their position is that in many cases inductive reasoning and semantic cognition are just different names for the same thing. However, in our view, although knowledge is very important to an understanding of thinking, there are limits to what can be explained by recourse to knowledge and the processes by which it is attained. First, we will describe some effects, our own and other people's, which appear to challenge accounts that equate thinking with semantic cognition. Then we will speculate as to what kinds of account might best capture those effects.

The literature on deductive reasoning contains the clearest evidence that there is more to thinking than semantic cognition. For example, Handley et al. (2004) used a belief bias task where 10-year-old participants were asked to reason about arguments the validity and believability of whose conclusions had been orthogonally manipulated. Participants also completed measures of inhibitory control and working memory. Successful performance on this task calls for the inhibition of outputs from semantic cognition, and Handley et al. observed that inhibitory control and working memory were independent predictors of the ability to respond in accord with logical validity.

Of course, R&M make no claims about deduction. However, some of our own work asks whether inductive reasoning can be wholly captured by fast and parallel knowledge-based processes or whether slow, resource-demanding processes also play a role. For example, Feeney (2007) studied inductive projection using arguments with multiple premises. Such arguments can be used to study whether people are sensitive to diversity and amount of evidence when evaluating inductive arguments, and sensitivity to these phenomena has been modelled in wholly similarity-based ways (Osherson et al. 1990; Sloman 1993). Feeney showed that a measure of IQ is associated with people's sensitivity to these principles. The results are complex, but particularly in the case of diversity, those participants who scored highest on the IQ test tended to be most sensitive to the diversity of the premises. One interpretation of correlations between IQ and performance on particular thinking tasks is that they indicate the involvement of slow, symbol-manipulating processes in thinking (see Stanovich 1999). That is, inductive reasoning is more than semantic cognition, and is based on more than processes that allow for the calculation of similarity between representations.

A related finding concerns when sensitivity to properties of the premises of an inductive argument develops. Wilburn and Feeney (2007) have shown that sensitivity to diversity begins to emerge at age 7, whereas sensitivity to amount of evidence does not begin to emerge until age 13. We interpret this finding as suggesting that in a category-based inductive argument, sensitivity to amount of evidence requires the reasoner to know that larger samples make for sounder inferences, whereas sensitivity to diversity can be demonstrated on the basis of similarity calculations alone. This finding also suggests that there is more to thinking than mere similarity.

Like R&M (*Semantic Cognition*, Ch. 8), we have also been concerned with the effects of knowledge about causal relations on inductive generalisation. A particularly interesting case comes from Medin et al. (2003), who demonstrated the category-based conjunction fallacy. They compared strength ratings for the following argument:

Lead has Property X, therefore pipes and plumbers have Property X

to the mean strength ratings for the causally *near* generalisation from lead to pipes and to the causally *distant* generalisation from lead to plumbers. (We term lead and pipes *causally distant* because the reasoner has to infer the involvement of pipes to explain the transmission of Property X from lead to plumbers.) Medin et al. (2003) demonstrated that, on average, people commit the conjunction fallacy. That is, the strength rating for the argument with the conjunctive conclusion is higher than the average strength rating for other two arguments.

Feeney et al., (2007) followed up on this finding and showed that the near generalisation from lead to pipes is rated strongest, whereas the distant generalisation from pipes to plumbers is rated weakest. In addition, we found that participants highest in IQ were more likely to rate the near generalisation stronger than the conjunctive argument. In further follow-up experiments (Crisp et al., under review) we asked participants to concurrently perform a working memory task whilst rating generalisation strength. The secondary task increased rates of the conjunction fallacy observed when ratings for the conjunctive argument were compared to the distant case, but not when compared to the near case. Our interpretation of these findings is that in the distant case, people resisted the conjunction fallacy because they explicitly reasoned about causal relations and reconstructed the causal chain linking, for example, lead to plumbers. Having reconstructed the causal chain, they assigned equally high-strength ratings to distant and conjunctive arguments. A concurrent task impeded their ability to engage in this causal reasoning in the distant case, whereas it had no effect in the near case because the stronger causal relation was immediately available. The same basic pattern was obtained when participants were encouraged to answer quickly. Thus, the individual differences, secondary task, and speeded task data suggest that some effects of knowledge on thinking are moderated by processes that are associated with IQ and working memory, and which take time.

