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Learning Maximal Entropy Models from finite size datasets: a fast Data-Driven algorithm allows to sample from the posterior distribution.[1] ULISSE FERRARI, Institut de la Vision, Sorbonne Universités, UPMC, INSERM U968, CNRS, UMRΩ_{-}, Paris, F-75012, France. — A maximal entropy model provides the least constrained probability distribution that reproduces experimental averages of an observables set. In this work we characterize the learning dynamics that maximizes the log-likelihood in the case of large but finite datasets. We first show how the steepest descent dynamics is not optimal as it is slowed down by the inhomogeneous curvature of the model parameters space. We then provide a way for rectifying this space which relies only on dataset properties and does not require large computational efforts. We conclude by solving the long-time limit of the parameters dynamics including the randomness generated by the systematic use of Gibbs sampling. In this stochastic framework, rather than converging to a fixed point, the dynamics reaches a stationary distribution, which for the rectified dynamics reproduces the posterior distribution of the parameters. We sum up all these insights in a "rectified" Data-Driven algorithm that is fast and by sampling from the parameters posterior avoids both under- and over-fitting along all the directions of the parameters space. Through the learning of pairwise Ising models from the recording of a large population of retina neurons, we show how our algorithm outperforms the steepest descent method.

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