AN ARTIFACT INTELLIGENCE FOR NEURO-IMAGING

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1 INTRODUCTION

Neuro-imaging has drawn a great attention of research recently, especially investigating the measurable markers of behavior, health or disorder. It enables us to identify corresponding brain regions and their interaction to internal and external impacts. We proposed an AI that can predict assessments from multiple domains (in-train data), including:

1. Source-based morphometry (SBM) loadings, which are weights from ICA decomposition of gray matter concentration maps.
2. Static functional network connectivity (FNC) matrices, which are cross-correlation values among 53 components from GIG-ICA.
3. Spatial maps (SM) which are subject-level 3D images of 53 spatial networks.

The AI are able to perform multiple outputs prediction, which assist neuro-imaging specialists analyse subject-level MRI images. The features of the AI include:

- Human-machine interaction visualization of MRI images, including 2-D slices and 3-D spatial maps.
- Predicted domain-expert values for each subject-level instance.

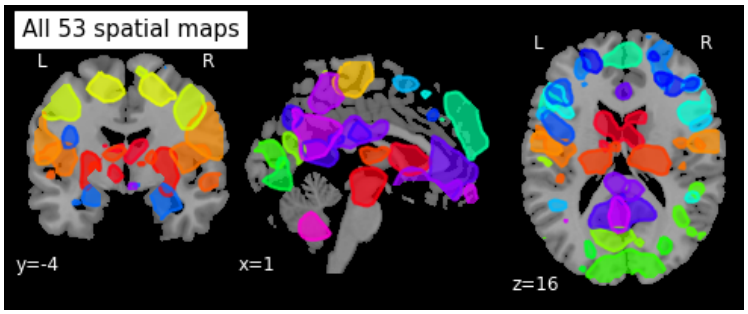

Figure 1: A sample of human-machine interaction visualization

1.1 DATA DESCRIPTION

The dataset under investigation is a part of Kaggle's competition (1), provided by Tri-institutional Georgia State University/Georgia Institute of Technology/Emory University. The total train size is 167 Gb, which includes 3 sources of input. The proposed AI will predict the age and additional 4 domain-expert values $v_i, i \in \{1, 2, 3, 4\}$. The evaluation of models is provided as feature-weighted absolute errors, which is

$$\text{score} = \sum_f w_f \left(\frac{\sum_i |v_{f,i} - \hat{v}_{f,i}|}{\sum_i \hat{v}_{f,i}} \right),$$

where $w_f = (.3, .175, .175, .175, .175)$

1.2 METHODOLOGY DESCRIPTION

The AI includes two sub-intelligences, which are:

1. Machine learning module uses SBM loadings and FNC to predict multiple outcomes. The backbone model is tree-boosted model called gradient boosting machine (GBM) (2) with hyper-parameter optimization (3).
2. Deep learning convolution neural network extracts feature maps from MRI images. We will investigate several the transferability of state-of-the-art architects, such as Inception-Resnet-v2, Xception and SENet. (4; 5; 6)

1.3 PRELIMINARY RESULT

We are currently achieve a score of 0.16358 (low is 0.196, best is 0.15612) with only stand-alone GBM module.

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