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Predictive processing

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Overview

- Why does the brain need predictive processing?
- Evidence for predictions in the brain
- Theories of predictive processing
    - Predictive coding
    - Bayesian brain
    - Free energy
- Implementations in the brain
    - Probabilistic population codes
    - Sampling hypothesis
    - Prediction errors

Why does the brain need predictive processing?

- Brain helps agents to achieve beneficial states (e.g. finding food, avoiding danger, reproduction).

- To be able to do this brain needs to:
  - Know current state of the world
  - Anticipate changes in the world
  - Derive consequences of possible actions that can be taken

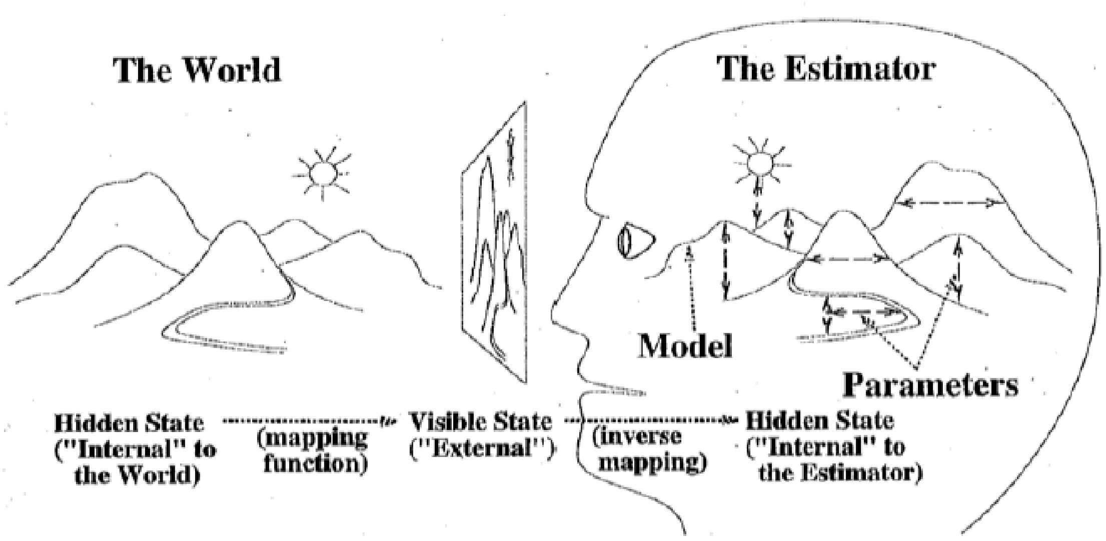
- Possible due to structure in the world and causal relationships (physics)

Why does the brain need predictive processing?

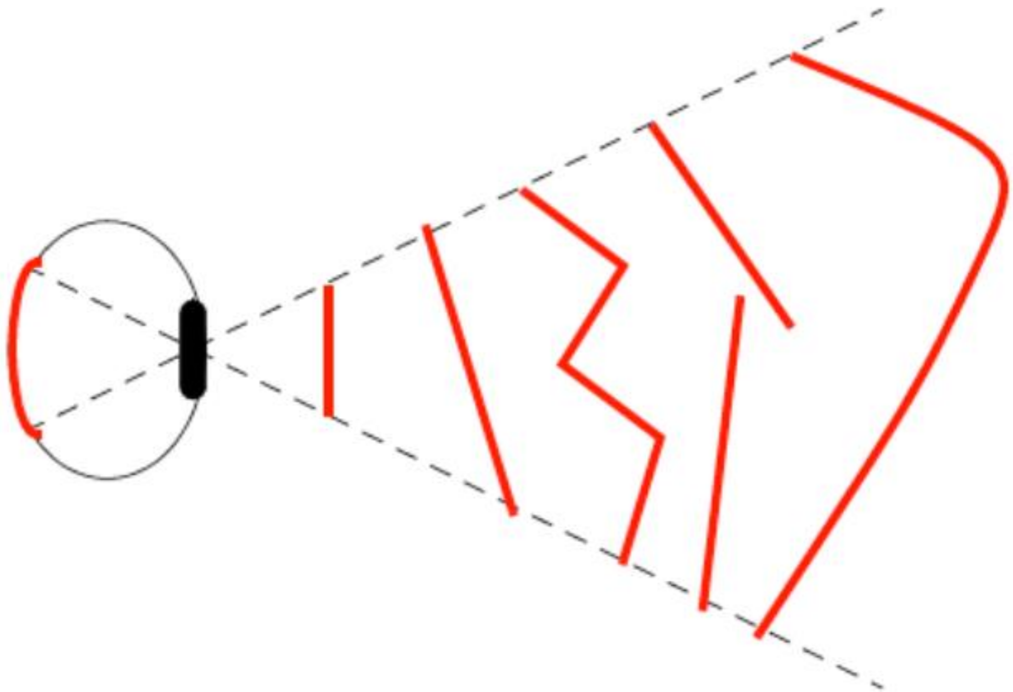
- Fully knowing the state of the world at time T and the causal relationships between different elements in the world would enable us to exactly predict the consequences of our actions and enables us to choose best action.

- Problem is we don't know exact state and don't have the capacity to know every relationship.

- Cannot observe whole world, but get noisy and ambiguous sensory information from which we need to infer underlying state of the world.

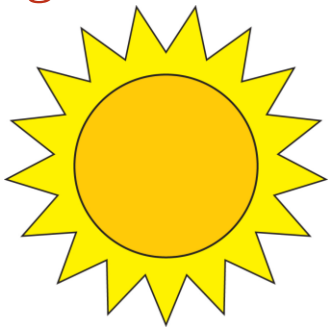


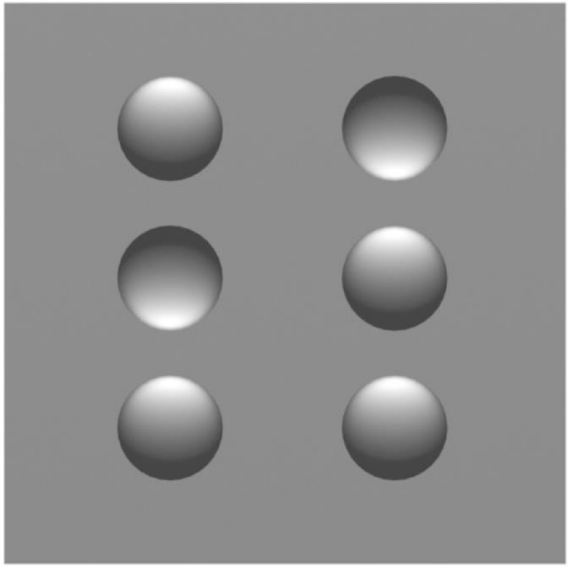
Ambiguity in the brain



Same sensory obsevation can be caused by many different underlying states.

Influence of prior knowledge



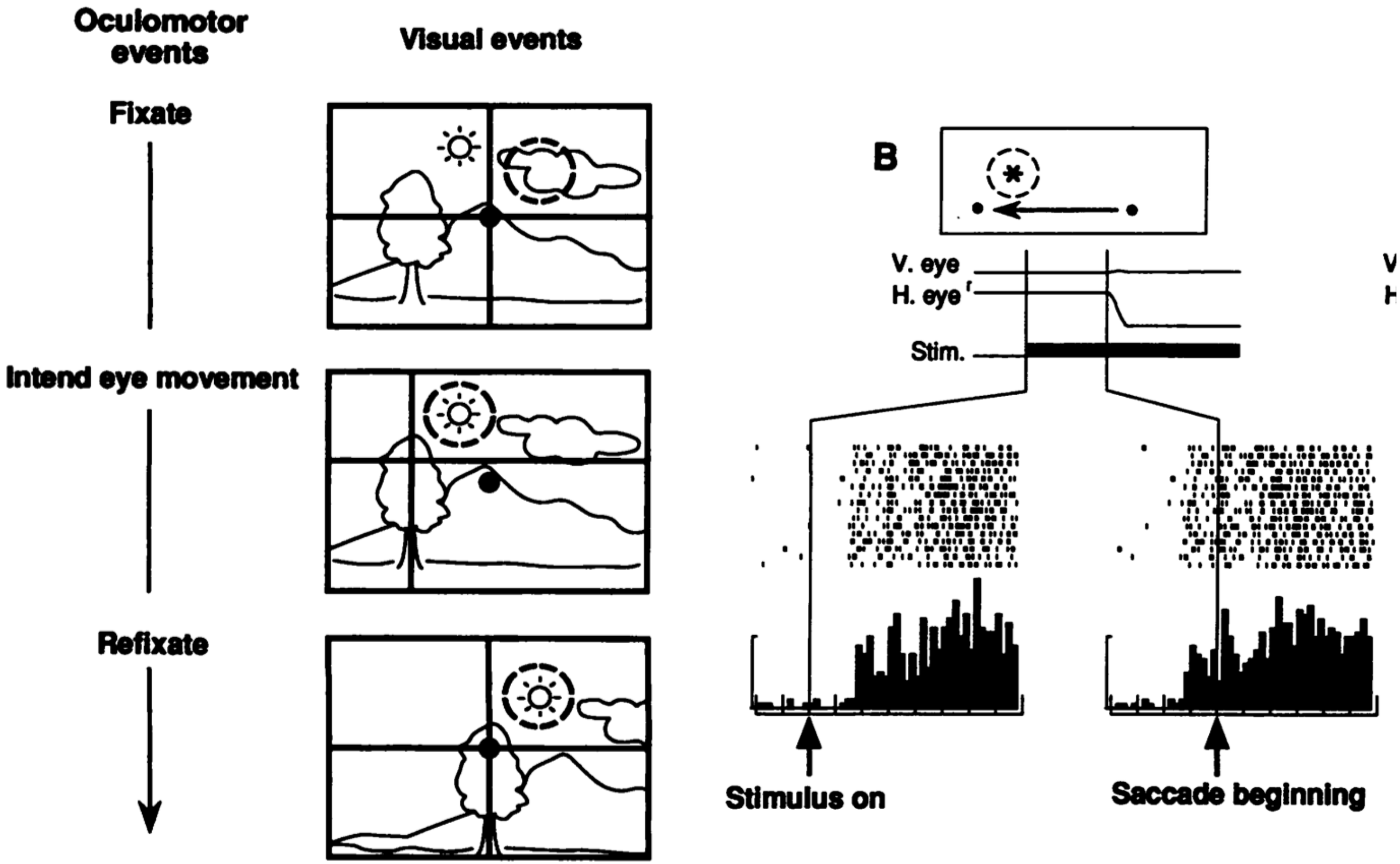


Many underlying causes unlikely.

Prior knowledge helps to resolve ambiguity.

Hollow face illusion

Predictions in the brain



LIP neurons predict the sensory consequences of intended action!

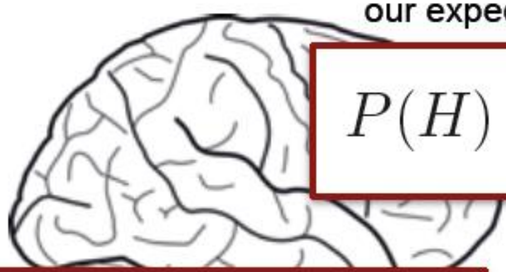
Duhamel JR, Colby CL, Goldberg ME. The updating of the representation of visual space in parietal cortex by intended eye movements. Science. 1992 Jan 3;255(5040):90-2.

Theories of predictive processing

- Bayesian brain
- Predictive coding
- Free energy principle

All based around learning a model of the world

Bayesian brain



our expectations

$$P(H)$$

our (noisy) sensations

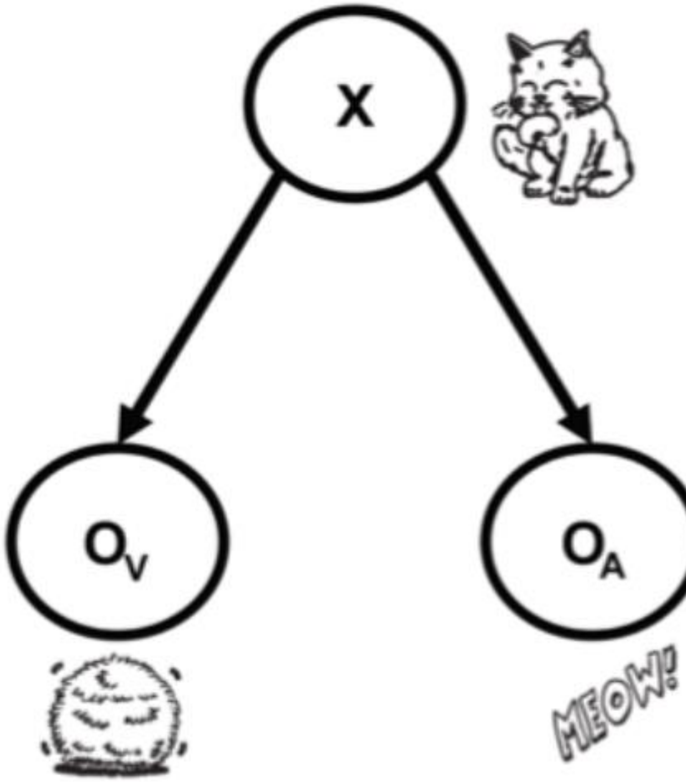
$$P(D \mid H)$$

$$P(H \mid D) = \frac{P(D \mid H)P(H)}{P(D)}$$

Requires: incorporating prior knowledge

Vilares and Kording, Ann N Y Acad Sci, 2011

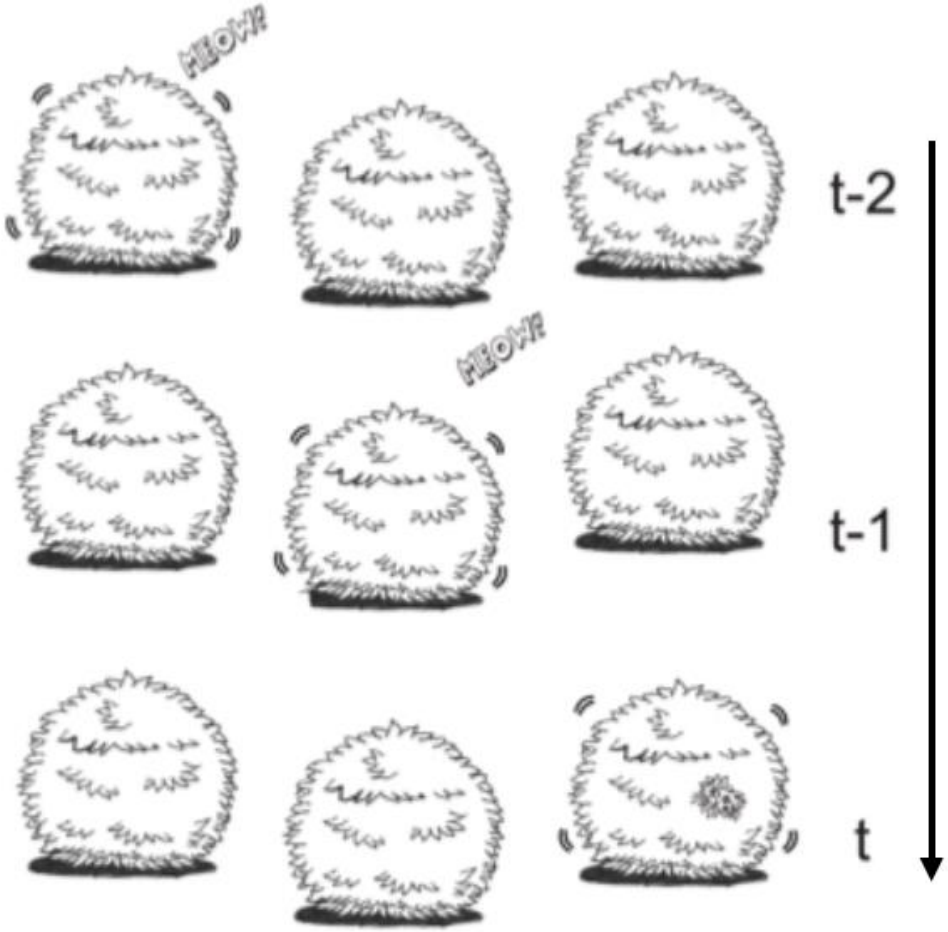
Requires: combining cues



$$P(\text{position}, \text{vision}, \text{audition}) = P(\text{position})P(\text{audition} \mid \text{position})P(\text{vision} \mid \text{position})$$

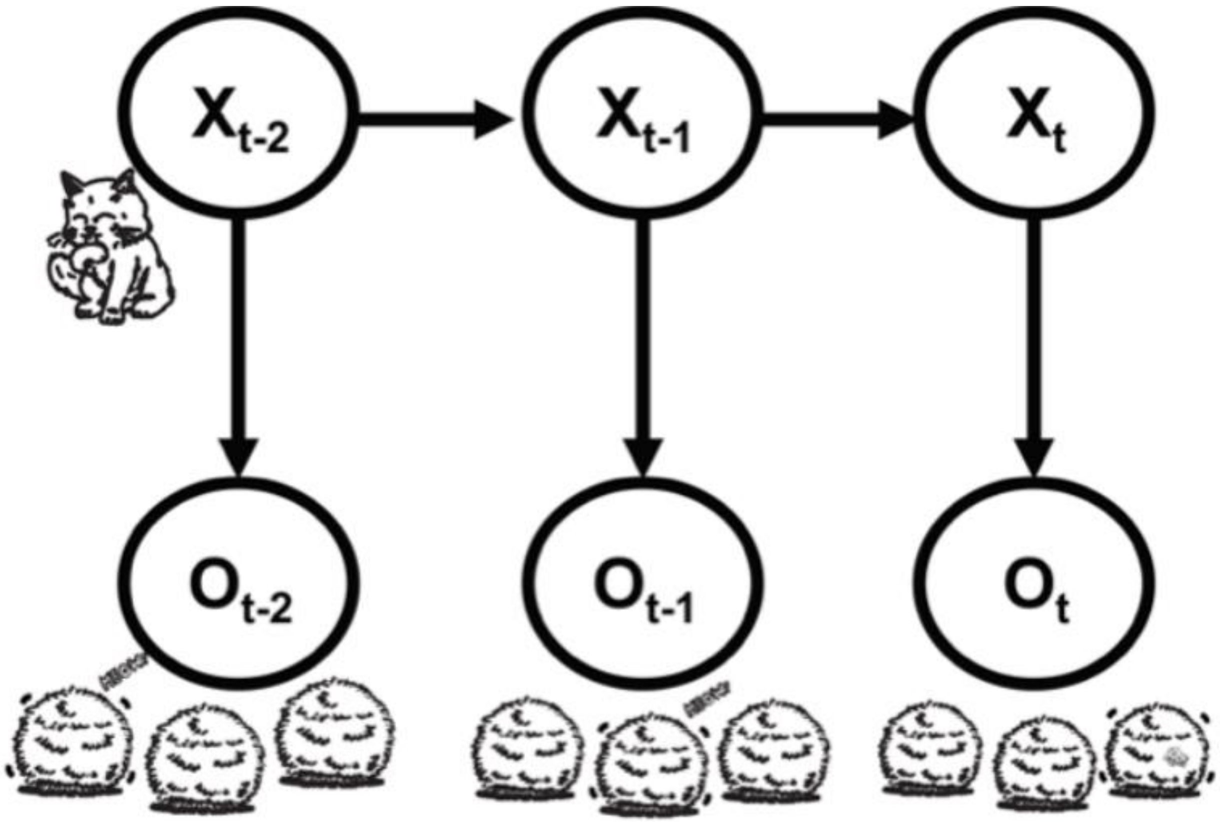
Vilares and Kording, Ann N Y Acad Sci, 2011

Modelling temporal structure



Vilares and Kording, Ann N Y Acad Sci, 2011

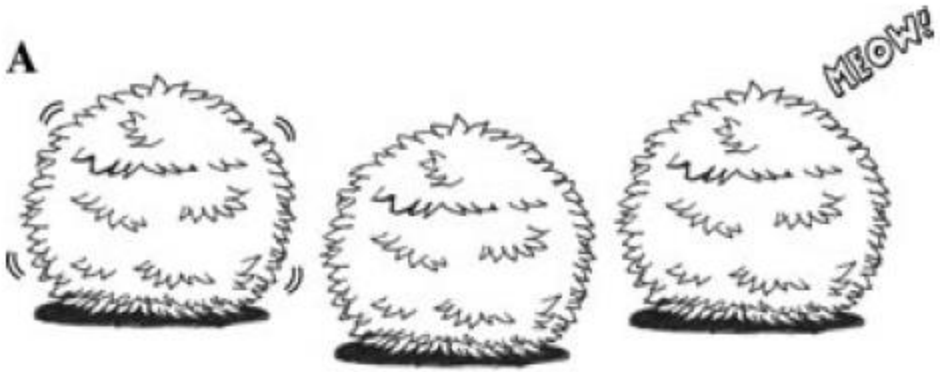
Modelling temporal structure



Best described by hidden Markov model (discrete) or Kalman filter (continuous)

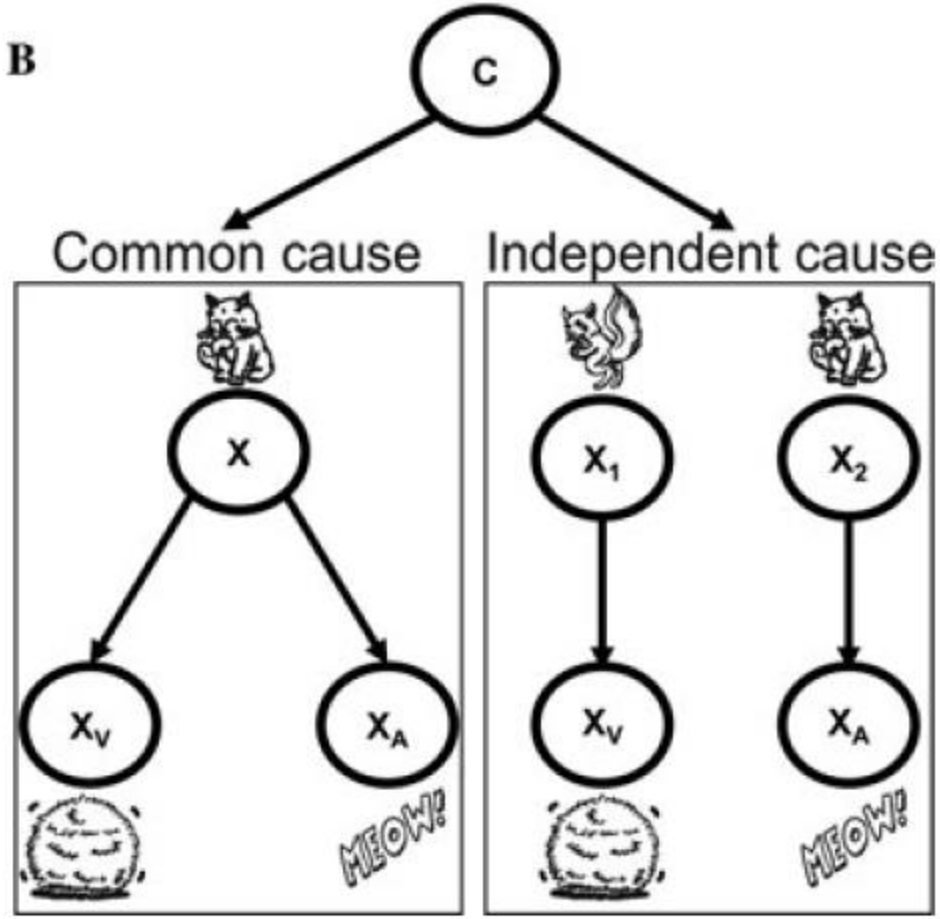
Vilares and Kording, Ann N Y Acad Sci, 2011

Inferring causal structure



How many hidden causes?

Inferring causal structure



Vilares and Kording, Ann N Y Acad Sci, 2011

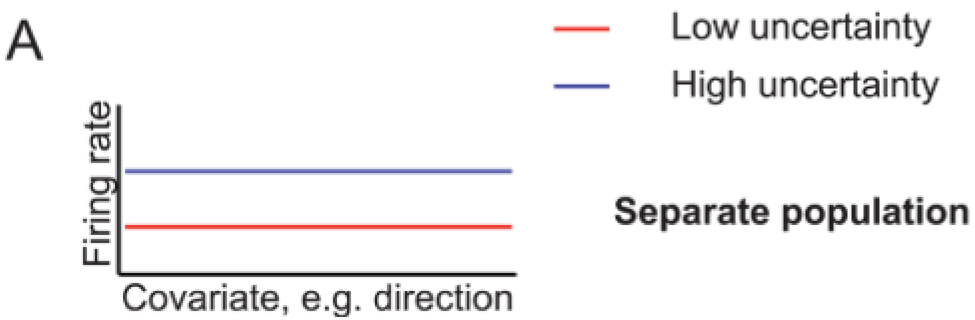
Neural implementation

To do Bayesian inference the brain needs to

- Represent uncertainty
- Combine probabilities

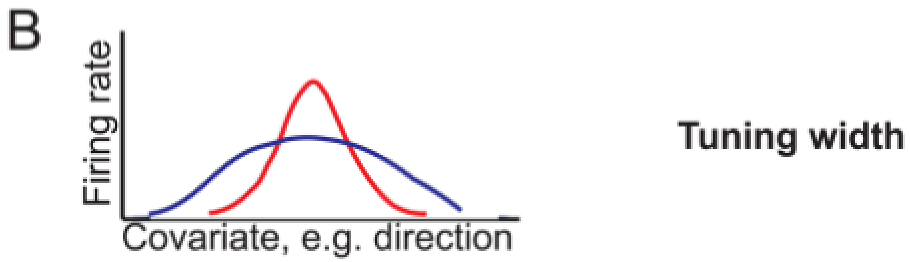
How does could the brain implement this?

Representing uncertainty



Separate neurons code only for uncertainty.

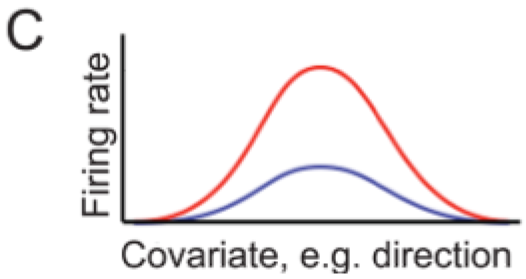
Supported by dopaminergic neurons representing uncertainty in reward.



Tuning curves of neurons change with certainty.

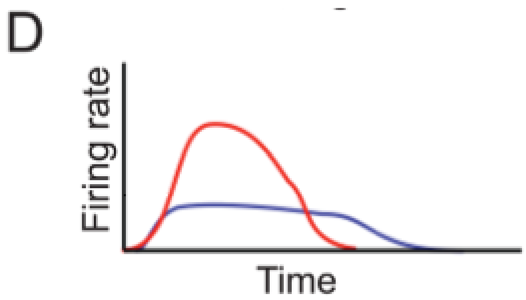
Supported by wider spatial frequency tuning curves in darkness (more uncertainty).

Vilares and Kording, Ann N Y Acad Sci, 2011



Probabilistic population codes

Populations of neurons encode probability distributions. Poisson firing fundamentally probabilistic.

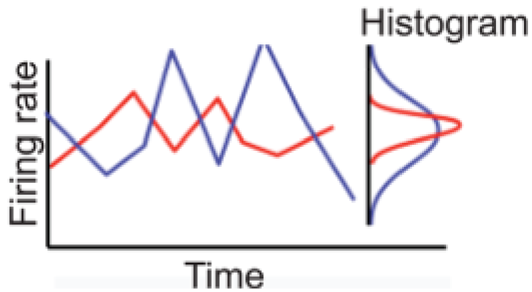


Relative timing change

Neurons fire short and strong during low uncertainty and long but weak during high uncertainty.

Vilares and Kording, Ann N Y Acad Sci, 2011

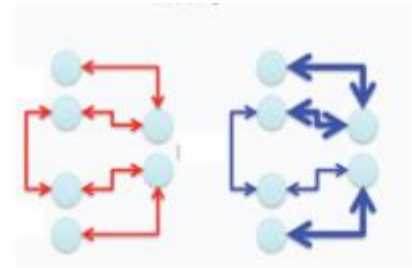
E



Sampling

Width of firing rate distribution represents uncertainty.

F



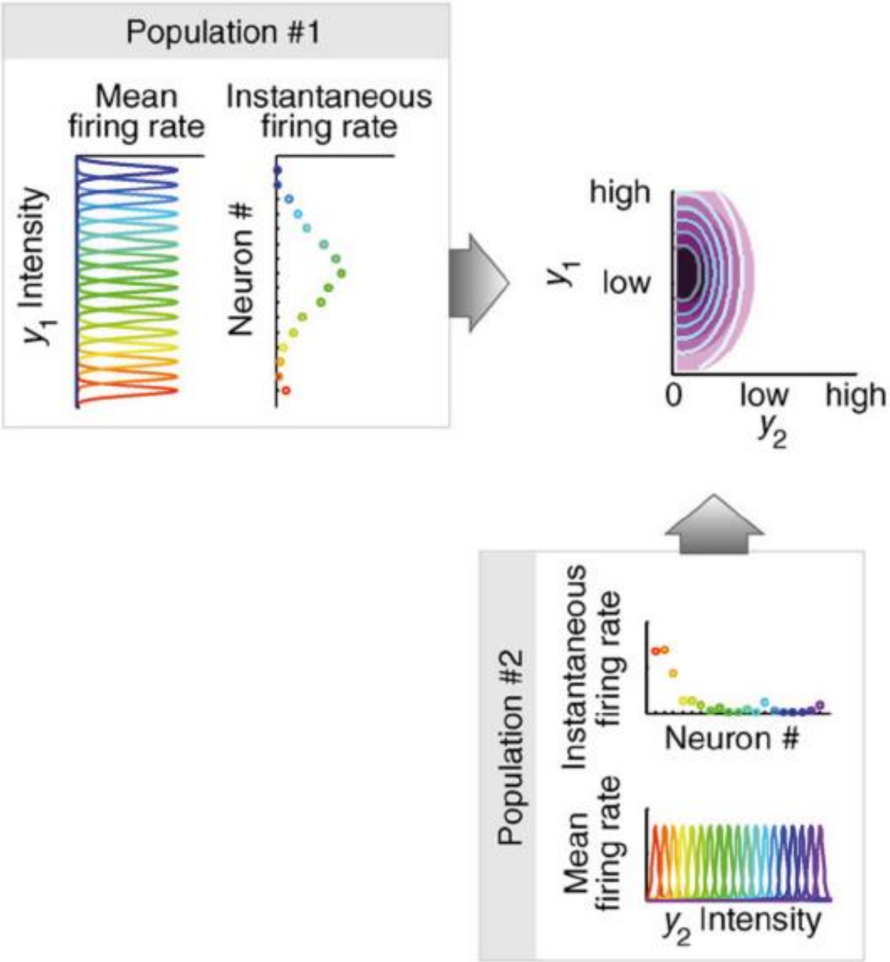
Changed functional connectivity

Uncertainty represented in connectivity between neurons.

Especially important for prior knowledge.

Vilares and Kording, Ann N Y Acad Sci, 2011

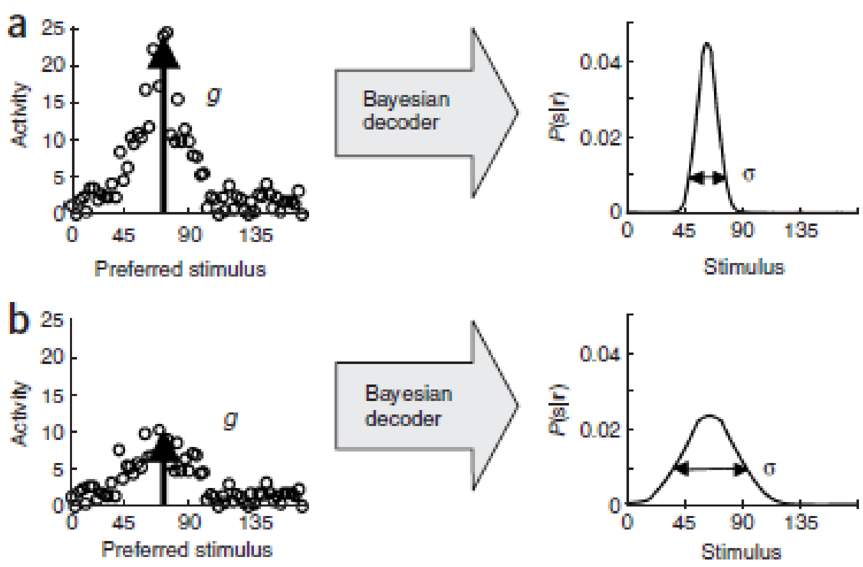
Probabilistic population codes



- Neurons represent parameters of distribution
- Number of parameters increases exponentially with more complex distributions

Fiser, J., Berkes, P., Orbán, G., & Lengyel, M. (2010). Trends in Cognitive Sciences.

Probabilistic population codes

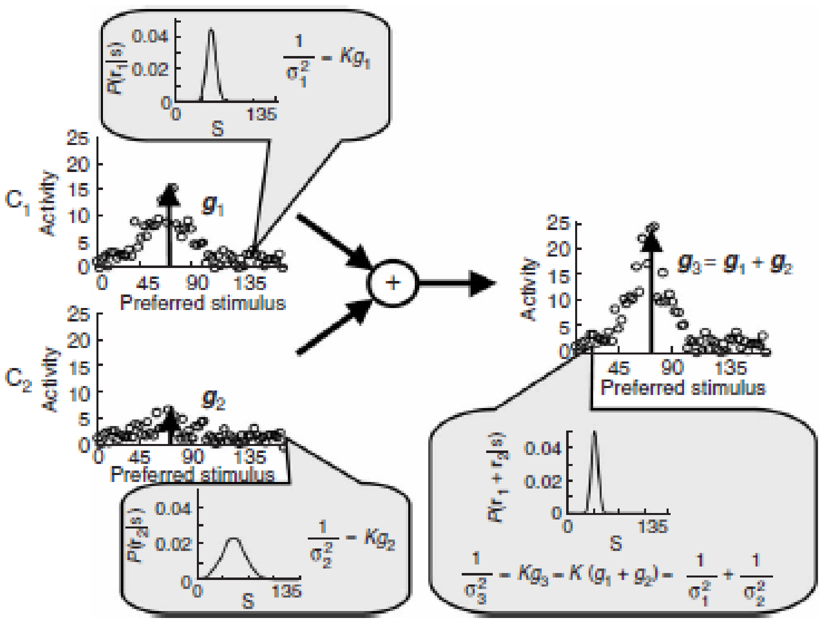


- In neurons with poisson variability the uncertainty is modulated by the gain

$$p(s|\mathbf{r}) \propto p(\mathbf{r}|s)p(s)$$

$$p(s|\mathbf{r}) \propto \prod_i \frac{e^{-f_i(s)} f_i(s)^{r_i}}{r_i!} p(s)$$

Probabilistic population codes



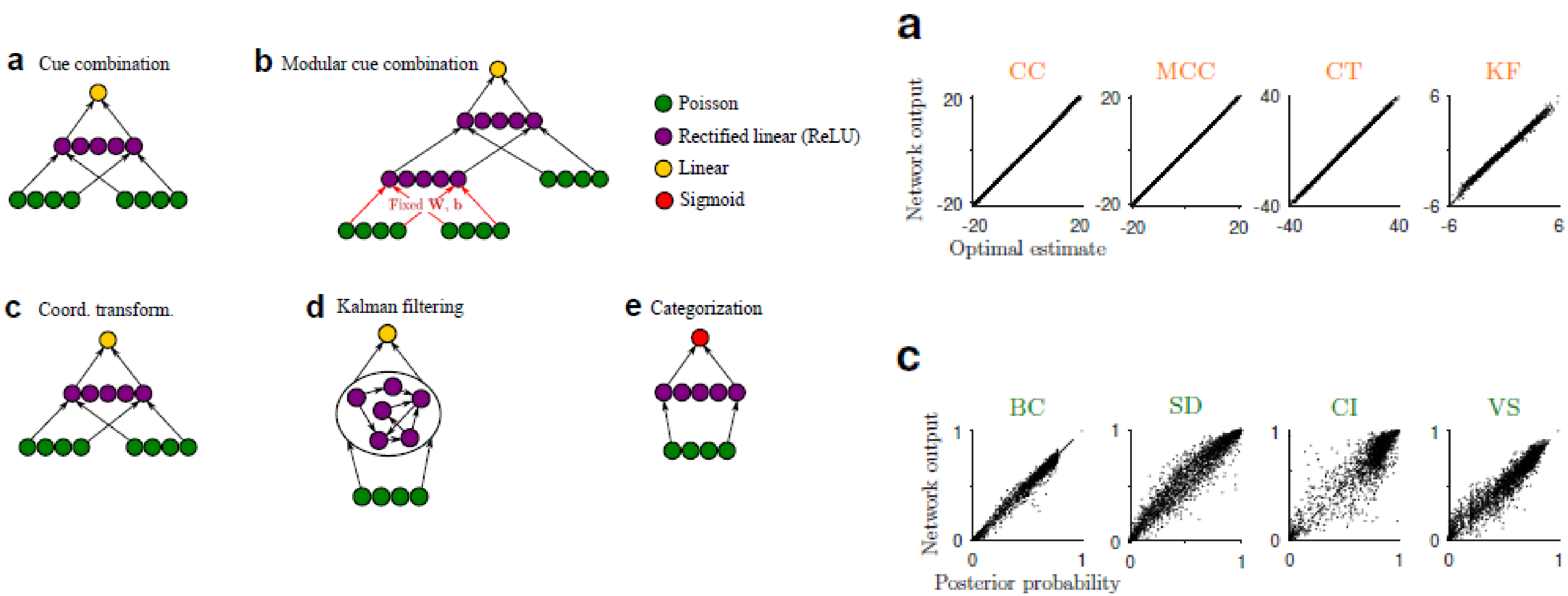
- Performing cue integration with these neurons is simple

- In this case these neurons have the nice property that adding activity leads to optimal Bayesian estimate

$$\mu_3 = \frac{\sigma_2^2}{\sigma_1^2+\sigma_2^2}\mu_1 + \frac{\sigma_1^2}{\sigma_1^2+\sigma_2^2}\mu_2$$

$$\frac{1}{\sigma_3^2} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}$$

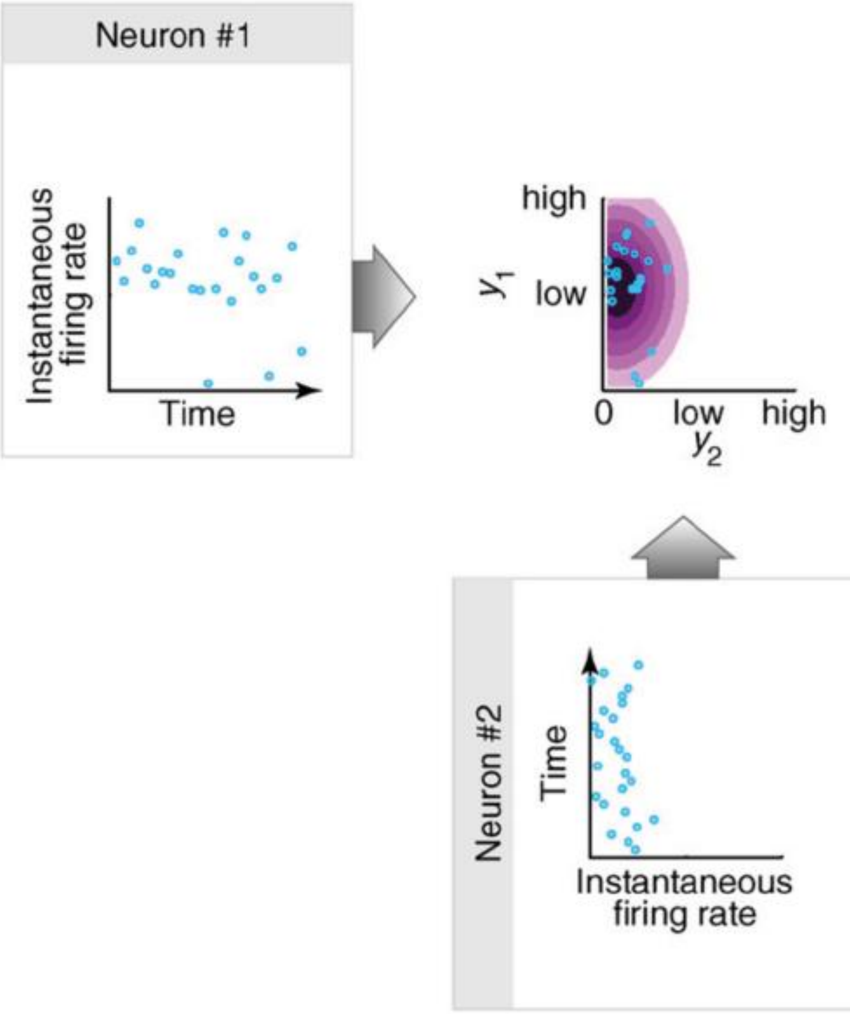
Simple neural network can do probabilistic inference



- Neural network trained with non probabilistic feedback is able to give probabilistic estimations

- No need for probabilistic population code, but how does network do this?

Sampling hypothesis



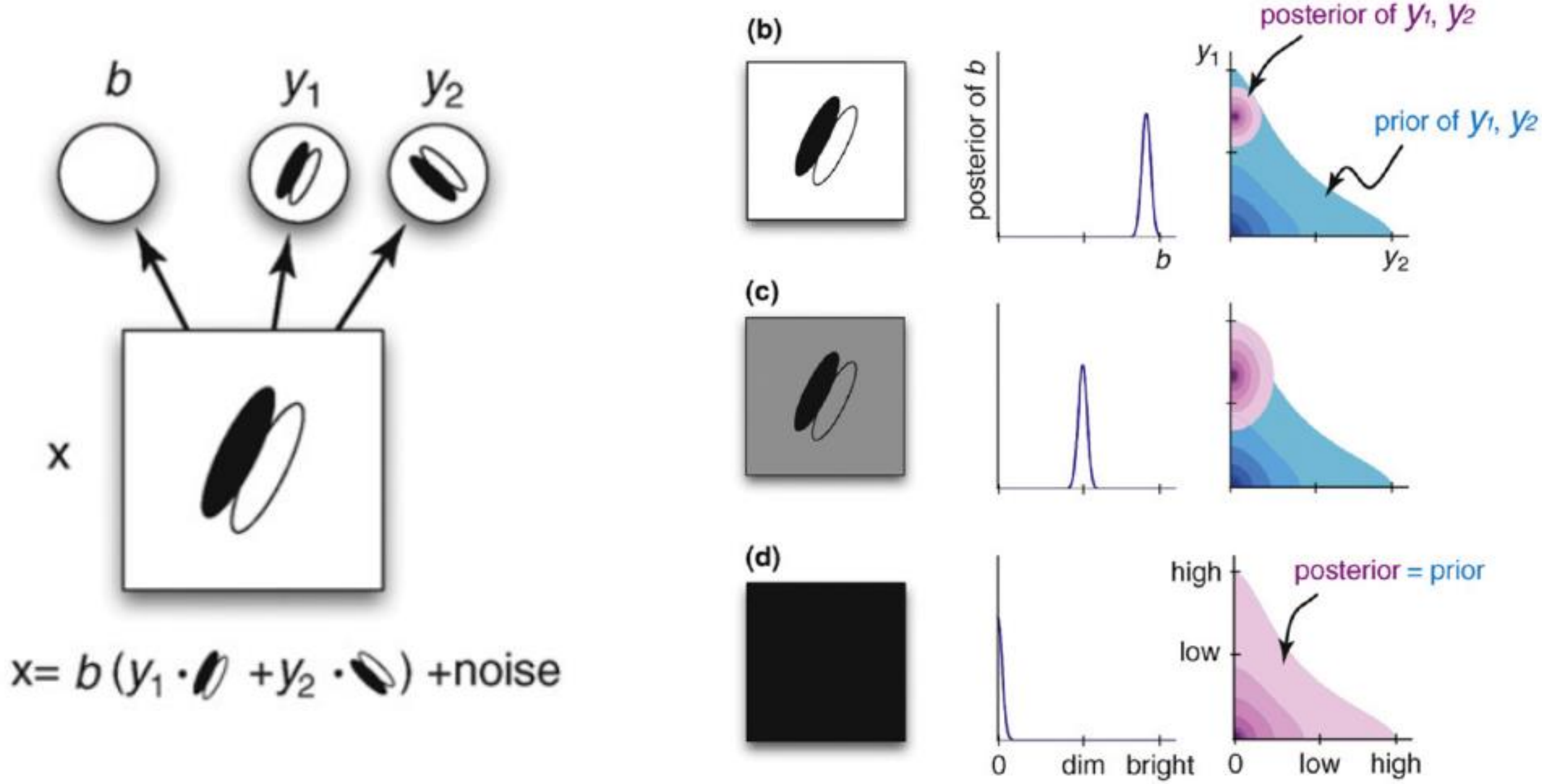
- Firing rates represent samples of a distribution

- Need to take multiple samples which takes time

- But is able to represent any distribution without expontial increase of parameters

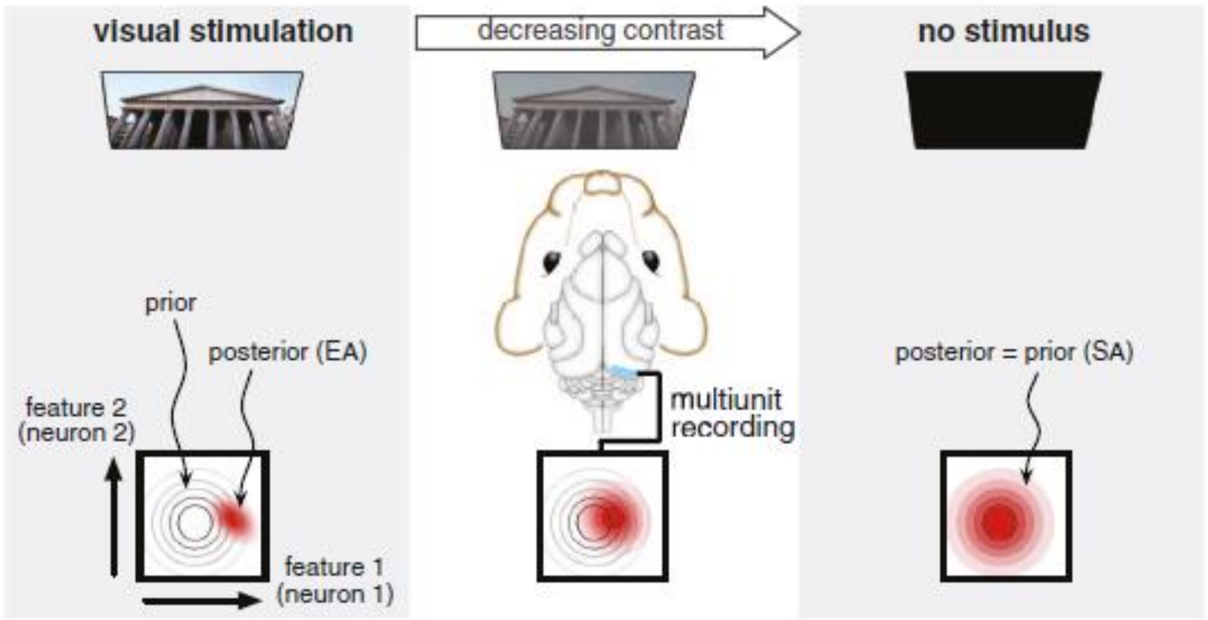
Fiser, J., Berkes, P., Orbán, G., & Lengyel, M. (2010). Trends in Cognitive Sciences.

Combining prior with likelihood



Fiser, J., Berkes, P., Orbán, G., & Lengyel, M. (2010). Trends in Cognitive Sciences.

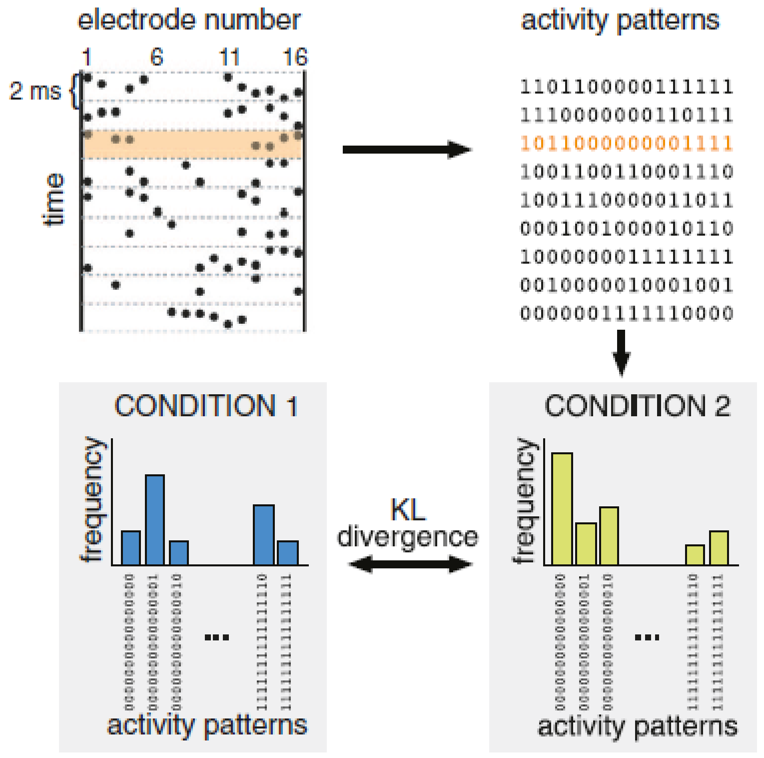
Using prior knowledge



$P(\text{features}|\text{input, model})$ $\quad$ $P(\text{features}|\text{model})$

Prior should adapt to match frequency of features in natural world.

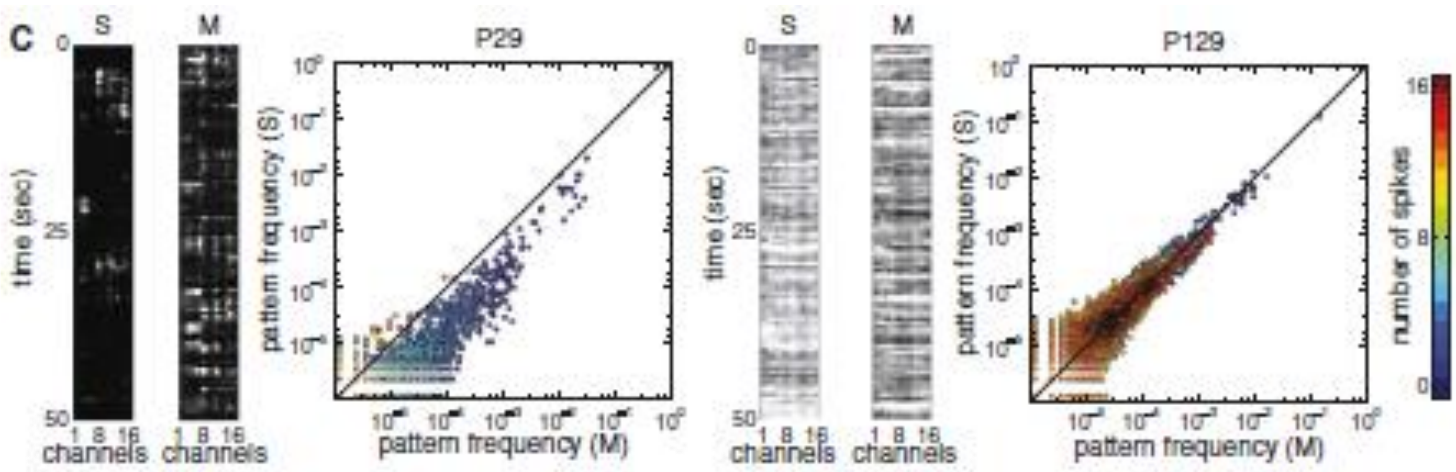
Using prior knowledge

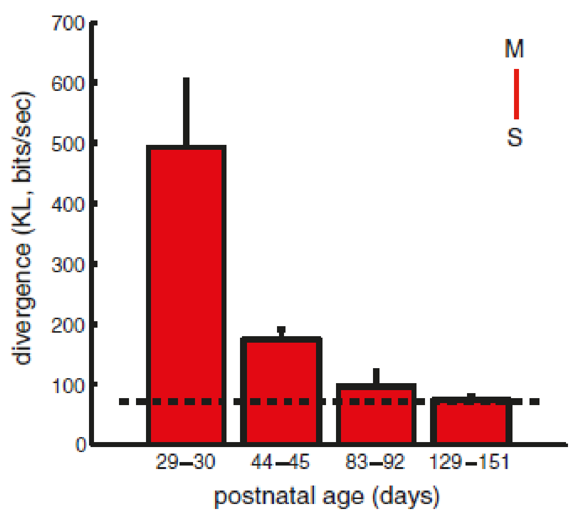


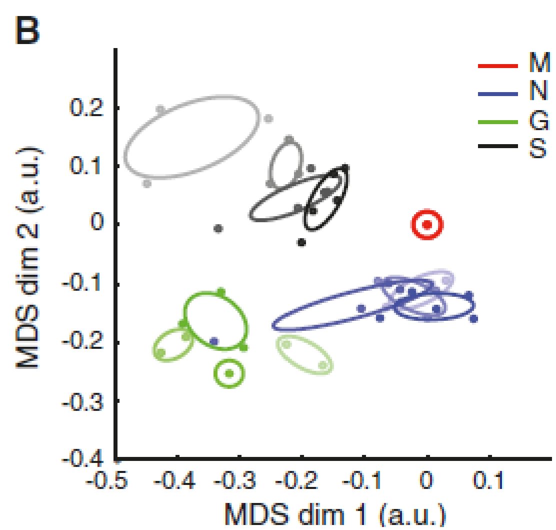
$P(\text{features}|\text{input, model})$ $P(\text{features}|\text{model})$

$$D(p||q) = \sum_x p(x) \log \frac{p(x)}{q(x)}$$

Using prior knowledge



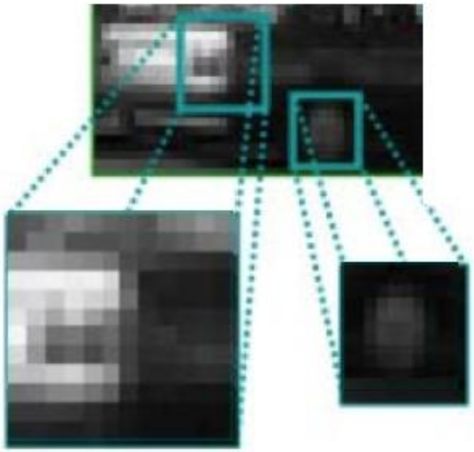




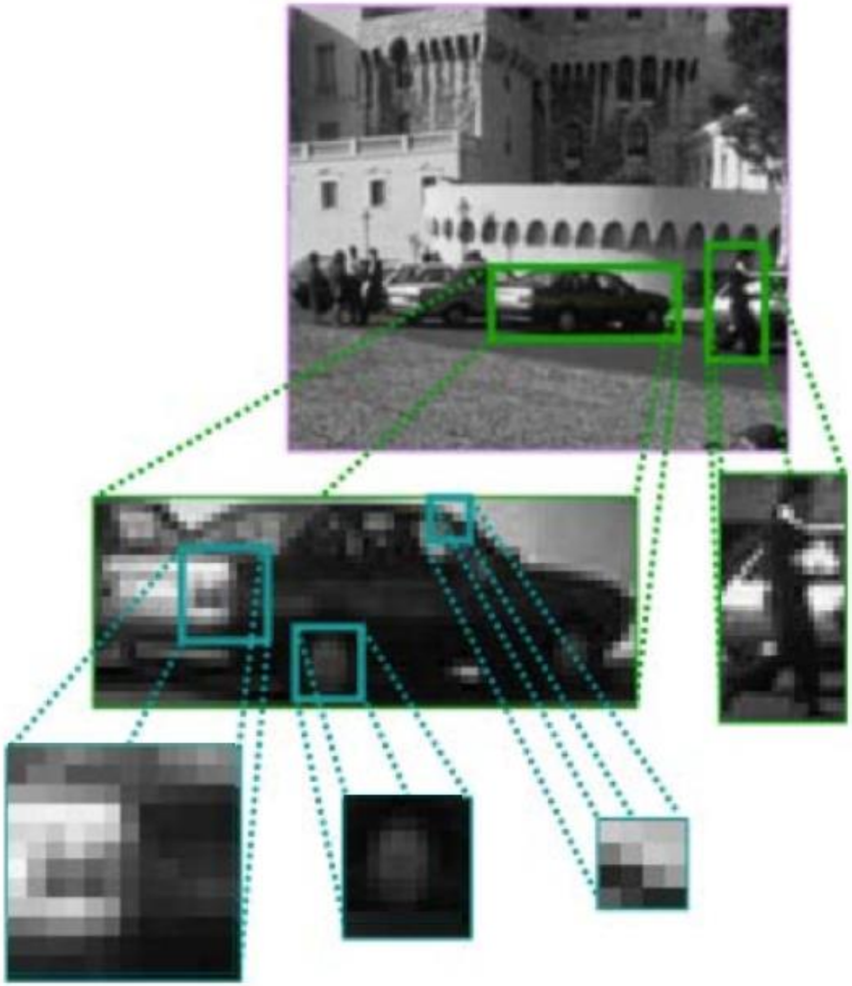
Distributions of natural movies and SA converge over time.

Hierarchical inference

Hierarchical inference



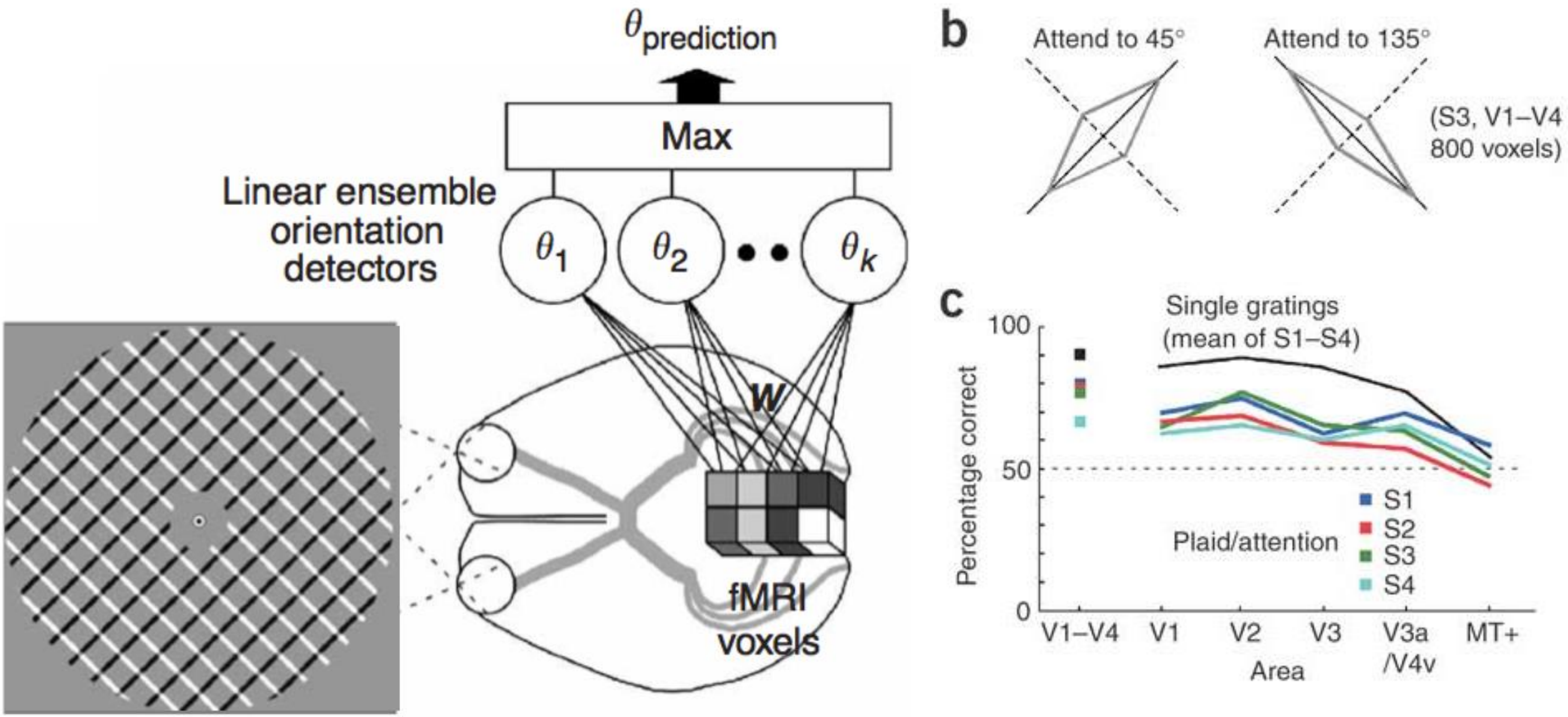
Hierarchical inference



Higher areas have information that can help processing in lower areas.

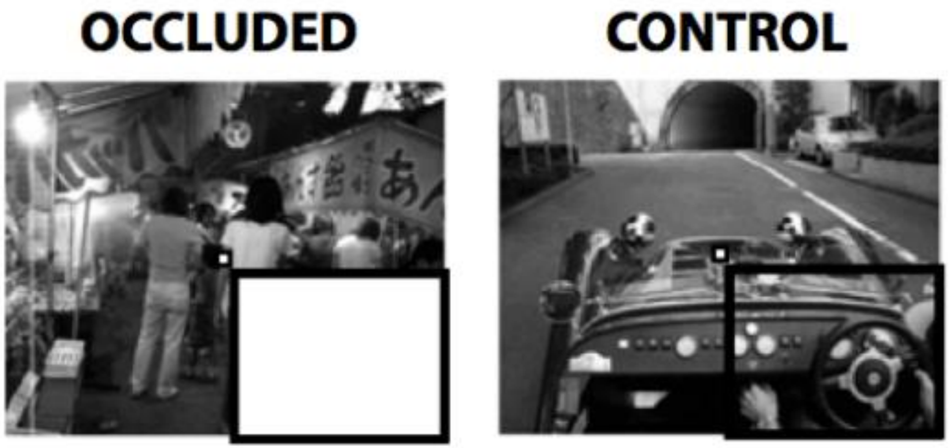
Evidence for feedback in the brain

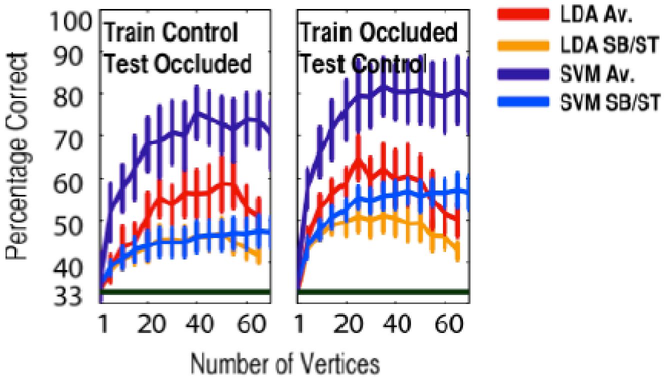
Attention modulates
early responses



Kamitani and Tong, Nature Neuroscience, 2005

Evidence for feedback in the brain





Smith FW, Muckli L. Nonstimulated early visual areas carry information about surrounding context. PNAS. 2010 Nov 16;107(46):20099–103.

- Context changes early visual responses
- Even occluded area allows prediction of the scene
- Feedback from other areas can be spatial precise or diffuse

Predictive coding

– Initially introduced as mechanism to reduce noise in the retina (1982).

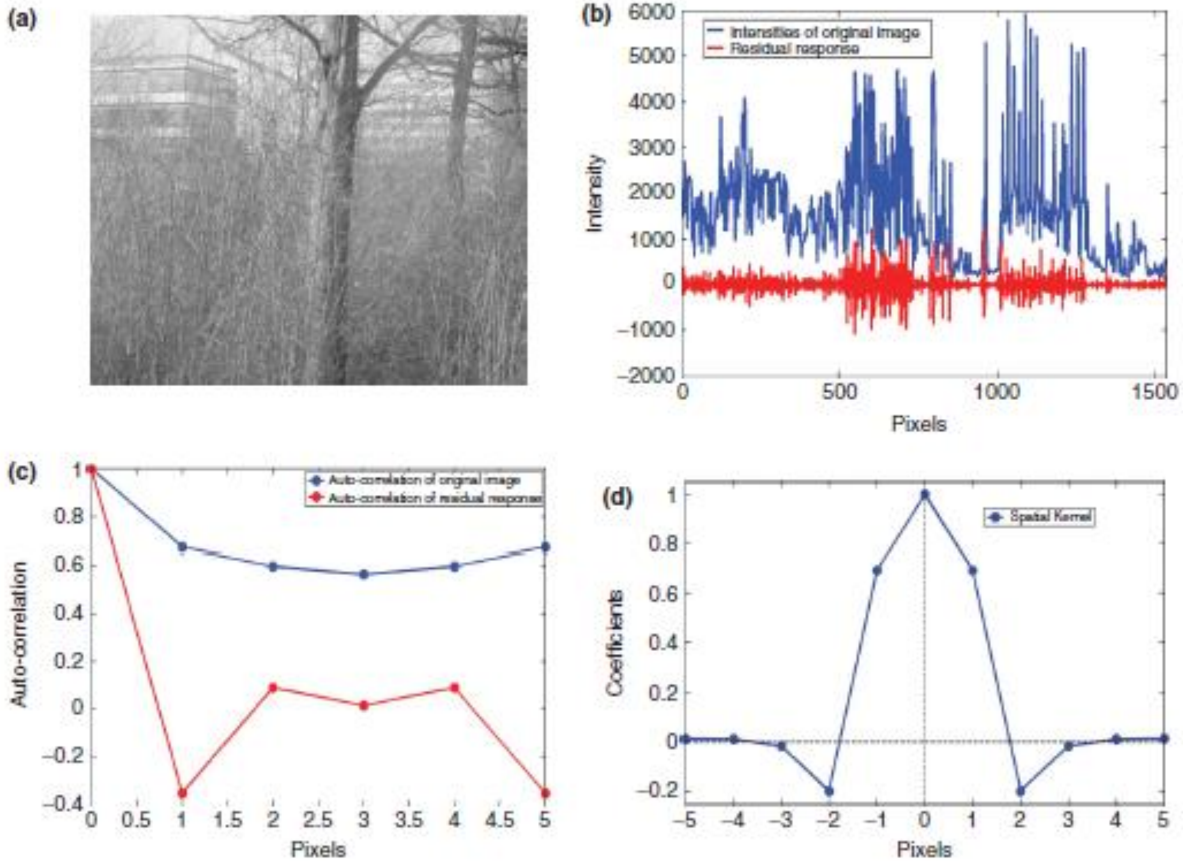
Predictive coding: a fresh view of inhibition in the retina

By M. V. Srinivasan[1,2]†, S. B. Laughlin[1] and A. Dubs[1]

– Predictions are made about upcoming sensory input.

– Resources can be focussed on processing what cannot be predicted yet (prediction error).

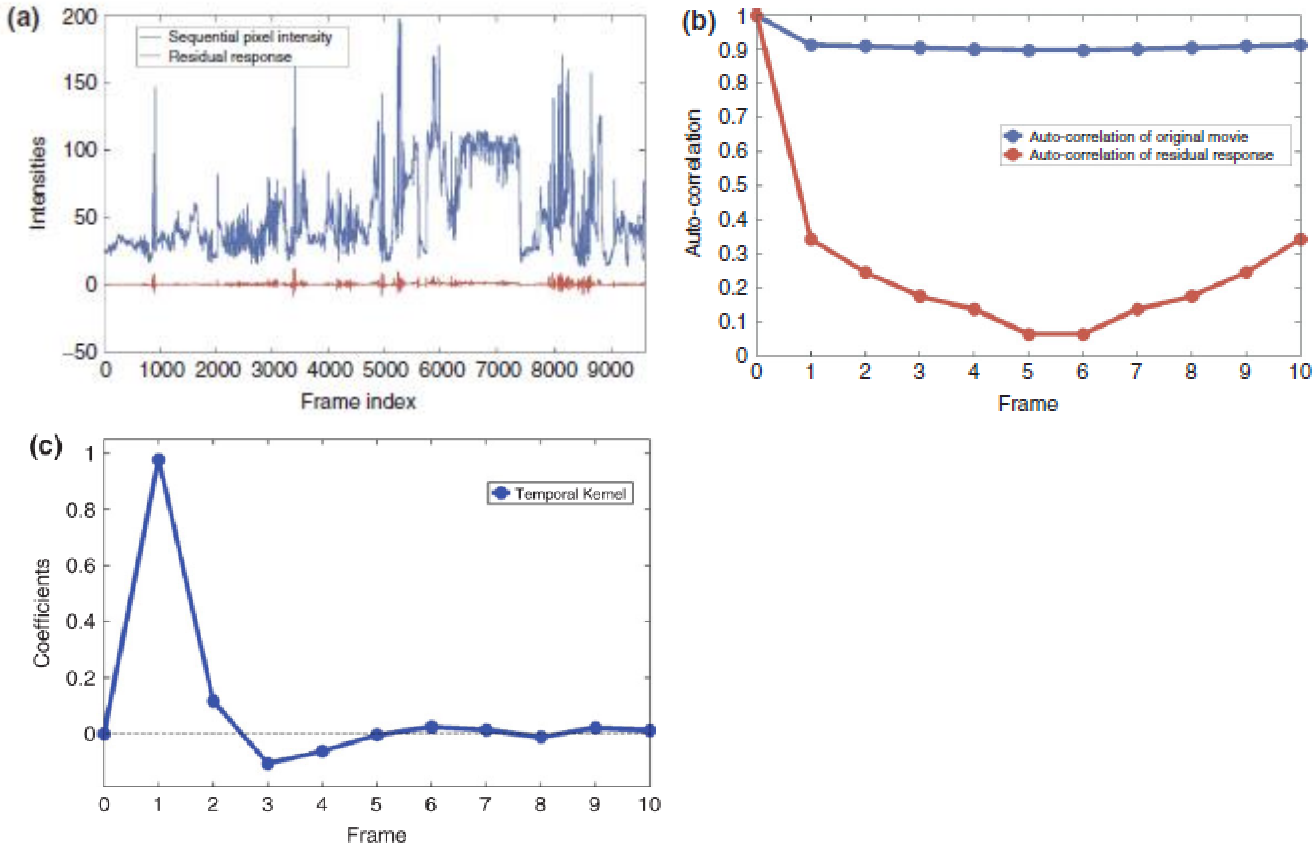
Reducing spatial redundancy



There is a lot of spatial and temporal redundancy in natural images and movies. Predictive coding is a way of efficiently reducing this redundancy.

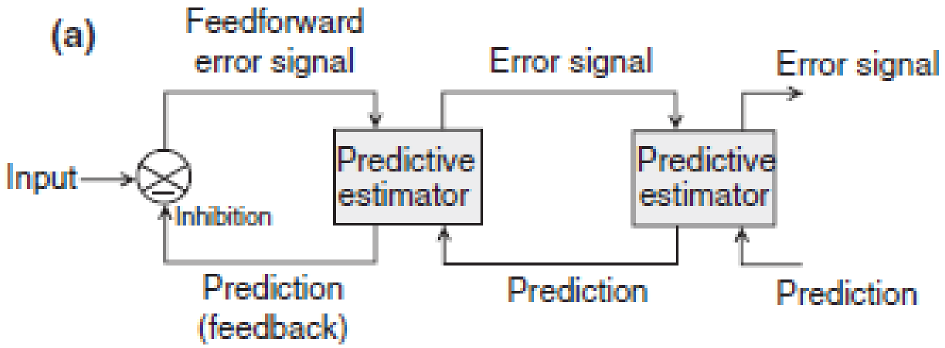
Huang, Y., & Rao, R. P. N. (2011). Predictive coding. WIRES Cognitive Science

Reducing temporal redundancy



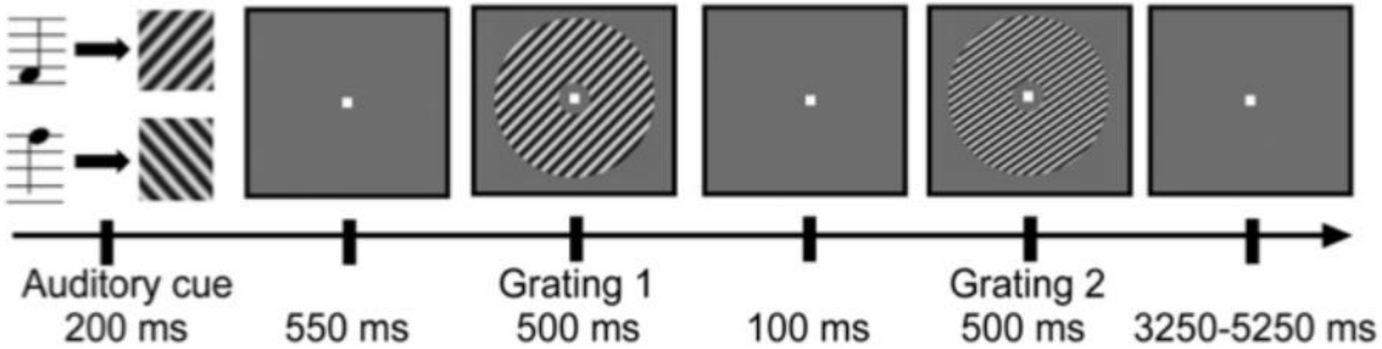
Huang, Y., & Rao, R. P. N. (2011). Predictive coding. WIRES Cognitive Science

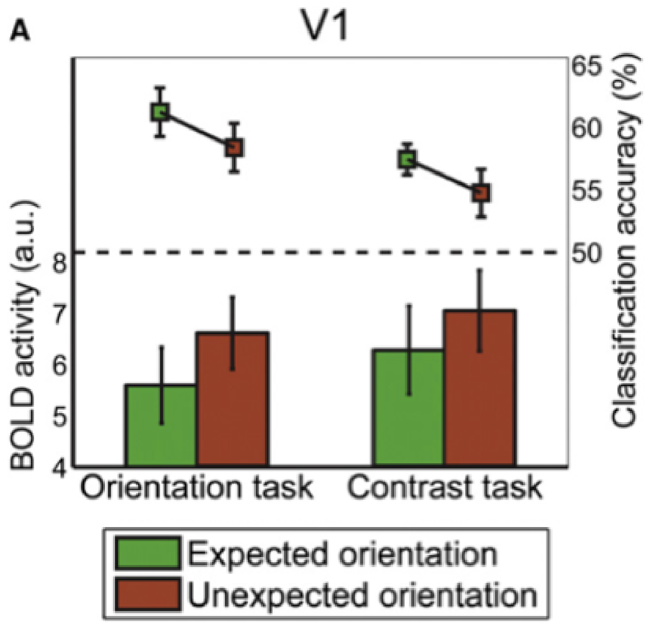
Predictive coding can explain Gabor wavelets



Rao RP, Ballard DH. Predictive coding in the visual cortex: a functional interpretation of some extra-classical receptive-field effects. Nat. Neurosci. 1999 Jan;2(1):79–87.

Evidence from fMRI

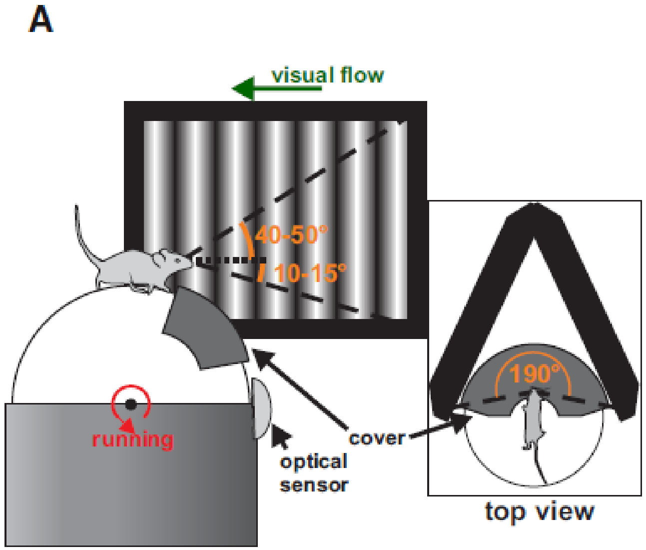




- Activity lower for expected stimuli
- But decoding better

Kok P, Jehee JFM, de Lange FP. Less is more: expectation sharpens representations in the primary visual cortex. Neuron. 2012 Jul 26;75(2):265–70.

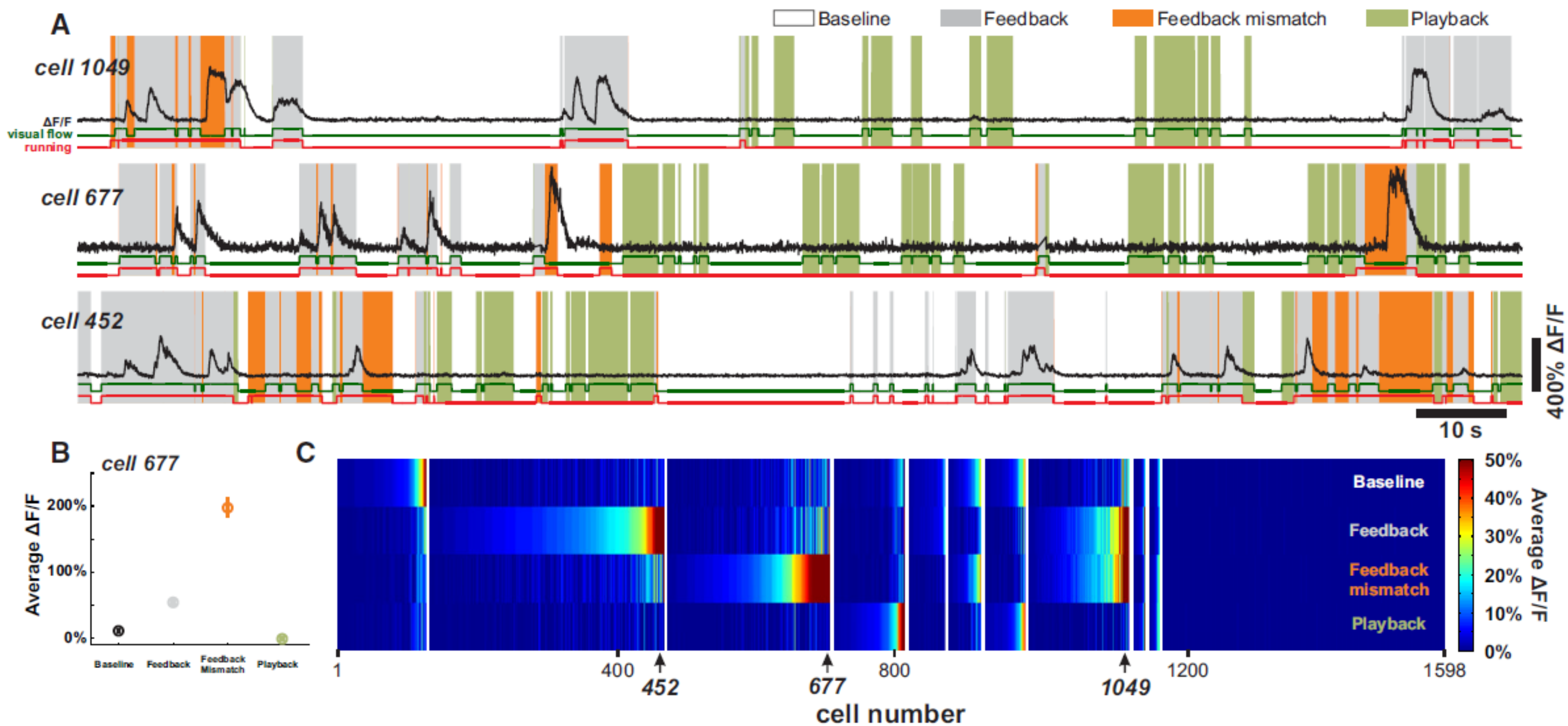
Predictive coding in neurons



- Experiment in rodents.
- Moving grating shown when animal runs.
- Prediction errors induced by manipulating visual flow.

Keller, G. B., Bonhoeffer, T., & Hübener, M. (2012). Sensorimotor mismatch signals in primary visual cortex of the behaving mouse. *Neuron*, *74*(5), 809-815.

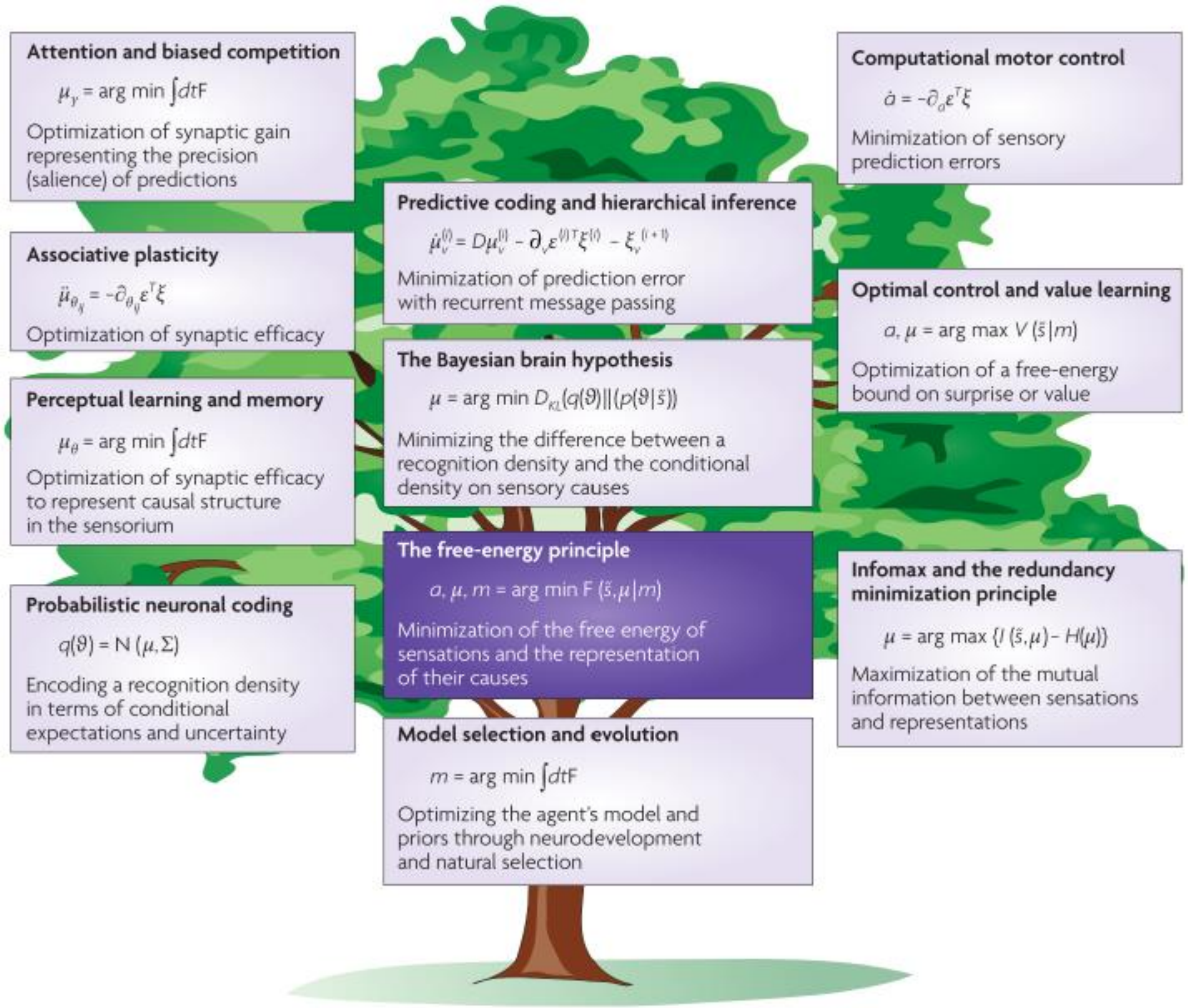
Predictive coding in neurons



Fraction of neurons responsive to prediction errors.

Keller, G. B., Bonhoeffer, T., & Hübener, M. (2012). Sensorimotor mismatch signals in primary visual cortex of the behaving mouse. *Neuron*, *74*(5), 809-815.

Free energy principle



Friston, K. J. (2010). The free-energy principle: a unified brain theory? Nature Reviews. Neuroscience, 11(2), 127–138

Free energy principle

- Theory introduced by Karl Friston that tries to explain how organisms tend to strive against the second law of thermodynamics.

- Isolated systems tend to become more chaotic over time, but because of energy input organisms are able to go create order.

- Brain helps to seek out a restricted number of beneficial states.

- Animals try to minimise their **surprise** by minimising **free energy**.

Free energy principle

- We try to infer hidden states of the world **θ** from our sensations **s**

- Organism tries to form an internal model **m**, that tries to explain the link between sensations and underlying hidden states of the world:

$$p(\mathbf{s}, \boldsymbol{\theta}) = p(\mathbf{s} \mid \boldsymbol{\theta})p(\boldsymbol{\theta})$$

- Hidden states **θ** are unknown so we integrate them out to get the model evidence

$$p(\mathbf{s}) = \int p(\mathbf{s} \mid \boldsymbol{\theta})p(\boldsymbol{\theta})d\boldsymbol{\theta}$$

- When making dependency on **m** explicit this is equivalent to:

$$p(\mathbf{s} \mid m)$$

Free energy principle

- Free energy principle is equivalent to variational Bayes method
- In variational Bayes we try to find an approximating density **q** that approximates the posterior $p(\boldsymbol{\theta} \mid \mathrm{s}, m)$
- Can be done by mimizing the **free energy**

$$\underbrace{F}_{\text{free energy}} = \underbrace{-\log p(\mathrm{s} \mid m)}_{\text{surprise}} + \underbrace{D_{\mathrm{KL}}(q(\boldsymbol{\theta} \mid \boldsymbol{\mu}) || p(\boldsymbol{\theta} \mid \mathrm{s}, m))}_{\text{divergence}} \geq \underbrace{-\log p(\mathrm{s} \mid m)}_{\text{surprise}}$$

- Divergence between **q** and posterior is minimized.
- Gives an upper bound on **surprise** which is the negative log model evidence

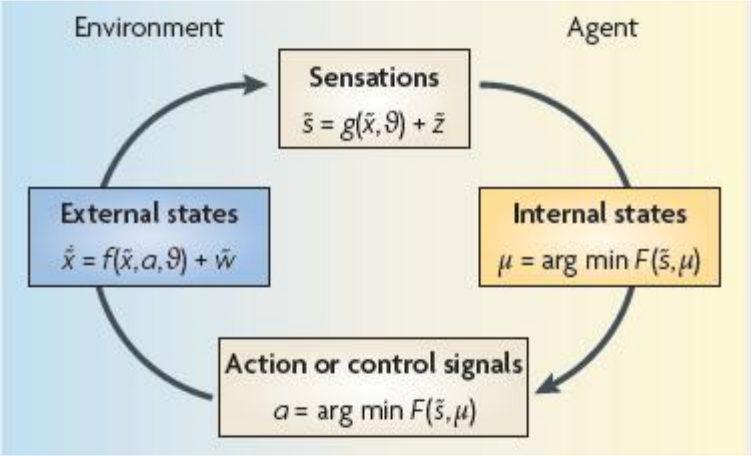
Free energy principle

- We can minimize free energy by adapting internal states to optimise predictions

$$\boldsymbol{\mu} = \arg\min_{\boldsymbol{\mu}} F \geq -\log p(\mathbf{s} \mid m)$$

- Or take actions to minimise prediction errors

$$\mathbf{a}^* = \arg\min_{\mathbf{a}} F \geq -\log p(\mathbf{s} \mid m)$$



- Underlines organisms tendency to avoid risky ‘uncertain’ situations, but raises questions about exploratory behavior

Conclusions

- Brain could use structure in the world to improve perception
- Abundant behavioral evidence that people use prior knowledge and account for uncertainty in their observations
- Different theories that account for these findings, similar in some aspects, but different in others
- How predictive processing is implemented in the brain remains mainly an open question
- Evidence for and against different implementations
- Need for experiments that can dissociate between different theories

Required reading

Vilares, I., & Kording, K. (2011). Bayesian models: the structure of the world, uncertainty, behavior, and the brain. *Annals of the New York Academy of Sciences*, *1224*(1), 22-39.

Huang, Y., & Rao, R. P. (2011). Predictive coding. *Wiley Interdisciplinary Reviews: Cognitive Science*, *2*(5), 580-593.

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