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L^p Metric Criteria For Directed Convergence

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We discuss a new form of Bayesian inference where the object is to resolve stable substructures in a given environment, such as a feature or a system of related features. This is in contrast to classical statistical inference where the object is to infer overall statistics of the environment. The method, called *directed convergence strategy* employs metric criteria to accept or reject instantaneous input measures, in order to facilitate the convergence of a sequence of instantaneous conclusion measures. The limit measure is the stable resolved structure. Another difference between classical Bayesian inference and directed convergence is that now we no longer view the prior as being fixed. In fact, at each stage the current conclusion serves as a new prior for the purpose of calculating the Bayesian posterior to be used for the next updating. This, together with the selective acceptance of inputs, facilitates convergence. The appropriate type of convergence in this context is weak convergence of probability measure. But it is more computationally efficient to represent measures 'locally' as their Radon-Nikodym derivatives, and then formulate criteria for directed convergence (i.e., for acceptance or rejection of input measures), in terms of L^p metrics. In this article we show that such a formulation is possible, in fact we develop specific L^p criteria for directed convergence. This work generalizes L^∞ criteria for directed convergence obtained by Bennett and Cohen.