Спортивный анализ данных. Платформа Kaggle

Урок 6. Feature Engineering, Feature Selection, part II

Домашнее задание:

Продолжим работу с данными, которые были использованы ранее, возьмем за основу набор данных с дополнительными признаками, которые были созданы в предыдущем задании (оставить все признаки, вне зависимости от того, добавляют они качества или нет).

Задание 0: Выбрать любимую модель и схему валидации решения, зафиксировать базовое качество модели.

Задание 1: Использовать внутренний способ для оценки важности признаков алгоритма, вывести его в виде диаграммы.

Задание 2: Удалить признаки с нулевой или маленькой важностью, переобучить модель и оценить изменение качества.

Задание 3: Использовать permutation importance , выполнить задание 1 и 2.

Задание 4: Использовать shap, выполнить задание 1 и 2.

Задание 5: Построить shap.summary_plot и shap.decision_plot для небольшой группы примеров (определить размер самостоятельно) и проанализировать влияние признаков на поведение модели.

Подключение библиотек и скриптов

import datetime import warnings import numpy as np import pandas as pd import matplotlib as mpl import matplotlib.pyplot as plt import seaborn as sns

pd.set_option('display.max_rows', 500) pd.set_option('display.max_columns', 500) pd.set_option('display.width', 1000)

Модель

import xgboost as xgb import catboost as cb

Метрика

from sklearn.metrics import roc_auc_score, auc from sklearn.model_selection import KFold, StratifiedKFold, train_test_split, cross_val_score

warnings.simplefilter("ignore") %matplotlib inline

В [1]:
```
import datetime
import warnings
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns

# Модель
import xgboost as xgb
import catboost as cb

# Метрика
from sklearn.metrics import roc_auc_score, auc
from sklearn.model_selection import KFold, StratifiedKFold, train_test_split, cross_val_score

warnings.simplefilter("ignore")
%matplotlib inline
```

В [2]:
```
# 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)
```

В [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
```

В [4]:
```
# input
TRAIN_DATASET_PATH = '../../data/assignment_2_train.csv'
TEST_DATASET_PATH = '../../data/assignment_2_test.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 данныхМ
df_train.head(2)
```

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

Out[5]:

	TransactionID	isFraud	TransactionDT	TransactionAmt	ProductCD	card1	card2	card3	card4	card5	card6	addr1	addr2	dist1	dist2	P
0	2987000	0	86400	68.5	W	13926	NaN	150.0	discover	142.0	credit	315.0	87.0	19.0	NaN	
1	2987001	0	86401	29.0	W	2755	404.0	150.0	mastercard	102.0	credit	325.0	87.0	NaN	NaN	

В [6]:
```
# Тестовые данные
# leaderboard = pd.read_csv(TEST_DATASET_PATH)
# df_test =reduce_mem_usage(leaderboard)  # Уменьшаем размер данных

# df_test.head(2)
```

В [7]:
```
df_train.set_index('TransactionID', inplace=True)
# X_test['DistrictId'] = X_test['DistrictId'].astype(str)
# target = df_train["isFraud"]
df_train.head(2)
```

Out[7]:

	isFraud	TransactionDT	TransactionAmt	ProductCD	card1	card2	card3	card4	card5	card6	addr1	addr2	dist1	dist2	P_er
TransactionID															
2987000	0	86400	68.5	W	13926	NaN	150.0	discover	142.0	credit	315.0	87.0	19.0	NaN	
2987001	0	86401	29.0	W	2755	404.0	150.0	mastercard	102.0	credit	325.0	87.0	NaN	NaN	

Числовых признаки

В [8]:
```
numerical_features = df_train.select_dtypes(exclude=["category"])
numerical_features = numerical_features.columns.tolist()
#numerical_features.remove('TransactionID')
numerical_features.remove('isFraud')
#numerical_features
```

В [9]:
```
# Общее количество записей в датафрейме = 180 000
# Исключаем такие поля содержащие меньше 100 000 значений,
# из предположения, что значение этих полей несущественно (всегда можно этот параметр проварьировать).

# numerical_features = [
# # 'TransactionID',  # Индекс
# # 'isFraud',  # Целевой параметр
# 'TransactionDT',  # Временя совершения транзакции
# 'TransactionAmt',  # Сумма транзакции
# 'card1', 'card2', 'card3', 'card5', 'addr1', 'addr2',
# 'C1', 'C2', 'C3', 'C4', 'C5', 'C6', 'C7', 'C8', 'C9', 'C10', 'C11', 'C12', 'C13', 'C14', 'D1', 'D4', 'D10', 'D15', #'D
# 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20', 'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28',
# 'V30', 'V31', 'V32', 'V33', 'V34', 'V35', 'V36', 'V37', 'V38', 'V39', 'V40', 'V41', 'V42', 'V43', 'V44', 'V45', 'V46',
# 'V48', 'V49', 'V50', 'V51', 'V52', 'V53', 'V54', 'V55', 'V56', 'V57', 'V58', 'V59', 'V60', 'V61', 'V62', 'V63', 'V64',
# 'V66', 'V67', 'V68', 'V69', 'V70', 'V71', 'V72', 'V73', 'V74', 'V75', 'V76', 'V77', 'V78', 'V79', 'V80', 'V81', 'V82',
# 'V84', 'V85', 'V86', 'V87', 'V88', 'V89', 'V90', 'V91', 'V92', 'V93', 'V94', 'V95', 'V96', 'V97', 'V98', 'V99','V100',
# 'V102','V103','V104','V105','V106','V107','V108','V109','V110','V111','V112','V113','V114','V115','V116','V117','V118',
# 'V120','V121','V122','V123','V124','V125','V126','V127','V128','V129','V130','V131','V132','V133','V134','V135','V136',
# 'V280','V281','V282','V283','V284','V285','V286','V287','V288','V289','V290','V291','V292','V293','V294','V295','V296',
# 'V298','V299','V300','V301','V302','V303','V304','V305','V306','V307','V308','V309','V310','V311','V312','V313','V314',
# 'V316','V317','V318','V319','V320','V321']
```

Обрабатка категориальные признаков

В [10]:
```
catigorical_features = df_train.select_dtypes(include=["category"])
catigorical_features = catigorical_features.columns.tolist()
# catigorical_features
```

В [11]:
```
# 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
# ]
```

В [12]:
```
# Каждой категории сопоставляет целое число (номер категории) - https://dyakonov.org/2016/08/03/python-категориальные-пр
from sklearn.preprocessing import LabelEncoder

def catigorical_features_prepare(df, cat_features_drop = 0, catigorical_features=[]):
    # Подготовка категориальных признаков
    if catigorical_features == []:
        catigorical_features = df.select_dtypes(include=["category"])
        catigorical_features = catigorical_features.columns.tolist()

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

    le = LabelEncoder()
    # создаём новые категориальные признаки - каждой категории сопоставляем целое число (номер категории)
    for cat_colname in df[catigorical_features].columns:
        le.fit(df[cat_colname])
        df[cat_colname+'_le'] = le.transform(df[cat_colname])

    # список новых категориальных признаков
    catigorical_features_le = catigorical_features.copy()
    for key, value in enumerate(catigorical_features):
        catigorical_features_le[key] = value + '_le'

    print(catigorical_features)
    # удаляем необработанные категориальные признаки при необходимости
    if cat_features_drop == 1:
        df.drop(catigorical_features, axis=1, inplace=True)

    return df, catigorical_features_le
```

В [13]:
```
data = df_train.copy()
data, catigorical_features_le = catigorical_features_prepare(data, catigorical_features)
data[catigorical_features_le].head(2)
```

```
['ProductCD', 'card4', 'card6', 'P_emaildomain', 'R_emaildomain', 'M1', 'M2', 'M3', 'M4', 'M5', 'M6', 'M7', 'M8', 'M9']
```

Out[13]:

	ProductCD_le	card4_le	card6_le	P_emaildomain_le	R_emaildomain_le	M1_le	M2_le	M3_le	M4_le	M5_le	M6_le	M7_le	M8_le	M
TransactionID														
2987000	4	2	2	0	0	1	1	1	2	0	1	2	2	
2987001	4	3	2	17	0	2	2	2	0	1	1	2	2	

В [14]:
```
# data = df_train.copy()
# data, catigorical_features_le = catigorical_features_prepare(data)
# data[catigorical_features_le + catigorical_features].head(2)
```

В [15]:
```
# data = df_train.copy()
# data, catigorical_features_le = catigorical_features_prepare(data, 1)
# data[catigorical_features_le].head(2)
```

Продолжим работу с данными, которые были использованы ранее, возьмьем за основу набор данных с дополнительными признаками, которые были созданы в предыдущем задании (оставить все признаки, вне зависимости от того, добавляют они качества или нет).

Добавляем поля из 5 урока задание 1

В [16]:
```
def function(x):
    base_date = datetime.datetime(2017, 10, 1)
    new_date = base_date + datetime.timedelta(seconds=x)
    year = new_date.year
    month = new_date.month
    week_day = new_date.weekday()
    hour = new_date.hour
    day = new_date.day

    return year, month, week_day, hour, day
```

В [17]:
```
task_1_fields = ['year', 'month', 'week_day', 'hour', 'day']
```

В [18]:
```
data['year'], data['month'], data['week_day'], data['hour'], data['day']  = \
zip(*data['TransactionDT'].map(function))
```

В [19]:
```
data[task_1_fields].head(2)
```

Out[19]:

	year	month	week_day	hour	day
TransactionID					
2987000	2017	10	0	0	2
2987001	2017	10	0	0	2

Добавляем поля из 5 урока задание 2

В [20]:
```
## Предыдущий вариант
# data['card2_1'] = data['card2'].fillna('.0', inplace=False)
# data['card1_card2'] = data.agg(lambda x: f"{x['card1']}{x['card2_1']}", axis=1)
# data['card1_card2_card_3_card_5'] = \
#     data.agg(lambda x: f"{x['card1_card2']} {x['card3']}{x['card5']}", axis=1)
# data['card1_card2_card_3_card_5_addr1_addr2'] = \
#     data.agg(lambda x: f"{x['card1_card2_card_3_card_5']}{x['addr1']} {x['addr2']}", axis=1)
```

В [21]:
```
task_2 = ['card1', 'card2', 'card3', 'card5','addr1','addr2']
data[task_2].dtypes
#data.dtypes
```

Out[21]:
```
card1      int16
card2    float32
card3    float32
card5    float32
addr1    float32
addr2    float32
dtype: object
```

В [22]:
```
data['card1_1'] = data['card1'].astype(float)
data['card2_1'] = data['card2'].fillna(0, inplace=False)
#data[task_2 + ['card1_1', 'card2_1']].dtypes
data['card1_card2'] = data.agg(lambda x: x['card1_1'] + x['card2_1'], axis=1)
data['card1_card2_card_3_card_5'] = data.agg(lambda x: x['card1_card2'] + x['card3'] + x['card5'], axis=1)
data['card1_card2_card_3_card_5_addr1_addr2'] = \
    data.agg(lambda x: x['card1_card2_card_3_card_5'] + x['addr1'] + x['addr2'], axis=1)
```

В [23]:
```
task_2_fields = ['card1_card2', 'card1_card2_card_3_card_5', 'card1_card2_card_3_card_5_addr1_addr2']
```

В [24]:
```
data[task_2_fields].head(2)
```

Out[24]:

	card1_card2	card1_card2_card_3_card_5	card1_card2_card_3_card_5_addr1_addr2
TransactionID			
2987000	13926.0	14218.0	14620.0
2987001	3159.0	3411.0	3823.0

Добавляем поля из 5 урока задание 3

В [25]:
```
freq_encoder = data["card1"].value_counts(normalize=True)
data["card1_freq_enc"] = data["card1"].map(freq_encoder)
freq_encoder = data["card2"].value_counts(normalize=True)
data["card2_freq_enc"] = data["card2"].map(freq_encoder)
freq_encoder = data["card3"].value_counts(normalize=True)
data["card3_freq_enc"] = data["card3"].map(freq_encoder)
freq_encoder = data["card4"].value_counts(normalize=True)
```

В [26]:
```
data["card4_freq_enc"] = data["card4"].map(freq_encoder)
freq_encoder = data["card5"].value_counts(normalize=True)
```

В [27]:
```
data["card5_freq_enc"] = data["card5"].map(freq_encoder)
freq_encoder = data["card6"].value_counts(normalize=True)
```

В [28]:
```
data["card6_freq_enc"] = data["card6"].map(freq_encoder)
freq_encoder = data["addr1"].value_counts(normalize=True)
```

В [29]:
```
data["addr1_freq_enc"] = data["addr1"].map(freq_encoder)
freq_encoder = data["addr2"].value_counts(normalize=True)
data["addr2_freq_enc"] = data["addr2"].map(freq_encoder)
```

В [30]:
```
# task_3_fields = ['card1', 'card1_freq_enc', 'card2', 'card2_freq_enc', 'card3', 'card3_freq_enc', \
#       'card4', 'card4_freq_enc', 'card5', 'card5_freq_enc', 'card6', 'card6_freq_enc', \
#       'addr1', 'addr1_freq_enc', 'addr2', 'addr2_freq_enc']
```

В [31]:
```
task_3_fields = [
'card1_freq_enc',
'card2_freq_enc',
'card3_freq_enc',
'card4_freq_enc',
'card5_freq_enc',
'card6_freq_enc',
'addr1_freq_enc',
'addr2_freq_enc'
]
```

В [32]:
```
data[task_3_fields].head(2)
# Функция map применяет функцию к каждому элементу последовательности и возвращает итератор с результатами.
```

Out[32]:

	card1_freq_enc	card2_freq_enc	card3_freq_enc	card4_freq_enc	card5_freq_enc	card6_freq_enc	addr1_freq_enc	addr2_freq_enc
TransactionID								
2987000	0.000061	NaN	0.879737	0.013211	0.000274	0.317939	0.042773	0.982344
2987001	0.001244	0.006855	0.879737	0.302783	0.054723	0.317939	0.080004	0.982344

Добавляем поля из 5 урока задание 4

В [33]:
```
temp = data.groupby('card1')['TransactionAmt'].agg(['mean']).rename({'mean':'TransactionAmt_card1_mean'},axis=1)
data = pd.merge(data,temp,on='card1',how='left')
temp = data.groupby('card2')['TransactionAmt'].agg(['mean']).rename({'mean':'TransactionAmt_card2_mean'},axis=1)
data = pd.merge(data,temp,on='card2',how='left')
temp = data.groupby('card3')['TransactionAmt'].agg(['mean']).rename({'mean':'TransactionAmt_card3_mean'},axis=1)
data = pd.merge(data,temp,on='card3',how='left')
temp = data.groupby('card5')['TransactionAmt'].agg(['mean']).rename({'mean':'TransactionAmt_card5_mean'},axis=1)
data = pd.merge(data,temp,on='card5',how='left')

temp = data.groupby('card4')['TransactionAmt'].agg(['mean']).rename({'mean':'TransactionAmt_card4_mean'},axis=1)
data = pd.merge(data,temp,on='card4',how='left')
temp = data.groupby('card6')['TransactionAmt'].agg(['mean']).rename({'mean':'TransactionAmt_card6_mean'},axis=1)
data = pd.merge(data,temp,on='card6',how='left')

temp = data.groupby('card1_card2')['TransactionAmt'].agg(['mean']).\
rename({'mean':'TransactionAmt_card1_card2_mean'},axis=1)
data = pd.merge(data,temp,on='card1_card2',how='left')

temp = data.groupby('card1_card2_card_3_card_5')['TransactionAmt'].agg(['mean']).\
rename({'mean':'TransactionAmt_card1_card2_card_3_card_5_mean'},axis=1)
data = pd.merge(data,temp,on='card1_card2_card_3_card_5',how='left')

temp = data.groupby('card1_card2_card_3_card_5_addr1_addr2')['TransactionAmt'].agg(['mean']).\
rename({'mean':'TransactionAmt_card1_card2_card_3_card_5_addr1_addr2_mean'},axis=1)
data = pd.merge(data,temp,on='card1_card2_card_3_card_5_addr1_addr2',how='left')
```

В [34]:
```
task_4_fields = ['TransactionAmt_card1_mean',
 'TransactionAmt_card2_mean',
 'TransactionAmt_card3_mean',
 'TransactionAmt_card5_mean',
 'TransactionAmt_card4_mean',
 'TransactionAmt_card6_mean',
 'TransactionAmt_card1_card2_mean',
 'TransactionAmt_card1_card2_card_3_card_5_mean',
 'TransactionAmt_card1_card2_card_3_card_5_addr1_addr2_mean',
]
```

В [35]:
```
data[task_4_fields].head(2)
```

Out[35]:

	TransactionAmt_card1_mean	TransactionAmt_card2_mean	TransactionAmt_card3_mean	TransactionAmt_card5_mean	TransactionAmt_card4_mean
0	193.227280	NaN	140.340759	123.384491	220.508194
1	229.588074	198.800095	140.340759	190.203415	126.019066

Добавляем поля из 5 урока задание 5

В [36]:
```
temp = data.groupby('card1')['D15'].agg(['mean']).rename({'mean':'D15_card1_mean'},axis=1)
data = pd.merge(data,temp,on='card1',how='left')
temp = data.groupby('card2')['D15'].agg(['mean']).rename({'mean':'D15_card2_mean'},axis=1)
data = pd.merge(data,temp,on='card2',how='left')
temp = data.groupby('card3')['D15'].agg(['mean']).rename({'mean':'D15_card3_mean'},axis=1)
data = pd.merge(data,temp,on='card3',how='left')
temp = data.groupby('card5')['D15'].agg(['mean']).rename({'mean':'D15_card5_mean'},axis=1)
data = pd.merge(data,temp,on='card5',how='left')
temp = data.groupby('card4')['D15'].agg(['mean']).rename({'mean':'D15_card4_mean'},axis=1)
data = pd.merge(data,temp,on='card4',how='left')
temp = data.groupby('card6')['D15'].agg(['mean']).rename({'mean':'D15_card6_mean'},axis=1)
data = pd.merge(data,temp,on='card6',how='left')
```

В [37]:
```
temp = data.groupby('card1_card2')['D15'].agg(['mean']).\
rename({'mean':'D15_card1_card2_mean'},axis=1)
data = pd.merge(data,temp,on='card1_card2',how='left')

temp = data.groupby('card1_card2_card_3_card_5')['D15'].agg(['mean']).\
rename({'mean':'D15_card1_card2_card_3_card_5_mean'},axis=1)
data = pd.merge(data,temp,on='card1_card2_card_3_card_5',how='left')

