



THE WEIZMANN INSTITUTE OF SCIENCE  
FACULTY OF MATHEMATICS AND COMPUTER SCIENCE

Machine Learning and Statistics Seminar

Room 1 ,Ziskind Building  
on Wednesday, Dec 13, 2017  
at 11:15

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Overcoming Intractability in Learning

Abstract:

Machine learning has recently been revolutionized by the introduction of Deep Neural Networks. However, from a theoretical viewpoint these methods are still poorly understood. Indeed the key challenge in Machine Learning today is to derive rigorous results for optimization and generalization in deep learning. In this talk I will present several tractable approaches to training neural networks. At the second part I will discuss a new sequential algorithm for decision making that can take into account the structure in the action space and is more tuned with realistic decision making scenarios.

I will present our work that provides some of the first positive results and yield new, provably efficient, and practical algorithms for training certain types of neural networks. In a second work I will present a new online algorithm that learns by sequentially sampling random networks and asymptotically converges, in performance, to the optimal network. Our approach improves on previous random features based learning in terms of sample/computational complexity, and expressiveness. In a more recent work we take a different perspective on this problem. I will provide sufficient conditions that guarantee tractable learning, using the notion of refutation complexity. I will then discuss how this new idea can lead to new interesting generalization bounds that can potentially explain generalization in settings that are not always captured by classical theory.

In the setting of reinforcement learning I will present a recently developed new algorithm for decision making in a metrical action space. As an application, we consider a dynamic pricing problem in which a seller is faced with a stream of patient buyers. Each buyer buy at the lowest price in a certain time window. We use our algorithm to achieve an optimal regret, improving on previously known regret bound.