



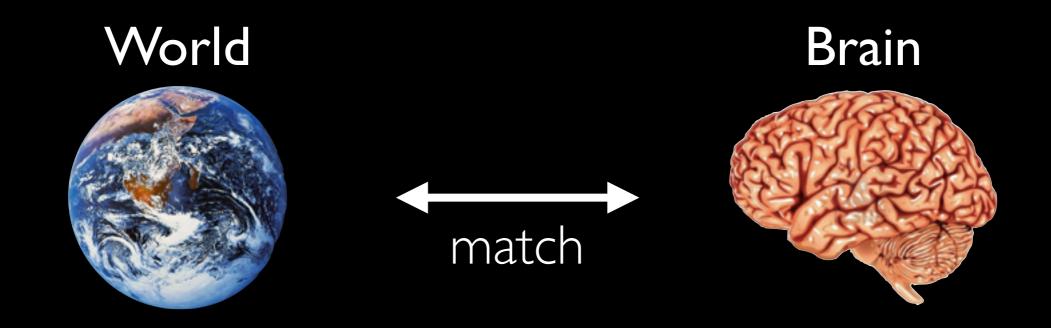
Inferring Inference

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part of the MICrONS project with Tolias, Bethge, Patel, Zemel, Urtasun, Xu, Siapas, Paninski, Baraniuk, Reid, Seung

NICE workshop 2017





Hypothesis:

The brain

approximates probabilistic inference

over a probabilistic graphical model

using a message-passing algorithm

implicit in population dynamics

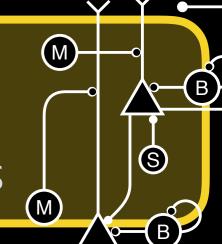
What algorithms can we learn from the brain?

Architectures?

cortex, hippocampus, cerebellum, basal ganglia, ...

Transformations?

nonlinear dynamics from population responses



Learning rules?

short and long-term plasticity

Principles: Details:

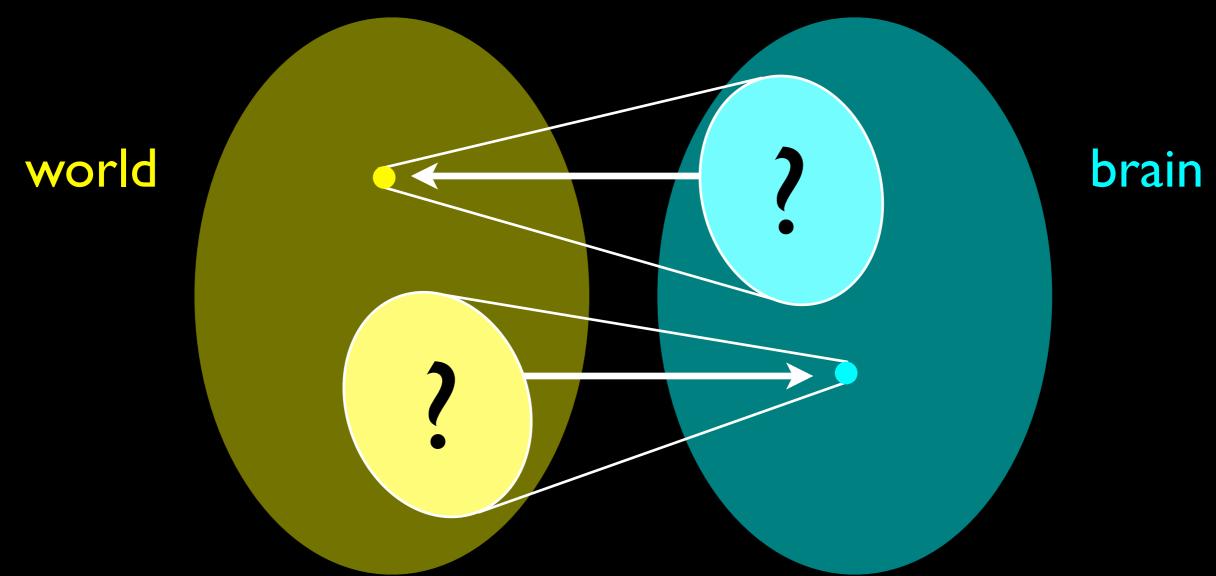
Probabilistic Graphical models

Nonlinear Message-passing inference

Distributed Multiplexed across neurons

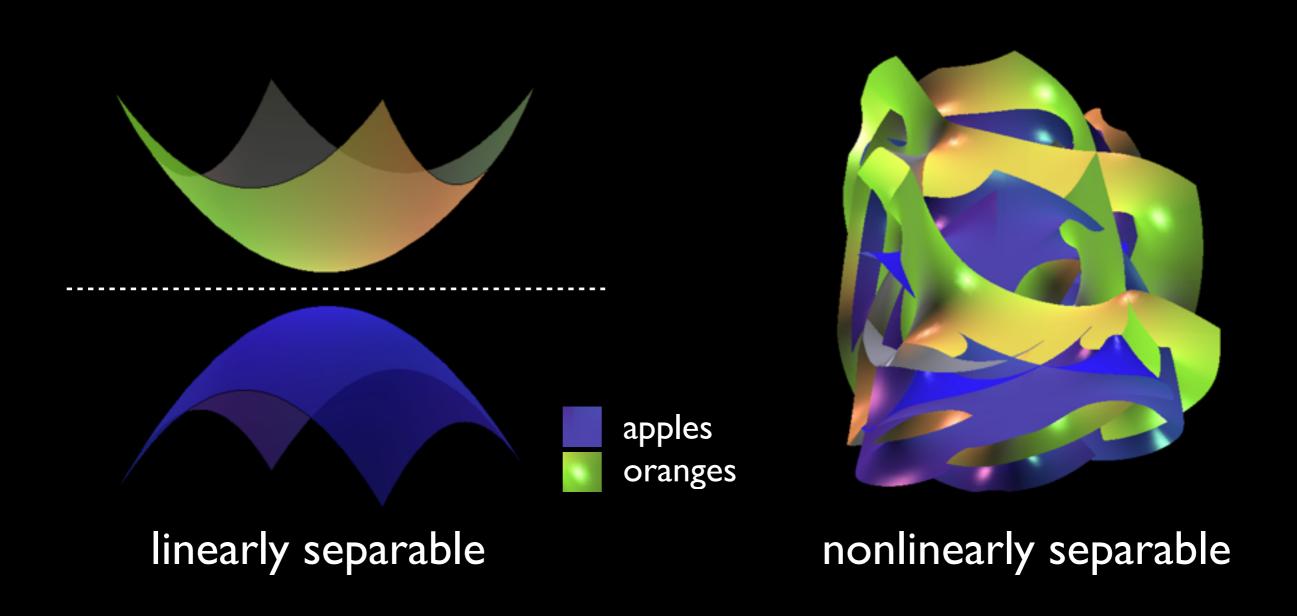
Events in the world can cause many neural responses. Neural responses can be caused by many events.

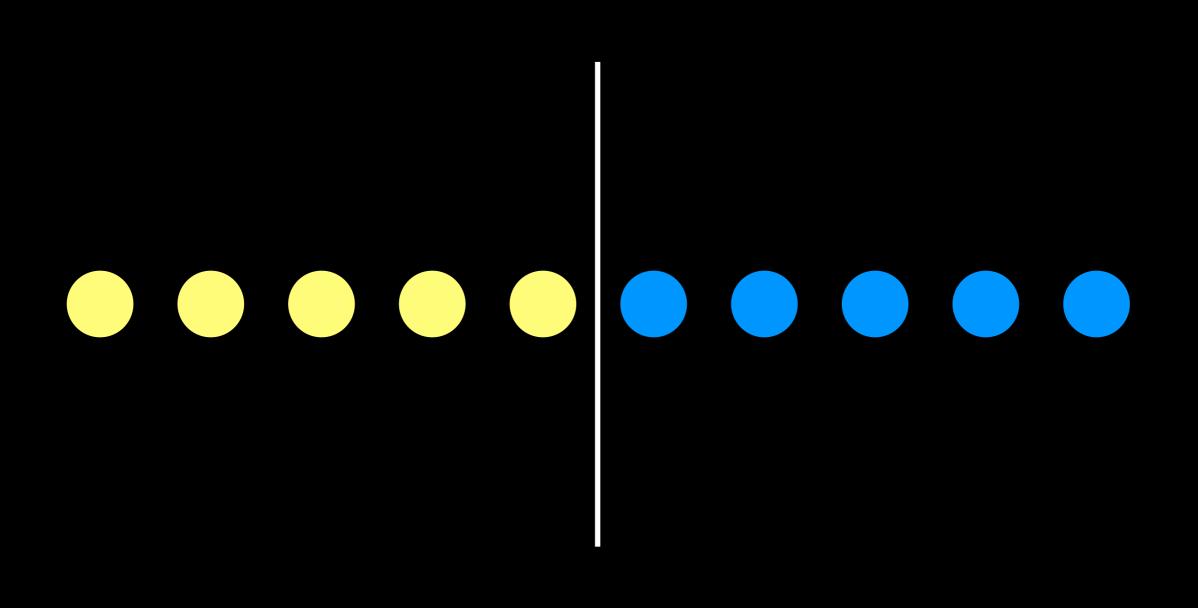
So neural computation is inevitably statistical. This provides us with mathematical predictions.

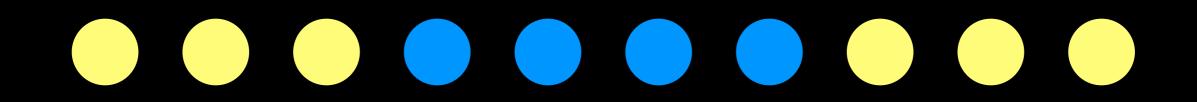


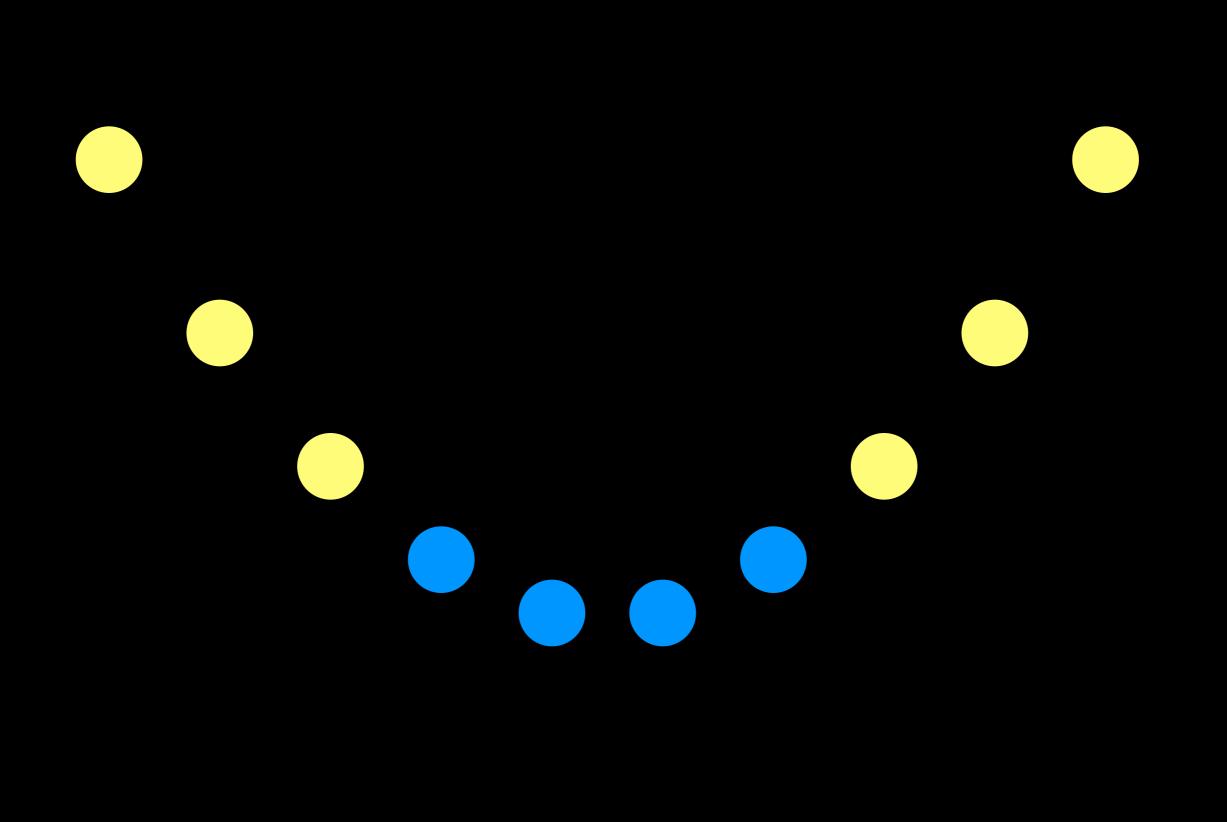
Why does it matter whether processing is linear or nonlinear?

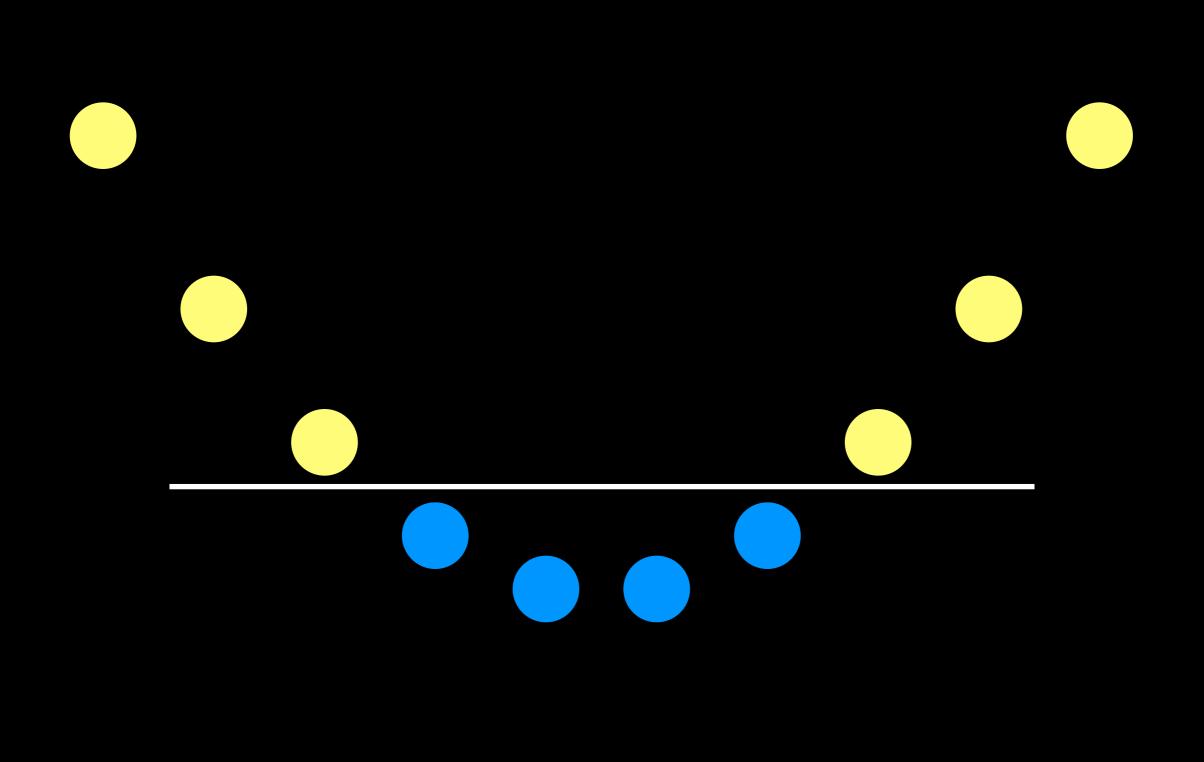
If all computation were linear we wouldn't need a brain.







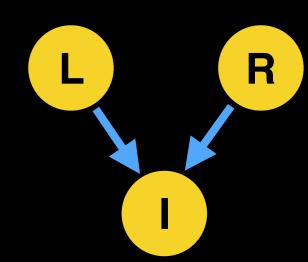




Two sources of nonlinearities

Relationships between latent variables

Image = Light × Reflectance



Relationships between uncertainties

posteriors generally have nonlinear dependencies even for the simplest variables

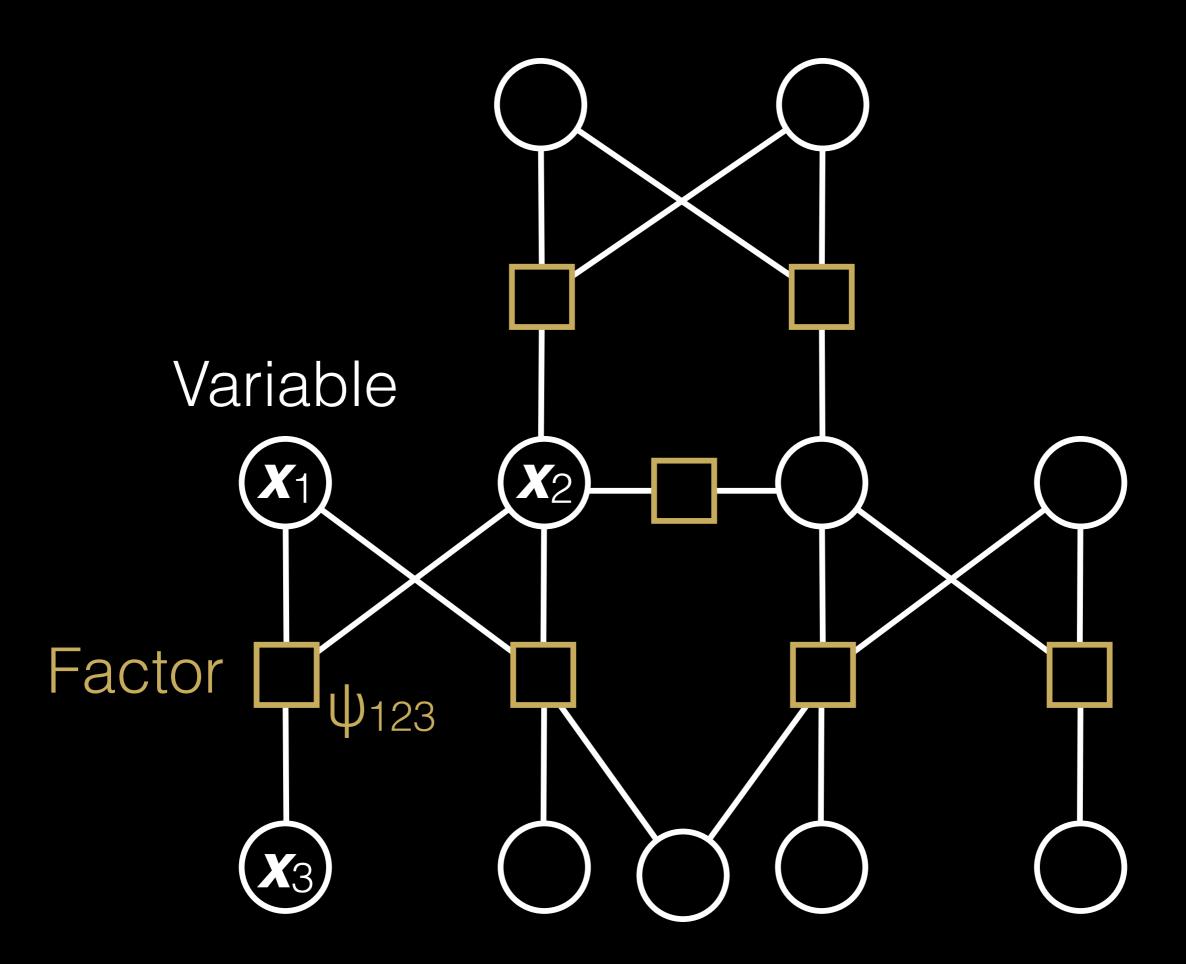
Product rule: $p(x,y) = p(x) \cdot p(y)$

Sum rule: $L(x) = \log \sum_{y} \exp L(x,y)$

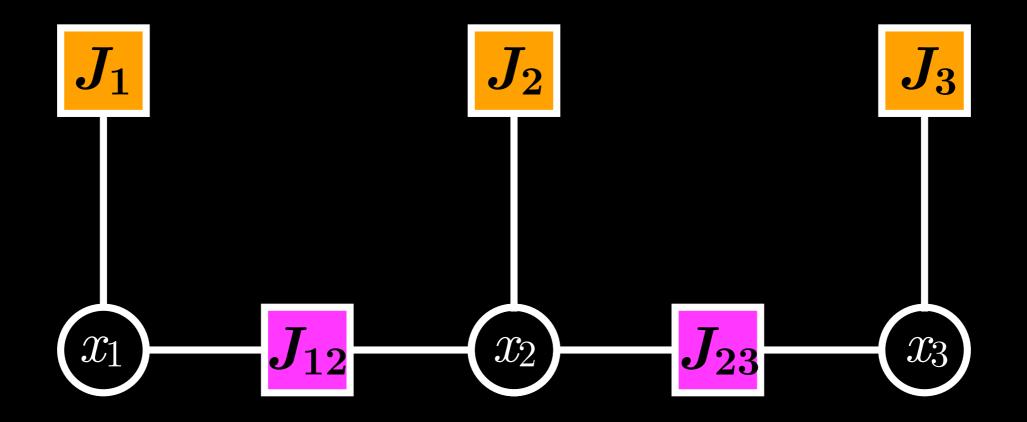
Probabilistic Graphical Models:

Simplify joint distribution $p(\boldsymbol{x}|\boldsymbol{r})$ by specifying how variables interact

$$p(\boldsymbol{x}|\boldsymbol{r}) \propto \prod_{\alpha} \psi_{\alpha}(\boldsymbol{x}_{\alpha})$$



Example: Pairwise Markov Random Field



$$p(\boldsymbol{x}) = \frac{1}{Z} \prod_{\boldsymbol{s} \in V} e^{\boldsymbol{J_s(\boldsymbol{x_s})}} \prod_{(\boldsymbol{s},\boldsymbol{t}) \in E} e^{\boldsymbol{J_{st}(\boldsymbol{x_{st}})}}$$

Approximate inference by message-passing:

- Localize information so it is actionable
- Summarize statistics relevant for targets
- Send that information along graph
- Iteratively update factors with new information

general equation interactions
$$\theta_{i,t+1} = f(\theta_{it}, \{\theta_{jt}\}_{j \in N_i} | G, J)$$

posterior parameters posterior for neighbors

message-passing parameters

Example message-passing algorithms

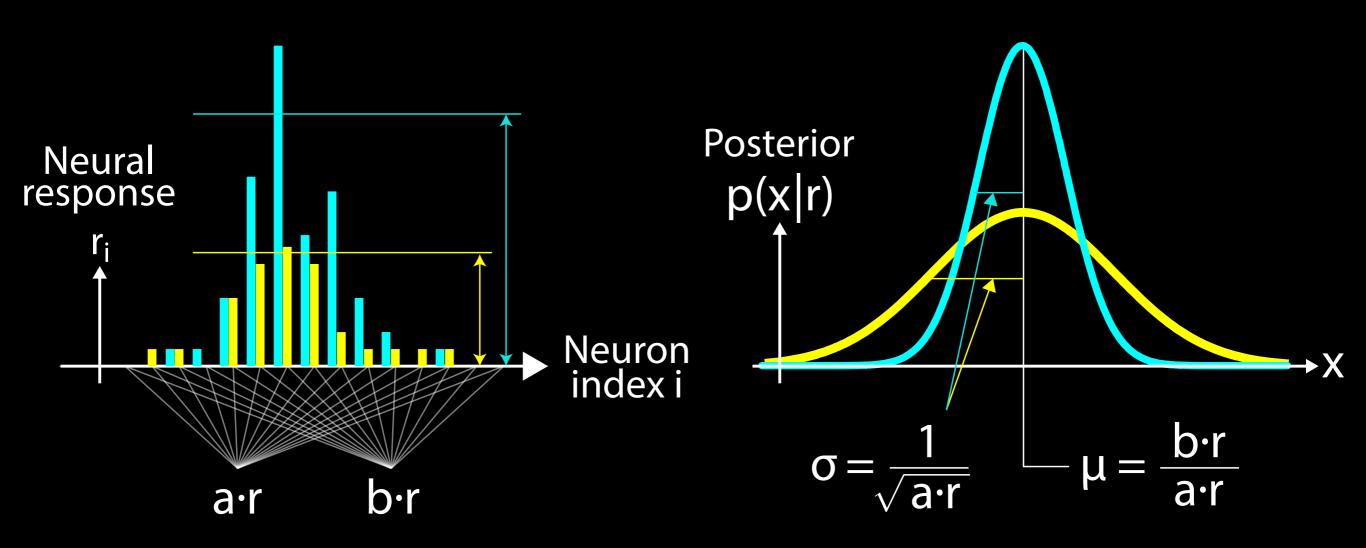
- Mean-field (assumes variables are independent)
- Belief propagation (assumes tree graph)
- Expectation propagation (updates parametric posterior)

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Brain's clever tricks?

Spatial representation of uncertainty

(e.g. Probabilistic Population Codes, PPCs)



Pattern of activity represents probability.

More spikes generally means more certainty

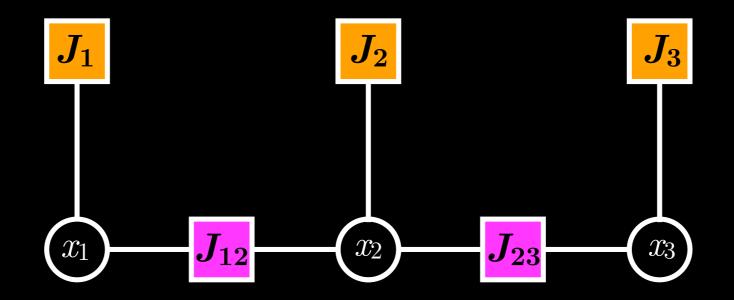
Message-passing updates

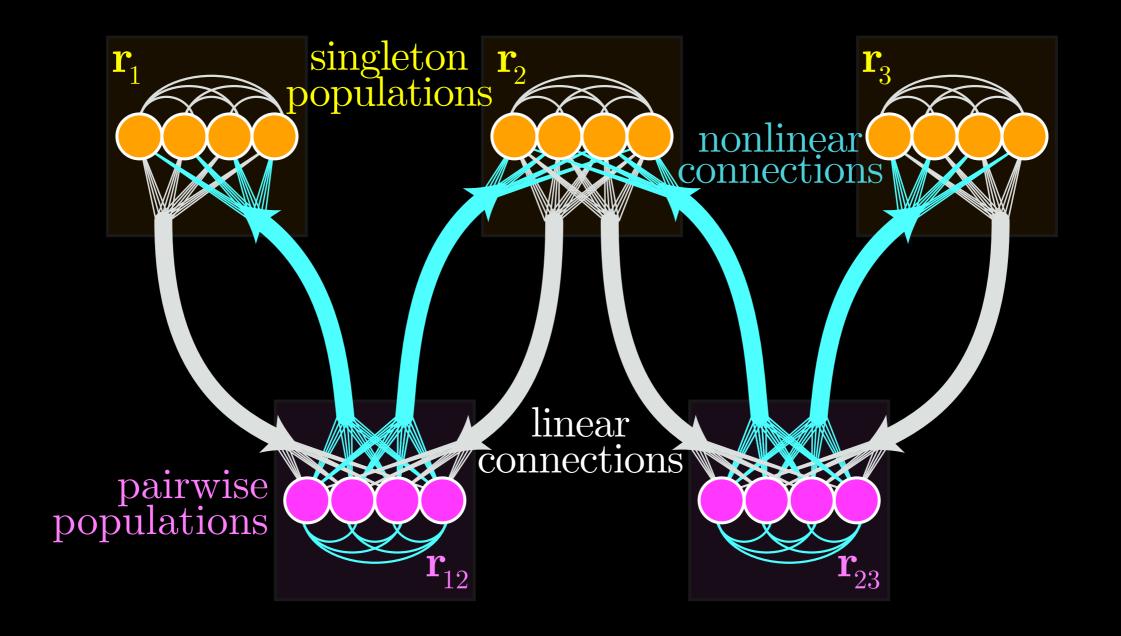
$$\boldsymbol{\theta}_{i,t+1} = \boldsymbol{f}(\boldsymbol{\theta}_{it}, \{\boldsymbol{\theta}_{jt}\}_{j \in N_i} | G, \boldsymbol{J})$$

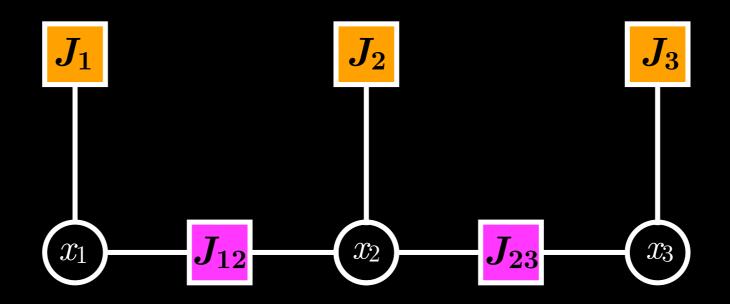
$$r=U\mathbf{\Theta}+\mathbf{\eta}$$
 embedding

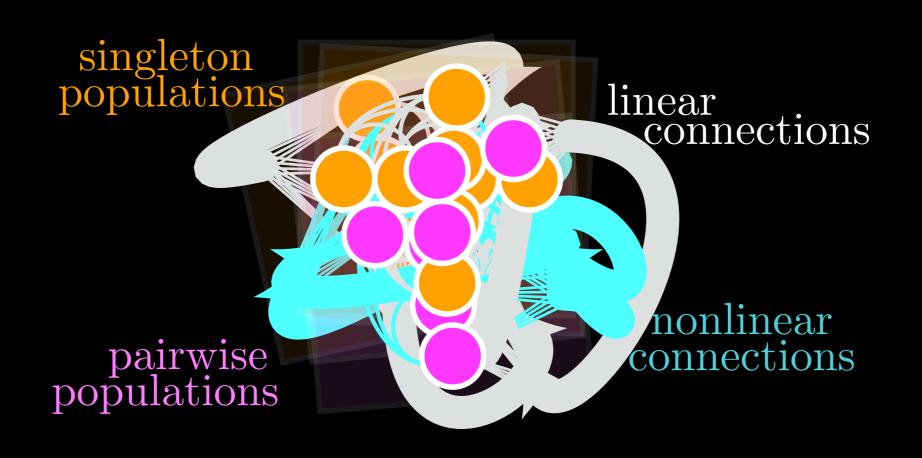
$$\dot{m{r}} = m{F}(m{r}_t)$$

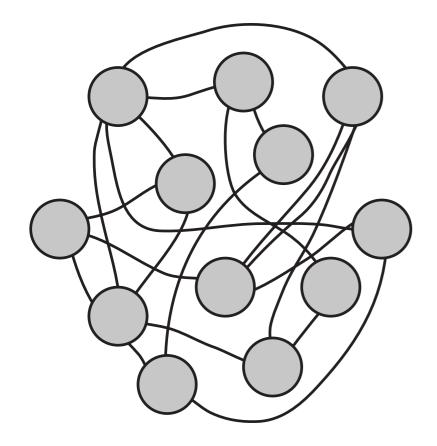
Neural dynamics

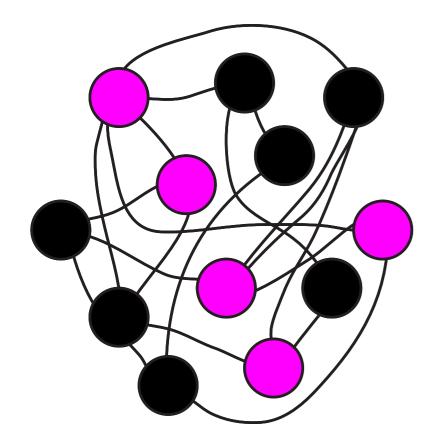


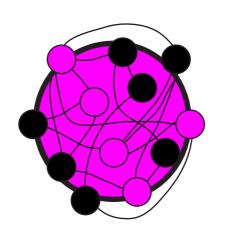


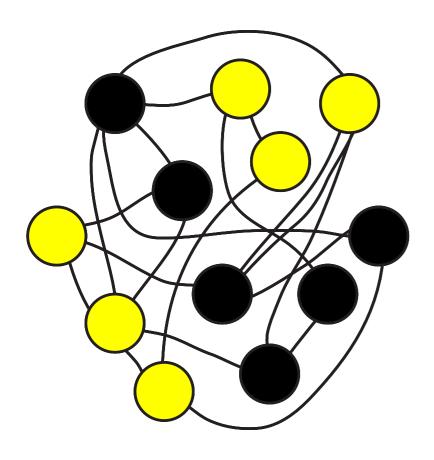






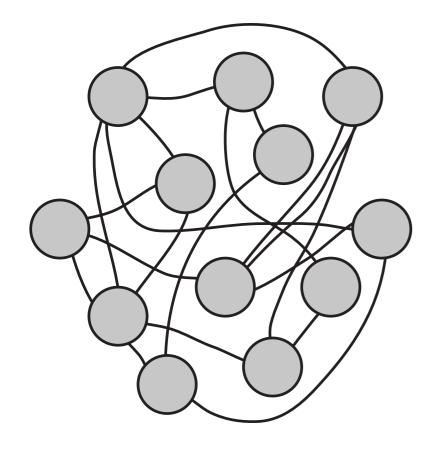


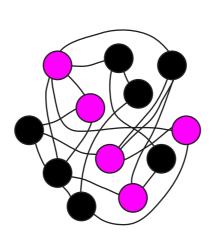


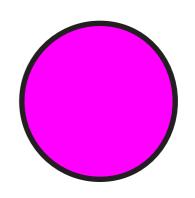


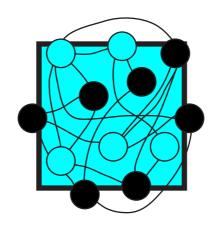
Neural encoding

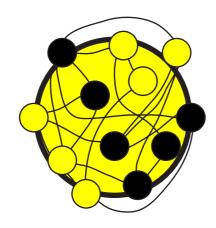
Information encoded





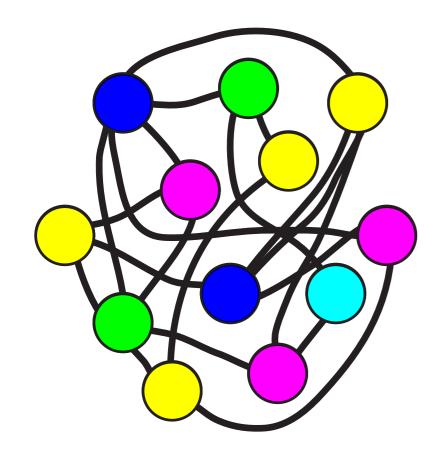


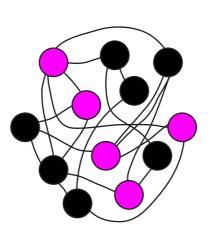


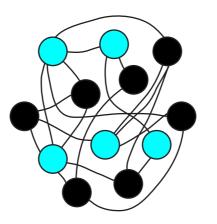


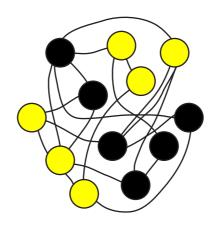
Neural encoding

Information encoded

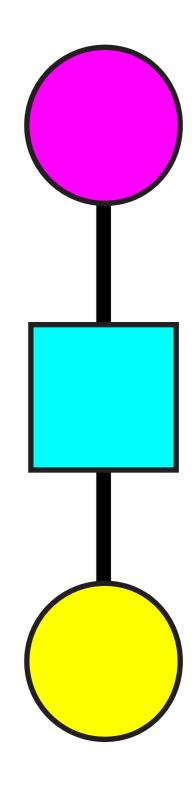






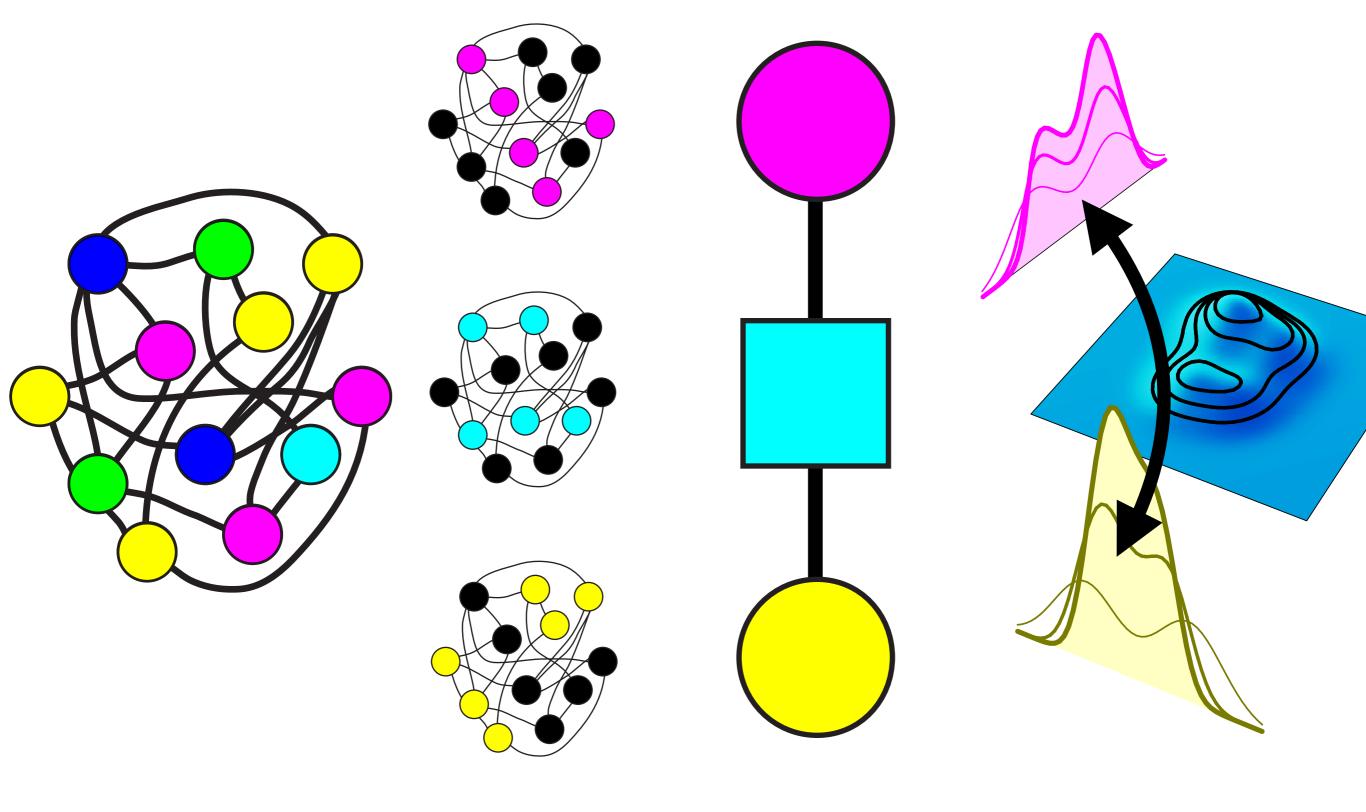


Neural encoding



Information interactions

Neural interactions

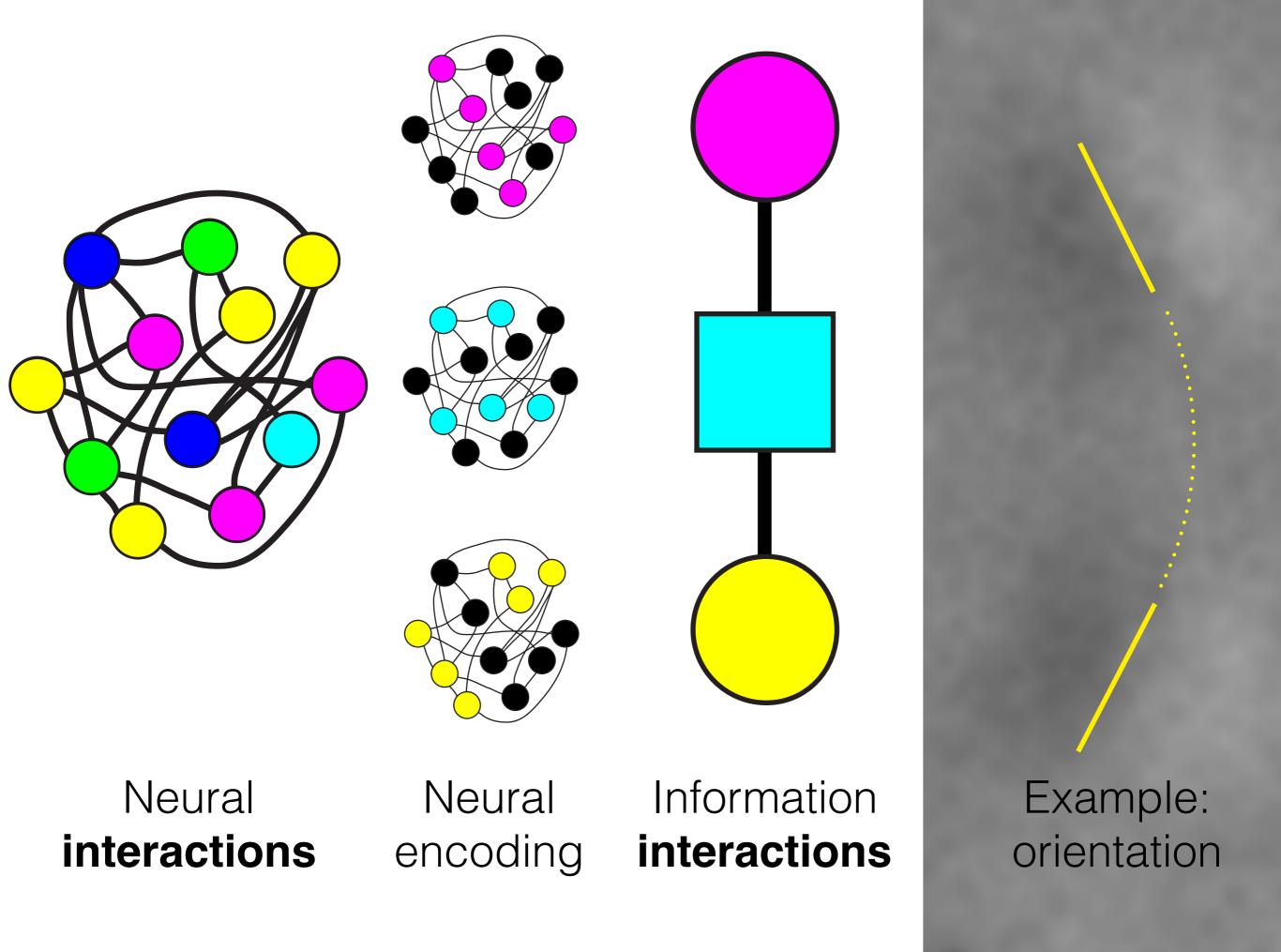


Neural interactions

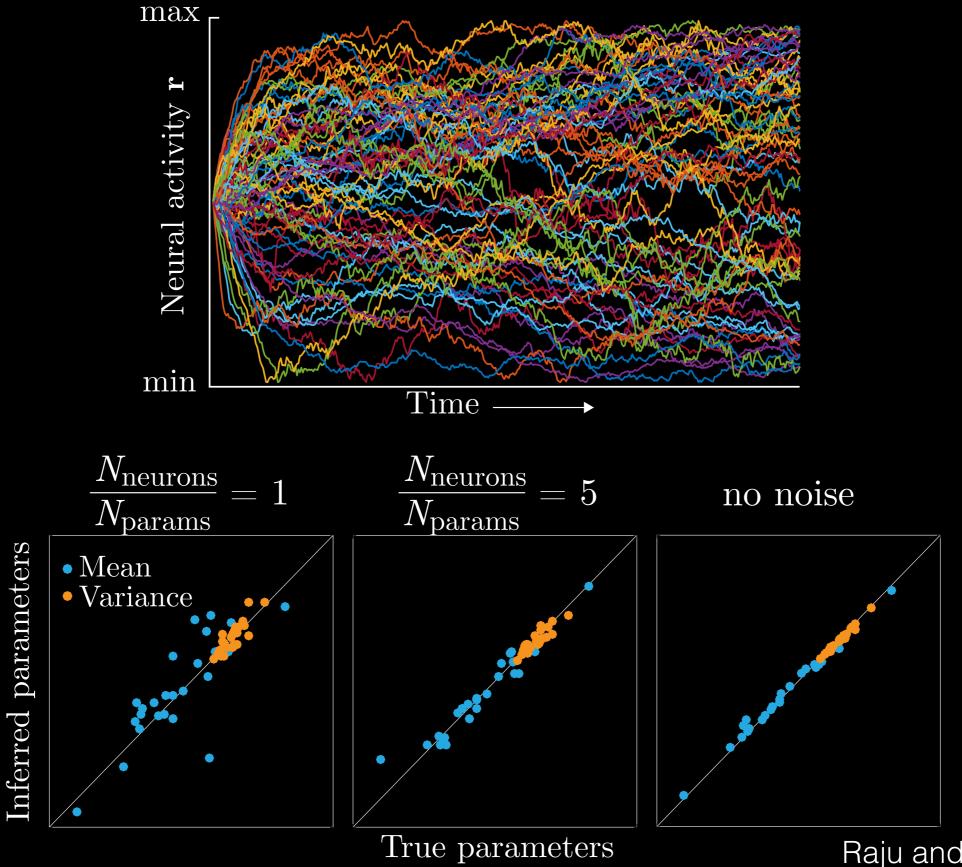
Neural encoding

Information interactions

Probability distributions



Network activity can implicitly perform inference



Raju and Pitkow 2016

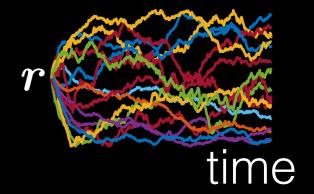
Simulated brain

$$\dot{b}_{it} = -b_{it} + \sigma \left(\sum_{j} W \left[J_{ij}, b_{it}, b_{jt} \right] b_{jt} + h_{it} \right)$$

$$W \left[J_{ij}, b_{i}, b_{j} \right] = 2J_{ij} + 4J_{ij}^{2} (1 - 2b_{i})(1 - b_{j})$$

$$\mathbf{r}_{t+1} = \sigma \left(A \mathbf{r}_t + B \mathbf{h}_t - \theta \right)$$

Encode



Inferring inference

$$\hat{\boldsymbol{b}} = V\boldsymbol{r} + c$$

$$\hat{W}[J_{ij}, b_i, b_j] = \sum_{\alpha\beta\gamma} G_{\alpha\beta\gamma} J_{ij}^{\alpha} b_i^{\beta} b_j^{\gamma}$$

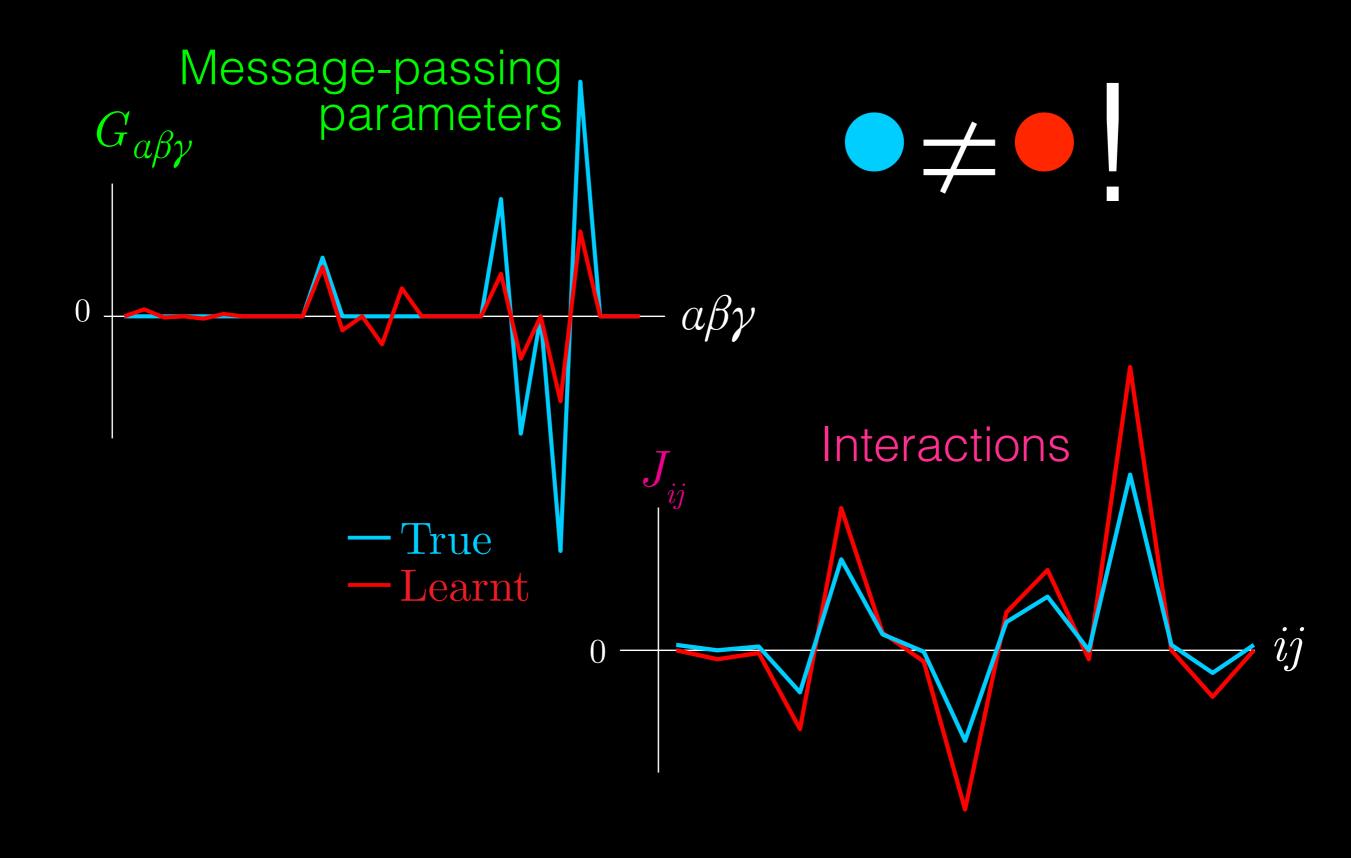
Message-passing Interactions parameters

Decode

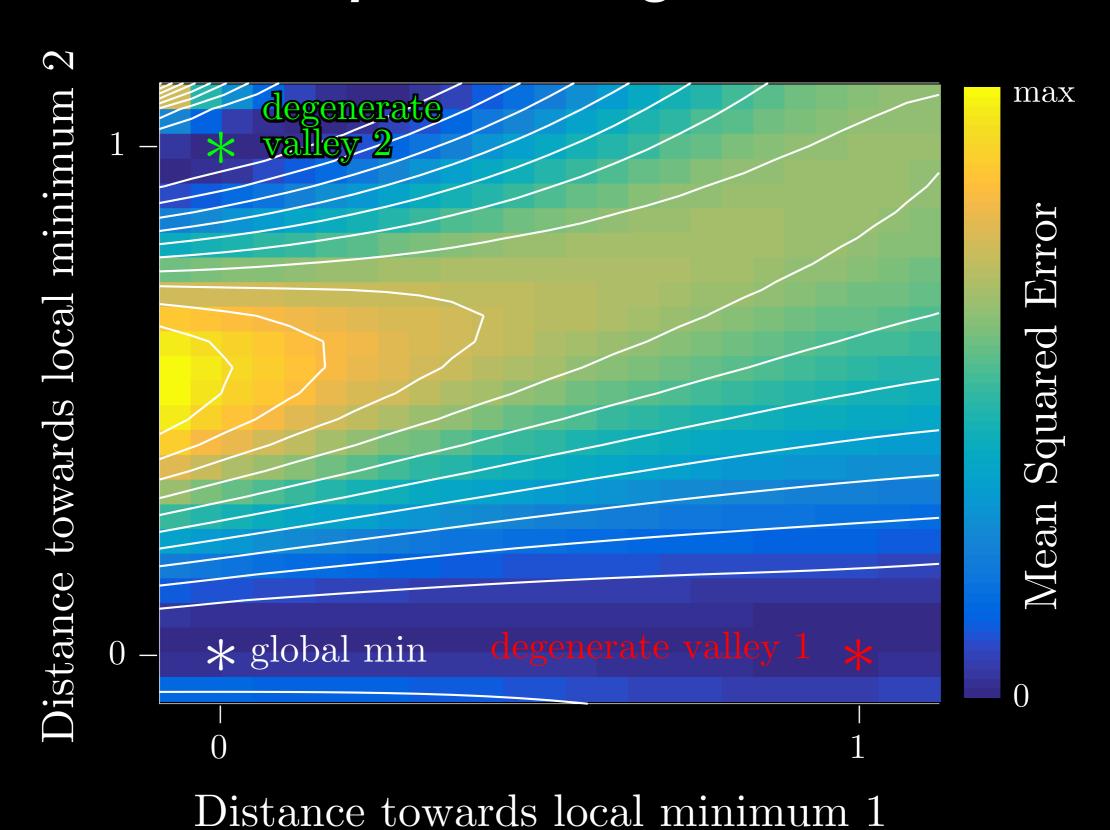
Fit*

*within family

Recovery results for simulated brain



Analysis reveals degenerate family of *equivalent* algorithms



From *simulated* neural data we have recovered:

how variables are encoded

Representation

which variables interact

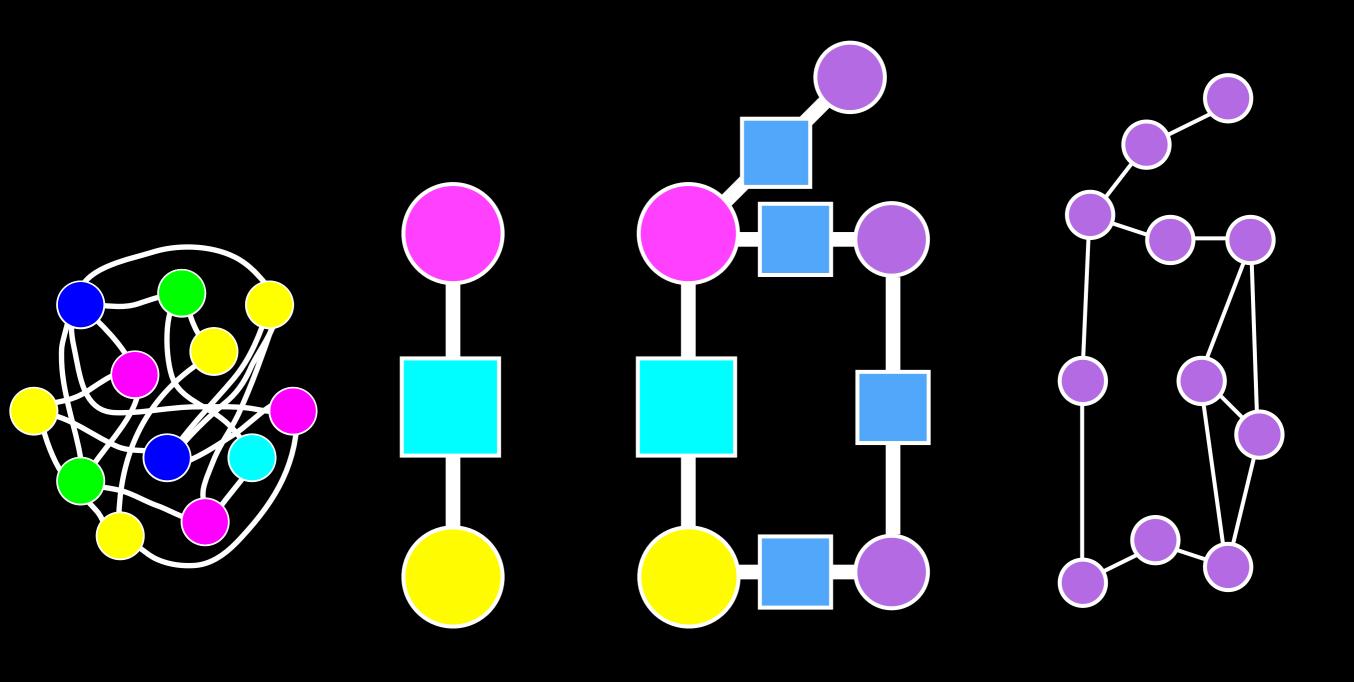
how they interact

Graphical model

how the interactions are used

Message-Passing algorithm

Applying message-passing to novel tasks



Brain neural network

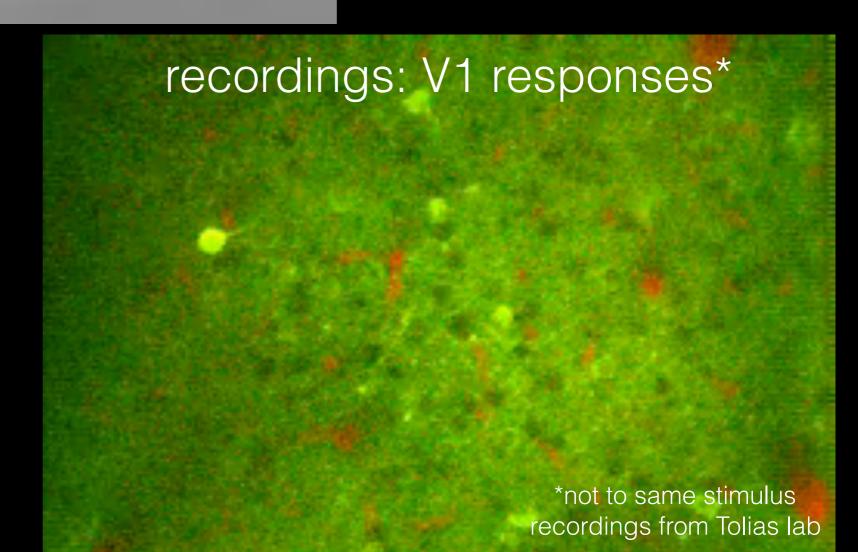
Message passing nonlinearity

Apply to new graphical OR novel neural model structure

Relax to network

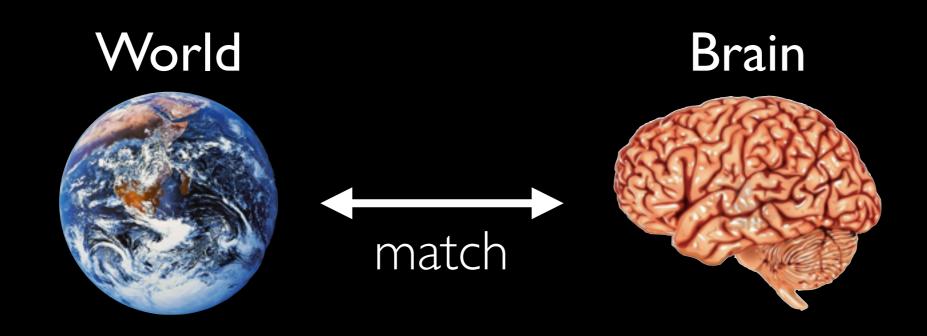
Next up: applying methods to real brains

stimulus: orientation field



mementos:

- Neurons can perform inference implicitly in a graphical model distributed across a population.
- New method to discover message-passing algorithms by modeling transformations of decoded task variables



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