temp = data.groupby('card1_card2_card_3_card_5_addr1_addr2')['D15'].agg(['mean']).\
rename({'mean':'D15_card1_card2_card_3_card_5_addr1_addr2_mean'},axis=1)
data = pd.merge(data,temp,on='card1_card2_card_3_card_5_addr1_addr2',how='left')
```

В [38]:
```
task_5_fields = [
 'D15_card1_mean',
 'D15_card2_mean',
 'D15_card3_mean',
 'D15_card5_mean',
 'D15_card4_mean',
 'D15_card6_mean',
 'D15_card1_card2_mean',
 'D15_card1_card2_card_3_card_5_mean',
 'D15_card1_card2_card_3_card_5_addr1_addr2_mean',
]
```

В [39]:
```
data[task_5_fields].head(2)
```

Out[39]:

	D15_card1_mean	D15_card2_mean	D15_card3_mean	D15_card5_mean	D15_card4_mean	D15_card6_mean	D15_card1_card2_mean	D15_card1_car
0	0.400000	NaN	168.466583	101.575760	114.041664	108.7519	236.111115	
1	114.811768	123.450722	168.466583	110.602066	139.496765	108.7519	114.397659	

Добавляем поля из 5 урока задание 6

В [40]:
```
import math
# print(math.modf(45.8978))

def function(x):
    x = math.modf(x)
    return x[1], x[0]
```

В [41]:
```
data['TransactionAmr_intager'], data['TransactionAmr_fractional'] = zip(*data['TransactionAmt'].map(function))
data['TransactionAmr_log'] = np.log(data['TransactionAmt'])
```

В [42]:
```
task_6_fields = [
 'TransactionAmr_intager',
 'TransactionAmr_fractional',
 'TransactionAmr_log',
]
```

В [43]:
```
data[task_6_fields].head(2)
```

Out[43]:

	TransactionAmr_intager	TransactionAmr_fractional	TransactionAmr_log
0	68.0	0.5	4.226834
1	29.0	0.0	3.367296

Добавляем поля из 5 урока задание 7

В [44]:
```
freq_encoder = data["P_emaildomain"].value_counts(normalize=True)
data["P_emaildomain_freq_enc"] = data["P_emaildomain"].map(freq_encoder)
freq_encoder = data["R_emaildomain"].value_counts(normalize=True)
data["R_emaildomain_freq_enc"] = data["R_emaildomain"].map(freq_encoder)
```

В [45]:
```
task_7_fields = [
 'P_emaildomain_freq_enc',
 'R_emaildomain_freq_enc'
]
```

В [46]:
```
data[task_7_fields].head(2)
```

Out[46]:

	P_emaildomain_freq_enc	R_emaildomain_freq_enc
0	0.158000	0.665
1	0.373322	0.665

В [47]:
```
#data[["P_emaildomain", "P_emaildomain_freq_enc", "R_emaildomain", "R_emaildomain_freq_enc"]].head(2)
```

В [48]:
```
#catigorical_features
```

В [49]:
```
#data.drop(catigorical_features, axis=1, inplace=True)
```

В [50]:
```
#data.drop(catigorical_features_le, axis=1, inplace=True)
```

В [51]:
```
data.head(2)
```

Out[51]:

	isFraud	TransactionDT	TransactionAmt	ProductCD	card1	card2	card3	card4	card5	card6	addr1	addr2	dist1	dist2	P_emaildomain
0	0	86400	68.5	W	13926	NaN	150.0	discover	142.0	credit	315.0	87.0	19.0	NaN	Unknown
1	0	86401	29.0	W	2755	404.0	150.0	mastercard	102.0	credit	325.0	87.0	NaN	NaN	gmail.com

Задание 0:

Выбрать любимую модель и схему валидации решения, зафиксировать базовое качество модели.

В [52]:
```
new_categorical_features = []
new_numerical_features = []
new_categorical_features = task_1_fields + task_2_fields + \
        task_3_fields + \
        task_4_fields + task_5_fields + task_6_fields + task_7_fields
new_numerical_features = numerical_features
```

В [53]:
```
#new_categorical_features
```

В [54]:
```
#new_numerical_features
```

В [55]:
```
#target = data["isFraud"]
target = df_train["isFraud"]
from pprint import pprint
#pprint(numerical_features)
#pprint(new_categorical_features)
```

В [56]:
```
df_data = data[new_numerical_features + new_categorical_features]
#df_data_xgb = data[new_numerical_features + new_categorical_features]
#df_data = df_data.drop(["isFraud"], axis=1)
```

В [57]:
```
df_data[['card2', 'card5', 'addr1', 'addr1','D15']].isnull().sum(axis = 0)
```

Out[57]:
```
card2     2611
card5      953
addr1    19433
addr1    19433
D15      48819
dtype: int64
```

В [58]:
```
df_data[new_categorical_features] = df_data[new_categorical_features].astype(str)
```

В [59]:
```
# df_data[new_categorical_features].dtypes
```

В [60]:
```
# catigorical_features
```

В [61]:
```
# df_data[task_1_fields + new_categorical_features].isnull().sum(axis = 0)
```

В [62]:
```
x_train, x_test = train_test_split(
    df_data, train_size=0.75, random_state=27
)
y_train, y_test = train_test_split(
    target, train_size=0.75, random_state=27
)
print("x_train.shape = {} rows, {} cols".format(*x_train.shape))
print("x_test.shape = {} rows, {} cols".format(*x_test.shape))
```

```
x_train.shape = 135000 rows, 417 cols
x_test.shape = 45000 rows, 417 cols
```

В [63]:
```
train_scores = pd.DataFrame({"target": y_train})
test_scores = pd.DataFrame({"target": y_test})
```

CatBoost с категориальными признаками

В [64]:
```
cb_params = {
    "n_estimators": 1000,
    "loss_function": "Logloss",
    "eval_metric": "AUC",
    "task_type": "CPU",
    #"max_bin": 20,
    "verbose": 10,
    "max_depth": 6,
    "l2_leaf_reg": 100,
    "early_stopping_rounds": 50,
    "thread_count": 6,
    "random_seed": 42
}
```

В [65]:
```
cb_model = cb.CatBoostClassifier(**cb_params)
```

В [66]:
```
eval_sets= [
    (x_train[new_numerical_features + new_categorical_features], y_train),
    (x_test[new_numerical_features + new_categorical_features], y_test)
]
```

Фиксируем базовое качество модели

CatBoost с категориальными параметрами

В [67]:
```
cb_model.fit(
    x_train[new_numerical_features + new_categorical_features],
    y_train,
    cat_features = new_categorical_features,
    eval_set=eval_sets)
```

```
0:      test: 0.6636502 test1: 0.6467941        best: 0.6467941 (0)     total: 1.38s    remaining: 23m 2s
10:     test: 0.8084001 test1: 0.8062021        best: 0.8124208 (8)     total: 9.33s    remaining: 13m 58s
20:     test: 0.8278173 test1: 0.8224416        best: 0.8224416 (20)    total: 16.9s    remaining: 13m 8s
30:     test: 0.8444114 test1: 0.8425265        best: 0.8425265 (30)    total: 24.9s    remaining: 12m 57s
40:     test: 0.9073914 test1: 0.8781701        best: 0.8781701 (40)    total: 32.2s    remaining: 12m 34s
50:     test: 0.9343021 test1: 0.8879807        best: 0.8879807 (50)    total: 41.4s    remaining: 12m 51s
60:     test: 0.9494424 test1: 0.8962046        best: 0.8962757 (59)    total: 52.1s    remaining: 13m 21s
70:     test: 0.9651329 test1: 0.9068694        best: 0.9070937 (69)    total: 1m 4s    remaining: 13m 57s
80:     test: 0.9723898 test1: 0.9083662        best: 0.9084802 (79)    total: 1m 14s   remaining: 14m 7s
90:     test: 0.9753955 test1: 0.9106510        best: 0.9106510 (90)    total: 1m 26s   remaining: 14m 19s
100:    test: 0.9771578 test1: 0.9133678        best: 0.9133678 (100)   total: 1m 35s   remaining: 14m 8s
110:    test: 0.9783415 test1: 0.9158490        best: 0.9158490 (110)   total: 1m 44s   remaining: 13m 56s
120:    test: 0.9795755 test1: 0.9171541        best: 0.9171541 (120)   total: 1m 54s   remaining: 13m 50s
130:    test: 0.9801937 test1: 0.9181217        best: 0.9181217 (130)   total: 2m 2s    remaining: 13m 32s
140:    test: 0.9807749 test1: 0.9188409        best: 0.9188409 (140)   total: 2m 10s   remaining: 13m 16s
150:    test: 0.9812258 test1: 0.9197386        best: 0.9197386 (150)   total: 2m 18s   remaining: 12m 59s
160:    test: 0.9814089 test1: 0.9203767        best: 0.9203767 (160)   total: 2m 26s   remaining: 12m 44s
170:    test: 0.9815614 test1: 0.9213180        best: 0.9213182 (169)   total: 2m 35s   remaining: 12m 34s
180:    test: 0.9821573 test1: 0.9221660        best: 0.9221660 (180)   total: 2m 44s   remaining: 12m 22s
190:    test: 0.9826765 test1: 0.9231819        best: 0.9231819 (190)   total: 2m 52s   remaining: 12m 10s
200:    test: 0.9834777 test1: 0.9248686        best: 0.9248686 (200)   total: 3m 1s    remaining: 11m 59s
210:    test: 0.9845254 test1: 0.9262655        best: 0.9262655 (210)   total: 3m 10s   remaining: 11m 52s
220:    test: 0.9854267 test1: 0.9279512        best: 0.9279512 (220)   total: 3m 20s   remaining: 11m 45s
230:    test: 0.9855285 test1: 0.9286111        best: 0.9286111 (230)   total: 3m 28s   remaining: 11m 33s
240:    test: 0.9857794 test1: 0.9294683        best: 0.9294683 (240)   total: 3m 37s   remaining: 11m 24s
250:    test: 0.9859708 test1: 0.9300731        best: 0.9300793 (249)   total: 3m 46s   remaining: 11m 16s
260:    test: 0.9864066 test1: 0.9309452        best: 0.9309452 (260)   total: 3m 55s   remaining: 11m 8s
270:    test: 0.9863569 test1: 0.9315543        best: 0.9315543 (270)   total: 4m 4s    remaining: 10m 57s
280:    test: 0.9864288 test1: 0.9321745        best: 0.9321745 (280)   total: 4m 12s   remaining: 10m 47s
290:    test: 0.9868088 test1: 0.9326213        best: 0.9326213 (290)   total: 4m 22s   remaining: 10m 38s
300:    test: 0.9869564 test1: 0.9326982        best: 0.9326996 (299)   total: 4m 30s   remaining: 10m 27s
310:    test: 0.9873767 test1: 0.9337689        best: 0.9337689 (310)   total: 4m 38s   remaining: 10m 16s
320:    test: 0.9875914 test1: 0.9344141        best: 0.9344141 (320)   total: 4m 47s   remaining: 10m 7s
330:    test: 0.9882342 test1: 0.9348737        best: 0.9348737 (330)   total: 4m 55s   remaining: 9m 57s
340:    test: 0.9885841 test1: 0.9353380        best: 0.9353380 (340)   total: 5m 4s    remaining: 9m 48s
350:    test: 0.9886882 test1: 0.9357538        best: 0.9357546 (349)   total: 5m 12s   remaining: 9m 37s
360:    test: 0.9886772 test1: 0.9359328        best: 0.9359329 (359)   total: 5m 20s   remaining: 9m 27s
370:    test: 0.9886349 test1: 0.9361602        best: 0.9361602 (370)   total: 5m 28s   remaining: 9m 16s
380:    test: 0.9888924 test1: 0.9365848        best: 0.9365848 (380)   total: 5m 37s   remaining: 9m 7s
390:    test: 0.9889856 test1: 0.9368113        best: 0.9368172 (389)   total: 5m 45s   remaining: 8m 57s
400:    test: 0.9896560 test1: 0.9371506        best: 0.9371565 (397)   total: 5m 53s   remaining: 8m 48s
410:    test: 0.9898325 test1: 0.9373081        best: 0.9373082 (406)   total: 6m 3s    remaining: 8m 40s
420:    test: 0.9902869 test1: 0.9378299        best: 0.9378332 (419)   total: 6m 11s   remaining: 8m 31s
430:    test: 0.9906586 test1: 0.9381421        best: 0.9381421 (430)   total: 6m 20s   remaining: 8m 22s
440:    test: 0.9908990 test1: 0.9385374        best: 0.9385458 (439)   total: 6m 29s   remaining: 8m 13s
450:    test: 0.9911212 test1: 0.9387707        best: 0.9387707 (450)   total: 6m 38s   remaining: 8m 5s
460:    test: 0.9914541 test1: 0.9392929        best: 0.9392929 (460)   total: 6m 47s   remaining: 7m 56s
470:    test: 0.9917144 test1: 0.9395791        best: 0.9395792 (464)   total: 6m 56s   remaining: 7m 47s
480:    test: 0.9918528 test1: 0.9397499        best: 0.9397499 (480)   total: 7m 4s    remaining: 7m 38s
490:    test: 0.9919738 test1: 0.9399424        best: 0.9399600 (486)   total: 7m 13s   remaining: 7m 29s
500:    test: 0.9919939 test1: 0.9400716        best: 0.9400716 (500)   total: 7m 22s   remaining: 7m 20s
510:    test: 0.9921460 test1: 0.9405449        best: 0.9405449 (510)   total: 7m 30s   remaining: 7m 11s
520:    test: 0.9922689 test1: 0.9406928        best: 0.9406928 (520)   total: 7m 39s   remaining: 7m 2s
530:    test: 0.9924586 test1: 0.9408987        best: 0.9408987 (530)   total: 7m 47s   remaining: 6m 53s
540:    test: 0.9926464 test1: 0.9410705        best: 0.9410717 (536)   total: 7m 56s   remaining: 6m 43s
550:    test: 0.9927146 test1: 0.9411234        best: 0.9411245 (547)   total: 8m 4s    remaining: 6m 34s
560:    test: 0.9929298 test1: 0.9412742        best: 0.9412742 (560)   total: 8m 12s   remaining: 6m 25s
570:    test: 0.9929336 test1: 0.9412766        best: 0.9412766 (570)   total: 8m 20s   remaining: 6m 15s
580:    test: 0.9929361 test1: 0.9412771        best: 0.9412778 (572)   total: 8m 27s   remaining: 6m 6s
590:    test: 0.9929389 test1: 0.9412855        best: 0.9412856 (581)   total: 8m 35s   remaining: 5m 56s
600:    test: 0.9929416 test1: 0.9412942        best: 0.9412942 (600)   total: 8m 42s   remaining: 5m 47s
610:    test: 0.9929439 test1: 0.9413006        best: 0.9413006 (610)   total: 8m 50s   remaining: 5m 37s
620:    test: 0.9929445 test1: 0.9413004        best: 0.9413006 (610)   total: 8m 57s   remaining: 5m 28s
630:    test: 0.9929498 test1: 0.9413164        best: 0.9413164 (629)   total: 9m 5s    remaining: 5m 18s
640:    test: 0.9929513 test1: 0.9413240        best: 0.9413243 (638)   total: 9m 12s   remaining: 5m 9s
650:    test: 0.9929532 test1: 0.9413291        best: 0.9413291 (650)   total: 9m 20s   remaining: 5m
660:    test: 0.9929549 test1: 0.9413373        best: 0.9413380 (658)   total: 9m 27s   remaining: 4m 51s
670:    test: 0.9929569 test1: 0.9413455        best: 0.9413455 (669)   total: 9m 35s   remaining: 4m 41s
680:    test: 0.9929594 test1: 0.9413521        best: 0.9413521 (680)   total: 9m 42s   remaining: 4m 32s
690:    test: 0.9929607 test1: 0.9413570        best: 0.9413570 (689)   total: 9m 49s   remaining: 4m 23s
700:    test: 0.9929609 test1: 0.9413575        best: 0.9413575 (699)   total: 9m 56s   remaining: 4m 14s
710:    test: 0.9929618 test1: 0.9413621        best: 0.9413621 (710)   total: 10m 3s   remaining: 4m 5s
720:    test: 0.9929624 test1: 0.9413647        best: 0.9413647 (719)   total: 10m 11s  remaining: 3m 56s
730:    test: 0.9929616 test1: 0.9413621        best: 0.9413651 (727)   total: 10m 18s  remaining: 3m 47s
740:    test: 0.9929611 test1: 0.9413608        best: 0.9413651 (727)   total: 10m 25s  remaining: 3m 38s
750:    test: 0.9929599 test1: 0.9413564        best: 0.9413651 (727)   total: 10m 33s  remaining: 3m 29s
760:    test: 0.9929606 test1: 0.9413584        best: 0.9413651 (727)   total: 10m 40s  remaining: 3m 21s
770:    test: 0.9929607 test1: 0.9413588        best: 0.9413651 (727)   total: 10m 47s  remaining: 3m 12s
Stopped by overfitting detector  (50 iterations wait)

bestTest = 0.9413650674
bestIteration = 727
```

```
Shrink model to first 728 iterations.
```

Out[67]:
```
<catboost.core.CatBoostClassifier at 0x55c2b07160>
```

Базовое качество модели:

- bestTest = 0.945278915
- bestIteration = 787

XGBoost

В отличие от CatBoost или LGBM, XGBoost не может обрабатывать категориальные функции сам по себе, он принимает только числовые значения, подобные случайному лесу. Поэтому перед подачей категориальных данных в XGBoost необходимо выполнить различные кодировки, такие как кодирование меток, среднее кодирование или однократное кодирование.

В [101]:
```python
# Модель
import xgboost as xgb
# Метрика
from sklearn.metrics import roc_auc_score, auc
from sklearn.model_selection import KFold, StratifiedKFold, train_test_split, cross_val_score
```

В [102]:
```python
df_data_xgb = data[new_numerical_features + new_categorical_features]
```

В [103]:
```python
# df_data_xgb['card1_card2']
```

В [104]:
```python
# df_data_xgb[new_categorical_features].dtypes
```

В [105]:
```python
df_data_xgb['card1_card2'] = df_data_xgb.card1_card2.replace('', np.nan).astype(float)
df_data_xgb['card1_card2_card_3_card_5'] = df_data_xgb.card1_card2_card_3_card_5.replace('', np.nan).astype(float)
df_data_xgb['card1_card2_card_3_card_5_addr1_addr2'] = df_data_xgb.card1_card2_card_3_card_5_addr1_addr2.replace('', np.
df_data_xgb['card4_freq_enc'] = df_data_xgb.card4_freq_enc.replace('', np.nan).astype(float)
df_data_xgb['card6_freq_enc'] = df_data_xgb.card6_freq_enc.replace('', np.nan).astype(float)
df_data_xgb['addr1_freq_enc'] = df_data_xgb.addr1_freq_enc.replace('', np.nan).astype(float)
```

В [107]:
```python
# df_data_xgb[new_categorical_features].dtypes
```

В [108]:
```python
x_train_xgb, x_test_xgb = train_test_split(
    df_data_xgb, train_size=0.75, random_state=27
)
y_train_xgb, y_test_xgb = train_test_split(
    target, train_size=0.75, random_state=27
)
print("x_train.shape = {} rows, {} cols".format(*x_train_xgb.shape))
print("x_test.shape = {} rows, {} cols".format(*x_test_xgb.shape))
```

