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Improving the Explanation Capabilities of Advisory Systems[1]

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Abstract

A major limitation of current advisory systems (e.g., intelligent tutoring systems and expert systems) is their restricted ability to give explanations. The goal of our research is to develop and evaluate a *flexible* explanation facility, one that can dynamically generate responses to questions not anticipated by the system's designers and that can tailor these responses to individual users. To achieve this flexibility, we are developing a large knowledge base, a viewpoint construction facility, and a modeling facility.

In the long term we plan to build and evaluate advisory systems with flexible explanation facilities for scientists in numerous domains. In the short term, we are focusing on a single complex domain in biological science, and we are working toward two important milestones: 1) building and evaluating an advisory system with a flexible explanation facility for freshman-level students studying biology, and 2) developing general methods and tools for building similar explanation facilities in other domains.

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1 Research Objectives

The goal of our research is to develop and evaluate a *flexible* explanation facility that can dynamically generate responses to questions not anticipated by the system's designers and that can tailor these responses to individual users. Previous advisory systems have lacked these capabilities for a variety of reasons. In this section we will describe the problems of current advisory systems, the solutions to these problems that we propose, and our research activities for achieving those solutions.

Problems. The explanation facilities of current advisory systems are inflexible for two reasons:

- Inadequate domain knowledge: At least two factors limit the adequacy of the knowledge base as a source of "raw materials" for flexibly generating explanations: small size and task specificity. Although small size is an obvious limitation, few research projects have built a large-scale knowledge base as their "starting point" for research on explanation. Furthermore, because the knowledge for most advisory systems supports only a single task, most research on explanation has overlooked issues outside the task requirements, such as answering a range of questions, explaining terminology, and customizing explanations for specific users [22]. (For notable exceptions see work by Moore and Swartout [33, 24].)

- Inability to reorganize knowledge: Little work has been done to develop methods to select coherent packets of knowledge from a knowledge base, and even less on the reorganization of portions of the knowledge base to improve specific explanations. These issues have been avoided by "hardwiring" knowledge structures that are suitable for the limited explanations required by a particular advisory system. (For notable exceptions see work by McKeown [21] and Suthers [32].)

Solutions. We are developing a five-part solution to the problems of current advisory systems. Our solution comprises: (1) constructing a knowledge base which is large-scale and contains very fine-grained representations, (2) selecting and organizing knowledge with viewpoints and models, (3) generating new viewpoints on demand, (4) constructing and simulating models and using them to explain the behavior of mechanisms, and (5) generating explanations which relate new information to what the user already knows. We discuss each of these in turn.

First, we have built an extensive knowledge base for one area of biology — college-level anatomy and physiology of plants [26]. Although it is under constant development, it is already one of the largest knowledge bases in existence. (Our knowledge base currently contains about 3,000 frames and over 28,000 facts.) Unlike knowledge bases built with instructional frames [14] or hypertext [10], our knowledge base consists of "atomic facts" that our explanation facility can combine in different ways to produce different explanations.

Second, we are developing methods for selecting information from the knowledge base and organizing it into a coherent bundle appropriate to the situation at hand. One organizing structure is that of *viewpoints*, which provide coherent descriptions of objects or processes. For instance, the viewpoint "photosynthesis as a production process" selects and organizes facts to explain how photosynthesis produces glucose from carbon dioxide and water. Another organizing structure is that of *models*, which are built from viewpoints and support computer simulation. For example, an energy flow model of the plant includes the viewpoints "photosynthesis as an energy transduction process" and "respiration as an energy transfer process," and it allows an advisory system to predict and explain the effects of changes in light wavelength on a plant's photosynthetic or respiratory rate under a variety of specific circumstances.

Third, we are developing methods to automatically generate *new* viewpoints. This ability is important because, as system designers, we cannot anticipate all the viewpoints necessary for effective explanations. For example, Table 1 lists several viewpoints on photosynthesis and the situations in which they might arise. Our question answering facility will be able to construct these viewpoints by selecting and reorganizing the individual facts comprising existing viewpoints in the knowledge base (see [1]).

Fourth, we are developing methods for automatically constructing and simulating models and interpreting the consequences of simulations. These methods use existing methods of qualitative reasoning, but add two new capabilities: constructing models from large knowledge bases and generating explanations from these models. This will allow our explanation facility to answer "what-if" questions that were unanticipated when the knowledge base was built (see [28]).

