



Reference: <https://www.kaggle.com/nroman/lgb-single-model-lb-0-9419>
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Importing necessary library

```
In [1]: import pandas as pd
import numpy as np
import multiprocessing
import warnings
import matplotlib.pyplot as plt
import seaborn as sns
import lightgbm as lgb
import gc
from time import time
import datetime
from tqdm import tqdm_notebook
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import KFold, TimeSeriesSplit
from sklearn.metrics import roc_auc_score
warnings.simplefilter('ignore')
sns.set()
%matplotlib inline
```

Importing datasets

```
In [2]: sub = pd.read_csv("../input/ieee-fraud-detection/sample_submission.csv")
```

```
In [3]: train_id = pd.read_csv("../input/ieee-fraud-detection/train_identity.csv")
train_tr = pd.read_csv("../input/ieee-fraud-detection/train_transaction.csv")
```

```
In [4]: train_id.head(5)
```

Out[4]:

	TransactionID	id_01	id_02	id_03	id_04	id_05	id_06	id_07	id_08
0	2987004	0.0	70787.0	NaN	NaN	NaN	NaN	NaN	NaN
1	2987008	-5.0	98945.0	NaN	NaN	0.0	-5.0	NaN	NaN
2	2987010	-5.0	191631.0	0.0	0.0	0.0	0.0	NaN	NaN
3	2987011	-5.0	221832.0	NaN	NaN	0.0	-6.0	NaN	NaN
4	2987016	0.0	7460.0	0.0	0.0	1.0	0.0	NaN	NaN



5 rows × 41 columns

In [5]:

```
train_id.head(5)
```

Out[5]:

	TransactionID	id_01	id_02	id_03	id_04	id_05	id_06	id_07	id_08
0	2987004	0.0	70787.0	NaN	NaN	NaN	NaN	NaN	NaN
1	2987008	-5.0	98945.0	NaN	NaN	0.0	-5.0	NaN	NaN
2	2987010	-5.0	191631.0	0.0	0.0	0.0	0.0	NaN	NaN
3	2987011	-5.0	221832.0	NaN	NaN	0.0	-6.0	NaN	NaN
4	2987016	0.0	7460.0	0.0	0.0	1.0	0.0	NaN	NaN

5 rows × 41 columns

In [6]:

```
train_id.shape, train_tr.shape
```

Out[6]:

```
((144233, 41), (590540, 394))
```

In [7]:

```
test_id = pd.read_csv("../input/ieee-fraud-detection/  
test_identity.csv")  
test_tr = pd.read_csv("../input/ieee-fraud-detection/  
test_transaction.csv")
```

In [8]:

```
test_id.shape, test_tr.shape
```

Out[8]:

```
((141907, 41), (506691, 393))
```

Merging transaction and Identity

In [9]:

```
train = pd.merge(train_tr, train_id, on='TransactionID', how='left')  
test = pd.merge(test_tr, test_id, on='TransactionID', how='left')  
  
del test_id, test_tr, train_id, train_tr  
gc.collect()
```

Out[9]:

15

```
In [10]: train.head(5)
```

Out[10]:

	TransactionID	isFraud	TransactionDT	TransactionAmt	ProductCD	card
0	2987000	0	86400	68.5	W	1392
1	2987001	0	86401	29.0	W	2755
2	2987002	0	86469	59.0	W	4663
3	2987003	0	86499	50.0	W	1813
4	2987004	0	86506	50.0	H	4497

5 rows × 434 columns

```
In [11]: train.shape, test.shape
```

Out[11]: ((590540, 434), (506691, 433))

From below we can see that there are a lot of features with almost 99% nan values

```
In [12]: train.isna().sum()
```

Out[12]:

TransactionID	0
isFraud	0
TransactionDT	0
TransactionAmt	0
ProductCD	0
...	
id_36	449555
id_37	449555
id_38	449555
DeviceType	449730
DeviceInfo	471874

