# G2M Case Study

Virtual Internship

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# Background –G2M(cab industry) case study

- XYZ is a private equity 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.

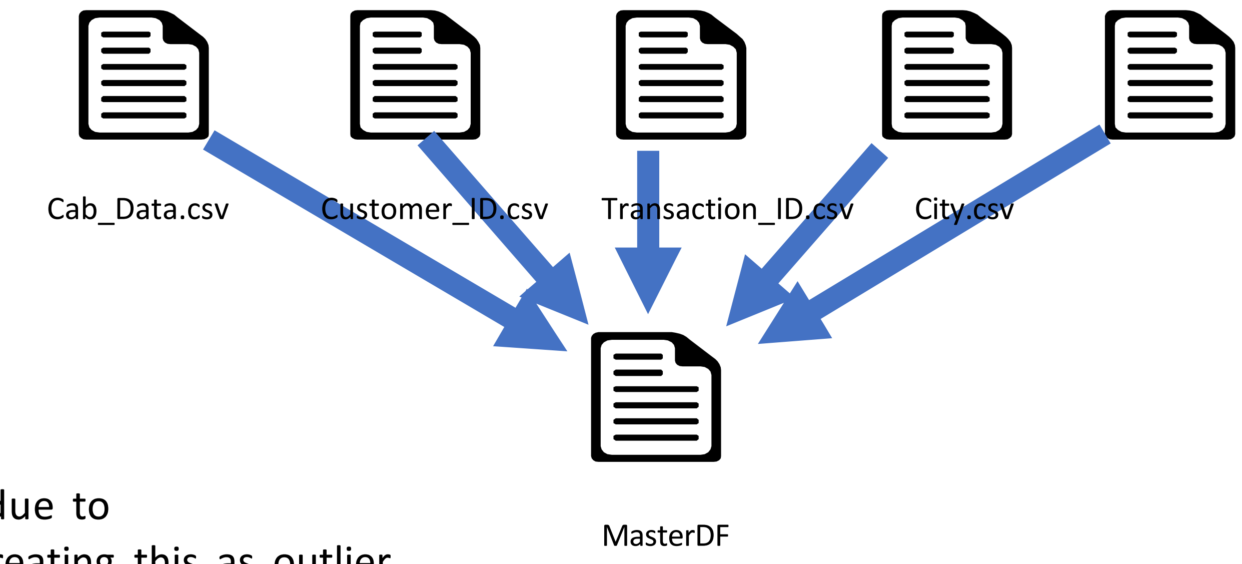
- Objective : Provide actionable insights to help XYZ firm in identifying the right company for making investment.

The analysis has been divided into four parts:

- Data Understanding
- Forecasting profit and number of rides for each cab type
- Finding the most profitable Cab company
- Recommendation for investment

# Data Exploration

- 24 Features( including 9 derived features)
- Timeframe of the data: 2016-01-31 to 2018-12-31
- Total data points :355,032




**Assumptions:**

- Outliers are present in Price_Charged feature but due to unavailability of trip duration details ,we are not treating this as outlier.

- Profit of rides are calculated keeping other factors constant and only Price_Charged and Cost_of_Trip features used to calculate profit.

- Users feature of city dataset is treated as number of cab users in the city. we have assumed that this can be other cab users as well(including Yellow and Pink cab)

In [1]:
```python
import pandas as pd
import numpy as np
import datetime as dt
import matplotlib.pyplot as plt
```

In [2]:
```python
#at first lets read all csv files and assign them to a variable to ease our job
#and lets review them with head method and count some important values to have a basic insight
#we have an error that cant convert 8,405,837 to int or float so we need to change it with 8.405,837
city=pd.read_csv(r"C:\Users\Abdullah\week2 datasets\City.csv")
city["Population"] = city["Population"].apply(lambda x: x.replace(',', ''))
city["Population"].apply(lambda x: int(x))
city["Users"] = city["Users"].apply(lambda x: x.replace(',', ''))
city["Population"].apply(lambda x: int(x))
city.drop_duplicates(keep="first")


city.head()
```

Out[2]:

| | 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 |

In [3]:
```python
cab_data=pd.read_csv(r"C:\Users\Abdullah\week2 datasets\Cab_Data.csv")
cab_data['Date of Travel'] = pd.to_datetime(cab_data['Date of Travel'],unit = 'D',origin = '1899-12-30')
cab_data.drop_duplicates(keep="first")
cab_data.dropna(how='all')
#if there is a row contains all nan value we drop it
cab_data.head(5)
```

Out[3]:

| | Transaction ID | Date of Travel | Company | City | KM Travelled | Price Charged | Cost of Trip |
|---|---|---|---|---|---|---|---|
| 0 | 10000011 | 2016-01-08 | Pink Cab | ATLANTA GA | 30.45 | 370.95 | 313.635 |
| 1 | 10000012 | 2016-01-06 | Pink Cab | ATLANTA GA | 28.62 | 358.52 | 334.854 |
| 2 | 10000013 | 2016-01-02 | Pink Cab | ATLANTA GA | 9.04 | 125.20 | 97.632 |
| 3 | 10000014 | 2016-01-07 | Pink Cab | ATLANTA GA | 33.17 | 377.40 | 351.602 |
| 4 | 10000015 | 2016-01-03 | Pink Cab | ATLANTA GA | 8.73 | 114.62 | 97.776 |

In [4]:
```python
cab_data["City"].value_counts()
```

Out[4]:
```
NEW YORK NY       99885
CHICAGO IL        56625
LOS ANGELES CA    48033
WASHINGTON DC     43737
BOSTON MA         29692
SAN DIEGO CA      20488
SILICON VALLEY     8519
SEATTLE WA         7997
ATLANTA GA         7557
DALLAS TX          7017
MIAMI FL           6454
AUSTIN TX          4896
ORANGE COUNTY      3982
DENVER CO          3825
NASHVILLE TN       3010
SACRAMENTO CA      2367
PHOENIX AZ         2064
TUCSON AZ          1931
PITTSBURGH PA      1313
Name: City, dtype: int64
```

In [5]:
```python
customer_id=pd.read_csv(r"C:\Users\Abdullah\week2 datasets\Customer_ID.csv")

customer_id.drop_duplicates(keep="first")

customer_id.head(5)
```

Out[5]:

| | 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 [6]:
```python
customer_id["Gender"].value_counts()
```

Out[6]:
```
Male      26562
Female    22609
Name: Gender, dtype: int64
```

In [7]:
```python
transaction_id=pd.read_csv(r"C:\Users\Abdullah\week2 datasets\Transaction_ID.csv")
transaction_id.drop_duplicates(keep="first")

transaction_id.head(5)
```

Out[7]:

| | 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 [8]:
```python
transaction_id["Payment_Mode"].value_counts()
```

Out[8]:
```
Card    263991
Cash    176107
Name: Payment_Mode, dtype: int64
```

In [9]:
```python
#now lets check data quality if there are NaN or null values and see the data types
a=[(city.isnull().sum()),city.info()]
b=[(cab_data.isnull().sum()),cab_data.info()]
c=[(customer_id.isnull().sum()),customer_id.info()]
d=[(transaction_id.isnull().sum()),transaction_id.info()]
print(a,b,c,d)
```

```
<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
<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  datetime64[ns]
 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: datetime64[ns](1), float64(3), int64(1), object(2)
memory usage: 19.2+ MB
<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
<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
[City          0
Population    0
Users         0
dtype: int64, None] [Transaction ID    0
Date of Travel    0
Company           0
City              0
KM Travelled      0
Price Charged     0
Cost of Trip      0
dtype: int64, None] [Customer ID           0
Gender                0
Age                   0
Income (USD/Month)    0
dtype: int64, None] [Transaction ID    0
Customer ID       0
Payment_Mode      0
dtype: int64, None]
```

In [10]:
```python
#at first glance it seems yellow cab is better at profit per km
#added a column named "Profit per km" in order to determine which company is better per km profit
cab_data["Profit per KM"]=(cab_data["Price Charged"]-cab_data["Cost of Trip"])/(cab_data["KM Travelled"])
cab_data.head(3)
```

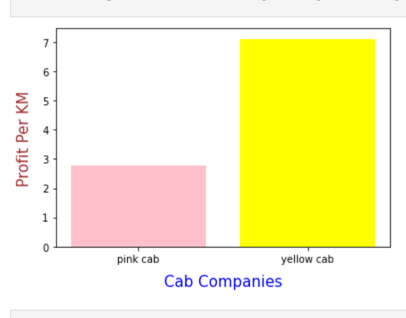
Out[10]:

| | Transaction ID | Date of Travel | Company | City | KM Travelled | Price Charged | Cost of Trip | Profit per KM |
|---|---|---|---|---|---|---|---|---|
| 0 | 10000011 | 2016-01-08 | Pink Cab | ATLANTA GA | 30.45 | 370.95 | 313.635 | 1.882266 |
| 1 | 10000012 | 2016-01-06 | Pink Cab | ATLANTA GA | 28.62 | 358.52 | 334.854 | 0.826904 |
| 2 | 10000013 | 2016-01-02 | Pink Cab | ATLANTA GA | 9.04 | 125.20 | 97.632 | 3.049558 |

In [11]:
```python
#now lets find average profit per km by company name to determine which cab is preferrable based on our hypotes
pc=cab_data.loc[cab_data["Company"]=="Pink Cab","Profit per KM"].mean()
yc=cab_data.loc[cab_data["Company"]=="Yellow Cab","Profit per KM"].mean()
strpc=str(pc)
stryc=str(yc)
print("Average Profit for KM for Pink Cab is "+ strpc," ","Average Profit for KM for Yellow Cab is "+ stryc)
```

```
Average Profit for KM for Pink Cab is 2.769907700396525   Average Profit for KM for Yellow Cab is 7.10550780835
3063
```

In [12]:
```python
plt.xlabel("Cab Companies",fontsize=15,color='blue',labelpad=10)
plt.ylabel("Profit Per KM",fontsize=15,color='brown',labelpad=10)
plt.bar(["pink cab","yellow cab"],[pc,yc],color=["pink","yellow"]);


#as we see yellow cab has much profit per KM comparing to pink cab
```




In [13]:
```python
#so lets create master data using 4 dataframe to one using joins based on common columns
merged1=pd.merge(city,cab_data,on='City',how='outer')
merged2=pd.merge(customer_id,transaction_id,on='Customer ID',how='outer')
merged2.head()
```

