Neuroimaging data from multiple sources in PRoNTo v3.0: spatiotemporal patterns of face processing

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Introduction

- Different brain regions and time-windows have been implicated in face processing [1]. Here we investigated the spatiotemporal nature of face processing using multimodal machine learning modelling implemented in the third version of the "Pattern Recognition for Neuroimaging Toolbox" (PRoNTo v3.0) [2].
- Data from different imaging techniques with both high spatial (fMRI) and temporal (EEG and MEG) resolution were combined in the models.
- Multiple Kernel Learning (MKL) classification models [3] were used to learn the contribution of the different brain regions and time windows to discriminate between faces (famous or unfamiliar) vs. non-faces stimuli, providing information about the overall spatiotemporal pattern involved in face processing.

Methods

Dataset: publicly available multimodal dataset [4] containing EEG, MEG and fMRI neuroimaging data from 16 healthy participants (7 women, mean age = 26.37 years).

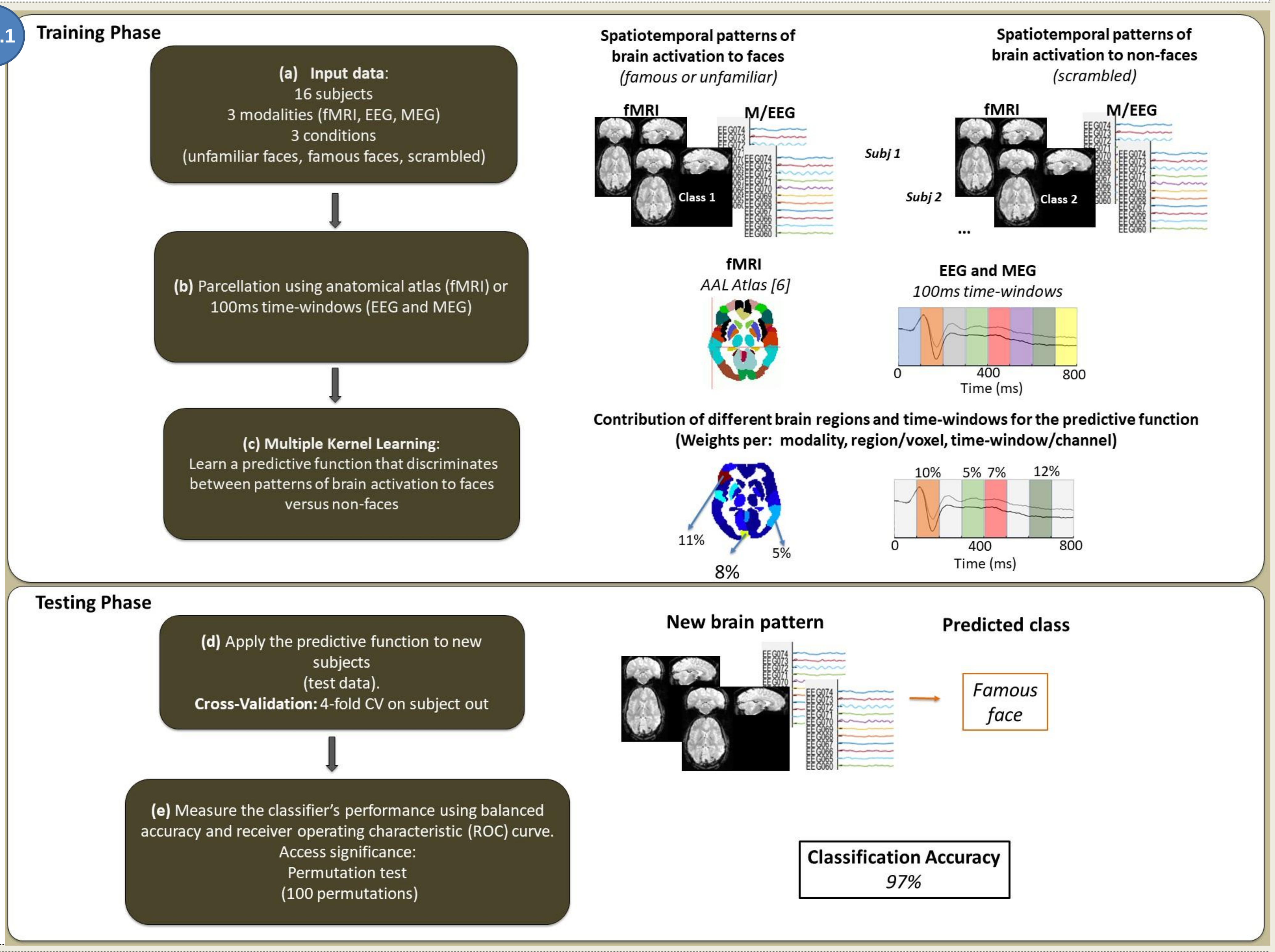
Task: perceptual task with images of famous and unfamiliar faces, and scrambled stimuli [4].

Pre-processing. Data were pre-processed using SPM12 software as in Henson et al. [5]

Models: two MKL models were implemented in PRoNTo v3.0 [2]. **Model 1** was trained to discriminate between spatiotemporal patterns of brain activation to *unfamiliar* faces *vs.* *scrambled* stimuli and **Model 2** to discriminate between spatiotemporal patterns of brain activation to *famous* faces *vs.* *scrambled* stimuli.

Fig.1 **Multiple Kernel Learning (MKL) Framework in PRoNTo v3.0.**

(a) Input data: fMRI beta images, M/EEG traces and the corresponding label of their experimental conditions **(b) Segmentation of the beta images and the EEG/MEG traces** based on spatial or temporal coordinates. **(c) MKL training:** the MKL model simultaneously learns: (1) the contribution of each region (kernel/regions weights for fMRI) and of each each time-window (kernel/time-windows weights for EEG and MEEG). (2) the contribution of each feature within each the region or time window (voxels weights for fMRI and weights for time points across channels for EEG and MEEG). The contribution of each modality is computed adding all kernel weights for the specific modality. All kernels were normalized and mean centered. **(d) MKL test:** given the fMRI beta images and EEG/MEG traces of a test subject, the MKL model predicts its corresponding experimental condition. **(e) Model performance:** the classification performance is evaluated using accuracy and ROC curve.



Results

MKL classification model 1: unfamiliar faces versus scrambled

Balance accuracy: 81.25% (p = 0.001); ROC/AUC: 0.89

Fig.2 fMRI Total weight: 27.4%

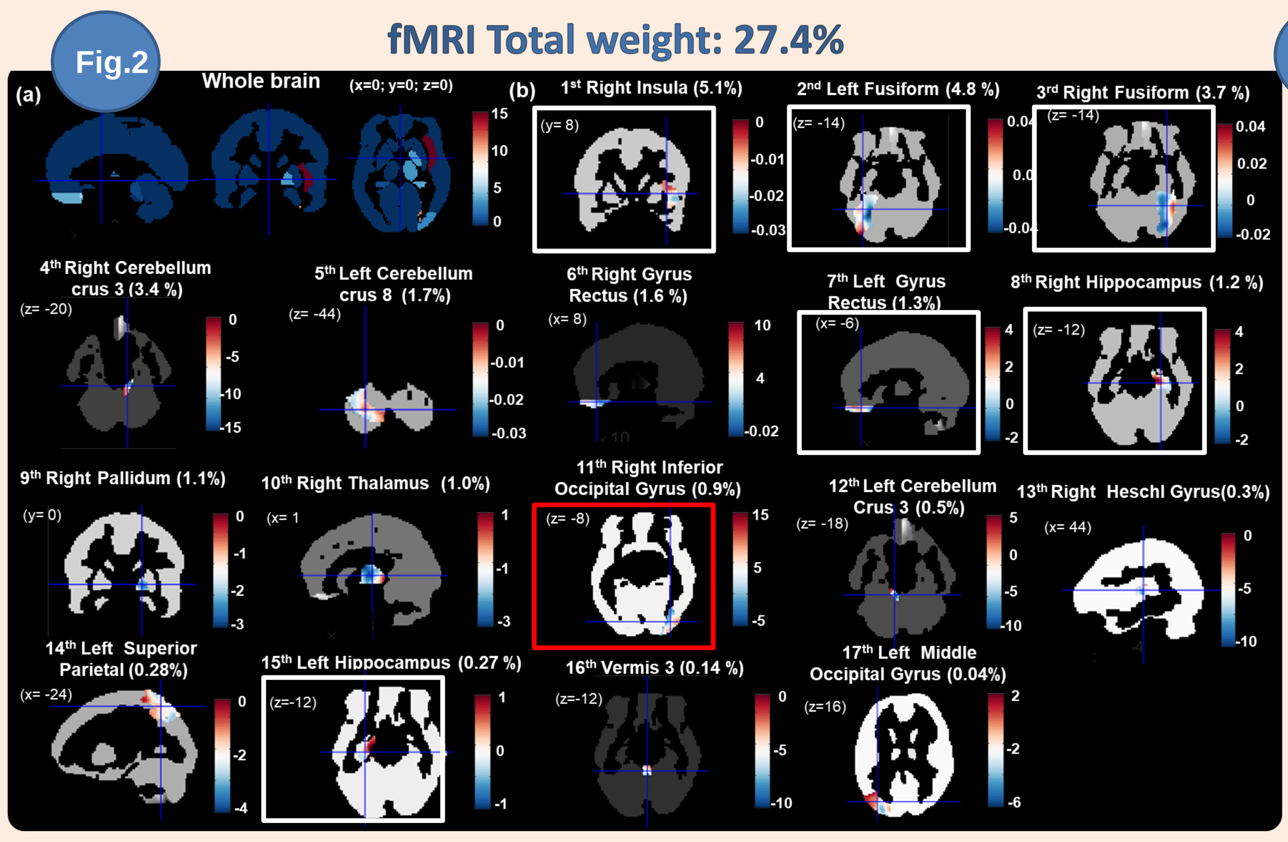
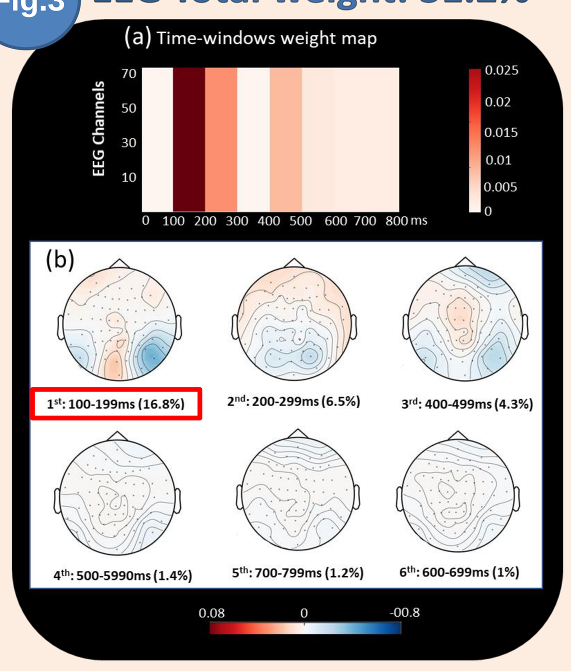
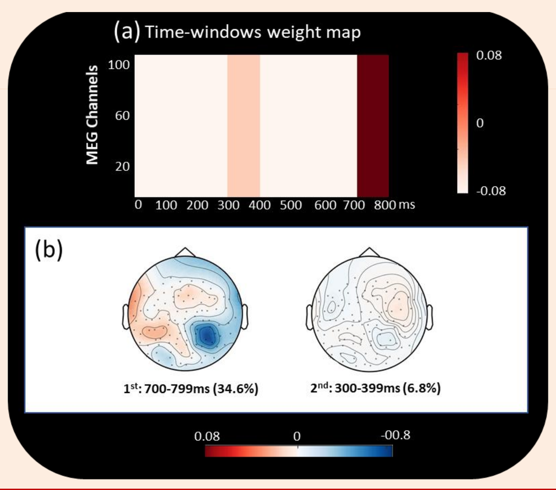


Fig.3 EEG Total weight: 31.2%



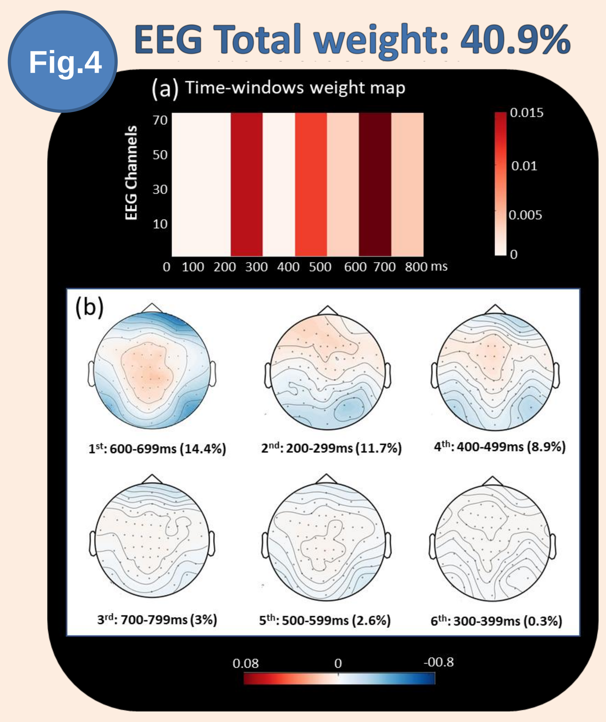
MEG Total weight: 41.4%



MKL classification model 2: famous faces versus scrambled

Balance accuracy: 96.88% (p = 0.001); ROC/AUC: 0.95

Fig.4 EEG Total weight: 40.9%



MEG Total weight: 6.8%

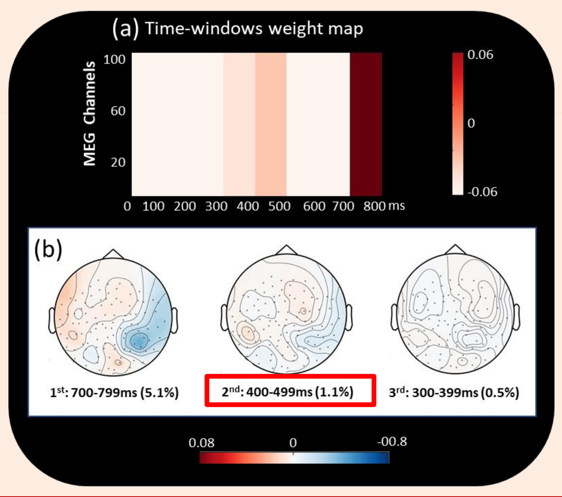


Fig.5 fMRI Total weight: 52.3%

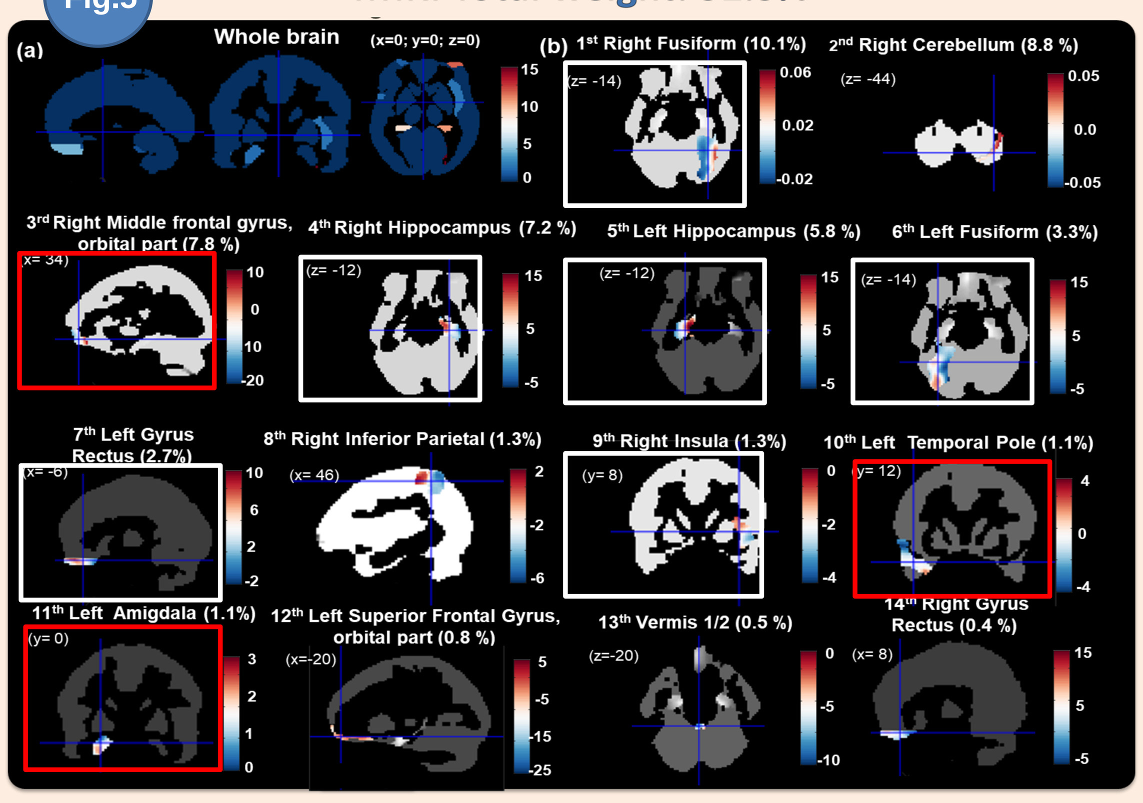


Fig.2 Fig.5 **fMRI:** (a) Whole brain map showing the kernel weights per region; the color bar represents the full range of kernel weights. (b) Images showing the voxels weights within the regions that contributed to the MKL classification model in sagittal or axial plane slices ("x" or "z" MNI coordinates, respectively). The regions ranked by the MKL classification model as relevant for discriminating between patterns of brain activity to faces (unfamiliar or famous) versus scrambled are shown; the regions' weights (%) are shown in parentheses. The color bars represent the full range of voxel weights within each region. Brain regions previously described as important to faces' processing are highlighted in: 1) white if identified by both models. 2) red if identified by only one model.

Fig.3 Fig.4 **EEG and MEG:** (a) Time-window map showing the kernel weights per time-window; the color bar represents the full range of kernel weights. (b) Topographical 2D maps of the scalp showing the channels weights within the time-windows that were ranked by the MKL classification models as relevant for the predictive function. The time-windows' weights (%) are shown in parentheses. The color bars represent the full range of channels weights within each time-window. Time-windows previously described as important to faces' processing are highlighted in red if identified by only one model. The other time-windows were identified by both models.

MAIN RESULTS

- Higher performance found for model 2 (famous faces vs. scrambled) than for model 1 (unfamiliar faces vs. scrambled).
- Spatial patterns of brain activity contributed more to discriminate *famous* faces versus scrambled stimuli**.**
- The regions and time-windows identified by the two models were similar, although some regions and time-windows were identified by only one of the two models.

Conclusions

- Faces' familiarity plays a role in the discriminability between spatiotemporal patterns of brain activity to faces versus non-faces stimuli.
- Processing famous faces may involve the activation of multiple brain regions in parallel.
- Processing famous and unfamiliar faces may involve similar but yet different networks and dynamics.
- The multimodal machine-learning framework applied here provides a new approach to uncover fine-grained characterization of the spatiotemporal dynamics underlying faces processing.

References

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Department of Computer Science: www.ucl.ac.uk/computer-science/
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- A video related to this Poster can be found in: https://www.dropbox.com/sh/q7p2fq700ugaj53/AAB-61PVRSh5Hgq7rn7850IGa?dl=0