Project: Fastage Fraud Detection

In [ ]:
```
# Import libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [ ]:
```
# Read Data
data = pd.read_csv("../Data/raw/fastag-data.csv")

# View
data.head()
```

Out[ ]:

	Transaction_ID	Timestamp	Vehicle_Type	FastagID	TollBoothID	Lane_Type	Vehicle_
0	1	1/6/2023 11:20	Bus	FTG-001-ABC-121	A-101	Express	
1	2	1/7/2023 14:55	Car	FTG-002-XYZ-451	B-102	Regular	
2	3	1/8/2023 18:25	Motorcycle	NaN	D-104	Regular	
3	4	1/9/2023 2:05	Truck	FTG-044-LMN-322	C-103	Regular	
4	5	1/10/2023 6:35	Van	FTG-505-DEF-652	B-102	Express	

In [ ]:
```
# Shape
data.shape
```

Out[ ]:
```
(5000, 13)
```

In [ ]:
```
# Check for duplicates
data.duplicated().sum()
```

Out[ ]:
```
0
```

In [ ]:
```
# Metainformation
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   Transaction_ID        5000 non-null   int64 
 1   Timestamp             5000 non-null   object
 2   Vehicle_Type          5000 non-null   object
 3   FastagID              4451 non-null   object
 4   TollBoothID           5000 non-null   object
 5   Lane_Type             5000 non-null   object
 6   Vehicle_Dimensions    5000 non-null   object
 7   Transaction_Amount    5000 non-null   int64 
 8   Amount_paid           5000 non-null   int64 
 9   Geographical_Location 5000 non-null   object
 10  Vehicle_Speed         5000 non-null   int64 
 11  Vehicle_Plate_Number  5000 non-null   object
 12  Fraud_indicator       5000 non-null   object
dtypes: int64(4), object(9)
memory usage: 507.9+ KB
```

- *Dataset contains 5000 records for fastag transactions, there are no missing values in dataset except for the column 'FastageID'.*

In [ ]:

```
# Analyze the missing FastagID
data[data.FastagID.isnull()]
```

Out[ ]:

	Transaction_ID	Timestamp	Vehicle_Type	FastagID	TollBoothID	Lane_Type	Vehi
2	3	1/8/2023 18:25	Motorcycle	NaN	D-104	Regular	
9	10	1/15/2023 7:30	Motorcycle	NaN	D-104	Regular	
16	17	1/22/2023 16:45	Motorcycle	NaN	D-104	Regular	
23	24	1/29/2023 3:05	Motorcycle	NaN	D-104	Regular	
30	31	2/5/2023 13:20	Motorcycle	NaN	D-104	Regular	
...	...	...	...	...	...	...	
4966	4967	8/31/2023 6:08	Motorcycle	NaN	D-106	Regular	
4973	4974	12/27/2023 19:04	Motorcycle	NaN	D-106	Regular	
4980	4981	4/20/2023 6:01	Motorcycle	NaN	D-106	Regular	
4987	4988	8/19/2023 18:57	Motorcycle	NaN	D-106	Regular	
4994	4995	12/14/2023 6:53	Motorcycle	NaN	D-106	Regular	

549 rows × 13 columns

In [ ]:

```
# Transaction amount with no FastagID
transaction_amt = data[data.FastagID.isnull()]['Transaction_Amount'].unique()
amt_paid = data[data.FastagID.isnull()]['Amount_paid'].unique()

transaction_amt, amt_paid
```

Out[ ]:

```
(array([0], dtype=int64), array([0], dtype=int64))
```

- *All of these transactions without FastagID has zero for amount paid.*
- *Meaning, there is no record for amount paid for these transactions. so, lets drop all rows with missing FastagID.*

In [ ]:

```
# Drop missing FastagId rows.
data = data.dropna(axis=0).copy()
```

In [ ]:

```
# Unique values in IDs, and categorical data.
data.nunique()
```

```
Out[ ]: Transaction_ID          4451
        Timestamp               4008
        Vehicle_Type               7
        FastagID                4451
        TollBoothID                4
        Lane_Type                  2
        Vehicle_Dimensions         3
        Transaction_Amount        20
        Amount_paid               23
        Geographical_Location      5
        Vehicle_Speed             85
        Vehicle_Plate_Number    4451
        Fraud_indicator            2
        dtype: int64
```

```
In [ ]: for col in data.select_dtypes(include='object').columns:
            print(col)
            print(data[col].unique())
            print('--' * 10)
```

```
Timestamp
['1/6/2023 11:20' '1/7/2023 14:55' '1/9/2023 2:05' ... '2/5/2023 5:08'
 '2/20/2023 20:34' '3/10/2023 0:59']
--------------------
Vehicle_Type
['Bus ' 'Car' 'Truck' 'Van' 'Sedan' 'SUV' 'Motorcycle']
--------------------
FastagID
['FTG-001-ABC-121' 'FTG-002-XYZ-451' 'FTG-044-LMN-322' ...
 'FTG-447-PLN-109' 'FTG-458-VFR-876' 'FTG-459-WSX-543']
--------------------
TollBoothID
['A-101' 'B-102' 'C-103' 'D-106']
--------------------
Lane_Type
['Express' 'Regular']
--------------------
Vehicle_Dimensions
['Large' 'Small' 'Medium']
--------------------
Geographical_Location
['13.059816123454882, 77.77068662374292'
 '13.042660878688794, 77.47580097259879'
 '12.84197701525119, 77.67547528176169'
 '12.936687032945434, 77.53113977439017'
 '13.21331620748757, 77.55413526894684']
--------------------
Vehicle_Plate_Number
['KA11AB1234' 'KA66CD5678' 'KA11GH3456' ... 'KA33WX6789' 'KA35YZ0123'
 'KA37AB3456']
--------------------
Fraud_indicator
['Fraud' 'Not Fraud']
--------------------
```

```
In [ ]: # Convert date into datetime type
        data['Timestamp'] = pd.to_datetime(data.Timestamp)
```

```
In [ ]: # Convert columns
        data.rename(columns={col: col.lower() for col in data.columns.tolist()}, inplace
```

```
# rename
data.rename(columns={
    'fastagid': 'fastag_id',
    'tollboothid': 'tollbooth_id',
    'vehicle_dimensions': 'vehicle_size'
}, inplace=True)
```

In [ ]:
```
# Check data types
data.dtypes
```

Out[ ]:
```
transaction_id                   int64
timestamp               datetime64[ns]
vehicle_type                    object
fastag_id                       object
tollbooth_id                    object
lane_type                       object
vehicle_size                    object
transaction_amount               int64
amount_paid                      int64
geographical_location           object
vehicle_speed                    int64
vehicle_plate_number            object
fraud_indicator                 object
dtype: object
```

In [ ]:
```
# Summary descriptions
columns = ['transaction_amount', 'amount_paid', 'vehicle_speed']
fraud_desc = data[data.fraud_indicator == 'Fraud'][columns].describe()
notfraud_desc = data[data.fraud_indicator == 'Not Fraud'][columns].describe()

pd.concat([fraud_desc, notfraud_desc], axis=1, keys=['Fraudulent', 'Non-Fraudule
```

Out[ ]:

	Fraudulent				
	transaction_amount	**amount_paid**	**vehicle_speed**	**transaction_amount**	**amount_pa**
count	983.000000	983.000000	983.000000	3468.000000	3468.0000
mean	193.555443	92.838250	68.340793	177.348616	177.3486
std	97.465586	35.230277	16.832977	104.256672	104.2566
min	60.000000	0.000000	20.000000	0.000000	0.0000
25%	120.000000	90.000000	55.000000	110.000000	110.0000
50%	145.000000	100.000000	68.000000	130.000000	130.0000
75%	300.000000	110.000000	82.000000	300.000000	300.0000
max	350.000000	190.000000	118.000000	350.000000	350.0000

In [ ]:
```
# Datetime
data['timestamp'].dt.year.unique() # 2023 data
```

Out[ ]:
```
array([2023])
```

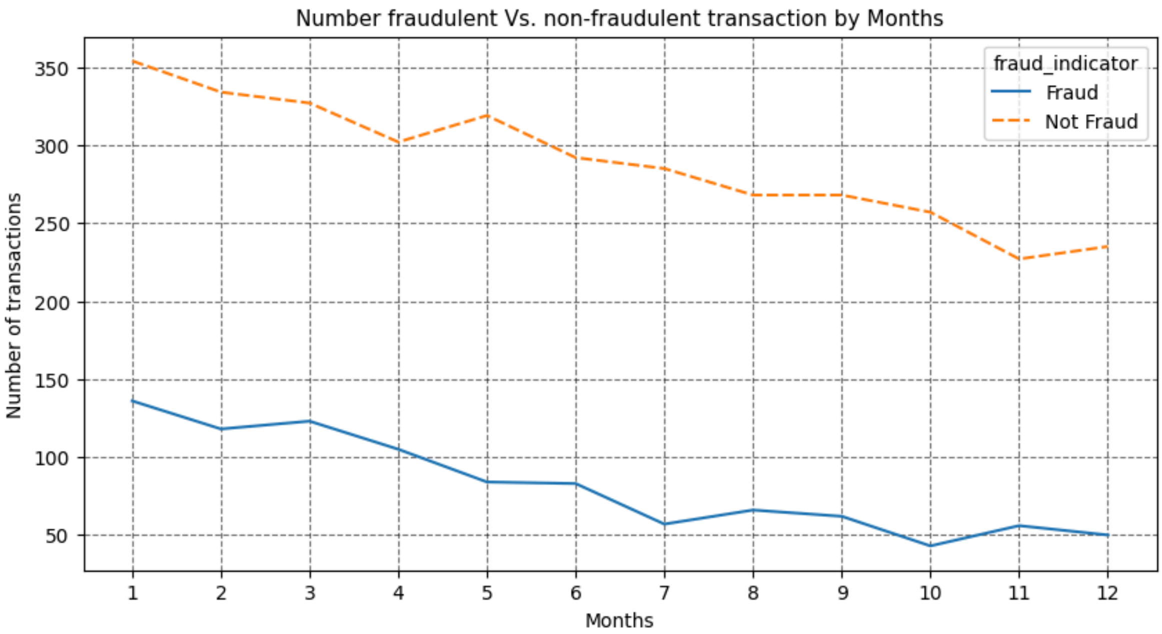
```
In [ ]: # Total days of records
        data['timestamp'].dt.date.nunique()
```

```
Out[ ]: 365
```

```
In [ ]: # Create new columns
        data['month'] = data['timestamp'].dt.month
        data['weekday'] = data['timestamp'].dt.weekday
        data['hour'] = data['timestamp'].dt.hour
        data['is_month_end'] = data['timestamp'].dt.is_month_end.astype('int')
        data['is_month_start'] = data['timestamp'].dt.is_month_start.astype('int')
        data['quarter'] = data['timestamp'].dt.quarter
        data['day_month'] = data['timestamp'].dt.strftime(date_format='%d-%m')
```

```
In [ ]: # Datetime analysis - Number of fraudulent transaction in each month
        # data preparation
        monthly_n_transactions = pd.pivot_table(data, values='transaction_id', index='mc

        # for label ticks
        hours = sorted(data.hour.unique().tolist())
        months = sorted(data.month.unique().tolist())
```

```
In [ ]: # plot
        plt.figure(figsize=(10, 5))
        sns.lineplot(monthly_n_transactions)

        plt.title('Number fraudulent Vs. non-fraudulent transaction by Months', size=11)
        plt.xlabel('Months')
        plt.ylabel('Number of transactions')

        plt.grid(ls='--', c="#181818", alpha=0.6)
        plt.xticks(ticks=months);
```



- *The lineplot compares the count of total fraudulent and non-fraudulent transactions over months(from 1 to 12) in year 2023.*
- *The line plot represents the decreasing trend in overall fastag transactions.*

- *The line plot shows, the highest number of fraudulent as well as non-fraudulent transaction in January, while the octobar has lowest fraudulent transaction.*

In [ ]:
```
# What is fraction of monthly contribution in total fraudulent transactions?
pct_fraud = (monthly_n_transactions['Fraud'] * 100 / monthly_n_transactions['Fra
pct_fraud.columns = ['Month', 'Fraud_Percent']

pct_fraud.sort_values(by='Fraud_Percent', ascending=False)
```

Out[ ]:

	Month	Fraud_Percent
0	1	13.835198
2	3	12.512716
1	2	12.004069
3	4	10.681587
4	5	8.545270
5	6	8.443540
7	8	6.714140
8	9	6.307223
6	7	5.798576
10	11	5.696846
11	12	5.086470
9	10	4.374364

- *The first quarter (the first four months of the year-January, February, March and April) seems to have hightest fraudelent transaction over the year 2023.*

In [ ]:
```
# What happened in January?
jan_23 = data[data.month == 1]

jan_23[jan_23.fraud_indicator=='Fraud'].groupby(by='day_month').count()['transac
```

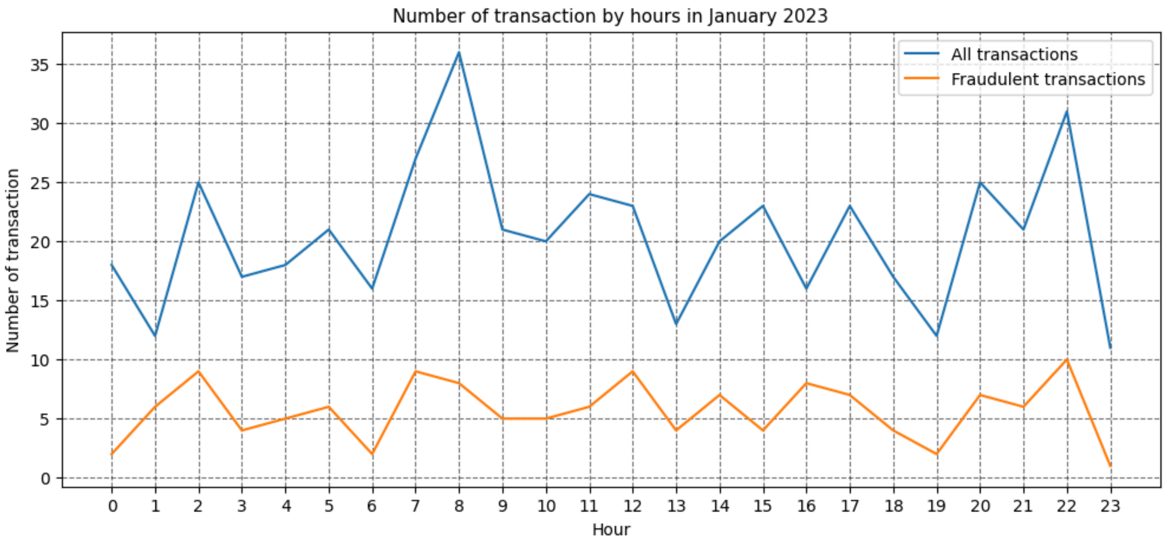
Out[ ]:
```
day_month
15-01    9
03-01    7
24-01    7
23-01    7
07-01    7
Name: transaction_id, dtype: int64
```

In [ ]:
```
# day-name: 0 -> Monday, 1 -> Tuesday, 2 -> Wednesday, 3 -> Thursday, 4 -> Frida
jan_23.loc[jan_23.day_month == '15-01', 'weekday'].head(1)
```

Out[ ]:
```
126    6
Name: weekday, dtype: int32
```

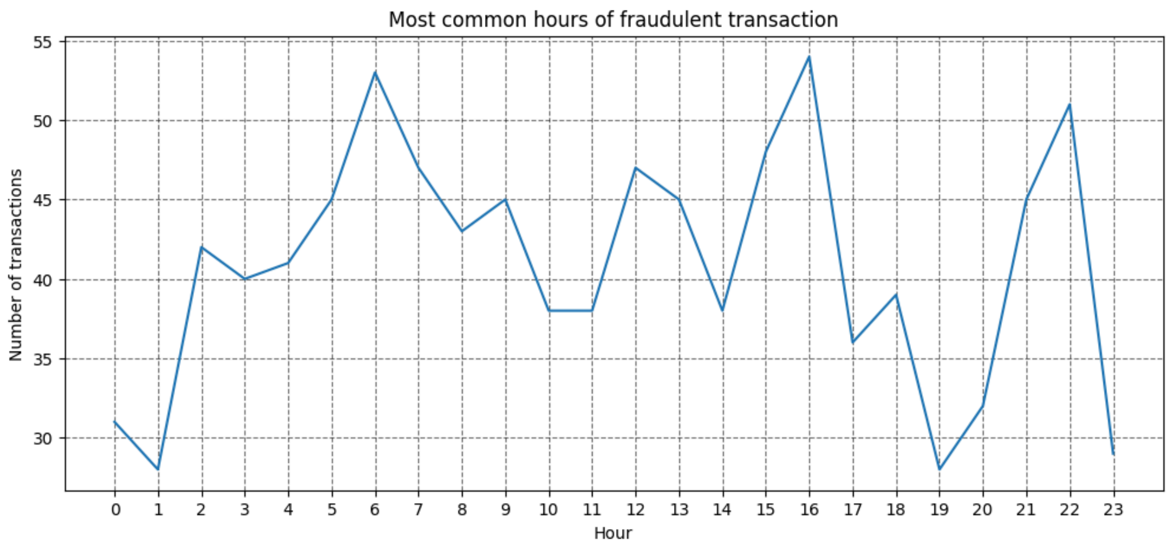
- *The highest fraudulent transaction observed on Sunday, 15th January.*

In [ ]:
```
# What are the most common hours for fraudulent transaction in January?

# Data preparation
pivot_nt = pd.pivot_table(jan_23, values='transaction_id', columns='fraud_indica
pivot_nt['total_transactions'] = pivot_nt['Fraud'] + pivot_nt['Not Fraud']

# plot
plt.figure(figsize=(12, 5))
sns.lineplot(pivot_nt['total_transactions'], label='All transactions')
sns.lineplot(pivot_nt['Fraud'], label='Fraudulent transactions')

plt.title('Number of transaction by hours in January 2023', size=11)
plt.xlabel('Hour')
plt.ylabel('Number of transaction')
plt.grid(ls='--', c="#181818", alpha=0.6)
plt.xticks(ticks=hours, color='#000')
plt.show()
```



- *The above lineplot shows the total number of hourly transaction in January 2023.*
- *The highest fraudulent transactions are observed at the peakest hours in January.*

In [ ]:
```
# What is the most common hour for fraudulent transaction in
pivot_nt = pd.pivot_table(data, values='transaction_id', columns='fraud_indicato

plt.figure(figsize=(12, 5))
sns.lineplot(pivot_nt['Fraud'])

plt.title('Most common hours of fraudulent transaction')
plt.xlabel('Hour')
plt.ylabel('Number of transactions')

plt.grid(ls='--', c="#181818", alpha=0.6)
plt.xticks(ticks=hours);
```

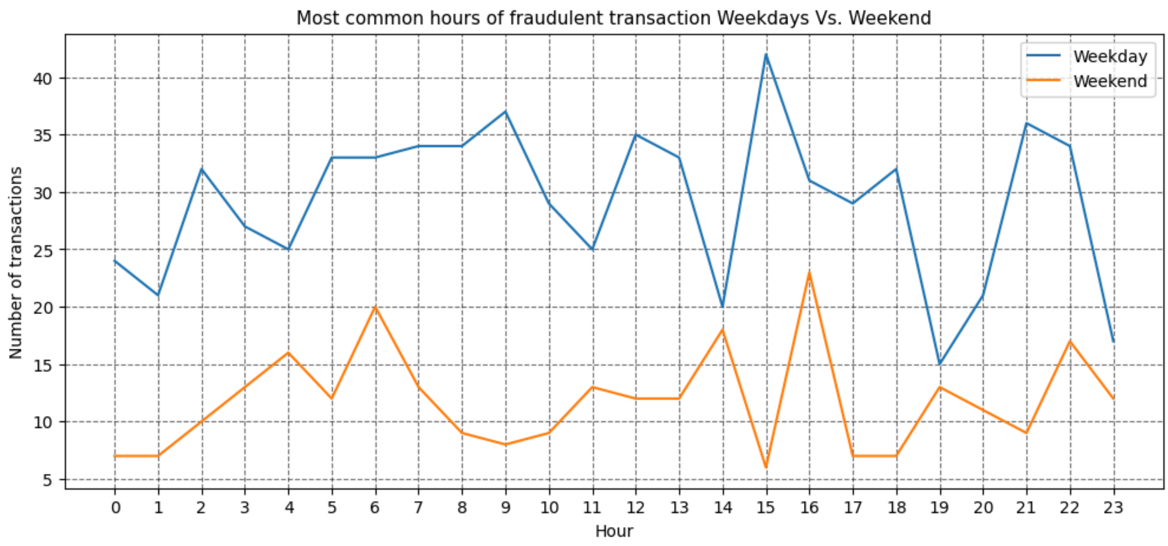


- *The line plot has some noticeable peaks at around Early mornings (around 2nd and 6th hour), and late evening (around 16th and 22th hour).*
- *Lunchtime (around 12th hour) could be another peak.*
- *This might happend because these are the peak traffic hours.*

There might be difference in patterns for weeekdays and weekends. Let's analysis further for days of the week.

In [ ]:

```
# Is there any difference in fraud patterns for weekdays and weekends.

# Data preparation
# filter data
fraud_data = data[data.fraud_indicator=='Fraud']
weekdays = fraud_data[fraud_data.weekday <= 4]
weekends = fraud_data[fraud_data.weekday > 4]

# Get the count of transaction by hour
weekdays_grp = weekdays.groupby(by='hour')['transaction_id'].count()
weekends_grp = weekends.groupby(by='hour')['transaction_id'].count()


plt.figure(figsize=(12, 5))
sns.lineplot(weekdays_grp, label='Weekday')
sns.lineplot(weekends_grp, label='Weekend')

plt.title('Most common hours of fraudulent transaction Weekdays Vs. Weekend', si
plt.xlabel('Hour')
plt.ylabel('Number of transactions')

plt.grid(ls='--', c="#181818", alpha=0.6)
plt.xticks(ticks=hours);
```



- *The above line graph shows the fraud transactions patterns for weekdays and weekends.*
- *The number of transactions on weekends are less compare to weekdays.*
- *The main difference can observed at the 15th hour, which has highest peak for weekdays however, lowest for the weekends, this might happend becuase it is not busy traffic hour on weekends.*
- *Similary, the hours that has lowest peak on weekdays has highest peak for weekends (around 14th, and 19th hour)*
- *Overall pattern of early mornings and late evening highest fraudulent transaction can observed in both*

In [ ]:
```
# Earlier we saw that the first four months have higher rate of fraudulent trans
data.groupby(by=['fraud_indicator', 'quarter'])['transaction_id'].count()
```

Out[ ]:
```
fraud_indicator  quarter
Fraud            1           377
                 2           272
                 3           185
                 4           149
Not Fraud        1          1015
                 2           913
                 3           821
                 4           719
Name: transaction_id, dtype: int64
```

In [ ]:
```
# Total transaction amount and acutal amount paid by quarter.
grp_data = data.groupby(by=['fraud_indicator', 'quarter'])[['transaction_amount'
```

In [ ]:
```
grp_data['amt_paid_percent'] = grp_data['amount_paid'] * 100 / grp_data['transac
grp_data = grp_data.reset_index()
```

In [ ]:
```
grp_data
```

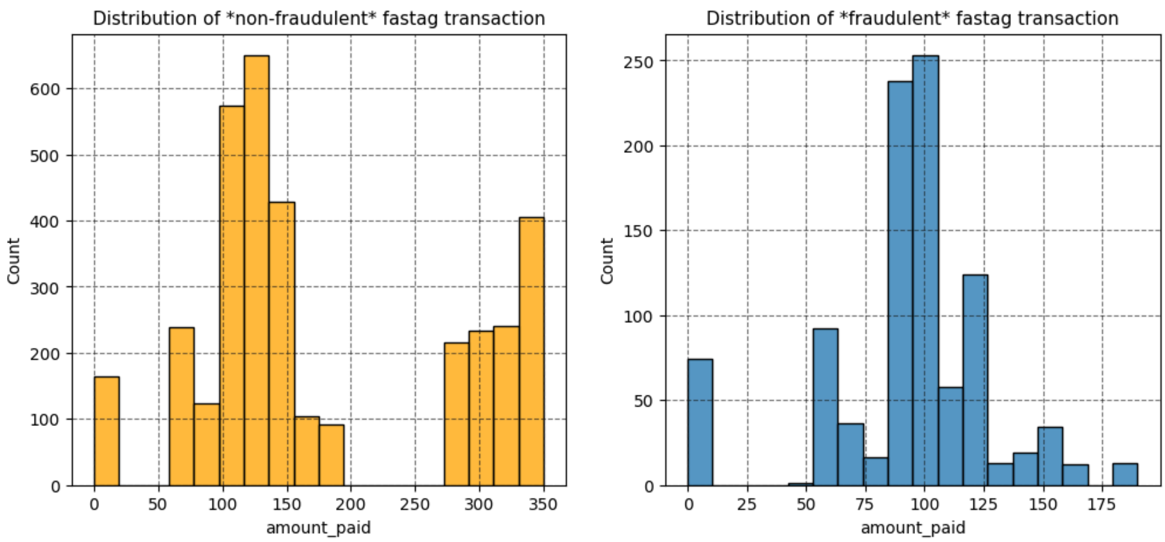
Out[ ]:

	fraud_indicator	quarter	transaction_amount	amount_paid	amt_paid_percent
0	Fraud	1	75305	35755	47.480247
1	Fraud	2	51880	24900	47.995374
2	Fraud	3	35275	16985	48.150248
3	Fraud	4	27805	13620	48.983996
4	Not Fraud	1	183010	183010	100.000000
5	Not Fraud	2	160625	160625	100.000000
6	Not Fraud	3	142865	142865	100.000000
7	Not Fraud	4	128545	128545	100.000000

The rate of actual amount paid in fraudulent transaction is always less than 50% for all the quarters, whereas in genuine transactions is 100%.

In [ ]:

```
# Distribution of amount paid
non_fraudulent_amount = data[data['fraud_indicator'] == 'Not Fraud']['amount_pai
fraudulent_amount = data[data['fraud_indicator'] == 'Fraud']['amount_paid']

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 5))
sns.histplot(non_fraudulent_amount, bins=18, color='orange', ax=ax1)
sns.histplot(fraudulent_amount, bins=18, ax=ax2)

ax1.grid(ls='--', c="#181818", alpha=0.6)
ax2.grid(ls='--', c="#181818", alpha=0.6)

ax1.set_title('Distribution of *non-fraudulent* fastag transaction', size=11)
ax2.set_title('Distribution of *fraudulent* fastag transaction', size=11);
```



- *Histogram plot shows the distribution of amount paid in non-fraudulent transaction(left) and fraudulent transaction(right).*
- *The graph shows multiple groups for both transaction, which represent the multi-model distribution.*

In [ ]:
```
# Vehicle type
data.vehicle_type.unique()
```

Out[ ]:
```
array(['Bus ', 'Car', 'Truck', 'Van', 'Sedan', 'SUV', 'Motorcycle'],
      dtype=object)
```

Notice, 'Bus ' it is with the space. So, let's clean the data by removing the extra whitespaces in data.

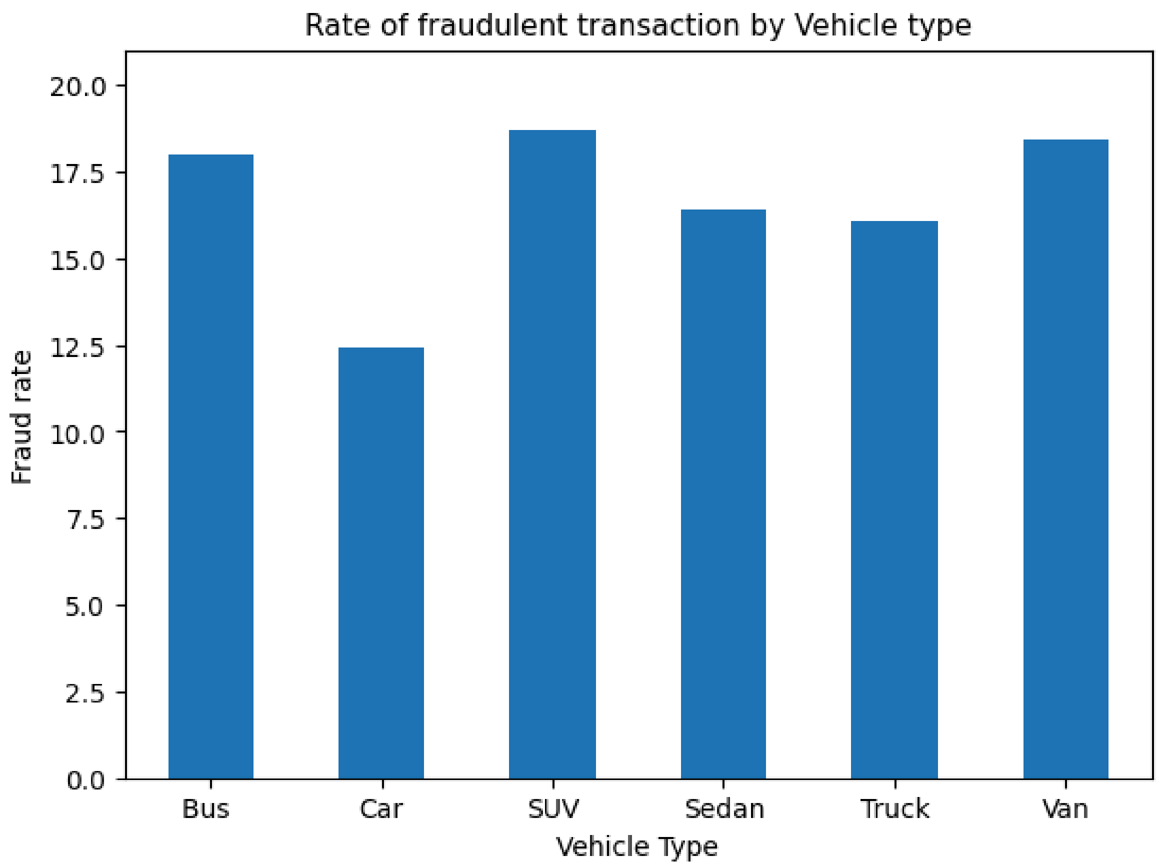
In [ ]:
```
# Remove whitespace.
columns = ['vehicle_type', 'lane_type', 'vehicle_size', 'fraud_indicator']

data[columns] = data[columns].apply(lambda x: x.str.strip())
```

In [ ]:
```
# Examine the data for Motorcycle.
type_filter = data.vehicle_type == 'Motorcycle'
print(data[type_filter]['transaction_amount'].value_counts())
print("--"*10)
print(data[type_filter]['fraud_indicator'].value_counts())
```

```
transaction_amount
0    165
Name: count, dtype: int64
--------------------
fraud_indicator
Not Fraud    165
Name: count, dtype: int64
```

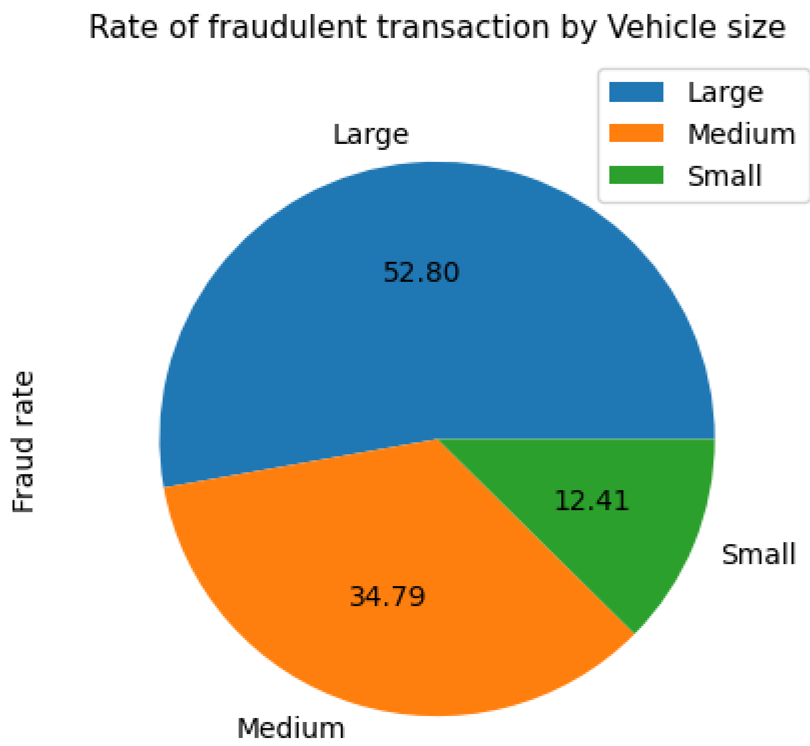
You see, for the motorcycle type of vehicle has no transaction charges, so it has no fraud indicator. We can say that, if vehicle type is Motorcycle, then there will no fraud.

In [ ]:
```
# Calcuate the rate of fraudulent transaction by vehicle type.
# Data preparation
vehicle_type_pivot = pd.pivot_table(fraud_data, values='transaction_id', index='
fraud_rate = vehicle_type_pivot['Fraud'] * 100/ fraud_data.shape[0]

# Plot

fraud_rate.plot(kind='bar', figsize=(7, 5))

plt.ylim(ymax=21)
plt.title('Rate of fraudulent transaction by Vehicle type', size=11)
plt.xlabel('Vehicle Type')
plt.ylabel('Fraud rate')

plt.xticks(rotation='horizontal')
plt.show()
```

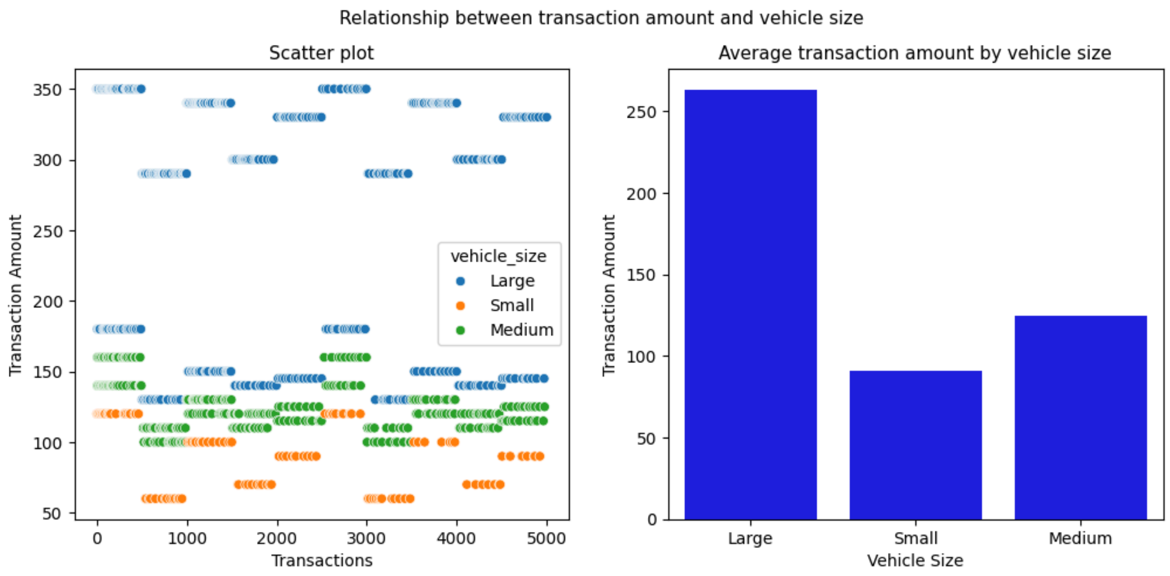


In [ ]:

```
# Calcuate the rate of fraudulent transaction by vehicle size.
# Data preparation
vehicle_type_pivot = pd.pivot_table(fraud_data, values='transaction_id', index='
fraud_rate = vehicle_type_pivot['Fraud'] * 100/ fraud_data.shape[0]

# Plot

fraud_rate.plot(kind='pie', figsize=(7, 5), autopct='%.2f', radius=0.9)

plt.title('Rate of fraudulent transaction by Vehicle size', size=11)
plt.legend()
plt.ylabel('Fraud rate')
plt.show()
```

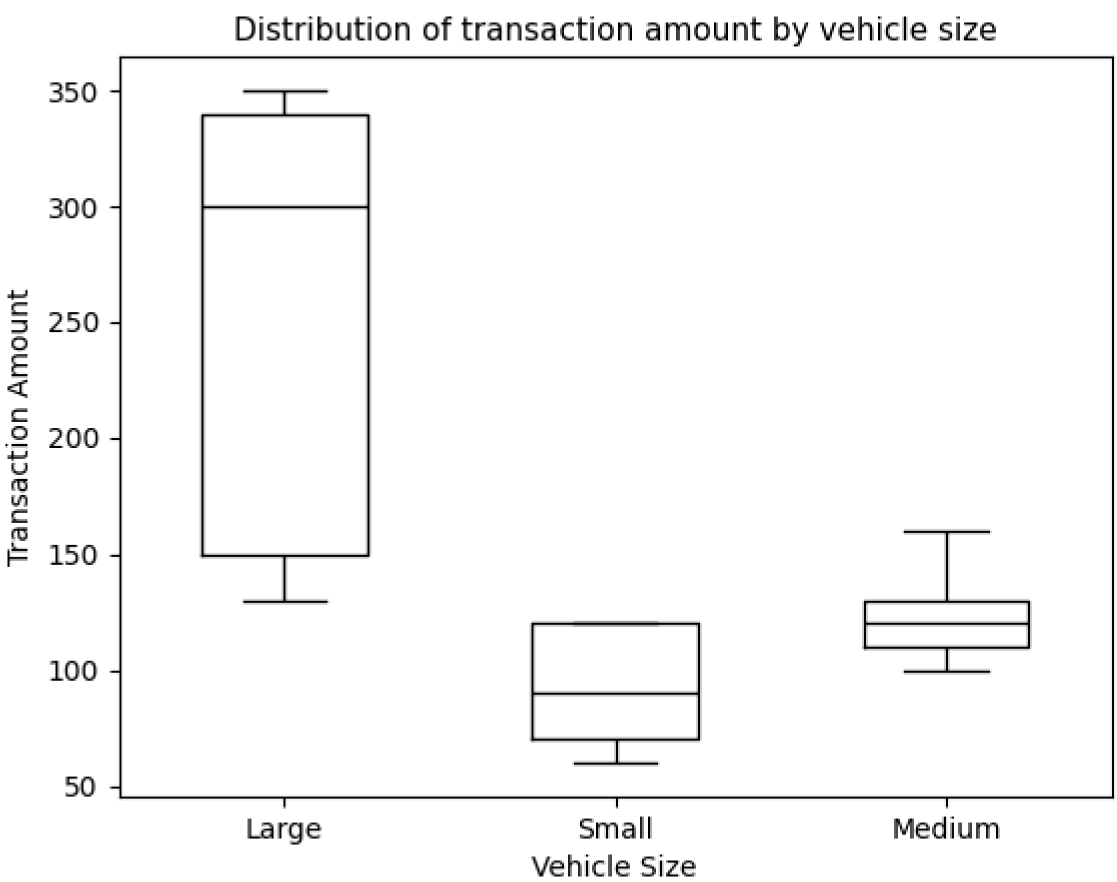


In [ ]:
```
# Does transaction amount depends on size of the vehicle?
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 5))

sns.scatterplot(fraud_data, x='transaction_id', y='transaction_amount', hue='veh
sns.barplot(fraud_data, x='vehicle_size', y='transaction_amount', estimator='mea

# labels
fig.suptitle("Relationship between transaction amount and vehicle size", size=11
ax1.set_title('Scatter plot', size=11)
ax2.set_title("Average transaction amount by vehicle size", size=11)

ax1.set_xlabel('Transactions')
ax2.set_xlabel('Vehicle Size')

ax1.set_ylabel('Transaction Amount')
ax2.set_ylabel('Transaction Amount');
```



- *The scatter plot shows the relationship between the transaction amount and vehicle size.*
- *The plot shows that linear relation between transaction amount and size of the vehicle because the amount increases as size or dimensions of the vehicle increase.*

In [ ]:
```
# Distribution of transaction amount for fraudulent transaction by vehicle size.
sns.boxplot(fraud_data, x='vehicle_size', y='transaction_amount', width=0.5, col

# labels
plt.title("Distribution of transaction amount by vehicle size", size=11)
plt.xlabel('Vehicle Size')
plt.ylabel('Transaction Amount');
```



- *The boxplot represents the distribution and variation in transaction amount over different size of vehicles.*
- *The variation in mean value of transaction amount for different vehicle size represent the relation between them.*
- *Large vehicle tends to have large transaction amount but with large variation.*

In [ ]:
```
# What is rate of fradulent transaction for differnt lane types
data.lane_type.value_counts()
```

Out[ ]:
```
lane_type
Regular    2309
Express    2142
Name: count, dtype: int64
```

In [ ]:
```
data.groupby(by=['lane_type', 'fraud_indicator'])['transaction_id'].count()
```

Out[ ]:
```
lane_type  fraud_indicator
Express    Fraud               490
           Not Fraud          1652
Regular    Fraud               493
           Not Fraud          1816
Name: transaction_id, dtype: int64
```

In [ ]:
```
# What is fraudent transaction amount for different type of lanes?
pd.pivot_table(data, values='transaction_amount', columns='lane_type', index='fr
```

Out[ ]:

lane_type	Express	Regular
fraud_indicator		
Fraud	189.989796	197.099391
Not Fraud	187.230630	168.359031

- *The lane data is pretty balance and has no significant effect on fraudulent transaction.*
- *As we can see that the number of fraudulent transaction on both express and regular lane type is almost equal to ~490.*
- *However, there is significant difference in average transaction amount on regular lane type for fraudulent and genuine transactions.*

In [ ]:
```
# Tollbooth ID
data.tollbooth_id.nunique()
```

Out[ ]:
```
4
```

In [ ]:
```
# What is rate of fraudulent transaction by tollbooth.
a = pd.pivot_table(data, values='transaction_id', index='tollbooth_id', columns=
a['pct_fraud'] = a['Fraud'] * 100 / (a['Fraud'] + a['Not Fraud'])
a.sort_values(by='pct_fraud', ascending=False)
```

Out[ ]:

fraud_indicator	Fraud	Not Fraud	pct_fraud
tollbooth_id			
B-102	367	1065	25.628492
C-103	333	1093	23.352034
A-101	283	1145	19.817927
D-106	0	165	0.000000

In [ ]:

```
# Examine the data for tollbooth_id 'D-106' where, fraud rate is 0%.
data[data.tollbooth_id == 'D-106']['fraud_indicator'].value_counts()
```

Out[ ]:

```
fraud_indicator
Not Fraud    165
Name: count, dtype: int64
```

In [ ]:

```
# Get the unique value in attributes for tollbooth ID D-106, if it is only value
data[data.tollbooth_id == 'D-106'].apply(lambda x: x.unique()[0] if len(x.unique
```

Out[ ]:

```
transaction_id                  165
timestamp                       165
vehicle_type             Motorcycle
fastag_id                       165
tollbooth_id                  D-106
lane_type                   Regular
vehicle_size                  Small
transaction_amount                0
amount_paid                       0
geographical_location             4
vehicle_speed                    56
vehicle_plate_number            165
fraud_indicator           Not Fraud
month                            12
weekday                           7
hour                             24
is_month_end                      2
is_month_start                    2
quarter                           4
day_month                       118
dtype: object
```

- *The tollboothID 'D-106' is for a particular vehicle type which is Motorcycle, and Regular lane type.*
- *The Motorcycle has no transaction charges and hence it has no fraudulent trasactions activities.*

In [ ]:

```
fraud_data.groupby(by=['tollbooth_id', 'geographical_location'])['transaction_id
```

Out[ ]:
```
tollbooth_id  geographical_location
A-101         12.84197701525119, 77.67547528176169     56
              12.936687032945434, 77.53113977439017    48
              13.042660878688794, 77.47580097259879    59
              13.059816123454882, 77.77068662374292    75
              13.21331620748757, 77.55413526894684     45
B-102         12.84197701525119, 77.67547528176169     83
              12.936687032945434, 77.53113977439017    67
              13.042660878688794, 77.47580097259879    69
              13.059816123454882, 77.77068662374292    99
              13.21331620748757, 77.55413526894684     49
C-103         12.84197701525119, 77.67547528176169     92
              12.936687032945434, 77.53113977439017    53
              13.042660878688794, 77.47580097259879    71
              13.059816123454882, 77.77068662374292    72
              13.21331620748757, 77.55413526894684     45
Name: transaction_id, dtype: int64
```

In [ ]:
```
fraud_data.groupby(by=['tollbooth_id', 'vehicle_size'])['transaction_id'].count(
```

Out[ ]:
```
tollbooth_id  vehicle_size
A-101         Large             2
              Medium          161
              Small           120
B-102         Large           184
              Medium          181
              Small             2
C-103         Large           333
Name: transaction_id, dtype: int64
```

In [ ]:
```
data.groupby(by=['tollbooth_id', 'vehicle_size'])['transaction_id'].count()
pd.pivot_table(data, 'transaction_id', 'tollbooth_id', ['fraud_indicator', 'vehi
```

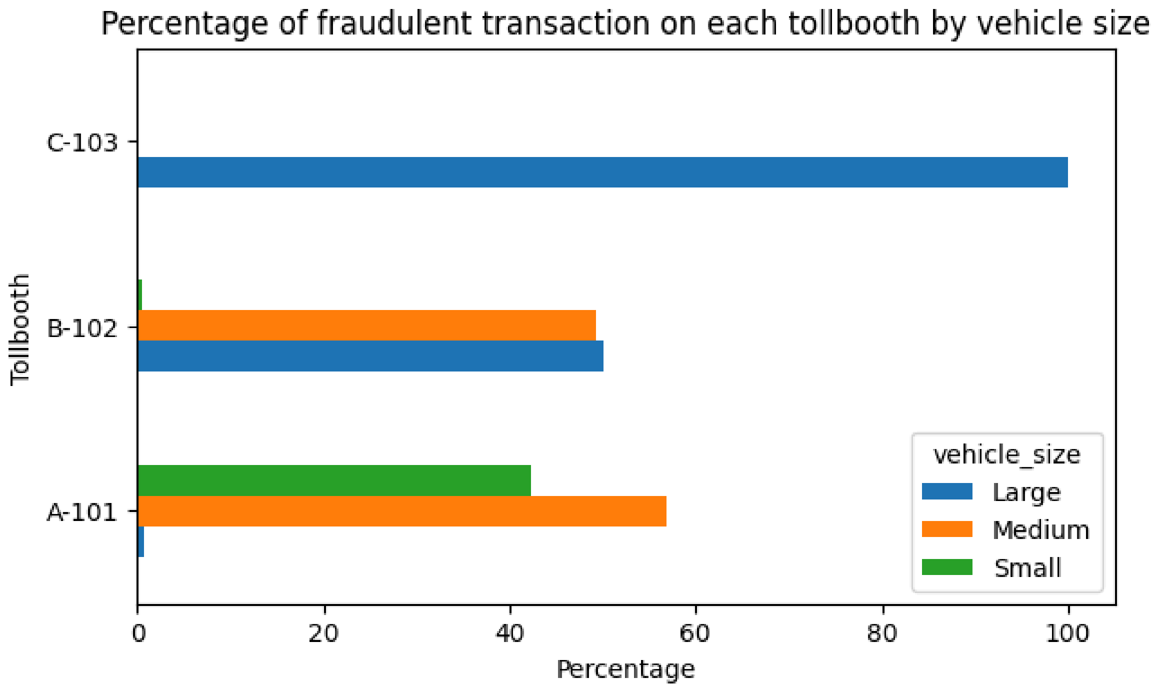
Out[ ]:

fraud_indicator	Fraud										
vehicle_type	Bus	Car	SUV	Sedan	Truck	Van	Bus	Car	Motorcycle	SUV	Sedan
tollbooth_id											
A-101	2	120	0	161	0	0	2	590	0	0	553
B-102	0	2	184	0	0	181	0	2	0	530	0
C-103	175	0	0	0	158	0	537	0	0	0	0
D-106	0	0	0	0	0	0	0	0	165	0	0

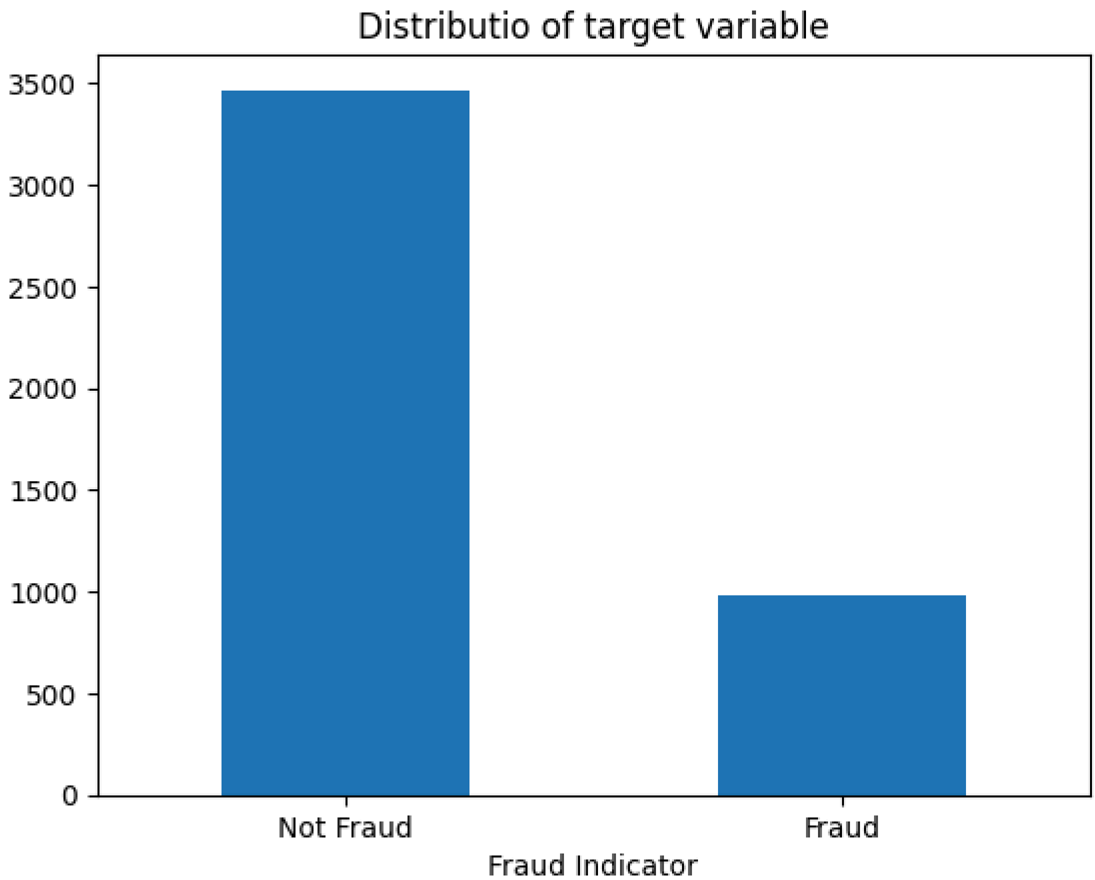
In [ ]:
```
# What is rate of fraudulent transaction for vehicle size on each tollbooth?
a = pd.pivot_table(fraud_data, values='transaction_id', index=['tollbooth_id', '
b = pd.pivot_table(fraud_data, values='transaction_id', index=['tollbooth_id'],
b.columns = ['Total Fraud']
pct_vehicle_size = (a['Fraud'] * 100 / b['Total Fraud'])
```

In [ ]:
```
# plot
pct_vehicle_size.unstack().plot(kind='barh',
                                figsize=(7, 4),
                                xlabel='Percentage',
                                ylabel='Tollbooth',
                                title="Percentage of fraudulent transaction on e
```

```
plt.show()
```



In [ ]:
```
# Distribution of target variable.
data.fraud_indicator.value_counts().plot(kind='bar', xlabel='Fraud Indicator', t
plt.xticks(rotation='horizontal');
```



- *The bar shows that there is imbalance in distribution of the target variable.*

In [ ]:
```
# Create a new variable for state of the vehicle registration state.
data['vehicle_reg_state'] = data['vehicle_plate_number'].apply(lambda x: x[:2])
```

In [ ]:
```
n_frauds = data.fraud_indicator.value_counts().iloc[0]
n_not_frauds = data.fraud_indicator.value_counts().iloc[1]
```

In [ ]:
```
a = pd.pivot_table(data, values='transaction_id', columns='fraud_indicator', ind
a['pct_fraud'] = a['Fraud'] * 100 / n_frauds
a['pct_not_fraud'] = a['Not Fraud'] * 100 / n_not_frauds
```

In [ ]:
```
a
```

Out[ ]:

fraud_indicator	Fraud	Not Fraud	pct_fraud	pct_not_fraud
vehicle_reg_state				
AP	68	334	1.960784	33.977620
BR	6	15	0.173010	1.525941
DL	12	94	0.346021	9.562564
GA	93	346	2.681661	35.198372
GJ	16	89	0.461361	9.053917
HR	5	16	0.144175	1.627670
KA	623	1933	17.964245	196.642930
KL	14	85	0.403691	8.646999
MH	92	344	2.652826	34.994914
MP	2	11	0.057670	1.119023
RJ	7	14	0.201845	1.424212
TN	31	146	0.893887	14.852492
TS	8	14	0.230681	1.424212
UP	4	17	0.115340	1.729400
WB	2	10	0.057670	1.017294

In [ ]:
```
data['lat'] = data['geographical_location'].apply(lambda x: x.split(',')[0])
data['long'] = data['geographical_location'].apply(lambda x: x.split(',')[1])
```

Data Preprocessing

In [ ]:
```
# Feature selection
cat_columns = ['vehicle_type','tollbooth_id', 'lane_type', 'vehicle_size', 'vehi
num_columns = ['transaction_amount', 'amount_paid', 'lat', 'long', 'vehicle_spee
```

In [ ]:
```
# Split data into X and y
X = data[cat_columns + num_columns]
y = data['fraud_indicator']
y = y.apply(lambda x: x =='Fraud' ).astype('int')
```

```
# Split data into traning and validation dataset.
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_
```

In [ ]:
```
# One hot encoding
from sklearn.preprocessing import OneHotEncoder

oh_en = OneHotEncoder()
oh_en.fit(x_train[cat_columns])

# Transform the training and test dataset
cat_x_train = oh_en.transform(x_train[cat_columns]).toarray()
cat_x_test = oh_en.transform(x_test[cat_columns]).toarray()
```

In [ ]:
```
cat_x_train_df = pd.DataFrame(cat_x_train, columns=oh_en.get_feature_names_out()
cat_x_test_df = pd.DataFrame(cat_x_test, columns=oh_en.get_feature_names_out())
```

In [ ]:
```
# Scale the numerical data
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(x_train[num_columns])

# Transform the training and test dataset
num_x_train = scaler.transform(x_train[num_columns])
num_x_test = scaler.transform(x_test[num_columns])
```

In [ ]:
```
num_x_train_df = pd.DataFrame(num_x_train, columns=scaler.get_feature_names_out(
num_x_test_df = pd.DataFrame(num_x_test, columns=scaler.get_feature_names_out())
```

In [ ]:
```
# final datasets
final_x_train = pd.concat([cat_x_train_df, num_x_train_df], axis=1)
final_x_test = pd.concat([cat_x_test_df, num_x_test_df], axis=1)
```

Model selection

In [ ]:
```
# Import libraries
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier,
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from xgboost import XGBClassifier
from sklearn.svm import SVC

# metrics for model evaluations
from sklearn.metrics import accuracy_score, f1_score, precision_score, confusion
from sklearn.model_selection import cross_val_score
```

In [ ]:
```
# Model selection with default settings
models = {
    'linear-models' : LogisticRegression(random_state=42),
    'd-tree' : DecisionTreeClassifier(random_state=42),
    'random-forest': RandomForestClassifier(random_state=42),
    'gradient-boost': GradientBoostingClassifier(random_state=42),
    'extra-tree': ExtraTreesClassifier(random_state=42),
```

```
    'neighbors': KNeighborsClassifier(),
    'naive-bayes': GaussianNB(),
    'xgb-clf': XGBClassifier(random_state=42),
    'svc': SVC(random_state=42)
}

model_scores = []
for name, model in models.items():

    scores = cross_val_score(estimator=model, X=final_x_train, y=y_train, cv=10,
    model_scores.append((name, scores.mean(), scores.std()))
```

In [ ]:
```
pd.DataFrame(model_scores, columns=['classifier', 'f1 score', 'std']).style.high
```

Out[ ]:

	classifier	f1 score	std
0	linear-models	0.947163	0.018358
1	d-tree	0.994355	0.005538
2	random-forest	0.985736	0.006085
3	gradient-boost	0.989572	0.006710
4	extra-tree	0.974523	0.010059
5	neighbors	0.818936	0.030235
6	naive-bayes	0.280534	0.019259
7	xgb-clf	0.995297	0.003643
8	svc	0.927298	0.017929

Decision tree algorithms out perform the model, by giving accuracy greater than 97% for almost all of the ensembles. There is higher chances that model might overfit the training data. To evaluate performance of model further, let us use the precision score on selected algorithm.

- Random forest
- Decision tree
- Xgboost

In [ ]:
```
# Model evaluation
def get_score(y_true, y_preds):

    # Compute scores
    precision = precision_score(y_true, y_preds)
    f1score = f1_score(y_true, y_preds)
    accuracy = accuracy_score(y_true, y_preds)
    class_report = confusion_matrix(y_true, y_preds)

    return precision, f1score, accuracy, class_report

def eval_clf(classifier):
    clf = classifier.fit(final_x_train, y_train)
    y_preds = clf.predict(final_x_test)
    return clf, get_score(y_test, y_preds)
```

```
In [ ]: # Random Forest Classifier
rf_clf = RandomForestClassifier(n_estimators=200, max_depth=3, random_state=42)
rf_clf, (precision, f1score, accuracy, class_report) = eval_clf(rf_clf)

print("Precision:: %.3f" %precision)
print("F1 Score:: %.3f" %f1score)
print("Accuracy:: %.3f" %accuracy)
print(class_report)
```

```
Precision:: 1.000
F1 Score:: 0.370
Accuracy:: 0.829
[[1041    0]
 [ 228   67]]
```

```
In [ ]: # Decision Tree Classifier
dt_clf = DecisionTreeClassifier(max_depth=3, random_state=42)
dt_clf, (precision, f1score, accuracy, class_report) = eval_clf(dt_clf)

print("Precision:: %.3f" %precision)
print("F1 Score:: %.3f" %f1score)
print("Accuracy:: %.3f" %accuracy)

print(class_report)
```

```
Precision:: 1.000
F1 Score:: 0.852
Accuracy:: 0.943
[[1041    0]
 [  76  219]]
```

```
In [ ]: # XGBoost Classifier
xgb_clf = XGBClassifier(n_estimators=200, max_depth=3, learning_rate=0.1, random
xgb_clf, (precision, f1score, accuracy, class_report) = eval_clf(xgb_clf)

print("Precision: %.3f" %precision)
print("F1 Score: %.3f" %f1score)
print("Accuracy: %.3f" %accuracy)

print(class_report)
```

```
Precision: 1.000
F1 Score: 0.986
Accuracy: 0.994
[[1041    0]
 [   8  287]]
```

Hyperparameter tunning

```
In [ ]: from sklearn.model_selection import GridSearchCV, RandomizedSearchCV

scale_positive_weight = (y_train==0).sum() / (y_train==1).sum()

# Model definiation
xgb_clf = XGBClassifier(objective='binary:logistic', scale_pos_weight=scale_posi

params = {
    'max_depth': range(3, 11, 2),
    'learning_rate': [0.1, 0.01, 0.02],
    'n_estimators': range(200, 1200, 100),
```

```python
    'gamma': [0.01, 0.1],
    'subsample': [0.4, 0.5, 0.6, 0.7]
}


# define grid search algorithm
grid_model = GridSearchCV(estimator=xgb_clf, param_grid=params, scoring='f1_macr

# fit the mdoel
grid_model.fit(final_x_train, y_train)
```

Out[ ]:

```
▸ GridSearchCV

▸ best_estimator_: XGBClassifier

    ▸ XGBClassifier
```

In [ ]:

```python
# Make prediction using this model and find the score.
y_preds = grid_model.predict_proba(final_x_test)[0:, 1]
y_preds = np.array([1 if y_t > 0.6 else 0 for y_t in y_preds])
score = f1_score(y_test, y_preds)
print(score)
```

Model evaluation

In [ ]:

```python
# Get the best estimator
final_xgb_model = grid_model.best_estimator_

# fit the model on the best model
final_xgb_model.fit(final_x_train, y_train)
y_predicts = final_xgb_model.predict(final_x_test)
print('Score: %.3f' %f1_score(y_test, y_predicts))
```

```
Score: 0.990
```