NEURAL DATA ANALYSIS

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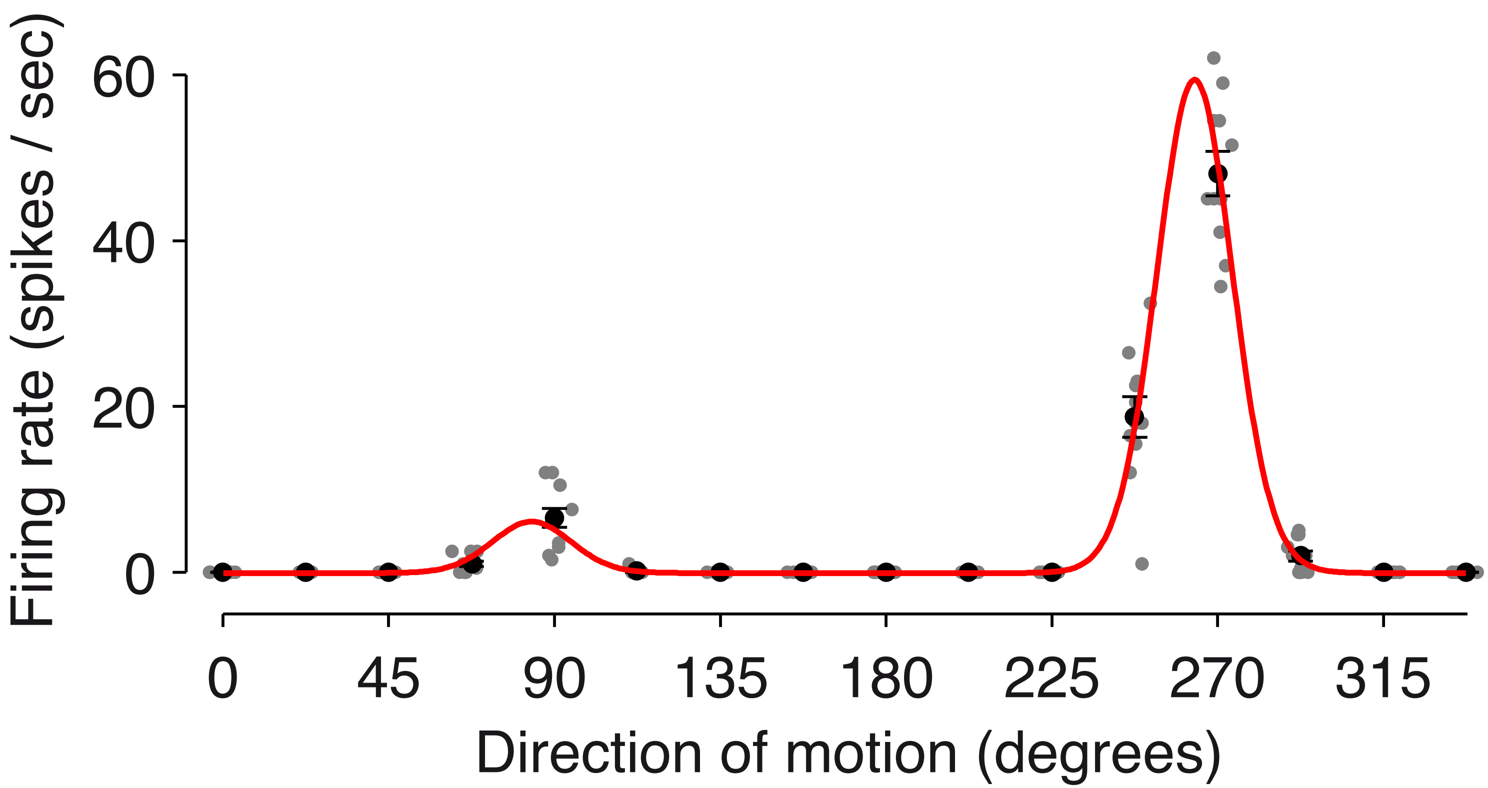
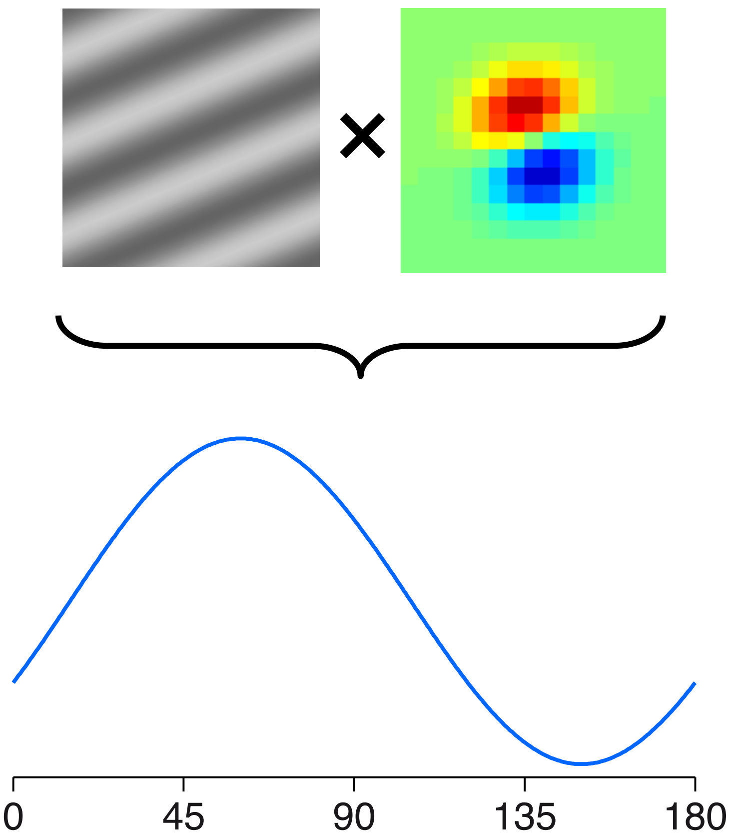
ORIENTATION/ DIRECTION TUNING



ORIENTATION TUNING
THE STANDARD MODEL

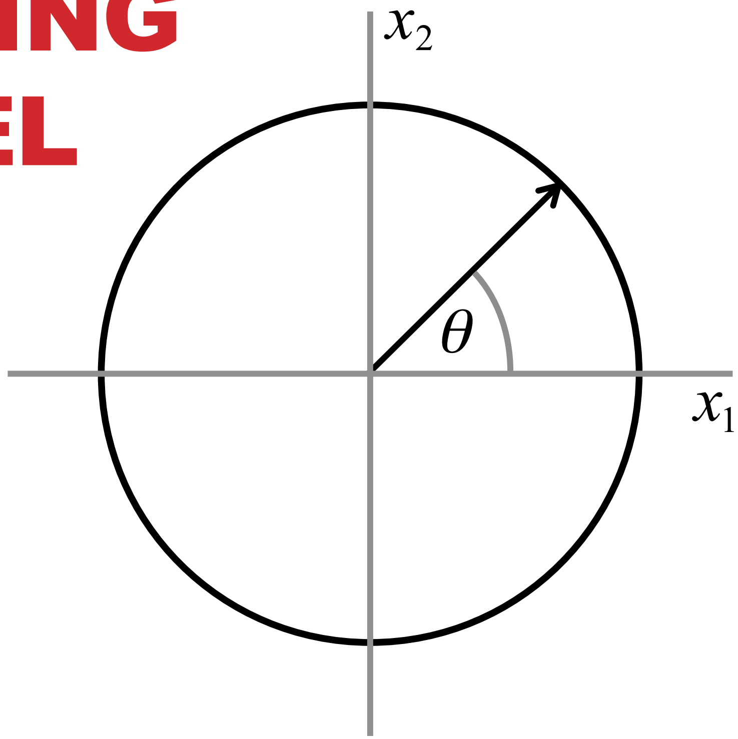


ORIENTATION TUNING AS A LINEAR MODEL

Represent orientation as 2D vector of unit length

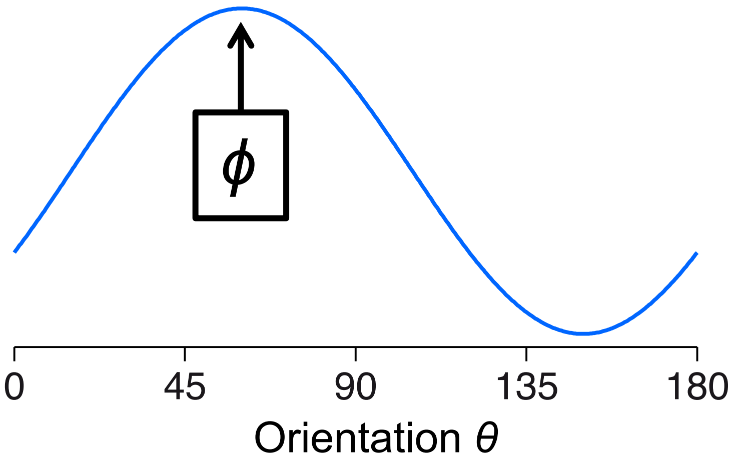
$$f(\mathbf{x}) = a + \mathbf{b}^{\mathrm{T}}\mathbf{x}$$

$$\mathbf{b} = \beta \begin{bmatrix} \cos\phi \\ \sin\phi \end{bmatrix} \qquad \mathbf{x} = \begin{bmatrix} \cos\theta \\ \sin\theta \end{bmatrix}$$



Equivalent to:

$$f(\theta) = a + \beta\cos(\theta - \phi)$$



LINEAR MODEL IN FOURIER DOMAIN

Use 0th (mean) and 2nd (orientation) Fourier components as basis functions:

$$v_{jk} = \frac{1}{\sqrt{N}} \exp\left(\frac{2\pi ijk}{N}\right) \qquad j = 1, \cdots, N \qquad k = \{0, 2\}$$

two cycles since we expect there are to peaks on the tuning graph.

Tuning curve can be written as:

complex conjugate

$$\mathbf{f} = q_0 + q_2 \mathbf{v}_2 + \overline{q}_2 \overline{\mathbf{v}}_2$$

Preferred orientation: $\phi = \arg(q_2)$

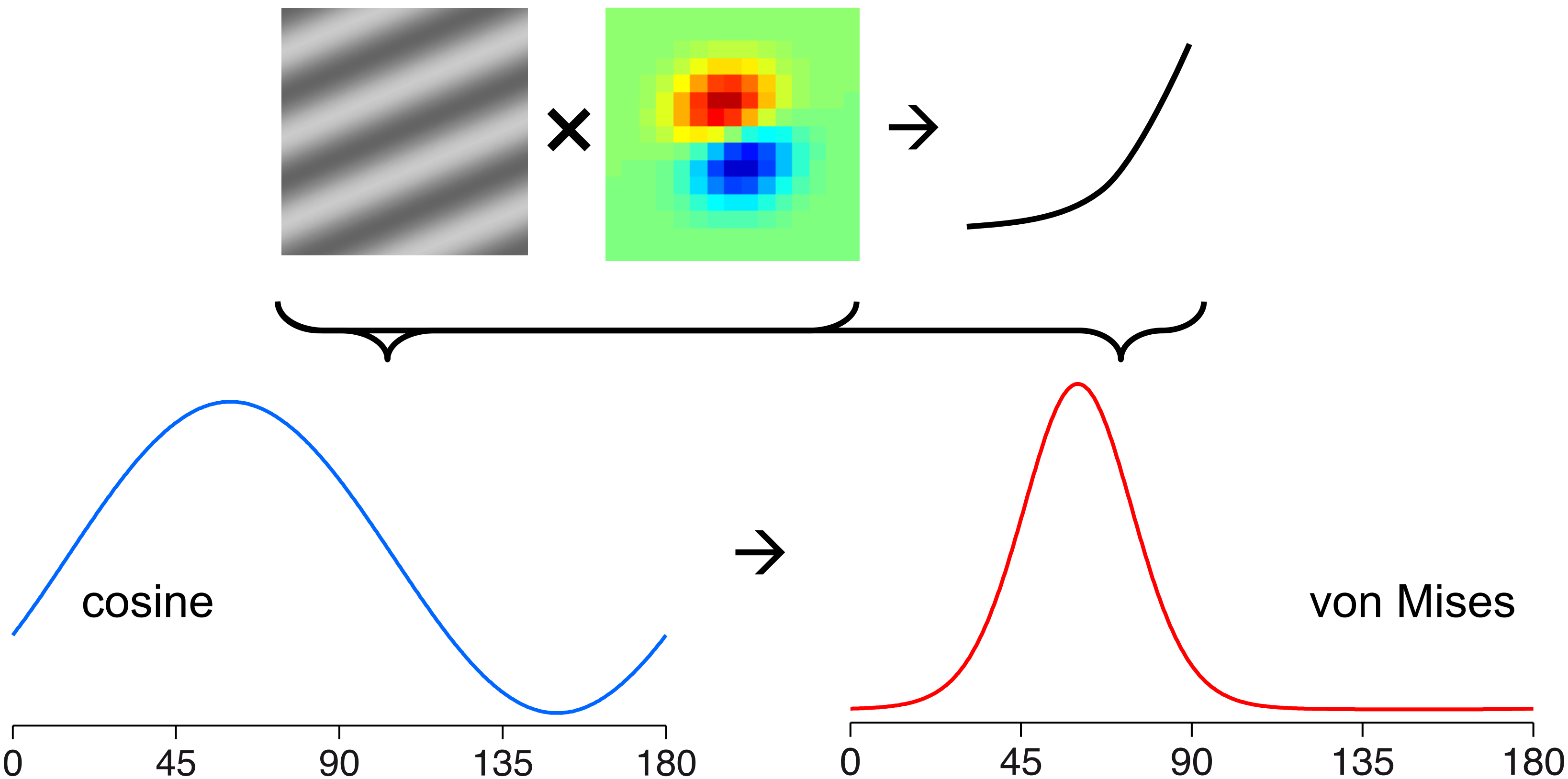
LINEAR-NONLINEAR (LN) MODEL

$$f(\theta) = \exp[\alpha + \kappa(\cos(2(\theta - \phi)) - 1)]$$

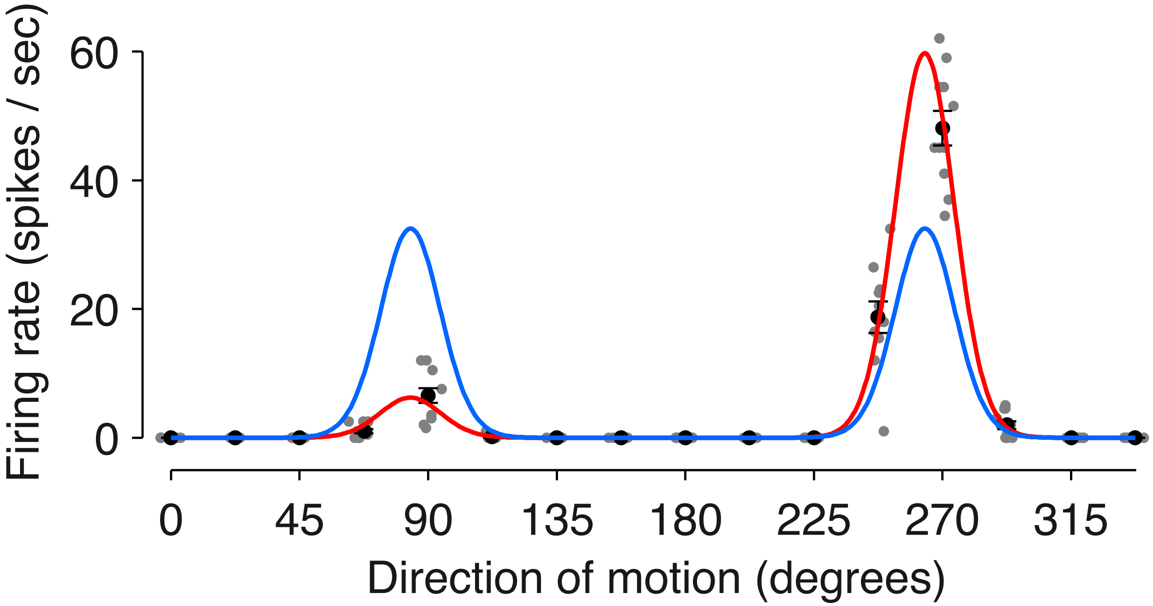
basis function

tuning curve

exponential



DIRECTION SELECTIVITY



Ratio of preferred and null direction:

$$\exp(2\nu)$$

Add the first harmonic to the von Mises model

$$f(\theta) = \exp[\alpha + \kappa(\cos(2(\theta - \phi)) - 1) + \nu(\cos(\theta - \phi) - 1)]$$

FITTING TUNING CURVES TO DATA

How do we learn these models?

Linear: project on Fourier components

Von Mises

- Gaussian additive noise: Least squares
- Poisson noise: Maximum likelihood

→ Gradient descent

LINEAR MODEL

Project on 0th (mean) and 2nd (orientation) Fourier components:

$$v_{jk} = \frac{1}{\sqrt{N}} \exp\left(\frac{2\pi ijk}{N}\right) \qquad j = 1, \cdots, N \qquad k = \{0, 2\}$$

$$q_k = \mathbf{v}_k^* \mathbf{m}$$

$\mathbf{m}$: average spike counts
$\mathbf{v}_k^*$: complex conjugate transpose

The tuning curve is then again given by:

$$\mathbf{f} = q_0 + q_2 \mathbf{v}_2 + \overline{q}_2 \overline{\mathbf{v}}_2$$

→ **Equivalent to taking Fourier transform and inverse Fourier Transform, ignoring all other components**

POISSON MODEL

Log-likelihood:

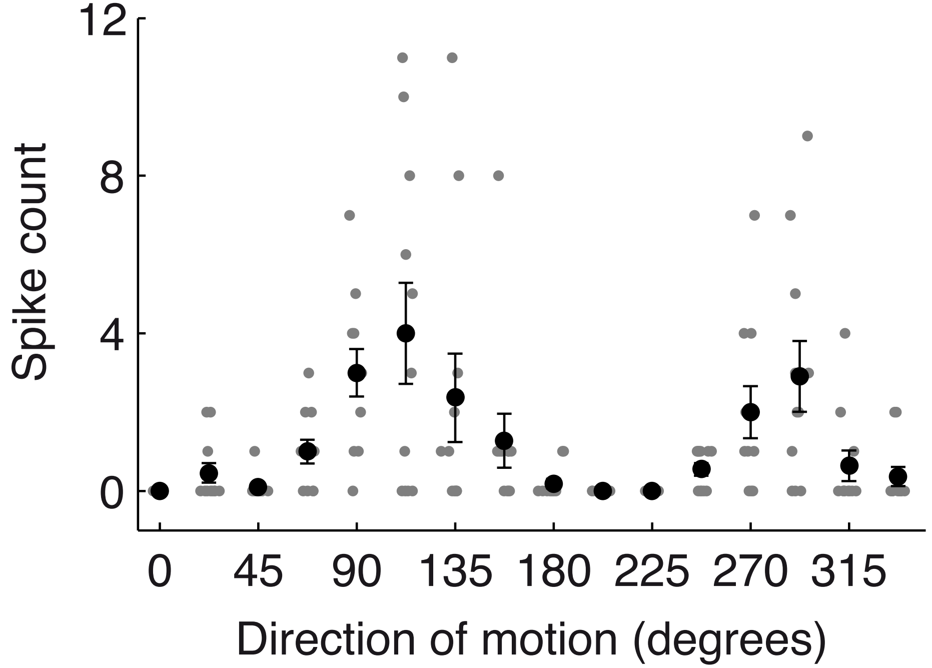
$$p(k) = \frac{\lambda^k}{k!}\exp(-\lambda) \qquad \text{where } \lambda = f(\theta)$$

$$\log p(k) = k\log\lambda - \lambda + \text{const}$$

Differentiate with respect to tuning parameters $\alpha, \kappa, \nu, \phi$ **and maximize**

SIGNIFICANCE TESTING

Is this cell tuned significantly?



There is no "ready to use" statistical test for this problem.

REVIEW: HYPOTHESIS TESTING

Example: Student's *t* test

- **Compute test statistic:** $t = \dfrac{\mu}{\sigma_{\mu}}$
- **Compare measured value of *t* to its distribution under the null hypothesis of no effect**
- ***p* value: probability of observing a value of *t* as extreme or more extreme under the null distribution**
- ***p* < α: significant effect (α usually 0.05)**

TEST FOR TUNING

Build our own hypothesis test: permutation test.

Use linear model and $|q_2|$ as test statistic.

Derive null distribution from the measured data by randomly shuffling trial labels
→ under the null hypothesis of no tuning all trials are equivalent.

Run 1000 iterations

Count the fraction of runs that produce $|q_2|$ larger than observed with trial labels intact.

TEST TUNING: EXAMPLE

Null distribution based on 1000 iterations with labels shuffled.

***p* < 0.001 → cell is tuned**