

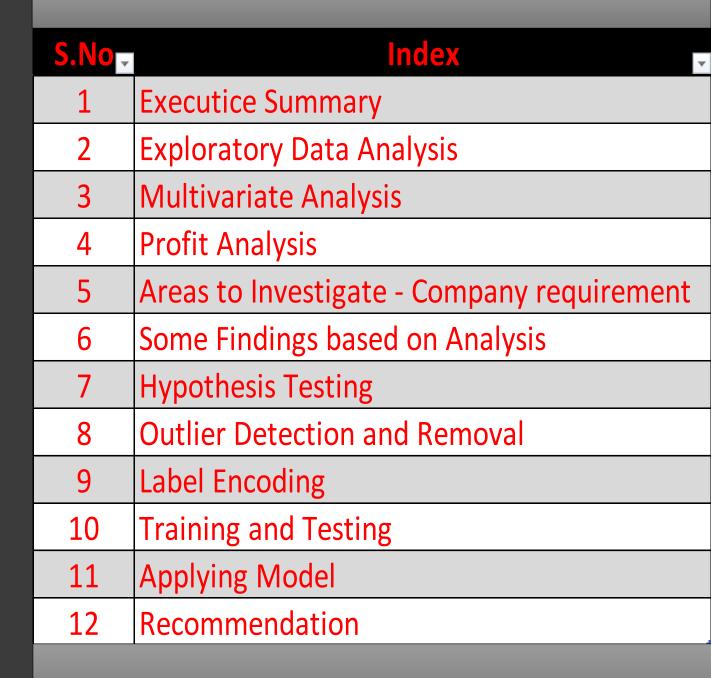
# Exploratory Data Analysis G2M Case Study

16/06/2022

Ramya Mercy Rajan

Batch: LISUM 10:30, Data Science

# Agenda





#### About Project :

The purpose of this Project is making suggestion on "Investment" for a Company XYZ in United States of America by analyzing and investigating the records of two Cab Companies based on the informations provided.

#### The Client: XYZ

XYZ is a private firm in US. Due to remarkable growth in the Cab Industry in last few years and multiple key players in the market, it is planning for an investment in Cab industry and as per their Go-to-Market(G2M) strategy they want to understand the market before taking final decision.

#### **≻**About Project :

The purpose of this Project is making suggestion on "Investment" for a Company XYZ in United States of America by analysing and investigating the records of two Cab Companies based on the information's provided.

#### **≻The Client : XYZ**

XYZ is a private firm in US. Due to remarkable growth in the Cab Industry in last few years and multiple key players in the market, as it is planning for an investment in Cab industry and as per their Go-to-Market(G2M) strategy they want to understand the market before taking final decision.

#### **≻**Project delivery:

Provided with multiple data sets that contains information on 2 cab companies. Each file (data set) provided represents different aspects of the customer profile. XYZ is interested in using actionable insights to help them identify the right company to make their investment.

- > Provided 4 individual data sets.
- > Time period of data is from 31/01/2016 to 31/12/2018.
- > Below are the list of datasets which are provided for the analysis:
  - 1) Cab\_Data.csv this file includes details of transaction for 2 cab companies.
  - 2) **Customer\_ID.csv** this is a mapping table that contains a unique identifier which links the customer's demographic details.
  - 3) **Transaction\_ID.csv** this is a mapping table that contains transaction to customer mapping and payment mode
  - 4) City.csv this file contains the list of US cities, their population and the number of cab users.

#### ➤ Analysis made :

Create multiple hypothesis

#### > Areas to Investigated :

- 1. Which company has maximum cab users at a particular time period?
- 2. Does margin proportionally increase with increase in number of customers?
- 3. What are the attributes of these customer segments?

#### Topic covered as per requirement

- 1. Review the Source Documentation
- 2. Understand the field names and data types
- 3. Identify relationships across the files
- 4. Field/feature transformations
- 5. Determine which files should be joined versus which ones should be appended
- 6. Create master data and explain the relationship
- 7. Identify and remove duplicates
- Perform other analysis like NA value and outlier detection

### **Exploratory Data Analysis**

- Data Sets: 4 individual datasets are given
- 1. Cab\_Data.csv (359392 Rows and 7 Columns)

This file contains the Cab Companies Information.