Length: 434, dtype: int64

Sorting features on basis of TransactionDT

```
In [13]: train = train.sort_values('TransactionDT')
```

Taking all features

Initially I will start with all the features and then will drop most of the features

	TransactionID	isFraud	TransactionDT	TransactionAmt	ProductCD	card
0	2987000	0	86400	68.5	W	1392
1	2987001	0	86401	29.0	W	2755
2	2987002	0	86469	59.0	W	4663
3	2987003	0	86499	50.0	W	1813
4	2987004	0	86506	50.0	H	4497
5	2987005	0	86510	49.0	W	5937
6	2987006	0	86522	159.0	W	1230
7	2987007	0	86529	422.5	W	1269
8	2987008	0	86535	15.0	H	2803
9	2987009	0	86536	117.0	W	1739

```
In [21]:
target = train["isFraud"]
train.drop(["isFraud"], axis=1, inplace=True)
```

Concatinating train and test as one dataframe

```
In [22]:
train = pd.concat([train, test])
```

```
In [23]:
train.drop(["TransactionID", "TransactionDT"], axis=1
, inplace=True)
train.shape
```

```
Out[23]:
(1097231, 431)
```

Here I will treat all features as categorical except TransationAmt

```
In [24]:
neglect = ["TransactionAmt"]
```

```
In [25]:
useful_features = [col for col in train.columns if col
not in neglect]
```

This block of code count every features and drop original features

Dropping below features as these seems to be repeating

```
In [26]:
dropping1=["D8_count_dist", "V138_count_dist", "V139
_count_dist", "V140_count_dist", "V141_count_dist",\
"V146_count_dist" "V147_count_dist" "V14
```

V140_count_dist", "V147_count_dist", "V148_count_dist", "V149_count_dist", "V144_count_dist", \n
"V145_count_dist", "V150_count_dist", "V151_count_dist", "V152_count_dist", "V153_count_dist", \n
"V154_count_dist", "V155_count_dist", "V156_count_dist", "V157_count_dist", "V158_count_dist", \n
"V159_count_dist", "V160_count_dist", "V161_count_dist", "V162_count_dist", "V163_count_dist", \n
"V164_count_dist", "V165_count_dist", "V166_count_dist", "V168_count_dist", "V170_count_dist", \n
"V171_count_dist", "V172_count_dist", "V173_count_dist", "V174_count_dist", "V175_count_dist", \n
"V176_count_dist", "V177_count_dist", "V178_count_dist", "V179_count_dist", "V180_count_dist", \n
"V181_count_dist", "V182_count_dist", "V183_count_dist", "V184_count_dist", "V185_count_dist", \n
"V186_count_dist", "V187_count_dist", "V188_count_dist", "V189_count_dist", "V190_count_dist" \n
"V191_count_dist", "V192_count_dist", "V193_count_dist", "V194_count_dist", "V195_count_dist", \n
"V196_count_dist", "V197_count_dist", "V198_count_dist", "V199_count_dist", "V200_count_dist", \n
"V201_count_dist", "V202_count_dist", "V203_count_dist", "V204_count_dist", "V205_count_dist", \n
"V206_count_dist", "V207_count_dist", "V208_count_dist", "V209_count_dist", "V210_count_dist", \n
"V211_count_dist", "V212_count_dist", "V213_count_dist", "V214_count_dist", "V215_count_dist", \n
"V216_count_dist", "V218_count_dist", "V219_count_dist", "V221_count_dist", "V222_count_dist", \n
"V223_count_dist", "V224_count_dist", "V225_count_dist", "V226_count_dist", "V227_count_dist", \n
"V228_count_dist", "V229_count_dist", "V230_count_dist", "V231_count_dist", "V232_count_dist", \n
"V233_count_dist", "V234_count_dist", "V235_count_dist", "V236_count_dist", "V237_count_dist", \n
"V205_count_dist", "V205_count_dist", "V205_count_dist", "V205_count_dist", "V205_count_dist", \n
"V238_count_dist", "V239_count_dist", "V240_count_dist", "V241_count_dist", "V242_count_dist", \n
"V243_count_dist", "V244_count_dist", "V245_count_dist", "V246_count_dist", "V247_count_dist", \n
"V248_count_dist", "V249_count_dist", "V250_count_dist", "V251_count_dist", "V252_count_dist", \n
"V253_count_dist", "V254_count_dist", "V255_count_dist", "V256_count_dist", "V257_count_dist", \n
"V258_count_dist", "V259_count_dist", "V260_count_dist", "V261_count_dist", "V262_count_dist", \n
"V263_count_dist", "V264_count_dist", "V265_count_dist", "V266_count_dist", "V267_count_dist", \n
"V268_count_dist", "V269_count_dist", "V270_count_dist", "V271_count_dist", "V272_count_dist", \n
"V273_count_dist", "V274_count_dist", "V275_count_dist", "V276_count_dist", "V277_count_dist", \n
"V278_count_dist", "V323_count_dist", "V324_count_dist", "V325_count_dist", "V326_count_dist", \n
"V327_count_dist", "V328_count_dist", "V329_count_dist", "V330_count_dist", "V331_count_dist", \n
"V332 count dist". "V333 count dist". "V334 count dist".

```

    "id_04_count_dist", "id_06_count_dist",
    "id_08_count_dist", "id_10_count_dist", "id_22_count_dist", "id_27_count_dist", "id_29_count_dist",
    "id_36_count_dist", "id_37_count_dist", "id_38_count_dist"]

```

```

In [27]: dropping = []
         for i in dropping1:
             dropping.append(i.replace("_count_dist", ""))

```

```

In [28]: dropping

```

```

Out[28]: ['D8',
          'V138',
          'V139',
          'V140',
          'V141',
          'V146',
          'V147',
          'V148',
          'V149',
          'V144',
          'V145',
          'V150',
          'V151',
          'V152',
          'V153',
          'V154',
          'V155',
          'V156',
          'V157',
          'V158',
          'V159',
          'V160',
          'V161',
          'V162',
          'V163',
          'V164',
          'V165',
          'V166',
          'V168',
          'V170',
          'V171',
          'V172',
          'V173',
          'V174',
          'V175',
          'V176',
          'V177',
          'V178',

```


'V179',
'V180',
'V181',
'V182',
'V183',
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'V188',
'V189',
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'V277',
'V278',
'V323',
'V324',
'V325',
'V326',
'V327',
'V328',
'V329',
'V330',
'V331',
'V332',
'V333',
'V334',
'V335',
'V336'

```
    'V237',  
    'V238',  
    'V239',  
    'id_04',  
    'id_06',  
    'id_08',  
    'id_10',  
    'id_22',  
    'id_27',  
    'id_29',  
    'id_36',  
    'id_37',  
    'id_38']
```

```
In [29]: train = train.drop(dropping, axis=1)
```

```
In [30]: i=0  
for feature in useful_features:  
    # Count encoded separately for train and test  
    train[feature + '_count_dist'] = np.log(train[feature].map(train[feature].value_counts(dropna=False)))  
    train.drop([feature], axis=1, inplace=True)  
    print("Done" + str(i))  
    i+=1
```

```
Done0  
Done1  
Done2  
Done3  
Done4  
Done5  
Done6  
Done7  
Done8  
Done9  
Done10  
Done11  
Done12  
Done13  
Done14  
Done15  
Done16  
Done17  
Done18  
Done19  
Done20  
Done21  
Done22  
Done23  
Done24  
Done25  
Done26
```

Done27
Done28
Done29
Done30
Done31
Done32
Done33

```
-----  
-----  
KeyError                                Traceback  
  (most recent call last)  
    /opt/conda/lib/python3.6/site-packages/pandas/core/indexes/base.py in get_loc(self, key, method, tolerance)  
    e)
```

```
2896         try:  
2897             # try to convert the key to a pandas index
```



IEEE_fraud_Play_with_Count_lightGbm_[0.9428]

Python notebook using data from [IEEE-CIS Fraud Detection](#) · 12 views · 36m ago



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```
pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()  
ine.get_loc()
```

```
pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()  
ine.get_loc()
```

```
pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get_item()  
bs.hashtable.PyObjectHashTable.get_item()
```

```
pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get_item()  
bs.hashtable.PyObjectHashTable.get_item()
```

KeyError: 'D8'

During handling of the above exception, another exception occurred:

```
KeyError                                Traceback  
  (most recent call last)  
    <ipython-input-30-eccd76ef1c1f> in <module>  
      3  
      4         # Count encoded separately for train  
      and test  
----> 5         train[feature + '_count_dist'] = np.log(train[feature].map(train[feature].value_counts(dropna=False)))  
      6         train.drop([feature], axis=1, inplace=True)  
      )  
      7         print("Done" + str(i))
```

```
/opt/conda/lib/python3.6/site-packages/pandas/core/frame.py in __getitem__(self, key)  
2978         if self.columns.nlevels > 1:  
2979             return self._getitem_multilevel(key)  
el(key)  
-> 2980         indexer = self.columns.get_loc(key)  
y)  
2981         if is_integer(indexer):
```

Ver
6

```

2982         indexer = [indexer]

/opt/conda/lib/python3.6/site-packages/pandas/core/indexes/base.py in get_loc(self, key, method, tolerance)
2897         return self._engine.get_loc(key)
2898     except KeyError:
-> 2899         return self._engine.get_loc(self._maybe_cast_indexer(key))
2900     indexer = self.get_indexer([key], method=method, tolerance=tolerance)
2901     if indexer.ndim > 1 or indexer.size > 1:

pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()

```

Notebook

Data

Output

Comments

```

pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get_item()

```

```

pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get_item()

```

KeyError: 'D8'

In [31]: `len(dropping)`

Out[31]: 168

Below we can see that all I am left with is count

In [32]: `train.head(4)`

Out[32]:

	TransactionAmt	D9	D10	D11	D12	D13	D14	D15	M1
0	68.5	NaN	13.0	13.0	NaN	NaN	NaN	0.0	T
1	29.0	NaN	0.0	NaN	NaN	NaN	NaN	0.0	NaN
2	59.0	NaN	0.0	315.0	NaN	NaN	NaN	315.0	T
3	50.0	NaN	84.0	NaN	NaN	NaN	NaN	111.0	NaN

In [33]: `train.shape`

Out[33]: (1097231, 271)

```
In [34]: #X = train.sort_values('TransactionDT').drop(['isFraud', 'TransactionDT', 'TransactionID'], axis=1)#
#y = train.sort_values('TransactionDT')['isFraud']
#test = test.sort_values('TransactionDT').drop(['TransactionDT', 'TransactionID'], axis=1)
```

```
In [35]: #del train
#gc.collect()
```

Again separating data into train and test

```
In [36]: X = train.iloc[:590540, :]
test = train.iloc[590540:, :]
```

```
In [37]: y=target
```

Train test and split

```
In [38]: # Training and Validation Set
#from sklearn.model_selection import train_test_split
#X_train, X_valid, y_train, y_valid = train_test_split(
train, target, test_size=0.20, random_state=23)
```

Lightgbm

```
In [39]: from catboost import CatBoostRegressor
categorical_var = np.where(train.dtypes != np.float)[
0]
print('\nCategorical Variables indices : ',categorical_var)
```

```
Categorical Variables indices : [ 8  9 10 11 12
13 14 15 16 214 217 218 224 228 229 230 232 233
234 235 236]
```

```
In [40]: del train
```

```
In [41]: params = {'num_leaves': 491,
'min_child_weight': 0.03454472573214212,
'feature_fraction': 0.2707454001646042}
```

```

        'feature_fraction': 0.5797454081040243,
        'bagging_fraction': 0.4181193142567742,
        'min_data_in_leaf': 106,
        'objective': 'binary',
        'max_depth': -1,
        'learning_rate': 0.006883242363721497,
        'boosting_type': "gbdt",
        'bagging_seed': 11,
        'metric': 'auc',
        'verbosity': -1,
        'reg_alpha': 0.3899927210061127,
        'reg_lambda': 0.6485237330340494,
        'random_state': 47
    }

```

In [42]:

```

folds = TimeSeriesSplit(n_splits=5)

aucs = list()
feature_importances = pd.DataFrame()
feature_importances['feature'] = X.columns

training_start_time = time()
for fold, (trn_idx, test_idx) in enumerate(folds.split(X, y)):
    start_time = time()
    print('Training on fold {}'.format(fold + 1))

    trn_data = lgb.Dataset(X.iloc[trn_idx], label=y.iloc[trn_idx])
    val_data = lgb.Dataset(X.iloc[test_idx], label=y.iloc[test_idx])
    clf = lgb.train(params, trn_data, 10000, valid_sets = [trn_data, val_data], verbose_eval=1000, early_stopping_rounds=500)

    feature_importances['fold_{}'.format(fold + 1)] = clf.feature_importance()
    aucs.append(clf.best_score['valid_1']['auc'])

    print('Fold {} finished in {}'.format(fold + 1, str(datetime.timedelta(seconds=time() - start_time))))
    print('-' * 30)
    print('Training has finished.')
    print('Total training time is {}'.format(str(datetime.timedelta(seconds=time() - training_start_time))))
    print('Mean AUC:', np.mean(aucs))
    print('-' * 30)

```

Training on fold 1

```

-----
-----
ValueError                                Traceback
  (most recent call last)
<ipython-input-42-9e31bbac3c4c> in <module>
     12     trn_data = lgb.Dataset(X.iloc[trn_idx], 1

```

```

abel=y.iloc[trn_idx])
    13     val_data = lgb.Dataset(X.iloc[test_idx],
        label=y.iloc[test_idx])
--> 14     clf = lgb.train(params, trn_data, 10000,
        valid_sets = [trn_data, val_data], verbose_eval=1000
, early_stopping_rounds=500)
    15
    16     feature_importances['fold_{}'.format(fold
+ 1)] = clf.feature_importance()

/opt/conda/lib/python3.6/site-packages/lightgbm/engine.py in train(params, train_set, num_boost_round, valid_sets, valid_names, fobj, feval, init_model, feature_name, categorical_feature, early_stopping_rounds, evals_result, verbose_eval, learning_rates, keep_training_booster, callbacks)
    195     # construct booster
    196     try:
--> 197         booster = Booster(params=params, train_set=train_set)
    198         if is_valid_contain_train:
    199             booster.set_train_data_name(train_data_name)

/opt/conda/lib/python3.6/site-packages/lightgbm/basic.py in __init__(self, params, train_set, model_file, silent)
    1550         self.handle = ctypes.c_void_p()
    1551         _safe_call(_LIB.LGBM_BoosterCreate(
-> 1552             train_set.construct().handle,
    1553             c_str(params_str),
    1554             ctypes.byref(self.handle)))

/opt/conda/lib/python3.6/site-packages/lightgbm/basic.py in construct(self)
    999             init_score=self.init_score, predictor=self._predictor,
    1000             silent=self.silent, feature_name=self.feature_name,
-> 1001             categorical_feature=self.categorical_feature, params=self.params)
    1002         if self.free_raw_data:
    1003             self.data = None

/opt/conda/lib/python3.6/site-packages/lightgbm/basic.py in _lazy_init(self, data, label, reference, weight, group, init_score, predictor, silent, feature_name, categorical_feature, params)
    727
    728     categorical_feature,
--> 729     self.pandas_categorical)
    730     label = _label_from_pandas(label)
    731     self.data_has_header = False

```



```

/opt/conda/lib/python3.6/site-packages/lightgbm/basic.py in _data_from_pandas(data, feature_name, categorical_feature, pandas_categorical)
    275         msg = ("DataFrame.dtypes for data
must be int, float or bool.\n"
    276               "Did not expect the data t
ypes in fields ")
--> 277         raise ValueError(msg + ', '.join(
bad_fields))
    278         data = data.values.astype('float')
    279     else:

```

ValueError: DataFrame.dtypes for data must be int, float or bool.
Did not expect the data types in fields M1, M2, M3, M4, M5, M6, M7, M8, M9, id_12, id_15, id_16, id_23, id_28, id_30, id_31, id_33, id_34, id_35, DeviceType, DeviceInfo

In [43]:

```

feature_importances['average'] = feature_importances
[ ['fold_{}'.format(fold + 1) for fold in range(folds.
n_splits) ] ].mean(axis=1)
feature_importances.to_csv('feature_importances.csv')

plt.figure(figsize=(16, 16))
sns.barplot(data=feature_importances.sort_values(by=
'average', ascending=False).head(50), x='average', y=
'feature');
plt.title('50 TOP feature importance over {} folds av
erage'.format(folds.n_splits));

```

```

-----
-----
KeyError                                Traceback
(most recent call last)
<ipython-input-43-1195e33b4c10> in <module>
----> 1 feature_importances['average'] = feature_imo
rtances[ ['fold_{}'.format(fold + 1) for fold in range
(folds.n_splits) ] ].mean(axis=1)
      2 feature_importances.to_csv('feature_importanc
es.csv')
      3
      4 plt.figure(figsize=(16, 16))
      5 sns.barplot(data=feature_importances.sort_val
ues(by='average', ascending=False).head(50), x='avera
ge', y='feature');

/opt/conda/lib/python3.6/site-packages/pandas/core/fr
ame.py in __getitem__(self, key)

```

This kernel has been released under the [Apache 2.0](#) open source license.

Did you find this Kernel useful?

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0

Data

Data Sources

IEEE-CIS Fraud Detection

sample_submission.csv	507k x 2
test_identity.csv	142k x 41
test_transaction.csv	507k x 393
train_identity.csv	144k x 41
train_transaction.csv	591k x 394



IEEE-CIS Fraud Detection

Can you detect fraud from customer transactions?

Last Updated: 2 months ago

About this Competition

In this competition you are predicting the probability that an online transaction is fraudulent, as denoted by the binary target `isFraud`.

The data is broken into two files `identity` and `transaction`, which are joined by `TransactionID`. Not all transactions have corresponding identity information.

Categorical Features - Transaction

- `ProductCD`
- `card1 - card6`
- `addr1, addr2`
- `P_emaildomain`
- `R_emaildomain`
- `M1 - M9`

Categorical Features - Identity

- `DeviceType`
- `DeviceInfo`
- `id_12 - id_38`

The `TransactionDT` feature is a `timedelta` from a given reference datetime (not an actual timestamp).

You can read more about the data from [this post by the competition host](#).

Output Files

New Dataset

New Notebook

Download All



Output Files

ieee_cis_fraud_detection_1.csv

About this file

This file was created from a Kernel, it does not have a description.

ieee_cis_fraud_detection_1.csv



1	TransactionID	isFraud
2	3663549	0.5
3	3663550	0.5
4	3663551	0.5
5	3663552	0.5
6	3663553	0.5
7	3663554	0.5
8	3663555	0.5
9	3663556	0.5
10	3663557	0.5
11	3663558	0.5
12	3663559	0.5
13	3663560	0.5
14	3663561	0.5
15	3663562	0.5
16	3663563	0.5
17	3663564	0.5
18	3663565	0.5
19	3663566	0.5
20	3663567	0.5
21	3663568	0.5
22	3663569	0.5
23	3663570	0.5
24	3663571	0.5
25	3663572	0.5
26	3663573	0.5
27	3663574	0.5
28	3663575	0.5
29	3663576	0.5
30	3663577	0.5
31	3663578	0.5

Comments (0)



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