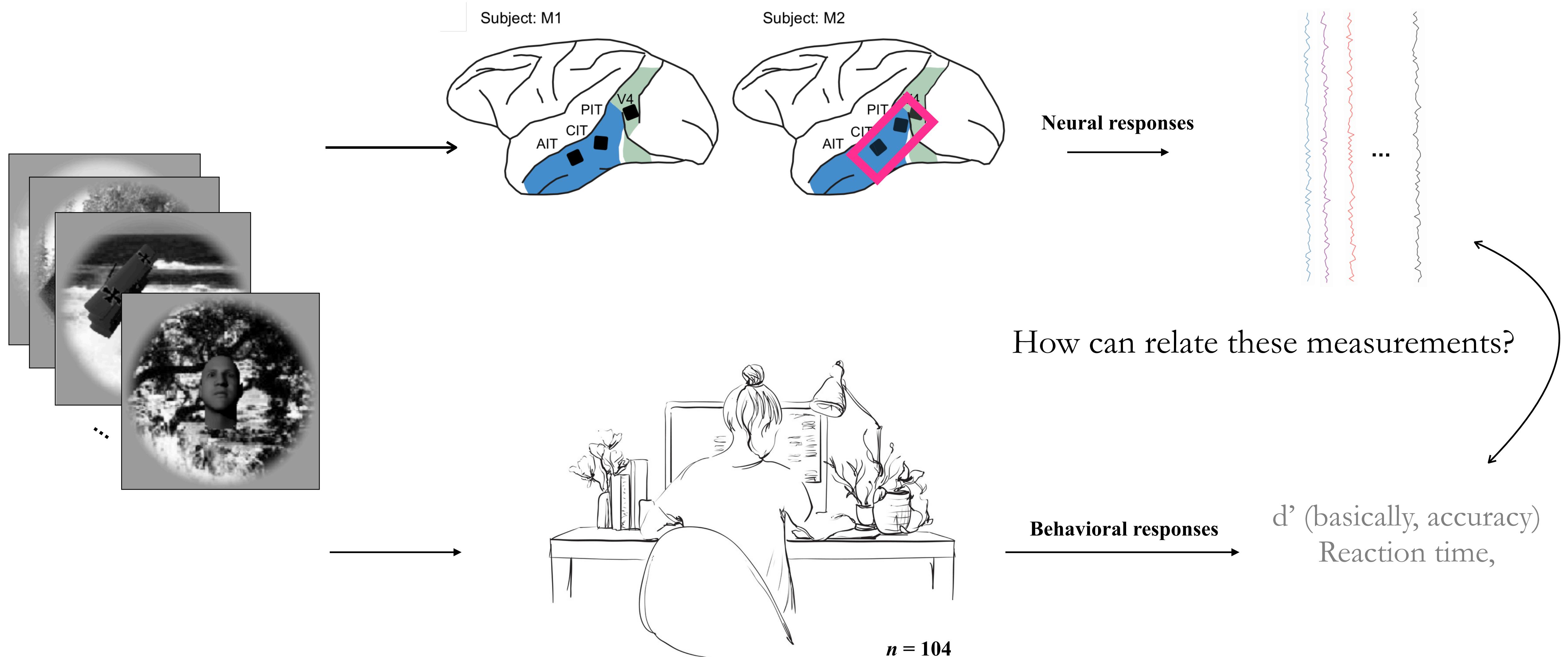


# Non-parametric model comparisons

- i. Building a linking function between the brain and behavior
- ii. Representational Similarity Analysis (RSA)
- iii. Linear mappings between responses to shared inputs
- iv. A familiar visualization :)

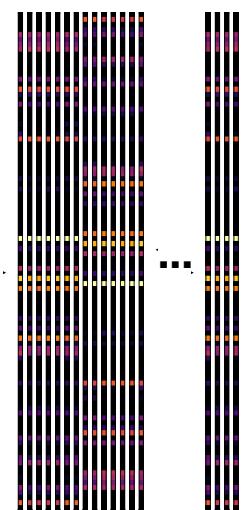
# Building a linking function

# Majaj et al. 2015



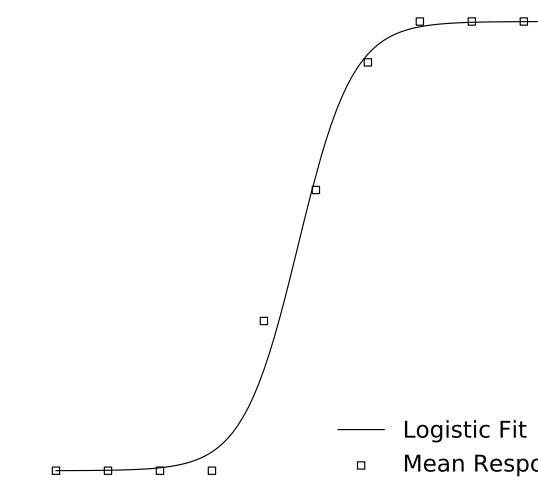
# Building a linking function between neural and human behavior

N feature vectors  
(i.e. neural responses)



Tran-test split

Build Logistic  
Regression model  
on training data



Determine performance  
on test data

e.g. [0,1,0, 1, 1 ... 0]

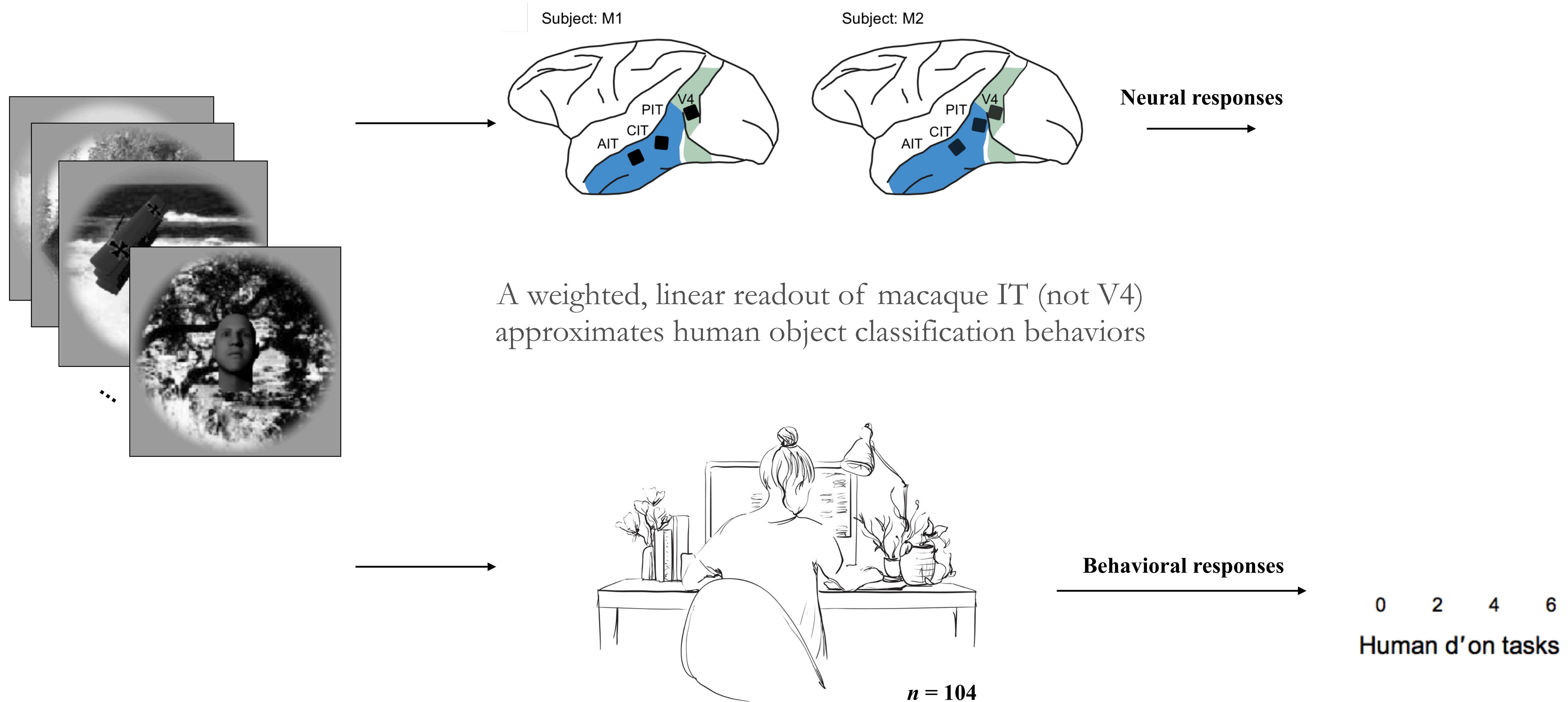
Compute d' from  
Model behavior

e.g. 3.1

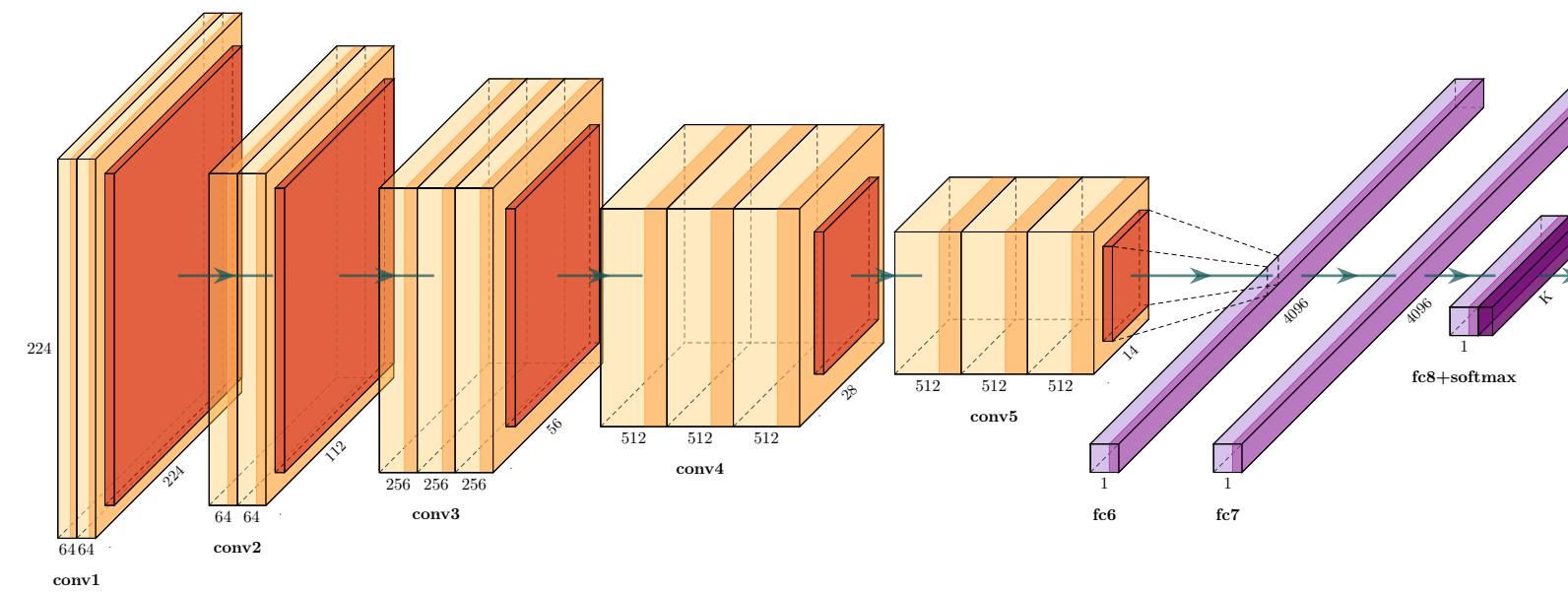
For each object classification task:

1. Segregate feature vectors (i.e. neural responses) training and testing data
2. Build logistic regression model to predict object (e.g. face001 vs. not face001)
3. Determine performance on test data
4. Compute  $d'$  (a more sophisticated accuracy measure) from model performance

# Majaj et al. 2015



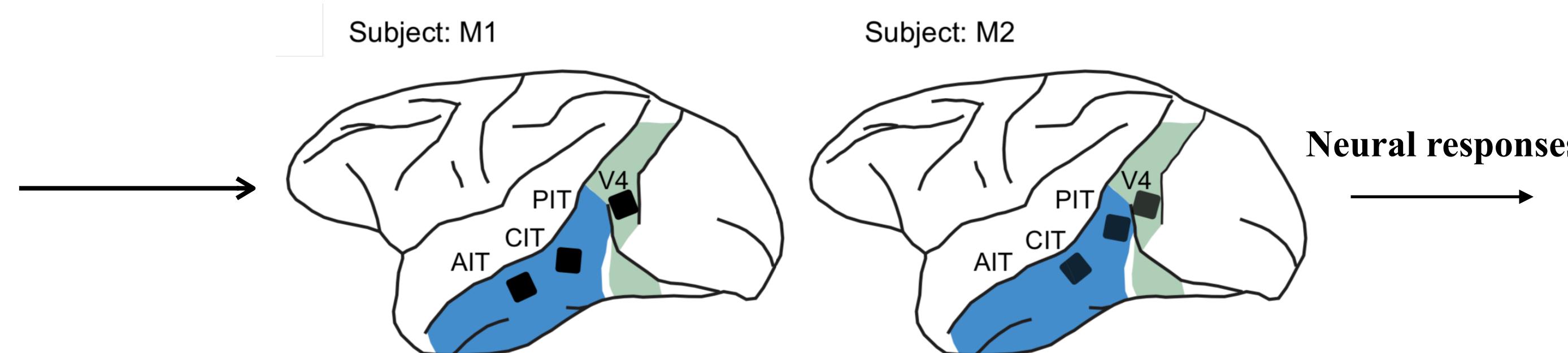
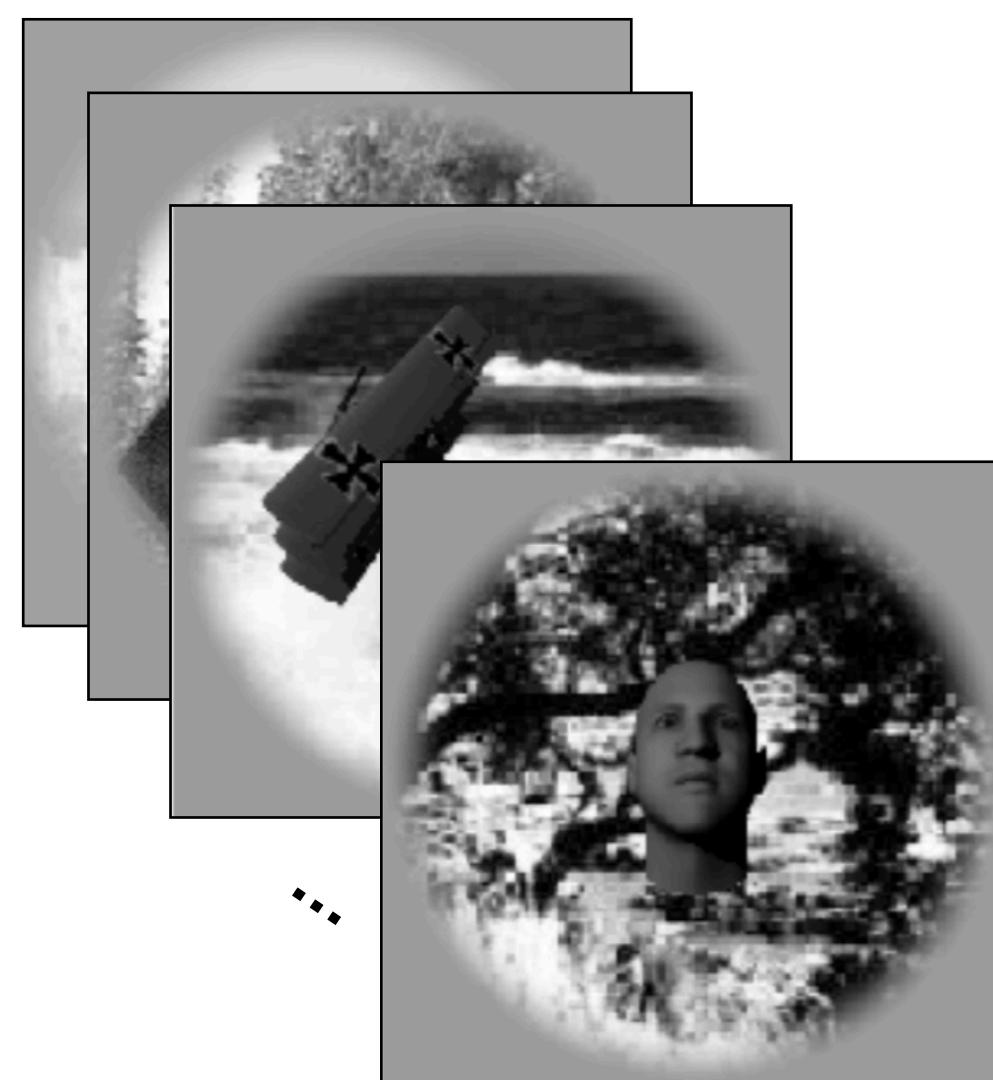
# Representational Similarity Analysis (RSA)



Convolutional Neural Networks (CNNs) predict neural responses throughout the VVS directly from experimental stimuli

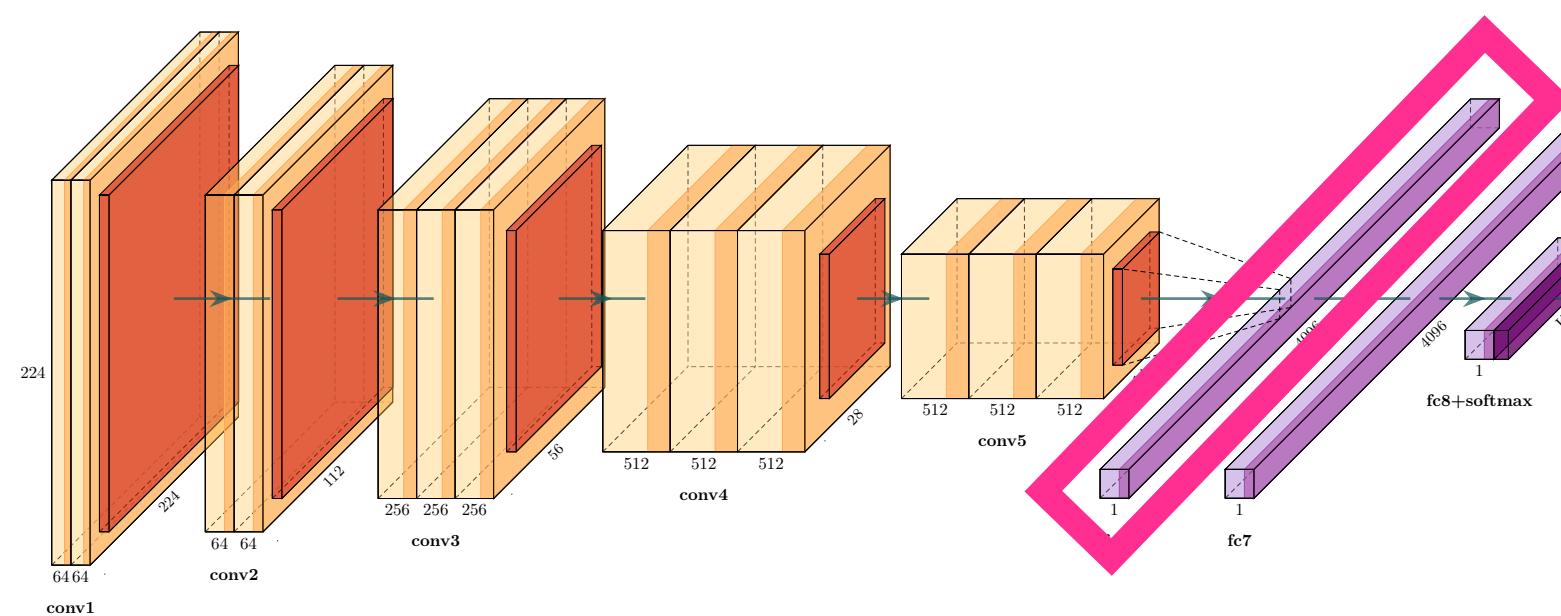
V1: Cadena et al. 2019 | V4: Bashivan et al. 2019 | IT: Yamins et al. 2014 | Behavior: Rajalingham 2018

168 (neurons) x 64 (objects)

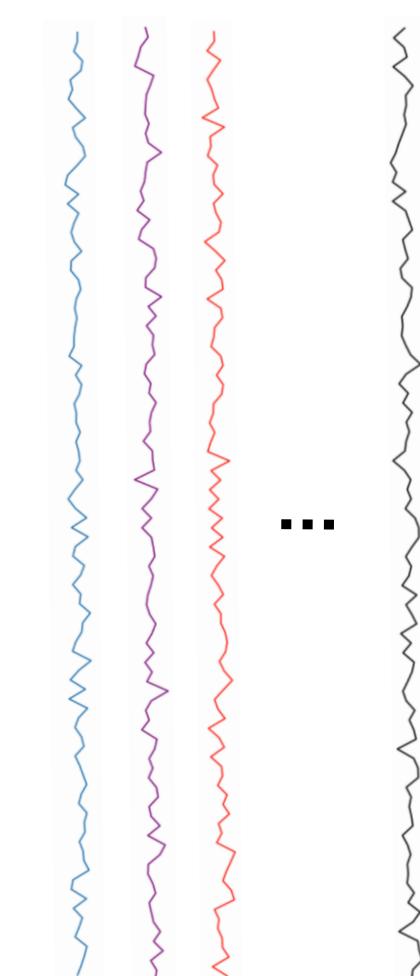
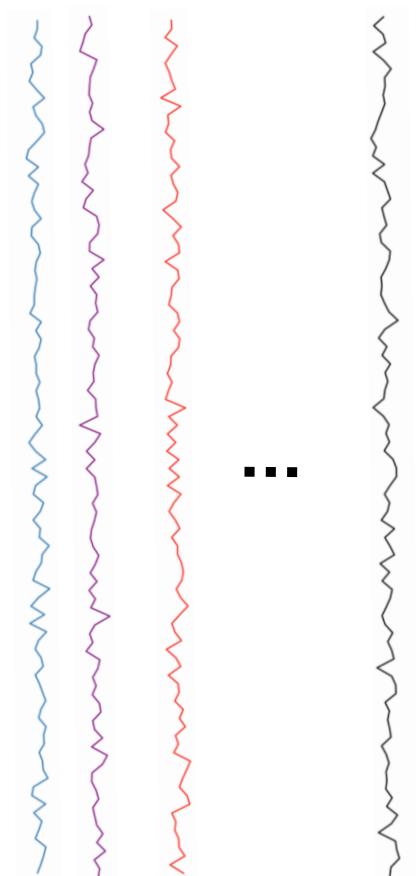


How can relate these measurements?

4096 ("neurons") x 64 (objects)



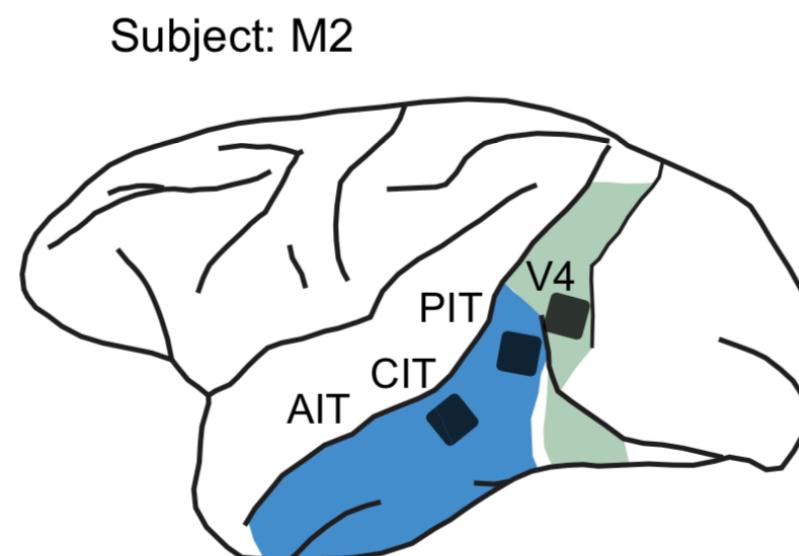
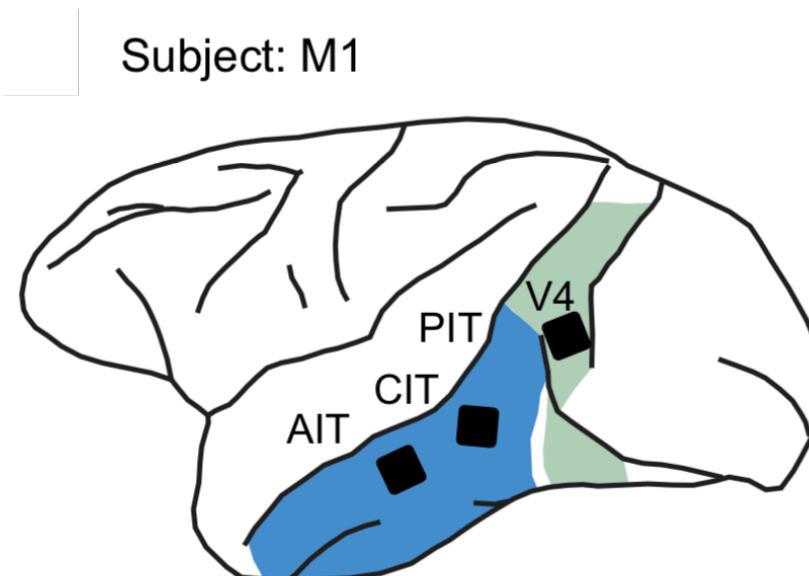
Model responses



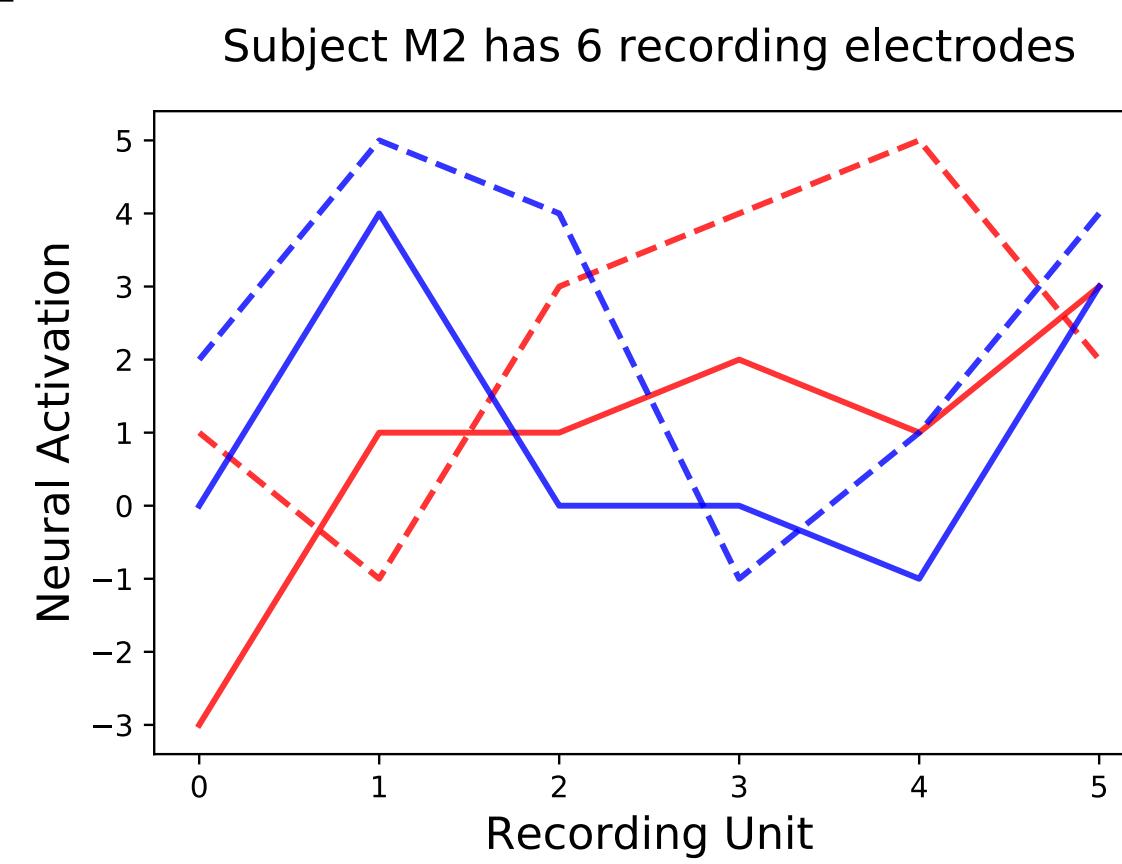
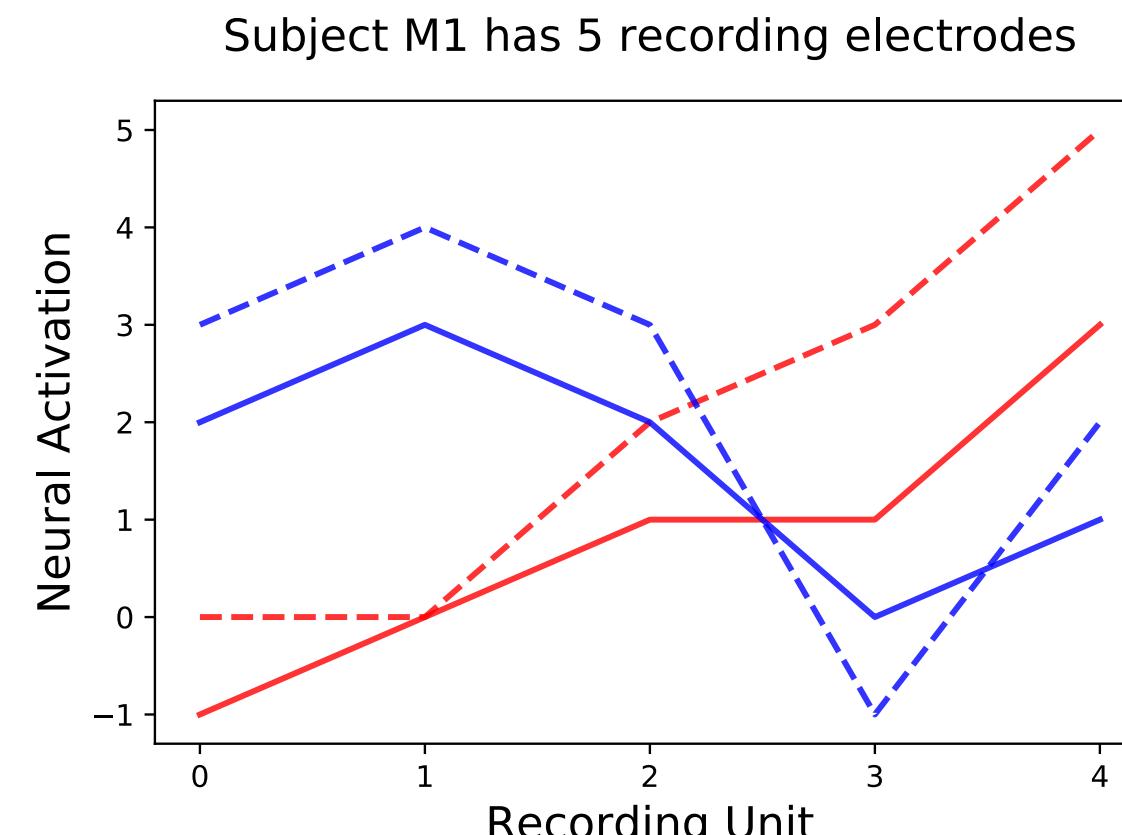
In order to compare model and neural responses, here we can

- i. preserves task relevant information (e.g. relationship between stimuli)
- ii. while being agnostic to units of measurement (e.g. n neurons)

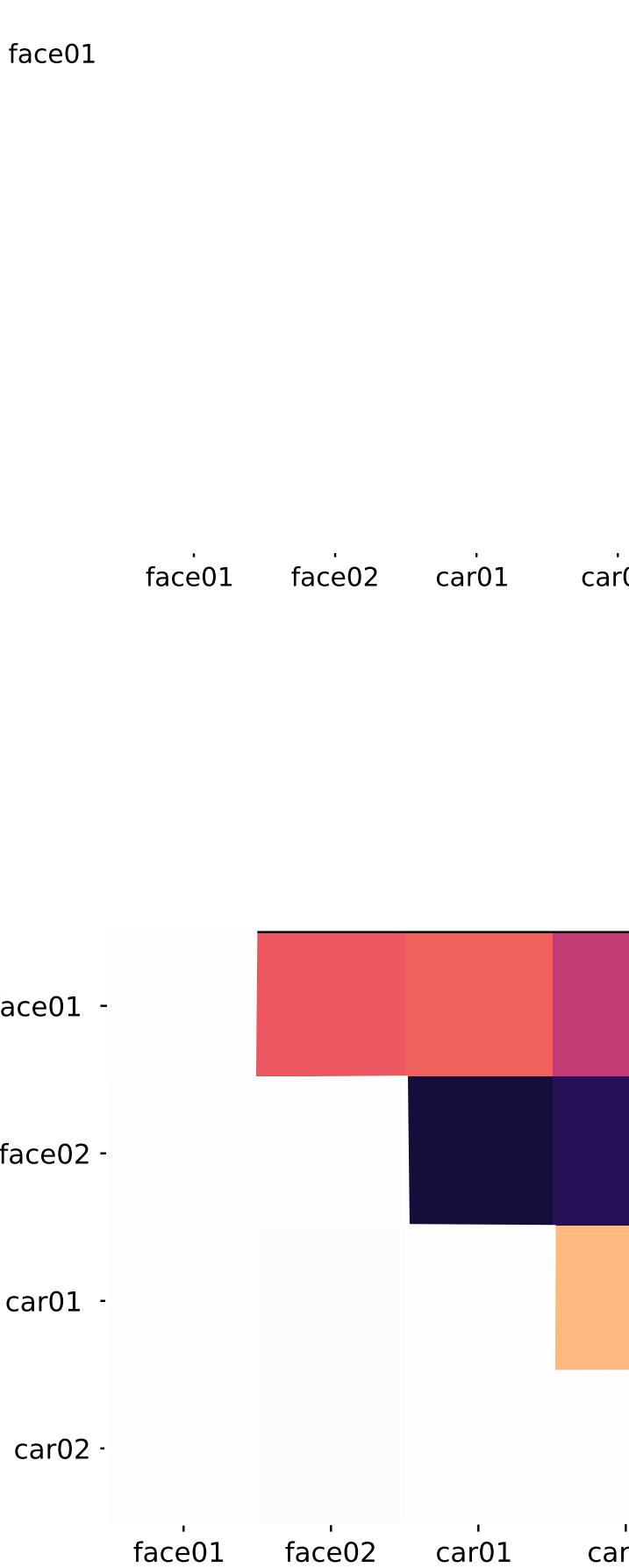
Let's work through an example that's simpler, but still a real problem:  
Compare neural responses across monkeys with different number of electrodes



Data in native format has mismatched dimensions but there seems to be shared structure



Generate a Representation Dissimilarity Matrix (RDM) —pairwise  $1-r$

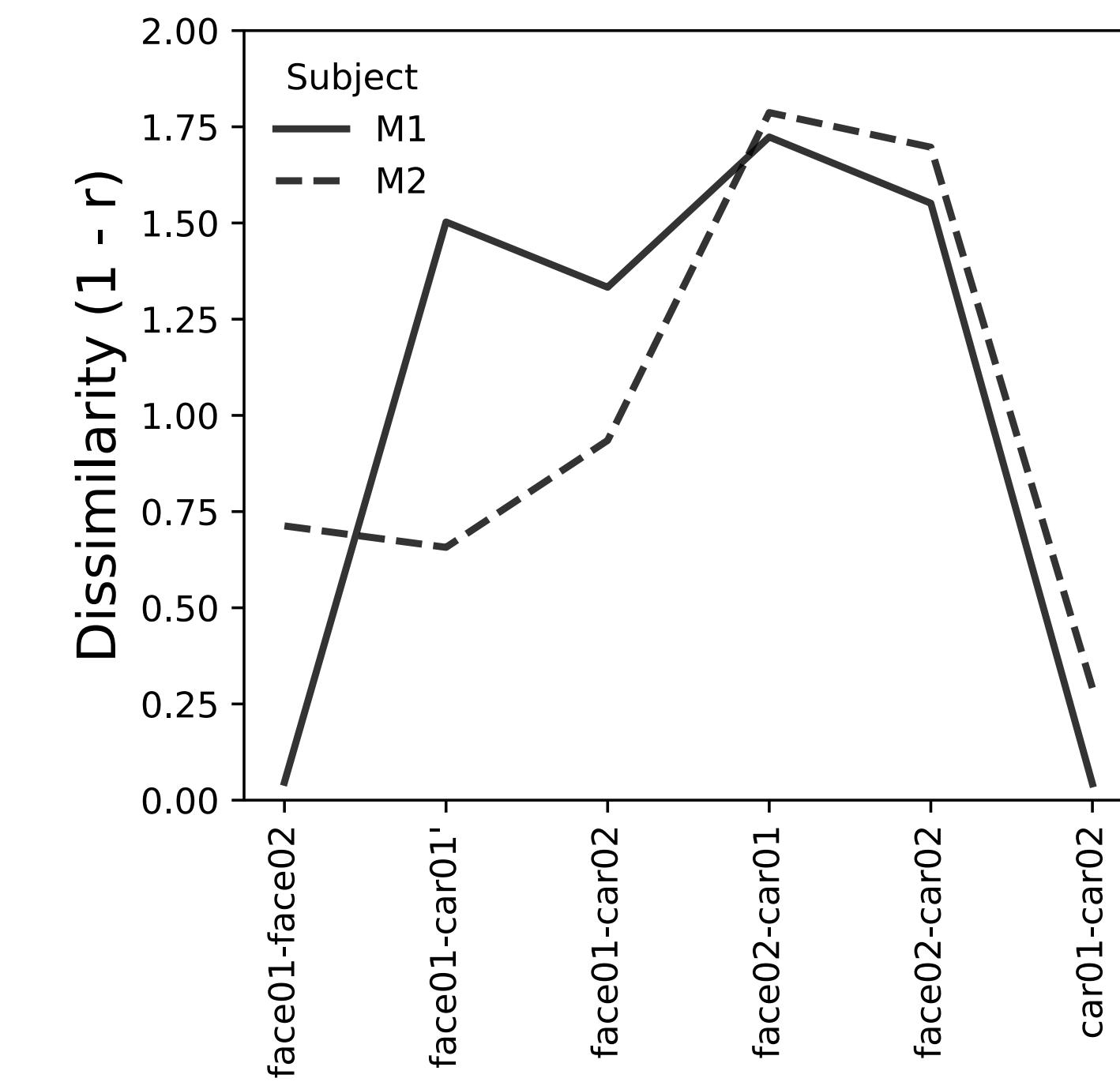


Extract off-diagonal



Compute correlation between off-diagonals from M1 & M2 RDMs

Correlation between different measurements of the same phenomena ( $r = 0.73, p < .05$ )



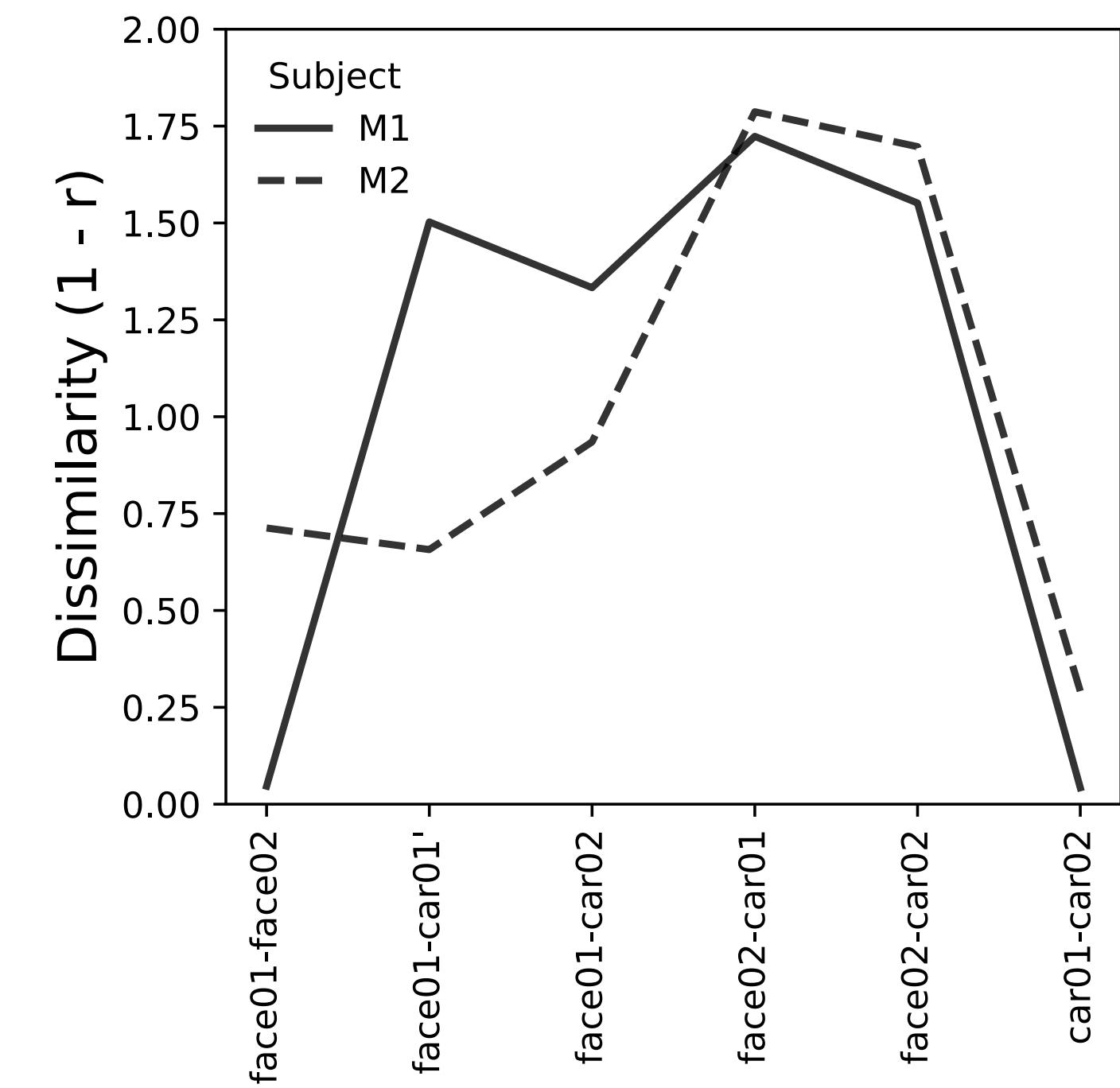
# This protocol is called a Representational Similarity Analysis (RSA)

## How do we generate p values?

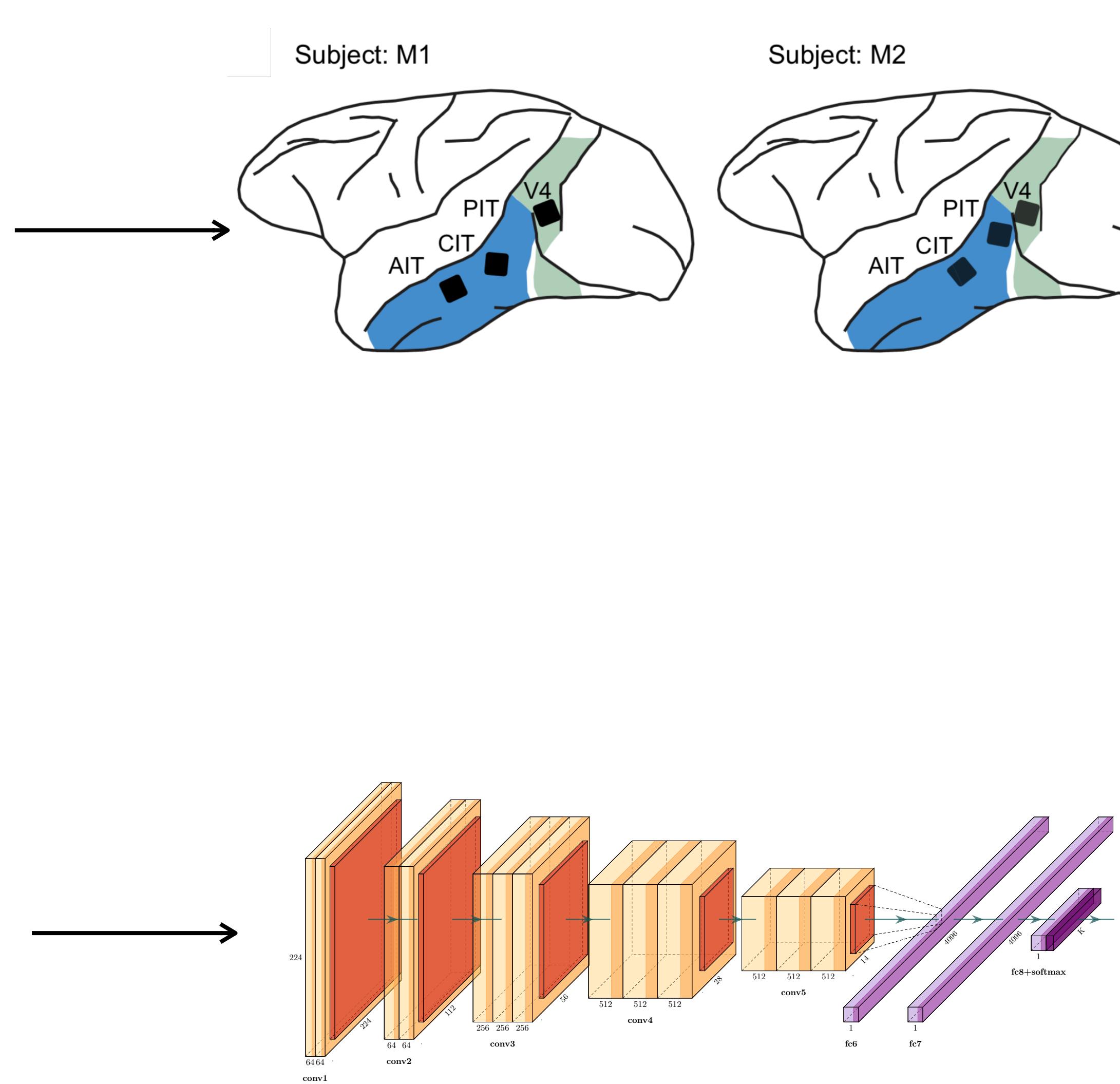
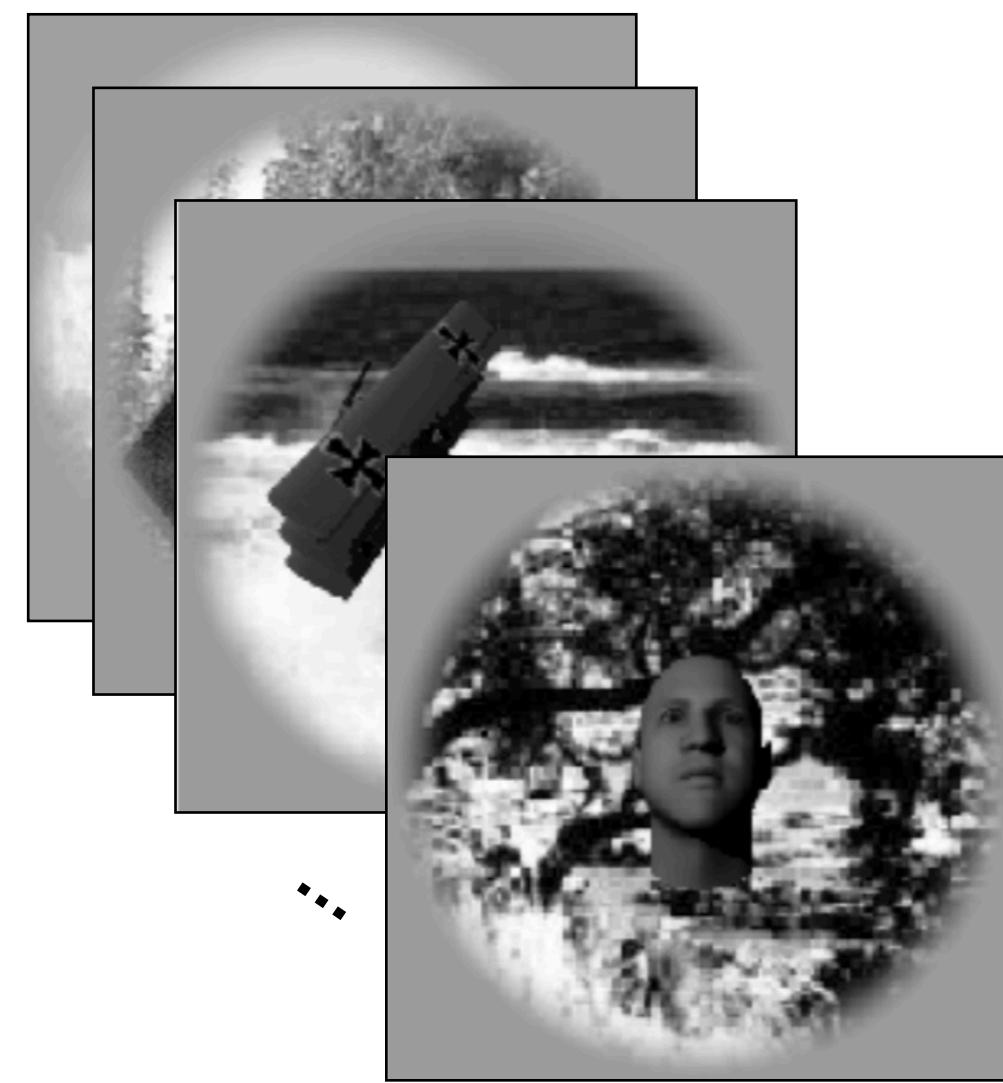
- We generate an empirical null: compute correlation between shuffled RDMs for n iterations
- Compute probability of observed  $r$  directly
- $p\_value = \text{mean}(\text{empirical\_null} > r\_{\text{observed}})$

Typically we only report this final (RSA) correlation value

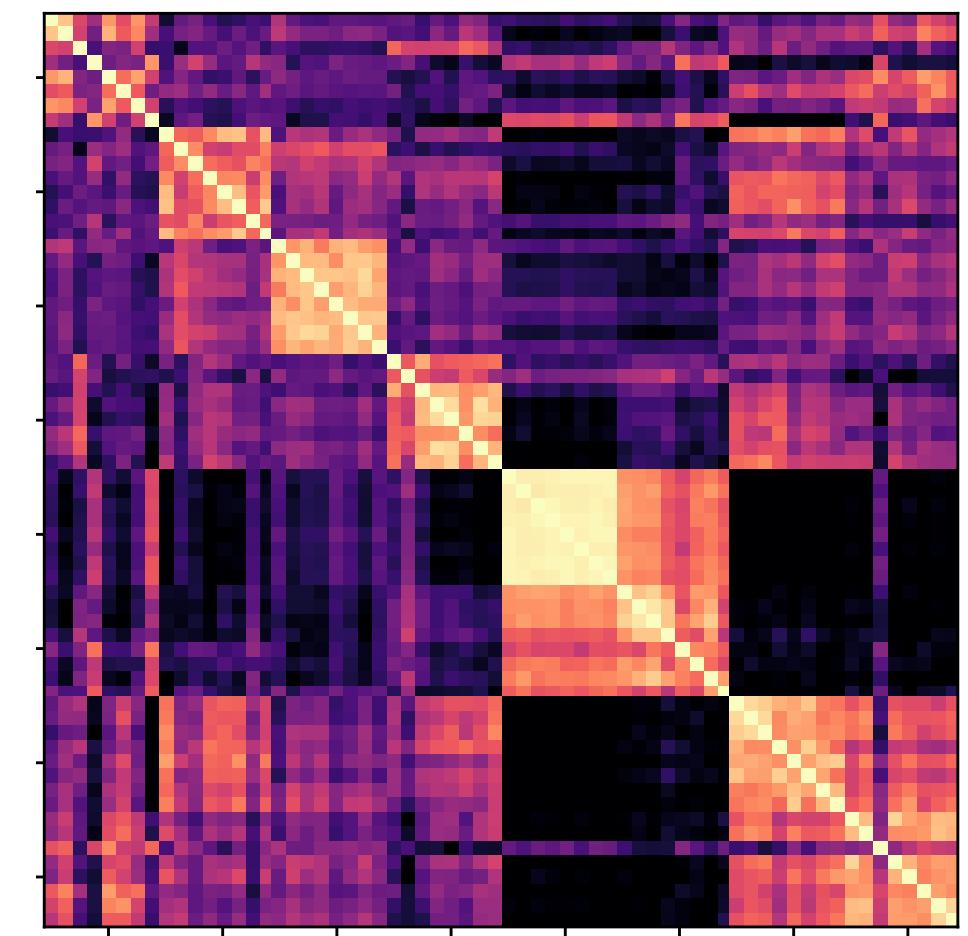
Correlation between different measurements  
of the same phenomena ( $r = 0.73, p < .05$ )



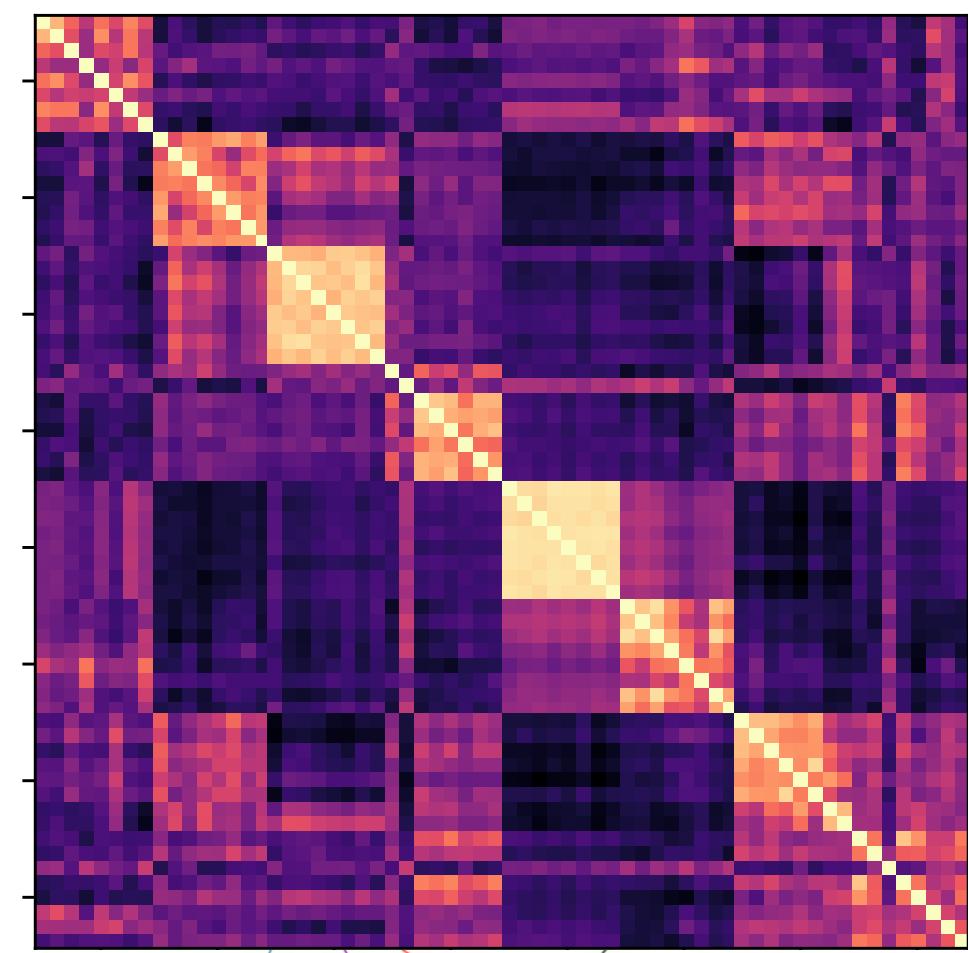
Now lets go back to the model comparison we're interested in



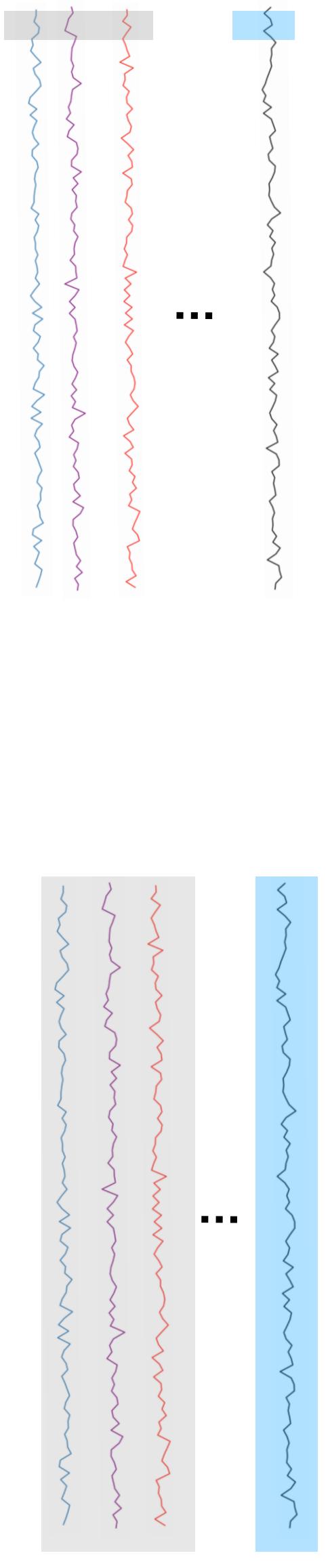
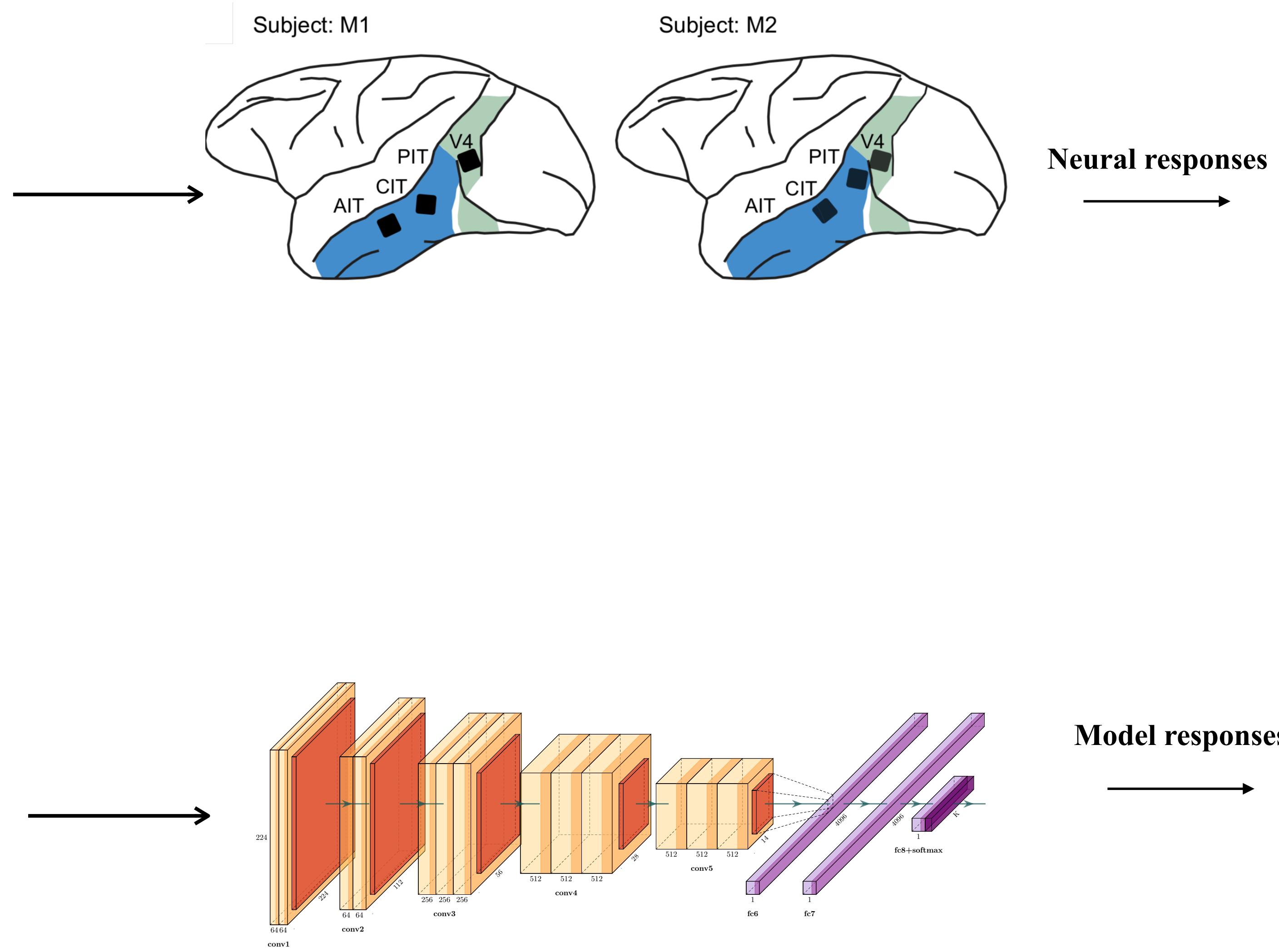
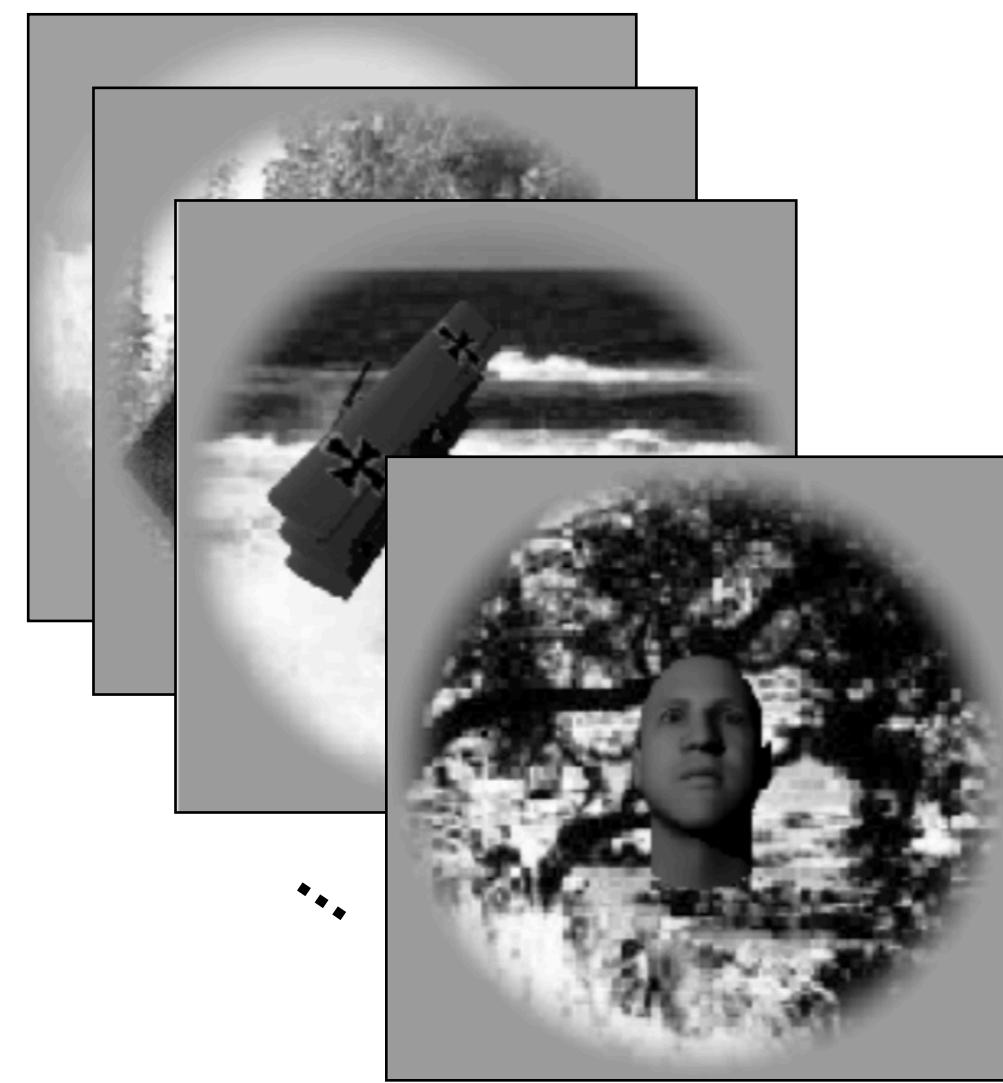
Neural (IT) Dissimilarity Matrices

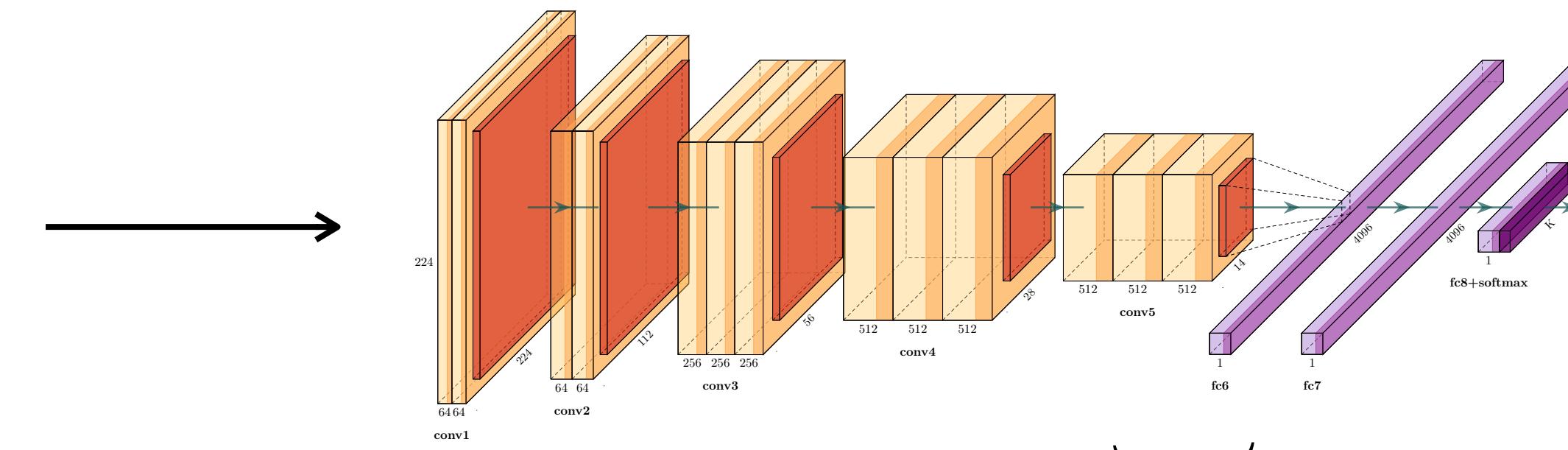
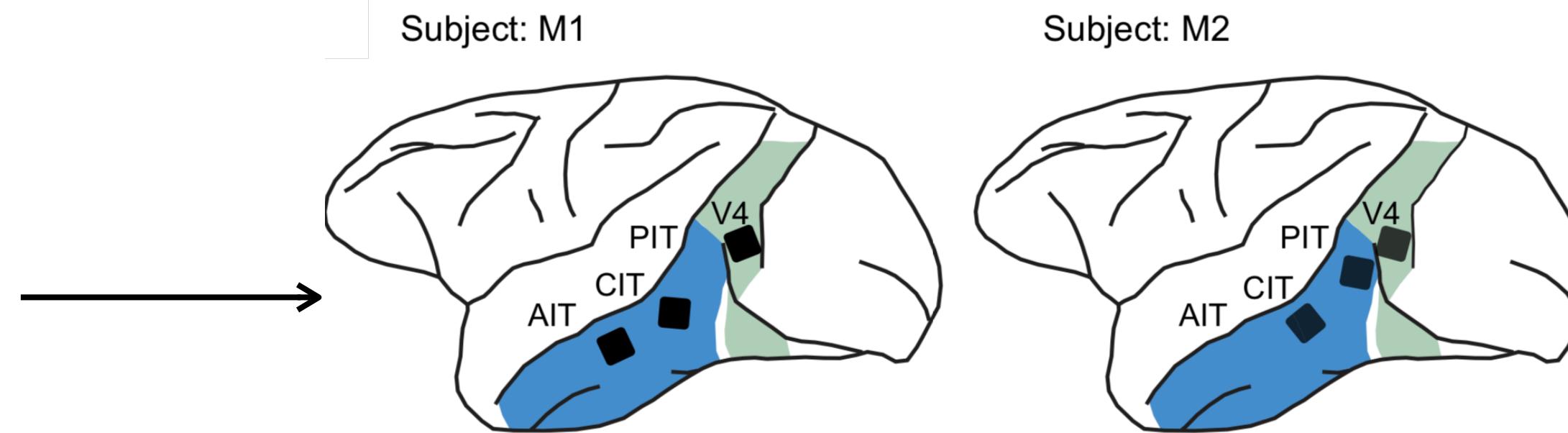
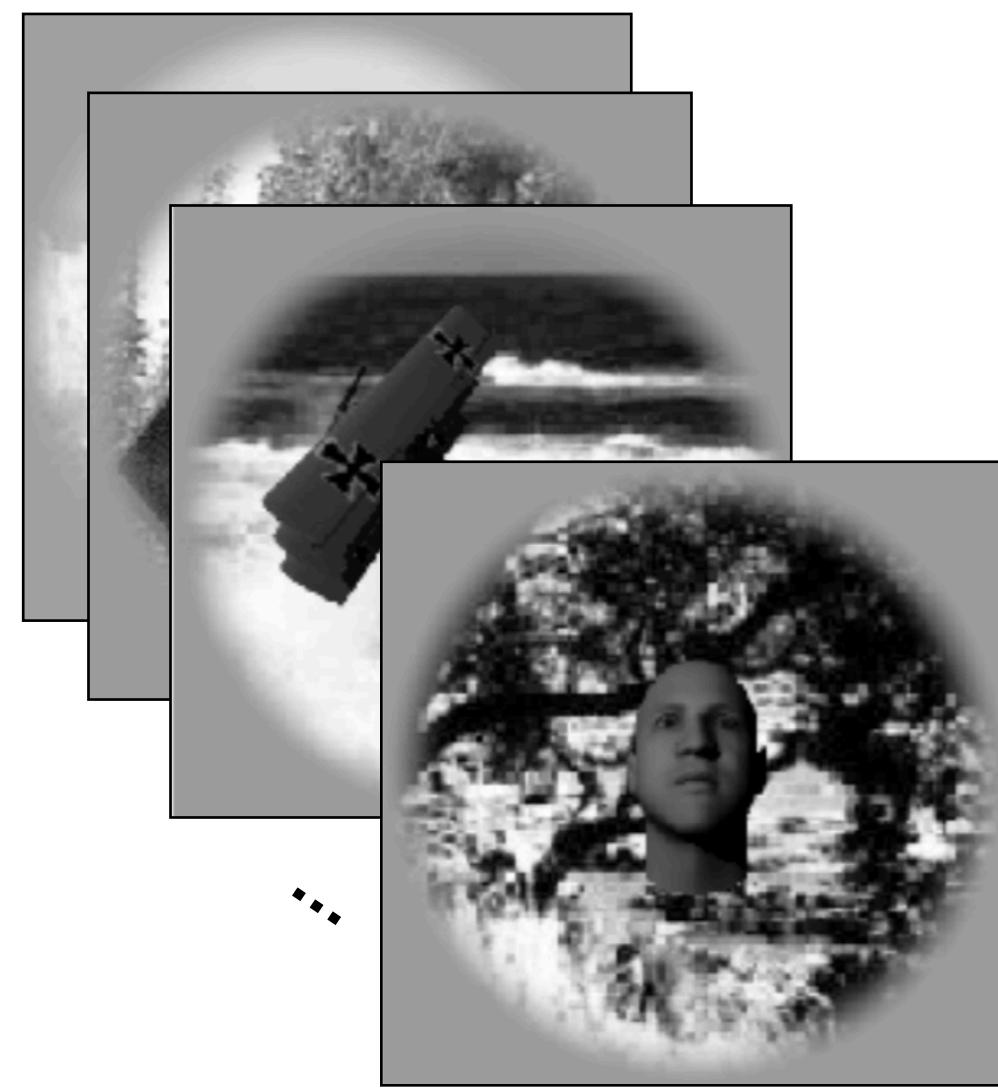


Model (fc6) Dissimilarity Matrices



Learning a mapping between responses  
to shared stimuli





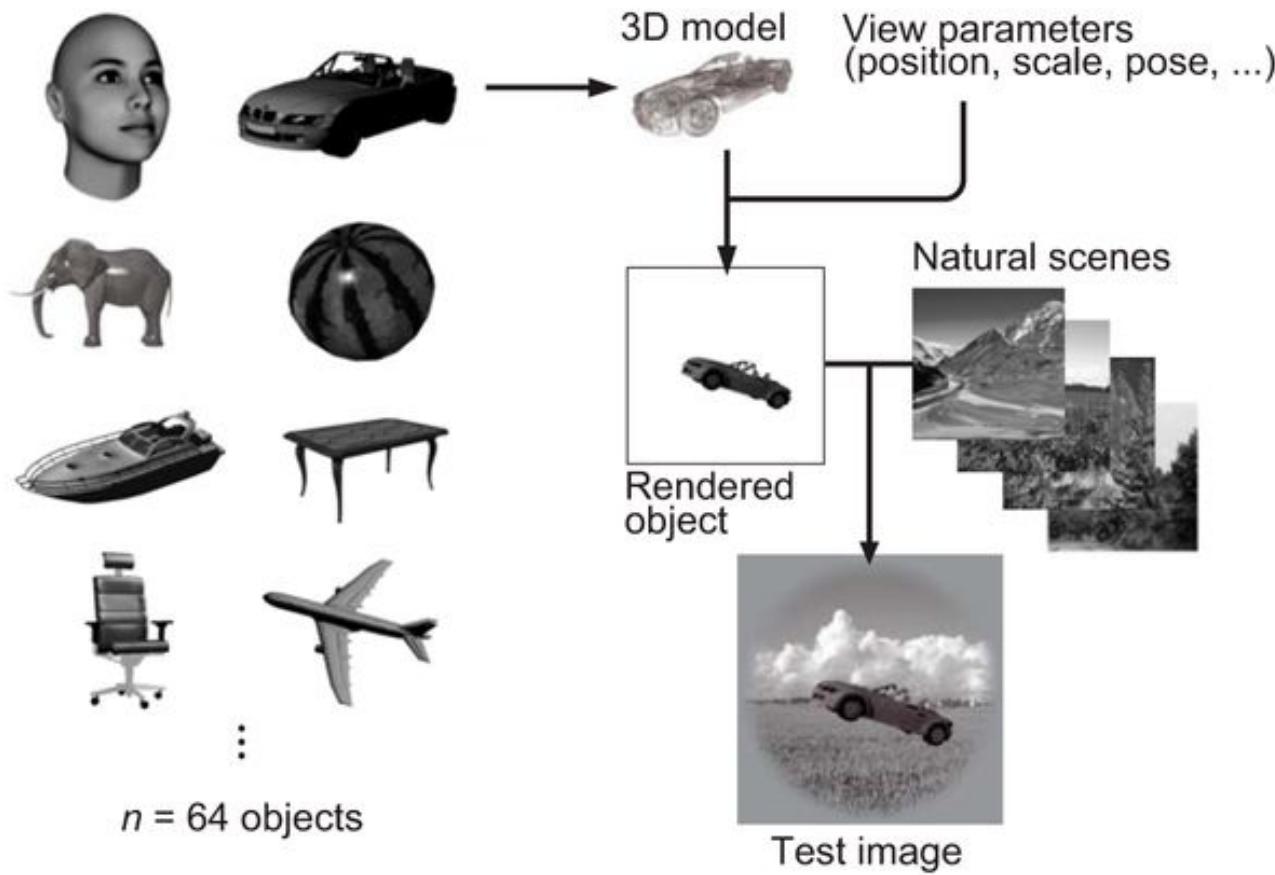
↑ “V4 like”      “IT like”

$\text{pool1}$  -  
 $\text{conv2}_1$  -  
 $\text{conv2}_2$  -  
 $\text{pool2}$  -  
 $\text{conv3}_1$  -  
 $\text{conv3}_2$  -  
 $\text{pool3}$  -  
 $\text{conv4}_1$  -  
 $\text{conv4}_2$  -  
 $\text{pool4}$  -  
 $\text{conv5}_1$  -  
 $\text{conv5}_2$  -  
 $\text{pool5}$  -  
 $\text{conv4}_3$  -  
 $\text{conv5}_3$  -  
 $\text{pool6}$  -  
 $\text{fc7}$  -  
 $\text{fc8}$  -

# Using computational models as a common metric space across data types

What if we want to create a whole new behavioral experiment,  
but still make use of the same images and neural data?

# Generating a novel task that leverages previous data



Majaj et al. 2015

Typical Objects

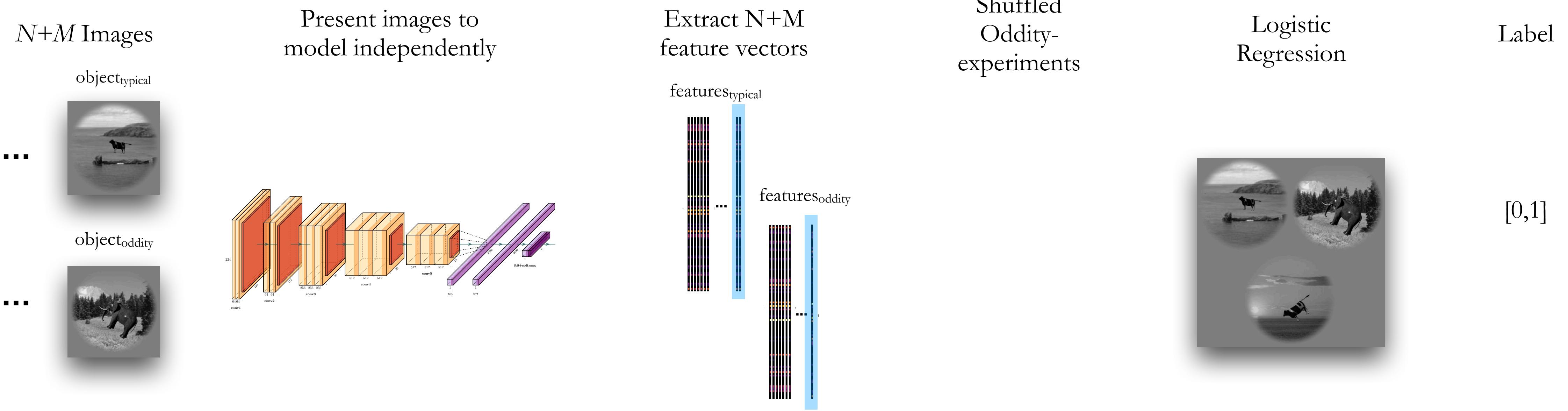


Oddity

Single Trial

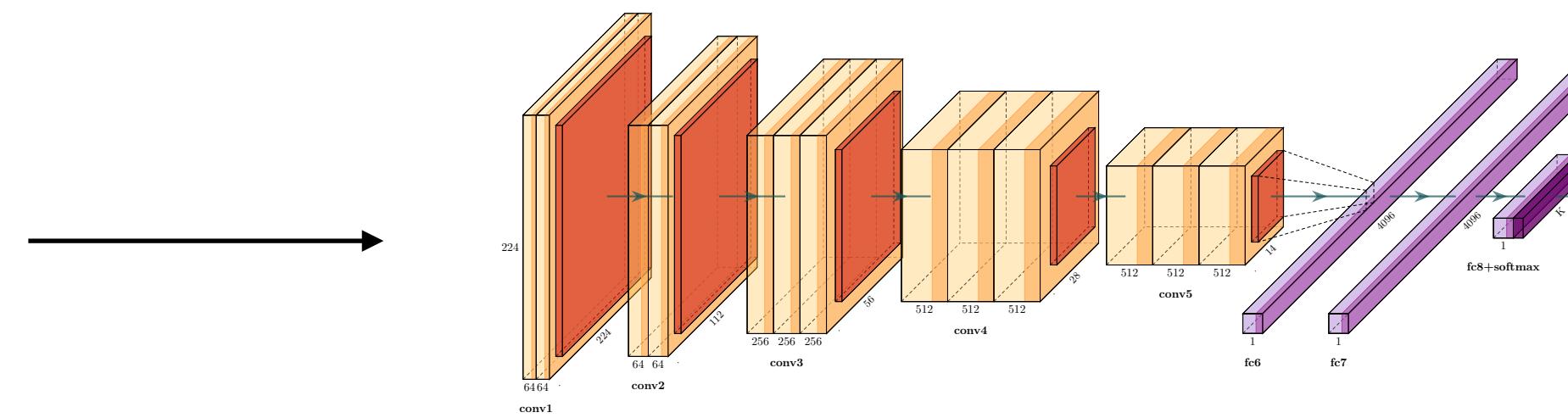


# Experimental Protocol

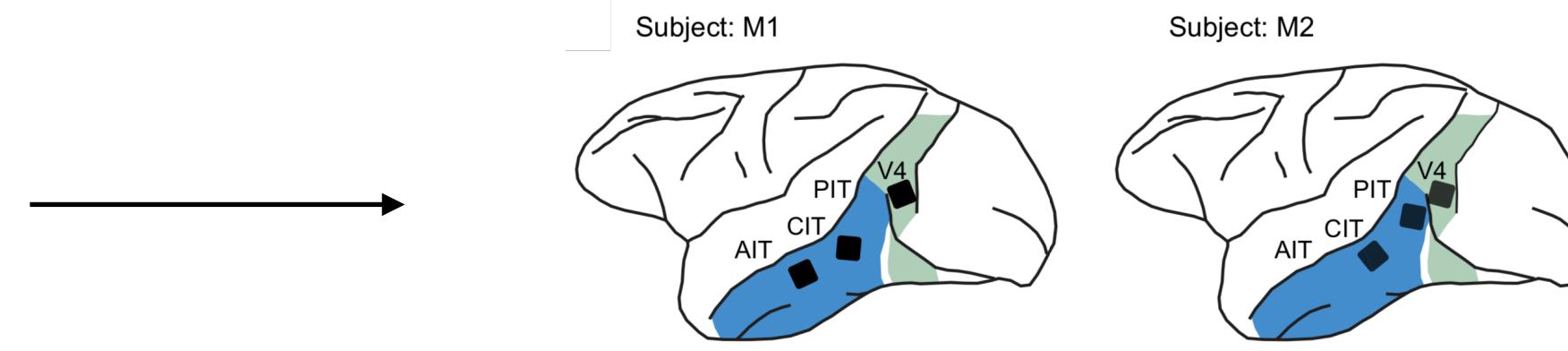


For each trial (e.g. cow\_image34, cow\_image75, elephan\_image34):

1. Pass all  $N$  examples of  $object_{typical}$  and all  $M$  examples of  $object_{oddity}$  to model
2. Extract these  $M+N$  feature vectors from an “IT like” layer
3. Hold out *this trial* feature vectors (e.g. cow\_features34, cow\_features75, elephant\_features34)
4. Generate training data/oddity experiments: sampling without replacement from typical and oddity features
5. Build logistic regression model from pseudo-experiments
6. Evaluate model on this trial (e.g. cow\_image34, cow\_image75, elephan\_image34)
7. Repeat over  $n$  permutations



**Model responses**



**Neural responses**



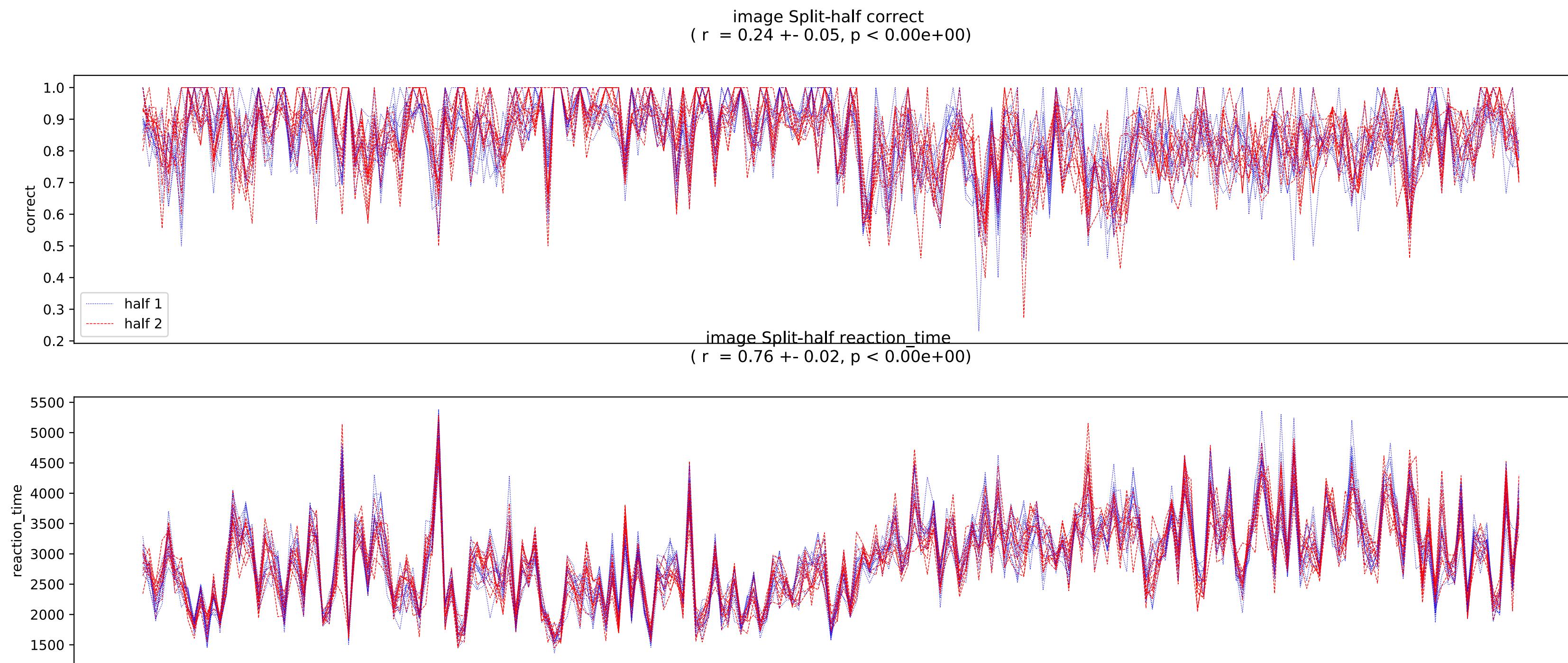
**n = 297**

**Behavioral responses**

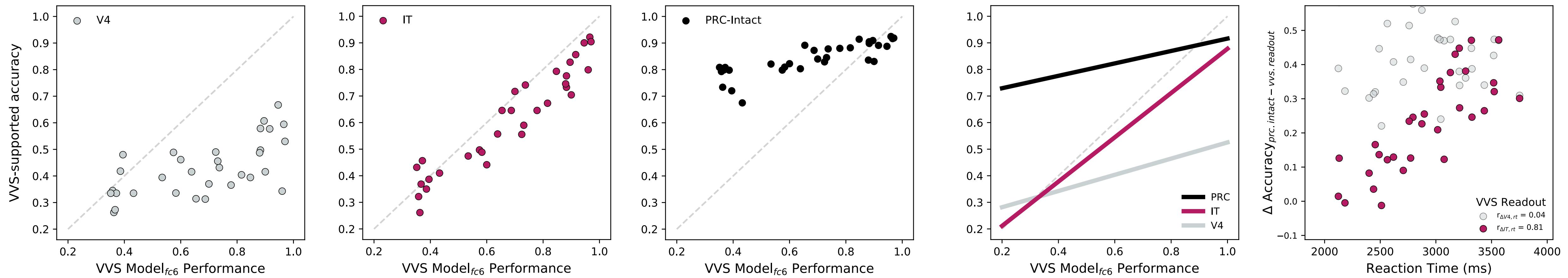
3-way oddity tasks

# A quick note on reliability

- What's the most variance we could hope a model could explain?
  - The variance that's reliably evident in different samples of the data
  - Often called the split-half reliability, or referred to as the “noise ceiling”
- When we can, we should look at reliability across multiple resolutions



# Relating neural, model, and behavioral data



- But you've already seen this, haven't you :)

# Questions?