Our preferred explanation for these findings is that there are at least two types of thinking (see Evans 2006; Sloman 1996; Stanovich 1999), a fast and associative form of thinking, and a slower and sequential type of thinking. The first type of thinking performs, among other operations, similarity calculations, whereas the second type applies rules and makes some (but not all) inferences about causal relations. It has been studied by researchers interested in models (Johnson-Laird 2006), rules (Rips 1994), or simulations (Evans & Over 2004) for reasoning. R&M's models of semantic cognition appear more relevant to the first type of thinking than they do to the second.

Impressed as we are by R&M's book, we cannot see how their current models can capture our data. Of course, R&M have anticipated our concerns and questions (see *Semantic Cognition*, pp. 371–73), but it may take another book to convince us of their answer.

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Context, categories and modality: Challenges for the Rumelhart model

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Abstract: Three issues are raised in this commentary. First, the mapping of semantic information into the different layers could be done in a more realistic way by using the *Context* layer to represent situational contexts. Second, a way to differentiate category membership information from other property information needs to be considered. Finally, the issue of modal knowledge is raised.

The parallel distributed processing (PDP) approach to modeling cognition has provided a healthy redress of the balance between empiricist and rationalist accounts of human thought. Following Chomsky's demolition of behaviorist theories of thought and language, it was assumed for many years that the mind was a symbol-processing machine, following algorithmic, syntactic rules to solve problems, achieve goals, and so forth. The discovery that PDP networks can behave in systematic rule-following ways has been matched by growing evidence that in many important respects our psychological processes are also only approximately rule-governed, so that a felicitous marrying of model and data has been achieved. In *Semantic Cognition*, Rogers and McClelland (2004) show how the Rumelhart model can learn to accurately associate properties with their respective noun concepts, while at the same time showing the general influence of the similarity structure of the knowledge being represented. Just as Rosch (1978) proposed, the mind is sensitive to the correlational structure of the world and the concepts we learn correspond to the complex covariation of different properties across semantic domains. The Rumelhart model provides the missing mechanism for how this arises, while at the same time modeling a wide range of now familiar prototype effects such as basic levels, typicality and category-based induction.

As presented, the model does not aim to represent the actual contents of anyone's semantic memory, and so there is still much detail to explore and develop. The following comments are suggestions about directions in which the model could usefully be taken, both to demonstrate its explanatory power and test its limits.

Use of the Context Relation layer. The *Context* or *Relation* layer is currently used to determine the type of relation between the noun concept (e.g., *pine*) and a property (e.g., *ISA tree, CAN grow, IS tall*). This use of the *Context* layer appears arbitrary and could lead to difficulties in a more realistic conceptual domain. The *Context* layer is clearly a vital part of the architecture of the model and cannot be omitted. But perhaps the *Context* layer might more usefully encode just that – context. Barsalou (2003) has reviewed evidence that the properties generated to a noun concept relate to an imagined situational context – so that, for example, very different properties would be generated for a car seen in a parking lot versus a car from the point of view of a driver. Typicality structure can also be highly context dependent (Barsalou 1987; Roth & Shoben 1983). Output property units could then encode whole properties (can grow, is tall) undifferentiated by their syntax. Syntactic form is a poor guide to the relatedness of properties. In the model most of the "is" relations were visually based. But in real life an "is" relation can encode any number of non-perceptual and abstract properties such as *is valuable*, *is annoying*, or *is bad for your health.* Grouping properties by syntax may not correspond to any real-world structure. An alternative suggestion to try here would be to use the *Context* layer to input the type of property (part, appearance, function, behavior, origin, etc.) using semantic rather than syntactic criteria to determine types.