Out[13]:

| | Customer ID | Gender | Age | Income (USD/Month) | Transaction ID | Payment_Mode |
|---|---|---|---|---|---|---|
| 0 | 29290 | Male | 28 | 10813 | 10000011 | Card |
| 1 | 29290 | Male | 28 | 10813 | 10351127 | Cash |
| 2 | 29290 | Male | 28 | 10813 | 10412921 | Card |
| 3 | 27703 | Male | 27 | 9237 | 10000012 | Card |
| 4 | 27703 | Male | 27 | 9237 | 10320494 | Card |

In [14]:
```python
merged1.head()
```

Out[14]:

| | City | Population | Users | Transaction ID | Date of Travel | Company | KM Travelled | Price Charged | Cost of Trip | Profit per KM |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | NEW YORK NY | 8405837 | 302149 | 10000139.0 | 2016-01-08 | Pink Cab | 17.85 | 242.90 | 198.135 | 2.507843 |
| 1 | NEW YORK NY | 8405837 | 302149 | 10000140.0 | 2016-01-09 | Pink Cab | 25.30 | 407.21 | 255.530 | 5.995257 |
| 2 | NEW YORK NY | 8405837 | 302149 | 10000141.0 | 2016-01-06 | Pink Cab | 16.32 | 236.41 | 186.048 | 3.085907 |
| 3 | NEW YORK NY | 8405837 | 302149 | 10000142.0 | 2016-01-04 | Pink Cab | 12.43 | 194.61 | 144.188 | 4.056476 |
| 4 | NEW YORK NY | 8405837 | 302149 | 10000143.0 | 2016-01-09 | Pink Cab | 29.70 | 434.57 | 350.460 | 2.831987 |

In [15]:
```python
#NOW WE HAVE A MASTER DF MERGING TO MERGED DATAFRAME
masterdf=pd.merge(merged1,merged2,on='Transaction ID',how='outer')
masterdf.dropna
masterdf.head(12)
```

Out[15]:

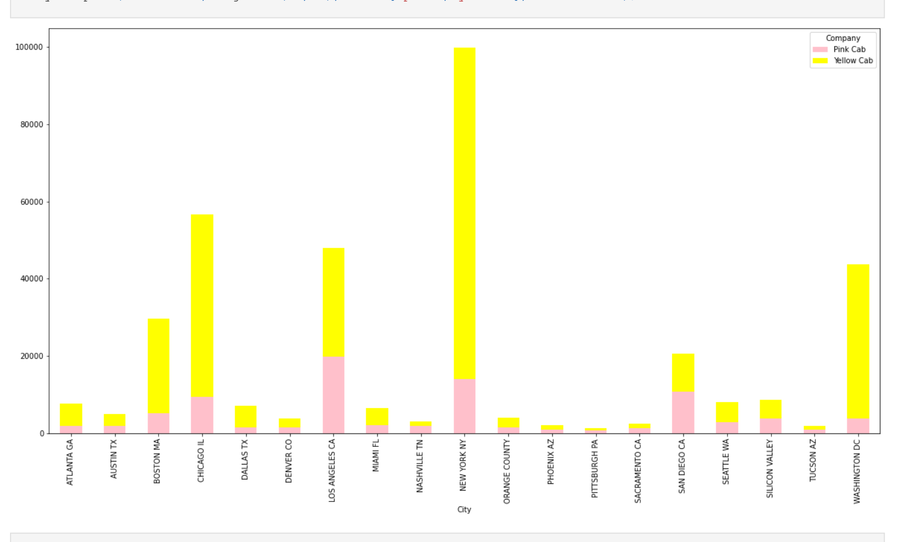
| | City | Population | Users | Transaction ID | Date of Travel | Company | KM Travelled | Price Charged | Cost of Trip | Profit per KM | Customer ID | Gender | Age | Income (USD/Month) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | NEW YORK NY | 8405837 | 302149 | 10000139.0 | 2016-01-08 | Pink Cab | 17.85 | 242.90 | 198.135 | 2.507843 | 2416.0 | Male | 28.0 | 21399.0 |
| 1 | NEW YORK NY | 8405837 | 302149 | 10000140.0 | 2016-01-09 | Pink Cab | 25.30 | 407.21 | 255.530 | 5.995257 | 2060.0 | Male | 18.0 | 8149.0 |
| 2 | NEW YORK NY | 8405837 | 302149 | 10000141.0 | 2016-01-06 | Pink Cab | 16.32 | 236.41 | 186.048 | 3.085907 | 1451.0 | Male | 35.0 | 23989.0 |
| 3 | NEW YORK NY | 8405837 | 302149 | 10000142.0 | 2016-01-04 | Pink Cab | 12.43 | 194.61 | 144.188 | 4.056476 | 1609.0 | Male | 30.0 | 23036.0 |
| 4 | NEW YORK NY | 8405837 | 302149 | 10000143.0 | 2016-01-09 | Pink Cab | 29.70 | 434.57 | 350.460 | 2.831987 | 2927.0 | Male | 33.0 | 14520.0 |
| 5 | NEW YORK NY | 8405837 | 302149 | 10000144.0 | 2016-01-12 | Pink Cab | 19.00 | 305.81 | 214.700 | 4.795263 | 2626.0 | Male | 18.0 | 30401.0 |
| 6 | NEW YORK NY | 8405837 | 302149 | 10000145.0 | 2016-01-02 | Pink Cab | 2.10 | 37.18 | 21.420 | 7.504762 | 502.0 | Male | 28.0 | 15285.0 |
| 7 | NEW YORK NY | 8405837 | 302149 | 10000146.0 | 2016-01-03 | Pink Cab | 16.52 | 290.52 | 168.504 | 7.385956 | 2571.0 | Male | 33.0 | 4620.0 |
| 8 | NEW YORK NY | 8405837 | 302149 | 10000147.0 | 2016-01-08 | Pink Cab | 27.30 | 439.40 | 294.840 | 5.295238 | 769.0 | Male | 63.0 | 29758.0 |
| 9 | NEW YORK NY | 8405837 | 302149 | 10000148.0 | 2016-01-06 | Pink Cab | 24.70 | 325.27 | 276.640 | 1.968826 | 373.0 | Male | 27.0 | 5070.0 |
| 10 | NEW YORK NY | 8405837 | 302149 | 10000149.0 | 2016-01-02 | Pink Cab | 32.64 | 498.60 | 349.248 | 4.575735 | 533.0 | Male | 52.0 | 15974.0 |
| 11 | NEW YORK NY | 8405837 | 302149 | 10000150.0 | 2016-01-03 | Pink Cab | 28.84 | 465.87 | 299.936 | 5.753606 | 1217.0 | Male | 51.0 | 3122.0 |

In [16]:
```python
#LETS CHECK THE CORRELATIONS BETWEEN COLUMNS IN DF BEFORE VISUALIZING THE RELEVANT ONES
masterdf.corr()
```

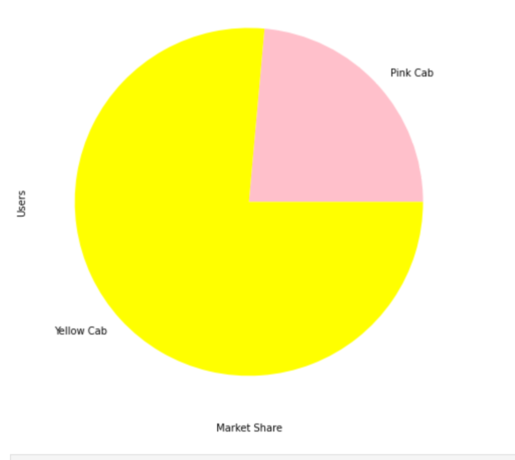
Out[16]:

| | Transaction ID | KM Travelled | Price Charged | Cost of Trip | Profit per KM | Customer ID | Age | Income (USD/Month) |
|---|---|---|---|---|---|---|---|---|
| Transaction ID | 1.000000 | -0.001429 | -0.052902 | -0.003462 | -0.110524 | -0.021289 | -0.001060 | -0.000935 |
| KM Travelled | -0.001429 | 1.000000 | 0.835753 | 0.981848 | -0.000538 | 0.000389 | -0.000369 | -0.000544 |
| Price Charged | -0.052902 | 0.835753 | 1.000000 | 0.859812 | 0.473222 | -0.177324 | -0.003084 | 0.003228 |
| Cost of Trip | -0.003462 | 0.981848 | 0.859812 | 1.000000 | 0.031053 | 0.003077 | -0.000189 | -0.000633 |
| Profit per KM | -0.110524 | -0.000538 | 0.473222 | 0.031053 | 1.000000 | -0.394133 | -0.006428 | 0.008159 |
| Customer ID | -0.021289 | 0.000389 | -0.177324 | 0.003077 | -0.394133 | 1.000000 | -0.002161 | -0.005834 |
| Age | -0.001060 | -0.000369 | -0.003084 | -0.000189 | -0.006428 | -0.002161 | 1.000000 | -0.000573 |
| Income (USD/Month) | -0.000935 | -0.000544 | 0.003228 | -0.000633 | 0.008159 | -0.005834 | -0.000573 | 1.000000 |

In [31]:
```python
#CHECKED COMPANY'S TOTAL USERS FOR EACH CITY
citysum=masterdf.groupby(by=['City','Company']).count()['Users'].unstack("Company")

citysum.plot(kind="bar", figsize=(20,10),color=["pink","yellow"],stacked=True);
```




In [30]:
```python
# total market share
#as we see yellow cab dominates the current market .
piesum=masterdf.groupby(('Company'))
piesum=piesum.count()['Users']
plt.xlabel('Market Share')
piesum.plot(kind="pie",colors=["pink","yellow"],figsize=(10,8));
```




In [19]:
```python
masterdf["Income (USD/Month)"].mean()
masterdf["Income (USD/Month)"].max()
```

Out[19]:
```
35000.0
```

In [20]:
```python
#now lets check the relation between income and cab usage stats
#to categorize incomes we found the mean income value above
#mean value is 15000 , max val is 35000 so we categorize income below;


def incomecomparison(income):
    if income <10000:
        return "Poor"
    elif income <=25000:
        return "Mid income"
    else:
        return "Rich"

a=masterdf["Income (USD/Month)"].apply(incomecomparison)
```

