NEURAL DATA ANALYSIS

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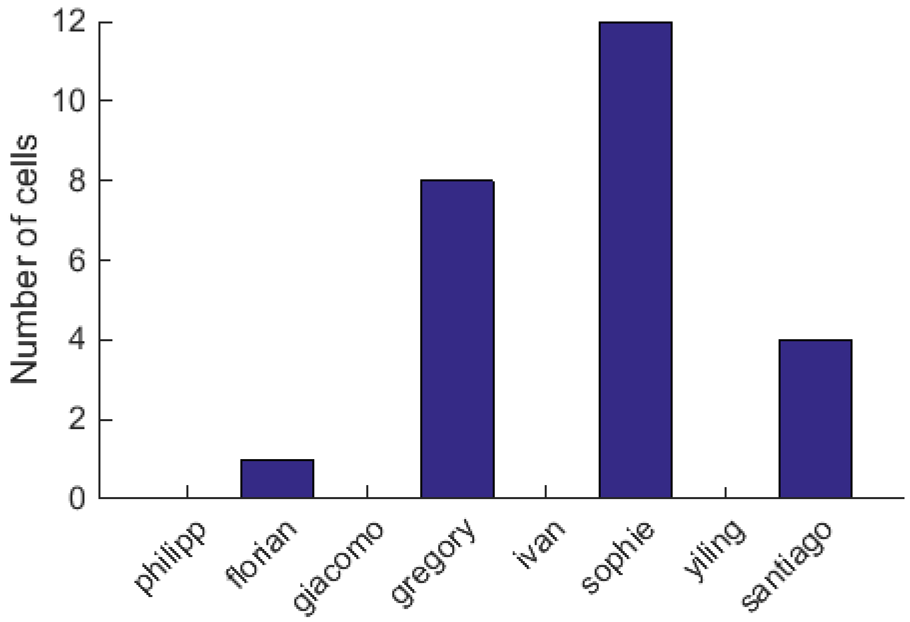
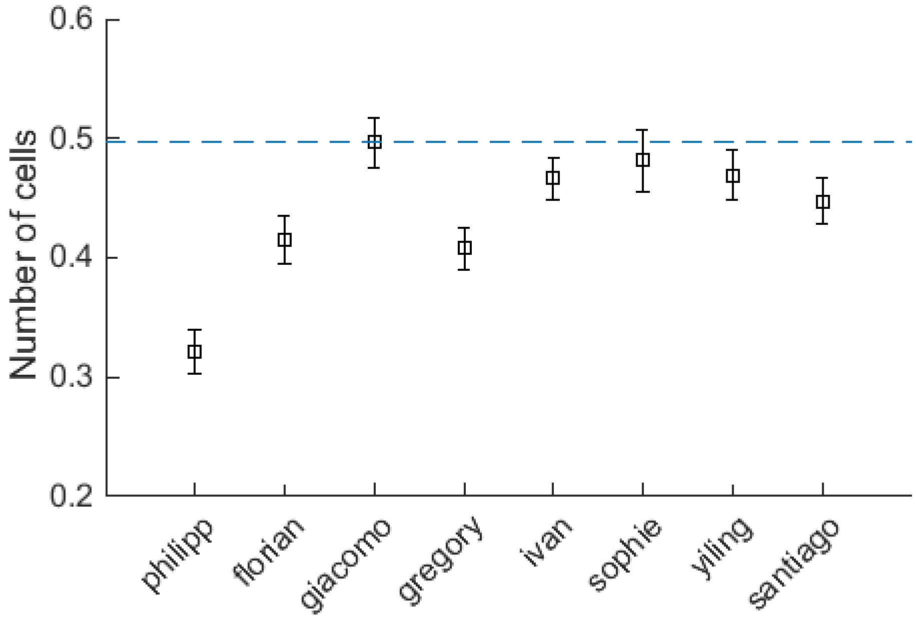
COMPUTATIONAL VISION AND NEUROSCIENCE GROUP

NOT ALL CODE RUNS ON ALL CELLS

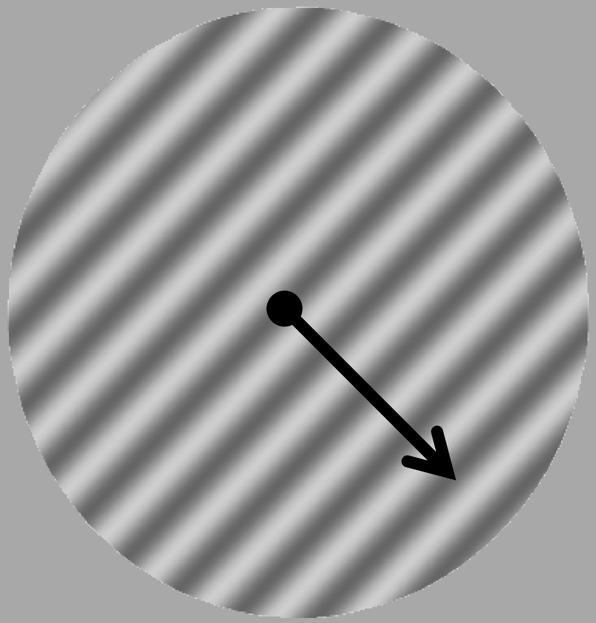


THE WINNER IS...



