Homework 2 - IEEE Fraud Detection

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

In [1]:
```
# TODO: code and runtime results
%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#To display atmost 1000 rows
pd.options.display.max_rows=1000
```

In [2]:
```
# ********** LOADING DATA FILES *****************
#importing train_transaction.csv file
train_trans= pd.read_csv('train_transaction.csv')

#importing train_identity.csv file
train_id= pd.read_csv('train_identity.csv')

#creating a transaction dataframe with required columns only
df_trans = train_trans[['TransactionID','TransactionDT','TransactionAmt',
                'ProductCD','card4','card6','P_emaildomain',
                'R_emaildomain','addr1','addr2','dist1','dist2','isFraud']]

#creating an identity dataframe with required columns only
df_identity = train_id[['TransactionID','DeviceType','DeviceInfo']]

#merging modified transaction and identity dataframe based on the TransactionID
combined_df = pd.merge(df_trans,df_identity,how='outer',on='TransactionID')

#replace NAN with appropriate values in combined data frame
set1 = ["addr1","addr2","dist1","dist2"]
set2 = ["card4","card6",'P_emaildomain','R_emaildomain','DeviceType','DeviceInfo']
combined_df[set1] = combined_df[set1].replace({np.nan:-9999})
combined_df[set2] = combined_df[set2].replace({np.nan:'unknown'})
```

In [8]:
```
# ********** CHECKING DATA *****************
print('Size of data:',combined_df.size,combined_df.shape)
print('*'*70)
print('Null values:',combined_df.isna().sum())
print('*'*70)
print(combined_df.describe())
print('*'*70)
print('# of duplicated rows',combined_df.duplicated().sum())
print('*'*70)
combined_df.head()
```

```
Size of data: 8858100 (590540, 15)
**********************************************************************
Null values: TransactionID     0
TransactionDT     0
TransactionAmt    0
ProductCD         0
card4             0
card6             0
P_emaildomain     0
R_emaildomain     0
addr1             0
addr2             0
dist1             0
dist2             0
isFraud           0
DeviceType        0
DeviceInfo        0
dtype: int64
**********************************************************************
       TransactionID  TransactionDT  TransactionAmt          addr1  \
count   5.905400e+05   5.905400e+05   590540.000000  590540.000000
mean    3.282270e+06   7.372311e+06      135.027176    -854.145890
std     1.704744e+05   4.617224e+06      239.162522    3237.124485
min     2.987000e+06   8.640000e+04        0.251000   -9999.000000
25%     3.134635e+06   3.027058e+06       43.321000     184.000000
50%     3.282270e+06   7.306528e+06       68.769000     272.000000
75%     3.429904e+06   1.124662e+07      125.000000     327.000000
max     3.577539e+06   1.581113e+07    31937.391000     540.000000

                addr2          dist1          dist2        isFraud
count  590540.000000  590540.000000  590540.000000  590540.000000
mean    -1035.388580   -5916.825842   -9347.128159       0.034990
std      3171.575553    4969.215023    2502.421591       0.183755
min     -9999.000000   -9999.000000   -9999.000000       0.000000
25%        87.000000   -9999.000000   -9999.000000       0.000000
50%        87.000000   -9999.000000   -9999.000000       0.000000
75%        87.000000       5.000000   -9999.000000       0.000000
max       102.000000   10286.000000   11623.000000       1.000000
**********************************************************************
# of duplicated rows 0
**********************************************************************
```

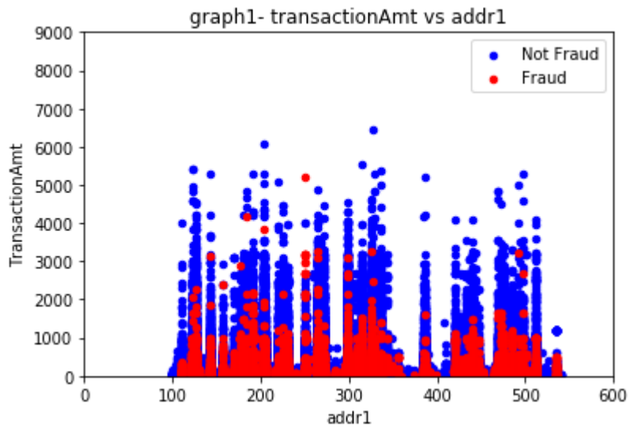
Out[8]:

	TransactionID	TransactionDT	TransactionAmt	ProductCD	card4	card6	P_emaildomain	R_emaildomain	addr1	addr2	dist1	dist2	isFraud	DeviceType	DeviceInfo
0	2987000	86400	68.5	W	discover	credit	unknown	unknown	315.0	87.0	19.0	-9999.0	0	unknown	unknown
1	2987001	86401	29.0	W	mastercard	credit	gmail.com	unknown	325.0	87.0	-9999.0	-9999.0	0	unknown	unknown
2	2987002	86469	59.0	W	visa	debit	outlook.com	unknown	330.0	87.0	287.0	-9999.0	0	unknown	unknown
3	2987003	86499	50.0	W	mastercard	debit	yahoo.com	unknown	476.0	87.0	-9999.0	-9999.0	0	unknown	unknown
4	2987004	86506	50.0	H	mastercard	credit	gmail.com	unknown	420.0	87.0	-9999.0	-9999.0	0	mobile	SAMSUNG SM-G892A Build/NRD90M

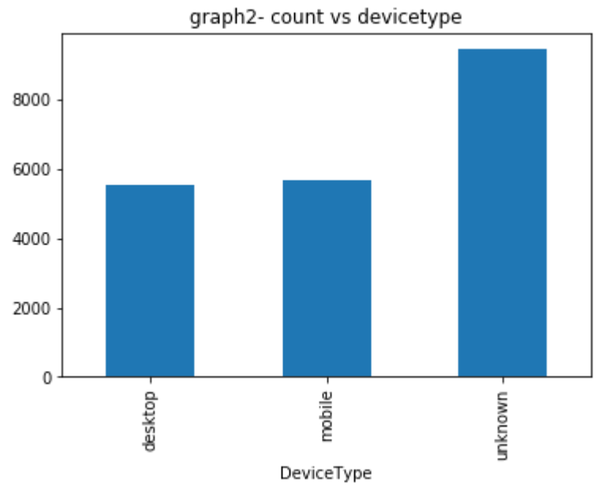
In [4]:
```
#Creating a dataframe with isFraud value as 1
isFraud_True=combined_df[combined_df['isFraud'] == 1]

#Creating a dataframe with isFraud value as 0
isFraud_False=combined_df.loc[combined_df['isFraud'] == 0]
```

In [5]:
```
#Creating scatter plot for non fraud and fraud transactions using addr1 and TransactionAmt on x and y axis respectively
ax=isFraud_False.plot(kind='scatter',y='TransactionAmt',x='addr1',label='Not Fraud',color='blue')
isFraud_True.reset_index().plot(kind='scatter', y='TransactionAmt', x='addr1',
                                color='red', label='Fraud', ax=ax)
ax.set_title("graph1- transactionAmt vs addr1")
ax.set_ylim((0, 9000))
ax.set_xlim((0, 600))
```

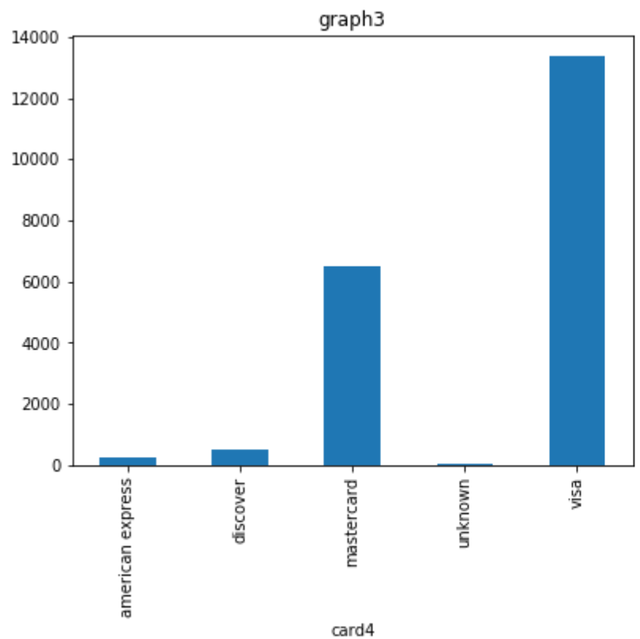
Out[5]: (0, 600)

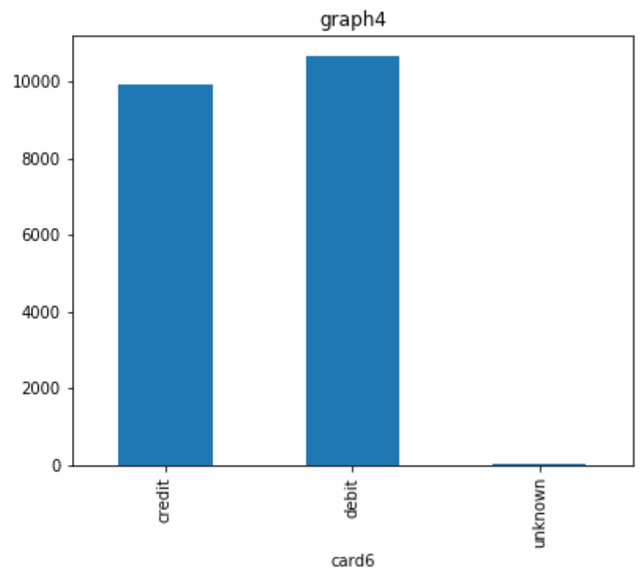


In [6]:
```
#creating bar graphs for device type vs count of the device type
isFraud_True.groupby('DeviceType')['DeviceType'].count().plot(kind='bar',title='graph2- count vs devicetype')
plt.show()
```

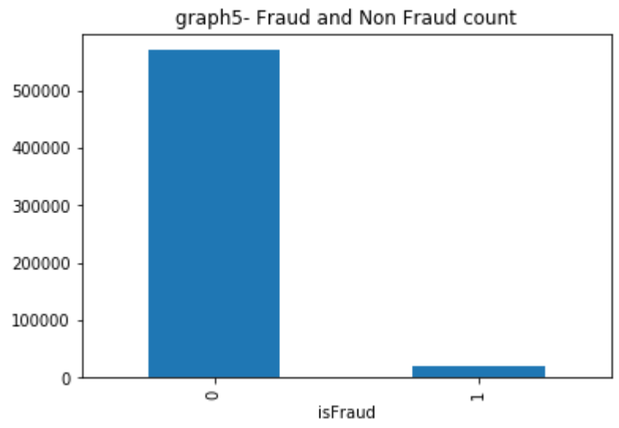


In [7]:
```
#creating bar graphs for card4 and card6 vs count
fig = plt.figure(figsize=(14,5))
ax1 = fig.add_subplot(121)
ax2 = fig.add_subplot(122)
isFraud_True.groupby('card4')['card4'].count().plot(ax=ax1,kind='bar',title='graph3')
isFraud_True.groupby('card6')['card6'].count().plot(kind='bar',title='graph4')
plt.show()
```





In [8]:
```
#creating bar graphs for fraud and non fraud transactions
combined_df.groupby('isFraud')['isFraud'].count().plot(kind='bar',title='graph5- Fraud and Non Fraud count')
plt.show()
```



According to the graph1, considering only the addr1 as the location we can notice that the fraudulent transactions are made for lower transaction amounts compared to the genuine transactions.From graph2, it is evident that the fraud transactions are slightly more for mobiles on comparison with desktop. From graph3, we see that fraudulent transactions are made more using the visa card. From graph4, we notice that fraudulent transactions are made more using credit card. Another interesting observation is that the fraudulent transactions are much less in number (from graph5)

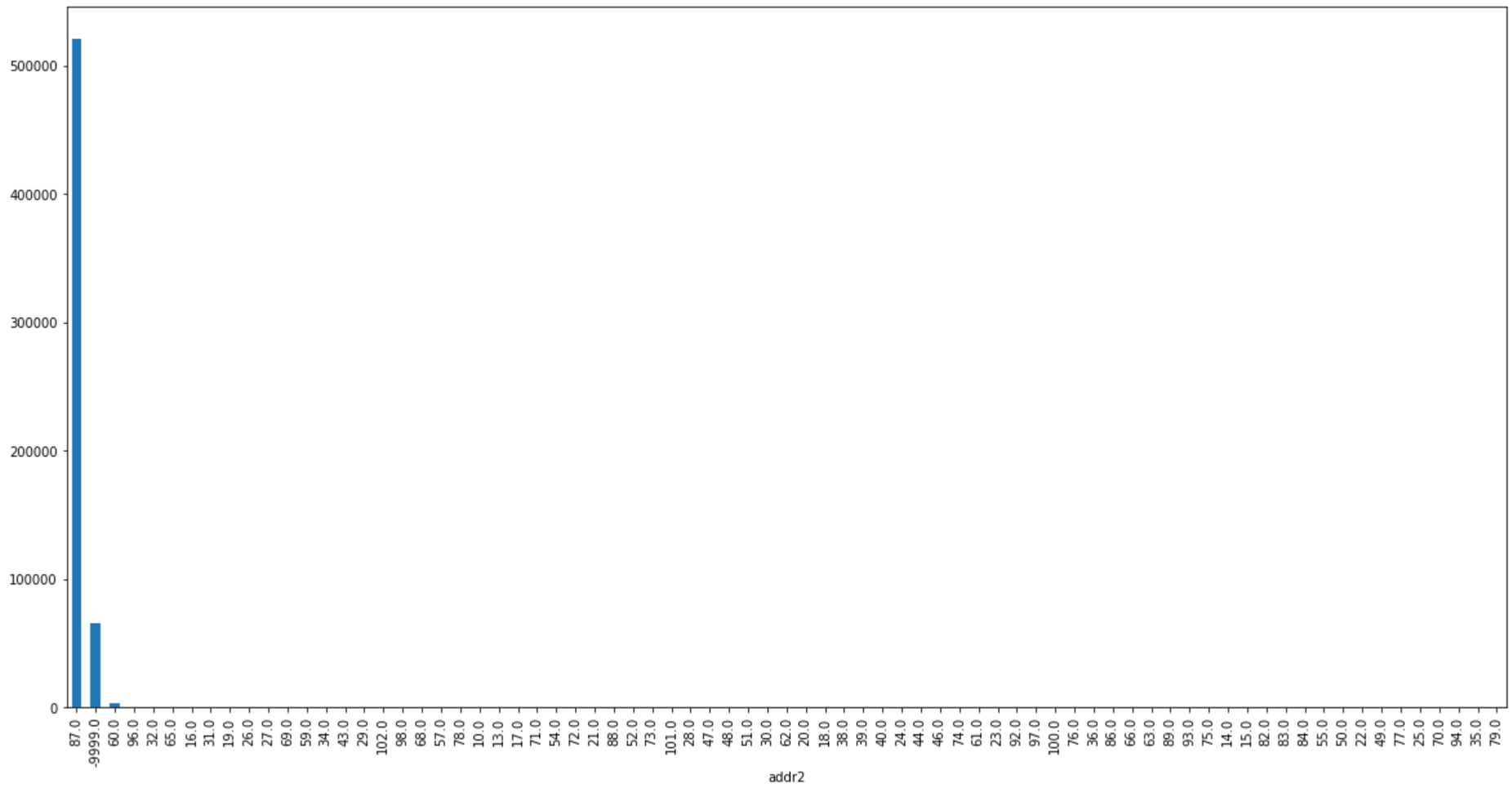
Part 2 - Transaction Frequency

In [9]:
```
# TODO: code to generate the frequency graph

#  Finding the units of 'TransactionDT'
print('Time difference:',combined_df['TransactionDT'].max()-combined_df['TransactionDT'].min())
print('Time difference:',(combined_df['TransactionDT'].max()-combined_df['TransactionDT'].min())//(60*60*24))

# We can assume the data to be in second and can capture data between ~182 days.
# Creating day column
combined_df['day'] = (combined_df['TransactionDT']//(60*60*24)-1)%7
#Creating hour column
combined_df['hour'] = (combined_df['TransactionDT']//(60*60))%24
```

```
Time difference: 15724731
Time difference: 181.99920138888888
```

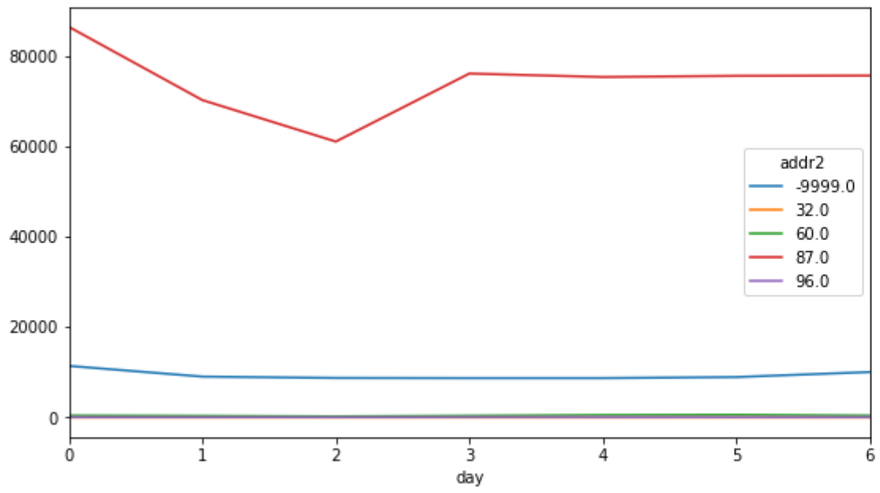
In [10]:
```
# Distibution of total transactions
fig = plt.figure(figsize=(20,10))

combined_df.groupby('addr2')['day'].count().sort_values(ascending=False).plot(kind='bar')
freq_countries_list = combined_df.groupby('addr2')['day'].count().sort_values(ascending=False).head().index.values

print('The most frequent countries are:',freq_countries_list)

print('**********graph1- frequency vs addr2**********')
```

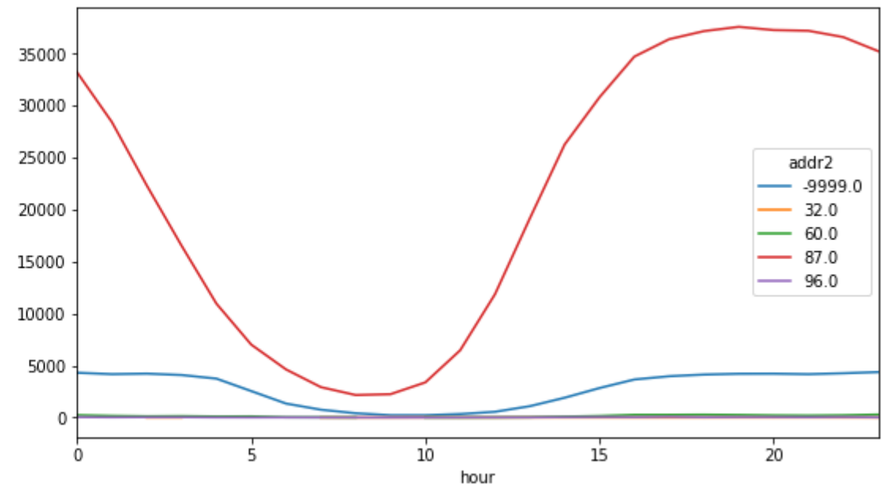
```
The most frequent countries are: [   87. -9999.    60.    96.    32.]
**********graph1- frequency vs addr2**********
```



In [11]:
```
# Distibution of transactions for most frequent countries.

fig = plt.figure(figsize=(20,5))
ax1 = fig.add_subplot(121)
ax2 = fig.add_subplot(122)

freq_countries = combined_df[combined_df['addr2'].isin(list(freq_countries_list))]

freq_countries.groupby(['day','addr2']).count()['TransactionAmt'].unstack().plot(ax=ax1)
freq_countries.groupby(['hour','addr2']).count()['TransactionAmt'].unstack().plot(ax=ax2)
print('**********graph2**********')
plt.show()

plt.show()
```

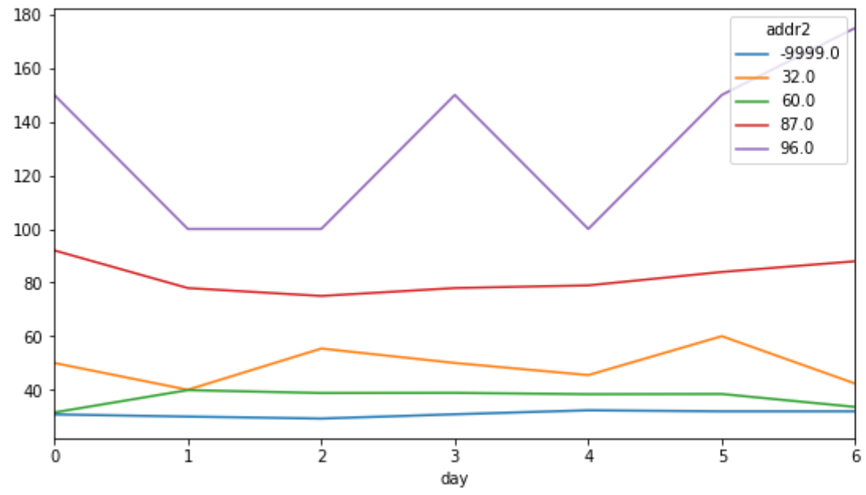
**********graph2**********

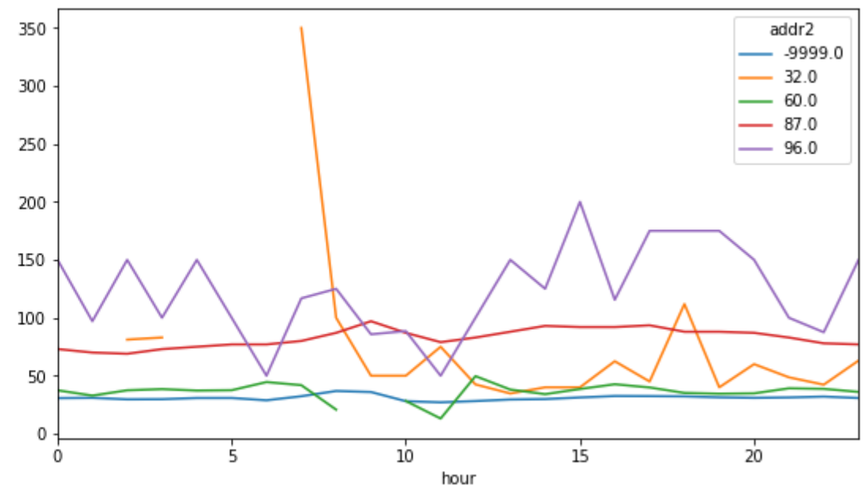




In [12]:
```
# Distibution of transctions for most frequent countries with amount.

fig = plt.figure(figsize=(20,5))
ax1 = fig.add_subplot(121)
ax2 = fig.add_subplot(122)

fre_countries = combined_df[combined_df['addr2'].isin(list(freq_countries_list))]

fre_countries.groupby(['day','addr2']).median()['TransactionAmt'].unstack().plot(ax=ax1)
fre_countries.groupby(['hour','addr2']).median()['TransactionAmt'].unstack().plot(ax=ax2)
print('**********************************graph3*****************************')
plt.show()

plt.show()
```

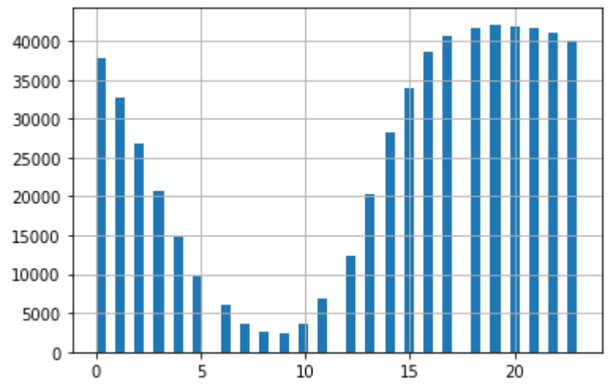
**********graph3**********





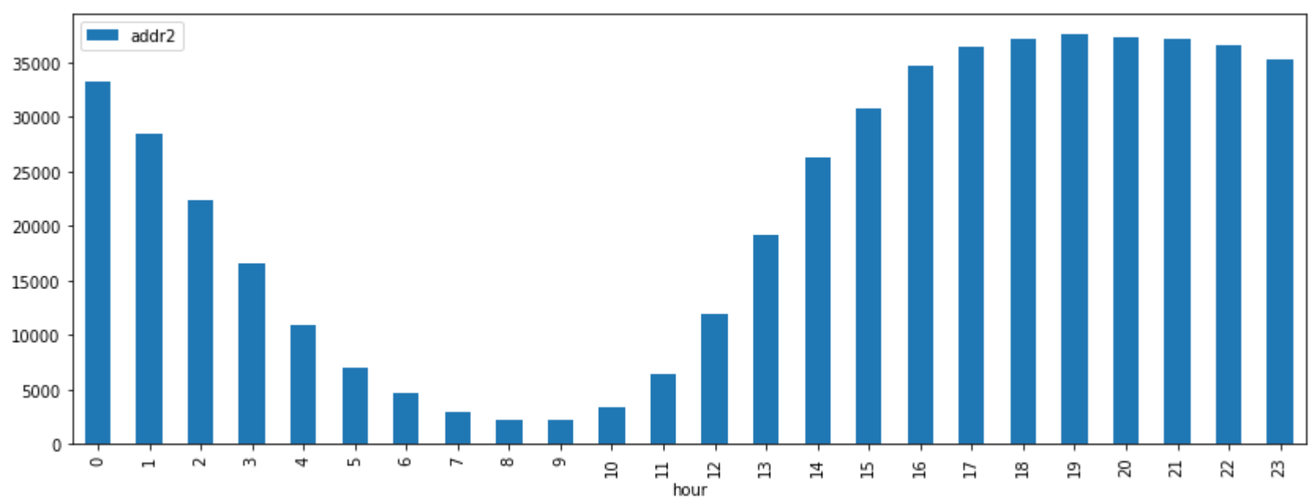
In [14]:
```
#histograms for hour vs frequency
hr_df=combined_df.filter(['hour','addr2'])
hr_df['hour'].hist(bins=50)
print('**********************************graph4- addr2 vs hour**************************************')
```

```
**********************************graph4- addr2 vs hour**************************************
```



In [19]:
```
#Frequency distribution of transactions by time for the most frequent country code
freq_addr=hr_df['addr2'].value_counts().idxmax()

#creating a  data frame based on most frequent address
freq_df=hr_df.loc[hr_df['addr2'] == freq_addr]
freq_df.groupby('hour').count().plot(kind='bar',legend=True,label='Most Frequent Address vs time',figsize=(14,5))
'''graph5- Frequency distribution of transactions by time for the most frequent country code '''
```

Out[19]: 'graph5- Frequency distribution of transactions by time for the most frequent country code '



From graph1, we find that the most frequent country code is 87. From graph5, we see that the most active hours are from 14:00 to 19:00 since the transaction activity is increasing steadily. So this is the waking hours of the most frequent country code. We see that transaction activity at 19:00 is the highest and it slowly starts decreasing. The graph resembles a sine wave.

Part 3 - Product Code

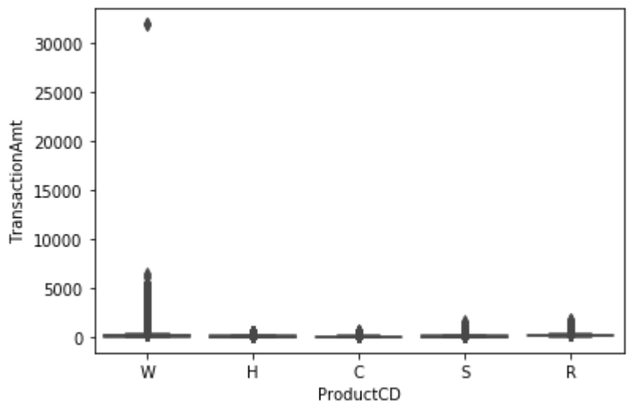
In [15]:
```
# TODO: code to analyze prices for different product codes
```

In [15]:
```
combined_df.groupby('ProductCD')['TransactionAmt'].describe()
```

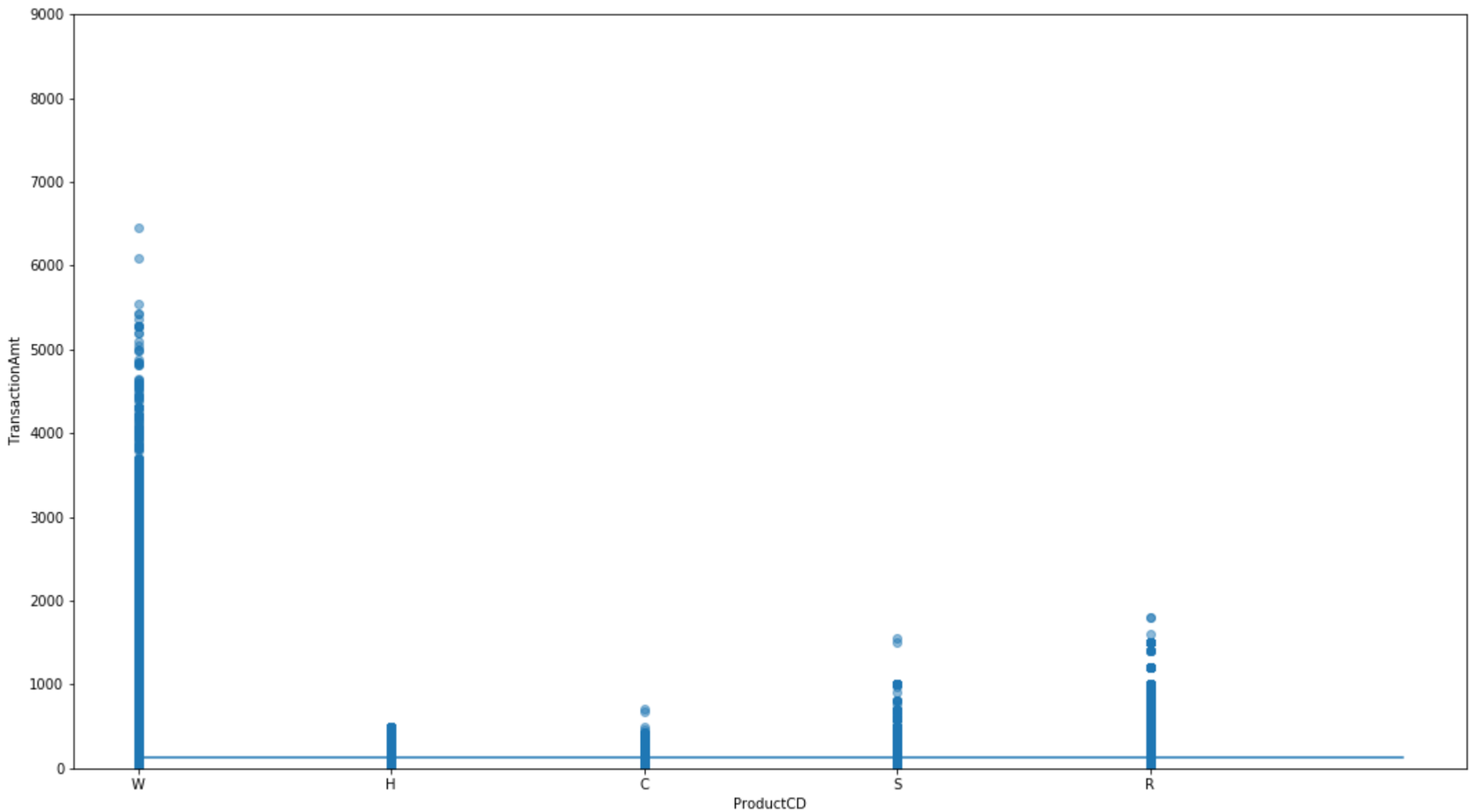
Out[15]:

ProductCD	count	mean	std	min	25%	50%	75%	max
C	68519.0	42.872353	38.943070	0.251	18.423	31.191	54.102	712.896
H	33024.0	73.170058	61.950955	15.000	35.000	50.000	100.000	500.000
R	37699.0	168.306188	142.035568	25.000	100.000	125.000	200.000	1800.000
S	11628.0	60.269487	80.546775	5.000	20.000	35.000	80.000	1550.000
W	439670.0	153.158554	268.733692	1.000	49.000	78.500	146.000	31937.391

In [16]:
```
#Creating a boxplot for TransactionAmt vs ProductCD
s = sns.boxplot( x="ProductCD", y="TransactionAmt",data=combined_df, palette="Set1",showfliers=True)
```



In [17]:
```
amt_mean=combined_df['TransactionAmt'].mean()
x= combined_df['ProductCD']
y= combined_df['TransactionAmt']
plt.figure(figsize=(18,10))
plt.scatter(x, y, alpha=0.5)
plt.plot([0, 5], [amt_mean, amt_mean])
plt.ylim(0, 9000)
plt.xlabel('ProductCD')
plt.ylabel('TransactionAmt')
plt.show()
```



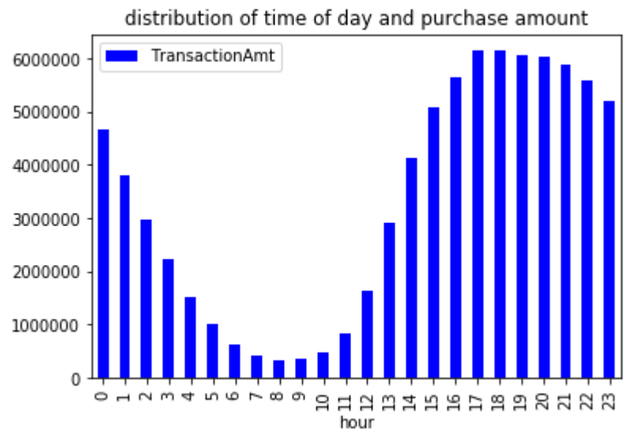
From the boxplots for all the productCD, we see that the Product Code W corresponds with the highest transaction amount and H corresponds with the lowest transaction amount. Hence, W corresponds with the most expensive products and H with the cheapest products.

Part 4 - Correlation Coefficient

In [18]:
```
# TODO: code to calculate correlation coefficient

#filtering out the merged dataset with transaction amount and hours as columns
time_df=combined_df.filter(['TransactionAmt','hour'])
sum_df=time_df.groupby('hour').sum().reset_index()

#printing the correlation matrix
print('**********correlation coefficient*********')
print(sum_df.corr())

#plotting bar graph of distribution of time of day and purchase amount
time_amt=sum_df.plot(kind='bar',y='TransactionAmt',x='hour',color='blue')
time_amt.set_title("distribution of time of day and purchase amount")
```

```
**********correlation coefficient*********
                    hour  TransactionAmt
hour            1.000000        0.642117
TransactionAmt  0.642117        1.000000
```

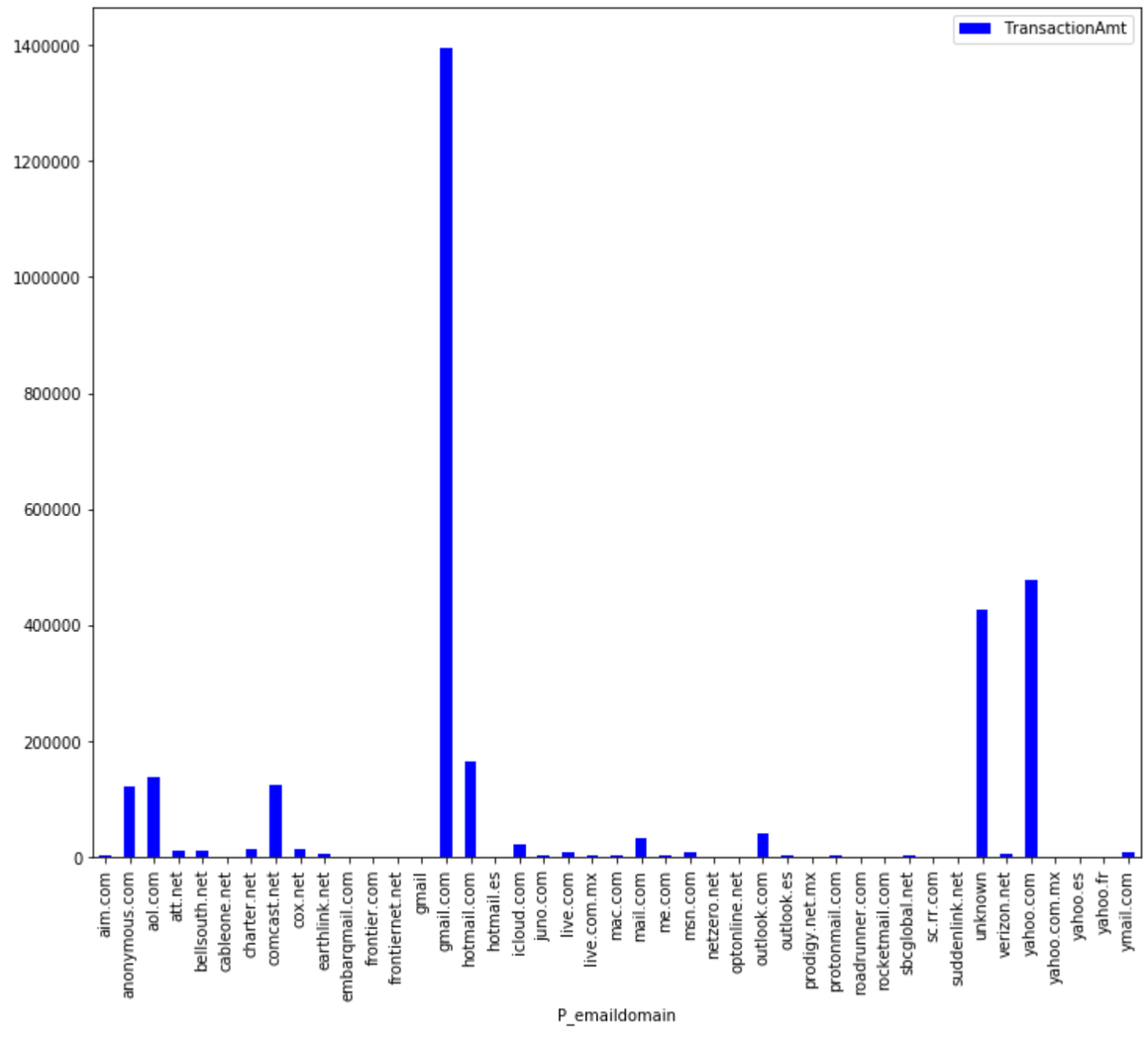
Out[18]: Text(0.5, 1.0, 'distribution of time of day and purchase amount')



The correlation of time of the day to purchase amount is 0.642117

Part 5 - Interesting Plot

In [26]:
```
#filtering out the merged dataset with transaction amount and hours as columns
email_df=isFraud_True.filter(['P_emaildomain','TransactionAmt'])
#sum_df=card_df.groupby('card4').sum().reset_index()
email_df.describe
emaildomain_df=email_df.groupby('P_emaildomain').sum().reset_index()
graph=emaildomain_df.plot(kind='bar',y='TransactionAmt',x='P_emaildomain',color='blue', figsize=(12,10))
```



From this graph, we can deduce that among the fraudulent transactions, gmail.com corresponds with highest transaction amount. This is followed by yahoo.com. Interesting thing that can be noticed over here is that a lot of transactions have NAN as P_emaildomain which is also the third highest in the bar graph plotted above

Part 6 - Prediction Model

In [27]:
```
from sklearn.preprocessing import LabelEncoder
import random
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestRegressor
```

In [28]:
```
train_trans= pd.read_csv('train_transaction.csv')
train_id= pd.read_csv('train_identity.csv')

#merging transaction and identity data frames
final_df = pd.merge(train_trans,train_id,how='outer',on='TransactionID')

# ********** CHECKING DATA *****************
print('Size of data:',final_df.size,final_df.shape)
print('*'*70)
print('Null values:',final_df.isna().sum())
print('*'*70)
print(final_df.describe())
print('*'*70)
print('# of duplicated rows',final_df.duplicated().sum())
print('*'*70)
final_df.head()
```

```
Size of data: 256294360 (590540, 434)
**********************************************************************
Null values: TransactionID         0
isFraud               0
TransactionDT         0
TransactionAmt        0
ProductCD             0
card1                 0
card2              8933
card3              1565
card4              1577
card5              4259
card6              1571
addr1             65706
addr2             65706
dist1            352271
dist2            552913
P_emaildomain     94456
R_emaildomain    453249
C1                    0
C2                    0
C3                    0
C4                    0
C5                    0
C6                    0
C7                    0
C8                    0
C9                    0
C10                   0
C11                   0
C12                   0
C13                   0
C14                   0
D1                 1269
D2               280797
D3               262878
D4               168922
D5               309841
D6               517353
D7               551623
D8               515614
D9               515614
D10               76022
D11              279287
D12              525823
D13              528588
D14              528353
D15               89113
M1               271100
M2               271100
M3               271100
M4               281444
M5               350482
M6               169360
M7               346265
M8               346252
M9               346252
```

V1	279287
V2	279287
V3	279287
V4	279287
V5	279287
V6	279287
V7	279287
V8	279287
V9	279287
V10	279287
V11	279287
V12	76073
V13	76073
V14	76073
V15	76073
V16	76073
V17	76073
V18	76073
V19	76073
V20	76073
V21	76073
V22	76073
V23	76073
V24	76073
V25	76073
V26	76073
V27	76073
V28	76073
V29	76073
V30	76073
V31	76073
V32	76073
V33	76073
V34	76073
V35	168969
V36	168969
V37	168969
V38	168969
V39	168969
V40	168969
V41	168969
V42	168969
V43	168969
V44	168969
V45	168969
V46	168969
V47	168969
V48	168969
V49	168969
V50	168969
V51	168969
V52	168969
V53	77096
V54	77096
V55	77096
V56	77096
V57	77096

V58	77096
V59	77096
V60	77096
V61	77096
V62	77096
V63	77096
V64	77096
V65	77096
V66	77096
V67	77096
V68	77096
V69	77096
V70	77096
V71	77096
V72	77096
V73	77096
V74	77096
V75	89164
V76	89164
V77	89164
V78	89164
V79	89164
V80	89164
V81	89164
V82	89164
V83	89164
V84	89164
V85	89164
V86	89164
V87	89164
V88	89164
V89	89164
V90	89164
V91	89164
V92	89164
V93	89164
V94	89164
V95	314
V96	314
V97	314
V98	314
V99	314
V100	314
V101	314
V102	314
V103	314
V104	314
V105	314
V106	314
V107	314
V108	314
V109	314
V110	314
V111	314
V112	314
V113	314
V114	314

V115	314
V116	314
V117	314
V118	314
V119	314
V120	314
V121	314
V122	314
V123	314
V124	314
V125	314
V126	314
V127	314
V128	314
V129	314
V130	314
V131	314
V132	314
V133	314
V134	314
V135	314
V136	314
V137	314
V138	508595
V139	508595
V140	508595
V141	508595
V142	508595
V143	508589
V144	508589
V145	508589
V146	508595
V147	508595
V148	508595
V149	508595
V150	508589
V151	508589
V152	508589
V153	508595
V154	508595
V155	508595
V156	508595
V157	508595
V158	508595
V159	508589
V160	508589
V161	508595
V162	508595
V163	508595
V164	508589
V165	508589
V166	508589
V167	450909
V168	450909
V169	450721
V170	450721
V171	450721

V172	450909
V173	450909
V174	450721
V175	450721
V176	450909
V177	450909
V178	450909
V179	450909
V180	450721
V181	450909
V182	450909
V183	450909
V184	450721
V185	450721
V186	450909
V187	450909
V188	450721
V189	450721
V190	450909
V191	450909
V192	450909
V193	450909
V194	450721
V195	450721
V196	450909
V197	450721
V198	450721
V199	450909
V200	450721
V201	450721
V202	450909
V203	450909
V204	450909
V205	450909
V206	450909
V207	450909
V208	450721
V209	450721
V210	450721
V211	450909
V212	450909
V213	450909
V214	450909
V215	450909
V216	450909
V217	460110
V218	460110
V219	460110
V220	449124
V221	449124
V222	449124
V223	460110
V224	460110
V225	460110
V226	460110
V227	449124
V228	460110

V229	460110
V230	460110
V231	460110
V232	460110
V233	460110
V234	449124
V235	460110
V236	460110
V237	460110
V238	449124
V239	449124
V240	460110
V241	460110
V242	460110
V243	460110
V244	460110
V245	449124
V246	460110
V247	460110
V248	460110
V249	460110
V250	449124
V251	449124
V252	460110
V253	460110
V254	460110
V255	449124
V256	449124
V257	460110
V258	460110
V259	449124
V260	460110
V261	460110
V262	460110
V263	460110
V264	460110
V265	460110
V266	460110
V267	460110
V268	460110
V269	460110
V270	449124
V271	449124
V272	449124
V273	460110
V274	460110
V275	460110
V276	460110
V277	460110
V278	460110
V279	12
V280	12
V281	1269
V282	1269
V283	1269
V284	12
V285	12

V286	12
V287	12
V288	1269
V289	1269
V290	12
V291	12
V292	12
V293	12
V294	12
V295	12
V296	1269
V297	12
V298	12
V299	12
V300	1269
V301	1269
V302	12
V303	12
V304	12
V305	12
V306	12
V307	12
V308	12
V309	12
V310	12
V311	12
V312	12
V313	1269
V314	1269
V315	1269
V316	12
V317	12
V318	12
V319	12
V320	12
V321	12
V322	508189
V323	508189
V324	508189
V325	508189
V326	508189
V327	508189
V328	508189
V329	508189
V330	508189
V331	508189
V332	508189
V333	508189
V334	508189
V335	508189
V336	508189
V337	508189
V338	508189
V339	508189
id_01	446307
id_02	449668
id_03	524216

```
id_04             524216
id_05             453675
id_06             453675
id_07             585385
id_08             585385
id_09             515614
id_10             515614
id_11             449562
id_12             446307
id_13             463220
id_14             510496
id_15             449555
id_16             461200
id_17             451171
id_18             545427
id_19             451222
id_20             451279
id_21             585381
id_22             585371
id_23             585371
id_24             585793
id_25             585408
id_26             585377
id_27             585371
id_28             449562
id_29             449562
id_30             512975
id_31             450258
id_32             512954
id_33             517251
id_34             512735
id_35             449555
id_36             449555
id_37             449555
id_38             449555
DeviceType        449730
DeviceInfo        471874
dtype: int64
**********************************************************************
       TransactionID        isFraud  TransactionDT  TransactionAmt  \
count   5.905400e+05  590540.000000   5.905400e+05   590540.000000
mean    3.282270e+06       0.034990   7.372311e+06      135.027176
std     1.704744e+05       0.183755   4.617224e+06      239.162522
min     2.987000e+06       0.000000   8.640000e+04        0.251000
25%     3.134635e+06       0.000000   3.027058e+06       43.321000
50%     3.282270e+06       0.000000   7.306528e+06       68.769000
75%     3.429904e+06       0.000000   1.124662e+07      125.000000
max     3.577539e+06       1.000000   1.581113e+07    31937.391000

              card1          card2          card3          card5  \
count  590540.000000  581607.000000  588975.000000  586281.000000
mean     9898.734658     362.555488     153.194925     199.278897
std      4901.170153     157.793246      11.336444      41.244453
min      1000.000000     100.000000     100.000000     100.000000
25%      6019.000000     214.000000     150.000000     166.000000
50%      9678.000000     361.000000     150.000000     226.000000
75%     14184.000000     512.000000     150.000000     226.000000
```

```
max     18396.000000     600.000000     231.000000     237.000000

              addr1          addr2  ...          id_17         id_18  \
count  524834.000000  524834.000000  ...  139369.000000  45113.000000
mean      290.733794      86.800630  ...     189.451377     14.237337
std       101.741072       2.690623  ...      30.375360      1.561302
min       100.000000      10.000000  ...     100.000000     10.000000
25%       204.000000      87.000000  ...     166.000000     13.000000
50%       299.000000      87.000000  ...     166.000000     15.000000
75%       330.000000      87.000000  ...     225.000000     15.000000
max       540.000000     102.000000  ...     229.000000     29.000000

              id_19          id_20        id_21        id_22        id_24  \
count  139318.000000  139261.000000  5159.000000  5169.000000  4747.000000
mean      353.128174     403.882666   368.269820    16.002708    12.800927
std       141.095343     152.160327   198.847038     6.897665     2.372447
min       100.000000     100.000000   100.000000    10.000000    11.000000
25%       266.000000     256.000000   252.000000    14.000000    11.000000
50%       341.000000     472.000000   252.000000    14.000000    11.000000
75%       427.000000     533.000000   486.500000    14.000000    15.000000
max       671.000000     661.000000   854.000000    44.000000    26.000000

            id_25        id_26         id_32
count  5132.000000  5163.000000  77586.000000
mean    329.608924   149.070308     26.508597
std      97.461089    32.101995      3.737502
min     100.000000   100.000000      0.000000
25%     321.000000   119.000000     24.000000
50%     321.000000   149.000000     24.000000
75%     371.000000   169.000000     32.000000
max     548.000000   216.000000     32.000000

[8 rows x 403 columns]
**************************************************************************
# of duplicated rows 0
**************************************************************************
```

Out[28]:

	TransactionID	isFraud	TransactionDT	TransactionAmt	ProductCD	card1	card2	card3	card4	card5	...	id_31	id_32	id_33	id_34	id_35	id_36	id_37	id_38	DeviceType	DeviceInfo
0	2987000	0	86400	68.5	W	13926	NaN	150.0	discover	142.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	2987001	0	86401	29.0	W	2755	404.0	150.0	mastercard	102.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	2987002	0	86469	59.0	W	4663	490.0	150.0	visa	166.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	2987003	0	86499	50.0	W	18132	567.0	150.0	mastercard	117.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	2987004	0	86506	50.0	H	4497	514.0	150.0	mastercard	102.0	...	samsung browser 6.2	32.0	2220x1080	match_status:2	T	F	T	T	mobile	SAMSUNG SM-G892A Build/NRD90M

5 rows × 434 columns

In [29]:
```
#filtering out final merged data frame by using only certain columns
cols = ['ProductCD','card1','card2','card3','card4','card5','card6','addr1','addr2','P_emaildomain','R_emaildomain','M1',
                'M2','M3','M4','M5','M6','M7','M8','M9','DeviceType','DeviceInfo','id_12','id_13',
                'id_14','id_15','id_16','id_17','id_18','id_19','id_20','id_21','id_22','id_23',
                 'id_24','id_25','id_26','id_27','id_28','id_29','id_30','id_31',
                 'id_32','id_33','id_34','id_35','id_36','id_37','id_38','TransactionDT','TransactionAmt','isFraud','TransactionID','C1','C2','C3']

final_df=final_df.filter(cols)
```

In [30]:
```
print('Null values:',final_df.isna().sum())
```

```
Null values: ProductCD             0
card1                  0
card2               8933
card3               1565
card4               1577
card5               4259
card6               1571
addr1              65706
addr2              65706
P_emaildomain      94456
R_emaildomain     453249
M1                271100
M2                271100
M3                271100
M4                281444
M5                350482
M6                169360
M7                346265
M8                346252
M9                346252
DeviceType        449730
DeviceInfo        471874
id_12             446307
id_13             463220
id_14             510496
id_15             449555
id_16             461200
id_17             451171
id_18             545427
id_19             451222
id_20             451279
id_21             585381
id_22             585371
id_23             585371
id_24             585793
id_25             585408
id_26             585377
id_27             585371
id_28             449562
id_29             449562
id_30             512975
id_31             450258
id_32             512954
id_33             517251
id_34             512735
id_35             449555
id_36             449555
id_37             449555
id_38             449555
TransactionDT          0
TransactionAmt         0
isFraud                0
TransactionID          0
C1                     0
C2                     0
C3                     0
dtype: int64
```

In [31]:
```
numeric_cols=['card2','card3','card5','addr1','addr2','id_13','id_14','id_17','id_18','id_19','id_20','id_21','id_22','id_24','id_25','id_26','id_32','C1','C2','C3']
```

In [32]:
```
#replacing numeric columns with mean
for x in numeric_cols:
 final_df[x].fillna((final_df[x].mean()), inplace=True)
```

In [33]:
```
str_cols=['card4','card6','P_emaildomain','R_emaildomain','id_15','id_16','id_23','id_27','id_28','id_29','id_30','id_31','id_33','id_34','id_35','id_36','id_37','id_38','DeviceType',
'DeviceInfo']
```

In [35]:
```
#replacing other columns with "no record"
for x in str_cols:
 final_df[x].fillna("no record", inplace=True)
```

In [36]:
```
fin_cols = ['ProductCD','card1','card2','card3','card4','card5','card6','addr1','addr2','P_emaildomain','R_emaildomain','M1',
                'M2','M3','M4','M5','M6','M7','M8','M9','DeviceType','DeviceInfo','id_12','id_13',
                'id_14','id_15','id_16','id_17','id_18','id_19','id_20','id_21','id_22','id_23',
                 'id_24','id_25','id_26','id_27','id_28','id_29','id_30','id_31',
                 'id_32','id_33','id_34','id_35','id_36','id_37','id_38','TransactionDT','TransactionAmt','TransactionID','C1','C2','C3']

enc = ['ProductCD','card1','card2','card3','card4','card5','card6','addr1','addr2','P_emaildomain','R_emaildomain','M1',
                'M2','M3','M4','M5','M6','M7','M8','M9','DeviceType','DeviceInfo','id_12','id_13',
                'id_14','id_15','id_16','id_17','id_18','id_19','id_20','id_21','id_22','id_23',
                 'id_24','id_25','id_26','id_27','id_28','id_29','id_30','id_31',
                 'id_32','id_33','id_34','id_35','id_36','id_37','id_38','C1','C2','C3']
```

In [37]:
```
#create label encoders for categorical features
for x in enc:
 labelenc = LabelEncoder()
 final_df[x] = labelenc.fit_transform(final_df[x].astype('str'))
```

In [38]:
```
final_df['TransactionDT']=(final_df['TransactionDT']//(60*60))%24
```

In [39]:
```
#importing test_identity.csv file
test_id= pd.read_csv('test_identity.csv')

#importing test_transaction.csv file
test_trans= pd.read_csv('test_transaction.csv')
```

In [40]:
```
#have two data sets now :Combine test_trans and test_id with transactionID as commmon
test_final=pd.merge(test_trans,test_id,how='outer',on='TransactionID')
test_final=test_final.filter(fin_cols)
#clean data

#replacing numeric columns with mean
for x in numeric_cols:
 test_final[x].fillna((test_final[x].mean()), inplace=True)


for x in str_cols:
 test_final[x].fillna("no record", inplace=True)

#create label encoders for categorical features
for x in enc:
 labelenc = LabelEncoder()
 test_final[x] = labelenc.fit_transform(test_final[x].astype('str'))


#merged data frame; change dt to hourly range
test_final['TransactionDT']=pd.to_datetime(test_final['TransactionDT'],unit='s')
test_final['TransactionDT']=test_final['TransactionDT'].dt.hour
```

In [41]:
```
y=final_df.isFraud.copy()
X=final_df.drop('isFraud', axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_state=0)
# KNN
# classifier = KNeighborsClassifier(n_neighbors=5)
# classifier.fit(X_train, y_train)
# y_pred = classifier.predict(X_test)
# pr1 = classifier.predict(test_final)
```

In [42]:
```
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators=20, random_state=0)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
confmatrix = metrics.confusion_matrix(y_test, y_pred)
print(confmatrix)
```

```
[[170921    120]
 [  3265   2856]]
```

In [46]:
```
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
#using the test data to predict isFraud
pr1 = classifier.predict(test_final)
```

```
Accuracy: 0.9808931938000248
```

In [45]:
```
out=pd.DataFrame(pr1,test_final.TransactionID,['isFraud'])
out.to_csv('out.csv')
```

Training dataset for transaction and identity are merged to form final dataframe. This data frame is filtered out by only considering few columns which would be relevant for prediction. After this the dataset is cleaned by replacing NANs with appropriate values in numerical as well object columns. Label encoders are used for all the columns. Test data is also cleaned and irrelevant columns are removed. Random forest classifier is used to predict the isFraud for test dataset. Accuracy is 0.98

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/aishwaryavhs07 (https://www.kaggle.com/aishwaryavhs07)

Highest Rank: 5681

Score: 0.6020

Number of entries: 5

Overview Data Notebooks Discussion Leaderboard Rules Team My Submissions **Submit Predictions**

5678	alexey0308	0.6074	1	2mo
5679	Zhengyang Xu	0.6045	2	2mo
5680	Chaitra Hegde	0.6028	10	4h
5681	Hemasai Aishwarya Vijayaku...	0.6020	5	6h

Your Best Entry ↑

Your submission scored 0.5398, which is not an improvement of your best score. Keep trying!

5682	Niharika Tippabhatla	0.5980	2	10h
5683	Binayak Ranjan Das	0.5959	1	6h
5684	Debapriya Mukherjee	0.5947	1	7h
5685	Siddhanth Parikh	0.5935	5	25m
5686	Sushravya	0.5927	2	4h
5687	salimelawad	0.5925	2	2mo