The Third Pao-Lu Hsu Lecture on Statistical Machine Learning

The MOE-Microsoft Key Laboratory of Statistics and Information Technology of Peking University organizes a lecture series to promote the research on statistical learning.

Several times a year, an eminent person from China or abroad, in statistics, machine learning, data mining, pattern recognition, and other related fields will be invited to give a talk.

Students, researchers, and community members are welcome to attend. The lectures are free of charge.

We are pleased and honored to have Prof. Peter Bartlett from UC Berkeley to give the third talk, as described below.

Time: 2:00pm-3:00pm, July 14, 2010
Place: Lijiao Building 103, Peking University (北京大学理教103)
Joint Lab Web Site: http://iria.pku.edu.cn/PMSIT/

Talk: Optimal Online Prediction in Adversarial Environments
Speaker: Prof. Peter Bartlett (Statistics and EECS, UC Berkeley)

Abstract:
In many prediction problems, including those that arise in computer security and computational finance, the process generating the data is best modeled as an adversary with whom the predictor competes. The predictor's aim is to minimize the regret, or the difference between the predictor's performance and the best performance among some comparison class, whereas the adversary aims to maximize the predictor's regret. Even decision problems that are not inherently adversarial can be usefully modeled in this way, since the assumptions are sufficiently weak that effective prediction strategies for adversarial settings are very widely applicable.

The first part of this talk presents two examples of online decision problems of this kind: a resource allocation problem from computational finance and a reactive approach to managing an enterprise's information security risks. In both cases, we present efficient strategies with near-

optimal performance.

The second part of the talk presents results on the regret of optimal strategies. These results are closely related to finite sample analyses of prediction strategies for probabilistic settings, where the data are chosen iid from an unknown probability distribution. In particular, we show that the optimal online regret is closely related to the behavior of empirical minimization in a probabilistic setting, but with a non-iid stochastic process generating the data. This allows the application of techniques from the analysis of the performance of empirical minimization in an iid setting, which relates the optimal regret to a measure of complexity of the comparison class that is similar to the Rademacher averages that have been studied in the iid setting.

Bio:

Peter Bartlett is a professor in the Computer Science Division and the Department of Statistics at the University of California at Berkeley. He is the co-author, with Martin Anthony, of the book Learning in Neural Networks: Theoretical Foundations, has edited three other books, and has co-authored many papers in the areas of machine learning and statistical learning theory. He has served as an associate editor of the journals Machine Learning, Mathematics of Control Signals and Systems, the Journal of Machine Learning Research, the Journal of Artificial Intelligence Research, and the IEEE Transactions on Information Theory, as a member of the editorial boards of Machine Learning, the Journal of Artificial Intelligence Research, and Foundations and Trends in Machine Learning, and as a member of the steering committees of the Conference on Computational Learning Theory and the Algorithmic Learning Theory Workshop. He has consulted to a number of organizations, including General Electric, Telstra, Polaris Wireless and SAC Capital Advisors. In 2001, he was awarded the Malcolm McIntosh Prize for Physical Scientist of the Year in Australia, for his work in statistical learning theory. He has been a Miller Institute Visiting Research Professor in Statistics and Computer Science at U.C. Berkeley, a fellow, senior fellow and professor in the Research School of Information Sciences and Engineering at the Australian National University's Institute for Advanced Studies, and an honorary professor in the School of Information Technology and Electrical Engineering at the University of Queensland. His research interests include machine learning, statistical learning theory, and adaptive control.