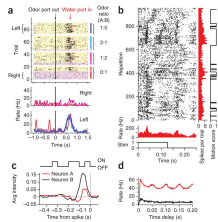
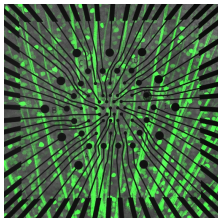


# A bit about reverse correlation stimulus design and analysis

Yonatan Aljadeff, University of Chicago  
aljadeff@uchicago.edu

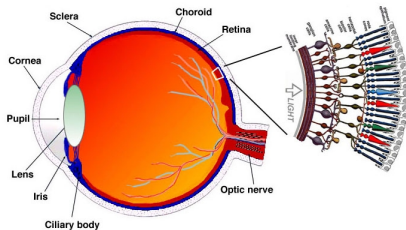
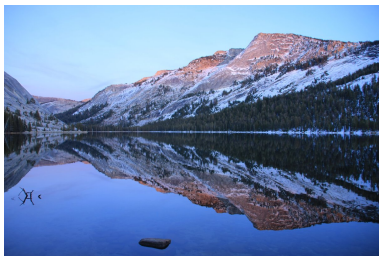
1/27/2016, UCSD



# Outline:

- ▶ Reverse correlation experiments and linear non-linear models
- ▶ Why use white noise?
- ▶ Why not use white noise?
- ▶ Analysis of responses to non-white noise stimuli
  - ▶ synthetic model
  - ▶ rat thalamus

# Reverse correlation experiments:



The model we will construct:

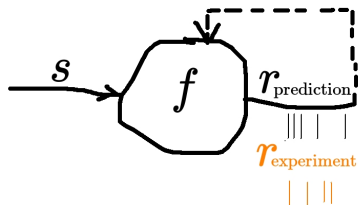
$$\text{response}(t) = f[\text{stimulus}(t' < t), \text{response}(t' < t)]$$

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If by knowing  $f$  we can predict responses to stimuli that weren't used to fit  $f$  we have hope to understand the computation the cell is performing.

Important model assumptions: no explicit time dependence (no adaptation), fixed stimulus statistics

# Two steps of constructing model

## 1. dimensionality reduction

$$\text{response}(t) = f[\text{stimulus}(t' < t)]$$

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We want to focus on stimulus statistics, so small number = 1.

The first component is the Spike  
Triggered Average:

$$\varphi_{\text{STA}} = \left( \frac{1}{N_{\text{spike}}} \sum_{t=t_{\text{spike}}} s(t) \right) - \langle s \rangle$$

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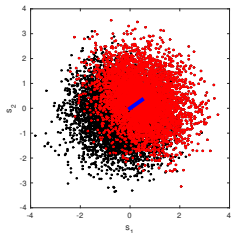
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# Two steps of constructing model

## 2. fitting nonlinearity

We use Bayes' rule:

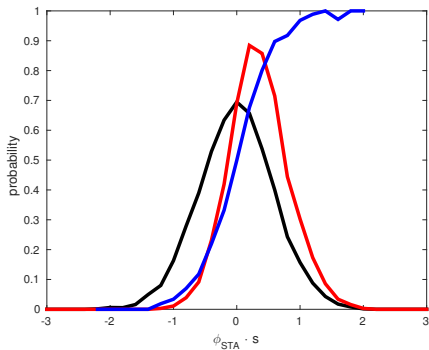
$$r(t) = p(\text{spike}|s)$$

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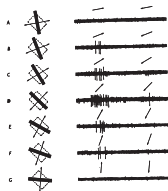
$$\begin{aligned}r(t) &= p(\text{spike}|s) \\ &= \frac{p(s|\text{spike})p(\text{spike})}{p(s)}\end{aligned}$$



# Why use white noise stimuli?

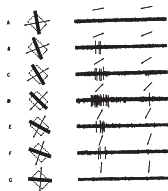
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Avoid *putting the answer in*



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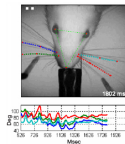
Makes analysis easy

$$\begin{aligned} r(t) &= f[\varphi_{STA} \cdot s] \\ p(\text{spike}|s) &= \frac{p(s|\text{spike})p(\text{spike})}{p(s)} \end{aligned}$$

# Why not use white noise stimuli?

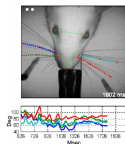
# Why not use white noise stimuli?

active sensing  
(self generated stimulus)

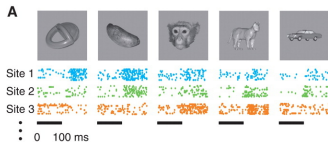


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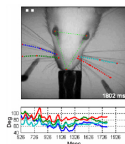


some neurons will never spike

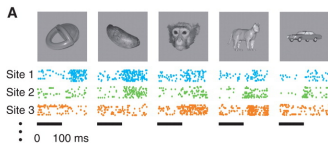


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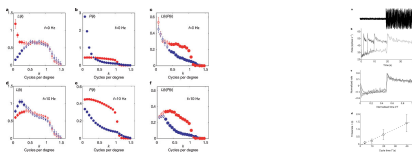
active sensing  
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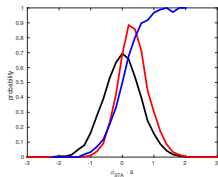
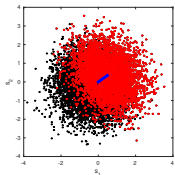
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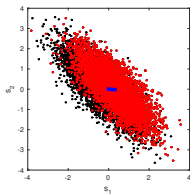
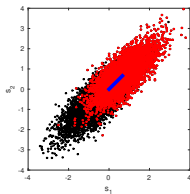
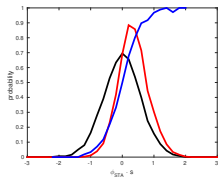
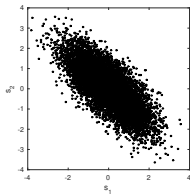
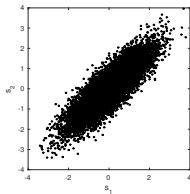
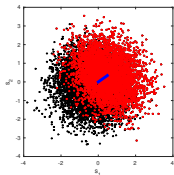
ask questions about  
adaptation, optimal processing ...



# What is the big deal?



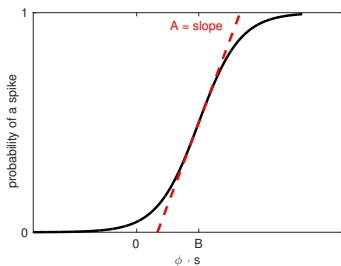
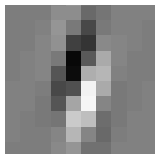
# What is the big deal?



# A simple exercise, model

$$p(\text{spike}|s) = \frac{1}{1 + \exp[-A(\phi \cdot s - B)]}$$

$\phi =$



# A simple exercise, stimulus

white noise



10×10 patches from



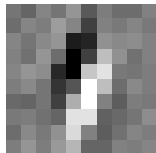
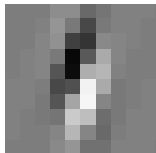
strongly correlated  
Gaussians



# Spike Triggered Average

$\phi$

STA computed from  
responses to white  
noise



STA computed from  
responses to  
correlated noise



# Decorrelation

Analyze responses with decorrelated stimulus  $\tilde{s}$

$$C = \text{cov}(S) = \frac{1}{T} \sum_{t=1}^T s(t)s(t)^\top$$

$$\tilde{s}(t) = C^{-\frac{1}{2}} s(t)$$

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# Decorrelation

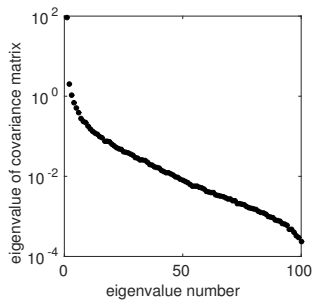
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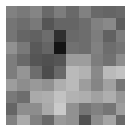
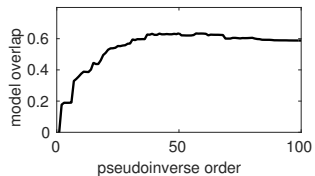
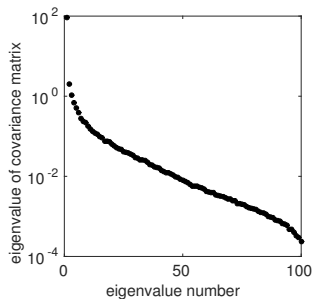
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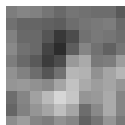
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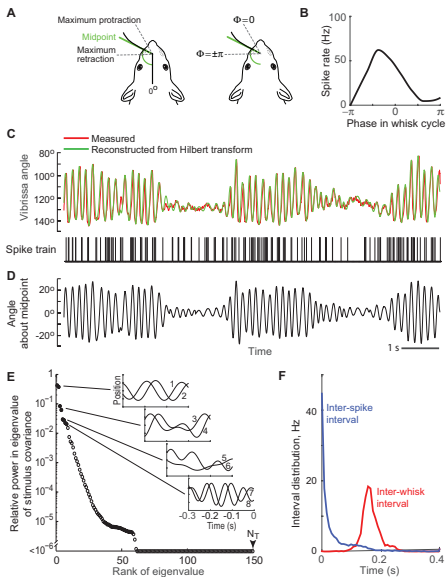


computed from full inverse

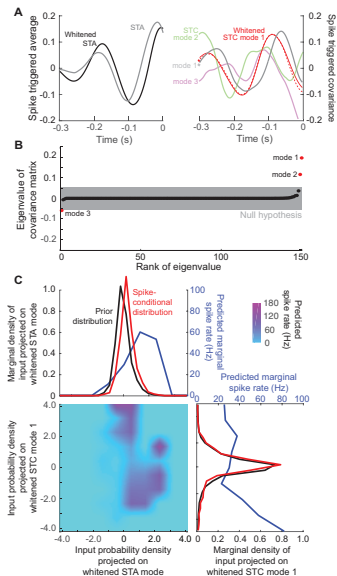


computed from pseudoinverse

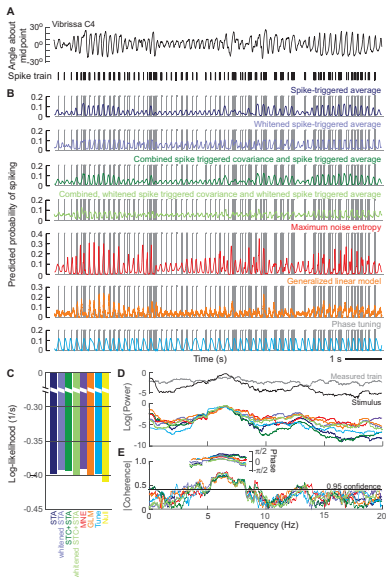
# Rat thalamus data



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## Conclusion

Think about stimulus design and the appropriate analyses methods the stimulus you choose implies.

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