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

In [2]:
```
#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]:
```
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]:
```
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]:
```
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]:
```
customer_id["Gender"].value_counts()
```

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

In [7]:
```
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]:
```
transaction_id["Payment_Mode"].value_counts()
```

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

In [9]:
```
#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]:
```
#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)
```

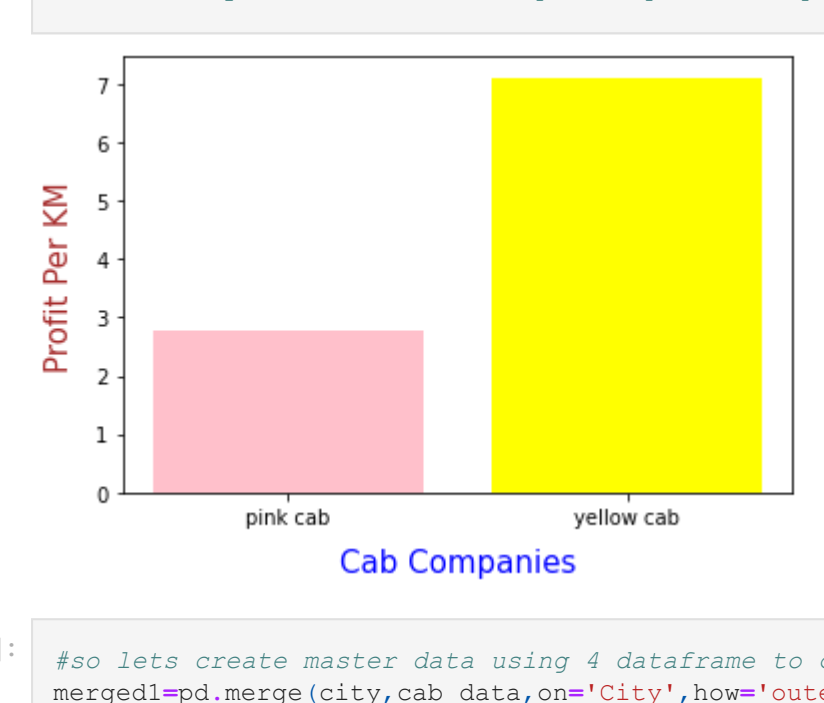
Out[10]:

	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]:
```
#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]:
```
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]:
```
#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]:
```
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]:
```
#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]:

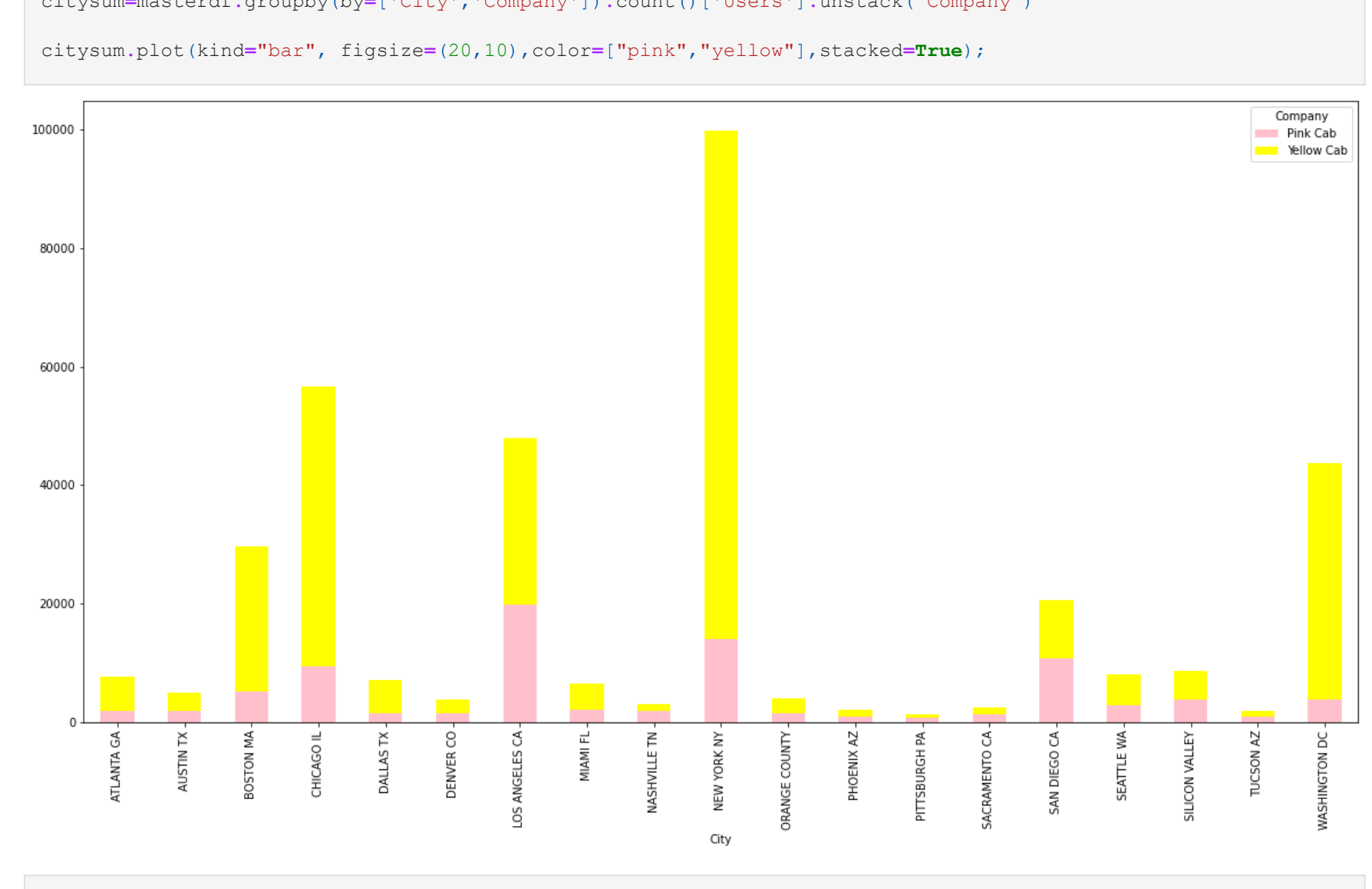
	City	Population	Users	Transaction ID	Date of Travel	Company	KM Travelled	Price Charged	Cost of Trip	Profit per KM	Customer ID	Gender	Age	Income (USD/Month)
0	NEW YORK NY	8405837	302149	10000139.0	2016-01-08	Pink Cab	17.85	242.90	198.135	2.507843	2416.0	Male	28.0	21399.0
1	NEW YORK NY	8405837	302149	10000140.0	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]:
```
#LETS CHECK THE CORRELATIONS BETWEEN COLUMNS IN DF BEFORE VISUALIZING THE RELEVANT ONES
masterdf.corr()
```

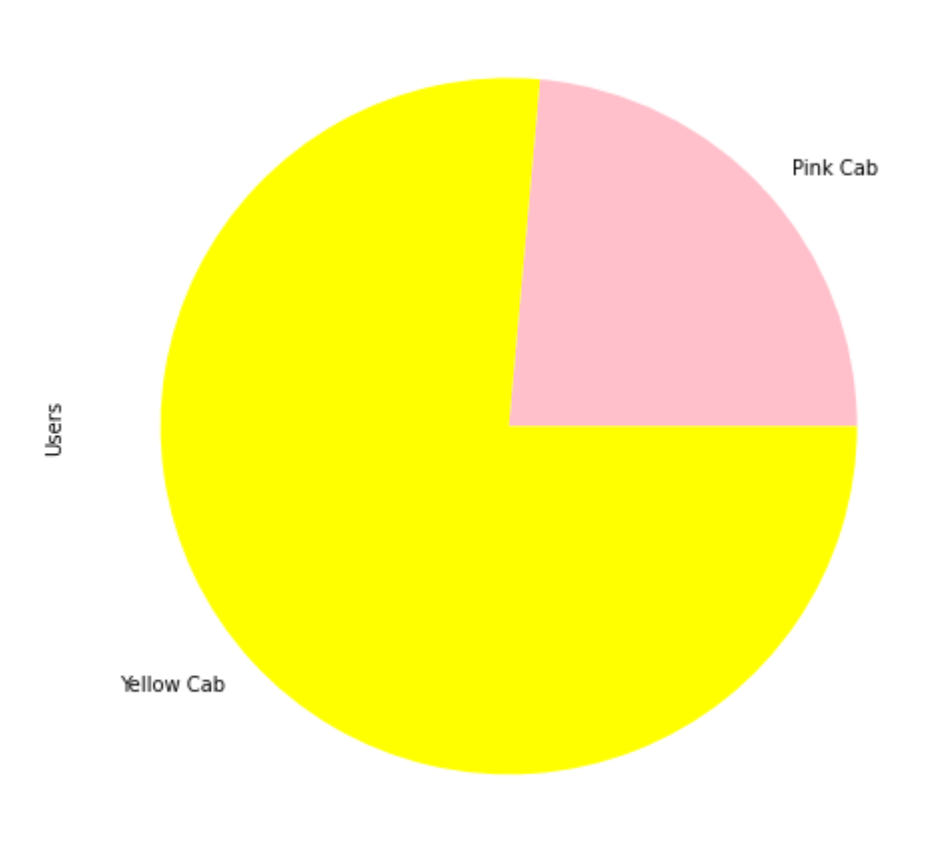
Out[16]:

	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]:
```
#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]:
```
