Summary of *A tutorial on the free-energy framework for modelling perception and learning* by Rafal Bogacz

Marco Casari

University of Turin

Complex system in neuroscience, 12 December 2023

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1. Prior predictions are compared to stimuli and the model parameters are updated considering prediction errors, features corresponding to receptive fields in the the primary sensory cortex are learned.
2. Weight stimuli by their noise, learn features using their covariance, implement attentional modulation changing the variance of attended features.
3. Synaptic strenght is changed proportionally to activities of pre-synaptic and post-synaptic neurons.
4. Minimization of free energy can be seen as the base of many theories of perception.

Working hypotheses

- Local computation.

1. The state of a neuron is determined only by the synaptic weight and the state of its input neurons.

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3. The state of a neuron is the result of the application of a monotonic function to the linear combination of states and synaptic weights of input neurons.

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1. The model describes the inference of a single variable from a single sensory input.
2. In general inferred variable and sensory input are related by some smooth function.
3. Sensory input and stimulus are drafted from the same space.
4. Information gained and constantly updated from previous experience.

Exact solution of the inference problem

- Bayes theorem:

$$p(v|u) = \frac{p(v)p(u|v)}{p(u)} \quad . \tag{1}$$

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2. In general marginal likelihood is difficult to evaluate.
3. Complex calculations and infinite nodes are needed to represent each value of the posterior.

Approximated solution of the inference problem

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Neural implementation

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Learning model parameters

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Learning relation between variable and stimulus

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└─Single variable model
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Free energy framework

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Multiple variables model

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Learning parameters

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Hierarchical structure implementation

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Recover local plasticity

Conclusion