CISC 3250
Systems Neuroscience

Representations in the brain

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JMH 328A

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 concept, 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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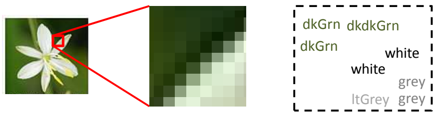
Computational representations describing a visual object

- 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

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Computational representations numeric encoding of a visual object

Each pixel represents color as

- red intensity (0-255) + green intensity (0-255) + blue intensity (0-255)
- 1,000,000 x 3 -> 3,000,000 color numbers
- Category can be represented by a single number, but more (~1,000,000) numbers to choose from

floss	flour	flower	flume	flute	foam
5501	5502	5503	5504	5505	5506

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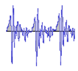
Computer storage

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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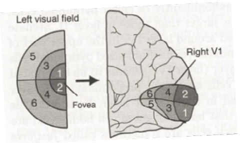
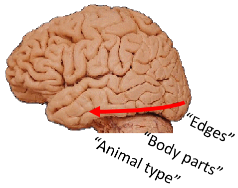
Data in the brain

- Neural location related to information encoded



- Progression of encoding for increasingly complex concepts



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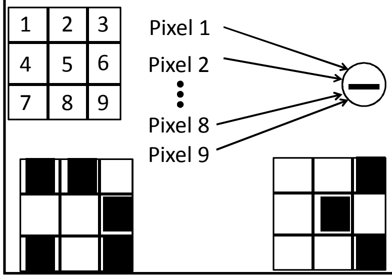
Interacting representations: feedforward network

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



w_1=-1
w_2=-1
w_3=-1
w_4=1
w_5=1
w_6=1
w_7=-1
w_8=-1
w_8=-1

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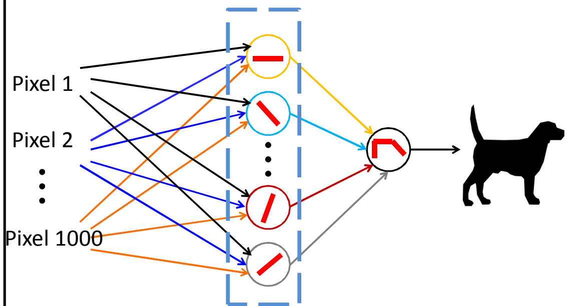
Feed-forward network



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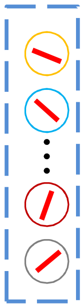
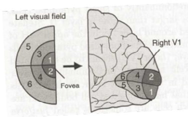
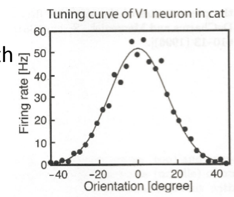
Cortical organization and feature organization



Nearby neurons respond to similar features



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



Henry et al., *J Neurophys* 1974.

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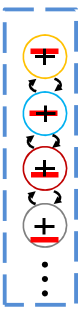
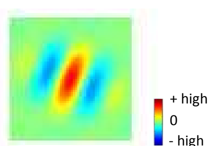
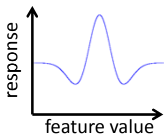
Lateral connections: surround suppression



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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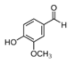
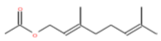
The pathway for smell processing



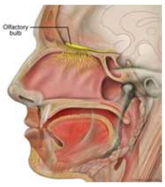
vanilla



rose

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

Chemical shape detection



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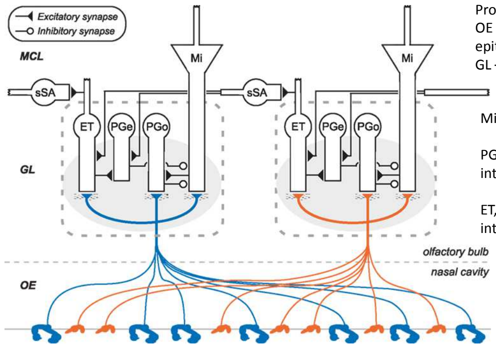
The neuroscience of smell: example inhibition with interneurons



Processing layers:
OE – olfactory epithelium
GL – glomerulus

Mi – Mitral cell

PGe/o – inhib. interneurons

ET, sSA – excit. interneurons

Imam et al. Frontiers Neurosci 2012

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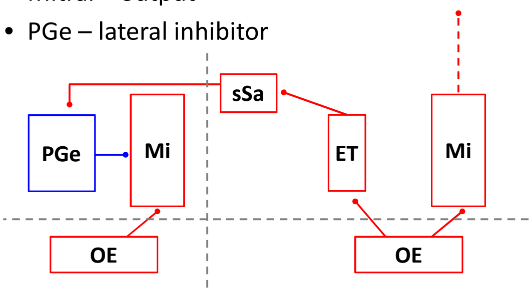
Simplified circuit

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



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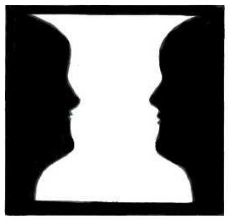
Competition on behavior level

Opposing interpretations of scene
Ocular competition



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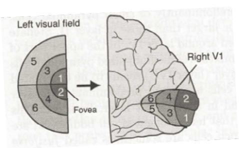
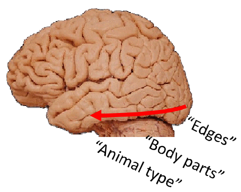
Data in the brain

- Neural location related to information encoded



- Progression of encoding for increasingly complex concepts



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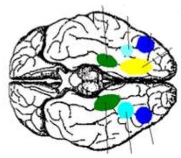
Classes of representation

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

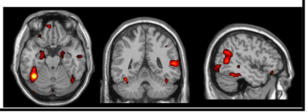
- Every neuron/region plays a part

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, grape

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Coding on a scale: sparsity

high firing / mid firing / not firing

mood (sad – happy)

age (0 – 100)

amount hair (bald – long)

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Coding on a scale: distributed

high firing / mid firing / not firing

mood (sad – happy)

age (0 – 100)

amount hair (bald – long)

freckles (some – lots)

What does this encode?

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

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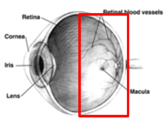
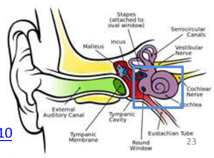
Biology of information coding

- 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

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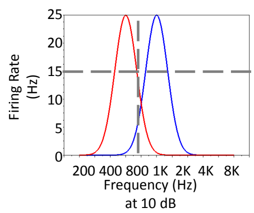
Decoding with tuning curves

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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Decoding by "population coding"

Each neuron votes for its most-preferred feature

- $\hat{s}_{dir} = \sum_i r_i s_i^{pref}$

r – spiking rate
s – encoded feature

"Normalized" firing rate

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

Used in neural prosthetic technologies

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Population coding to find direction of motion

Non-normalized population coding

- $\hat{s}_{dir} = \sum_i r_i s_i^{pref}$

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

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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: $\sum_j \hat{r}_j$

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

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

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

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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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Linear algebra

- Math on lists of numbers
  - Firing rates of multiple neurons
  - x,y,z directions/locations encoded by neurons
  - Multiple features (mood, hair, age) of percept

r	1	4	1	0
	$\downarrow$	$\rightarrow$	$\uparrow$	$\leftarrow$
$\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 0 \\ -1 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -1 \\ 0 \end{bmatrix}$

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

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Matrices and weighted sums

r	1	4	1	0
	$\downarrow$	$\rightarrow$	$\uparrow$	$\leftarrow$
$\begin{bmatrix} x \\ y \end{bmatrix}$	$\begin{bmatrix} 0 \\ -1 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -1 \\ 0 \end{bmatrix}$

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

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

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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Linear algebra

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

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