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# The emerging perceptual representation of faces decoded from human neuromagnetic recordings


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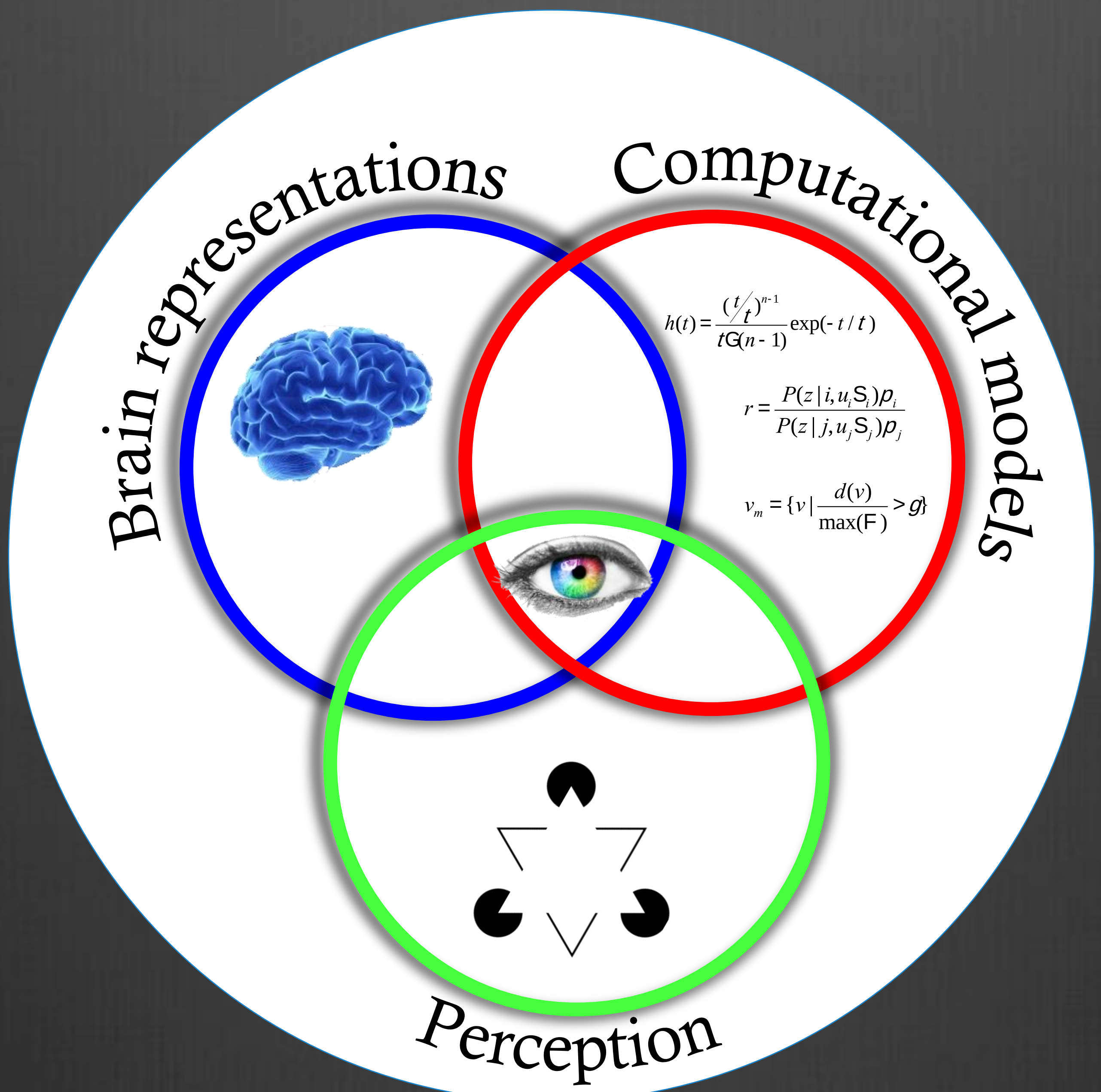
# Introduction

- Faces are singularly important stimuli for social primates
- We effortlessly extract a range of information about an individual from their face: identity, age, gender, health, attractiveness, emotional state, intent, etc.
- It's known that considerable neural resources (a "module"?) devoted to visual processing of faces.
- The brain is solving a tough problem. Understanding how it does it requires an understanding of how the solution operates at different levels of processing…

# Aim of the study: bridge computational model, perception, and neuronal representations of faces




## Constructing a computational model

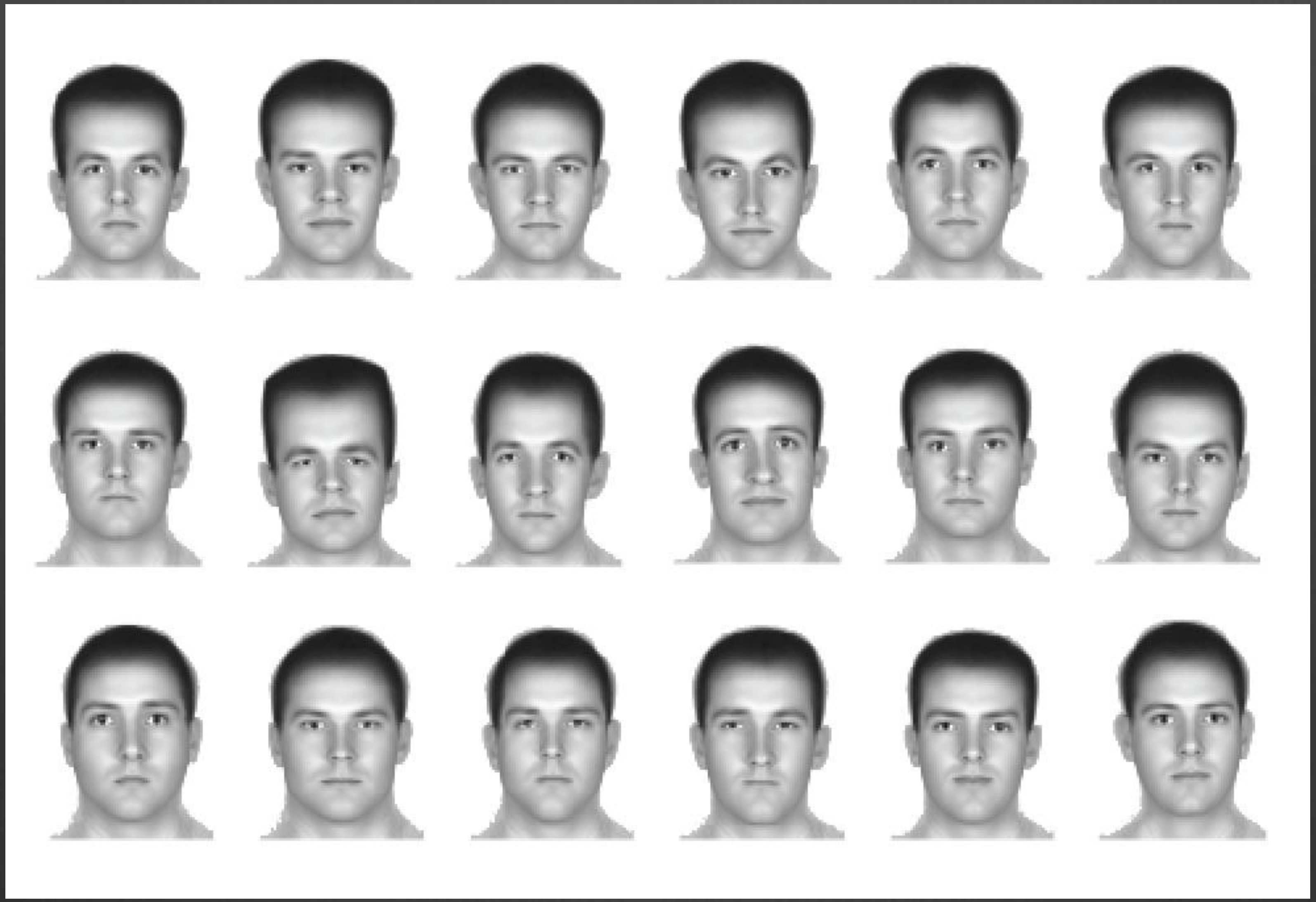
# Generative model of faces

- Valentine (1991) proposed "face-space", where a face is a point in a multi-dimensional space the dimensions of which are measured in relation to an "average face". Explains e.g. other-race effects.

- The idea of a norm-based code can be combined with digital morphing to generate a generative model of faces:

    - Establish common key-points on a set of faces.
    - Faces are represented as vector of the key-point x & y values
    - Express all vectors relative to the average "face"

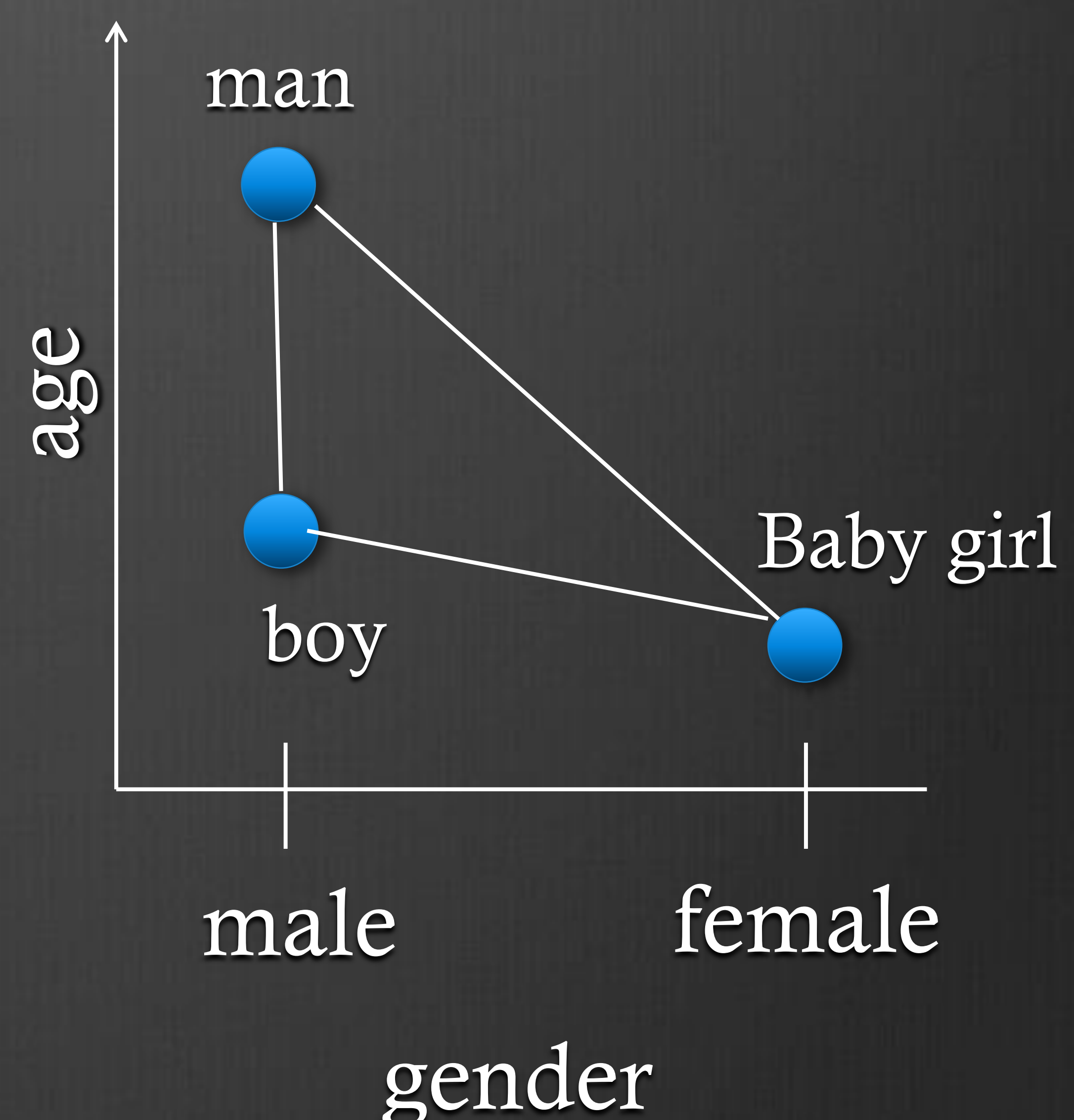
# The unusual suspects



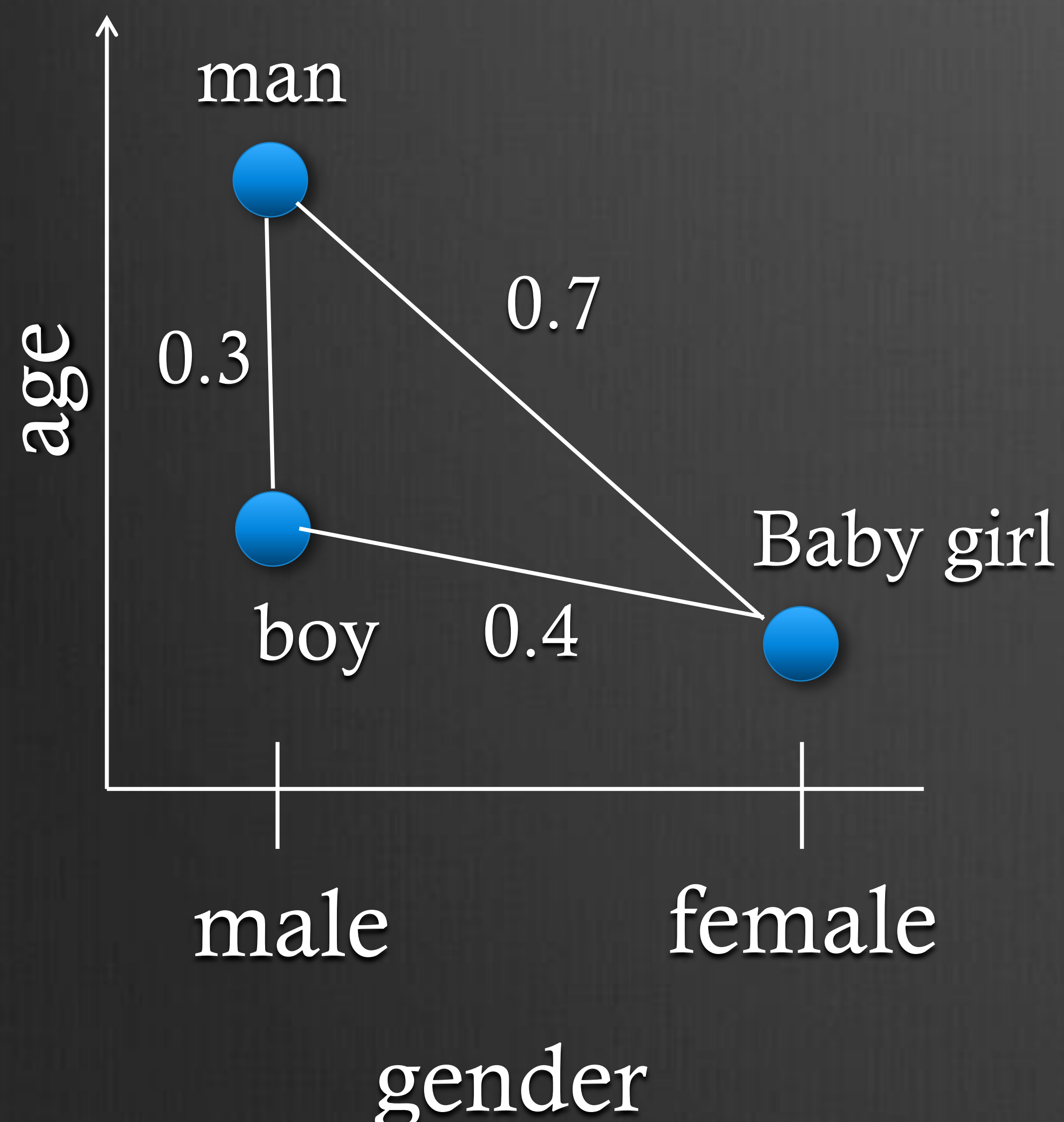
- Model based on images of Scottish policeman
- 18 face exemplars generated by morphing “average face” into registration with a random key-point vectors (i.e. random locations in the multi-dimensional model “facespace”.

# Measuring representational geometry

- High dimensional space describing "what a representation cares about", e.g. retinotopic location, colour, semantic category, etc.
- Individual stimulus exemplars occupy points in representational space.
- Distances between exemplars describe their relationship.
- Representational geometry is important because :
  - The nature of the organization hints at why the brain might use this coding scheme (Carlson et al., 2014a).
  - We can examine how information might be "read out" from the representation? (Carlson et al., 2014b).



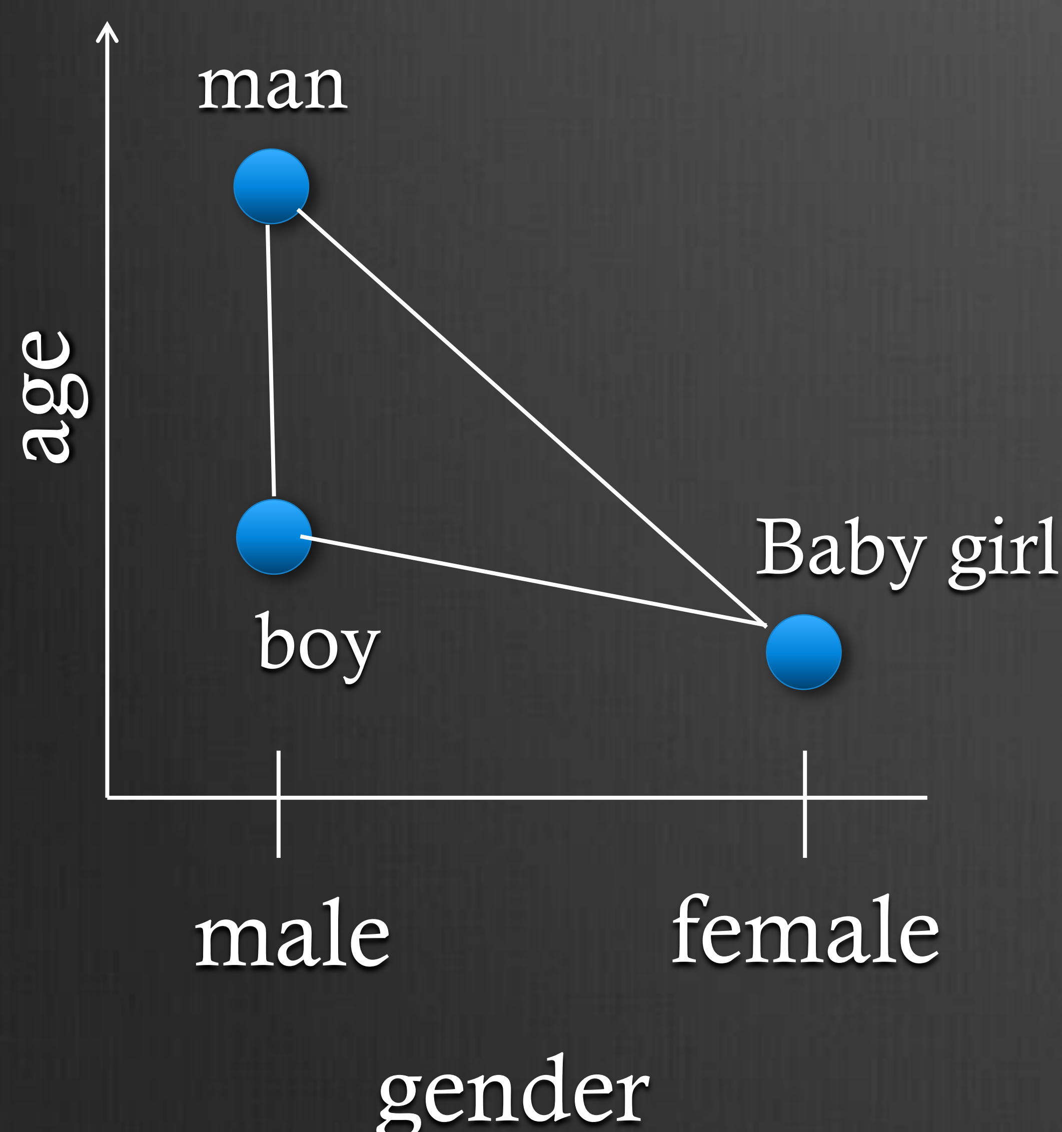
# Representational geometry

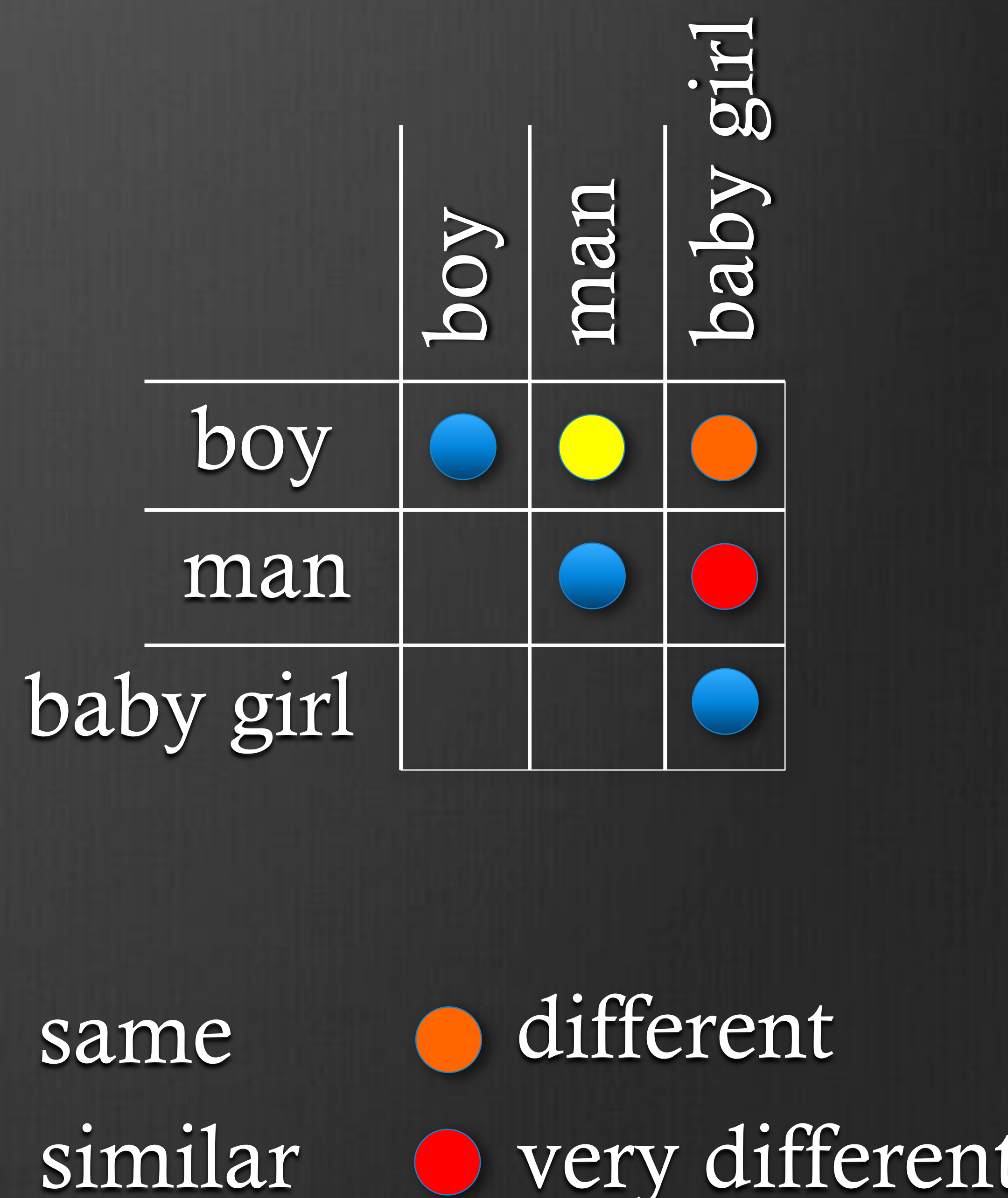



| | boy | man | baby girl |
|---|---|---|---|
| boy | 0.0 | 0.3 | 0.4 |
| man | | 0.0 | 0.7 |
| baby girl | | | 0.0 |

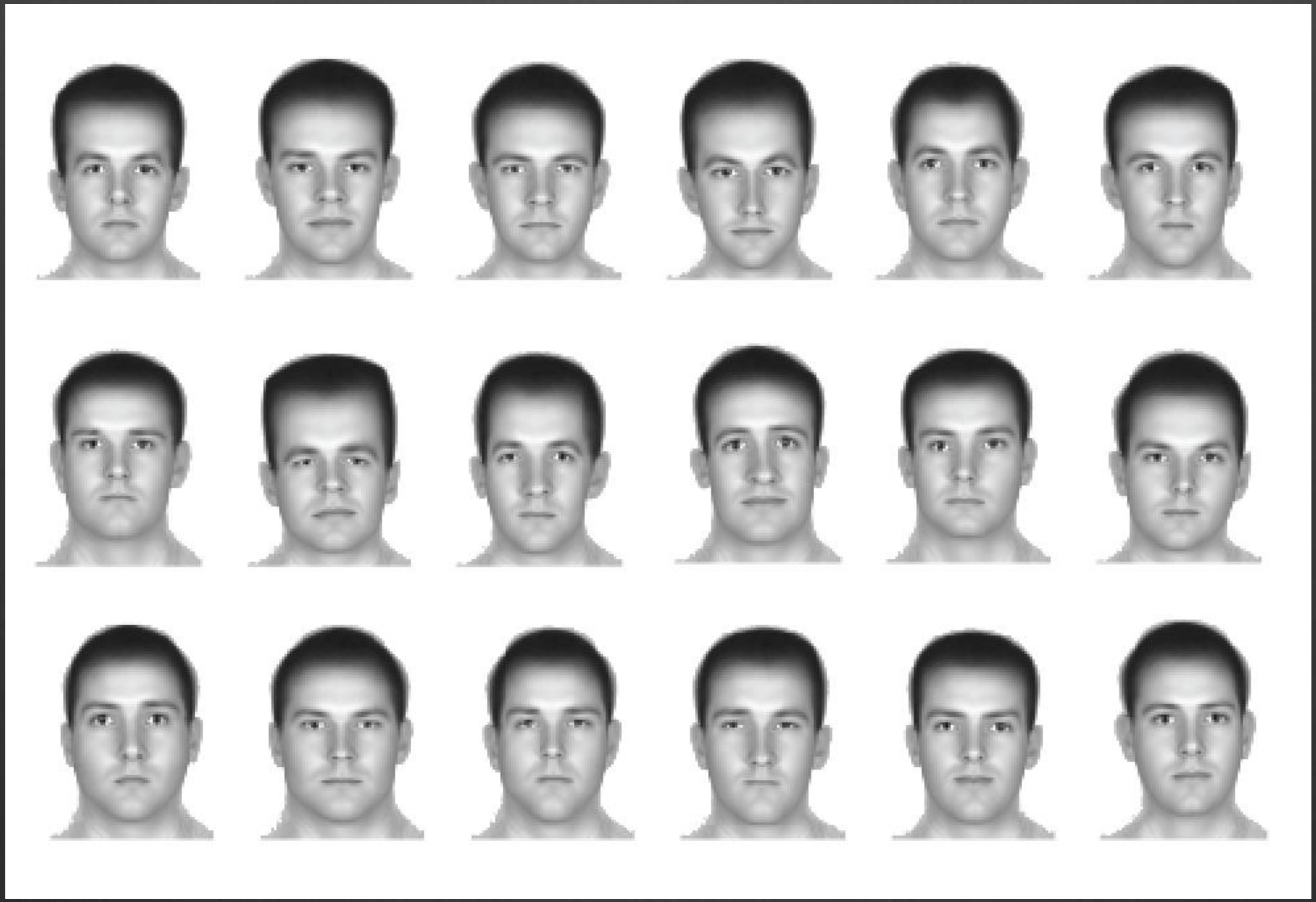
Formally described using a dissimilarity matrix (distance in the space)

# Representational geometry



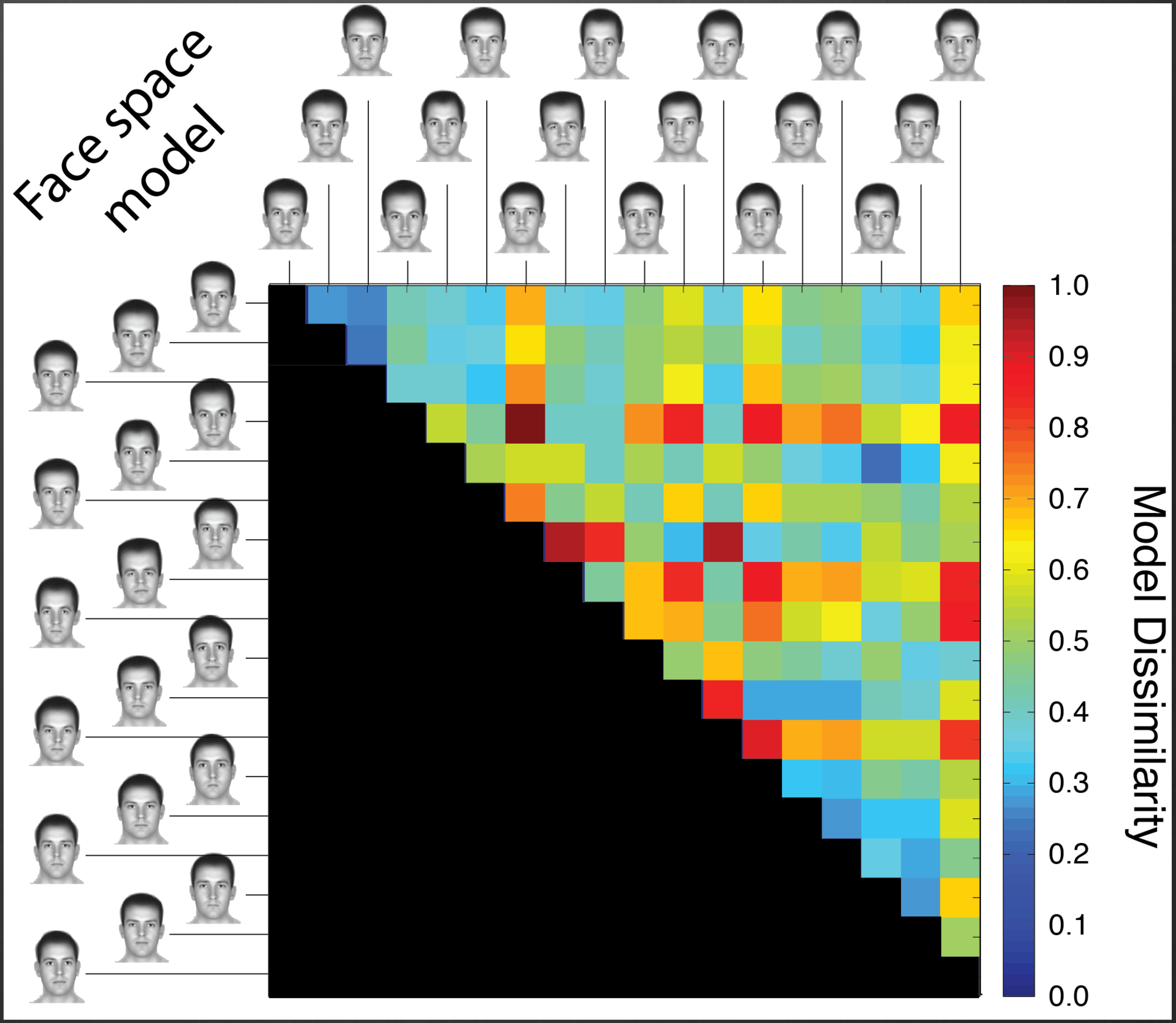



# The representational geometry of model faces

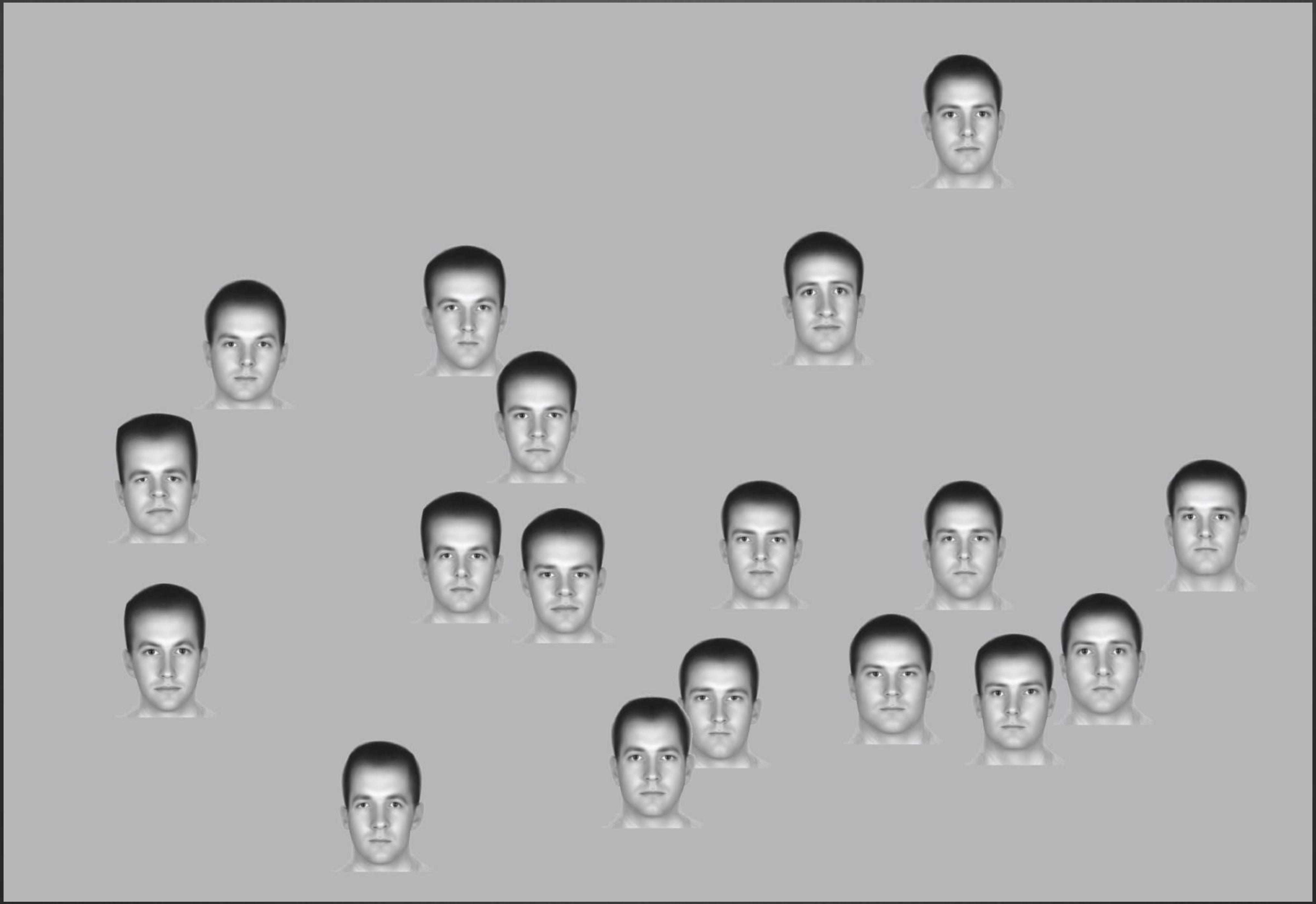


# Model face dissimilarity

- Facespace model dissimilarity matrix (DSM)
- Shows model difference between all possible face pairs
- Color represents difference (Euclidean distance in facespace)

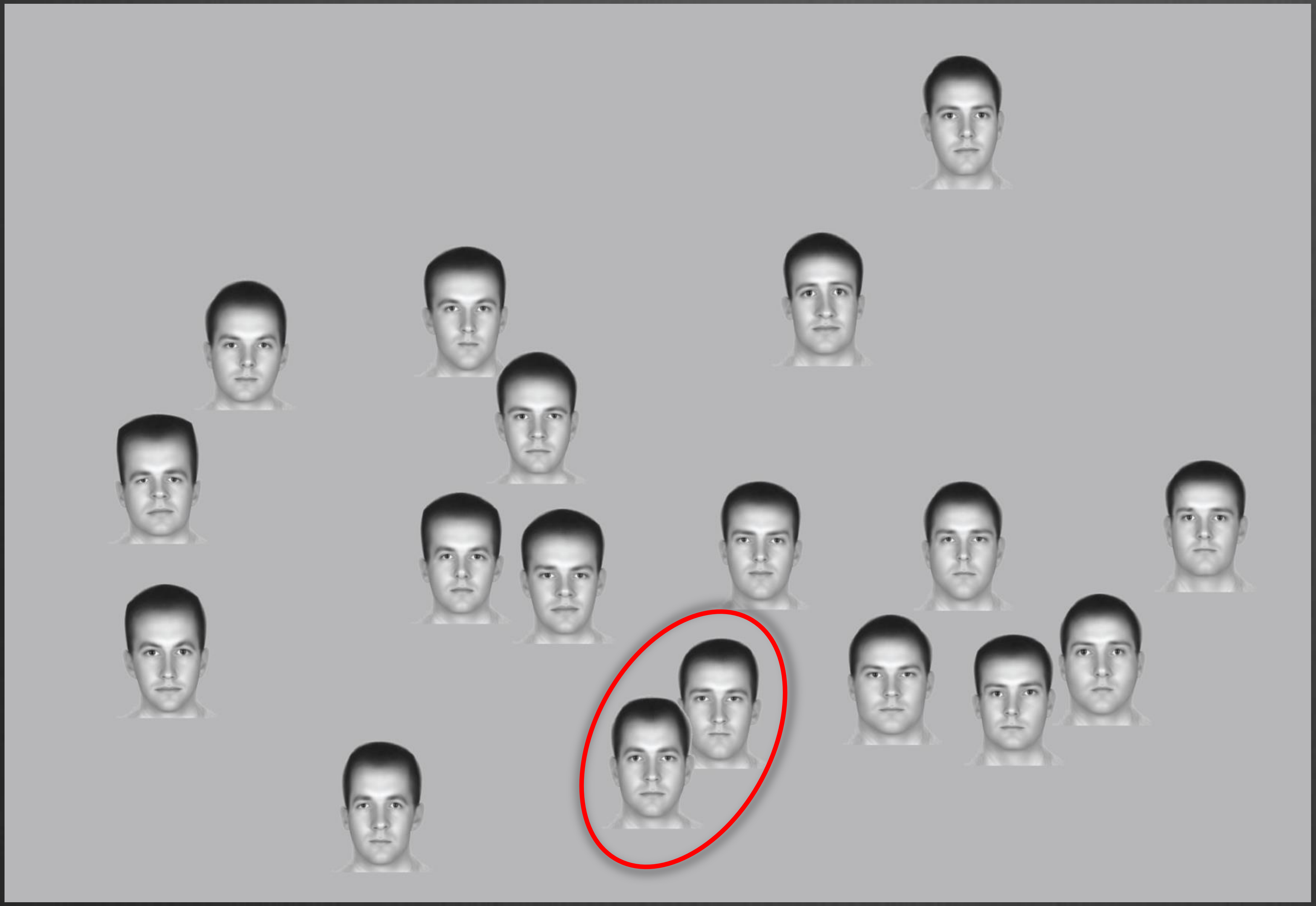


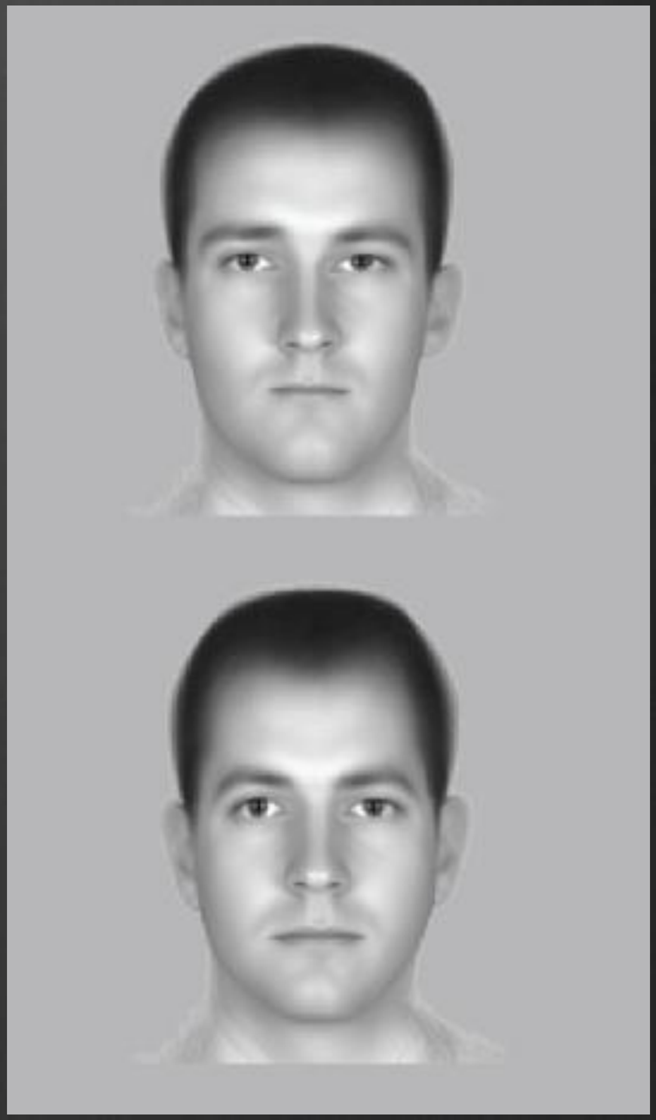
# Generative "face space" model



"Flattened" Multidimensional scaling representation

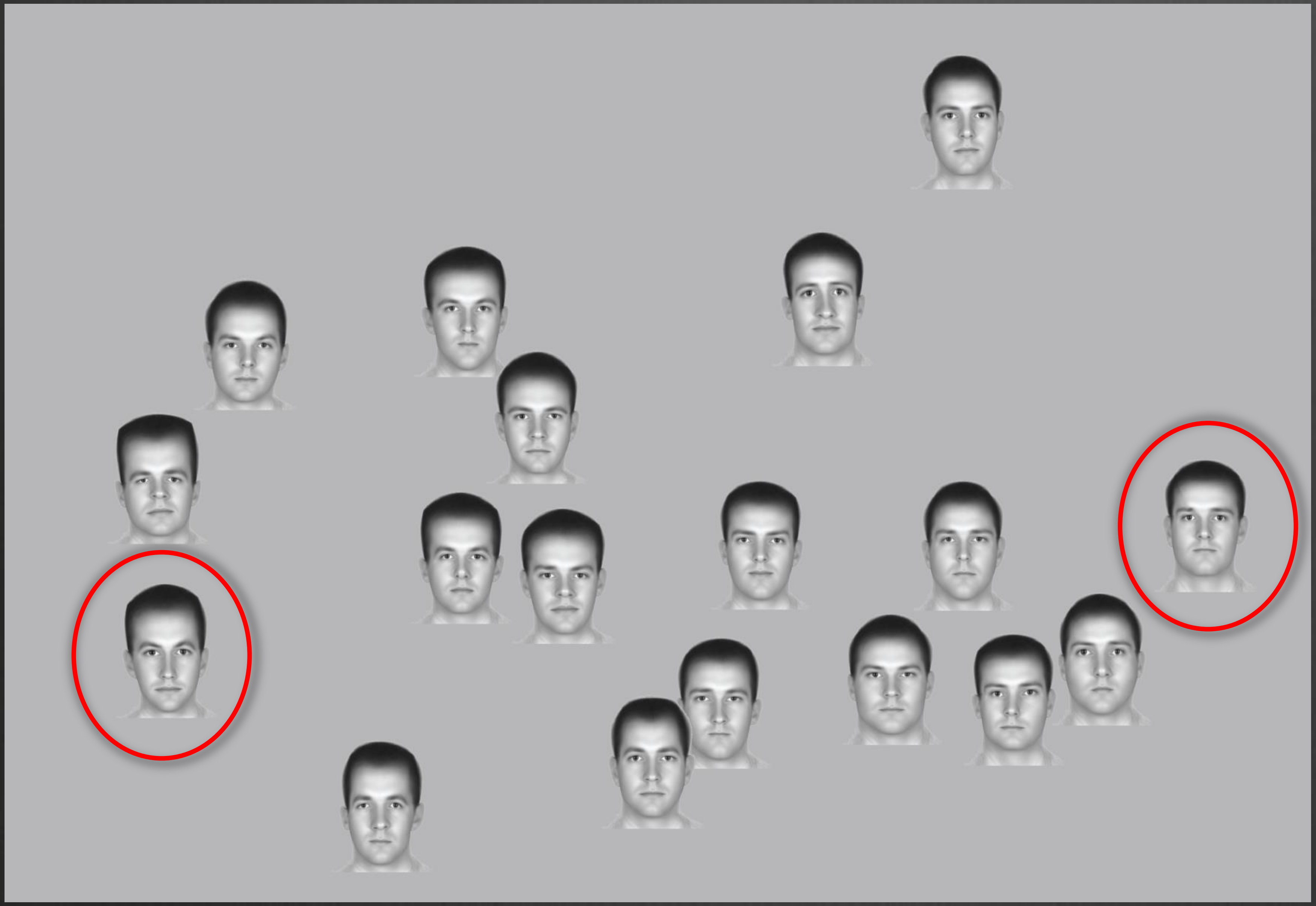
# Generative model "face space"





Distance represents model dissimilarity: close = similar

# Generative model "face space"



Distance represents model dissimilarity: far = dissimilar

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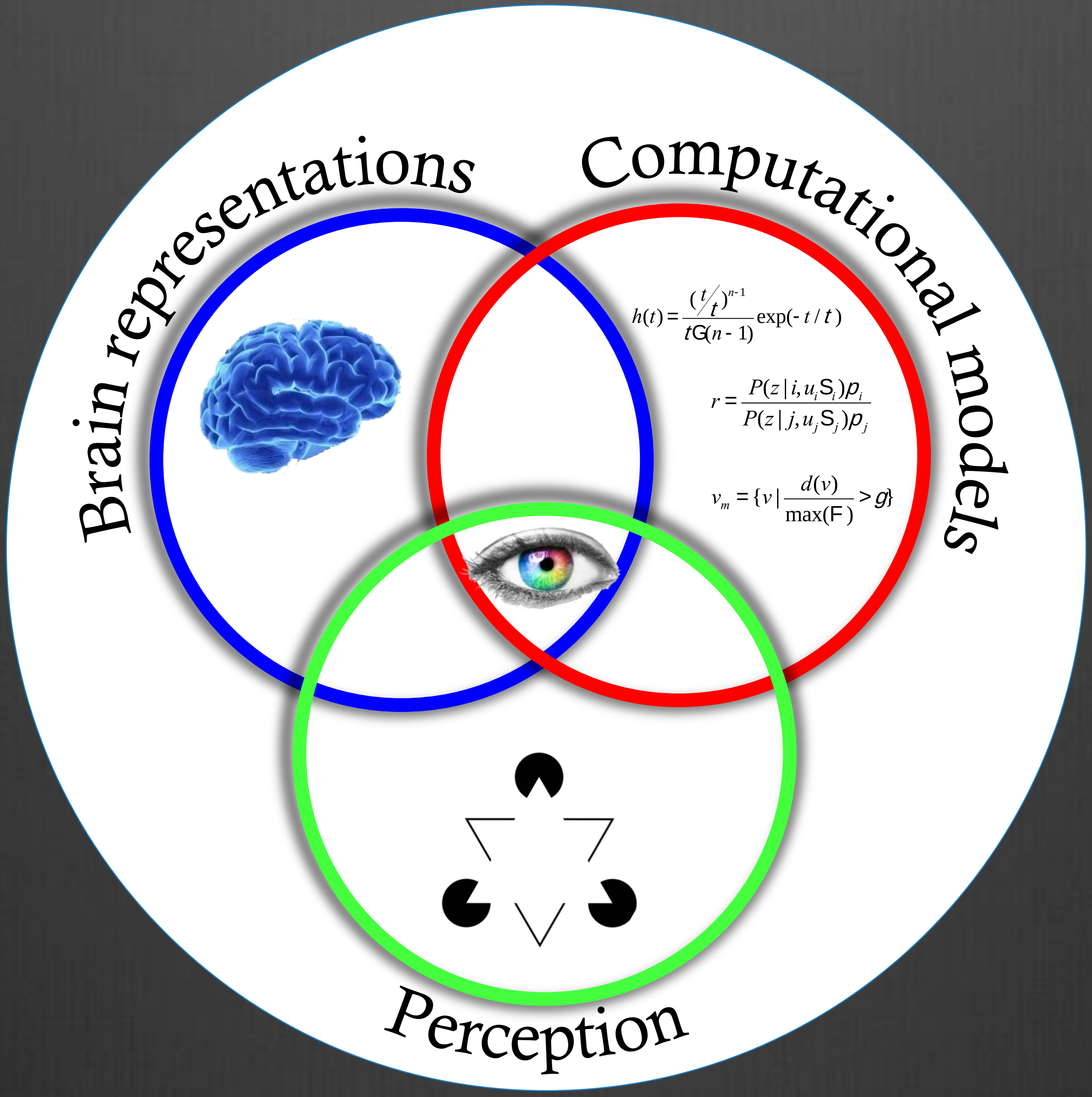
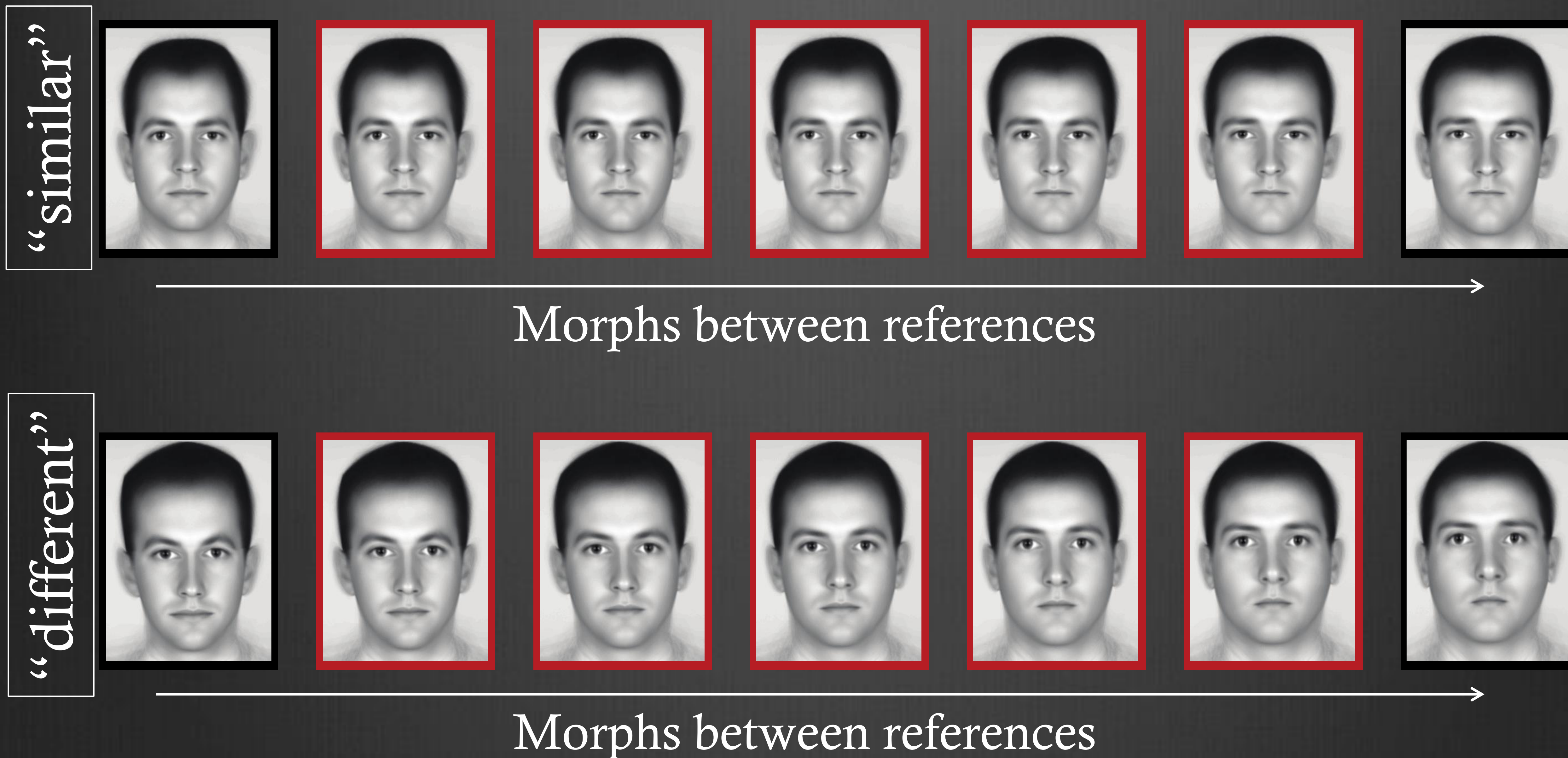


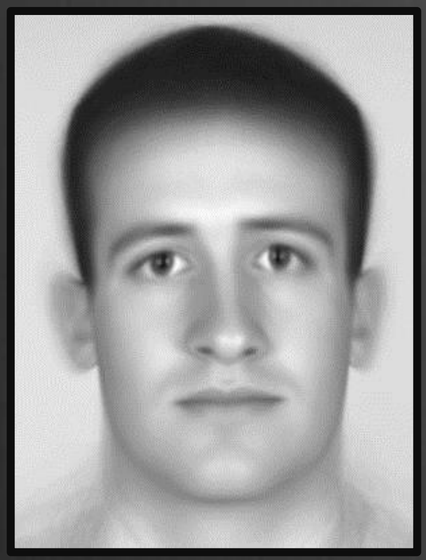

# Measuring perception

# Constructing perceptual model

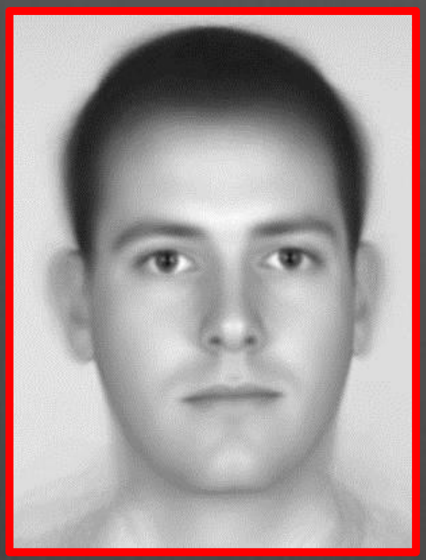



- Individual pairs of reference faces from the generative model vary in terms of perceptual similarity
- Using the model, we can generate morphs between reference faces

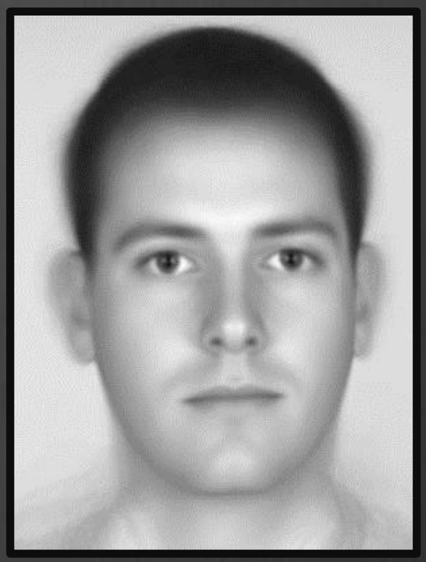
# Measuring distances in perceptual space



Reference face #1 from generative model



Target “morph” between references

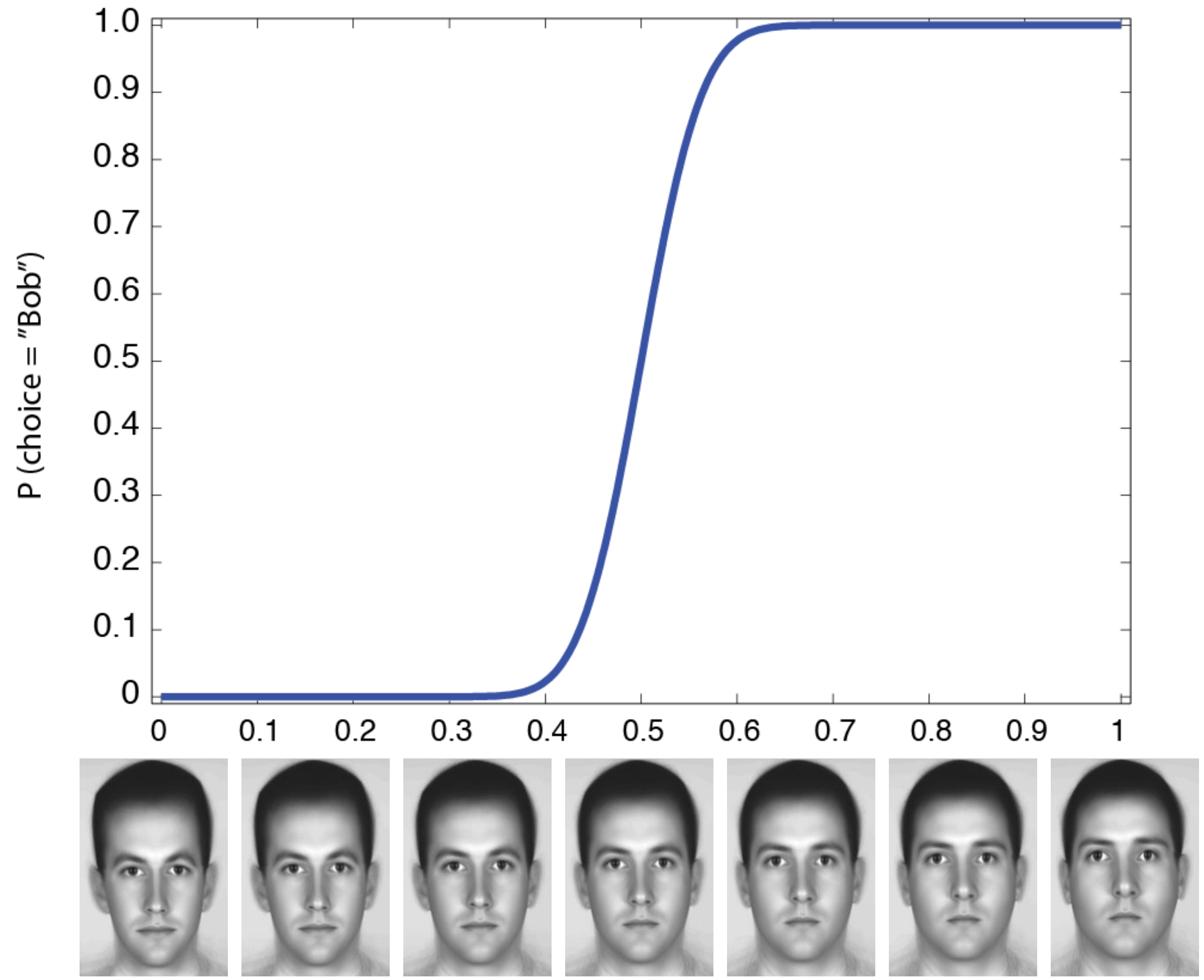


Reference face #2 from generative model

## Brother identification task:

- Target face is an interpolated  morph between two reference faces
- Target is presented flanked by two reference faces for three seconds
- Subject’s task is choose which reference is more similar (i.e. who is the target’s brother?)
- Measure performance varying for mixture morphs (e.g. 60% reference 1, 40% reference 2)

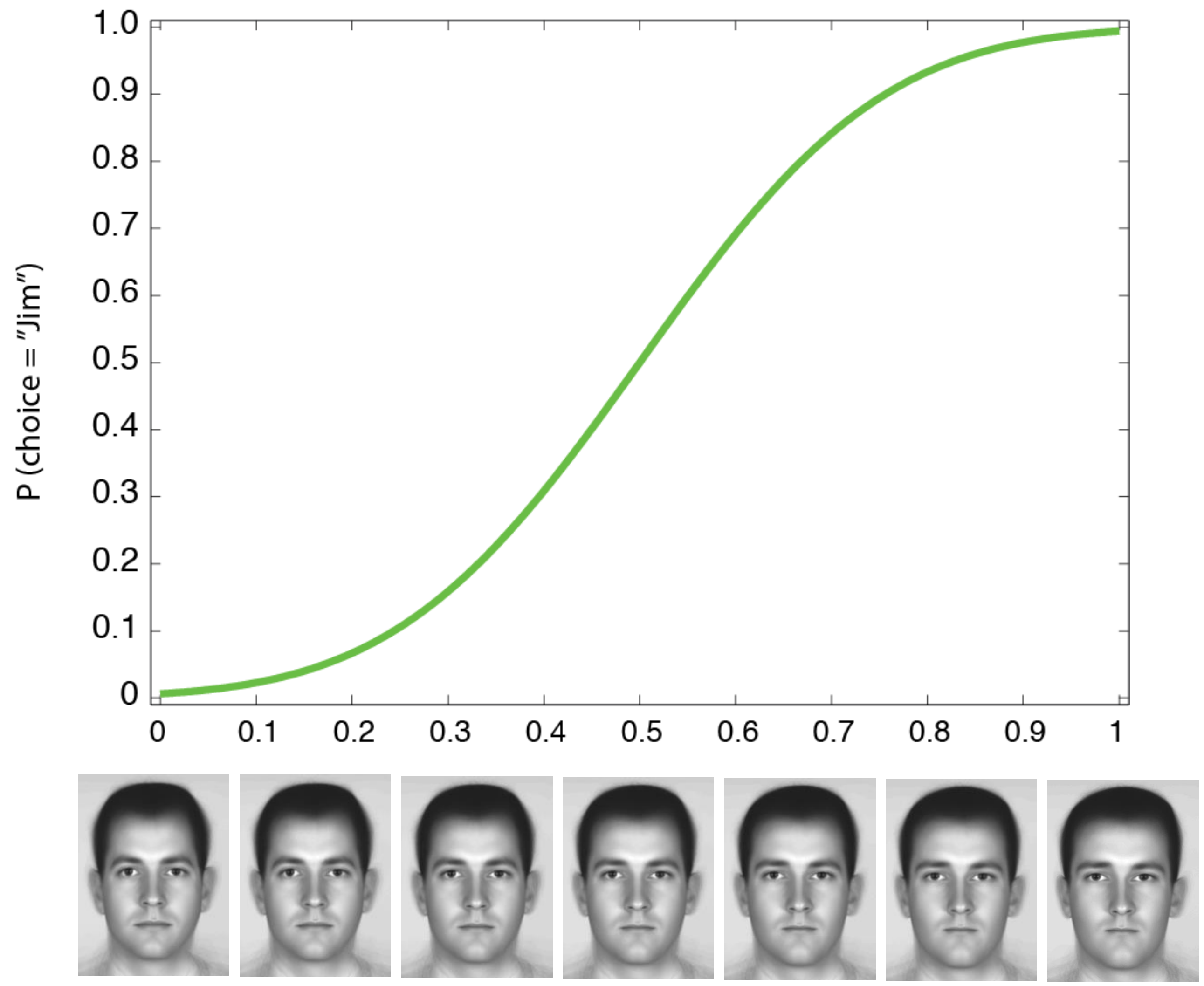
# Measuring distances in perceptual space




Brother identification task measures human sensitivity to face pairs

- If faces are highly dissimilar, there will be few confusions for the extreme morphs.
- Steep psychometric function means faces are highly discriminable

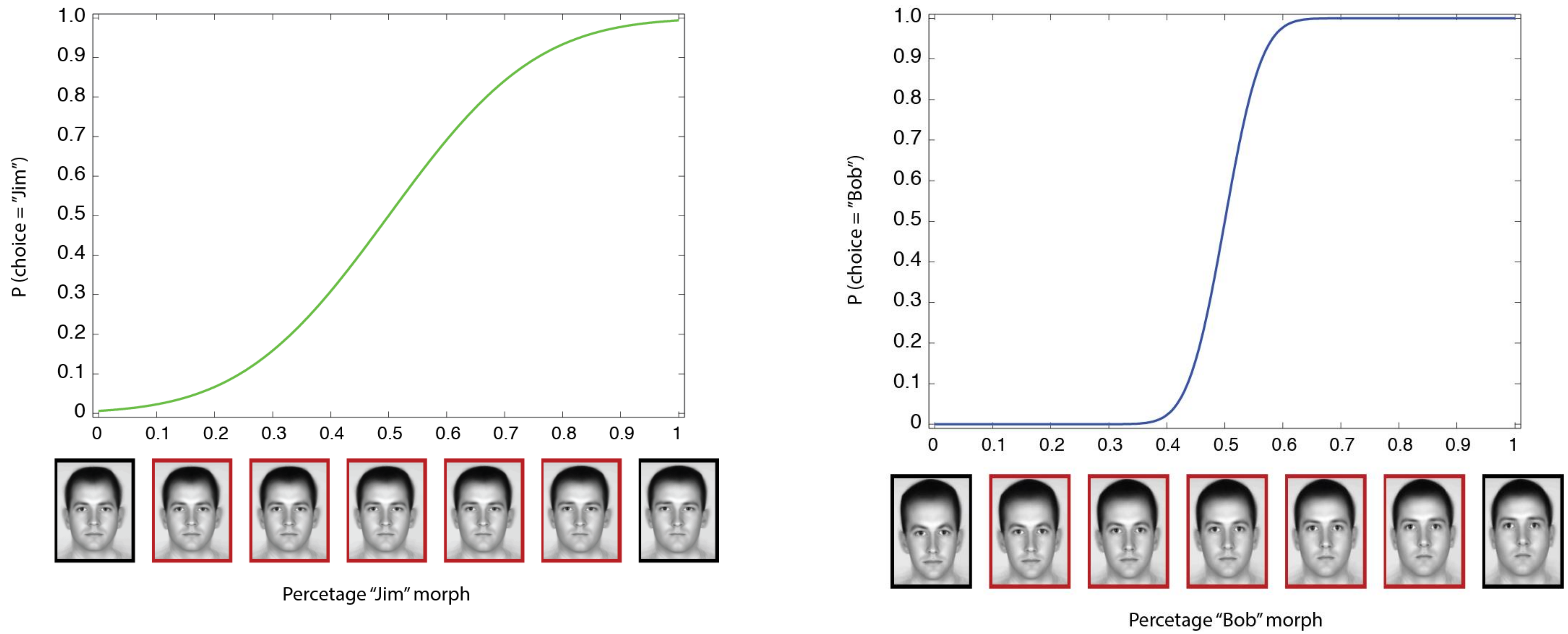
# Measuring distances in perceptual space




Brother identification task measures human sensitivity to face pairs

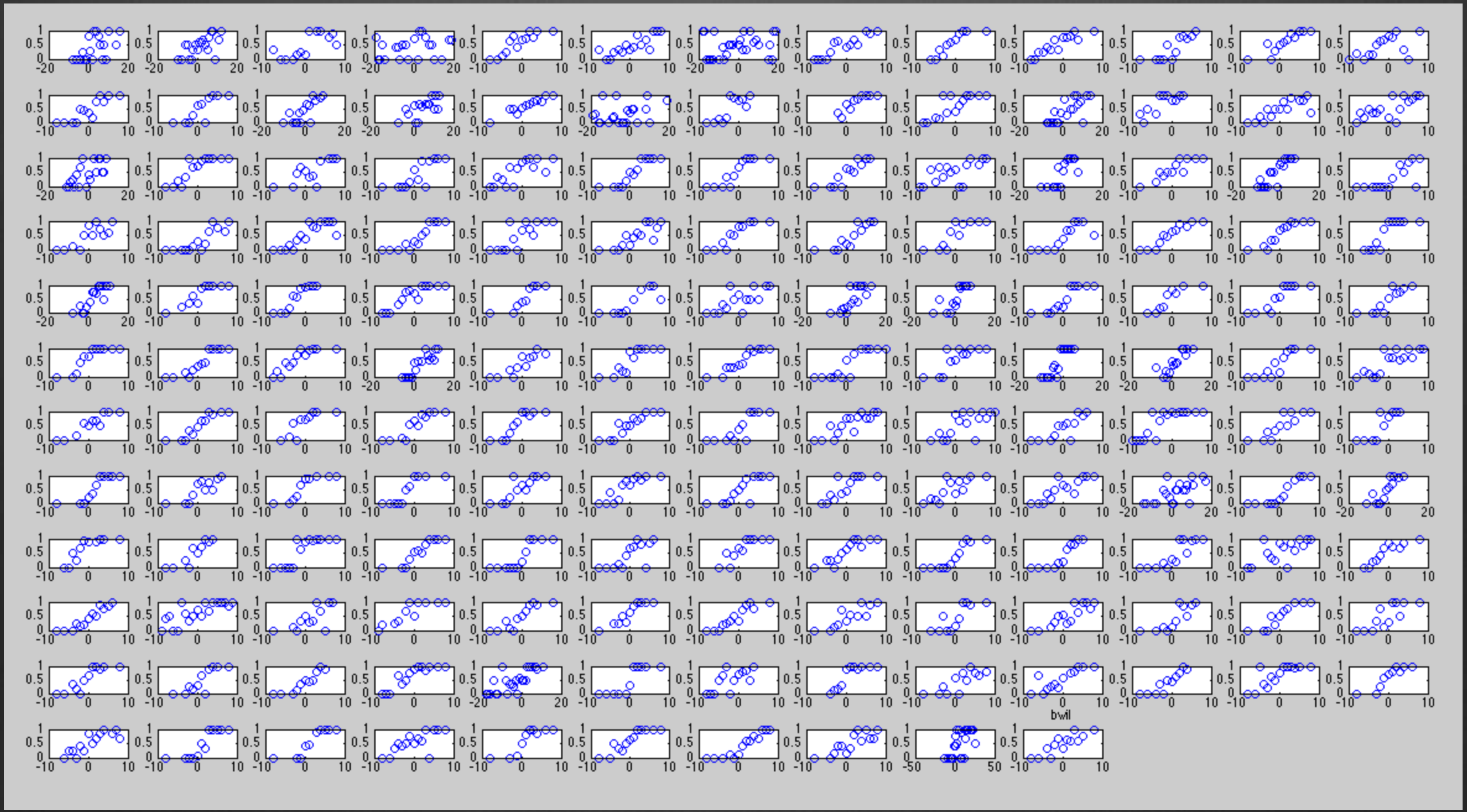
- If faces are very similar, there will be more confusions between faces, even at the extremes.
- Shallow psychometric function means faces are less discriminable

# Measuring distances in perceptual space




- Shallow psychometric function = close in perceptual face space
- Steep psychometric function = far in perceptual face space

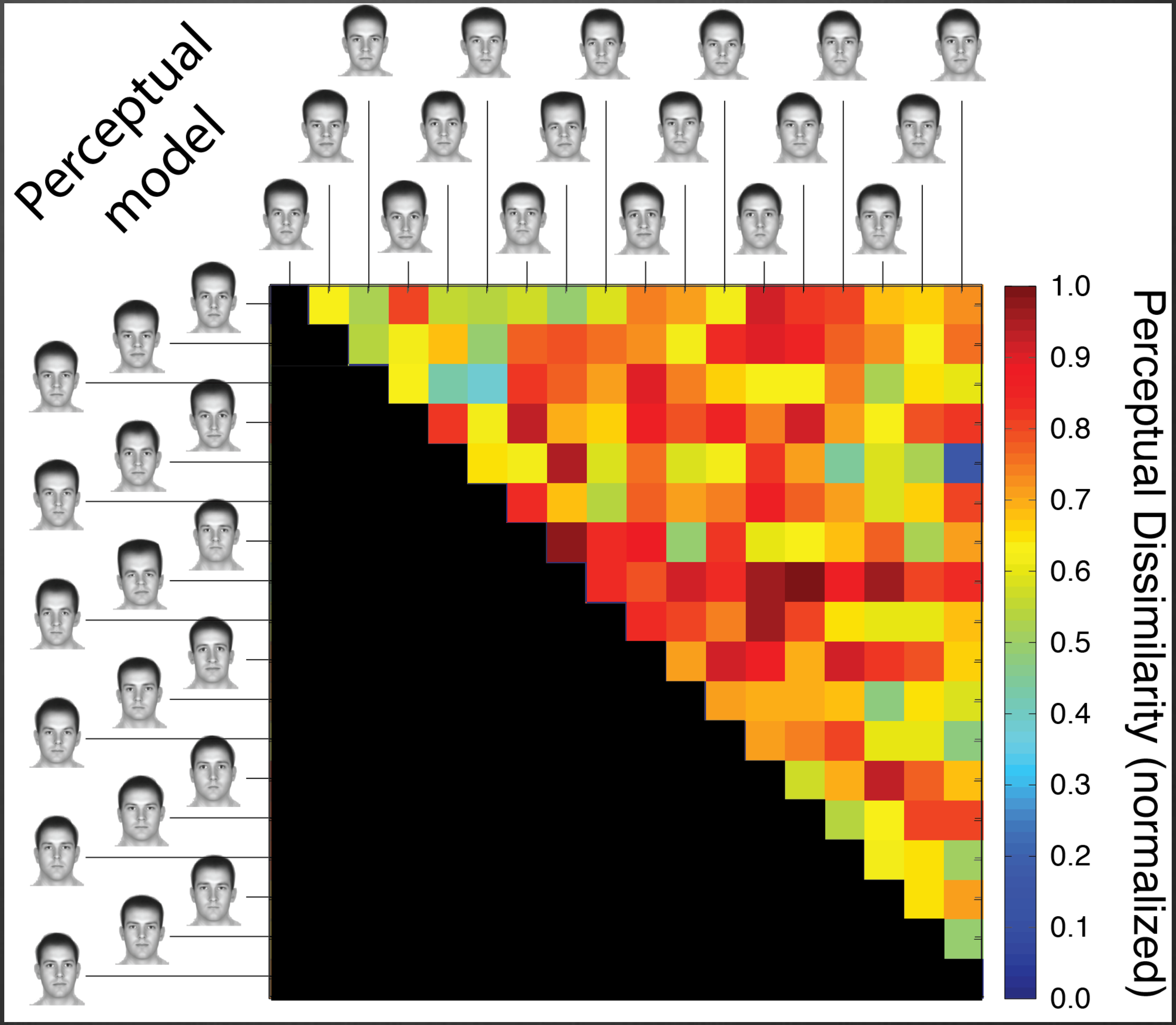
# A non trivial experiment!



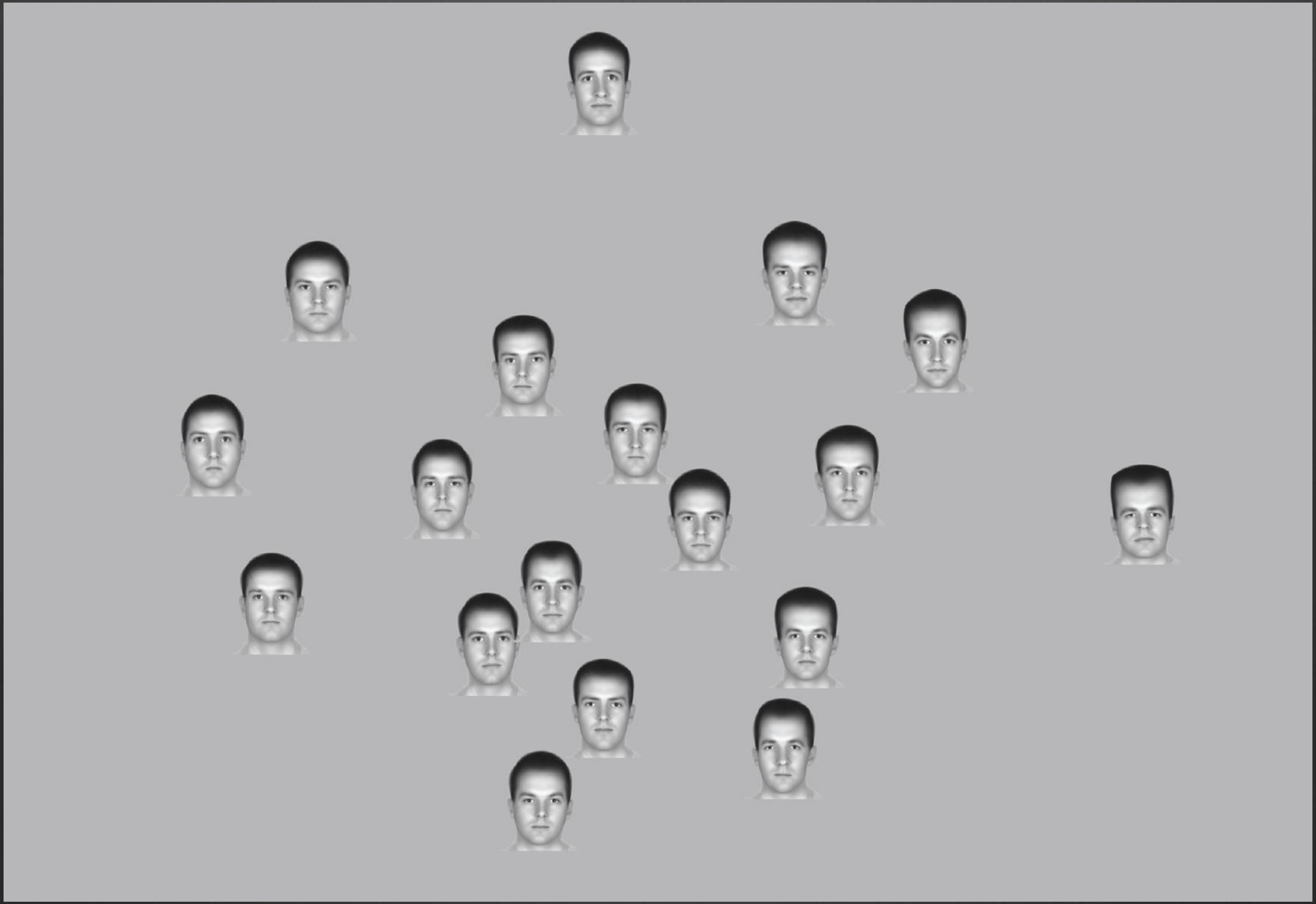
- Psychometric functions for 153 pairwise combinations of faces!
- 17 one hour testing sessions  (n = 7)

# Perceptual model of faces

- Perceptual dissimilarity matrix (DSM)
- Shows perceptual difference between all possible face pairs
- Color represents difference/distance in perceptual space

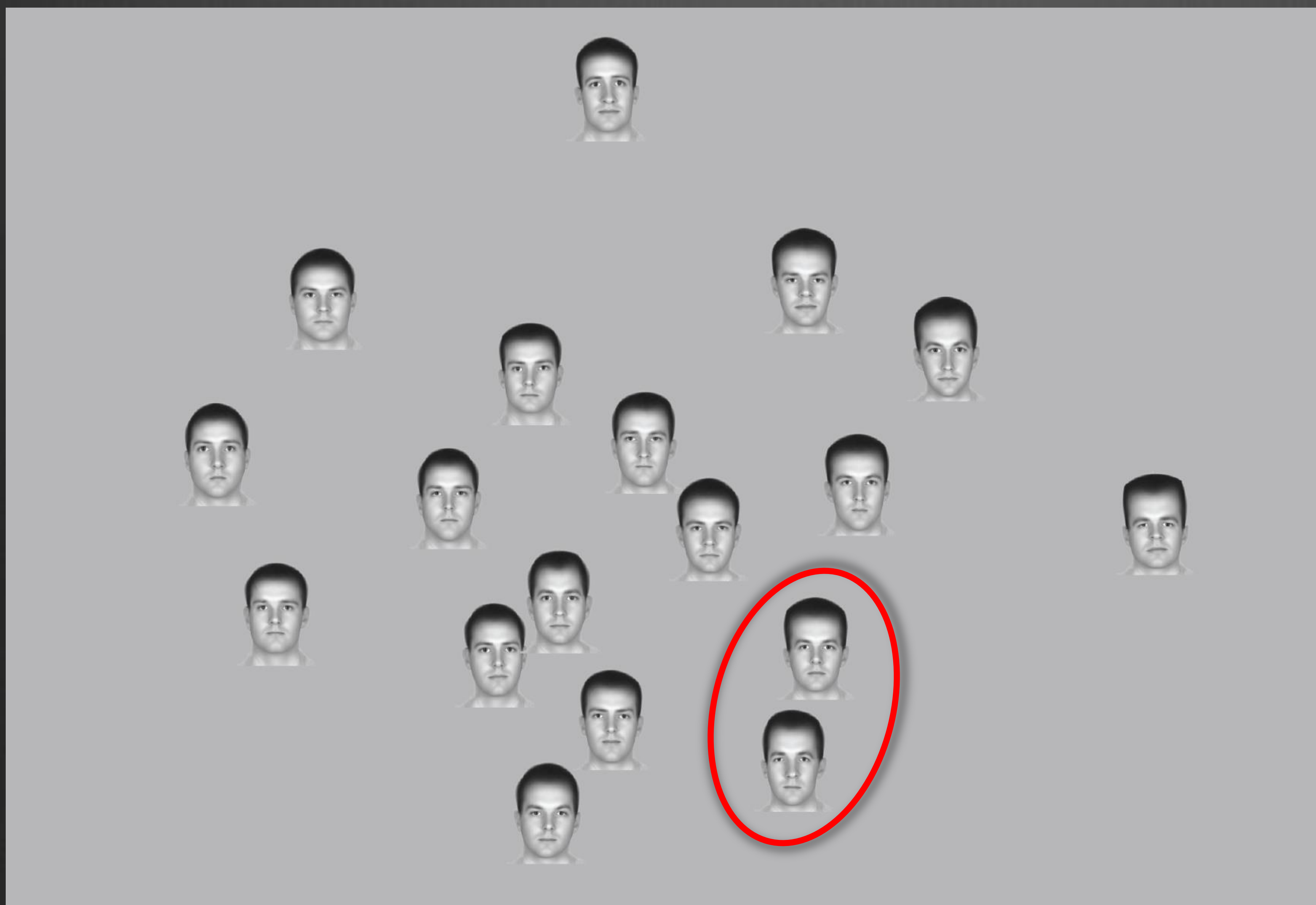


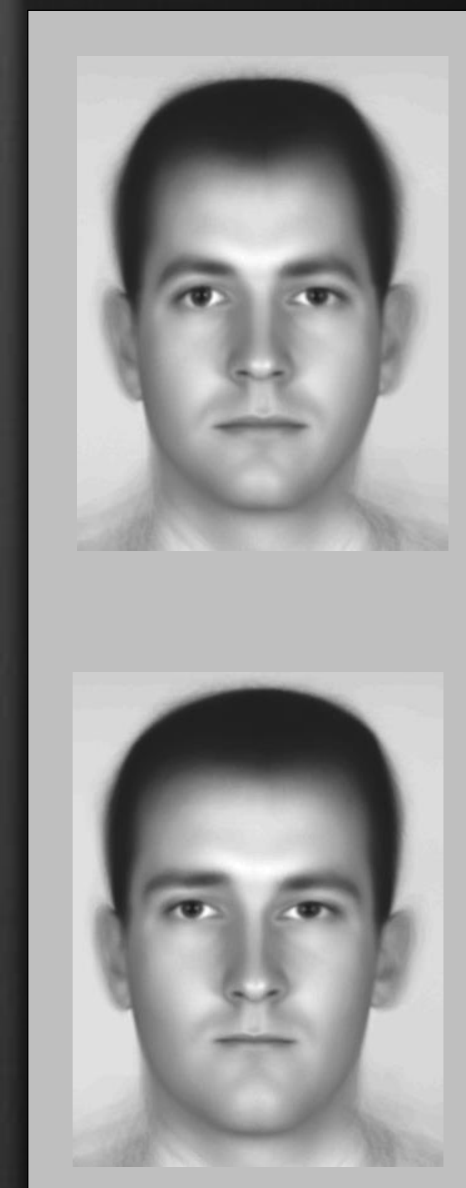
# Perceptual “face space”



“Flattened” Multidimensional scaling representation

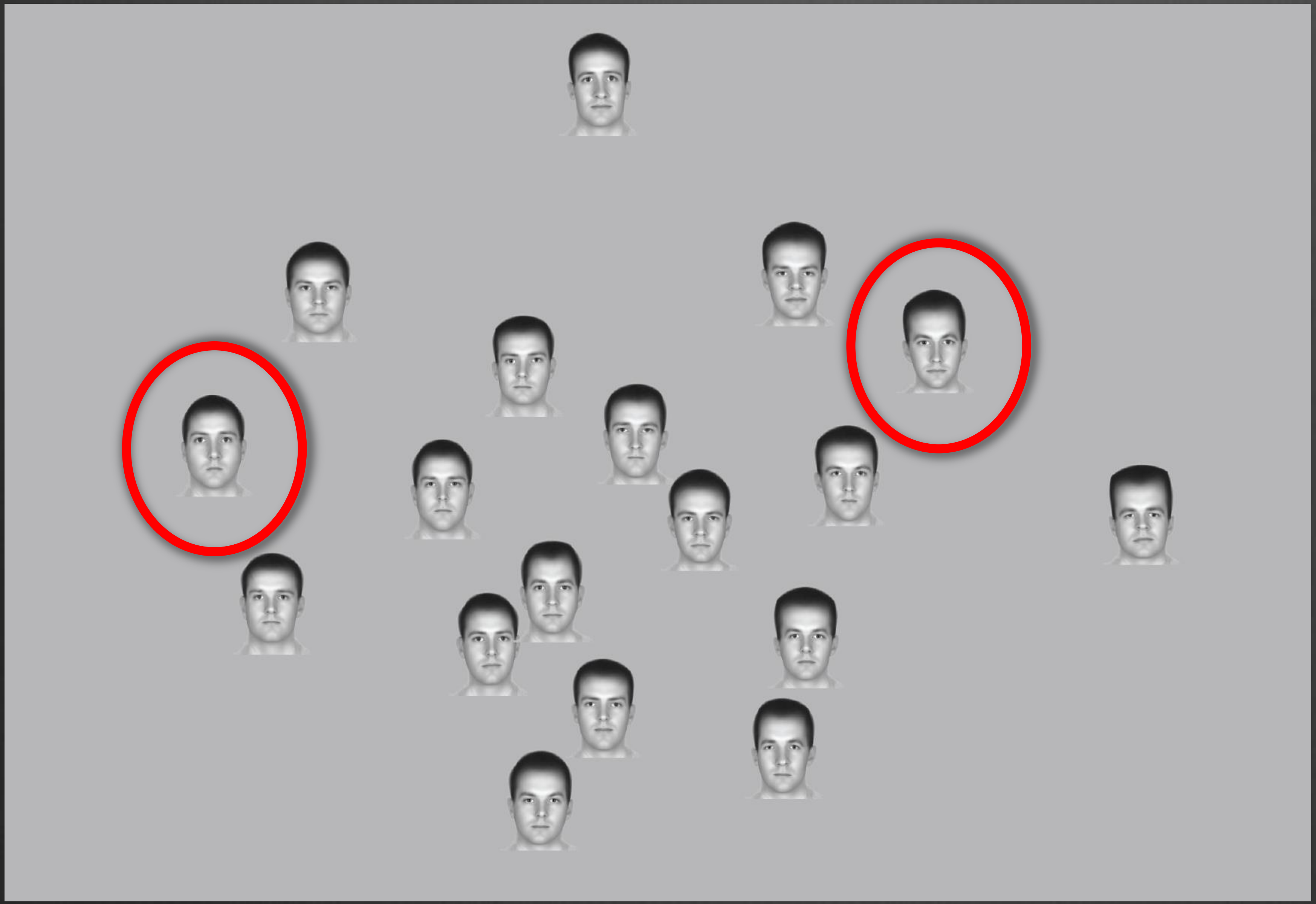
# Perceptual “face space”

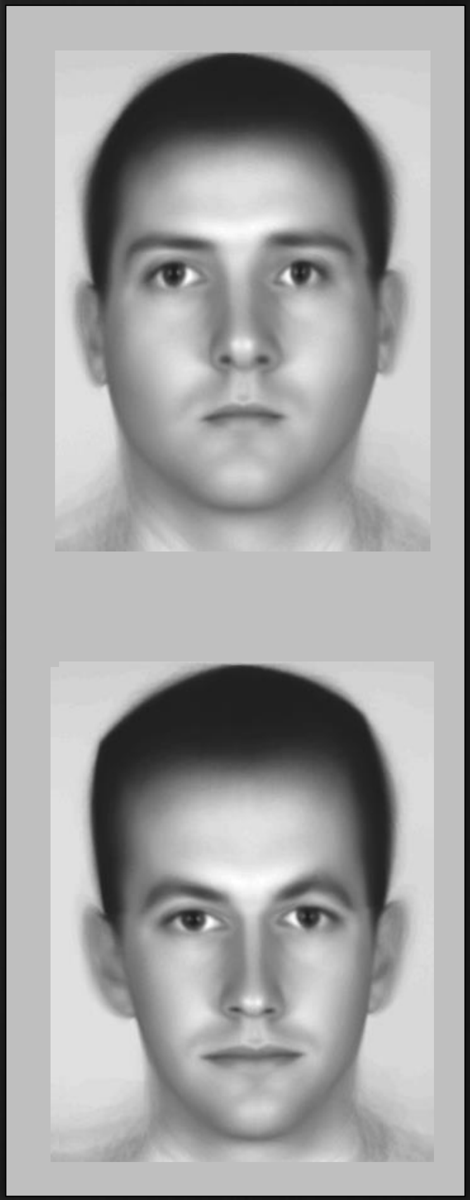




Distance represents model dissimilarity: close = similar

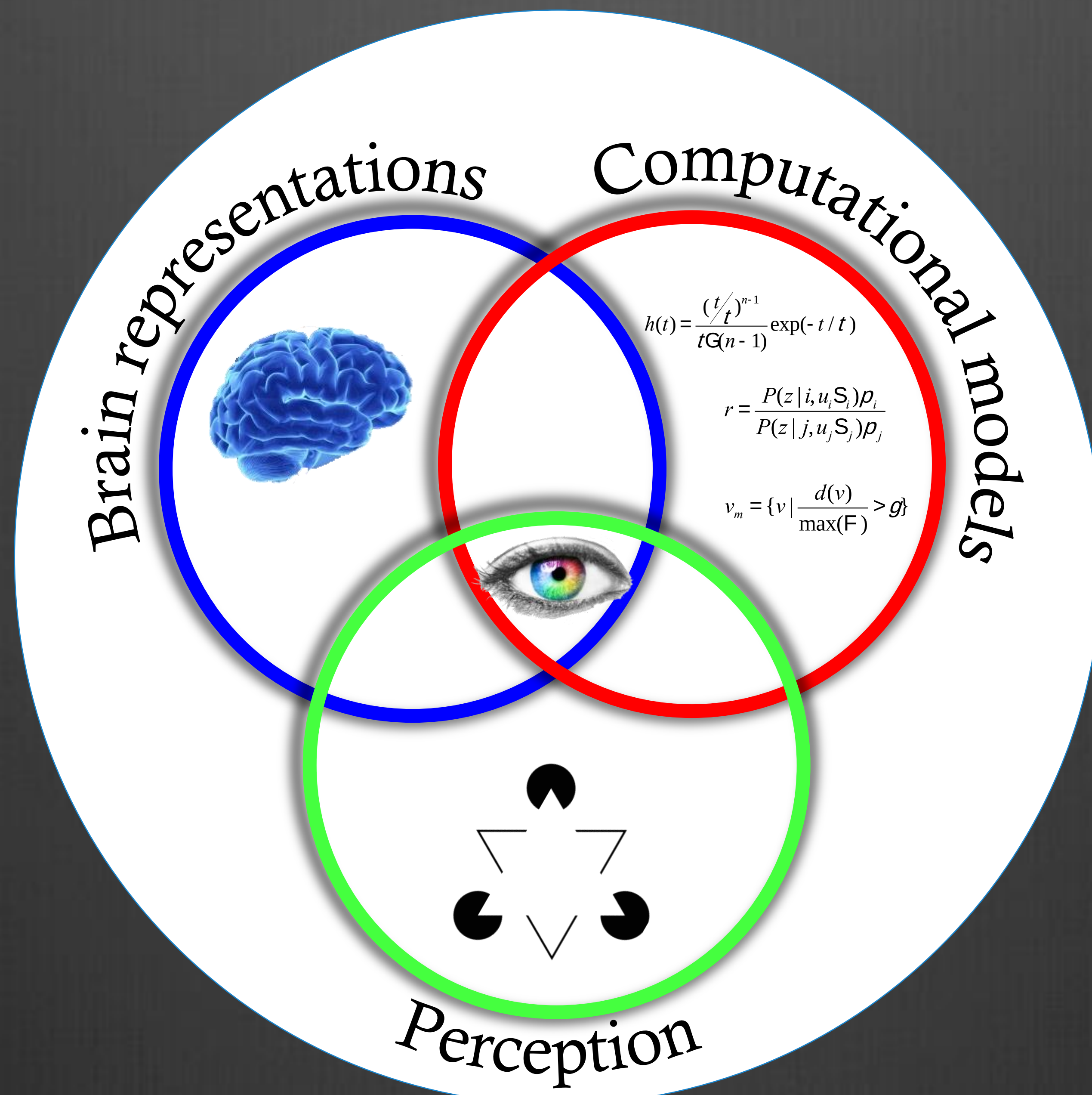
# Perceptual "face space"





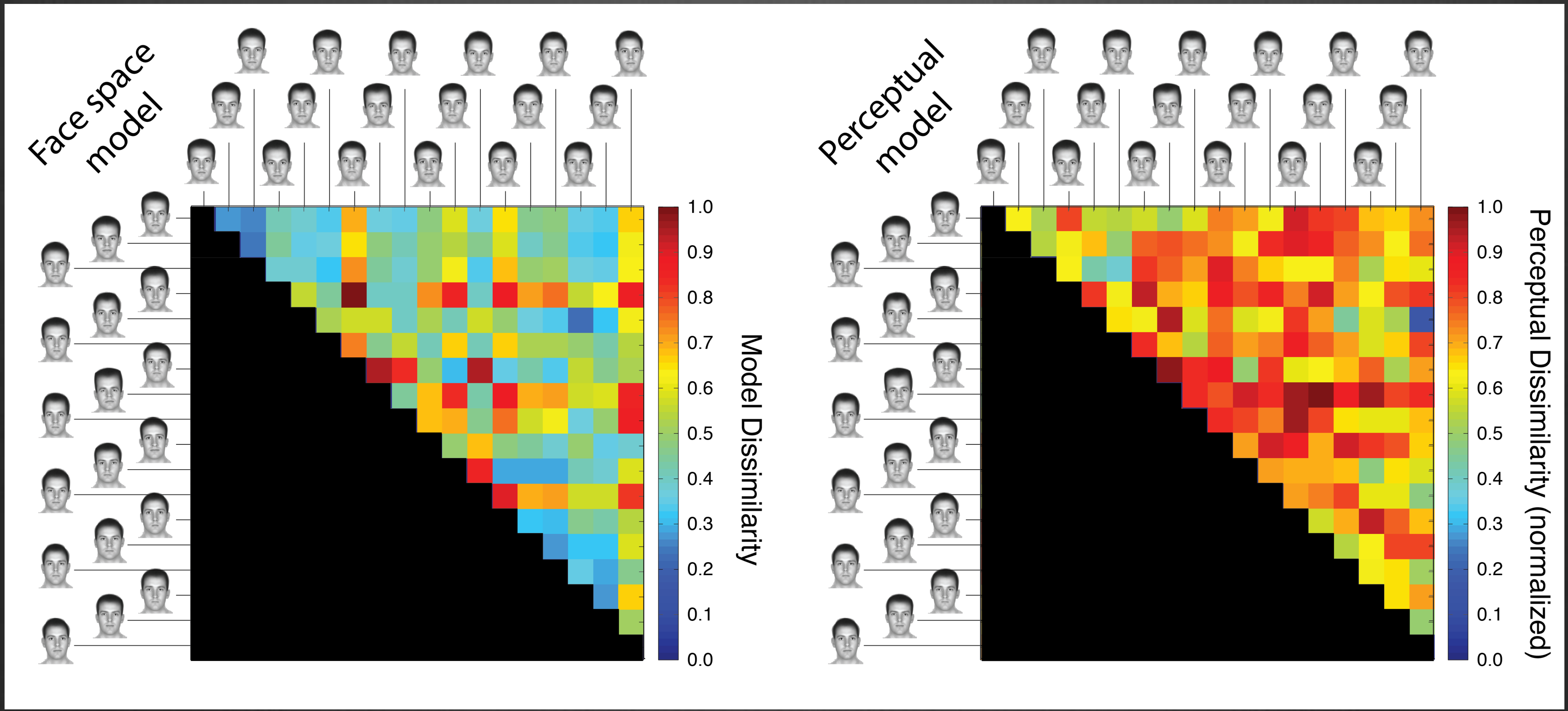
Distance represents model dissimilarity: far = dissimilar

