

THREE PAPERS ON BOOSTING: AN INTRODUCTION

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The notion of boosting originated in the Machine Learning literature in the 1980's [4]. The goal of boosting is to improve the generalization performance of weak (or base) learning algorithms by combining them in a certain way. The first algorithm of this type was discovered by Schapire [3] and then the second one by Freund [1]. Schapire and Freund [2] came up with the idea of a more practical version of boosting and invented the algorithm called AdaBoost that combines simple classification rules into much more powerful and precise classification algorithms. For a fixed number of iterations, AdaBoost runs the weak (or base) learning algorithm on resampled original data sets in a sequential manner and then combines the resulting learning algorithms through a weighted summation at the end of the iteration. Gradually, it became clear that AdaBoost is a special case of a more general statistical methodology of combining simple estimates in classification or regression into more complex and more precise ones. The study of statistical properties of these methods has been conducted in several directions since then in both the machine learning and statistics communities.

The problem of consistency of AdaBoost is posed by Leo Breiman in the first paper in this issue of *The Annals of Statistics*. Breiman studies one ingredient needed to prove the consistency, the convergence properties of AdaBoost as a numerical method in the population case. This paper has been circulated for a couple of years as a preprint and its results were also covered in the Wald Lectures delivered by Breiman at the IMS Annual Meeting in 2002 in Banff, Canada. The papers by Jiang, Lugosi and Vayatis, and Zhang, published below with discussions, consider various versions of boosting and give answers to the consistency question posed by Breiman.

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Received May 2003; revised May 2003.