Category information is not just another property. Categorical *ISA* relations have traditionally been treated very differently in studies of semantic memory from other properties. Knowing the category membership of an item will normally provide a much broader range of useful inferences about it than will knowledge of a salient property. The *ISA* relation captures the kind of thing that the item is, whereas properties just capture a particular property. Category information is also verified more rapidly (Hampton 1984). The model does not reflect this difference structurally, although it is notable that all of the input items reappear as *ISA* output units. How could the model be asked whether it had learned the properties of superordinate categories – for example, that trees have roots or that fish have gills?

Quantification and modality. A difficulty for any similarity-based model is the handling of extensional reasoning and quantified statements. When it has mastered its knowledge domain, the model will correctly verify that a robin is a robin, a robin is a bird, and a robin is red. It will not be able to explain, however, that *a robin is a robin* is tautologically true, *a robin is a bird* is necessarily true (assuming that any non-bird could never resemble a robin sufficiently to belong in that class), whereas *a robin is red* is generically true – only being true of most adult robins (or in Europe only of adult males). Knowledge of what actually exists is not primarily the job of semantic memory, but the model clearly lacks a way to handle truth under different quantifiers.

Failure to consider the truth of statements extensionally is quite possibly an advantage of the model given that people are also bad at it, and succumb to similarity-based "non-logical" effects when reasoning about category membership (e.g., Hampton 1982; Jönsson & Hampton 2006). But it would be worth exploring whether the model can learn the difference between properties that are necessarily true and those that are typically true.

The reverse side of the coin is whether the model can determine which properties can be expected to co-occur and which may not. Suppose that backpropagation to representation is used to find a representation of an item that is large and yellow, and has petals, as opposed to an item that has roots, gills, and feathers. Can it be demonstrated that some representations are found rapidly and with low residual error (even although the properties have not co-occurred in the training set), whereas others are impossible to represent without a high degree of error. Modal intuitions of necessity and possibility (Rips 2001) are an important aspect of semantic cognition, and it would be a bonus for the research program to show how the network can also match such intuitions.

Structured models of semantic cognition

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Abstract: Rogers & McClelland (R&M) criticize models that rely on structured representations such as categories, taxonomic hierarchies, and schemata, but we suggest that structured models can account for many of the phenomena that they describe. Structured approaches and parallel distributed processing (PDP) approaches operate at different levels of analysis, and may ultimately be compatible, but structured models seem more likely to offer immediate insight into many of the issues that R&M discuss.

It is widely accepted that cognition can be understood at multiple levels of analysis, but there are different claims about the nature of these levels (Broadbent 1985; Marcus 2001; Rumelhart & McClelland 1985; Smolensky 1988). In *Semantic Cognition* (2004), Rogers & McClelland (R&M) appear to suggest that parallel distributed processing (PDP) approaches and structured approaches lead to proposals at the same level of analysis, and are therefore competitors. Like some previous researchers (Smolensky 1988), we believe that these two paradigms are compatible, and that they aim for explanations at different levels of analysis.

Since R&M treat structured approaches as the competition, they naturally emphasize the problems they see with structured models of cognition. Among other criticisms, they suggest that structured approaches cannot capture typicality, exceptions, and the graded inferences that are characteristic of human learning (*Semantic Cognition*, p. 44); that there are few attempts to explain how taxonomic hierarchies might be acquired (pp. 13, 31); and that structured approaches do not explain why people make very different inferences when reasoning about different kinds of properties (e.g., "has cold blood" vs. "weighs ten tons," p. 34).

If PDP approaches and structured approaches operate at different levels of analysis, then many phenomena (e.g., graded inferences and learning) will turn out to be compatible with