- a) Number of Cab Companies-2
- b) Names of Cab Companies Yellow Cab and Pink Cab
- c) Date of Travel
- d) City
- e) Kilometres Travelled
- f) Price Charged by each company
- g) Cost of Trip

### **Exploratory Data Analysis**

#### 2. Customer\_ID.csv (49171 Rows and 4Columns)

This file contains the customer's demographic details.

- a) Customer ID
- b) Gender
- c) Age
- d) Income

#### 3. City.csv (20 Rows and 3Columns)

This file contains list of US cities, their population and number of cab users.

- a) US cities
- b) Population
- c) Number of cab users

### **Exploratory Data Analysis**

#### 4. Transaction\_ID.csv (440098 Rows and 3Columns)

This file contains list of

- a) Transaction ID
- b) Customer ID
- c) Payment\_Mode
- Data Preprocessing- There was no Null Values and Duplicate values in the four datasets.
- Outliers was found in the feature Price Charged and rectified.
- Additional Features
  - The feature "Date of Travel" was not in a proper format and was corrected using datetime.timedelta() function. A new "Date" column was created after correction of the old feature "Date of Travel".
  - The Profit column was created by finding the difference between Price Charged and Cost of Trip. Profit was considered as my target variable.
  - ➤ Age Groups column was created using class intervals format(Bins) in order to know the age groups performance on other features.
- Statistical measure was checked on every datasets in order to know the Count, Mean, Std, Min and Max.

### Multivariate Analysis

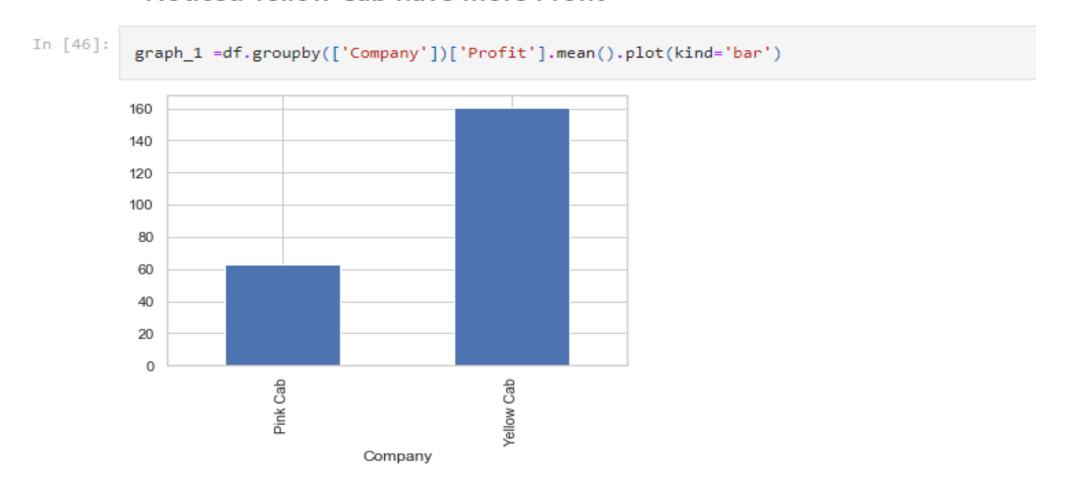
• Multivariate analysis was made to check the relationship between Profit and other features .

In [45]:	<pre>df.groupby(['Company','Price Charged','Cost of Trip','Age','KM Travelled'])['Profit'].mean()</pre>					
Out[45]:	Company	Price Charged	Cost of Trip	Age	KM Travelled	
	Pink Cab	15.60	21.3840	34	1.98	-5.7840
		15.75	24.7800	32	2.10	-9.0300
		16.38	19.3800	43	1.90	-3.0000
		16.53	19.2000	57	1.92	-2.6700
		16.76	19.9820	18	1.94	-3.2220
						•••
	Yellow Cab	1981.05	556.9092	37	41.81	1424.1408
		1993.83	594.7200	60	47.20	1399.1100
		2013.95	580.6080	64	43.20	1433.3420
		2016.70	571.4280	37	43.29	1445.2720
		2048.03	584.0640	18	46.80	1463.9660
	Name: Profi	t, Length: 3593	86, dtype: flo	at64		

