Homework 2 - IEEE Fraud Detection

Part 0 - Setup that is required to run the code (Required to load data)

```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A

Enter your authorization code:
··········
Mounted at /content/gdrive
```

```
cd '/content/gdrive/My Drive/Semester I/Data Science Fundamentals/Submission'
```

```
/content/gdrive/My Drive/Semester I/Data Science Fundamentals/Submission
```

```
import pandas as pd
TRAIN_TRANSACTION_DATA = pd.read_csv('train_transaction.csv')
TRAIN_IDENTITY_DATA = pd.read_csv('train_identity.csv')
Skiena_Columns= ['TransactionID','TransactionDT','TransactionAmt','ProductCD','card4','card6','P_emaildomain','R_emaildomain','addr1','addr2','dist1','dist2','DeviceType','DeviceInfo','isFraud']

#JOIN with IDENTITY COLUMN

TRAIN_TRANSACTION_DATA_FINAL = pd.merge(pd.DataFrame(TRAIN_TRANSACTION_DATA),pd.DataFrame(TRAIN_IDENTITY_DATA), how='left', on = 'TransactionID')

#EXTRACTING COLUMNS IN THE ASSIGMENT

TRAIN_TRANSACTION_DATA_SKIENA=TRAIN_TRANSACTION_DATA_FINAL[Skiena_Columns]
```

For all parts below, answer all parts as shown in the Google document for Homework 2. Be sure to include both code that justifies your answer as well as text to answer the questions. We also ask that code be commented to make it easier to follow.

Part 1 - Fraudulent vs Non-Fraudulent Transaction

Part 1(a) - Preprocessing

```
TRAIN_TRANSACTION_DATA_SKIENA.head(5)
```

	TransactionID	TransactionDT	TransactionAmt	ProductCD	card4	card6	P_emaildomain	R_emaildomain	addr1	addr2	dist1	dist2	DeviceType	DeviceInfo	isFraud
0	2987000	86400	68.5	W	discover	credit	NaN	NaN	315.0	87.0	19.0	NaN	NaN	NaN	0
1	2987001	86401	29.0	W	mastercard	credit	gmail.com	NaN	325.0	87.0	NaN	NaN	NaN	NaN	0
2	2987002	86469	59.0	W	visa	debit	outlook.com	NaN	330.0	87.0	287.0	NaN	NaN	NaN	0
3	2987003	86499	50.0	W	mastercard	debit	yahoo.com	NaN	476.0	87.0	NaN	NaN	NaN	NaN	0
4	2987004	86506	50.0	H	mastercard	credit	gmail.com	NaN	420.0	87.0	NaN	NaN	mobile	SAMSUNG SM-G892A	0

```
pd.Series(TRAIN_TRANSACTION_DATA_SKIENA['addr1'].unique()).sort_values().head(5)
```

```
113    100.0
239    101.0
154    102.0
277    104.0
289    105.0
dtype: float64
```

```
pd.Series(TRAIN_TRANSACTION_DATA_SKIENA['addr2'].unique()).sort_values().head(5)
```

```
50    10.0
9     13.0
34    14.0
14    15.0
13    16.0
dtype: float64
```

```
pd.Series(TRAIN_TRANSACTION_DATA_SKIENA['dist1'].unique()).sort_values().head(5)
```

```
4     0.0
19    1.0
10    2.0
5     3.0
7     4.0
dtype: float64
```

```
pd.Series(TRAIN_TRANSACTION_DATA_SKIENA['dist2'].unique()).sort_values().head(5)
```

```
17     0.0
31     1.0
16     2.0
126    3.0
14     4.0
dtype: float64
```

```
from sklearn import preprocessing
import numpy as np

# PREPROCESSING
#P_emaildomain, R_emaildomain and DeviceInfo with LabelEncoder since they contain String fields that can be labelled.

# Moreover, fields like emaildomain can go huge and hence OneHot Encoding is not a good idea
```

```
le_p = preprocessing.LabelEncoder()
le_p.fit(np.unique(TRAIN_TRANSACTION_DATA_SKIENA['P_emaildomain'].astype(str)))

le_r = preprocessing.LabelEncoder()
le_r.fit(np.unique(TRAIN_TRANSACTION_DATA_SKIENA['R_emaildomain'].astype(str)))

le_d = preprocessing.LabelEncoder()
le_d.fit(np.unique(TRAIN_TRANSACTION_DATA_SKIENA['DeviceInfo'].astype(str)))

TRAIN_TRANSACTION_DATA_SKIENA['R_emaildomain']=pd.DataFrame(TRAIN_TRANSACTION_DATA_SKIENA['R_emaildomain'].astype(str)).apply(le_r.transform)
TRAIN_TRANSACTION_DATA_SKIENA['P_emaildomain']=pd.DataFrame(TRAIN_TRANSACTION_DATA_SKIENA['P_emaildomain'].astype(str)).apply(le_p.transform)
TRAIN_TRANSACTION_DATA_SKIENA['DeviceInfo']=pd.DataFrame(TRAIN_TRANSACTION_DATA_SKIENA['DeviceInfo'].astype(str)).apply(le_d.transform)

##Shown above, addr1 and addr2 does not contain 0 and hence 0 can be put for nan values
##Shown above, dist1 and dist2 does contain 0 and hence -1 should be put for nan values
TRAIN_TRANSACTION_DATA_SKIENA['dist2'].fillna(-1.0,inplace=True)
TRAIN_TRANSACTION_DATA_SKIENA['dist1'].fillna(-1.0,inplace=True)
TRAIN_TRANSACTION_DATA_SKIENA['addr2'].fillna(0.0,inplace=True)
TRAIN_TRANSACTION_DATA_SKIENA['addr1'].fillna(0.0,inplace=True)



## TransactionDT looks like a timestamp in seconds and hence it is wise to extract data it contains in hours and use that


Onehot_hour=pd.DataFrame(pd.to_datetime(TRAIN_TRANSACTION_DATA_SKIENA['TransactionDT'],unit='s').dt.hour)
Onehot_hour.columns=['hour']
TRAIN_TRANSACTION_DATA_SKIENA['hour']=pd.DataFrame(Onehot_hour)


## ProductCD, card4 and card6 and DeviceType contains limited set values and can strongly influence decision making which will be shown further
## Hence separate features for them using OneHot Encoding
Onehot=pd.DataFrame(pd.get_dummies(TRAIN_TRANSACTION_DATA_SKIENA['ProductCD']))
TRAIN_TRANSACTION_DATA_SKIENA=TRAIN_TRANSACTION_DATA_SKIENA.join(Onehot)
Onehot=pd.DataFrame(pd.get_dummies(TRAIN_TRANSACTION_DATA_SKIENA['card4']))
TRAIN_TRANSACTION_DATA_SKIENA=TRAIN_TRANSACTION_DATA_SKIENA.join(Onehot)
Onehot=pd.DataFrame(pd.get_dummies(TRAIN_TRANSACTION_DATA_SKIENA['card6']))
TRAIN_TRANSACTION_DATA_SKIENA=TRAIN_TRANSACTION_DATA_SKIENA.join(Onehot)
Onehot=pd.DataFrame(pd.get_dummies(TRAIN_TRANSACTION_DATA_SKIENA['DeviceType']))
TRAIN_TRANSACTION_DATA_SKIENA=TRAIN_TRANSACTION_DATA_SKIENA.join(Onehot)

TRAIN_TRANSACTION_DATA_SKIENA.drop(columns=['card4','card6','ProductCD','DeviceType','TransactionDT'],inplace=True)
```

Data after preprocessing and cleaning

```
TRAIN_TRANSACTION_DATA_SKIENA.head(10)
```

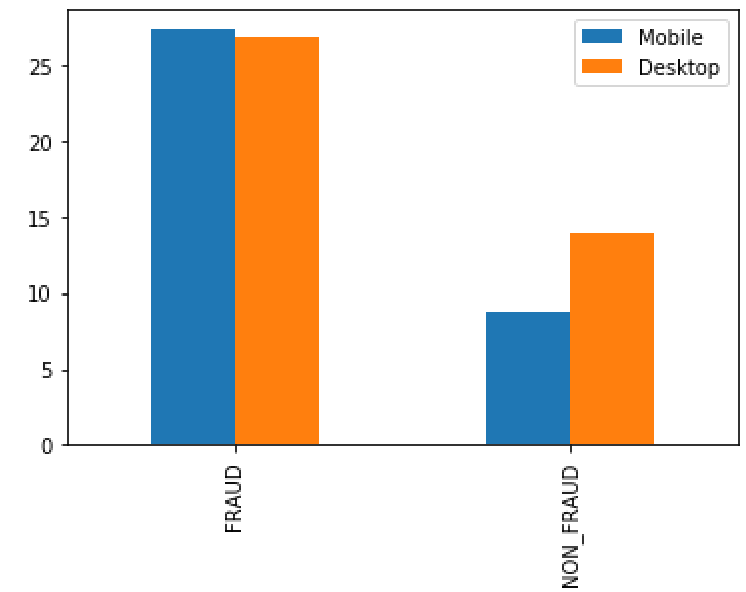
	TransactionID	TransactionAmt	P_emaildomain	R_emaildomain	addr1	addr2	dist1	dist2	DeviceInfo	isFraud	hour	C	H	R	S	W	american express	discover	mastercard	visa	charge card	credit	debit
0	2987000	68.5	32	32	315.0	87.0	19.0	-1.0	1742	0	0	0	0	0	0	1	0	1	0	0	0	1	0
1	2987001	29.0	16	32	325.0	87.0	-1.0	-1.0	1742	0	0	0	0	0	0	1	0	0	1	0	0	1	0
2	2987002	59.0	36	32	330.0	87.0	287.0	-1.0	1742	0	0	0	0	0	0	1	0	0	0	1	0	0	1
3	2987003	50.0	54	32	476.0	87.0	-1.0	-1.0	1742	0	0	0	0	0	0	1	0	0	1	0	0	0	1
4	2987004	50.0	16	32	420.0	87.0	-1.0	-1.0	954	0	0	0	1	0	0	0	0	0	1	0	0	1	0
5	2987005	49.0	16	32	272.0	87.0	36.0	-1.0	1742	0	0	0	0	0	0	1	0	0	0	1	0	0	1
6	2987006	159.0	54	32	126.0	87.0	0.0	-1.0	1742	0	0	0	0	0	0	1	0	0	0	1	0	0	1
7	2987007	422.5	29	32	325.0	87.0	-1.0	-1.0	1742	0	0	0	0	0	0	1	0	0	0	1	0	0	1
8	2987008	15.0	1	32	337.0	87.0	-1.0	-1.0	1727	0	0	0	1	0	0	0	0	0	0	1	0	0	1
9	2987009	117.0	54	32	204.0	87.0	19.0	-1.0	1742	0	0	0	0	0	0	1	0	0	1	0	0	0	1

TransactionID can be skipped as that is a simple identity field and it will not influence a fraudulent nature of transaction.