Finally, we are developing methods to automatically generate *integrative explanations*, which explicitly relate new information to what the user already knows. This is important to advisory systems because the coherence of an explanation depends upon the particular situation. Our system will record the discourse with each user and will explain new topics

Viewpoint on Photosynthesis	*Contextual Situation*
as a destructive process	To explain the effects of the first oxygen producing plants on other organisms during evolution.
as an essential process in ecosystem energy flow	To explain how almost all living things depend on photosynthesis for deriving energy from an abiotic source.
as a magnesium-utilizing process	To explain the effects of magnesium deficiency on the plant.
as an enabling process	To explain how photosynthesis is important for any processes which use glucose or oxygen.
as a constructive process	To explain how photosynthesis is vitally important to plant growth and reproduction.

Table 1: A few of the viewpoints on photosynthesis and the teaching situations in which they might be appropriate.

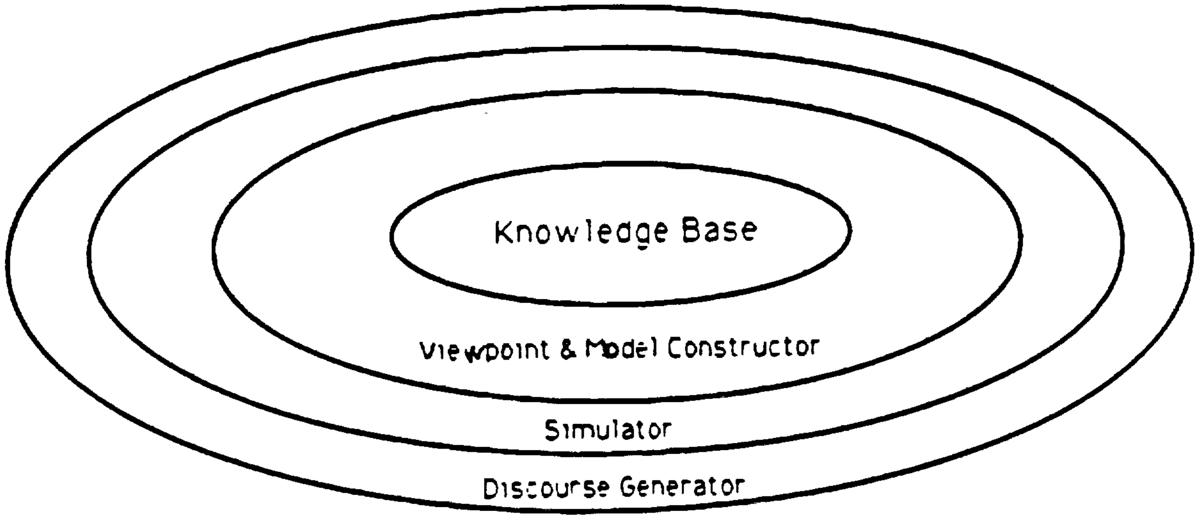

Figure 1: The layered design of our proposed advisory system. Each layer of software can access and use any layers within it.

in ways that relate to that user's knowledge and interests (see [18]).

2 The Design of Our Advisory System

An advisory system that simply provides facts to a user fails to take advantage of established techniques for effective communication. These techniques include treating the user as an active learner, grounding new information within a relevant context, and conveying information in appropriate ways through an interface which is intuitively easy to use. If the advisory system is to be used in a learning situation, it also needs to motivate the user with an appealing environment.

To provide these capabilities, our advisory system is designed with layers of software between the knowledge base and the user, each providing an essential capability for a flexible, reactive advisory system (see Figure 1). The outermost layer is the *discourse generator*, which interacts with the user by presenting focused information and encouraging the user to ask questions and to explore additional issues germane to the topic. To generate the relevant knowledge within an appropriate context and provide alternate modes of presentation, the discourse generator uses information from the inner layers. The *modeler and simulator* predict and explain the behavior of biological systems by using computational models to answer "what if" and "why" questions; they permit the user to directly investigate the predictions of a model by manipulating its parameters. The *viewpoint constructor* selects and organizes domain information into coherent explanations. Many of these viewpoints may be directly encoded in the *knowledge base.* Others will be constructed by reorganizing the facts comprising existing structures.

This section describes the capabilities of each layer of software, and our current prototypes, beginning with the knowledge base.

