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 [25]:
```
# TODO: code and runtime results
```

In [420]:
```
import pandas as pd
# import the seaborn module
import seaborn as sns
# import the matplotlib module
import matplotlib.pyplot as plt
import datetime
import numpy as np
from matplotlib.ticker import PercentFormatter
import os
import missingno as msno # visualize the distribution of NaN values
import warnings
pd.options.mode.chained_assignment = None
warnings.filterwarnings("ignore", category=DeprecationWarning)
%matplotlib inline
```

In [424]:
```
#reading the file train_(identity,transaction)
train_idt= pd.read_csv("train_identity.csv")
train_txn= pd.read_csv("train_transaction.csv")
```

In [28]:
```
#reading the file test_(identity,transaction)
test_idt= pd.read_csv('test_identity.csv')
test_txn= pd.read_csv('test_transaction.csv')
```

Cheking the data frames idt and txn to filter out relevant column

for parts 1 to 5 need the below columns 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, …)

In [29]:
```
#Filtering out required columns from idt
idt_filt = ['TransactionID','DeviceType','DeviceInfo']
train_idt = train_idt[idt_filt]
test_idt = test_idt[idt_filt]
```

In [30]:
```
#Filtering out required columns from txn
train_txn_filt = ['TransactionID','TransactionDT','TransactionAmt','ProductCD','card4','card6','P_emaildomain','R_emaildomain','addr1','addr2','dist1','dist2','isFraud']
train_txn = train_txn[train_txn_filt]

test_txn_filt = ['TransactionID','TransactionDT','TransactionAmt','ProductCD','card4','card6','P_emaildomain','R_emaildomain','addr1','addr2','dist1','dist2']
test_txn = test_txn[test_txn_filt]
```

In [31]:
```
#merge both train files idt and txn based on common entity 'TransactionID'
train_df = pd.merge(train_txn, train_idt,on='TransactionID', how='left')
#train_df=train_df.drop_duplicates()

#merge both test files idt and txn based on common entity 'TransactionID'
test_df = pd.merge(test_txn,test_idt, on='TransactionID', how='left')

print('Shape of Training Set: ' + str(train_df.shape))
print('Shape of Test Set: ' + str(test_df.shape))
```

```
Shape of Training Set: (590540, 15)
Shape of Test Set: (506691, 14)
```

In [32]:
```
del train_idt, train_txn, test_idt, test_txn
```

In [33]:
```
#Checking Nullity and Data Completeness
import missingno as msno
msno.matrix(train_df)
plt.title('Data Completenss Check in Training Set', size = 40)
```

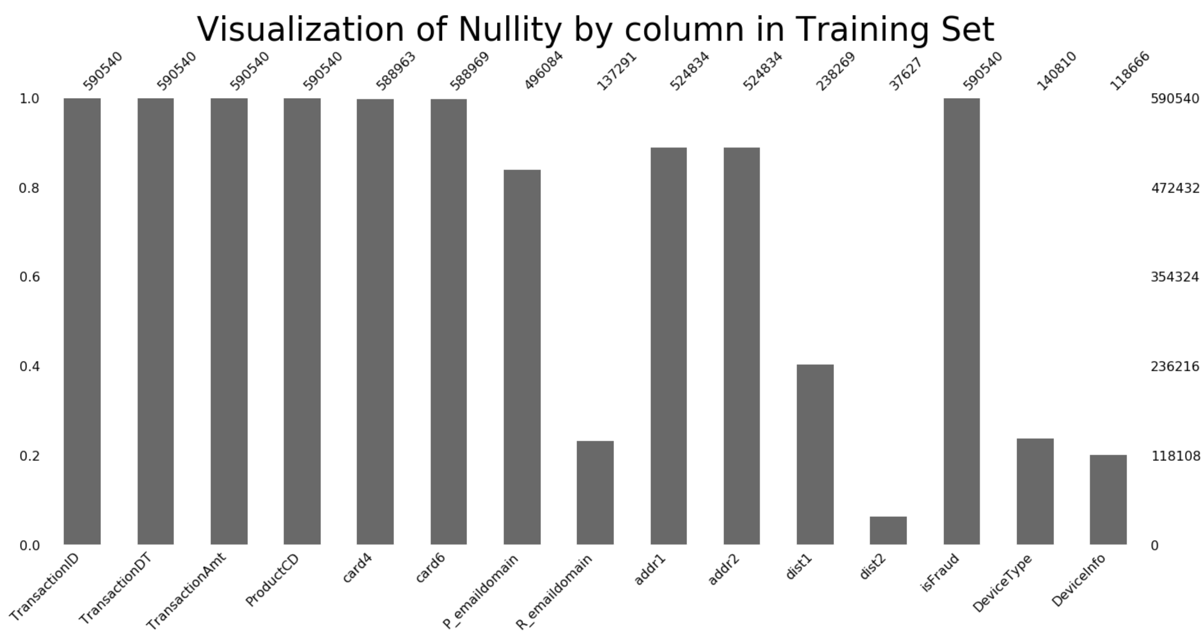
Out[33]:
```
Text(0.5, 1.0, 'Data Completenss Check in Training Set')
```

-->From Above plot we observe that dist2, dist1, R_emaildomain, DeviceType, DeviceInfo are alomst empty, lets investigate further to see what number of non null values are present in each variable

In [34]:
```
from tabulate import tabulate
print("Percentage Null Values in each column")
print(train_df.isna().mean().round(4) * 100)

msno.bar(train_df)
plt.title('Visualization of Nullity by column in Training Set', size = 4
0)
```

```
Percentage Null Values in each column
TransactionID      0.00
TransactionDT      0.00
TransactionAmt     0.00
ProductCD          0.00
card4              0.27
card6              0.27
P_emaildomain     15.99
R_emaildomain     76.75
addr1             11.13
addr2             11.13
dist1             59.65
dist2             93.63
isFraud            0.00
DeviceType        76.16
DeviceInfo        79.91
dtype: float64
```

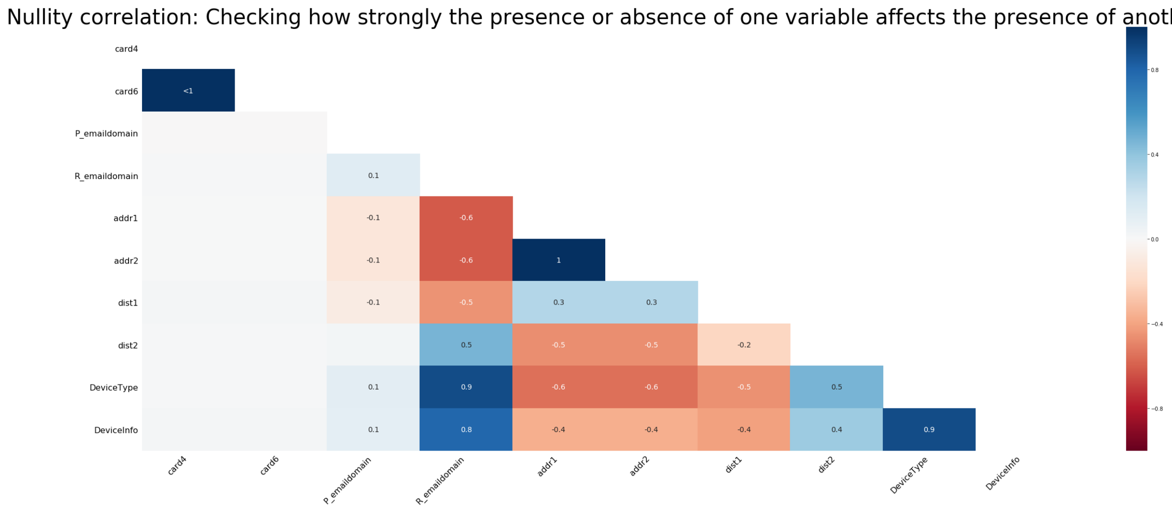
Out[34]:
```
Text(0.5, 1.0, 'Visualization of Nullity by column in Training Set')
```



-->We clearly observe that columns dist2 has 94% nullls, dist1 has 60% nulls, DeviceType has 76% nulls, DeviceInfo has 80% nulls, Remaildomain has 77% nulls, investigating further how does the nullity of one column are related to other columns

In [35]:
```
msno.heatmap(train_df,figsize= (40,15))
plt.title('Nullity correlation: Checking how strongly the presence or ab
sence of one variable affects the presence of another', size = 40)
```

Out[35]:
```
Text(0.5, 1, 'Nullity correlation: Checking how strongly the presence o
r absence of one variable affects the presence of another')
```



-->From the above Nullity by column Visualization we observe that: --> The TransactionID, TransactionDT, TransactionAmt, ProductCD, IsFraud,dist1 which are completely filled or unfilled are not included in the vislualization -->addr1 and addr2 have nullity realtion =1, if one is present other is present and viceversa --> dist2, addr1, addr2 are only partially complete --> DeviceType and DeviceInfo als have high nullity relation ~0.9 --> DeviceType and Remaildomain als have high nullity relation ~0.9 **We conclude that we can keep either addr1 or addr2**

In [36]:
```
#Dropping dist1, dist2, DeviceType,DeviceInfo, R_emaildomain as they are
mostly NUll Values
train_df= train_df.drop(['dist1','dist2','DeviceType','DeviceInfo','R_em
aildomain'], axis=1)
test_df = test_df.drop(['dist1','dist2','DeviceType','DeviceInfo','R_ema
ildomain'], axis=1)

train_df['addr1']= train_df['addr1'].astype(str)
train_df['addr2']= train_df['addr2'].astype(str)

test_df['addr1']= test_df['addr1'].astype(str)
test_df['addr2']= test_df['addr2'].astype(str)
```

Reducing the Memory size by converting the columns to appropriate type and replacing null, NaN values of numerical varibales by -999

In [37]:
```
def reduce_memory(df):
    original_mem_usg = df.memory_usage().sum() / 1024**2
    print("Memory usage of orginal properties dataframe is :",original_m
em_usg," MB")
    NAlist = [] # Keeps track of columns that have missing values filled
in.
    for col in df.columns:
        if df[col].dtype != object:  # Exclude strings

            # make variables for Int, max and min
            IsInt = False
            mx = df[col].max()
            mn = df[col].min()

            #Integer does not support NA, therefore, NA needs to be fill
ed

            if not np.isfinite(df[col]).all():
               NAlist.append(col)
               df[col].fillna(-999,inplace=True)

            # test if column can be converted to an integer
            asint = df[col].fillna(0).astype(np.int64)
            result = (df[col] - asint)
            result = result.sum()
            if result > -0.01 and result < 0.01:
                IsInt = True


            # Make Integer/unsigned Integer datatypes
            if IsInt:
                if mn >= 0:
                    if mx < 255:
                        df[col] = df[col].astype(np.uint8)
                    elif mx < 65535:
                        df[col] = df[col].astype(np.uint16)
                    elif mx < 4294967295:
                        df[col] = df[col].astype(np.uint32)
                    else:
                        df[col] = df[col].astype(np.uint64)
                else:
                    if mn > np.iinfo(np.int8).min and mx < np.iinfo(np.i
nt8).max:
                        df[col] = df[col].astype(np.int8)
                    elif mn > np.iinfo(np.int16).min and mx < np.iinfo(n
p.int16).max:
                        df[col] = df[col].astype(np.int16)
                    elif mn > np.iinfo(np.int32).min and mx < np.iinfo(n
p.int32).max:
                        df[col] = df[col].astype(np.int32)
                    elif mn > np.iinfo(np.int64).min and mx < np.iinfo(n
p.int64).max:
                        df[col] =df[col].astype(np.int64)

            # Make float datatypes 32 bit
            else:
```

```
                df[col] = df[col].astype(np.float32)

    # Print final result
    print("___MEMORY USAGE AFTER COMPLETION:___")
    mem_usg = df.memory_usage().sum() / 1024**2
    print("Memory usage is: ",mem_usg," MB")
    print("This is ",100*mem_usg/original_mem_usg,"% of the initial siz
e")
    return df

#Reducing Memory For training and test data
train=reduce_memory(train_df)

test=reduce_memory(test_df)
```

```
Memory usage of orginal properties dataframe is : 49.560089111328125  M
B
___MEMORY USAGE AFTER COMPLETION:___
Memory usage is:  38.859615325927734  MB
This is  78.4090909090909 % of the initial size
Memory usage of orginal properties dataframe is : 38.65745544433594  MB
___MEMORY USAGE AFTER COMPLETION:___
Memory usage is:  32.85883712768555  MB
This is  85.0 % of the initial size
```

In [38]:
```
#Keeping a backup for train and test
train_bkup = train.copy()
test_bkup = test.copy()
```

In [39]:
```
#Run this cell in case test and train needs to be brought back to origin
al shape
train=train_bkup.copy()
test= test_bkup.copy()
```

Part 1 Continued...

Filter out your data to examine just the fraudulent transactions. For each field above, examine the distribution of the values, and explain any interesting insight you get from this. How do the distributions on fraudulent transactions compare to the non-fraudulent ones?

Checking Numeric AND Categorical Columns

In [40]:
```
cols=train.columns
num_cols=train._get_numeric_data().columns
cat_cols=list(set(cols)-set(num_cols))
print("Numeric Columns:",num_cols)
print("Categoric Columns:",cat_cols)
```

```
Numeric Columns: Index(['TransactionID', 'TransactionDT', 'TransactionA
mt', 'isFraud'], dtype='object')
Categoric Columns: ['card6', 'ProductCD', 'card4', 'addr1', 'addr2', 'P
_emaildomain']
```

To handle Time period of the data, let's look at the country code distribution of the data

In [41]:
```
country_zone = train.groupby(['addr2'])['TransactionID'].count()
cnt= pd.DataFrame(country_zone*100 / country_zone.sum())
cnt=cnt.reset_index()
cnt.columns = ['addr2', 'Percentage_Transactions']


df1 = cnt.sort_values('Percentage_Transactions',ascending = False)
df1.head(5)
```

Out[41]:

	addr2	Percentage_Transactions
65	87.0	88.136451
74	nan	11.126427
43	60.0	0.522234
71	96.0	0.108037
23	32.0	0.015410

We can see that 88% of the data comes from Country code 87 and 11 % are null which accounts to 99% of all data so its safe to take any base timesamp and convert TimestampDt to date format

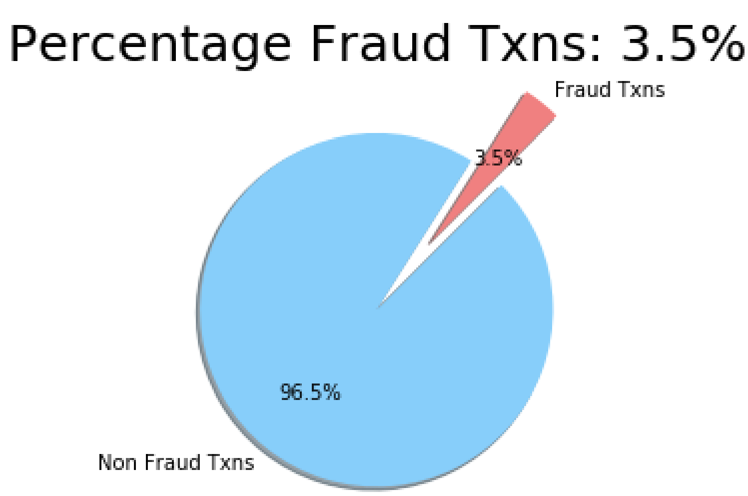
The TransactionDT feature is timedelta from a given reference datetime (not an actual timestamp). Let's assume the start time is from Jan 19,2019

In [42]:
```
st_dt = datetime.datetime.strptime('2019-01-19', '%Y-%m-%d')
train['TransactionDT'] = train['TransactionDT'].apply(lambda x: (st_dt +
datetime.timedelta(seconds = x)))
test['TransactionDT'] = test['TransactionDT'].apply(lambda x: (st_dt + d
atetime.timedelta(seconds = x)))

#Converting Date to 'yy-mm-dd hh-mm-ss' format
#train_df['TransactionDT']= pd.to_datetime(train_df['TransactionDT'],uni
t='s')
```

Checking Percentage of Fraud Samples in the training Set

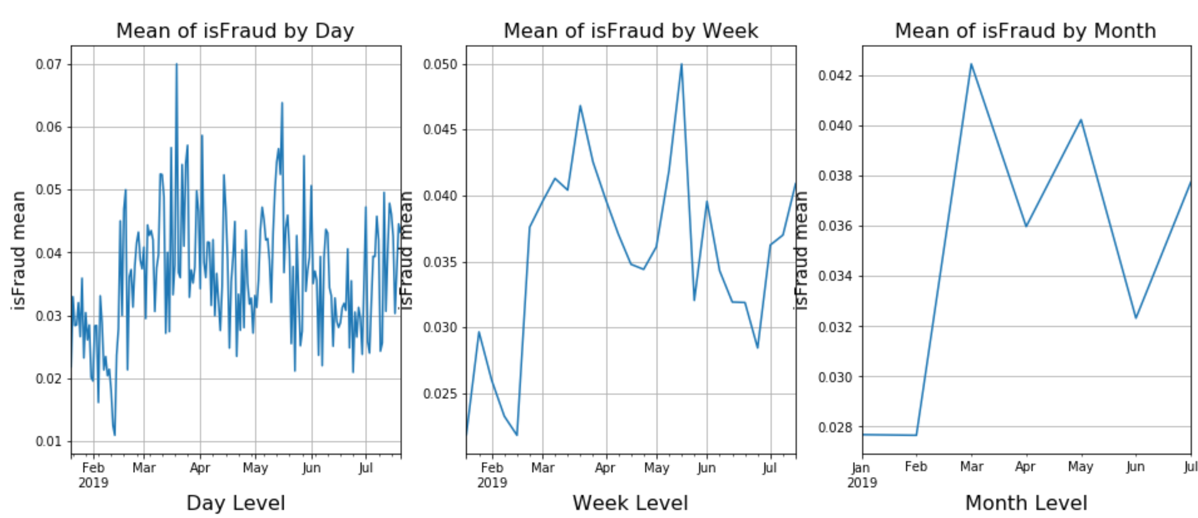
In [43]:
```
#Filtering Fraud and nonFraud Transactions
fraud_txn = train.loc[train['isFraud'] == 1]
non_fraud_txn = train.loc[train['isFraud'] == 0]

print('Total Data frame Shape: '+ str(train.shape))
print('Fraud_Txns Data frame Shape: ' + str(fraud_txn.shape))
print('Non_Fraud_Txns Data frame Shape: ' + str(non_fraud_txn.shape))

print('')
total_rws= train.shape[0]
fraud_rws= fraud_txn.shape[0]

plt.title('Percentage Fraud Txns: '+ str(round(fraud_rws*100/total_rws,2
))+'%', size = 25)


import matplotlib.pyplot as plt

# Data to plot
labels = 'Fraud Txns', 'Non Fraud Txns'
sizes = [fraud_rws,total_rws-fraud_rws]
colors = ['lightcoral', 'lightskyblue']
explode = (0.5, 0)  # explode 1st slice

# Plot
plt.pie(sizes, explode=explode, labels=labels, colors=colors,
autopct='%1.1f%%', shadow=True, startangle=45)
plt.axis('equal')
plt.show()
```

```
Total Data frame Shape: (590540, 10)
Fraud_Txns Data frame Shape: (20663, 10)
Non_Fraud_Txns Data frame Shape: (569877, 10)
```



In [44]:
```
import matplotlib.gridspec as gridspec

fig = plt.figure(figsize=(16, 6))
gs = gridspec.GridSpec(1, 3)

axes = plt.subplot(gs[0, 0])
train.set_index('TransactionDT').resample('D').mean()['isFraud'].plot(ax
=axes).set_ylabel('isFraud mean', fontsize=14)
axes.set_title('Mean of isFraud by Day', fontsize=16)
axes.set_xlabel('Day Level', fontsize=16)
plt.grid(True)

fig.add_subplot(axes)


axes = plt.subplot(gs[0, 1])
train.set_index('TransactionDT').resample('W').mean()['isFraud'].plot(ax
=axes).set_ylabel('isFraud mean', fontsize=14);
axes.set_title('Mean of isFraud by Week', fontsize=16)
axes.set_xlabel('Week Level', fontsize=16)
plt.grid(True)

fig.add_subplot(axes)

axes = plt.subplot(gs[0, 2])
train.set_index('TransactionDT').resample('M').mean()['isFraud'].plot(ax
=axes).set_ylabel('isFraud mean', fontsize=14);
axes.set_title('Mean of isFraud by Month', fontsize=16)
axes.set_xlabel('Month Level', fontsize=16)
plt.grid(True)

fig.add_subplot(axes)
```

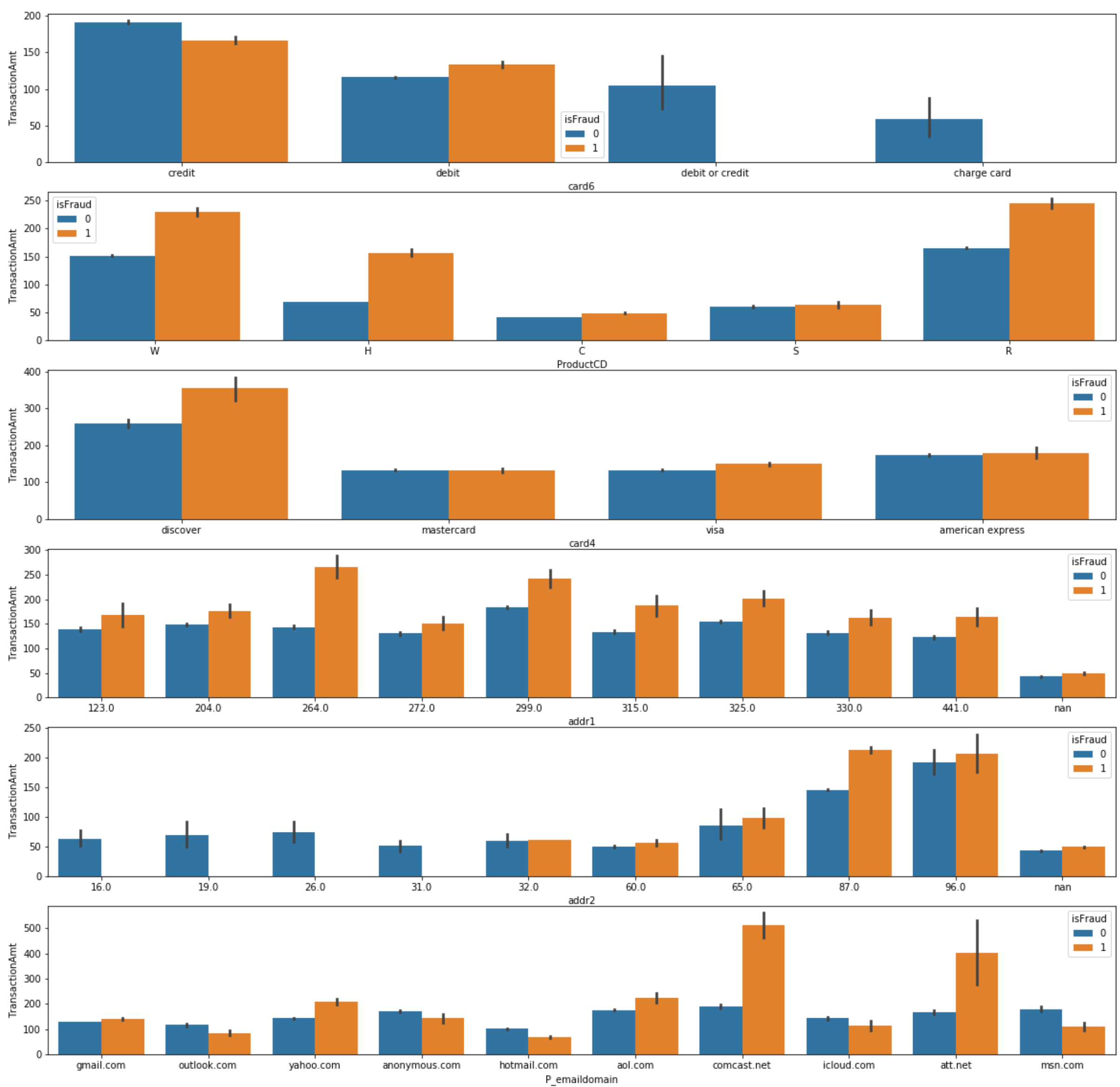
Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x11cbe0748>



From above we observe the following : --> The probaility of Fraud spikes at the mid of the month --> It will be interesting to see if week of the month plays a role in determining Fraud

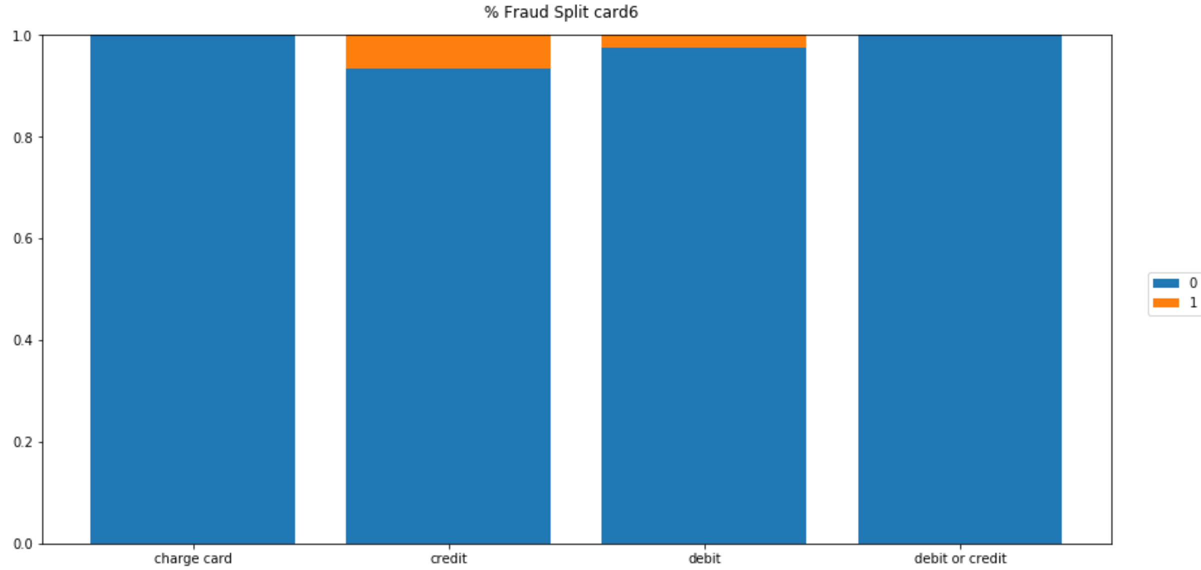
Plotting Transaction Amount for Fraud v/s Non Fraud for all the categorical Variable

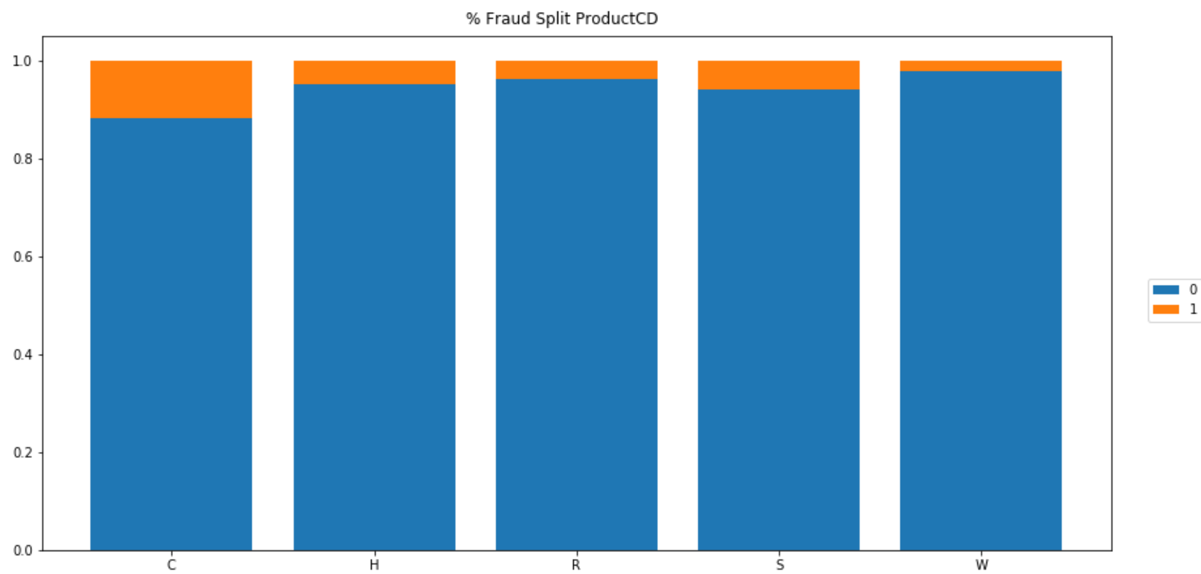
In [46]:
```
fig = plt.figure(figsize=(20, 20))

tot_plots=len(cat_cols)
i=1
for var in cat_cols:

    plt.subplot(tot_plots, 1, i)
    pick=train[var].value_counts()[:10].index
    temp=train.loc[train[var].isin(pick)]
    sns.barplot(x=var, y="TransactionAmt",hue="isFraud",data=temp)
    i=i+1
```

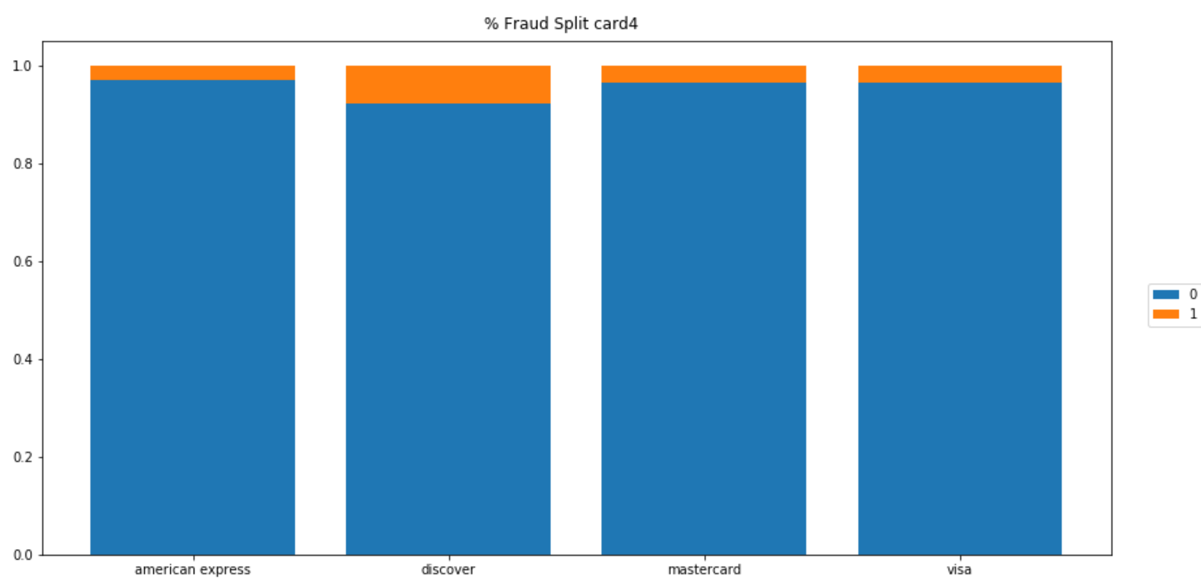


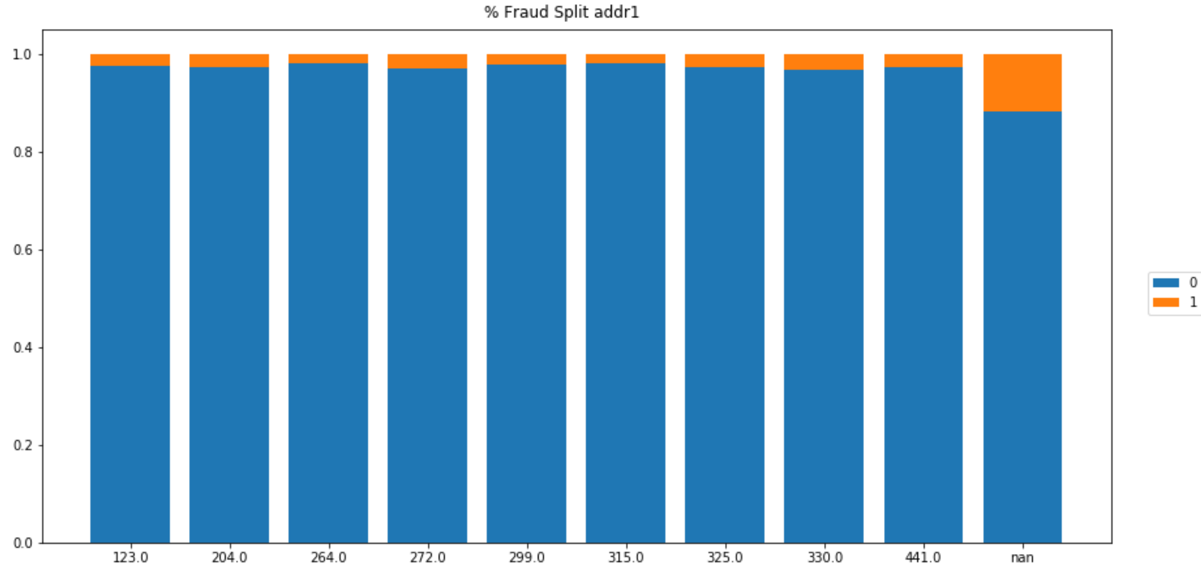
% Fraud on each category Level

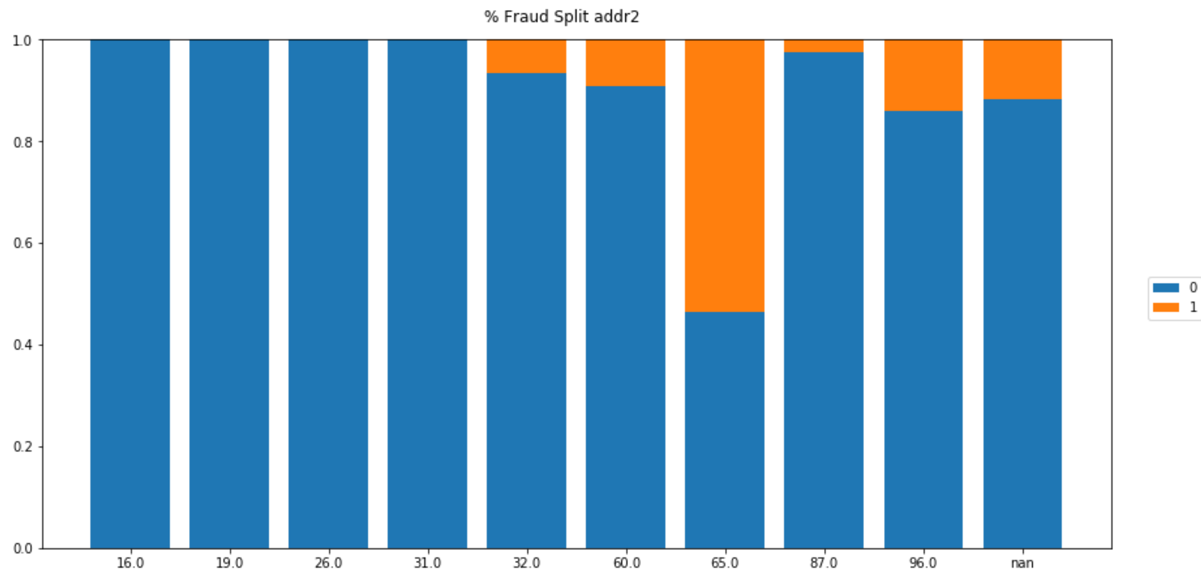
In [47]:
```
import dexplot as dxp

for var in cat_cols:
    #Selecting Top 10 most used var
    pick=train[var].value_counts()[:10].index
    temp=train.loc[train[var].isin(pick)]
    dxp.aggplot(agg=var, data=temp,hue='isFraud', normalize=var,stacked=
True,title="% Fraud Split " + var)
```

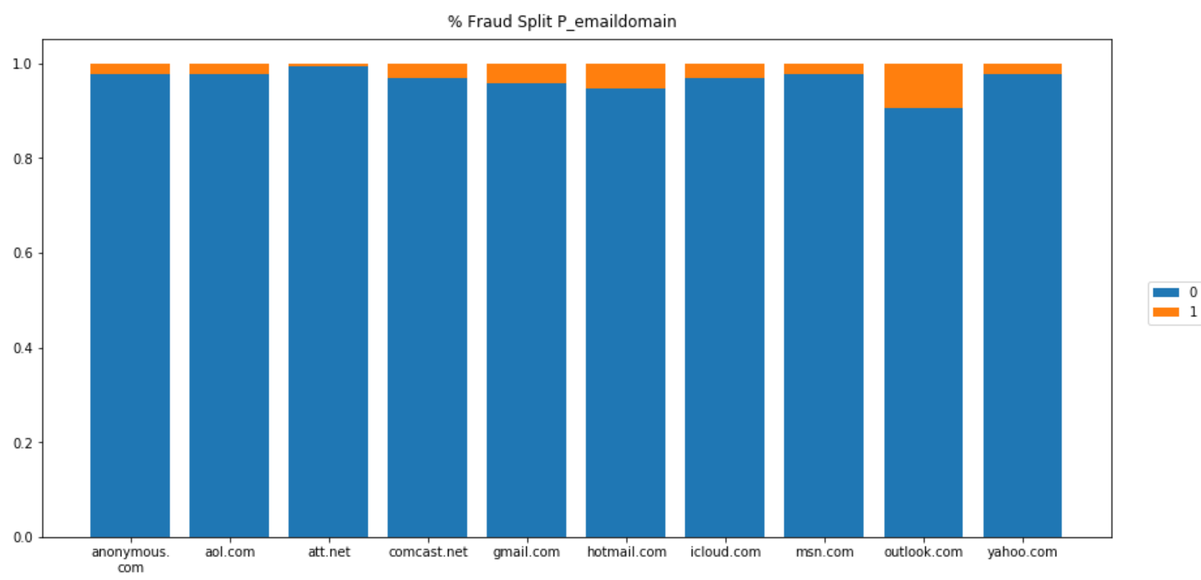

% Fraud Split card6
1.0
0.8
0.6
0.4
0.2
0.0
charge card
credit
debit
debit or credit
0
1


% Fraud Split ProductCD
1.0
0.8
0.6
0.4
0.2
0.0
C
H
R
S
W
0
1


% Fraud Split card4
1.0
0.8
0.6
0.4
0.2
0.0
american express
discover
mastercard
visa
0
1

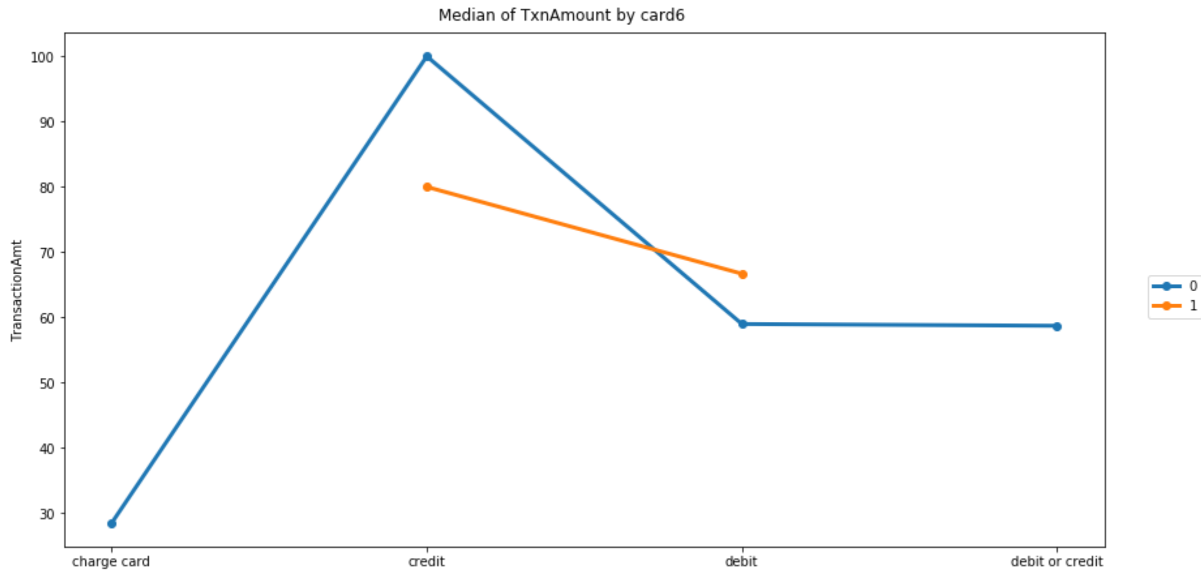

% Fraud Split addr1
1.0
0.8
0.6
0.4
0.2
0.0
123.0
204.0
264.0
272.0
299.0
315.0
325.0
330.0
441.0
nan
0
1

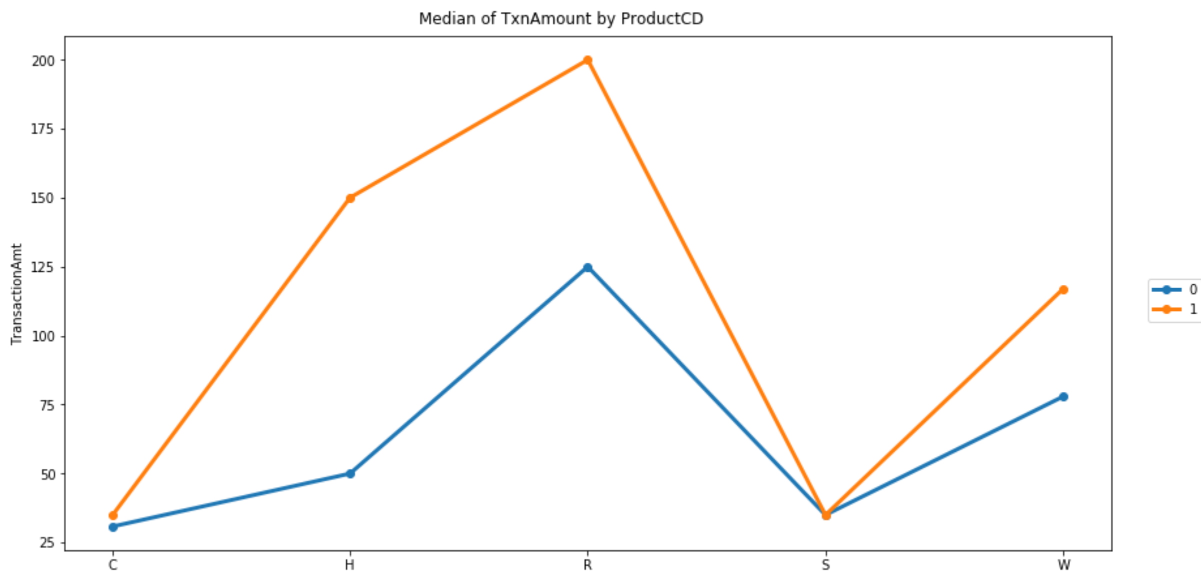

% Fraud Split addr2
1.0
0.8
0.6
0.4
0.2
0.0
16.0
19.0
26.0
31.0
32.0
60.0
65.0
87.0
96.0
nan
0
1

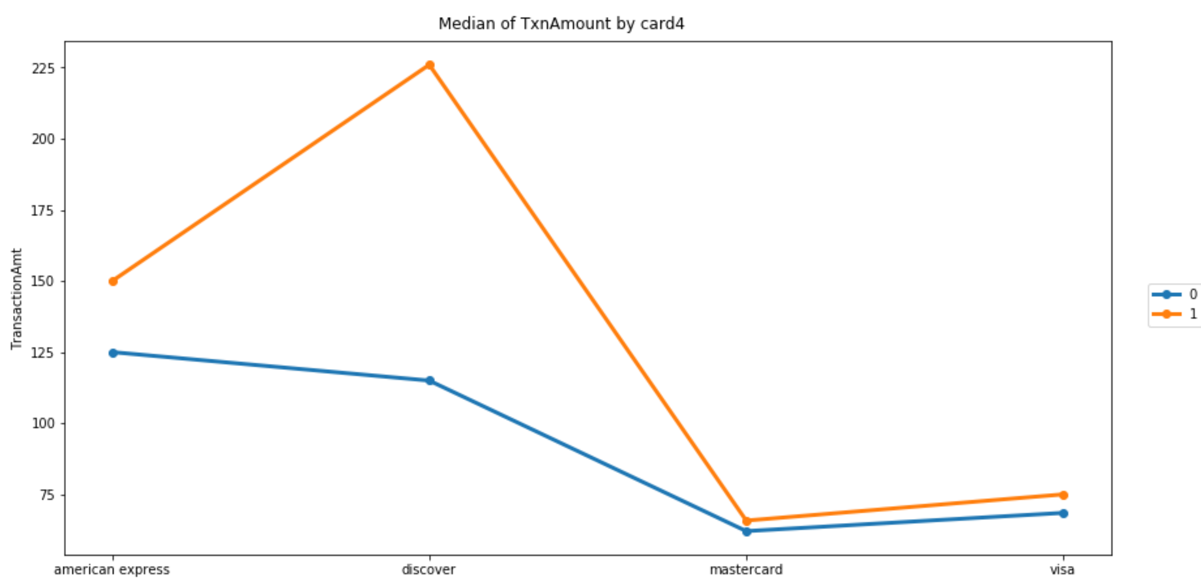

% Fraud Split P_emaildomain
1.0
0.8
0.6
0.4
0.2
0.0
anonymous.
com
aol.com
att.net
comcast.net
gmail.com
hotmail.com
icloud.com
msn.com
outlook.com
yahoo.com
0
1

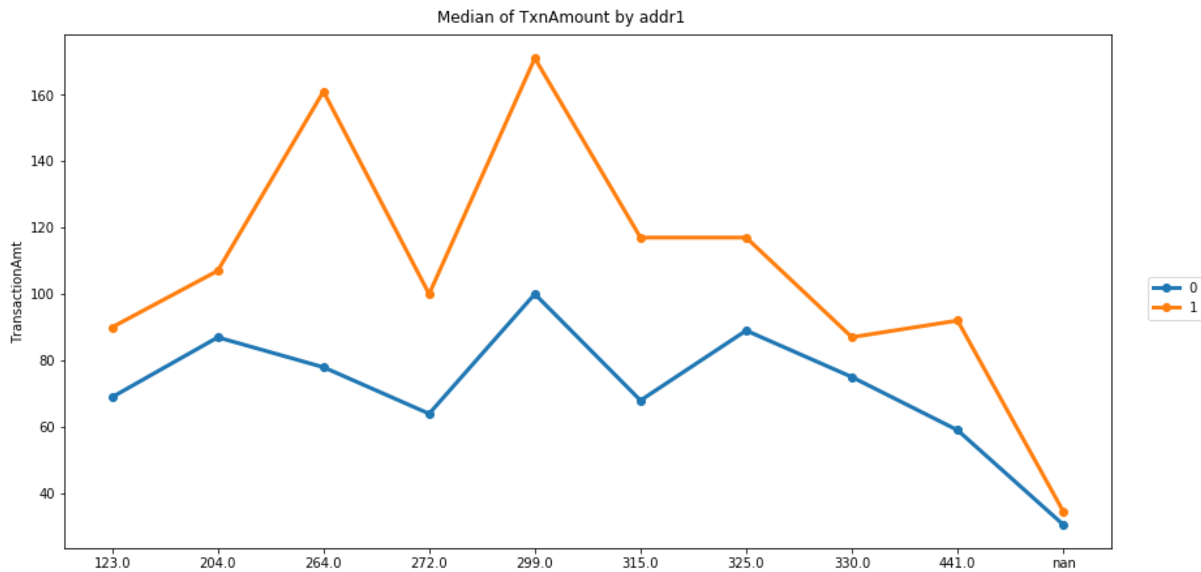
Checking the Median Transaction Amount across all cateogries to determine if there are any alerts

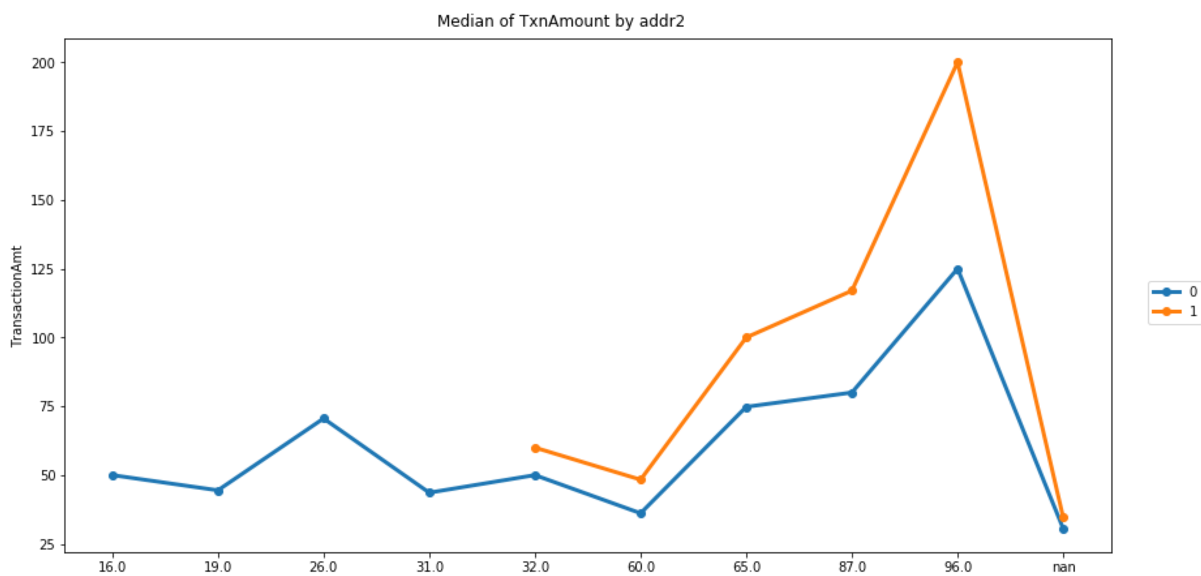
In [48]:
```
for var in cat_cols:
    #Selecting Top 10 most used var
    pick=train[var].value_counts()[:10].index
    temp=train.loc[train[var].isin(pick)]
    dxp.aggplot(agg='TransactionAmt', data=temp, groupby=var, hue='isFraud', kind='line', aggfunc='median',title="Median of TxnAmount by " + var)
```

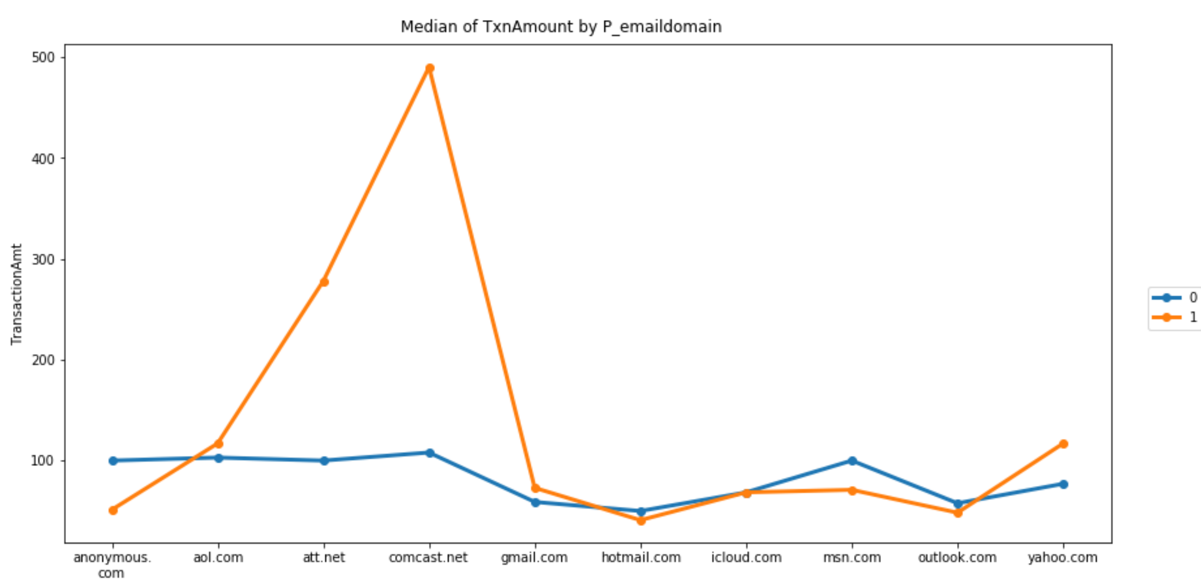

Median of TxnAmount by card6
TransactionAmt
100
90
80
70
60
50
40
30
charge card
credit
debit
debit or credit
0
1


Median of TxnAmount by ProductCD
TransactionAmt
200
175
150
125
100
75
50
25
C
H
R
S
W
0
1


Median of TxnAmount by card4
TransactionAmt
225
200
175
150
125
100
75
american express
discover
mastercard
visa
0
1







##Observations: --> addr2= 65 has 50% of its transactions as Fraud --> Product Code "C" has highest percentage of fraud comapred to other products --> There are more Credit Card Frauds than Debit Card Frauds --> Median of trnsaction amount for Fraud cases is on a higher side

Part 2 - Transaction Frequency

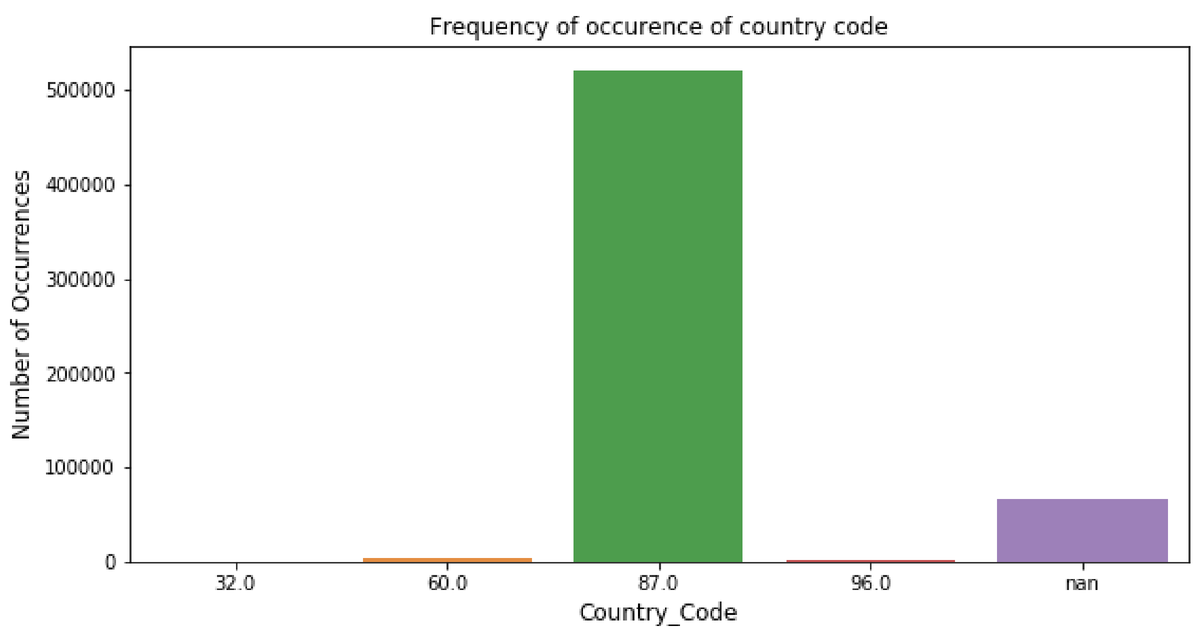
In [49]:
```
# TODO: code to generate the frequency graph
```

The addr2 field gives a code (but not name) associated with the country of the purchaser. TransactionDT shows the time passed from some reference for each transaction. By looking at the time of day of the transactions, we can infer what waking hours are associated with the country relative to the reference time. Analyze the frequency distribution of transactions by time for the most frequent country code, as per the addr2 field. Plot this distribution. Explain your findings.

In [50]:
```
#Filtering only addr2 and Date columns for ditribution visualization
addr2_dt = train[['addr2','TransactionDT']]
addr2_dt= pd.DataFrame(addr2_dt)
```

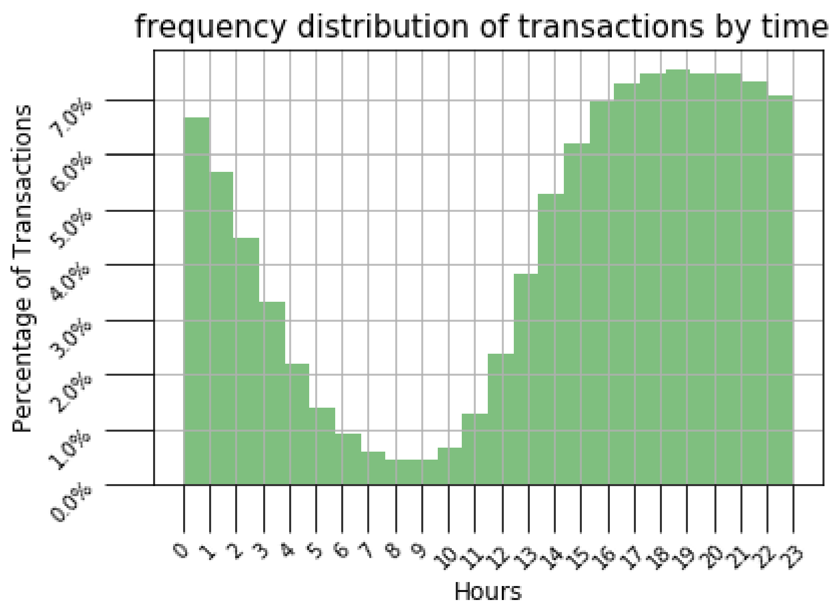
In [51]:
```
#Adding hour column
import datetime
addr2_dt['hours'] = addr2_dt.TransactionDT.dt.hour
```

In [52]:
```
# Plotting a bar graph of the number of occurences of each unique addr2
 in the column 'addr2'
addr2_count  = addr2_dt['addr2'].value_counts()
addr2_count = addr2_count[:5,]
plt.figure(figsize=(10,5))
sns.barplot(addr2_count.index, addr2_count.values, alpha=0.9)
plt.title('Frequency of occurence of country code')
plt.ylabel('Number of Occurrences', fontsize=12)
plt.xlabel('Country_Code', fontsize=12)
plt.show()
```

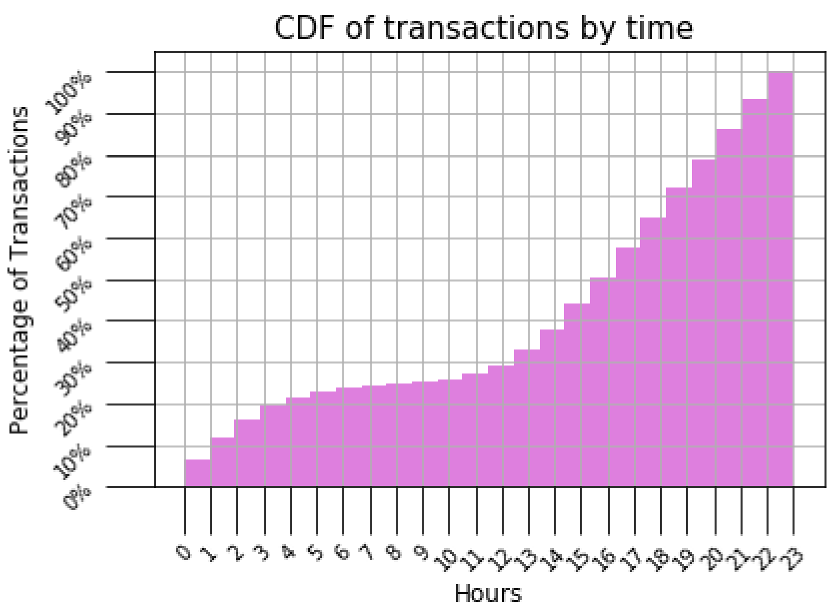


From above graph we observe that addr2 = "87" is the most frequent country code

In [53]:
```
freq_country= addr2_dt.loc[addr2_dt['addr2'] == '87.0']['hours']
#.hist(column='hours', bins=24)

### Plotting the PDF
plt.hist(freq_country, weights=np.ones(len(freq_country)) / len(freq_cou
ntry),bins =24,density=True, histtype='stepfilled',
                           cumulative=0, label='Empirical',facecolor='g'
, alpha=0.5)
plt.gca().yaxis.set_major_formatter(PercentFormatter(1))

plt.title('frequency distribution of transactions by time ',fontsize=15)
plt.ylabel('Percentage of Transactions', fontsize=12)
plt.xlabel('Hours', fontsize=12)
plt.xticks(np.arange(0,24,1))
plt.grid(True)
plt.tick_params(axis ='x', rotation = 45,length =24)
plt.tick_params(axis ='y', rotation = 45,length =24)
```



In [54]:
```
### Plotting the PDF
plt.hist(freq_country, weights=np.ones(len(freq_country)) / len(freq_cou
ntry),bins =24,density=True, histtype='stepfilled',
                           cumulative=1, label='Empirical',facecolor='m'
, alpha=0.5)
plt.gca().yaxis.set_major_formatter(PercentFormatter(1))

plt.title('CDF of transactions by time ',fontsize=15)
plt.ylabel('Percentage of Transactions', fontsize=12)
plt.xlabel('Hours', fontsize=12)
plt.xticks(np.arange(0,24,1))
plt.yticks(np.arange(0,1.1,0.1))
plt.grid(True)
plt.tick_params(axis ='x', rotation = 45,length =24)
plt.tick_params(axis ='y', rotation = 45,length =24)
```



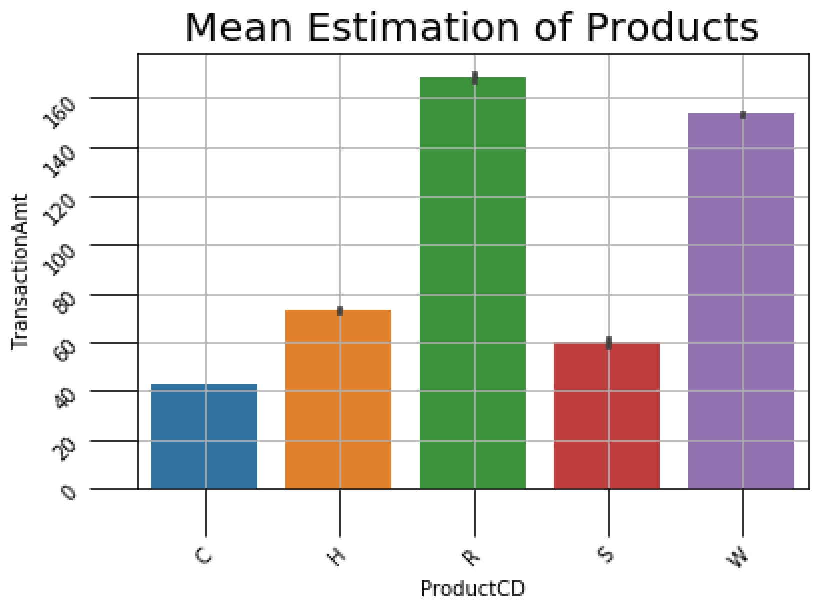
Findings: From the above distribution of transactions by time for the country code =87 we observe below: --> Peak hits at 4pm and remains almost flat till 8pm, ~40% txns are done in this window --> Transactions continously drop after 8pm till morning 6 am, ~20% txns are done from 8pm till midnight, ~10% txns are done from midnight till morning 6am --> Transactions hits the lowest at 8am, reamins almost flat between 6am to 11am, ~ 5% txns are done in this window --> We observe a steep increase since 11am till 4pm, ~ 25% txns are done in this window

Part 3 - Product Code

In [55]:
```
# TODO: code to analyze prices for different product codes
```

ProductCD refers to a product code. Make your best educated guess on which codes correspond to the most expensive products and which to the cheapest products. Justify with analysis.

In [56]:
```
sns.barplot(x="ProductCD", y="TransactionAmt",
            data=train.sort_values("ProductCD"));
plt.title(' Mean Estimation of Products ',fontsize=20)
plt.grid(True)
plt.tick_params(axis ='x', rotation = 45,length =24)
plt.tick_params(axis ='y', rotation = 45,length =24)
```



In [65]:
```
print('Checking the Amount Quantile for each ProductCD')
round(train[['ProductCD', 'TransactionAmt']].groupby('ProductCD').quanti
le([.25, .5, .75,1]),2).transpose()
```

Checking the Amount Quantile for each ProductCD

Out[65]:

ProductCD	C				H				R			
	0.25	**0.50**	**0.75**	**1.00**	**0.25**	**0.50**	**0.75**	**1.00**	**0.25**	**0.50**	**0.75**	**1.00**
TransactionAmt	18.42	31.19	54.1	712.9	35.0	50.0	100.0	500.0	100.0	125.0	200.0	1800.0

From the above Mean Estimation PLot and Quantile Plot we observe below: --> The most expensive Product is R with a median value of 125, mean value of 165 and more than 25% items are sold at price >=200 --> The most cheapest Product is C with a median value of 30.8, mean value of 40 and 75% items are sold at price <= 53

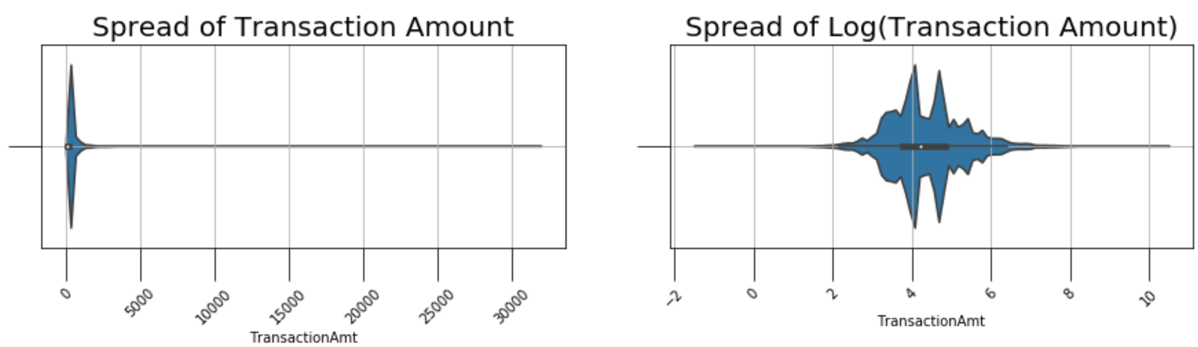
Part 4 - Correlation Coefficient

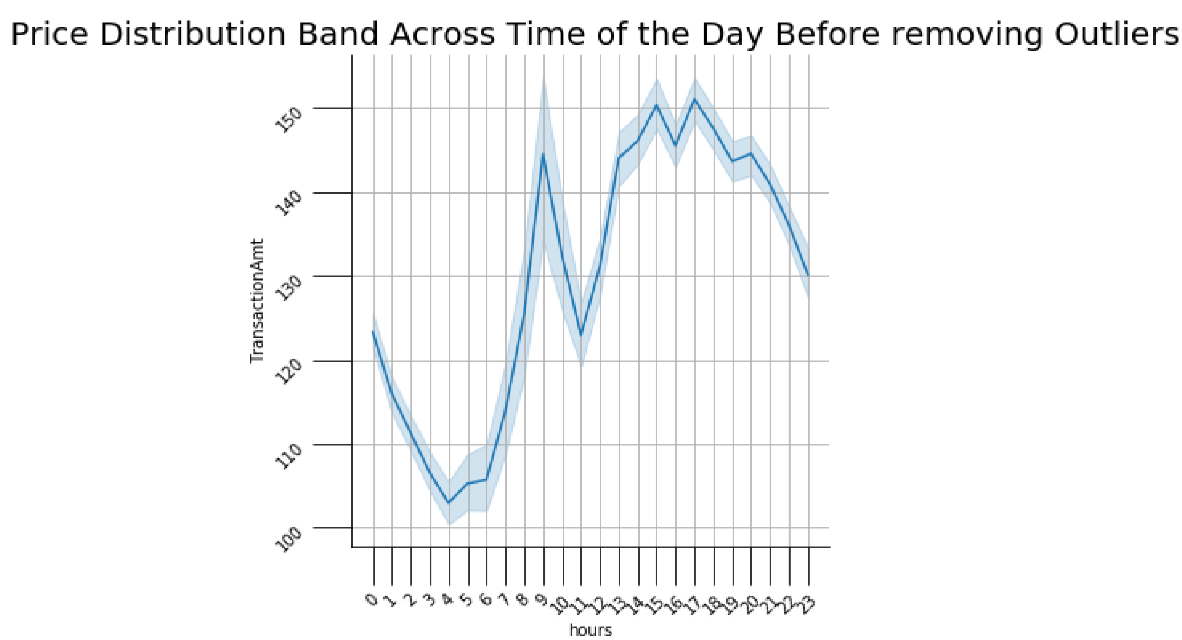
In [66]:
```
# TODO: code to calculate correlation coefficient
```

Plot the distribution between the time of day and the purchase amount. What is the correlation coefficient? Note that some cleaning is necessary to get a meaningful time of day.

In [67]:
```
#Filtering only addr2 and Date columns for ditribution visualization
dt_price = train[['TransactionDT','TransactionAmt']]
dt_price= pd.DataFrame(dt_price)

#Adding hour column

dt_price['hours'] = dt_price.TransactionDT.dt.hour
```

In [80]:
```
plt.figure(figsize= (15,6))
plt.subplot(2,2,1)
sns.violinplot(x=dt_price['TransactionAmt'])
plt.title('Spread of Transaction Amount',fontsize=20)
plt.grid(True)
plt.tick_params(axis ='x', rotation = 45,length =24)
plt.tick_params(axis ='y', rotation = 45,length =24)


plt.subplot(2,2,2)
sns.violinplot(x=np.log(dt_price['TransactionAmt']))
plt.title('Spread of Log(Transaction Amount)',fontsize=20)
plt.grid(True)
plt.tick_params(axis ='x', rotation = 45,length =24)
plt.tick_params(axis ='y', rotation = 45,length =24)

sns.relplot(x="hours", y="TransactionAmt", kind="line", data=dt_price)
plt.title(' Price Distribution Band Across Time of the Day Before removi
ng Outliers',fontsize=20)
plt.grid(True)
plt.xticks(np.arange(0,24,1))
plt.tick_params(axis ='x', rotation = 45,length =24)
plt.tick_params(axis ='y', rotation = 45,length =24)
```





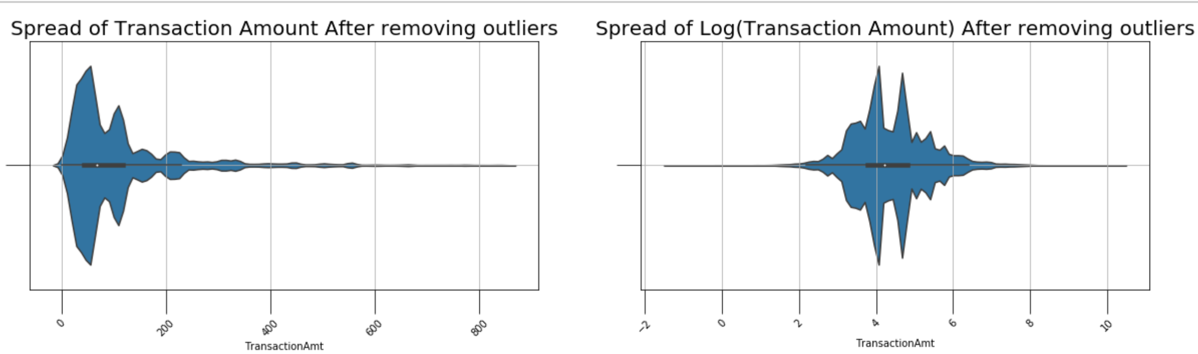
From the above Scatter Plot we observe that beyond the transaction amount 200, the data is very sparse and there are outliers

Finding Z score and removing the data points that are beyond 3Sigma for finding correlation

In [82]:
```
from scipy.stats import zscore
threshold= 3
dt_price["Price_zscore"] = zscore(dt_price["TransactionAmt"])
dt_price["is_outlier"] = dt_price["Price_zscore"].apply(
  lambda x: x <= -threshold or x >= threshold
)
#Filtering out data points that are beyond 3sigma

dt_price_filt= dt_price[dt_price['Price_zscore'] < threshold]
print(" ")
print('\033[1m' + "Shape Before Filtering:", dt_price.shape)
print('\033[1m' + "Shape After Filtering:", dt_price_filt.shape)
```

```
Shape Before Filtering: (590540, 5)
Shape After Filtering: (580447, 5)
```

In [86]:
```
plt.figure(figsize= (20,10))
plt.subplot(2,2,1)
sns.violinplot(x=dt_price_filt['TransactionAmt'])
plt.title('Spread of Transaction Amount After removing outliers',fontsiz
e=20)
plt.grid(True)
plt.tick_params(axis ='x', rotation = 45,length =24)
plt.tick_params(axis ='y', rotation = 45,length =24)


plt.subplot(2,2,2)
sns.violinplot(x=np.log(dt_price['TransactionAmt']))
plt.title('Spread of Log(Transaction Amount) After removing outliers',fo
ntsize=20)
plt.grid(True)
plt.tick_params(axis ='x', rotation = 45,length =24)
plt.tick_params(axis ='y', rotation = 45,length =24)
```



Finding Correlation on two levels, one at Hourly Level , other at ranking Hour based on Early Morning, Morning to Evening, Evening to Midnight and Midnight to Morning

In [89]:
```
from scipy.stats import pearsonr,spearmanr
# calculate Pearson's correlation
dt_price_filt = dt_price_filt[np.isfinite(dt_price_filt['hours'])]
dt_price_filt['hours']= dt_price_filt['hours'].astype(int)

binning= [-1,5,8,12,15,19,23]
dt_price_filt['hr_bucket'] = pd.cut(x=dt_price_filt['hours'], bins= binn
ing,labels=[1,2,3,5,6,4])

median_hr= dt_price_filt.groupby('hours', as_index=False)['TransactionAm
t'].median()

median_hrbuk= dt_price_filt.groupby('hr_bucket', as_index=False)['Transa
ctionAmt'].median()

corr, _ = pearsonr(median_hr['hours'], median_hr['TransactionAmt'])
print('\033[1m' + 'Pearsons correlation on Hour Level: %.3f' % corr)

corr, _ = spearmanr(median_hr['hours'], median_hr['TransactionAmt'])
print('\033[1m' + 'Spearmans correlation on Hour Level: %.3f' % corr)


corr, _ = pearsonr(median_hrbuk['hr_bucket'], median_hrbuk['TransactionA
mt'])
print('\033[1m' + 'Pearsons correlation on HourBucket: %.3f' % corr)

corr, _ = spearmanr(median_hrbuk['hr_bucket'], median_hrbuk['Transaction
Amt'])
print('\033[1m' + 'Spearmans correlation on HourBucket: %.3f' % corr)
```

```
Pearsons correlation on Hour Level: 0.513
Spearmans correlation on Hour Level: 0.478
Pearsons correlation on HourBucket: 0.824
Spearmans correlation on HourBucket: 0.794
```

Part 5 - Interesting Plot

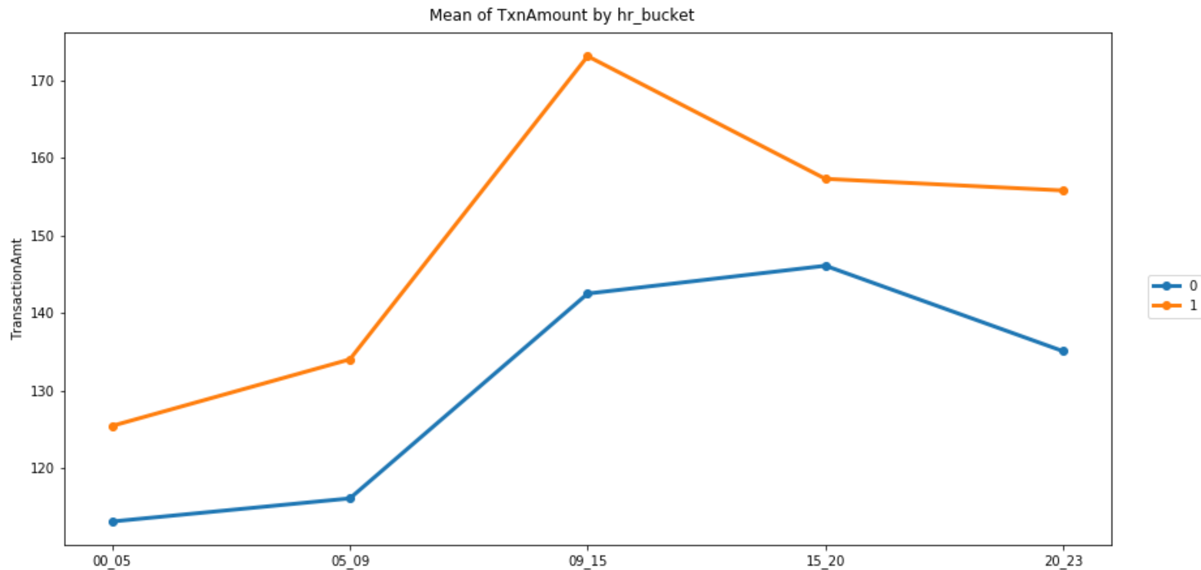
In [90]:
```
# TODO: code to generate the plot here.
```

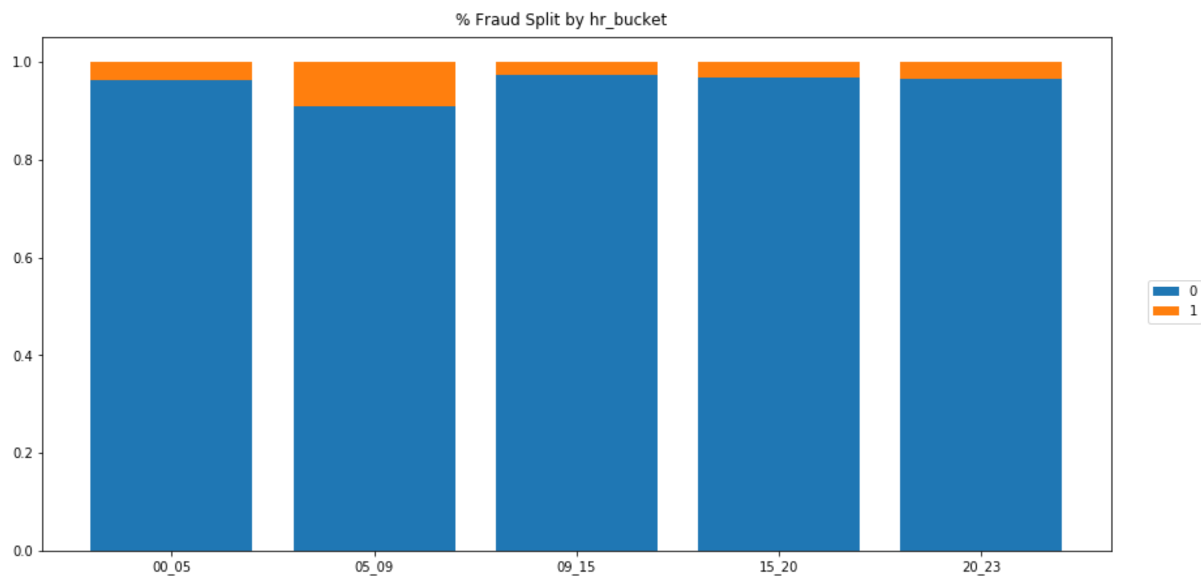
Create a plot of your own using the dataset that you think reveals something very interesting. Explain what it is, and anything else you learned.

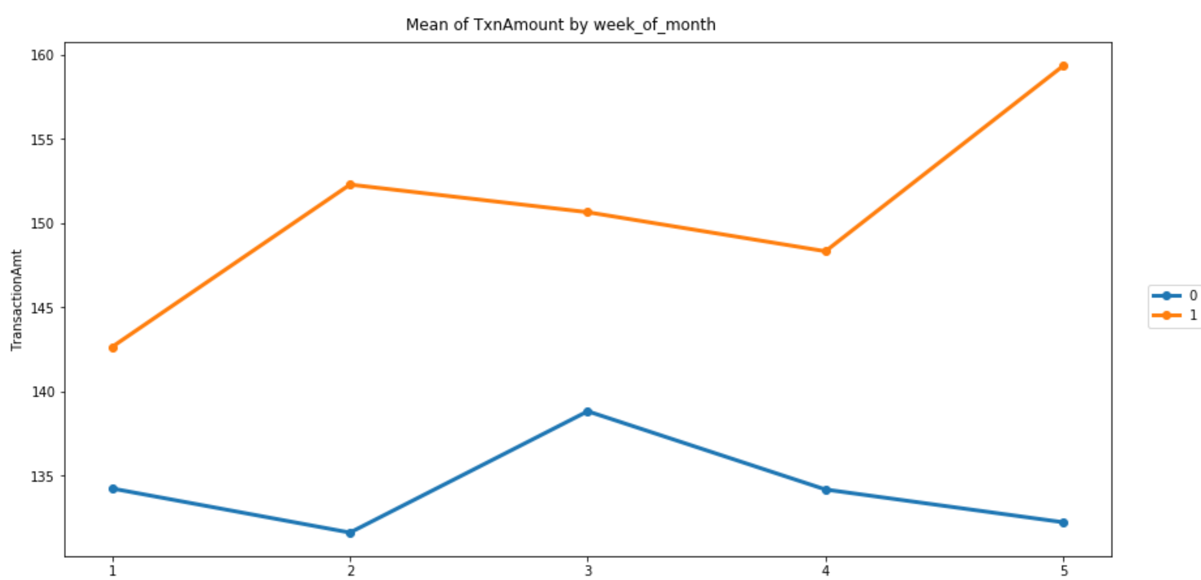
#Adding Time of the day as a variable #Adding Weekofthe Month as a variable

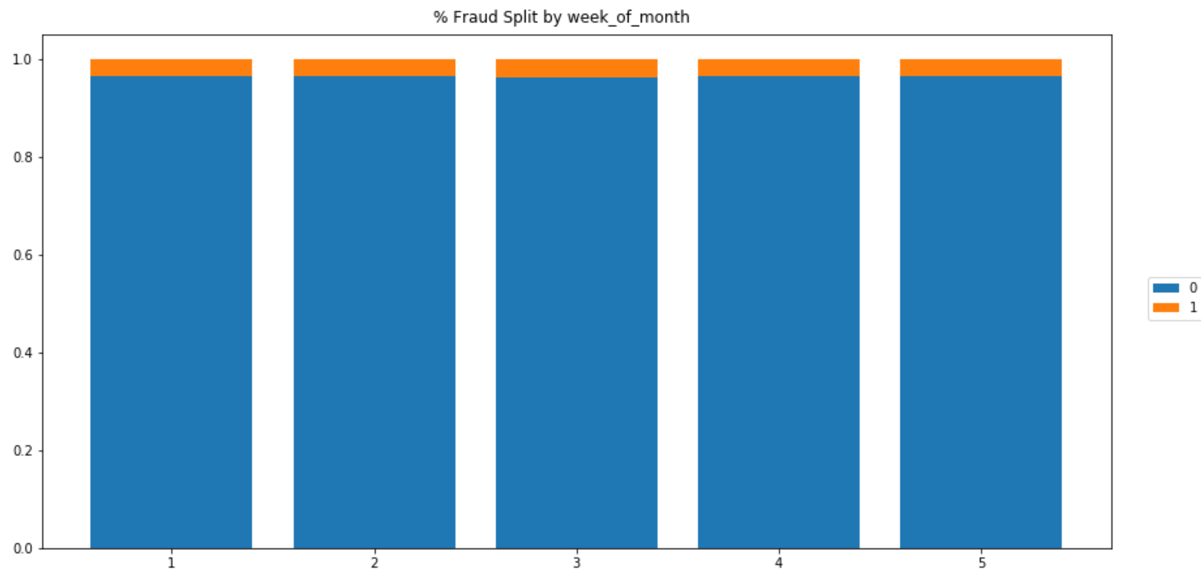
In [91]:
```
#Time of the day
train['hrs'] = train.TransactionDT.dt.hour
train['hrs']= train['hrs'].astype(int)

binning= [-1,5,9,15,20,23]
buk_nm= ['00_05','05_09','09_15','15_20','20_23']
train['hr_bucket'] = pd.cut(x=train['hrs'], bins= binning,labels=buk_nm)

train['week_of_month'] = (train.TransactionDT.dt.day -1)//7 +1
train['week_of_month']= train['week_of_month'].astype(str)

#train['Month_Week']= train.TransactionDT.dt.weekday
#train['Month_WeekDay']= train['Month_Week'].astype(str)

# train['Month']= train.TransactionDT.dt.month
# train['Month']= train['Month'].astype(str)


print('\033[1m' + 'Plotting TxnAmount V/s  [hr_bucket, week_of_month, Mo
nth] to see if there is any pattern')

var= 'hr_bucket'
dxp.aggplot(agg='TransactionAmt', data=train, groupby=var, hue='isFraud'
, kind='line', aggfunc='mean',title="Mean of TxnAmount by " + var)
dxp.aggplot(agg=var, data=train,hue='isFraud', normalize=var,stacked=Tru
e,title="% Fraud Split by " + var)

var= 'week_of_month'
dxp.aggplot(agg='TransactionAmt', data=train, groupby=var, hue='isFraud'
, kind='line', aggfunc='mean',title="Mean of TxnAmount by " + var)
dxp.aggplot(agg=var, data=train,hue='isFraud', normalize=var,stacked=Tru
e,title="% Fraud Split by " + var)

# var= 'Month'
# dxp.aggplot(agg='TransactionAmt', data=train, groupby=var, hue='isFrau
d', kind='line', aggfunc='mean',title="Mean of TxnAmount by " + var)
# dxp.aggplot(agg=var, data=train,hue='isFraud', normalize=var,stacked=T
rue,title="% Fraud Split by " + var)

train['week_of_month']= train['week_of_month'].astype(str)
# train['Month']= train['Month'].astype(str)
train['hr_bucket']= train['hr_bucket'].astype(str)
```

Plotting TxnAmount V/s [hr_bucket, week_of_month, Month] to see if the re is any pattern









From above Plots we observe following: --> During Mid of the Month Fraud Txn amount is 2X of the Non Fraud Txn amount --> During Early Morning from 5am - 9am, ~20% of the transactions are fraud --> Week_of_MOnth and Hour_Bucket could be a good predictor

In [92]:
```
#Time of the day
test['hrs'] = test.TransactionDT.dt.hour
test['hrs']= test['hrs'].astype(int)

binning= [-1,5,9,15,20,23]
buk_nm= ['00_05','05_09','09_15','15_20','20_23']
test['hr_bucket'] = pd.cut(x=test['hrs'], bins= binning,labels=buk_nm)

test['week_of_month'] = (test.TransactionDT.dt.day -1)//7 +1
test['week_of_month']= test['week_of_month'].astype(str)

test['hr_bucket']= test['hr_bucket'].astype(str)
```

Part 6 - Prediction Model

In [93]:
```
# TODO: code for your final model
```

Now, try to build a prediction model that works to solve the task. You are allowed to use additional variables from the dataset if you wish. Perhaps it will use linear regression. Perhaps it will preprocess features (e.g. normalize or scale the input vector, convert non-numerical value into float, or do a special treatment of missing values). Perhaps it will use a different machine learning approach (e.g. nearest neighbors, random forests).

Feature Preparation

In [94]:
```
from sklearn import preprocessing
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
```

In [103]:
```
def print_train_test_columns(train, test):
    print(train.shape)
    print('\033[1m' + "Features in Training Set")
    print(list(train.columns))

    print(' ')
    print(test.shape)
    print('\033[1m' + "Features in Test Set")
    print(list(test.columns))

print_train_test_columns(train, test)
```

```
(590540, 14)
Features in Training Set
['TransactionID', 'TransactionDT', 'TransactionAmt', 'ProductCD', 'card
4', 'card6', 'P_emaildomain', 'addr1', 'addr2', 'isFraud', 'hrs', 'hr_b
ucket', 'week_of_month', 'TxnAmt_Log']

(506691, 13)
Features in Test Set
['TransactionID', 'TransactionDT', 'TransactionAmt', 'ProductCD', 'card
4', 'card6', 'P_emaildomain', 'addr1', 'addr2', 'hrs', 'hr_bucket', 'we
ek_of_month', 'TxnAmt_Log']
```

For categorical Columns if its NA or na or null replacing it with 'empty'

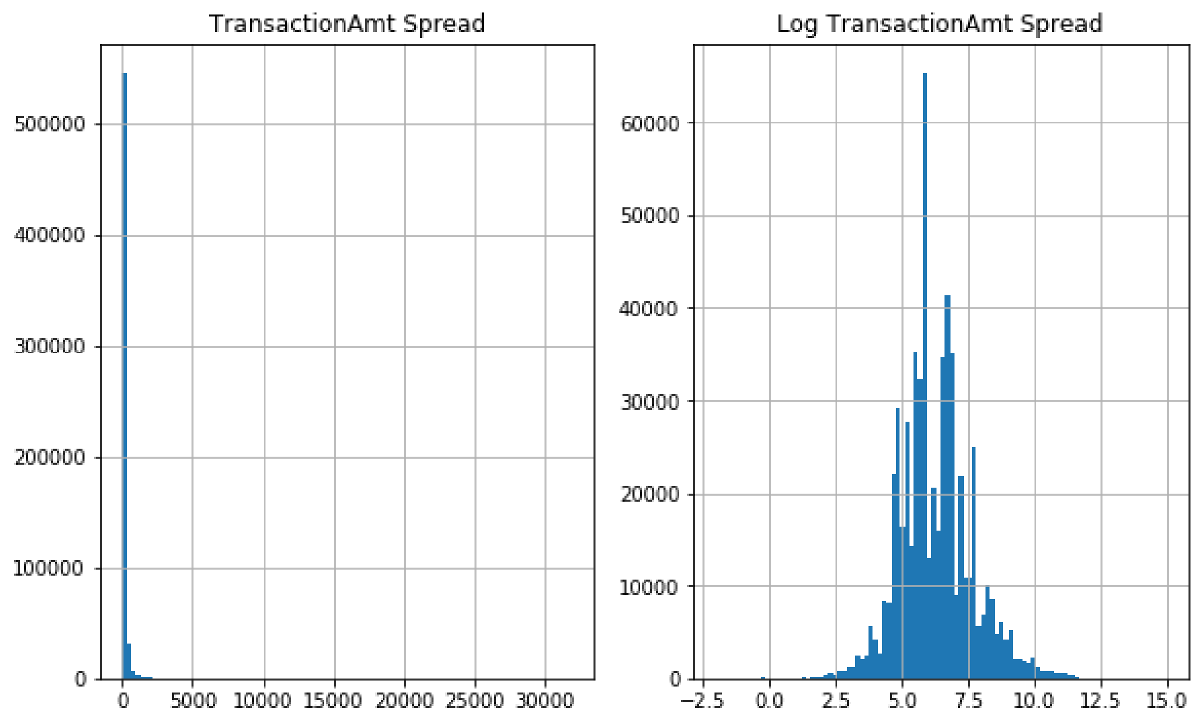
In [100]:
```
##For Training Set
cols=train.columns
num_cols=train._get_numeric_data().columns
cat_cols=list(set(cols)-set(num_cols))

for col in cat_cols:
    train[col]=train[col].fillna('empty')

##For Test Set
cols=test.columns
num_cols=test._get_numeric_data().columns
cat_cols=list(set(cols)-set(num_cols))

for col in cat_cols:
    test[col]=test[col].fillna('empty')
```

As we saw in Part4 that Transaction Amount has lot of outliers so we will introduce a new varibale for amount in the log scale

In [101]:
```
train['TxnAmt_Log']= np.log2(train['TransactionAmt'])
test['TxnAmt_Log']= np.log2(test['TransactionAmt'])

test_id= pd.DataFrame(test['TransactionID'])
```

In [125]:
```
plt.figure(figsize=(10,6))
plt.subplot(1,2,1)
plt.title('TransactionAmt Spread')
(train_on['TransactionAmt']).hist(bins=100)

plt.subplot(1,2,2)
plt.title('Log TransactionAmt Spread')
np.log2(train_on['TransactionAmt']).hist(bins=100)
```

Out[125]: <matplotlib.axes._subplots.AxesSubplot at 0x1639bafd0>



Dropping redundant Columns from the Feature set

In [349]:
```
drop_columns = ['TransactionID', 'TransactionDT','addr1']
train_on=[]
train_on = train.drop(drop_columns, axis=1)
print(train_on.shape)

test_on=[]
test_on = test.drop(drop_columns, axis=1)
print(test_on.shape)
```

```
(590540, 11)
(506691, 10)
```

Reducing the number of categories in the categorical variable of Training Set

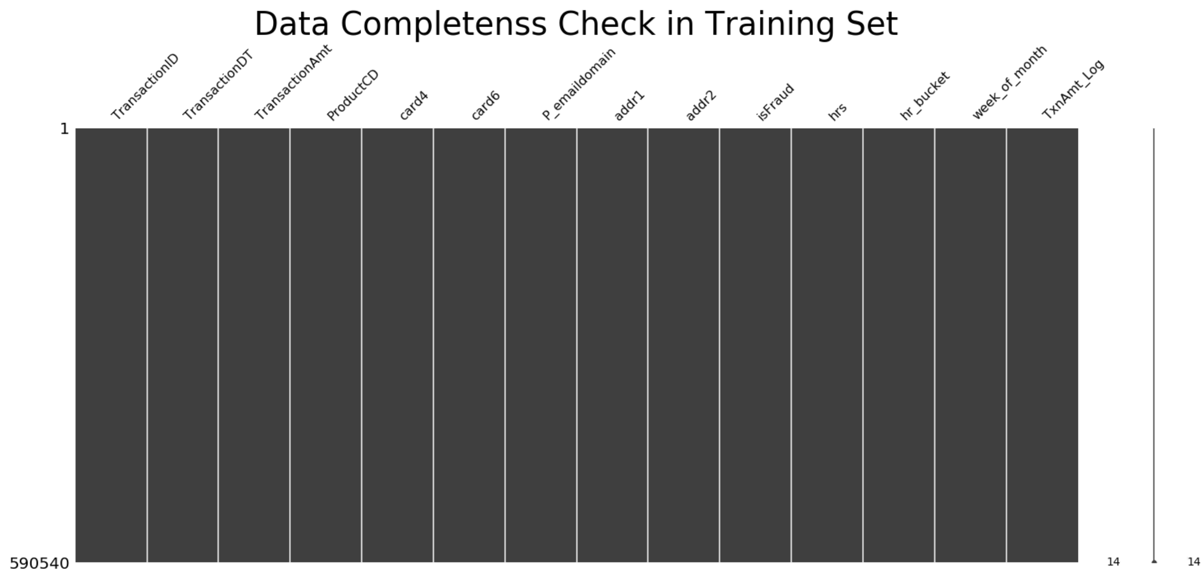
In [350]:

```
cols=train_on.columns
num_cols=train_on._get_numeric_data().columns
cat_cols=list(set(cols)-set(num_cols))

for cat in cat_cols:
    print("There are "+ str(train_on[cat].nunique()) + " unique " + cat)

#Reducing the categories in the following Variables:
reduce_levels_cat= ['addr2','P_emaildomain']

for var in reduce_levels_cat:
    freq='count'
    var_c = train_on.groupby(var).size().rename_axis(var).reset_index(na
me=freq)
    var_c= pd.DataFrame(var_c)
    var_c = var_c.sort_values(by=freq, ascending=False)
    var_c['cumulative_percentage'] = 100*var_c[freq].cumsum()/var_c[freq
].sum()

    thres= 80
    var_c = var_c[var_c['cumulative_percentage'] <= thres]
    filt = list(var_c[var])
    train_on[var]= train_on[var].apply(lambda i: i if i in filt else 'ot
her')

print(' ')
print('\033[1m' + "After Labelling Adjustment")
for cat in cat_cols:
    print("There are "+ str(train_on[cat].nunique()) + " unique " + cat)
```

```
There are 5 unique card6
There are 5 unique ProductCD
There are 5 unique week_of_month
There are 5 unique card4
There are 5 unique hr_bucket
There are 75 unique addr2
There are 60 unique P_emaildomain

After Labelling Adjustment
There are 5 unique card6
There are 5 unique ProductCD
There are 5 unique week_of_month
There are 5 unique card4
There are 5 unique hr_bucket
There are 1 unique addr2
There are 5 unique P_emaildomain
```

In [351]:
```
#Checking Nullity and Data Completeness
import missingno as msno
msno.matrix(train)
plt.title('Data Completenss Check in Training Set', size = 40)
```

Out[351]:
```
Text(0.5, 1.0, 'Data Completenss Check in Training Set')
```



Reducing the number of categories in the categorical variable of Test Set

In [352]:
```
cols=test_on.columns
num_cols=test_on._get_numeric_data().columns
cat_cols=list(set(cols)-set(num_cols))


for cat in cat_cols:
    print("There are "+ str(test_on[cat].nunique()) + " unique " + cat)

#Reducing the categories in the following Variables:
reduce_levels_cat= ['addr2','P_emaildomain']

for var in reduce_levels_cat:
    freq='count'
    var_c = test_on.groupby(var).size().rename_axis(var).reset_index(nam
e=freq)
    var_c= pd.DataFrame(var_c)
    var_c = var_c.sort_values(by=freq, ascending=False)
    var_c['cumulative_percentage'] = 100*var_c[freq].cumsum()/var_c[freq
].sum()

    thres= 80
    var_c = var_c[var_c['cumulative_percentage'] <= thres]
    filt = list(var_c[var])
    test_on[var]= test_on[var].apply(lambda i: i if i in filt else 'othe
r')

print(' ')
print('\033[1m' + "After Labelling Adjustment")
for cat in cat_cols:
    print("There are "+ str(test_on[cat].nunique()) + " unique " + cat)
```

```
There are 4 unique card6
There are 5 unique ProductCD
There are 5 unique week_of_month
There are 5 unique card4
There are 5 unique hr_bucket
There are 1 unique addr2
There are 5 unique P_emaildomain

After Labelling Adjustment
There are 4 unique card6
There are 5 unique ProductCD
There are 5 unique week_of_month
There are 5 unique card4
There are 5 unique hr_bucket
There are 1 unique addr2
There are 3 unique P_emaildomain
```

In [353]:
```
print_train_test_columns(train_on,test_on)
```

```
(590540, 11)
Features in Training Set
['TransactionAmt', 'ProductCD', 'card4', 'card6', 'P_emaildomain', 'add
r2', 'isFraud', 'hrs', 'hr_bucket', 'week_of_month', 'TxnAmt_Log']

(506691, 10)
Features in Test Set
['TransactionAmt', 'ProductCD', 'card4', 'card6', 'P_emaildomain', 'add
r2', 'hrs', 'hr_bucket', 'week_of_month', 'TxnAmt_Log']
```

Creating onehotencoder for the categorical Variables in Training and Test Set

In [354]:
```
y= train_on['isFraud']
train_on = train_on.drop(['isFraud'], axis=1)
```

In [355]:
```
one_hot_vectors_train = pd.get_dummies(train_on)

one_hot_vectors_test= pd.get_dummies(test_on)
```

In [356]:
```
print_train_test_columns(one_hot_vectors_train,one_hot_vectors_test)
```

```
(590540, 34)
Features in Training Set
['TransactionAmt', 'hrs', 'TxnAmt_Log', 'ProductCD_C', 'ProductCD_H',
 'ProductCD_R', 'ProductCD_S', 'ProductCD_W', 'card4_american express',
'card4_discover', 'card4_empty', 'card4_mastercard', 'card4_visa', 'car
d6_charge card', 'card6_credit', 'card6_debit', 'card6_debit or credi
t', 'card6_empty', 'P_emaildomain_empty', 'P_emaildomain_gmail.com', 'P
_emaildomain_hotmail.com', 'P_emaildomain_other', 'P_emaildomain_yahoo.
com', 'addr2_other', 'hr_bucket_00_05', 'hr_bucket_05_09', 'hr_bucket_0
9_15', 'hr_bucket_15_20', 'hr_bucket_20_23', 'week_of_month_1', 'week_o
f_month_2', 'week_of_month_3', 'week_of_month_4', 'week_of_month_5']

(506691, 31)
Features in Test Set
['TransactionAmt', 'hrs', 'TxnAmt_Log', 'ProductCD_C', 'ProductCD_H',
 'ProductCD_R', 'ProductCD_S', 'ProductCD_W', 'card4_american express',
'card4_discover', 'card4_empty', 'card4_mastercard', 'card4_visa', 'car
d6_charge card', 'card6_credit', 'card6_debit', 'card6_empty', 'P_email
domain_gmail.com', 'P_emaildomain_other', 'P_emaildomain_yahoo.com', 'a
ddr2_other', 'hr_bucket_00_05', 'hr_bucket_05_09', 'hr_bucket_09_15',
 'hr_bucket_15_20', 'hr_bucket_20_23', 'week_of_month_1', 'week_of_mont
h_2', 'week_of_month_3', 'week_of_month_4', 'week_of_month_5']
```

In [357]:
```
training_features_sel=list(set(one_hot_vectors_train.columns).intersecti
on(one_hot_vectors_test.columns))
print('Final Features Selected for Training the Model')
print(' ')
print('\033[1m' + str(training_features_sel))
```

```
Final Features Selected for Training the Model

['ProductCD_W', 'hrs', 'week_of_month_3', 'ProductCD_S', 'P_emaildomain
_yahoo.com', 'P_emaildomain_other', 'hr_bucket_20_23', 'card4_empty',
 'week_of_month_5', 'ProductCD_R', 'card6_charge card', 'card6_debit',
 'week_of_month_4', 'P_emaildomain_gmail.com', 'TxnAmt_Log', 'Transacti
onAmt', 'card4_discover', 'card4_visa', 'week_of_month_2', 'card6_empt
y', 'card4_mastercard', 'ProductCD_C', 'addr2_other', 'ProductCD_H', 'w
eek_of_month_1', 'hr_bucket_00_05', 'hr_bucket_09_15', 'card4_american
 express', 'hr_bucket_15_20', 'card6_credit', 'hr_bucket_05_09']
```

In [358]:
```
pick_features= ['ProductCD_W', 'hrs', 'week_of_month_3', 'ProductCD_S',
'P_emaildomain_yahoo.com', 'P_emaildomain_other',
                'hr_bucket_20_23', 'card4_empty', 'week_of_month_5', 'Pr
oductCD_R', 'card6_charge card',
                'card6_debit', 'week_of_month_4', 'P_emaildomain_gmail.c
om', 'TxnAmt_Log', 'TransactionAmt',
                'card4_discover', 'card4_visa', 'week_of_month_2', 'card
6_empty', 'card4_mastercard',
                'ProductCD_C', 'addr2_other', 'ProductCD_H', 'week_of_mo
nth_1', 'hr_bucket_00_05',
                'hr_bucket_09_15', 'card4_american express', 'hr_bucket_
15_20', 'card6_credit', 'hr_bucket_05_09']
```

In [359]:
```
train_final_features= one_hot_vectors_train[pick_features]
test_final_features=one_hot_vectors_test[pick_features]
```

Checking Correlation Matrix of the Variables in Training Set

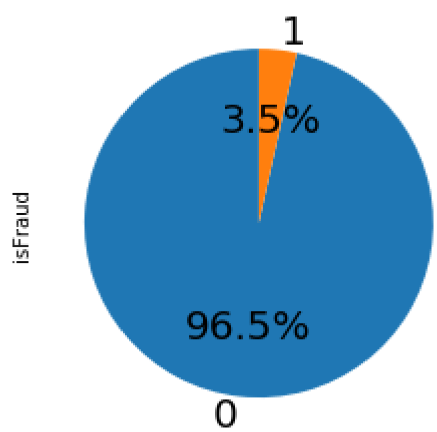
In [360]:
```python
# Compute the correlation matrix
corr = train_final_features.corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)


# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[360]: <matplotlib.axes._subplots.AxesSubplot at 0x1318d9588>

In [361]:
```
X=train_final_features.copy()

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=44)
```

In [362]:
```
y.value_counts().plot(kind='pie',autopct='%1.1f%%',startangle=90, shadow
=False,  legend = False, fontsize=20)
```

Out[362]: <matplotlib.axes._subplots.AxesSubplot at 0x12bea8588>



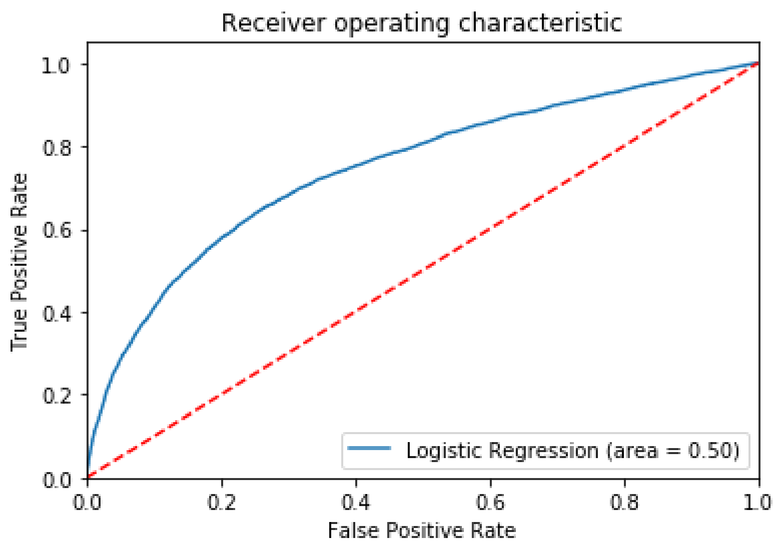
As we can observe Minority Fraud samples are only 3.5%, so its a highly unblanaced class set

Implementing the Model with UnBalanced Classes

Modelling without OverSampling the minority class

In [363]:
```
logreg = LogisticRegression()
logreg.fit(X_train, y_train)

from sklearn.metrics import accuracy_score
y_pred = logreg.predict(X_test)
#print('\033[1m' + 'Accuracy of logistic regression classifier on test s
et: {:.2f}'.format(logreg.score(X_test, y_test)))
#print(round(100*accuracy_score(y_test, y_pred), 2))

print('\033[1m' + 'Accuracy of logistic regression classifier on test se
t: ' + str(round(100*accuracy_score(y_test, y_pred), 2)) + '%')


prob = logreg.predict_proba(X_test)



from sklearn.metrics import confusion_matrix

confusion_matrix = confusion_matrix(y_test, y_pred)
print('\033[1m' + 'Confusion Matrix')
print(confusion_matrix)

from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))

from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve

logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,
1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_ro
c_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```

```
Accuracy of logistic regression classifier on test set: 96.53%
Confusion Matrix
[[171015      3]
 [  6139      5]]
              precision    recall  f1-score   support

           0       0.97      1.00      0.98    171018
           1       0.62      0.00      0.00      6144

    accuracy                           0.97    177162
   macro avg       0.80      0.50      0.49    177162
weighted avg       0.95      0.97      0.95    177162
```



We observe that the Model is able not able to predict the Non Fraud Class, as the f1-score for Fraud =0 , this is probably because the Fraud samples are very less in our training set, hence we need to upsample the fraud cases

Implementing the Model with Balanced Classes

Over-sampling the Minority Class

In [364]:
```
import sys
import warnings
if not sys.warnoptions:
    warnings.simplefilter("ignore")

from imblearn.over_sampling import SMOTE

os = SMOTE(random_state=0)

columns = X_train.columns
os_data_X,os_data_y=os.fit_sample(X_train, y_train)
os_data_X = pd.DataFrame(data=os_data_X,columns=columns )
os_data_y= pd.DataFrame(data=os_data_y,columns=['isFraud'])

# we can Check the numbers of our data
print('\033[1m' + "# Oversampled data is ",len(os_data_X))
print('\033[1m' + "# Non Fraud in oversampled data",len(os_data_y[os_dat
a_y['isFraud']==0]))
print('\033[1m' + "# Fraud",len(os_data_y[os_data_y['isFraud']==1]))
print('\033[1m' + "Proportion of Non Fraud data in oversampled data is "
,len(os_data_y[os_data_y['isFraud']==0])/len(os_data_X))
print('\033[1m' + "Proportion of Fraud data in oversampled data is ",len
(os_data_y[os_data_y['isFraud']==1])/len(os_data_X))
```

```
# Oversampled data is  797718
# Non Fraud in oversampled data 398859
# Fraud 398859
Proportion of Non Fraud data in oversampled data is  0.5
Proportion of Fraud data in oversampled data is  0.5
```

Logistic Regression Model Fitting

In [365]:
```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics

X_train, X_test, y_train, y_test = train_test_split(os_data_X, os_data_y
['isFraud'], test_size=0.3, random_state=42)
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[365]:
```
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, verbos
e=0,
                   warm_start=False)
```

Predicting the test set results and calculating the accuracy

In [366]:
```
from sklearn.metrics import accuracy_score
y_pred = logreg.predict(X_test)
print('\033[1m' + 'Accuracy of logistic regression classifier on test se
t: {:.2f}'.format(logreg.score(X_test, y_test)))
#print(round(100*accuracy_score(y_test, y_pred), 2))

prob = logreg.predict_proba(X_test)
```

```
Accuracy of logistic regression classifier on test set: 0.70
```

Confusion Matrix

In [367]:
```
from sklearn.metrics import confusion_matrix

confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

```
[[89924 29540]
 [41992 77860]]
```

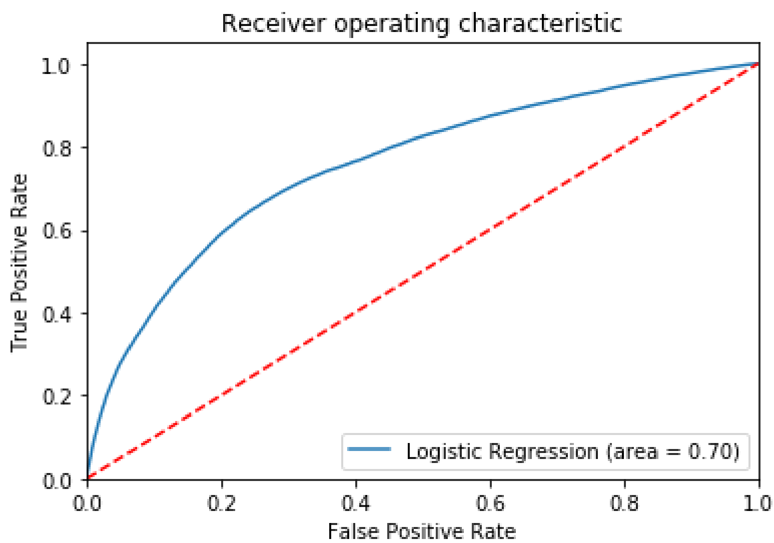
Compute precision, recall, F-measure and support

In [368]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.68      0.75      0.72    119464
           1       0.72      0.65      0.69    119852

    accuracy                           0.70    239316
   macro avg       0.70      0.70      0.70    239316
weighted avg       0.70      0.70      0.70    239316
```

ROC Curve

In [369]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve

logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,
1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_ro
c_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```



In [370]:
```
y_pred= pd.DataFrame(y_pred)
y_pred.columns = ['is_Fraud']
y_pred.groupby('is_Fraud').size().rename_axis('is_Fraud').reset_index(na
me='count')
```

Out[370]:

	is_Fraud	count
0	0	131916
1	1	107400

Predicting Fraud in the Test Data

In [200]:
```
Test_Features=test_final_features.copy()
```

In [201]:
```
test_pred= pd.DataFrame(logreg.predict_proba(Test_Features)[:,1])
```

In [203]:
```
submission=pd.DataFrame()
submission= test_id.copy()
```

In [204]:
```
submission['isFraud']=round(test_pred,3)
```

In [205]:
```
submission.shape
```

Out[205]:
```
(506691, 2)
```

In [206]:
```
submission.head()
```

Out[206]:

	TransactionID	isFraud
0	3663549	0.285
1	3663550	0.202
2	3663551	0.302
3	3663552	0.501
4	3663553	0.292

In [208]:
```
file_version= 'submission_2.csv'
```

In [214]:
```
submission.to_csv('/Users/mehar/Downloads/Stony_Brook_University/Fall201
9/DataScience/ieee-fraud-detection/Submission/'+ str(file_version), inde
x=False)
```

Applying XGBoost Algorithm

Finding Top Contributing features

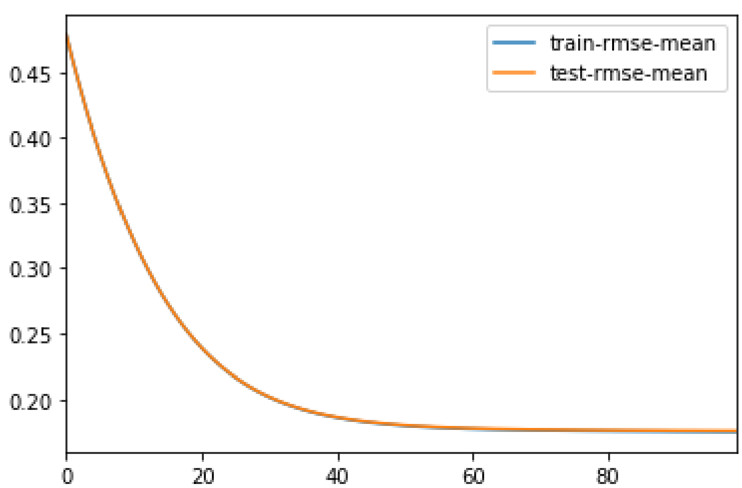
In [373]:
```
x_train, x_test, y_train, y_test = train_test_split(train_on, y, test_si
ze=0.2, random_state=123)
```

In [374]:

```
from sklearn import model_selection, preprocessing
import xgboost as xgb

for c in x_train.columns:
    if x_train[c].dtype == 'object':
        lbl = preprocessing.LabelEncoder()
        lbl.fit(list(x_train[c].values))
        x_train[c] = lbl.transform(list(x_train[c].values))

for c in x_test.columns:
    if x_test[c].dtype == 'object':
        lbl = preprocessing.LabelEncoder()
        lbl.fit(list(x_test[c].values))
        x_test[c] = lbl.transform(list(x_test[c].values))

xgb_params = {
    'eta': 0.05,
    'max_depth': 5,
    'subsample': 0.7,
    'colsample_bytree': 0.7,
    'objective': 'reg:linear',
    'eval_metric': 'rmse',
    'silent': 1
}

dtrain = xgb.DMatrix(x_train, y_train)
dtest = xgb.DMatrix(x_test)

cv_output = xgb.cv(xgb_params, dtrain, num_boost_round=100, early_stoppi
ng_rounds=20,
    verbose_eval=50, show_stdv=False)
cv_output[['train-rmse-mean', 'test-rmse-mean']].plot()
```

```
[0]     train-rmse:0.478292     test-rmse:0.478302
[50]    train-rmse:0.179743     test-rmse:0.180166
[99]    train-rmse:0.175101     test-rmse:0.175849
```

Out[374]: <matplotlib.axes._subplots.AxesSubplot at 0x16bb4f5f8>

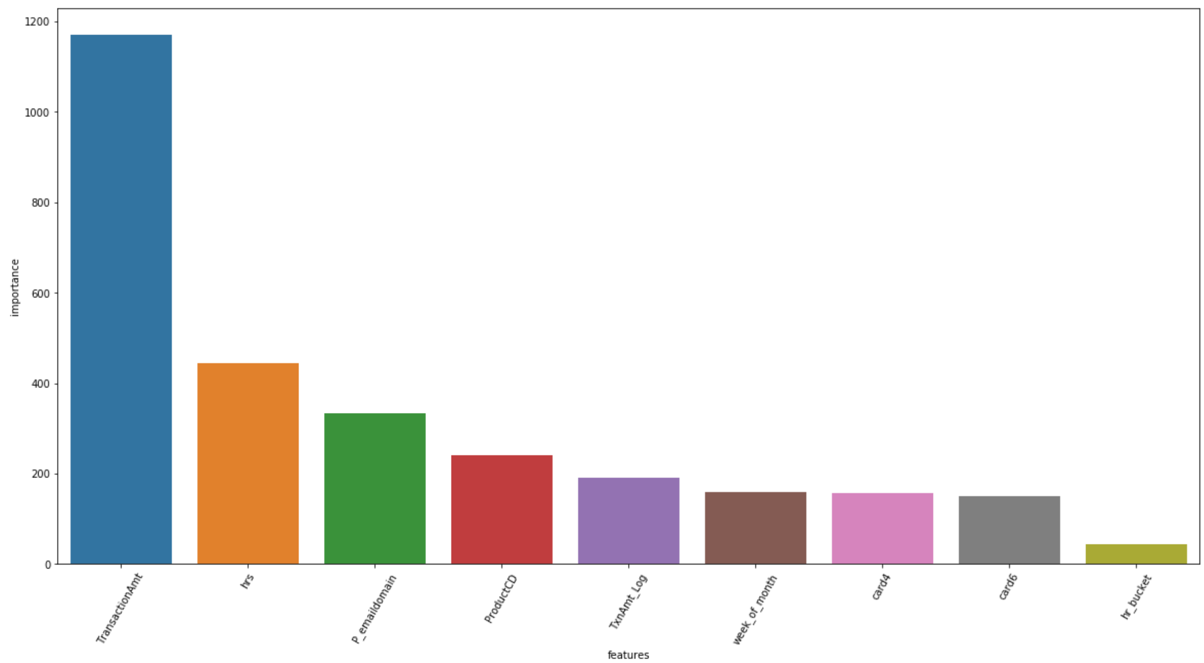


In [375]:
```
num_boost_rounds = len(cv_output)
model = xgb.train(dict(xgb_params, silent=0), dtrain, num_boost_round= n
um_boost_rounds)
```

```
[19:20:42] WARNING: src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
```

In [376]:
```
featureImportance = model.get_fscore()
features = pd.DataFrame()
features['features'] = featureImportance.keys()
features['importance'] = featureImportance.values()
features.sort_values(by=['importance'],ascending=False,inplace=True)
fig,ax= plt.subplots()
fig.set_size_inches(20,10)
plt.xticks(rotation=60)
sns.barplot(data=features.head(30),x="features",y="importance",ax=ax,ori
ent="v")
```

Out[376]: <matplotlib.axes._subplots.AxesSubplot at 0x172331f98>



In [390]:
```
ypred = model.predict(dtest,ntree_limit=model.best_ntree_limit)
```

In [395]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_test, ypred)
```

Root Mean Square Error

In [413]:
```
print('MSE'+ str(mse))
```

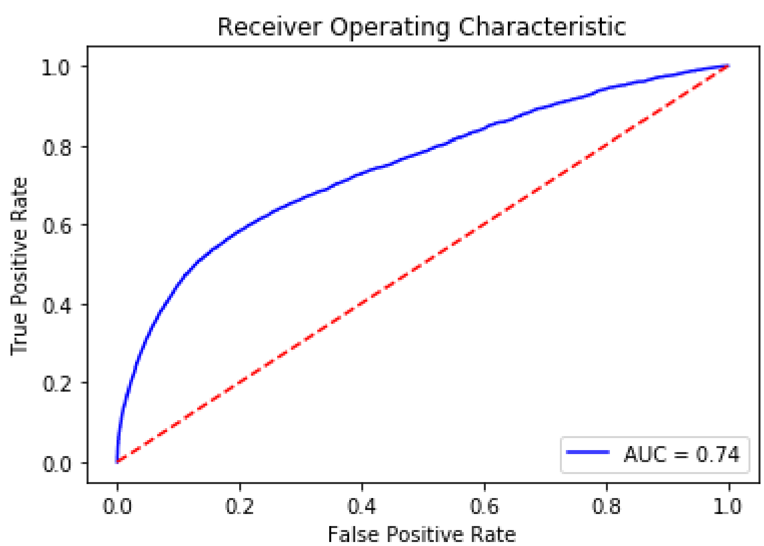
```
MSE0.032094926
```

In [399]:
```
for c in test_on.columns:
    if test_on[c].dtype == 'object':
        lbl = preprocessing.LabelEncoder()
        lbl.fit(list(test_on[c].values))
        test_on[c] = lbl.transform(list(test_on[c].values))
```

In [401]:
```
test_submission= xgb.DMatrix(test_on)
```

In [403]:
```
submission_pred = model.predict(test_submission,ntree_limit=model.best_n
tree_limit)
submission_pred=pd.DataFrame(submission_pred)
```

In [405]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve

from sklearn import metrics
def buildROC(target_test,test_preds):
    fpr, tpr, threshold = metrics.roc_curve(target_test, test_preds)
    roc_auc = metrics.auc(fpr, tpr)
    plt.title('Receiver Operating Characteristic')
    plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1],'r--')
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.gcf().savefig('roc.png')

buildROC(y_test,ypred)
```



In [410]:
```
submission=pd.DataFrame()
submission= test_id.copy()

submission['isFraud']=round(submission_pred,3)

submission.shape

submission.head()

file_version= 'submission_xgboost.csv'

submission.to_csv(file_version, index=False)
```

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.

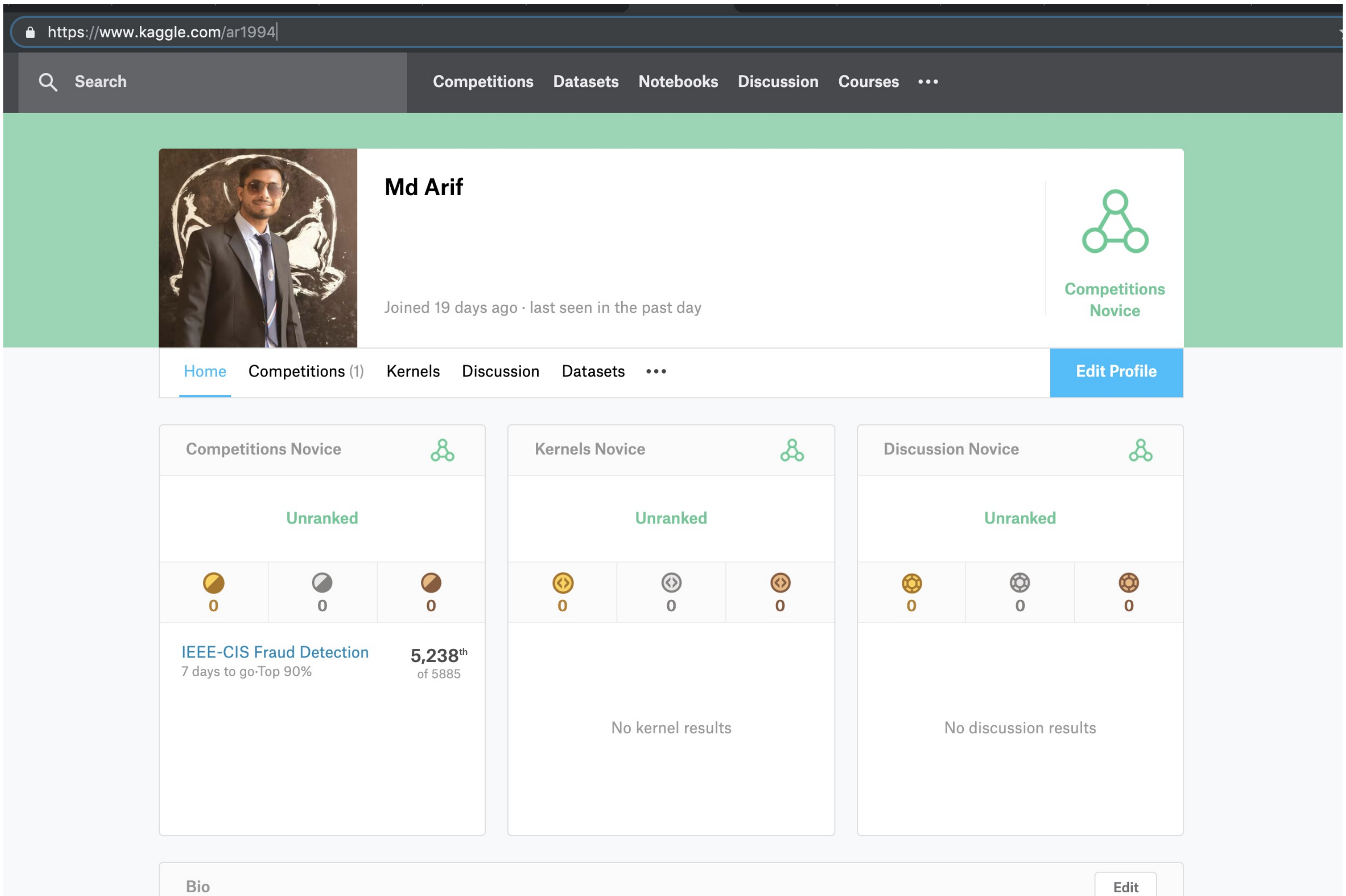
Kaggle Link: https://www.kaggle.com/ar1994 (https://www.kaggle.com/ar1994)

Highest Rank: 5238

Score: 0.8161

Number of entries: 3

INCLUDE IMAGE OF YOUR KAGGLE RANKING


https://www.kaggle.com/ar1994
Search
Competitions
Datasets
Notebooks
Discussion
Courses
Md Arif
Joined 19 days ago · last seen in the past day
Competitions Novice
Home
Competitions (1)
Kernels
Discussion
Datasets
Edit Profile
Competitions Novice
Unranked
0
0
0
IEEE-CIS Fraud Detection
7 days to go·Top 90%
5,238th
of 5885
Kernels Novice
Unranked
0
0
0
No kernel results
Discussion Novice
Unranked
0
0
0
No discussion results
Bio
Edit

References

https://towardsdatascience.com/building-a-logistic-regression-in-python-step-by-step-becd4d56c9c8 (https://towardsdatascience.com/building-a-logistic-regression-in-python-step-by-step-becd4d56c9c8)

https://www.kaggle.com/inversion/ieee-simple-xgboost (https://www.kaggle.com/inversion/ieee-simple-xgboost)