DSF IEEE

September 26, 2019

1 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.

1.1 Part 1 - Fraudulent vs Non-Fraudulent Transaction

```
In [190]: #Importing Pandas
          import pandas as pd
```

```
In [191]: # Read Identity CSV
          df_identity = pd.read_csv(r'I:\Data Science Fundamentals\train_identity.csv')
```

```
In [192]: # Read Transaction CSV
          df_transaction=pd.read_csv(r'I:\Data Science Fundamentals\train_transaction.csv')
```

```
In [193]: # Crop the Identity CSV to columns needed
          identity_columns=df_identity[['TransactionID','DeviceType','DeviceInfo']]
```

```
In [194]: identity_columns.head(2)
```

```
Out[194]:    TransactionID DeviceType                     DeviceInfo
          0        2987004     mobile  SAMSUNG SM-G892A Build/NRD90M
          1        2987008     mobile                     iOS Device
```

```
In [195]: # Convert the Timedelta from a default timestamp
          #df_transaction['TransactionDT']=pd.to_datetime(df_transaction['TransactionDT'], unit='s')
```

```
In [196]: # Crop the Transaction CSV to columns needed
          transaction_columns=df_transaction[['TransactionID','TransactionDT','TransactionAmt','Product
```

```
In [197]: transaction_columns.head(2)
```

```
Out[197]:    TransactionID  TransactionDT  TransactionAmt ProductCD  isFraud  \
          0        2987000          86400            68.5         W        0
          1        2987001          86401            29.0         W        0

                  card4   card6 P_emaildomain R_emaildomain  addr1  addr2  dist1  dist2
          0    discover  credit           NaN           NaN  315.0   87.0   19.0    NaN
          1  mastercard  credit     gmail.com           NaN  325.0   87.0    NaN    NaN
```

```
In [198]: # Complete Column List
          df_transaction_identity=transaction_columns.merge(identity_columns,how='outer')
```

In [199]: df_transaction_identity.head(10)

Out[199]:

	TransactionID	TransactionDT	TransactionAmt	ProductCD	isFraud	\
0	2987000	86400	68.5	W	0	
1	2987001	86401	29.0	W	0	
2	2987002	86469	59.0	W	0	
3	2987003	86499	50.0	W	0	
4	2987004	86506	50.0	H	0	
5	2987005	86510	49.0	W	0	
6	2987006	86522	159.0	W	0	
7	2987007	86529	422.5	W	0	
8	2987008	86535	15.0	H	0	
9	2987009	86536	117.0	W	0	

	card4	card6	P_emaildomain	R_emaildomain	addr1	addr2	dist1	\
0	discover	credit	NaN	NaN	315.0	87.0	19.0	
1	mastercard	credit	gmail.com	NaN	325.0	87.0	NaN	
2	visa	debit	outlook.com	NaN	330.0	87.0	287.0	
3	mastercard	debit	yahoo.com	NaN	476.0	87.0	NaN	
4	mastercard	credit	gmail.com	NaN	420.0	87.0	NaN	
5	visa	debit	gmail.com	NaN	272.0	87.0	36.0	
6	visa	debit	yahoo.com	NaN	126.0	87.0	0.0	
7	visa	debit	mail.com	NaN	325.0	87.0	NaN	
8	visa	debit	anonymous.com	NaN	337.0	87.0	NaN	
9	mastercard	debit	yahoo.com	NaN	204.0	87.0	19.0	

	dist2	DeviceType	DeviceInfo
0	NaN	NaN	NaN
1	NaN	NaN	NaN
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	mobile	SAMSUNG SM-G892A Build/NRD90M
5	NaN	NaN	NaN
6	NaN	NaN	NaN
7	NaN	NaN	NaN
8	NaN	mobile	iOS Device
9	NaN	NaN	NaN

In [200]:

```
#Filter Fraud Transactions
Fraud_Transactions_Boolean=df_transaction_identity['isFraud']==1
Fraud_Transactions=df_transaction_identity[Fraud_Transactions_Boolean]
#Filter Non-Fraudulent Transactions
Non_Fraud_Transactions_Boolean=df_transaction_identity['isFraud']==0
Non_Fraud_Transactions=df_transaction_identity[Non_Fraud_Transactions_Boolean]
```

In [201]: Fraud_Transactions.head(10)

Out[201]:

	TransactionID	TransactionDT	TransactionAmt	ProductCD	isFraud	\
203	2987203	89760	445.000	W	1	
240	2987240	90193	37.098	C	1	
243	2987243	90246	37.098	C	1	
245	2987245	90295	37.098	C	1	
288	2987288	90986	155.521	C	1	
367	2987367	92350	225.000	R	1	
405	2987405	92999	90.570	C	1	

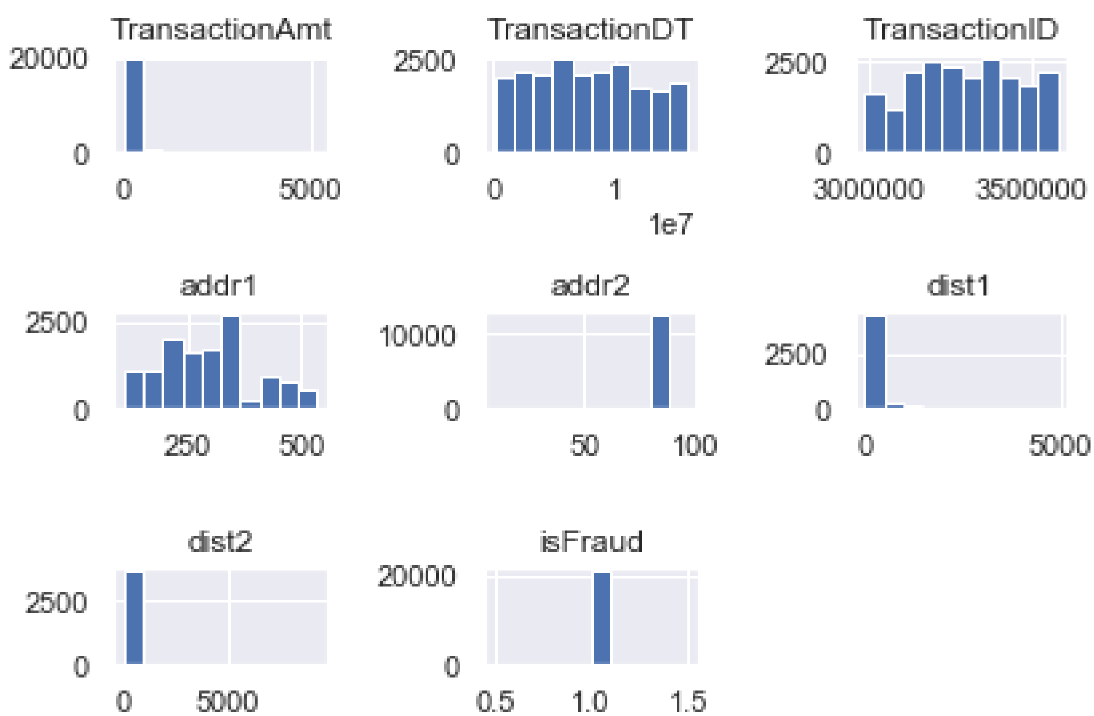
```
630        2987630          97843          12.326         C         1
683        2987683          99584         124.344         C         1
736        2987736         100591         100.000         W         1

          card4   card6 P_emaildomain R_emaildomain  addr1  addr2  dist1  \
203        visa  credit       aol.com           NaN  251.0   87.0    NaN
240        visa  credit   hotmail.com   hotmail.com    NaN    NaN    NaN
243        visa  credit   hotmail.com   hotmail.com    NaN    NaN    NaN
245        visa  credit   hotmail.com   hotmail.com    NaN    NaN    NaN
288        visa  credit   outlook.com   outlook.com    NaN    NaN    NaN
367  mastercard  credit     gmail.com     gmail.com  472.0   87.0    NaN
405  mastercard  credit     gmail.com     gmail.com    NaN    NaN    NaN
630  mastercard   debit     gmail.com     gmail.com    NaN    NaN    NaN
683  mastercard   debit     gmail.com     gmail.com    NaN    NaN    NaN
736        visa  credit     yahoo.com           NaN  231.0   87.0    NaN

     dist2 DeviceType                 DeviceInfo
203    NaN        NaN                        NaN
240    NaN     mobile  Redmi Note 4 Build/MMB29M
243    NaN     mobile  Redmi Note 4 Build/MMB29M
245    NaN     mobile  Redmi Note 4 Build/MMB29M
288    NaN     mobile                        NaN
367    NaN    desktop                    rv:52.0
405    NaN     mobile                        NaN
630    7.0    desktop                    Windows
683    7.0    desktop                    Windows
736    NaN        NaN                        NaN
```

In [202]:
```
Non_Fraud_Transactions.head(10)
```

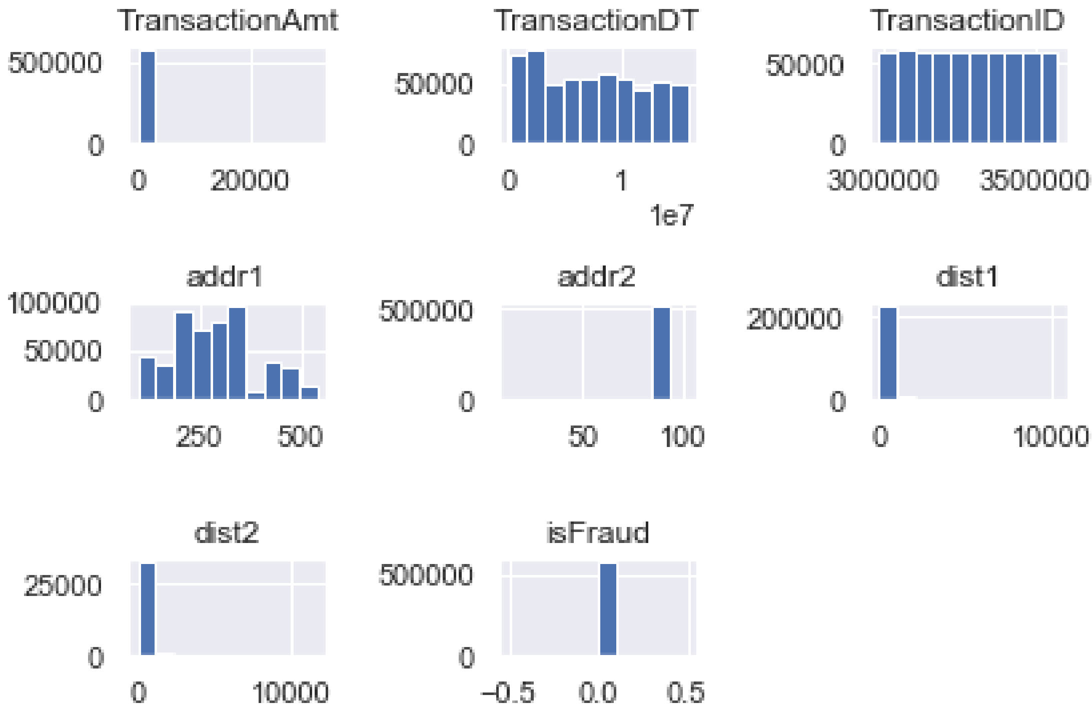
Out[202]:
```
   TransactionID  TransactionDT  TransactionAmt ProductCD  isFraud  \
0        2987000          86400            68.5         W        0
1        2987001          86401            29.0         W        0
2        2987002          86469            59.0         W        0
3        2987003          86499            50.0         W        0
4        2987004          86506            50.0         H        0
5        2987005          86510            49.0         W        0
6        2987006          86522           159.0         W        0
7        2987007          86529           422.5         W        0
8        2987008          86535            15.0         H        0
9        2987009          86536           117.0         W        0

        card4   card6 P_emaildomain R_emaildomain  addr1  addr2  dist1  \
0    discover  credit           NaN           NaN  315.0   87.0   19.0
1  mastercard  credit     gmail.com           NaN  325.0   87.0    NaN
2        visa   debit   outlook.com           NaN  330.0   87.0  287.0
3  mastercard   debit     yahoo.com           NaN  476.0   87.0    NaN
4  mastercard  credit     gmail.com           NaN  420.0   87.0    NaN
5        visa   debit     gmail.com           NaN  272.0   87.0   36.0
6        visa   debit     yahoo.com           NaN  126.0   87.0    0.0
7        visa   debit      mail.com           NaN  325.0   87.0    NaN
8        visa   debit anonymous.com           NaN  337.0   87.0    NaN
9  mastercard   debit     yahoo.com           NaN  204.0   87.0   19.0

   dist2 DeviceType                       DeviceInfo
```

```
0     NaN         NaN                              NaN
1     NaN         NaN                              NaN
2     NaN         NaN                              NaN
3     NaN         NaN                              NaN
4     NaN      mobile   SAMSUNG SM-G892A Build/NRD90M
5     NaN         NaN                              NaN
6     NaN         NaN                              NaN
7     NaN         NaN                              NaN
8     NaN      mobile                      iOS Device
9     NaN         NaN                              NaN
```

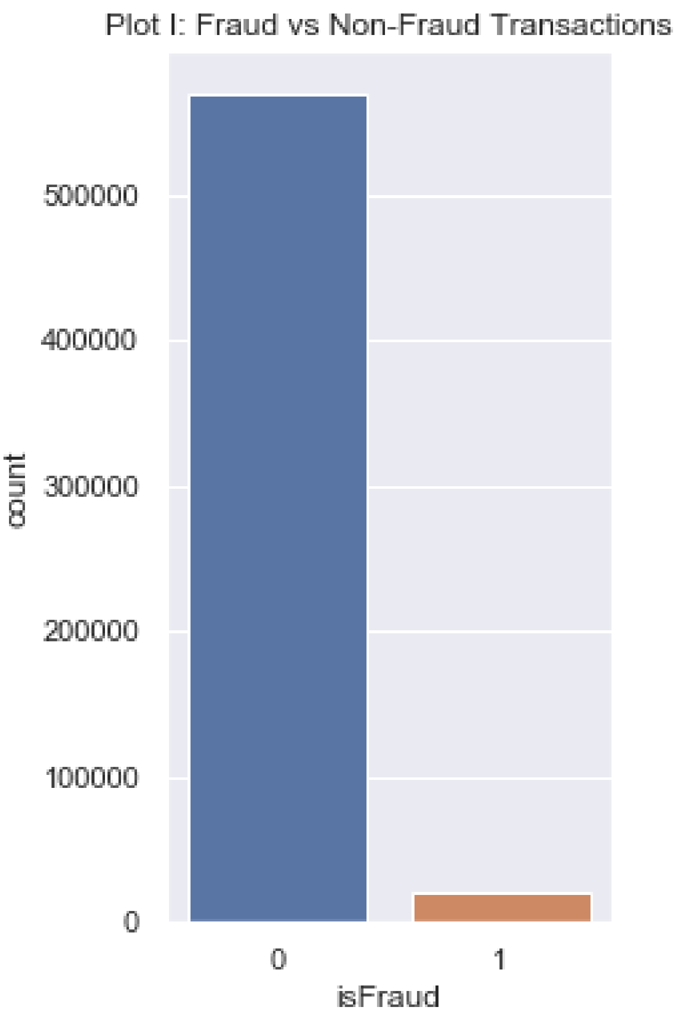
In [203]:
```python
# Import matplotlib to examine distributions
import matplotlib.pyplot as plt
# Import numpy to get better histogram distributions
import numpy as np
# Histogram for Fraudulent Transactions
hists = Fraud_Transactions.hist()
plt.tight_layout()
```



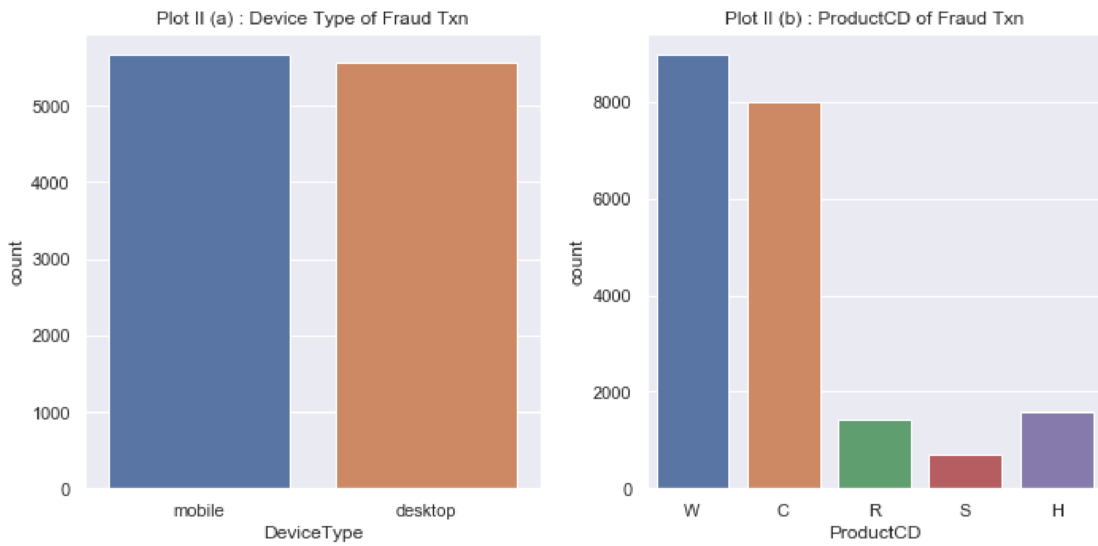
In [204]:
```python
# Import matplotlib to examine distributions
import matplotlib.pyplot as plt
# Histogram for Non Fraudulent Transactions
hists = Non_Fraud_Transactions.hist()
plt.tight_layout()
```



In [205]:
```
# Importing seaborn for doing plotting
import seaborn as sns
# Now,let's get the count of Fraud vs Non-Fraud Transactions
# https://seaborn.pydata.org/generated/seaborn.countplot.html
f, axes = plt.subplots(1, 1, figsize=(3, 6))
isFraud = sns.countplot(x='isFraud', data=df_transaction_identity)
plt.title("Plot I: Fraud vs Non-Fraud Transactions")
plt.show()
```

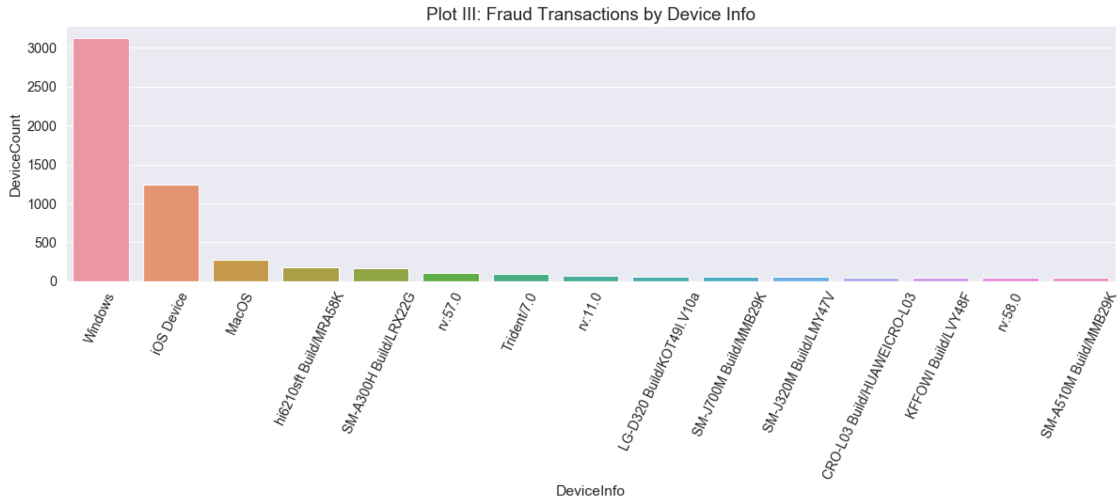



```
In [206]: # For Plot II, I will plot the Fraud Transactions according to the DeviceType, and the Produc
          f, axes = plt.subplots(1, 2, figsize=(10, 5))
          DeviceType = sns.countplot(x='DeviceType', data=Fraud_Transactions, ax=axes[0]).set_title("Plo
          ProductCD = sns.countplot(x='ProductCD', data=Fraud_Transactions, ax=axes[1]).set_title("Plot
          plt.tight_layout()
```



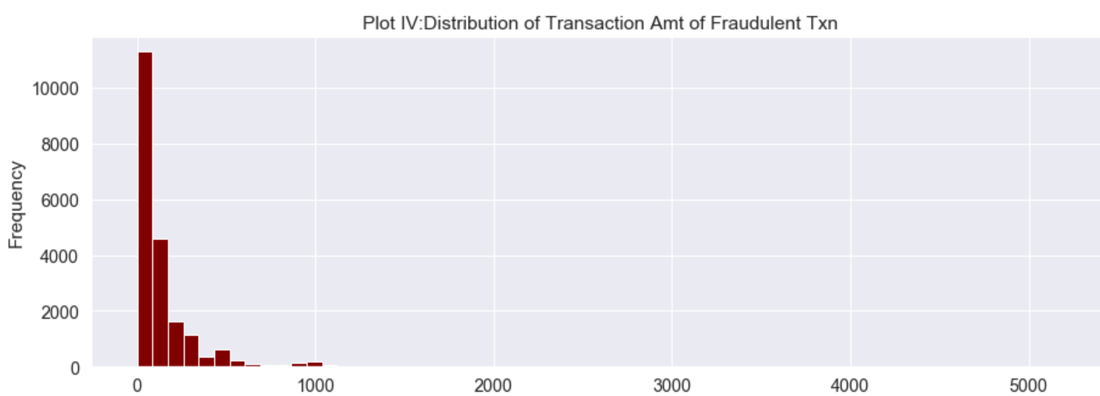
**Observation: From Plot II (a), it can be established that its hard to distinguish between the number of fraud transactions, that occured on mobile and desktop, as they are almost equal. Also, from Plot II (b), it can be confirmed that the products having ProductCD 'W' have highest number of fraud transactions.

