This dissertation studies a fundamental open challenge in deep learning theory, christened "the generalization puzzle". Central to the tremendous empirical success of deep learning is the ability of massively overparameterized deep networks (i.e., networks with millions of more parameters than training datapoints) to learn patterns from training data that generalize well to test data. This success however flies in the face of classical learning theory which suggests that such complex overparameterized models should generalize miserably. What explains this counterintuitive behavior?

A natural approach to deciphering this puzzle is to use the learning-theoretic tool of uniform convergence to derive generalization bounds that depend on some parameter-count-independent measure of complexity of deep networks.

We pursue this direction in the first part of this thesis, by studying measures of complexity such as distance from initialization and the width of the minimum found in the training loss. We relate these quantities to generalization bounds with improved dependencies on the parameter count.

In the second part of the thesis however, we take a step back from the above pursuit and cast doubt on the ability of uniform convergence bounds to explain generalization in deep learning. Specifically, we show that in some example deep learning settings, uniform convergence bounds cannot do any better than providing a vacuous (i.e., uninformative) generalization bound.

Keeping in mind this negative result, for future work, we first propose to understand the failure of uniform convergence in simpler setups (e.g., one with a "linearized" network). Then, in such a setup, we would like to overcome the failure of uniform convergence at least under milder constraints (e.g., derive meaningful bounds assuming access to extra unlabeled data). This exploration would then hopefully spark new ideas on how to go beyond the limits of uniform convergence to explain generalization in the standard deep learning setting.

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Thesis Summary:
https://drive.google.com/open?id=1NtzYDghbvnQbZVRC2Kvh8P8WzQ3Qi32