2.1 A Knowledge Base for Biology

At the core of any advisory system is a knowledge base. It contains both the information to be communicated to the user and the information required for effective comunication, such as the background knowledge required to understand particular concepts.

For many domains, building a knowledge base is difficult and time consuming. To avoid this difficulty, most system designers have built advisory systems in subject areas for which a small knowledge base will suffice [35, 34, 4, 7, 6, 29, 16, 27, 25]. These subjects fall into two categories. The first is task-specific subjects that focus on a single application of knowledge. For example, the Guidon system [9] teaches diagnosis of infectious blood diseases. Teaching other tasks, such as how to determine a patient's prognosis, would require substantial changes to the system because Guidon is specialized for its single task. The second category of subjects is formally characterizable subjects that require only a small set of logical rules or axioms. For example, the GEOMETRY system [2] requires only a few rules of introductory geometry. However, the fundamental knowledge in a field like biology is neither committed to performing a single task nor formally characterizable with a small set of axioms. We believe that we con overcome the inherent difficulty in building a large knowledge base for two reasons: 1) we have developed sophisticated software that assists us in viewing and editing large, fine-grained knowledge bases; 2) we have used this software to build a large knowledge base, and applied our prototype systems for explanation generation to it.

2.2 The Viewpoint Constructor

A knowledge base for basic science must represent multiple *viewpoints* of each concept. For example, encoded in the Biology Knowledge Base are many different viewpoints of photosynthesis. Two of these, which we mentioned earlier, are "photosynthesis as a production process" and "photosynthesis as an energy transduction process." The knowledge base also contains more focused viewpoints that are appropriate in certain situations, such as "photosynthesis as a *glucose* production process" and "photosynthesis as an *oxygen* production process."

Figure 2 suggests why viewpoints are useful and even essential. The figure shows just part of the knowledge about photosynthesis that is encoded in our Biology Knowledge Base. Taken altogether, the totality of knowledge about photosynthesis is incoherent — there are so many facts about photosynthesis that some focus is necessary. Viewpoints provide this focus. The figure shows the two viewpoints of "photosynthesis as production" and "photosynthesis as energy transduction," highlighted with solid and dashed bold lines, respectively. Each collects and organizes facts about the basic process of photosynthesis that are relevant to that particular point of view and omits the large number of other facts that are irrelevant from that point of view. For example, "photosynthesis as production" focuses on the compounds, oxygen and glucose, that are produced by photosynthesis and on the compounds, carbon dioxide and water, that are its raw materials, and omits intermediate compounds, such as ATP that participate in photosynthesis but are, overall, neither produced nor consumed. This viewpoint also omits much other information about photosynthesis that is irrelevant to viewing photosynthesis as production.

A viewpoint, then, is a collection of facts about a particular concept that are all relevant within a particular context. The focus that viewpoints provide is critical because an arbitrary collection of facts is usually incoherent, even when the facts all pertain to the same topic. For example, describing photosynthesis as "a process that converts light energy into glucose and oxygen" is not patently incorrect but is confused or incoherent in that it intermixes facts from the viewpoints of energy flow and material flow. It is better to say that photosynthesis converts light energy into chemical bond energy (the energy transduction viewpoint), or that it converts carbon dioxide and water into glucose and oxygen (the production viewpoint). The *viewpoint constructor* is the part of our system that processes requests for viewpoints and produces the appropriate collection of facts selected from all facts in the knowledge base.

Many researchers acknowledge that viewpoints are a useful way of organizing knowledge. However, most methods for retrieving viewpoints from a knowledge base assume that each viewpoint is explicitly encoded [33, 23, 20]. Unfortunately, the difficulty of explicitly encoding viewpoints increases combinatorially with the number of concepts in the knowledge base. In

