Forecast of the loss of clients in the Bank

Content

Project Description

Company "Beta bank" has faced the loss of the clients. The clients are started to terminate the contracts with the bank every month. The quantity of clients who terminated the contact with the bank is not sufficient compare to the total quantity of clients. Marketing department of bank calculated that keep the currents clients is cheaper than to pull the new one to come.

It's required to make a prediction of the loss of clients in nearest time. The historical data provided and has the information on clients behavior and contract termination with bank.

It's required to train the model and get the **"F1** score as high as possible. The value of **F1** equal to 0.59 or higher should be achieved.

Additionally it's required to check *AUC-ROC* scores of models and compare it.

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

Data preparation

Libraries import

In [1]:
```
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import r2_score
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import accuracy_score
from sklearn.utils import shuffle

from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV
import numpy as np
```

In [2]:
```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter(action='ignore', category=DeprecationWarning)
warnings.simplefilter(action='ignore', category=RuntimeWarning)
```

Data loading and overview

In [3]:
```
data = pd.read_csv('Churn.csv')
data.head(15)
```

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estima
0	1	15634602	Hargrave	619	France	Female	42	2.0	0.00	1	1	1	
1	2	15647311	Hill	608	Spain	Female	41	1.0	83807.86	1	0	1	
2	3	15619304	Onio	502	France	Female	42	8.0	159660.80	3	1	0	
3	4	15701354	Boni	699	France	Female	39	1.0	0.00	2	0	0	
4	5	15737888	Mitchell	850	Spain	Female	43	2.0	125510.82	1	1	1	
5	6	15574012	Chu	645	Spain	Male	44	8.0	113755.78	2	1	0	
6	7	15592531	Bartlett	822	France	Male	50	7.0	0.00	2	1	1	
7	8	15656148	Obinna	376	Germany	Female	29	4.0	115046.74	4	1	0	
8	9	15792365	He	501	France	Male	44	4.0	142051.07	2	0	1	
9	10	15592389	H?	684	France	Male	27	2.0	134603.88	1	1	1	
10	11	15767821	Bearce	528	France	Male	31	6.0	102016.72	2	0	0	
11	12	15737173	Andrews	497	Spain	Male	24	3.0	0.00	2	1	0	
12	13	15632264	Kay	476	France	Female	34	10.0	0.00	2	1	0	
13	14	15691483	Chin	549	France	Female	25	5.0	0.00	2	0	0	
14	15	15600882	Scott	635	Spain	Female	35	7.0	0.00	2	1	1	

In [4]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           9091 non-null   float64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(3), int64(8), object(3)
memory usage: 1.1+ MB
```

In [5]:

```
data.sort_values(by='Tenure')
```

Out[5]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember
6546	6547	15633840	Henderson	781	France	Male	20	0.0	125023.10	2	1	1
2622	2623	15787026	Onwuatuegwu	627	Germany	Male	27	0.0	185267.45	2	1	1
886	887	15591711	Sleeman	739	Spain	Male	38	0.0	128366.44	1	1	0
4532	4533	15739194	Manfrin	548	Spain	Male	38	0.0	178056.54	2	1	0
8213	8214	15748352	Endrizzi	598	Spain	Male	34	0.0	104488.17	1	0	1
...	...	...	...	...	...	...	...	...	...	...	...	...
9944	9945	15703923	Cameron	744	Germany	Male	41	NaN	190409.34	2	1	1
9956	9957	15707861	Nucci	520	France	Female	46	NaN	85216.61	1	1	0
9964	9965	15642785	Douglas	479	France	Male	34	NaN	117593.48	2	0	0
9985	9986	15586914	Nepean	659	France	Male	36	NaN	123841.49	2	1	0
9999	10000	15628319	Walker	792	France	Female	28	NaN	130142.79	1	1	0

10000 rows × 14 columns

In [6]:

```
data.query('Tenure == "NaN"')['RowNumber'].count()
```

Out[6]:

```
0
```

In [7]:

```
data['Tenure'] = data['Tenure'].fillna(0)
data.sort_values(by='Tenure')
```

Out[7]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Est
9999	10000	15628319	Walker	792	France	Female	28	0.0	130142.79	1	1	0	
6220	6221	15716926	Macleod	807	France	Male	33	0.0	101952.97	2	1	0	
6221	6222	15603554	Berkeley	513	France	Female	45	0.0	164649.52	3	1	0	
6223	6224	15679429	Bell	694	France	Male	32	0.0	91956.49	1	1	1	
6225	6226	15742172	Williamson	598	Germany	Male	32	0.0	123938.60	2	1	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
7579	7580	15649101	Reeves	601	France	Male	40	10.0	127847.86	1	0	0	
7565	7566	15623369	Clifton	708	France	Male	52	10.0	105355.81	1	1	0	
1619	1620	15770309	McDonald	656	France	Male	18	10.0	151762.74	1	0	1	
3135	3136	15753874	Kent	694	France	Male	37	10.0	143835.47	1	0	1	
4863	4864	15640491	Raff	464	France	Female	33	10.0	147493.70	2	1	0	

10000 rows × 14 columns

In [8]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           10000 non-null  float64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(3), int64(8), object(3)
memory usage: 1.1+ MB
```

In [9]:

```
# deletion of useles columns
data = data.drop(columns = ['RowNumber','CustomerId','Surname'])
```

In [10]:

```
data.head()
```

Out[10]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2.0	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1.0	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8.0	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1.0	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2.0	125510.82	1	1	1	79084.10	0

Conclusion

1) Data successfully imported;

2) Useless columns were deleted;

3) nulls filled with zeros;

4) prepared dataset has 11 columns and 10000 rows.

Models training

Encoding of categorical data

In [11]:
```
data_s = data.copy()
```

In [12]:
```
data_s = pd.get_dummies(data_s,drop_first=True)
```

In [13]:
```
data_s.head(10)
```

Out[13]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Geography_Germany	Geography_Spain
0	619	42	2.0	0.00	1	1	1	101348.88	1	0	0
1	608	41	1.0	83807.86	1	0	1	112542.58	0	0	1
2	502	42	8.0	159660.80	3	1	0	113931.57	1	0	0
3	699	39	1.0	0.00	2	0	0	93826.63	0	0	0
4	850	43	2.0	125510.82	1	1	1	79084.10	0	0	1
5	645	44	8.0	113755.78	2	1	0	149756.71	1	0	1
6	822	50	7.0	0.00	2	1	1	10062.80	0	0	0
7	376	29	4.0	115046.74	4	1	0	119346.88	1	1	0
8	501	44	4.0	142051.07	2	0	1	74940.50	0	0	0
9	684	27	2.0	134603.88	1	1	1	71725.73	0	0	0

In [14]:
```
features = data_s.drop(columns='Exited')
target = data_s['Exited']
```

Dataset splitting on samples

In [15]:
```
features_train,features_valid_temp,target_train,target_valid_temp = train_test_split(
    features,target,test_size=0.4, random_state=12345)
```

In [16]:
```
features_valid,features_test,target_valid,target_test = train_test_split(features_valid_temp,target_valid_temp,test_size=0.5, ra
```

Random forest Model training

In [17]:
```
rf_model = RandomForestClassifier(random_state=12345)
rf_model.fit(features_train,target_train)
rf_predictions= rf_model.predict(features_valid)
```

In [18]:
```
confusion_matrix(target_valid,rf_predictions)
```

Out[18]:
```
array([[1521,   61],
       [ 222,  196]], dtype=int64)
```

In [19]:
```
rf_f1_score = f1_score(target_valid, rf_predictions)
rf_f1_score
```

Out[19]:
```
0.5807407407407408
```

In [20]:
```
recall_score(target_valid, rf_predictions)
```

Out[20]:
```
0.4688995215311005
```

In [21]:
```
precision_score(target_valid, rf_predictions)
```

Out[21]:
```
0.7626459143968871
```

In [22]:
```
accuracy_score(target_valid, rf_predictions)
```

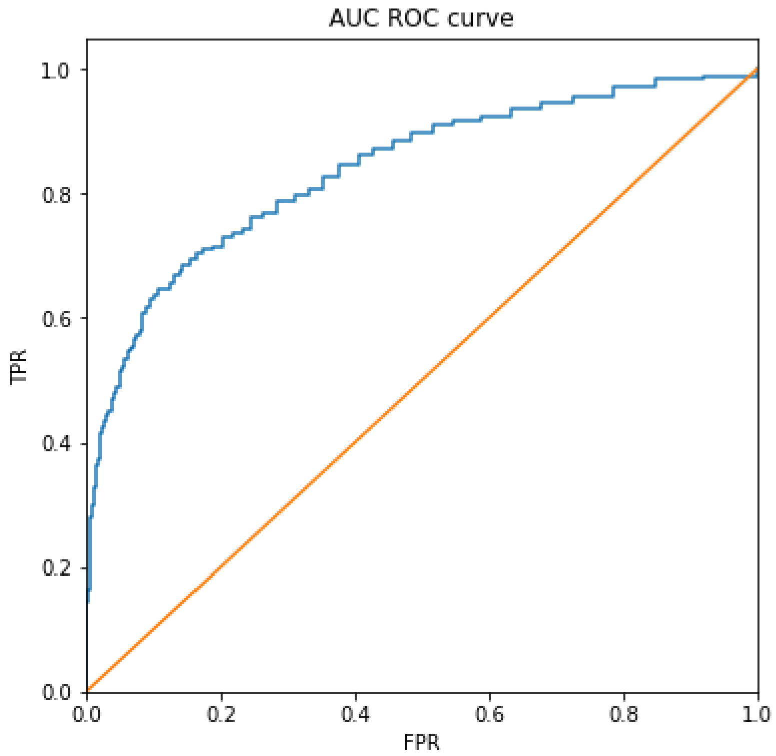
Out[22]:
```
0.8585
```

Plotting of random forest model auc roc curve

In [23]:

```
rf_probabilities_valid = rf_model.predict_proba(features_valid)
precision, recall, thresholds = roc_curve(target_valid, rf_probabilities_valid[:, 1])

plt.figure(figsize=(6, 6))
plt.step( precision,recall, where='post')
plt.plot([0.0,1.0],[0.0,1.0])
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('AUC ROC curve')
plt.show()
```



In [24]:

```
roc_auc_score(target_valid,rf_probabilities_valid[:, 1])
```

Out[24]:

```
0.8424114893025
```

Conclusions:

Random Forest model was successfully trained and has the following scores: 1) F1 - 0.53

2) AUC ROC - 0.81

3) recall_score - 0.418

4) precision_score - 0.73

5) accuracy_score - 0.84

Combat to imbalance

Logistic Regression model training with balanced weight

In [25]:
```
lr_model = LogisticRegression(random_state=12345, solver='liblinear',class_weight='balanced')
lr_model.fit(features_train,target_train)
lr_predictions= lr_model.predict(features_valid)
```

In [26]:
```
lr_f1_score = f1_score(target_valid, lr_predictions)
lr_f1_score
```

Out[26]:
```
0.4514056224899599
```

In [27]:
```
recall_score(target_valid, lr_predictions)
```

Out[27]:
```
0.6722488038277512
```

In [28]:
```
precision_score(target_valid, lr_predictions)
```

Out[28]:
```
0.33978234582829503
```

In [29]:
```
accuracy_score(target_valid, lr_predictions)
```

Out[29]: 0.6585

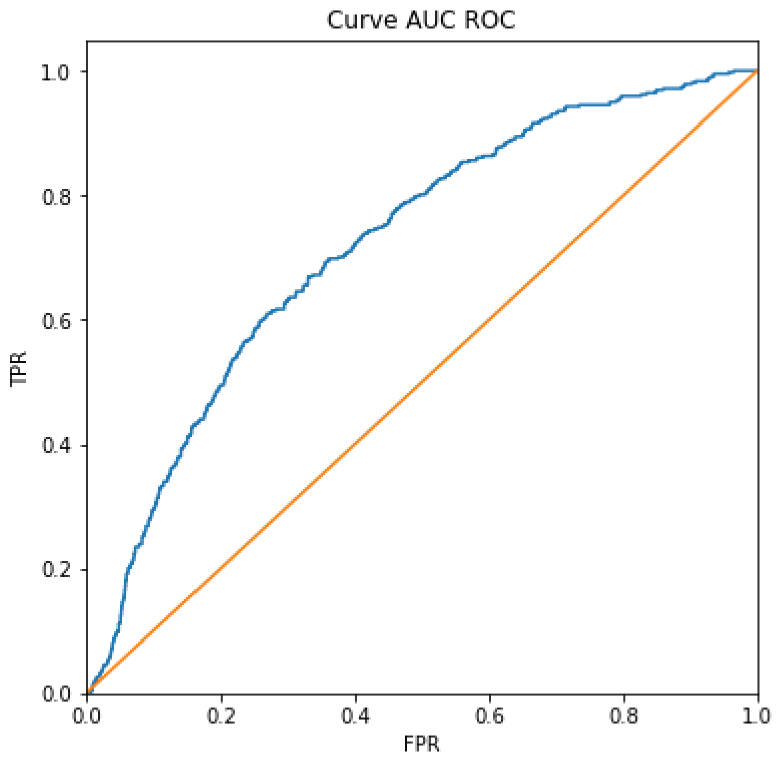
In [30]:
```
confusion_matrix(target_valid,lr_predictions)
```

