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

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Introduction

- Predictive coding model of Rao and Ballard.

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- Free-energy model of Friston.
- Hebbian plasticity.
- Free energy minimization.

Working hypotheses

1. Local computation.

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3. Basic neuronal computation.

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- Sensory input $p(u|v)$ is affected by gaussian noise and it has mean $g(v)$ and variance Σ_u.
- Prior knowledge of the feature $p(v)$ follows a gaussian distribution with mean v_p and variance Σ_p.

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- Bayes theorem:

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- No implementation in simple biological systems.

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- Prediction errors:

$$\varepsilon_p = \frac{v - v_p}{\Sigma_p} \quad , \tag{4}$$

$$\varepsilon_u = \frac{u - g(v)}{\Sigma_u} \quad . \tag{5}$$

Neural implementation

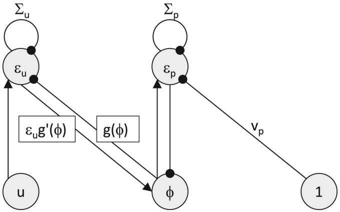

Fig. 3 from article: network implementation of the dynamical system

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

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- Equivalent to maximize negative free energy with respect to parameters:

$$\frac{\partial F}{\partial v_p} = \frac{\phi - v_p}{\Sigma_p} \quad , \tag{7}$$

$$\frac{\partial F}{\partial \Sigma_p} = \frac{1}{2}\left(\frac{(\phi - v_p)^2}{\Sigma_p^2} - \frac{1}{\Sigma_p}\right) \quad , \tag{8}$$

$$\frac{\partial F}{\partial \Sigma_u} = \frac{1}{2}\left(\frac{(u - g(\phi))^2}{\Sigma_u^2} - \frac{1}{\Sigma_u}\right) \quad . \tag{9}$$

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- Hebbian plasticity is satisfied using prediction errors.

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- Gradient of negative free energy for learning:

$$\frac{\partial F}{\partial \theta} = \frac{u - \theta h(\phi)}{\Sigma_u} h(\phi) = \varepsilon_u h(\phi) \quad . \tag{12}$$

Free energy framework

- Minimization of Kullback-Leibler divergence:

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

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- Definition of negative free energy:

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- For the models discussed in the paper: $q(v) = \delta(v - \phi)$.

Multiple variables model

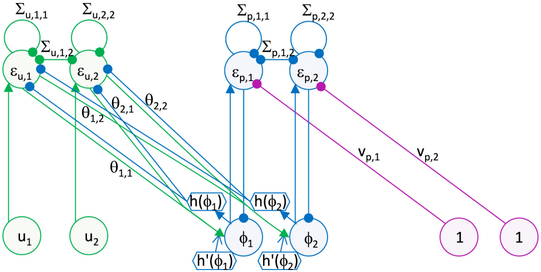

Fig. 5 from article: example of a model with 2 features and 2 stimuli. Same equations in matrix notation, but local plasticity is not satisfied.

Hierarchical structure implementation

- Parallel to structure of cortical areas.

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- Generalized equations for the inference task:

$$\dot{\vec{\phi}}_i = -\vec{\varepsilon}_i + h'(\vec{\phi}_i) \times \mathbf{\Theta}_{i-1}^{\mathsf{T}} \vec{\varepsilon}_{i-1} \quad , \tag{15}$$

$$\dot{\vec{\varepsilon}}_i = \vec{\phi}_i - \mathbf{\Theta}_i h(\vec{\phi}_{i+1}) - \mathbf{\Sigma}_i \vec{\varepsilon}_i \quad . \tag{16}$$

- Generalized equations for the learning task:

$$\frac{\partial F}{\partial \mathbf{\Sigma}_i} = \frac{1}{2}(\vec{\varepsilon}_i \vec{\varepsilon}_i^{\mathsf{T}} - \mathbf{\Sigma}_i^{-1}) \quad , \tag{17}$$

$$\frac{\partial F}{\partial \mathbf{\Theta}_i} = \vec{\varepsilon}_i h(\vec{\phi}_{i+1})^{\mathsf{T}} \quad . \tag{18}$$

Recover local plasticity

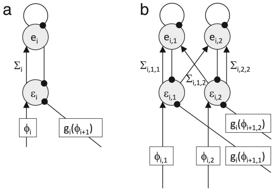

Fig. 7 from article: networks satisfying local plasticity for (a) single variable model and (b) multiple variables model. They implement the generalized dynamical system

$$\begin{cases} \dot{\vec{\varepsilon}}_i = \vec{\phi}_i - g_i(\vec{\phi}_{i+1}) - \vec{e}_i \\ \dot{\vec{e}}_i = \mathbf{\Sigma}_i \vec{\varepsilon}_i - \vec{e}_i \end{cases} . \tag{19}$$

Conclusion

- Stimuli weighted by noise.
- Learn covariance of stimuli.
- Attentional modulation.