Meta learning

Meta learning is a subfield of machine learning where automatic learning algorithms are applied to metadata about machine learning experiments. As of 2017 the term had not found a standard interpretation, however the main goal is to use such metadata to understand how automatic learning can become flexible in solving learning problems, hence to improve the performance of existing learning algorithms or to learn (induce) the learning algorithm itself, hence the alternative term **learning to learn**.

Flexibility is important because each learning algorithm is based on a set of assumptions about the data, its inductive bias.[3] This means that it will only learn well if the bias matches the learning problem. A learning algorithm may perform very well in one domain, but not on the next. This poses strong restrictions on the use of machine learning or data mining techniques, since the relationship between the learning problem (often some kind of database) and the effectiveness of different learning algorithms is not yet understood.

By using different kinds of metadata, like properties of the learning problem, algorithm properties (like performance measures), or patterns previously derived from the data, it is possible to learn, select, alter or combine different learning algorithms to effectively solve a given learning problem. Critiques of meta learning approaches bear a strong resemblance to the critique of metaheuristic, a possibly related problem. A good analogy to meta-learning, and the inspiration for Jürgen Schmidhuber's early work (1987) and Yoshua Bengio et al.'s work (1991), considers that genetic evolution learns the learning procedure encoded in genes and executed in each individual's brain. In an open-ended hierarchical meta learning system[1] using genetic programming, better evolutionary methods can be learned by meta evolution, which itself can be improved by meta meta evolution, etc.