Statistical Physics of Energy-Based generative models

Energy-based models (EBMs) are powerful generative machine learning models that are able to encode the complex distribution of a dataset in the Gibbs-Boltzmann distribution of a model energy function. This means that, if properly trained, they can be used to synthesize new samples that resemble those of the dataset as closely as possible, but also that this energy function can be used to "learn" something about the building mechanisms of the dataset under study. Indeed, EBMs can be considered a powerful modeling tool for arbitrary data if one were able to map complex energy functions defined in a neural network into spin-interaction Hamiltonians that can be explored using standard statistical physics tools. Such an approach has long been used in physics for inverse Ising problems. The goal now is to extend this approach to more complex energy functions that can encode all higher order correlations in complex data. While this program is very encouraging, training good EBMs is particularly challenging, mainly because they rely on long Monte Carlo sampling processes to estimate the log-likelihood gradient. In my talk, I will present some results on the interpretability of shallow EBMs and discuss how computational statistical physics is a valuable tool for understanding and improving and controlling the training of EBMs.

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