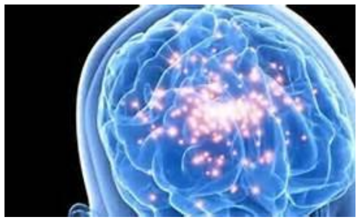
CISC 3250 Systems Neuroscience

Representations in the brain



Professor Daniel Leeds
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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"

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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

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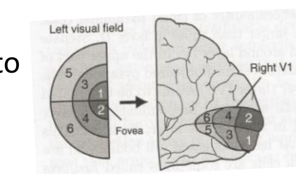
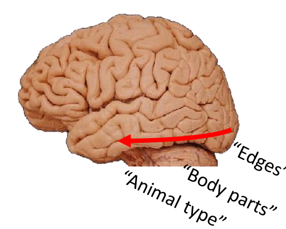
Data in the brain

- Neural location related to information encoded



- Progression of encoding for increasingly complex concepts



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Simple outline of vision pathway

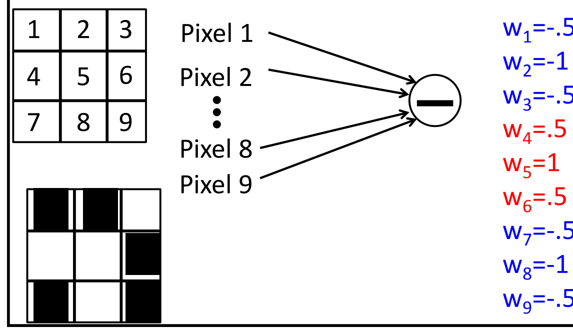
1. Retina: pixel detectors
2. Primary visual cortex (V1): edge detectors
3. Second-cortical layer (V2?): edge combination detectors

. . .

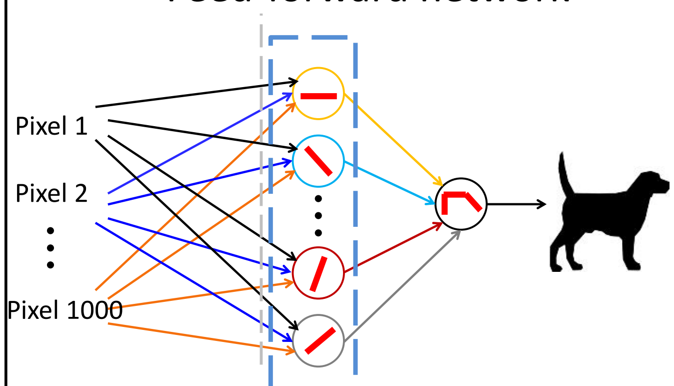
N. Higher-cortical layer: Full-object detectors

Interacting representations: feedforward network

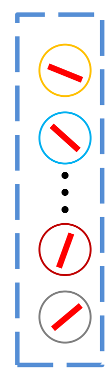
- More-complex information/features computed from simpler information/features



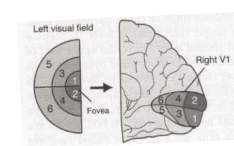
Feed-forward network



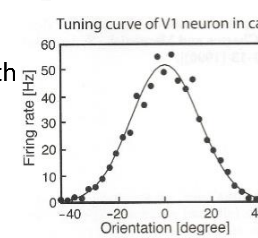
Cortical organization and feature organization



Nearby neurons respond to similar features

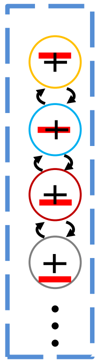


Neuron can respond with intermediate rates to features deviating from maximum preference

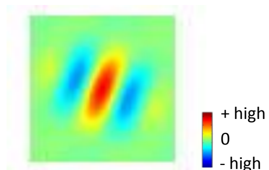


Henry et al., *J Neurophys* 1974.

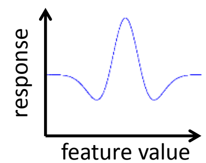
Lateral connections: surround suppresion



Neuron can have suppressed response for features deviant from maximum preference



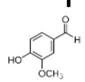
Typical V1 receptive field



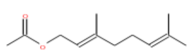
Suppression/competition with interneurons

- 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

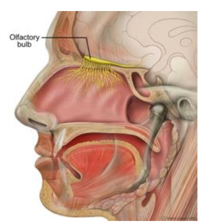
Chemical shape detection

Olfactory bulb (in cortex)

Orbitofrontal cortex

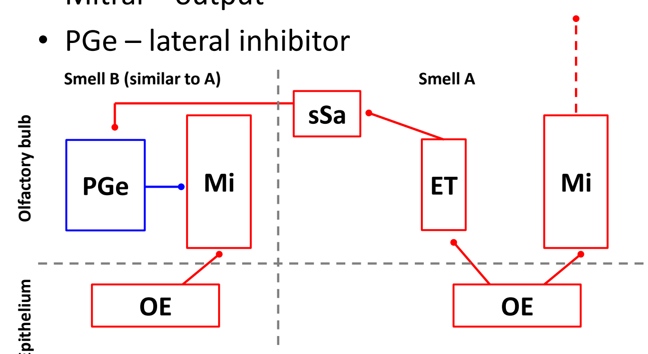
Amygdala

Hippocampus



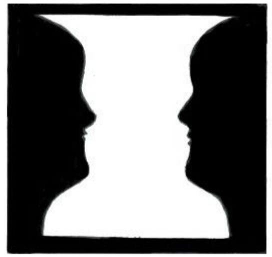
Simplified circuit

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



Competition on behavior level

Opposing interpretations of scene



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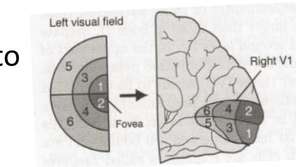
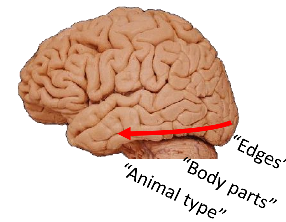
Data in the brain

- Neural location related to information encoded



- Progression of encoding for increasingly complex concepts



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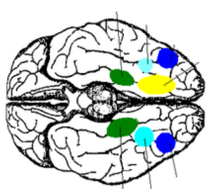
Classes of representation

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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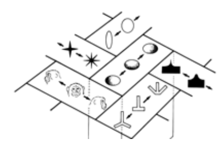
Classes of representation

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

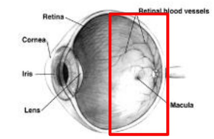
banana — apple — pear

- Complete distributed coding: 2^n things

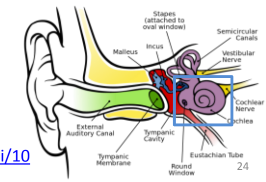
banana, orange, lime, blueberry, apple, lemon, pear, No fruit

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 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

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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**

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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**

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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)

0 .1 .2 – light
0 .2 .4 – middle
0 .4 .8 – lots
freckles
(some – lots)

What does this encode? 0 .4 .8

If each of *n* neurons is coding on a scale, at most *n* distinguishable concepts can be encoded

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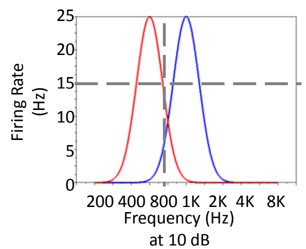
Decoding with tuning curves

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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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

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

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

If $r^{min} = 1, r^{max} = 6$ for →
Then $\hat{r} = \frac{4-1}{6} = \frac{3}{6} = 0.5$

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

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

Another example

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

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

Decoding large neural codes

Information from neuron patterns

- Happy 
- Sad 
- Angry 
- Nervous 

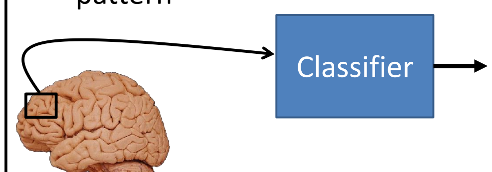
Overlay of multiple patterns and noise

- What mood is this?

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