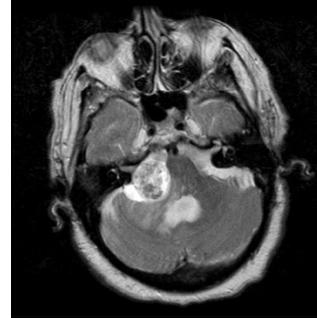
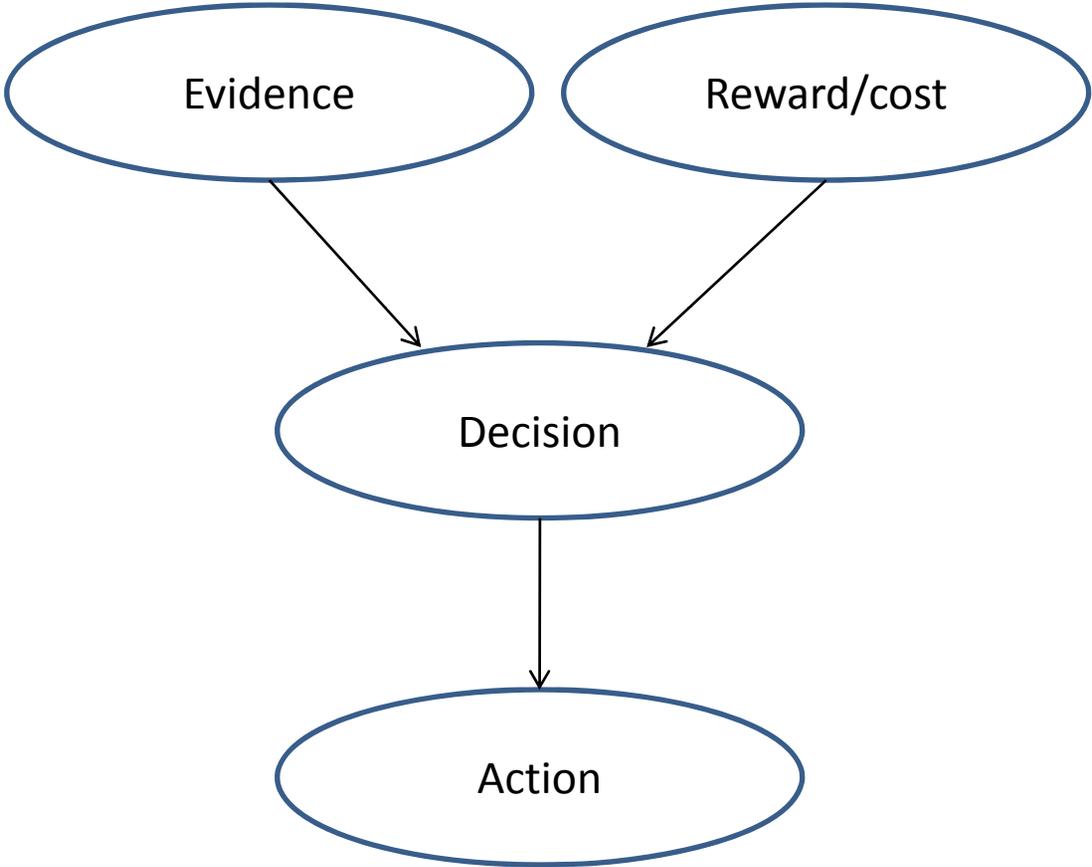


Decision-making

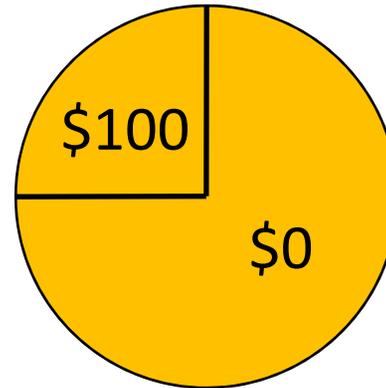
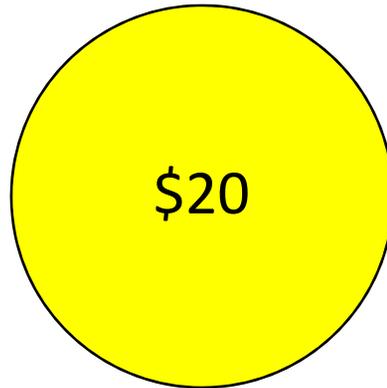
Lecture 7

Types of decisions

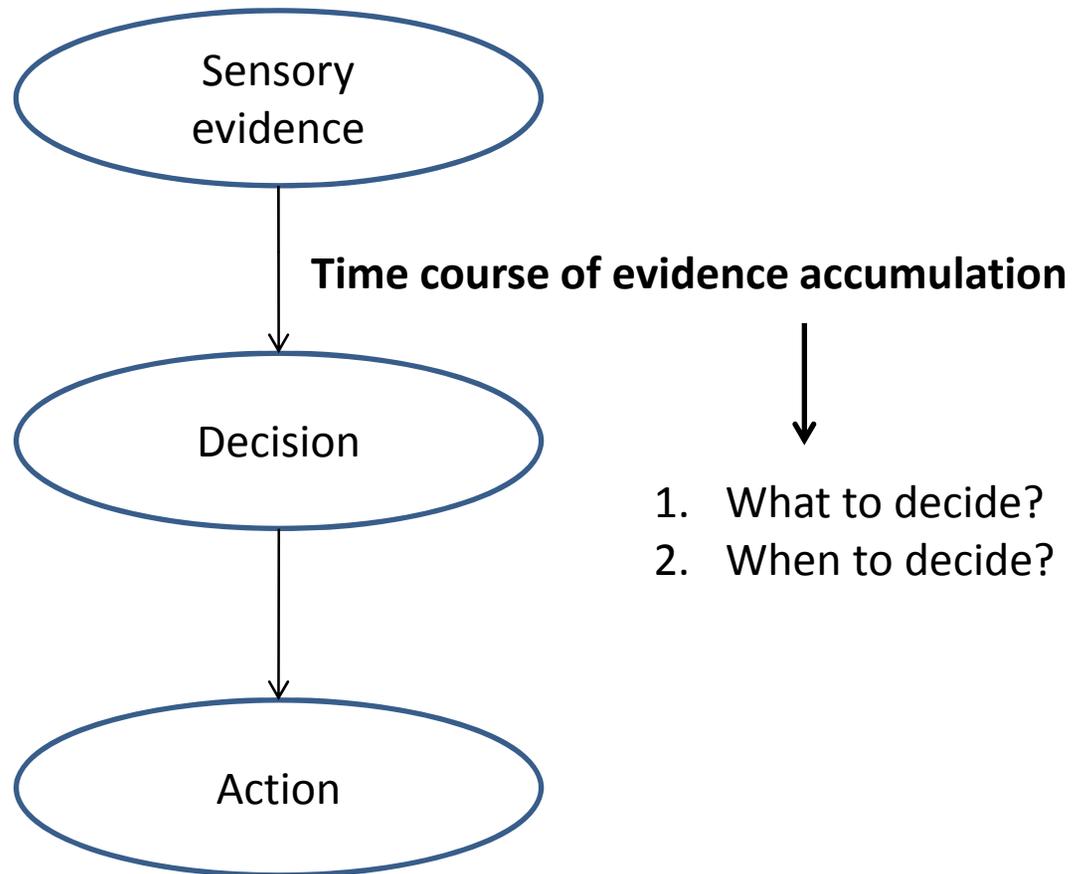




Reward-based decisions



Perceptual decisions



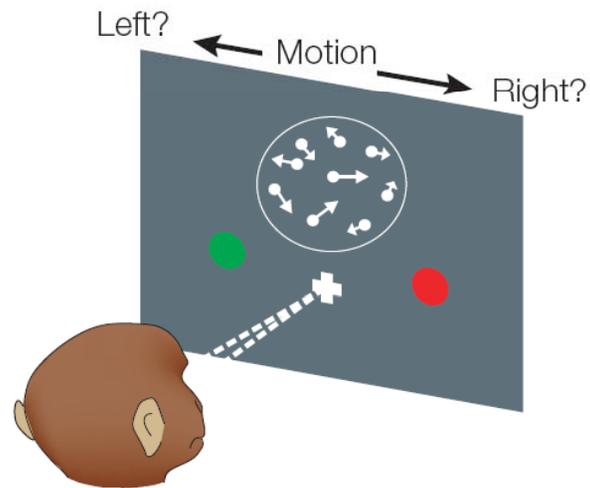
Multiple alternatives

APPETIZERS			
春卷	1. Roast Pork Egg Roll (1)	1.00	
春卷	2. Shrimp Egg Roll (1)	1.10	
春卷	3. Boneless Bar-B-Q Spare Ribs (Sm)4.85 (Lg)7.75		
春卷	4. Bar-B-Q Spare Ribs (Sm)4.80 (Lg)9.20		
春卷	5. Fanta! Shrimp (1)	1.00	
春卷	6. Fried Wonton (10)	2.35	
春卷	7. Shrimp Toast (4)	2.65	
春卷	8. Fried Dumplings (7)	(Order) 3.85	
春卷	9. Steamed Dumpling (7)	(Order) 3.85	
春卷	9a. Cold Sesame Noodles	4.50	
春卷	10. Teriyaki Beef on Stick	(3)3.35 (6)6.35	
春卷	10a. Bar-B-Q Chicken on Stick	(4)2.75 (8)5.25	
春卷	11. Fried Chicken Wings		
春卷	12. Szechuan Sauce (12)	3.75	
春卷	12.a. Fried Shrimp	8.50	
春卷	12.a. Fried Shrimp	4.25	
SOUPS (w. Fried Noodles)		Sm.	Lg.
春卷	10. Wonton Soup	1.20	2.20
春卷	14. Egg Drop Soup	1.10	2.15
春卷	15. Wonton w. Egg Drop Soup	1.60	2.65
春卷	16. Chicken Noodle Soup	1.10	2.10
春卷	17. Chicken Rice Soup	1.10	2.10
春卷	18. House Special Soup	4.75	
春卷	19. Hot & Spicy Soup	1.75	3.35
春卷	20. Vegetable Soup	1.10	2.10
春卷	21. Shrimp or Beef Yat Gaw Mein	3.75	
春卷	22. Chicken or Pork Yat Gaw Mein	3.50	
CHOW MEIN (w. Fried Noodles and White Rice)		Sm.	Lg.
春卷	23. Chicken Chow Mein	2.80	5.40
春卷	24. Pork Chow Mein	2.80	5.40
春卷	25. Beef Chow Mein	3.00	5.60
春卷	26. Shrimp Chow Mein	3.35	6.60
春卷	27. Vegetable Chow Mein	2.30	4.20
春卷	28. Subgum Chicken Chow Mein	3.25	6.20
春卷	29. Subgum Shrimp Chow Mein	3.50	6.60
春卷	30. Lobster Chow Mein	4.75	9.20
春卷	31. House Special Chow Mein	3.75	7.20
CHOP SUEY (w. White Rice)		Sm.	Lg.
春卷	32. Pork Chop Suey	2.85	5.50
春卷	33. Chicken Chop Suey	2.95	5.80
春卷	34. Vegetable Chop Suey	2.50	4.80
春卷	35. Beef Chop Suey	3.35	6.35
春卷	36. Shrimp Chop Suey	3.65	6.95
春卷	37. Lobster Chop Suey	4.85	9.30
春卷	38. House Special Chop Suey	3.75	7.20
FRIED RICE		Sm.	Lg.
春卷	39. Roast Pork Fried Rice	2.80	5.30
春卷	40. Chicken Fried Rice	2.90	5.45
春卷	41. Vegetable Fried Rice	2.45	4.60
春卷	42. Beef Fried Rice	3.25	6.15
春卷	43. Shrimp Fried Rice	3.45	6.75
春卷	44. Lobster Fried Rice	4.70	8.85
春卷	45. Young Chow Fried Rice	3.55	6.80
春卷	45a. Plain Fried Rice	2.15	4.15
LO MEIN (Soft Noodles)		Sm.	Lg.
春卷	46. Vegetable Lo Mein	2.50	4.65
春卷	47. Roast Pork Lo Mein	3.10	6.00
春卷	48. Chicken Lo Mein	3.20	6.15
春卷	49. Beef Lo Mein	3.35	6.25
春卷	50. Shrimp Lo Mein	3.65	6.95
春卷	51. Lobster Lo Mein	4.75	8.55
春卷	52. House Special Lo Mein	4.25	7.95
PORK (w. White Rice)		Sm.	Lg.
春卷	53. Roast Pork w. Chinese Veg.	3.20	6.20
春卷	54. Roast Pork w. Pepper Onion	3.50	6.80
春卷	55. Roast Pork w. Snow Peas	3.90	7.50
春卷	56. Roast Pork w. Broccoli	3.75	7.20
春卷	57. Roast Pork w. Almond Ding	3.75	7.20
春卷	58. Roast Pork w. Mushroom	3.75	7.20
春卷	59. Roast Pork w. Oyster Sauce	3.79	7.20
春卷	59a. Roast Pork w. Mixed Vegetable	3.95	7.35
CHICKEN (w. White Rice)		Sm.	Lg.
春卷	60. Chicken w. Chinese Veg.	3.25	6.30
春卷	61. Moo Gao Gai Pan	3.45	6.55
春卷	62. Chicken w. Snow Peas	3.95	7.95
春卷	63. Chicken w. Broccoli	3.85	7.35
春卷	64. Chicken w. Almond Ding	3.85	7.25
春卷	65. Chicken w. Black Bean Sc	3.75	7.20
春卷	66. Chicken w. Oyster Sauce	3.75	7.20
春卷	67. Chicken w. Curry Sauce	3.95	7.35
春卷	67.a. Plain Broccoli	3.25	6.00
春卷	67.b. Chicken w. Mixed Vegetable	4.00	7.75
BEEF (w. White Rice)		Sm.	Lg.
春卷	68. Beef w. Chinese Veg.	3.85	6.95
春卷	69. Pepper Steak w. Onion	3.95	7.50
春卷	70. Beef w. Pepper & Tomato	3.95	7.25
春卷	71. Beef w. Snow Peas	4.20	7.85
春卷	72. Beef w. Broccoli	4.20	7.85
春卷	73. Beef w. Mushroom	4.00	7.70
春卷	74. Beef w. Oyster Sauce	4.00	7.70
春卷	75. Curry Beef w. Onion	4.00	7.70
春卷	75a. Beef w. Mixed Vegetables	4.00	7.75
SHRIMP (w. White Rice)		Sm.	Lg.
春卷	76. Lobster Sauce	2.25	4.20
春卷	77. Shrimp w. Lobster Sauce	4.55	8.70
春卷	78. Shrimp w. Chinese Veg.	4.45	8.50
春卷	79. Shrimp w. Pepper & Tomato	4.55	8.70
春卷	80. Shrimp w. Broccoli	4.55	8.70
春卷	81. Shrimp w. Almond Ding	4.25	8.20
春卷	82. Shrimp w. Snow Peas	4.75	9.20
春卷	83. Shrimp w. Mushrooms	4.50	8.70
春卷	84. Shrimp w. Curry Sauce	4.50	8.70
春卷	85. Shrimp w. Black Bean Sauce	4.50	8.70
春卷	85a. Shrimp w. Mixed Vegetables	4.65	8.75
EGG FOO YOUNG (w. White Rice)		Sm.	Lg.
春卷	86. Mushroom Egg Foo Young	4.95	
春卷	87. Roast Pork Egg Foo Young	5.00	
春卷	88. Chicken Egg Foo Young	5.00	
春卷	89. Shrimp Egg Foo Young	6.45	
春卷	90. House Special Egg Foo Young	6.25	
SWEET & SOUR (w. White Rice)		Sm.	Lg.
春卷	91. Sweet & Sour Pork	3.90	7.35
春卷	92. Sweet & Sour Chicken	3.90	7.35
春卷	93. Sweet & Sour Shrimp	4.50	8.70
春卷	94. Sweet & Sour Combination (Order)	7.95	
春卷	95. French Fries (Sm.) 1.35 (Lg.) 2.55		
春卷	96. Fortune Cookies (Per Bag) 0.50		
春卷	97. Almond Cookies (Per Bag) 0.50		
春卷	98. Finest Home Made Crispy Noodles 0.50		
春卷	99. Boiled Rice (Pt) 0.75 (Qt) 1.50		
★ HOT & SPICY			

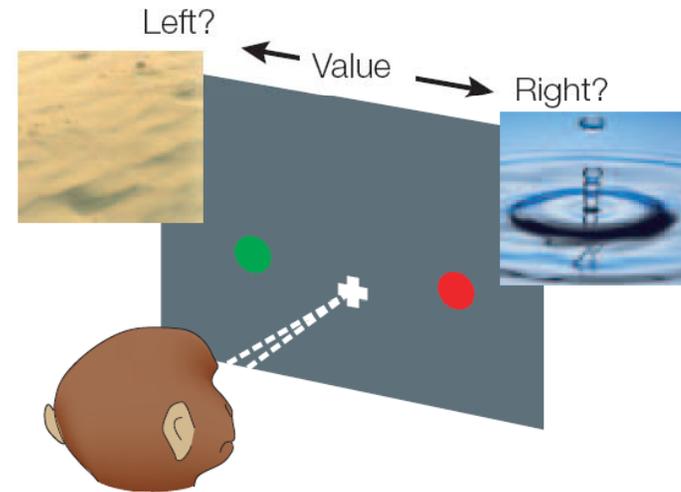


Physiology: binary choice

a Perceptual discrimination task



c Free-choice task

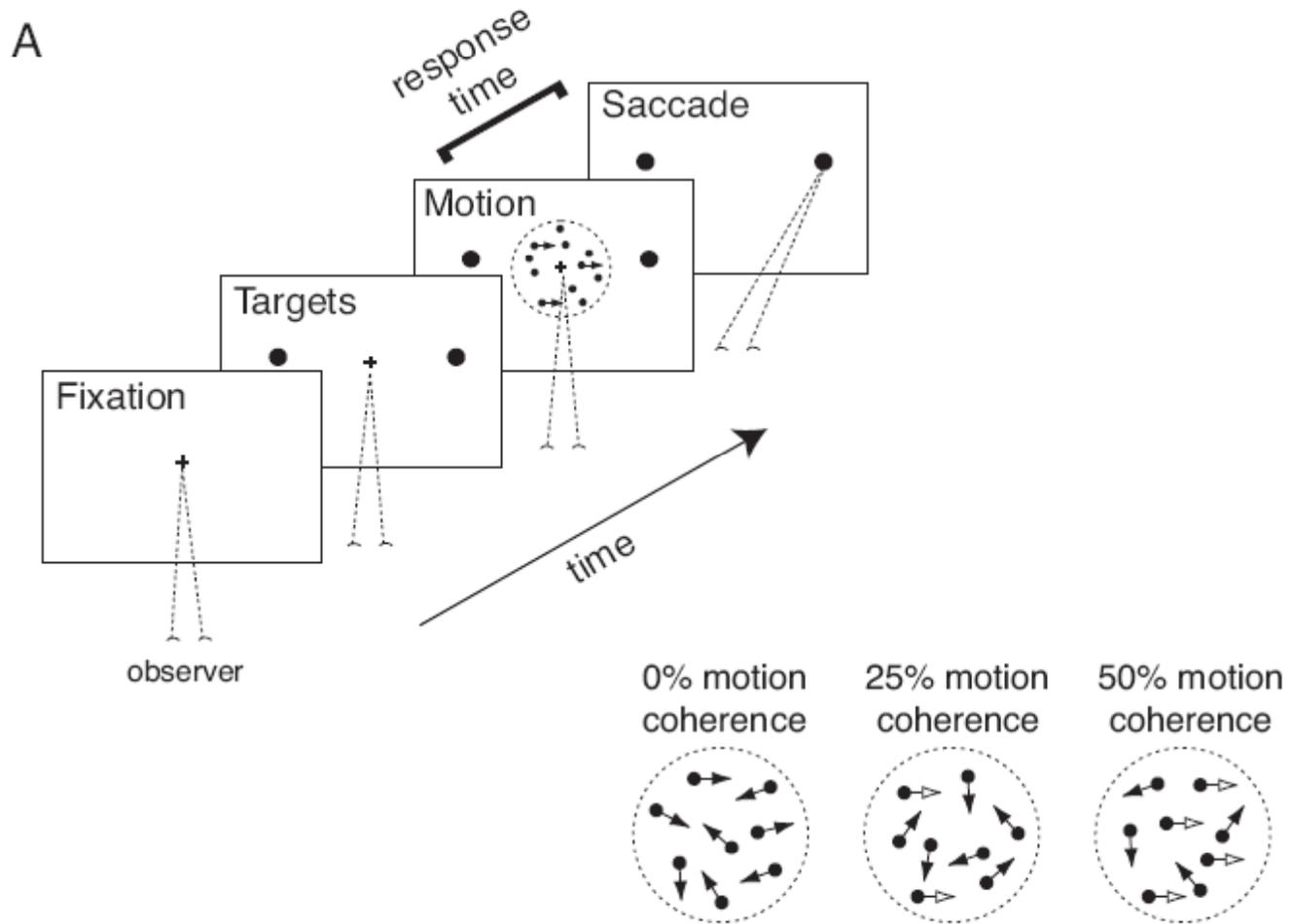


Sugrue, Corrado, Newsome, 2005

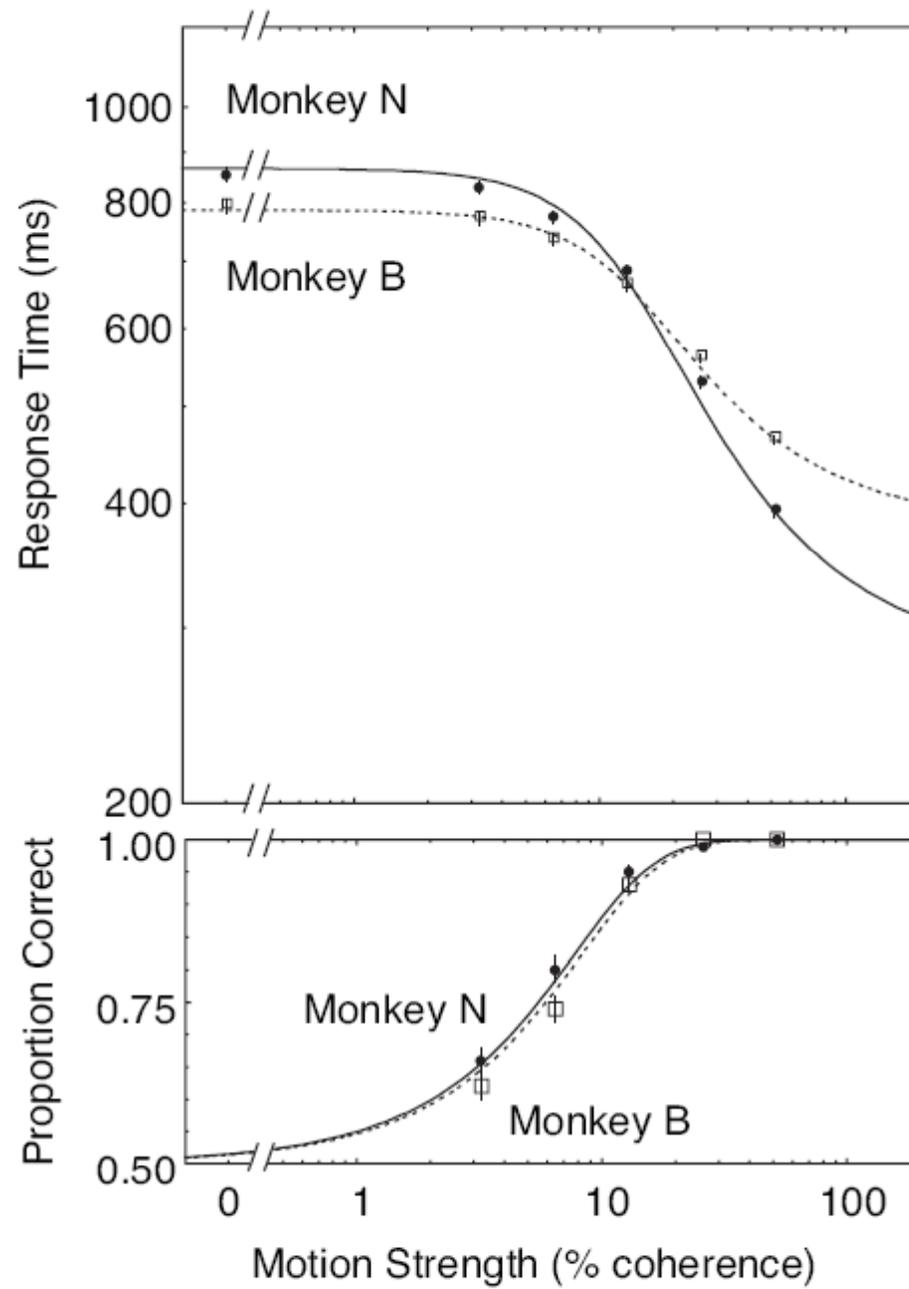
Types of experiments

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

Motion discrimination – response time



Palmer, Huk, Shadlen 2005

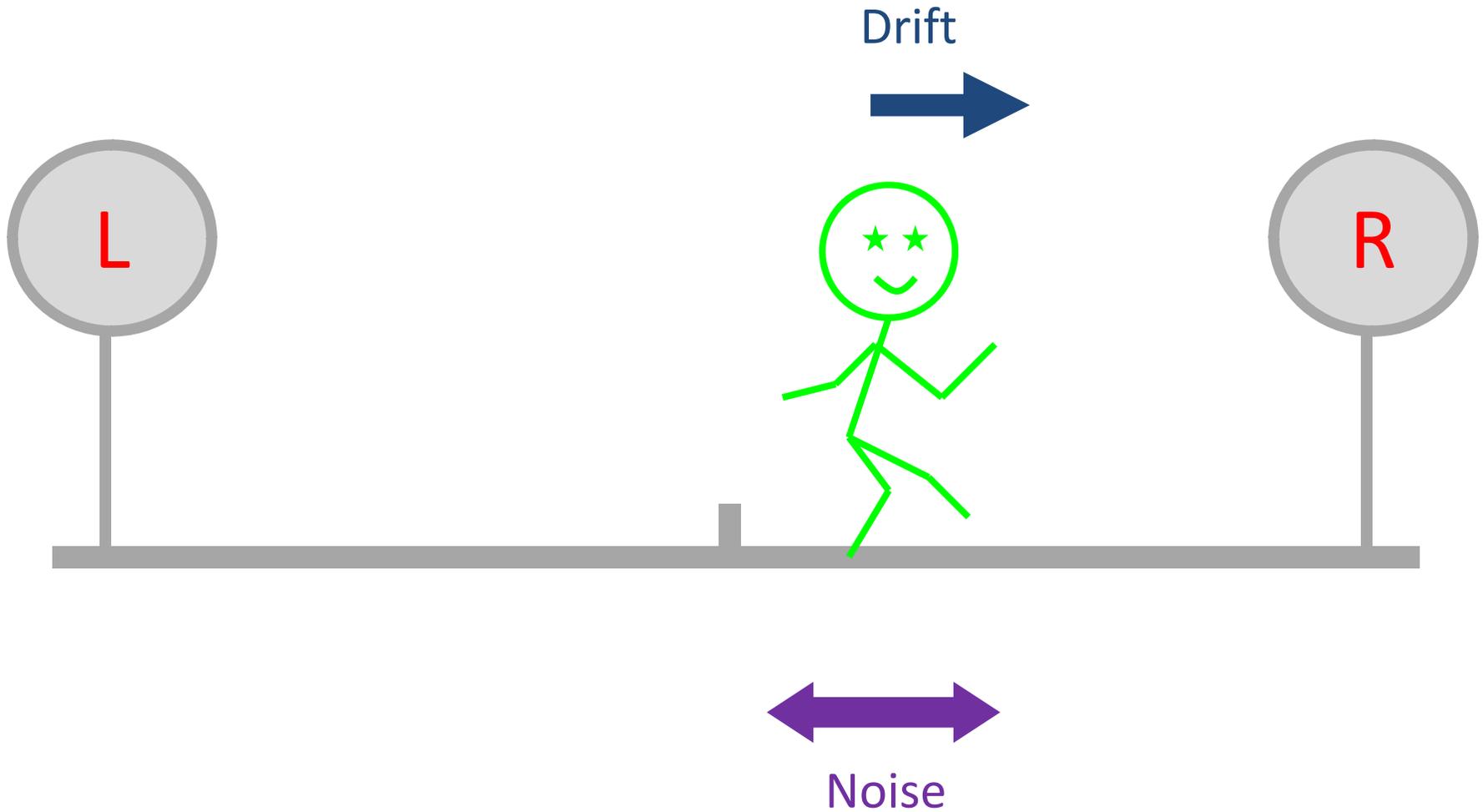


Types of models

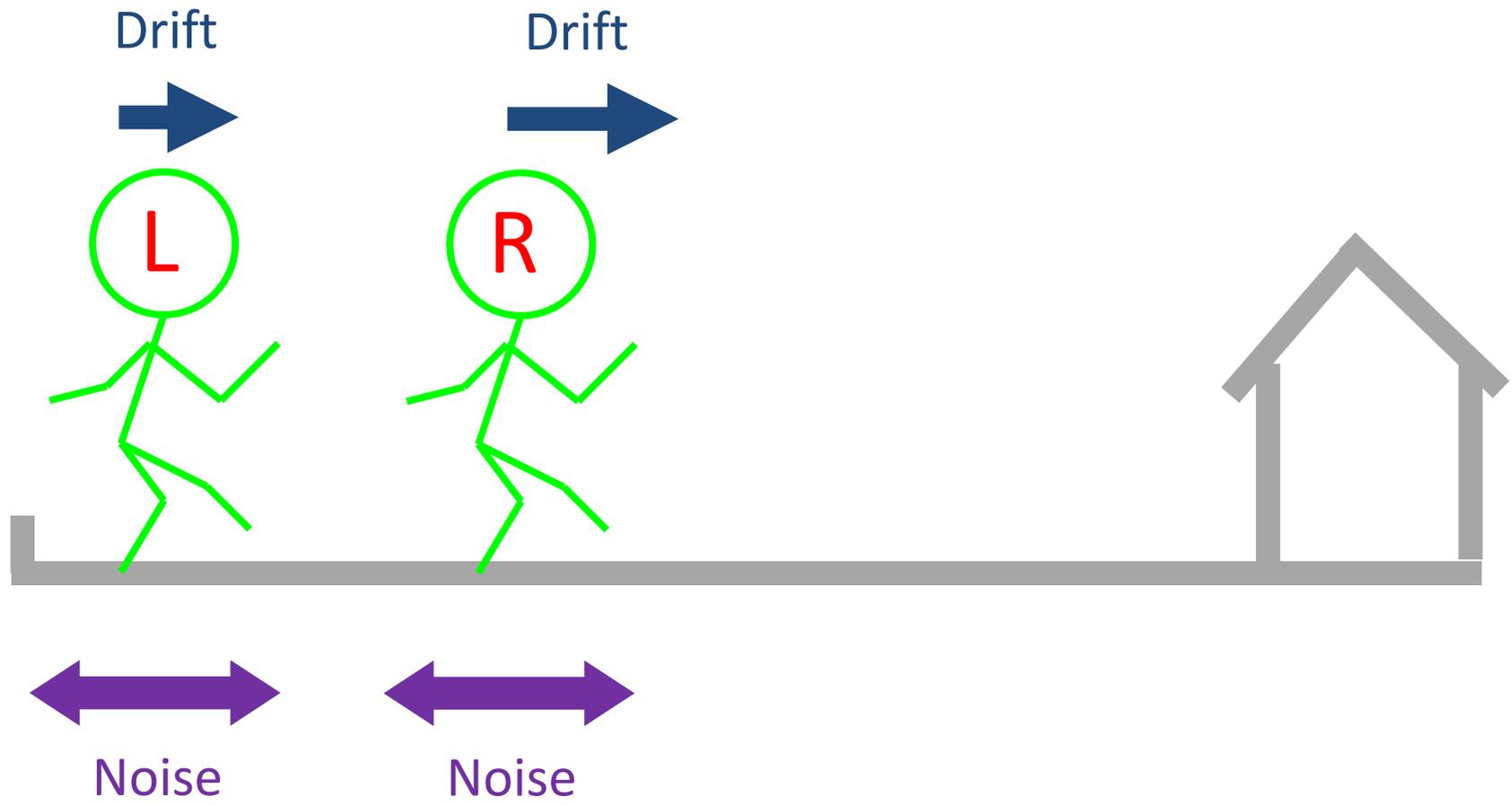
- Diffusion models
- Race (accumulator) models
- Bayesian models

- Behavioral models
- Neural models

Diffusion model



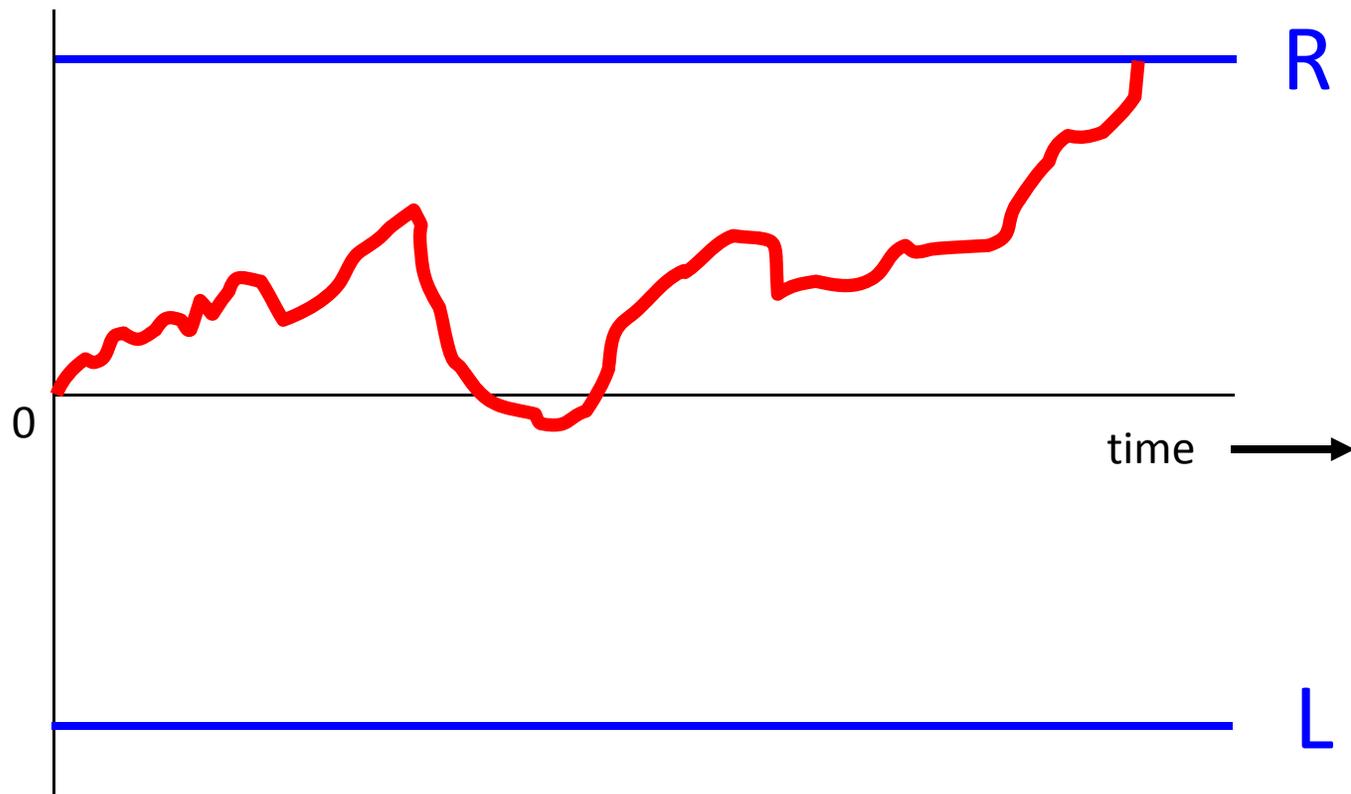
Race model

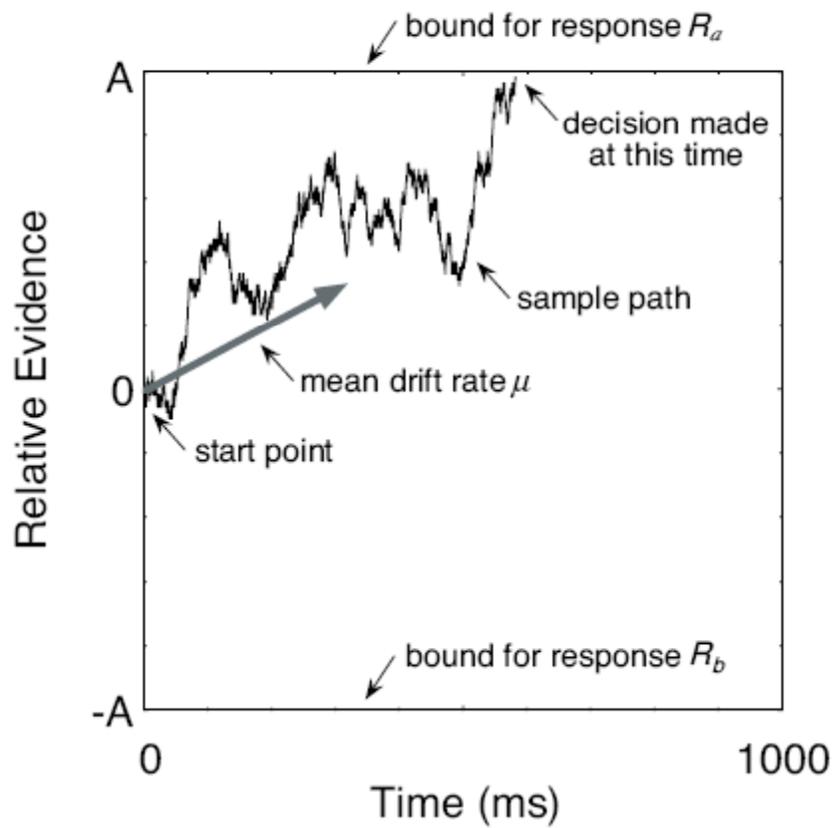


Pros and cons

- **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



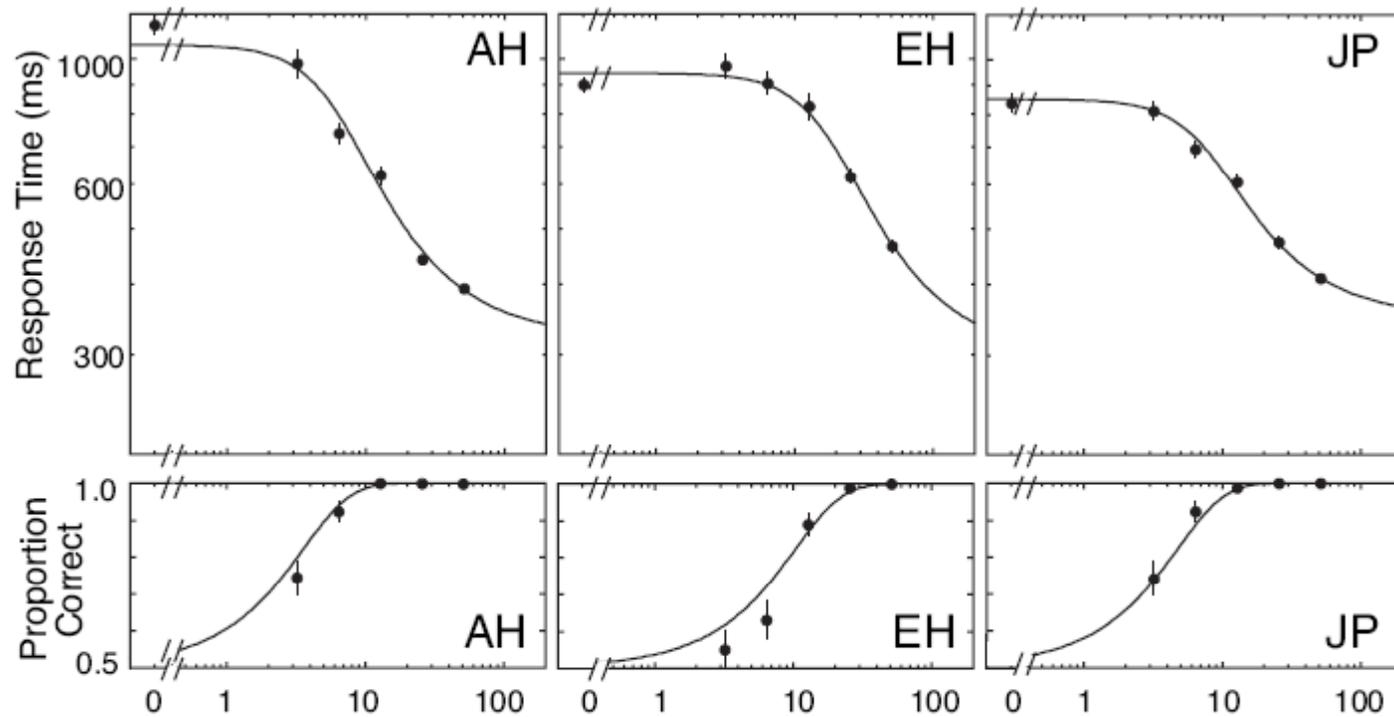


$$\mu' = kx$$

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

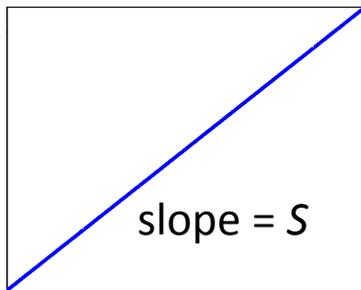
$$t_T(x) = \frac{A'}{kx} \tanh(A'kx) + t_R$$

Binary choice – response time



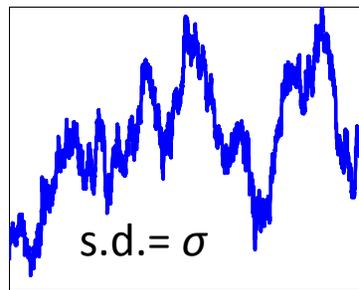
Leaky accumulator model

Integration



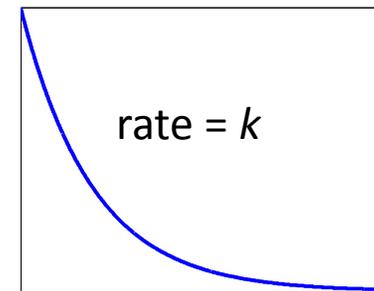
$$\frac{dx}{dt} = S$$

White noise



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

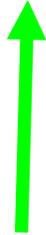
Leakage



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

Leaky accumulator model

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



i 'th unit's change
in time dt

Leaky accumulator model

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

i 'th signal
(drift)

Leaky accumulator model

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



i 'th unit's leakage

Leaky accumulator model

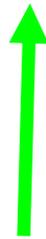
$$dx_i = \left(S_i - kx_i \right) dt + \sigma dW_i$$



white noise
into i 'th unit

Leaky accumulator model

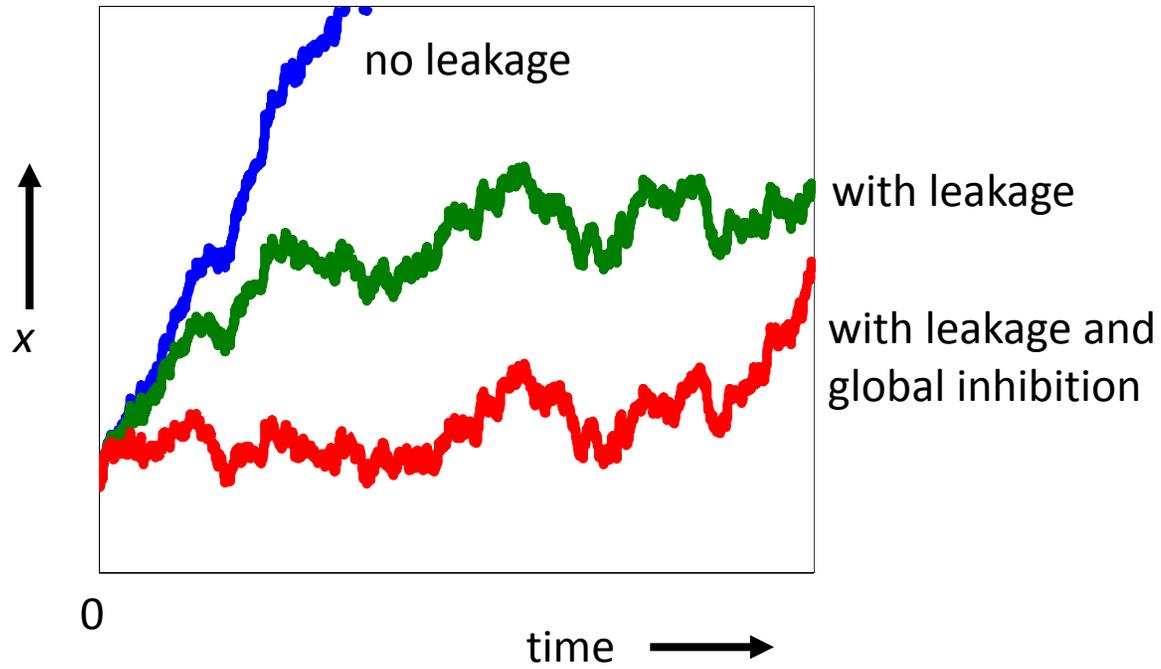
$$dx_i = \left(S_i - kx_i - w \sum_{j \neq i} x_j \right) dt + \sigma dW_i$$



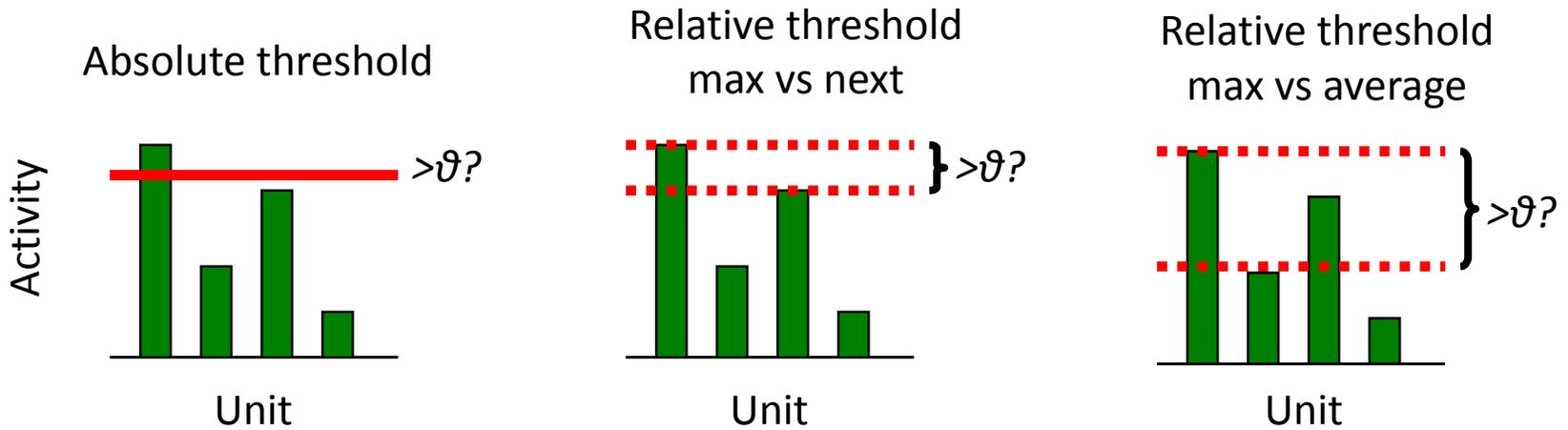
global inhibition

Leaky accumulator model

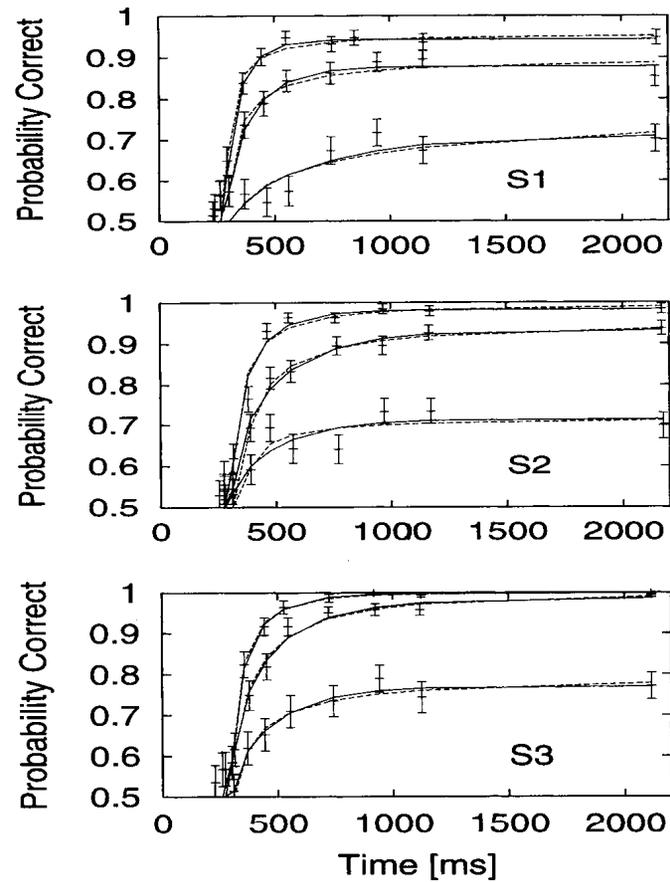
Typical behavior



When to decide?



Binary choice – Response signal



Problems with existing models

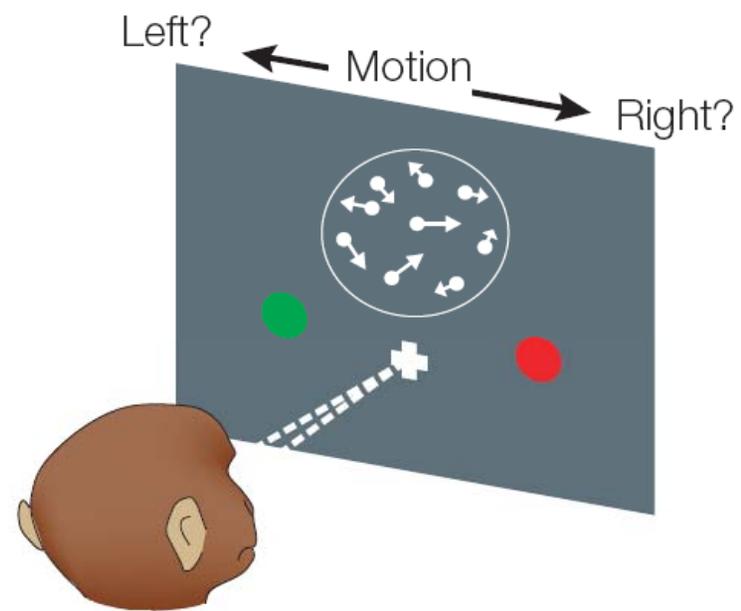
- Limited to binary or discrete choice
- Uncertainty not encoded
- What if certainty changes over time or over trials?
- No normative solution

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?



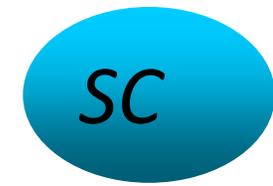
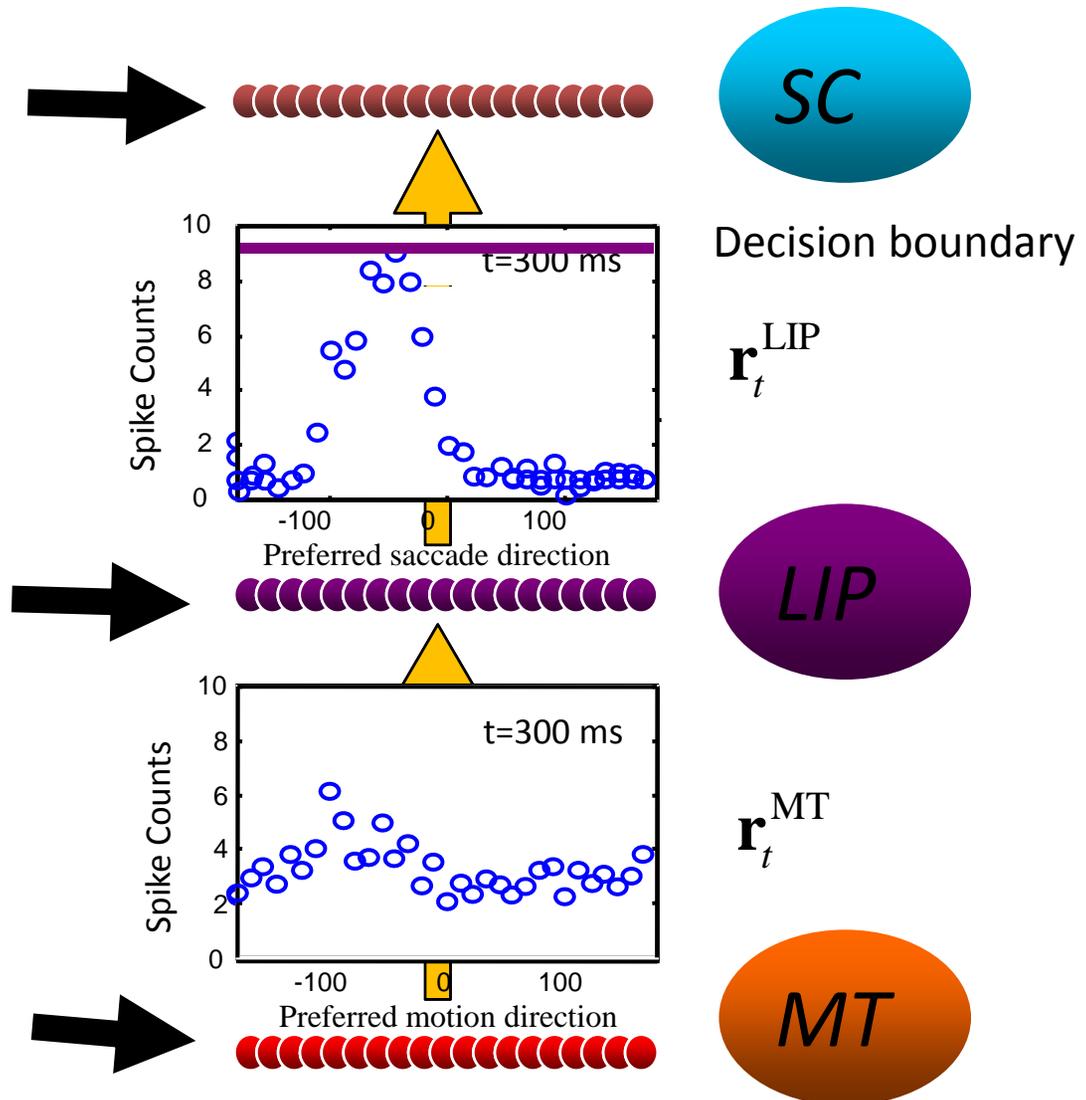
Single Trial Network Architecture Activity

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



Decision boundary

$$\mathbf{r}_t^{\text{LIP}}$$



$$\mathbf{r}_t^{\text{MT}}$$



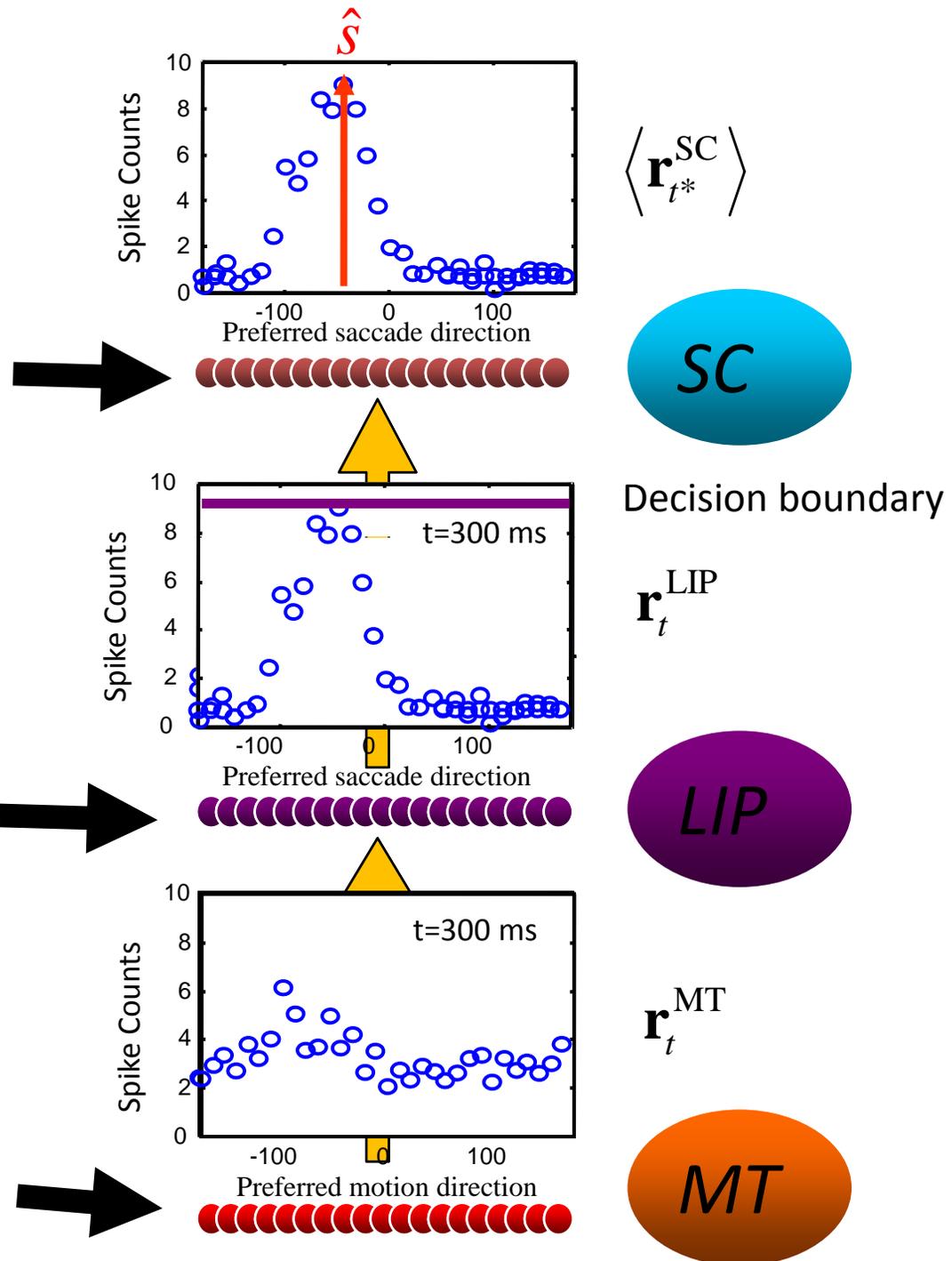
Single-Trial Activity

Action selection : attractor dynamics

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

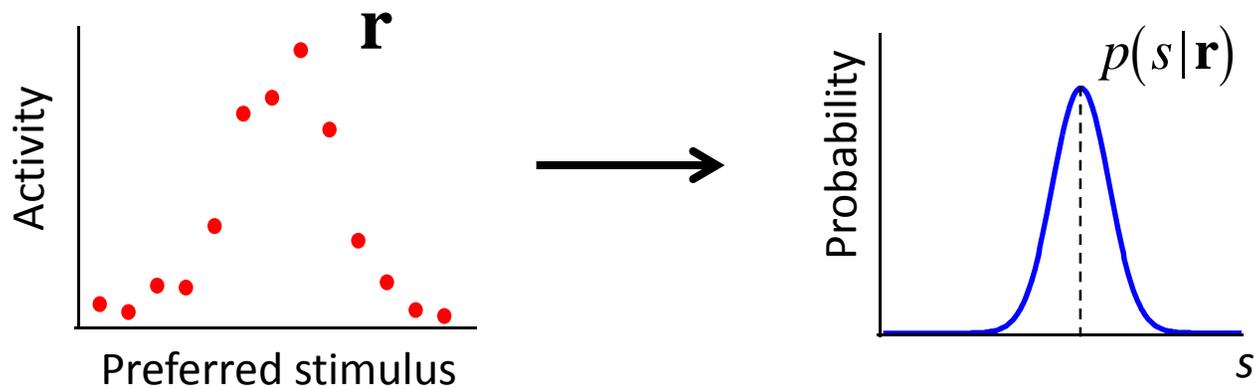
Termination rule: Stop integration when peak activity reaches a preset bound

Sensory data: 100 direction-selective neurons



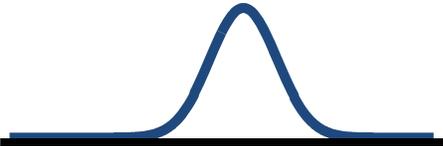
Why is such a network near-optimal?

Probability distributions from neural activity

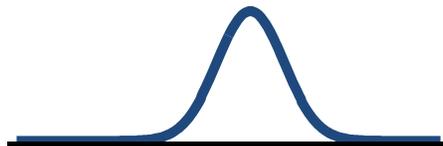


$$p(s|\mathbf{r}) \propto p(\mathbf{r}|s)p(s)$$

Time 1 evidence



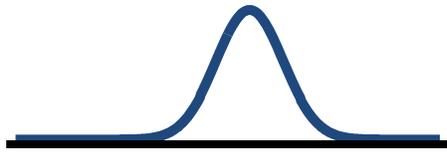
Time 2 evidence



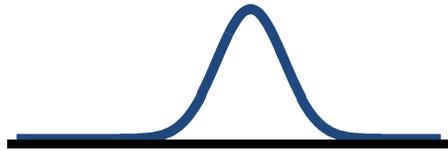
Time 3 evidence



Time 1 evidence $p(s | t = 1)$



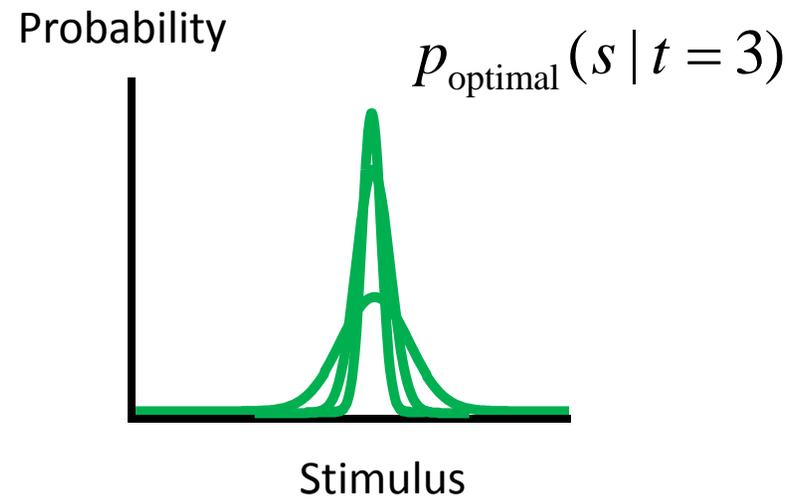
Time 2 evidence $p(s | t = 2)$



Time 3 evidence $p(s | t = 3)$



Optimal evidence
accumulation



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:

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

How can LIP compute and represent this probability distribution?

Poisson-like neural variability

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

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

Integration over time is optimal

in decision area

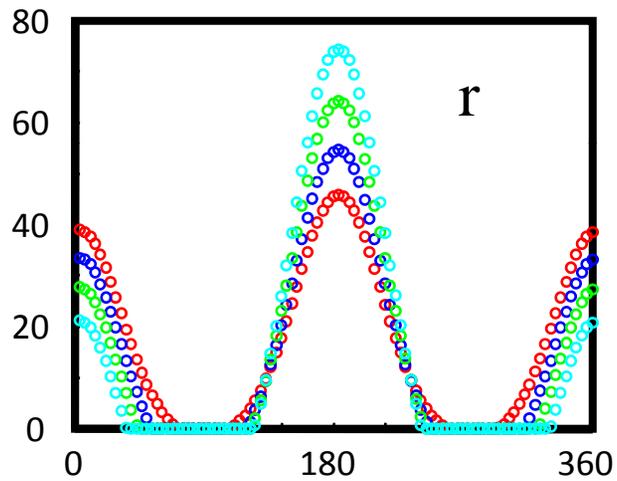
sensory input

$$p(s | \mathbf{r}_{t=1} + \dots + \mathbf{r}_{t=T}) \propto p(s | \mathbf{r}_{t=1}) \cdots p(s | \mathbf{r}_{t=T})$$

- 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

Firing rate (Hz)

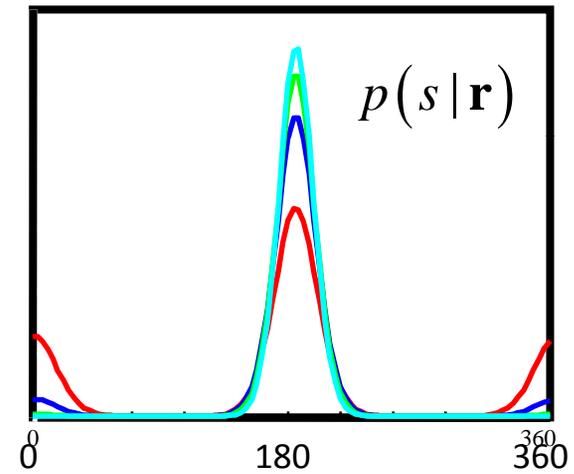


Preferred saccade direction (°)

OUT

IN

Probability



Saccade direction (°)

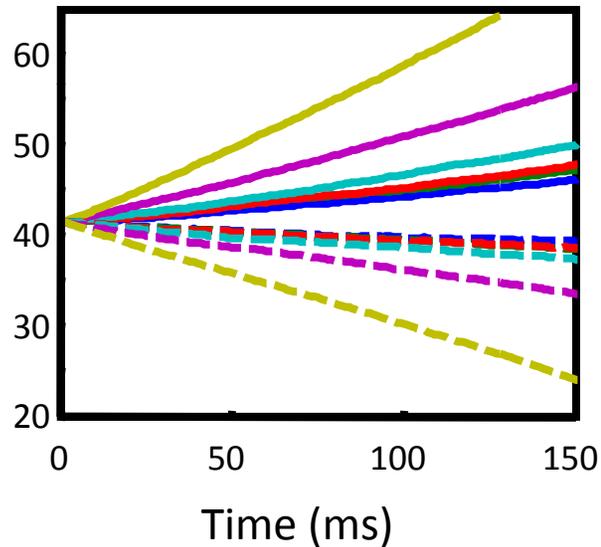
Bayes



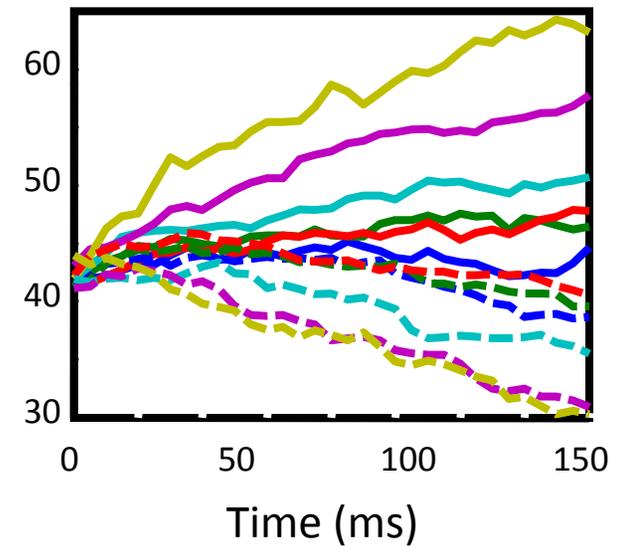
- 200 ms
- 150 ms
- 100 ms
- 50 ms

Binary Choice: Activity of IN and OUT neurons

Firing rate (Hz)



Firing rate (Hz)

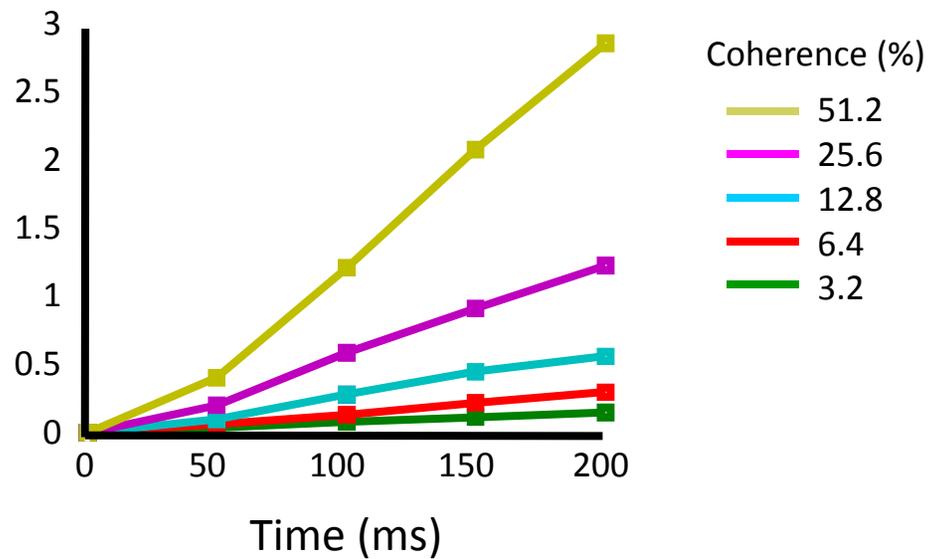


Data from Roitman and Shadlen (2002)

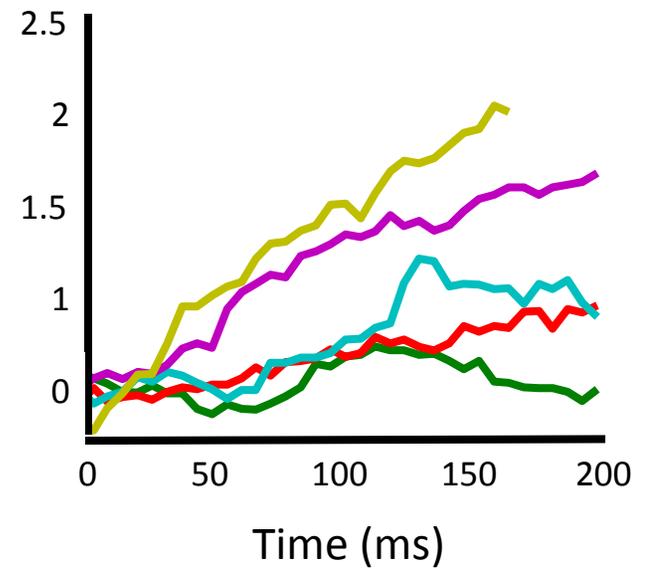
Log odds grow linearly in time

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

Log odds



Log odds



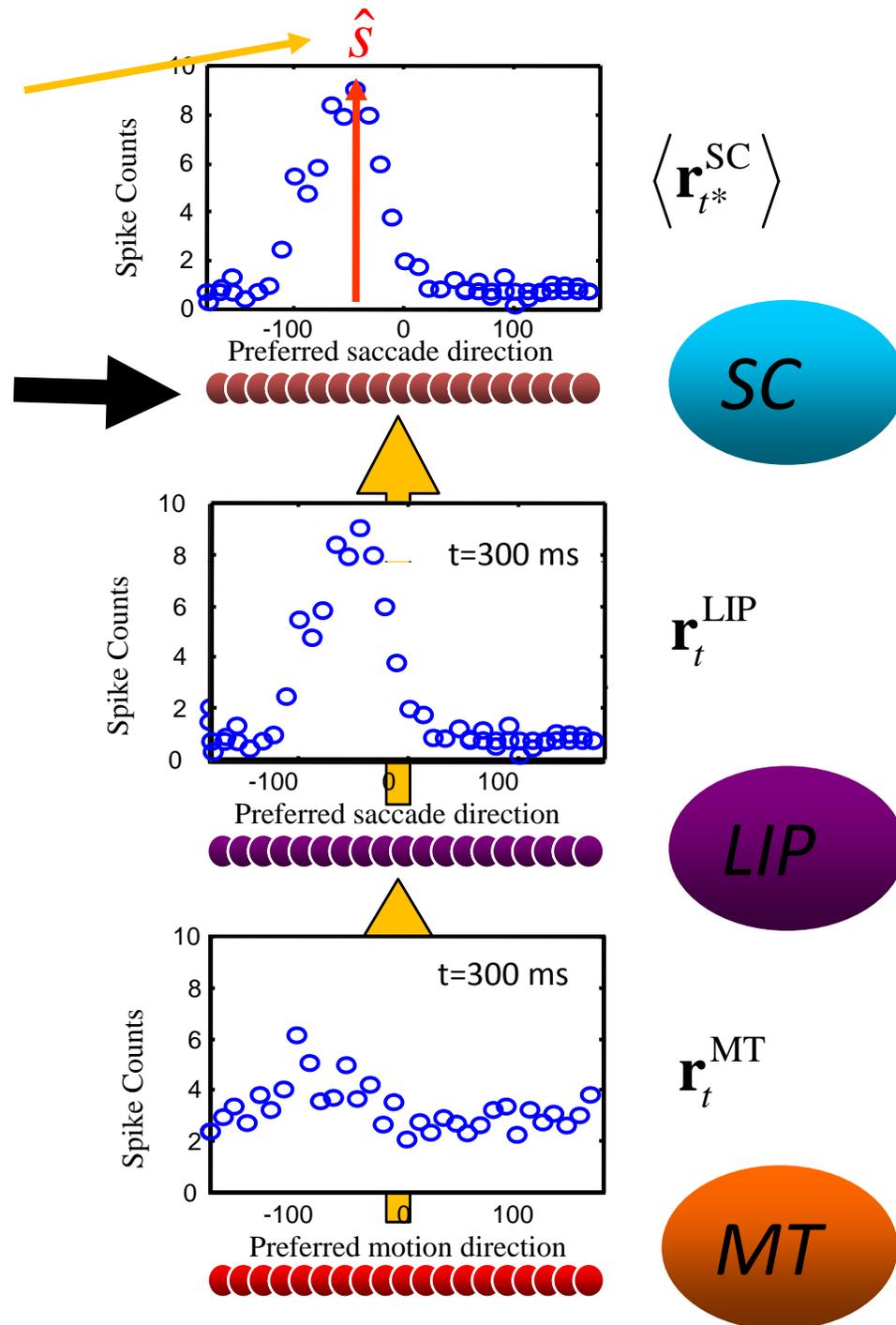
Optimal Action Selection

- 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 → 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)

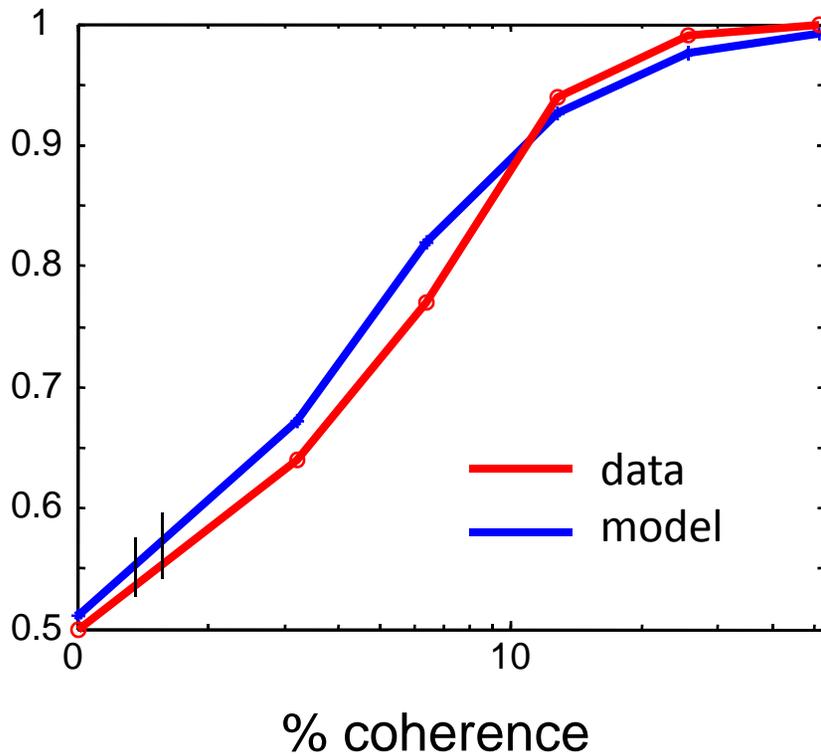
Maximum-likelihood estimate

Action selection : attractor dynamics

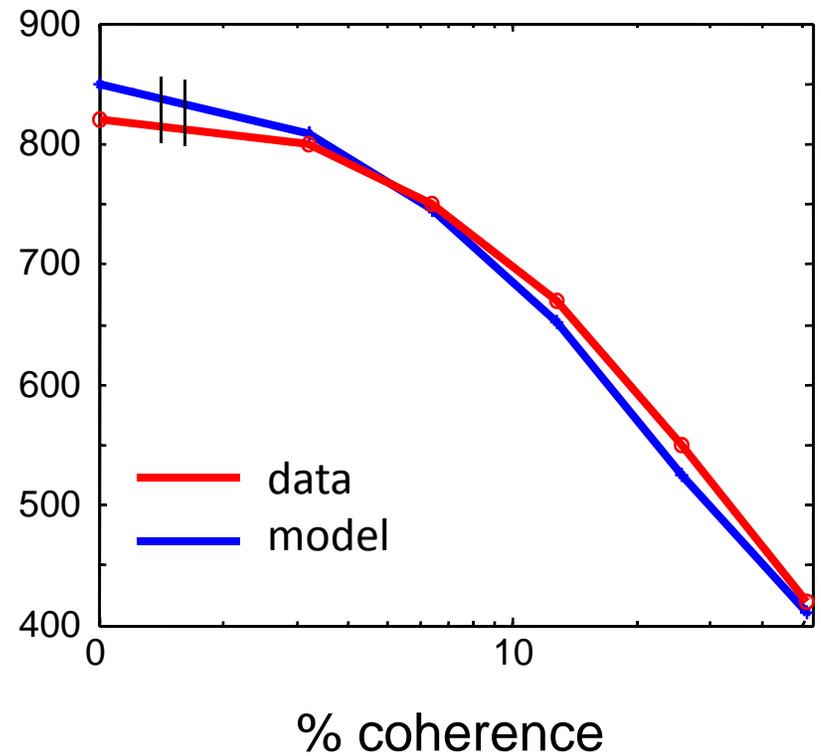


Binary Choice: Performance and Reaction Time

Probability correct



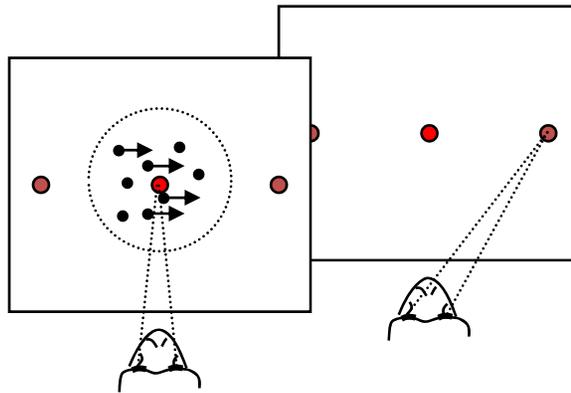
Reaction time (ms)



Data from Mazurek, Roitman, Ditterich, Shadlen, 2003

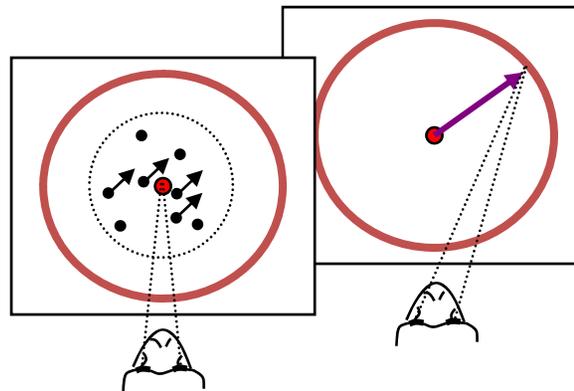
Beyond binary?

Binary



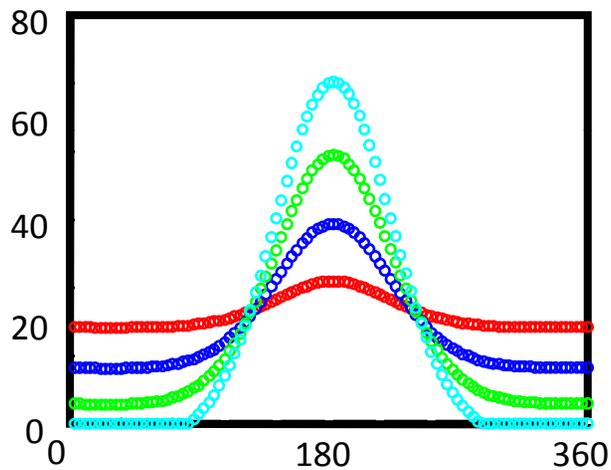
e.g. Roitman and Shadlen (2002)

Continuous



Continuous choice: Distribution encoded in LIP

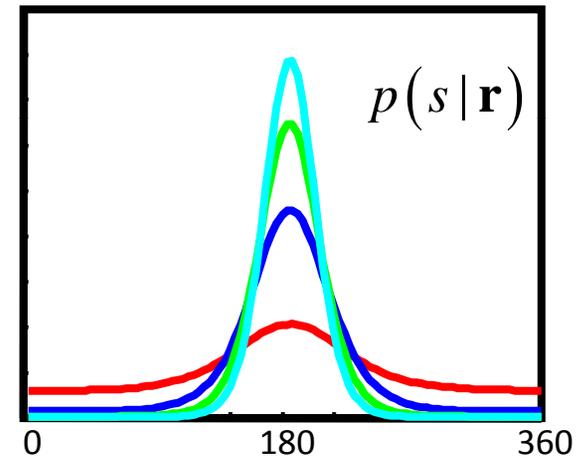
Firing rate (Hz)



Preferred saccade direction (°)

Probability

Bayes
→



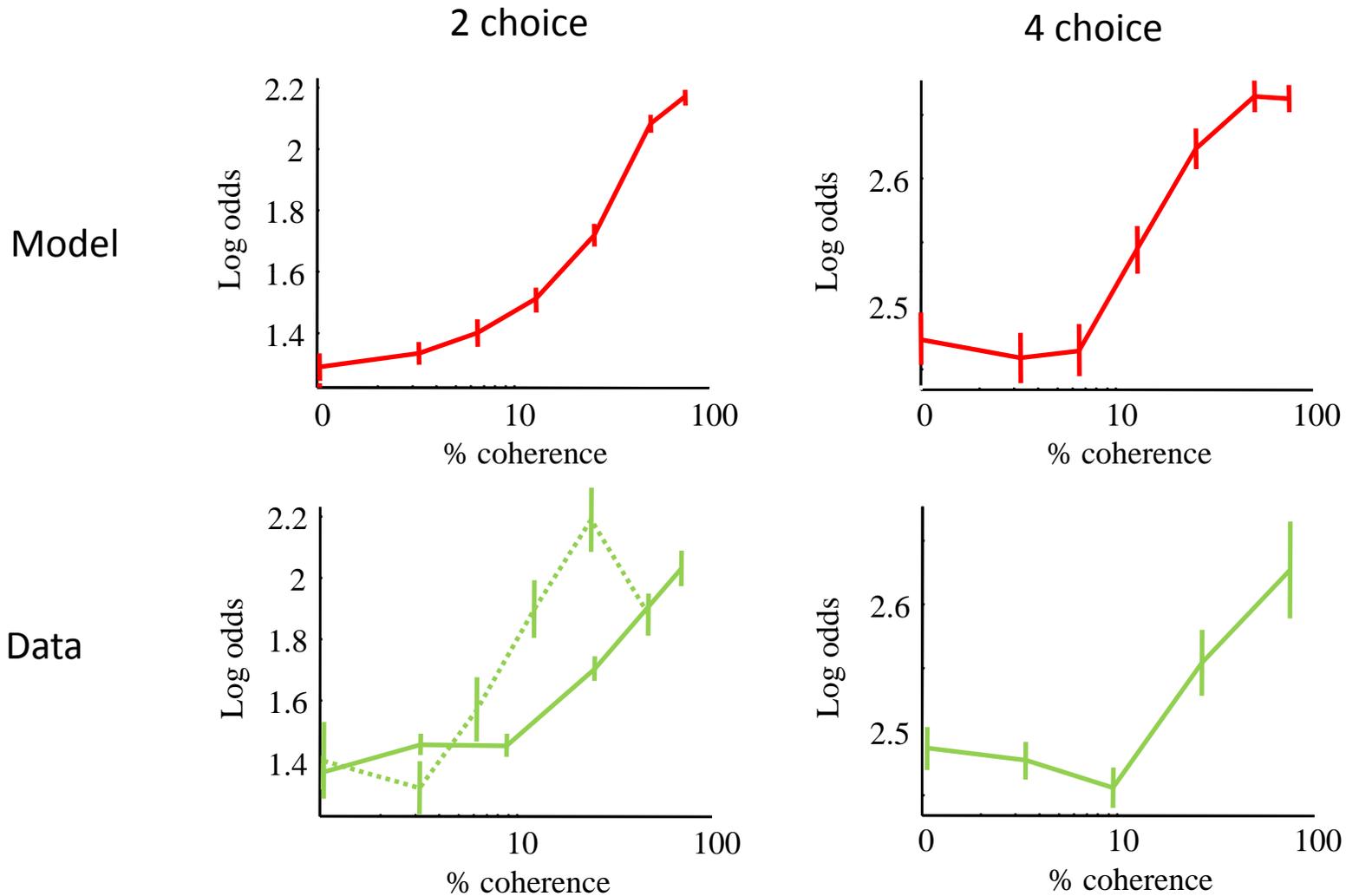
Saccade direction (°)

- 200 ms
- 150 ms
- 100 ms
- 50 ms

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

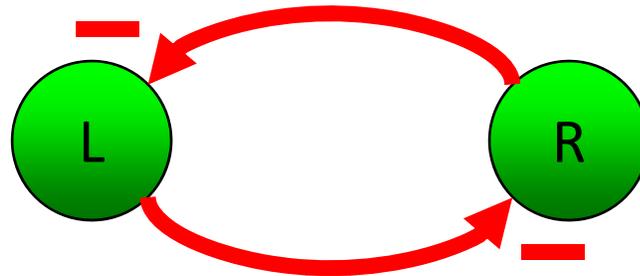


Data from Roitman and Shadlen (2002)

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