```
x_train.shape = 135000 rows, 417 cols
x_test.shape = 45000 rows, 417 cols
```

В [109]:
```python
x_train_xgb[new_categorical_features].head(2)
```

Out[109]:

	year	month	week_day	hour	day	card1_card2	card1_card2_card_3_card_5	card1_card2_card_3_card_5_addr1_addr2	card1_freq_enc	card
141582	2017	11	4	18	3	7452.0	7828.0	8348.0	0.000311	
131503	2017	10	1	2	31	3505.0	3881.0	4267.0	0.000094	

В [110]:
```python
df_data_xgb.head(2)
```

Out[110]:

	TransactionDT	TransactionAmt	card1	card2	card3	card5	addr1	addr2	dist1	dist2	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C1
0	86400	68.5	13926	NaN	150.0	142.0	315.0	87.0	19.0	NaN	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	2.0	0.(
1	86401	29.0	2755	404.0	150.0	102.0	325.0	87.0	NaN	NaN	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.(

В [111]:
```
xgb_params = {
    "booster": "gbtree",
    "objective": "binary:logistic",
    "eval_metric": "auc",
    "n_estimators": 1000,
    "learning_rate": 0.1,
    "reg_lambda": 10,
    "max_depth": 4,
    "gamma": 10,
    "nthread": 6,
    "seed": 27
}

# eval_sets= [
#     (x_train_xgb[new_numerical_features], y_train),
#     (x_train_xgb[new_numerical_features], y_test)
# ]
```

В [112]:
```
eval_sets= [
    (x_train_xgb[new_numerical_features + new_categorical_features], y_train_xgb),
    (x_test_xgb[new_numerical_features + new_categorical_features], y_test_xgb)
]
```

В [113]:
```
# x_train_xgb[new_categorical_features].dtypes
```

В [114]:
```
xgb_model_0 = xgb.XGBClassifier(**xgb_params)

xgb_model_0.fit(
    y=y_train_xgb,
    X=x_train_xgb[new_numerical_features + new_categorical_features],
    early_stopping_rounds=50,
    eval_set=eval_sets,
    eval_metric="auc",
    verbose=10
)
```

```
[0]     validation_0-auc:0.70651        validation_1-auc:0.69725
[10]    validation_0-auc:0.80401        validation_1-auc:0.79680
[20]    validation_0-auc:0.84378        validation_1-auc:0.83655
[30]    validation_0-auc:0.87470        validation_1-auc:0.86655
[40]    validation_0-auc:0.88669        validation_1-auc:0.87788
[50]    validation_0-auc:0.89773        validation_1-auc:0.88661
[60]    validation_0-auc:0.90369        validation_1-auc:0.89161
[70]    validation_0-auc:0.90805        validation_1-auc:0.89508
[80]    validation_0-auc:0.91243        validation_1-auc:0.89797
[90]    validation_0-auc:0.91543        validation_1-auc:0.90039
[100]   validation_0-auc:0.91730        validation_1-auc:0.90168
[110]   validation_0-auc:0.91958        validation_1-auc:0.90340
[120]   validation_0-auc:0.92139        validation_1-auc:0.90478
[130]   validation_0-auc:0.92350        validation_1-auc:0.90643
[140]   validation_0-auc:0.92465        validation_1-auc:0.90756
[150]   validation_0-auc:0.92684        validation_1-auc:0.90905
[160]   validation_0-auc:0.92779        validation_1-auc:0.90968
[170]   validation_0-auc:0.92782        validation_1-auc:0.90967
[180]   validation_0-auc:0.92789        validation_1-auc:0.90977
[190]   validation_0-auc:0.92789        validation_1-auc:0.90977
[200]   validation_0-auc:0.92789        validation_1-auc:0.90977
[210]   validation_0-auc:0.92789        validation_1-auc:0.90977
[220]   validation_0-auc:0.92789        validation_1-auc:0.90977
```

Out[114]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eval_metric='auc',
              gamma=10, gpu_id=-1, importance_type='gain',
              interaction_constraints='', learning_rate=0.1, max_delta_step=0,
              max_depth=4, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=1000, n_jobs=6, nthread=6,
              num_parallel_tree=1, random_state=27, reg_alpha=0, reg_lambda=10,
              scale_pos_weight=1, seed=27, subsample=1, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

Базовое качество модели:

[180] validation_0-auc:0.92789 validation_1-auc:0.90977

Задание 1:

Использовать внутренний способ для оценки важности признаков алгоритма, вывести его в виде диаграммы.

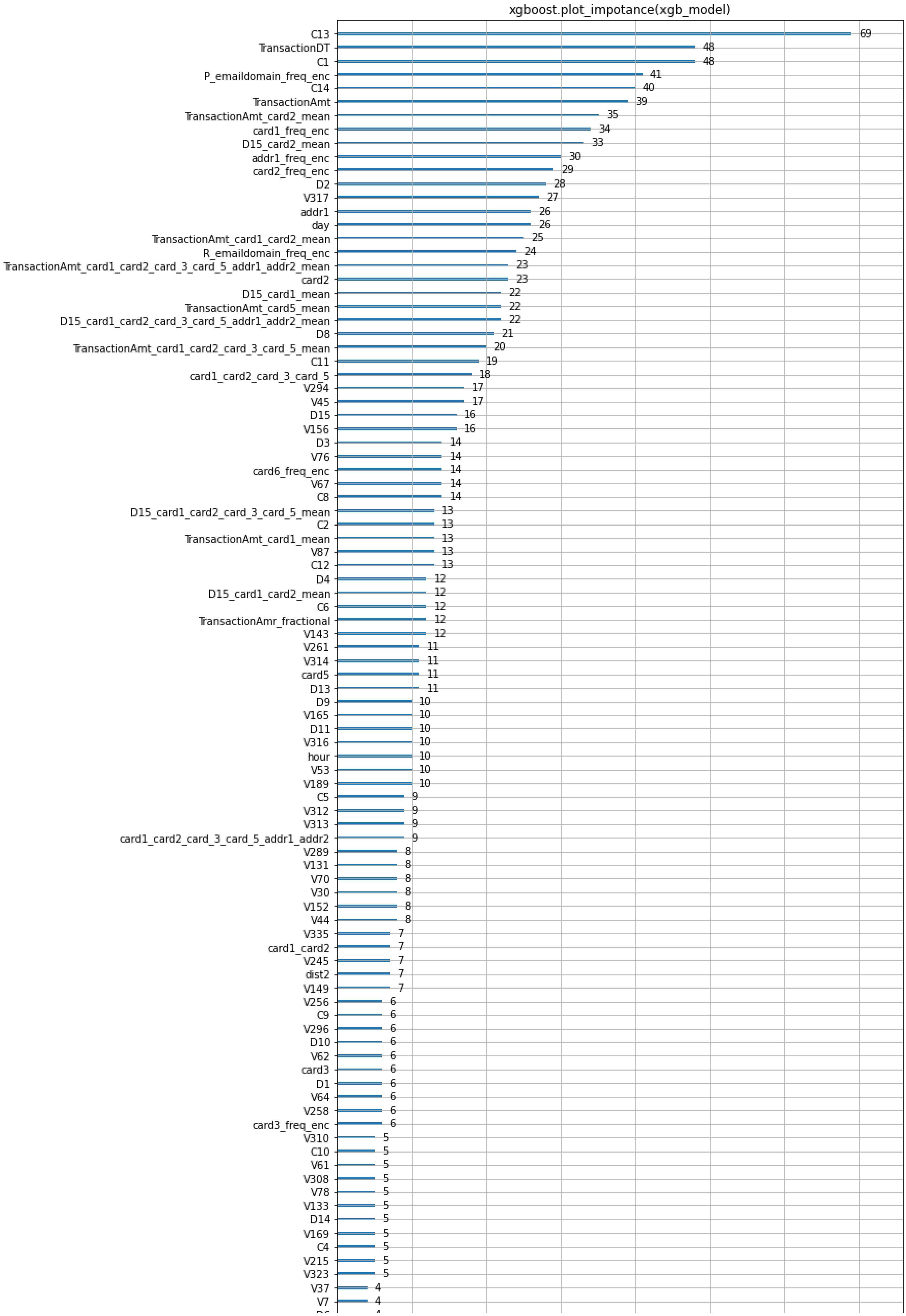
Важность и выбор функций с помощью XGBoost в Python

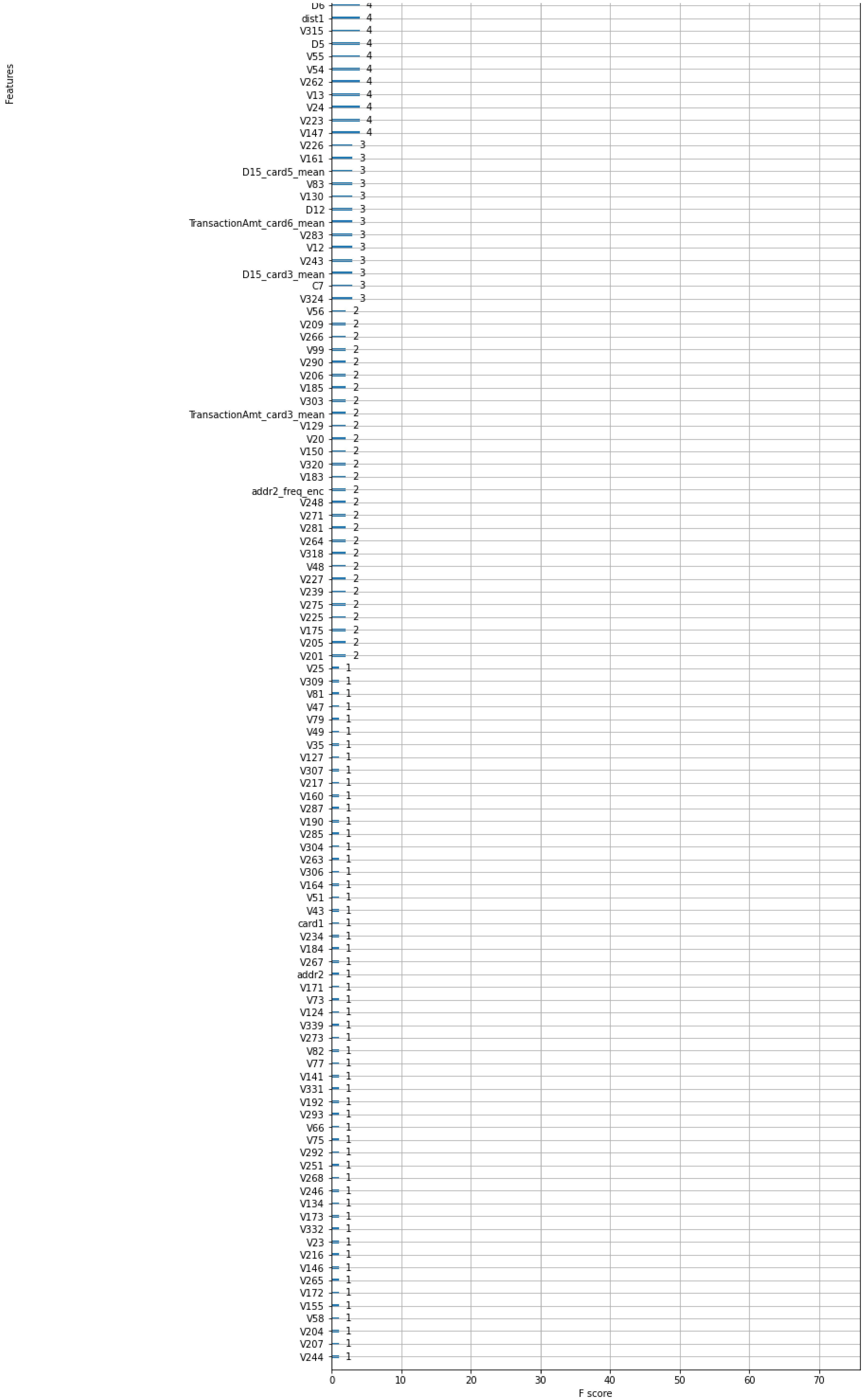
- [https://www.machinelearningmastery.ru/feature-importance-and-feature-selection-with-xgboost-in-python/ (https://www.machinelearningmastery.ru/feature-importance-and-feature-selection-with-xgboost-in-python/)](https://www.machinelearningmastery.ru/feature-importance-and-feature-selection-with-xgboost-in-python/)

В [81]:
```
# pprint(x_train_xgb.columns.tolist())
```

В [82]:
```python
# plot feature importance using built-in function
from numpy import loadtxt
from xgboost import XGBClassifier
from xgboost import plot_importance
from matplotlib import pyplot

