American Express - Default Prediction

- 대회 내용 : 고객이 미래의 채무 불이행 여부를 예측
- 대회 링크: https://www.kaggle.com/competitions/amex-default-prediction)
- 코드 참조 링크: https://www.kaggle.com/code/wanko5452/catboost-md-10-gpu-0-794-lb)
- 대회 평가 : M = 0.5 * (G + D)
 - G: Normalized Gini Coefficient
 D: 4%에서의 기본 비율(default rate)
- 데이터 셋
 - train_data: 16.39 GB, test_data: 33.82 GB

학습 목표

• CatBoost 알고리즘을 활용한 데이터 EDA 부터, 기본 모델을 만들어 제출해봅니다.

목차

01. 라이브러리 불러오기

02. 함수 정의

03. 데이터 불러오기

04. 모델 구축 및 학습

05. 모델 학습 후, 정보 확인

06. 제출

01. 라이브러리 불러오기

목차로 이동하기

In [1]:

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

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

from catboost import CatBoostClassifier

import gc
import datetime
from IPython.display import display
import warnings
```

Vaex.ml

- vaex.ml의 API는 scikit-learn에 근접하면서, 데이터 처리를 수행하기 위한 더 나은 성능과 기능을 제공
- 사용 가능한 데이터보다 더 큰 RAM 에 대해

In [2]:

```
import vaex
vaex.multithreading.thread_count_default = 8
import vaex.ml

from cycler import cycler

from colorama import Fore, Back, Style
```

In [3]:

```
# config
MAX_DEPTH = 10
ITERATIONS = 28000

DATA_PATH = '../input/amex-data-integer-dtypes-parquet-format/' # denoised data fr
LABELS_PATH = '../input/amex-default-prediction/train_labels.csv' # original data so

TEST_FEAT_PATH = '../input/amex-denoised-aggregated-features/test_feat.parquet' # aggregated_features/train_feat.parquet'
```

02. 함수 정의

목차로 이동하기

- 데이터 불러오기
- 특성 중요도 그리기
- 평가 지표

특성 중요도 그리기

In [4]:

```
def plot feature importance(importance, names, model type, n=50, figsize=(16,10)):
    # 특징명과 특징의 중요도로 배열을 만든다.
    feature importance = np.array(importance)
    feature names = np.array(names)
    # 딕셔너리를 이용하여 데이터 프레임을 생성
    data={'feature names':feature names,'feature importance':feature importance}
    fi df = pd.DataFrame(data)
    # 특징 중요도를 정렬
    fi df.sort values(by=['feature importance'], ascending=False,inplace=True)
    fi df = fi df[:n]
    # Define size of bar plot
    plt.figure(figsize=figsize)
    # Plot Searborn bar chart
    sns.barplot(x=fi_df['feature_importance'], y=fi_df['feature_names'])
    # 그래프의 레이브를 추가
    plt.title(model type + ' FEATURE IMPORTANCE')
    plt.xlabel('FEATURE IMPORTANCE')
    plt.ylabel('FEATURE NAMES')
    plt.tight_layout()
    plt.show()
    return fi df.feature names
```

amex 평가 지표

In [5]:

```
def amex metric(y true: np.array, y pred: np.array) -> float:
    # count of positives and negatives
    n pos = y true.sum()
    n neg = y true.shape[0] - n pos
    # sorting by describing prediction values
    indices = np.argsort(y_pred)[::-1]
    preds, target = y_pred[indices], y_true[indices]
    # filter the top 4% by cumulative row weights
    weight = 20.0 - \text{target} * 19.0
    cum_norm_weight = (weight / weight.sum()).cumsum()
    four pct filter = cum norm weight <= 0.04
    # default rate captured at 4%
    d = target[four pct filter].sum() / n pos
    # weighted Gini coefficient
    lorentz = (target / n pos).cumsum()
    gini = ((lorentz - cum norm weight) * weight).sum()
    # max weighted Gini coefficient
    gini_max = 10 * n_neg * (1 - 19 / (n_pos + 20 * n_neg))
    # normalized weighted Gini coefficient
    g = gini / gini max
    return 0.5 * (g + d)
```

In [6]:

```
# TEST_FEAT_PATH = '../input/amex-denoised-aggregated-features/test_feat.parquet'
# TRAIN_FEAT_PATH = '../input/amex-denoised-aggregated-features/train_feat.parquet'

def get_data(read_from_cache=True):
    train = pd.read_parquet(TRAIN_FEAT_PATH)
    test = pd.read_parquet(TEST_FEAT_PATH)
    return train, test
```

03. 데이터 불러오기

목차로 이동하기

```
In [7]:
# LABELS PATH = '../input/amex-default-prediction/train labels.csv'
target = pd.read_csv(LABELS_PATH).target.values
train, test = get data(read from cache=True)
print(f"target shape: {target.shape}, train shape: {train.shape}, test shape: {test.
target shape: (458913,), train shape: (458913, 469), test shape: (9246
21, 469)
 • [B, D, P, R, S]_X_last
 • [B, D, P, R, S]_X_min
 • [B, D, P, R, S]_X_max
 • [B, D, P, R, S]_X_avg
In [8]:
# train columns 확인
features = [f for f in train.columns if f != 'customer_ID' and f != 'target']
features
Out[8]:
['B_1_last',
 'B 2 last',
 'B 3 last',
 'B_4_last',
 'B 5 last',
 'B_6_last',
 'B_7_last',
 'B 8 last',
 'B 9 last',
 'B_10_last',
 'B_11_last',
 'B_12_last',
 'B 13 last',
 'B 14 last',
 'B_15_last',
 'B 16 last',
```

04. 모델 구축 및 학습

목차로 이동하기

'B_17_last',
'B 18 last'.

In [9]:

```
param = {
    "objective": "Logloss",
    "learning_rate": 0.01,
    "n estimators": ITERATIONS,
    #"eval_metric": "AUC", #AmexMetric(),
#'colsample_bylevel': 0.10506469029379303,
    "max_depth": MAX_DEPTH,
    #"12 leaf_reg": 15,
    "od_type": "Iter",
    "od wait": 600,
    #"boosting_type": "Ordered",
    #"bootstrap type": "MVS",
    "task_type": "GPU",
    #"devices":'0:1',
    #"auto class weights": "Balanced",
    #"grow_policy": "Lossguide",
    #"leaf_estimation_method": "Gradient",
    #"leaf estimation iterations": 15,
    #"leaf_estimation_backtracking": "Armijo",
    "use best model": True,
    #"scale pos weight": 20,
    #"score function": "L2"
}
```

```
In [10]:
```

```
cv folds = 5
ONLY_FIRST_FOLD = False
score list, y pred list = [], []
kf = StratifiedKFold(n splits=cv folds)
for fold, (idx tr, idx va) in enumerate(kf.split(train, target)):
    X_tr, X_va, y_tr, y_va, model = None, None, None, None, None
                                         # 시작 시간
    start_time = datetime.datetime.now()
    X_tr = train.iloc[idx_tr][features]
    X va = train.iloc[idx va][features]
    y tr = target[idx tr]
    y va = target[idx va]
    with warnings.catch warnings():
        warnings.filterwarnings('ignore', category=UserWarning)
        model = CatBoostClassifier(**param)
        model.fit(X tr, y tr,
                  eval\_set = [(X_va, y_va)],
                  metric period=100
    X tr, y tr = None, None
    y_va_pred = model.predict_proba(X_va)[:,1]
    score = amex_metric(y_va, y_va_pred)
    n_trees = model.best_iteration_
    if n trees is None: n trees = model.n estimators
    print(f"{Fore.GREEN}{Style.BRIGHT}Fold {fold} | {str(datetime.datetime.now() - s
          f" {n trees:5} trees |"
          f"
                            Score = {score:.5f}{Style.RESET_ALL}")
    score_list.append(score)
    y pred list.append(model.predict proba(test[features])[:,1])
    qc.collect()
    if ONLY FIRST FOLD: break # we only want the first fold
print(f"{Fore.GREEN}{Style.BRIGHT}OOF Score:
                                                                    {np.mean(score_li
gc.collect()
```

```
0:
        learn: 0.6791702
                                test: 0.6792409 best: 0.6792409 (0)
total: 65.8ms
                remaining: 30m 43s
        learn: 0.2710022
100:
                                test: 0.2752627 best: 0.2752627 (10
0)
        total: 6.2s
                        remaining: 28m 31s
        learn: 0.2370489
200:
                                test: 0.2438037 best: 0.2438037 (20
        total: 12.8s
                      remaining: 29m 27s
0)
        learn: 0.2269402
300:
                                test: 0.2357646 best: 0.2357646 (30
0)
        total: 18.4s
                      remaining: 28m 15s
400:
        learn: 0.2214221
                                test: 0.2321372 best: 0.2321372 (40
        total: 24.4s remaining: 27m 59s
0)
                                test: 0.2299194 best: 0.2299194 (50
500:
        learn: 0.2173831
        total: 30s
                        remaining: 27m 29s
0)
600:
        learn: 0.2140748
                                test: 0.2284084 best: 0.2284084 (60
0)
        total: 36s
                        remaining: 27m 23s
700:
        learn: 0.2111725
                                test: 0.2272325 best: 0.2272325 (70
        total: 41.6s
0)
                        remaining: 27m 1s
800:
        learn: 0.2086000
                                test: 0.2263073 best: 0.2263073 (80
        total: 48.2s
                        remaining: 27m 17s
0)
        learn: 0.2062820
                                test: 0.2255653 best: 0.2255653 (90
900:
```

05. 모델 학습 후, 정보 확인

<u>목차로 이동하기</u>

학습 파라미터 확인

```
In [11]:
```

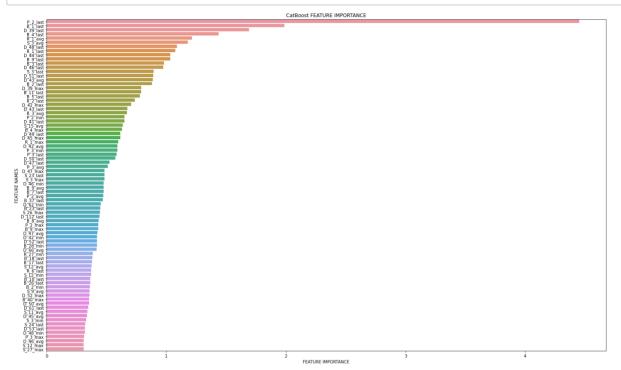
```
model.get_all_params()
```

```
Out[11]:
{'nan_mode': 'Min',
 'gpu_ram_part': 0.95,
 'eval metric': 'Logloss',
 'iterations': 28000,
 'leaf estimation method': 'Newton',
 'observations to bootstrap': 'TestOnly',
 'od pval': 0,
 'grow policy': 'SymmetricTree',
 'boosting_type': 'Plain',
 'feature_border_type': 'GreedyLogSum',
 'bayesian matrix reg': 0.1000000149011612,
 'devices': '-1',
 'pinned memory bytes': '104857600',
 'force unit auto pair weights': False,
 '12 leaf reg': 3,
 'random strength': 1,
 'od_type': 'Iter',
 'rsm': 1,
 'boost from average': False,
 'gpu_cat_features_storage': 'GpuRam',
 'fold_size_loss_normalization': False,
 'model size reg': 0.5,
 'pool_metainfo_options': {'tags': {}},
 'use best model': True,
 'meta 12 frequency': 0,
 'od wait': 600,
 'class names': [0, 1],
 'random seed': 0,
 'depth': 10,
 'border count': 128,
 'min fold size': 100,
 'data_partition': 'DocParallel',
 'bagging temperature': 1,
 'classes_count': 0,
 'auto class weights': 'None',
 'leaf estimation backtracking': 'AnyImprovement',
 'best model min trees': 1,
 'min data in leaf': 1,
 'add_ridge_penalty_to_loss_function': False,
 'loss_function': 'Logloss',
 'learning rate': 0.009999999776482582,
 'meta 12 exponent': 1,
 'score_function': 'Cosine',
 'task type': 'GPU',
 'leaf_estimation_iterations': 10,
 'bootstrap_type': 'Bayesian',
 'max_leaves': 1024}
```

특성 중요도 확인