STIMULUS

Drifting gratings presented in trials



Parameters:

- 2 sec per trial
- 16 directions of motion
- Diameter: 2 deg
- Eccentricity: ~2-3 deg
- Speed: 3.4 cycles / sec
- Spatial frequency: 3 cycles / deg

STRATEGIES FOR ANALYZING DATA

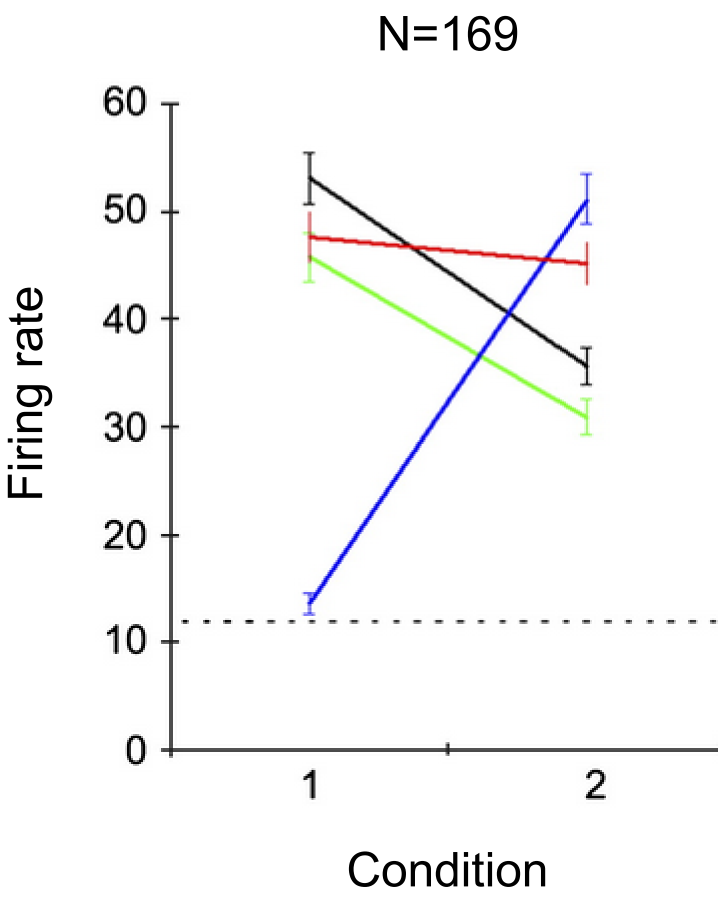
Look at raw data

Visualize spikes

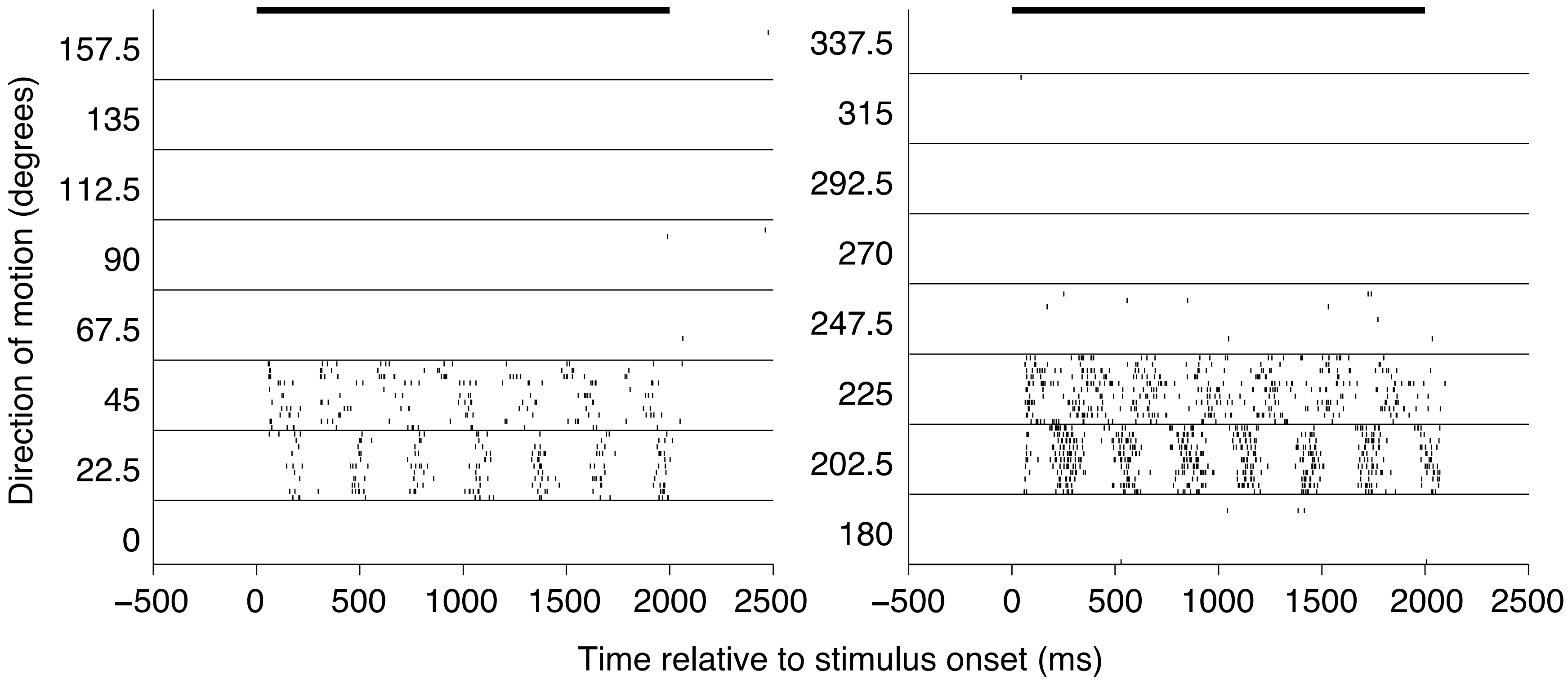
Do not look at

- Fitted tuning functions
- Adaptation indices
- Population averages
- Population histograms

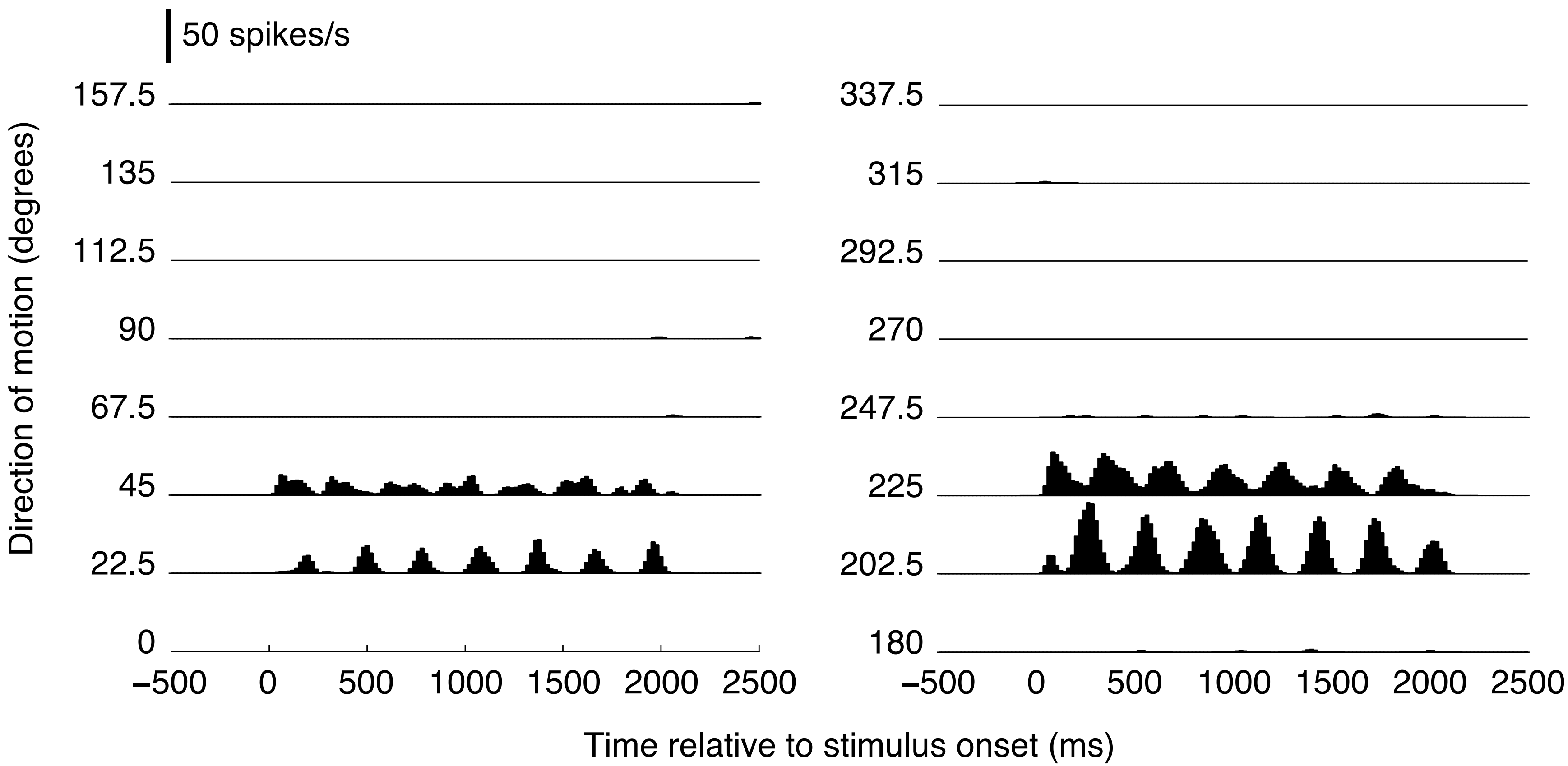
until you spent considerable time looking at raw data and examples



SPIKE RASTERS

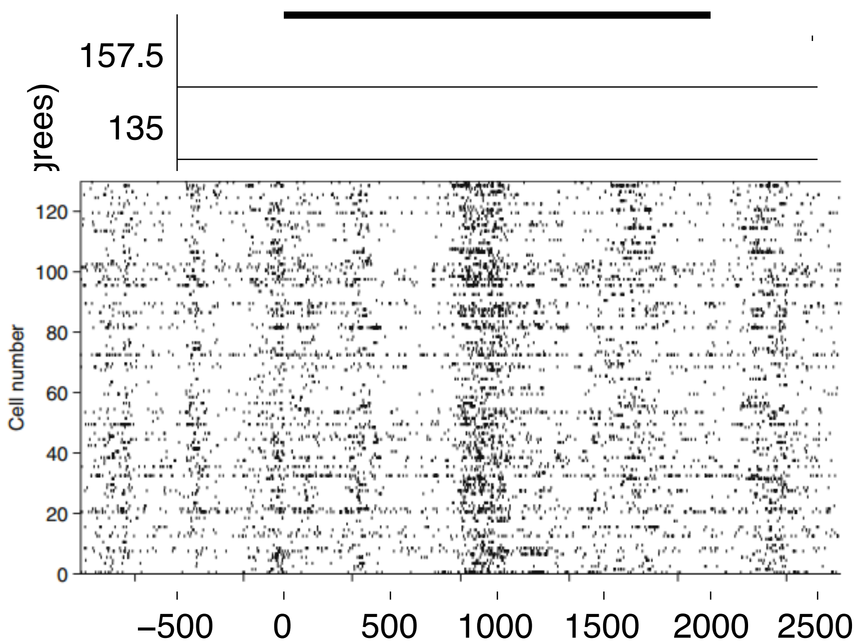


PERI-STIMULUS TIME HISTOGRAM



PSTH & SPIKE RASTERS

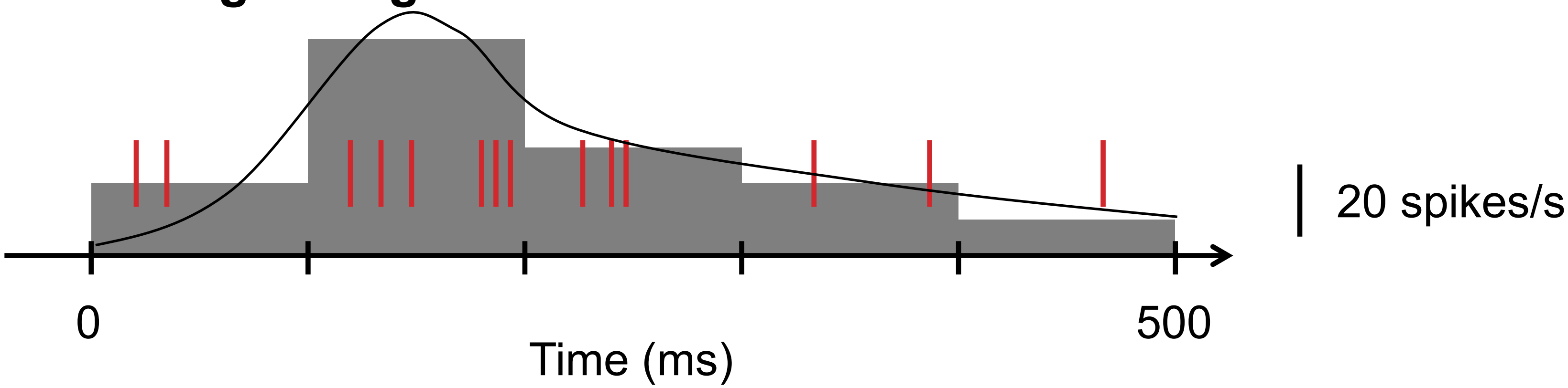
- **Repeated measurements of spike trains with a reference time to align on**
  - Stimulus
  - Onset of Movement/Saccade
- **Event-related single neuron rate dynamics**
- **Population raster plot**
  - population dynamics
- **Align on LFP phase?**



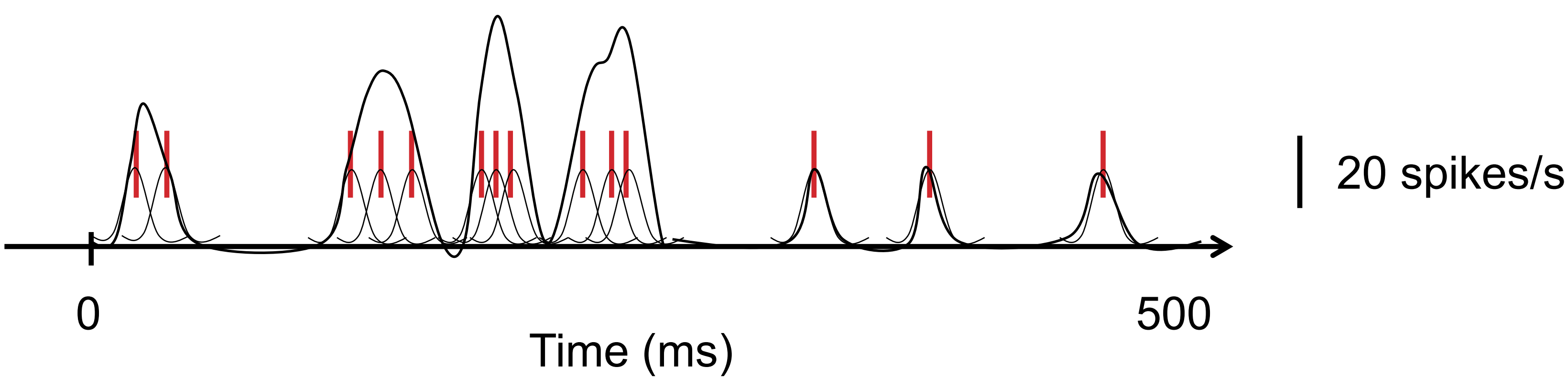
Kelly et al 2010

PSTH/SDF – HOW TO

1. **Average firing rate in a bin**



2. **Directly estimate spike density**



WINDOW SIZE

Optimal gaussian window

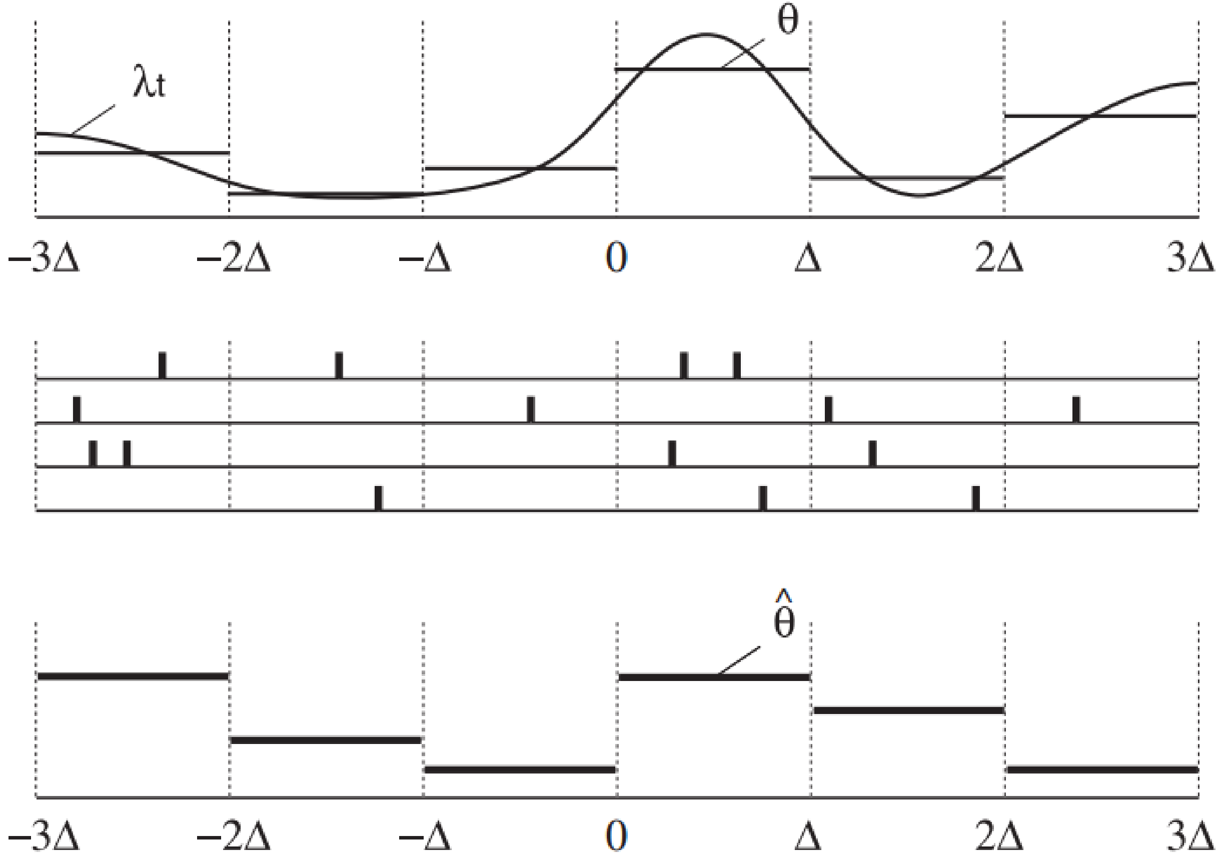
Gaussian process

BARS

Bayesian binning

Reviewed by Cunningham et al. 2009

BIN SIZE SELECTION



$$\theta = \frac{1}{\Delta}\int_0^{\Delta} \lambda_t dt$$

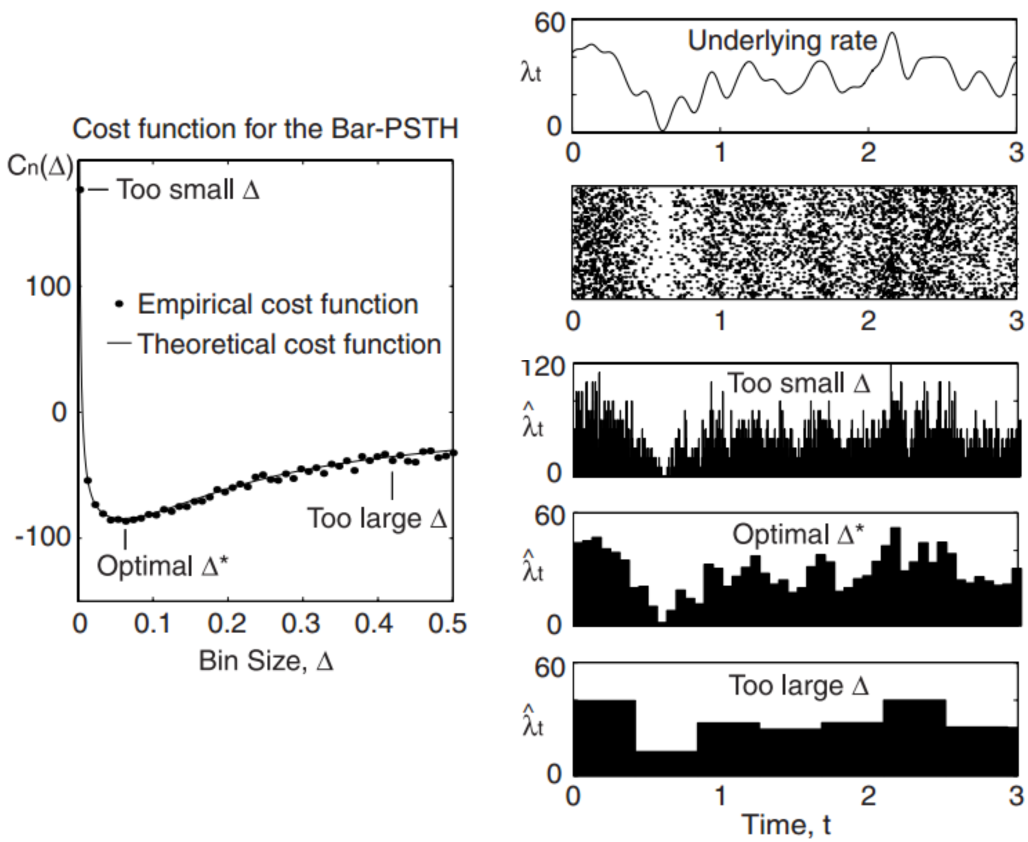
$$\hat{\theta} = \frac{k}{n\Delta}$$

BIN SIZE SELECTION

- **Divide the observation period T into N bins of width Δ.**
- **Count the number of spikes k_i from all n trials that fall into i-th bin**
- **Compute $k = \frac{1}{N}\sum_i^N k_i$ and $v = \frac{1}{N}\sum_i^N \left(k_i - \bar{k}\right)^2$**
- **Compute $C_n(\Delta) = \frac{2\bar{k}-v}{(n\Delta)^2}$** 2*mean- variance , and normalized with bin size ?
- **Search for Δ^* that minimizes $C_n(\Delta)$**

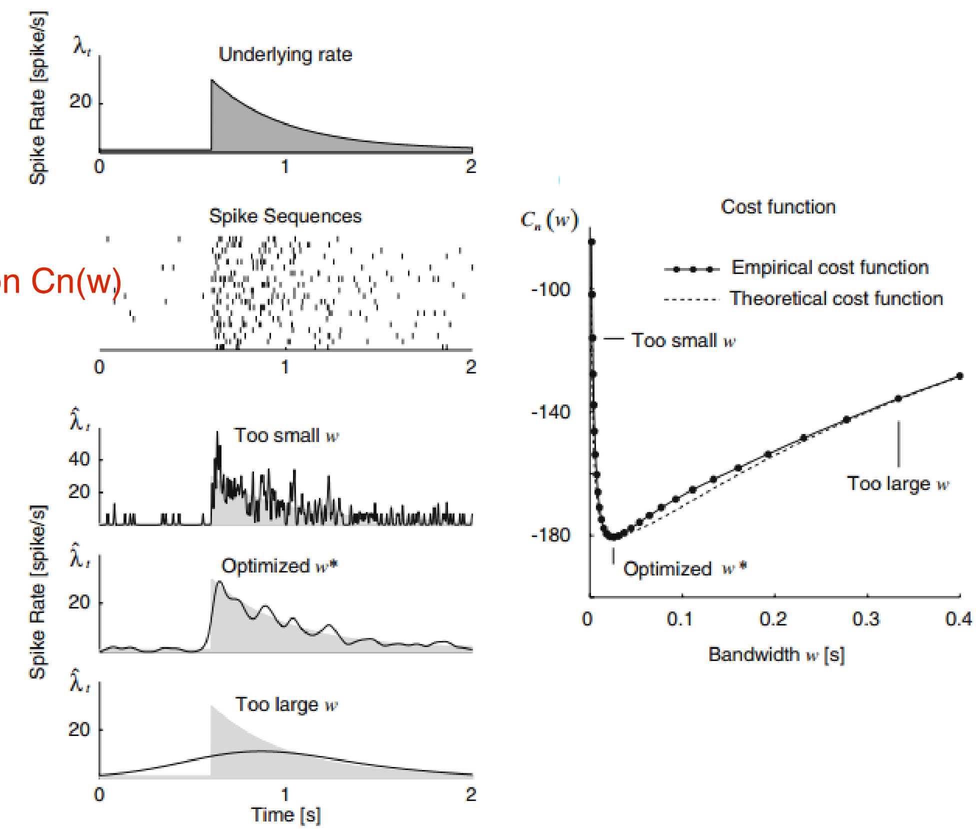
Shimazaki & Shinomoto 2007

BIN SIZE SELECTION



OPTIMAL KERNEL WIDTH

Minimize cost function Cn(w)



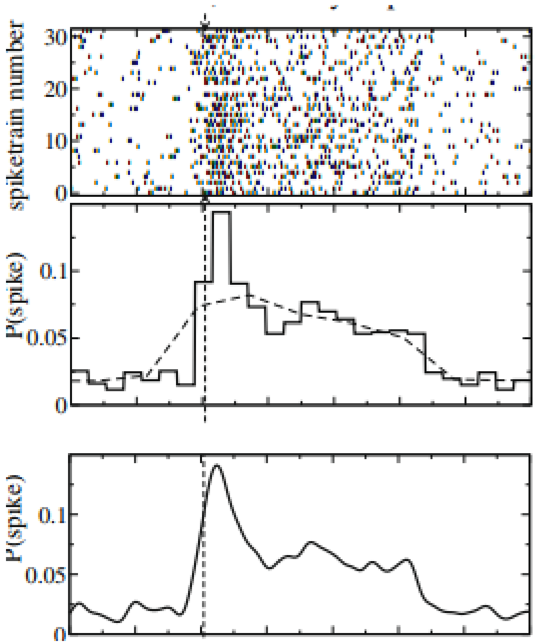
$$n^2 C_n(\omega) = \frac{N}{\omega} + \frac{2}{\omega} \sum_{i<j} \left[\exp\left(-\frac{(t_i - t_j)^2}{4\omega^2} \right) - 2\sqrt{2} \exp\left(-\frac{(t_i - t_j)^2}{2\omega^2} \right) \right]$$

Shimazaki & Shinimoto 2010

PROBLEMS WITH PSTH/SDF

- **Problems with PSTH approaches**
  - Sharp transients
  - Many bins where rate is constant

- **Problems with SDFs** ?
  - Sharp transients are blurred

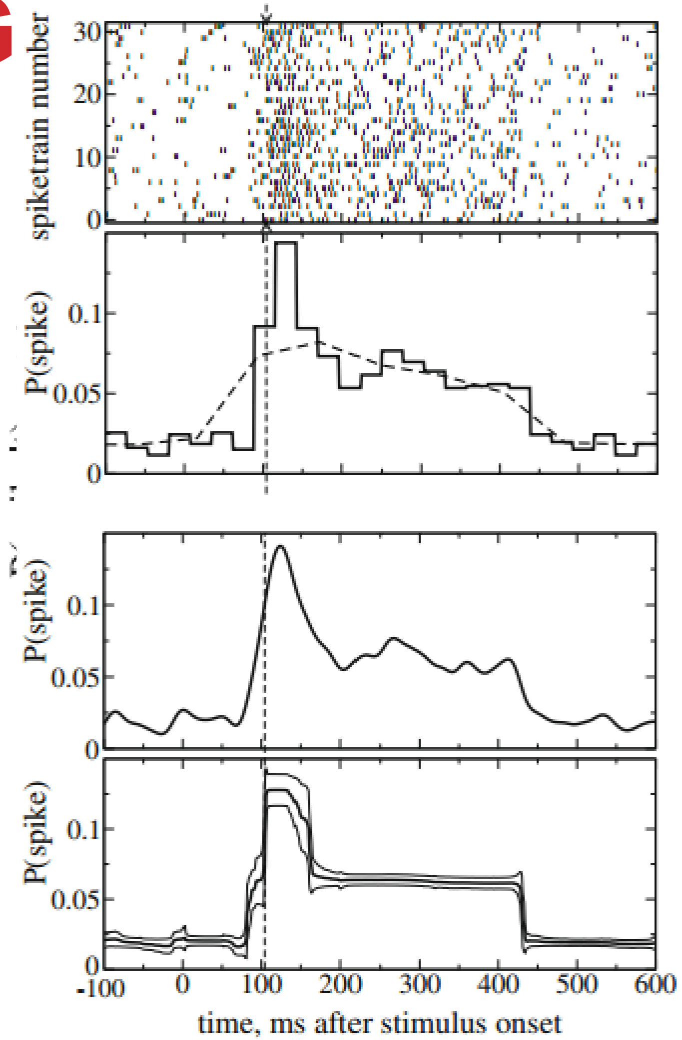


BAYESIAN BINNING

- **Model PSTH as sequence of intervals with constant firing probability**

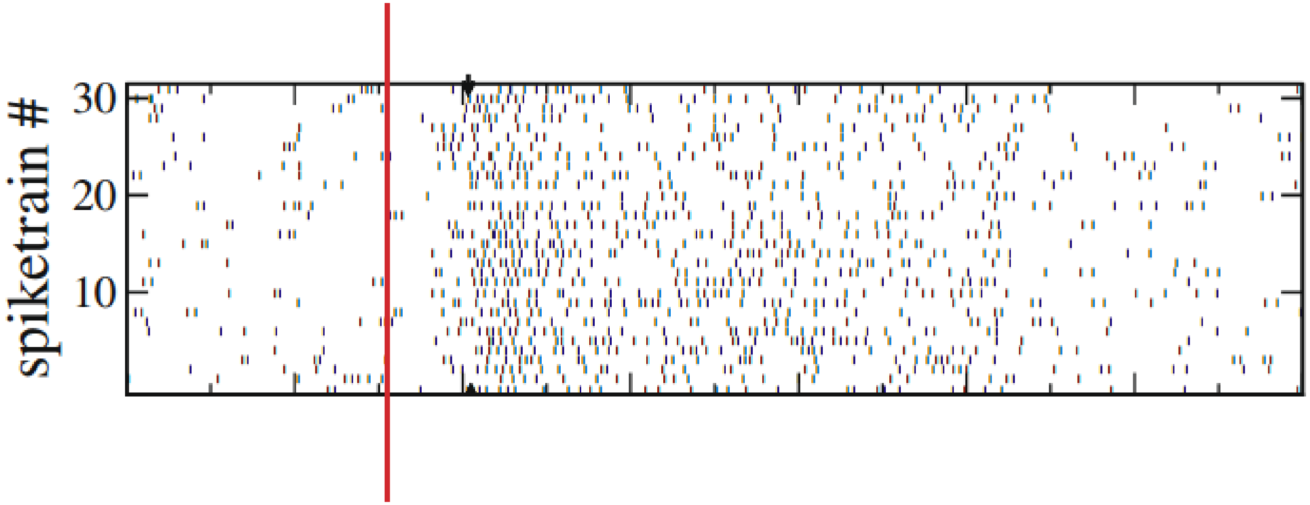
$$P(\vec{z}^i | \{f_m\}, \{k_m\}, M) = \prod_{m=0}^{M} f_m^{s(\vec{z}^i, m)} (1 - f_m)^{g(\vec{z}^i, m)}$$

- **Bayesian inference for model parameters by computing posterior**
- **Dynamic programming**
- **Code online: http://mloss.org/software/view/67/**



Endres et al. 2008/2010

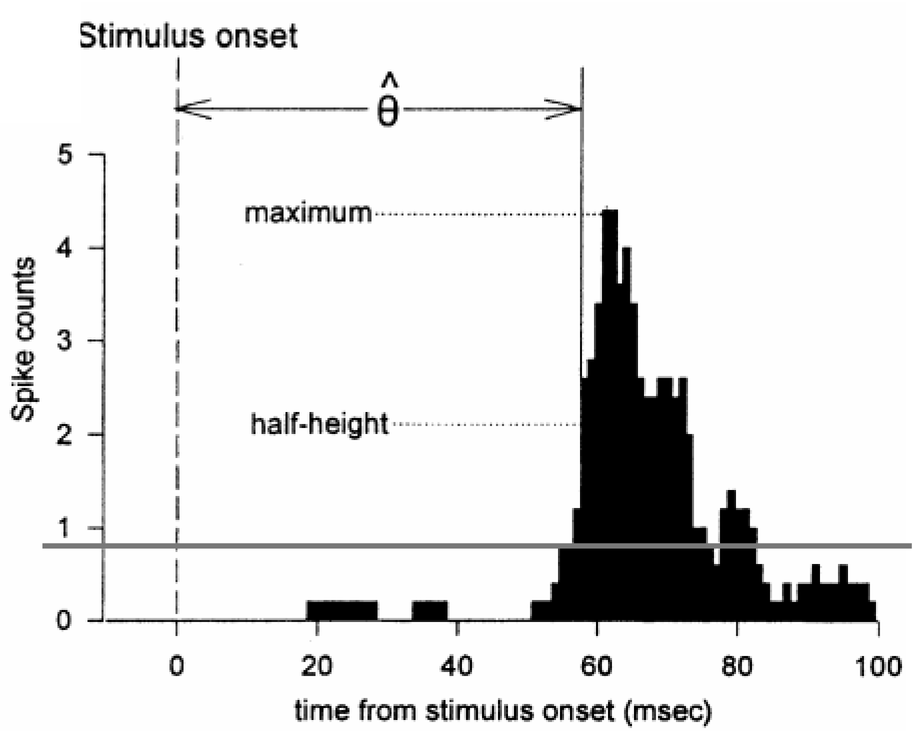
LATENCY DETECTION



„Latency is where is the signal starts“

LATENCY DETECTION

- **Non-parametric estimation as half height of peak firing rate**
- **Threshold criterion above spontaneous firing**



Friedman & Priebe 1998

LATENCY DETECTION

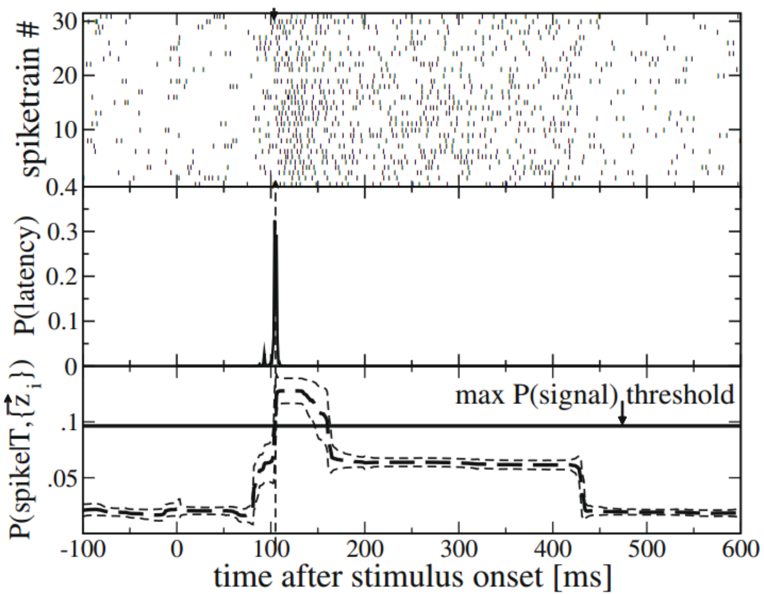
- **Change point detection**

$$s(t) = Poisson(\lambda_1), t \in [0, \theta)$$

$$s(t) = Poisson(\lambda_2), t \in [\theta, \kappa)$$

- **Bayesian binning**

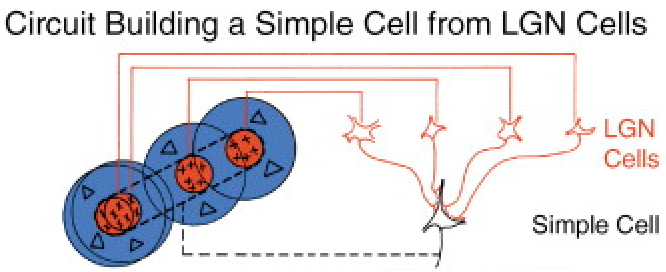
$$P(\text{excitatory latency at } t | \{k_m\}, \{f_m\}, M, S) = \begin{cases} 1 & \text{if } \exists\, k_j \in \{k_m\} : k_j + 1 = t \\ & \text{and } f_j \geqslant S \text{ and } \forall\, i < j : f_i < S \\ 0 & \text{otherwise} \end{cases}$$



SIMPLE OR COMPLEX CELL?

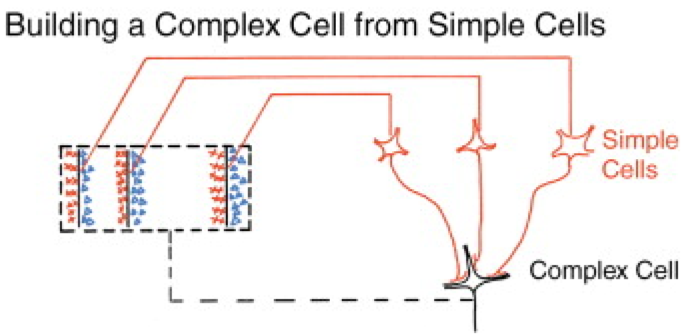
Simple cells:

- Selective for spatial frequency and orientation
- Modulated by phase of a grating



Complex cells:

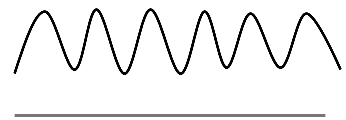
- Selective for spatial frequency and orientation
- Invariant to phase of the grating

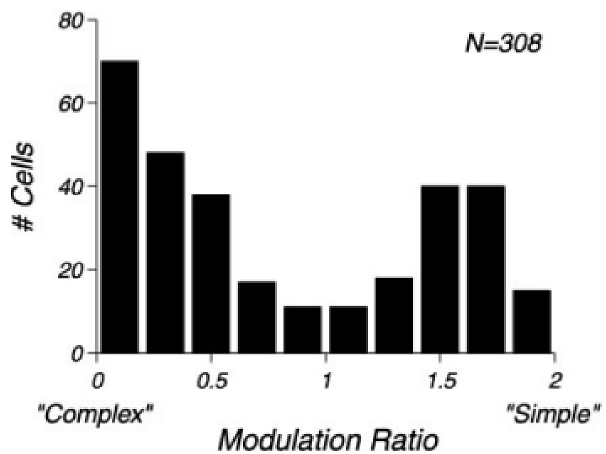


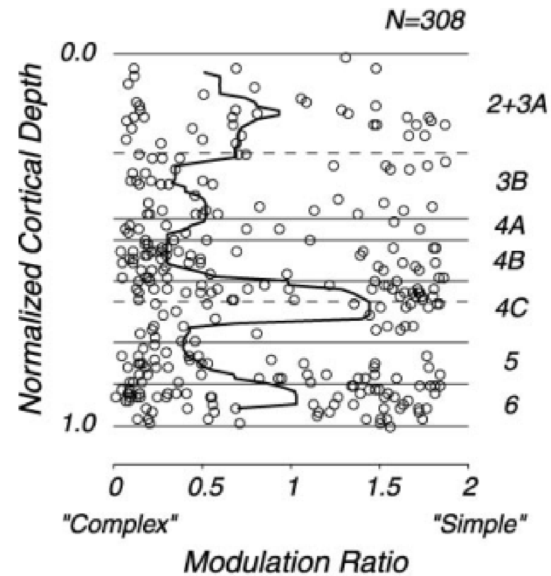
LINEARITY INDEX

Compare oscillation at stimulus frequency to DC component

$$LI = \frac{F_1}{F_0}$$







Ringach et al. 2002

SIMPLE OR COMPLEX?