**Introduction**

**The first reason is statistical**.

A learning algorithm can be viewed as searching a space H of hypotheses to identify the best hypothesis in the space. The statistical problem arises when the amount of training data available is too small compared to the size of the hypothesis space.

**The second reason is computational.**

Many learning algorithms work by performing some form of local search that may get stuck in local optima. For example, neural network algorithms employ gradient descent to minimize an error function over the training data, and decision tree algorithms employ a greedy splitting rue to grow the decision tree. In case where there is enough training data (so that the statistical problem is absent), it may still very difficult computationally for the learning algorithm to find the best hypothesis.

**The third reason is representational.**

In the most applications of machine learning, the true function f cannot be represented by any of the hypotheses in H. By forming weighted sums of the hypotheses drawn from H, it may be possible to expand the space of representable functions.

Diagram

Description automatically generated

**Methods for Constructing Ensembles**

1. **Bayesian Voting**
2. **Manipulating the Training Examples**
3. **Manipulating the Input Feature**
4. **Manipulating the Output Targets**
5. **Injecting Randomness**

**Comparing Different Ensembles Methods**

**Conclusions**

**Ensembles are well-established as a method for obtaining highly accurate classifiers by combining less accurate ones. This paper has provided a brief survey of methods for constructing ensembles and reviewed the three fundamental reasons why ensemble methods are able to out-perform any single classifier within the ensemble. The paper has also provided some experimental results to elucidate one of the reasons why AdaBoost performs so well.**