#### Load Data Set

We are doing a 70-30 split

```
test = read.csv("test.csv")
train = read.csv("train.csv")
test_completer = read.csv("test_completer.csv")
train_completer = read.csv("train_completer.csv")
                  779 obs. of 18 variables:
## 'data.frame':
                         : int 1000100000...
## $ converter
## $ PTGENDER
                         : chr "Male" "Female" "Male" "Female" ...
## $ AGE
                         : num 81.1 68 71.2 63.5 82.2 71.6 72.1 75 83.7 77.1 ...
## $ PTEDUCAT
                         : int 16 16 18 15 20 20 14 16 18 17 ...
## $ PTMARRY
                         : chr "Married" "Married" "Married" ...
                               "LMCI" "EMCI" "LMCI" "EMCI" ...
## $ DX.bl
                         : chr
## $ CDRSB
                         : num 4 0.5 1.5 0.5 1.5 2.5 1.5 1 1 0 ...
## $ FAQ
                         : int 0090481000...
## $ MMSE
                         : int 26 28 29 29 24 26 27 29 29 28 ...
## $ ADAS11
                         : num 18 5 6 9 12.3 ...
## $ ADAS13
                         : num 32 8 11 12 20.3 ...
## $ ADASQ4
                         : int 9243564555...
                         : int 18 46 32 45 29 28 44 37 30 33 ...
## $ RAVLT.immediate
   $ RAVLT.learning
                         : int
                               4 6 6 8 0 3 8 8 0 4 ...
                         : int 6664567274 ...
## $ RAVLT.forgetting
## $ RAVLT.perc.forgetting: num 100 50 66.7 33.3 83.3 ...
## $ LDELTOTAL
                         : int 4 10 5 8 2 2 9 20 6 8 ...
## $ TRABSCOR
                         : int 217 60 79 54 155 66 159 53 44 180 ...
## 'data.frame':
                  779 obs. of 18 variables:
## $ converter
                         : Factor w/ 2 levels "0", "1": 2 1 1 1 2 1 1 1 1 1 ...
## $ PTGENDER
                         : Factor w/ 2 levels "Female", "Male": 2 1 2 1 2 2 2 1 1 2 ...
## $ AGE
                         : num 81.1 68 71.2 63.5 82.2 71.6 72.1 75 83.7 77.1 ...
## $ PTEDUCAT
                         : int 16 16 18 15 20 20 14 16 18 17 ...
## $ PTMARRY
                         : Factor w/ 4 levels "Divorced", "Married", ...: 2 2 2 2 2 2 2 2 1 2 ...
                         : Factor w/ 2 levels "EMCI", "LMCI": 2 1 2 1 2 2 1 1 2 2 ...
## $ DX.bl
                         : num 4 0.5 1.5 0.5 1.5 2.5 1.5 1 1 0 ...
## $ CDRSB
                         : int 0090481000...
## $ FAQ
## $ MMSE
                         : int 26 28 29 29 24 26 27 29 29 28 ...
## $ ADAS11
                         : num 18 5 6 9 12.3 ...
                         : num 32 8 11 12 20.3 ...
## $ ADAS13
## $ ADASQ4
                         : int 9243564555 ...
## $ RAVLT.immediate
                        : int 18 46 32 45 29 28 44 37 30 33 ...
## $ RAVLT.learning
                         : int 4668038804...
## $ RAVLT.forgetting
                         : int 6664567274 ...
## $ RAVLT.perc.forgetting: num 100 50 66.7 33.3 83.3 ...
## $ LDELTOTAL
                         : int 4 10 5 8 2 2 9 20 6 8 ...
## $ TRABSCOR
                         : int 217 60 79 54 155 66 159 53 44 180 ...
                  189 obs. of 18 variables:
## 'data.frame':
## $ converter
                         : Factor w/ 2 levels "0", "1": 2 2 1 1 2 1 1 2 1 1 ...
## $ PTGENDER
                         : Factor w/ 2 levels "Female", "Male": 1 2 2 2 2 2 2 1 2 ...
                         : num 72.8 78.8 73.5 74.8 74.8 72.4 57.8 85.6 81.4 79.8 ...
## $ AGE
```

```
$ PTEDUCAT
                            : int 12 20 12 15 12 14 20 20 18 14 ...
##
    $ PTMARRY
                            : Factor w/ 4 levels "Divorced", "Married", ...: 1 2 2 1 2 2 2 2 2 2 ...
##
    $ DX.bl
                            : Factor w/ 2 levels "EMCI", "LMCI": 2 2 2 1 2 2 2 2 1 2 ...
    $ CDRSB
                                   2 1.5 1.5 0.5 2.5 2 1.5 4 0.5 1.5 ...
##
##
    $ FAQ
                             int
                                   1 3 0 0 6 0 1 19 0 0 ...
    $ MMSE
                                   28 29 27 29 25 29 28 27 29 29 ...
##
                             int
    $ ADAS11
                                   7.33 15.67 8.67 6 12 ...
##
                            : num
    $ ADAS13
##
                            : num
                                   10.3 22.7 17.7 9 23 ...
##
    $ ADASQ4
                             int
                                   3 6 7 2 10 6 7 6 3 3 ...
                                   44 31 34 48 22 30 33 24 51 37 ...
##
    $ RAVLT.immediate
                            : int
    $ RAVLT.learning
                            : int
                                   9 3 4 7 4 5 5 1 10 3 ...
    $ RAVLT.forgetting
                                   8 5 7 6 6 6 6 6 9 6 ...
##
                             int
    $ RAVLT.perc.forgetting: num
                                   61.5 71.4 77.8 54.5 100 ...
                                   3 6 4 11 0 4 5 3 11 6 ...
##
    $ LDELTOTAL
                            : int
    $ TRABSCOR
                                  112 134 107 108 125 300 70 143 75 69 ...
                            : int
```

#### Fit Random Forest

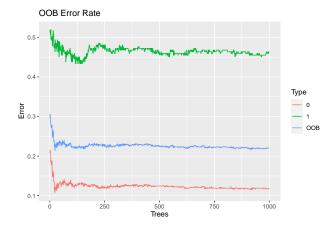
```
##
  Call:
    randomForest(formula = converter ~ ., data = train, mtry = mtry.value,
##
                                                                                   importance = TRUE, prox
                  Type of random forest: classification
##
                         Number of trees: 1000
## No. of variables tried at each split: 4
##
##
           OOB estimate of error rate: 22.08%
##
  Confusion matrix:
##
       0
           1 class.error
## 0 482
          64
               0.1172161
```

• Out of Bag Error rate here is 100% - 22.08% = 77.92%. This means that 77.92% of the OOB samples were correctly classified by the random forest. Just as a reminder, OOB is used to make predictions on the data. It is the "testing" data.

#### **Optimality of Trees**

0.4635193

## 1 108 125



• As we can observe from the graph above. The default number of trees in R is 500 and after 500 trees, the error seems to stabilize. We will decide to stick to 500 trees.

#### MTRY Value Search

#### ## [1] 4

Table 1: OOB Error Rate for Different MTRY Values

MTRY	OOB Error
1	0.222
2	0.221
3	0.218
4	0.214
5	0.221
6	0.220
7	0.218
8	0.231
9	0.221
10	0.234

• Here we are finding different values of mtry which give the lowest OOB-error. We set values of mtry from 1 to 10 and noticed that an mtry of 1 has the lowest OOB-error.

#### Final Random Forest Model

0.4549356

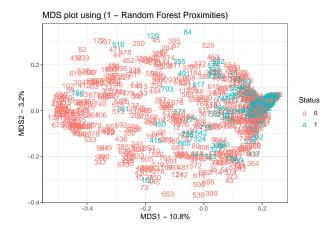
## 1 106 127

```
##
## Call:
   randomForest(formula = converter ~ ., data = train, mtry = 4,
                                                                       importance = TRUE, proximity = T
##
                  Type of random forest: classification
##
                        Number of trees: 500
## No. of variables tried at each split: 4
##
##
           OOB estimate of error rate: 22.34%
## Confusion matrix:
           1 class.error
      0
## 0 478 68
              0.1245421
```

	0	1	class.error
0	478	68	0.1245421
1	106	127	0.4549356

• The final model on the training set appears to be struggling with correctly classifying people who are not going to develop Alzheimer's Disease in the next 5 years. Basically, the type 2 error is at 53%.

#### **MDS Plot**



- Just as a reminder, MDS aims to represent the pairwise dissimilarities or distances between data points in a lower-dimensional space while preserving the original distances as much as possible.
- In the above MDS plot, we can see that there is a clear distinction between groups but there appears to be overlaps in some areas. There are converters in the non-converter groups and vice versa.

#### Predict on Test Data

## [1] 0.8

• The accuracy of our random forest model on the test set is 79%.

## Sensitivity Analysis

#### MTRY Value Search

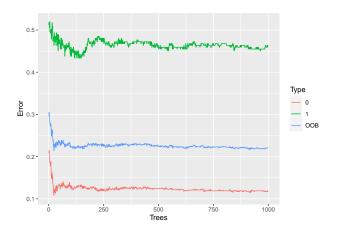
```
## [1] 0.2169312 0.1904762 0.1904762 0.2010582 0.2169312 0.2116402 0.2010582 ## [8] 0.2010582 0.2275132 0.2169312
```

## [1] 0.1904762

## [1] 2 3

# Random Forest Model

### **Optimality of Trees**



### Final Random Forest Model

### Predict on Test Data

## [1] 0.7654321