CISC 3250
Systems Neuroscience

Representations in the brain

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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
  - texture, temperature

We call each piece of information a “feature”

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

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

Pixel 1

Pixel 2

Pixel 3

Pixel 4

Pixel 5

Pixel 6

Pixel 7

Pixel 8

Pixel 9

Edge detector in action

Feed-forward network

Pixel 1

Pixel 2

Pixel 3

Pixel 4

Pixel 5

Pixel 6

Pixel 7

Pixel 8

Pixel 9

Pixel 1000

Pixel 10
Cortical organization and feature organization

Nearby neurons respond to similar features

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


Lateral connections: surround suppression

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

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

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
- "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 (\( g_{\text{step}} \) 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)

**Coding on a scale: sparsity**
- Typically we will say "sparsity" is using at most 10% of available neurons
Coding on a scale: distributed + overlapping

### Responses for each property add together

<table>
<thead>
<tr>
<th>Mood</th>
<th>Age</th>
<th>Hair</th>
</tr>
</thead>
<tbody>
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<td>Sad</td>
<td>(0-100)</td>
<td>Bald</td>
</tr>
<tr>
<td>Ambivalent</td>
<td></td>
<td>Mid-hair</td>
</tr>
<tr>
<td>Happy</td>
<td></td>
<td>Long</td>
</tr>
</tbody>
</table>

What does this encode? 0 .4 .8

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

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What does this encode? 1 .5 1.5

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
Coding on a scale: distributed + overlapping

Responses for each property add together

- Mood: sad (0.1) – happy (0.9)
- Age: young (0.1) – old (0.9)
- Amount of hair: bald (0.5) – long (0.5)
- Freckles: some (0.1) – lots (0.9)

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.

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.

Population coding to find direction of motion

Non-normalized population coding:

\[ s_{\text{dir}} = \sum_i r_i s^\text{pref}_i \]

Adding lists of numbers

\[
\begin{align*}
\begin{bmatrix} x \\ y \end{bmatrix} & = \begin{bmatrix} 0 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ -1 \end{bmatrix} \\
\end{align*}
\]
Population coding to find direction of motion

Non-normalized population coding

\[ S_{dir} = \sum_i r_i s_i^{pref} \]

\[ s_{\text{pref}}^{[x,y]} = \begin{bmatrix} 0 & 1 & 0 & -1 \\ -1 & 0 & 1 & 0 \end{bmatrix} \]

\[ s^{[x,y]} = 1 \begin{bmatrix} 0 \\ -1 \end{bmatrix} + 4 \begin{bmatrix} 4 \\ 0 \end{bmatrix} + 1 \begin{bmatrix} 0 \\ 1 \end{bmatrix} + 0 \begin{bmatrix} -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \end{bmatrix} \]

“Normalized” firing rate

\[ \hat{r}_i = \frac{r_i - r_{\text{min}}}{r_{\text{max}} - r_{\text{min}}} \]

\[ r_{\text{max}} = 60 \text{ Hz}, \quad r_{\text{min}} = 0 \text{ Hz} \]

\[ r \]

\[ 1 \quad 4 \quad 1 \quad 0 \]

\[ \hat{s}_{\text{pref}}^{[x,y]} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \]

Normalized firing rates

\[ r_{\text{min}} = 0 \text{ Hz}, \quad r_{\text{max}} = 60 \text{ Hz} \]

\[ r \]

\[ 30 \quad 30 \quad 10 \quad 0 \]

\[ \hat{s}_{\text{pref}}^{[x,y]} = \begin{bmatrix} 0 & 1 & 0 & -1 \\ -1 & 0 & 1 & 0 \end{bmatrix} \]

Population coding to find direction of motion

“Normalized” pop’n coding

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

\[ \hat{r} = \frac{\hat{r}_i}{\sum_j \hat{r}_j s_j^{pref}} \]

\[ \hat{r} \]

\[ 0.05 \quad 0.5 \quad 0.05 \quad 0 \]

\[ \hat{s}_{\text{pref}}^{[x,y]} = \begin{bmatrix} 0 & 1 & 0 & -1 \\ -1 & 0 & 1 & 0 \end{bmatrix} \]
Another example
Assume for all neurons $r_{\text{min}}=10\text{ Hz}, r_{\text{max}}=100\text{ Hz}$

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

Find most-favored motion direction, do not amplify motion distance.