

Decoding Neural Activity

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1. Neuro-syntax:

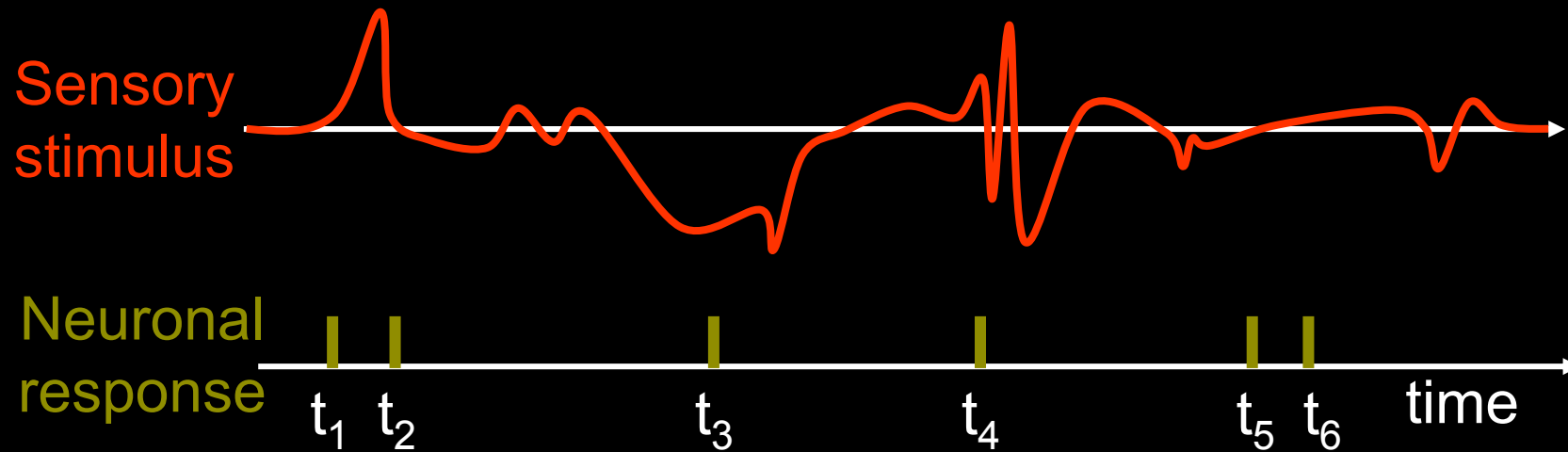
What is basic 'syntactic' unit of the neuronal response?

2. Neuro-semantics:

What 'semantic' features do these syntactic units represent?

Outline

- Neurosyntax
 - Information theory
- Neurosemantics
 - Systems identification
- Biological 'case study'
 - Whisker system



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$P[\text{spike train} \mid \text{sensory stimulus}]$

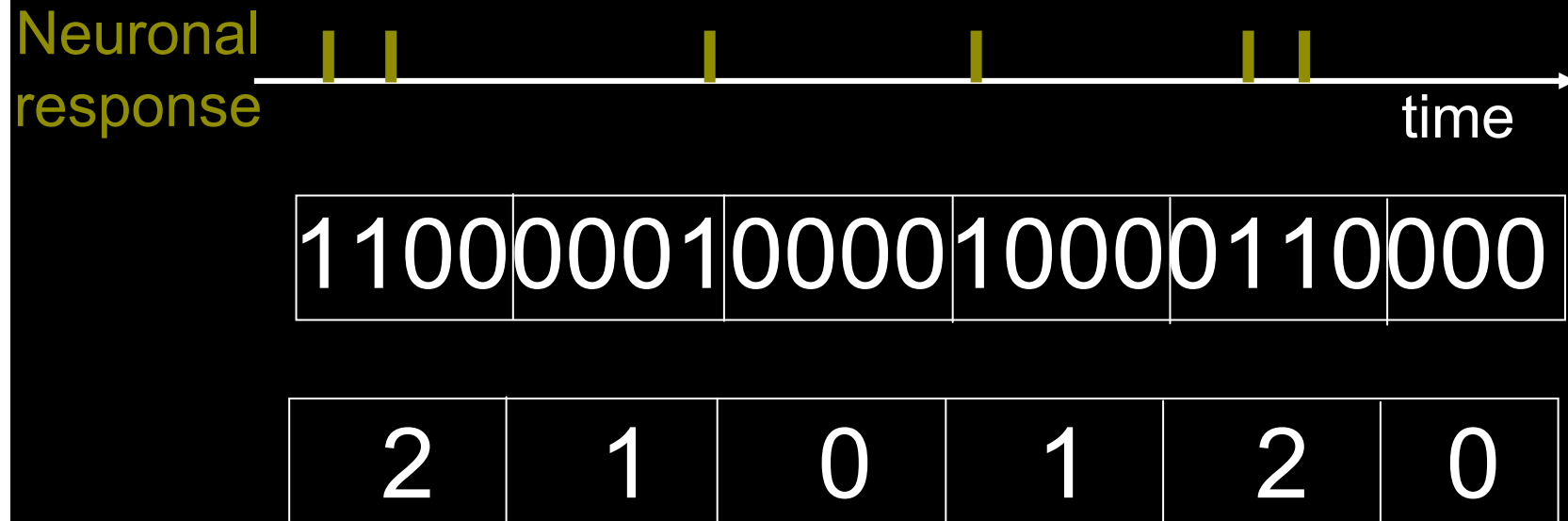
Spike train $\mathbf{r} = \{t_1, t_2, \dots, t_N\}$
 $= (r_1, r_2, \dots, r_L)$

Stimulus $\mathbf{s} = (s_1, s_2, \dots, s_T)$

Possible simplifications

- Coarse-grain the response?
- Ignore higher order statistical structure?

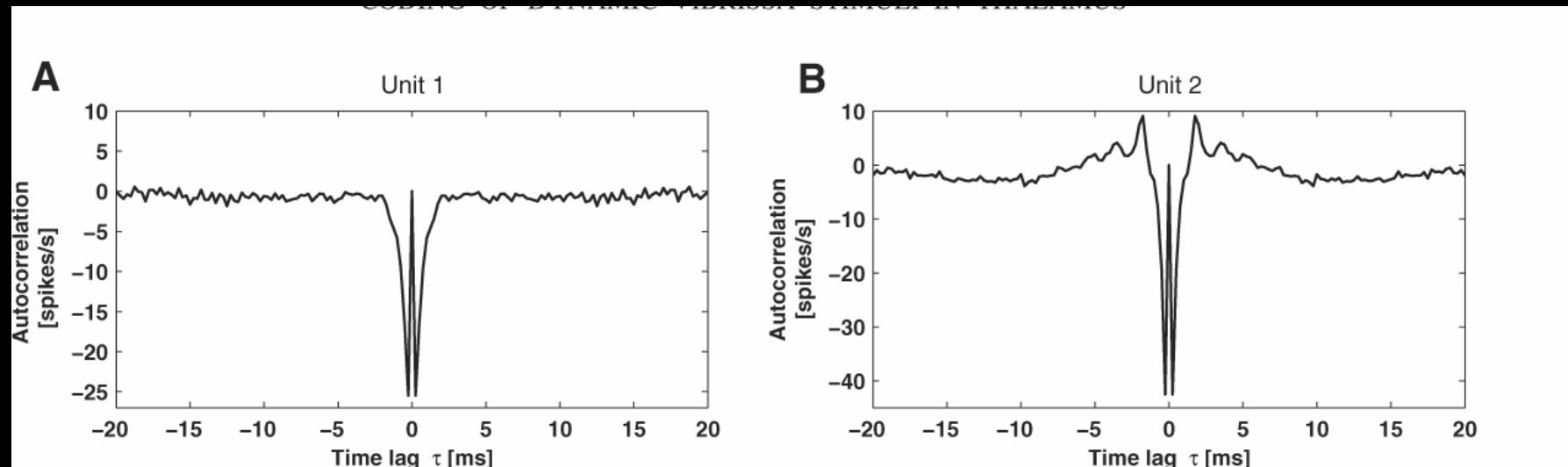
Coarse graining



Spike count hypothesis: The key information-bearing unit of the spike train is the number of spikes (**spike count**) fired within a time window (long enough to include several spikes). *Corollary.* Precise timing of spikes within the window is just noise.

Higher order statistical structure

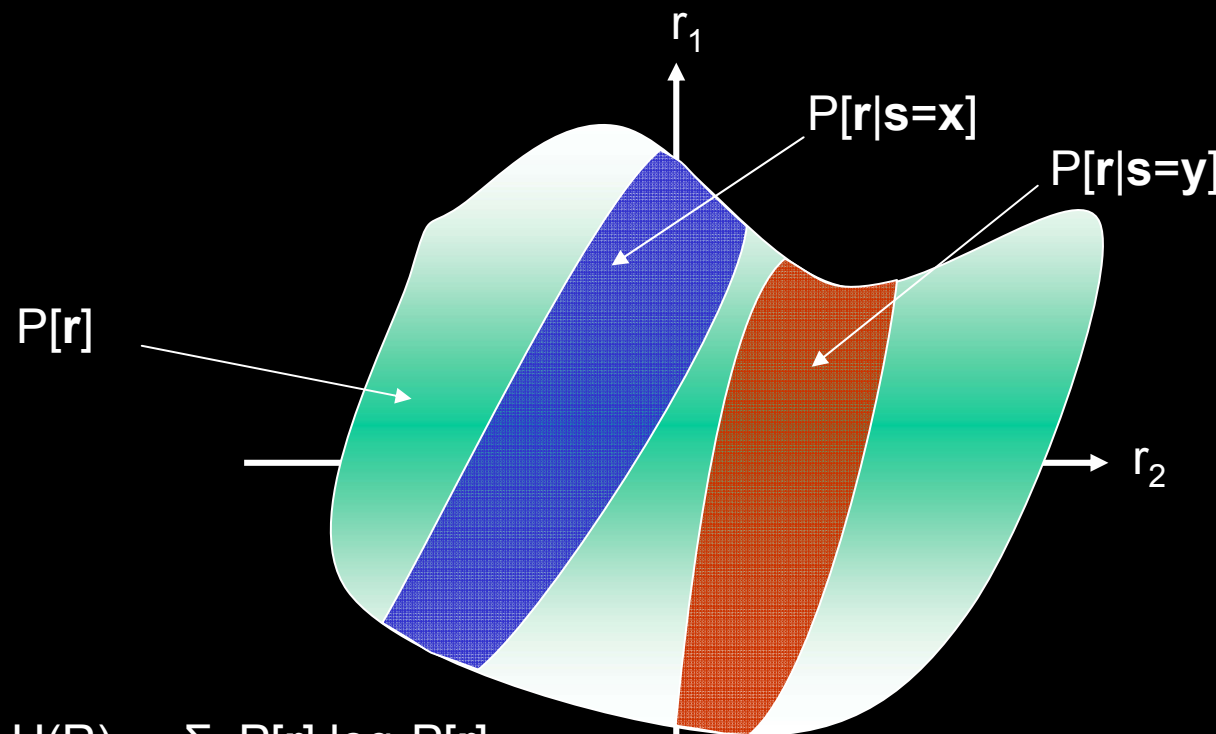
- Correlation here defined as:
 - $P[(r_1, r_2, \dots, r_N) | \mathbf{s}] \neq P[r_1 | \mathbf{s}] P[r_2 | \mathbf{s}] \dots P[r_N | \mathbf{s}]$
 - ‘noise correlation’
- Uncorrelated ‘rate’ model:
 - $P[(r_1, r_2, \dots, r_N) | \mathbf{s}] = P[r_1 | \mathbf{s}] P[r_2 | \mathbf{s}] \dots P[r_N | \mathbf{s}]$



Testing coding hypotheses

- Spike count hypothesis:
 - Predicts that precise spike timing adds nothing to the “information” available from the spike count
- Rate coding hypothesis:
 - Predicts that no “information” lost by neglecting correlations

Information Theory



$H(\mathbf{R}) = -\sum_{\mathbf{r}} P[\mathbf{r}] \log_2 P[\mathbf{r}]$
Response entropy

$$H(\mathbf{R}|\mathbf{s}) = -\sum_{\mathbf{r}} P[\mathbf{r}|\mathbf{s}] \log_2 P[\mathbf{r}|\mathbf{s}]$$

$$H[\mathbf{R}|\mathbf{S}] = -\sum_{\mathbf{s}} P[\mathbf{s}] H[\mathbf{R}|\mathbf{s}]$$

