bank_customer_churn_modeling

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1 Data Science

1.1 Bank Customer Churn Modeling

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In [0]:
```
# Basic Libraries
import numpy as np
import pandas as pd
import operator
import re
import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter("ignore")

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats

# Preprocessing
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.pipeline import _name_estimators
from sklearn.base import BaseEstimator
from sklearn.base import ClassifierMixin
from sklearn.base import clone
from sklearn.externals import six

# Evaluation
from sklearn import metrics
from sklearn import linear_model, datasets
from sklearn.metrics import accuracy_score, log_loss
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.neighbors import LocalOutlierFactor
```

```
# Classifier (machine learning algorithm)
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis, QuadraticDiscrimi
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.neural_network import MLPClassifier

from sklearn.base import BaseEstimator
from sklearn.base import ClassifierMixin
from sklearn.externals import six
from sklearn.base import clone
from sklearn.pipeline import _name_estimators
```

2 Read data

https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling

```
In [2]: from google.colab import drive
        drive.mount('/content/gdrive')
        dataset = pd.read_csv("gdrive/My Drive/Colab Notebooks/Churn_Modelling.csv", header = (

Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/co
```

```
In [0]: # dataset = pd.read_csv('../input/Churn_Modelling.csv', header = 0)
```

```
In [4]: # Tmp data
        dataset_tmp = dataset.copy()
        dataset_tmp.head()
```

```
Out[4]:    RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age  \
        0          1    15634602  Hargrave          619    France  Female   42
        1          2    15647311      Hill          608     Spain  Female   41
        2          3    15619304      Onio          502    France  Female   42
        3          4    15701354      Boni          699    France  Female   39
        4          5    15737888  Mitchell          850     Spain  Female   43

           Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
        0       2       0.00              1          1               1
        1       1   83807.86              1          0               1
        2       8  159660.80              3          1               0
```

```
3       1       0.00              2           0               0
4       2  125510.82              1           1               1

   EstimatedSalary  Exited
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

3 Functions

```
In [0]: class MajorityVoteClassifier(BaseEstimator, ClassifierMixin):
            """ A majority vote ensemble classifier
            Parameters
            classifiers : array-like, shape = [n_classifiers]  Different classifiers for the e
            vote : str, {'classlabel', 'probability'} (default='label')
              If 'classlabel' the prediction is based on the argmax of class labels. Else if '
            weights : array-like, shape = [n_classifiers], optional (default=None)
              If a list of `int` or `float` values are provided, the classifiers are weighted
            """
            def __init__(self, classifiers, vote='classlabel', weights=None):
                self.classifiers = classifiers
                self.named_classifiers = {key: value for key, value in _name_estimators(classi
                self.vote = vote
                self.weights = weights
            def fit(self, X, y):
                """ Fit classifiers. Parameters
                X : {array-like, sparse matrix}, shape = [n_samples, n_features] Matrix of tra
                y : array-like, shape = [n_samples] Vector of target class labels.
                Returns self : object
                """
                if self.vote not in ('probability', 'classlabel'):
                    raise ValueError("vote must be 'probability' or 'classlabel'" "; got (vote=
                if self.weights and len(self.weights) != len(self.classifiers):
                    raise ValueError('Number of classifiers and weights must be equal''; got %
                    (len(self.weights), len(self.classifiers)))
                # Use LabelEncoder to ensure class labels start with 0, which is important for
                self.lablenc_ = LabelEncoder()
                self.lablenc_.fit(y)
                self.classes_ = self.lablenc_.classes_
                self.classifiers_ = []
                for clf in self.classifiers:
                    fitted_clf = clone(clf).fit(X, self.lablenc_.transform(y))
                    self.classifiers_.append(fitted_clf)
                return self
            def predict(self, X):
```

```python
        """ Predict class labels for X.
        Parameters
        ----------
        X : {array-like, sparse matrix}, shape = [n_samples, n_features] Matrix of tra
        Returns ----------
        maj_vote : array-like, shape = [n_samples] Predicted class labels.
        """
        if self.vote == 'probability':
            maj_vote = np.argmax(self.predict_proba(X), axis=1)
        else:  # 'classlabel' vote
            #  Collect results from clf.predict calls
            predictions = np.asarray([clf.predict(X) for clf in self.classifiers_]).T
            maj_vote = np.apply_along_axis( lambda x: np.argmax(np.bincount(x, weights=
                                      axis=1,
                                      arr=predictions)
        maj_vote = self.lablenc_.inverse_transform(maj_vote)
        return maj_vote
    def predict_proba(self, X):
        """ Predict class probabilities for X.
        X : {array-like, sparse matrix}, shape = [n_samples, n_features]
            Training vectors, where n_samples is the number of samples and n_features
        Returns
        avg_proba : array-like, shape = [n_samples, n_classes] Weighted average probab
        """
        probas = np.asarray([clf.predict_proba(X)  for clf in self.classifiers_])
        avg_proba = np.average(probas, axis=0, weights=self.weights)
        return avg_proba
    def get_params(self, deep=True):
        """ Get classifier parameter names for GridSearch"""
        if not deep:
            return super(MajorityVoteClassifier, self).get_params(deep=False)
        else:
            out = self.named_classifiers.copy()
            for name, step in six.iteritems(self.named_classifiers):
                for key, value in six.iteritems(step.get_params(deep=True)):
                    out['%s__%s' % (name, key)] = value
            return out

# Split Train and Test and check shape
def SplitDataFrameToTrainAndTest(DataFrame, TrainDataRate, TargetAtt):
    # gets a random TrainDataRate % of the entire set
    training = DataFrame.sample(frac=TrainDataRate, random_state=1)
    # gets the left out portion of the dataset
    testing = DataFrame.loc[~DataFrame.index.isin(training.index)]

    X_train = training.drop(TargetAtt, 1)
    y_train = training[[TargetAtt]]
    X_test = testing.drop(TargetAtt, 1)
```

```
    y_test = testing[[TargetAtt]]
    return X_train, y_train, X_test, y_test

def PrintTrainTestInformation(X_train, y_train, X_test, y_test):
    print("Train rows and columns : ", X_train.shape)
    print("Test rows and columns : ", X_test.shape)

def DrawJointPlot(DataFrame, XAtt, yAtt, bins = 20):
    sns.set(color_codes=True)
    sns.distplot(data[XAtt], bins=bins);
    df = pd.DataFrame(DataFrame, columns=[XAtt,yAtt])
    df = df.reset_index(drop=True)
    sns.jointplot(x=XAtt, y=yAtt, data=df)

def DrawBoxplot2(DataFrame, xAtt, yAtt, hAtt="N/A"):
    plt.figure()
    if(hAtt == "N/A"):
        sns.boxplot(x=xAtt, y=yAtt,  data=DataFrame)
    else:
        sns.boxplot(x=xAtt, y=yAtt,  hue=hAtt,  data=DataFrame)
    plt.show()

def DrawBarplot(DataFrame, att):
    Distribution = DataFrame[att].value_counts()
    Distribution = pd.DataFrame({att:Distribution.index, 'Freq':Distribution.values})
    Distribution = Distribution.sort_values(by=att, ascending=True)
    plt.bar(Distribution[att], Distribution["Freq"])
    plt.xticks(Distribution[att])
    plt.ylabel('Frequency')
    plt.title('Barplot of ' + att)
    plt.show()

def DrawCountplot(DataFrame, att, hatt="N/A"):
    if(hatt == "N/A"):
        sns.countplot(x=att, data=DataFrame)
    else:
        sns.countplot(x=att, hue=hatt, data=DataFrame)
    plt.show()

def DrawHistogram(DataFrame, att):
    plt.figure()
    DataFrame[att].hist(edgecolor='black', bins=20)
    plt.title(att)
    plt.show()

# Detect outlier in each feature
def DetectOutlierByIQR(DataFrame, AttList, Rate = 3.0):
    OutlierIdx = []
```

```
    for att in AttList:
        AttData = DataFrame.loc[:, att]
        lowerq = AttData.quantile(0.25)
        upperq = AttData.quantile(0.75)
        IQR = upperq - lowerq
        threshold_upper = (IQR * Rate) + upperq
        threshold_lower = lowerq - (IQR * Rate)
        AttOutlierIdx = set(AttData[AttData.apply(lambda x: x > threshold_upper
                                                  or x < threshold_lower)].index.get_
        OutlierIdx = set(OutlierIdx) | AttOutlierIdx
        # print("Min, Max and IQR : %f, %f, and %f" % (AttData.min(), AttData.max(), I
        # print("Upper Fence and Lower Fence : %f and %f" % (threshold_lower, threshol
        # print("OutlierIdx : " + str(OutlierIdx))
        # print(att + " "  + str(len(AttOutlierIdx)) + " Outlier Idx : " + str(AttOutl

    OutlierIdx = list(OutlierIdx)
    OutlierIdx = sorted(OutlierIdx)
    return OutlierIdx

# Detect outlier in group features
def DetectOutlierByLOF(DataFrame, AttList, LOFThresh=3.0, neighbors = 10):
    clf = LocalOutlierFactor(n_neighbors=neighbors)
    AttData = DataFrame.loc[:, AttList].values
    y_pred = clf.fit_predict(AttData)
    AttData_scores = -1 * clf.negative_outlier_factor_
    LOFFactorData = pd.DataFrame(AttData_scores, columns=['LOF'])
    LOFFactorData = LOFFactorData.sort_values('LOF', ascending=False)
    LOFFactorData = LOFFactorData.reset_index(drop=False)
    # print(LOFFactorData.loc[0:10, :])
    OutlierThreshold = LOFThresh
    SuspectOutlierData = LOFFactorData[LOFFactorData['LOF'].apply(lambda x: x > Outlie
    OutlierIdx = SuspectOutlierData.loc[:, 'index'].tolist()
    # print("OutlierIdx : " + str(OutlierIdx))
    return OutlierIdx, LOFFactorData

def RemoveRowsFromDataFrame(DataFrame, RowIdxList = []):
    DataFrame = DataFrame.drop(RowIdxList)
    DataFrame = DataFrame.reset_index(drop=True)
    return DataFrame

def NaiveBayesLearning(DataTrain, TargetTrain):
    NBModel = GaussianNB()
    NBModel.fit(DataTrain, TargetTrain.values.ravel())
    return NBModel

def NaiveBayesTesting(NBModel,DataTest, TargetTest):
    PredictTest = NBModel.predict(DataTest)
    Accuracy = accuracy_score(TargetTest, PredictTest)
```

```python
    return Accuracy, PredictTest

def LogisticRegressionLearning(DataTrain, TargetTrain):
    logreg = LogisticRegression()
    # Training by Logistic Regression
    logreg.fit(DataTrain, TargetTrain.values.ravel())
    return logreg

def LogisticRegressionTesting(LRModel,DataTest, TargetTest):
    logreg = LRModel
    PredictTest = logreg.predict(DataTest)
    Accuracy = accuracy_score(TargetTest, PredictTest)
    # print('Logistic regression accuracy: {:.3f}'.format(Accuracy))
    return Accuracy, PredictTest

def RandomForestLearning(DataTrain, TargetTrain):
    rf = RandomForestClassifier()
    rf.fit(DataTrain, TargetTrain.values.ravel())
    return rf

def RandomForestTesting(RFModel,DataTest, TargetTest):
    PredictTest = RFModel.predict(DataTest)
    Accuracy = accuracy_score(TargetTest, PredictTest)
    # print('Random Forest Accuracy: {:.3f}'.format(accuracy_score(TargetTest, Predict
    return Accuracy, PredictTest

def SVMLearning(DataTrain, TargetTrain, ClassifierType = " "):
    if(ClassifierType == 'Linear'):
        svc = SVC(kernel="linear", C=0.025)
        # print('SVM Linear processing')
    # Radial basis function kernel
    elif (ClassifierType == 'RBF'):
        svc = SVC(gamma=2, C=1)
        # print('SVM RBF processing')
    else:
        svc = SVC()
        # print('SVM Default processing')
    svc.fit(DataTrain, TargetTrain.values.ravel())
    return svc

def SVMTesting(SVMModel, DataTest, TargetTest):
    PredictTest = SVMModel.predict(DataTest)
    Accuracy = accuracy_score(TargetTest, PredictTest)
    # print('Support Vector Machine Accuracy: {:.3f}'.format(accuracy_score(TargetTest
    return Accuracy, PredictTest

def KNNLearning(DataTrain, TargetTrain, K = 3):
    neigh = KNeighborsClassifier(n_neighbors=K)
```

```
    neigh.fit(DataTrain, TargetTrain.values.ravel())
    return neigh

def KNNTesting(KNNModel,DataTest, TargetTest):
    PredictTest = KNNModel.predict(DataTest)
    Accuracy = accuracy_score(TargetTest, PredictTest)
    # print('KNN Accuracy: {:.3f}'.format(accuracy_score(TargetTest, PredictTest)))
    return Accuracy, PredictTest

def ANNLearning(DataTrain, TargetTrain):
    ANNModel = MLPClassifier(alpha=1)
    ANNModel.fit(DataTrain, TargetTrain.values.ravel())
    return ANNModel

def ANNTesting (ANNModel, DataTest, TargetTest):
    PredictTest = ANNModel.predict(DataTest)
    Accuracy = accuracy_score(TargetTest, PredictTest)
    # print('Neural Net Accuracy: {:.3f}'.format(Accuracy))
    return Accuracy, PredictTest