# plot feature importance
fig, ax = plt.subplots(1, 1, figsize=(10, 50))
xgb.plot_importance(xgb_model,ax=ax)
plt.title("xgboost.plot_impotance(xgb_model)")
pyplot.show()
```





Задание 2:

Удалить признаки с нулевой или маленькой важностью, переобучить модель и оценить изменение качества.

В [145]:
```
# task_2_numerical_features = new_numerical_features.copy()
```

В [146]:
```
task_2_numerical_features = ['C13',  # 68
 'TransactionDT',  # 48
 'C1',  # 48
 'P_emaildomain_freq_enc',  # 41
 'C14',  # 40
 'TransactionAmt',  # 39
 'TransactionAmt_card2_mean',  # 35
 'card1_freq_enc',  # 34
 'D15_card2_mean',  # 33
 'addr1_freq_enc',  # 30
 'card2_freq_enc',  # 29
 'D2',  # 28
 'V317',  # 27
 'addr1',  # 26
 'day',  # 26
 'TransactionAmt_card1_card2_mean',  # 25
 'R_emaildomain_freq_enc',  # 24
 'TransactionAmt_card1_card2_card_3_card_5_addr1_addr2_mean',  # 23
 'card2',  # 23
 'D15_card1_mean',  # 22
 'TransactionAmt_card5_mean',  # 22
 'D15_card1_card2_card_3_card_5_addr1_addr2_mean',  # 22
 'D8',  #21
 'TransactionAmt_card1_card2_card_3_card_5_mean',  # 20

 'C11',  # 19
 'card1_card2_card_3_card_5',  # 18
 'V294',  # 17
 'V45',
 'D15',  # 16
 'V156',
 'D3',  # 14
 'V76',
 'card6_freq_enc',
 'V67',
 'C8',
 'D15_card1_card2_card_3_card_5_mean',  # 13
 'C2',
 'TransactionAmt_card1_mean',
 'V87',
 'C12',
 'D4', # 12
 'D15_card1_card2_mean',
 'C6',
 'TransactionAmr_fractional',
 'V143',  # 11
 'V261',
 'V314',
 'card5',
 'D13',

 'D9',  # 10
 'V165',
 'D11',
 'V316',
 'hour',
 'V53',
 'V189',
 'C5',  # 9
 'V312',
 'V313',
 'card1_card2_card_3_card_5_addr1_addr2',
 'V289', # 8
 'V131',
 'V70',
 'V30',
 'V152',
 'V44',
 'V335',  # 7
 'card1_card2',
 'V245',
 'dist2',
 'V149',
 'V256',  # 6
 'C9',
 'V296',
 'D10',
 'V62',
 'card3',
 'D1',
 'V64',
 'V258',
 'card3_freq_enc',
 'V310',  # 5
 'C10',
 'V61',
 'V308',
 'V78',
```

```
'V133',
'D14',
'V169',
'C4',
'V215',
'V323',

'V37',  # 4
'V7',
'D6',
'dist1',
'V315',
'D5',
'V55',
'V54',
'V262',
'V13',
'V24',
'V223',
'V147',
'V226', # 3
'V161',
'D15_card5_mean',
'V83',
'V130',
'D12',
'TransactionAmt_card6_mean',
'V283',
'V12',
'V243',
'D15_card3_mean',
'C7',
'V324',
'V56',  # 2
'V209',
'V266',
'V99',
'V290',
'V206',
'V185',
'V303',
'TransactionAmt_card3_mean',
'V129',
'V20',
'V150',
'V320',
'V183',
'addr2_freq_enc',
'V248',
'V271',
'V281',
'V264',
'V318',
'V48',
'V227',
'V239',
'V275',
'V225',
'V175',
'V205',
'V201',

'V25',  #1
'V309',
'V81',
'V47',
'V79',
'V49',
'V35',
'V127',
'V307',
'V217',
'V160',
'V287',
'V190',
'V285',
'V304',
'V263',
'V306',
'V164',
'V51',
'V43',
'card1',
'V234',
'V184',
'V267',
'addr2',
'V171',
```

```
 'V73',
 'V124',
 'V339',
 'V273',
 'V82',
 'V77',
 'V141',
 'V331',
 'V192',
 'V293',
 'V66',
 'V75',
 'V292',
 'V251',
 'V268',
 'V246',
 'V134',
 'V173',
 'V332',
 'V23',
 'V216',
 'V146',
 'V265',
 'V172',
 'V155',
 'V58',
 'V204',
 'V207',
 'V244',
]
```

В [147]:
```
#task_2_numerical_features
```

В [148]:
```
# t = set(task_2_numerical_features)
# task_2_numerical_features = list(t)
# task_2_numerical_features
```

В [149]:
```
df_data_xgb_task_2 = df_data_xgb[task_2_numerical_features]
```

В [150]:
```
x_train_xgb, x_test_xgb = train_test_split(
    df_data_xgb_task_2, train_size=0.75, random_state=27
)
y_train_xgb, y_test_xgb = train_test_split(
    target, train_size=0.75, random_state=27
)
print("x_train.shape = {} rows, {} cols".format(*df_data_xgb_task_2.shape))
print("x_test.shape = {} rows, {} cols".format(*df_data_xgb_task_2.shape))
```

```
x_train.shape = 180000 rows, 201 cols
x_test.shape = 180000 rows, 201 cols
```

В [151]:
```
eval_sets= [
    (x_train_xgb[task_2_numerical_features], y_train_xgb),
    (x_test_xgb[task_2_numerical_features], y_test_xgb)
]
```

В [152]:
```
xgb_model_1 = xgb.XGBClassifier(**xgb_params)

xgb_model_1.fit(
    y=y_train_xgb,
    X=x_train_xgb[task_2_numerical_features],
    early_stopping_rounds=50,
    eval_set=eval_sets,
    eval_metric="auc",
    verbose=10
)
```

