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Generalization limits of deep neural networks in identity effects learning

A key open problem in the mathematical foundations of deep learning is understanding *generalization*, informally defined as the ability of neural networks to successfully perform a given task outside the training set. Motivated by this challenge and by applications to cognitive science, we consider the problem of learning *identity effects*, i.e., classifying whether a pair of objects is identical or not, and present a theory aimed at rigorously identifying the generalization limits of deep learning for this task.

First, we will illustrate a general *rating impossibility* theorem that identifies settings where machine learning algorithms are provably unable to generalize outside the training set. Then, we will show how to apply this theorem to popular deep learning architectures such as feed-forward, recurrent and graph neural networks trained via stochastic gradient descent or Adam. For graph neural networks, we will also present a *rating possibility* theorem that establishes sufficient conditions for the existence of architectures able to generalize outside the training set. Finally, we will illustrate numerical experiments that either validate our theoretical findings or identify gaps between theory and practice.

This presentation is based on joint work with Giuseppe A. D'Inverno, Matthew Liu, Mirco Ravanelli, and Paul Tupper.