Learning through atypical “phase transitions” in overparameterized neural networks

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One of the most debated themes in machine learning is how to characterize deep neural network performances. These are highly overparameterized devices in which the number of parameters far exceed the number of data points whose abilities can be studied in terms of the structure of the loss landscape and by focusing on how the learning algorithms minimizing the loss affect their generalization properties. In this talk I will specialize on a non-convex model of random features (i.e. a two layer neural network) in order to shed new light on the mistery of overparameterization: given the large amount of connection weights to be adjusted, one would expect them to overfit the training dataset but, surprisingly, this is not the evidence. Once the choice of model has been justified, I will illustrate why having a way to geometrically characterize solutions in the energy landscape in terms of their stability parameter is highly correlated with the network performances. Thus, with the support of an analytical conjecture, we identify a novel (non-equilibrium) phase transition in the geometrical structure of the error counting loss, i.e. what we call the "Local Entropy" transition. It is controlled by the degree of overparameterization of the system and is definitely different from the common SAT/UNSAT threshold. It coincides wih the detection of locally entropic minima of solutions which seems to be highly attractive to the learning algorithms exhibiting good generalization properties.