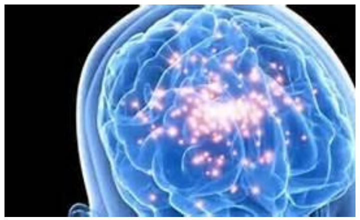
CISC 3250
Systems Neuroscience

Representations in the brain



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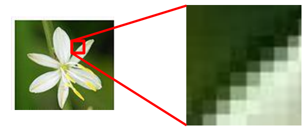
JMH 332

Computational representations describing a visual object

- A picture is worth a million pixels
  - Digital picture broken into a grid of boxes – pixels
  - Each pixel contains a color



dkGrn dkdkGrn
dkGrn white
white
grey
ltGrey grey

- Translate from pixels to category label:

floss flour flower flume flute foam

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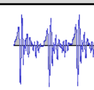
Computer storage

Memory for data

- Information stored as billions of numbers (giga-bytes)
- Groups of numbers stored in sequence represent single concept
  - flower 1000 x 1000 x 3 matrix
- Each piece of information has location in memory
  - flower starts at address 100,000,5000
  - song1 starts at address 103,000,5000

Memory

⋮
flower: 1,1,red
1,1,green
1,1,blue
1,2,red
1,2,green
1,2,blue
⋮
1000,1000,red
1000,1000,green
1000,1000,blue
song1: sound at 0ms
sound at 10ms
sound at 20ms



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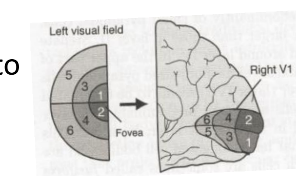
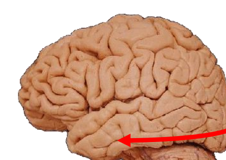
Data in the brain

- Neural location related to information encoded



- Progression of encoding for increasingly complex concepts



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Simple outline of vision pathway

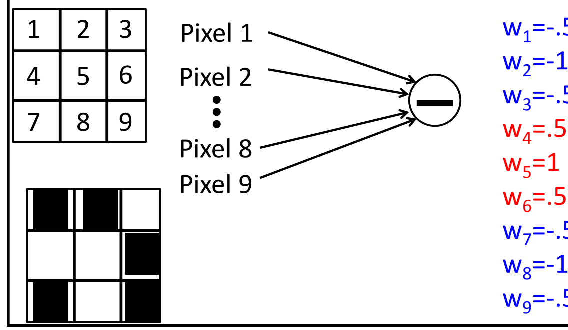
1. Retina: pixel detectors
2. Primary visual cortex (V1): edge detectors
3. Second-cortical layer (V2?): edge combination detectors

. . .

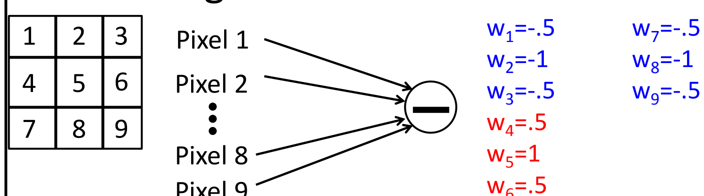
N. Higher-cortical layer: Full-object detectors

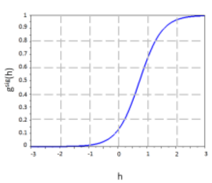
Interacting representations: feedforward network

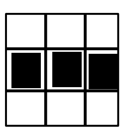
- More-complex information/features computed from simpler information/features



Edge detector in action

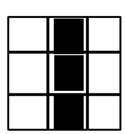






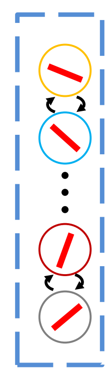
p_1=0, p_2=0, p_3=0,
p_4=1, p_5=1, p_6=1,
p_7=0, p_8=0, p_9=0

h=.5+1+.5=2
g(2)=0.95

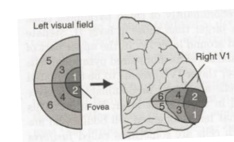


p_1=0, p_2=1, p_3=0,
p_4=0, p_5=1, p_6=0,
p_7=0, p_8=1, p_9=0

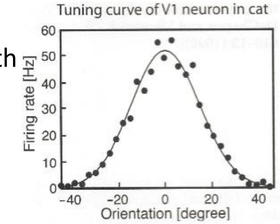
Cortical organization and feature organization



Nearby neurons respond to similar features



Tuning curve of V1 neuron in cat

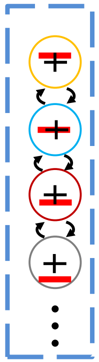


Neuron can respond with intermediate rates to features deviating from maximum preference

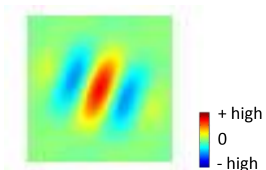
Can be supported by local excitation

Henry et al., *J Neurophys* 1974.

