Спортивный анализ данных. Платформа Kaggle

Урок 2. Обзор основных алгоритмов машинного обучения, используемых в соревнованиях

Домашнее задание:

В домашнем задании, будем обучать разные алгоритмы машинного обучения. Для этого, нужно предварительно зафиксировать схему валидации решения (можете выбрать любую, которую знаете). Выбранную схему валидации нужно использовать во всех задачах этого домашнего задания. Метрика качества - **ROC AUC**, целевая переменная - **isFraud**.

Ссылка на данные - https://drive.google.com/file/d/1gMEVl47pIoV1-AseB9doQ6DZNJrY3NkW/view?usp=sharing (https://drive.google.com/file/d/1gMEVl47pIoV1-AseB9doQ6DZNJrY3NkW/view?usp=sharing)

Задание 1: отобрать только числовые признаки и обучить модель XGBoost с параметром booster = gbtree. Обучать алгоритм до тех пор, пока метрика качества не перестанет улучшаться на валидационной выборке в течение определенного числа итераций (выбрать значение самостоятельно).

Задание 2: обработать категориальные признаки любым способом (который вы знаете) и добавить их к данным. Выполнить задание 1.

Задание 4: для числовых признаков обучить модель LightGBM. Обучать алгоритм до тех пор, пока метрика качества не перестанет улучшаться на валидационной выборке в течение определенного числа итераций (выбрать значение самостоятельно).

Задание 5: обработать категориальные признаки любым способом (который вы знаете) и добавить их к данным. Выполнить задание 4.

Задание 6: обработать категориальные признаки встроенным методом в LightGBM. Выполнить задание 4. Сделать выводы о качестве работы алгоритма, по сравнению с пунктом 5.

Задание 7: для числовых признаков обучить модель CatBoost. Обучать алгоритм до тех пор, пока метрика качества не перестанет улучшаться на валидационной выборке в течение определенного числа итераций (выбрать значение самостоятельно).

Задание 8: обработать категориальные признаки любым способом (который вы знаете) и добавить их к данным. Выполнить задание 7.

Задание 9: обработать категориальные признаки встроенным методом в CatBoost. Выполнить задание 7. Сделать выводы о качестве работы алгоритма, по сравнению с пунктом 8.

Задание 10: построить ROC-кривую для всех построенных алгоритмов на обучающей и тестовой выборке. Сделать выводы о работе алгоритмов с точки зрения качества на тестовой выборке и с точки зрения переобучения.

Задание на повторение:

Задание не обязательно к выполнению, но очень рекомендуется для понимания набора данных, этот набор данных будет использован и для следующего домашнего задания.

Задание 1: Построить график распределения времени совершения транзакции для обучающей / тестовой выборки, сделать выводы о том, как разбиты данные и какие виды валидации могут подойти для данной задачи.

Задание 2: построить scatter-plot зависимости суммы транзакции от времени совершения транзакции. Построить графики для обучающей выборки и для тестовой выборки, для обучающей выборки - построить как для целевой переменной = 0, так и для переменной = 1. Сделать выводы.

Задание 3: построить распределение признака TransactionAmt в логарифмическом масштабе, сделать выводы о близости распредления к нормальному распределению. Построить распределение признака в логарифмическому масштабе для обучающей выборк и для тестовой выборки, сделать выводы.

Задание 4: построить распределение признака целевой переменной в зависимости от значений категориальных признаков ProductCD, card4, card6. Сделать выводы.

Подключение библиотек и скриптов

B [1]:
```
from typing import List, Optional
from tqdm import tqdm

import numpy as np
import pandas as pd
# разварачиваем выходной дисплей, чтобы увидеть больше столбцов и строк а pandas DataFrame
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)
#pd.options.display.max_info_columns = 400
#pd.options.display.max_columns = 300

import matplotlib as mpl
import matplotlib.pyplot as plt

import seaborn as sns
import scipy.stats as st
from scipy.stats import probplot, ks_2samp

from sklearn.metrics import roc_auc_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import KFold, cross_val_score
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.utils.validation import check_is_fitted

import missingno as msno  # Missingo предлагает быстрый и простой способ по визуализации отсутствующих зна

import xgboost as xgb

%matplotlib inline
```

B [2]:
```
#Нарисовать граф с Graphviz в Jupyter Notebook
#http://diginal.ru/python/narisovat-graf-s-graphviz-v-jupyter-notebook/
import sys
sys.path #можно посмотреть что в PATH
#graphviz_path = '...\\Anaconda3\\Library\\bin\\graphviz'  #не забыть понравить ... и поставить двойные юн
graphviz_path = 'C:\\ProgramData\\Anaconda3\\Library\\bin\\graphviz'

sys.path.insert(0, graphviz_path)
#sys.path.remove(graphviz_path) - если что-то пошло не так и путь нужно удалить
!dot -V  #проверить, что всё работает - должен вывести версию graphviz
```

```
dot - graphviz version 2.38.0 (20140413.2041)
```

B [3]:
```
def reduce_mem_usage(df):
    '''Сокращение размера датафрейма за счёт изменения типа данных'''

    start_mem = df.memory_usage().sum() / 1024**2
    print('Memory usage of dataframe is {:.2f} MB'.format(start_mem))

    for col in df.columns:
        col_type = df[col].dtype

        if col_type != object:
            c_min = df[col].min()
            c_max = df[col].max()
            if str(col_type)[:3] == 'int':
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(np.int8).max:
                    df[col] = df[col].astype(np.int8)
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinfo(np.int16).max:
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.int32).max:
                    df[col] = df[col].astype(np.int32)
                elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.int64).max:
                    df[col] = df[col].astype(np.int64)
            else:
                if c_min > np.finfo(np.float32).min and c_max < np.finfo(np.float32).max:
                    df[col] = df[col].astype(np.float32)
                else:
                    df[col] = df[col].astype(np.float64)
        else:
            df[col] = df[col].astype('category')

    end_mem = df.memory_usage().sum() / 1024**2
    print('Memory usage after optimization is: {:.2f} MB'.format(end_mem))
    print('Decreased by {:.1f}%'.format(100 * (start_mem - end_mem) / start_mem))

    return df
```

Пути к директориям и файлам

В [4]:
```
# input
TRAIN_DATASET_PATH = './data/assignment_2_train.csv'
TEST_DATASET_PATH = './data/assignment_2_test.csv'

# output
#PREP_DATASET_PATH = './assignment1_data/data_prep.csv'
```

Загрузка данных

В [5]:
```
# Тренировочные данные
# train = pd.read_csv(TRAIN_DATASET_PATH, header = none)  # если надо скрыть названия столбцов
train = pd.read_csv(TRAIN_DATASET_PATH)
df_train =reduce_mem_usage(train)  # Уменьшаем размер данных
# Тестовые данные
test = pd.read_csv(TEST_DATASET_PATH)
df_test =reduce_mem_usage(test)  # Уменьшаем размер данных
```

```
Memory usage of dataframe is 541.08 MB
Memory usage after optimization is: 262.48 MB
Decreased by 51.5%
Memory usage of dataframe is 300.60 MB
Memory usage after optimization is: 145.83 MB
Decreased by 51.5%
```

Размерности датасетов

В [6]:
```
print("train.shape = {} rows, {} cols".format(*train.shape))
print("test.shape = {} rows, {} cols".format(*test.shape))
```

```
train.shape = 180000 rows, 394 cols
test.shape = 100001 rows, 394 cols
```

Числовые признаки

В [7]:
```
numerical_features = train.select_dtypes(include=['float32', 'float64', 'int8', 'int16', 'int32']).columns
print(numerical_features)
```

```
Index(['TransactionID', 'isFraud', 'TransactionDT', 'TransactionAmt', 'card1', 'card2', 'card3', 'card5',
'addr1', 'addr2',
       ...
       'V330', 'V331', 'V332', 'V333', 'V334', 'V335', 'V336', 'V337', 'V338', 'V339'], dtype='object', l
ength=380)
```

Категориальные признаки

В [8]:
```
#categorical_features = train.select_dtypes(include=[np.object])
categorical_features = train.select_dtypes(include=['category'])
print(f"Categorical Feature Count {categorical_features.shape[1]}")
categorical_features.head(n=2)
```

```
Categorical Feature Count 14
```

Out[8]:

	ProductCD	card4	card6	P_emaildomain	R_emaildomain	M1	M2	M3	M4	M5	M6	M7	M8	M9
0	W	discover	credit	NaN	NaN	T	T	T	M2	F	T	NaN	NaN	NaN
1	W	mastercard	credit	gmail.com	NaN	NaN	NaN	NaN	M0	T	T	NaN	NaN	NaN

В [9]:
```
#df_train.select_dtypes(include='object').columns
df_train.select_dtypes(include='category').columns
```

Out[9]:
```
Index(['ProductCD', 'card4', 'card6', 'P_emaildomain', 'R_emaildomain', 'M1', 'M2', 'M3', 'M4', 'M5', 'M
6', 'M7', 'M8', 'M9'], dtype='object')
```

Тренировочный датасет

Обзор целевой переменной

В [10]:
```
target = 'isFraud'
df_train[target].value_counts()  # Количество различных значений признака 'Credit Default'
```

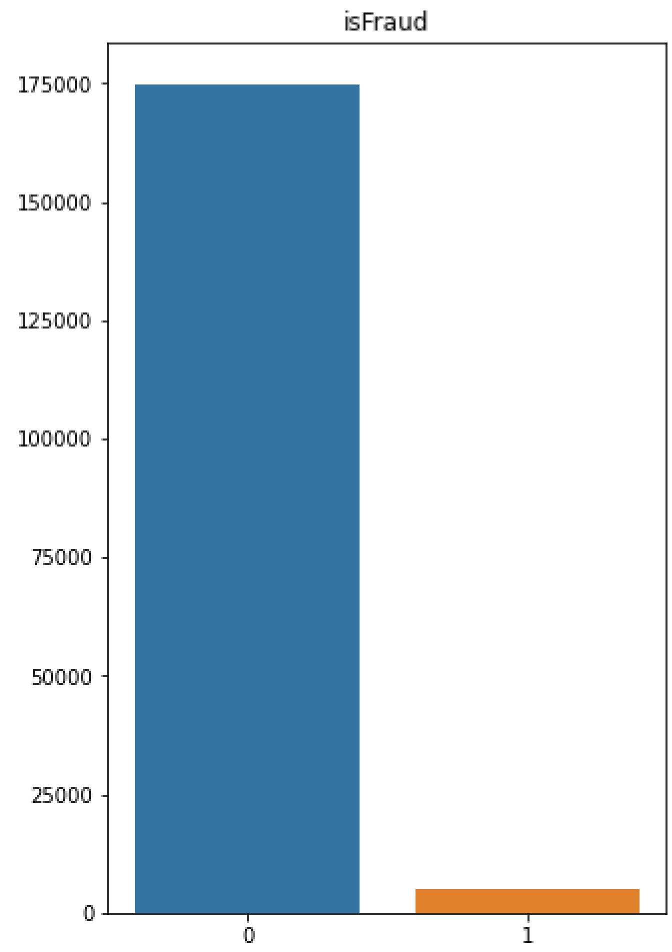
Out[10]:
```
0    174859
1      5141
Name: isFraud, dtype: int64
```

В [11]:
```
counts = df_train[target].value_counts()

plt.figure(figsize=(5,8))
plt.title(target)
sns.barplot(counts.index, counts.values)

plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following v
ariables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



В [12]:
```
#pd.options.display.max_info_columns = 400
#pd.options.display.max_columns = 400
```

В [13]:
```
train.info()
# Идея 1. Рассматривать только те параметры у которых кол-во непустых значений > 100000 (50000).
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180000 entries, 0 to 179999
Columns: 394 entries, TransactionID to V339
dtypes: category(14), float32(376), int16(1), int32(2), int8(1)
memory usage: 262.5 MB
```

В [14]:
```
#train.dtypes
```

В [15]:
```
train.head()
# 86400 - 1 day, 0:00:00
#train.tail()
```

Out[15]:

	TransactionID	isFraud	TransactionDT	TransactionAmt	ProductCD	card1	card2	card3	card4	card5	card6	addr1	addı
0	2987000	0	86400	68.5	W	13926	NaN	150.0	discover	142.0	credit	315.0	87.
1	2987001	0	86401	29.0	W	2755	404.0	150.0	mastercard	102.0	credit	325.0	87.
2	2987002	0	86469	59.0	W	4663	490.0	150.0	visa	166.0	debit	330.0	87.
3	2987003	0	86499	50.0	W	18132	567.0	150.0	mastercard	117.0	debit	476.0	87.
4	2987004	0	86506	50.0	H	4497	514.0	150.0	mastercard	102.0	credit	420.0	87.

Тестовый датасет

В [16]:
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100001 entries, 0 to 100000
Columns: 394 entries, TransactionID to V339
dtypes: category(14), float32(376), int16(1), int32(2), int8(1)
memory usage: 145.8 MB
```

В [17]:
```
#test.dtypes
```

В [18]:
```
test.head()
```

Out[18]:

	TransactionID	isFraud	TransactionDT	TransactionAmt	ProductCD	card1	card2	card3	card4	card5	card6	addr1	addr2	d
0	3287000	1	7415038	226.000000	W	12473	555.0	150.0	visa	226.0	credit	299.0	87.0	1
1	3287001	0	7415054	3072.000000	W	15651	417.0	150.0	visa	226.0	debit	330.0	87.0	I
2	3287002	0	7415081	319.950012	W	13844	583.0	150.0	visa	226.0	credit	126.0	87.0	
3	3287003	0	7415111	171.000000	W	11556	309.0	150.0	visa	226.0	debit	181.0	87.0	
4	3287004	0	7415112	107.949997	W	10985	555.0	150.0	visa	226.0	debit	231.0	87.0	

Базовые статистики

В [19]:
```
# Тренировочный датасет
train.describe().T
```

Out[19]:

	count	mean	std	min	25%	50%	75%	max
TransactionID	180000.0	3.077000e+06	5.196167e+04	2987000.000	3.032000e+06	3.077000e+06	3.121999e+06	3.166999e+06
isFraud	180000.0	2.856111e-02	1.665699e-01	0.000	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
TransactionDT	180000.0	1.909818e+06	1.039029e+06	86400.000	1.091681e+06	1.884075e+06	2.693196e+06	3.958317e+06
TransactionAmt	180000.0	1.294917e+02	2.065206e+02	0.292	4.400000e+01	7.500000e+01	1.250000e+02	5.278950e+03
card1	180000.0	9.860226e+03	4.910778e+03	1001.000	6.019000e+03	9.633000e+03	1.418200e+04	1.839600e+04
card2	177389.0	3.683454e+02	1.589787e+02	100.000	2.150000e+02	3.750000e+02	5.140000e+02	6.000000e+02
card3	179997.0	1.534064e+02	1.153677e+01	100.000	1.500000e+02	1.500000e+02	1.500000e+02	2.310000e+02
card5	179047.0	2.003184e+02	4.058468e+01	100.000	1.660000e+02	2.260000e+02	2.260000e+02	2.370000e+02
addr1	160567.0	2.911745e+02	1.022446e+02	100.000	2.040000e+02	2.990000e+02	3.300000e+02	5.400000e+02
addr2	160567.0	8.655991e+01	3.963716e+00	10.000	8.700000e+01	8.700000e+01	8.700000e+01	1.020000e+02
dist1	60605.0	1.262432e+02	3.862911e+02	0.000	3.000000e+00	9.000000e+00	2.600000e+01	7.068000e+03
dist2	14458.0	2.409624e+02	5.478262e+02	0.000	7.000000e+00	2.700000e+01	2.180000e+02	9.103000e+03

В [20]:
```
# Тестовый датасет
# test.describe().T
```

Создаём набор числовых признаков

В [21]:
```
numerical_features = train.select_dtypes(include=['float32', 'float64', 'int8', 'int16', 'int32']).columns
```

В [22]:
```
# Общее количество записей в датафрейме = 180 000
# Исключаем такие поля содержащие меньше 100 000 значений,
# из предполажения, что значение этих полей несущественно (всегда можно этот параметр проварьировать).

numerical_features_1 = [
#'TransactionID',  # Индекс
#'isFraud',  # Целевой параметр
'TransactionDT',  # Временя совершения транзакции
'TransactionAmt',  # Сумма транзакции
'card1',
'card2',
'card3',
'card5',
'addr1',
'addr2',
#'dist1', ## < 100 000
#'dist2', ## <  50 000
'C1',
'C2',
'C3',
'C4',
'C5',
'C6',
'C7',
'C8',
'C9',
'C10',
'C11',
'C12',
'C13',
'C14',
'D1',
#'D2', ## < 100 000
#'D3', ## < 100 000
'D4',
#'D5', ## < 100 000
#'D6', ## <  50 000
#'D7', ## <  50 000
#'D8', ## <  50 000
#'D9', ## <  50 000
'D10',
'D11', ## <  50 000
#'D12', ## <  50 000
#'D13', ## <  50 000
#'D14', ## <  50 000
'D15']
#
numerical_features_2 = [
#'V1', ## < 100 000
#'V2', ## < 100 000
#'V3', ## < 100 000
#'V4', ## < 100 000
#'V5', ## < 100 000
#'V6', ## < 100 000
#'V7', ## < 100 000
#'V8', ## < 100 000
#'V9', ## < 100 000
#'V10', ## < 100 000
#'V11', ## < 100 000
'V12',
'V13',
'V14',
'V15',
'V16',
'V17',
'V18',
'V19',
'V20',
'V21',
'V22',
'V23',
'V24',
'V25',
'V26',
'V27',
'V28',
'V29',
'V30',
'V31',
'V32',
'V33',
'V34',
'V35',
'V36',
'V37',
```

```
'V38',
'V39',
'V40',
'V41',
'V42',
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'V48',
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'V110',
'V111',
'V112',
'V113',
'V114',
'V115',
'V116',
'V117',
'V118',
'V119',
'V120',
'V121',
'V122',
```

```
'V123',
'V124',
'V125']
#
numerical_features_3 = ['V126',
'V127',
'V128',
'V129',
'V130',
'V131',
'V132',
'V133',
'V134',
'V135',
'V136',
'V137',
#'V138', ## <  50 000
#'V139', ## <  50 000
#'V140', ## <  50 000
#'V141', ## <  50 000
#'V142', ## <  50 000
#'V143', ## <  50 000
#'V144', ## <  50 000
#'V145', ## <  50 000
#'V146', ## <  50 000
#'V147', ## <  50 000
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#'V188', ## <  100 000
#'V189', ## <  100 000
#'V190', ## <  100 000
#'V191', ## <  100 000
#'V192', ## <  100 000
#'V193', ## <  100 000
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#'V195', ## <  100 000
#'V196', ## <  100 000
#'V197', ## <  100 000
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#'V201', ## <  100 000
#'V202', ## <  100 000
#'V203', ## <  100 000
#'V204', ## <  100 000
#'V205', ## <  100 000
#'V206', ## <  100 000
```

```
#'V207', ## <  100 000
#'V208', ## <  100 000
#'V209', ## <  100 000
#'V210', ## <  100 000
#'V211', ## <  100 000
#'V212', ## <  100 000
#'V213', ## <  100 000
#'V214', ## <  100 000
#'V215', ## <  100 000
#'V216', ## <  100 000
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#'V218', ## <  100 000
#'V219', ## <  100 000
#'V220', ## <  100 000
#'V221', ## <  100 000
#'V222', ## <  100 000
#'V223', ## <  100 000
#'V224', ## <  100 000
#'V225', ## <  100 000
#'V226', ## <  100 000
#'V227', ## <  100 000
#'V228', ## <  100 000
#'V229'  ## <  100 000
]
#
numerical_features_4 = [
#'V230', ## <  100 000
#'V231', ## <  100 000
#'V232', ## <  100 000
#'V233', ## <  100 000
#'V234', ## <  100 000
#'V235', ## <  100 000
#'V236', ## <  100 000
#'V237', ## <  100 000
#'V238', ## <  100 000
#'V239', ## <  100 000
#'V240', ## <  100 000
#'V241', ## <  100 000
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#'V246', ## <  100 000
#'V247', ## <  100 000
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#'V263', ## <  100 000
#'V264', ## <  100 000
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#'V269', ## <  100 000
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#'V272', ## <  100 000
#'V273', ## <  100 000
#'V274', ## <  100 000
#'V275', ## <  100 000
#'V276', ## <  100 000
#'V277', ## <  100 000
#'V278', ## <  100 000
#'V279', ## <  100 000
'V280',
'V281',
'V282',
'V283',
'V284',
'V285',
'V286',
'V287',
'V288',
```

```
'V289',
'V290',
'V291',
'V292',
'V293',
'V294',
'V295',
'V296',
'V297',
'V298',
'V299',
'V300',
'V301',
'V302',
'V303',
'V304',
'V305',
'V306',
'V307',
'V308',
'V309',
'V310',
'V311',
'V312',
'V313',
'V314',
'V315',
'V316',
'V317',
'V318',
'V319',
'V320',
'V321'
#'V322', ## < 50 000
#'V323', ## < 50 000
#'V324', ## < 50 000
#'V325', ## < 50 000
#'V326', ## < 50 000
#'V327', ## < 50 000
#'V328', ## < 50 000
#'V329', ## < 50 000
#'V330', ## < 50 000
#'V331', ## < 50 000
#'V332', ## < 50 000
#'V333', ## < 50 000
#'V334', ## < 50 000
#'V335', ## < 50 000
#'V336', ## < 50 000
#'V337', ## < 50 000
#'V338', ## < 50 000
#'V339'  ## < 50 000
]
```

В [23]:

```
numerical_features = numerical_features_1 + numerical_features_2 + numerical_features_3 + numerical_featur
#numerical_features
```

В [24]:

```
df_num_features = df_train[numerical_features]
df_num_features.hist(figsize=(50, 80), bins=50, grid=True)
# для более подробного анализа графиков, можно выводить гистограммы для небольших груп признаков
```

Out[24]:

```
array([[<AxesSubplot:title={'center':'TransactionDT'}>,
        <AxesSubplot:title={'center':'TransactionAmt'}>,
        <AxesSubplot:title={'center':'card1'}>,
        <AxesSubplot:title={'center':'card2'}>,
        <AxesSubplot:title={'center':'card3'}>,
        <AxesSubplot:title={'center':'card5'}>,
        <AxesSubplot:title={'center':'addr1'}>,
        <AxesSubplot:title={'center':'addr2'}>,
        <AxesSubplot:title={'center':'C1'}>,
        <AxesSubplot:title={'center':'C2'}>,
        <AxesSubplot:title={'center':'C3'}>,
        <AxesSubplot:title={'center':'C4'}>,
        <AxesSubplot:title={'center':'C5'}>,
        <AxesSubplot:title={'center':'C6'}>],
       [<AxesSubplot:title={'center':'C7'}>,
        <AxesSubplot:title={'center':'C8'}>,
        <AxesSubplot:title={'center':'C9'}>,
        <AxesSubplot:title={'center':'C10'}>,
        <AxesSubplot:title={'center':'C11'}>,
```

В [25]:

```
#df_num_features = df_train[numerical_features_1]
#df_num_features.hist(figsize=(50, 80), bins=50, grid=True)
```

В [26]:
```
#pd.set_option('display.max_rows', 50)
#df_num_features = df_train[numerical_features_2]
#df_num_features.hist(figsize=(50, 80), bins=50, grid=True)
```

В [27]:
```
#df_num_features = df_train[numerical_features_3]
#df_num_features.hist(figsize=(50, 80), bins=50, grid=True)
```

В [28]:
```
#df_num_features = df_train[numerical_features_4]
#df_num_features.hist(figsize=(25, 50), bins=50, grid=True)
```

В [29]:
```
#train_num_features = []
#train_num_features = train[numerical_features]
#print(f"Continuous Feature Count {len(numerical_features)}")
```

В [30]:
```
#df_num_features = df_train.select_dtypes(include=['float32', 'float64', 'int8', 'int16', 'int32'])

#df_num_features.hist(figsize=(25, 150), bins=50, grid=True)
```

Задание 1:

Отобрать только числовые признаки и обучить модель XGBoost с параметром booster = gbtree. Обучать алгоритм до тех пор, пока метрика качества не перестанет улучшаться на валидационной выборке в течение определенного числа итераций (выбрать значение самостоятельно).

В [31]:
```
import xgboost as xgb
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
```

В [32]:
```
data = df_train[numerical_features]
target = df_train["isFraud"]

print(data.shape)
print(target.shape)
```

```
(180000, 195)
(180000,)
```

В [33]:
```
x_train, x_valid = train_test_split(
    data, train_size=0.8, random_state=1
)
y_train, y_valid = train_test_split(
    target, train_size=0.8, random_state=1
)
print("x_train.shape = {} rows, {} cols".format(*x_train.shape))
print("x_valid.shape = {} rows, {} cols".format(*x_valid.shape))
```

```
x_train.shape = 144000 rows, 195 cols
x_valid.shape = 36000 rows, 195 cols
```

В [34]:
```
#data.head(10)
```

XGBoost API

В [35]:
```
# Задача бинарной классификации
params = {
    "booster": "gbtree",  # бостинг над решающими деревьями (1:14:25)
    "objective": "binary:logistic", # бинарная крос-энтропия
    "eval_metric": "auc",  # метрика качества - ROC AUC
    "learning_rate": 0.1,  # скорсть обучения
    "n_estimators": 1000,  # число деревьев
     # регуляризация
    "reg_lambda": 100,  # регуляризация (то что используется при F2-штрафе (1:15:10))
    "max_depth": 4,  # глубина дерева
    "gamma": 10,  # min-е улучшение функции потерь при котором мы будем делать разбиени (1:15:40)
    "nthread": 6, # число ядер
    "seed": 27
}
```

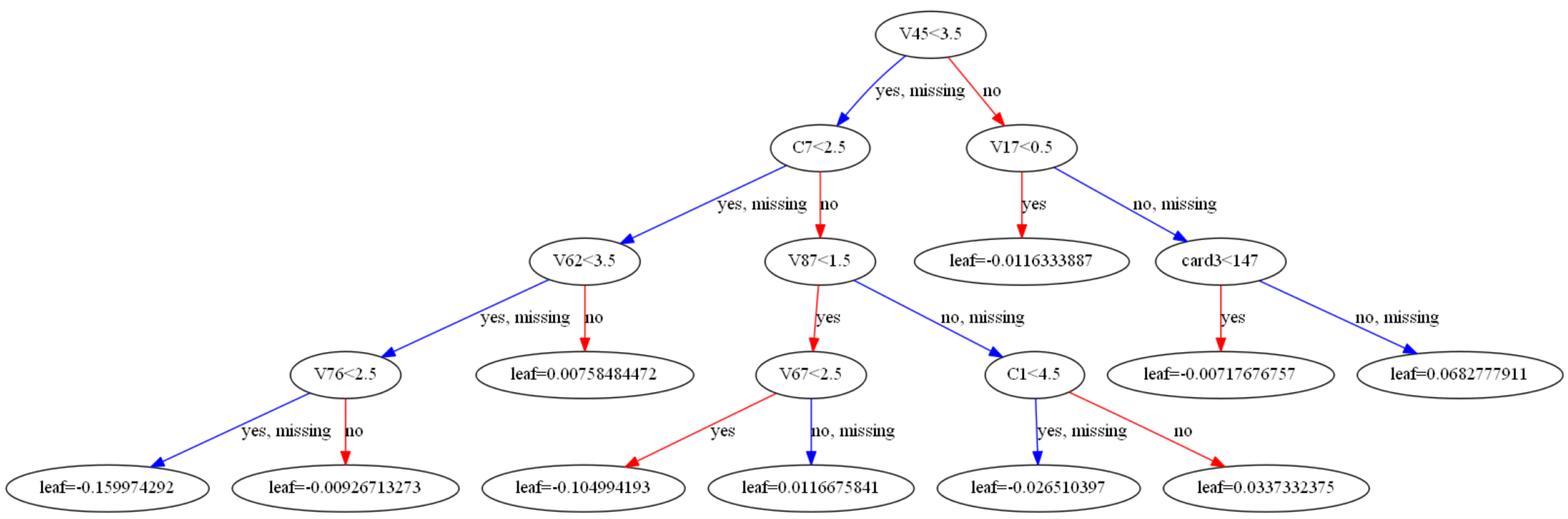
В [36]:
```
# DMatrix - специальный формат данных XGBoost API
dtrain = xgb.DMatrix(
    data=x_train, label=y_train
)

dvalid = xgb.DMatrix(
    data=x_valid, label=y_valid
)
```

В [37]:
```
model = xgb.train(
    params=params,
    dtrain=dtrain,  #dmatrix - наш dataframe
    num_boost_round=1000,  # max кол-во итераций, к! мы готовы ждать, обычно ~10000
    early_stopping_rounds=50, # max кол-во итераций к! мы ждём, если качество не увеличивается
    evals=[(dtrain, "train"), (dvalid, "valid")],  # выборки на к! мы отслеживаем качество
    verbose_eval=50,  # Как часто выводим на экран статистику
    maximize=True,  # True -Чем выше значение метрики , тем она лучше
)
```

```
[23:22:59] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:541:
Parameters: { n_estimators } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[0]     train-auc:0.61944       valid-auc:0.61748
[50]    train-auc:0.88098       valid-auc:0.87410
[100]   train-auc:0.89956       valid-auc:0.88869
[150]   train-auc:0.90526       valid-auc:0.89390
[200]   train-auc:0.90734       valid-auc:0.89603
[222]   train-auc:0.90734       valid-auc:0.89603
```

В [38]:
```
fig, axes = plt.subplots(1, 1, figsize=(40, 40))
xgb.plot_tree(model, num_trees=2, ax=axes)
```

Out[38]: <AxesSubplot:>



В [39]:
```
#fig, axes = plt.subplots(1, 1, figsize=(40, 40))
#xgb.plot_tree(model, num_trees=2, ax=axes, rankdir='LR')
```

XGBoost Linear

В [40]:
```
params = {
    "booster": "gblinear",
    "objective": "binary:logistic",
    "eval_metric": "auc",
    "learning_rate": 0.1,
    "n_estimators": 1000,
    "reg_lambda": 100,
    "max_depth": 4,
    "gamma": 10,
    "nthread": 6,
    "seed": 27,
    #"target_type_": "BINARY"
}
```

В [41]:
```
model = xgb.train(
    params=params,
    dtrain=dtrain,
    num_boost_round=2000,
    early_stopping_rounds=50,
    evals=[(dtrain, "train"), (dvalid, "valid")],
    verbose_eval=50,
    maximize=True,
)
```

```
[23:23:51] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:541:
Parameters: { gamma, max_depth, n_estimators } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[0]     train-auc:0.57739       valid-auc:0.58001
[50]    train-auc:0.70224       valid-auc:0.70682
[100]   train-auc:0.70739       valid-auc:0.71209
[150]   train-auc:0.71012       valid-auc:0.71480
[200]   train-auc:0.71218       valid-auc:0.71679
[250]   train-auc:0.71379       valid-auc:0.71839
[300]   train-auc:0.71508       valid-auc:0.71966
[350]   train-auc:0.71612       valid-auc:0.72068
[400]   train-auc:0.71697       valid-auc:0.72153
[450]   train-auc:0.71766       valid-auc:0.72222
[500]   train-auc:0.71823       valid-auc:0.72279
```

XGBoost Cross-Validation

В [42]:
```
cv_result = xgb.cv(
    params=params,
    dtrain=dtrain,
    num_boost_round=1000,
    early_stopping_rounds=50,
    verbose_eval=50,
    stratified=True,  # Стратифицированное разбиение (1:23:40)
    metrics="auc",
    maximize=True,
    shuffle=True, # Нужно перемешивать или нет
    nfold=3,  # кол-во фолдов кросвалидации (1:23:50)
)
```

```
[23:26:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:541:
Parameters: { gamma, max_depth, n_estimators } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[23:26:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:541:
Parameters: { gamma, max_depth, n_estimators } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[23:26:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:541:
Parameters: { gamma, max_depth, n_estimators } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.
```

В [43]:
```
cv_result
```

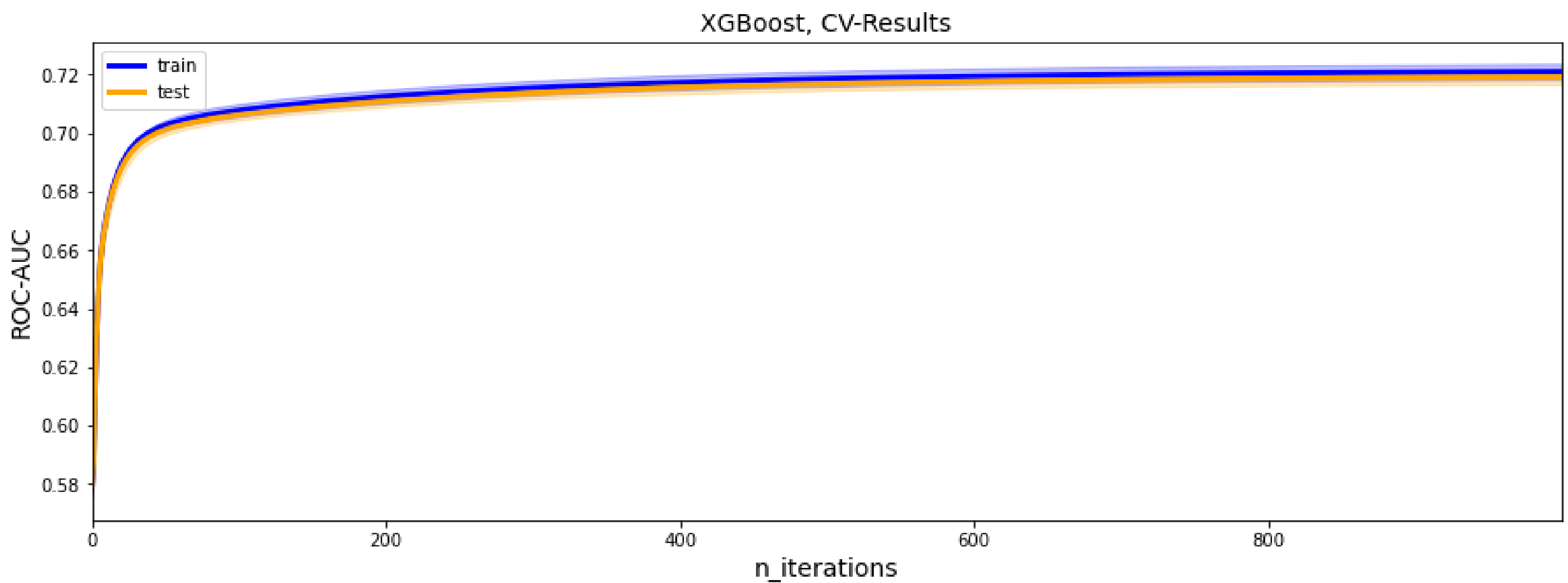
Out[43]:

	train-auc-mean	train-auc-std	test-auc-mean	test-auc-std
0	0.578999	0.002918	0.579163	0.003918
1	0.586861	0.003081	0.586678	0.004061
2	0.606123	0.003416	0.605677	0.003996
3	0.626972	0.002903	0.626617	0.005459
4	0.640686	0.002669	0.640145	0.005501
...	...	...	...	...
995	0.721022	0.002743	0.719283	0.002636
996	0.721024	0.002743	0.719285	0.002636
997	0.721026	0.002743	0.719287	0.002636
998	0.721028	0.002743	0.719289	0.002637
999	0.721029	0.002744	0.719290	0.002637

1000 rows × 4 columns

В [44]:
```
# Построение доверительного интервала
fig = plt.figure(figsize=(15, 5))
plt.plot(cv_result["train-auc-mean"], color="blue", linewidth=3, label="train")
plt.plot(cv_result["test-auc-mean"], color="orange", linewidth=3, label="test")
plt.fill_between( # метод позволяет построить доверительный интервал
    x=cv_result.index,  # то что мы хотим отложить (1:28:03)
    y1=cv_result["train-auc-mean"] - cv_result["train-auc-std"],  # границы доверительного интервала
    y2=cv_result["train-auc-mean"] + cv_result["train-auc-std"],  # границы доверительного интервала
    alpha=0.25, color="blue"
)
plt.fill_between(
    x=cv_result.index,
    y1=cv_result["test-auc-mean"] - cv_result["test-auc-std"],
    y2=cv_result["test-auc-mean"] + cv_result["test-auc-std"],
    alpha=0.25, color="orange"
)
plt.title("XGBoost, CV-Results", size=14)
plt.xlabel("n_iterations", size=14)
plt.xlim(0, cv_result.index.max())
plt.ylabel("ROC-AUC", size=14)
plt.legend(loc="best")
```

Out[44]: `<matplotlib.legend.Legend at 0x6d85e1790>`



XGBoost sklearn-API

В [45]:
```
model = xgb.XGBClassifier(**params)
model.fit(
    X=x_train,
    y=y_train,
    eval_set=[(x_train, y_train), (x_valid, y_valid)],
    early_stopping_rounds=50,
    eval_metric="auc",
    verbose=50
)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\xgboost\sklearn.py:888: UserWarning: The use of label encoder
in XGBClassifier is deprecated and will be removed in a future release. To remove this warning, do the fo
llowing: 1) Pass option use_label_encoder=False when constructing XGBClassifier object; and 2) Encode you
r labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[23:29:26] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:541:
Parameters: { gamma, max_depth } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[0]     validation_0-auc:0.57697        validation_1-auc:0.57932
[50]    validation_0-auc:0.70223        validation_1-auc:0.70680
[100]   validation_0-auc:0.70739        validation_1-auc:0.71208
[150]   validation_0-auc:0.71012        validation_1-auc:0.71480
[200]   validation_0-auc:0.71217        validation_1-auc:0.71679
[250]   validation_0-auc:0.71379        validation_1-auc:0.71838
[300]   validation_0-auc:0.71508        validation_1-auc:0.71966
[350]   validation_0-auc:0.71612        validation_1-auc:0.72068
[400]   validation_0-auc:0.71697        validation_1-auc:0.72153
[450]   validation_0-auc:0.71766        validation_1-auc:0.72223
[500]   validation_0-auc:0.71823        validation_1-auc:0.72279
[550]   validation_0-auc:0.71870        validation_1-auc:0.72325
[600]   validation_0-auc:0.71909        validation_1-auc:0.72364
[650]   validation_0-auc:0.71942        validation_1-auc:0.72396
[700]   validation_0-auc:0.71969        validation_1-auc:0.72424
[750]   validation_0-auc:0.71991        validation_1-auc:0.72448
[800]   validation_0-auc:0.72011        validation_1-auc:0.72467
[850]   validation_0-auc:0.72027        validation_1-auc:0.72483
[900]   validation_0-auc:0.72041        validation_1-auc:0.72497
[950]   validation_0-auc:0.72054        validation_1-auc:0.72510
[999]   validation_0-auc:0.72064        validation_1-auc:0.72520
```

Out[45]:
```
XGBClassifier(base_score=0.5, booster='gblinear', colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None, eval_metric='auc',
              gamma=10, gpu_id=-1, importance_type='gain',
              interaction_constraints=None, learning_rate=0.1,
              max_delta_step=None, max_depth=4, min_child_weight=None,
              missing=nan, monotone_constraints=None, n_estimators=1000,
              n_jobs=6, nthread=6, num_parallel_tree=None, random_state=27,
              reg_alpha=0, reg_lambda=100, scale_pos_weight=1, seed=27,
              subsample=None, tree_method=None, validate_parameters=1,
              verbosity=None)
```

ROCAUC - https://rebeccabilbro.github.io/xgboost-and-yellowbrick/ (https://rebeccabilbro.github.io/xgboost-and-yellowbrick/)

В [46]:
```
#!pip install yellowbrick
```

В [47]:
```
#from yellowbrick.classifier import ClassBalance, ROCAUC, ClassificationReport, ClassPredictionError
#rocauc = ROCAUC(model, size=(1080, 720), classes=numerical_features)

#rocauc.score(x_valid, y_valid)
#r = rocauc.poof()
```

Задание 2:

Обработать категориальные признаки любым способом (который вы знаете) и добавить их к данным. Выполнить задание 1.

XGBoost В отличие от CatBoost или LGBM, XGBoost не может обрабатывать категориальные функции сам по себе, он принимает только числовые значения.

Все о категориальном кодировании переменных - https://www.machinelearningmastery.ru/all-about-categorical-variable-encoding-305f3361fd02/ (https://www.machinelearningmastery.ru/all-about-categorical-variable-encoding-305f3361fd02/)

2.1 Обработать категориальные признаки любым способом (который вы знаете) и добавить их к данным.

В [48]:
```
df_train.select_dtypes(include='object').columns
df_train.select_dtypes(include='category').columns
```

Out[48]:
```
Index(['ProductCD', 'card4', 'card6', 'P_emaildomain', 'R_emaildomain', 'M1', 'M2', 'M3', 'M4', 'M5', 'M
6', 'M7', 'M8', 'M9'], dtype='object')
```

В [49]:
```
catigorical_features = [
'ProductCD',  # 180000 non-null  category
'card4',  # 179992 non-null  category
'card6',  # 179993 non-null  category
'P_emaildomain',  # 151560 non-null  category
'R_emaildomain',  # 60300 non-null   category
'M1',  # 61749 non-null   category
'M2',  # 61749 non-null   category
'M3',  # 61749 non-null   category
'M4',  # 83276 non-null   category
'M5',  # 61703 non-null   category
'M6',  # 105652 non-null  category
'M7',  # 31652 non-null   category
'M8',  # 31652 non-null   category
'M9'  # 31652 non-null   category
]
#catigorical_features_1 = ['ProductCD', 'card4', 'card6', 'P_emaildomain', 'R_emaildomain', 'M1', 'M2', 'M
```

В [50]:
```
data = []
data = df_train[numerical_features + catigorical_features]
#data = df_train[catigorical_features]
```

В [51]:
```
print(data.shape)
```

```
(180000, 209)
```

Приведение типов

В [52]:
```
#for colname in catigorical_features:
#     df_train[colname] = df_train[colname].astype(str)

#df_train['ProductCD'] = df_train['ProductCD'].astype(str)
```

В [53]:
```
data[catigorical_features].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180000 entries, 0 to 179999
Data columns (total 14 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   ProductCD      180000 non-null  category
 1   card4          179992 non-null  category
 2   card6          179993 non-null  category
 3   P_emaildomain  151560 non-null  category
 4   R_emaildomain  60300 non-null   category
 5   M1             61749 non-null   category
 6   M2             61749 non-null   category
 7   M3             61749 non-null   category
 8   M4             83276 non-null   category
 9   M5             61703 non-null   category
 10  M6             105652 non-null  category
 11  M7             31652 non-null   category
 12  M8             31652 non-null   category
 13  M9             31652 non-null   category
dtypes: category(14)
memory usage: 2.4 MB
```

В [54]:
```
data[catigorical_features].isna().sum()  # просматриваем пропуски
```

Out[54]:
```
ProductCD              0
card4                  8
card6                  7
P_emaildomain      28440
R_emaildomain     119700
M1                118251
M2                118251
M3                118251
M4                 96724
M5                118297
M6                 74348
M7                148348
M8                148348
M9                148348
dtype: int64
```

Оработка пропусков в категориалиных признаках

В [55]:
```
# заполняем пропуски в категориалиных признаках
for feature in catigorical_features:
    data[feature] = data[feature].cat.add_categories('Unknown')
    data[feature].fillna('Unknown', inplace =True)
```

```
<ipython-input-55-cb6ea9ab320f>:3: 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.ht
ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy)
  data[feature] = data[feature].cat.add_categories('Unknown')
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\series.py:4517: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.ht
ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy)
  return super().fillna(
```

Обзор значений категориальных признаков

В [56]:
```
#cat_colname = 'ProductCD'
#print(str(cat_colname) + '\n\n' + str(data[cat_colname].value_counts()))
```

В [57]:
```
for cat_colname in data[catigorical_features].columns:
    print(str(cat_colname) + '\n\n' + str(data[cat_colname].value_counts()) + '\n' + '*' * 40 + '\n')
```

```
ProductCD

W          110340
H           22422
R           21926
C           21664
S            3648
Unknown         0
Name: ProductCD, dtype: int64
****************************************

card4

visa                118295
mastercard           54501
american express      4818
discover              2378
Unknown                  8
Name: card4, dtype: int64
****************************************
```

В [58]:
```
data[catigorical_features].isna().sum()  # просматриваем пропуски
```

Out[58]:
```
ProductCD        0
card4            0
card6            0
P_emaildomain    0
R_emaildomain    0
M1               0
M2               0
M3               0
M4               0
M5               0
M6               0
M7               0
M8               0
M9               0
dtype: int64
```

В [59]:
```
data[catigorical_features].head()
```

Out[59]:

	ProductCD	card4	card6	P_emaildomain	R_emaildomain	M1	M2	M3	M4	M5	M6	
0	W	discover	credit	Unknown	Unknown	T	T	T	M2	F	T	Unl
1	W	mastercard	credit	gmail.com	Unknown	Unknown	Unknown	Unknown	M0	T	T	Unl
2	W	visa	debit	outlook.com	Unknown	T	T	T	M0	F	F	
3	W	mastercard	debit	yahoo.com	Unknown	Unknown	Unknown	Unknown	M0	T	F	Unl
4	H	mastercard	credit	gmail.com	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	Unl

В [60]:
```
#for c in catigorical_features:
#    print(data[c].unique())
```

В [61]:
```
# Каждой категории сопоставляем целое число (номер категории) - https://dyakonov.org/2016/08/03/python-кат
from sklearn.preprocessing import LabelEncoder
'''
le = LabelEncoder()
le.fit(data.ProductCD)
data['ProductCD_le'] = le.transform(data.ProductCD)
print(str('ProductCD_le') + '\n\n' + str(data[cat_colname].value_counts()) + str(data['ProductCD'].value_c
'''
```

Out[61]:
```
"\nle = LabelEncoder()\nle.fit(data.ProductCD)\ndata['ProductCD_le'] = le.transform(data.ProductCD)\nprin
t(str('ProductCD_le') + '\n\n' + str(data[cat_colname].value_counts()) + str(data['ProductCD'].value_coun
ts()))\n"
```

В [62]:
```
le = LabelEncoder()
for cat_colname in data[catigorical_features].columns:
    le.fit(data[cat_colname])
    data[cat_colname+'_le'] = le.transform(data[cat_colname])
```

```
<ipython-input-62-450a2fdcc54b>:4: 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.ht
ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy)
  data[cat_colname+'_le'] = le.transform(data[cat_colname])
```

В [63]:
```
le = LabelEncoder()
for cat_colname in data[catigorical_features].columns:
    print(str(cat_colname+'_le') + '\n\n' + str(data[cat_colname+'_le'].value_counts()) + '\n' + '*' * 40
```

```
ProductCD_le

4    110340
1     22422
2     21926
0     21664
3      3648
Name: ProductCD_le, dtype: int64
****************************************

card4_le

4    118295
3     54501
1      4818
2      2378
0         8
Name: card4_le, dtype: int64
****************************************
```

В [64]:
```
data[catigorical_features].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180000 entries, 0 to 179999
Data columns (total 14 columns):
 #   Column         Non-Null Count   Dtype   
---  ------         --------------   -----   
 0   ProductCD      180000 non-null  category
 1   card4          180000 non-null  category
 2   card6          180000 non-null  category
 3   P_emaildomain  180000 non-null  category
 4   R_emaildomain  180000 non-null  category
 5   M1             180000 non-null  category
 6   M2             180000 non-null  category
 7   M3             180000 non-null  category
 8   M4             180000 non-null  category
 9   M5             180000 non-null  category
 10  M6             180000 non-null  category
 11  M7             180000 non-null  category
 12  M8             180000 non-null  category
 13  M9             180000 non-null  category
dtypes: category(14)
memory usage: 2.4 MB
```

2.2 Повторно выполняем задание 1 (с учётом категориальных признаков)

В [65]:
```
data_new = data
data_new = data_new.drop(catigorical_features, axis=1)

data_new.columns
```

Out[65]:
```
Index(['TransactionDT', 'TransactionAmt', 'card1', 'card2', 'card3', 'card5', 'addr1', 'addr2', 'C1', 'C
2',
       ...
       'R_emaildomain_le', 'M1_le', 'M2_le', 'M3_le', 'M4_le', 'M5_le', 'M6_le', 'M7_le', 'M8_le', 'M9_l
e'], dtype='object', length=209)
```

В [66]:
```
target = df_train["isFraud"]
```

В [67]:
```
x_train, x_valid = train_test_split(
    data_new, train_size=0.8, random_state=1
)
y_train, y_valid = train_test_split(
    target, train_size=0.8, random_state=1
)
print("x_train.shape = {} rows, {} cols".format(*x_train.shape))
print("x_valid.shape = {} rows, {} cols".format(*x_valid.shape))
```

```
x_train.shape = 144000 rows, 209 cols
x_valid.shape = 36000 rows, 209 cols
```

