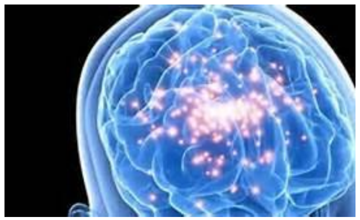
CISC 3250 Systems Neuroscience

Representations in the brain



Professor Daniel Leeds
dleeds@fordham.edu
JMH 332

How do we represent our world? Diverse sensations

Dog

- Body parts
  - tail, ears, legs
- Sounds
  - bark, whimper, pant
- Feel
  - fur

Flower

- Appearance
  - color, size, shape
- Smell
- Feel
  - texture, temperature

We call each piece of information a "feature"

2

How do we represent our world? One sensation, multiple levels

Song

- Meaning of words
- Pitch/melody
- Rhythm
- Language
- Singer identity

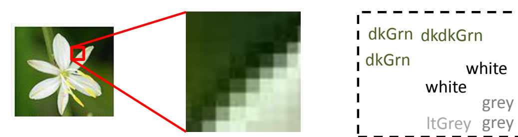
Dance

- Body part
  - arms, hands, legs
- Direction
  - forward, to-the-left
- Timing
  - order of moves, speed

3

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



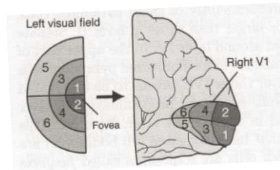
- Translate from pixels to category label:

floss flour flower flume flute foam

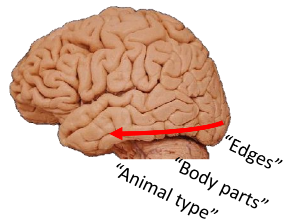
4

Data in the brain

- Neural location related to information encoded



- Progression of encoding for increasingly complex concepts



Simple outline of vision pathway

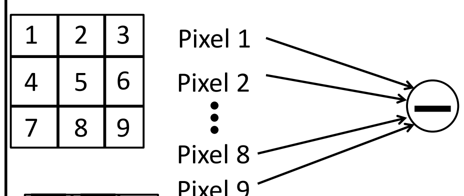
1. Retina: pixel detectors
2. Primary visual cortex (V1): edge detectors
3. Second-cortical layer (V2?): edge combination detectors

. . .

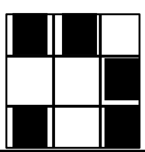
N. Higher-cortical layer: Full-object detectors

Interacting representations: feedforward network

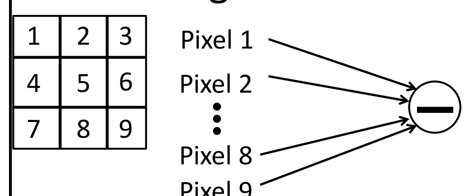
- More-complex information/features computed from simpler information/features



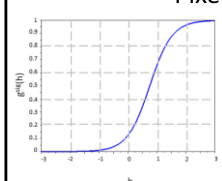
w_1=-.5
w_2=-1
w_3=-.5
w_4=.5
w_5=1
w_6=.5
w_7=-.5
w_8=-1
w_9=-.5

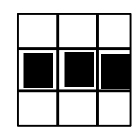


Edge detector in action



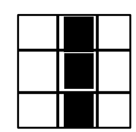
w_1=-.5
w_2=-1
w_3=-.5
w_4=.5
w_5=1
w_6=.5
w_7=-.5
w_8=-1
w_9=-.5





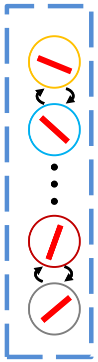
p_1=0, p_2=0, p_3=0,
p_4=1, p_5=1, p_6=1,
p_7=0, p_8=0, p_9=0

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

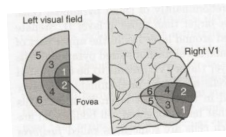


p_1=0, p_2=1, p_3=0,
p_4=0, p_5=1, p_6=0,
p_7=0, p_8=1, p_9=0

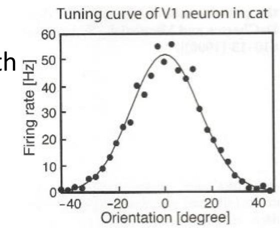
Cortical organization and feature organization



Nearby neurons respond to similar features



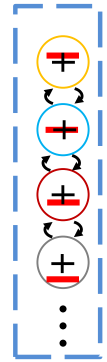
Neuron can respond with intermediate rates to features deviating from maximum preference



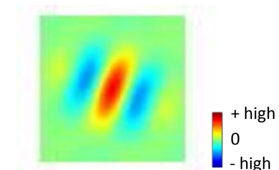
Can be supported by local excitation

Henry et al., *J Neurophys* 1974.

