ANALYSE MULTI-TABLEAUX.
FEATURING:
PLAIN MULTI-TABLES PCA
SUM-PCA, MULTIPLE FACTOR ANALYSIS, STATIS, ETC.

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La Famille Multi-Tableaux

Biblio. Allez voir à www.utdallas.edu/~herve

A87: STATIS & DISTATIS

A71, A59: DISTATIS

C71: Rv Coefficient

C40: Multiple Factor Analysis

C33: STATIS

CNAM: 7 NOVEMBRE 2011

- Principal Component Analysis + Frills

Main Theme: What are multi-table analysis?

Main ideas:

– Good pictures help.
– Project parts of a data table

Variation 1: Tables and sub-tables

Variation 2: Preprocessing tables (*Z*-scores)

Variation 3: sum-PCA, MFA

Variation 4: Optimal weights for tables: STATIS

Variation 5: Extensions of STATIS

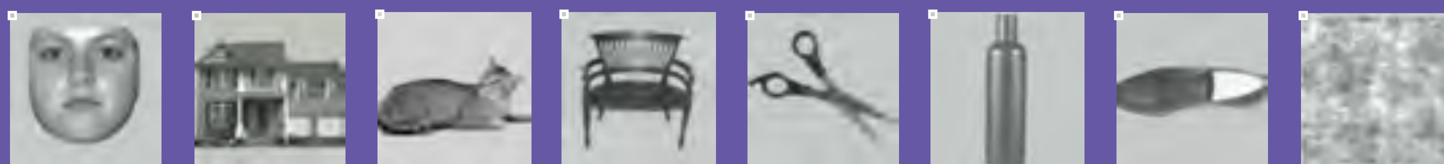
- "I am reading in the brain …"

START WITH AN EXAMPLE OF MULTI-TABLE ANALYSIS

OBJECT AND FACE PERCEPTION IN VT CORTEX

Haxby et al. (2001) *Science 293,* 2425-2429

- 8 categories of objects
  - faces, houses, cats, chairs, scissors, bottles, shoes, scrambled faces



A scan = 64 × 64 × 40 = 163,840 voxels

Keep only the "sensitive voxels" ≈ 500 per subject
(not critical for this story)

AN EXAMPLE: LOOKING IN THE BRAIN

- From Haxby *et al*. (2001)
  - small participant sample (*N* = 6)
  - simple 1-back memory task
  - 8 visual categories:

  - 7 scans for each category per block; 8 blocks in 12 superblocks (672 scans total)
  - Magnet parameters: gradient EPI on GE 3T scanner, TR = 2500ms, 40 3.5 mm sagittal images, FOV 24 cm, TE = 30 ms, flip angle 90º

SOURCE DATA

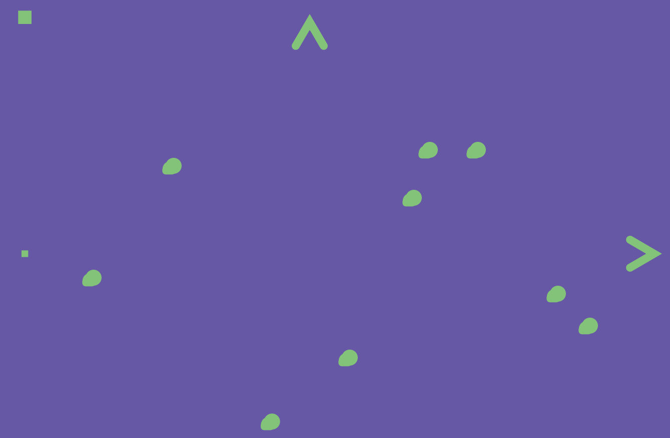
- A map with the categories

What do we want?

General idea: things are points in a (Euclidean!) space

DIMENSIONS

Euclidean Model



1,2,3 PCA

Why PCA?

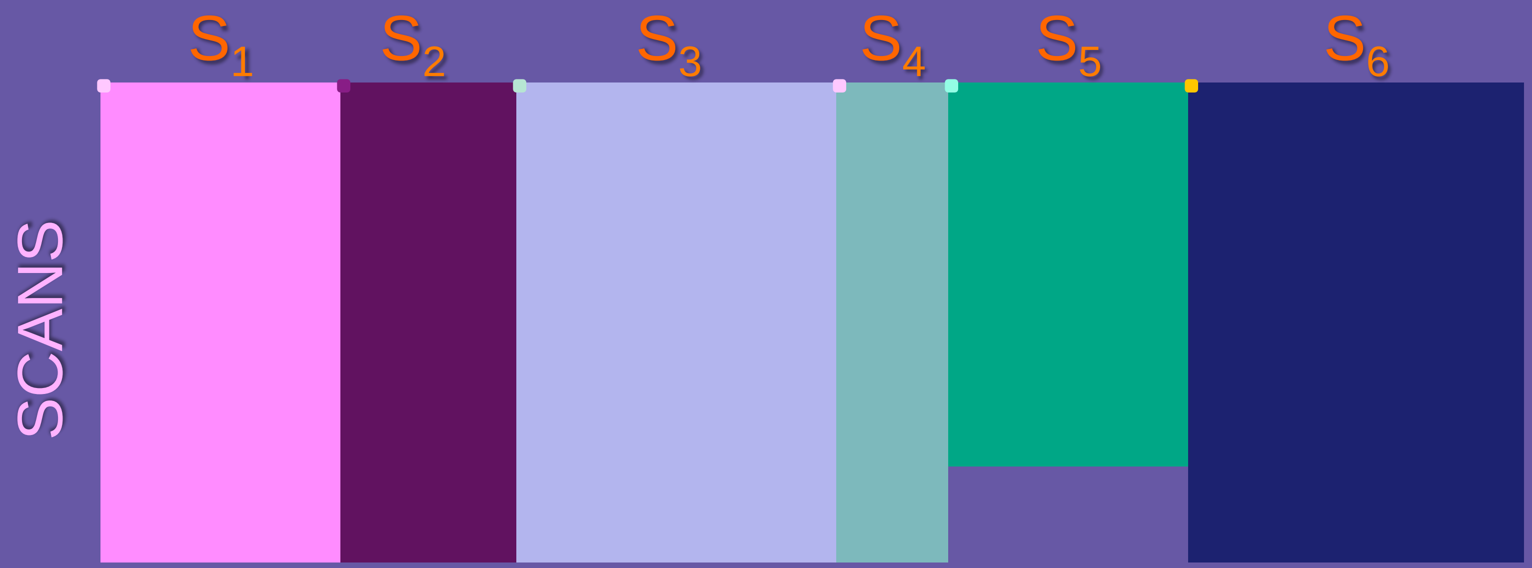
THE EUCLIDEAN WORLD *IS* BEAUTIFUL
IT WORKS WITH THE PYTHAGOREAN THEOREM!

- Mean, variance, inertia are *natural* (cosines and contributions).
- We love to minimize sum of squares
  (and the eigen-world is *magic*).
- Good routines means very large data sets.
- Easy Duality (What does that mean ????)
- Generalizes beautifully (masses, weights, …)
- And if it is multivariate normal we are *in Paradise!*

PCA: WHY EUCLIDEAN?

Back to the data: What is the structure

- DATA MATRIX



6 PARTICIPANTS

WITH DIFFERENT # OF VARIABLES (VOXELS)

[577, 464, 307, 675, 422,348]

- One participant = One block / subtable

One row = One scan

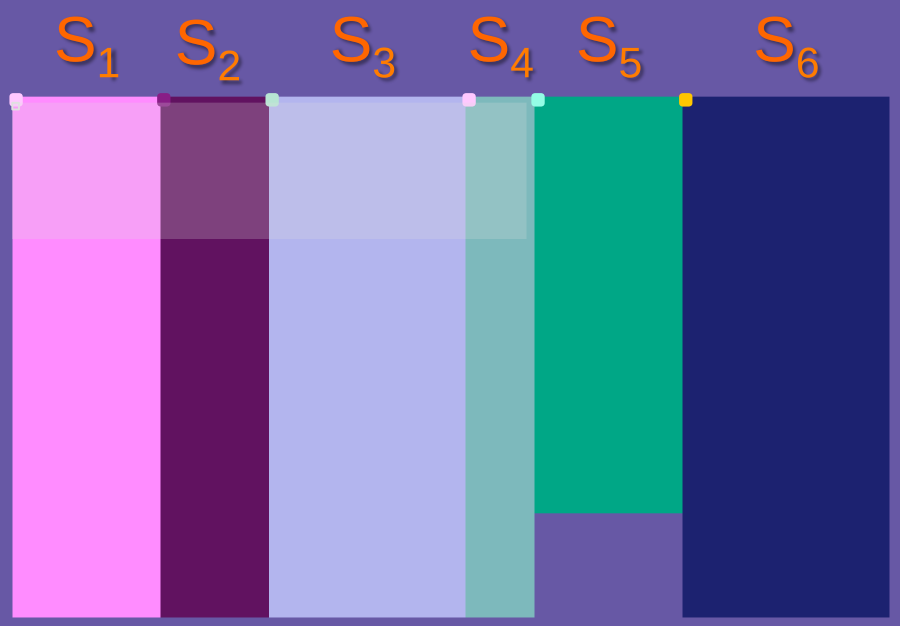
One column = one voxel of a participant

We want to look at everybody together

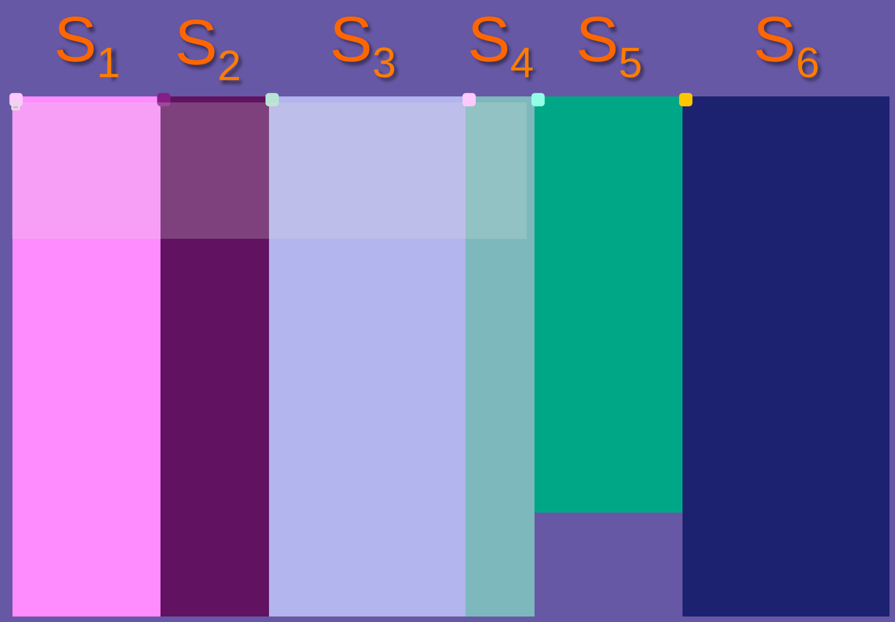
but also at each subject alone

STRUCTURES

How to analyze these data



How to analyze? Compute category means



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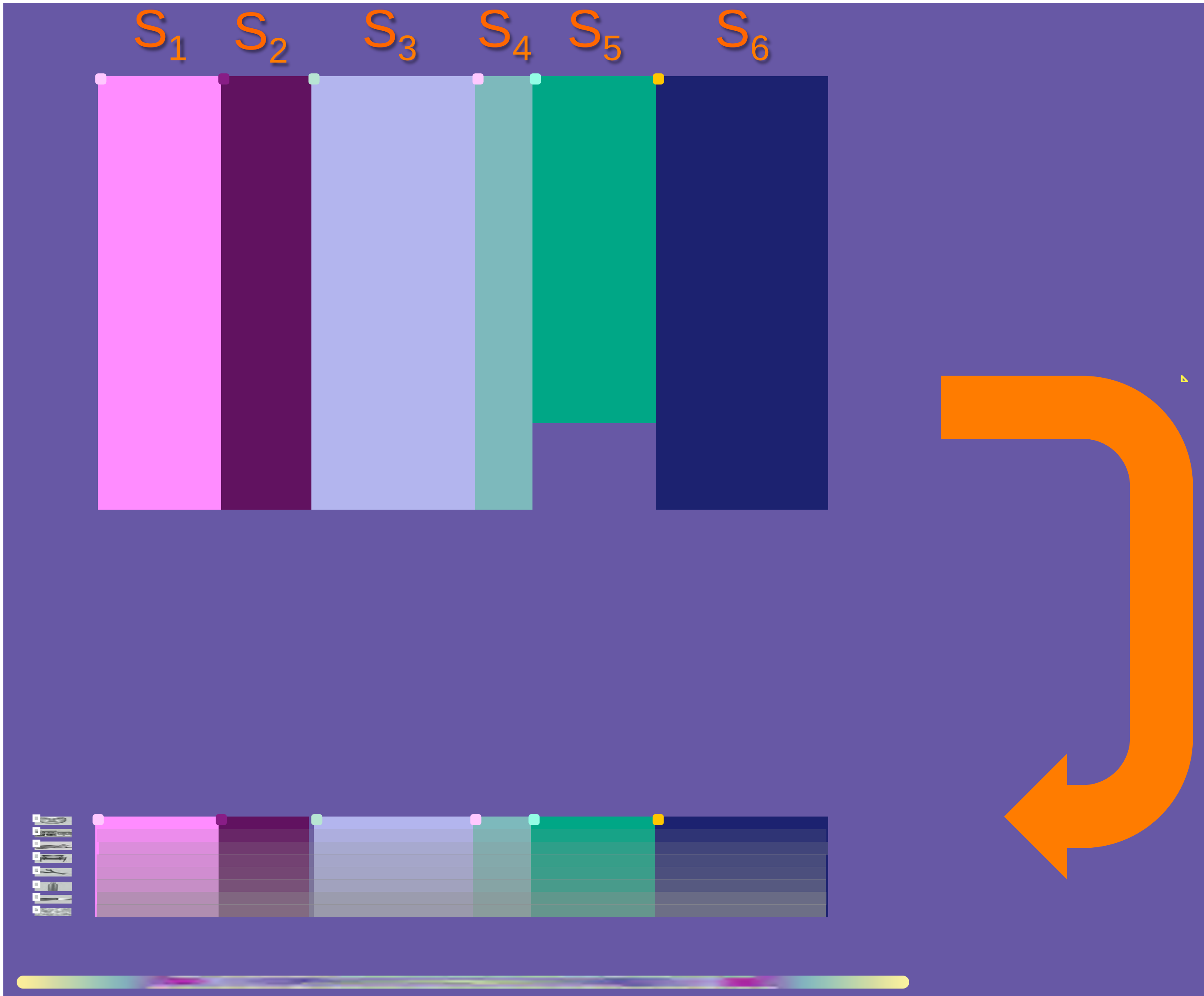

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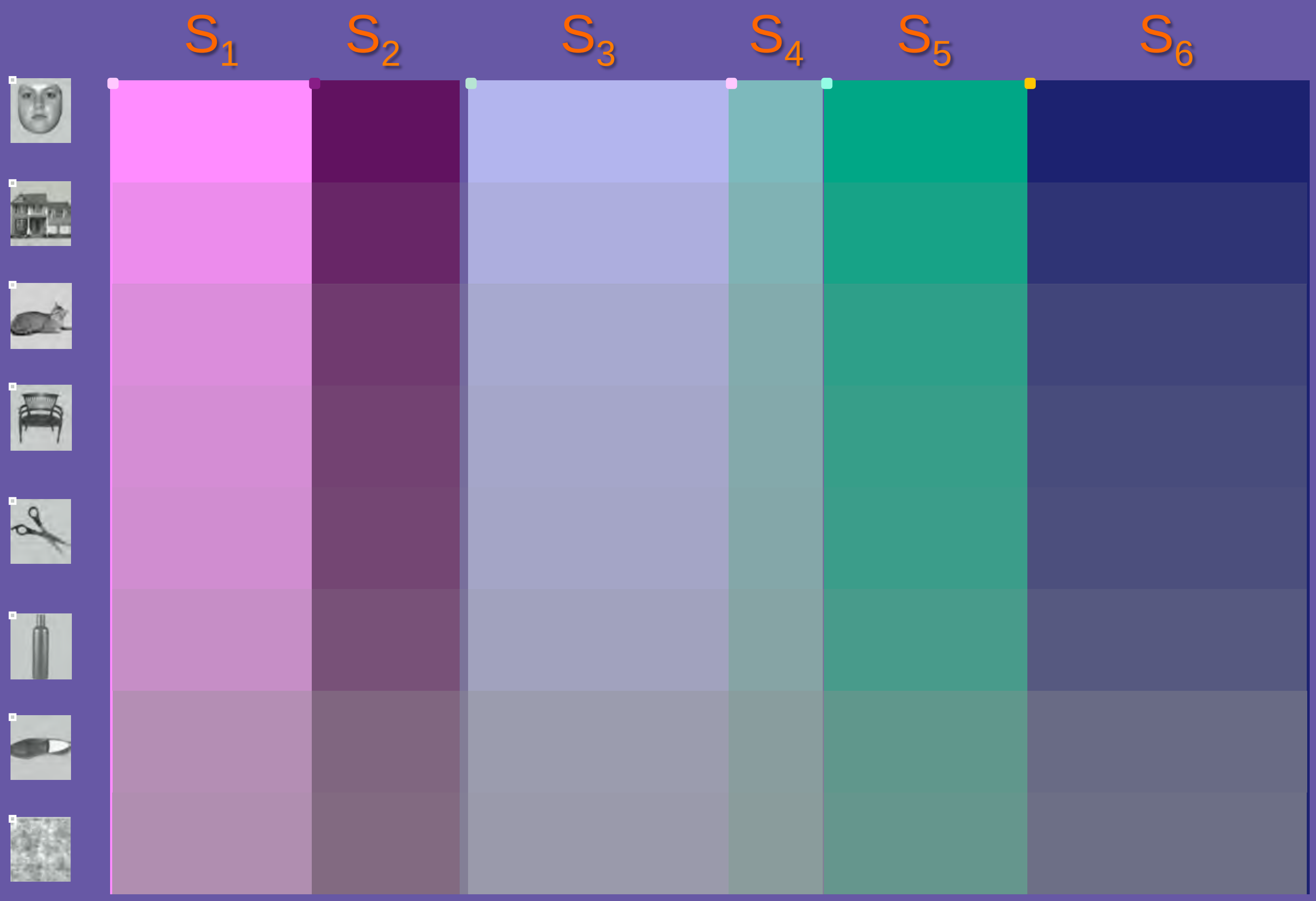
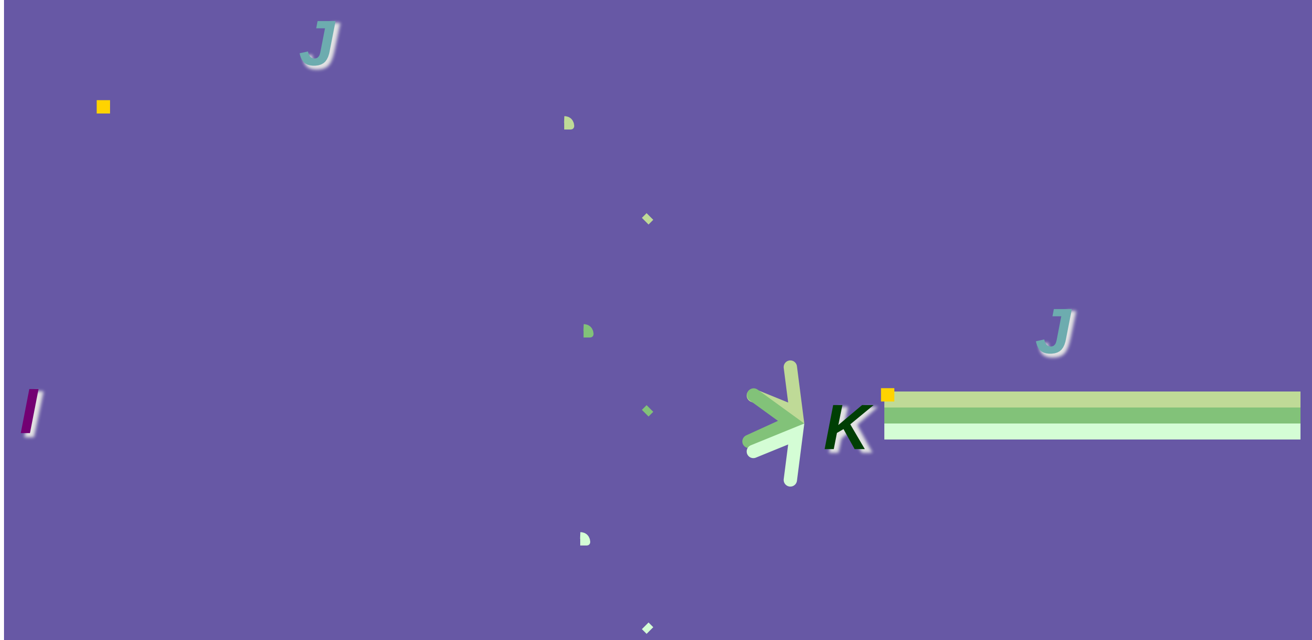


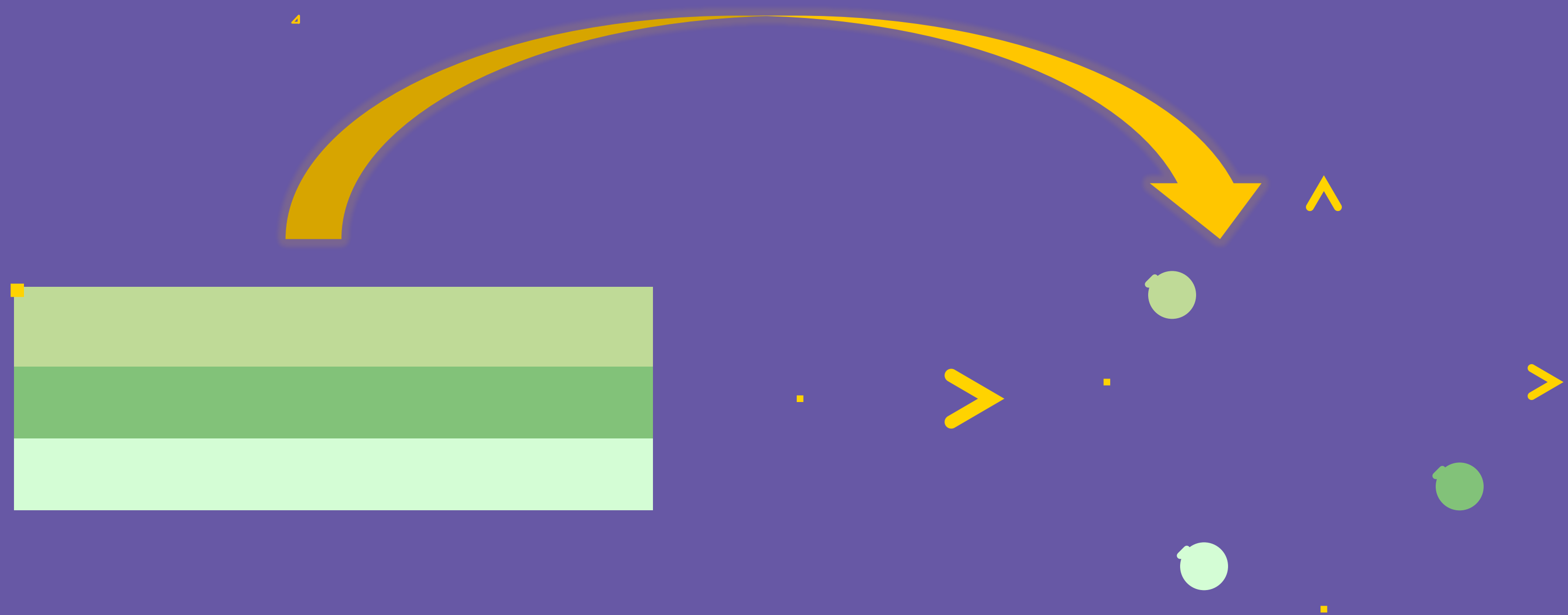
DATA: 6 SUBJECTS BY 8 CATEGORIES: AVERAGE ACTIVATION PER CATEGORY

Step one: Compute barycenter.



THE BEAUTY OF EUCLID …

Mix the variables to get “better variables”
(separate the groups best and independent)
Then plot the observations



Pause Principal Component Analysis (PCA)

Step two project the observation (supplementary rows)

THE BEAUTY OF EUCLID …

Multi-Block Approach

Project the blocks

4, 5, 6 MULTIBLOCK …

Start with a *I* rows by *J column* data matrix: **X**

TIME FOR SOME EQUATIONS

Start with a *I* rows by *J columns* data matrix: **X**

And **X** is made of blocks (sub-tables):

$$\mathbf{X} = [\, \mathbf{X}_1 , \ldots , \mathbf{X}_k , \ldots , \mathbf{X}_K \,]$$

with $\mathbf{X}_k$ being an I by J_K matrix

TIME FOR SOME EQUATIONS

PCA (i.e., singular value decomposition) of **X**

$$\mathbf{X} = [\,\mathbf{X}_1, \ldots, \mathbf{X}_k, \ldots, \mathbf{X}_K\,]$$

gives

$$\mathbf{X} = \mathbf{P}\boldsymbol{\Delta}\mathbf{Q}^T \text{ with } \mathbf{P}^T\mathbf{P} = \mathbf{Q}^T\mathbf{Q} = \mathbf{I}$$

PCA: THE EQUATIONS

From

$$\mathbf{X} = \mathbf{P}\boldsymbol{\Delta}\mathbf{Q}^{T} \text{ with } \mathbf{P}^{T}\mathbf{P} = \mathbf{Q}^{T}\mathbf{Q} = \mathbf{I}$$

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We got

1. Factor scores (rows): $\mathbf{F} = \mathbf{P\Delta} = \mathbf{XQ}$

PCA: The equations

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$$\mathbf{X} = \mathbf{P\Delta Q}^T \text{ with } \mathbf{P}^T\mathbf{P} = \mathbf{Q}^T\mathbf{Q} = \mathbf{I}$$

We got

1. Factor scores (rows): $\mathbf{F} = \mathbf{P\Delta} = \mathbf{XQ}$
2. Loadings (columns): $\mathbf{Q}$

PCA: The equations

From

$$\mathbf{X} = \mathbf{P\Delta Q}^T \text{ with } \mathbf{P}^T\mathbf{P} = \mathbf{Q}^T\mathbf{Q} = \mathbf{I}$$

We got (with L as rank of **X**)

1. Factor scores (rows) is I by L: $\mathbf{F} = \mathbf{P\Delta} = \mathbf{XQ}$
2. Loadings (columns) is J by L: **Q**

   with

$\mathbf{Q} = [\,\mathbf{Q}_1, \ldots, \mathbf{Q}_k, \ldots, \mathbf{Q}_K\,]$

with $\mathbf{Q}_k$ being an L by J_K matrix (corresponds to $\mathbf{X}_k$)

PCA: The equations

Getting to the "tables' projection"

So: $\mathbf{X} = \mathbf{P\Delta Q}^{T} = \mathbf{P\Delta} [\,\mathbf{Q}_1, \ldots, \mathbf{Q}_k, \ldots, \mathbf{Q}_K\,]^{T}$

1. Factor scores (rows): $\mathbf{F} = \mathbf{P\Delta} = \mathbf{XQ}$
2. Loadings (columns): $\mathbf{Q}$

MULTI-TABLES PROJECTIONS

Getting to the "tables' projection"

So: $\mathbf{X} = \mathbf{P\Delta Q}^T = \mathbf{P\Delta} [\, \mathbf{Q}_1 , \ldots , \mathbf{Q}_k , \ldots , \mathbf{Q}_K \,]^T$

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Give

$$\mathbf{F} = \mathbf{XQ} = \mathbf{X}\,[\,\mathbf{Q}_1, \ldots, \mathbf{Q}_k, \ldots, \mathbf{Q}_K\,]$$

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Give

$$\mathbf{F} = \mathbf{XQ} = \mathbf{X}\, [\, \mathbf{Q}_1 , \ldots , \mathbf{Q}_k , \ldots , \mathbf{Q}_K\,]$$

$$= [\, \mathbf{X}_1 , \ldots , \mathbf{X}_k , \ldots , \mathbf{X}_K\,] \times [\, \mathbf{Q}_1 , \ldots , \mathbf{Q}_k , \ldots , \mathbf{Q}_K\,]$$

Getting to the "tables' projection"

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Give

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$$= [\,\mathbf{X}_1, \ldots, \mathbf{X}_k, \ldots, \mathbf{X}_K\,] \times [\,\mathbf{Q}_1, \ldots, \mathbf{Q}_k, \ldots, \mathbf{Q}_K\,]$$

$$= \mathbf{X}_1\mathbf{Q}_1 + \ldots + \mathbf{X}_k\mathbf{Q}_k + \ldots + \mathbf{X}_K\mathbf{Q}_K$$

Getting to the "tables' projection"

So from $\mathbf{X} = \mathbf{P\Delta Q}^T = \mathbf{P\Delta}\,[\,\mathbf{Q}_1\,, \ldots\,, \mathbf{Q}_k\,, \ldots\,, \mathbf{Q}_K\,]^T$

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I want the compromise factor score as mean of tables

$$\mathbf{F} = 1/K \sum \mathbf{F}_k$$

MULTI-TABLES PROJECTIONS

Getting to the “tables’ projection”

So from $\mathbf{X} = \mathbf{P}\boldsymbol{\Delta}\mathbf{Q}^T = \mathbf{P}\boldsymbol{\Delta}\,[\,\mathbf{Q}_1, \ldots, \mathbf{Q}_k, \ldots, \mathbf{Q}_K\,]^T$

we got

$$\mathbf{F} = \mathbf{X}_1\mathbf{Q}_1 + \ldots + \mathbf{X}_k\mathbf{Q}_k + \ldots + \mathbf{X}_K\mathbf{Q}_K$$

I want the compromise factor score as mean of tables

$$\mathbf{F} = 1/K \sum \mathbf{F}_k$$

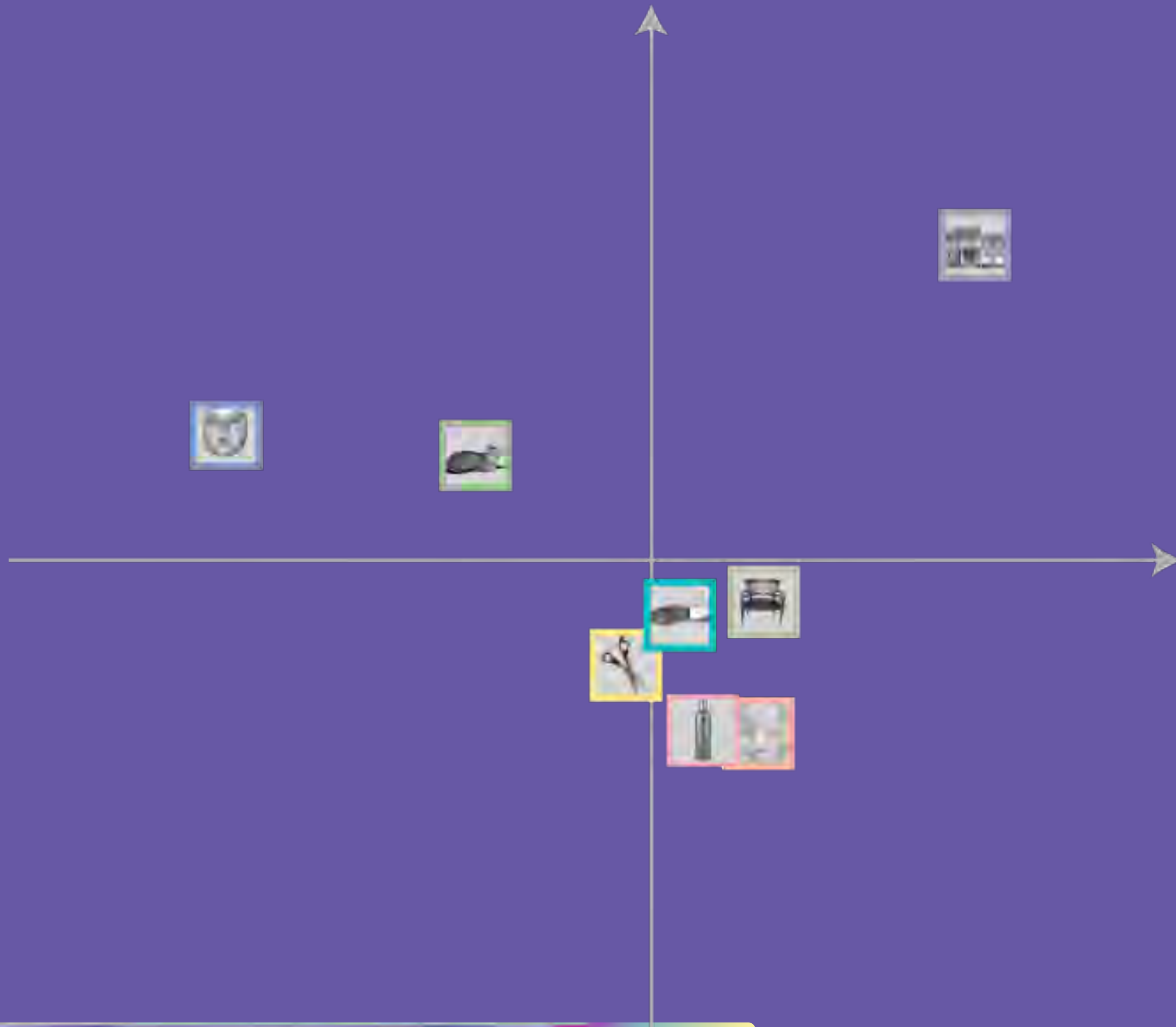
So:

$$\mathbf{F}_k = K\,\mathbf{X}_k\mathbf{Q}_k$$

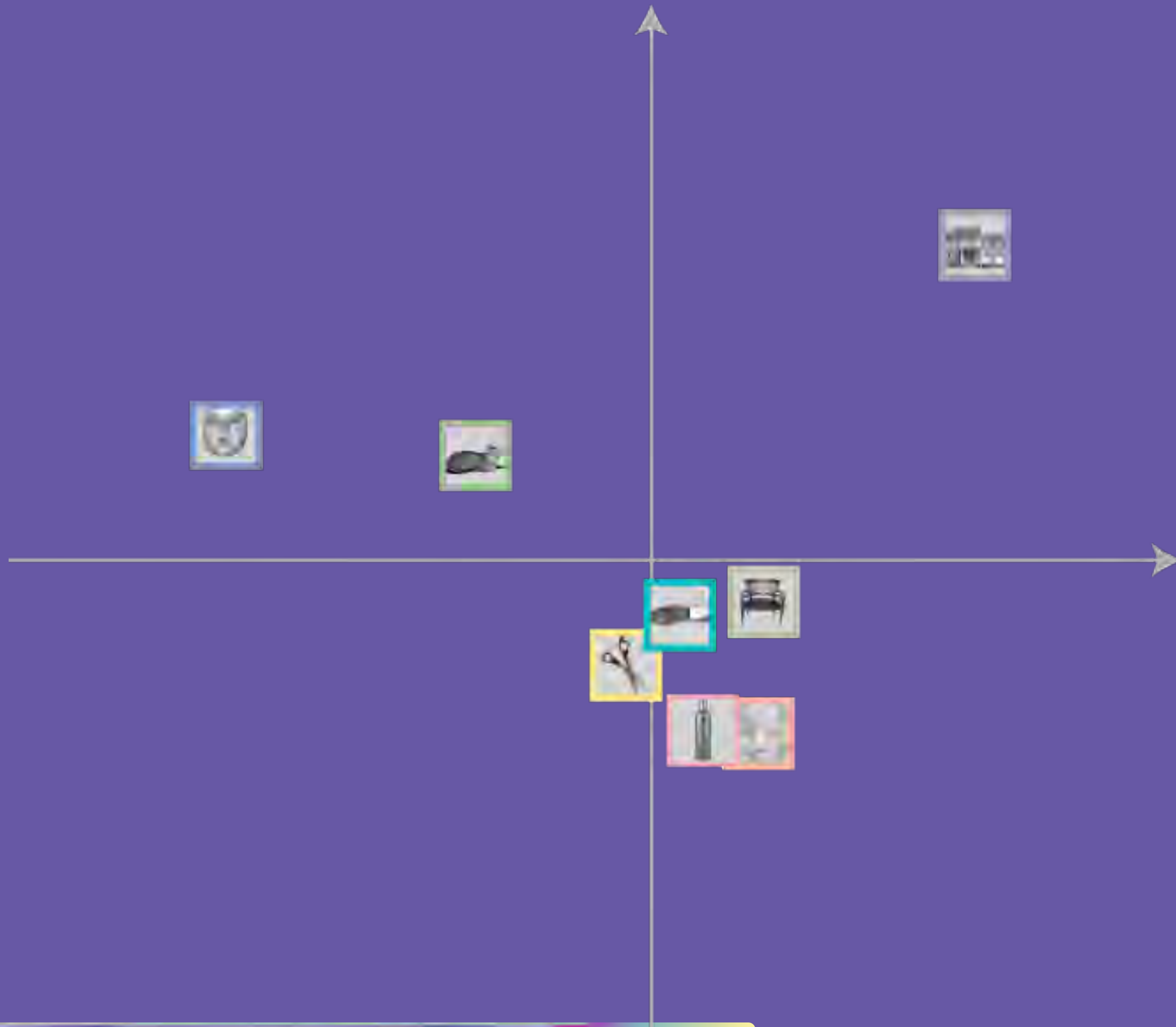
MULTI-TABLES PROJECTIONS

READY FOR THE PICTURES?

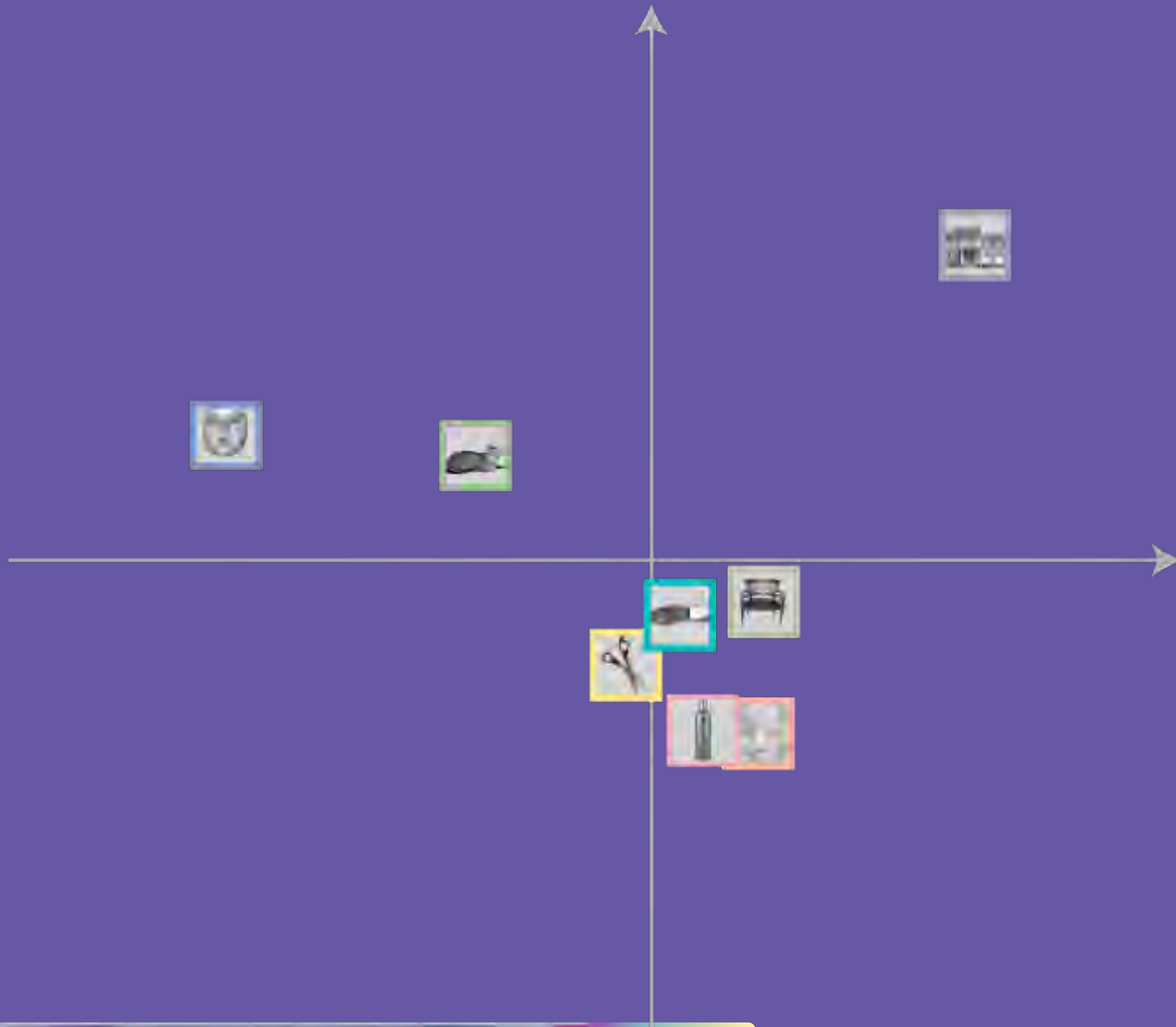
ALTOGETHER RESULTS



CATEGORIES



PRETTY



BUT, SO WHAT?

- Call for a test?
- Sampling distribution?

How stable is this (is $p < .05$?)

Remember Cohen's The earth is round $p < .05$

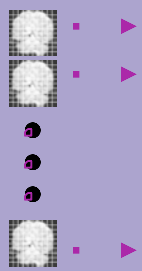
- Get confidence Intervals

USE BOOTSTRAP

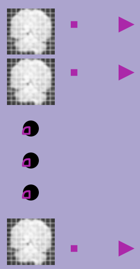
Bootstrap

THE SAMPLE *IS* THE POPULATION

BOOTSTRAP: START WITH A DATA TABLE

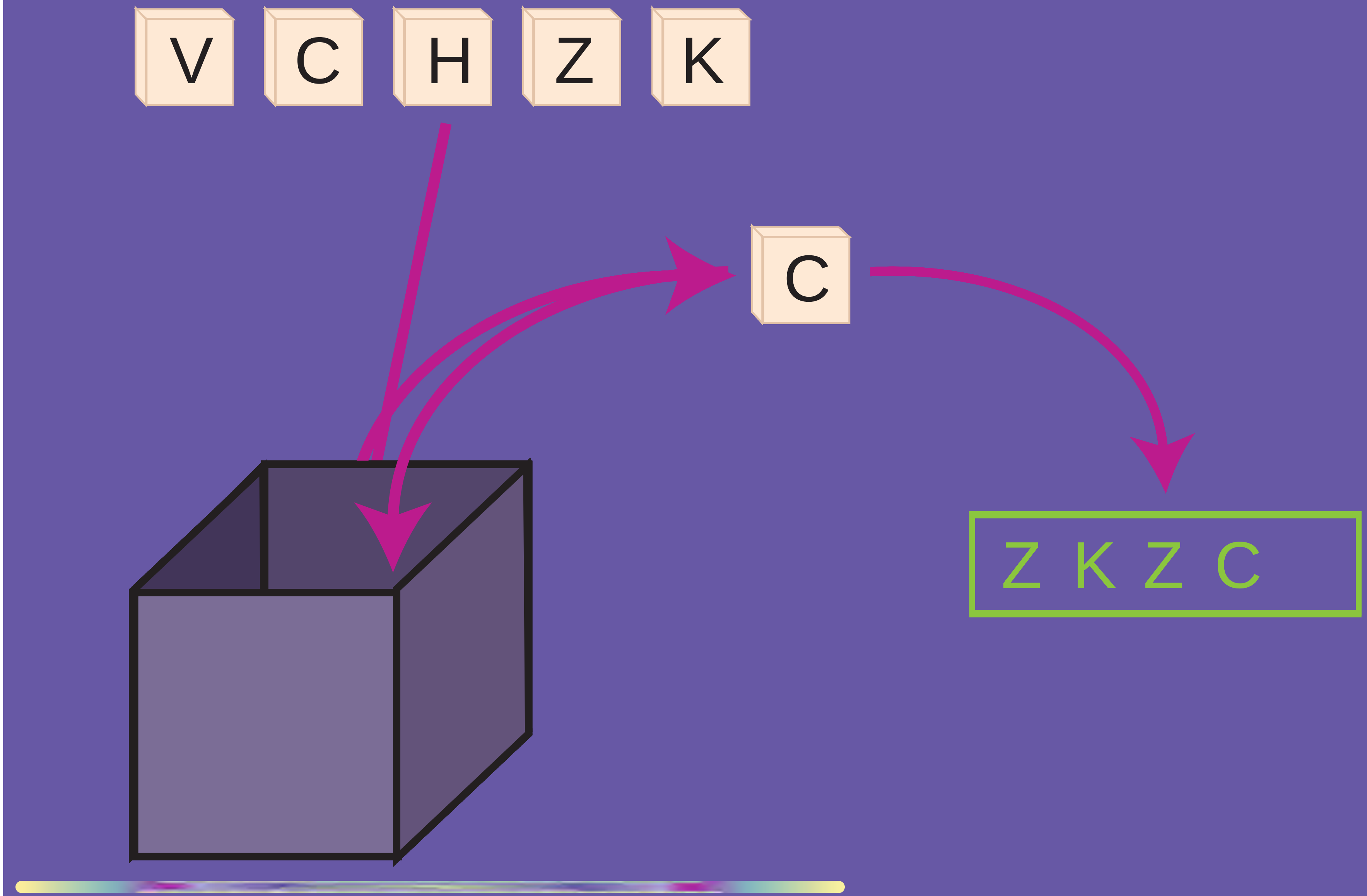


BOOTSTRAP: DO THE ANALYSIS

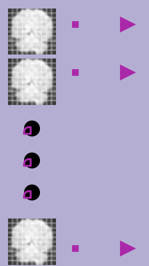


BOOTSTRAP: DO THE ANALYSIS

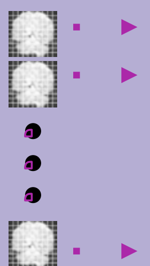
Bootstrap: Generate bootstrap sample



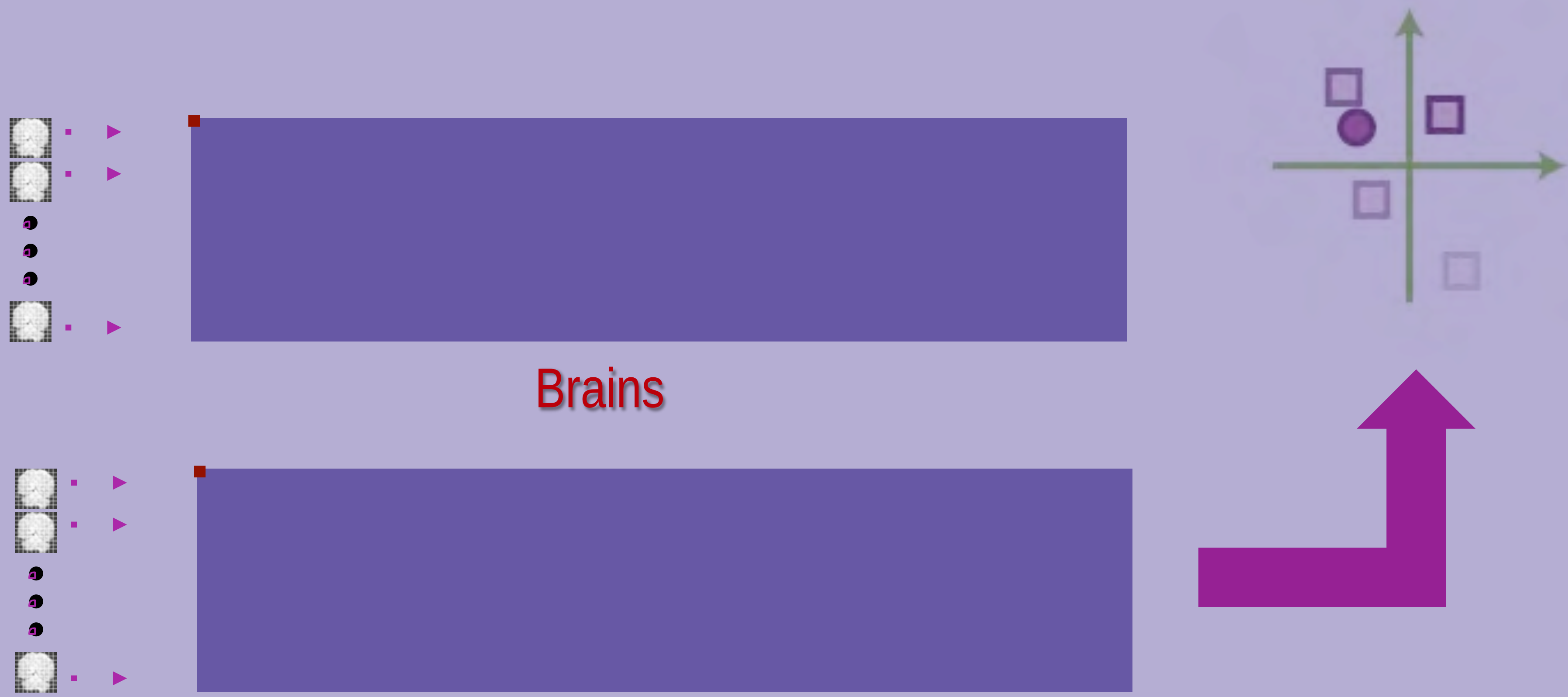
Drawing with Replacement



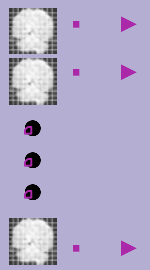
Brains



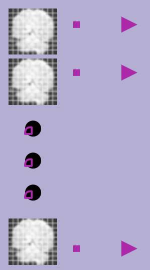
So get bootstrap sample



Project bootstrap sample onto original



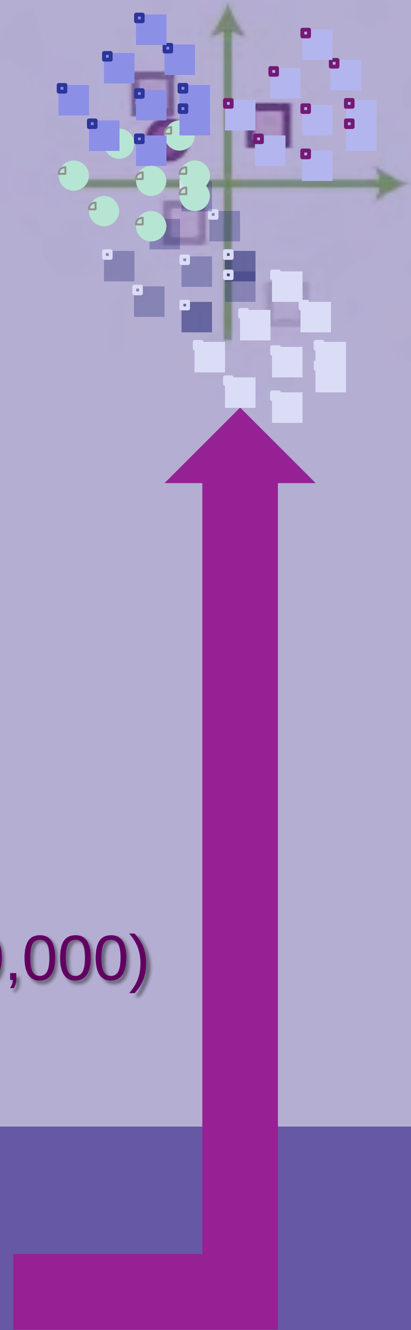
Brains

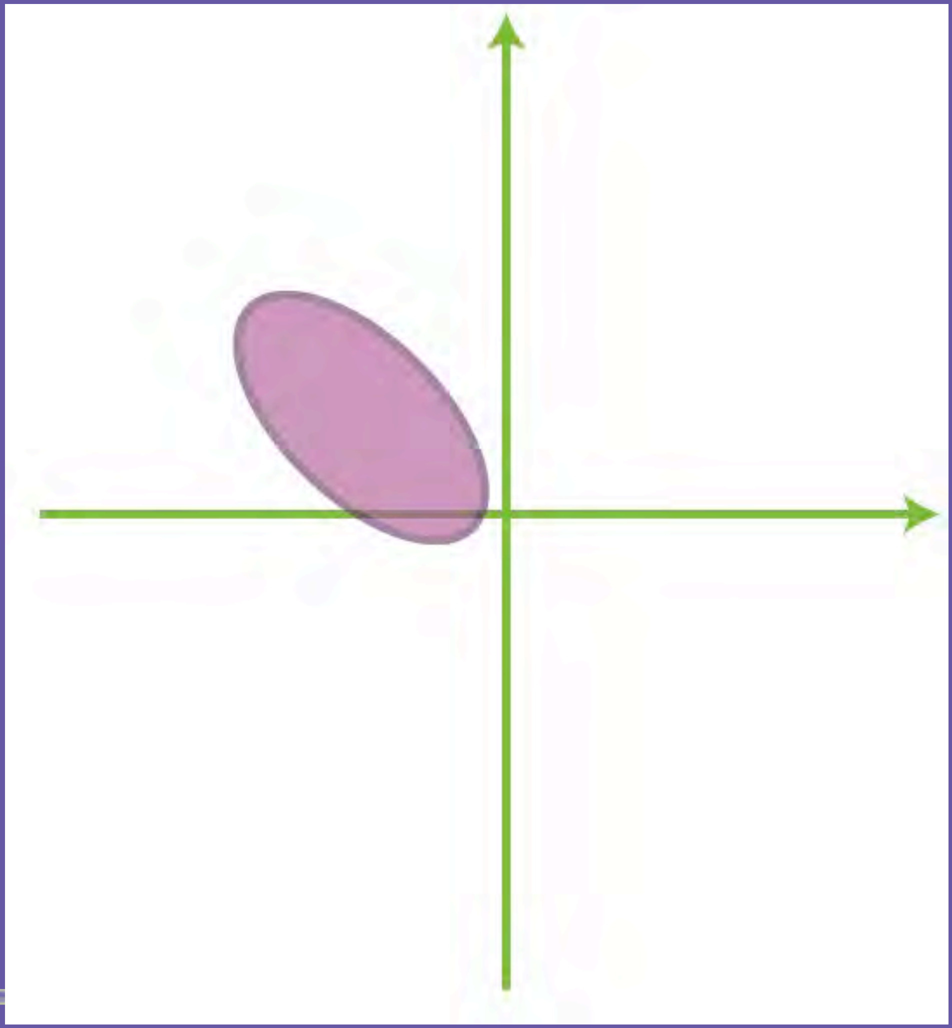


Keep on with more bootstrap samples

Brains

A lot o' times (e.g.,10,000)





Fit a 95% ellipsoid: confidence interval

- 1. Bootstrap the participants
- 2. Bootstrap the scans
- 3. put all that together.
- 4. Project in the common space

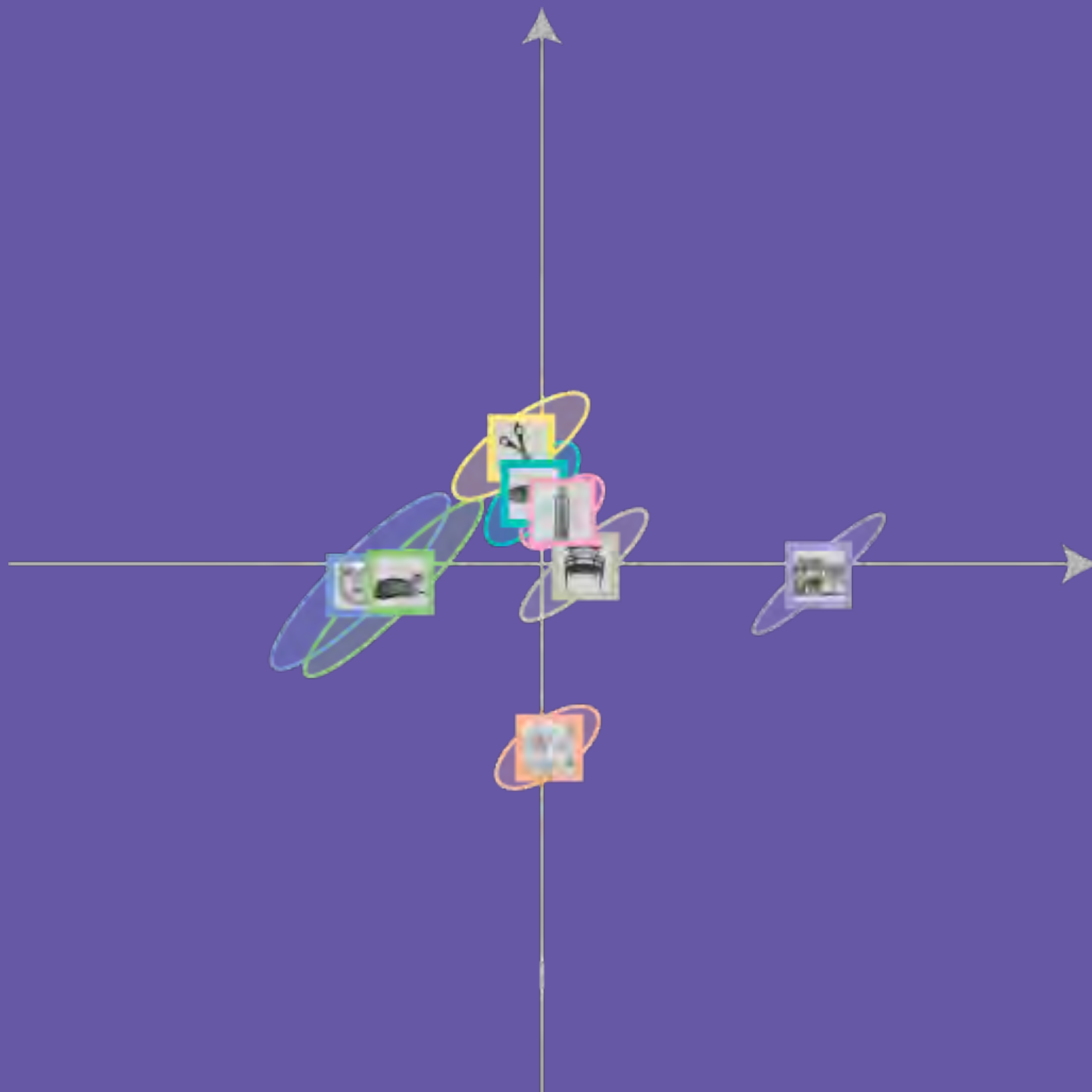
DOUBLE BOOTSTRAP

Between Category Confidence Intervals
The earth is round!

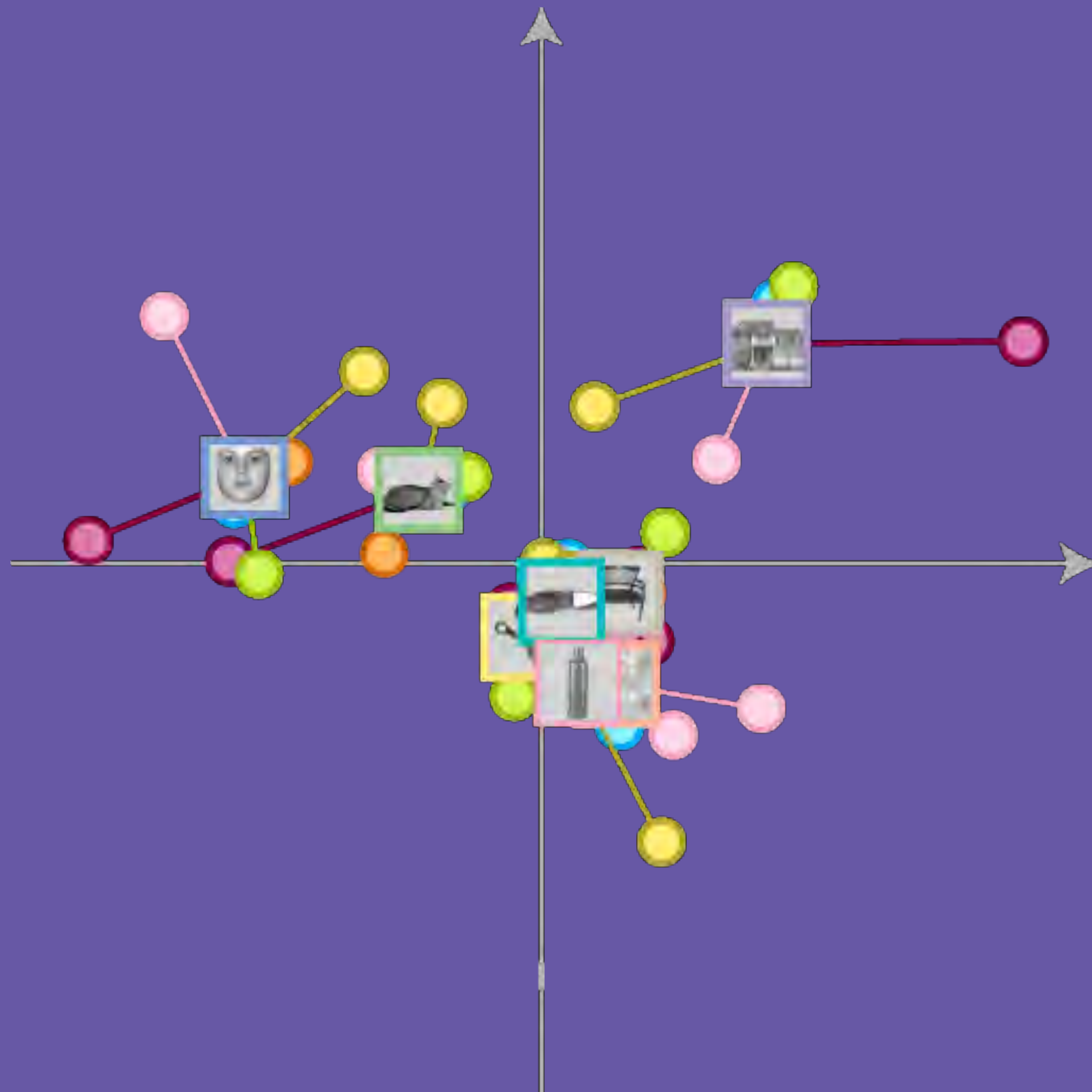
- Look at one participant (#3)

  Use Block projection

BACK TO THE PRESENT!



S3 Confidence Interval



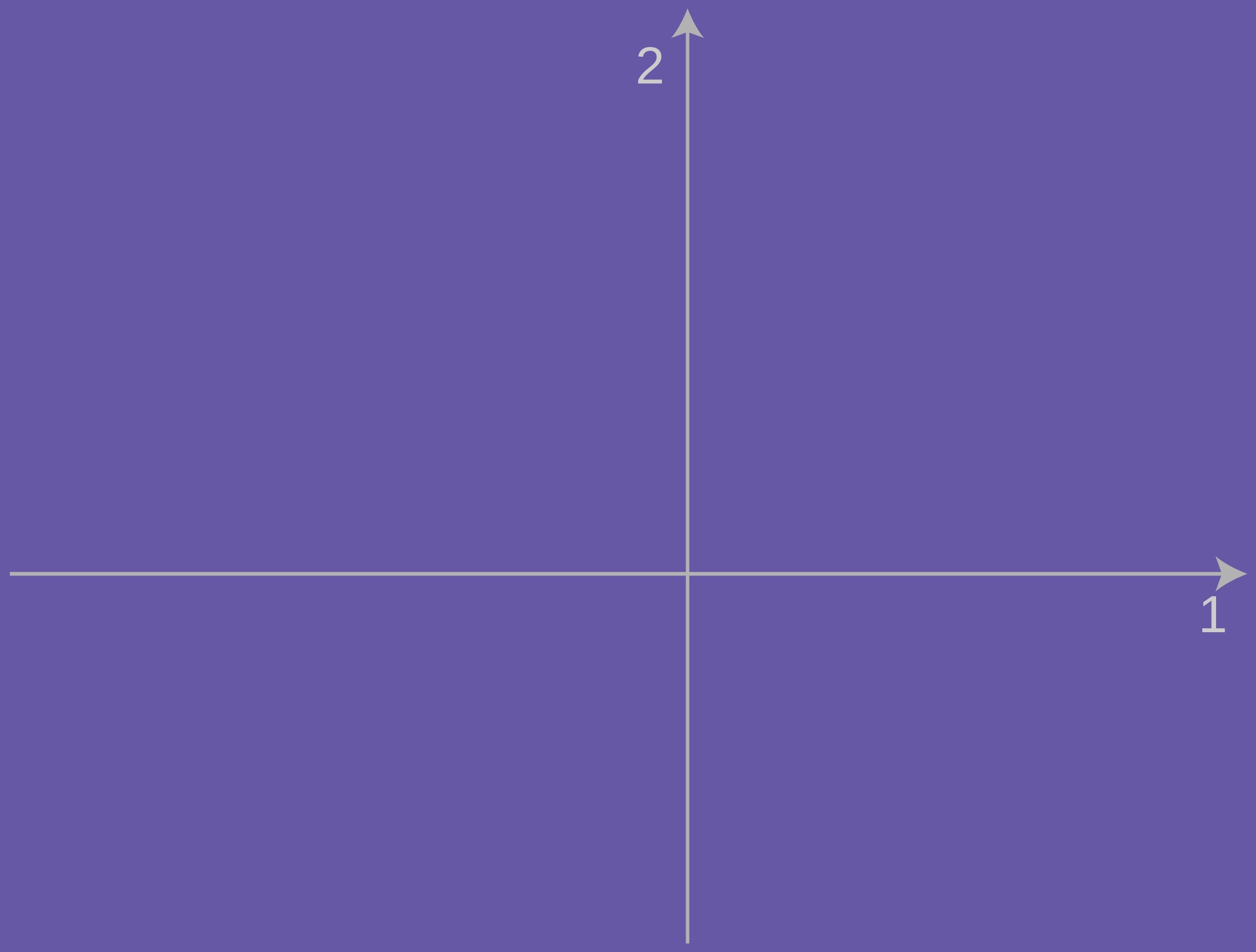
CATEGORIES AS BARYCENTER OF SUBJECT TABLES

- Brain or Image?

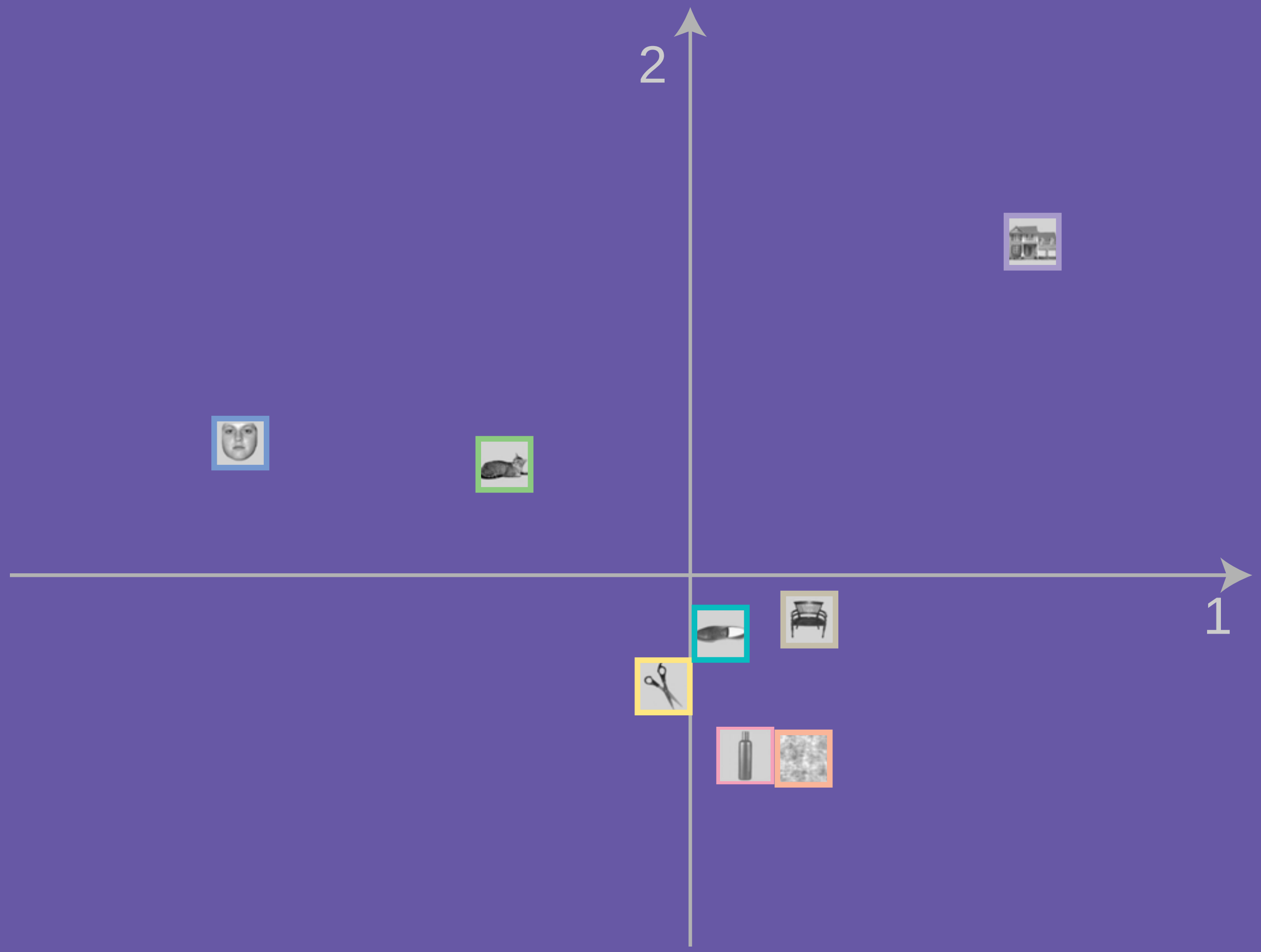
WHERE DOES THE CATEGORIZATION COME FROM?

- Project the images onto the brain space

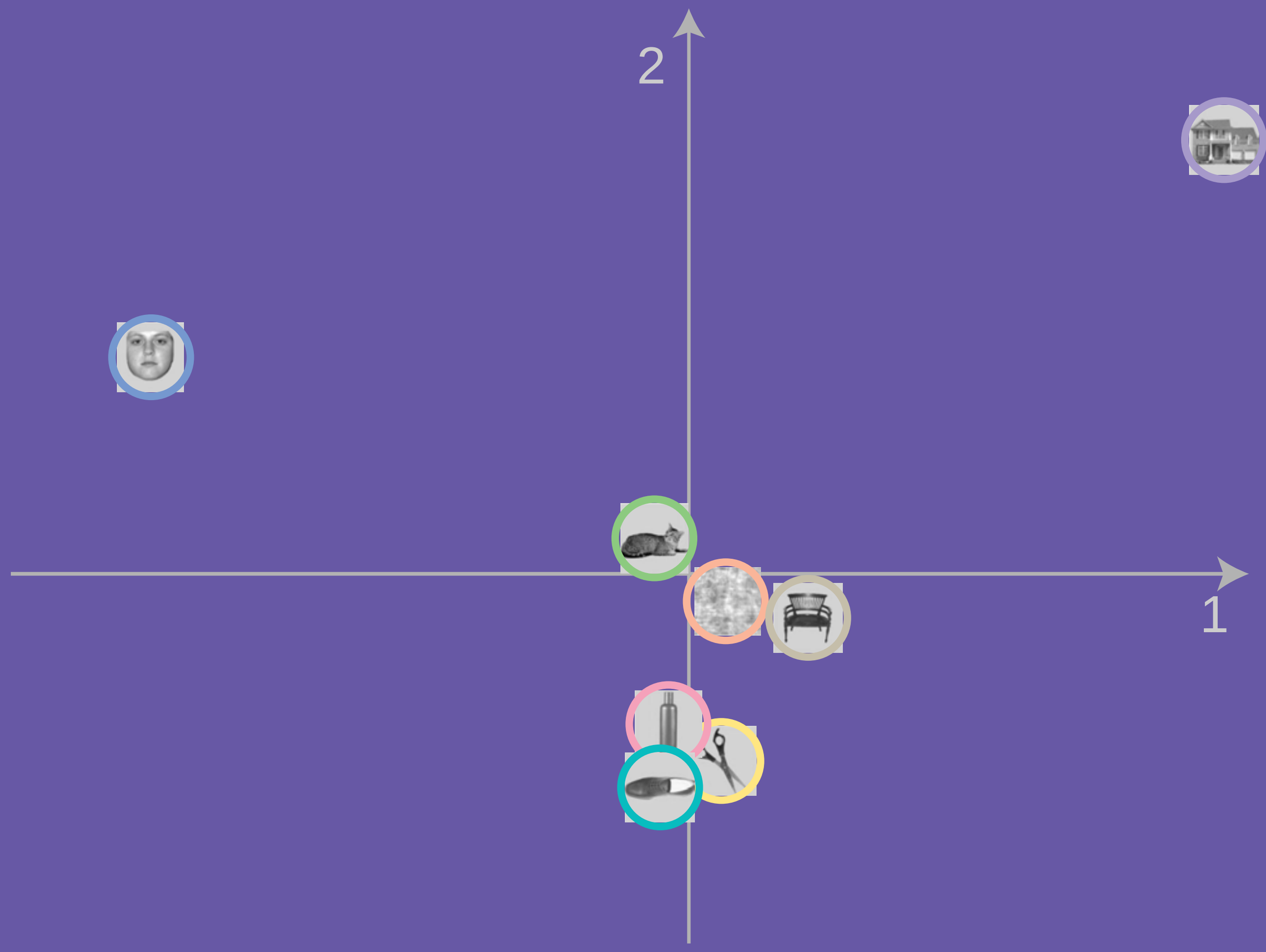
REDO THE ANALYSIS WITH THE IMAGES



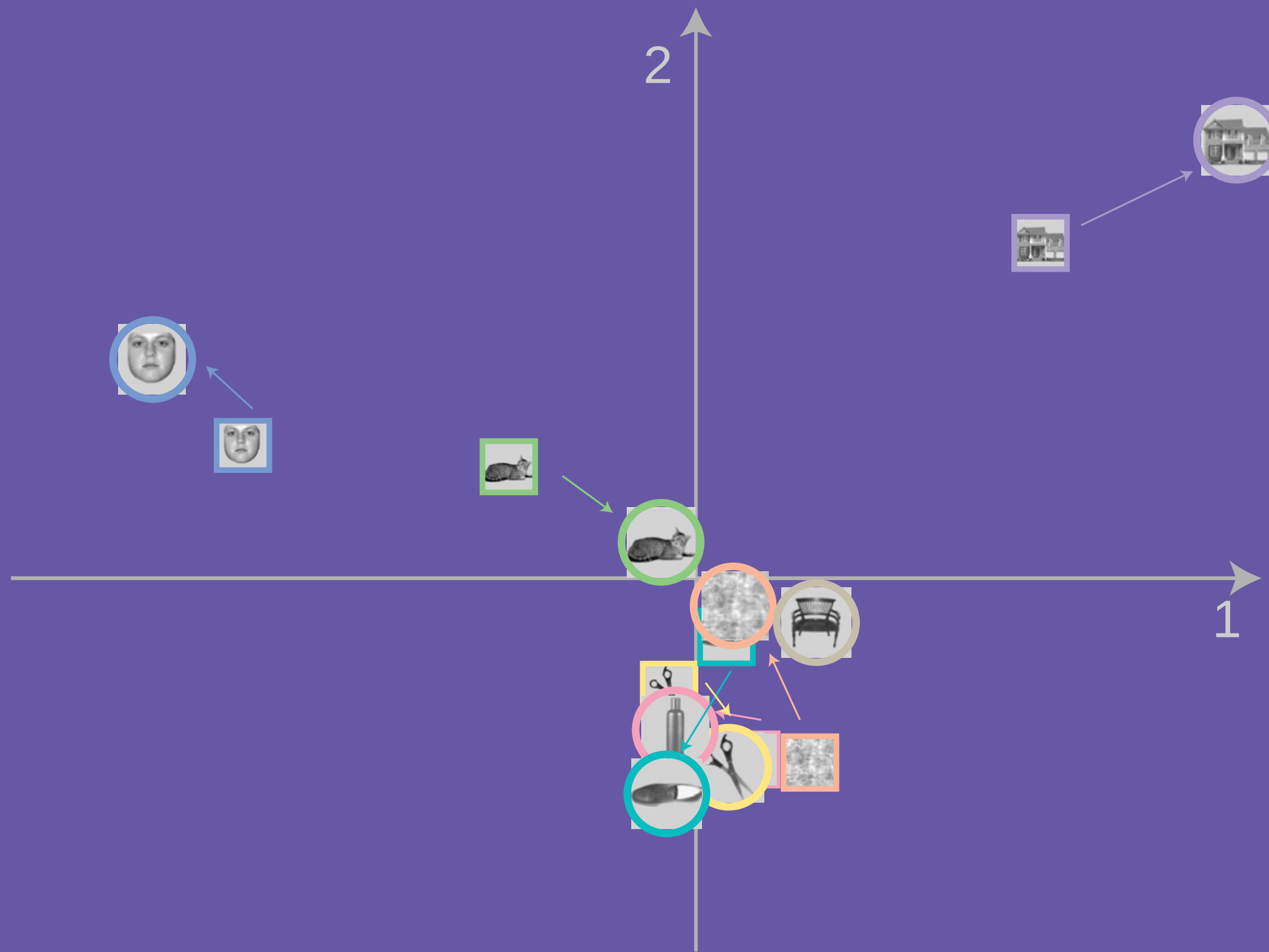
Haxby 1



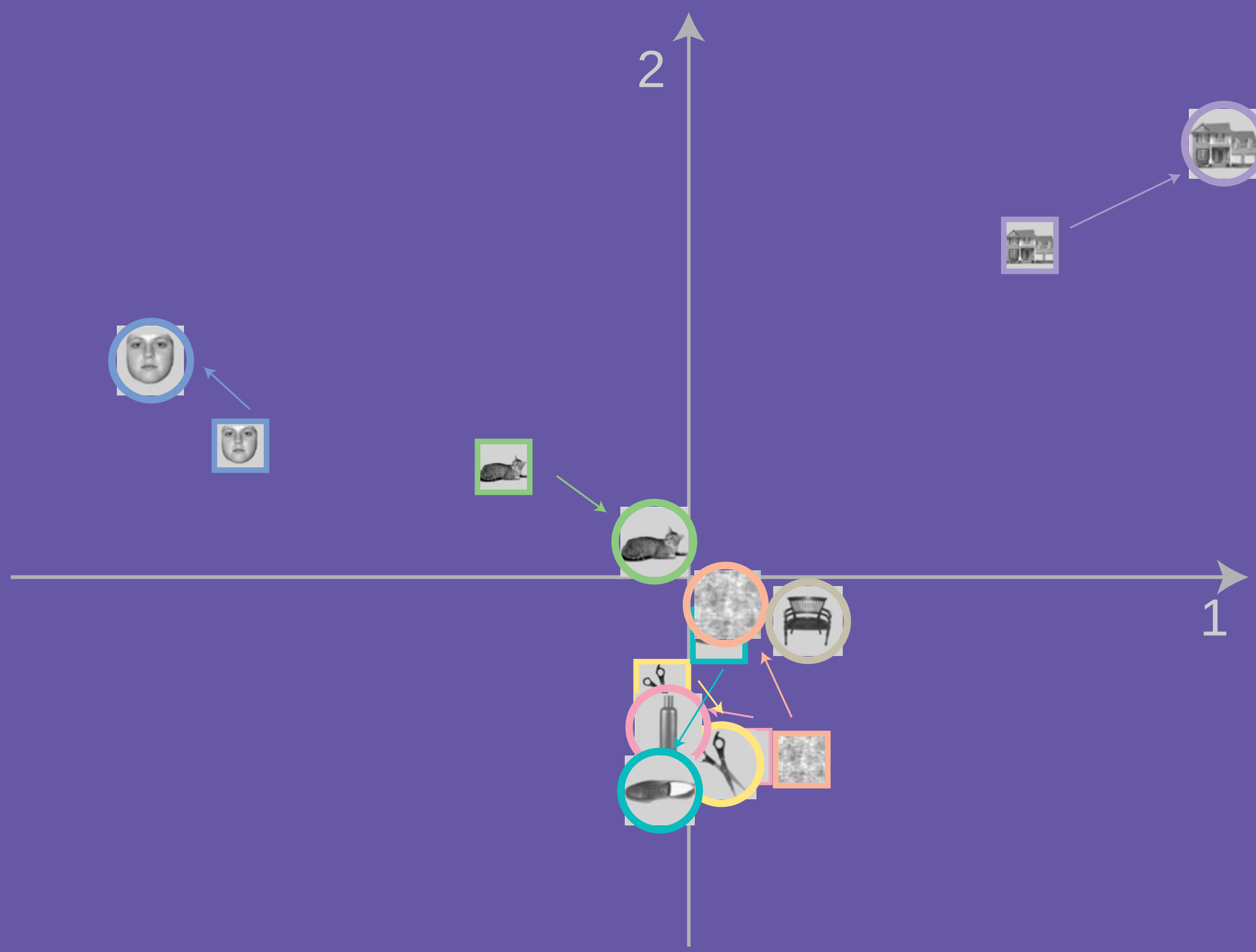
The brain space



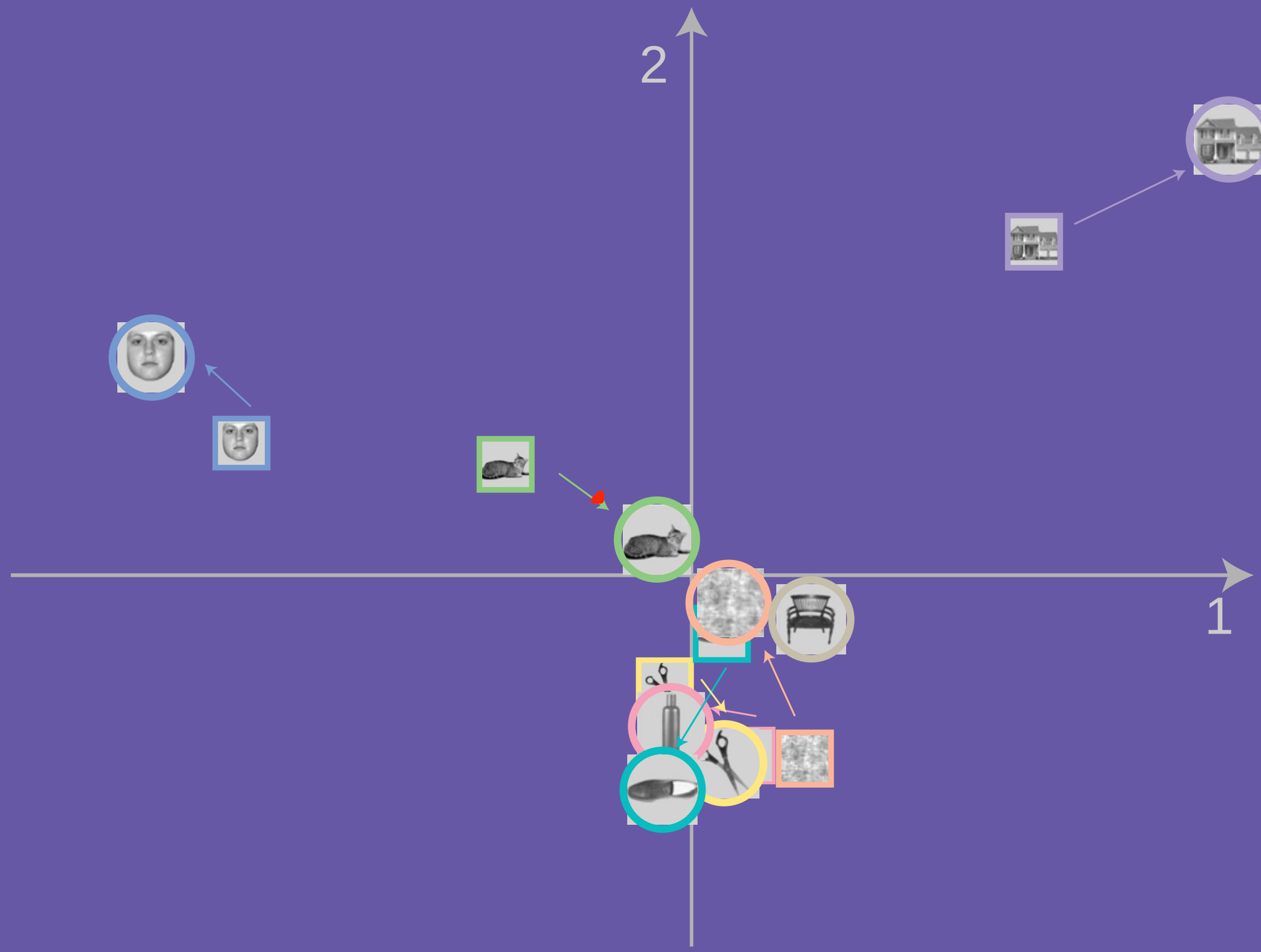
THE IMAGE PROJECTED ONTO THE BRAIN SPACE



Brain and images in brain space



IMAGES IN THE BRAIN SPACE



FOR THE BRAIN CATS LOOK LIKE HUMANS
CATS HAVE FACES!

- Cats have faces!

Finale: Variation 1

VARIATION 2

Dogs and monkeys have faces too?

- Try other types of faces
- Same design as in 2001
- But: Use anatomical definitions
- Use 3 Regions of Interest (ROIs)

Dogs and monkeys have faces

- 10 Participants
- 7 categories
- Block design (8 runs × 7 blocks)
- Task: one back
- 3T scanner/TR=2s/

FACES AND OBJECTS

- 1. Medial occipital (MO) includes:
  calcarine cortex

- 2. Inferior occipital (IO) includes:
  lateral object sensitive regions

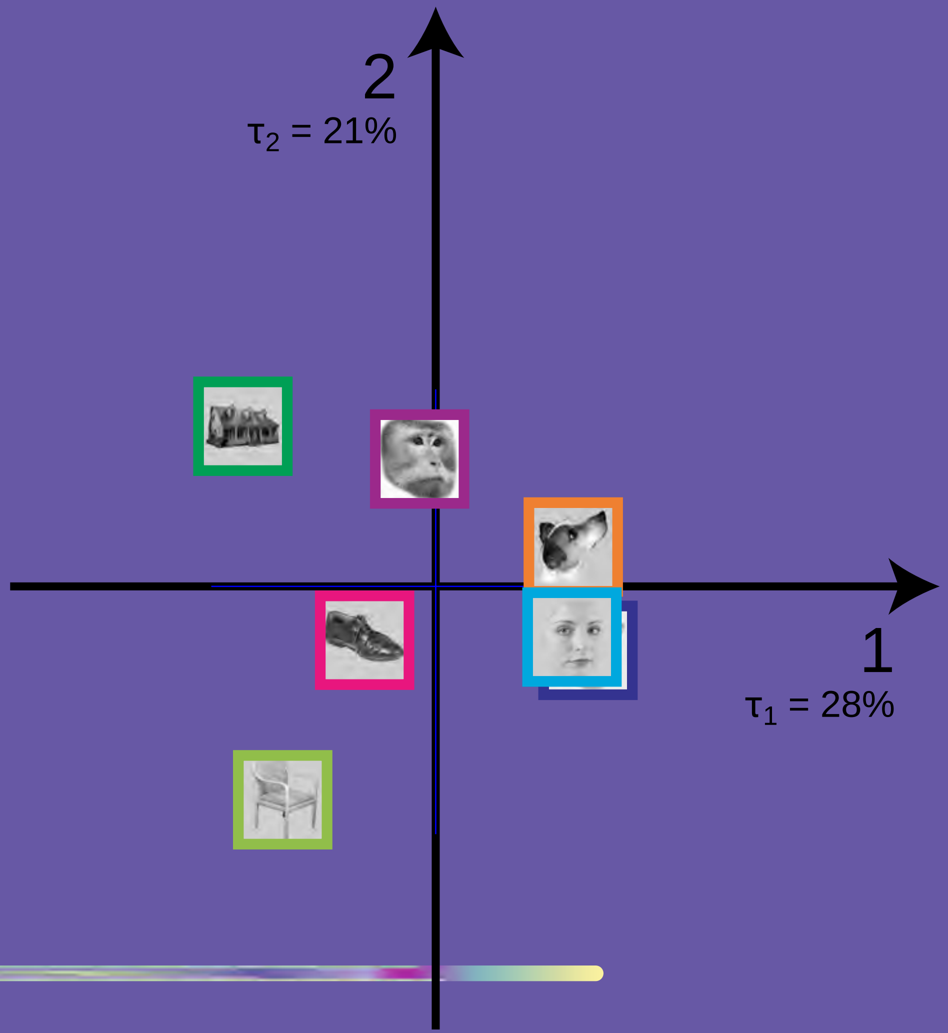
- 3. Ventro Temporal (VT) includes:
  inferior temporal, fusiform, parahippocampal gyri

Three Anatomical ROIs: From Low Level to High Level Vision

- **Implies different # of voxels per subjects**
- Medial Occipital (MO): 435 to 1261 voxels
- Inferior Occipital (IO) : 688 to 1859 voxels
- Ventro-Temporal (VT): 2791 to 4815 voxels

ANATOMICAL ROIs

All Rois



What are the dimensions?

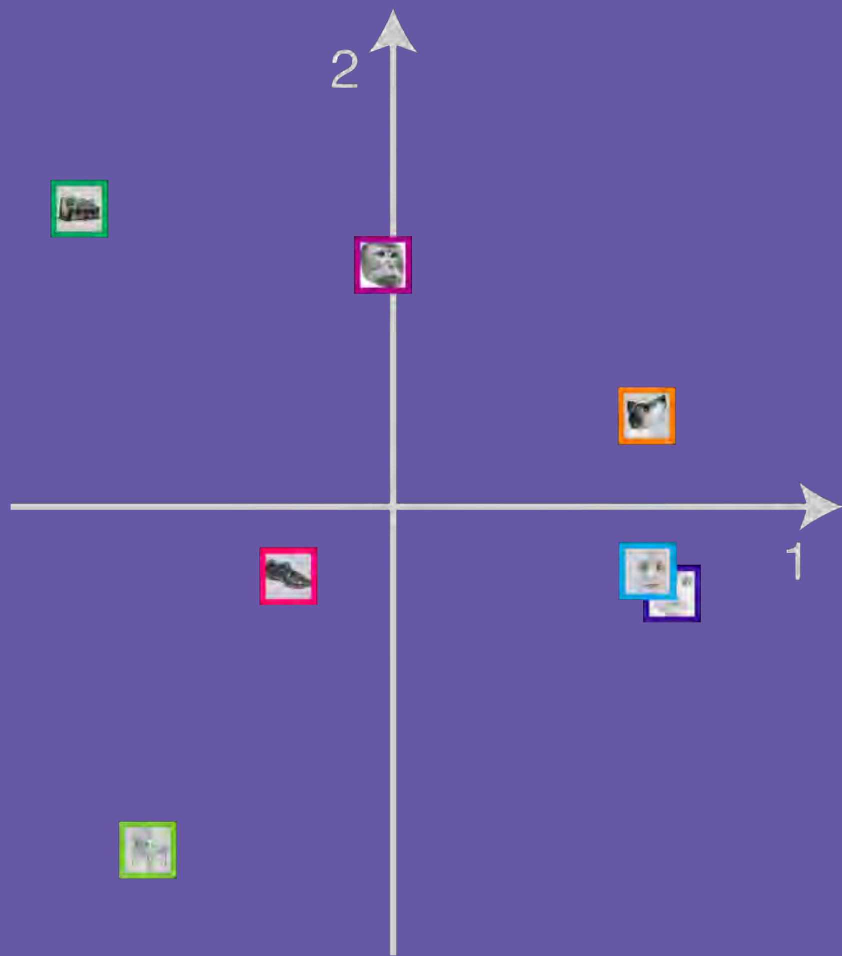
- Dimension 1: Faces vs. non faces (semantic?)

WHAT ARE THE DIMENSIONS?

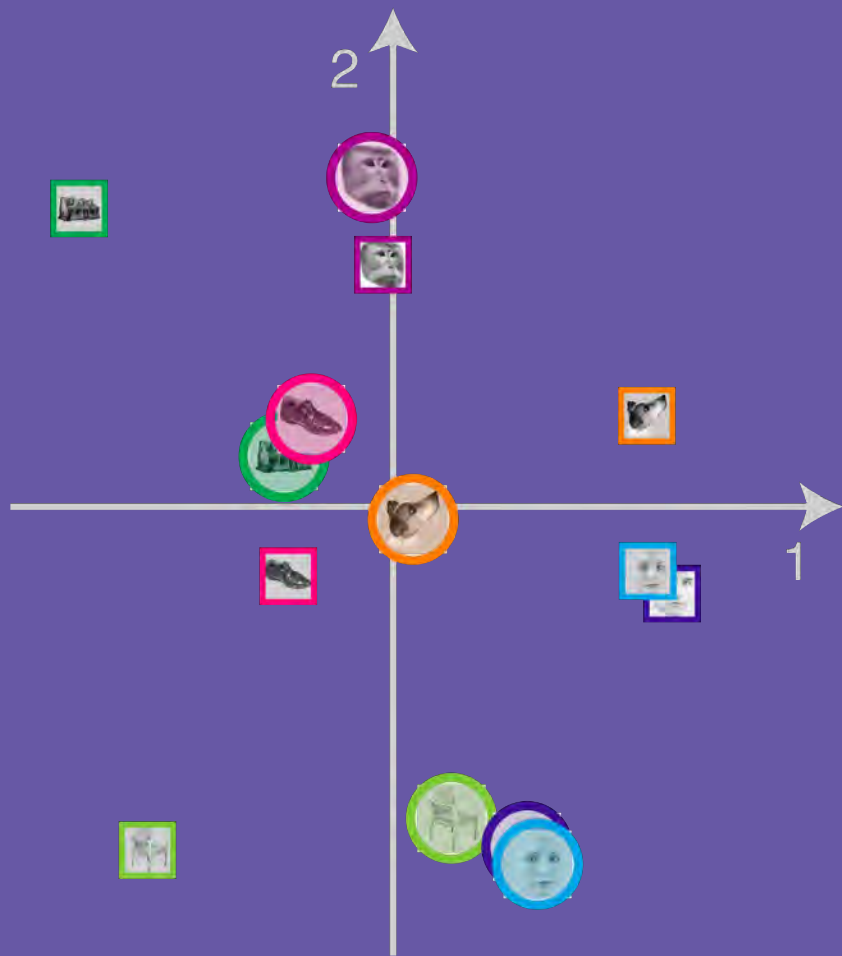
- Dimension 1: Faces vs non faces (semantic?)

- Dimension 2: Low level again?

What are the dimensions?



MONKEY–DOG: BRAIN CATEGORIES

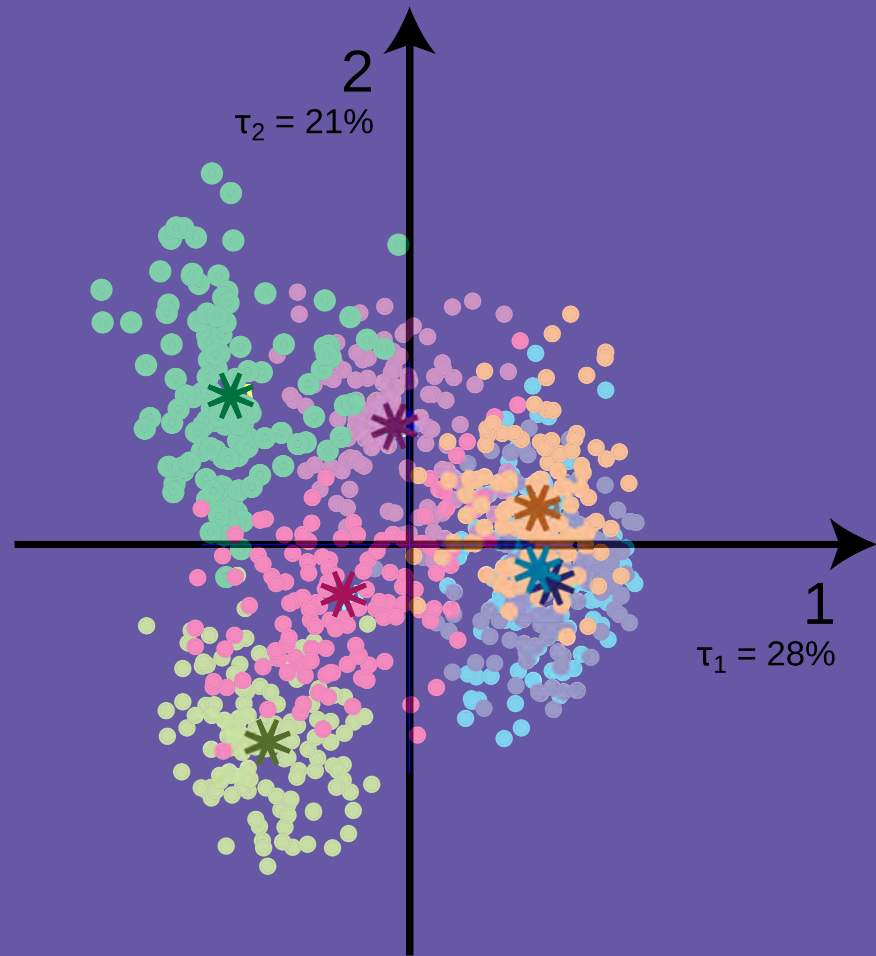


Monkey–Dog: With the pictures

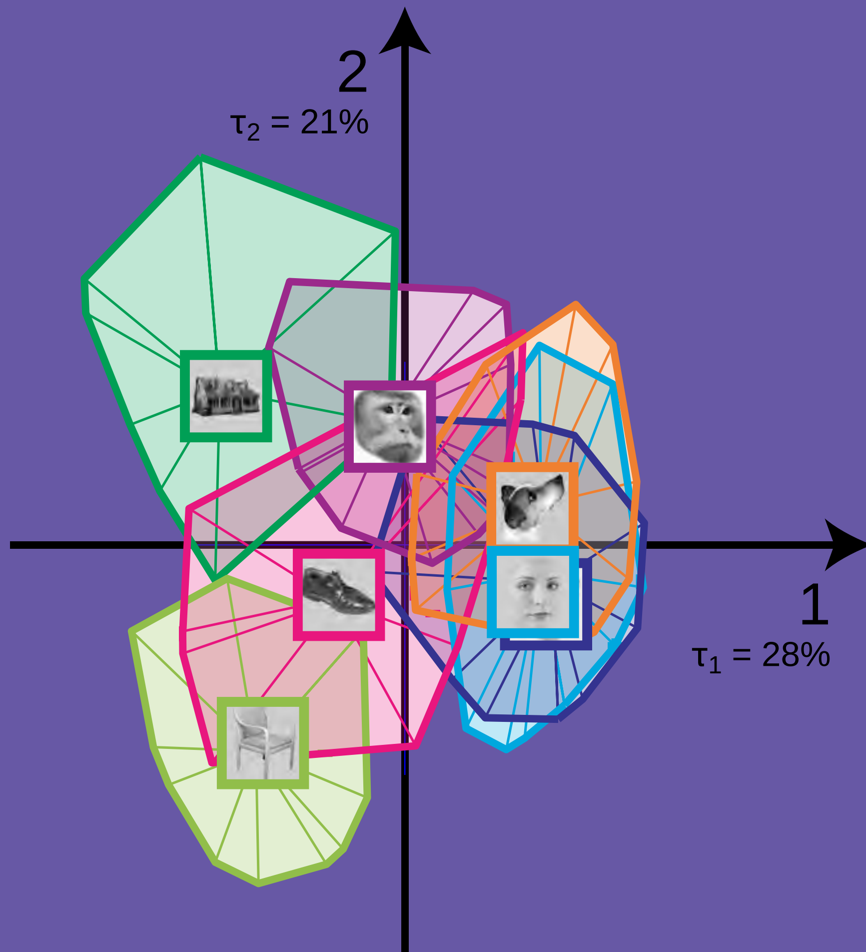
- Dimension 1: Semantic
- Dimension 2: Low Level

DIMENSIONS

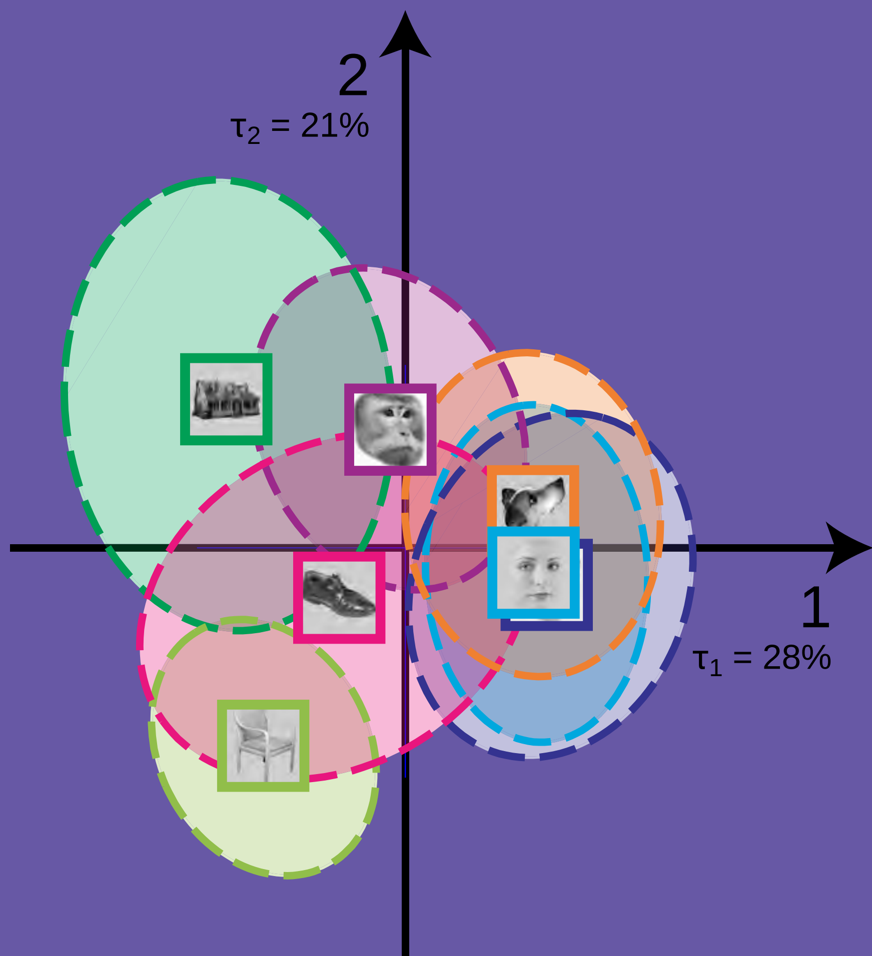
- One scan is one point.
- Look at the scans



All Rois. Observations



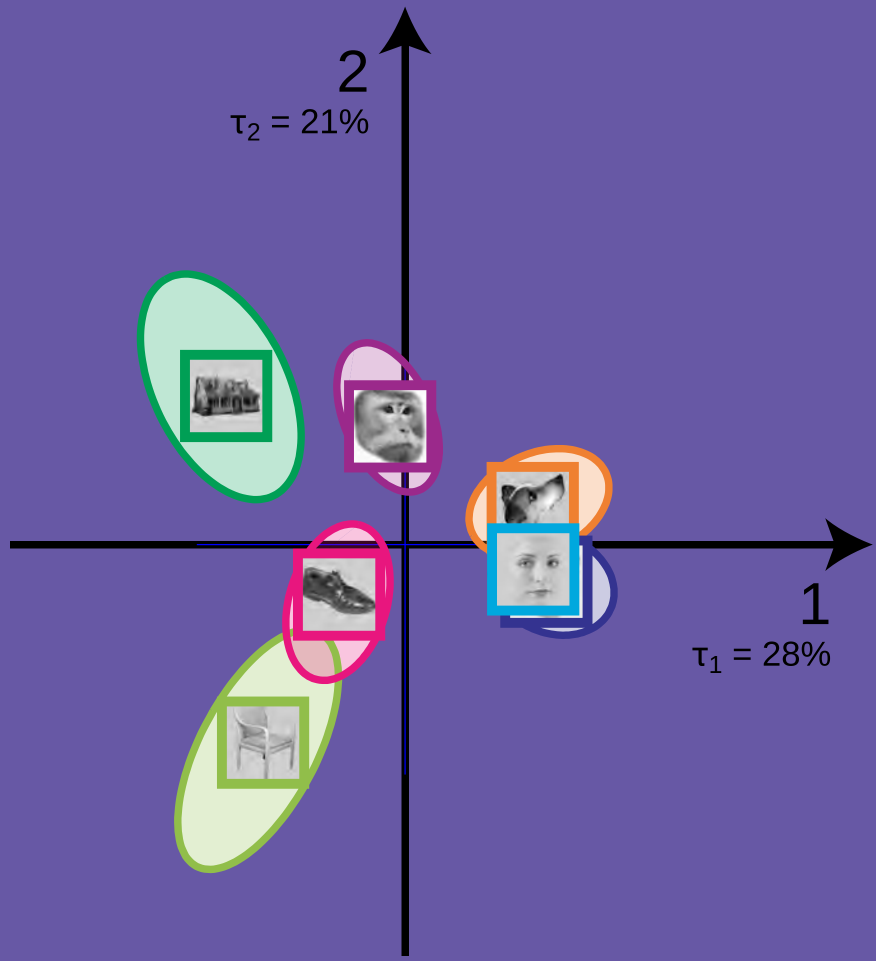
All Rois Convex Hulls



All Rois Tolerance Intervals

Is the earth round?

Bootstrap again for confidence intervals



All Rois Confidence Intervals

How good is the prediction for new scans

BADA: Jackknife Take Row or block 1 …

J

I - 1

BADA: Jackknife Take Row or Block 1 …

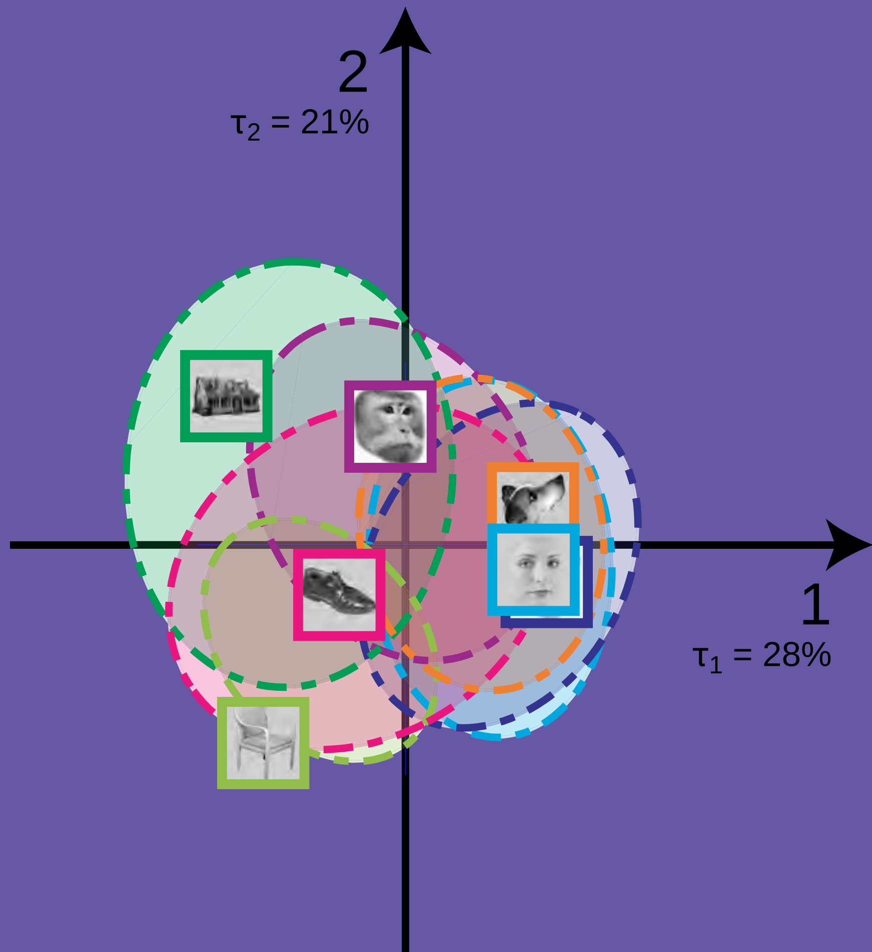
BADA: JACKKNIFE ...

MULTI-TABLE: JACKKNIFE …

PREDICTION: Do not use scans from the same block!

➔**Jackknife the whole block**

THE DANGERS OF TIME CORRELATION

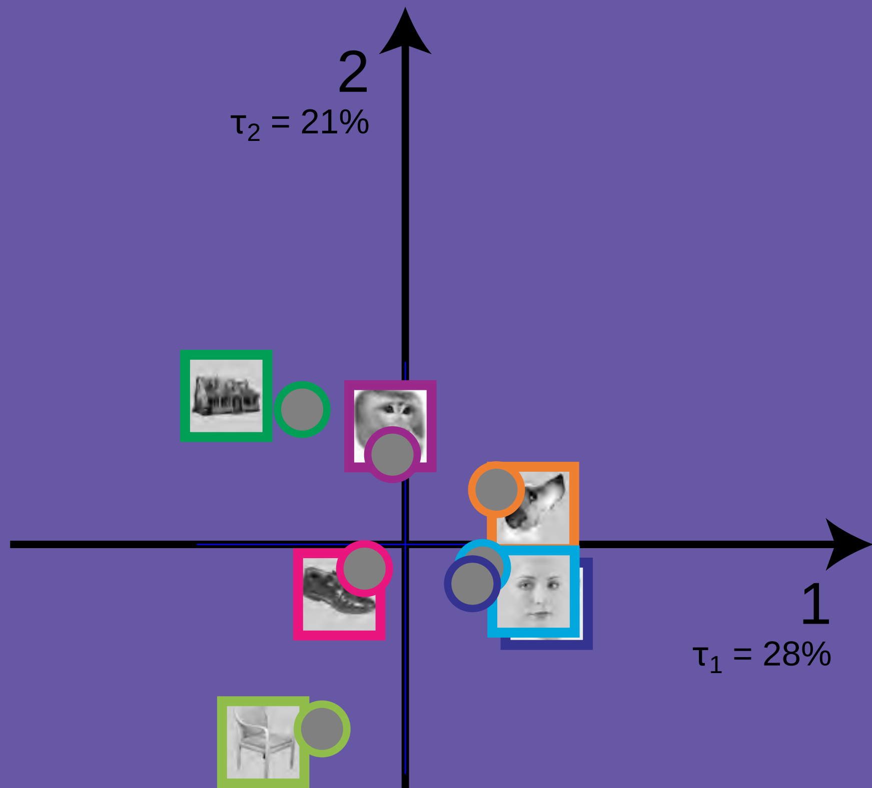


All Rois: Prediction Intervals

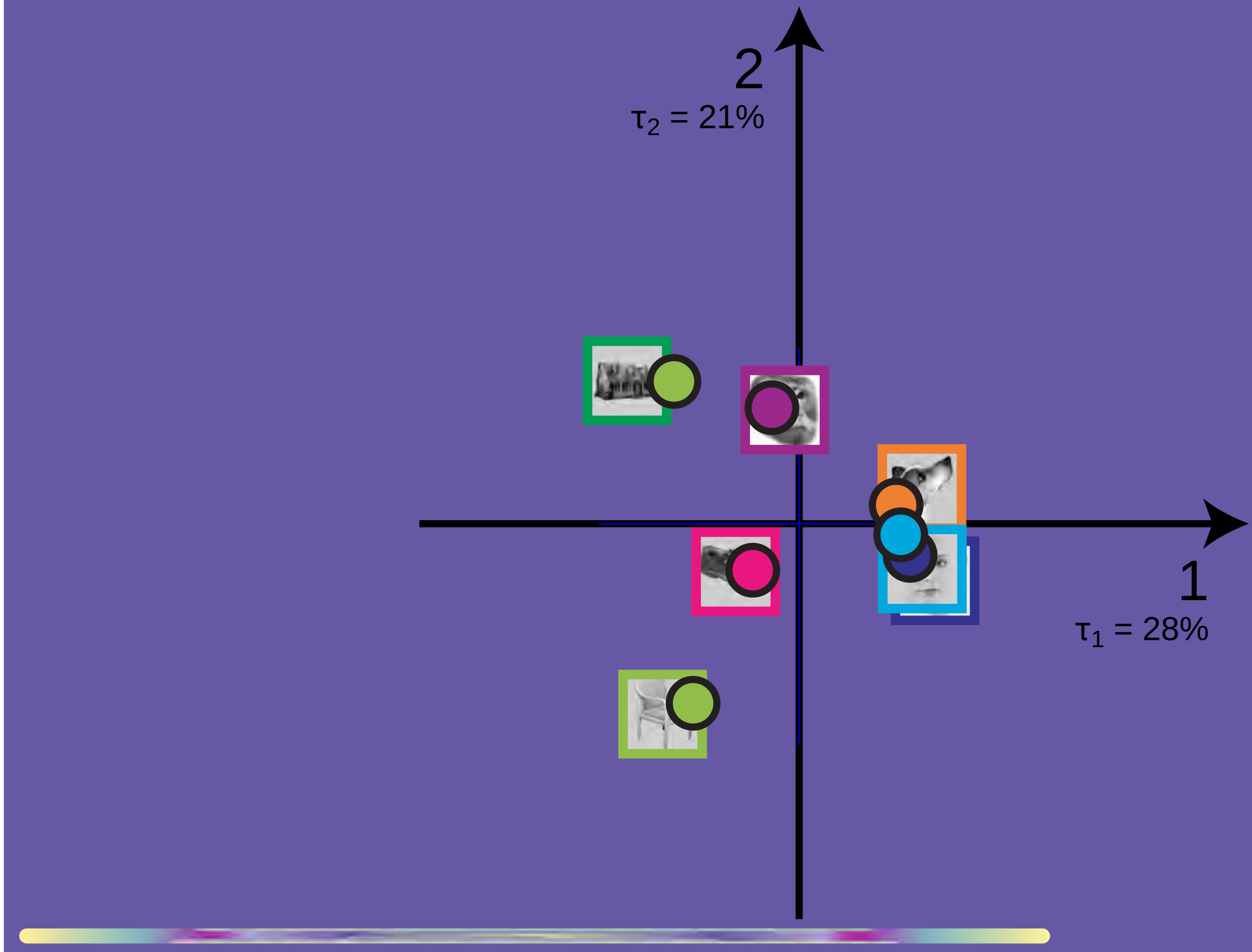
What about the ROIs?

3 ROIS

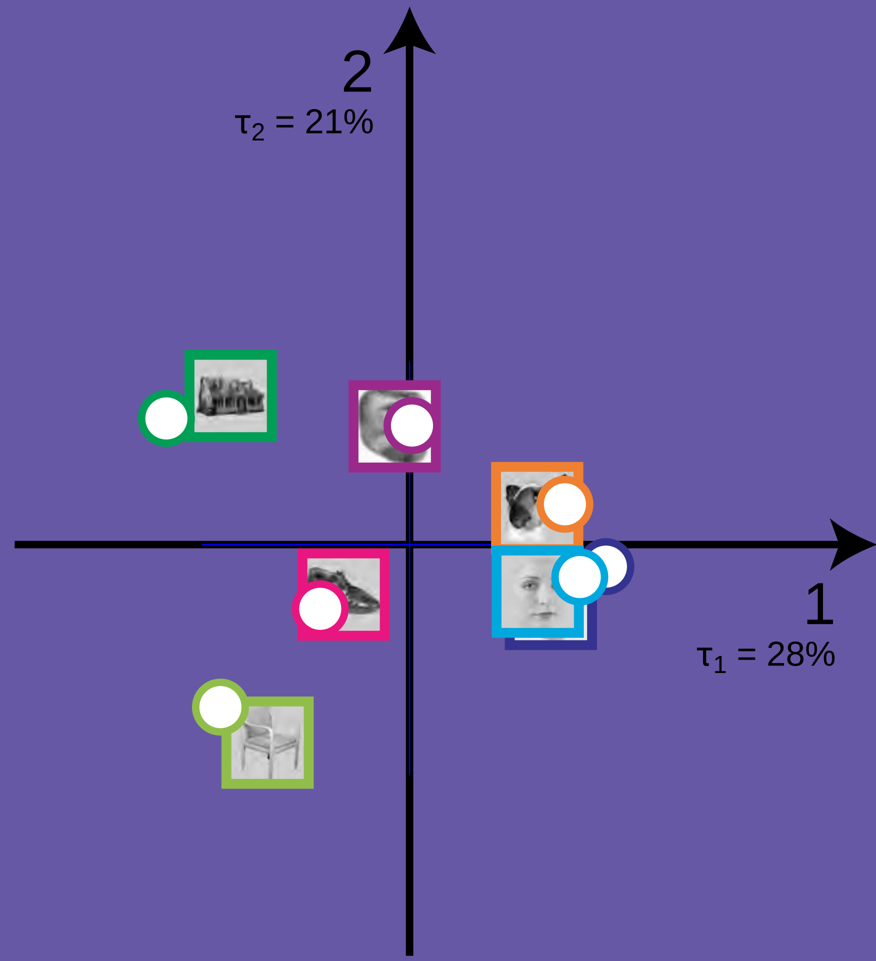
MO → IO → VT



Roi: Medio-Occipital (MO)



Roi: Inferior Occipital (IO)



Roi: Ventro Temporal (VT)

THE BRAIN BECOMES MORE "SEMANTIC" AS WE GO DEEPER IN THE VENTRAL STREAM

FINALE VARIATION 2:

BRAIN AND IMAGES:

- Data from Denise Park

VARIATION 3: CATEGORIZATION, BRAIN AND AGE

VARIATION 3:

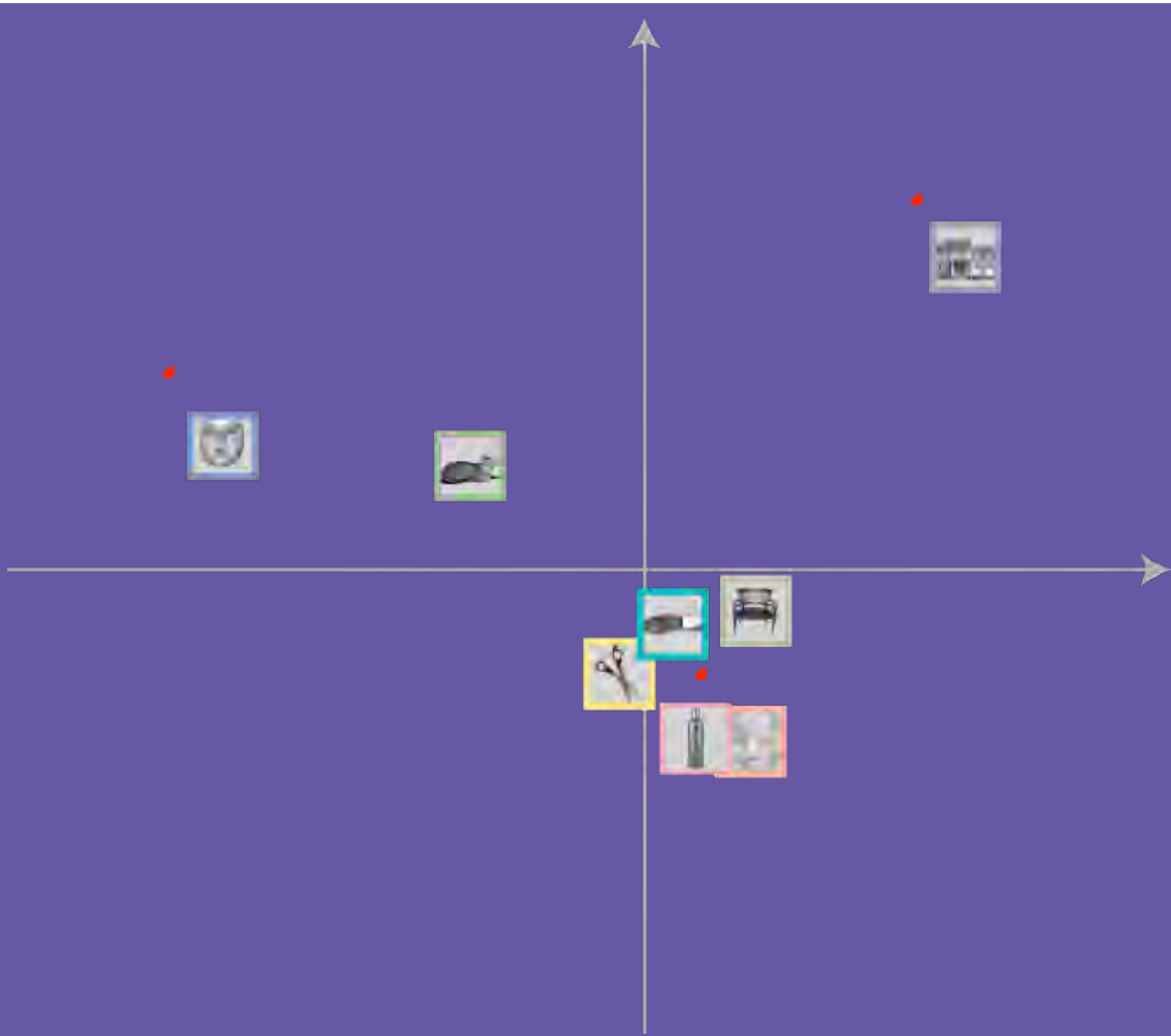
Flatter brain space as we mature?

Question: Does the brain changes its categorization strategy with age

Main idea:

Replicate Haxby (2001)

with old and young participants



Back to Haxby 2001, Abdi et al. (2009)

Pick up three categories

- *F*MRI Brain Reading Experiment:

- GOAL:

  evaluate age effects on brain reading

DESIGN

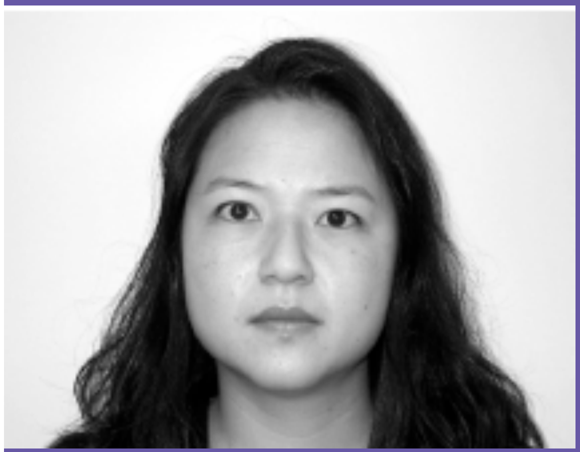
- Passive viewing of Pictures

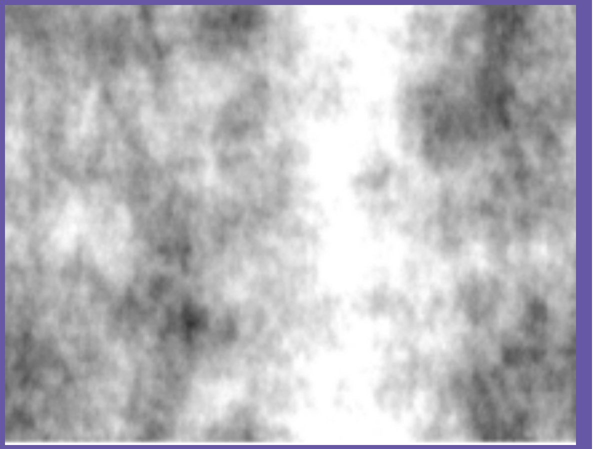
60 FACES : 30 Female & 30 Male

60 HOUSES : 30 Residential & 30 Apartment

60 SCRAMBLE

DESIGN: STIMULI





STIMULI

- One Run
- 4 blocks × 3 Categories = 12 Blocks
- **Order of Pictures**

  randomized **for each participant**

DESIGN

- 3.0T Siemens Allegra scanner

DESIGN: MATERIAL

PARTICIPANTS

YOUNG		OLD	
Male	Female	Male	Female

	Young	Old	
Men	50	41	91
Women	47	53	100
	97	94	191

Design: participants

- 180 Pictures into 2+2+1 = 5 categories
  - **60 Faces**

    30 male & 30 female faces
  - **60 Houses**

    30 multiple & single houses
  - **60 Scramble pictures**

- 191 Participants into 2×2 = 4 categories
  - Young and Old participants
  - Male and Female participants

DESIGN: RECAP

- **Anatomical ROIs**.

  ventral visual cortex including (usual suspects):

  fusiform, inferior temporal,

  lingual, parahippocampal,

  and occipital regions

USUAL PREPROCESSING +

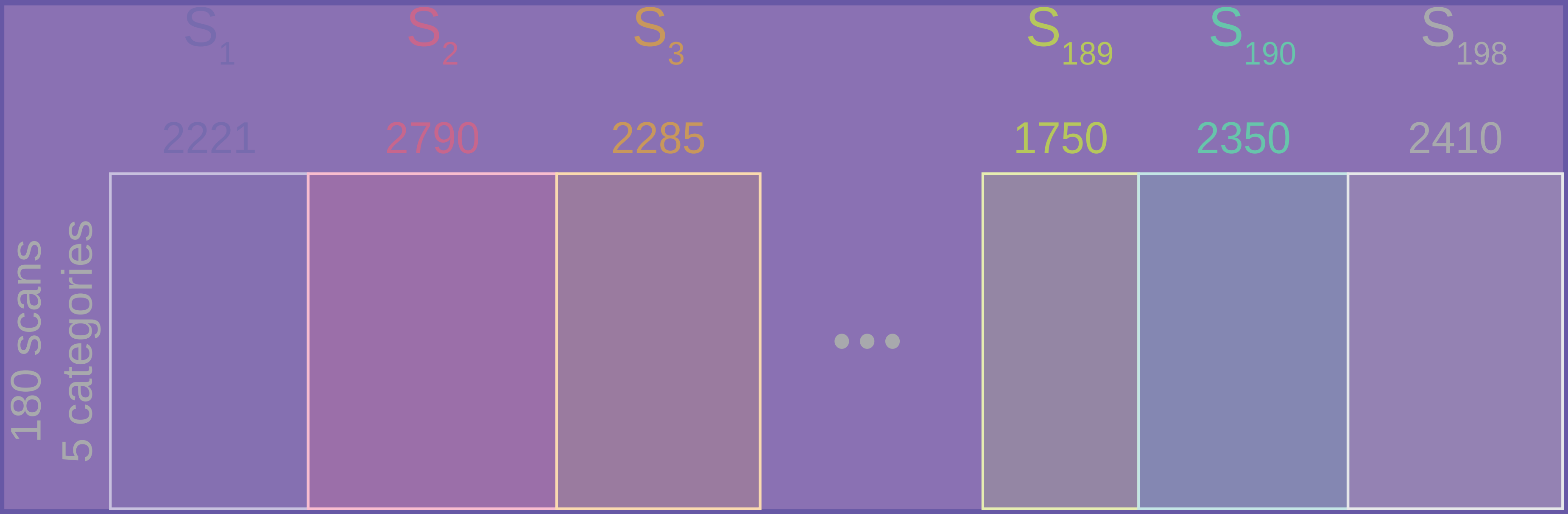
- 180 rows
- 191 Blocks: One Block = One Participant

  anatomical ROIs

  implies different # of voxels per participant

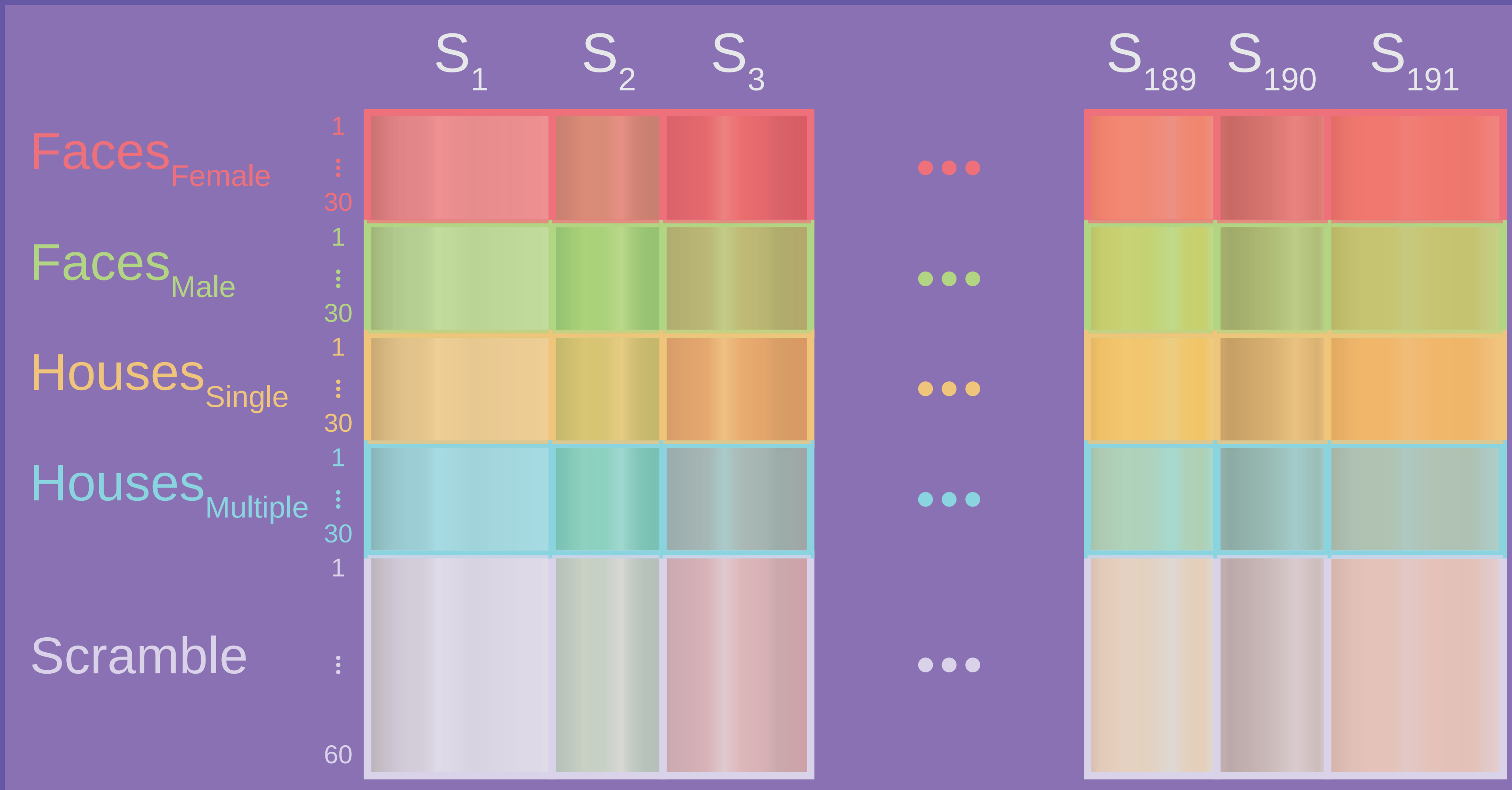
- Total number of voxels = 264,395

METHOD: MUBADA
(MULTIBLOCK BARYCENTRIC DISCRIMINANT ANALYSIS)



Total # of Voxels
2221 + 2790 + … + 2350 + 2410 = 506,375

180 SCANS FROM 5 CATEGORIES
191 PARTICIPANTS (97 YOUNG, 94 OLDS)



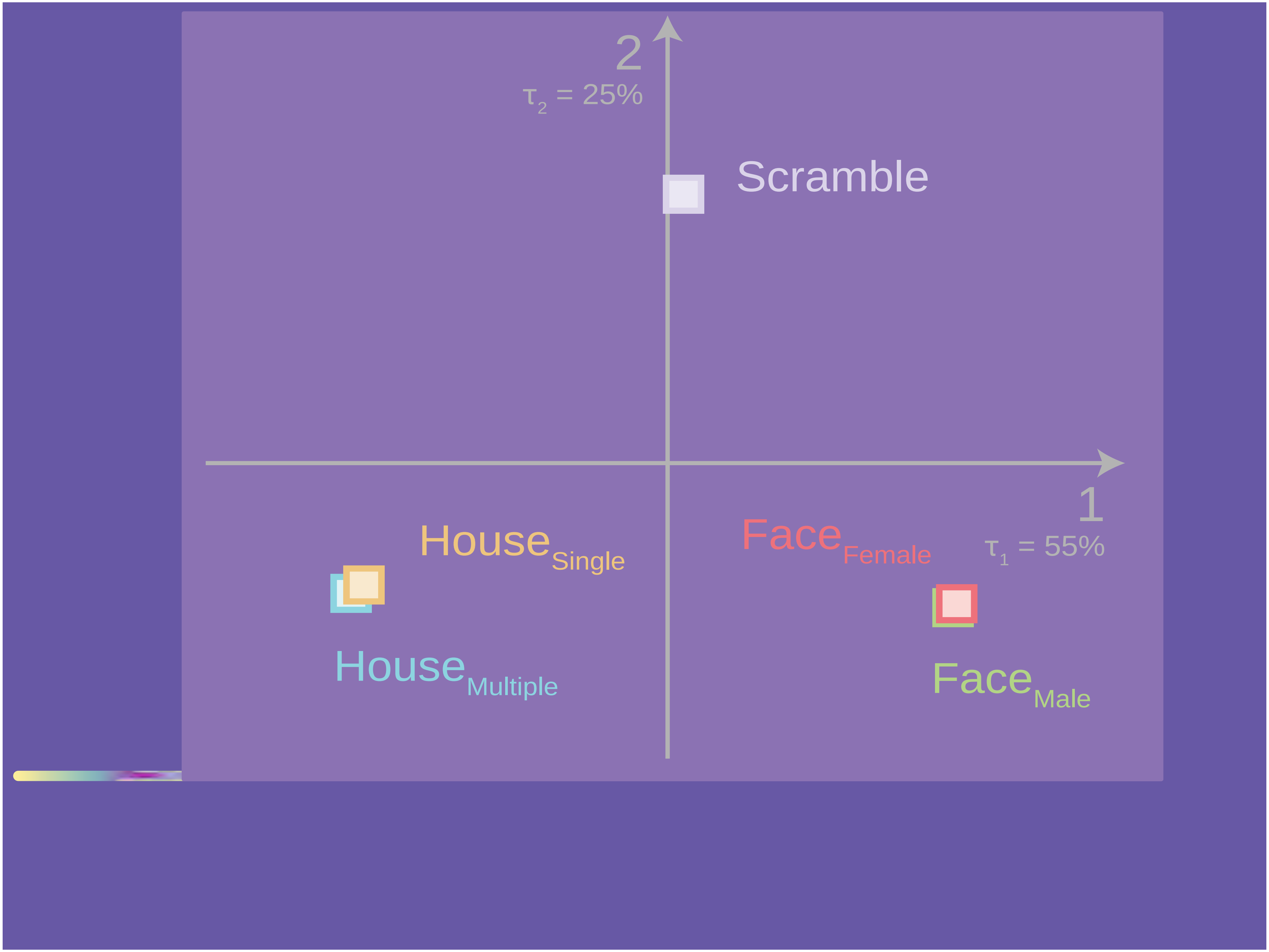
DATA STRUCTURE

- Block normalization:
  Do a PCA of each block
  equalize the first component
  (singular value normalization, kind of *Z*-score)

Problem of Different Variance Per subject

Run a barycentric discriminant analysis (BADA)

RESULTS FROM MULTI-TABLE


2
τ2 = 25%
Scramble
1
τ1 = 55%
HouseSingle
FaceFemale
HouseMultiple
FaceMale

FIXED EFFECT MODEL

CONFUSION MATRICE

TOLERANCE ELLIPSOIDS

RANDOM EFFECT MODEL

CONFUSION MATRICE

PREDICTION ELLIPSOIDS

CONFIDENCE ELLIPSOIDS

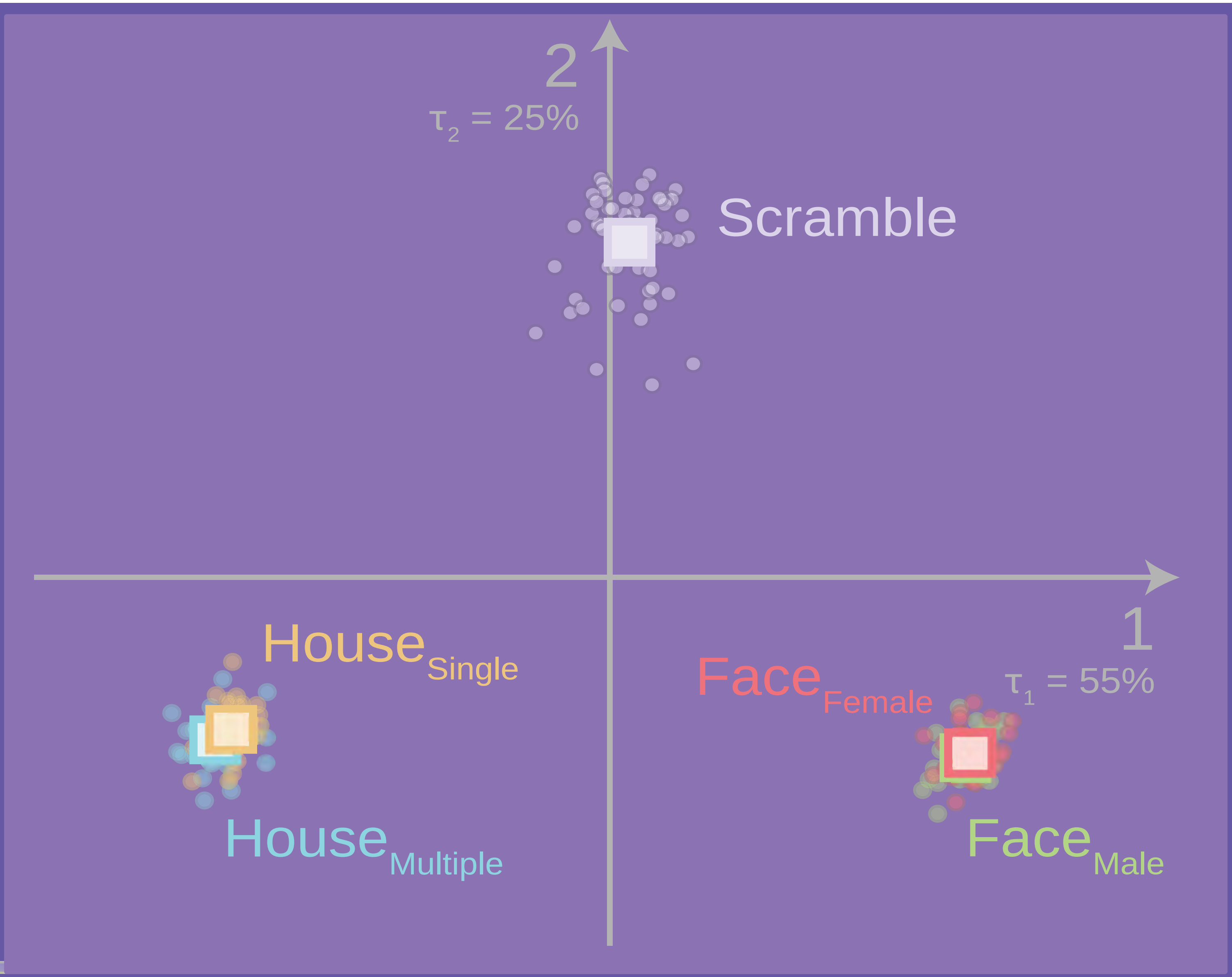
RESULTS: HOW GOOD IS THE MODEL?

FIXED EFFECT MODEL

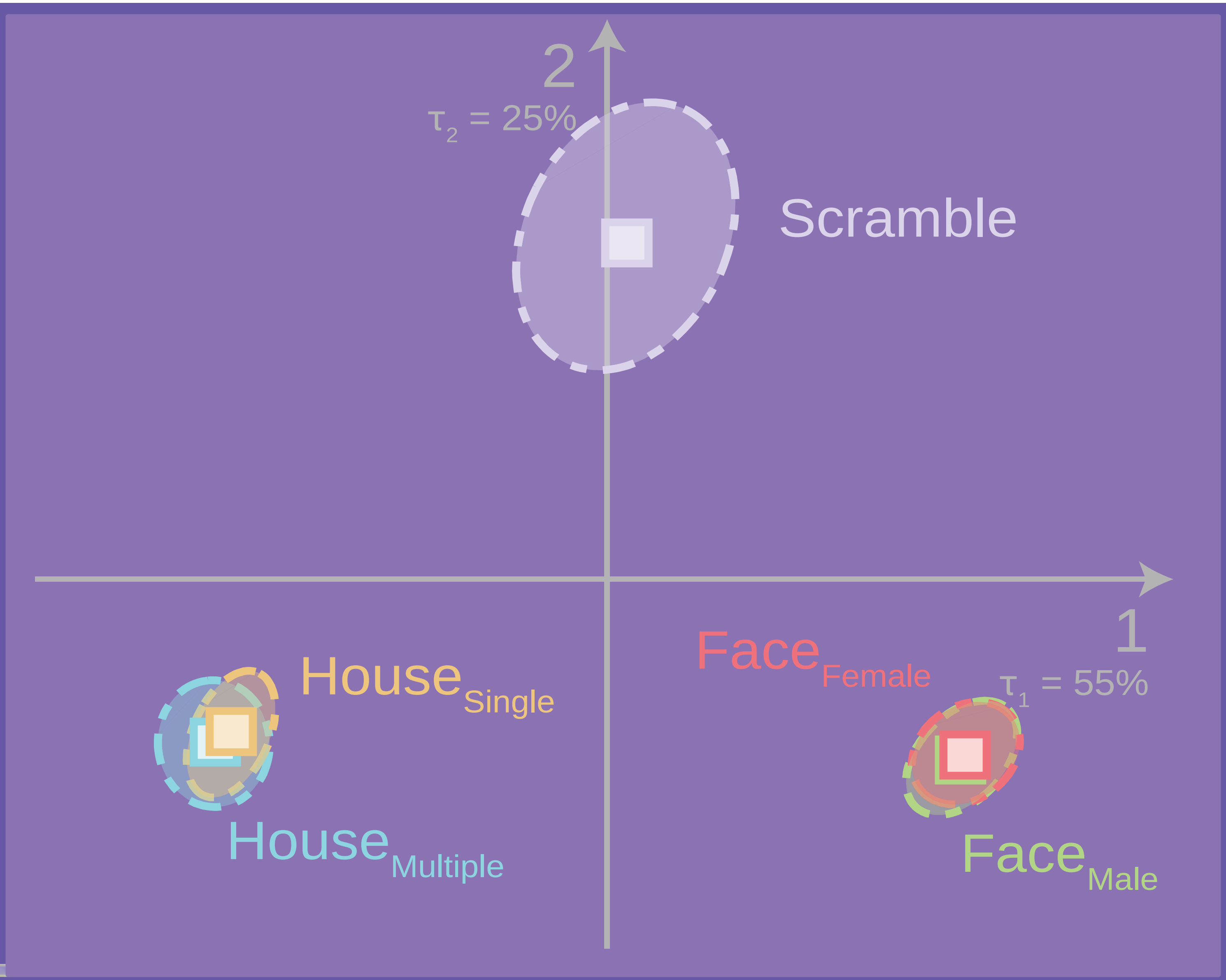
CONFUSION MATRICE

TOLERANCE ELLIPSOIDS

RESULTS: HOW GOOD IS THE MODEL?

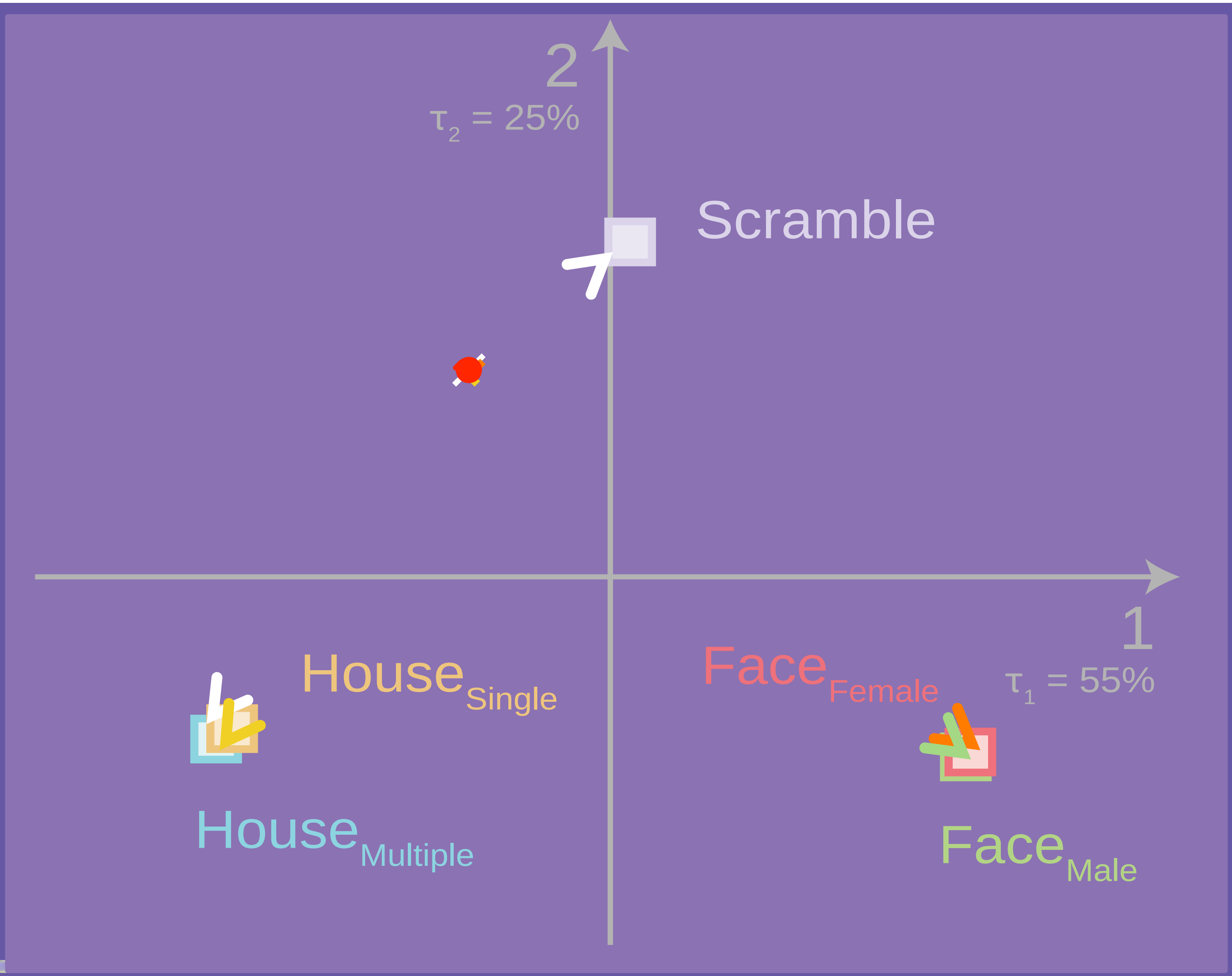


ONE DOT = ONE PICTURE

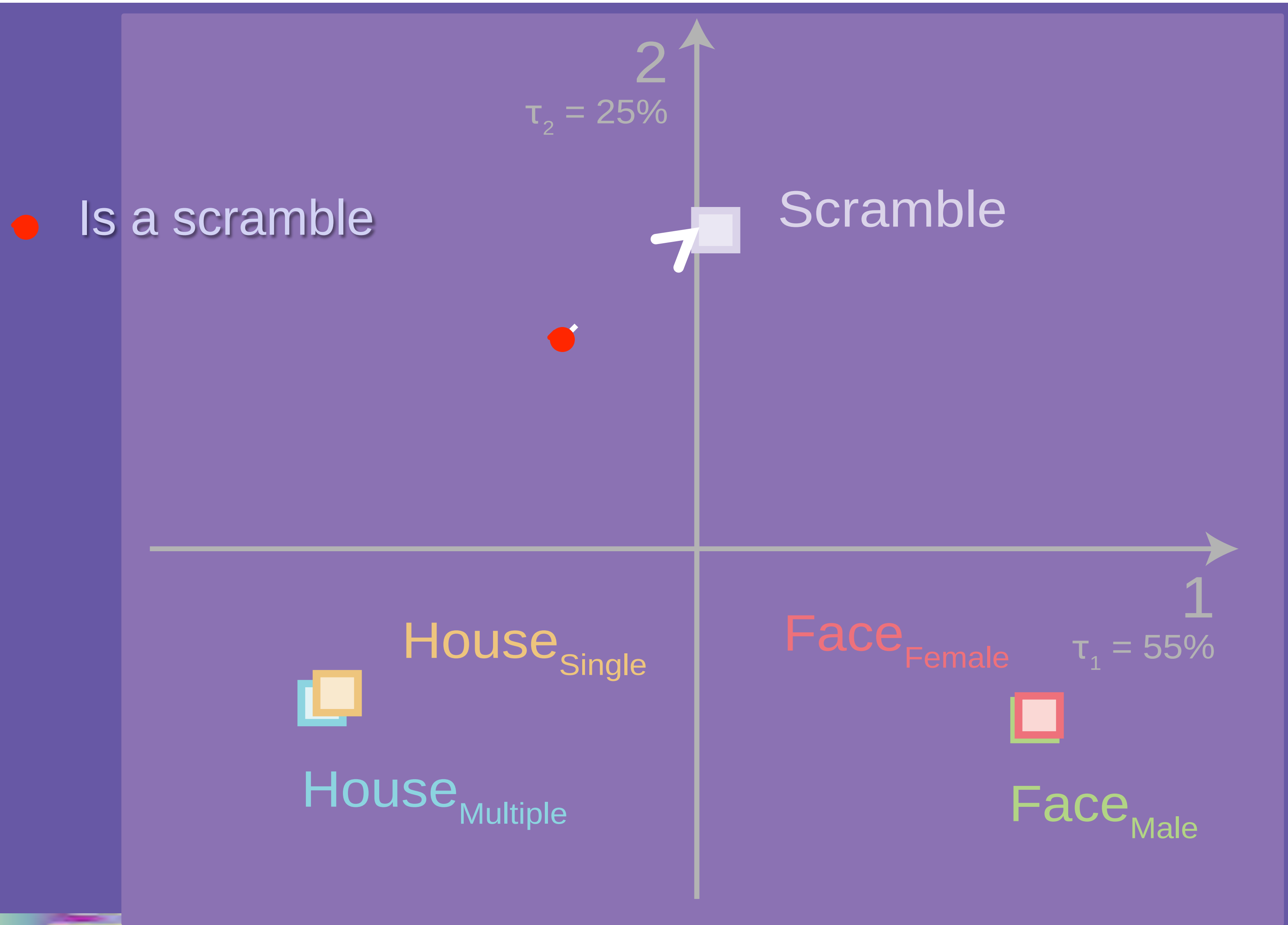


95% Tolerance Ellipses
(95% of the scans are in the ellipse)

How to Classify Observations
(What category of picture was watched)



Assigning scans to categories



Assigning scans to categories

Fixed Effect Model

Actual Classification

Predicted Classification

	F-m	F-f	H-b	H-s	Scr
F-m					
F-f					
H-b					
H-s					
Scr					

Fixed Effect Model

Actual Classification

Predicted Classification	F-m	F-f	H-b	H-s	Scr
F-m	*30*	0	0	0	0
F-f	0	*30*	0	0	0
H-b	0	0	*30*	0	0
H-s	0	0	0	*30*	5
Scr	0	0	0	0	*60*

180 = 100%

Barycentric Discriminant Analysis

RANDOM EFFECT MODEL
Use Jackknife + Bootstrap

CONFUSION MATRICE
PREDICTION ELLIPSOIDS
CONFIDENCE ELLIPSOIDS

RESULTS: HOW GOOD IS THE MODEL?

JACKKNIFE (LEAVE ONE OUT: LOO)

BADA: JACKKNIFE... ONE ROW AT A TIME

Random Effect Model

Actual Classification

Predicted Classification

	F-m	F-f	H-b	H-s	Scr
F-m	*13*	14	0	0	0
F-f	17	*16*	0	0	0
H-b	0	0	*13*	17	0
H-s	0	0	17	*13*	0
Scr	0	0	0	0	*60*

115 = 64%

BARYCENTRIC DISCRIMINANT ANALYSIS

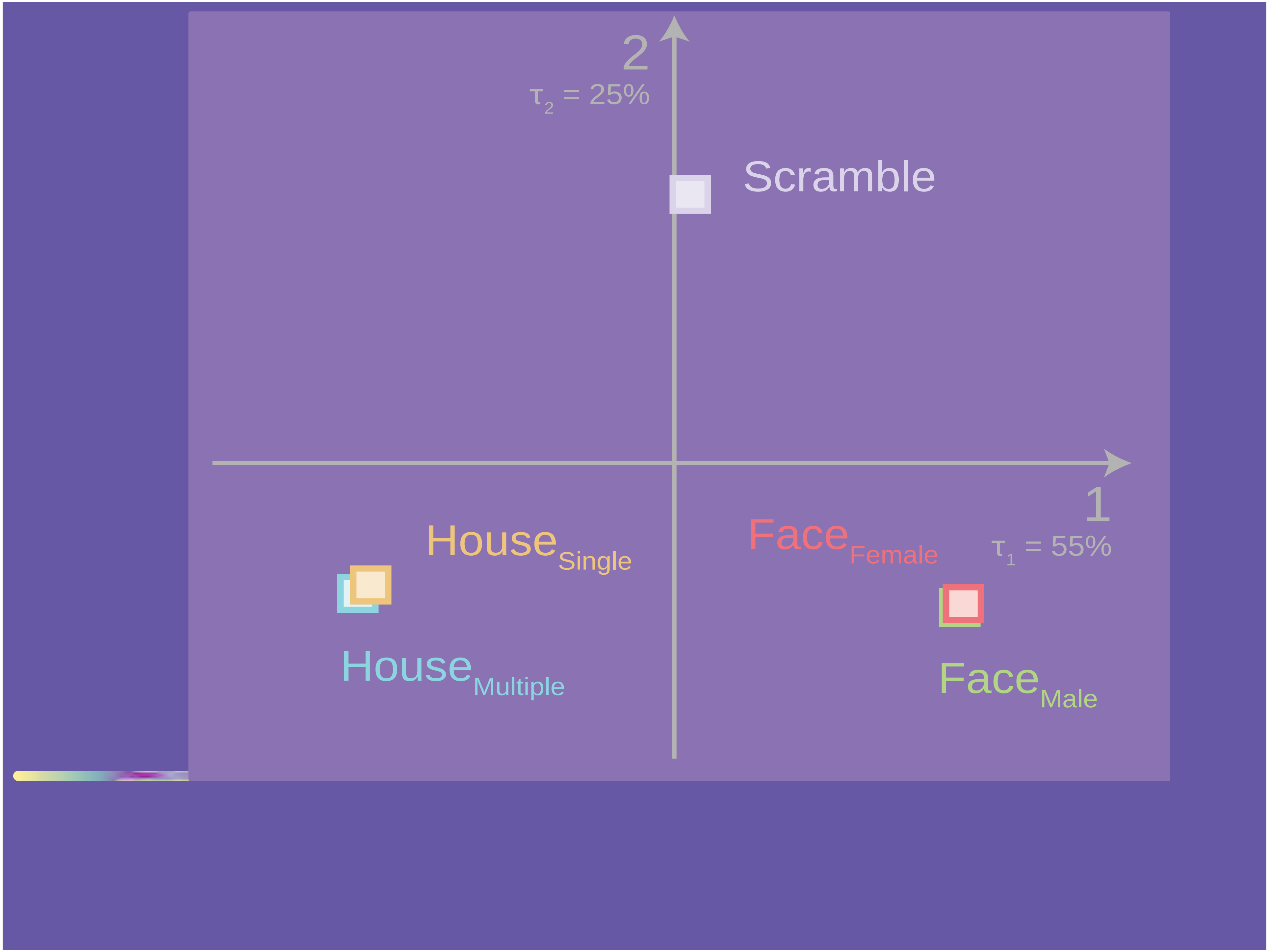
Random Effect Model

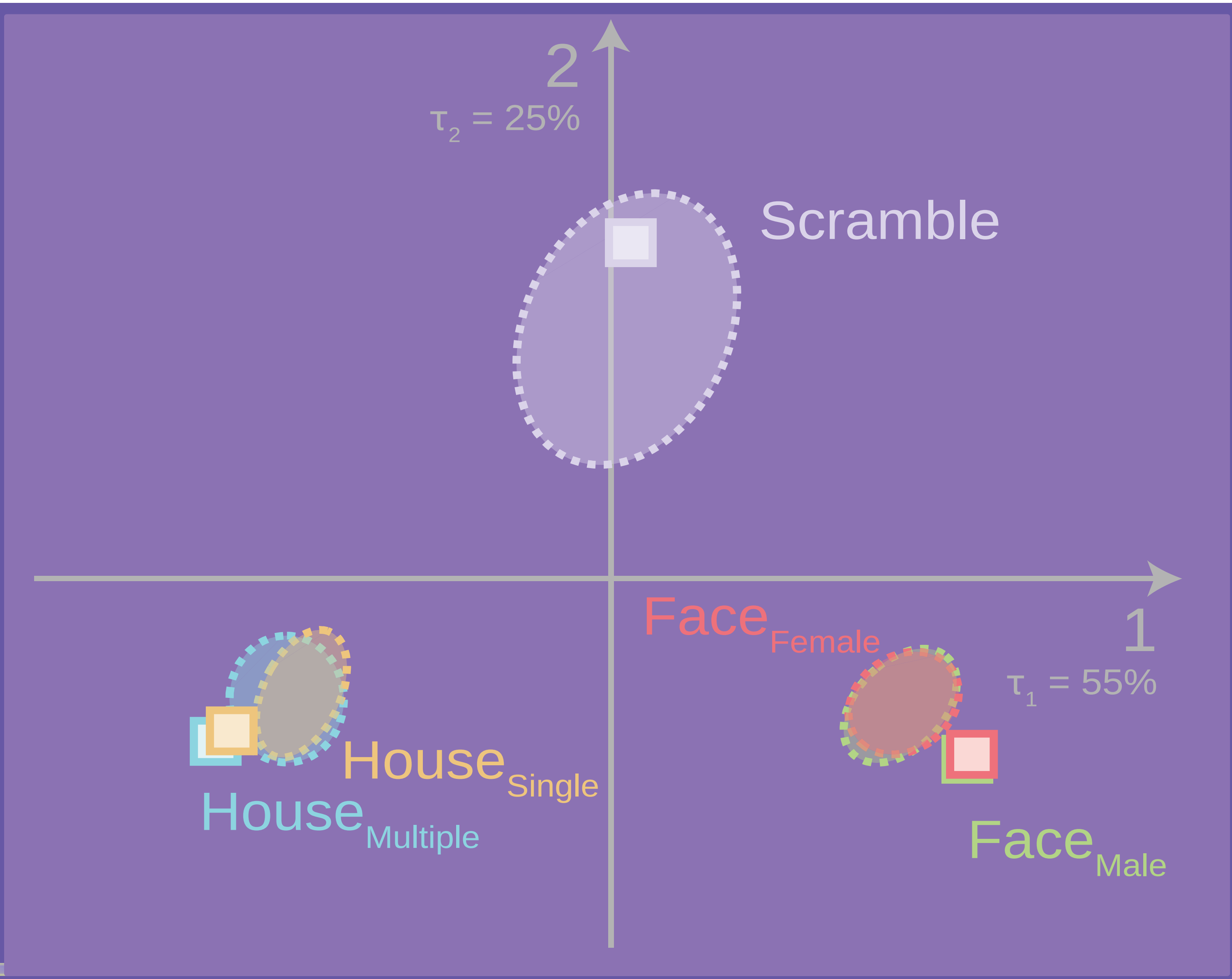
Actual Classification

Predicted Classification	F-m	F-f	H-b	H-s	Scr
F-m	*13*	14	0	0	0
F-f	17	*16*	0	0	0
H-b	0	0	*13*	17	0
H-s	0	0	17	*13*	0
Scr	0	0	0	0	*60*

115 = 64%

BARYCENTRIC DISCRIMINANT ANALYSIS


2
τ2 = 25%
Scramble
1
τ1 = 55%
House Single
Face Female
House Multiple
Face Male

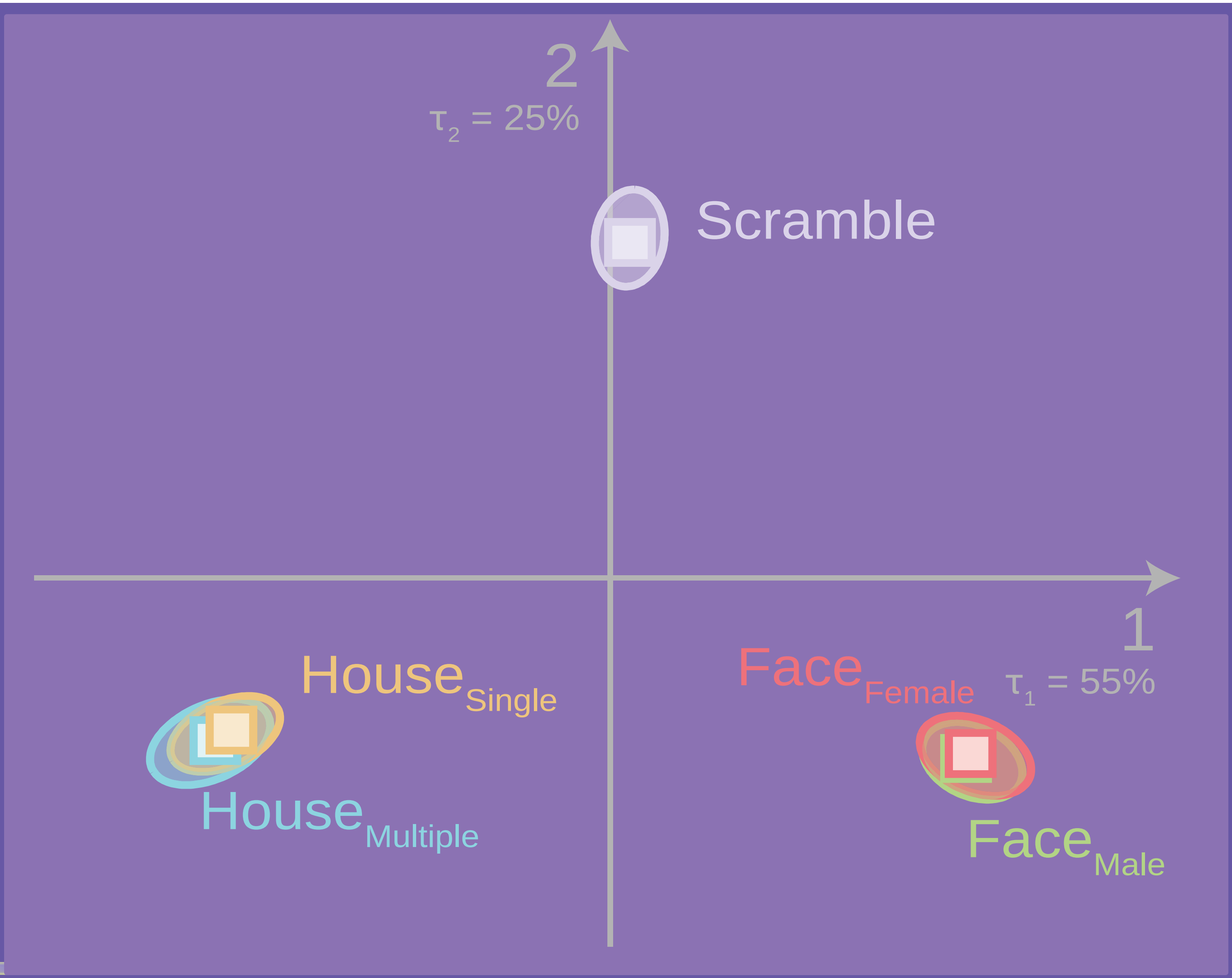


Prediction Ellipses

- Redo the analysis 10,000 times
  with resampling (bootstrap)
  the participants and the scans
  (participants and scans are random)

Project and compute ellipsoids:
Confidence ellipsoids

HOW STABLE IS THE SOLUTION
IS THE EARTH ROUND $p < .05$



95%

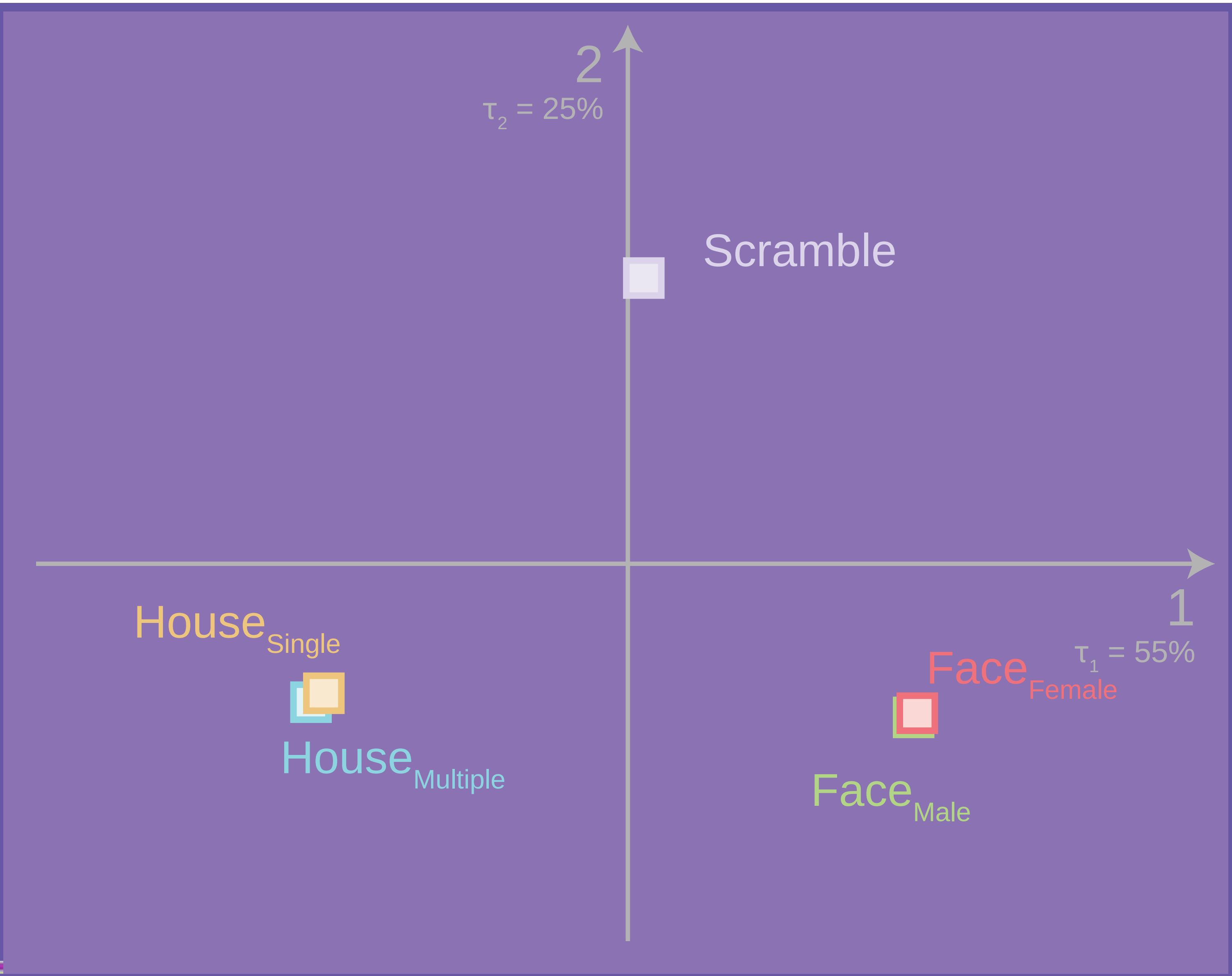
BOOTSTRAP CONFIDENCE INTERVALS

- Look at differences between old & Young

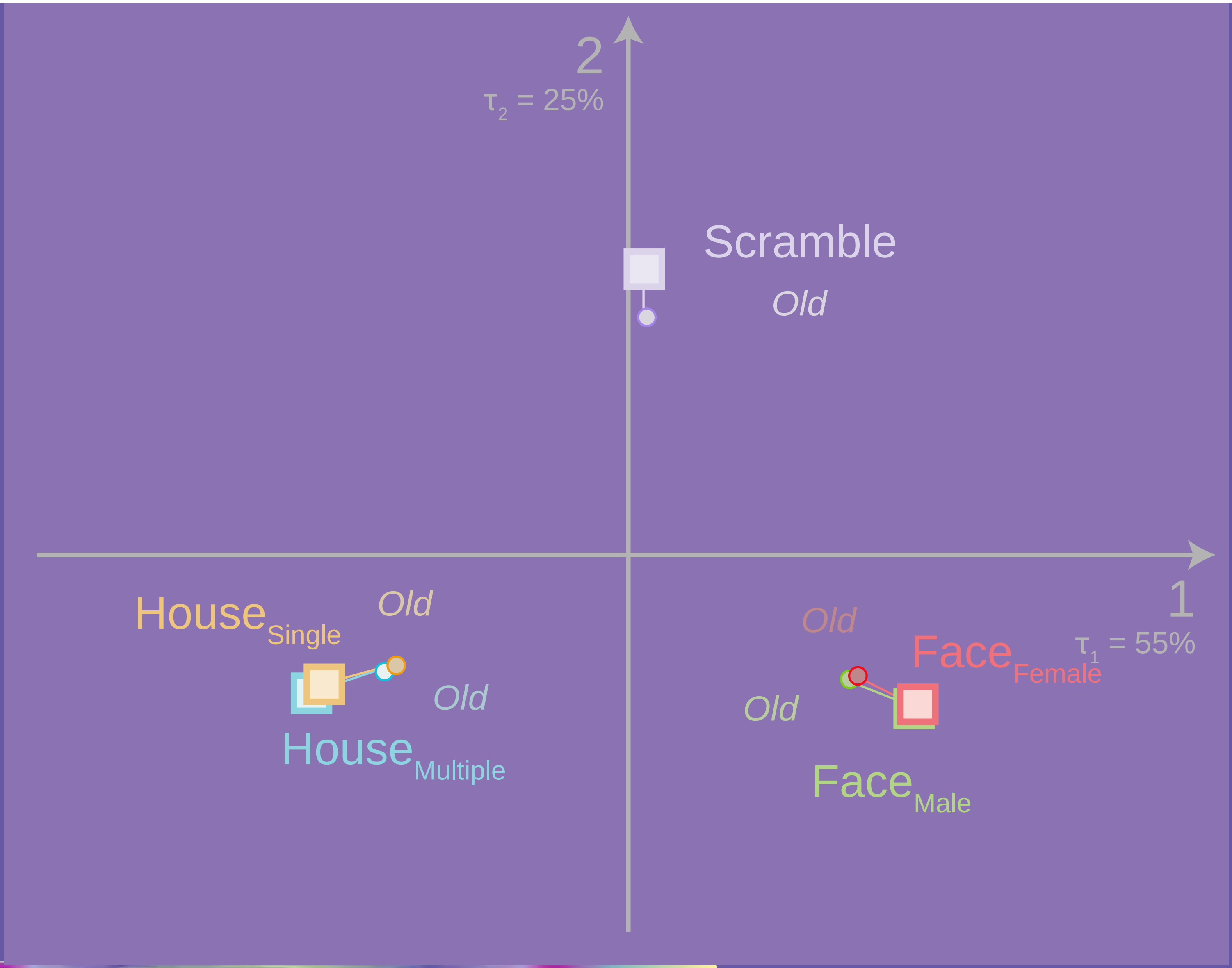
Block projection

- Dedifferentiation hypothesis prediction:
  Youngs more distinctive than Olds

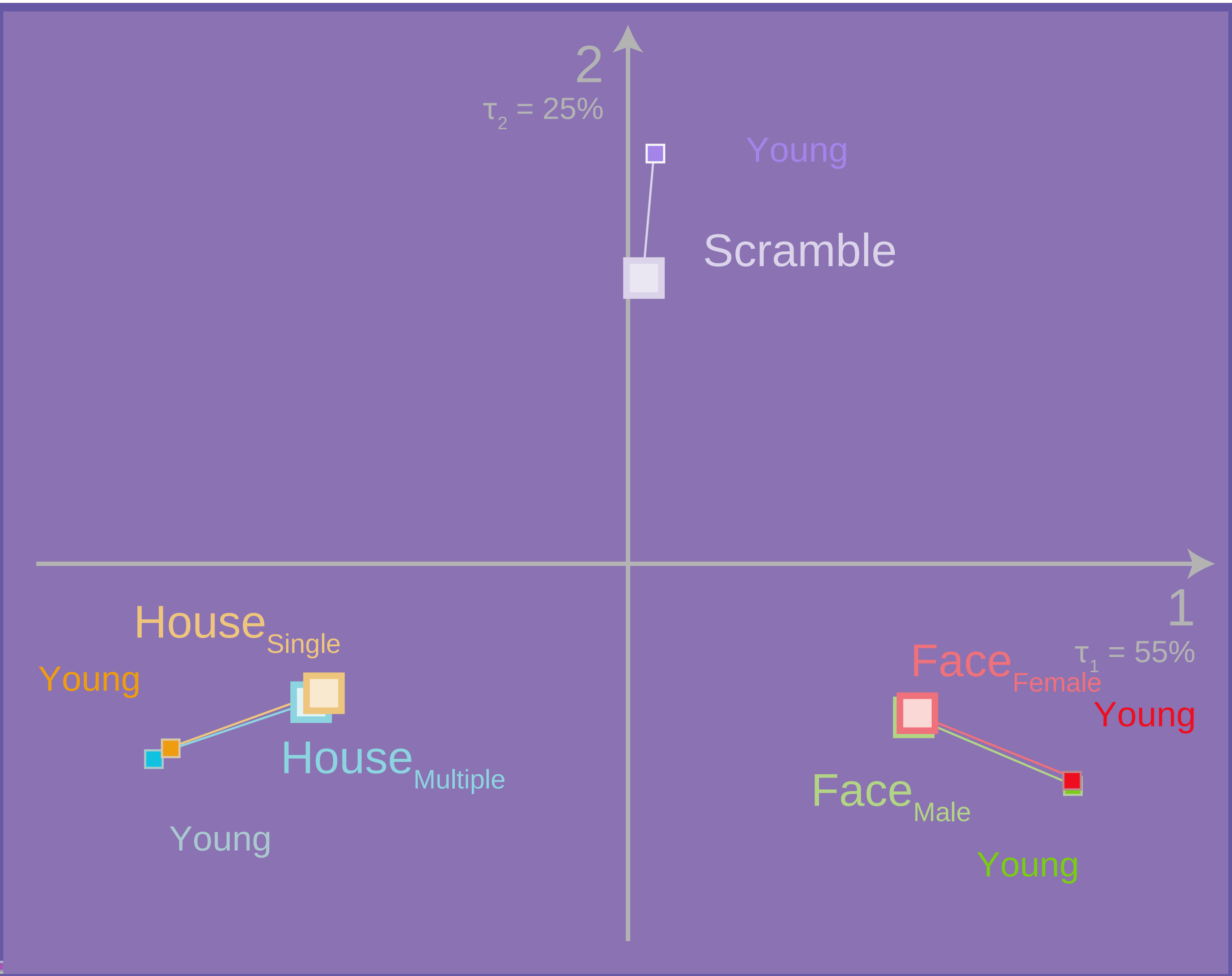
OLD AND YOUNG: 97 YOUNG, 94 OLD



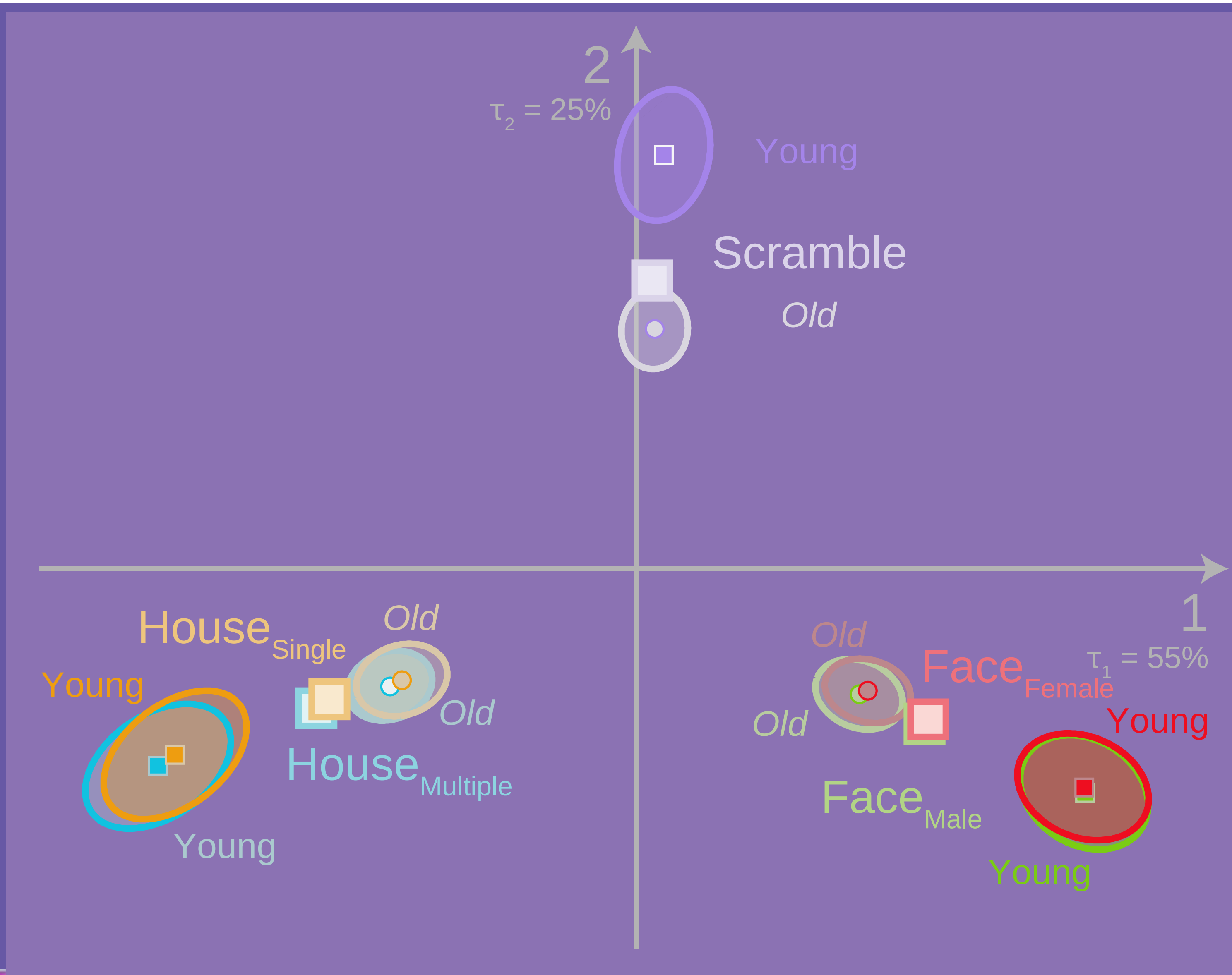
Block Projections: Barycenters



BLOCK PROJECTIONS: BARYCENTERS



BLOCK PROJECTIONS: BARYCENTERS



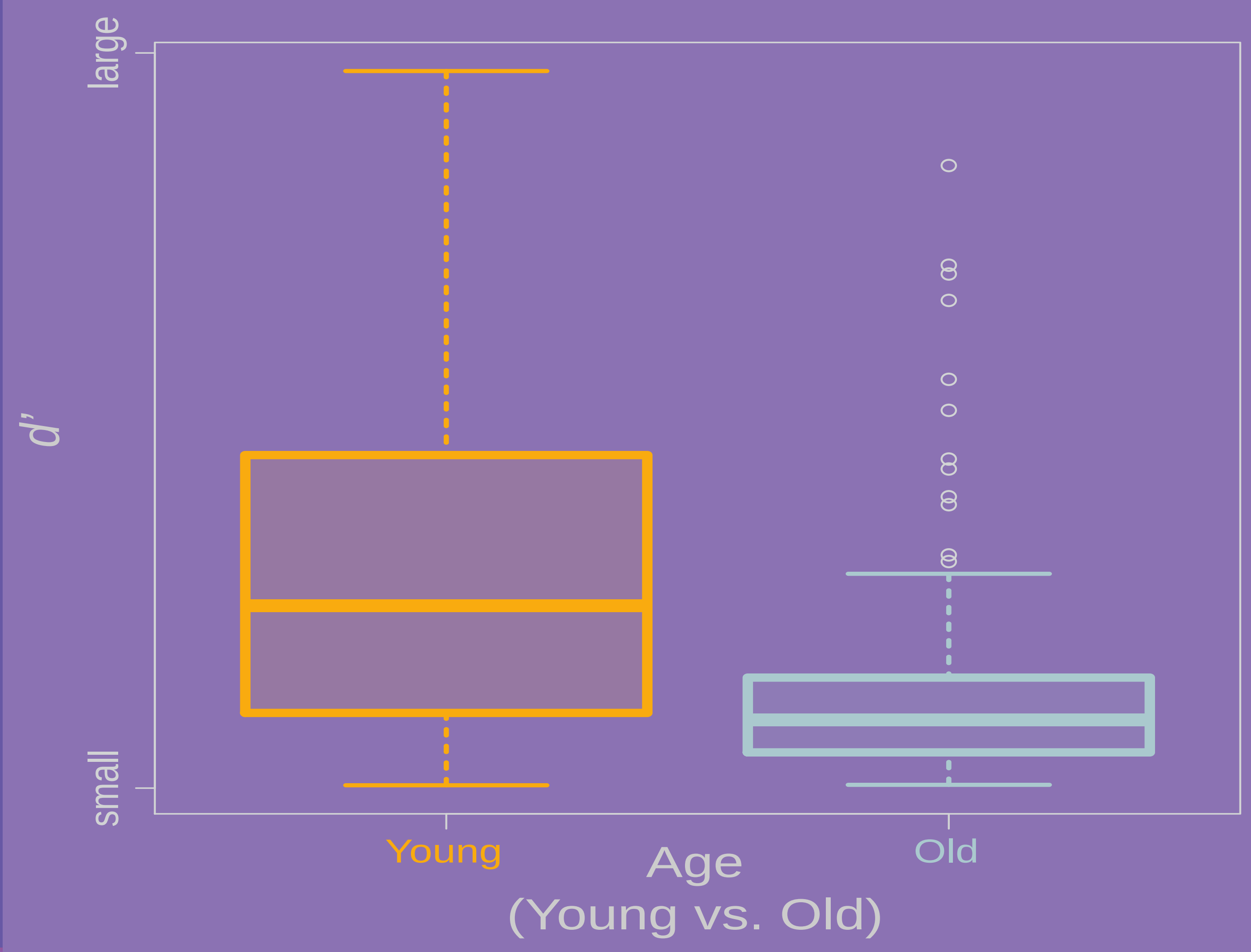
BLOCK PROJECTIONS: BARYCENTERS

OLD ≠ YOUNG ($p < .01$)

Is the brain less efficient?

Less able to *differentiate* between categories?

WHY?



d'
large
small
Young
Old
Age
(Young vs. Old)

- Older participants are less efficient.

- ***WHY?***

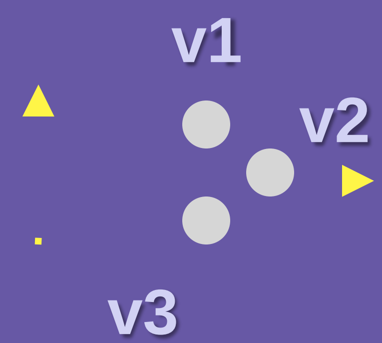
MEASURING EFFICIENCY?

- Sphericity:
  A measure of coding efficiency?

SPHERICITY STORY

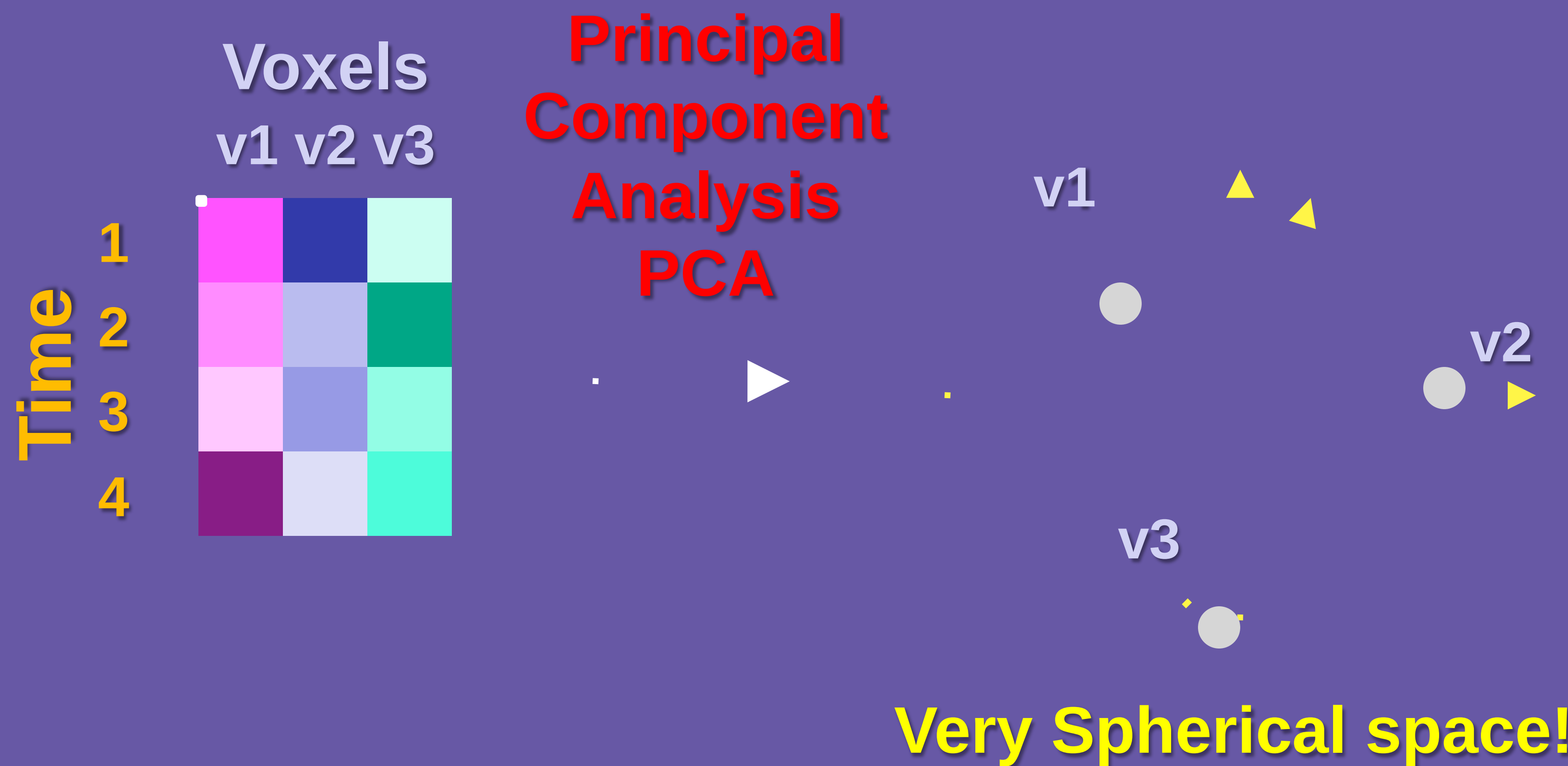
But What Is *"Sphericity"*?

Principal Component Analysis PCA



Very flat space!

Lack of sphericity: inefficient code

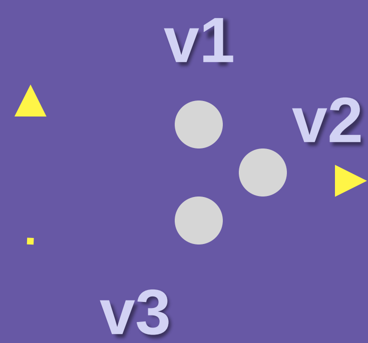


Sphericity: Efficient code

- One number

$$\frac{(10 + 10 + 10)^2}{3\,(10^2 + 10^2 + 10^2)} = 1$$

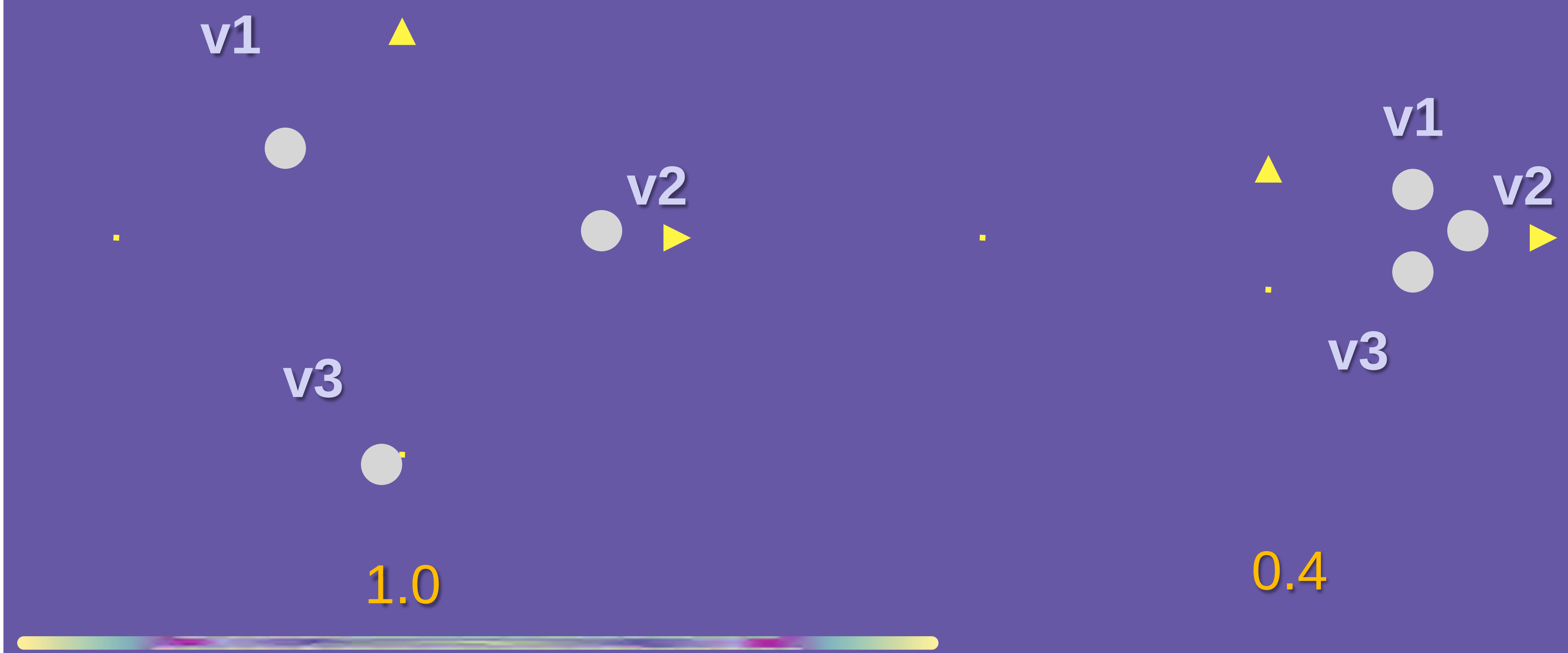
SPHERICITY = 1 (MAX)



$$\frac{10 + 1^{\ 2}}{3\ \ 10^2 + 1^2} \quad .4$$

FLATTER = .4

- One number gets the pattern.



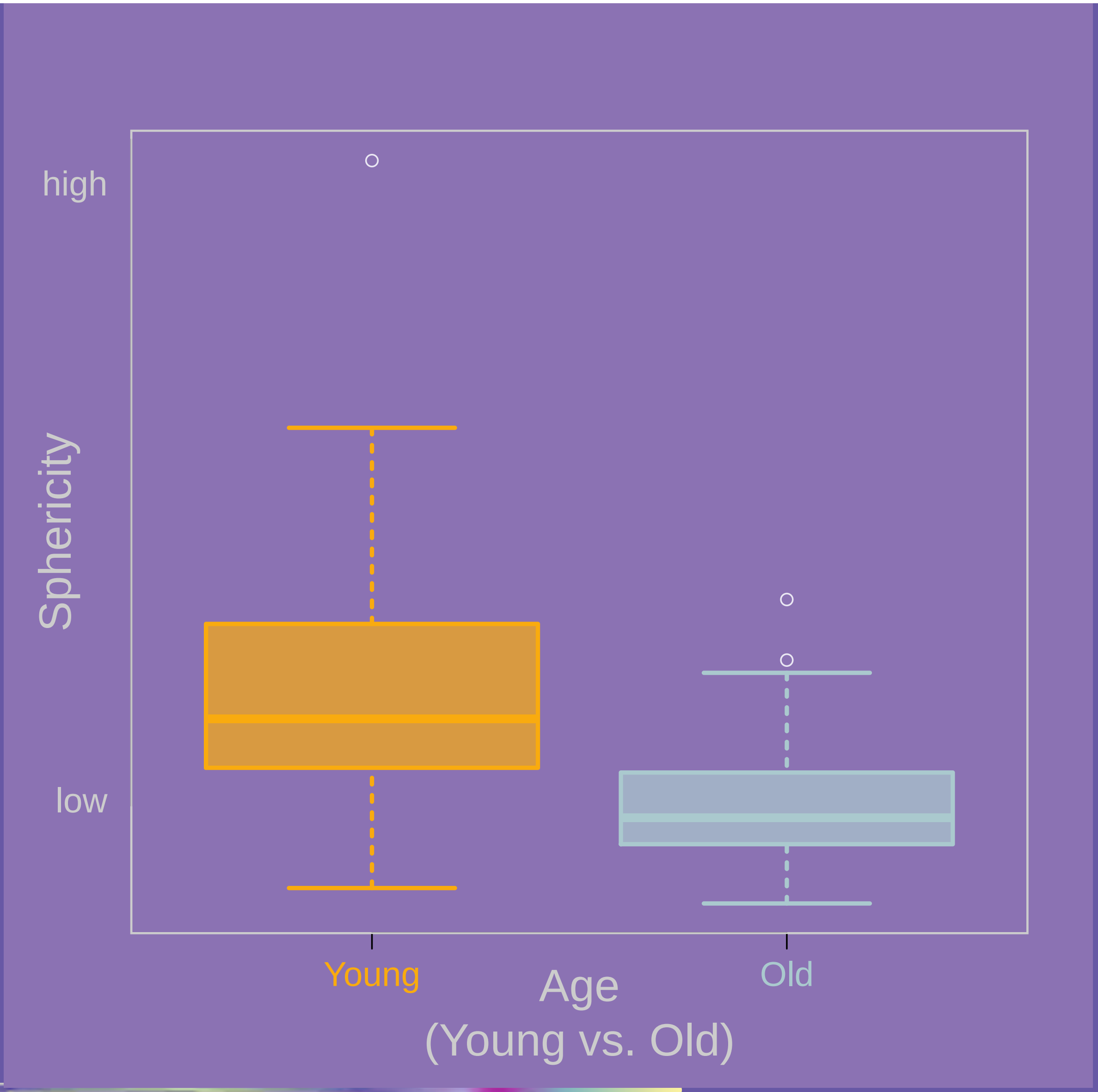
SPHERICITY GOES FROM 1 TO 0

- Efficient (differentiated) code: Spherical

- Inefficient code: Flat (less spherical)

SPHERICITY: IN A NUTSHELL

- Compute sphericity index per participant
- Plot by Age



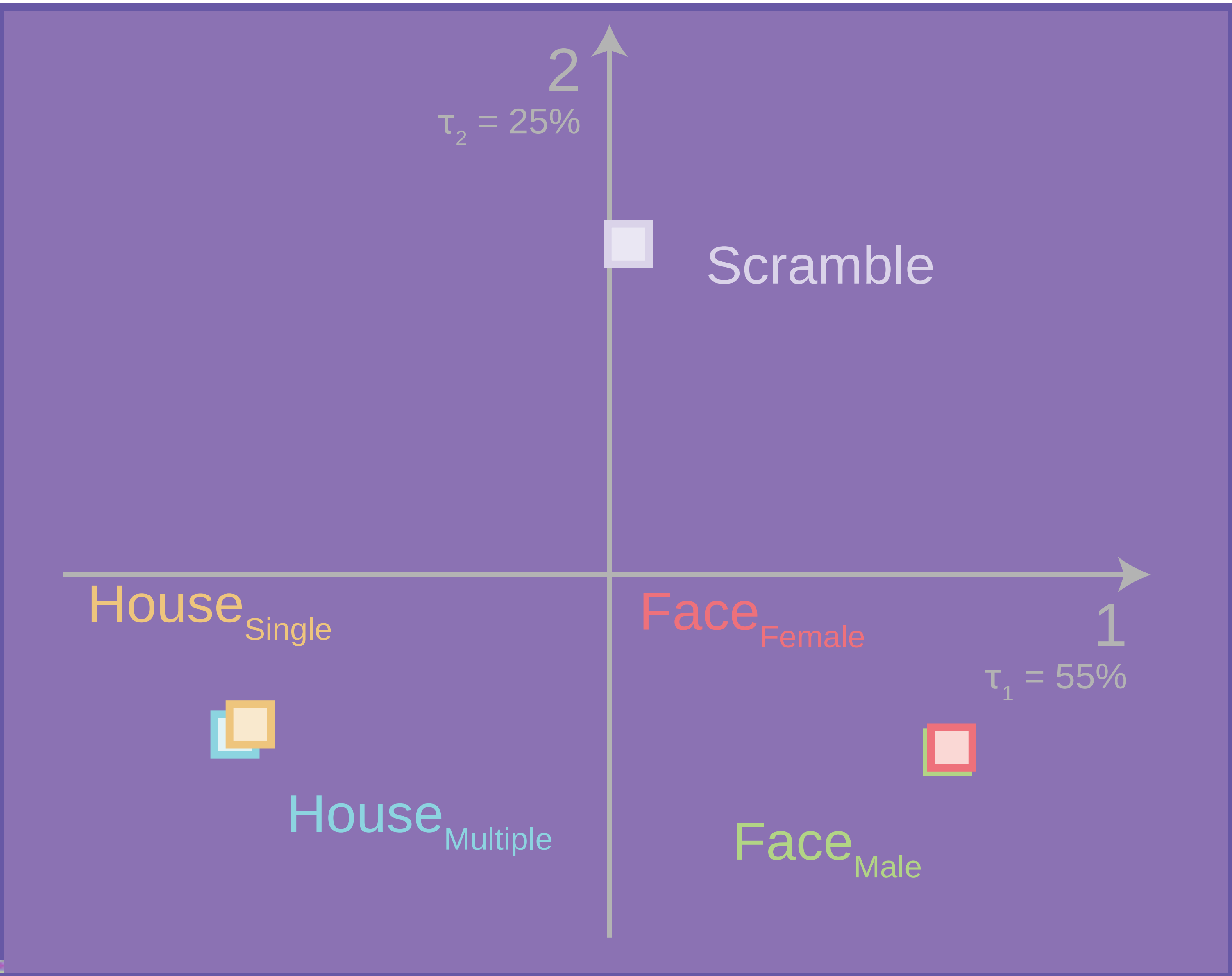
SPHERICITY OLD & YOUNG
(P < .00001)

NOW WE DECIDED TO LOOK AT SEX!

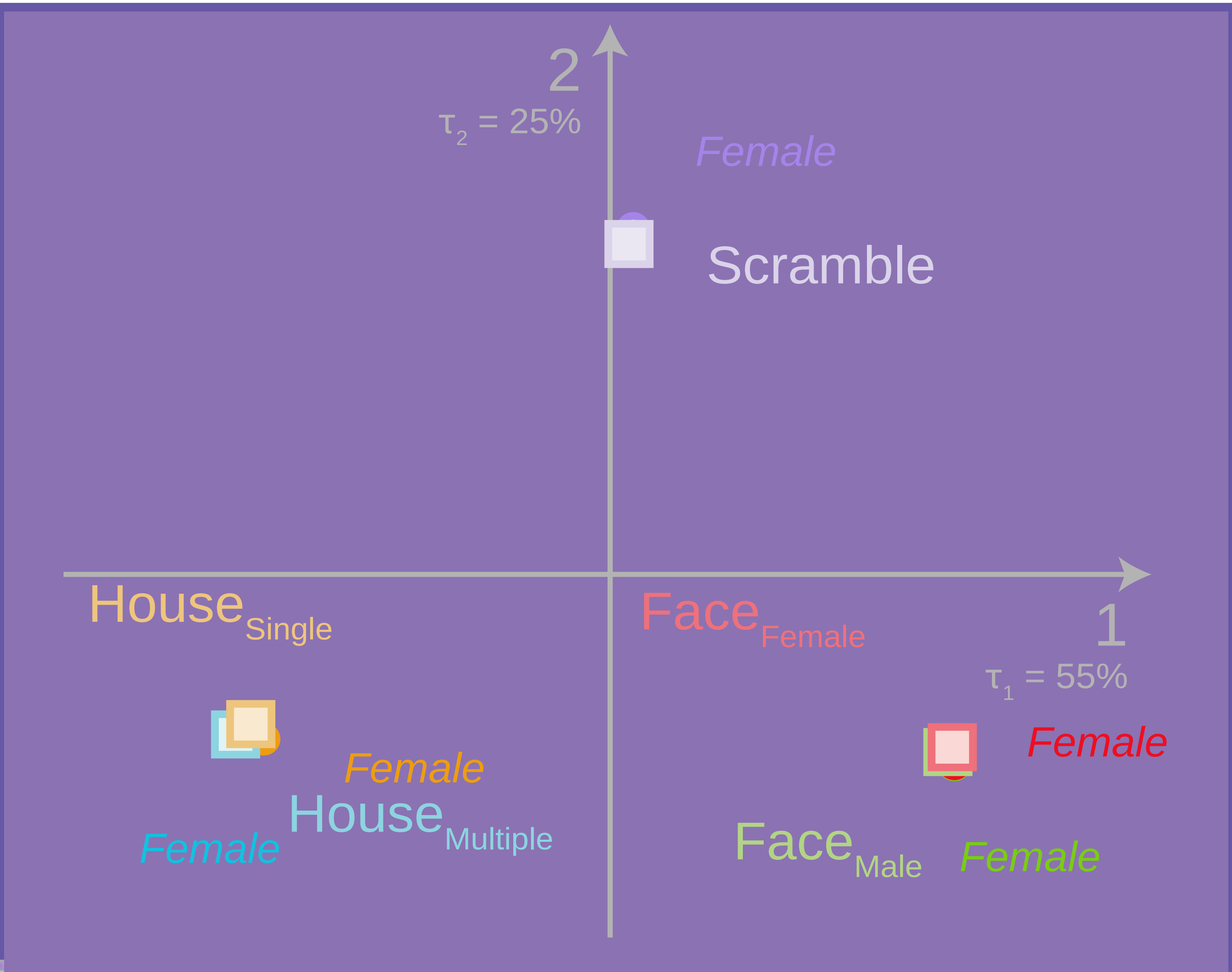
- Now you are paying attention!

I MEAN *GENDER*

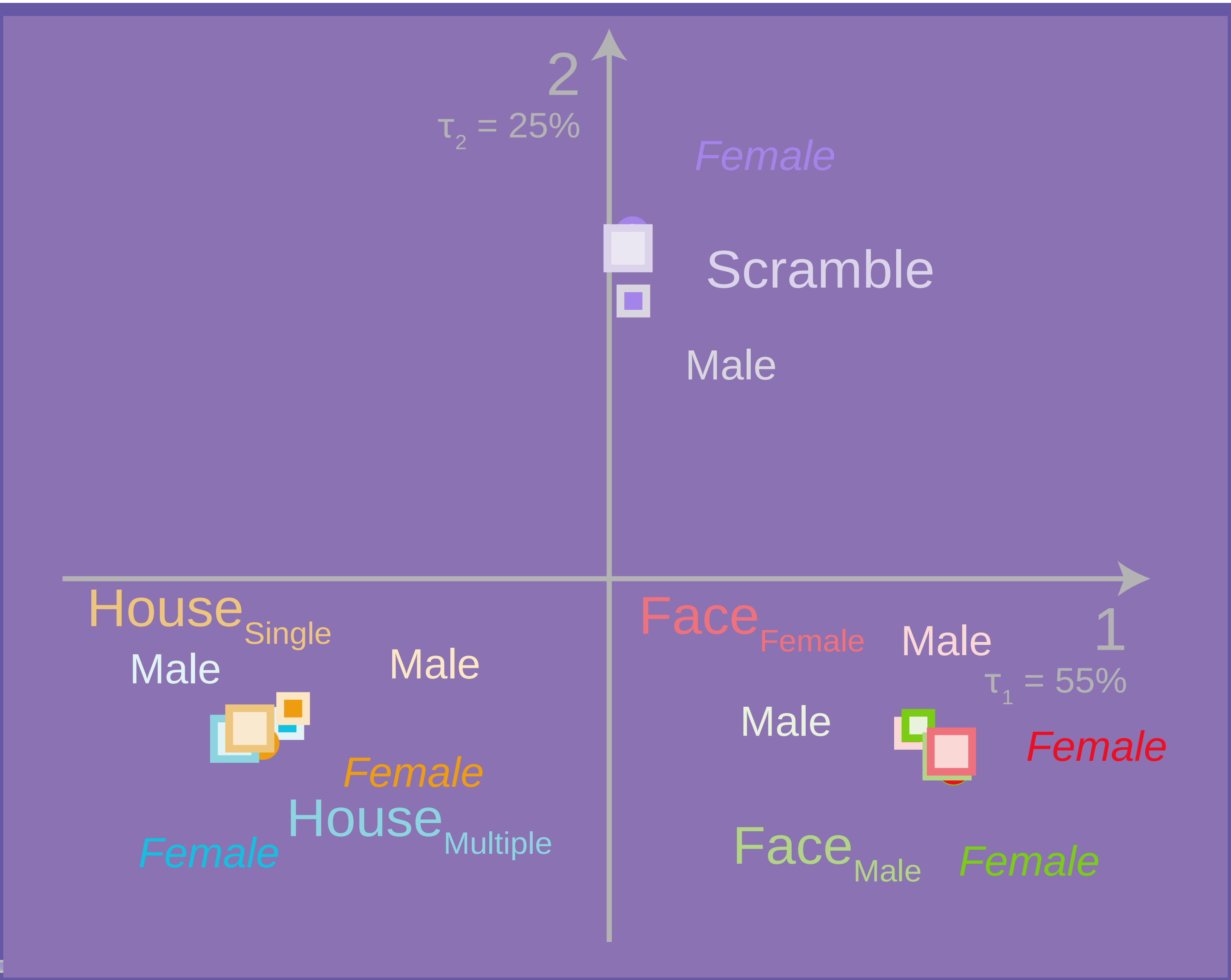
WHAT ABOUT GENDER?



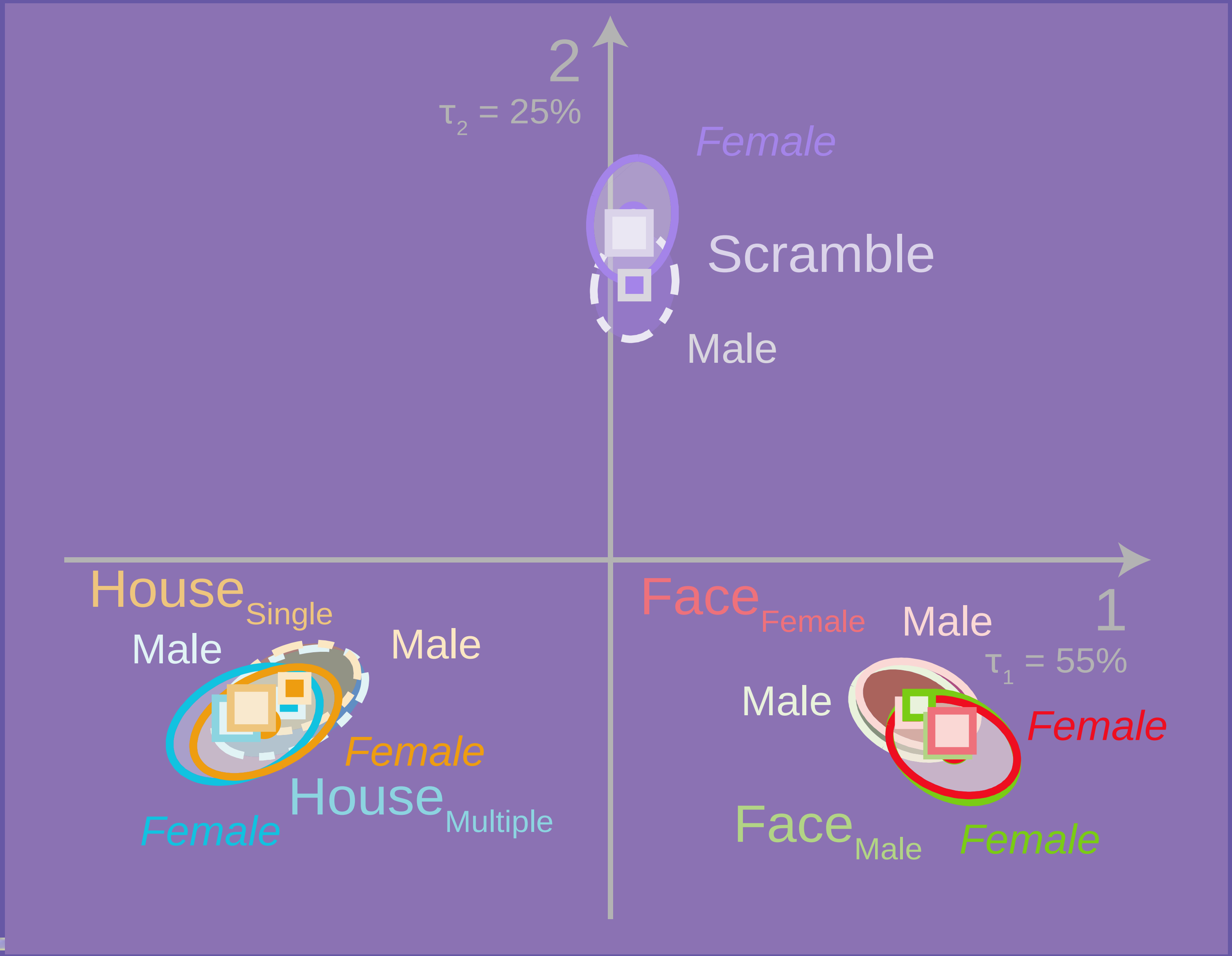
Gender Effects?



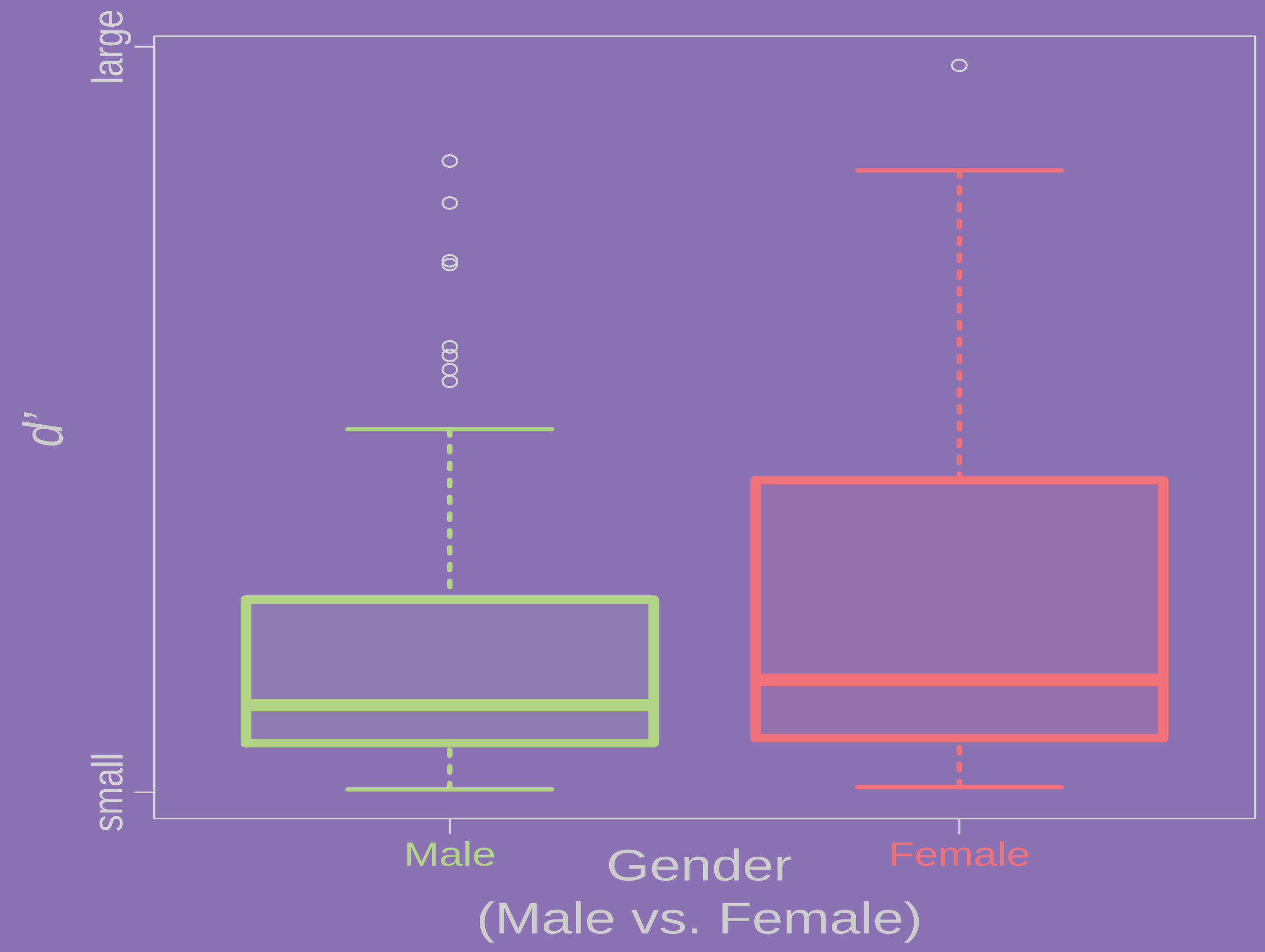
Gender Effects: Women.



Gender Effects: Women & Men.

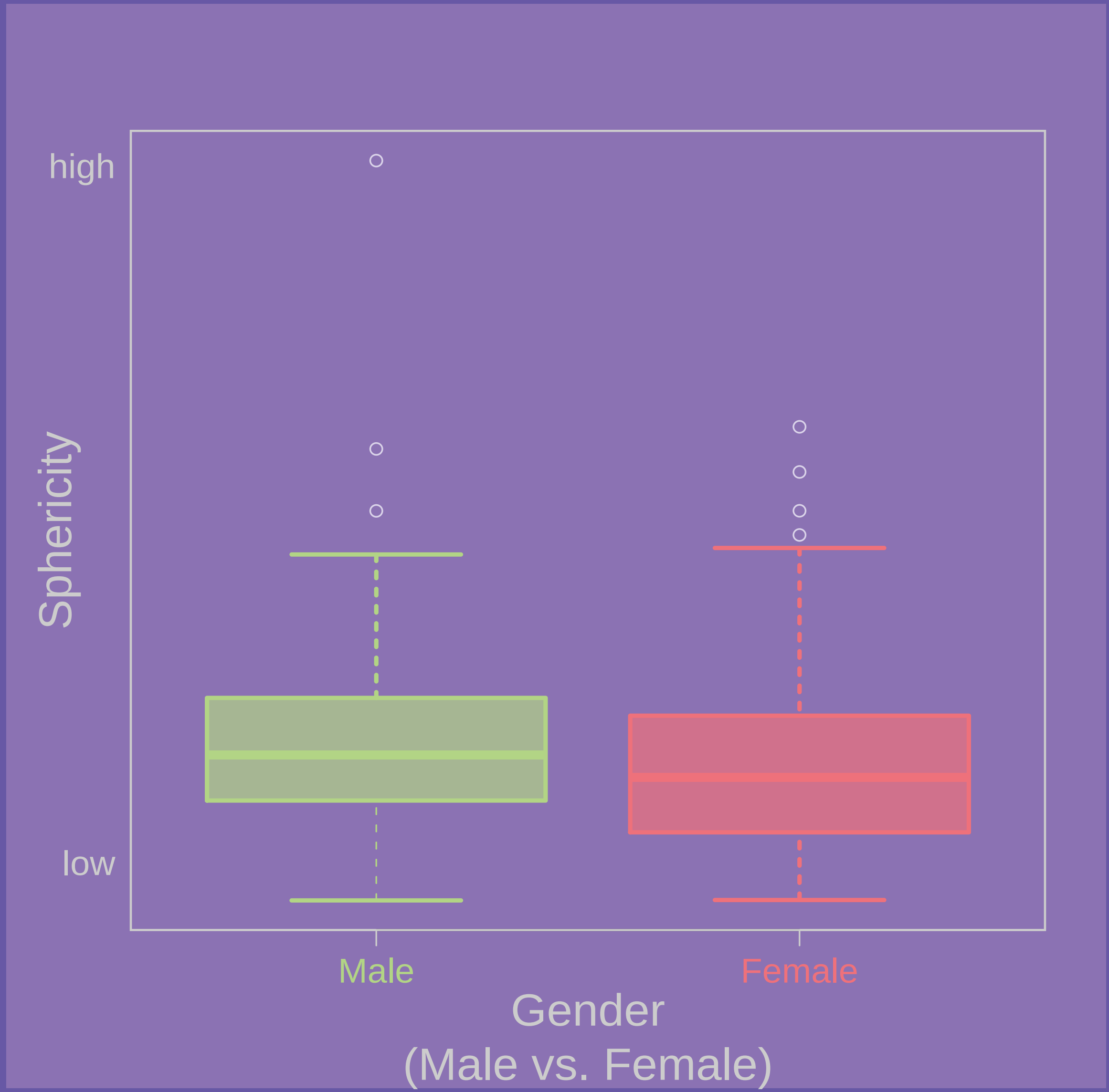


GENDER EFFECTS: *NS.*



D' BY GENDER

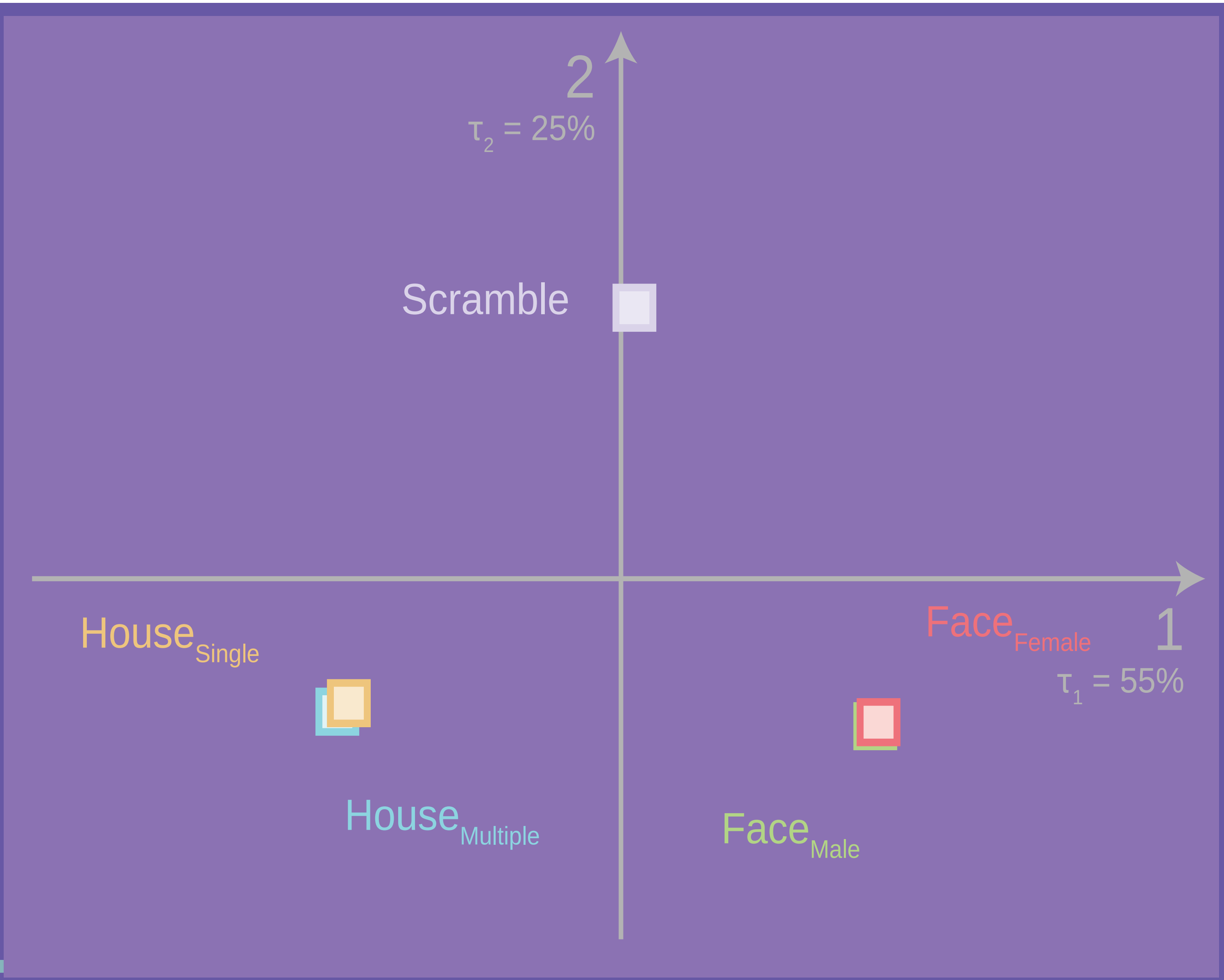
SPHERICITY



Sphericity men & women

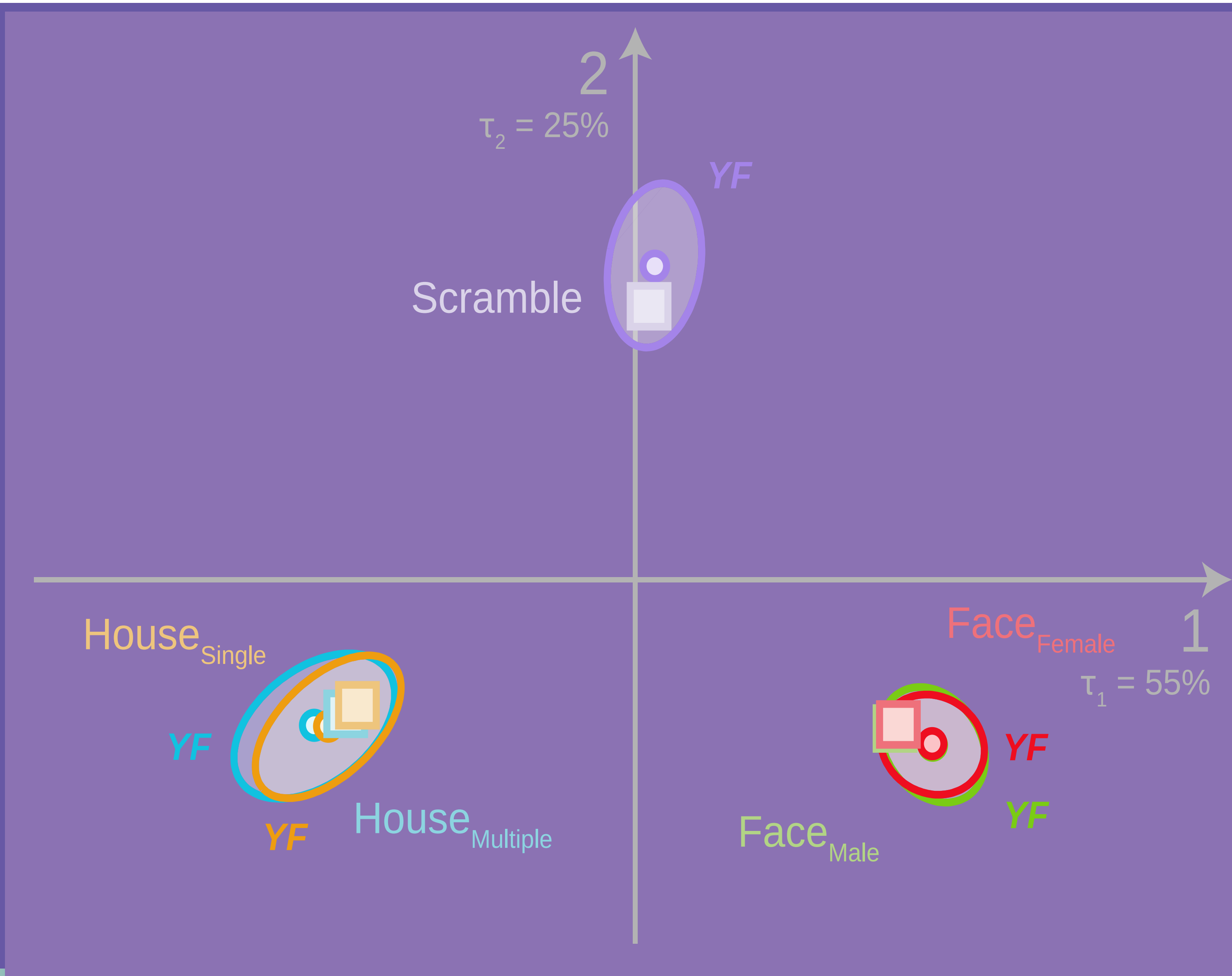
(*p* > .50)

AGE & GENDER

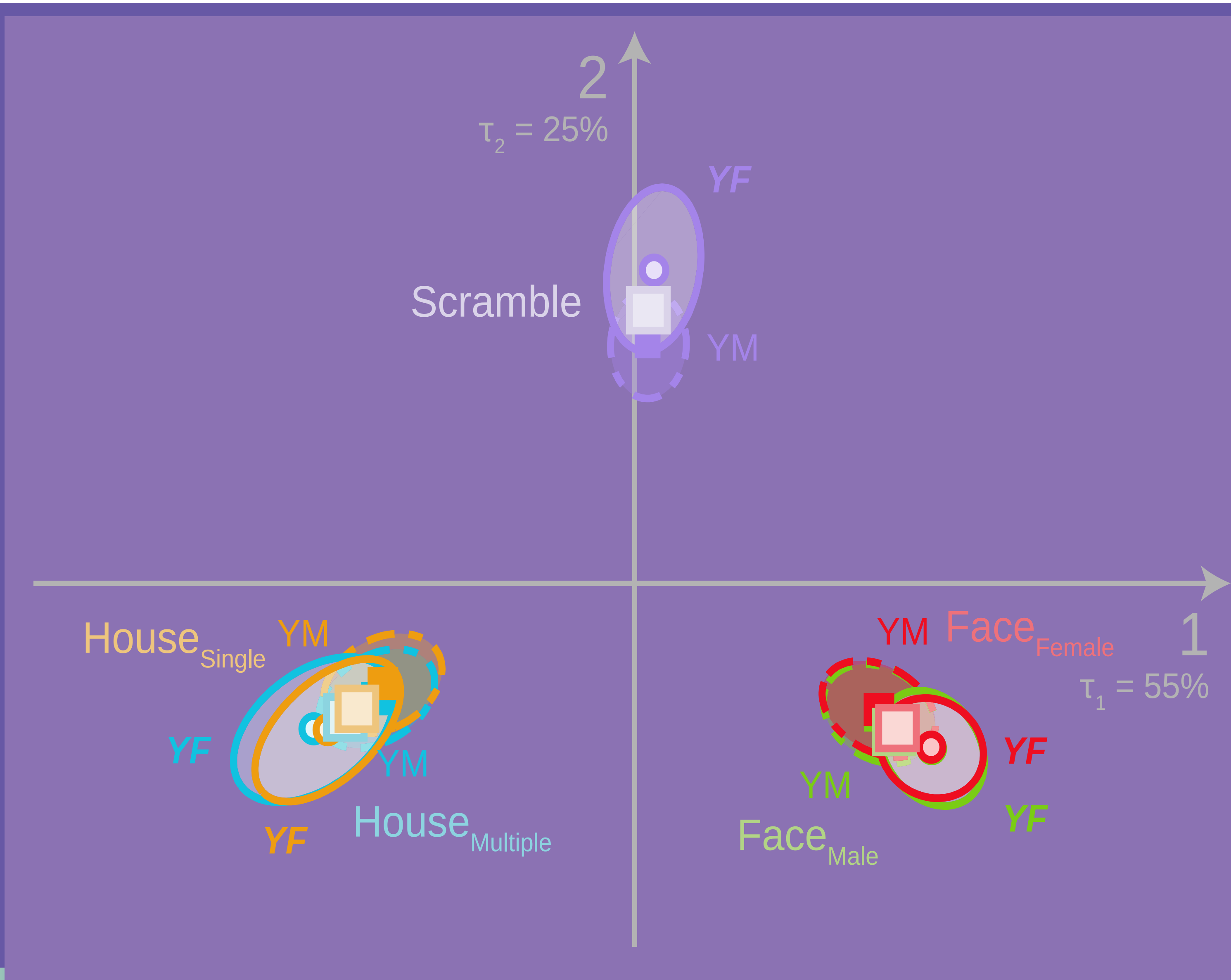


2
τ2 = 25%
Scramble
HouseSingle
FaceFemale
1
τ1 = 55%
HouseMultiple
FaceMale

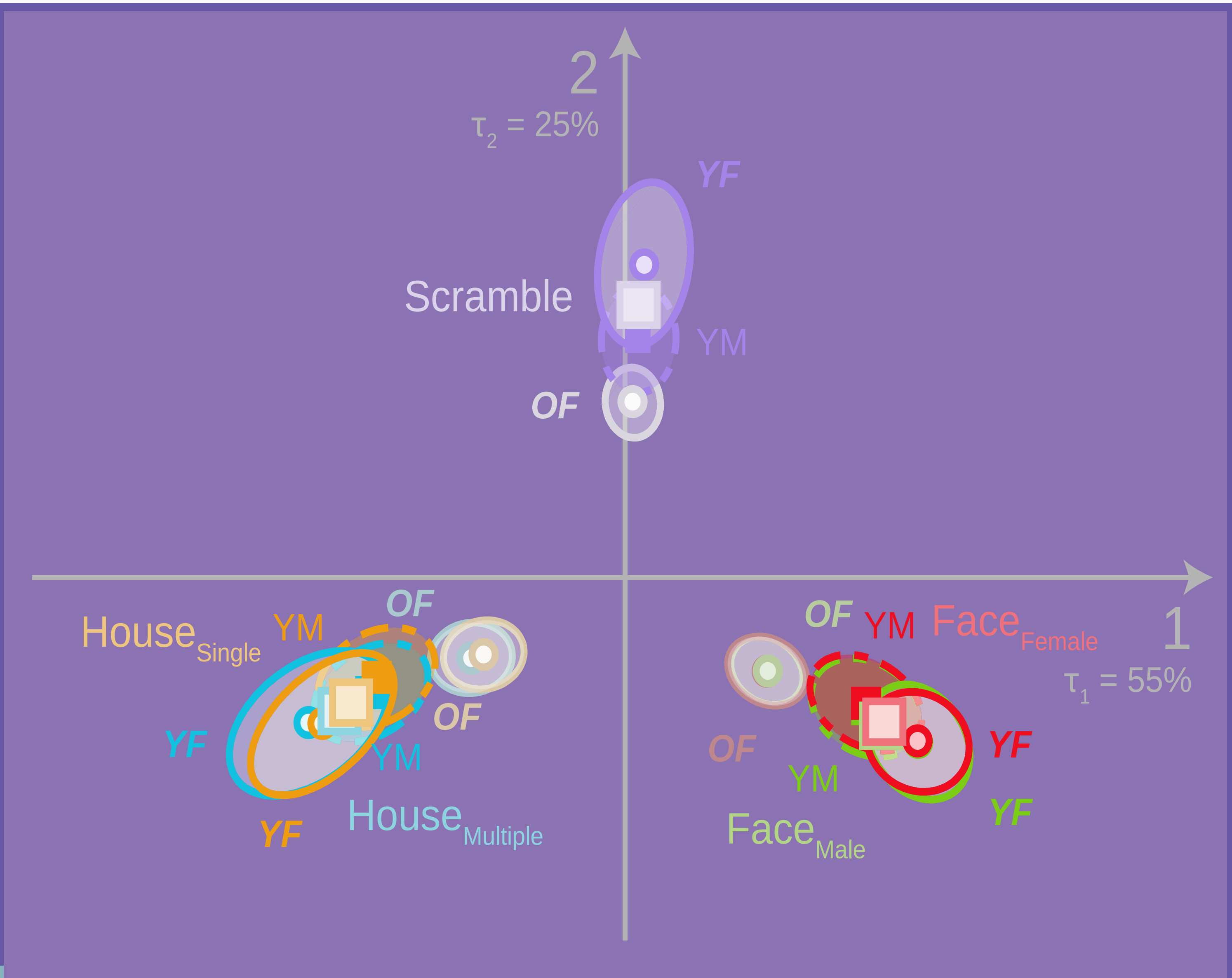
Age & Gender


2
τ2 = 25%
YF
Scramble
House Single
YF
YF
House Multiple
Face Female
1
τ1 = 55%
YF
YF
Face Male

Age & Gender

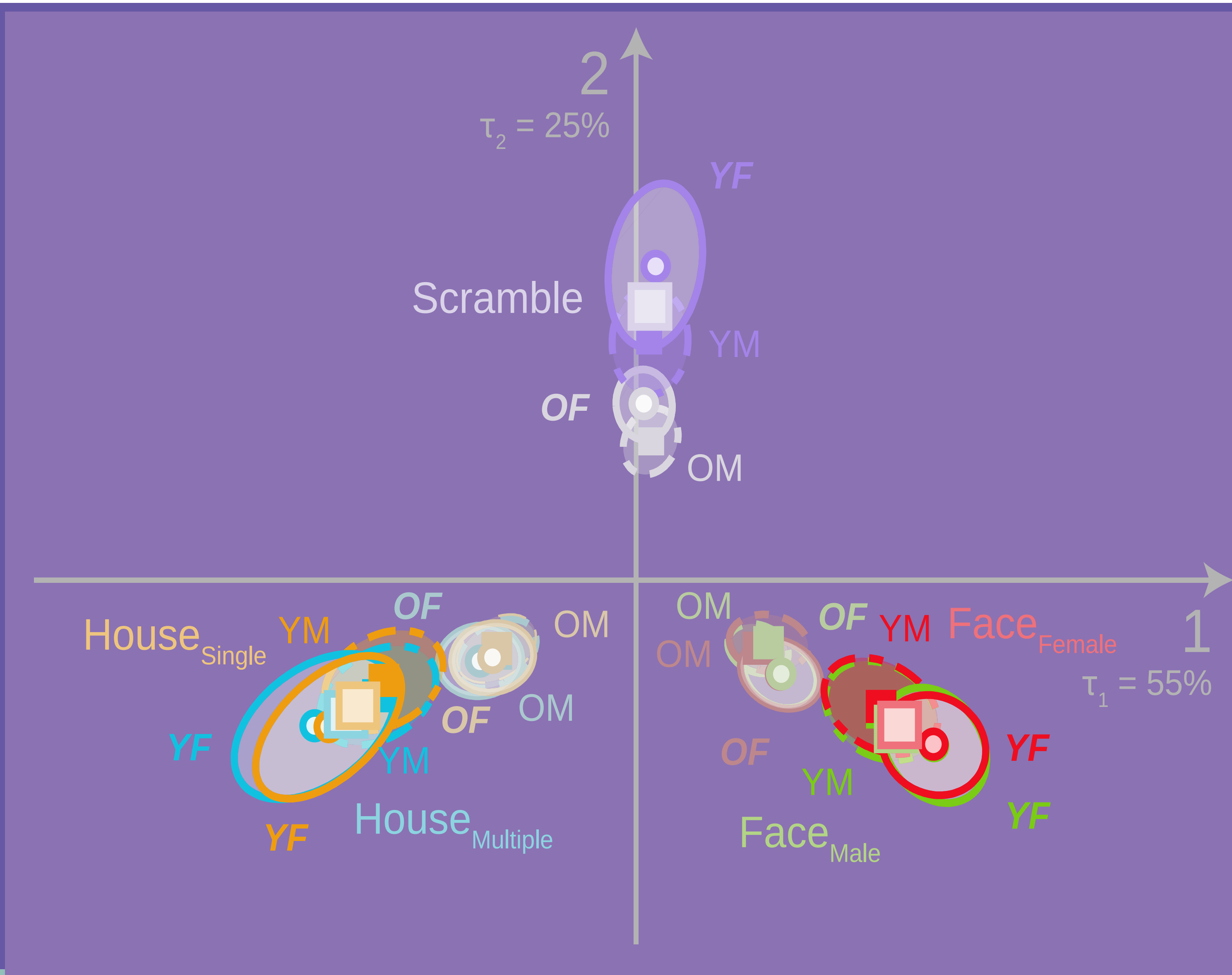

2
τ2 = 25%
YF
Scramble
YM
1
τ1 = 55%
HouseSingle
YM
YF
YM
YF
HouseMultiple
YM
FaceFemale
YF
YM
YF
FaceMale

AGE & GENDER

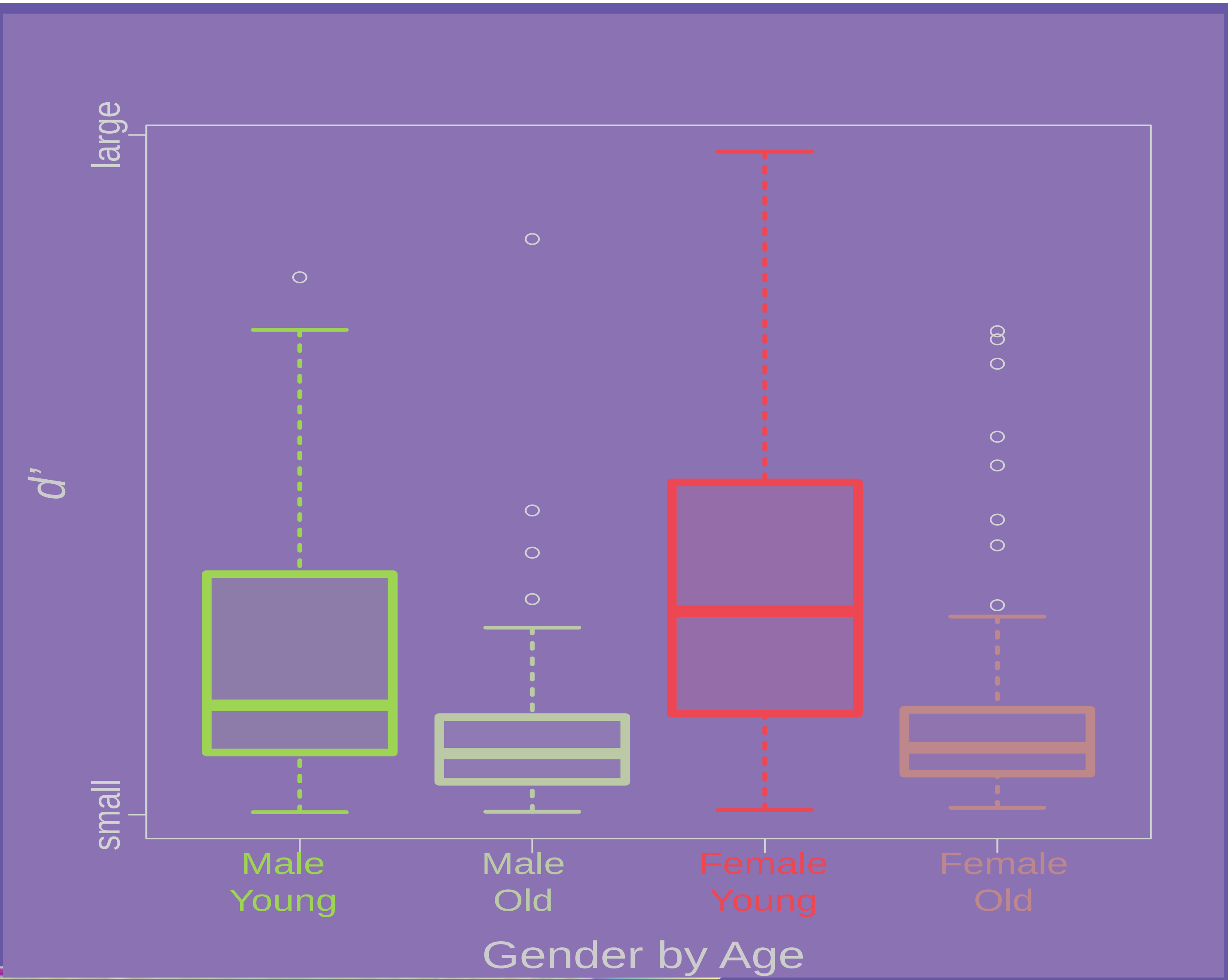


2
τ2 = 25%
YF
Scramble
YM
OF
House Single
YM
OF
OF
YF
YM
YF
House Multiple
OF
YM
Face Female
1
τ1 = 55%
OF
YF
YM
YF
Face Male

Age & Gender

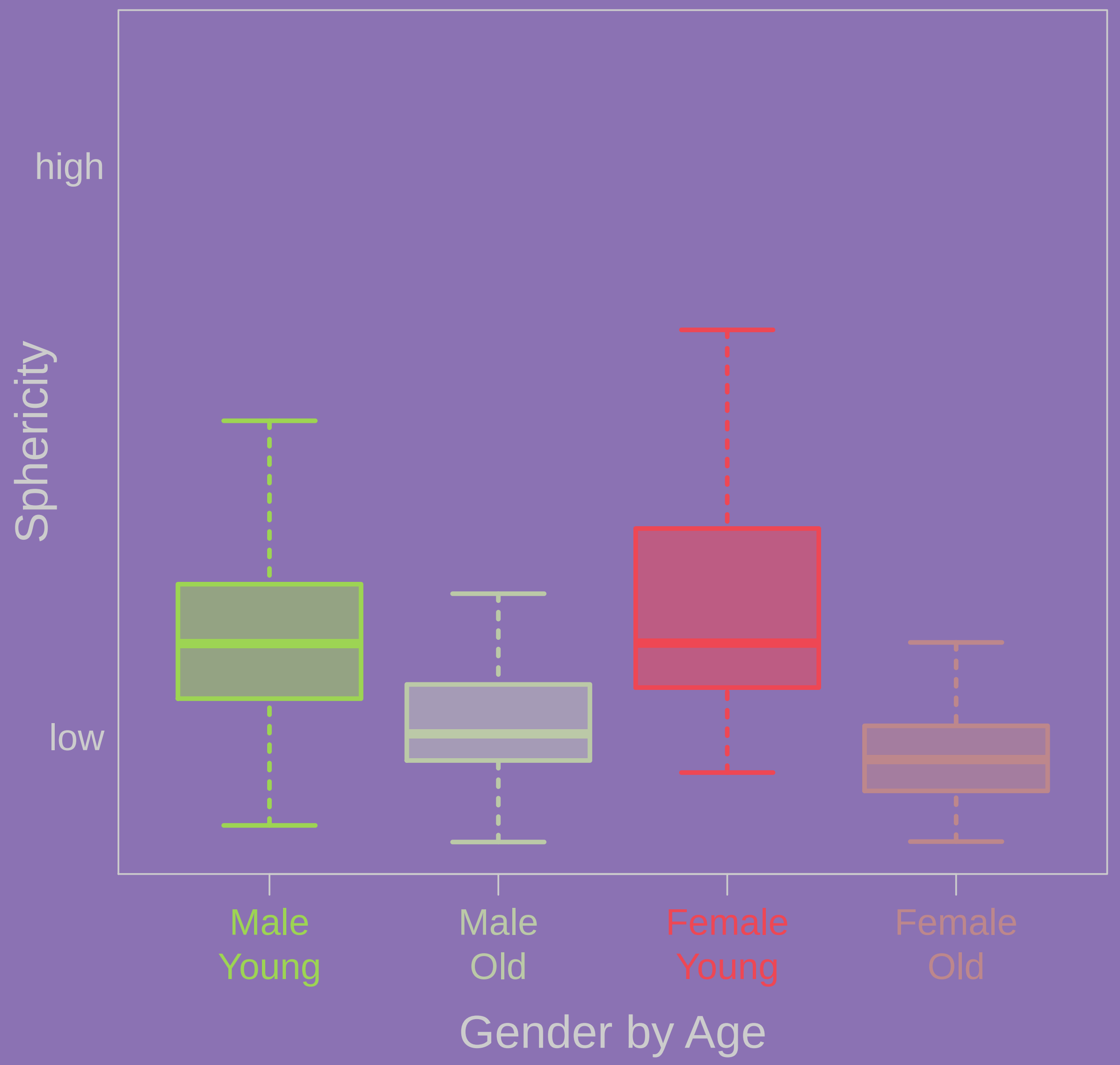

2
τ2 = 25%
YF
Scramble
YM
OF
OM
1
τ1 = 55%
House Single
YM
OF
OM
OF
OM
YF
YM
YF
House Multiple
OM
OM
OF
YM
Face Female
OF
YF
YM
YF
Face Male

Age & Gender



large
small
d'
Male
Young
Male
Old
Female
Young
Female
Old
Gender by Age

SPHERICITY


high
low
Sphericity
Male
Young
Male
Old
Female
Young
Female
Old
Gender by Age

- Very clear effect of age
- As predicted by dedifferentiation
- Effect of age correlates with sphericity
- Subtle effect of Gender
- Stronger in young people

For pattern classifiers: Power in numbers

Finale: Variation 3: Flatter Brains

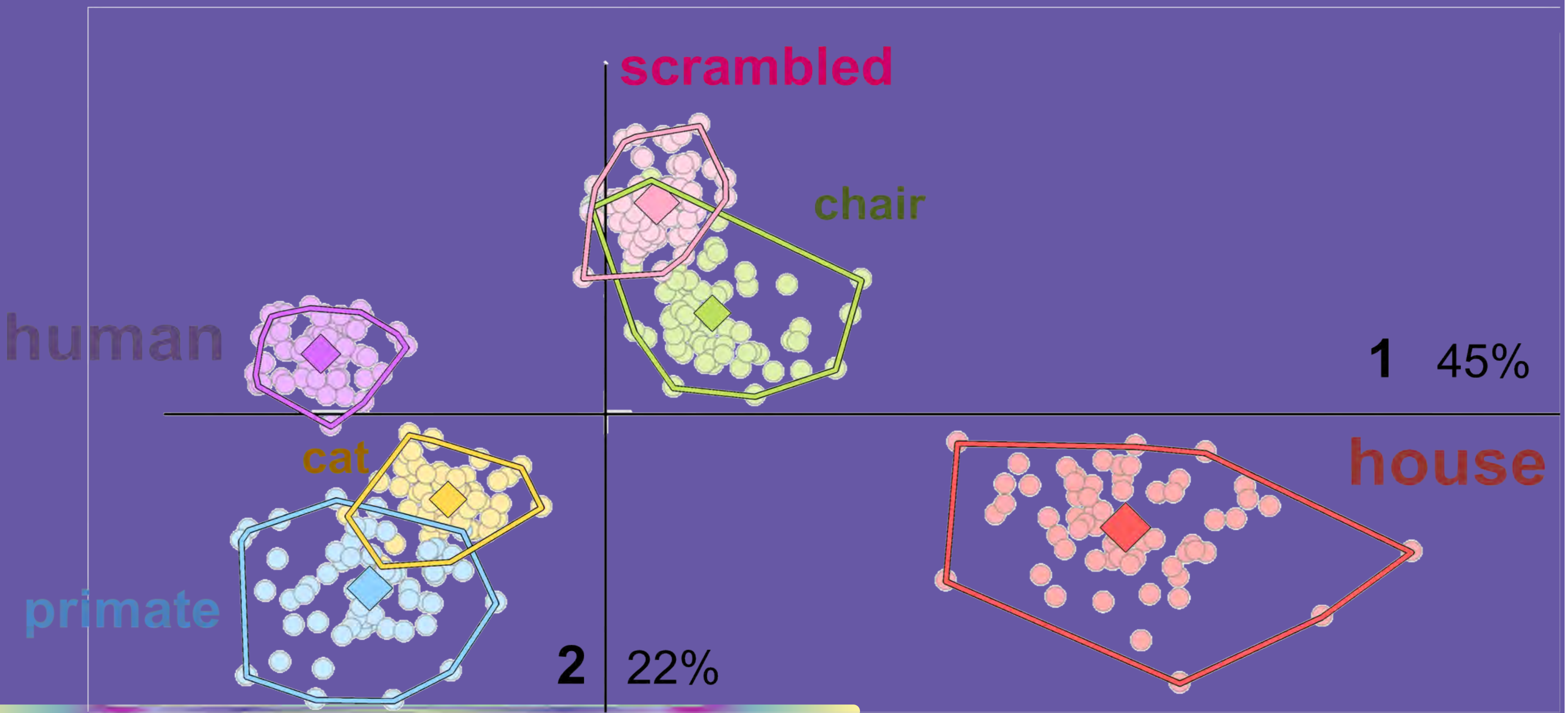
Variation 4: Age and Categories

Do categories change with age?

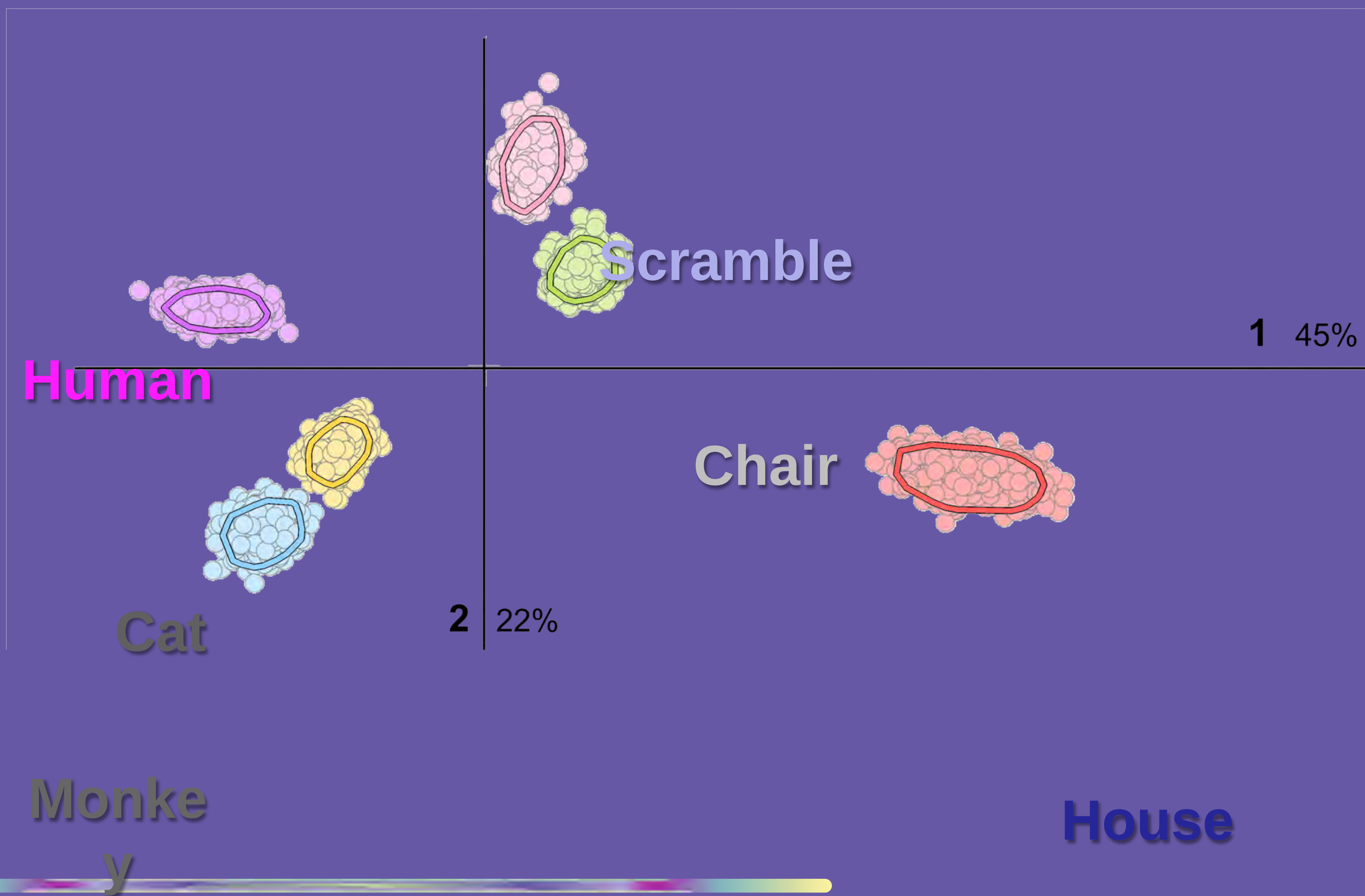
SIX CATEGORIES. 64 IMAGES PER CATEGORY
BLOCK DESIGN
35 YOUNG & 35 OLD PARTICIPANTS

(RIECK, BEATON, ABDI, & PARK, *SFN*, 2011)

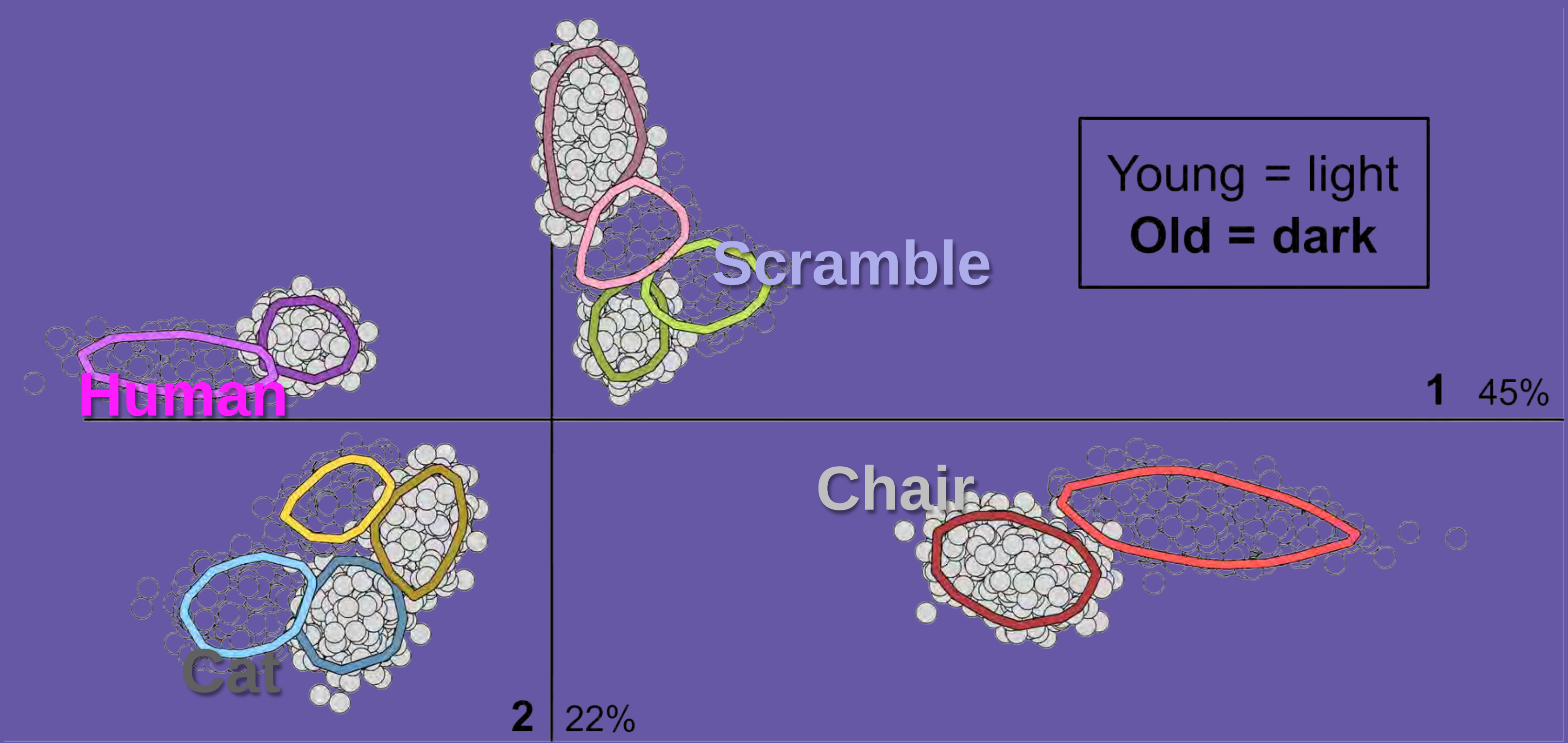
WHERE TO LOOK



Tolerance. Dimensions 1 & 2 All



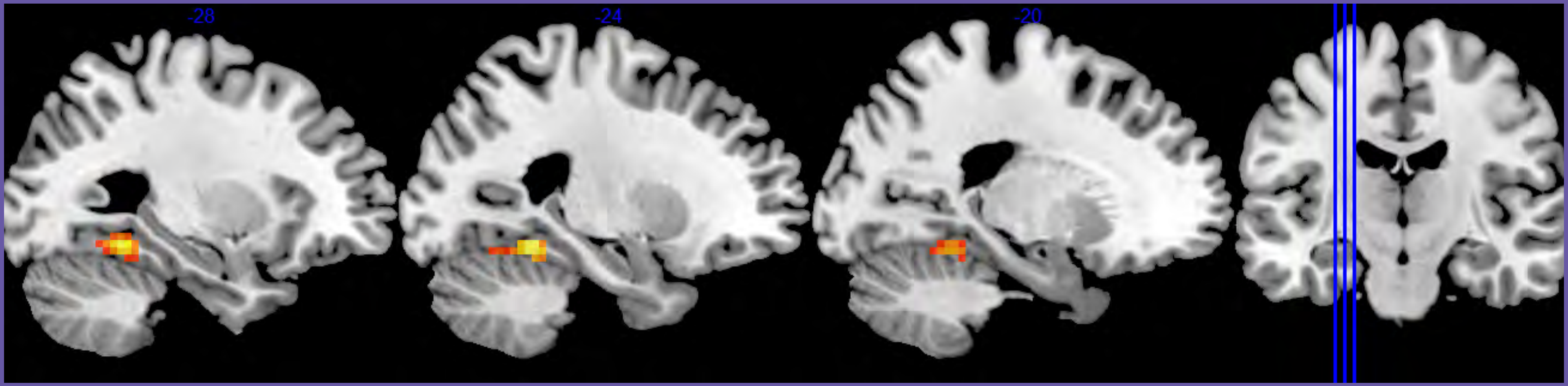
CONFIDENCE. DIMENSIONS 1 & 2 ALL



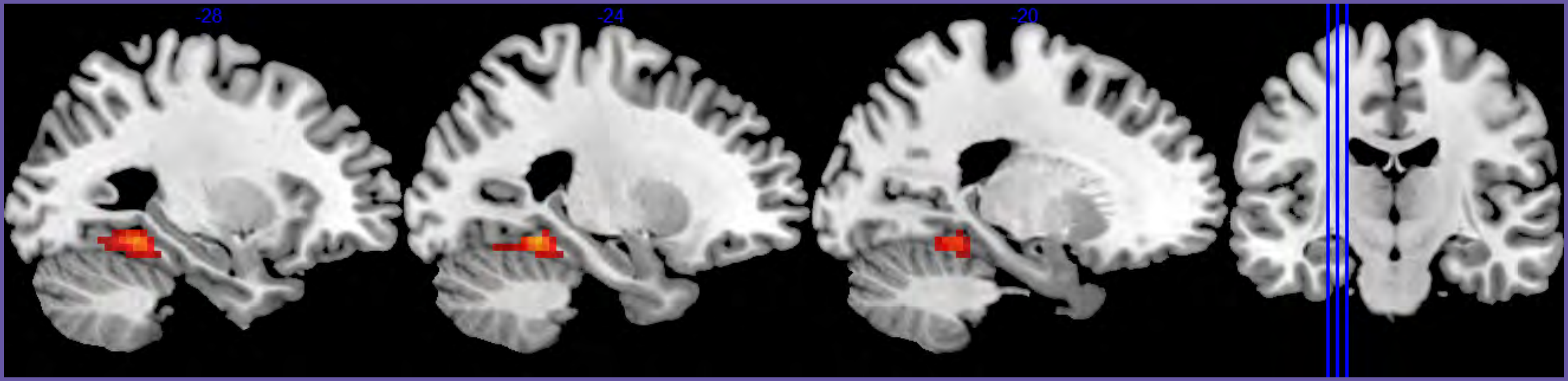
House

Monke
y

DIMENSIONS 1 & 2. BY AGE

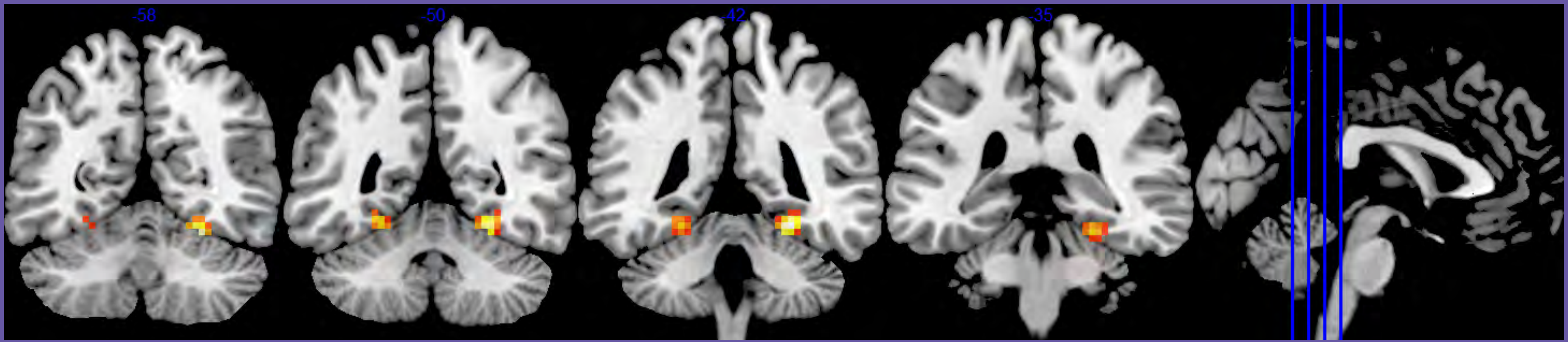


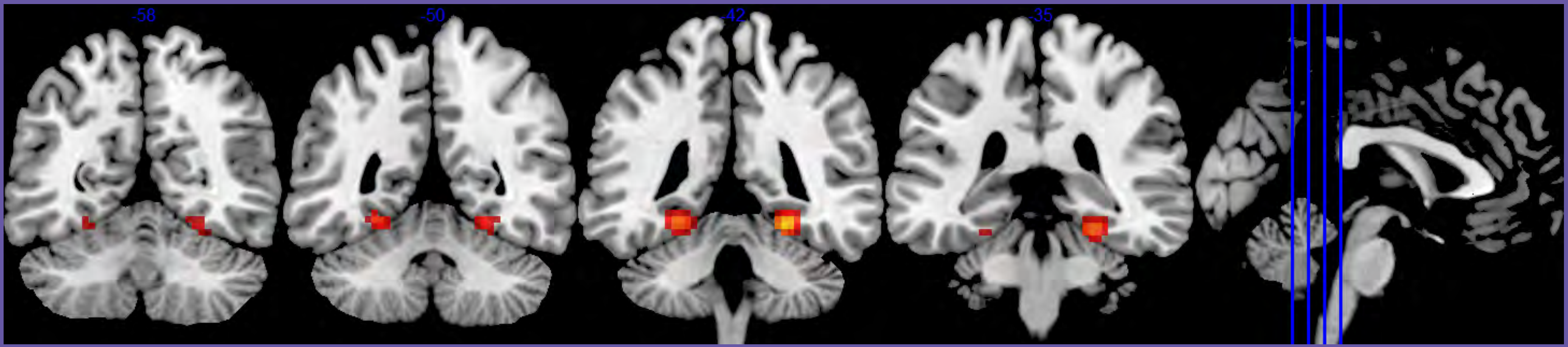
Young. Top Voxels # 153



Old. Top Voxels # 295

THE BRAIN. TOP CONTRIBUTIONS (15% VAR) LIGHTER IS MORE





CORONAL. 15% VARIANCE. DE-DIFERRENCIATION

Time for a Pause