В [68]:
```
# Задача бинарной классификации
params = {
    "booster": "gbtree",  # бостинг над решающими деревьями (1:14:25)
    "objective": "binary:logistic", # бинарная крос-энтропия
    "eval_metric": "auc",  # метрика качества - ROC AUC
    "learning_rate": 0.1,  # скорсть обучения
    "n_estimators": 1000,  # число деревьев
     # регуляризация
    "reg_lambda": 100,  # регуляризация (то что используется при F2-штрафе (1:15:10))
    "max_depth": 4,  # глубина дерева
    "gamma": 10,  # min-е улучшение функции потерь при которм мы будем делать разбиени (1:15:40)
    "nthread": 6, # число ядер
    "seed": 27
}
```

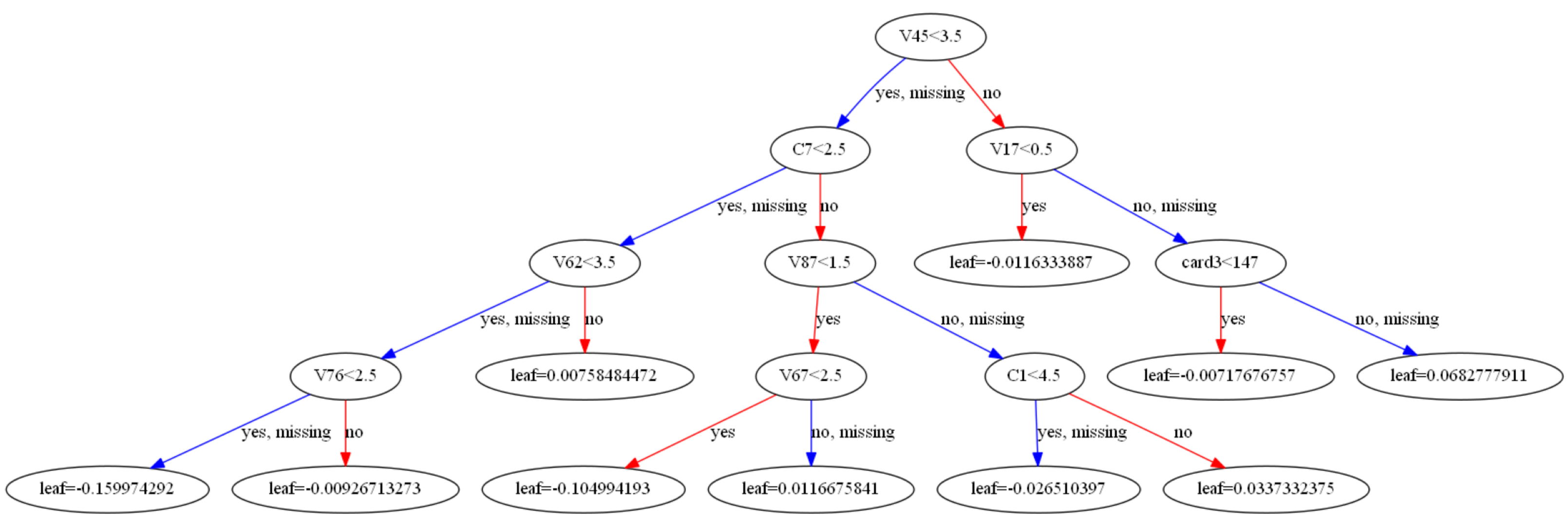
В [69]:
```
# DMatrix - специальный формат данных XGBoost API
dtrain = xgb.DMatrix(
    data=x_train, label=y_train
)

dvalid = xgb.DMatrix(
    data=x_valid, label=y_valid
)
```

В [70]:
```
model = xgb.train(
    params=params,
    dtrain=dtrain,  #dmatrix - наш dataframe
    num_boost_round=1000,  # max кол-во итераций, к! мы готовы ждать, обычно ~10000
    early_stopping_rounds=50, # max кол-во итераций к! мы ждём, если качество не увеличивается
    evals=[(dtrain, "train"), (dvalid, "valid")],  # выборки на к! мы отслеживаем качество
    verbose_eval=50,  # Как часто выводим на экран статистику
    maximize=True,  # True -Чем выше значение метрики , тем она лучше
)
```

```
[23:30:57] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:541:
Parameters: { n_estimators } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[0]     train-auc:0.61944       valid-auc:0.61748
[50]    train-auc:0.88791       valid-auc:0.88177
[100]   train-auc:0.90881       valid-auc:0.89788
[150]   train-auc:0.91700       valid-auc:0.90469
[200]   train-auc:0.91819       valid-auc:0.90576
[211]   train-auc:0.91819       valid-auc:0.90576
```

В [71]:
```
fig, axes = plt.subplots(1, 1, figsize=(40, 40))
xgb.plot_tree(model, num_trees=2, ax=axes)
```

Out[71]: <AxesSubplot:>



Результат

Было (значение из Задания 1 без учёта категориальных признаков):

```
[200]    train-auc:0.90734    valid-auc:0.89603
```

Стало (с учётом категориальных признаков):

```
[200]    train-auc:0.91819    valid-auc:0.90576
```

Вывод:

Вывод:

```
1. XGBoost - не умеет самостоятельно обрабатывать категориальные признаки, поэтому их необходимо
 обрабатывать вручную.
2. Значение метрики качества модели увеличилось с - {[200]  train-auc:0.90734  valid-auc:0.8960
3}, для набора данных
в котором не использавались категориальные признаки, до значений - {[200]  train-auc:0.91819  val
id-auc:0.90576}.

Таким образом использование обработанных категориальных признаков, позволило достигнуть лучшего р
езультата.
```

Задание 4:

Для числовых признаков обучить модель LightGBM. Обучать алгоритм до тех пор, пока метрика качества не перестанет улучшаться на валидационной выборке в течение определенного числа итераций (выбрать значение самостоятельно)

В [72]:
```
import lightgbm as lgb

from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
```

В [73]:
```
data = df_train[numerical_features]
#data = data.drop(["TransactionID", "isFraud"], axis=1)
target = df_train["isFraud"]

print("data.shape = {} rows, {} cols".format(*data.shape))
print(data.shape)
print(target.shape)
```

```
data.shape = 180000 rows, 195 cols
(180000, 195)
(180000,)
```

В [74]:
```
x_train, x_valid = train_test_split(
    data, train_size=0.8, random_state=1
)
y_train, y_valid = train_test_split(
    target, train_size=0.8, random_state=1
)
print("x_train.shape = {} rows, {} cols".format(*x_train.shape))
print("x_valid.shape = {} rows, {} cols".format(*x_valid.shape))
```

```
x_train.shape = 144000 rows, 195 cols
x_valid.shape = 36000 rows, 195 cols
```

LightGBM API

В [75]:
```
params = {
    "boosting_type": "gbdt",  # gradient boosting tree decision tree
    "objective": "binary",
    "metric": "auc",
    "learning_rate": 0.01,
    "n_estimators": 200,  # число деревьев
    "n_jobs": 6,
    "seed": 27
}
```

В [76]:
```
dtrain = lgb.Dataset(
    data=x_train, label=y_train
)
dvalid = lgb.Dataset(
    data=x_valid, label=y_valid
)

model = lgb.train(
    params=params,
    train_set=dtrain,
    num_boost_round=200,
    valid_sets=[dtrain, dvalid],
    categorical_feature="auto",
    early_stopping_rounds=50,
    verbose_eval=10
)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\lightgbm\engine.py:151: UserWarning: Found `n_estimators` in p
arams. Will use it instead of argument
  warnings.warn("Found `{}` in params. Will use it instead of argument".format(alias))

[LightGBM] [Info] Number of positive: 4139, number of negative: 139861
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing was 0.082456 second
s.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 15073
[LightGBM] [Info] Number of data points in the train set: 144000, number of used features: 193
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.028743 -> initscore=-3.520195
[LightGBM] [Info] Start training from score -3.520195
Training until validation scores don't improve for 50 rounds
[10]    training's auc: 0.829902        valid_1's auc: 0.829728
[20]    training's auc: 0.859873        valid_1's auc: 0.857996
[30]    training's auc: 0.86686 valid_1's auc: 0.860833
[40]    training's auc: 0.869993        valid_1's auc: 0.862705
[50]    training's auc: 0.872168        valid_1's auc: 0.863933
[60]    training's auc: 0.876123        valid_1's auc: 0.86884
[70]    training's auc: 0.880097        valid_1's auc: 0.873166
[80]    training's auc: 0.882318        valid_1's auc: 0.874728
[90]    training's auc: 0.885935        valid_1's auc: 0.878646
[100]   training's auc: 0.889005        valid_1's auc: 0.880191
[110]   training's auc: 0.891749        valid_1's auc: 0.881675
[120]   training's auc: 0.894707        valid_1's auc: 0.884775
[130]   training's auc: 0.896842        valid_1's auc: 0.885973
[140]   training's auc: 0.89819 valid_1's auc: 0.887065
[150]   training's auc: 0.899129        valid_1's auc: 0.887711
[160]   training's auc: 0.900417        valid_1's auc: 0.888376
[170]   training's auc: 0.902062        valid_1's auc: 0.889872
[180]   training's auc: 0.903385        valid_1's auc: 0.890734
[190]   training's auc: 0.904655        valid_1's auc: 0.891744
[200]   training's auc: 0.906055        valid_1's auc: 0.893405
Did not meet early stopping. Best iteration is:
[200]   training's auc: 0.906055        valid_1's auc: 0.893405
```

В [77]:
```
params["boosting_type"] = "goss"

model = lgb.train(
    params=params,  # GOSS - Gradient Based One Side Sampling (случайный отбор на основе градиентов)
    train_set=dtrain,
    num_boost_round=200,
    valid_sets=[dtrain, dvalid],
    categorical_feature="auto",
    early_stopping_rounds=50,
    verbose_eval=10
)
```

```
[LightGBM] [Info] Number of positive: 4139, number of negative: 139861
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing was 0.059360 second
s.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 15073
[LightGBM] [Info] Number of data points in the train set: 144000, number of used features: 193
[LightGBM] [Info] Using GOSS
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.028743 -> initscore=-3.520195
[LightGBM] [Info] Start training from score -3.520195
Training until validation scores don't improve for 50 rounds
[10]	training's auc: 0.829902	valid_1's auc: 0.829728
[20]	training's auc: 0.859873	valid_1's auc: 0.857996
[30]	training's auc: 0.86686 valid_1's auc: 0.860833
[40]	training's auc: 0.869993	valid_1's auc: 0.862705
[50]	training's auc: 0.872168	valid_1's auc: 0.863933
[60]	training's auc: 0.876123	valid_1's auc: 0.86884
[70]	training's auc: 0.880097	valid_1's auc: 0.873166
[80]	training's auc: 0.882318	valid_1's auc: 0.874728
[90]	training's auc: 0.885935	valid_1's auc: 0.878646
[100]	training's auc: 0.889005	valid_1's auc: 0.880191
[110]	training's auc: 0.892023	valid_1's auc: 0.88333
[120]	training's auc: 0.895691	valid_1's auc: 0.885122
[130]	training's auc: 0.897215	valid_1's auc: 0.88681
[140]	training's auc: 0.898855	valid_1's auc: 0.887692
[150]	training's auc: 0.900143	valid_1's auc: 0.889119
[160]	training's auc: 0.902012	valid_1's auc: 0.890495
[170]	training's auc: 0.904004	valid_1's auc: 0.891495
[180]	training's auc: 0.905815	valid_1's auc: 0.892908
[190]	training's auc: 0.907035	valid_1's auc: 0.89398
[200]	training's auc: 0.908304	valid_1's auc: 0.894809
Did not meet early stopping. Best iteration is:
[200]	training's auc: 0.908304	valid_1's auc: 0.894809
```

LightGBM Cross-Validation

В [78]:
```
cv_result = lgb.cv(
    params=params,
    train_set=dtrain,
    num_boost_round=200,
    categorical_feature="auto",
    early_stopping_rounds=50,
    verbose_eval=10,
    stratified=True,
    shuffle=True,
    nfold=5,
)
```

```
[LightGBM] [Info] Number of positive: 3312, number of negative: 111888

C:\ProgramData\Anaconda3\lib\site-packages\lightgbm\engine.py:530: UserWarning: Found `n_estimators` in
params. Will use it instead of argument
  warnings.warn("Found `{}` in params. Will use it instead of argument".format(alias))
```

В [79]:
```
cv_result
```

Out[79]:
```
{'auc-mean': [0.7767344021563523,
  0.7813921893780746,
  0.7881130202738797,
  0.7974385108839965,
  0.8095428652804602,
  0.8129991309656089,
  0.8164208967704789,
  0.817641476781113,
  0.818318094269275,
  0.8195217860156259,
  0.8225287398645305,
  0.8227115335726687,
  0.8230399114195862,
  0.8244361301980682,
  0.8314746147243863,
  0.8376470766758211,
  0.8381938228426478,
  0.8418451271532108,
  0.8420269526176115,
```

LightGBM Sklearn-API

В [80]:
```
model = lgb.LGBMClassifier(**params)
y = model.fit(
    X=x_train,
    y=y_train,
    eval_set=[(x_train, y_train), (x_valid, y_valid)],
    early_stopping_rounds=25,
    eval_metric="auc",
    verbose=10
)
print('-'*50)
print(y)
```

```
Training until validation scores don't improve for 25 rounds
[10]	training's auc: 0.829902	valid_1's auc: 0.829728
[20]	training's auc: 0.859873	valid_1's auc: 0.857996
[30]	training's auc: 0.86686	valid_1's auc: 0.860833
[40]	training's auc: 0.869993	valid_1's auc: 0.862705
[50]	training's auc: 0.872168	valid_1's auc: 0.863933
[60]	training's auc: 0.876123	valid_1's auc: 0.86884
[70]	training's auc: 0.880097	valid_1's auc: 0.873166
[80]	training's auc: 0.882318	valid_1's auc: 0.874728
[90]	training's auc: 0.885935	valid_1's auc: 0.878646
[100]	training's auc: 0.889005	valid_1's auc: 0.880191
[110]	training's auc: 0.892023	valid_1's auc: 0.88333
[120]	training's auc: 0.895691	valid_1's auc: 0.885122
[130]	training's auc: 0.897215	valid_1's auc: 0.88681
[140]	training's auc: 0.898855	valid_1's auc: 0.887692
[150]	training's auc: 0.900143	valid_1's auc: 0.889119
[160]	training's auc: 0.902012	valid_1's auc: 0.890495
[170]	training's auc: 0.904004	valid_1's auc: 0.891495
[180]	training's auc: 0.905815	valid_1's auc: 0.892908
[190]	training's auc: 0.907035	valid_1's auc: 0.89398
[200]	training's auc: 0.908304	valid_1's auc: 0.894809
Did not meet early stopping. Best iteration is:
[200]	training's auc: 0.908304	valid_1's auc: 0.894809
--------------------------------------------------
LGBMClassifier(boosting_type='goss', learning_rate=0.01, metric='auc',
               n_estimators=200, n_jobs=6, objective='binary', seed=27)
```

Задание 5:

Обработать категориальные признаки любым способом (который вы знаете) и добавить их к данным. Выполнить задание 4

Обрабатывае категориальные признаки также как и XGBoost

В [81]:
```
data = []
data = df_train[numerical_features + catigorical_features]

# заполняем пропуски в категориалиных признаках
for feature in catigorical_features:
    data[feature] = data[feature].cat.add_categories('Unknown')
    data[feature].fillna('Unknown', inplace =True)

# Каждой категории сопоставляет целое число (номер категории) - https://dyakonov.org/2016/08/03/python-кам
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
for cat_colname in data[catigorical_features].columns:
    le.fit(data[cat_colname])
    data[cat_colname+'_le'] = le.transform(data[cat_colname])
```

```
<ipython-input-81-56759bab4f67>:6: 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.ht
ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy)
  data[feature] = data[feature].cat.add_categories('Unknown')
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\series.py:4517: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.ht
ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy)
  return super().fillna(
<ipython-input-81-56759bab4f67>:15: 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.ht
ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy)
  data[cat_colname+'_le'] = le.transform(data[cat_colname])
```

В [82]:
```
####
data_new = data
data_new = data_new.drop(catigorical_features, axis=1)

data_new.columns
```