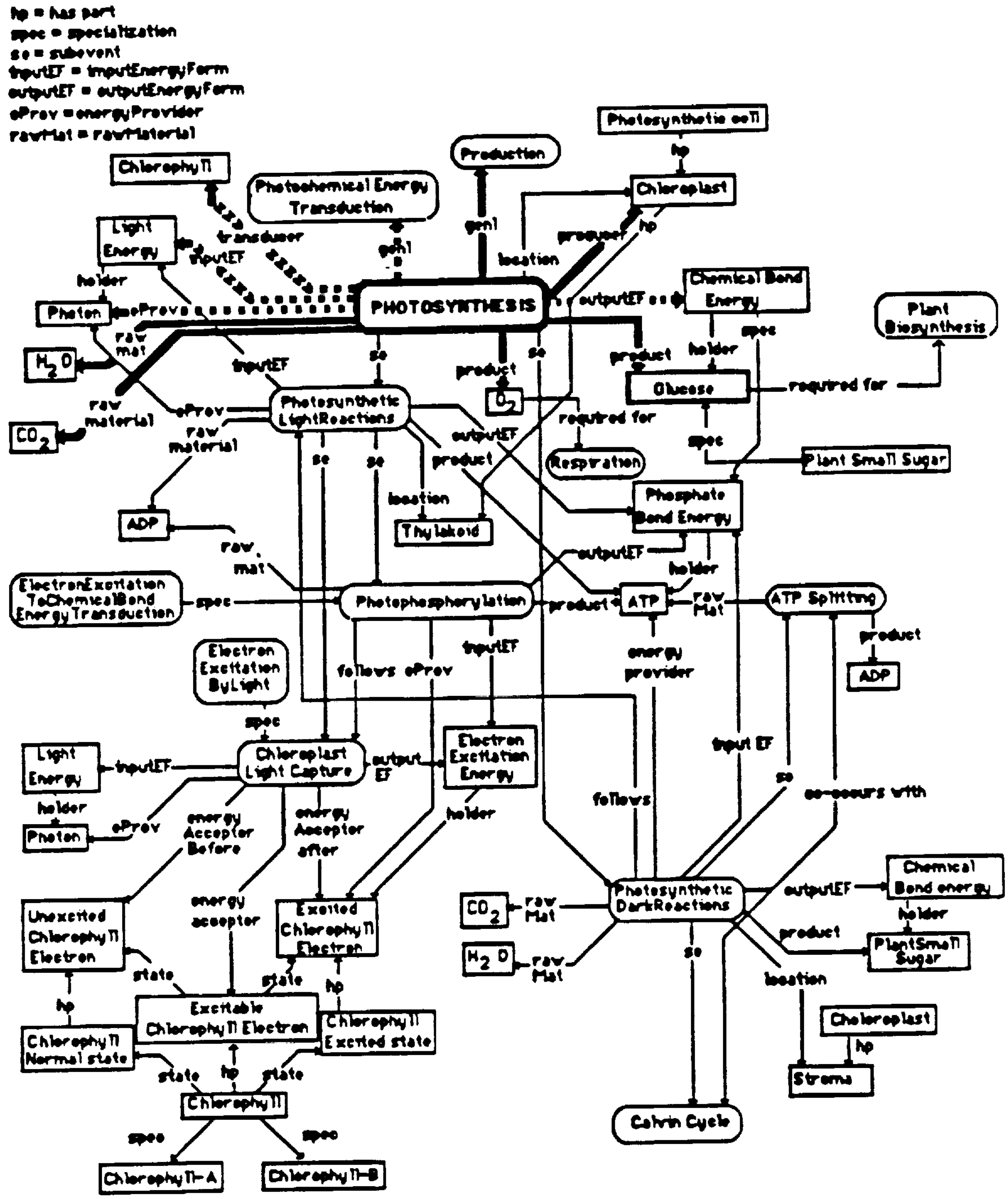

Figure 2: A small portion of the knowledge about photosynthesis represented in the Biology Knowledge Base. These labelled graphs, or "semantic networks", are widely used in artificial intelligence. Each fact is a relation (depicted as a labeled arc or line) between two concepts (depicted as labeled boxes). Solid bold lines represent information that is part of the viewpoint "photosynthesis as production", while the dotted bold lines represent the viewpoint of "photosynthesis as energy transduction".

addition, relying on pre-encoded viewpoints is inflexible because new viewpoints cannot be created as needed.

Our solution to this problem is to enable the advisory system to dynamically generate viewpoints when they are needed. We have experimented with methods for doing this using abstract specifications for points of view, called *view types*. For example, the *structural* view type specifies methods for constructing viewpoints concerning an object's parts and their interconnections, such as the viewpoint "endosperm as part of a seed." Similarly, the *functional* view type specifies methods for constructing viewpoints concerning the role of an object in a process, such as "chloroplast as the producer in photosynthesis."

View types can also be combined. The *structural-functional* view type specifies how the individual parts of an object participate in the subevents of some process. For example, a structural-functional description of angiosperm sexual reproduction would discuss how each part of the flower (sepals, petals, stamen, and carpels) participates in some event of the reproductive process (e.g., pollinator attraction, pollen formation, and pollination).

We believe that a relatively small number of such view types is sufficient to characterize and produce many viewpoints within the natural sciences. Support for this conjecture is preliminary but encouraging. First, we found that our view types and their combinations are sufficient to characterize over fifty definitions chosen at random from the glossary of a biology textbook. Second, we have successfully used view types in a prototype system for generating viewpoints [1, 30]. These viewpoints constitute answers to a wide range of definational questions (e.g., "What is C3-photosynthesis?") and comparative questions (e.g., "What is the difference between mitosis and meiosis?").

2.3 The Modeler and Simulator

Our advisory system will use computational models to predict and explain the behavior of complex biological systems. This capability is very important because it can tie together otherwise disparate and uninteresting facts into an explanation of how something works.

Most computational models in biology are *quantitative* models, which interrelate a system's parameters using differential equations. Although these models are precise, they can also be intractable, especially if some of the equations are nonlinear. Moreover, because quantitative models require complete numeric data, model builders must assume precise values for parameters for which little precise data may be known. Finally, the quantitative details often obscure the more important qualitative principles.

During the past ten years, research on *qualitative* models has addressed these problems [15, 13, 11]. Instead of using exact relationships and values, qualitative models employ qualitative relationships, such as "water potential increases with turgor," and qualitative values, such as "cell turgor is positive and decreasing." Approximations like these are frequently sufficient to express essential information about a system when complete knowledge is unavailable or unneccessary. They also enable a qualitative simulator to characterize the behavior of a system, much as a human reasoner could, without knowing or needing exact relationships or values. For example, a qualitative simulator with a model of a plant's water flow could predict that "excessive transpiration from a plant caused by increasing temperatures will be countered by closing of the stomata" without knowing the original concentration of water in the plant or the exact rate of transpiration. Qualitative models have been used in advisory systems for steam-plant operation [31], weather prediction [5], circuit diagnosis [3, 35], and many other domains.

We are extending the research on qualitative reasoning in two ways. First, while previous research assumes that a model is given *a priori*, we are developing methods for constructing models as needed. In order to support a wide range of questions, our knowledge base must provide a vast array of viewpoints and levels of detail. However, overly detailed models, while perhaps capable of answering many questions, can be inefficient or even intractable, and excess detail would make their predictions opaque. Our program uses each question to decide which perspectives and abstractions are needed, constructs a model from these pieces, and simulates this model to answer the question (see [28]). Such a model not only answers the question, but also highlights the knowledge supporting the answer and provides transparent, explainable answers.

Second, we are developing methods to generate in-depth explanations of qualitative reasoning. A major shortcoming of current simulators (both qualitative and quantitative) is that they generate extensive details about a model's behaviors but little overview or explanation. Our system will provide concise and focused textual answers to a range of questions about a model and its behaviors. For example, we expect to provide multilevel overviews of both a model and its behaviors which highlight their most important features and compare and contrast different behaviors (if there is more than one). We also expect to provide an explanation of the mechanisms by which a model causes its behaviors, grounded in familiar physical principles, and how a model would respond to changed circumstances (see [19]).

2.4 The Explanation Generator

Our overriding goal is to develop and evaluate a *flexible* explanation facility that can dynamically generate responses to questions not anticipated by the system's designers and that can tailor these responses to individual users. We are building an explanation generator that will achieve flexibility in three ways. First, it will produce *integrative explanations* that relate new information to the user's existing knowledge. In producing an integrative explanation, we can define three networks of relevant concepts and relations. The *target* network is the set of concepts and relations that a system seeks to communicate to the user. The *base* network is the set of concepts and relations that model what the user already understands and is relevant in some way to the target. The *linking* network is the set of concepts and relations that relate the target to the base. To produce an integrative explanation, our system will determine the relevant target, linking, and base networks, and it will organize the knowledge in the linking and target networks in a manner that facilitates their integration into the base network.

Opportunism is the second way that our explanation generator will achieve flexibility. The system will actively seek opportunities to include important information in the domain that is closely related to the topic being explained but is unknown to the user. For example, suppose the system were explaining embryo sac formation to a user, and noticed that two participants in this process, a megaspore and a megaspore mother cell, are both kinds of botanical cells. It can recognize this as an opportunity to discuss the difference between haploid and diploid cells, an important distinction in biology. Moreover, rather than interjecting this discussion in the middle of another topic, the system can relocate it to an appropriate place in its explanation.

