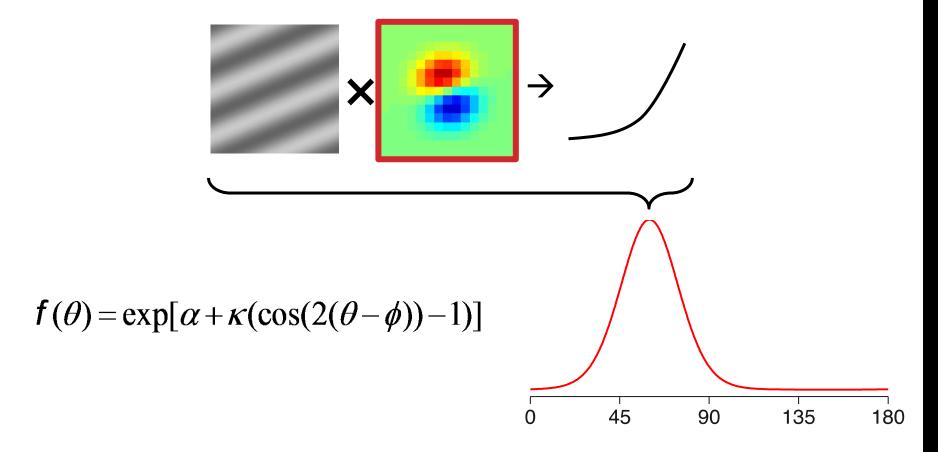
NEURAL DATA ANALYSIS

ALEXANDER ECKER, PHILIPP BERENS, MATTHIAS BETHGE

COMPUTATIONAL VISION AND NEUROSCIENCE GROUP

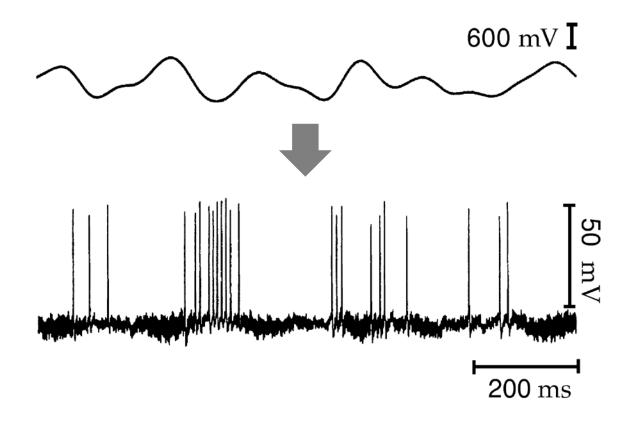
RECEPTIVE FIELDS

WHAT MAKES A NEURON FIRE?WHERE?

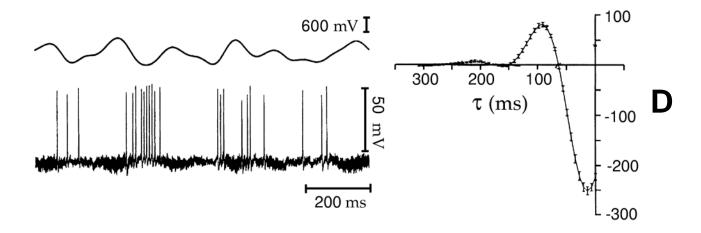


WHAT MAKES A NEURON FIRE <u>WHEN</u>?

