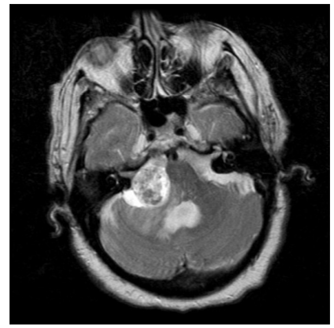
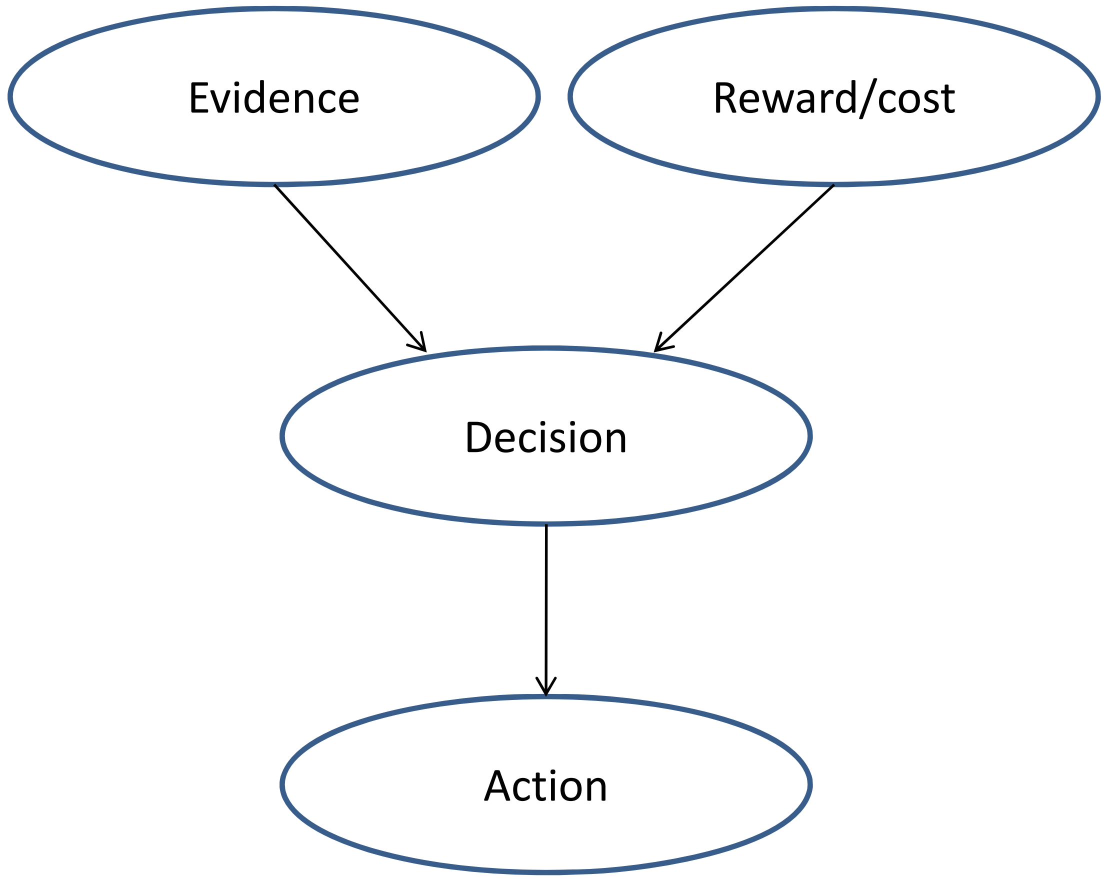
Decision-making

