

SYDE 556/750

Simulating Neurobiological Systems
Lecture 3: Population Representation

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UNIVERSITY OF
WATERLOO

FACULTY OF
ENGINEERING



Visual Cortex



Mapping receptive fields

cell activity

behavior

overall



ongoing













































































NEF Principle 1: Representation

NEF Principle 1 – Representation

Groups (“populations”, or “ensembles”) of neurons *represent* values via nonlinear encoding and linear decoding.

Lossless Codes

INTERNATIONAL ALPHABET FLAGS, PHONETIC ALPHABET, MORSE CODE AND SEMAPHORE ALPHABET																		
A ALFA  <small>Alphabet: 1st letter</small>	B BRAVO  <small>Alphabet: 2nd letter</small>	C CHARLIE  <small>Alphabet: 3rd letter</small>	D DELTA  <small>Alphabet: 4th letter</small>	E ECHO  <small>Alphabet: 5th letter</small>	F FOXTROT  <small>Alphabet: 6th letter</small>	G GOLF  <small>Alphabet: 7th letter</small>	H HOTEL  <small>Alphabet: 8th letter</small>	I INDIA  <small>Alphabet: 9th letter</small>	J JULIETT  <small>Alphabet: 10th letter</small>									
K KILO  <small>Alphabet: 11th letter</small>	L LIMA  <small>Alphabet: 12th letter</small>	M MIKE  <small>Alphabet: 13th letter</small>	N NOVEMBER  <small>Alphabet: 14th letter</small>	O OSCAR  <small>Alphabet: 15th letter</small>	P PAPA  <small>Alphabet: 16th letter</small>	Q QUEBEC  <small>Alphabet: 17th letter</small>	R ROMEO  <small>Alphabet: 18th letter</small>	S SIERRA  <small>Alphabet: 19th letter</small>	T TANGO  <small>Alphabet: 20th letter</small>									
U UNIFORM  <small>Alphabet: 21st letter</small>	V VICTOR  <small>Alphabet: 22nd letter</small>	W WHISKEY  <small>Alphabet: 23rd letter</small>	X XRAY  <small>Alphabet: 24th letter</small>	Y YANKEE  <small>Alphabet: 25th letter</small>	Z ZULU  <small>Alphabet: 26th letter</small>	SEMAPHORE ALPHABET  <small>Alphabet: 1st letter</small>									 <small>Alphabet: 2nd letter</small>	 <small>Alphabet: 3rd letter</small>	 <small>Alphabet: 4th letter</small>	 <small>Alphabet: 5th letter</small>
NAVAL NUMERAL FLAGS, PHONETIC NUMERALS AND MORSE CODE																		
1 ONE  <small>Alphabet: 1st numeral</small>	2 TWO  <small>Alphabet: 2nd numeral</small>	3 THREE  <small>Alphabet: 3rd numeral</small>	4 FOUR  <small>Alphabet: 4th numeral</small>	5 FIVE  <small>Alphabet: 5th numeral</small>	6 SIX  <small>Alphabet: 6th numeral</small>	7 SEVEN  <small>Alphabet: 7th numeral</small>	8 EIGHT  <small>Alphabet: 8th numeral</small>	9 NINE  <small>Alphabet: 9th numeral</small>	0 ZERO  <small>Alphabet: 10th numeral</small>									
INTERNATIONAL NUMERAL PENNANTS																		
1 "Pennant One"  <small>Alphabet: 1st pennant</small>	2 "Pennant Two"  <small>Alphabet: 2nd pennant</small>	3 "Pennant Three"  <small>Alphabet: 3rd pennant</small>	4 "Pennant Four"  <small>Alphabet: 4th pennant</small>	5 "Pennant Five"  <small>Alphabet: 5th pennant</small>	6 "Pennant Six"  <small>Alphabet: 6th pennant</small>	7 "Pennant Seven"  <small>Alphabet: 7th pennant</small>	8 "Pennant Eight"  <small>Alphabet: 8th pennant</small>	9 "Pennant Nine"  <small>Alphabet: 9th pennant</small>	0 "Pennant Zero"  <small>Alphabet: 10th pennant</small>									
NAVAL SPECIAL FLAGS AND PENNANTS																		
International Answer  <small>Alphabet: 1st special flag</small>	Code  <small>Alphabet: 2nd special flag</small>	Black Pennant  <small>Alphabet: 3rd special flag</small>	Corpus  <small>Alphabet: 4th special flag</small>	Designation  <small>Alphabet: 5th special flag</small>	Division  <small>Alphabet: 6th special flag</small>	Emergency  <small>Alphabet: 7th special flag</small>	Flotilla  <small>Alphabet: 8th special flag</small>	Formation  <small>Alphabet: 9th special flag</small>										
Interrogative  <small>Alphabet: 10th special flag</small>	Negative  <small>Alphabet: 11th special flag</small>	Preparative  <small>Alphabet: 12th special flag</small>	Port  <small>Alphabet: 13th special flag</small>	Speed  <small>Alphabet: 14th special flag</small>	Squadron  <small>Alphabet: 15th special flag</small>	Starboard  <small>Alphabet: 16th special flag</small>	Station  <small>Alphabet: 17th special flag</small>	Submarine  <small>Alphabet: 18th special flag</small>	Tow  <small>Alphabet: 19th special flag</small>									
First Substitute  <small>Alphabet: 20th special flag</small>	Second Substitute  <small>Alphabet: 21st special flag</small>	Third Substitute  <small>Alphabet: 22nd special flag</small>	Fourth Substitute  <small>Alphabet: 23rd special flag</small>															

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Encoding: $a = f(x)$

Decoding: $x = f^{-1}(a)$

Binary numbers: Nonlinear encoding, linear decoding

- Represent a natural number between 0 and $2^n - 1$ as n binary digits.

Binary numbers: Nonlinear encoding, linear decoding

- ▶ Represent a natural number between 0 and $2^n - 1$ as n binary digits.
- ▶ **Nonlinear encoding**

$$a_i = (f(x))_i = \begin{cases} 1 & \text{if } x - 2^i \lfloor \frac{x}{2^i} \rfloor \geq 2^{i-1}, \\ 0 & \text{otherwise.} \end{cases}$$

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$$x = f^{-1}(\mathbf{a}) = \sum_{i=0}^{n-1} 2^i a_i = \mathbf{F}\mathbf{a} = \begin{pmatrix} 1 & 2 & \dots & 2^{n-1} \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_{n-1} \end{pmatrix}.$$

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- This is a **distributed code**. But, **not robust** against additive noise!

Lossy codes

- **Lossy code**

Inverse f^{-1} does not exist, instead *approximate* the represented value

Encoding: $\mathbf{a} = f(\mathbf{x})$

Decoding: $\mathbf{x} \approx g(\mathbf{a})$

Lossy codes

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- ▶ **Examples**

- ▶ Audio, image, and video coding schemes (MP3, JPEG, H.264)

- ▶ Basis transformation onto first n principal components (PCA)

Lossy codes

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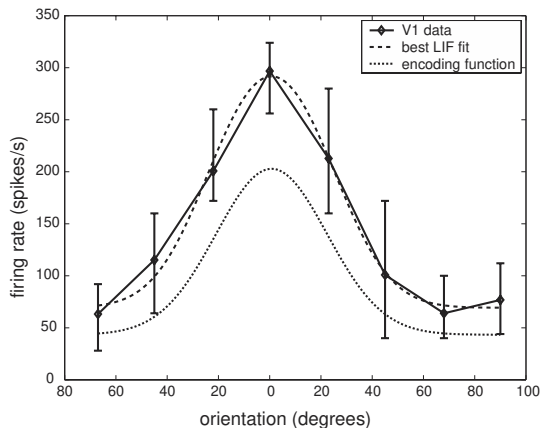
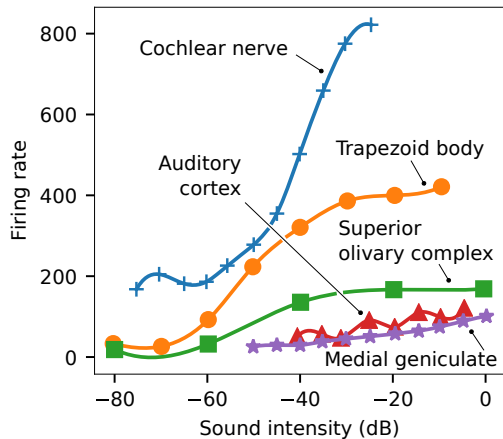
- ▶ **Examples**

- ▶ Audio, image, and video coding schemes (MP3, JPEG, H.264)

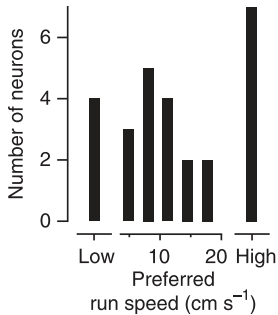
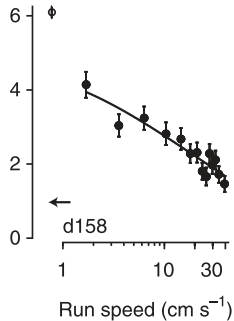
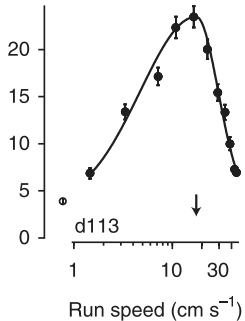
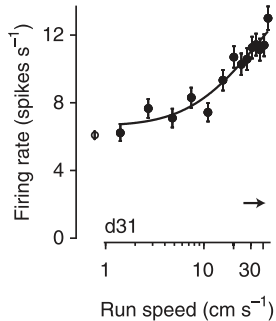
- ▶ Basis transformation onto first n principal components (PCA)

- ▶ **Neural Representations**

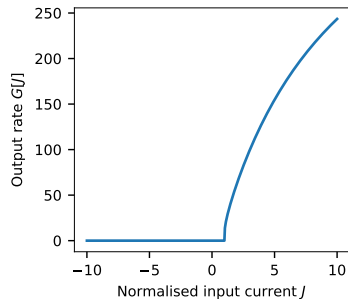
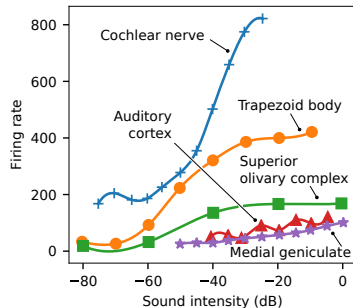
Tuning curves (I)



Tuning curves (II)



- Last lecture: response curves:
 $a = G(J)$
- This lecture: tuning curves:
 $a = f(x) = G(J_i(x))$
- What sort of function can we try for $J_i(x)$?

