bank_customer_churn_modeling

January 28, 2019

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, AdaBoostCla
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.ensemble import BaggingClassifier

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
```

1 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
```

2 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):
        """ 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)
    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))
```

3 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
```

3.1 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	

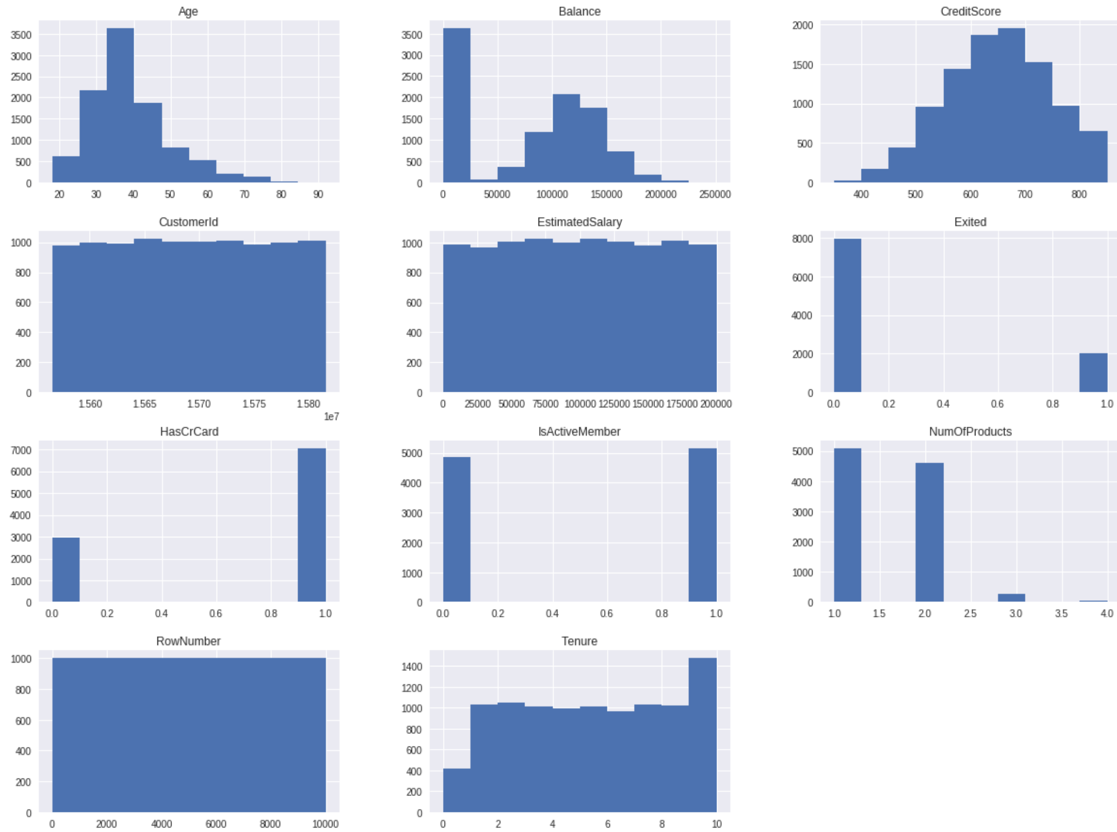
```
max    9999.000000  1.581569e+07   850.000000    92.000000    10.000000

                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'])
```

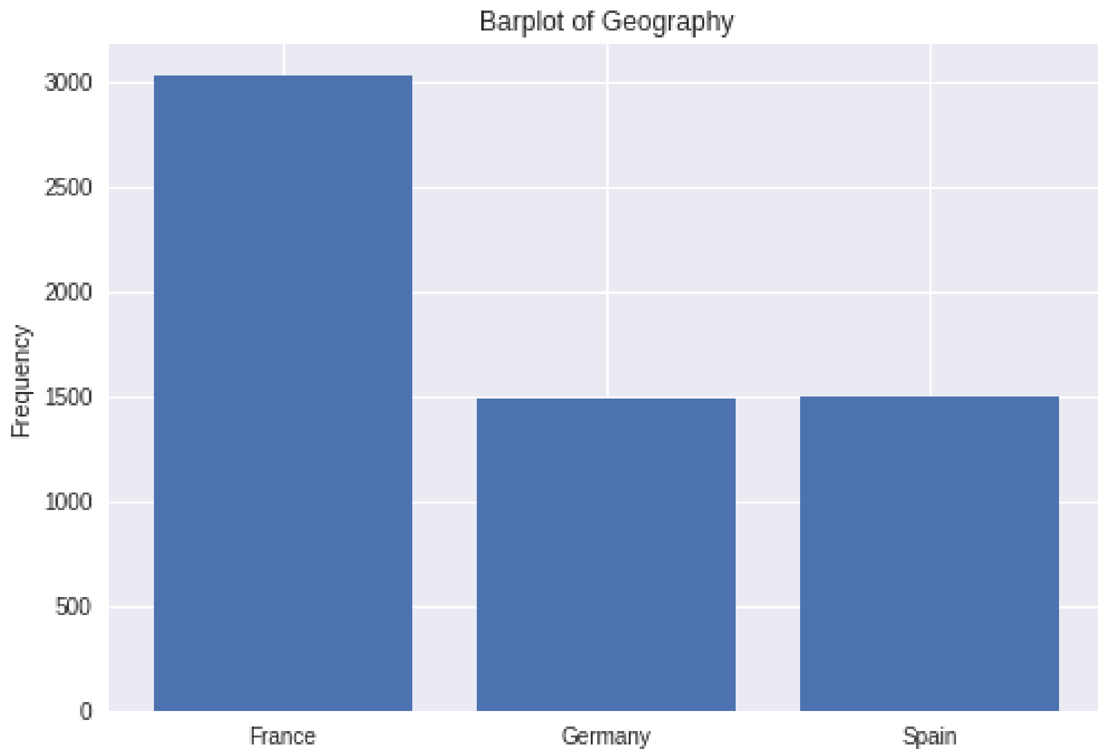
Out[11]:
```
       Surname Geography Gender
count     6000      6000   6000
unique    2246         3      2
top      Smith    France   Male
freq        23      3026   3259
```

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

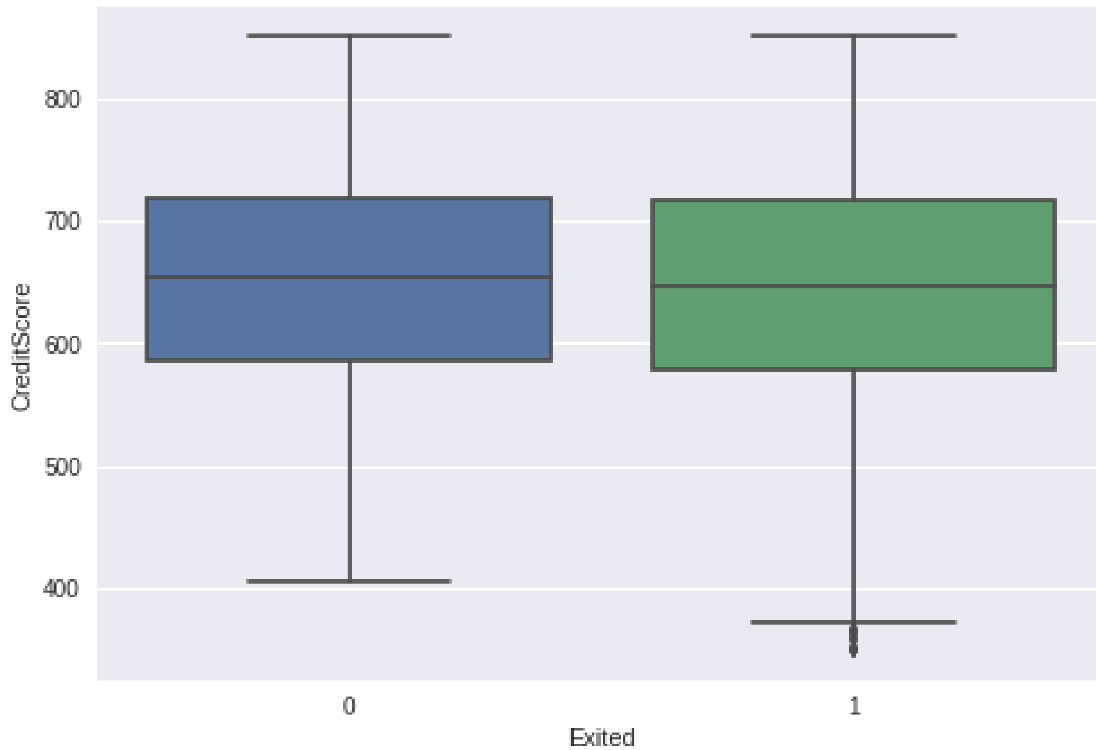
Out[12]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f97fdf0af98>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd490400>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd438a58>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f97fd3ea0f0>,
        <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)
```

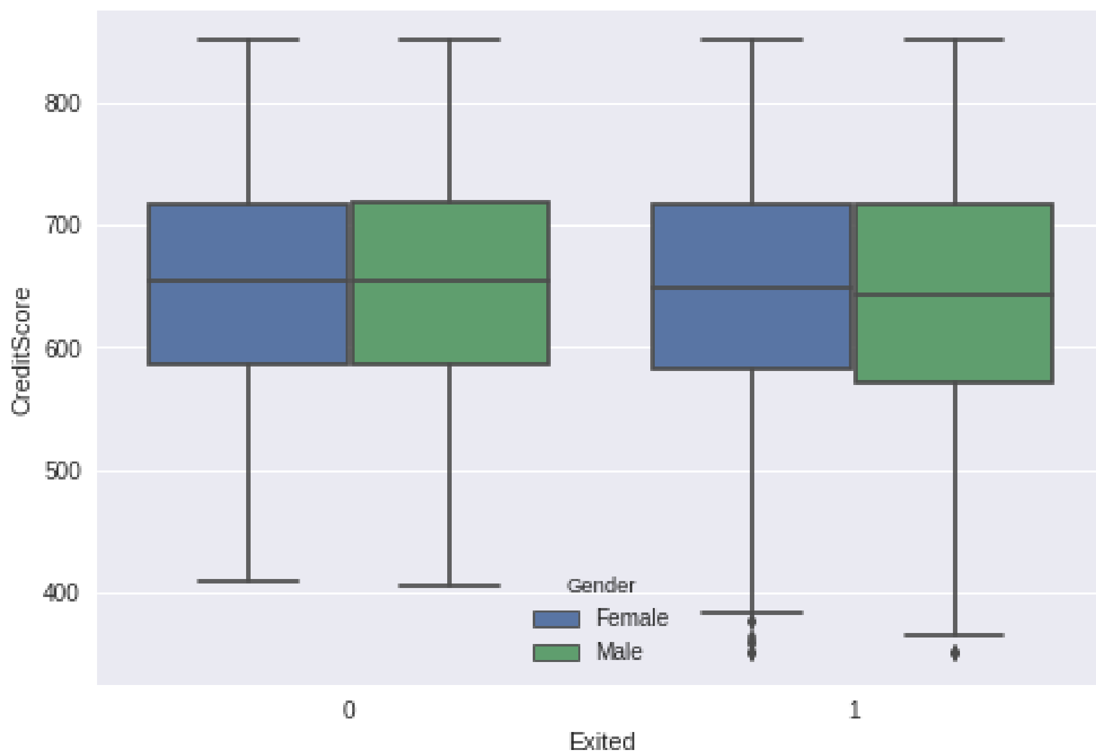



```
In [13]: DrawBarplot(data_train, 'Geography')
```

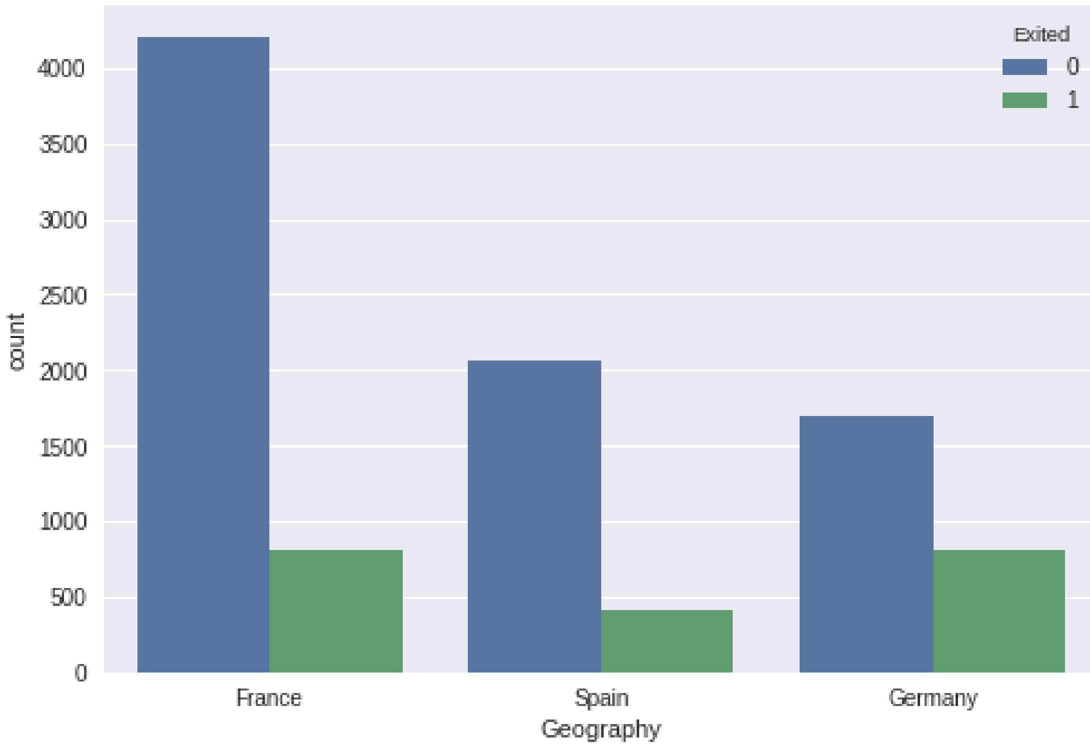


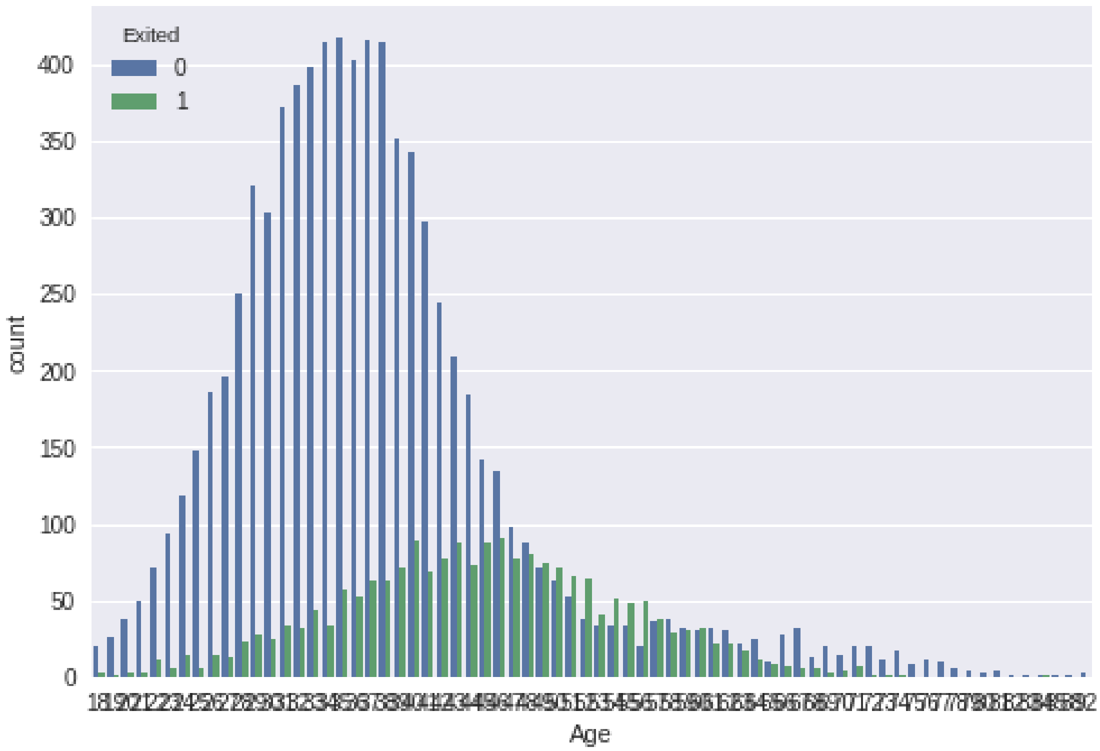

```
In [14]: DrawBoxplot2(dataset, xAtt = 'Exited', yAtt='CreditScore')
         DrawBoxplot2(dataset, xAtt = 'Exited', yAtt='CreditScore', hAtt='Gender')
```


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')
```

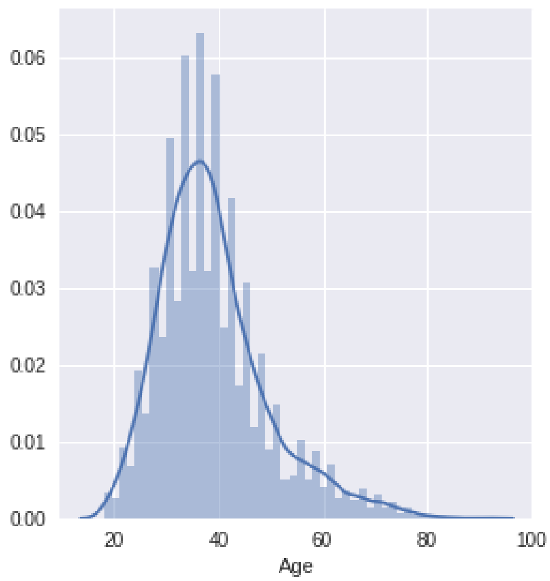


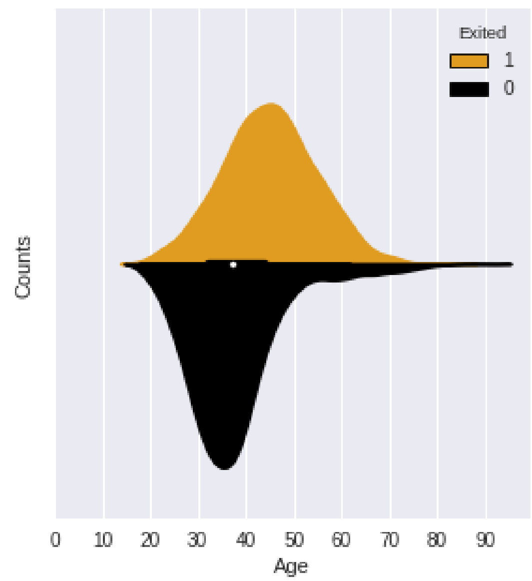



```
In [16]: dataset['CategoricalCreditScore'] = pd.qcut(dataset['CreditScore'], 3)
         print (dataset[['CategoricalCreditScore', 'Exited']].groupby(['CategoricalCreditScore
```

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

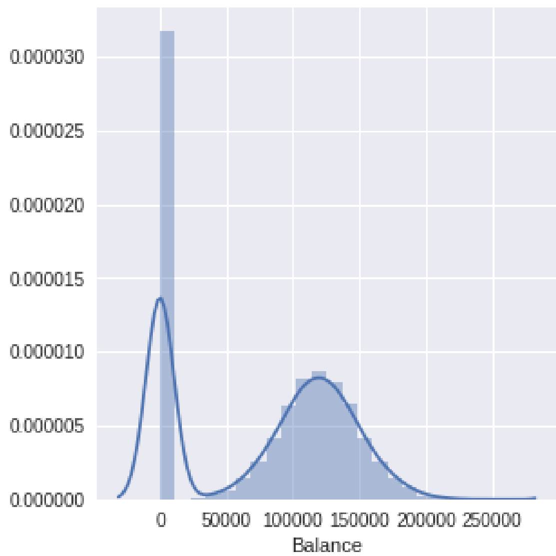
```
In [17]: ContPlot(dataset[['Age','Exited']].copy().dropna(axis=0),
                   'Age', 'Exited', {0: "black", 1: "orange"} , [1, 0], range(0,100,10))

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

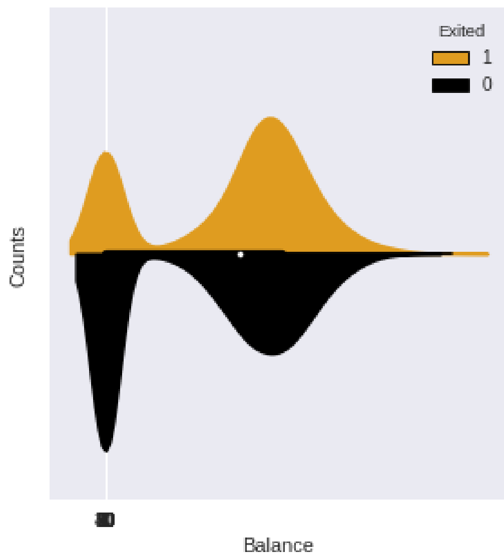





```
   CategoricalAge    Exited
0  (17.999, 31.0]  0.076307
1    (31.0, 35.0]  0.093206
2    (35.0, 40.0]  0.149603
3    (40.0, 46.0]  0.285967
4    (46.0, 92.0]  0.459416
```