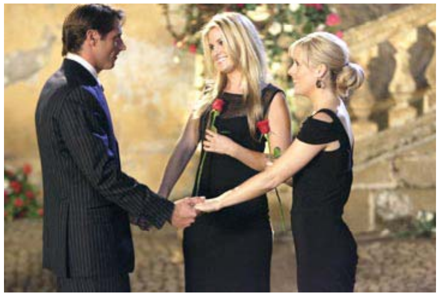
Lecture 7

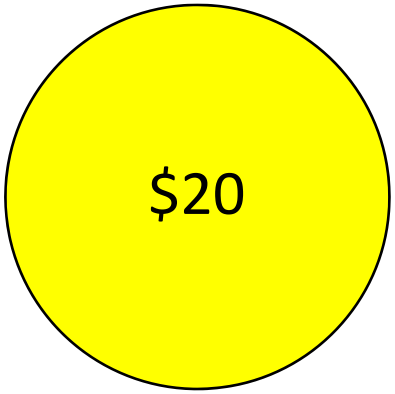
Types of decisions

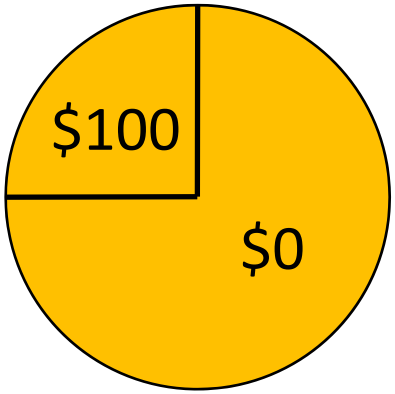



Evidence
Reward/cost
Decision
Action

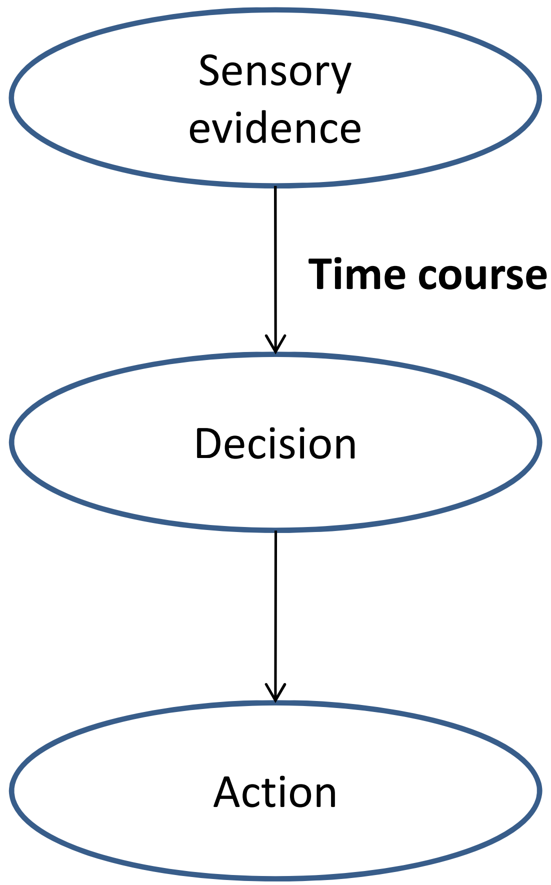
Reward-based decisions







Perceptual decisions

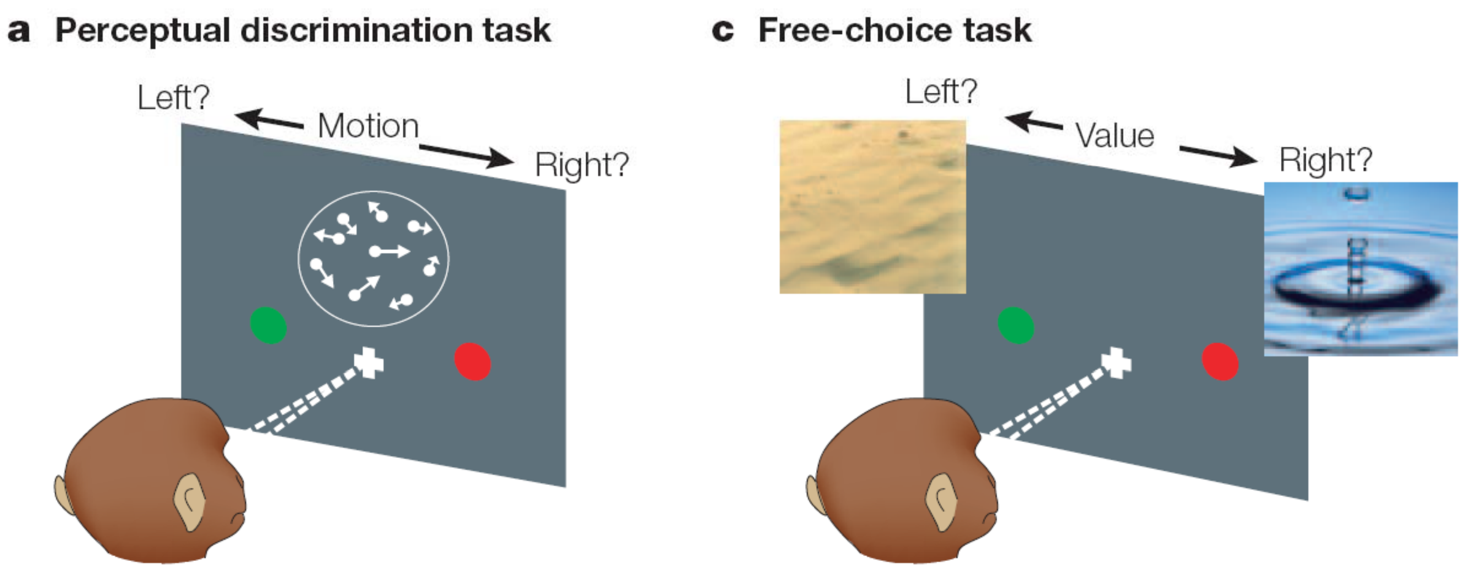


Time course of evidence accumulation

1. What to decide?
2. When to decide?

Multiple alternatives

Physiology: binary choice

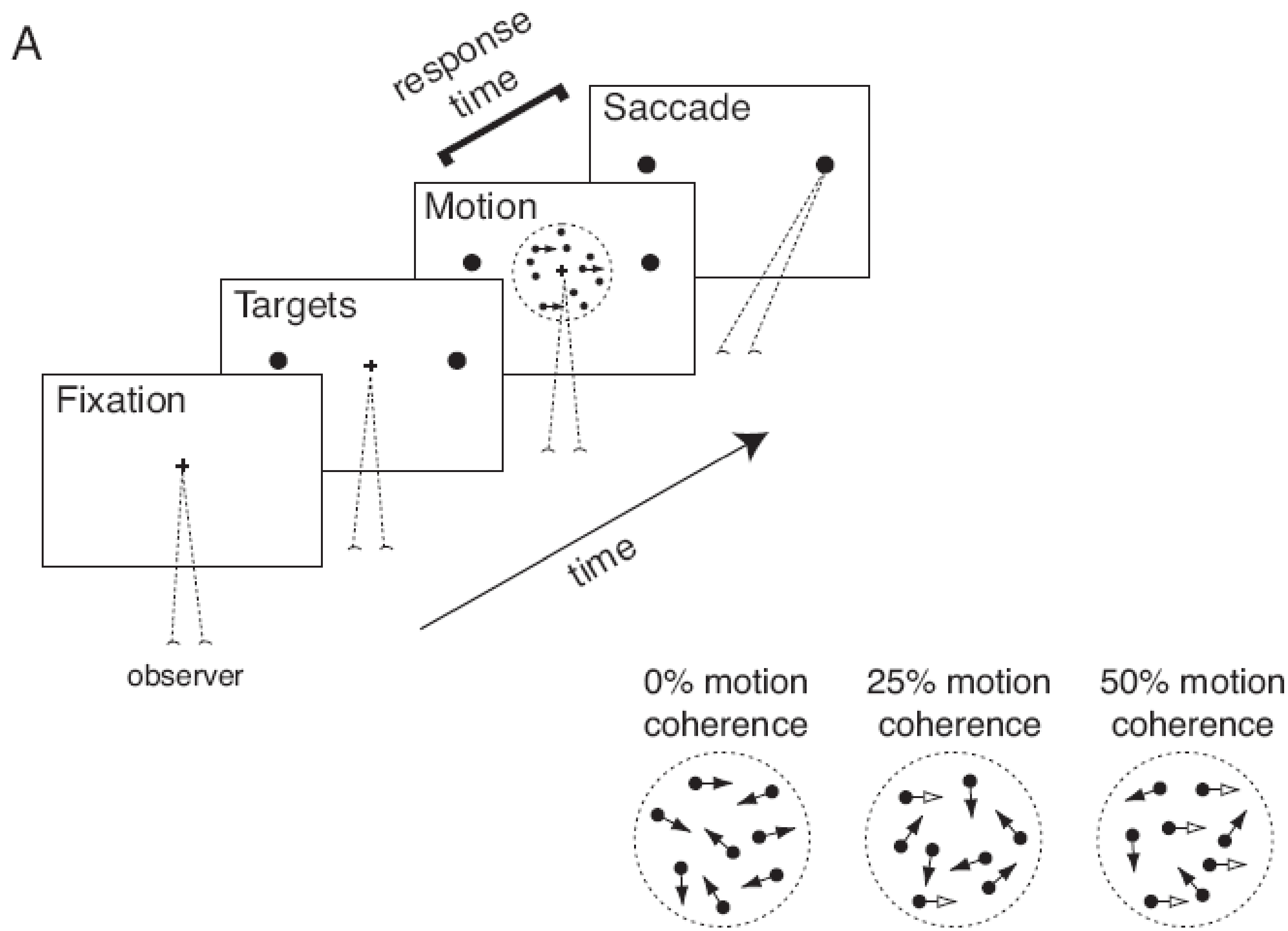


Sugrue, Corrado, Newsome, 2005

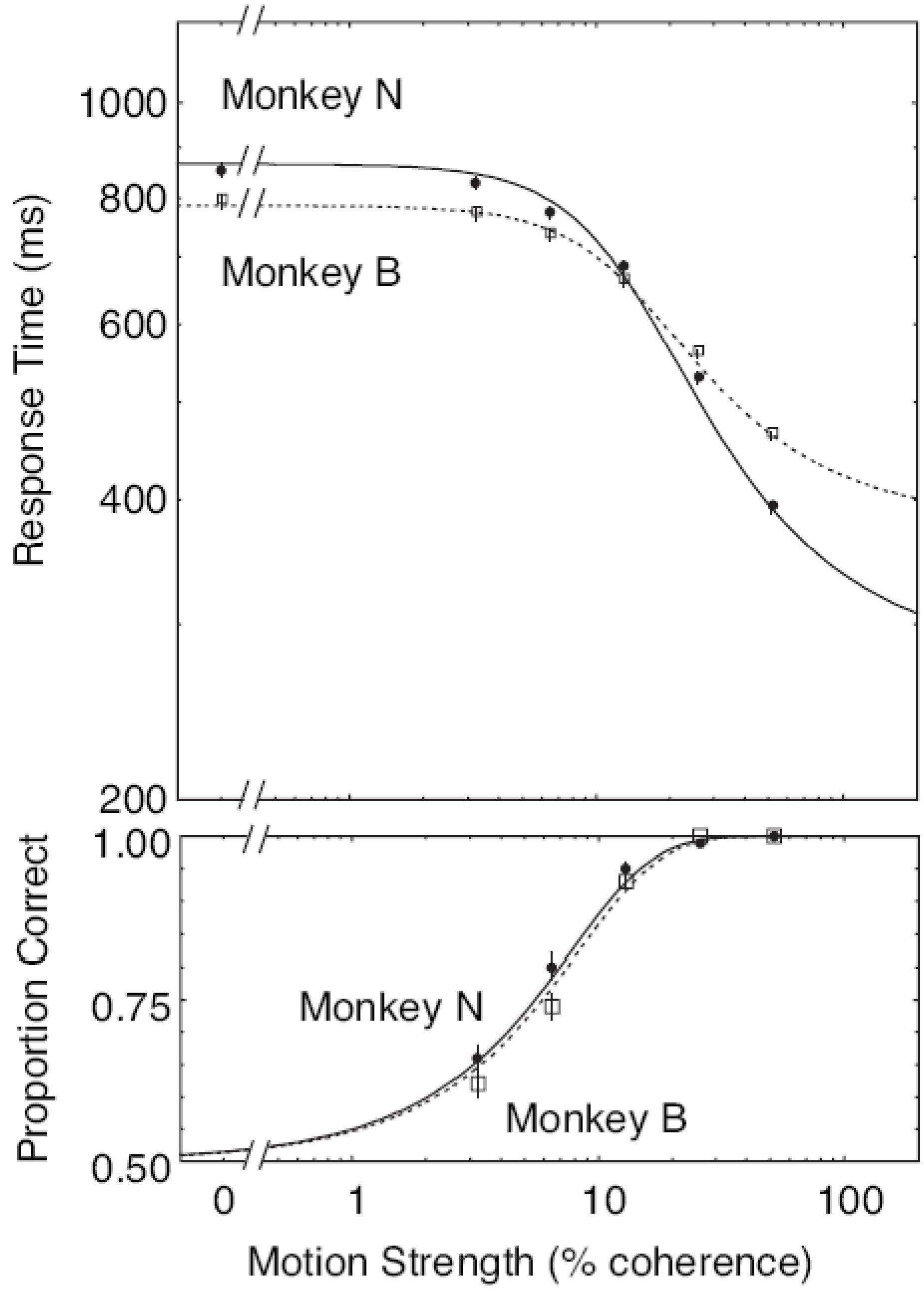
Types of experiments

- Response time procedure (free response protocol): unlimited time
- Response signal procedure (interrogation protocol): limited time

Motion discrimination – response time



Palmer, Huk, Shadlen 2005



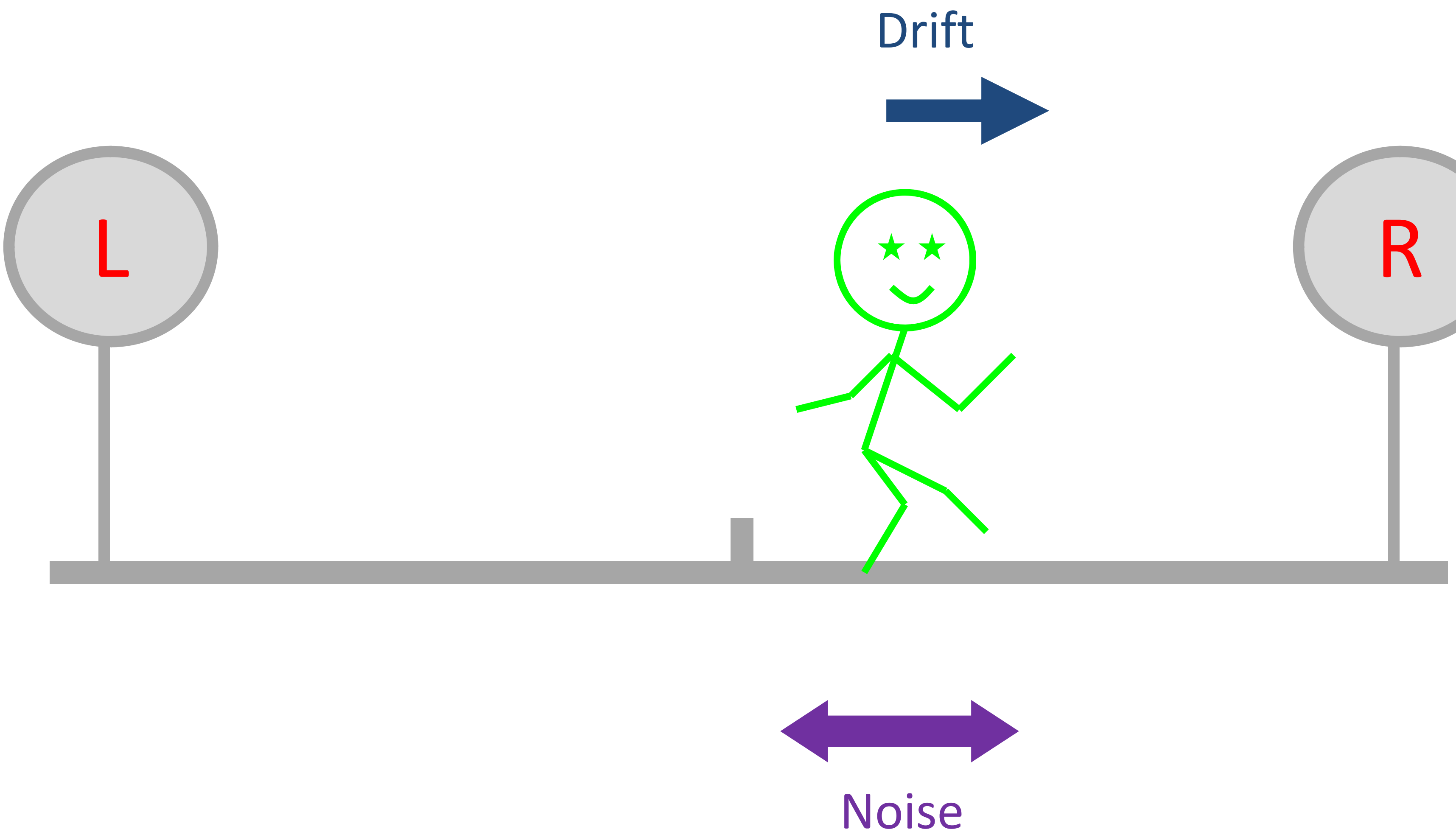
Monkey N
Monkey B
Response Time (ms)
1000
800
600
400
200
Proportion Correct
1.00
0.75
0.50
Monkey N
Monkey B
0
1
10
100
Motion Strength (% coherence)

Types of models

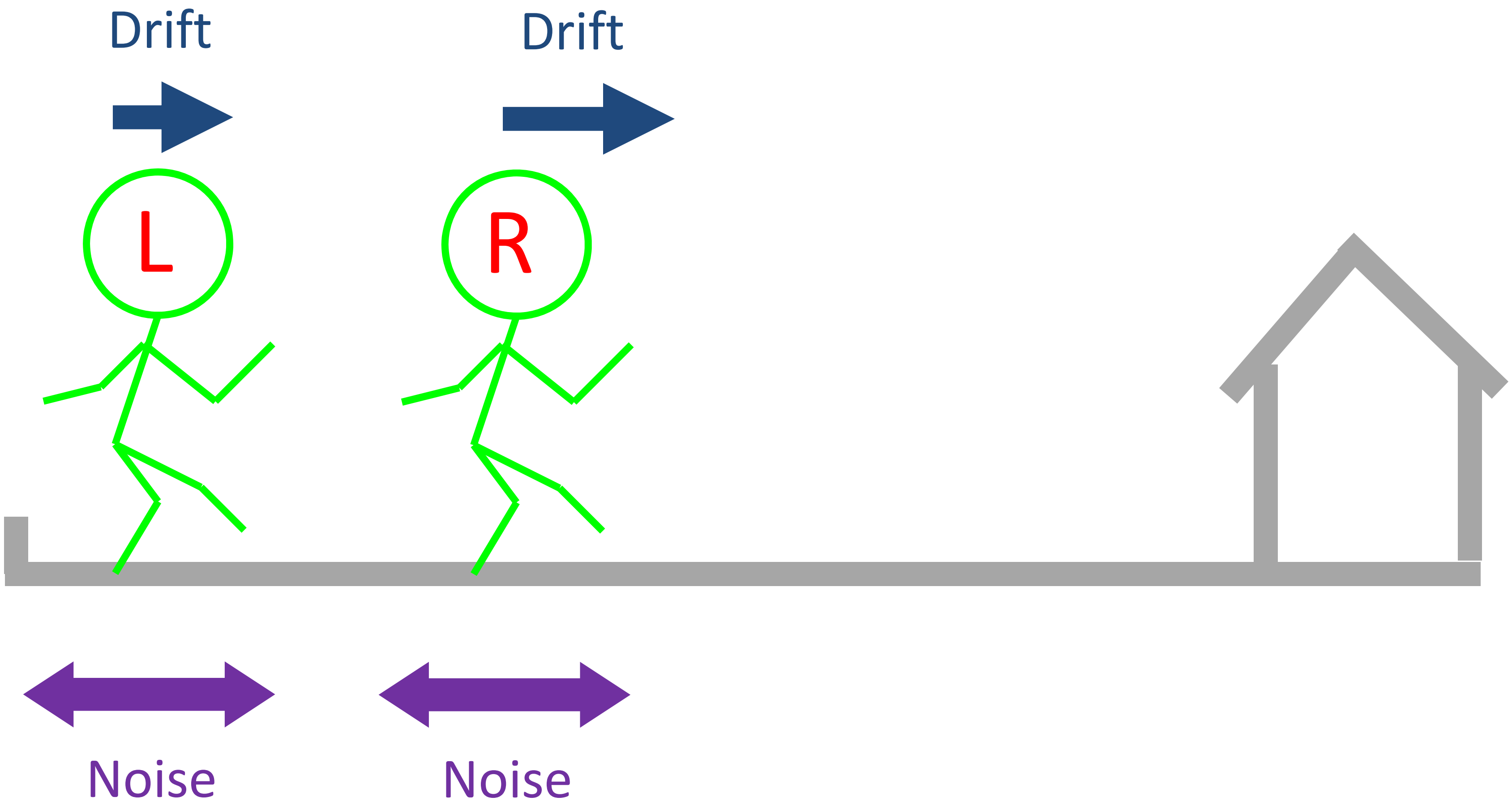
- Diffusion models
- Race (accumulator) models
- Bayesian models

- Behavioral models
- Neural models

Diffusion model



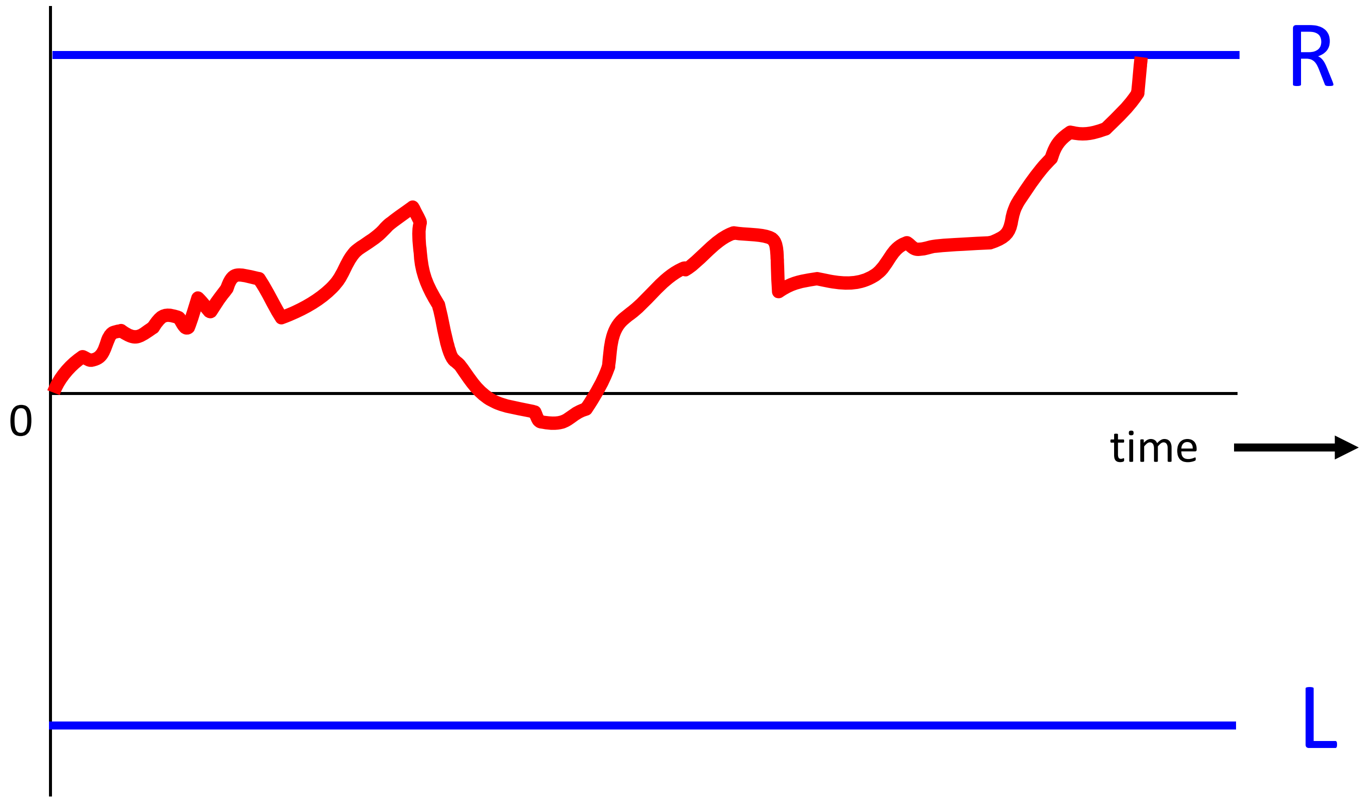
Race model

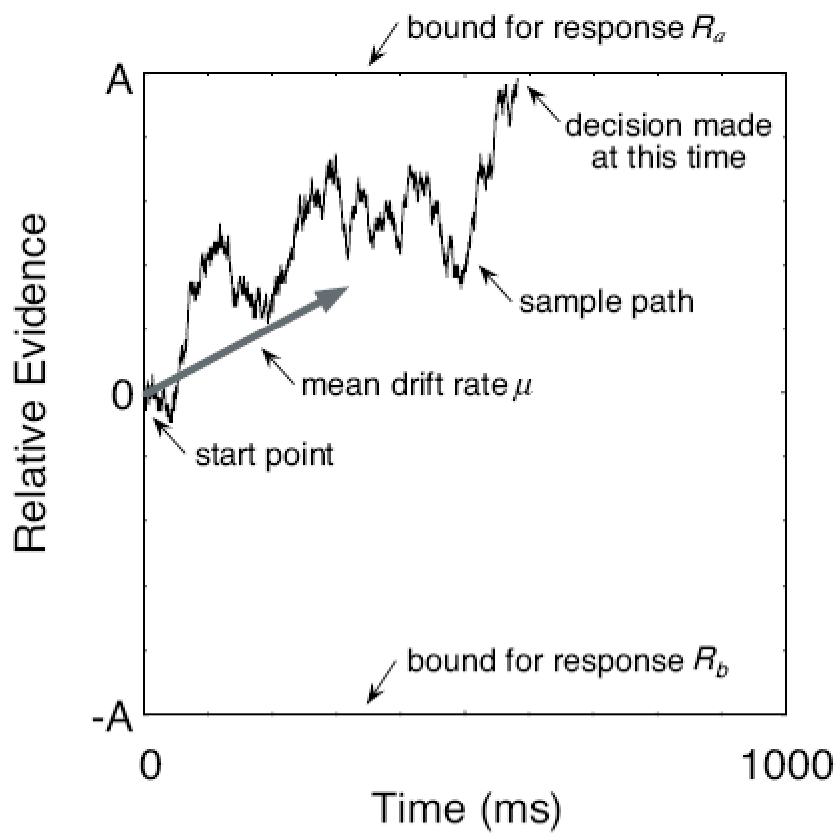


Pros and cons

- Diffusion models (Wald; Gold/Shadlen; Ratcliff)
  - Simple
  - Good description of psychophysics
  - What is the decision variable?
- Accumulator models (Usher/McClelland; McMillen/Holmes)
  - Neural flavor
  - More parameters
  - Worse fit to the data?

Diffusion model





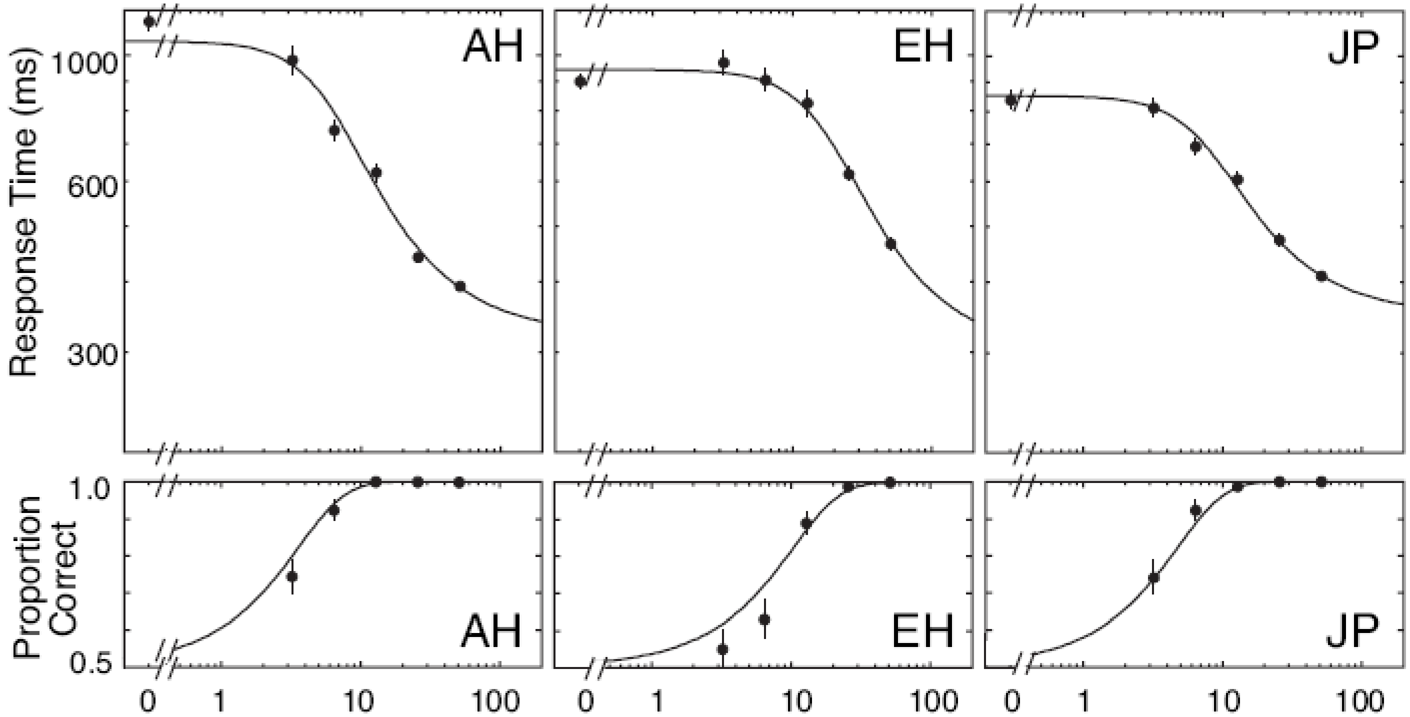
$$\mu' = kx$$

$$P_C(x) = \frac{1}{1+e^{-2A'k|x|}}.$$

$$t_T(x) = \frac{A'}{kx}\tanh(A'kx) + t_R$$

Palmer, Huk, Shadlen 2005

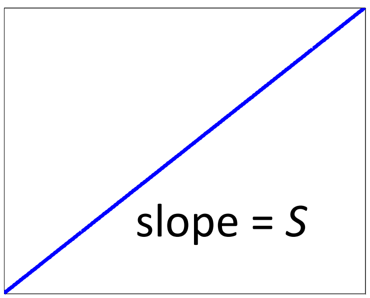
Binary choice – response time



Palmer, Huk, Shadlen 2005

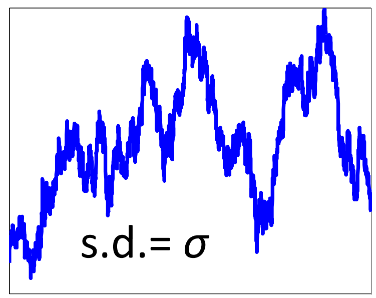
Leaky accumulator model

Integration



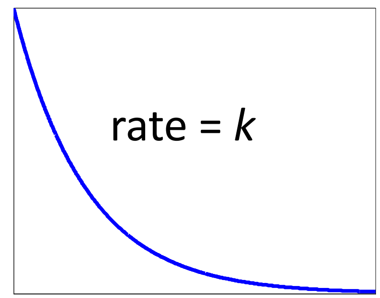
$$\frac{dx}{dt} = S$$

White noise



$$\frac{dx}{dt} = \text{white noise}$$

Leakage



$$\frac{dx}{dt} = -kx$$

Leaky accumulator model

$$dx_i = \left(\qquad\qquad\qquad \right) dt$$

i'th unit's change
in time *dt*

Leaky accumulator model

$$dx_i = \left(S_i \qquad\qquad\qquad\qquad \right) dt$$

i'th signal
(drift)

Leaky accumulator model

$$dx_i = \left(S_i - kx_i \qquad\qquad\qquad \right) dt$$

i'th unit's leakage

Leaky accumulator model

$$dx_i = \left(S_i - kx_i \qquad\qquad\qquad \right) dt + \sigma dW_i$$

white noise
into *i*'th unit

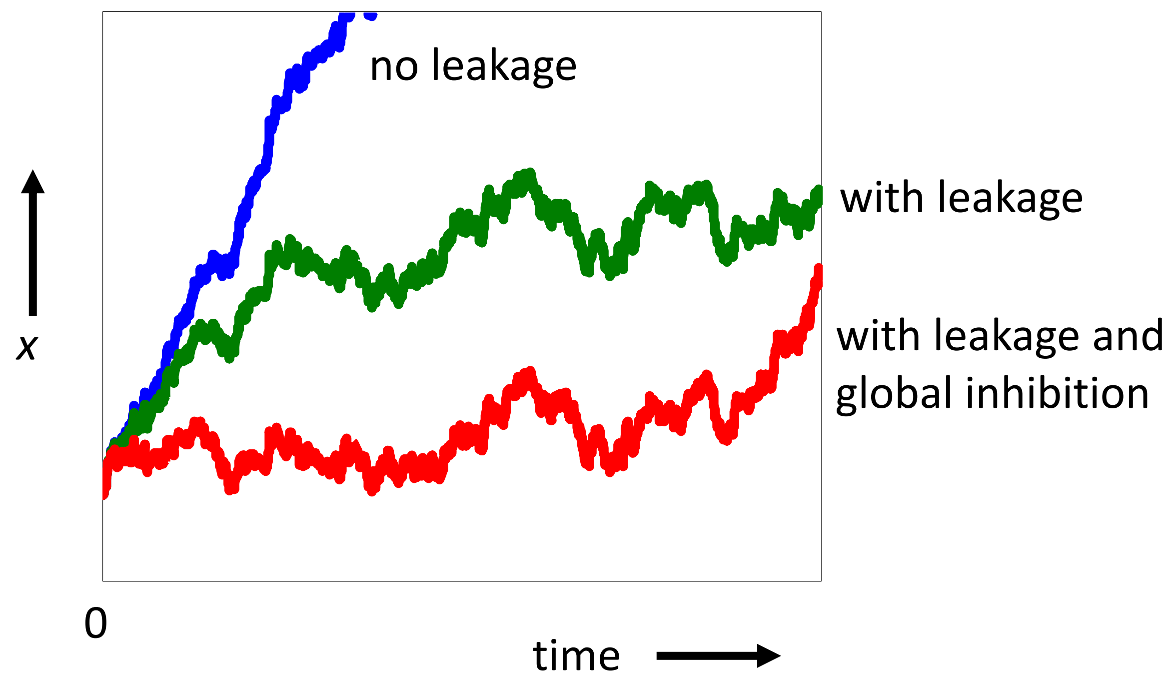
Leaky accumulator model

$$dx_i = \left(S_i - kx_i - w\sum_{j \neq i} x_j \right) dt + \sigma dW_i$$

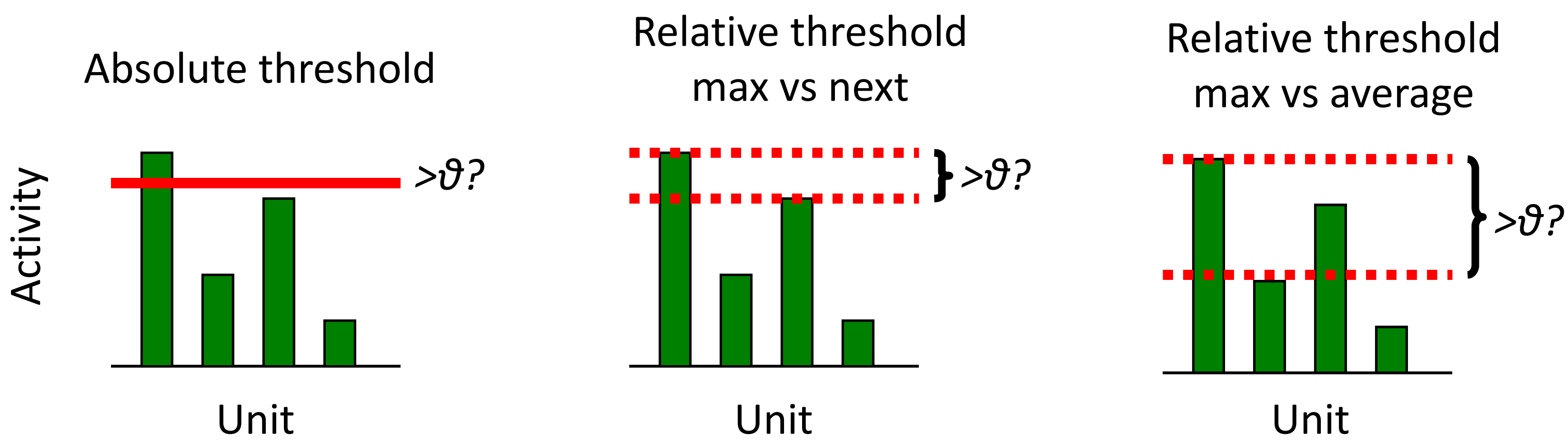
global inhibition

Leaky accumulator model

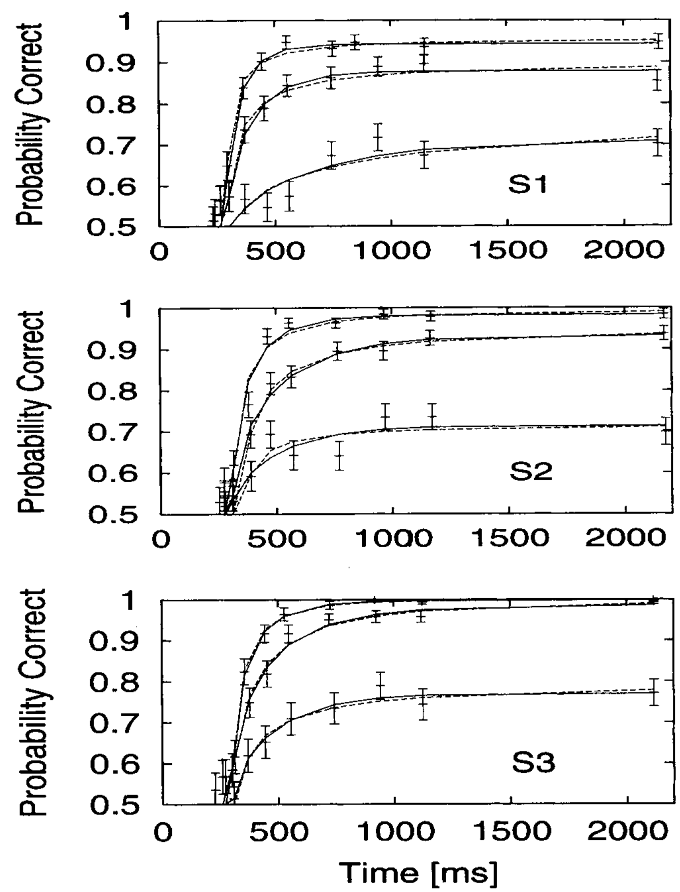
Typical behavior



When to decide?



Binary choice – Response signal



Usher and McClelland, 2001

Problems with existing models

- Limited to binary or discrete choice
- Uncertainty not encoded
- What if certainty changes over time or over trials?
- No normative solution

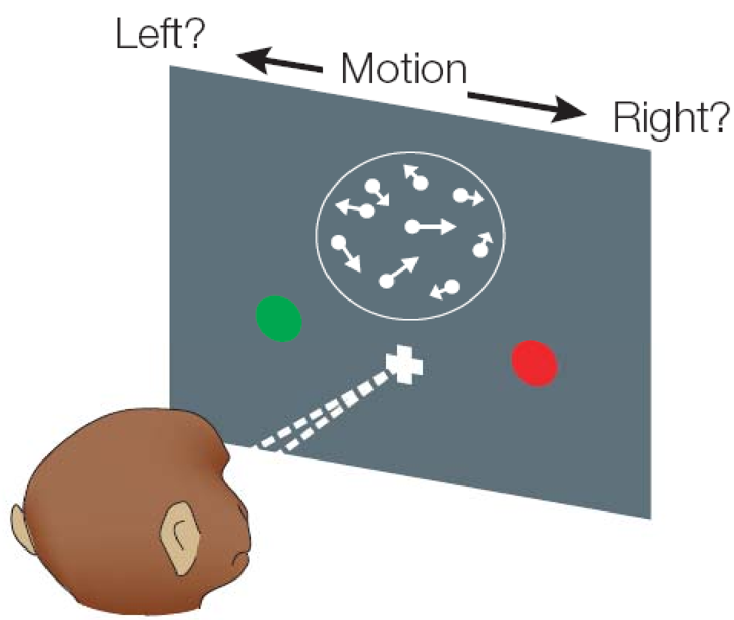
Stages of decision-making

Two stages to decision-making:

1. Accumulating the evidence
2. Action selection

- Can we build a neural network that performs accumulation and action selection optimally for any number of choices? No neural model is known beyond two choices.
- Would this network account for existing data?

Beck, Ma, et al., 2008



Left?
Motion
Right?

Single-Trial Activity

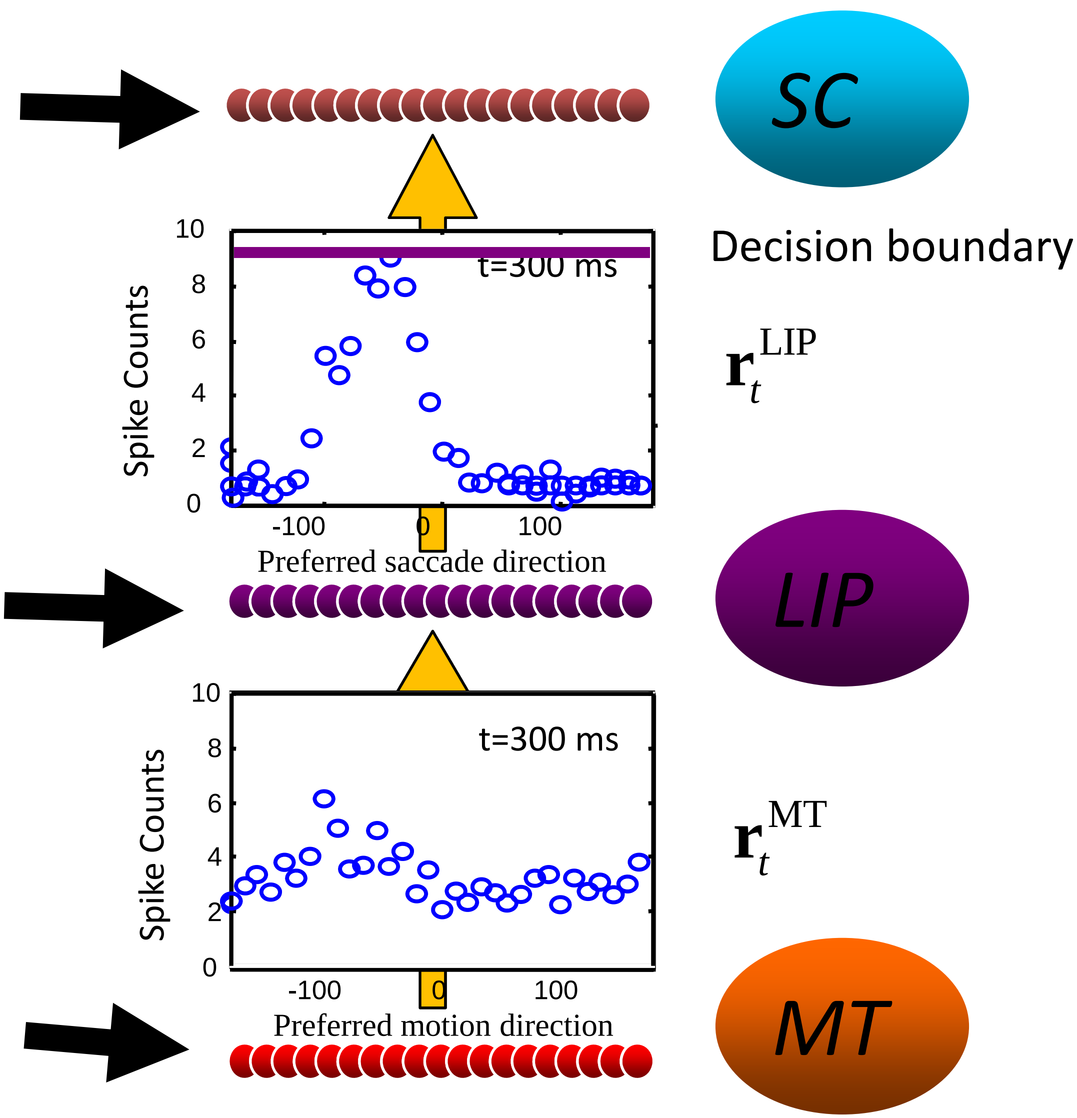
Network Architecture

Action selection : attractor dynamics

Integration: 100 spiking (LNP) neurons with lateral connections and long time constant

Termination rule: Stop integration when peak activity reaches a preset bound

Sensory data: 100 direction-selective neurons



Single-Trial Activity

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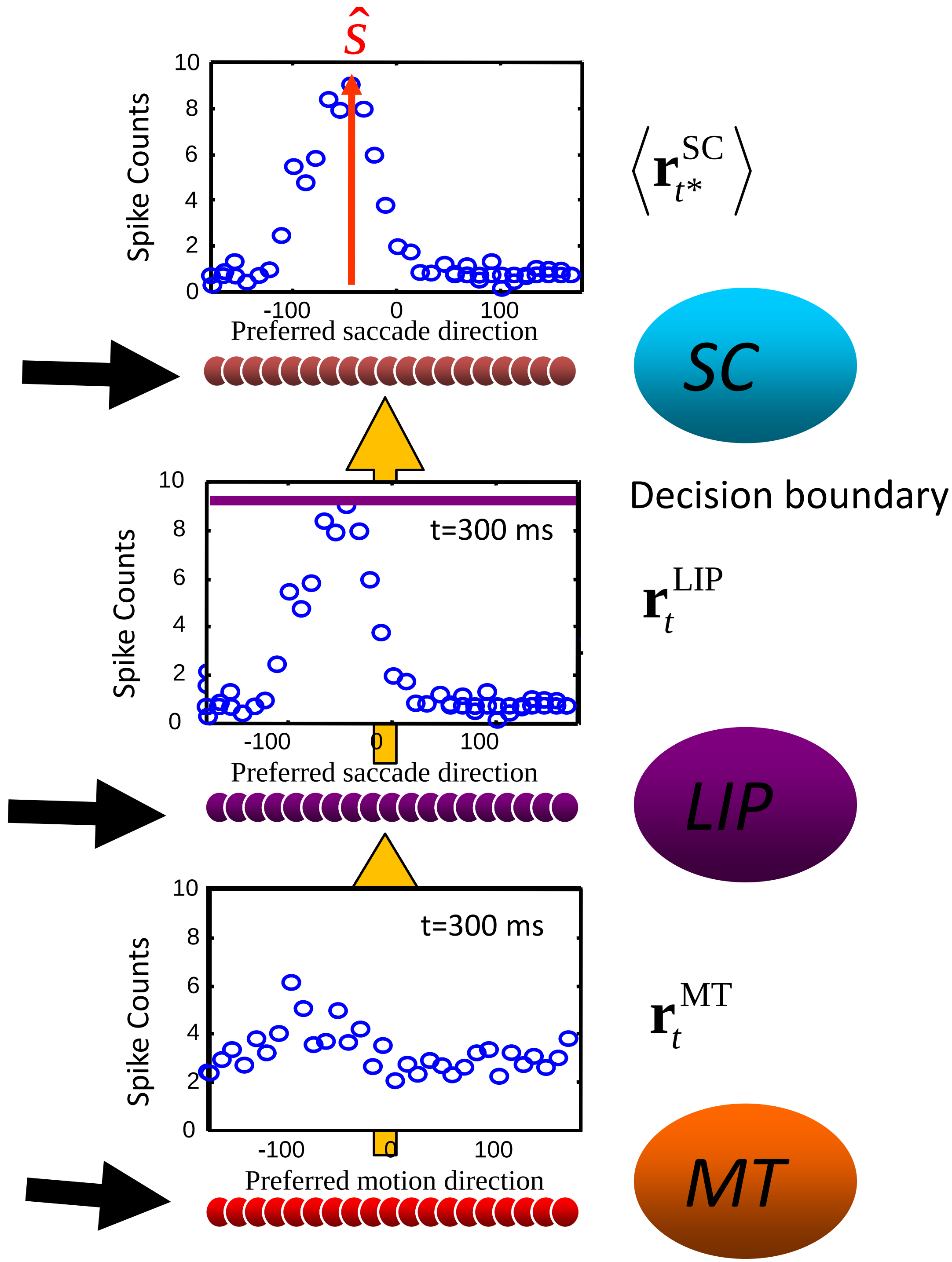
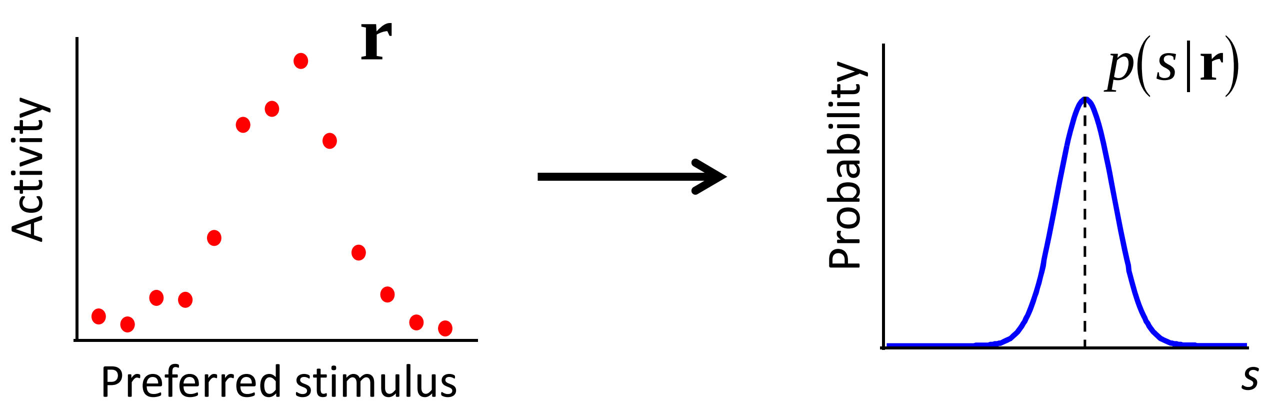


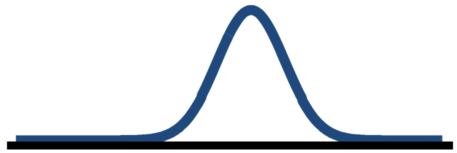
Why is such a network near-optimal?

Probability distributions from neural activity

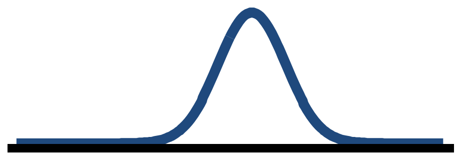


$$p(s \mid \mathbf{r}) \propto p(\mathbf{r} \mid s)\, p(s)$$

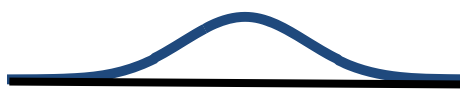
Time 1 evidence



Time 2 evidence

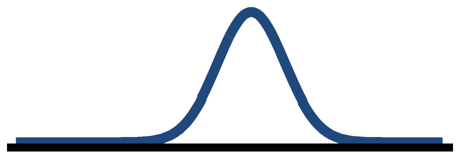


Time 3 evidence



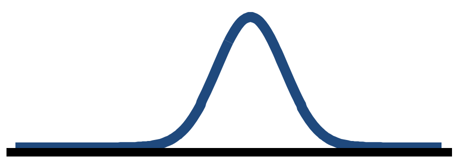
Time 1 evidence

$$p(s \mid t = 1)$$



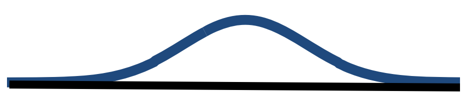
Time 2 evidence

$$p(s \mid t = 2)$$



Time 3 evidence

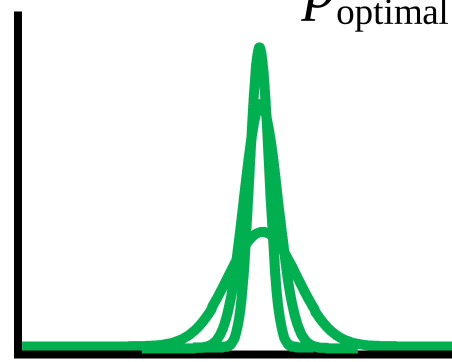
$$p(s \mid t = 3)$$



Optimal evidence accumulation

Probability

$$p_{\mathrm{optimal}}(s \mid t = 3)$$



Stimulus

Bayesian evidence accumulation

Given the pattern of activity from MT since the beginning of a trial, the optimal decision should be based on the posterior distribution:

$$p\left(s \mid \mathbf{r}_t^{\mathrm{MT}},\ldots,\mathbf{r}_1^{\mathrm{MT}}\right) \propto p\left(\mathbf{r}_t^{\mathrm{MT}} \mid s\right)\ldots p\left(\mathbf{r}_2^{\mathrm{MT}} \mid s\right) p\left(\mathbf{r}_1^{\mathrm{MT}} \mid s\right)$$

How can LIP compute and represent this probability distribution?

Poisson-like neural variability

$$p(\mathbf{r} \mid s) = \varphi(\mathbf{r}) e^{\mathbf{h}(s)\cdot\mathbf{r}}$$

- Includes independent Poisson
- Allows for Fano factors different from 1
- Allows for correlated variability
- Kernel **h**(*s*) determined by tuning curves and correlation structure of population
- Makes optimal cue integration easy to implement

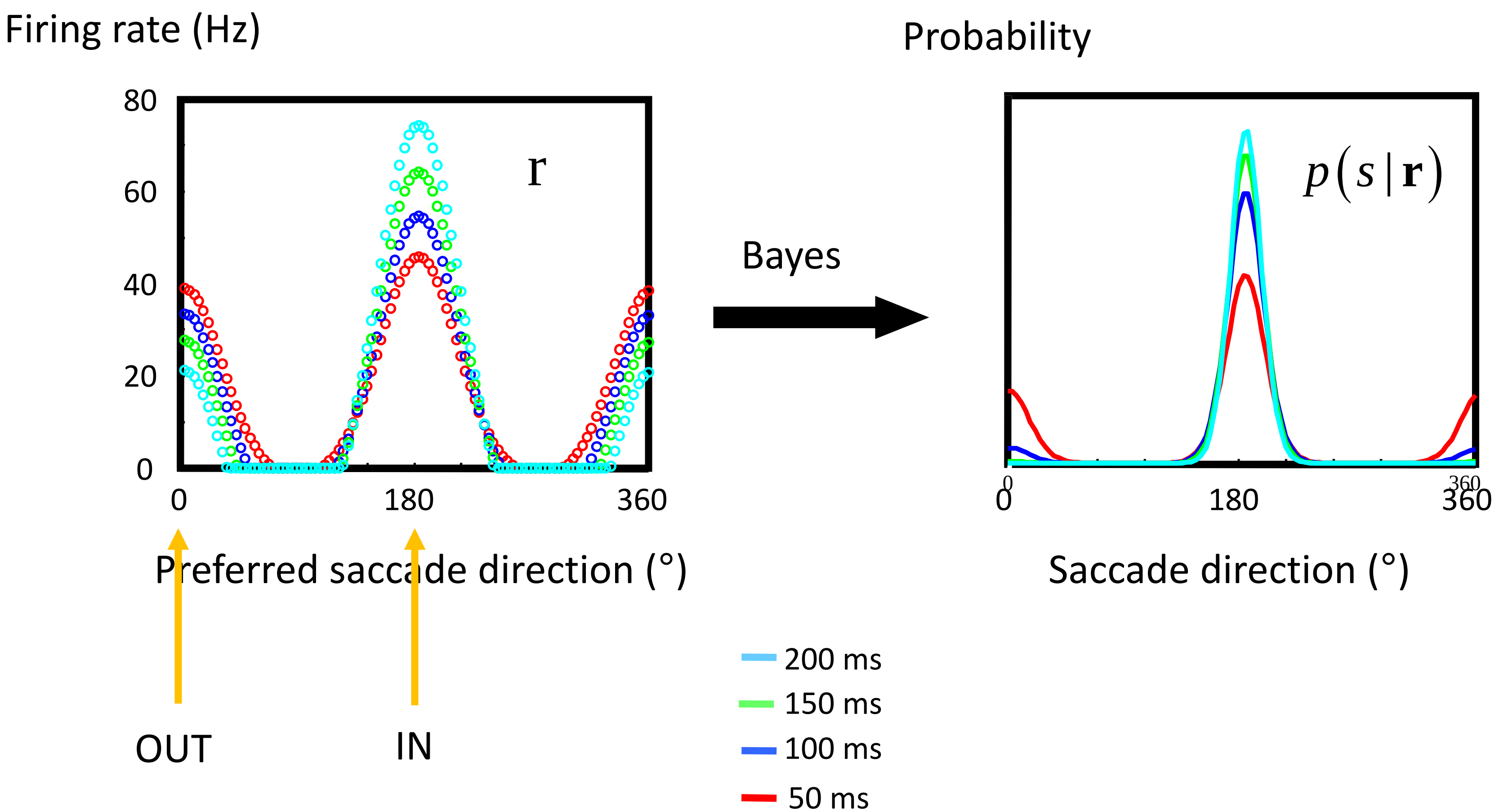
Integration over time is optimal

sensory input

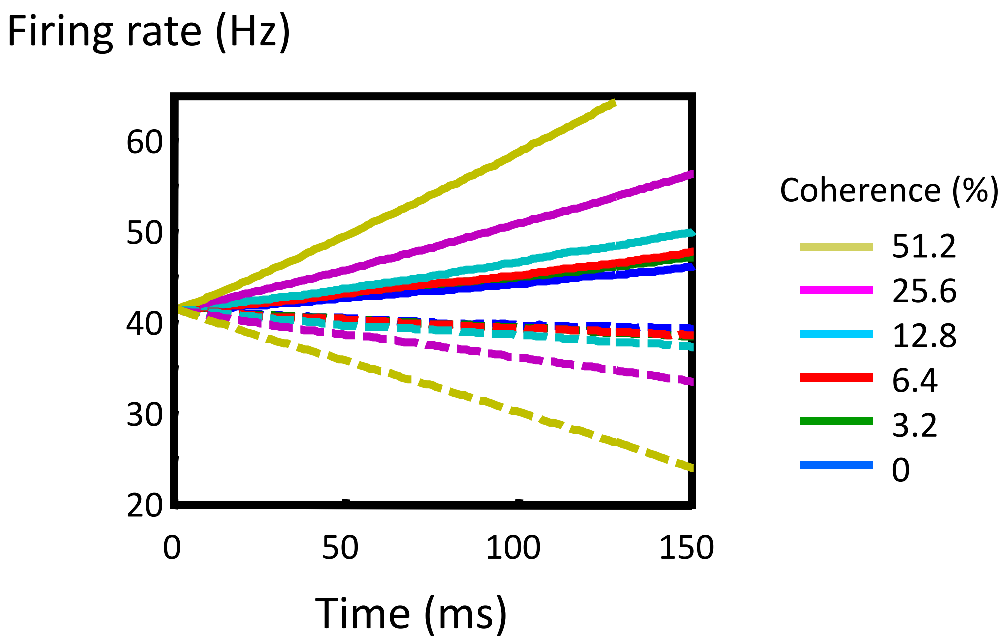
$$p(s \mid \overbrace{\mathbf{r}_{t=1} + \ldots + \mathbf{r}_{t=T}}^{\text{in decision area}}) \propto p(s \mid \mathbf{r}_{t=1}) \cdots p(s \mid \mathbf{r}_{t=T})$$

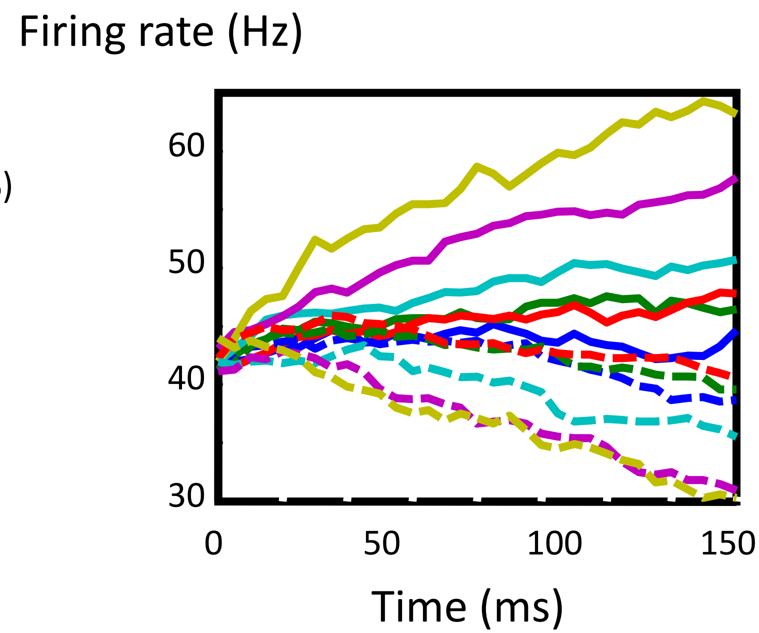
- Integrating neural activity over time corresponds to multiplying the encoded probability distributions, which is the condition for optimality.
- If LIP performs temporal integration, it encodes the optimal posterior distribution at all times.

Binary Choice:
Distribution Encoded in LIP



Binary Choice:
Activity of IN and OUT neurons

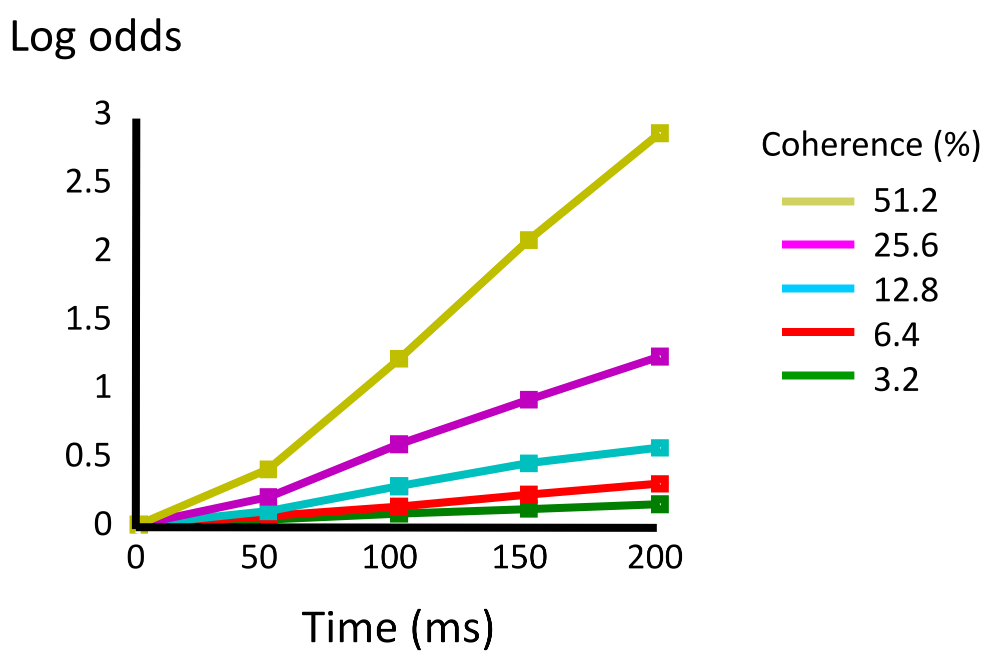


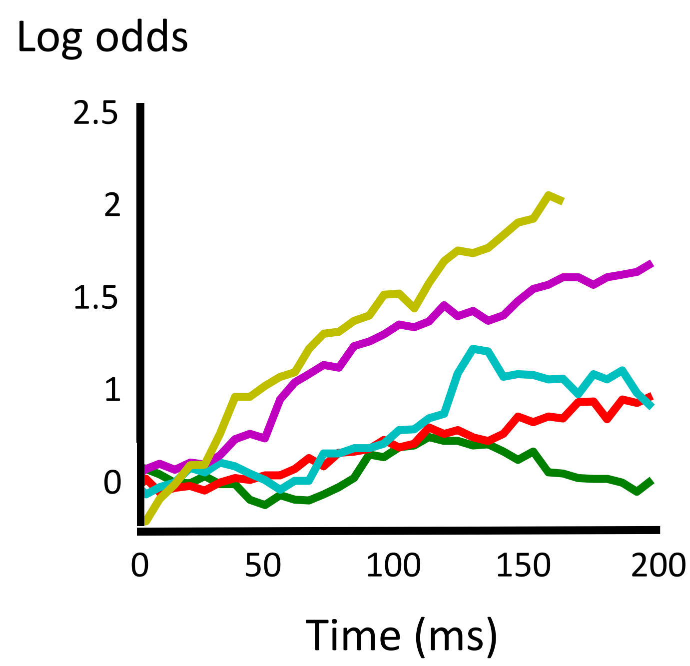


Data from Roitman and Shadlen (2002)

Log odds grow linearly in time

$$\log \frac{p\left(s=0^\circ \mid r_0, r_{180}\right)}{p\left(s=180^\circ \mid r_0, r_{180}\right)} \propto r_0 - r_{180}$$





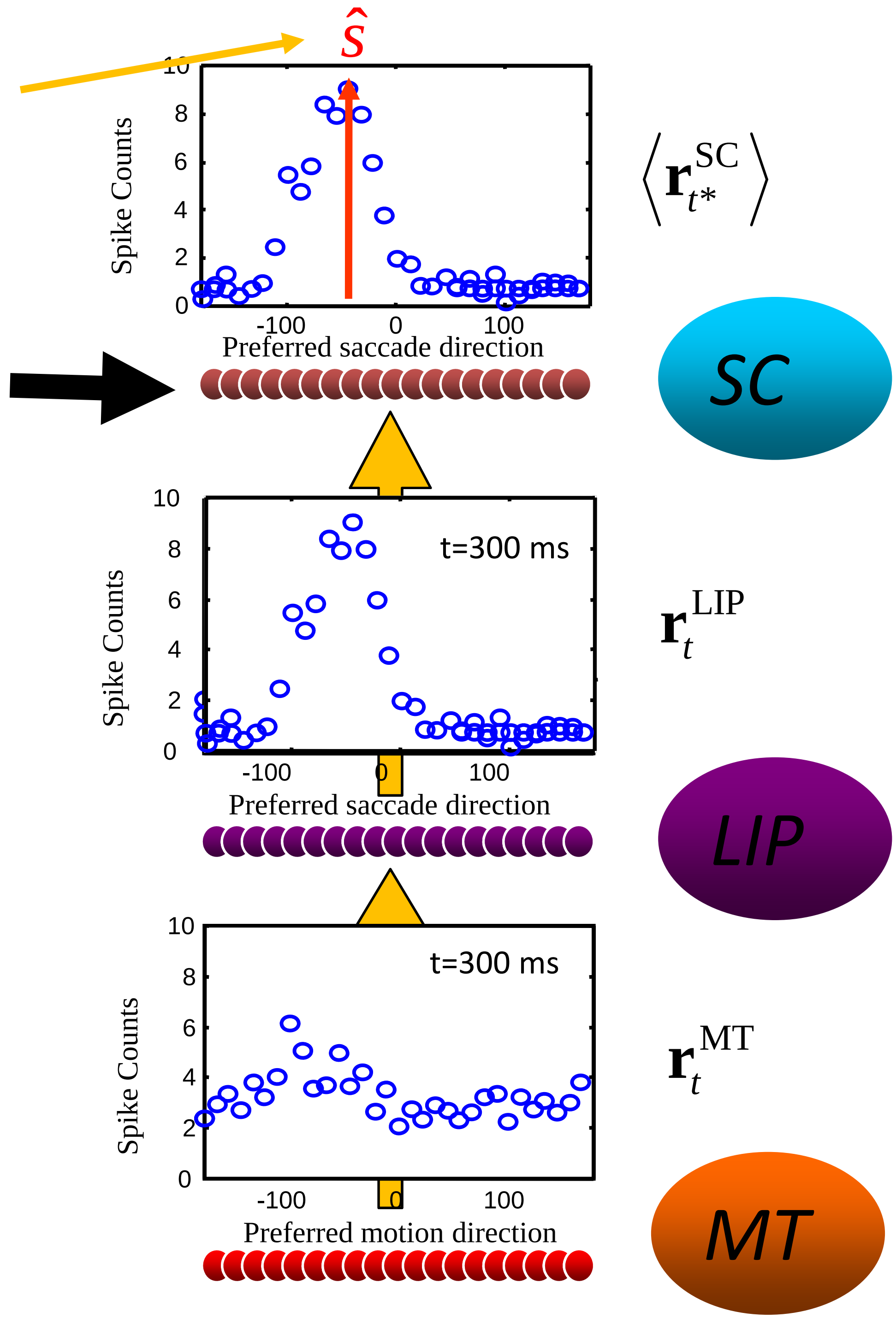
Optimal Action Selection

- LIP encodes the optimal posterior distribution at all times. But how is it read out optimally?
- Which action is the most likely to be right $\rightarrow$ maximum-likelihood estimate
- Can the SC take LIP activity at decision time and generate the maximum-likelihood saccade?
- For general noise distributions, the answer is no.
- However, if the noise is Poisson-like, then a solution exists.
- A network with a line attractor can be tuned to recover the maximum-likelihood estimate.

  (Deneve, Latham, Pouget 1999)

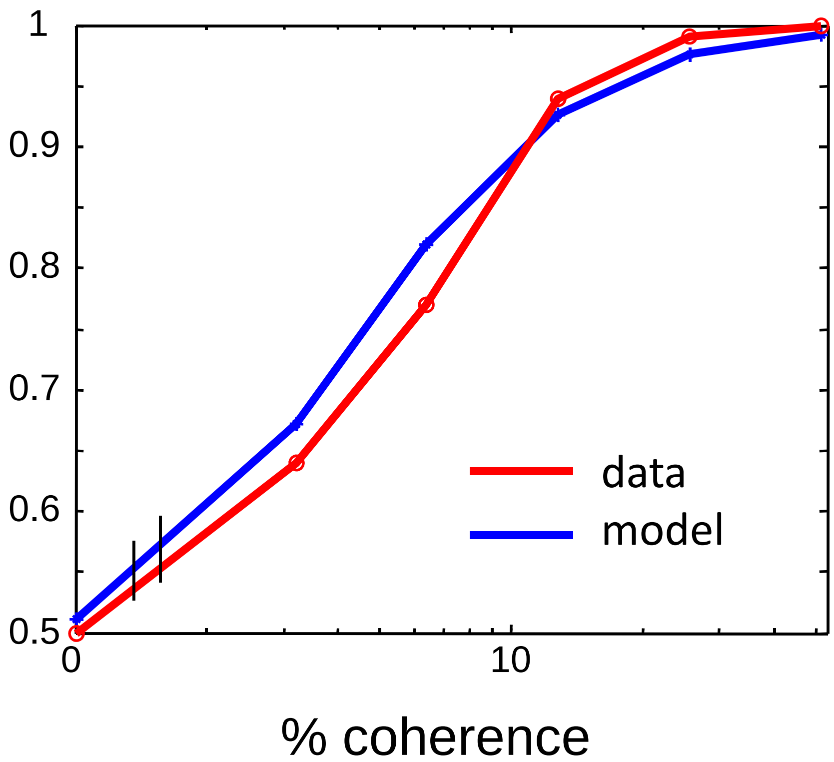
Maximum-likelihood estimate

Action selection : attractor dynamics

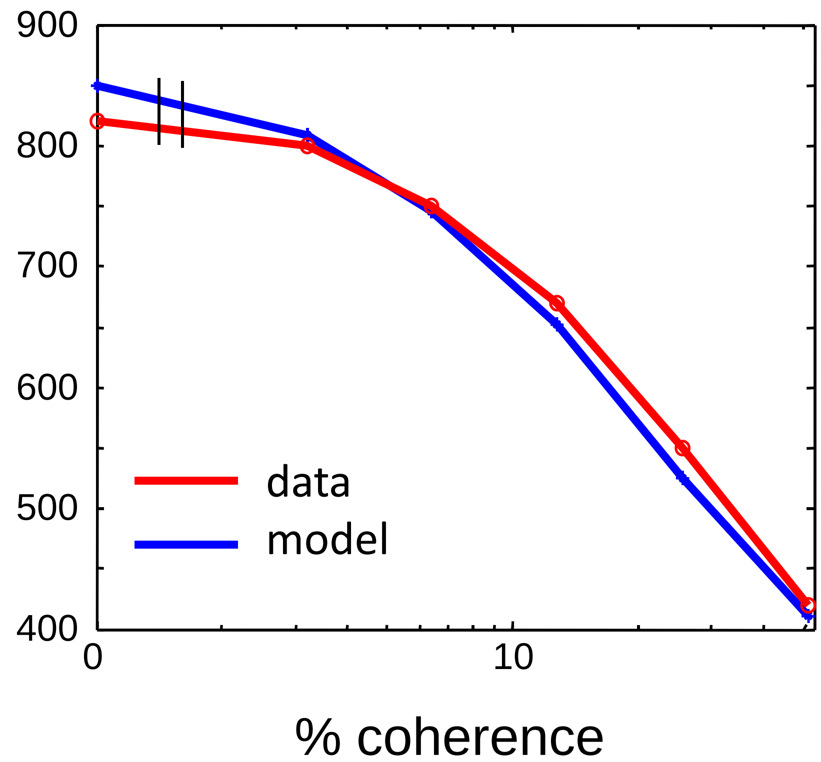


Binary Choice:
Performance and Reaction Time

Probability correct



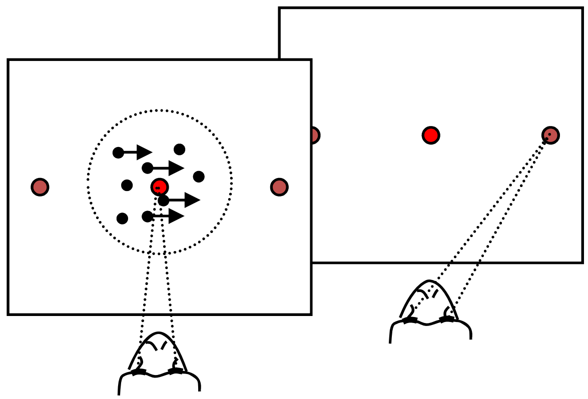
Reaction time (ms)



Data from Mazurek, Roitman, Ditterich, Shadlen, 2003

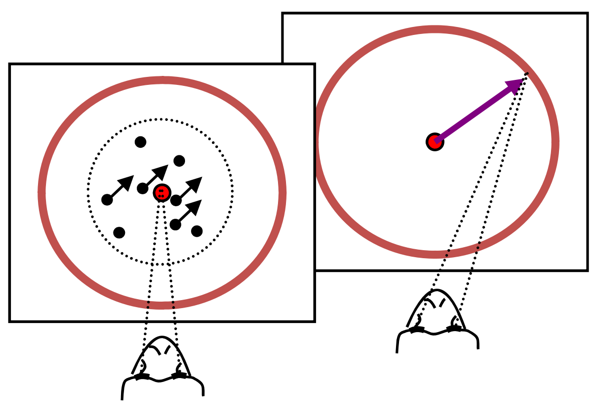
Beyond binary?

Binary

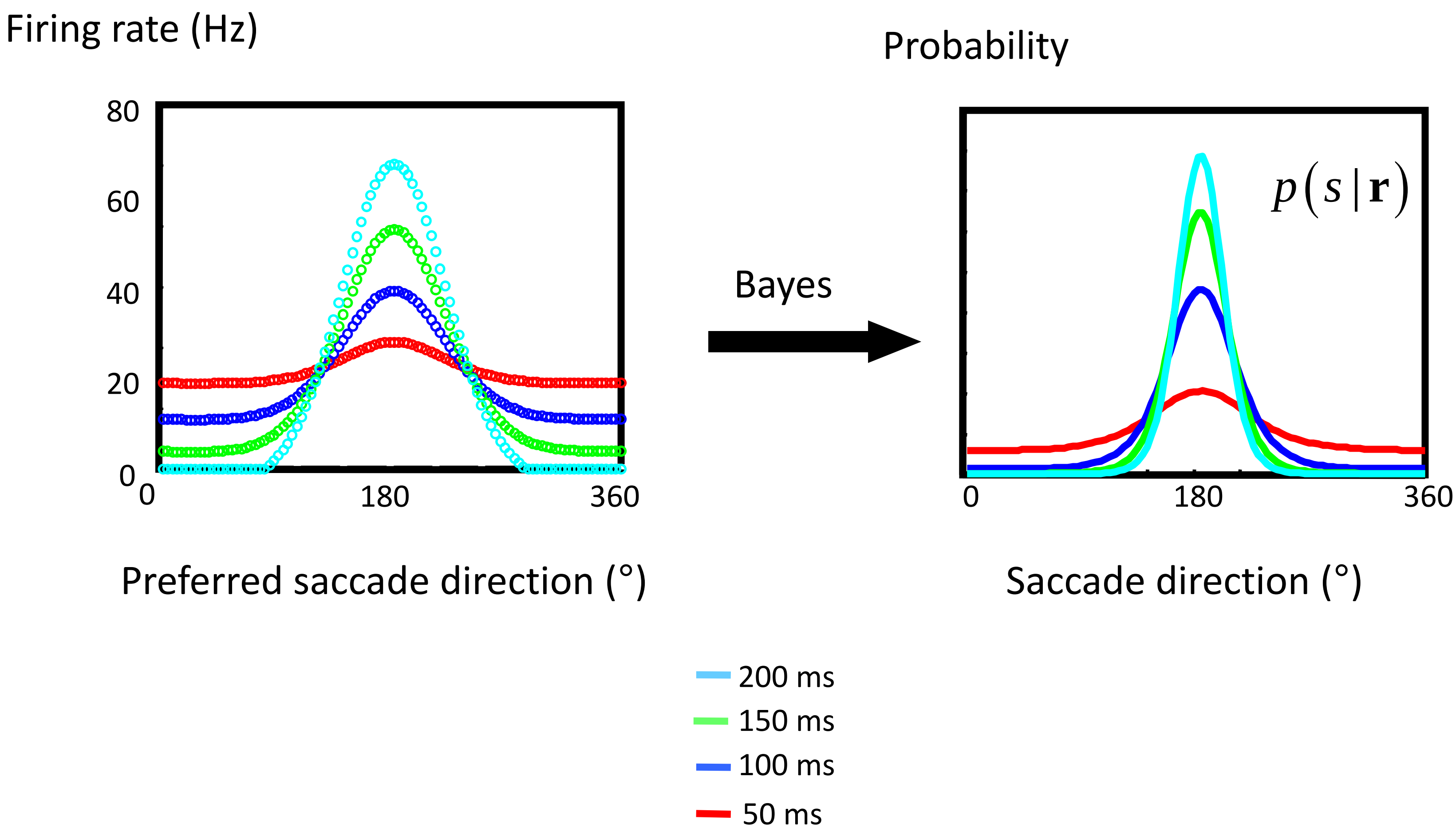


e.g. Roitman and Shadlen (2002)

Continuous



Continuous choice:
Distribution encoded in LIP



Experimental predictions

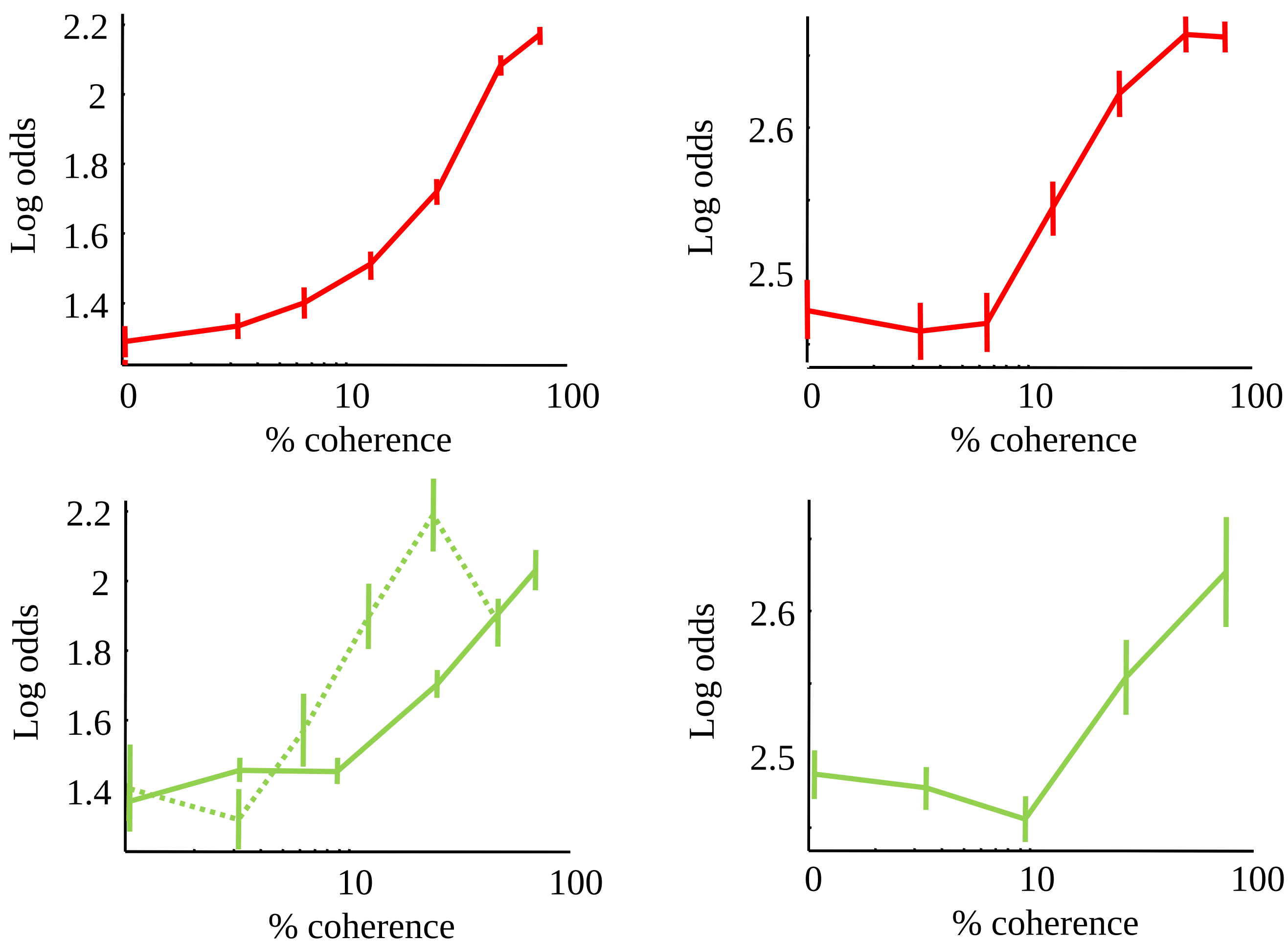
- Continuous case: width of population activity does not change over time
- LIP encodes a probability distribution over the stimulus. This distribution reflects both the reliability of the evidence and the performance of the animal.
- Same weights regardless of coherence or number of choices

Log odds at decision time

2 choice | 4 choice

Model

Data

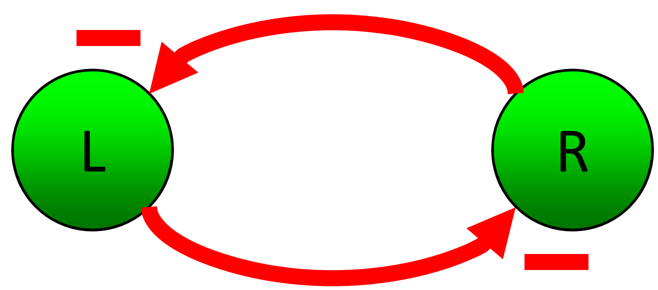


Data from Roitman and Shadlen (2002)

Data from Churchland et al. (2008)

The role of inhibition

- Bayesian model: Inhibition is needed only to keep neurons in their dynamical range.
- Other models: mutual inhibition essential.
- Open question



Conclusions

- Decision-making
  - Reward-based vs perceptual
  - Response time vs response signal
  - Binary vs multiple alternatives/continuous
  - Uncertainty can change over time or trials
- Diffusion models
- Accumulator models
- Bayesian models