Decoding and Classification of Category-Specific Visual Stimuli in the Fusiform Gyrus Using fMRI Data and Machine Learning

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Outline

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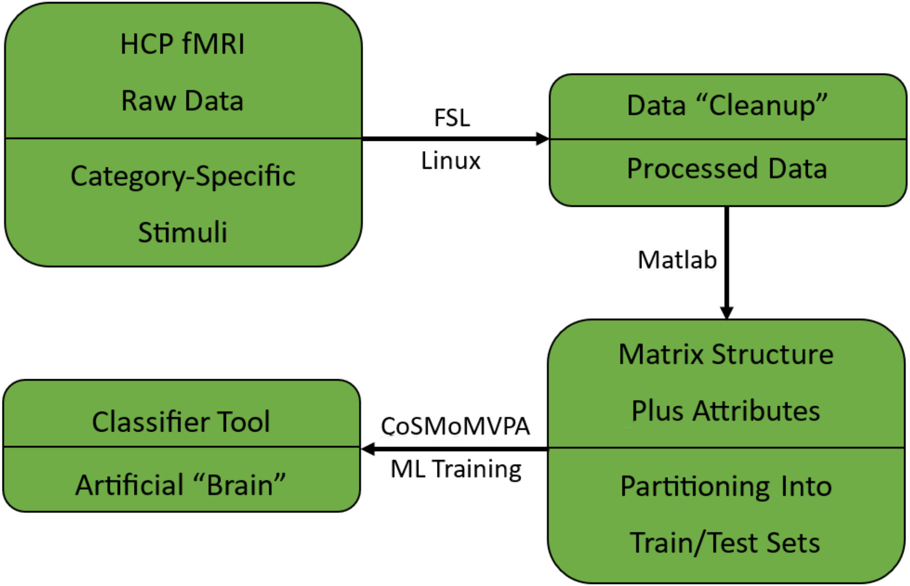
Compact Run-Through



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Decoding

- To connect neural patterns with specific human functions
- From brain activation to identifying object of perception
- Certain areas are linked to category-specific stimuli processing
- Assessment of baseline BOLD signal magnitude (*UPA*)
- Comparison of pattern distributions (*MVPA*)

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- Support Vector Machine algorithm to determine boundaries

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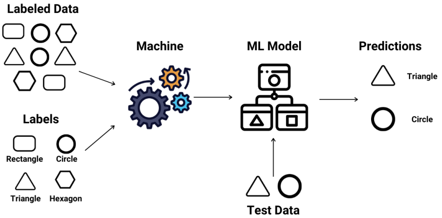

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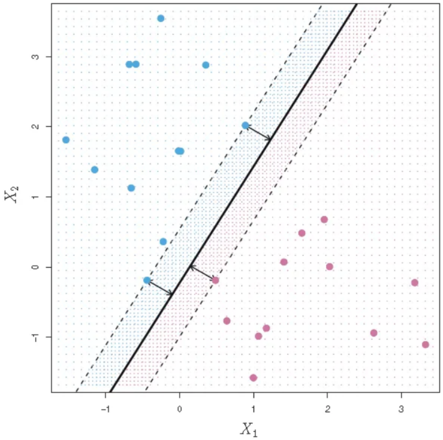
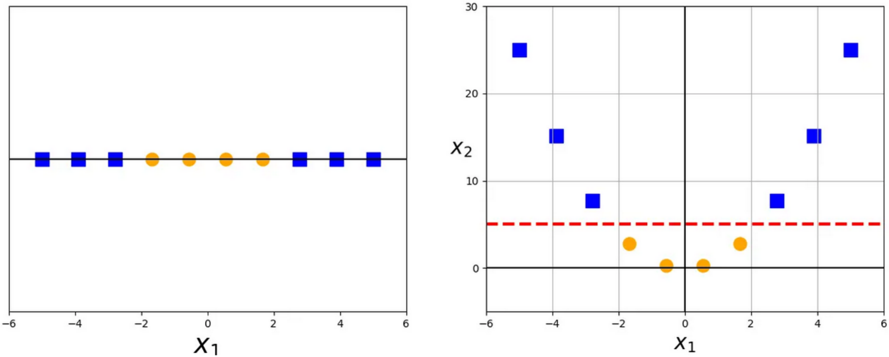


SVM - Linear Separation

SVM - Linear Separation - Kernel Trick



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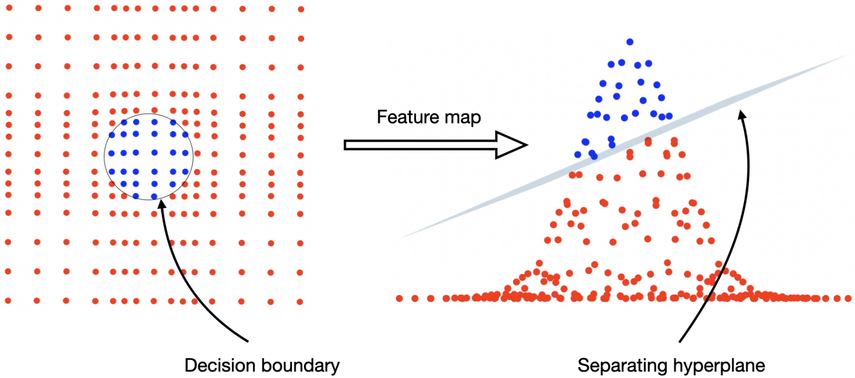
SVM - Non-Linear Separation - Kernel Trick



SVM - Non-Linear Separation - Kernel Trick

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The Fusiform Gyrus

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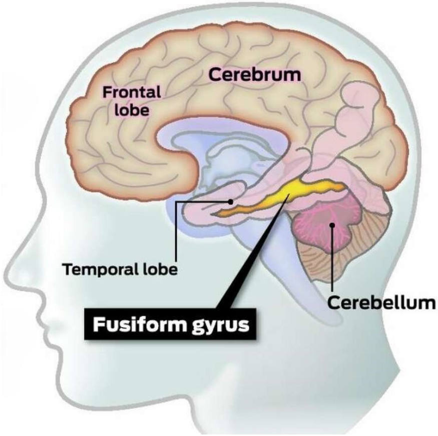
- Home to the Fusiform Face Area (*FFA*) and the Parahippocampal Place Area (*PPA*), partly
- Category selectivity is more localized and stronger, based on literature



The Fusiform Gyrus Location in the Human Brain (*Saggital Plane*)

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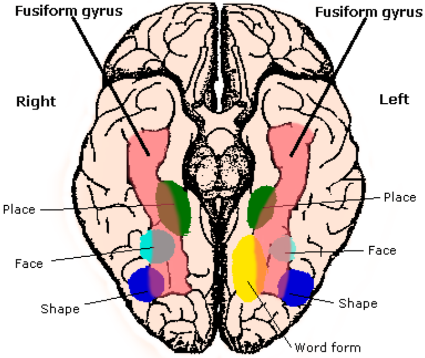

The Fusiform Gyrus Location in the Human Brain (*Horizontal Plane*)

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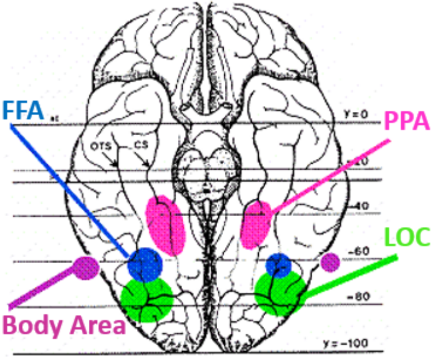

Category-Specific Stimulus Information Processing Centers

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Why fMRI?

- High spatial resolution (mm), ideal for studying localized functions
- Whole brain coverage, highlighting interaction among regions
- Measures BOLD signal, indirectly associated with neuronal activity
- Low temporal resolution, allowing the study of longer-term brain processes (s), but potential problem for quick responses

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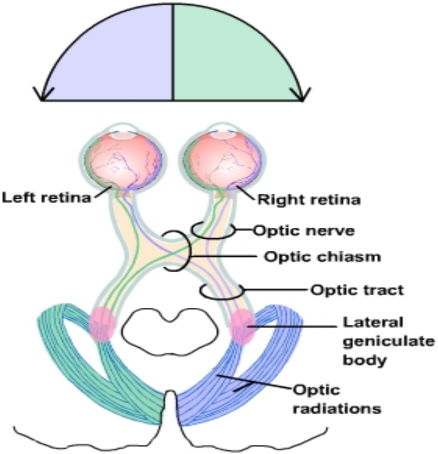
Visual Information Processing

- Visual information route from the eyes to the visual cortex
- Distinction based on motion
- Assigned to category-specific information processing centers



Visual Information Flow to V1

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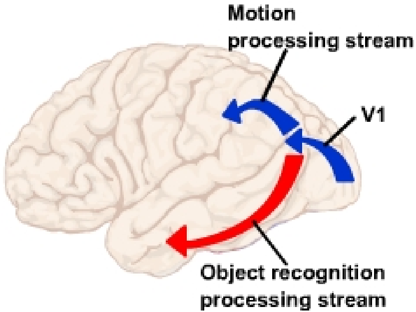

Ventral and Dorsal Information Streams

Visual Information Processing

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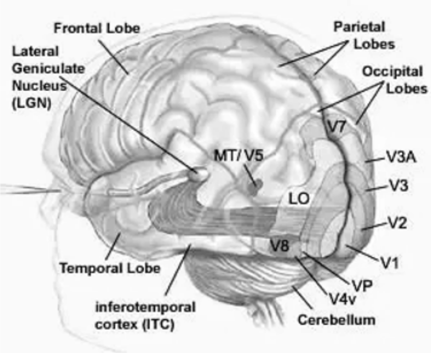
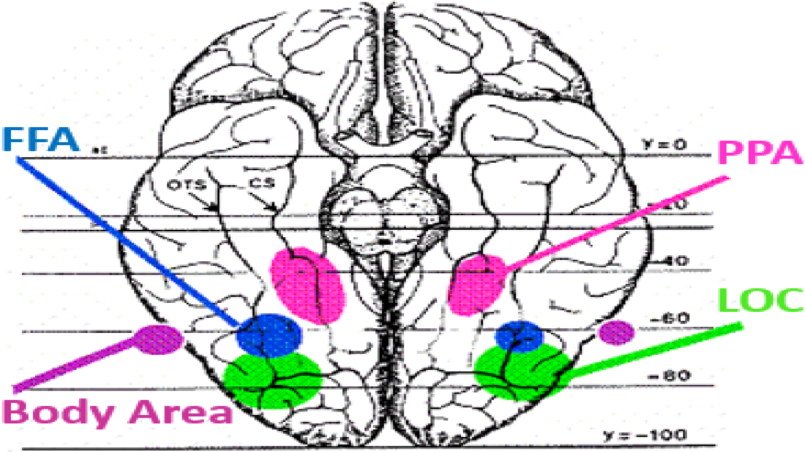


Brain Region Specialization Regarding Visual Information Processing

Category-Specific Information Processing Centers

- Fusiform Face Area - Occipital Face Area
  Parahippocampal Place Area - Latteral Occipital Cortex
  Extrastriate Body Area - Fusiform Body Area



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NMR Signal

- Scanner generates a powerful magnetic field $\vec{B}_0$
- Magnetic moments of nonzero spin nuclei (protons - water) weakly align with $\vec{B}_0$, creating a net macroscopic magnetization $\vec{M}_0$
- Coil transmits RF transverse magnetic field pulse at resonant frequency tipping $\vec{M}_0$ from alignment
- $\vec{M}_0$ precesses around $\vec{B}_0$ to return to equilibrium
- Rotating M_{xy} component generates oscillating magnetic field inducing current, producing signal

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T1 Relaxation

- The process by which the z component of the net magnetization M returns to its initial maximum value M_0 parallel to B_0

- Measured T1, modified by blood inflow relocating spins in-and-out of the imaging plane, is termed T1*

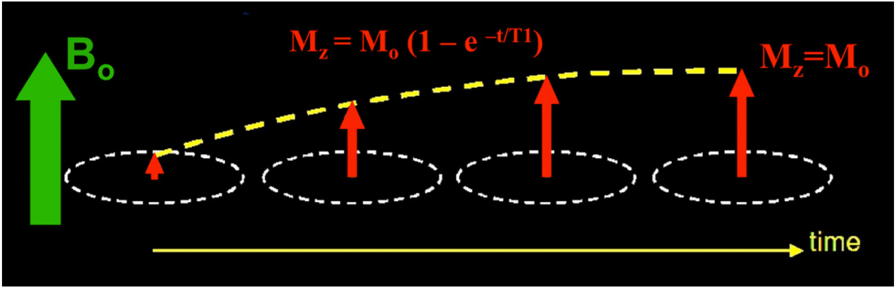

Illustration of T1 Relaxation

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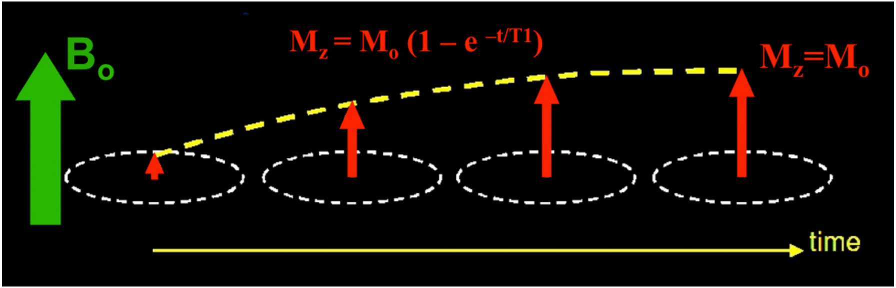
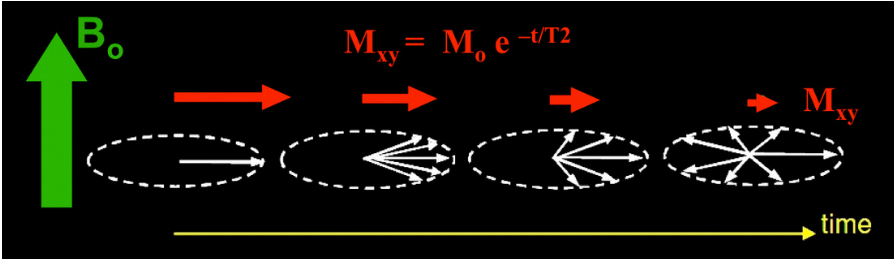


Illustration of T1 Relaxation

T2 Relaxation

- T2 is the time constant for dephasing of trasverse magnerization M_{xy}

- Following an RF pulse spin distribution is conserved, from the z axis to phase coherence in the xy plane, leading to precession of spins at the Larmor frequency



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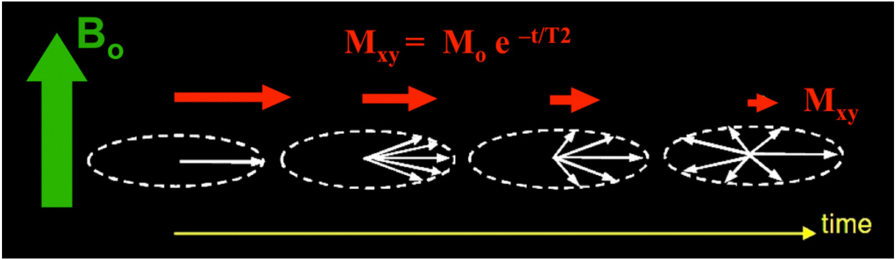
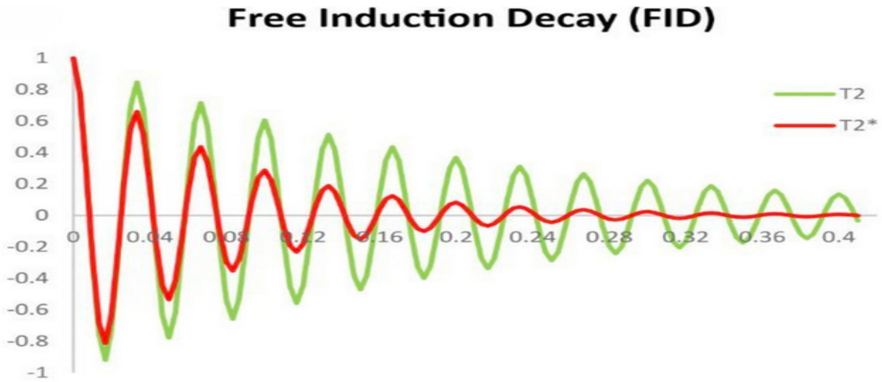


Illustration of T2 Relaxation

T2* Relaxation



- "Effective" T2* is much shorter than "natural" T2 due to inhomogeneities in the main magnetic field

BOLD Signal

- Blood Oxygen-Level Dependent Signal
- Detects changes in HbR driven by localized changed in blood flow and blood oxygenation
- HbR is paramagnetic, making it a naturally occurring contrast agent
- Neural activity reduces the OEF which increases MR signal locally

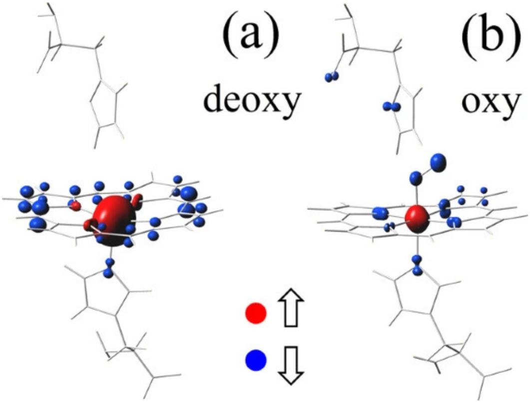


Illustration of Oxyhemoglobin and Deoxyhemoglobin Magnetic Moment Density

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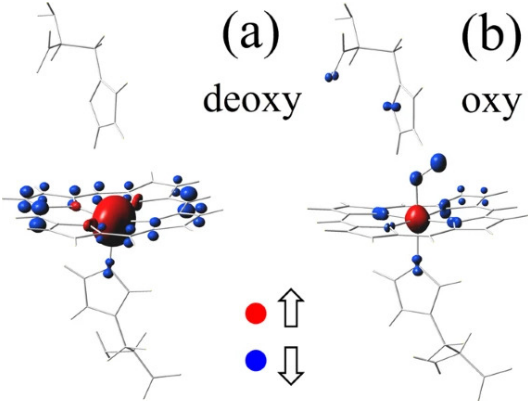

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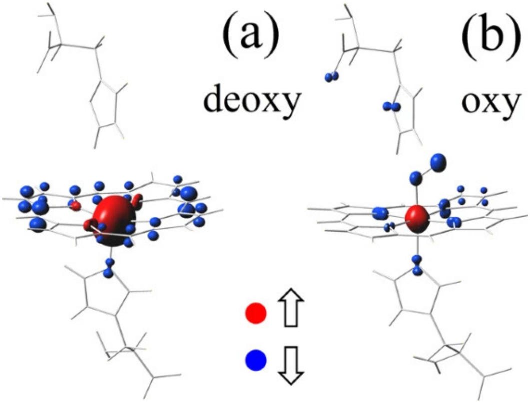

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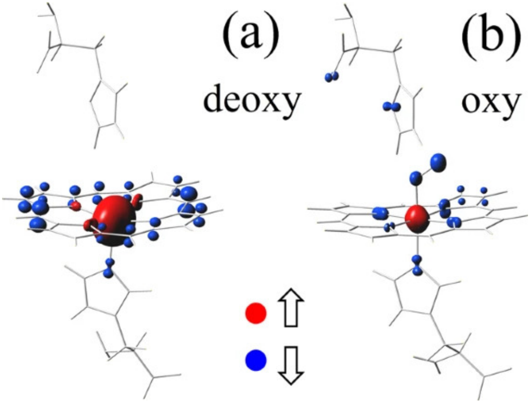

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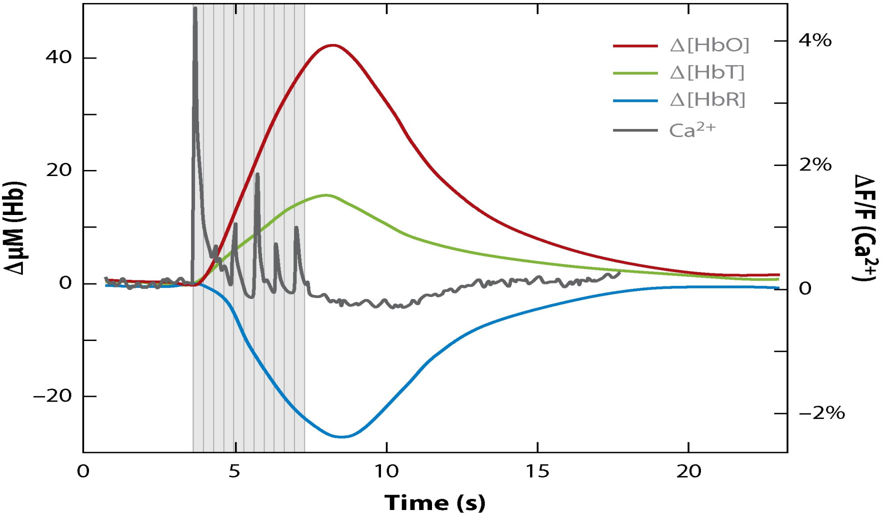
BOLD Response



Stimulus-Evoked Response in Somatosensory Cortex of Rats

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The Human Connectome Project (*HCP*)

- Five-year effort to characterize brain connectivity, function and their variability in healthy adults
- Multiple imaging modalities: dMRI, r-fMRI, t-fMRI, T1w and T2w MRI, MEG, and EEG
- 1200 subjects, 300 sibships mostly including a mono- or di-zygotic twin pair

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Task-fMRI Battery of the HCP

Neural systems targeted by the tests:

- Visual and Somatosensory-Motor Systems
- **Category-Specific Representation**
- Language Function (semantic and phonological processing)
- Attention Systems
- **Working Memory/Cognitive Control System**
- Emotion Processing
- Decision-Making/Reward Processing
- Episodic Memory Systems

Working Memory Task

- Subjects presented with blocks of trials that consisted of pictures of places, tools, faces, and body parts
- N-Back paradigm was utilized
- Every 2 blocks separated by a fixation period
- 8 blocks per run, 2 runs per subject

Segment Type	Duration (s)	N-Back Paradigm	Target Category
Setup	10	-	-
Cue	2.5	-	-
Task	25	2-Back	Body
Cue	2.5	-	-
Task	25	0-Back	Face
Fixation	15	-	-
Cue	2.5	-	-
Task	25	2-Back	Tools
Cue	2.5	-	-
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The Hemodynamic Response Function

- Impulse stimulus produces acute hemodynamic response function (*HRF*)
- Lasting stimulus produces boxcar HRF
- HRF shape can be modelled with a Gamma Distribution

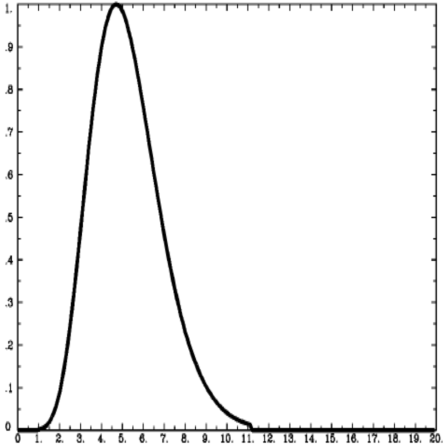

Illustration of Acute HRF.

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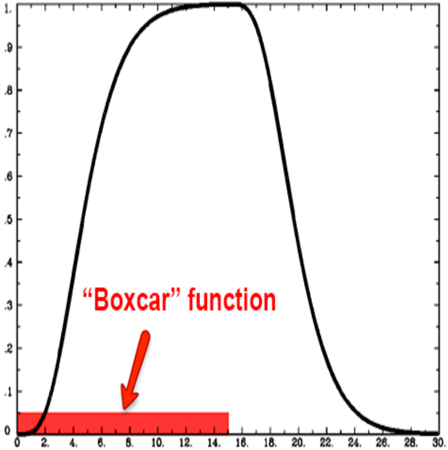

Illustration of Boxcar HRF.

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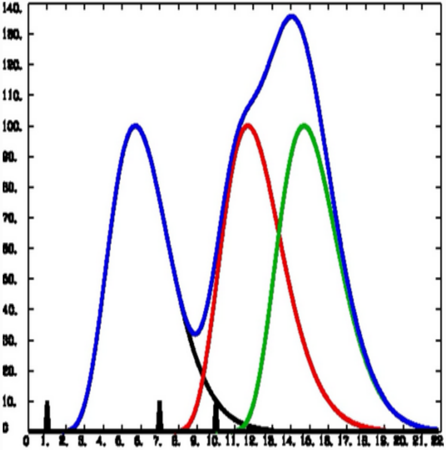

HRF Overlap and Fitting.

Analysis Process Overview

- General Linear Model fitting to the BOLD signal time-series
- Original explanatory variables (*EV*) defined by the experiment
- Beta-weights corresponding to each EV
- Contrast of parameter estimates (*COPE*) selected by researcher

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

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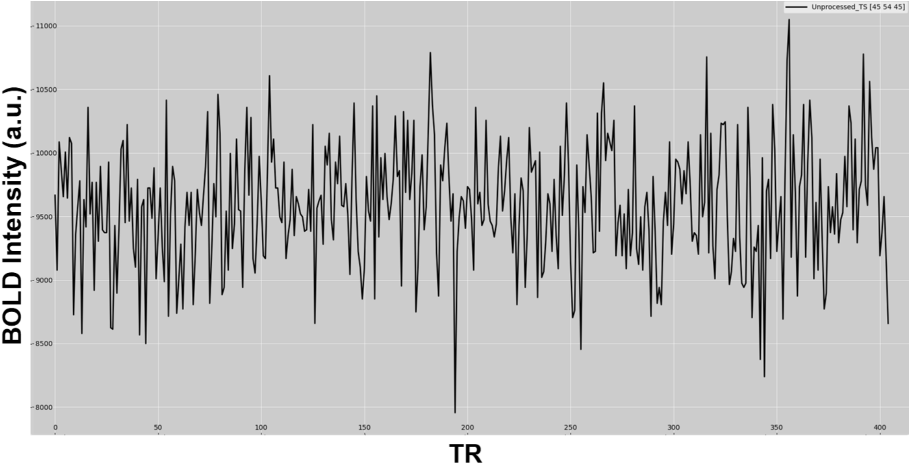
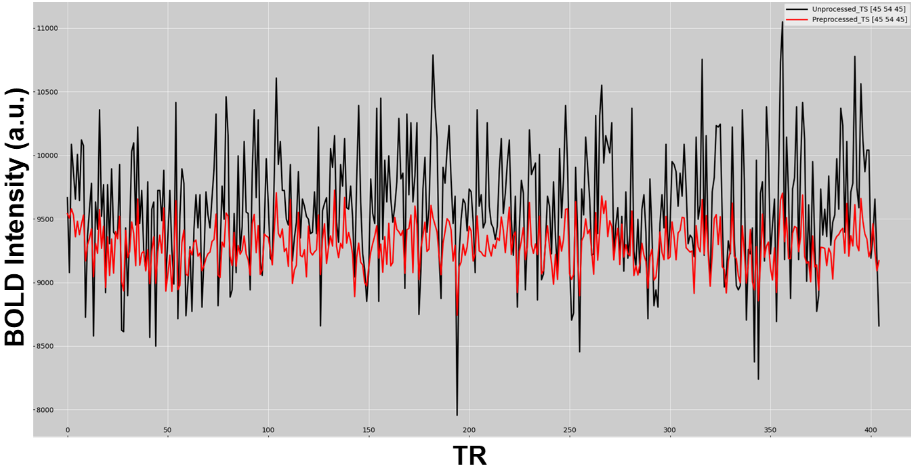


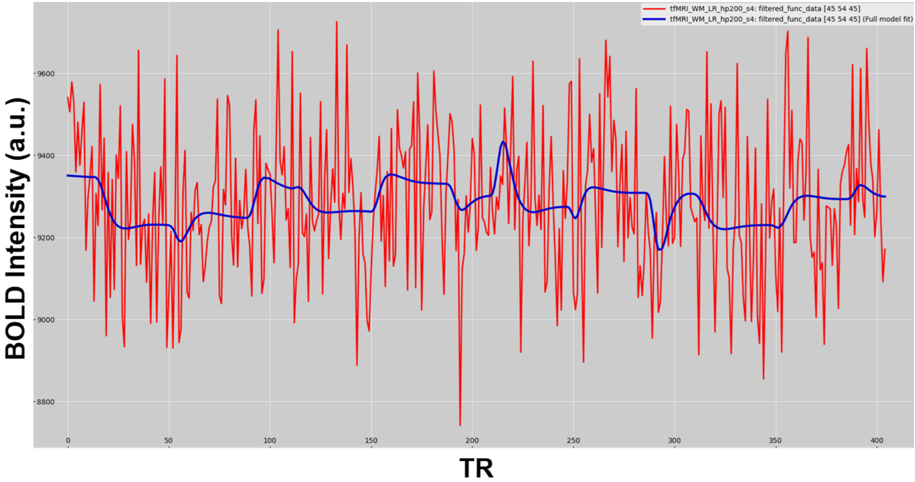
Preprocessed BOLD Time-Series.

- Unprocessed Versus Preprocessed BOLD Time-Series



Fitted BOLD Time-Series.

- Preprocessed Versus Fitted BOLD Time-Series



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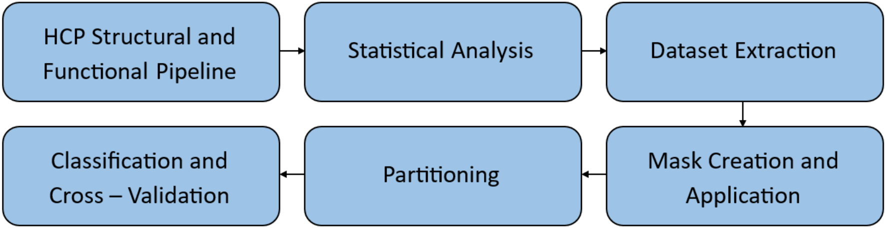
Pipeline Overview

- Starting point is HCP preprocessed data
- Smoothing changed to 4mm
- Singal-to-noise ratio increase, registrastion to MNI-152, enables statistical comparisons

- Two analyses conducted (20s)
- N-Back combination, 4 copes/run, 2 chunks/subject (2C), 160 patterns total
- N-Back distinction, 8 copes/run, 4 chunks/subject (4C), 320 patterns total



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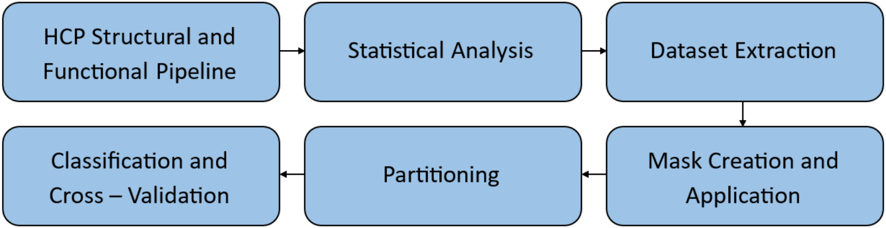

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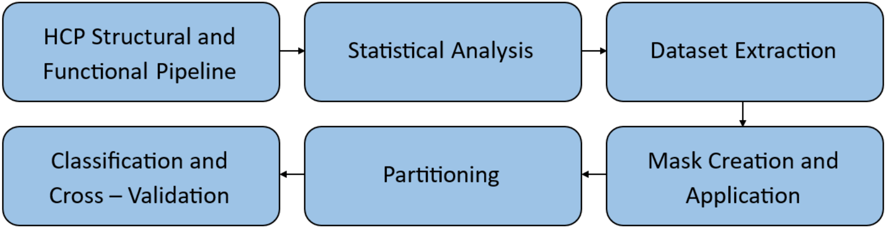

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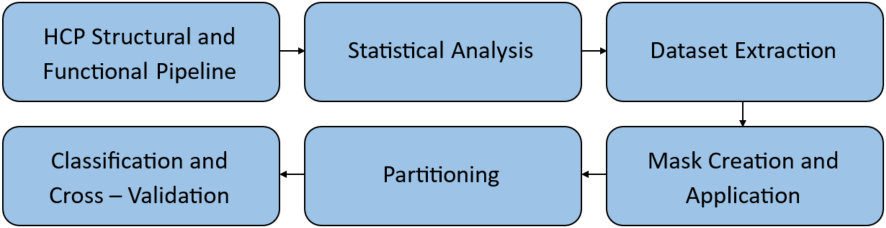

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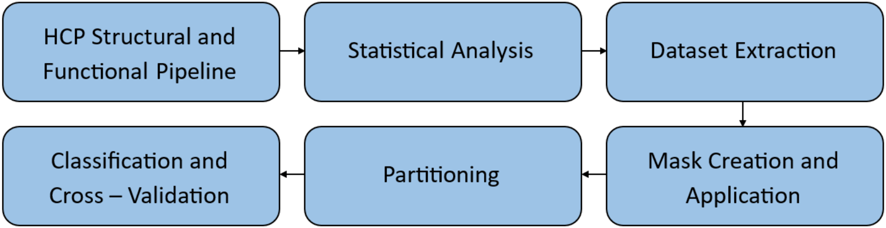

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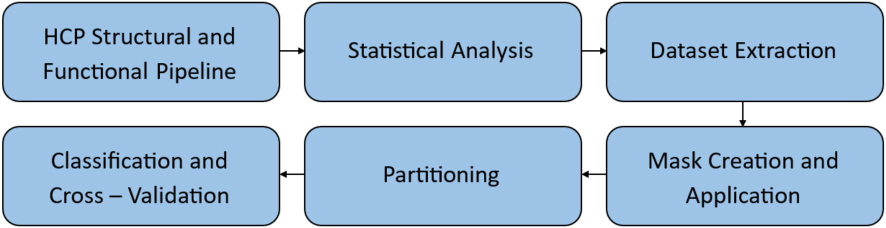
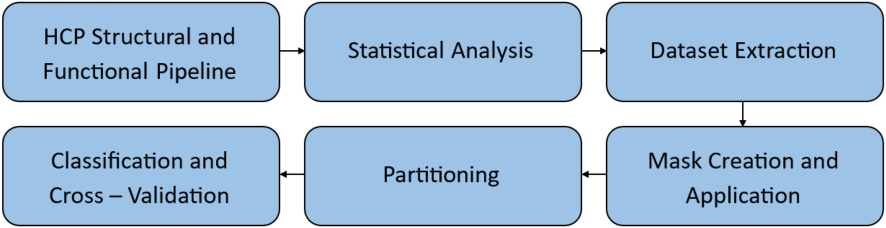


Extraction and Masks

- From separate copes across different runs of various subjects into one dataset structure
- Samples by Features matrix with attributes, targets, labels, chunks (**320 X 900k**)
- Two masks created for FFA and PPA with 12 voxel radius
- Application of masks, focus on specific region, data is manageable (**320 X 1k**)



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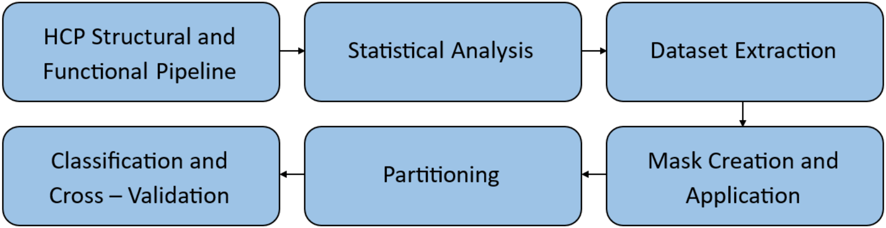

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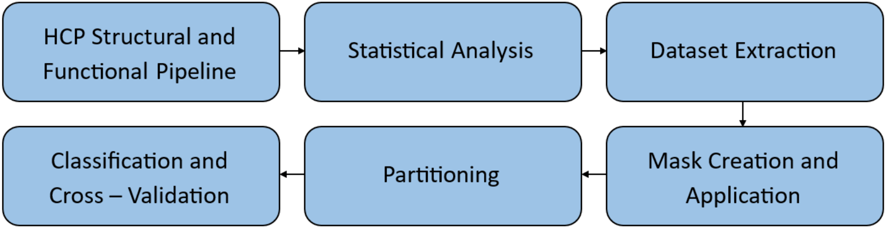

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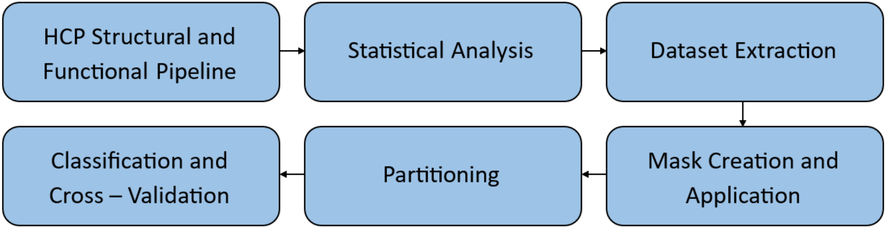
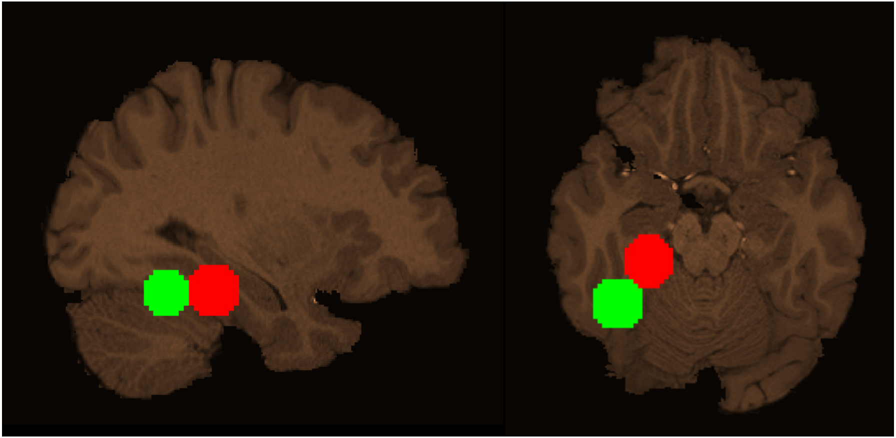


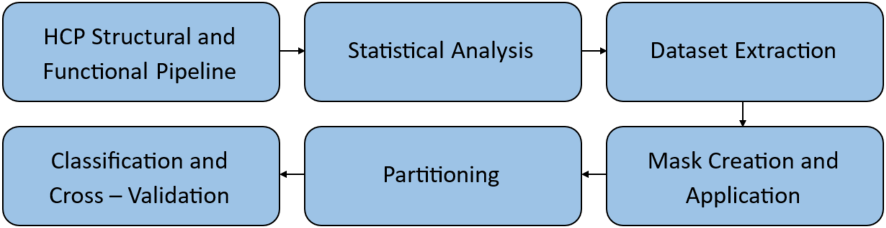
Illustration of Masks



FSL Snapshots of FFA (green) and PPA (red) Masks at Maximum Overlap in the Saggital and Horizontal Planes

Partitioning, Classification and Cross-Validation

- Partition data into folds, based on chunks
- Each fold contains independent train and test sets (80/20)
- SVM classification
- Predict test set targets/labels
- Repeat across multiple folds (cross-validate)



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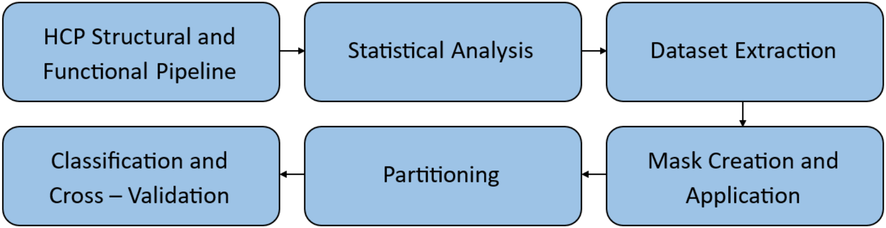

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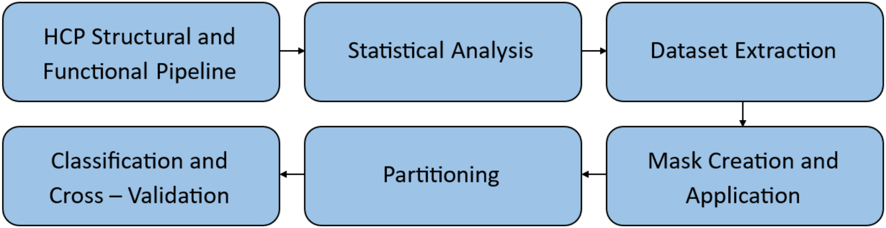

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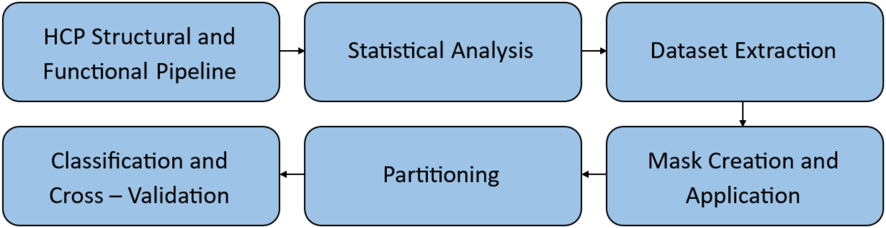

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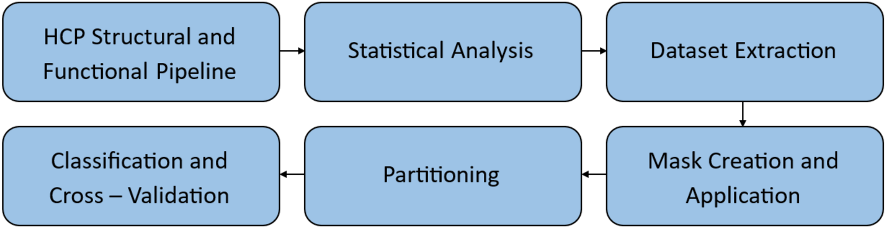

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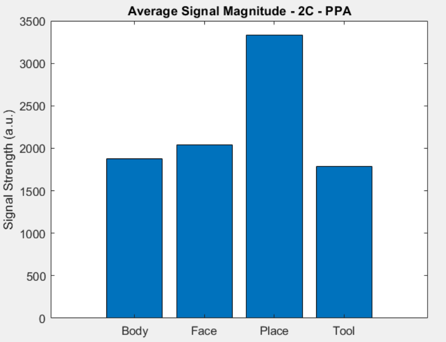
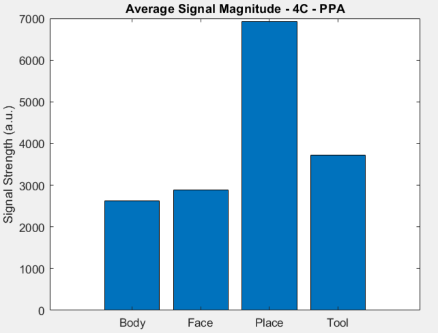
Category-Secific BOLD Signal (*UPA*) - PPA





- Average magnitude of brain activation in the PPA across different stimulus categories in the 2C and 4C analyses
- UPA based on COPE values - Statistical value of BOLD over time and voxels
- Baseline signal for the region's specificity stands out, with higher magnitude

Classifier Performance Variables

- Classification accuracy was treated as a function of three variables:
- Chunks Per Subject
- Fold Count
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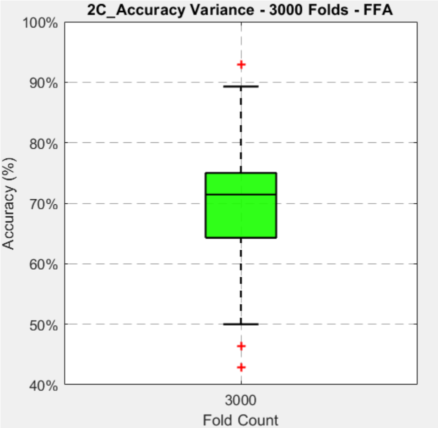
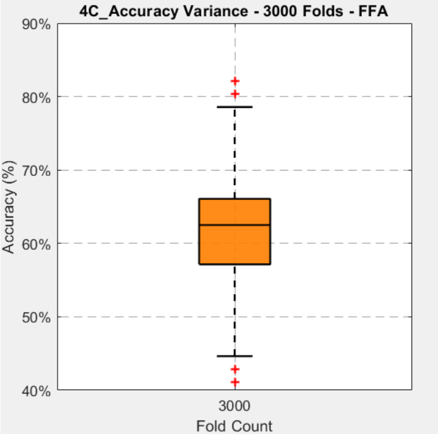
MVPA - FFA - 3000 Folds Analysis

- Mean: 70% σ: 8.4%
  Median: 71.4%

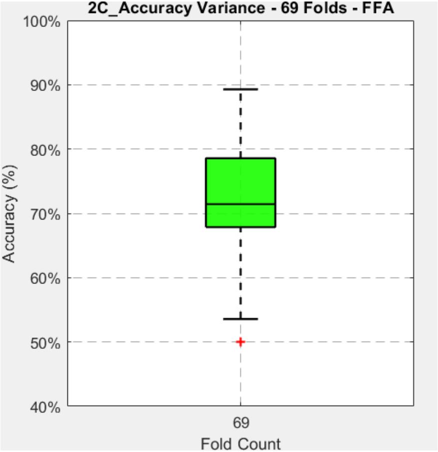
- Mean: 61.9% σ: 6.3%
  Median: 62.5%



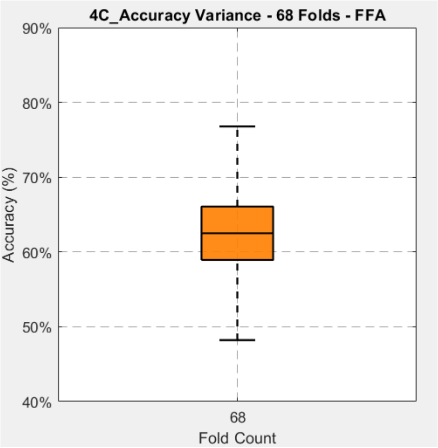


MVPA - FFA - Practical Fold Count

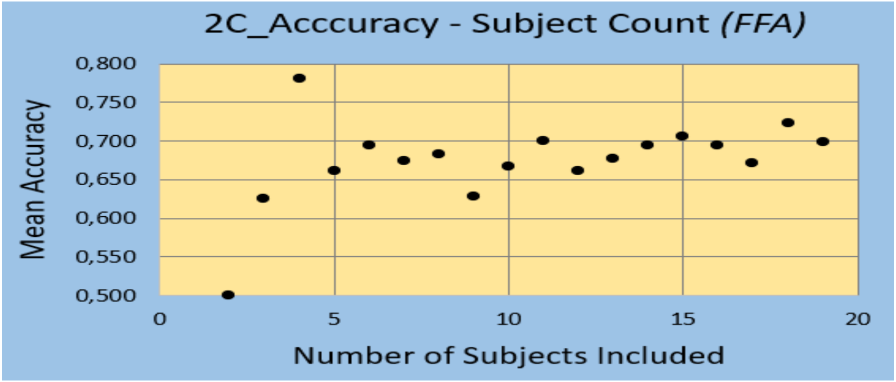
- Mean: 72.3% σ: 8.0%
  Median: 71.4%



- Mean: 62.2% σ: 6.0%
  Median: 62.5%



MVPA - FFA - 2C Subject Count



- Surprisingly accurate at 2 subjects only (50%)
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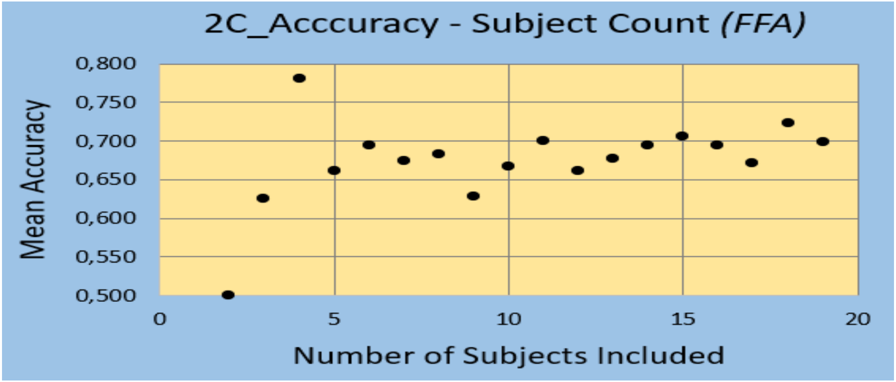

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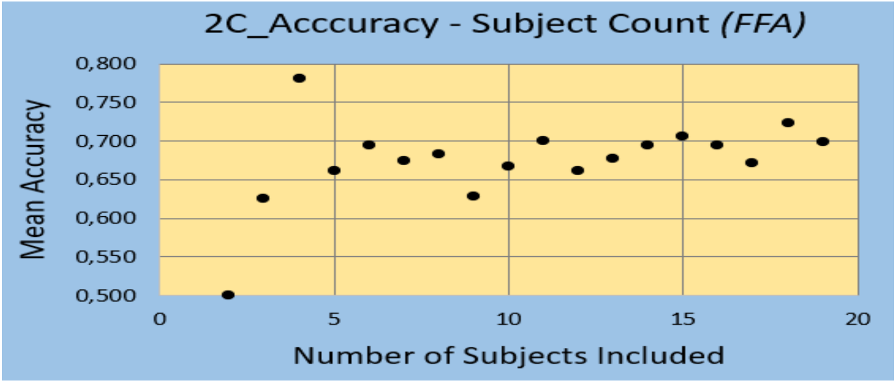

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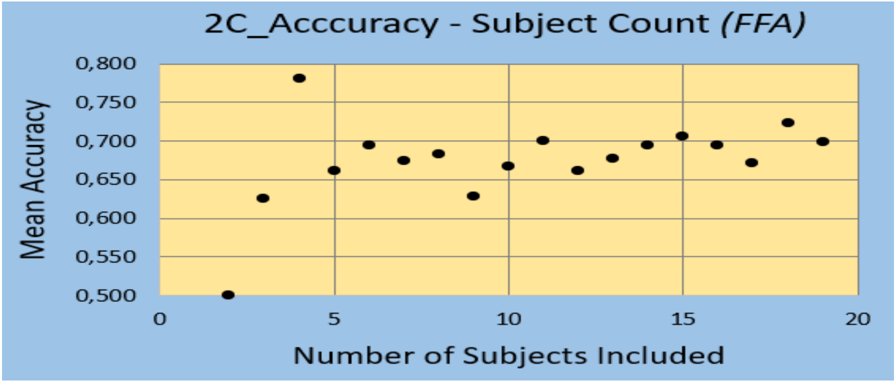

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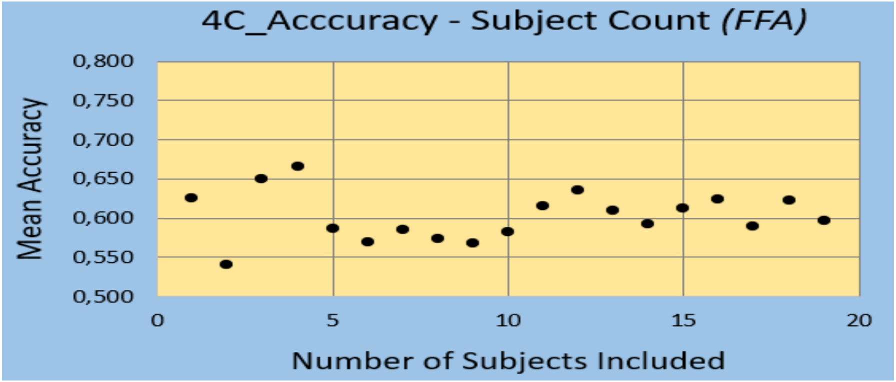

- Similar overperformance before 5 subjects
- Stabilizes around 57% initially at 5 subjects
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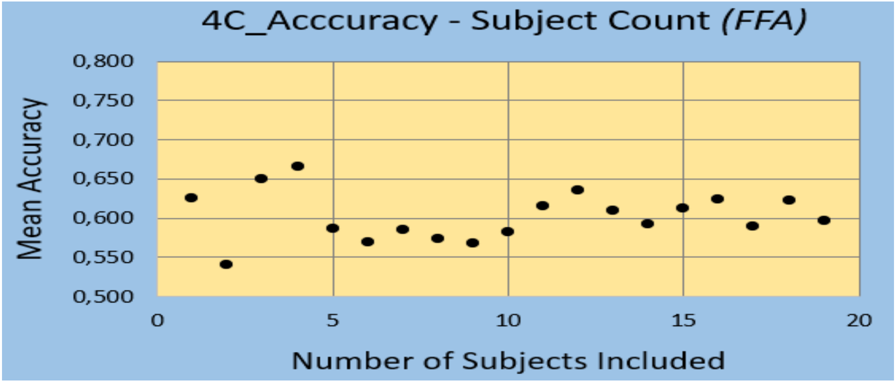

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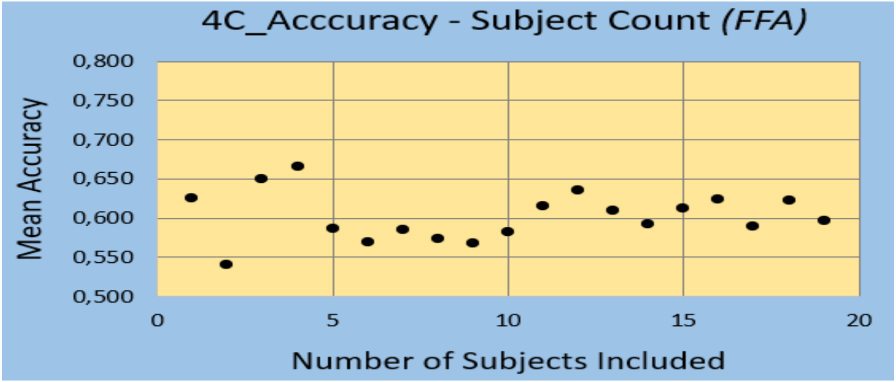

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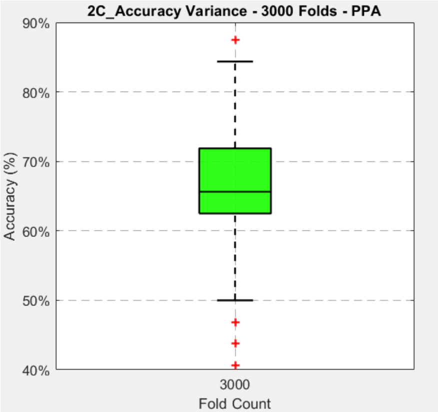
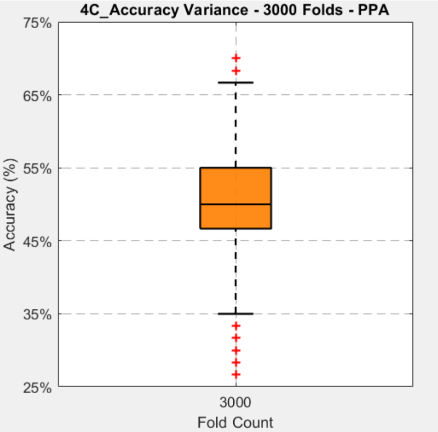
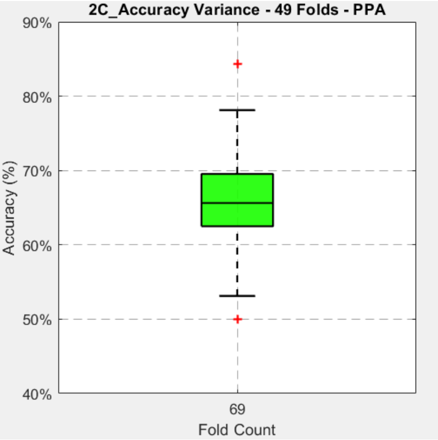


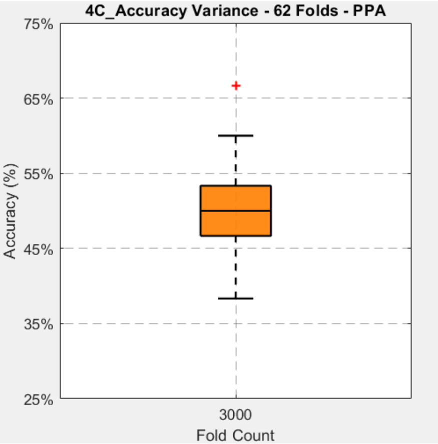


MVPA - PPA - Practical Fold Count

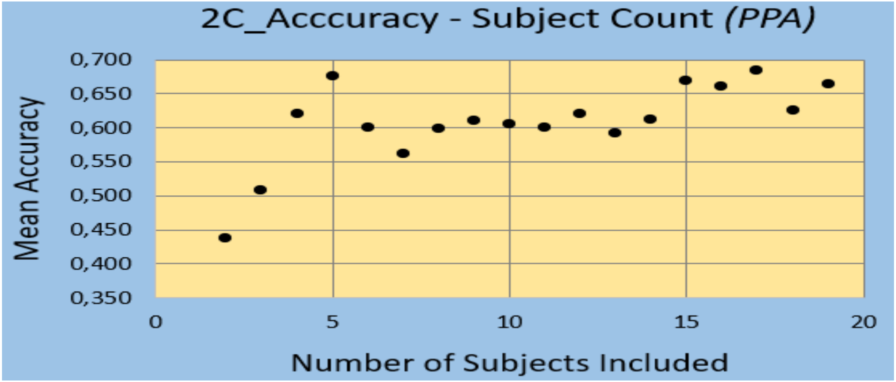
- Mean: 66.4% σ: 7.0%
  Median: 65.6%



- Mean: 50.1% σ: 5.7%
  Median: 50.0%

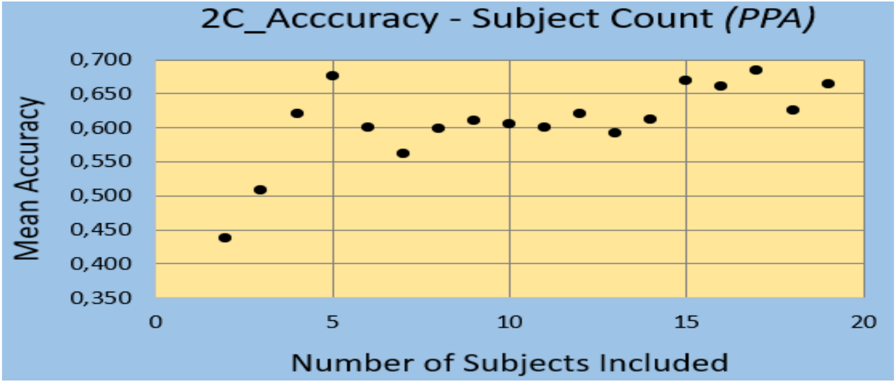


MVPA - PPA - 2C Subject Count



- Rapid linear increase until 5 subjects
- Overperformance at 5 (67.5%), cannot be generalized
- Consistency over 5 subjects around 60%
- Approaches optimal accuracy at 15 subjects (66.8% - 66.4%)

MVPA - PPA - 2C Subject Count



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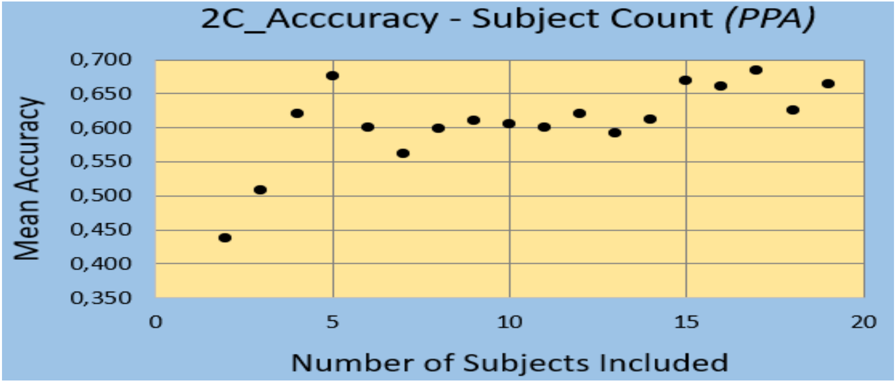

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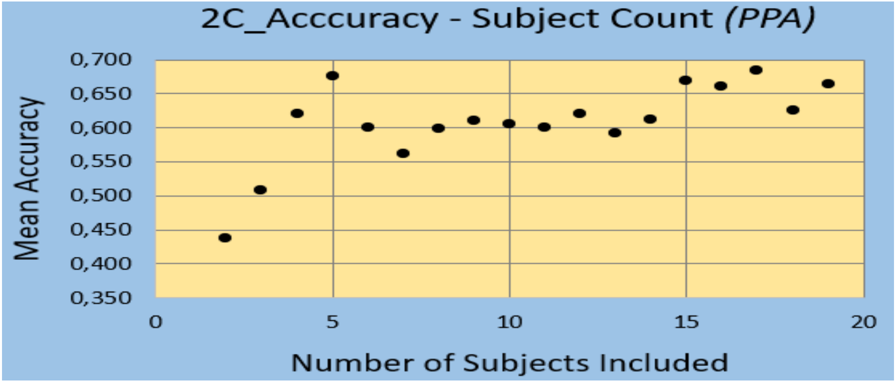

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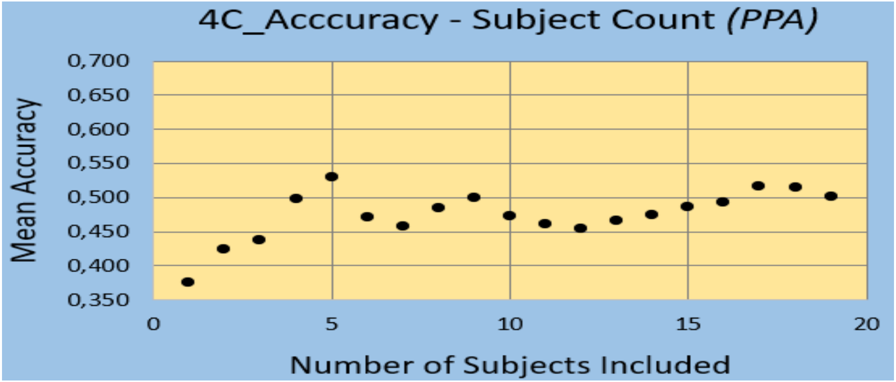
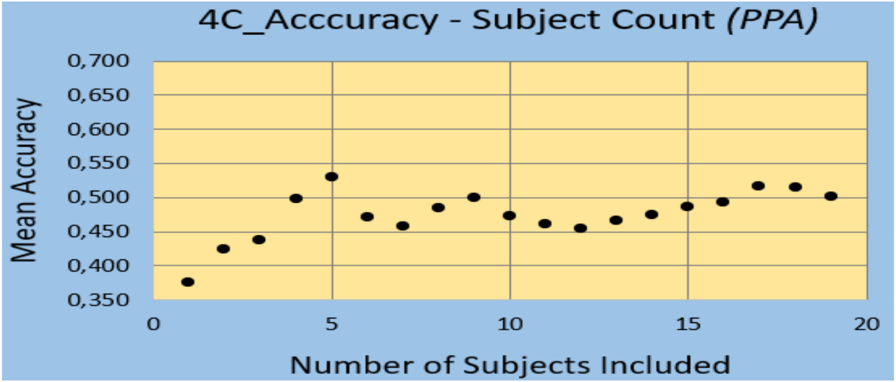
MVPA - PPA - 4C Subject Count



- Similar pattern showing even more stability
- Linear increase into irregularity at 5
- Oscillation around optimal accuracy (50.1%)

MVPA - PPA - 4C Subject Count



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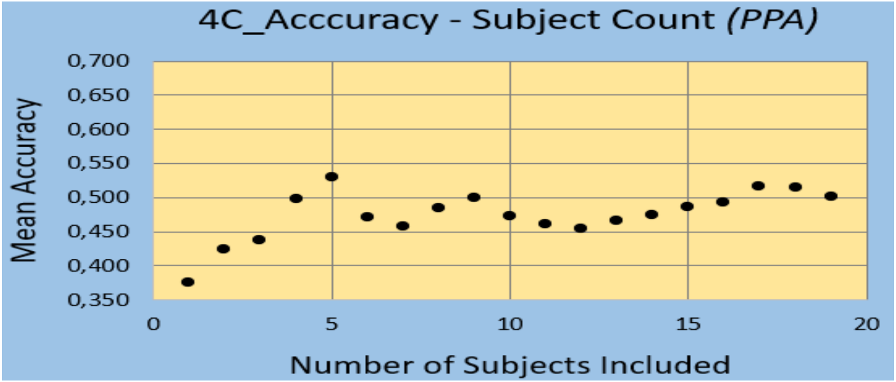

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- Automated data extraction and consolidation
- Linked base signal to performance
- Significance of reasearcher's choice of data interpretation proven
- Provided framework for tool's optimal performance, efficiency, practicality

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- Cross-model decoding
- Utilization of more specialized data
- Expansion to other brain regions, not only visual
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License

Everything can be found on the **GitHub** repository:
https://github.com/kasapakis-nk/BSc_Thesis_MVPA_Decoding_Classification

Thank You!

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nkasapak@auth.gr

https://github.com/kasapakis-nk