# Continuous Data Plot
def ContPlot(df, feature_name, target_name, palettemap, hue_order, feature_scale):
    df['Counts'] = "" # A trick to skip using an axis (either x or y) on splitting vio
    fig, [axis0,axis1] = plt.subplots(1,2,figsize=(10,5))
    sns.distplot(df[feature_name], ax=axis0);
    sns.violinplot(x=feature_name, y="Counts", hue=target_name, hue_order=hue_order, da
                   palette=palettemap, split=True, orient='h', ax=axis1)
    axis1.set_xticks(feature_scale)
    plt.show()

# Categorical/Ordinal Data Plot
def CatPlot(df, feature_name, target_name, palettemap):
    fig, [axis0,axis1] = plt.subplots(1,2,figsize=(10,5))
    df[feature_name].value_counts().plot.pie(autopct='%1.1f%%',ax=axis0)
    sns.countplot(x=feature_name, hue=target_name, data=df,
                  palette=palettemap,ax=axis1)
    plt.show()

def MachineLearningModelEvaluate(X_train, y_train, X_test, y_test):
    NBModel = NaiveBayesLearning(X_train, y_train)
    NBAccuracy,NBPredictTest = NaiveBayesTesting(NBModel,X_test, y_test)
    print('Naive Bayes accuracy: {:.3f}'.format(NBAccuracy))

    LRModel = LogisticRegressionLearning(X_train, y_train)
    LRAccuracy,LRPredictTest = LogisticRegressionTesting(LRModel,X_test, y_test)
    print('Logistic Regression accuracy: {:.3f}'.format(LRAccuracy))

    RFModel = RandomForestLearning(X_train, y_train)
```

```
RFAccuracy,RFPredictTest = RandomForestTesting(RFModel,X_test, y_test)
print('Random Forest accuracy: {:.6f}'.format(RFAccuracy))

LiSVMModel = SVMLearning(X_train, y_train)
LiSVMAccuracy,LiSVMPredictTest = SVMTesting(LiSVMModel, X_test, y_test)
print('Linear SVM accuracy: {:.6f}'.format(LiSVMAccuracy))

RBFSVMModel = SVMLearning(X_train, y_train, 'RBF')
RBFSVMAccuracy,RBFSVMPredictTest = SVMTesting(RBFSVMModel, X_test, y_test)
print('RBF SVM accuracy: {:.6f}'.format(RBFSVMAccuracy))

KNNModel = KNNLearning(X_train, y_train)
KNNAccuracy,KNNPredictTest = KNNTesting(KNNModel,X_test, y_test)
print('K Nearest Neighbor accuracy: {:.6f}'.format(KNNAccuracy))

ANNModel = ANNLearning(X_train, y_train)
ANNAccuracy, ANNPredictTest = ANNTesting(ANNModel, X_test, y_test)
print('ANN accuracy: {:.6f}'.format(ANNAccuracy))
```

4 Checking missing values

- Fill missing value: Median / Mode, Label Encode / Dummies

In [6]:
```
# Checking the percentage of missing values in each variable
(dataset.isnull().sum()/len(dataset)*100)
```

Out[6]:
```
RowNumber          0.0
CustomerId         0.0
Surname            0.0
CreditScore        0.0
Geography          0.0
Gender             0.0
Age                0.0
Tenure             0.0
Balance            0.0
NumOfProducts      0.0
HasCrCard          0.0
IsActiveMember     0.0
EstimatedSalary    0.0
Exited             0.0
dtype: float64
```

4.1 Preparation and EDA

In [7]:
```
# Split Train and Test and check shape
data_train, target_train, data_test, target_test = SplitDataFrameToTrainAndTest(datase
PrintTrainTestInformation(data_train, target_train, data_test, target_test)
```

```
Train rows and columns :  (6000, 13)
Test rows and columns :  (4000, 13)
```

```
In [8]: # Check column types
        data_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6000 entries, 9953 to 2374
Data columns (total 13 columns):
RowNumber          6000 non-null int64
CustomerId         6000 non-null int64
Surname            6000 non-null object
CreditScore        6000 non-null int64
Geography          6000 non-null object
Gender             6000 non-null object
Age                6000 non-null int64
Tenure             6000 non-null int64
Balance            6000 non-null float64
NumOfProducts      6000 non-null int64
HasCrCard          6000 non-null int64
IsActiveMember     6000 non-null int64
EstimatedSalary    6000 non-null float64
dtypes: float64(2), int64(8), object(3)
memory usage: 656.2+ KB
```

```
In [9]: print(" List of unique values in Surname : ")
        print(dataset['Surname'].unique())
        print(" List of unique values in Geography : ")
        print(dataset['Geography'].unique())
        print(" List of unique values in Gender : ")
        print(dataset['Gender'].unique())

        #Special Field
        print(" List of unique values in NumOfProducts : ")
        print(dataset['NumOfProducts'].unique())
```

```
 List of unique values in Surname :
['Hargrave' 'Hill' 'Onio' ... 'Kashiwagi' 'Aldridge' 'Burbidge']
 List of unique values in Geography :
['France' 'Spain' 'Germany']
 List of unique values in Gender :
['Female' 'Male']
 List of unique values in NumOfProducts :
[1 3 2 4]
```

```
In [10]: # Numerical data distribution
         data_train.describe()
```

Out[10]:

	RowNumber	CustomerId	CreditScore	Age	Tenure
count	6000.000000	6.000000e+03	6000.000000	6000.000000	6000.000000
mean	5000.534667	1.569090e+07	652.017833	38.801333	5.021667
std	2877.924946	7.201902e+04	96.171969	10.409335	2.888469
min	4.000000	1.556570e+07	350.000000	18.000000	0.000000
25%	2501.250000	1.562812e+07	586.000000	32.000000	3.000000
50%	4995.500000	1.569189e+07	655.000000	37.000000	5.000000
75%	7483.500000	1.575351e+07	718.000000	44.000000	8.000000
max	9999.000000	1.581569e+07	850.000000	92.000000	10.000000

	Balance	NumOfProducts	HasCrCard	IsActiveMember
count	6000.000000	6000.000000	6000.000000	6000.000000
mean	76069.556590	1.524667	0.702333	0.521833
std	62709.267925	0.576582	0.457270	0.499565
min	0.000000	1.000000	0.000000	0.000000
25%	0.000000	1.000000	0.000000	0.000000
50%	96598.420000	1.000000	1.000000	1.000000
75%	127671.927500	2.000000	1.000000	1.000000
max	238387.560000	4.000000	1.000000	1.000000

	EstimatedSalary
count	6000.000000
mean	99470.172248
std	57622.657250
min	11.580000
25%	50343.395000
50%	99482.980000
75%	149170.417500
max	199992.480000

In [11]:
```
data_train.describe(include=['O'])
```

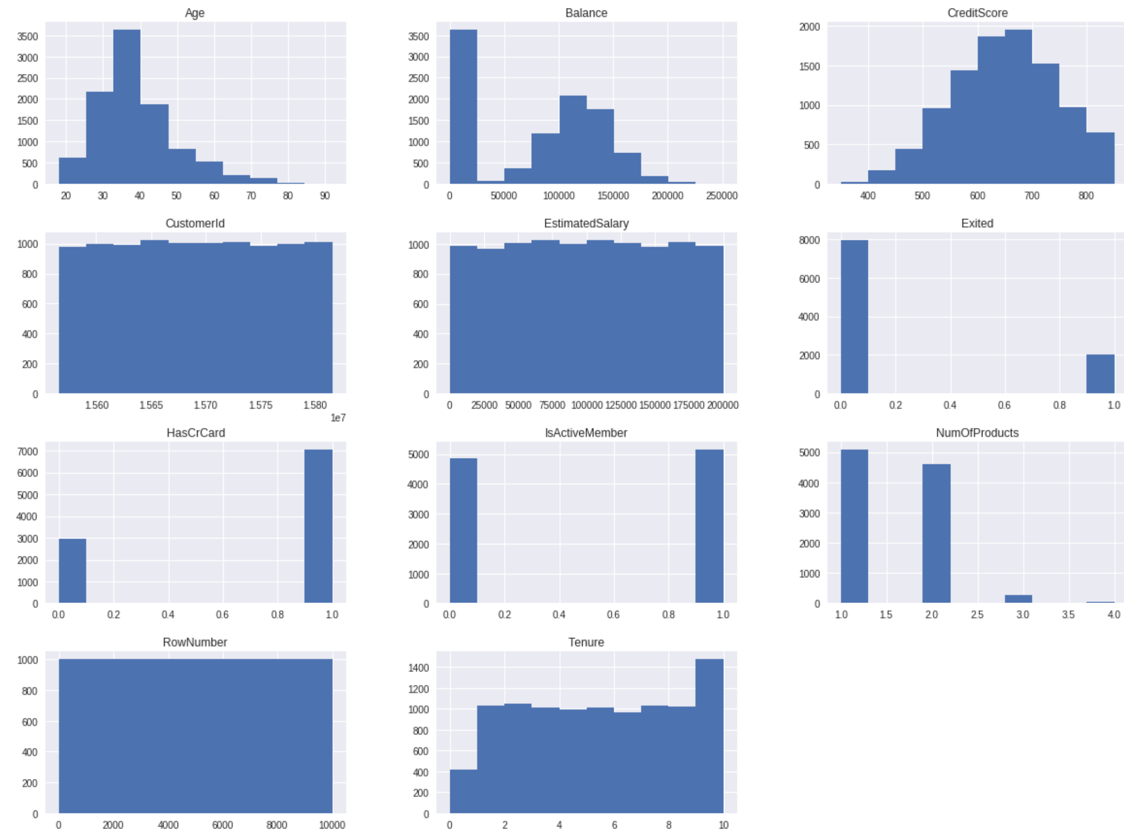
Out[11]:

	Surname	Geography	Gender
count	6000	6000	6000
unique	2246	3	2
top	Smith	France	Male
freq	23	3026	3259

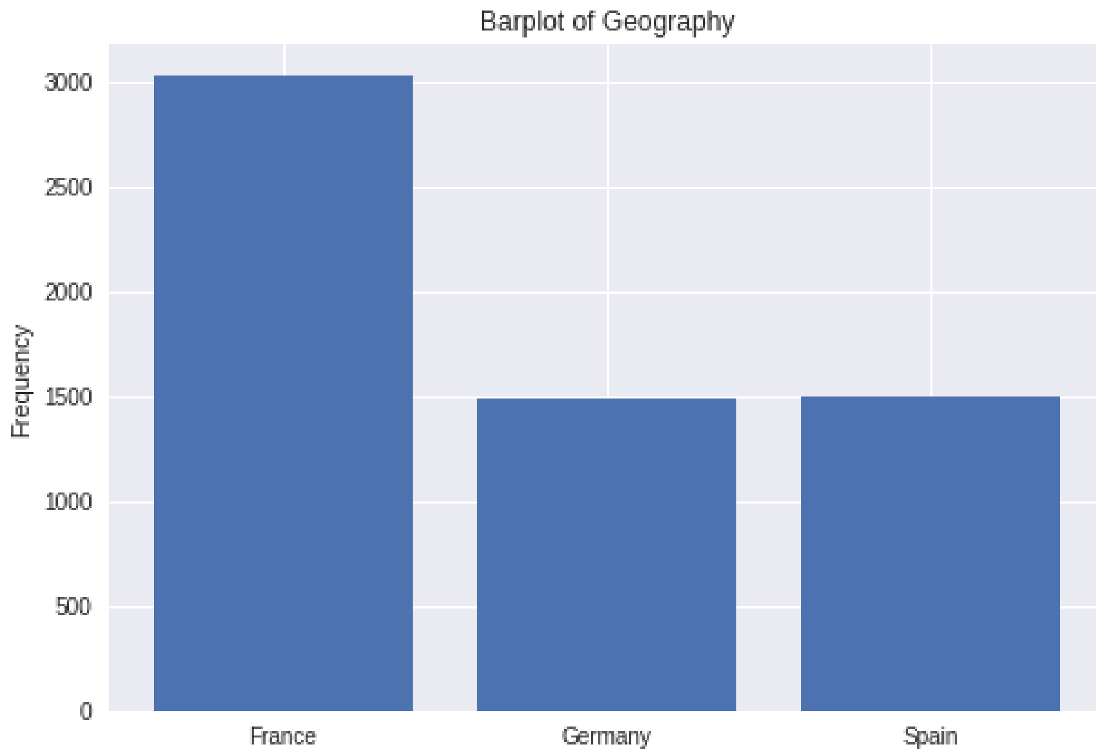
In [12]:
```
dataset.hist(bins=10, figsize=(20,15))
```

Out[12]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f97fdf0af98>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd490400>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd438a58>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd3ea0f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd40d748>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd3b4da0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd364400>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd388a90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd388ac8>],
```

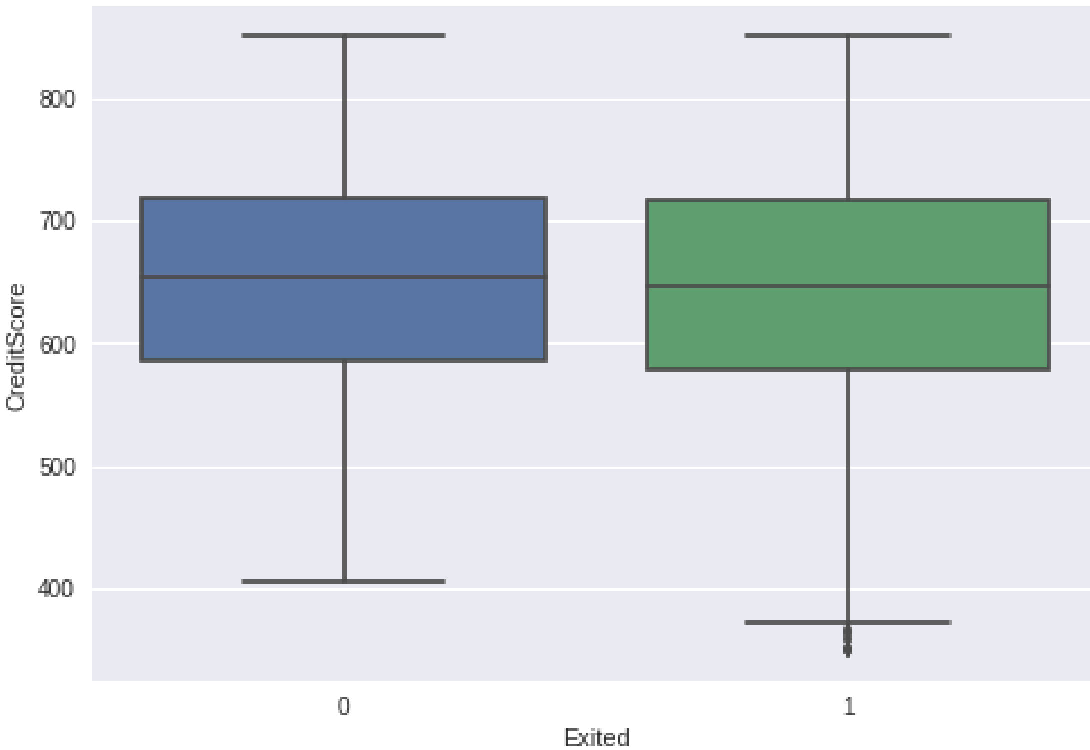
```
[<matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd2de748>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd306da0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd2b5438>]],
dtype=object)
```

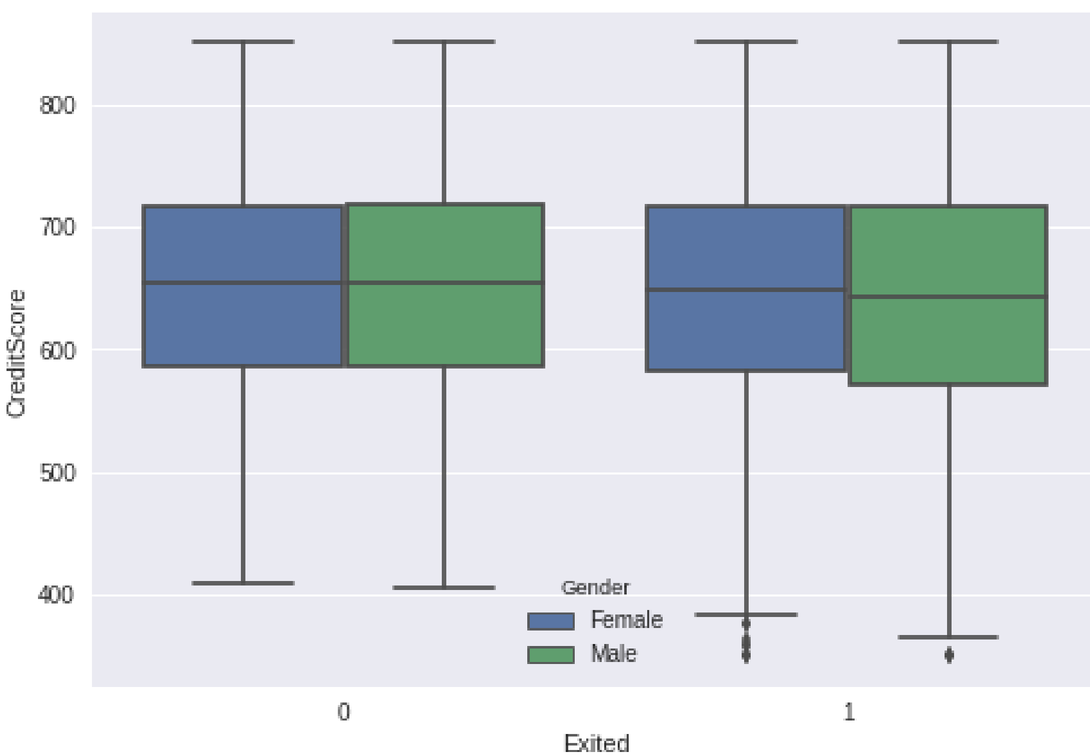



```
In [13]: DrawBarplot(data_train, 'Geography')
```

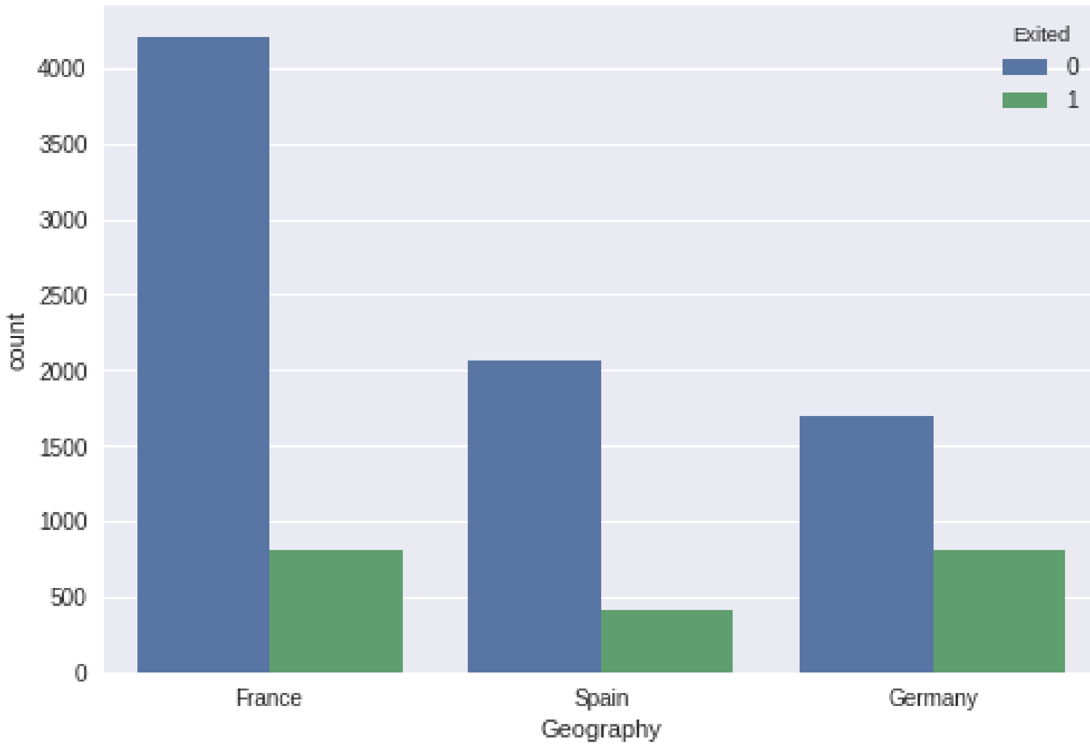


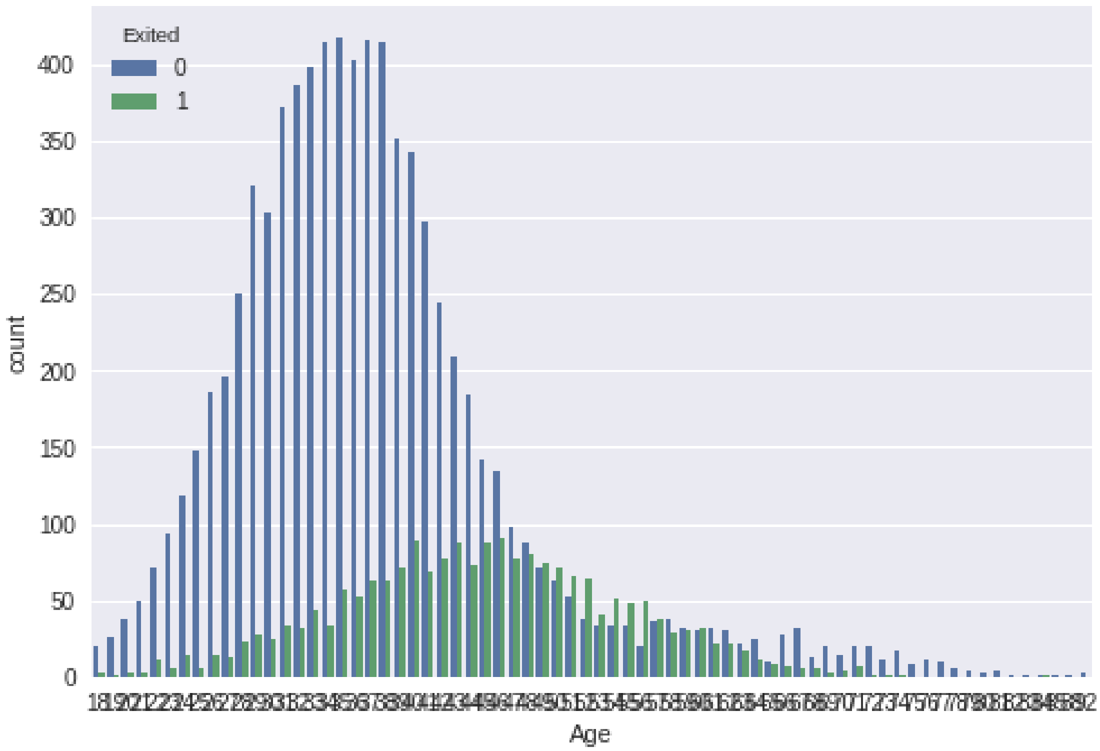

```
In [14]: DrawBoxplot2(dataset, xAtt = 'Exited', yAtt='CreditScore')
         DrawBoxplot2(dataset, xAtt = 'Exited', yAtt='CreditScore', hAtt='Gender')
```


800
700
600
500
400
CreditScore
0
1
Exited


800
700
600
500
400
CreditScore
Gender
Female
Male
0
1
Exited

```
In [15]: DrawCountplot(dataset, 'Geography', 'Exited')
         DrawCountplot(dataset, 'Age', 'Exited')
```



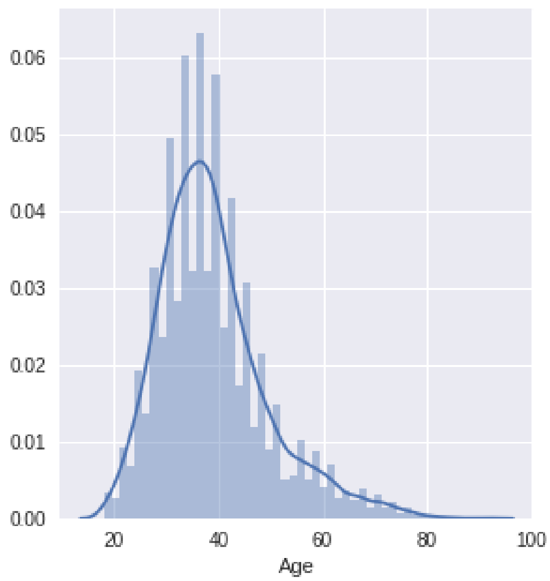


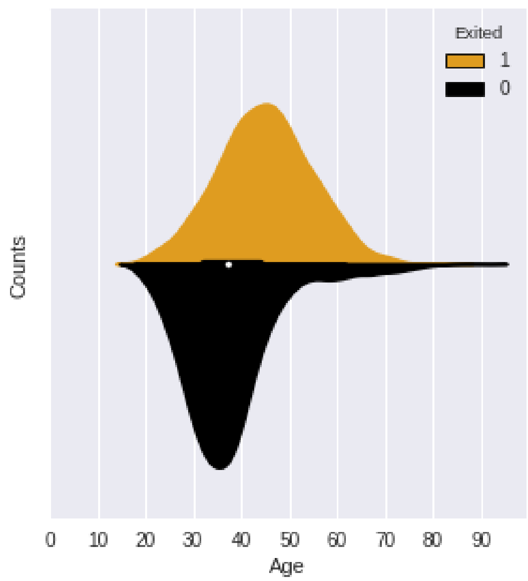

```
In [16]: dataset['CategoricalCreditScore'] = pd.qcut(dataset['CreditScore'], 3)
         print (dataset[['CategoricalCreditScore', 'Exited']].groupby(['CategoricalCreditScore
```

```
  CategoricalCreditScore    Exited
0       (349.999, 608.0]  0.215284
1         (608.0, 695.0]  0.197660
2         (695.0, 850.0]  0.198002
```

```
In [17]: ContPlot(dataset[['Age','Exited']].copy().dropna(axis=0),
                   'Age', 'Exited', {0: "black", 1: "orange"} , [1, 0], range(0,100,10))

         dataset['CategoricalAge'] = pd.qcut(dataset['Age'], 5, duplicates='drop')
         print (dataset[['CategoricalAge', 'Exited']].groupby(['CategoricalAge'], as_index=Fals
```

