Modern machine learning models such as deep networks typically contain more parameters than training data. While this overparameterization results in ill-posed problems, these models often perform well in practice and are successfully deployed in data-driven applications. In this talk I will present theoretical results demystifying this success. We show that, neural networks trained by the gradient based algorithms (1) are provably robust to noise/corruption on a constant fraction of the labels and (2) provably generalize to test data despite overparameterization. We discuss the role of the dataset and model for driving such desirable behavior.

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