In [207]:
```
# For Plot III, I am trying to plot the Fraud Transactions according to the DeviceInfo. As the
# I will limit the graph to the top 15 devices
# Ref: https://seaborn.pydata.org/generated/seaborn.barplot.html
# Ref: https://s3.amazonaws.com/assets.datacamp.com/blog_assets/Python_Seaborn_Cheat_Sheet.pd
fraud = pd.DataFrame()
fraud['DeviceCount'] = Fraud_Transactions.groupby(['DeviceInfo'])['DeviceInfo'].count()
fraud['DeviceInfo'] = fraud.index
group_top = fraud.sort_values(by='DeviceCount',ascending=False).head(15)

plt.figure(figsize=(20, 5))
sns.set(color_codes=True)
sns.set(font_scale = 1.3)
ax = sns.barplot(x="DeviceInfo", y="DeviceCount", data=group_top)

font_size= {'size': 'large'}
ax.set_title("Plot III: Fraud Transactions by Device Info", **font_size)
xt = plt.xticks(rotation=65)
```



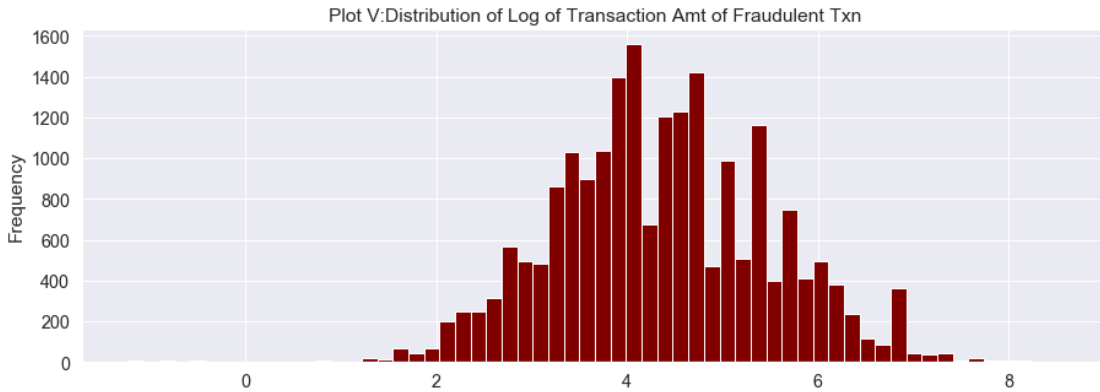
**Observation: From Plot III, it can be established that Fraud transaction cases come mostly from Windows and iOS devices. This is predictable given the vast majority of all transactions come from those systems.

```
In [208]: # For Plot IV,I am first plotting the distribution of Transaction Amt of Fraudulent Txn
          Fraud_Transactions['TransactionAmt'] \
              .plot(kind='hist',
                    bins=60,
                    figsize=(15, 5),
                    color="maroon",
                    title='Plot IV:Distribution of Transaction Amt of Fraudulent Txn')
          plt.show()
```




```
In [209]: # For Plot V,I am plotting the distribution of Log of Transaction Amt of Fraudulent Txn, as i
          Fraud_Transactions['TransactionAmt'] \
              .apply(np.log) \
              .plot(kind='hist',
                    bins=60,
                    figsize=(15, 5),
                    color="maroon",
```

```
                title='Plot V:Distribution of Log of Transaction Amt of Fraudulent Txn')
        plt.show()
```



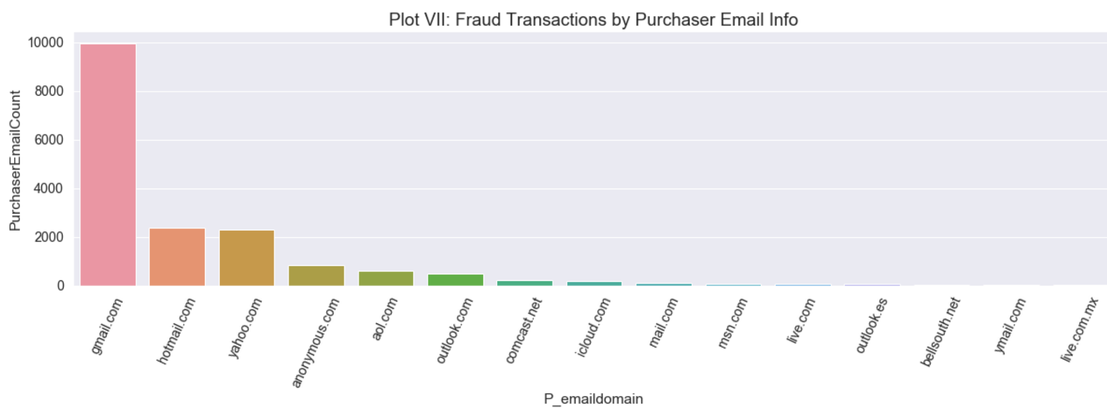
**From Plot V, it can be concluded that taking the log gives us a better distribution, as the transaction amounts lies within a narrow range.

```
In [210]: # For Plot VI,I am plotting the distribution of the card merchant as well as the card type of
          f, axes = plt.subplots(1, 2, figsize=(14, 6))
          sns.set(color_codes=True)
          card4 = sns.countplot(x='card4', data=Fraud_Transactions, ax=axes[0]).set_title("Plot VI (a)
          card6 = sns.countplot(x='card6', data=Fraud_Transactions, ax=axes[1]).set_title("Plot VI (b)
```

**From Plot VI(a), it can be established that maximum fraud transactions occur when the card merchant is VISA. Also, from Plot VI(b), we see more fraud happening in debit transactions.

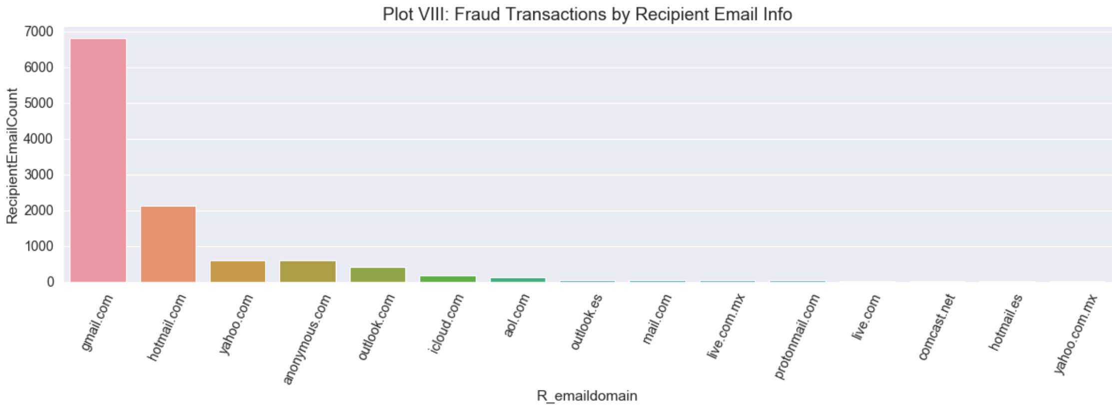
```
In [211]: # For Plot VII, I am plotting the Fraud Transactions according to the Purchaser Email Domain.
          # I will limit the graph to the top 15 email domains
          fraud = pd.DataFrame()
          fraud['PurchaserEmailCount'] = Fraud_Transactions.groupby(['P_emaildomain'])['P_emaildomain']
          fraud['P_emaildomain'] = fraud.index
```

```
group_top = fraud.sort_values(by='PurchaserEmailCount',ascending=False).head(15)

plt.figure(figsize=(20, 5))
sns.set(color_codes=True)
sns.set(font_scale = 1.3)
ax = sns.barplot(x="P_emaildomain", y="PurchaserEmailCount", data=group_top)

font_size= {'size': 'large'}
ax.set_title("Plot VII: Fraud Transactions by Purchaser Email Info", **font_size)
xt = plt.xticks(rotation=65)
```



**From Plot VII, we see that most of the purchaser email domain associated with fraud transactions come from gmail.com

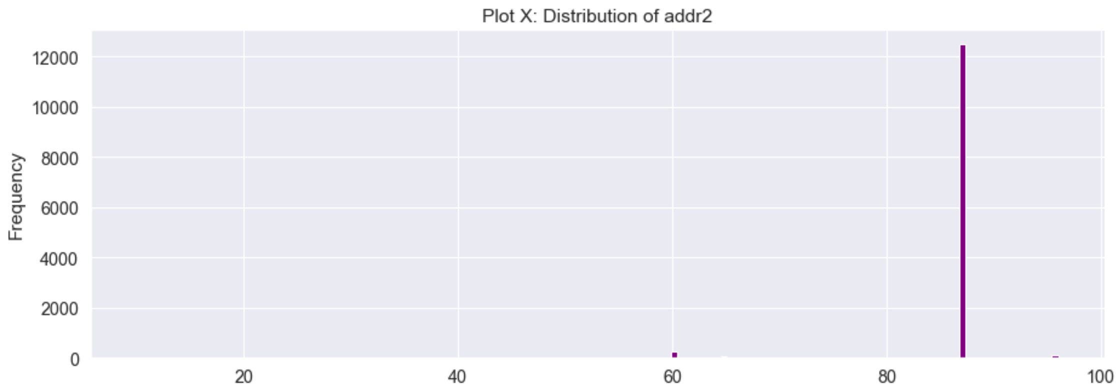
In [212]:
```
# For Plot VIII, I am plotting the Fraud Transactions according to the Recipient Email Domain
# I will limit the graph to the top 15 email domains
fraud = pd.DataFrame()
fraud['RecipientEmailCount'] = Fraud_Transactions.groupby(['R_emaildomain'])['R_emaildomain']
fraud['R_emaildomain'] = fraud.index
group_top = fraud.sort_values(by='RecipientEmailCount',ascending=False).head(15)

plt.figure(figsize=(20, 5))
sns.set(color_codes=True)
sns.set(font_scale = 1.3)
ax = sns.barplot(x="R_emaildomain", y="RecipientEmailCount", data=group_top)

font_size= {'size': 'large'}
ax.set_title("Plot VIII: Fraud Transactions by Recipient Email Info", **font_size)
xt = plt.xticks(rotation=65)
```



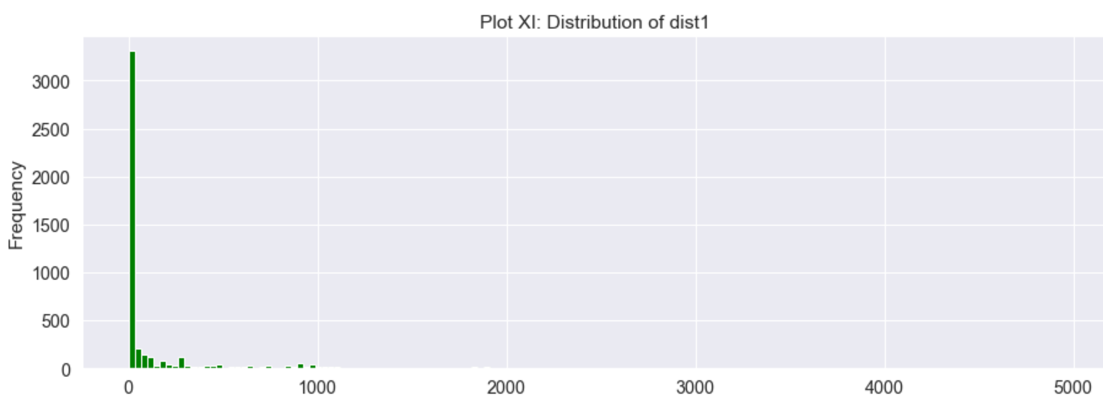
**From Plot VIII, we see that most of the receiver email domain associated with fraud transactions come from gmail.com, as well.

In [213]:
```
# For Plot IX,I am plotting the distribution of the addr1 field associated with Fraudulent Txn
Fraud_Transactions['addr1'] \
    .plot(kind='hist',
          bins=150,
          figsize=(15, 5),
          color="teal",
          title='Plot IX: Distribution of addr1')
plt.show()
```

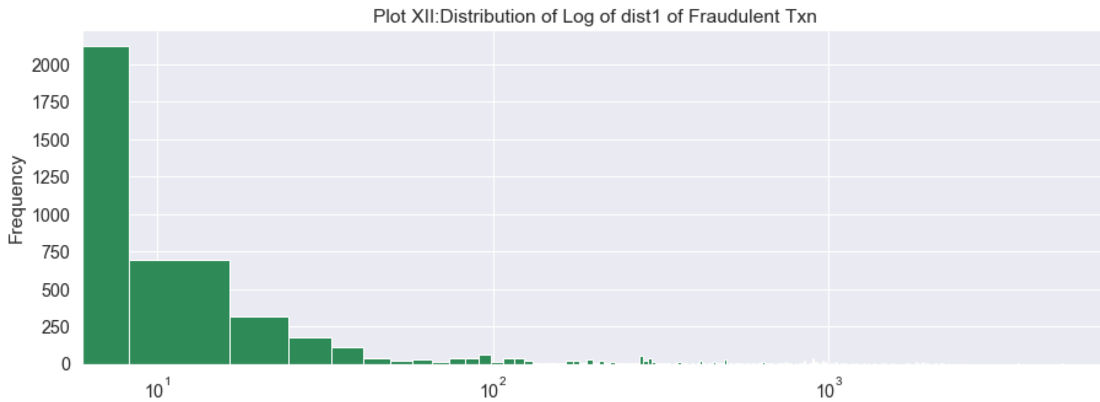
In [214]:
```
# For Plot X,I am plotting the distribution of the addr2 field associated with Fraudulent Txn
Fraud_Transactions['addr2'] \
    .plot(kind='hist',
          bins=150,
          figsize=(15, 5),
          color="purple",
          title='Plot X: Distribution of addr2')
plt.show()
```




```
In [215]: # For Plot XI,I am plotting the distribution of dist1 of Fraudulent Txn
          Fraud_Transactions['dist1'] \
              .plot(kind='hist',
                    bins=150,
                    figsize=(15, 5),
                    color="green",
                    title='Plot XI: Distribution of dist1')
          plt.show()
```

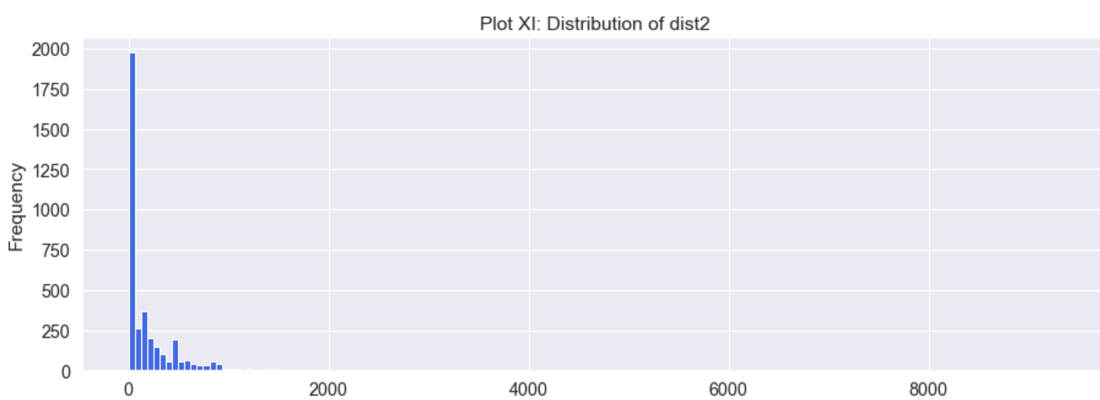



```
In [216]: #  For Plot XII,I am plotting the log of distribution of dist1 of Fraudulent Txn
          Fraud_Transactions['dist1'] \
              .plot(kind='hist',
                    bins=600,
                    figsize=(15, 5),
                    color="seagreen",
                    title='Plot XII:Distribution of Log of dist1 of Fraudulent Txn', logx="true")
          plt.show()
```

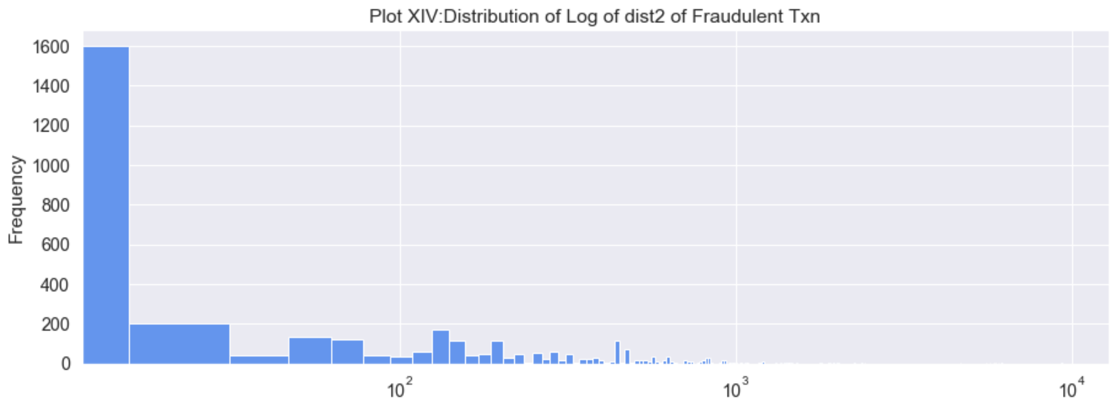


**From Plot XII, it can be concluded that taking the log gives us a better distribution, as the dist1 values lies within a narrow range.

In [217]:
```
# For Plot XIII,I am plotting the distribution of dist2 of Fraudulent Txn
Fraud_Transactions['dist2'] \
    .plot(kind='hist',
          bins=150,
          figsize=(15, 5),
          color="royalblue",
          title='Plot XI: Distribution of dist2')
plt.show()
```

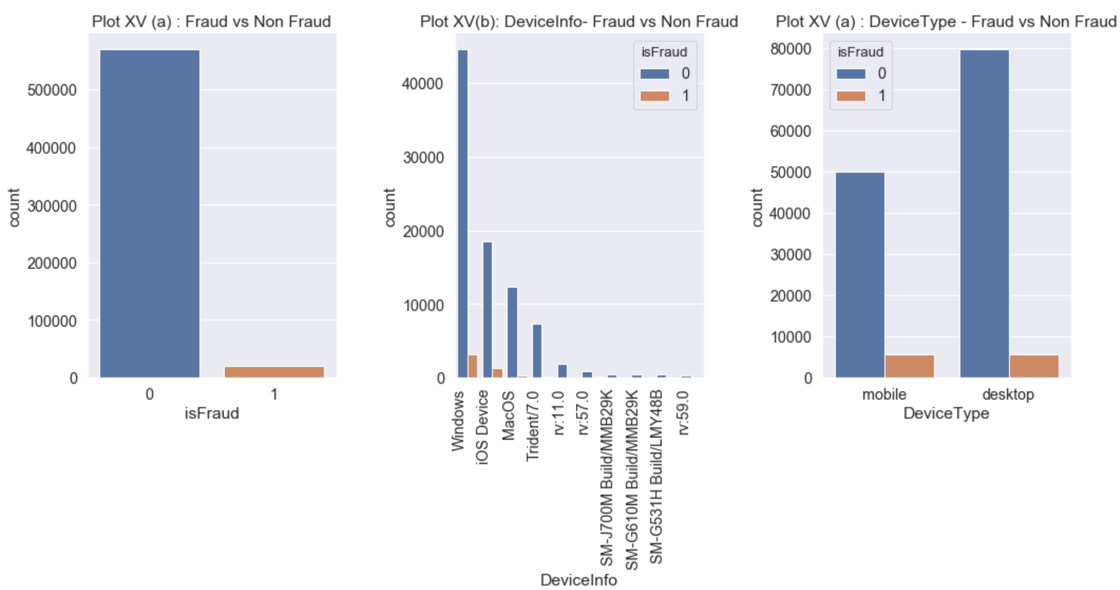


In [218]:
```
#  For Plot XIV,I am plotting the log of distribution of dist2 of Fraudulent Txn
Fraud_Transactions['dist2'] \
    .plot(kind='hist',
          bins=600,
          figsize=(15, 5),
          color="cornflowerblue",
          title='Plot XIV:Distribution of Log of dist2 of Fraudulent Txn', logx="true")
plt.show()
```



**From Plot XIV, it can be concluded that taking the log gives us a better distribution, as the dist2 values lies within a narrow range, just like dist1.

In [219]:
```
# Plot XV Fraud vs Non Fraud for DeviceInfo and DeviceType
f, axes = plt.subplots(1, 3, figsize=(15, 8))
isFraud = sns.countplot(x='isFraud', data=df_transaction_identity, ax=axes[0]).set_title("Plot
DeviceInfo = sns.countplot(x='DeviceInfo', hue="isFraud", data=df_transaction_identity, order=
DeviceInfo.set_xticklabels(DeviceInfo.get_xticklabels(), rotation=90, ha="right")
DeviceInfo.set_title("Plot XV(b): DeviceInfo- Fraud vs Non Fraud")
DeviceType = sns.countplot(x='DeviceType', hue="isFraud", data=df_transaction_identity, ax=axe
plt.tight_layout()
```

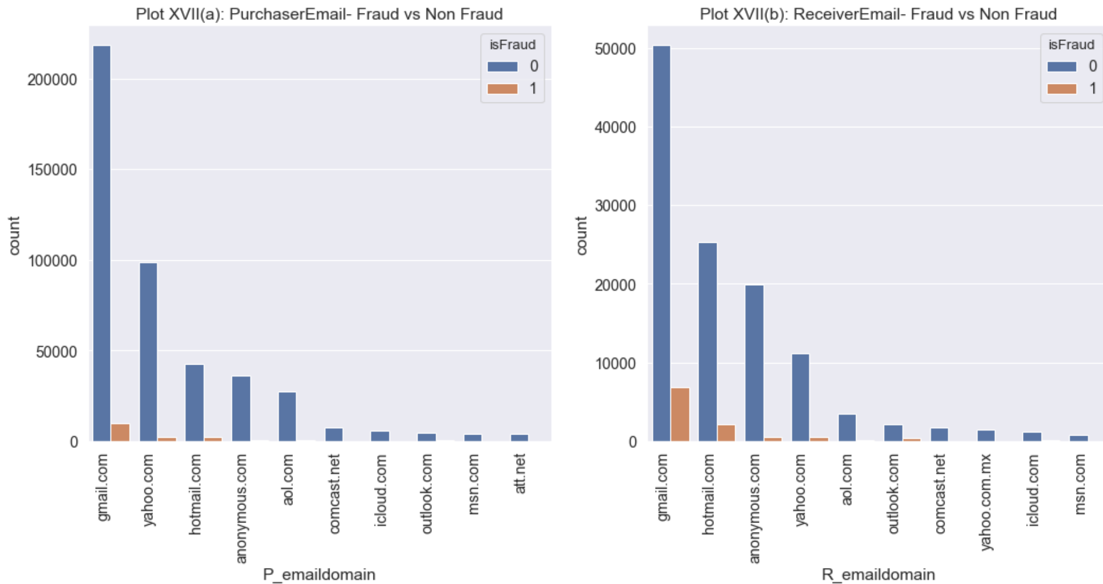


**From Plot XV, we can make (a) Fraud Transactions are very less compared to Non-Fraud Transactions. (b) Althought the number of fraud transactions is very high for Windows devices, but again, the number of non-fraud transactions is also very high. (c) Desktop has a larger number of non-fraud transactions, compared to mobile, while the number of fraud transactions is comparable in both the cases.

```
In [220]: # Plot XVI Fraud vs Non Fraud for CardType,CardMerchant and ProductCD
          f, axes = plt.subplots(1, 3, figsize=(15, 8))
          ProductCD = sns.countplot(x='ProductCD', hue="isFraud", data=df_transaction_identity, ax=axes
          CardMerchant = sns.countplot(x='card4', hue="isFraud", data=df_transaction_identity, ax=axes[
          CardType = sns.countplot(x='card6', hue="isFraud", data=df_transaction_identity, ax=axes[0]).s
          plt.tight_layout()
```

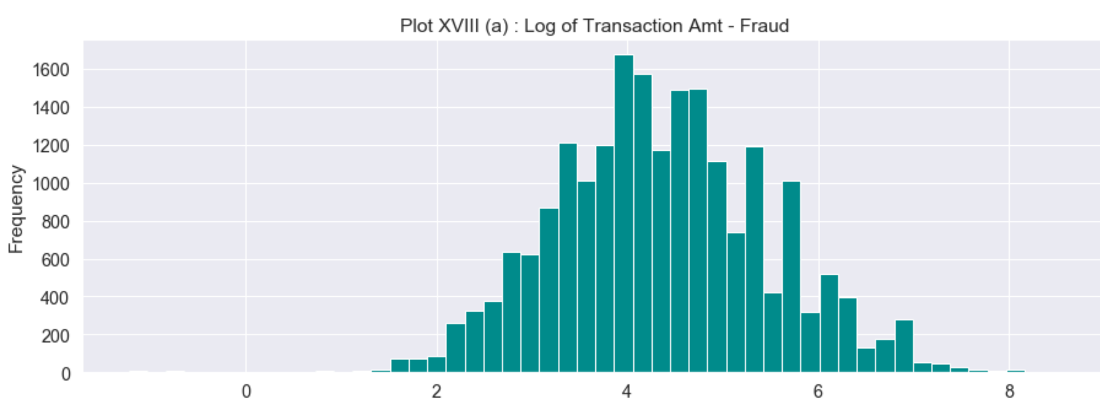
**From Plot XVI, the following observations can be made: (a) Debit has a larger number of non-fraud transactions, compared to credit, while the number of fraud transactions is comparable in both the cases. (b) Both Discover and Amex have hardly any fraud transactions. (c) Products with code 'C' has the highest proportion of Fraud Transactions.

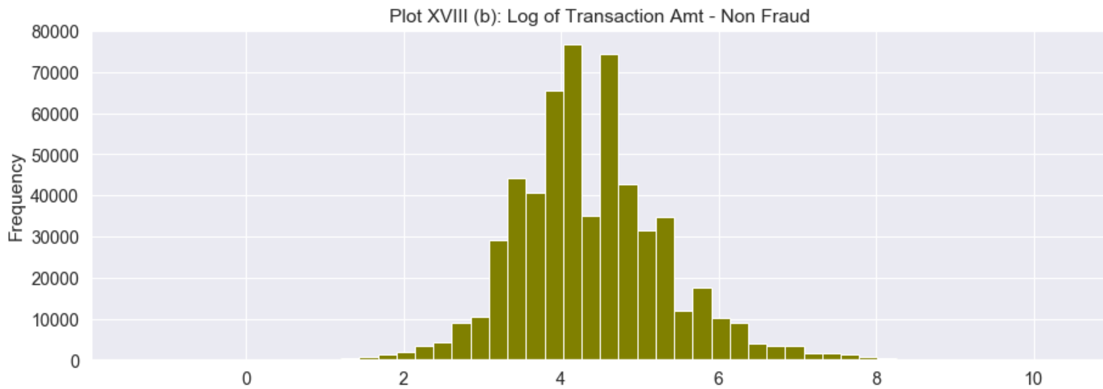
```
In [221]: # Plot XVII Fraud vs Non Fraud for PurchaserEmail and ReceiverEmail
          f, axes = plt.subplots(1, 2, figsize=(15, 8))
          PurchaserEmail = sns.countplot(x='P_emaildomain', hue="isFraud", data=df_transaction_identity
          PurchaserEmail.set_xticklabels(PurchaserEmail.get_xticklabels(), rotation=90, ha="right")
          PurchaserEmail.set_title("Plot XVII(a): PurchaserEmail- Fraud vs Non Fraud")
          ReceiverEmail = sns.countplot(x='R_emaildomain', hue="isFraud", data=df_transaction_identity,
          ReceiverEmail.set_xticklabels(ReceiverEmail.get_xticklabels(), rotation=90, ha="right")
          ReceiverEmail.set_title("Plot XVII(b): ReceiverEmail- Fraud vs Non Fraud")
          plt.tight_layout()
```



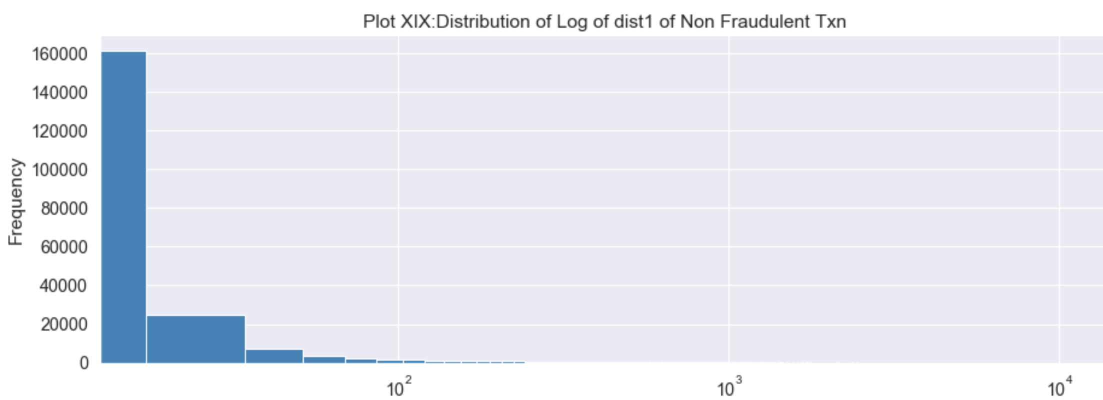
From Plot XVII, we can make the following observations: (a) For both Purchaser Email and Receiver Email, we see that both gmail.com and hotmail.com are in top 3 of email service providers, meaning, that these are the most used services. (b) We also see the presence of a domain called 'anonymous.com', which might be used by people who don't want to reveal their information.

```
In [222]: # Plot XVIII Fraud vs Non Fraud for Log of Transaction Amount
          Fraud_Transactions['TransactionAmt'].apply(np.log).plot(kind='hist',bins=50, figsize=(15,5),
                                                                  title='Plot XVIII (a) : Log of Transaction Am
          plt.show()
          Non_Fraud_Transactions['TransactionAmt'].apply(np.log).plot(kind='hist', bins=50, figsize=(15
          plt.show()
```

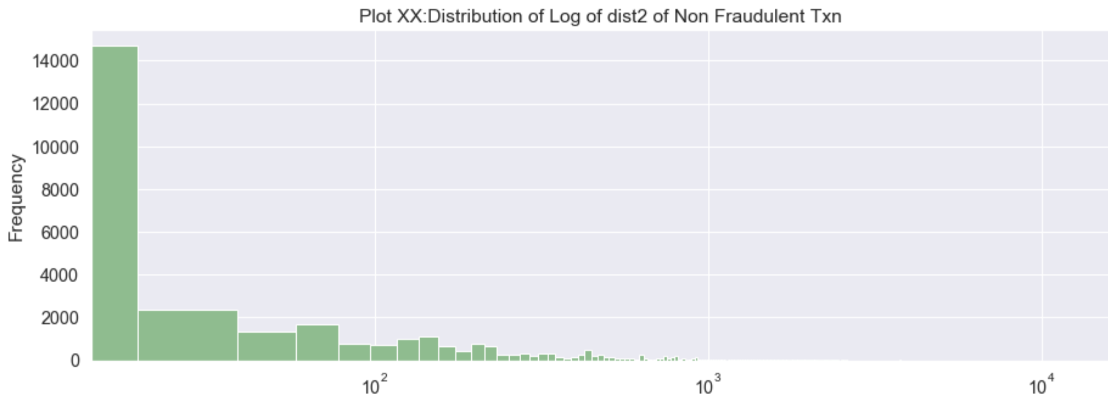




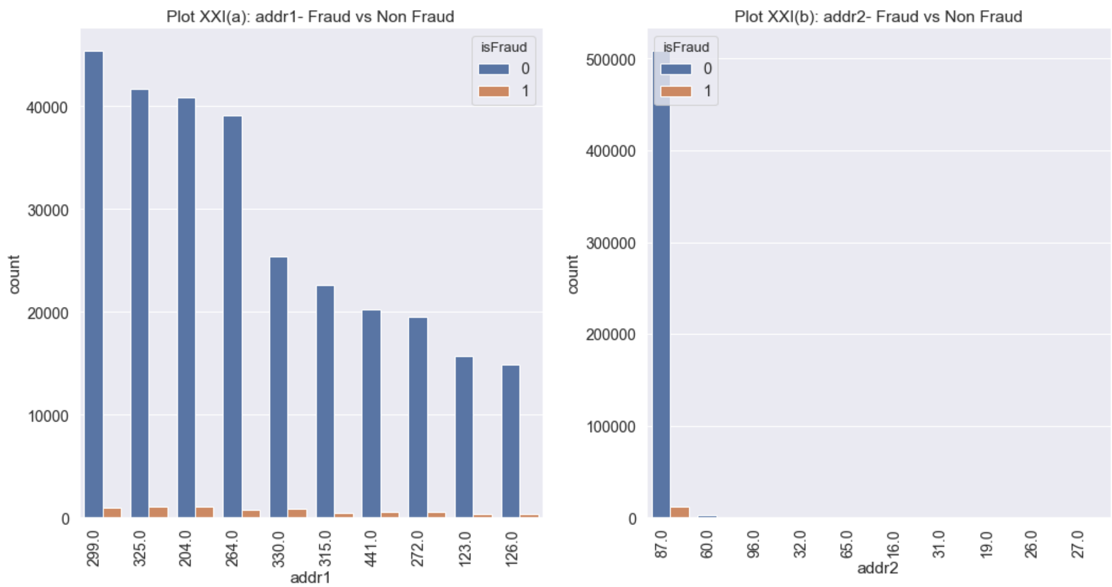

```
In [223]: # Plot XIX Non Fraud for Log of dist1
          # Check Plot XII for Fraud for Log of dist1
          Non_Fraud_Transactions['dist1'] \
              .plot(kind='hist',
                    bins=600,
                    figsize=(15, 5),
                    color="steelblue",
                    title='Plot XIX:Distribution of Log of dist1 of Non Fraudulent Txn', logx="true")
          plt.show()
```




```
In [224]: # For Plot XX,I am plotting the distribution of dist2 of Non Fraudulent Txn
          # Check Plot XIV for Fraudulent Txn
          Non_Fraud_Transactions['dist2'] \
              .plot(kind='hist',
                    bins=600,
                    figsize=(15, 5),
                    color="darkseagreen",
                    title='Plot XX:Distribution of Log of dist2 of Non Fraudulent Txn', logx="true")
          plt.show()
```




```
In [225]: # Plot XXI Fraud vs Non Fraud for addr1 and addr2
          f, axes = plt.subplots(1, 2, figsize=(15, 8))
          Address1 = sns.countplot(x='addr1', hue="isFraud", data=df_transaction_identity,order=pd.value
          Address1.set_xticklabels(Address1.get_xticklabels(), rotation=90, ha="right")
          Address1.set_title("Plot XXI(a): addr1- Fraud vs Non Fraud")
          Address2 = sns.countplot(x='addr2', hue="isFraud", data=df_transaction_identity,order=pd.value
          Address2.set_xticklabels(Address2.get_xticklabels(), rotation=90, ha="right")
          Address2.set_title("Plot XXI(b): addr2- Fraud vs Non Fraud")
          plt.tight_layout()
```



