Чем лучше бустить? Тестируем алгоритмы бустинга в бою.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
!pip install catboost
```

```
Requirement already satisfied: catboost in /usr/local/lib/python3.7/dist-packages (0.25)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.7/dist-packages (from catboost) (1.19.5)
Requirement already satisfied: graphviz in /usr/local/lib/python3.7/dist-packages (from catboost) (0.10.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from catboost) (1.4.1)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from catboost) (1.15.0)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-packages (from catboost) (3.2.2)
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.7/dist-packages (from catboost) (1.1.5)
Requirement already satisfied: plotly in /usr/local/lib/python3.7/dist-packages (from catboost) (4.4.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib->catboost) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->catbo
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->catboost) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->catboost) (1.3.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.24.0->catboost) (2018.9)
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.7/dist-packages (from plotly->catboost) (1.3.3)
```

Часть 1. EDA, Часть 2. Preprocessing & Feature Engineering

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

from sklearn.preprocessing import LabelEncoder
```

```
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split,cross_val_score, StratifiedKFold, GridSearchCV
from sklearn.metrics import accuracy_score,confusion_matrix,roc_auc_score,roc_curve,classification_report, precision_score, recall_score, f1_sc
from xgboost.sklearn import XGBClassifier
from catboost import CatBoostClassifier
from lightgbm import LGBMClassifier
```

```
%matplotlib inline
plt.rcParams["figure.figsize"] = (12,8)
```

```
data = pd.read_csv('/content/drive/MyDrive/STUDY/otus/HW/3/WA_Fn-UseC_-Telco-Customer-Churn.csv')
```

```
data.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBa
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	

проверка на дубликаты

```
data[data.duplicated(['customerID'], keep=False)]
```

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBacl

```
data.describe()
```

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

```
data.columns
```

```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
```

```
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

```
data.tail()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	Onlin
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	DSL	Yes	
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	No	
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	DSL	Yes	
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes	Fiber optic	No	
7042	3186-AJIEK	Male	0	No	No	66	Yes	No	Fiber optic	Yes	

проверим на пропуски

```
data.isnull().sum()
```

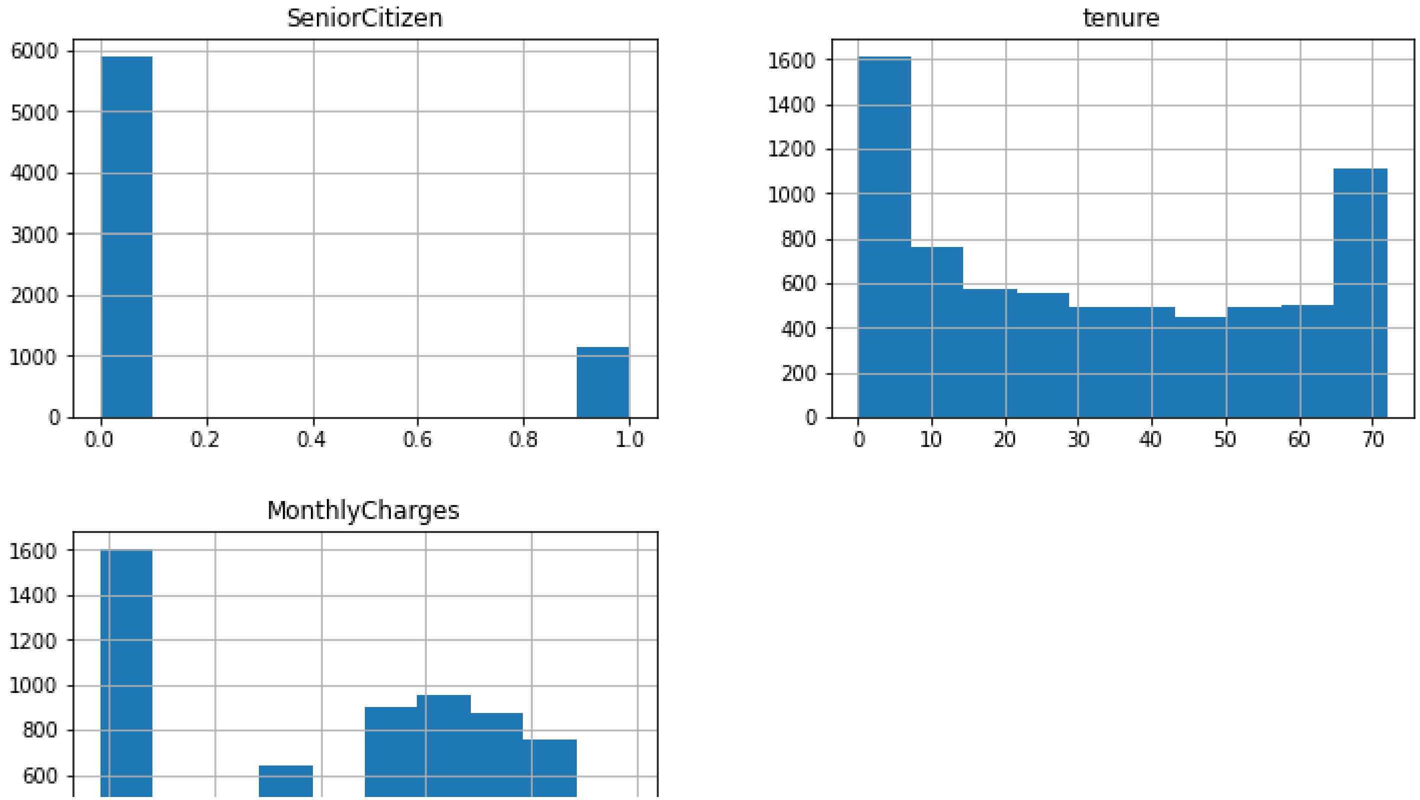
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

удалим лишнюю колонку

```
data.drop(columns=['customerID'], inplace = True)
```

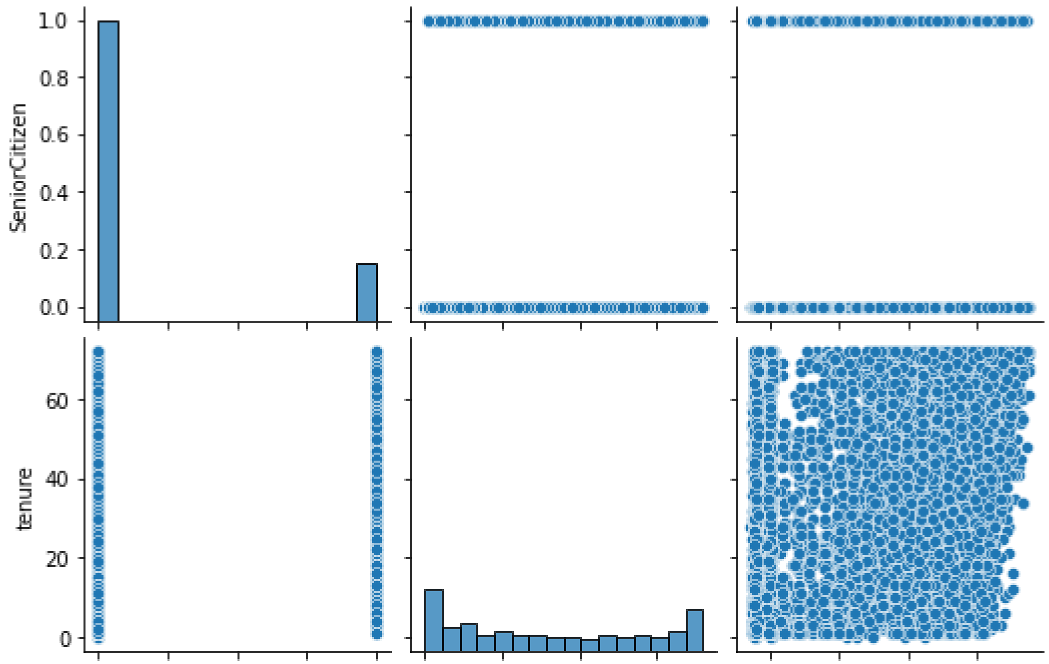
```
data.hist()
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f4a20ff90d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f4a20fc8710>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f4a20f82d90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f4a20f45450>]],
      dtype=object)
```




```
sns.pairplot(data)
```

<seaborn.axisgrid.PairGrid at 0x7f4a20dd05d0>



Target: Churn

```
data['Churn'].value_counts().plot(kind='bar', label='Churn').legend()
plt.title('Распределение оттока клиентов')
```

```
Text(0.5, 1.0, 'Распределение оттока клиентов')
```

оцифруем целевую переменную

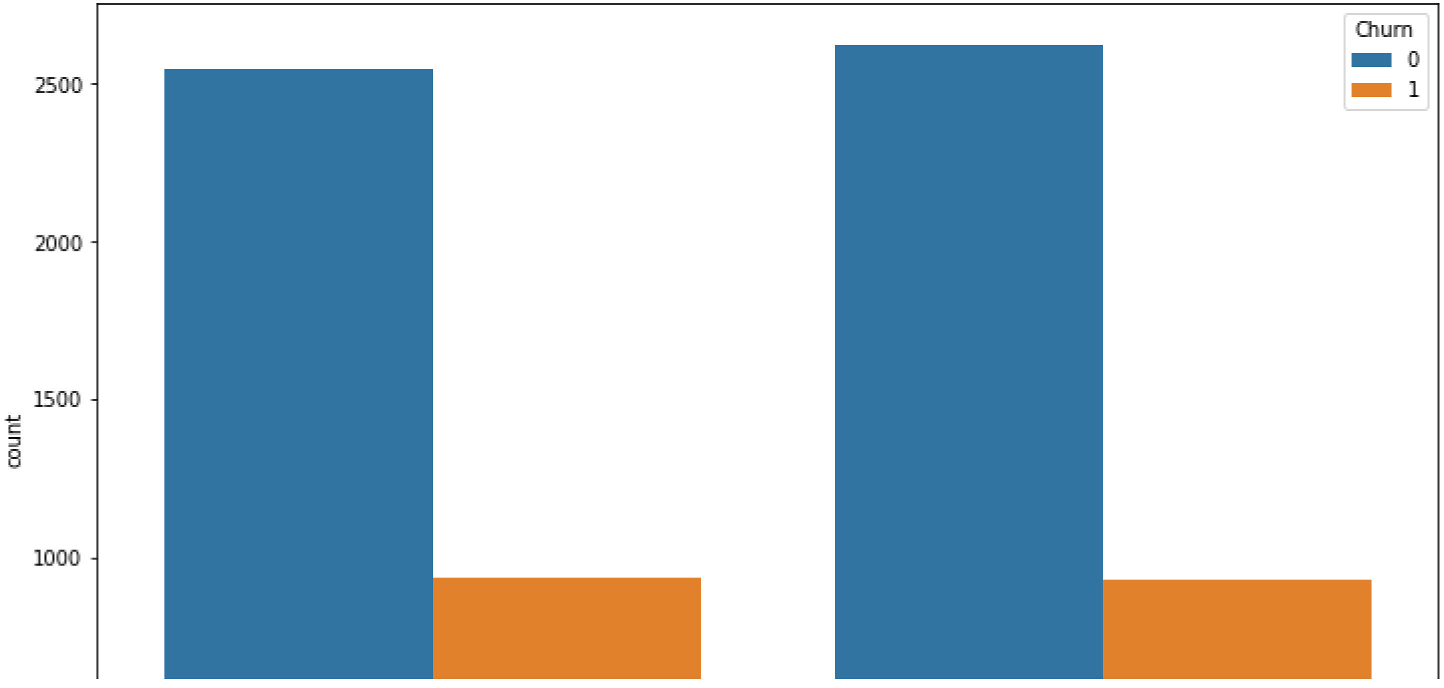
```
data['Churn'] = data['Churn'].apply(lambda x: 1 if x == 'Yes' else 0)
```

gender

```
data.gender.value_counts()
```

```
Male      3555
Female    3488
Name: gender, dtype: int64
```

```
sns.countplot(x='gender', hue='Churn', data=data);
```



закодируем, используя label encoder. Его т.к. будем работать с "деревянными" моделями

```
le = LabelEncoder()
```

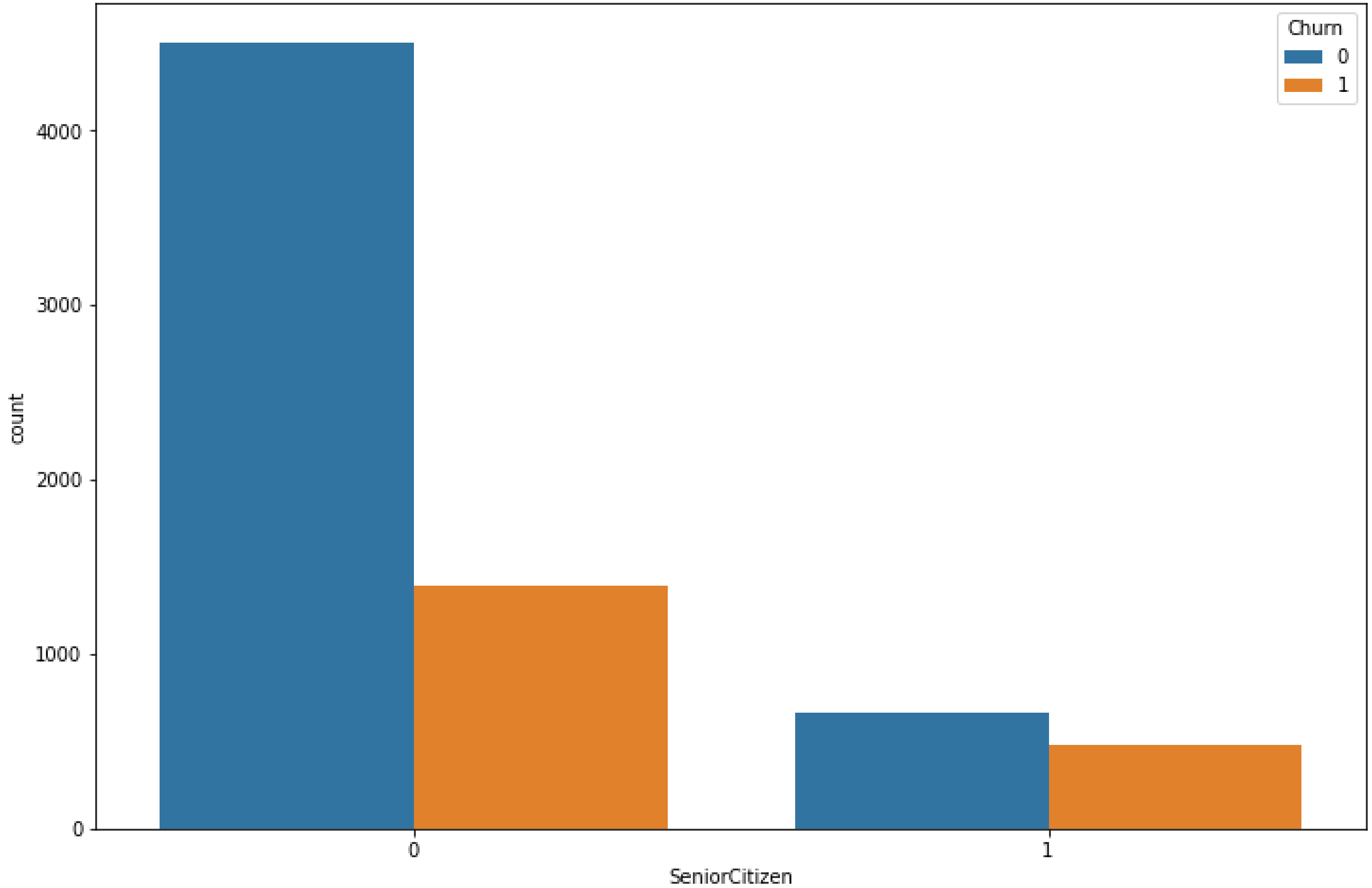
```
data.gender = le.fit_transform(data.gender)
```

SeniorCitizen