Out[30]:
```
array([[1036,  546],
       [ 137,  281]], dtype=int64)
```

Plotting of logistic regression model auc roc curve

In [31]:
```
lr_probabilities_valid = lr_model.predict_proba(features_valid)
precision, recall, thresholds = roc_curve(target_valid, lr_probabilities_valid[:, 1])


plt.figure(figsize=(6, 6))
plt.step( precision,recall, where='post')
plt.plot([0.0,1.0],[0.0,1.0])
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Curve AUC ROC')
plt.show()
```



In [32]:
```
roc_auc_score(target_valid,lr_probabilities_valid[:, 1])
```

Out[32]:
```
0.7193909955903435
```

Conclusion

Logistic regression model with balanced class weight has the following scores:

1) F1 - 0.48

2) AUC ROC - 0.75

3) recall_score - 0.37

4) precision_score - 0.73

5) accuracy_score - 0.69

Upsampling

In [33]:
```
features_zeros = features_train[target_train==0]
features_ones = features_train[target_train==1]
target_zeros = target_train[target_train==0]
target_ones = target_train[target_train==1]
n= 15
```

In [34]:
```
features_upsampled = pd.concat([features_zeros]+[features_ones]*n)
target_upsampled = pd.concat([target_zeros]+[target_ones]*n)
```

In [35]:
```
features_upsampled,target_upsampled = shuffle(features_upsampled,target_upsampled,random_state=12345)
```

Random forest model training on upsampled data

In [36]:
```
rf_up_model = RandomForestClassifier(random_state=12345)
rf_up_model.fit(features_upsampled,target_upsampled)
rf_up_predictions= rf_up_model.predict(features_valid)
rf_up_f1_score = f1_score(target_valid, rf_up_predictions)
rf_up_f1_score
```

Out[36]:
```
0.5932885906040269
```

In [37]:
```
confusion_matrix(target_valid,rf_up_predictions)
```

Out[37]:
```
array([[1476,  106],
       [ 197,  221]], dtype=int64)
```

In [38]:
```
recall_score(target_valid, rf_up_predictions)
```

Out[38]:
```
0.5287081339712919
```

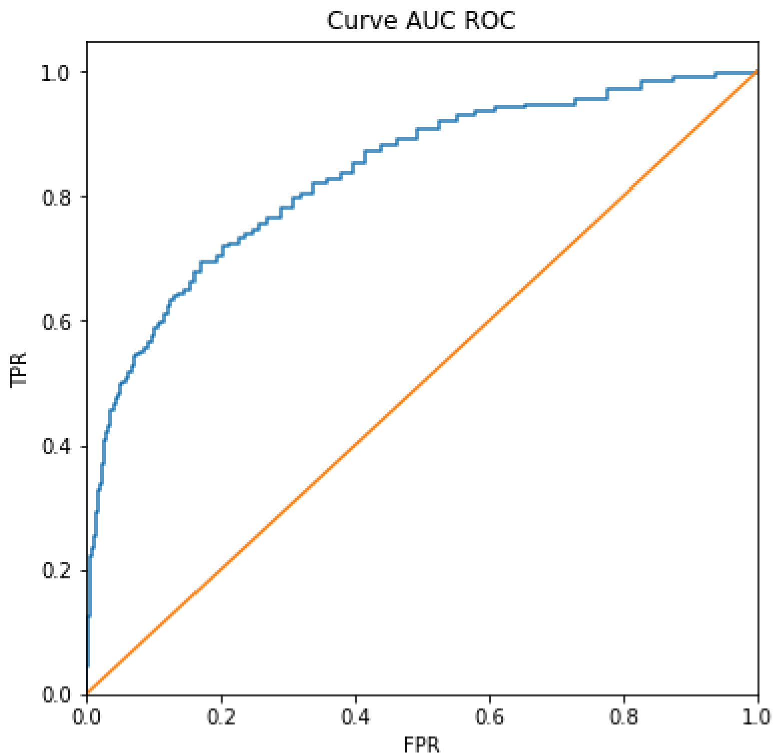
In [39]:
```
precision_score(target_valid, rf_up_predictions)
```

Out[39]:
```
0.6758409785932722
```

Plotting of upsampled rf model auc roc curve

In [40]:
```
rf_up_probabilities_valid = rf_up_model.predict_proba(features_valid)
precision, recall, thresholds = roc_curve(target_valid, rf_up_probabilities_valid[:, 1])

plt.figure(figsize=(6, 6))
plt.step( precision,recall, where='post')
plt.plot([0.0,1.0],[0.0,1.0])
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Curve AUC ROC')
plt.show()
```



In [41]:
```
roc_auc_score(target_valid,rf_up_probabilities_valid[:, 1])
```

Out[41]:
```
0.8381833001651353
```

In [42]:
```
accuracy_score(target_valid, rf_up_predictions)
```

Out[42]:
```
0.8485
```

Conclusion

Random forest model on upsampled data has the following scores:

1) F1 - 0.57

2) AUC ROC - 0.808

3) recall_score - 0.50

4) precision_score - 0.65

5) accuracy_score - 0.84

Downsampling

In [43]:
```
features_zeros = features_train[target_train==0]
features_ones = features_train[target_train==1]
target_zeros = target_train[target_train==0]
target_ones = target_train[target_train==1]
m= 0.02
```

In [44]:
```
features_downsampled = pd.concat(
        [features_zeros.sample(frac=m, random_state=12345)] + [features_ones])
target_downsampled = pd.concat(
        [target_zeros.sample(frac=m, random_state=12345)] + [target_ones])
```

In [45]:
```
features_downsampled,target_downsampled = shuffle(features_upsampled,target_upsampled,random_state=12345)
```

In [46]:
```
rf_dn_model = RandomForestClassifier(random_state=12345)
rf_dn_model.fit(features_downsampled,target_downsampled)
rf_dn_predictions= rf_dn_model.predict(features_valid)
rf_dn_f1_score = f1_score(target_valid, rf_dn_predictions)
rf_dn_f1_score
```

Out[46]: 0.5850340136054422

In [47]:
```
confusion_matrix(target_valid,rf_dn_predictions)
```

Out[47]:
```
array([[1480,  102],
       [ 203,  215]], dtype=int64)
```

In [48]:
```
rf_dn_probabilities_valid = rf_dn_model.predict_proba(features_valid)
precision_score(target_valid, rf_dn_predictions)
```

Out[48]: 0.6782334384858044

In [49]:
```
recall_score(target_valid, rf_dn_predictions)
```

Out[49]: 0.5143540669856459

In [50]:
```
roc_auc_score(target_valid,rf_dn_probabilities_valid[:, 1])
```

Out[50]: 0.837675947713209

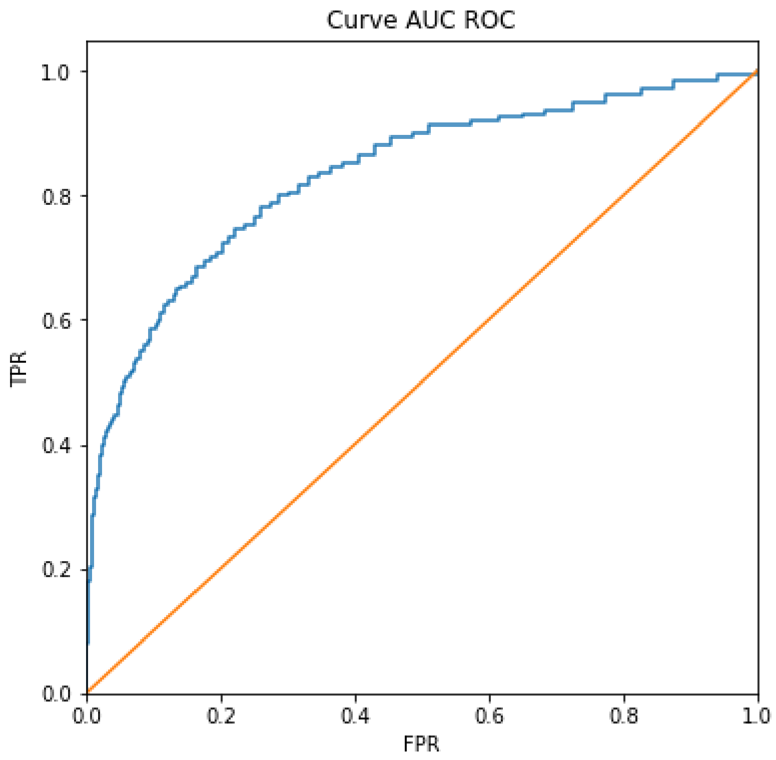
In [51]:
```
accuracy_score(target_valid, rf_dn_predictions)
```

Out[51]: 0.8475

Plotting of downsampled rf model auc roc curve

In [52]:
```
probabilities_valid = rf_dn_model.predict_proba(features_valid)
precision, recall, thresholds = roc_curve(target_valid, probabilities_valid[:, 1])

plt.figure(figsize=(6, 6))
plt.step( precision,recall, where='post')
plt.plot([0.0,1.0],[0.0,1.0])
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Curve AUC ROC')
plt.show()
```



Conclusion

Random forest model with downsampling has the follwoing scores:

1) F1 - 0.55

2) AUC ROC - 0.81

3) recall_score - 0.47

4) precision_score - 0.66

5) accuracy_score - 0.84

Hyperparameters tuning

In [53]:

```
%%time

models = [RandomForestClassifier,DecisionTreeClassifier]

f1_best=0
for c in models:
        for d in range(2):
            if d == 0:
                e = features_downsampled
                f = target_downsampled
                g = 'downsampled'
            elif d == 1:
                e = features_upsampled
                f = target_upsampled
                g = 'upsampled'
            else:
                e = features_train
                f = target_train
                g = 'train'
            for depth in range (10,210,50):
                if c == RandomForestClassifier:
                    for estimators in range (10,210,50):
                        tuned_model = c(n_estimators = estimators , max_depth = depth, random_state=12345,
                                        class_weight ='balanced')
                        tuned_model.fit(e,f)
                        tuned_predictions= tuned_model.predict(features_valid)
                        F1_temp = f1_score(target_valid, tuned_predictions)
                        if f1_best < F1_temp:
                            f1_best = F1_temp
                            best_model = c
                            best_features = g
                            best_depth = depth
                            best_estimators = estimators
                elif c == DecisionTreeClassifier:
                    tuned_model = c(max_depth = depth, random_state=12345,class_weight ='balanced')
                    tuned_model.fit(e,f)
                    tuned_predictions= tuned_model.predict(features_valid)
                    F1_temp = f1_score(target_valid, tuned_predictions)
                    if f1_best < F1_temp:
                        f1_best = F1_temp
                        best_model = c
                        best_features = g
                        best_depth = depth
```

```
                        best_estimators = estimators
print(f1_best,'\n',best_model,'\n',best_features,'\n',best_depth,'\n',best_estimators)
```

```
0.6293103448275862
 <class 'sklearn.ensemble._forest.RandomForestClassifier'>
 upsampled
 10
 60
CPU times: total: 41 s
Wall time: 41.1 s
```

In [54]:
```
tuned_model = best_model(n_estimators = best_estimators, max_depth =best_depth, random_state=12345, class_weight = 'balanced')
tuned_model.fit(e, f)
tuned_predictions = tuned_model.predict(features_valid)
```

In [55]:
```
tuned_f1 = f1_score(target_valid, tuned_predictions)
tuned_f1
```

Out[55]:
```
0.6293103448275862
```

In [56]:
```
accuracy_score(target_valid, tuned_predictions)
```

Out[56]:
```
0.828
```

In [57]:
```
recall_score(target_valid, tuned_predictions)
```

Out[57]:
```
0.6985645933014354
```

In [58]:
```
tuned_probabilities_valid = tuned_model.predict_proba(features_valid)
roc_auc_score(target_valid,tuned_probabilities_valid[:, 1])
```

Out[58]:
```
0.8502728059085768
```

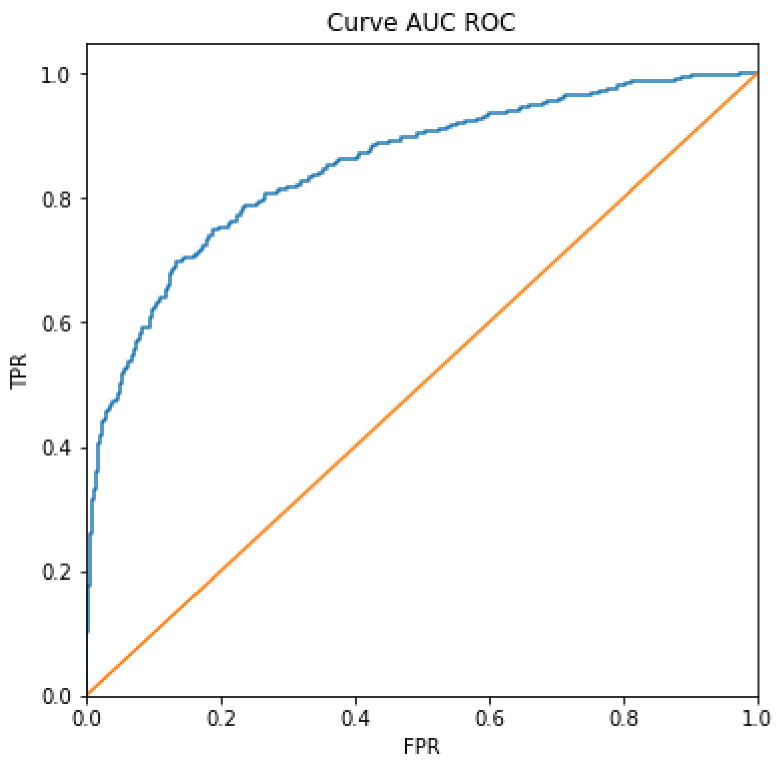
In [59]:
```
precision_score(target_valid, tuned_predictions)
```

Out[59]:
```
0.5725490196078431
```

Plotting of AUC ROC curve of tuned model

In [60]:
```
tuned_probabilities_valid = tuned_model.predict_proba(features_valid)
precision, recall, thresholds = roc_curve(target_valid, tuned_probabilities_valid[:, 1])
```

```
plt.figure(figsize=(6, 6))
plt.step(precision,recall, where='post')
plt.plot([0.0,1.0],[0.0,1.0])
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Curve AUC ROC')
plt.show()
```



Conclusions

Using hyperparamters tuning the model has the following scores:

1) F1 ~ 0.629

2) AUC ROC ~ 0.85

3) recall_score ~ 0.44

4) precision_score ~ 0.57

5) accuracy_score ~ 0.828

Selection of best model

In [61]:
```
models_df = pd.DataFrame({'model_name': ['rf_model','lr_model','rf_up_model','rf_dn_model','tuned_model'],
                          'model': [rf_model,lr_model,rf_up_model,rf_dn_model,tuned_model],
                          'F1': [rf_f1_score,lr_f1_score,rf_up_f1_score,rf_dn_f1_score,tuned_f1] })
```

In [62]:
```
models_df = models_df.sort_values(by = 'F1', ascending = 0).reset_index(drop = True)
models_df
```

Out[62]:

	model_name	model	F1
0	tuned_model	(DecisionTreeClassifier(max_depth=10, max_feat...	0.629310
1	rf_up_model	(DecisionTreeClassifier(max_features='sqrt', r...	0.593289
2	rf_dn_model	(DecisionTreeClassifier(max_features='sqrt', r...	0.585034
3	rf_model	(DecisionTreeClassifier(max_features='sqrt', r...	0.580741
4	lr_model	LogisticRegression(class_weight='balanced', ra...	0.451406

In [63]:
```
best_model = models_df['model'][0]
best_model
```

Out[63]:
```
▾ RandomForestClassifier
RandomForestClassifier(class_weight='balanced', max_depth=10, n_estimators=60,
                       random_state=12345)
```

Conclusion

1) Five models were trained and compared:

- random forest model;

- linear regression with class balance;
- random forest with class upsampling;
- random forest with class downsampling;
- random forest with hyperparamters tuning.

2) Best F1 score was achieved using tuned model. The model was selected for testing.

Model testing

In [64]:
```
best_model.fit(features_upsampled, target_upsampled)
test_predictions = best_model.predict(features_test)
print( 'Test_f1:', f1_score(target_test,test_predictions))
```

```
Test_f1: 0.5982905982905982
```

In [65]:
```
accuracy_score(target_test, test_predictions)
```

Out[65]:
```
0.812
```

In [66]:
```
recall_score(target_test, test_predictions)
```

Out[66]:
```
0.6619385342789598
```

In [67]:
```
test_probabilities = best_model.predict_proba(features_test)
roc_auc_score(target_test,test_probabilities[:, 1])
```

Out[67]:
```
0.8544157968192292
```

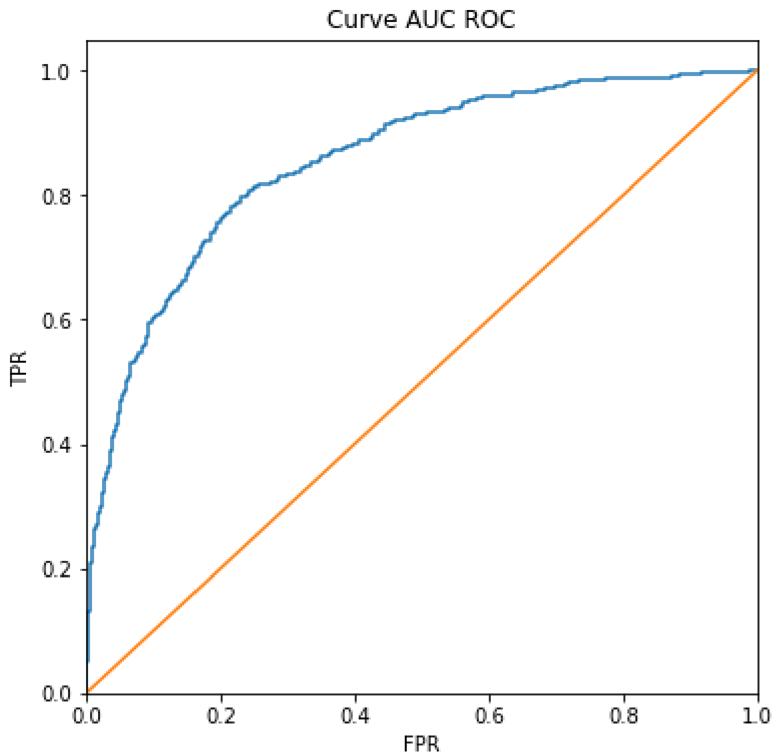
In [68]:
```
precision_score(target_test, test_predictions)
```

Out[68]:
```
0.5458089668615984
```

In [69]:
```
test_probabilities = best_model.predict_proba(features_test)
precision, recall, thresholds = roc_curve(target_test, test_probabilities[:, 1])

plt.figure(figsize=(6, 6))
```

```
plt.step(precision,recall, where='post')
plt.plot([0.0,1.0],[0.0,1.0])
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Curve AUC ROC')
plt.show()
```



Conclusion

Testing of the model with highest F1 score on valid sample has the following scores:

1) F1 ~ 0.598

2) AUC ROC ~ 0.85

3) recall_score ~ 0.67

4) precision_score ~ 0.54

5) accuracy_score ~ 0.81

General conclusion

1) Data was successfully imported, prepared and encoded.

2) Dataset was splat on train, valid and test samples.

3) Five models were train, four of them were using the different tools for combat to imbalance of classes:

- balancing of weight of classes;
- upsampling;
- down sampling;

4) The best model was selected after comparison. The model has tuned hyperparameters and balanced class weight.

5) The main goal was achieved - the F1 score is above 0.59.