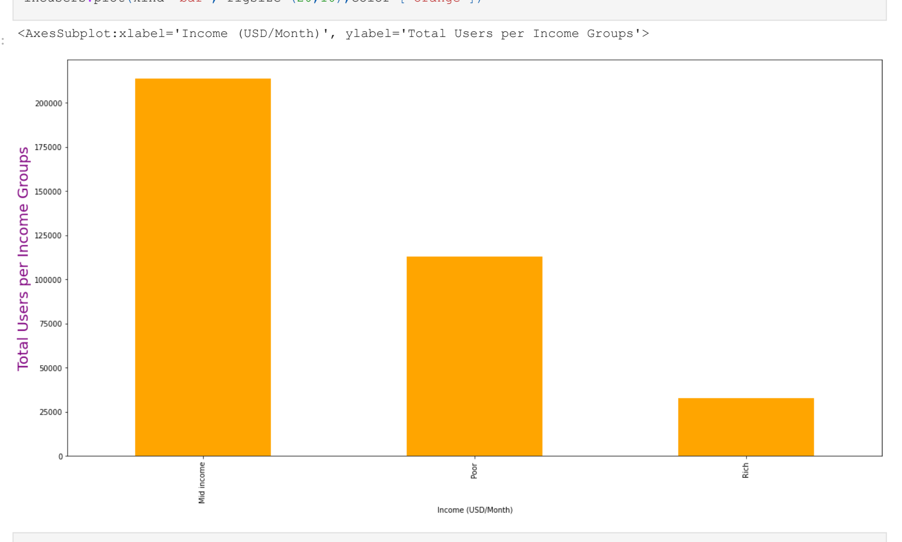
In [21]:
```python
masterdf["Income (USD/Month)"]=a
masterdf.head()
```

Out[21]:

| | City | Population | Users | Transaction ID | Date of Travel | Company | KM Travelled | Price Charged | Cost of Trip | Profit per KM | Customer ID | Gender | Age | Income (USD/Month) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | NEW YORK NY | 8405837 | 302149 | 10000139.0 | 2016-01-08 | Pink Cab | 17.85 | 242.90 | 198.135 | 2.507843 | 2416.0 | Male | 28.0 | Mid income |
| 1 | NEW YORK NY | 8405837 | 302149 | 10000140.0 | 2016-01-09 | Pink Cab | 25.30 | 407.21 | 255.530 | 5.995257 | 2060.0 | Male | 18.0 | Poor |
| 2 | NEW YORK NY | 8405837 | 302149 | 10000141.0 | 2016-01-06 | Pink Cab | 16.32 | 236.41 | 186.048 | 3.085907 | 1451.0 | Male | 35.0 | Mid income |
| 3 | NEW YORK NY | 8405837 | 302149 | 10000142.0 | 2016-01-04 | Pink Cab | 12.43 | 194.61 | 144.188 | 4.056476 | 1609.0 | Male | 30.0 | Mid income |
| 4 | NEW YORK NY | 8405837 | 302149 | 10000143.0 | 2016-01-09 | Pink Cab | 29.70 | 434.57 | 350.460 | 2.831987 | 2927.0 | Male | 33.0 | Mid income |

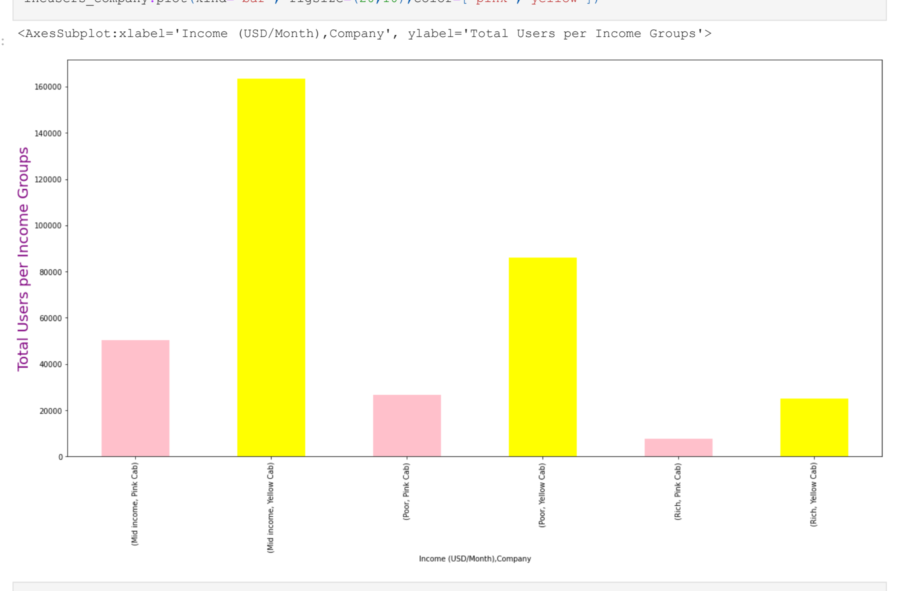
In [22]:
```python
#total users per income groups
incusers=masterdf.groupby("Income (USD/Month)").count()['Users']
incusers.to_frame()
plt.ylabel('Total Users per Income Groups',fontsize=20,color="purple")
incusers.plot(kind="bar", figsize=(20,10),color=["orange"])
```

Out[22]:
```
<AxesSubplot:xlabel='Income (USD/Month)', ylabel='Total Users per Income Groups'>
```



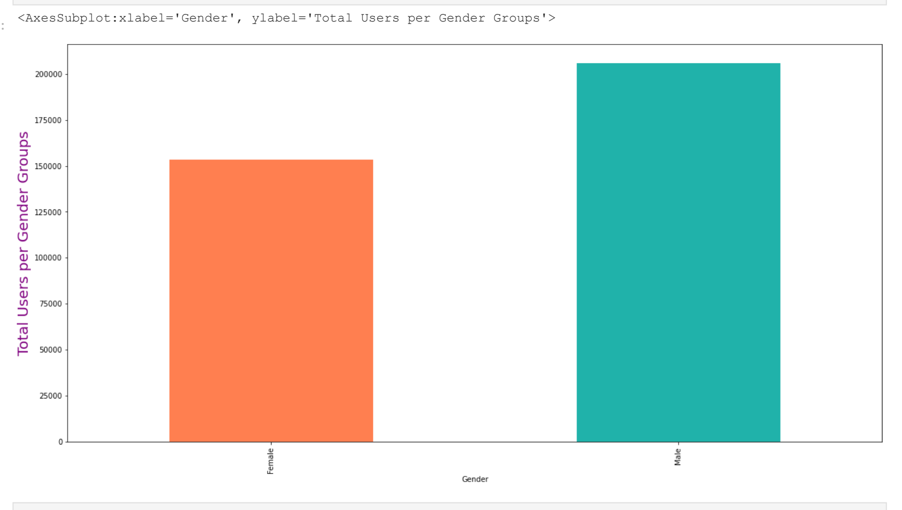

In [33]:
```python
#total users per income groups for each company
#yellow cab has largest number of user in the mid income group which prefers using cab more than other income g
incusers_company=masterdf.groupby(["Income (USD/Month)","Company"]).count()['Users']
incusers_company.to_frame()
plt.ylabel('Total Users per Income Groups',fontsize=20,color="purple")
incusers_company.plot(kind="bar", figsize=(20,10),color=["pink","yellow"])
```

Out[33]:
```
<AxesSubplot:xlabel='Income (USD/Month),Company', ylabel='Total Users per Income Groups'>
```



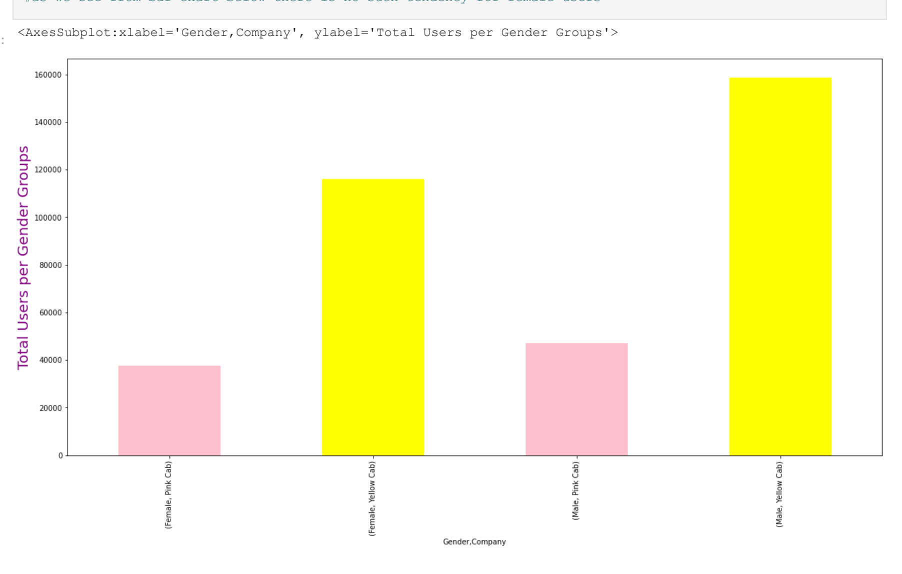

In [23]:
```python
#first i took a glance to total users per genders
genusers=masterdf.groupby("Gender").count()['Users']
genusers.to_frame()
plt.ylabel('Total Users per Gender Groups',fontsize=20,color="purple")
genusers.plot(kind="bar", figsize=(20,10),color=["coral","lightseagreen"])
```

Out[23]:
```
<AxesSubplot:xlabel='Gender', ylabel='Total Users per Gender Groups'>
```




In [24]:
```python
#female users have a tendency to use pink cab more often?
gender_cab=masterdf.groupby(by=['Gender','Company']).count()['Users']
gender_cab.to_frame()
plt.ylabel('Total Users per Gender Groups',fontsize=20,color="purple")
gender_cab.plot(kind="bar",stacked=True, figsize=(20,10),color=("pink","yellow"))
#as we see from bar chart below there is no such tendency for female users
```

Out[24]:
```
<AxesSubplot:xlabel='Gender,Company', ylabel='Total Users per Gender Groups'>
```




## now lets checked the total cab users per year

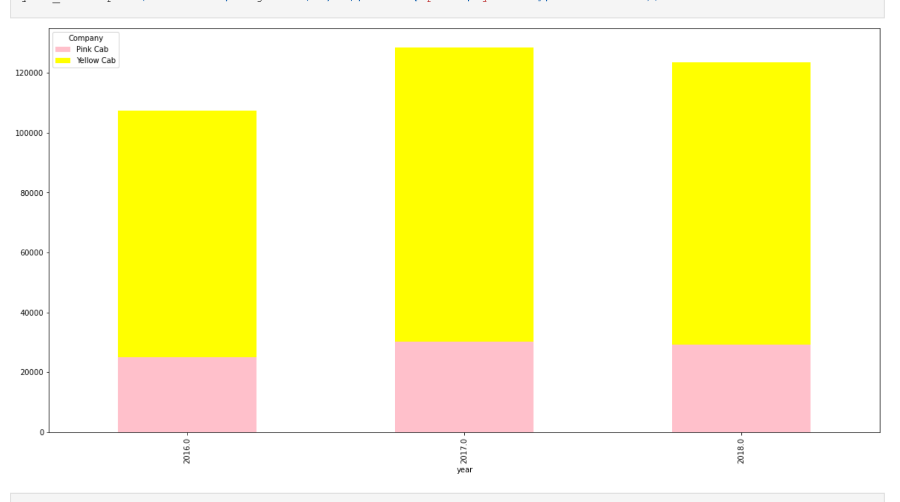
## code failed !!

## in order to divide datetime to year i used another method below

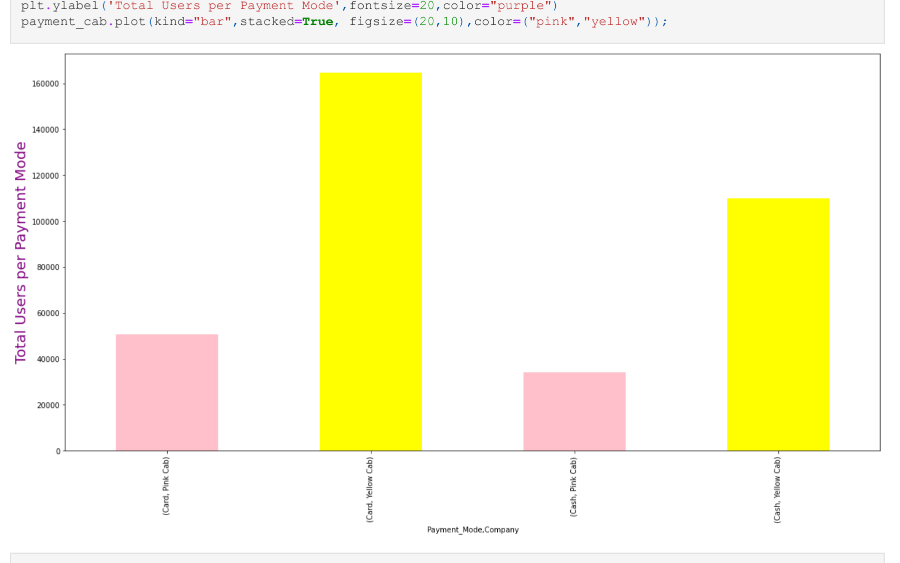
dfcopy=masterdf.copy() t2016=pd.date_range("2016-01-01", periods=365, freq="D").to_series().array t2017=pd.date_range("2017-01-01", periods=365, freq="D").to_series().array t2018=pd.date_range("2018-01-01", periods=365, freq="D").to_series().array def yearindicator(i): for i in dfcopy["Date of Travel"]: if i in t2016: return "2016" elif i in t2017: return "2017" elif i in t2018: return "2018" else: return "error"

time_user=dfcopy["Date of Travel"].apply(yearindicator) time_user

In [34]:
```python
#now lets checked the total cab users per year
#i added a new column called "year"
#as we see yellow cab has more users than pink cab in each year
masterdf['year'] = masterdf['Date of Travel'].dt.year
masterdf['year']
year_users=masterdf.groupby(by=['year','Company']).count()['Users'].unstack("Company")
year_users.plot(kind="bar", figsize=(20,10),color=["pink","yellow"],stacked=True);
```




In [35]:
```python
#lets check cab company's total users per payment mode
payment_cab=masterdf.groupby(by=['Payment_Mode','Company']).count()['Users']
payment_cab.to_frame()
plt.ylabel('Total Users per Payment Mode',fontsize=20,color="purple")
payment_cab.plot(kind="bar",stacked=True, figsize=(20,10),color=("pink","yellow"));
```



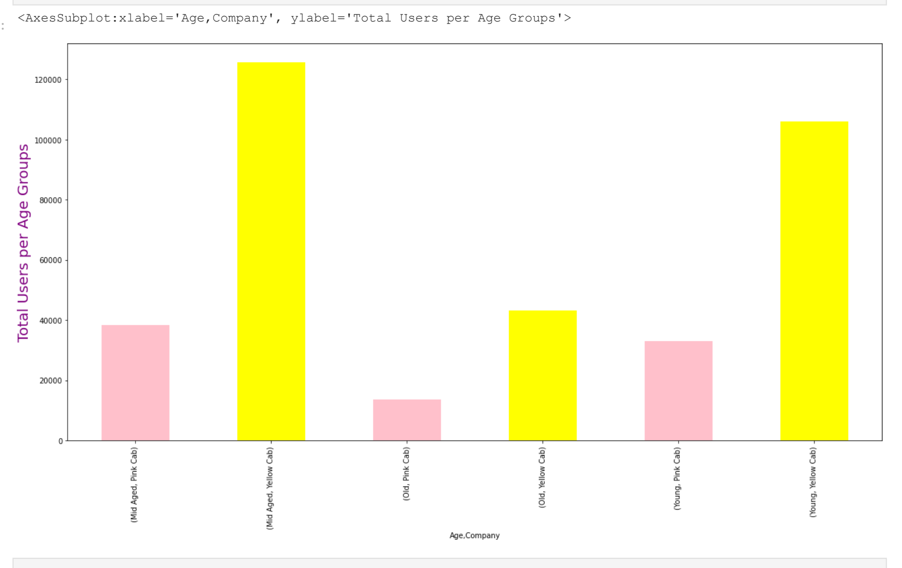

In [27]:
```python
#age and cab using relation diagram
#ages grouped into 3 different group using a simple function
def agecomparison(age):
    if age <30:
        return "Young"
    elif age <=50:
        return "Mid Aged"
    else:
        return "Old"

a=masterdf["Age"].apply(agecomparison)
masterdf["Age"]=a
masterdf.head()
```

Out[27]:

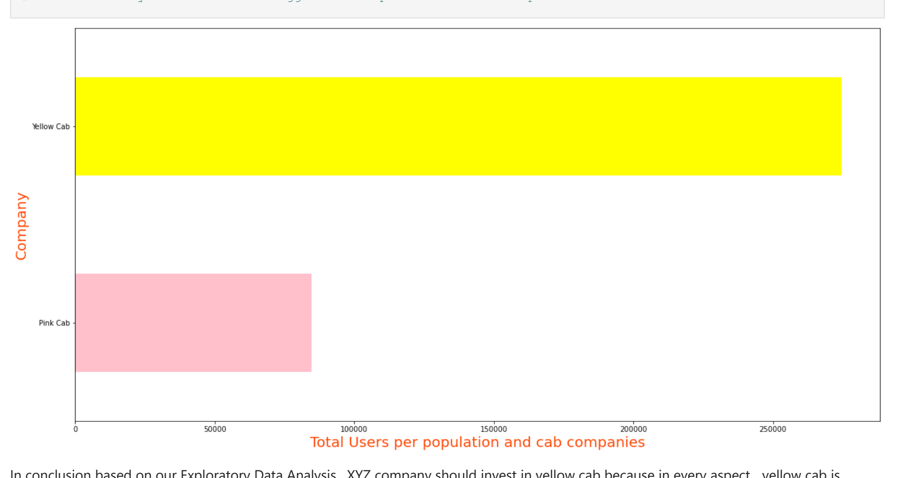
| | City | Population | Users | Transaction ID | Date of Travel | Company | KM Travelled | Price Charged | Cost of Trip | Profit per KM | Customer ID | Gender | Age | Income (USD/Month) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | NEW YORK NY | 8405837 | 302149 | 10000139.0 | 2016-01-08 | Pink Cab | 17.85 | 242.90 | 198.135 | 2.507843 | 2416.0 | Male | Young | Mid income |
| 1 | NEW YORK NY | 8405837 | 302149 | 10000140.0 | 2016-01-09 | Pink Cab | 25.30 | 407.21 | 255.530 | 5.995257 | 2060.0 | Male | Young | Poor |
| 2 | NEW YORK NY | 8405837 | 302149 | 10000141.0 | 2016-01-06 | Pink Cab | 16.32 | 236.41 | 186.048 | 3.085907 | 1451.0 | Male | Mid Aged | Mid income |
| 3 | NEW YORK NY | 8405837 | 302149 | 10000142.0 | 2016-01-04 | Pink Cab | 12.43 | 194.61 | 144.188 | 4.056476 | 1609.0 | Male | Mid Aged | Mid income |
| 4 | NEW YORK NY | 8405837 | 302149 | 10000143.0 | 2016-01-09 | Pink Cab | 29.70 | 434.57 | 350.460 | 2.831987 | 2927.0 | Male | Mid Aged | Mid income |

In [28]:
```python
#yellow cab is preferred mostly by mid aged users
age_cab=masterdf.groupby(by=['Age','Company']).count()['Users']
age_cab.to_frame()
plt.ylabel('Total Users per Age Groups',fontsize=20,color="purple")
age_cab.plot(kind="bar",stacked=True, figsize=(20,10),color=("pink","yellow"))
```

Out[28]:
```
<AxesSubplot:xlabel='Age,Company', ylabel='Total Users per Age Groups'>
```




In [36]:
```python
pop_cab=masterdf.groupby(by=['Company']).count()['Population']
pop_cab.to_frame()
plt.xlabel('Total Users per population and cab companies',fontsize=20,color="orangered")
plt.ylabel('Cab Companies',fontsize=20,color="orangered")

pop_cab.plot(kind="barh",stacked=True, figsize=(20,10),color=("pink","yellow"));
#as we can see yellow cab has a bigger market potential than the pink cab
```




In conclusion based on our Exploratory Data Analysis , XYZ company should invest in yellow cab because in every aspect , yellow cab is better and having more potential than the pink cab has.

In [ ]:

In [ ]: