Understanding the Process

How are credit cards used and what can we understand about their use to identify credit card fraud?

There are many ways to use credit cards. Some people use them for everyday purchases, such as gas or groceries. Other people use them for larger purchases, such as a new television or a vacation. And still others use them for emergencies, such as when their car breaks down or they have unexpected medical bills. Whatever the occasion people tend to follow certain trends in their spending.

Aside from trends in purchases there are also trends in where and how the cards are used. A person could regularly use their card in a specific city one day or they only use the chip on the card instead of using it for online purchases. All of these trends can be monitored to help identify potential fraud.

If there are suddenly large purchases being made on a credit card that is usually only used for small transactions, that could be a sign of fraud. Or if the card is being used in a city where the person doesn't live or work, that could also be suspicious.

Libraries for this project

I like to dedicate a block to the libraries used in project. This will be the first step.

In [1]:

```
# linear algebra
import numpy as np

# data processing library
import pandas as pd

# pyplot from matplotlib
import matplotlib.pyplot as plt

# high level visualization package
import seaborn as sns

# import library to generate training and testing datasets
from sklearn.model_selection import train_test_split

# import library to help scale features in the datsets
from sklearn.preprocessing import StandardScaler

# import K Nearest Neighbors
from sklearn.neighbors import KNeighborsClassifier
```

Understanding the Data

Now that we have an understanding of some nuances to credit card usage lets take a look at the data. The next step is loading the data into a dataframe and viewing the raw data. Our data is stored in a csv so all we have to do is read the csv into a dataframe.

In [10]:

```
# read csv file to dataframe
df = pd.read_csv(r'./input/credit-card-fraud/card_transdata.csv')

# display dataframe
df
```

Out[10]:

	distance_from_home	distance_from_last_transaction	ratio_to_median_purchase_price	repeat_retailer	used_chip	used_pin_numbe
0	57.877857	0.311140	1.945940	1.0	1.0	0.
1	10.829943	0.175592	1.294219	1.0	0.0	0.
2	5.091079	0.805153	0.427715	1.0	0.0	0.
3	2.247564	5.600044	0.362663	1.0	1.0	0.
4	44.190936	0.566486	2.222767	1.0	1.0	0.
...	...	...	...	...	...	

	distance_from_home	distance_from_last_transaction	ratio_to_median_purchase_price	repeat_retailer	used_chip	used_pin_numbe
999995	2.207101	0.112651	1.626798	1.0	1.0	0.
999996	19.872726	2.683904	2.778303	1.0	1.0	0.
999997	2.914857	1.472687	0.218075	1.0	1.0	0.
999998	4.258729	0.242023	0.475822	1.0	0.0	0.
999999	58.108125	0.318110	0.386920	1.0	1.0	0.

1000000 rows × 8 columns

There are 1 million entries and 8 columns. The 8 columns are:

- distance_from_home - Distance from home where transaction occured
- distance_from_last_transaction - Distance from where last transaction occured
- ratio_to_median_purchase_price - Ratio of purchased price transaction to median purchase price
- repeat_retailer - Has historically purchased from retailer (1 = Yes / 0 = No)
- used_chip - Was chip used in transaction (1 = Yes / 0 = No)
- used_pin_number - Was PIN used to complete transaction (1 = Yes / 0 = No)
- online_order - Was transaction an online order (1 = Yes / 0 = No)
- fraud - Was transaction fraudulent (1 = Yes / 0 = No)

Based on how the data has been organized we can assume it doesn't represent a single client. It is a collection of transactions from many clients derived from a combination of data sources.

Variables relating to distance have no unit of measure attached to them but, we can assume this data uses the same unit of measure. We care more about relations between distance and other variables.

The data type of all variabes are float. I prefer the boolean values be integers and will change those later on.

Let's take a closer look at each variable.

In [11]:

```
df.describe()
```

Out[11]:

	distance_from_home	distance_from_last_transaction	ratio_to_median_purchase_price	repeat_retailer	used_chip	used_pin_nu
count	1000000.000000	1000000.000000	1000000.000000	1000000.000000	1000000.000000	1000000.0
mean	26.628792	5.036519	1.824182	0.881536	0.350399	0.1
std	65.390784	25.843093	2.799589	0.323157	0.477095	0.3
min	0.004874	0.000118	0.004399	0.000000	0.000000	0.0
25%	3.878008	0.296671	0.475673	1.000000	0.000000	0.0
50%	9.967760	0.998650	0.997717	1.000000	0.000000	0.0
75%	25.743985	3.355748	2.096370	1.000000	1.000000	0.0
max	10632.723672	11851.104565	267.802942	1.000000	1.000000	1.0

The count of each column is exactly 1 million which is a great indicator that we don't have any missing values.

Approximately 88% of transactions were with a repeat retailer. 35% used a chip. 10% used a pin. 65 % were online orders, that matches with the chip transactions.

Only 8.7% of transactions were fraudulant.

There's a pretty large gap between the minimum distance and max distance. The next step is grouping the distance and ratio values and generating a group so we can compare the values to the number of fraudulant cases.

I used the percentage values from the describe() function to determine the grouping for each variable.

In [12]:
```python
# create temporary dataframe
df_temp = df

# how distance from home groups are organized
dfh_groups = [0, 10, 25, 100, 1000, 5000, 11000]

# how distance from last transaction groups are organized
dflt_groups = [0, 1, 2, 3, 100, 1000, 5000, 12000]

# how ratio to median purchase groups are organized
rtmpp_groups = [0, .5, 1, 1.5, 2, 10, 50, 100, 200, 250, 300]

# split distance into groups
df_temp['dist_home_group'] = pd.cut(df['distance_from_home'], dfh_groups)
df_temp['dist_trans_group'] = pd.cut(df['distance_from_last_transaction'], dflt_groups)
df_temp['rtmpp_group'] = pd.cut(df['ratio_to_median_purchase_price'], rtmpp_groups)

# check number of entries with distances
print("Distance from Home ")
print(df_temp['dist_home_group'].value_counts().sort_index())
print("\n")
print("Distance from last transaction")
print(df_temp['dist_trans_group'].value_counts().sort_index())
print("\n")
print("Ratio to median purchase price")
print(df_temp['rtmpp_group'].value_counts().sort_index())
```

```
Distance from Home
(0, 10]          500934
(10, 25]         242427
(25, 100]        206850
(100, 1000]       49303
(1000, 5000]        483
(5000, 11000]         3
Name: dist_home_group, dtype: int64


Distance from last transaction
(0, 1]           500294
(1, 2]           149981
(2, 3]            79373
(3, 100]         265092
(100, 1000]        5204
(1000, 5000]         55
(5000, 12000]         1
Name: dist_trans_group, dtype: int64


Ratio to median purchase price
(0.0, 0.5]        264451
(0.5, 1.0]        236428
(1.0, 1.5]        143620
(1.5, 2.0]         91758
(2.0, 10.0]       245829
(10.0, 50.0]       17724
(50.0, 100.0]        179
(100.0, 200.0]         9
(200.0, 250.0]         0
(250.0, 300.0]         2
Name: rtmpp_group, dtype: int64
```

In [13]:
```python
# count number fraudulant transactions in distance group.
df_temp.groupby(['dist_home_group'])['fraud'].apply(lambda fraud: (fraud==1).sum())
```

Out[13]:
```
dist_home_group
(0, 10]          35759
(10, 25]         15844
(25, 100]        13593
(100, 1000]      21996
(1000, 5000]       210
(5000, 11000]        1
Name: fraud, dtype: int64
```

In [14]:
```python
# Visualize the count of fraudulant transactions for columns 'dis_home_group',
```

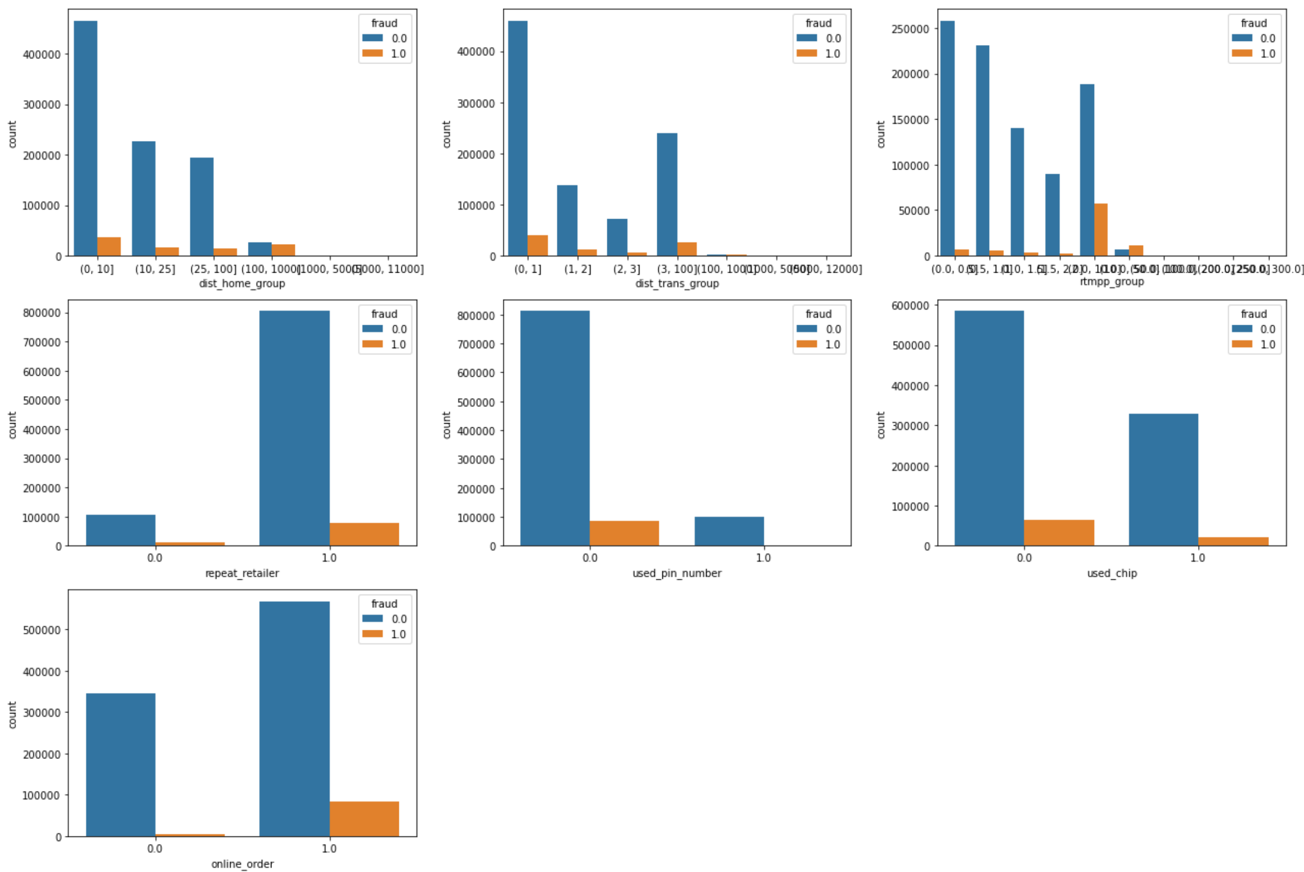
```python
cols = [ 'dist_home_group', 'dist_trans_group', 'rtmpp_group', 'repeat_retailer',
        'used_pin_number', 'used_chip', 'online_order']

n_rows = 3
n_cols = 3

# The subplot grid and the figure size of each graph
# This returns a Figure (fig) and an Axes Object (axs)
fig, axs = plt.subplots(n_rows, n_cols, figsize=(n_cols*6,n_rows*4))

# Iterates through the matrix and places a graph
for r in range(0,n_rows):
    for c in range(0,n_cols):
        # prevents out of range error and hides graph template
        if r == 2 and c > 0:
            fig.delaxes(axs[r][c])
            fig.delaxes(axs[r][c+1])
            break
        i = r*n_cols+ c #index to go through the number of columns
        ax = axs[r][c] #Show where to position each subplot
        sns.countplot(x=df_temp[cols[i]], hue=df_temp["fraud"], ax=ax)
        ax.legend(title="fraud", loc='upper right')

plt.tight_layout()    #tight_layout
```



Based on these graphs, there is a relation to high dollar purchases and fraudulant transactions. This makes sense. A scammer would want to extract as much money as they could before the card is blocked.

Fraud and repeated retailers suggests scammers using a retailer they are familiar with. If making purchases in person they know the stock or they are familiar with with the online purchasing process.

It is no surprise fraudulant transactions occur without the chip or pin. Online orders allow more anonymous purchases and are quicker to process.

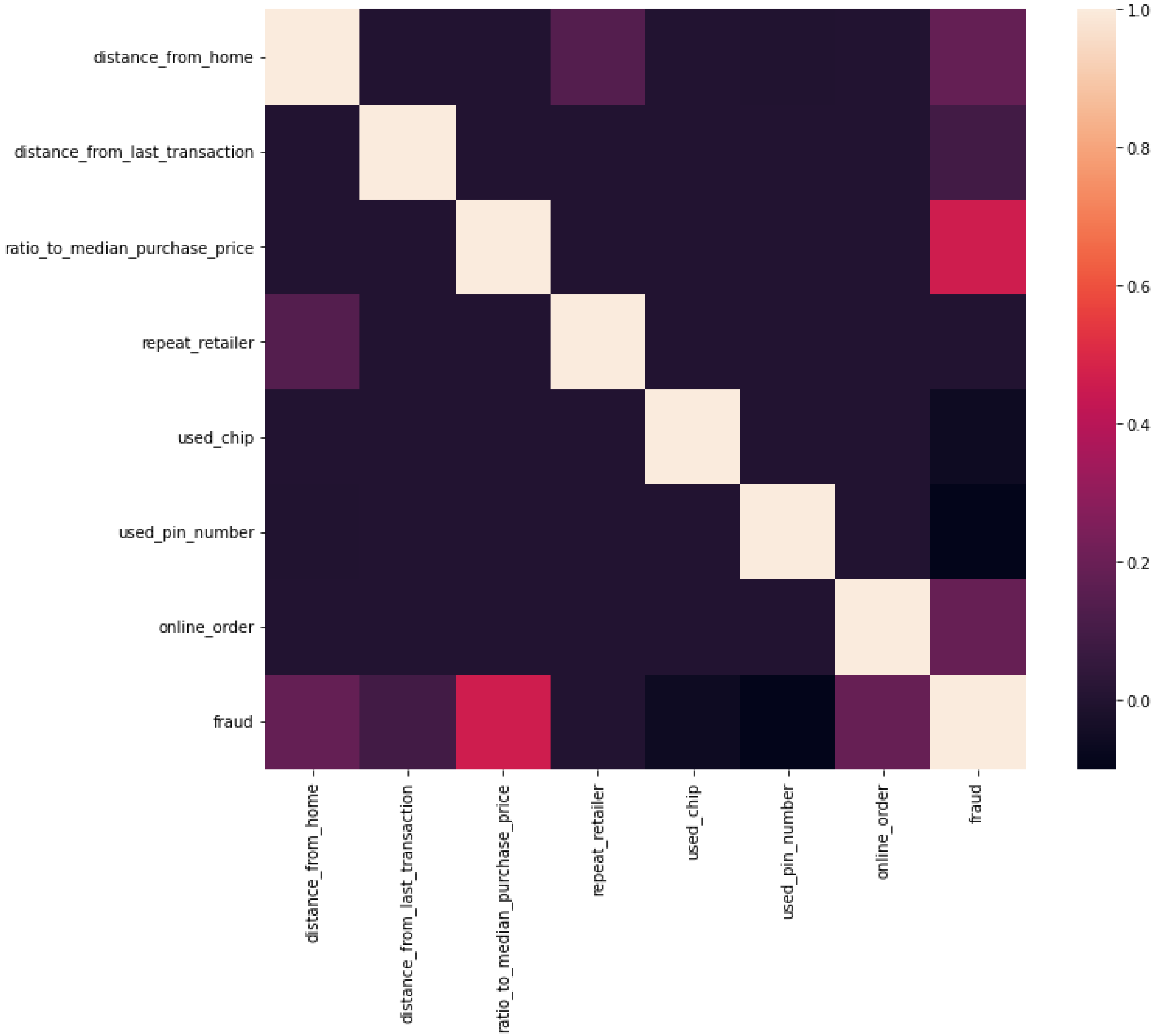
Next let's observe any correlation between variables.

In [15]:

```python
# Generate correlation matrix
cormat = df_temp.corr()
```

```
# setup figure size
fig = plt.figure(figsize = (12, 9))

# assign data to a heatmap
sns.heatmap(cormat, square = True)
plt.show()
```



Anomaly Detection with Classification Algorithm

We will be using K Nearest Neighbors to detect whether fraud occured or not.

In [16]:

```
# split data into independent 'X' and dependent 'Y' variables
X = df.iloc[:, 0:6].values
Y = df.iloc[:, 7].values

# split dataset into 80% training set and 20% testing set
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, random_state = 0)

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

print("completed")
```

```
completed
```

In [17]:

```
# create a KNN classifier container and place the training data into it.
knn = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
```

```python
knn.fit(X_train, Y_train)

# predict fraudulant transaction on test set
final_pred = knn.predict(X_train)

# print score
print('Accuracy Score of KNN: ' + str(knn.score(X_train, Y_train)))
```

```
Accuracy Score of KNN: 0.96784625
```

In [ ]: