



# INSIDE OUT ML: CLASSIFY FMRI BY EMOTION



**Predicting Emotion States and Priming Conditions**

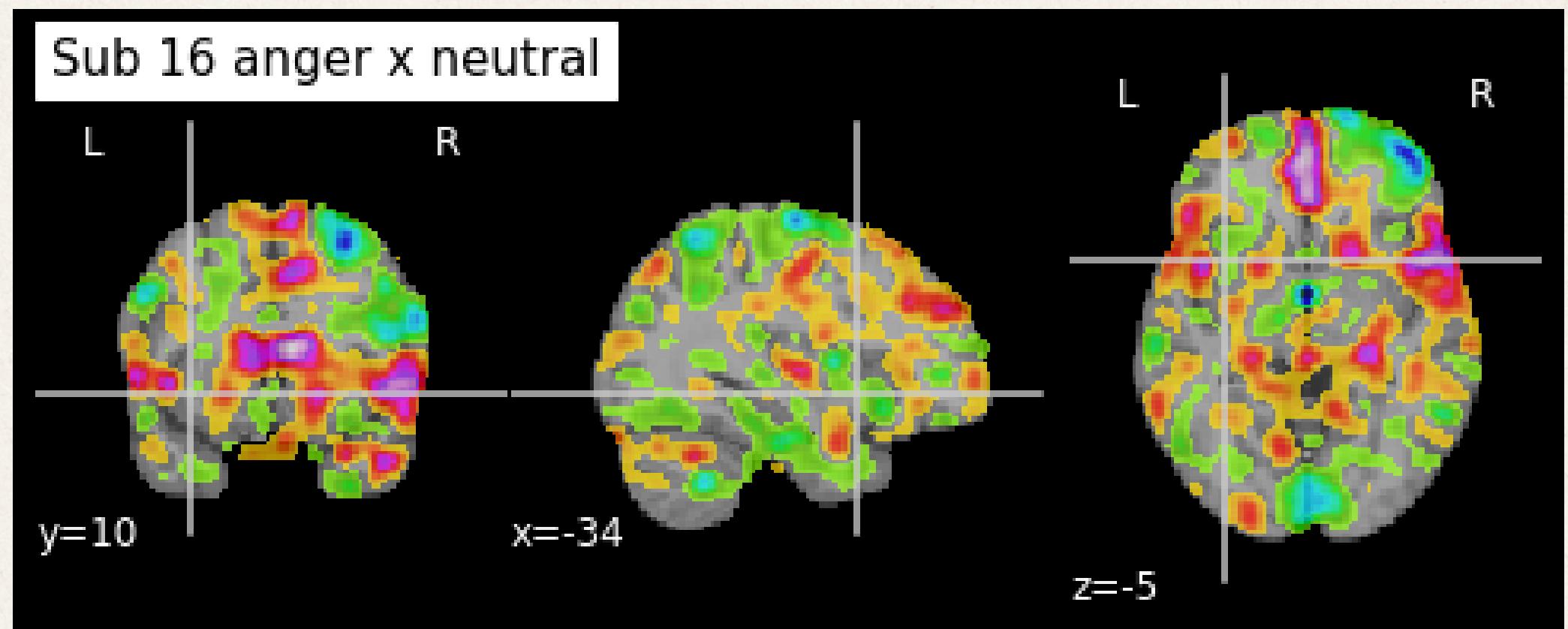
**NAME OF PROJECT:**  
NEURO-CV-EMOTION

**PRESENTED BY:**  
Anissa Vaughn

**PRESENTED TO:**  
Dr. Uzair Ahmad

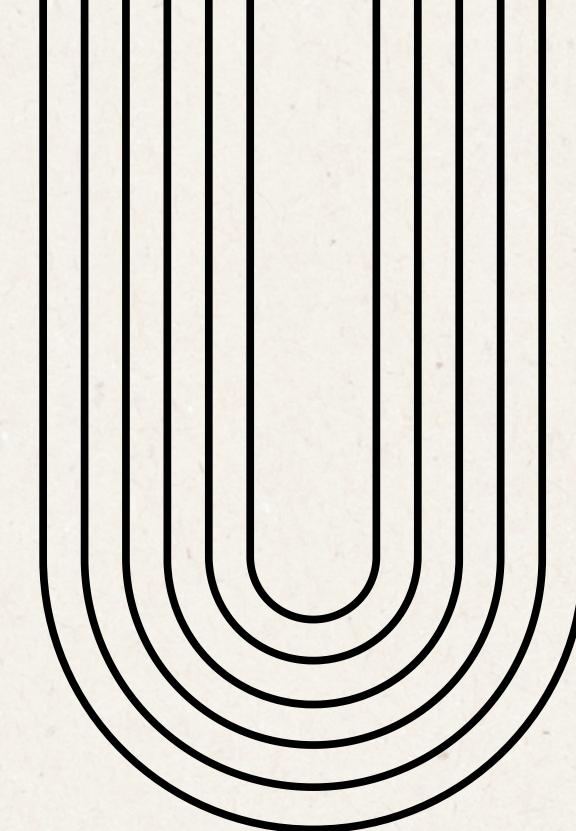
# About This Dataset

- **Source:** Northeastern University's Affective and Brain Sciences Lab
- **Participants:** 30 individuals underwent fMRI scans
  - Each underwent 9 trials: one for each emotion × priming combination
- **Task:** Participants were shown emotionally evocative images after hearing a word.
  - **Emotions:** anger, fear, disgust
  - **Priming Conditions:**
    - Incongruent: Emotion word does not match the image
      - fearful word → disgusting image
    - Congruent: Emotion word matches the image
      - angry word → angry image
    - Neutral: Emotionally neutral word before the image
- **Dataset:**
  - Preprocessed 3D beta maps from fMRI
  - Each map reflects voxelwise brain activation levels
  - Map Dimensions:  $91 \times 109 \times 91$  voxels per map
  - Sample Size: 270 total images
  - $30 \text{ subjects} \times 3 \text{ emotions} \times 3 \text{ priming conditions}$



**Figure 1:** fmri image at coordinates  $(-34, 10, -5)$  represented as a ROI mask for Subject 16. Shown angry image after neutral word.

# Research Objectives



**Overall:** Investigate how statistical and domain-specific feature extraction (parcellation and projection) techniques impact multi-class fMRI classification of emotional states



## Goal # 1

Identify optimal feature extraction technique for classification



## Goal # 2

Identify relationships between features, classes and regions of the brain

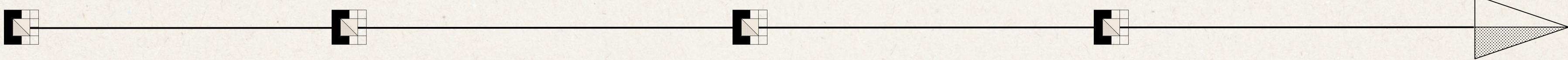


## Goal # 3

Identify how to manage autocorrelation and bias-variance

# Data Preprocessing

How was the raw .nii.gz images prepared for analysis?



## **Load data:**

### **Nibabel**

Store NIfTI files  
into np.arrays  
of voxel data

## **Assess Feature Extraction Methods**

Use cost functions, run  
time and ROI count to  
select best methods

## **Parcellation Maps:**

### **Nilearn**

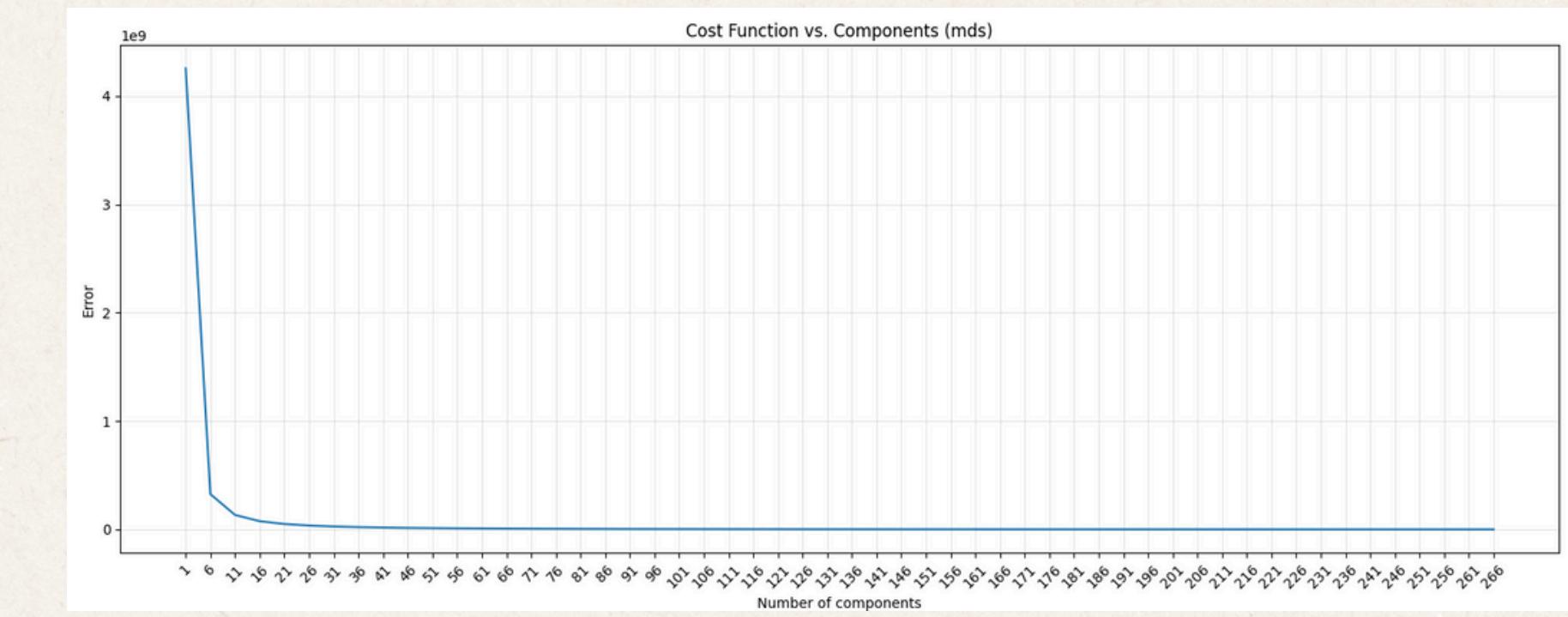
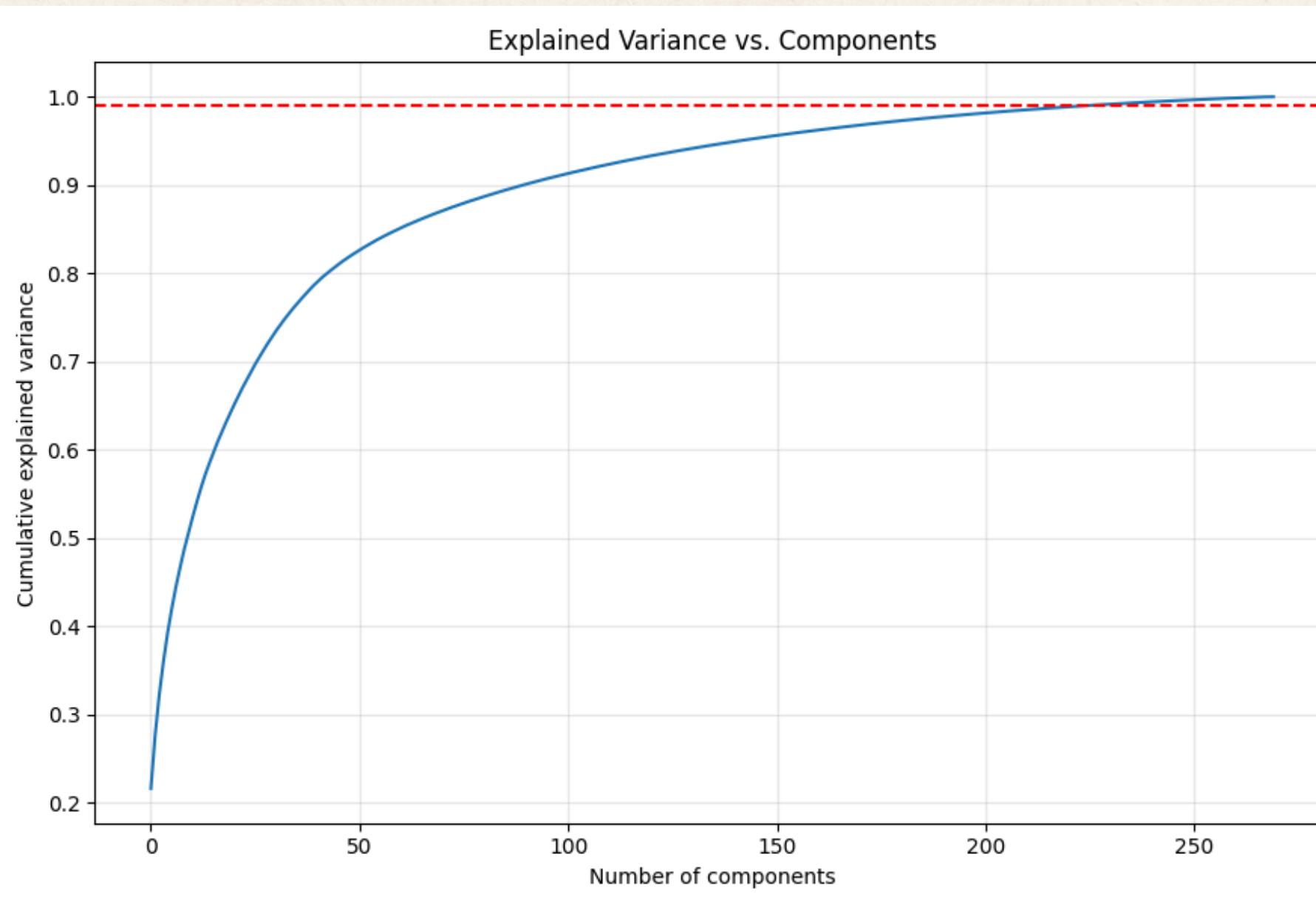
Reduce data to one  
value per brain region  
of interest (ROI)

## **Dimension Reduction:**

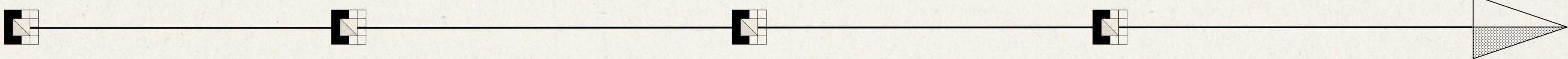
### **Sci-kit Learn**

Reduce scaled data to  
best components for  
explained variance

# Preprocessing Step: Cost Functions



# Investigation



## Homogeneity of Variance

Identify features that variance changes across target classes

## Multicollinearity

Identify features with high VIF values and correlation coefficients to other input feautres

## Autocorrelation

Identify input features with high correlation to subject ID due to relatedness

## Logistic Regression

Conduct Multi-class classification on emotion and priming classes. leverging Logistic Regression

