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 [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','ProductCD','isFraud','card4','card6','P_emaildomain','R_emaildomai
n','addr1','addr2','dist1','dist2']]
```

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

Out[197]:

	TransactionID	TransactionDT	TransactionAmt	ProductCD	isFraud	card4	card6	P_emaildomain	R_emaildomain	addr1	addr2	dist1	dist2
0	2987000	86400	68.5	W	0	discover	credit	NaN	NaN	315.0	87.0	19.0	NaN
1	2987001	86401	29.0	W	0	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	card4	card6	P_emaildomain	R_emaildomain	addr1	addr2	dist1	dist2	DeviceType	DeviceInfo
0	2987000	86400	68.5	W	0	discover	credit	NaN	NaN	315.0	87.0	19.0	NaN	NaN	NaN
1	2987001	86401	29.0	W	0	mastercard	credit	gmail.com	NaN	325.0	87.0	NaN	NaN	NaN	NaN
2	2987002	86469	59.0	W	0	visa	debit	outlook.com	NaN	330.0	87.0	287.0	NaN	NaN	NaN
3	2987003	86499	50.0	W	0	mastercard	debit	yahoo.com	NaN	476.0	87.0	NaN	NaN	NaN	NaN
4	2987004	86506	50.0	H	0	mastercard	credit	gmail.com	NaN	420.0	87.0	NaN	NaN	mobile	SAMSUNG SM-G892A Build/NRD90M
5	2987005	86510	49.0	W	0	visa	debit	gmail.com	NaN	272.0	87.0	36.0	NaN	NaN	NaN
6	2987006	86522	159.0	W	0	visa	debit	yahoo.com	NaN	126.0	87.0	0.0	NaN	NaN	NaN
7	2987007	86529	422.5	W	0	visa	debit	mail.com	NaN	325.0	87.0	NaN	NaN	NaN	NaN
8	2987008	86535	15.0	H	0	visa	debit	anonymous.com	NaN	337.0	87.0	NaN	NaN	mobile	iOS Device
9	2987009	86536	117.0	W	0	mastercard	debit	yahoo.com	NaN	204.0	87.0	19.0	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]:
```python
Fraud_Transactions.head(10)
```

Out[201]:

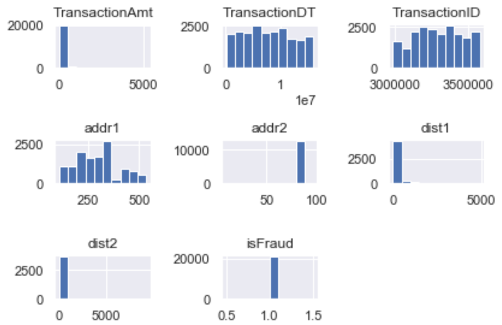
	TransactionID	TransactionDT	TransactionAmt	ProductCD	isFraud	card4	card6	P_emaildomain	R_emaildomain	addr1	addr2	dist1	dist2	DeviceType	DeviceInfo
203	2987203	89760	445.000	W	1	visa	credit	aol.com	NaN	251.0	87.0	NaN	NaN	NaN	NaN
240	2987240	90193	37.098	C	1	visa	credit	hotmail.com	hotmail.com	NaN	NaN	NaN	NaN	mobile	Redmi Note 4 Build/MMB29M
243	2987243	90246	37.098	C	1	visa	credit	hotmail.com	hotmail.com	NaN	NaN	NaN	NaN	mobile	Redmi Note 4 Build/MMB29M
245	2987245	90295	37.098	C	1	visa	credit	hotmail.com	hotmail.com	NaN	NaN	NaN	NaN	mobile	Redmi Note 4 Build/MMB29M
288	2987288	90986	155.521	C	1	visa	credit	outlook.com	outlook.com	NaN	NaN	NaN	NaN	mobile	NaN
367	2987367	92350	225.000	R	1	mastercard	credit	gmail.com	gmail.com	472.0	87.0	NaN	NaN	desktop	rv:52.0
405	2987405	92999	90.570	C	1	mastercard	credit	gmail.com	gmail.com	NaN	NaN	NaN	NaN	mobile	NaN
630	2987630	97843	12.326	C	1	mastercard	debit	gmail.com	gmail.com	NaN	NaN	NaN	7.0	desktop	Windows
683	2987683	99584	124.344	C	1	mastercard	debit	gmail.com	gmail.com	NaN	NaN	NaN	7.0	desktop	Windows
736	2987736	100591	100.000	W	1	visa	credit	yahoo.com	NaN	231.0	87.0	NaN	NaN	NaN	NaN

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

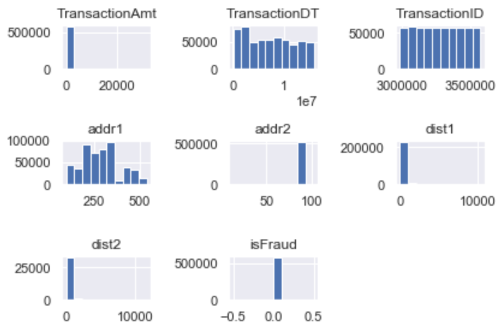
Out[202]:

	TransactionID	TransactionDT	TransactionAmt	ProductCD	isFraud	card4	card6	P_emaildomain	R_emaildomain	addr1	addr2	dist1	dist2	DeviceType	DeviceInfo
0	2987000	86400	68.5	W	0	discover	credit	NaN	NaN	315.0	87.0	19.0	NaN	NaN	NaN
1	2987001	86401	29.0	W	0	mastercard	credit	gmail.com	NaN	325.0	87.0	NaN	NaN	NaN	NaN
2	2987002	86469	59.0	W	0	visa	debit	outlook.com	NaN	330.0	87.0	287.0	NaN	NaN	NaN
3	2987003	86499	50.0	W	0	mastercard	debit	yahoo.com	NaN	476.0	87.0	NaN	NaN	NaN	NaN
4	2987004	86506	50.0	H	0	mastercard	credit	gmail.com	NaN	420.0	87.0	NaN	NaN	mobile	SAMSUNG SM-G892A Build/NRD90M
5	2987005	86510	49.0	W	0	visa	debit	gmail.com	NaN	272.0	87.0	36.0	NaN	NaN	NaN
6	2987006	86522	159.0	W	0	visa	debit	yahoo.com	NaN	126.0	87.0	0.0	NaN	NaN	NaN
7	2987007	86529	422.5	W	0	visa	debit	mail.com	NaN	325.0	87.0	NaN	NaN	NaN	NaN
8	2987008	86535	15.0	H	0	visa	debit	anonymous.com	NaN	337.0	87.0	NaN	NaN	mobile	iOS Device
9	2987009	86536	117.0	W	0	mastercard	debit	yahoo.com	NaN	204.0	87.0	19.0	NaN	NaN	NaN

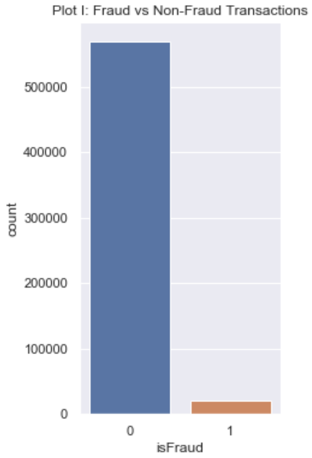
In [203]:
```python
# Import matplotlib to examine distributions
import matplotlib.pyplot as plt
# Import numpy to get better histogram distributions
import numpy as np
# Histogram for Fraudulent Transactions
hists = Fraud_Transactions.hist()
plt.tight_layout()
```



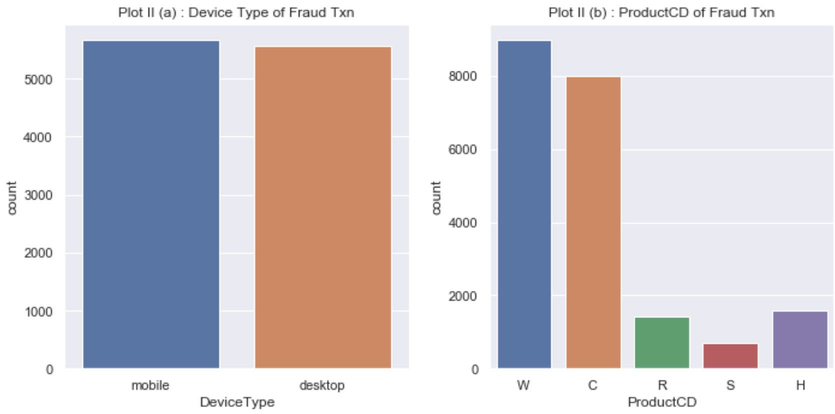
In [204]:
```python
# Import matplotlib to examine distributions
import matplotlib.pyplot as plt
# Histogram for Non Fraudulent Transactions
hists = Non_Fraud_Transactions.hist()
plt.tight_layout()
```



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()
```

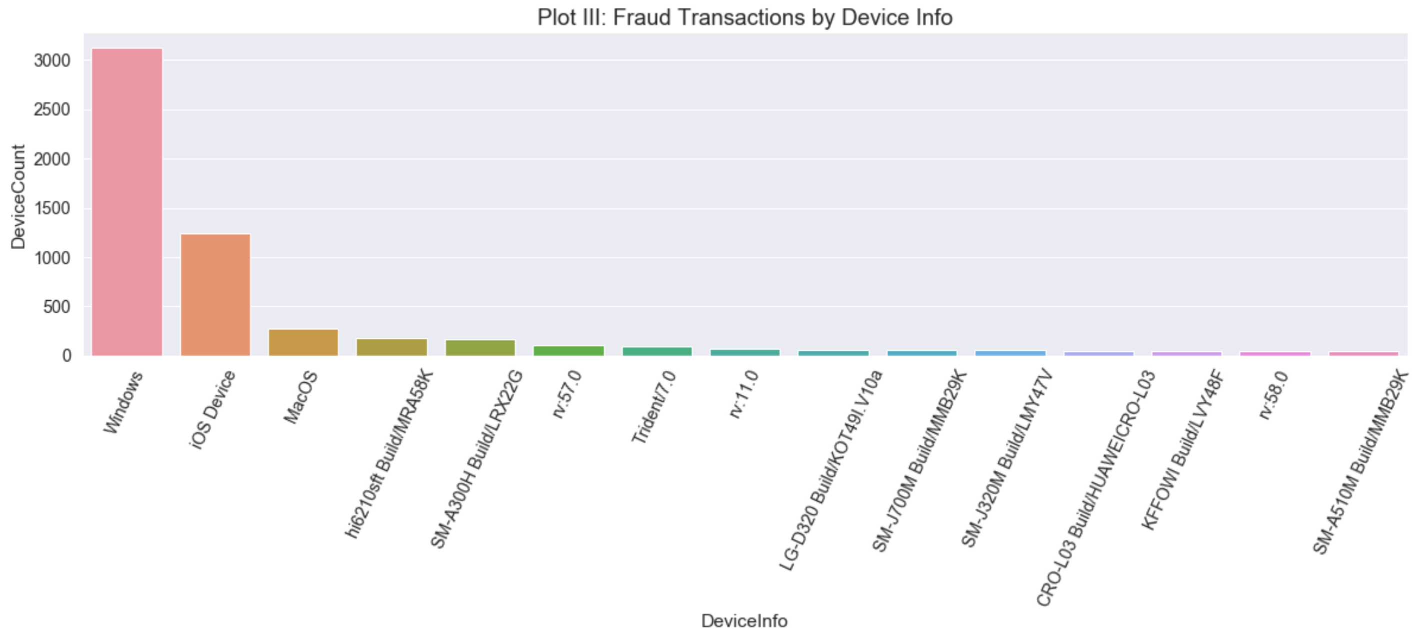


In [206]:
```
# For Plot II, I will plot the Fraud Transactions according to the DeviceType, and the ProductCD
f, axes = plt.subplots(1, 2, figsize=(10, 5))
DeviceType = sns.countplot(x='DeviceType', data=Fraud_Transactions, ax=axes[0]).set_title("Plot II (a) : Device Type of Fraud Txn")
ProductCD =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



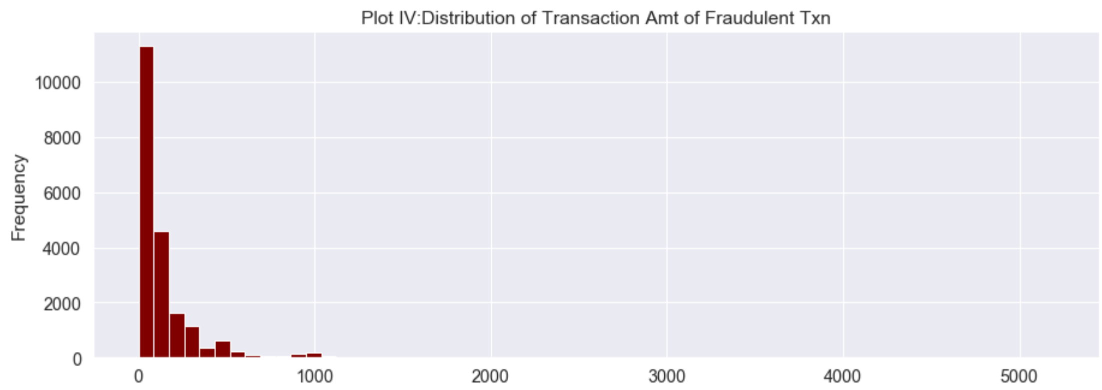
**Observation: From Plot II (a), it can be established that its hard to distinguish between the number of fraud transactions, that occured on mobile and desktop, as they are almost equal. Also, from Plot II (b), it can be confirmed that the products having ProductCD 'W' have highest number of fraud transactions.

In [207]:
```
# For Plot III, I am trying to plot the Fraud Transactions according to the DeviceInfo. As there are too many device types,
# 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.pdf
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)
```

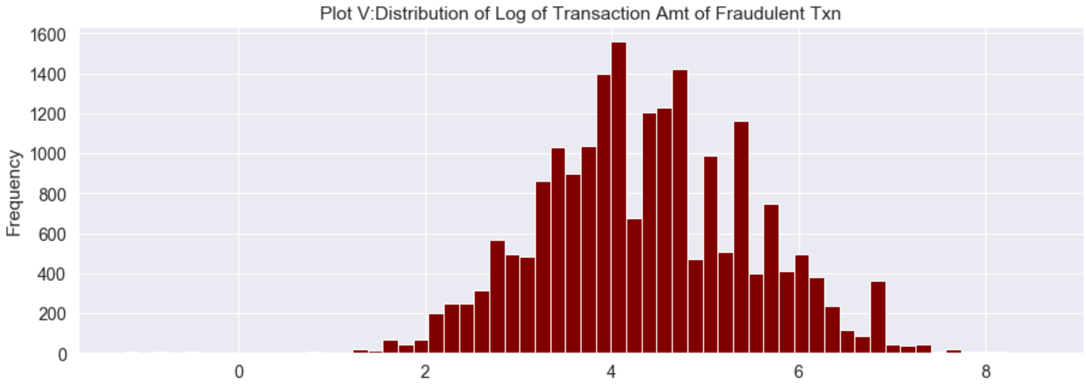


**Observation: From Plot III, it can be established that Fraud transaction cases come mostly from Windows and iOS devices. This is predictable given the vast majority of all transactions come from those systems.

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()
```