Finally, our explanation generator will achieve *organizational flexibility.* Such flexibility is desirable for two reasons. First, a generator should be able to introduce prerequisite material and elaborations at appropriate positions in the explantion. Second, it should be able to place material that is familiar to the user earlier in the explanation and material that is new to the user later. To achieve organizational flexibility, the generator takes a *delayed-commitment* approach: it delays organizational commitments as long as possible. Initially, the propositions of the explanation are organized very loosely. As the explanation develops, the generator adds new propositions and gradually arranges them in an order that is most suitable for the user.

We are aided in our efforts to construct an explanation generator by previous research results on user modeling and natural language generation. An *overlay* model [8] represents what the user knows as a subset of the concepts in the knowledge base. The explanation generator initializes the user model with basic concepts covered in previous courses and lessons, and updates the model based upon explanations that it generates and questions the user asks. Also, we are using the FUF system [12] for converting explanation structures into English. FUF, which has been in development at Columbia for the past seven years, employs one of the largest machine grammars ever constructed and provides wide linguistic coverage.

We have constructed a prototype system, which provides integrative explanations, opportunism, and organization flexibility [17, 18]. We have used this system to produce multi-paragraph explanations from portions of the Biology Knowledge Base. Because the system is not restricted to schemas, it generates different explanations for different users. The system's output was favorably evaluated by a domain expert, who found the explanations both accurate and clear.

3 Evaluating and Generalizing Our Results

Our long-term objective is to build advisory systems for complex domains that compete well with human advisors. Although we cannot meet this objective soon, we believe we can build and evaluate the core components of an advisory system that competes well with textbooks for an important portion of a course, and that meeting this short-term objective is a critical milestone for achieving our long-term objective.

We plan to evaluate our advisory system by using it to help teach an introductory biology course at the University of Texas at Austin. In addition to introductory material, the system will explain advanced material that has not been covered in the classroom or assigned readings.

The evaluation will be based on data from the following experiment. Users will be paid to spend extra time in the course studying the advanced material with the help of the advisory system. When the users are comfortable using the system, we will give them several assignments. Each assignment will require answers and explanations for a range of technical questions on both the introductory and advanced material. (These questions will be formulated by a biologist who is not affiliated with our project. Our research team will not know the questions beforehand.) To complete their assignments, the users will be randomly assigned to three groups. Users in the "traditional" group will be permitted to use any standard (non-human) resources, such as textbooks and laboratory equipment. The "advisory" group will be allowed to use only the advisory system, and the "eclectic" group will be allowed to use both traditional sources and the system.

We will compare the performance of the three groups of users on correctness and completeness of answers and on efficiency of task completion. The users' answers and explanations will be judged by the teaching staff for the biology course, who will not be apprised of the users' identity or group. If a benefit for the advisory system is found, we will separately analyze user performance on the introductory material to see if a benefit exists even when the material has been covered in the classroom. Including the eclectic group will further allow us to ascertain whether there is a synergistic effect among the three sources of information — classroom, textbook, and advisory system. The users' proficiency in terms of the amount of time used to complete the assignment will be measured, controlling for the correctness of the users' responses. For each of the three groups, we will also measure the users' interest in the advanced materials taught. This assessment will be based on questions from standard course evaluations.

Based on the results of our evaluation, we will generalize our research results to help others build advisory systems in a range of domains. This will involve removing dependencies on the domain of biology that our experience will no doubt reveal and re-implementing those parts of our system that contributed most to its success, to improve its portability and ease of reuse.

4 Summary

The primary results of this research will be the following: (1) an explanation facility for college-level biology, (2) a critical evaluation of the explanation facility based upon its use in an introductory biology course at the University of Texas, and (3) general methods and tools for building similar explanation facilities in other domains.

During the last six years, we have built a very large knowledge base for one area of biology and we have developed prototype systems for each component of our proposed explanation facility. From this experience, we have learned how to structure large knowledge bases using viewpoints and models, and we have created a foundation on which to build a flexible explanation facility.

Our proposed explanation facility will dynamically generate responses to unanticipated questions and tailor these responses to individual users. This flexibility will encourage a user to ask questions and request clarification or detail. In the future we expect this functionality to be the foundation for a wide range of computer-based advisory and research tools, such as intelligent databases, electronic libraries, and simulated laboratories.

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