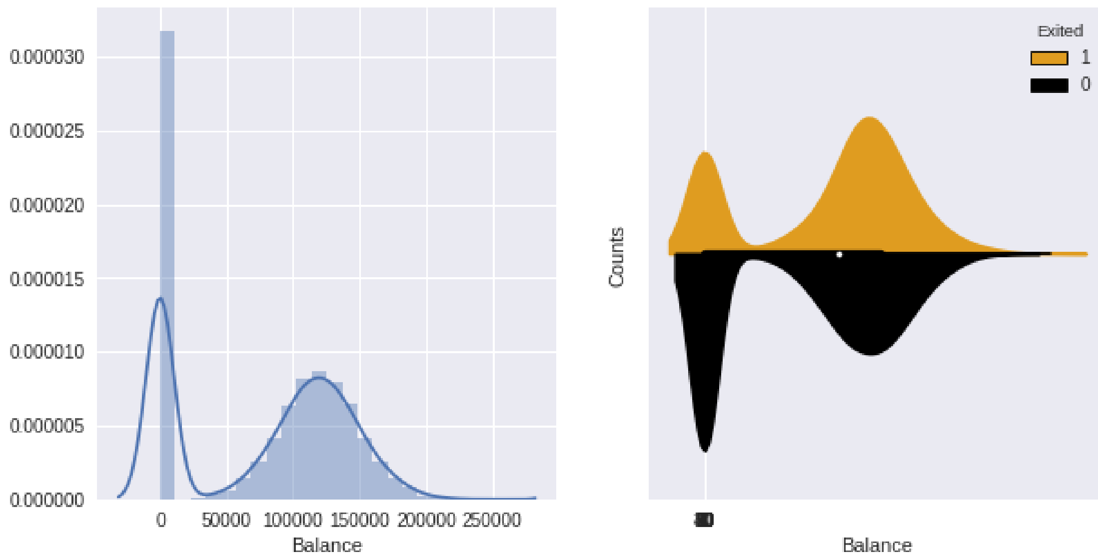





```
   CategoricalAge    Exited
0  (17.999, 31.0]  0.076307
1    (31.0, 35.0]  0.093206
2    (35.0, 40.0]  0.149603
3    (40.0, 46.0]  0.285967
4    (46.0, 92.0]  0.459416
```

```
In [18]: ContPlot(dataset[['Balance','Exited']].copy().dropna(axis=0),
                  'Balance', 'Exited', {0: "black", 1: "orange"} , [1, 0], range(0,100,10))

         dataset['CategoricalBalance'] = pd.qcut(dataset['Balance'], 3, duplicates='drop')
         print (dataset[['CategoricalBalance', 'Exited']].groupby(['CategoricalBalance'], as_i
```



	CategoricalBalance	Exited
0	(-0.001, 118100.59]	0.183441
1	(118100.59, 250898.09]	0.244224

5 Encoder

In [19]:
```
data_encoder = dataset.copy()
data_encoder['Geography'] = LabelEncoder().fit_transform(data_encoder['Geography'])
# data_encoder['Surname'] = LabelEncoder().fit_transform(data_encoder['Surname'])
# data_encoder['Gender'] = LabelEncoder().fit_transform(data_encoder['Gender'])
data_encoder = data_encoder.join(pd.get_dummies(data_encoder['Gender'], prefix='Gende
data_encoder = data_encoder.drop('Gender', axis=1)

data_encoder.loc[ data_encoder['Balance'] <= 118100.59, 'Balance'] = 0
data_encoder.loc[ data_encoder['Balance'] > 118100.59, 'Balance'] = 1

data_encoder.head(10)
```

Out[19]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Age	Tenure	\
0	1	15634602	Hargrave	619	0	42	2	
1	2	15647311	Hill	608	2	41	1	
2	3	15619304	Onio	502	0	42	8	
3	4	15701354	Boni	699	0	39	1	
4	5	15737888	Mitchell	850	2	43	2	
5	6	15574012	Chu	645	2	44	8	
6	7	15592531	Bartlett	822	0	50	7	
7	8	15656148	Obinna	376	1	29	4	

```
8           9    15792365        He          501          0   44       4
9          10    15592389        H?          684          0   27       2

   Balance  NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  Exited  \
0      0.0              1          1               1        101348.88       1
1      0.0              1          0               1        112542.58       0
2      1.0              3          1               0        113931.57       1
3      0.0              2          0               0         93826.63       0
4      1.0              1          1               1         79084.10       0
5      0.0              2          1               0        149756.71       1
6      0.0              2          1               1         10062.80       0
7      0.0              4          1               0        119346.88       1
8      1.0              2          0               1         74940.50       0
9      1.0              1          1               1         71725.73       0

  CategoricalCreditScore  CategoricalAge      CategoricalBalance  \
0         (608.0, 695.0]    (40.0, 46.0]     (-0.001, 118100.59]
1       (349.999, 608.0]    (40.0, 46.0]     (-0.001, 118100.59]
2       (349.999, 608.0]    (40.0, 46.0]  (118100.59, 250898.09]
3         (695.0, 850.0]    (35.0, 40.0]     (-0.001, 118100.59]
4         (695.0, 850.0]    (40.0, 46.0]  (118100.59, 250898.09]
5         (608.0, 695.0]    (40.0, 46.0]     (-0.001, 118100.59]
6         (695.0, 850.0]    (46.0, 92.0]     (-0.001, 118100.59]
7       (349.999, 608.0]  (17.999, 31.0]     (-0.001, 118100.59]
8       (349.999, 608.0]    (40.0, 46.0]  (118100.59, 250898.09]
9         (608.0, 695.0]  (17.999, 31.0]  (118100.59, 250898.09]

   Gender_Female  Gender_Male
0              1            0
1              1            0
2              1            0
3              1            0
4              1            0
5              0            1
6              0            1
7              1            0
8              0            1
9              0            1
```

In [20]:
```python
AttList = ["RowNumber", "CustomerId", "Surname", "CategoricalCreditScore", "Categorica
data_encoder = data_encoder.drop(AttList, axis=1)
data_encoder.head()
```

Out[20]:
```
   CreditScore  Geography  Age  Tenure  Balance  NumOfProducts  HasCrCard  \
0          619          0   42       2      0.0              1          1
1          608          2   41       1      0.0              1          0
2          502          0   42       8      1.0              3          1
3          699          0   39       1      0.0              2          0
```

```
4          850          2   43        2      1.0               1          1

   IsActiveMember  EstimatedSalary  Exited  Gender_Female  Gender_Male
0               1        101348.88       1              1            0
1               1        112542.58       0              1            0
2               0        113931.57       1              1            0
3               0         93826.63       0              1            0
4               1         79084.10       0              1            0
```

In [21]:
```python
# Split Train and Test and check shape
data_train_encoder, target_train_encoder, data_test_encoder, target_test_encoder = Spl
PrintTrainTestInformation(data_train_encoder, target_train_encoder, data_test_encoder
```

```
Train rows and columns :  (6000, 11)
Test rows and columns :  (4000, 11)
```

5.1 Classification by trainditional models

In [0]:
```python
X_train = data_train_encoder
y_train = target_train_encoder
X_test = data_test_encoder
y_test = target_test_encoder
```

In [23]:
```python
MachineLearningModelEvaluate(X_train, y_train, X_test, y_test)
```

```
Naive Bayes accuracy: 0.770
Logistic Regression accuracy: 0.785
Random Forest accuracy: 0.839500
Linear SVM accuracy: 0.798250
RBF SVM accuracy: 0.798250
K Nearest Neighbor accuracy: 0.736250
ANN accuracy: 0.797750
```

6 Approach 1 (Feature Selection)

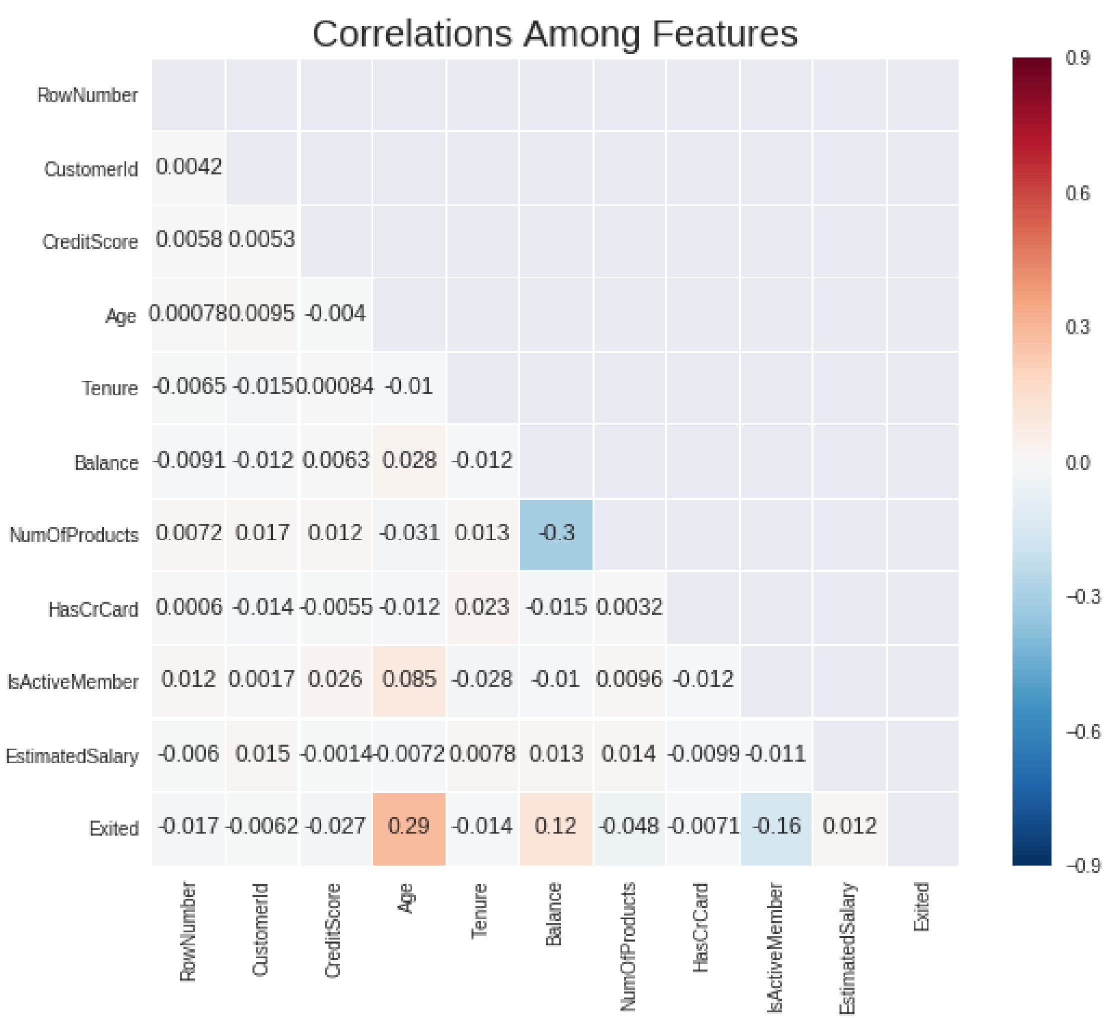
7 Correlation

In [24]:
```python
## get the most important variables.
corr = dataset.corr()**2
corr.Exited.sort_values(ascending=False)
```

Out[24]:
```
Exited            1.000000
Age               0.081409
IsActiveMember    0.024376
Balance           0.014050
NumOfProducts     0.002287
```