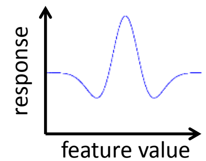
Lateral connections: surround suppresion



Neuron can have suppressed response for features deviant from maximum preference



Typical V1 receptive field



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Suppression/competition with interneurons

- In common cortical circuits, there are feedforward excitatory inputs and lateral inhibitory inputs
- Relative weighting achieves balance between activation and suppression

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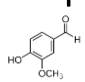
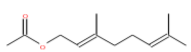
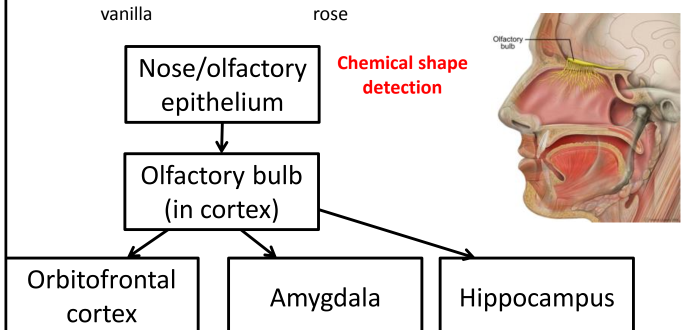
The pathway for smell processing



vanilla



rose



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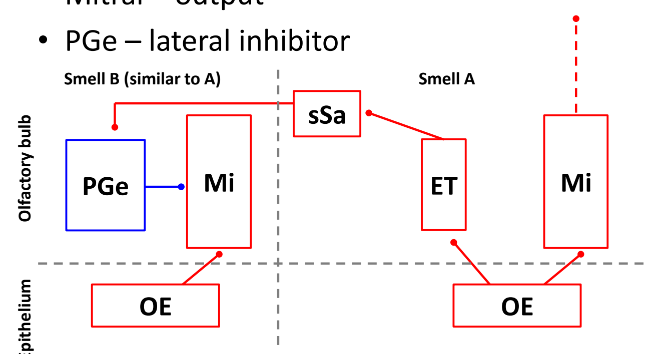
Simplified circuit

- Olfactory Epithelium (OE) – input
- Mitral – output
- PGe – lateral inhibitor



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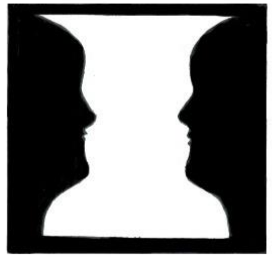
Competition on behavior level

Opposing interpretations of scene



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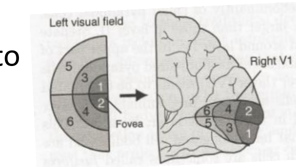
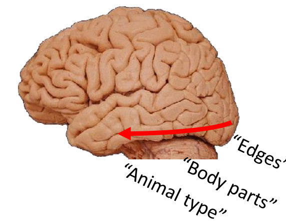
Data in the brain

- Neural location related to information encoded



- Progression of encoding for increasingly complex concepts



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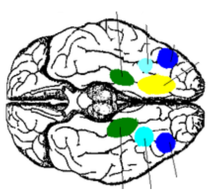
Classes of representation

Local representation

- Neural level: “grandmother” cell
- “Region” level: face region, place region



Parahippocampal place area

Fusiform face area

Visual word form area

Lateral occipital cortex (shapes)

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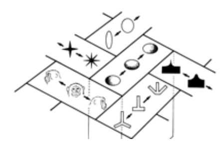
Classes of representation

Fully distributed representation

- Every neuron/region plays a part

Sparsely-distributed representation

- Neural level: hyper-column for perceptual feature



Tanaka 2003, columns of neurons for shape types in IT

- “Region” level: face network in medial temporal, lateral temporal, anterior parietal

Principles of information coding: binary

How many things can we represent with *n* binary (g^{step} activation function) neurons?

- Complete sparse coding: n things

firing / not firing

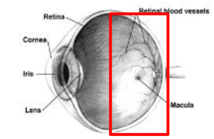
banana   apple   pear

- Complete distributed coding: 2^n things

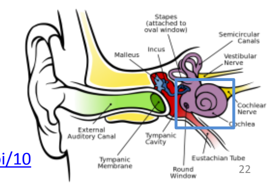
banana   blueberry
orange   apple   pear
lime   lemon   No fruit

Biology of sparse coding

- Preserving energy – higher spiking rate requires higher energy
- Representational fan-out
  - ~1 million neurons in retina -> ~140 million neurons in V1 (primary visual cortex)



  - ~50,000 neurons in cochlea -> 1.6 million neurons in A1 (primary auditory cortex)



http://www.plosbiology.org/article/info:doi/10.1371/journal.pbio.0030137

Coding on a scale: sparsity

high firing / mid firing / not firing

sad / ambi-valent / happy — mood (sad – happy)

young / mid-age / old — age (0 – 100)

bald / mid-hair / hairy — amount hair (bald – long)

Typically we will say "sparsity" is using at most 10% of available neurons

Coding on a scale: distributed + overlapping

high firing / mid firing / not firing

sad / ambi-valent / happy — mood (sad – happy)

young / mid-age / old — age (0 – 100)

bald / mid-hair / hairy — amount hair (bald – long)

What does this encode?

Coding on a scale: distributed + overlapping

Responses for each property add together

1 - 1 Hz – sad	- 1 1 Hz – young	- - 1 Hz – bald
25 – 25 Hz – neutral	- 25 25 Hz – middle	- - 25 Hz – middle
50 – 50 Hz – happy	- 50 50 Hz – old	- - 50 Hz – full-hair
mood (sad – happy)	age (0 – 100)	amount hair (bald – long)

How do we encode: happy (100%), mid-age (50%), light hair (1%)?

$$\sum_j level_j \; pattern_j$$

Coding on a scale: distributed + overlapping

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How do we encode: happy (100%), mid-age (50%), light hair (1%)?

$$\sum_j level_j \; pattern_j$$

n1	n2	n3	
50	0	50	happy
0	25	25	mid-age
0	0	5	light hair
50	**25**	**80**	

Coding on a scale: distributed + overlapping

Responses for each property add together

1 – 1 Hz – sad	- 1 1 Hz – young	- - 1 Hz – bald
25 – 25 Hz – neutral	- 25 25 Hz – middle	- - 25 Hz – middle
50 – 50 Hz – happy	- 50 50 Hz – old	- - 50 Hz – full-hair
mood (sad – happy)	age (0 – 100)	amount hair (bald – long)

How do we encode: sad (5%), mid-age (50%), hairy (100%)?

$$\sum_j level_j \; pattern_j$$

Coding on a scale: distributed + overlapping

Responses for each property add together

1 – 1 Hz – sad	- 1 1 Hz – young	- - 1 Hz – bald
25 – 25 Hz – neutral	- 25 25 Hz – middle	- - 25 Hz – middle
50 – 50 Hz – happy	- 50 50 Hz – old	- - 50 Hz – full-hair
mood (sad – happy)	age (0 – 100)	amount hair (bald – long)

How do we encode: sad (5%), mid-age (50%), hairy (100%)?

$$\sum_j level_j \; pattern_j$$

n1	n2	n3	
2.5	0	2.5	happy
0	25	25	mid-age
0	0	50	light hair
2.5	**25**	**77.5**	

Coding on a scale: distributed + overlapping

Responses for each property add together

mood (sad – happy)	age (0 – 100)	amount hair (bald – long)
1 – 1 Hz – sad	- 1 1 Hz – young	- - 1 Hz – bald
25 – 25 Hz – neutral	- 25 25 Hz – middle	- - 25 Hz – middle
50 – 50 Hz – happy	- 50 50 Hz – old	- - 50 Hz – full-hair

What does this encode? 0 20 40

What does this encode? 50 20 75

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Decoding large neural codes

Information from neuron patterns

- Happy 
- Old 
- Hairy 
- Loud 

Overlay of multiple patterns and noise

- What property is this?

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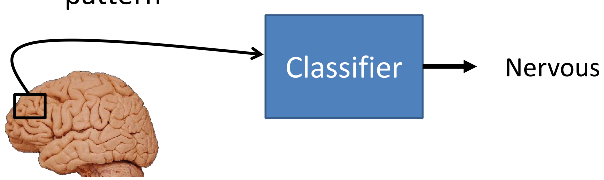
Decoding large neural codes

Classifier:

- If consistent response, can learn pattern
- If irrelevant response, cannot learn helpful pattern



Method:

- 500 trials – measure mood, record brain responses
- Make classifier from neural patterns in trials 1-250
- Find accuracy to predict mood in trials 251-500

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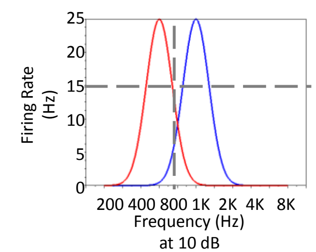
Decoding with tuning curves

Use spiking rates from multiple neurons to determine encoded feature



- 15 Hz firing rate for red neuron means sound 400 or 800 Hz (at 10 dB)
- 15 Hz for red and 6 Hz for blue requires sound 800 Hz (at 10 dB)

Actual decoding incorporates noise/natural variability in spiking

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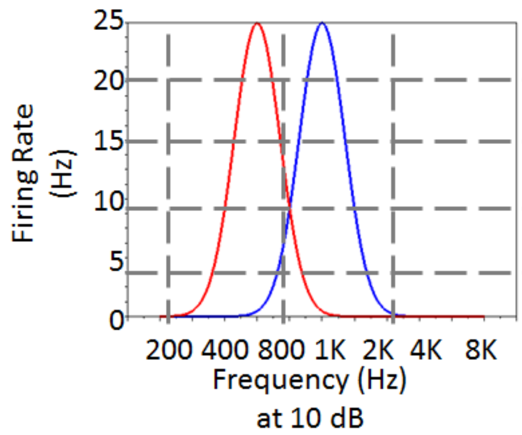

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Population coding to find direction of motion

Non-normalized population coding

- $s_{dir} = \sum_i r_i s_i^{pref}$

r	1	4	1	0
	↓	→	↑	←
s^{pref} $\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 0 \\ -1 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -1 \\ 0 \end{bmatrix}$

$s_{dir} =$

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Population coding to find direction of motion

"Normalized" firing rate

- $\hat{r}_i = \dfrac{r_i - r_i^{min}}{r_i^{max} - r_i^{min}}$

If $r^{min} = 1, r^{max} = 6$ for →
Then $\hat{r}_i = \frac{4-1}{6-1} = \frac{3}{5} = 0.6$

Normalized $\hat{r}$ will always be between 0 and 1

r	4
	→
s^{pref} $\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$

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Normalized firing rates

r^{min}=0 Hz, r^{max}=60 Hz

r	30	30	10	0
	↓	→	↑	←
s^{pref} $\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 0 \\ -1 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -1 \\ 0 \end{bmatrix}$

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Population coding to find direction of motion

“Normalized” pop’n coding

For $\hat{s}_{pop}$, divide normalized rate by sum of all rates in neural population: $\sum_j \hat{r}_j$

- $\hat{s}_{pop} = \sum_i \frac{\hat{r}_i}{\sum_j \hat{r}_j} s_i^{pref}$

$\hat{r}$	0.05	0.5	0.05	0
	↓	→	↑	←
s^{pref} $\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 0 \\ -1 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -1 \\ 0 \end{bmatrix}$

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Population coding to find direction of motion

“Normalized” pop’n coding

For $\hat{s}_{pop}$, divide normalized rate by sum of all rates in neural population: $\sum_j \hat{r}_j$

- $\hat{s}_{pop} = \sum_i \frac{\hat{r}_i}{\sum_j \hat{r}_j} s_i^{pref}$

$\hat{r}$	0.05	0.5	0.05	0
	↓	→	↑	←
s^{pref} $\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 0 \\ -1 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -1 \\ 0 \end{bmatrix}$

$$\sum_j \hat{r}_j = 0.05 + 0.5 + 0.05 + 0 = 0.6$$

$$\begin{bmatrix} x \\ y \end{bmatrix} = \frac{0.05}{0.6}\begin{bmatrix} 0 \\ -1 \end{bmatrix} + \frac{0.5}{0.6}\begin{bmatrix} 1 \\ 0 \end{bmatrix} + \frac{0.05}{0.6}\begin{bmatrix} 0 \\ 1 \end{bmatrix} + 0\begin{bmatrix} -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.83 \\ 0 \end{bmatrix}$$

Find most-favored motion direction, do no amplify motion distance

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Another example

Assume for all neurons r^{min}=10 Hz, r^{max}=100 Hz

r	50	70	10	30
	↓	→	↑	←
$\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 0 \\ -1 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -1 \\ 0 \end{bmatrix}$

Linear algebra

- Left matrix: data
  - Rows: different data points
  - Columns: different features
- Right matrix: column contains weights for weighted sum

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Matrices and weighted sums

r 1 4 1 0

$$\begin{bmatrix} x \\ y \end{bmatrix} \quad \begin{bmatrix} 0 \\ -1 \end{bmatrix} \quad \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad \begin{bmatrix} -1 \\ 0 \end{bmatrix}$$

$$1\begin{bmatrix} 0 \\ -1 \end{bmatrix} + 4\begin{bmatrix} 1 \\ 0 \end{bmatrix} + 1\begin{bmatrix} 0 \\ 1 \end{bmatrix} + 0\begin{bmatrix} -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 1 & 0 & -1 \\ -1 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 4 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \end{bmatrix}$$

Matrix multiplication:
Sum {left row x right column}

$$\begin{bmatrix} a & b & c \\ d & e & f \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} ax + by + cz \\ dx + ey + fz \end{bmatrix}$$

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