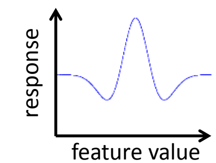
Lateral connections: surround suppresion



Neuron can have suppressed response for features deviant from maximum preference



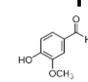
Typical V1 receptive field



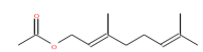
Suppression/competition with interneurons

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

The pathway for smell processing



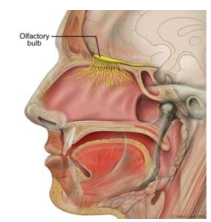
vanilla



rose

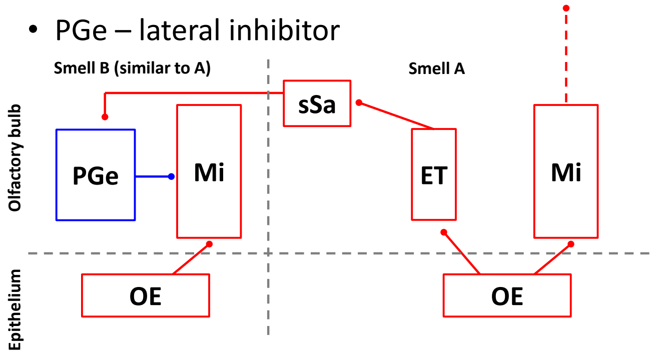
Nose/olfactory epithelium → Olfactory bulb (in cortex) → Orbitofrontal cortex; Amygdala; Hippocampus

Chemical shape detection



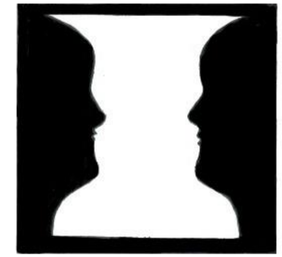
Simplified circuit

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



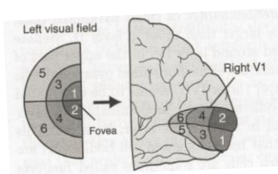
Competition on behavior level

Opposing interpretations of scene

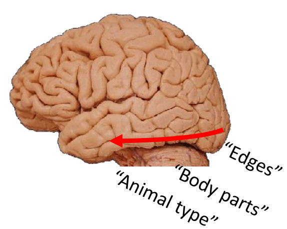


Data in the brain

- Neural location related to information encoded



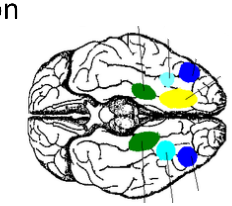
- Progression of encoding for increasingly complex concepts



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)

Classes of representation

Fully distributed representation

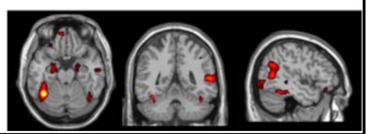
- Every neuron/region plays a part

Sparsely-distributed representation

- Neural level: hyper-column for perceptual feature

Tanaka 2003, columns of neurons for shape types in IT

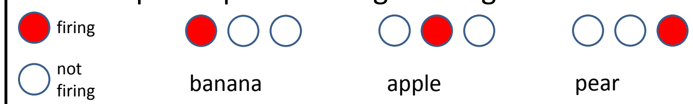
- "Region" level: face network in medial temporal, lateral temporal, anterior parietal



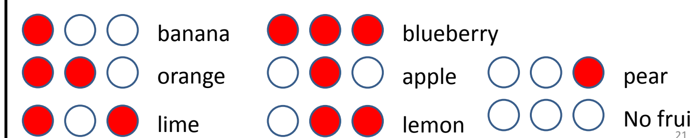
Principles of information coding: binary

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

- Complete sparse coding: n things

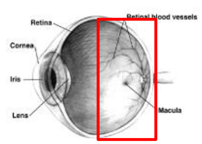


- Complete distributed coding: 2^n things

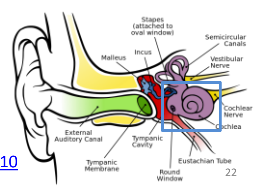


Biology of sparse coding

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

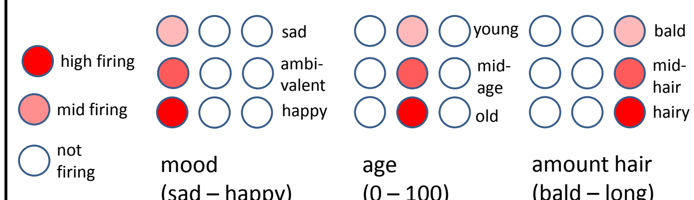


  - ~50,000 neurons in cochlea -> 1.6 million neurons in A1 (primary auditory cortex)



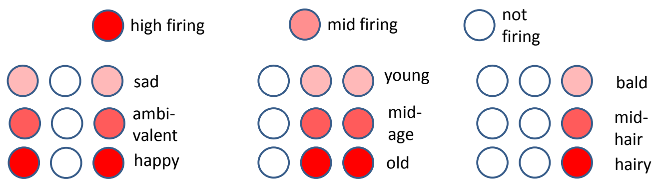
http://www.plosbiology.org/article/info:doi/10.1371/journal.pbio.0030137

Coding on a scale: sparsity



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

Coding on a scale: distributed + overlapping



mood
(sad – happy)

age
(0 – 100)

amount hair
(bald – long)

What does this encode? 

Coding on a scale: distributed + overlapping

Responses for each property add together

.1 0 .1 – sad
.5 0 .5 – neutral
.9 0 .9 – happy
mood
(sad – happy)

0 .1 .1 – young
0 .5 .5 – middle
0 .9 .9 – old
age
(0 – 100)

0 0 .1 – bald
0 0 .5 – middle
0 0 .9 – full-hair
amount hair
(bald – long)

How do we encode: sad (0), mid-age (.5), hairy (1.0)?

$\sum_j level_j\ pattern_j$

n1	n2	n3
0	0	0
0	.5	.5
0	0	1
0	**.5**	**1.5**

Coding on a scale: distributed + overlapping

Responses for each property add together

.1 0 .1 – sad
.5 0 .5 – neutral
.9 0 .9 – happy
mood
(sad – happy)

0 .1 .1 – young
0 .5 .5 – middle
0 .9 .9 – old
age
(0 – 100)

0 0 .1 – bald
0 0 .5 – middle
0 0 .9 – full-hair
amount hair
(bald – long)

How do we encode: happy-ish (.8), young-ish (.2), some-hair (0.5)? $\sum_j level_j\ pattern_j$

n1	n2	n3
.8	0	.8
0	.2	.2
0	0	.5
.9	**.2**	**1.5**

Coding on a scale: distributed + overlapping

Responses for each property add together

.1 0 .1 – sad
.5 0 .5 – neutral
.9 0 .9 – happy
mood
(sad – happy)

0 .1 .1 – young
0 .5 .5 – middle
0 .9 .9 – old
age
(0 – 100)

0 0 .1 – bald
0 0 .5 – middle
0 0 .9 – full-hair
amount hair
(bald – long)

What does this encode? 0 .4 .8

What does this encode? 1 .5 1.5

Coding on a scale: distributed + overlapping

Responses for each property add together

.1 0 .1 – sad	0 .1 .1 – young	0 0 .1 – bald
.5 0 .5 – neutral	0 .5 .5 – middle	0 0 .5 – middle
.9 0 .9 – happy	0 .9 .9 – old	0 0 .9 – full-hair
mood (sad – happy)	age (0 – 100)	amount hair (bald – long)

What does this encode? 0 .4 .8 (Neuron 1, Neuron 2, Neuron 3)

Very sad: contributes: 0 x [1 0 1] = 0 0 0

Middle-age: contributes .4 x [0 1 1] = 0 .4 .4

Middle-hair: contributes .4 x [0 0 1] = 0 0 .4

Summing together: 0 .4 .8

30

Coding on a scale: distributed + overlapping

Responses for each property add together

.1 0 .1 – sad	0 .1 .1 – young	0 0 .1 – bald
.5 0 .5 – neutral	0 .5 .5 – middle	0 0 .5 – middle
.9 0 .9 – happy	0 .9 .9 – old	0 0 .9 – full-hair
mood (sad – happy)	age (0 – 100)	amount hair (bald – long)

What does this encode? 1 .5 1.5 (Neuron 1, Neuron 2, Neuron 3)

Very happy: contributes 1 x [1 0 1] = 1 0 1

Middle-age: contributes .5 x [0 1 1] = 0 .5 .5

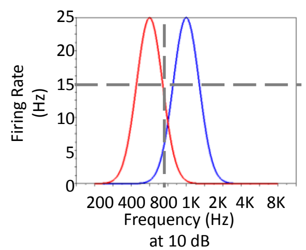
Bald: contributes 0 x [0 0 1] = 0 0 0

Summing together: 1 .5 1.5

31

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

34

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

$s_{dir} =$

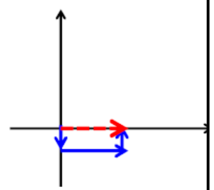
37

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



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

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

Normalized firing rates

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

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

Normalized firing rates

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

	0.5	0.5	0.16	0
r	30	30	10	0
	↓	→	↑	←
s^{pref} $\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 0 \\ -1 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -1 \\ 0 \end{bmatrix}$

$$\begin{bmatrix} \mathbf{0.5} \\ \mathbf{0} \end{bmatrix}$$

Population coding to find direction of motion

"Normalized" pop'n coding

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

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

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

45

Population coding to find direction of motion

"Normalized" pop'n coding

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

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

$\hat{r}$		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

46

Another example

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

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

Another example

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

r	50	70	10	30
	↓	→	↑	←
$\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 0 \\ -1 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -1 \\ 0 \end{bmatrix}$
	$\frac{50-10}{100}$	$\frac{70-10}{100}$	$\frac{10-10}{100}$	$\frac{30-10}{100}$
$\hat{r}$	0.4	0.6	0	0.2
	$\frac{.4}{1.2}$	$\frac{.6}{1.2}$	$\frac{0}{1.2}$	$\frac{.2}{1.2}$
$\hat{r}^{pop}$	0.33	0.5	0	0.16

.4+.6+.2 = 1.2

$\hat{s}^{pop} = \begin{bmatrix} .34 \\ -.33 \end{bmatrix}$

48

A third example

Assume for all neurons
r^{min}=20 Hz, r^{max}=80 Hz

r	20	20	30	50
	↓	→	↑	←
$\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 0 \\ -1 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -1 \\ 0 \end{bmatrix}$
	$\frac{20-20}{80}$	$\frac{20-20}{80}$	$\frac{30-20}{80}$	$\frac{50-20}{80}$
$\hat{r}$	0	0	0.13	0.38
	$\frac{0}{.51}$	$\frac{0}{.51}$	$\frac{.13}{.52}$	$\frac{.38}{.51}$
$\hat{r}^{pop}$	0	0	.26	0.76

.13+.38 = .51

$$\hat{s}^{pop} = \begin{bmatrix} -.76 \\ .26 \end{bmatrix}$$

49

Decoding large neural codes

Information from neuron patterns

- Happy 
- Old 
- Hairy 
- Loud 

Overlay of multiple patterns and noise

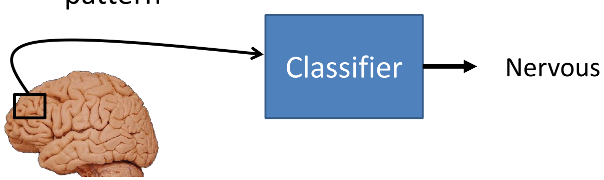
- What property is this?

52

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

53