customer_churn_project_english

It is necessary to predict whether the client will leave the bank in the near future or not. We have been provided with historical data on customer behavior and termination of agreements with the bank.

Let us construct a model with an extremely large *F1*-measure. To pass the project successfully, you need to bring the metric to 0.59. Check the *F1*-measure on the test set.

Additionally, we measure *AUC-ROC*, compare its value with *F1*-measure.

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

Data preparation

Import libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import re as re

from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV

from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score, roc_auc_score, roc_curve, precision_score, recall_score, precision_recall_curve, accuracy_score
from sklearn.utils import shuffle

from catboost import CatBoostClassifier
from catboost import Pool, cv

from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler

import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
#data = pd.read_csv("/workspaces/Data-Science/Dataset/Churn_Modelling.csv")
data = pd.read_csv('/media/aleksey/A6B828A60EB3956D/Data science/Dataset/Churn_Modelling.csv')
data.head(10)
```

Out[2]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0
5	6	15574012	Chu	645	Spain	Male	44	8	113755.78	2	1	0	149756.71	1
6	7	15592531	Bartlett	822	France	Male	50	7	0.00	2	1	1	10062.80	0
7	8	15656148	Obinna	376	Germany	Female	29	4	115046.74	4	1	0	119346.88	1
8	9	15792365	He	501	France	Male	44	4	142051.07	2	0	1	74940.50	0
9	10	15592389	H?	684	France	Male	27	2	134603.88	1	1	1	71725.73	0

In [3]:

```
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  int64  
 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(2), int64(9), object(3)
memory usage: 1.1+ MB
```

Data exploration Churn_Modelling.csv

In [4]:

```
data.head()
```

Out[4]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

Features:

RowNumber - the index of the row in the data

CustomerId - unique customer identifier

Surname - surname

CreditScore - credit rating

Geography - country of residence

Gender - gender

Age - age

Tenure - how many years a person has been a client of the bank

Balance - account balance

NumOfProducts - the number of bank products used by the client

HasCrCard - availability of a credit card

IsActiveMember - client activity

EstimatedSalary - estimated salary

Target column:

Exited - the fact of the client's departure

In [5]:
```
data.columns = [re.sub(r'(?<!^)(?=[A-Z])', '_', i).lower() for i in data.columns]#Let's convert the names of the columns to the snake register
data.columns
```

Out[5]:
```
Index(['row_number', 'customer_id', 'surname', 'credit_score', 'geography',
       'gender', 'age', 'tenure', 'balance', 'num_of_products', 'has_cr_card',
       'is_active_member', 'estimated_salary', 'exited'],
      dtype='object')
```

In [6]:
```
data.columns = ['row_number', 'customer_id', 'surname', 'credit_score', 'geography',
       'gender', 'age', 'tenure', 'balance', 'num_of_products', 'has_cr_card',
       'is_active_member', 'estimated_salary', 'exited']#Let's convert the names of the columns to the snake register
data.columns
```

Out[6]:
```
Index(['row_number', 'customer_id', 'surname', 'credit_score', 'geography',
       'gender', 'age', 'tenure', 'balance', 'num_of_products', 'has_cr_card',
       'is_active_member', 'estimated_salary', 'exited'],
      dtype='object')
```

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   row_number        10000 non-null  int64  
 1   customer_id       10000 non-null  int64  
 2   surname           10000 non-null  object 
 3   credit_score      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  int64  
 8   balance           10000 non-null  float64
 9   num_of_products   10000 non-null  int64  
 10  has_cr_card       10000 non-null  int64  
 11  is_active_member  10000 non-null  int64  
 12  estimated_salary  10000 non-null  float64
 13  exited            10000 non-null  int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

Consider the presence of rare and outliers by analyzing through the method .describe()

In [8]:
```
data.describe(include='all')
```

Out[8]:

	row_number	customer_id	surname	credit_score	geography	gender	age	tenure	balance	num_of_products	has_cr_card	is_active_member	estimated_sala
count	10000.00000	1.000000e+04	10000	10000.000000	10000	10000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.0000
unique	NaN	NaN	2932	NaN	3	2	NaN	NaN	NaN	NaN	NaN	NaN	Na
top	NaN	NaN	Smith	NaN	France	Male	NaN	NaN	NaN	NaN	NaN	NaN	Na
freq	NaN	NaN	32	NaN	5014	5457	NaN	NaN	NaN	NaN	NaN	NaN	Na
mean	5000.50000	1.569094e+07	NaN	650.528800	NaN	NaN	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.2398
std	2886.89568	7.193619e+04	NaN	96.653299	NaN	NaN	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.4928
min	1.00000	1.556570e+07	NaN	350.000000	NaN	NaN	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.5800
25%	2500.75000	1.562853e+07	NaN	584.000000	NaN	NaN	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.1100
50%	5000.50000	1.569074e+07	NaN	652.000000	NaN	NaN	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.9150
75%	7500.25000	1.575323e+07	NaN	718.000000	NaN	NaN	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.2475
max	10000.00000	1.581569e+07	NaN	850.000000	NaN	NaN	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.4800

- No anomalies

In [9]:
```
data.groupby('exited')['customer_id'].count()# consider the target feature. One in four leaves the bank
```

Out[9]:
```
exited
0    7963
1    2037
Name: customer_id, dtype: int64
```

In [10]:
```
data[data['balance']==0].groupby('exited')['customer_id'].count()# Every sixth client with a zero balance leaves the bank
```

Out[10]:
```
exited
0    3117
1     500
Name: customer_id, dtype: int64
```

Check for duplicates

In [11]:
```
data.duplicated().sum()
```

Out[11]:
```
0
```

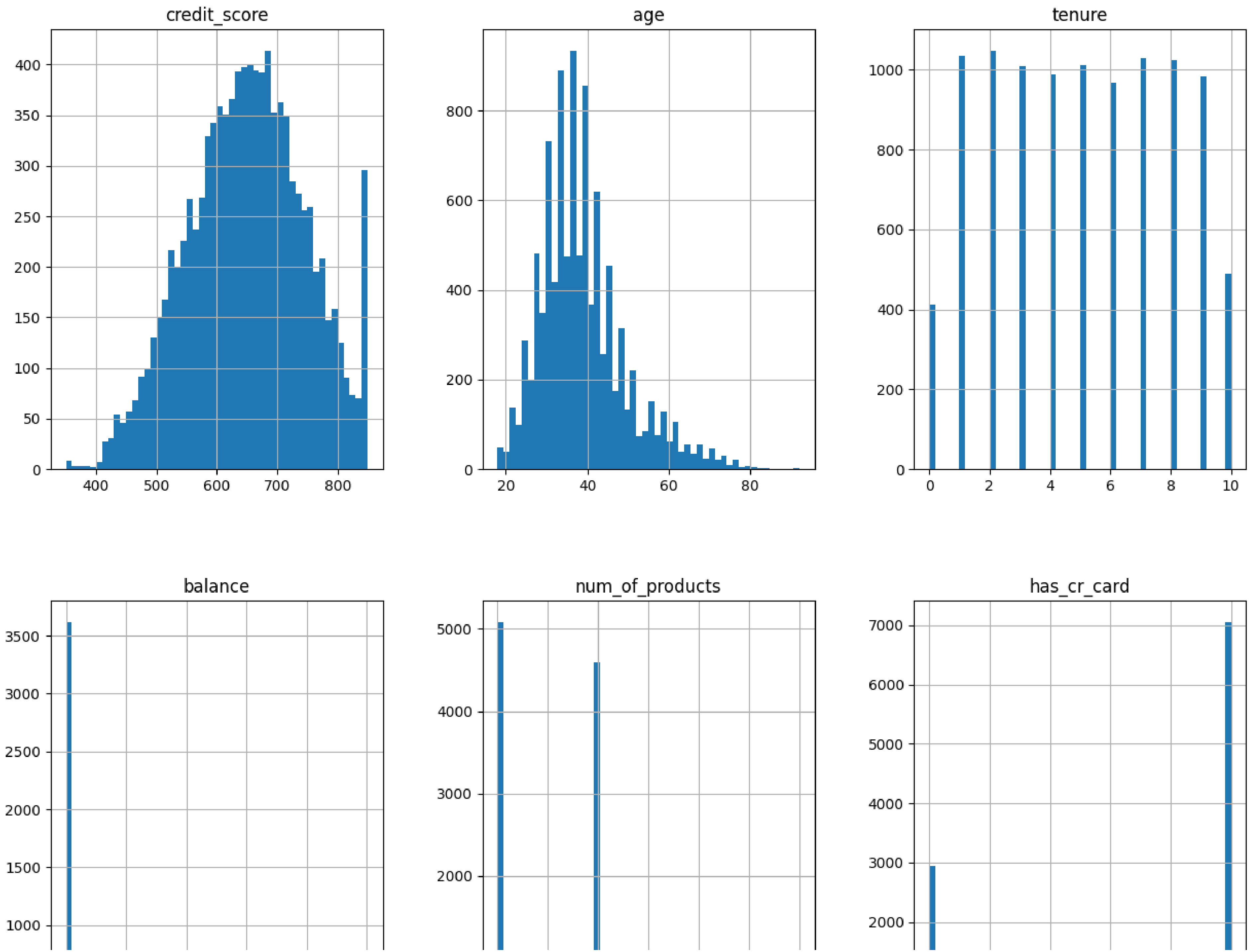
Remove non-informative columns not needed for the model row_number, customer_id, surname

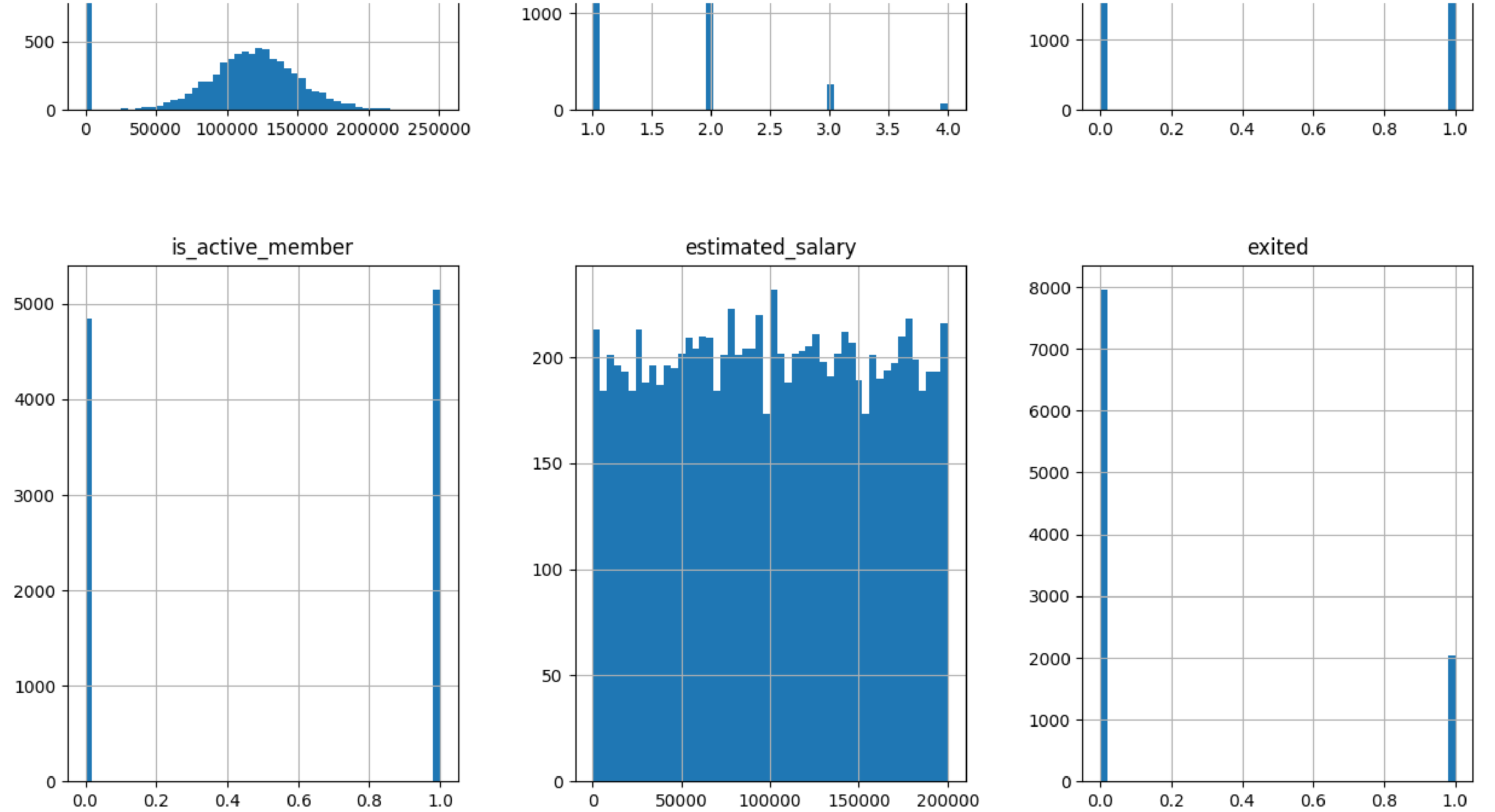
In [12]:
```
data = data.drop(['row_number', 'customer_id', 'surname'], axis=1).copy()
data.head()
```

Out[12]:

	credit_score	geography	gender	age	tenure	balance	num_of_products	has_cr_card	is_active_member	estimated_salary	exited
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

In [13]:
```
data.hist(bins=50, figsize=(15, 20))#built a common histogram for all numeric columns
plt.show()
```


credit_score
age
tenure
balance
num_of_products
has_cr_card



Findings

1. Out of 10,000 customers, 2,037 customers left the bank.
2. Column names are changed to snake and lowercase
3. Anomalies were not detected
4. There is an imbalance of classes. The number of customer exits is approximately four times less than the remaining
5. People with zero balances are more likely to leave the bank

Problem research

Clients started leaving the bank. A little, but noticeable. Banking marketers figured it was cheaper to keep current customers than to attract new ones. It is necessary to predict whether the client will leave the bank in the near future or not.

1. Let us construct a model with an extremely large value of the F1-measure. Let's check the F1-measure on the test sample.
2. Additionally, we measure the AUC-ROC, compare its value with the F1-measure.
3. We have an imbalance of classes, correctness (accuracy) does not suit us. To solve this problem, I propose to use the algorithms of Logistic Regression, Random Forest and Decision Tree, Catboost

One-hot Encoding

In [14]:
```
def unique_values(data):
    for column in data :
        if data[column].dtypes == 'object':
            print(f'{column}:{data[column].unique()}:{len(data[column].unique())}')
unique_values(data)
```

