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# Generalization in deep nets: an empirical perspective

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**Abstract:** The power of neural networks lies in their ability to perform well on data that wasn't seen during training, a phenomena known as "generalization." Classical learning theory predicts that models generalize when they are under-parameterized, i.e., when the training set contains more samples than the number of model parameters. But strangely, neural nets generalize even when they have many more parameters than training data, and the underlying reasons for this good behavior remain elusive. Numerous rigorous attempts have been made to explain generalization, but available bounds are still quite loose, and analysis does not always lead to true understanding. The goal of this talk is to make generalization more intuitive. Using visualization methods, we discuss the mystery of generalization, the geometry of loss landscapes, and how the curse (or, rather, the blessing) of dimensionality causes optimizers to settle into minima that generalize well.