

# Inferring Attentional State and Kinematics from Motor Cortical Firing Rates

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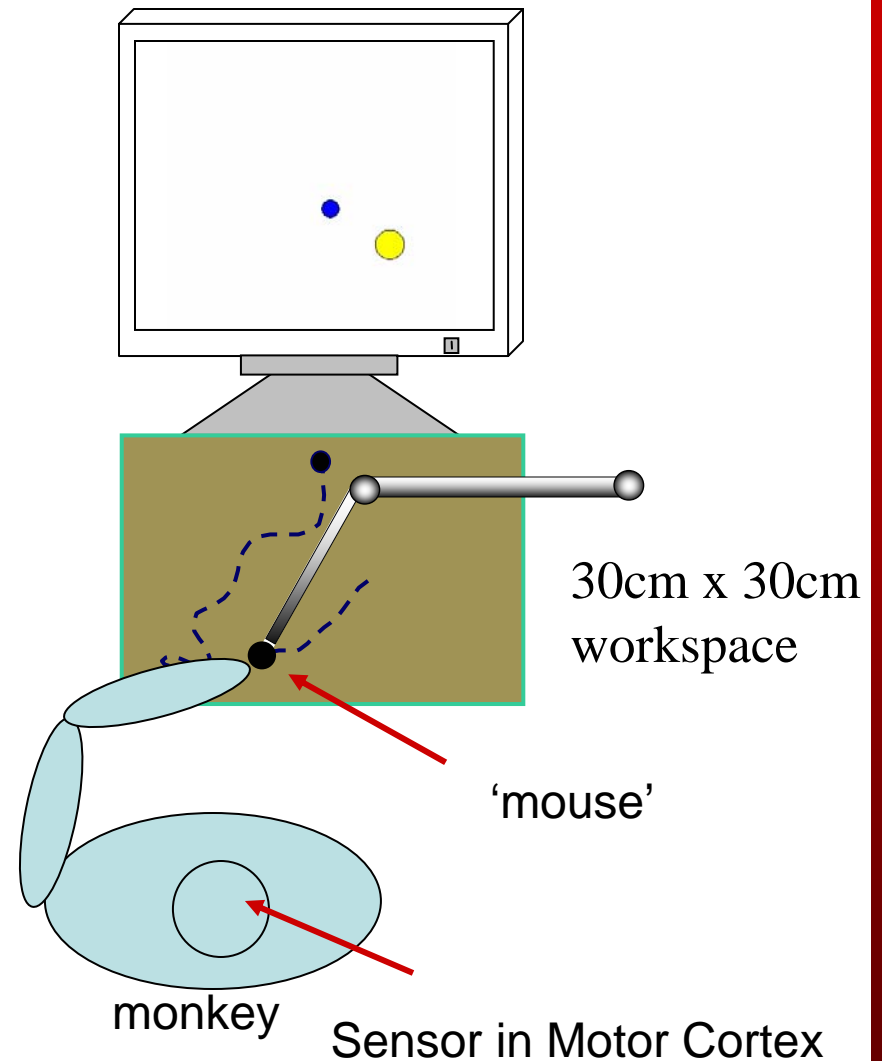


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# Background: Neural Decoding.

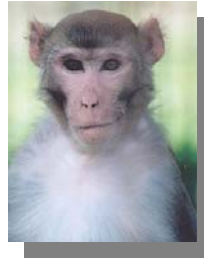
- Trained implanted monkeys perform a task.
- Motor cortical neural population firing rates and hand position are recorded.
- GOAL: Reconstruct hand position from neural firing rates.
- SOLVED!

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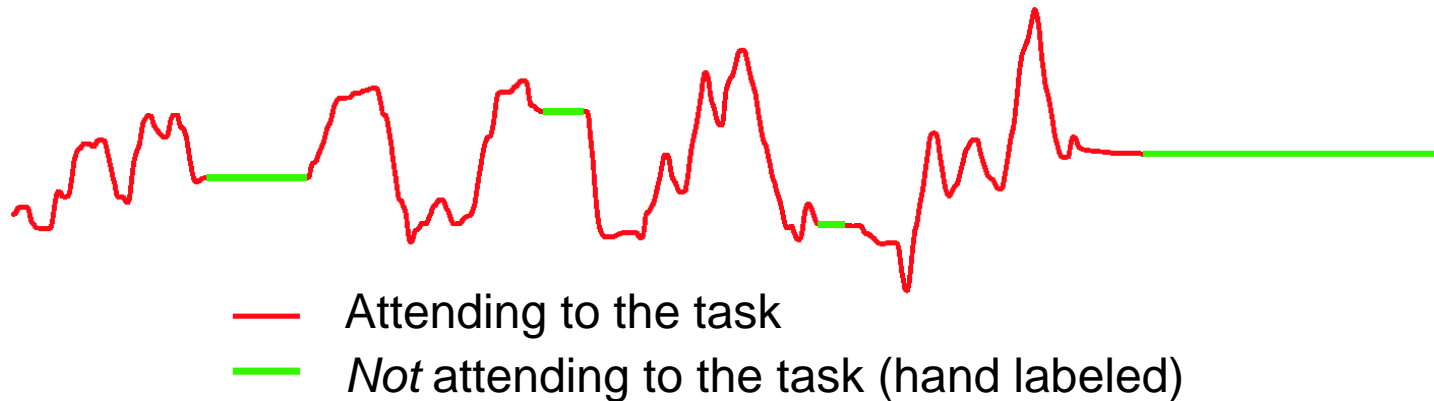


# What's the Problem?

Sometimes the monkey performs its task, sometimes it does not.



We call this the “**attentional state**” of the monkey.



Decoders fail in non-attending regions.



## Solution: Decode Both

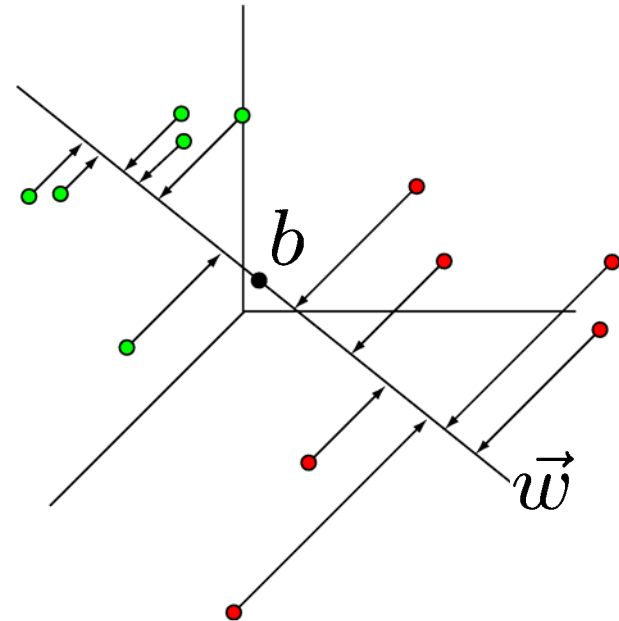
- Probabilistically switch between *decoding* when the monkey attends to the task and *not decoding* when the monkey attends away from the task.
- Use only neural firing rates of *same* cells.
- Need:
  - Attentional State Classifier
    - Distinguish two states (attending/not attending)
  - Hand Position Estimation
    - Recover hand position from neural firing rates

**Motivation: neuroprosthetic on/off switch or click signal**



# Classifying Attentional State

- A supervised learning task
  - Data label pairs
    - Data: firing rate history
      - 20 bins(~1.4 sec.)
    - Label: attentional state
      - Attending, Not Attending
- A Fisher linear separator was learned.
  - Of the form  $\text{sign}(\langle \vec{z}, \vec{w} \rangle + b)$
  - Sufficient to noisily distinguish attending and non-attending states.



# Attentional State Classification Performance

- Classifier output on test data (thresholded):

96.5% Correct (4823/5000)

3.5% Incorrect (177/5000)

		True Label	
		Attending	Not Attending
Predicted Label	Attending	3088	157
	Not Attending	20	1735

*"confusion matrix"*



# Recursive Bayesian Decoding

$\vec{x}_t$  = hand position at time  $t$  (state)

$\vec{z}_t$  = neural firing rates at time  $t$  (observation)

$$p(\vec{x}_t | \vec{z}_{0:t}) \approx p(\vec{z}_t | \vec{x}_t) \int p(\vec{x}_t | \vec{x}_{t-1}) p(\vec{x}_{t-1} | \vec{z}_{0:t-1}) \delta \vec{x}_{t-1}$$

posterior  
at time  $t$

likelihood /  
observation  
model

state model

posterior  
at time  $t-1$



# Augmenting the State

$\gamma_t \in \{+1, -1\}$  is the attentional state of the monkey at time  $t$

$\vec{s}_t = \{\vec{x}_t, \gamma_t\}$  (state)

$$p(\vec{s}_t | \vec{z}_{0:t}) \approx p(\vec{z}_t | \vec{s}_t) \int p(\vec{s}_t | \vec{s}_{t-1}) p(\vec{s}_{t-1} | \vec{z}_{0:t-1}) \delta \vec{s}_{t-1}$$

Diagram illustrating the components of the state augmentation equation:

- $p(\vec{s}_t | \vec{z}_{0:t})$ : posterior at time  $t$
- $p(\vec{z}_t | \vec{s}_t)$ : likelihood / observation model
- $p(\vec{s}_t | \vec{s}_{t-1})$ : state model
- $p(\vec{s}_{t-1} | \vec{z}_{0:t-1})$ : posterior at time  $t-1$





# Modifying the state model.

$$p(\vec{s}_t | \vec{z}_{0:t}) \approx p(\vec{z}_t | \vec{s}_t) \int p(\vec{s}_t | \vec{s}_{t-1}) p(\vec{s}_{t-1} | \vec{z}_{0:t-1}) \delta \vec{s}_{t-1}$$

$$p(\vec{s}_t | \vec{s}_{t-1}) \rightarrow p(\vec{x}_t | \vec{x}_{t-1}, \gamma_{t-1}) p(\gamma_t | \gamma_{t-1})$$

Linear Gaussian model when attending, constant when not attending.

Attentional state transition probabilities learned from training data counts.



# Modifying the observation model.

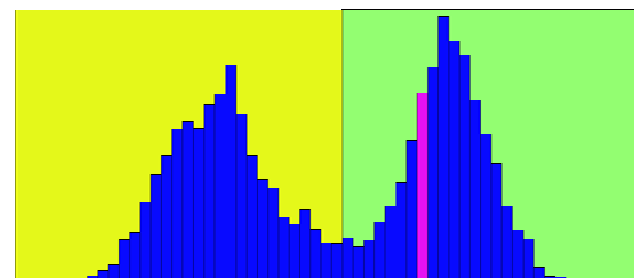
$$p(\vec{s}_t | \vec{z}_{0:t}) \approx p(\vec{z}_t | \vec{s}_t) \int p(\vec{s}_t | \vec{s}_{t-1}) p(\vec{s}_{t-1} | \vec{z}_{0:t-1}) \delta \vec{s}_{t-1}$$

$$p(\vec{s}_t | \vec{s}_{t-1}) \rightarrow p(\vec{x}_t | \vec{x}_{t-1}, \gamma_{t-1}) p(\gamma_t | \gamma_{t-1})$$

$$p(\vec{z}_t | \vec{s}_t) \rightarrow p(\vec{z}_t | \vec{x}_t) p(\vec{z}_t | \gamma_t)$$

Linear Gaussian

Attending Not Attending



$\langle \vec{z}, \vec{w} \rangle$

Likelihood of firing rate as a function of attentional state determined by Fisher linear discriminant.



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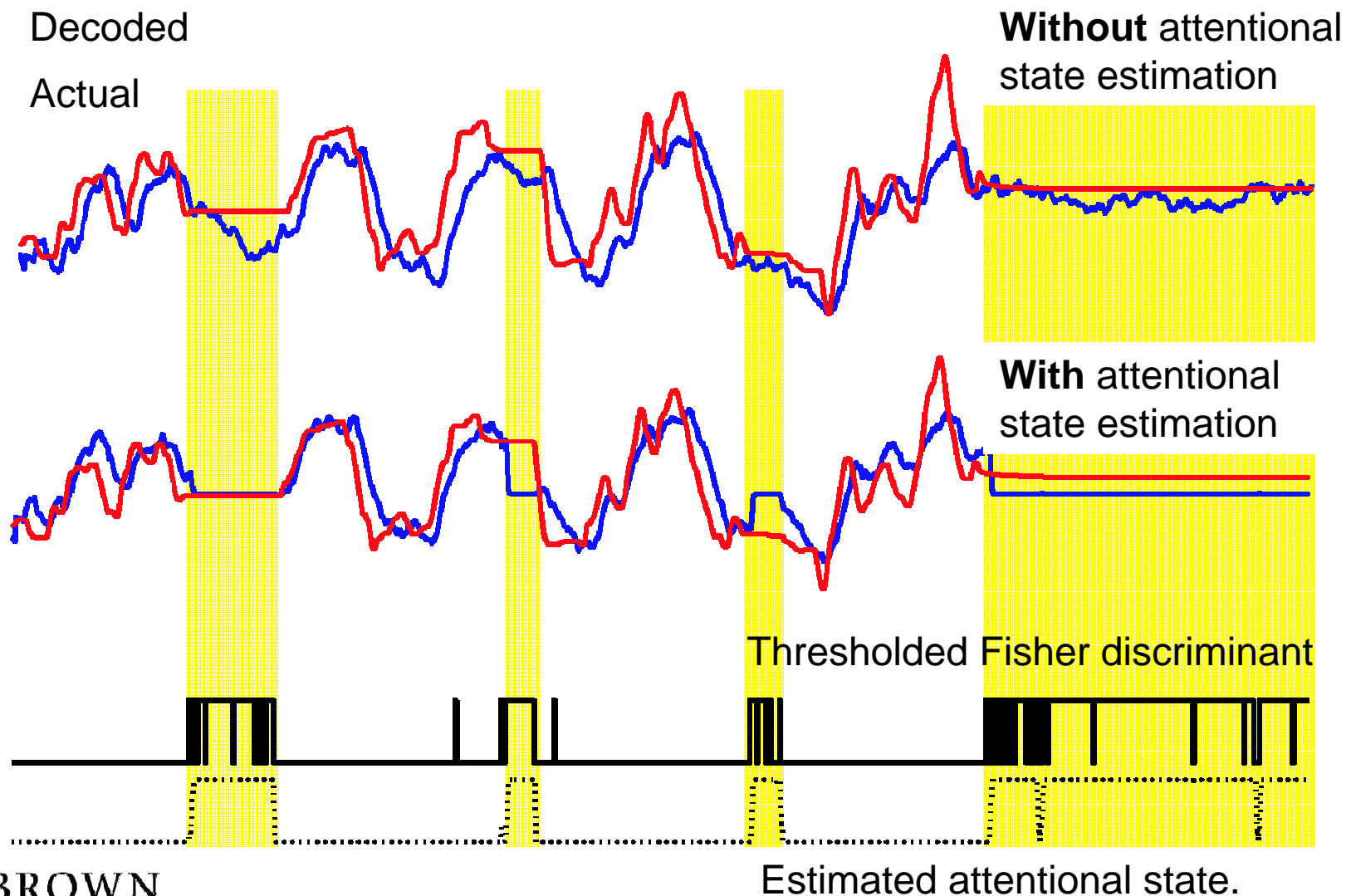
# Decoding Design Choices

- Monte Carlo integration (particle filter).
- What to “decode” when the monkey’s attention shifts from the task.
- How to score the decoding improvement.
  - Correlation coefficient and MSE are unsuitable for comparing DC signals.
  - We use a modified metric that assigns a correlation coefficient of 1 and an MSE of 0 when two signals are both constant.



# Example decoding results

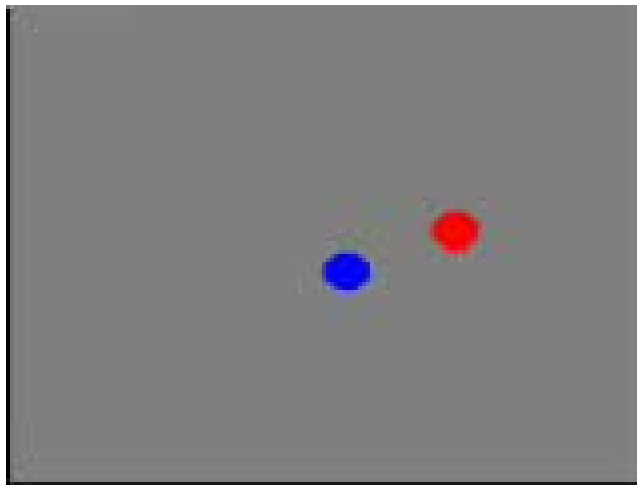
- Decoded
- Actual



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# Decoding Results

	X cc	Y cc	X mse	Y mse
Particle Filter	0.34	0.32	29.39	36.62
Switching PF	0.76	0.68	8.39	8.68
Kalman Filter	0.45	0.45	34.74	17.64



## Attentional State

- Attending
- Not Attending

## Hand Position

- Decoded
- Actual



# Conclusions and Comments

Attentional state (discrete) and hand kinematics (continuous) can be decoded simultaneously from motor cortical firing rates (same cells).

A simple linear discriminant can be used to distinguish attentional states.

Attentional state decoding could be used as a an on/off switch or click signal for neural prosthetics.



# Future Work and Thanks

- Open Questions:
  - How many states can be decoded from this cortical area?
  - What is happening when the monkey attends away?

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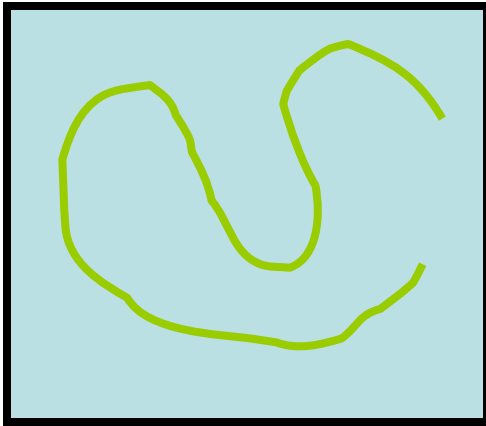
Thank You. Questions?



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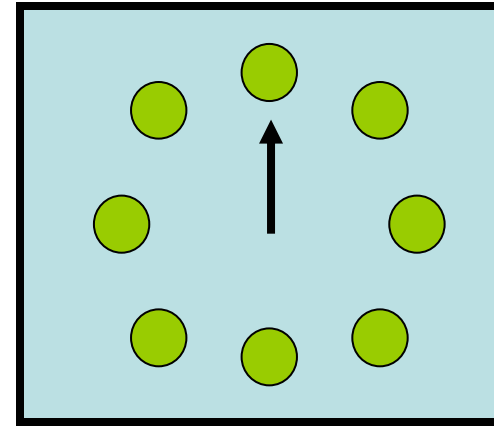


# Problem – Discrete state decoding needed



- Continuous (Mouse Cursor)

- Population vector
- Linear filter
- Particle filter
- Kalman filter



- Discrete States (Mouse Click)

- ML Bayes
- Discriminative classifier

**On/Off Switch**  
**Click**



# Motivation

*Supervised on/off switch*



*Hover "click"*

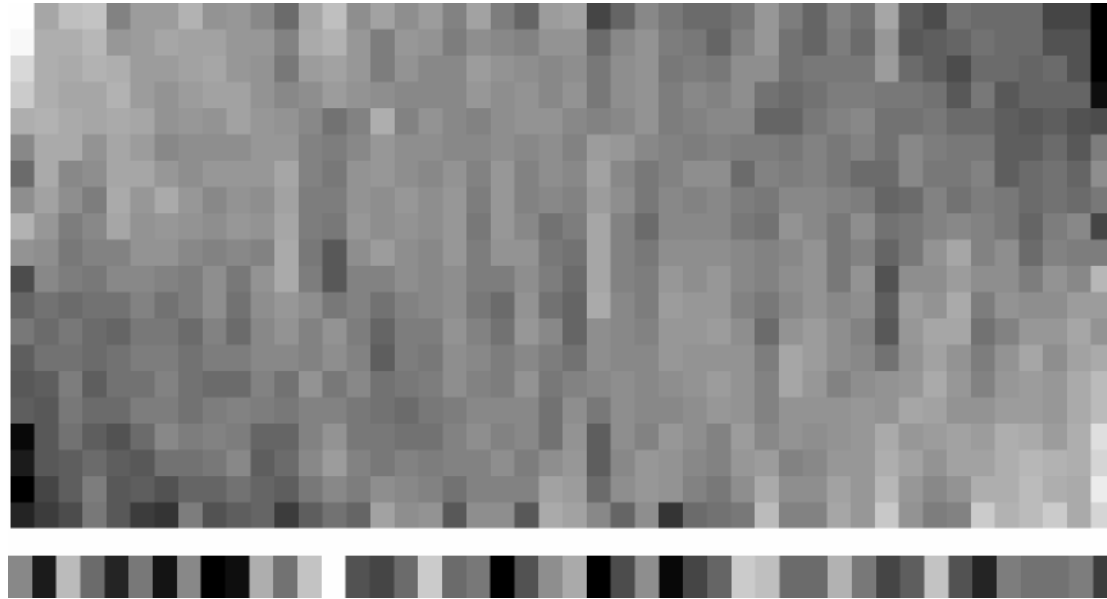


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*From wired.com with thanks to Cyberkinetics, Inc.*

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# Fisher Linear Discriminant Details



$$p(\gamma_i|\vec{z}_i) = \frac{p(\gamma_i)G(w^\top \vec{z}_i; \mu_i, \sigma_i)}{\sum_j p(\gamma_j)G(w^\top \vec{z}_j; \mu_j, \sigma_j)}$$

$$p(\vec{z}_i|\gamma_i) = \frac{p(\gamma_i|\vec{z}_i)p(\vec{z}_i)}{p(\gamma_i)}$$



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# Particle Filter Estimation of State

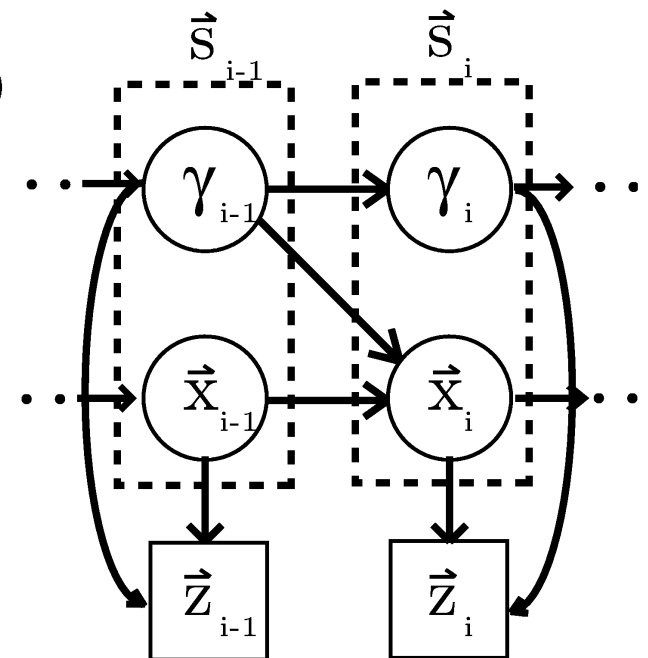
- Given only cell firing rates, estimate hand position and attentional state

$$p(\vec{s}_i | \vec{s}_{i-1:1}, \vec{z}_{i:1}) = \kappa p(\vec{z}_i | \vec{s}_i) \int p(\vec{s}_i | \vec{s}_{i-1}) p(\vec{s}_{i-1} | \vec{z}_{i-1}) \delta \vec{s}_{i-1}$$

$$\begin{aligned} p(\vec{s}_i | \vec{s}_{i-1}) &= p(\vec{x}_i, \gamma_i | \vec{x}_{i-1}, \gamma_{i-1}) \\ &= p(\vec{x}_i | \vec{x}_{i-1}, \gamma_{i-1}) p(\gamma_i | \gamma_{i-1}) \end{aligned}$$

where

$$\begin{aligned} p(\vec{z}_i | \vec{s}_i) &= p(\vec{z}_i | \vec{x}_i, \gamma_i) \\ &= p(\vec{z}_i | \vec{x}_i) p(\vec{z}_i | \gamma_i) \end{aligned}$$



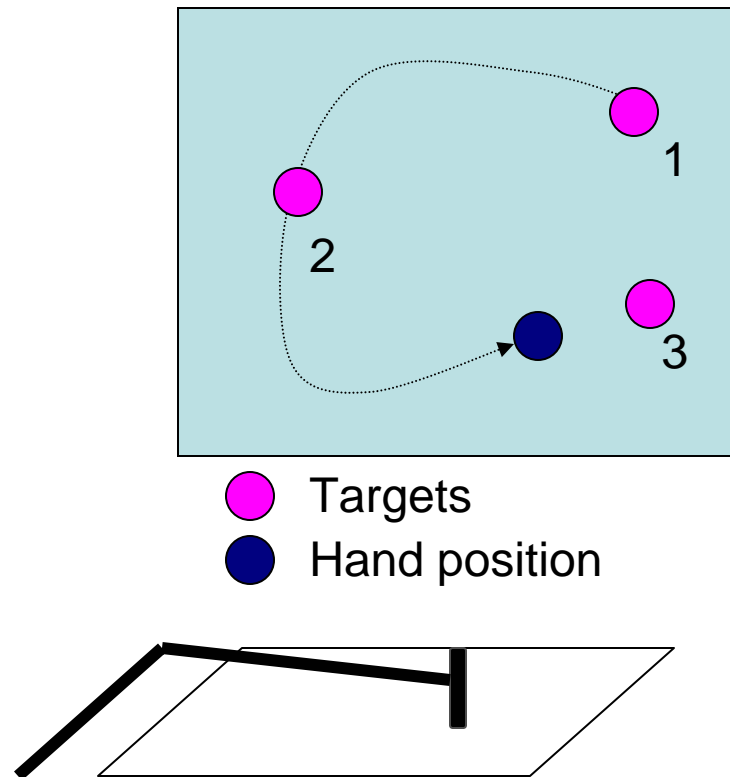
# Data

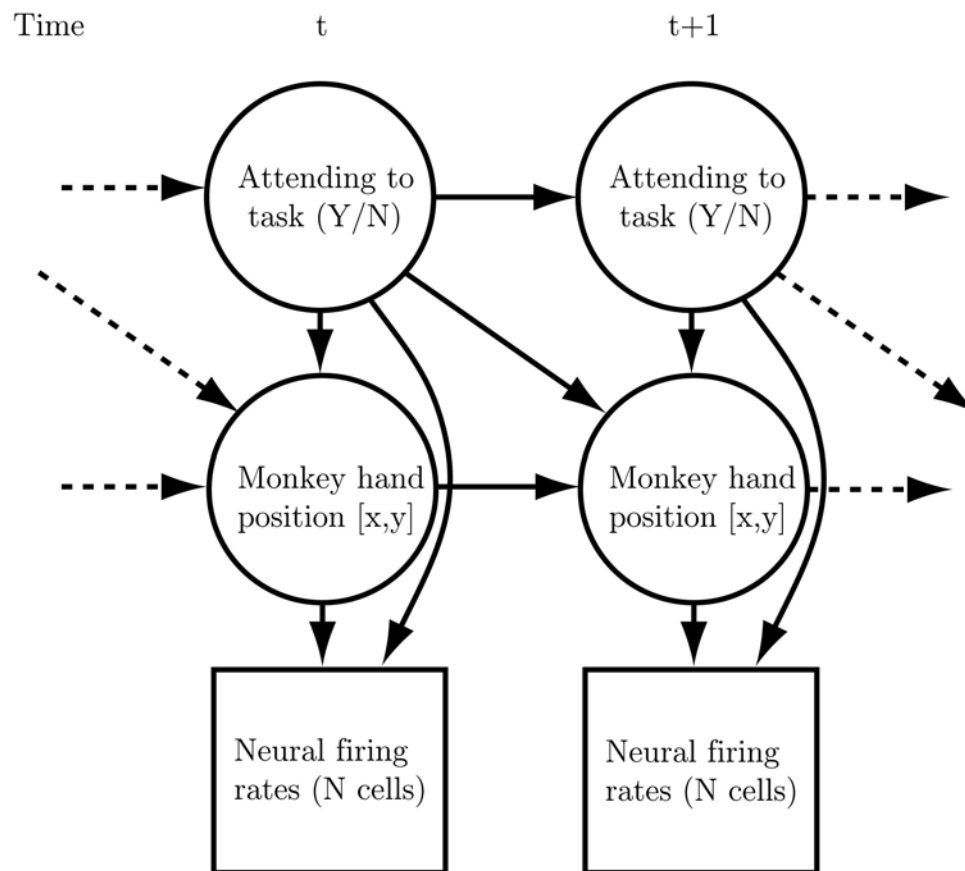
- Linear classifier parameter tuning
  - Separate 42 cell, 10 minute recording used to determine optimal history for attentional state classification (20 70msec. bins) (cross-validated using held-out data)
- Decoding results
  - Single monkey
  - Single recording session
  - Pinball task
  - 15000 70msec. bins for training, 5000 bins for testing



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