```
geography:['France' 'Spain' 'Germany']:3
gender:['Female' 'Male']:2
```

Converting categorical features to numerical will help the direct coding technique, or One-Hot Encoding display. The OHE technique converts categorical features into numerical features in two stages:

1. A new column is created for each characteristic value;
2. If the category is suitable for the object, 1 is assigned, if not, 0. The new features are called dummy variables, or dummy features. For direct encoding, the pandas library has the pd.get_dummies() function. Let's convert the categorical features of the gender and geography columns with the One-hot Encoding method into numerical ones.

In [15]:
```
data.groupby('gender')['estimated_salary'].count()# consider the target feature
```

Out[15]:
```
gender
Female    4543
Male      5457
Name: estimated_salary, dtype: int64
```

In [16]:
```
data.groupby('geography')['estimated_salary'].count()#consider the target feature
```

Out[16]:
```
geography
France     5014
Germany    2509
Spain      2477
Name: estimated_salary, dtype: int64
```

In [17]:
```
data['gender'] = pd.get_dummies(data["gender"], drop_first=True)
```

In [18]:
```
pd.get_dummies(data["geography"], drop_first=True)
```

Out[18]:

	Germany	Spain
0	0	0
1	0	1
2	0	0
3	0	0
4	0	1
...	...	...
9995	0	0
9996	0	0
9997	0	0
9998	1	0
9999	0	0

10000 rows × 2 columns

In [19]:
```
data_ohe = pd.get_dummies(data["geography"], drop_first=True)
```

In [20]:
```
data = pd.concat([data, data_ohe], axis=1)#add new columns from geography

data.head()
```

Out[20]:

	credit_score	geography	gender	age	tenure	balance	num_of_products	has_cr_card	is_active_member	estimated_salary	exited	Germany	Spain
0	619	France	0	42	2	0.00	1	1	1	101348.88	1	0	0
1	608	Spain	0	41	1	83807.86	1	0	1	112542.58	0	0	1
2	502	France	0	42	8	159660.80	3	1	0	113931.57	1	0	0
3	699	France	0	39	1	0.00	2	0	0	93826.63	0	0	0
4	850	Spain	0	43	2	125510.82	1	1	1	79084.10	0	0	1

In [21]:
```
data = data.drop(['geography'], axis=1).copy()#remove the geography column
data.head()
```

Out[21]:

	credit_score	gender	age	tenure	balance	num_of_products	has_cr_card	is_active_member	estimated_salary	exited	Germany	Spain
0	619	0	42	2	0.00	1	1	1	101348.88	1	0	0
1	608	0	41	1	83807.86	1	0	1	112542.58	0	0	1
2	502	0	42	8	159660.80	3	1	0	113931.57	1	0	0
3	699	0	39	1	0.00	2	0	0	93826.63	0	0	0
4	850	0	43	2	125510.82	1	1	1	79084.10	0	0	1

Divide the data into samples

In [22]:
```
# separate 20% of the data for the test sample of the sample (for model validation)
```

In [23]:
```
target = data['exited']
features = data.drop(['exited'] , axis=1)
features_other, features_test, target_other, target_test = train_test_split(
    features, target, test_size=0.2, random_state=12345)
```

In [24]:
```
# separate 25% of the data (from other) to split into training and validation sets
```

In [25]:
```
features_train, features_valid, target_train, target_valid = train_test_split(
    features_other, target_other, test_size=0.25, random_state=12345)
```

In [26]:
```
print('Training sample size', len(features_train))
print('Validation sample size', len(features_valid))
print('Test sample size', len(features_test))
```

```
Training sample size 6000
Validation sample size 2000
Test sample size 2000
```

Feature scaling

If the data contains quantitative features with different ranges of values, then the algorithm may decide that features with large values and ranges are more important. To avoid this traps, signs are scaled - brought to the same scale.

In [27]:
```
numeric = ['credit_score', 'age', 'tenure', 'balance', 'num_of_products', 'estimated_salary']

scaler = StandardScaler()
scaler.fit(features_train[numeric])

features_train[numeric] = scaler.transform(features_train[numeric])
features_train.head()
```

Out[27]:

	credit_score	gender	age	tenure	balance	num_of_products	has_cr_card	is_active_member	estimated_salary	Germany	Spain
492	-0.134048	0	-0.078068	-0.357205	0.076163	0.816929	0	1	0.331571	0	0
6655	-1.010798	1	0.494555	0.676673	0.136391	-0.896909	1	1	-0.727858	0	0
4287	0.639554	1	1.353490	-1.391083	0.358435	-0.896909	1	1	-0.477006	1	0
42	-0.990168	0	2.116987	-1.046457	0.651725	-0.896909	1	1	-0.100232	0	0
8178	0.567351	0	0.685430	0.676673	0.813110	0.816929	1	1	0.801922	0	0

In [28]:
```
features_valid[numeric] = scaler.transform(features_valid[numeric])
features_valid.head()
```

Out[28]:

	credit_score	gender	age	tenure	balance	num_of_products	has_cr_card	is_active_member	estimated_salary	Germany	Spain
2358	0.175393	1	0.399118	-1.391083	1.385698	-0.896909	0	1	-1.466761	0	0
8463	-1.299609	1	0.971741	-1.046457	-1.232442	-0.896909	1	0	0.254415	0	1
163	0.711757	0	-0.268942	-1.046457	-1.232442	0.816929	1	1	0.122863	0	1
3074	-0.391916	0	0.494555	0.332047	0.672529	-0.896909	1	0	0.585847	1	0
5989	0.165078	0	1.353490	1.710552	0.536522	-0.896909	0	0	1.462457	0	0

In [29]:

```
features_test[numeric] = scaler.transform(features_test[numeric])
features_test.head()
```

Out[29]:

	credit_score	gender	age	tenure	balance	num_of_products	has_cr_card	is_active_member	estimated_salary	Germany	Spain
7867	-0.123733	0	0.685430	-0.701831	-1.232442	-0.896909	1	1	0.980212	0	1
1402	1.083087	1	-0.937002	1.021300	0.858518	-0.896909	1	0	-0.390486	0	0
8606	1.598822	1	0.303681	-0.012579	-1.232442	0.816929	1	1	-0.435169	0	1
8885	0.165078	1	0.589993	-0.357205	0.412100	0.816929	1	1	1.017079	0	1
6494	0.484834	1	-1.032439	0.676673	-1.232442	0.816929	1	1	-1.343558	0	0

Examining models without imbalance

In [30]:

```
#for the convenience of output in the future - we will collect the indicators in lists
tabl_model = []
tabl_prec = []
tabl_not = []
tabl_roc_auc = []
```

Logistic Regression Model

In [31]:

```
model = LogisticRegression(solver = 'liblinear', penalty = 'l2', multi_class ='auto', fit_intercept=True, dual=False, C=10,
                           random_state=12345, max_iter=1000)
model.fit(features_train, target_train) # train the model on the training data
predicted_valid = model.predict(features_valid)
print("F1:", f1_score(target_valid, predicted_valid))# calculate the quality of the model on the validation set

probabilities_valid = model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1: 0.30393996247654786
AUC_ROC = 0.770
```

In [32]:

```
tabl_prec.append(round(f1_score(target_valid, predicted_valid), 2))
tabl_roc_auc.append(round(auc_roc, 2))
```

```
tabl_model.append('LogisticRegression')
tabl_not.append('without_imbalance')
```

Small value F1. We will select parameters and disassemble with an imbalance later

Decision tree model

In [33]:
```
%%time
1 + 1
best_model = None
best_result = 0
for depth in range(1, 15):
        model = DecisionTreeClassifier(max_depth=depth) # train the model with a given tree depth
        model.fit(features_train, target_train)
        predicted_valid = model.predict(features_valid)
        result = f1_score(target_valid, predicted_valid)
        if result > best_result:
                best_model = model
                best_result = result

print("F1 best model:", best_result)
print("max_depth best model:", best_model)

probabilities_valid = best_model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1 best model: 0.5543307086614172
max_depth best model: DecisionTreeClassifier(max_depth=7)
AUC_ROC = 0.827

CPU times: user 332 ms, sys: 76 ms, total: 408 ms
Wall time: 274 ms
```

In [34]:
```
tabl_prec.append(round((best_result), 2))
tabl_roc_auc.append(round(auc_roc, 2))
tabl_model.append('DecisionTreeClassifier')
tabl_not.append('without_imbalance')
```

Much better, but consider other models

Random forest model

In [35]:
```
%%time
1 + 1

best_result = 0
for est in range(10, 101, 10):
    for depth in range(1, 30):
        for samples_split in range(2, 51, 10):
            model = RandomForestClassifier(max_depth=depth, min_samples_split=samples_split, n_estimators=est, random_state=12345)
            model.fit(features_train, target_train)
```

```
            predicted_valid = model.predict(features_valid)
            result = f1_score(target_valid, predicted_valid)
            if result > best_result:
                best_model = model
                best_result = result
```

```
CPU times: user 7min 18s, sys: 760 ms, total: 7min 19s
Wall time: 7min 20s
```

In [36]:
```
best_model
```

Out[36]:
```
RandomForestClassifier
RandomForestClassifier(max_depth=17, min_samples_split=12, n_estimators=30,
                       random_state=12345)
```

In [37]:
```
best_result
```

Out[37]:
```
0.5819935691318328
```

In [38]:
```
print("F1:", best_result)
tabl_prec.append(round(best_result, 2))

probabilities_valid = best_model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))

tabl_roc_auc.append(round(auc_roc, 2))
tabl_model.append('RandomForestClassifier')
tabl_not.append('without_imbalance')
```

```
F1: 0.5819935691318328
AUC_ROC = 0.843
```

This RandomForestClassifier model has the best result so far

CatBoostClassifier

In [39]:
```
model = CatBoostClassifier(verbose=100, random_state=12345)
model.fit(features_train, target_train)

predicted_valid = model.predict(features_valid)
print("F1:", f1_score(target_valid, predicted_valid))

probabilities_valid = model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
Learning rate set to 0.022141
0:      learn: 0.6754999        total: 57.8ms   remaining: 57.7s
100:    learn: 0.3343972        total: 234ms    remaining: 2.08s
200:    learn: 0.3110064        total: 455ms    remaining: 1.81s
300:    learn: 0.2963858        total: 670ms    remaining: 1.56s
400:    learn: 0.2844886        total: 831ms    remaining: 1.24s
500:    learn: 0.2741070        total: 1.07s    remaining: 1.06s
600:    learn: 0.2646223        total: 1.25s    remaining: 827ms
700:    learn: 0.2550124        total: 1.42s    remaining: 604ms
800:    learn: 0.2456157        total: 1.57s    remaining: 391ms
900:    learn: 0.2361567        total: 1.72s    remaining: 189ms
999:    learn: 0.2277176        total: 1.86s    remaining: 0us
F1: 0.596875
AUC_ROC = 0.864
```

In [40]:
```
tabl_prec.append(round(f1_score(target_valid, predicted_valid), 2))
tabl_roc_auc.append(round(auc_roc, 2))
tabl_model.append('CatBoostClassifier')
tabl_not.append('without_imbalance')
```

F1 measure is larger than in all other models

In [41]:
```
table_models = (pd.DataFrame({'Model':tabl_model, 'F1 score':tabl_prec, 'ROC-AUC':tabl_roc_auc, 'Notice': tabl_not}).sort_values(by='F1 score', ascendi
                reset_index(drop=True))
table_models
```

Out[41]:

	Model	F1 score	ROC-AUC	Notice
0	CatBoostClassifier	0.60	0.86	without_imbalance
1	RandomForestClassifier	0.58	0.84	without_imbalance
2	DecisionTreeClassifier	0.55	0.83	without_imbalance
3	LogisticRegression	0.30	0.77	without_imbalance

Findings

1. Transformed categorical features into numerical ones using direct coding technique, or One-Hot Encoding mapping.
2. Divided the data into samples in the ratio 60-20-20
3. Brought signs to a single scale to avoid the trap
4. We studied the models without taking into account the imbalance. The models CatBoostClassifier, RandomForestClassifier performed best
5. Compared parameters f1 and ROC-AUC models

Struggling with imbalance

In [42]:
```
data.groupby('exited')['exited'].count()# Let's look at the target. One in four leaves the bank. There is a class imbalance
```

Out[42]:
```
exited
0    7963
1    2037
Name: exited, dtype: int64
```

class_weight='balanced'

Logistic Regression Model

In [43]:
```
model = LogisticRegression(solver = 'liblinear', penalty = 'l2', multi_class ='auto', fit_intercept=True, dual=False, C=10,
                           random_state=12345, max_iter=1000, class_weight='balanced')
model.fit(features_train, target_train)
predicted_valid = model.predict(features_valid)
print("F1:", f1_score(target_valid, predicted_valid))

probabilities_valid = model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1: 0.4821428571428571
AUC_ROC = 0.772
```

In [44]:
```
tabl_prec.append(round(f1_score(target_valid, predicted_valid), 2))
tabl_roc_auc.append(round(auc_roc, 2))
tabl_model.append('LogisticRegression')
tabl_not.append('class_weight')
```

Decision tree model

In [45]:
```
%%time
1 + 1
best_model = None
best_result = 0
for depth in range(1, 15):
        model = DecisionTreeClassifier(max_depth=depth, random_state=12345, class_weight='balanced')
        model.fit(features_train, target_train)
        predicted_valid = model.predict(features_valid)
        result = f1_score(target_valid, predicted_valid)
        if result > best_result:
                best_model = model
                best_result = result

print("F1 best model:", best_result)
print("max_depth best model:", best_model)

probabilities_valid = best_model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1 best model: 0.5572441742654509
max_depth best model: DecisionTreeClassifier(class_weight='balanced', max_depth=6, random_state=12345)
AUC_ROC = 0.807

CPU times: user 420 ms, sys: 96 ms, total: 516 ms
Wall time: 297 ms
```

In [46]:
```
tabl_prec.append(round((best_result), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('DecisionTreeClassifier')
tabl_not.append('class_weight')
```

Random forest model

In [47]:
```
%%time
1 + 1

model = RandomForestClassifier(class_weight='balanced', max_depth=17, min_samples_leaf=2, min_samples_split=12,
                               n_estimators=30,random_state=12345)

model.fit(features_train, target_train)
predicted_valid = model.predict(features_valid)
print("F1:", f1_score(target_valid, predicted_valid))

probabilities_valid = best_model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1: 0.583547557840617
AUC_ROC = 0.807

CPU times: user 184 ms, sys: 0 ns, total: 184 ms
Wall time: 184 ms
```

In [48]:
```
tabl_prec.append(round(f1_score(target_valid, predicted_valid), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('RandomForestClassifier')
tabl_not.append('class_weight')
```

By adding the class_weight='balanced' parameter, a rare class will have more weight.

In [49]:
```
table_models = (pd.DataFrame({'Model':tabl_model, 'F1 score':tabl_prec, 'ROC-AUC':tabl_roc_auc, 'Notice': tabl_not}).sort_values(by='F1 score', ascendi
                  reset_index(drop=True))
table_models
```

Out[49]:

	Model	F1 score	ROC-AUC	Notice
0	CatBoostClassifier	0.60	0.86	without_imbalance
1	RandomForestClassifier	0.58	0.84	without_imbalance
2	RandomForestClassifier	0.58	0.81	class_weight
3	DecisionTreeClassifier	0.56	0.81	class_weight
4	DecisionTreeClassifier	0.55	0.83	without_imbalance
5	LogisticRegression	0.48	0.77	class_weight
6	LogisticRegression	0.30	0.77	without_imbalance

Comparison:

Two models (DecisionTreeClassifier, LogisticRegression) increased the F1 measure and the ROC-AUC indicator using the class_weight='balanced' parameter

upsampling.

In [50]:
```
oversample = SMOTE(random_state=12345)
```

In [51]:
```
features_upsampled, target_upsampled = oversample.fit_resample(features_train, target_train)
```

In [52]:
```
print('Upsampled validation sample size', len(features_upsampled))
```

```
Upsampled validation sample size 9562
```

Logistic Regression Model

In [53]:
```
model = LogisticRegression(solver='liblinear', random_state=12345)
model.fit(features_upsampled, target_upsampled)
predicted_valid = model.predict(features_valid)
print("F1:", f1_score(target_valid, predicted_valid))

probabilities_valid = model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1: 0.479108635097493
AUC_ROC = 0.765
```

In [54]:
```
tabl_prec.append(round(f1_score(target_valid, predicted_valid), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('LogisticRegression')
tabl_not.append('upsampling')
```

Decision tree model

In [55]:
```
%%time
1 + 1
best_model = None
best_result = 0
for depth in range(1, 15):
        model = DecisionTreeClassifier(max_depth=depth)
        model.fit(features_upsampled, target_upsampled)
        predicted_valid = model.predict(features_valid)
        result = f1_score(target_valid, predicted_valid)
        if result > best_result:
                best_model = model
                best_result = result

print("F1 best model:", best_result)
print("max_depth лучшей модели:", best_model)

probabilities_valid = best_model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1 best model: 0.5567226890756302
max_depth лучшей модели: DecisionTreeClassifier(max_depth=5)
AUC_ROC = 0.821

CPU times: user 612 ms, sys: 104 ms, total: 716 ms
Wall time: 459 ms
```

In [56]:
```
tabl_prec.append(round((best_result), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('DecisionTreeClassifier')
tabl_not.append('upsampling')
```

Random forest model.

In [57]:
```
%%time
1 + 1
model = RandomForestClassifier(max_depth=17, min_samples_leaf=2, min_samples_split=12,
                       n_estimators=30, random_state=12345)

model.fit(features_upsampled, target_upsampled)
predicted_valid = model.predict(features_valid)
print("F1:", f1_score(target_valid, predicted_valid))

probabilities_valid = model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1: 0.5842696629213483
AUC_ROC = 0.843

CPU times: user 424 ms, sys: 0 ns, total: 424 ms
Wall time: 432 ms
```

In [58]:
```
tabl_prec.append(round(f1_score(target_valid, predicted_valid), 2))
```

```
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('RandomForestClassifier')
tabl_not.append('upsampling')
```

CatBoostClassifier

In [59]:
```
model = CatBoostClassifier(verbose=100, random_state=12345)
model.fit(features_upsampled, target_upsampled)
predicted_valid = model.predict(features_valid)
print("F1:", f1_score(target_valid, predicted_valid))

auc_roc = roc_auc_score(target_valid, predicted_valid)
print('ROC-AUC:', auc_roc)
```

```
Learning rate set to 0.027016
0:	learn: 0.6778800	total: 2.94ms	remaining: 2.94s
100:	learn: 0.3859493	total: 318ms	remaining: 2.83s
200:	learn: 0.3243032	total: 595ms	remaining: 2.36s
300:	learn: 0.2843332	total: 821ms	remaining: 1.91s
400:	learn: 0.2568472	total: 1.03s	remaining: 1.53s
500:	learn: 0.2364721	total: 1.24s	remaining: 1.23s
600:	learn: 0.2198285	total: 1.45s	remaining: 963ms
700:	learn: 0.2067733	total: 1.66s	remaining: 709ms
800:	learn: 0.1963333	total: 1.87s	remaining: 464ms
900:	learn: 0.1869532	total: 2.13s	remaining: 234ms
999:	learn: 0.1778376	total: 2.43s	remaining: 0us
F1: 0.6022727272727274
ROC-AUC: 0.7397137902368233
```

In [60]:
```
tabl_prec.append(round(f1_score(target_valid, predicted_valid), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('CatBoostClassifier')
tabl_not.append('upsampling')
```

In [61]:
```
table_models = (pd.DataFrame({'Model':tabl_model, 'F1 score':tabl_prec, 'ROC-AUC':tabl_roc_auc, 'Notice': tabl_not}).sort_values(by='F1 score', ascendi
                  reset_index(drop=True))
table_models
```

Out[61]:

	Model	F1 score	ROC-AUC	Notice
0	CatBoostClassifier	0.60	0.86	without_imbalance
1	CatBoostClassifier	0.60	0.74	upsampling
2	RandomForestClassifier	0.58	0.84	without_imbalance
3	RandomForestClassifier	0.58	0.81	class_weight
4	RandomForestClassifier	0.58	0.84	upsampling
5	DecisionTreeClassifier	0.56	0.81	class_weight
6	DecisionTreeClassifier	0.56	0.82	upsampling
7	DecisionTreeClassifier	0.55	0.83	without_imbalance
8	LogisticRegression	0.48	0.77	class_weight
9	LogisticRegression	0.48	0.77	upsampling
10	LogisticRegression	0.30	0.77	without_imbalance

Comparison:

By increasing the sample, we improved the LogisticRegression, DecisionTreeClassifier model. For CatBoostClassifier and RandomForestClassifier models, values are worse than before debalancing

downsampling. Sample reduction

In [62]:
```
downsample = RandomUnderSampler(random_state=12345)
```

In [63]:
```
features_downsampled, target_downsampled = downsample.fit_resample(features_train, target_train)
```

In [64]:
```
print('Size of the downsampled validation sample', len(features_downsampled))
```

```
Size of the downsampled validation sample 2438
```

Logistic Regression Model

In [65]:
```
model = LogisticRegression(solver='liblinear', random_state=12345)
model.fit(features_downsampled, target_downsampled)
predicted_valid = model.predict(features_valid)
print("F1:", f1_score(target_valid, predicted_valid))

probabilities_valid = model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1: 0.4763603925066905
AUC_ROC = 0.774
```

In [66]:
```
tabl_prec.append(round(f1_score(target_valid, predicted_valid), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('LogisticRegression')
tabl_not.append('downsampled')
```

Decision tree model

In [67]:
```
%%time
1 + 1
best_model = None
best_result = 0
for depth in range(1, 15):
        model = DecisionTreeClassifier(max_depth=depth)
        model.fit(features_downsampled, target_downsampled)
        predicted_valid = model.predict(features_valid)
        result = f1_score(target_valid, predicted_valid)
        if result > best_result:
                best_model = model
                best_result = result

print("F1 best model:", best_result)
print("max_depth best model:", best_model)

probabilities_valid = best_model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1 best model: 0.549718574108818
max_depth best model: DecisionTreeClassifier(max_depth=6)
AUC_ROC = 0.813

CPU times: user 228 ms, sys: 28 ms, total: 256 ms
Wall time: 210 ms
```

In [68]:
```
tabl_prec.append(round((best_result), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('DecisionTreeClassifier')
tabl_not.append('downsampled')
```

Random forest model

In [69]:
```
%%time
1 + 1
model = RandomForestClassifier(max_depth=17, min_samples_leaf=2, min_samples_split=12,
                       n_estimators=30, random_state=12345)
model.fit(features_downsampled, target_downsampled)
predicted_valid = model.predict(features_valid)
print("F1:", f1_score(target_valid, predicted_valid))

probabilities_valid = model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
F1: 0.5436893203883495
AUC_ROC = 0.838

CPU times: user 128 ms, sys: 0 ns, total: 128 ms
Wall time: 125 ms
```

In [70]:
```
tabl_prec.append(round(f1_score(target_valid, predicted_valid), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('RandomForestClassifier')
tabl_not.append('downsampled')
```

CatBoostClassifier

In [71]:
```
model = CatBoostClassifier(verbose=100, random_state=12345)
model.fit(features_downsampled, target_downsampled)
predicted_valid = model.predict(features_valid)
print("F1:", f1_score(target_valid, predicted_valid))

probabilities_valid = model.predict_proba(features_valid)[:, 1]
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("AUC_ROC = {:.3f}\n".format(auc_roc))
```

```
Learning rate set to 0.015073
0:      learn: 0.6858003        total: 2.1ms    remaining: 2.1s
100:    learn: 0.4611947        total: 100ms    remaining: 891ms
200:    learn: 0.4195959        total: 203ms    remaining: 806ms
300:    learn: 0.3960656        total: 342ms    remaining: 794ms
400:    learn: 0.3775319        total: 492ms    remaining: 735ms
500:    learn: 0.3599686        total: 623ms    remaining: 620ms
600:    learn: 0.3440070        total: 721ms    remaining: 479ms
700:    learn: 0.3277725        total: 819ms    remaining: 349ms
800:    learn: 0.3132693        total: 960ms    remaining: 238ms
900:    learn: 0.2992471        total: 1.12s    remaining: 123ms
999:    learn: 0.2868099        total: 1.23s    remaining: 0us
F1: 0.5731108930323846
AUC_ROC = 0.853
```

In [72]:
```
tabl_prec.append(round(f1_score(target_valid, predicted_valid), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('CatBoostClassifier')
tabl_not.append('downsampled')
```

In [73]:
```
table_models = (pd.DataFrame({'Model':tabl_model, 'F1 score':tabl_prec, 'ROC-AUC':tabl_roc_auc, 'Notice': tabl_not}).sort_values(by='F1 score', ascendi
                  reset_index(drop=True))
table_models
```

Out[73]:

	Model	F1 score	ROC-AUC	Notice
0	CatBoostClassifier	0.60	0.86	without_imbalance
1	CatBoostClassifier	0.60	0.74	upsampling
2	RandomForestClassifier	0.58	0.84	without_imbalance
3	RandomForestClassifier	0.58	0.81	class_weight
4	RandomForestClassifier	0.58	0.84	upsampling
5	CatBoostClassifier	0.57	0.85	downsampled
6	DecisionTreeClassifier	0.56	0.81	class_weight
7	DecisionTreeClassifier	0.56	0.82	upsampling
8	DecisionTreeClassifier	0.55	0.83	without_imbalance
9	DecisionTreeClassifier	0.55	0.81	downsampled
10	RandomForestClassifier	0.54	0.84	downsampled
11	LogisticRegression	0.48	0.77	class_weight
12	LogisticRegression	0.48	0.77	upsampling
13	LogisticRegression	0.48	0.77	downsampled
14	LogisticRegression	0.30	0.77	without_imbalance

Comparison:

Significantly worse performance for all models except LogisticRegression.

Changing the qualification threshold

The boundary where the negative class ends and the positive class begins is called the threshold. By default it is 0.5, but you can change it.

Logistic Regression Model

In [74]:

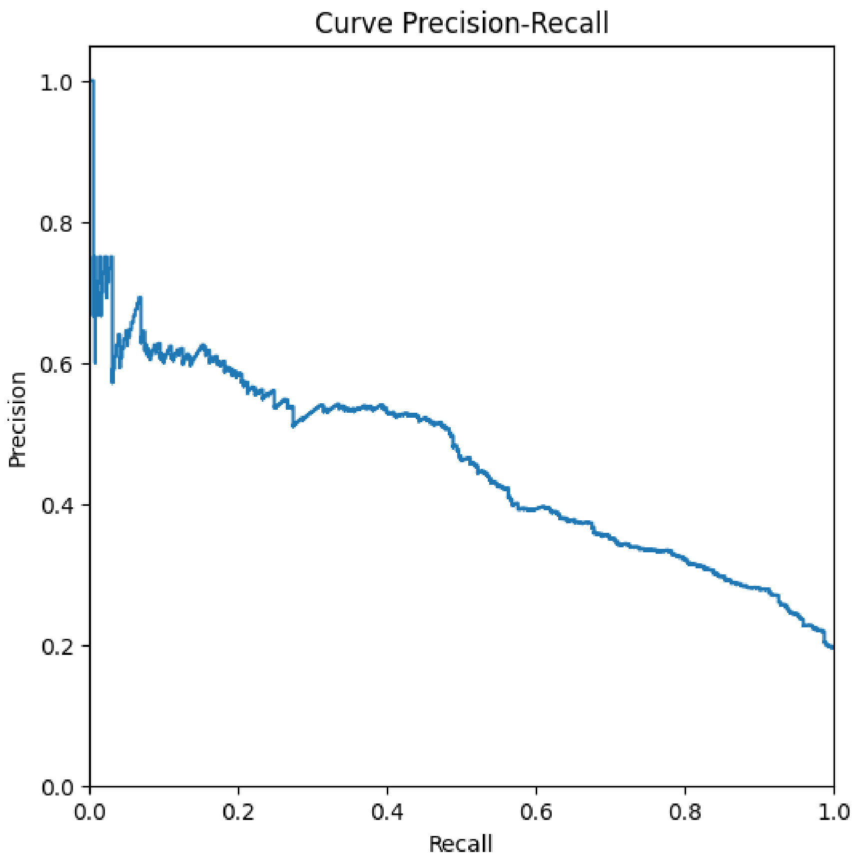
```
model = LogisticRegression(random_state=12345, solver='liblinear')
model.fit(features_train, target_train)
probabilities_valid = model.predict_proba(features_valid)[:, 1]

best_f1 = 0
for threshold in np.arange(0, 0.95, 0.05):
    predicted_valid = probabilities_valid > threshold
    precision = precision_score(target_valid, predicted_valid)
    recall = recall_score(target_valid, predicted_valid)
    F1 = f1_score(target_valid, predicted_valid)
    print("threshold = {:.2f} | precision = {:.3f}, recall = {:.3f}, F1 = {:.3f}".format(threshold, precision, recall, F1))
    if F1>best_f1:
        best_f1 = F1
```

```
auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("ROC-AUC = {:.3f}".format(auc_roc))
print("F1-мера = {:.3f}".format(best_f1))
```

```
threshold = 0.00 | precision = 0.196, recall = 1.000, F1 = 0.327
threshold = 0.05 | precision = 0.218, recall = 0.987, F1 = 0.357
threshold = 0.10 | precision = 0.265, recall = 0.926, F1 = 0.412
threshold = 0.15 | precision = 0.314, recall = 0.813, F1 = 0.453
threshold = 0.20 | precision = 0.356, recall = 0.696, F1 = 0.471
threshold = 0.25 | precision = 0.397, recall = 0.575, F1 = 0.470
threshold = 0.30 | precision = 0.458, recall = 0.514, F1 = 0.484
threshold = 0.35 | precision = 0.518, recall = 0.442, F1 = 0.477
threshold = 0.40 | precision = 0.537, recall = 0.368, F1 = 0.437
threshold = 0.45 | precision = 0.512, recall = 0.274, F1 = 0.357
threshold = 0.50 | precision = 0.570, recall = 0.207, F1 = 0.304
threshold = 0.55 | precision = 0.616, recall = 0.156, F1 = 0.249
threshold = 0.60 | precision = 0.618, recall = 0.107, F1 = 0.183
threshold = 0.65 | precision = 0.684, recall = 0.066, F1 = 0.121
threshold = 0.70 | precision = 0.609, recall = 0.036, F1 = 0.068
threshold = 0.75 | precision = 0.727, recall = 0.020, F1 = 0.040
threshold = 0.80 | precision = 0.750, recall = 0.008, F1 = 0.015
threshold = 0.85 | precision = 1.000, recall = 0.005, F1 = 0.010
threshold = 0.90 | precision = 1.000, recall = 0.003, F1 = 0.005
ROC-AUC = 0.770
F1-мера = 0.484
```

In [75]:

```
probabilities_valid = model.predict_proba(features_valid)
precision, recall, thresholds = precision_recall_curve(target_valid, probabilities_valid[:, 1])

plt.figure(figsize=(6, 6))
plt.step(recall, precision, where='post')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Curve Precision-Recall')

plt.show()
```



For a threshold of 0.30, the highest F1 and ROC-AUC

In [76]:
```
tabl_prec.append(round(best_f1, 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('LogisticRegression')
tabl_not.append('threshold=0.3')
```

In [77]:
```
table_models = (pd.DataFrame({'Model':tabl_model, 'F1 score':tabl_prec, 'ROC-AUC':tabl_roc_auc, 'Notice': tabl_not}).sort_values(by='F1 score', ascendi
                  reset_index(drop=True))
table_models
```

Out[77]:

	Model	F1 score	ROC-AUC	Notice
0	CatBoostClassifier	0.60	0.86	without_imbalance
1	CatBoostClassifier	0.60	0.74	upsampling
2	RandomForestClassifier	0.58	0.84	without_imbalance
3	RandomForestClassifier	0.58	0.81	class_weight
4	RandomForestClassifier	0.58	0.84	upsampling
5	CatBoostClassifier	0.57	0.85	downsampled
6	DecisionTreeClassifier	0.56	0.81	class_weight
7	DecisionTreeClassifier	0.56	0.82	upsampling
8	DecisionTreeClassifier	0.55	0.83	without_imbalance
9	DecisionTreeClassifier	0.55	0.81	downsampled
10	RandomForestClassifier	0.54	0.84	downsampled
11	LogisticRegression	0.48	0.77	class_weight
12	LogisticRegression	0.48	0.77	upsampling
13	LogisticRegression	0.48	0.77	downsampled
14	LogisticRegression	0.48	0.77	threshold=0.3
15	LogisticRegression	0.30	0.77	without_imbalance

Decision tree model

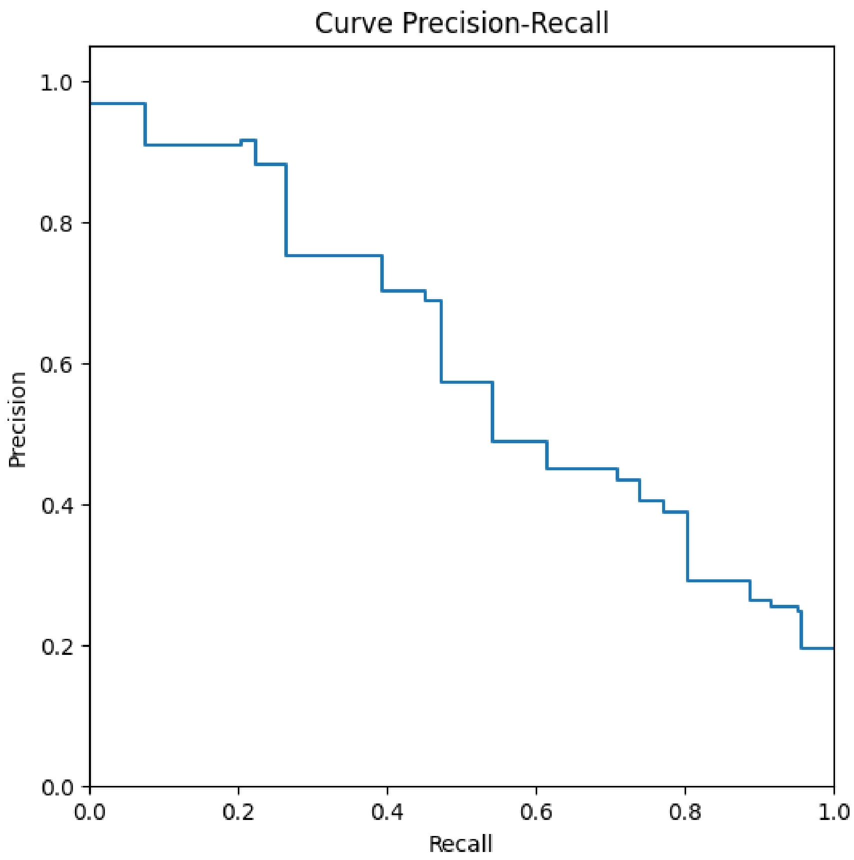
In [78]:

```
%%time
1 + 1
model = DecisionTreeClassifier(max_depth=5)
model.fit(features_train, target_train)
probabilities_valid = model.predict_proba(features_valid)[:, 1]

best_f1 = 0
for threshold in np.arange(0, 0.95, 0.05):
    predicted_valid = probabilities_valid > threshold
    precision = precision_score(target_valid, predicted_valid)
    recall = recall_score(target_valid, predicted_valid)
    F1 = f1_score(target_valid, predicted_valid)
    print("threshold = {:.2f} | precision = {:.3f}, recall = {:.3f}, F1 = {:.3f}".format(threshold, precision, recall, F1))
    if F1>best_f1:
        best_f1 = F1

auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("ROC-AUC = {:.3f}".format(auc_roc))
print("F1-мера = {:.3f}".format(best_f1))
```

```
threshold = 0.00 | precision = 0.194, recall = 0.992, F1 = 0.325
threshold = 0.05 | precision = 0.248, recall = 0.957, F1 = 0.393
threshold = 0.10 | precision = 0.389, recall = 0.803, F1 = 0.524
threshold = 0.15 | precision = 0.389, recall = 0.803, F1 = 0.524
threshold = 0.20 | precision = 0.434, recall = 0.724, F1 = 0.543
threshold = 0.25 | precision = 0.573, recall = 0.542, F1 = 0.557
threshold = 0.30 | precision = 0.573, recall = 0.542, F1 = 0.557
threshold = 0.35 | precision = 0.573, recall = 0.542, F1 = 0.557
threshold = 0.40 | precision = 0.688, recall = 0.473, F1 = 0.561
threshold = 0.45 | precision = 0.688, recall = 0.473, F1 = 0.561
threshold = 0.50 | precision = 0.701, recall = 0.450, F1 = 0.548
threshold = 0.55 | precision = 0.751, recall = 0.394, F1 = 0.517
threshold = 0.60 | precision = 0.873, recall = 0.263, F1 = 0.405
threshold = 0.65 | precision = 0.873, recall = 0.263, F1 = 0.405
threshold = 0.70 | precision = 0.880, recall = 0.263, F1 = 0.406
threshold = 0.75 | precision = 0.880, recall = 0.263, F1 = 0.406
threshold = 0.80 | precision = 0.880, recall = 0.263, F1 = 0.406
threshold = 0.85 | precision = 0.916, recall = 0.223, F1 = 0.358
threshold = 0.90 | precision = 0.908, recall = 0.202, F1 = 0.331
ROC-AUC = 0.821
F1-мера = 0.561
CPU times: user 96 ms, sys: 0 ns, total: 96 ms
Wall time: 96.8 ms
```

In [79]:

```python
probabilities_valid = model.predict_proba(features_valid)
precision, recall, thresholds = precision_recall_curve(target_valid, probabilities_valid[:, 1])

plt.figure(figsize=(6, 6))
plt.step(recall, precision, where='post')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Curve Precision-Recall')
plt.show()
```



For a threshold of 0.4, the highest F1

In [80]:
```
tabl_prec.append(round(best_f1, 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('DecisionTreeClassifier')
tabl_not.append('threshold=0.4')
```

In [81]:
```
table_models = (pd.DataFrame({'Model':tabl_model, 'F1 score':tabl_prec, 'ROC-AUC':tabl_roc_auc, 'Notice': tabl_not}).sort_values(by='F1 score', ascendi
                  reset_index(drop=True))
table_models
```

Out[81]:

	Model	F1 score	ROC-AUC	Notice
0	CatBoostClassifier	0.60	0.86	without_imbalance
1	CatBoostClassifier	0.60	0.74	upsampling
2	RandomForestClassifier	0.58	0.84	upsampling
3	RandomForestClassifier	0.58	0.84	without_imbalance
4	RandomForestClassifier	0.58	0.81	class_weight
5	CatBoostClassifier	0.57	0.85	downsampled
6	DecisionTreeClassifier	0.56	0.82	upsampling
7	DecisionTreeClassifier	0.56	0.82	threshold=0.4
8	DecisionTreeClassifier	0.56	0.81	class_weight
9	DecisionTreeClassifier	0.55	0.83	without_imbalance
10	DecisionTreeClassifier	0.55	0.81	downsampled
11	RandomForestClassifier	0.54	0.84	downsampled
12	LogisticRegression	0.48	0.77	upsampling
13	LogisticRegression	0.48	0.77	downsampled
14	LogisticRegression	0.48	0.77	class_weight
15	LogisticRegression	0.48	0.77	threshold=0.3
16	LogisticRegression	0.30	0.77	without_imbalance

Random forest model

In [82]:

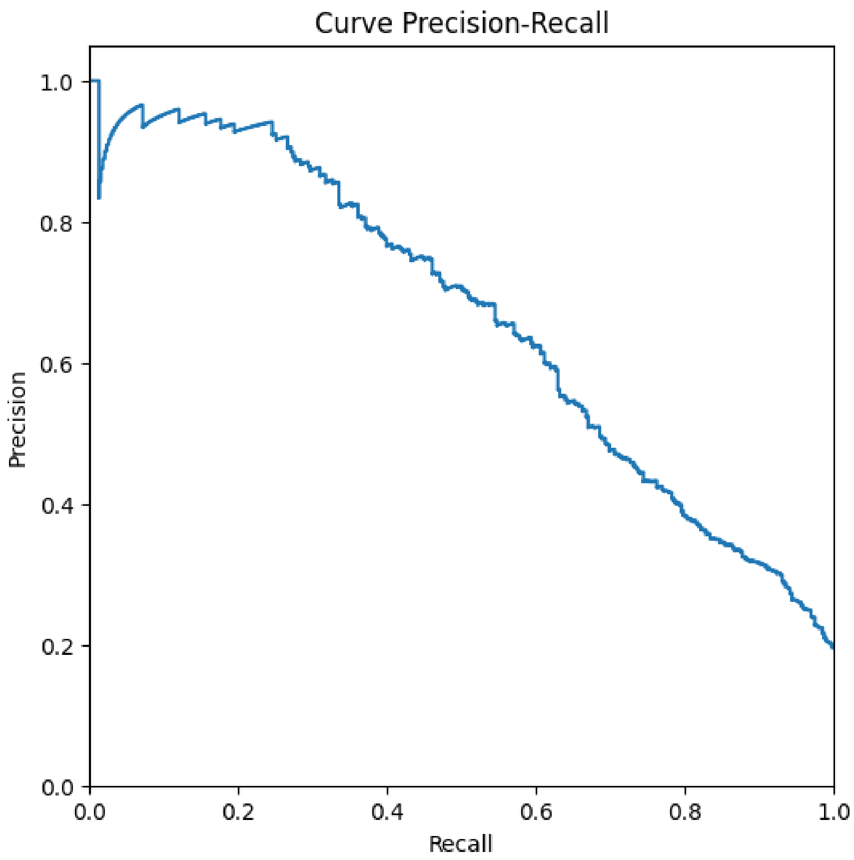
```
%%time
1 + 1
model = RandomForestClassifier(max_depth=17, min_samples_leaf=2, min_samples_split=12,
                               n_estimators=30, random_state=12345)

model.fit(features_train, target_train)
probabilities_valid = model.predict_proba(features_valid)[:, 1]

best_f1 = 0

for threshold in np.arange(0, 0.95, 0.05):
    predicted_valid = probabilities_valid > threshold
    precision = precision_score(target_valid, predicted_valid)
    recall = recall_score(target_valid, predicted_valid)
    F1 = f1_score(target_valid, predicted_valid)
    print("threshold = {:.2f} | precision = {:.3f}, recall = {:.3f}, F1 = {:.3f}".format(threshold, precision, recall, F1))
    if F1>best_f1:
        best_f1 = F1

auc_roc = roc_auc_score(target_valid, probabilities_valid)
```

```
print("ROC-AUC = {:.3f}".format(auc_roc))
print("F1-мера = {:.3f}".format(best_f1))
```

```
threshold = 0.00 | precision = 0.198, recall = 0.997, F1 = 0.331
threshold = 0.05 | precision = 0.251, recall = 0.959, F1 = 0.398
threshold = 0.10 | precision = 0.313, recall = 0.908, F1 = 0.465
threshold = 0.15 | precision = 0.360, recall = 0.829, F1 = 0.502
threshold = 0.20 | precision = 0.422, recall = 0.770, F1 = 0.545
threshold = 0.25 | precision = 0.479, recall = 0.698, F1 = 0.568
threshold = 0.30 | precision = 0.543, recall = 0.642, F1 = 0.589
threshold = 0.35 | precision = 0.628, recall = 0.596, F1 = 0.612
threshold = 0.40 | precision = 0.683, recall = 0.540, F1 = 0.603
threshold = 0.45 | precision = 0.706, recall = 0.478, F1 = 0.570
threshold = 0.50 | precision = 0.760, recall = 0.430, F1 = 0.549
threshold = 0.55 | precision = 0.784, recall = 0.389, F1 = 0.520
threshold = 0.60 | precision = 0.822, recall = 0.355, F1 = 0.496
threshold = 0.65 | precision = 0.866, recall = 0.315, F1 = 0.462
threshold = 0.70 | precision = 0.886, recall = 0.279, F1 = 0.424
threshold = 0.75 | precision = 0.941, recall = 0.243, F1 = 0.386
threshold = 0.80 | precision = 0.944, recall = 0.171, F1 = 0.290
threshold = 0.85 | precision = 0.951, recall = 0.100, F1 = 0.181
threshold = 0.90 | precision = 0.941, recall = 0.041, F1 = 0.078
ROC-AUC = 0.843
F1-мера = 0.612
CPU times: user 276 ms, sys: 0 ns, total: 276 ms
Wall time: 279 ms
```

In [83]:

```
probabilities_valid = model.predict_proba(features_valid)
precision, recall, thresholds = precision_recall_curve(target_valid, probabilities_valid[:, 1])

plt.figure(figsize=(6, 6))
plt.step(recall, precision, where='post')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Curve Precision-Recall')
plt.show()
```



For a threshold of 0.35, the highest F1

In [84]:
```
tabl_prec.append(round(best_f1, 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('RandomForestClassifier')
tabl_not.append('threshold=0.35')
```

In [85]:
```
%%time
1 + 1
model = CatBoostClassifier(verbose=100, random_state=12345)

model.fit(features_train, target_train)
probabilities_valid = model.predict_proba(features_valid)[:, 1]

best_f1 = 0

for threshold in np.arange(0, 0.95, 0.05):
    predicted_valid = probabilities_valid > threshold
    precision = precision_score(target_valid, predicted_valid)
```

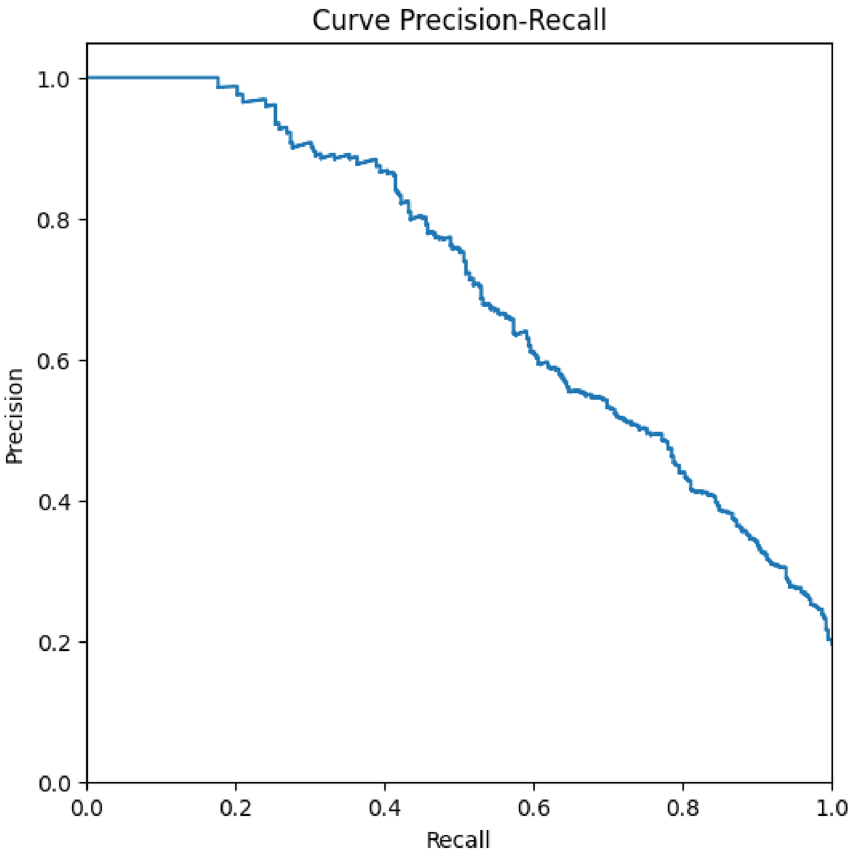
```
    recall = recall_score(target_valid, predicted_valid)
    F1 = f1_score(target_valid, predicted_valid)
    print("threshold = {:.2f} | precision = {:.3f}, recall = {:.3f}, F1 = {:.3f}".format(threshold, precision, recall, F1))
    if F1>best_f1:
        best_f1 = F1

auc_roc = roc_auc_score(target_valid, probabilities_valid)
print("ROC-AUC = {:.3f}".format(auc_roc))
print("F1-мера = {:.3f}".format(best_f1))
```

```
Learning rate set to 0.022141
0:      learn: 0.6754999        total: 5.13ms   remaining: 5.12s
100:    learn: 0.3343972        total: 193ms    remaining: 1.72s
200:    learn: 0.3110064        total: 335ms    remaining: 1.33s
300:    learn: 0.2963858        total: 533ms    remaining: 1.24s
400:    learn: 0.2844886        total: 757ms    remaining: 1.13s
500:    learn: 0.2741070        total: 902ms    remaining: 898ms
600:    learn: 0.2646223        total: 1.1s     remaining: 733ms
700:    learn: 0.2550124        total: 1.3s     remaining: 556ms
800:    learn: 0.2456157        total: 1.45s    remaining: 359ms
900:    learn: 0.2361567        total: 1.66s    remaining: 182ms
999:    learn: 0.2277176        total: 1.87s    remaining: 0us
threshold = 0.00 | precision = 0.196, recall = 1.000, F1 = 0.327
threshold = 0.05 | precision = 0.281, recall = 0.944, F1 = 0.433
threshold = 0.10 | precision = 0.364, recall = 0.877, F1 = 0.515
threshold = 0.15 | precision = 0.433, recall = 0.803, F1 = 0.562
threshold = 0.20 | precision = 0.501, recall = 0.752, F1 = 0.601
threshold = 0.25 | precision = 0.542, recall = 0.696, F1 = 0.609
threshold = 0.30 | precision = 0.588, recall = 0.621, F1 = 0.604
threshold = 0.35 | precision = 0.634, recall = 0.575, F1 = 0.603
threshold = 0.40 | precision = 0.672, recall = 0.545, F1 = 0.602
threshold = 0.45 | precision = 0.723, recall = 0.514, F1 = 0.601
threshold = 0.50 | precision = 0.767, recall = 0.488, F1 = 0.597
threshold = 0.55 | precision = 0.801, recall = 0.453, F1 = 0.578
threshold = 0.60 | precision = 0.821, recall = 0.422, F1 = 0.557
threshold = 0.65 | precision = 0.867, recall = 0.402, F1 = 0.549
threshold = 0.70 | precision = 0.878, recall = 0.368, F1 = 0.519
threshold = 0.75 | precision = 0.887, recall = 0.320, F1 = 0.470
threshold = 0.80 | precision = 0.902, recall = 0.284, F1 = 0.432
threshold = 0.85 | precision = 0.960, recall = 0.246, F1 = 0.391
threshold = 0.90 | precision = 0.987, recall = 0.199, F1 = 0.332
ROC-AUC = 0.864
F1-мера = 0.609
CPU times: user 5.09 s, sys: 452 ms, total: 5.54 s
Wall time: 2.04 s
```

In [86]:

```
probabilities_valid = model.predict_proba(features_valid)
precision, recall, thresholds = precision_recall_curve(target_valid, probabilities_valid[:, 1])

plt.figure(figsize=(6, 6))
plt.step(recall, precision, where='post')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
```

```
plt.title('Curve Precision-Recall')
plt.show()
```



The highest score with a threshold of 0.25

In [87]:
```
tabl_prec.append(round(best_f1, 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('CatBoostClassifier')
tabl_not.append('threshold=0.25')
```

In [88]:
```
table_models = (pd.DataFrame({'Model':tabl_model, 'F1 score':tabl_prec, 'ROC-AUC':tabl_roc_auc, 'Notice': tabl_not}).sort_values(by='F1 score', ascendi
                  reset_index(drop=True))
table_models
```

Out[88]:

	Model	F1 score	ROC-AUC	Notice
0	CatBoostClassifier	0.61	0.86	threshold=0.25
1	RandomForestClassifier	0.61	0.84	threshold=0.35
2	CatBoostClassifier	0.60	0.86	without_imbalance
3	CatBoostClassifier	0.60	0.74	upsampling
4	RandomForestClassifier	0.58	0.81	class_weight
5	RandomForestClassifier	0.58	0.84	upsampling
6	RandomForestClassifier	0.58	0.84	without_imbalance
7	CatBoostClassifier	0.57	0.85	downsampled
8	DecisionTreeClassifier	0.56	0.81	class_weight
9	DecisionTreeClassifier	0.56	0.82	upsampling
10	DecisionTreeClassifier	0.56	0.82	threshold=0.4
11	DecisionTreeClassifier	0.55	0.83	without_imbalance
12	DecisionTreeClassifier	0.55	0.81	downsampled
13	RandomForestClassifier	0.54	0.84	downsampled
14	LogisticRegression	0.48	0.77	upsampling
15	LogisticRegression	0.48	0.77	class_weight
16	LogisticRegression	0.48	0.77	downsampled
17	LogisticRegression	0.48	0.77	threshold=0.3
18	LogisticRegression	0.30	0.77	without_imbalance

Comparison:

Changing the qualification threshold was able to significantly improve the models.

Conclusion

We have determined the two most successful models - CatBoostClassifier with the best F1-measure and ROC-AUC measure obtained with threshold=0.25 and RandomForestClassifier with threshold 0.3. Let's try to find the optimal hyperparameters for it. 1. In addition, we found that if there is an imbalance for our task, the best option is to change the threshold for RandomForestClassifier and a little for CatBoostClassifier. 2. The increase in the sample proved to be better than its decrease. But not suitable for CatBoostClassifier and RandomForestClassifier

Hyperparameter optimization for random forest model

Stage 1. RandomizedSearchCV

You can start with the RandomizedSearchCV algorithm, which allows you to pretty roughly explore wide ranges of values. We will check on the sample (other), with the class_weight = {1:3.5} parameter using cross-validation. We get the base model, we will check it by the F1-measure.

In [89]:

```
%%time
1 + 1
n_estimators = [int(x) for x in np.linspace(start = 2, stop = 100, num = 25)]
max_features = ['log2', 'sqrt']
max_depth = [int(x) for x in np.linspace(start = 1, stop = 20, num = 20)]
min_samples_split = [int(x) for x in np.linspace(start = 2, stop = 50, num = 25)]
min_samples_leaf = [int(x) for x in np.linspace(start = 2, stop = 50, num = 25)]
bootstrap = [True, False]
class_weight = [{1:3.5}, {1:3.6}, {1:3.4},]
#As we work, we generate a param_dist entity containing, for each hyperparameter, the range of values to be tested
param_dist = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap,
             'class_weight': class_weight}
model = RandomizedSearchCV(RandomForestClassifier(),
                        param_dist,
                        n_iter = 100,
                        cv = 5,
                        verbose = 1,
                        n_jobs=-1,
                        random_state=12345,
                        scoring = 'f1')
model.fit(features_other, target_other)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
CPU times: user 1.4 s, sys: 184 ms, total: 1.58 s
Wall time: 57.4 s
```

Out[89]:

```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier
```

- **With parameter values n_iter = 100 and cv = 5, we created 500 RF models by randomly selecting combinations of the above hyperparameters**
- **In order to find out in what range of values it is worth continuing the search, we can easily get a dataframe containing the results of the RandomizedSearchCV algorithm.**

In [90]:

```
rs_df = pd.DataFrame(model.cv_results_).sort_values('rank_test_score').reset_index(drop=True)
rs_df = rs_df.drop([
            'mean_fit_time',
            'std_fit_time',
            'mean_score_time',
            'std_score_time',
```

```
            'params',
            'split0_test_score',
            'split1_test_score',
            'split2_test_score',
            'std_test_score'],
            axis=1)
rs_df
```

Out[90]:

	param_n_estimators	param_min_samples_split	param_min_samples_leaf	param_max_features	param_max_depth	param_class_weight	param_bootstrap	split3_test_score	split4_test_score
0	91	34	4	log2	8	{1: 3.4}	True	0.619760	0.640118
1	83	34	8	log2	19	{1: 3.4}	True	0.633484	0.635015
2	83	30	8	log2	10	{1: 3.6}	False	0.628492	0.647383
3	55	8	6	log2	11	{1: 3.6}	False	0.622807	0.640580
4	42	36	2	sqrt	15	{1: 3.5}	True	0.626687	0.640580
...	...	...	...	...	...	...	...	...	...
95	91	50	34	sqrt	1	{1: 3.6}	True	0.568012	0.526718
96	42	50	16	log2	1	{1: 3.5}	False	0.515235	0.567119
97	2	24	4	log2	17	{1: 3.6}	True	0.519774	0.543011
98	59	40	28	sqrt	1	{1: 3.4}	False	0.558870	0.526316
99	22	28	34	log2	1	{1: 3.5}	False	0.488372	0.528160

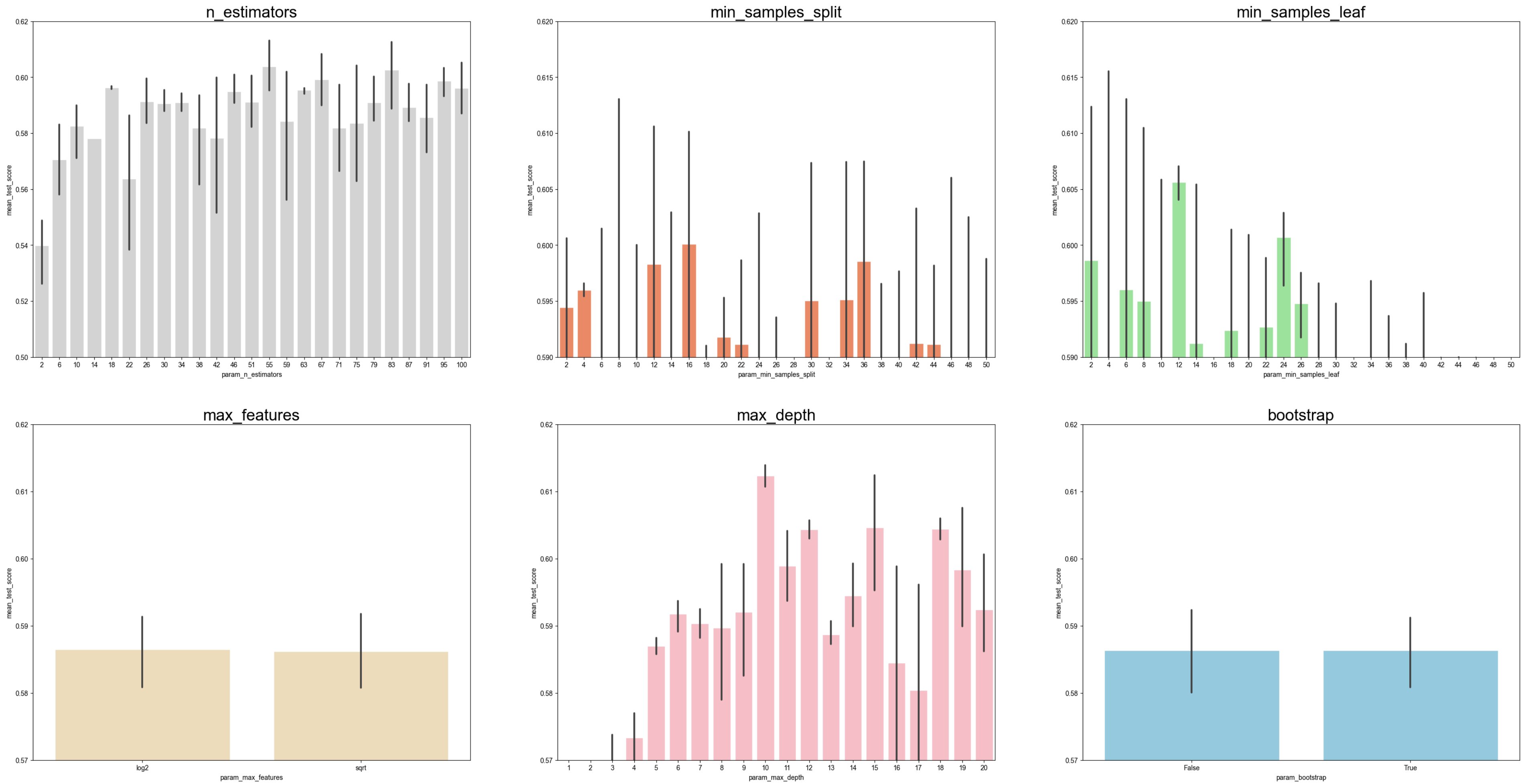
100 rows × 11 columns

Now let's create bar graphs, on which, along the x-axis, the values of hyperparameters are located, and along the y-axis, the average values shown by the models. This will allow you to understand which hyperparameter values, on average, perform best.

In [91]:

```
fig, axs = plt.subplots(ncols=3, nrows=2)
sns.set(style="whitegrid", color_codes=True, font_scale = 2)
fig.set_size_inches(40,20)
sns.barplot(x='param_n_estimators', y='mean_test_score', data=rs_df, ax=axs[0,0], color='lightgrey')
axs[0,0].set_ylim([.5,.62])
axs[0,0].set_title('n_estimators')

sns.barplot(x='param_min_samples_split', y='mean_test_score', data=rs_df, ax=axs[0,1], color='coral')
axs[0,1].set_ylim([.59,.62])
axs[0,1].set_title('min_samples_split')

sns.barplot(x='param_min_samples_leaf', y='mean_test_score', data=rs_df, ax=axs[0,2], color='lightgreen')
axs[0,2].set_ylim([.59,.62])
axs[0,2].set_title('min_samples_leaf')

sns.barplot(x='param_max_features', y='mean_test_score', data=rs_df, ax=axs[1,0], color='wheat')
axs[1,0].set_ylim([.57,.62])
axs[1,0].set_title('max_features')
```

```
sns.barplot(x='param_max_depth', y='mean_test_score', data=rs_df, ax=axs[1,1], color='lightpink')
axs[1,1].set_ylim([.57,.62])
axs[1,1].set_title('max_depth')

sns.barplot(x='param_bootstrap',y='mean_test_score', data=rs_df, ax=axs[1,2], color='skyblue')
axs[1,2].set_ylim([.57,.62])
axs[1,2].set_title('bootstrap')

plt.show()
```



Analyzing the graphs, you can see some patterns:

1. **n_estimators - choose the best parameters 55, 67, 83**
2. **min_samples_split - choose the best parameters 12, 16, 36**
3. **min_samples_leaf - choose the best parameters 4, 8, 12.**

4. max_features - variant of log2 and sqrt
5. max_depth - choose the best parameters 10, 15, 18
6. bootstrap - True and False option

Stage 2. Hyperparameter optimization. GridSearchCV

In [92]:

```
%%time
1 + 1
n_estimators = [55, 67, 83]
max_features = ['log2', 'sqrt']
max_depth = [10, 15, 18]
min_samples_split = [12, 16, 36]
min_samples_leaf = [4, 8, 12]
bootstrap = [True, False]
class_weight = [{1:3.5}, {1:3.6}, {1:3.4},]
param_dist = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap,
             'class_weight': class_weight}
model = GridSearchCV(RandomForestClassifier(),
                     param_dist,
                     cv = 3,
                     verbose = 1,
                     n_jobs=-1)
model.fit(features_other, target_other)
```

```
Fitting 3 folds for each of 972 candidates, totalling 2916 fits
CPU times: user 5.89 s, sys: 548 ms, total: 6.44 s
Wall time: 6min 29s
```

Out[92]:

```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

The best model is stored in the best*estimator* attribute

gsearch.best*estimator* The score of the best model obtained through cross-validation is stored in the best*score* attribute

gsearch.best*score* The parameters of the best model are stored in the attribute best*params*

gsearch.best*params* Thus, having once trained the GridSearchCV object, we immediately get both the best model and the best hyperparameters and the model score obtained using cross-validation. And there is no need for additional training of the model and determination of metrics for the selected validation set.

In [93]:

```
model.best_estimator_
```

Out[93]:

```
RandomForestClassifier
RandomForestClassifier(class_weight={1: 3.4}, max_depth=18, max_features='log2',
                       min_samples_leaf=4, min_samples_split=12,
                       n_estimators=67)
```

In [94]:

```
model.best_score_
```

Out[94]:

```
0.8513761830033811
```

Above the threshold of 0.59 on the validation set and the test set. Let's try on a test sample and see how the model behaves on unfamiliar data

Hyperparameter optimization for the CatBoostClassifier model

Let's try to set up Catboost using cross-validation. We get the base model, we will check it by the F1-measure.

In [95]:

```
model_cat = CatBoostClassifier(custom_loss=['F1'], random_seed=12345, logging_level='Silent')
```

In [96]:

```
model_cat.fit(features_train, target_train, eval_set=(features_valid, target_valid))
```

Out[96]:

```
<catboost.core.CatBoostClassifier at 0x7fb367d264f0>
```

Let's cross-validate using the built-in Pool function

In [97]:

```
cv_params = model_cat.get_params()
cv_params.update({'loss_function': 'Logloss'})
cv_data = cv(Pool(features_train, target_train),cv_params)
```

In [98]:

```
cv_params
```

Out[98]:

```
{'random_seed': 12345,
 'logging_level': 'Silent',
 'custom_loss': ['F1'],
 'loss_function': 'Logloss'}
```

In [99]:

```
print('F1-мера: {}'.format(np.max(cv_data['test-F1-mean'])))
```

```
F1-мера: 0.5978681578885929
```

In [100…

```
probabilities_valid = model_cat.predict_proba(features_valid)[:, 1]

auc_roc = roc_auc_score (target_valid, probabilities_valid)

print("AUC:", auc_roc)
```

```
AUC: 0.867969334895306
```

Above the threshold of 0.59 on the validation set and the test set. Good readings of the ROC-AUC metric Let's try it on a test set and see how the model behaves on unfamiliar data

Conclusion

We selected optimal hyperparameters with the best F1-measure for RandomForestClassifier(class_weight='balanced', max_depth=19, min_samples_leaf=2, min_samples_split=10,n_estimators=30, random_state=12345)

Model testing

RandomForestClassifier

In [101…

```
model = RandomForestClassifier(class_weight={1: 3.4}, max_depth=18, min_samples_leaf=4,
                       min_samples_split=12, n_estimators=83,
                       random_state=12345)

model_rfc1 = model.fit(features_train, target_train)
predicted_test = model_rfc1.predict(features_test)
print("F1= {:.3f}\n".format(f1_score(target_test, predicted_test)))

probabilities_test = model.predict_proba(features_test)[:, 1]
auc_roc = roc_auc_score(target_test, probabilities_test)
print("AUC_ROC = {:.3f}\n".format(auc_roc))

print("Accuracy = {:.3f}\n".format(accuracy_score(target_test, predicted_test)))

print("Recall = {:.3f}\n".format(recall_score(target_test, predicted_test)))

print("Precision= {:.3f}\n".format(precision_score(target_test, predicted_test)))
```

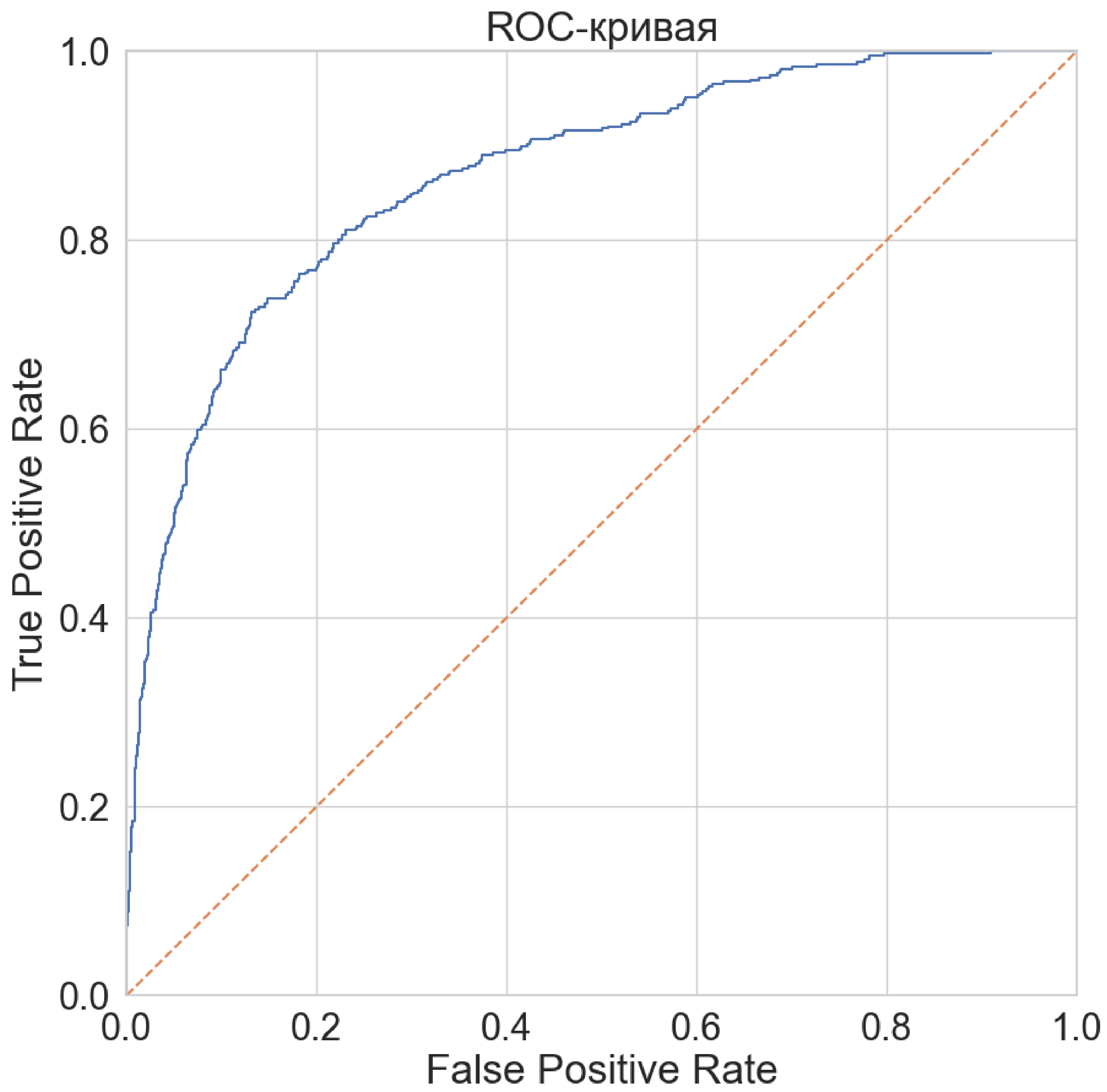
```
F1= 0.636

AUC_ROC = 0.868

Accuracy = 0.851

Recall = 0.611

Precision= 0.662
```

To find out how much our model differs from the random one, let's calculate the area under the ROC curve - AUCZROC (Area Under Curve ROC). This is a new quality metric that ranges from 0 to 1. The AUCZROC of a random model is 0.5.

In [102…

```
fpr, tpr, thresholds = roc_curve(target_test, probabilities_test)

plt.figure(figsize=(10, 10))
plt.plot(fpr, tpr, linestyle='-')
plt.plot([0, 1], [0, 1], linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title('ROC-кривая')
plt.show()

auc_roc = roc_auc_score(target_test, probabilities_test)

print("AUC:", auc_roc)
```


ROC-кривая
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
True Positive Rate
False Positive Rate

```
AUC: 0.8682316193493542
```

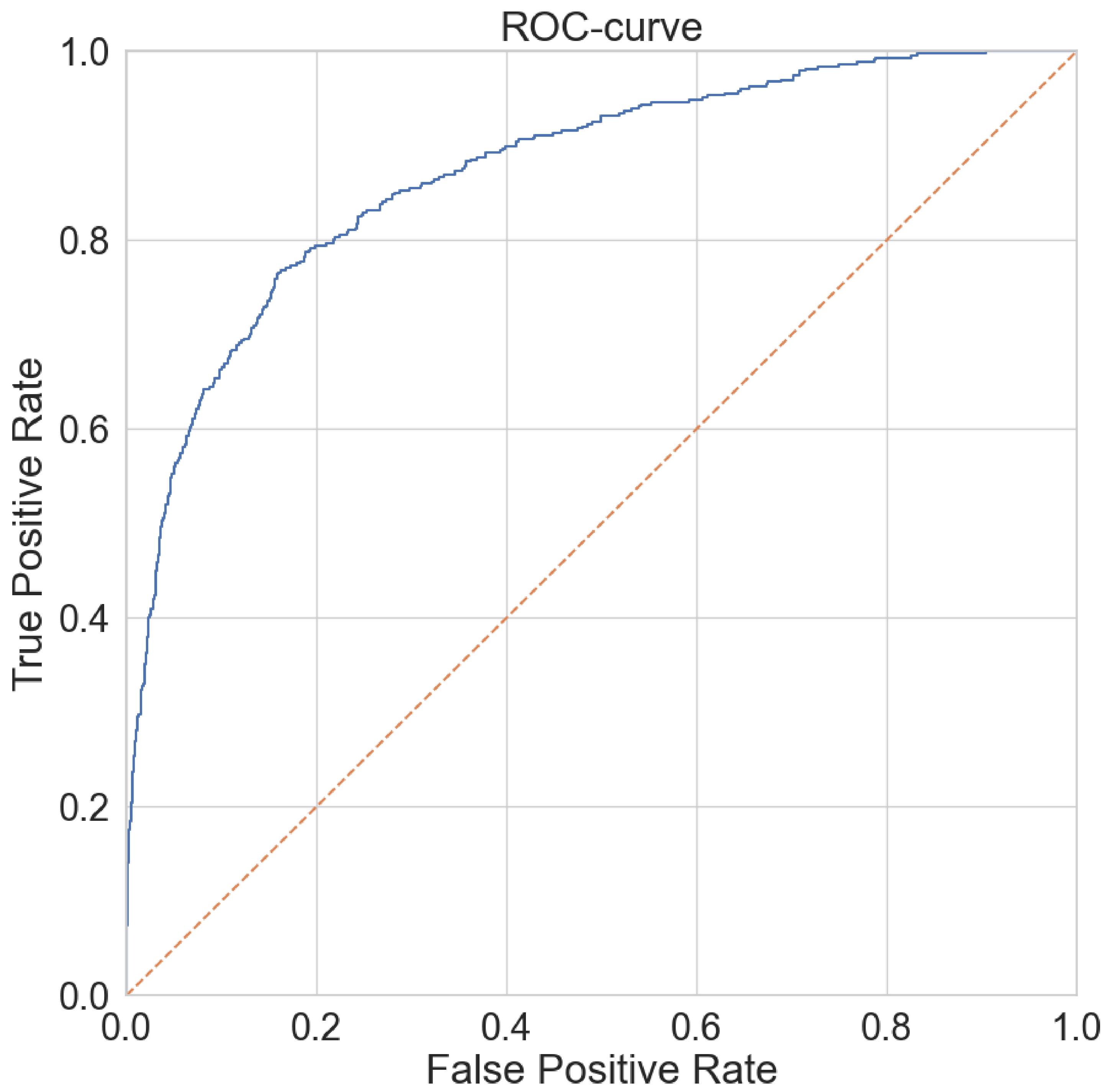
In [103…
```python
tabl_prec.append(round(f1_score(target_test, predicted_test), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('RandomForestClassifier')
tabl_not.append('test')
```

CatBoostClassifier

In [104…
```python
model_cat = CatBoostClassifier(random_seed=42,logging_level= 'Silent',custom_loss= ['F1'], loss_function= 'Logloss')
model_cat = model_cat.fit(features_train, target_train)
predicted_test = model_cat.predict(features_test)
print("F1= {:.3f}\n".format(f1_score(target_test, predicted_test)))

probabilities_test = model_cat.predict_proba(features_test)[:, 1]
auc_roc = roc_auc_score(target_test, probabilities_test)
print("AUC_ROC = {:.3f}\n".format(auc_roc))

print("Accuracy = {:.3f}\n".format(accuracy_score(target_test, predicted_test)))

print("Recall = {:.3f}\n".format(recall_score(target_test, predicted_test)))

print("Precision= {:.3f}\n".format(precision_score(target_test, predicted_test)))
```

```
F1= 0.591

AUC_ROC = 0.873

Accuracy = 0.860

Recall = 0.473

Precision= 0.786
```

In [105…
```python
fpr, tpr, thresholds = roc_curve(target_test, probabilities_test)

plt.figure(figsize=(10, 10))
plt.plot(fpr, tpr, linestyle='-')
plt.plot([0, 1], [0, 1], linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC-curve')
plt.show()

auc_roc = roc_auc_score(target_test, probabilities_test)

print("AUC:", auc_roc)
```


ROC-curve
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate

```
AUC: 0.8729050383297775
```

In [106…
```
tabl_prec.append(round(f1_score(target_test, predicted_test), 2))
tabl_roc_auc.append(round(auc_roc,2))
tabl_model.append('CatBoostClassifier')
tabl_not.append('test')
```

In [107…
```
table_models = (pd.DataFrame({'Model':tabl_model, 'F1 score':tabl_prec, 'ROC-AUC':tabl_roc_auc, 'Notice': tabl_not}).sort_values(by='F1 score', ascendi
                  reset_index(drop=True))
table_models
```

Out[107]:

	Model	F1 score	ROC-AUC	Notice
0	RandomForestClassifier	0.64	0.87	test
1	RandomForestClassifier	0.61	0.84	threshold=0.35
2	CatBoostClassifier	0.61	0.86	threshold=0.25
3	CatBoostClassifier	0.60	0.74	upsampling
4	CatBoostClassifier	0.60	0.86	without_imbalance
5	CatBoostClassifier	0.59	0.87	test
6	RandomForestClassifier	0.58	0.81	class_weight
7	RandomForestClassifier	0.58	0.84	upsampling
8	RandomForestClassifier	0.58	0.84	without_imbalance
9	CatBoostClassifier	0.57	0.85	downsampled
10	DecisionTreeClassifier	0.56	0.82	upsampling
11	DecisionTreeClassifier	0.56	0.82	threshold=0.4
12	DecisionTreeClassifier	0.56	0.81	class_weight
13	DecisionTreeClassifier	0.55	0.83	without_imbalance
14	DecisionTreeClassifier	0.55	0.81	downsampled
15	RandomForestClassifier	0.54	0.84	downsampled
16	LogisticRegression	0.48	0.77	upsampling
17	LogisticRegression	0.48	0.77	downsampled
18	LogisticRegression	0.48	0.77	threshold=0.3
19	LogisticRegression	0.48	0.77	class_weight
20	LogisticRegression	0.30	0.77	without_imbalance

In [108…
```
model_cat.feature_importances_
```

Out[108]:
```
array([11.41660844,  3.05358441, 18.84085193,  7.43120884, 13.65095016,
       18.49680806,  1.12665484,  6.98735623, 10.81494697,  6.24856825,
        1.93246187])
```

In [109…
```
model_rfc1.feature_importances_
```

Out[109]:
```
array([0.09894422, 0.02281794, 0.30112186, 0.05756063, 0.13047728,
       0.16040435, 0.01282303, 0.05518014, 0.10138008, 0.04774879,
       0.01154167])
```

In [110…
```
features_test.columns
```

Out[110]:
```
Index(['credit_score', 'gender', 'age', 'tenure', 'balance', 'num_of_products',
       'has_cr_card', 'is_active_member', 'estimated_salary', 'Germany',
       'Spain'],
      dtype='object')
```

In [111…
```
f1_table = pd.DataFrame({'name':features_test.columns,'f1_table':model_rfc1.feature_importances_,'f2_table':model_cat.feature_importances_})
f1_table.sort_values('f1_table',ascending=False)
```

Out[111]:

	name	f1_table	f2_table
2	age	0.301122	18.840852
5	num_of_products	0.160404	18.496808
4	balance	0.130477	13.650950
8	estimated_salary	0.101380	10.814947
0	credit_score	0.098944	11.416608
3	tenure	0.057561	7.431209
7	is_active_member	0.055180	6.987356
9	Germany	0.047749	6.248568
1	gender	0.022818	3.053584
6	has_cr_card	0.012823	1.126655
10	Spain	0.011542	1.932462

Conclusion

The most important signs that bank marketers should pay attention to:

1. **customer age**
2. **the number of bank products used by the client**
3. **account balance**
4. **estimated salary**
5. **credit score**

To predict churn, you can use a model based on the Random Forest algorithm with the parameters RandomForestClassifier(class_weight={1: 3.4}, max_depth=18, min_samples_leaf=4,min_samples_split=12, n_estimators=83) and the CatBoostClassifier model(random_seed=42,logging_level= 'Silent',custom_loss= ['F1'], loss_function= 'Logloss')