# 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 [ ]:

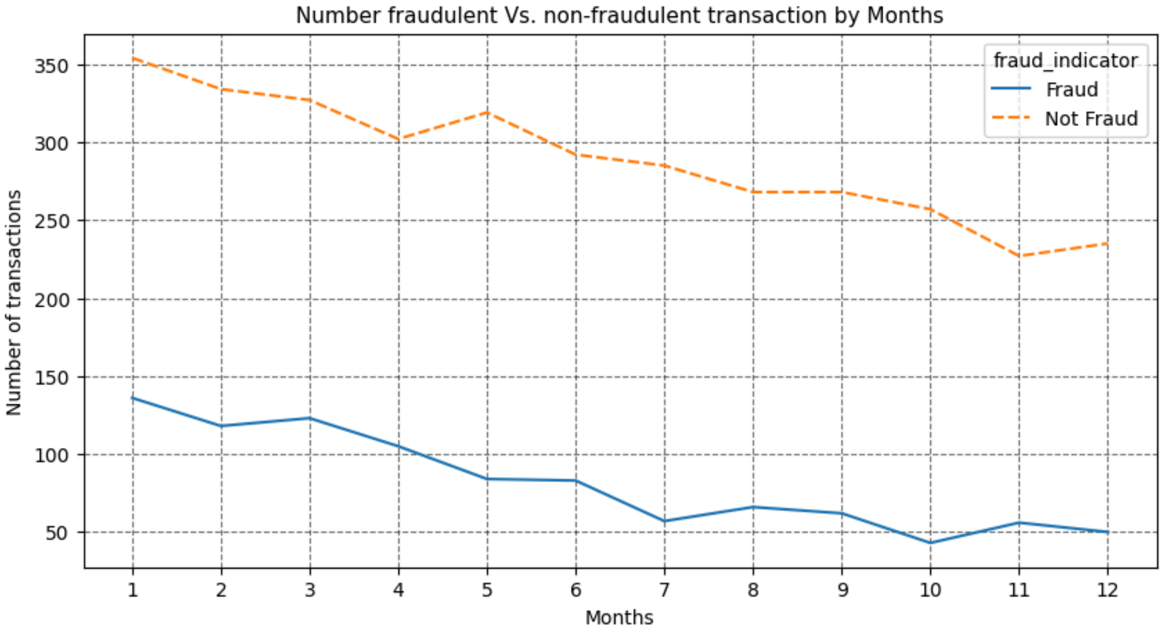
```
# Create new columns
data['month'] = data['timestamp'].dt.month
data['weekday'] = data['timestamp'].dt.weekday
data['hour'] = data['timestamp'].dt.hour
data['is_month_end'] = data['timestamp'].dt.is_month_end.astype('int')
data['is_month_start'] = data['timestamp'].dt.is_month_start.astype('int')
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
```

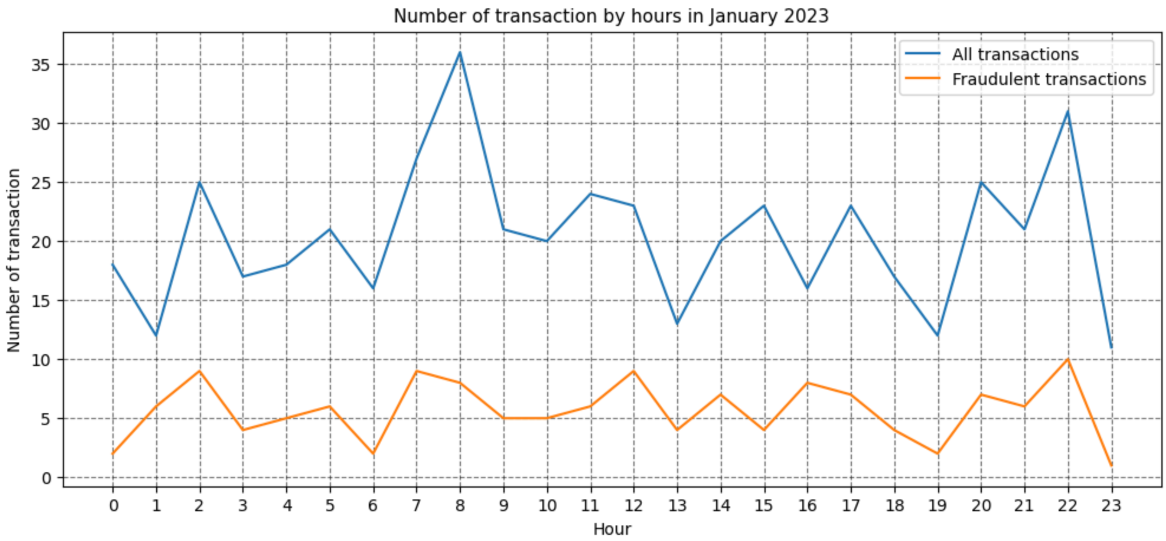
In [ ]:
```
# day-name: 0 -> Monday, 1 -> Tuesday, 2 -> Wednesday, 3 -> Thursday, 4 -> Frida
jan_23.loc[jan_23.day_month == '15-01', 'weekday'].head(1)
```

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

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

In [ ]:

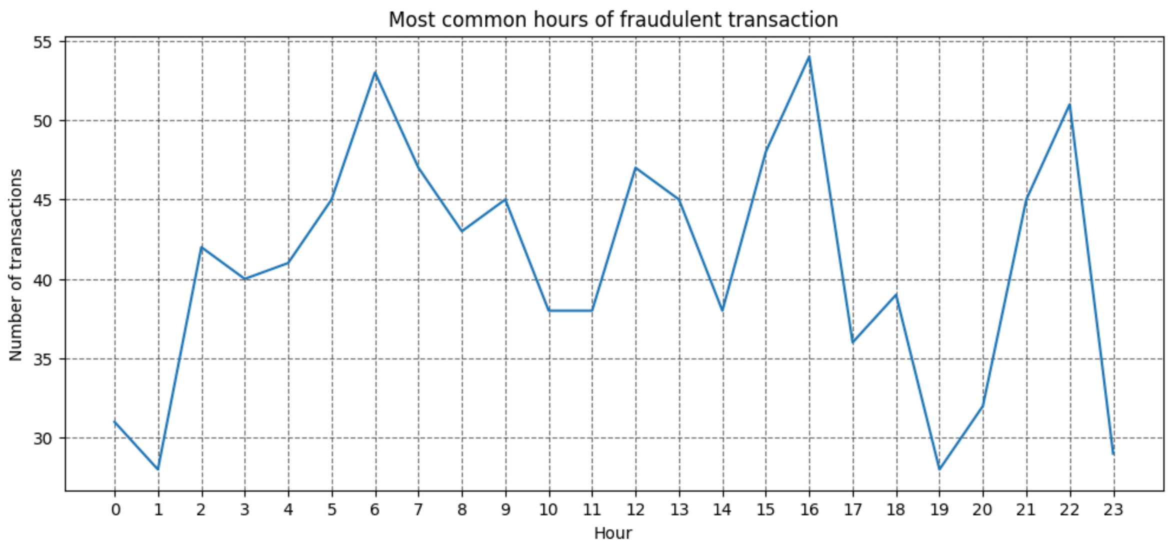
```python
# What are the most common hours for fraudulent transaction in January?

# 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 [ ]:

```python
# 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);
```

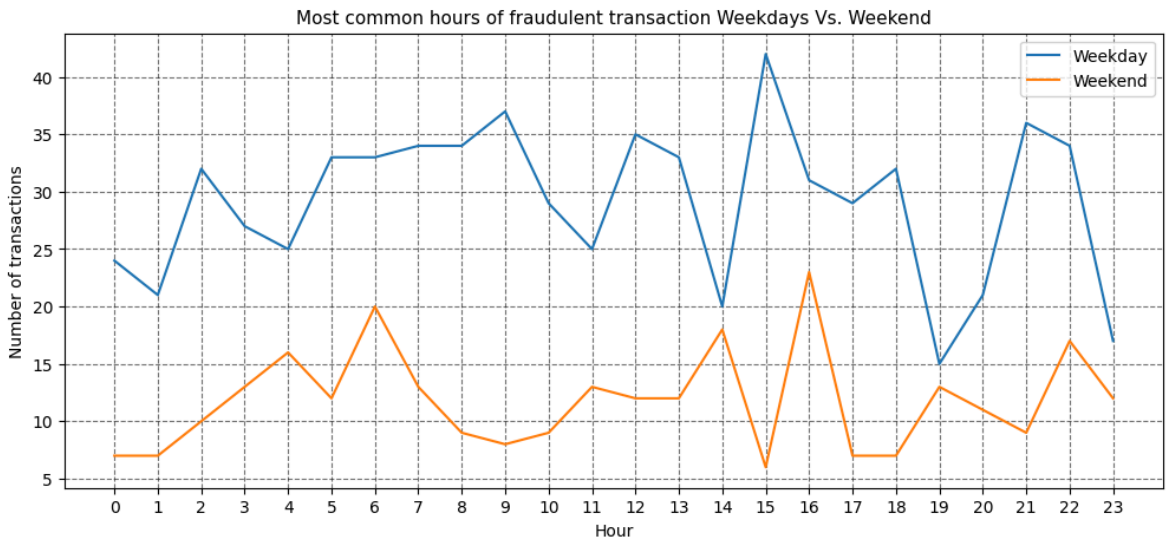



- *The line plot has some noticeable peaks at around Early mornings (around 2nd and 6th hour), and late evening (around 16th and 22th hour).*
- *Lunchtime (around 12th hour) could be another peak.*
- *This might happend because these are the peak traffic hours.*

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
```

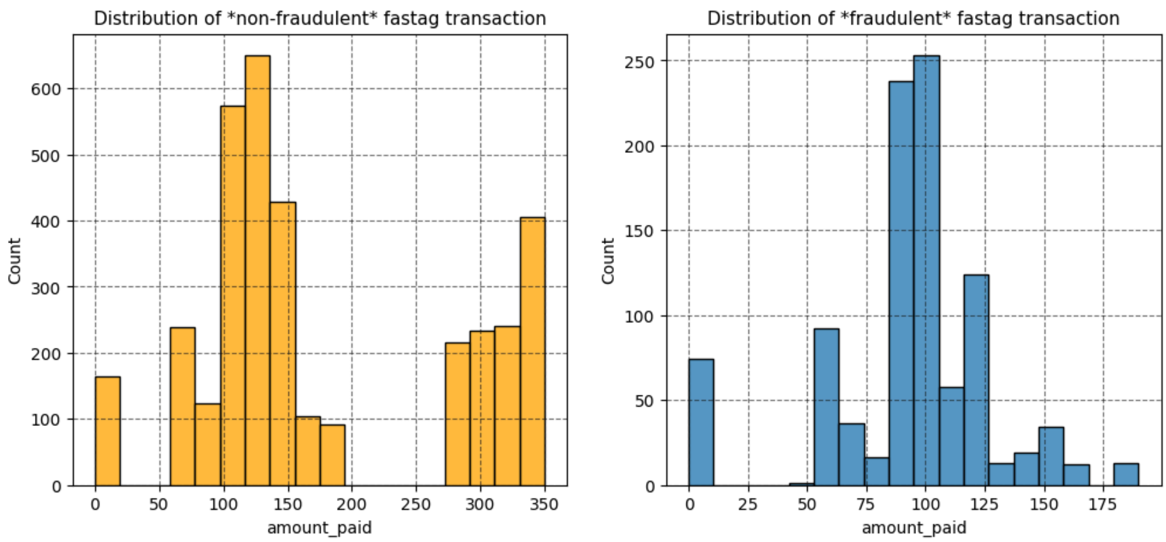
Out[ ]:

| | 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.*

To be Continue...