How Do Psychologists Think Anyhow?

John Black and Arthur Graesser
Yale University and California State University at Fullerton

What do psychologists know and how do they use that knowledge to answer questions?[1] These are two of the issues we have had to address as part of a project to design an intelligent computer assisted instruction (ICAI) system that will help people learn about psychology. Questions like these are critical for any ICAI system, because central to the design of such systems is determining how knowledge of the domain is to be represented, determining what that knowledge is, and determining how that knowledge is to be used to interact with the students (e.g., to answer student questions).

Several ICAI systems address these issues for rule-based domains like electronics (e.g., Brown and Burton, 1975), arithmetic (Brown and Burton, 1978), algebra (Sleeman, 1982), and computer programming (Soloway, Rubin, Woolf, Bonar and Johnson, 1982); but how to address them is less clear for non-rule-based domains like psychology, history, literary studies, law, and management of organizations. In fact, domains like medical diagnosis are probably less rule-based than current expert systems (e.g., Shortliffe, 1976) make them appear, and are thus more like psychology than algebra. We have approached these issues of how to represent expert knowedge in non-rule-based domains by trying to devise an ICAI system that contains knowledge about psychology in a form that allows it to intelligently answer student questions as a human expert would (or perhaps better).

Psychological Thinking

The kinds of knowledge and reasoning used by psychologists to answer questions is illustrated by the following "think aloud" protocol of a cognitive psychologist (who is a faculty member at a research university) determining how to answer a student question. The psychologist was given the background and student question, then gave the following verbal report of his thoughts (which we have edited slightly) as he figured out how to answer the student:

> ***Background:*** The student asking the question is in a class that has just learned about depth of processing and elaboration theories of memory.
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> ***Student Question:*** I'm taking Spanish and I was wondering if using imagery is a good way to learn the vocabulary?
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> ***Psychologist's Reasoning:*** Well, imagery is a deep processing task, so by depth of processing theory, imagery should give good memories... Ah, I'm remembering that there is an experiment about this by Atkinson and Raugh. They found that interacting images is the critical thing. That is, the subjects had to form images of the English words, then form images of the Spanish words' sounds, and then show the images interacting. Just forming images by themselves was not good enough they had to be interacting ... The example I remember (I'm not sure it's right) is "horse -- caballo." Here the image is of a horse kicking an eye because "caballo" sort of sounds like "eye." So I need to tell the student about this study and that they must use interacting images... Ah, I can explain this using elaboration, because the interacting images provide elaborative connections between the words...

So what is going on here? Our psychologist starts out by trying to relate the query to the depth of

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processing theory of memory (probably because he has been told that the student knows that theory), then realizes that he knows of an experiment that directly addresses the strategy of using images to learn vocabulary. He retrieves from memory the details of the relevant experiment and realizes that the results provide more specific information about exactly how to use images to learn vocabulary -- namely, use interacting images. But how is he to explain this to the student? The depth of processing theory does not have a clear way of explaining why interacting images would be better than images alone, so he retrieves what he knows about the elaboration theory of memory (the other theory he has been told the student knows) and realizes that that theory provides an explanation. His eventual answer to the student is to describe the specific experimental result and rationalize it using the elaboration theory of memory.

Note that the crucial information for the answer is provided by the memory for a specific expert, not by the models. Thus the important reasoning here is case-based reasoning rather than rule-based reasoning, because the experiment is a specific case or observation and the needed specific rule is stored as part of the memory for that case. If this had been a rule-based domain, then the expert would have merely derived the answer using the rules stored as part of the knowledge representation of the model -- perhaps citing a case to illustrate the rule. However, such complete models are rare in fields like psychology, so case-based reasoning seems to dominate. Thus experts in fields like psychology seem to have a mental representation composed of cases (memories for specific experiments) that are organized so that they can be accessed directly to answer queries. These specific cases also seem to have links to various explanatory frameworks (e.g., the depth of processing and elaboration theories of memory) that can provide explanations for the results of the experiments.

