# Библиотеки Python для Data Science: продолжение

# Итоговый проект на тему: "Credit Default"

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In [1]:
```
import numpy as np
import pandas as pd

import matplotlib
from matplotlib import pyplot as plt
%matplotlib inline

import seaborn as sns

rc_params = {'figure.figsize': [11, 4.5], 'lines.linewidth': 2.5}

matplotlib.rcParams.update(rc_params)
sns.set_theme(style="whitegrid")
sns.set_context("notebook", font_scale=1.2, rc=rc_params)
```

In [2]:
```
from scipy.stats import chi2_contingency, mannwhitneyu
```

In [3]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split, StratifiedKFold, GridSearchCV
from sklearn.metrics import accuracy_score, classification_report, plot_confusion_matrix, plot_precision_recall_
```

In [4]:
```
import xgboost as xgb, lightgbm as lgbm, catboost as catb
```

## Импорт данных

In [5]:
```
TRAIN_DATASET_PATH = './data/credit-default/train.csv'
TEST_DATASET_PATH = './data/credit-default/test.csv'
```

In [6]:
```
df = pd.read_csv(TRAIN_DATASET_PATH)
test_df = pd.read_csv(TEST_DATASET_PATH)
display(df.shape, test_df.shape)
```

```
(7500, 17)
(2500, 16)
```

## Целевые классы

Credit Default - факт невыполнения кредитных обязательств (0 - погашен вовремя, 1 - просрочка)

In [7]:
```
target = 'Credit Default'
FREQ_NAME = 'Chance of Default'  # Обозначение частоты события "1". Ниже встретится сокращение CoD = Chance of D
target_counts = df[target].value_counts(normalize=True)
target_disbalance = target_counts.loc[0] / target_counts.loc[1]
print(target_counts, target_disbalance, sep='\n****\n')
```

```
0    0.718267
1    0.281733
Name: Credit Default, dtype: float64
****
2.5494557501183155
```

## Вспомогательные функции

In [8]:
```
# Возвращает частоту единичной целевой переменной для каждого значения категориального признака (пропуски считаю
def feature_target_counts(df, features, na_value='NA', target=target, freq_name=FREQ_NAME):
    result_df = df.filter(features + [target]).fillna(na_value).value_counts().unstack(fill_value=0)
    result_df['Count'] = result_df[0] + result_df[1]
    result_df['Share %'] = round(result_df['Count'] * 100 / df.shape[0], 2)
    result_df[freq_name] = result_df[1] / result_df['Count']
    return result_df
```

In [9]:
```python
# Возвращает частоту единичной целевой переменной для интервала распределения признака (на базе квантилей)
def get_quantile_freq(df, feature, nbins, target=target, freq_name=FREQ_NAME):
    _feature_df = df.filter([feature, target]).dropna()
    quantile_df = pd.DataFrame(_feature_df[feature].quantile(np.linspace(0, 1, nbins+1)))
    quantile_df[feature].iloc[[0, -1]] = np.NINF, np.inf
    quantile_df = quantile_df.reset_index().rename(columns = {'index': 'Quantile'})
    _feature_df['Feature Bin'] = pd.cut(_feature_df[feature], bins = quantile_df[feature], labels=False)
    return feature_target_counts(_feature_df, ['Feature Bin'], target=target, freq_name=freq_name).join(quantile
```

In [10]:
```python
# Используется для генерации target encoding-признака, сопоставляющего исходному значению признака
# частоту единичной целевой переменной соответствующего интервала распределения (из функции get_quantile_freq)
def get_feature_freq(df, quantile_freq, na_value=None, freq_name=FREQ_NAME):
    feature = quantile_freq.columns[-1]
    _feature_df = pd.DataFrame({'Feature Bin': pd.cut(df[feature], bins=quantile_freq[feature].tolist() + [np.in
    result_df = pd.merge(_feature_df, quantile_freq.reset_index().filter(['Feature Bin', freq_name]), how='left'
    if na_value is not None:
        result_df[freq_name].fillna(na_value, inplace=True)
    return result_df[freq_name].values
```

# Признаки: анализ существующих, генерация дополнительных

In [11]:
```python
feature_candidates = []  # Здесь будем собирать кандидатов в признаки модели
```

In [12]:
```python
# Предварительная значимость числовых признаков исходя из корреляции с целевой переменной
target_corr = df.corr()[target].abs().sort_values(ascending=False)[1:]
print(target_corr)
```

```
Credit Score                    0.442050
Current Loan Amount             0.226522
Annual Income                   0.101375
Number of Open Accounts         0.028884
Tax Liens                       0.024368
Years of Credit History         0.020567
Number of Credit Problems       0.020088
Current Credit Balance          0.019522
Monthly Debt                    0.018480
Maximum Open Credit             0.014275
Months since last delinquent    0.002598
Bankruptcies                    0.001648
Name: Credit Default, dtype: float64
```

In [13]:
```python
# Список категориальных признаков:
set(df.columns) - set(target_corr.index) - {target}
```

Out[13]:
```
{'Home Ownership', 'Purpose', 'Term', 'Years in current job'}
```

In [14]:
```python
# Признаки с пропущенными значениями
print(df.columns[df.apply(lambda x: x.isnull().any())].sort_values().tolist())
```

```
['Annual Income', 'Bankruptcies', 'Credit Score', 'Months since last delinquent', 'Years in current job']
```

## Credit Score

In [15]:
```python
feature_name = 'Credit Score'
df[feature_name].isnull().value_counts(normalize=True)
```

Out[15]:
```
False    0.7924
True     0.2076
Name: Credit Score, dtype: float64
```

In [16]:
```python
# Сразу заметим, что пропущенные значения признака Credit Score совпадают с пропущенными значениями Annual Incom
all(df['Credit Score'].isnull() == df['Annual Income'].isnull())
```

Out[16]:
```
True
```

**Примечание**: вне данного ноутбука была сделана попытка заполнить пропущенные значения Credit Score и Annual Income через регрессию по другим признакам, но значения R2 в районе ~0.3 показались недостаточными для практического применения этого метода.

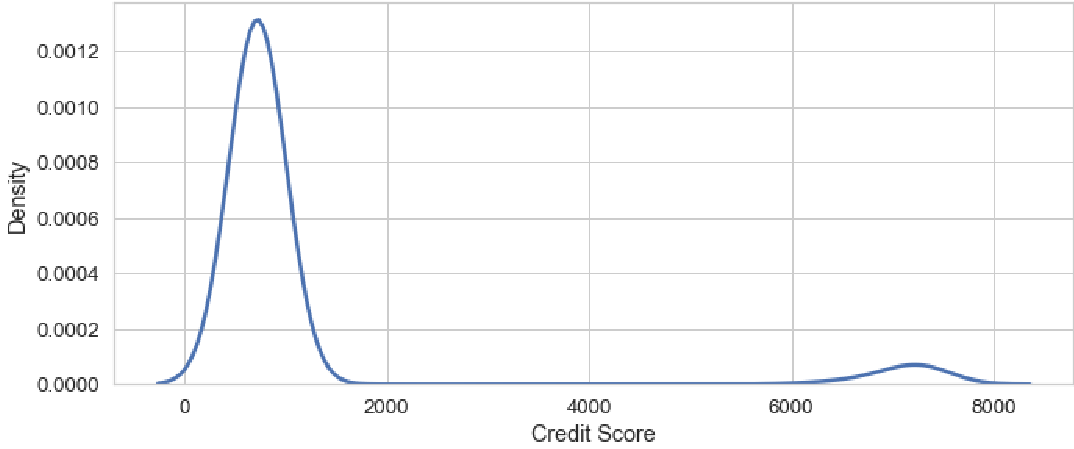
In [17]:
```python
# Запомним значение частоты дефолта для данных, у которых пропущен кредитный рейтинг и значения годового дохода,
credit_score_missing_freq = df.loc[df[feature_name].isnull(), target].mean()
```

```
credit_score_missing_freq
```

Out[17]: 0.3397559409120103

In [18]:

```
sns.kdeplot(data=df, x=feature_name);
```




In [19]:

```
# Выясним, как влияет "расположение на шкале" на целевую переменную
feature_df = df.assign(Tag=np.sign(df[feature_name] - 4000).map({-1: 'Low', 1: 'High'}))
feature_target_counts(feature_df, ['Tag'], 'Missing').sort_values(FREQ_NAME, ascending=False)
```

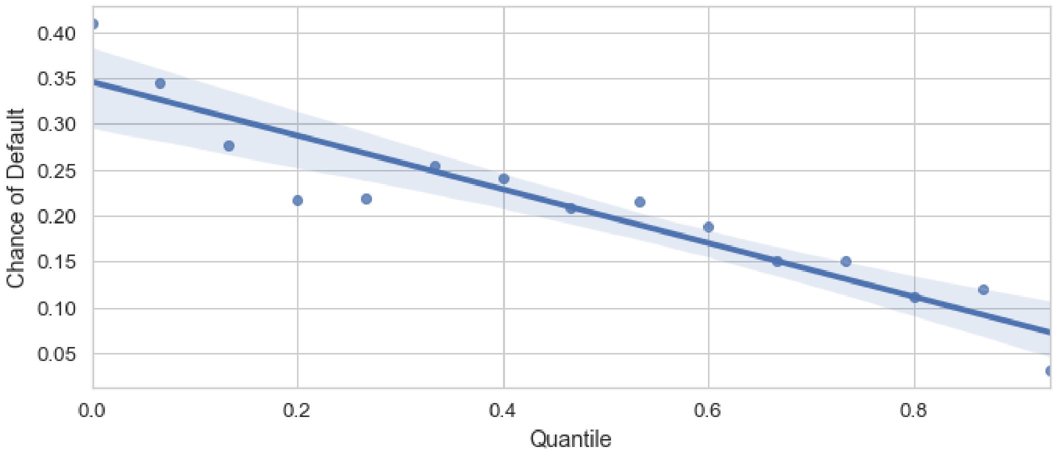
Out[19]:

| Credit Default | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|
| **Tag** | | | | | |
| **High** | 0 | 400 | 400 | 5.33 | 1.000000 |
| **Missing** | 1028 | 529 | 1557 | 20.76 | 0.339756 |
| **Low** | 4359 | 1184 | 5543 | 73.91 | 0.213603 |

Как видим, "десятикратные" показатели рейтинга однозначно свидетельствуют о ненадежности клиента.

In [20]:

```
# Посмотрим, как частота дефолта меняется в квантилях распределения "нижней кривой" признака
qfreq_df = get_quantile_freq(df[df[feature_name] < 4000], feature_name, nbins=15)
sns.regplot(data=qfreq_df, x='Quantile', y=FREQ_NAME);
```




In [21]:

```
# Создадим признак Credit Score CoD, в котором значению Credit Score сопоставлена частота единичной целевой пере
feature_freq_name = f"{feature_name} CoD"
df[feature_freq_name] = get_feature_freq(df, qfreq_df, na_value=credit_score_missing_freq)
test_df[feature_freq_name] = get_feature_freq(test_df, qfreq_df, na_value=credit_score_missing_freq)
```

In [22]:

```
# Учтем высокий риск "десятикратных" значений основного признака
df.loc[df[feature_name] > 4000, feature_freq_name] = 1.0
test_df.loc[test_df[feature_name] > 4000, feature_freq_name] = 1.0
```

In [23]:

```
df.filter([feature_name, feature_freq_name]).corr()
```

Out[23]:

| | Credit Score | Credit Score CoD |
|---|---|---|
| **Credit Score** | 1.00000 | 0.91332 |
| **Credit Score CoD** | 0.91332 | 1.00000 |

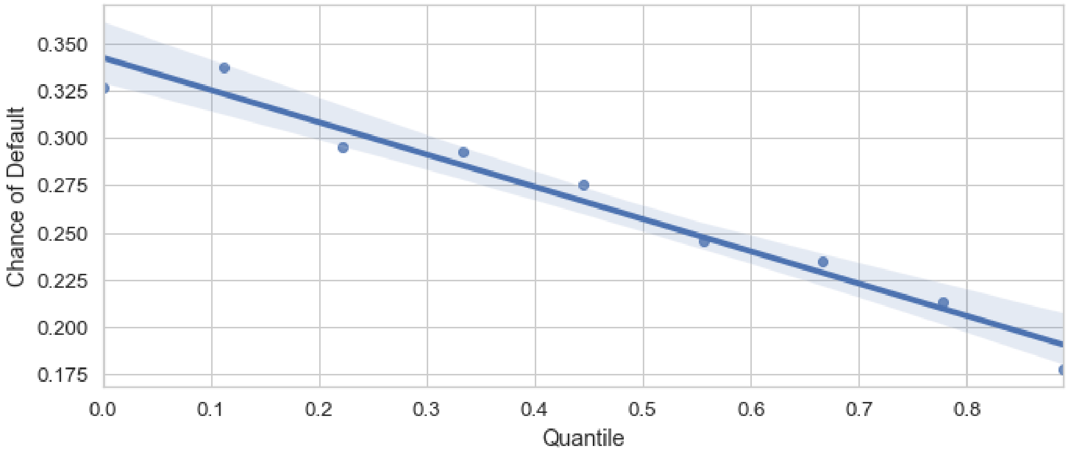
In [24]:
```
# Корреляция двух признаков большая, оставим только сгенерированный через целевую переменную
feature_candidates.append(feature_freq_name)
```

## Annual Income - годовой доход

In [25]:
```
feature_name = 'Annual Income'
df[feature_name].isnull().value_counts(normalize=True)
```

Out[25]:
```
False    0.7924
True     0.2076
Name: Annual Income, dtype: float64
```

In [26]:
```
# Создадим признак Annual Income CoD, аналогичный по построению Credit Score CoD
qfreq_df = get_quantile_freq(df, feature_name, nbins=9)
sns.regplot(data=qfreq_df, x='Quantile', y=FREQ_NAME)
feature_freq_name = f"{feature_name} CoD"
df[feature_freq_name] = get_feature_freq(df, qfreq_df, na_value=credit_score_missing_freq)
test_df[feature_freq_name] = get_feature_freq(test_df, qfreq_df, na_value=credit_score_missing_freq)
```




In [27]:
```
df.filter([feature_name, feature_freq_name]).corr()
```

Out[27]:

| | Annual Income | Annual Income CoD |
|---|---|---|
| **Annual Income** | 1.000000 | -0.826125 |
| **Annual Income CoD** | -0.826125 | 1.000000 |

In [28]:
```
feature_candidates.append(feature_freq_name)
```

## Current Loan Amount - текущая сумма кредита

In [29]:
```
feature_name = 'Current Loan Amount'
```

In [30]:
```
# Есть странное значение 99999999, обозначающее какое-то особое состояние
(df[feature_name] == 99999999).value_counts()
```

Out[30]:
```
False    6630
True      870
Name: Current Loan Amount, dtype: int64
```

In [31]:
```
# Как можно убедиться, "особое состояние" = "уверенность в погашении кредита"
feature_df = df.assign(Tag=df[feature_name] == 99999999)
feature_target_counts(feature_df, ['Tag'])
```

Out[31]:

| Credit Default | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|

| Credit Default | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|
| **Tag** | | | | | |
| **False** | 4517 | 2113 | 6630 | 88.4 | 0.318703 |
| **True** | 870 | 0 | 870 | 11.6 | 0.000000 |

In [32]:
```
# Создадим особый признак
new_feature_name = f"{feature_name} Low Risk"
df[new_feature_name] = (df[feature_name] == 99999999).astype(np.uint8)
test_df[new_feature_name] = (test_df[feature_name] == 99999999).astype(np.uint8)
```

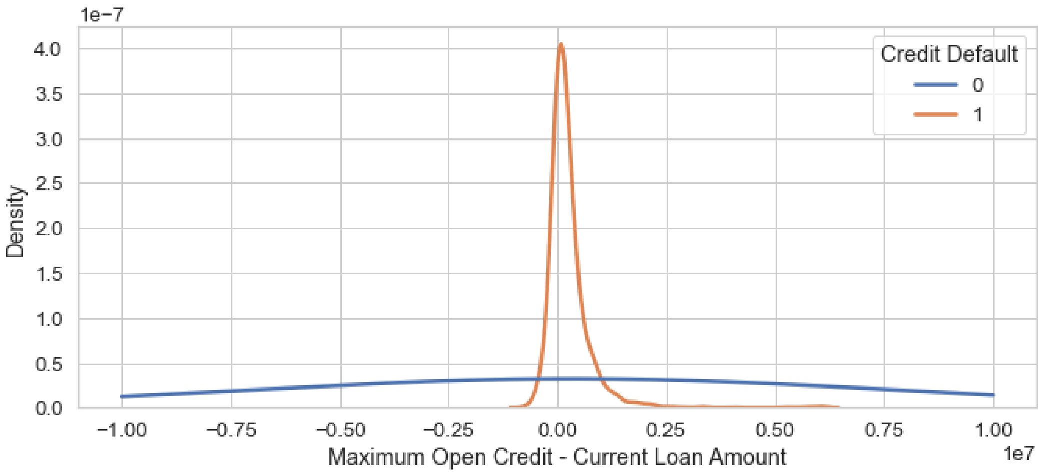
In [33]:
```
feature_candidates.append(new_feature_name)  # сам признак используем далее
```

## Maximum Open Credit - наибольший открытый кредит

Сравнение с Current Loan Amount может быть полезно для разделения целевой переменной.

In [34]:
```
feature_name = 'Maximum Open Credit'
cross_feature_name = 'Maximum Open Credit - Current Loan Amount'
df[cross_feature_name] = df[feature_name] - df['Current Loan Amount']
test_df[cross_feature_name] = test_df[feature_name] - test_df['Current Loan Amount']
```

In [35]:
```
sns.kdeplot(data=df, x=cross_feature_name, hue=target, clip=(-1e7, 1e7));
```




In [36]:
```
# Убедимся в отсутствии эквивалентность мат. ожадиний в исследуемых группах, с помощью критерия Манна-Уитни.
mannwhitneyu(
    df.loc[df[target] == 0, cross_feature_name].values,
    df.loc[df[target] == 1, cross_feature_name].values
)
```

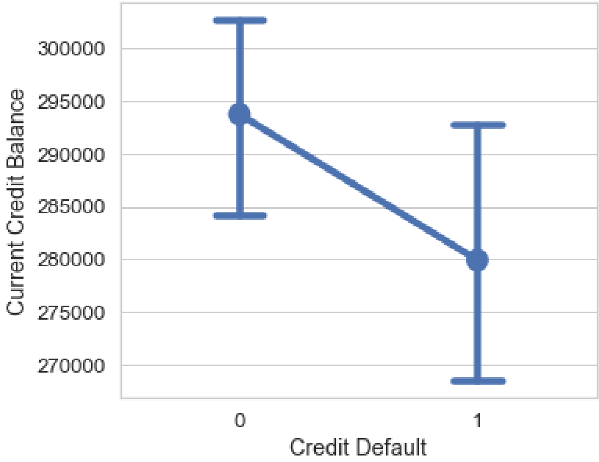
Out[36]:
```
MannwhitneyuResult(statistic=5371067.5, pvalue=7.317532151695133e-05)
```

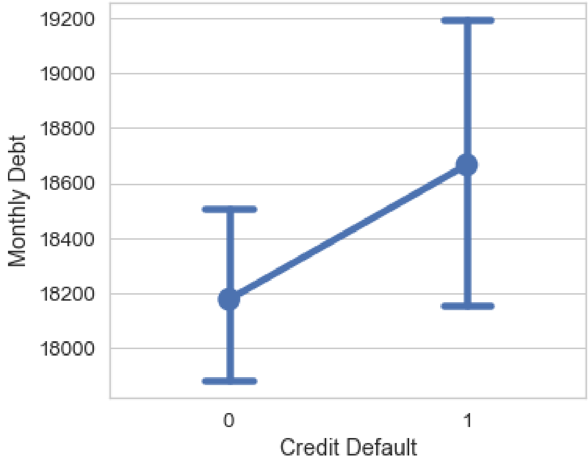
In [37]:
```
df.loc[(df['Current Loan Amount Low Risk'] == 1), cross_feature_name] = df.loc[(df['Current Loan Amount Low Risk
test_df.loc[(test_df['Current Loan Amount Low Risk'] == 1), cross_feature_name] = test_df.loc[(test_df['Current
```

In [38]:
```
feature_candidates.append(cross_feature_name)
```

## Current Credit Balance - текущий кредитный баланс и Monthly Debt - ежемесячный долг

In [39]:
```
# Оба признака не особенно эффективно разделяют целевую переменную
fig, ax = plt.subplots(1,2)
sns.pointplot(data=df, x=target, y='Current Credit Balance', capsize=.2, ax=ax[0])
sns.pointplot(data=df, x=target, y='Monthly Debt', capsize=.2, ax=ax[1])
fig.tight_layout()
```




In [40]:

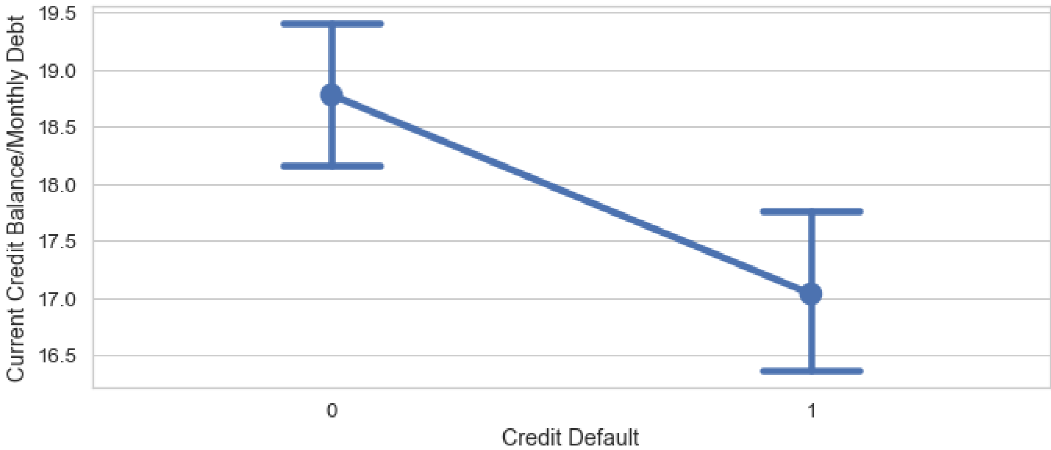
```
# Создадим синтетический признак частного от деления 'Current Credit Balance' на 'Monthly Debt'
df.loc[df['Monthly Debt'] == 0, 'Monthly Debt'] = np.NaN
df['Current Credit Balance/Monthly Debt'] = df['Current Credit Balance'] / df['Monthly Debt']
df['Current Credit Balance/Monthly Debt'].fillna(df['Current Credit Balance/Monthly Debt'].max(), inplace=True)
df['Monthly Debt'].fillna(0, inplace=True)
```

In [41]:

```
test_df.loc[df['Monthly Debt'] == 0, 'Monthly Debt'] = np.NaN
test_df['Current Credit Balance/Monthly Debt'] = test_df['Current Credit Balance'] / test_df['Monthly Debt']
test_df['Current Credit Balance/Monthly Debt'].fillna(test_df['Current Credit Balance/Monthly Debt'].max(), inpl
test_df['Monthly Debt'].fillna(0, inplace=True)
```

In [42]:

```
# Ситетический признак разделяем немного лучше
sns.pointplot(data=df, x=target, y='Current Credit Balance/Monthly Debt', capsize=.2);
```




In [43]:

```
feature_candidates.append('Current Credit Balance/Monthly Debt')
```

## Tax Liens - налоговые обременения

In [44]:

```
feature_name = 'Tax Liens'
agg_df = feature_target_counts(df, [feature_name])
agg_df
```

Out[44]:

| Credit Default | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|
| Tax Liens | | | | | |
| **0.0** | 5301 | 2065 | 7366 | 98.21 | 0.280342 |
| **1.0** | 59 | 24 | 83 | 1.11 | 0.289157 |
| **2.0** | 15 | 15 | 30 | 0.40 | 0.500000 |
| **3.0** | 5 | 5 | 10 | 0.13 | 0.500000 |
| **4.0** | 3 | 3 | 6 | 0.08 | 0.500000 |
| **5.0** | 1 | 1 | 2 | 0.03 | 0.500000 |

| Credit Default | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|
| **Tax Liens** | | | | | |
| **6.0** | 2 | 0 | 2 | 0.03 | 0.000000 |
| **7.0** | 1 | 0 | 1 | 0.01 | 0.000000 |

In [45]:
```
# Группы мало пригодны для разделения целевой переменной
chi2, p, dof, ex = chi2_contingency(agg_df.loc[[0,1], [0,1]])
p
```

Out[45]: 0.956212700856196

## Number of Credit Problems - количество проблем с кредитом

In [46]:
```
feature_name = 'Number of Credit Problems'
agg_df = feature_target_counts(df, [feature_name])
agg_df
```

Out[46]:

| Credit Default | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|
| **Number of Credit Problems** | | | | | |
| **0.0** | 4654 | 1815 | 6469 | 86.25 | 0.280569 |
| **1.0** | 641 | 241 | 882 | 11.76 | 0.273243 |
| **2.0** | 60 | 33 | 93 | 1.24 | 0.354839 |
| **3.0** | 21 | 14 | 35 | 0.47 | 0.400000 |
| **4.0** | 3 | 6 | 9 | 0.12 | 0.666667 |
| **5.0** | 3 | 4 | 7 | 0.09 | 0.571429 |
| **6.0** | 4 | 0 | 4 | 0.05 | 0.000000 |
| **7.0** | 1 | 0 | 1 | 0.01 | 0.000000 |

In [47]:
```
chi2, p, dof, ex = chi2_contingency(agg_df.loc[[0,1], [0,1]])
p
```

Out[47]: 0.6783214582441461

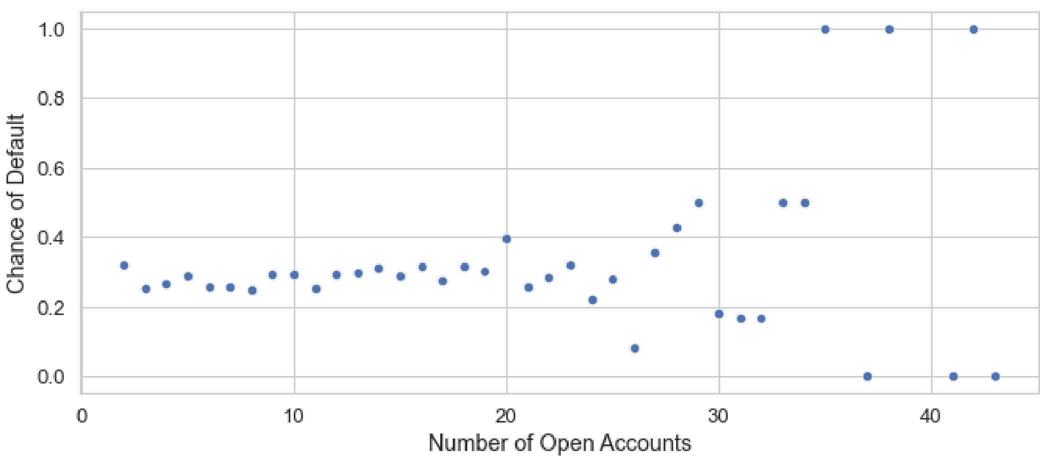
In [48]:
```
chi2, p, dof, ex = chi2_contingency(agg_df.loc[[0,2], [0,1]])
p
```

Out[48]: 0.14293426550821686

Такая же история, группы либо малочисленные, либо не разделяют целевую переменную в достаточной мере.

## Number of Open Accounts - количество открытых счетов

In [49]:
```
feature_name = 'Number of Open Accounts'
sns.scatterplot(data=feature_target_counts(df, [feature_name]), x=feature_name, y=FREQ_NAME);
```



In [50]:
```python
# Начиная с некоторого значения признака, в данном случае, с 13, заметно отличие частоты дефолта
agg_df = feature_target_counts(df.assign(Over_12 =(df[feature_name] > 12)), ['Over_12'])
agg_df
```

Out[50]:

| Credit Default | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|
| **Over_12** | | | | | |
| **False** | 3692 | 1382 | 5074 | 67.65 | 0.272369 |
| **True** | 1695 | 731 | 2426 | 32.35 | 0.301319 |

In [51]:
```python
# Убедимся, что частоты не согласованы
chi2, p, dof, ex = chi2_contingency(agg_df.iloc[[0, 1], [0,1]])
p
```

Out[51]: 0.009886126527020072

In [52]:
```python
new_feature_name = f"{feature_name} Over 12"
df[new_feature_name] = (df[feature_name] > 12).astype(np.uint8)
test_df[new_feature_name] = (test_df[feature_name] > 12).astype(np.uint8)
```

In [53]:
```python
feature_candidates.append(new_feature_name)
```

## Years in current job - количество лет на текущем месте работы

In [54]:
```python
feature_name = 'Years in current job'
feature_target_counts(df, [feature_name]).sort_values(FREQ_NAME, ascending=False)
```

Out[54]:

| Credit Default | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|
| **Years in current job** | | | | | |
| **NA** | 234 | 137 | 371 | 4.95 | 0.369272 |
| **6 years** | 302 | 124 | 426 | 5.68 | 0.291080 |
| **< 1 year** | 404 | 159 | 563 | 7.51 | 0.282416 |
| **1 year** | 362 | 142 | 504 | 6.72 | 0.281746 |
| **5 years** | 371 | 145 | 516 | 6.88 | 0.281008 |
| **7 years** | 285 | 111 | 396 | 5.28 | 0.280303 |
| **4 years** | 338 | 131 | 469 | 6.25 | 0.279318 |
| **10+ years** | 1688 | 644 | 2332 | 31.09 | 0.276158 |
| **3 years** | 450 | 170 | 620 | 8.27 | 0.274194 |
| **2 years** | 512 | 193 | 705 | 9.40 | 0.273759 |
| **8 years** | 247 | 92 | 339 | 4.52 | 0.271386 |
| **9 years** | 194 | 65 | 259 | 3.45 | 0.250965 |

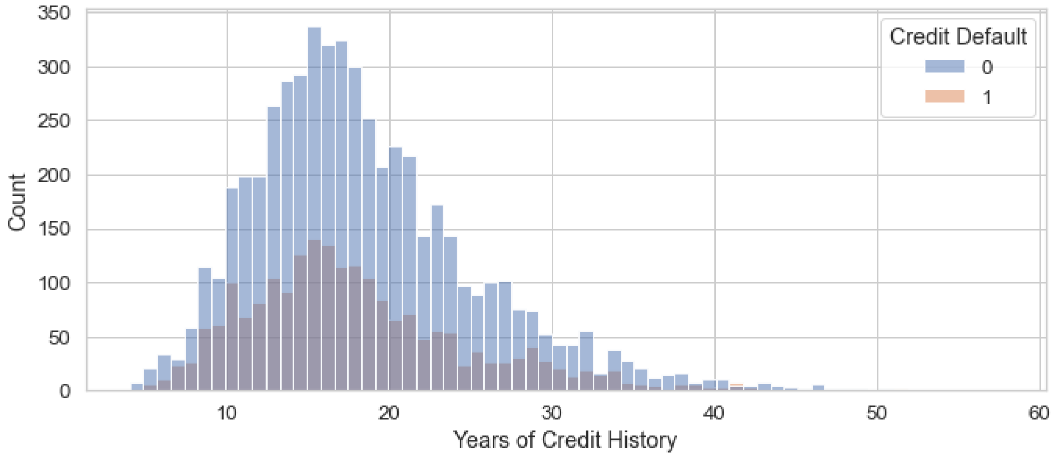
In [55]:
```python
# Создадим признак пропущенного значения, а значения самого признака не будем использовать
feature_missing_name = f"{feature_name} Missing"
df[feature_missing_name] = df[feature_name].isnull().astype(np.uint8)
test_df[feature_missing_name] = test_df[feature_name].isnull().astype(np.uint8)
```

In [56]:
```python
feature_candidates.append(feature_missing_name)
```

## Years of Credit History - количество лет кредитной истории

In [57]:
```python
feature_name = 'Years of Credit History'
```

In [58]:
```python
sns.histplot(data=df, x=feature_name, hue=target);
```




In [59]:
```
mannwhitneyu(
    df.loc[df[target] == 0, feature_name].values,
    df.loc[df[target] == 1, feature_name].values
)
```

Out[59]:
```
MannwhitneyuResult(statistic=5461129.5, pvalue=0.003171215731103466)
```

In [60]:
```
feature_candidates.append(feature_name)
```

## Months since last delinquent - количество месяцев с последней просрочки платежа

In [61]:
```
feature_name = 'Months since last delinquent'
df[feature_name].isnull().value_counts(normalize=True)
```

Out[61]:
```
True     0.544133
False    0.455867
Name: Months since last delinquent, dtype: float64
```

In [62]:
```
feature_df = df.filter([feature_name, 'Annual Income', target]).copy()
feature_df['Tag'] = 10 * feature_df['Annual Income'].isnull() + feature_df[feature_name].isnull()
feature_target_counts(feature_df, ['Tag'])
```

Out[62]:

| Credit Default | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|
| **Tag** | | | | | |
| **0** | 2003 | 733 | 2736 | 36.48 | 0.267909 |
| **1** | 2356 | 851 | 3207 | 42.76 | 0.265357 |
| **10** | 433 | 250 | 683 | 9.11 | 0.366032 |
| **11** | 595 | 279 | 874 | 11.65 | 0.319222 |

In [63]:
```
# Отметим несколько большую частоту дефолта в данных, у которых отсутствует значение Annual Income, но ненулевое
new_feature_name = f"{feature_name} Special"
df[new_feature_name] = ((10 * df['Annual Income'].isnull() + df[feature_name].isnull() == 10)).astype(np.uint8)
test_df[new_feature_name] = (10 * df['Annual Income'].isnull() + test_df[feature_name].isnull() == 10).astype(np
```

In [64]:
```
feature_target_counts(df, [new_feature_name])
```

Out[64]:

| Credit Default | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|
| **Months since last delinquent Special** | | | | | |
| **0** | 4954 | 1863 | 6817 | 90.89 | 0.273287 |
| **1** | 433 | 250 | 683 | 9.11 | 0.366032 |

In [65]:
```
feature_candidates.append(new_feature_name)
```

## Bankruptcies - банкротства

In [66]:
```
# Группы не особо помогают разделить целевую переменную
feature_target_counts(df, ['Bankruptcies'], -1)
```

Out[66]:

| Credit Default<br>Bankruptcies | 0 | 1 | Count | Share % | Chance of Default |
|---|---|---|---|---|---|
| **-1.0** | 10 | 4 | 14 | 0.19 | 0.285714 |
| **0.0** | 4782 | 1878 | 6660 | 88.80 | 0.281982 |
| **1.0** | 569 | 217 | 786 | 10.48 | 0.276081 |
| **2.0** | 20 | 11 | 31 | 0.41 | 0.354839 |
| **3.0** | 5 | 2 | 7 | 0.09 | 0.285714 |
| **4.0** | 1 | 1 | 2 | 0.03 | 0.500000 |

## Purpose / Term / Home Ownership

In [67]:
```
# Создадим новый признак, принимающий значения частоты дефолта, в зависимости от сочетания значений Purpose, Ter
new_feature_name = 'Purpose/Term/Home Ownership CoD'
```

In [68]:
```
agg_df = (
    feature_target_counts(df, ['Purpose', 'Term', 'Home Ownership'])
    .sort_values('Share %', ascending=False)
    .filter(['Share %', FREQ_NAME])
    .reset_index()
    .rename(columns={FREQ_NAME: new_feature_name, 'Share %': f"{new_feature_name} Share"})
)
agg_df.head(7)
```

Out[68]:

| Credit Default | Purpose | Term | Home Ownership | Purpose/Term/Home Ownership CoD Share | Purpose/Term/Home Ownership CoD |
|---|---|---|---|---|---|
| **0** | debt consolidation | Short Term | Rent | 27.35 | 0.268649 |
| **1** | debt consolidation | Short Term | Home Mortgage | 26.35 | 0.188259 |
| **2** | debt consolidation | Long Term | Home Mortgage | 11.84 | 0.382883 |
| **3** | debt consolidation | Long Term | Rent | 7.16 | 0.472998 |
| **4** | debt consolidation | Short Term | Own Home | 4.80 | 0.230556 |
| **5** | other | Short Term | Rent | 3.77 | 0.265018 |
| **6** | home improvements | Short Term | Home Mortgage | 2.96 | 0.171171 |

In [69]:
```
df = pd.merge(df, agg_df, how='left')
df[new_feature_name].fillna(credit_score_missing_freq, inplace=True)
test_df = pd.merge(test_df, agg_df, how='left')
test_df[new_feature_name].fillna(credit_score_missing_freq, inplace=True)
```

In [70]:
```
feature_candidates.append(new_feature_name)
```

# Базовая модель

## Корреляция признаков-кандидатов с целевой переменной и между собой

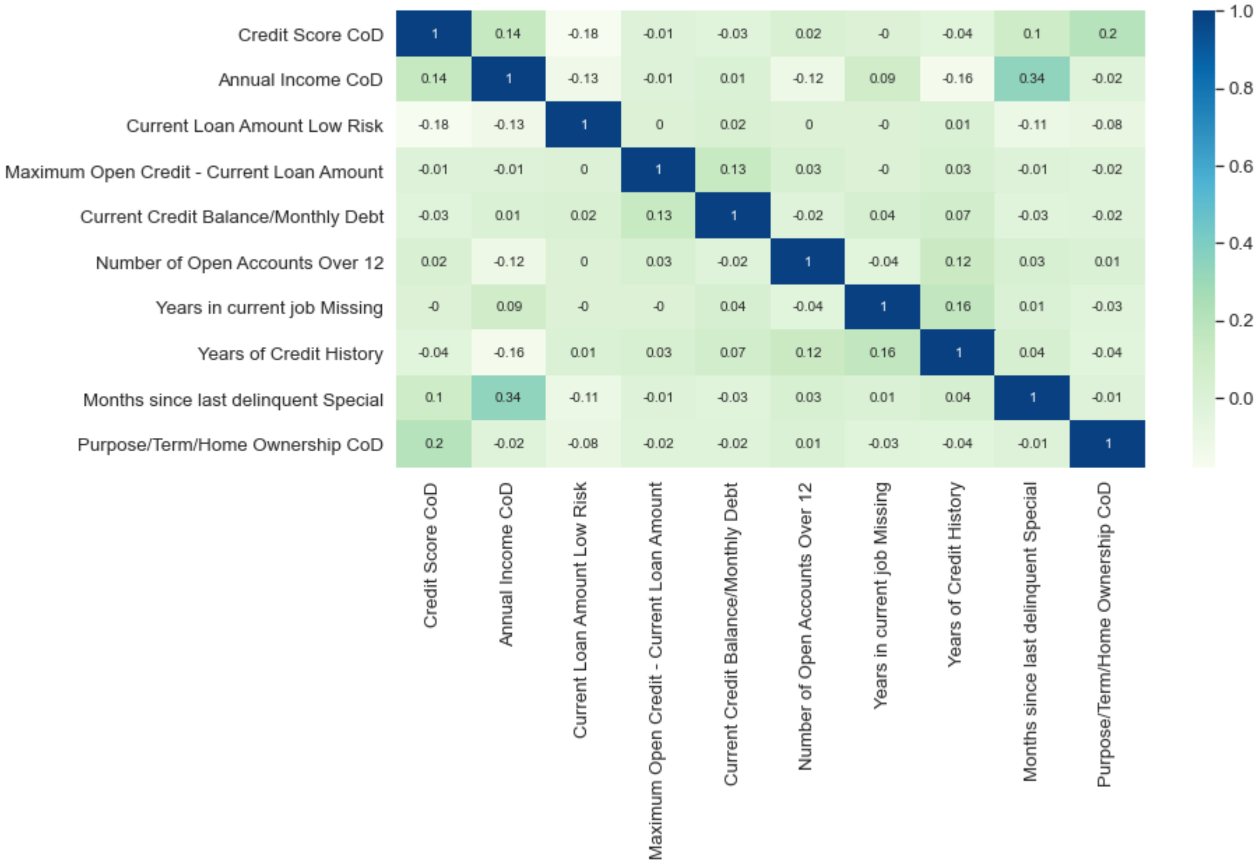
In [71]:
```
df.filter(feature_candidates + [target]).corr()[target].abs().sort_values(ascending=False)[1:]
```

Out[71]:
```
Credit Score CoD                       0.428685
Purpose/Term/Home Ownership CoD        0.232629
Current Loan Amount Low Risk           0.226871
Annual Income CoD                      0.119038
Months since last delinquent Special   0.059316
Years in current job Missing           0.044393
```

```
Current Credit Balance/Monthly Debt         0.036132
Number of Open Accounts Over 12             0.030106
Years of Credit History                     0.020567
Maximum Open Credit - Current Loan Amount   0.016367
Name: Credit Default, dtype: float64
```

In [72]:
```
feature_corr_matrix = df.filter(feature_candidates).corr().round(2)
```

In [73]:
```
sns_plot = sns.heatmap(feature_corr_matrix, annot=True, cmap='GnBu', annot_kws={"fontsize":10})
sns_plot.figure.set_size_inches((12, 6))
```




In [74]:
```
# Считаем, что все кандидаты годятся
use_features = feature_candidates
```

## Наборы данных для моделей

In [75]:
```
X = df.filter(use_features)
y = df[target]
```

In [76]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=True, stratify=y, random_state=
X_train.shape, X_test.shape
```

Out[76]:
```
((5250, 10), (2250, 10))
```

In [77]:
```
basic_model = DecisionTreeClassifier(random_state=2020, max_depth=5)
```

# Балансировка

Сравним методы Tomeklinks, SMOTE и задание весов классов базовой модели

## Tomeklinks

In [78]:
```
from imblearn.under_sampling import TomekLinks

tl = TomekLinks()
X_train_balanced, y_train_balanced = tl.fit_sample(X_train, y_train)
```

```
y_train_balanced.value_counts()
```

Out[78]:
```
0    3100
1    1479
Name: Credit Default, dtype: int64
```

In [79]:
```
basic_model.fit(X_train_balanced, y_train_balanced)
print(classification_report(y_test, basic_model.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.77      0.98      0.86      1616
           1       0.81      0.25      0.39       634

    accuracy                           0.77      2250
   macro avg       0.79      0.61      0.62      2250
weighted avg       0.78      0.77      0.73      2250
```

## SMOTE

In [80]:
```
from imblearn.over_sampling import SMOTE

smote = SMOTE()
X_train_balanced, y_train_balanced = smote.fit_sample(X_train, y_train)

y_train_balanced.value_counts()
```

Out[80]:
```
1    3771
0    3771
Name: Credit Default, dtype: int64
```

In [81]:
```
basic_model.fit(X_train_balanced, y_train_balanced)
print(classification_report(y_test, basic_model.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.82      0.73      0.77      1616
           1       0.46      0.59      0.52       634

    accuracy                           0.69      2250
   macro avg       0.64      0.66      0.65      2250
weighted avg       0.72      0.69      0.70      2250
```

## Задание весов классов

In [82]:
```
basic_model = DecisionTreeClassifier(random_state=2020, max_depth=5, class_weight={0:1, 1:target_disbalance})
basic_model.fit(X_train, y_train)
pred_train = basic_model.predict(X_train)
pred_test = basic_model.predict(X_test)
print(f'Accuracy на трейне {accuracy_score(y_train, pred_train)}')
print(f'Accuracy на тесте {accuracy_score(y_test, pred_test)}')
print(classification_report(y_train, basic_model.predict(X_train)))
print(classification_report(y_test, basic_model.predict(X_test)))
```

```
Accuracy на трейне 0.7346666666666667
Accuracy на тесте 0.7368888888888889
              precision    recall  f1-score   support

           0       0.82      0.81      0.81      3771
           1       0.53      0.54      0.53      1479

    accuracy                           0.73      5250
   macro avg       0.67      0.68      0.67      5250
weighted avg       0.74      0.73      0.74      5250

              precision    recall  f1-score   support

           0       0.82      0.82      0.82      1616
           1       0.53      0.53      0.53       634

    accuracy                           0.74      2250
   macro avg       0.67      0.67      0.67      2250
weighted avg       0.74      0.74      0.74      2250
```

> Далее будем использовать веса классов

In [83]:
```
basic_model.fit(X, y)
basic_df = pd.DataFrame({'Id': test_df.index.values, target: basic_model.predict(test_df.filter(use_features))})
basic_df.to_csv('avidclam_submit_basic.csv', index=False)
```

**Kaggle Score = 0.48945**

# Модели бустинга

Сразу зададим "улучшенные" параметры

## XGBoost

In [84]:
```
%%time
model_xgb = xgb.XGBClassifier(
    booster='gbtree',
    tree_method='hist',
    importance_type='total_gain',
    random_state=2020,
    scale_pos_weight=target_disbalance,
    learning_rate=0.07,
    max_depth=5,
    n_estimators=100,
    reg_lambda=30
)
model_xgb.fit(X_train, y_train)
print(classification_report(y_train, model_xgb.predict(X_train)))
print(classification_report(y_test, model_xgb.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.87      0.75      0.81      3771
           1       0.53      0.71      0.60      1479

    accuracy                           0.74      5250
   macro avg       0.70      0.73      0.70      5250
weighted avg       0.77      0.74      0.75      5250

              precision    recall  f1-score   support

           0       0.84      0.73      0.78      1616
           1       0.49      0.64      0.55       634

    accuracy                           0.71      2250
   macro avg       0.66      0.69      0.67      2250
weighted avg       0.74      0.71      0.72      2250

Wall time: 229 ms
```

## LightGBM

In [85]:
```
%%time
model_lgbm = lgbm.LGBMClassifier(
    random_state=2020,
    class_weight={0:1, 1:target_disbalance},
    learning_rate=0.07,
    max_depth=5,
    n_estimators=100,
    reg_lambda=30,
    num_leaves=30
)
model_lgbm.fit(X_train, y_train)
print(classification_report(y_train, model_lgbm.predict(X_train)))
print(classification_report(y_test, model_lgbm.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.86      0.75      0.80      3771
           1       0.52      0.70      0.60      1479

    accuracy                           0.73      5250
   macro avg       0.69      0.73      0.70      5250
weighted avg       0.77      0.73      0.74      5250

              precision    recall  f1-score   support

           0       0.84      0.74      0.78      1616
           1       0.49      0.64      0.55       634

    accuracy                           0.71      2250
   macro avg       0.66      0.69      0.67      2250
weighted avg       0.74      0.71      0.72      2250
```

```
Wall time: 201 ms
```

### CatBoost

In [86]:

```
%%time
frozen_params = {
    'silent':True,
    'random_state':2020,
    'eval_metric':'F1',
    'l2_leaf_reg': 50,
    'class_weights': [1, target_disbalance],
    'iterations': 100,
    'max_depth': 5
}
model_cb = catb.CatBoostClassifier(**frozen_params)
model_cb.fit(X_train, y_train)
print(classification_report(y_train, model_cb.predict(X_train)))
print(classification_report(y_test, model_cb.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.85      0.72      0.78      3771
           1       0.48      0.66      0.56      1479

    accuracy                           0.71      5250
   macro avg       0.66      0.69      0.67      5250
weighted avg       0.74      0.71      0.72      5250

              precision    recall  f1-score   support

           0       0.83      0.72      0.77      1616
           1       0.47      0.63      0.54       634

    accuracy                           0.69      2250
   macro avg       0.65      0.68      0.65      2250
weighted avg       0.73      0.69      0.71      2250

Wall time: 470 ms
```

## Подбор гиперпараметров

Ни одна из моделей радикально не опередила другие по метрикам, для подбора гиперпараметров возьмем LightGBM, так как она имеет преимущество в скорости.

model = lgbm.LGBMClassifier(random_state=2020) param_grid={ 'class_weight': [{0:1, 1:target_disbalance*k} for k in (0.9, 1)], 'learning_rate': [0.07, 0.1], 'max_depth': [5, 6], 'n_estimators': [70, 100, 200], 'reg_lambda': [20, 30, 50], 'num_leaves': [20, 30, 70], } cv = StratifiedKFold(n_splits=3, random_state=31, shuffle=True) grid_search = GridSearchCV(model, param_grid, scoring='', cv=cv, n_jobs=-1, verbose=1) grid_search.fit(X_train, y_train) best_model = grid_search.best_estimator_ print(classification_report(y_test, best_model.predict(X_test)))Лучшие параметры: {'class_weight': {0: 1, 1: 2.294510175106484}, 'learning_rate': 0.07, 'max_depth': 5, 'n_estimators': 200, 'num_leaves': 70, 'reg_lambda': 20}Метрики на трейне: precision recall f1-score support 0 0.87 0.81 0.84 3771 1 0.60 0.69 0.64 1479 accuracy 0.78 5250 macro avg 0.73 0.75 0.74 5250 weighted avg 0.79 0.78 0.79 5250

Метрики на тесте:

precision recall f1-score support 0 0.82 0.78 0.80 1616 1 0.51 0.58 0.54 634 accuracy 0.72 2250 macro avg 0.67 0.68 0.67 2250 weighted avg 0.74 0.72 0.73 2250

## Финальная модель и экспорт данных

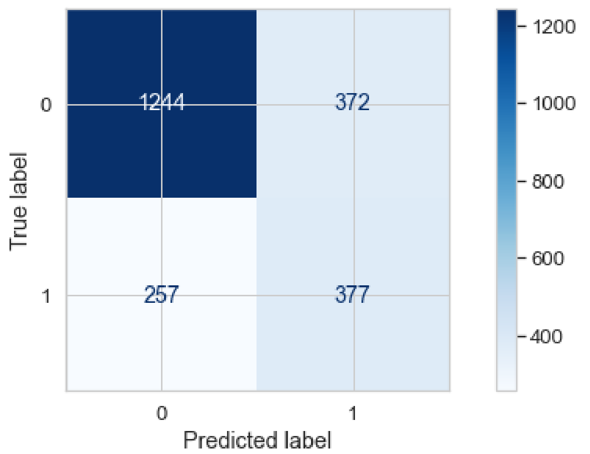
В финальной модели немного скорректированы параметры для снижения переобучения и повышения Precision (балансом Precision/Recall можно управлять, меняя class_weight).

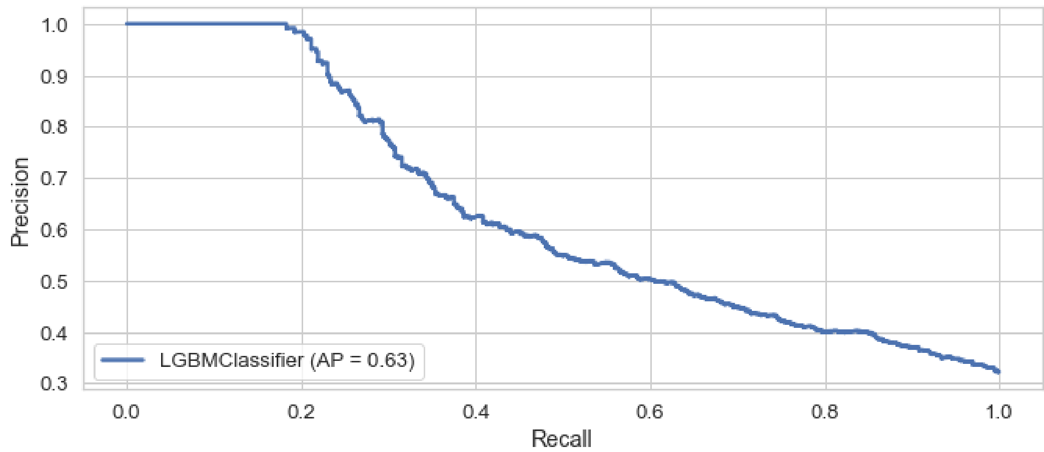
In [87]:

```
final_params = {'class_weight': {0: 1, 1: target_disbalance*.92},
                'learning_rate': 0.07,
                'max_depth': 5,
                'n_estimators': 200,
                'num_leaves': 20,
                'reg_lambda': 50}
final_model = lgbm.LGBMClassifier(random_state=2020, **final_params)
final_model.fit(X_train, y_train)
print(classification_report(y_train, final_model.predict(X_train)))
print(classification_report(y_test, final_model.predict(X_test)))
plot_confusion_matrix(final_model, X_test, y_test, cmap=plt.cm.Blues)
plot_precision_recall_curve(final_model, X_test, y_test);
```

```
              precision    recall  f1-score   support

           0       0.86      0.79      0.83      3771
           1       0.56      0.68      0.62      1479

    accuracy                           0.76      5250
```

```
   macro avg       0.71      0.74      0.72      5250
weighted avg       0.78      0.76      0.77      5250

              precision    recall  f1-score   support

           0       0.83      0.77      0.80      1616
           1       0.50      0.59      0.55       634

    accuracy                           0.72      2250
   macro avg       0.67      0.68      0.67      2250
weighted avg       0.74      0.72      0.73      2250
```




In [88]:

```
final_model.fit(X, y)
final_df = pd.DataFrame({'Id': test_df.index.values, target: final_model.predict(test_df.filter(use_features))})
final_df.to_csv('avidclam_submit.csv', index=False)
```

**Kaggle Score: 0.54244**