G2M insight for Cab Investment firm

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In [49]:
```
# import all the packages that are required.

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import datetime as dt
from scipy import stats
```

In [3]:
```
# reading the csv files

cab_data = pd.read_csv('.\DataSets-main\Cab_Data.csv')
city= pd.read_csv('.\DataSets-main\City.csv')
cust_id = pd.read_csv('.\DataSets-main\Customer_ID.csv')
trans_id= pd.read_csv('.\DataSets-main\Transaction_ID.csv')
```

CAB Data

In [21]:
```
cab_data.head()
```

Out[21]:

	Transaction ID	Date of Travel	Company	City	KM Travelled	Price Charged	Cost of Trip
0	10000011	42377	Pink Cab	ATLANTA GA	30.45	370.95	313.635
1	10000012	42375	Pink Cab	ATLANTA GA	28.62	358.52	334.854
2	10000013	42371	Pink Cab	ATLANTA GA	9.04	125.20	97.632
3	10000014	42376	Pink Cab	ATLANTA GA	33.17	377.40	351.602
4	10000015	42372	Pink Cab	ATLANTA GA	8.73	114.62	97.776

In [23]:
```
cab_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 359392 entries, 0 to 359391
Data columns (total 7 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   Transaction ID  359392 non-null  int64  
 1   Date of Travel  359392 non-null  int64  
 2   Company         359392 non-null  object 
 3   City            359392 non-null  object 
 4   KM Travelled    359392 non-null  float64
 5   Price Charged   359392 non-null  float64
 6   Cost of Trip    359392 non-null  float64
dtypes: float64(3), int64(2), object(2)
memory usage: 19.2+ MB
```

In [25]:

```
# cab dataset shape

print("Number of rows:", cab_data.shape[0])
print("Number of columns:",cab_data.shape[1])
```

```
Number of rows: 359392
Number of columns: 7
```

In [107…

```
# Cab data description

cab_data.describe()
```

Out[107]:

	Transaction ID	KM Travelled	Price Charged	Cost of Trip
count	3.593920e+05	359392.000000	359392.000000	359392.000000
mean	1.022076e+07	22.567254	423.443311	286.190113
std	1.268058e+05	12.233526	274.378911	157.993661
min	1.000001e+07	1.900000	15.600000	19.000000
25%	1.011081e+07	12.000000	206.437500	151.200000
50%	1.022104e+07	22.440000	386.360000	282.480000
75%	1.033094e+07	32.960000	583.660000	413.683200
max	1.044011e+07	48.000000	2048.030000	691.200000

In [117…

```
# Now check the type

cab_data.dtypes
```

Out[117]:

```
Transaction ID             int64
Date of Travel    datetime64[ns]
Company                   object
City                      object
KM Travelled             float64
Price Charged            float64
Cost of Trip             float64
dtype: object
```

In [27]:
```
# cab data column names

cab_data.columns
```

Out[27]:
```
Index(['Transaction ID', 'Date of Travel', 'Company', 'City', 'KM Travelle
d',
       'Price Charged', 'Cost of Trip'],
      dtype='object')
```

In [32]:
```
# unique values in categorical columns -campany

print(cab_data['Company'].unique())
```

```
['Pink Cab' 'Yellow Cab']
```

In [64]:
```
# categorical columns -city

print(cab_data['City'].unique())
```

```
['ATLANTA GA' 'AUSTIN TX' 'BOSTON MA' 'CHICAGO IL' 'DALLAS TX' 'DENVER CO'
 'LOS ANGELES CA' 'MIAMI FL' 'NASHVILLE TN' 'NEW YORK NY' 'ORANGE COUNTY'
 'PHOENIX AZ' 'PITTSBURGH PA' 'SACRAMENTO CA' 'SAN DIEGO CA' 'SEATTLE WA'
 'SILICON VALLEY' 'TUCSON AZ' 'WASHINGTON DC']
```

In [34]:
```
# cab data min and max dates

print("Minimum Date: ", cab_data['Date of Travel'].min())
print("Maximum Date: ", cab_data['Date of Travel'].max())
```

```
Minimum Date:  42377
Maximum Date:  43465
```

In [25]:
```
# Traveling date handling

from datetime import datetime

min_date = cab_data ['Date of Travel'].min()
max_date = cab_data ['Date of Travel'].max()

trans_min = datetime.fromordinal(datetime(1900, 1, 27).toordinal() + min_dat
trans_max = datetime.fromordinal(datetime(1899, 12, 30).toordinal() + max_da

print(trans_min)
print(trans_max)
```

```
30-01-2016
31-12-2018
```

In [26]:
```
def handle_date(date):
    convert = datetime.fromordinal(datetime(1900, 1, 30).toordinal() + date
    return datetime.strptime(convert, "%d-%m-%Y")
```

In [29]:
```
cab_data
```

Out[29]:

	Transaction ID	Date of Travel	Company	City	KM Travelled	Price Charged	Cost of Trip
0	10000011	2016-02-06	Pink Cab	ATLANTA GA	30.45	370.95	313.6350
1	10000012	2016-02-04	Pink Cab	ATLANTA GA	28.62	358.52	334.8540
2	10000013	2016-01-31	Pink Cab	ATLANTA GA	9.04	125.20	97.6320
3	10000014	2016-02-05	Pink Cab	ATLANTA GA	33.17	377.40	351.6020
4	10000015	2016-02-01	Pink Cab	ATLANTA GA	8.73	114.62	97.7760
...	...	...	...	...	...	...	...
359387	10440101	2018-02-06	Yellow Cab	WASHINGTON DC	4.80	69.24	63.3600
359388	10440104	2018-02-02	Yellow Cab	WASHINGTON DC	8.40	113.75	106.8480
359389	10440105	2018-02-03	Yellow Cab	WASHINGTON DC	27.75	437.07	349.6500
359390	10440106	2018-02-03	Yellow Cab	WASHINGTON DC	8.80	146.19	114.0480
359391	10440107	2018-01-31	Yellow Cab	WASHINGTON DC	12.76	191.58	177.6192

359392 rows × 7 columns

In [108…

```
#checking for missing values

print("\n Missing values in Cab Dataset \n",cab_data.isnull().sum())
```

```
 Missing values in Cab Dataset 
 Transaction ID    0
Date of Travel    0
Company           0
City              0
KM Travelled      0
Price Charged     0
Cost of Trip      0
dtype: int64
```

There is no missing values in cab data

City Data

In [109…

```
city.head()
```

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Out[109]:

	City	Population	Users
0	NEW YORK NY	8,405,837	302,149
1	CHICAGO IL	1,955,130	164,468
2	LOS ANGELES CA	1,595,037	144,132
3	MIAMI FL	1,339,155	17,675
4	SILICON VALLEY	1,177,609	27,247

In [110…

```
city.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   City        20 non-null     object
 1   Population  20 non-null     object
 2   Users       20 non-null     object
dtypes: object(3)
memory usage: 608.0+ bytes
```

In [112…

```
# Now check the type

city.dtypes
```

Out[112]:

```
City          object
Population    object
Users         object
dtype: object
```

In [125…

```
# city dataset shape

print("Number of rows:", city.shape[0])
print("Number of columns:",city.shape[1])
```

```
Number of rows: 20
Number of columns: 3
```

In [119…

```
city.columns
```

Out[119]: Index(['City', 'Population', 'Users'], dtype='object')

In [120…

```
# checking missing values

print("\n Missing values in City Dataset \n",city.isnull().sum())
```

```
 Missing values in City Dataset 
 City          0
Population    0
Users         0
dtype: int64
```

There is no missing values in city dataset.

In [123…

```
# Attribute 'Population' should be an integer

city['Population'] = [x.replace(',','') for x in city['Population']]
city['Population'] = city['Population'].astype(float)

# Attribute 'Users' should be an integer

city['Users'] = [x.replace(',','') for x in city['Users']]
city['Users'] = city['Users'].astype(float)
```

In [124…

```
# City Description

city.describe()
```

Out[124]:

	Population	Users
count	2.000000e+01	20.000000
mean	1.231592e+06	64520.650000
std	1.740127e+06	83499.375289
min	2.489680e+05	3643.000000
25%	6.086372e+05	11633.250000
50%	7.845590e+05	23429.000000
75%	1.067041e+06	91766.000000
max	8.405837e+06	302149.000000

In [68]:

```
city['Users'] = city['Users'].replace(",","", regex=True).astype(int)
city['Population'] = city['Population'].replace(",","", regex=True).astype(i
city
```

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Out[68]:

	City	Population	Users
0	NEW YORK NY	8405837	302149
1	CHICAGO IL	1955130	164468
2	LOS ANGELES CA	1595037	144132
3	MIAMI FL	1339155	17675
4	SILICON VALLEY	1177609	27247
5	ORANGE COUNTY	1030185	12994
6	SAN DIEGO CA	959307	69995
7	PHOENIX AZ	943999	6133
8	DALLAS TX	942908	22157
9	ATLANTA GA	814885	24701
10	DENVER CO	754233	12421
11	AUSTIN TX	698371	14978
12	SEATTLE WA	671238	25063
13	TUCSON AZ	631442	5712
14	SAN FRANCISCO CA	629591	213609
15	SACRAMENTO CA	545776	7044
16	PITTSBURGH PA	542085	3643
17	WASHINGTON DC	418859	127001
18	NASHVILLE TN	327225	9270
19	BOSTON MA	248968	80021

Customer ID data

In [126…

```
cust_id.head()
```

Out[126]:

	Customer ID	Gender	Age	Income (USD/Month)
0	29290	Male	28	10813
1	27703	Male	27	9237
2	28712	Male	53	11242
3	28020	Male	23	23327
4	27182	Male	33	8536

In [127…

```
cust_id.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49171 entries, 0 to 49170
Data columns (total 4 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   Customer ID          49171 non-null  int64 
 1   Gender               49171 non-null  object
 2   Age                  49171 non-null  int64 
 3   Income (USD/Month)  49171 non-null  int64 
dtypes: int64(3), object(1)
memory usage: 1.5+ MB
```

In [128…

```
 #checking datatype

cust_id.dtypes
```

Out[128]:

```
Customer ID            int64
Gender                object
Age                    int64
Income (USD/Month)     int64
dtype: object
```

In [129…

```
#number of rows and colmns

print("Number of rows:", cust_id.shape[0])
print("Number of columns:",cust_id.shape[1])
```

```
Number of rows: 49171
Number of columns: 4
```

In [134…

```
#checking missing values

print("\n Missing values in Transaction Dataset \n",trans_id.isnull().sum())
```

```
 Missing values in Transaction Dataset 
 Transaction ID    0
Customer ID       0
Payment_Mode      0
dtype: int64
```

There is no missing values in Customer dataset

In [132…

```
#column names

cust_id.columns
```

Out[132]:

```
Index(['Customer ID', 'Gender', 'Age', 'Income (USD/Month)'], dtype='objec
t')
```

In [136…

```
cust_id['Gender'].unique()
```

Out[136]:

```
array(['Male', 'Female'], dtype=object)
```

In [137…

```
#Customer description

cust_id.describe()
```

Out[137]:

	Customer ID	Age	Income (USD/Month)
count	49171.000000	49171.000000	49171.000000
mean	28398.252283	35.363121	15015.631856
std	17714.137333	12.599066	8002.208253
min	1.000000	18.000000	2000.000000
25%	12654.500000	25.000000	8289.500000
50%	27631.000000	33.000000	14656.000000
75%	43284.500000	42.000000	21035.000000
max	60000.000000	65.000000	35000.000000

Transaction ID Data

In [138…

```
trans_id.head()
```

Out[138]:

	Transaction ID	Customer ID	Payment_Mode
0	10000011	29290	Card
1	10000012	27703	Card
2	10000013	28712	Cash
3	10000014	28020	Cash
4	10000015	27182	Card

In [139…

```
trans_id.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 440098 entries, 0 to 440097
Data columns (total 3 columns):
 #   Column          Non-Null Count   Dtype 
---  ------          --------------   ----- 
 0   Transaction ID  440098 non-null  int64 
 1   Customer ID     440098 non-null  int64 
 2   Payment_Mode    440098 non-null  object
dtypes: int64(2), object(1)
memory usage: 10.1+ MB
```

In [140…

```
#Checking datatype

trans_id.dtypes
```

Out[140]:

```
Transaction ID     int64
Customer ID        int64
Payment_Mode      object
dtype: object
```

In [141…

```
#Number of rows and columns
```

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```
print("Number of rows:", trans_id.shape[0])
print("Number of columns:",trans_id.shape[1])
```

```
Number of rows: 440098
Number of columns: 3
```

In [142…

```
#Column names

trans_id.columns
```

Out[142]:

```
Index(['Transaction ID', 'Customer ID', 'Payment_Mode'], dtype='object')
```

In [144…

```
trans_id['Payment_Mode'].unique()
```

Out[144]:

```
array(['Card', 'Cash'], dtype=object)
```

In [145…

```
#checking missing values

print("\n Missing values in Transaction Dataset \n",trans_id.isnull().sum())
```

```
 Missing values in Transaction Dataset 
 Transaction ID    0
Customer ID       0
Payment_Mode      0
dtype: int64
```

There is no missing values in Transaction Id dataset

In [148…

```
#transcation descruption

trans_id.describe(include = 'all', datetime_is_numeric=True)
```

Out[148]:

	Transaction ID	Customer ID	Payment_Mode
count	4.400980e+05	440098.000000	440098
unique	NaN	NaN	2
top	NaN	NaN	Card
freq	NaN	NaN	263991
mean	1.022006e+07	23619.513120	NaN
std	1.270455e+05	21195.549816	NaN
min	1.000001e+07	1.000000	NaN
25%	1.011004e+07	3530.000000	NaN
50%	1.022006e+07	15168.000000	NaN
75%	1.033008e+07	43884.000000	NaN
max	1.044011e+07	60000.000000	NaN

Creating Master Data

Loading [MathJax]/extensions/Safe.js

We have merged all dataset safely without lossing any data.

In [4]:
```
# merged all datasets

master_data = cab_data.merge(trans_id, on= 'Transaction ID').merge(
    cust_id, on ='Customer ID').merge(city, on = 'City')

master_data
```

Out[4]:

	Transaction ID	Date of Travel	Company	City	KM Travelled	Price Charged	Cost of Trip	Customer ID
0	10000011	42377	Pink Cab	ATLANTA GA	30.45	370.95	313.6350	29290
1	10351127	43302	Yellow Cab	ATLANTA GA	26.19	598.70	317.4228	29290
2	10412921	43427	Yellow Cab	ATLANTA GA	42.55	792.05	597.4020	29290
3	10000012	42375	Pink Cab	ATLANTA GA	28.62	358.52	334.8540	27703
4	10320494	43211	Yellow Cab	ATLANTA GA	36.38	721.10	467.1192	27703
...	...	...	...	...	...	...	...	...
359387	10307228	43162	Yellow Cab	WASHINGTON DC	38.40	668.93	525.3120	51406
359388	10319775	43203	Yellow Cab	WASHINGTON DC	3.57	67.60	44.5536	51406
359389	10347676	43287	Yellow Cab	WASHINGTON DC	23.46	331.97	337.8240	51406
359390	10358624	43314	Yellow Cab	WASHINGTON DC	27.60	358.23	364.3200	51406
359391	10370709	43342	Yellow Cab	WASHINGTON DC	34.24	453.11	427.3152	51406

359392 rows × 14 columns

In [70]:
```
# masterdata detailed info

master_data.info
```

```
Out[70]: <bound method DataFrame.info of         Transaction ID Date of Travel     C
ompany           City  \
0             10000011     2016-02-06    Pink Cab     ATLANTA GA
1             10351127     2018-08-19  Yellow Cab     ATLANTA GA
2             10412921     2018-12-22  Yellow Cab     ATLANTA GA
3             10000012     2016-02-04    Pink Cab     ATLANTA GA
4             10320494     2018-05-20  Yellow Cab     ATLANTA GA
...                ...            ...         ...            ...
359387        10307228     2018-04-01  Yellow Cab  WASHINGTON DC
359388        10319775     2018-05-12  Yellow Cab  WASHINGTON DC
359389        10347676     2018-08-04  Yellow Cab  WASHINGTON DC
359390        10358624     2018-08-31  Yellow Cab  WASHINGTON DC
359391        10370709     2018-09-28  Yellow Cab  WASHINGTON DC

        KM Travelled  Price Charged  Cost of Trip  Customer ID Payment_Mode
\
0              30.45         370.95      313.6350        29290         Card
1              26.19         598.70      317.4228        29290         Cash
2              42.55         792.05      597.4020        29290         Card
3              28.62         358.52      334.8540        27703         Card
4              36.38         721.10      467.1192        27703         Card
...              ...            ...           ...          ...          ...
359387         38.40         668.93      525.3120        51406         Cash
359388          3.57          67.60       44.5536        51406         Cash
359389         23.46         331.97      337.8240        51406         Card
359390         27.60         358.23      364.3200        51406         Cash
359391         34.24         453.11      427.3152        51406         Card

        Gender  Age  Income (USD/Month)  Population   Users
0         Male   28               10813      814885   24701
1         Male   28               10813      814885   24701
2         Male   28               10813      814885   24701
3         Male   27                9237      814885   24701
4         Male   27                9237      814885   24701
...        ...  ...                 ...         ...     ...
359387  Female   29                6829      418859  127001
359388  Female   29                6829      418859  127001
359389  Female   29                6829      418859  127001
359390  Female   29                6829      418859  127001
359391  Female   29                6829      418859  127001

[359392 rows x 14 columns]>
```

In [71]:
```
# checking no of missing values in each column

master_data.isna().sum()
```

Loading [MathJax]/extensions/Safe.js

Out[71]:
```
Transaction ID        0
Date of Travel        0
Company               0
City                  0
KM Travelled          0
Price Charged         0
Cost of Trip          0
Customer ID           0
Payment_Mode          0
Gender                0
Age                   0
Income (USD/Month)    0
Population            0
Users                 0
dtype: int64
```

As a conclusion here is no missing values after merging all datasets.

In [46]:
```
#number of rows and columns in master dataset

master_data.shape
```

Out[46]:
```
(359392, 14)
```

In [48]:
```
#checking unique values of Company

print(master_data.Company.unique())
print(master_data.Company.value_counts())
```

```
['Pink Cab' 'Yellow Cab']
Yellow Cab    274681
Pink Cab       84711
Name: Company, dtype: int64
```

In [42]:
```
import xlrd
master_data['Year']=pd.DatetimeIndex(master_data['Date_of_Travel']).year
master_data['Month']=pd.DatetimeIndex(master_data['Date_of_Travel']).month
```

Check the correlation

In [9]:
```
import warnings
warnings.filterwarnings("ignore")

data_corr = master_data.corr()
data_corr
```

Out[9]:

	Transaction ID	Date of Travel	KM Travelled	Price Charged	Cost of Trip	Customer ID	Age	(USD
Transaction ID	1.000000	0.993030	-0.001429	-0.052902	-0.003462	-0.016912	-0.001267	-0
Date of Travel	0.993030	1.000000	-0.001621	-0.055559	-0.004484	-0.017653	-0.001346	-0
KM Travelled	-0.001429	-0.001621	1.000000	0.835753	0.981848	0.000389	-0.000369	-0
Price Charged	-0.052902	-0.055559	0.835753	1.000000	0.859812	-0.177324	-0.003084	0
Cost of Trip	-0.003462	-0.004484	0.981848	0.859812	1.000000	0.003077	-0.000189	-0
Customer ID	-0.016912	-0.017653	0.000389	-0.177324	0.003077	1.000000	-0.004735	-0
Age	-0.001267	-0.001346	-0.000369	-0.003084	-0.000189	-0.004735	1.000000	0
Income (USD/Month)	-0.001570	-0.001368	-0.000544	0.003228	-0.000633	-0.013608	0.003907	1

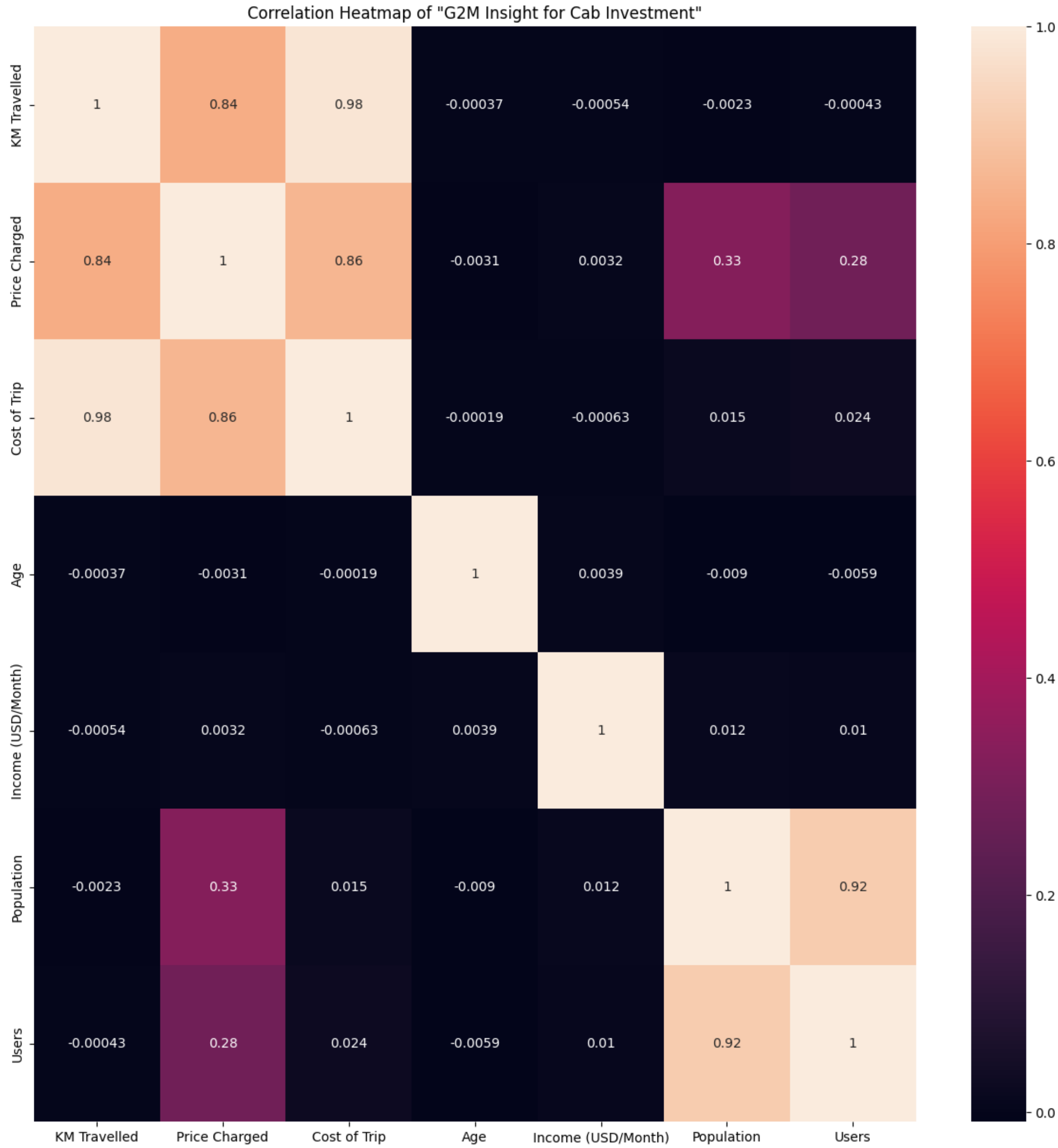
In [94]:

```
#correlation matrix

plt.figure(figsize=(15,15))
plt.title('Correlation Heatmap of "G2M Insight for Cab Investment"')
sb.heatmap(master_data[['KM Travelled', 'Price Charged', 'Cost of Trip', 'Ag
```

Out[94]:

```
<Axes: title={'center': 'Correlation Heatmap of "G2M Insight for Cab Invest
ment"'}>
```



From above map there is a correlation between:

- KM travelled is highly correlated with Price Changed and Cost of Trip.

In [81]:
```
sb.pairplot(data=master_data[['KM Travelled', 'Price Charged', 'Cost of Trip
plt.show()
```

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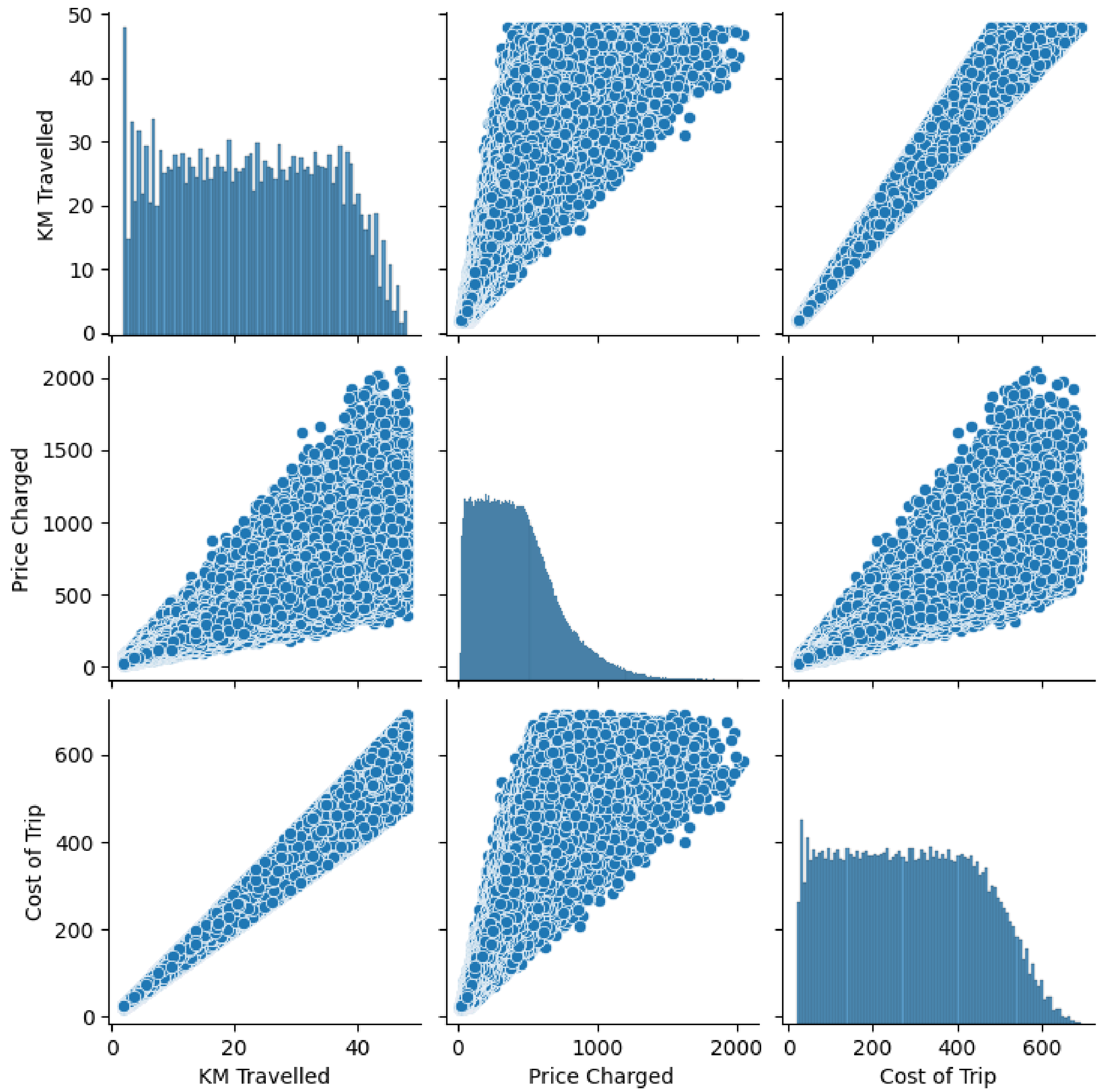
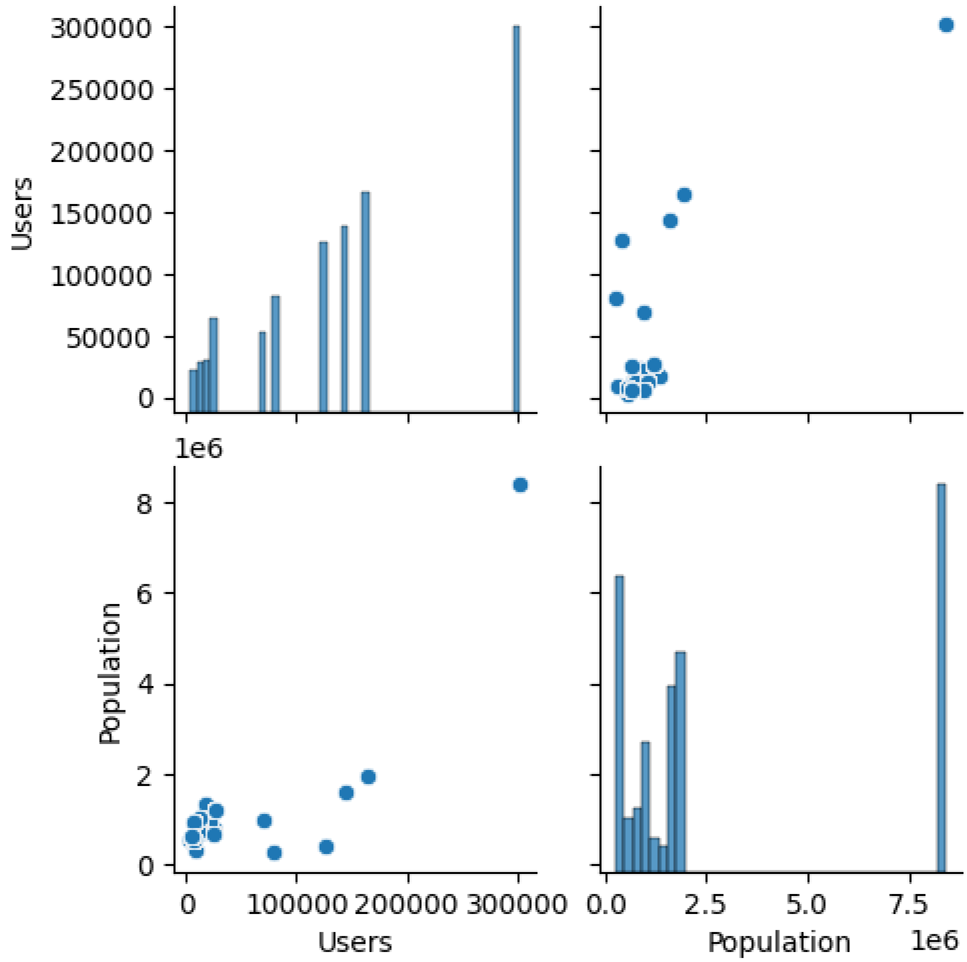


- Users are related to population

In [82]:
```
sb.pairplot(data=master_data[['Users','Population']])
plt.show()
```



FEATURE ANALYSIS

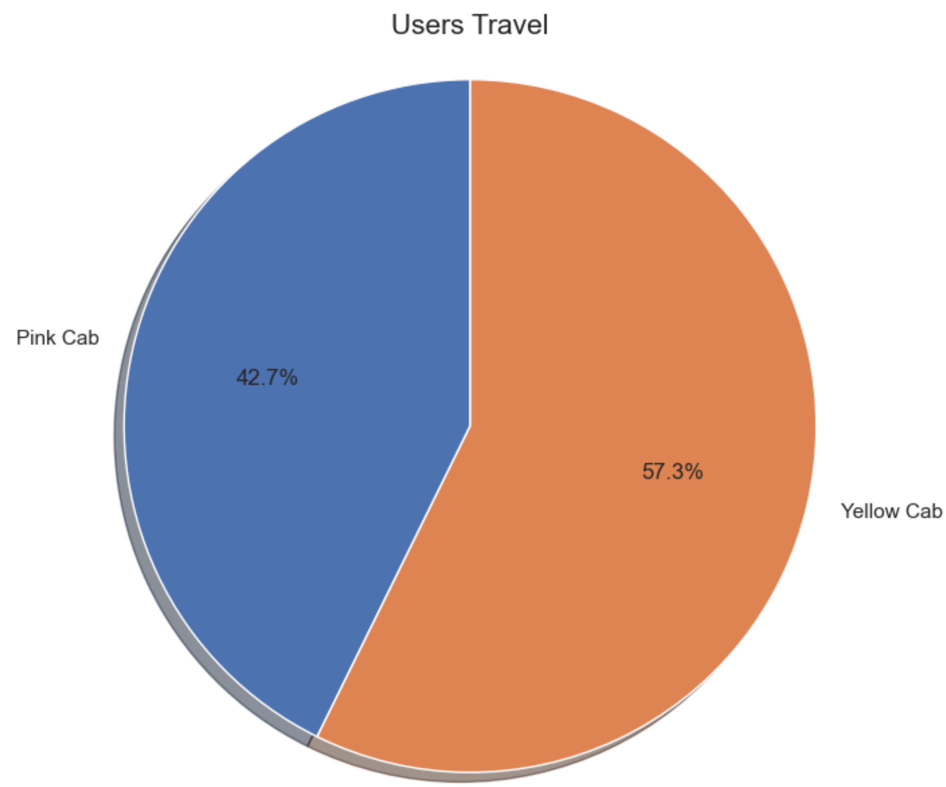
1.Number of users

In [147…

```
#plotting number of users of pink and yellow company

user=master_data.groupby('Company')
avg_user = user.Users.mean()
index = avg_user.index
value = avg_user.values
figp, axp = plt.subplots(figsize=(10,7))
axp.pie(value , labels=index, autopct='%1.1f%%',shadow=True, startangle=90,)
axp.axis('equal')

plt.title('Users Travel', fontsize = 15)
plt.show()
```



CONCLUSION: Number of yellow cab users(57%) are more than pink cab(42%)

2. Profit Margin

In [124…

```
company = master_data.groupby('Company')
price_charged = company['Price Charged'].mean()
cost_trip = company['Cost of Trip'].mean()
c = cost_trip.index
c_v = cost_trip.values
c_p = price_charged.values

plt.style.use('fivethirtyeight')
plt.figure(figsize = (4, 4))
plt.bar(c, c_p, edgecolor='black', label="Revenue")
plt.bar(c, c_v, edgecolor='black', label="Profit")
plt.title('Profit Margin')
plt.ylabel('Price Charged')
plt.xlabel('Cost of Trip')
plt.legend()
plt.show()
```

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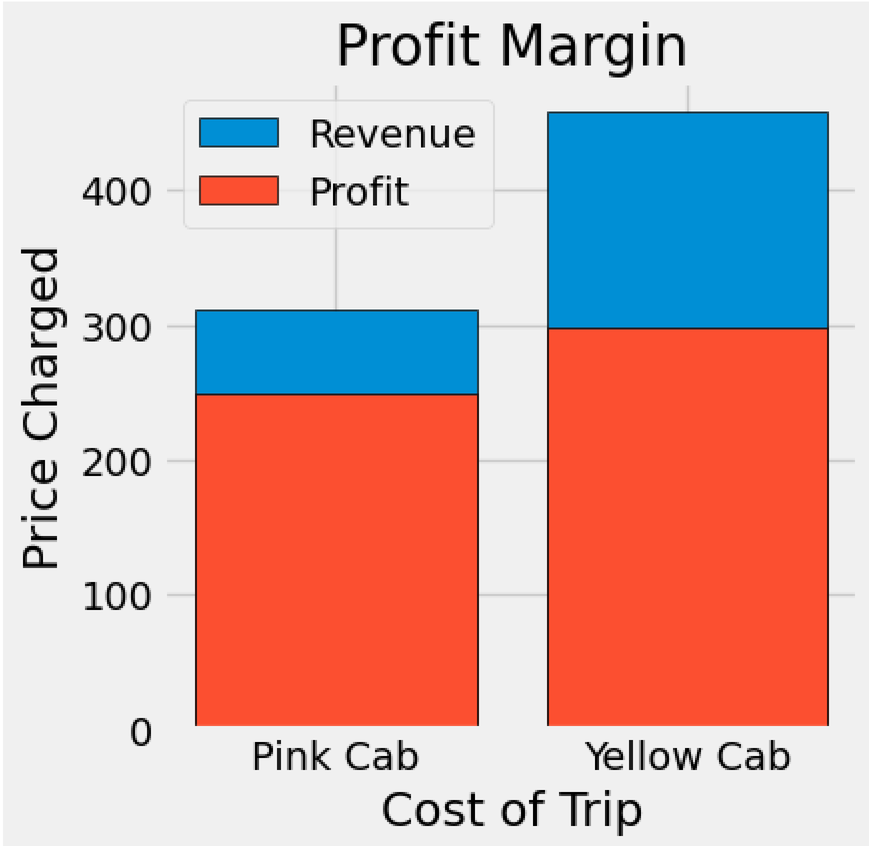


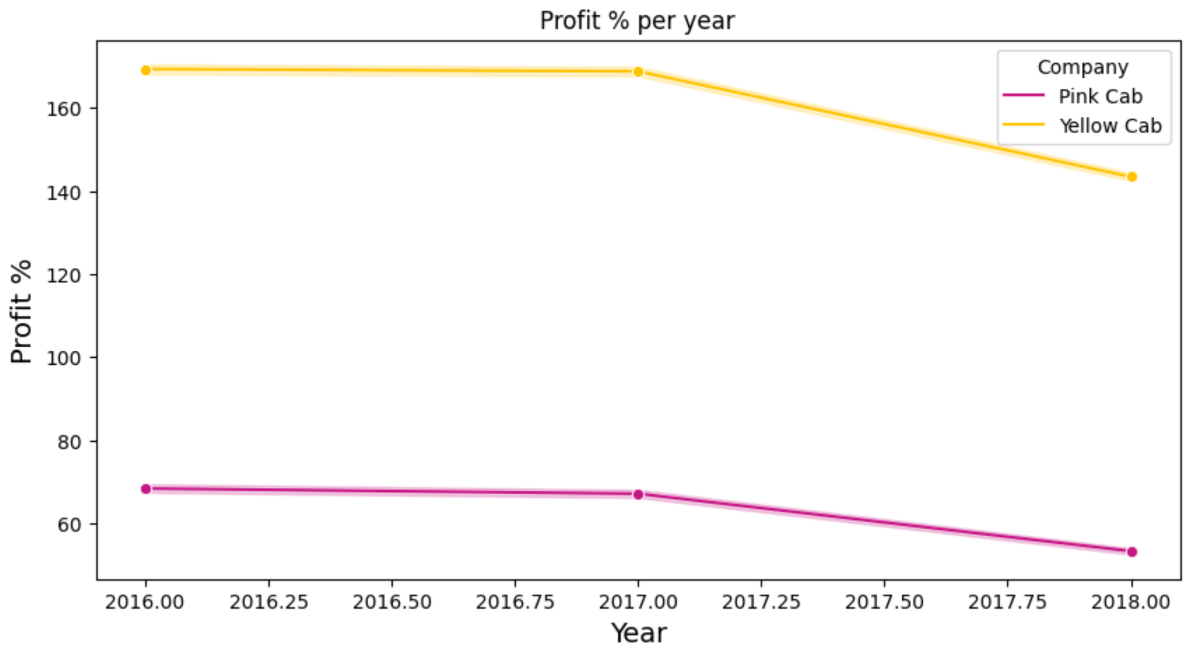
CONCLUSION: In contrast to the Pink cab, the Yellow cab has a higher profit margin

In [27]:
```
# calculating the profit of each transaction

master_data['Profit'] = master_data['Price Charged'] -master_data['Cost of T
```

In [40]:
```
#profit per year

plt.figure(figsize = (10, 5))
sb.lineplot(x='Year', y='Profit', hue="Company", data=master_data, marker='c
plt.xlabel("Year", size=14)
plt.ylabel("Profit %", size=14)
plt.title("Profit % per year")
plt.show()
```



CONCLUSION: From the line graph we can conclude

- In comparison to 2018, both companies' profits were higher in 2016.
- In the year 2018, PINK cab had higher profits than YELLOW cab.
- From 2016 to 2017, the profit margin stayed consistent and it was dropped after 2017.

In [24]:
```
#profit per month

plt.figure(figsize = (10, 5))
sb.lineplot(x='Travel_month', y='Profit', hue="Company", data=master_data, m
plt.xlabel("Month", size=14)
plt.ylabel("Profit %", size=14)
plt.title("Profit % per month")
plt.show()
```

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CONCLUSION: From the line graph we can conclude

- The middle of the year appears to have been profitable for YELLOW cab.
- PINK Cab has made more profit at the beginning and end of the year.
- In pink cab,profit was going up and down consistently while in yellow cab it was declined over the months and later it went up.

3.KM Travelled Distribution

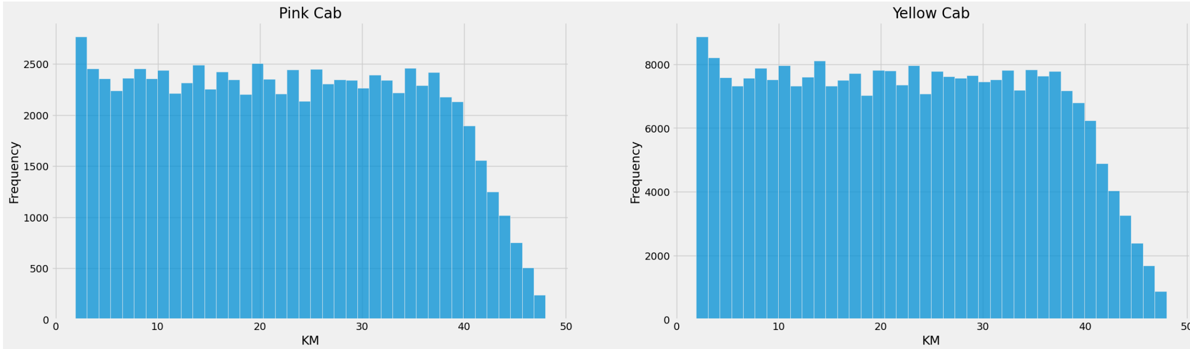
In [126…

```
#number of KM travelled in both cabs

fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(25,7))
sb.histplot(data=PinkCab, x='KM Travelled', bins=40, ax=ax1)
ax1.set_title('Pink Cab', fontsize=20)
ax1.set_xlabel('KM')
ax1.set_ylabel('Frequency')
sb.histplot(data=YellowCab, x='KM Travelled', bins=40, ax=ax2)
ax2.set_title('Yellow Cab', fontsize=20)
ax2.set_xlabel('KM')
ax2.set_ylabel('Frequency')
```

Out[126]:

```
Text(0, 0.5, 'Frequency')
```

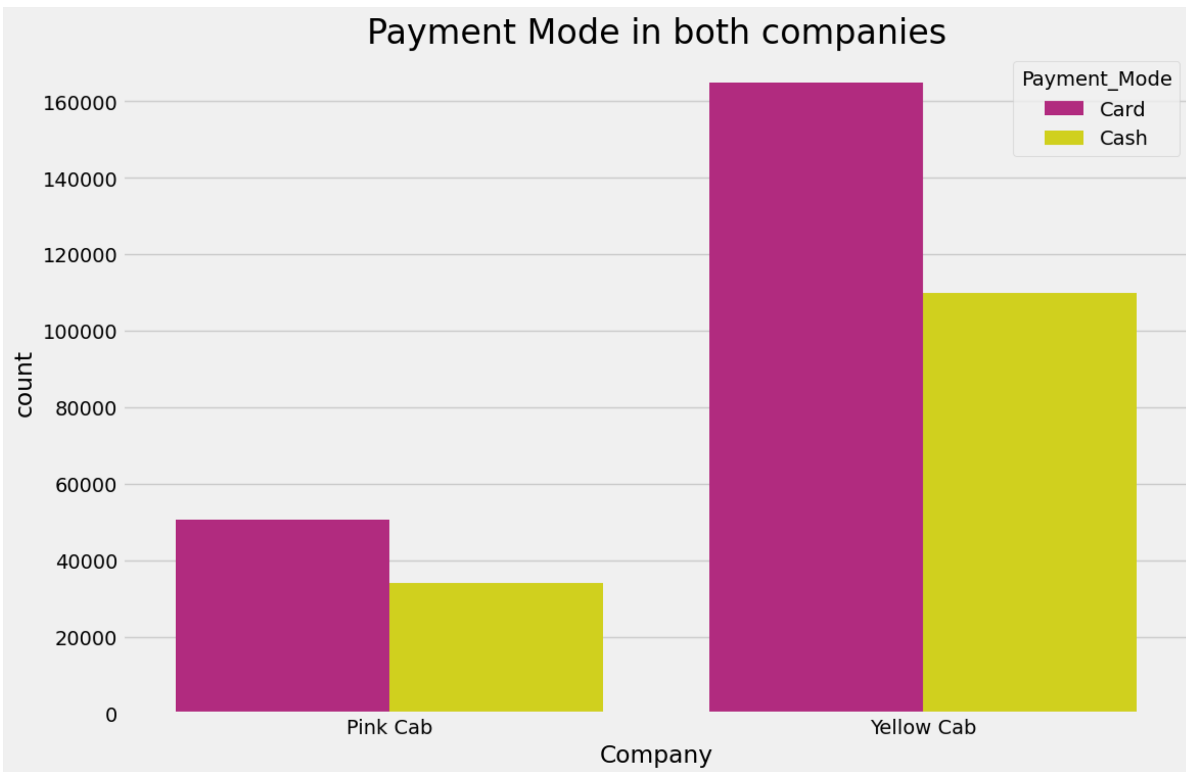


CONCLUSION: Most of the rides are in the range of approximately 2 to 48 KM.

4.Mode of Payment

In [143…

```
plt.figure(figsize = (12, 8))
ax = sb.countplot(x="Company", hue="Payment_Mode", data=master_data,palette=
plt.title('Payment Mode in both companies', fontsize=24)
plt.show()
```



CONCLUSION: Users prefered to pay with a card more than cash.

5. Price charged

In [170…

```
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(20,7))
sb.histplot(data=PinkCab, x='Price Charged', bins=40, ax=ax1)
ax1.set_title('Pink Cab', fontsize=20)
ax1.set_xlabel('Price Charged')
l('Frequency')
```

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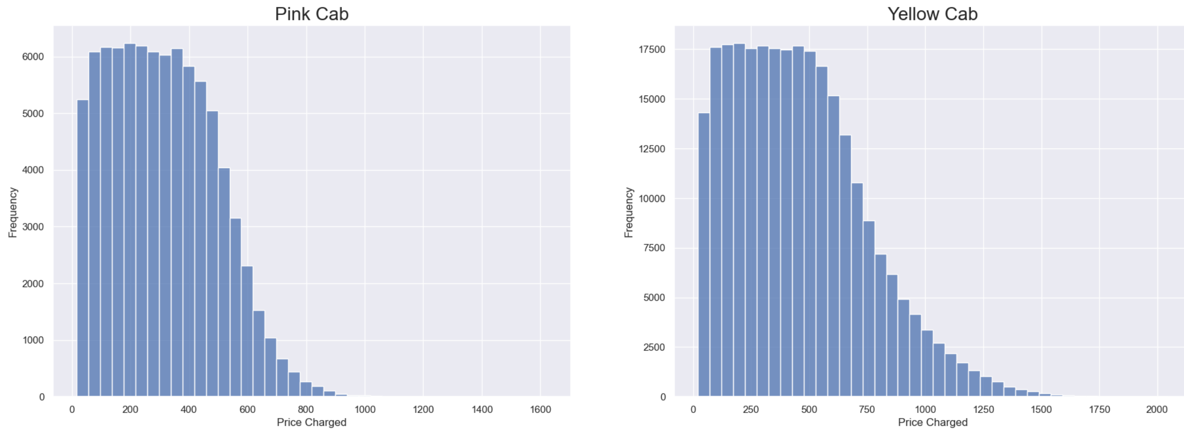
```
sb.histplot(data=YellowCab, x='Price Charged', bins=40, ax=ax2)
ax2.set_title('Yellow Cab', fontsize=20)
ax2.set_xlabel('Price Charged')
ax2.set_ylabel('Frequency')
```

Out[170]: Text(0, 0.5, 'Frequency')

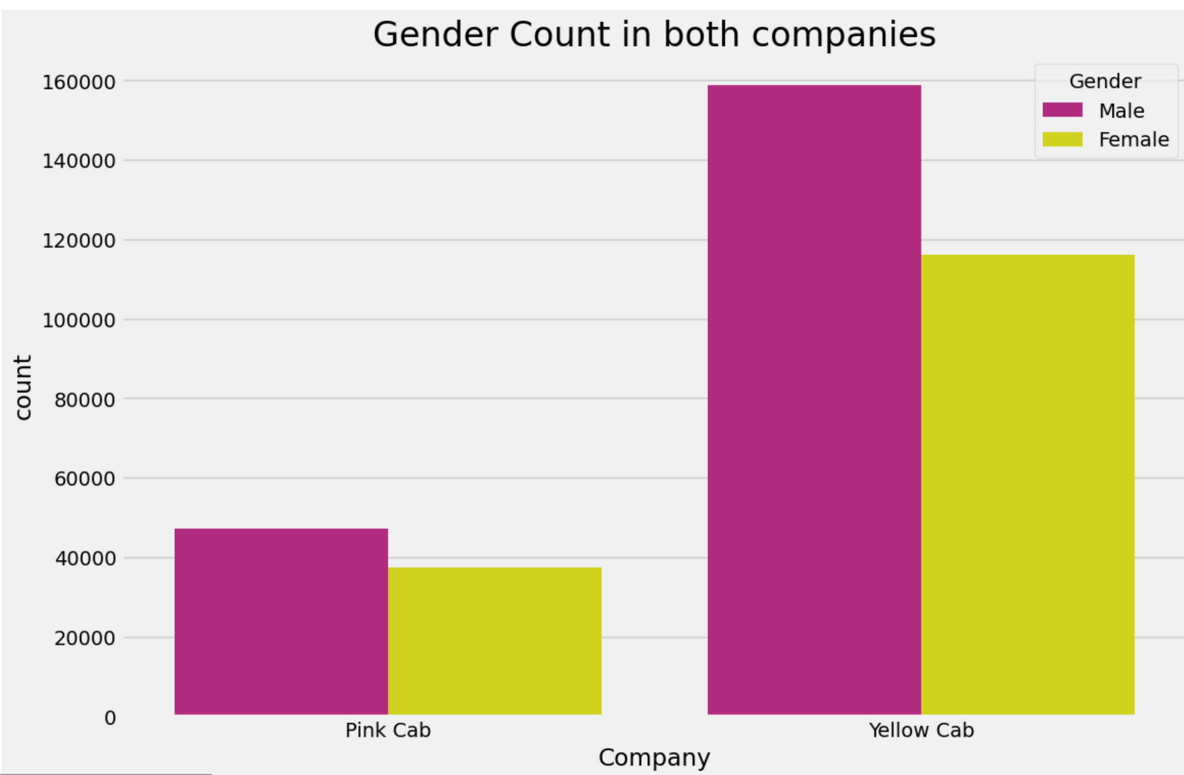


CONCLUSION: Price charged per trip is more for YELLOW cab compared to PINK cab

6. Gender Count

In [141…
```
# comparing male and female travel frequency

plt.figure(figsize = (12, 8))
ax = sb.countplot(x="Company", hue="Gender", data=master_data, palette=['#C7
plt.title('Gender Count in both companies', fontsize=24)
plt.show()
```



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CONCLUSION:

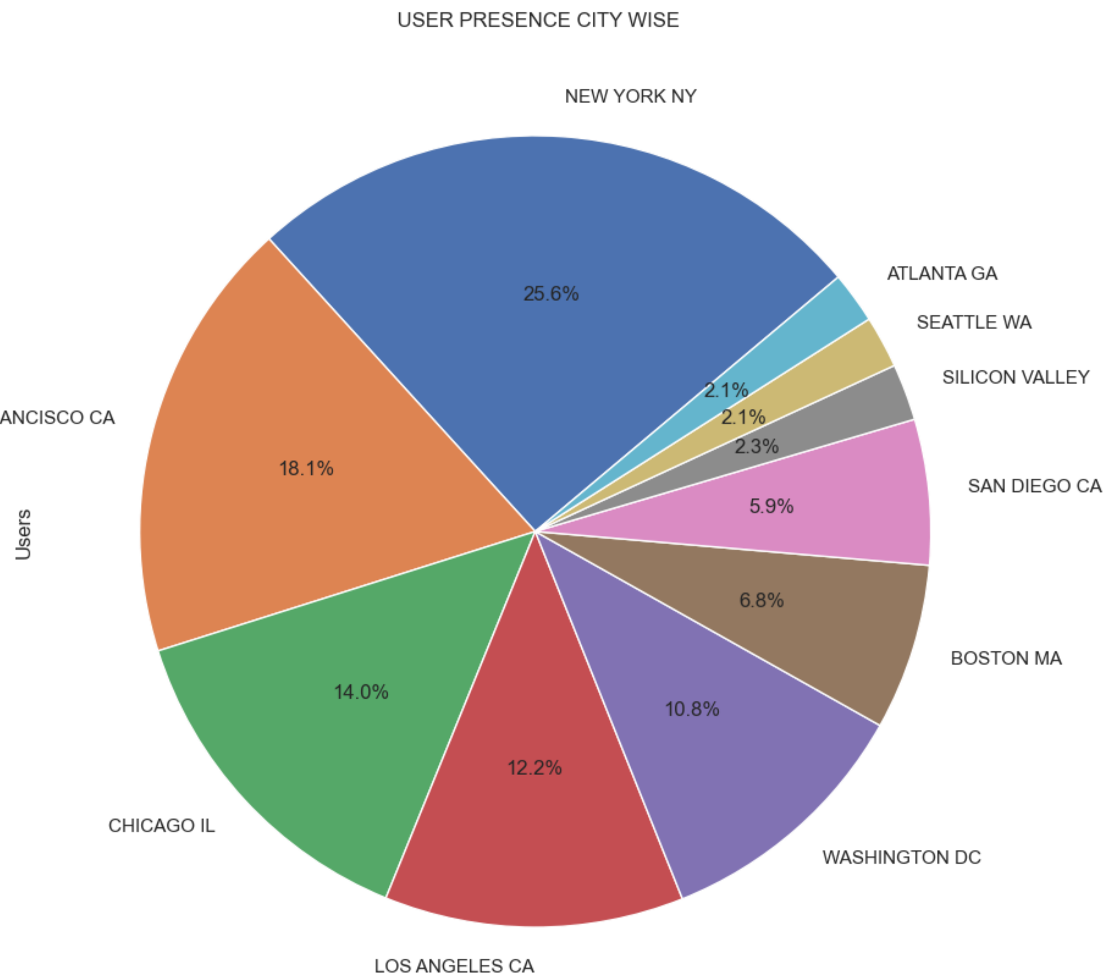
- In both companies, males have travelled more compared to females.
- Yellow cabs are preferred by customers.

7.User per city

In [157…

```
# top 10 cities by users
plt.title(" USER PRESENCE CITY WISE")
city.groupby("City")["Users"].sum().sort_values(ascending=False).head(10).pl
```

Out[157]: `<Axes: title={'center': ' USER PRESENCE CITY WISE'}, ylabel='Users'>`



CONCLUSION: The majority of cab users are in New York City (25%), followed by San Francisco (18%), and Chicago (14%).

8.Checking Outliers of column values

In [173…

```
# To check the outliers we use boxplots.
```

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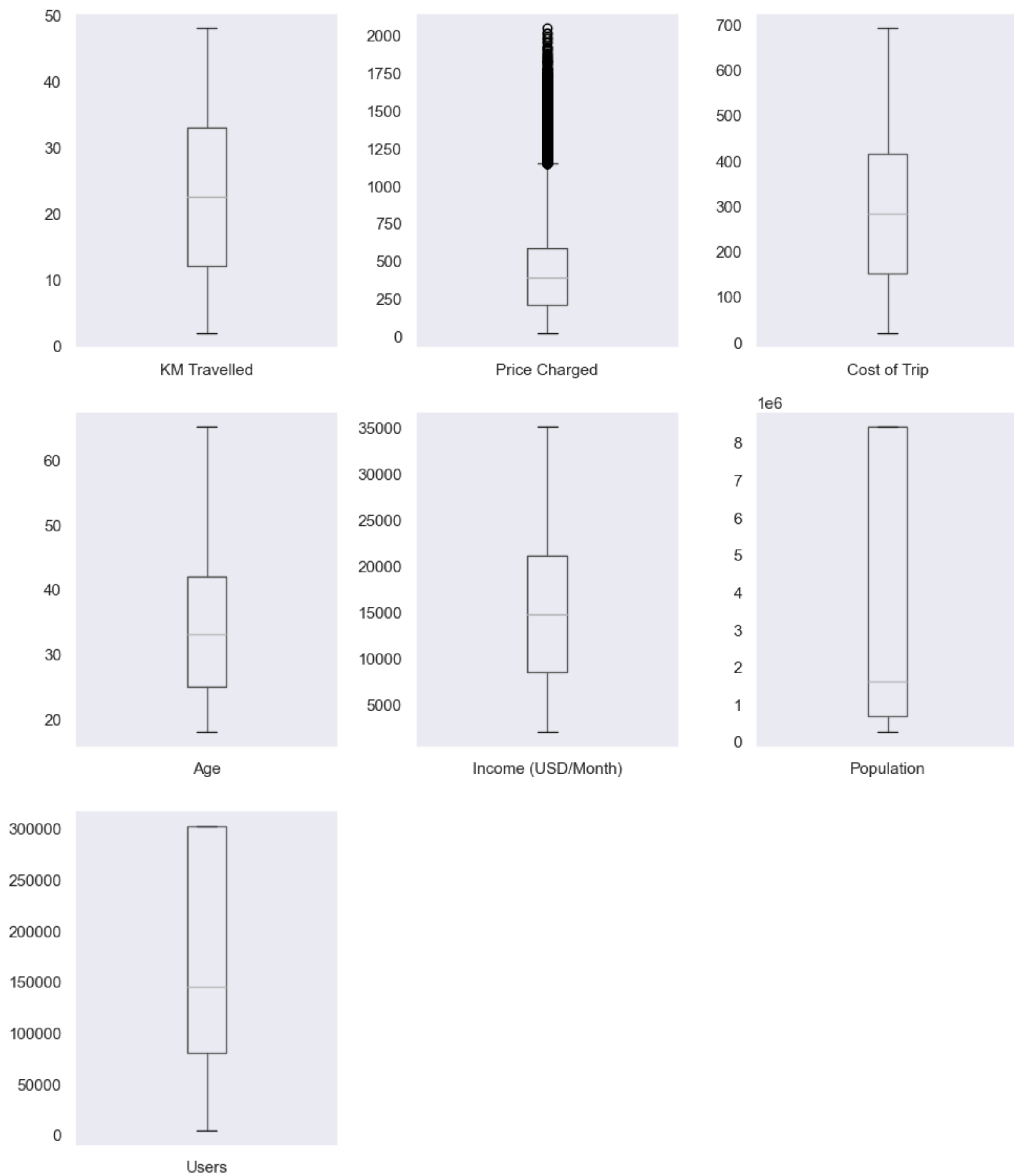
```python
master_data.columns.values
cols = ['KM Travelled', 'Price Charged', 'Cost of Trip',
        'Age', 'Income (USD/Month)',
       'Population', 'Users']


plt.figure(figsize=(10,15))

for i, col in enumerate(cols):
    plt.subplot(4,3,i+1)
    master_data.boxplot(col)
    plt.grid()
    plt.tight_layout()
```



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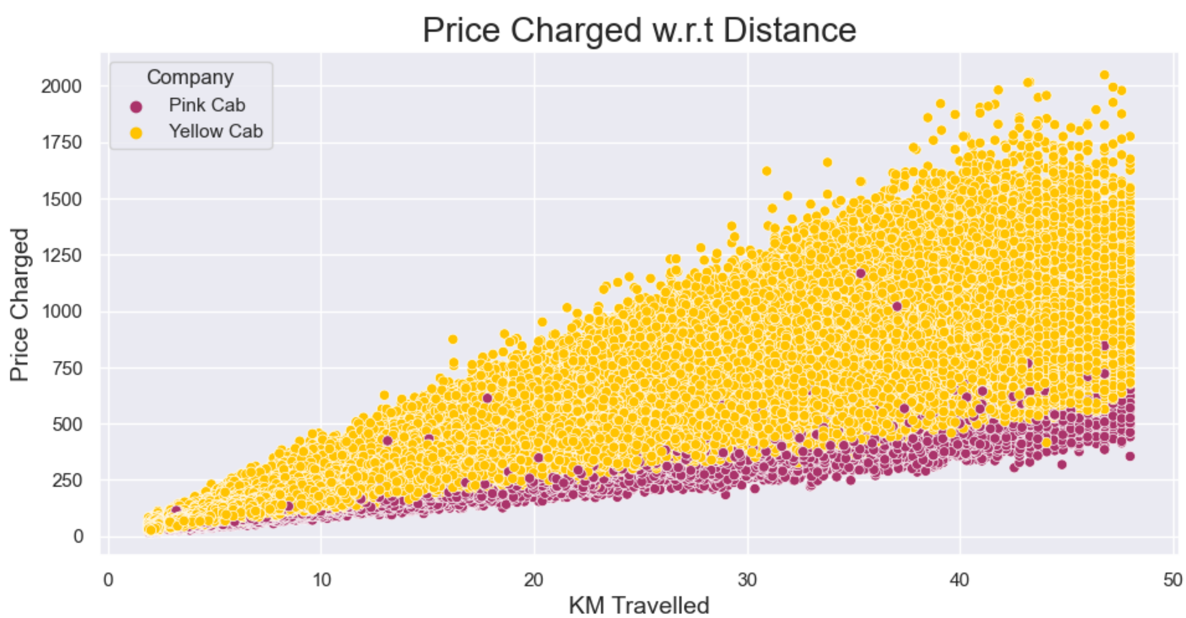
CONCLUSION: From above boxplot price charged has some outliers while compared with other values

9. Price charged with respect to Distance

In [176…
```
plt.figure(figsize = (10, 5))

sb.scatterplot(data=master_data, x='KM Travelled', y='Price Charged', hue='C
plt.title('Price Charged w.r.t Distance',fontsize = 20)
plt.ylabel('Price Charged',fontsize = 14)
plt.xlabel('KM Travelled',fontsize = 14)
plt.show()
```



CONCLUSION: The scatter plot above demonstrates a linear relationship between the price charged and the distance travelled for both cab campanies.

Hypothesis

Hypothesis 1 : Is there any gender-based difference in profit?

H0(Null Hypothesis):There is no difference based on gender in both cab companies.

H1(Alternate Hypothesis):There is difference based on gender in both cab companies.

Pink Cab

In [56]:
```
a = master_data[(master_data.Gender=='Male')&(master_data.Company=='Pink Cab
b = master_data[(master_data.Gender=='Female')&(master_data.Company=='Pink C
print(a.shape[0],b.shape[0])
```

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```
_, p_value = stats.ttest_ind(a.values, b.values, equal_var=True)

print('P value is ', p_value)

if(p_value<0.05):
    print('We accept alternative hypothesis (H1) that there is a difference
else:
    print('We accept null hypothesis (H0) that there is no difference based
```

```
47231 37480
P value is  0.115153059004258
We accept null hypothesis (H0) that there is no difference based on gender
for Pink Cab
```

Yellow Cab

In [58]:

```
a = master_data[(master_data.Gender=='Male')&(master_data.Company=='Yellow C
b = master_data[(master_data.Gender=='Female')&(master_data.Company=='Yellow
print(a.shape[0],b.shape[0])

_, p_value = stats.ttest_ind(a.values, b.values, equal_var=True)

print('P value is ', p_value)

if(p_value<0.05):
    print('We accept alternative hypothesis (H1) that there is a difference
else:
    print('We accept null hypothesis (H0) that there is no difference based
```

```
158681 116000
P value is  6.060473042494056e-25
We accept alternative hypothesis (H1) that there is a difference based on g
ender for Yellow Cab
```

As a conclusion there is no difference regarding Gender in both cab companies.

Hypothesis 2 : Is there any difference in Profit regarding Age.

H0(Null Hypothesis):There is no difference regarding Age in both cab companies.

H1(Alternate Hypothesis):There is difference regarding Age in both cab companies.

Pink Cab

In [54]:

```
a = master_data[(master_data.Age <= 60)&(master_data.Company=='Pink Cab')].g
b = master_data[(master_data.Age >= 60)&(master_data.Company=='Pink Cab')].g
print(a.shape[0],b.shape[0])

_, p_value = stats.ttest_ind(a.values,
                             b.values,
                             equal_var=True)

print('P value is ', p_value)

                                05):
```

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```
    print('We accept alternative hypothesis (H1) that there is a difference 
else:
    print('We accept null hypothesis (H0) that there is no difference regarc
```

```
80125 5429
P value is  0.4816748536155634
We accept null hypothesis (H0) that there is no difference regarding age fo
r Pink Cab
```

Yellow Cab

In [59]:
```
a = master_data[(master_data.Age <= 60)&(master_data.Company=='Yellow Cab')]
b = master_data[(master_data.Age >= 60)&(master_data.Company=='Yellow Cab')]
print(a.shape[0],b.shape[0])

_, p_value = stats.ttest_ind(a.values,
                             b.values,
                             equal_var=True)

print('P value is ', p_value)

if(p_value<0.05):
    print('We accept alternative hypothesis (H1) that there is a difference 
else:
    print('We accept null hypothesis (H0) that there is no difference regarc
```

```
260356 17257
P value is  6.328485471267631e-05
We accept alternative hypothesis (H1) that there is a difference regarding
age for Yellow Cab
```

Summary

I found that there are no null values in the master dataframe. The above Exploratory Data Analysis finds various dynamics of the data of two cab companies,that is Pink Cab and Yellow Cab.

- **Yellow Cab is noticeably earning much Profit than Pink Cab.**
- **Yellow cab is preferred by the customers over Pink cab.**
- **Yellow Cab is more popular than Pink Cab overall.**

To sum up, Yellow cab would be the preferred one to invest in.