Fraud_Detection_Notebook

June 8, 2019

1 Extracting The Country From The I.P Adress

Before we can do any data analysis and model creation, let us add a new column called 'country' in the fraud data table that indicates from which country did the user purchase the item. We can do this by using the ip_address table, i.e if an I.P address falls within a certain range, then we can find the country of origin.

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import random

from datetime import datetime, time
import time
```

In [2]:
```
fraud_data = pd.read_csv("Fraud_Data.csv")
ip_address_to_country = pd.read_csv("IpAddress_to_Country.csv")

display(fraud_data.head(5))
display(ip_address_to_country.head(5))
```

	user_id	signup_time	purchase_time	purchase_value	\
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	34	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	16	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	15	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	44	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	39	

	device_id	source	browser	sex	age	ip_address	class
0	QVPSPJUOCKZAR	SEO	Chrome	M	39	7.327584e+08	0
1	EOGFQPIZPYXFZ	Ads	Chrome	F	53	3.503114e+08	0
2	YSSKYOSJHPPLJ	SEO	Opera	M	53	2.621474e+09	1
3	ATGTXKYKUDUQN	SEO	Safari	M	41	3.840542e+09	0
4	NAUITBZFJKHWW	Ads	Safari	M	45	4.155831e+08	0

```
   lower_bound_ip_address  upper_bound_ip_address    country
0              16777216.0                16777471  Australia
1              16777472.0                16777727      China
2              16777728.0                16778239      China
3              16778240.0                16779263  Australia
4              16779264.0                16781311      China
```

```
In [3]: def ip_to_country(ip_address):
            lower_bound = ip_address_to_country['lower_bound_ip_address'] <= ip_address
            upper_bound = ip_address_to_country['upper_bound_ip_address'] >= ip_address

            if len(ip_address_to_country[lower_bound & upper_bound]['country'].values) > 0:
                return ip_address_to_country[lower_bound & upper_bound]['country'].values[0]
            else:
                return 'None'
```

```
In [4]: start_time = time.time()
        fraud_data['country'] = np.vectorize(ip_to_country)(fraud_data['ip_address'])
        print("Time taken to complete process (seconds): %s" % (time.time() - start_time))
```

```
Time taken to complete process (seconds): 444.6918411254883
```

```
In [5]: fraud_data.head(15)
```

Out[5]:

	user_id	signup_time	purchase_time	purchase_value	\
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	34	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	16	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	15	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	44	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	39	
5	159135	2015-05-21 06:03:03	2015-07-09 08:05:14	42	
6	50116	2015-08-01 22:40:52	2015-08-27 03:37:57	11	
7	360585	2015-04-06 07:35:45	2015-05-25 17:21:14	27	
8	159045	2015-04-21 23:38:34	2015-06-02 14:01:54	30	
9	182338	2015-01-25 17:49:49	2015-03-23 23:05:42	62	
10	199700	2015-07-11 18:26:54	2015-10-28 21:59:40	13	
11	73884	2015-05-29 16:22:02	2015-06-16 05:45:58	58	
12	79203	2015-06-16 21:19:35	2015-06-21 03:29:59	18	
13	299320	2015-03-03 19:17:07	2015-04-05 12:32:36	50	
14	82931	2015-02-16 02:50:30	2015-04-16 00:56:47	15	

	device_id	source	browser	sex	age	ip_address	class	country
0	QVPSPJUOCKZAR	SEO	Chrome	M	39	7.327584e+08	0	Japan
1	EOGFQPIZPYXFZ	Ads	Chrome	F	53	3.503114e+08	0	United States
2	YSSKYOSJHPPLJ	SEO	Opera	M	53	2.621474e+09	1	United States
3	ATGTXKYKUDUQN	SEO	Safari	M	41	3.840542e+09	0	None
4	NAUITBZFJKHWW	Ads	Safari	M	45	4.155831e+08	0	United States

```
5   ALEYXFXINSXLZ     Ads  Chrome   M   18  2.809315e+09      0         Canada
6   IWKVZHJOCLPUR     Ads  Chrome   F   19  3.987484e+09      0           None
7   HPUCUYLMJBYFW     Ads   Opera   M   34  1.692459e+09      0  United States
8   ILXYDOZIHOOHT     SEO      IE   F   43  3.719094e+09      0          China
9   NRFFPPHZYFUVC     Ads      IE   M   31  3.416747e+08      0  United States
10  TEPSJVVXGNTYR     Ads  Safari   F   35  1.819009e+09      0  United States
11  ZTZZJUCRDOCJZ  Direct  Chrome   M   32  4.038285e+09      0           None
12  IBPNKSMCKUZWD     SEO  Safari   M   33  4.161541e+09      0           None
13  RMKQNVEWGTWPC  Direct  Safari   M   38  3.178510e+09      0         Brazil
14  XKIFNYUZMBWFU     SEO      IE   M   24  4.203488e+09      0           None
```

```
In [6]: #Save the fraud data with country column
        fraud_data.to_csv("fraud_data_with_country.csv")
```

To save a bit of time, there is a file called fraud_data_with_country that is the result of running the above cells. If it takes too long to find the country from the ip address for 151,000 rows, simply run the cell below.

```
In [3]: #If fraud_data_with_country.csv file exists simply load it into a dataframe
        fraud_data = pd.read_csv("fraud_data_with_country.csv", index_col = 0)
```

2 Exploratory Data Analysis

```
In [4]: print("Number of Rows: \t\t" + str(len(fraud_data)))
        print("Number of Unique User IDs: \t" + str(len(fraud_data.index.unique())))
        print("Number of Unique Device IDs: \t" + str(len(fraud_data['device_id'].unique())))
```

```
Number of Rows:                 151112
Number of Unique User IDs:         151112
Number of Unique Device IDs:          137956
```

Based on the above table, we can conclude that there exists at least one device that is used by multiple users. If there are multiple users that try to make a transaction from the same device, then the transaction might be fraudulent. Let's take a sample of the devices where there were used by more than 2 users.

```
In [5]: device_ids = (fraud_data.groupby('device_id')['user_id'].count() > 1)
        duplicated_device_ids = np.array(device_ids[device_ids == True].index)
        np.random.shuffle(duplicated_device_ids)

        for device_id in duplicated_device_ids[0:10]:
            if len(fraud_data[fraud_data['device_id'] == device_id]) > 2:
                display(fraud_data[fraud_data['device_id'] == device_id])
```

```
        user_id          signup_time        purchase_time  purchase_value  \
16080     89282  2015-01-12 05:38:30  2015-01-12 05:38:31              10
28029     56660  2015-01-12 05:38:28  2015-01-12 05:38:29              10
```

```
29457    196694  2015-01-12 05:38:31  2015-01-12 05:38:32              10
37861    390533  2015-01-12 05:38:26  2015-03-24 05:42:39              10
81068    228713  2015-01-12 05:38:32  2015-01-12 05:38:33              10
94498     39903  2015-01-12 05:38:27  2015-01-12 05:38:28              10
97853     13822  2015-01-12 05:38:35  2015-01-12 05:38:36              10
100964   222104  2015-01-12 05:38:29  2015-01-12 05:38:30              10
109669   173800  2015-01-12 05:38:34  2015-01-12 05:38:35              10
140752   164891  2015-01-12 05:38:33  2015-01-12 05:38:34              10

            device_id  source browser sex  age    ip_address  class  \
16080   VGCGSGCJILYYI  Direct  Chrome   M   39  3.744589e+09      1
28029   VGCGSGCJILYYI  Direct  Chrome   M   39  3.744589e+09      1
29457   VGCGSGCJILYYI  Direct  Chrome   M   39  3.744589e+09      1
37861   VGCGSGCJILYYI  Direct  Chrome   M   39  3.744589e+09      0
81068   VGCGSGCJILYYI  Direct  Chrome   M   39  3.744589e+09      1
94498   VGCGSGCJILYYI  Direct  Chrome   M   39  3.744589e+09      1
97853   VGCGSGCJILYYI  Direct  Chrome   M   39  3.744589e+09      1
100964  VGCGSGCJILYYI  Direct  Chrome   M   39  3.744589e+09      1
109669  VGCGSGCJILYYI  Direct  Chrome   M   39  3.744589e+09      1
140752  VGCGSGCJILYYI  Direct  Chrome   M   39  3.744589e+09      1

                 country
16080   Korea Republic of
28029   Korea Republic of
29457   Korea Republic of
37861   Korea Republic of
81068   Korea Republic of
94498   Korea Republic of
97853   Korea Republic of
100964  Korea Republic of
109669  Korea Republic of
140752  Korea Republic of


        user_id          signup_time        purchase_time  purchase_value  \
14202     94701  2015-01-05 08:08:37  2015-01-05 08:08:38              12
49546    143809  2015-01-05 08:08:35  2015-01-05 08:08:36              12
57356    163168  2015-01-05 08:08:32  2015-01-19 10:13:44              12
59514    190985  2015-01-05 08:08:43  2015-01-05 08:08:44              12
69932     50055  2015-01-05 08:08:38  2015-01-05 08:08:39              12
88237     72269  2015-01-05 08:08:40  2015-01-05 08:08:41              12
89781    315717  2015-01-05 08:08:36  2015-01-05 08:08:37              12
110523   264878  2015-01-05 08:08:34  2015-01-05 08:08:35              12
124254     9168  2015-01-05 08:08:41  2015-01-05 08:08:42              12
126713   328379  2015-01-05 08:08:33  2015-01-05 08:08:34              12
128611   380729  2015-01-05 08:08:39  2015-01-05 08:08:40              12
128671   219587  2015-01-05 08:08:42  2015-01-05 08:08:43              12
130826    67477  2015-01-05 08:08:44  2015-01-05 08:08:45              12
```

```
           device_id source browser sex  age    ip_address  class  \
14202   ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
49546   ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
57356   ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      0
59514   ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
69932   ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
88237   ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
89781   ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
110523  ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
124254  ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
126713  ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
128611  ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
128671  ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1
130826  ROGEGTJRATEKV    SEO   Opera   M   37  2.751388e+09      1

             country
14202   United States
49546   United States
57356   United States
59514   United States
69932   United States
88237   United States
89781   United States
110523  United States
124254  United States
126713  United States
128611  United States
128671  United States
130826  United States


        user_id          signup_time        purchase_time  purchase_value  \
6463     232759  2015-01-06 00:05:53  2015-01-06 00:05:54              15
26526    326442  2015-01-06 00:05:49  2015-01-06 00:05:50              15
70352    201313  2015-01-06 00:05:52  2015-01-06 00:05:53              15
100683   330259  2015-01-06 00:05:51  2015-01-06 00:05:52              15
104182   293688  2015-01-06 00:05:48  2015-05-03 01:13:05              15
135857    59988  2015-01-06 00:05:50  2015-01-06 00:05:51              15

           device_id source browser sex  age    ip_address  class country
6463    KLCMFZVFBRYOP    Ads  Chrome   M   36  1.819146e+07      1   Japan
26526   KLCMFZVFBRYOP    Ads  Chrome   M   36  1.819146e+07      1   Japan
70352   KLCMFZVFBRYOP    Ads  Chrome   M   36  1.819146e+07      1   Japan
100683  KLCMFZVFBRYOP    Ads  Chrome   M   36  1.819146e+07      1   Japan
104182  KLCMFZVFBRYOP    Ads  Chrome   M   36  1.819146e+07      0   Japan
135857  KLCMFZVFBRYOP    Ads  Chrome   M   36  1.819146e+07      1   Japan
```

As I suspect, a device that is used by more than 2 users (or 10 users) is strongly correlated to a fraudulent transaction. Interestingly, after running the above cell multiple times, I notice that the time difference between signup and purchase time for fraudulent transactions is usually one second. This might be an important factor in determining whether a transaction is fraudulent. Let's add it to our fraud data before we analyse the devices that have more than 2 users.

```
In [6]: def date_diff_in_seconds(index):
            date1 = datetime.strptime(fraud_data.iloc[index]['signup_time'], '%Y-%m-%d %H:%M:%S'
            date2 = datetime.strptime(fraud_data.iloc[index]['purchase_time'], '%Y-%m-%d %H:%M:%
            time_delta = date2 - date1

            return time_delta.days * 24 * 3600 + time_delta.seconds

        fraud_data['time_duration (secs)'] = np.vectorize(date_diff_in_seconds)(fraud_data.index
        fraud_data.head(5)
```

Out[6]:

	user_id	signup_time	purchase_time	purchase_value	\
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	34	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	16	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	15	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	44	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	39	

	device_id	source	browser	sex	age	ip_address	class	country	\
0	QVPSPJUOCKZAR	SEO	Chrome	M	39	7.327584e+08	0	Japan	
1	EOGFQPIZPYXFZ	Ads	Chrome	F	53	3.503114e+08	0	United States	
2	YSSKYOSJHPPLJ	SEO	Opera	M	53	2.621474e+09	1	United States	
3	ATGTXKYKUDUQN	SEO	Safari	M	41	3.840542e+09	0	None	
4	NAUITBZFJKHWW	Ads	Safari	M	45	4.155831e+08	0	United States	

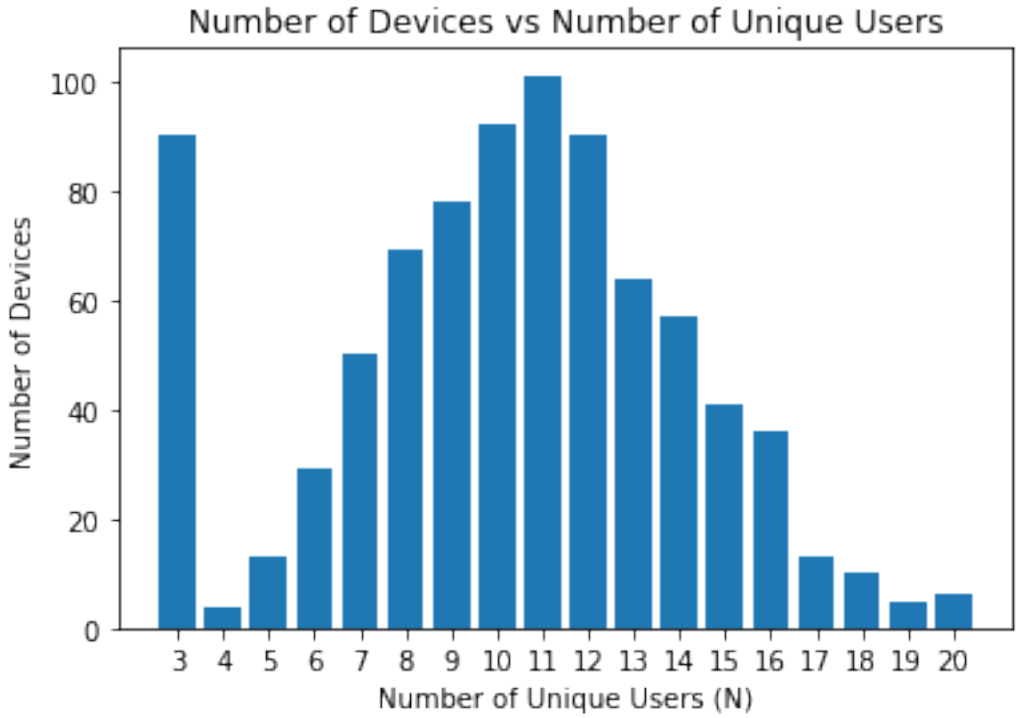
	time_duration (secs)
0	4506682
1	17944
2	1
3	492085
4	4361461

Now lets analyse the devices that have more than 2 users.

```
In [8]: num_unique_users_to_device_id \
        = fraud_data[['user_id', 'device_id']].groupby('device_id').count()

        num_unique_users_to_device_id.rename(columns = {'user_id': 'num_unique_user_ids'},
                                             inplace = True)

        minimum_num_users = num_unique_users_to_device_id['num_unique_user_ids'].min()
        maximum_num_users = num_unique_users_to_device_id['num_unique_user_ids'].max()

        print("Minimum number of users per device id: %d" % minimum_num_users)
```

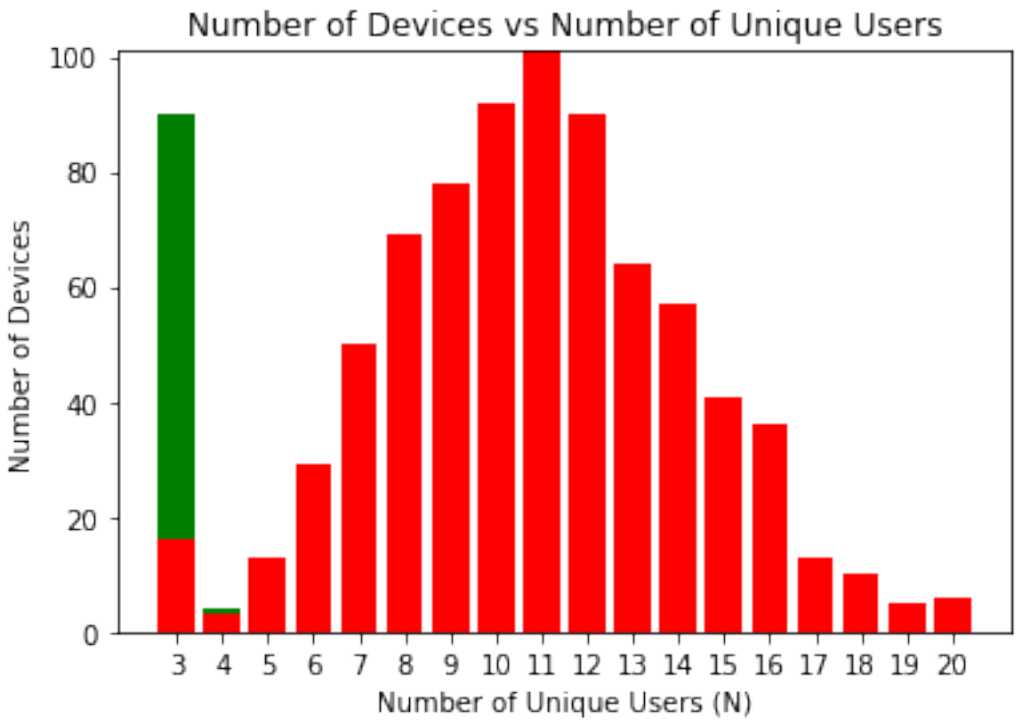
```
print("Maximum number of users per device id: %d" % maximum_num_users)

count_devices_to_num_users = []
for num_users in range(3, 21):
    num_user_condition = (num_unique_users_to_device_id['num_unique_user_ids']
                          == num_users)
    num = num_unique_users_to_device_id[num_user_condition].shape[0]
    count_devices_to_num_users.append(num)

plt.bar([x for x in range(3, 21)], count_devices_to_num_users)
plt.xticks([x for x in range(3, 21)])
plt.title("Number of Devices vs Number of Unique Users")
plt.xlabel("Number of Unique Users (N)")
plt.ylabel("Number of Devices")
plt.show()
```

```
Minimum number of users per device id: 1
Maximum number of users per device id: 20
```



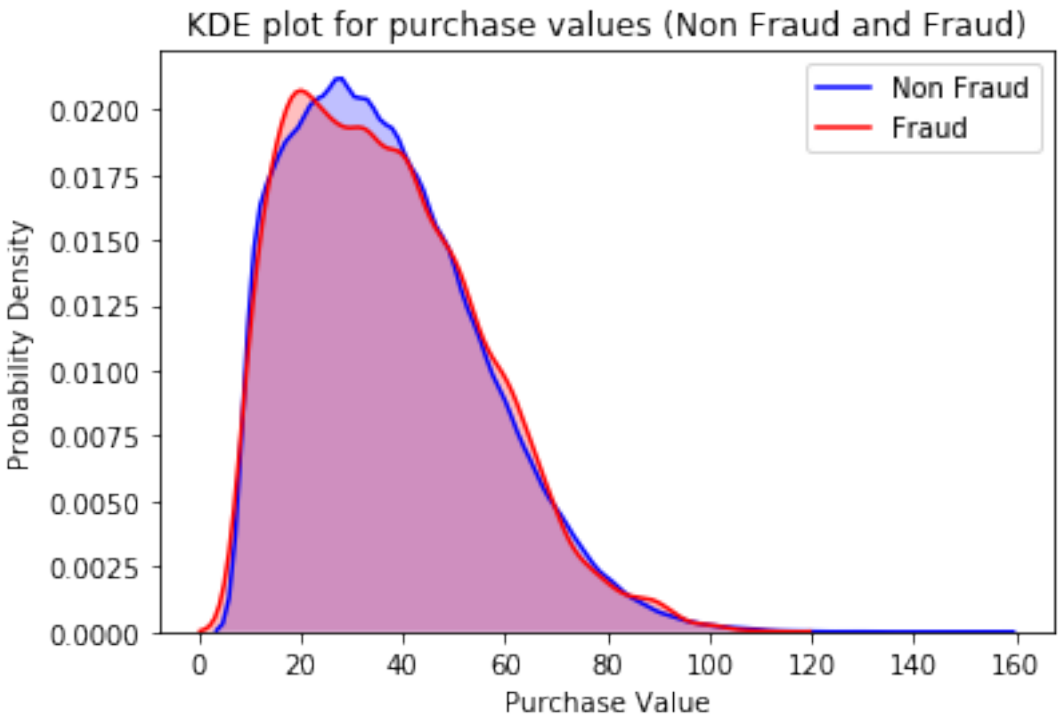
The above cell simply generates a bar graph where the y-axis is the number of devices and the x-axis is the number of unique users using a device. What is interesting about this graph is that looks normally distributed where the mean number of users for a single device is about 11. For each number of unique users, we would like to know what proportion of the devices are associated to fraud. The next two cells will answer our question.

```
In [9]: device_id_is_fraudulant \
        = fraud_data[['device_id', 'class']].groupby(['device_id']).agg(lambda x:x.value_counts(

        fraud_user_condition = device_id_is_fraudulant['class'] == 1

        count_devices_associated_with_fraud      = []
        count_devices_to_num_users               = []
        count_devices_not_associated_with_fraud  = []

        for num_users in range(3, 21):
            num_user_condition = (num_unique_users_to_device_id['num_unique_user_ids'] == num_us

            num = num_unique_users_to_device_id[num_user_condition].shape[0]
            count_devices_to_num_users.append(num)

            num_fraud = num_unique_users_to_device_id[num_user_condition & fraud_user_condition]
            count_devices_associated_with_fraud.append(num_fraud)

            count_devices_not_associated_with_fraud.append(num - num_fraud)

In [10]: plt.bar([x for x in range(3, 21)], count_devices_associated_with_fraud, color = 'red')
         plt.bar([x for x in range(3, 21)], count_devices_not_associated_with_fraud,
                 bottom = count_devices_associated_with_fraud, color = 'green')
         plt.xticks([x for x in range(3, 21)])
         plt.title("Number of Devices vs Number of Unique Users")
         plt.xlabel("Number of Unique Users (N)")
         plt.ylabel("Number of Devices")
         plt.show()
```



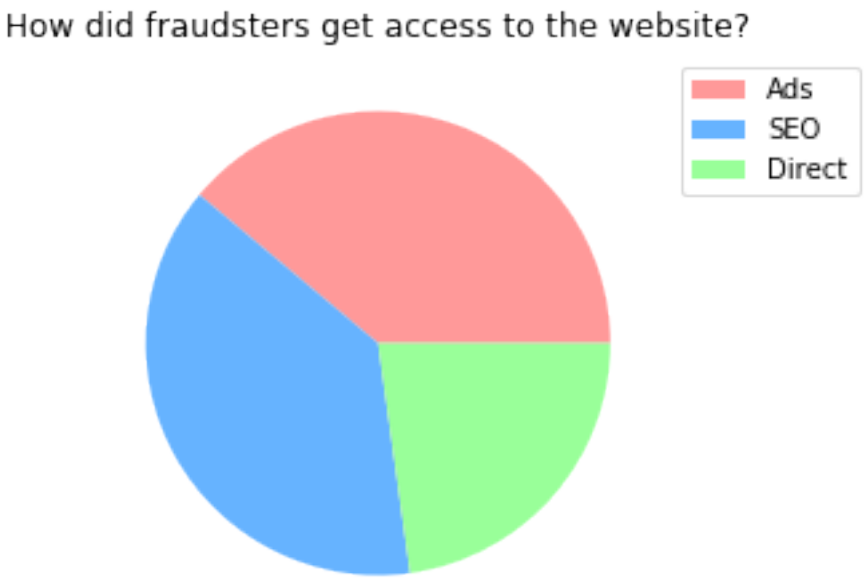
Most devices that have 3 unique users are not associated to fraudulent transactions. A possible reason could be that there is a family (eg father, mother, and single child) sharing a single device. All devices that have 5 or more unique users are associated with fraud. This means that the number of unique users on a device is an important factor in detecting fraudulant transactions. Let us look at purchase value, and see if it is also an important feature in detecting fraud.

```
In [11]: non_fraudulent_transactions = fraud_data[fraud_data['class'] == 0]
         fraudulent_transactions     = fraud_data[fraud_data['class'] == 1]

         non_fraudulent_transactions['purchase_value']
         sns.kdeplot(non_fraudulent_transactions['purchase_value'], shade = True, color = 'blue'
         sns.kdeplot(fraudulent_transactions['purchase_value'], shade = True, color = 'red', lab

         plt.title("KDE plot for purchase values (Non Fraud and Fraud)")
         plt.ylabel("Probability Density")
         plt.xlabel("Purchase Value")

         plt.show()
```



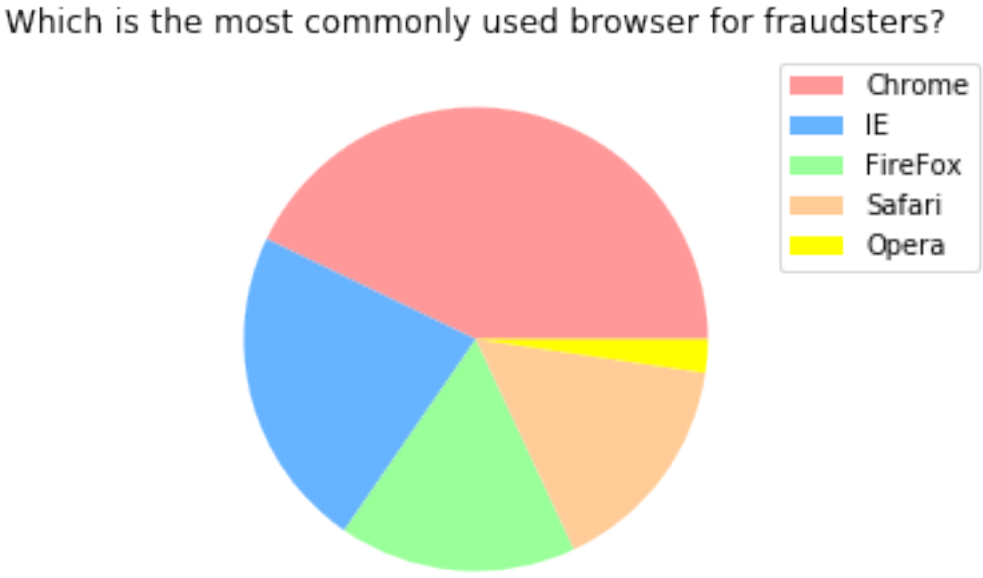
The KDE plot demonstrates that the distribution between fraudulent and non fraudulent transactions, in terms of its purchase value, is very similar with one another. Therefore, purchase value on its own will not be useful in determining fraud based on the data that we have. Lets focus more on fraudelent transactions see what tools do fraudsters use to make a transaction.

```
In [56]: plt.pie(fraud_data[fraud_data['class'] == 1]['source'].value_counts(),
                 colors = ['#ff9999','#66b3ff','#99ff99'])
         plt.title("How did fraudsters get access to the website?")
         plt.legend(['Ads', 'SEO', 'Direct'], bbox_to_anchor = (1.0, 1.0))
         plt.show()
```



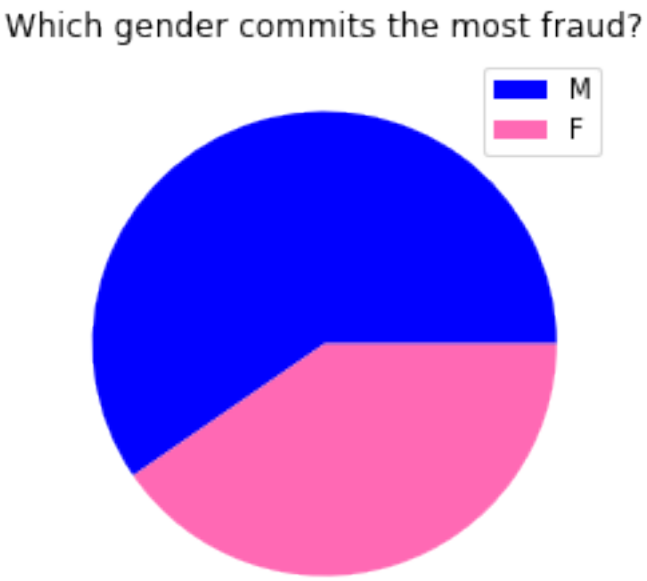
Most of them got access to the website through advertisements, and search engine optimizations.

```
In [57]: plt.pie(fraud_data[fraud_data['class'] == 1]['browser'].value_counts(),
                 colors = ['#ff9999','#66b3ff','#99ff99','#ffcc98', 'yellow'])
         plt.title("Which is the most commonly used browser for fraudsters?")
         plt.legend(['Chrome', 'IE', 'FireFox', 'Safari', 'Opera'], bbox_to_anchor=(1.0, 1.0))
         plt.show()
```



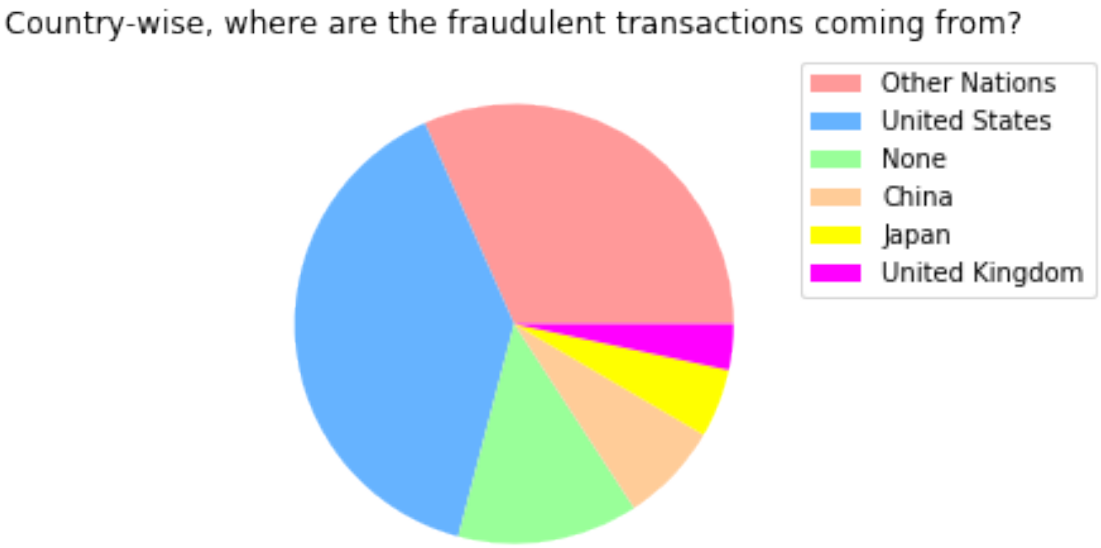
Most of them use Chrome, Internet Explorer, and FireFox as their browser to access the website.

```
In [14]: plt.pie(fraud_data[fraud_data['class'] == 1]['sex'].value_counts(), colors = ['blue', '
         plt.title("Which gender commits the most fraud?")
         plt.legend(['M', 'F'])
         plt.show()
```



Most fraudsters are male.

```
In [15]: series = fraud_data[fraud_data['class'] == 1]['country'].value_counts()
         country_to_fraud_count = pd.DataFrame(series)
         dictionary = {'Other Nations': 0}

         for country in country_to_fraud_count.index:
             if country_to_fraud_count.loc[country].values[0] > 450:
                 dictionary[country] = country_to_fraud_count.loc[country].values[0]
             else:
                 dictionary['Other Nations'] += country_to_fraud_count.loc[country].values[0]

         country_to_fraud_count = pd.Series(dictionary)
         plt.pie(country_to_fraud_count,
                 colors = ['#ff9999','#66b3ff','#99ff99','#ffcc98', 'yellow', 'magenta'])
         plt.title("Country-wise, where are the fraudulent transactions coming from?")
         plt.legend(['Other Nations', 'United States', 'None', 'China', 'Japan', 'United Kingdom
         plt.show()
```



3 Model Creation

3.1 Preprocessing Step

As a preprocessing step, we will add the number of unique users column into our fraud_data dataframe. This number is associated to a device ID (i.e how many unique users are using a device).

```
In [16]: fraud_data['num_unique_users_for_device'] \
         = fraud_data['device_id'].apply(lambda x: num_unique_users_to_device_id.loc[x])

         fraud_data.head(10)
```

Out[16]:

	user_id	signup_time	purchase_time	purchase_value	\
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	34	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	16	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	15	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	44	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	39	
5	159135	2015-05-21 06:03:03	2015-07-09 08:05:14	42	
6	50116	2015-08-01 22:40:52	2015-08-27 03:37:57	11	
7	360585	2015-04-06 07:35:45	2015-05-25 17:21:14	27	
8	159045	2015-04-21 23:38:34	2015-06-02 14:01:54	30	
9	182338	2015-01-25 17:49:49	2015-03-23 23:05:42	62	

device_id	source	browser	sex	age	ip_address	class	country	\

```
0  QVPSPJUOCKZAR    SEO  Chrome   M   39  7.327584e+08      0          Japan
1  EOGFQPIZPYXFZ    Ads  Chrome   F   53  3.503114e+08      0  United States
2  YSSKYOSJHPPLJ    SEO   Opera   M   53  2.621474e+09      1  United States
3  ATGTXKYKUDUQN    SEO  Safari   M   41  3.840542e+09      0           None
4  NAUITBZFJKHWW    Ads  Safari   M   45  4.155831e+08      0  United States
5  ALEYXFXINSXLZ    Ads  Chrome   M   18  2.809315e+09      0         Canada
6  IWKVZHJOCLPUR    Ads  Chrome   F   19  3.987484e+09      0           None
7  HPUCUYLMJBYFW    Ads   Opera   M   34  1.692459e+09      0  United States
8  ILXYDOZIHOOHT    SEO      IE   F   43  3.719094e+09      0          China
9  NRFFPPHZYFUVC    Ads      IE   M   31  3.416747e+08      0  United States

   time_duration (secs)  num_unique_users_for_device
0               4506682                            1
1                 17944                            1
2                     1                           12
3                492085                            1
4               4361461                            1
5               4240931                            1
6               2177825                            1
7               4268729                            1
8               3594200                            1
9               4943753                            1
```

Filter out the fraud dataframe so that have the columns that are of most interest in detecting fraud and one hot encode all categorical variables.

```
In [17]: columns_of_interest = ['num_unique_users_for_device', 'time_duration (secs)',
                               'purchase_value', 'source','browser', 'sex', 'age',
                               'country','class']

         modified_fraud_data = fraud_data[columns_of_interest].copy()
         modified_fraud_data = pd.get_dummies(modified_fraud_data)
         column_list = list(modified_fraud_data)

         for i in range(0,3):
             column_list[i], column_list[4] = column_list[4], column_list[i]

         modified_fraud_data = modified_fraud_data[column_list]
         modified_fraud_data.head(10)
```

```
Out[17]:    class  num_unique_users_for_device  time_duration (secs)  age  \
         0      0                            1               4506682   39
         1      0                            1                 17944   53
         2      1                           12                     1   53
         3      0                            1                492085   41
         4      0                            1               4361461   45
         5      0                            1               4240931   18
         6      0                            1               2177825   19
```

```
7      0                          1              4268729   34
8      0                          1              3594200   43
9      0                          1              4943753   31

   purchase_value  source_Ads  source_Direct  source_SEO  browser_Chrome  \
0              34           0              0           1               1
1              16           1              0           0               1
2              15           0              0           1               0
3              44           0              0           1               0
4              39           1              0           0               0
5              42           1              0           0               1
6              11           1              0           0               1
7              27           1              0           0               0
8              30           0              0           1               0
9              62           1              0           0               0

   browser_FireFox  ...  country_United States  country_Uruguay  \
0                0  ...                      0                0
1                0  ...                      1                0
2                0  ...                      1                0
3                0  ...                      0                0
4                0  ...                      1                0
5                0  ...                      0                0
6                0  ...                      0                0
7                0  ...                      1                0
8                0  ...                      0                0
9                0  ...                      1                0

   country_Uzbekistan  country_Vanuatu  country_Venezuela  country_Viet Nam  \
0                   0                0                  0                 0
1                   0                0                  0                 0
2                   0                0                  0                 0
3                   0                0                  0                 0
4                   0                0                  0                 0
5                   0                0                  0                 0
6                   0                0                  0                 0
7                   0                0                  0                 0
8                   0                0                  0                 0
9                   0                0                  0                 0

   country_Virgin Islands (U.S.)  country_Yemen  country_Zambia  \
0                              0              0               0
1                              0              0               0
2                              0              0               0
3                              0              0               0
4                              0              0               0
5                              0              0               0
6                              0              0               0
```

```
7                            0              0              0
8                            0              0              0
9                            0              0              0

   country_Zimbabwe
0                 0
1                 0
2                 0
3                 0
4                 0
5                 0
6                 0
7                 0
8                 0
9                 0

[10 rows x 197 columns]
```

3.2 Logistic Regression

```
In [59]: from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LogisticRegression
         from sklearn import preprocessing
         from sklearn.metrics import recall_score, accuracy_score, f1_score, precision_score, ro

         x_train, x_val_test, y_train, y_val_test = train_test_split(modified_fraud_data[column_
                                                                     modified_fraud_data['class'
                                                                     test_size = 0.30)
         x_val = x_val_test[0:len(x_val_test) // 2]
         y_val = y_val_test[0:len(x_val_test) // 2]

         x_test = x_val_test[len(x_val_test) // 2:]
         y_test = y_val_test[len(x_val_test) // 2:]

         scaler = preprocessing.MinMaxScaler()
         scaler = scaler.fit(x_train)

         x_train_minmax = scaler.transform(x_train)
         x_val_minmax   = scaler.transform(x_val)
         x_test_minmax  = scaler.transform(x_test)
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:323: DataConversionWarning:
  return self.partial_fit(X, y)
```

```
In [60]: model = LogisticRegression(penalty = 'l1', C = 3)
```

```
In [61]: model.fit(x_train_minmax, y_train)
         y_predict = model.predict(x_val_minmax)
```

```
        print("Validation Results")
        print("-------------")
        print("Accurcay: \t %f"  %(accuracy_score(y_val, y_predict)))
        print("Recall: \t %f"    %(recall_score(y_val, y_predict)))
        print("F1 Score: \t %f"  %(f1_score(y_val, y_predict)))
        print("Precision: \t %f" %(precision_score(y_val, y_predict)))
        print("AUC score: \t %f" %(roc_auc_score(y_val, y_predict)))
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Defa
  FutureWarning)


Validation Results
-------------
Accurcay:          0.951383
Recall:          0.514656
F1 Score:          0.660296
Precision:          0.920894
AUC score:          0.755094
```

```
In [62]: y_predict = model.predict(x_test_minmax)

        print("Test Results")
        print("-------------")
        print("Accurcay: \t %f"  %(accuracy_score(y_test, y_predict)))
        print("Recall: \t %f"    %(recall_score(y_test, y_predict)))
        print("F1 Score: \t %f"  %(f1_score(y_test, y_predict)))
        print("Precision: \t %f" %(precision_score(y_test, y_predict)))
        print("AUC score: \t %f" %(roc_auc_score(y_test, y_predict)))
```

```
Test Results
-------------
Accurcay:          0.951207
Recall:          0.527897
F1 Score:          0.666867
Precision:          0.905151
AUC score:          0.761129
```

```
In [63]: #Examine the weights in the logistic regression model (First 10)
        predictors = column_list[1:]
        print("Features \t\t\t\t Absolute Value Weight")
        print("-----------------------------------------------------------------")
        for i, weight in enumerate(model.coef_[0, 0:10]):
            print("{:50s} {:10f}".format(predictors[i], abs(weight)))

        #len(column_list[1:])
```

```
Features                                    Absolute Value Weight
-------------------------------------------------------------
num_unique_users_for_device                              10.326834
time_duration (secs)                                      0.608034
age                                                       0.122542
purchase_value                                            0.073701
source_Ads                                                0.727852
source_Direct                                             0.500312
source_SEO                                                0.775373
browser_Chrome                                            0.742193
browser_FireFox                                           0.722369
browser_IE                                                0.721169
```

3.3 Decision Tree

```
In [33]: from sklearn.tree import DecisionTreeClassifier, export_graphviz

         x_train, x_val_test, y_train, y_val_test = train_test_split(modified_fraud_data[column_
                                                                     modified_fraud_data['class'
                                                                     test_size = 0.30)
         x_val = x_val_test[0:len(x_val_test) // 2]
         y_val = y_val_test[0:len(x_val_test) // 2]

         x_test = x_val_test[len(x_val_test) // 2:]
         y_test = y_val_test[len(x_val_test) // 2:]

In [34]: model = DecisionTreeClassifier(criterion = 'entropy', max_depth = 10)

In [35]: _ = model.fit(x_train, y_train)
         export_graphviz(model, out_file = "tree.dot", feature_names = column_list[1:], class_na
         # For the visual representation of the tree, look at tree.png file. The image file was
         # converter that uses graphviz.

In [36]: y_predict = model.predict(x_val)

         print("Validation Results")
         print("-------------")
         print("Accurcay: \t %f"  %(accuracy_score(y_val, y_predict)))
         print("Recall: \t %f"    %(recall_score(y_val, y_predict)))
         print("F1 Score: \t %f"  %(f1_score(y_val, y_predict)))
         print("Precision: \t %f" %(precision_score(y_val, y_predict)))
         print("AUC score: \t %f" %(roc_auc_score(y_val, y_predict)))

Validation Results
-------------
Accurcay:          0.954912
Recall:          0.543260
F1 Score:          0.700117
```

```
Precision:          0.984323
AUC score:          0.771166
```

```
In [37]: y_predict = model.predict(x_test)

         print("Test Results")
         print("-------------")
         print("Accurcay: \t %f"  %(accuracy_score(y_test, y_predict)))
         print("Recall: \t %f"    %(recall_score(y_test, y_predict)))
         print("F1 Score: \t %f"  %(f1_score(y_test, y_predict)))
         print("Precision: \t %f" %(precision_score(y_test, y_predict)))
         print("AUC score: \t %f" %(roc_auc_score(y_test, y_predict)))
```

```
Test Results
-------------
Accurcay:          0.957074
Recall:          0.553688
F1 Score:          0.709118
Precision:          0.985869
AUC score:          0.776430
```