Out[82]:
```
Index(['TransactionDT', 'TransactionAmt', 'card1', 'card2', 'card3', 'card5', 'addr1', 'addr2', 'C1', 'C
2',
       ...
       'R_emaildomain_le', 'M1_le', 'M2_le', 'M3_le', 'M4_le', 'M5_le', 'M6_le', 'M7_le', 'M8_le', 'M9_l
e'], dtype='object', length=209)
```

В [83]:
```
x_train, x_valid = train_test_split(
    data_new, train_size=0.8, random_state=1
)
y_train, y_valid = train_test_split(
    target, train_size=0.8, random_state=1
)
print("x_train.shape = {} rows, {} cols".format(*x_train.shape))
print("x_valid.shape = {} rows, {} cols".format(*x_valid.shape))
```

```
x_train.shape = 144000 rows, 209 cols
x_valid.shape = 36000 rows, 209 cols
```

В [84]:
```
dtrain = lgb.Dataset(
    data=x_train, label=y_train
)
dvalid = lgb.Dataset(
    data=x_valid, label=y_valid
)

model = lgb.train(
    params=params,
    train_set=dtrain,
    num_boost_round=1000,
    valid_sets=[dtrain, dvalid],
    categorical_feature="auto",
    early_stopping_rounds=50,
    verbose_eval=10
)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\lightgbm\engine.py:151: UserWarning: Found `n_estimators` in
params. Will use it instead of argument
  warnings.warn("Found `{}` in params. Will use it instead of argument".format(alias))

[LightGBM] [Info] Number of positive: 4139, number of negative: 139861
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing was 0.086151 secon
ds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 15236
[LightGBM] [Info] Number of data points in the train set: 144000, number of used features: 207
[LightGBM] [Info] Using GOSS
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.028743 -> initscore=-3.520195
[LightGBM] [Info] Start training from score -3.520195
Training until validation scores don't improve for 50 rounds
[10]    training's auc: 0.830267        valid_1's auc: 0.830224
[20]    training's auc: 0.85899 valid_1's auc: 0.858742
[30]    training's auc: 0.868745        valid_1's auc: 0.865245
[40]    training's auc: 0.871826        valid_1's auc: 0.866352
[50]    training's auc: 0.877573        valid_1's auc: 0.871756
```

В [85]:
```
cv_result = lgb.cv(
    params=params,
    train_set=dtrain,
    num_boost_round=1000,
    categorical_feature="auto",
    early_stopping_rounds=50,
    verbose_eval=10,
    stratified=True,
    shuffle=True,
    nfold=5,
)
```

```
[LightGBM] [Info] Number of positive: 3312, number of negative: 111888

C:\ProgramData\Anaconda3\lib\site-packages\lightgbm\engine.py:530: UserWarning: Found `n_estimators` in
params. Will use it instead of argument
  warnings.warn("Found `{}` in params. Will use it instead of argument".format(alias))
```

В [86]:
```
cv_result
```

Out[86]:
```
{'auc-mean': [0.776732105173379,
  0.7813907812101026,
  0.7880309351449395,
  0.7972522606708969,
  0.8054336055619178,
  0.8126760744552666,
  0.8158976570201389,
  0.8176204301180772,
  0.8182379659283499,
  0.8200505296922083,
  0.8205130605204612,
  0.820819269417251,
  0.823710008479857,
  0.8245248204159173,
  0.8349770727876745,
  0.8439672477441397,
  0.8447880912384381,
  0.8460303064549249,
  0.8464812031077417,
```

Результат

Было (значение из Задания 4 (LightGBM Cross-Validation) без учёта категориальных признаков):

```
[200]    training's auc: 0.906055    valid_1's auc: 0.893405
[200]    cv_agg's auc: 0.893526 + 0.00634967 # LightGBM   ([200] train-auc:0.90734 valid-auc:0.89
603 # XGBoost)
```

Стало (с учётом категориальных признаков):

```
[200]    training's auc: 0.915969    valid_1's auc: 0.901176
[200]    cv_agg's auc: 0.901872 + 0.00498726 # LightGBM    ([200] train-auc:0.91819 valid-auc:0.9
0576 # XGBoost)
```

Вывод:

```
Значение метрики качества модели увеличилось с - {[200]    cv_agg's auc: 0.893526 + 0.00634967},
для набора данных в котором не использавались категориальные признаки,
до значений - {[200]    cv_agg's auc: 0.901872 + 0.00498726}.

Таким образом использование обработанных категориальных признаков, позволило достигнуть лучшего р
езультата.
```

В [ ]:
```

```

Задание 6:

Обработать категориальные признаки встроенным методом в LightGBM. Выполнить задание 4. Сделать выводы о качестве работы алгоритма, по сравнению с пунктом 5

LightGBM Sklearn-API с обработанными вручную категориальными признаками (задание 5)

В [87]:
```
# Выполним LightGBM Sklearn-API для применения в задание 6
model = lgb.LGBMClassifier(**params)
model.fit(
    X=x_train,  # используем обработанный датафрэйм из предыдущего занятия
    y=y_train,
    eval_set=[(x_train, y_train), (x_valid, y_valid)],
    early_stopping_rounds=25,
    eval_metric="auc",
    verbose=10
)
```

```
Training until validation scores don't improve for 25 rounds
[10]	training's auc: 0.830267	valid_1's auc: 0.830224
[20]	training's auc: 0.85899	valid_1's auc: 0.858742
[30]	training's auc: 0.868745	valid_1's auc: 0.865245
[40]	training's auc: 0.871826	valid_1's auc: 0.866352
[50]	training's auc: 0.877573	valid_1's auc: 0.871756
[60]	training's auc: 0.880594	valid_1's auc: 0.874296
[70]	training's auc: 0.882865	valid_1's auc: 0.875916
[80]	training's auc: 0.884931	valid_1's auc: 0.877509
[90]	training's auc: 0.893909	valid_1's auc: 0.88362
[100]	training's auc: 0.897756	valid_1's auc: 0.886242
[110]	training's auc: 0.900059	valid_1's auc: 0.888187
[120]	training's auc: 0.901987	valid_1's auc: 0.889596
[130]	training's auc: 0.903725	valid_1's auc: 0.890804
[140]	training's auc: 0.904956	valid_1's auc: 0.892603
[150]	training's auc: 0.905909	valid_1's auc: 0.89401
[160]	training's auc: 0.908898	valid_1's auc: 0.896229
[170]	training's auc: 0.909918	valid_1's auc: 0.897507
[180]	training's auc: 0.911831	valid_1's auc: 0.898807
[190]	training's auc: 0.913846	valid_1's auc: 0.899947
[200]	training's auc: 0.915969	valid_1's auc: 0.901176
Did not meet early stopping. Best iteration is:
[200]	training's auc: 0.915969	valid_1's auc: 0.901176
```

Out[87]:
```
LGBMClassifier(boosting_type='goss', learning_rate=0.01, metric='auc',
               n_estimators=200, n_jobs=6, objective='binary', seed=27)
```

Обработака категориальных признакав встроенным методом LightGBM (задание 6)

В [88]:
```
data = []
data = df_train[numerical_features + catigorical_features]
```

В [89]:
```
x_train, x_valid = train_test_split(
    data, train_size=0.8, random_state=1
)
y_train, y_valid = train_test_split(
    target, train_size=0.8, random_state=1
)
print("x_train.shape = {} rows, {} cols".format(*x_train.shape))
print("x_valid.shape = {} rows, {} cols".format(*x_valid.shape))
```

```
x_train.shape = 144000 rows, 209 cols
x_valid.shape = 36000 rows, 209 cols
```

LightGBM Sklearn-API

В [90]:
```
model = lgb.LGBMClassifier(**params)
model.fit(
    X=x_train,
    y=y_train,
    eval_set=[(x_train, y_train), (x_valid, y_valid)],
    early_stopping_rounds=25,
    eval_metric="auc",
    verbose=10
)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\lightgbm\basic.py:1286: UserWarning: Overriding the parameters
from Reference Dataset.
  warnings.warn('Overriding the parameters from Reference Dataset.')
C:\ProgramData\Anaconda3\lib\site-packages\lightgbm\basic.py:1098: UserWarning: categorical_column in par
am dict is overridden.
  warnings.warn('{} in param dict is overridden.'.format(cat_alias))

Training until validation scores don't improve for 25 rounds
[10]	training's auc: 0.83002	valid_1's auc: 0.829868
[20]	training's auc: 0.859856	valid_1's auc: 0.858051
[30]	training's auc: 0.866844	valid_1's auc: 0.861242
[40]	training's auc: 0.871268	valid_1's auc: 0.865083
[50]	training's auc: 0.877034	valid_1's auc: 0.870163
[60]	training's auc: 0.886489	valid_1's auc: 0.876019
[70]	training's auc: 0.890624	valid_1's auc: 0.878833
[80]	training's auc: 0.893321	valid_1's auc: 0.881282
[90]	training's auc: 0.895349	valid_1's auc: 0.882706
[100]	training's auc: 0.898623	valid_1's auc: 0.885333
[110]	training's auc: 0.900894	valid_1's auc: 0.887276
[120]	training's auc: 0.902637	valid_1's auc: 0.889401
[130]	training's auc: 0.90459	valid_1's auc: 0.891104
[140]	training's auc: 0.906315	valid_1's auc: 0.892637
[150]	training's auc: 0.907901	valid_1's auc: 0.894407
[160]	training's auc: 0.910167	valid_1's auc: 0.896012
[170]	training's auc: 0.911974	valid_1's auc: 0.897424
[180]	training's auc: 0.913239	valid_1's auc: 0.898483
[190]	training's auc: 0.914821	valid_1's auc: 0.899961
[200]	training's auc: 0.916621	valid_1's auc: 0.901497
Did not meet early stopping. Best iteration is:
[200]	training's auc: 0.916621	valid_1's auc: 0.901497
```

Out[90]:
```
LGBMClassifier(boosting_type='goss', learning_rate=0.01, metric='auc',
               n_estimators=200, n_jobs=6, objective='binary', seed=27)
```

Результат

без учёта категориальных признаков:

```
[200]    training's auc: 0.906055    valid_1's auc: 0.893405

LGBMClassifier(boosting_type='goss', learning_rate=0.01, metric='auc',
               n_estimators=200, n_jobs=6, objective='binary', seed=27)
```

Обработка категориальных признаков вручную (LightGBM Sklearn-API):

```
Best iteration is:
[200]    training's auc: 0.915969    valid_1's auc: 0.901176

LGBMClassifier(boosting_type='goss', learning_rate=0.01, metric='auc',
               n_estimators=200, n_jobs=6, objective='binary', seed=27)
```

Обработать категориальные признаки встроенным методом LightGBM (Sklearn-API):

```
Best iteration is:
[200]    training's auc: 0.916621    valid_1's auc: 0.901497

LGBMClassifier(boosting_type='goss', learning_rate=0.01, metric='auc',
               n_estimators=200, n_jobs=6, objective='binary', seed=27)
```

Вывод

```
Значение метрики качества модели незначительно улучшилось.
[200]	training's auc: 0.906055	valid_1's auc: 0.893405 - без учёта категориальных признако
в.
[200]	training's auc: 0.915969	valid_1's auc: 0.901176 - при обработке категориальных призн
аков вручную.
[200]	training's auc: 0.916621	valid_1's auc: 0.901497 - при обработке категориальные призн
аков
встроенным методом LightGBM.

LightGBM хорошо работает с категориальными признаками даже без их предварительной обработки.
При обработке категориальных признаков вручную, результат зависит от качества обработки признако
в.
```

Задание 7:

Для числовых признаков обучить модель CatBoost. Обучать алгоритм до тех пор, пока метрика качества не перестанет улучшаться на валидационной выборке в течение определенного числа итераций (выбрать значение самостоятельно).

В [91]:
```
import catboost as cb

from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
```

В [92]:
```
data = df_train[numerical_features]
#data = data.drop(["TransactionID", "isFraud"], axis=1)
target = df_train["isFraud"]

print("data.shape = {} rows, {} cols".format(*data.shape))
#print(data.shape)
#print(target.shape)
```

```
data.shape = 180000 rows, 195 cols
```

В [93]:
```
x_train, x_valid = train_test_split(
    data, train_size=0.8, random_state=1
)
y_train, y_valid = train_test_split(
    target, train_size=0.8, random_state=1
)
print("x_train.shape = {} rows, {} cols".format(*x_train.shape))
print("x_valid.shape = {} rows, {} cols".format(*x_valid.shape))
```

```
x_train.shape = 144000 rows, 195 cols
x_valid.shape = 36000 rows, 195 cols
```

CatBoost Sklearn-API

В [94]:
```
cb_params = {
    "n_estimators": 1000,
    "loss_function": "Logloss",
    "eval_metric": "AUC",
    "task_type": "CPU",
    "max_bin": 20,
    "verbose": 10,  # Как часто выводим на экран статистику
    "max_depth": 6,
    "l2_leaf_reg": 100,
    "early_stopping_rounds": 50,
    "thread_count": 6,
    "random_seed": 42
}
```

В [95]:
```
model = cb.CatBoostClassifier(**cb_params)
model.fit(x_train, y_train, eval_set=[(x_train, y_train), (x_valid, y_valid)])
```

```
0:      test: 0.6428916 test1: 0.6337011        best: 0.6337011 (0)     total: 261ms    remaining: 4m 2
0s
10:     test: 0.7903512 test1: 0.7760513        best: 0.7761566 (9)     total: 1.33s    remaining: 1m 5
9s
20:     test: 0.8337795 test1: 0.8310485        best: 0.8310485 (20)    total: 2.04s    remaining: 1m 3
4s
30:     test: 0.8457567 test1: 0.8421181        best: 0.8421181 (30)    total: 2.59s    remaining: 1m 2
1s
40:     test: 0.8508974 test1: 0.8474832        best: 0.8474832 (40)    total: 3.42s    remaining: 1m 2
0s
50:     test: 0.8527125 test1: 0.8485145        best: 0.8493058 (41)    total: 4.16s    remaining: 1m 1
7s
60:     test: 0.8535528 test1: 0.8486150        best: 0.8493058 (41)    total: 4.84s    remaining: 1m 1
4s
70:     test: 0.8571808 test1: 0.8513373        best: 0.8513373 (70)    total: 5.45s    remaining: 1m 1
1s
80:     test: 0.8608275 test1: 0.8544776        best: 0.8546970 (79)    total: 6.11s    remaining: 1m 9
s
90:     test: 0.8637865 test1: 0.8568108        best: 0.8568108 (90)    total: 6.81s    remaining: 1m 8
```

В [96]:
```
model = cb.CatBoostClassifier(**cb_params)
model.fit(
    X=x_train,
    y=y_train,
    eval_set=[(x_train, y_train), (x_valid, y_valid)],
    plot=True
)
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))
```

Model Cross-Validation

В [97]:
```
cv_data = cb.cv(
    #cb.Pool(x_train, y_train, cat_features=["var_67_categorical"]),
    cb.Pool(x_train, y_train),
    cb_params,
    plot=True
)
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))
```

В [98]:
```
cv_data.head()
```

Out[98]:

	iterations	test-AUC-mean	test-AUC-std	test-Logloss-mean	test-Logloss-std	train-Logloss-mean	train-Logloss-std
0	0	0.692885	0.002207	0.640846	0.000013	0.640843	0.000025
1	1	0.694013	0.004397	0.596069	0.000037	0.596066	0.000081
2	2	0.723899	0.001748	0.553569	0.000118	0.553566	0.000111
3	3	0.730961	0.007147	0.515403	0.000727	0.515405	0.000706
4	4	0.734457	0.006221	0.480692	0.000363	0.480686	0.000320

В [99]:
```
print('Best validation accuracy score: {:.2f}±{:.2f} on step {}'.format(
    np.max(cv_data['test-AUC-mean']),
    cv_data['test-AUC-std'][np.argmax(cv_data['test-AUC-mean'])],
    np.argmax(cv_data['test-AUC-mean'])
))
```

```
Best validation accuracy score: 0.89±0.00 on step 999
```

Применение модели

В [100]:
```
predictions = model.predict(x_valid)
predictions_probs = model.predict_proba(x_valid)

print(predictions[:10])
print(predictions_probs[:10])
```

```
[0 0 0 0 0 0 0 0 0 0]
[[0.98311737 0.01688263]
 [0.99512308 0.00487692]
 [0.99578802 0.00421198]
 [0.99354988 0.00645012]
 [0.9808637  0.0191363 ]
 [0.99523593 0.00476407]
 [0.98952062 0.01047938]
 [0.98967758 0.01032242]
 [0.98904561 0.01095439]
 [0.98870075 0.01129925]]
```

