Title: Efficient encoding and decoding: a variational autoencoder framework

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The efficient coding approach proposes that neural systems represent as much sensory information as biological constraints allows. It aims at formalizing encoding as a constrained optimal process. A different approach, that aims at formalizing decoding, proposes that neural systems instantiate a generative model of the sensory world. Here, we put forth a normative framework that characterizes neural systems as jointly optimizing encoding and decoding. It takes the form of a variational autoencoder: sensory stimuli are encoded in the noisy activity of neurons to be interpreted by a flexible decoder; encoding must allow for an accurate stimulus reconstruction from neural activity. Jointly, neural activity is required to represent the statistics of latent features which are mapped by the decoder into distributions over sensory stimuli; decoding correspondingly optimizes the accuracy of the generative model. This framework results in a family of encoding-decoding models, indexed by a measure of the stimulus-induced deviation from spontaneous activity, which result in equally accurate generative models. Each member of this family predicts a specific relation between properties of the sensory neurons—such as the arrangement of the tuning curve means (preferred stimuli) and widths (degrees of selectivity) in the population—as a function of the statistics of the sensory world. Our approach thus generalizes the efficient coding approach. Notably, here, the form of the constraint on the optimization derives from the requirement of an accurate generative model, while in efficient coding models it is defined arbitrarily. Finally, we characterize the family of models we obtain through other measures of performance, such as the error in stimulus reconstruction. We find that a range of models admit comparable maximal performance; in particular, a population of sensory neurons with broad tuning curves as observed experimentally can yield both low reconstruction stimulus error and an accurate generative model.