Principal Differences in Structure-Mapping

The Contribution of Non-Classical Models

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Abstract: *Recent research in metaphor and analogy, as variously embodied in such systems as Sapper, LISA, Copycat and TableTop, speak to the importance of three principles of cross-domain mapping that have received limited attention in, what might be termed, the classical analogy literature. These principles are that: (i) high-level analogies arise out of nascent, lower-level analogies automatically recognized by memory processes; (ii) analogy is memory-situated inasmuch as it occurs* in situ *within the vast interconnected tapestry of long-term semantic memory, and may potentially draw upon any knowledge fragment; and (iii), this memory-situatedness frequently makes analogy necessarily dependent on some form of attributive grounding to secure its analogical interpretations. In this paper we discuss various arguments, pro and con, for the computational and cognitive reality of these principles.*

1. Introduction

Over the last few years, we have been examining the computational capabilities of models of analogy (see Veale & Keane, 1993, 1994, 1997; Veale *et al.*, 1996). Some models of analogy, like the original version of the Structure-Mapping Engine (SME; Falkenhainer, Forbus & Gentner, 1989), have been concerned with producing optimal solutions to the computational problems of structure mapping, although more recently, many models have adopted a more heuristic approach to improve performance at the expense of optimality; models like the Incremental Analogy Machine (IAM; Keane & Brayshaw, 1988; Keane *et al.*, 1994), the Analogical Constraint Mapping Engine (ACME; Holyoak & Thagard, 1989), Greedy-SME (see Forbus & Oblinger, 1990) and Incremental-SME (see Forbus, Ferguson & Gentner, 1994). These *classical structure-mapping models* have also been predominantly concerned with modelling the details of a corpus of psychological studies on analogy.

In contrast, there is a different *non-classical* tradition that has concentrated on capturing key properties of analogising, with less reference to the mainstream psychological literature (e.g., the Copycat system of Hoftstadter *et al.* 1995; the TableTop system of Hofstadter & French, 1995; and the AMBR system of Kokinov, 1994). Recently, there has been something of a confluence of these two traditions as models have emerged that exhibit many of the parallel processing properties of non-classical approach with the computational and empirical constraints of classical models; models like Sapper (see Veale & Keane, 1993, 1994, 1997; Veale *et al.*, 1996) and LISA (see Hummel and Holyoak, 1997). While these models are clearly different to classical models, it is not immediately obvious whether they are just algorithmic variations on the same computational-level theme, or whether they constitute a significant departure regarding the *principles of analogy*. In this paper, using Sapper as a focus, we argue that there are at least three principles on which Sapper differs from wholly classical models. We also argue from a computational perspective that Sapper offers several performance efficiencies over optimal and sub-optimal classical models.

2. Principal Differences

Sapper accepts most of the computational-level assertions made about structure mapping, such as the importance of isomorphism, structural consistency and systematicity (see Keane *et al.*, 1994, for a computational-level account). A ongoing discussion with several researchers in the field has helped to define its differences in-principle from classical models (c.f. Ferguson, Forbus & Gentner, 1997; Thagard, 1997). In summary, they are that:

- *Analogies are forever nascent in human memory*: that human memory is continually preparing for future analogies by establishing potential mappings between domains of knowledge
- *Mapping is memory-situated*: that mapping occurs within a richly elaborated, tangle of conceptual knowledge in long-term memory
- *Attributes are important to mapping*: that attribute/category information plays a crucial role in securing both the relevance *and* tractability of an analogical mapping.

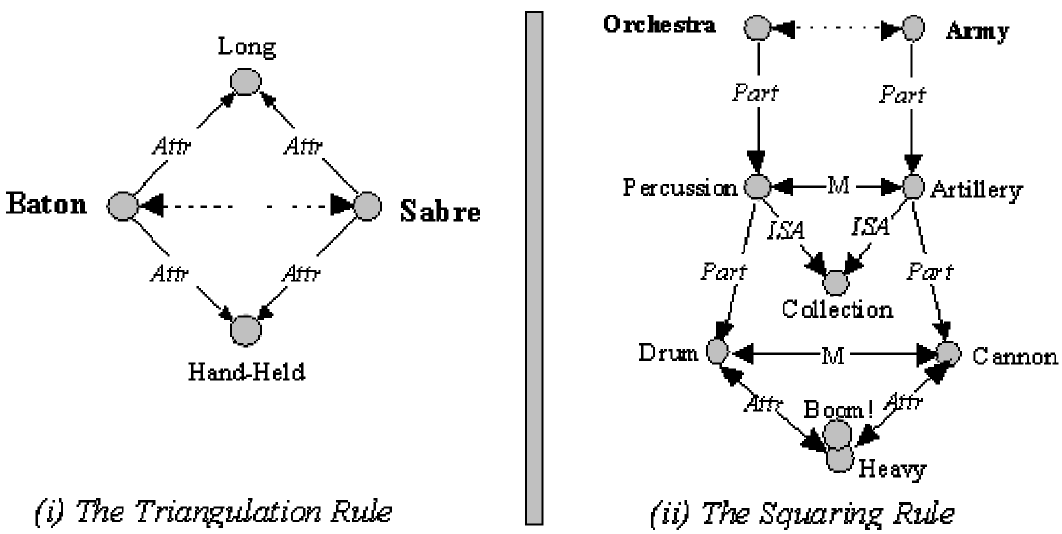

Figure 1: The Triangulation Rule (i) and the Squaring Rule (ii) augment semantic memory with additional bridges (denoted M)*, indicating potential future mappings.*

At present, the psychological literature is silent on many of these points. In this paper, we address these issues by outlining each of the principles in more detail and evaluating the computational and psychological evidence of relevance to them.

2.1. Nascent Analogies

The picture Sapper creates of the analogy process is quite different from the goal-driven, *just-in-time* construction of analogies associated with the classical models. In the classical tradition, all analogising occurs when current processing demands it, a proposal that is most obvious in the centrality given to pragmatic constraints (see

Holyoak & Thagard, 1989; Keane 1985; Forbus & Oblinger, 1990). In these models, mappings are constructed when the system goes into "analogy mode" and are not prepared in advance of an analogy-making session. In contrast, Sapper models analogy-making as a constant background activity where potential mappings are continually and pro-actively prepared in memory, to be exploited when particular processing goals demand them to be used. Analogies are thus forever nascent in Sapper's long-term memory.

Sapper forms analogies using spreading-activation within a semantic network model of long-term memory, by exploiting *conceptual bridges* that have been established between concepts in this network. These bridges record potential mappings between concepts and are automatically added by Sapper to its semantic network when the structural neighbourhoods of two concepts share some local regularity of structure. Such bridges are highly tentative when initially formed, and thus remain dormant inasmuch as they are not used by "normal" spreading activation in the network. But dormant bridges can be awakened, and subsequently used for spreading activation, when some proposed analogical correspondence between the concepts is made by the cognitive agent.

The regularities of structure which Sapper exploits to recognize new *bridge-sites* in long-term memory are captured in two rules that are graphically illustrated in Figure 1: the triangulation and squaring rules. The *triangulation rule* asserts that:

> *If memory already contains two linkages L_{ij} and L_{kj} of semantic type L forming two sides of a triangle between the concept nodes C_i, C_j and C_k, then complete the triangle and augment memory with a new bridge linkage B_{ik}.*

For example, in Figure 1(i), when concepts *baton* and *sabre* have the shared predicates long and HANDHELD the triangulation rule will add a bridge between them, which may subsequently be exploited by an analogy. In predicate calculus notation, this could be interpreted as asserting that when two concepts partake in two or more instances of predications which are otherwise identical, they become candidates for an analogical mapping, e.g., that *long(baton) & handheld(baton)* and *long(sabre) & handheld(sabre)* suggest that *baton* and *sabre* are candidates for an entity mapping in a later analogy. Memory is thus seen by Sapper as pro-actively exploiting perceptual similarities to pave the way for future structural analogies and metaphors; much like Hofstadter & French (1995) then, Sapper views analogy and metaphor as outcrops of low-level perception.

The structural integrity of these analogical outcrops is enforced by the *squaring rule*, which works at a higher level over collections of bridges between concepts:

> *If B_{ik} is a conceptual bridge, and if there already exists the linkages L_{mi} and L_{nk} of the predicate type L, forming three sides of a square between the concept nodes C_i, C_k, C_m and C_n, then complete the square and augment long-term memory with a new bridge linkage B_{mn}.*

For example, in Figure 1(ii) the bridges established using triangulation between *percussion* -> *artillery* and *drum* -> *cannon*, support the formation of an additional bridge between *orchestra* and *army* using the squaring rule. The intuition here is that correspondences based on low-level semantic features can support yet higher-level correspondences (see Hofstadter *et al.* 1995; Hummel & Holyoak, 1997).

The proposal that analogies are forever nascent in human memory may seem computationally implausible because it suggests a proliferation of conceptual bridges that would quickly overwhelm our memories with irrelevant conceptual structure. In practice, this does not seem to be the case. In performance experiments, we have shown that as a knowledge-base grows so too does the number of bridges, but in a polynomially modest fashion (see Veale *et al.* 1996). Indeed, the notion of a conceptual bridge is a compelling one that seems to have emerged independently from multiple researchers in the field (e.g., Veale & Keane, 1993; Eskridge, 1994; Hofstadter *et al.* 1995). From a psychological perspective, some have argued that forming potential mappings in advance of an analogy is implausible (e.g., see Ferguson *et al.,* 1997). While we know of no evidence that directly supports or denies the bridging stance, it does gel with certain broad phenomena. The inherent flexibility and speed of people's analogical mapping, even within relatively large domains, suggests that some pre-compiled correspondences are used, otherwise the mapping problem approaches intractability; this is especially so when slippage and re-representation in these domains is also implicated. Similarly, Hofstadter and his team's characterisation of people's alacrity in performing conceptual slippage between different entities is more consistent with this account than classical models would be.

2.2. Mapping is Memory-Situated

Sapper sees the mapping process as being essentially *memory-situated*, that is, that the generation of mapping-rich interpretations can only be carried out within a long-term memory of richly interconnected concepts. In character, this is quite different to classical models which see analogues as delineated bundles of knowledge, segregated parcels of predications that are retrieved from memory and mapped in "another place" (usually a temporary working memory). In some cases, this knowledge-bundling seems more plausible than in others. For instance, it makes some sense in the encoding of episodic event sequences (typically, used in bench-marking analogy models), although even in these cases many of the properties of object-centred concepts (i.e., those typically expressed at a linguistic level via nouns rather than verbs) seem to be unnaturally suppressed. This bundling makes less sense in other cases, as in the profession domains used in Sapper where objects (such as General, Surgeon, Scalpel, Army, etc.) are the focal points of the representation, and relations are hung between them. In turn, this has led to the objection that Sapper's test domains inappropriately include "the whole of semantic memory" in the domain representation (c.f. Thagard, 1997). We would argue that this is entirely the point; natural analogy is performed within large, elaborated domains involving many predicates with few clear boundaries on relevance. Since clever analogies and metaphors surprise and delight us by the unexpected ways in which they relate the dissimilar, the mapping device is frequently itself the relevance mechanism. Let's consider then how Sapper forms analogies in a memory-situated fashion.