```
[0]	validation_0-auc:0.70651	validation_1-auc:0.69725
[10]	validation_0-auc:0.80401	validation_1-auc:0.79680
[20]	validation_0-auc:0.84378	validation_1-auc:0.83655
[30]	validation_0-auc:0.87470	validation_1-auc:0.86655
[40]	validation_0-auc:0.88669	validation_1-auc:0.87788
[50]	validation_0-auc:0.89773	validation_1-auc:0.88661
[60]	validation_0-auc:0.90369	validation_1-auc:0.89160
[70]	validation_0-auc:0.90805	validation_1-auc:0.89507
[80]	validation_0-auc:0.91243	validation_1-auc:0.89797
[90]	validation_0-auc:0.91543	validation_1-auc:0.90039
[99]	validation_0-auc:0.91709	validation_1-auc:0.90143
```

Out[152]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eval_metric='auc',
              gamma=10, gpu_id=-1, importance_type='gain',
              interaction_constraints='', learning_rate=0.1, max_delta_step=0,
              max_depth=4, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=6, nthread=6,
              num_parallel_tree=1, random_state=27, reg_alpha=0, reg_lambda=10,
              scale_pos_weight=1, seed=27, subsample=1, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

Базовое качество модели:

[180] validation_0-auc:0.92789 validation_1-auc:0.90977 (417 cols)

Учёт вклада полей в модель (F score):

```
> 20 [110]    validation_0-auc:0.90674    validation_1-auc:0.88975 (24 cols)
> 10 [160]    validation_0-auc:0.92392    validation_1-auc:0.90668 (49 cols)
> 4 [150]    validation_0-auc:0.92500    validation_1-auc:0.90742 (92 cols)
> 1 [150]    validation_0-auc:0.92549    validation_1-auc:0.90781 (146 cols)
= 1 [180]    validation_0-auc:0.92789    validation_1-auc:0.90976 (201 cols)
```

Задание 3:

Использовать permutation importance , выполнить задание 1 и 2.

https://habr.com/ru/company/otus/blog/464695/ (https://habr.com/ru/company/otus/blog/464695/) - Интерпретируемая модель машинного обучения. Часть 1

В [115]:
```
from copy import deepcopy

xgb_params = deepcopy(xgb_params)
xgb_params["n_estimators"] = 100
```

В [153]:
```
conda install -c conda-forge eli5
```

```
Collecting package metadata (current_repodata.json): ...working... done
Note: you may need to restart the kernel to use updated packages.
Solving environment: ...working... done

# All requested packages already installed.
```

В [158]:
```
df_data_xgb = data[new_numerical_features + new_categorical_features]
```

В [159]:
```
df_data_xgb['card1_card2'] = df_data_xgb.card1_card2.replace('', np.nan).astype(float)
df_data_xgb['card1_card2_card_3_card_5'] = df_data_xgb.card1_card2_card_3_card_5.replace('', np.nan).astype(float)
df_data_xgb['card1_card2_card_3_card_5_addr1_addr2'] = df_data_xgb.card1_card2_card_3_card_5_addr1_addr2.replace('', np.
df_data_xgb['card4_freq_enc'] = df_data_xgb.card4_freq_enc.replace('', np.nan).astype(float)
df_data_xgb['card6_freq_enc'] = df_data_xgb.card6_freq_enc.replace('', np.nan).astype(float)
df_data_xgb['addr1_freq_enc'] = df_data_xgb.addr1_freq_enc.replace('', np.nan).astype(float)
```

В [160]:
```
x_train_xgb, x_test_xgb = train_test_split(
    df_data_xgb, train_size=0.75, random_state=27
)
y_train_xgb, y_test_xgb = train_test_split(
    target, train_size=0.75, random_state=27
)
print("x_train.shape = {} rows, {} cols".format(*x_train_xgb.shape))
print("x_test.shape = {} rows, {} cols".format(*x_test_xgb.shape))
```

```
x_train.shape = 135000 rows, 417 cols
x_test.shape = 45000 rows, 417 cols
```

В [161]:
```
eval_sets= [
    (x_train_xgb[new_numerical_features + new_categorical_features], y_train_xgb),
    (x_test_xgb[new_numerical_features + new_categorical_features], y_test_xgb)
]
```

В [162]:
```
xgb_model_0 = xgb.XGBClassifier(**xgb_params)

xgb_model_0.fit(
    y=y_train_xgb,
    X=x_train_xgb[new_numerical_features + new_categorical_features],
    early_stopping_rounds=50,
    eval_set=eval_sets,
    eval_metric="auc",
    verbose=10
)
```

```
[0]	validation_0-auc:0.70651	validation_1-auc:0.69725
[10]	validation_0-auc:0.80401	validation_1-auc:0.79680
[20]	validation_0-auc:0.84378	validation_1-auc:0.83655
[30]	validation_0-auc:0.87470	validation_1-auc:0.86655
[40]	validation_0-auc:0.88669	validation_1-auc:0.87788
[50]	validation_0-auc:0.89773	validation_1-auc:0.88661
[60]	validation_0-auc:0.90369	validation_1-auc:0.89161
[70]	validation_0-auc:0.90805	validation_1-auc:0.89508
[80]	validation_0-auc:0.91243	validation_1-auc:0.89797
[90]	validation_0-auc:0.91543	validation_1-auc:0.90039
[99]	validation_0-auc:0.91709	validation_1-auc:0.90144
```

Out[162]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eval_metric='auc',
              gamma=10, gpu_id=-1, importance_type='gain',
              interaction_constraints='', learning_rate=0.1, max_delta_step=0,
              max_depth=4, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=6, nthread=6,
              num_parallel_tree=1, random_state=27, reg_alpha=0, reg_lambda=10,
              scale_pos_weight=1, seed=27, subsample=1, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

В [119]:
```
import eli5
from eli5.sklearn import PermutationImportance

# perm = PermutationImportance(model, random_state=27).fit(val_x, val_y)
# perm = PermutationImportance(model, scoring='roc_auc', random_state=27).fit(val_x, val_y)
# eli5.show_weights(perm, feature_name = val_X.columns.tolist())
```

В [122]:
```
perm_0 = PermutationImportance(xgb_model_0, random_state=27).fit(x_test_xgb, y_test_xgb)
```

В [132]:
```
eli5.show_weights(perm_0, feature_names = x_test_xgb.columns.tolist(), top = 100)
```

Out[132]:

Weight	Feature
0.0034 ± 0.0004	C13
0.0016 ± 0.0001	V317
0.0012 ± 0.0003	C1
0.0006 ± 0.0001	C8
0.0005 ± 0.0002	V30
0.0004 ± 0.0001	C14
0.0004 ± 0.0001	V67
0.0003 ± 0.0004	TransactionDT
0.0003 ± 0.0001	C11
0.0003 ± 0.0001	P_emaildomain_freq_enc
0.0003 ± 0.0001	D2
0.0003 ± 0.0002	D15_card2_mean
0.0003 ± 0.0000	V156
0.0003 ± 0.0000	V294
0.0003 ± 0.0002	V70
0.0003 ± 0.0001	V258
0.0002 ± 0.0001	C4
0.0002 ± 0.0001	V45
0.0002 ± 0.0000	V308
0.0002 ± 0.0001	card2_freq_enc
0.0002 ± 0.0001	V62
0.0002 ± 0.0001	V314
0.0002 ± 0.0001	card1_freq_enc
0.0002 ± 0.0002	addr1_freq_enc
0.0002 ± 0.0001	card3
0.0002 ± 0.0001	V313
0.0002 ± 0.0001	TransactionAmt
0.0002 ± 0.0001	addr1
0.0002 ± 0.0000	V261
0.0002 ± 0.0000	V289
0.0002 ± 0.0002	card1_card2_card_3_card_5
0.0002 ± 0.0001	C5
0.0002 ± 0.0001	TransactionAmt_card1_card2_card_3_card_5_addr1_addr2_mean
0.0002 ± 0.0001	D15_card1_card2_card_3_card_5_addr1_addr2_mean
0.0002 ± 0.0001	C12
0.0002 ± 0.0001	TransactionAmt_card2_mean
0.0002 ± 0.0001	C2
0.0002 ± 0.0001	V283
0.0002 ± 0.0001	V143
0.0002 ± 0.0001	R_emaildomain_freq_enc
0.0002 ± 0.0001	V87
0.0001 ± 0.0001	D15
0.0001 ± 0.0000	V133
0.0001 ± 0.0000	V78
0.0001 ± 0.0001	card2
0.0001 ± 0.0001	card5
0.0001 ± 0.0001	V131
0.0001 ± 0.0001	V149
0.0001 ± 0.0001	C6
0.0001 ± 0.0000	V134
0.0001 ± 0.0001	D15_card1_mean
0.0001 ± 0.0001	D14
0.0001 ± 0.0000	C10
0.0001 ± 0.0001	TransactionAmt_card1_card2_card_3_card_5_mean
0.0001 ± 0.0000	card1_card2_card_3_card_5_addr1_addr2
0.0001 ± 0.0000	D3
0.0001 ± 0.0000	V335
0.0001 ± 0.0001	D8
0.0001 ± 0.0000	TransactionAmt_card1_mean
0.0001 ± 0.0000	V312
0.0001 ± 0.0001	V61
0.0001 ± 0.0001	D9
0.0001 ± 0.0000	hour
0.0001 ± 0.0000	V262
0.0001 ± 0.0001	V310
0.0001 ± 0.0000	D15_card5_mean
0.0001 ± 0.0000	V13
0.0001 ± 0.0000	V287
0.0001 ± 0.0001	D15_card1_card2_mean
0.0001 ± 0.0000	V281
0.0001 ± 0.0000	TransactionAmr_fractional
0.0001 ± 0.0000	V51
0.0001 ± 0.0001	V152
0.0001 ± 0.0001	V225
0.0001 ± 0.0000	V129
0.0000 ± 0.0000	V47
0.0000 ± 0.0001	V49
0.0000 ± 0.0001	V189
0.0000 ± 0.0000	V79
0.0000 ± 0.0002	TransactionAmt_card1_card2_mean
0.0000 ± 0.0001	V245
0.0000 ± 0.0000	TransactionAmt_card3_mean
0.0000 ± 0.0000	V296
0.0000 ± 0.0000	V243
0.0000 ± 0.0000	V171
0.0000 ± 0.0000	C7
0.0000 ± 0.0000	D4
0.0000 ± 0.0000	V24
0.0000 ± 0.0001	V54
0.0000 ± 0.0001	card1_card2
0.0000 ± 0.0000	V239
0.0000 ± 0.0001	V141
0.0000 ± 0.0000	D1
0.0000 ± 0.0001	V64
0.0000 ± 0.0000	V303
0.0000 ± 0.0000	addr2
0.0000 ± 0.0000	V37
0.0000 ± 0.0000	V204
0.0000 ± 0.0000	V309
0.0000 ± 0.0000	V248

… 317 more …

В [135]:
```
task_3_numerical_features = [
'C13',  # 0.0034 ± 0.0004
'V317',  # 0.0016 ± 0.0001
'C1',  # 0.0012 ± 0.0003
'C8',  # 0.0006 ± 0.0001
'V30',  # 0.0005 ± 0.0002
'C14',  # 0.0004 ± 0.0001
'V67',  # 0.0004 ± 0.0001
'TransactionDT',  # 0.0003 ± 0.0004
'C11',  # 0.0003 ± 0.0001
'P_emaildomain_freq_enc',  # 0.0003 ± 0.0001