Device Type and Fradulent nature

```
TRAIN_T_D_FRAUD = TRAIN_TRANSACTION_DATA_SKIENA['isFraud']>0.02
TRAIN_T_D_NON_FRAUD = TRAIN_TRANSACTION_DATA_SKIENA['isFraud']<=0.02
TRAIN_T_D_FRAUD_DATA = TRAIN_TRANSACTION_DATA_SKIENA[TRAIN_T_D_FRAUD]
TRAIN_T_D_NON_FRAUD_DATA = TRAIN_TRANSACTION_DATA_SKIENA[TRAIN_T_D_NON_FRAUD]
TRAIN_TRANSACTION_DATA_FRAUD_TID = TRAIN_T_D_FRAUD_DATA['TransactionID']
TRAIN_TRANSACTION_DATA_NONFRAUD_TID = TRAIN_T_D_NON_FRAUD_DATA['TransactionID']


FRAUD_DEVICE_TYPE_MOBILE = TRAIN_T_D_FRAUD_DATA.loc[TRAIN_T_D_FRAUD_DATA['mobile']==1]
FRAUD_DEVICE_TYPE_DESKTOP = TRAIN_T_D_FRAUD_DATA.loc[TRAIN_T_D_FRAUD_DATA['desktop']==1]
NON_FRAUD_DEVICE_TYPE_MOBILE = TRAIN_T_D_NON_FRAUD_DATA.loc[TRAIN_T_D_NON_FRAUD_DATA['mobile']==1]
NON_FRAUD_DEVICE_TYPE_DESKTOP = TRAIN_T_D_NON_FRAUD_DATA.loc[TRAIN_T_D_NON_FRAUD_DATA['desktop']==1]

FRAUD_DEVICE_TYPE_COUNT_MOBILE = pd.DataFrame(FRAUD_DEVICE_TYPE_MOBILE).shape[0]
FRAUD_DEVICE_TYPE_COUNT_DESKTOP = FRAUD_DEVICE_TYPE_DESKTOP.shape[0]
FRAUD_DEVICE_TYPE_COUNT_TOTAL = TRAIN_T_D_FRAUD_DATA.shape[0]


NON_FRAUD_DEVICE_TYPE_COUNT_MOBILE = pd.DataFrame(NON_FRAUD_DEVICE_TYPE_MOBILE).shape[0]
NON_FRAUD_DEVICE_TYPE_COUNT_DESKTOP = NON_FRAUD_DEVICE_TYPE_DESKTOP.shape[0]
NON_FRAUD_DEVICE_TYPE_COUNT_TOTAL = TRAIN_T_D_NON_FRAUD_DATA.shape[0]

MOB = { 'NON_FRAUD':(NON_FRAUD_DEVICE_TYPE_COUNT_MOBILE*100.0/NON_FRAUD_DEVICE_TYPE_COUNT_TOTAL),'FRAUD':(FRAUD_DEVICE_TYPE_COUNT_MOBILE*100.0/FRAUD_DEVICE_TYPE_COUNT_TOTAL)}
DESK = { 'NON_FRAUD':(NON_FRAUD_DEVICE_TYPE_COUNT_DESKTOP*100.0/NON_FRAUD_DEVICE_TYPE_COUNT_TOTAL),'FRAUD':(FRAUD_DEVICE_TYPE_COUNT_DESKTOP*100.0/FRAUD_DEVICE_TYPE_COUNT_TOTAL)}
Q1_DEVICETYPE = pd.DataFrame({'Mobile': MOB,'Desktop': DESK})

Q1_DEVICETYPE.plot.bar()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98ca803780>
```



The above graph shows that in fraudulent transactions, Mobile and Desktop contributed equally whereas in non fraduent cases Mobile had a fairly small share which goes into proving that Mobile was used for a lot of fraudulent activities(about 28%) as compared to that of non fradulent (about 8%) and can possibly be used as a feature.

TransactionDT can be converted to hour and used to analyse fradulent behaviour

```
DT_FRAUD=pd.DataFrame(TRAIN_T_D_FRAUD_DATA.groupby('hour').size()/TRAIN_T_D_FRAUD_DATA.groupby('hour').size().sum())
DT_NON_FRAUD=pd.DataFrame(TRAIN_T_D_NON_FRAUD_DATA.groupby('hour').size()/TRAIN_T_D_NON_FRAUD_DATA.groupby('hour').size().sum())
DT_FRAUD.columns=['Fraud']
DT_FRAUD['Non Fraud'] = DT_NON_FRAUD
DT_FRAUD.plot.line()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98c9ea23c8>
```

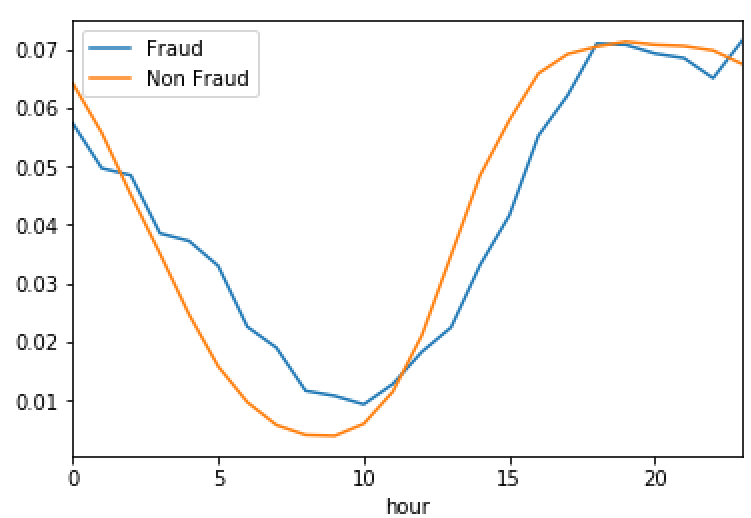
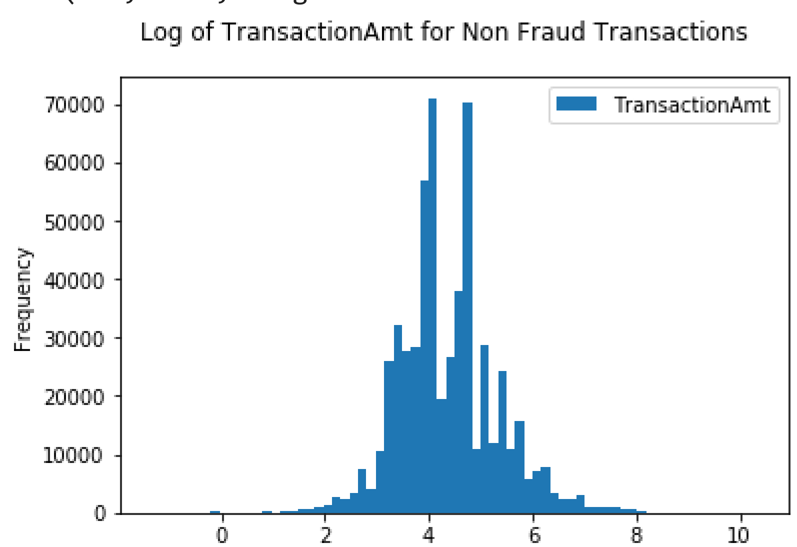


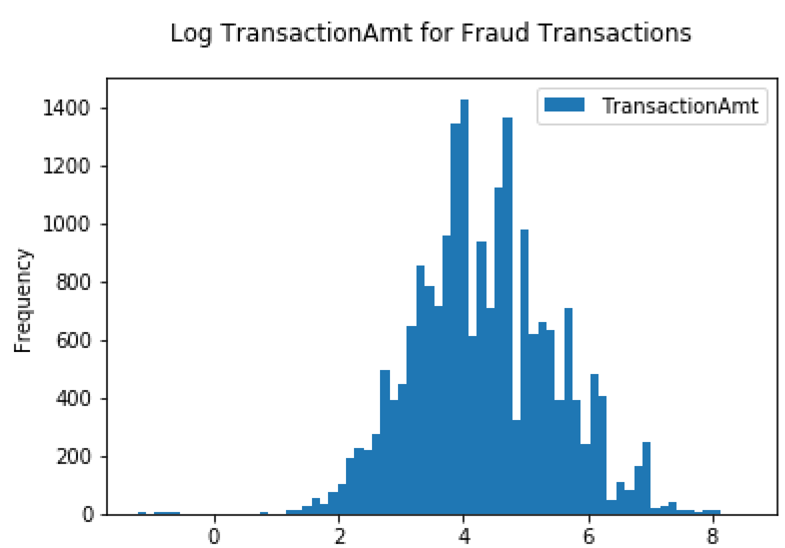
Figure shows that TransactionDT or 'hour of transaction' followed the same pattern. Therefore, there was nothing that the hour of

```
AMT_FRAUD=pd.DataFrame(TRAIN_T_D_FRAUD_DATA['TransactionAmt'])
AMT_NON_FRAUD=pd.DataFrame(TRAIN_T_D_NON_FRAUD_DATA['TransactionAmt'])
```

```
import pylab as pl
np.log(AMT_NON_FRAUD).plot.hist(bins=70)
pl.suptitle("Log of TransactionAmt for Non Fraud Transactions")

np.log(AMT_FRAUD).plot.hist(bins=70)
pl.suptitle("Log TransactionAmt for Fraud Transactions")
```

```
Text(0.5, 0.98, 'Log TransactionAmt for Fraud Transactions')
```





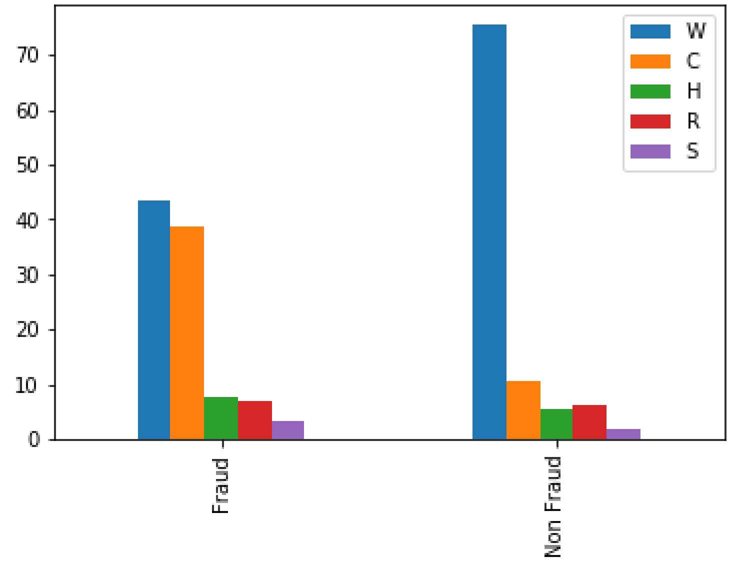
Transaction Amt also shows a similar trend and hence is not a suitable candidate for feature.

Note: Log is taken because transaction values are too large

```
FRAUD_PRODUCT_CD = pd.DataFrame((TRAIN_T_D_FRAUD_DATA[['W','C','H','R','S']].sum() * 100/TRAIN_T_D_FRAUD_DATA[['W','C','H','R','S']].sum().sum()))
FRAUD_PRODUCT_CD.columns = ['Fraud']
FRAUD_PRODUCT_CD['Fraud'] = pd.DataFrame(FRAUD_PRODUCT_CD)
NON_FRAUD_PRODUCT_CD = pd.DataFrame(TRAIN_T_D_NON_FRAUD_DATA[['W','C','H','R','S']].sum() * 100 /TRAIN_T_D_NON_FRAUD_DATA[['W','C','H','R','S']].sum().sum())
```

```
FRAUD_PRODUCT_CD['Non Fraud'] = pd.DataFrame(NON_FRAUD_PRODUCT_CD)
FRAUD_PRODUCT_CD.transpose().plot.bar()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98bfb350b8>
```



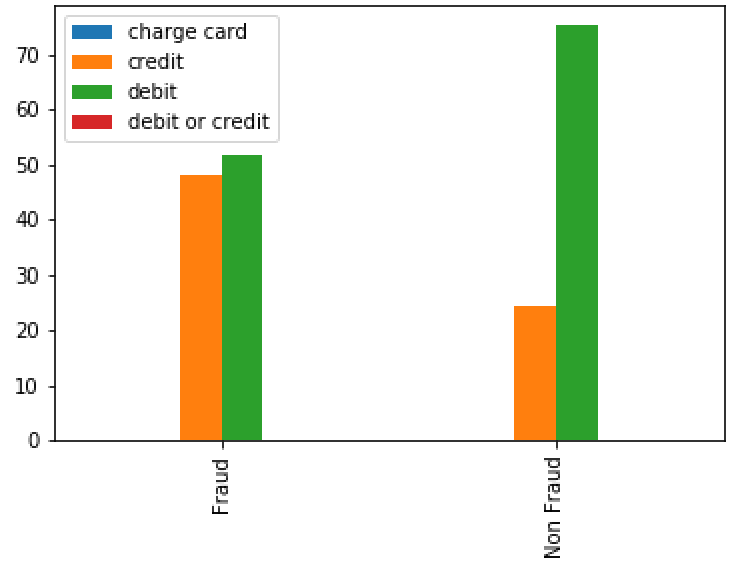
NonFraud Transactions are dominated by W product type.

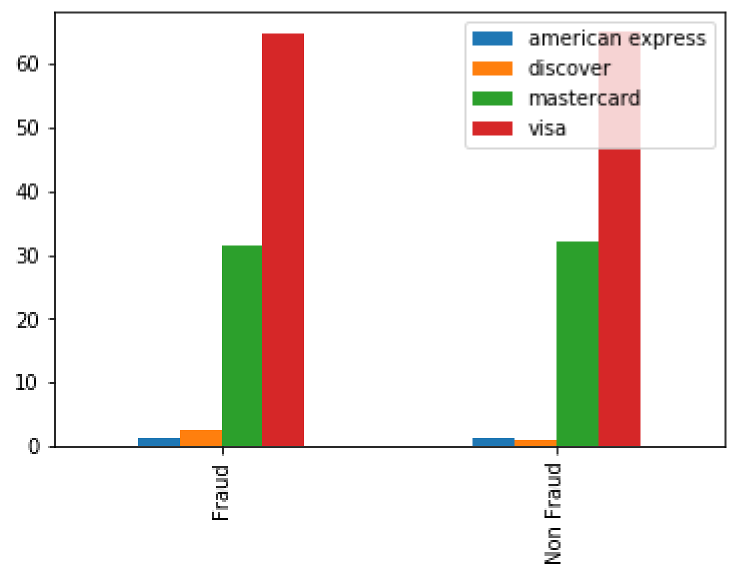
In case of fraudulent transactions, there is an unexpected rise in the percent of ProductType C. This can be used as feature and a purchase of Product Type C has a much higher chance of it being C when compare to other product types.

```
NON_FRAUD_CARD_4= TRAIN_T_D_NON_FRAUD_DATA[['american express', 'discover', 'mastercard', 'visa']][(TRAIN_T_D_NON_FRAUD_DATA['american express']==1) |
                                                                                (TRAIN_T_D_NON_FRAUD_DATA['discover']==1) |
                                                                                (TRAIN_T_D_NON_FRAUD_DATA['mastercard']==1)|
                                                                                (TRAIN_T_D_NON_FRAUD_DATA['visa']==1)
                                                                               ].sum()*100/TRAIN_T_D_NON_FRAUD_DATA.shape[0]
NON_FRAUD_CARD_6= TRAIN_T_D_NON_FRAUD_DATA[['charge card', 'credit', 'debit', 'debit or credit']][(TRAIN_T_D_NON_FRAUD_DATA['charge card']==1) |
                                                                                (TRAIN_T_D_NON_FRAUD_DATA['credit']==1) |
                                                                                (TRAIN_T_D_NON_FRAUD_DATA['debit']==1)|
                                                                                (TRAIN_T_D_NON_FRAUD_DATA['debit or credit']==1)
                                                                               ].sum()*100/TRAIN_T_D_NON_FRAUD_DATA.shape[0]
FRAUD_CARD_4= TRAIN_T_D_FRAUD_DATA[['american express', 'discover', 'mastercard', 'visa']][
                                                                                (TRAIN_T_D_FRAUD_DATA['american express']==1) |
                                                                                (TRAIN_T_D_FRAUD_DATA['discover']==1) |
                                                                                (TRAIN_T_D_FRAUD_DATA['mastercard']==1)|
                                                                                (TRAIN_T_D_FRAUD_DATA['visa']==1)
                                                                               ].sum()*100/TRAIN_T_D_FRAUD_DATA.shape[0]
FRAUD_CARD_6= TRAIN_T_D_FRAUD_DATA[['charge card', 'credit', 'debit', 'debit or credit']][
                                                                                (TRAIN_T_D_FRAUD_DATA['charge card']==1) |
                                                                                (TRAIN_T_D_FRAUD_DATA['credit']==1) |
                                                                                (TRAIN_T_D_FRAUD_DATA['debit']==1)|
                                                                                (TRAIN_T_D_FRAUD_DATA['debit or credit']==1)
                                                                               ].sum()*100/TRAIN_T_D_FRAUD_DATA.shape[0]

NON_FRAUD_CARD_6 = pd.DataFrame(NON_FRAUD_CARD_6)
FRAUD_CARD_6 = pd.DataFrame(FRAUD_CARD_6)
FRAUD_CARD_6.columns = ['Fraud']
FRAUD_CARD_6['Non Fraud']  = NON_FRAUD_CARD_6
FRAUD_CARD_6.transpose().plot.bar()


NON_FRAUD_CARD_4 = pd.DataFrame(NON_FRAUD_CARD_4)
FRAUD_CARD_4 = pd.DataFrame(FRAUD_CARD_4)
FRAUD_CARD_4.columns = ['Fraud']
```

```
FRAUD_CARD_4['Non Fraud']  = NON_FRAUD_CARD_4
FRAUD_CARD_4.transpose().plot.bar()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98bf772828>
```





The card4 column shows cardtype. "credit" card shown an unexpected rise in percent in fraudulent cases and hence can be used as feature. "debit" on the other hand, shows a decrease in percent in case of fraudulent cases making a "debit" transaction much safer that "credit"

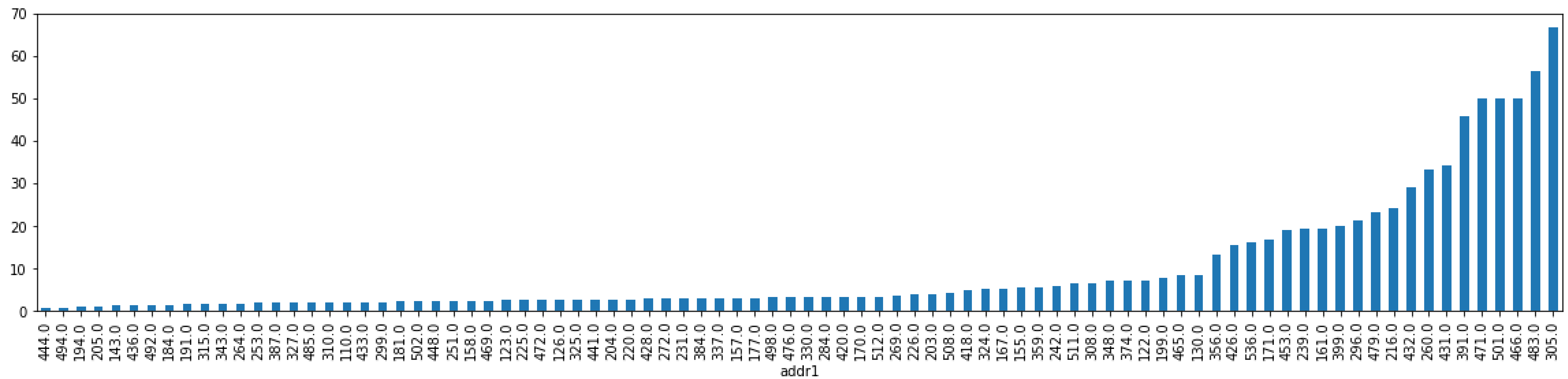
Company issuing the card in card6 columns reveals no fruitful info,

```
np.log(TRAIN_T_D_NON_FRAUD_DATA[TRAIN_T_D_NON_FRAUD_DATA['addr1']!=0.0].groupby('addr1').size().sort_values()).tail(100).plot.bar(figsize=(25,4))
```

```
A=pd.DataFrame(TRAIN_T_D_FRAUD_DATA[TRAIN_T_D_FRAUD_DATA['addr1']>1.0].groupby('addr1').size())
B=pd.DataFrame(TRAIN_T_D_NON_FRAUD_DATA[TRAIN_T_D_NON_FRAUD_DATA['addr1']!=0.0].groupby('addr1').size())

A.columns=['Fraud']
```

```
A['Non Fraud']= pd.DataFrame(B)
A['percent']= A['Fraud']*100/(A['Fraud'] + A['Non Fraud'])
A['percent'].sort_values().plot.bar(figsize=(20,4))
A.sort_values(by='percent').tail(7)
```

addr1	Fraud	Non Fraud	percent
431.0	13	25	34.210526
391.0	16	19	45.714286
471.0	1	1	50.000000
501.0	2	2	50.000000
466.0	1	1	50.000000
483.0	13	10	56.521739
305.0	6	3	66.666667

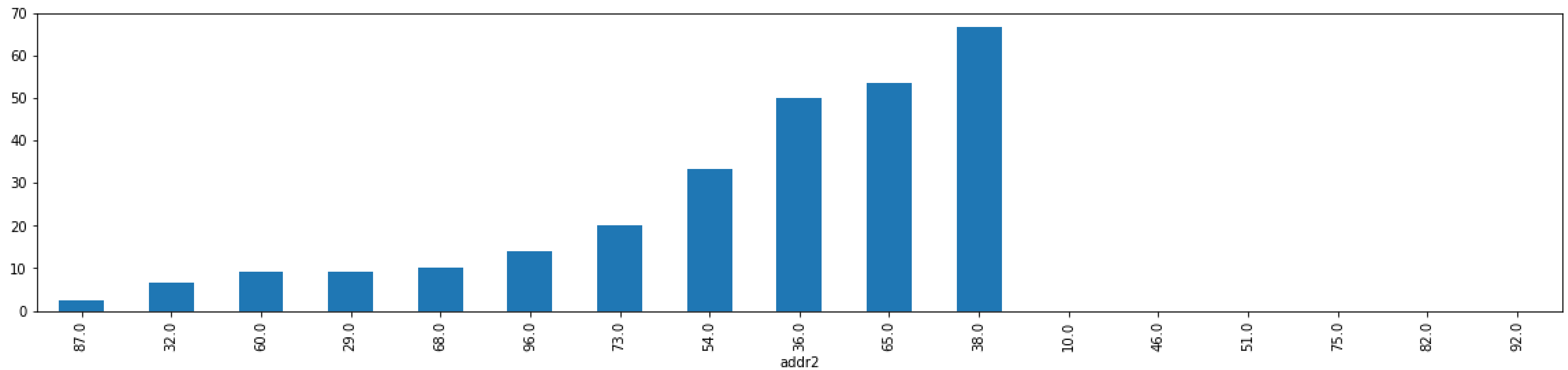


In areas with addr1 as 391, 471, 501, 466, 483, 395 there is more than 45% fraudulent traffic

```
np.log(TRAIN_T_D_NON_FRAUD_DATA[TRAIN_T_D_NON_FRAUD_DATA['addr2']!=0.0].groupby('addr2').size()).tail(100).plot.bar(figsize=(25,4))
```

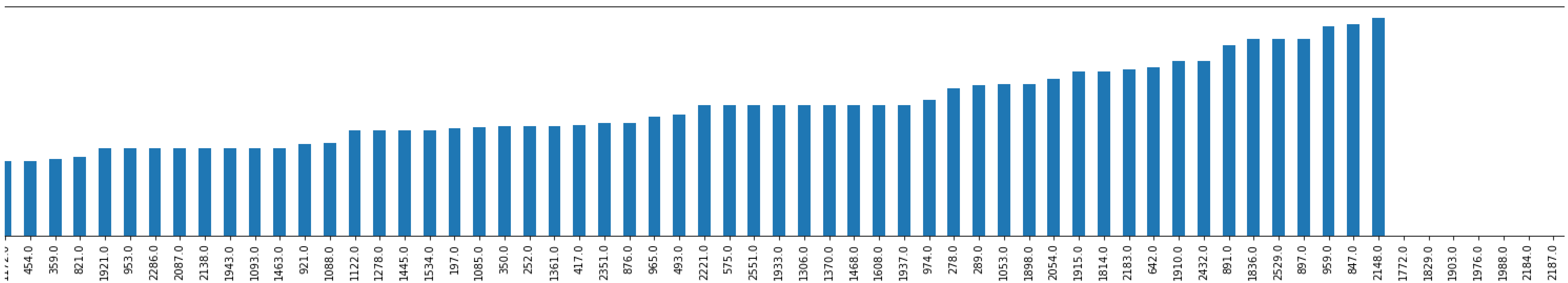
```
A=pd.DataFrame(TRAIN_T_D_FRAUD_DATA[TRAIN_T_D_FRAUD_DATA['addr2']!=0.0].groupby('addr2').size())
B=pd.DataFrame(TRAIN_T_D_NON_FRAUD_DATA[TRAIN_T_D_NON_FRAUD_DATA['addr2']!=0.0].groupby('addr2').size())

A.columns=['Fraud']
A['Non Fraud']= pd.DataFrame(B)

A['percent']= A['Fraud']*100/(A['Fraud'] + A['Non Fraud'])
A['percent'].sort_values().plot.bar(figsize=(20,4))
A.sort_values(by='percent').tail(7)
```

	Fraud	Non Fraud	percent
addr2			
38.0	2	1.0	66.666667
10.0	8	NaN	NaN
46.0	3	NaN	NaN
51.0	4	NaN	NaN
75.0	1	NaN	NaN
82.0	1	NaN	NaN
92.0	2	NaN	NaN



66% transactions with addr2 are fraudulent

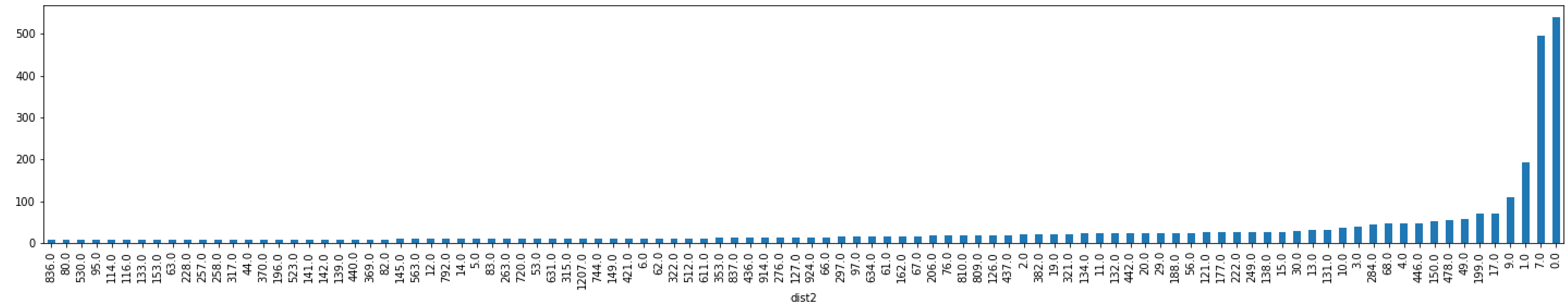
```
A=pd.DataFrame(TRAIN_T_D_FRAUD_DATA[TRAIN_T_D_FRAUD_DATA['dist1']!=-1.0].groupby('dist1').size())
B=pd.DataFrame(TRAIN_T_D_NON_FRAUD_DATA[TRAIN_T_D_NON_FRAUD_DATA['dist1']!=-1.0].groupby('dist1').size())
A.columns=['Fraud']

A['Non Fraud']= pd.DataFrame(B)

A['percent']= A['Fraud']*100/(A['Fraud'] + A['Non Fraud'])
A['percent'].sort_values().plot.bar(figsize=(200,4))
A.sort_values(by='percent').tail(7)
```



70+ % transactions through with dist 1 as '2148' are fraudulent

```
TRAIN_T_D_FRAUD_DATA[TRAIN_T_D_FRAUD_DATA['dist2']!=-1.0].groupby('dist2').size().sort_values().tail(100).plot.bar(figsize=(25,4))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98ba6c8d30>
```



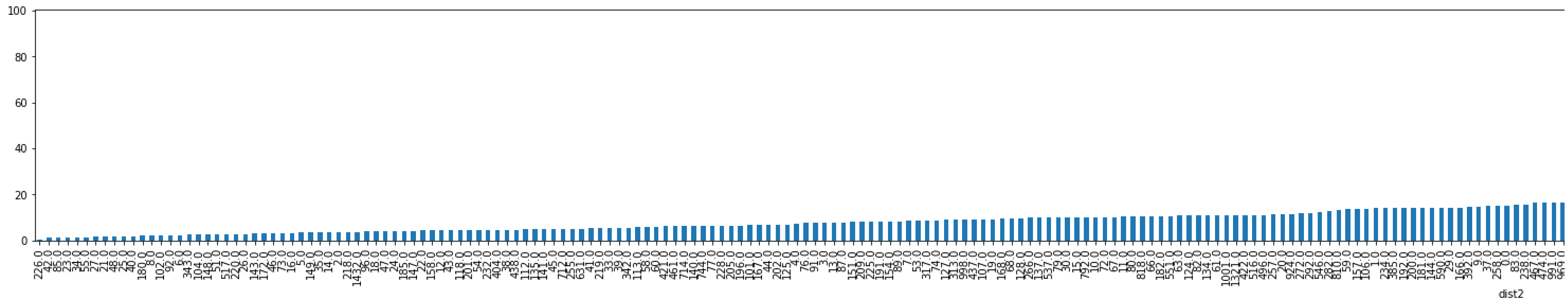

```
A=pd.DataFrame(TRAIN_T_D_NON_FRAUD_DATA[TRAIN_T_D_NON_FRAUD_DATA['dist2']!=-1.0].groupby('dist2').size())
B=pd.DataFrame(TRAIN_T_D_FRAUD_DATA[TRAIN_T_D_FRAUD_DATA['dist2']!=-1.0].groupby('dist2').size())
A.columns=['Non Fraud']
A['Fraud']= pd.DataFrame(B)

A['percent']= A['Fraud']*100/(A['Fraud'] + A['Non Fraud'])
```

```
TRAIN_T_D_FRAUD_DATA.groupby('dist2').size().head(200).tail(25)
```

```
dist2
293.0     5
295.0     1
297.0    15
313.0     1
315.0     9
317.0     7
321.0    21
322.0    10
333.0     1
339.0     3
342.0     3
343.0     2
348.0     4
351.0     1
353.0    12
354.0     1
355.0     1
361.0     2
367.0     1
369.0     8
370.0     7
371.0     5
377.0     2
382.0    21
384.0     1
dtype: int64
```

```
A.dropna(subset=['percent'], inplace=True)
A['percent'].sort_values().plot.bar(figsize=(50,4))

A.sort_values(by='percent').tail(5)
```

	Non Fraud	Fraud	percent
dist2			
249.0	7	26.0	78.787879
1176.0	1	4.0	80.000000
2018.0	1	4.0	80.000000
1459.0	1	5.0	83.333333
382.0	1	21.0	95.454545

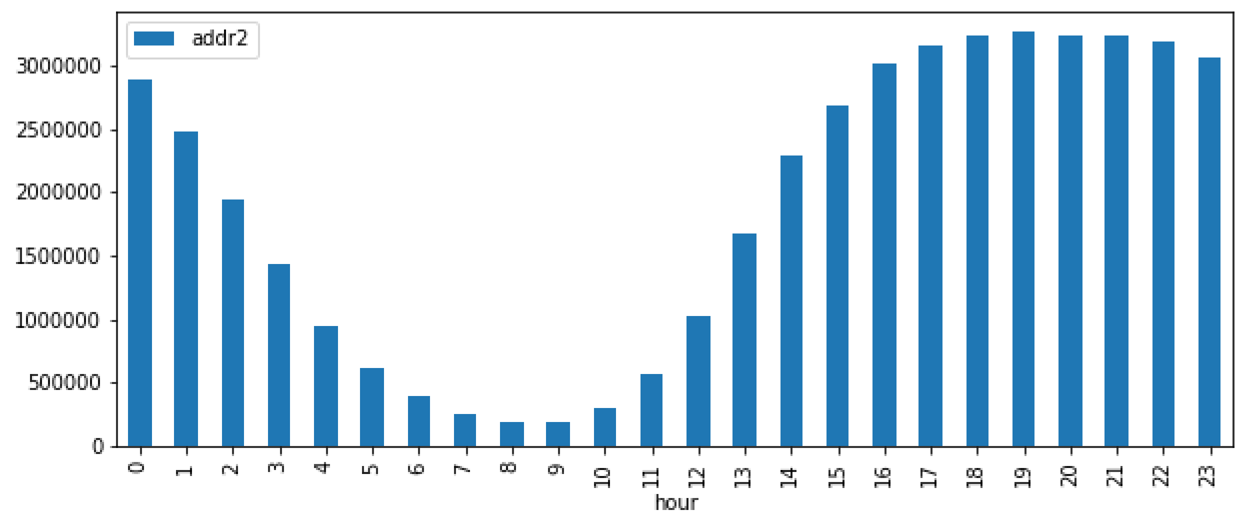


95% of the transactions reported for 382 dist2 are fraud

Part 2 - Transaction Frequency

```
TRAIN_TRANSACTION_TRANSACTIONDT_ADDR2 = TRAIN_TRANSACTION_DATA_SKIENA[['hour', 'addr2']]
COUNT_OF_ADDR2=pd.DataFrame(TRAIN_TRANSACTION_TRANSACTIONDT_ADDR2.groupby('addr2').size())
COUNT_OF_ADDR2.columns=['Count']
COUNT_OF_ADDR2.sort_values(by='Count').tail(1)
TRAIN_TRANSACTION_TRANSACTIONDT_ADDR2_MAX_FREQ_EIGHTY_SEVEN_HOUR_CRITERIA = TRAIN_TRANSACTION_TRANSACTIONDT_ADDR2.loc[TRAIN_TRANSACTION_TRANSACTIONDT_ADDR2['addr2']==87.0]
TRAIN_TRANSACTION_TRANSACTIONDT_ADDR2_MAX_FREQ_EIGHTY_SEVEN_HOUR_CRITERIA.groupby('hour').sum().plot.bar(figsize=(10,4))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98b73e6198>
```

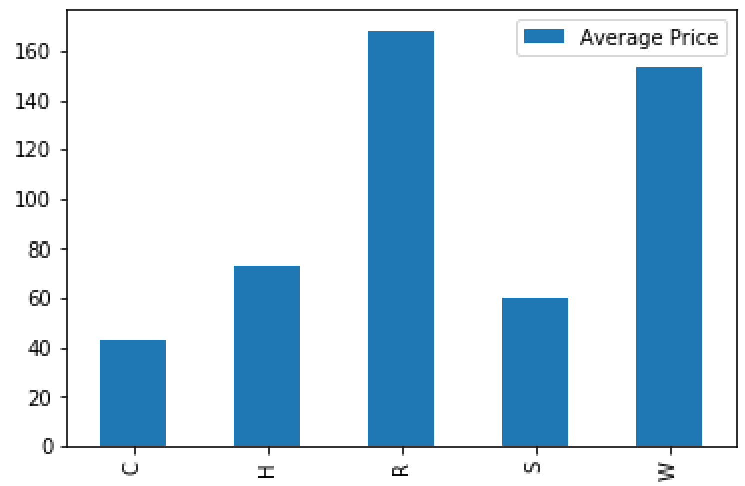


- **The highest data is for addr2 which is most probably a country code. This data was discussed and heavily supported in kaggle's discussion threads. https://www.kaggle.com/c/ieee-fraud-detection/discussion/102910#latest-595293**
- **The article discusses the waking time of an average american https://whygetupearly.com/whats-the-average-bedtime-for-adults/**
- **The average american wakes up at 6:30am and sleeps at 11:30pm. Roughly estimating these two to be from 5 to 12, the waking hours relative to this data is 0 to 5 and 12 to 23.**

Part 3 - Product Code

```
W_COST = TRAIN_TRANSACTION_DATA_SKIENA.loc[TRAIN_TRANSACTION_DATA_SKIENA['W']==1]
C_COST = TRAIN_TRANSACTION_DATA_SKIENA.loc[TRAIN_TRANSACTION_DATA_SKIENA['C']==1]
H_COST = TRAIN_TRANSACTION_DATA_SKIENA.loc[TRAIN_TRANSACTION_DATA_SKIENA['H']==1]
R_COST = TRAIN_TRANSACTION_DATA_SKIENA.loc[TRAIN_TRANSACTION_DATA_SKIENA['R']==1]
S_COST = TRAIN_TRANSACTION_DATA_SKIENA.loc[TRAIN_TRANSACTION_DATA_SKIENA['S']==1]
MeanH=H_COST['TransactionAmt'].sum()/H_COST.shape[0]
MeanW=W_COST['TransactionAmt'].sum()/W_COST.shape[0]
MeanC=C_COST['TransactionAmt'].sum()/C_COST.shape[0]
MeanR=R_COST['TransactionAmt'].sum()/R_COST.shape[0]
MeanS=S_COST['TransactionAmt'].sum()/S_COST.shape[0]
cost = {'H':MeanH,'W':MeanW,'C':MeanC,'R':MeanR,'S':MeanS}
COST = pd.DataFrame({'Average Price': cost})
COST.plot.bar()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98ba268f60>
```

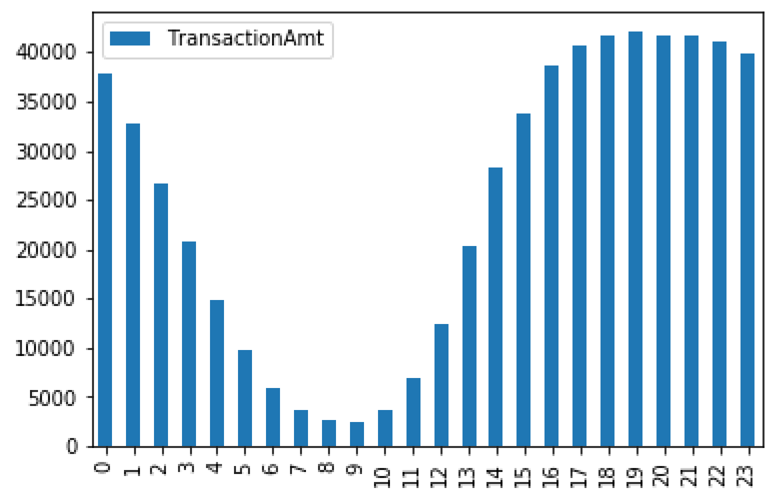


- **Product type R seems expensive at around 168 avg cost per unit.**
- **Product type C seems cheapest at around 40 avg cost per unit.**
- **The above graph shows average price of each product type.**
- **It is calculated using mean. (Total Transaction AMT in ProductCD)/(All respective ProductCD transactions)**

Part 4 - Correlation Coefficient

```
TOD_AND_AMT = TRAIN_TRANSACTION_DATA_SKIENA[['TransactionAmt','hour']].groupby('hour').size()
TOD_AND_AMT=pd.DataFrame(TOD_AND_AMT)
TOD_AND_AMT.columns=['Amt']
TOD_AND_AMT['hour']=pd.DataFrame(TRAIN_TRANSACTION_DATA_SKIENA['hour'].unique())
TOD=pd.DataFrame()
TOD['Amt']=TOD_AND_AMT['Amt']
TOD['Time']=TOD_AND_AMT['hour']
TOD=pd.DataFrame()
TOD=pd.DataFrame(np.array(TRAIN_TRANSACTION_DATA_SKIENA[['TransactionAmt','hour']].groupby('hour').size()))
pd.DataFrame(np.array(TRAIN_TRANSACTION_DATA_SKIENA[['TransactionAmt','hour']].groupby('hour').size()))
TOD.columns = ['TransactionAmt']
TOD.plot.bar()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98b979cdd8>
```




```
TRAIN_TRANSACTION_DATA_SKIENA.corr()
```

	TransactionID	TransactionAmt	P_emaildomain	R_emaildomain	addr1	addr2	dist1	dist2	DeviceInfo	isFraud	hour	C	H	R	S	
TransactionID	1.000000	0.012025	0.015285	0.088160	-0.005017	-0.001855	0.005670	-0.027466	0.066017	0.014166	0.011143	-0.008696	-0.170191	-0.120515	0.013181	0.15
TransactionAmt	0.012025	1.000000	-0.013181	0.058434	0.088535	0.138022	0.022934	-0.027575	0.075637	0.011320	0.044532	-0.139600	-0.062948	0.036336	-0.044301	0.12
P_emaildomain	0.015285	-0.013181	1.000000	0.286664	0.076013	0.116611	0.014883	-0.031981	0.085509	-0.024056	-0.001973	-0.118461	-0.047909	-0.108924	0.062906	0.15
R_emaildomain	0.088160	0.058434	0.286664	1.000000	0.252682	0.385129	0.066599	-0.126005	0.306556	-0.085760	0.014322	-0.390946	-0.131891	-0.352287	-0.062281	0.57
addr1	-0.005017	0.088535	0.076013	0.252682	1.000000	0.686815	0.045157	-0.116555	0.240398	-0.106814	0.044692	-0.665220	0.065225	0.068293	0.051054	0.39
addr2	-0.001855	0.138022	0.116611	0.385129	0.686815	1.000000	0.070498	-0.176882	0.362016	-0.161030	0.068837	-0.980583	0.082148	0.093755	0.042913	0.61
dist1	0.005670	0.022934	0.014883	0.066599	0.045157	0.070498	1.000000	-0.020250	0.060156	-0.006110	0.013012	-0.071775	-0.048217	-0.051734	-0.028077	0.11
dist2	-0.027466	-0.027575	-0.031981	-0.126005	-0.116555	-0.176882	-0.020250	1.000000	-0.083646	0.028497	-0.013003	0.182953	-0.013050	0.049604	0.060337	-0.17
DeviceInfo	0.066017	0.075637	0.085509	0.306556	0.240398	0.362016	0.060156	-0.083646	1.000000	-0.075975	0.043407	-0.356720	-0.223015	-0.201364	-0.081754	0.51
isFraud	0.014166	0.011320	-0.024056	-0.085760	-0.106814	-0.161030	-0.006110	0.028497	-0.075975	1.000000	-0.013112	0.161442	0.016784	0.004030	0.018515	-0.13
hour	0.011143	0.044532	-0.001973	0.014322	0.044692	0.068837	0.013012	-0.013003	0.043407	-0.013112	1.000000	-0.067444	-0.010328	0.025797	-0.001383	0.04
C	-0.008696	-0.139600	-0.118461	-0.390946	-0.665220	-0.980583	-0.071775	0.182953	-0.356720	0.161442	-0.067444	1.000000	-0.088175	-0.094608	-0.051346	-0.61
H	-0.170191	-0.062948	-0.047909	-0.131891	0.065225	0.082148	-0.048217	-0.013050	-0.223015	0.016784	-0.010328	-0.088175	1.000000	-0.063555	-0.034493	-0.41
R	-0.120515	0.036336	-0.108924	-0.352287	0.068293	0.093755	-0.051734	0.049604	-0.201364	0.004030	0.025797	-0.094608	-0.063555	1.000000	-0.037009	-0.44
S	0.013181	-0.044301	0.062906	-0.062281	0.051054	0.042913	-0.028077	0.060337	-0.081754	0.018515	-0.001383	-0.051346	-0.034493	-0.037009	1.000000	-0.24
W	0.159403	0.129420	0.153244	0.573873	0.399576	0.610559	0.116051	-0.174496	0.518354	-0.135549	0.040947	-0.618477	-0.415478	-0.445786	-0.241940	1.00
american express	-0.058901	0.019018	-0.061991	-0.183317	0.029235	0.042338	-0.023694	0.027108	-0.113827	-0.004095	0.013509	-0.043241	0.068770	0.329347	0.047344	-0.20
discover	-0.010789	0.058336	0.002476	-0.004431	0.021937	0.038281	-0.000578	-0.002168	-0.007695	0.024564	0.007295	-0.038667	0.016137	0.043613	0.051864	-0.02
mastercard	0.021545	-0.007578	0.007615	0.026854	-0.061151	-0.061860	-0.011432	-0.001411	0.009776	-0.002463	0.003857	0.061909	-0.041748	-0.068985	0.008260	0.01
visa	-0.008009	-0.010665	0.007319	0.019229	0.048108	0.041762	0.017892	-0.004330	0.019555	-0.001741	-0.007705	-0.041499	0.021502	-0.022153	-0.030497	0.04
charge card	-0.003180	-0.001591	0.001607	0.001469	-0.004270	-0.009856	-0.000998	0.013652	-0.001129	-0.000960	0.000710	0.010764	-0.001227	0.002807	-0.000714	-0.00
credit	-0.085406	0.133600	-0.090122	-0.214080	-0.080808	-0.121353	-0.038128	0.055340	-0.162482	0.100508	0.014528	0.124961	0.158221	0.270933	0.100840	-0.35
debit	0.080943	-0.133598	0.089796	0.212316	0.080997	0.121127	0.038777	-0.054728	0.161062	-0.099779	-0.013303	-0.124729	-0.156148	-0.268458	-0.099619	0.35
debit or credit	-0.002566	-0.000923	-0.003394	0.002396	-0.005095	0.002563	-0.000487	-0.000729	0.002164	-0.001357	-0.002494	-0.002582	-0.001735	-0.001861	-0.001010	0.00
desktop	-0.130888	-0.072824	-0.121292	-0.426603	-0.205462	-0.324809	-0.081327	0.149001	-0.325876	0.067522	-0.007298	0.330585	0.298906	0.387804	0.261108	-0.70
mobile	-0.062545	-0.088364	-0.067994	-0.285654	-0.286094	-0.420950	-0.063898	0.086958	-0.399630	0.117027	-0.063032	0.411074	0.251641	0.184270	0.040440	-0.55

- **Transaction Amt shows similar pattern to the activity and hence complements each other.**

- **When people are awake they make more purchases.**
- **The correlation below transactionamt and hour is 0.04**

Part 5 - Interesting Plot

```
W_ANALYSIS=TRAIN_TRANSACTION_DATA_SKIENA.loc[TRAIN_TRANSACTION_DATA_SKIENA['W']==1]
NON_W_ANALYSIS=TRAIN_TRANSACTION_DATA_SKIENA.loc[TRAIN_TRANSACTION_DATA_SKIENA['W']!=1]
W_ANALYSIS.loc[W_ANALYSIS['dist2']!=-1].sum().sum()
```

```
0.0
```

```
NON_W_ANALYSIS.loc[NON_W_ANALYSIS['dist1']!=-1].sum().sum()
```

```
0.0
```

- **The above analysis shows that there is no data in dist2 for Product code : 'W'**
- **The above analysis also shows that there is no data in dist1 for Product code : 'H','C','R','S'**
- **There is a school of thought (https://www.kaggle.com/c/ieee-fraud-detection/discussion/107791) that puts 'ProductCD' as a type of transaction.**
- **If that were true, and give the high percent for ProductCD 'W', it is probably the mode of online payment using 'Web' and hence the high number.**

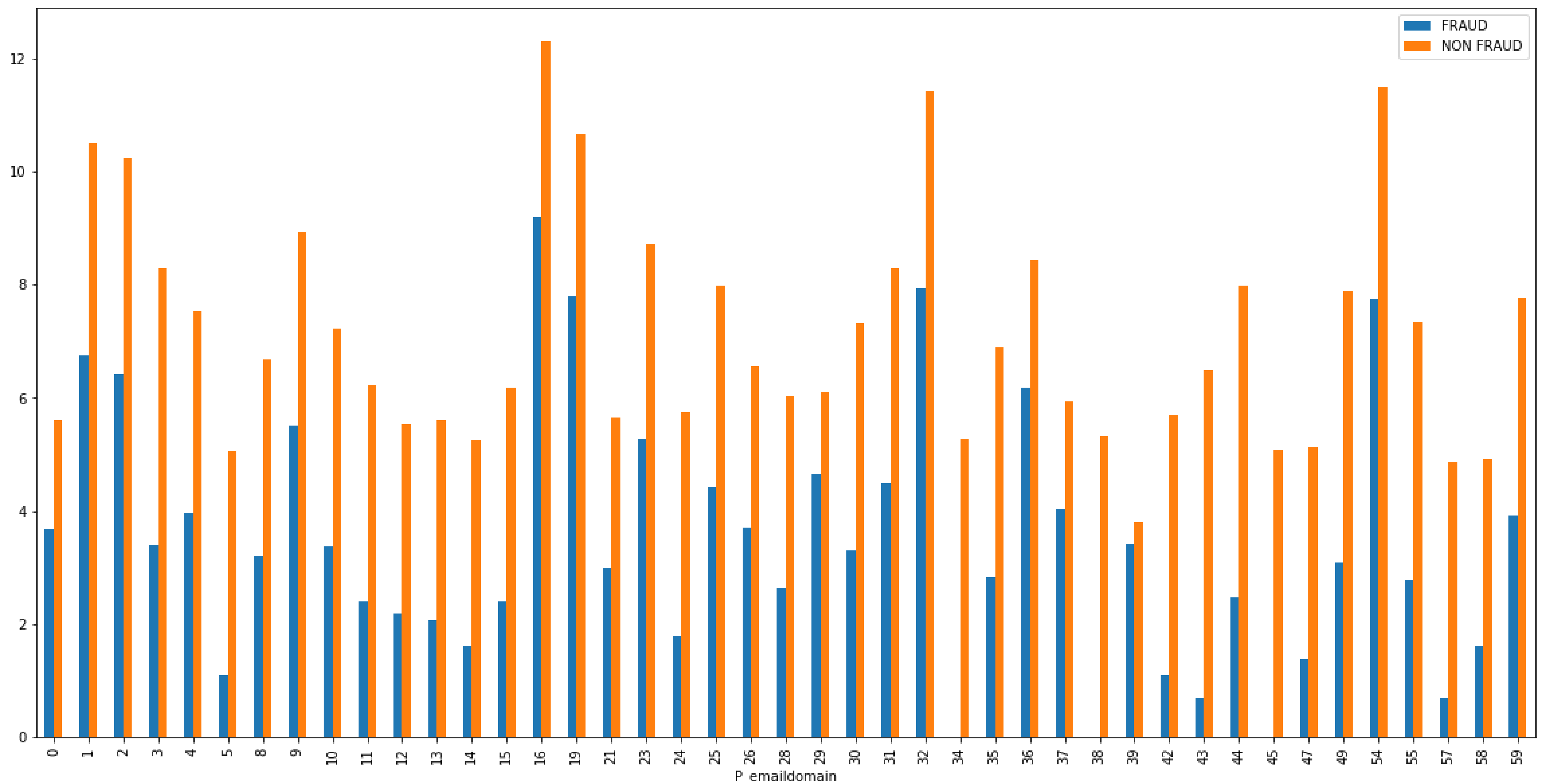
```
plt.subplots(figsize=(20,10))
FRAUD_P=pd.DataFrame(TRAIN_T_D_FRAUD_DATA.groupby('P_emaildomain').size())
```

```
plt.subplots(figsize=(20,10))
NON_FRAUD_P=pd.DataFrame(TRAIN_T_D_NON_FRAUD_DATA.groupby('P_emaildomain').size())
```

```
FRAUD_P['NON FRAUD'] = pd.DataFrame(TRAIN_T_D_NON_FRAUD_DATA.groupby('P_emaildomain').size())
```

```
np.log(FRAUD_P).plot.bar(figsize=(20,10))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98ab9f9588>
```

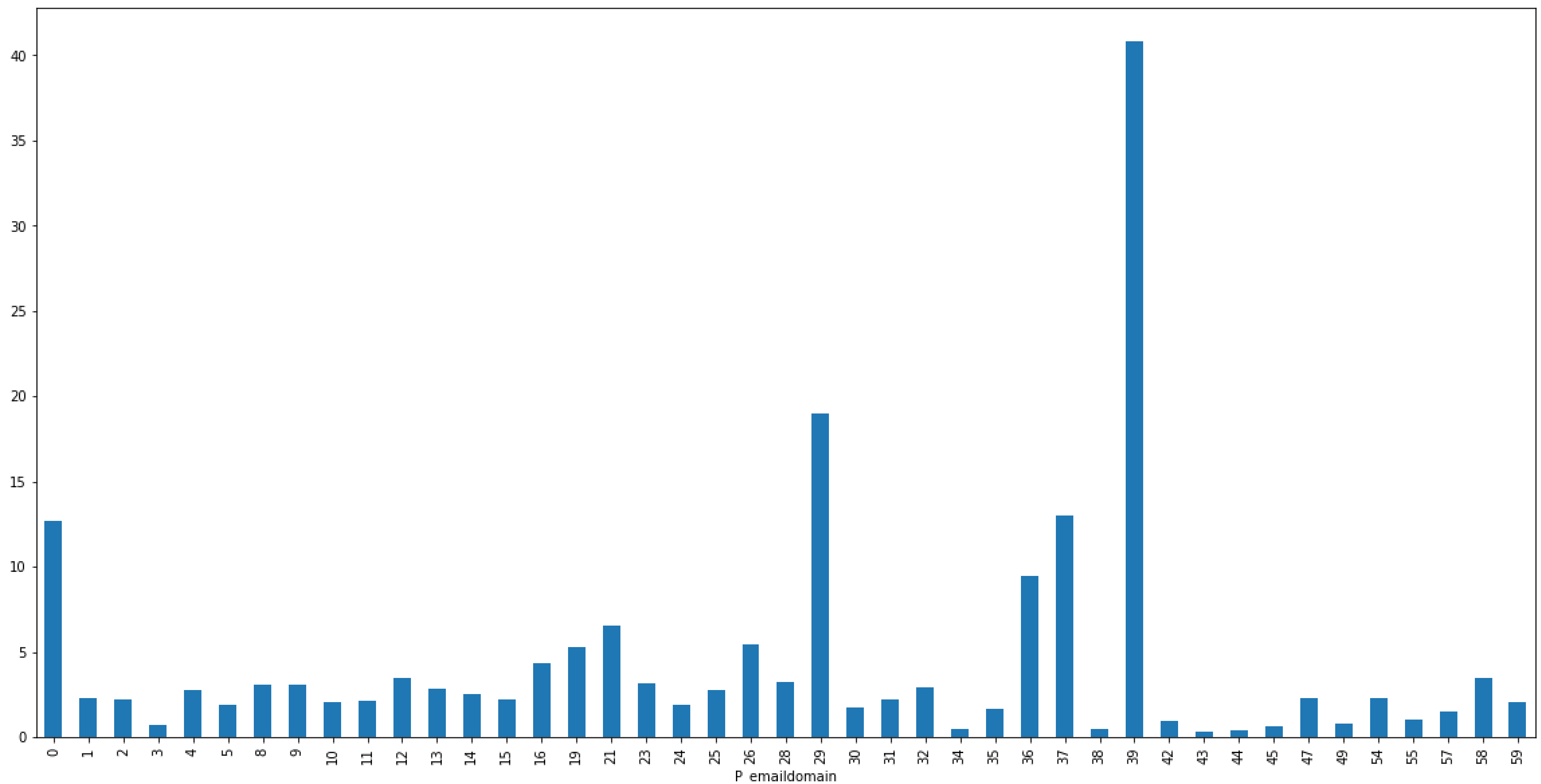



```
FRAUD_P['ratio']=FRAUD_P['FRAUD']/FRAUD_P['NON FRAUD']
```

```
FRAUD_P['percent']=FRAUD_P['FRAUD']* 100/(FRAUD_P['NON FRAUD']+FRAUD_P['FRAUD'])
```

```
FRAUD_P['percent'].plot.bar(figsize=(20,10))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98ab3ffe10>
```




```
le_p.inverse_transform([39,29,0,37])
```

```
array(['protonmail.com', 'mail.com', 'aim.com', 'outlook.es'],
      dtype=object)
```

```
TRAIN_TRANSACTION_DATA_SKIENA[TRAIN_TRANSACTION_DATA_SKIENA['P_emaildomain']==39].groupby('isFraud').size()
```

```
isFraud
0    45
1    31
dtype: int64
```

- **Another insight that one can find by analysing the P_emaildomain or Purchaser's email domain is that there is one email domain which stands out "protonmail"**

- **40% transactions made by protonmail are fraudulent.**
- **There are 31 fraudulent transaction of protonmail and 45 non fraudulent.**
- **Following closely are 'mail.com', 'aim.com' and 'outlook.es'**

Part 6 - Prediction Model

```
TRAIN = TRAIN_TRANSACTION_DATA_SKIENA.copy(deep=False)
TRAIN['R_emaildomain'] = le_r.inverse_transform(TRAIN['R_emaildomain'])
TRAIN['P_emaildomain'] = le_p.inverse_transform(TRAIN['P_emaildomain'])
TRAIN['R_emaildomain']='R_'+TRAIN['R_emaildomain'].astype(str)
TRAIN['P_emaildomain']='P_'+TRAIN['P_emaildomain'].astype(str)
Onehot=pd.DataFrame(pd.get_dummies(TRAIN['R_emaildomain']))
TRAIN=TRAIN.join(Onehot)
Onehot=pd.DataFrame(pd.get_dummies(TRAIN['P_emaildomain']))
TRAIN=TRAIN.join(Onehot)
```

```
TRAIN.drop(columns=['R_emaildomain','P_emaildomain'], inplace=True)
```

```
### Load data

import pandas as pd
TEST_TRANSACTION_DATA = pd.read_csv('test_transaction.csv')
TEST_IDENTITY_DATA = pd.read_csv('test_identity.csv')
```

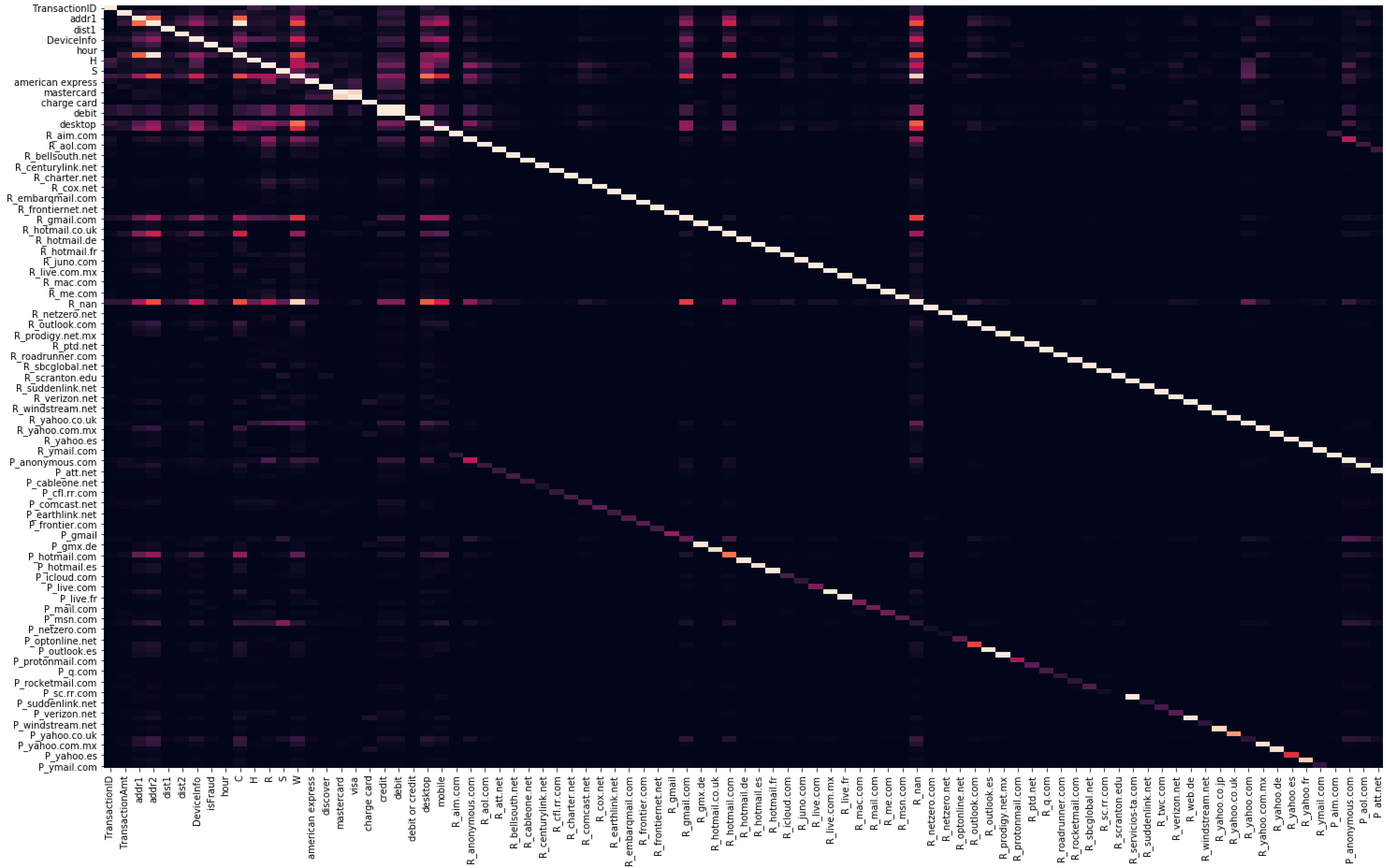
```
TEST_TRANSACTION_DATA_FINAL = pd.merge(pd.DataFrame(TEST_TRANSACTION_DATA),pd.DataFrame(TEST_IDENTITY_DATA), how='left', on = 'TransactionID')

#Extracting only for skiena's columns
Skiena_Columns= ['TransactionID','TransactionDT','TransactionAmt','ProductCD','card4','card6','P_emaildomain','R_emaildomain','addr1','addr2','dist1','dist2','DeviceType','DeviceInfo']
TEST_TRANSACTION_DATA_SKIENA=TEST_TRANSACTION_DATA_FINAL[Skiena_Columns]

##Drop DeviceInfo

TEST_TRANSACTION_DATA_SKIENA.drop(columns=['DeviceInfo'], inplace=True)
```

```
#Cleaning
TEST_TRANSACTION_DATA_SKIENA['R_emaildomain']='R_'+TEST_TRANSACTION_DATA_SKIENA['R_emaildomain'].astype(str)
TEST_TRANSACTION_DATA_SKIENA['P_emaildomain']='P_'+TEST_TRANSACTION_DATA_SKIENA['P_emaildomain'].astype(str)
TEST_TRANSACTION_DATA_SKIENA['dist2'].fillna(-1.0,inplace=True)
TEST_TRANSACTION_DATA_SKIENA['dist1'].fillna(-1.0,inplace=True)
TEST_TRANSACTION_DATA_SKIENA['addr2'].fillna(0.0,inplace=True)
TEST_TRANSACTION_DATA_SKIENA['addr1'].fillna(0.0,inplace=True)

#Onehot encoding

Onehot=pd.DataFrame(pd.get_dummies(TEST_TRANSACTION_DATA_SKIENA['R_emaildomain']))
TEST_TRANSACTION_DATA_SKIENA=TEST_TRANSACTION_DATA_SKIENA.join(Onehot)
Onehot=pd.DataFrame(pd.get_dummies(TEST_TRANSACTION_DATA_SKIENA['P_emaildomain']))
TEST_TRANSACTION_DATA_SKIENA=TEST_TRANSACTION_DATA_SKIENA.join(Onehot)
Onehot=pd.DataFrame(pd.get_dummies(TEST_TRANSACTION_DATA_SKIENA['ProductCD']))
TEST_TRANSACTION_DATA_SKIENA=TEST_TRANSACTION_DATA_SKIENA.join(Onehot)
Onehot=pd.DataFrame(pd.get_dummies(TEST_TRANSACTION_DATA_SKIENA['card4']))
TEST_TRANSACTION_DATA_SKIENA=TEST_TRANSACTION_DATA_SKIENA.join(Onehot)
Onehot=pd.DataFrame(pd.get_dummies(TEST_TRANSACTION_DATA_SKIENA['card6']))
```

```
TEST_TRANSACTION_DATA_SKIENA=TEST_TRANSACTION_DATA_SKIENA.join(Onehot)
Onehot=pd.DataFrame(pd.get_dummies(TEST_TRANSACTION_DATA_SKIENA['DeviceType']))
TEST_TRANSACTION_DATA_SKIENA=TEST_TRANSACTION_DATA_SKIENA.join(Onehot)


#Drop one hot encoded columns

TEST_TRANSACTION_DATA_SKIENA.drop(columns=['card4','card6','ProductCD','R_emaildomain','P_emaildomain','DeviceType'],inplace=True)

#Cleaning transactiondt

Onehot_hour=pd.DataFrame(pd.to_datetime(TEST_TRANSACTION_DATA_SKIENA['TransactionDT'],unit='s').dt.hour)

Onehot_hour.columns=['hour']

TEST_TRANSACTION_DATA_SKIENA['hour']=pd.DataFrame(Onehot_hour)

TEST_TRANSACTION_DATA_SKIENA.drop(columns=['TransactionDT'],inplace=True)

#### TEST DATA SETUP END #################
```

```
import matplotlib.pyplot as plt
plt.subplots(figsize=(50,15))
import seaborn as sns
sns.heatmap(np.abs(TRAIN.corr()))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98b988eac8>
```



The above heatmap shows that all columns are not required. Hence, only few columns with correlation greater > 0.4 absolute value

Two models are trained below to predict. Logistic and Linear Regression

```
from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.model_selection import train_test_split

from sklearn import metrics

COLS=['mobile','desktop','credit','debit','W','R','H','C',
      'P_yahoo.com','P_hotmail.com','P_gmail.com'
      ,'R_yahoo.com','R_hotmail.com','R_gmail.com',
      'addr1','addr2','dist1','dist2']
X=TRAIN[COLS]
Y=TRAIN_TRANSACTION_DATA_SKIENA['isFraud']

X_TRAIN, X_TEST, Y_TRAIN, Y_TEST = train_test_split(X, Y, test_size=0.3)

clf = LogisticRegression(solver='lbfgs')
clf.fit(X_TRAIN, Y_TRAIN)

PREDS = clf.predict(X_TEST)

print(metrics.classification_report(Y_TEST, PREDS))
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:947: ConvergenceWarning: lbfgs failed to converge. Increase the number of iterations.
  "of iterations.", ConvergenceWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1437: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted sa
  'precision', 'predicted', average, warn_for)
              precision    recall  f1-score   support

           0       0.97      1.00      0.98    171044
           1       0.00      0.00      0.00      6118

    accuracy                           0.97    177162
   macro avg       0.48      0.50      0.49    177162
weighted avg       0.93      0.97      0.95    177162
```

Write your answer here

```
reg = LinearRegression().fit(X_TRAIN, Y_TRAIN)
import numpy as np;
y_pred = reg.predict(X_TEST)

mae = metrics.mean_absolute_error(Y_TEST, y_pred)
msq = metrics.mean_squared_error(Y_TEST, y_pred)
rmse = np.sqrt(metrics.mean_squared_error(Y_TEST, y_pred))

print('Mean Absolute Error:'+str(mae))
print('Mean Squared Error:'+str(msq))
print('Root Mean Squared Error:'+str(rmse))
```

```
Mean Absolute Error:0.06468942445833634
Mean Squared Error:0.03186813942038352
Root Mean Squared Error:0.17851649621360913
```

```
SAMPLE_SUBMISSION = pd.read_csv('sample_submission.csv')
TRANSACTIONIDS_JOIN = pd.merge(pd.DataFrame(SAMPLE_SUBMISSION),pd.DataFrame(TEST_TRANSACTION_DATA_SKIENA), how='left', on = 'TransactionID')
TRANSACTIONIDS_JOIN=TRANSACTIONIDS_JOIN[COLS]

FRAUD_COLUMN_LOG=clf.predict(TRANSACTIONIDS_JOIN)
FRAUD_COLUMN_LIN= reg.predict(TRANSACTIONIDS_JOIN)
KAGGLE_UPLOAD_LOG=pd.DataFrame()
KAGGLE_UPLOAD_LIN=pd.DataFrame()
KAGGLE_UPLOAD_LOG['TransactionID']=SAMPLE_SUBMISSION['TransactionID']
KAGGLE_UPLOAD_LIN['TransactionID']=SAMPLE_SUBMISSION['TransactionID']
FRAUD_COLUMN_LOG= pd.DataFrame(FRAUD_COLUMN_LOG)
FRAUD_COLUMN_LIN= pd.DataFrame(FRAUD_COLUMN_LIN)
FRAUD_COLUMN_LOG.columns=['isFraud']
FRAUD_COLUMN_LIN.columns=['isFraud']
KAGGLE_UPLOAD_LOG['isFraud']=pd.DataFrame(FRAUD_COLUMN_LOG['isFraud'])
KAGGLE_UPLOAD_LIN['isFraud']=pd.DataFrame(FRAUD_COLUMN_LIN['isFraud'])

KAGGLE_UPLOAD_LIN.to_csv("LinearRegression.csv")
KAGGLE_UPLOAD_LIN.to_csv("LogisticRegression.csv")
```

Part 7 - Final Result

Report the rank, score, number of entries, for your highest rank. Include a snapshot of your best score on the leaderboard as confirmation. Be sure to provide a link to your Kaggle profile. Make sure to include a screenshot of your ranking. Make sure your profile includes your face and affiliation with SBU.

Kaggle Link: https://www.kaggle.com/abdullahmitkar

Highest Rank: 5343

Score: 0.8057

Number of entries: 4

INCLUDE IMAGE OF YOUR KAGGLE RANKING

```
import cv2
plt.subplots(figsize=(50,15))
img=cv2.imread('Capture_Kaggle.PNG')
plt.imshow(img)
```

<matplotlib.image.AxesImage at 0x7f98b74bc7f0>