Importing libraries and modules

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, ExtraTreesClassifier, S
from sklearn.neighbors import KNeighborsClassifier
import xgboost as xgb
from sklearn.preprocessing import PolynomialFeatures, LabelEncoder, FunctionTransformer,OneHotEn
from imblearn.over_sampling import  SMOTENC
from imblearn.pipeline import Pipeline
from sklearn.decomposition import PCA
from sklearn.compose import ColumnTransformer
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, roc_curve, a
from sklearnex import patch_sklearn
patch_sklearn()
import warnings
warnings.filterwarnings('ignore')
```

```
Intel(R) Extension for Scikit-learn* enabled (https://github.com/intel/scikit-learn-intelex)
```

We want to unite our colors for plots so we'll use seaborns palette for this

In [2]:
```
# define sns palette
sns.set_palette('cubehelix')
sns.color_palette('cubehelix')
```

Out[2]:

Data Loading, Preprocessing and EDA

First we'll need to load our training data and test data(Saved for later)

In [3]:
```
df_train = pd.read_csv('train.csv')
df_test = pd.read_csv('test.csv')
```

Let's Check our training dataframe

In [4]:
```
df_train
```

Out[4]:

	id	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfP
0	0	15674932	Okwudilichukwu	668	France	Male	33.0	3	0.00	
1	1	15749177	Okwudiliolisa	627	France	Male	33.0	1	0.00	
2	2	15694510	Hsueh	678	France	Male	40.0	10	0.00	
3	3	15741417	Kao	581	France	Male	34.0	2	148882.54	
4	4	15766172	Chiemenam	716	Spain	Male	33.0	5	0.00	
...	...	...	...	...	...	...	...	...	...	
165029	165029	15667085	Meng	667	Spain	Female	33.0	2	0.00	
165030	165030	15665521	Okechukwu	792	France	Male	35.0	3	0.00	
165031	165031	15664752	Hsia	565	France	Male	31.0	5	0.00	
165032	165032	15689614	Hsiung	554	Spain	Female	30.0	7	161533.00	
165033	165033	15732798	Ulyanov	850	France	Male	31.0	1	0.00	

165034 rows × 14 columns

We check for information about our data

In [5]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 165034 entries, 0 to 165033
Data columns (total 14 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   id               165034 non-null  int64
 1   CustomerId       165034 non-null  int64
 2   Surname          165034 non-null  object
 3   CreditScore      165034 non-null  int64
 4   Geography        165034 non-null  object
 5   Gender           165034 non-null  object
 6   Age              165034 non-null  float64
 7   Tenure           165034 non-null  int64
 8   Balance          165034 non-null  float64
 9   NumOfProducts    165034 non-null  int64
 10  HasCrCard        165034 non-null  float64
 11  IsActiveMember   165034 non-null  float64
 12  EstimatedSalary  165034 non-null  float64
 13  Exited           165034 non-null  int64
dtypes: float64(5), int64(6), object(3)
memory usage: 17.6+ MB
```

We found out that there are object type columns, so we'll need to save them in a list, so we can label encode them, we'll also make a list of numerical columns.

In [6]:
```
categorical_cols = df_train.select_dtypes(include=['object']).columns
numerical_cols = df_train.select_dtypes(exclude=['object']).columns
```

Using Label encoder we label encode our categorical columns in the whole dataset, I use this step just to measure the importance of each features and their distribution, however I'm willing to use one hot encoding to encode the categorical columns and train the model on it later on.

In [7]:
```
# merge train and test
df = pd.concat([df_train, df_test])
# Label encoding the categorical variables
df_encoded = df.copy()
le = LabelEncoder()
for col in categorical_cols:
    df_encoded[col] = le.fit_transform(df[col])
```

Retake the train and test data after encoding

In [8]:
```
df_train_encoded = df_encoded[:len(df_train)]
df_train_encoded
```

Out[8]:

	id	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProduct
0	0	15674932	1992	668	0	1	33.0	3	0.00	
1	1	15749177	1993	627	0	1	33.0	1	0.00	
2	2	15694510	1217	678	0	1	40.0	10	0.00	
3	3	15741417	1341	581	0	1	34.0	2	148882.54	
4	4	15766172	483	716	2	1	33.0	5	0.00	
...	...	...	...	...	...	...	...	...	...	
165029	165029	15667085	1758	667	2	0	33.0	2	0.00	
165030	165030	15665521	1986	792	0	1	35.0	3	0.00	
165031	165031	15664752	1211	565	0	1	31.0	5	0.00	
165032	165032	15689614	1215	554	2	0	30.0	7	161533.00	
165033	165033	15732798	2648	850	0	1	31.0	1	0.00	