# 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]:
```
masterdf["Income (USD/Month)"].mean()
masterdf["Income (USD/Month)"].max()
```

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

In [20]:
```
#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)
```

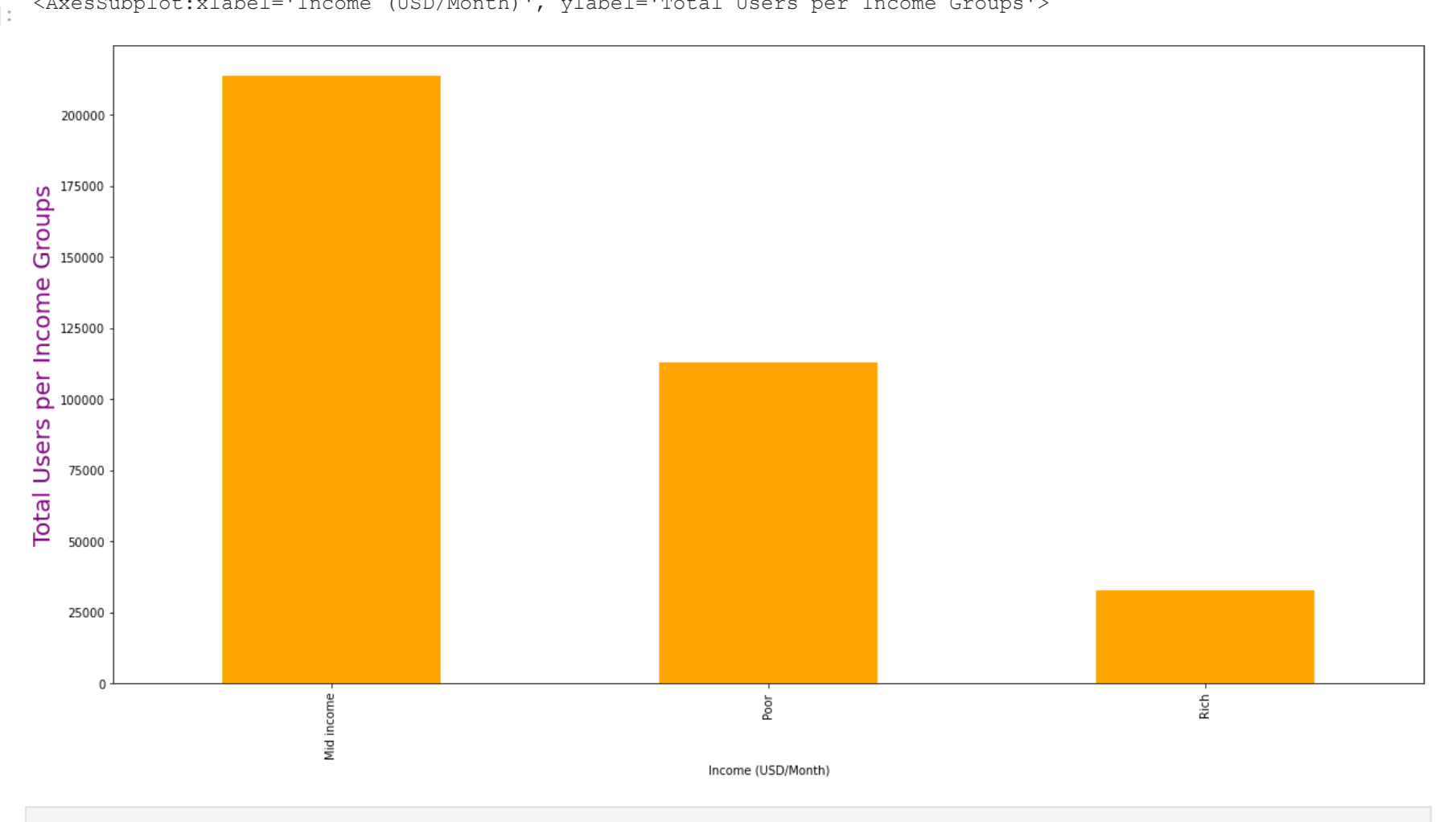
In [21]:
```
masterdf["Income (USD/Month)"]=a
masterdf.head()
```

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

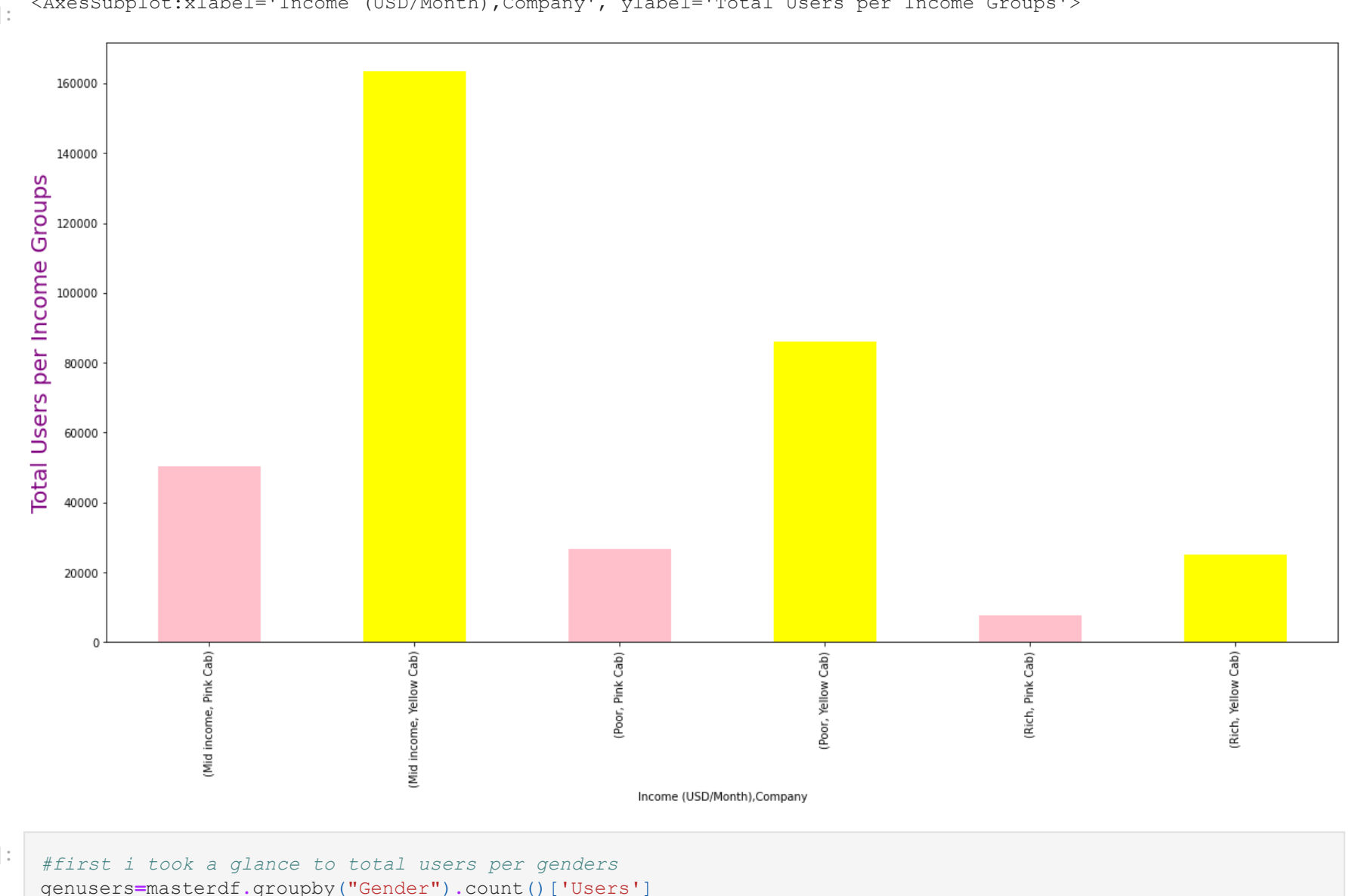
In [22]:
```
#total users per income groups
incusers=masterdf.groupby("Income (USD/Month)").count()['Users']
incusers.to_frame()
plt.ylabel('Total Users per Income Groups',fontsize=20,color="purple")
incusers.plot(kind="bar", figsize=(20,10),color=["orange"])
```

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



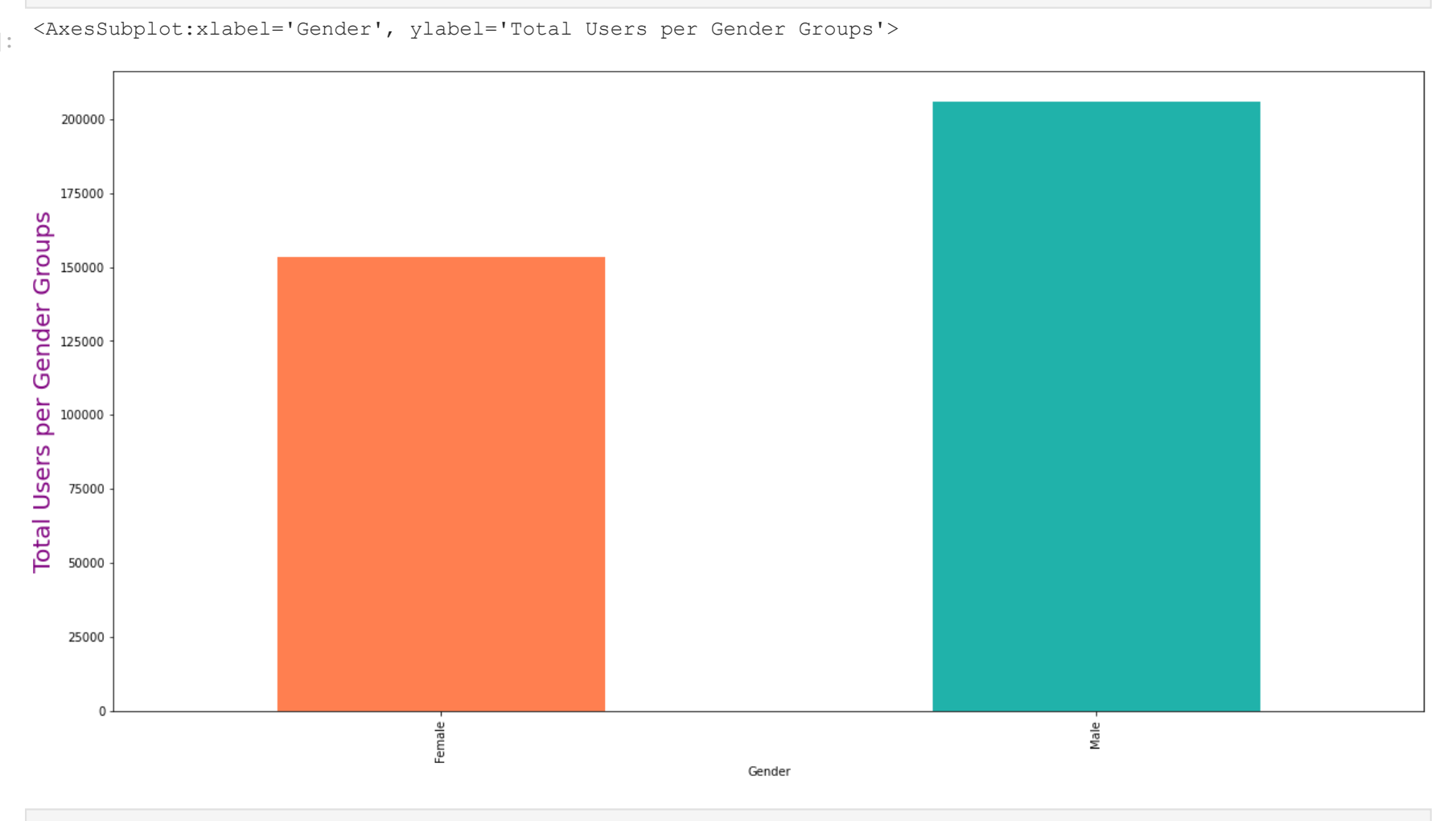
In [33]:
```
#total users per income groups for each company
#yellow cab has largest number of user in the mid income group which prefers using cab more than other income g
incusers_company=masterdf.groupby(["Income (USD/Month)","Company"]).count()['Users']
incusers_company.to_frame()
plt.ylabel('Total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



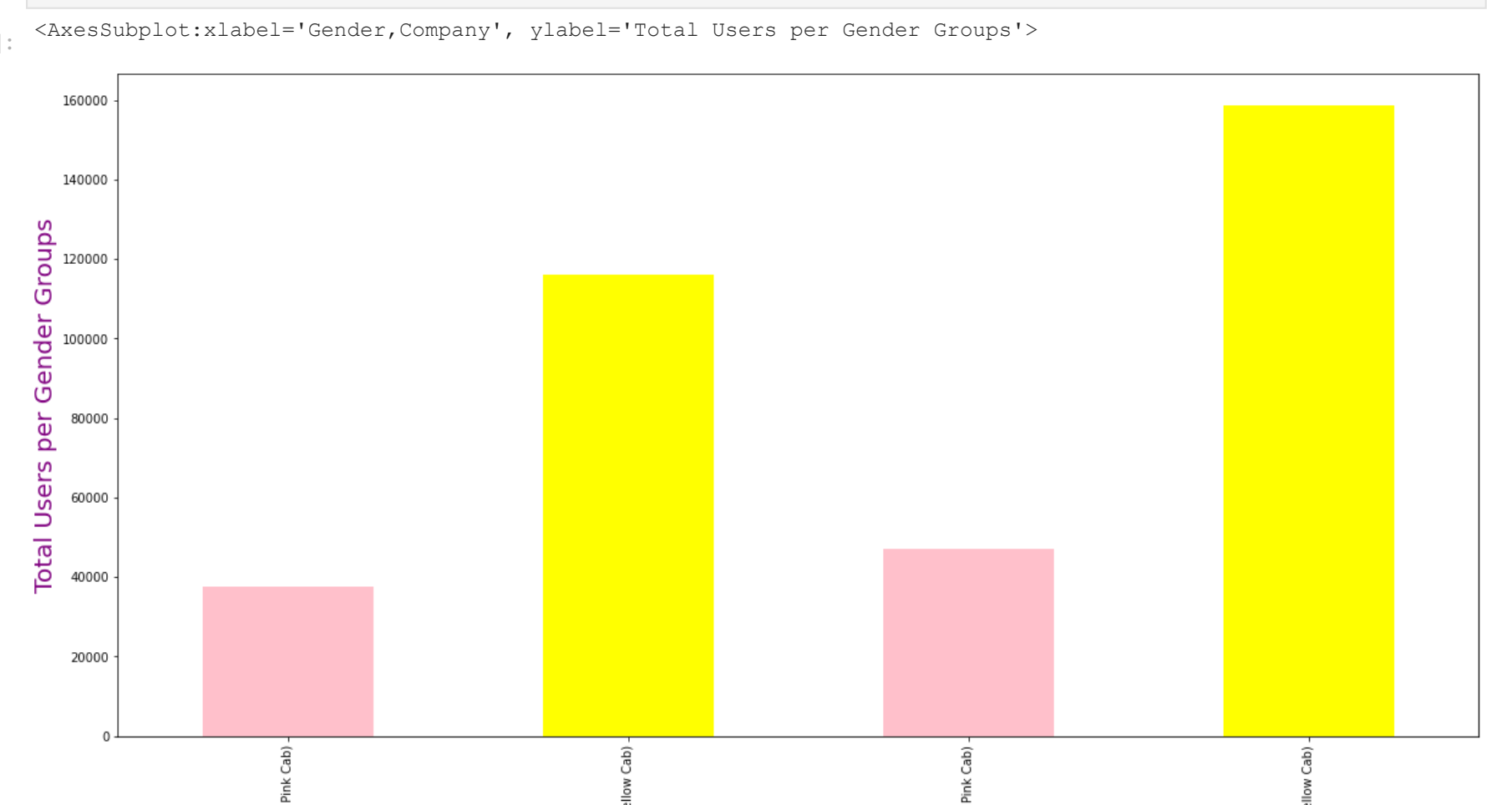
In [23]:
```
#first i took a glance to total users per genders
genusers=masterdf.groupby("Gender").count()['Users']
genusers.to_frame()
plt.ylabel('Total Users per Gender Groups',fontsize=20,color="purple")
genusers.plot(kind="bar", figsize=(20,10),color=["coral","lightseagreen"])
```

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



In [24]:
```
#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

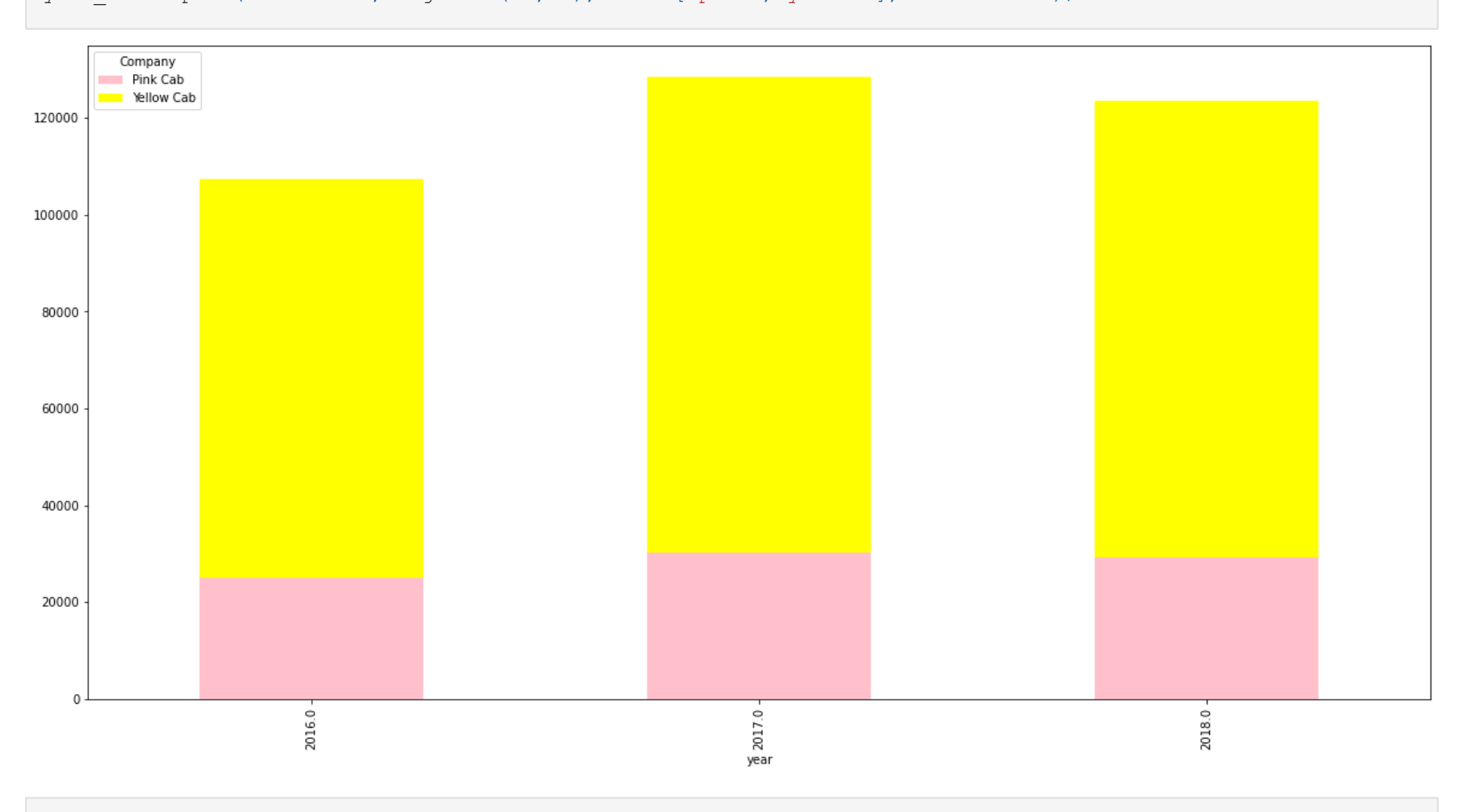
code failed !!

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

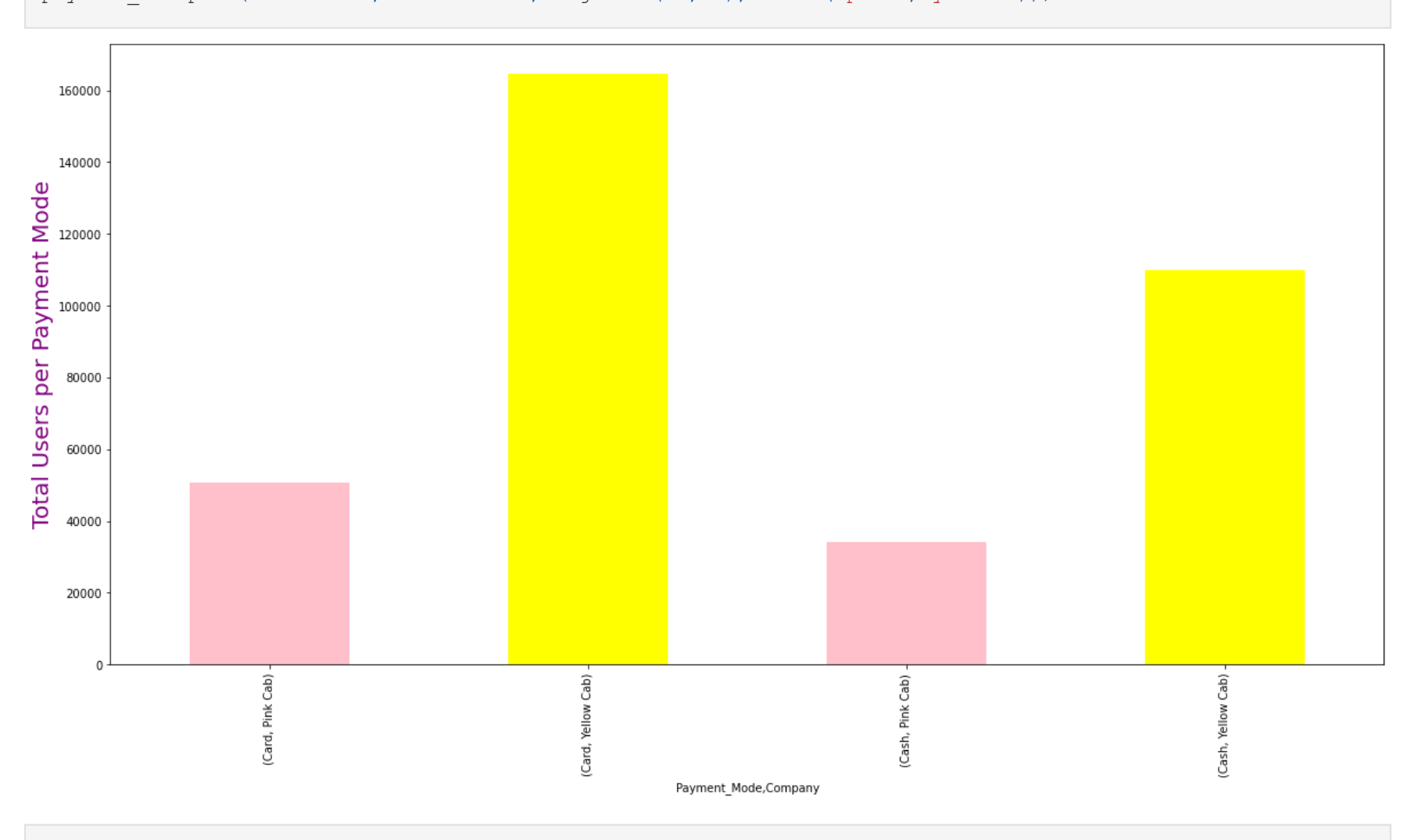
dfcopy=masterdf.copy() t2016=pd.date_range("2016-01-01", periods=365, freq="D").to_series().array t2017=pd.date_range("2017-01-01", periods=365, freq="D").to_series().array t2018=pd.date_range("2018-01-01", periods=365, freq="D").to_series().array def yearindicator(i): for i in dfcopy["Date of Travel"]: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



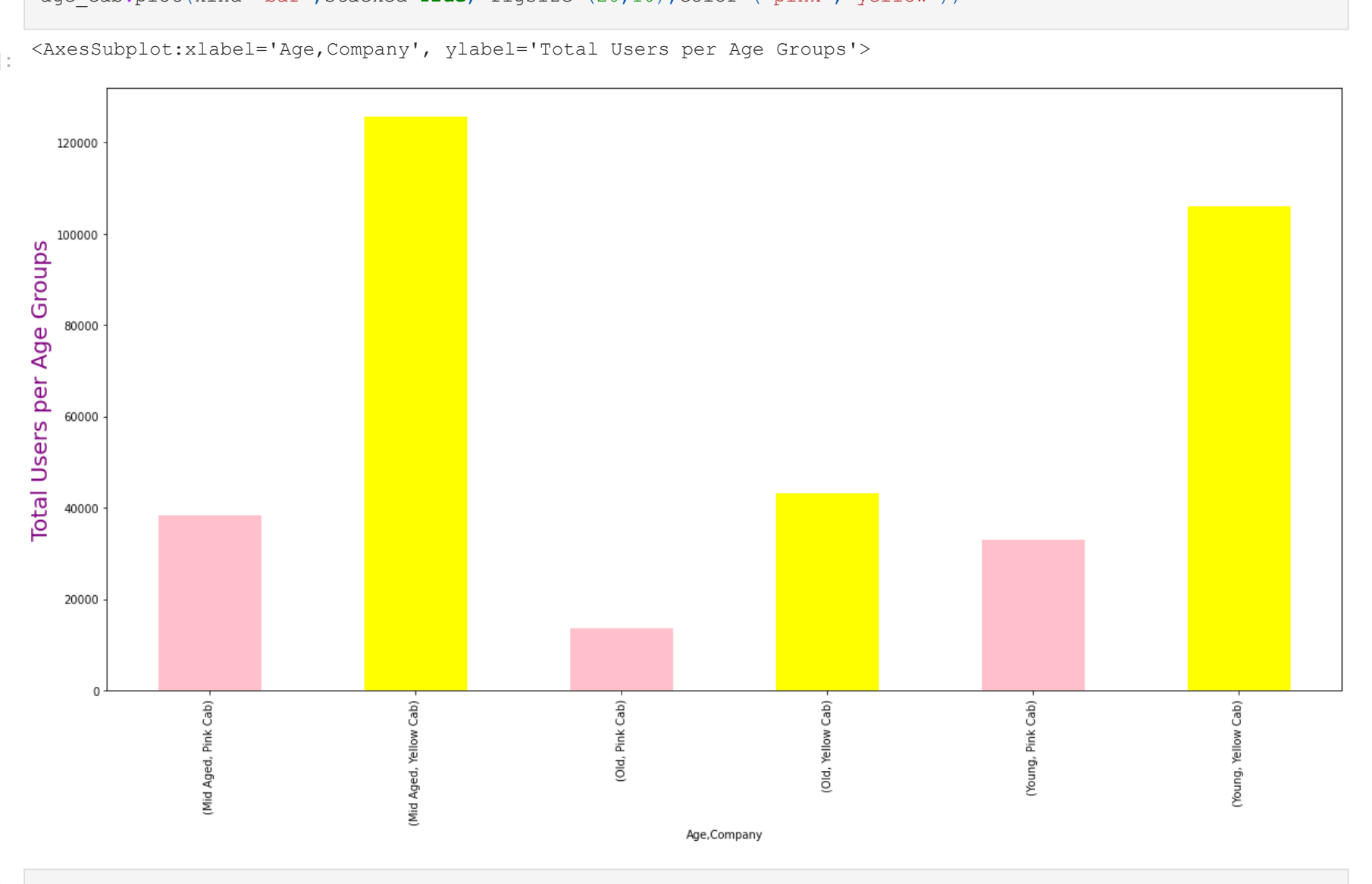
In [27]:
```
#age and cab using relation diagram
#ages grouped into 3 different group using a simple function
def agecomparison(age):
    if age <30:
        return "Young"
    elif age <=50:
        return "Mid Aged"
    else:
        return "Old"

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

Out[27]:

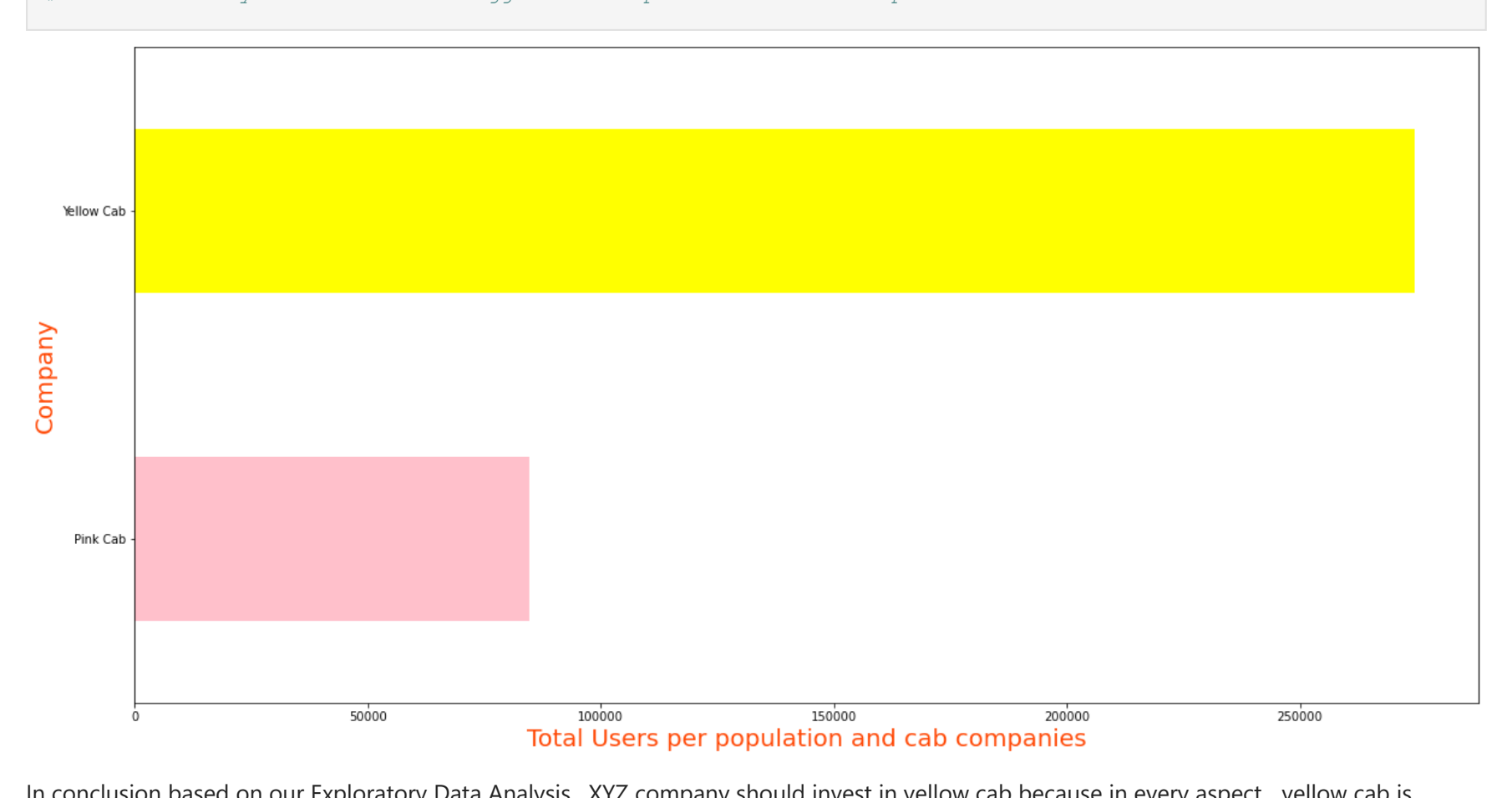
	City	Population	Users	Transaction ID	Date of Travel	Company	KM Travelled	Price Charged	Cost of Trip	Profit per KM	Customer ID	Gender	Age	Income (USD/Month)
0	NEW YORK NY	8405837	302149	10000139.0	2016-01-08	Pink Cab	17.85	242.90	198.135	2.507843	2416.0	Male	Young	Mid income
1	NEW YORK NY	8405837	302149	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]:
```
#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]:
```
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 [ ]: