# Classification challenge on Alzheimer's Disease using MRIs and Gene Expression data

May 3, 2023

#### The problem

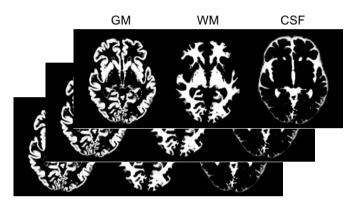
- AD affects about 55M people in the world\*
  - → need for early diagnosis

- AD (macro-)stages
  - CTL (Controls): no deficit
  - MCI (Mild Cognitive Impairment): few deficits
  - AD (Alzheimer's Disease): dementia

#### "Hints" from different types of data

- Demographic (age, gender, instruction, ...)
- Clinical evaluation (cognitive tests)
- CSF (Cerebrospinal fluid)
- Medical imaging (MRIs, PETs, DTIs, ...)
- Transcriptomics (gene expression, ...)

#### Features from MRIs



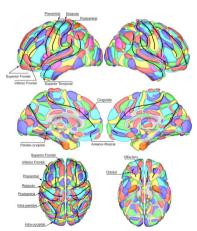
Tissue segmentation, bias correction and spatial normalization





Inter-subject registration (group template)





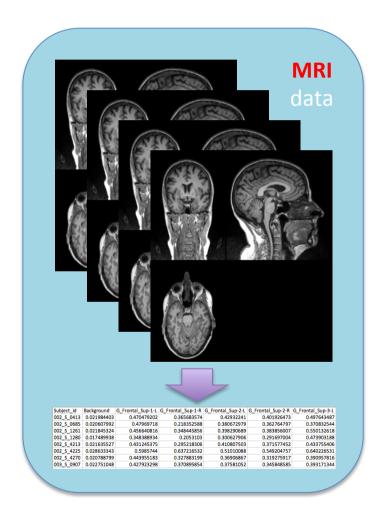
**AICHA Atlas** 

Average grey matter densities obtained from each anatomical region defined in an atlas

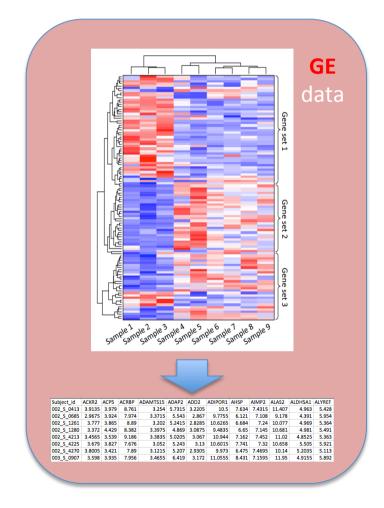


All images mapped to a common space (MNI), providing a voxel-wise correspondence across subjects

#### **Combined Data**







#### You will receive

- 3 training datasets for 3 different binary classification problems. These are to be used for training 3 separate classifiers, experimenting different classifiers, feature selection methods, etc. and validating them through cross-validation
- 3 test datasets (one for each binary problem) to test the classifier and provide the obtained predictions

#### Training data

- 1) ADCTLtrain.csv: training data for binary classification problem to discriminate AD vs. CN patients
  - a) First column: ID of the patient
  - b) Columns from 2 to 430: MRI+GE features
  - c) Last column: Label (patient classification: 'AD' or 'CTL')

Overall 164 patients: 81 AD and 83CTL

- **2) ADMCItrain.csv**: training data for binary classification problem to discriminate AD vs. MCI patients
  - a) First column: ID of the patient
  - b) Columns from 2 to 64: MRI+GE features
  - c) Last column: Label (patient classification: 'AD' or 'MCI')

Overall 172 patients: 82 AD and 90 MCI

- **3) MCICTLtrain.csv**: training data for binary classification problem to discriminate MCI vs. CTL patients
  - a) First column: ID of the patient
  - b) Columns from 2 to 594: MRI+GE features
  - c) Last column: Label (patient classification: 'MCI' or 'CTL')

Overall 172 patients: 90 MCI and 82 CTL

### Example of training dataset

| ID       | Background | Precentral_L |       | ABCA7 | AGTRAP | •••   | Labels |
|----------|------------|--------------|-------|-------|--------|-------|--------|
| ADCTL001 | •••        | •••          |       | •••   |        |       | AD     |
| ADCTL002 | •••        | •••          |       | •••   | •••    |       | AD     |
| ADCTL003 | •••        | •••          |       | •••   | •••    |       | AD     |
| ADCTL004 | •••        | •••          |       | •••   | •••    |       | AD     |
| ADCTL005 | •••        | •••          |       | •••   | •••    |       | AD     |
| ADCTL006 | •••        | •••          |       | •••   |        |       | AD     |
| ADCTL007 | •••        | •••          |       | •••   |        |       | AD     |
| ADCTL008 | •••        | •••          |       | •••   | •••    |       | AD     |
| ADCTL009 | •••        | •••          |       | •••   | •••    |       | AD     |
| ADCTL010 | •••        | •••          |       | •••   | •••    |       | AD     |
| •••      |            | •••          | • • • | •••   |        | • • • | •••    |

#### Test data

- 1) ADCTLtest.csv: test data for binary classification problem to discriminate AD vs. CTL patients
  - a) First column: ID of the patient
  - b) Columns from 2 to 430: MRI+GE features

Overall 41 patients

- **2) ADMCItest.csv**: test data for binary classification problem to discriminate AD vs. MCI patients
  - a) First column: ID of the patient
  - b) Columns from 2 to 64: MRI+GE features

Overall 41 patients

- **3) MCICTLtest.csv**: test data for binary classification problem to discriminate MCI vs. CTL patients
  - a) First column: ID of the patient
  - b) Columns from 2 to 594: MRI+GE features

Overall 43 patients

#### Your submission will consist of

#### For each binary classification problem

1. Two CSV files whose name are formatted as:

```
StudentRegistrationNumber_FamilyName_*res.csv
StudentRegistrationNumber_FamilyName_*feat.csv
where * denotes the classification problem (ADCTL, ADMCI, or MCICTL)
```

- 1.a) The first file will contain three columns
  - the IDs of the test observation;
  - the predicted labels;
  - the probabilities of the predicted labels;
- 1.b) The second file will contain the column index in the training data files (from 2 to end-1) of the selected features. If features are somehow pre-transformed, describe the transformation in the presentation file (see below).
- 2. <u>A presentation in PDF</u> with up to 6 pages, in which you describe how you obtained the model. It is NOT mandatory to choose the same classification model for the three different binary problems; just choose the one that leads to the most promising results.
- 3. <u>The R macro</u> (script) named *StudentRegistrationNumber\_FamilyName\_*solution.R used to obtain the results.

#### The winner is...

- For each binary problem, the results will be ranked according to
  - AUC (e.g., auc R function from pROC) and
  - MCC (e.g., mcc R function from mltools)

$$AUC = \int_{0}^{1} Sens(x)dx, \quad x = 1 - Spec$$
 Uses the ROC curve to exhibit the trade-off between the classifier's TP and FP rates

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TN + FN)(TN + FP)(TN + FN)}}$$
 Correlation coefficient between observed and predicted binary classifications

#### Other metrics

$$Acc = \frac{TP + TN}{TP + FN + FP + TN}$$

Percentage of correctly classified samples

$$Spec = \frac{TN}{TN + FP}$$

Percentage of negative samples correctly identified

$$Sens = \frac{TP}{TP + FN}$$

Percentage of positive samples correctly classified (Recall or TPR)

$$Prec = \frac{TP}{TP + FP}$$

Percentage of positive samples correctly classified, considering the set of all the samples classified as positive

$$F_1 = \frac{2 \cdot Prec \cdot Sens}{Prec + Sens}$$

Compromise between sensitivity and precision

$$BA = \frac{Spec + Sens}{2}$$

Mean of Specificity and Sensitivity

#### Example results

A) Performance on the training datasets:

|            | Acc   | Sens  | Spec  | Prec  | F1    | AUC   | MCC   | ВА    |
|------------|-------|-------|-------|-------|-------|-------|-------|-------|
| AD vs CTL  | 0.902 | 0.926 | 0.880 | 0.882 | 0.904 | 0.969 | 0.806 | 0.903 |
| AD vs MCI  | 0.977 | 0.976 | 0.978 | 0.976 | 0.976 | 0.993 | 0.953 | 0.977 |
| MCI vs CTL | 0.826 | 0.867 | 0.780 | 0.812 | 0.839 | 0.884 | 0.651 | 0.824 |

## B) Performance on the test datasets using the classifier trained on the training data:

|            |       |       |       |       |       |       |       | ВА    |
|------------|-------|-------|-------|-------|-------|-------|-------|-------|
|            | Acc   | Sens  | Spec  | Prec  | F1    | AUC   | MCC   |       |
| AD vs CTL  | 0.829 | 0.857 | 0.800 | 0.818 | 0.837 | 0.888 | 0.659 | 0.829 |
| AD vs MCI  | 0.643 | 0.700 | 0.591 | 0.609 | 0.651 | 0.761 | 0.292 | 0.645 |
| MCI vs CTL | 0.628 | 0.545 | 0.714 | 0.667 | 0.600 | 0.801 | 0.263 | 0.630 |