```
In [12]:
```

```
top_n = plot_feature_importance(model.feature_importances_, features,'CatBoost', n=8
print(f'Mean CV score for {MAX_DEPTH} max_depth: {np.mean(score_list)}')
```



Mean CV score for 10 max_depth: 0.7933820749798006

In [13]:

```
# 5개 데이터 셋에 대한 평
print(f'LGBM baseline: {np.mean([0.79605, 0.79674, 0.79362, 0.79283, 0.79442])}')
```

LGBM baseline: 0.794732

예측값의 확인

In [14]:

```
np.exp((np.log(y_pred_list[0])+np.log(y_pred_list[1])+np.log(y_pred_list[2])+np.log(
Out[14]:
```

```
array([0.01859136, 0.00176784, 0.03999009, ..., 0.3929696 , 0.4208918 , 0.04277044])
```

Out[16]:

0.25215407968337267

```
In [17]:
```

```
list(top_n)
```

Out[17]:

```
['P_2_last',
 'B_1_last',
 'D_39_last',
 'B 4_last',
 'R_1_avg',
 'S_3_avg',
 'D_48_last',
 'R 1 last',
 'D_44_last',
 'B_9_last',
 'B 3 last',
 'D_46_last',
 'S_3_last',
 'D_51_last',
 'D 43_avg',
 'B_2_last',
 'D_39_max',
 'B_11_last',
 'B 5 last',
 'R 2 last',
 'D_42_max',
 'D_43_last',
 'R_3_avg',
 'P_2_min',
 'D_41_last',
 'S 15 avg',
 ^{\prime}B_{4}_{max'}
 'D_49_last',
 'D_45_max',
 'R 1 max',
 'D_42_avg',
 'P_3_min',
 'P 3 last',
 'D_50_last',
 'D_47_last',
 'P_3_avg',
 'D 47 max',
 'S_23_last',
 'S_3_max',
 'D_46_min',
 'B_9_avg',
 'B_7_last',
 'P_2_avg',
 'B_37_last',
 'D_62_min',
 'B_23_last',
 'S 26 max',
 'D 112 last',
 'B_8_avg',
 'P_2_max',
 'B_9_max',
 'D_47_avg',
 'D 42 min',
 'D_52_last',
```

```
'B_28_min',
'D_66_avg',
'R 27 min',
'B_18_last',
'B 17 last',
'S_12_avg',
'R_6_last',
'S 12 min',
'B 10 last',
'B_26_last',
'B_2_min',
'S_9_avg',
'D_52_max',
'B_40_max',
'D_50_avg',
'D 61 last',
'S_11_avg',
'D_45_avg',
'S 3 min',
'S 24 last',
'D_53_last',
'D_48_min',
'P_3_max',
'D 46 avg',
'S 12 max',
'C 27 mav'1
```

06. 제출

목차로 이동하기

In [18]:

In [19]:

sub

Out[19]:

	customer_ID	prediction
0	00000469ba478561f23a92a868bd366de6f6527a684c9a	0.018591
1	00001bf2e77ff879fab36aa4fac689b9ba411dae63ae39	0.001768
2	0000210045da4f81e5f122c6bde5c2a617d03eef67f82c	0.039990
3	00003b41e58ede33b8daf61ab56d9952f17c9ad1c3976c	0.221594
4	00004b22eaeeeb0ec976890c1d9bfc14fd9427e98c4ee9	0.828064
924616	ffff952c631f2c911b8a2a8ca56ea6e656309a83d2f64c	0.010519
924617	ffffcf5df59e5e0bba2a5ac4578a34e2b5aa64a1546cd3	0.799683
924618	ffffd61f098cc056dbd7d2a21380c4804bbfe60856f475	0.392970
924619	ffffddef1fc3643ea179c93245b68dca0f36941cd83977	0.420892
924620	fffffa7cf7e453e1acc6a1426475d5cb9400859f82ff61	0.042770

924621 rows × 2 columns