```
data.SeniorCitizen.value_counts()
```

```
0    5901
1    1142
Name: SeniorCitizen, dtype: int64
```

```
sns.countplot(x='SeniorCitizen', hue='Churn', data=data);
```



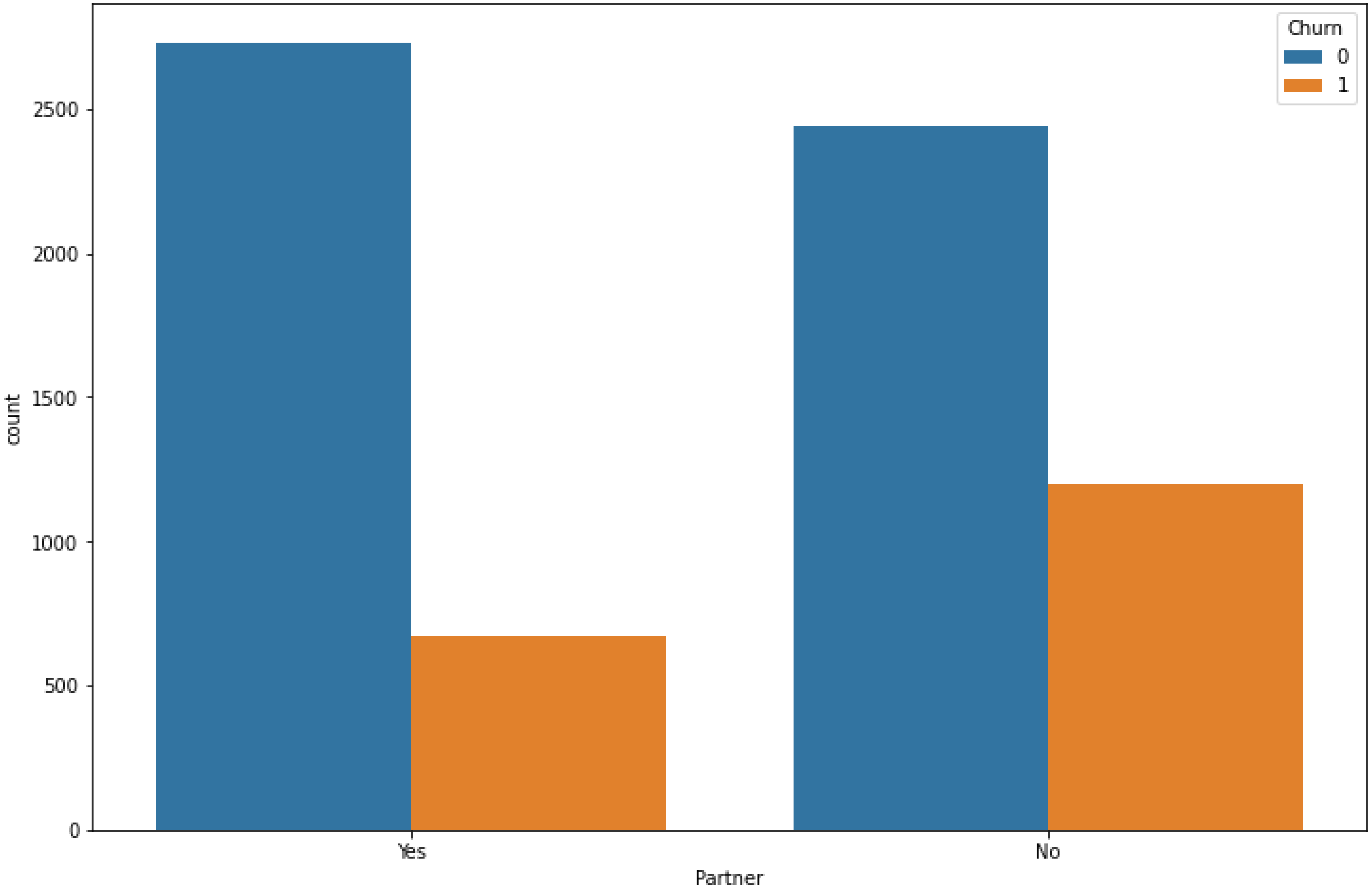

```
data.SeniorCitizen = le.fit_transform(data.SeniorCitizen)
```

Partneer

```
data.Partner.value_counts()
```

```
No     3641
Yes    3402
Name: Partner, dtype: int64
```

```
sns.countplot(x='Partner', hue='Churn', data=data);
```



интересный признак, люди без партнера чаще уходят от оператора, возможно это связано с тем, что одному проще сменить оператора. В паре нужно менять всем,т.к. звонки между одним и тем же оператором - дешевле

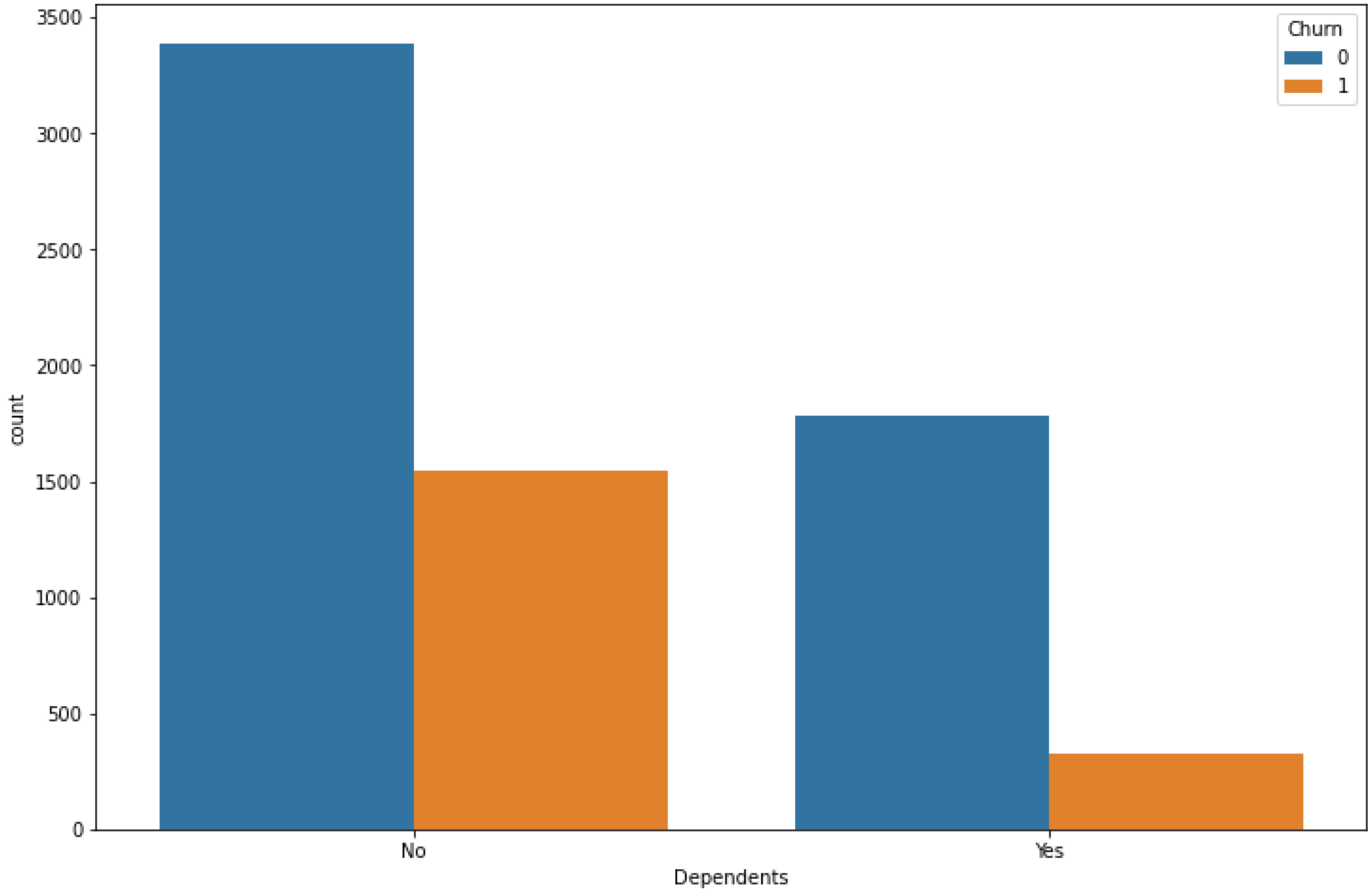
```
data.Partner = le.fit_transform(data.Partner)
```

Dependents

```
data.Dependents.value_counts()
```

```
No     4933
Yes    2110
Name: Dependents, dtype: int64
```

```
sns.countplot(x='Dependents', hue='Churn', data=data);
```



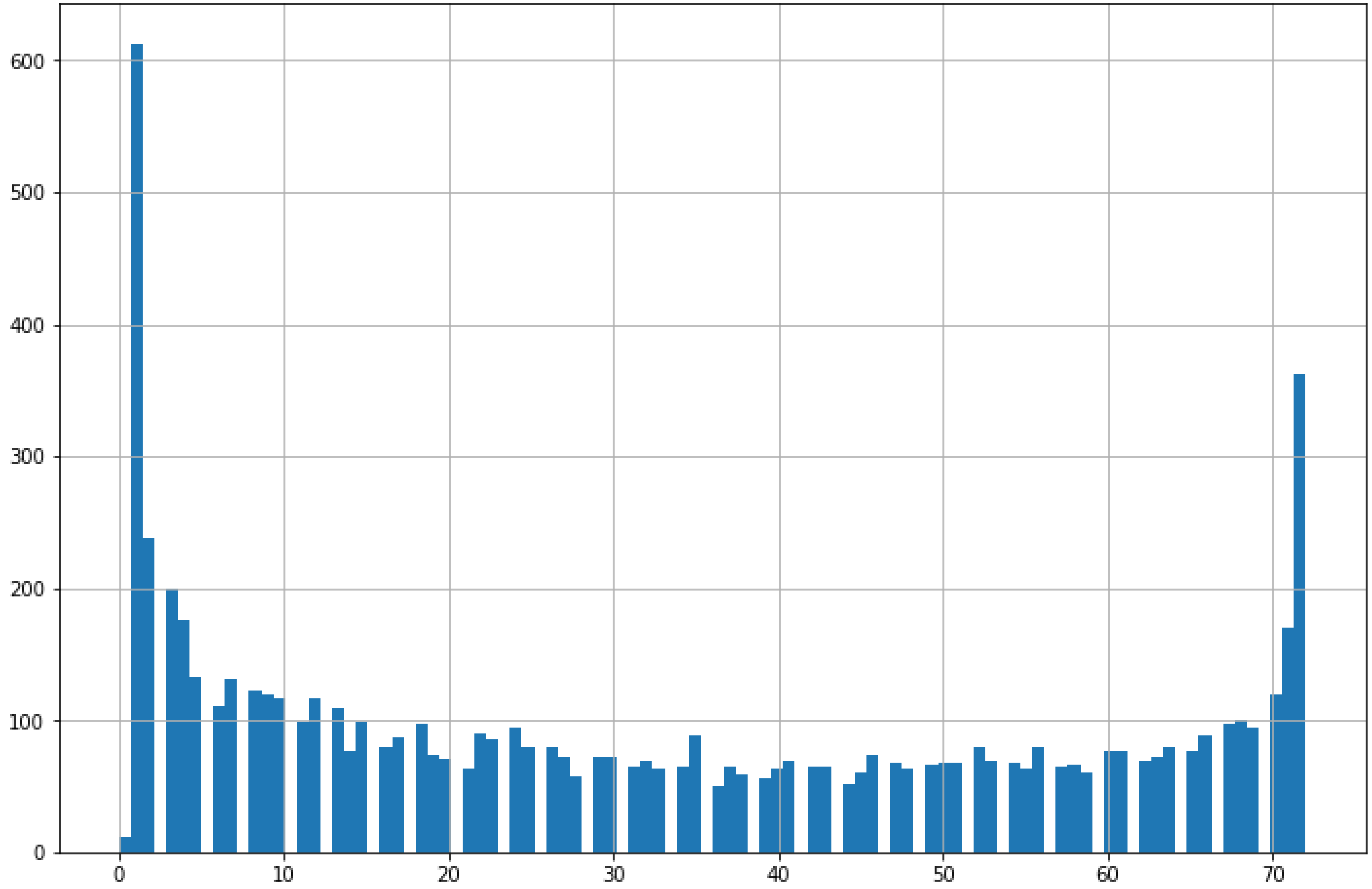
клиенты без иждивенцев чаще уходят

