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Towards Autism detection on brain structural MRI scans using deep unsupervised learning methods

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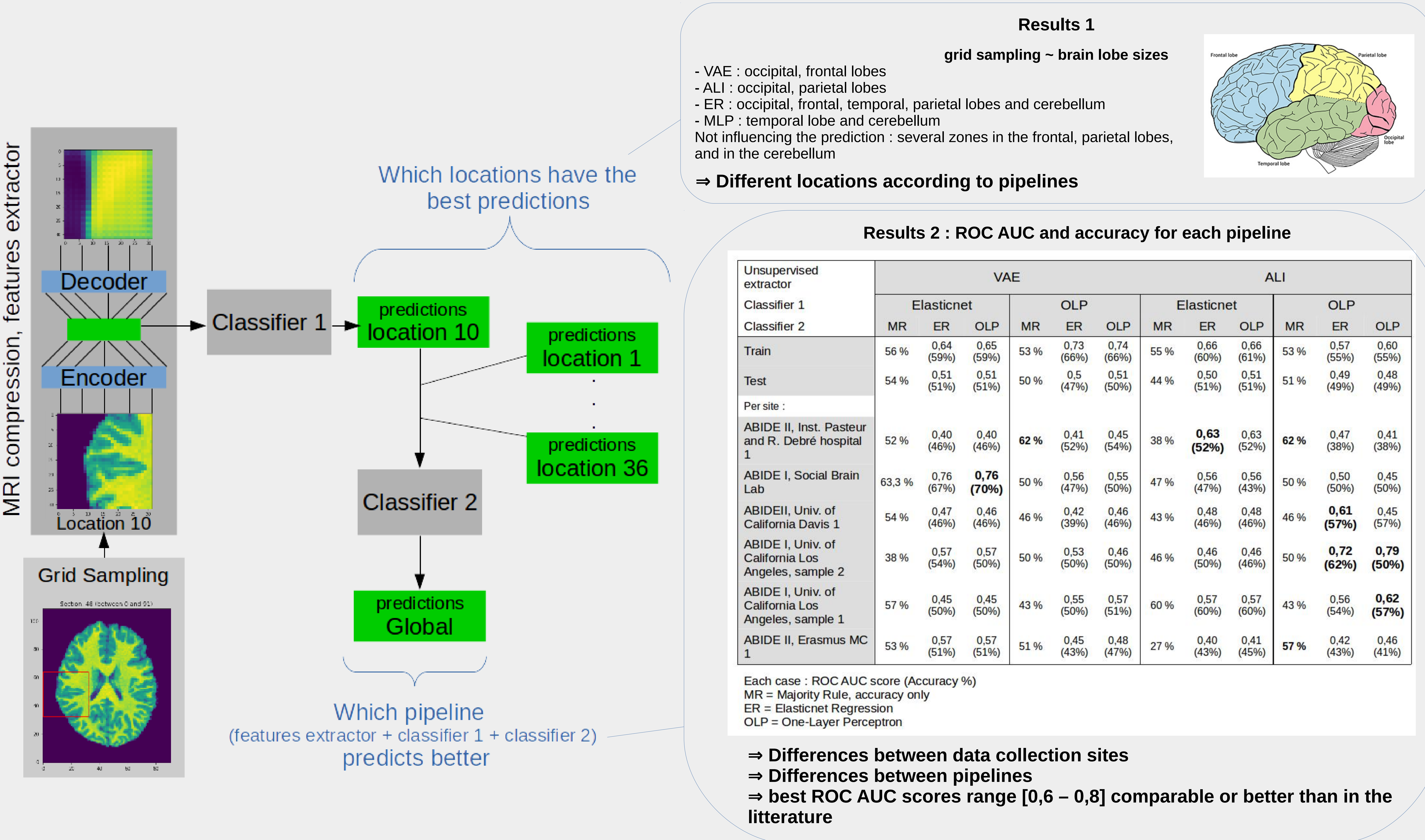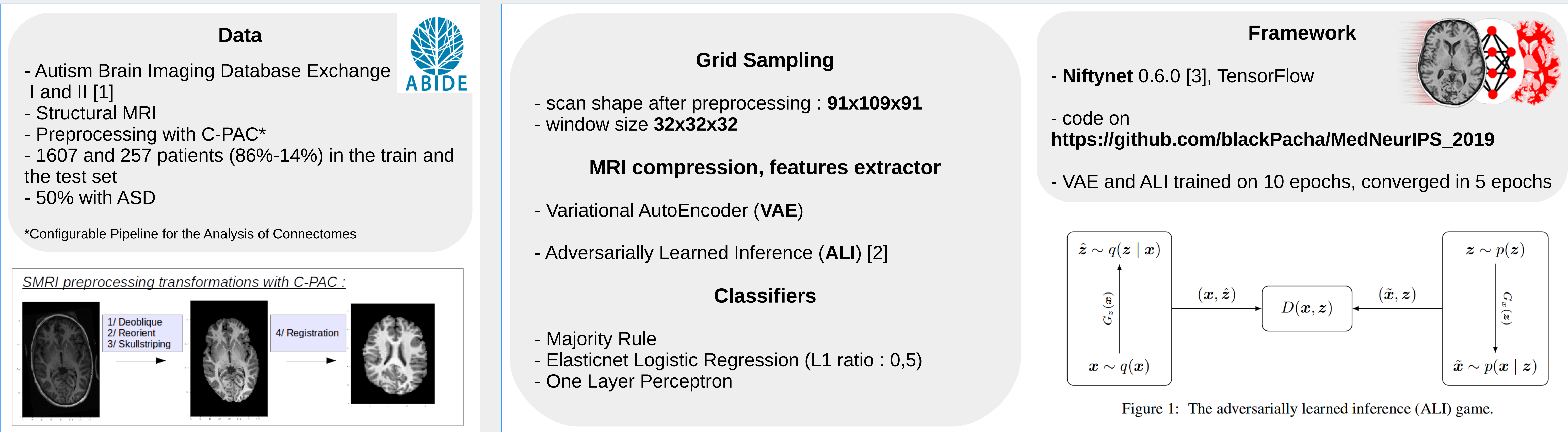**Margaux Luck,** University of Montréal, Mila, margaux.luck@gmail.com

Abstract

Autism Spectrum Disorder (ASD) is a relatively common neurodevelopmental condition that for which we currently lack any objective biomarkers. The study of patient brain MRI data has the potential to reveal regions of dysfunction that may serve as biomarkers to supplement current clinician-based diagnoses. In this paper, we propose **a method that enhances the diagnosis of ASD by compressing structural MRI from the open science Autism Brain Imaging Database Exchange (ABIDE, 892 ASD, 972 non-ASD) to obtain a representation of the brain that is relevant for the prediction of ASD using unsupervised deep learning models.** Our experimental evaluation demonstrates promising performance on the task of automated ASD diagnosis on ABIDE.

Data

- Autism Brain Imaging Database Exchange I and II [1]
- Structural MRI
- Preprocessing with C-PAC*
- 1607 and 257 patients (86%-14%) in the train and the test set
- 50% with ASD

*Configurable Pipeline for the Analysis of Connectomes

SMRI preprocessing transformations with C-PAC :

1/ Deoblique
2/ Reorient
3/ Skullstriping
4/ Registration

Grid Sampling

- scan shape after preprocessing : **91x109x91**
- window size **32x32x32**

MRI compression, features extractor

- Variational AutoEncoder (**VAE**)

- Adversarially Learned Inference (**ALI**) [2]

Classifiers

- Majority Rule
- Elasticnet Logistic Regression (L1 ratio : 0,5)
- One Layer Perceptron

Framework

- **Niftynet** 0.6.0 [3], TensorFlow

- code on **https://github.com/blackPacha/MedNeurIPS_2019**

- VAE and ALI trained on 10 epochs, converged in 5 epochs

Figure 1: The adversarially learned inference (ALI) game.

MRI compression, features extractor

Decoder / Encoder / Location 10 / Grid Sampling / Section 46 (sectioon 0 and 90)

Which locations have the best predictions

Classifier 1 → predictions location 10 → predictions location 1 ⋮ predictions location 36

Classifier 2 → predictions Global

Which pipeline
(features extractor + classifier 1 + classifier 2)
predicts better

Results 1

grid sampling ~ brain lobe sizes

- VAE : occipital, frontal lobes
- ALI : occipital, parietal lobes
- ER : occipital, frontal, temporal, parietal lobes and cerebellum
- MLP : temporal lobe and cerebellum
Not influencing the prediction : several zones in the frontal, parietal lobes, and in the cerebellum

⇒ **Different locations according to pipelines**

Results 2 : ROC AUC and accuracy for each pipeline

Unsupervised extractor	VAE						ALI					
Classifier 1	Elasticnet			OLP			Elasticnet			OLP		
Classifier 2	MR	ER	OLP	MR	ER	OLP	MR	ER	OLP	MR	ER	OLP
Train	56 %	0,64 (59%)	0,65 (59%)	53 %	0,73 (66%)	0,74 (66%)	55 %	0,66 (60%)	0,66 (61%)	53 %	0,57 (55%)	0,60 (55%)
Test	54 %	0,51 (51%)	0,51 (51%)	50 %	0,5 (47%)	0,51 (50%)	44 %	0,50 (51%)	0,51 (51%)	51 %	0,49 (49%)	0,48 (49%)
Per site :												
ABIDE II, Inst. Pasteur and R. Debré hospital 1	52 %	0,40 (46%)	0,40 (46%)	**62 %**	0,41 (52%)	0,45 (54%)	38 %	**0,63 (52%)**	0,63 (52%)	**62 %**	0,47 (38%)	0,41 (38%)
ABIDE I, Social Brain Lab	63,3 %	0,76 (67%)	**0,76 (70%)**	50 %	0,56 (47%)	0,55 (50%)	47 %	0,56 (47%)	0,56 (50%)	50 %	0,50 (50%)	0,45 (50%)
ABIDEII, Univ. of California Davis 1	54 %	0,47 (46%)	0,46 (46%)	46 %	0,42 (39%)	0,46 (46%)	43 %	0,48 (46%)	0,48 (46%)	46 %	**0,61 (57%)**	0,45 (57%)
ABIDE I, Univ. of California Los Angeles, sample 2	38 %	0,57 (54%)	0,57 (50%)	50 %	0,53 (50%)	0,46 (50%)	46 %	0,46 (50%)	0,46 (46%)	50 %	**0,72 (62%)**	**0,79 (50%)**
ABIDE I, Univ. of California Los Angeles, sample 1	57 %	0,45 (50%)	0,45 (50%)	43 %	0,55 (50%)	0,57 (51%)	60 %	0,57 (60%)	0,57 (60%)	43 %	0,56 (54%)	**0,62 (57%)**
ABIDE II, Erasmus MC 1	53 %	0,57 (51%)	0,57 (51%)	51 %	0,45 (43%)	0,48 (47%)	27 %	0,40 (43%)	0,41 (45%)	**57 %**	0,42 (43%)	0,46 (41%)

Each case : ROC AUC score (Accuracy %)
MR = Majority Rule, accuracy only
ER = Elasticnet Regression
OLP = One-Layer Perceptron

⇒ **Differences between data collection sites**
⇒ **Differences between pipelines**
⇒ **best ROC AUC scores range [0,6 – 0,8] comparable or better than in the litterature**

Conclusion

PoC : deep learning could be useful for ASD diagnosis
⇒ could raise new paths of research on finding Autism neurological markers
Pipeline on brain sMRI providing weak locations of the brain areas involved in good prediction of ASD

Limitations & Future work

- findings very preliminary
- should be compared with more classic models as baselines on ABIDE I and II
- should take into account the data collection sites and other modalities like functional MRI during training

References
[1] ABIDE data collection :
« The autism brain imaging data exchange: towards a large-scale evaluation of the intrinsic brain architecture in autism. » Di Martino et al., Molecular Psychiatry 2014
« Enhancing studies of the connectome in autism using the autism brain imaging data exchange II. » Di Martino et al., Scientific data 2017
[2] ALI : « Adversarially Learned Infeence » Dumoulin, Belghazi et al., ICLR 2017
[3] NiftyNet : « NiftyNet : a deep-learning platform for medical imaging. » Gibson, Li et al., Computer Methods and Programs in Biomedecine, volume 158, May 2018, pages 113-122