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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- In this presentation the main topics of the paper are presented, in the same order they appear in the paper.

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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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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 to the inference problem

- Bayes theorem:

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

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1. Knowledge of feature depending on a given stimulus is the posterior. Prior knowledge on the feature is the prior, distribution of stimulus is the likelihood.
2. In general, marginal likelihood is difficult to evaluate.
3. Complex calculations and infinite nodes are needed to represent each value of the posterior.

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- Most likely value of the feature is a scalar variable $\phi \in \Omega_v$.

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1. Evaluating the mode of the posterior instead of the whole function is more biologically plausible.
2. The most likely feature value is the fixed point of the gradient descent method applied to the negative free energy.
3. Prediction errors are introduced as new variables to extend the dynamical system and satisfy Hebbian plasticity.

Neural implementation

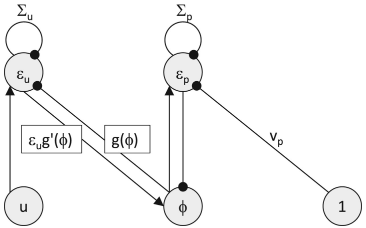
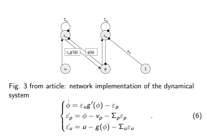


Fig. 3 from article: network implementation of the dynamical system

$$\begin{cases} \dot{\phi} = \varepsilon_u g'(\phi) - \varepsilon_p \\ \dot{\varepsilon_p} = \phi - v_p - \Sigma_p \varepsilon_p \\ \dot{\varepsilon_u} = u - g(\phi) - \Sigma_u \varepsilon_u \end{cases} . \tag{6}$$



- Note that all three hypotheses are satisfied.

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- Hebbian plasticity is satisfied using prediction errors.

1. Model parameters are mean and variance of variables.
2. The fixed point of this dynamical system exists only as sample mean over the occured events of perception.
3. Without prediction errors, the computation is still local.

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1. Only one parameter is considered without loss of generality.
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3. Same consideration of model parameters apply to the relation parameter.

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- Minimization of Kullback-Leibler divergence:

$$KL(q(v)||p(u|v)) = \int_{\Omega_v} q(v) \ln\left(\frac{q(v)}{p(v|u)}\right) \mathrm{d}v \quad . \quad (13)$$

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2. Minimize KL divergence or maximize negative free energy to learn most likely model value, maximize marginal likelihood or maximize negative free energy to learn model parameters.
3. Equation (3) is recovered using delta function centered in the most likely feature value as probability distribution.

Multiple variables model

└Multiple variables model

Learning parameters

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Hierarchical structure implementation

Hierarchical structure implementation

Recover local plasticity

Recover local plasticity

Conclusion

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