CatBoost API

В [101]:
```
#train_pool = cb.Pool(x_train, y_train, cat_features=["var_67_categorical"])
#valid_pool = cb.Pool(x_valid, y_valid, cat_features=["var_67_categorical"])
train_pool = cb.Pool(x_train, y_train)
valid_pool = cb.Pool(x_valid, y_valid)
```

В [102]:
```
model = cb.CatBoostClassifier(**cb_params)
model.fit(train_pool, eval_set=valid_pool)
```

```
0:      test: 0.6337011 best: 0.6337011 (0)     total: 168ms    remaining: 2m 47s
10:     test: 0.7760513 best: 0.7761566 (9)     total: 1.33s    remaining: 1m 59s
20:     test: 0.8310485 best: 0.8310485 (20)    total: 2s       remaining: 1m 33s
30:     test: 0.8421181 best: 0.8421181 (30)    total: 2.48s    remaining: 1m 17s
40:     test: 0.8474832 best: 0.8474832 (40)    total: 2.98s    remaining: 1m 9s
50:     test: 0.8485145 best: 0.8493058 (41)    total: 3.84s    remaining: 1m 11s
60:     test: 0.8486150 best: 0.8493058 (41)    total: 4.65s    remaining: 1m 11s
70:     test: 0.8513373 best: 0.8513373 (70)    total: 5.22s    remaining: 1m 8s
80:     test: 0.8544776 best: 0.8546970 (79)    total: 5.78s    remaining: 1m 5s
90:     test: 0.8568108 best: 0.8568108 (90)    total: 6.29s    remaining: 1m 2s
100:    test: 0.8580264 best: 0.8580264 (100)   total: 6.78s    remaining: 1m
110:    test: 0.8598111 best: 0.8598719 (109)   total: 7.29s    remaining: 58.4s
120:    test: 0.8606391 best: 0.8606391 (120)   total: 7.79s    remaining: 56.6s
130:    test: 0.8615384 best: 0.8615384 (130)   total: 8.3s     remaining: 55.1s
140:    test: 0.8633281 best: 0.8633281 (140)   total: 8.8s     remaining: 53.6s
150:    test: 0.8665500 best: 0.8665500 (150)   total: 9.32s    remaining: 52.4s
160:    test: 0.8685733 best: 0.8685733 (160)   total: 9.84s    remaining: 51.3s
170:    test: 0.8697402 best: 0.8697402 (170)   total: 10.3s    remaining: 50.1s
180:    test: 0.8708745 best: 0.8708745 (180)   total: 10.9s    remaining: 49.1s
```

Задание 8:

Обработать категориальные признаки любым способом (который вы знаете) и добавить их к данным. Выполнить задание 7.

Обрабатывае категориальные признаки также как и XGBoost

В [103]:
```
data = []
data = df_train[numerical_features + catigorical_features]

# заполняем пропуски в категориалиных признаках
for feature in catigorical_features:
    data[feature] = data[feature].cat.add_categories('Unknown')
    data[feature].fillna('Unknown', inplace =True)

# Каждой категории сопоставляем целое число (номер категории) - https://dyakonov.org/2016/08/03/python-кам
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
for cat_colname in data[catigorical_features].columns:
    le.fit(data[cat_colname])
    data[cat_colname+'_le'] = le.transform(data[cat_colname])

target = df_train["isFraud"]

#train.dtypes
```

```
<ipython-input-103-8bac6da628fd>:6: 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.ht
ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy)
  data[feature] = data[feature].cat.add_categories('Unknown')
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\series.py:4517: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.ht
ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy)
  return super().fillna(
<ipython-input-103-8bac6da628fd>:15: 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.ht
ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy)
  data[cat_colname+'_le'] = le.transform(data[cat_colname])
```

В [104]:
```
data_new = data
data_new = data_new.drop(catigorical_features, axis=1)

data_new.columns
```

Out[104]:
```
Index(['TransactionDT', 'TransactionAmt', 'card1', 'card2', 'card3', 'card5', 'addr1', 'addr2', 'C1', 'C
2',
       ...
       'R_emaildomain_le', 'M1_le', 'M2_le', 'M3_le', 'M4_le', 'M5_le', 'M6_le', 'M7_le', 'M8_le', 'M9_l
e'], dtype='object', length=209)
```

В [105]:
```
x_train, x_valid = train_test_split(
    data_new, train_size=0.8, random_state=1
)
y_train, y_valid = train_test_split(
    target, train_size=0.8, random_state=1
)
print("x_train.shape = {} rows, {} cols".format(*x_train.shape))
print("x_valid.shape = {} rows, {} cols".format(*x_valid.shape))
```

```
x_train.shape = 144000 rows, 209 cols
x_valid.shape = 36000 rows, 209 cols
```

В [106]:
```
model = cb.CatBoostClassifier(**cb_params)
model.fit(x_train, y_train, eval_set=[(x_train, y_train), (x_valid, y_valid)])
```

```
0:	test: 0.5634650 test1: 0.5649556	best: 0.5649556 (0)	total: 216ms	remaining: 3m 3
5s
10:	test: 0.7976306 test1: 0.7909441	best: 0.7920496 (9)	total: 1.41s	remaining: 2m 6
s
20:	test: 0.8415536 test1: 0.8356316	best: 0.8356316 (20)	total: 2.54s	remaining: 1m 5
8s
30:	test: 0.8464893 test1: 0.8416125	best: 0.8416125 (30)	total: 3.55s	remaining: 1m 5
0s
40:	test: 0.8492076 test1: 0.8448612	best: 0.8448612 (40)	total: 4.44s	remaining: 1m 4
3s
50:	test: 0.8547717 test1: 0.8515601	best: 0.8515601 (50)	total: 5.38s	remaining: 1m 4
0s
60:	test: 0.8567688 test1: 0.8514909	best: 0.8518652 (59)	total: 6.09s	remaining: 1m 3
3s
70:	test: 0.8602788 test1: 0.8540535	best: 0.8540570 (68)	total: 6.78s	remaining: 1m 2
8s
80:	test: 0.8637868 test1: 0.8585103	best: 0.8585103 (80)	total: 7.67s	remaining: 1m 2
7s
90:	test: 0.8666512 test1: 0.8609496	best: 0.8609496 (90)	total: 8.61s	remaining: 1m 2
```

CatBoost API

В [107]:
```
train_pool = cb.Pool(x_train, y_train)
valid_pool = cb.Pool(x_valid, y_valid)
```

В [108]:
```
model = cb.CatBoostClassifier(**cb_params)
model.fit(train_pool, eval_set=valid_pool)
```

```
0:	test: 0.5649556 best: 0.5649556 (0)	total: 148ms	remaining: 2m 27s
10:	test: 0.7909441 best: 0.7920496 (9)	total: 978ms	remaining: 1m 27s
20:	test: 0.8356316 best: 0.8356316 (20)	total: 1.46s	remaining: 1m 8s
30:	test: 0.8416125 best: 0.8416125 (30)	total: 1.95s	remaining: 1m
40:	test: 0.8448612 best: 0.8448612 (40)	total: 2.46s	remaining: 57.6s
50:	test: 0.8515601 best: 0.8515601 (50)	total: 2.97s	remaining: 55.2s
60:	test: 0.8514909 best: 0.8518652 (59)	total: 3.46s	remaining: 53.2s
70:	test: 0.8540535 best: 0.8540570 (68)	total: 4.01s	remaining: 52.5s
80:	test: 0.8585103 best: 0.8585103 (80)	total: 4.51s	remaining: 51.2s
90:	test: 0.8609496 best: 0.8609496 (90)	total: 5.03s	remaining: 50.2s
100:	test: 0.8632508 best: 0.8634941 (98)	total: 5.53s	remaining: 49.2s
110:	test: 0.8643263 best: 0.8643263 (110)	total: 6.03s	remaining: 48.3s
120:	test: 0.8653065 best: 0.8653065 (120)	total: 6.55s	remaining: 47.6s
130:	test: 0.8666361 best: 0.8666361 (130)	total: 7.06s	remaining: 46.8s
140:	test: 0.8695659 best: 0.8695659 (140)	total: 7.6s	remaining: 46.3s
150:	test: 0.8716204 best: 0.8716204 (150)	total: 8.14s	remaining: 45.8s
160:	test: 0.8732946 best: 0.8732946 (160)	total: 8.69s	remaining: 45.3s
170:	test: 0.8748241 best: 0.8748304 (169)	total: 9.19s	remaining: 44.5s
180:	test: 0.8766481 best: 0.8766481 (180)	total: 9.73s	remaining: 44.1s
```

Результат

Было (значение из *задания 7* без учёта категориальных признаков):

```
bestTest = 0.8841871945 bestIteration = 780
```

Стало (с учётом категориальных признаков):

```
bestTest = 0.8921156772 bestIteration = 529
```

Вывод:

```
Значение метрики качества модели улучшилось.
Было: {bestTest = 0.8841871945 bestIteration = 780}, для набора данных в котором не использавалис
ь
категориальные признаки.
Стало: {bestTest = 0.8921156772 bestIteration = 529}, для набора данных в котором использавались
категориальные признаки обработанные вручную.

Таким образом использование обработанных категориальных признаков, позволило достигнуть лучшего р
езультата.
```

Задание 9:

Обработать категориальные признаки встроенным методом в CatBoost. Выполнить задание 7. Сделать выводы о качестве работы алгоритма, по сравнению с пунктом 8.

CatBoost API

В [109]:
```
from pprint import pprint
data = []
#data = df_train[numerical_features + catigorical_features]
data = df_train[catigorical_features + numerical_features]

# CatBoost отказался принимать NaN-значения (пропуски) в категориальных признаках,
# поэтому заполняем пропуски в категориалиных признаках
for feature in catigorical_features:
    data[feature] = data[feature].cat.add_categories('Unknown')
    data[feature].fillna('Unknown', inplace =True)

pprint(type(data.columns))
pprint(data.columns)
```

```
<class 'pandas.core.indexes.base.Index'>
Index(['ProductCD', 'card4', 'card6', 'P_emaildomain', 'R_emaildomain', 'M1', 'M2', 'M3', 'M4', 'M5',
       ...
       'V312', 'V313', 'V314', 'V315', 'V316', 'V317', 'V318', 'V319', 'V320', 'V321'], dtype='object', l
ength=209)

<ipython-input-109-9aad4995db54>:9: 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.ht
ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy)
  data[feature] = data[feature].cat.add_categories('Unknown')
```

В [110]:
```
x_train, x_valid = train_test_split(
    data, train_size=0.8, random_state=1
)
y_train, y_valid = train_test_split(
    target, train_size=0.8, random_state=1
)
print("x_train.shape = {} rows, {} cols".format(*x_train.shape))
print("x_valid.shape = {} rows, {} cols".format(*x_valid.shape))
print(catigorical_features)
```

```
x_train.shape = 144000 rows, 209 cols
x_valid.shape = 36000 rows, 209 cols
['ProductCD', 'card4', 'card6', 'P_emaildomain', 'R_emaildomain', 'M1', 'M2', 'M3', 'M4', 'M5', 'M6', 'M
7', 'M8', 'M9']
```

В [111]:
```
train_pool = cb.Pool(x_train, y_train, cat_features=catigorical_features)
valid_pool = cb.Pool(x_valid, y_valid, cat_features=catigorical_features)
```

В [112]:
```
model = cb.CatBoostClassifier(**cb_params)
model.fit(train_pool, eval_set=valid_pool)
```

```
0:      test: 0.5447932 best: 0.5447932 (0)     total: 708ms    remaining: 11m 47s
10:     test: 0.8067101 best: 0.8067101 (10)    total: 3.56s    remaining: 5m 20s
20:     test: 0.8147418 best: 0.8160923 (17)    total: 6.16s    remaining: 4m 47s
30:     test: 0.8332325 best: 0.8332325 (30)    total: 8.72s    remaining: 4m 32s
40:     test: 0.8390837 best: 0.8390837 (40)    total: 11.3s    remaining: 4m 23s
50:     test: 0.8444603 best: 0.8444603 (50)    total: 13.8s    remaining: 4m 17s
60:     test: 0.8482172 best: 0.8482607 (57)    total: 16.5s    remaining: 4m 13s
70:     test: 0.8518190 best: 0.8521914 (69)    total: 19.1s    remaining: 4m 10s
80:     test: 0.8531991 best: 0.8531991 (80)    total: 21.7s    remaining: 4m 6s
90:     test: 0.8530414 best: 0.8532376 (87)    total: 24.2s    remaining: 4m 2s
100:    test: 0.8580223 best: 0.8581058 (98)    total: 26.8s    remaining: 3m 58s
110:    test: 0.8594502 best: 0.8594502 (110)   total: 29.4s    remaining: 3m 55s
120:    test: 0.8631692 best: 0.8631692 (120)   total: 31.9s    remaining: 3m 52s
130:    test: 0.8647246 best: 0.8647246 (130)   total: 34.6s    remaining: 3m 49s
140:    test: 0.8670810 best: 0.8670810 (140)   total: 37.2s    remaining: 3m 46s
150:    test: 0.8702482 best: 0.8702482 (150)   total: 39.8s    remaining: 3m 43s
160:    test: 0.8727569 best: 0.8727569 (160)   total: 42.4s    remaining: 3m 41s
170:    test: 0.8742531 best: 0.8742531 (170)   total: 45s      remaining: 3m 37s
180:    test: 0.8762383 best: 0.8762383 (180)   total: 47.5s    remaining: 3m 34s
```

Результат

Было (значение из *задания 7* без учёта категориальных признаков):

```
bestTest = 0.8841871945 bestIteration = 780
```

Было (значение из *задания 7*, с учётом категориальных признаков обработанных вручную):

```
bestTest = 0.8921156772 bestIteration = 529
```

Стало (с учётом категориальных признаков обработанных встроенным методом CatBoost):

```
bestTest = 0.8954842045 bestIteration = 884
```

Вывод:

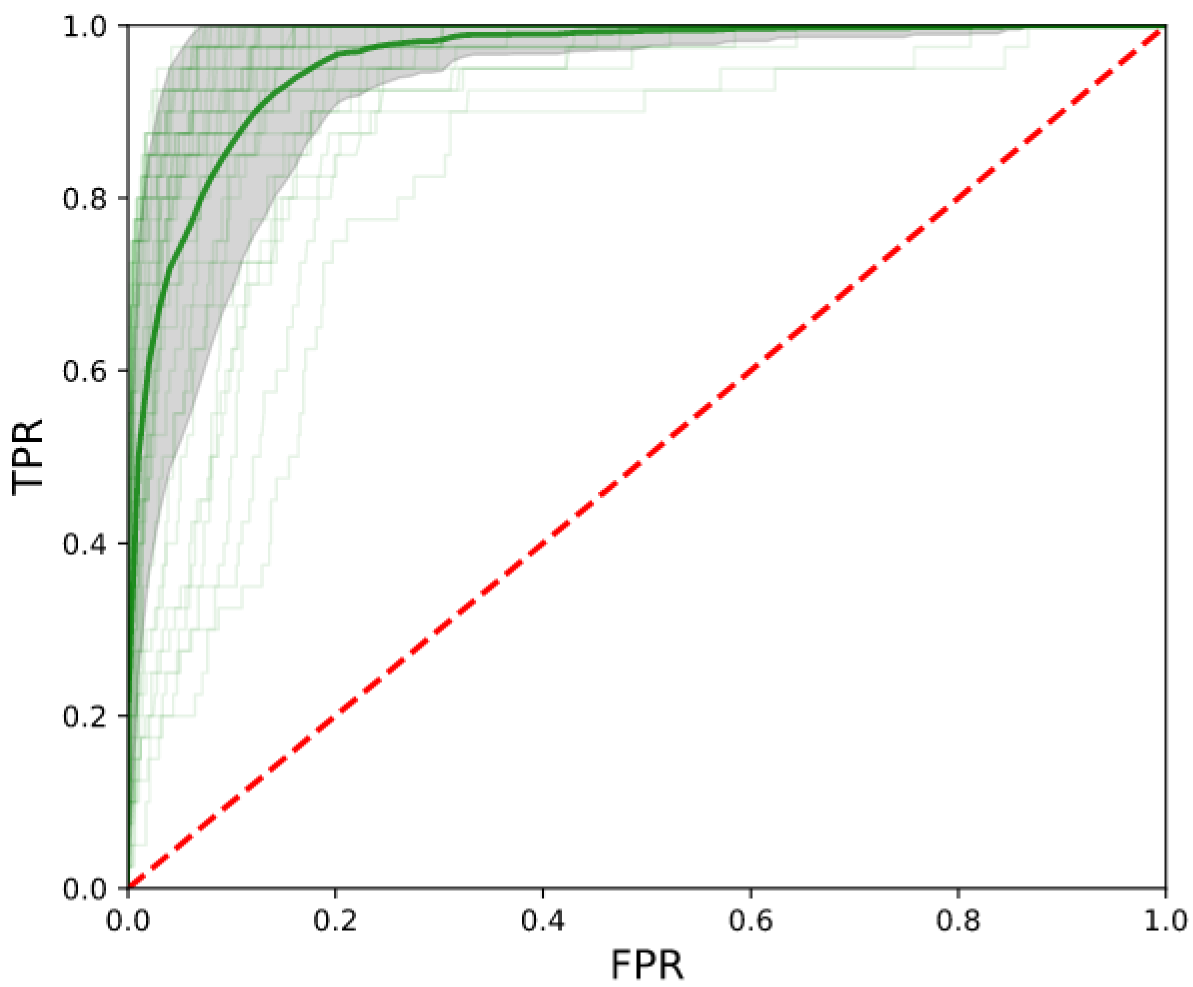
```
Значение метрики качества модели улучшилось.
Было: {bestTest = 0.8841871945 bestIteration = 780}, для набора данных в котором не использовалис
ь
категориальные признаки.
Было: {bestTest = 0.8841871945 bestIteration = 780}, для набора данных в котором использавались
категориальные признаки обработанные вручную.
Стало: {bestTest = 0.8954842045 bestIteration = 884}, для набора данных в котором использавались
категориальные признаки обработанные встроенным методом CatBoost.

Таким образом использование категориальных признаков, позволило достигнуть лучшего результата.
При обработке категориальных признаков вручную, результат зависит от качества обработки признако
в.
```

Задание 10:

Построить ROC-кривую для всех построенных алгоритмов на обучающей и тестовой выборке. Сделать выводы о работе алгоритмов с точки зрения качества на тестовой выборке и с точки зрения переобучения.

Графичекая характеристика качества бинарного классификатора, отображает зависимость доли верных положительных классификаций True Positive Rate (TPR) от доли ложных положительных классификаций False Positive Rate (FPR).

$$TPR = \frac{TP}{TP+FN} \quad FPR = \frac{FP}{FP+TN}$$



ROCAUC - [https://rebeccabilbro.github.io/xgboost-and-yellowbrick/¶ (https://rebeccabilbro.github.io/xgboost-and-yellowbrick/%C2%B6)](https://rebeccabilbro.github.io/xgboost-and-yellowbrick/%C2%B6)

В [113]:
```
#!pip install scikit-plot  # Successfully installed scikit-plot-0.3.7
```

В [114]:
```
import scikitplot as skplt
import matplotlib.pyplot as plt
"""
y_true = # ground truth labels
y_probas = # predicted probabilities generated by sklearn classifier

skplt.metrics.plot_roc_curve(y_true, y_probas)
plt.show()
"""
```

Out[114]:
```
'\ny_true = # ground truth labels\ny_probas = # predicted probabilities generated by sklearn classifier\n\nskplt.metrics.plot_roc_curve(y_true, y_probas)\nplt.show() \n'
```

Как построить кривую ROC (кривая ошибок)

- https://coderoad.ru/25009284/как-plot-ROC-кривая-в-Puthon (https://coderoad.ru/25009284/%D0%BA%D0%B0%D0%BA-plot-ROC-%D0%BA%D1%80%D0%B8%D0%B2%D0%B0%D1%8F-%D0%B2-Puthon)

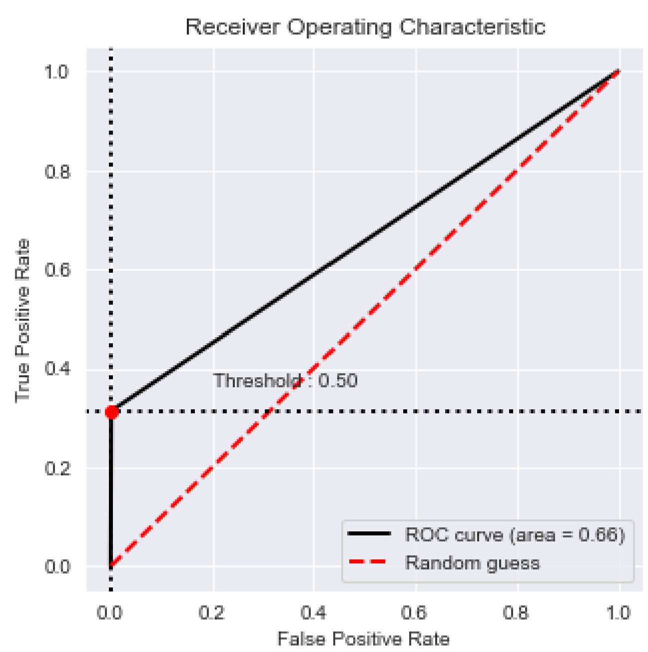
  Количественную интерпретацию ROC даёт показатель AUC (англ. area under ROC curve, площадь под ROC-кривой) — площадь, ограниченная ROC-кривой и осью доли ложных положительных классификаций.

В [115]:
```
#!pip install plot-metric  # Successfully installed colorlover-0.3.0 plot-metric-0.0.6
```

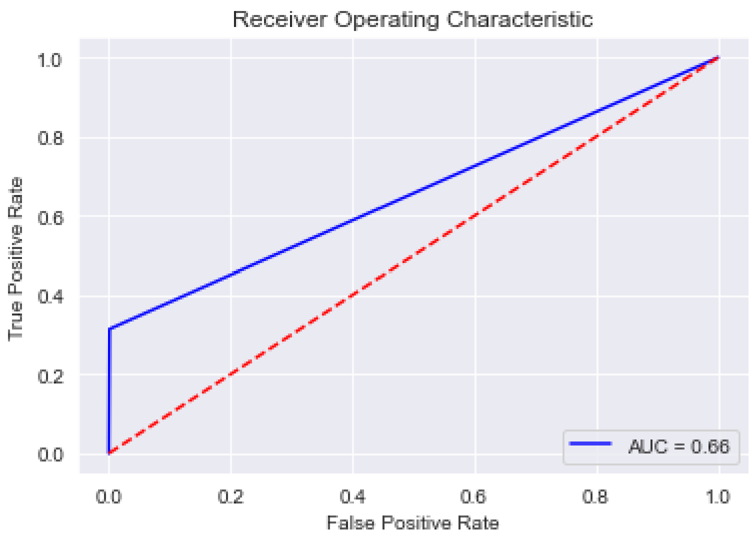
XGBoost plot Roc кривая

В [116]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score

TRAIN_DATASET_PATH = './data/assignment_2_train.csv'
train = pd.read_csv(TRAIN_DATASET_PATH)

numerical_features = train.select_dtypes(include=['float32', 'float64', 'int8', 'int16', 'int32']).columns

data = train[numerical_features]
target = train['isFraud']

x_train, x_valid = train_test_split(data, train_size=0.8, random_state=1)
y_train, y_valid = train_test_split(target, train_size=0.8, random_state=1)

params = {
    "booster": "gbtree",
    "objective": "binary:logistic",
    "eval_metric": "auc",
    "learning_rate": 0.1,
    "n_estimators": 1000,
    "reg_lambda": 100,
    "max_depth": 4,
    "gamma": 10,
    "nthread": 6,
    "seed": 27
}

model = xgb.XGBClassifier(**params)
model.fit(
    X=x_train,
    y=y_train,
    eval_set=[(x_train, y_train), (x_valid, y_valid)],
    early_stopping_rounds=50,
    eval_metric="auc",
    verbose=10
)
# make predictions for test data
y_pred = model.predict(x_valid)
preds = [round(value) for value in y_pred]
y_test = list(y_valid)

from plot_metric.functions import BinaryClassification
# Visualisation with plot_metric
bc = BinaryClassification(y_test, y_pred, labels=["Class 1", "Class 2"])

# Figures
plt.figure(figsize=(5,5))
bc.plot_roc_curve()
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\xgboost\sklearn.py:888: UserWarning: The use of label encoder
in XGBClassifier is deprecated and will be removed in a future release. To remove this warning, do the fo
llowing: 1) Pass option use_label_encoder=False when constructing XGBClassifier object; and 2) Encode you
r labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)

[0]	validation_0-auc:0.64988	validation_1-auc:0.65040
[50]	validation_0-auc:0.87698	validation_1-auc:0.86934
[100]	validation_0-auc:0.89150	validation_1-auc:0.88314
[150]	validation_0-auc:0.89855	validation_1-auc:0.88944
[198]	validation_0-auc:0.89855	validation_1-auc:0.88944
```



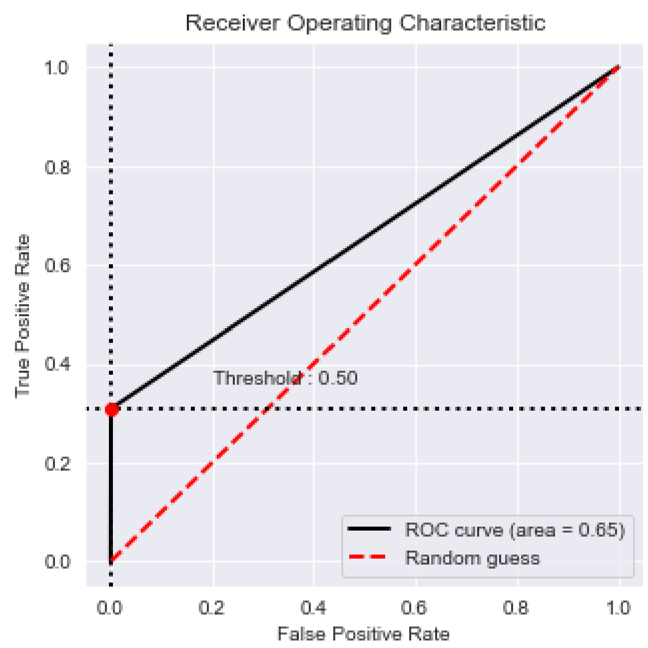
В [117]:
```
#XGBoost plot Roc кривая
from sklearn import metrics
def buildROC(target_test,test_preds):
    fpr, tpr, threshold = metrics.roc_curve(target_test, test_preds)
    roc_auc = metrics.auc(fpr, tpr)
    plt.title('Receiver Operating Characteristic')
    plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1],'r--')
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.gcf().savefig('roc.png')

buildROC(y_test, y_pred)
```



LightGBM plot Roc кривая

В [118]:
```
params = {
    "boosting_type": "gbdt",  # gradient boosting tree decision tree
    "objective": "binary",
    "metric": "auc",
    "learning_rate": 0.01,
    "n_estimators": 200,  # число деревьев
    "n_jobs": 6,
    "seed": 27
}

model = lgb.LGBMClassifier(**params)
y = model.fit(
    X=x_train,
    y=y_train,
    eval_set=[(x_train, y_train), (x_valid, y_valid)],
    early_stopping_rounds=25,
    eval_metric="auc",
    verbose=10
)

# make predictions for test data
y_pred = model.predict(x_valid)
preds = [round(value) for value in y_pred]
y_test = list(y_valid)

from plot_metric.functions import BinaryClassification
# Visualisation with plot_metric
bc = BinaryClassification(y_test, y_pred, labels=["Class 1", "Class 2"])

# Figures
plt.figure(figsize=(5,5))
bc.plot_roc_curve()
plt.show()
```

```
Training until validation scores don't improve for 25 rounds
[10]    training's auc: 0.833851        valid_1's auc: 0.83047
[20]    training's auc: 0.83805 valid_1's auc: 0.833559
[30]    training's auc: 0.865735        valid_1's auc: 0.860417
[40]    training's auc: 0.873545        valid_1's auc: 0.867133
[50]    training's auc: 0.878139        valid_1's auc: 0.869278
[60]    training's auc: 0.881281        valid_1's auc: 0.872269
[70]    training's auc: 0.88287 valid_1's auc: 0.874168
[80]    training's auc: 0.884983        valid_1's auc: 0.875948
[90]    training's auc: 0.886449        valid_1's auc: 0.876993
[100]   training's auc: 0.888211        valid_1's auc: 0.87777
[110]   training's auc: 0.889141        valid_1's auc: 0.879241
[120]   training's auc: 0.891341        valid_1's auc: 0.88049
[130]   training's auc: 0.892671        valid_1's auc: 0.881388
[140]   training's auc: 0.893938        valid_1's auc: 0.882437
[150]   training's auc: 0.895089        valid_1's auc: 0.883594
[160]   training's auc: 0.896685        valid_1's auc: 0.884503
[170]   training's auc: 0.898   valid_1's auc: 0.885442
[180]   training's auc: 0.899499        valid_1's auc: 0.886509
[190]   training's auc: 0.901372        valid_1's auc: 0.888111
[200]   training's auc: 0.903402        valid_1's auc: 0.890431
Did not meet early stopping. Best iteration is:
[200]   training's auc: 0.903402        valid_1's auc: 0.890431
```

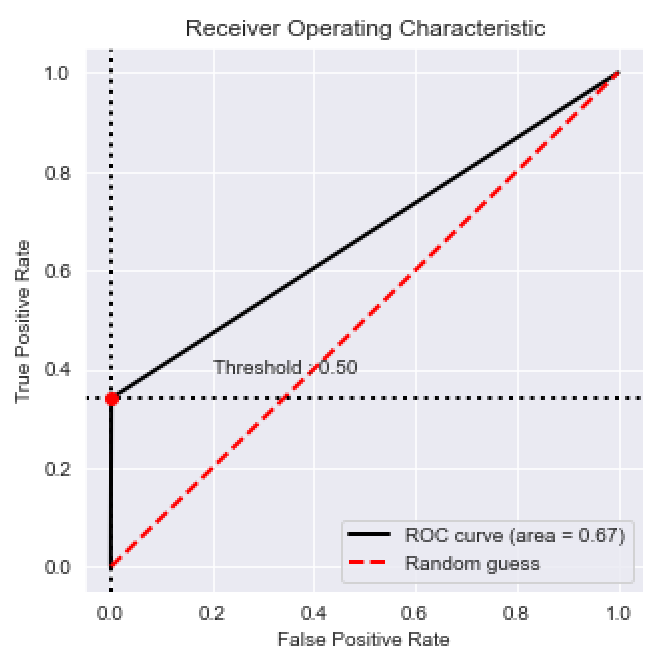


CatBoost plot Roc кривая

В [119]:
```
cb_params = {
    "n_estimators": 1000,
    "loss_function": "Logloss",
    "eval_metric": "AUC",
    "task_type": "CPU",
    "max_bin": 20,
    "verbose": 10,  # Как часто выводим на экран статистику
    "max_depth": 6,
    "l2_leaf_reg": 100,
    "early_stopping_rounds": 50,
    "thread_count": 6,
    "random_seed": 42
}

model = cb.CatBoostClassifier(**cb_params)
model.fit(
    X=x_train,
    y=y_train,
    eval_set=[(x_train, y_train), (x_valid, y_valid)],
    plot=True
)

# make predictions for test data
y_pred = model.predict(x_valid)
preds = [round(value) for value in y_pred]
y_test = list(y_valid)

from plot_metric.functions import BinaryClassification
# Visualisation with plot_metric
bc = BinaryClassification(y_test, y_pred, labels=["Class 1", "Class 2"])

# Figures
plt.figure(figsize=(5,5))
bc.plot_roc_curve()
plt.show()
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))

0:      test: 0.7615702 test1: 0.7487818       best: 0.7487818 (0)     total: 271ms    remaining: 4m 31s
10:     test: 0.8199551 test1: 0.8109260       best: 0.8109260 (10)    total: 1.61s    remaining: 2m 25s
20:     test: 0.8247723 test1: 0.8111688       best: 0.8132692 (13)    total: 2.49s    remaining: 1m 56s
30:     test: 0.8412945 test1: 0.8324845       best: 0.8325651 (29)    total: 3.35s    remaining: 1m 44s
40:     test: 0.8457663 test1: 0.8371246       best: 0.8371246 (40)    total: 4.34s    remaining: 1m 41s
50:     test: 0.8486648 test1: 0.8402671       best: 0.8402671 (50)    total: 5.16s    remaining: 1m 35s
60:     test: 0.8521082 test1: 0.8454715       best: 0.8454715 (60)    total: 5.89s    remaining: 1m 30s
70:     test: 0.8530905 test1: 0.8476468       best: 0.8477893 (66)    total: 6.62s    remaining: 1m 26s
80:     test: 0.8569671 test1: 0.8503087       best: 0.8505791 (77)    total: 7.35s    remaining: 1m 23s
90:     test: 0.8585353 test1: 0.8515643       best: 0.8517219 (85)    total: 8.16s    remaining: 1m 21s
100:    test: 0.8586887 test1: 0.8519240       best: 0.8519240 (100)   total: 8.92s    remaining: 1m 19s
110:    test: 0.8590225 test1: 0.8521876       best: 0.8521876 (110)   total: 9.66s    remaining: 1m 17s
120:    test: 0.8602266 test1: 0.8535461       best: 0.8535461 (120)   total: 10.4s    remaining: 1m 15s
130:    test: 0.8609379 test1: 0.8534412       best: 0.8539267 (126)   total: 11.2s    remaining: 1m 14s
140:    test: 0.8635243 test1: 0.8564968       best: 0.8564968 (140)   total: 12.1s    remaining: 1m 13s
150:    test: 0.8648355 test1: 0.8577926       best: 0.8577926 (150)   total: 12.8s    remaining: 1m 12s
160:    test: 0.8656122 test1: 0.8584703       best: 0.8584703 (160)   total: 13.6s    remaining: 1m 10s
170:    test: 0.8677959 test1: 0.8609653       best: 0.8609653 (170)   total: 14.4s    remaining: 1m 9s
180:    test: 0.8692329 test1: 0.8621425       best: 0.8621425 (180)   total: 15.2s    remaining: 1m 8s
190:    test: 0.8712665 test1: 0.8641418       best: 0.8641418 (190)   total: 16.1s    remaining: 1m 8s
200:    test: 0.8726949 test1: 0.8662755       best: 0.8662755 (200)   total: 16.8s    remaining: 1m 6s
210:    test: 0.8732719 test1: 0.8669972       best: 0.8670129 (209)   total: 17.5s    remaining: 1m 5s
220:    test: 0.8740828 test1: 0.8679158       best: 0.8679158 (220)   total: 18.4s    remaining: 1m 4s
230:    test: 0.8752694 test1: 0.8694482       best: 0.8694482 (230)   total: 19.3s    remaining: 1m 4s
240:    test: 0.8762000 test1: 0.8702477       best: 0.8702477 (240)   total: 20.3s    remaining: 1m 4s
250:    test: 0.8769197 test1: 0.8711710       best: 0.8711710 (250)   total: 21.5s    remaining: 1m 4s
260:    test: 0.8780661 test1: 0.8722234       best: 0.8722234 (260)   total: 22.5s    remaining: 1m 3s
270:    test: 0.8785734 test1: 0.8726973       best: 0.8726973 (270)   total: 23.7s    remaining: 1m 3s
280:    test: 0.8791970 test1: 0.8732220       best: 0.8732220 (280)   total: 24.8s    remaining: 1m 3s
290:    test: 0.8795761 test1: 0.8736619       best: 0.8736619 (290)   total: 25.7s    remaining: 1m 2s
300:    test: 0.8802929 test1: 0.8741459       best: 0.8741459 (300)   total: 26.6s    remaining: 1m 1s
310:    test: 0.8806125 test1: 0.8743971       best: 0.8743971 (310)   total: 27.6s    remaining: 1m 1s
320:    test: 0.8810562 test1: 0.8749600       best: 0.8749600 (320)   total: 28.4s    remaining: 1m
330:    test: 0.8815025 test1: 0.8754622       best: 0.8754622 (330)   total: 29.2s    remaining: 59s
340:    test: 0.8820375 test1: 0.8759854       best: 0.8759854 (340)   total: 30.1s    remaining: 58.1s
350:    test: 0.8824273 test1: 0.8763297       best: 0.8763297 (350)   total: 30.9s    remaining: 57s
360:    test: 0.8828578 test1: 0.8766108       best: 0.8766108 (360)   total: 31.8s    remaining: 56.2s
370:    test: 0.8831448 test1: 0.8769312       best: 0.8769312 (370)   total: 32.7s    remaining: 55.4s
380:    test: 0.8833236 test1: 0.8769932       best: 0.8769932 (380)   total: 33.6s    remaining: 54.6s
390:    test: 0.8836360 test1: 0.8773386       best: 0.8773386 (390)   total: 34.4s    remaining: 53.6s
400:    test: 0.8838959 test1: 0.8776269       best: 0.8776269 (400)   total: 35.1s    remaining: 52.5s
410:    test: 0.8843848 test1: 0.8780858       best: 0.8780858 (410)   total: 35.9s    remaining: 51.5s
420:    test: 0.8845889 test1: 0.8783579       best: 0.8783579 (420)   total: 36.7s    remaining: 50.5s
430:    test: 0.8849388 test1: 0.8786424       best: 0.8786424 (430)   total: 37.5s    remaining: 49.5s
440:    test: 0.8849870 test1: 0.8786815       best: 0.8786821 (437)   total: 38.1s    remaining: 48.4s
450:    test: 0.8851595 test1: 0.8788994       best: 0.8788994 (450)   total: 38.9s    remaining: 47.4s
```

```
460:	test: 0.8854453 test1: 0.8791895	best: 0.8791895 (460)	total: 39.9s	remaining: 46.6s
470:	test: 0.8855147 test1: 0.8792454	best: 0.8792530 (469)	total: 41.2s	remaining: 46.2s
480:	test: 0.8856238 test1: 0.8793408	best: 0.8793418 (479)	total: 42.5s	remaining: 45.8s
490:	test: 0.8857518 test1: 0.8793905	best: 0.8793908 (484)	total: 43.3s	remaining: 44.9s
500:	test: 0.8857680 test1: 0.8793909	best: 0.8793912 (499)	total: 44.3s	remaining: 44.1s
510:	test: 0.8857783 test1: 0.8793968	best: 0.8793968 (510)	total: 45.3s	remaining: 43.3s
520:	test: 0.8857887 test1: 0.8793975	best: 0.8793979 (519)	total: 46.6s	remaining: 42.9s
530:	test: 0.8857984 test1: 0.8793972	best: 0.8793979 (519)	total: 47.6s	remaining: 42.1s
540:	test: 0.8858063 test1: 0.8793986	best: 0.8793991 (539)	total: 48.3s	remaining: 41s
550:	test: 0.8858137 test1: 0.8793982	best: 0.8793991 (539)	total: 48.9s	remaining: 39.9s
560:	test: 0.8858394 test1: 0.8794220	best: 0.8794220 (560)	total: 49.7s	remaining: 38.9s
570:	test: 0.8858472 test1: 0.8794212	best: 0.8794224 (564)	total: 50.4s	remaining: 37.9s
580:	test: 0.8858531 test1: 0.8794218	best: 0.8794224 (564)	total: 51.6s	remaining: 37.2s
590:	test: 0.8859000 test1: 0.8794178	best: 0.8794224 (564)	total: 53s	remaining: 36.7s
600:	test: 0.8859472 test1: 0.8794552	best: 0.8794556 (599)	total: 54.1s	remaining: 35.9s
610:	test: 0.8860457 test1: 0.8794817	best: 0.8794817 (610)	total: 55.1s	remaining: 35.1s
620:	test: 0.8861257 test1: 0.8795332	best: 0.8795332 (620)	total: 56.2s	remaining: 34.3s
630:	test: 0.8861311 test1: 0.8795381	best: 0.8795385 (629)	total: 57.7s	remaining: 33.7s
640:	test: 0.8861839 test1: 0.8795650	best: 0.8795650 (640)	total: 59s	remaining: 33s
650:	test: 0.8862157 test1: 0.8795842	best: 0.8795842 (650)	total: 1m	remaining: 32.4s
660:	test: 0.8862393 test1: 0.8796079	best: 0.8796079 (660)	total: 1m 1s	remaining: 31.6s
670:	test: 0.8862472 test1: 0.8796122	best: 0.8796155 (665)	total: 1m 2s	remaining: 30.8s
680:	test: 0.8862565 test1: 0.8796256	best: 0.8796283 (675)	total: 1m 3s	remaining: 29.9s
690:	test: 0.8862538 test1: 0.8796317	best: 0.8796317 (690)	total: 1m 4s	remaining: 28.9s
700:	test: 0.8862446 test1: 0.8796393	best: 0.8796394 (696)	total: 1m 5s	remaining: 27.8s
710:	test: 0.8862420 test1: 0.8796461	best: 0.8796461 (710)	total: 1m 6s	remaining: 26.8s
720:	test: 0.8863133 test1: 0.8797133	best: 0.8797134 (717)	total: 1m 6s	remaining: 25.9s
730:	test: 0.8863237 test1: 0.8797282	best: 0.8797282 (730)	total: 1m 8s	remaining: 25.2s
740:	test: 0.8863317 test1: 0.8797449	best: 0.8797449 (740)	total: 1m 9s	remaining: 24.4s
750:	test: 0.8863350 test1: 0.8797462	best: 0.8797464 (749)	total: 1m 11s	remaining: 23.6s
760:	test: 0.8863366 test1: 0.8797489	best: 0.8797489 (760)	total: 1m 12s	remaining: 22.7s
770:	test: 0.8863456 test1: 0.8797628	best: 0.8797628 (770)	total: 1m 13s	remaining: 21.9s
780:	test: 0.8863445 test1: 0.8797663	best: 0.8797663 (780)	total: 1m 14s	remaining: 21s
790:	test: 0.8863487 test1: 0.8797683	best: 0.8797683 (790)	total: 1m 16s	remaining: 20.1s
800:	test: 0.8863531 test1: 0.8797724	best: 0.8797728 (798)	total: 1m 17s	remaining: 19.3s
810:	test: 0.8863556 test1: 0.8797760	best: 0.8797761 (808)	total: 1m 18s	remaining: 18.4s
820:	test: 0.8863594 test1: 0.8797778	best: 0.8797780 (817)	total: 1m 19s	remaining: 17.4s
830:	test: 0.8863605 test1: 0.8797777	best: 0.8797782 (825)	total: 1m 20s	remaining: 16.4s
840:	test: 0.8863579 test1: 0.8797833	best: 0.8797833 (840)	total: 1m 21s	remaining: 15.4s
850:	test: 0.8863613 test1: 0.8797838	best: 0.8797839 (849)	total: 1m 21s	remaining: 14.4s
860:	test: 0.8863650 test1: 0.8797862	best: 0.8797862 (860)	total: 1m 22s	remaining: 13.4s
870:	test: 0.8863653 test1: 0.8797896	best: 0.8797896 (870)	total: 1m 23s	remaining: 12.4s
880:	test: 0.8863680 test1: 0.8797912	best: 0.8797912 (880)	total: 1m 24s	remaining: 11.4s
890:	test: 0.8863696 test1: 0.8797913	best: 0.8797915 (889)	total: 1m 25s	remaining: 10.5s
900:	test: 0.8863716 test1: 0.8797975	best: 0.8797975 (900)	total: 1m 26s	remaining: 9.49s
910:	test: 0.8863728 test1: 0.8797982	best: 0.8797986 (904)	total: 1m 27s	remaining: 8.54s


920:	test: 0.8864293 test1: 0.8797988	best: 0.8798000 (915)	total: 1m 28s	remaining: 7.63s
930:	test: 0.8864308 test1: 0.8798193	best: 0.8798193 (930)	total: 1m 30s	remaining: 6.7s
940:	test: 0.8865382 test1: 0.8798970	best: 0.8798970 (940)	total: 1m 31s	remaining: 5.76s
950:	test: 0.8865720 test1: 0.8799345	best: 0.8799345 (950)	total: 1m 33s	remaining: 4.82s
960:	test: 0.8867638 test1: 0.8800468	best: 0.8800468 (960)	total: 1m 34s	remaining: 3.85s
970:	test: 0.8869668 test1: 0.8802774	best: 0.8802774 (970)	total: 1m 35s	remaining: 2.87s
980:	test: 0.8872719 test1: 0.8806114	best: 0.8806114 (980)	total: 1m 36s	remaining: 1.88s
990:	test: 0.8875976 test1: 0.8809324	best: 0.8809324 (990)	total: 1m 37s	remaining: 888ms
999:	test: 0.8879360 test1: 0.8812724	best: 0.8812724 (999)	total: 1m 38s	remaining: 0us

bestTest = 0.8812724143
bestIteration = 999
```



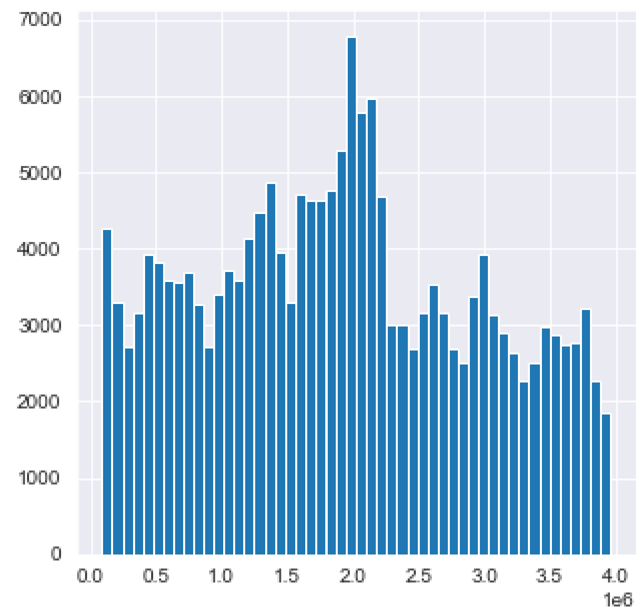
Задание на повторение:

Задание не обязательно к выполнению, но очень рекомендуется для понимания набора данных, этот набор данных будет использован и для следующего домашнего задания.

Задание 1: Построить график распределения времени совершения транзакции ("TransactionDT") для обучающей / тестовой выборки, сделать выводы о том, как разбиты данные и какие виды валидации могут подойти для данной задачи.

В [123]:
```
df_num_features = train['TransactionDT']
df_num_features.hist(figsize=(5, 5), bins=50, grid=True)
# для более подробного анализа графиков, можно выводить гистограммы для небольших груп признаков
```

Out[123]:
```
<AxesSubplot:>
```



Задание 2: построить scatter-plot зависимости суммы транзакции ("TransactionAmt"?) от времени совершения транзакции. Построить графики для обучающей выборки и для тестовой выборки, для обучающей выборки - построить как для целевой переменной = 0, так и для переменной = 1. Сделать выводы.

В [139]:
```
#scatter plot lib example using matplotlbimport numpy as np
import matplotlib.pyplot as plt# Create data
#N = 100
x = train['TransactionAmt']
y = train['TransactionDT']
print(train['TransactionAmt'].isna().sum())
print(train['TransactionDT'].isna().sum())
print(x.head(2))
print(y.head(2))
x = list(x)
y = list(y)
print(len(x))
print(len(y))


colors = (0, 100, 255)
area = np.pi*3  # Plot
```

```
0
0
0    68.5
1    29.0
Name: TransactionAmt, dtype: float64
0    86400
1    86401
Name: TransactionDT, dtype: int64
180000
180000
```

В [1]:
```
"""
plt.scatter(x, y, s=area, c=colors, alpha=0.5)
plt.title('Scatter plot example using matplotlib')
plt.xlabel('x')
plt.ylabel('y')

plt.show()"""
```

Out[1]:
```
"\nplt.scatter(x, y, s=area, c=colors, alpha=0.5)\nplt.title('Scatter plot example using matplotlib')\npl
t.xlabel('x')\nplt.ylabel('y')\n\nplt.show()"
```

Задание 3: построить распределение признака TransactionAmt в логарифмическом масштабе, сделать выводы о близости распредления к нормальному распределению. Построить распределение признака в логарифмическому масштабе для обучающей выборк и для тестовой выборки, сделать выводы.

Задание 4: построить распределение признака целевой переменной в зависимости от значений категориальных признаков ProductCD, card4, card6. Сделать выводы.

В [ ]:

```
```