Using population decoding to understand neural content and coding
Motivation

We have some great theory about how the brain works
We run an experiment and make neural recordings
We get a bunch of data...

How can we convert data into answers?
What do I want from a data analysis method?

Clear answers to:

**Neural content**: What information is in a brain region?

**Neural coding**: What features of the activity contain information?
Talk Outline

What is population decoding?

Using decoding to understand **neural content**

Using decoding to understand **neural coding**

How to analyze your own data
Neural population decoding

**Decoding:** Predict stimulus/behavior from neural activity

\[ f(\text{neural activity}) \rightarrow \text{stimulus} \]

Decoding approaches have been used for 30 years

- Motor system: e.g., Georgopoulos et al, 1986
- Hippocampus: e.g., Wilson and McNaughton, 1993
- Computational work: e.g., Salinas and Abbott, 1994

Alternative names for decoding:

- Multivariate Pattern Analysis (MVPA)
- Readout
Training the classifier

Learning association between neural activity an image

Pattern Classifier

neuron 1
euron 2
euron 3
neuron n
Training the classifier

Learning association between neural activity and an image

Pattern Classifier

neuron 1
neuron 2
neuron 3
neuron n
Using the classifier

Pattern Classifier

Prediction

neuron 1
neuron 2
neuron 3
neuron n

“Correct”
Using the classifier

“Incorrect”

Prediction

Pattern Classifier
Using the classifier

Pattern Classifier

neuron 1
neuron 2
neuron 3
neuron n
Symbols:
- \( L \) : features
- \( X \) : stimuli

Data:
- Stimuli set \( \{X_1, \ldots, X_n\} \)
- Feature set \( \{L_1, \ldots, L_m\} \)
- Feature indices \( \{l_1, \ldots, l_m\} \)

Indexing:
- \( i \) : feature index
- \( j \) : stimulus index

Features:
- \( f(j) \) : feature extracted
- \( f(j) \) : feature vector
- \( f(j) \) : feature map

Stimuli:
- \( x(j) \) : stimulus
- \( x(j) \) : stimulus vector
- \( x(j) \) : stimulus map

Indices:
- \( l \) : feature index
- \( n \) : feature index
- \( m \) : feature index

Expansion:
- \( x(j) \) : stimulus
- \( x(j) \) : stimulus vector
- \( x(j) \) : stimulus map

Reduction:
- \( f(j) \) : feature extracted
- \( f(j) \) : feature vector
- \( f(j) \) : feature map

Pattern recognition:
- \( f(j) \) : feature vector
- \( f(j) \) : feature map
- \( f(j) \) : feature set

Matrix:
- \( A \) : feature matrix
- \( A \) : feature vector
- \( A \) : feature map

Source:

Courtesy of MIT Press. Used with permission.
Pseudo-populations
Maximum Correlation Coefficient Classifier

Neuron 1
Neuron 2
Neuron 3
Neuron 4
Neuron 5
Neuron 6

Trials
Maximum Correlation Coefficient Classifier

Neuron 1
Neuron 2
Neuron 3
Neuron 4
Neuron 5
Neuron 6

Learned prototypes

Test point
Decoding can be viewed as assessing the information available to downstream neurons.
Neural content
A simple experiment

Seven objects:

132 neurons recorded from IT

Zhang, Meyers, Bichot, Serre, Poggio, and Desimone, PNAS, 2011
Applying decoding

Train
Applying decoding

100 ms bins, sample every 10 ms
Basic decoding results

![Graph showing classification accuracy over time](image-url)
Basic results are similar to other methods.
Confusion matrices
Generally robust to the choice of classifier

![Classification accuracy over time](image)
Abstract/invariant representations

The ability to form abstract representations is essential for complex behavior.
Example: position invariance

Hung, Kreiman, Poggio, and DiCarlo, Science, 2005
Face identification invariant to head pose

Stimulus set: 25 individuals, 8 head poses per individual

Face identification invariant to head pose

Train
Left Profile

Test
Same Pose

Test
Pose Invariance

Courtesy of Society for Neuroscience. License CC BY.
Face identification invariant to head pose

ML/MF

AL

AM

Posterior

Anterior

Courtesy of Society for Neuroscience. License CC BY.
Learning abstract category information

Summary of neural content

Decoding offers a way to clearly see information flow over time

For assessing basic information, decoding often yields similar results as other methods

Decoding allows one to assess whether information is contained in an abstract/invariant format, which is not possible with other methods
Neural coding
Motivating study

Meyers, Qi, Constantinidis, PNAS, 2012
Monkeys were first trained to passively fixate
Monkeys were first trained to passively fixate.
Monkeys then engaged in a delayed-match-to-sample task (DMS task)

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

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

<table>
<thead>
<tr>
<th>Time (ms)</th>
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<tbody>
<tr>
<td>0</td>
</tr>
<tr>
<td>1000</td>
</tr>
<tr>
<td>1500</td>
</tr>
<tr>
<td>3000</td>
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<tr>
<td>3500</td>
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<td>5000</td>
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<tr>
<td>6000</td>
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</tbody>
</table>

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

Train
Decoding applied

500 ms bins, sample every 50 ms
Decoding is based on 750 neurons
Decoding match/nonmatch information

![Graph showing classification accuracy over time for Passive fixation and DMS task](image)

Is the new information widely distributed?

Passive fixation

DMS task

![Graphs showing Max \(\eta^2\) vs. Time (ms) for Passive fixation and DMS task.](image)

Courtesy of Proceedings of the National Academy of Sciences. Used with permission.
Compact/sparse coding of information

Training set

Neuron 1
Neuron 2
Neuron 3
Neuron 4
Neuron 5
Neuron 6

Labels M N N M
Compact/sparse coding of information

Training set

<table>
<thead>
<tr>
<th>Neuron 1</th>
<th>Neuron 2</th>
<th>Neuron 3</th>
<th>Neuron 4</th>
<th>Neuron 5</th>
<th>Neuron 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Orange</td>
<td>Green</td>
<td>Orange</td>
<td>Red</td>
<td>Blue</td>
<td>Yellow</td>
</tr>
</tbody>
</table>

Labels: M N N M

Test set

...
Compact/sparse coding of information

Neuron 1  Neuron 2  Neuron 3  Neuron 4  Neuron 5  Neuron 6

Training set

Test set

Labels

M  N  N  M

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Compact/sparse coding of information

![Diagram of neuron coding](image)

**Neuron 1**
**Neuron 4**
**Neuron 6**

**Labels**
M  N  N  M

**Training set**

**Test set**

...
Is the new information widely distributed?

Using only the 8 most selective neurons

Excluding the 128 most selective neurons

Implications for analyzing data

Decoding Results

Averaged ROC Results

Selectivity value

Frequency
Is information contained in a dynamic population code?

Mazor and Laurent 2005; Meyers et al, 2008; King and Dehaene 2014
Decoding applied
Decoding applied

Time (ms)

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

0 | 1000 | 1500 | 3000 | 3500 | 5000 | 6000

Test | Test
Dynamic population coding
Dynamic population coding

Passive fixation

DMS task

Courtesy of Proceedings of the National Academy of Sciences. Used with permission.
The dynamics can be seen in individual neurons.

Is information coded in high firing rates or patterns?

**Poisson Naïve Bayes Classifier**
Total activity and pattern

**Minimum Angle Classifier**
Pattern only

**Total Population Activity Classifier**
Total activity only

\[
\text{Decision Rule} \quad \arg \max_c \log((w_c)^T x - n\overline{w}_c)
\]

\[
\arg \max_c \frac{w_c^T x}{\|w_c\| \|x\|}
\]

\[
\arg \max_c |\overline{w}_c - \overline{x}|
\]

**w_c** are the classification weights for class c

**x** is the test point to be classifier
Is information coded in high firing rates or patterns?

Pose specific face identification

Poisson Naïve Bayes – Total activity and pattern
Minimum Angle – Pattern only
Total Population Activity - Total activity only

Meyers, Borzello, Freiwald, Tsao, 2015
Independent neuron code?

Data courtesy of the DiCarlo lab; see Ami Patel’s MEng thesis.
Precision of the neural code (temporal coding)

(basic results – clearly room to explore this further)

See Meyers et al, COSYNE, 2009
Summary of neural coding

Decoding allows you examine many questions in neural coding including:

• Compact/sparse coding

• Dynamic population coding

• Independent neural code

• Temporal precision/temporal coding
Decoding can be applied to other types of data

MEG/EEG (LFPs, ECog)
  - New tutorial on readout.info

fMRI
  - Princeton-mvpa-toolbox
  - PyMVPA
  - The decoding toolbox

Continuous decoding
  - nSTAT

Figure removed due to copyright restrictions. Please see the video. Source: Figure 2, Isik, Leyla, Ethan M. Meyers, Joel Z. Leibo, and Tomaso Poggio. "The dynamics of invariant object recognition in the human visual system." Journal of neurophysiology 111, no. 1 (2014): 91-102.
Limitations of decoding

Hypothesis based – could be overlooking information that is not explicitly tested for

Just because information is present, doesn’t mean it’s used

Decoding focuses on the computational and algorithmic/representational levels, does not give a mechanistic explanation of the phenomena

Decoding methods can be computationally intensive, analyses can be slow to run
The Neural Decoding Toolbox (NDT)

Makes it easy to do decoding in MATLAB:

1  binned_file = 'Binned_data.mat';
2  ds = basic_DS(binned_file, 'stimulus_ID', 20);
3  cl = max_correlation_coefficient_CL;
4  fps{1} = zscore_normalize_FP;
5  cv = standard_resample_cv(ds, cl, fps)
6  DECODING_RESULTS = cv.run_cv_decoding;

Open Science philosophy: open source for reproducible results
• The code open source for reproducible results
• Hope to encourage open science culture, so please share your data

www.readout.info

Meyers, Front Neuroinfo, 2013
The Neural Decoding Toolbox Design

**Toolbox design: 4 abstract classes**

1. **Datasource**: creates training and test splits
   - E.g., can examine the effects from different binning schemes

2. **Preprocessors**: learn parameters from training data apply them to the training and test data
   - E.g., can examine sparse/compact coding

3. **Classifiers**: learn from training data and make predictions on test data
   - E.g., can examine whether information is in high firing rates or patterns

4. **Cross-validators**: run the training/test cross-validation cycle
Getting started with your own data

You can use the NDT on your own data by putting your data into ‘raster format’
Questions?

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[www.readout.info](http://www.readout.info)