Noise entropy

$$I(\mathbf{S};\mathbf{R}) = H(\mathbf{R}) - H(\mathbf{R}|\mathbf{S})$$

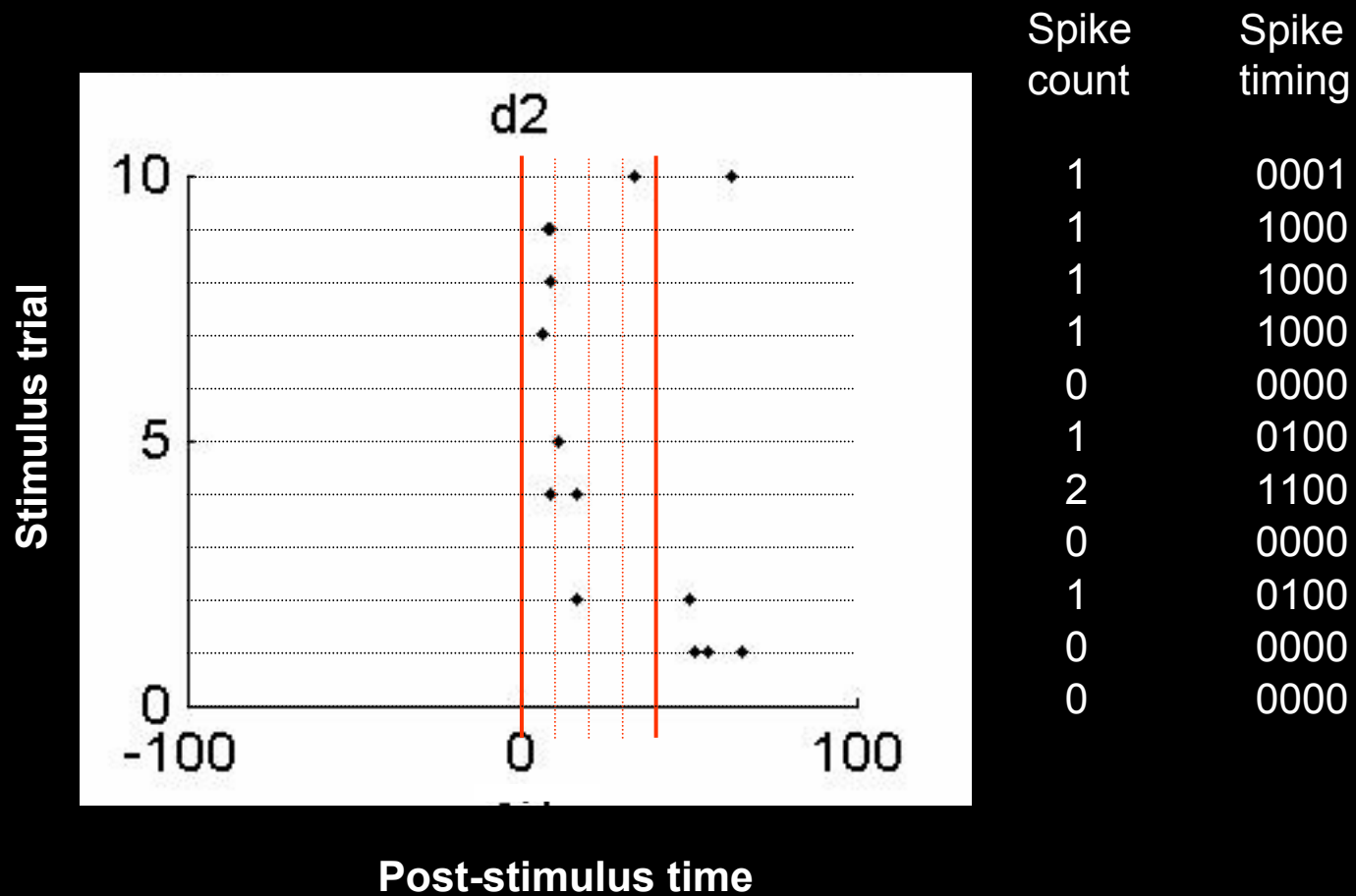
Mutual Information

Estimating mutual information

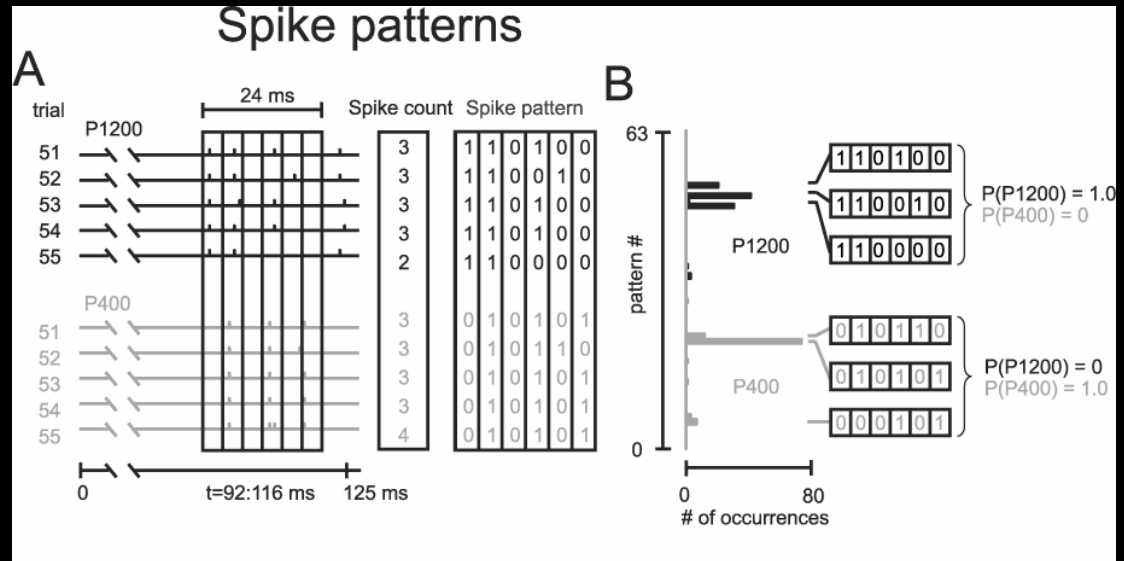
Static stimuli

Dynamic stimuli

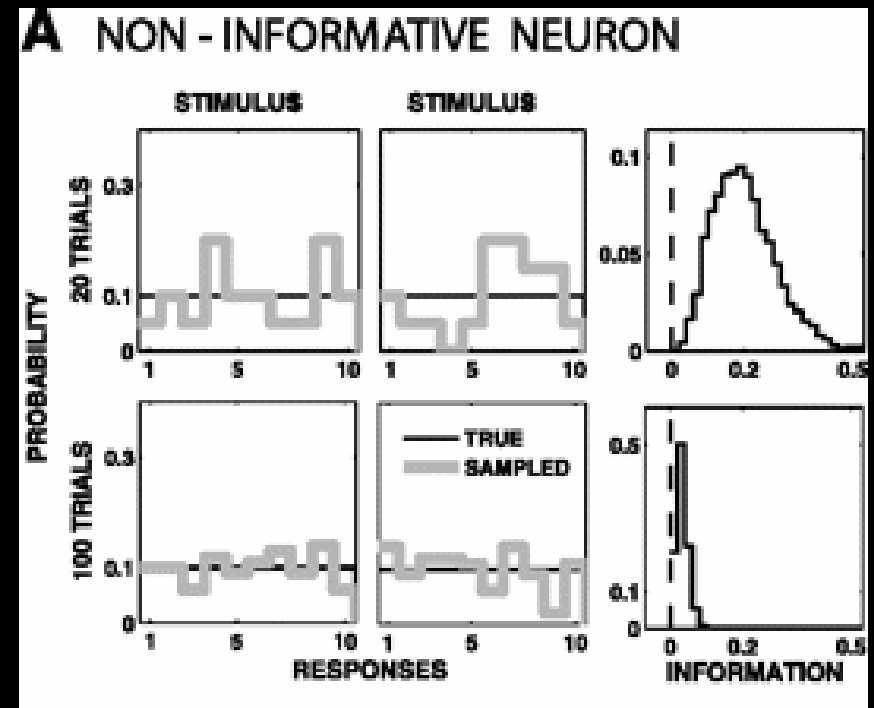
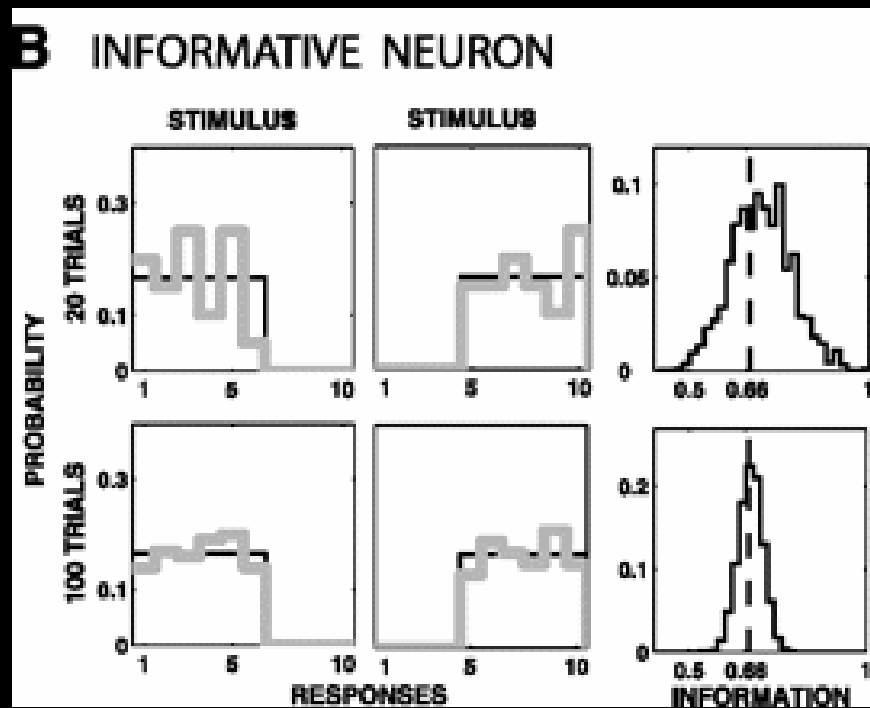
Estimating $I(S;R)$ – static stimuli

