Learning Representation by Integrating Case-based and Inductive Learning

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This paper describes a machine learning approach combining case-based reasoning with inductive learning in order to learn representation of problem solving context. The essence of this approach is the use of conceptual clustering to both facilitate efficient retrieval of cases and to induce concepts representing generalizations of context. In addition, learning by examples is used to acquire rules to guide adaptation of retrieved cases. The concepts induced via clustering are used to represent generalized context in the learning and application of acquired adaptation rules.

Machine Learning supports the solution of complex reasoning tasks by capturing knowledge of how similar problems were previously solved. Such knowledge is often local, suggesting how to solve parts of the problem independent of the other parts of the problem or their solutions. A major source of complexity in these problems, however, is the interaction between the different parts of the problem. To avoid this problem, the overall problem solving context must be taken into account when solving the individual parts of the problem. This requires representing and reasoning about context.

The case-based reasoning approach to learning addresses this issue by retrieving an entire solution to a problem similar to the current one and adapting it to the new problem. This approach, however, can only represent context in its most specific form — a specific case. The knowledge contained in a case is only known to be valid in this case's problem solving context and it is unclear how to transfer this knowledge to another context. Our approach combines case-based reasoning and inductive learning to learn a more general representation of context:

- Our case memory is organized using conceptual clustering. Classes are formed by hierarchically clustering cases to minimize intra-cluster distance and maximize inter-cluster distance. Describing each class is a COBWEB-style *probabilistic concept*, containing conditional probabilities of each attribute-value assignment given the class. This allows individual cases to be matched against clusters allowing efficient case-memory update and retrieval by recursively searching the hierarchy.

- Case adaptation is guided by heuristics which are acquired via supervised learning. Terms in the conditions of adaptation rules are represented using version spaces which are refined via Mitchell's candidate elimination algorithm.

- Classes formed by clustering cases in the case memory are used to represent generalizations of context. Together, the induced concepts and the induced hierarchy form a language which can be used for reasoning about context. Concepts from this language appear in the conditions of adaptation rules, restricting application of these rules to the appropriate context. The induced hierarchy allows the context portion of these rules to be generalized using the candidate elimination algorithm.

The induced concept language described above and particularly the induced generalization hierarchy allow us to efficiently represent and search the hypothesis space using version spaces. This use of a restrictive language to constrain learning is an example of inductive bias. We are, in effect, using the self-organizing characteristics of our case memory to perform constructive induction and learn inductive bias.