Title
The Role of Existing Knowledge in Generalization

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Consider what general lesson one might learn from these two examples:

In 1980, the US refused to sell grain to the Soviet Union if the Soviet Union did not withdraw its troops from Afghanistan. The Soviet Union paid a higher price to buy grain from Argentina and did not withdraw from Afghanistan.

In 1983, Australia refused to sell uranium to France, unless France ceased nuclear testing in the South Pacific. France paid a higher price to buy uranium from South Africa and continued nuclear testing.

Several generalizations are possible. One might learn "When an English-speaking nation threatens a country that exports arms, a country in the Southern Hemisphere will help out." Another might learn "When a country that exports a commodity supplied by several countries tries to coerce a country by refusing to sell the commodity, then the commodity will be purchased at a higher price from an alternate supplier." The latter rule is consistent with existing knowledge of economics and politics.

A number of psychological studies (e.g.., Hume and Pazzani, 1994; Murphy and Medin, 1985; Pazzani, 1991) have shown that concepts consistent with existing knowledge are easier for people to learn and are preferred to concepts not consistent with existing knowledge. Several researchers (e.g., Mitchell, Keller and Kedar-Cabelli, 1986; Pazzani and Kibler, 1992) have shown there is an advantage for computer learning algorithms in using existing knowledge to bias learning. A variety of different forms of existing knowledge have been identified in philosophy, psychology and artificial intelligence. These include:

- Knowledge of specific mechanisms: This includes knowledge of physical and social causality as well as predictive rules in economics, biology etc. The philosopher Kant pointed out the importance of this form of knowledge in perceiving causality. Pazzani (1991) describes a series of experiments that show the importance of knowledge of existing causal factors in human learning. This form of knowledge serves as the basis of the machine learning method called Explanation-Based Learning (Mitchell et al., 1986).

- General knowledge of causality: Shultz et al. (1986) have shown that even young children have a set of heuristics that help them learn new causal rules. Some of these heuristics are related to philosophical principles described by Hume. This form of knowledge was shown to be useful in OCCAM (Pazzani, 1990), a cognitive modeling system.

- Overhypotheses (Goodman, 1983): Overhypotheses represent a general form of knowledge, such as "All gemstones are uniform in color" that facilitate learning more specific rules, such as "All emeralds are green." Machine learning systems have exploited this type of knowledge in the form of determinations (Russell, 1989). A similar notion, knowledge of variability, has been shown experimentally to bias human learners (Holland et al., 1986).

Although it is generally agreed that these types of knowledge are used by human learners, there are a number of issues that require further research. For example, most cognitive models that use existing knowledge make the unrealistic assumption that this existing knowledge consists of logical rules described by necessary and sufficient conditions. In addition, adequate models have not yet been developed to explain how a learner initially acquires the knowledge that is used to constrain later learning.

References

Goodman, N. (1983). *Fact, fiction and forecast, fourth edition.* Cambridge, MA: Harvard University Press.

Holland, J., Holyoak, K., Nisbett, R., & Thagard, P. (1986). *Induction.* Cambridge, MA: MIT Press.

Hume, T. & Pazzani, M. (1994). *Learning sets of causally related concepts.* ICS TR-94-21, UC Irvine.

Mitchell, T., Keller, R., & Kedar-Cabelli, S. (1986). Explanation-based learning: A unifying view. *Machine Learning, 1,* 47–80.

Murphy, G., & Medin, D. (1985). The role of theories in conceptual coherence. *Psychology Review, 92.*

Pazzani, M. (1990). *Creating a memory of causal relationships: An integration of empirical and explanation-based learning* Hillsdale, NJ: Lawrence Erlbaum

Pazzani, M. (1991). The influence of prior knowledge on concept acquisition: Experimental and computational results. *Journal of Experimental Psychology: Learning, Memory & Cognition, 17, 3,* 416-432.

Pazzani, M., & Kibler, D. (1992). The role of prior knowledge in inductive learning. *Machine Learning.9.*

Russell, S. (1989). *Analogical and inductive reasoning.* London: Pitman Press.

Shultz, T., Fisher, G., Pratt, C., & Rulf, S. (1986). Selection of causal rules. *Child Development, 57.*