ONLINE SUBJECT EVALUATIONS ARE NOW OPEN

http://web.mit.edu/subjectevaluation

• You have until Monday, Dec. 16 at 9 AM
• Please evaluate all subjects in your list
• Don’t forget your TAs
• Write comments

Your feedback is read and valued!

Also, class projects due December 11th
email them to: shimon.ullman@gmail.com
Using machine learning to understand biological vision and learning

Ethan Meyers
Vision and learning: computers and brains

<table>
<thead>
<tr>
<th>Vision</th>
<th>Computers</th>
<th>Brains</th>
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<tr>
<td></td>
<td>Mike Jones</td>
<td>Winrich Freiwald</td>
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<td></td>
<td>Yann LeCun</td>
<td>Elias Issa</td>
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<td>Learning</td>
<td>Andrew Barto</td>
<td>Charles Cadieu</td>
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<td>Yael Niv</td>
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<td>Larry Abbot</td>
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<td>Haim Sompolinsky</td>
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Tomaso Poggio
Shimon Ullman
Shihab Shamma
Vision and learning: computers and brains

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![Diagram showing the relationship between vision and learning in computers and brains.](attachment:diagram.png)
Machine learning applied to neural data

Decoding (readout/MVPA):

\[\text{stimulus} = f(\text{neuronal response}); \quad P(S|R)\]

Encoding:

\[\text{neural response} = g(\text{stimulus}); \quad P(R|S)\]
Decoding was used to analyze the data (training the classifier)

Learning association between neural activity and an image

Pattern Classifier
Decoding was used to analyze the data (training the classifier)

Learning association between neural activity an image

Pattern Classifier
Decoding was used to analyze the data (testing the classifier)

“Correct”

Prediction

Pattern Classifier

neuron 1
neuron 2
neuron 3
neuron n
Decoding was used to analyze the data (testing the classifier)

Test set

- neuron 1
- neuron 2
- neuron 3
- neuron n

Prediction

Pattern Classifier

“Incorrect”
Outline

• BCI to study learning in the motor cortex

• MVPA to study vision in human fMRI data

• Population decoding to study high level learning and vision in macaque monkeys
Outline

- BCI to study learning in the motor cortex
- MVPA to study vision in human fMRI data
- Population decoding to study high level learning and vision in macaque monkeys
Ferrier (1874), Penfield (1937)
What is coded by the motor cortex?

Muscle/joint activation
- Evarts (1968)
- Scott and Kalaska (1995)

Direction of movement
- Moran and Schwartz (1999)

Complex motor sequences
Direction tuning in cortex

\[ f(\mathbf{v}) = b_0 + b_x v_x + b_y v_y \]

\[ = b_0 + \mathbf{b}^T \mathbf{v} \]

\[ = b_0 + \|\mathbf{b}\| \|\mathbf{v}\| \cos \theta_{vb} \]

Georgopoulos et al. (1982)
Population vector - offline decoding

\[ f_i(\mathbf{v}) = b_{i0} + b_{ix}v_x + b_{iy}v_y \]
\[ = b_{i0} + \mathbf{b}_i^T \mathbf{v} \]

Call \( \mathbf{b}_i \) the ‘preferred direction’ of neuron \( i \)

Decoded movement direction at time \( t \) is:

\[ \mathbf{v}(t) = \sum_{i}^{n} (f_i(t) - b_{i0}) \mathbf{b}_i \]

Georgopoulos et al. (1986)
Monkey controls robotic arm using brain signals sent over Internet
Elizabeth A. Thomson, News Office

December 6, 2000

Monkeys in North Carolina have remotely operated a robotic arm 600 miles away in MIT's Touch Lab -- using their brain signals.

The feat is based on a neural-recording system reported in the November 16 issue of Nature. In that system, tiny electrodes implanted in the animals' brains detected their brain signals as they controlled a robot arm to reach for a piece of food.

According to the scientists from Duke University Medical Center, MIT and the State University of New York (SUNY) Health Science Center, the new system could form the basis for a brain-machine interface that would allow paralyzed patients to control the movement of prosthetic limbs.
Surrogates (2009)

TOMATOMETER

* 39%

Though it sports a slick look and feel, Surrogates fails to capitalize on a promising premise, relying instead on mindless action and a poor script.

Average Rating: 5.4/10
Reviews Counted: 112
Fresh: 44 | Rotten: 68

AUDIENCE

38%

liked it

Average Rating: 3.1/5
User Ratings: 293,681

MY RATING

WANT TO SEE IT  NOT INTERESTED

Add a Review (Optional)

http://www.youtube.com/watch?v=Z1_h9RaL0es
Closed-loop decoding
Differences between hand control and brain control

Taylor et al, Science 2002
Decoding in humans

Blackrock array

Video1  News 6

Hochberg et al. (2006)
Using BCIs to studying learning

Optimal decoder (PDs) is different for hand and brain control

Is it possible to change the coding properties of neurons?
Operant conditioning to control neurons

Fetz and Baker (1973)
Using BCIs to study learning

Jarosiewicz, Chase, Fraser, Villiste, Kass and Schwartz, PNAS, 2008

Ganguly and Carmena, PLoS Biology, 2009
Plasticity in BCIs: Jarosiewicz et al, 2008

A

B

C

<table>
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<tr>
<th>Calibration</th>
<th>Control</th>
<th>Perturb</th>
<th>Washout</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obtains original dPDs</td>
<td>Uses original dPDs</td>
<td>Uses reassigned dPDs</td>
<td>Uses original dPDs</td>
</tr>
</tbody>
</table>
Expected effect of perturbation on cursor movement
Effect of perturbation on cursor movement

The graph shows the perturbation direction in millimeters (y-axis) as a function of the target direction in millimeters (x-axis) for different conditions labeled as C, EP, LP, EW, and LW. The bars on the right indicate the deviation in millimeters for 25% and 50% perturbations.
Possible neural compensation mechanisms

1) **Re-aiming:** the monkey could have aimed the cursor to offset the perturbation caused by the reassignment, disregarding the relative contributions of the rotated vs. non-rotated units to the error.
Possible neural compensation mechanisms

1) **Re-aiming:** the monkey could have aimed the cursor to offset the perturbation caused by the reassignment, disregarding the relative contributions of the rotated vs. non-rotated units to the error.

2) **Re-weighting:** the rotated units could have suppressed their contribution to the population vector by firing at baseline rate everywhere; i.e. by *decreasing their modulation depths*
Possible neural compensation mechanisms

1) **Re-aiming**: the monkey could have aimed the cursor to offset the perturbation caused by the reassignment, disregarding the relative contributions of the rotated vs. non-rotated units to the error.

2) **Re-weighting**: the rotated units could have suppressed their contribution to the population vector by firing at baseline rate everywhere; i.e. by decreasing their modulation depths.

3) **Re-mapping**: the rotated units could have shifted their actual PDs (activation functions) toward their reassigned dPDs (labels).
Testing for these possibilities

\[ f = b_0 + b_x v_x + b_y v_y + b_z v_z + \varepsilon \]

Recalculate (offline) neuron’s PD during the perturbation session
Evidence for re-weighting

$$f = b_0 + b_x v_x + b_y v_y + b_z v_z + \epsilon$$

[Graph showing Modulation depth]
Evidence for re-aiming and re-mapping

Re-aiming appears as a shift in all PDs in the direction of the perturbation:

Deflection caused by perturbation

Target

Re-aiming (PD)
Summary: Jarosiewicz et al

Improved brain control of the cursor after the perturbation was due to: re-weighting, re-aiming, and re-mapping
Performance increased over days

Accuracy

Speed
Neural activity formed a stable map

There was a high correlation between the increase in decoding performance and the neural activity stabilization.
Using a random decoding

A  Created a random decoder.
   - Performance on motor control was poor on day 1

B  Performance on the random decoding improved over time
Switching between two different decoders
Summary: BCI to study plasticity

• It is possible to decode neural activity to control external devices
  – i.e., closed loop brain computer interfaces work

• Neurons can change their tuning properties to improve their performance on BCI tasks

• Perhaps reinforcement learning mechanisms are involved (see Yael Niv’s talk)
  – Also see:
Outline

• BCI to study learning in the motor cortex

• MVPA to study vision in human fMRI data

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How MVPA works (Haxby et al, Science 2001)
Detailed visual information can be extracted.

Kamitani and Tong (2005)
Using encoding models of visual information

- Encoding models can estimate voxel parameters (e.g., voxel’s retinotopic location, spatial frequency and orientation)
  - Kay et al, 2008, was able to decode 820 of 1000 novel images correctly
  - Miyawaki et al, 2008 could reconstruct images
Nishimoto et al, Current Biology, 2011

http://www.youtube.com/watch?v=HVL8GrUs_E
Beyond detailed visual information

- Decoding what people are:
  - Attending to
  - Imagining
  - Recalling from memories
  - Assessing semantic content of nouns
Decoding what subjects are attending to

Kamitani and Tong (2005)
Decoding imagined categories

A. Perception Blocks

B. Imagery Blocks

Decoding imagined categories

Recalled episodic memory

Polyn et al (2005)
Predicting novel nouns

\[ y_v(w) = \sum_{i=1}^{25} c_{iv} f_i(w) \]

Predicting novel nouns

77% classification accuracy (chance 50%)

Mitchell et al. (2008)
Summary

• MVPA can be used to:
  – Extract detailed visual information
  – Decode:
    • Attended objects
    • Freely Recalled memory
    • Novel nouns

• Reliable method for gaining insight into a range of neuroscience questions
Outline

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Decoding visual information from IT

Hung et al (2005)
Work with Freiwald & Tsao

Same orientation

Different orientation
Incorporation of new information into prefrontal cortical activity after learning working memory tasks

Ethan M. Meyers\textsuperscript{a,1}, Xue-Lian Qi\textsuperscript{b}, and Christos Constantinidis\textsuperscript{b}
The prefrontal cortex (PFC) is involved in working memory, task learning, and executive function.
1. How does the information content change after learning a new task?

2. How is information coded in neural activity?

3. Are there regions differences within dorsolateral PFC?
Monkeys were first trained to passively fixate
Monkeys were first trained to passively fixate

Fixation    1\textsuperscript{st} stimulus    1\textsuperscript{st} delay    2\textsuperscript{nd} stimulus    2\textsuperscript{nd} delay    Reward

![Diagram](image)

Time (ms)
Monkeys then engaged in a delayed-match-to-sample task (DMS task)

<table>
<thead>
<tr>
<th>Fixation</th>
<th>1st stimulus</th>
<th>1st delay</th>
<th>2nd stimulus</th>
<th>2nd delay</th>
<th>Choice targets/saccade</th>
</tr>
</thead>
</table>

Time (ms)

0 1000 1500 3000 3500 5000 6000
Monkeys then engaged in a delayed-match-to-sample task (DMS task)
Spatial task: PAMSe taskation

Fixation  1<sup>st</sup> stimulus  1<sup>st</sup> delay  2<sup>nd</sup> stimulus  2<sup>nd</sup> delay  Choice targets/ R saccade

0  1000  1500  3000  3500  5000  6000
Time (ms)
Population Decoding
Decoding applied

Fixation  1st stimulus  1st delay  2nd stimulus  2nd delay  Choice targets/saccade

Time (ms)

0  1000  1500  3000  3500  5000  6000
Decoding applied

Fixation 1\textsuperscript{st} stimulus 1\textsuperscript{st} delay 2\textsuperscript{nd} stimulus 2\textsuperscript{nd} delay Choice targets/saccade

Time (ms)

500 ms bins, sample every 50 ms
What types of information are in PFC?

Visual information

Match/nonmatch information

10°

Analyzed pseudo-population of 750/600 neurons
Decoding visual information (feature task)
Decoding visual information (spatial task)
Decoding match/nonmatch information

![Graph showing classification accuracy over time for Passive fixation and DMS task with shaded areas representing variability.](image)
Decoding match/nonmatch information

[Graph showing classification accuracy over time for passive fixation and DMS task.]
1. How does the information content change after learning a new task?

Answer:

Visual information remains largely unchanged
There is a large increase in task-relevant information
How is information coded in neural activity?

a) Sparse vs. distributed information
b) Dynamic vs. static population coding
c) Dedicated neurons vs. multiplexing
Is the new information widely distributed?

Passive fixation

Feature task
Is the new information widely distributed?

Passive fixation

DMS task

Spatial task
Is the new information widely distributed?

Using only the 8 most selective neurons
Is the new information widely distributed?

Using only the 8 most selective neurons

Excluding the 64 most selective neurons

Spatial task
How is information coded in neural activity? (dynamics)

DMS Task

Meyers, et al., 2008 Add more refs
Is information contained in a dynamic population code?

Decoding applied

Fixation  1st stimulus  1st delay  2nd stimulus  2nd delay  Choice targets/saccade

Time (ms)

Test
Decoding applied

Fixation  1\textsuperscript{st} stimulus  1\textsuperscript{st} delay  2\textsuperscript{nd} stimulus  2\textsuperscript{nd} delay  Choice targets/saccade

0  1000  1500  3000  3500  5000  6000

Test
Dynamic population coding

Feature task
Dynamic population coding

Passive fixation

Feature task
Dynamic population coding

Passive fixation

DMS task

Spatial task
The dynamics can be seen in individual neurons.

**Feature task**

**Spatial task**
Do neurons become specialized to new information or do they multiplex information?

- Find highly selective match/nonmatch neurons (ANOVA, $p < 10^{-6.5}$)
- 50 neurons feature task
- 18 neurons spatial task
- Use highly selective match/nonmatch neurons to decode visual information
Highly selective match/nonmatch neurons also contain stimulus information
How is information coded in neural activity?

**Answer:**

Information is contained in a dynamic population code, where at each point in time, a small number of neurons contain all the information present in the larger population.

These neurons contain information about multiple variables.
Are there regions differences within lateral PFC?

Domain specific theories
(Wilson et al., 1993 Science; O'Scalaidhe et al., Science 1997; Romanski et al., Nat Neuro, 2002)

Integrative theories
(Rao, et al., Science 1997; Rainer et al., PNAS 1998)

The debate continues
(O'Reilly, 2010 TINS, Wilson et al., 2010 TINS).
Dorsolateral vs. ventrolateral PFC visual information

Passive fixation

DMS task

Spatial task
Dorsolateral vs. ventrolateral PFC match/nonmatch information

Passive fixation

Classification Accuracy

Time (ms)

Dorsal
Ventral

DMS task

Time (ms)

Feature task
Dorsolateral vs. ventrolateral PFC match/nonmatch information

Passive fixation

Classification Accuracy

Time (ms)

Dorsal
Ventral

DMS task

Classification Accuracy

Time (ms)

Spatial task
Summary
Visual information then is largely unchanged; there is a large after-learning effect on task information.
Visual information is largely unchanged; there is a large increase in task-relevant information.

How is information coded dynamically in a neural population code?
Visual information is largely unchanged; there is a large increase in task-relevant information.

Information is contained in a compact dynamic population code.

3. Visual information is primarily in dorsal PFC, while task relevant information is widespread.
Conclusions

Using machine learning is a powerful way to analyze neural data

Thanks to:

B. Jarosiewicz for providing some slides
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