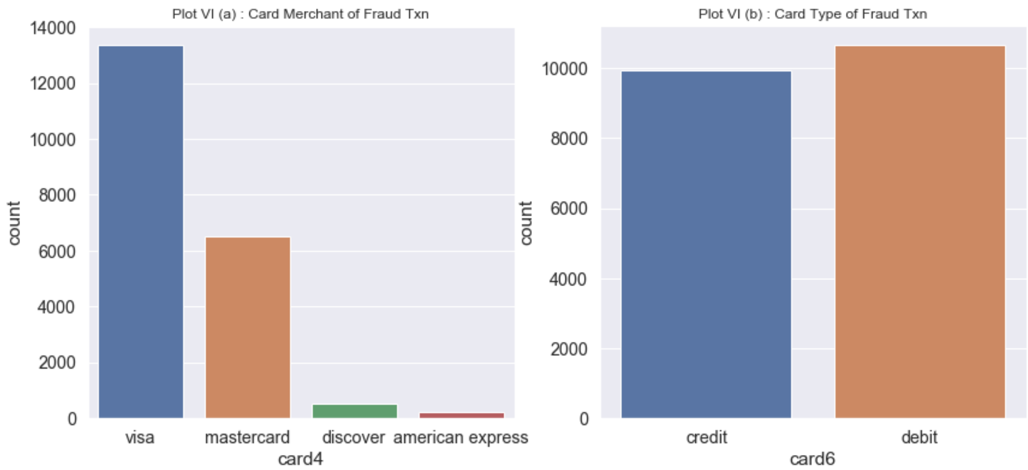


In [209]:
```
# For Plot V,I am plotting the distribution of Log of Transaction Amt of Fraudulent Txn, as it gives a better distribution
Fraud_Transactions['TransactionAmt'] \
    .apply(np.log) \
    .plot(kind='hist',
          bins=60,
          figsize=(15, 5),
          color="maroon",
        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



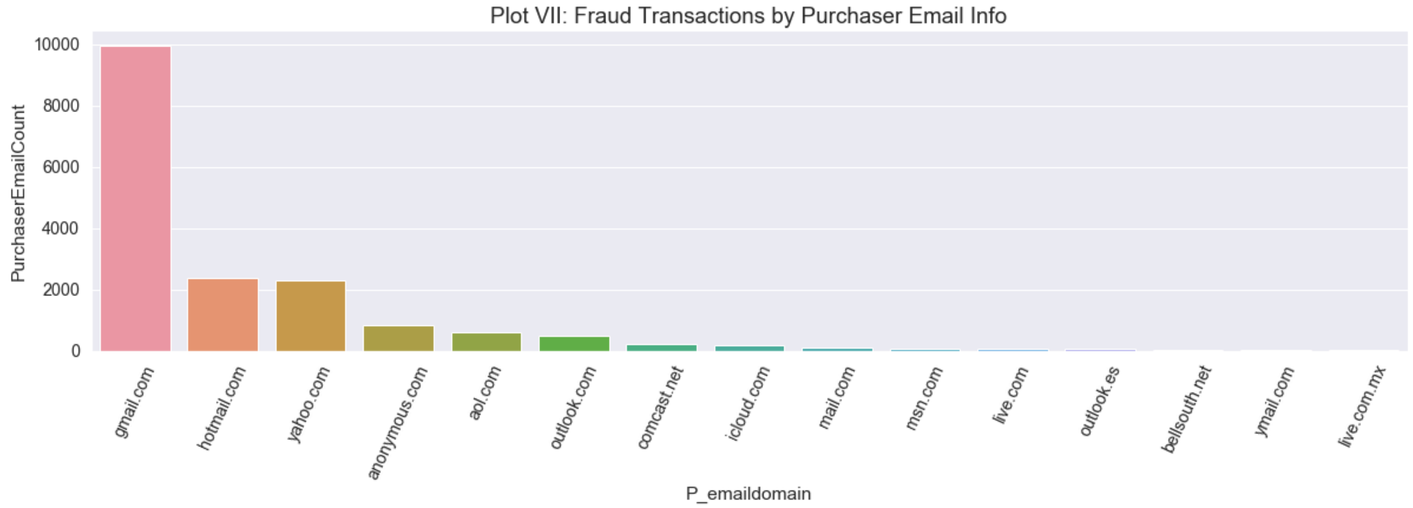
**From Plot V, it can be concluded that taking the log gives us a better distribution, as the transaction amounts lies within a narrow range.

In [210]:
```
# For Plot VI,I am plotting the distribution of the card merchant as well as the card type of Fraud Txn
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) : Card Merchant of Fraud Txn")
card6 = sns.countplot(x='card6', data=Fraud_Transactions, ax=axes[1]).set_title("Plot VI (b) : Card Type of Fraud Txn")
```



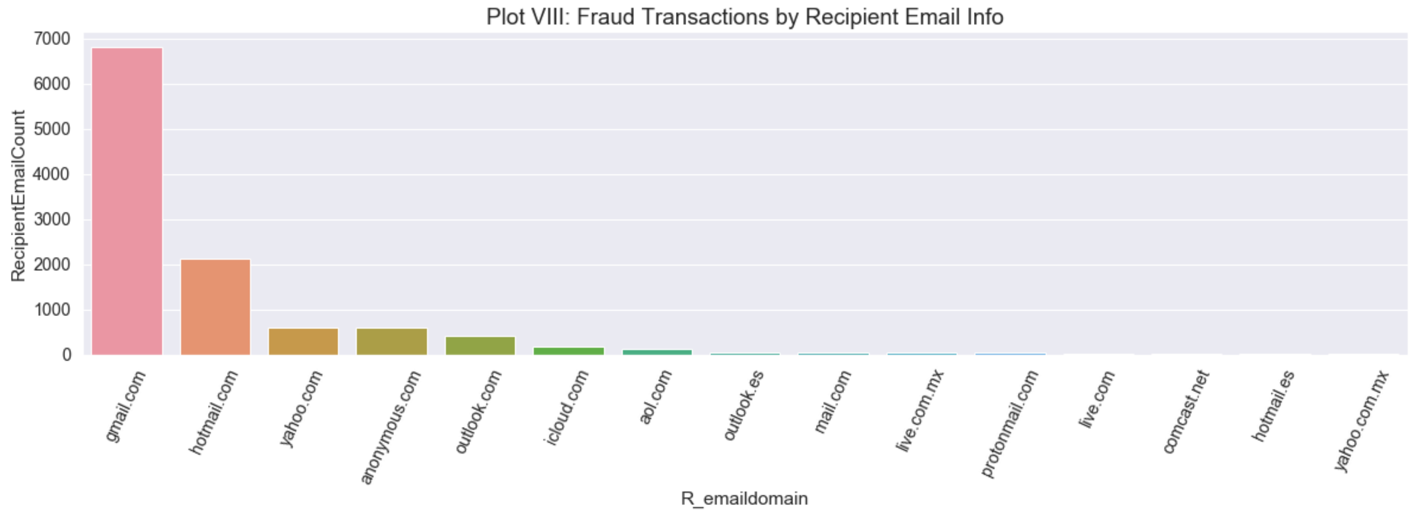
**From Plot VI(a), it can be established that maximum fraud transactions occur when the card merchant is VISA. Also, from Plot VI(b), we see more fraud happening in debit transactions.

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



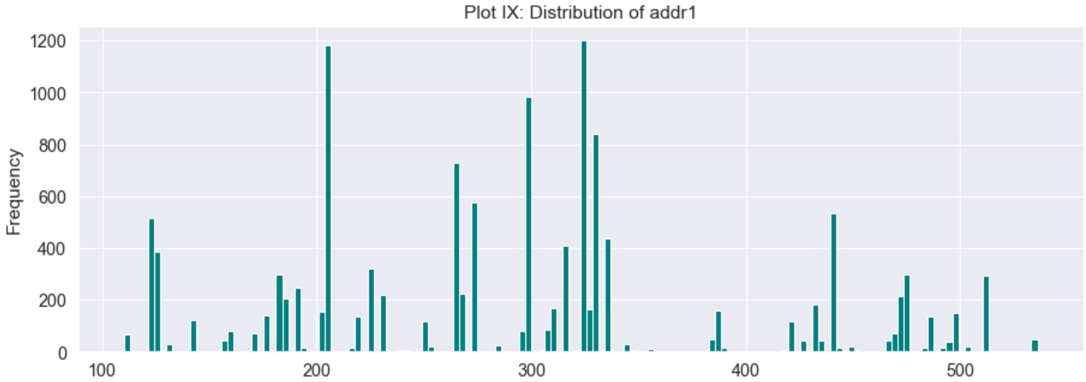
**From Plot VII, we see that most of the purchaser email domain associated with fraud transactions come from gmail.com

In [212]:
```
# For Plot VIII, I am plotting the Fraud Transactions according to the Recipient Email Domain. As there are too many such types,
# I will limit the graph to the top 15 email domains
fraud = pd.DataFrame()
fraud['RecipientEmailCount'] = Fraud_Transactions.groupby(['R_emaildomain'])['R_emaildomain'].count()
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)
```

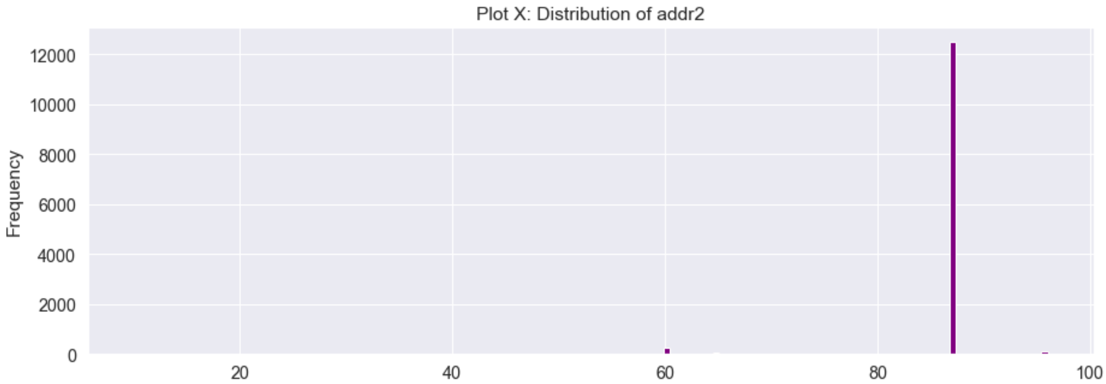


**From Plot VIII, we see that most of the receiver email domain associated with fraud transactions come from gmail.com, as well.

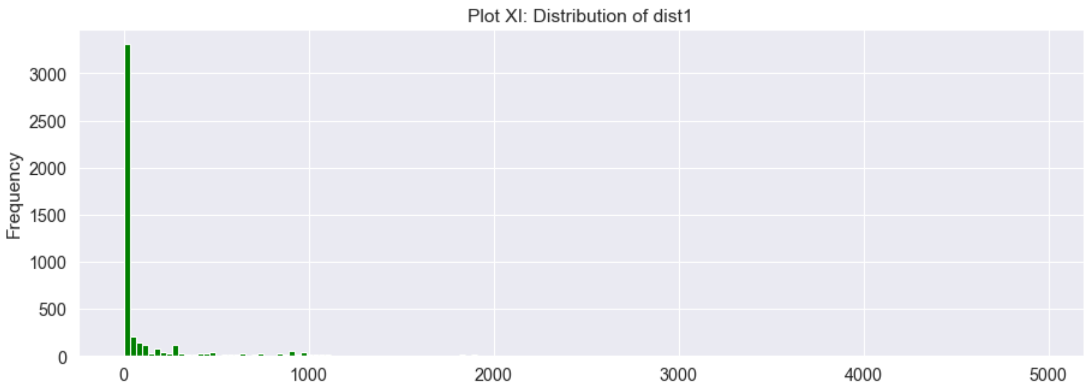
In [213]:
```
# For Plot IX,I am plotting the distribution of the addr1 field associated with Fraudulent Txn
Fraud_Transactions['addr1'] \
    .plot(kind='hist',
          bins=150,
          figsize=(15, 5),
          color="teal",
          title='Plot IX: Distribution of addr1')
plt.show()
```



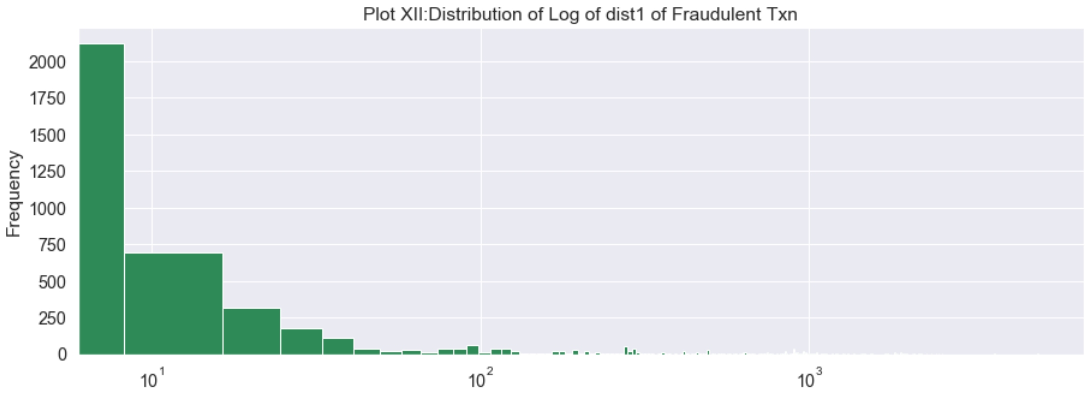
In [214]:
```
# For Plot X,I am plotting the distribution of the addr2 field associated with Fraudulent Txn
Fraud_Transactions['addr2'] \
    .plot(kind='hist',
          bins=150,
          figsize=(15, 5),
          color="purple",
          title='Plot X: Distribution of addr2')
plt.show()
```



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()
```

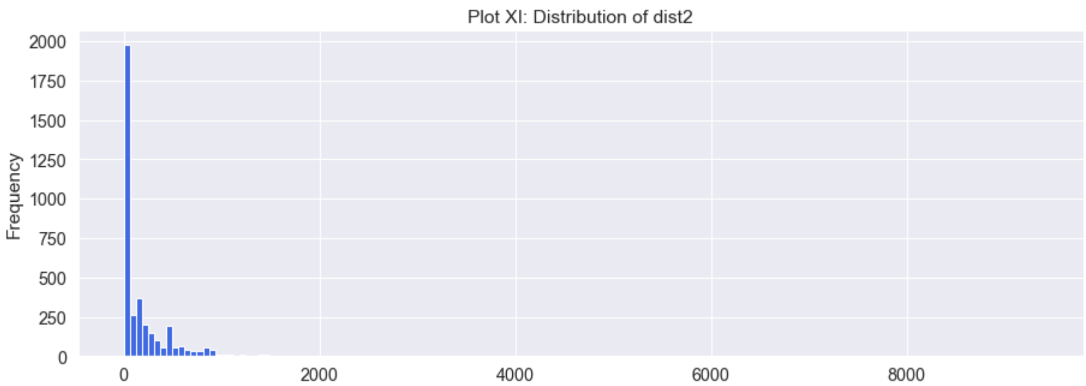


In [216]:
```
#  For Plot XII,I am plotting the log of distribution of dist1 of Fraudulent Txn
Fraud_Transactions['dist1'] \
    .plot(kind='hist',
          bins=600,
          figsize=(15, 5),
          color="seagreen",
          title='Plot XII:Distribution of Log of dist1 of Fraudulent Txn', logx="true")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

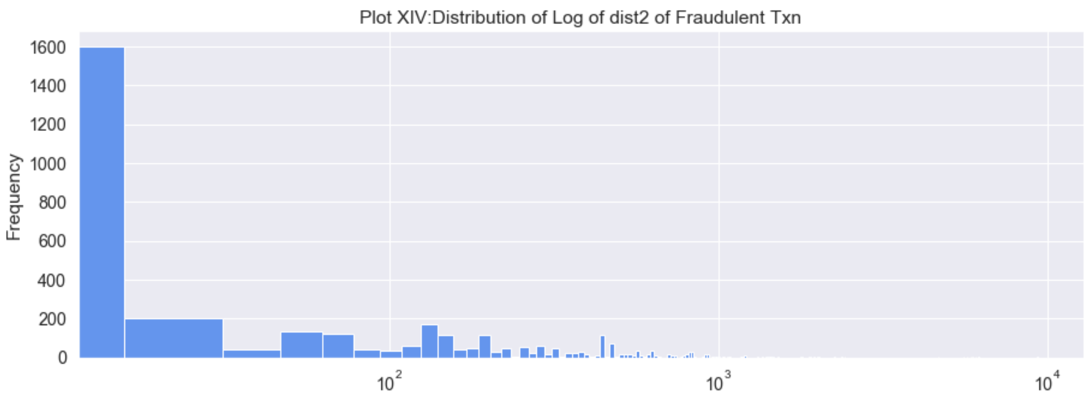


**From Plot XII, it can be concluded that taking the log gives us a better distribution, as the dist1 values lies within a narrow range.

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()
```

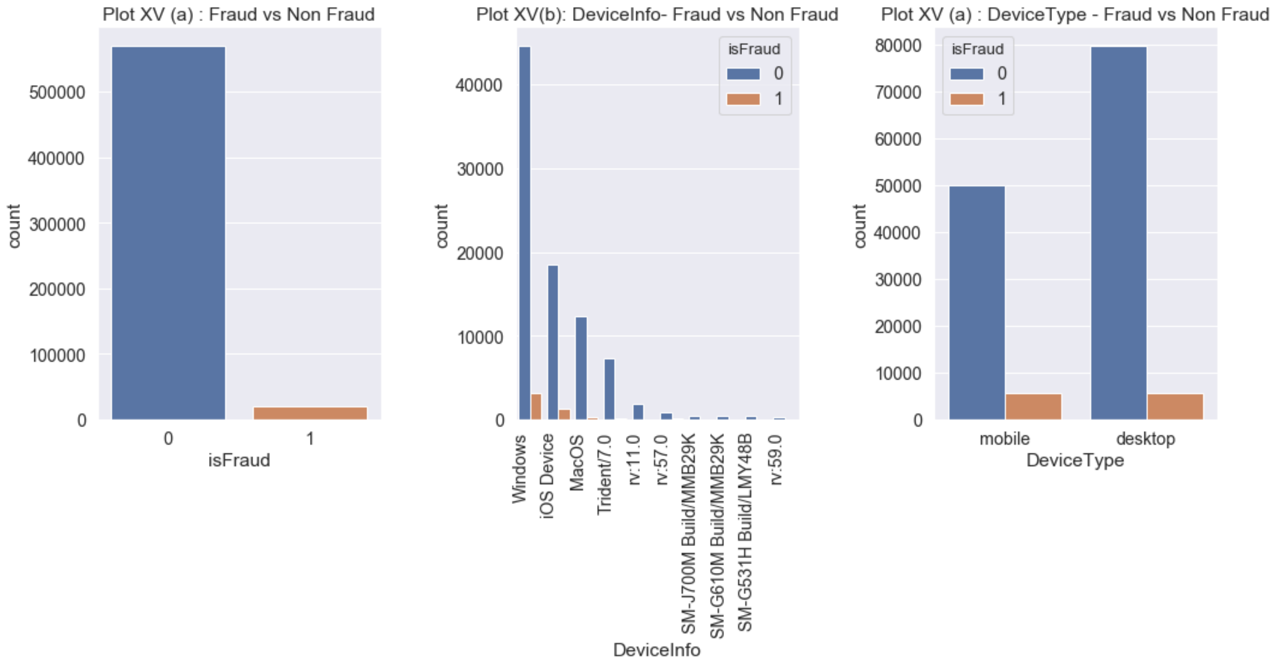


In [218]:
```
#  For Plot XIV,I am plotting the log of distribution of dist2 of Fraudulent Txn
Fraud_Transactions['dist2'] \
    .plot(kind='hist',
          bins=600,
          figsize=(15, 5),
          color="cornflowerblue",
          title='Plot XIV:Distribution of Log of dist2 of Fraudulent Txn', 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]:
```python
# 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 XV (a) : Fraud vs Non Fraud")
DeviceInfo = sns.countplot(x='DeviceInfo', hue="isFraud", data=df_transaction_identity, order=pd.value_counts(df_transaction_identity['DeviceInfo']).iloc[:10].index, ax=axes[1])#.set_title("Plot XV (b) : ProductCD - Fraud vs Non Fraud")
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=axes[2]).set_title("Plot XV (a) : DeviceType - Fraud vs Non Fraud")
plt.tight_layout()
```

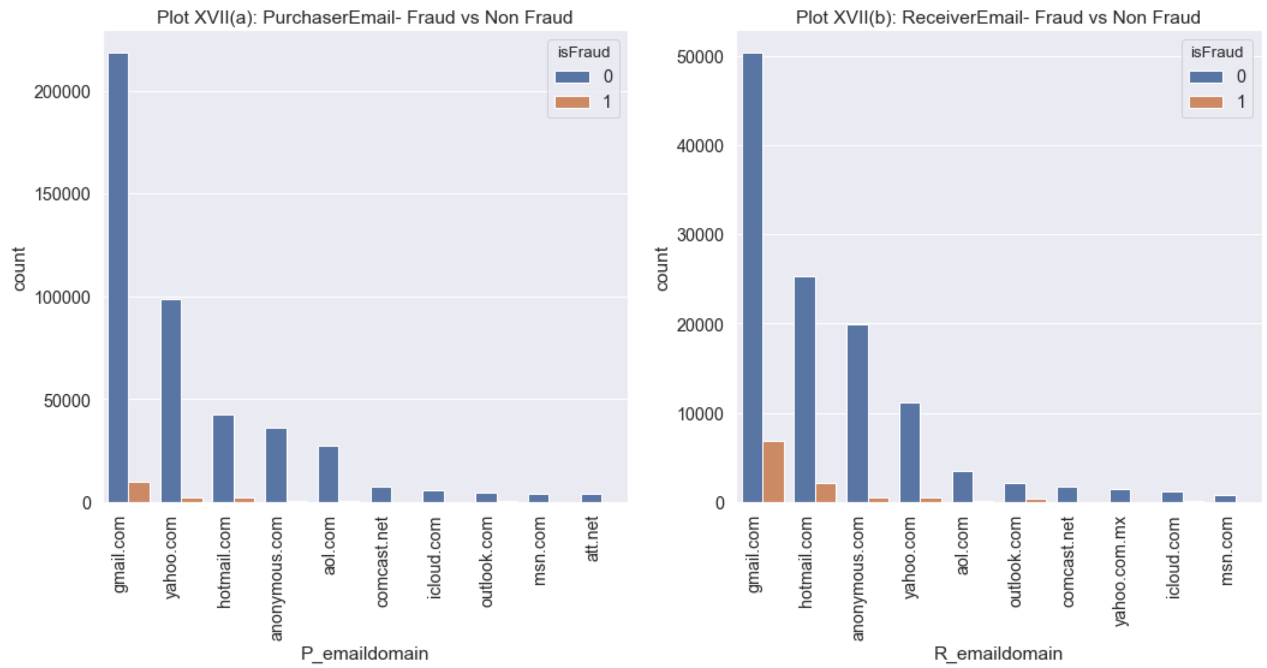


**From Plot XV, we can make (a) Fraud Transactions are very less compared to Non-Fraud Transactions. (b) Althought the number of fraud transactions is very high for Windows devices, but again, the number of non-fraud transactions is also very high. (c) Desktop has a larger number of non-fraud transactions,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

In [220]:
```python
# 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[2]).set_title("Plot XVI (b) : ProductCD - Fraud vs Non Fraud")
CardMerchant = sns.countplot(x='card4', hue="isFraud", data=df_transaction_identity, ax=axes[1]).set_title("Plot XVI (b) : CardMerchant - Fraud vs Non Fraud")
CardType = sns.countplot(x='card6', hue="isFraud", data=df_transaction_identity, ax=axes[0]).set_title("Plot XVI (a) : CardType - Fraud vs Non Fraud")
plt.tight_layout()
```

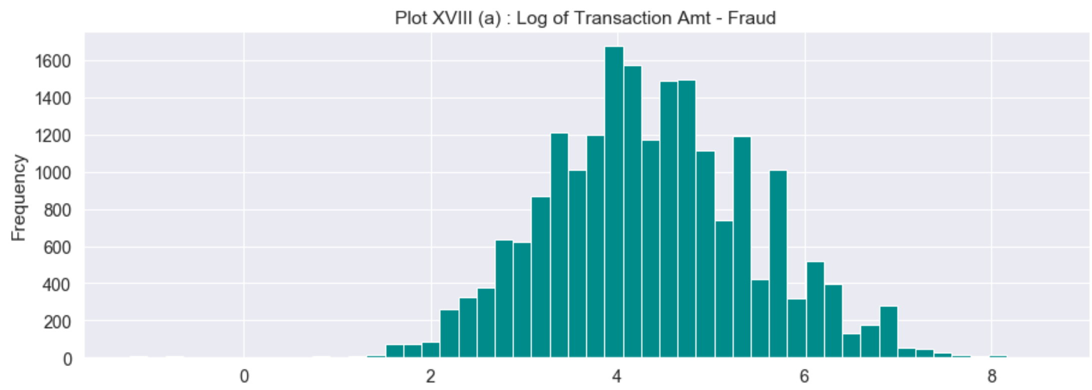
**From Plot XVI, the following observations can be made: (a) Debit has a larger number of non-fraud transactions, compared to credit, while the number of fraud transactions is comparable in both the cases. (b) Both Discover and Amex have hardly any fraud transactions. (c) Products with code 'C' has the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

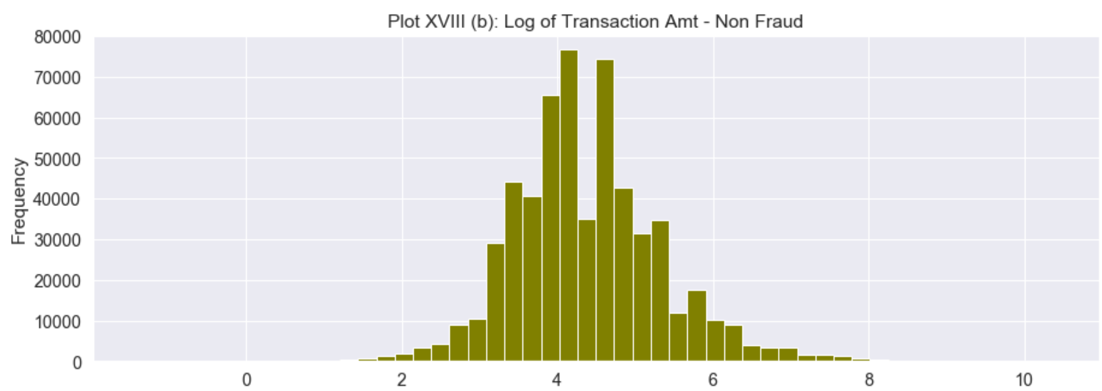
In [221]:
```
# Plot XVII Fraud vs Non Fraud for PurchaserEmail and ReceiverEmail
f, axes = plt.subplots(1, 2, figsize=(15, 8))
PurchaserEmail = sns.countplot(x='P_emaildomain', hue="isFraud", data=df_transaction_identity,order=pd.value_counts(df_transaction_identity['P_emaildomai
n']).iloc[:10].index, ax=axes[0])
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,order=pd.value_counts(df_transaction_identity['R_emaildomai
n']).iloc[:10].index, ax=axes[1])
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.

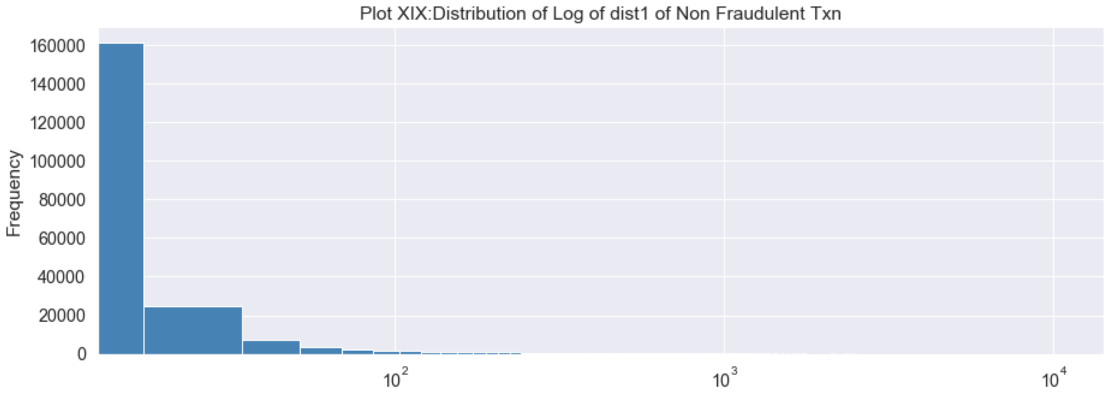
In [222]:
```
# Plot XVIII Fraud vs Non Fraud for Log of Transaction Amount
Fraud_Transactions['TransactionAmt'].apply(np.log).plot(kind='hist',bins=50, figsize=(15,5),
                                                        title='Plot XVIII (a) : Log of Transaction Amt - Fraud', color='darkcyan')
plt.show()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





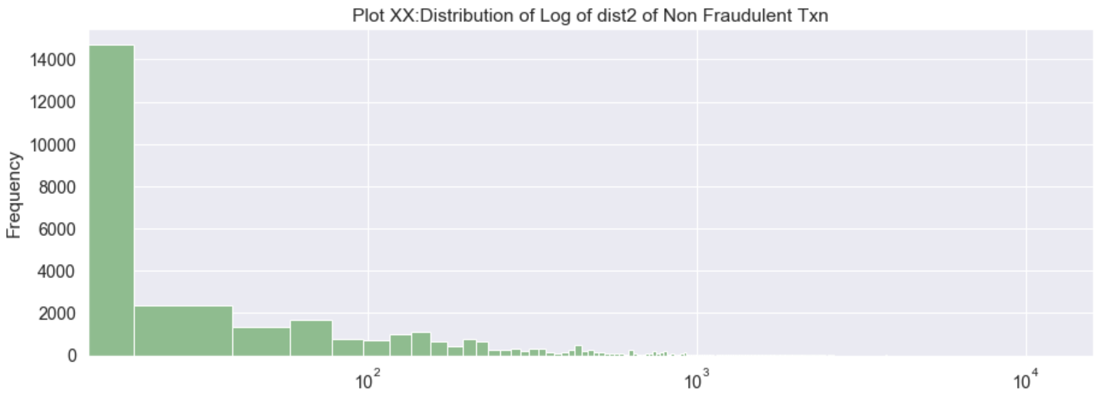
In [223]:

```
# 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_counts(df_transaction_identity['addr1']).iloc[:10].index,
ax=axes[0])
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_counts(df_transaction_identity['addr2']).iloc[:10].index,
ax=axes[1])
Address2.set_xticklabels(Address2.get_xticklabels(), rotation=90, ha="right")
Address2.set_title("Plot XXI(b): addr2- Fraud vs Non Fraud")
plt.tight_layout()
```

Part 2 - Transaction Frequency

In [226]:
```
# At the start of Task 2, first I am figuring out the addr2 value, having the maximum frequency
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 corresponding to the value we got previously
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 + datetime.timedelta(seconds = x)))
except:
    print("Ok")
```

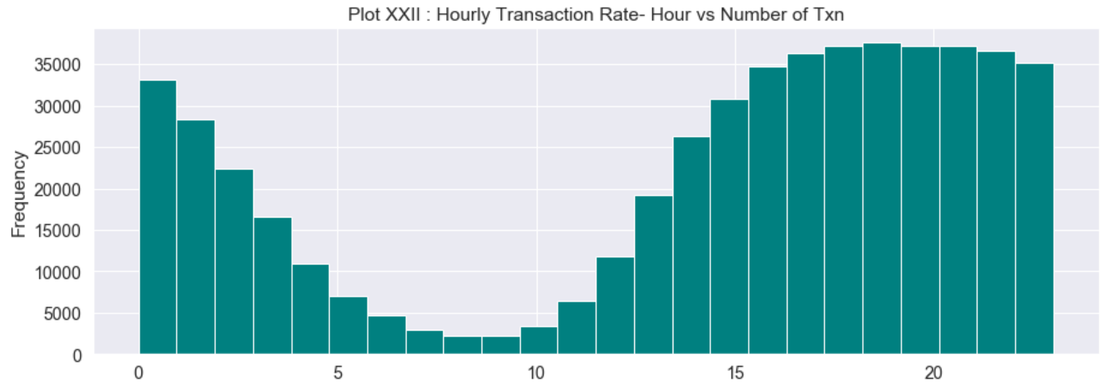
In [231]:
```
# After I get a proper datetime, now I add another field to max_addr2 dataframe, which will give me the hour of the transaction
try:
    max_addr2['hour']=pd.DatetimeIndex(max_addr2['TransactionDT']).hour
except:
    print("Ok")
```

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

Out[232]:

	TransactionID	TransactionDT	TransactionAmt	ProductCD	isFraud	card4	card6	P_emaildomain	R_emaildomain	addr1	addr2	dist1	dist2	DeviceType	DeviceInfo	hour
590538	3577538	2018-06-01 23:58:08	117.00	W	0	mastercard	debit	aol.com	NaN	387.0	87.0	3.0	NaN	NaN	NaN	23
590539	3577539	2018-06-01 23:58:51	279.95	W	0	mastercard	credit	gmail.com	NaN	299.0	87.0	NaN	NaN	NaN	NaN	23

In [233]:
```
# For Plot XXII,I am plotting the distribution of number of transactions vs the hour of the day
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()
```

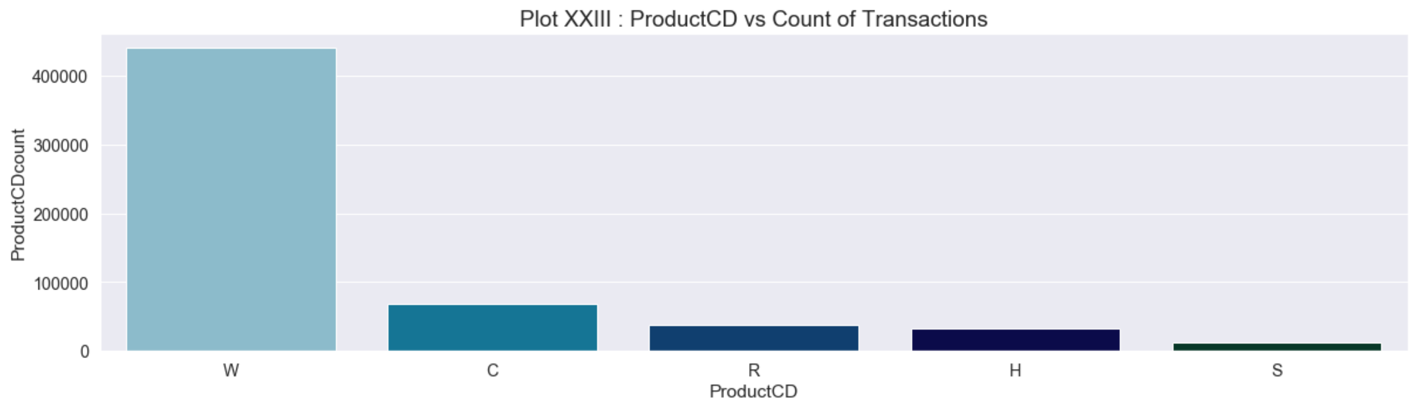


**Observation: From the hourly transaction rate which plots the number of transactions vs the hour of the day, it can be seen that the number of transactions start reducing from the 4th hour till the 12th hour. Hence, we can conclude that the people are generally awake from the 13th hour to 23rd hour,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

Part 3 - Product Code

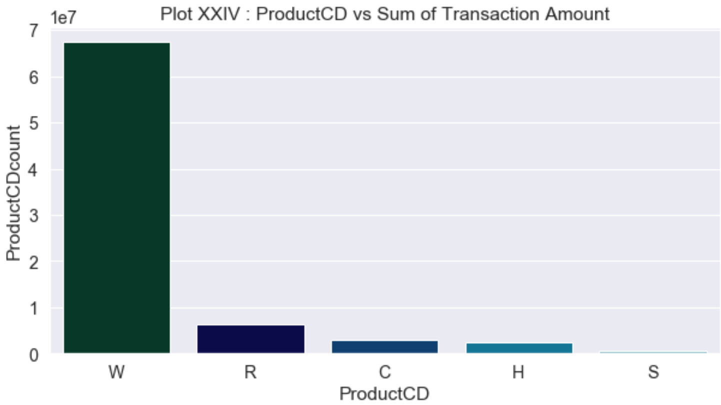
In [234]:
```
# At the start of Task 3, I am first getting the count of transactions per productcd
complete_data = pd.DataFrame()
complete_data['ProductCDcount'] = df_transaction_identity.groupby(['ProductCD'])['ProductCD'].count()
complete_data['ProductCD'] = complete_data.index
group_top = complete_data.sort_values(by='ProductCDcount',ascending=False)

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')
```



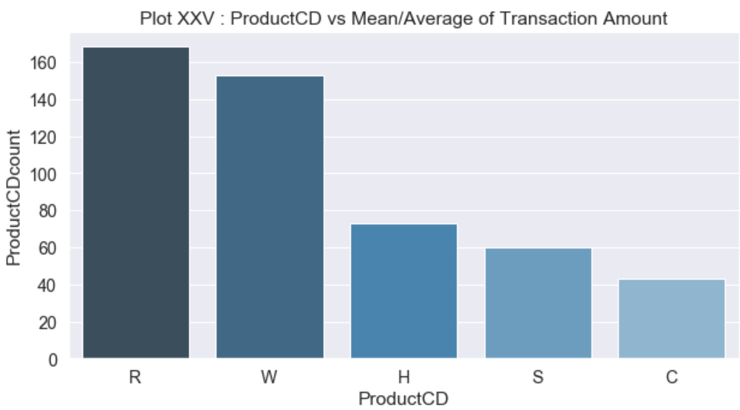
In [235]:
```
# Then, I am calculating the sum of transaction amounts per productcd
complete_data = pd.DataFrame()
complete_data['ProductCDcount'] = df_transaction_identity.groupby(['ProductCD'])['TransactionAmt'].sum()
complete_data['ProductCD'] = complete_data.index
group_top = complete_data.sort_values(by='ProductCDcount',ascending=False)

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'])['TransactionAmt'].mean()
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.

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(lambda x: (startdate + datetime.timedelta(seconds = x)))
except:
    print("Ok")
```

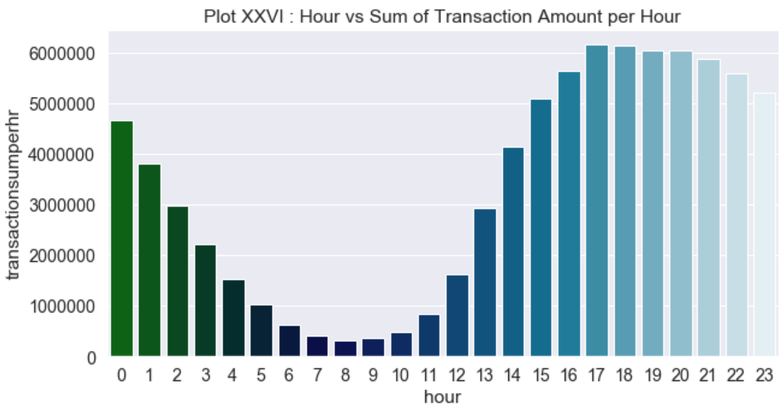
In [238]:
```
# After I get a proper datetime, now I add another field to max_addr2 dataframe, which will give me the hour of the transaction
try:
    df_transaction_identity['hour']=pd.DatetimeIndex(df_transaction_identity['TransactionDT']).hour
except:
    print("Ok")
```

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

	TransactionID	TransactionDT	TransactionAmt	ProductCD	isFraud	card4	card6	P_emaildomain	R_emaildomain	addr1	addr2	dist1	dist2	DeviceType	DeviceInfo	hour
0	2987000	2017-12-02 00:00:00	68.5	W	0	discover	credit	NaN	NaN	315.0	87.0	19.0	NaN	NaN	NaN	0
1	2987001	2017-12-02 00:00:01	29.0	W	0	mastercard	credit	gmail.com	NaN	325.0	87.0	NaN	NaN	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'])['TransactionAmt'].sum()
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')



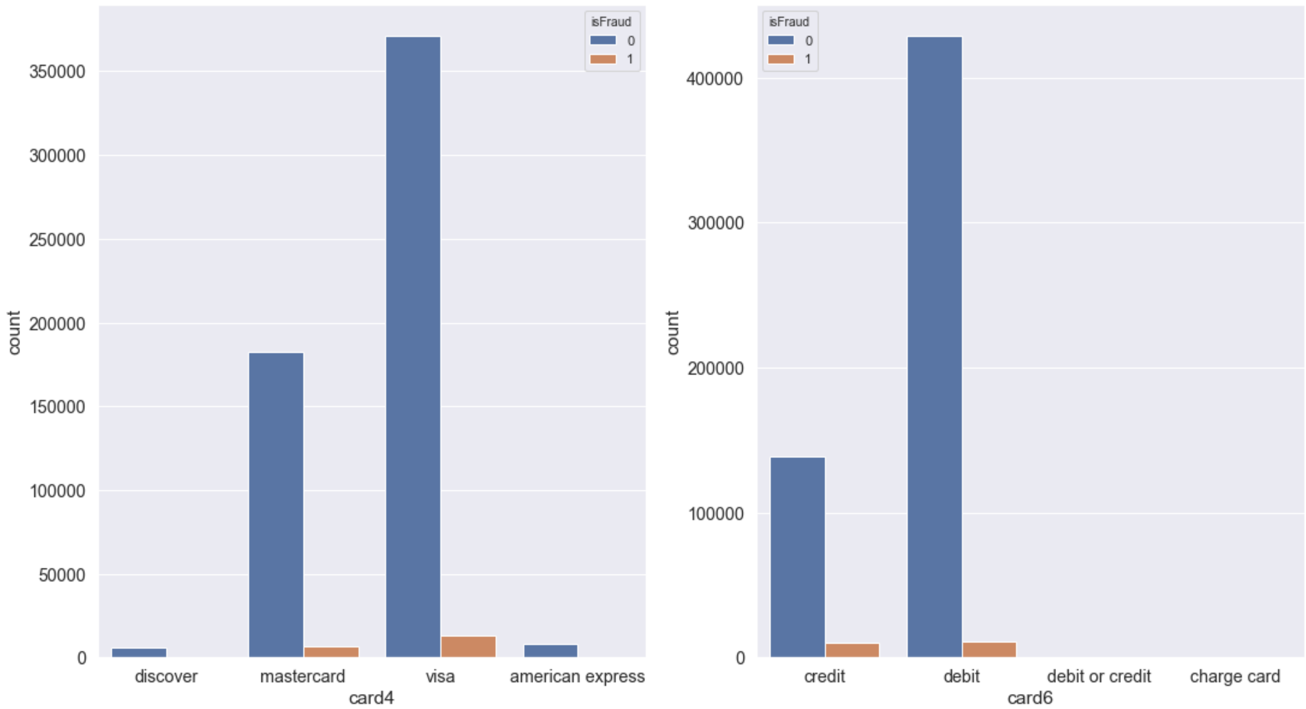
In [242]:
```
hr_amount=df_transaction_identity[['hour','TransactionAmt']]
hr_amount.corr(method='pearson')
```
Out[242]:

	hour	TransactionAmt
hour	1.000000	0.044532
TransactionAmt	0.044532	1.000000

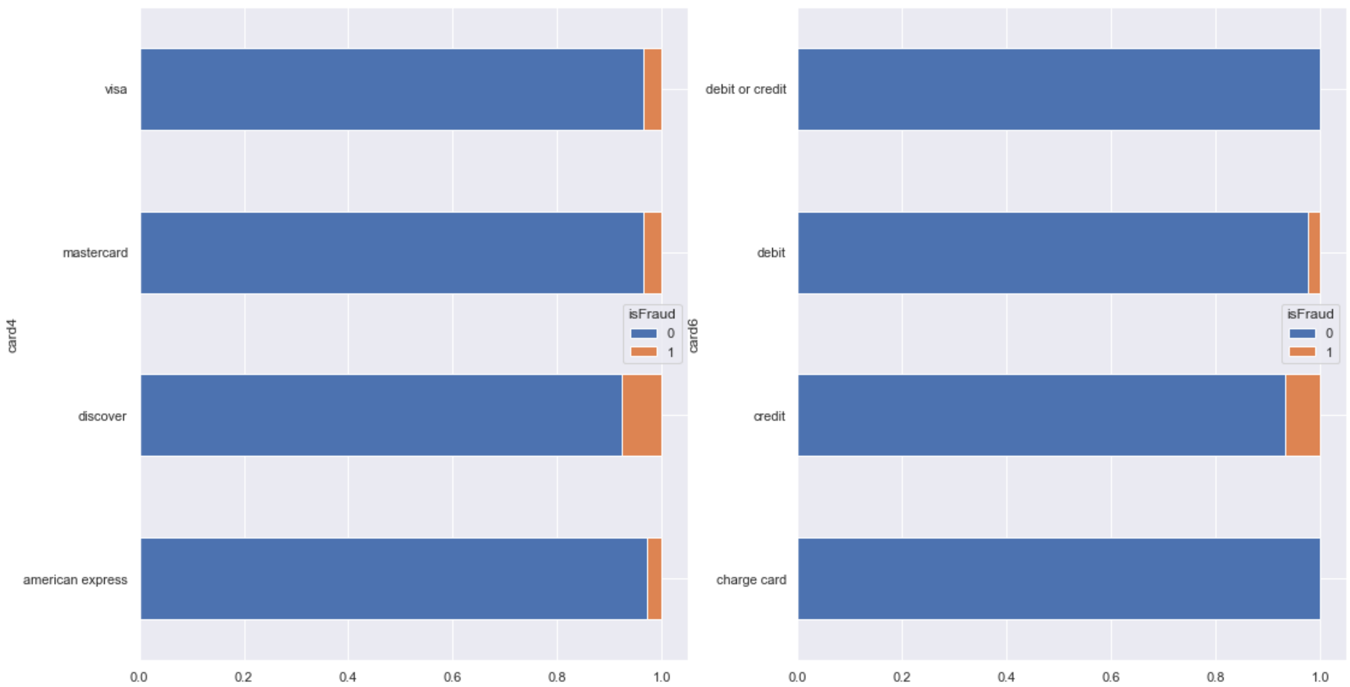
**For Task 4, I plotted Plot XXVI, to show the distribution of time of day and the purchase amount. Also the correlation coefficient is calculated above, which comes out to be 0.044532, by Pearson method

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).unstack()
p = props.plot(kind='barh', stacked='True', ax=axes[0])

props = df_transaction_identity.groupby("card6")['isFraud'].value_counts(normalize=True).unstack()
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.

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	card2	card3	card4	card5	...	id_31	id_32	id_33	id_34	id_35	id_36	id_37	id_38	Dev
0	2987000	0	86400	68.5	W	13926	NaN	150.0	discover	142.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	2987001	0	86401	29.0	W	2755	404.0	150.0	mastercard	102.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	2987002	0	86469	59.0	W	4663	490.0	150.0	visa	166.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	2987003	0	86499	50.0	W	18132	567.0	150.0	mastercard	117.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
4	2987004	0	86506	50.0	H	4497	514.0	150.0	mastercard	102.0	...	samsung browser 6.2	32.0	2220x1080	match_status:2	T	F	T	T	
5	2987005	0	86510	49.0	W	5937	555.0	150.0	visa	226.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
6	2987006	0	86522	159.0	W	12308	360.0	150.0	visa	166.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
7	2987007	0	86529	422.5	W	12695	490.0	150.0	visa	226.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
8	2987008	0	86535	15.0	H	2803	100.0	150.0	visa	226.0	...	mobile safari 11.0	32.0	1334x750	match_status:1	T	F	F	T	
9	2987009	0	86536	117.0	W	17399	111.0	150.0	mastercard	224.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

10 rows × 434 columns

In [247]:
```
# Drop the columns which have more than 60% null values as they will not contribute much to the prediction model
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]:
```
# Loading Test Identity
identity_test=pd.read_csv(r'I:\Data Science Fundamentals\test_identity.csv')
```

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

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

In [252]:
```
# 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]:
```
# Fill Null Values with -999
model_df = model_df.fillna(-999)
test_transaction_identity = test_transaction_identity.fillna(-999)
```

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

In [255]:
```
# 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]:
```
# 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-becd4d56c9c8
# Ref: https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html
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='TransactionID')
submit['isFraud'] = logisticreg.predict_proba(test_transaction_identity)[:,1]
submit.to_csv('Logisticreg_submission.csv')
submit.head()
```

Out[257]:

TransactionID	isFraud
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->0.8969
# 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='TransactionID')
submit['isFraud'] = xgbmodel.predict_proba(test_transaction_identity)[:,1]
submit.to_csv('XGB_submission.csv')
submit.head()
```

Out[259]:

TransactionID	isFraud
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.

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 (https://www.kaggle.com/kaustavsbu)](https://www.kaggle.com/kaustavsbu)

Highest Rank: 4837

Score: 0.8969

Number of entries: 2

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

4829	**JuneKim**	0.8975	7	24d
4830	**WERimagin**	0.8975	1	1mo
4831	**Torbjørn Ringholm**	0.8972	5	1mo
4832	**Jonathan Lee**	0.8971	2	1mo
4833	**broz**	0.8971	3	2mo
4834	**Grant White**	0.8970	15	19d
4835	**Ayush**	0.8969	15	2mo
4836	**Jung HyunWoo**	0.8969	3	1mo
4837	**Kaustav**	0.8969	2	~10s

Your Best Entry

You advanced 486 places on the leaderboard!

Your submission scored 0.8969, which is an improvement of your previous score of 0.7872. Great job! Tweet this!

4838	**Matti Pekari**	0.8967	1	9d
4839	**wssholmes**	0.8967	5	1mo