```
data.Dependents = le.fit_transform(data.Dependents)
```

tenure

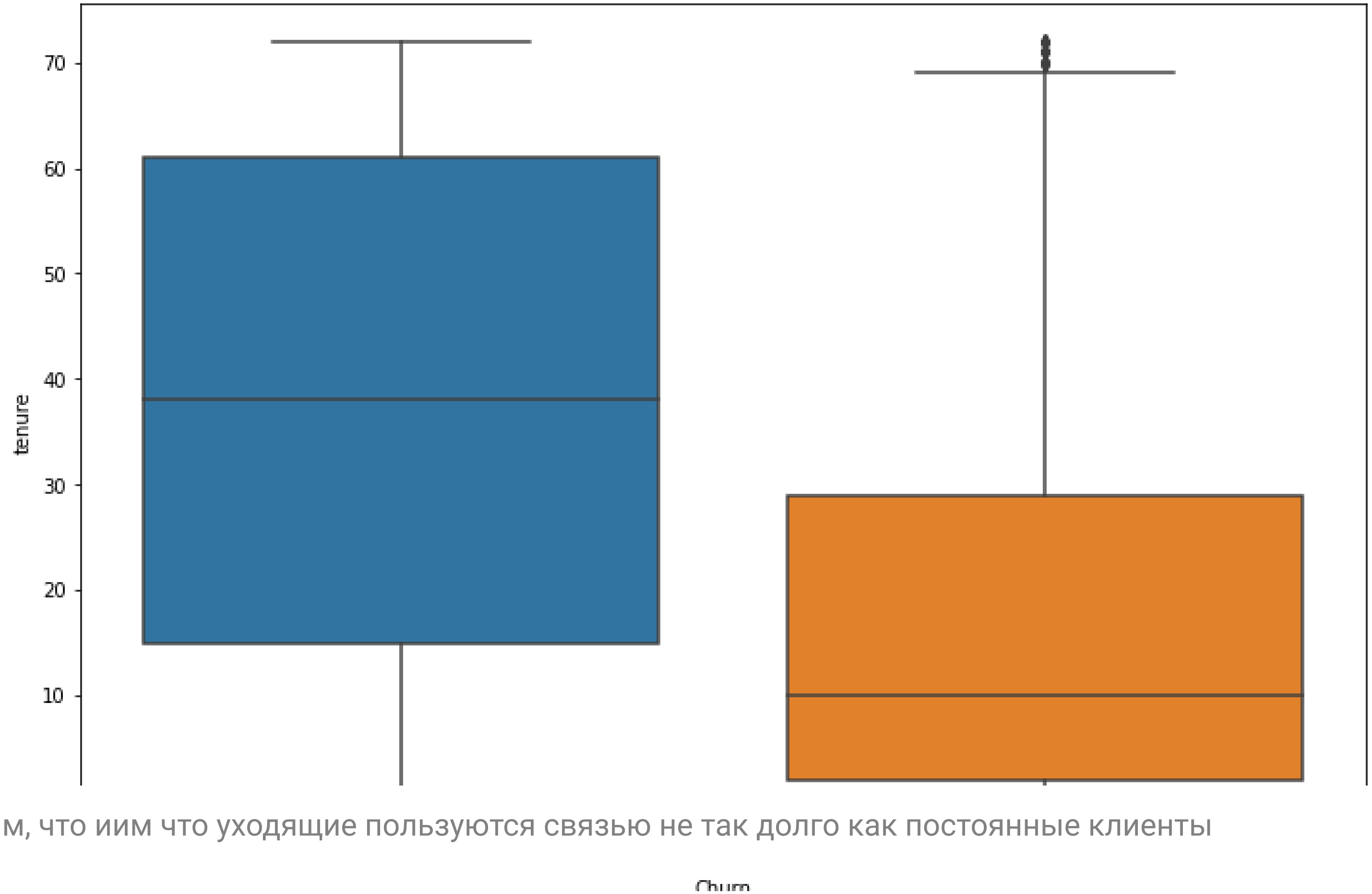
```
data.tenure.hist(bins = 100)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4a1579ea10>
```




```
sns.boxplot(x='Churn', y='tenure', data=data)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f4a15676a50>



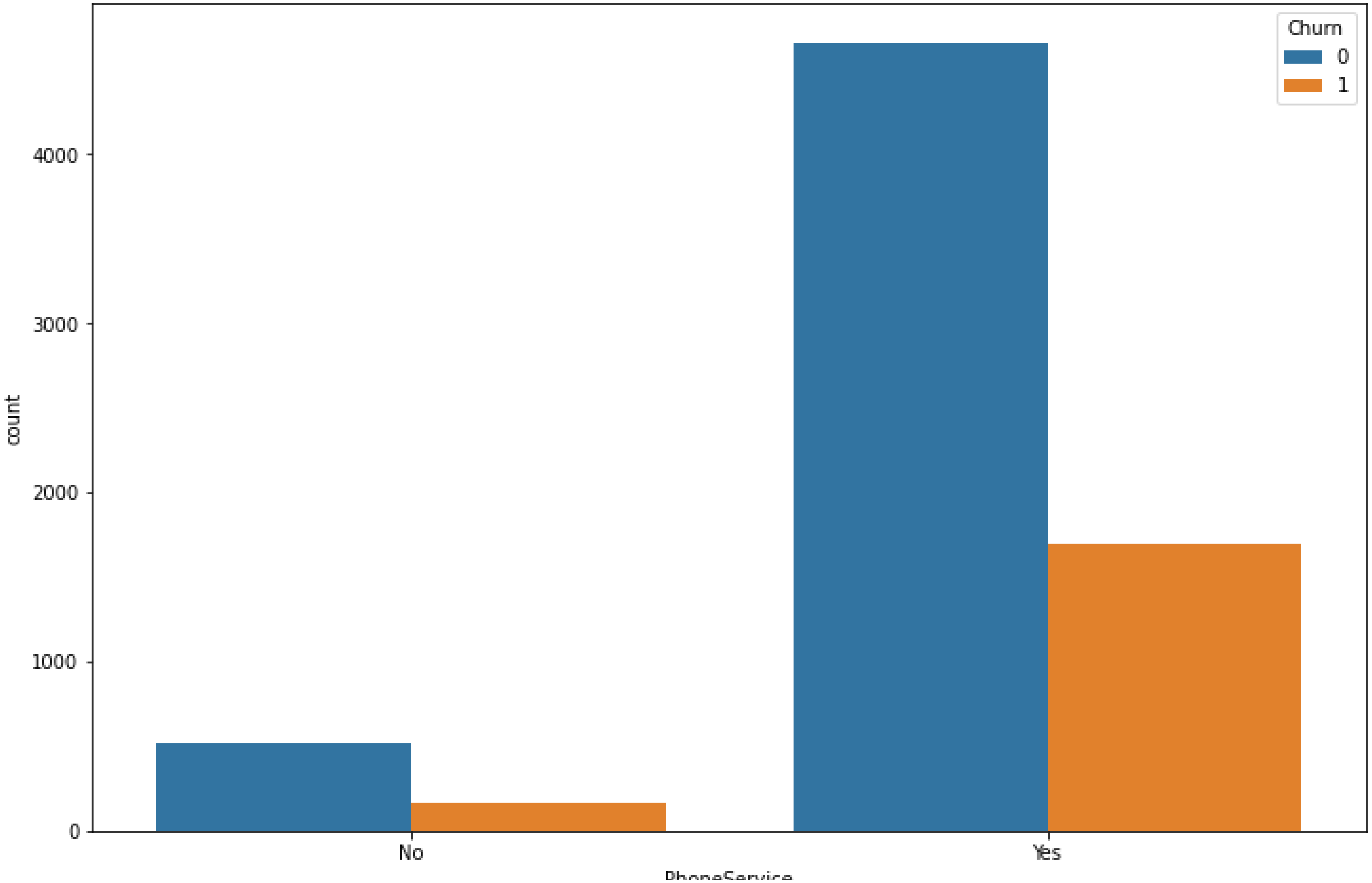
видим, что иим что уходящие пользуются связью не так долго как постоянные клиенты

PhoneService

```
data.PhoneService.value_counts()
```

```
Yes    6361
No      682
Name: PhoneService, dtype: int64
```

```
sns.countplot(x='PhoneService', hue='Churn', data=data);
```



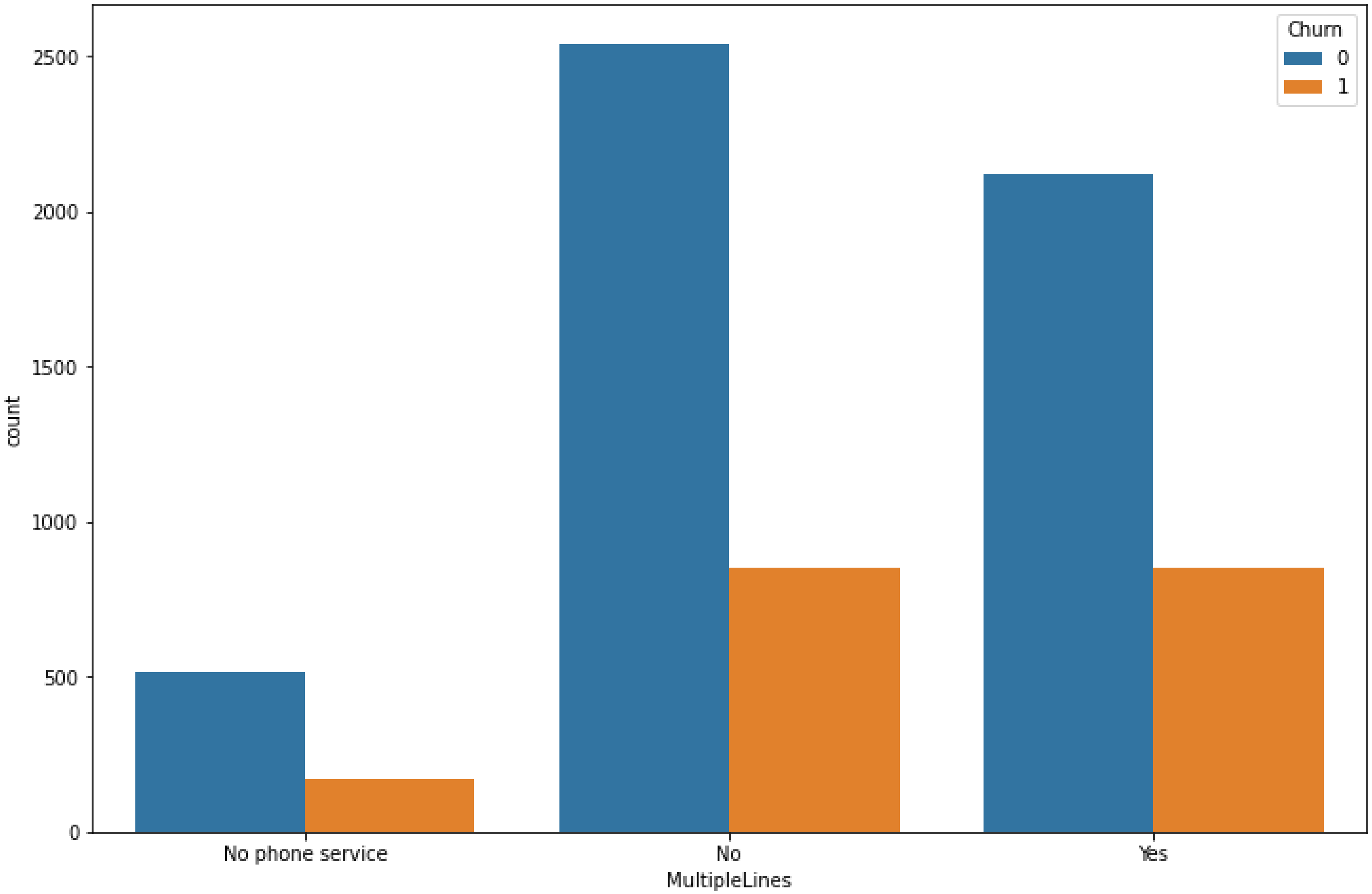

```
data.PhoneService = le.fit_transform(data.PhoneService)
```

MultipleLines

```
data.MultipleLines.value_counts()
```

```
No                  3390
Yes                 2971
No phone service     682
Name: MultipleLines, dtype: int64
```

```
sns.countplot(x='MultipleLines', hue='Churn', data=data);
```




```
data.MultipleLines = le.fit_transform(data.MultipleLines)
```

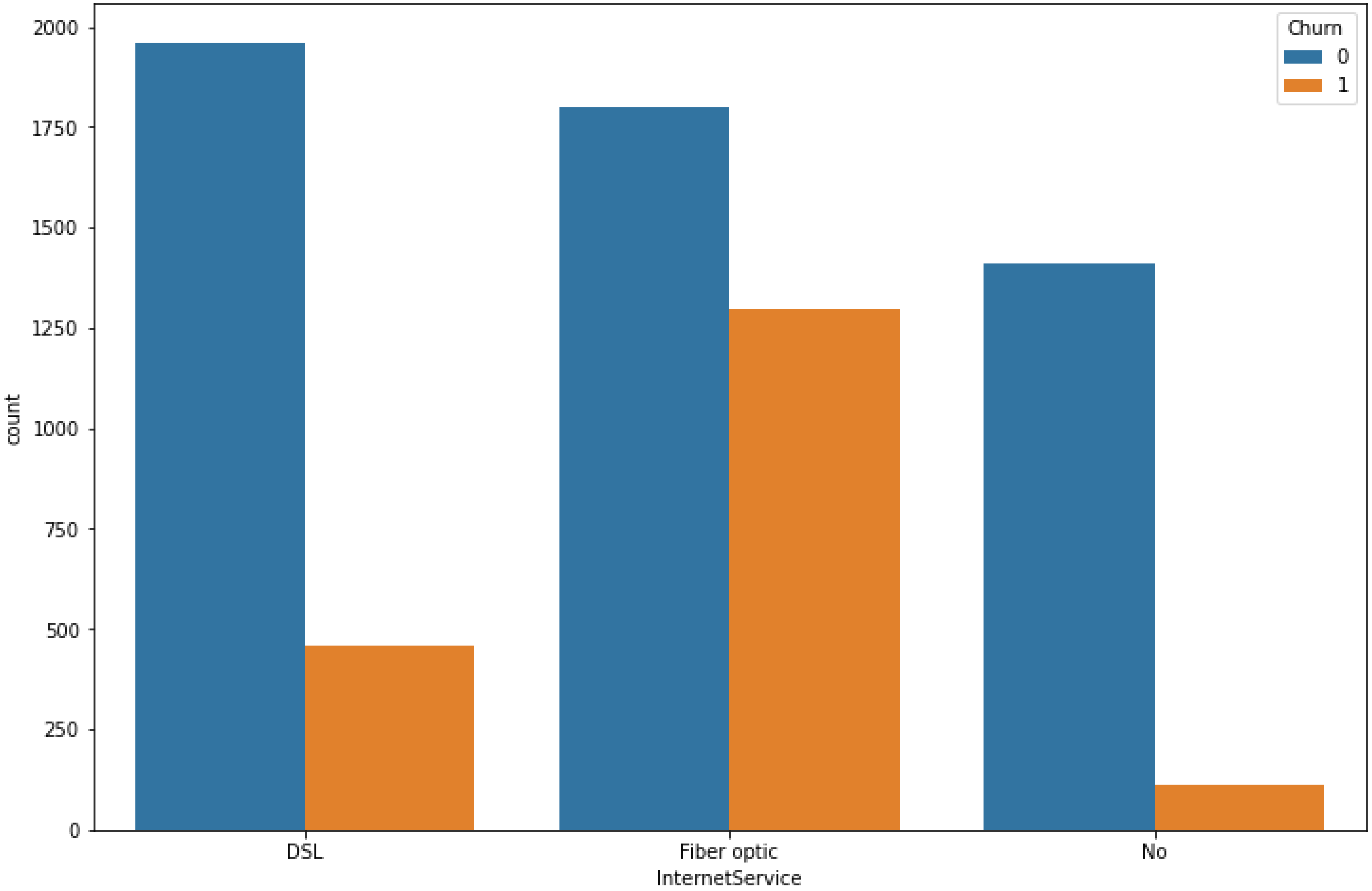
InternetService

```
data.InternetService.value_counts()
```

```
Fiber optic    3096
DSL            2421
```

```
No              1526
Name: InternetService, dtype: int64
```

```
sns.countplot(x='InternetService', hue='Churn', data=data);
```



интересное замечание, клиенты с оптоволокном лидируют по оттоку..

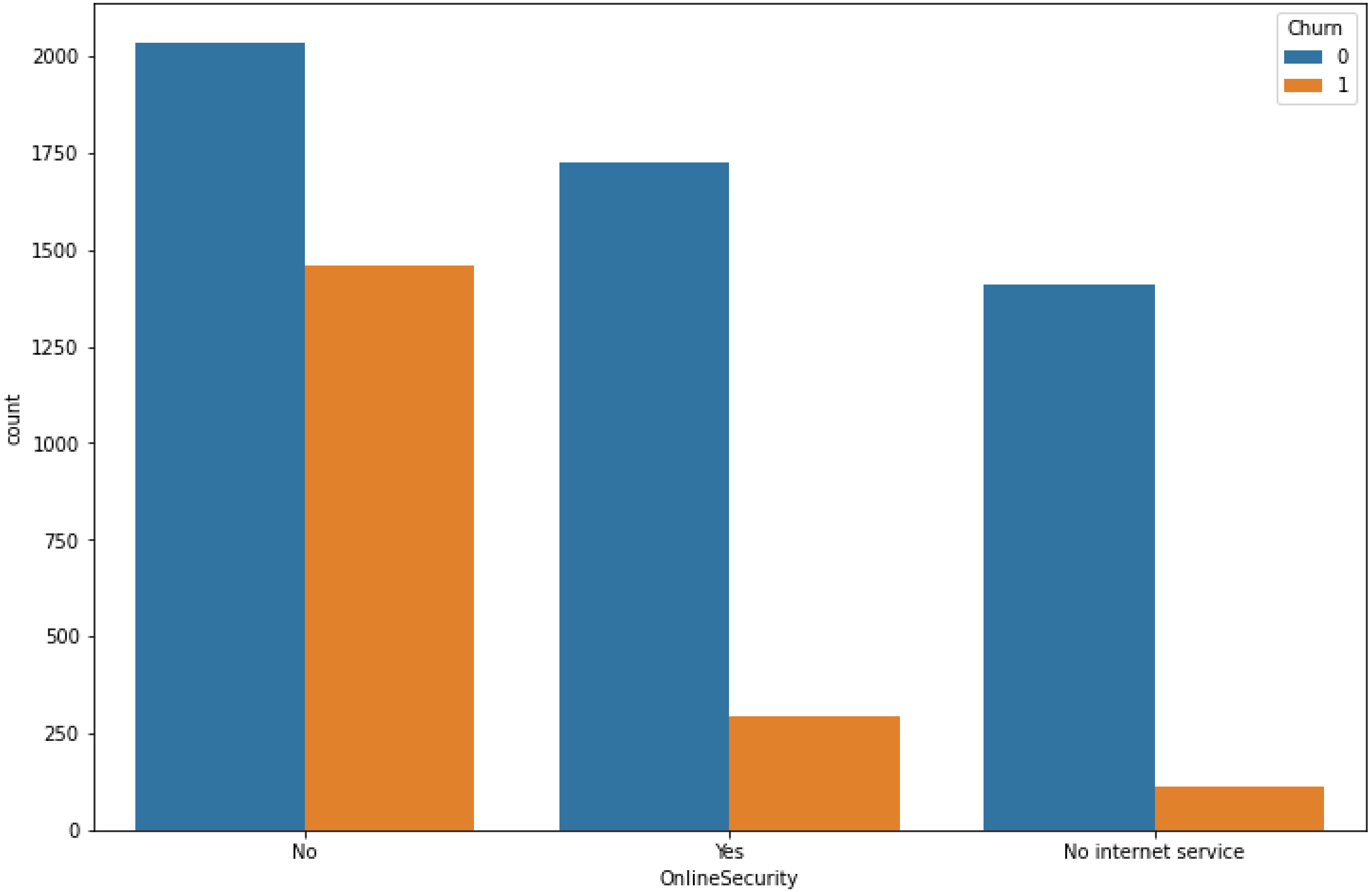
```
data.InternetService = le.fit_transform(data.InternetService)
```

OnlineSecurity

```
data.OnlineSecurity.value_counts()
```

```
No                     3498
Yes                    2019
No internet service    1526
Name: OnlineSecurity, dtype: int64
```

```
sns.countplot(x='OnlineSecurity', hue='Churn', data=data);
```



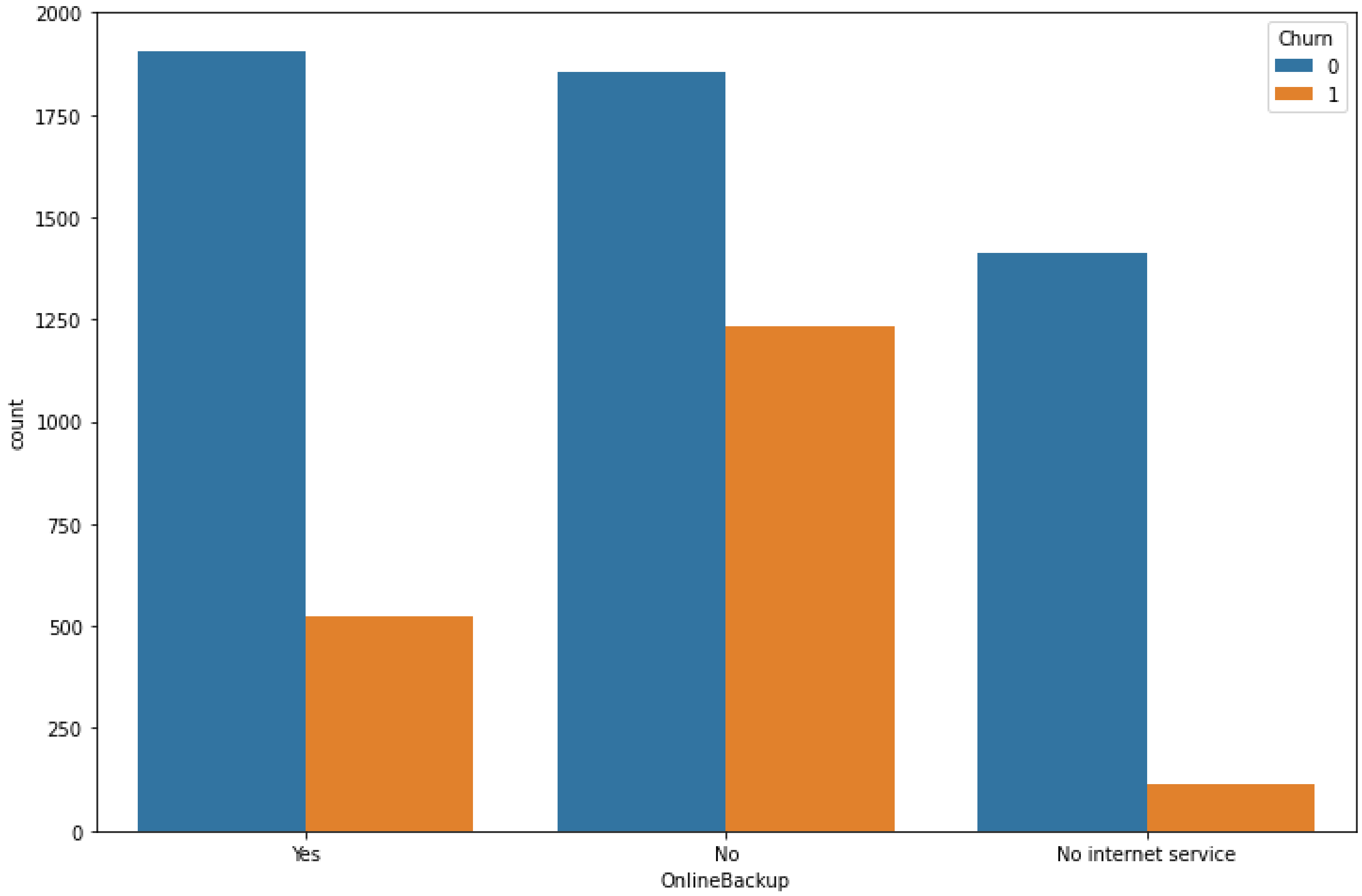

```
data.OnlineSecurity = le.fit_transform(data.OnlineSecurity)
```

OnlineBackup

```
data.OnlineBackup.value_counts()
```

```
No                     3088
Yes                    2429
No internet service    1526
Name: OnlineBackup, dtype: int64
```

```
sns.countplot(x='OnlineBackup', hue='Churn', data=data);
```



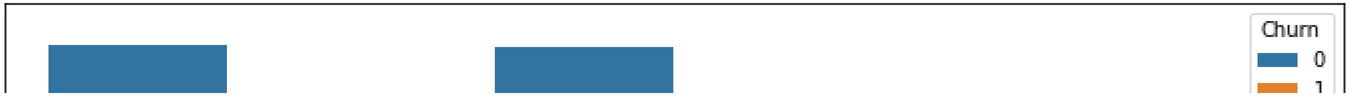
```
data.OnlineBackup = le.fit_transform(data.OnlineBackup)
```

DeviceProtection

```
data.DeviceProtection.value_counts()
```

```
No                     3095
Yes                    2422
No internet service    1526
Name: DeviceProtection, dtype: int64
```

```
sns.countplot(x='DeviceProtection', hue='Churn', data=data);
```



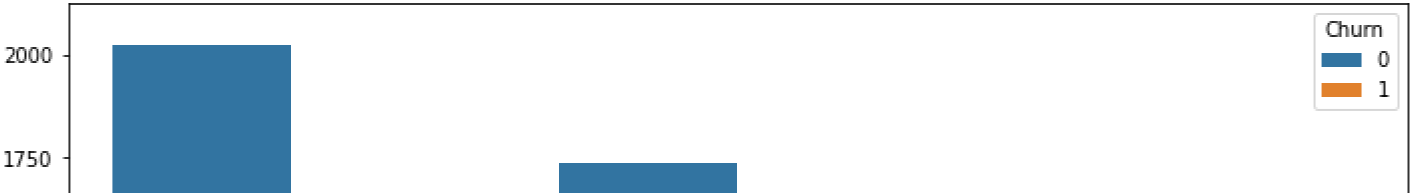

```
data.DeviceProtection = le.fit_transform(data.DeviceProtection)
```

TechSupport


```
data.TechSupport.value_counts()
```

```
No                     3473
Yes                    2044
No internet service    1526
Name: TechSupport, dtype: int64
```

```
sns.countplot(x='TechSupport', hue='Churn', data=data);
```




```
data.TechSupport = le.fit_transform(data.TechSupport)
```

StreamingTV

```
data.StreamingTV.value_counts()
```

```
No                     2810
Yes                    2707
No internet service    1526
Name: StreamingTV, dtype: int64
```

```
sns.countplot(x='StreamingTV', hue='Churn', data=data);
```

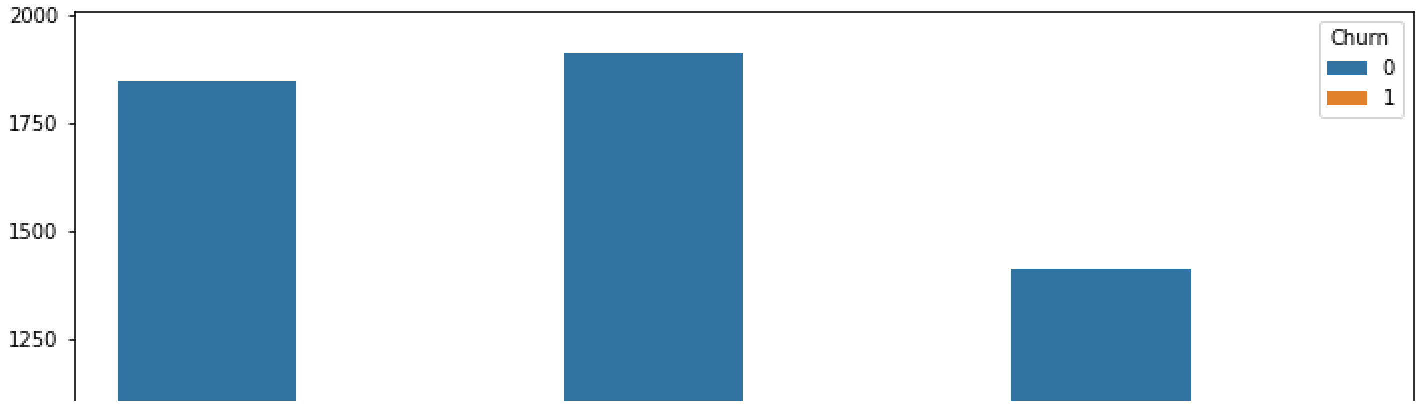

```
data.StreamingTV = le.fit_transform(data.StreamingTV)
```

StreamingMovies

```
data.StreamingMovies.value_counts()
```

```
No                     2785
Yes                    2732
No internet service    1526
Name: StreamingMovies, dtype: int64
```

```
sns.countplot(x='StreamingMovies', hue='Churn', data=data);
```




```
data.StreamingMovies = le.fit_transform(data.StreamingMovies)
```

```
data.head()
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	Device
0	0	0	1	0	1	0	1	0	0	2	
1	1	0	0	0	34	1	0	0	2	0	
2	1	0	0	0	2	1	0	0	2	2	
3	1	0	0	0	45	0	1	0	2	0	
4	0	0	0	0	2	1	0	1	0	0	

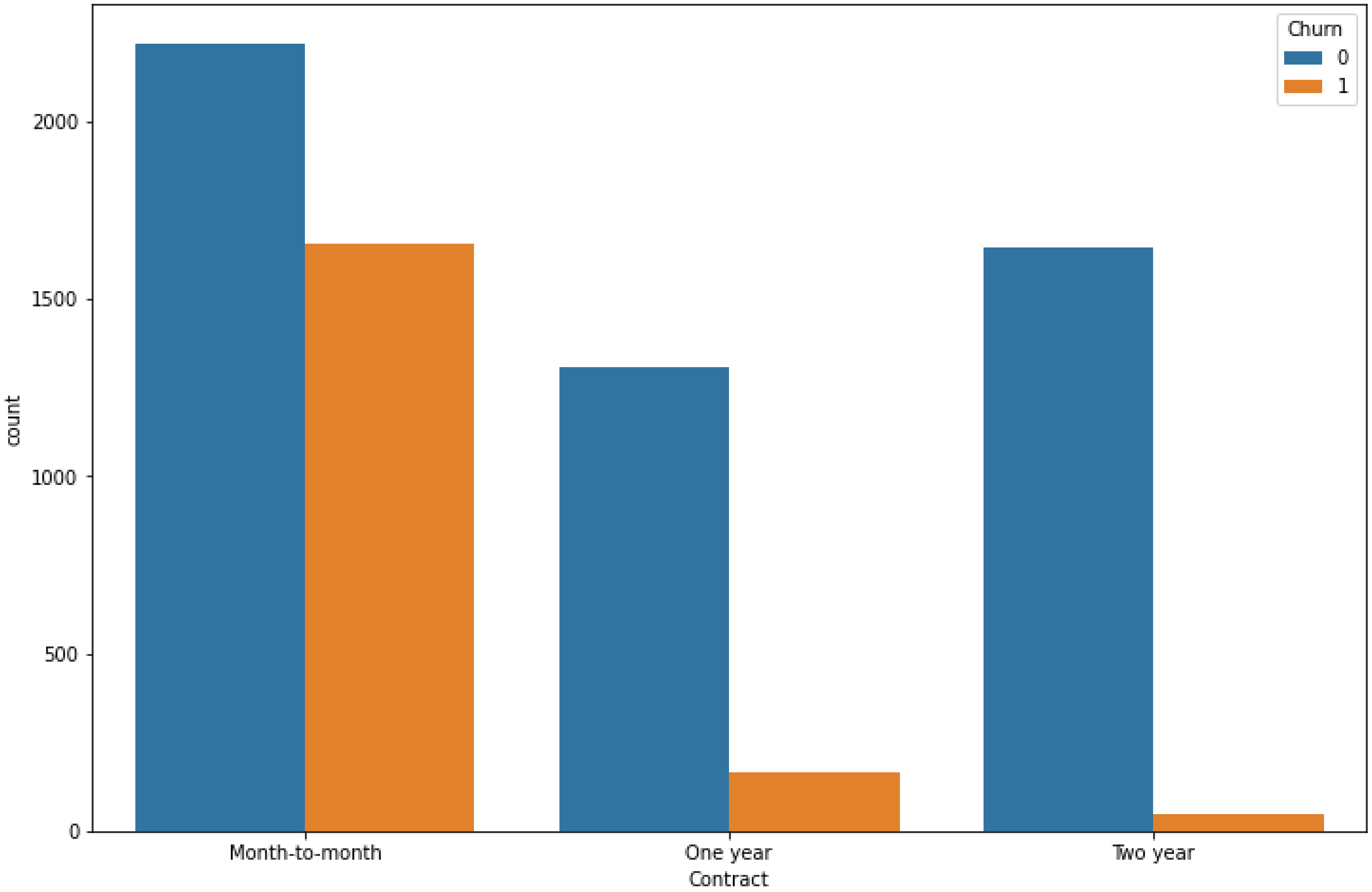
Contract

```
data.Contract.value_counts()
```

```
Month-to-month    3875
Two year          1695
```

```
One year          1473
Name: Contract, dtype: int64
```

```
sns.countplot(x='Contract', hue='Churn', data=data);
```



крутой признак, месячники уходят чаще

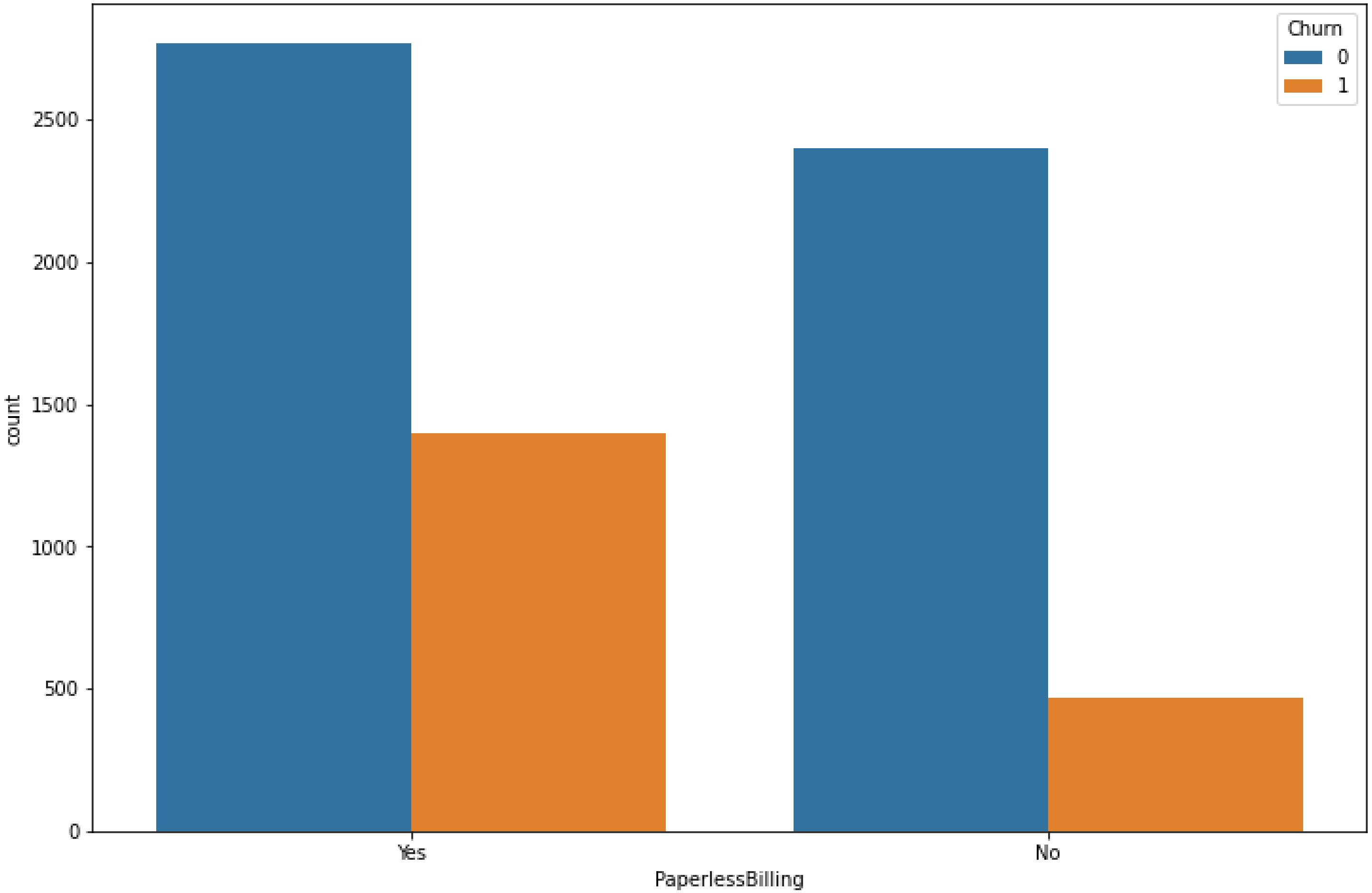
```
data.Contract = le.fit_transform(data.Contract)
```

PaperlessBilling

```
data.PaperlessBilling.value_counts()
```

```
Yes    4171
No     2872
Name: PaperlessBilling, dtype: int64
```

```
sns.countplot(x='PaperlessBilling', hue='Churn', data=data);
```




```
data.PaperlessBilling = le.fit_transform(data.PaperlessBilling)
```

PaymentMethod

```
data.PaymentMethod.value_counts()
```

```
Electronic check             2365
Mailed check                 1612
Bank transfer (automatic)    1544
Credit card (automatic)      1522
Name: PaymentMethod, dtype: int64
```

```
sns.countplot(x='PaymentMethod', hue='Churn', data=data);
```

электронные чеки это плохо...

```
data.PaymentMethod = le.fit_transform(data.PaymentMethod)
```

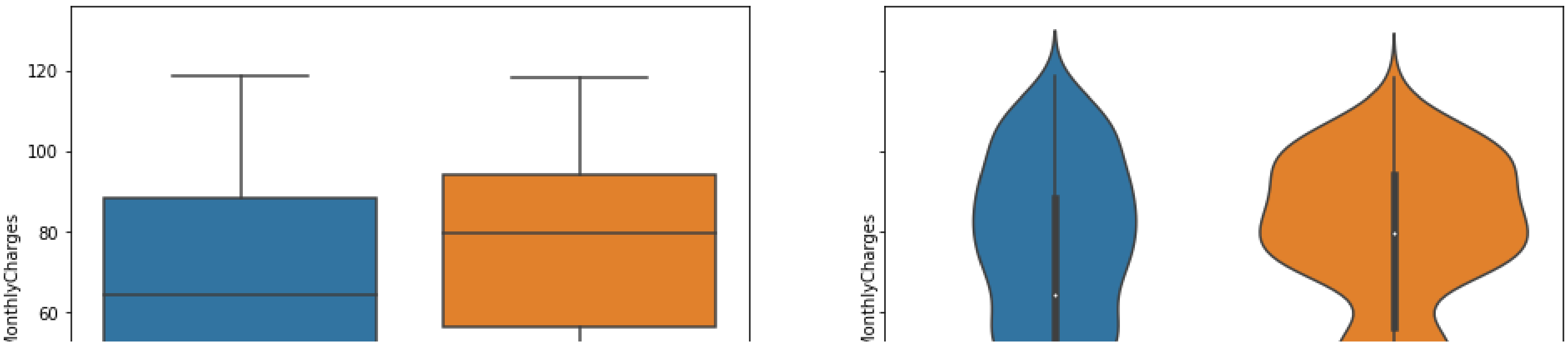
```
data.head()
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	Device
0	0	0	1	0	1	0	1	0	0	2	
1	1	0	0	0	34	1	0	0	2	0	
2	1	0	0	0	2	1	0	0	2	2	
3	1	0	0	0	45	0	1	0	2	0	
4	0	0	0	0	2	1	0	1	0	0	

MonthlyCharges TotalCharges

```
_, axes = plt.subplots(1, 2, sharey=True, figsize=(16,6))

sns.boxplot(x='Churn', y='MonthlyCharges', data=data, ax=axes[0]);
sns.violinplot(x='Churn', y='MonthlyCharges', data=data, ax=axes[1]);
```



преобразуем total_charges во float

```
data['TotalCharges']
```

```
0         29.85
1        1889.5
2        108.15
3       1840.75
4        151.65
          ...
7038     1990.5
7039     7362.9
7040     346.45
7041      306.6
7042     6844.5
Name: TotalCharges, Length: 7043, dtype: object
```

```
data[data['TotalCharges'].str.match(' ') == False]
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	Dev
0	0	0	1	0	1	0	1	0	0	2	
1	1	0	0	0	34	1	0	0	2	0	
2	1	0	0	0	2	1	0	0	2	2	
3	1	0	0	0	45	0	1	0	2	0	
4	0	0	0	0	2	1	0	1	0	0	
...	...	...	...	...	...	...	...	...	...	...	
7038	1	0	1	1	24	1	2	0	2	0	
7039	0	0	1	1	72	1	2	1	0	2	

```
data = data[data['TotalCharges'].str.match(' ') == False]
```

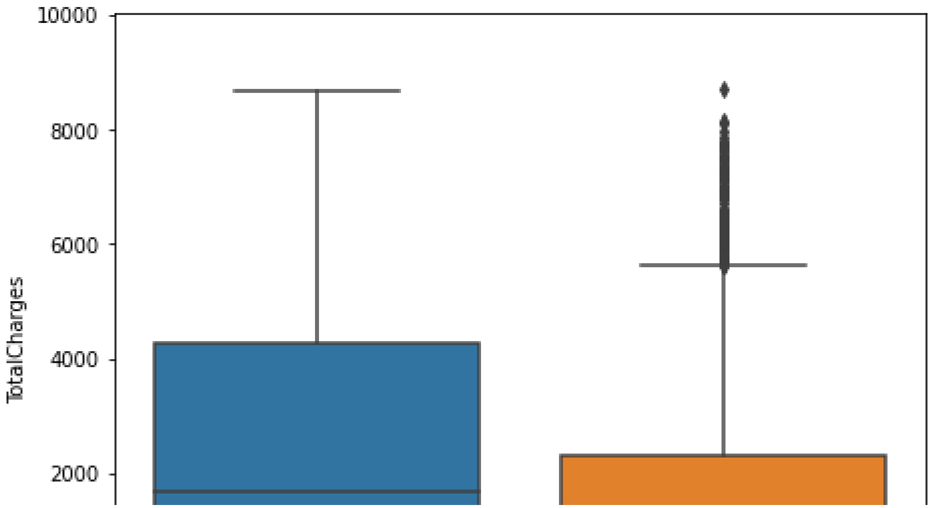
```
data['TotalCharges'] = data['TotalCharges'].astype('float64')
```

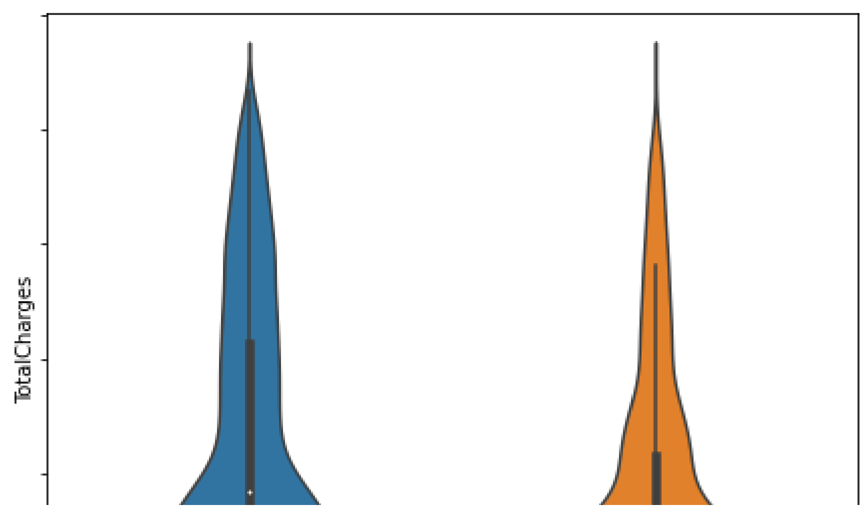
```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cop
  """Entry point for launching an IPython kernel.
```

```
_, axes = plt.subplots(1, 2, sharey=True, figsize=(16,6))

sns.boxplot(x='Churn', y='TotalCharges', data=data, ax=axes[0]);
sns.violinplot(x='Churn', y='TotalCharges', data=data, ax=axes[1]);
```






```
data.TotalCharges.corr(data.MonthlyCharges)
```

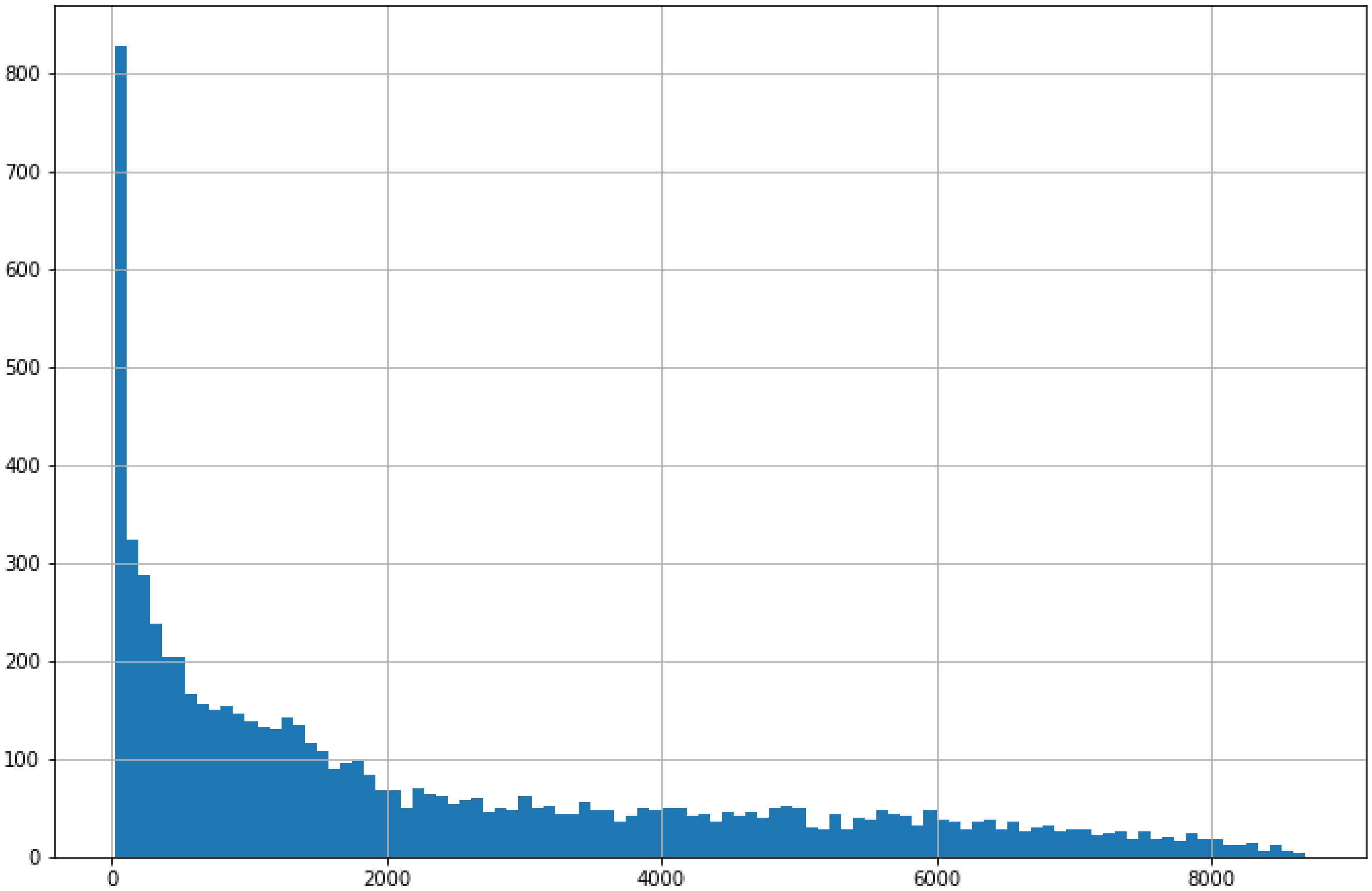
```
0.6510648032262024
```

```
data.MonthlyCharges.hist(bins = 100)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4a152d2f10>
```

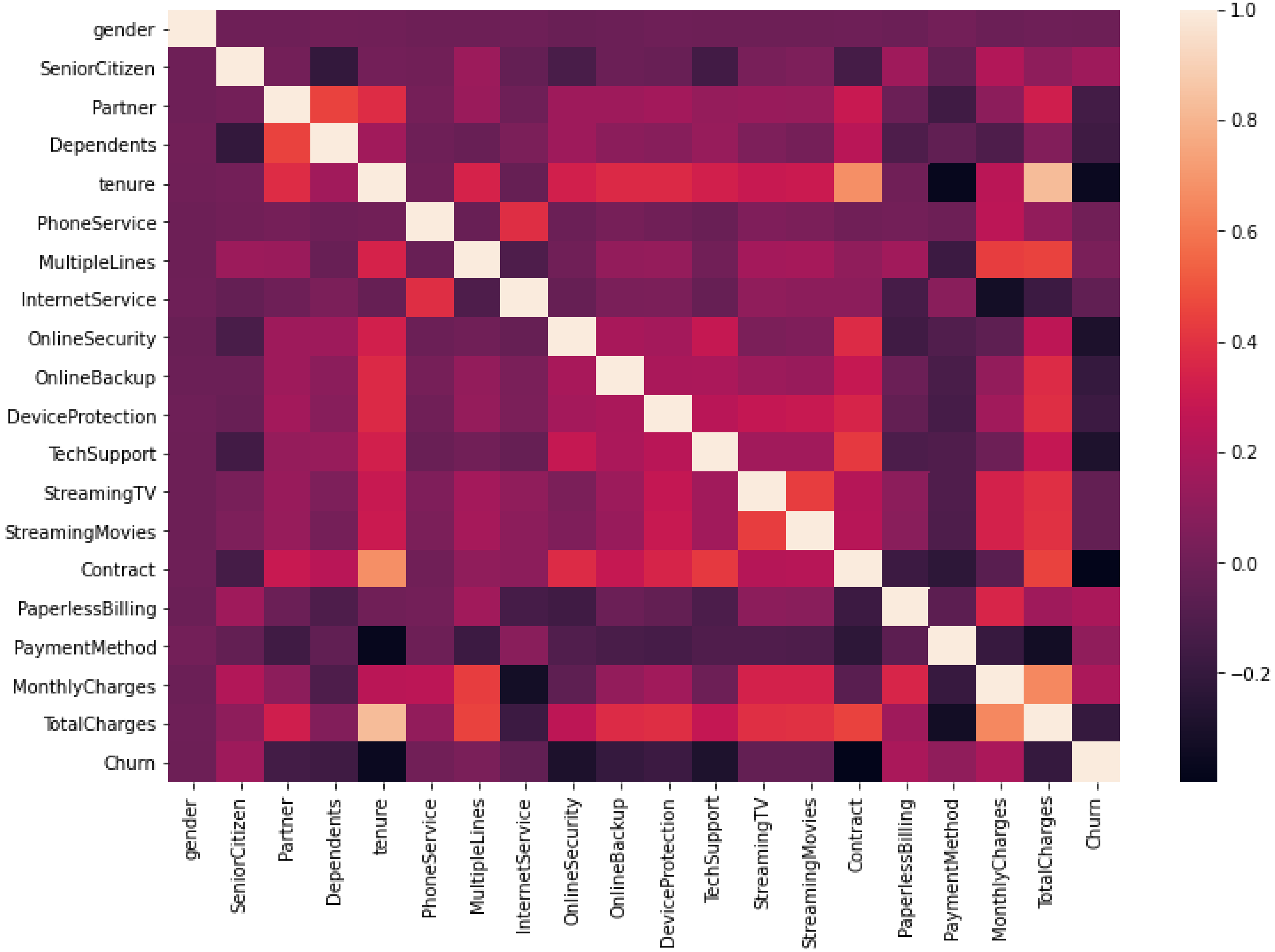

```
data.TotalCharges.hist(bins = 100)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4a1318de10>
```




```
corr_matrix = data.corr()
```

```
sns.heatmap(corr_matrix);
```



Часть 3.Who's the mightiest of them all?

функция качества модели

```
def quality(prediction_y, true_y):
    accuracy = accuracy_score(prediction_y, true_y)
    precision = precision_score(prediction_y, true_y)
    recall = recall_score(prediction_y, true_y)
    f1 = f1_score(prediction_y, true_y)
    print("Accuracy:  {:.3f}\nPrecision: {:.3f}\nRecall:    {:.3f}\nF1-score:  {:.3f}".format(
        accuracy, precision, recall, f1
    ))
```

функция построения кривой roc_auc

```
def plot_roc_curve(prob_prediction, actual):
    fpr, tpr, thresholds = roc_curve(y_test, prob_prediction)
    auc_score = roc_auc_score(y_test, prob_prediction)

    plt.plot(fpr, tpr, label='ROC curve ')
    plt.plot([0, 1], [0, 1])
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC AUC: {:.3f}'.format(auc_score))
    plt.show()
```

sklearn RandomForest

```
X_train, X_test, y_train, y_test = train_test_split(
    data.drop(['Churn'], axis = 1), data.Churn, test_size=0.3, random_state=2021, stratify=data.Churn.values)
```

```
clfRF = RandomForestClassifier()
clfRF.fit(X_train, y_train)
```

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
```

```
                            max_leaf_nodes=None, max_samples=None,
                            min_impurity_decrease=0.0, min_impurity_split=None,
                            min_samples_leaf=1, min_samples_split=2,
                            min_weight_fraction_leaf=0.0, n_estimators=100,
                            n_jobs=None, oob_score=False, random_state=None,
                            verbose=0, warm_start=False)
```

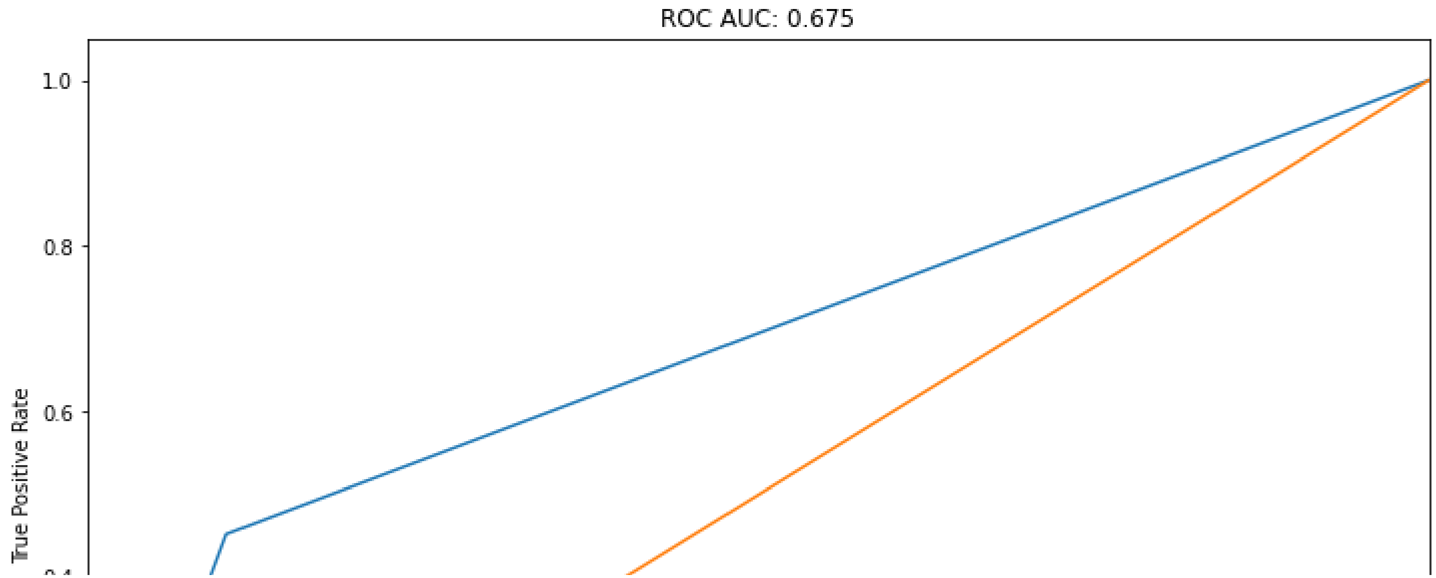
```
predRF = clfRF.predict(X_test)
```

```
print("Train quality:")
quality(clfRF.predict(X_train), y_train)
print("\nTest quality:")
quality(predRF, y_test)
```

```
    Train quality:
    Accuracy:  0.998
    Precision: 0.994
    Recall:    0.997
    F1-score:  0.995

    Test quality:
    Accuracy:  0.779
    Precision: 0.453
    Recall:    0.614
    F1-score:  0.521
```

```
plot_roc_curve(predRF, y_test)
```



XGBoost

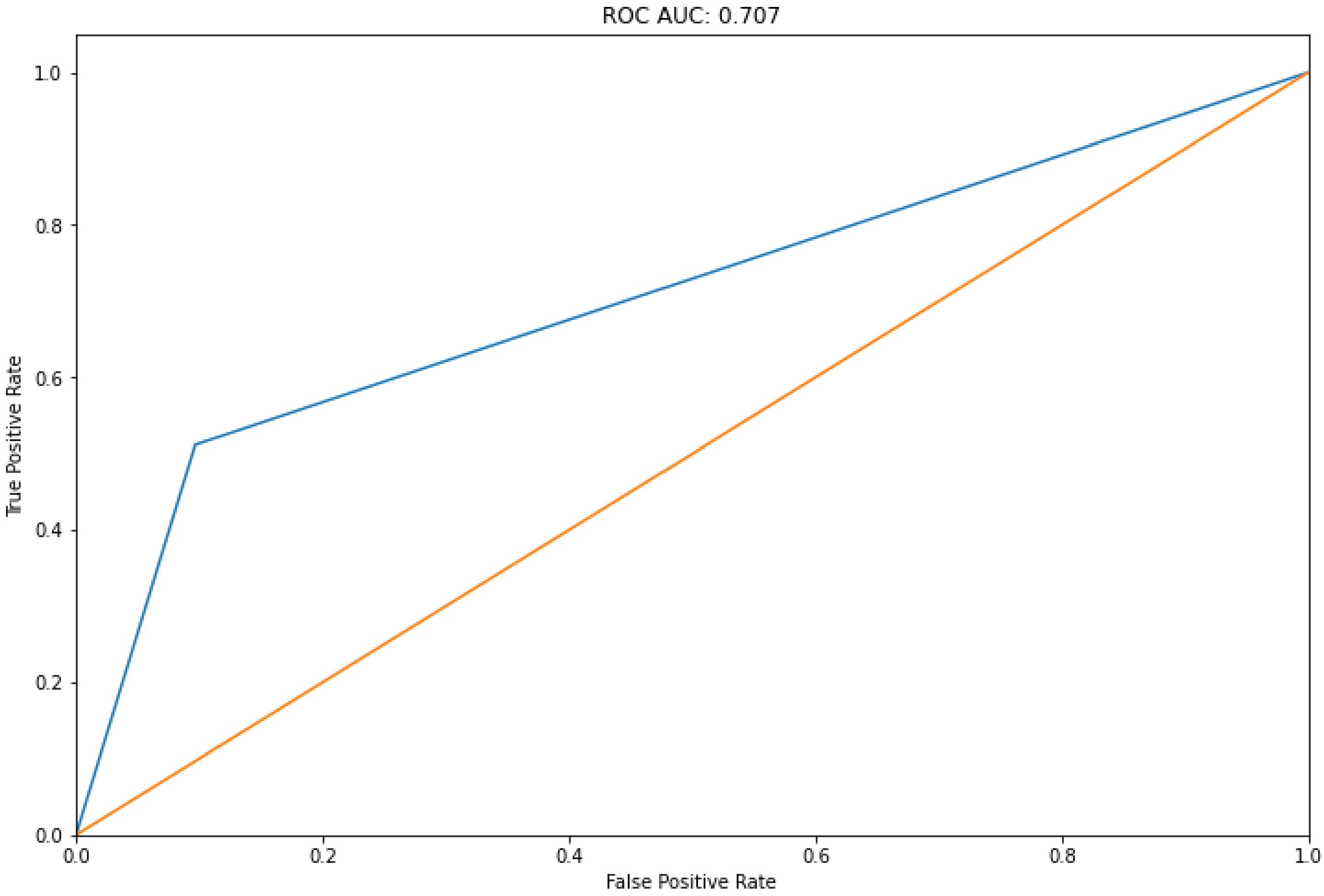
```
clfXGB = XGBClassifier()
clfXGB.fit(X_train, y_train)
predXGB = clfXGB.predict(X_test)
```

```
print("Train quality:")
quality(clfXGB.predict(X_train), y_train)
print("\nTest quality:")
quality(predXGB, y_test)
```

```
Train quality:
Accuracy:  0.825
Precision: 0.563
Recall:    0.719
F1-score:  0.631

Test quality:
Accuracy:  0.799
Precision: 0.512
Recall:    0.657
F1-score:  0.575
```

```
plot_roc_curve(predXGB, y_test)
```



CatBost

```
clfcat = CatBoostClassifier(eval_metric='AUC')
clfcat.fit(X_train, y_train, silent= True)
predcat = clfcat.predict(X_test)
```

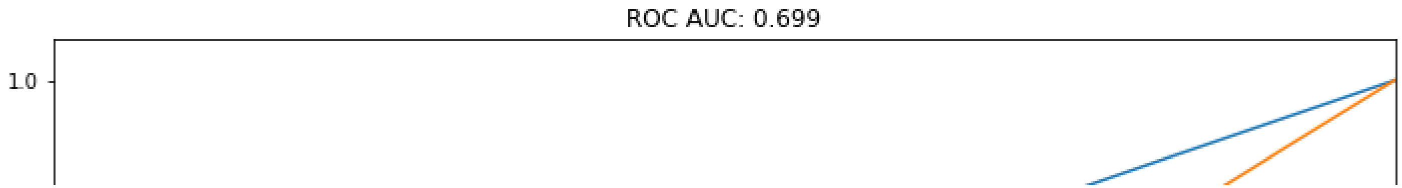
```
print("Train quality:")
```

```
print("Train quality:")
quality(clfcat.predict(X_train), y_train)
print("\nTest quality:")
quality(predcat, y_test)
```

```
Train quality:
Accuracy:  0.880
Precision: 0.694
Recall:    0.828
F1-score:  0.755

Test quality:
Accuracy:  0.789
Precision: 0.506
Recall:    0.627
F1-score:  0.560
```

```
plot_roc_curve(predcat, y_test)
```



LightGBM

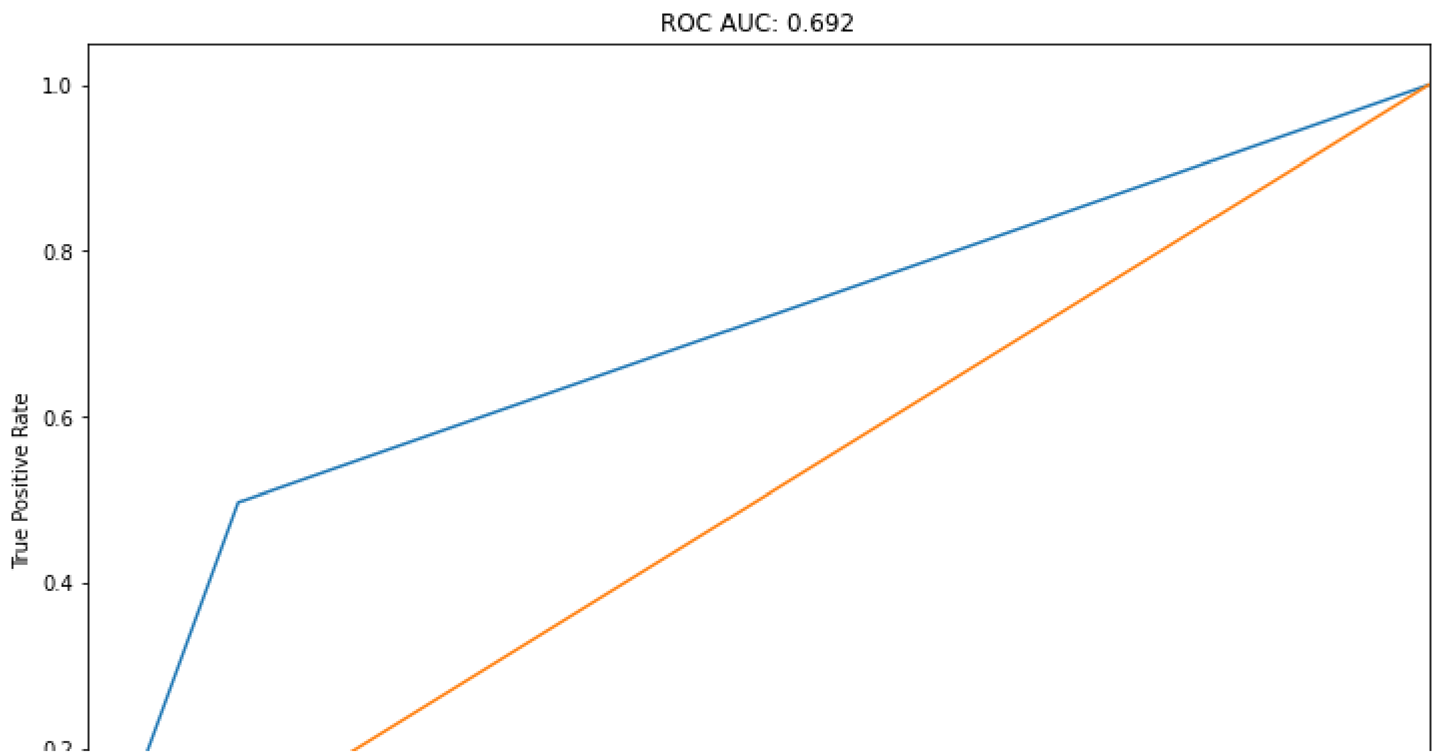
```
clfLBM = LGBMClassifier()
clfLBM.fit(X_train, y_train)
predLBM = clfLBM.predict(X_test)
```

```
print("Train quality:")
quality(clfLBM.predict(X_train), y_train)
print("\nTest quality:")
quality(predLBM, y_test)
```

```
Train quality:
Accuracy:  0.889
Precision: 0.722
Recall:    0.836
F1-score:  0.775

Test quality:
Accuracy:  0.784
Precision: 0.497
Recall:    0.616
F1-score:  0.550
```

```
plot_roc_curve(predLBM, y_test)
```



sklearn RandomForest, XGBoost, CatBost, LightGBM (настройка гиперпараметров)

Инициализируем страифицированную разбивку нашего датасета для валидации

```
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
```

sklearn RandomForest

```
parameters = {'max_features': [4, 7, 10, 13], 'min_samples_leaf': [1, 3, 5, 7], 'max_depth': [5,10,15,20]}
rfc = RandomForestClassifier(n_estimators=100, random_state=42,
                             n_jobs=-1, oob_score=True)
gcv_rf = GridSearchCV(rfc, parameters, n_jobs=-1, cv=skf, verbose=1)
gcv_rf.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 64 candidates, totalling 320 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:   19.2s
[Parallel(n_jobs=-1)]: Done 196 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done 320 out of 320 | elapsed:  2.9min finished
GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=42, shuffle=True),
             error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jobs=-1,
                                              oob_score=True, random_state=42,
                                              verbose=0, warm_start=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'max_depth': [5, 10, 15, 20],
                         'max_features': [4, 7, 10, 13],
                         'min_samples_leaf': [1, 3, 5, 7]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=1)
```

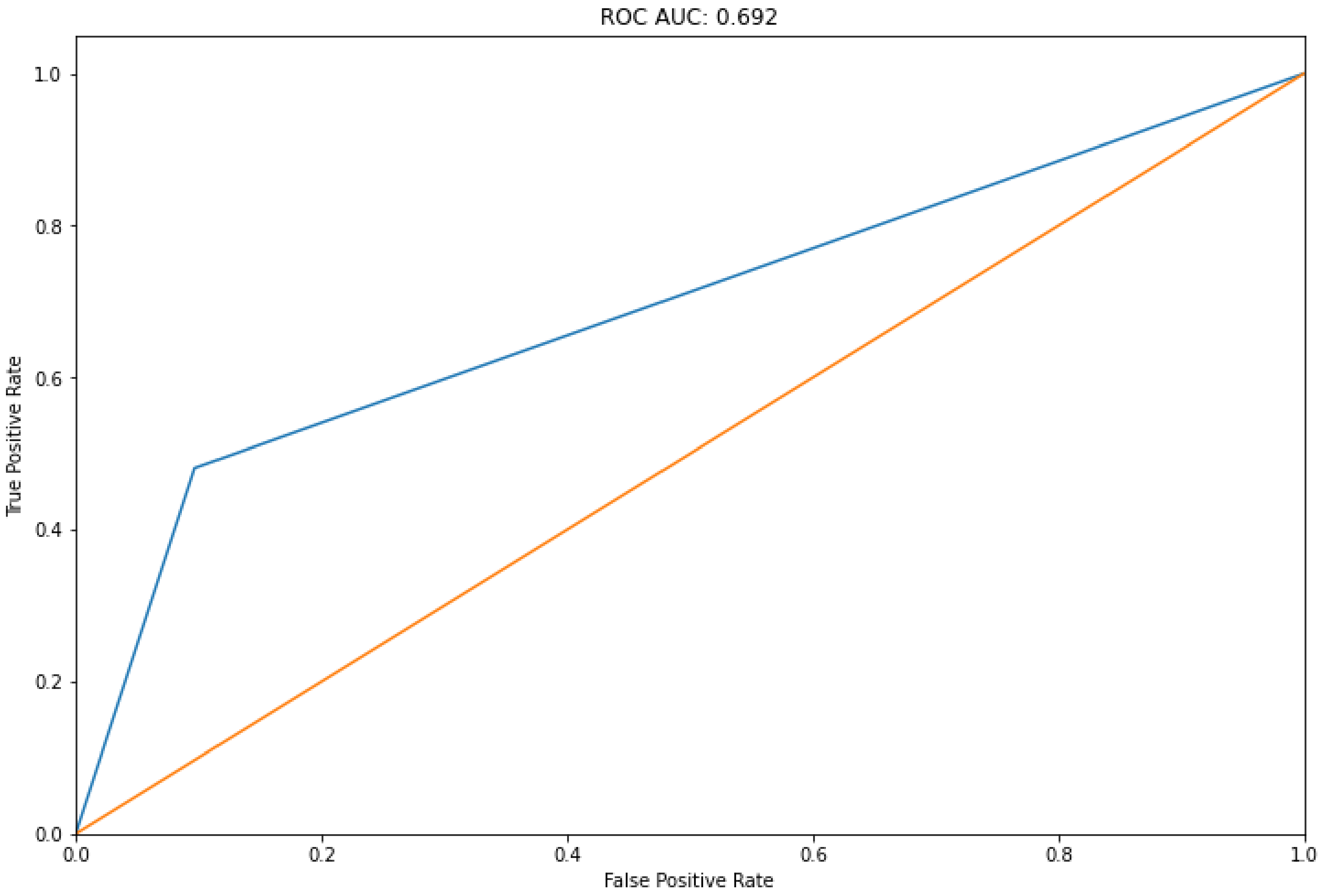
```
print("Train quality:")
quality(gcv_rf.predict(X_train), y_train)
print("\nTest quality:")
quality(gcv_rf.predict(X_test), y_test)
```

```
Train quality:
Accuracy:  0.869
Precision: 0.633
Recall:    0.834
F1-score:  0.720

Test quality:
Accuracy:  0.791
Precision: 0.481
```

```
    Recall:    0.643
    F1-score:  0.550
```

```
plot_roc_curve(gcv_rf.predict(X_test), y_test)
```



XGBoost

```
xgbc = XGBClassifier(n_estimators=100, random_state=42,
                             n_jobs=-1, oob_score=True)
gcv_x = GridSearchCV(xgbc, parameters, n_jobs=-1, cv=skf, verbose=1)
gcv_x.fit(X_train, y_train)
```

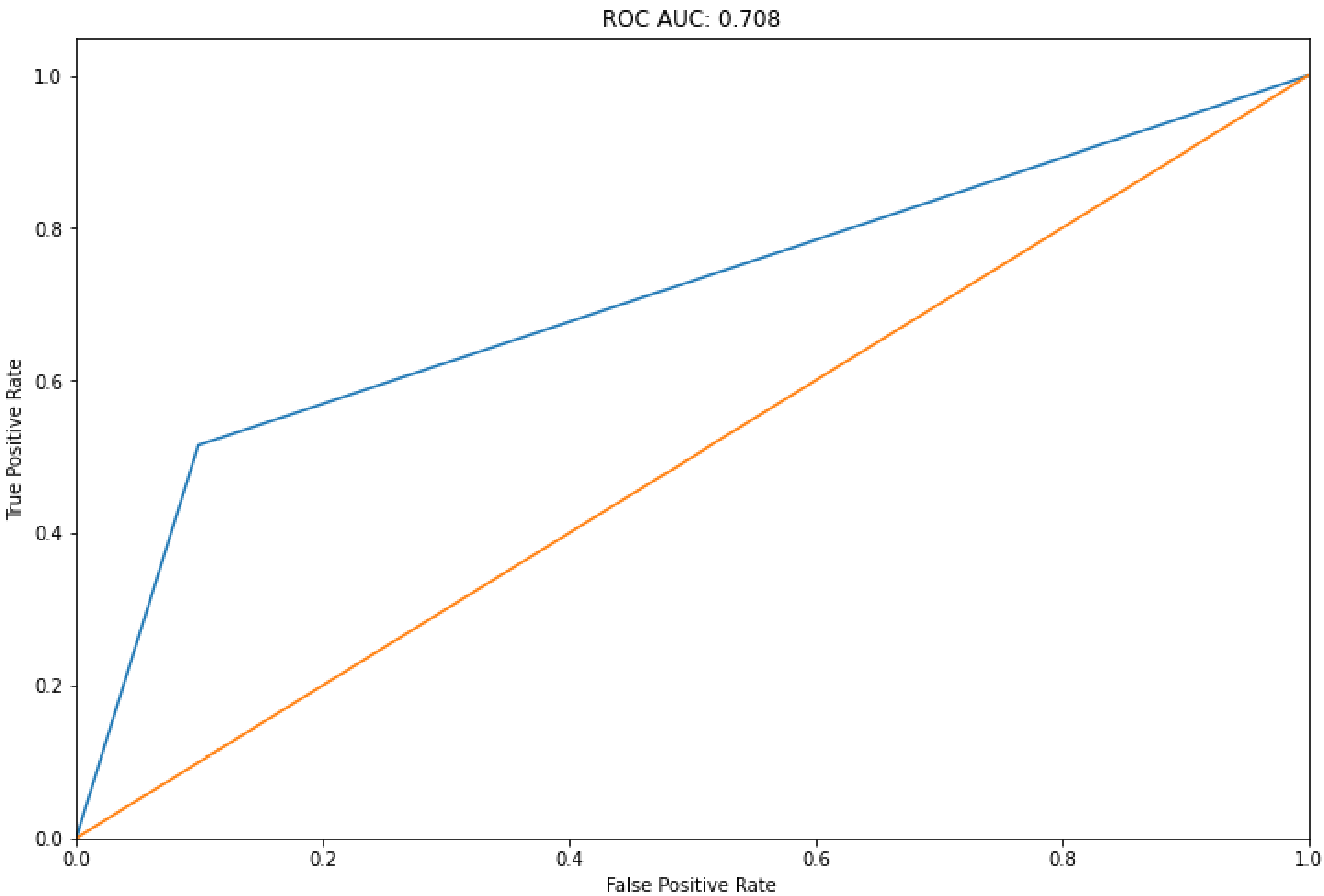
```
Fitting 5 folds for each of 64 candidates, totalling 320 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:   17.0s
[Parallel(n_jobs=-1)]: Done 196 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 320 out of 320 | elapsed:  4.9min finished
GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=42, shuffle=True),
             error_score=nan,
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     colsample_bylevel=1, colsample_bynode=1,
                                     colsample_bytree=1, gamma=0,
                                     learning_rate=0.1, max_delta_step=0,
                                     max_depth=3, min_child_weight=1,
                                     missing=None, n_estimators=100, n_jobs=-1,
                                     nthread=None, objective='binary:logistic',
                                     oob_score=True, random_state=42,
                                     reg_alpha=0, reg_lambda=1,
                                     scale_pos_weight=1, seed=None, silent=None,
                                     subsample=1, verbosity=1),
             iid='deprecated', n_jobs=-1,
             param_grid={'max_depth': [5, 10, 15, 20],
                         'max_features': [4, 7, 10, 13],
                         'min_samples_leaf': [1, 3, 5, 7]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=1)
```

```
print("Train quality:")
quality(gcv_x.predict(X_train), y_train)
print("\nTest quality:")
quality(gcv_x.predict(X_test), y_test)
```

```
Train quality:
Accuracy:  0.856
Precision: 0.635
Recall:    0.782
F1-score:  0.700

Test quality:
Accuracy:  0.798
Precision: 0.515
Recall:    0.652
F1-score:  0.576
```

```
plot_roc_curve(gcv_x.predict(X_test), y_test)
```



CatBost

```
param_cat = {'iterations': [1,5,10,20,50], 'subsample': [0.66, 0.8,1], 'max_depth': [5,10,15,20]}
catc = CatBoostClassifier(random_state=42,
                             eval_metric='AUC')
gcv_c = GridSearchCV(catc, param_cat, n_jobs=-1, cv=skf, verbose=1)
gcv_c.fit(X_train, y_train)
     1:      total: 3.78ms   remaining: 90.7ms
```

```
2:      total: 5.03ms   remaining: 78.8ms
3:      total: 6.82ms   remaining: 78.5ms
4:      total: 8.62ms   remaining: 77.6ms
5:      total: 10.4ms   remaining: 76.3ms
6:      total: 12.3ms   remaining: 75.3ms
7:      total: 14ms     remaining: 73.6ms
8:      total: 16ms     remaining: 72.7ms
9:      total: 17.8ms   remaining: 71.2ms
10:     total: 19.6ms   remaining: 69.4ms
11:     total: 21.5ms   remaining: 68ms
12:     total: 23.4ms   remaining: 66.5ms
13:     total: 25.2ms   remaining: 64.7ms
14:     total: 27ms     remaining: 63ms
15:     total: 28.8ms   remaining: 61.2ms
16:     total: 30.6ms   remaining: 59.4ms
17:     total: 32.4ms   remaining: 57.6ms
18:     total: 34.2ms   remaining: 55.8ms
19:     total: 36ms     remaining: 54ms
20:     total: 37.9ms   remaining: 52.4ms
21:     total: 39.8ms   remaining: 50.6ms
22:     total: 41.5ms   remaining: 48.8ms
23:     total: 43.3ms   remaining: 47ms
24:     total: 45.1ms   remaining: 45.1ms
25:     total: 46.9ms   remaining: 43.3ms
26:     total: 48.8ms   remaining: 41.5ms
27:     total: 50.5ms   remaining: 39.7ms
28:     total: 52.4ms   remaining: 38ms
29:     total: 54.2ms   remaining: 36.1ms
30:     total: 56ms     remaining: 34.3ms
31:     total: 57.7ms   remaining: 32.5ms
32:     total: 59.4ms   remaining: 30.6ms
33:     total: 61.2ms   remaining: 28.8ms
34:     total: 62.9ms   remaining: 27ms
35:     total: 64.8ms   remaining: 25.2ms
36:     total: 66.6ms   remaining: 23.4ms

37:     total: 68.3ms   remaining: 21.6ms
38:     total: 70.1ms   remaining: 19.8ms
39:     total: 71.8ms   remaining: 18ms
40:     total: 73.7ms   remaining: 16.2ms
41:     total: 75.5ms   remaining: 14.4ms
42:     total: 77.2ms   remaining: 12.6ms
43:     total: 78.9ms   remaining: 10.8ms
44:     total: 80.7ms   remaining: 8.96ms
45:     total: 82.5ms   remaining: 7.17ms
```

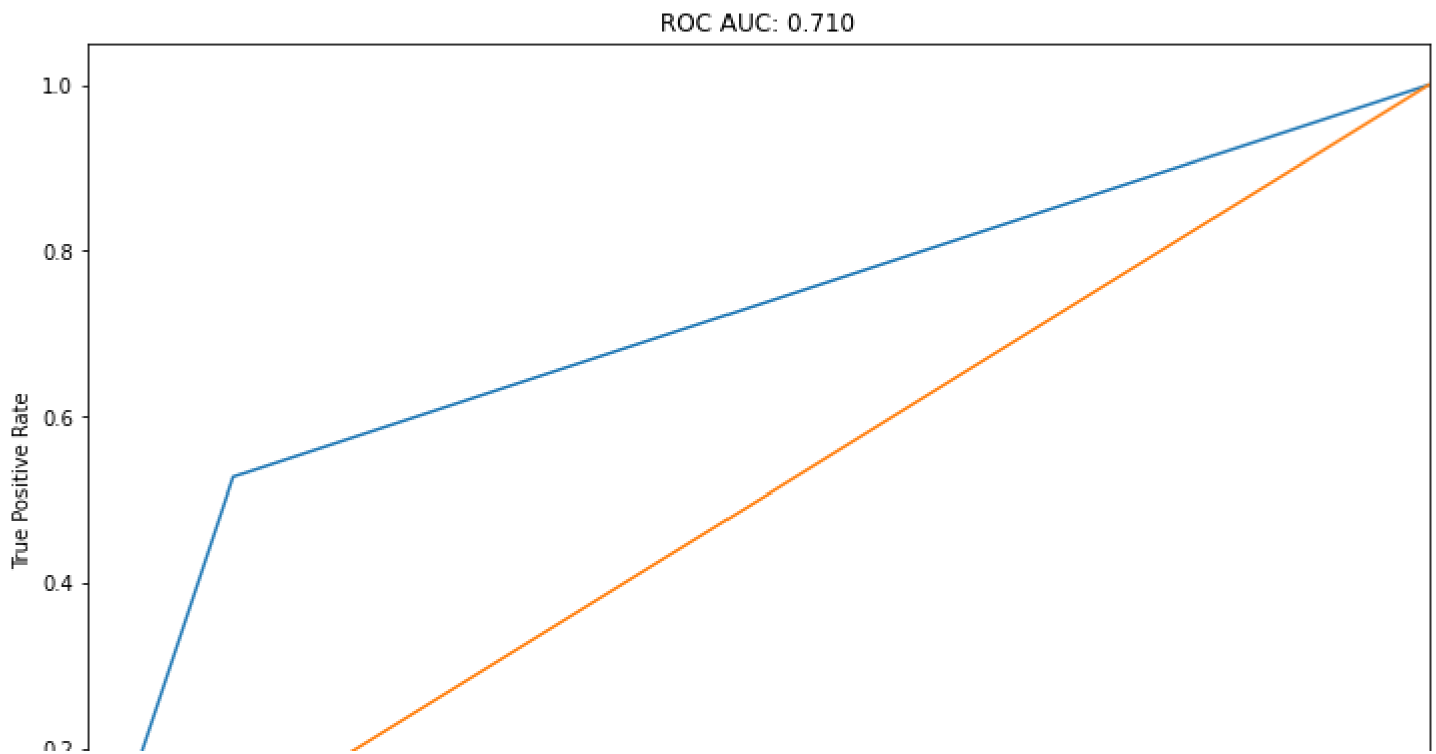
```
46:     total: 84.3ms   remaining: 5.38ms
47:     total: 86.1ms   remaining: 3.59ms
48:     total: 87.8ms   remaining: 1.79ms
49:     total: 89.6ms   remaining: 0us
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:  5.4min finished
GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=42, shuffle=True),
             error_score=nan,
             estimator=<catboost.core.CatBoostClassifier object at 0x7f4a152a5950>,
             iid='deprecated', n_jobs=-1,
             param_grid={'iterations': [1, 5, 10, 20, 50],
                         'max_depth': [5, 10, 15, 20],
                         'subsample': [0.66, 0.8, 1]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=1)
```

```
print("Train quality:")
quality(gcv_c.predict(X_train), y_train)
print("\nTest quality:")
quality(gcv_c.predict(X_test), y_test)
```

```
Train quality:
Accuracy:  0.832
Precision: 0.583
Recall:    0.732
F1-score:  0.649

Test quality:
Accuracy:  0.795
Precision: 0.528
Recall:    0.638
F1-score:  0.578
```

```
plot_roc_curve(gcv_c.predict(X_test), y_test)
```



LightGBM

```
gbmc = LGBMClassifier(n_estimators=100, random_state=42,
                             n_jobs=-1, oob_score=True)
gcv_l = GridSearchCV(gbmc, parameters, n_jobs=-1, cv=skf, verbose=1)
gcv_l.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 64 candidates, totalling 320 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:    4.6s
[Parallel(n_jobs=-1)]: Done 196 tasks      | elapsed:   21.8s
[Parallel(n_jobs=-1)]: Done 320 out of 320 | elapsed:   36.9s finished
GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=42, shuffle=True),
             error_score=nan,
             estimator=LGBMClassifier(boosting_type='gbdt', class_weight=None,
                                      colsample_bytree=1.0,
                                      importance_type='split',
                                      learning_rate=0.1, max_depth=-1,
                                      min_child_samples=20,
```

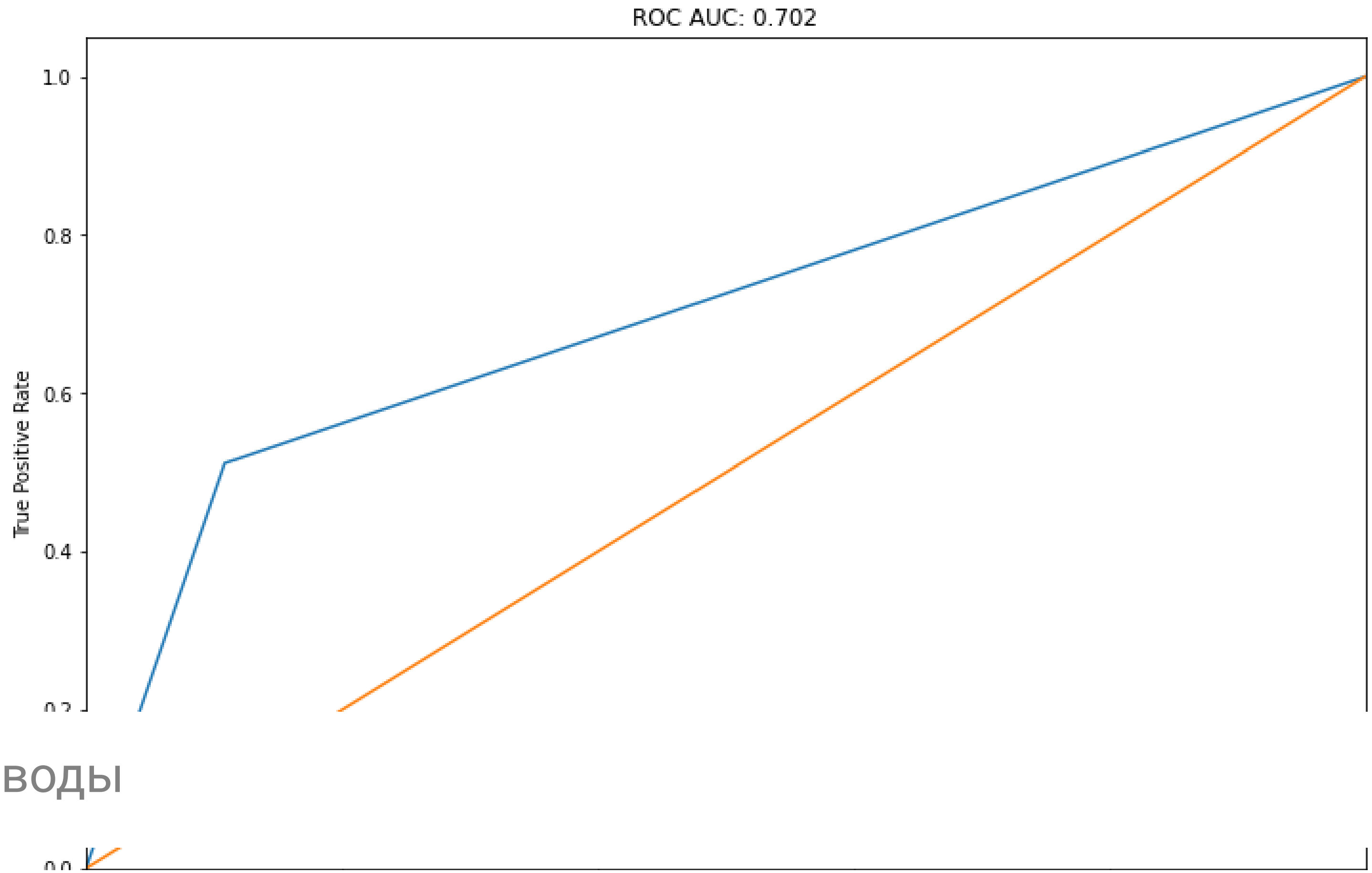
```
                                        min_child_weight=0.001,
                                        min_split_gain=0.0, n_estimators=100,
                                        n_jobs=-1, num_leaves=31, objective=None,
                                        oob_score=True, random_state=42,
                                        reg_alpha=0.0, reg_lambda=0.0,
                                        silent=True, subsample=1.0,
                                        subsample_for_bin=200000,
                                        subsample_freq=0),
                 iid='deprecated', n_jobs=-1,
                 param_grid={'max_depth': [5, 10, 15, 20],
                             'max_features': [4, 7, 10, 13],
                             'min_samples_leaf': [1, 3, 5, 7]},
                 pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                 scoring=None, verbose=1)
```

```
print("Train quality:")
quality(gcv_l.predict(X_train), y_train)
print("\nTest quality:")
quality(gcv_l.predict(X_test), y_test)
```

```
    Train quality:
    Accuracy:  0.855
    Precision: 0.635
    Recall:    0.778
    F1-score:  0.699

    Test quality:
    Accuracy:  0.791
    Precision: 0.512
    Recall:    0.631
    F1-score:  0.565
```

```
plot_roc_curve(gcv_l.predict(X_test), y_test)
```



Выводы

- без настроек гимперпараметров победила модель XGBOOST auc = 0,707, 2 место - catbost auc = 0,699 (если смотреть по метрике ROC_AUC)
- с настройками гиперпараметров на кросс валидации победила также модель CATBOST auc = 0,710, 2 место XGBOOST auc = 0,708

Вопрос: не могу понять, почему такое низкое качество выдали мои модели? Дело в настроцках фич?

0s completed at 10:49 PM