**01 Problem:** Dependent samples (same subject)

**03/10**

**Solution:** Hierarchical K-Fold Cross Validation:  
prevent data leaks of same subject in test and train splits

**02 Problem:** Bias-Variance Tradeoff

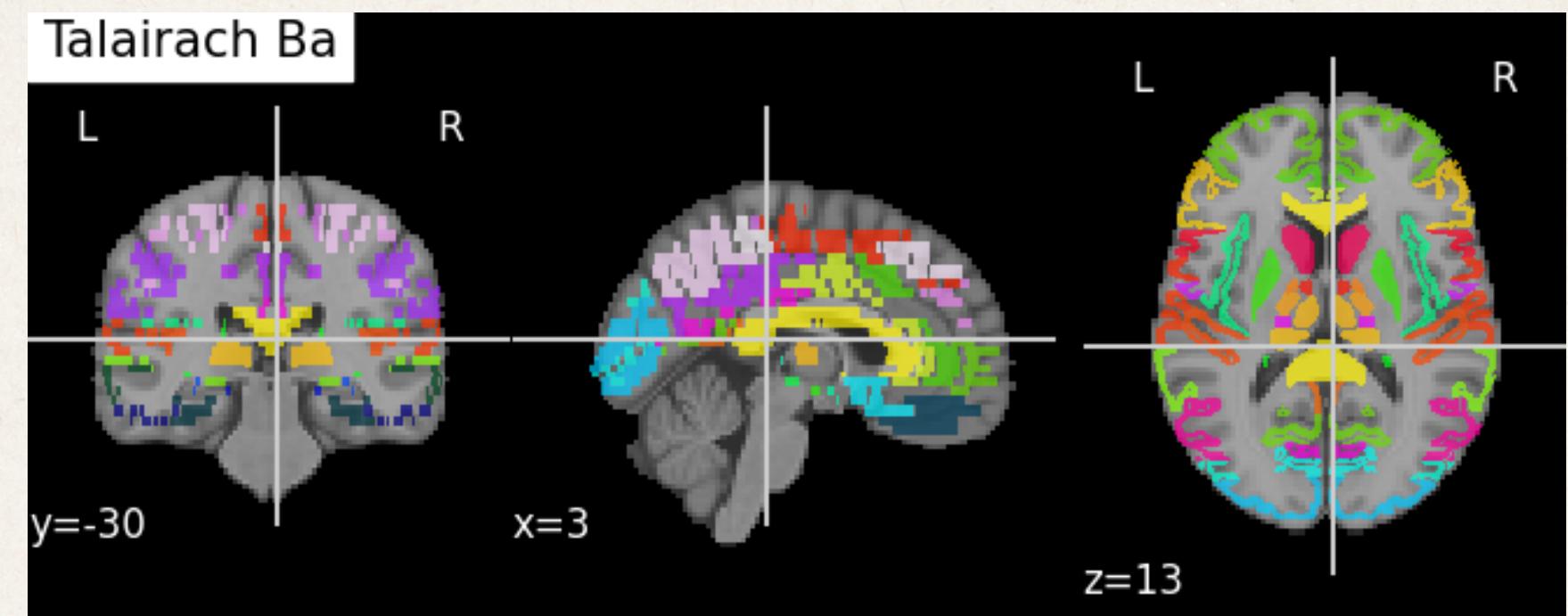
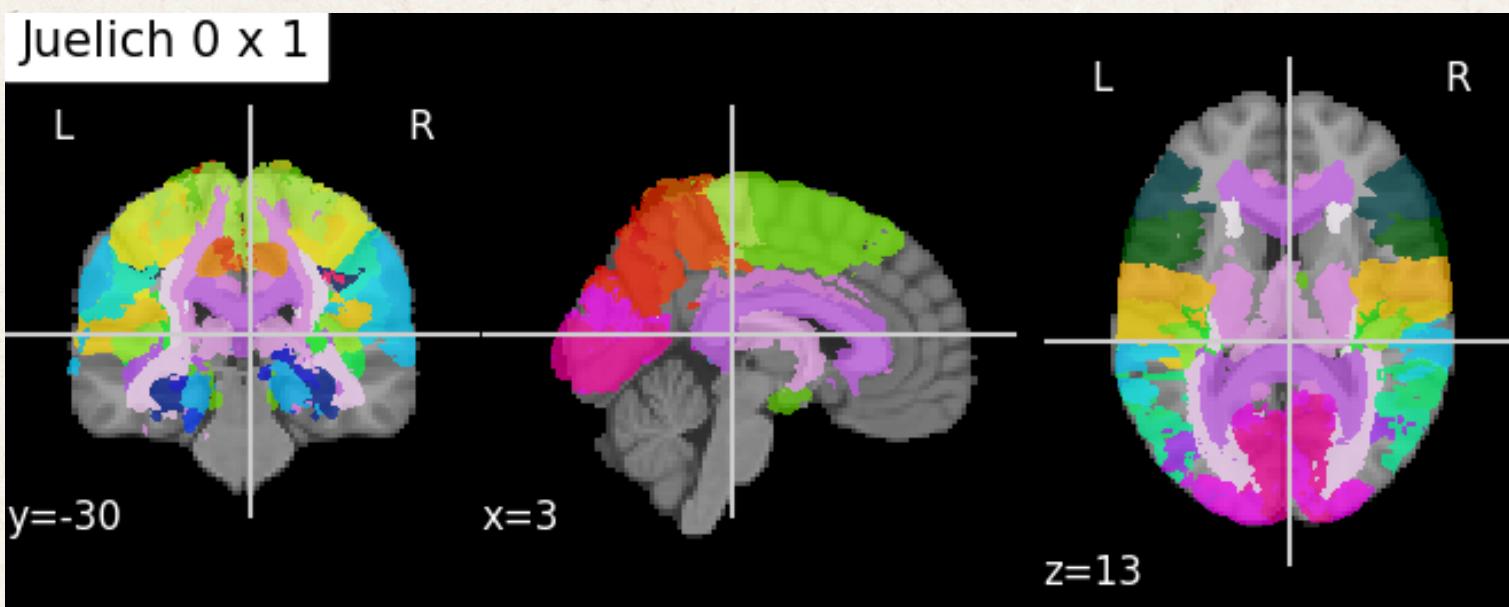
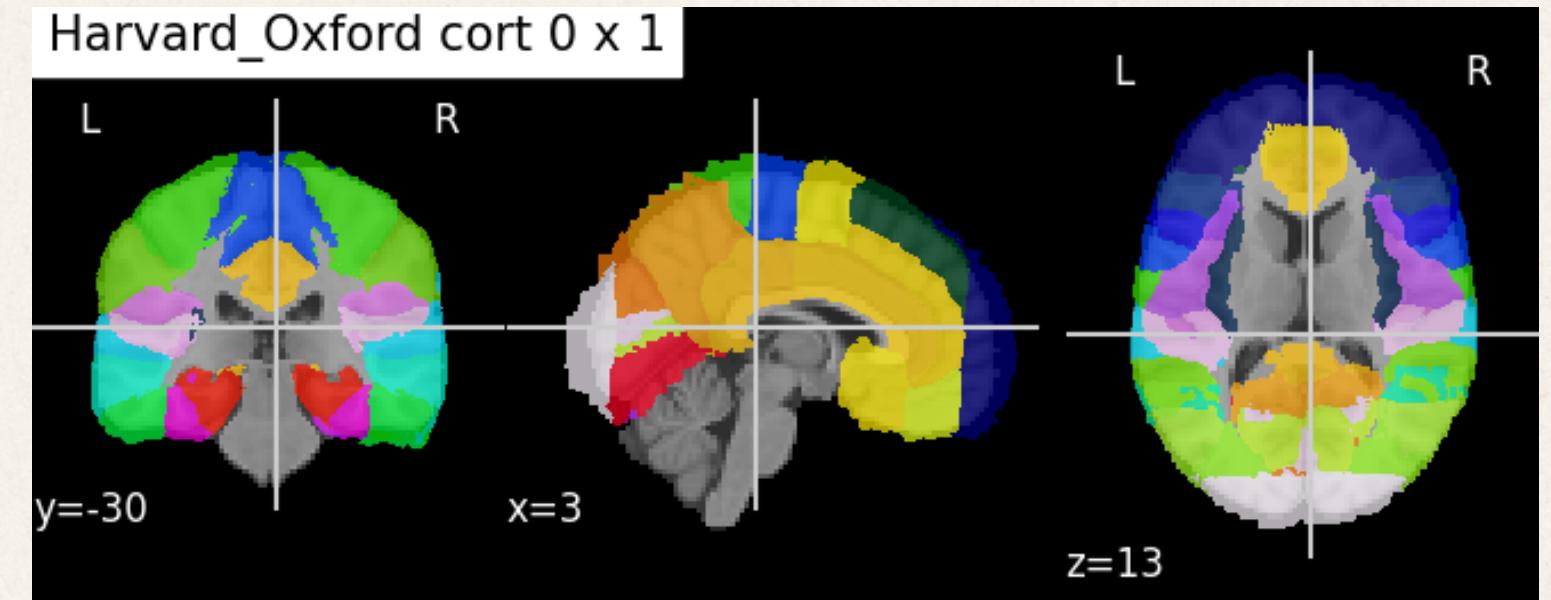
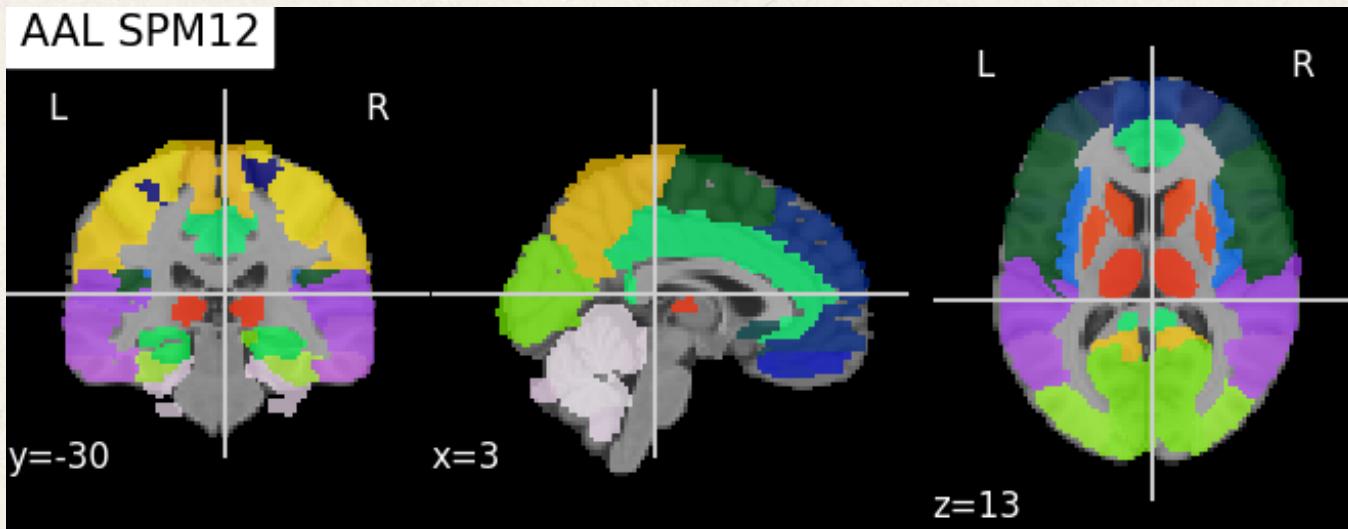
**Solution:** Calculate test and train metrics to identify overfitting

**03 Problem:** Explainability and Feature Importance

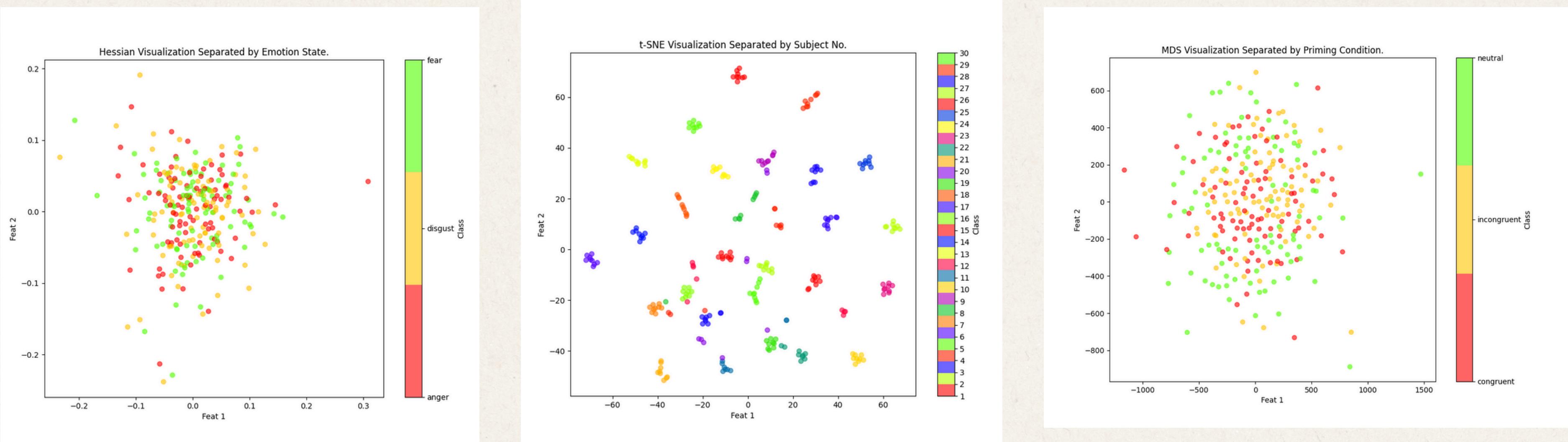
**Solution:** Choose appropriate model for classification task and output coefficients

# Model Training

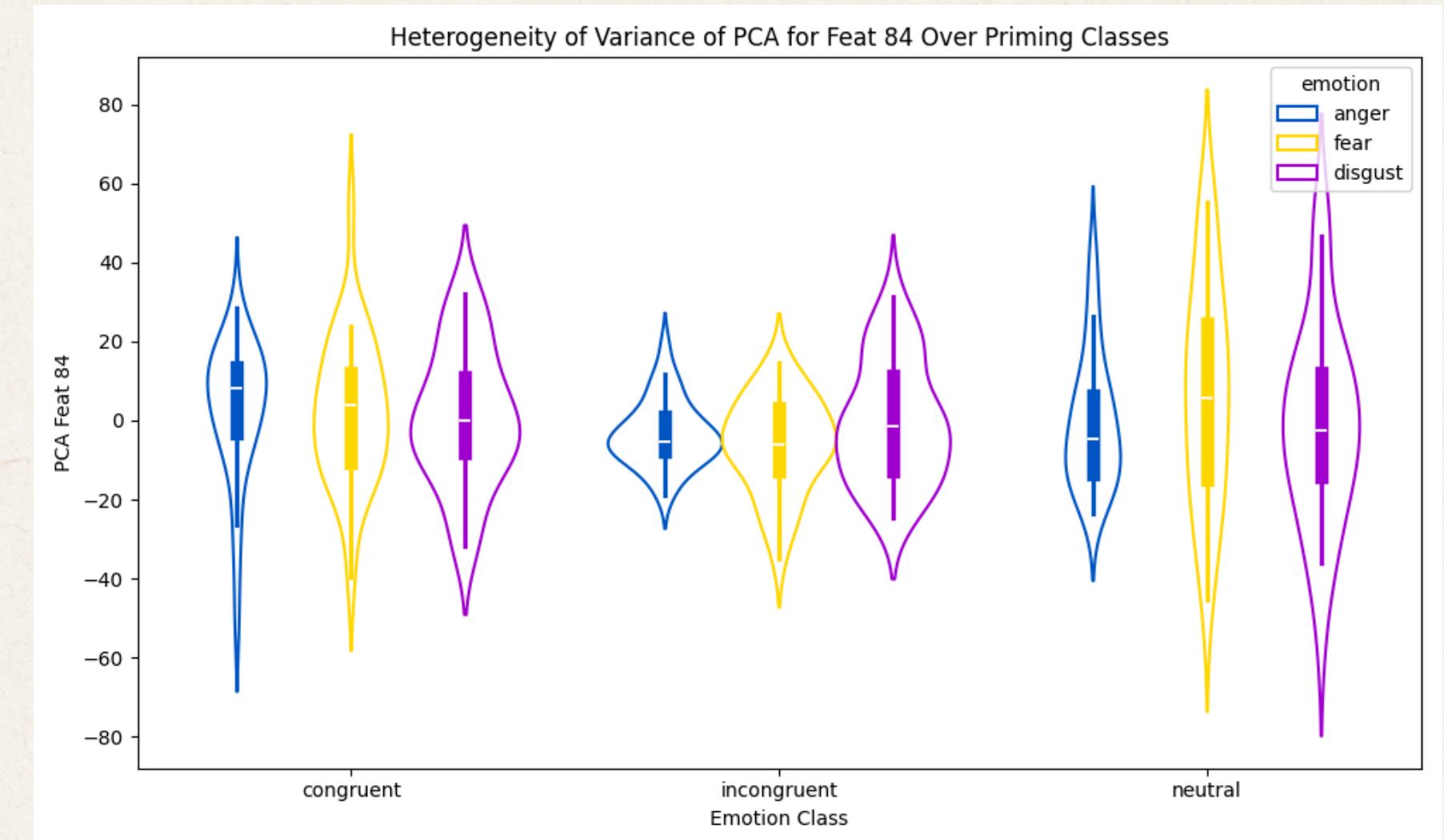
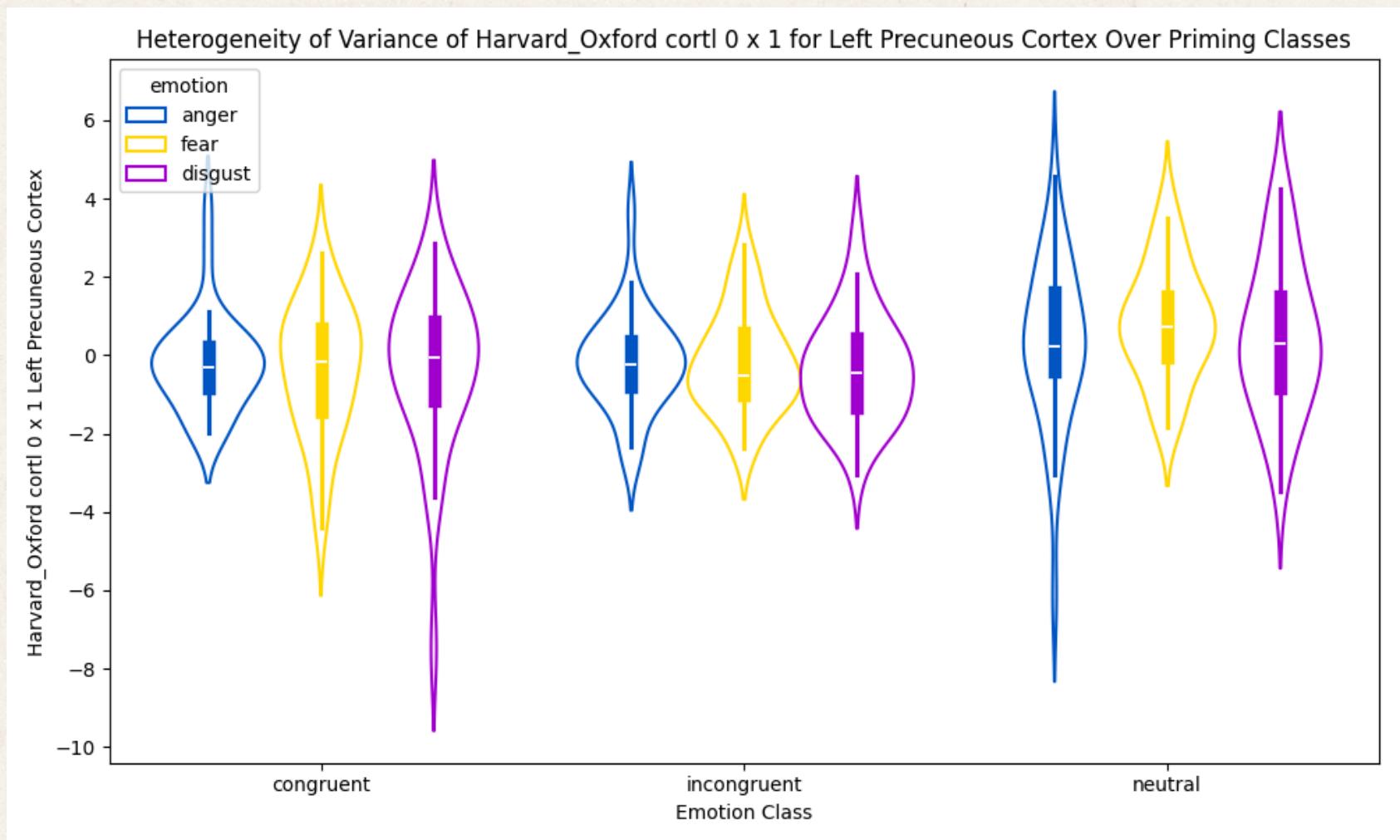
# Brain Parcellation Visualizations



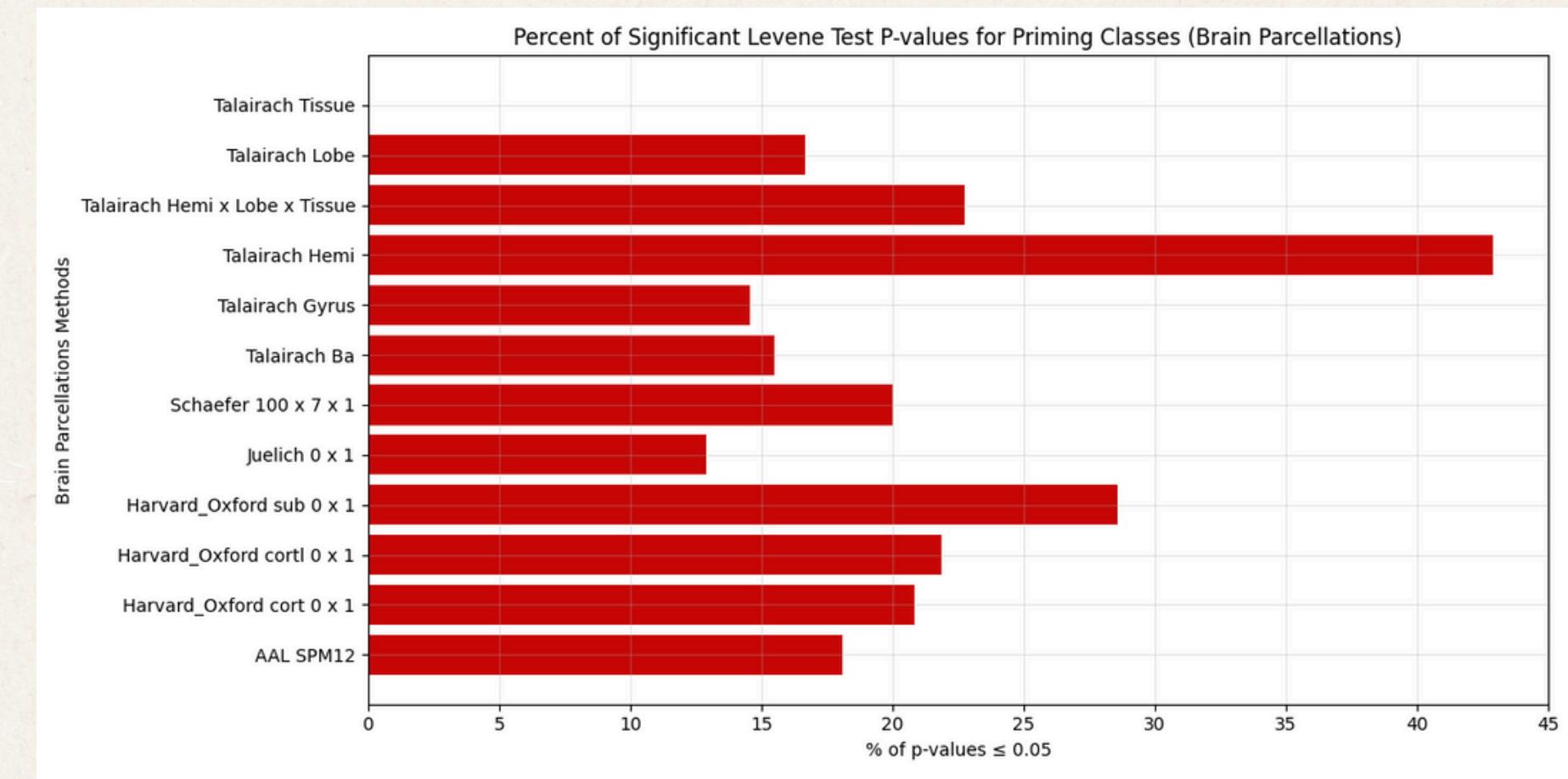
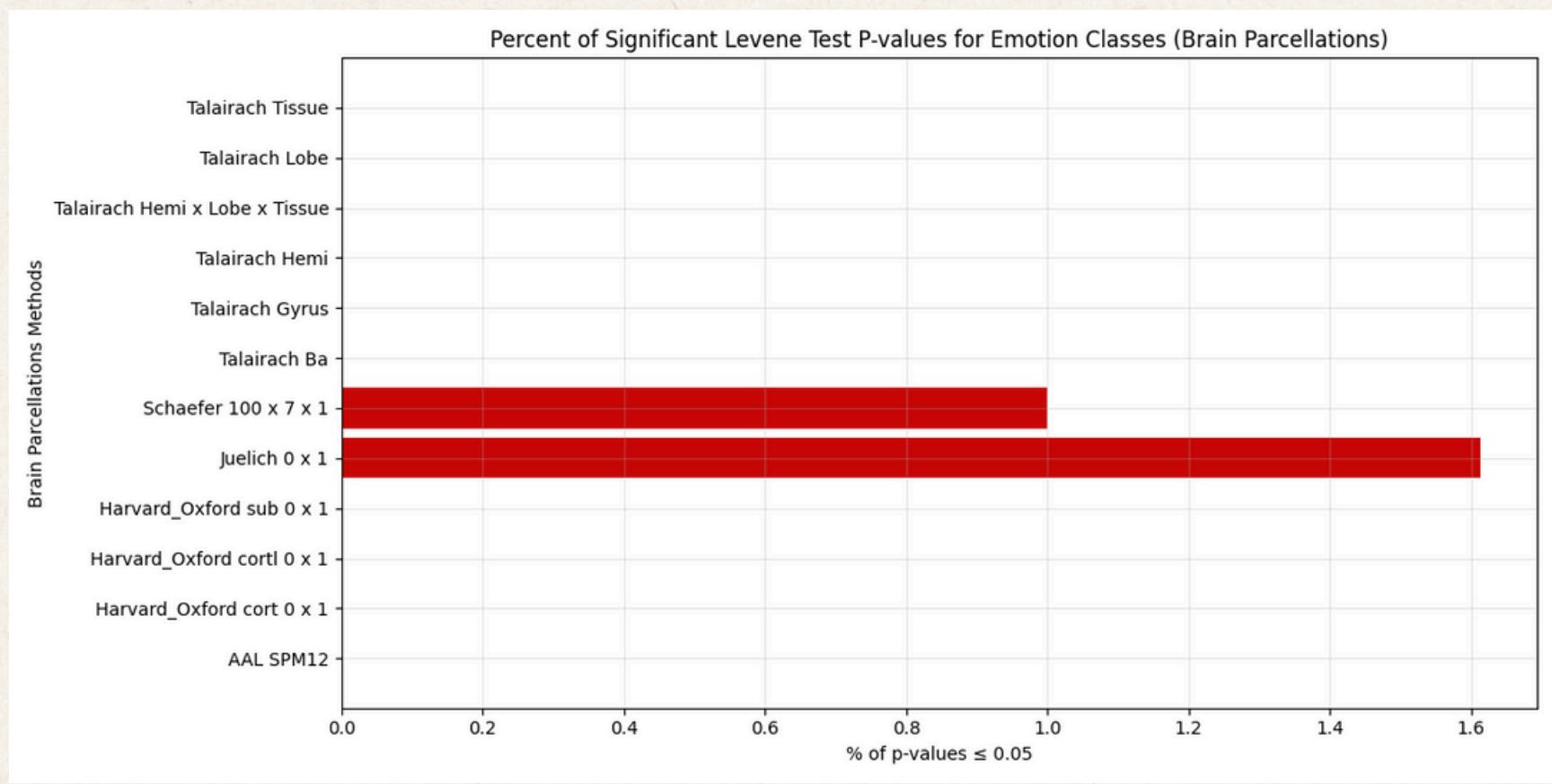
# Geometric Projection Visualizations



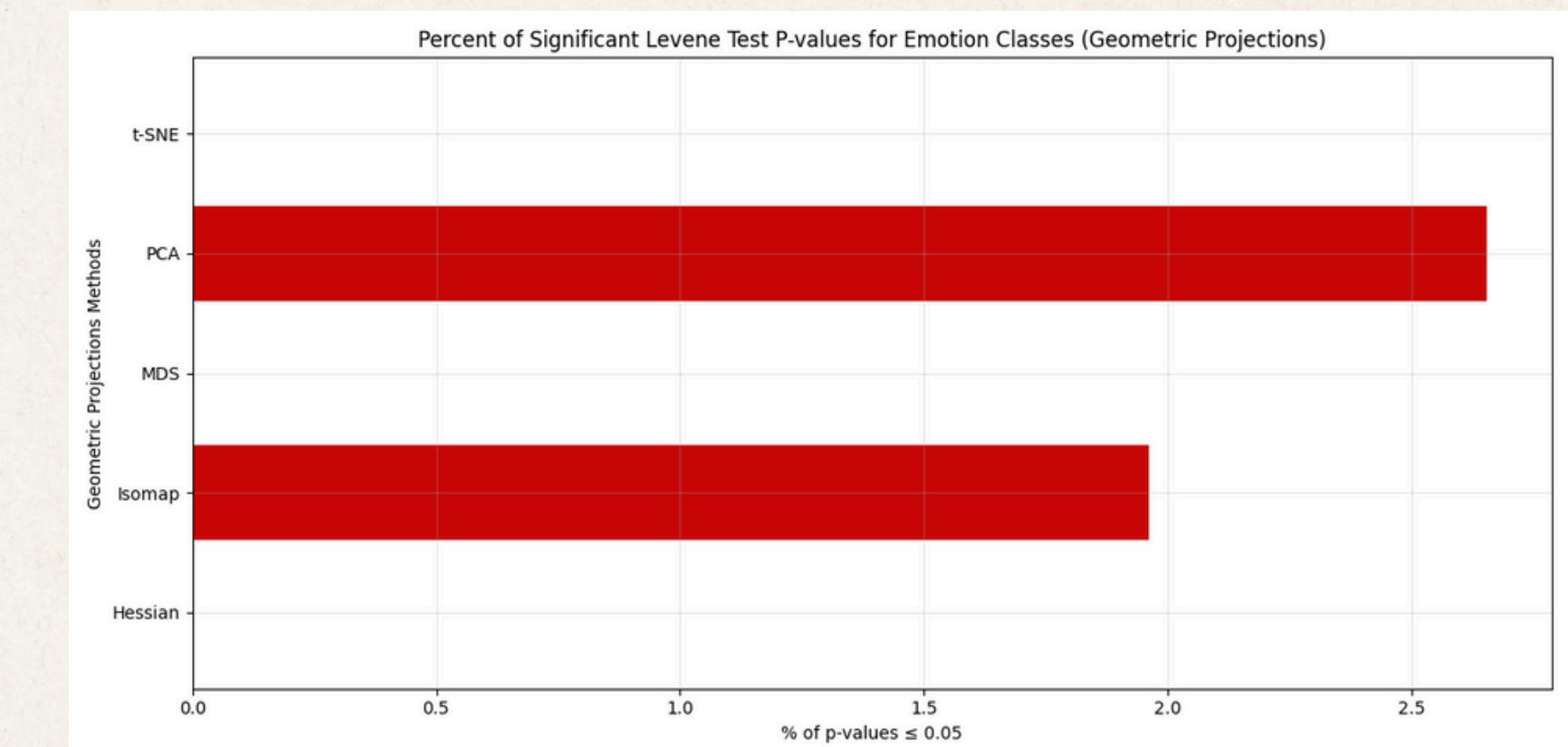
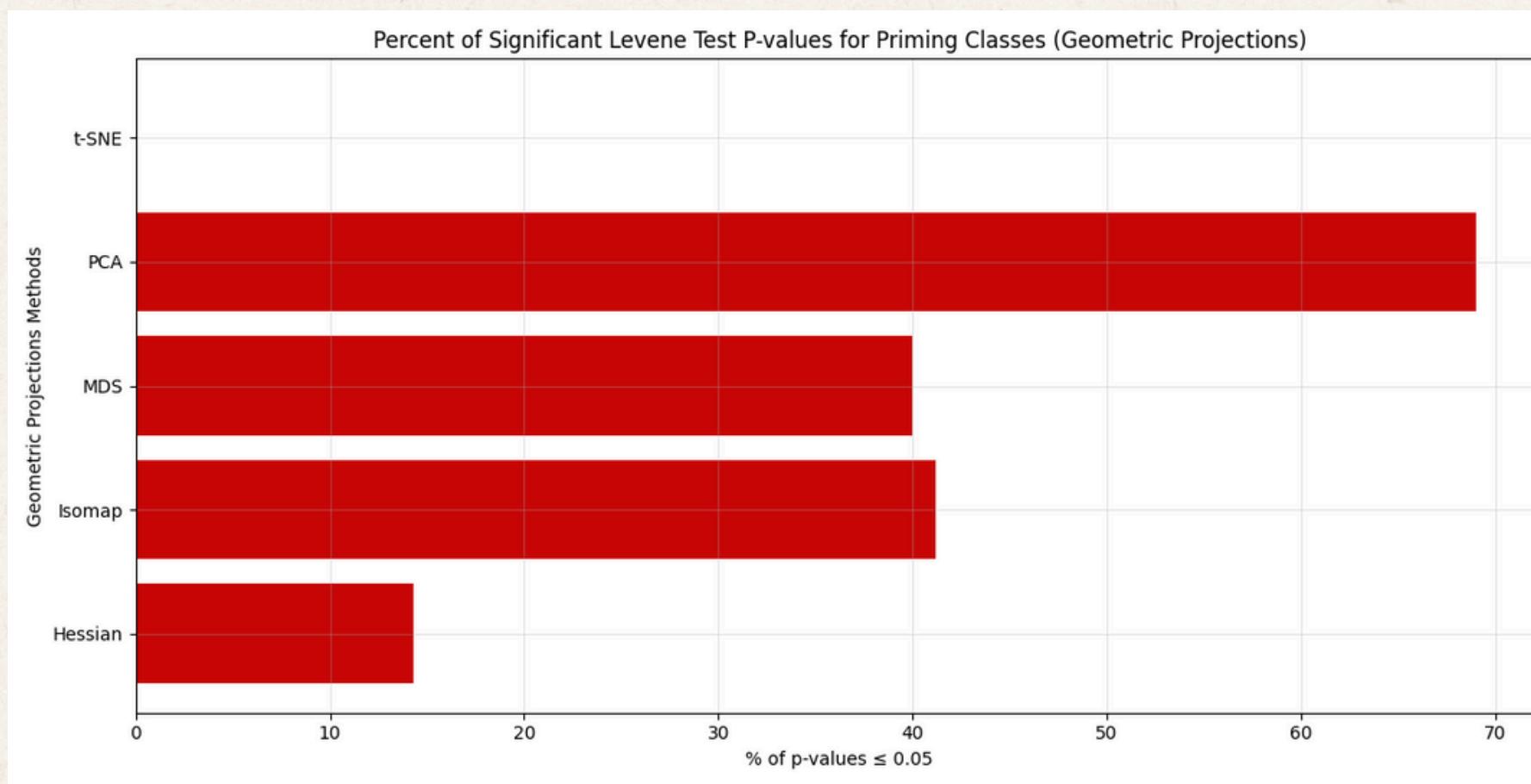
# Heterogeneity of Variance



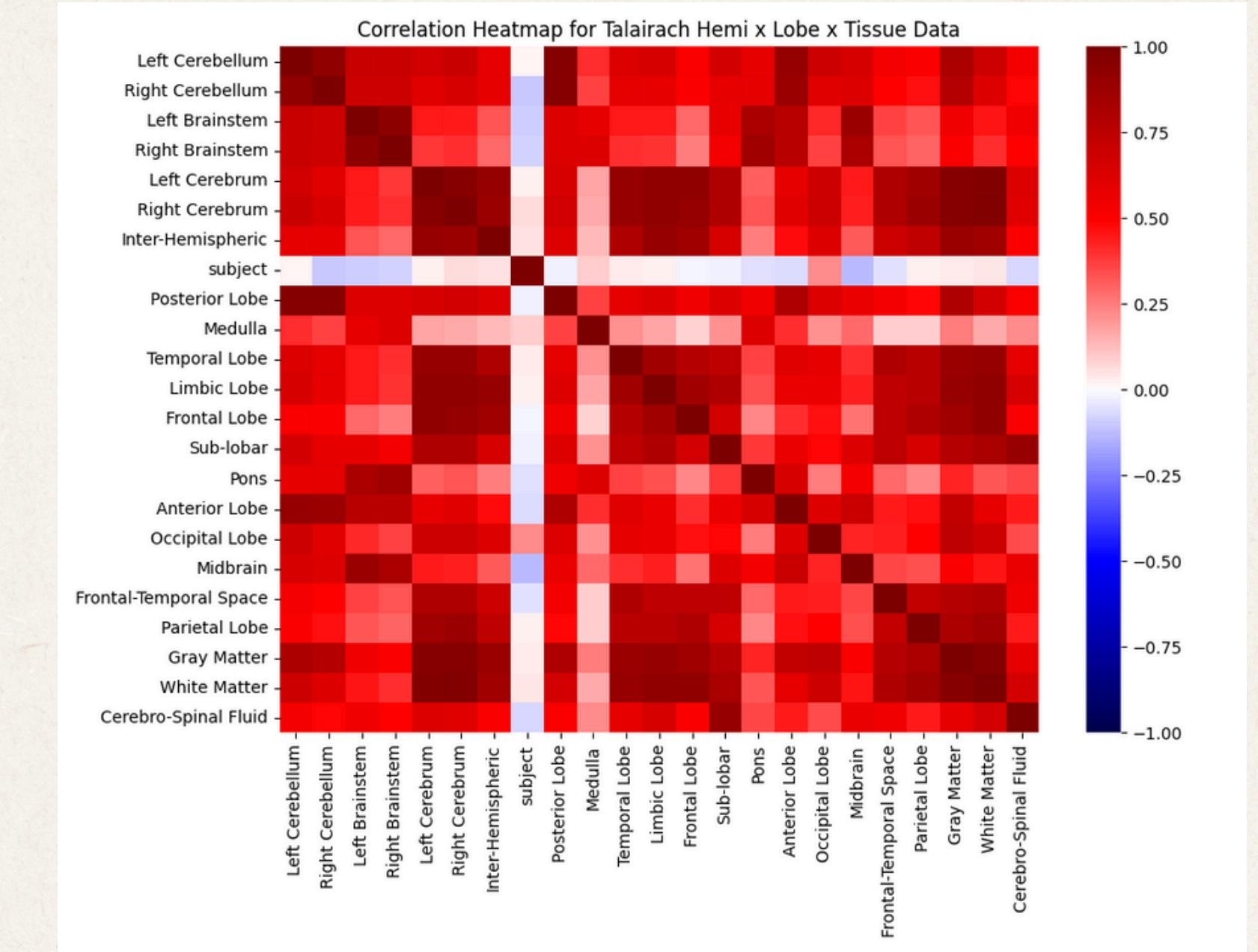
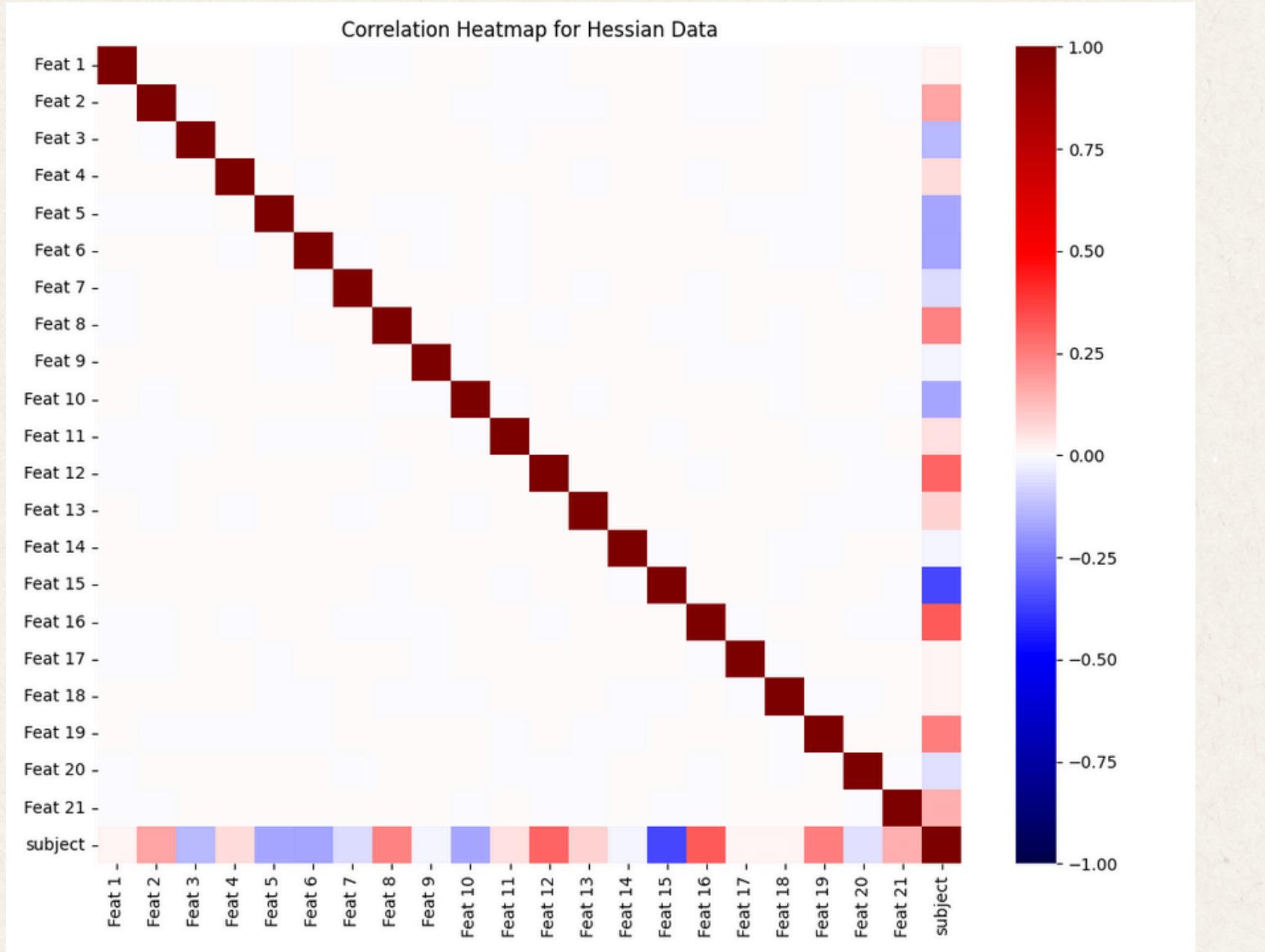
# Heterogeneity of Variance pt. 2



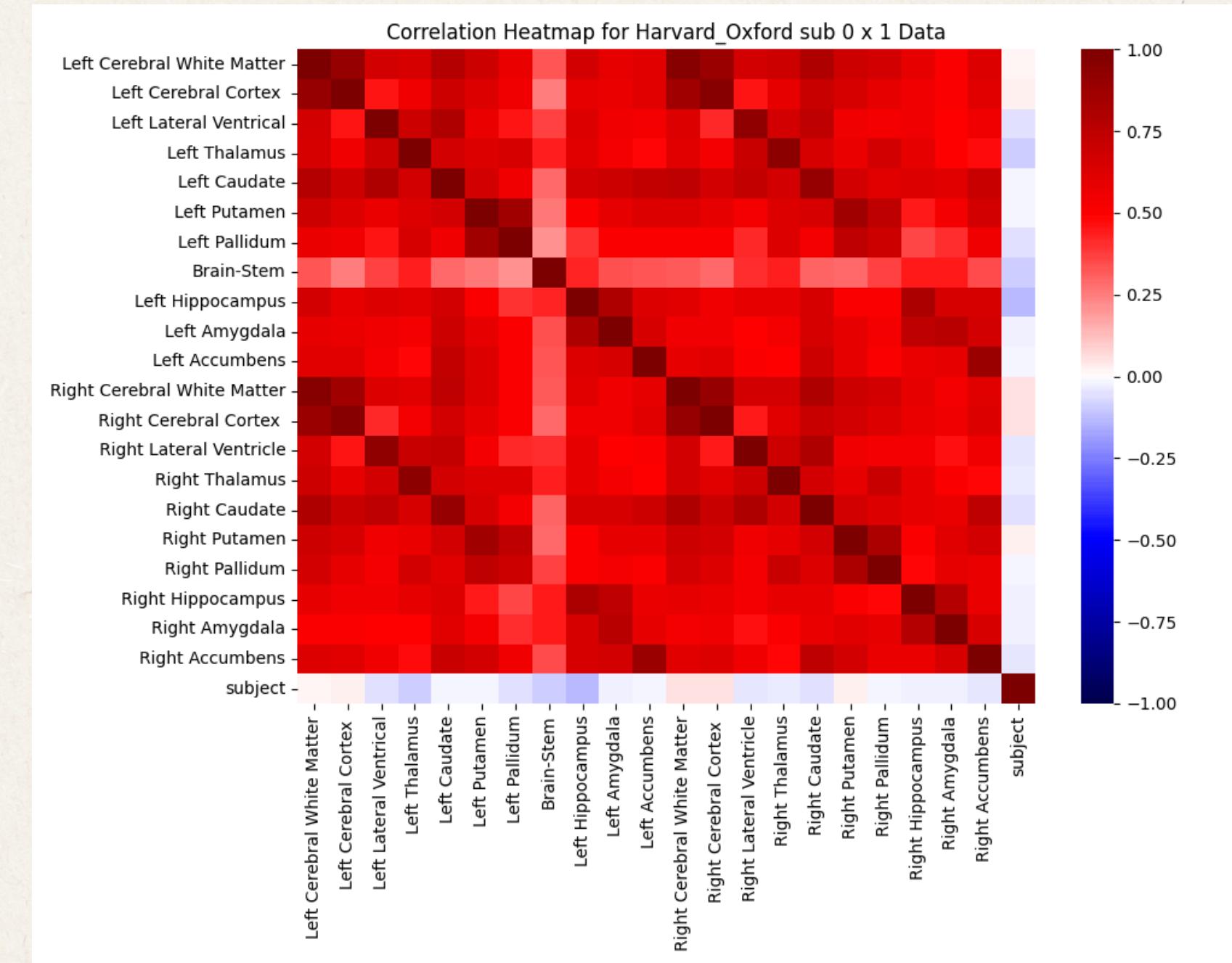
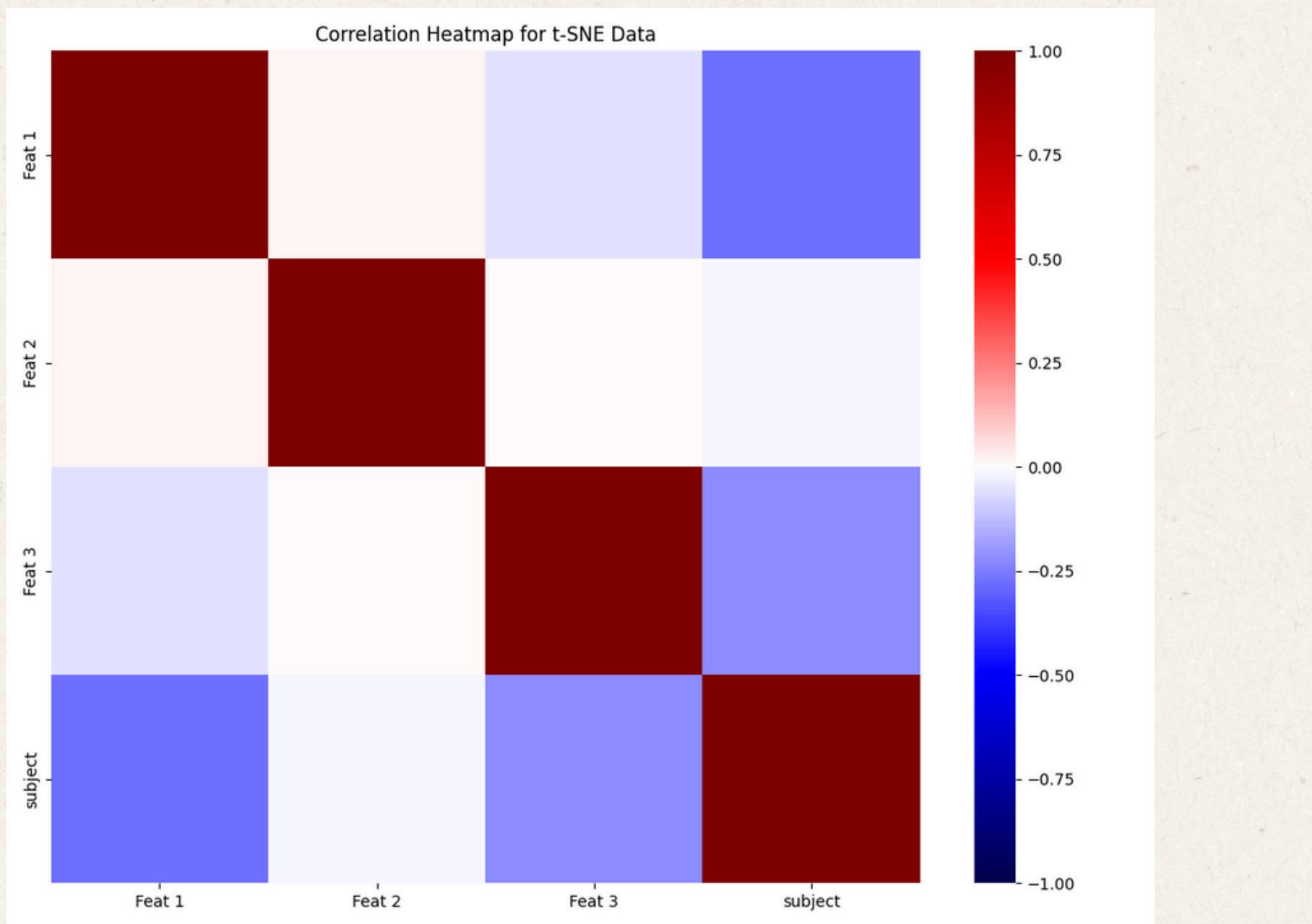
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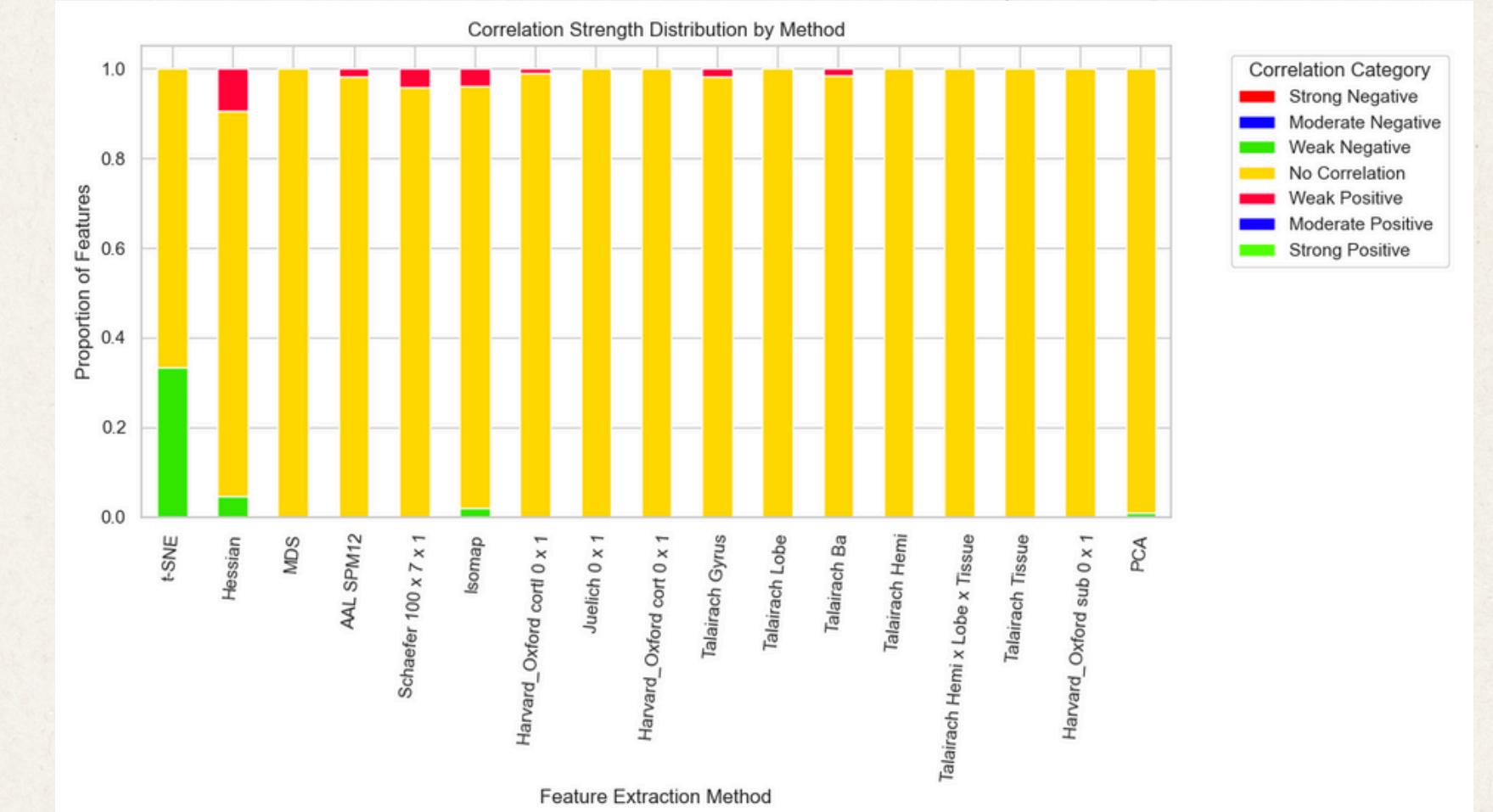
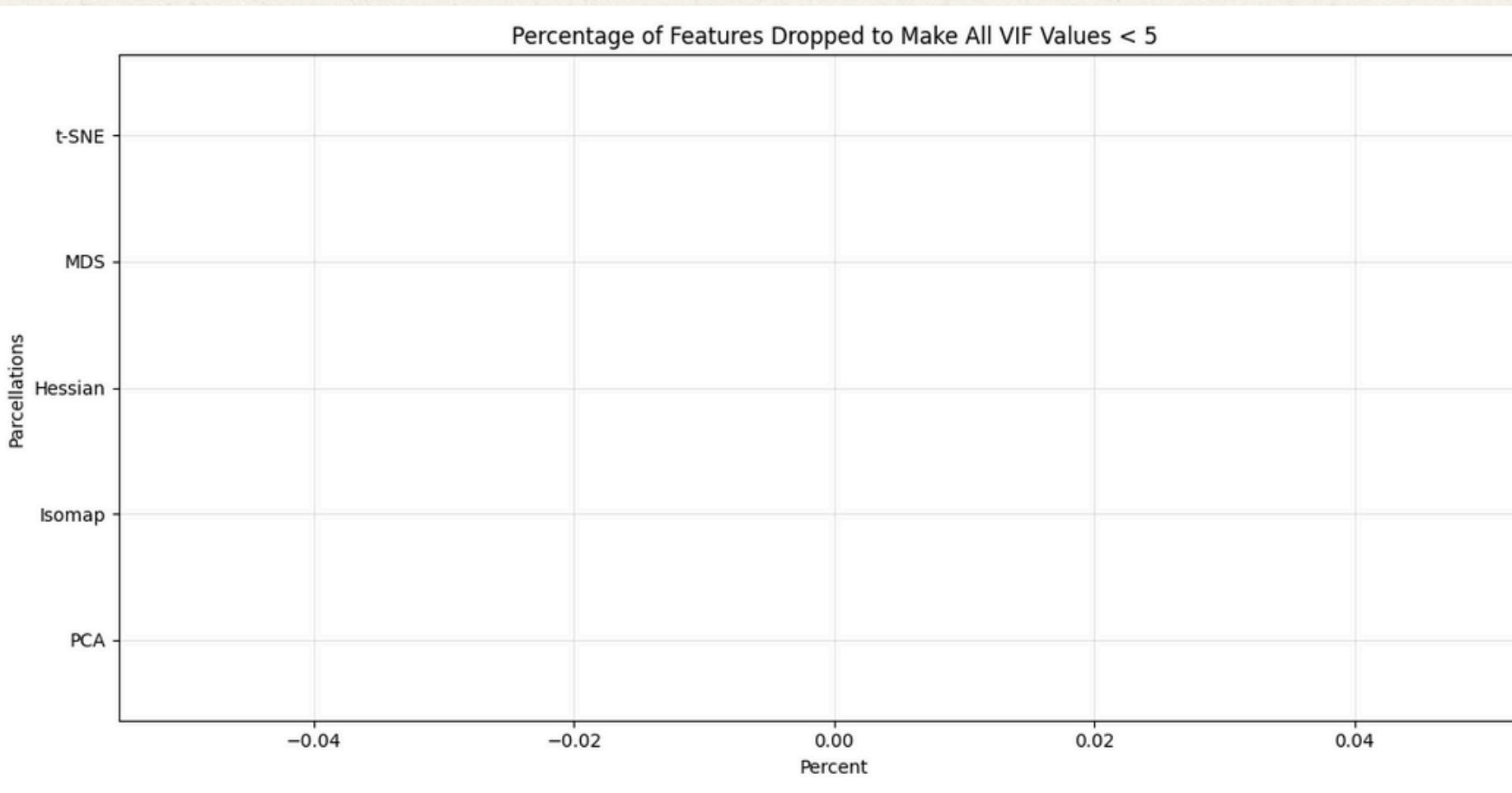
# Multicollinearity



# Multicollinearity



# Multicollinearity



# Thank you