Alzheimer’s Disease and Cognitive Impairment Prediction

ELIUD OMOLLO

In [1]:
```
#numpy and pandas
import pandas as pd
import numpy as np
```

In [2]:
```
#visualization
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [3]:
```
#preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import PolynomialFeatures
```

In [4]:
```
#Regressions
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
```

In [5]:
```
#classification
from sklearn.linear_model import LogisticRegressionCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.pipeline import Pipeline
```

In [6]:
```
#Regression model metrics
from sklearn.metrics import r2_score
from sklearn.model_selection import cross_val_score
```

In [7]:
```
#classification metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
```

In [8]:
```
#regularization
from sklearn.linear_model import LassoCV
from sklearn.linear_model import RidgeCV
from sklearn.decomposition import PCA
```

In [9]:
```
#cross validation
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold
```

In [10]:
```
#utilities
from sklearn.model_selection import train_test_split
```

In [11]:
```
#global random state
rnd_state = 41
```

In [12]:
```
import warnings
import sklearn.exceptions
warnings.filterwarnings("ignore", category=sklearn.exceptions.UndefinedMetricWarn
```

FUNCTIONS

Imputing Functions

In [13]:
```
#impute missing numerical data with mean
def imputeWithMean(dataFrame):
    nullCols = dataFrame.columns[dataFrame.isnull().any()].tolist()
    for col in nullCols:
        col_mean = dataFrame[col].mean()
        dataFrame[col] = dataFrame[col].fillna(col_mean)
    return dataFrame
```

In [14]:
```
#We will add new columns that tracks changes from the baseline data
#if there is no change, function will record zero, otherwise function will record

def trackBaseline(dataFrame):
    #check if a baseline col exists
    blColArray  = []
    for col in list(dataFrame):
        if '_bl' in col:
            blColArray.append(col)
        else:
            blCol = col+'_bl'
            if blCol in list(dataFrame):
                #create a new column and populate the column with 0 if no change,
                f = lambda x: 1 if x[col] != x[blCol] else 0
                #create a new cols with the new values
                dataFrame[col+'_chg'] = dataFrame.apply(f, axis = 1)
    #drop all the baseline columns
    dataFrame = dataFrame.drop(blColArray, axis=1)
    return dataFrame
```

Encoding Function

In [15]:
```
#function to encode categorical data:
# Target will be encoded with label encoding
#Features will be encoded using one hot encoding for features

def encodeData(dataFrame, target):
    catCols = []
    #encode the target
    from sklearn import preprocessing
    le = preprocessing.LabelEncoder()
    dataFrame[target] =  le.fit_transform(dataFrame[target])
    cat = le.inverse_transform([0, 1, 2])

    #encode features
    feat = [x for x in list(dataFrame) if x !=target]
    for col in feat:
        if dataFrame[col].dtype.kind == 'O':
            catCols.append(col)
    catDf = dataFrame[catCols]
    catDf_en = pd.get_dummies(catDf, drop_first= True)

    dataFrame = dataFrame.drop(catCols, axis= 1)
    dataFrame = pd.concat([dataFrame, catDf_en], axis=1)
    return dataFrame, cat
```

Standardize Data function

In [16]:
```
#function to standardize the the test and train data using the mean and std of th
def dataScaler(train, test, target):

    features = [x for x in list(train) if (x !=target)]
    mean = np.mean(train.loc[:, features])
    std = np.std(train.loc[:, features])
    f = lambda x: (x-mean)/std

    train_n = train.apply(f, axis = 1)
    train_n[target] = train[target]

    test_n  = test.apply(f, axis = 1)
    test_n[target] = test[target]
    return train_n , test_n
```

Model Evaluation

In [17]:
```
#function to evaluate and plot various models

def modelAnalyzer(X_train, y_train, X_test, y_test):
    scores = {}
    f1_scores = {}
    precision_scores = {}
    recall_scores = {}

    models = dict(
        lgr =LogisticRegressionCV(Cs=10, random_state=rnd_state, penalty='l2', cv
        ld = LinearDiscriminantAnalysis(),
        qd =QuadraticDiscriminantAnalysis(),
        knn= KNeighborsClassifier(),
        rnd = RandomForestClassifier(random_state= rnd_state, max_depth=None, max_
        )
    def fitpredict(model, suf):
        #fit data
        model.fit(X_train, y_train)

        #make predictions
        y_predict_train  = model.predict(X_train)
        y_predict_test  = model.predict(X_test)

        #store values
        #scores[name +'_train_score_' + str(suf)] = model.score(X_train, y_train)
        scores[name +'_test_score_' + str(suf)] = model.score(X_test, y_test)

        #calculate and store f1-scores
        #f1_scores[name +'_train_f1_' + str(suf)] = f1_score(y_train,y_predict_tr
        f1_scores[name +'_test_f1_' + str(suf)] = f1_score(y_test,y_predict_test,


        #calculate and store precision scores
        #precision_scores[name +'_train_precision_' + str(suf)] = precision_score
        precision_scores[name +'_test_precision_' + str(suf)] = precision_score(y_

        #calculate and store recall scores
        #recall_scores[name +'_train_recall_' + str(suf)] = recall_score(y_test,y_
        recall_scores[name +'_test_recall_' + str(suf)] = recall_score(y_test,y_p

    for name, model in models.items():
        if name in ['lgr', 'ld', 'qd']:
            fitpredict(model, '')
        elif name in ['knn','rnd']:
            params = {}
            params['knn'] =  {'n_neighbors': [2, 5, 10, 20]}
            params['rnd'] = {'n_estimators': [5, 10, 20, 30, 40]}
            for key, paramDict in params.items():
                 for k, param in paramDict.items():
                        for item in param:
                            if name == key:
                                model = model.set_params(**{k: item})
                                suf = str(key) + '_' + str(item)
                                fitpredict(model, suf )
        else:
            pass
```

```
    scoresDF = pd.DataFrame.from_records([scores])
    f1_scoresDF = pd.DataFrame.from_records([f1_scores])
    pscoresDF = pd.DataFrame.from_records([precision_scores])
    rscoresDF = pd.DataFrame.from_records([recall_scores])
    return scoresDF,  f1_scoresDF, pscoresDF , rscoresDF
```

Visualization Functions

In [18]:
```
#Plot histogram given a dataframe and a colum. The histogram is colored by target
def histPlot(dataFrame, col, grouby):
    plt.figure()
    grouped = dataFrame.groupby(grouby)
    colors = ['blue', 'red', 'green']

    for i, group in enumerate(grouped):
        plt.subplot(1,1, 1)
        plt.hist(group[1][col], color=colors[i], label= group[1][grouby])
        plt.xlabel(col)
        plt.title(col + ' HISTOGRAM')
        plt.legend()
```

In [19]:
```
#Plot scatter given a dataframe and a colum. The scatterplot is colored by target
def scatterPlot(dataFrame, xcol, ycol, groupby):
    fig = plt.figure()
    ax = fig.add_axes([0.1, 0.1,1.0, 1.0 ])
    colors = {0:'green', 1:'cyan', 2:'red', 3:'green', 4: 'magenta'}
    categories = dataFrame.groupby(groupby)
    for key, category in categories:
        category.plot(ax=ax, kind='scatter', x=xcol, y=ycol, label=key, color=col
    ax.set_title('Scatter plot of ' + xcol + ' vs ' + ycol)
    plt.show()
```

In [20]:
```
#Function to plot missing data
def plotMissingData(dataFrame):
    miss_data = {col: (pd.isnull(dataFrame[col]).sum()/dataFrame.shape[0])*100 fo
    miss_data_df = pd.DataFrame.from_dict(data=miss_data, orient='index')
    g = sns.factorplot(x=miss_data_df.index , y=0, data=miss_data_df, kind= 'bar'
    g.set_xticklabels(rotation=90, fontsize=10)
    g.set_xlabels('Feature')
    g.set_ylabels('% of Missing data')
    plt.show()
```

In [21]:
```
#Plot collineariLity
def plot_collinearity(df, cols):
    fig, ax = plt.subplots(1,1, figsize=(10,8))
    sns.heatmap(np.corrcoef(df.T), ax=ax)
    ax.set_xticklabels(cols, rotation='vertical')
    ax.set_yticklabels(cols[::-1], rotation='horizontal')
    plt.show()
```

BASELINE MODEL

Import data and drop any unnecessary columns

In [22]:
```
adnimergeDF= pd.read_csv('data\ADNIMERGE.csv')
#Drop those columns since they do not add value to the model or they present inte
#for example, SITE is the location where the test was done or they are collinear
dropCols= ['PTID','VISCODE', 'SITE','COLPROT', 'ORIGPROT', 'EXAMDATE', 'FLDSTRENG
           'FLDSTRENG_bl', 'FSVERSION_bl',
            'Years_bl','Month','Month_bl' ,'M','update_stamp',
            'EcogPtMem', 'EcogPtLang',
            'EcogPtVisspat', 'EcogPtPlan', 'EcogPtOrgan', 'EcogPtDivatt',
            'EcogPtTotal', 'EcogSPMem', 'EcogSPLang', 'EcogSPVisspat', 'EcogSPPla
            'EcogSPOrgan', 'EcogSPDivatt', 'EcogSPTotal', 'EcogPtMem_bl', 'EcogPt
            'EcogPtPlan_bl', 'EcogPtOrgan_bl', 'EcogPtDivatt_bl', 'EcogPtTotal_bl
            'EcogSPMem_bl', 'EcogSPLang_bl', 'EcogSPVisspat_bl', 'EcogSPPlan_bl',
            'EcogSPOrgan_bl', 'EcogSPDivatt_bl', 'EcogSPTotal_bl',
            'RAVLT_immediate', 'RAVLT_learning', 'RAVLT_forgetting','RAVLT_perc_f
            'RAVLT_immediate_bl','RAVLT_learning_bl', 'RAVLT_forgetting_bl', 'RAV
            'ADAS11', 'ADAS13', 'ADAS11_bl', 'ADAS13_bl'
          ]
adnimergeDF= adnimergeDF.drop(dropCols, axis=1)
```

In [23]:
```
adnimergeDF.shape
```

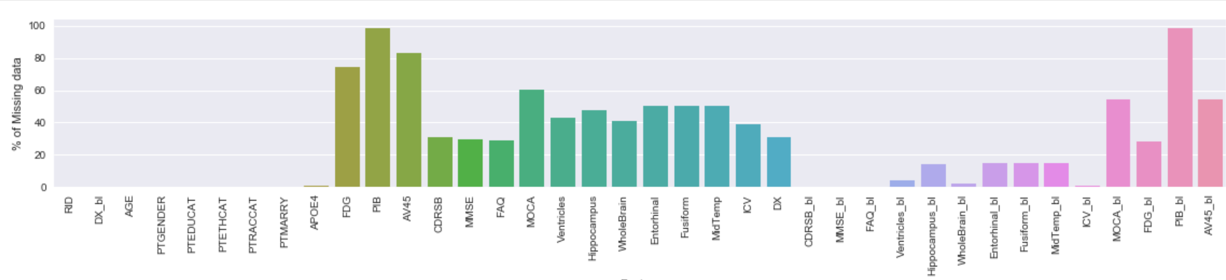
Out[23]:
```
(13017, 38)
```

In [24]:
```
adnimergeDF.columns
```

Out[24]:
```
Index(['RID', 'DX_bl', 'AGE', 'PTGENDER', 'PTEDUCAT', 'PTETHCAT', 'PTRACCAT',
       'PTMARRY', 'APOE4', 'FDG', 'PIB', 'AV45', 'CDRSB', 'MMSE', 'FAQ',
       'MOCA', 'Ventricles', 'Hippocampus', 'WholeBrain', 'Entorhinal',
       'Fusiform', 'MidTemp', 'ICV', 'DX', 'CDRSB_bl', 'MMSE_bl', 'FAQ_bl',
       'Ventricles_bl', 'Hippocampus_bl', 'WholeBrain_bl', 'Entorhinal_bl',
       'Fusiform_bl', 'MidTemp_bl', 'ICV_bl', 'MOCA_bl', 'FDG_bl', 'PIB_bl',
       'AV45_bl'],
      dtype='object')
```

Plot missing data

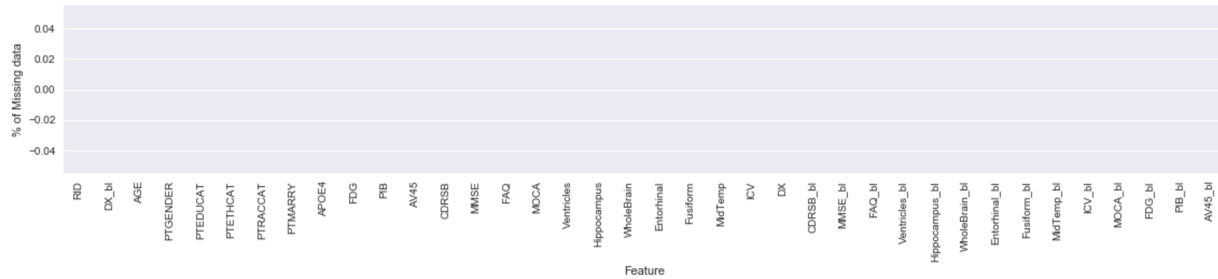
In [25]:
```
plotMissingData(adnimergeDF)
```



In [26]:
```
#We are going to rows with null values for Target data 'DX','DX_bl'
adnimergeDF = adnimergeDF.dropna(subset=['DX','DX_bl'], axis=0, how='any')
```

Impute missing data

In [27]:
```
#impute and plot missing data using our functios
adnimergeDF = imputeWithMean(adnimergeDF)
#returns null. All missing data imputed
plotMissingData(adnimergeDF)
```



In [28]:
```
#Create a baseline change column using our function. Recal that the baseline func
#that records 0 if no change occurred in the baseline and the current measurement
blData_final  = trackBaseline(adnimergeDF)
```

In [29]:
```
#We now have new fields with the suffix "_chg". These fields contain 0 if no chang
blData_final.columns
```

Out[29]:
```
Index(['RID', 'AGE', 'PTGENDER', 'PTEDUCAT', 'PTETHCAT', 'PTRACCAT', 'PTMARRY',
       'APOE4', 'FDG', 'PIB', 'AV45', 'CDRSB', 'MMSE', 'FAQ', 'MOCA',
       'Ventricles', 'Hippocampus', 'WholeBrain', 'Entorhinal', 'Fusiform',
       'MidTemp', 'ICV', 'DX', 'FDG_chg', 'PIB_chg', 'AV45_chg', 'CDRSB_chg',
       'MMSE_chg', 'FAQ_chg', 'MOCA_chg', 'Ventricles_chg', 'Hippocampus_chg',
       'WholeBrain_chg', 'Entorhinal_chg', 'Fusiform_chg', 'MidTemp_chg',
       'ICV_chg', 'DX_chg'],
      dtype='object')
```

Perform one hot encoding on categorical data

In [30]:
```
#Perform One hot encoding on categorical data using our function. Also does label
blData_final, cat = encodeData(blData_final, 'DX')
```

In [31]:
```
#Display inverse encoding
print(cat)
```

```
['CN' 'Dementia' 'MCI']
```

In [32]:
```
#Our final data
blData_final.head()
```

Out[32]:

	RID	AGE	PTEDUCAT	APOE4	FDG	PIB	AV45	CDRSB	MMSE	FAQ	...	PTRACC
0	2	74.3	16	0.0	1.36926	1.781869	1.195086	0.0	28.0	0.0	...	
1	3	81.3	18	1.0	1.09079	1.781869	1.195086	4.5	20.0	10.0	...	
2	3	81.3	18	1.0	1.06360	1.781869	1.195086	6.0	24.0	12.0	...	
3	3	81.3	18	1.0	1.10384	1.781869	1.195086	3.5	17.0	17.0	...	
4	3	81.3	18	1.0	1.03871	1.781869	1.195086	8.0	19.0	14.0	...	

5 rows × 47 columns

In [33]:
```
blData_final.describe()
```

Out[33]:

	RID	AGE	PTEDUCAT	APOE4	FDG	PIB	AV45
count	8910.000000	8910.000000	8910.000000	8910.000000	8910.000000	8910.000000	8910.000000
mean	2212.596857	73.747374	15.958361	0.544924	1.208160	1.781869	1.195086
std	1859.793954	7.014481	2.837294	0.658405	0.098701	0.066626	0.111252
min	2.000000	54.400000	4.000000	0.000000	0.636804	1.095000	0.814555
25%	605.000000	69.500000	14.000000	0.000000	1.208160	1.781869	1.195086
50%	1257.000000	73.700000	16.000000	0.000000	1.208160	1.781869	1.195086
75%	4335.000000	78.700000	18.000000	1.000000	1.208160	1.781869	1.195086
max	5296.000000	91.400000	20.000000	2.000000	1.753320	2.927500	2.669210

8 rows × 47 columns

BASELINE EXPLORATORY DATA ANALYSIS: OVERALL

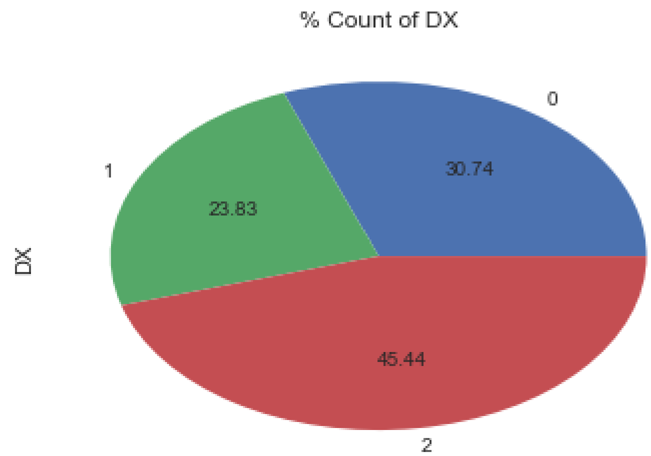
:

Train/Test Split

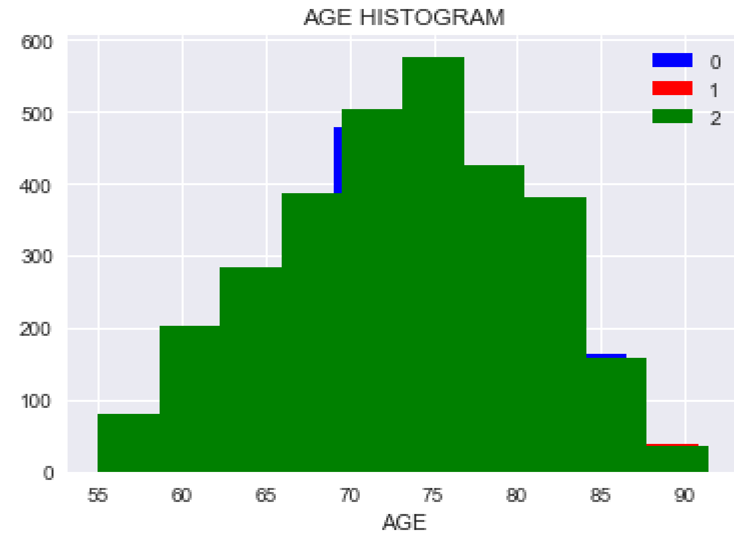
In [34]:
```
#Split the data into  75% train and 25% test splits
X = blData_final.drop('RID', axis = 1)
train, test = train_test_split(X, test_size=0.25, random_state=rnd_state)
```

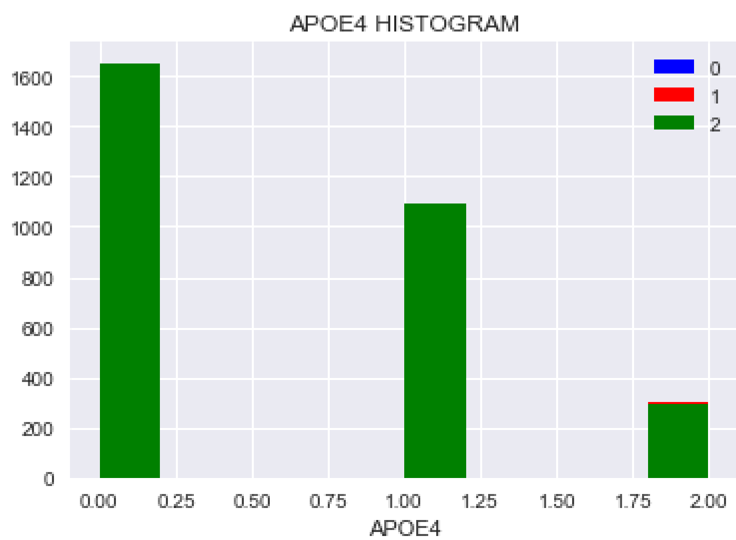
In [35]:
```
train['DX'].value_counts(sort=False).plot.pie(autopct='%.2f').set_title('% Count 
print('Pie Chart of DX Distrubution')
plt.show()
```

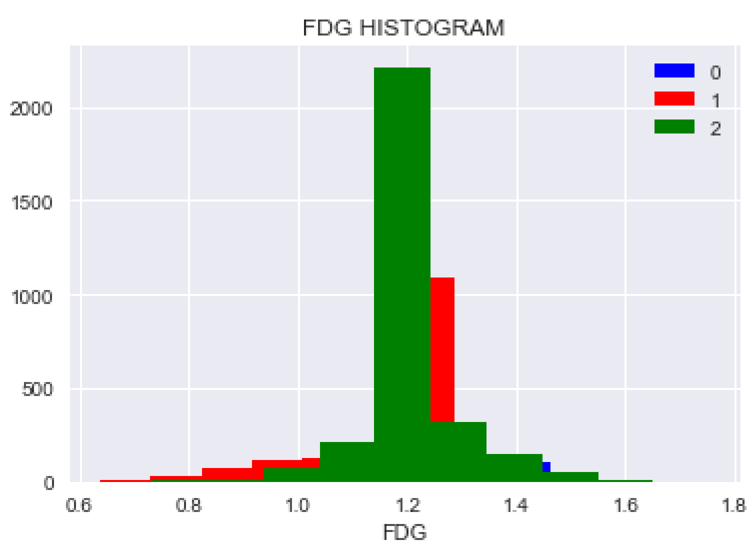
```
Pie Chart of DX Distrubution
```

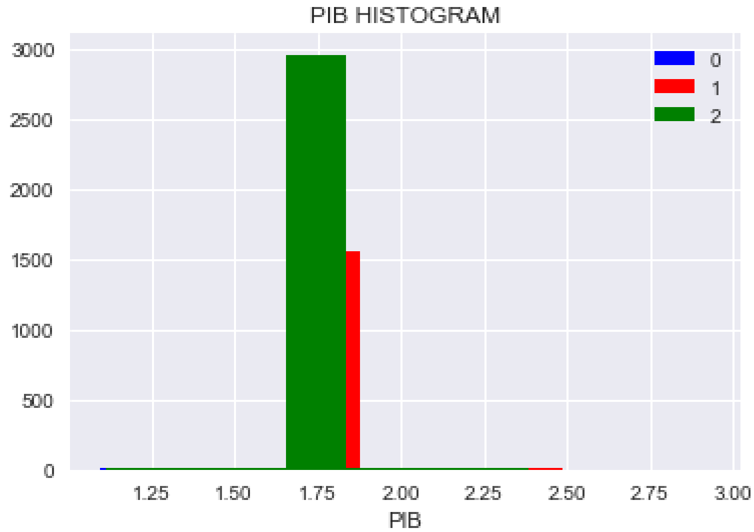


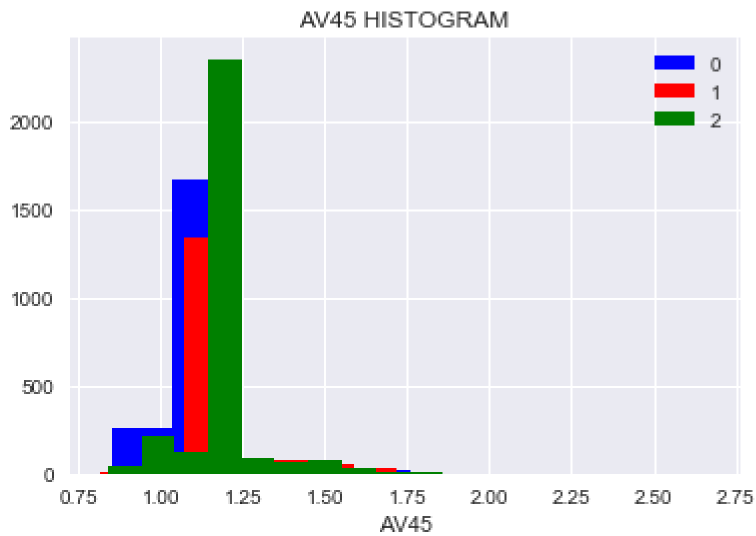
In [36]:
```
numCols = ['AGE','APOE4', 'FDG', 'PIB', 'AV45', 'CDRSB', 'MMSE', 'FAQ', 'MOCA',
           'Ventricles', 'Hippocampus', 'WholeBrain', 'Entorhinal', 'Fusiform',
           'MidTemp', 'ICV']
for col in numCols:
    histPlot(train, col, 'DX')
```

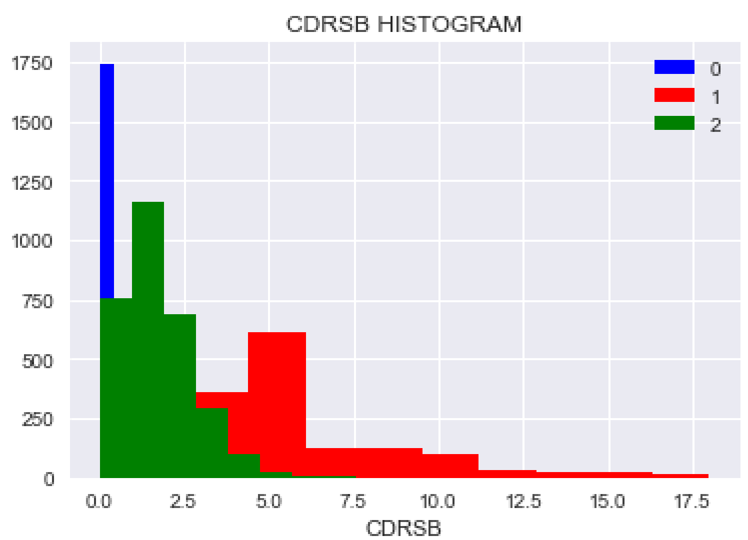


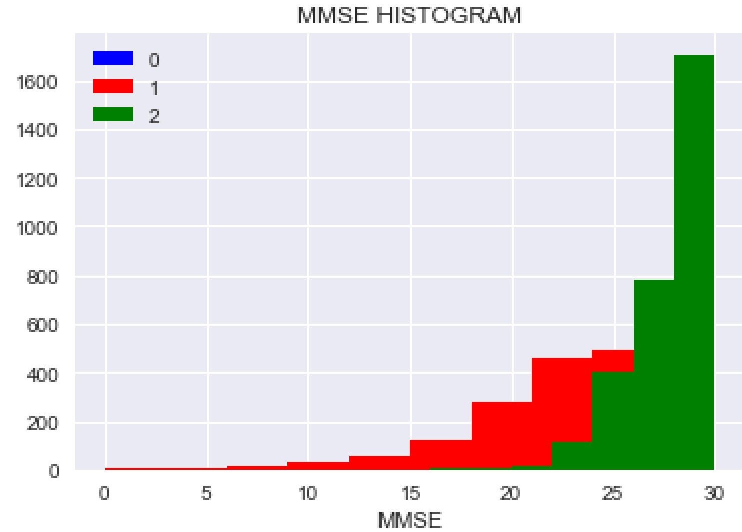


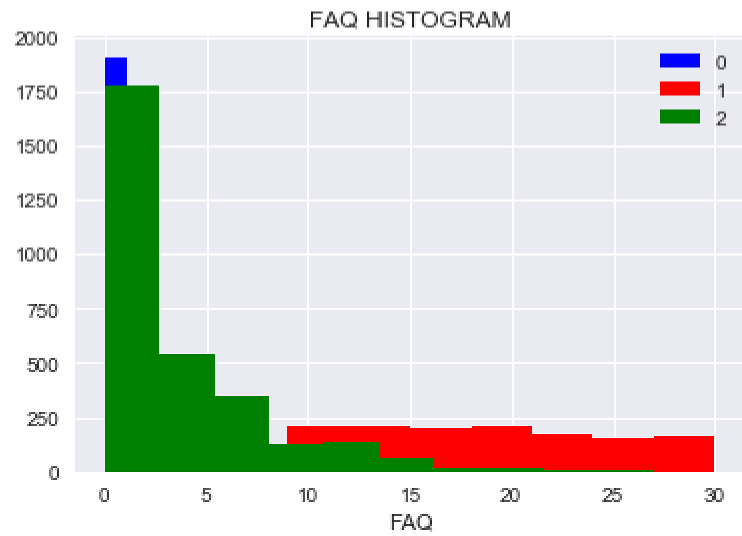


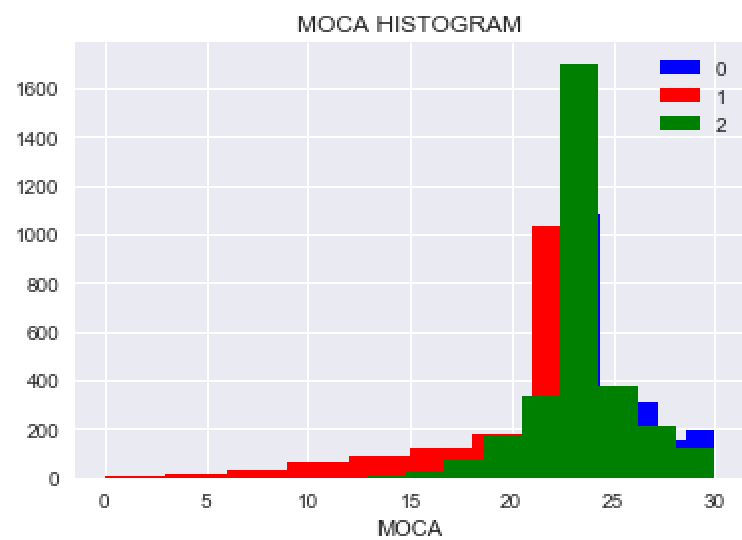

PIB HISTOGRAM
0
1
2
3000
2500
2000
1500
1000
500
0
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
PIB

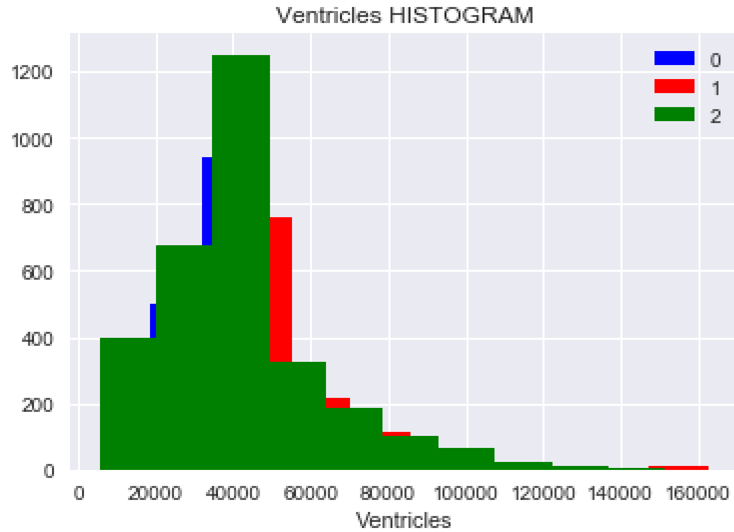

AV45 HISTOGRAM
0
1
2
2000
1500
1000
500
0
0.75
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
AV45

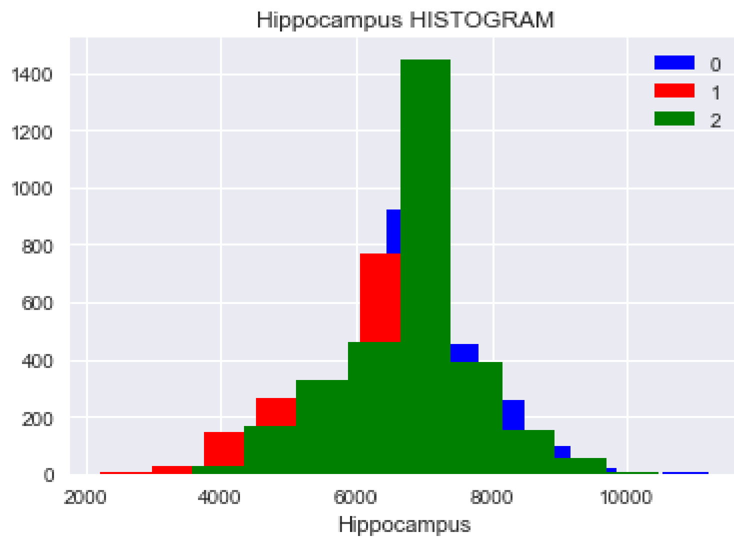

CDRSB HISTOGRAM
0
1
2
1750
1500
1250
1000
750
500
250
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
CDRSB

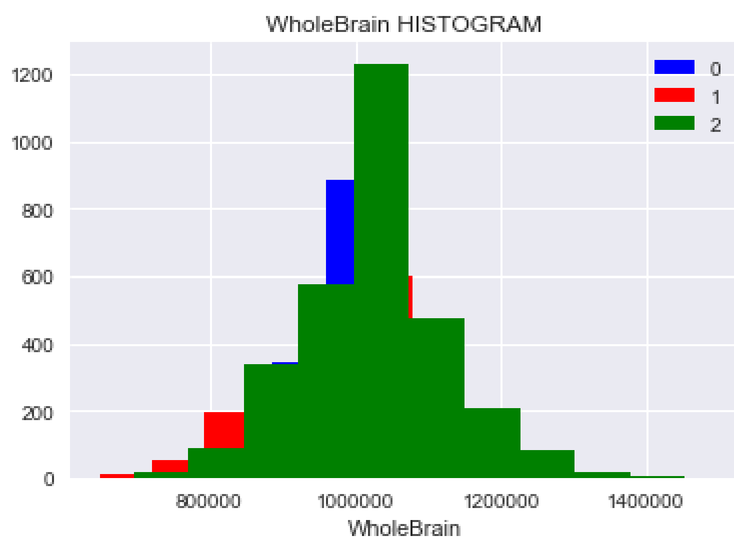

MMSE HISTOGRAM
0
1
2
1600
1400
1200
1000
800
600
400
200
0
0
5
10
15
20
25
30
MMSE

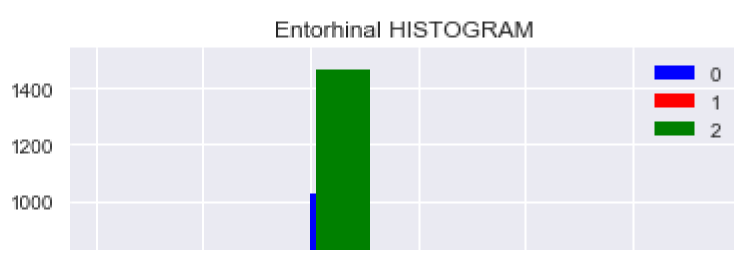

FAQ HISTOGRAM
2000
1750
1500
1250
1000
750
500
250
0
0
1
2
0
5
10
15
20
25
30
FAQ

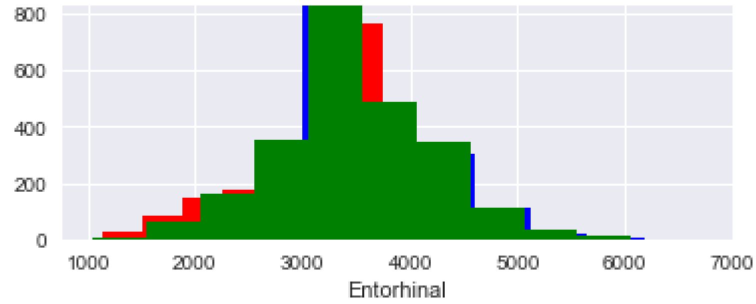

MOCA HISTOGRAM
0
1
2
1600
1400
1200
1000
800
600
400
200
0
0
5
10
15
20
25
30
MOCA

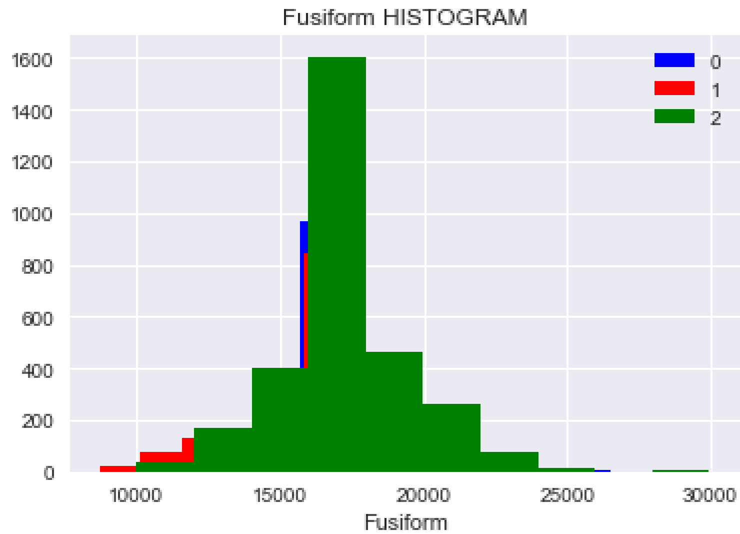

Ventricles HISTOGRAM
0
1
2
0
200
400
600
800
1000
1200
0
20000
40000
60000
80000
100000
120000
140000
160000
Ventricles

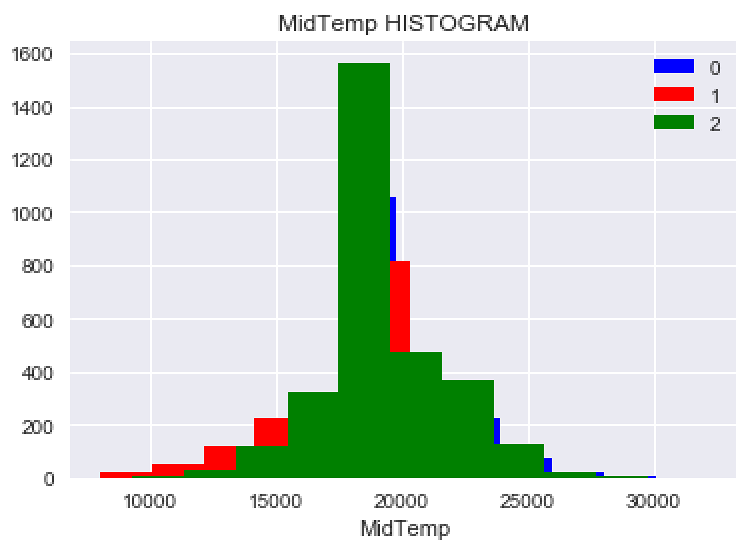

Hippocampus HISTOGRAM
0
1
2
0
200
400
600
800
1000
1200
1400
2000
4000
6000
8000
10000
Hippocampus

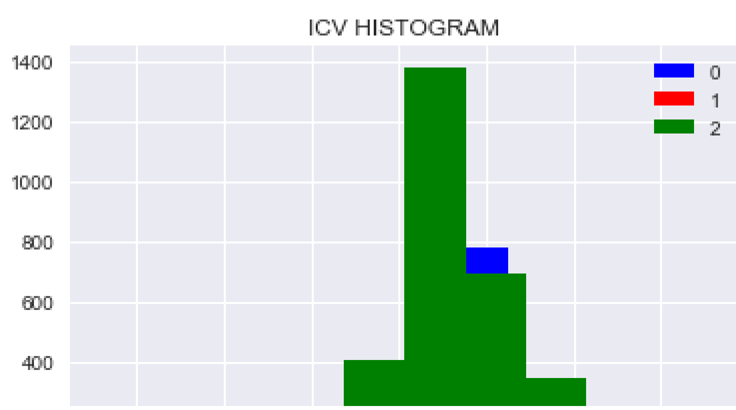

WholeBrain HISTOGRAM
0
1
2
0
200
400
600
800
1000
1200
800000
1000000
1200000
1400000
WholeBrain

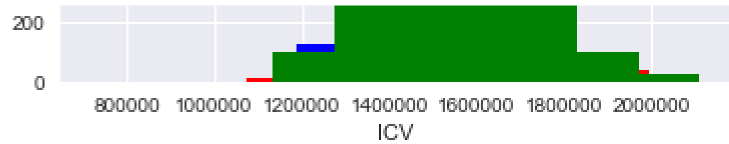

Entorhinal HISTOGRAM
0
1
2
1000
1200
1400


0
200
400
600
800
1000
2000
3000
4000
5000
6000
7000
Entorhinal

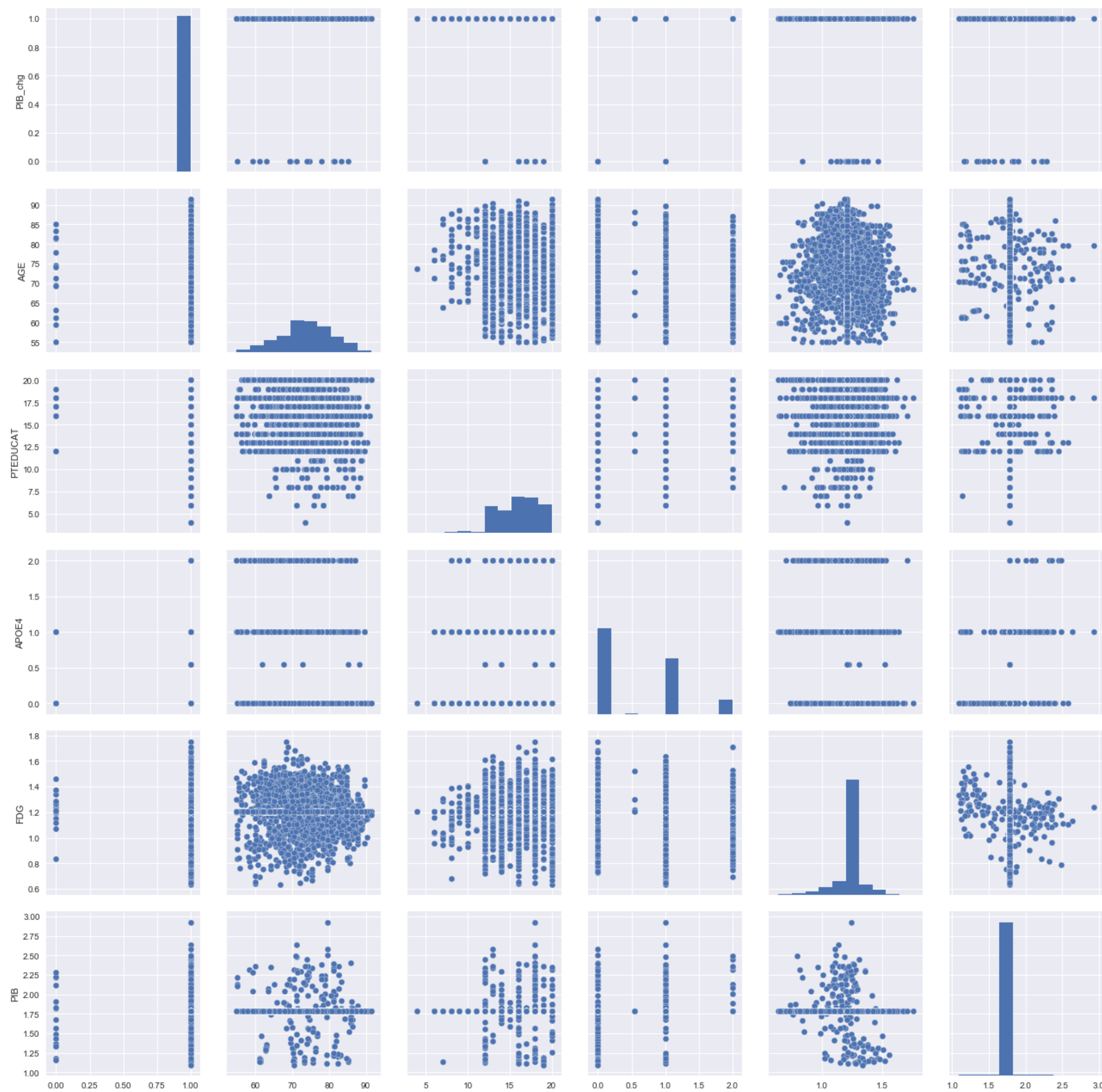

Fusiform HISTOGRAM
0
1
2
0
200
400
600
800
1000
1200
1400
1600
10000
15000
20000
25000
30000
Fusiform


MidTemp HISTOGRAM
0
1
2
0
200
400
600
800
1000
1200
1400
1600
10000
15000
20000
25000
30000
MidTemp


ICV HISTOGRAM
0
1
2
400
600
800
1000
1200
1400



In [37]:
```
g = sns.pairplot(train.iloc[:, np.r_[19, 0:5]] ,palette='muted',size=3)
```



BASELINE EXPLORATORY DATA ANALYSIS: COGNITIVE TESTS

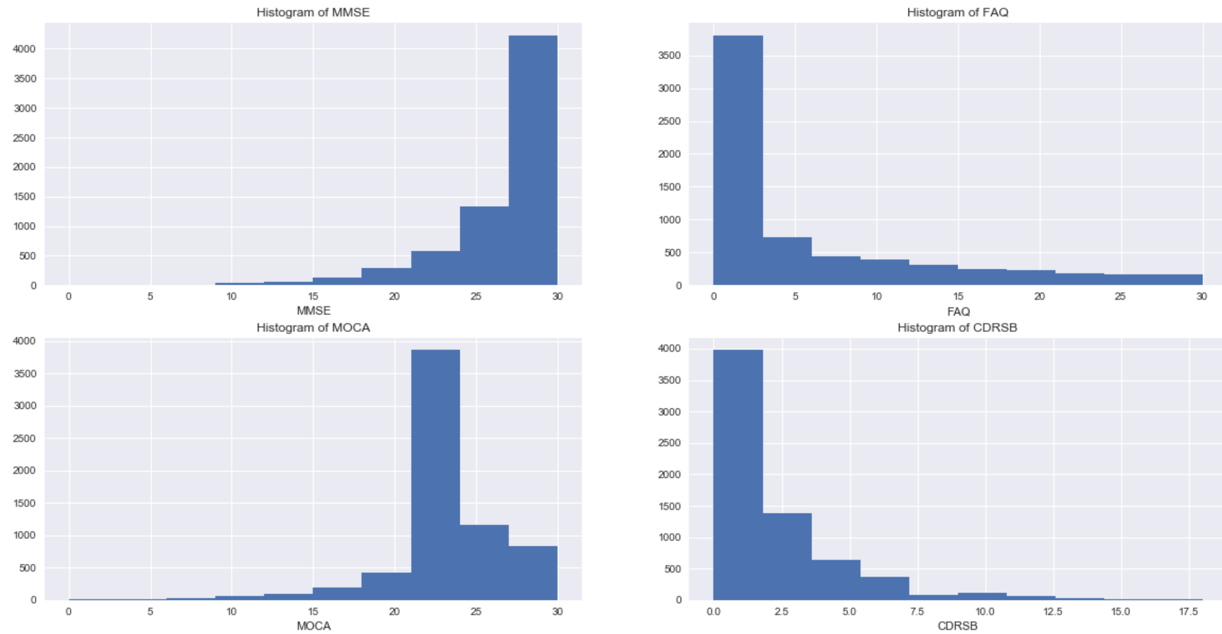
:

Cognitive Tests

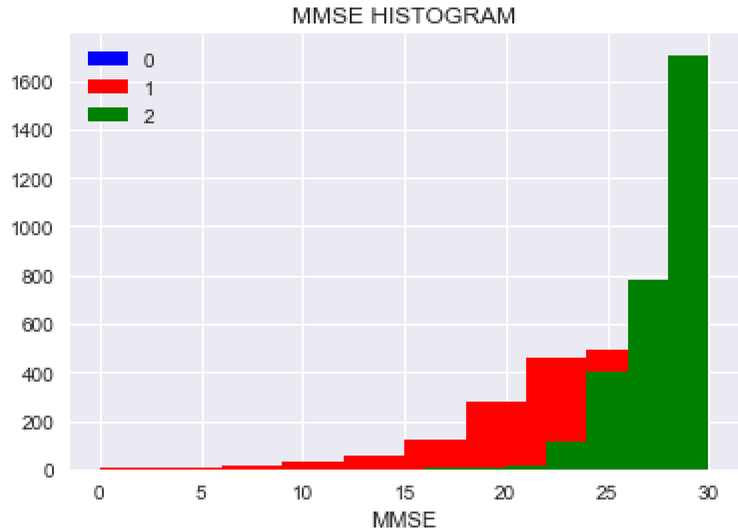
MMSE : Mini Mental State Exam
FAQ: Functional Activities Questionnaire
MOCA : Montreal Cognitive Assessment
CDRSB : Clinical Dementia Rating

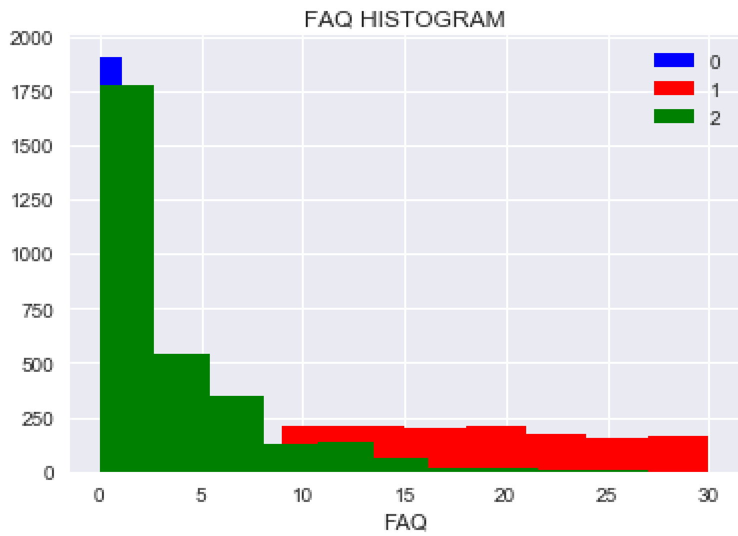
In [38]:
```
#Explanatory data analysis on Cognitive scores
cogCols = ['MMSE', 'FAQ', 'MOCA','CDRSB']
print('HISTOGRAM OF COGNITIVE TESTS')
plt.figure(figsize=(20, 10))
for k, p in enumerate(cogCols):
    plt.subplot(2,2, k+1)
    plt.xlabel(p)
    plt.title('Histogram of ' + p)
    train[p].hist()
plt.show()
```

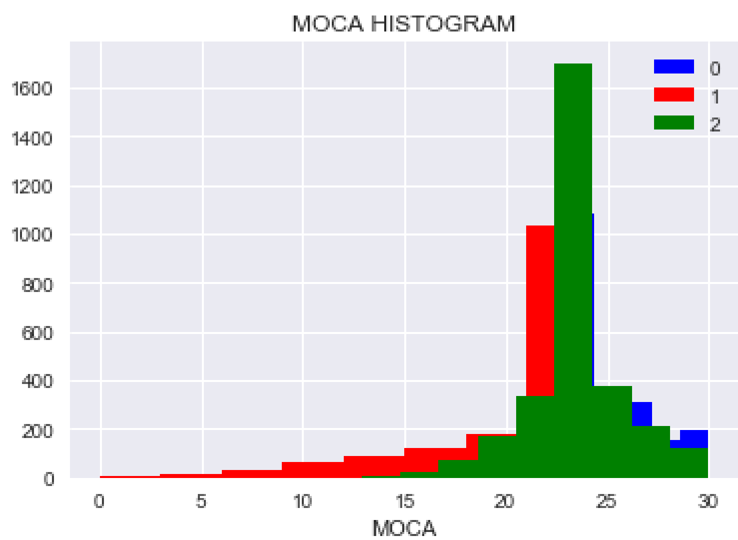
```
HISTOGRAM OF COGNITIVE TESTS
```

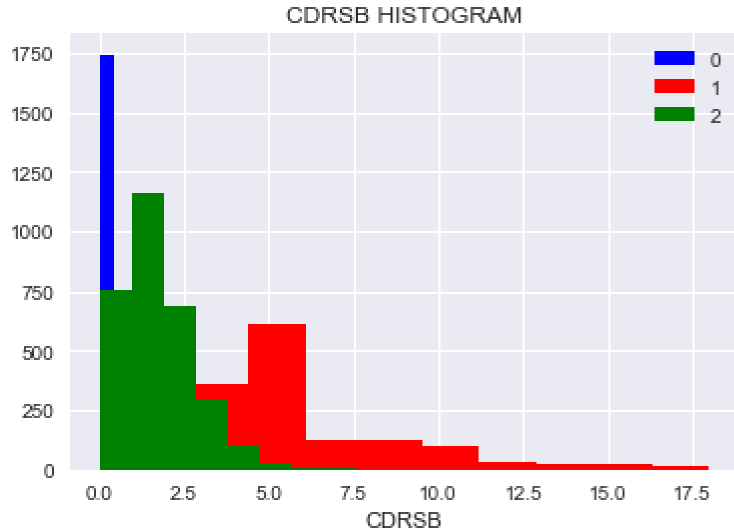


In [39]:
```
for i, col in enumerate(cogCols):
    histPlot(train, col, 'DX')
```



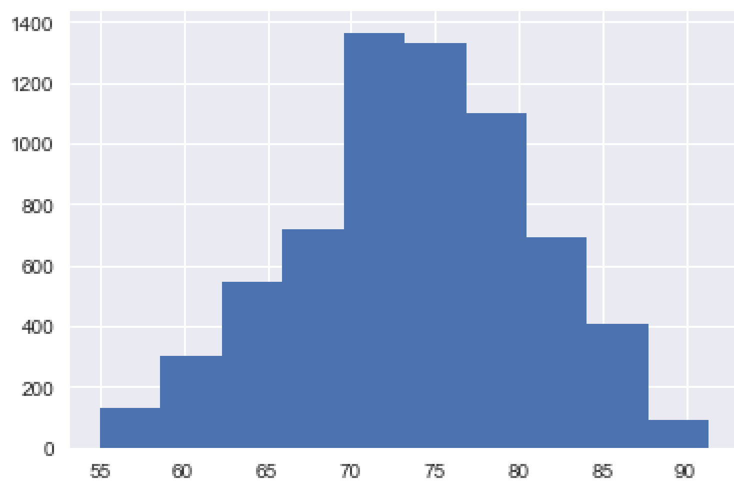






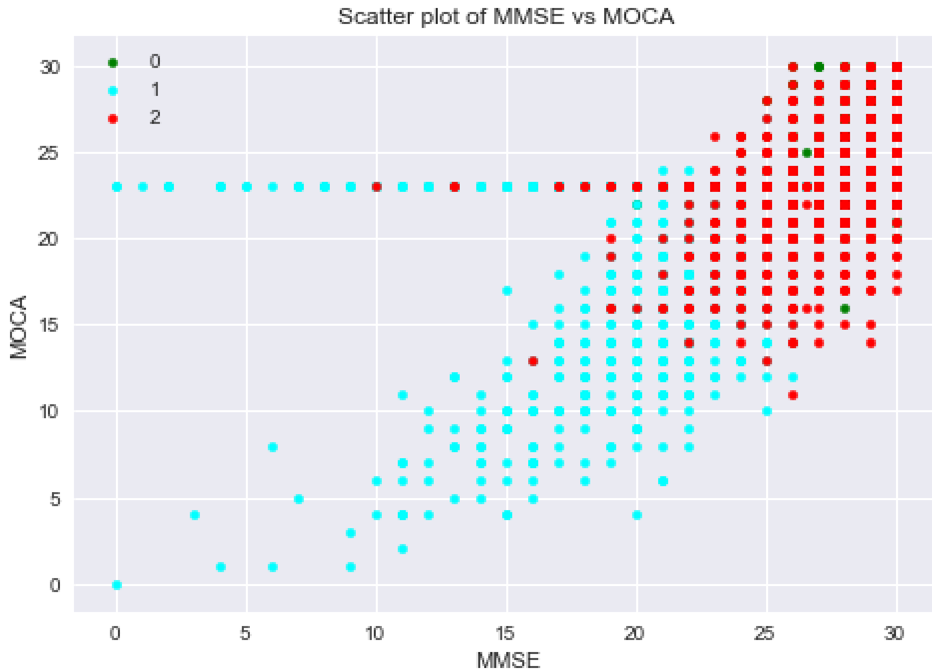
In [40]:
```
train['AGE'].hist()
print('Pie Chart of DX Distrubution')
plt.show()
```

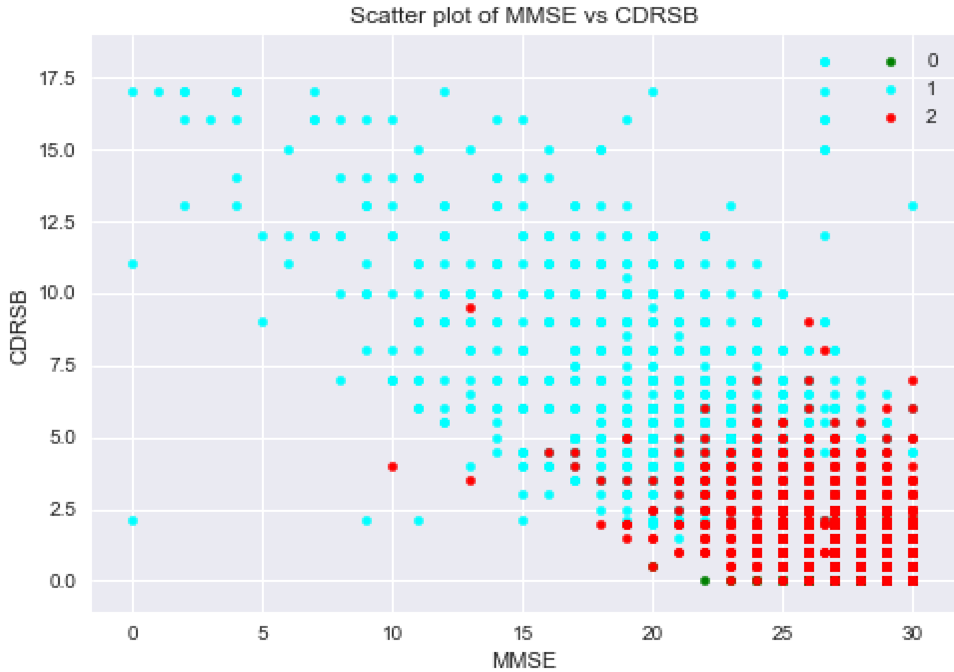
```
Pie Chart of DX Distrubution
```

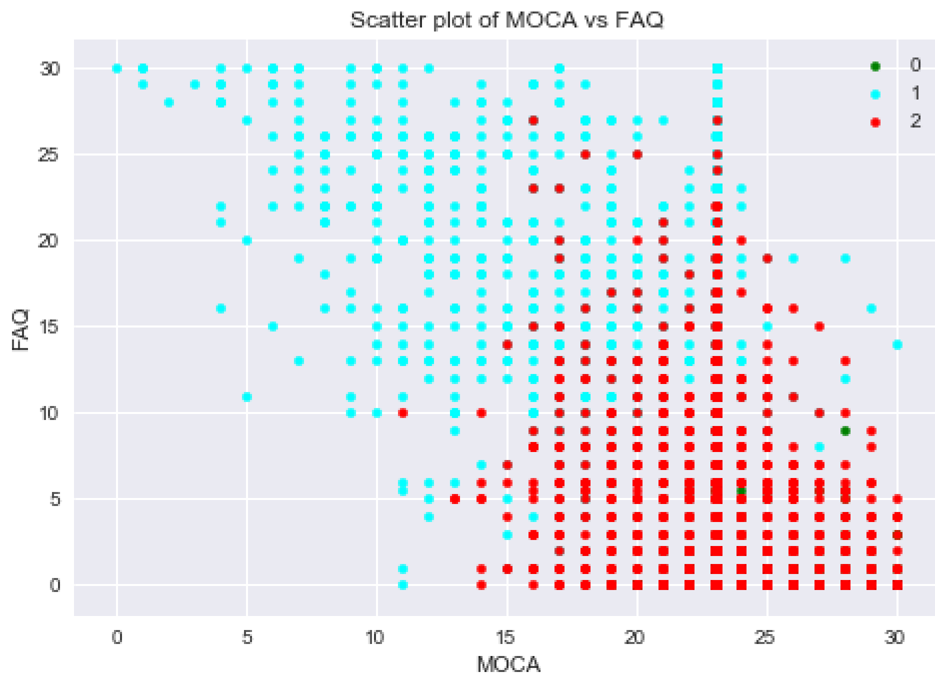


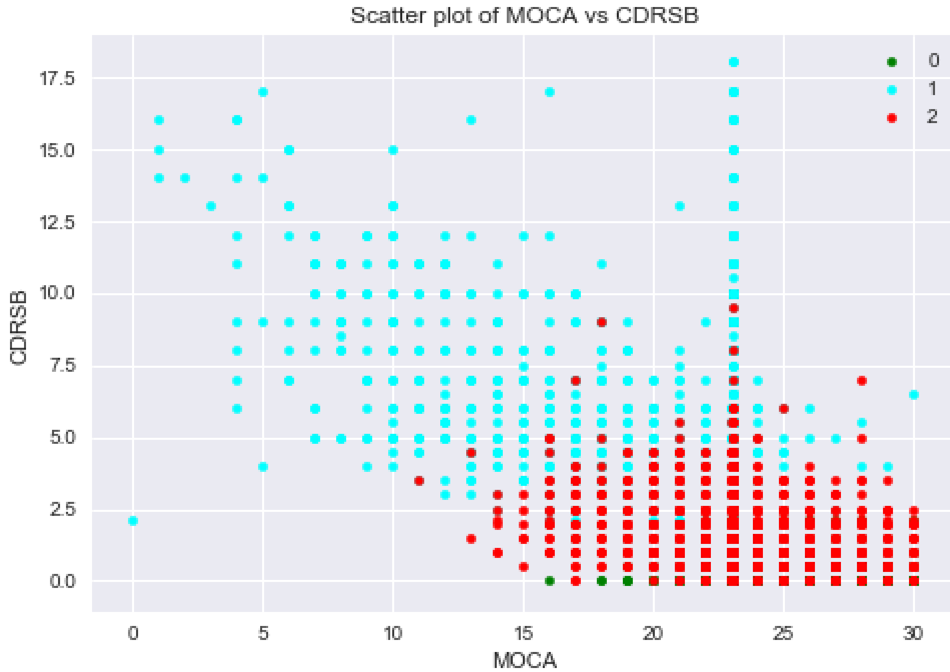
['CN' 'Dementia' 'MCI'] = [0, 1, 2] From the histogram distribution, observe the following:
1: MMSE: Subjects with scores less than 17, had dimentia(encoded 1)
2: MOCA: Subjects with scores less than 15, had dimentia(encoded 1).
3: FAQ: Subjects with scores greater than 28 had dimentia(encoded 1).
4: CDRSB: Subjects with scores greater than 8 had dimentia(encoded 1).
CDRSB Official Guidelines: Score
0-18 --- Mild
19-36 -- Moderate
37-54 -- Severe

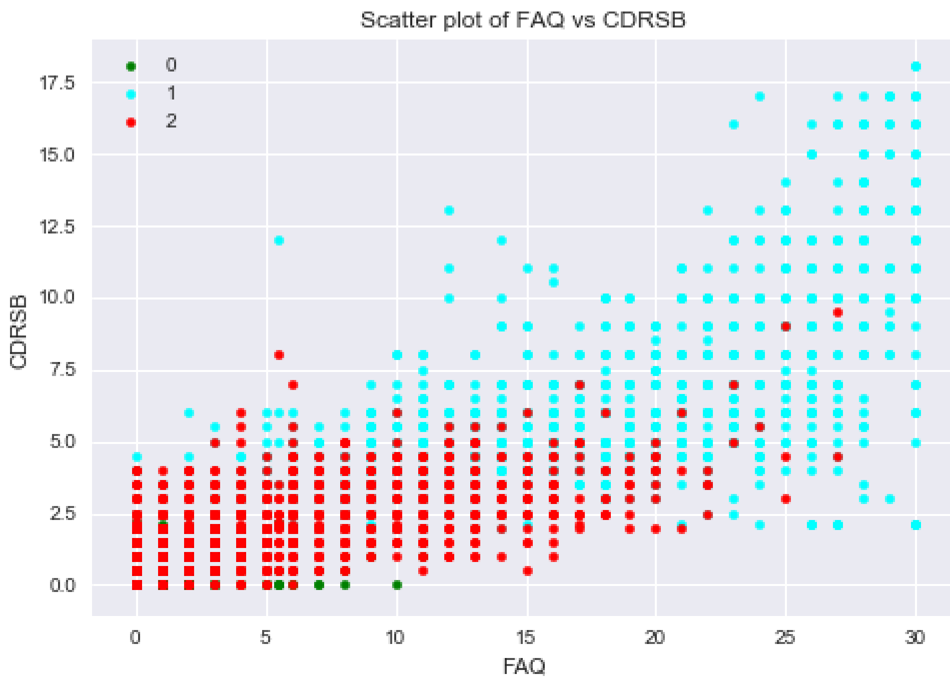
In [41]:
```
pairs = [('MMSE', 'MOCA'), ('MMSE', 'FAQ'), ('MMSE', 'CDRSB'), ('MOCA', 'FAQ'), (
for k, p in enumerate(pairs):
    scatterPlot(train, p[0], p[1], 'DX')
```



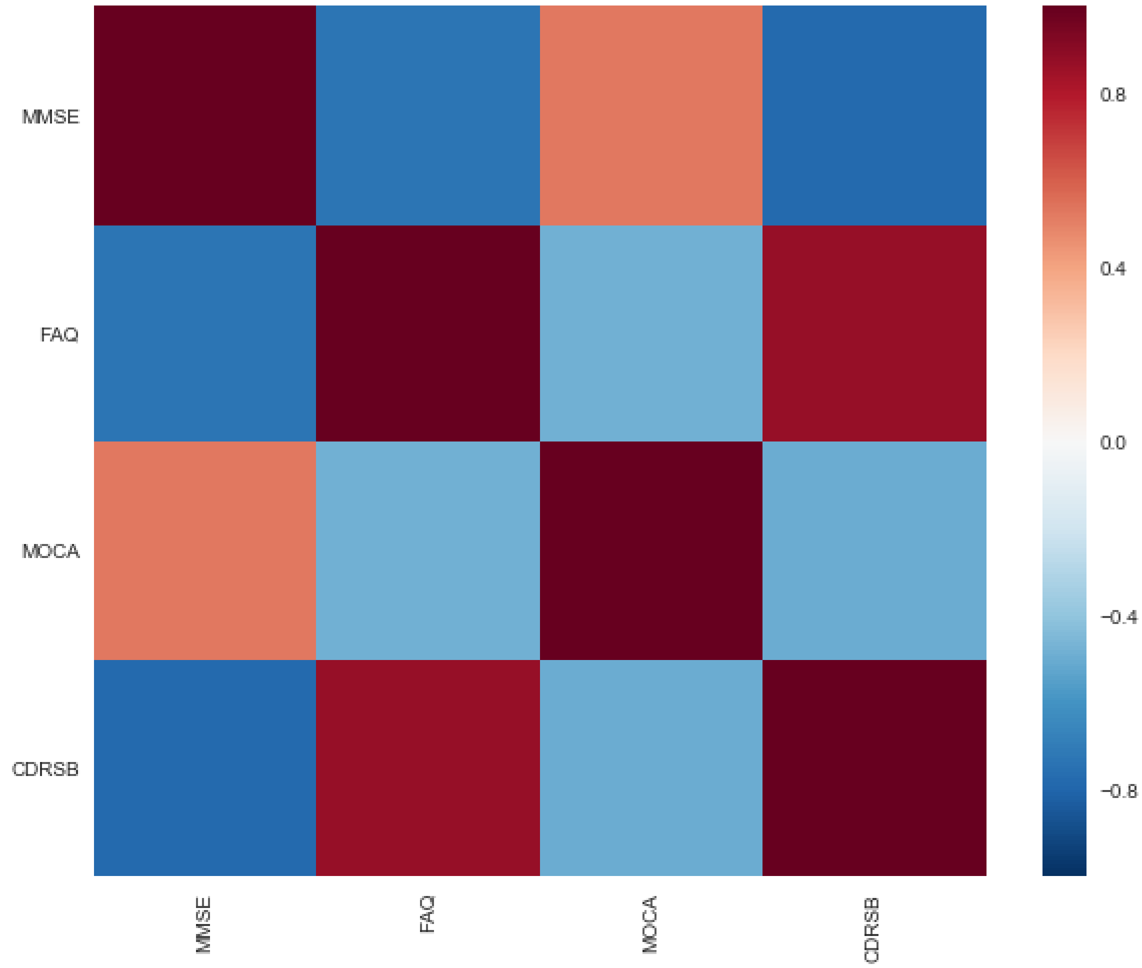

Scatter plot of MMSE vs CDRSB
CDRSB
MMSE
0
1
2
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
5
10
15
20
25
30


Scatter plot of MOCA vs FAQ
FAQ
MOCA
0
1
2
30
25
20
15
10
5
0
0
5
10
15
20
25
30


Scatter plot of MOCA vs CDRSB
CDRSB
MOCA
0
1
2
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
0
5
10
15
20
25
30


Scatter plot of FAQ vs CDRSB
CDRSB
FAQ
0
1
2
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
0
5
10
15
20
25
30

In [42]:
```
#We will use our function to plot collinearity
plot_collinearity(train[cogCols] , cogCols)
```



Observed collinearity: 'MMSE', 'FAQ', 'MOCA','CDRSB' Features without collinearity
No collinearity: 'MMSE' with 'MOCA'
No collinearity: 'FAQ' with 'MOCA'
No collinearity: 'MOCA' with 'CDRSB', MMSE and 'FAQ'

BASELINE PREDICTIONS

:

In [43]:
```
#Use the custom function we created to standardize the data
#Recall we are standardizing the data using the mean and standard deviation of th
train, test = dataScaler(train, test, 'DX')
```

In [44]:
```
train.describe()
```

Out[44]:

	AGE	APOE4	AV45	AV45_chg	CDRSB	CDRSB_chg	
count	6.682000e+03	6.682000e+03	6.682000e+03	6.682000e+03	6.682000e+03	6.682000e+03	668
mean	5.908151e-14	1.719001e-16	4.585387e-13	2.606249e-16	-9.705230e-16	-1.465787e-16	
std	1.000075e+00	1.000075e+00	1.000075e+00	1.000075e+00	1.000075e+00	1.000075e+00	
min	-2.670551e+00	-8.238791e-01	-3.398385e+00	-2.980707e+00	-7.941728e-01	-9.889861e-01	
25%	-6.088465e-01	-8.238791e-01	-4.310785e-03	3.354909e-01	-7.941728e-01	-9.889861e-01	
50%	2.555613e-03	-8.238791e-01	-4.310785e-03	3.354909e-01	-4.191118e-01	-9.889861e-01	
75%	7.134883e-01	6.928090e-01	-4.310785e-03	3.354909e-01	3.310104e-01	1.011137e+00	
max	2.505039e+00	2.209497e+00	1.314385e+01	3.354909e-01	5.956927e+00	1.011137e+00	

8 rows × 46 columns

Using Cognitive Test to determine Cognitive State

In [45]:
```
#Use our model analyzer function evaluate the performance of each test
cogTests = ['MMSE', 'FAQ', 'MOCA','CDRSB']
cogScoresDF = {}
for cogTest in cogTests:
    xx_train = train[cogTest].values.reshape(-1, 1)
    yy_train = train['DX']
    xx_test = test[cogTest].values.reshape(-1, 1)
    yy_test = test['DX']
    cogScoresDF[cogTest] = modelAnalyzer(xx_train,yy_train, xx_test, yy_test )
```

In [46]:
```
mm= cogScoresDF['MMSE'][0].T
fq= cogScoresDF['FAQ'][0].T
mo = cogScoresDF['MOCA'][0].T
cd = cogScoresDF['CDRSB'][0].T
```

In [47]:
```
mm
```

Out[47]:

	0
knn_test_score_knn_10	0.633303
knn_test_score_knn_2	0.535009
knn_test_score_knn_20	0.622980
knn_test_score_knn_5	0.633303
ld_test_score_	0.572262
lgr_test_score_	0.640036
qd_test_score_	0.631508
rnd_test_score_rnd_10	0.642280
rnd_test_score_rnd_20	0.641831
rnd_test_score_rnd_30	0.641831
rnd_test_score_rnd_40	0.641831
rnd_test_score_rnd_5	0.641831

In [48]:
```
mm_f1 = cogScoresDF['MMSE'][1].T
fq_f1 = cogScoresDF['FAQ'][1].T
mo_f1 = cogScoresDF['MOCA'][1].T
cd_f1  = cogScoresDF['CDRSB'][1].T
```

In [49]:
```
cd_f1
```

Out[49]:

	0
knn_test_f1_knn_10	0.845661
knn_test_f1_knn_2	0.609434
knn_test_f1_knn_20	0.863338
knn_test_f1_knn_5	0.863338
ld_test_f1_	0.851588
lgr_test_f1_	0.863338
qd_test_f1_	0.801292
rnd_test_f1_rnd_10	0.862402
rnd_test_f1_rnd_20	0.863338
rnd_test_f1_rnd_30	0.863338
rnd_test_f1_rnd_40	0.863338
rnd_test_f1_rnd_5	0.862402

In [50]:
```
mm_r = cogScoresDF['MMSE'][2].T
fq_r = cogScoresDF['FAQ'][2].T
mo_r = cogScoresDF['MOCA'][2].T
cd_r  = cogScoresDF['CDRSB'][2].T
```

In [51]:
```
cd_r
```

Out[51]:

	0
knn_test_precision_knn_10	0.848751
knn_test_precision_knn_2	0.750116
knn_test_precision_knn_20	0.872471
knn_test_precision_knn_5	0.872471
ld_test_precision_	0.870294
lgr_test_precision_	0.872471
qd_test_precision_	0.814605
rnd_test_precision_rnd_10	0.871759
rnd_test_precision_rnd_20	0.872471
rnd_test_precision_rnd_30	0.872471
rnd_test_precision_rnd_40	0.872471
rnd_test_precision_rnd_5	0.871759

**Effect of Combining all cognitive scores together

In [52]:
```
#New we look at the effect of combining all scores together
#Use our model analyzer function evaluate the performance of each test
#define input and target
X_train_acog = train[['MMSE', 'FAQ', 'MOCA','CDRSB']]
y_train_acog = train['DX']
X_test_acog = test[['MMSE', 'FAQ', 'MOCA','CDRSB']]
y_test_acog = test['DX']

#User our model analyzer function to generate values
scoresDF,  f1_scoresDF, pscoresDF , rscoresDF  = modelAnalyzer(X_train_acog, y_tr
```

In [53]:
```
scoresDF.T
```

Out[53]:

	0
knn_test_score_knn_10	0.864004
knn_test_score_knn_2	0.806104
knn_test_score_knn_20	0.864452
knn_test_score_knn_5	0.857720
ld_test_score_	0.761221
lgr_test_score_	0.850987
qd_test_score_	0.792190
rnd_test_score_rnd_10	0.847397
rnd_test_score_rnd_20	0.850987
rnd_test_score_rnd_30	0.852334
rnd_test_score_rnd_40	0.853680
rnd_test_score_rnd_5	0.843806

In [54]:
```
f1_scoresDF.T
```

Out[54]:

	0
knn_test_f1_knn_10	0.864290
knn_test_f1_knn_2	0.803608
knn_test_f1_knn_20	0.864698
knn_test_f1_knn_5	0.857966
ld_test_f1_	0.757529
lgr_test_f1_	0.850739
qd_test_f1_	0.790886
rnd_test_f1_rnd_10	0.847768
rnd_test_f1_rnd_20	0.851300
rnd_test_f1_rnd_30	0.852600
rnd_test_f1_rnd_40	0.854038
rnd_test_f1_rnd_5	0.844035

In [55]:
```
pscoresDF.T
```

Out[55]:

	0
knn_test_precision_knn_10	0.866368
knn_test_precision_knn_2	0.811765
knn_test_precision_knn_20	0.866041
knn_test_precision_knn_5	0.859841
ld_test_precision_	0.792176
lgr_test_precision_	0.851895
qd_test_precision_	0.798219
rnd_test_precision_rnd_10	0.849616
rnd_test_precision_rnd_20	0.852613
rnd_test_precision_rnd_30	0.853933
rnd_test_precision_rnd_40	0.856244
rnd_test_precision_rnd_5	0.844936

In [56]:
```
rscoresDF.T
```

Out[56]:

	0
knn_test_recall_knn_10	0.864004
knn_test_recall_knn_2	0.806104
knn_test_recall_knn_20	0.864452
knn_test_recall_knn_5	0.857720
ld_test_recall_	0.761221
lgr_test_recall_	0.850987
qd_test_recall_	0.792190
rnd_test_recall_rnd_10	0.847397
rnd_test_recall_rnd_20	0.850987
rnd_test_recall_rnd_30	0.852334
rnd_test_recall_rnd_40	0.853680
rnd_test_recall_rnd_5	0.843806

CHAPTER 2: Using ADNI MERGE to determine Cognitive State

In [59]:
```
#We will use our custom function model analyzer
X_train_adni = train.drop('DX', axis=1)
y_train_adni = train['DX']
X_test_adni = test.drop('DX', axis=1)
y_test_adni = test['DX']

#User our model analyzer function to generate values
scoresDF_adni,  f1_scoresDF_adni, pscoresDF_adni , rscoresDF_adni  = modelAnalyze
```

```
C:\Users\EliudOmollo\Anaconda3\lib\site-packages\sklearn\discriminant_analysis.
py:695: UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")
```

In [60]:
```
scoresDF_adni.T
```

Out[60]:

	0
knn_test_score_knn_10	0.837074
knn_test_score_knn_2	0.791293
knn_test_score_knn_20	0.837971
knn_test_score_knn_5	0.830341
ld_test_score_	0.857720
lgr_test_score_	0.899461
qd_test_score_	0.490126
rnd_test_score_rnd_10	0.908438
rnd_test_score_rnd_20	0.912029
rnd_test_score_rnd_30	0.909336
rnd_test_score_rnd_40	0.909785
rnd_test_score_rnd_5	0.890485

In [61]:
```
f1_scoresDF_adni.T
```

Out[61]:

	0
knn_test_f1_knn_10	0.836977
knn_test_f1_knn_2	0.788412
knn_test_f1_knn_20	0.837105
knn_test_f1_knn_5	0.829810
ld_test_f1_	0.857731
lgr_test_f1_	0.899278
qd_test_f1_	0.402712
rnd_test_f1_rnd_10	0.908779
rnd_test_f1_rnd_20	0.912271
rnd_test_f1_rnd_30	0.909533
rnd_test_f1_rnd_40	0.909969
rnd_test_f1_rnd_5	0.890644

In [62]:
```
pscoresDF_adni.T
```

Out[62]:

	0
knn_test_precision_knn_10	0.841671
knn_test_precision_knn_2	0.800564
knn_test_precision_knn_20	0.848889
knn_test_precision_knn_5	0.836373
ld_test_precision_	0.873729
lgr_test_precision_	0.900618
qd_test_precision_	0.749065
rnd_test_precision_rnd_10	0.909358
rnd_test_precision_rnd_20	0.913245
rnd_test_precision_rnd_30	0.910662
rnd_test_precision_rnd_40	0.911195
rnd_test_precision_rnd_5	0.891381

In [63]:
```
rscoresDF_adni.T
```

Out[63]:

	0
knn_test_recall_knn_10	0.837074
knn_test_recall_knn_2	0.791293
knn_test_recall_knn_20	0.837971
knn_test_recall_knn_5	0.830341
ld_test_recall_	0.857720
lgr_test_recall_	0.899461
qd_test_recall_	0.490126
rnd_test_recall_rnd_10	0.908438
rnd_test_recall_rnd_20	0.912029
rnd_test_recall_rnd_30	0.909336
rnd_test_recall_rnd_40	0.909785
rnd_test_recall_rnd_5	0.890485

CHAPTER 2: EFFECT OF MERGING MEDICAL HISTORY

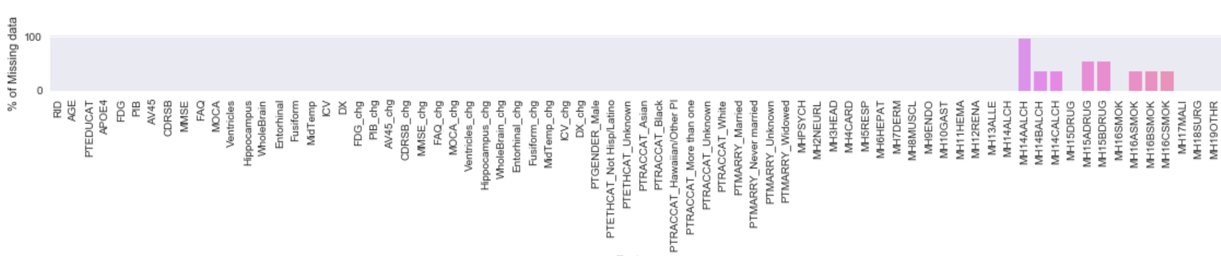
In [64]:
```
#import Medical History
medHistDF_r = pd.read_csv('data\MEDHIST.csv', low_memory=False)

#We are going to add columns that add value to the predictions
medHistDF = medHistDF_r.iloc[: , np.r_[2, 10:37]]
```

In [65]:
```
#CHAPTER
#Merge all the data into one dataframe
data = pd.merge(blData_final, medHistDF, on='RID', how='inner')
data.shape
```

Out[65]: (14170, 74)

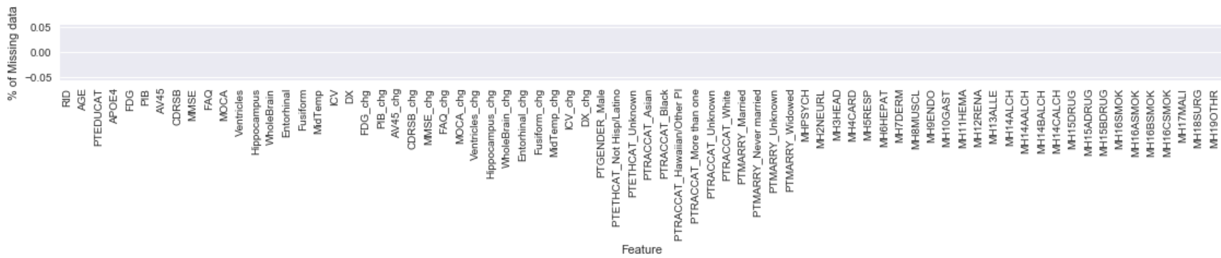
In [66]:
```
plotMissingData(data)
```



In [67]:
```
#impute the missing data
```

In [68]:
```
from sklearn.preprocessing import Imputer
imp = Imputer(missing_values=np.nan, strategy='mean', axis=1)
data_imp = pd.DataFrame(imp.fit_transform(data))
data_imp.columns = data.columns
data_imp.index = data.index
```

In [69]:
```
#confirm that no null values exist and all columns imputed using our function
plotMissingData(data_imp)
```



In [70]:
```
#Split the data into  75% train and 25% test splits
train, test = train_test_split(data_imp, test_size=0.25, random_state=rnd_state)
```

In [71]:
```
#Use the custom function we created to standardize the data
#Recall we are standardizing the data using the mean and standard deviation of th
train, test = dataScaler(train, test, 'DX')
```

In [72]:
```
train.describe()
```

Out[72]:

	AGE	APOE4	AV45	AV45_chg	CDRSB	CDRSB_chg	
count	1.062700e+04	1.062700e+04	1.062700e+04	1.062700e+04	1.062700e+04	1.062700e+04	10
mean	-6.059152e-14	4.487904e-16	-1.403934e-12	-3.163410e-17	-2.966031e-15	-1.141000e-15	
std	1.000047e+00	1.000047e+00	1.000047e+00	1.000047e+00	1.000047e+00	1.000047e+00	
min	-2.892716e+00	-7.963365e-01	-3.566121e+00	-3.628958e+00	-7.556487e-01	-1.007841e+00	
25%	-5.578285e-01	-7.963365e-01	9.347270e-03	2.755612e-01	-7.556487e-01	-1.007841e+00	
50%	3.726774e-03	-7.963365e-01	9.347270e-03	2.755612e-01	-3.724458e-01	9.922200e-01	
75%	6.835042e-01	7.623756e-01	9.347270e-03	2.755612e-01	2.023585e-01	9.922200e-01	
max	2.575059e+00	2.321088e+00	1.386020e+01	2.755612e-01	6.142003e+00	9.922200e-01	

8 rows × 74 columns

In [73]:
```
#using our custom model analyzer to evaluate function

X_train_comp = train.drop('DX', axis=1)
y_train_comp = train['DX']
X_test_comp = test.drop('DX', axis=1)
y_test_comp = test['DX']

#Applying our model analyzer
scores_comp,  f1_scores_comp, pscores_comp , rscores_comp  =  modelAnalyzer(X_tra
```

```
C:\Users\EliudOmollo\Anaconda3\lib\site-packages\sklearn\discriminant_analysis.
py:387: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
C:\Users\EliudOmollo\Anaconda3\lib\site-packages\sklearn\discriminant_analysis.
py:695: UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")
```

In [74]:
```
scores_comp.T
```

Out[74]:

	0
knn_test_score_knn_10	0.842224
knn_test_score_knn_2	0.842506
knn_test_score_knn_20	0.847587
knn_test_score_knn_5	0.843635
ld_test_score_	0.886255
lgr_test_score_	0.914197
qd_test_score_	0.497036
rnd_test_score_rnd_10	0.947502
rnd_test_score_rnd_20	0.951454
rnd_test_score_rnd_30	0.953712
rnd_test_score_rnd_40	0.954558
rnd_test_score_rnd_5	0.938188

In [75]:
```
f1_scores_comp.T
```

Out[75]:

	0
knn_test_f1_knn_10	0.841609
knn_test_f1_knn_2	0.841319
knn_test_f1_knn_20	0.845893
knn_test_f1_knn_5	0.842657
ld_test_f1_	0.886308
lgr_test_f1_	0.914307
qd_test_f1_	0.414943
rnd_test_f1_rnd_10	0.947614
rnd_test_f1_rnd_20	0.951416
rnd_test_f1_rnd_30	0.953648
rnd_test_f1_rnd_40	0.954520
rnd_test_f1_rnd_5	0.938161

In [76]:
```
pscores_comp.T
```

Out[76]:

	0
knn_test_precision_knn_10	0.841499
knn_test_precision_knn_2	0.851224
knn_test_precision_knn_20	0.850936
knn_test_precision_knn_5	0.843563
ld_test_precision_	0.896598
lgr_test_precision_	0.915399
qd_test_precision_	0.780897
rnd_test_precision_rnd_10	0.947801
rnd_test_precision_rnd_20	0.951697
rnd_test_precision_rnd_30	0.954241
rnd_test_precision_rnd_40	0.955109
rnd_test_precision_rnd_5	0.938455

In [77]:
```
rscores_comp.T
```

Out[77]:

	0
knn_test_recall_knn_10	0.842224
knn_test_recall_knn_2	0.842506
knn_test_recall_knn_20	0.847587
knn_test_recall_knn_5	0.843635
ld_test_recall_	0.886255
lgr_test_recall_	0.914197
qd_test_recall_	0.497036
rnd_test_recall_rnd_10	0.947502
rnd_test_recall_rnd_20	0.951454
rnd_test_recall_rnd_30	0.953712
rnd_test_recall_rnd_40	0.954558
rnd_test_recall_rnd_5	0.938188

In [ ]:
```

```