On the relationship between structure in the data and what deep learning can learn

Abstract:

The past five years have seen a dramatic increase in the performance of recognition systems due to the introduction of deep architectures for feature learning and classification. However, the mathematical reasons for this success remain elusive. In this talk we will briefly survey some existing theory of deep learning. In particular, we will focus on data structure based theory and discuss two recent developments.

The first work studies the generalization error of deep neural network. We will show how the generalization error of deep networks can be bounded via their classification margin. We will also discuss the implications of our results for the regularization of the networks. For example, the popular weight decay regularization guarantees the margin preservation, but it leads to a loose bound to the classification margin. We show that a better regularization strategy can be obtained by directly controlling the properties of the network's Jacobian matrix.

The second work focuses on solving minimization problems with neural networks. Relying on recent recovery techniques developed for settings in which the desired signal belongs to some low-dimensional set, we show that using a coarse estimate of this set leads to faster convergence of certain iterative algorithms with an error related to the accuracy of the set approximation. Our theory ties to recent advances in sparse recovery, compressed sensing and deep learning. In particular, it provides an explanation for the successful approximation of the ISTA (iterative shrinkage and thresholding algorithm) solution by neural networks with layers representing iterations.

Joint work with Guillermo Sapiro, Miguel Rodrigues, Jure Sokolic, Alex Bronstein and Yonina Eldar.