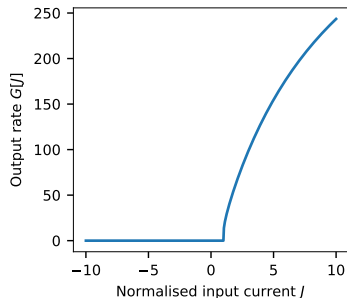
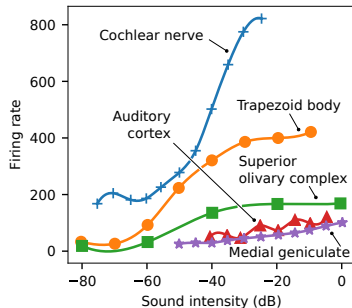


- Last lecture: response curves:
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- This lecture: tuning curves:
 $a = f(x) = G(J_i(x))$
- What sort of function can we try for $J_i(x)$?
- Introduce a gain α_i and a bias J_i^{bias} :

$$J_i(x) = \alpha_i x + J_i^{\text{bias}}$$

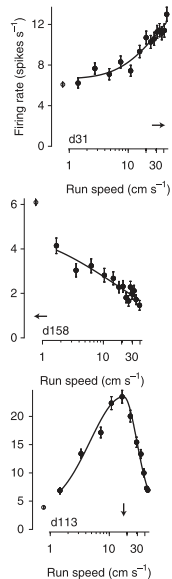
$$a_i(x) = G(\alpha_i x + J_i^{\text{bias}})$$

- α_i controls the slope
- J_i^{bias} shifts curve left and right



- Does this work for all tuning curves?

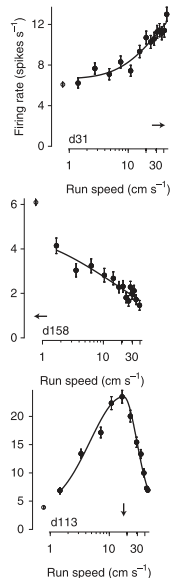
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$$a_i(x) = G(\alpha_i x + J_i^{\text{bias}})$$

- a) increasing: Yes!

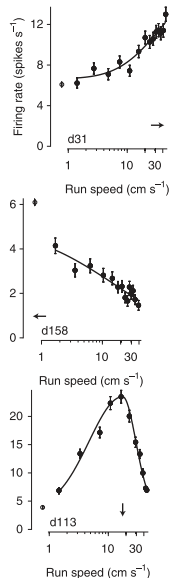


- Does this work for all tuning curves?

$$a_i(x) = G(\alpha_i x + J_i^{\text{bias}})$$

- a) increasing: Yes!
- b) decreasing: Yes! (just let α_i be negative)
 - or, better yet, introduce e_i which is either 1 or -1 and keep α_i to be always positive. This keeps the two ideas (slope and increase/decreasing) separate.

$$a_i(x) = G(\alpha_i(e_i x) + J_i^{\text{bias}})$$



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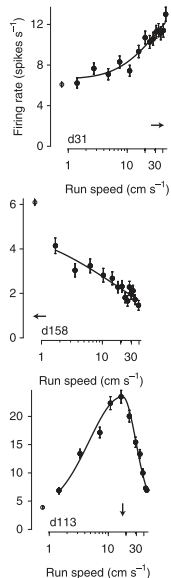
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- c) preferred stimulus: Need some sort of similarity measure
 - But it shouldn't be too complicated. So far we've only needed to introduce multiplication and addition, which are both things we're pretty sure neurons can do, so let's avoid adding anything else if we don't have to. Ideas?

$$a_i(x) = G(\alpha_i \text{sim}(e_i, x) + J_i^{\text{bias}})$$



Encoders: Preferred Direction Vectors

- ▶ The represented value x doesn't have to be a scalar
- ▶ What if it's a vector?

Encoders: Preferred Direction Vectors

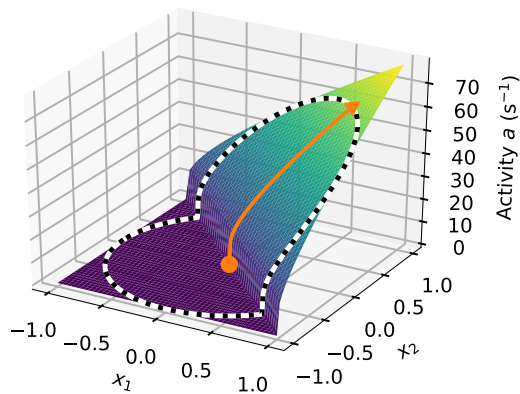
- ▶ The represented value x doesn't have to be a scalar
- ▶ What if it's a vector?
- ▶ There's a simple similarity-like measure for vectors: the dot product

$$\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{i=0}^d x_i y_i = \cos(\angle(\mathbf{x}, \mathbf{y})) \|\mathbf{x}\| \|\mathbf{y}\|$$

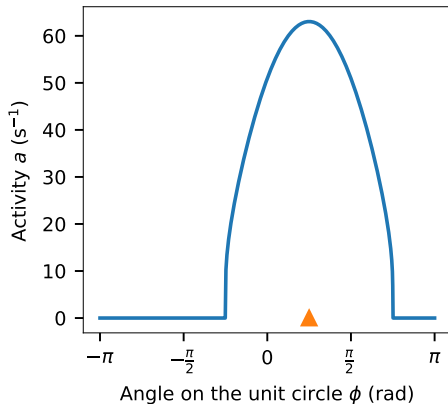
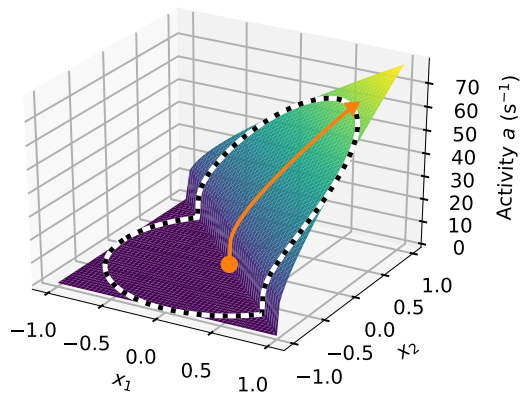
$$a_i(\mathbf{x}) = G(\alpha_i \langle \mathbf{e}_i, \mathbf{x} \rangle + J_i^{\text{bias}})$$

- ▶ Constrain \mathbf{e}_i to be a unit vector
 - ▶ Note that for scalar x , the only two unit vectors are $+1$ and -1
 - ▶ So the increasing / decreasing scenario is a special case of this!

Preferred Directions in Higher Dimensions: Representing 2D Values



Preferred Directions in Higher Dimensions: Representing 2D Values



Decoding

- ▶ Non-linear Encoding and Linear Decoding

$$\mathbf{a}_i = G[\alpha_i \langle \mathbf{x}, \mathbf{e}_i \rangle + J_i^{\text{bias}}],$$
$$\hat{\mathbf{x}} = \mathbf{D}\mathbf{a}$$

Encoding

Decoding

- ▶ How do we find \mathbf{D} ?

Decoding

- Non-linear Encoding and Linear Decoding

$$\mathbf{a}_i = G[\alpha_i \langle \mathbf{x}, \mathbf{e}_i \rangle + J_i^{\text{bias}}],$$

Encoding

$$\hat{\mathbf{x}} = \mathbf{D}\mathbf{a}$$

Decoding

- How do we find \mathbf{D} ?
- Least-squares minimization

$$\arg \min_{\mathbf{D}} E = \frac{1}{|\mathbb{X}|} \int_{\mathbb{X}} \|\mathbf{x} - \hat{\mathbf{x}}\| \, d\mathbf{x} = \frac{1}{|\mathbb{X}|} \int_{\mathbb{X}} \|\mathbf{x} - \mathbf{D}\mathbf{a}(\mathbf{x})\| \, d\mathbf{x}$$

Decoding via Least-squares Minimization

- Find the minimum decoding error

$$\arg \min_{\mathbf{D}} E = \frac{1}{|\mathbb{X}|} \int_{\mathbb{X}} \|\mathbf{x} - \hat{\mathbf{x}}\| \, d\mathbf{x} = \frac{1}{|\mathbb{X}|} \int_{\mathbb{X}} \|\mathbf{x} - \mathbf{D}\mathbf{a}(\mathbf{x})\| \, d\mathbf{x}$$

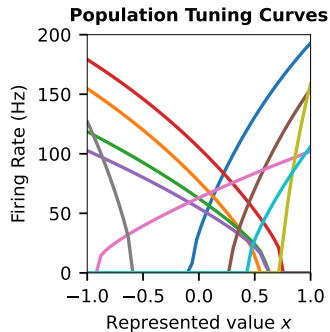
- We can do this analytically, or sample:

$$\arg \min_{\mathbf{D}} E = \frac{1}{N} \sum_{i=0}^N \|\mathbf{x}_i - \mathbf{D}\mathbf{a}(\mathbf{x}_i)\|$$

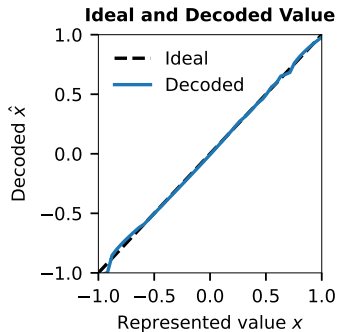
Decoding via Least-squares Minimization

- ▶ Let's write this in matrix form, where $\mathbf{A}_{ik} = a_i(x_k)$ and $\mathbf{X} = (x_1, \dots, x_N)$
- ▶ We want $\mathbf{A}^T \mathbf{D}^T = \mathbf{X}^T$
- ▶ So $\mathbf{A} \mathbf{A}^T \mathbf{D}^T = \mathbf{A} \mathbf{X}^T$
- ▶ $(\mathbf{A} \mathbf{A}^T)^{-1} \mathbf{A} \mathbf{A}^T \mathbf{D}^T = (\mathbf{A} \mathbf{A}^T)^{-1} \mathbf{A} \mathbf{X}^T$
- ▶ $\mathbf{D}^T = (\mathbf{A} \mathbf{A}^T)^{-1} \mathbf{A} \mathbf{X}^T$
- ▶ In Python, `D = np.linalg.lstsq(A.T, X.T, rcond=None)[0].T`
- ▶ (where \mathbf{A} is a $n \times N$ array and \mathbf{X} is a $d \times N$ array)

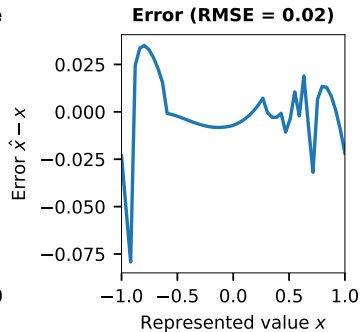
Decoding



A



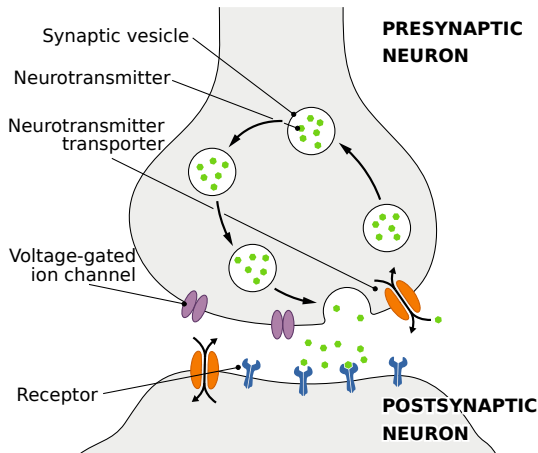
$\mathbf{A}^T \mathbf{D}^T$



$\mathbf{A}^T \mathbf{D}^T - \mathbf{X}^T$

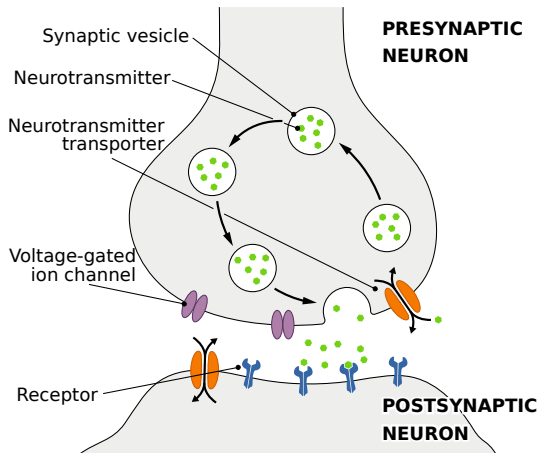
Sources of Noise in Biological Neural Networks

- ▶ **Axonal jitter**
Active axonal spike propagation
- ▶ **Vesicle release failure**
10-30% of pre-synaptic events cause post-synaptic current
- ▶ **Neurotransmitter per vesicle**
Varying amounts of neurotransmitter
- ▶ **Ion channel noise**
Ion-channels are “binary”, stochastic
- ▶ **Thermal noise**
- ▶ **Network effects**
Simple, noise-free inhibitory/excitatory networks produce irregular spike trains



Sources of Noise in Biological Neural Networks

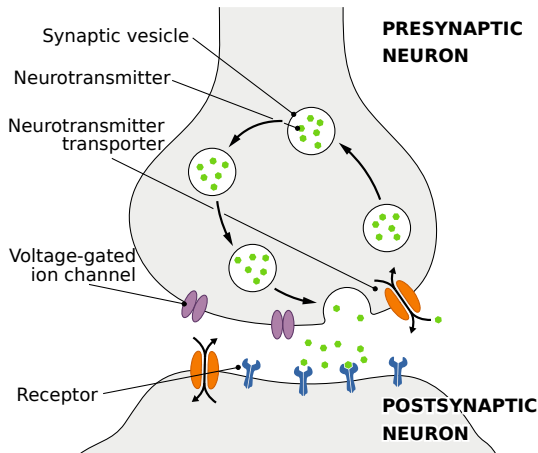
- ▶ **Axonal jitter**
Active axonal spike propagation
- ▶ **Vesicle release failure**
10-30% of pre-synaptic events cause post-synaptic current
- ▶ **Neurotransmitter per vesicle**
Varying amounts of neurotransmitter
- ▶ **Ion channel noise**
Ion-channels are “binary”, stochastic
- ▶ **Thermal noise**
- ▶ **Network effects**
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▶ **How to model?**

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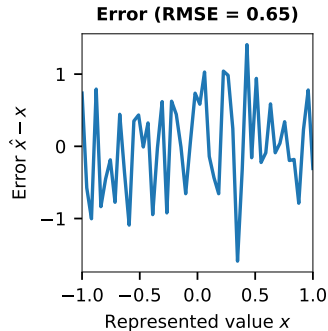
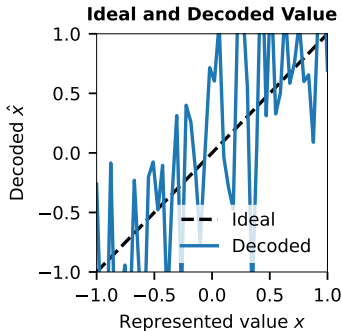
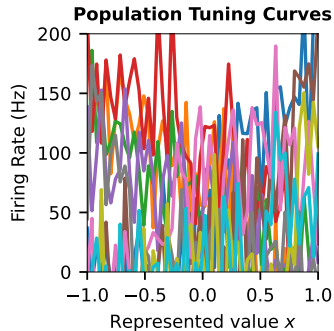
- ▶ **How to model?** Gaussian noise