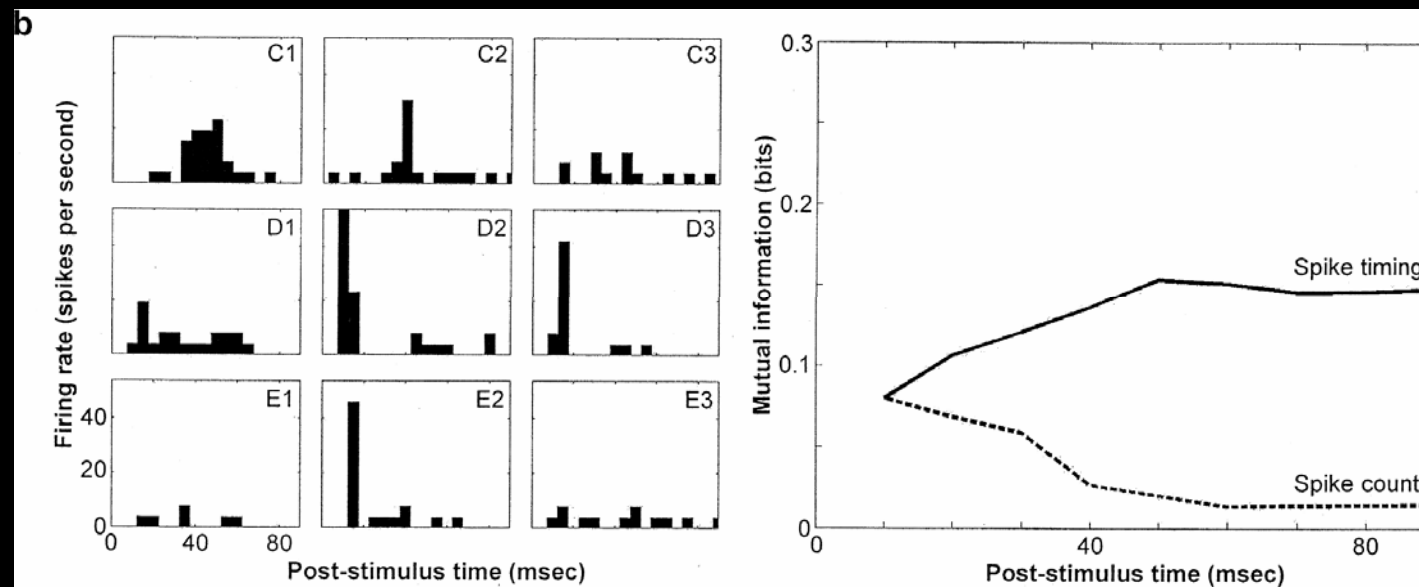
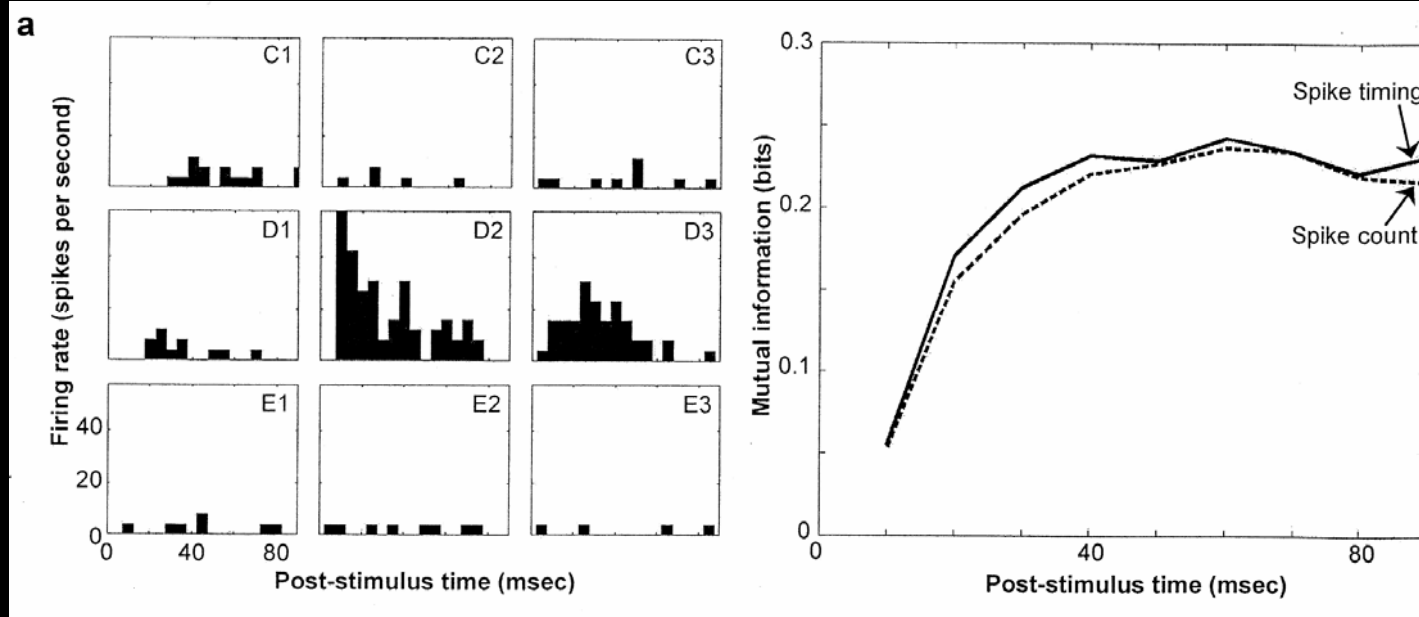


$$H(R|S) = -\sum_s P[s] \sum_r P[r|s] \log_2 P[r|s]$$

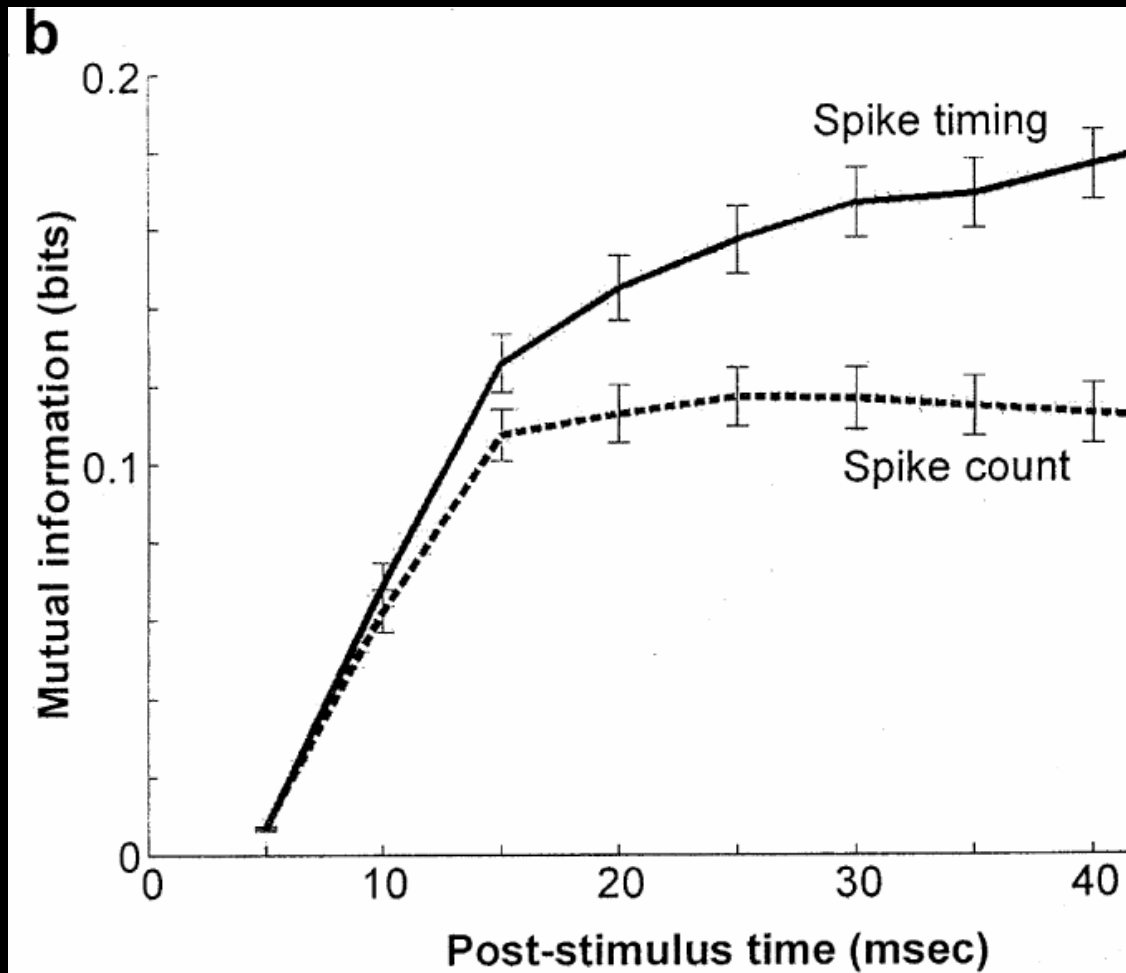


Sampling bias



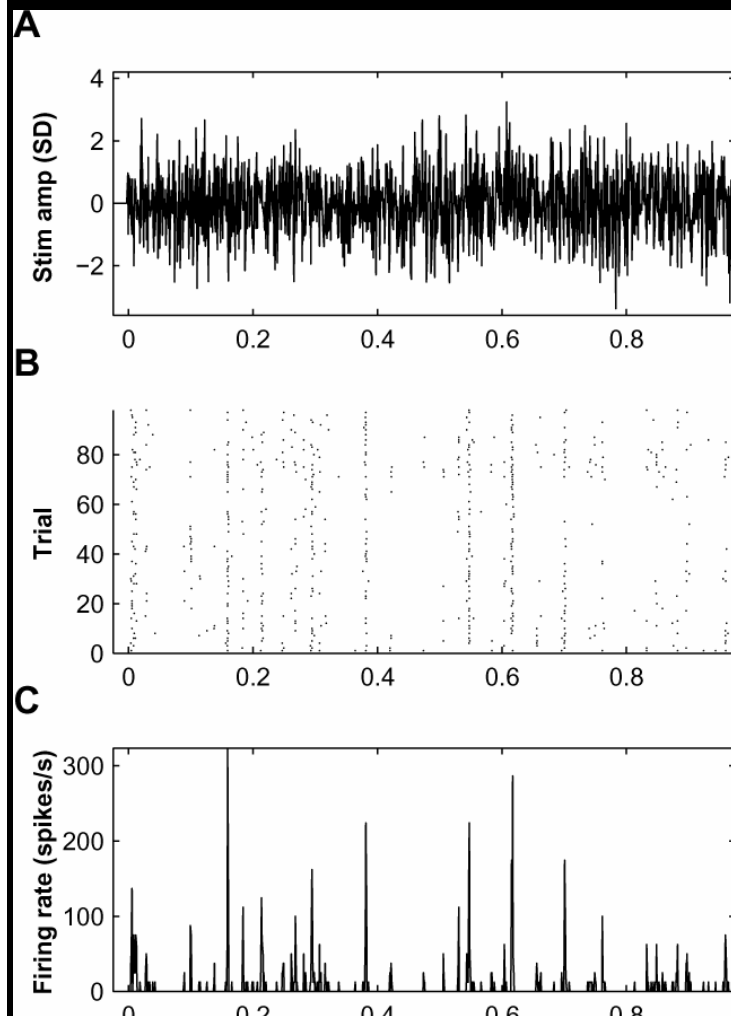


Panzeri et al (2001) *Neuron*
 Petersen et al (2001) *Neuron*

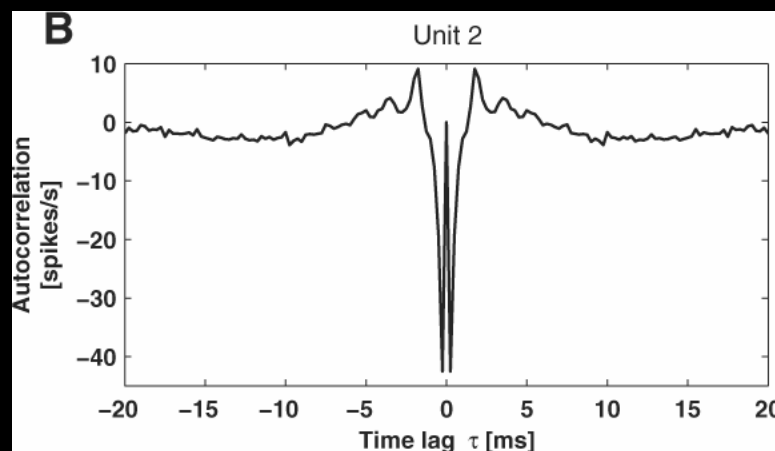


Panzeri et al (2001) *Neuron*
Petersen et al (2001) *Neuron*

Rates vs Correlations



- Correlated model:
 $P(r_1, r_2, \dots, r_N | s) \neq P[r_1 | s] P[r_2 | s] \dots P[r_N | s]$
- Uncorrelated 'rate' model:
 $P(r_1, r_2, \dots, r_N | s) = P[r_1 | s] P[r_2 | s] \dots P[r_N | s]$



Assessing correlations

- Encoding framework (Schneidman et al., 2003)
- Decoding framework (Nirenberg et al., 2001)
- Information breakdown (Pola et al., 2003)

Encoding framework

- Uncorrelated model:

$$P_{\text{ind}}[(r_1, r_2, \dots, r_N) | \mathbf{s}] = P[r_1 | \mathbf{s}] P[r_2 | \mathbf{s}] \dots P[r_N | \mathbf{s}]$$

- Estimate $I(\mathbf{S}; \mathbf{R})$ using $P_{\text{ind}}[\mathbf{s} | \mathbf{r}]$ instead of $P[\mathbf{s} | \mathbf{r}]$

$$\rightarrow I_{\text{ind}}(\mathbf{S}; \mathbf{R})$$

$$I_{\text{cor}}(\mathbf{S}; \mathbf{R}) = I(\mathbf{S}; \mathbf{R}) - I_{\text{ind}}(\mathbf{S}; \mathbf{R})$$

- I_{cor} tells us how much the presence of noise correlations changes $I(\mathbf{S}; \mathbf{R})$ compared to a hypothetical neural system with identical PSTH but zero noise correlations.

Decoding framework

- Bayesian decoding:
$$P[\mathbf{s}|\mathbf{r}] = P[\mathbf{r}|\mathbf{s}] P[\mathbf{s}] / P[\mathbf{r}]$$
- Use $P_{\text{ind}}[\mathbf{r}|\mathbf{s}]$ instead of $P[\mathbf{r}|\mathbf{s}]$
- Upper bound on $I(\mathbf{S};\mathbf{R})$ that will be lost:
$$\Delta I(\mathbf{S};\mathbf{R}) = \sum_{\mathbf{r}} P[\mathbf{r}] \sum_{\mathbf{s}} P[\mathbf{s}|\mathbf{r}] \log_2 P[\mathbf{s}|\mathbf{r}] / P_{\text{ind}}[\mathbf{s}|\mathbf{r}]$$
- ΔI tells us, If a hypothetical downstream decoding circuit attempts to decode using a model that includes PSTHs but ignores noise correlations, upper bound on how much $I(\mathbf{S};\mathbf{R})$ will be lost.