The *ECALP* System

We have been working on an ICAI system that we call ***ECALP***, for Expert Computer Assisted Learning of Psychology. While it is far from adequate to do the kinds of reasoning shown in our protocols of actual reasoning by psychologists, it does show a few of the needed features in rudimentary form. ***ECALP*** is implemented as a PROLOG program that uses two levels of representation to embody psychological knowledge -- a conceptual packet level and an explanatory packet level.

The conceptual packet level contains interrelated packets of information each using conceptual graph structures (Graesser, 1981) to represent experimental results (e.g., Byrne and Nelson found that the proportion of similar attitudes was more important in causing attraction than was the number of similar attitudes) and general facts (e.g., person X familiar with person Y causes X to be attracted to Y). Each conceptual packet has six information slots: one that contains a pattern describing when the packet will be relevant, another slot that contains a unique identifier, a third slot that is the category of the packet (e.g., event or state), a fourth slot is a list of links from other packets (e.g., is a consequence of, is an implication of), a fifth slot is a list of links to other packets (e.g., causes, implies), and the sixth slot provides alternative ways of expressing the packet information to the student. The first slot provides the mechanism needed to access the conceptual packet directly when relevant queries arise and the fifth slot provides access to other relevant conceptual and explanatory packets.

The explanatory packet level contains interrelated packets of information that organize the information at the conceptual packet level that relates to the various relevant explanatory frameworks. The explanatory packets contain six information slots: one slot containing the names used to describe the explanatory framework (e.g., depth of processing, levels of processing), another slot describing the general phenomena addressed by the framework (e.g., human memory), a third slot describing the type of explanatory framework (e.g., theory, model, hypothesis, or folklore), a fourth slot containing indexing links to the conceptual packets that describe the mechanisms of the framework, a fifth slot containing indexing links to conceptual packets that describe the predictions of the framework, and a sixth slot that provides indexing links to conceptual packets that describe experimental results providing evidence related to the explanatory framework.

Using this two level representation, the question-answering procedures given in Graesser and Murachver (in press), and a simple definite clause grammar (Pereira and Warren, 1980; McCord, 1982), we have been able to get ***ECALP*** to flexibly answer questions of the following kinds:

1. What does X mean?
2. Is the answer to X YES or NO?
3. How does X occur?
4. Why does X occur (or X exist)?
5. What are the consequences of X occuring (or existing)?
6. What is the evidence for X?
7. According to theory T, <question>?

With these capabilities ***ECALP*** can serve as an expert consultant on psychology (to a limited extent at this time) that the student can try out ideas on and use to seek further information. When the student first broaches a topic (e.g., human memory or interpersonal attraction), ***ECALP*** gives the student a few key concepts that the student can then use to guide further queries (e.g., asking what various terms mean) and to derive ideas of their own which ***ECALP*** can evaluate (e.g., Is semantic encoding remembered better than acoustic encoding?). The teaching strategy used in ***ECALP*** is to try to establish a learning environment |n which the students can themselves generate most of the ideas about a topic. The reason for this is that if students can generate ideas themselves, then they will know and remember those ideas beter than if they were merely told the ideas (Jacoby, 1978; Black and McGuigan, 1983; Carroll and Carrithers, 1983). We believe that ICAI systems that exploit the potentially powerful learning mechanisms of such generation effects will be more effective than other ICAI systems, but this is an hypothesis that needs to be empirically evaluated.

Conclusions

In our investigation of psychology, we have found that ICAI systems for such non-rule-based fields need knowledge representations of specific cases in addition to the rules represented in current rule-based ICAI systems. We have implemented a prototype of one such system (***ECALP***) that uses cases and rules to answer student queries about psychology. This system also embodies the teaching strategy that we think is potentially the most powerful: namely, presenting the student with a few key ideas and then having them generate the rest.

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