Sapper performs analogical mapping by spreading activation through its semantic memory, pin-pointing cross-domain bridges that might potentially contribute to a final interpretation (see Appendix A for the algorithm). The algorithm first performs a bi-directional breadth-first search from the root nodes of the source (S) and target (T) domains in memory, to seek out all relevant bridges that might potentially connect both domains and thus finds an intermediate set of candidate matches (or *pmaps*, in SME parlance). To avoid a combinatorial explosion, this search is limited to a fixed horizon `H` of relational links (usually `H = 6`) while employing the same predicate identicality constraint as SME for determining structural isomorphism. Then, the richest pmap (i.e., the pmap containing the largest number of cross-domain mappings) is chosen as a seed to anchor the overall interpretation, while other pmaps are folded into this seed if they are consistent with the evolving interpretation, in descending order of the richness of those pmaps (in a manner that corresponds closely to Greedy-SME). The use of *memory-situatedness* in combination with the other features of Sapper delivers effective performance on mapping these analogies.

Tests of Sapper relative to other models have been performed on a corpus of 105 metaphors between profession domains (e.g., *"A Surgeon is a Butcher"*), where these domains contain an average of 120 predications each (on average, 70 of these are attributional, coding taxonomic position and descriptive properties). Sapper's long-term memory for these profession domains is coded via a semantic network of 300+ nodes with just over 1,600 inter-concept relations. Table I shows that Sapper performs better than other classical models in these domains (SME and ACME return no results for many examples in an extended time-frame, though Greedy-SME fares much better), three caveats should be stated to qualify these results. Firstly, although the average pmap measurement for Optimal-SME is clearly quite poor (inasmuch as it over-complicates the interpretation process immensely), it does underestimate its adequacy on some individual metaphors; as Ferguson (1997) has noted, Optimal-SME can map some metaphors with smaller pmap sets, e.g., *Hacker as Sculptor* from 49 pmaps in 1,077 seconds, *Accountant as Sculptor* from 43 pmaps in 251 seconds, and *Butcher as Sculptor* from 47 pmaps in 443 seconds. Second, other models can do better if they use tailored re-representations of Sapper's domains (in which, for example, attributions are ignored), but this raises problems as to the theoretical import of such re-representations. Third, these results establish whether the tested models can find some interpretation for a given metaphor but they say nothing about quality of the analogy returned.

Aspect	***Optimal-SME***	***Greedy-SME***	***ACME***	***Sapper (Vanilla)***	***Sapper (Optimal)***
Avg. # of mid-level pmaps	269 per metaphor	269 per metaphor	12,657 per metaphor	18 per metaphor	18 per metaphor
Avg. run-time per metaphor	N/A – worst case $O(2^{269})$ seconds	17 seconds	N/A in time-frame	12.5 seconds	720 seconds

Table I*: Comparative evaluation of SME, ACME and Sapper*

For each test metaphor, there is an optimal set of cross-domain matches, so to assess the quality of a given interpretation, one needs to note how many of the produced matches actually intersect with this optimal set (as generated by the exhaustive variant of Sapper profiled in Table I), taking into account the number of "ghost mappings" (i.e., matches included in the interpretation that should not have been generated).

Table II shows some quality results for the more efficient structure mappers, Vanilla Sapper and Greedy-SME (Greedy-SIM is our simulation of Greedy-SME earlier reported in Veale & Keane, 1997, and Greedy-SME is based on an analysis of the outputs provided to us by the SME Group). Three measures of quality are used (borrowing some terms from the field of information retrieval, e.g., Van Rijsbergen, 1979). *Recall* is the total number of optimal mappings generated measured as a percentage of the total number of optimal mappings available. *Precision* is the number of optimal mappings generated measured as a percentage of the total number of optimal mappings generated by the model. Recall indicates the productivity (or under-productivity) of a model, while precision indicates over-productivity (or the propensity to generate "ghost mappings"). Finally, we measured the percentage of times a perfect, optimal interpretation was produced by the model.

Aspect	***Sapper***	***Greedy-SIM***	***Greedy-SME***
Merge complexity	$O(\|\Pi\|\log_2(\|\Pi\|) + \|\Pi\|)$	$O(\|\Pi\|\log_2(\|\Pi\|) + \|\Pi\|)$	$O(\|\Pi\|\log_2(\|\Pi\|) + \|\Pi\|)$
Precision	0.95	0.56	0.60
Recall	0.95	0.72	0.72
% times optimal	77%	0%	0%

Table II: Precision and Recall for Sapper, Greedy-SIM (our simulation) and Greedy-SME

The results shown in Tables I and II lead one to conclude that while Sapper and Greedy-SME take roughly the same time to process metaphors, the quality of the latter lags behind the former. Our analyses suggest that the specific features underlying the proposed principles contribute to Sapper's better performance, namely: its pre-preparation of potential mappings in memory, the use of a richly elaborated semantic memory and its exploitation of low-level similarity (the final issue to which we now turn).

2.3. Attributes Are Important

The third main difference in principle that emerges from Sapper is its emphasis on attribute knowledge (also a cornerstone of the FARG models of Hofstadter *et al.*, 1995). For Sapper, attribute knowledge is always *necessary* to ground the mapping process, whereas in non-classical models it tends to be merely *sufficient*.

A central tenet of structure mapping theory (see Gentner, 1983) is that analogy rests on relational rather than attribute mappings, although the, sometimes misleading, influence of attribute mappings have been well-recognised (Gentner, Ratterman & Forbus, 1993; Gentner & Toupin, 1986; Keane, 1985; Markman & Gentner, 1993). Originally, in Optimal-SME, analogies were found using analogy match-rules which explicitly ignored attribute correspondences (unless they the arguments to relational matches; see Falkenhainer et al., 1989) and literally-similar comparisons were handled by literal-similarity rules that matched both relations and attributes. More recently, SME uses literal-similarity rules for both analogies and literally-similar comparisons (see e.g., Markman & Gentner, 1993; Forbus, Gentner & Law, 1995). So, if a comparison yields mainly systematic relational matches then it is an analogy, whereas if it yields more attribute than relational matches then it is literally similar. However, even though literal-similarity rules are used, attribute information is typically only sufficient in the formation of analogies, rather than necessary. If attribute matches are absent then SME will find a systematic relational interpretation for the two domains, and if they are present then it will find the same systematic relational interpretation *along* with any consistent attribute matches .

In contrast, Sapper proposes a strong causal role for the grounding of high-level correspondences in initial attribute correspondences. This model will simply not find any matches unless they are, in some way, grounded in attribute knowledge. The triangulation rule establishes a candidate set of mappings using category information that anchors the later construction of the analogy, so that correspondences established by the squaring rule are built on the bridges found by the triangulation rule. Thus, Sapper assumes that categories exist to enable people to infer shared causal properties among objects.

There are several psychological and computational observations that support this emphasis on the importance of attributes. First, as we already know, human memory has a tendency to retrieve analogues with have attribute overlap (see e.g., Keane, 1987; Gentner, Ratterman & Forbus, 1993; Holyoak & Koh, 1987), which must mean that many everyday analolgies rely heavily on attribute overlaps (unlike the *attribute-lite* analogies used to illustrate most analogies, like the atom/solar system and heat-flow/water-flow examples).

Second, category information constrains the computational exercise of finding a structure mapping. When reasoning about two analogical situations, people will intuitively seek to map elements within categories; for instance, when mapping Irangate to Watergate, presidents will map to presidents, patsies to patsies, reporters to reporters, and so on. With these initial, tentative mappings in mind, the structure-mapping exercise that follows may be greatly curtailed in its combinatorial scope (for supporting psychological evidence see Goldstone & Medin, 1994; Ratcliff & McKoon, 1989).

Third, the triangulation of attributive information allows Sapper to model an important aspect of metaphor interpretation that has largely been ignored in most classical structure-mapping models, namely *domain incongruence* (Ortony, 1979; Tourangeau & Sternberg, 1981). The same attribute can possess different meanings in different domains and this plurality of meaning serves to ground a metaphor between these domains. For instance, when one claims that a "tie is too loud", the attribute LOUD is being used in an acoustic and a visual sense; a GARISH tie is one whose colours invoke a visual counterpart of the physical unease associated with loud, clamorous noises. But for LOUD to be seen as a metaphor for GARISH such attributes must possess an internal semantic structure to facilitate the mapping between both. That is, attributes may possess attributes on their own (e.g., both LOUD and GARISH may be associated with SENSORY, INTENSE and UNCOMFORTABLE). The division between structure and attribution is not as clean a break then as classical models predict; rather structure blends into attribution and both should be handled homogenously. This homogeniety is perhaps one of the strongest features of non-classical models.

This asserted centrality of attribute information in the mapping process may seem to be contradicted by evidence of aptness ratings on analogy, which show that apt analogies have few attribute overlaps (see Gentner and Clement, 1988; also soundness, see Gentner, Ratterman & Forbus, 1993) . However, there is a possibility that these ratings may just reflect a folk theory of analogy. More plausibly, since we argue that the role of attributes is to ground high-level structure in low-level preception, the effect of this grounding may not be apparent to subjects, particularly when this grounding occurs at a significant recursive remove (e.g., H = 5). Ultimately then, these aptness ratings may tell us nothing about what actually facilitates the process of structural mapping.

3. Conclusions

In this paper, we have tried to show that a very different computational treatment of structure mapping in a localist semantic-memory diverges from so-called classical models of analogy in three important respects. Models like Sapper promote the idea that memory is continuously laying the groundwork for analogy formation, that analogical mapping should be memory-situated, and that attribute correspondences play a key role in the mapping process. Computationally, it is clear that at least one instantiation of these ideas does a very good job at dealing with the computational intractability of structure mapping, albeit in a sub-optimal fashion. Our experiments, both on our own profession domain metaphors (in which Sapper out-performs other models) and the benchmark analogies of other models (such as *Karla as Zerdia* and *Socrates as Midwife*, where Sapper does at least as well as SME and ACME), suggest that of all the attempts at sub-optimal mappings it seems to offer the best all-round performance. Psychologically, much needs to be established to determine if these ideas are indeed the case. It clearly presents an interesting a fruitful direction for future research.

To conclude, should readers wish to examine the experimental data used in this research, it can be obtained (in Sapper, SME and ACME formats) from the first author's web-site: *http://www.compapp.dcu.ie/~tonyv/metaphor.html*. A Prolog implementation of the Sapper model is also available from this location.

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Appendix A: Pseudo-code of the Sapper Algorithm

Function Sapper::Stage-I (T:S, H)

Let $\Pi \leftarrow \varnothing$
Spread Activation from roots T and S in long-term memory to a horizon H
  When a wave of activation from T meets a wave from S at a bridge T':S'
    linking a target domain concept T' to a source concept S' then:
      Determine a chain of relations R that links T' to T and S' to S
      If R is found, then the bridge T':S' is balanced relative to T:S, do:
        Generate a partial interpretation π of the metaphor T:S as follows:
          For every tenor concept t between T' and T as linked by R do
            Align t with the equivalent concept s between S' and S
            Let $\pi \leftarrow \pi \cup \{t{:}s\}$
          Let $\Pi \leftarrow \Pi \cup \{\pi\}$
Return Π, a set of intermediate-level pmaps for the metaphor T:S

Function Sapper::Stage-II (T:S, Π)

  Once all partial interpretations $\Pi = \{\pi_i\}$ have been gathered, do:
    Evaluate the quality (e.g., mapping richness) of each interpretation π_i
      Sort all partial interpretations $\{\pi_i\}$ in descending order of quality.
      Choose the first interpretation Γ as a seed for overall interpretation.
        Work through every other pmap π_i in descending order of quality:
          If it is coherent to merge π_i with Γ (i.e., w.r.t. 1-to-1ness) then:
            Let $\Gamma \leftarrow \Gamma \cup \pi_i$
          Otherwise discard π_i
      *When $\{\pi_i\}$ is exhausted, **Return** Γ, the Sapper interpretation of T:S*