Information Breakdown

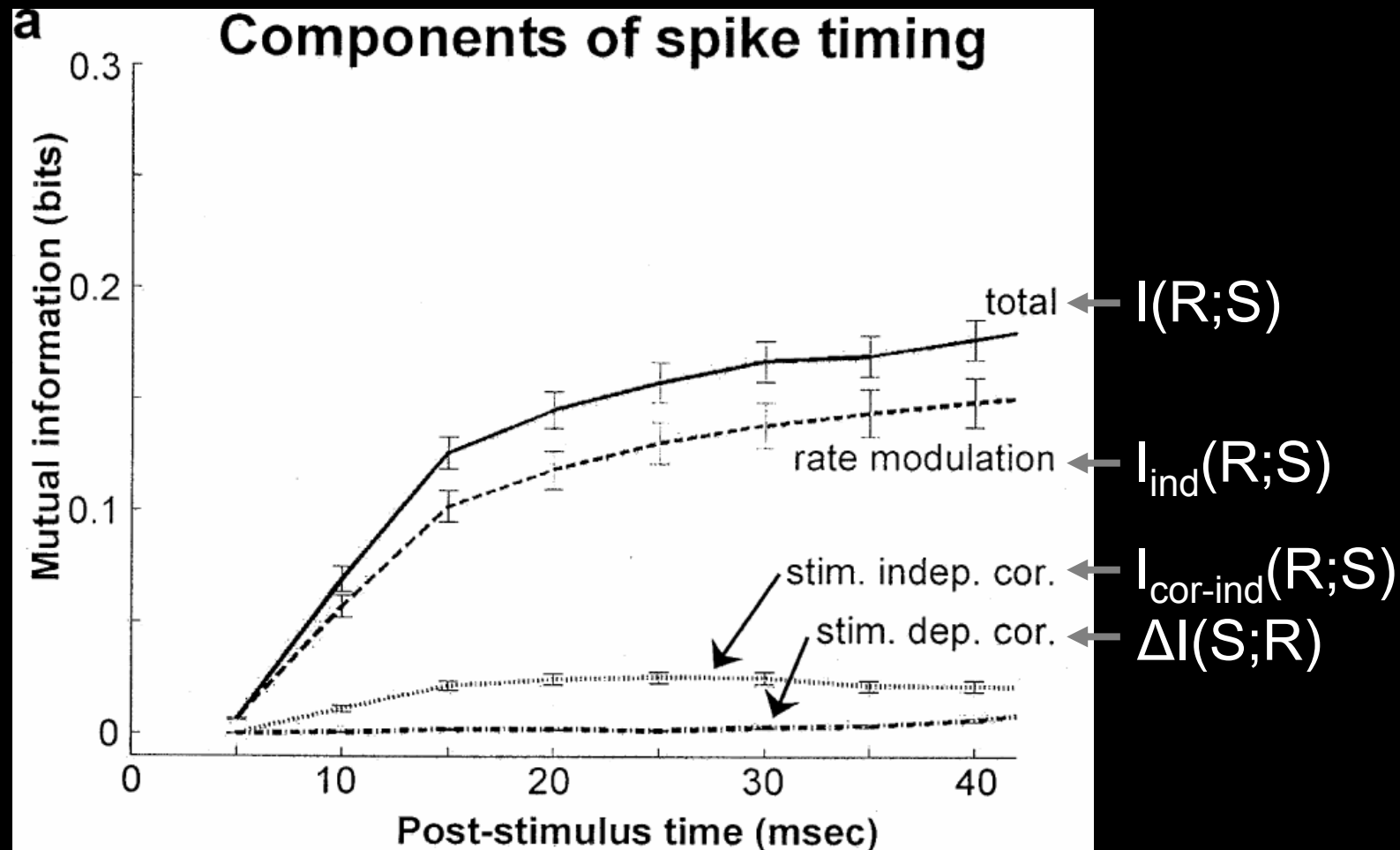
$$I(S;R) = I_{\text{ind}}(S;R) + I_{\text{cor-ind}}(S;R) + I_{\text{cor-dep}}(S;R)$$

Link to encoding framework:

$$I_{\text{cor}}(S;R) = I_{\text{cor-ind}}(S;R) + I_{\text{cor-dep}}(S;R)$$

Link to decoding framework:

$$\Delta I(S;R) = I_{\text{cor-dep}}(S;R)$$

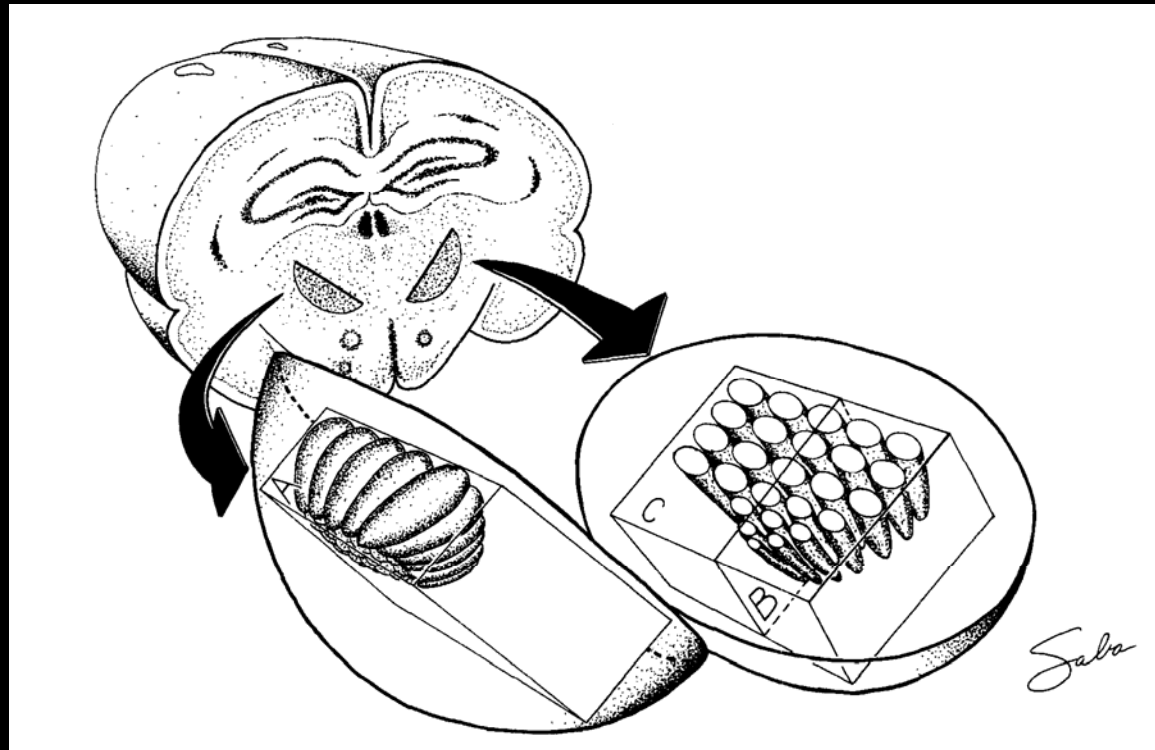


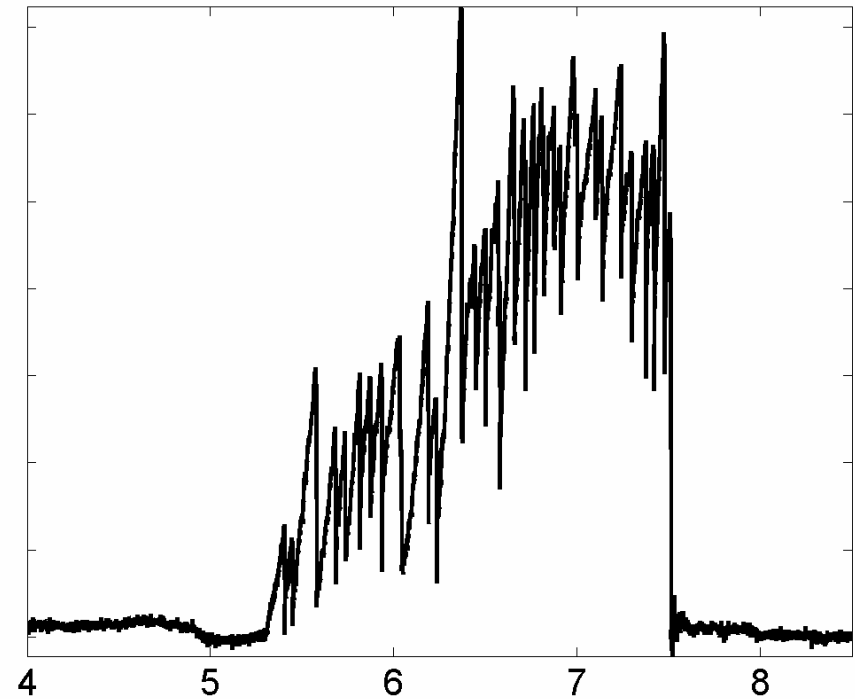
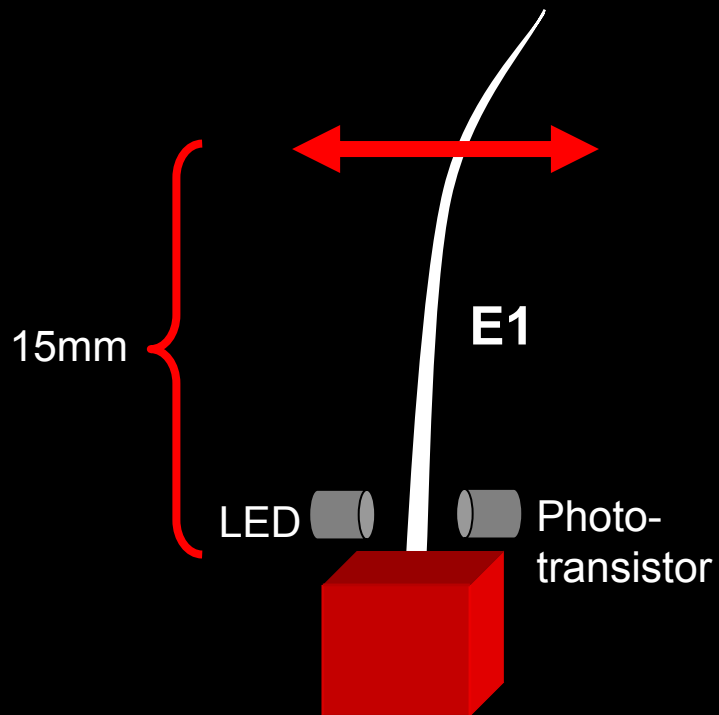
Panzeri et al (2001) *Neuron*
Petersen et al (2001) *Neuron*

Case study

Whisker system

Ventro-posterior medial nucleus (VPM)





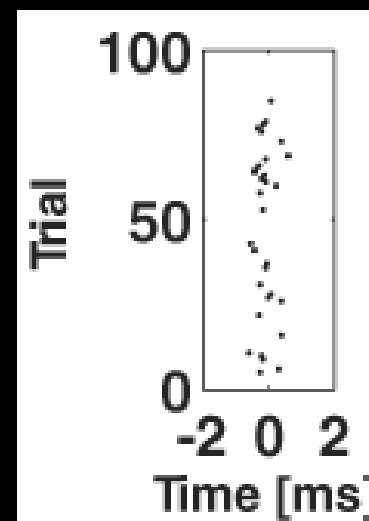
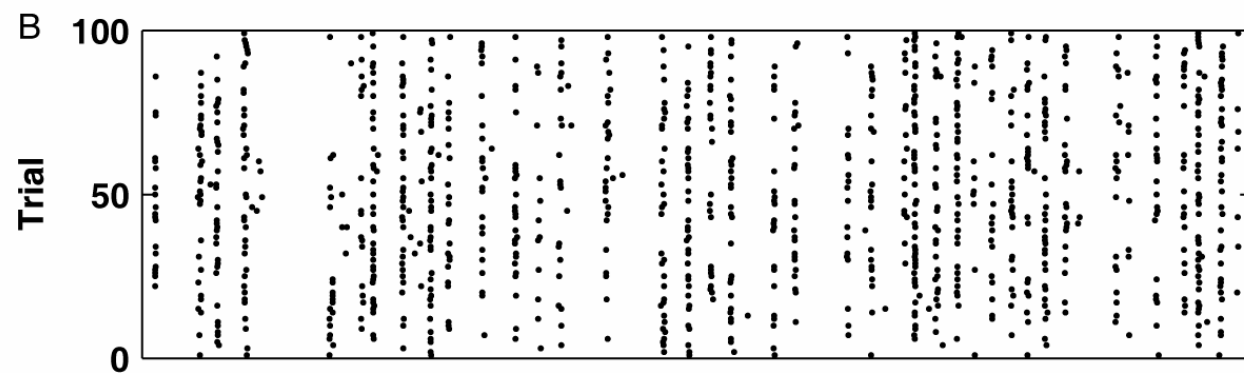
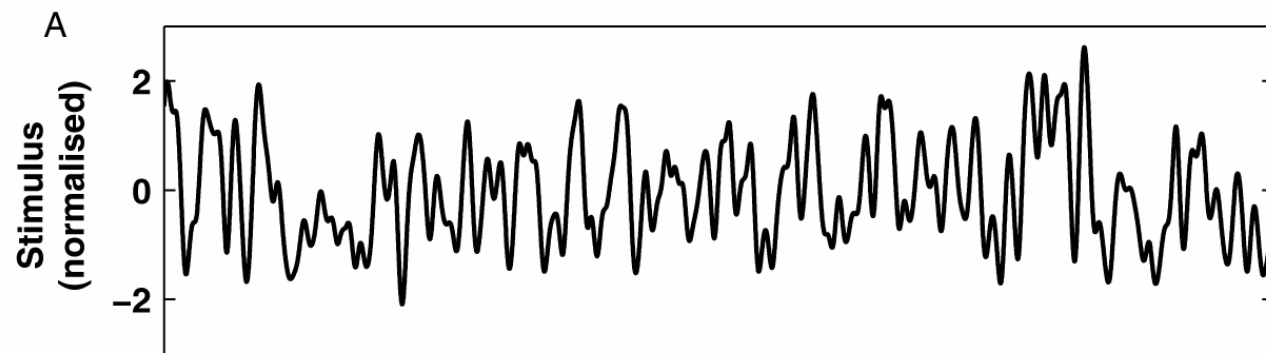
Space-to-time transformation:
Object texture to whisker vibration

How is high band-width
information about whisker
vibrations squeezed through the
subcortical bottleneck?

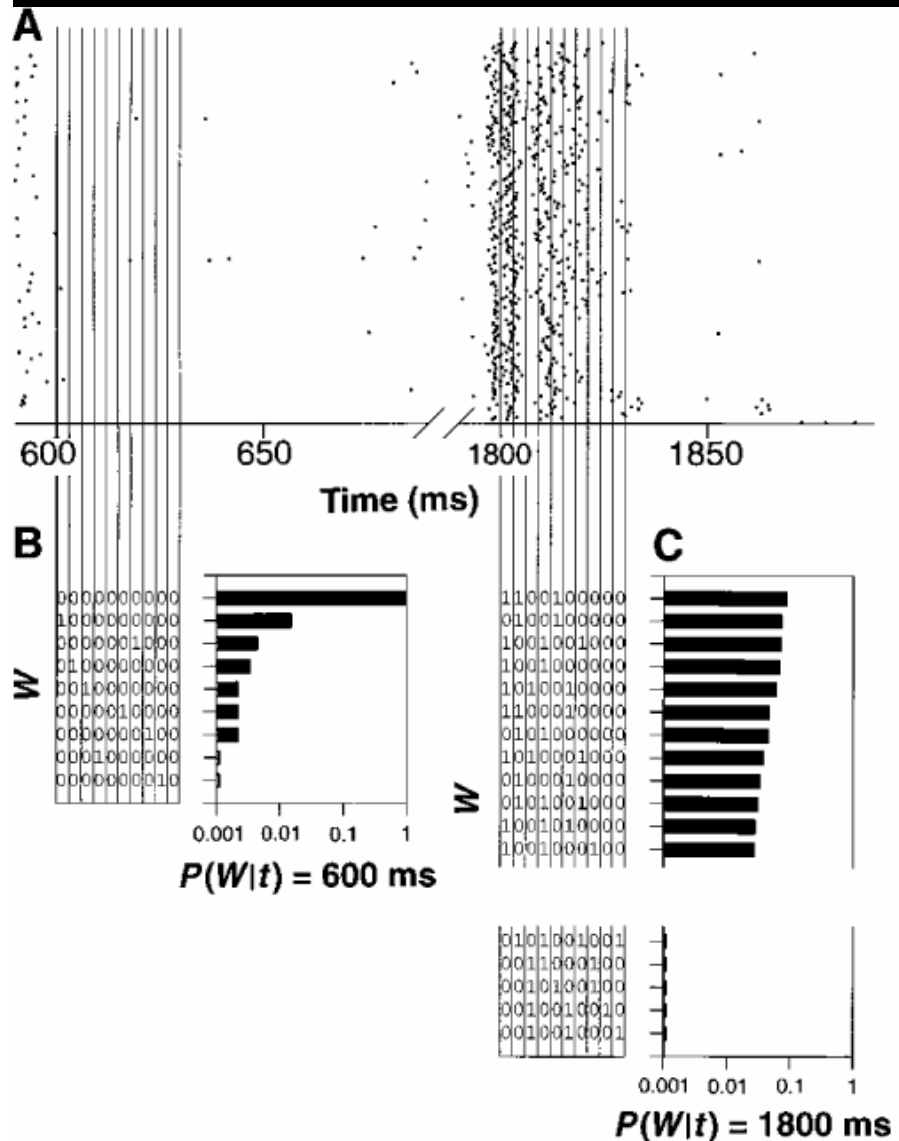
Stimulus: (Smoothed) white noise

Preparation: anaesthetised, adult rat

Recordings : VPM thalamus



Strong et al (1998)



Standard:

$$I(S;R) = H(R) - H(R|S)$$

$$H(R|S) = \sum_s P[s] H[R|s]$$

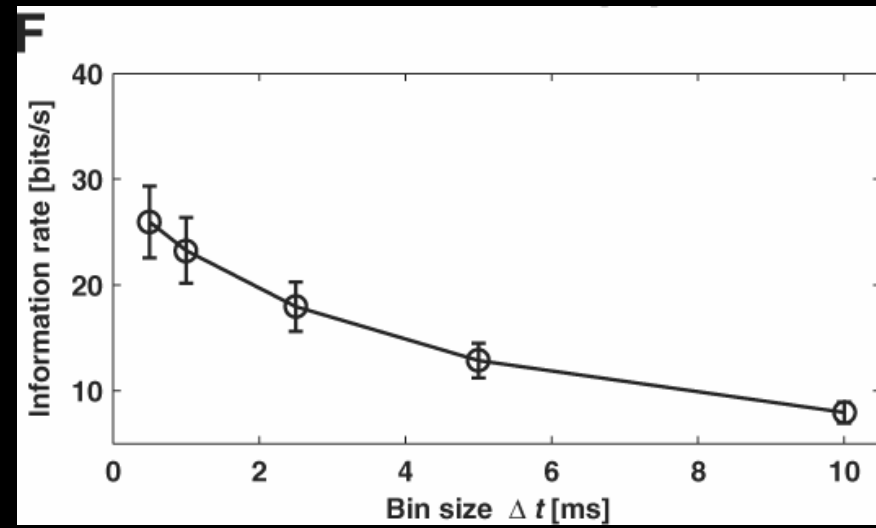
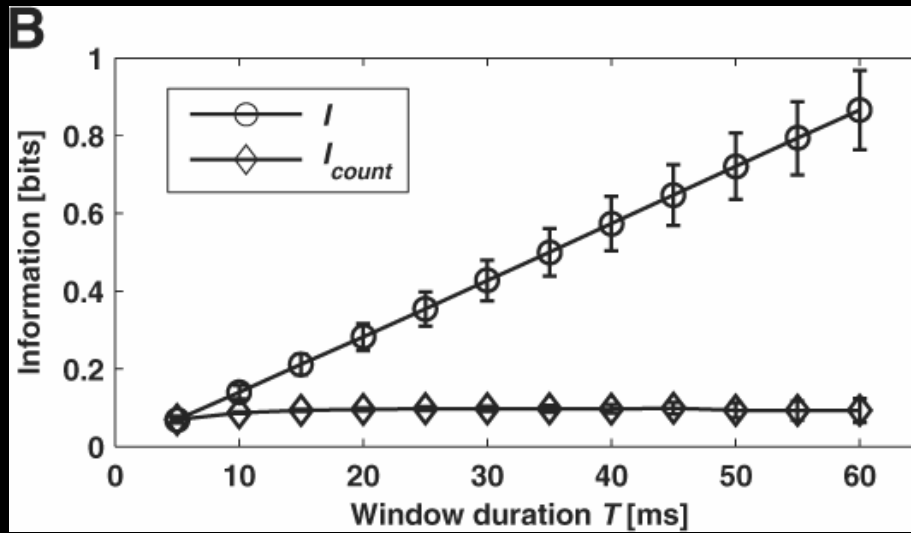
$$H(R|s) = -\sum_r P[r|s] \log_2 P[r|s]$$

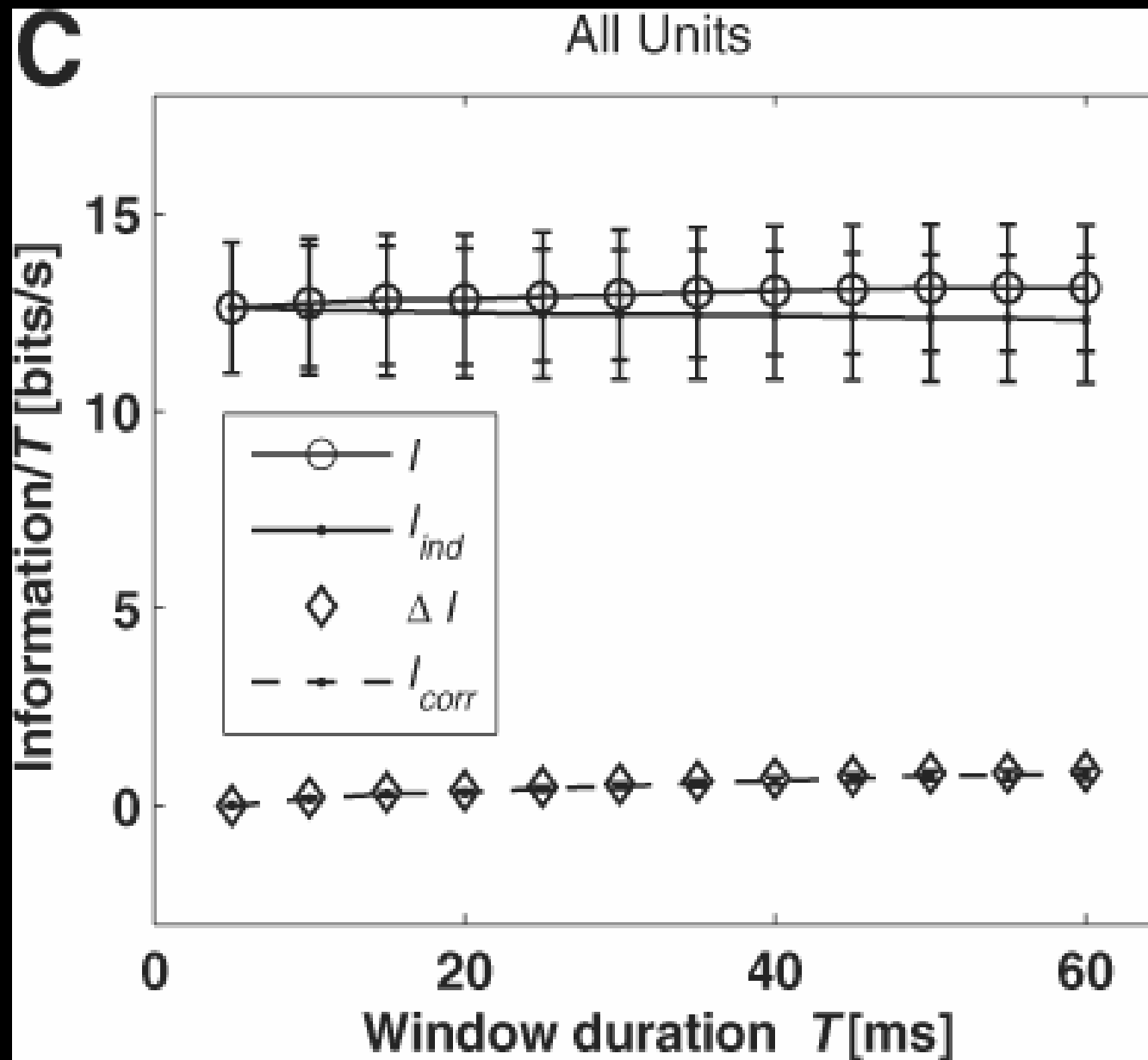
Strong et al. (1998):

$$P[r|s] \rightarrow P[r|t]$$

$$H(R|s) \rightarrow H(R|t)$$

$$H(R|S) \rightarrow \langle H(R_t) \rangle_t$$





Montemurro et al (2007) *J Neurophysiol*

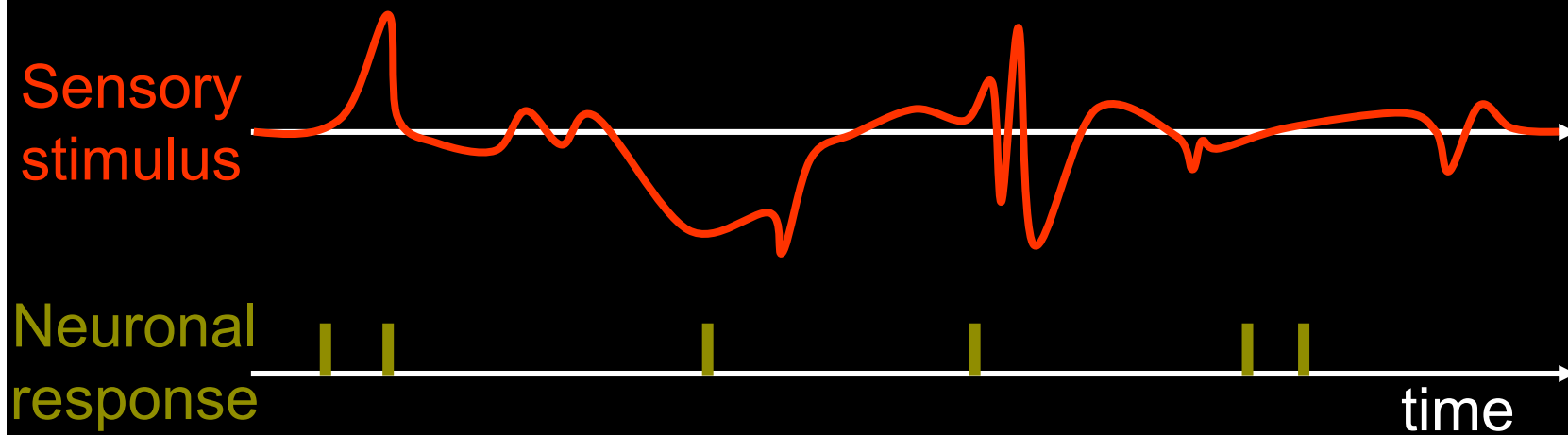
Summary: whisker-syntax

- Millisecond precise spike timing
- Major syntactic element of code is time-dependent firing rate (PSTH)
- Temporal noise correlations have small effect on coding

Role of correlations in other systems

- Retina:
 - Nirenberg et al (2001) Nature
 - Puchalla et al (2005) Neuron
- Primary visual cortex:
 - Golledge et al (2003) Neuroreport
 - Montani et al (2007) J Neurosci
- Primary somatosensory cortex:
 - Petersen et al (2001) Neuron

Neurosemantics



Assuming, $P[(r_1, r_2, \dots, r_N) | \mathbf{s}] \approx P[r_1 | \mathbf{s}] P[r_2 | \mathbf{s}] \dots P[r_N | \mathbf{s}]$

$P(r_t | \mathbf{s}_t) = ?$

$\mathbf{s}_t = (s_{t-L}, s_{t-L+1}, \dots, s_t)$

Possible approaches

- LNP model

$$P[r_t | \mathbf{s}_t] = g(k_t)$$

$$k_t = \mathbf{s}_t \cdot \mathbf{f}$$

- Multi-feature LNP model

$$P[r_t | \mathbf{s}_t] = g(k_t^1, k_t^2, \dots)$$

$$k_t^i = \mathbf{s}_t \cdot \mathbf{f}^i$$

- Spike-feedback model

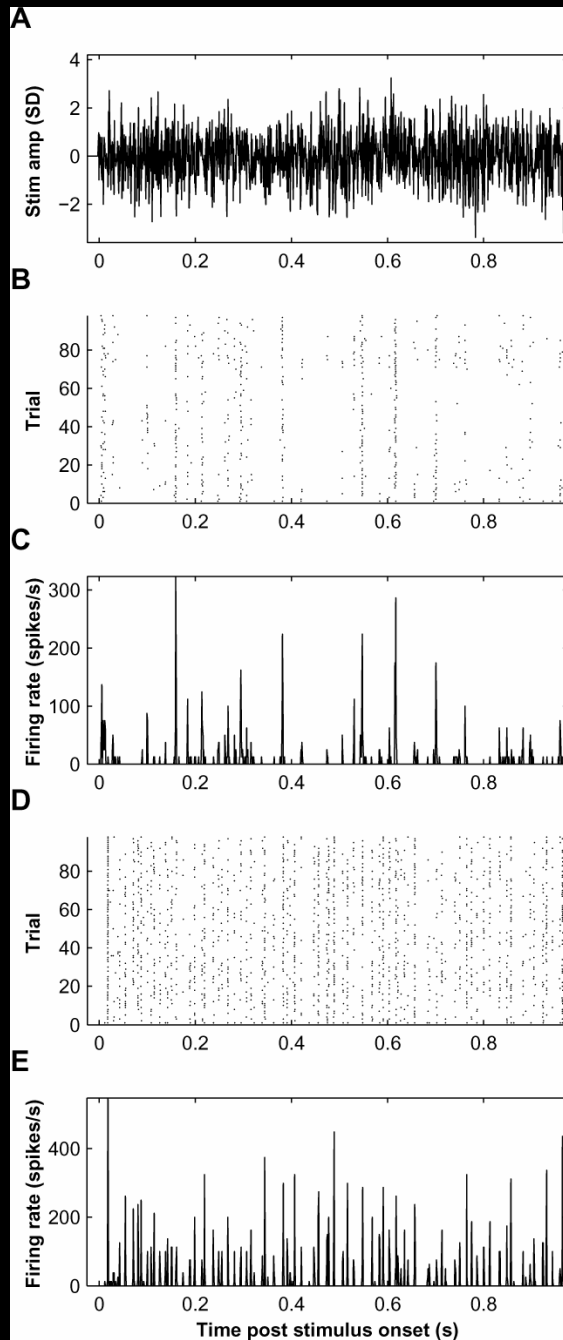
$$P[r_t | \mathbf{s}_t] = g(k_t, m_t)$$

$$m_t = (r_{t-L}, r_{t-L+1}, \dots, r_{t-1}) \cdot \mathbf{h}$$

- Adaptive models

AIM

What temporal (kinetic) features of the whisker stimulus are neurons in VPM sensitive to?



Special cases

kernels

Position

$$r(t) = g[s(t)]$$

$$\mathbf{f} = [1]$$

Velocity

$$r(t) = g[s(t) - s(t - \delta t)]$$

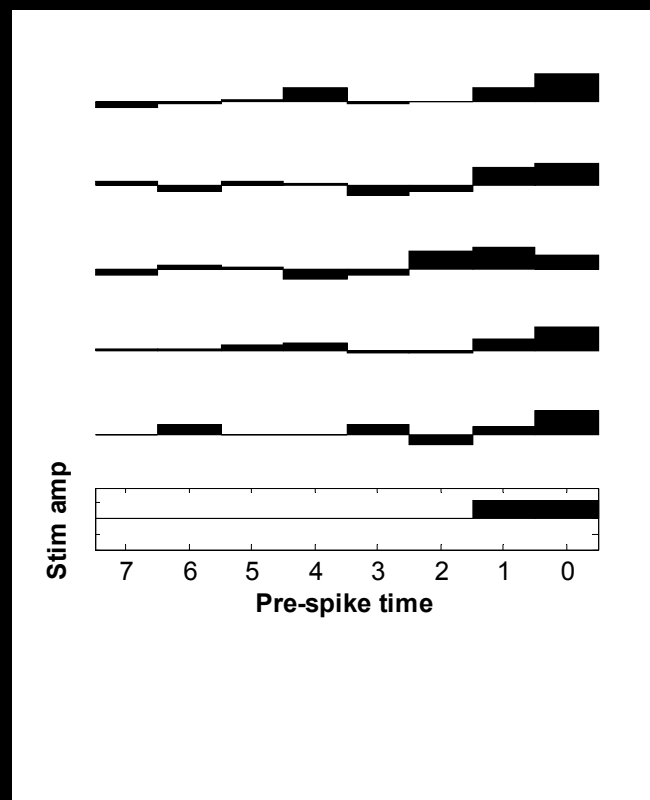
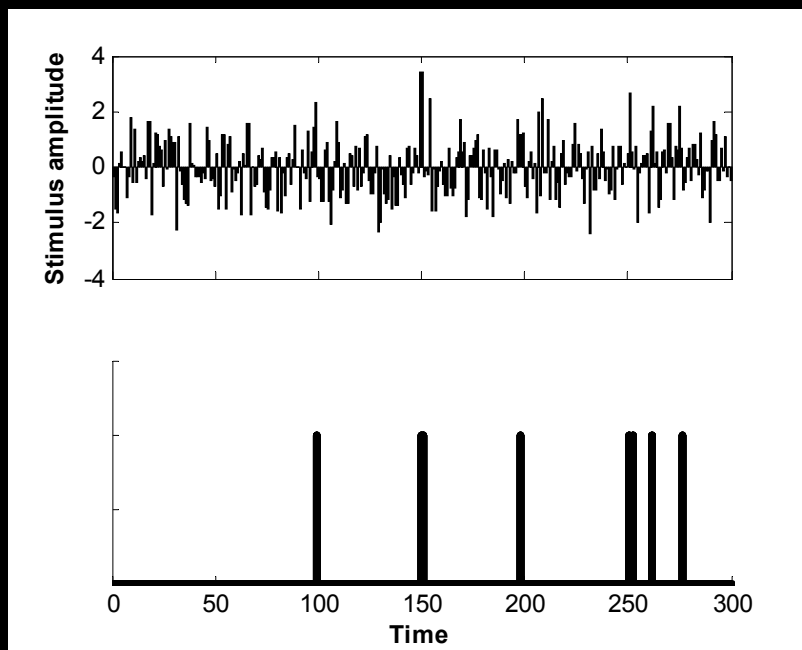
$$\mathbf{f} = [-1, 1]$$

Acceler.

$$r(t) = g\left[\frac{1}{2} s(t) - s(t - \delta t) + \frac{1}{2} s(t - 2\delta t)\right]$$

$$\mathbf{f} = [-1/2, 1, -1/2]$$

Fitting the kernel: Spike-triggered averaging



Theory

For the LNP model

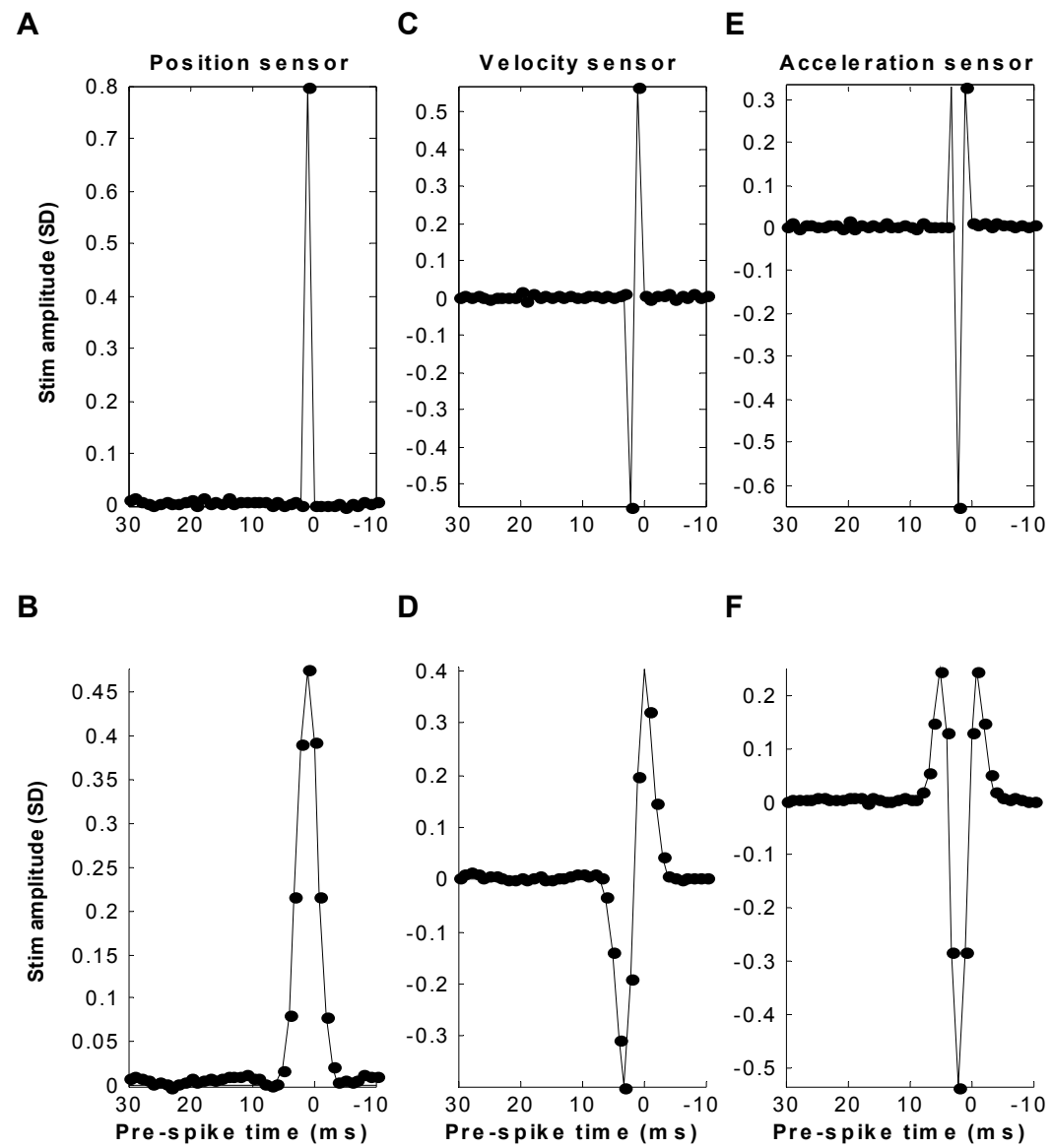
$$P[r_t | \mathbf{s}_t] = g(k_t), \quad k_t = \mathbf{s}_t \cdot \mathbf{f}$$

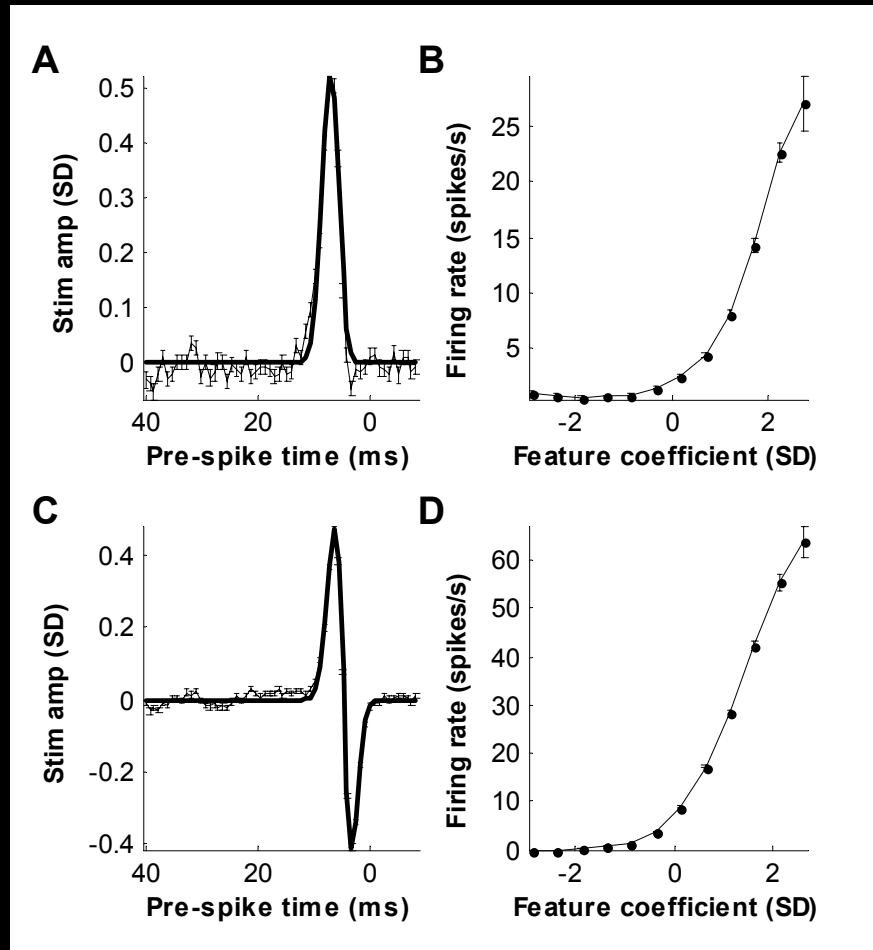
If,

- stimulus is white noise
- $\langle g[k] \rangle \neq \langle g[-k] \rangle$

Then,

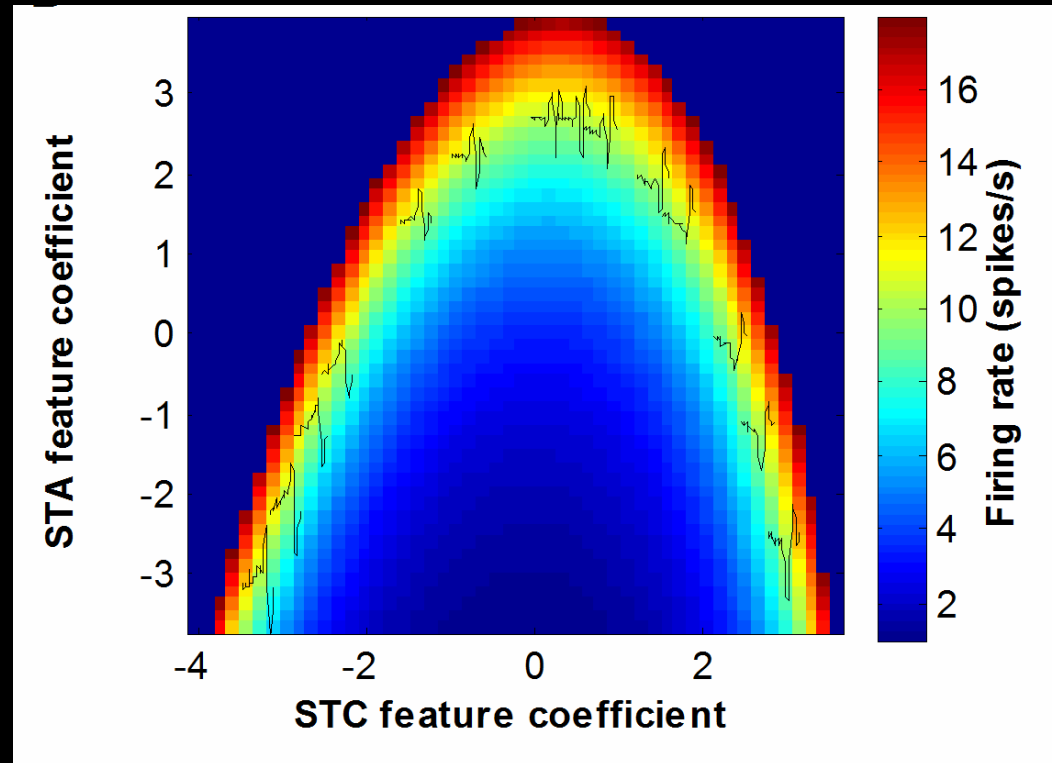
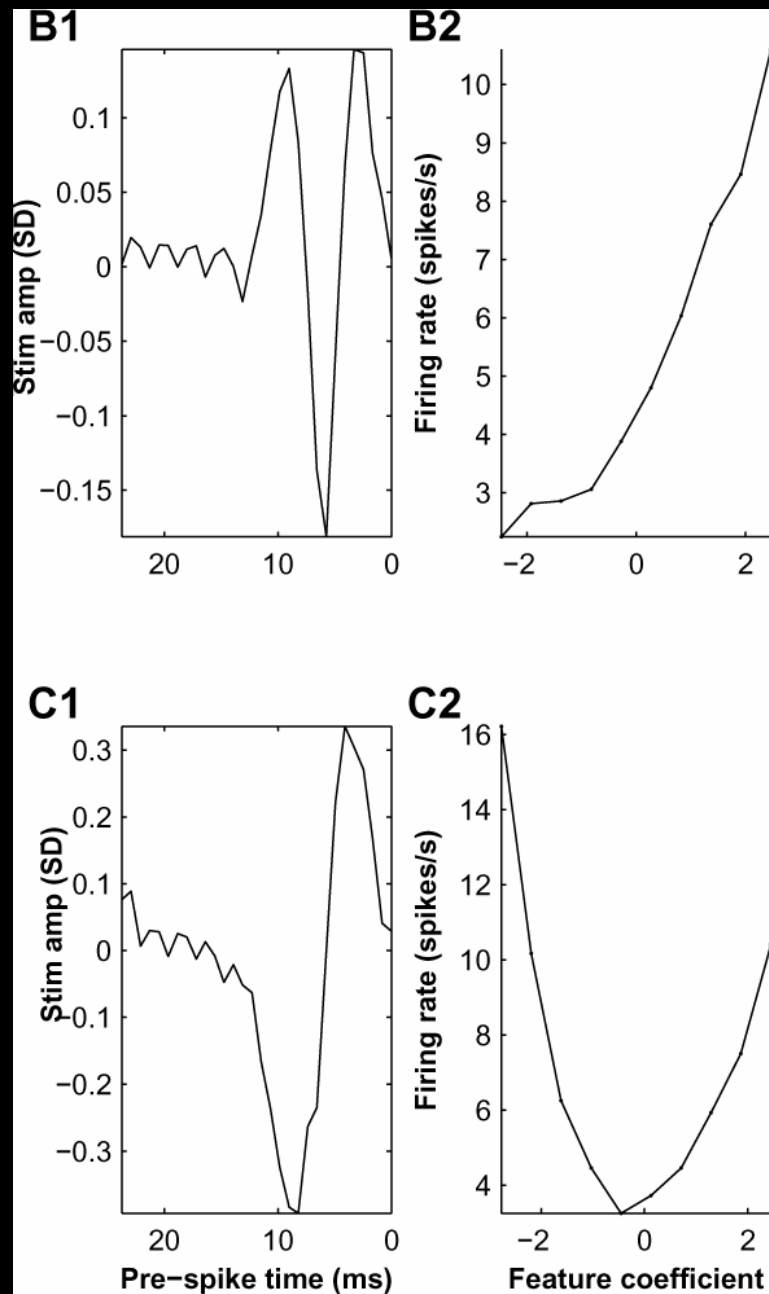
Spike-triggered average is
unbiased estimate of kernel $\mathbf{f}$

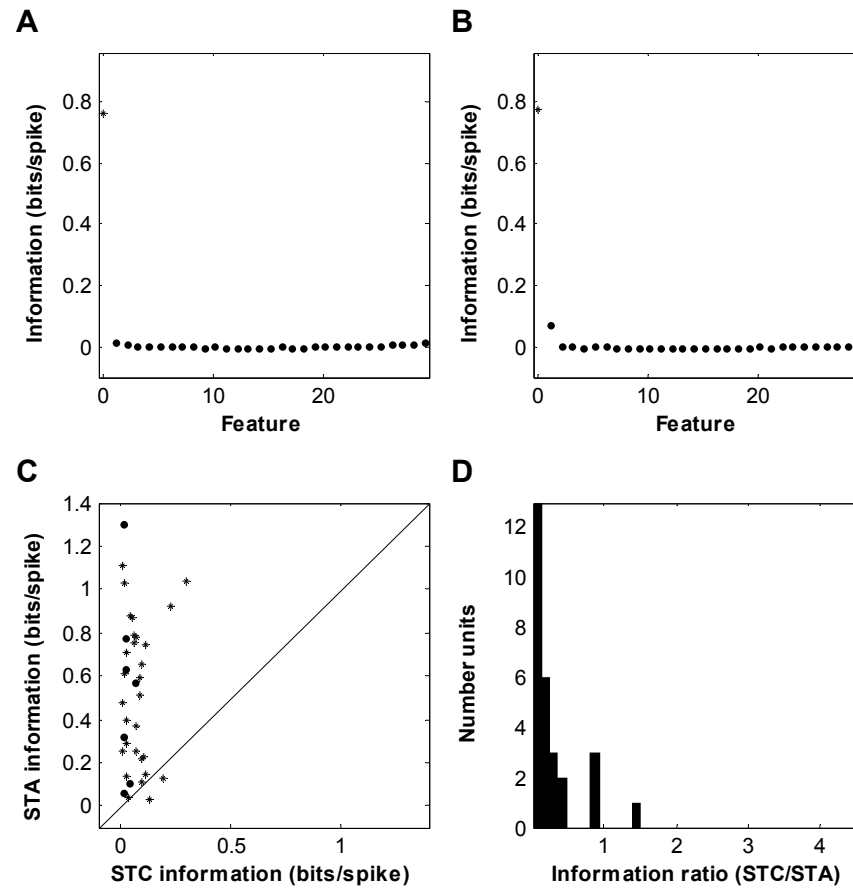




How accurate is the LNP model?

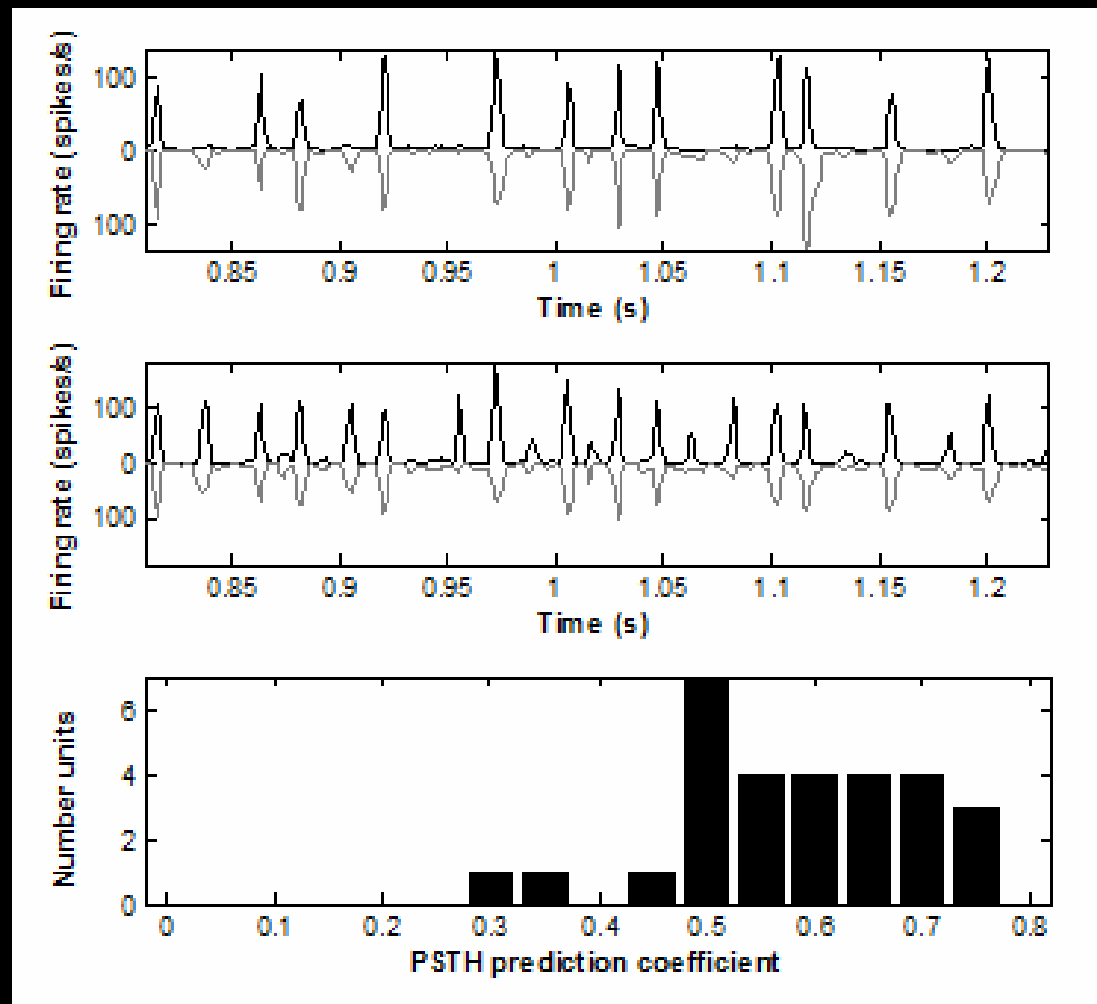
- Non-linear approaches:
 - Maximum likelihood fitting of spike feedback (Paninski) model
 - Spike-triggered covariance analysis

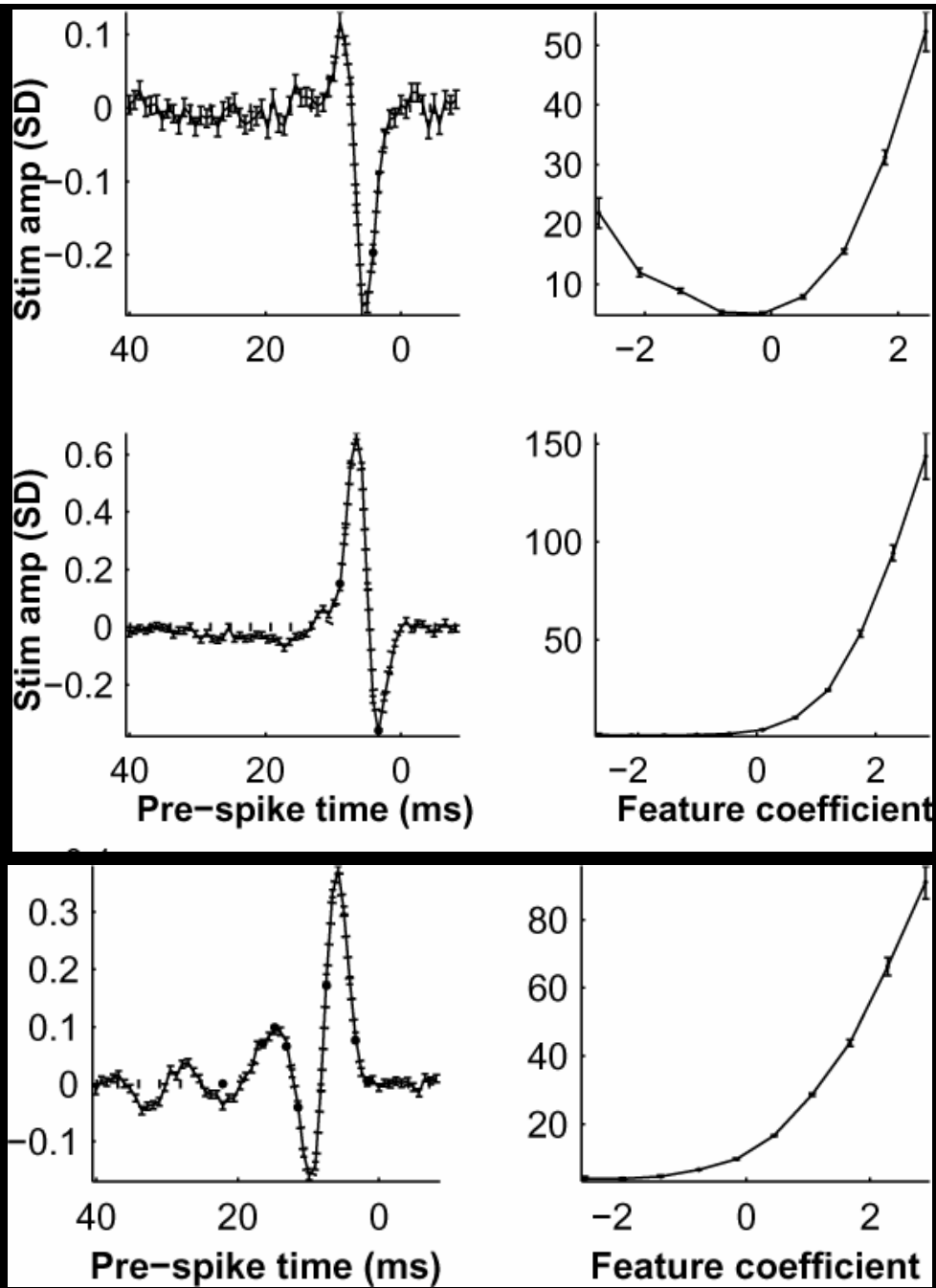




PSTH prediction using
LNP model:

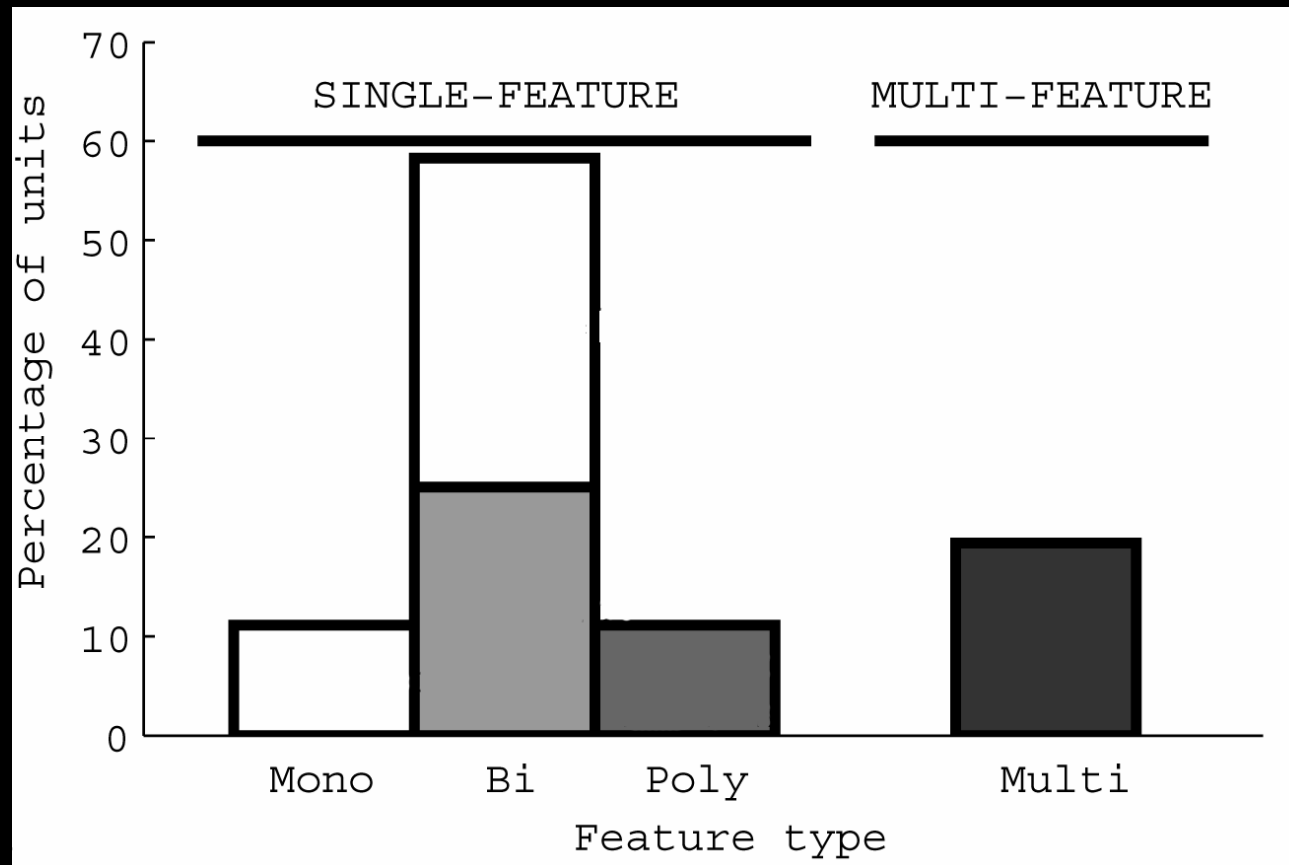
$$P[r_t | \mathbf{s}_t] = g(k_t), \quad k_t = \mathbf{s}_t \cdot \mathbf{f}$$





Petersen et al (2008) *Neuron*

Distributed code for whisker motion



Summary

- Syntax-semantics approach:
 - What is the basic 'syntactic' element of the response?
 - Information theory
 - What stimulus features does that syntactic element signify?
 - White noise analysis
- Whisker syntax:
 - Millisecond precise spike timing
 - Spikes code independently
- Whisker semantics:
 - Accuracy of LNP model
 - Distributed code for whisker motion