Example: weakly electric fish electrosensory lateral-line lobe



LINEAR MODEL



$$r_{\text{ext}}(t) = \int_{0}^{\infty} D(\tau) s(t - \tau) d\tau$$

Receptive field kernel

Stimulus

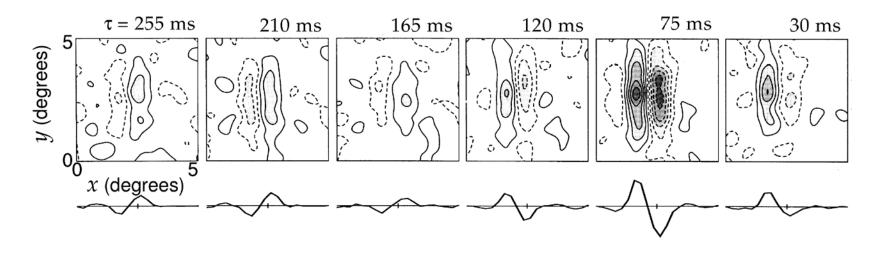
WIENER/VOLTERRA EXPANSION

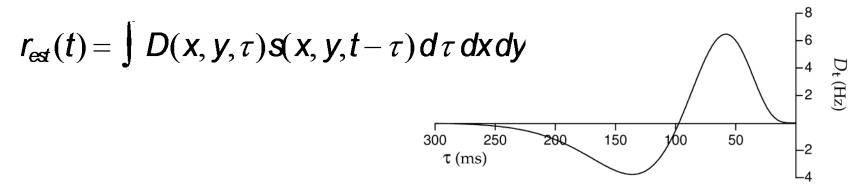
$$r_{est}(t) = r_0 + \int D(\tau)s(t-\tau)d\tau$$

$$+ \int D(\tau_1, \tau_2)s(t-\tau_1)s(t-\tau_2)d\tau_1d\tau_2$$

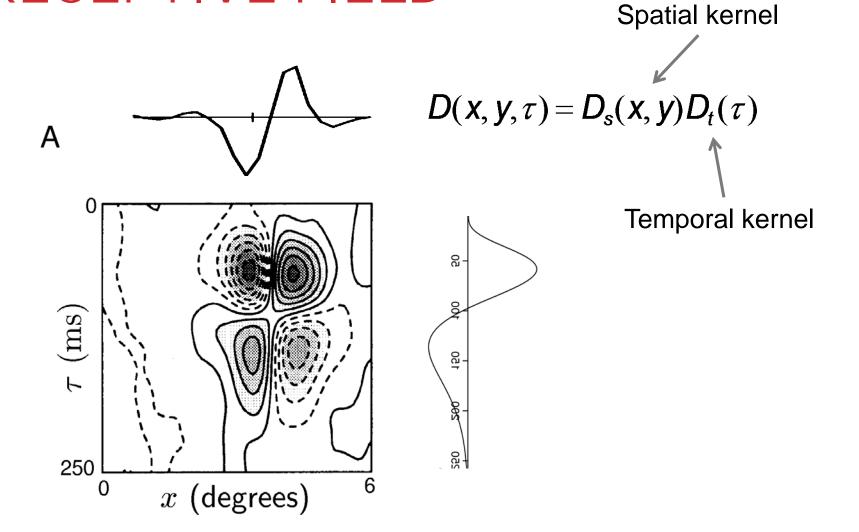
$$+ \int D(\tau_1, \tau_2, \tau_3)s(t-\tau_1)s(t-\tau_2)s(t-\tau_3)d\tau_1d\tau_2d\tau_3$$
+ ...

V1 SIMPLE CELL

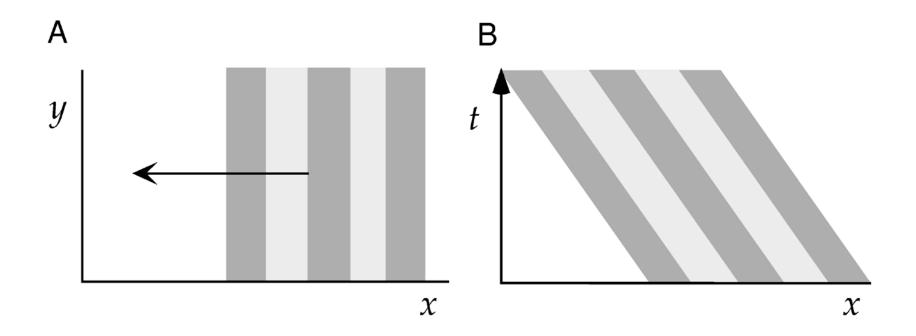




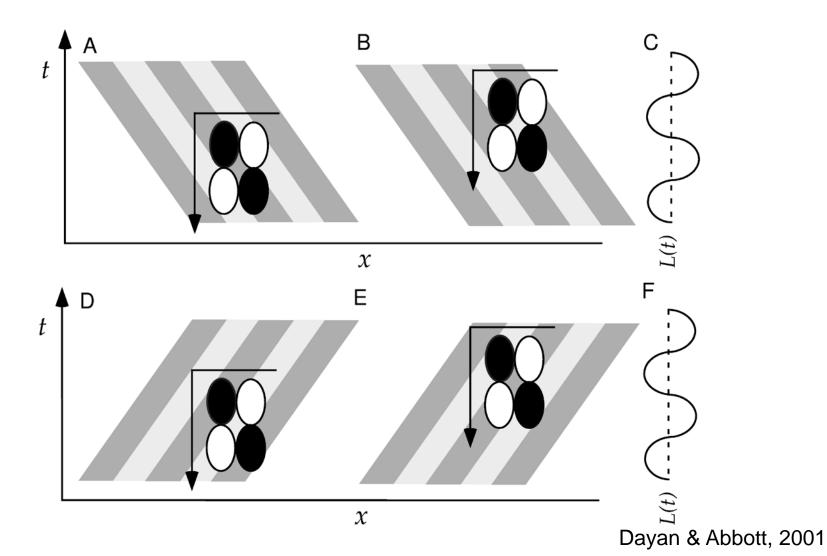
SPACE-TIME SEPARABLE RECEPTIVE FIELD



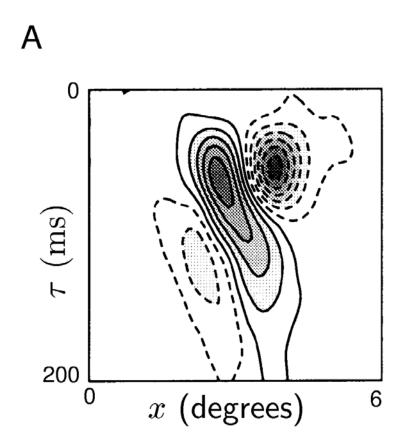
MOVING GRATING IN SPACE-TIME DIAGRAM



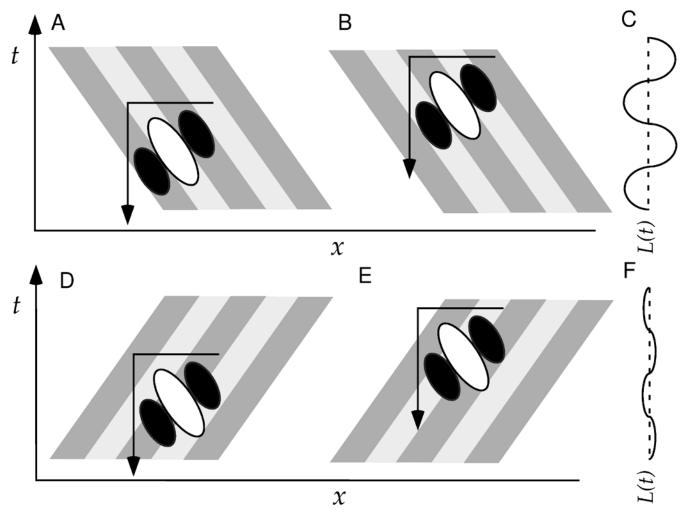
SPACE-TIME SEPARABLE RESPONSE



NON-SEPARABLE: DIRECTION SELECTIVITY



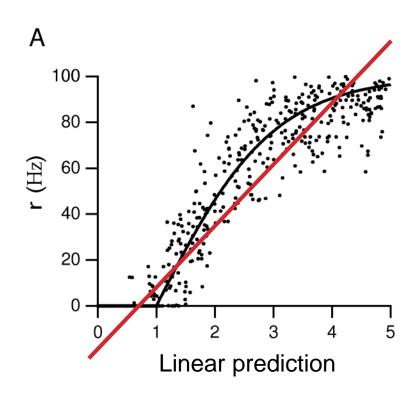
NON-SEPARABLE RESPONSE



BEYOND LINEAR

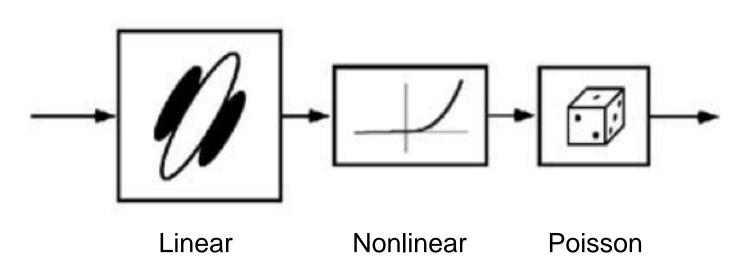
- 1. Linear-nonlinear-Poisson (LNP) model
- 2. Energy model (complex cells)

LNP MODEL: STATIC NONLINEARITY



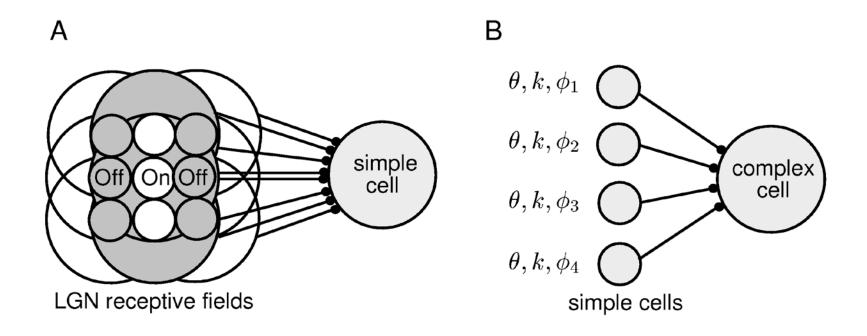
THE LNP MODEL

Simple cell

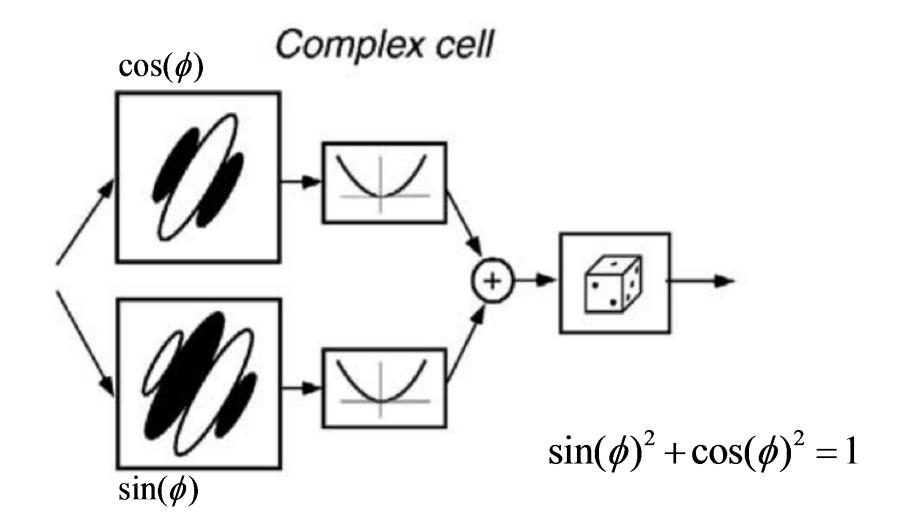


 $y \sim \text{Poisson}(\exp(r))$

COMPLEX CELLS: HUBEL & WIESEL MODEL



COMPLEX CELLS: THE ENERGY MODEL



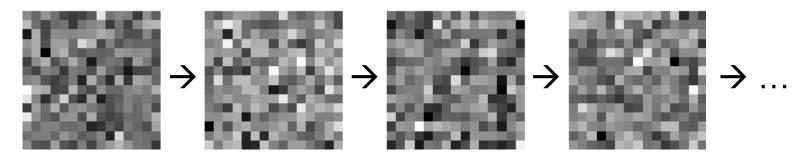
LEARNING RECEPTIVE FIELDS

LEARNING RECEPTIVE FIELD MODELS

- 1. Spike-triggered average
- 2. Maximum likelihood
- 3. Spike-triggered covariance

SPECIAL CASE

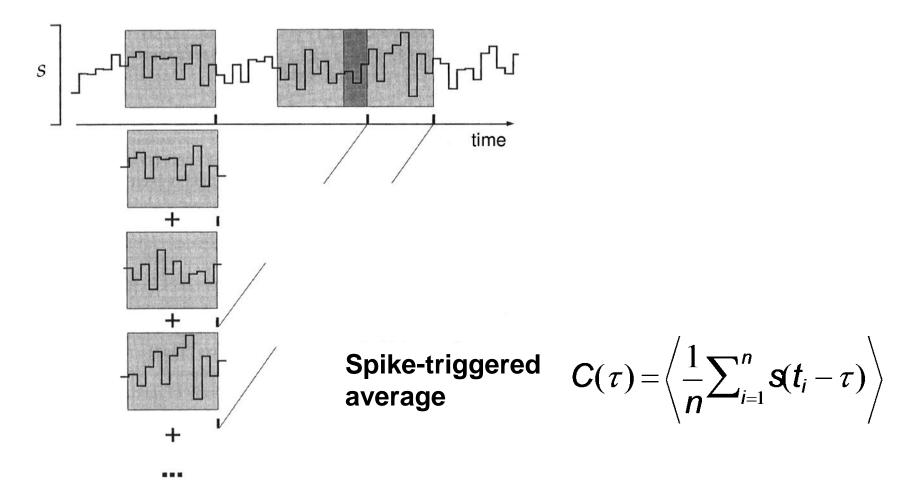
1. White noise stimulus



2. Linear receptive field

 \Rightarrow $D(\tau) \sim C(\tau)$, $C(\tau)$: Spike-triggered average (STA)

SPIKE-TRIGGERED AVERAGE



ESTIMATING RECEPTIVE FIELDS

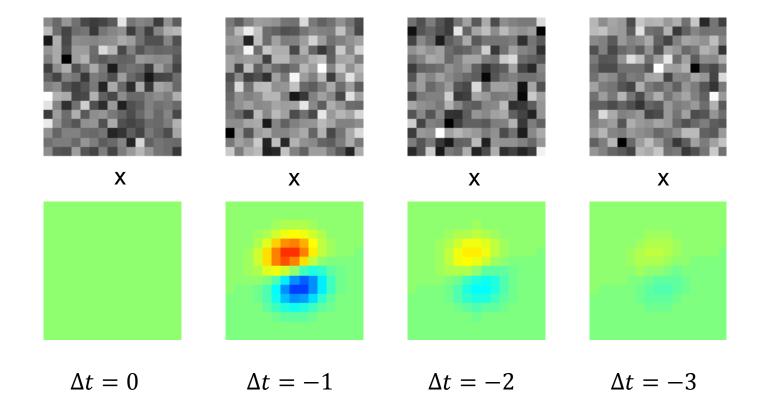
Continuous representation (integrals)

$$r_{ext}(t) = \int D_s(x, y) D_t(\tau) s(x, y, t - \tau) d\tau dx dy$$

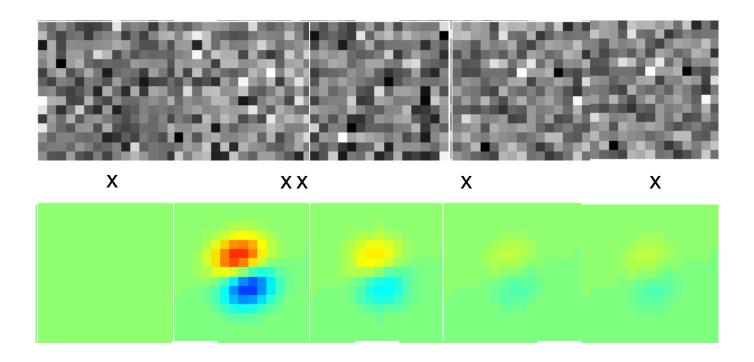
Discretize space and time (sums)

$$r(t) = \sum_{i} \sum_{j} \sum_{k} D_{ijk} s_{ijk}(t)$$

SPATIO-TEMPORAL RECEPTIVE FIELDS



SPATIO-TEMPORAL RECEPTIVE FIELDS



$$\Rightarrow r_t = \mathbf{w}^{\mathrm{T}} \mathbf{S}_t$$

ESTIMATING RECEPTIVE FIELDS

Maximum likelihood: minimize the negative log-likelihood

$$y_t \sim \text{Poisson}(\lambda), \quad \lambda = \exp(\mathbf{w}^T \mathbf{s}_t)$$

$$P(y_t \mid \mathbf{w}) = \frac{\lambda^{y_t}}{y_t!} \exp(-\lambda)$$

Negative log-likelihood:

$$L(w) = -\log P(y_t | w)$$

$$= -y_t \log \lambda + \log(y_t!) + \lambda$$

$$\frac{\partial L(w)}{\partial w} = ...$$

SPIKE-TRIGGERED COVARIANCE

SPIKE-TRIGGERED COVARIANCE

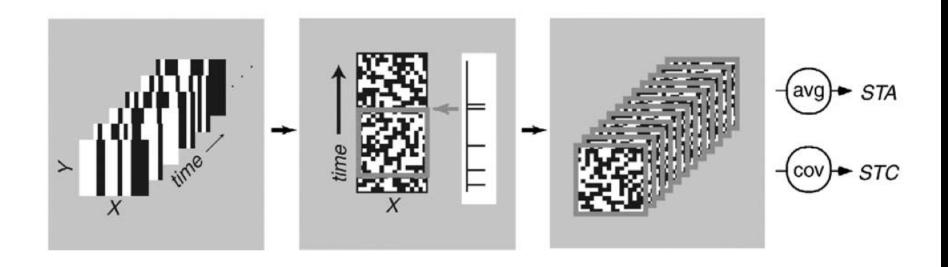
e.g. Rust et al. (2005), Neuron

Spike-triggered covariance:
$$C_{ij}(\tau) = \left\langle \frac{1}{n} \sum_{t} s_i(t-\tau) s_j(t-\tau) \right\rangle$$

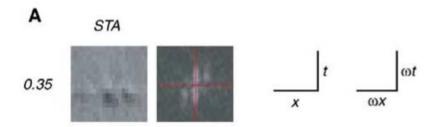
Visualize eigenvectors of C_{ii} with largest (smallest) variance

→ Capture non-linear response properties (e.g. complex cell)

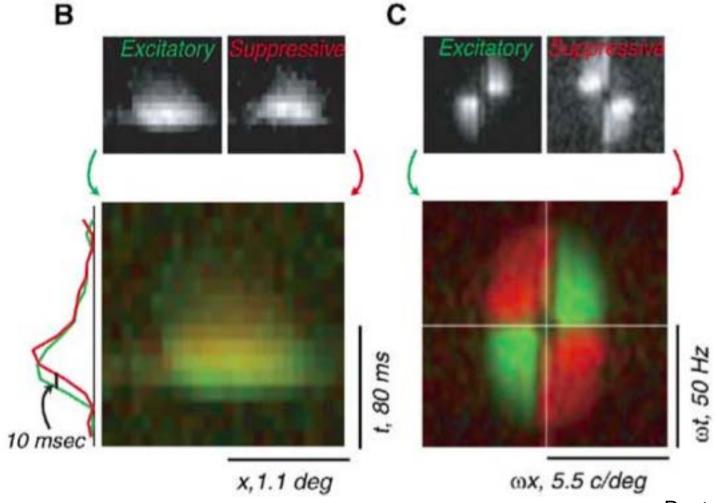
SPIKE-TRIGGERED COVARIANCE (RUST 2005)



SPIKE-TRIGGERED COVARIANCE (COMPLEX CELL)



SPIKE-TRIGGERED COVARIANCE (RUST 2005)



SPIKE-TRIGGERED COVARIANCE (RUST 2005)

