IEEE Fraud Detection

Part 1 - Fraudulent vs Non-Fraudulent Transaction

```
# TODO: code and runtime results
from google.colab import files
files.upload()
!pip install -q kaggle
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
!kaggle competitions download -c ieee-fraud-detection
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in

```
Saving kaggle.json to kaggle (2).json
Warning: Looks like you're using an outdated API Version, please consider updating (serv
train_transaction.csv.zip: Skipping, found more recently modified local copy (use --forc
train_identity.csv.zip: Skipping, found more recently modified local copy (use --force t
test_transaction.csv.zip: Skipping, found more recently modified local copy (use --force
test_identity.csv.zip: Skipping, found more recently modified local copy (use --force to
sample_submission.csv.zip: Skipping, found more recently modified local copy (use --forc
```

Write your answer here

```
import pandas as pd
transactions = pd.read_csv('train_transaction.csv.zip')
transactions.shape
identities = pd.read_csv('train_identity.csv.zip')
identities.shape
identities.head()
```

	TransactionID	id_01	id_02	id_03	id_04	id_05	id_06	id_07	id_08	id_09	id_1
0	2987004	0.0	70787.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
1	2987008	-5.0	98945.0	NaN	NaN	0.0	-5.0	NaN	NaN	NaN	Na
2	2987010	-5.0	191631.0	0.0	0.0	0.0	0.0	NaN	NaN	0.0	0.
3	2987011	-5.0	221832.0	NaN	NaN	0.0	-6.0	NaN	NaN	NaN	Na
4	2987016	0.0	7460.0	0.0	0.0	1.0	0.0	NaN	NaN	0.0	0.

```
fraudTransactions = transactions[transactions['isFraud'] == 1]
nonFraudTransactions = transactions[transactions['isFraud'] == 0]
```

```
fraudTransactions1 = fraudTransactions[['TransactionID','TransactionDT','TransactionAmt','
                                        'P_emaildomain','R_emaildomain','addr1','addr2','d
identitiesWithDTDI = identities[['TransactionID','DeviceType', 'DeviceInfo']]
fraudTransactions1WithIdentities = pd.merge(fraudTransactions1, identitiesWithDTDI, on='Tr

nonFraudTransactions1 = nonFraudTransactions[['TransactionID','TransactionDT','Transaction
                                        'P_emaildomain','R_emaildomain','addr1','addr2','d
nonFraudTransactions1WithIdentities = pd.merge(nonFraudTransactions1, identitiesWithDTDI,
fraudTransactions1WithIdentities.describe()
fraudTransactions1WithIdentities.head()

fraudTransactions1.shape
nonFraudTransactions1.shape
nonFraudTransactions1WithIdentities.shape
fraudTransactions1WithIdentities['DeviceInfo'].value_counts()
```

```
Windows                                 3121
iOS Device                              1240
MacOS                                    278
hi6210sft Build/MRA58K                   180
SM-A300H Build/LRX22G                    169
rv:57.0                                  103
Trident/7.0                               96
rv:11.0                                   76
LG-D320 Build/KOT49I.V10a                 61
SM-J700M Build/MMB29K                     60
SM-J320M Build/LMY47V                     57
CRO-L03 Build/HUAWEICRO-L03               51
KFFOWI Build/LVY48F                       51
rv:58.0                                   49
SM-A510M Build/MMB29K                     45
rv:59.0                                   44
Moto G (4) Build/NPJ25.93-14.7            40
SM-J500M Build/LMY48B                     39
SM-G920P Build/NRD90M                     39
SM-G610M Build/MMB29K                     37
Moto G (5) Plus Build/NPNS25.137-15-11    35
VS5012 Build/NRD90M                       34
SM-G950F Build/NRD90M                     34
SM-G531H Build/LMY48B                     33
SM-G955U Build/NRD90M                     33
Hisense L675 Build/MRA58K                 32
Moto E (4) Plus Build/NMA26.42-69         32
SM-G935F Build/NRD90M                     31
Moto Z2 Play Build/NPSS26.118-19-14       30
SM-J701M Build/NRD90M                     30
                                        ...
M4 SS4450 Build/MRA58K                     1
SAMSUNG SM-G925P Build/MMB29K              1
Beat                                       1
SM-N950U Build/R16NW                       1
SAMSUNG SM-J730GM Build/NRD90M             1
LG-SP320                                   1
LG-M327 Build/NRD90U                       1
SM-T530                                    1
rv:45.0                                    1
MotoG3 Build/MPI24.65-33.1-2               1
rv:61.0                                    1
Moto G (5) Plus Build/NPNS25.137-92-8      1
SM-T285M                                   1
SAMSUNG SM-G935A Build/NRD90M              1
ALCATEL                                    1
HUAWEI RIO-L03 Build/HUAWEIRIO-L03         1
SAMSUNG SM-G930F Build/NRD90M              1
LG-H420 Build/LRX21Y                       1
4047G Build/NRD90M                         1
SM-G900F Build/KOT49H                      1
P5526A Build/NRD90M                        1
SAMSUNG SM-N900W8 Build/LRX21V             1
iPhone                                     1
E2104                                      1
H1711 Build/HUAWEIH1711                    1
LG-H542 Build/MRA58K                       1
```

```
AERIAL                                       1
A5002                                        1
LG-H870 Build/NRD90U                         1
VTR-L09 Build/HUAWEIVTR-L09                  1
Name: DeviceInfo, Length: 420, dtype: int64
```

It looks like the most number of fraudulent transactions have been done through a Windows PC, with iOS comes a distant 2nd with around 1200 fraudulent transactions.

```
fraudTransactions1['TransactionAmt'].value_counts()
```

```
117.000     719
59.000      646
150.000     561
100.000     523
49.000      469
200.000     423
226.000     390
300.000     355
50.000      353
171.000     272
77.000      266
39.000      242
335.000     234
445.000     231
107.950     221
97.000      213
250.000     205
29.000      201
554.000     179
994.000     175
92.000      145
141.000     143
500.000     141
34.000      140
15.000      137
280.000     135
25.000      131
75.000      128
87.000      113
54.000      106
           ...
191.913       1
36.438        1
17.952        1
114.230       1
355.440       1
58.898        1
177.985       1
9.591         1
244.950       1
39.025        1
11.435        1
295.596       1
794.950       1
33.490        1
385.990       1
93.818        1
7.255         1
15.741        1
106.500       1
39.178        1
570.000       1
3076.970      1
109.127       1
28.579        1
17.082        1
73.838        1
```

```
117.456       1
46.786        1
355.000       1
13.381        1
Name: TransactionAmt, Length: 2515, dtype: int64
```

Here we get a very **interesting insight**. The** maximum number** of fraudulent transactions has beer **117**. It means that it's **easy** to do a fraudulent transaction for a **particular product**.

Same is the case for **some other items** with a particular price tag.

We perform this operation **only on the Transaction table** as when we join the table with the Identity ta **11k from 21k**, which I feel is a significant reduction in the sample size.

```
1 fraudTransactions1['ProductCD'].value_counts()
```

```
W    8969
C    8008
H    1574
R    1426
S     686
Name: ProductCD, dtype: int64
```

```
1 fraudTransactions1['card4'].value_counts()
```

```
visa                 13373
mastercard            6496
discover               514
american express       239
Name: card4, dtype: int64
```

When we take it as a percentage

The most fraudulent transactions have been done through the **visa** card

On the second place is a distant mastercard with as many as half the transactions than that done thro

All the other values are too few relative to **mastercard** and **visa**

```
1 nonFraudTransactions1['card4'].value_counts()
```

```
visa                 371394
mastercard           182721
american express       8089
discover               6137
Name: card4, dtype: int64
```

When we look for the percentage,

- Visa and mastercard have similar percentage of fraudulent transactions out of overall transactic
- 8% of all Discover card transactions are fraudulent which is quite high for a reputed firm.
- American Express stands at around 5%

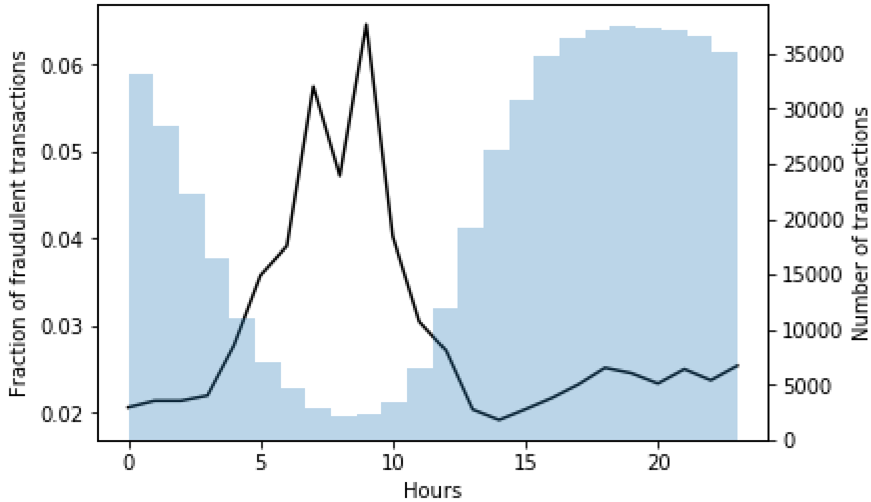
```
nonFraudTransactions1['card6'].value_counts()
```

```
debit               429264
credit              139036
debit or credit         30
charge card             15
Name: card6, dtype: int64
```

Part 2 - Transaction Frequency

```
trnFreq = transactions[['TransactionID', 'TransactionDT', 'addr2', 'isFraud']]
trnFreq.head()
trnFreq['addr2'].value_counts()
trnFreq['TransactionDT'].value_counts()

trnFreq87 = trnFreq[trnFreq['addr2'] == 87.0]
import matplotlib.pyplot as plt

import numpy as np
def make_hour_feature(df, tname='TransactionDT'):

    hours = df[tname] / (3600)
    encoded_hours = np.floor(hours) % 24
    return encoded_hours

trnFreq87['hours'] = make_hour_feature(trnFreq87)
plt.plot(trnFreq87.groupby('hours').mean()['isFraud'], color='k')
ax = plt.gca()
ax2 = ax.twinx()
_ = ax2.hist(trnFreq87['hours'], alpha=0.3, bins=24)
ax.set_xlabel('Hours')
ax.set_ylabel('Fraction of fraudulent transactions')

ax2.set_ylabel('Number of transactions')

```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:16: 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: http://pandas.pydata.org/pandas-docs/stable/indexi
  app.launch_new_instance()
Text(0, 0.5, 'Number of transactions')
```



Double-click (or enter) to edit

TransactionID

DeviceType (mobile/desktop/...)

DeviceInfo (Windows/MacOS/…)

TransactionDT (time delta from reference)

TransactionAmt (amount in USD)

ProductCD (product code - W/C/H/R/...)

card4 (card issuer)

card6 (debit/credit)

P_emaildomain (purchaser email)

R_emaildomain (recipient email)

addr1 / addr2 (billing region / billing country)

dist1 / dist2 (some form of distance - address, zip code, IP, phone, …)

```
# TODO: code to generate the frequency graph
```

Write your answer here

Part 3 - Product Code

```
transactions.head()
transactionsProdAmt = transactions[['TransactionID', 'TransactionAmt', 'ProductCD']]
transactionsProdAmt.head()
transactionsProdAmt['TransactionAmt'].value_counts()
transactionsProdAmt.groupby('ProductCD')['TransactionAmt'].mean()
```

```
ProductCD
C     42.872353
H     73.170058
R    168.306188
S     60.269487
W    153.158554
Name: TransactionAmt, dtype: float64
```

The product code R corresponds to the most expensive products with the mean of all the amounts cc

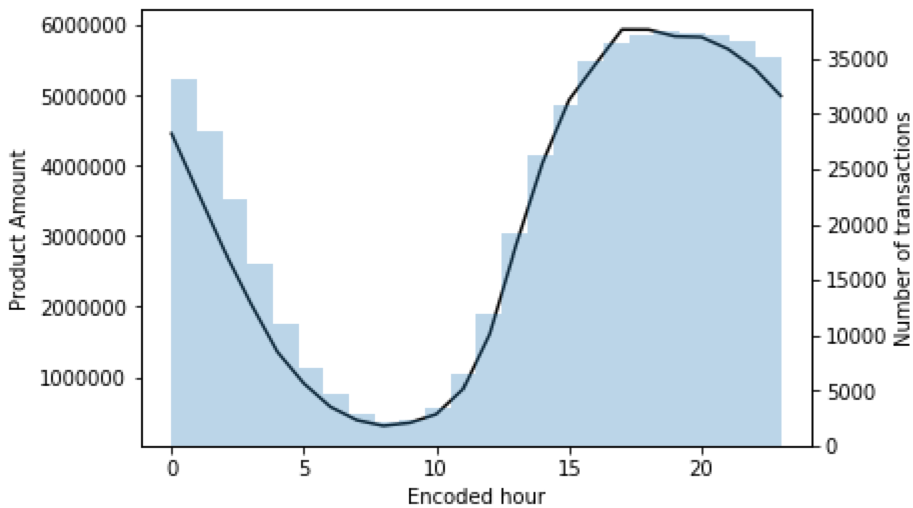
The product code C corresponds to the least expensive products with the mean of 42.87

Part 4 - Correlation Coefficient

```
# TODO: code to calculate correlation coefficient
todAmt = transactions[['TransactionID', 'TransactionDT', 'addr2', 'TransactionAmt','Produc
todAmt.head()
todAmt['addr2'].value_counts()
todAmt['TransactionDT'].value_counts()


todAmt87 = todAmt[todAmt['addr2'] == 87.0]
import matplotlib.pyplot as plt

import numpy as np
def make_hour_feature(df, tname='TransactionDT'):
    hours = df[tname] / (3600)
    encoded_hours = np.floor(hours) % 24
    return encoded_hours

todAmt87['hours'] = make_hour_feature(todAmt87)
plt.plot(todAmt87.groupby('hours')['TransactionAmt'].sum(), color='k')
ax = plt.gca()
ax2 = ax.twinx()
_ = ax2.hist(todAmt87['hours'], alpha=0.3, bins=24)
```

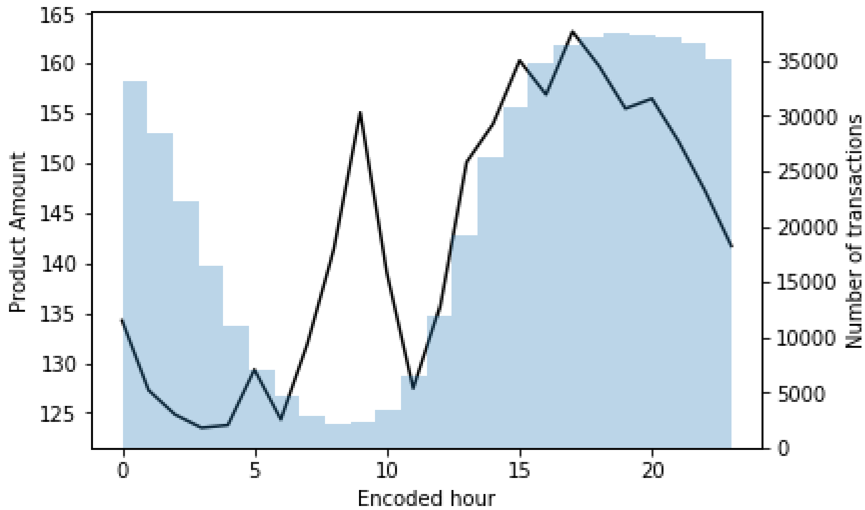
```
ax.set_xlabel('Encoded hour')
ax.set_ylabel('Product Amount')
ax2.set_ylabel('Number of transactions')

from scipy.stats import pearsonr
hour = []
for i in range(24):
  hour.append(i)
todAmt87SumGB = todAmt87.groupby('hours')['TransactionAmt'].sum()
todAmt87SumGB.describe()
list(todAmt87SumGB)
corr,_ = pearsonr(hour,todAmt87SumGB)
print('Pearsons correlation considering sum of Transaction Amount: %.3f' % corr)

```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:26: 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: http://pandas.pydata.org/pandas-docs/stable/indexi
Pearsons correlation considering sum of Transaction Amount: 0.651
```




```
plt.plot(todAmt87.groupby('hours')['TransactionAmt'].mean(), color='k')
axM = plt.gca()
axM2 = axM.twinx()
_ = axM2.hist(todAmt87['hours'], alpha=0.3, bins=24)
axM.set_xlabel('Encoded hour')
axM.set_ylabel('Product Amount')
axM2.set_ylabel('Number of transactions')

todAmt87MeanGB = todAmt87.groupby('hours')['TransactionAmt'].mean()
todAmt87MeanGB.describe()
list(todAmt87MeanGB)
corr,_ = pearsonr(hour,todAmt87MeanGB)
print('Pearsons correlation considering mean of Transaction Amount: %.3f' % corr)
```

```
Pearsons correlation considering mean of Transaction Amount: 0.756
```



Write your answer here

Part 5 - Interesting Plot

```
# TODO: code to generate the plot here.
```

The plots of time of day vs product is interesting and it's getting a correlation co-efficient of 0.65

Also, the plost of card6 variable vs isFraud is interesting. The percentage of number of fraudulent trar than that of debit card!!!! Beware credit card holders!

Part 6 - Prediction Model

Write your answer here

```
# TODO: code for your final model
import seaborn as sns
sns.countplot(x='isFraud',hue = 'card6', data=transactions)
transactionAmtByFraudness = transactions.groupby('isFraud')['TransactionAmt'].sum()
list(transactionAmtByFraudness)

transactions.isnull().sum()
transactions.groupby('isFraud').mean()

```

```
from sklearn.model_selection import train_test_split
cleanup_Prod = {"ProductCD":     {"C": 4, "H": 2, "S": 3, "R":4, "W":5}}
cleanup_card6 = {"card6": {"debit":1, "credit":2, "debit or credit":3, "charge card": 4}}
todAmtReplaced = todAmt87.replace(cleanup_Prod)
feature_cols = ['TransactionAmt', 'hours', 'ProductCD']

X = todAmtReplaced[feature_cols] # Features
y = todAmtReplaced.isFraud # Target variable
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state=0)

#split dataset in features and target variable

from sklearn.linear_model import LogisticRegression

# instantiate the model (using the default parameters)
logreg = LogisticRegression()

# fit the model with data
logreg.fit(X_train,y_train)

```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarni
  FutureWarning)
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```


```
todAmtReplaced['card6'].fillna(0, inplace=True)
todAmtReplaced['card6'].isna().sum()
transactions['DeviceType'].value_counts()
```

```
transactions_test = pd.read_csv('test_transaction.csv.zip')
transactions_test.replace(cleanup_Prod, inplace=True)

```

```
transactions_test['hours'] = make_hour_feature(transactions_test)
cleanup_Prod = {"ProductCD":     {"C": 4, "H": 2, "S": 3, "R":4, "W":5}}
```

```
transactions_test.head()
transactions_test_columns = transactions_test[['TransactionAmt', 'hours', 'ProductCD']]
transactions_test_columns.head()
```

	TransactionAmt	hours	ProductCD
0	31.95	0.0	5
1	49.00	0.0	5
2	171.00	0.0	5
3	284.95	0.0	5
4	67.95	0.0	5

```
y_pred=logreg.predict(transactions_test_columns)

sampleSubmission = pd.read_csv("sample_submission.csv.zip")
sampleSubmission['isFraud'] = y_pred
sampleSubmission.head()

sampleSubmission.to_csv("sampleSubmission1.csv")
sampleSubmission.head()
```

	TransactionID	isFraud
0	3663549	0
1	3663550	0
2	3663551	0
3	3663552	0
4	3663553	0

Part 7 - Final Result

Score: 0.88