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ABSTRACT

This paper draws from several disciplines to provide a foundation for making progress toward a unified conception of thinking in science education. Areas covered include: (1) the philosophy of science (discussing contextual realism); (2) cognitive psychology (describing development of scientific thinking skills); and (3) artificial intelligence (including machine learning). It is suggested that the mechanism of prediction should be incorporated into current learning and instructional theories in science education. Finally, research results exploring the role of prediction as part of an instructional strategy are discussed. A total of 28 references is appended. (YP)

TOWARD A UNIFIED CONCEPTION OF THINKING:

PREDICTION WITHIN A COGNITIVE SCIENCE PERSPECTIVE

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Toward A Unified Conception of Thinking:
Prediction Within A Cognitive Science Perspective

A cognitive science perspective on anything is, by definition, interdisciplinary. Gardner (1985) includes philosophy, psychology, artificial intelligence, linguistics, anthropology, and neuroscience as the disciplines included in cognitive science. Together, these individual cognitive sciences contribute to a unified cognitive science. In this paper I rely mostly on philosophy, psychology, and artificial intelligence as the basis for my remarks.

Making progress toward a unified conception of thinking has proven very difficult, perhaps because until recently there have been no systematic attempts to focus many disciplines on the same goal. Because cognitive science defines itself as an interdisciplinary effort, I think it offers more hope that we will make important progress toward a unified conception of thinking. It is important at the outset to clarify what I mean by a unified conception of thinking. I use the phrase "unified conception of thinking" in the sense that we have a unified conception in science of mechanics or genetics or kinetic theory, etc.; in other words that there is widespread agreement about basic principles among those who use the knowledge for basic and applied research. I do not mean by "unified conception of thinking" that we are trying to define thinking or problem solving in some broad, general, "contentless" way. A recent paper by Perkins and Saloman (1989) provides a historical sketch of the long-standing controversy between generalist and specialist camps, concluding that a synthesis is needed to join subject-matter instruction with thinking-skills instruction.

I try in this paper to use contemporary work in philosophy, psychology, and artificial intelligence in providing a brief overview of some ideas that, taken together, can provide a reasonable foundation for making progress toward a unified conception of thinking in science education.

Philosophy of Science

My pocket Funk and Wagnalls (1980) defines philosophy as "The inquiry into the most comprehensive principles of reality in general, or of some sector of it, as human knowledge or human values." In many ways the beginnings of cognitive science emphasized the need for philosophy. The crucial role of "representation" in the mind's new science requires that we understand relations between a discipline and how the mind structures and uses that knowledge in problem solving. Gardner (1985) notes that,..." philosophy participates in the disciplinary matrix by virtue of its dialectical role: a dialectic within the discipline and a dialectic between the analysis put forth by philosophers, on the one hand, and the empirical findings and theories put forth by scientists, on the other" (p. 87).

Rather than selecting one of the better known contemporary cognitive philosophers such as Dennett (1978) or Fodor(1983) or Putnam (1983) to lay the philosophical foundation here, I have selected Schlagel (1986), a somewhat lesser-known philosopher of science. His approach, which he calls "contextual realism", fully acknowledges the importance of cognitive science while avoiding the language games approach of Wittgenstein and his followers. Schlagel relies heavily on concepts such as "limiting conditions" and "complementarity" in modern physics in sketching out his view of a meta-physical framework for modern science. He concludes that the context of modern philosophy must be tied closely to modern science and to our growing understanding of our inner world:

> These developments indicate, in my opinion, that physical reality consists of a series of levels, each composed of distinct layers of entities with unique properties that account, to some extent, for the kinds of structures and interactions one finds on the succeeding higher levels.... While this conception of inexhaustible, irreducible contexts or levels will probably be replaced in the future by a more adequate meta-physical model, in the meantime, rather than attempting to collapse reality into one dimension, which invariably blinds the investigator to the significance of other contexts, we should assume that the universe consists of an endless nexus of domains with innumerable structures and features. Experimentation and theory construction have been the most successful means so far in providing partial glimpses of this reality, as refracted through our cognitive-linguistic frames, but we should not assume these means are final. (Schlagel, 1986, pp. 294-5)

From the standpoint of science education Schlagel's contextual realism offers a framework that I think can be embraced by many workers in the field, particularly those who embraced much of Piaget's work at an earlier time. This brief paper does not allow a detailed description of contextual realism so the reader who wants more details should spend a weekend with Contextual Realism.

In the next two sections I draw from cognitive psychology and artificial intelligence to complete my sketch of the foundation needed to describe contributions toward a unified conception of thinking.

Cognitive Psychology

The beginnings of modern cognitive psychology including the study of information processing using the computer as metaphor for mind, is described in Gardner's (1985) excellent historical account of cognitive science. The work of a handful of individuals during the 1950's broke the stranglehold of behaviorism on American psychology. Since that time cognitive psychology has increasingly dominated nearly all areas, including science education. During the 1960's and throughout much of the 1970's Piaget's work was the dominant force in science education and since the late 1970's various forms of the information-processing model have become more common. The current emphasis on misconceptions in science education combines many of the assumptions and techniques from Piaget's work with ideas associated with information-processing theory.

From the very large body of literature in cognitive psychology I have selected two sources that seem to me to have particular relevance to our goal of moving toward a unified conception of thinking in science education. A book by Kuhn, Amsel, and O'Loughlin (1988) on the development of scientific thinking and a book by Holland, Holyoak, Nisbett, and Thagard (1986) on induction represent an important knowledge base for science education.

In The Development of Scientific Thinking Skills, Kuhn, et al. (1988) reduce the process of learning science to relating evidence with theory. By implication, they argue that this is, or should be, the focus of science learning for children. In coordinating theory and evidence they note that a fundamental ability is, "to think about a theory, rather than only think with it" (p. 219). Without an awareness of the theory, the individual is unable to assess the bearing of evidence on it. I think this is true whether the "theory" is consistent with scientifically-accepted knowledge or if the "theory" is based on misconceptions.

Each of us has theories and models that are used to interpret the world around us. These theories are based on a combination of knowledge derived from our sensory interaction with our physical world and from knowledge mediated by other persons. The misconceptions research clearly shows that regular science instruction has a modest effect in helping most students recognize the limitations in their conceptions of the world. Prescientific views of the world are indeed resistant to many and repeated efforts by science teachers, at least for modes of instruction not designed to specifically target the misconceptions.

Kuhn, et al. (1988) found that the situation is complex when subjects are asked to coordinate theory and evidence, with the majority of subjects unable to acknowledge discrepancies between the two. Many strategies were used by the subjects to maintain theory-evidence consistency, especially "adjusting" the evidence through selective attention or simply ignoring discrepant evidence entirely. When the theory was held less strongly, discrepant evidence was more effective in causing the subjects to alter the theory. Most interesting was Kuhn et al's. claim that the subjects did not seem to consciously acknowledge the adjustments in the theory:

> Thus, we witnessed the adjustment of theories to fit evidence, as well as the "adjustment" of evidence to fit theories, but in neither case is either the discrepancy itself or the adjustment made in response to it acknowledged by the subject, and the subject appears to lack conscious control of the operation of these adjustment mechanisms in his or her thinking. (Kuhn, Amsel, and O'Loughlin, 1988, p. 221).

Helping students gain conscious control of the "adjustment mechanisms" referred to by Kuhn et al. seems to me a critical goal for science education. Awareness of one's thought mechanisms would very likely contribute to changes in one's theories or models about how nature operates. By itself, metacognition is not a sufficient condition for changing misconceptions and developing more scientifically-accurate conceptions of nature, but the evidence suggests it is a necessary condition. Kuhn et al. (1988) note, "Making contact with these inferior strategies, and getting subjects to see their limitations, must be given as much, if not more, attention than developing new strategies that will replace them" (p. 233). Following this advice would require much greater emphasis, than is currently given, to teacher diagnosis of students' current knowledge states and related activities that help students become aware of the kinds of problems inherent in their conceptions of nature.

In the second part of this section on psychology the nature of, and research on, induction are briefly overviewed. Much of the content is drawn from the important work on induction by Holland, Holyoak, Nisbett, and Thagard (1986). In their excellent book, Holland et al. (1986) define the domain of induction as that which includes "all inferential processes that expand knowledge in the face of uncertainty" (p. 1). In spite of the obvious importance of inductive processes in scientific discovery, relatively little modern work in philosophy or psychology has been devoted to the study of induction. Popper (1961) and others since the 1930's discouraged its study in philosophy and the behaviorist tradition in America did the same for psychology during the first half of this century.

Holland et al's approach is decidedly computational, although their inquiry reflects the authors' fields of study (computer science, cognitive and social psychology, and philosophy of science) in a way that results in a broad-based, integrated theory of induction. Following the lead of Peirce and Dewey, they assume, "the central problem of induction is to specify processing constraints that will ensure that the inferences drawn by a cognitive system will tend to be plausible and relevant to the system's goals" (p. 5). Their emphasis on goals and context rather than the simple syntax of induction place their theory within the pragmatism concerned with problem solving and associated with Dewey and Peirce. One can see that their emphasis on goals and context is important in trying to make progress toward a unified theory or conception of thinking in science education. The goals of science and science education as well as the context in which science education occurs must be carefully considered.

Holland et al. (1986) tie induction very closely to problem solving, noting that their position is largely consistent with Newell and Simon's (1972) theory. However, they emphasize that, "It is now clear that general methods such as means-ends analysis are insufficient to account for expert problem-solving skill" (p. 10). They go on to say, "Human expertise is critically dependent on specialized methods and representations of knowledge about the relevant domain" (p. 10). This has been supported by many expert-novice studies, including the domains of physics (Larkin, McDermott, Simon, and Simon, 1980), chemistry (Camacho and Good, 1989), and biology (Smith and Good, 1984).

Holland et al. take the notion of mental model as the focus of their analysis of induction and problem solving. They prefer mental model over schema (or script, frame, and concept) because of its greater flexibility. Within the mental model notion are the necessary mechanisms for coordinating and integrating schemes, (or scripts, etc.) namely, condition-action (i.e., if-then) rules. Holland et al. stress the role of rules in what they call the most important learning mechanism, prediction:

> Rules are a natural vehicle for what we take to be the most fundamental learning mechanism: prediction-based evaluation of the knowledge store.... A rule that leads to a successful prediction should be strengthened some way, increasing the likelihood of its use in the future; one that leads to error should be modified or discarded. Predictions about the attainment of goals will normally be the most powerful source of feedback. (p. 16)

The central role of prediction in Holland et al's. theory of induction is analogous to the role of prediction in the science learning cycle described by Good (1987). Prediction-based evaluation of the knowledge store described by Holland et al. is precisely the mechanism inserted into the well-known science learning cycle, recently described in detail by Lawson, Abraham, and Renner (1989), by this author in order to encourage students in science classes to become more aware of their own conceptions and to put their conceptions (predictions) to the test in the science lab and with fellow students. It was hypothesized (Good and Lavoie, 1986) that a prediction-based learning cycle in science classes would offer the following advantages:

> 1) Students will be encouraged to organize their existing knowledge.
> 2) Students will become more aware of the diversity of opinions held by their peers.
> 3) There will be greater commitment by students to follow up on their efforts.
> 4) Teachers can use students' predictions to aid in assessment of their understandings.
> 5) Predictions can be used as a type of pretest by which to judge initial understanding and later progress. (pp. 24-35)

More will be said later in the paper about efforts to test these conjectures.

The final chapters of Induction: Processes of Inference, Learning, and Discovery by Holland et al. (1986) focus on analogy and scientific discovery, topics of great importance to science educators. The authors note that analogy is a top-down mechanism for constructing mental models and that, "Analogy differs from other generative mechanisms in that it is less directly focused on the current problem situation" (p. 288). Although the potential of analogical reasoning and problem solving has long been recognized it is only recently that considerable attention has been focused in this direction. Gick and Holyoak (1980) called attention to the difficulty problem solvers have in retrieving or noticing the relevance of source analogs unless someone (i.e., a teacher) calls attention to the analogy. This suggests that science curriculum materials and teacher education materials will have to assist students in their efforts to find and use analogies that might be useful in learning new science principles and concepts. More will be said of learning by analogy in the next section on machine learning.

In their chapter on scientific discovery, Holland et al. argue that scientific theories can be viewed as systems of rules in mental models and that analogy is the primary means of theory construction. They also note that central problems in the philosophy of science are, "continuous with key issues in cognitive psychology and artificial intelligence" (p. 335). Their observation supports my approach in this paper and, I think, should guide any attempt to formulate a unified conception of thinking for science education.

Holland et al. mention that the best known computational work on scientific discovery, i.e., the discovery of natural laws, is the BACON series of programs by Langley et al. (1987). In an earlier paper (Good, 1984), I reviewed that series of programs and noted that such computational analysis of the nature of scientific discovery had potential for aiding science educators in their work. What was apparent from the work reported by Langley et al. (1987) was that scientific discovery could be explained as a form of problem solving, reducing much of the mystery long associated with well-known discoveries of laws in science.

Artificial Intelligence

The third area that serves as a foundation for developing a unified conception of thinking in science education is artificial intelligence (AI). In an earlier paper (Good, 1987) I sketched an overview of AI and

ICAI (intelligent computer-assisted instruction) and identified machine learning as, "Probably the most difficult long-range problem facing the field of AI in general and ICAI in particular" (p. 337). The specific problem referred to here has been called "brittleness", or the rapid deterioration in the performance of expert systems when they face problems slightly outside their knowledge base. This section of the paper relies heavily on the two main texts on machine learning, both by the same authors, Michalski, Carbonel, and Mitchell (1983, 1986). The 40 or so authors who contributed to these two works include such well-known experts as John Anderson, Frederick Hayes-Roth, Dedre Gentner, John Holland, Douglas Lenat, Donald Michie, Allen Newell, Herbert Simon, and Patrick Winston.

An inspection of the contents of each of the texts on machine learning shows a concern with issues similar to those of concern to science education researchers interested in how people learn science. Learning by observation, analogy, and discovery are prominent among the various issues.

In the 1986 text the authors note that, "current AI systems have very limited learning abilities or none at all" (p. 4). The nearly total reliance on deductive rules prohibit the current systems to draw inductive inferences from the information provided. Errors are repeated endlessly. Since one of the most striking abilities of human intelligence is to improve with time, learning from errors along the way, it is fair to say that machines cannot be considered intelligent until they learn how to improve over time, adapting effectively to changing information environments.

Michalski, Carbonell, and Mitchell (1986) chose to define learning as, ..."constructing or modifying representations of what is being experienced" (p. 10). They clarify "experienced" by noting that internal thought processes can be the subject of learning, not just the sensory stimuli from the environment. Notice that from this definition of learning, constructing a representation of some "reality", rather than improving performance, becomes the focal point of the process.

Michalski et al. (1986) define the quality of learning in terms of three dimensions for evaluating the constructed representations: validity, effectiveness, and abstraction level. Validity is the degree of accuracy between representation and reality, effectiveness is a measure of how well the representation achieves a goal, and abstraction level defines the explanatory power of the representation. Recall in the section on philosophy of science that Schlagel (1986) referred to levels of reality (context) such as Newton's system for representing reality and Einstein's system for representing reality. Einstein's system achieved a higher level of abstraction and explanatory power.

The many different aspects of machine learning make it impossible to adequately summarize them in this brief paper but one set of programs is particularly relevant to science education. The four systems - BACON, GLAUBER, STAHL, and DALTON are described by Langley et al. (1986) in the 1986 text on machine learning. BACON focuses on the discovery of empirical laws by analyzing observational data GLAUBER formulates qualitative laws, STAHL infers the components of substances (in the chemical sense), and DALTON formulates structural models. Each of these components of scientific discovery is known to be an important part of the overall process and Langley et al. (1986) are interested in exploring the relations among the systems as well as refining each system.

The extent to which knowledge gained from machine learning systems such as these, relates to what we can do to help students learn science, remains to be seen. One thing that it seems to do is help to clarify the complex processes involved in something like scientific discovery. There are many other types of learning, but data-driven pattern search is clearly an important part of what most science educators say they value. An interesting theory by Margolis (1987) reduces cognition to pattern recognition and search, not a particularly new idea, but his development of the theory is interesting and consistent with the emphasis on data-driven machine learning systems researched by Langley et al. (1986).

I close this section by returning to the brittleness problem identified earlier. Holland (1986) analyzes the problem and concludes that, for machine learning, induction is the only way of making important advances. He specifies rule-based classifier systems as the inductive approach needed, noting a number of important differences with the normal rule-based expert systems. The details of his machine learning approach are not what I want to focus on here. What is important to recognize is that the brittleness problem is what is often called "lack of transfer" in human learning studies. Holland (1986) notes that, "when a system uses a model to generate expectations or predictions, it can use subsequent verification or falsification of the predictions to guide revisions of the model (toward better prediction)...." (p. 599). Holland recognizes that the key to escaping brittleness in a machine learning system is to focus on predictions using a model in order to verify or falsify. In the final section in this paper I use this focus on prediction to develop a model of science learning that reflects many of the ideas set forth earlier in this paper.

Putting It Together

My original thesis in this paper was that making progress toward a unified conception of thinking would require the kind of interdisciplinary approach represented by cognitive science. The disciplines I selected for this process, philosophy of science, cognitive psychology, and artificial intelligence, do not include all possible knowledge bases, but they include much of what I think is necessary to consider. Examples of work from social psychology and linguistics would undoubtedly make my plea for an interdisciplinary approach more appealing to a wider audience, but only so much can be attempted in a paper like this.

The thinking in science that I want to stress here is consistent with the positions in philosophy of science (Schlagel, 1986), cognitive psychology (Kuhn, Amsel, and O'Loughlin, 1988; Holland, Holyoak, Nisbett, and Thagard, 1986), and machine learning (Michalski, Carbonell, and Mitchell, 1983, 1986) that have been identified earlier in the paper. Each of these important works provides guidance for constructing a foundation designed to support a unified conception of thinking in science education.

It is not an accident that I ended the previous sentence with science education. The local or domain-specific knowledge of interest, such as physics, chemistry, biology, etc., will determine what kind of thinking is most appropriate for the learning task at hand. A unified conception of thinking in science education will be different than a unified conception of thinking in literature, history, economics, etc. because the knowledge base, heuristics for problem solving, etc. are different. Accepting this at the outset will make our task of achieving a unified conception of thinking in science education, a reasonable one. I acknowledge the work done by Sternberg (1986) and many others before him on identifying the common characteristics of human reasoning , but to proceed in a pragmatic way it is necessary to be specific in response to the question, "thinking about what"?

Of the many important ideas found in the five texts that I have focused on in this paper, there is one that is of particular interest to me. Holland et al. (1986), in their description of a framework for induction, identify the central characteristic of the dynamics of an effective inductive system. Part of the following quote was used in an earlier section of this paper.

> Rules are a natural vehicle for what we take to be the most fundamental learning mechanism: prediction-based evaluation of the knowledge store. A realistic inductive system cannot be expected to leap to optimal inductive inferences. There must be mechanisms that evaluate candidate structures, discarding some, storing others, and modifying those that already exist. The evaluation mechanism compares the predicted consequences of applying a knowledge structure with the actual outcome of that application. Condition-action rules are obviously well-suited for making predictions. A rule that leads to a successful prediction should be strengthened in some way, increasing the likelihood of its use in the future; one that leads to error should be modified or discarded. Predictions about the attainment of goals will normally be the most powerful source of feedback. (p. 16)

The mechanism of prediction is what I want to concentrate on in the remainder of this paper. An emphasis on this mechanism, prediction, should be incorporated into current learning and instructional theories in science education.

An overview of a learning theory that many science educators feel has promise for science education, was presented by Osborne and Wittrock (1983). Their Generative Learning Model has considerable appeal because it incorporates many of the important features of Piaget's constructionist approach, with some of the general ideas of information-processing theory, into a framework that is compatible with long-held ideas about the nature of science and science education. Their learning theory is generally compatible with an instructional theory that originated with Robert Karplus and his colleagues in their work with Science Curriculum Improvement Study in the early 1960's (see Lawson, Abraham, and Renner, 1989 for an excellent, in-depth overview of the learning cycle). The learning cycle has its roots mainly in the developmental work (genetic epistemology) of Jean Piaget, although the monograph by Lawson et al. (1989) provides an update and considers future directions.

The mechanism of prediction is not emphasized either in the generative learning theory or in the learning cycle approach to instruction. In addition to the evidence already presented in support of the central role of the mechanism of prediction in a science learning theory, I would like to describe an ongoing project designed to explore the role of prediction in science classrooms. Based on earlier ideas and research on the nature and use of prediction skills of high school biology students (Lavoie and Good, 1988), a group of university faculty and graduate students at Louisiana State University and secondary science teachers, began in 1987 to explore the role of prediction as part of an instructional strategy in middle grades physical sciences classes. As described in Good et al. (1988), the project was designed to explore the following questions:

1. Will students' prescientific concepts (misconceptions) be revealed in a modified learning cycle that uses prediction as the beginning phase?
2. Will students' predictions about common "science systems" (e.g., pendulum, electric circuit) encourage debate and argumentation prior to experimentation?
3. Does a prediction phase in a science learning cycle increase student involvement in exploration and later phases?
4. Can prediction sheets be used by science teachers as an effective tool to assess misconceptions held by students?
5. What factors seem to contribute to effective learning in science learning cycles with and without a prediction phase?

Question one has been answered affirmatively. By using prediction sheets based on the misconceptions research literature, teachers and students can become aware of specific conceptions held by students in the class. This is considered to be an important first step in helping students construct more scientifically-accurate concepts about nature. Work during the 1988-89 school year has expanded to other classrooms, including high school physics, to further test the feasibility of systematic use of prediction sheets with students. The results so far indicate an acceptance by teachers of regular use of prediction sheets by all students as a first step in identifying misconceptions. So questions one and four have been answered in the affirmative.

Question two is not as easy to answer with a clear-cut yes. Most of the results to this point indicate that it depends heavily on how the teacher chooses to use the prediction sheets. There seems to be much more success when teachers ask students to form groups of four or five students and discuss their predictions (after each student has completed a prediction sheet) than when whole-class discussions are attempted. It is clear that many students will defend their position vigorously. In one physics class during the small-group discussion phase, one student became so involved in argumentation about various predictions that she got up and left the group over a disagreement. I don't recall the last time I heard about a student in a science class (physics) getting so personally involved in a similar discussion that she or he took such a social risk. Although more data from different types of classrooms will be needed to test replicability of results, at this point I am confident that students' predictions about science systems in content areas like force, electricity, and heat, can be used by teachers to encourage discussion and debate among the students.

For question three, a qualified yes is the appropriate answer at this point. A formal prediction phase preceding lab work does seem to focus students' attention on investigations designed to test their predictions. Although this procedure emphasizes verification over pure discovery, it is important to recognize that students are testing or attempting to verify their predictions rather than an outside expert's assertions. This focuses on what Kuhn et al. (1988) stressed was the most important characteristic of science, theory-experiment coordination. The physical science teachers in eighth- and ninth-grade classes said their use of a prediction phase prior to lab work seemed to have a motivating and a focusing effect on their students, compared to classes that did not use a prediction phase.

Question five is a broad question that asks about factors, in addition to a prediction phase, that contribute to effective science learning. The many suggestions described in Lawson et al. (1989), Osborne & Wittrock (1983), and other documents on effective science strategies can be used to help answer this question. It is important to realize that any one technique or factor of interest, by itself, will not be enough to make overall, lasting differences in students' conceptions about and attitudes toward science. Treatment must be interpreted broadly, as in the science learning cycle (Lawson et al., 1989) and the generative learning theory (Osborne & Wittrock, 1983), if we are to achieve important, lasting improvements in science education.

I am convinced, for theoretical as well as empirical reasons, that a formal prediction phase is necessary in any science learning theory that focuses on students' prior conceptions. The multi-disciplinary approach that I have argued for in this paper is needed to establish a solid, consistent base for a unified theory of thinking in science education.

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