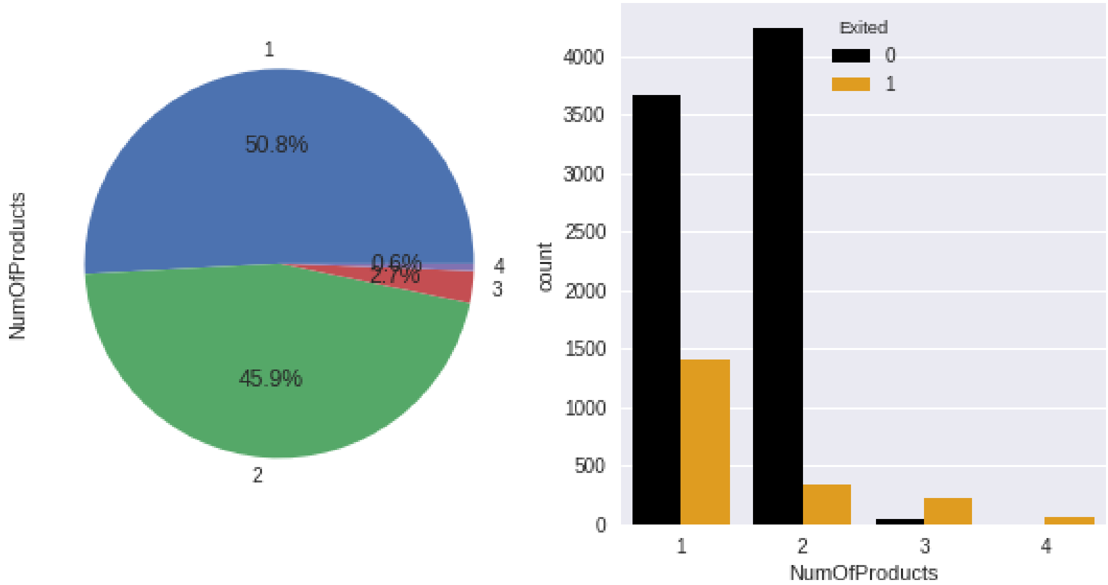
```
CreditScore        0.000734
RowNumber          0.000275
Tenure             0.000196
EstimatedSalary    0.000146
HasCrCard          0.000051
CustomerId         0.000039
Name: Exited, dtype: float64
```

In [25]:
```python
# Heatmeap to see the correlation between features.
# Generate a mask for the upper triangle (taken from seaborn example gallery)
mask = np.zeros_like(dataset.corr(), dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
# plot
plt.subplots(figsize = (10,8))
sns.heatmap(dataset.corr(), annot=True, mask = mask, cmap = 'RdBu_r', linewidths=0.1,
plt.title("Correlations Among Features", y = 1.03,fontsize = 20);
```



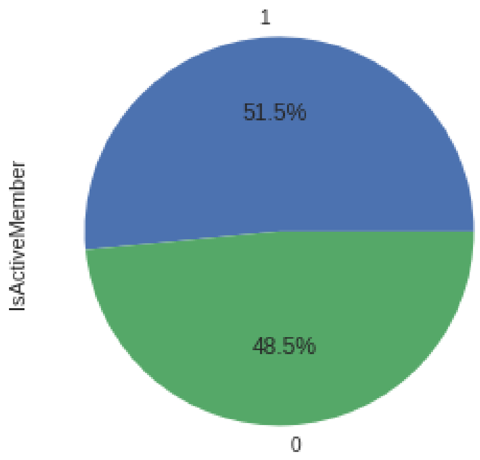
```
In [26]: print(dataset[['NumOfProducts', 'Exited']].groupby(['NumOfProducts'], as_index=False)
         CatPlot(dataset, 'NumOfProducts','Exited', {0: "black", 1: "orange"} )
```

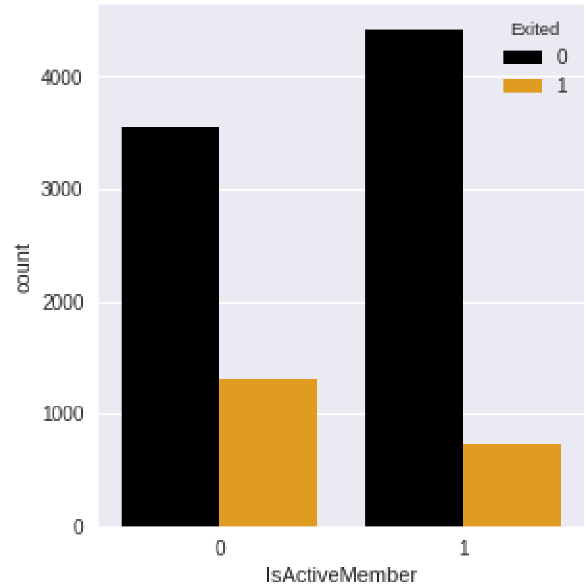
```
   NumOfProducts    Exited
3              4  1.000000
2              3  0.827068
0              1  0.277144
1              2  0.075817
```




```
In [27]: print(dataset[['IsActiveMember', 'Exited']].groupby(['IsActiveMember'], as_index=Fals
         CatPlot(dataset, 'IsActiveMember','Exited', {0: "black", 1: "orange"} )
```

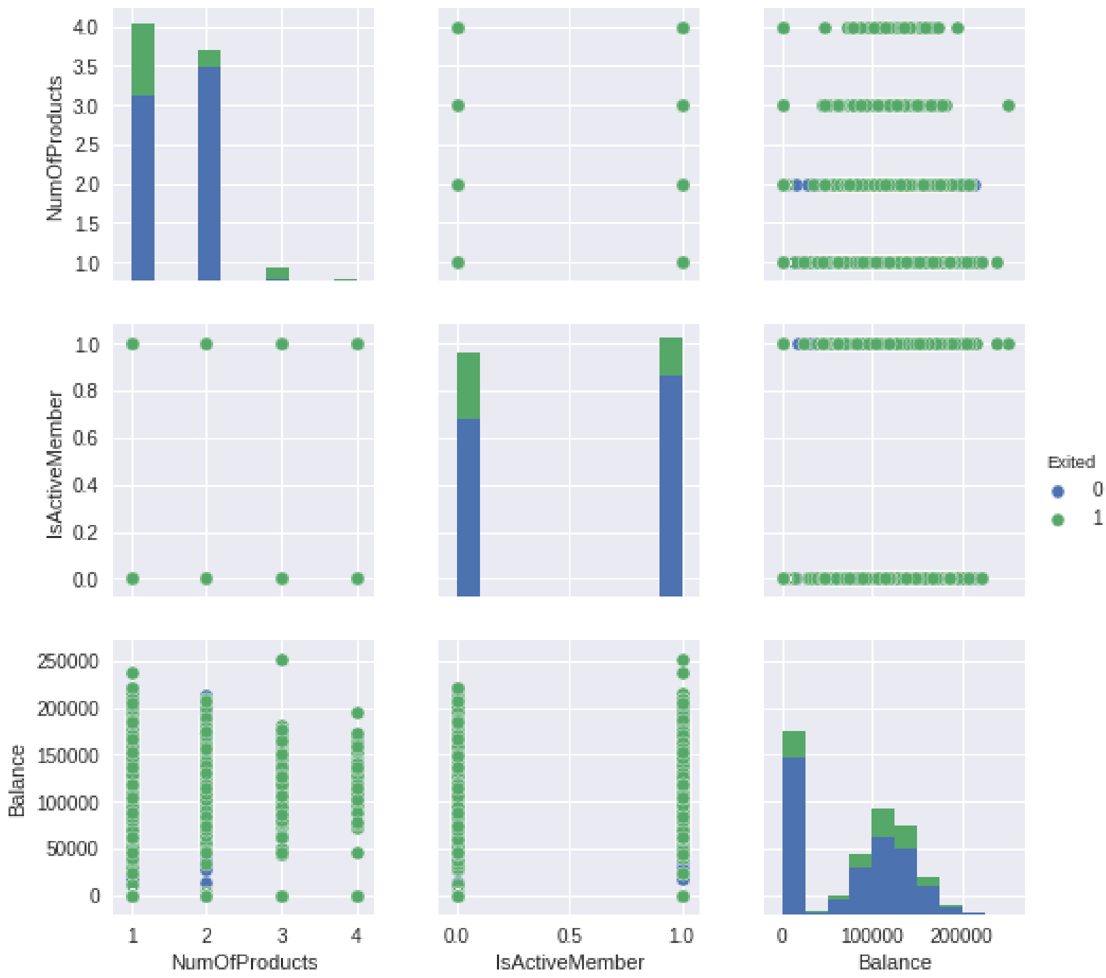
```
   IsActiveMember    Exited
0               0  0.268509
1               1  0.142691
```





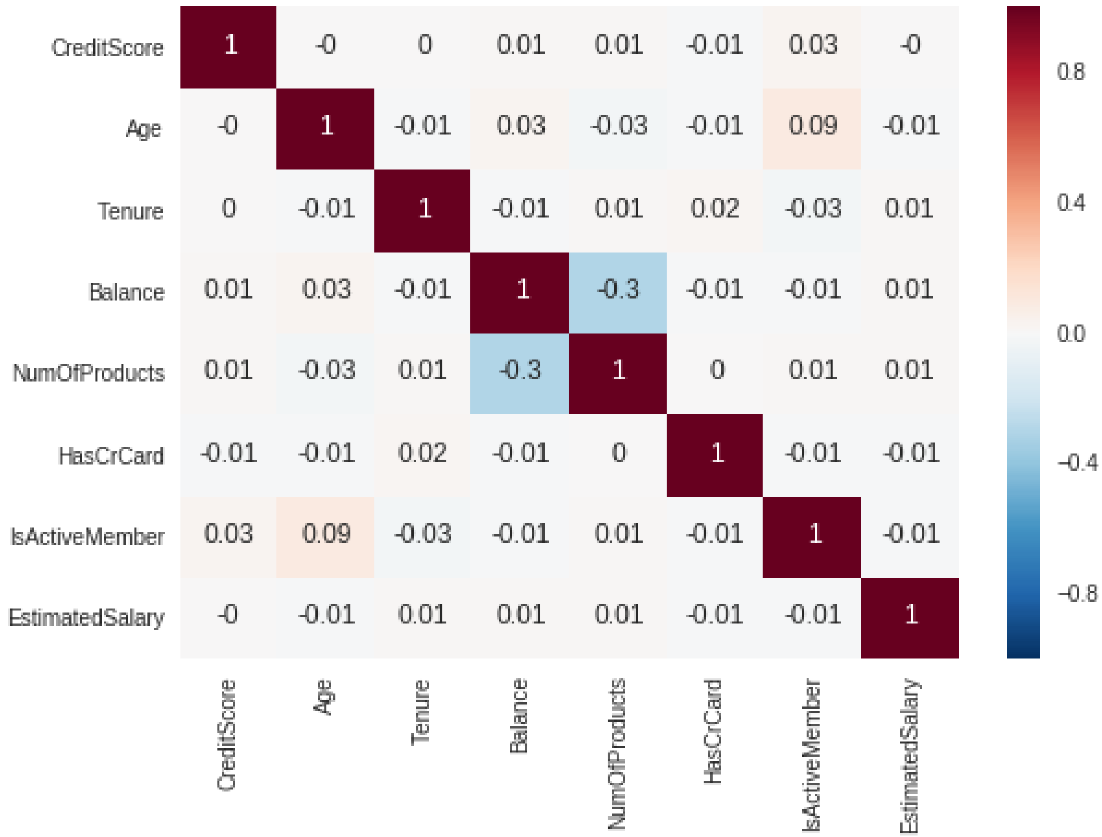

```
In [28]: # https://seaborn.pydata.org/generated/seaborn.pairplot.html
         sns.pairplot(dataset, vars=["NumOfProducts", "IsActiveMember", "Balance"], hue="Exitec
```

```
Out[28]: <seaborn.axisgrid.PairGrid at 0x7f97f8b54198>
```




```
In [29]: AttList = ["CreditScore",         "Age",          "Tenure",         "Balance",          "Nu
         correlation_matrix = dataset[AttList].corr().round(2)
         # annot = True to print the values inside the square
         sns.heatmap(data=correlation_matrix, annot=True)

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7f97f8ef3dd8>
```



In [30]:
```
data_encoder_feselection = data_encoder.copy()
# AttList = ["Surname", "RowNumber", "CustomerId"]
# data_encoder_feselection = data_encoder_feselection.drop(AttList,  axis=1)
print(data_encoder_feselection.shape)
data_encoder_feselection.head()
```

```
(10000, 12)
```

Out[30]:
```
   CreditScore  Geography  Age  Tenure  Balance  NumOfProducts  HasCrCard  \
0          619          0   42       2      0.0              1          1
1          608          2   41       1      0.0              1          0
2          502          0   42       8      1.0              3          1
3          699          0   39       1      0.0              2          0
4          850          2   43       2      1.0              1          1

   IsActiveMember  EstimatedSalary  Exited  Gender_Female  Gender_Male
0               1        101348.88       1              1            0
1               1        112542.58       0              1            0
2               0        113931.57       1              1            0
3               0         93826.63       0              1            0
4               1         79084.10       0              1            0
```

In [31]:
```
# Split Train and Test and check shape
data_train_encoder_feselection, target_train_encoder_feselection, data_test_encoder_fe
PrintTrainTestInformation(data_train_encoder_feselection, target_train_encoder_featsele
```

```
Train rows and columns :  (6000, 11)
Test rows and columns :  (4000, 11)
```

In [32]:
```
# Retest all traditional classification approaches
X_train = data_train_encoder
y_train = target_train_encoder
X_test = data_test_encoder
y_test = target_test_encoder

MachineLearningModelEvaluate(X_train, y_train, X_test, y_test)
```

```
Naive Bayes accuracy: 0.770
Logistic Regression accuracy: 0.785
Random Forest accuracy: 0.846000
Linear SVM accuracy: 0.798250
RBF SVM accuracy: 0.798250
K Nearest Neighbor accuracy: 0.736250
ANN accuracy: 0.798000
```

In [33]:
```
# Retest all traditional classification approaches
X_train = data_train_encoder_feselection
y_train = target_train_encoder_feselection
X_test = data_test_encoder_feselection
y_test = target_test_encoder_feselection

MachineLearningModelEvaluate(X_train, y_train, X_test, y_test)
```

```
Naive Bayes accuracy: 0.770
Logistic Regression accuracy: 0.785
Random Forest accuracy: 0.840000
Linear SVM accuracy: 0.798250
RBF SVM accuracy: 0.798250
K Nearest Neighbor accuracy: 0.736250
ANN accuracy: 0.797500
```

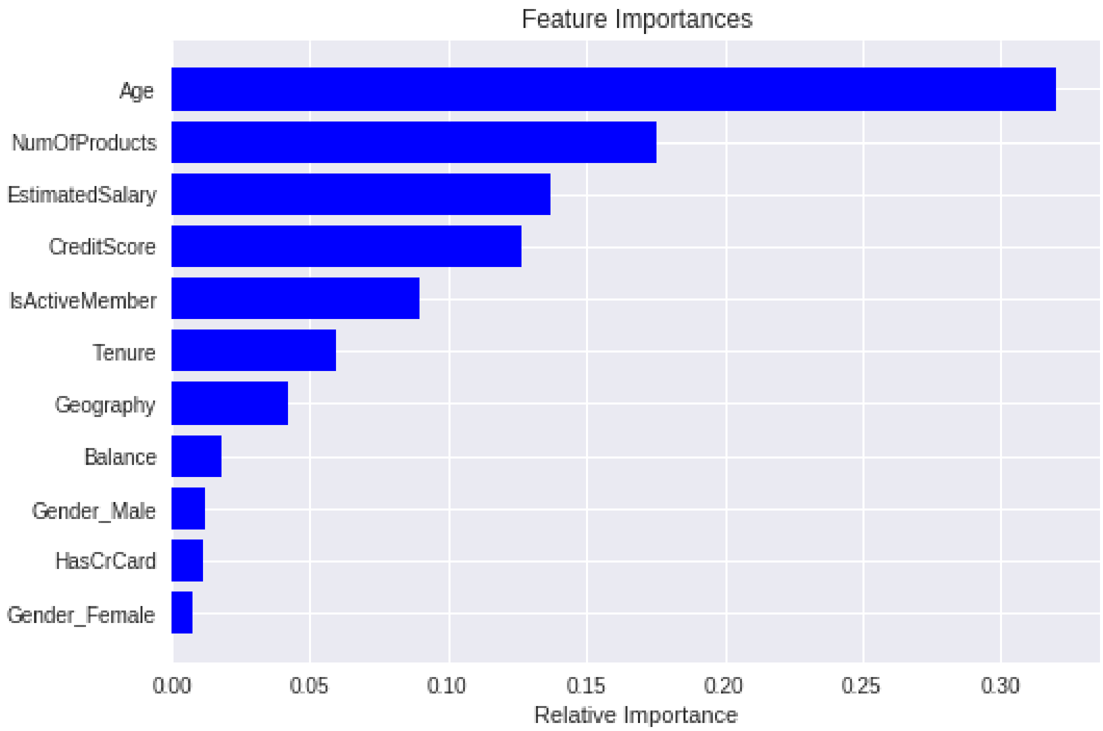
7.1 Feature Importances

In [71]:
```
model = RandomForestRegressor(random_state=1, max_depth=10)
model.fit(data_train_encoder,target_train_encoder.values.ravel())

print(data_train_encoder.shape)
features = data_train_encoder.columns
```

```
importances = model.feature_importances_
indices = np.argsort(importances)[-len(features):]  # top features
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='b', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```

```
(6000, 11)
```




```
In [72]: # Get numerical feature importances
         feature_list = list(data_train_encoder.columns)
         importances = list(model.feature_importances_)
         # List of tuples with variable and importance
         feature_importances = [(feature, round(importance, 2)) for feature, importance in zip
         # Sort the feature importances by most important first
         feature_importances = sorted(feature_importances, key = lambda x: x[1], reverse = True
         # Print out the feature and importances
         [print('Variable: {:20} Importance: {}'.format(*pair)) for pair in feature_importances
```

```
Variable: Age                  Importance: 0.32
Variable: NumOfProducts        Importance: 0.18
Variable: EstimatedSalary      Importance: 0.14
```

```
Variable: CreditScore          Importance: 0.13
Variable: IsActiveMember       Importance: 0.09
Variable: Tenure               Importance: 0.06
Variable: Geography            Importance: 0.04
Variable: Balance              Importance: 0.02
Variable: HasCrCard            Importance: 0.01
Variable: Gender_Female        Importance: 0.01
Variable: Gender_Male          Importance: 0.01
```

```
In [74]: # Split Train and Test and check shape
         AttSelection = ["Age", "NumOfProducts", "EstimatedSalary", "CreditScore", "Tenure", "(
                         "Exited"]

         data_train_encoder_feselection02, target_train_encoder_feselection02, data_test_encode
         PrintTrainTestInformation(data_train_encoder_feselection02, target_train_encoder_fesel
```

```
Train rows and columns :  (6000, 7)
Test rows and columns :  (4000, 7)
```

```
In [75]: # Retest all traditional classification approaches
         X_train = data_train_encoder_feselection02
         y_train = target_train_encoder_feselection02
         X_test = data_test_encoder_feselection02
         y_test = target_test_encoder_feselection02

         MachineLearningModelEvaluate(X_train, y_train, X_test, y_test)
```

```
Naive Bayes accuracy: 0.767
Logistic Regression accuracy: 0.784
Random Forest accuracy: 0.830750
Linear SVM accuracy: 0.798250
RBF SVM accuracy: 0.798250
K Nearest Neighbor accuracy: 0.736000
ANN accuracy: 0.798750
```

```
In [38]: from sklearn.feature_selection import RFE
         from sklearn.linear_model import LogisticRegression
         import pandas as pd
         from sklearn.svm import SVR

         # Retest all traditional classification approaches
         X_train = data_train_encoder
         y_train = target_train_encoder
         X_test = data_test_encoder
         y_test = target_test_encoder
```

```
LRModel = LogisticRegressionLearning(X_train, y_train)
model = LRModel
rfe = RFE(model, 10)
rfe = rfe.fit(X_train, y_train.values.ravel())

feature_list = list(X_train.columns)
RankStatistics = pd.DataFrame(columns=['Attributes', 'Ranking', 'Support'])
for i, att, rank, suppport in zip(range(len(feature_list)), feature_list, rfe.ranking_
    RankStatistics.loc[i] = [att, rank, suppport]
RankStatistics = RankStatistics.sort_values('Ranking')

RankStatistics
```

Out[38]:

	Attributes	Ranking	Support
0	CreditScore	1	True
1	Geography	1	True
2	Age	1	True
3	Tenure	1	True
4	Balance	1	True
5	NumOfProducts	1	True
6	HasCrCard	1	True
7	IsActiveMember	1	True
9	Gender_Female	1	True
10	Gender_Male	1	True
8	EstimatedSalary	2	False

In [39]:

```
# Split Train and Test and check shape
AttSelection = RankStatistics[(RankStatistics["Support"] == True)]
AttSelection = list(filter(lambda a: a not in ["CustomerId", "Surname"], AttSelection
AttSelection = AttSelection + ['Exited']

data_train_encoder_feselection03, target_train_encoder_feselection03, data_test_encode
PrintTrainTestInformation(data_train_encoder_feselection03, target_train_encoder_fesel
```

```
Train rows and columns :  (6000, 10)
Test rows and columns :  (4000, 10)
```

In [40]:

```
# Retest all traditional classification approaches
X_train = data_train_encoder_feselection03
y_train = target_train_encoder_feselection03
X_test = data_test_encoder_feselection03
y_test = target_test_encoder_feselection03

MachineLearningModelEvaluate(X_train, y_train, X_test, y_test)
```

```
Naive Bayes accuracy: 0.818
Logistic Regression accuracy: 0.803
Random Forest accuracy: 0.841000
```

```
Linear SVM accuracy: 0.795500
RBF SVM accuracy: 0.798250
K Nearest Neighbor accuracy: 0.772750
ANN accuracy: 0.806750
```

8 Approach 2 (Feature Reduction)

In [41]:
```python
# Feature Reduction: Dimensionality Reduction with PCA.
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

AttRemoved = ["RowNumber", "CustomerId", "Surname", "HasCrCard", "Gender_Male", "Gende
DataFrame = data_encoder
hr_vars = DataFrame.columns.values.tolist()
hr_vars = list(filter(lambda a: a not in AttRemoved, hr_vars))
targets = ['Exited']
features = [i for i in hr_vars if i not in targets]

# Separating out the features
x = DataFrame.loc[:, features].values
# Separating out the target
y = DataFrame.loc[:, ['Exited']].values
# Standardizing the features
x = StandardScaler().fit_transform(x)

nSelectedFeature = len(hr_vars) - 1
SelectedAttList = []
for i in range(1, nSelectedFeature + 1):
    SelectedAttList.append("principal component" + str(i))


pca = PCA(n_components=nSelectedFeature)
principalComponents = pca.fit_transform(x)
principalDf = pd.DataFrame(data=principalComponents, columns=SelectedAttList)
PCAdf = pd.concat([principalDf, DataFrame[targets]], axis=1)
PCAdf = PCAdf.dropna()
PCAdata = PCAdf

PCAdata.head(10)
```

Out[41]:
```
   principal component1  principal component2  principal component3  \
0             -0.210853              0.884002              1.446764
1             -0.569838              1.195424              0.047422
2              0.869274             -1.103759              0.016253
3              1.128893             -0.151478              1.081788
```

```
4           -1.923635             1.451394            -1.077486
5            0.847114            -0.370761            -1.909737
6            0.937177             1.788649             0.042209
7            3.409745            -1.006174             0.435076
8           -0.565255             0.566436             1.276217
9           -1.303973            -0.089951             1.253032

   principal component4  principal component5  principal component6  \
0              0.278925             -0.634165              0.096706
1              0.380679              0.028651             -1.688115
2              1.523084              0.787701              0.617678
3             -0.534498             -0.756419             -0.618177
4             -1.795071             -0.735991             -0.963920
5              0.815389              0.614184             -0.434943
6             -1.637323              0.347318              1.693827
7              2.204620              1.414215             -1.814186
8              1.057400              0.478299              0.262575
9             -1.072287             -0.924581             -0.059585

   principal component7  principal component8  Exited
0             -0.253957             -0.944001       1
1             -0.447760             -1.349368       0
2              0.319225              2.904623       1
3              1.185436              0.322298       0
4             -0.146821              0.122698       0
5              0.884744             -0.210759       1
6              0.486942              0.326536       0
7             -0.327603              2.408140       1
8             -0.764268              1.755141       0
9             -1.356978              0.445756       0
```

In [42]:
```
PCAdata_train, PCAtarget_train, PCAdata_test, PCAtarget_test = SplitDataFrameToTrainAr
PrintTrainTestInformation(PCAdata_train, PCAtarget_train, PCAdata_test, PCAtarget_tes
```

```
Train rows and columns :  (6000, 8)
Test rows and columns :  (4000, 8)
```

In [43]:
```
# Retest all traditional classification approaches
X_train = PCAdata_train
y_train = PCAtarget_train
X_test = PCAdata_test
y_test = PCAtarget_test

MachineLearningModelEvaluate(X_train, y_train, X_test, y_test)
```

```
Naive Bayes accuracy: 0.827
Logistic Regression accuracy: 0.802
Random Forest accuracy: 0.839000
```

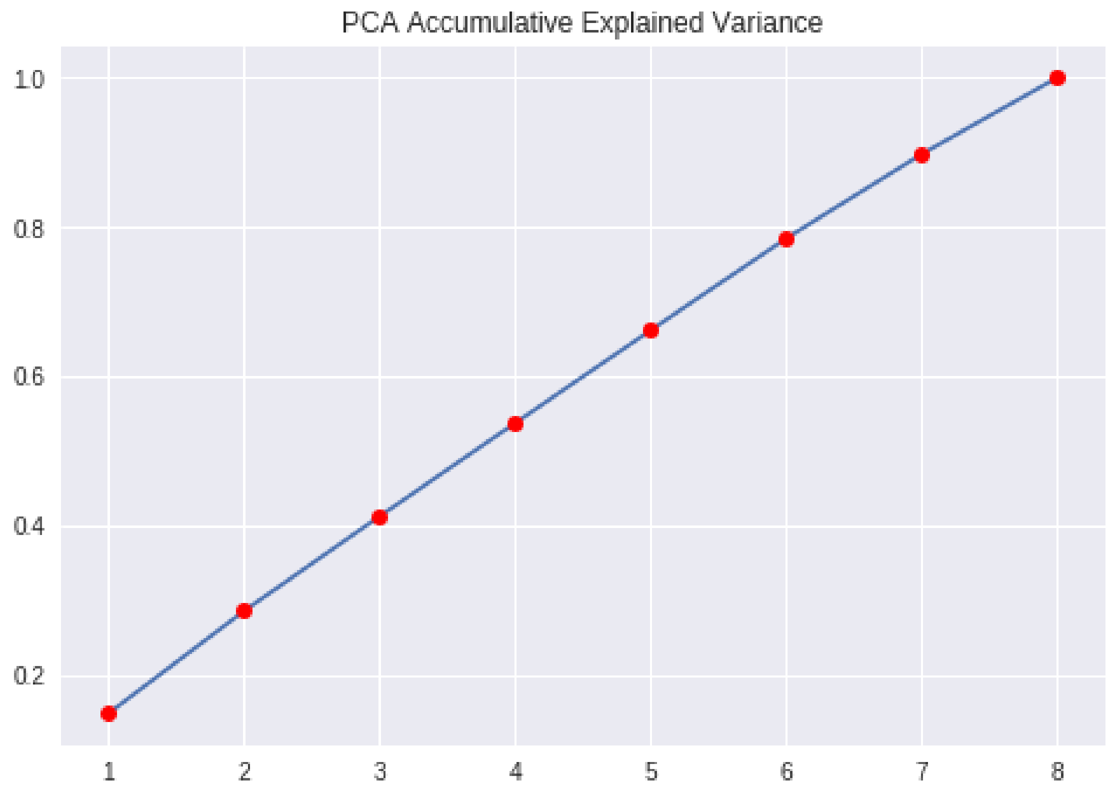
```
Linear SVM accuracy: 0.853500
RBF SVM accuracy: 0.810500
K Nearest Neighbor accuracy: 0.817500
ANN accuracy: 0.850500
```

In [44]:
```python
import matplotlib.pyplot as plt

cum_explained_var = []
for i in range(0, len(pca.explained_variance_ratio_)):
    if i == 0:
        cum_explained_var.append(pca.explained_variance_ratio_[i])
    else:
        cum_explained_var.append(pca.explained_variance_ratio_[i] +
                                 cum_explained_var[i - 1])

x_val = range(1, len(cum_explained_var) + 1)
y_val = cum_explained_var

fig = plt.figure()
plt.plot(x_val, y_val)
plt.plot(x_val, y_val, 'or')
plt.title("PCA Accumulative Explained Variance")
plt.xticks(range(1, len(cum_explained_var) + 1))
plt.grid(True)
plt.show()
```




