles in different parts of the system. The other is one reasoning act as a support or a regulation for primary reasoning. Examples of the former one include:

1. For explanation and concept categorization

   Since there is the persistent need for explanations of categorization and similarity mapping rather than just give the outcome of classification and mapping, Rissland (Rissland 2006) proposes applying statistical methods to propose concepts and classifications, and symbolic methods to provide precedent-based explanations and hypothesis to test them out.

   Moreover, the explanation itself can either be knowledge-based or similarity-based. Falkenhainer (Falkenhainer 1990) provides a unified approach to explanation and theory formation by integrating deduction, abduction, and analogy. A similarity-driven explanation can facilitate knowledge-based explanation by (1) proposing explanations of phenomena by their similarity to understood phenomena (2) smoother adaptability to unanticipated or underspecified events (3) enabling transfer of knowledge from one domain to another (4) extend or revise imperfect theories when they fail to produce an explanation.

2. CBR can be incorporated as one component of a multi-strategy reasoning system

The second case has more examples:
In CBR systems, there are many possible combinations between case-based reasoning and rule-based reasoning: case guided rule interpretation; rule-guided CBR; rule or case-based metareasoing about CBR performance, etc.

Under the structure mapping theory, K. Forbus et al. (Forbus, Mostek, T. and Ferguson, R 2002) integrate analogical processing and first-principles reasoning (i.e., rules or axioms plus logical inference). The key idea is to use an analogy ontology that provides a formal, declarative representation of the contents and results of analogical reasoning. By the ontology, analogical operations can be formulated in the same way as standard logical inference. Analogical processing systems in turn can call on the services of first-principles reasoners for creating cases and validating their conjectures. This is an exemplar of facilitating analogical reasoning by first-principles reasoning. K. Forbus et al. (Forbus, Gentner, D., Everett, J. and Wu, M. 1997) also put forward an information-level model and logic directed evaluation model of analogical inference.

CBR can even be integrated with analogical reasoning. In (Mostek, Forbus, K, and Meverden, C. 2000), CBR dynamically extract cases for analogical reasoning from general-purpose knowledge bases, and dynamically expand them during the course of analogical reasoning. This is case-based reasoning directed analogical reasoning.

Finally, previous section introduced a meta-control version of the implementation of fluid analogies theory: Metacat, a system amplifying Copycat by monitoring and explicitly articulating, patterns in their own thinking (Marshall 2006). Specifically, these functional extensions include:

- Explicit temporal record of the most important processing events that occur during a run, which is continually examined by codelets for patterns, in much the same way that codelets examine letter-strings for patterns.
- Constructing an abstract description of an answer in terms of the key concepts and events that led to its discovery.
- By monitoring its own processing, Metacat can recognize when it has become stuck in a rut

To realize these benefits, three new components are inserted: the Episodic Memory, the Themespace, and the Temporal Trace. *The Episodic Memory* contains descriptions of analogies in its long-term Episodic Memory. This description includes the four letter-strings of the analogy, as well as the rules, bridges, slippages, and other structures that give rise to the answer. *Themes* and the *Themespace* are short-term memory structures that describe the characteristics of mappings. Themes are composed of Slipnet concepts, created in Themespace in response to structure-building activity in the Workspace. The *Temporal Trace* is the locus for self-watching in short-term memory. It stores an explicit temporal record of the most important processing events that occur during problem solving, and allows Metacat to monitor the processing activity in the Workspace at a very abstract and highly chunked level of description.

Pattern-Clamping is key to Metacat's self-Control. Various patterns comprised of sets of themes, concepts, or codelet urgencies, can be clamped by the program in response to events in the Temporal Trace. Clamping a pattern alters the probabilities that certain types of codelets will run, or that certain types of Workspace structures will be built. In general, the purpose of clamping a pattern is to catalyze a series of events that reorganize the perceptual configuration of the Workspace in some way.

# 7. Comparisons between Similarity-based Systems

In this section, comparisons between previous discussed systems are presented for a holistic notion on similarity-based systems. The comparison starts from systems in SME family since it is the most extensive referred model. Other potential comparisons are given later.

## 7.1. SME and Other Models

The basic principle of SME is systematicity, so the first attempt is to compare with those systems which also adopt special cases of the systematicity principle. Carbonell's system (Carbonell, J .G. 1983) focuses on plans and goals as the high-order relations that give constraint to a system, and Holyoak's analogy theory (Holyoak 1984) makes a match based on the goal of a problem solver. In (Falkenhainer, Forbus, K.D., & Gentner, D. 1989), the authors claim that the limitations of goal-based system are that it has no notion of soundness, so the search space explodes. SME subsumes these by a domain independent mapping rules. Later research, however, shows that this domain independent assumption will also make the computation intractable (Forbus, D. 1990). SME takes no heuristic search. This is different from Winston's original matcher (Winston 1980) which does a heuristic search for a single best match. Winston's *later importance-dominated matching* (Winston 1982), however, instead of assembling global solutions from local matches as SME does, it constructs correspondences of local hypothesis by heuristic search, guided in part by functions which determine the similarity of parts. It is apparent that SME give more emphasis on global similarity.

Holyoak and Thagard's *ACME* (Analogical Constraint Mapping Engine) model (Holyoak, P. 1989) is a realization of their theory (Holyoak 1984) mentioned in the last paragraph. ACME endows the model with goals by embedding queries into the target description. Pragmatic theory (Forbus, D. 1990), a goal-version of SME, does not require the actual form of the candidate inference to be specified in advance. So the idea is filtering local matches in terms of goals for global matches.

Similarity-based reminding models ARCS (Thagard, G., & Gochfield. D. 1990) and MAC/FAC (Forbus, Gentner, D. & Law, K. 1994) are compared in (Law, K. and Gentner, D. 1994). Both models attempt to predict the fact that similarity-based retrieval is strongly influenced by surface similarity and weakly sensitive to structural consistency. In ARCS, an augmented subset of *WordNet* was used to make semantic similarity decisions. Two predicates in ARCS are considered semantically similar if their corresponding lexical concepts in WordNet are connected via links that denote particular relationships (basically, this is a connectionist approach). As claimed in (Law, K. and Gentner, D. 1994), they believe their experiments provide evidence that structure-mapping's identicality in MAC/FAC contains better models retrieval than Thagard et al's notion of semantic similarity.

Finally, there are agreements and discrepancies between Copycat and SME (Hofstadter, M. 1994)[1]. The main idea of systematicity is regulated by all sorts of pressure which can be seen as a kind of rules in Copycat. As for differences, the authors of Copycat list five major ones: other pressures in an analogy: (a) both superficial and abstract similarities that may not be parts of systematic wholes, but are still strong contenders in a competition; (b) any complex situation: many possible sets of relations that exhibit systematicity, and it is not explained how certain ones are considered for mapping and not others, on syntactic grounds alone. By contrast, in Copycat, the mechanisms for deciding which things to concentrate on and which mappings to make involve semantics; (c) SME not includes any notion of conceptual similarity or of slippage notions; (d) relies on a precise and unambiguous representation of situations in the language of predicate logic; (e) In Copycat, there is a clear distinction between answers that are immediately appealing (high-frequency answers) and answers that are insightful but hard to uncover (low-frequency but also low-temperature answers. In a brute-force system like SME, by contrast, the distinction between answers of superficial and obvious appeal and answers of deeper but more hidden appeal does not exist.
In summary, (a) and (e) concerns the equal significance of superficial similarity and relational similarity, (b), (c), (d) concerns that SME has no semantics in the syntactic structure. The first problem was identified by SME group and improvement had been made. The second is nevertheless hard to solve because they rely on a different view on semantics: SME's view of semantics might be a systematic symbolic structure whereas Copycat is on the fluid analogies theory.

### 7.2. Other Comparisons

Copycat and ACEM are similar in many ways: analogies emerge out of a competition among pressures (or "soft constraints"), involving a large number of local decisions that give rise to a larger coherent structuring. The systematicity in analogy-making should emerge from other pressures. However, ACME inherits more from SME. Like SME, ACME tries all syntactically plausible pairings; in ACME the pragmatic unit is set up by a human and then frozen for each new problem. Thus, like SME, ACME does not deal with another Copycat's main focus: how to automatically adapt to different situations. Since ACME's knowledge is set up ahead of time, the program's success, like that of SME, is totally dependent on the representations it is given.

Finally, systems such Copycat and Metacat on the fluid analogies theory have important differences from analogical reasoning system in that it is not the mechanism to simulate the analogical reasoning per se. Rather, it is context-sensitive concepts allowing analogies. It is an analogical perception rather than analogical reasoning.

## 8. Similarity and Tool Use: Conclusion and a Discussion

During the course of this survey, we discussed many theories, models, systems and issues related to similarity. Three distinct but interrelated theories stand out as the fundaments: case-based reasoning, structural mapping theory and fluid analogies theory. Although each theory embraces a

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s[1] We mentioned before that fluid analogies theory and structural mapping theory deal with distinct parts of analogy, so there is no direct conflict between two theories. But when it comes to realization, there may be some overlapping between two systems where the discrepancies come from.

large scope of topics, there are central issues in their cores. CBR considers how past experience can be used to solve new problems. Structural mapping theory gives the meaning of similarity (systematicity). Fluid analogies theory investigates the whole cognition from a new perspective.

How do the similarity insights of these theories get the relation with physical tool use problem? Before answering this question, we'd better answering what is physical tool use problem. Tool use (more precisely, using tools to build tools) and language are routinely cited as the paradigmatic behaviors involved in human-level cognition. However, language has received much more attention than tool use (Preston 1998). The reason behind this discrimination, I think, lies in that unlike language which is an independent cognitive faculty, tool use is mere the result of more general human ability—reasoning. Agent research always has two parts: representation and reasoning mechanism. Since physical tool use narrows the problem to the physical domain, it can only restrict the representation issue. But there is no notable line between tool use and other reasoning ability. In essence, physical tool use is in a larger picture of the study on how does an agent perform in a physical domain for some goals with or without the aid of tools.

In order to autonomously act in a physical domain, an agent should follow some cognitive processes. Situation assessment is the starting points. Then he should have a plan for solving problems stipulated by his goal. The plan may change during the action due to environmental feedback. Moreover, he may not even pursue his immediate goal when his behavior is just opportunistic to the environment.

## 8.1. Similarity Methods for Problem Solving

Similarity-based reasoning possibly comes into play for this problem solving scenario. Problem solving can be classified into two types: routine problems and creative problems. Routine problems refer to those that we encounter every day and involve a great deal of commonsense knowledge. Creative problems require a great many of efforts of thinking and often produce "clever" solutions. For routine problems, CBR may be useful because it provides a sample solution for the problems. This sample can provide an approximate direction for reasoning without being plagued by common sense for massive conclusions irrelevant to the problem at hand or relevant but just trivial facts. Also, CBR saves the extra time used for "searching from start" for those problems similar to the stored one.[2] Creative problems, on the other hand, need large scale switches between domains, thus analogy will be a favorable solution. It gives us what the so-called "insight" for a creative problem by mapping between two otherwise distinct problems.

## 8.2. Two Foundational Problems

To equip problem solving with similarity, two fundamental questions concerning the basis of similarity-based methods remain: what are the criteria to evaluate similarity and how to retrieve those which meet the similarity criteria. Systematicity proposed by structural mapping theory is an important criterion. Similarities of both problem description and solutions also follow the systematicity criteria. A problem is a goal description plus a group of constraints. So these

[2] In this sense, however, CBR has no difference from "problem solving by search" or traditional planning more than recording of past solutions (or may be put into system as a prior). It gives no new insight for knowledge representation, which still follows the tradition, say, predicate calculus.

constraints form a structure. The solution, e.g., a plan, also has structure implied in the description. Problem description structure is a criterion for retrieval whereas solution structure is the one for evaluation. However, many mappings are not too systematic, sometimes just naive or superficial. It is not always “more systematic is better” specified by SME. The choice of criteria is determined by a specific situation. The second question is about the retrieval strategy. There are three choices: first, examine all possible pairs, or parts of pairs directed by heuristics (search strategy); second, an analogical relation is a hard-coded connection, so just follow the connection; third, emergent pair matching, the quality of the matching is guaranteed by the random selecting pattern in terms of matching criteria (the strategy adopted by Copycat in fluid analogies theory). It is obvious that the second one is very inflexible but it exists prevalently as a cultural convention, such as the metaphor in our idiom. The contrast between search strategy and emergent strategy is similar to the contrast between genetic algorithm and local optimization. The first strategy has a tradeoff between the best matching and the computational complexity. The third strategy, on the other hand, can give better global matching in reasonable time.

## 8.3. Knowledge Representation

The knowledge representation issue for the physical tool use problem is how to represent physical domain. Physical domain is closely related to perception and motor control. The problem of how to project visual signals to concepts and concepts to motor control signals (this is also part of the symbol grounding problem) can be (partial) separated from knowledge representation for high-level reasoning.

K. Forbus in Qualitative Reasoning Group at Northwestern University also pursues research for knowledge representation for physical domain. He and his colleague propose *Qualitative Process Theory*-a representational model of *domain theory* (Forbus 1984). QP theory organizes domain theories around the notion of physical processes which affect objects by causing quantities associated with them to change, and communicate with each other through shared parameters. Physical processes are explicitly defined in terms of the individuals that give rise to them, the conditions under which they are true, and their direct consequences. They also develop *Qualitative Spatial Reasoning* model of spatial reasoning by diagrams representation with concrete detail (Forbus, Nielsen, P. and Faltings, B. 1991). This model is built on the *Poverty Conjecture*, i.e., there is no problem-independent, purely qualitative representation of space or shape. Consequently, the spatial representations consist of two parts (the *MD/PV* model): a metric diagram, which includes quantitative information and thus provides a substrate which can support mental image processing, and a place vocabulary, which makes explicit qualitative distinctions in shape and space relevant to the current task.

Apart from the representation model, they also combine analogy with this representation for physical domain. In (Forbus, D. 1986), they develop a computational model of human learning of physical domains. Qualitative Process theory is used to model portions of people's physical knowledge, and Structural Mapping theory is used to characterize the computations that move a learner from one representation to another. B. Falkenhainer’s PhD thesis studies physical analogies in his contextual structural mapping model. R. Ferguson, et al’s paper (Ferguson, K. 1995) focuses on a special physical problem: comprehend physics explanatory diagrams-juxtaposition diagrams, i.e., comparing two similar situations that vary in a carefully chosen way.

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