'D2',  # 0.0003 ± 0.0001
'D15_card2_mean',  # 0.0003 ± 0.0002
'V156',  # 0.0003 ± 0.0000
'V294',  # 0.0003 ± 0.0000
'V70',  # 0.0003 ± 0.0002
'V258',  # 0.0003 ± 0.0001
'C4',  # 0.0002 ± 0.0001
'V45',  # 0.0002 ± 0.0001
'V308',  # 0.0002 ± 0.0000
'card2_freq_enc',  # 0.0002 ± 0.0001

'V62',  # 0.0002 ± 0.0001
'V314',  # 0.0002 ± 0.0001
'card1_freq_enc',  # 0.0002 ± 0.0001
'addr1_freq_enc',  # 0.0002 ± 0.0002
'card3',  # 0.0002 ± 0.0001
'V313',  # 0.0002 ± 0.0001
'TransactionAmt',  # 0.0002 ± 0.0001
'addr1',  # 0.0002 ± 0.0001
'V261',  # 0.0002 ± 0.0000
'V289',  # 0.0002 ± 0.0000

'card1_card2_card_3_card_5',  # 0.0002 ± 0.0002
'C5',  # 0.0002 ± 0.0001
'TransactionAmt_card1_card2_card_3_card_5_addr1_addr2_mean',  # 0.0002 ± 0.0001
'D15_card1_card2_card_3_card_5_addr1_addr2_mean',  # 0.0002 ± 0.0001
'C12',  # 0.0002 ± 0.0001
'TransactionAmt_card2_mean',  # 0.0002 ± 0.0001
'C2',  # 0.0002 ± 0.0001
'V283',  # 0.0002 ± 0.0001
'V143',  # 0.0002 ± 0.0001
'R_emaildomain_freq_enc',  # 0.0002 ± 0.0001

'V87',  # 0.0002 ± 0.0001
'D15',  # 0.0001 ± 0.0001
'V133',  # 0.0001 ± 0.0000
'V78',  # 0.0001 ± 0.0000
'card2',  # 0.0001 ± 0.0001
'card5',  # 0.0001 ± 0.0001
'V131',  # 0.0001 ± 0.0001
'V149',  # 0.0001 ± 0.0001
'C6',  # 0.0001 ± 0.0001
'V134',  # 0.0001 ± 0.0000

'D15_card1_mean',  # 0.0001 ± 0.0001
'D14',  # 0.0001 ± 0.0001
'C10',  # 0.0001 ± 0.0000
'TransactionAmt_card1_card2_card_3_card_5_mean',  # 0.0001 ± 0.0001
'card1_card2_card_3_card_5_addr1_addr2',  # 0.0001 ± 0.0000
'D3',  # 0.0001 ± 0.0000
'V335',  # 0.0001 ± 0.0000
'D8',  # 0.0001 ± 0.0001
'TransactionAmt_card1_mean',  # 0.0001 ± 0.0000
'V312',  # 0.0001 ± 0.0000

'V61',  # 0.0001 ± 0.0001
'D9',  # 0.0001 ± 0.0001
'hour',  # 0.0001 ± 0.0000
'V262',  # 0.0001 ± 0.0000
'V310',  # 0.0001 ± 0.0001
'D15_card5_mean',  # 0.0001 ± 0.0000
'V13',  # 0.0001 ± 0.0000
'V287',  # 0.0001 ± 0.0000
'D15_card1_card2_mean',  # 0.0001 ± 0.0001
'V281',  # 0.0001 ± 0.0000

'TransactionAmr_fractional',  # 0.0001 ± 0.0000
'V51',  # 0.0001 ± 0.0000
'V152',  # 0.0001 ± 0.0001
'V225',  # 0.0001 ± 0.0001
'V129',  # 0.0001 ± 0.0000
]
```

В [139]:
```
df_data_xgb_task_3 = df_data_xgb[task_3_numerical_features]
```

В [140]:
```
x_train_xgb, x_test_xgb = train_test_split(
    df_data_xgb_task_3, train_size=0.75, random_state=27
)
y_train_xgb, y_test_xgb = train_test_split(
    target, train_size=0.75, random_state=27
)
print("x_train.shape = {} rows, {} cols".format(*df_data_xgb_task_2.shape))
print("x_test.shape = {} rows, {} cols".format(*df_data_xgb_task_2.shape))
```

```
x_train.shape = 180000 rows, 75 cols
x_test.shape = 180000 rows, 75 cols
```

В [142]:
```
eval_sets= [
    (x_train_xgb[task_3_numerical_features], y_train_xgb),
    (x_test_xgb[task_3_numerical_features], y_test_xgb)
]
```

В [143]:
```
xgb_model_2 = xgb.XGBClassifier(**xgb_params)

xgb_model_2.fit(
    y=y_train_xgb,
    X=x_train_xgb[task_3_numerical_features],
    early_stopping_rounds=50,
    eval_set=eval_sets,
    eval_metric="auc",
    verbose=10
)
```

```
[0]     validation_0-auc:0.66434        validation_1-auc:0.65607
[10]    validation_0-auc:0.80704        validation_1-auc:0.80065
[20]    validation_0-auc:0.84438        validation_1-auc:0.83775
[30]    validation_0-auc:0.87472        validation_1-auc:0.86862
[40]    validation_0-auc:0.88691        validation_1-auc:0.87857
[50]    validation_0-auc:0.89543        validation_1-auc:0.88609
[60]    validation_0-auc:0.90085        validation_1-auc:0.88962
[70]    validation_0-auc:0.90590        validation_1-auc:0.89280
[80]    validation_0-auc:0.90926        validation_1-auc:0.89497
[90]    validation_0-auc:0.91177        validation_1-auc:0.89663
[99]    validation_0-auc:0.91377        validation_1-auc:0.89831
```

Out[143]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eval_metric='auc',
              gamma=10, gpu_id=-1, importance_type='gain',
              interaction_constraints='', learning_rate=0.1, max_delta_step=0,
              max_depth=4, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=6, nthread=6,
              num_parallel_tree=1, random_state=27, reg_alpha=0, reg_lambda=10,
              scale_pos_weight=1, seed=27, subsample=1, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

Базовое качество модели:

[180] validation_0-auc:0.92789 validation_1-auc:0.90977 (417 cols)

Учёт вклада полей в модель (F score):

```
> 0 [99]    validation_0-auc:0.91377    validation_1-auc:0.89831 (75 cols)
```

Задание 4:

Использовать shap, выполнить задание 1 и 2.

Задание 5:

Построить shap.summary_plot и shap.decision_plot для небольшой группы примеров (определить размер самостоятельно) и проанализировать влияние признаков на поведение модели.

https://www.machinelearningmastery.ru/catboost-vs-light-gbm-vs-xgboost-5f93620723db/ (https://www.machinelearningmastery.ru/catboost-vs-light-gbm-vs-xgboost-5f93620723db/) - CatBoost против Light GBM против XGBoost

https://developer.nvidia.com/blog/leveraging-machine-learning-to-detect-fraud-tips-to-developing-a-winning-kaggle-solution/ (https://developer.nvidia.com/blog/leveraging-machine-learning-to-detect-fraud-tips-to-developing-a-winning-kaggle-solution/) - Leveraging Machine Learning to Detect Fraud: Tips to Developing a Winning Kaggle Solution

В [ ]: