Maximizing Revenue

October 7, 2024

1 Maximizing Revenue for Taxi Cab Drivers through Payment Type Analysis

2 Problem Statement

In the fast-paced taxi booking sector, making the most of revenue is essential for long-term success and driver happiness. Our goal is to use data-driven insights to maximise revenue streams for taxi drivers in order to meet this need. Our research aims to determine whether payment methods have an impact on fare pricing by focusing on the relationship between payment type and fare amount.

3 Objective

This project's main goal is to run an A/B test to examine the relationship between the total fare and the method of payment. We use Python hypothesis testing and descriptive statistics to extract useful information that can help taxi drivers generate more cash. In particular, we want to find out if there is a big difference in the fares for those who pay with credit cards versus those who pay with cash.

4 Research Question

Is there a relationship between total fare amount and payment type and can we nudge customers towards payment methods that generate higher revenue for drivers, without negatively impacting customer experience?

5 Importing Libraries

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as st
import warnings
import statsmodels.api as sm
warnings.filterwarnings('ignore')
```

6 Loading the Dataset

[2]:
```
taxi_data = pd.read_csv('yellow_tripdata_2020-01.csv')
```

[3]:
```
taxi_data.head()
```

[3]:
```
   VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
0       1.0  2020-01-01 00:28:15   2020-01-01 00:33:03              1.0
1       1.0  2020-01-01 00:35:39   2020-01-01 00:43:04              1.0
2       1.0  2020-01-01 00:47:41   2020-01-01 00:53:52              1.0
3       1.0  2020-01-01 00:55:23   2020-01-01 01:00:14              1.0
4       2.0  2020-01-01 00:01:58   2020-01-01 00:04:16              1.0

   trip_distance  RatecodeID store_and_fwd_flag  PULocationID  DOLocationID  \
0            1.2         1.0                  N           238           239
1            1.2         1.0                  N           239           238
2            0.6         1.0                  N           238           238
3            0.8         1.0                  N           238           151
4            0.0         1.0                  N           193           193

   payment_type  fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
0           1.0          6.0    3.0      0.5        1.47           0.0
1           1.0          7.0    3.0      0.5        1.50           0.0
2           1.0          6.0    3.0      0.5        1.00           0.0
3           1.0          5.5    0.5      0.5        1.36           0.0
4           2.0          3.5    0.5      0.5        0.00           0.0

   improvement_surcharge  total_amount  congestion_surcharge
0                    0.3         11.27                   2.5
1                    0.3         12.30                   2.5
2                    0.3         10.80                   2.5
3                    0.3          8.16                   0.0
4                    0.3          4.80                   0.0
```

7 Exploratory Data Analysis

We perform hypothesis between payment type and fare amount. so in this we pick only those columns which are related to both or can influence them.

[4]:
```
taxi_data.shape
```

[4]:
```
(6405008, 18)
```

[5]:
```
taxi_data.dtypes
```

[5]:
```
VendorID               float64
tpep_pickup_datetime    object
```

```
tpep_dropoff_datetime     object
passenger_count          float64
trip_distance            float64
RatecodeID               float64
store_and_fwd_flag        object
PULocationID               int64
DOLocationID               int64
payment_type             float64
fare_amount              float64
extra                    float64
mta_tax                  float64
tip_amount               float64
tolls_amount             float64
improvement_surcharge    float64
total_amount             float64
congestion_surcharge     float64
dtype: object
```

[6]:
```
taxi_data['tpep_pickup_datetime'] = pd.
 ↪to_datetime(taxi_data['tpep_pickup_datetime'])
taxi_data['tpep_dropoff_datetime'] = pd.
 ↪to_datetime(taxi_data['tpep_dropoff_datetime'])
```

[7]:
```
taxi_data.dtypes
```

[7]:
```
VendorID                          float64
tpep_pickup_datetime     datetime64[ns]
tpep_dropoff_datetime    datetime64[ns]
passenger_count                   float64
trip_distance                     float64
RatecodeID                        float64
store_and_fwd_flag                 object
PULocationID                        int64
DOLocationID                        int64
payment_type                      float64
fare_amount                       float64
extra                             float64
mta_tax                           float64
tip_amount                        float64
tolls_amount                      float64
improvement_surcharge             float64
total_amount                      float64
congestion_surcharge              float64
dtype: object
```

[8]:
```

```

```
taxi_data['duration'] = taxi_data['tpep_dropoff_datetime'] -␣
 ↪taxi_data['tpep_pickup_datetime']
taxi_data['duration'] = taxi_data['duration'].dt.total_seconds()/60
```

[9]:
```
taxi_data
```

[9]:

```
         VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
0             1.0  2020-01-01 00:28:15   2020-01-01 00:33:03              1.0
1             1.0  2020-01-01 00:35:39   2020-01-01 00:43:04              1.0
2             1.0  2020-01-01 00:47:41   2020-01-01 00:53:52              1.0
3             1.0  2020-01-01 00:55:23   2020-01-01 01:00:14              1.0
4             2.0  2020-01-01 00:01:58   2020-01-01 00:04:16              1.0
…             …                    …                    …               …
6405003       NaN  2020-01-31 22:51:00   2020-01-31 23:22:00              NaN
6405004       NaN  2020-01-31 22:10:00   2020-01-31 23:26:00              NaN
6405005       NaN  2020-01-31 22:50:07   2020-01-31 23:17:57              NaN
6405006       NaN  2020-01-31 22:25:53   2020-01-31 22:48:32              NaN
6405007       NaN  2020-01-31 22:44:00   2020-01-31 23:06:00              NaN

         trip_distance  RatecodeID store_and_fwd_flag  PULocationID  \
0                 1.20         1.0                  N           238
1                 1.20         1.0                  N           239
2                 0.60         1.0                  N           238
3                 0.80         1.0                  N           238
4                 0.00         1.0                  N           193
…                    …           …                  …             …
6405003           3.24         NaN                NaN           237
6405004          22.13         NaN                NaN           259
6405005          10.51         NaN                NaN           137
6405006           5.49         NaN                NaN            50
6405007          11.60         NaN                NaN           179

         DOLocationID  payment_type  fare_amount  extra  mta_tax  tip_amount  \
0                 239           1.0         6.00   3.00      0.5        1.47
1                 238           1.0         7.00   3.00      0.5        1.50
2                 238           1.0         6.00   3.00      0.5        1.00
3                 151           1.0         5.50   0.50      0.5        1.36
4                 193           2.0         3.50   0.50      0.5        0.00
…                   …             …            …      …        …           …
6405003           234           NaN        17.59   2.75      0.5        0.00
6405004            45           NaN        46.67   2.75      0.5        0.00
6405005           169           NaN        48.85   2.75      0.0        0.00
6405006            42           NaN        27.17   2.75      0.0        0.00
6405007           205           NaN        54.56   2.75      0.5        0.00

         tolls_amount  improvement_surcharge  total_amount  \
0                0.00                    0.3         11.27
```

```
1                0.00                    0.3         12.30
2                0.00                    0.3         10.80
3                0.00                    0.3          8.16
4                0.00                    0.3          4.80
…                 …                       …           …
6405003          0.00                    0.3         21.14
6405004         12.24                    0.3         62.46
6405005          0.00                    0.3         51.90
6405006          0.00                    0.3         30.22
6405007          0.00                    0.3         58.11

         congestion_surcharge   duration
0                         2.5   4.800000
1                         2.5   7.416667
2                         2.5   6.183333
3                         0.0   4.850000
4                         0.0   2.300000
…                          …        …
6405003                   0.0  31.000000
6405004                   0.0  76.000000
6405005                   0.0  27.833333
6405006                   0.0  22.650000
6405007                   0.0  22.000000

[6405008 rows x 19 columns]
```

Extracting only that columns which are required hypothesis testing

[10]:
```
taxi_data =␣
 ↪taxi_data[['passenger_count','payment_type','fare_amount','trip_distance','duration']]
```

[11]:
```
taxi_data.isnull().sum()
```

[11]:
```
passenger_count    65441
payment_type       65441
fare_amount            0
trip_distance          0
duration               0
dtype: int64
```

[12]:
```
(65441/len(taxi_data))*100
```

[12]:
```
1.021716132126611
```

[13]:
```
taxi_data.dropna(inplace = True)
```

[14]:
```
taxi_data
```

[14]:

	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1.0	1.0	6.0	1.20	4.800000
1	1.0	1.0	7.0	1.20	7.416667
2	1.0	1.0	6.0	0.60	6.183333
3	1.0	1.0	5.5	0.80	4.850000
4	1.0	2.0	3.5	0.00	2.300000
…	…	…	…	…	…
6339562	1.0	1.0	11.0	2.10	14.233333
6339563	1.0	1.0	13.0	2.13	19.000000
6339564	1.0	1.0	12.5	2.55	16.283333
6339565	1.0	2.0	8.5	1.61	9.633333
6339566	1.0	1.0	0.0	0.00	1.066667

[6339567 rows x 5 columns]

[15]:
```
taxi_data['passenger_count'] = taxi_data['passenger_count'].astype('int64')
```

[16]:
```
taxi_data
```

[16]:

	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1	1.0	6.0	1.20	4.800000
1	1	1.0	7.0	1.20	7.416667
2	1	1.0	6.0	0.60	6.183333
3	1	1.0	5.5	0.80	4.850000
4	1	2.0	3.5	0.00	2.300000
…	…	…	…	…	…
6339562	1	1.0	11.0	2.10	14.233333
6339563	1	1.0	13.0	2.13	19.000000
6339564	1	1.0	12.5	2.55	16.283333
6339565	1	2.0	8.5	1.61	9.633333
6339566	1	1.0	0.0	0.00	1.066667

[6339567 rows x 5 columns]

[17]:
```
taxi_data['payment_type'] = taxi_data['payment_type'].astype('int64')
```

[18]:
```
taxi_data
```

[18]:

	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1	1	6.0	1.20	4.800000
1	1	1	7.0	1.20	7.416667
2	1	1	6.0	0.60	6.183333
3	1	1	5.5	0.80	4.850000
4	1	2	3.5	0.00	2.300000
…	…	…	…	…	…
6339562	1	1	11.0	2.10	14.233333
6339563	1	1	13.0	2.13	19.000000

```
6339564                1             1          12.5           2.55  16.283333
6339565                1             2           8.5           1.61   9.633333
6339566                1             1           0.0           0.00   1.066667

[6339567 rows x 5 columns]
```

[19]:
```
taxi_data[taxi_data.duplicated()]
```

[19]:
```
         passenger_count  payment_type  fare_amount  trip_distance   duration
2056                   1             2          7.0           0.00   0.000000
2441                   1             1         52.0           0.00   0.200000
2446                   2             1          9.5           1.70  13.066667
2465                   1             1          4.0           0.40   3.083333
3344                   1             1          6.0           1.20   5.350000
…                    …             …            …              …         …
6339558                1             2          8.0           1.63   8.800000
6339559                1             1          8.5           1.81   8.016667
6339560                1             2          6.5           0.98   6.900000
6339562                1             1         11.0           2.10  14.233333
6339565                1             2          8.5           1.61   9.633333

[3331706 rows x 5 columns]
```

[20]:
```
taxi_data.drop_duplicates(inplace = True)
```

[21]:
```
taxi_data.shape
```

[21]:
```
(3007861, 5)
```

Now check the contibution/distribution of column passenger_count & payment_type they both make in the data. As both column has categorical data, even though it is encoded. By doing this we check what type of variables, values it consist in it before performing analysis.

[22]:
```
taxi_data['passenger_count'].value_counts(normalize = True)
```

[22]:
```
passenger_count
1    0.581981
2    0.190350
3    0.066360
5    0.062937
6    0.039272
4    0.036046
0    0.023033
7    0.000009
9    0.000006
8    0.000006
Name: proportion, dtype: float64
```

value_counts = Give frequency of value counts of the categorical data ....., normalize = This parameter is used to give percentage of the contribution/distribution.

[23]:
```
taxi_data['payment_type'].value_counts(normalize = True)
```

[23]:
```
payment_type
1    6.782670e-01
2    3.075731e-01
3    8.721480e-03
4    5.438084e-03
5    3.324622e-07
Name: proportion, dtype: float64
```

As we do not need more than 2 payment type and also no need more than 6 passengers at a time during cab booking.

[24]:
```
taxi_data =␣
↪taxi_data[(taxi_data['passenger_count']>0)&(taxi_data['passenger_count']<6)]
taxi_data = taxi_data[taxi_data['payment_type']<3]
```

[25]:
```
taxi_data.shape
```

[25]:
```
(2780283, 5)
```

[26]:
```
taxi_data['payment_type'].replace([1,2],['UPI','Cash'],inplace = True)
```

[27]:
```
taxi_data
```

[27]:

	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1	UPI	6.0	1.20	4.800000
1	1	UPI	7.0	1.20	7.416667
2	1	UPI	6.0	0.60	6.183333
3	1	UPI	5.5	0.80	4.850000
4	1	Cash	3.5	0.00	2.300000
…	…	…	…	…	…
6339555	3	UPI	10.0	2.09	14.800000
6339561	1	UPI	17.5	4.11	21.500000
6339563	1	UPI	13.0	2.13	19.000000
6339564	1	UPI	12.5	2.55	16.283333
6339566	1	UPI	0.0	0.00	1.066667

[2780283 rows x 5 columns]

Now we check out numerical data after filtering out categorical data.. For numerical data we use describe() function

[28]:
```
taxi_data.describe()
```

[28]:
```
       passenger_count   fare_amount  trip_distance      duration
count     2.780283e+06  2.780283e+06   2.780283e+06  2.780283e+06
mean      1.733386e+00  1.780567e+01   4.536729e+00  2.415478e+01
std       1.176652e+00  1.506997e+01   4.895890e+00  9.260031e+01
min       1.000000e+00 -5.000000e+02  -2.218000e+01 -2.770367e+03
25%       1.000000e+00  9.000000e+00   1.500000e+00  9.883333e+00
50%       1.000000e+00  1.300000e+01   2.730000e+00  1.573333e+01
75%       2.000000e+00  2.100000e+01   5.470000e+00  2.336667e+01
max       5.000000e+00  4.265000e+03   2.628800e+02  8.525117e+03
```

[29]:
```
taxi_data = taxi_data[taxi_data['fare_amount']>0]
taxi_data = taxi_data[taxi_data['trip_distance']>0]
taxi_data = taxi_data[taxi_data['duration']>0]
```

[30]:
```
taxi_data
```

[30]:

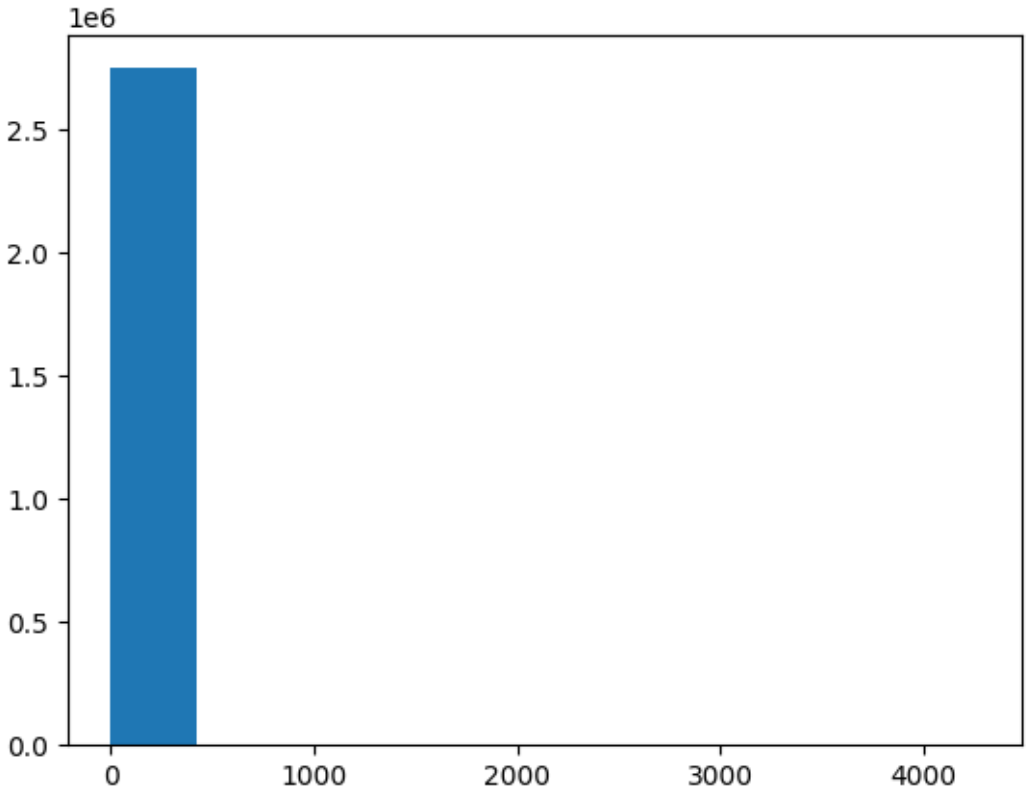
	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1	UPI	6.0	1.20	4.800000
1	1	UPI	7.0	1.20	7.416667
2	1	UPI	6.0	0.60	6.183333
3	1	UPI	5.5	0.80	4.850000
5	1	Cash	2.5	0.03	0.883333
…	…	…	…	…	…
6339550	4	UPI	10.5	2.40	12.383333
6339555	3	UPI	10.0	2.09	14.800000
6339561	1	UPI	17.5	4.11	21.500000
6339563	1	UPI	13.0	2.13	19.000000
6339564	1	UPI	12.5	2.55	16.283333

[2748932 rows x 5 columns]

Now checking whether outliers present in data or not (with the help of one of the function 'plt.hist'), whether it is in significant amount or we can ignore it. If it is significant no then we have to remove it..

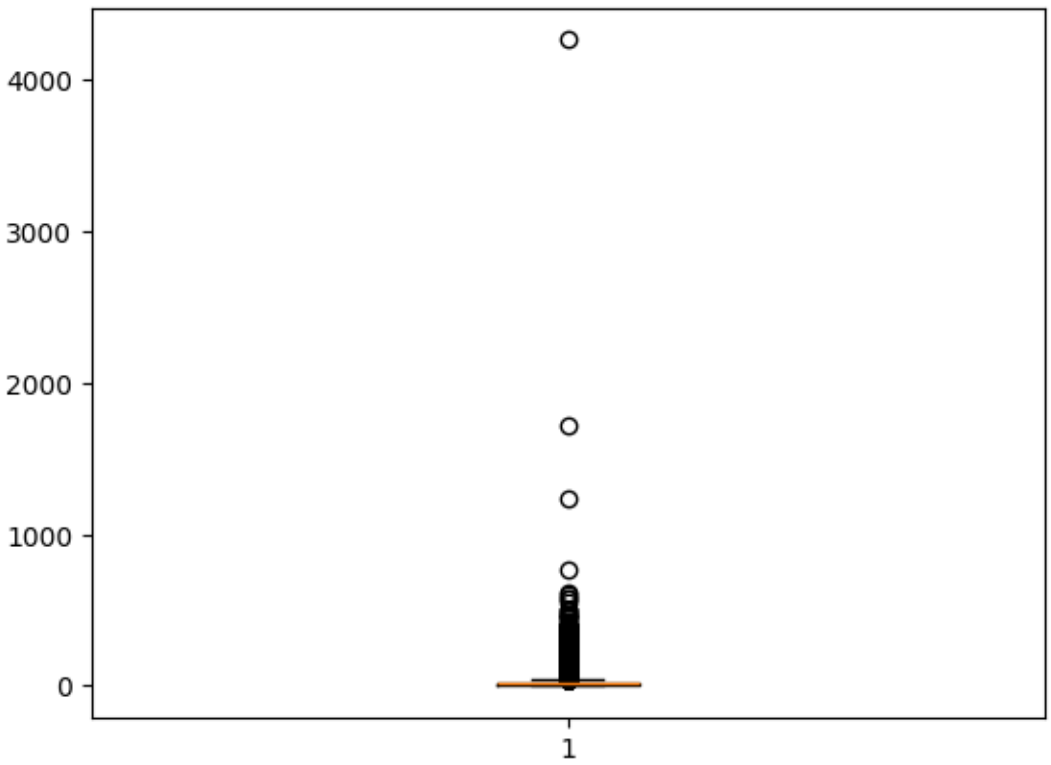
[31]:
```
plt.hist(taxi_data['fare_amount'])
```

[31]:
```
(array([2.748913e+06, 1.600000e+01, 1.000000e+00, 0.000000e+00,
        1.000000e+00, 0.000000e+00, 0.000000e+00, 0.000000e+00,
        0.000000e+00, 1.000000e+00]),
 array([1.000000e-02, 4.265090e+02, 8.530080e+02, 1.279507e+03,
        1.706006e+03, 2.132505e+03, 2.559004e+03, 2.985503e+03,
        3.412002e+03, 3.838501e+03, 4.265000e+03]),
 <BarContainer object of 10 artists>)
```



[32]:
```
plt.boxplot(taxi_data['fare_amount'])
```

[32]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x28bc7f4edb0>,
  <matplotlib.lines.Line2D at 0x28b8079fbc0>],
 'caps': [<matplotlib.lines.Line2D at 0x28b8079fec0>,
  <matplotlib.lines.Line2D at 0x28b807dc1a0>],
 'boxes': [<matplotlib.lines.Line2D at 0x28b8079f560>],
 'medians': [<matplotlib.lines.Line2D at 0x28b807dc470>],
 'fliers': [<matplotlib.lines.Line2D at 0x28b807dc770>],
 'means': []}
```



To remove outlier either we use z-score method or inter-quartile range.. In thos we use inter-quartile method bcz data doesnot seems to be normally distributed for z-score method to be used..

[33]:
```
for col in ['fare_amount','trip_distance','duration']:
    q1 = taxi_data[col].quantile(0.25)
    q3 = taxi_data[col].quantile(0.75)
    IQR = q3-q1

    lower_bound = q1-1.5*IQR
    upper_bound = q3+1.5*IQR

    taxi_data = taxi_data[(taxi_data[col]>=lower_bound) &␣
 ↪(taxi_data[col]<=upper_bound)]
```

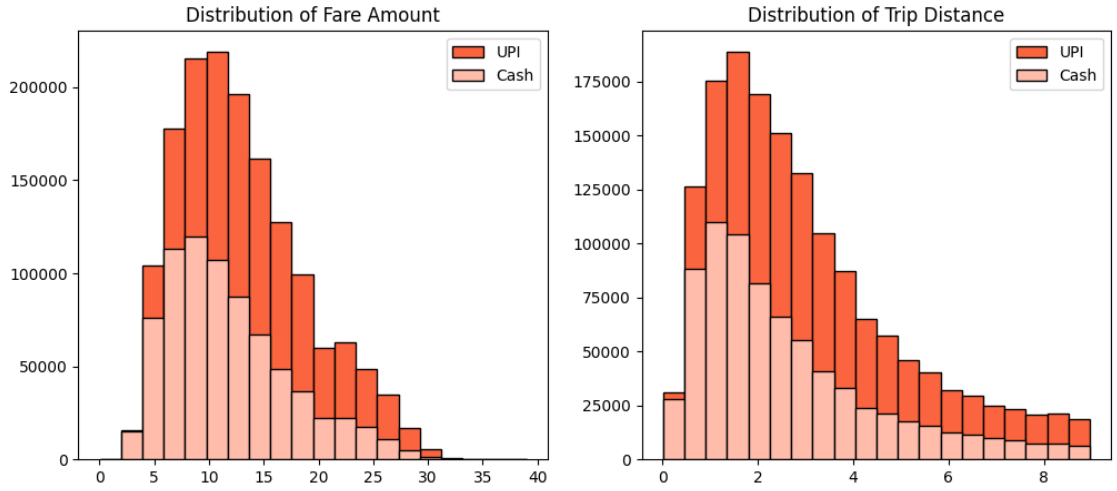
[34]:
```
taxi_data
```

[34]:

	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1	UPI	6.0	1.20	4.800000
1	1	UPI	7.0	1.20	7.416667
2	1	UPI	6.0	0.60	6.183333
3	1	UPI	5.5	0.80	4.850000
5	1	Cash	2.5	0.03	0.883333

```
...                    ...          ...          ...          ...          ...
6339550                4            UPI          10.5         2.40    12.383333
6339555                3            UPI          10.0         2.09    14.800000
6339561                1            UPI          17.5         4.11    21.500000
6339563                1            UPI          13.0         2.13    19.000000
6339564                1            UPI          12.5         2.55    16.283333

[2297908 rows x 5 columns]
```

[35]:
```
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.title('Distribution of Fare Amount')
plt.hist(taxi_data[taxi_data['payment_type']=='UPI']['fare_amount'], histtype=␣
 ↪'barstacked', bins = 20, edgecolor = 'k', color = '#FA643F', label = 'UPI')
plt.hist(taxi_data[taxi_data['payment_type']=='Cash']['fare_amount'], histtype=␣
 ↪'barstacked', bins = 20, edgecolor = 'k', color = '#FFBCAB', label = 'Cash')
plt.legend()

plt.subplot(1,2,2)
plt.title('Distribution of Trip Distance')
plt.hist(taxi_data[taxi_data['payment_type']=='UPI']['trip_distance'],␣
 ↪histtype= 'barstacked', bins = 20, edgecolor = 'k', color = '#FA643F', label␣
 ↪= 'UPI')
plt.hist(taxi_data[taxi_data['payment_type']=='Cash']['trip_distance'],␣
 ↪histtype= 'barstacked', bins = 20, edgecolor = 'k', color = '#FFBCAB', label␣
 ↪= 'Cash')
plt.legend()
plt.show()
```



Now checking mean, std of both parameter so we can compare it..

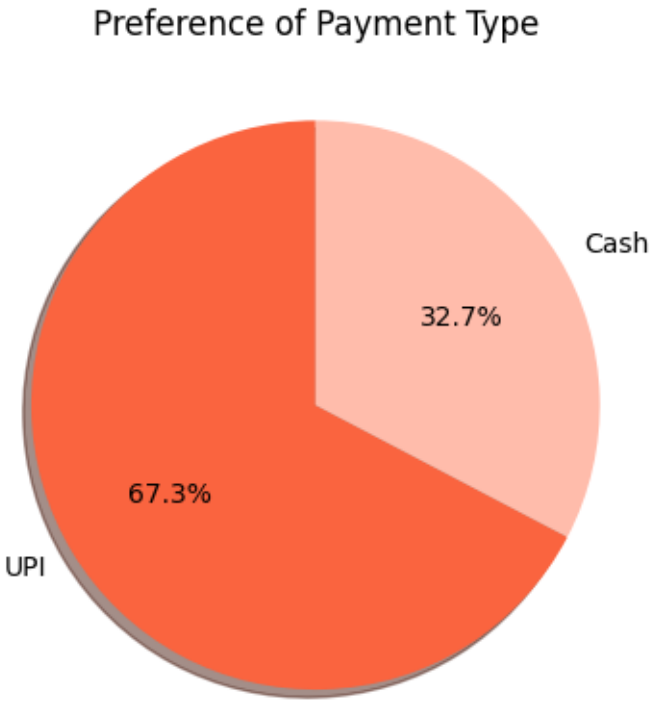
[36]:
```
taxi_data.groupby('payment_type').agg({'fare_amount':['mean','std'],␣
↪'trip_distance':['mean','std']})
```

[36]:

	fare_amount		trip_distance	
	mean	std	mean	std
payment_type				
Cash	11.758005	5.613038	2.602207	1.91372
UPI	13.112493	5.849281	2.992237	1.99274

Now we check in what percent customer pay through upi and also from cash. For it we use pie chart to depict it.

[37]:
```
plt.title('Preference of Payment Type')
plt.pie(taxi_data['payment_type'].value_counts(normalize = True), labels =␣
↪taxi_data['payment_type'].value_counts().index,
        startangle =90, shadow = True, autopct ='%1.1f%%', colors =␣
↪['#FA643F','#FFBCAB'])
plt.show()
```



Now check payment type(upi or cash) distribution on the basis of passenger count. We have max of 5 passengers, to depict this we use Stacked bar chart..

8 Passenger Count Analysis

1. Among UPI payments, rides with a single passenger (passenger_count = 1) comprise the largest proportion, constituting 40.08% of all UPI transactions.
2. Similarly, cash payments are predominantly associated with single-passenger rides, making up 20.04% of all cash transactions.
3. There is a noticeable decrease in the percentage of transactions as the passenger count increases, suggesting that larger groups are less likely to use taxis or may opt for alternative payment methods.
4. These insights emphasize the importance of considering both payment method and passenger count when analyzing transaction data, as they provide valuable insights into customer behavior and preferences.

[38]:
```
taxi_data.groupby(['payment_type','passenger_count'])[['passenger_count']].
↪count()
```

[38]:

		passenger_count
payment_type	passenger_count	
Cash	1	460550
	2	155472
	3	54506
	4	32715
	5	47626
UPI	1	909245
	2	327661
	3	122412
	4	63676
	5	124045

[39]:
```
passenger_count = taxi_data.
↪groupby(['payment_type','passenger_count'])[['passenger_count']].count()
passenger_count.rename(columns = {'passenger_count':'count'}, inplace = True)
passenger_count.reset_index(inplace = True)
```

[40]:
```
passenger_count['perc'] = passenger_count['count']/passenger_count['count'].
↪sum()*100
```

[41]:
```
passenger_count
```

[41]:

	payment_type	passenger_count	count	perc
0	Cash	1	460550	20.042143
1	Cash	2	155472	6.765806
2	Cash	3	54506	2.371984
3	Cash	4	32715	1.423686
4	Cash	5	47626	2.072581
5	UPI	1	909245	39.568381
6	UPI	2	327661	14.259100
7	UPI	3	122412	5.327106

```
8          UPI                4   63676   2.771042
9          UPI                5  124045   5.398171
```

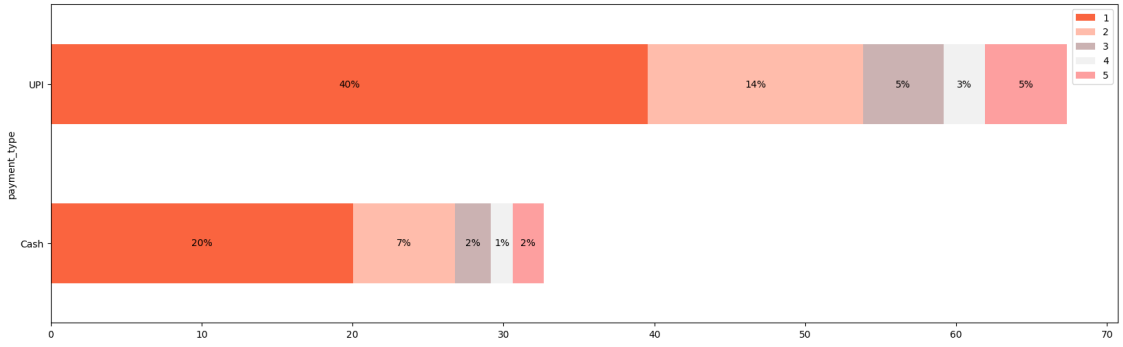
Now we have to plot this percentage value in a stacked bar chart. for this we create a custom dataset, to transform these values and then put it in the chart. At first we create an empty dataframe to store this data. If we directly make chart using that value without use of dataframe then we are not able to generate stacked bar chart, we could only create normal bar chart. Thats why we create dataframe.

[42]:
```
df = pd.DataFrame(columns = ['payment_type',1,2,3,4,5])
df['payment_type'] = ['Cash', 'UPI']
df.iloc[0,1:] = passenger_count.iloc[0:5,-1]
df.iloc[1,1:] = passenger_count.iloc[5:,-1]
df
```

[42]:

	payment_type	1	2	3	4	5
0	Cash	20.042143	6.765806	2.371984	1.423686	2.072581
1	UPI	39.568381	14.2591	5.327106	2.771042	5.398171

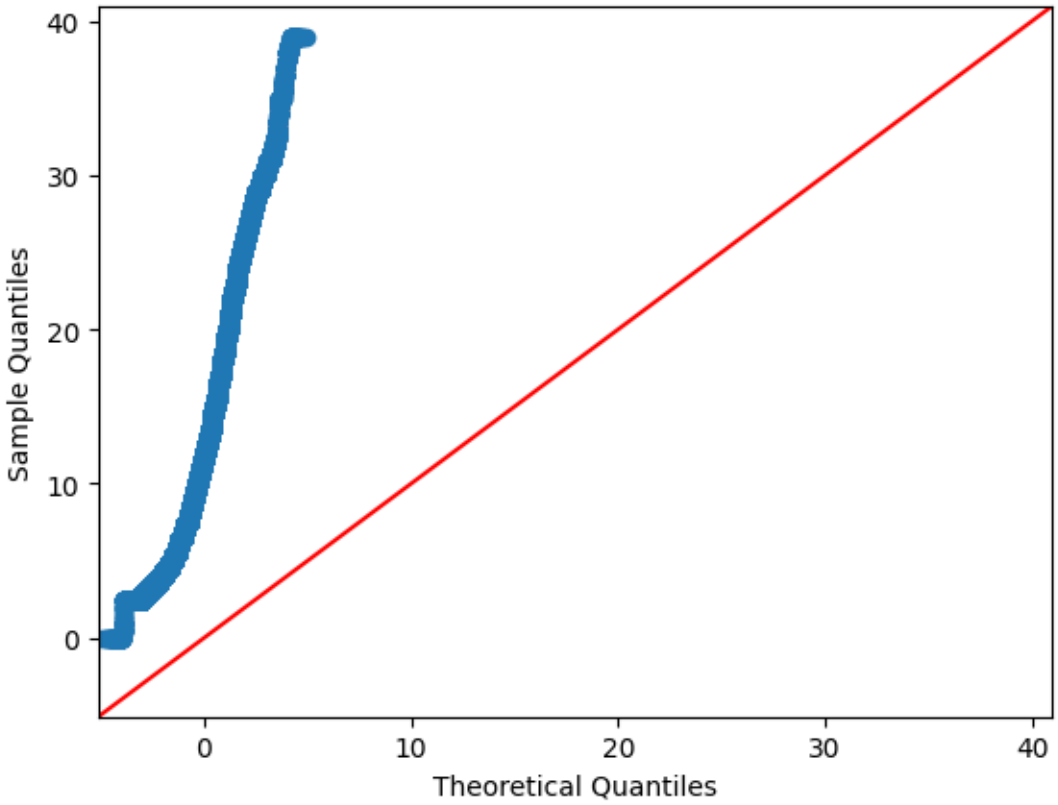
[43]:
```
fig, ax = plt.subplots(figsize=(20, 6))
df.plot(x ='payment_type', kind = 'barh', stacked = True, color =␣
↪['#FA643F','#FFBCAB','#CBB2B2','#F1F1F1','#Fd9F9F'], ax=ax)

# Add Pecentage Text

for p in ax.patches:
    width= p.get_width()
    height=p.get_height()
    x, y = p.get_xy()
    ax.text(x + width / 2,
            y + height / 2,
            '{:.0f}%'.format(width),
            horizontalalignment='center',
            verticalalignment='center')
```



9 Null Hypothesis: There is no difference in avg fare b/w customers who use upi and customers who use cash.

10 Alternate Hypothesis: There is difference in avg fare b/w customers who use upi and customers who use cash.

[44]:
```
sm.qqplot(taxi_data['fare_amount'], line = '45')
plt.show()
```



[45]:
```
UPI_sample = taxi_data[taxi_data['payment_type']=='UPI']['fare_amount']
Cash_sample = taxi_data[taxi_data['payment_type']=='Cash']['fare_amount']
```

[46]:
```
t_stats, p_value = st.ttest_ind(a = UPI_sample, b = Cash_sample, equal_var =␣
 ↪False)
print('T statistic:', t_stats, 'p-value:',p_value)
```

```
T statistic: 169.2111527245052 p-value: 0.0
```

#With a T-statistic of 169.2 and a P value less than 0.05, we reject null hypothesis, suggesting that there is indeed a significant difference in avg fare b/w the two payment methods.(we take significance value=0.05, means 5%)

[ ]: