Bayesian decision making using neural fields

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Abstract

Bayesian statistics has become a popular framework in various fields of experimental psychology such as signal detection theory, speech recognition, cue integration and decision making. However, it is still an open question how the human brain actually incorporates this functionality. One assumption is that the activities of populations of neurons encode probability distributions. Indeed, it has been shown that probabilistic decoding of neuronal activities can be used to predict overt behaviour in rat [5] and monkey [1]. However, in order to make statistically optimal decisions it is not only necessary to represent probability distributions, but also to transform likelihoods into beliefs (via Bayes' rule) and propagate beliefs between different levels of representation (via the marginalisation rule). Unlike biological neurons, Bayesian statistics does not involve any temporal dynamics. For example, Bayes' rule will fail for temporally misaligned signals. There are several theoretical extensions like hidden Markov models and dynamic Bayesian networks that remedy this situation, but again it is unclear how such mechanisms could be incorporated in the human brain.

Another approach is to implement decision making using neural fields, which have been applied successfully for explaining behavioural data [2, 6] and, in robotics, for dealing with complex uncertain environments [4]. Neural fields posses spatial structure and temporal dynamics similar to biological neural populations and, thus, provide temporal dynamics in a natural way. However, they do not necessarily incorporate Bayesian statistics. Here we show how two fundamental statistical laws (Bayes' rule and the marginalisation rule) can be implemented using neural fields. The result is a truly dynamic framework capable of Bayesian decision making, which is biologically plausible and which can easily be extended with non-Bayesian mechanisms such as learning and memory. We also show how this can be used in a model of goal inference and joint reasoning [3] in which Bayesian statistics is used to model decision making.

Keywords: Bayesian statistics; neural fields; decision making; goal inference

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