

8-15-1997

# A Human Learning Approach For Designing Adaptive Knowledge-Based Systems

Mukesh Rohatgi

*Old Dominion University, mxr100f@economy.bpa.odu.edu*

Follow this and additional works at: <http://aisel.aisnet.org/amcis1997>

---

## Recommended Citation

Rohatgi, Mukesh, "A Human Learning Approach For Designing Adaptive Knowledge-Based Systems" (1997). *AMCIS 1997 Proceedings*. 17.

<http://aisel.aisnet.org/amcis1997/17>

This material is brought to you by the Americas Conference on Information Systems (AMCIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in AMCIS 1997 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact [elibrary@aisnet.org](mailto:elibrary@aisnet.org).

# **A Human Learning Approach For Designing Adaptive Knowledge-Based Systems**

**Mukesh Rohatgi**

(mxr100f@economy.bpa.odu.edu)

IS Department, Old Dominion University

Norfolk, VA 23529

## **Abstract**

This paper explains our need for adaptive systems and outlines the conceptual model of a knowledge-based system that adapts through learning. The proposed model utilizes multiple human learning processes instead of ad hoc mathematical techniques to manifest its learning behavior. The incorporation of human learning processes in the design of machine learning systems is being referred to as "human learning approach."

## **Introduction**

Most computer-based systems are static in nature because their behavior is predetermined either by pre-planned software routines or by knowledge bases with unchanging knowledge content. Static systems have proven to be very brittle or short-lived when faced with changing demands of their environment. It has been claimed (Bruha, 1989) that in order to maintain their usefulness in dynamic environments, information systems should be adaptive, i.e., they should have the ability to change without being reprogrammed.

Systems can adapt either through learning or through evolution. In terms of time, learning mechanisms responsible for adaptation are more efficient when compared to slow evolutionary processes. The interest in creating learning systems dates back to mid-1950s but designers of computer-based learning systems have generally ignored existing research on human learning (Yadav, 1989). As a consequence, most learning systems in existence are (a) designed for specific applications, (b) rely on a single learning strategy, and (c) use mathematical techniques to support their learning mechanisms.

The purpose of this research is to show that it is feasible to utilize human learning processes as a basis for designing multistrategy machine learning systems capable of exhibiting adaptive behavior in dynamic environments. Our design philosophy calls for multiple learning processes derived from human learning behavior and is being referred to as the "human learning approach."

## **Rationale For Human Learning Approach**

The following assertions constitute our rationale for using "human learning approach" to design machine learning systems:

(a) Learning is among the most fundamental processes responsible for adaptation (Simon and Langley, 1989) implying that a learning system is also an adaptive system.

(b) Learning involves an interaction with the environment and results in acquisition of performance competencies to gain functional integration with the environment (Hunt and Sanders, 1986).

(c) Acquisition, modification, and discovery of knowledge are among the most fundamental aspects of a learning system (Michalski, 1986).

(d) Human learning is characterized by continuous interaction with the environment, knowledge acquisition, and knowledge manipulation (Barsalou, 1992; Gagne, 1986).

(e) Human beings are knowledge-intensive adaptive systems par excellence because they continuously attempt to achieve a better fit with their environments by acquiring, storing, and using vast amounts of complex knowledge (Barsalou, 1992).

Based on assertions (a) through (c) we can conclude the following:

Conclusion A. An adaptive computer-based system should be a learning system that interacts with its environment and gains functional integration with its environment through acquisition, modification, and discovery of knowledge.

Similarly, assertions (d) and (e) lead to the following conclusion:

Conclusion B. Human beings are adaptive systems because they have the capability to learn and their learning behavior is characterized by continuous interaction with their environment which results in acquisition, modification, and discovery of knowledge.

Similarities between the human learning behavior (conclusion B) and the requirements of a computer-based adaptive system (conclusion A) was the motivation behind the exploration of "human learning approach" for designing computer-based learning systems. The following subsections will briefly outline the conceptual development, implementation, and validation of "human learning approach" method for designing machine learning systems.

## Conceptual Model Of A Learning System Based On Human Learning

### **Approach**

A conceptual model for machine learning systems subscribing to the "human learning approach" was developed by operationalizing Gagne's human learning theory (Gagne, 1986). The operationalization was accomplished by creating a set of hierarchical learning levels that correspond to learning types observed in human beings (see Figure 1). The left column in Figure 1 lists the human learning types identified by Gagne, while the right column lists the corresponding learning levels appropriate for machine learning systems using the "human learning approach." There is a lack of one-to-one correspondence between the human learning types and the learning levels proposed for "human learning approach." This is because of the technological limitations involved in implementing

motor and sensory subsystems used by human beings to interact with their environment. Due to these limitations, the learning levels proposed for "human learning approach" should be interpreted differently. This is especially true for human learning types one through four. The following paragraph briefly outlines the functionality of each machine learning level shown in the right column of Figure 1.

Each learning level in the "human learning approach" model is responsible for acquiring, modifying or discovering a particular form of knowledge. Acquisition of descriptions corresponding to physical and conceptual object instances is accomplished by the object learning level while the association level is responsible for capturing relationships between two object types. The exemplar level attempts to capture knowledge that can be used to discriminate among similar object descriptions, whereas the concept level is responsible for creating a common description (a concept) for similar object descriptions. Principle learning is accomplished by generating complex concepts which are combinations of concept descriptions created at the concept or the prototype level. Finally, the knowledge acquired or discovered in form of object descriptions, relationship descriptions, concept descriptions, and conceptual combinations is used by the problem solving level either to revise, transform or to discover new concepts and principles.

Learning levels of the "human learning approach" hierarchy can also be understood as actions or processes invoked by a computer-based system to exhibit adaptive behavior through learning. The invocation sequence of these processes is determined by a control strategy which is similar to the hierarchical invocation sequence exhibited by human beings.

Initially, the control strategy for "human learning approach" invokes a lower level learning process (e.g., the process responsible for object learning) to acquire a lower level knowledge structure (e.g., an object description). The process continues by invoking higher level learning processes in succession to build higher level knowledge structures that are derived from knowledge structures acquired at lower levels. Any addition to the knowledge base, achieved either through acquisition, modification, or discovery initiates a new cycle of the invocation sequence.

GAGNE'S LEARNING TYPES	HLA LEARNING LEVELS
PROBLEM SOLVING	PROBLEM SOLVING LEVEL
PRINCIPLE LEARNING   LEVEL	CONCEPT COMBINATION
CONCEPT LEARNING	PROTOTYPE LEVEL
MULTIPLE DISCRIMINANT	EXEMPLAR LEVEL
VERBAL ASSOCIATION + CHAINING + STIMULUS RESPONSE	ASSOCIATION LEVEL
SIGNAL LEARNING	OBJECT LEVEL

Figure 1. Correspondence between Gagne's Human Learning Types and the Learning Levels of Human Learning Approach Model

### Validation Of Human Learning Approach

A prototype system called AKBS (Adaptive Knowledge-Based System) was implemented to demonstrate the feasibility of "human learning approach" design method. The concept of "human learning approach" for designing machine learning systems was validated through extensive experimentation with the prototype system. The purpose of experiments performed with the AKBS prototype was not only to demonstrate its learning capabilities but also to show that it has the capability to adapt its existing knowledge in the light of new inputs. It was shown that the prototype system is capable of exhibiting learning behavior by achieving the following:

- a. Acquisition of object descriptions;
- b. Acquisition of associative knowledge between object types;
- c. Learning of prototype-based concept descriptions;
- d. Dynamic updating of category prototypes with the acquisition of new knowledge;
- e. Discovering of complex concepts through conceptual combination;
- f. Dynamic updating of complex concepts to reflect the changes in the constituent concepts; and
- g. Using previously acquired, learned, or discovered knowledge to perform classification.

Object descriptions are acquired with the help of Object Level learning process within the context of a supervised learning environment. Instances described to the AKBS system can either belong to the same class or belong to many different classes. Each instance is described in terms of attribute-value pairs. For example, an instance belonging to the category ball may be described as  $object\_instance = \{(object\_type, physical), (label, ball), (color, blue), (shape, round), etc.\}$ . Descriptions with matching labels are agglomerated into a reduced exemplar representation (Barsalou, 1990) by the Exemplar Level learning process. Knowledge structures generated at the Exemplar Level serve as inputs for the Prototype Level learning process which abstracts the central tendency of category instances to generate a prototype-based concept description for each object class experienced by the AKBS system. Therefore, six instances, all labeled as ball, with three being red in color, two being green in color, and one being blue in color with rest of the attributes same as the instance described above will result in the generation of a prototype for the ball category and represented as  $prototype\_ball = \{(object\_type, physical), (label, ball), (color, red), (shape, round), etc.\}$ . Category prototypes are dynamically updated to reflect the new knowledge entering the knowledge base through the Object Level learning process. For example, if ten additional instances of green balls are described to the system then the color attribute of the prototype for ball will be updated to reflect the dominance of green color.

Attributes that belong to fewer than 10% of category instances are also dropped from the prototype description. Existence of multiple object categories in the AKBS knowledge base is required to trigger the Association Level or the Concept Combination Level learning process. The Association Level learning process works with rote learning mechanisms to acquire possible relationships that can exist between two objects. For example, the AKBS system can be told that a chair object and a table object are spatially related with each other.

On the other hand, the Concept Combination learning process uses a generative grammar to discover complex concepts which are combinations of two or more concepts. Therefore, the AKBS system is capable of combining concepts like flower and garden to generate a new complex concept called "flower garden" and heuristically discover a semantic interpretation for the concept by declaring that "flower garden" is a type of garden that contains (attribute) flowers (value).

The AKBS learning cycle culminates at the Problem Solving Level of the learning process hierarchy. Its purpose is to use the knowledge generated at the lower levels for solving problems by employing different problem-solving strategies. At present, the problem-solving capabilities of the AKBS system are limited to categorization. The reader can refer to Rohatgi (1994) for details regarding the classification experiments performed with the AKBS prototype system.

## **Conclusion**

The purpose of this paper was to suggest an alternate method for designing machine learning systems. The proposed method is significant in two aspects. It is significant

because the learning mechanisms used by the model are not ad hoc techniques specifically designed to optimize the performance of a learning system. Instead, the learning mechanisms are general and could function in any problem domain. The model is also significant because it supports multiple learning processes interlinked to achieve the overall goal of adaptability through acquisition, modification, and discovery of knowledge. Furthermore, the learning component is also integrated with a performance component through the problem solving processes embedded in the model.

## References

- Barsalou, L.W., "Cognitive Psychology: An Overview for Cognitive Scientists," Lawrence Erlbaum, Hillsdale, New Jersey, 1992.
- Barsalou, L. W., "On the Indistinguishability of Exemplar Memory and Abstraction in Category Representation," In *Advances in Social Cognition* (Vol. 3), T. K. Srull and R. S. Wyer (Eds.), Lawrence Erlbaum, Hillsdale, New Jersey, 1990.
- Bruha, I., "Defining Adaptive and Learning Systems," *Cybernetics and Systems: An International Journal* (20), 1989, pp. 77-88.
- Gagne, R. M., *The Conditions of Learning* (4th ed.), Holt, Rinehart, and Winston, New York, NY, 1986.
- Hunt, R.G. and Sanders, L.G., "Propaedeutics of Decision-Making: Supporting Managerial Learning and Innovation," *Decision Support Systems* (2), 1986, pp. 125-134.
- Michalski, R.S., "Understanding the Nature of Learning: Issues and Research Directions," In *Machine Learning: An Artificial Intelligence Approach* (Vol. 2), R.S. Michalski, J.G. Carbonell, and T.M. Mitchell (Eds.), Morgan Kaufmann Publishers, Palo Alto, CA, 1986.
- Rohatgi, M., "A human Learning Approach For Designing Adaptive Knowledge-Based Systems," Ph.D. Dissertation, Dept. of Information Systems, Texas Tech University, Lubbock, Texas, 1994.
- Simon, H.A. and Langley, P., "The Central Role of Learning in Cognition," In *Models of Thought* (Vol. 2), H.A. Simon (Ed.), 1989, pp. 102-115.
- Yadav, S. B., "A Human Learning Based Approach to Structuring and Acquiring Knowledge in Adaptive Knowledge-Based Systems," In *Proceedings of the Second Intl. Symp. on AI*, Monterrey, Mexico, Oct. 1989.