```
In [45]: AttSelection = PCAdata.columns.values.tolist()
         AttSelection = AttSelection[:15]
         if AttSelection[len(AttSelection)-1] != 'Exited' :
             AttSelection = AttSelection + ['Exited']
         print(AttSelection)

         PCAdata_train_feReduction, PCAtarget_train_feReduction, PCAdata_test_feReduction, PCA
         PrintTrainTestInformation(PCAdata_train_feReduction, PCAtarget_train_feReduction, PCAd

['principal component1', 'principal component2', 'principal component3', 'principal component4
Train rows and columns :  (6000, 8)
Test rows and columns :  (4000, 8)
```

```
In [46]: # Retest all traditional classification approaches
         X_train = PCAdata_train_feReduction
         y_train = PCAtarget_train_feReduction
         X_test = PCAdata_test_feReduction
         y_test = PCAtarget_test_feReduction

         MachineLearningModelEvaluate(X_train, y_train, X_test, y_test)
```

```
Naive Bayes accuracy: 0.827
Logistic Regression accuracy: 0.802
Random Forest accuracy: 0.839750
Linear SVM accuracy: 0.853500
RBF SVM accuracy: 0.810500
K Nearest Neighbor accuracy: 0.817500
ANN accuracy: 0.850750
```

9 *Outlier Removal Approach*

In [47]:
```
data_encoder.head()
```

Out[47]:
```
   CreditScore  Geography  Age  Tenure  Balance  NumOfProducts  HasCrCard  \
0          619          0   42       2      0.0              1          1
1          608          2   41       1      0.0              1          0
2          502          0   42       8      1.0              3          1
3          699          0   39       1      0.0              2          0
4          850          2   43       2      1.0              1          1

   IsActiveMember  EstimatedSalary  Exited  Gender_Female  Gender_Male
0               1        101348.88       1              1            0
1               1        112542.58       0              1            0
2               0        113931.57       1              1            0
3               0         93826.63       0              1            0
4               1         79084.10       0              1            0
```

In [48]:
```
data_encoder.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
CreditScore        10000 non-null int64
Geography          10000 non-null int64
Age                10000 non-null int64
Tenure             10000 non-null int64
Balance            10000 non-null float64
NumOfProducts      10000 non-null int64
HasCrCard          10000 non-null int64
IsActiveMember     10000 non-null int64
EstimatedSalary    10000 non-null float64
Exited             10000 non-null int64
Gender_Female      10000 non-null uint8
Gender_Male        10000 non-null uint8
dtypes: float64(2), int64(8), uint8(2)
memory usage: 800.9 KB
```

In [49]:
```
CheckOutlierAtt = ['CreditScore', 'Geography']
LOFOutlierIdx01,LOFFactorData01 = DetectOutlierByLOF(data_encoder, AttList=CheckOutli

print("Size of LOFOutlierIdx : " + str(len(LOFOutlierIdx01)))
print(LOFFactorData01.head())
```

```
Size of LOFOutlierIdx : 1656
   index           LOF
0   3871  9.000000e+09
1   9409  9.000000e+09
2    656  8.000000e+09
3     17  8.000000e+09
4    268  8.000000e+09
```

In [50]:
```
CheckOutlierAtt = ['Age', 'Tenure', 'Balance']
LOFOutlierIdx02,LOFFactorData02 = DetectOutlierByLOF(data_encoder, AttList=CheckOutli

print("Size of LOFOutlierIdx : " + str(len(LOFOutlierIdx02)))
print(LOFFactorData02.head())
```

```
Size of LOFOutlierIdx : 1020
   index           LOF
0   8174  8.000000e+09
1   5881  8.000000e+09
2   4402  8.000000e+09
3   7122  8.000000e+09
4   5228  8.000000e+09
```

In [51]:
```
CheckOutlierAtt = ['HasCrCard', 'IsActiveMember', 'EstimatedSalary']
LOFOutlierIdx03,LOFFactorData03 = DetectOutlierByLOF(data_encoder, AttList=CheckOutli

print("Size of LOFOutlierIdx : " + str(len(LOFOutlierIdx03)))
print(LOFFactorData03.head())
```

```
Size of LOFOutlierIdx : 0
   index       LOF
0   2813  2.275599
1   8397  2.226634
2   3470  2.079527
3   4132  2.013270
4   7478  2.001296
```

In [52]:
```
print('LOFOutlierIdx01 :' + str(LOFOutlierIdx01))
print('LOFOutlierIdx02 :' + str(LOFOutlierIdx02))
print('LOFOutlierIdx03 :' + str(LOFOutlierIdx03))
```

```
LOFOutlierIdx01 :[3871, 9409, 656, 17, 268, 4792, 6836, 5589, 2233, 6095, 7587, 1053, 8489, 224
LOFOutlierIdx02 :[8174, 5881, 4402, 7122, 5228, 6198, 3042, 2595, 4520, 5049, 7500, 8476, 3454
LOFOutlierIdx03 :[]
```

```
In [53]: OutlierIndex = set(LOFOutlierIdx01 + LOFOutlierIdx02 + LOFOutlierIdx03)
         OutlierIndex = list(OutlierIndex)
         print(len(OutlierIndex))
         print('OutlierIdx : ' + str(OutlierIndex))
```

```
2485
OutlierIdx : [2, 8195, 8194, 6, 8, 13, 15, 16, 17, 18, 19, 8213, 8217, 8220, 8222, 30, 32, 822
```

```
In [54]: data_encoder_mining = data_encoder.copy()
         print(data_encoder_mining.shape)
         data_encoder_mining = RemoveRowsFromDataFrame(data_encoder_mining,OutlierIndex)
         print(data_encoder_mining.shape)

         # feature selection
         # AttList = ["Surname", "RowNumber", "CustomerId"]
         # data_encoder_mining = data_encoder_mining.drop(AttList,  axis=1)
         # print(data_encoder_mining.shape)
```

```
(10000, 12)
(7515, 12)
```

```
In [55]: # Split Train and Test and check shape
         data_train_encoder_mining, target_train_encoder_mining, data_test_encoder_mining, targ
         PrintTrainTestInformation(data_train_encoder_mining, target_train_encoder_mining, data
```

```
Train rows and columns :  (4509, 11)
Test rows and columns :  (3006, 11)
```

```
In [56]: # Retest all traditional classification approaches
         X_train = data_train_encoder_mining
         y_train = target_train_encoder_mining
         X_test = data_test_encoder_mining
         y_test = target_test_encoder_mining

         MachineLearningModelEvaluate(X_train, y_train, X_test, y_test)
```

```
Naive Bayes accuracy: 0.791
Logistic Regression accuracy: 0.807
Random Forest accuracy: 0.858949
Linear SVM accuracy: 0.811045
RBF SVM accuracy: 0.811045
K Nearest Neighbor accuracy: 0.767132
ANN accuracy: 0.207917
```

10 Neural Network Approach

In [57]:
```
# Retest all traditional classification approaches
# X_train = data_train_encoder_mining
# y_train = target_train_encoder_mining
# X_test = data_test_encoder_mining
# y_test = target_test_encoder_mining

X_train = PCAdata_train_feReduction
y_train = PCAtarget_train_feReduction
X_test = PCAdata_test_feReduction
y_test = PCAtarget_test_feReduction

from keras.models import Sequential
from keras.layers import Dense
from keras.callbacks import ModelCheckpoint

seed = 42
np.random.seed(seed)

## Create our model
model = Sequential()

# 1st layer: 23 nodes, input shape[1] nodes, RELU
model.add(Dense(23, input_dim=X_train.shape[1], kernel_initializer='uniform', activati
# 2nd layer: 17 nodes, RELU
model.add(Dense(17, kernel_initializer='uniform', activation = 'relu'))
# 3nd layer: 15 nodes, RELU
model.add(Dense(15, kernel_initializer='uniform', activation='relu'))
# 4nd layer: 11 nodes, RELU
model.add(Dense(11, kernel_initializer='uniform', activation='relu'))
# 5nd layer: 9 nodes, RELU
model.add(Dense(9, kernel_initializer='uniform', activation='relu'))
# 6nd layer: 7 nodes, RELU
model.add(Dense(7, kernel_initializer='uniform', activation='relu'))
# 7nd layer: 5 nodes, RELU
model.add(Dense(5, kernel_initializer='uniform', activation='relu'))
# 8nd layer: 2 nodes, RELU
model.add(Dense(2, kernel_initializer='uniform', activation='relu'))
# output layer: dim=1, activation sigmoid
model.add(Dense(1, kernel_initializer='uniform', activation='sigmoid' ))
# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

NB_EPOCHS = 100
BATCH_SIZE = 23

# checkpoint: store the best model
```

```python
ckpt_model = 'pima-weights.best.hdf5'
checkpoint = ModelCheckpoint(ckpt_model, monitor='val_acc', verbose=1, save_best_only=
callbacks_list = [checkpoint]

print('Starting training...')
# train the model, store the results for plotting
history = model.fit(X_train,
                    y_train,
                    validation_data=(X_test, y_test),
                    epochs=NB_EPOCHS,
                    batch_size=BATCH_SIZE,
                    callbacks=callbacks_list,
                    verbose=0)
```

```
Using TensorFlow backend.


Starting training...

Epoch 00001: val_acc improved from -inf to 0.79825, saving model to pima-weights.best.hdf5

Epoch 00002: val_acc did not improve from 0.79825

Epoch 00003: val_acc did not improve from 0.79825

Epoch 00004: val_acc did not improve from 0.79825

Epoch 00005: val_acc improved from 0.79825 to 0.82400, saving model to pima-weights.best.hdf5

Epoch 00006: val_acc improved from 0.82400 to 0.82750, saving model to pima-weights.best.hdf5

Epoch 00007: val_acc did not improve from 0.82750

Epoch 00008: val_acc improved from 0.82750 to 0.84075, saving model to pima-weights.best.hdf5

Epoch 00009: val_acc improved from 0.84075 to 0.84325, saving model to pima-weights.best.hdf5

Epoch 00010: val_acc improved from 0.84325 to 0.84400, saving model to pima-weights.best.hdf5

Epoch 00011: val_acc improved from 0.84400 to 0.84625, saving model to pima-weights.best.hdf5

Epoch 00012: val_acc did not improve from 0.84625

Epoch 00013: val_acc improved from 0.84625 to 0.84875, saving model to pima-weights.best.hdf5

Epoch 00014: val_acc did not improve from 0.84875

Epoch 00015: val_acc did not improve from 0.84875
```

```
Epoch 00016: val_acc did not improve from 0.84875

Epoch 00017: val_acc improved from 0.84875 to 0.84975, saving model to pima-weights.best.hdf5

Epoch 00018: val_acc improved from 0.84975 to 0.85100, saving model to pima-weights.best.hdf5

Epoch 00019: val_acc did not improve from 0.85100

Epoch 00020: val_acc improved from 0.85100 to 0.85275, saving model to pima-weights.best.hdf5

Epoch 00021: val_acc did not improve from 0.85275

Epoch 00022: val_acc did not improve from 0.85275

Epoch 00023: val_acc did not improve from 0.85275

Epoch 00024: val_acc did not improve from 0.85275

Epoch 00025: val_acc did not improve from 0.85275

Epoch 00026: val_acc did not improve from 0.85275

Epoch 00027: val_acc did not improve from 0.85275

Epoch 00028: val_acc did not improve from 0.85275

Epoch 00029: val_acc did not improve from 0.85275

Epoch 00030: val_acc did not improve from 0.85275

Epoch 00031: val_acc did not improve from 0.85275

Epoch 00032: val_acc did not improve from 0.85275

Epoch 00033: val_acc did not improve from 0.85275

Epoch 00034: val_acc did not improve from 0.85275

Epoch 00035: val_acc did not improve from 0.85275

Epoch 00036: val_acc did not improve from 0.85275

Epoch 00037: val_acc did not improve from 0.85275

Epoch 00038: val_acc did not improve from 0.85275

Epoch 00039: val_acc did not improve from 0.85275
```

```
Epoch 00040: val_acc did not improve from 0.85275

Epoch 00041: val_acc did not improve from 0.85275

Epoch 00042: val_acc did not improve from 0.85275

Epoch 00043: val_acc did not improve from 0.85275

Epoch 00044: val_acc did not improve from 0.85275

Epoch 00045: val_acc did not improve from 0.85275

Epoch 00046: val_acc did not improve from 0.85275

Epoch 00047: val_acc did not improve from 0.85275

Epoch 00048: val_acc did not improve from 0.85275

Epoch 00049: val_acc did not improve from 0.85275

Epoch 00050: val_acc did not improve from 0.85275

Epoch 00051: val_acc did not improve from 0.85275

Epoch 00052: val_acc did not improve from 0.85275

Epoch 00053: val_acc did not improve from 0.85275

Epoch 00054: val_acc did not improve from 0.85275

Epoch 00055: val_acc did not improve from 0.85275

Epoch 00056: val_acc did not improve from 0.85275

Epoch 00057: val_acc did not improve from 0.85275

Epoch 00058: val_acc did not improve from 0.85275

Epoch 00059: val_acc did not improve from 0.85275

Epoch 00060: val_acc did not improve from 0.85275

Epoch 00061: val_acc did not improve from 0.85275

Epoch 00062: val_acc did not improve from 0.85275

Epoch 00063: val_acc did not improve from 0.85275
```

```
Epoch 00064: val_acc did not improve from 0.85275

Epoch 00065: val_acc did not improve from 0.85275

Epoch 00066: val_acc did not improve from 0.85275

Epoch 00067: val_acc did not improve from 0.85275

Epoch 00068: val_acc did not improve from 0.85275

Epoch 00069: val_acc did not improve from 0.85275

Epoch 00070: val_acc did not improve from 0.85275

Epoch 00071: val_acc did not improve from 0.85275

Epoch 00072: val_acc did not improve from 0.85275

Epoch 00073: val_acc did not improve from 0.85275

Epoch 00074: val_acc did not improve from 0.85275

Epoch 00075: val_acc did not improve from 0.85275

Epoch 00076: val_acc did not improve from 0.85275

Epoch 00077: val_acc did not improve from 0.85275

Epoch 00078: val_acc did not improve from 0.85275

Epoch 00079: val_acc did not improve from 0.85275

Epoch 00080: val_acc did not improve from 0.85275

Epoch 00081: val_acc did not improve from 0.85275

Epoch 00082: val_acc did not improve from 0.85275

Epoch 00083: val_acc did not improve from 0.85275

Epoch 00084: val_acc did not improve from 0.85275

Epoch 00085: val_acc did not improve from 0.85275

Epoch 00086: val_acc did not improve from 0.85275

Epoch 00087: val_acc did not improve from 0.85275
```

```
Epoch 00088: val_acc did not improve from 0.85275

Epoch 00089: val_acc did not improve from 0.85275

Epoch 00090: val_acc did not improve from 0.85275

Epoch 00091: val_acc did not improve from 0.85275

Epoch 00092: val_acc did not improve from 0.85275

Epoch 00093: val_acc did not improve from 0.85275

Epoch 00094: val_acc did not improve from 0.85275

Epoch 00095: val_acc did not improve from 0.85275

Epoch 00096: val_acc did not improve from 0.85275

Epoch 00097: val_acc did not improve from 0.85275

Epoch 00098: val_acc did not improve from 0.85275

Epoch 00099: val_acc did not improve from 0.85275

Epoch 00100: val_acc did not improve from 0.85275
```

11 *Bagging Boosting and Stacking*

```
In [58]: X = data_encoder_mining.copy()
         X = X.drop('Exited', 1)
         y = data_encoder_mining[['Exited']]
         X.head()
```

Out[58]:

	CreditScore	Geography	Age	Tenure	Balance	NumOfProducts	HasCrCard \
0	619	0	42	2	0.0	1	1
1	608	2	41	1	0.0	1	0
2	699	0	39	1	0.0	2	0
3	850	2	43	2	1.0	1	1
4	645	2	44	8	0.0	2	1

	IsActiveMember	EstimatedSalary	Gender_Female	Gender_Male
0	1	101348.88	1	0
1	1	112542.58	1	0
2	0	93826.63	1	0
3	1	79084.10	1	0
4	0	149756.71	0	1

```
In [0]: X = PCAdata.copy()
        X = X.drop('Exited', 1)
        y = PCAdata[['Exited']]
        X.head()

        X_train = PCAdata_train_feReduction
        y_train = PCAtarget_train_feReduction
        X_test = PCAdata_test_feReduction
        y_test = PCAtarget_test_feReduction
```

```
In [0]: NBModel = NaiveBayesLearning(X_train, y_train)
        LRModel = LogisticRegressionLearning(X_train, y_train)
        RFModel = RandomForestLearning(X_train, y_train)
        LiSVMModel = SVMLearning(X_train, y_train)
        RBFSVMModel = SVMLearning(X_train, y_train, 'RBF')
        KNNModel = KNNLearning(X_train, y_train)
        ANNModel = ANNLearning(X_train, y_train)
```

```
In [61]: from sklearn import model_selection
         print('5-fold cross validation:\n')
         labels = ['NaiveBayesLearning', 'LogisticRegressionLearning', 'RandomForestLearning',
                   'SVMLearningLinear', 'SVMLearningRBF', 'KNNLearning', 'ANNLearning']
         for clf, label in zip([NBModel, LRModel, RFModel, LiSVMModel, RBFSVMModel, KNNModel, A
             scores = model_selection.cross_val_score(clf, X, y.values.ravel(), cv=5, scoring=
             print("Accuracy: %0.2f (+/- %0.2f) [%s]" % (scores.mean(), scores.std(), label))
```

```
5-fold cross validation:

Accuracy: 0.82 (+/- 0.00) [NaiveBayesLearning]
Accuracy: 0.81 (+/- 0.00) [LogisticRegressionLearning]
Accuracy: 0.84 (+/- 0.00) [RandomForestLearning]
Accuracy: 0.86 (+/- 0.00) [SVMLearningLinear]
Accuracy: 0.82 (+/- 0.00) [SVMLearningRBF]
Accuracy: 0.83 (+/- 0.01) [KNNLearning]
Accuracy: 0.85 (+/- 0.01) [ANNLearning]
```

```
In [62]: from mlxtend.classifier import EnsembleVoteClassifier
         eclf = EnsembleVoteClassifier(clfs=[RFModel,
                                             LiSVMModel,
                                             ANNModel], weights=[1,1,1])

         labels = ['RandomForestLearning', 'SVMLearningLinear', 'ANNModel', 'Ensemble']
         for clf, label in zip([RFModel, LiSVMModel, ANNModel, eclf], labels):
             scores = model_selection.cross_val_score(clf, X, y.values.ravel(), cv=5,scoring='a
             print("Accuracy: %0.2f (+/- %0.2f) [%s]" % (scores.mean(), scores.std(), label))
```

```
Accuracy: 0.84 (+/- 0.01) [RandomForestLearning]
Accuracy: 0.86 (+/- 0.00) [SVMLearningLinear]
```

```
Accuracy: 0.84 (+/- 0.02) [ANNModel]
Accuracy: 0.86 (+/- 0.01) [Ensemble]
```

```
In [63]: # Majority Rule (hard) Voting

         mv_clf = MajorityVoteClassifier(classifiers=[RFModel, LiSVMModel, ANNModel])

         labels = ['RandomForestLearning', 'SVMLearningLinear', 'ANN', 'Majority voting']
         all_clf = [RFModel, LiSVMModel, ANNModel, mv_clf]

         for clf, label in zip(all_clf, labels):
             scores = cross_val_score(estimator=clf, X=X, y=y.values.ravel(), cv=5, scoring='ac
             print("ROC AUC: %0.2f (+/- %0.2f) [%s]" % (scores.mean(), scores.std(), label))
```

```
ROC AUC: 0.84 (+/- 0.01) [RandomForestLearning]
ROC AUC: 0.86 (+/- 0.00) [SVMLearningLinear]
ROC AUC: 0.84 (+/- 0.02) [ANN]
ROC AUC: 0.85 (+/- 0.00) [Majority voting]
```

```
In [64]: # Split Train and Test and check shape
         data_train_encoder_mining, target_train_encoder_mining, data_test_encoder_mining, targ
         PrintTrainTestInformation(data_train_encoder_mining, target_train_encoder_mining, data

         # Retest all traditional classification approaches
         X_train = data_train_encoder_mining
         y_train = target_train_encoder_mining
         X_test = data_test_encoder_mining
         y_test = target_test_encoder_mining
```

```
Train rows and columns :  (4509, 11)
Test rows and columns :  (3006, 11)
```

```
In [65]: tree = DecisionTreeClassifier(criterion='entropy', max_depth=None, random_state=1)
         bag = BaggingClassifier(base_estimator=RFModel,
                                 n_estimators=1000,
                                 max_samples=1.0,
                                 max_features=1.0,
                                 bootstrap=True,
                                 bootstrap_features=False,
                                 n_jobs=1,
                                 random_state=1)

         tree = tree.fit(X_train, y_train.values.ravel())
         y_train_pred = tree.predict(X_train)
         y_test_pred = tree.predict(X_test)
```

```
        tree_train = accuracy_score(y_train, y_train_pred)
        tree_test = accuracy_score(y_test, y_test_pred)
        print('Decision tree train/test accuracies %.3f/%.3f'
              % (tree_train, tree_test))

        bag = bag.fit(X_train, y_train.values.ravel())
        y_train_pred = bag.predict(X_train)
        y_test_pred = bag.predict(X_test)

        bag_train = accuracy_score(y_train, y_train_pred)
        bag_test = accuracy_score(y_test, y_test_pred)
        print('Bagging train/test accuracies %.3f/%.3f'
              % (bag_train, bag_test))
```

```
Decision tree train/test accuracies 1.000/0.788
Bagging train/test accuracies 0.957/0.874
```

```
In [66]: from sklearn.ensemble import AdaBoostClassifier

         tree = DecisionTreeClassifier(criterion='entropy', max_depth=None, random_state=1)
         ada = AdaBoostClassifier(base_estimator=tree, n_estimators=500, learning_rate=0.1, ran
         tree = tree.fit(X_train, y_train.values.ravel())
         y_train_pred = tree.predict(X_train)
         y_test_pred = tree.predict(X_test)

         tree_train = accuracy_score(y_train, y_train_pred)
         tree_test = accuracy_score(y_test, y_test_pred)
         print('Decision tree train/test accuracies %.3f/%.3f'% (tree_train, tree_test))

         ada = ada.fit(X_train, y_train.values.ravel())
         y_train_pred = ada.predict(X_train)
         y_test_pred = ada.predict(X_test)

         ada_train = accuracy_score(y_train, y_train_pred)
         ada_test = accuracy_score(y_test, y_test_pred)
         print('AdaBoost train/test accuracies %.3f/%.3f'
               % (ada_train, ada_test))
```

```
Decision tree train/test accuracies 1.000/0.788
AdaBoost train/test accuracies 1.000/0.789
```

```
In [67]: from mlxtend.classifier import StackingClassifier
         import matplotlib.gridspec as gridspec
         import itertools
         from mlxtend.plotting import plot_learning_curves
         from mlxtend.plotting import plot_decision_regions
```

```
lr = LogisticRegression()
sclf = StackingClassifier(classifiers=[RFModel, LiSVMModel, ANNModel], meta_classifie

label = ['RandomForestLearning', 'SVMLearningLinear', 'ANN', 'Stacking Classifier']
clf_list = [RFModel, LiSVMModel, ANNModel, sclf]


clf_cv_mean = []
clf_cv_std = []
for clf, label in zip(clf_list, label):
    scores = cross_val_score(clf, X, y.values.ravel(), cv=5, scoring='accuracy')
    print("Accuracy: %.2f (+/- %.2f) [%s]" %(scores.mean(), scores.std(), label))
    clf_cv_mean.append(scores.mean())
    clf_cv_std.append(scores.std())
    clf.fit(X, y.values.ravel())
```

```
Accuracy: 0.84 (+/- 0.01) [RandomForestLearning]
Accuracy: 0.86 (+/- 0.00) [SVMLearningLinear]
Accuracy: 0.84 (+/- 0.02) [ANN]
Accuracy: 0.84 (+/- 0.01) [Stacking Classifier]
```

12 Summaries

12.0.1 Using Bagging on RandomForest can make up to 87.4%