Required libraries

```
alzheimer-detection-and-classification
```

alzheimer-detection-and-classification

```
import pandas as pd
from scipy.io import arff
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
from sklearn import preprocessing
import numpy as np

from sklearn.metrics import confusion_matrix, accuracy_score, recall_score, roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.ensemble import (RandomForestClassifier, AdaBoostClassifier,
                              GradientBoostingClassifier, ExtraTreesClassifier)
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
import xgboost as xgb
from sklearn import metrics
from sklearn.metrics import mean_squared_error

import plotly.offline as py
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.tools as tls


FOLDS =10
%matplotlib inline
```

1. Declaration of functions

Graphing functions

```
# Function to graph number of people by age
def cont_age(field):
    plt.figure()
    g = None
    if field == "Age":
        df_query_mri = df[df["Age"] > 0]
        g = sns.countplot(df_query_mri["Age"])
        g.figure.set_size_inches(18.5, 10.5)
    else:
        g = sns.countplot(df[field])
        g.figure.set_size_inches(18.5, 10.5)

sns.despine()
```

```
<Figure size 432x288 with 0 Axes>
```

```
# Function to graph number of people per state [Demented, Nondemented]
def cont_Dementes(field):
    plt.figure()
    g = None
    if field == "Group":
        df_query_mri = df[df["Group"] >= 0]
        g = sns.countplot(df_query_mri["Group"])
        g.figure.set_size_inches(18.5, 10.5)
    else:
        g = sns.countplot(df[field])
        g.figure.set_size_inches(18.5, 10.5)

sns.despine()
```

```
<Figure size 432x288 with 0 Axes>
```

```
# 0 = F y 1= M
def bar_chart(feature):
    Demented = df[df['Group']==1][feature].value_counts()
    Nondemented = df[df['Group']==0][feature].value_counts()
    df_bar = pd.DataFrame([Demented,Nondemented])
    df_bar.index = ['Demented','Nondemented']
    df_bar.plot(kind='bar',stacked=True, figsize=(8,5))


def report_performance(model):

    model_test = model.predict(X_test)

    print("Confusion Matrix")
    print("{0}".format(metrics.confusion_matrix(y_test, model_test)))
    print("")
    print("Classification Report")
    print(metrics.classification_report(y_test, model_test))
```

2. Analysis of data

2.1 read dataset

```
data = '/kaggle/input/mri-and-alzheimers/oasis_longitudinal.csv'
df = pd.read_csv (data)
df.head()
```

	Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV
0	OAS2_0001	OAS2_0001_MR1	Nondemented	1	0	M	R	87	14	2.0	27.0	0.0	1987	0.696
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14	2.0	30.0	0.0	2004	0.681
2	OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12	NaN	23.0	0.5	1678	0.736
3	OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12	NaN	28.0	0.5	1738	0.713
4	OAS2_0002	OAS2_0002_MR3	Demented	3	1895	M	R	80	12	NaN	22.0	0.5	1698	0.701

```
df.describe()
```

	Visit	MR Delay	Age	EDUC	SES	MMSE	CDR	eTIV	nW
count	373.000000	373.000000	373.000000	373.000000	354.000000	371.000000	373.000000	373.000000	373.0000
mean	1.882038	595.104558	77.013405	14.597855	2.460452	27.342318	0.290885	1488.128686	0.7295
std	0.922843	635.485118	7.640957	2.876339	1.134005	3.683244	0.374557	176.139286	0.0371
min	1.000000	0.000000	60.000000	6.000000	1.000000	4.000000	0.000000	1106.000000	0.6440
25%	1.000000	0.000000	71.000000	12.000000	2.000000	27.000000	0.000000	1357.000000	0.7000
50%	2.000000	552.000000	77.000000	15.000000	2.000000	29.000000	0.000000	1470.000000	0.7290
75%	2.000000	873.000000	82.000000	16.000000	3.000000	30.000000	0.500000	1597.000000	0.7560
max	5.000000	2639.000000	98.000000	23.000000	5.000000	30.000000	2.000000	2004.000000	0.8370

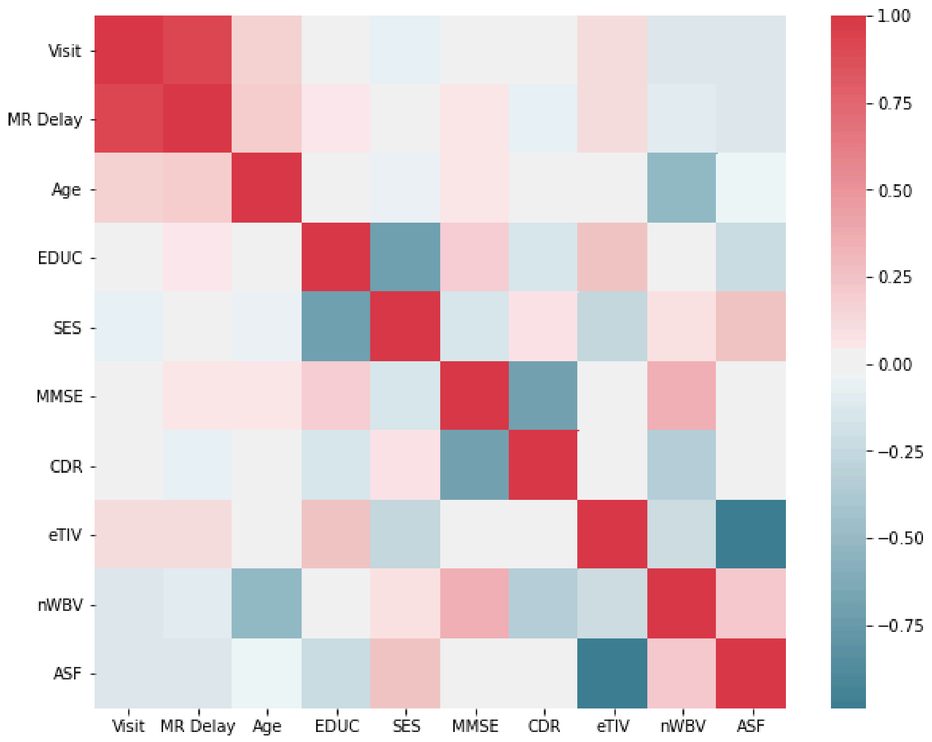
```
nd = pd.DataFrame(df['Group']=='Nondemented')
nd["Group"].value_counts()
```

```
True     190
False    183
Name: Group, dtype: int64
```

2.2 Correlation Analysis

```
f, ax = plt.subplots(figsize=(10, 8))
corr = df.corr(method = 'pearson')
sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool), cmap=sns.diverging_palette(220, 10, as_cmap=True),
            square=True, ax=ax)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f19f203b8d0>
```



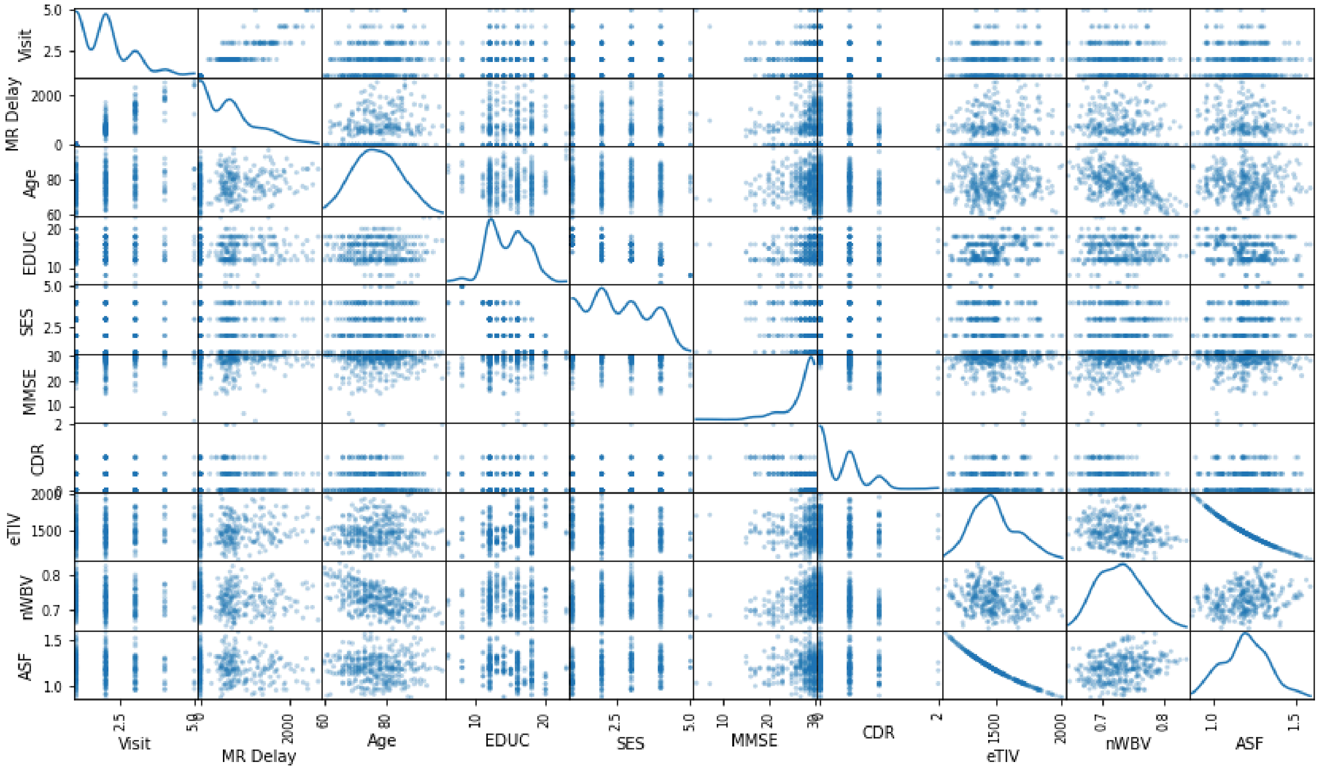
2.3 Correlation matrix

```
df.corr(method = 'pearson')
```

	Visit	MR Delay	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
Visit	1.000000	0.920009	0.183213	0.024615	-0.051622	-0.029078	0.002325	0.117428	-0.126682	-0.120399
MR Delay	0.920009	1.000000	0.205357	0.051630	-0.030813	0.065844	-0.062915	0.119624	-0.105586	-0.123545
Age	0.183213	0.205357	1.000000	-0.027886	-0.046857	0.055612	-0.026257	0.042348	-0.518359	-0.035067
EDUC	0.024615	0.051630	-0.027886	1.000000	-0.722647	0.194884	-0.153121	0.257015	-0.012200	-0.241752
SES	-0.051622	-0.030813	-0.046857	-0.722647	1.000000	-0.149219	0.076160	-0.261575	0.090095	0.255576
MMSE	-0.029078	0.065844	0.055612	0.194884	-0.149219	1.000000	-0.686519	-0.032084	0.341912	0.040052
CDR	0.002325	-0.062915	-0.026257	-0.153121	0.076160	-0.686519	1.000000	0.022819	-0.344819	-0.029340
eTIV	0.117428	0.119624	0.042348	0.257015	-0.261575	-0.032084	0.022819	1.000000	-0.210122	-0.988877
nWBV	-0.126682	-0.105586	-0.518359	-0.012200	0.090095	0.341912	-0.344819	-0.210122	1.000000	0.213476
ASF	-0.120399	-0.123545	-0.035067	-0.241752	0.255576	0.040052	-0.029340	-0.988877	0.213476	1.000000

2.4 Dispersion matrix

```
from pandas.plotting import scatter_matrix
scatter_matrix(df, alpha = 0.3, figsize = (14,8), diagonal = 'kde');
```



2.5 Graphs of all these correlations

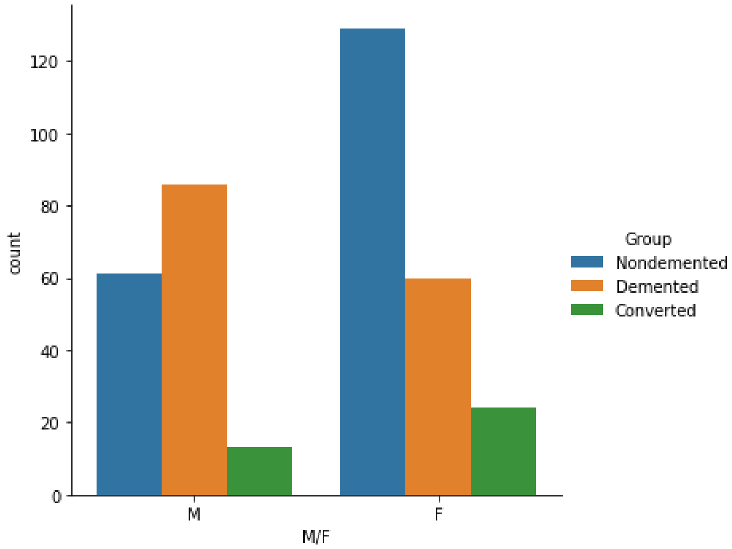
```
g = sns.PairGrid(df, vars=['Visit','MR Delay','M/F', 'Age', 'EDUC', 'SES', 'MMSE', 'eTIV', 'nWBV', 'ASF'],
                 hue='Group', palette='RdBu_r')
g.map(plt.scatter, alpha=0.8)
g.add_legend();
```

2.6 Miscellaneous Graphics

Number of Demented, Nondemented and Converted depending on the sex of the patient

```
import seaborn as sb
sb.catplot('M/F',data=df,hue='Group',kind="count")
```

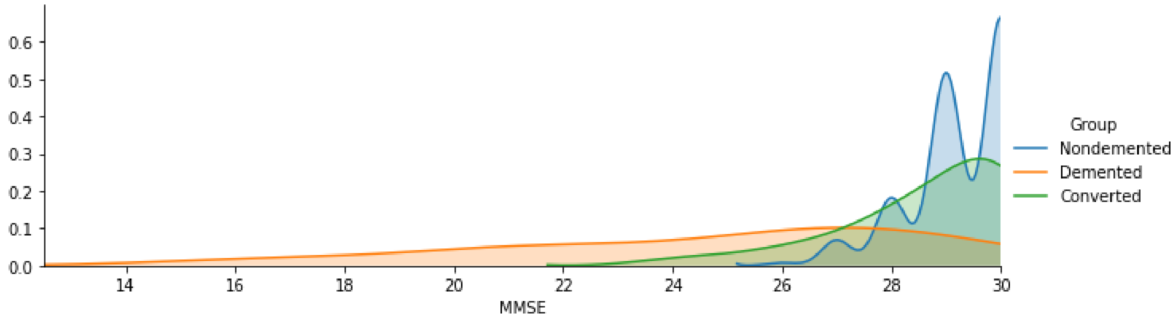
```
<seaborn.axisgrid.FacetGrid at 0x7f19dd23d690>
```



Variation of the dementia according to the MMSE depending on the scores of each patient

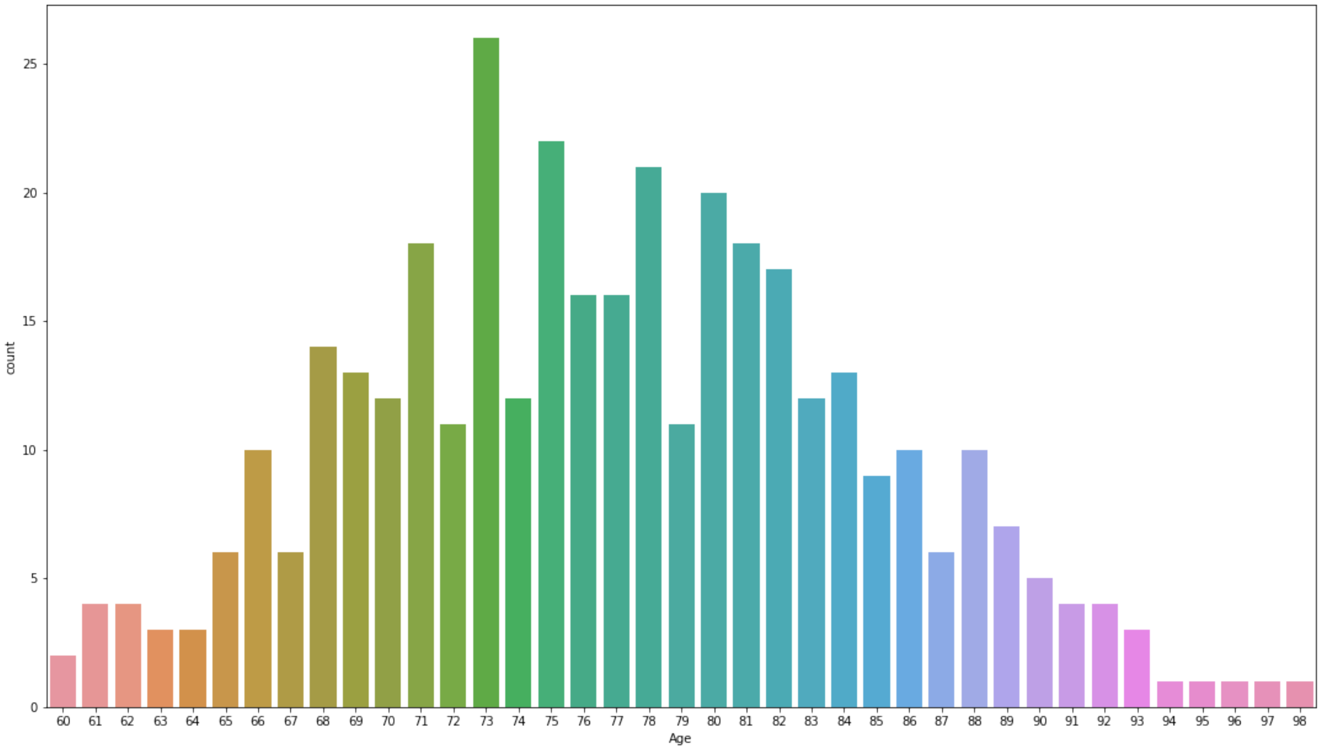
```
facet= sns.FacetGrid(df,hue="Group", aspect=3)
facet.map(sns.kdeplot,'MMSE',shade= True)
facet.set(xlim=(0, df['MMSE'].max()))
facet.add_legend()
plt.xlim(12.5)
```

```
(12.5, 30.0)
```



Number of patients of each age

```
cont_age("Age")
```



3.Preprocessing

Replace data Convert a Dement

```
df['Group'] = df['Group'].replace(['Converted'], ['Demented'])
df.head(3)
```

	Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV
0	OAS2_0001	OAS2_0001_MR1	Nondemented	1	0	M	R	87	14	2.0	27.0	0.0	1987	0.696
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14	2.0	30.0	0.0	2004	0.681
2	OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12	NaN	23.0	0.5	1678	0.736

3.1 Remove Useless Columns

```
df.drop(['Subject ID'], axis = 1, inplace = True, errors = 'ignore')
df.drop(['MRI ID'], axis = 1, inplace = True, errors = 'ignore')
df.drop(['Visit'], axis = 1, inplace = True, errors = 'ignore')
#for this study the CDR we eliminated it
df.drop(['CDR'], axis = 1, inplace = True, errors = 'ignore')
df.head(3)
```

	Group	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	eTIV	nWBV	ASF
0	Nondemented	0	M	R	87	14	2.0	27.0	1987	0.696	0.883
1	Nondemented	457	M	R	88	14	2.0	30.0	2004	0.681	0.876
2	Demented	0	M	R	75	12	NaN	23.0	1678	0.736	1.046

3.2 LabelEncoder

We are going to use Binarized LabelEncoder for our Binary attributes**

Which are sex and our class

```
# 1 = Demented, 0 = Nondemented
df['Group'] = df['Group'].replace(['Converted'], ['Demented'])

df['Group'] = df['Group'].replace(['Demented', 'Nondemented'], [1,0])
df.head(3)
```

	Group	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	eTIV	nWBV	ASF
0	0	0	M	R	87	14	2.0	27.0	1987	0.696	0.883
1	0	457	M	R	88	14	2.0	30.0	2004	0.681	0.876
2	1	0	M	R	75	12	NaN	23.0	1678	0.736	1.046

```
# 1= M, 0 = F

df['M/F'] = df['M/F'].replace(['M', 'F'], [1,0])
df.head(3)
```

	Group	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	eTIV	nWBV	ASF
0	0	0	1	R	87	14	2.0	27.0	1987	0.696	0.883
1	0	457	1	R	88	14	2.0	30.0	2004	0.681	0.876
2	1	0	1	R	75	12	NaN	23.0	1678	0.736	1.046

```
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
encoder.fit(df.Hand.values)
list(encoder.classes_)
#Transoformamos
encoder.transform(df.Hand.values)
df[['Hand']]=encoder.transform(df.Hand.values)
encoder2=LabelEncoder()
encoder2.fit(df.Hand.values)
list(encoder2.classes_)
```

```
[0]
```

3.3 Imputation of lost values

For various reasons, many real-world data sets contain missing values, often encoded as blanks, NaNs, or other placeholders. However, these data sets are incompatible with scikit-learn estimators that assume that all values in a matrix are numeric, and that they all have and have meaning. A basic strategy for using incomplete datasets is to discard rows and / or complete columns that contain missing values. However, this has the price of losing data that can be valuable (though incomplete). A better strategy is to impute the lost values, that is, to deduce them from the known part of the data.

The Imputer class provides basic strategies for imputation of missing values, using either the mean, the median or the most frequent value of the row or column in which the missing values are found. This class also allows different encodings of missing values.

Lost data

```
data_na = (df.isnull().sum() / len(df)) * 100
data_na = data_na.drop(data_na[data_na == 0].index).sort_values(ascending=False)[:30]
missing_data = pd.DataFrame({'Lost proportion (%)' :round(data_na,2)})
missing_data.head(20)
```

	Lost proportion (%)
SES	5.09
MMSE	0.54

```
from sklearn.impute  import SimpleImputer
# We perform it with the most frequent value
imputer = SimpleImputer ( missing_values = np.nan,strategy='most_frequent')

imputer.fit(df[['SES']])
df[['SES']] = imputer.fit_transform(df[['SES']])

# We perform it with the median
imputer = SimpleImputer ( missing_values = np.nan,strategy='median')

imputer.fit(df[['MMSE']])
df[['MMSE']] = imputer.fit_transform(df[['MMSE']])
```

```
from sklearn.impute  import SimpleImputer
# We perform it with the median
imputer = SimpleImputer ( missing_values = np.nan,strategy='median')

imputer.fit(df[['MMSE']])
df[['MMSE']] = imputer.fit_transform(df[['MMSE']])
```

3.4 Standardization

```
from sklearn.preprocessing import StandardScaler
df_norm = df
scaler = StandardScaler()
df_norm[['Age','MR Delay','M/F','Hand','EDUC','SES','MMSE','eTIV','nWBV','ASF']]=scaler.fit_transform(df[['Age','
```

```
df_norm.head(3)
```

	Group	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	eTIV	nWBV	ASF
0	0	-0.937715	1.153798	0.0	1.308738	-0.208132	-0.394466	-0.095686	2.836059	-0.905169	-2.265742
1	0	-0.217613	1.153798	0.0	1.439787	-0.208132	-0.394466	0.721664	2.932703	-1.309643	-2.316501
2	1	-0.937715	1.153798	0.0	-0.263856	-0.904394	-0.394466	-1.185486	1.079409	0.173429	-1.083784

3.5 Export them to then select the features

```
df_norm.to_csv('DatasetSelectionAttributes.csv', sep=',',index=False)
```

Remove Columns selected by boruta

```
df.drop(['Hand'], axis = 1, inplace = True, errors = 'ignore')
df.drop(['MR Delay'], axis = 1, inplace = True, errors = 'ignore')
```

```
df.head()
```

	Group	M/F	Age	EDUC	SES	MMSE	eTIV	nWBV	ASF
0	0	1.153798	1.308738	-0.208132	-0.394466	-0.095686	2.836059	-0.905169	-2.265742
1	0	1.153798	1.439787	-0.208132	-0.394466	0.721664	2.932703	-1.309643	-2.316501
2	1	1.153798	-0.263856	-0.904394	-0.394466	-1.185486	1.079409	0.173429	-1.083784
3	1	1.153798	-0.132806	-0.904394	-0.394466	0.176764	1.420506	-0.446765	-1.344830
4	1	1.153798	0.391392	-0.904394	-0.394466	-1.457936	1.193108	-0.770344	-1.170800

4.Modelling

```
data_test = df
```

```
X = data_test.drop(["Group"],axis=1)
y = data_test["Group"].values
X.head(3)
```

	M/F	Age	EDUC	SES	MMSE	eTIV	nWBV	ASF
0	1.153798	1.308738	-0.208132	-0.394466	-0.095686	2.836059	-0.905169	-2.265742
1	1.153798	1.439787	-0.208132	-0.394466	0.721664	2.932703	-1.309643	-2.316501
2	1.153798	-0.263856	-0.904394	-0.394466	-1.185486	1.079409	0.173429	-1.083784

```
# We divide our data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y,random_state = 0)
```

```
print("{0:0.2f}% Train".format((len(X_train)/len(data_test.index)) * 100))
print("{0:0.2f}% Test".format((len(X_test)/len(data_test.index)) * 100))
```

```
74.80% Train
25.20% Test
```

```
print("Original Demented : {0} ({1:0.2f}%)".format(len(df_norm.loc[df_norm['Group'] == 1]), 100 * (len(df_norm.lc
print("Original Nondemented : {0} ({1:0.2f}%)".format(len(df_norm.loc[df_norm['Group'] == 0]), 100 * (len(df_norm
print("")
print("Training Demented : {0} ({1:0.2f}%)".format(len(y_train[y_train[:] == 1]), 100 * (len(y_train[y_train[:] =
print("Training Nondemented : {0} ({1:0.2f}%)".format(len(y_train[y_train[:] == 0]), 100 * (len(y_train[y_train[:
print("")
print("Test Demented : {0} ({1:0.2f}%)".format(len(y_test[y_test[:] == 1]), 100 * (len(y_test[y_test[:] == 1]) /
print("Test Nondemented : {0} ({1:0.2f}%)".format(len(y_test[y_test[:] == 0]), 100 * (len(y_test[y_test[:] == 0])
```

```
Original Demented : 183 (49.06%)
Original Nondemented : 190 (50.94%)

Training Demented : 139 (49.82%)
Training Nondemented : 140 (50.18%)

Test Demented : 44 (46.81%)
Test Nondemented : 50 (53.19%)
```

4.1 Tuning Hyperparameters for better models

Before adjusting our models, we will look for the parameters that give us a high AUC

1. Random Forest

```
# Number of trees in random forest
n_estimators = range(10,250)
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = range(1,40)
# Minimum number of samples required to split a node
min_samples_split = range(3,60)


# Create the random grid
parameter_rf = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split}


model_forest = RandomForestClassifier(n_jobs=-1)
forest_random = RandomizedSearchCV(estimator = model_forest, param_distributions = parameter_rf, n_iter = 100, cv
                              verbose=2, random_state=42, n_jobs = -1, scoring='neg_mean_absolute_error')
forest_random.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 100 candidates, totalling 1000 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:    9.0s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:   26.3s
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 640 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 1000 out of 1000 | elapsed:  3.3min finished
RandomizedSearchCV(cv=10, error_score=nan,
                   estimator=RandomForestClassifier(bootstrap=True,
                                                    ccp_alpha=0.0,
                                                    class_weight=None,
                                                    criterion='gini',
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=0.0,
                                                    n_estimators=100, n_job...
                                                    oob_score=False,
                                                    random_state=None,
                                                    verbose=0,
                                                    warm_start=False),
                   iid='deprecated', n_iter=100, n_jobs=-1,
                   param_distributions={'max_depth': range(1, 40),
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_split': range(3, 60),
                                        'n_estimators': range(10, 250)},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=False, scoring='neg_mean_absolute_error',
                   verbose=2)
```

```
forest_random.best_params_
```

```
{'n_estimators': 46,
 'min_samples_split': 3,
 'max_features': 'sqrt',
 'max_depth': 20}
```

```
model_rf = forest_random.best_estimator_
model_rf =  RandomForestClassifier(n_estimators=60,min_samples_split=8,max_features='sqrt',max_depth= 37)
model_rf.fit(X_train,y_train)
```

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=37, max_features='sqrt',
```

```
                            max_leaf_nodes=None, max_samples=None,
                            min_impurity_decrease=0.0, min_impurity_split=None,
                            min_samples_leaf=1, min_samples_split=8,
                            min_weight_fraction_leaf=0.0, n_estimators=60,
                            n_jobs=None, oob_score=False, random_state=None,
                            verbose=0, warm_start=False)
```

```
test_score = cross_val_score(model_rf, X_train, y_train, cv=FOLDS, scoring='roc_auc').mean()
test_score
```

```
0.9000784929356358
```

```
test_score = cross_val_score(model_rf, X_train, y_train, cv=FOLDS, scoring='accuracy').mean()
test_score
```

```
0.8101851851851851
```

```
Predicted_rf= model_rf.predict(X_test)
test_recall = recall_score(y_test, Predicted_rf, pos_label=1)
fpr, tpr, thresholds = roc_curve(y_test, Predicted_rf, pos_label=1)
test_auc = auc(fpr, tpr)
```

**** 2. Extra Tree****

```
# Number of trees in random forest
n_estimators = range(50,280)
# Maximum number of levels in tree
max_depth =  range(1,40)
# Minimum number of samples required to split a node
min_samples_leaf = [3,4,5,6,7,8,9,10,15,20,30,40,50,60]
```

```
# Create the random grid
parameter_Et = {'n_estimators': n_estimators,
               'max_depth': max_depth,
               'min_samples_leaf': min_samples_leaf}
```

```
model_et = ExtraTreesClassifier(n_jobs=-1)
et_random = RandomizedSearchCV(estimator = model_et, param_distributions = parameter_rf, n_iter = 100, cv = FOLDS
                              verbose=2, random_state=42, n_jobs = -1, scoring='roc_auc')
et_random.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 100 candidates, totalling 1000 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:    5.1s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:   18.8s
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed:   52.7s
[Parallel(n_jobs=-1)]: Done 640 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done 1000 out of 1000 | elapsed:  2.6min finished
RandomizedSearchCV(cv=10, error_score=nan,
                   estimator=ExtraTreesClassifier(bootstrap=False,
                                                  ccp_alpha=0.0,
                                                  class_weight=None,
                                                  criterion='gini',
                                                  max_depth=None,
                                                  max_features='auto',
                                                  max_leaf_nodes=None,
                                                  max_samples=None,
                                                  min_impurity_decrease=0.0,
                                                  min_impurity_split=None,
                                                  min_samples_leaf=1,
                                                  min_samples_split=2,
                                                  min_weight_fraction_leaf=0.0,
                                                  n_estimators=100, n_jobs=-1,
                                                  oob_score=False,
                                                  random_state=None, verbose=0,
                                                  warm_start=False),
                   iid='deprecated', n_iter=100, n_jobs=-1,
```

```
                   param_distributions={'max_depth': range(1, 40),
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_split': range(3, 60),
                                        'n_estimators': range(10, 250)},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=False, scoring='roc_auc', verbose=2)
```

```
et_random.best_params_
```

```
{'n_estimators': 243,
 'min_samples_split': 4,
 'max_features': 'sqrt',
 'max_depth': 21}
```

3. AdaBoost

```
n_estimators = range(10,200)

learning_rate = [0.0001, 0.001, 0.01, 0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,0.95,1]


# Create the random grid
parameters_ada = {'n_estimators': n_estimators,
               'learning_rate': learning_rate}


model_ada = AdaBoostClassifier()

ada_random = RandomizedSearchCV(estimator = model_ada, param_distributions = parameters_ada, n_iter = 100, cv = F
                               verbose=2, random_state=42, n_jobs = -1, scoring='roc_auc')
ada_random.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 100 candidates, totalling 1000 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:    4.7s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:   19.2s
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed:   39.6s
[Parallel(n_jobs=-1)]: Done 640 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 1000 out of 1000 | elapsed:  1.8min finished
RandomizedSearchCV(cv=10, error_score=nan,
                   estimator=AdaBoostClassifier(algorithm='SAMME.R',
                                                base_estimator=None,
                                                learning_rate=1.0,
                                                n_estimators=50,
                                                random_state=None),
                   iid='deprecated', n_iter=100, n_jobs=-1,
                   param_distributions={'learning_rate': [0.0001, 0.001, 0.01,
                                                          0.1, 0.2, 0.3, 0.4,
                                                          0.5, 0.6, 0.7, 0.8,
                                                          0.9, 0.95, 1],
                                        'n_estimators': range(10, 200)},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=False, scoring='roc_auc', verbose=2)
```

```
ada_random.best_params_
```

```
{'n_estimators': 110, 'learning_rate': 0.6}
```

** 4. Gradient Boosting**

```
parameters_gb = {
    "loss":["deviance"],
    "learning_rate": [0.01, 0.025, 0.005,0.5, 0.075, 0.1, 0.15, 0.2,0.3,0.8,0.9],
    "min_samples_split": [0.01, 0.025, 0.005,0.4,0.5, 0.075, 0.1, 0.15, 0.2,0.3,0.8,0.9],
    "min_samples_leaf": [1,2,3,5,8,10,15,20,40,50,55,60,65,70,80,85,90,100],
    "max_depth":[3,5,8,10,15,20,25,30,40,50],
    "max_features":["log2","sqrt"],
    "criterion": ["friedman_mse",  "mae"],
    "subsample":[0.5, 0.618, 0.8, 0.85, 0.9, 0.95, 1.0],
    "n_estimators":range(1,100)
    }


model_gb= GradientBoostingClassifier()


gb_random = RandomizedSearchCV(estimator = model_gb, param_distributions = parameters_gb, n_iter = 100, cv = FOLD
                               verbose=2, random_state=42, n_jobs = -1, scoring='roc_auc')
gb_random.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 100 candidates, totalling 1000 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  58 tasks      | elapsed:    1.5s
[Parallel(n_jobs=-1)]: Done 512 tasks      | elapsed:   11.2s
[Parallel(n_jobs=-1)]: Done 993 out of 1000 | elapsed:   24.4s remaining:    0.2s
[Parallel(n_jobs=-1)]: Done 1000 out of 1000 | elapsed:   24.6s finished
RandomizedSearchCV(cv=10, error_score=nan,
                   estimator=GradientBoostingClassifier(ccp_alpha=0.0,
                                                        criterion='friedman_mse',
                                                        init=None,
                                                        learning_rate=0.1,
                                                        loss='deviance',
                                                        max_depth=3,
                                                        max_features=None,
                                                        max_leaf_nodes=None,
                                                        min_impurity_decrease=0.0,
                                                        min_impurity_split=None,
                                                        min_samples_leaf=1,
                                                        min_samples_split=2,
                                                        min_weight_fraction_leaf=0.0,
                                                        n_estimators=100,
                                                        n_it...
                                        'max_features': ['log2', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 3, 5, 8, 10,
                                                             15, 20, 40, 50, 55,
                                                             60, 65, 70, 80, 85,
                                                             90, 100],
                                        'min_samples_split': [0.01, 0.025,
                                                              0.005, 0.4, 0.5,
                                                              0.075, 0.1, 0.15,
                                                              0.2, 0.3, 0.8,
                                                              0.9],
                                        'n_estimators': range(1, 100),
                                        'subsample': [0.5, 0.618, 0.8, 0.85,
                                                      0.9, 0.95, 1.0]},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=False, scoring='roc_auc', verbose=2)
```

```
gb_random.best_params_
```

```
{'subsample': 1.0,
 'n_estimators': 30,
 'min_samples_split': 0.025,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 8,
 'loss': 'deviance',
 'learning_rate': 0.005,
 'criterion': 'mae'}
```

5. Support Vector

```
C = [0.001, 0.10, 0.1, 10, 25, 50,65,70,80,90, 100, 1000,2000,10000,20000,25000,30000,40000]

kernel =  ['rbf']

gamma =[1e-2, 1e-3, 1e-4, 1e-5,1e-6,1e-7,1e-8,1]


# Create the random grid
parameters_svm = {'C': C,
            'gamma': gamma,
             'kernel': kernel}


model_svm = SVC()
from sklearn.model_selection import GridSearchCV
svm_random = GridSearchCV(model_svm, parameters_svm,  cv = 20,
                               verbose=2, n_jobs = -1, scoring='roc_auc')
svm_random.fit(X, y)
```

```
Fitting 20 folds for each of 144 candidates, totalling 2880 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done 128 tasks      | elapsed:    0.8s
[Parallel(n_jobs=-1)]: Done 1096 tasks      | elapsed:    5.7s
[Parallel(n_jobs=-1)]: Done 2568 tasks      | elapsed:   20.4s
[Parallel(n_jobs=-1)]: Done 2880 out of 2880 | elapsed:   27.3s finished
GridSearchCV(cv=20, error_score=nan,
             estimator=SVC(C=1.0, break_ties=False, cache_size=200,
                           class_weight=None, coef0=0.0,
                           decision_function_shape='ovr', degree=3,
                           gamma='scale', kernel='rbf', max_iter=-1,
                           probability=False, random_state=None, shrinking=True,
                           tol=0.001, verbose=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'C': [0.001, 0.1, 0.1, 10, 25, 50, 65, 70, 80, 90, 100,
                               1000, 2000, 10000, 20000, 25000, 30000, 40000],
                         'gamma': [0.01, 0.001, 0.0001, 1e-05, 1e-06, 1e-07,
                                   1e-08, 1],
                         'kernel': ['rbf']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='roc_auc', verbose=2)
```

```
svm_random.best_params_
```

```
{'C': 20000, 'gamma': 1e-05, 'kernel': 'rbf'}
```

**6. xgboost **

```
param_xgb = {
        'silent': [False],
        'max_depth': [6, 10, 15, 20],
        'learning_rate': [0.001, 0.01, 0.1, 0.2, 0,3],
        'subsample': [0.5, 0.6, 0.7, 0.8, 0.9, 1.0],
        'colsample_bytree': [0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0],
        'colsample_bylevel': [0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0],
        'min_child_weight': [0.5, 1.0, 3.0, 5.0, 7.0, 10.0],
        'gamma': [0, 0.25, 0.5, 1.0],
        'reg_lambda': [0.1, 1.0, 5.0, 10.0, 50.0, 100.0],
        'n_estimators': [50,100,120]}


from sklearn.model_selection import GridSearchCV

model_xgb = xgb.XGBClassifier()
xgb_random = RandomizedSearchCV(estimator = model_xgb, param_distributions = param_xgb, n_iter = 100, cv = FOLDS,
                               verbose=2, random_state=42, n_jobs = -1, scoring='roc_auc')
xgb_random.fit(X_train.values, y_train)
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
Fitting 10 folds for each of 100 candidates, totalling 1000 fits
```

```
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    1.9s
[Parallel(n_jobs=-1)]: Done 856 tasks      | elapsed:   11.7s
[Parallel(n_jobs=-1)]: Done 1000 out of 1000 | elapsed:   13.2s finished
RandomizedSearchCV(cv=10, error_score=nan,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, gamma=None,
                                           gpu_id=None, importance_type='gain',
                                           interaction_constraints=None,
                                           learning_rate=None,
                                           max_delta_step=None, max_depth=None,
                                           min_child_weight=None, missing=nan,
                                           monotone_constraints=None,...
                                        'gamma': [0, 0.25, 0.5, 1.0],
                                        'learning_rate': [0.001, 0.01, 0.1, 0.2,
                                                          0, 3],
                                        'max_depth': [6, 10, 15, 20],
                                        'min_child_weight': [0.5, 1.0, 3.0, 5.0,
                                                             7.0, 10.0],
                                        'n_estimators': [50, 100, 120],
                                        'reg_lambda': [0.1, 1.0, 5.0, 10.0,
                                                       50.0, 100.0],
                                        'silent': [False],
                                        'subsample': [0.5, 0.6, 0.7, 0.8, 0.9,
                                                      1.0]},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=False, scoring='roc_auc', verbose=2)
```

```
xgb_random.best_params_
```

```
{'subsample': 0.9,
 'silent': False,
 'reg_lambda': 0.1,
 'n_estimators': 120,
 'min_child_weight': 1.0,
 'max_depth': 6,
 'learning_rate': 0.1,
 'gamma': 0,
 'colsample_bytree': 0.4,
 'colsample_bylevel': 0.7}
```

Selected Parameters

After running RandomizedSearchCV several times, we found the most acceptable parameters for each of our models. We will save these parameters to then make the adjustment of our models.

```
parameter_rf = forest_random.best_params_
```

```
parameter_et = et_random.best_params_
```

```
parameter_ada = ada_random.best_params_
```

```
parameter_gb = gb_random.best_params_
```

```
parameter_svm = svm_random.best_params_
```

```
parameter_xgb= xgb_random.best_params_
```

4. 2 Generating our models

So now let's prepare five learning models as our classification. All these models can be invoked conveniently through the Sklearn library and are listed below:

1. Random Forest Sorter

2. AdaBoost Classifier.
3. Gradient Boosting Classifer
4. Support Vector Machine
5. Extra Trees

```
model_rf = forest_random.best_estimator_

model_et = et_random.best_estimator_

model_ada = ada_random.best_estimator_

model_gb = gb_random.best_estimator_

model_svc = svm_random.best_estimator_

model_xgb= xgb_random.best_estimator_
```

```
kf = KFold(n_splits=FOLDS, random_state = 0, shuffle = True)
for i, (train_index, val_index) in enumerate(kf.split(X_train, y_train)):
    Xtrain, Xval = X_train.values[train_index], X_train.values[val_index]
    ytrain, yval = y_train[train_index], y_train[val_index]

    model_rf.fit(Xtrain, ytrain)
    model_et.fit(Xtrain, ytrain)
    model_ada.fit(Xtrain, ytrain)
    model_gb.fit(Xtrain, ytrain)
    model_svc.fit(Xtrain, ytrain)
    model_xgb.fit(Xtrain, ytrain)
```

5. Importance of characteristics

According to the Sklearn documentation, most classifiers are built with an attribute that returns important features by simply typing *. Feature_importances _ *. Therefore, we will invoke this very useful attribute through our graph of the function of the importance of the characteristic as such

```
rf_feature = model_rf.feature_importances_
ada_feature = model_ada.feature_importances_
gb_feature = model_gb.feature_importances_
et_feature = model_et.feature_importances_
xbg_feature = model_xgb.feature_importances_
```

```
cols = X.columns.tolist()
# Create a dataframe with features
feature_dataframe = pd.DataFrame( {'features': cols,
     'Random Forest feature importances': rf_feature,
      'AdaBoost feature importances': ada_feature,
    'Gradient Boost feature importances': gb_feature,
    'Extra Trees  feature importances': et_feature,
    'Xgboost feature importances': xbg_feature,
    })
```

```
xbg_feature
```

```
array([0.15925272, 0.08101212, 0.10553615, 0.09879456, 0.22974722,
       0.10138097, 0.11072818, 0.1135481 ], dtype=float32)
```

Graphics:

```
# Scatter plot
trace = go.Scatter(
    y = feature_dataframe['Random Forest feature importances'].values,
    x = feature_dataframe['features'].values,
    mode='markers',
    marker=dict(
        sizemode = 'diameter',
        sizeref = 1,
        size = 25,
#       size= feature_dataframe['AdaBoost feature importances'].values,
        #color = np.random.randn(500), #set color equal to a variable
        color = feature_dataframe['Random Forest feature importances'].values,
        colorscale='Portland',
        showscale=True
    ),
    text = feature_dataframe['features'].values
)
data = [trace]

layout= go.Layout(
    autosize= True,
    title= 'Random Forest Feature Importance',
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
        title= 'Feature Importance',
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig,filename='scatter2010')

# Scatter plot
trace = go.Scatter(
    y = feature_dataframe['Extra Trees  feature importances'].values,
    x = feature_dataframe['features'].values,
    mode='markers',
    marker=dict(
        sizemode = 'diameter',
        sizeref = 1,
        size = 25,
#       size= feature_dataframe['AdaBoost feature importances'].values,
        #color = np.random.randn(500), #set color equal to a variable
        color = feature_dataframe['Extra Trees  feature importances'].values,
        colorscale='Portland',
        showscale=True
    ),
    text = feature_dataframe['features'].values
)
data = [trace]

layout= go.Layout(
    autosize= True,
    title= 'Extra Trees Feature Importance',
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
```

```
        title= 'Feature Importance',
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig,filename='scatter2010')

# Scatter plot
trace = go.Scatter(
    y = feature_dataframe['AdaBoost feature importances'].values,
    x = feature_dataframe['features'].values,
    mode='markers',
    marker=dict(
        sizemode = 'diameter',
        sizeref = 1,
        size = 25,
#       size= feature_dataframe['AdaBoost feature importances'].values,
        #color = np.random.randn(500), #set color equal to a variable
        color = feature_dataframe['AdaBoost feature importances'].values,
        colorscale='Portland',
        showscale=True
    ),
    text = feature_dataframe['features'].values
)
data = [trace]

layout= go.Layout(
    autosize= True,
    title= 'AdaBoost Feature Importance',
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
        title= 'Feature Importance',
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig,filename='scatter2010')

# Scatter plot
trace = go.Scatter(
    y = feature_dataframe['Gradient Boost feature importances'].values,
    x = feature_dataframe['features'].values,
    mode='markers',
    marker=dict(
        sizemode = 'diameter',
        sizeref = 1,
        size = 25,
#       size= feature_dataframe['AdaBoost feature importances'].values,
        #color = np.random.randn(500), #set color equal to a variable
        color = feature_dataframe['Gradient Boost feature importances'].values,
        colorscale='Portland',
        showscale=True
    ),
    text = feature_dataframe['features'].values
)
data = [trace]

layout= go.Layout(
    autosize= True,
```

```
    title= 'Gradient Boosting Feature Importance',
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
        title= 'Feature Importance',
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig,filename='scatter2010')

trace = go.Scatter(
    y = feature_dataframe['Xgboost feature importances'].values,
    x = feature_dataframe['features'].values,
    mode='markers',
    marker=dict(
        sizemode = 'diameter',
        sizeref = 1,
        size = 25,
#       size= feature_dataframe['AdaBoost feature importances'].values,
        #color = np.random.randn(500), #set color equal to a variable
        color = feature_dataframe['Xgboost feature importances'].values,
        colorscale='Portland',
        showscale=True
    ),
    text = feature_dataframe['features'].values
)
data = [trace]

layout= go.Layout(
    autosize= True,
    title= 'XgboostFeature Importance',
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
        title= 'Feature Importance',
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig,filename='scatter2010')
```

```
# Create the new column that contains the average of the values.
feature_dataframe['mean'] = feature_dataframe.mean(axis= 1) # axis = 1 computes the mean row-wise
feature_dataframe.head(3)
```

	features	Random Forest feature importances	AdaBoost feature importances	Gradient Boost feature importances	Extra Trees feature importances	Xgboost feature importances	mean
0	M/F	0.038654	0.054545	0.037391	0.074301	0.159253	0.072829
1	Age	0.097803	0.109091	0.035709	0.080632	0.081012	0.080849
2	EDUC	0.096879	0.072727	0.103513	0.120405	0.105536	0.099812

```
y = feature_dataframe['mean'].values
x = feature_dataframe['features'].values
data = [go.Bar(
            x= x,
             y= y,
            width = 0.5,
            marker=dict(
               color = feature_dataframe['mean'].values,
            colorscale='Portland',
            showscale=True,
            reversescale = False
            ),
            opacity=0.6
        )]

layout= go.Layout(
    autosize= True,
    title= 'Barplots of Mean Feature Importance',
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
        title= 'Feature Importance',
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig, filename='bar-direct-labels')
```