Meta-Combiner

A *meta-combiner* is a form of ►ensemble learn-ing technique used with ►missing attribute val-ues. Its common topology involves base learners and classifiers at the first level, and meta-learner and meta-classifier at the second level. Th e meta-classifier com-bines the decisions of all the base classifiers.

Metaheuristic

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A metaheuristic is a set of concepts that can be used to define heuristic methods that can be applied to a wide set of different problems. In other words, a metaheuristic can be seen as a general algorithmic framework that can be applied to different optimization problems with relatively few modifications. Examples of metaheuristics include simulated annealing, tabu search, iterated local search, evolutionary algorithms, and ant colony optimization.

Metalearning

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Synonyms

Adaptive learning; Dynamic selection of bias; Learning to learn; Ranking learning methods; self-adaptive systems

Definition

Metalearning allows machine learning systems to benefit from their repetitive application. If a learning system fails to perform efficiently, one would expect the learning mechanism itself to adapt in case the same task is presented again. Metalearning differs from base-learning in the scope of the level of adaptation; whereas learning at the base-level is focused on accumulating experience on a specific task (e.g., credit rating, medical diagnosis, mine-rock discrimination, fraud detection, etc.), learning at the metalevel is concerned with accumulating experience on the performance of multiple applications of a learning system.

Briefly stated, the field of metalearning is focused on the relation between tasks or domains, and learn-ing algorithms. Rather than starting afresh on each new task, metalearning facilitates evaluation and comparison of learning algorithms on many different previous tasks, establishes benefits and disadvantages, and then recommends the learning algorithm, or combination of algorithms that maximizes some utility function on the new task. Th is problem can be seen as an algorithm selection task (Rice, 1976).

The utility or usefulness of a given learning algorithm is often determined through a mapping between characterization of the task and the algorithm's estimated performance (Brazdil & Henery, 1994). In general, met-alearning can recommend more than one algorithm. Typically, the number of recommended algorithms is significantly smaller than the number of all possible (available) algorithms (Brazdil, Giraud-Carrier, Soares, & Vilalta, 2009).

Motivation and Background

The application of machine learning systems to ►classification and ►regression tasks has become a standard, not only in research but also in commerce and industry (e.g., finance, medicine, and engineering). However, most successful applications are custom-designed, the result of skillful use of human exper-tise. This is due, in part, to the large, ever increasing number of available machine learning systems, their relative complexity, and the lack of systematic meth-ods for discriminating among them. Th e problem is further compounded by the fact that, in ►Knowledge Discovery from Databases, each operational phase (e.g., preprocessing, model generation) may involve a choice among various possible alternatives (e.g., progressive vs. random sampling, neural network vs. decision tree learning), as observed by Bernstein, Provost, and Hill (2005).