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Publication Date:
2018-02

Permanent Link:
https://doi.org/10.3929/ethz-b-000245071 →

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International Zurich Seminar on Information and Communication (IZS), February 21 – 23, 2018

Universal Batch Learning — Information Theoretical View

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Abstract

Universal learning with log-loss discussed in this talk follows information theoretical concepts of universal prediction and universal compression. However, the fact that in learning problems data features are given and the goal is to predict the outcome, requires an extension of the theory. In previous work we analyzed on-learning, so in this talk we focus on universal batch learning. In the stochastic setting we propose a minimax universal learning solution that minimizes the worst case log-loss regret. The resulting universal learning solution is a mixture over the models in the considered class. Utilizing the minimax theorem and information-theoretical tools, we also come up with a redundancy capacity theorem and an upper bound on the performance of the optimal solution. This performance bound on the generalization error decays as $O(\log N/N)$, where N is the sample size, instead of $O\left(\sqrt{\log N/N}\right)$ that I attained in statistical learning theory. Finally, we propose a setting for universal batch learning in the individual setting, based on the leaving-one-out (LOO) principle, and show its performance in some batch learning examples.