1.2 Part 2 - Transaction Frequency

```
In [226]: # At the start of Task 2, first I am figuring out the addr2 value, having the maximum frequen
          df_transaction_identity.addr2.mode()

Out[226]: 0    87.0
          dtype: float64
```

In [227]:
```
# Now I am filtering out the dataset, to create a new dataframe, having rows with addr2 value
max_addr2_bool=df_transaction_identity['addr2']==87
max_addr2=df_transaction_identity[max_addr2_bool]
```

In [228]:
```
# Checking if data is properly filtered
max_addr2.count()
```

Out[228]:
```
TransactionID     520481
TransactionDT     520481
TransactionAmt    520481
ProductCD         520481
isFraud           520481
card4             519100
card6             519103
P_emaildomain     428419
R_emaildomain      69932
addr1             520481
addr2             520481
dist1             238166
dist2              10710
DeviceType         78622
DeviceInfo         76083
dtype: int64
```

In [229]:
```
# Checking if data is properly filtered
df_transaction_identity.count()
```

Out[229]:
```
TransactionID     590540
TransactionDT     590540
TransactionAmt    590540
ProductCD         590540
isFraud           590540
card4             588963
card6             588969
P_emaildomain     496084
R_emaildomain     137291
addr1             524834
addr2             524834
dist1             238269
dist2              37627
DeviceType        140810
DeviceInfo        118666
dtype: int64
```

In [230]:
```
# Here I am converting the timedelta to a proper datetime using a reference start time
import warnings
warnings.filterwarnings('ignore')
try:
    import datetime
    START_DATE = '2017-12-01'
    startdate = datetime.datetime.strptime(START_DATE, '%Y-%m-%d')
    max_addr2['TransactionDT'] = max_addr2['TransactionDT'].apply(lambda x: (startdate + datet
except:
    print("Ok")
```

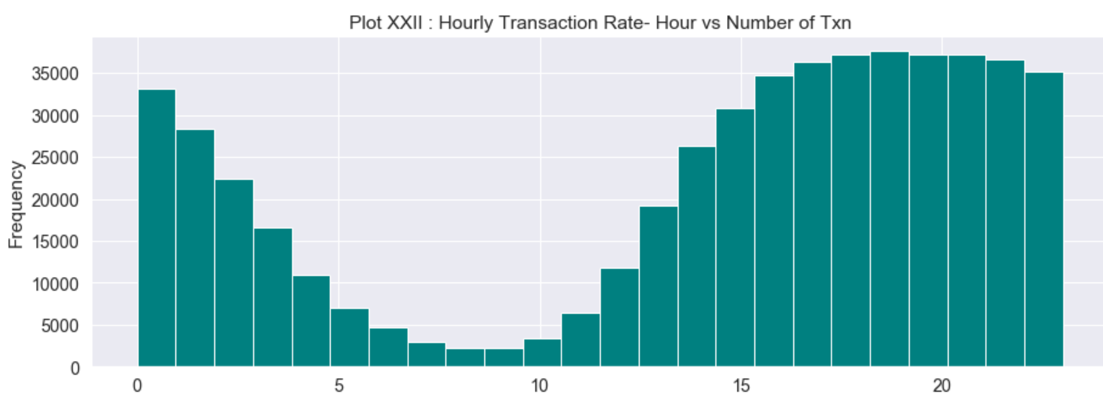
In [231]:
```
# After I get a proper datetime, now I add another field to max_addr2 dataframe, which will g
try:
```

```
    max_addr2['hour']=pd.DatetimeIndex(max_addr2['TransactionDT']).hour
except:
    print("Ok")
```

In [232]:
```
# Checking if that worked
max_addr2.tail(2)
```

Out[232]:
```
        TransactionID       TransactionDT  TransactionAmt ProductCD  isFraud  \
590538        3577538 2018-06-01 23:58:08          117.00         W        0
590539        3577539 2018-06-01 23:58:51          279.95         W        0

             card4   card6 P_emaildomain R_emaildomain  addr1  addr2  dist1  \
590538  mastercard   debit       aol.com           NaN  387.0   87.0    3.0
590539  mastercard  credit     gmail.com           NaN  299.0   87.0    NaN

        dist2 DeviceType DeviceInfo  hour
590538    NaN        NaN        NaN    23
590539    NaN        NaN        NaN    23
```

In [233]:
```
# For Plot XXII,I am plotting the distribution of number of transactions vs the hour of the da
max_addr2['hour'] \
    .plot(kind='hist',
          bins=24,
          figsize=(15, 5),
          color="teal",
          title='Plot XXII : Hourly Transaction Rate- Hour vs Number of Txn')
plt.show()
```



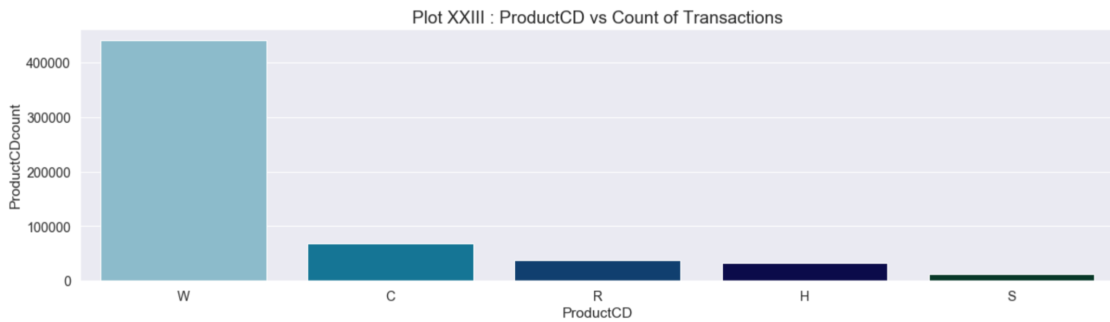
**Observation: From the hourly transaction rate which plots the number of transactions vs the hour of the day, it can be seen that the number of transactions start reducing from the 4th hour till the 12th hour. Hence, we can conclude that the people are generally awake from the 13th hour to 23rd hour, which continues from 0th hour to 3rd hour as well.

1.3 Part 3 - Product Code

In [234]:
```
# At the start of Task 3, I am first getting the count of transactions per productcd
complete_data = pd.DataFrame()
complete_data['ProductCDcount'] = df_transaction_identity.groupby(['ProductCD'])['ProductCD']
complete_data['ProductCD'] = complete_data.index
group_top = complete_data.sort_values(by='ProductCDcount',ascending=False)
```

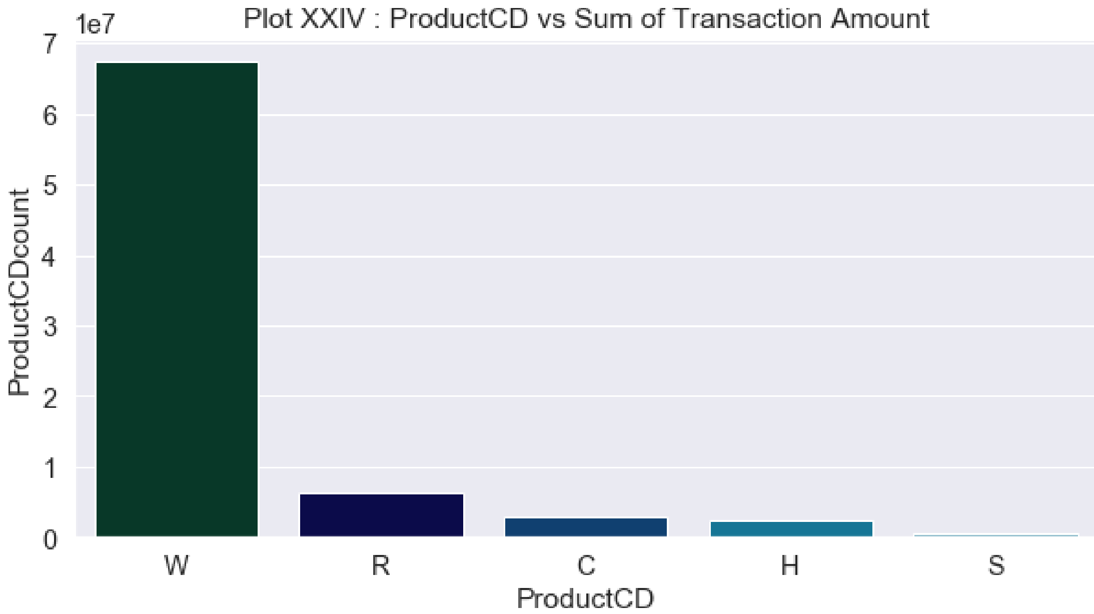
```
plt.figure(figsize=(20, 5))
sns.set(color_codes=True)
sns.set(font_scale = 1.3)
ax = sns.barplot(x="ProductCD", y="ProductCDcount",palette='ocean_r', data=group_top)

font_size= {'size': 'large'}
ax.set_title("Plot XXIII : ProductCD vs Count of Transactions", **font_size)
```

Out[234]: Text(0.5, 1.0, 'Plot XXIII : ProductCD vs Count of Transactions')

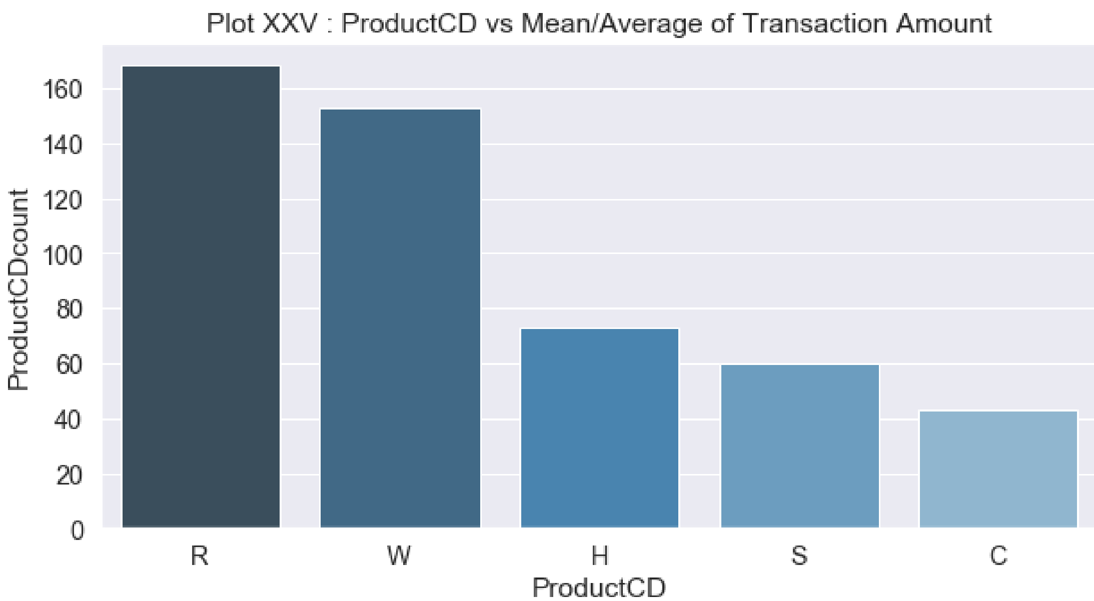


In [235]:
```
# Then, I am calculating the sum of transaction amounts per productcd
complete_data = pd.DataFrame()
complete_data['ProductCDcount'] = df_transaction_identity.groupby(['ProductCD'])['Transaction
complete_data['ProductCD'] = complete_data.index
group_top = complete_data.sort_values(by='ProductCDcount',ascending=False)

plt.figure(figsize=(10, 5))
sns.set(color_codes=True)
sns.set(font_scale = 1.3)
ax = sns.barplot(x="ProductCD", y="ProductCDcount",palette='ocean', data=group_top)

font_size= {'size': 'medium'}
ax.set_title("Plot XXIV : ProductCD vs Sum of Transaction Amount", **font_size)
```

Out[235]: Text(0.5, 1.0, 'Plot XXIV : ProductCD vs Sum of Transaction Amount')




```
In [236]: # Finally, I am calculating the average or mean of transaction amount per productcd
          sns.set_style('ticks')
          complete_data = pd.DataFrame()
          complete_data['ProductCDcount'] = df_transaction_identity.groupby(['ProductCD'])['Transaction
          complete_data['ProductCD'] = complete_data.index
          group_top = complete_data.sort_values(by='ProductCDcount',ascending=False)

          plt.figure(figsize=(10, 5))
          sns.set(color_codes=True)
          sns.set(font_scale = 1.3)
          ax = sns.barplot(x="ProductCD", y="ProductCDcount",palette='Blues_d', data=group_top)

          font_size= {'size': 'medium'}
          ax.set_title("Plot XXV : ProductCD vs Mean/Average of Transaction Amount", **font_size)

Out[236]: Text(0.5, 1.0, 'Plot XXV : ProductCD vs Mean/Average of Transaction Amount')
```



**Observation: From Plot XXV, we can see that the most expensive product is the product having ProductCD='R', and the least expensive is the product having ProductCD='C'. This is because, to find this, I first found out the count and sum of the transaction amounts per ProductCD, and then find out its mean/average, which, gives the most expensive and least expensive products.

1.4 Part 4 - Correlation Coefficient

In [237]:
```
# Task 4
# Here I am converting the timedelta to a proper datetime using a reference start time
try:
    import datetime
    START_DATE = '2017-12-01'
    startdate = datetime.datetime.strptime(START_DATE, '%Y-%m-%d')
    df_transaction_identity['TransactionDT'] = df_transaction_identity['TransactionDT'].apply
except:
    print("Ok")
```

In [238]:
```
# After I get a proper datetime, now I add another field to max_addr2 dataframe, which will g
try:
    df_transaction_identity['hour']=pd.DatetimeIndex(df_transaction_identity['TransactionDT'])
except:
    print("Ok")
```

In [239]:
```
df_transaction_identity.head(2)
```

Out[239]:
```
   TransactionID        TransactionDT  TransactionAmt ProductCD  isFraud  \
0        2987000 2017-12-02 00:00:00            68.5         W        0
1        2987001 2017-12-02 00:00:01            29.0         W        0

        card4   card6 P_emaildomain R_emaildomain  addr1  addr2  dist1  dist2  \
0    discover  credit           NaN           NaN  315.0   87.0   19.0    NaN
1  mastercard  credit     gmail.com           NaN  325.0   87.0    NaN    NaN
```

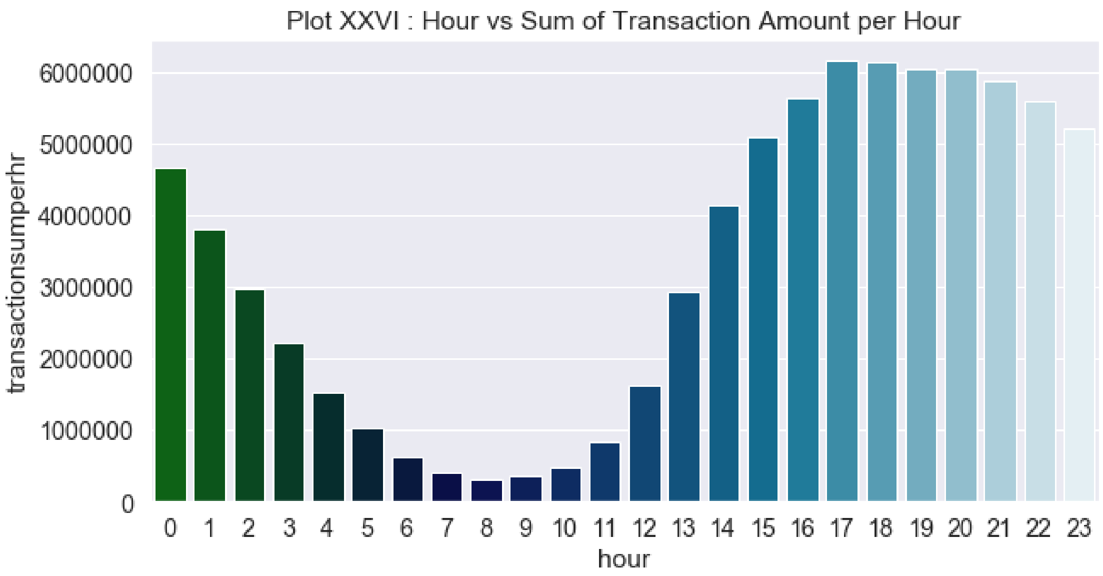
```
  DeviceType DeviceInfo  hour
0        NaN        NaN     0
1        NaN        NaN     0
```

In [240]:
```
df_transaction_identity['hour'].isnull().sum()
```

Out[240]:
```
0
```

In [241]:
```
# Then, I am calculating the sum of transaction amounts per productcd
complete_datas = pd.DataFrame()
complete_datas['transactionsumperhr'] = df_transaction_identity.groupby(['hour'])['Transactio
complete_datas['hour'] = complete_datas.index
group_top = complete_datas.sort_values(by='transactionsumperhr',ascending=False)

plt.figure(figsize=(10, 5))
sns.set(color_codes=True)
sns.set(font_scale = 1.3)
ax = sns.barplot(x="hour", y="transactionsumperhr",palette='ocean', data=group_top)

font_size= {'size': 'medium'}
ax.set_title("Plot XXVI : Hour vs Sum of Transaction Amount per Hour", **font_size)
```

Out[241]:
```
Text(0.5, 1.0, 'Plot XXVI : Hour vs Sum of Transaction Amount per Hour')
```



In [242]:
```
hr_amount=df_transaction_identity[['hour','TransactionAmt']]
hr_amount.corr(method='pearson')
```

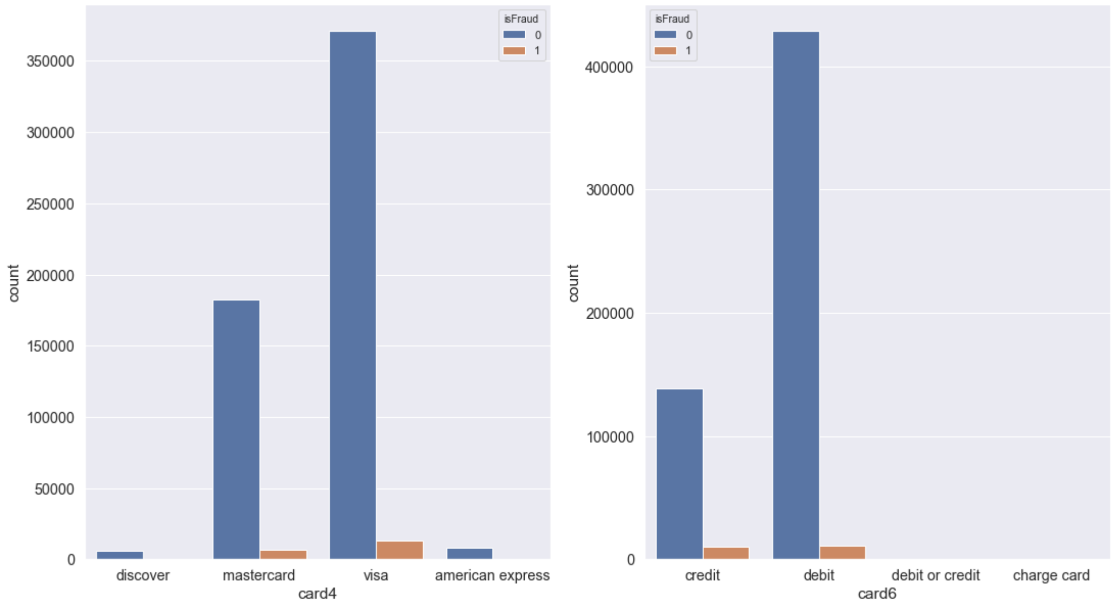
Out[242]:

	hour	TransactionAmt
hour	1.000000	0.044532
TransactionAmt	0.044532	1.000000

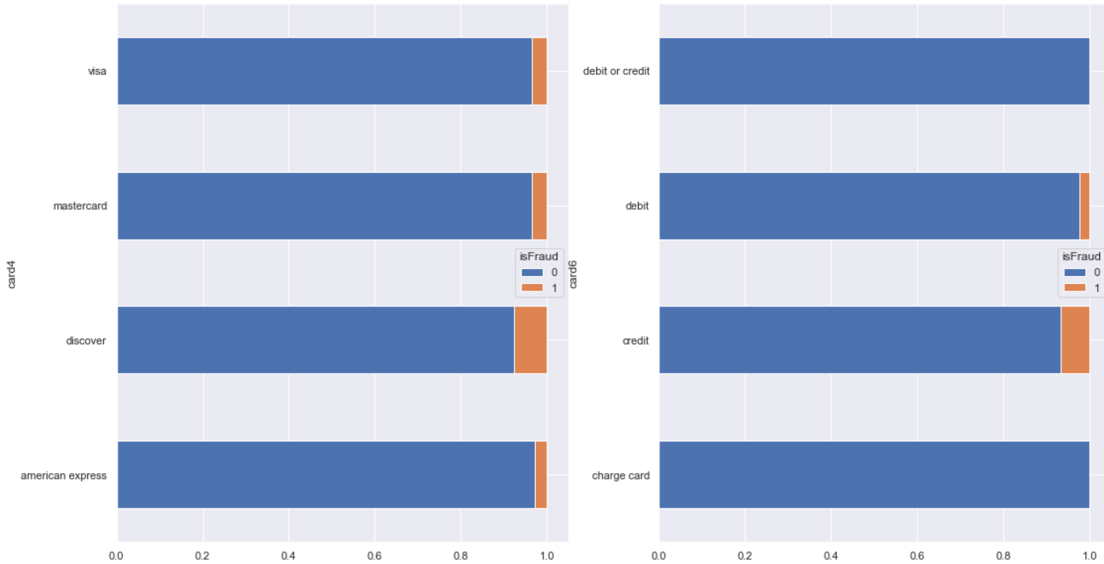
**For Task 4, I plotted Plot XXVI, to show the distribution of time of day and the purchase amount. Also the correlation coefficient is calculated above, which comes out to be 0.044532, by Pearson method

1.5 Part 5 - Interesting Plot

In [243]:
```
# In Task 5, I have first taken out the CardMerchant and CardType for Fraud vs Non-Fraud Txn
f, axes = plt.subplots(1, 2, figsize=(18, 10))
sns.set(color_codes=True)
card4 = sns.countplot(x='card4', hue="isFraud", data=df_transaction_identity, ax=axes[0])
card6 = sns.countplot(x='card6', hue="isFraud", data=df_transaction_identity, ax=axes[1])
```



In [244]:
```
# Then, I took the above Plot and showed it as percentage
f, axes = plt.subplots(1, 2, figsize=(18, 10))

props = df_transaction_identity.groupby("card4")['isFraud'].value_counts(normalize=True).unsta
p = props.plot(kind='barh', stacked='True', ax=axes[0])

props = df_transaction_identity.groupby("card6")['isFraud'].value_counts(normalize=True).unsta
p = props.plot(kind='barh', stacked='True', ax=axes[1])
```



**Observation: The above plots gives us some interesting information, which are as follows: (a) Visa has the highest number of Fraud Txns, but this number is only a minor proportion of all VISA transactions. (b) Discover, on the other hand, has very few Fraud transactions, yet it has the highest proportion of all Discover transactions, meaning, the chances that if a Txn is Discover, then chances that it is Fraud is the highest. (c) Although most Fraud transactions are done with Debit, yet when it comes to proportion of Fraud Transactions, Credit has the highest.

1.6 Part 6 - Prediction Model

In [245]:
```
# For Task 6, I start by merging the two CSVs

model_df= df_transaction.merge(df_identity, how='left', on='TransactionID')
```

In [246]:
```
model_df.head(10)
```

Out[246]:
```
   TransactionID  isFraud  TransactionDT  TransactionAmt ProductCD  card1  \
0        2987000        0          86400            68.5         W  13926
1        2987001        0          86401            29.0         W   2755
2        2987002        0          86469            59.0         W   4663
3        2987003        0          86499            50.0         W  18132
4        2987004        0          86506            50.0         H   4497
5        2987005        0          86510            49.0         W   5937
6        2987006        0          86522           159.0         W  12308
7        2987007        0          86529           422.5         W  12695
8        2987008        0          86535            15.0         H   2803
9        2987009        0          86536           117.0         W  17399

   card2  card3       card4  card5  ...                 id_31  id_32  \
0    NaN  150.0    discover  142.0  ...                   NaN    NaN
1  404.0  150.0  mastercard  102.0  ...                   NaN    NaN
2  490.0  150.0        visa  166.0  ...                   NaN    NaN
3  567.0  150.0  mastercard  117.0  ...                   NaN    NaN
4  514.0  150.0  mastercard  102.0  ...  samsung browser 6.2   32.0
5  555.0  150.0        visa  226.0  ...                   NaN    NaN
```

```
6   360.0  150.0        visa  166.0  ...                  NaN    NaN
7   490.0  150.0        visa  226.0  ...                  NaN    NaN
8   100.0  150.0        visa  226.0  ...   mobile safari 11.0   32.0
9   111.0  150.0  mastercard  224.0  ...                  NaN    NaN

       id_33           id_34  id_35 id_36 id_37  id_38  DeviceType  \
0        NaN             NaN    NaN   NaN   NaN    NaN         NaN
1        NaN             NaN    NaN   NaN   NaN    NaN         NaN
2        NaN             NaN    NaN   NaN   NaN    NaN         NaN
3        NaN             NaN    NaN   NaN   NaN    NaN         NaN
4  2220x1080  match_status:2      T     F     T      T      mobile
5        NaN             NaN    NaN   NaN   NaN    NaN         NaN
6        NaN             NaN    NaN   NaN   NaN    NaN         NaN
7        NaN             NaN    NaN   NaN   NaN    NaN         NaN
8   1334x750  match_status:1      T     F     F      T      mobile
9        NaN             NaN    NaN   NaN   NaN    NaN         NaN

                     DeviceInfo
0                           NaN
1                           NaN
2                           NaN
3                           NaN
4  SAMSUNG SM-G892A Build/NRD90M
5                           NaN
6                           NaN
7                           NaN
8                    iOS Device
9                           NaN

[10 rows x 434 columns]
```

In [247]:
```
# Drop the columns which have more than 60% null values as they will not contribute much to th
nullp = model_df.isnull().sum()/model_df.shape[0]*100

column_drop = np.array(nullp[nullp > 60].index)
```

In [248]:
```
# List of columns dropped
column_drop
```

Out[248]:
```
array(['dist2', 'R_emaildomain', 'D6', 'D7', 'D8', 'D9', 'D12', 'D13',
       'D14', 'V138', 'V139', 'V140', 'V141', 'V142', 'V143', 'V144',
       'V145', 'V146', 'V147', 'V148', 'V149', 'V150', 'V151', 'V152',
       'V153', 'V154', 'V155', 'V156', 'V157', 'V158', 'V159', 'V160',
       'V161', 'V162', 'V163', 'V164', 'V165', 'V166', 'V167', 'V168',
       'V169', 'V170', 'V171', 'V172', 'V173', 'V174', 'V175', 'V176',
       'V177', 'V178', 'V179', 'V180', 'V181', 'V182', 'V183', 'V184',
       'V185', 'V186', 'V187', 'V188', 'V189', 'V190', 'V191', 'V192',
       'V193', 'V194', 'V195', 'V196', 'V197', 'V198', 'V199', 'V200',
       'V201', 'V202', 'V203', 'V204', 'V205', 'V206', 'V207', 'V208',
       'V209', 'V210', 'V211', 'V212', 'V213', 'V214', 'V215', 'V216',
       'V217', 'V218', 'V219', 'V220', 'V221', 'V222', 'V223', 'V224',
       'V225', 'V226', 'V227', 'V228', 'V229', 'V230', 'V231', 'V232',
       'V233', 'V234', 'V235', 'V236', 'V237', 'V238', 'V239', 'V240',
       'V241', 'V242', 'V243', 'V244', 'V245', 'V246', 'V247', 'V248',
       'V249', 'V250', 'V251', 'V252', 'V253', 'V254', 'V255', 'V256',
```

```
'V257', 'V258', 'V259', 'V260', 'V261', 'V262', 'V263', 'V264',
'V265', 'V266', 'V267', 'V268', 'V269', 'V270', 'V271', 'V272',
'V273', 'V274', 'V275', 'V276', 'V277', 'V278', 'V322', 'V323',
'V324', 'V325', 'V326', 'V327', 'V328', 'V329', 'V330', 'V331',
'V332', 'V333', 'V334', 'V335', 'V336', 'V337', 'V338', 'V339',
'id_01', 'id_02', 'id_03', 'id_04', 'id_05', 'id_06', 'id_07',
'id_08', 'id_09', 'id_10', 'id_11', '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', 'DeviceType', 'DeviceInfo'],
dtype=object)
```

In [249]:
```python
# Loading Test Identity
identity_test=pd.read_csv(r'I:\Data Science Fundamentals\test_identity.csv')
```

In [250]:
```python
# Loading Test Transaction
transaction_test=pd.read_csv(r'I:\Data Science Fundamentals\test_transaction.csv')
```

In [251]:
```python
# Merging Both Transaction and Identity
test_transaction_identity= transaction_test.merge(identity_test, how='left', on='TransactionI
```

In [252]:
```python
# Drop Columns from both model_df and test_transaction_identity
model_df=model_df.drop(column_drop,axis=1)
test_transaction_identity=test_transaction_identity.drop(column_drop,axis=1)
```

In [253]:
```python
# Fill Null Values with -999
model_df = model_df.fillna(-999)
test_transaction_identity = test_transaction_identity.fillna(-999)
```

In [254]:
```python
# Create target(y_train) and feature variable(x_train)
y_train = model_df['isFraud']
x_train = model_df.drop('isFraud',axis=1)
```

In [255]:
```python
# Label Encoding
# Ref: https://codeloop.org/python-machine-learning-label-encoding/
# Ref: https://www.programcreek.com/python/example/93350/sklearn.preprocessing.LabelEncoder
from sklearn import preprocessing
for f in x_train.columns:
    if x_train[f].dtype=='object' or test_transaction_identity[f].dtype=='object':
        lbl = preprocessing.LabelEncoder()
        lbl.fit(list(x_train[f].values) + list(test_transaction_identity[f].values))
        x_train[f] = lbl.transform(list(x_train[f].values))
        test_transaction_identity[f] = lbl.transform(list(test_transaction_identity[f].values)
```

In [256]:
```python
# Create Baseline Model, that is, Logistic Regression, Kaggle Rank->5249, Score->0.79
# Ref: https://towardsdatascience.com/building-a-logistic-regression-in-python-step-by-step-b
# Ref: https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegress
from sklearn.linear_model import LogisticRegression
logisticreg = LogisticRegression()
logisticreg.fit(x_train, y_train)
```

Out[256]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [257]:
```
# Predict
submit = pd.read_csv(r'I:\Data Science Fundamentals\sample_submission.csv',index_col='Transac
submit['isFraud'] = logisticreg.predict_proba(test_transaction_identity)[:,1]
submit.to_csv('Logisticreg_submission.csv')
submit.head()
```

Out[257]:

	isFraud
TransactionID	
3663549	0.025644
3663550	0.029312
3663551	0.034953
3663552	0.030020
3663553	0.026786

In [258]:
```
# Create Second, hopefully, a better model, using XGB Classifier, Kaggle Rank->4837, Score->0
# Ref: https://xgboost.readthedocs.io/en/latest/python/python_api.html
# Ref: https://www.programcreek.com/python/example/99824/xgboost.XGBClassifier
from xgboost import XGBClassifier
xgbmodel = XGBClassifier()
xgbmodel.fit(x_train, y_train)
```

Out[258]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1,
       max_delta_step=0, max_depth=3, min_child_weight=1, missing=None,
       n_estimators=100, n_jobs=1, nthread=None,
       objective='binary:logistic', random_state=0, reg_alpha=0,
       reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
       subsample=1, verbosity=1)
```

In [259]:
```
# Predict
submit_xgb = pd.read_csv(r'I:\Data Science Fundamentals\sample_submission.csv',index_col='Tran
submit['isFraud'] = xgbmodel.predict_proba(test_transaction_identity)[:,1]
submit.to_csv('XGB_submission.csv')
submit.head()
```

Out[259]:

	isFraud
TransactionID	
3663549	0.005306
3663550	0.011927
3663551	0.015194
3663552	0.004945
3663553	0.011092

**Model Building Workflow: (1) I started off by first merging the two required CSVs. (2) Then, I found out the columns which have more than 60% null values as they will not contribute much to the prediction model. (3) After that, I loaded both the test files and merged them. (4) Next, I dropped the columns, which I found out from Step (2) from both the model and test dataframes. (5) After that, I decided to use Random Imputation to fill the Null Values, and replace them with -999. (6) Next, I created the target(y_train) and feature variable(x_train). (7) Then, I carried out the process of Label Encoding, which is used to normalize labels as well as to transform non-numerical labels (as long as they are hashable and comparable) to numerical labels. (8) After that, I decided to create a Baseline Model, to keep things simple. I did this by using Logistic Regression technique, and ran predictions on the sample_submission.csv file. This gave me a Kaggle rank of 5249 and score of 0.79. (9) Finally, I decided to create a better model using XGB Classifier. When I ran predictions on the sample_submission.csv file, I got a better Kaggle rank of 4837 and score of 0.8969.

attachment:Kaggle_Rank.jpg

Kaggle_Rank.jpg

1.7 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/kaustavsbu
Highest Rank: 4837
Score: 0.8969
Number of entries: 2