```
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
```

4 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]:
```
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]:
```
# 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)
```

4.1 Classification by trainditional models

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

In [23]:
```
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
```

5 Approach 1 (Feature Selection)

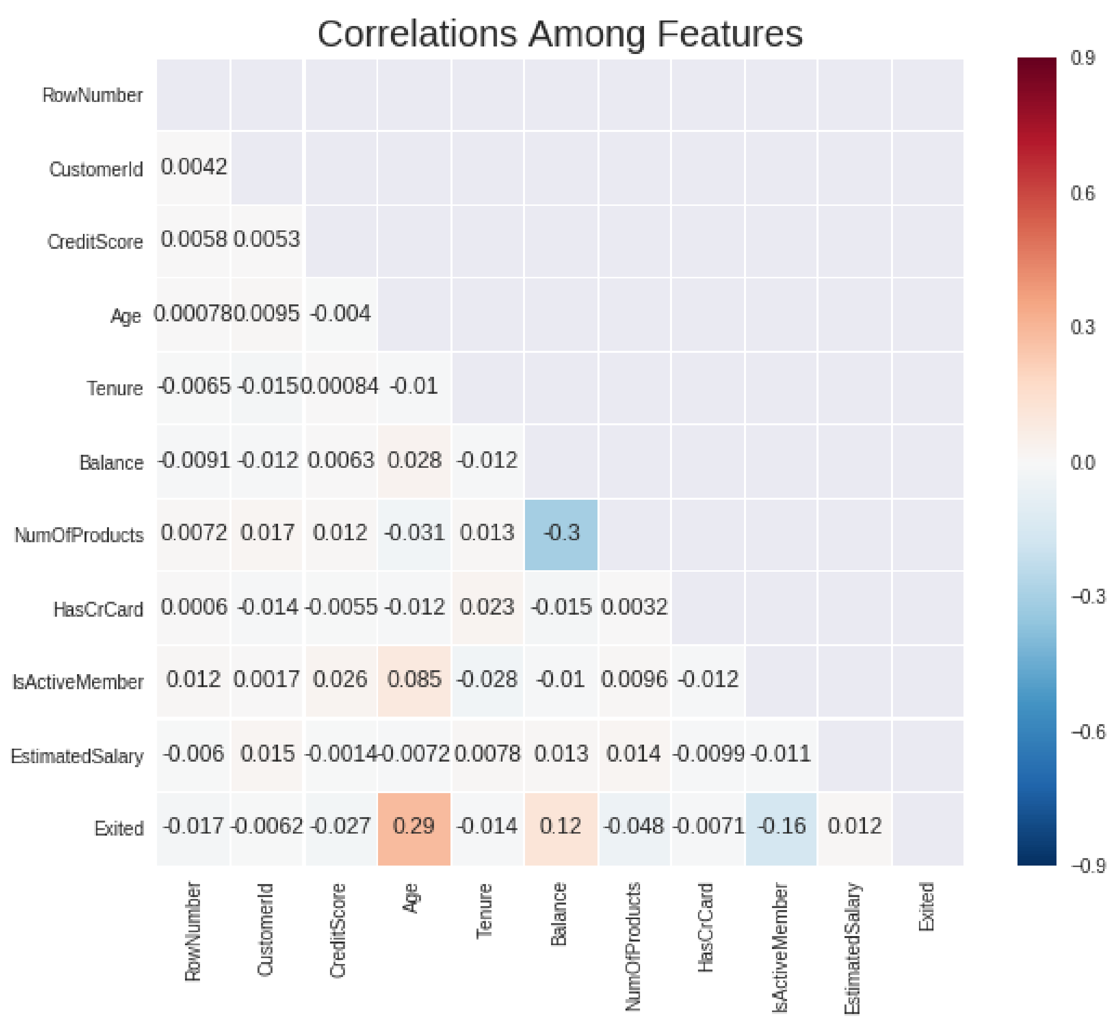
6 Correlation

In [24]:
```
## 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
```

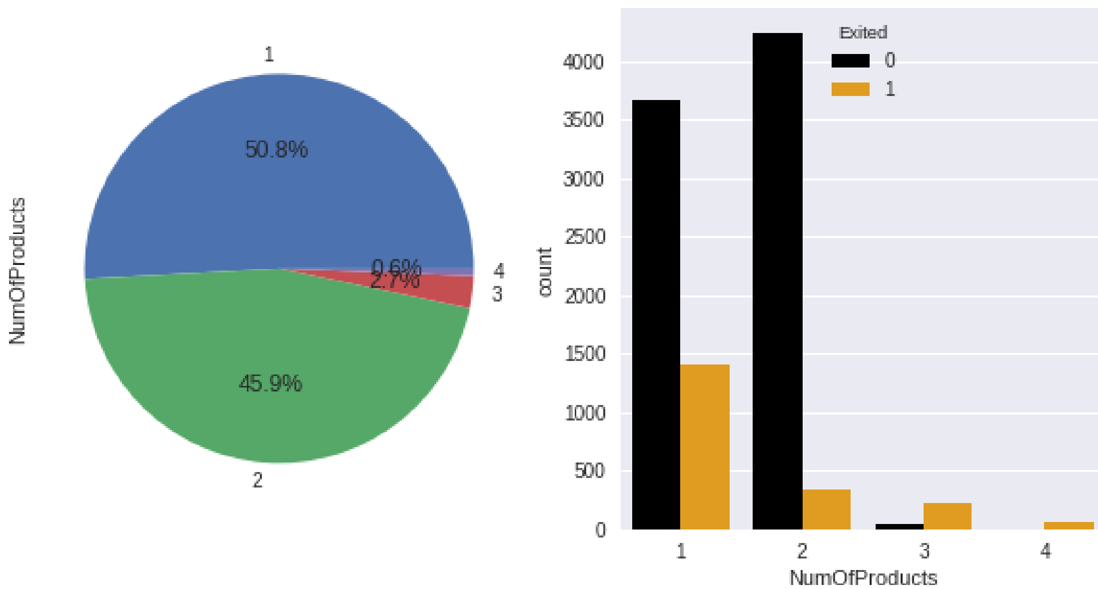
```
CreditScore        0.000734
RowNumber          0.000275
Tenure             0.000196
EstimatedSalary    0.000146
HasCrCard          0.000051
CustomerId         0.000039
Name: Exited, dtype: float64
```

In [25]:
```
# 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);
```



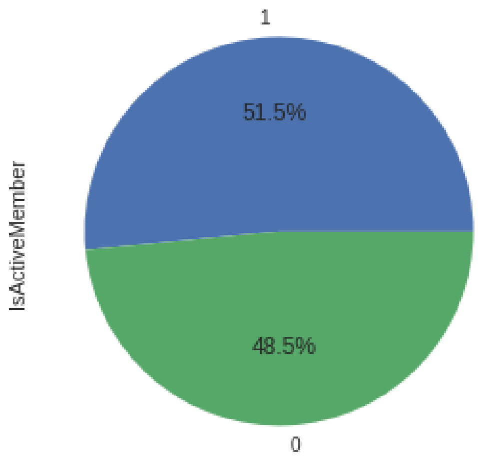
```
In [26]: print(dataset[['NumOfProducts', 'Exited']].groupby(['NumOfProducts'], as_index=False)
         CatPlot(dataset, 'NumOfProducts','Exited', {0: "black", 1: "orange"} )
```

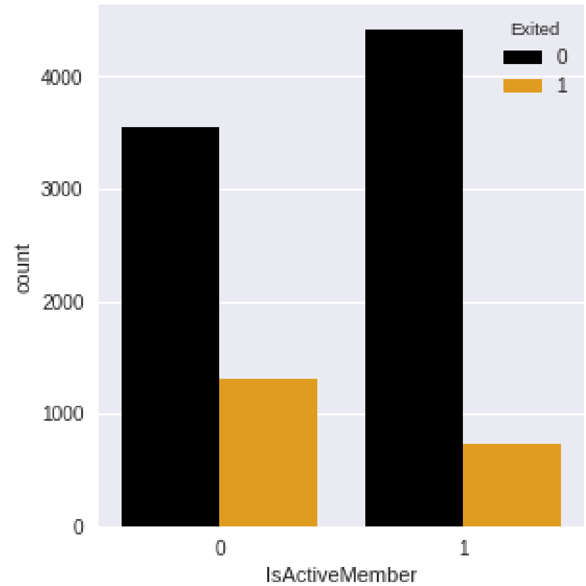
```
   NumOfProducts    Exited
3              4  1.000000
2              3  0.827068
0              1  0.277144
1              2  0.075817
```




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

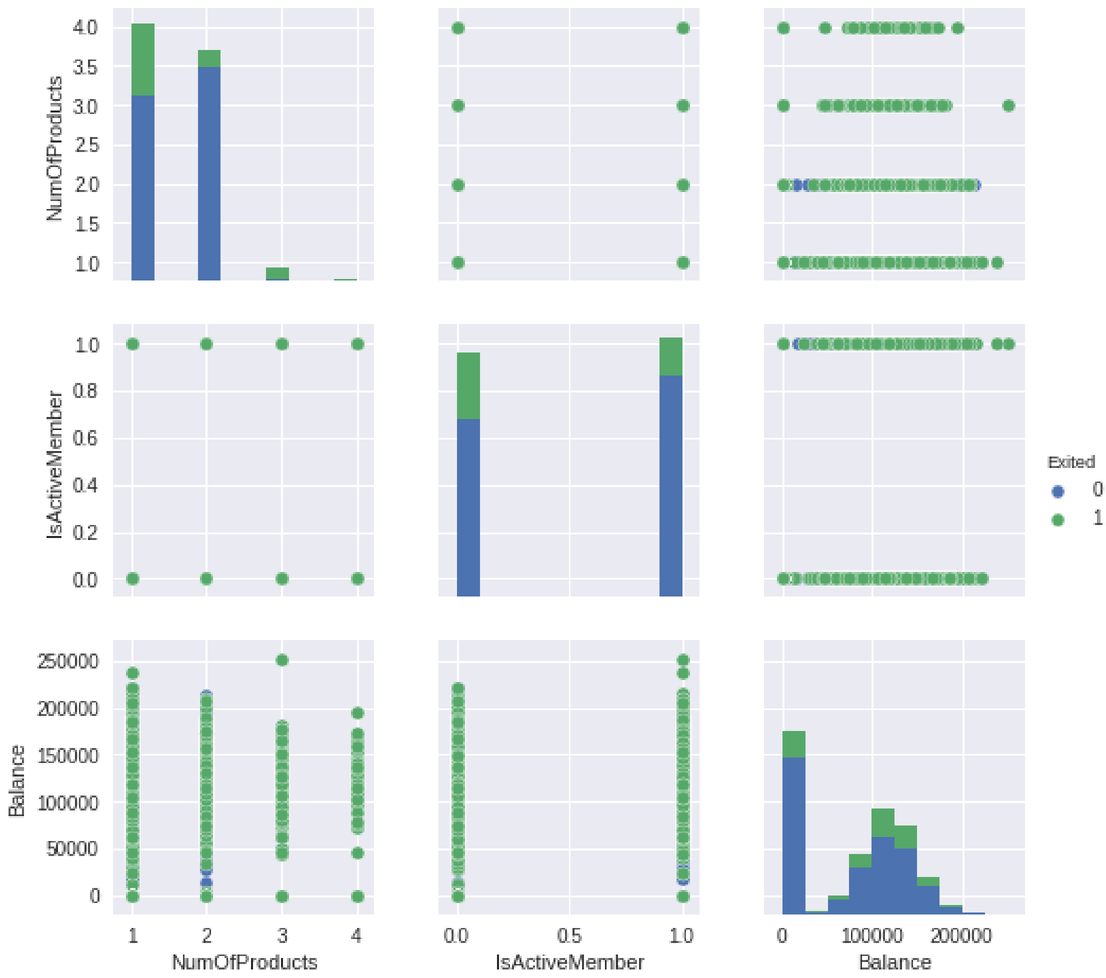
```
   IsActiveMember    Exited
0               0  0.268509
1               1  0.142691
```



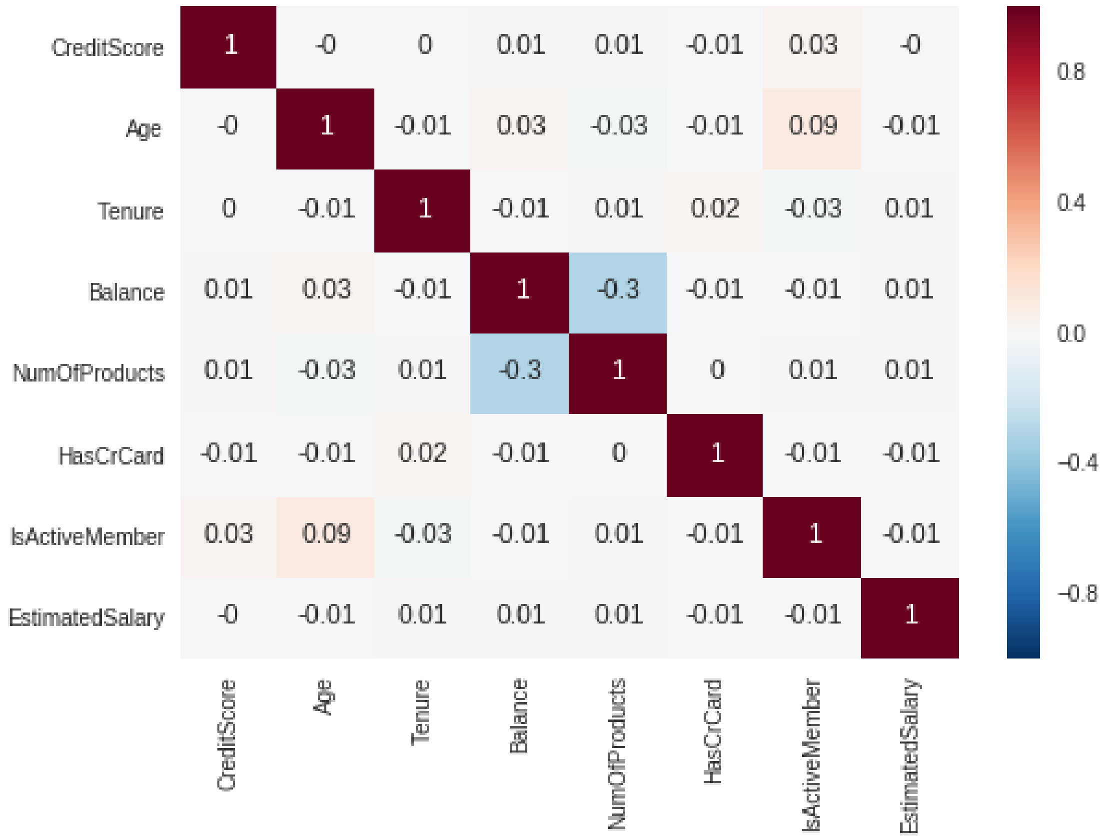



```
In [28]: # https://seaborn.pydata.org/generated/seaborn.pairplot.html
         sns.pairplot(dataset, vars=["NumOfProducts", "IsActiveMember", "Balance"], hue="Exited
```

```
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_feselec
```

```
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)
```

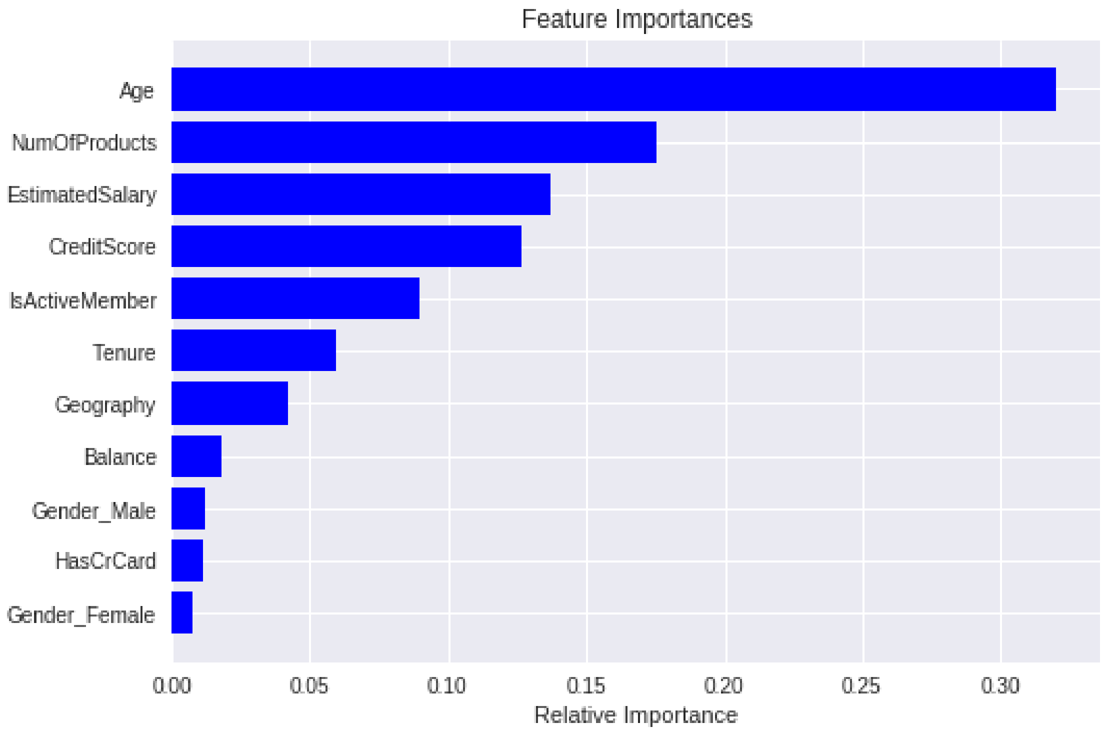
```
Naive Bayes accuracy: 0.770
Logistic Regression accuracy: 0.785
Random Forest accuracy: 0.840000
Linear SVM accuracy: 0.798250
RBF SVM accuracy: 0.798250
K Nearest Neighbor accuracy: 0.736250
ANN accuracy: 0.797500
```

6.1 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_fese]
```

```
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
```

7 Approach 2 (Feature Reduction)

In [41]:
```
# 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
```

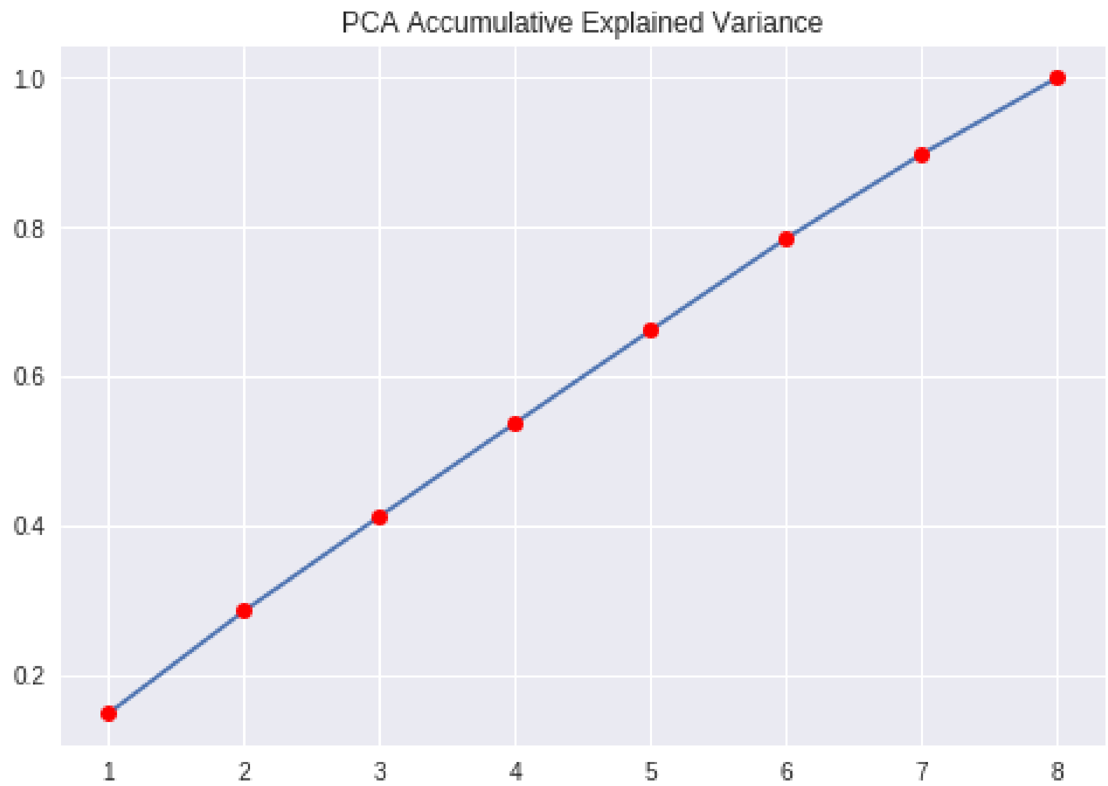
```
Train rows and columns :  (6000, 8)
Test rows and columns :  (4000, 8)
```

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, PCAt
         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
```

8 *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, 22
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, tar
         PrintTrainTestInformation(data_train_encoder_mining, target_train_encoder_mining, dat
```

```
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
```

9 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
```

10 *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
```

```python
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]
```

11 Summaries

Using Bagging on RandomForest can make up to 87.4%