165034 rows × 14 columns

Great! Now we can check our data again and describe it in order to get an overview of things like min, max, mean, std,.. etc

In [9]:
```
df_train_encoded.describe()
```

Out[9]:

	id	CustomerId	Surname	CreditScore	Geography	Gender	Age	
count	165034.0000	1.650340e+05	165034.000000	165034.000000	165034.000000	165034.000000	165034.000000	16
mean	82516.5000	1.569201e+07	1599.500188	656.454373	0.648545	0.564429	38.125888	
std	47641.3565	7.139782e+04	798.932859	80.103340	0.816574	0.495833	8.867205	
min	0.0000	1.556570e+07	0.000000	350.000000	0.000000	0.000000	18.000000	
25%	41258.2500	1.563314e+07	958.000000	597.000000	0.000000	0.000000	32.000000	
50%	82516.5000	1.569017e+07	1642.000000	659.000000	0.000000	1.000000	37.000000	
75%	123774.7500	1.575682e+07	2260.000000	710.000000	1.000000	1.000000	42.000000	
max	165033.0000	1.581569e+07	2888.000000	850.000000	2.000000	1.000000	92.000000	

Check for null values

In [10]:
```python
df_train_encoded.isnull().sum()
```

Out[10]:
```
id                 0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

All set! Now let's do some feature selection, we'll get the correlation of the features and show them in descending order, then we'll plot them using heatmap, doing this will help us to see which features are important for our model, and we which can we ignore.

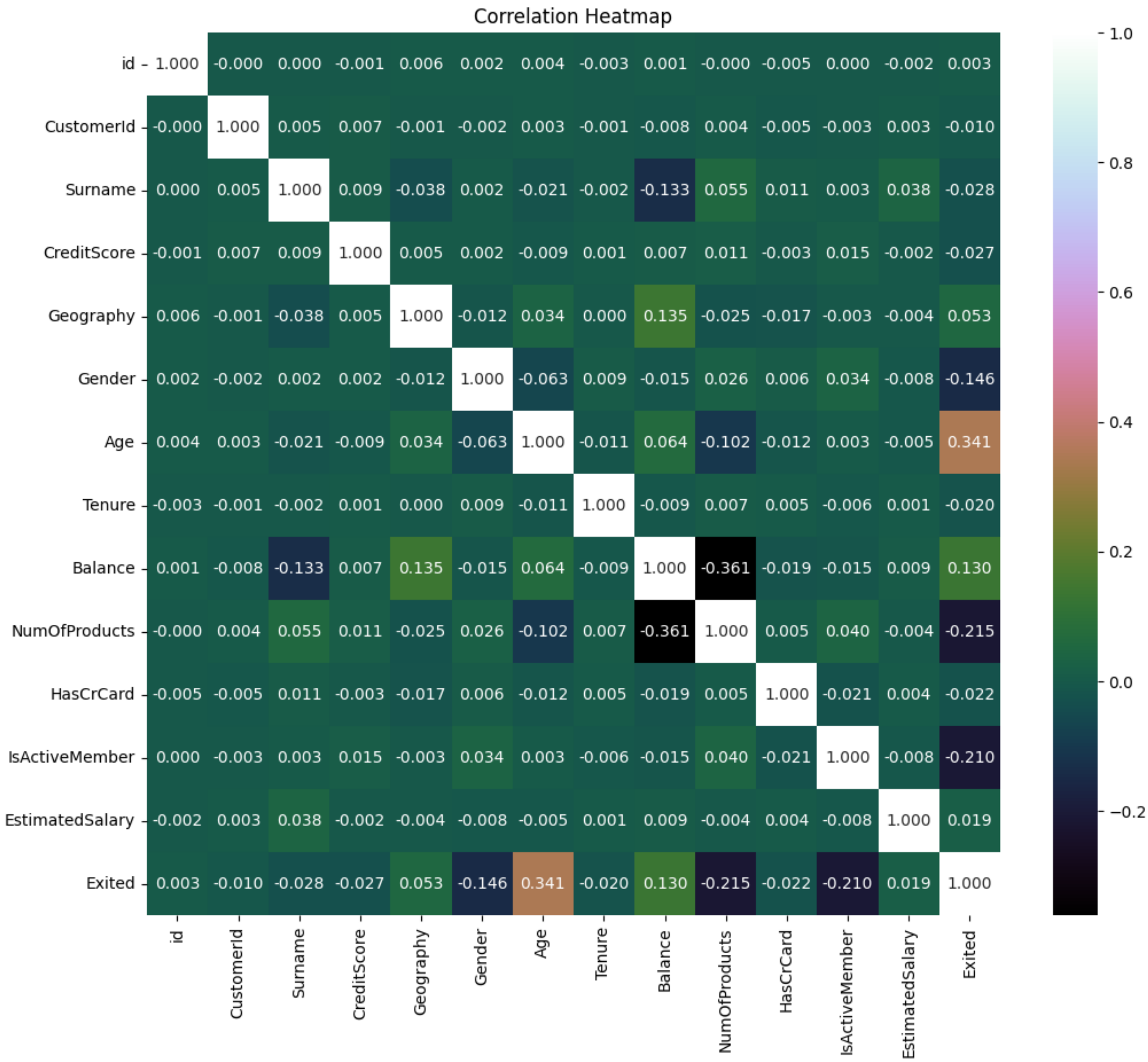
In [11]:
```python
corr = df_train_encoded.corr()
corr_descending = corr.sort_values(by='Exited', ascending=False)
corr_descending
```

Out[11]:

	id	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Bal
Exited	0.002512	-0.009947	-0.028248	-0.027383	0.053343	-0.146442	0.340768	-0.019565	0.12
Age	0.004039	0.002696	-0.020655	-0.008918	0.034110	-0.063139	1.000000	-0.010830	0.06
Balance	0.000606	-0.008348	-0.132849	0.006973	0.134642	-0.014699	0.064318	-0.009481	1.00
Geography	0.005552	-0.001249	-0.037736	0.005379	1.000000	-0.012092	0.034110	0.000276	0.13
EstimatedSalary	-0.001552	0.002891	0.037849	-0.001820	-0.004102	-0.007778	-0.005399	0.000971	0.00
id	1.000000	-0.000387	0.000349	-0.001201	0.005552	0.001929	0.004039	-0.002560	0.00
CustomerId	-0.000387	1.000000	0.005212	0.007364	-0.001249	-0.001944	0.002696	-0.001252	-0.00
Tenure	-0.002560	-0.001252	-0.002198	0.000942	0.000276	0.008767	-0.010830	1.000000	-0.00
HasCrCard	-0.004706	-0.005469	0.011043	-0.002828	-0.016715	0.006418	-0.012111	0.005327	-0.01
CreditScore	-0.001201	0.007364	0.008623	1.000000	0.005379	0.002310	-0.008918	0.000942	0.00
Surname	0.000349	0.005212	1.000000	0.008623	-0.037736	0.002098	-0.020655	-0.002198	-0.13
Gender	0.001929	-0.001944	0.002098	0.002310	-0.012092	1.000000	-0.063139	0.008767	-0.01
IsActiveMember	0.000418	-0.002934	0.003211	0.014790	-0.003493	0.033722	0.003320	-0.005532	-0.01