### Profit Analysis based on Companies

#### Observing Graph of Company vs Profit

Noticed Yellow Cab have more Profit



### Profit Analysis based Age

#### Observing Graph of Age vs Profit

- Noted Age groups from 20-49 creates more Profit

```
In [47]:
            graph_2 = df.groupby(['Age group'])['Profit'].mean().plot(kind='bar')
            140
            120
            100
             80
             60
             40
             20
              0
                             20 - 29
                                                         - 59
```

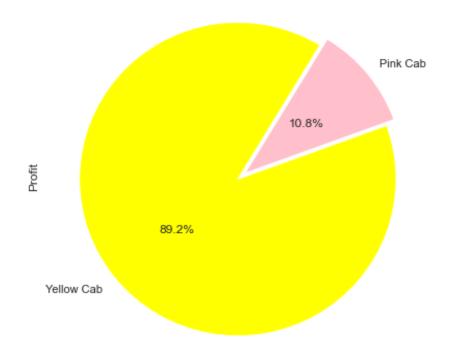
### Profit Analysis based on both Cabs

#### Profit per cabs

```
In [48]:
    plt.title("Profit made by both the Company's ")
    df.groupby('Company')['Profit'].sum().plot(kind='pie',y='Company',startangle=20,colors = ("pink", "yellow") ,figsize=(15,7),autopct='%1.1f%%',explode=
Out[48]:

Cut[48]:
```

Profit made by both the Company's



Q.1) Which company has maximum cab users at a particular time period?

```
In [52]:
         df.groupby([df['Date'].dt.year,'Company'])['Customer ID'].count()
        Date Company
Out[52]:
         2016 Pink Cab
                           25080
              Yellow Cab
                          82239
         2017 Pink Cab
                      30321
              Yellow Cab 98189
         2018 Pink Cah 29310
              Yellow Cab 94253
        Name: Customer ID, dtype: int64
```

In 2016, 2017 and 2018, Yellow cab has maximum customers

Which company made maximum Profit at a particular time period?

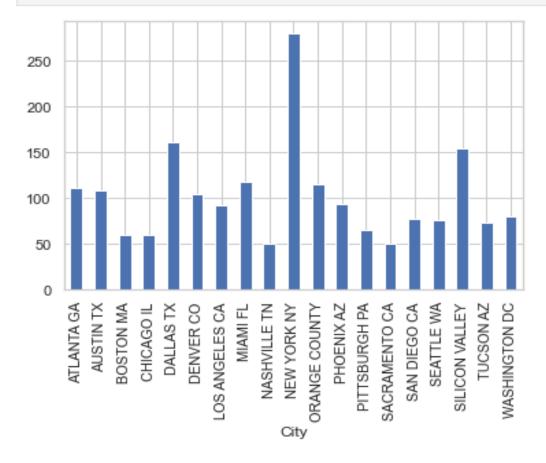
Q.2) Does margin proportionally increase with increase in number of customers?

```
In [55]:
         df.groupby([df['Date'].dt.year,'Company'])['Income (USD/Month)'].mean()
        Date Company
Out[55]:
         2016 Pink Cab
                           15124,241587
              Yellow Cab
                          15034.414900
         2017 Pink Cab
                          15058.789123
              Yellow Cab 15069.108974
         2018 Pink Cab
                          15003.528420
              Yellow Cab
                          15031.072146
        Name: Income (USD/Month), dtype: float64
```

- Outcome: Yellow Cab Company has got higher Income and Customers as compared to Pink Cab Company

Q.3) What are the attributes of these customer segments?

```
In [56]:
graph_3 = df.groupby(['City'])['Profit'].mean().plot(kind='bar')
```



# Rides to New York made maximum Profit

b) Yellow Cab Travelled more Kilometers as compared to Pink Cab. So Kilometers Travelled by each cab and the availability of more cabs can be an important factor of getting more Customers.

```
In [61]:
         df.groupby([df['Date'].dt.year,'Company'])['KM Travelled'].count()
        Date Company
Out[61]:
         2016 Pink Cab
                           25080
              Yellow Cab 82239
         2017 Pink Cab
                           30321
              Yellow Cab 98189
         2018 Pink Cab 29310
              Yellow Cab 94253
        Name: KM Travelled, dtype: int64
```

c) The Cost of Trip is higher for Yellow Cab as compared to Pink Cab because Yellow Cab had more trips and travelled more kilometers.

```
In [62]:
          df.groupby([df['Date'].dt.year,'Company'])['Cost of Trip'].count()
        Date Company
Out[62]:
         2016 Pink Cab
                            25080
               Yellow Cab
                            82239
         2017 Pink Cab
                            30321
                            98189
               Yellow Cab
         2018 Pink Cab
                            29310
               Yellow Cab 94253
         Name: Cost of Trip, dtype: int64
```

d) Yellow cab company has much more income than pink cab company, since it has more customers.

```
In [63]:
         df.groupby([df['Date'].dt.year,'Company'])['Income (USD/Month)'].count()
              Company
Out[63]:
         2016 Pink Cab
                          25080
              Yellow Cab
                         82239
         2017 Pink Cab 30321
              Yellow Cab
                           98189
         2018 Pink Cab
                      29310
              Yellow Cab
                         94253
         Name: Income (USD/Month), dtype: int64
```

e) When compared with Age group in the year 2016, 2017 and 2018 people aged between 20-39 might have used more cab services as compared to other Age groups.

```
In [65]:
          df.groupby([df['Date'].dt.year,'Age group'])['Profit'].count()
         Date
               Age group
Out[65]:
          2016
                              6606
                20 - 29
                             34704
                30 - 39
                             33884
                40 - 49
                             13885
                50 - 59
                            11445
                60 - 69
                            6795
         2017
               10 - 19
                             8208
                20 - 29
                           41717
                30 - 39
                            40004
               40 - 49
                             16899
                50 - 59
                             13554
                60 - 69
                            8128
         2018
               10 - 19
                           7623
                20 - 29
                             40009
                30 - 39
                             38847
                40 - 49
                             16233
                50 - 59
                             13088
                60 - 69
                              7763
         Name: Profit, dtype: int64
```

### Some Findings based on above Analysis:

- 1) Rides to which city made more Profit?
- -New York NY
- 2) Which City is in high demand for cab users?
- -New York NY
- 3) Which Company has more Users?
- -Yellow Cab with 302,149
- 4) Which City has highest Population?
- -New York Ny with 8,405,837

#### Hypothesis Testing: Payment Mode and Profit-Yellow Cab

- Hypothesis Testing based on Payment Mode and Profit

```
In [67]:
    cash = df[(df['Payment_Mode']=='Cash')&(df.Company=='Yellow Cab')].groupby('Transaction ID').Profit.mean()
    card = df[(df['Payment_Mode']=='Card')&(df.Company=='Yellow Cab')].groupby('Transaction ID').Profit.mean()
    print(cash.shape[0],card.shape[0])
    _, p_value = stats.ttest_ind(cash.values,card.values,equal_var=True)

    print('P value is ', p_value)

    if(p_value<0.05): # alpha value is 0.05 or 5%
        print("we are rejecting null hypothesis and it says that there is a difference regarding Payment Mode and Yellow Cab")
    else:
        print("We are accepting null hypothesis that there is no difference noted regarding Payment Mode and Yellow Cab")</pre>
```

109896 164785
P value is 0.2933060638298729
We are accepting null hypothesis that there is no difference noted regarding Payment Mode and Yellow Cab

#### Hypothesis Testing: Payment Mode and Profit-Pink Cab

```
In [68]:
    cash = df[(df['Payment_Mode']=='Cash')&(df.Company=='Pink Cab')].groupby('Transaction ID').Profit.mean()
    card = df[(df['Payment_Mode']=='Card')&(df.Company=='Pink Cab')].groupby('Transaction ID').Profit.mean()
    print(cash.shape[0],card.shape[0])
    _, p_value = stats.ttest_ind(cash.values,card.values,equal_var=True)

print('P value is ', p_value)

if(p_value<0.05):  # alpha value is 0.05 or 5%
    print("we are rejecting null hypothesis and it says that there is a difference regarding Payment Mode and Pink Cab")
else:
    print("We are accepting null hypothesis that there is no difference noted regarding Payment Mode and Pink Cab")</pre>
```

33992 50719
P value is 0.7900465828793288
We are accepting null hypothesis that there is no difference noted regarding Payment Mode and Pink Cab

#### **Hypothesis Testing: Age and Profit-Yellow Cak**

#### - Hypothesis Testing based on Age and Profit

```
In [69]:
    x = df[(df.Age <= 40)&(df.Company=='Yellow Cab')].groupby('Transaction ID').Profit.mean()
    y = df[(df.Age >= 40)&(df.Company=='Yellow Cab')].groupby('Transaction ID').Profit.mean()
    print(x.shape[0],y.shape[0])
    _, p_value = stats.ttest_ind(x.values,y.values,equal_var=True)

print('P value is ', p_value)

if(p_value<0.05):  # alpha value is 0.05 or 5%
    print("we are rejecting null hypothesis and it says that there is a difference regarding Age and Yellow Cab")
else:
    print("Ne are accepting null hypothesis that there is no difference noted regarding Age and Yellow Cab")</pre>
```

201029 82454
P value is 0.44246196729249976
We are accepting null hypothesis that there is no difference noted regarding Age and Yellow Cab

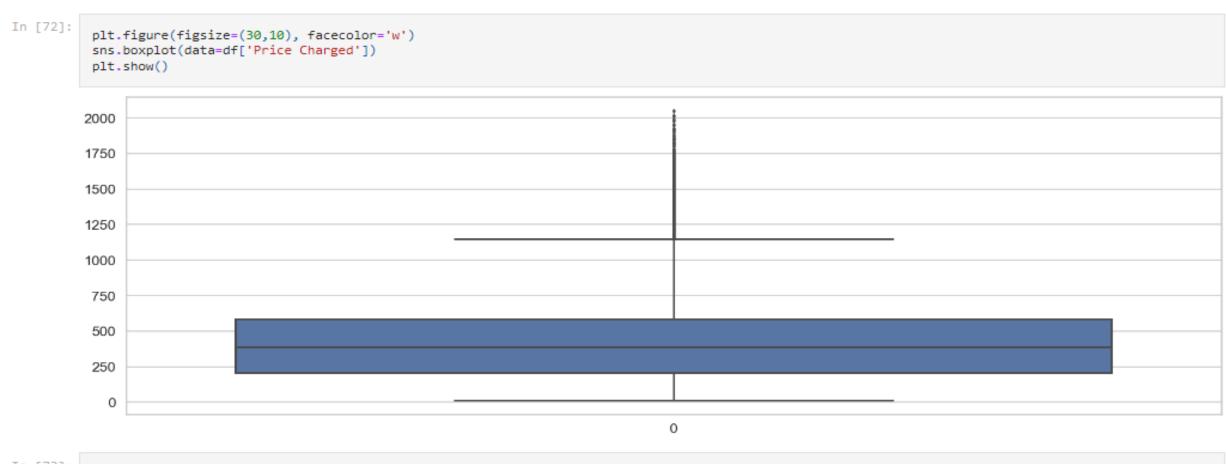
#### Hypothesis Testing: Age and Profit-Pink Cab

```
In [70]:
          x = df[(df.Age <= 40)&(df.Company=='Pink Cab')].groupby('Transaction ID').Profit.mean()</pre>
          y = df[(df.Age >= 40)&(df.Company=='Pink Cab')].groupby('Transaction ID').Profit.mean()
          print(x.shape[0],y.shape[0])
          , p value = stats.ttest ind(x.values,y.values,equal var=True)
          print('P value is ', p value)
          if(p value<0.05): # alpha value is 0.05 or 5%
              print("we are rejecting null hypothesis and it says that there is a difference regarding Age and Pink Cab")
          else:
              print("We are accepting null hypothesis that there is no difference noted regarding Age and Pink Cab")
```

62109 25336
P value is 0.09093510590632374
We are accepting null hypothesis that there is no difference noted regarding Age and Pink Cab

### Outliers detected and solved: Price Charged

Outlier Detection on Price Charged. - Noticed there are Outliers



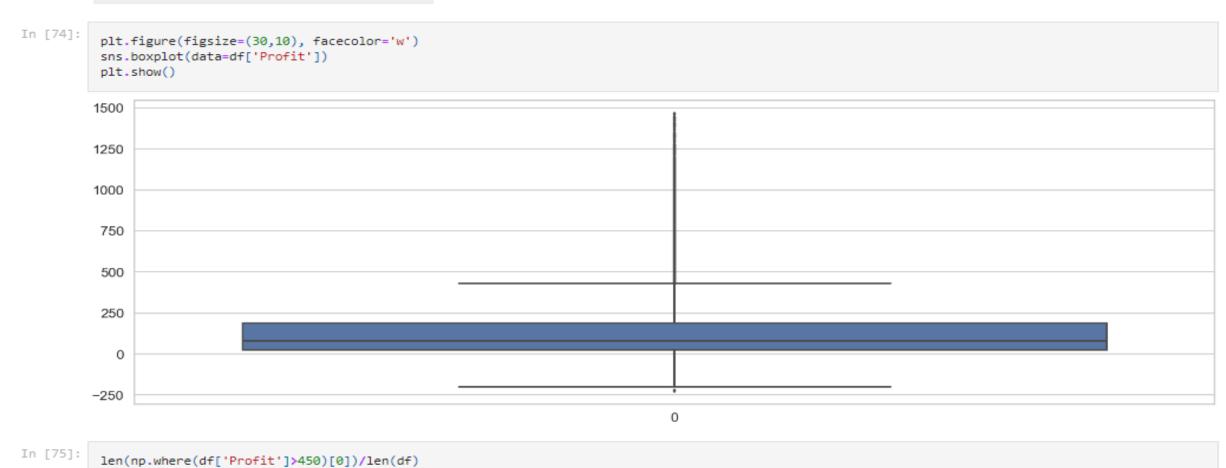
In [73]: len(np.where(df['Price Charged']>1200)[0])/len(df)

Out[73]: 0.012139947466832873

#### Outliers detected and solved: Profit

Outlier Detection on Profit. - Noticed there are Outliers

0.05926119668773929



#### Outliers detected and solved: Profit and Price Charged

```
In [79]:
          df['z_profit']=np.abs(stats.zscore(df.Profit))
          print("Removing Outliers: ", len(df[df['z_profit']>3]))
         Removing Outliers: 7244
In [80]:
          df = df[df['z profit']<3]
In [81]:
          df['z_price_charged']=np.abs(stats.zscore(df['Price Charged']))
          print("Removing Outliers: ", len(df[df['z price charged']>3]))
         Removing Outliers: 579
In [82]:
          df = df[df['z price charged']<3]</pre>
```

### Label Encoding done before applying Model

#### **Label Encoding**

```
In [87]:
           from sklearn.preprocessing import LabelEncoder
           lb= LabelEncoder()
In [88]:
           lb.fit(data['Company'])
           LabelEncoder()
Out[88]:
In [89]:
           classes= list(lb.classes )
In [90]:
           classes
          ['Pink Cab', 'Yellow Cab']
Out[90]:
In [91]:
           data['companies']= lb.fit transform(data['Company'])
In [92]:
           data.head(5)
Out[92]:
              Company
                                    KM Travelled
                                                  Price Charged Cost of Trip
                                                                               Profit Payment_Mode Gender Income (USD/Month)
                                                                                                                                  Population
                                                                                                                                              Users
                                                                                                                                                     Age companies
               Pink Cab ATLANTA GA
                                            30.45
                                                         370.95
                                                                   313.6350
                                                                             57.3150
                                                                                                Card
                                                                                                        Male
                                                                                                                            10813
                                                                                                                                      814,885 24,701
                                                                                                                                                       28
                                                                                                                                                                   0
          1 Yellow Cab ATLANTA GA
                                            26.19
                                                         598.70
                                                                   317.4228 281.2772
                                                                                                Cash
                                                                                                        Male
                                                                                                                            10813
                                                                                                                                      814,885 24,701
                                                                                                                                                       28
                                                                                                                                                                   1
             Yellow Cab ATLANTA GA
                                            42.55
                                                                                                                                                                   1
                                                         792.05
                                                                   597.4020
                                                                            194,6480
                                                                                                                            10813
                                                                                                                                                       28
                                                                                                Card
                                                                                                        Male
                                                                                                                                      814,885 24,701
               Pink Cab ATLANTA GA
                                            28.62
                                                         358.52
                                                                   334.8540
                                                                             23.6660
                                                                                                Card
                                                                                                        Male
                                                                                                                             9237
                                                                                                                                      814,885 24,701
                                                                                                                                                       27
                                                                                                                                                                   0
           4 Yellow Cab ATLANTA GA
                                            36.38
                                                         721.10
                                                                   467.1192 253.9808
                                                                                                Card
                                                                                                        Male
                                                                                                                                      814,885 24,701
```

#### 0 is for Pink Cab and 1 is for Yellow Cab

### Steps before applying Mode

Dropping Features ["Gender", "Payment\_Mode", "City"] so that I have only numerical values for modeling

```
In [95]:
           data.drop(["Gender","Payment_Mode","City",], axis=1, inplace=True)
In [96]:
           data.head()
Out[96]:
              Company KM Travelled Price Charged Cost of Trip
                                                                Profit Income (USD/Month) Population Users Age companies
              Pink Cab
                                                     313,6350
                              30.45
                                           370.95
                                                               57.3150
                                                                                     10813
                                                                                              814,885 24,701
                                                                                                                           0
          1 Yellow Cab
                              26,19
                                           598,70
                                                     317,4228 281,2772
                                                                                     10813
                                                                                              814,885 24,701
          2 Yellow Cab
                              42,55
                                           792.05
                                                     597,4020 194,6480
                                                                                     10813
                                                                                              814,885 24,701
                              28.62
          3 Pink Cab
                                           358.52
                                                     334,8540 23,6660
                                                                                      9237
                                                                                              814,885 24,701
                                                                                                                           0
                              36.38
          4 Yellow Cab
                                           721.10
                                                     467.1192 253.9808
                                                                                      9237
                                                                                              814,885 24,701
```

### Steps before applying Mode

#### String values noted while Normalizing

```
In [99]:
    data.Population = data.Population.str.replace(',','').astype(float)
    data.Users = data.Users.str.replace(',','').astype(float) # string values noted while normalizing
```

#### Splitting Data into Training and Test Set

### Steps before applying Model

#### Normalizing

```
In [106...
           scaler = MinMaxScaler()
           X train = scaler.fit transform(X train)
           X test = scaler.transform(X test)
In [107...
           from sklearn import datasets, linear model, metrics
           reg = linear model.LinearRegression()
           # train the model using the training sets
           reg.fit(X train, y train)
           # regression coefficients
           print('Coefficients: ', reg.coef )
          Coefficients: [ 6.20007014e-12    1.58726582e+03 -9.37039551e+02 -3.21844275e+02
            6.08291195e-13 3.12638804e-13 -3.41060513e-13 7.10542736e-14]
```

### Steps before applying Model

#### Cross Validation

```
In [108...
```

```
def get_cross_val(model, X_train, y_train, X_valid, y_valid):
   # Fit on train, predict on validation
    clf = model
   clf.fit(X train, y train)
   y_pred = clf.predict(X_valid)
   # Cross validation score over 10 folds
    scores = cross_val_score(clf, X_train, y_train, cv=10)
    print("Cross validation over 10 folds: ", sum(scores)/10.0)
    return y pred
```

### **Applying Model**

### **Applying Linear Regression Model**

```
In [109...
           Model = 'Linear Regression'
           lin predicted = reg.predict(X test)
           lin_acc_score = reg.score(X_train, y_train)
           print("LinearRegression:",lin_acc_score*100,'\n')
           get_cross_val(reg, X_train, y_train, X_test, y_test)
          LinearRegression: 100.0
          Cross validation over 10 folds: 1.0
          array([113.902 , 118.9316, 55. , ..., 27.682 , 246.5196, 146.3204])
Out [109...
```

#### Recommendation

From the data it is noted that the rides to New York have got more users which in turn have increased the income and profit of the firm.

It is well noted that Yellow cab is an outstanding performer as compared to Pink cab.

The demand for Yellow cab was higher as compared to Pink cab as it travelled longer kilometers as compared to pink cab and while taking the case of the availability for more cab was there even though many of yellow cab have gone for longer trips.

# G2M Case Study

## Thank You