NEF Principle 0: Noise

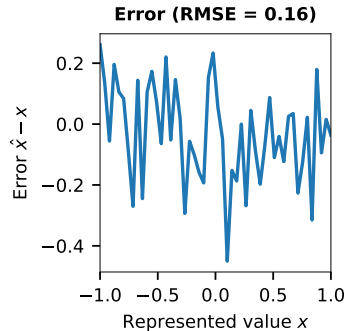
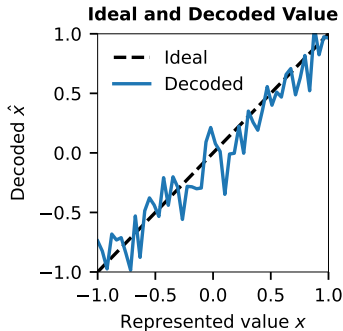
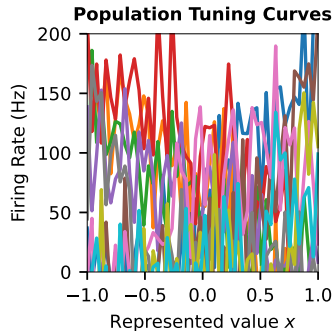
NEF Principle 0 – Noise

Biological neural systems are subject to significant amounts of noise from various sources. Any analysis of such systems must take the effects of noise into account.

Decoding Noisy \mathbf{A} Without Taking Noise Into Account



Decoding Noisy Δ Accounting for Noise

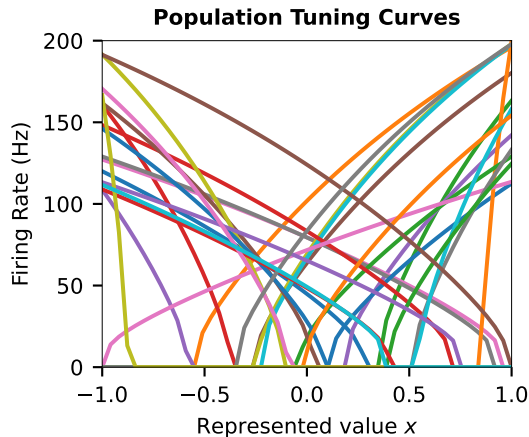


Summary: Building a model of neural representation (Encoding)

Encoding

- ▶ Select d , possible range $\mathbf{x} \in \mathbb{X}$, usually $\mathbb{X} = \{\mathbf{x} \mid \|\mathbf{x}\| \leq r, \mathbf{x} \in \mathbb{R}^d\}$ ($r = 1$)
- ▶ Select number of neurons n
- ▶ Select tuning curves, maximum rates
 $\Rightarrow \mathbf{e}_i, \alpha_i, J_i^{\text{bias}}$
 - ▶ Sample \mathbf{e}_i from unit-sphere
 - ▶ Uniformly distribute x -intercept, maximum rate
- ▶ Encoding equation:

$$a_i(\mathbf{x}) = G[\alpha_i \langle \mathbf{e}_i, \mathbf{x} \rangle + J_i^{\text{bias}}]$$



Summary: Building a model of neural representation (Decoding)

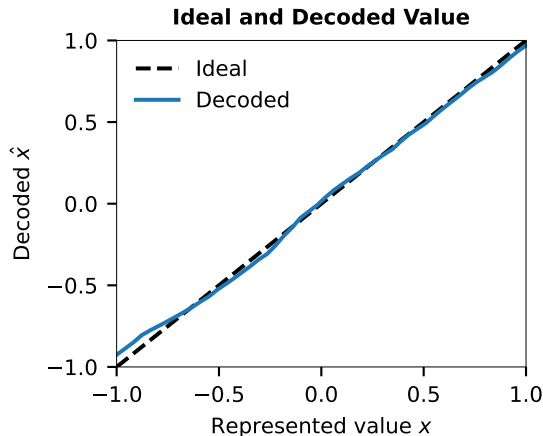
Decoding

- ▶ Uniformly sample N samples from \mathbb{X} , $\mathbf{X} = (\mathbf{x}_1, \dots, \mathbf{x}_N)$
- ▶ Compute \mathbf{A} , where $(\mathbf{A})_{ik} = a_i(\mathbf{x}_k)$
- ▶ Decoder computation:

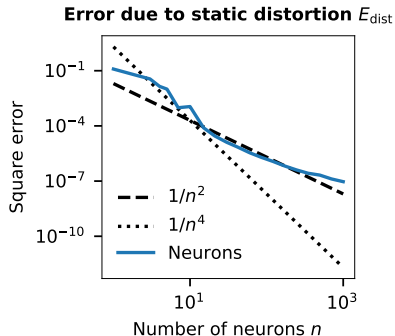
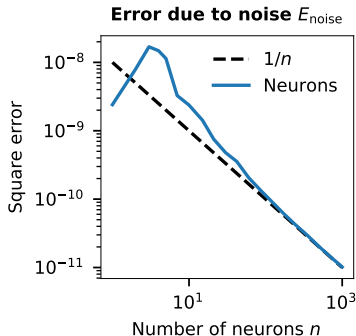
$$\mathbf{D}^T = (\mathbf{A}\mathbf{A}^T + N\sigma^2\mathbf{I})^{-1}\mathbf{A}\mathbf{X}^T$$

- ▶ Decoding equation:

$$\hat{\mathbf{X}} = \mathbf{D}\mathbf{A}$$

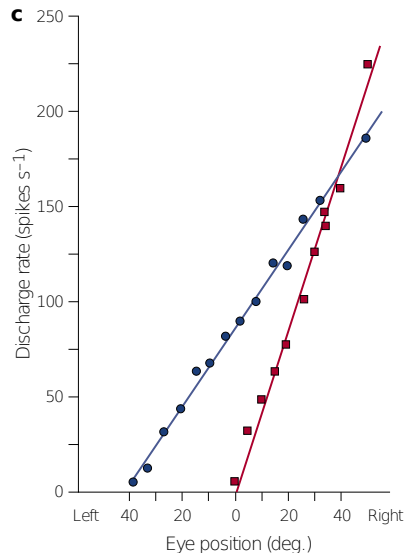
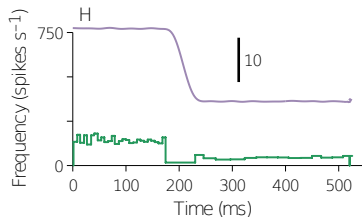
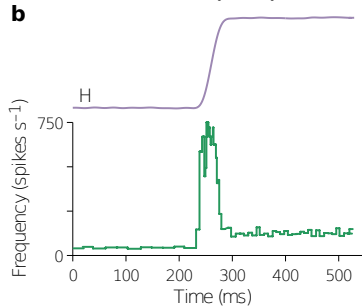
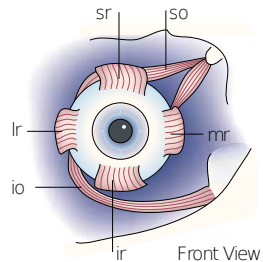
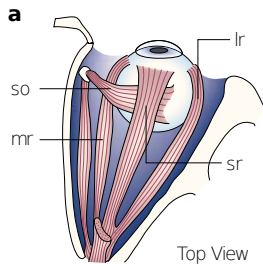


Analysing Sources of Errors



$$E = \underbrace{\frac{1}{2} \int_{-1}^1 \left(x - \sum_{i=1}^n d_i a_i(x) \right)^2 dx}_{E_{\text{dist}}} + \underbrace{\frac{1}{2} \sigma^2 \sum_{i=1}^n d_i^2}_{E_{\text{noise}}}$$

Example: Horizontal Eye Position (1D)



Example: Horizontal Eye Position (1D) (cont.)

► Step 1: System Description

- What is being represented?
 - x is the horizontal eye position
- What is the tuning curve shape?
 - Linear, low τ_{ref} , high τ_{RC}
 - $e_i \in \{1, -1\}$
 - Firing rates up to 300 s^{-1}

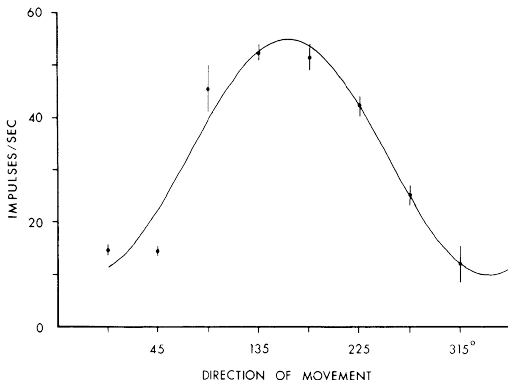
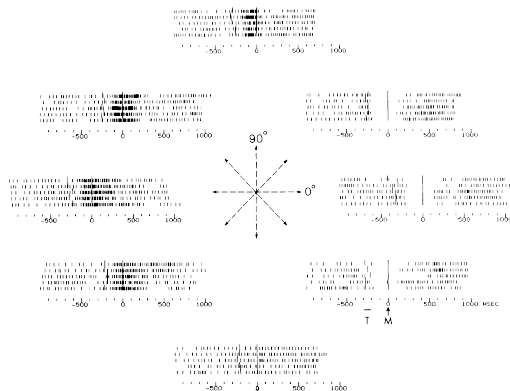
► Step 2: Design Specification

- Range of values
 - $\mathbb{X} = [-60, 60]$
- Amount of noise
 - About 20% of $\max(\mathbf{A})$

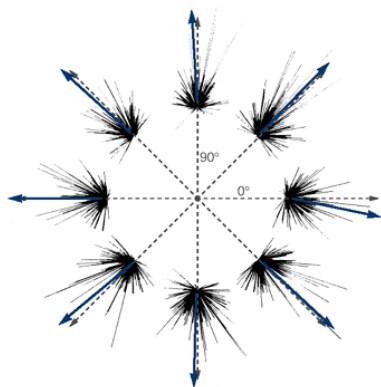
► Step 3: Implementation

- Choose tuning curve parameters
- Compute decoders

Example: Arm Movements (2D)



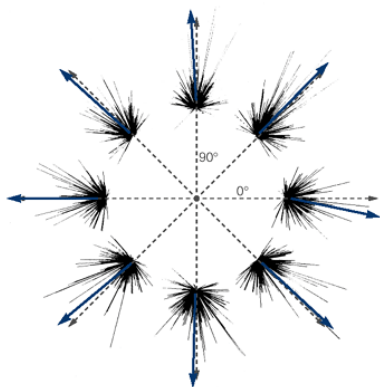
Example: Arm Movements (2D) (cont.)



- ▶ Experiment by Georgopoulos et al., 1982
- ▶ Preferred arm movement directions \mathbf{e}_i
- ▶ **Idea:** *Population Vectors*, decode using

$$\hat{\mathbf{x}} = \sum_{i=1}^n a_i(\mathbf{x}) \mathbf{e}_i = \mathbf{E} \mathbf{A}$$

Example: Arm Movements (2D) (cont.)

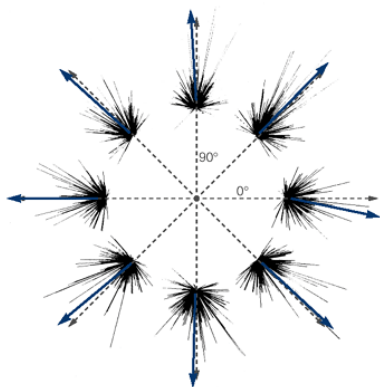


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- ⊕ Good direction estimate

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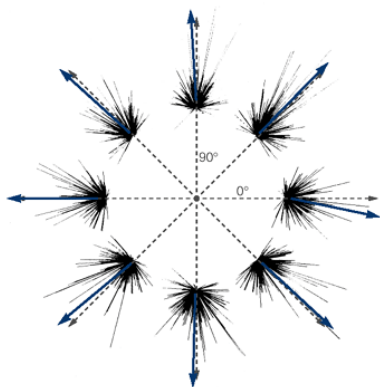


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- ⊖ Cannot reconstruct magnitude

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- + Good direction estimate
- Cannot reconstruct magnitude

The NEF does not use population vectors!

Example: Arm Movements (2D) (cont.)

► Step 1: System Description

- What is being represented?
 - \mathbf{x} the movement direction (or hand position)
- What is the tuning curve shape?
 - Bell-shaped
 - Encoders are randomly distributed along the unit circle
 - Firing rates up to 60 s^{-1}

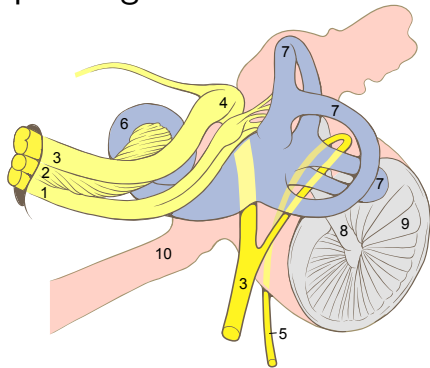
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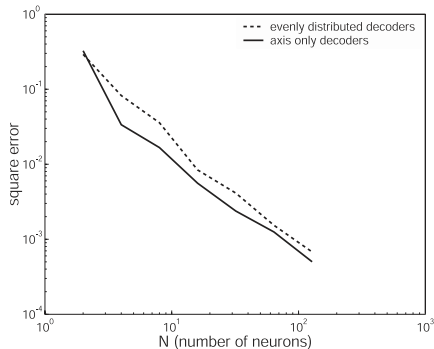
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Example: Higher Dimensional Representation

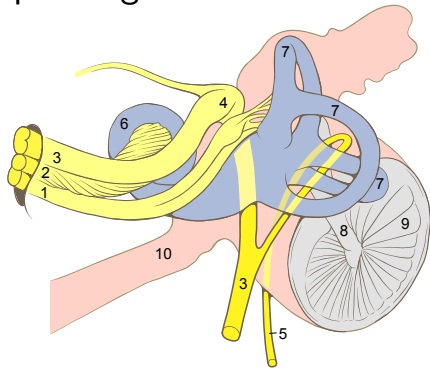


- ▶ Vestibular system senses head acceleration in 3D
- ▶ Axis aligned, must choose $\mathbf{e}_i \in \{[1, 0, 0], [-1, 0, 0], \dots, [0, 0, -1]\}$

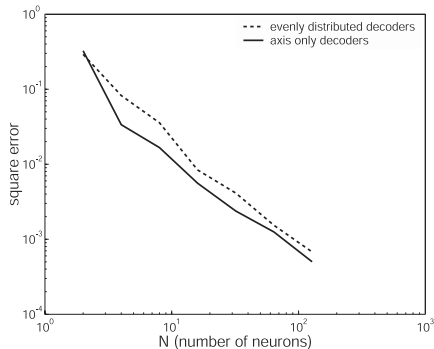


- ▶ Same as three 1D populations
- ▶ Slightly better precision

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- ▶ Same as three 1D populations
- ▶ Slightly better precision
- ▶ **Encoders affect accuracy**

Administration

- ▶ **Assignment 1 has been released.**

Image sources

Title slide

“The Ultimate painting.”

Author: Clark Richert.

From Wikimedia.