NumOfProducts	-0.000094	0.004380	0.054831	0.011361	-0.025123	0.026098	-0.102195	0.007335	-0.36

Heatmap helps us to see which features are important for our model with the help of correlation and color.

In [12]:
```python
plt.figure(figsize=(12, 10))
sns.heatmap(corr,annot=True, fmt='.3f', cmap='cubehelix')
plt.title('Correlation Heatmap')
plt.show()
```



I'm willing to ignore features with correlation between -0.01 and 0.01

In [13]:
```
selected_features = corr['Exited'][(corr['Exited'] > 0.01) | (corr['Exited'] < -0.01)].index
df_train_filtered = df_train_encoded[selected_features]
```

Now let's check the features we selected

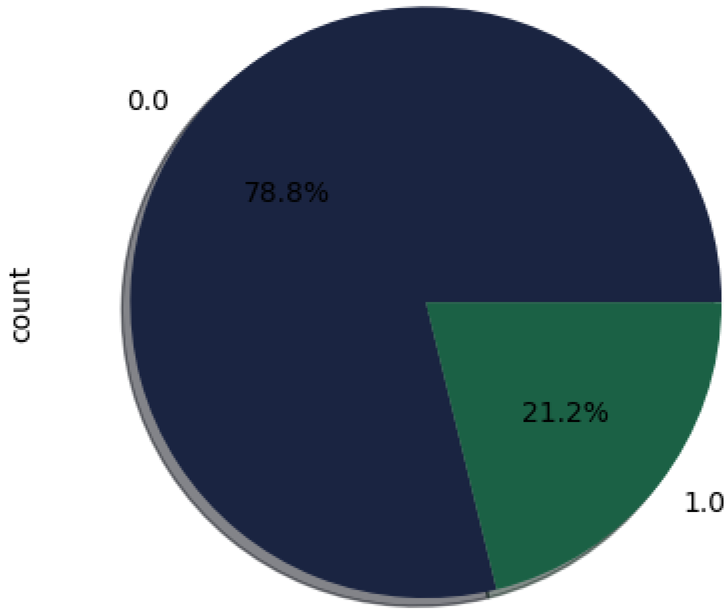
In [14]:
```
df_train_filtered.columns
```

Out[14]:
```
Index(['Surname', 'CreditScore', 'Geography', 'Gender', 'Age', 'Tenure',
       'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember',
       'EstimatedSalary', 'Exited'],
      dtype='object')
```

Looks great, let's see the balance of our target variable

In [15]:
```
# plot pie chart for exited
df_train_filtered['Exited'].value_counts().plot.pie(autopct='%1.1f%%', shadow=True)
```

Out[15]: <AxesSubplot: ylabel='count'>

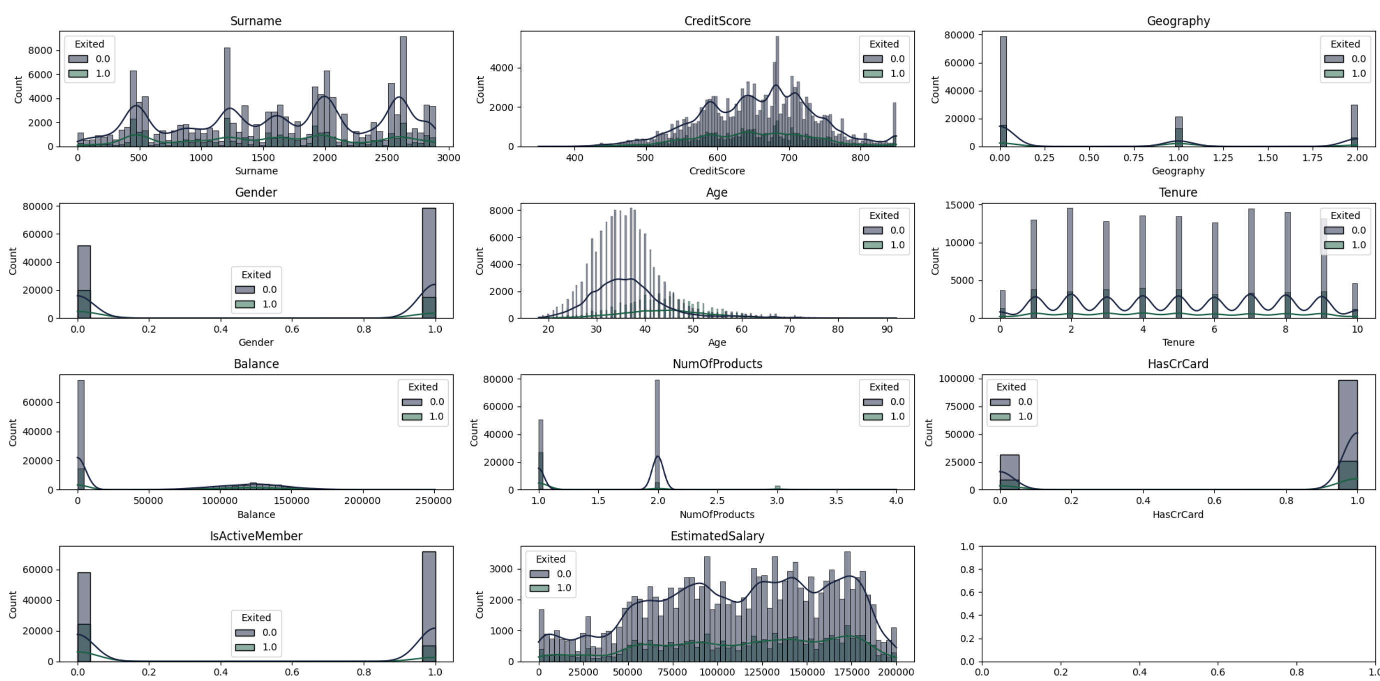


Wow, so unbalanced! we'll deal with that later, Let's check the distribution of our features

In [16]:
```
fig, ax = plt.subplots(nrows=(len(df_train_filtered.columns) - 1) // 3 + 1, ncols=3, figsize=(20,

for i, col in enumerate(df_train_filtered.columns):
    if col != 'Exited':
        sns.histplot(x=col, hue='Exited', data=df_train_filtered, ax=ax[i // 3, i % 3], kde=True)
        ax[i // 3, i % 3].set_title(col)

plt.tight_layout()
plt.show()
```

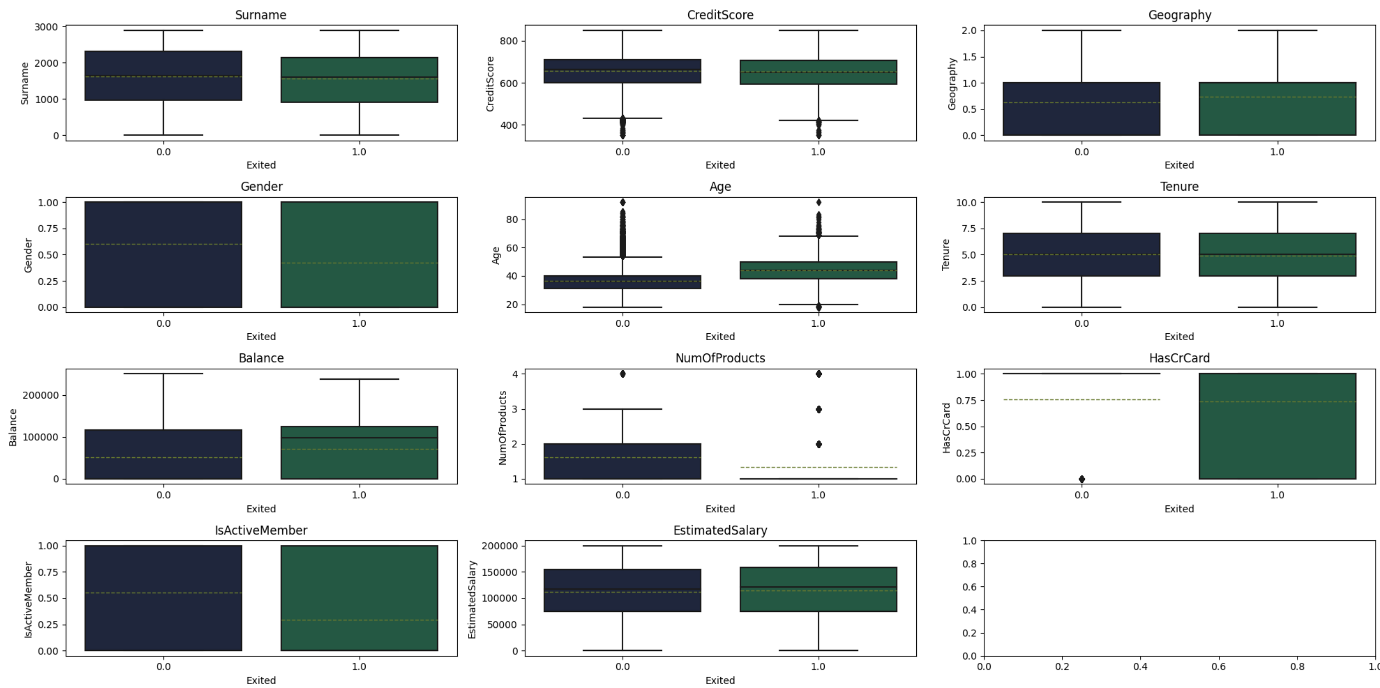


Now for the boxplots we can see the distribution of our features and grasp the outliers along with the 25% and 75% percentiles

In [17]:
```python
fig , ax = plt.subplots(nrows=(len(df_train_filtered.columns) - 1) // 3 + 1, ncols=3, figsize=(2

for i, col in enumerate(df_train_filtered.columns):
    if col != 'Exited':
        sns.boxplot(x='Exited', y=col, data=df_train_filtered, ax=ax[i // 3, i % 3], showmeans=T
        ax[i // 3, i % 3].set_title(col)

plt.tight_layout()
plt.show()
```



Time to specify our X(Features) and y(Target), we'll need to redefine our numerical and categorical columns as well after the feature selection, we'll read our data from the original dataframe

In [18]:
```python
X = df_train[selected_features].drop('Exited', axis=1)
y = df_train['Exited']
numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns
categorical_cols = X.select_dtypes(include=['object']).columns
```

Using SMOTENC To deal with the class imbalance, SMOTENC helps deal with categorical columns as well, unlike SMOTE.

In [19]:
```python
cat_indices = [X.columns.get_loc(col) for col in categorical_cols]
smote = SMOTENC(sampling_strategy='auto', random_state=42, categorical_features=cat_indices)
X, y = smote.fit_resample(X, y)
```

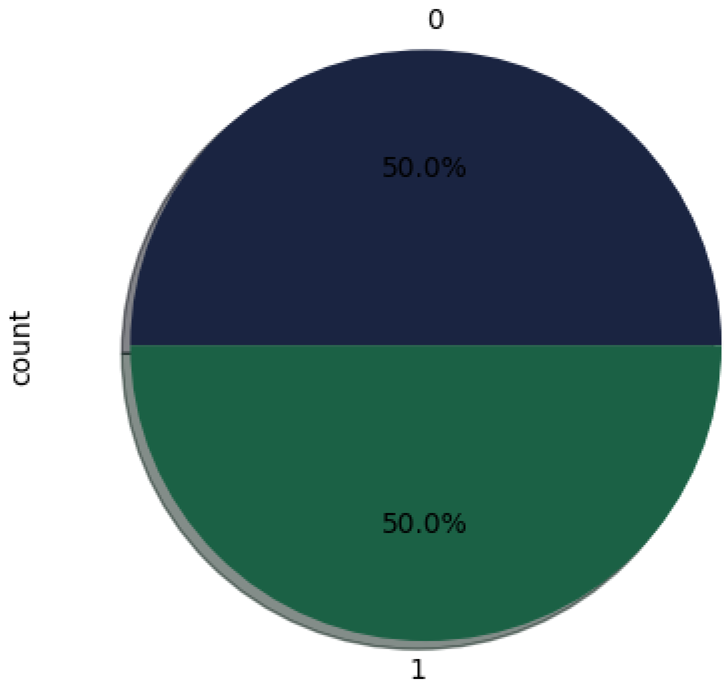
In [20]:
```python
print('Shape of X',X.shape)
print('Shape of y',y.shape)
```

```
Shape of X (260226, 11)
Shape of y (260226,)
```

Let's check the balance of our target again

In [21]:
```python
# plot pie chart for exited
y.value_counts().plot.pie(autopct='%1.1f%%', shadow=True)
```

Out[21]:
```
<AxesSubplot: ylabel='count'>
```



Perfectly balanced, As all things should be.

Time for the train test split

In [22]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,stratify=y, random_state
```

Model

Now we get to the model part, I'll make a pipeline doing some feature engineering and then use it to train the model

The pipeline Consists of:

1. A Preprocessor that encodes the categorical features using "OneHotEncoder", transforms the features using "Log1p" for skewed features, scales the features using "RobustScaler" for outliers, then applies PolynomialFeatures to the features to capture non-linear relationships between the features 2nd degree, and finally applies PCA to the features which will reduce the dimensionality of the data to 3 components, all helps to get better results.

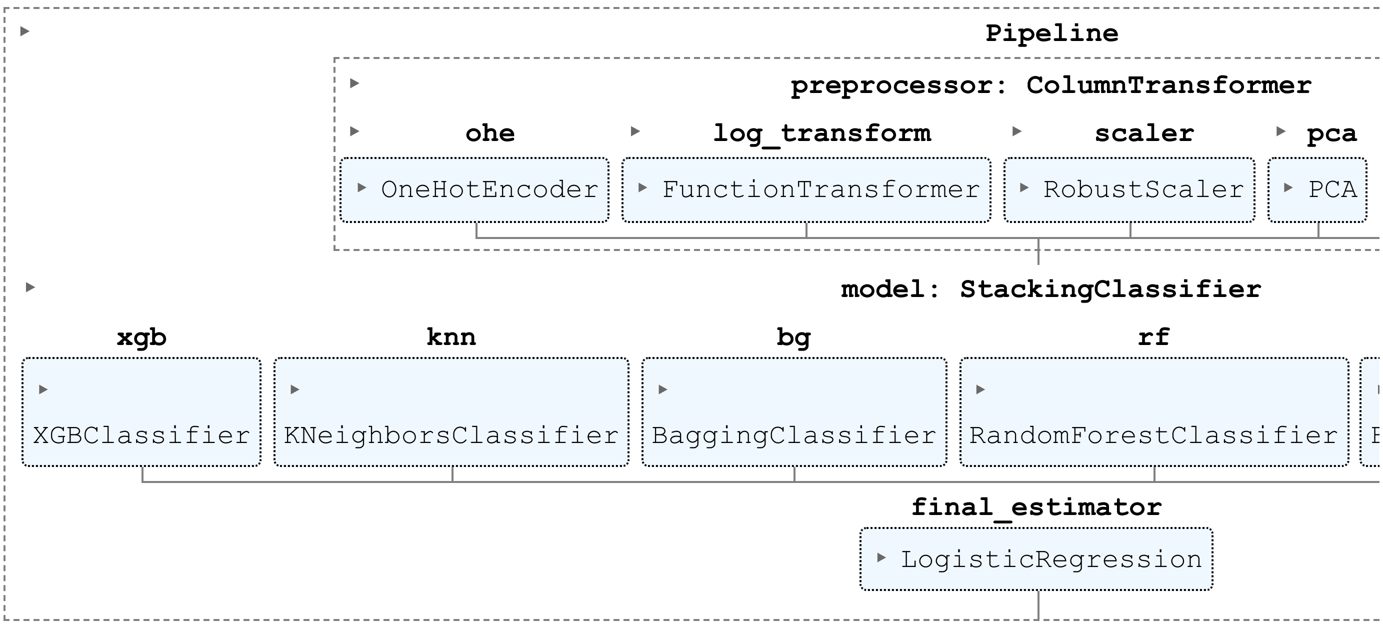
2. An ensemble of models using StackingClassifier which stacks the models in the order of XGB Classifier,KNN,Bagging Classifier, Random Forest Classifier, Extra Trees Classifier, Ada Boost Classifier, and all combining their predictions to get better results, with a final estimator of Logistic Regression.

In [25]:
```
# objects and assignments
ohe = OneHotEncoder(drop='first', handle_unknown='ignore')
scaler = RobustScaler()
rf = RandomForestClassifier(random_state=42)
knn = KNeighborsClassifier()
ada = AdaBoostClassifier (random_state=42)
ext = ExtraTreesClassifier(random_state=42)
xgbC = xgb.XGBClassifier(random_state=42)
bg = BaggingClassifier(random_state=42)
# The preprocessor
preprocessor = ColumnTransformer(
    transformers=[
        ('ohe', ohe, categorical_cols),
```

```
        ('log_transform', FunctionTransformer(np.log1p), numerical_cols),
        ('scaler', scaler, numerical_cols),
        ('pca', PCA(n_components=3), numerical_cols),
        ('poly', PolynomialFeatures(degree=2), numerical_cols),
    ]
)
# The ensemble model
ensemble = StackingClassifier(
    estimators=[
        ('xgb', xgbC),('knn', knn),('bg',bg),('rf',rf),('ext',ext),('ada',ada)
    ],
)
# The pipeline
model_pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('model', ensemble),
])
```

In [26]:
```
model_pipeline.fit(X_train, y_train)
```

Out[26]:



Let's predict our test data

In [27]:
```
y_pred = model_pipeline.predict(X_test)
```

Let's evaluate our model

In [28]:
```
# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
# Confusion matrix
confusion_matrix(y_test, y_pred)
# Classification report
print(classification_report(y_test, y_pred))
```

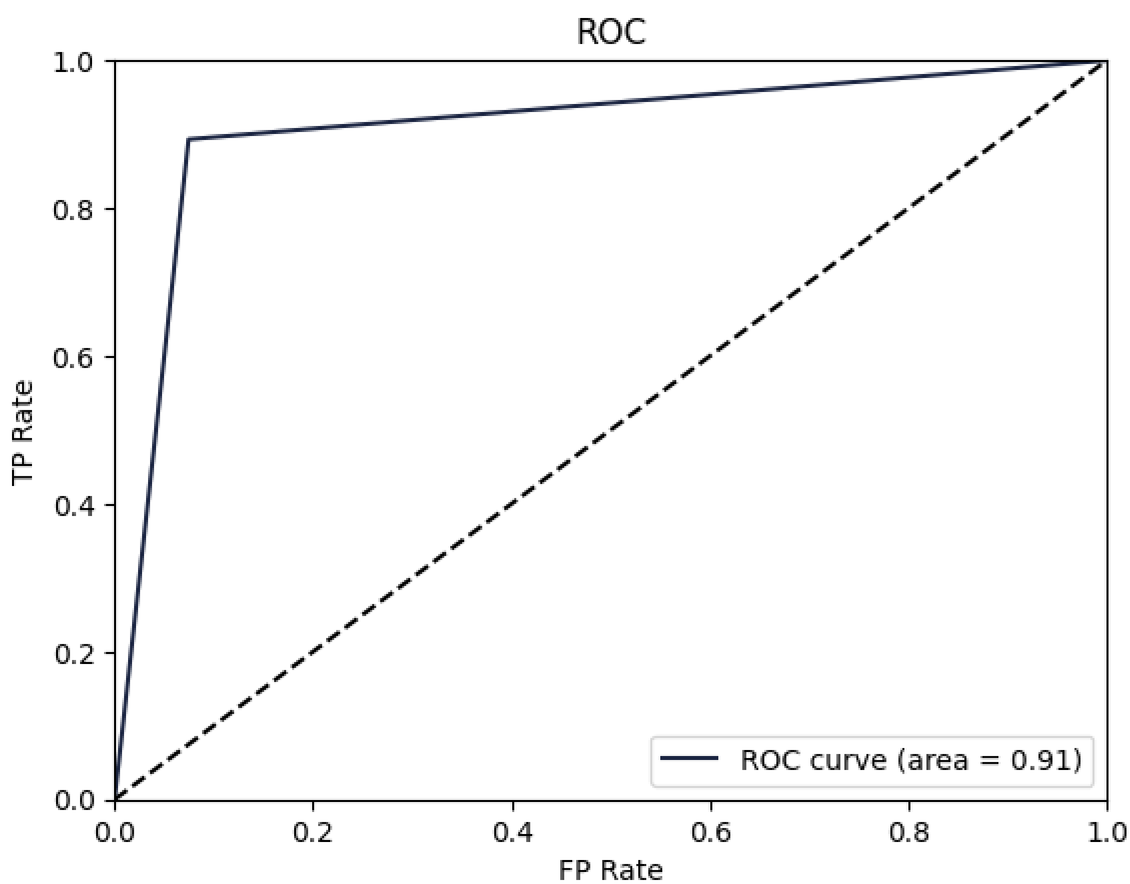
```
Accuracy: 0.9092149252584253
              precision    recall  f1-score   support

           0       0.90      0.93      0.91     26023
           1       0.92      0.89      0.91     26023

    accuracy                           0.91     52046
   macro avg       0.91      0.91      0.91     52046
weighted avg       0.91      0.91      0.91     52046
```

The score is quite good ! Let's plot the roc curve

In [29]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(fpr, tpr)
plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('FP Rate') # False Positive
plt.ylabel('TP Rate') # True Positive
plt.title('ROC')
plt.legend(loc="lower right")
plt.show()
```



Submission

Now let's use our model to submit the test data provided for the competition

In [30]:
```
X_sub = df_test
X_sub
```

Out[30]:

	id	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProduc
0	165034	15773898	Lucchese	586	France	Female	23.0	2	0.00	
1	165035	15782418	Nott	683	France	Female	46.0	2	0.00	
2	165036	15807120	K?	656	France	Female	34.0	7	0.00	
3	165037	15808905	O'Donnell	681	France	Male	36.0	8	0.00	
4	165038	15607314	Higgins	752	Germany	Male	38.0	10	121263.62	
...	...	...	...	...	...	...	...	...	...	
110018	275052	15662091	P'eng	570	Spain	Male	29.0	7	116099.82	
110019	275053	15774133	Cox	575	France	Female	36.0	4	178032.53	
110020	275054	15728456	Ch'iu	712	France	Male	31.0	2	0.00	
110021	275055	15687541	Yegorova	709	France	Female	32.0	3	0.00	
110022	275056	15663942	Tuan	621	France	Female	37.0	7	87848.39	

110023 rows × 13 columns

Let's select the same features as our train data

In [31]:
```
X_sub = X_sub[X_train.columns]
X_sub
```

Out[31]:

	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiv
0	Lucchese	586	France	Female	23.0	2	0.00	2	0.0	
1	Nott	683	France	Female	46.0	2	0.00	1	1.0	
2	K?	656	France	Female	34.0	7	0.00	2	1.0	
3	O'Donnell	681	France	Male	36.0	8	0.00	1	1.0	
4	Higgins	752	Germany	Male	38.0	10	121263.62	1	1.0	
...	...	...	...	...	...	...	...	...	...	
110018	P'eng	570	Spain	Male	29.0	7	116099.82	1	1.0	
110019	Cox	575	France	Female	36.0	4	178032.53	1	1.0	
110020	Ch'iu	712	France	Male	31.0	2	0.00	2	1.0	
110021	Yegorova	709	France	Female	32.0	3	0.00	1	1.0	
110022	Tuan	621	France	Female	37.0	7	87848.39	1	1.0	

110023 rows × 11 columns

Let's predict the provided test data probabilities

In [32]:
```
probabilities = model_pipeline.predict_proba(X_sub)
probabilities
```

Out[32]:
```
array([[0.98186745, 0.01813255],
       [0.13438906, 0.86561094],
       [0.96935999, 0.03064001],
       ...,
       [0.98882149, 0.01117851],
       [0.9631191 , 0.0368809 ],
       [0.91079268, 0.08920732]])
```

All we need to do now is read the submission dataframe and assign the probabilities to the 'Exited' column of the submission dataframe

In [33]:
```python
sub = pd.read_csv('sample_submission.csv')
sub['Exited'] = probabilities[:, 1]
sub
```

Out[33]:

	id	Exited
0	165034	0.018133
1	165035	0.865611
2	165036	0.030640
3	165037	0.187146
4	165038	0.459301
...	...	...
110018	275052	0.048794
110019	275053	0.127923
110020	275054	0.011179
110021	275055	0.036881
110022	275056	0.089207

110023 rows × 2 columns

Save the submission dataframe to csv file

In [34]:
```python
sub.to_csv('submission.csv', index=False)
```

That's it ! Thank you for reading. If you find this notebook useful, please consider UPVoting it.