# Aim of the study: bridge computational model, perception, and neuronal representations of faces



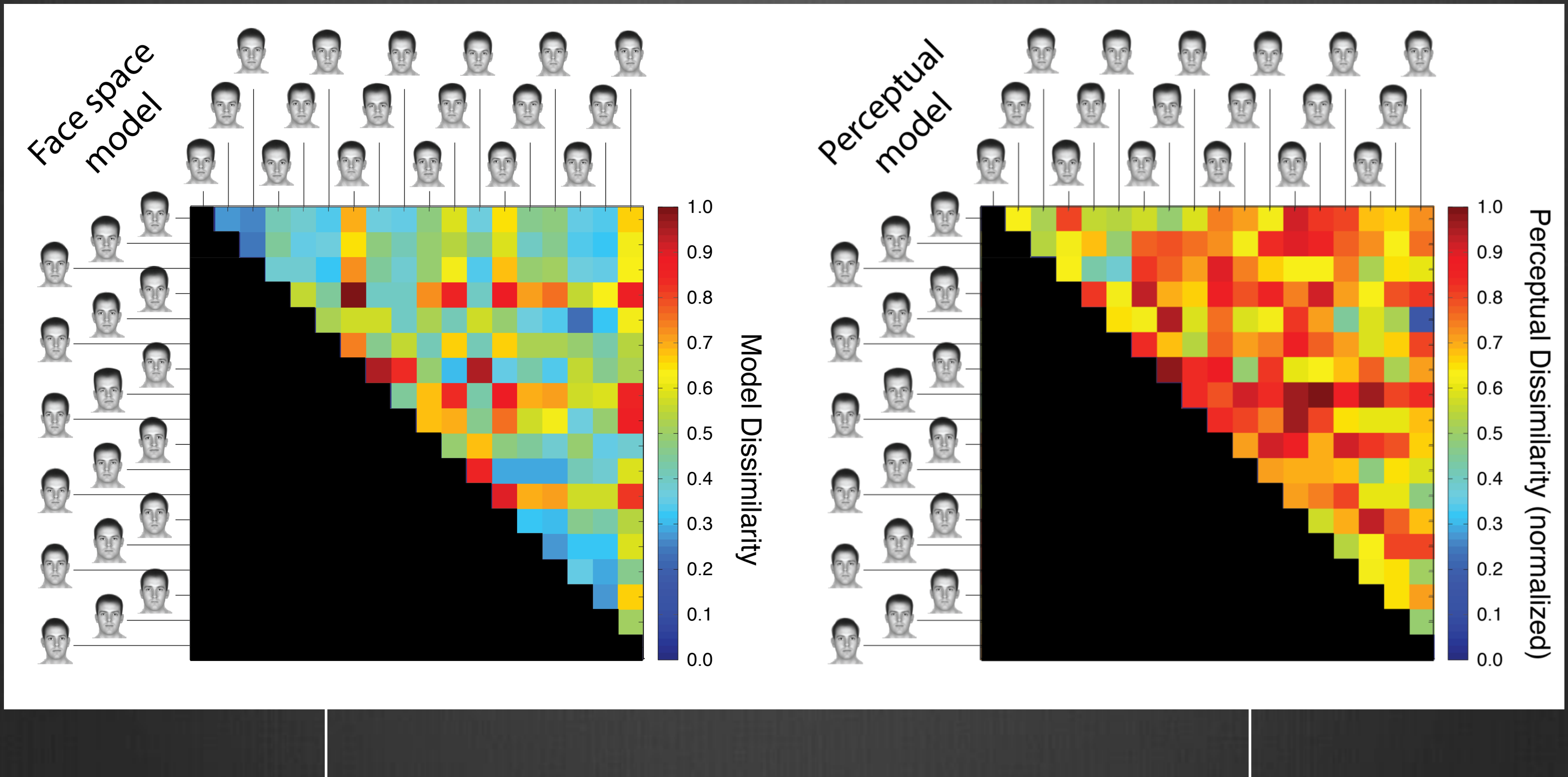

Linking model to perception

# Bridging computational model and perception




- Representational similarity analysis (RSA; Kriegeskorte, 2008)
- Non parametric correlations (Spearman) between DSM entries

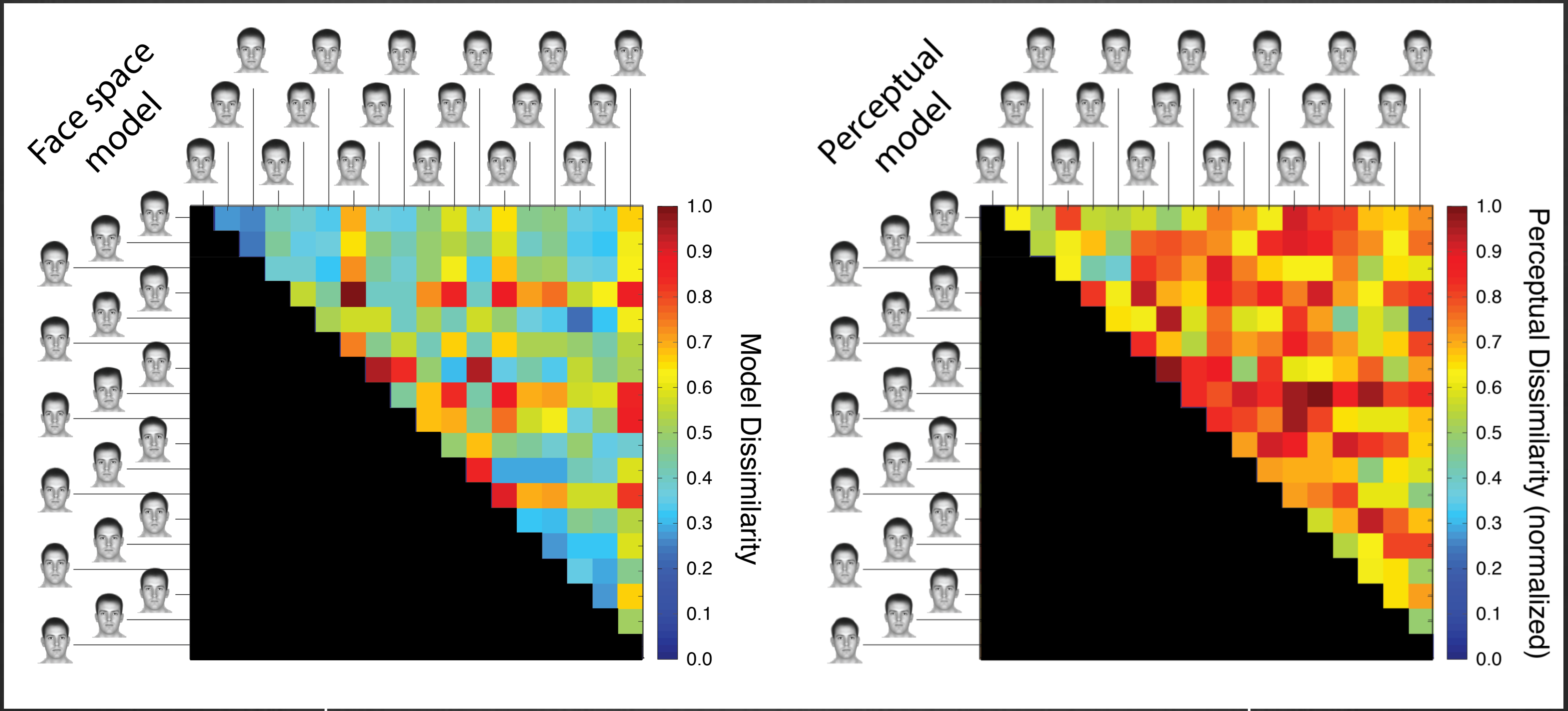
# Bridging computational model and perception




Spearman Rho = 0.49, $p < 0.001$ (bootstrap test)

Good (albeit imperfect) correspondence between model and perception

# Bridging computational model and perception




Spearman Rho = 0.49, $p < 0.001$ (bootstrap test)

- Dissociation between physical (generative model) and perception
- Differences can be used to study generative model features that are important for perceptual discrimination of faces

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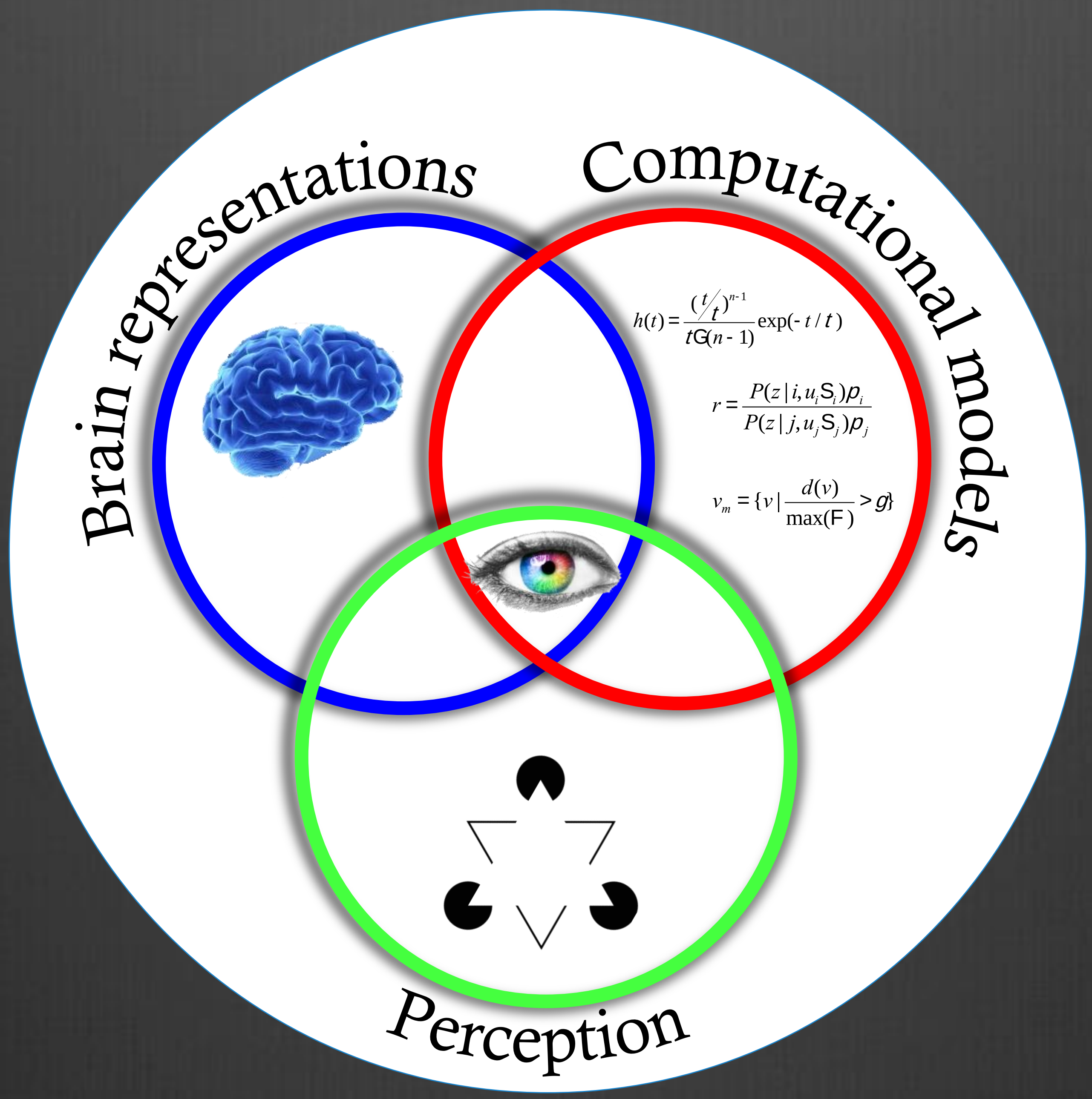
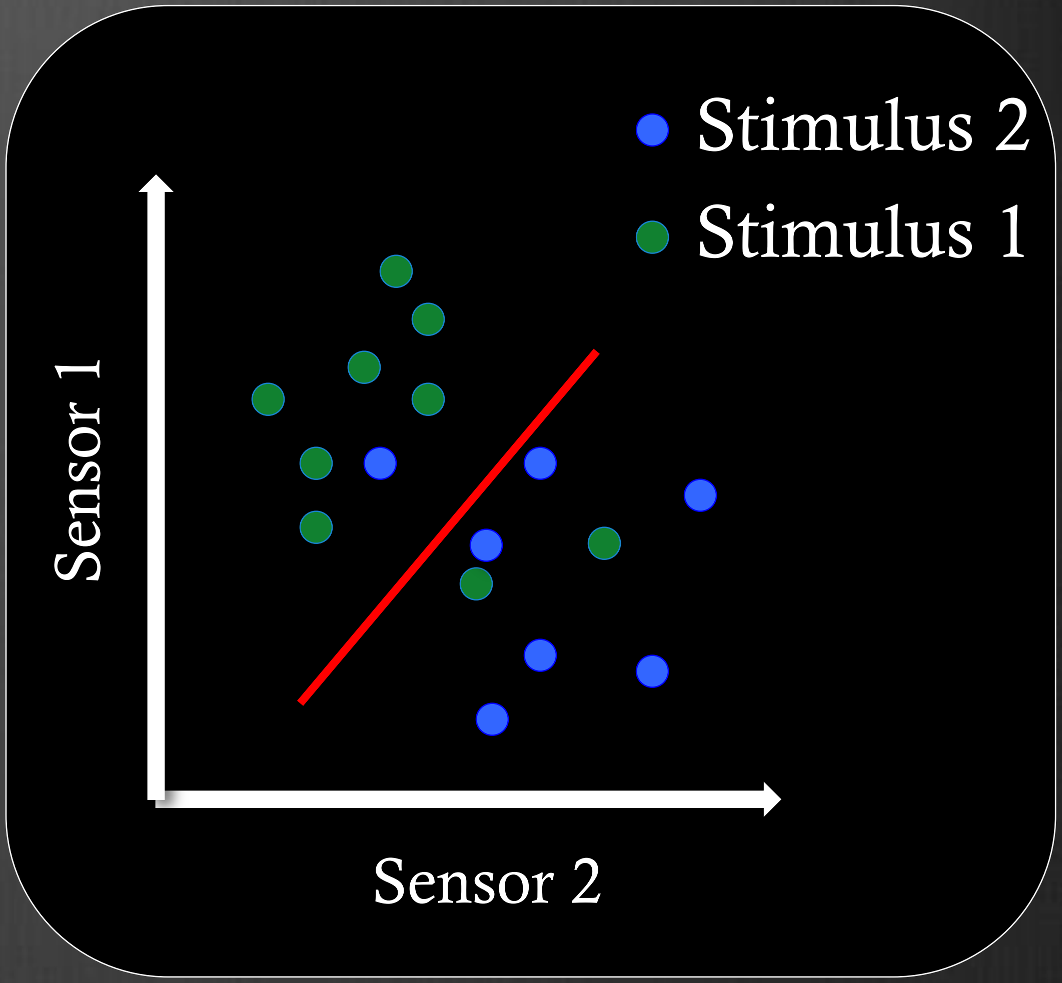



Measuring representational geometry of the brain

# Time resolved MEG decoding
(Carlson et al., 2011)

Use MVPA to measure the dissimilarity (i.e. decodability) between response patterns to stimuli as a function of time.



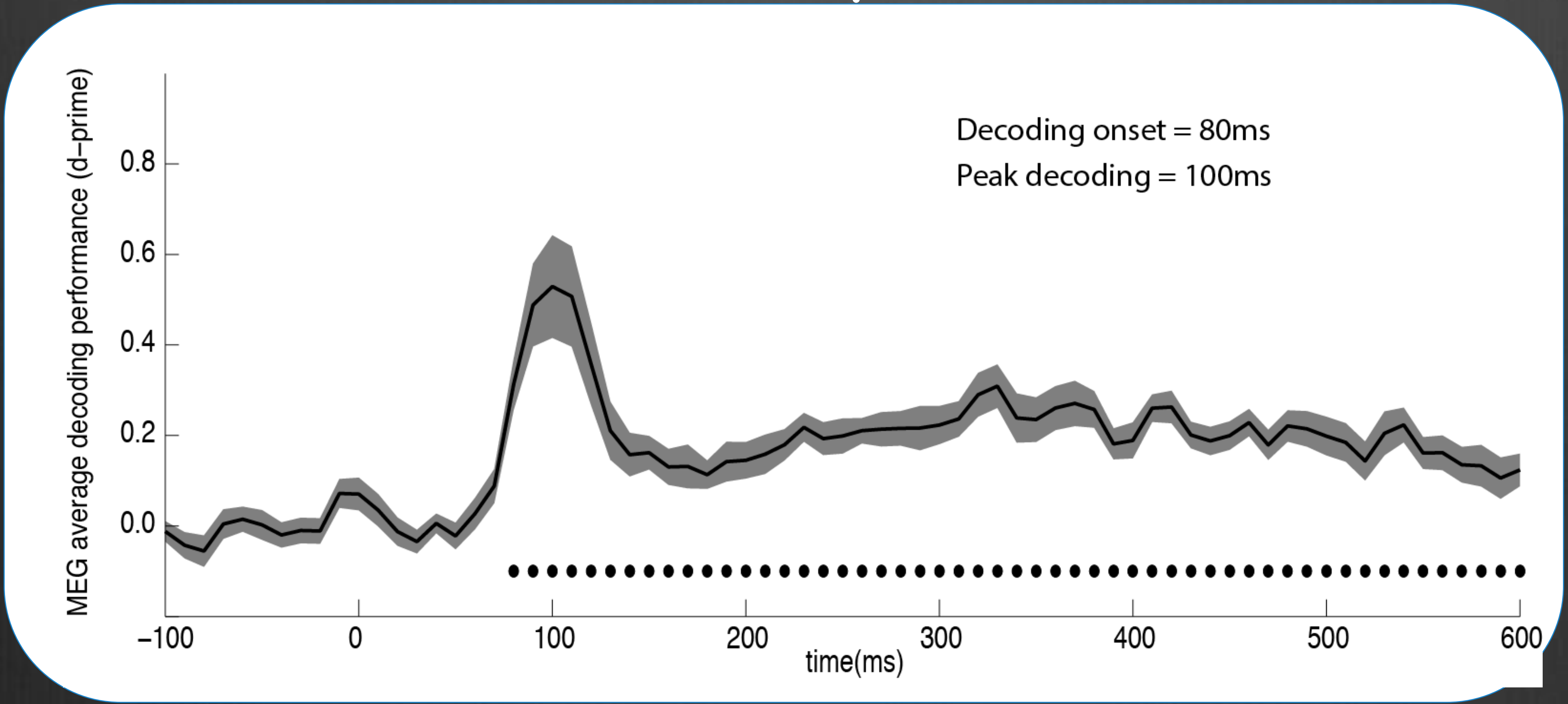

- Decoding done in sensor space (157 axial gradiometers) using Linear Discriminant Analysis Sliding window decoding (10ms resolution)

→

- Neural discriminability between faces on a moment to moment basis
- Analysis done for all possible face pairs to recover time varying representational geometry

# Decodability as a function of time

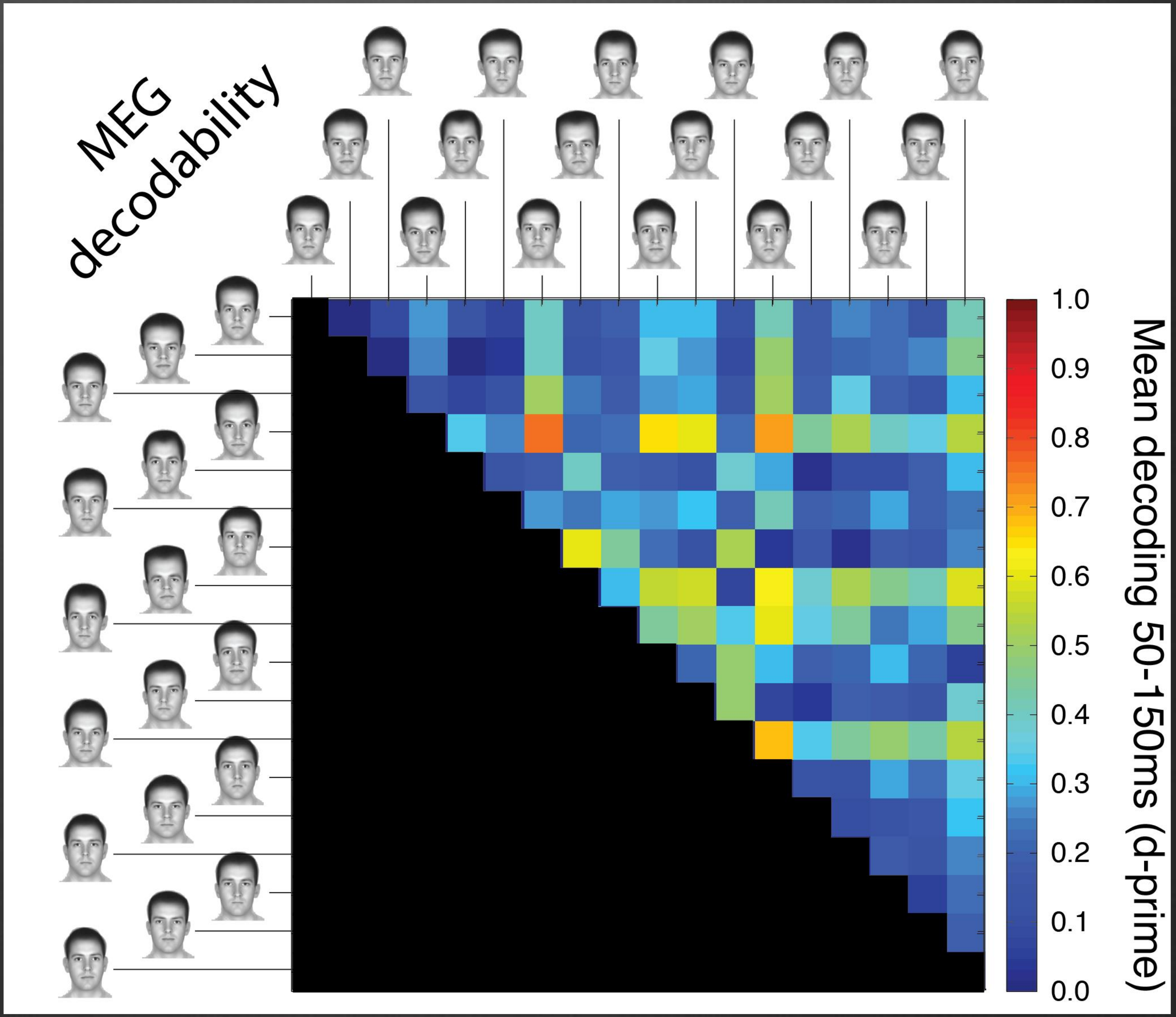
Average decodability for all possible




- We can decode individual face exemplars from neuromagnetic recordings!
- Onset accords with time for visual information to reach the cortex
- Peak decoding 100ms after stimulus onset

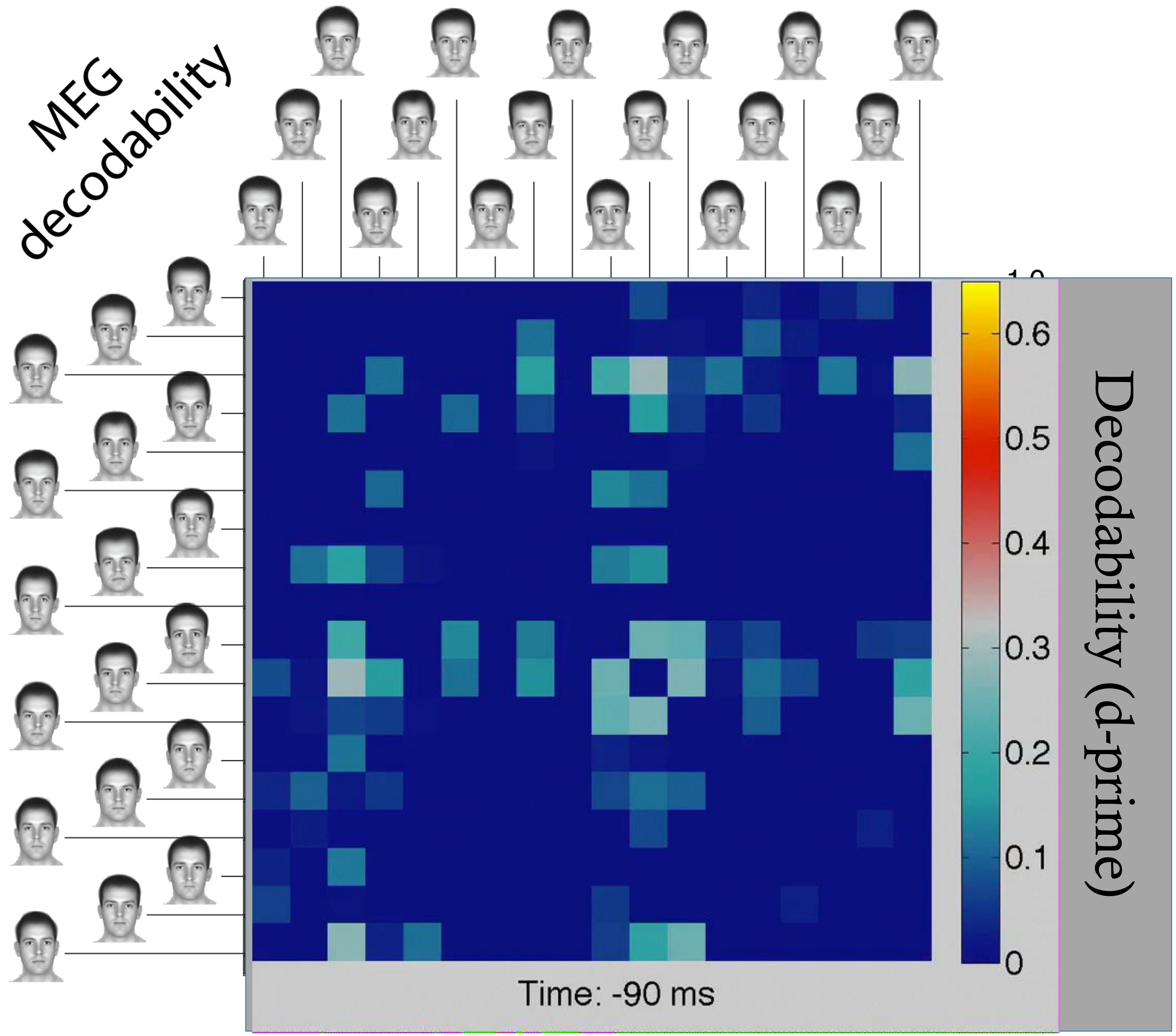
# Neural discriminability of face pairs

- Neural dissimilarity matrix (DSM) for time between 50 and 150ms
- Shows neural difference between all possible face pairs
- Color represents difference in representational space

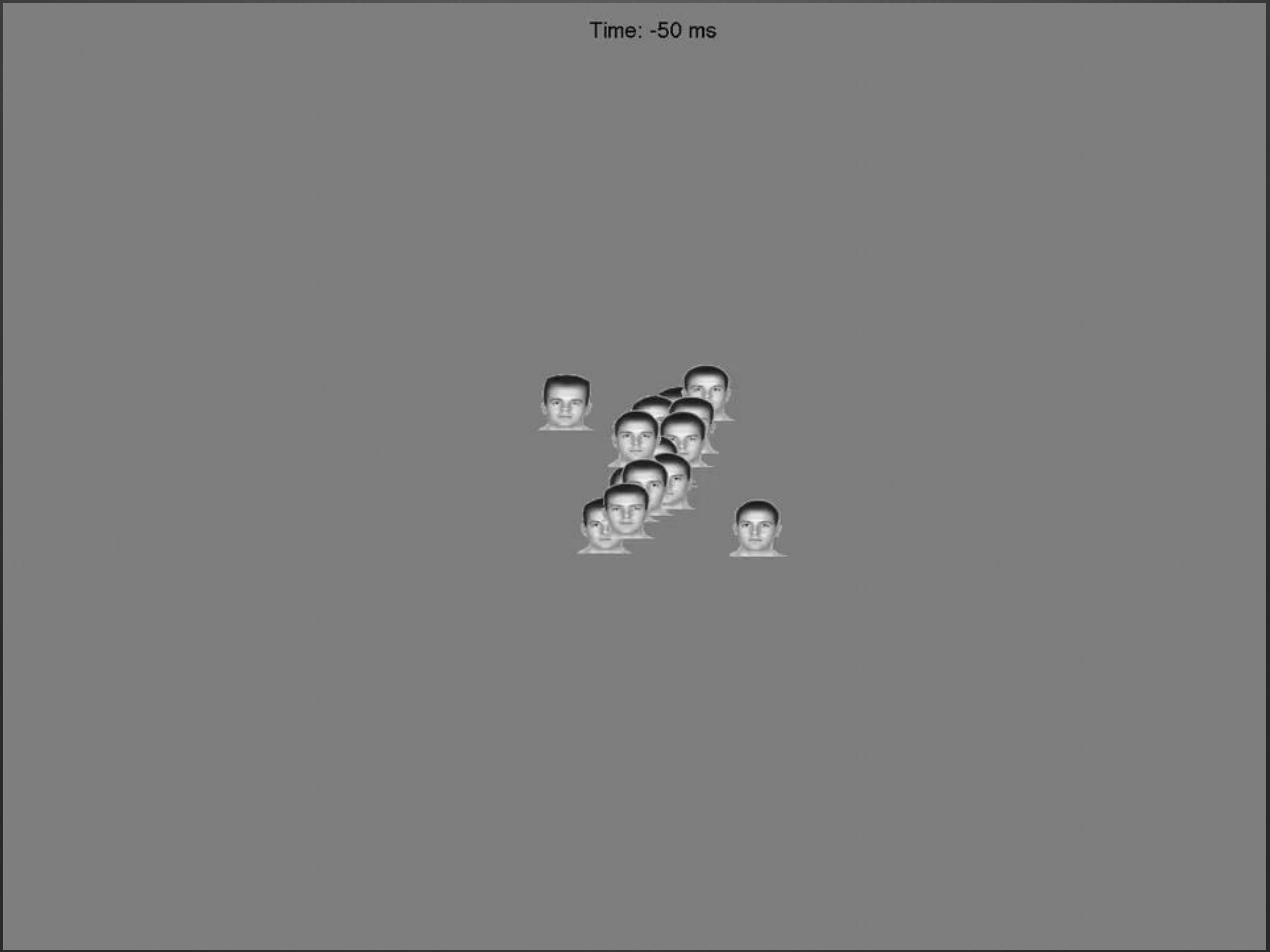


# Time varying MEG decoding

- Neural dissimilarity matrix (DSM)
- Shows neural difference between all possible face pairs
- Color represents difference/distance

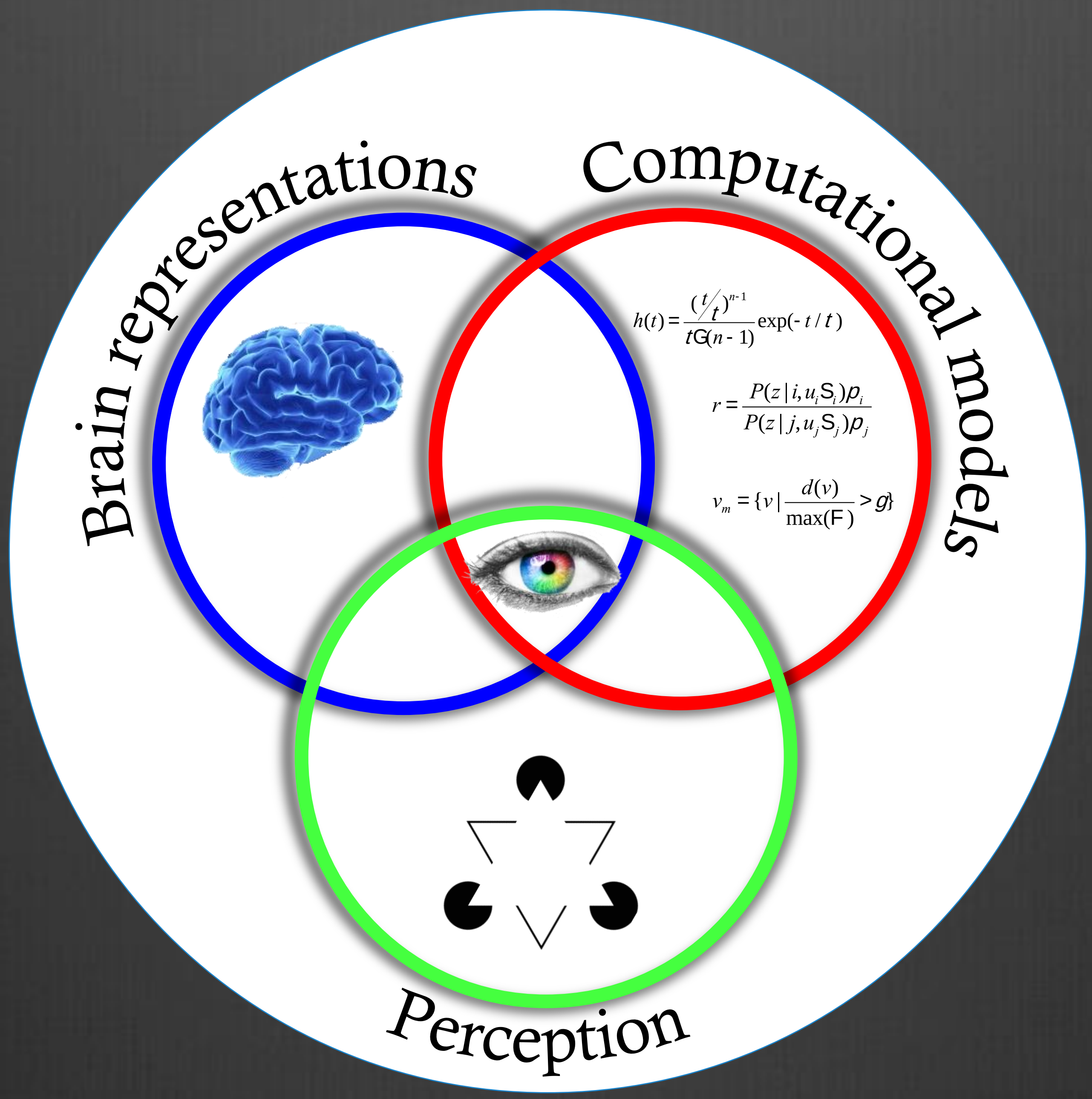


# Time varying representational geometry of faces



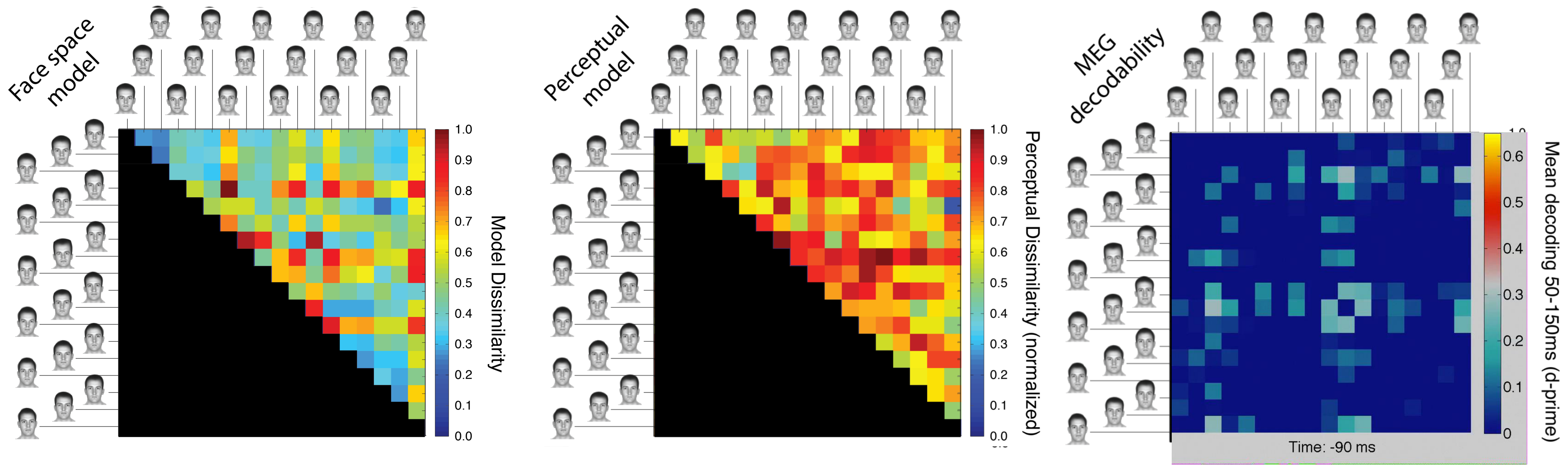

"Flattened" Multidimensional scaling representation

# Aim of the study: bridge computational model, perception, and neuronal representations of faces



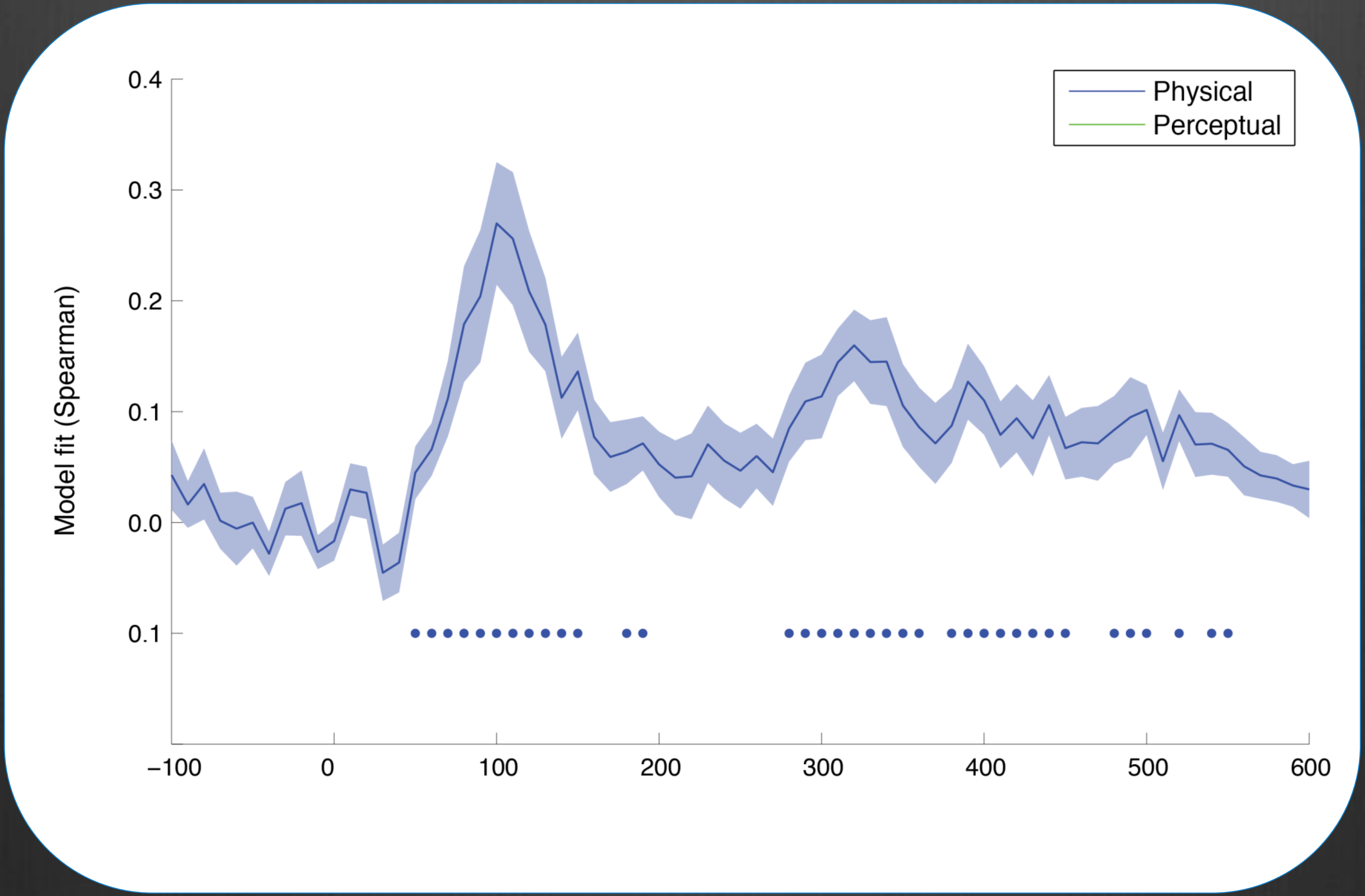

Linking brain representation to model

# Bridging computational model, perception and the brain



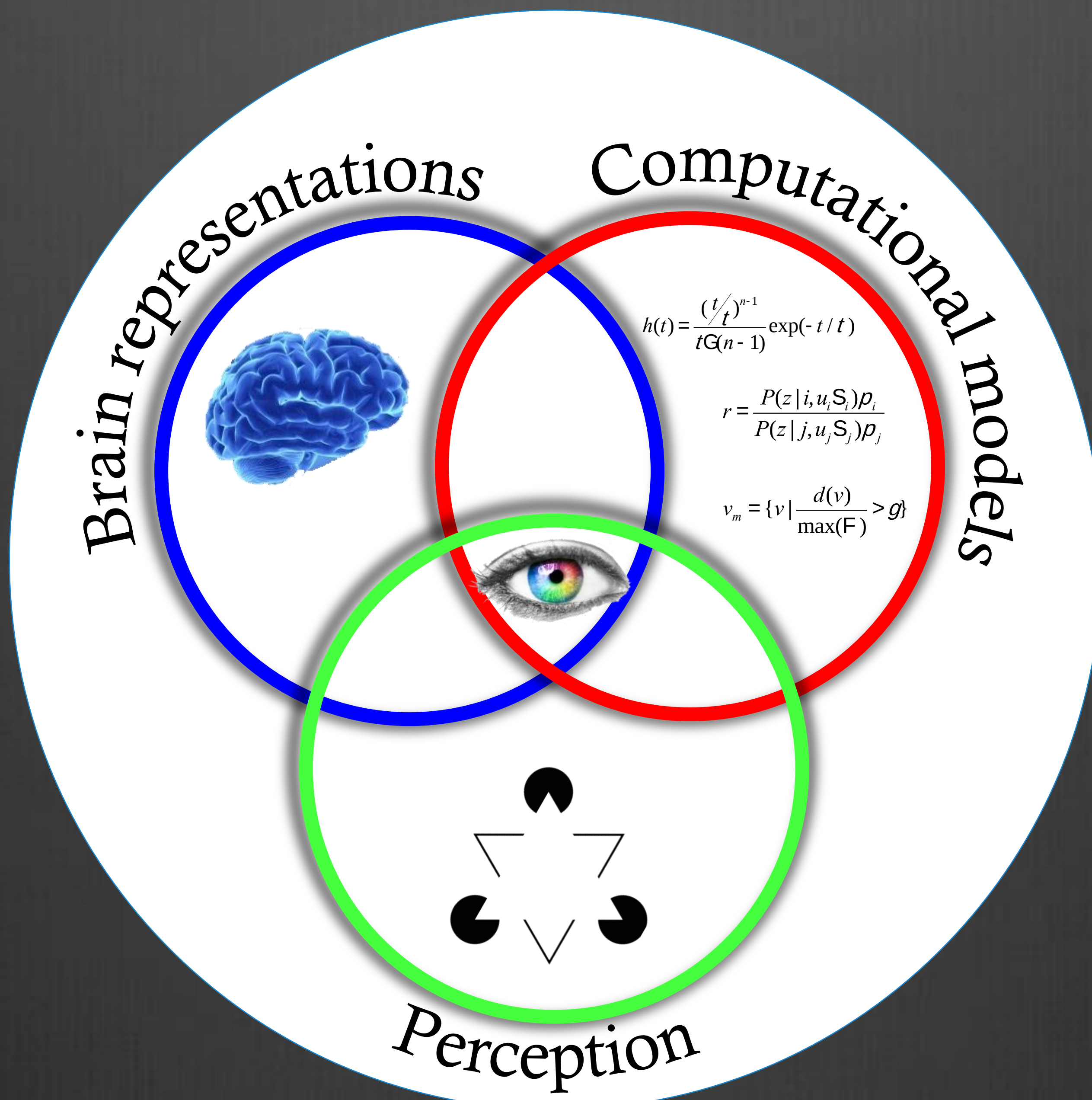

- Non parametric correlations (Spearman) between MEG and DSMs for each time point
- Time varying correlation between model/perception and neural stimulus representation (significance FDR < 0.05)

# Bridging computational (physical) model and neural representation of the stimulus



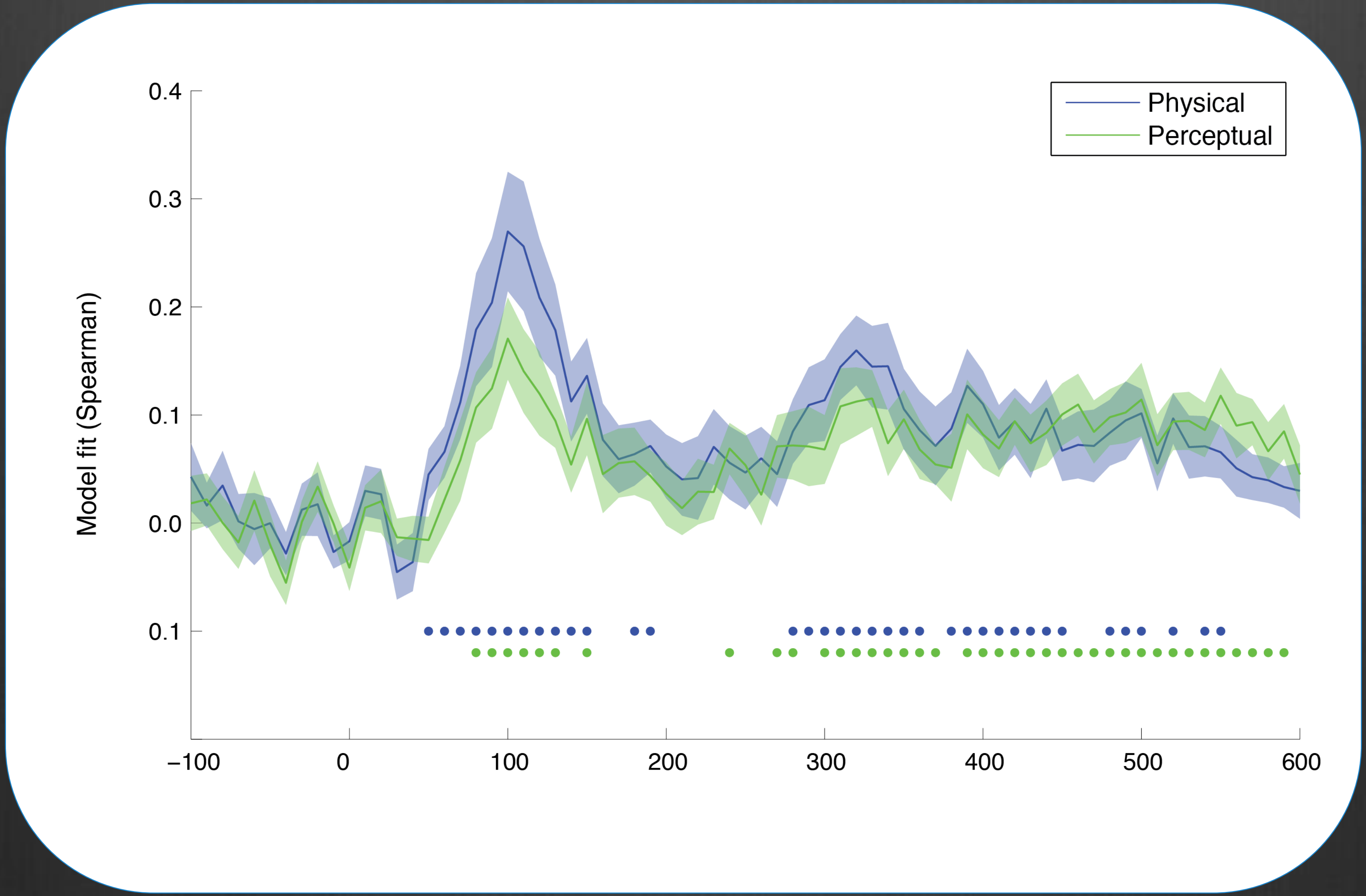

- Computation (physical) model corresponds well with MEG decodability early in time (~50ms post stimulus onset)

# Aim of the study: bridge computational model, perception, and neuronal representations of faces



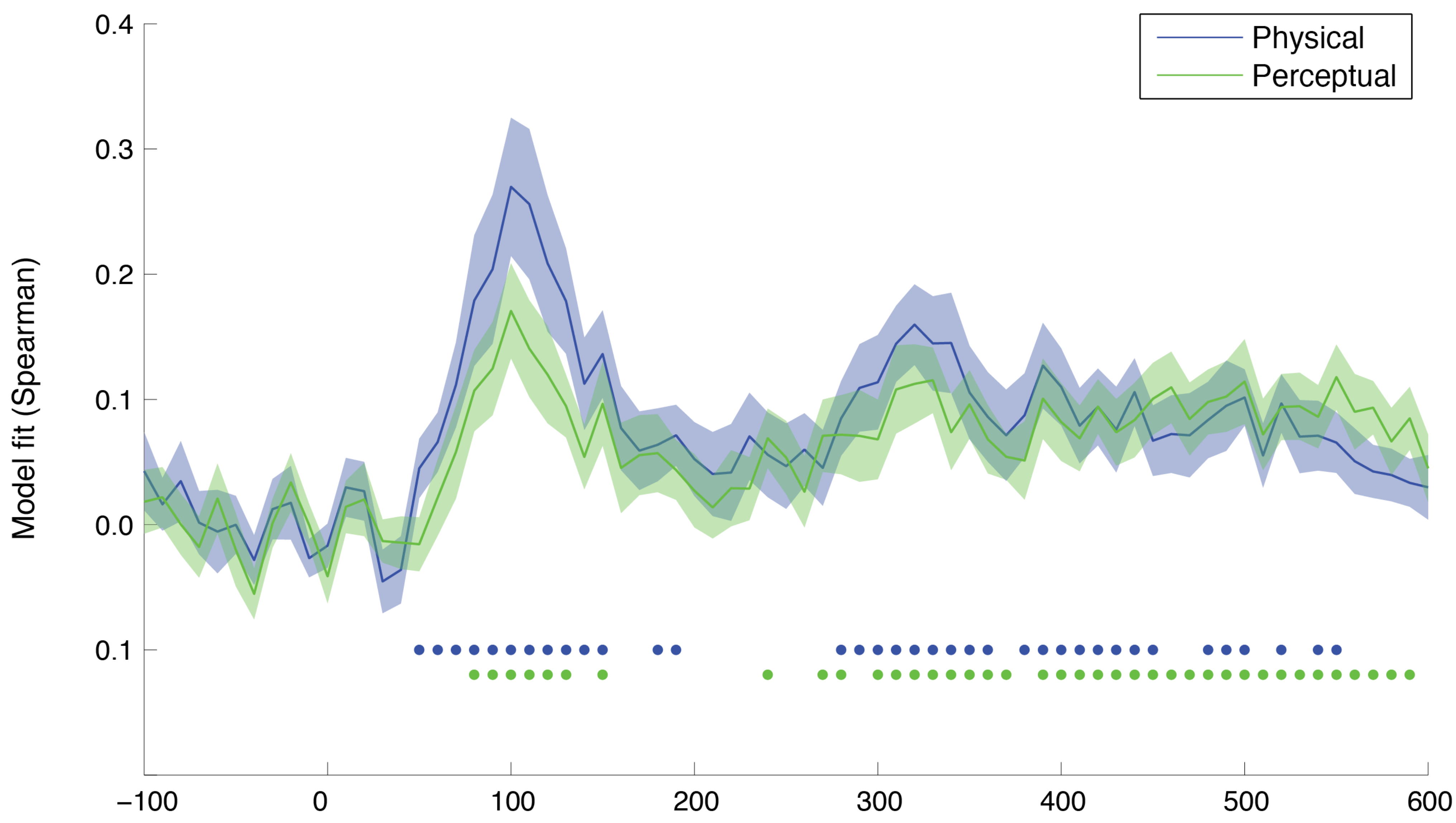

Linking brain representation to perception

# Bridging perception and neural representation of the stimulus



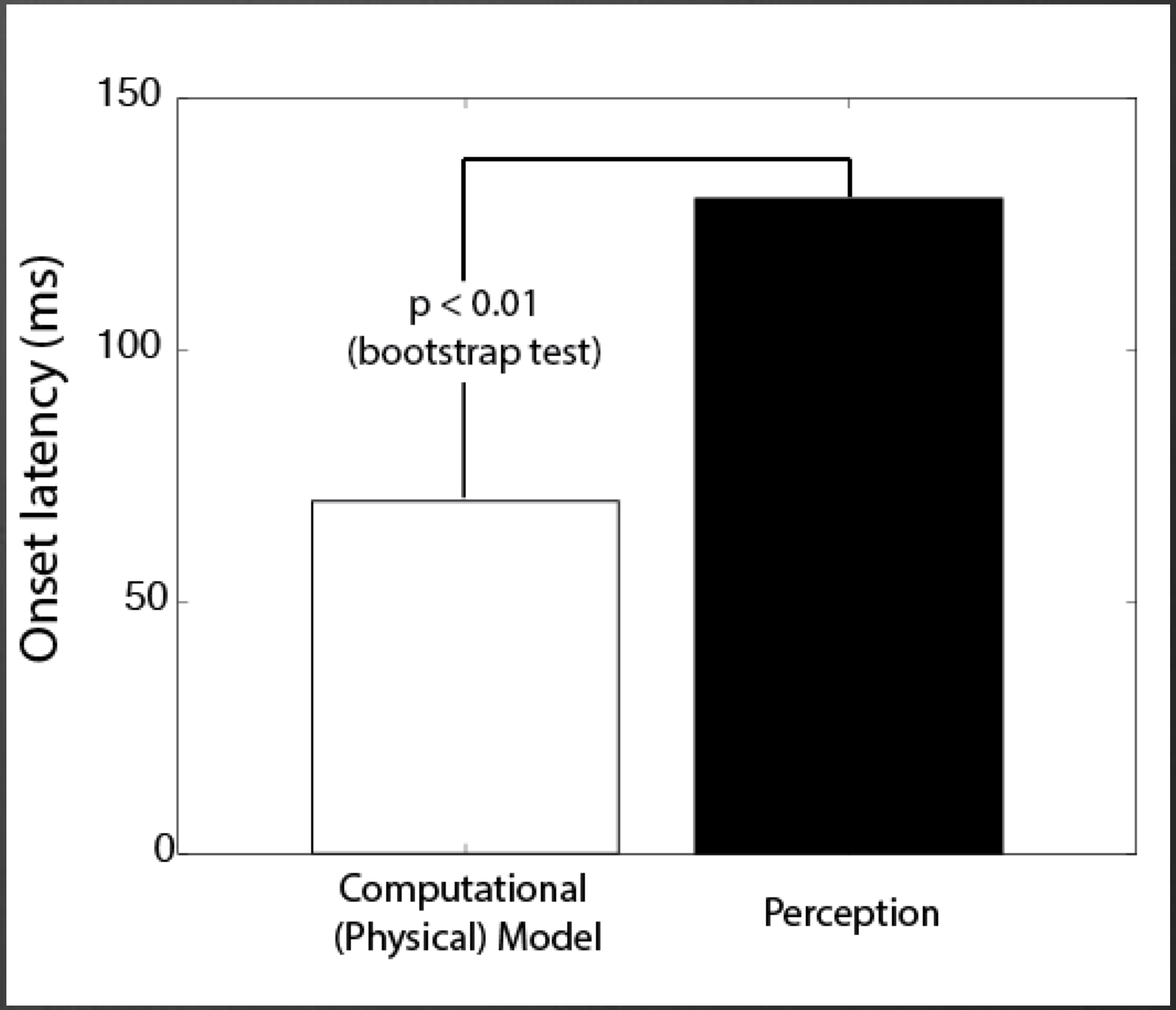

- Perception also corresponds well with MEG decodability early in time (~70ms post stimulus onset)

# Does the representation of physical features precede perception?



# Does the representation of physical features precede perception?

- Compute the onset latency for individual participants
- Non parametric Sign rank test for latency difference
- Suggests representation emphasizing physical features of faces precedes perceptual representation of face



# Summary/conclusions

- Framework for studying the relationship between computational models, perception and neuronal representation for faces.
- Analysis showed a correspondence between the generative model and perception
  - Future work could test alternative  models and work to determine model "features" are driving perception.
- Analysis showed a correspondence between the generative model/perception and brain's representation shortly after stimulus onset
- Perceptual representation emerged following representation of physical features, suggesting the brain first represents physical face features and then by emphasizing (and de-emphasizing) features forms a perceptual representation.

# Thanks to

Steven Dakin and the many students that assisted in data collection

Australian Government
Australian Research Council

Funding provided by the ARC

# ..and thank you for your attention!