Project: Cyclist Data Analysis

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Introduction

A fictional bike-share company in Chicago. The director of marketing believes the company's future success depends on maximizing the number of annual memberships. Therefore, your team wants to understand how casual riders and annual members use Cyclistic bikes differently. From these insights, your team will design a new marketing strategy to convert casual riders into annual members. But first, Cyclistic executives must approve your recommendations, so they must be backed up with compelling data insights and professional data visualizations.

Dataset Description

- Trip_id : Trip Id
- Start_time : start time of the trip
- End_time : end time of the trip
- Bike_id: Bike Id
- trip_duration : trip length
- from_station_id : starting station id
- from_station_name : starting station name
- to_station_id : starting station id
- to_station_name : starting station name
- usertype : subscriber or customar
- gender : male or female
- birthyear : user birthyear

Ask Phase

Following the steps of the data analysis process: **Ask**, Prepare, Process, Analyze, Share, and Act.

In this intial phase of our project we want to ask our stakeholders questions to fully understand our projects also identify questions to answer from our analysis, so our first approch is to **clearly** identify the business task then to introduce our question to the analysis

Statement of the business task

Design marketing strategies aimed at converting casual riders into annual members.

Question(s) for Analysis

> **Q1** How do annual members and casual riders use Cyclistic bikes differently?
>
> **Q2** Which age group has the most annual members ?
>
> **Q3** What do annaual users gain from the membership that casual users do not?

Prepare Phase

Following the steps of the data analysis process: Ask, **Prepare** , Process, Analyze, Share, and Act.

In the next phase after defining our objective we will gather and assess our data in other terms we will perform **Data Wrangling**, in which we will perform two steps, first we will load the data to our workspace, then we will proceed to assing the data and making sure that the quality and structure of it is right.

Data Gathering

Data was gathered from divvy trip data , we have choosen to work with the data of 2019 to drive our assumptions

Data assessment

let's take a look at our data to validate it's consistency, quality and structure

In [1]:
```
# importing important libararies
import numpy as np
import pandas as pd
from zipfile import ZipFile
import itertools
```

In [2]:
```
# extracting data in jupyter workspace
with ZipFile('specialization data.zip','r') as zip :
    zip.extractall()
```

In [3]:
```
#importing four quarters data
data_Q1 = pd.read_csv('Divvy_Trips_2019_Q1.csv')
data_Q2 = pd.read_csv('Divvy_Trips_2019_Q2.csv')
data_Q3 = pd.read_csv('Divvy_Trips_2019_Q3.csv')
data_Q4 = pd.read_csv('Divvy_Trips_2019_Q4.csv')
```

we will assess every dataset on its own but we will keep the generalize column names and data types over the datasets

we will start with the first quarter

In [4]:
```
data_Q1.head()
```

Out[4]:

	trip_id	start_time	end_time	bikeid	tripduration	from_station_id	from_station_name	to_station_id	to_station

	trip_id	start_time	end_time	bikeid	tripduration	from_station_id	from_station_name	to_station_id	to_station
0	21742443	2019-01-01 00:04:37	2019-01-01 00:11:07	2167	390.0	199	Wabash Ave & Grand Ave	84	Milwaukee Gra
1	21742444	2019-01-01 00:08:13	2019-01-01 00:15:34	4386	441.0	44	State St & Randolph St	624	Dearbo Van Bure
2	21742445	2019-01-01 00:13:23	2019-01-01 00:27:12	1524	829.0	15	Racine Ave & 18th St	644	Western Fillmor
3	21742446	2019-01-01 00:13:45	2019-01-01 00:43:28	252	1,783.0	123	California Ave & Milwaukee Ave	176	Clark St &
4	21742447	2019-01-01 00:14:52	2019-01-01 00:20:56	1170	364.0	173	Mies van der Rohe Way & Chicago Ave	35	Streete Gra

for starters bikeid, tripduration and usertype need to follow the standard naming conventions

trip_duration need to be in minutes not seconds as it will be easier to comprehend

birthyear need to be converted into age so we can devide the users into age groups and discover insights withen age group

In [5]:
```
data_Q1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 365069 entries, 0 to 365068
Data columns (total 12 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   trip_id            365069 non-null  int64  
 1   start_time         365069 non-null  object 
 2   end_time           365069 non-null  object 
 3   bikeid             365069 non-null  int64  
 4   tripduration       365069 non-null  object 
 5   from_station_id    365069 non-null  int64  
 6   from_station_name  365069 non-null  object 
 7   to_station_id      365069 non-null  int64  
 8   to_station_name    365069 non-null  object 
 9   usertype           365069 non-null  object 
 10  gender             345358 non-null  object 
 11  birthyear          347046 non-null  float64
dtypes: float64(1), int64(4), object(7)
memory usage: 33.4+ MB
```

we have missing data in both the gender and the birthyear, trip_duration,start_time and end_time types need to be adjusted

In [6]:
```
assert len(data_Q1.gender.unique()) == 3
assert len(data_Q1.usertype.unique()) == 2
```

we made sure there is no inconsistent data entries because in gender there is male,female and NaN hence '==3' but in usertype there is subscriber and customer hence '==2'

In [7]:
```
data_Q1.duplicated().sum()
```

Out[7]: 0

we have no duplicates in this dataset

Doing the same steps for the remaining quadrants

In [8]:
```
data_Q2.head()
```

Out[8]:

	01 - Rental Details Rental ID	01 - Rental Details Local Start Time	01 - Rental Details Local End Time	01 - Rental Details Bike ID	01 - Rental Details Duration In Seconds Uncapped	03 - Rental Start Station ID	03 - Rental Start Station Name	02 - Rental End Station ID	02 - Rental End Station Name	User Type	Member Gender	Mem De Mem Birth
0	22178529	2019-04-01 00:02:22	2019-04-01 00:09:48	6251	446.0	81	Daley Center Plaza	56	Desplaines St & Kinzie St	Subscriber	Male	19
1	22178530	2019-04-01 00:03:02	2019-04-01 00:20:30	6226	1,048.0	317	Wood St & Taylor St	59	Wabash Ave & Roosevelt Rd	Subscriber	Female	19
2	22178531	2019-04-01 00:11:07	2019-04-01 00:15:19	5649	252.0	283	LaSalle St & Jackson Blvd	174	Canal St & Madison St	Subscriber	Male	19
3	22178532	2019-04-01 00:13:01	2019-04-01 00:18:58	4151	357.0	26	McClurg Ct & Illinois St	133	Kingsbury St & Kinzie St	Subscriber	Male	19
4	22178533	2019-04-01 00:19:26	2019-04-01 00:36:13	3270	1,007.0	202	Halsted St & 18th St	129	Blue Island Ave & 18th St	Subscriber	Male	19

All columns names have to be changed to follow the standard naming convention

In [9]:
```
data_Q2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1108163 entries, 0 to 1108162
Data columns (total 12 columns):
 #   Column                                          Non-Null Count    Dtype  
---  ------                                          --------------    -----  
 0   01 - Rental Details Rental ID                   1108163 non-null  int64  
 1   01 - Rental Details Local Start Time            1108163 non-null  object 
 2   01 - Rental Details Local End Time              1108163 non-null  object 
 3   01 - Rental Details Bike ID                     1108163 non-null  int64  
 4   01 - Rental Details Duration In Seconds Uncapped 1108163 non-null  object 
 5   03 - Rental Start Station ID                    1108163 non-null  int64  
 6   03 - Rental Start Station Name                  1108163 non-null  object 
 7   02 - Rental End Station ID                      1108163 non-null  int64  
 8   02 - Rental End Station Name                    1108163 non-null  object 
 9   User Type                                       1108163 non-null  object 
 10  Member Gender                                   922609 non-null   object 
 11  05 - Member Details Member Birthday Year        927210 non-null   float64
dtypes: float64(1), int64(4), object(7)
memory usage: 101.5+ MB
```

missing data in gender and birth year also trip_duration, start and end time datatypes need to be fixed

In [10]:
```
assert len(data_Q2['Member Gender'].unique()) == 3
assert len(data_Q2['User Type'].unique()) == 2
```

we made sure there is no inconsistent data entries because in gender there is male,female and NaN hence '==3' but in usertype there is subscriber and customer hence '==2'

In [11]:
```
data_Q2.duplicated().sum()
```

Out[11]:
```
0
```

zero duplicates

In [12]:
```
data_Q3.head()
```

Out[12]:

	trip_id	start_time	end_time	bikeid	tripduration	from_station_id	from_station_name	to_station_id	to_station
0	23479388	2019-07-01 00:00:27	2019-07-01 00:20:41	3591	1,214.0	117	Wilton Ave & Belmont Ave	497	Kimball Belmo
1	23479389	2019-07-01 00:01:16	2019-07-01 00:18:44	5353	1,048.0	381	Western Ave & Monroe St	203	Western
2	23479390	2019-07-01 00:01:48	2019-07-01 00:27:42	6180	1,554.0	313	Lakeview Ave & Fullerton Pkwy	144	Larrabe Webs
3	23479391	2019-07-01 00:02:07	2019-07-01 00:27:10	5540	1,503.0	313	Lakeview Ave & Fullerton Pkwy	144	Larrabe Webs
4	23479392	2019-07-01 00:02:13	2019-07-01 00:22:26	6014	1,213.0	168	Michigan Ave & 14th St	62	McCormic

In [13]:
```
data_Q3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1640718 entries, 0 to 1640717
Data columns (total 12 columns):
 #   Column             Non-Null Count    Dtype  
---  ------             --------------    -----  
 0   trip_id            1640718 non-null  int64  
 1   start_time         1640718 non-null  object 
 2   end_time           1640718 non-null  object 
 3   bikeid             1640718 non-null  int64  
 4   tripduration       1640718 non-null  object 
 5   from_station_id    1640718 non-null  int64  
 6   from_station_name  1640718 non-null  object 
 7   to_station_id      1640718 non-null  int64  
 8   to_station_name    1640718 non-null  object 
 9   usertype           1640718 non-null  object 
 10  gender             1353368 non-null  object 
 11  birthyear          1362624 non-null  float64
dtypes: float64(1), int64(4), object(7)
memory usage: 150.2+ MB
```

usual missing data and datatypes need to be fixed

In [14]:
```
assert len(data_Q3.gender.unique()) == 3
assert len(data_Q3.usertype.unique()) == 2
```

we made sure there is no inconsistent data entries because in gender there is male,female and NaN hence '==3' but in usertype there is subscriber and customer hence '==2'

In [15]:
```
data_Q3.duplicated().sum()
```

Out[15]:
```
0
```

no duplicates here

In [16]:
```
data_Q4.head()
```

Out[16]:

	trip_id	start_time	end_time	bikeid	tripduration	from_station_id	from_station_name	to_station_id	to_station
0	25223640	2019-10-01 00:01:39	2019-10-01 00:17:20	2215	940.0	20	Sheffield Ave & Kingsbury St	309	Leav Armita
1	25223641	2019-10-01 00:02:16	2019-10-01 00:06:34	6328	258.0	19	Throop (Loomis) St & Taylor St	241	Morga
2	25223642	2019-10-01 00:04:32	2019-10-01 00:18:43	3003	850.0	84	Milwaukee Ave & Grand Ave	199	Wabash Gra
3	25223643	2019-10-01 00:04:32	2019-10-01 00:43:43	3275	2,350.0	313	Lakeview Ave & Fullerton Pkwy	290	Kedzie Pal
4	25223644	2019-10-01 00:04:34	2019-10-01 00:35:42	5294	1,867.0	210	Ashland Ave & Division St	382	Western Congres

In [17]:
```
data_Q4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 704054 entries, 0 to 704053
Data columns (total 12 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   trip_id            704054 non-null  int64  
 1   start_time         704054 non-null  object 
 2   end_time           704054 non-null  object 
 3   bikeid             704054 non-null  int64  
 4   tripduration       704054 non-null  object 
 5   from_station_id    704054 non-null  int64  
 6   from_station_name  704054 non-null  object 
 7   to_station_id      704054 non-null  int64  
 8   to_station_name    704054 non-null  object 
 9   usertype           704054 non-null  object 
 10  gender             637463 non-null  object 
 11  birthyear          642373 non-null  float64
dtypes: float64(1), int64(4), object(7)
memory usage: 64.5+ MB
```

In [18]:
```
assert len(data_Q4.gender.unique()) == 3
assert len(data_Q4.usertype.unique()) == 2
```

In [19]:
```
data_Q4.duplicated().sum()
```

Out[19]:
```
0
```

same changes in the past three datasets

So now we know the changes that need to be done to each dataset so we can analyze our data correctly, next step is data cleaning, it is time to take care of our problems

Process Phase

Following the steps of the data analysis process: Ask, Prepare , **Process** , Analyze, Share, and Act.

Now we start cleaning our data and processing it so we can produce valid visualizations and conclusions from it, Also this is the last step of **Data Wrangling** Data Cleaning

We will start by generalizing column names in the four datasets

In [20]:
```
for df in [data_Q1,data_Q3,data_Q4]:
    df.rename(columns = {'bikeid':'bike_id', 'tripduration':'trip_duration',
                         'usertype':'user_type'}, inplace = True)
```

In [21]:
```
general_col_names = data_Q1.columns
col_names_data_Q2=data_Q2.columns
for (i,v) in itertools.zip_longest(general_col_names,col_names_data_Q2):
    data_Q2.rename(columns = {v : i},inplace=True)
data_Q2.head()
```

Out[21]:

	trip_id	start_time	end_time	bike_id	trip_duration	from_station_id	from_station_name	to_station_id	to_static
0	22178529	2019-04-01 00:02:22	2019-04-01 00:09:48	6251	446.0	81	Daley Center Plaza	56	Despla
1	22178530	2019-04-01 00:03:02	2019-04-01 00:20:30	6226	1,048.0	317	Wood St & Taylor St	59	Waba Roo
2	22178531	2019-04-01 00:11:07	2019-04-01 00:15:19	5649	252.0	283	LaSalle St & Jackson Blvd	174	C M
3	22178532	2019-04-01 00:13:01	2019-04-01 00:18:58	4151	357.0	26	McClurg Ct & Illinois St	133	Kingsb
4	22178533	2019-04-01 00:19:26	2019-04-01 00:36:13	3270	1,007.0	202	Halsted St & 18th St	129	Blue Islar

Now we our datasets have the same column names, next let's fix the rest of the issues

In [22]:
```
combined_data=[data_Q1,data_Q2,data_Q3,data_Q4]
for df in combined_data:
    #fixing start and end time data types
    df['start_time'] = pd.to_datetime(df['start_time'])
    df['end_time'] = pd.to_datetime(df['end_time'])
```

```
    #converting trip into minutes
    df['duration'] = (df.end_time - df.start_time).dt.total_seconds() /60

    #adding age column and weekday for further invistagation
    df['Age']=2022 - df.birthyear
    df['weekday']=df.start_time.dt.day_name()

    #adding age groups
    df.loc[((df.Age <3)) , 'age_group'] = 'too young'
    df.loc[((df.Age >=3) & (df.Age <14)) , 'age_group'] = 'Kid'
    df.loc[((df.Age >=14) & (df.Age <21)) , 'age_group'] = 'Teen'
    df.loc[((df.Age >=21) & (df.Age <45)) , 'age_group'] = 'Adult'
    df.loc[((df.Age >=45)) , 'age_group'] = 'Senior'
    df.loc[((df.Age >90)) , 'age_group'] = 'too old'
```

In [23]:
```
data_Q1.head()
```

Out[23]:

	trip_id	start_time	end_time	bike_id	trip_duration	from_station_id	from_station_name	to_station_id	to_static
0	21742443	2019-01-01 00:04:37	2019-01-01 00:11:07	2167	390.0	199	Wabash Ave & Grand Ave	84	Milwauk G
1	21742444	2019-01-01 00:08:13	2019-01-01 00:15:34	4386	441.0	44	State St & Randolph St	624	Dearb Van Bu
2	21742445	2019-01-01 00:13:23	2019-01-01 00:27:12	1524	829.0	15	Racine Ave & 18th St	644	Weste Fillm
3	21742446	2019-01-01 00:13:45	2019-01-01 00:43:28	252	1,783.0	123	California Ave & Milwaukee Ave	176	Clark St
4	21742447	2019-01-01 00:14:52	2019-01-01 00:20:56	1170	364.0	173	Mies van der Rohe Way & Chicago Ave	35	Stree G

Now all of our data are prepared for further investigation just one last validation before we proceed to the analyze phase

we are going to search for inconsistent data entry which mean that we are searching for typos and outliers in

> - duration, user type, gender, Age

In [24]:
```
#duration
#lets see if there is any trips lessthan 0 minutes
for df in combined_data:
    assert min(df.duration) > 1
print('data is consistent')
```

```
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
Input In [24], in <cell line: 3>()
      1 #duration
      2 #lets see if there is any trips lessthan 0 minutes
      3 for df in combined_data:
----> 4     assert min(df.duration) > 1
      5 print('data is consistent')

AssertionError:
```

there is an error in data_Q4

In [25]:
```
data_Q4.query('duration < 1')
```

Out[25]:

	trip_id	start_time	end_time	bike_id	trip_duration	from_station_id	from_station_name	to_station_id	to
384478	25625830	2019-11-03 01:43:21	2019-11-03 01:09:56	4141	1,594.0	632	Clark St & Newport St	133	
384483	25625836	2019-11-03 01:46:01	2019-11-03 01:10:44	6329	1,483.0	373	Kedzie Ave & Chicago Ave	498	C
384485	25625838	2019-11-03 01:47:49	2019-11-03 01:02:40	964	891.0	229	Southport Ave & Roscoe St	87	
384486	25625839	2019-11-03 01:48:04	2019-11-03 01:16:48	2214	1,724.0	131	Lincoln Ave & Belmont Ave	131	
384487	25625841	2019-11-03 01:50:31	2019-11-03 01:04:25	4179	834.0	298	Lincoln Ave & Belle Plaine Ave	258	
384489	25625843	2019-11-03 01:51:59	2019-11-03 01:03:02	2920	663.0	460	Clark St & Bryn Mawr Ave	238	A
384490	25625844	2019-11-03 01:51:55	2019-11-03 01:04:33	3338	757.0	177	Theater on the Lake	327	
384491	25625845	2019-11-03 01:53:08	2019-11-03 01:04:53	2142	705.0	177	Theater on the Lake	327	
384492	25625846	2019-11-03 01:53:10	2019-11-03 01:04:53	5877	703.0	177	Theater on the Lake	327	
384493	25625847	2019-11-03 01:53:24	2019-11-03 01:06:08	3984	764.0	484	Monticello Ave & Irving Park Rd	484	M
384495	25625849	2019-11-03 01:55:33	2019-11-03 01:01:52	5059	379.0	109	900 W Harrison St	320	
384496	25625850	2019-11-03 01:57:48	2019-11-03 01:01:26	5310	217.0	340	Clark St & Wrightwood Ave	300	
384497	25625851	2019-11-03 01:58:17	2019-11-03 01:08:27	6133	609.0	301	Clark St & Schiller St	52	I

we see multiple entries where end date is earlier than start date, in our case since we relatively big dataset we will drop them

In [26]:
```
data_Q4.drop(data_Q4.query('duration < 1').index,axis = 0, inplace = True)
for df in combined_data:
```

```
    assert min(df.duration) > 1
print('duration is consistent')
```

```
duration is consistent
```

In [27]:

```
#user_type and gennder attributes
for df in combined_data:
    assert len(df.user_type.unique()) ==2
    # =3 because there is missing values which will be impelmented as nan
    assert len(df.gender.unique()) ==3
print('user type is consistent')
```

```
user type is consistent
```

In [28]:

```
#we will check Age for less than 2 years and above 100 years
for df in combined_data:
    assert min(df.Age) >2
    assert max(df.Age) <101
```

```
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
Input In [28], in <cell line: 2>()
      2 for df in combined_data:
      3     assert min(df.Age) >2
----> 4     assert max(df.Age) <101

AssertionError:
```

we have ages above 100 years old

In [29]:

```
Age_above_100=0
for df in combined_data:
    Age_above_100 += df.query('Age >100').shape[0]
Age_above_100
```

Out[29]:

```
1031
```

we can see that there is about 1000 inconsitent data entries in our data, let's drop them

In [30]:

```
for df in combined_data:
    df.drop(df.query('Age >100').index,axis = 0, inplace = True)
    assert min(df.Age) >2
    assert max(df.Age) <101
print('Age is clean')
```

```
Age is clean
```

Finally now our data is both consistent and clean, now we are ready to proceed to the next phase of our analysis and our most exciting one

Analyze Phase

Following the steps of the data analysis process: Ask, Prepare , Process , **Analyze**, Share, and Act.

Since our data is now complete, valid, accurate and consistent, we are now ready for the most exciting phase in our analysis, in which we visualize our data trends and reach an answer to our business problem, Also the main process of the analyze phase is Exploratory Data Analysis "EDA" so let's begin

Exploratory Data Analysis

Refresher on the business question "How do annual members and casual riders use Cyclistic bikes differently?"

now we need to view the attributes that help us reach a conclusion about the answer to this question

In [111…]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

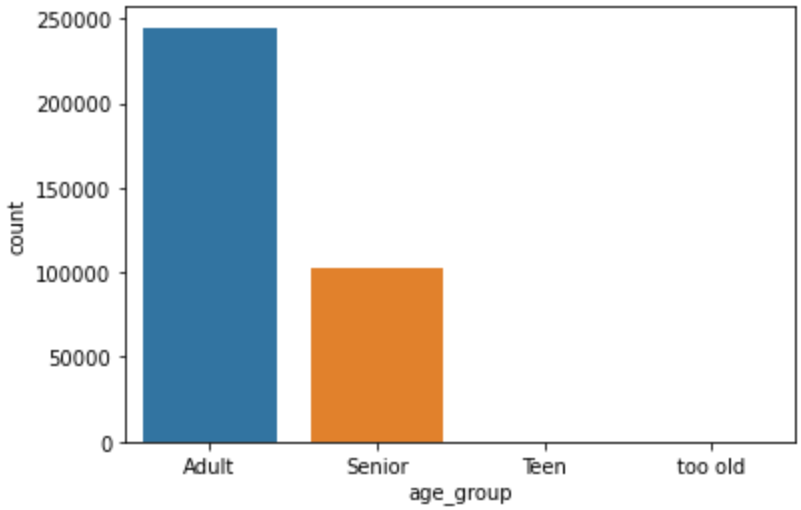
In [75]:
```
# creating a function that we pass the data to it and it creates plots over our four quart
# we pass the dataframes, attribute that we want to see over the four seasons and
# our most important attribute that we want to see it it's behavior related to other attri

def plot_relations(data,attribute_to_compare,compare_about):
    rows= len(data)//2
    cols=2
    dataset_name=['1st quarter','2nd quarter','3rd quarter','4th quarter']
    #setting up plot grid and colors
    fig, axes = plt.subplots(nrows=rows, ncols=cols, figsize=(10,15))
    color =['orangered']
    #adjusting plot margins
    plt.subplots_adjust(left=0.1,bottom=0.1, right=0.9, top=0.9, wspace=0.4, hspace=0.4)
    #loop to plot graphs in a grid
    #plot over the rows
    data_no = 0
    for i in range(rows) :
        #plot over the columns
        for j in range(cols):
            sns.countplot(data = data[data_no],x=attribute_to_compare,hue = compare_about,
                          ax =axes[i,j])

            axes[i,j].title.set_text('%s data'%(dataset_name[data_no]))
            #axes[i,j].set_ylabel('')
            #axes[i,j].set_xlabel(''%())
            axes[i-1,j-1].tick_params(axis='x', rotation=45)
            data_no = data_no + 1
```

In [64]:
```
#first lets see which age group uses the bikes the most
sns.countplot(data=data_Q1,x=data_Q1.age_group)
```

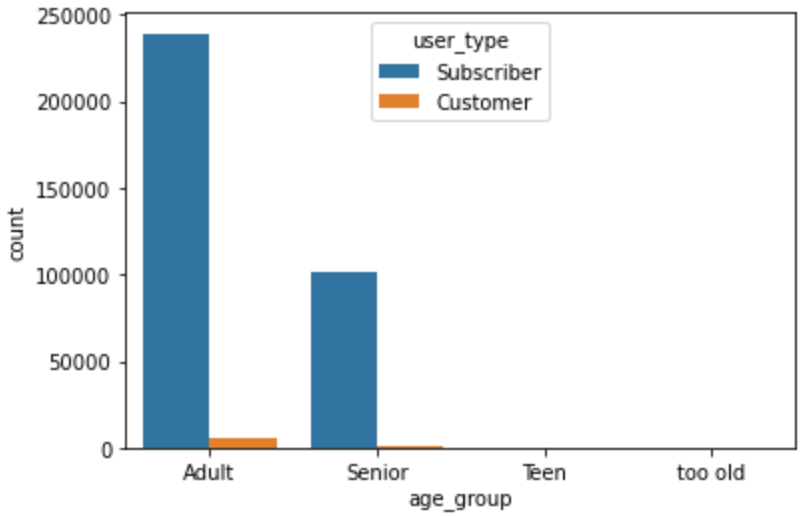
Out[64]:
```
<AxesSubplot:xlabel='age_group', ylabel='count'>
```



we see that adults are more than 50% of our users

In [65]:
```
#how many of age_groups are subscribers !?
sns.countplot(x=data_Q1.age_group,hue = data_Q1.user_type)
```

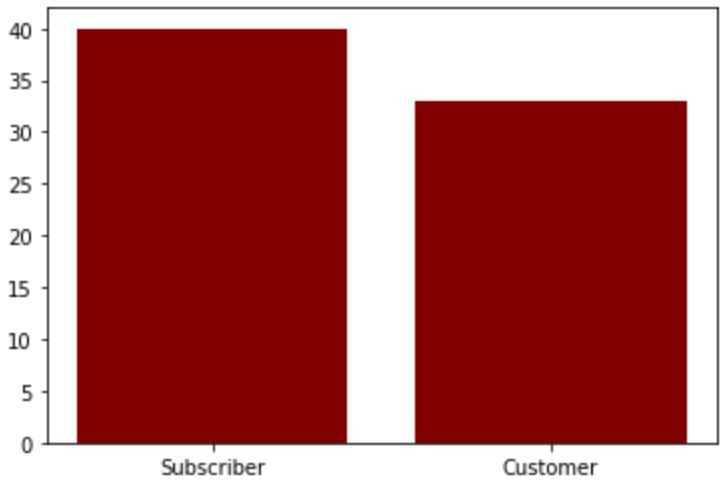
Out[65]:
```
<AxesSubplot:xlabel='age_group', ylabel='count'>
```



now we can see that most of our users are subscribers, but htis is only the first quarter of the year, so in other words we have low customers in the beginning of the year

In [110…
```
#what is the mean age for subscribers and customers ?
age_mean = [round(data_Q1[data_Q1.user_type == 'Subscriber']['Age'].mean()),round(data_Q1
plt.bar(['Subscriber','Customer'],age_mean,color='maroon')
```

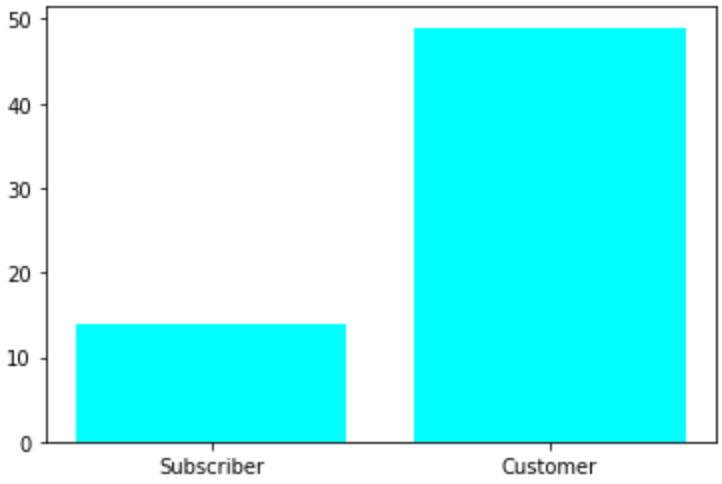
Out[110…
```
<BarContainer object of 2 artists>
```



average age for subscribers 40 years while for customers 33 years so our subscribers are usually older than our customers

In [106…
```
#how long do subscribers ride comparing to customers ?
duration_mean = [round(data_Q1[data_Q1.user_type == 'Subscriber']['duration'].mean()),
            round(data_Q1[data_Q1.user_type == 'Customer']['duration'].mean())]
plt.bar(['Subscriber','Customer'],duration_mean,color='Aqua')
```

Out[106…
```
<BarContainer object of 2 artists>
```

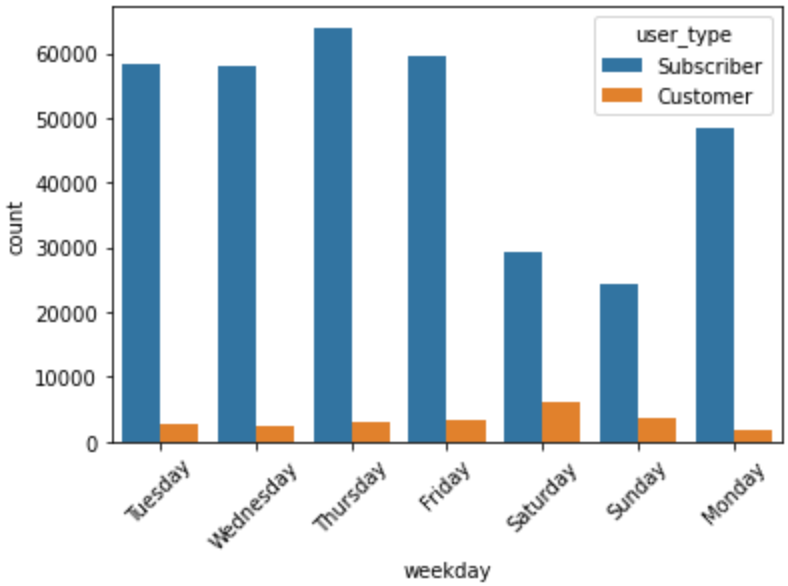


Surperisingly customers average trips are **435%** longer than subscribers this shows a point we can use in our marketing startegy

In [68]:
```
#last of the examination for one quadrant we see which day each user type prefers
sns.countplot(data_Q1.weekday, hue=data_Q1.user_type)
plt.xticks(rotation=45)
```

```
C:\Users\fahda\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resul
t in an error or misinterpretation.
  warnings.warn(
```

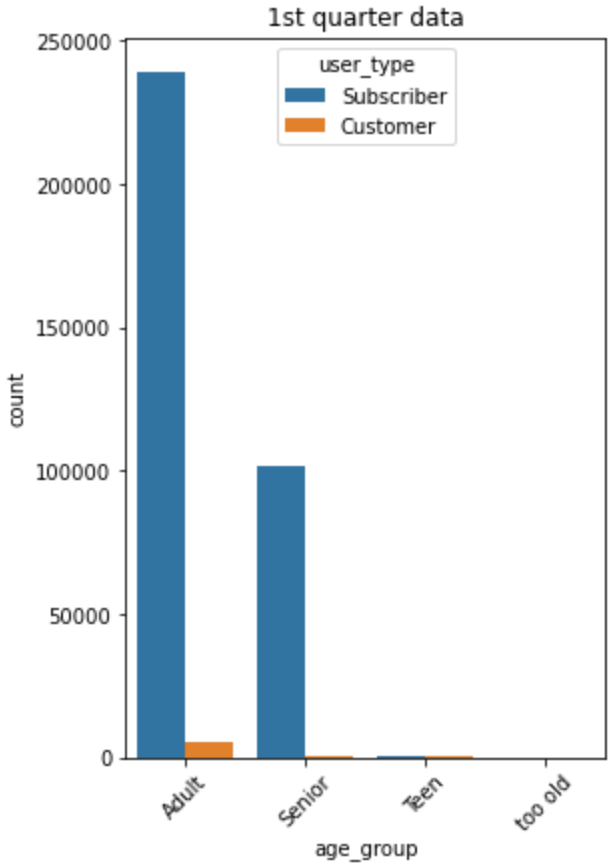
Out[68]:
```
(array([0, 1, 2, 3, 4, 5, 6]),
 [Text(0, 0, 'Tuesday'),
  Text(1, 0, 'Wednesday'),
  Text(2, 0, 'Thursday'),
  Text(3, 0, 'Friday'),
  Text(4, 0, 'Saturday'),
  Text(5, 0, 'Sunday'),
  Text(6, 0, 'Monday')])
```

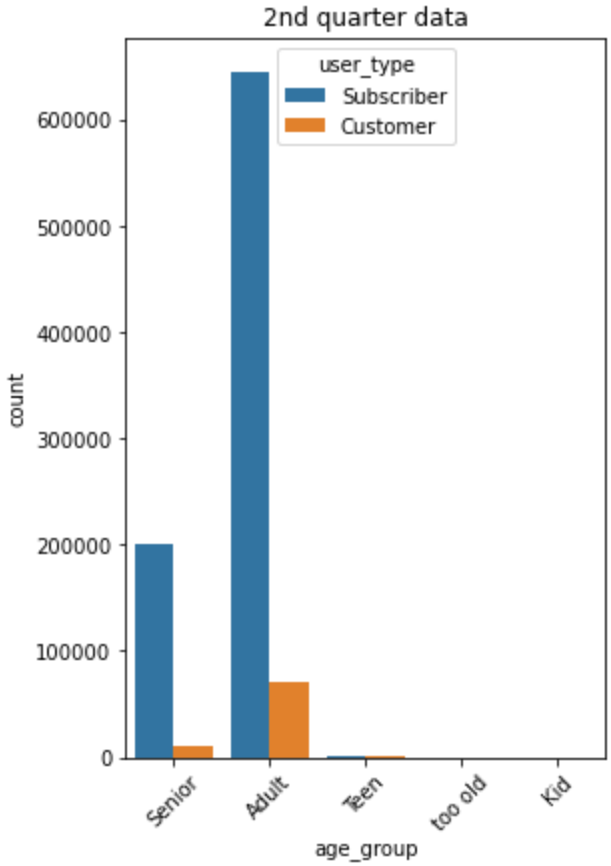


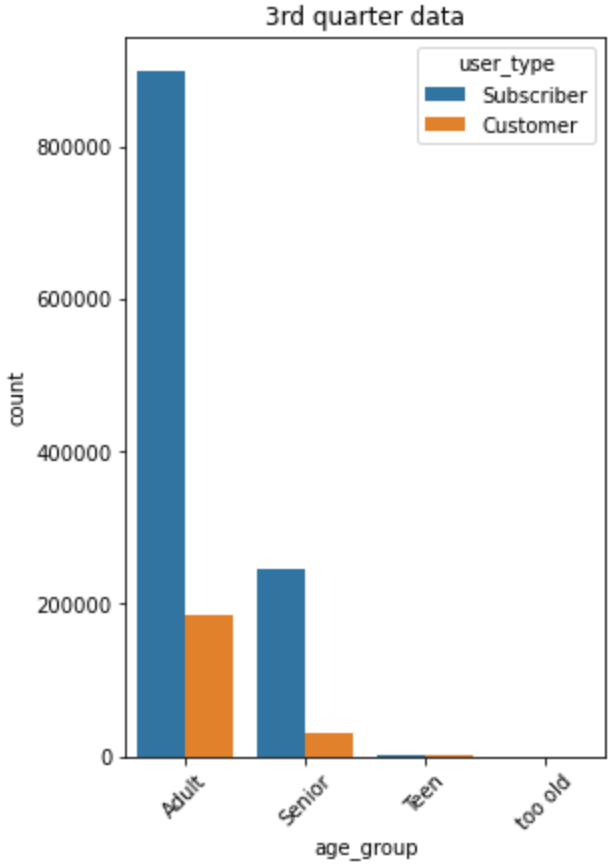
So we can see that Subscribers ride their bikes during the week but the tend to ignore it in the weekend days and customers are the complete oposite of that so maybe our subscribers take their bikes to work while our customers tend to enjoy it in the weekends

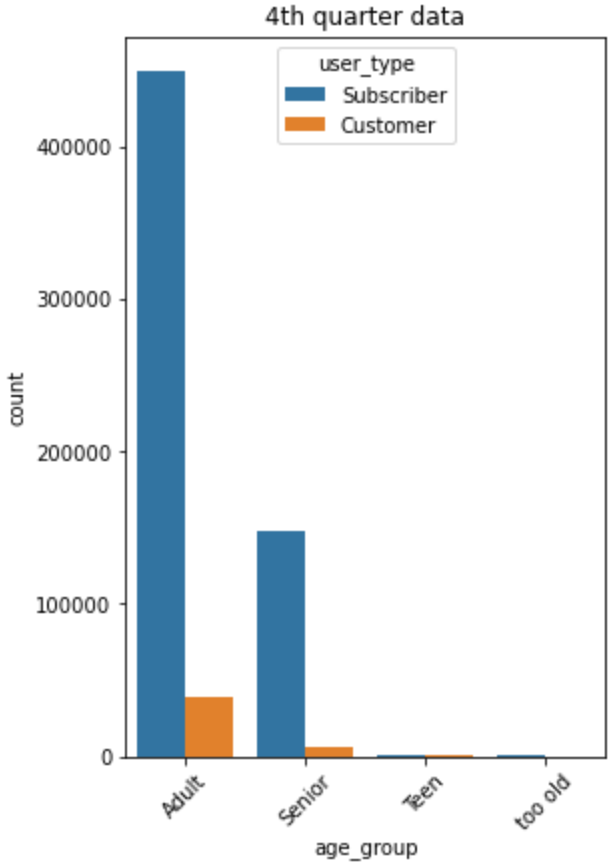
Now we will do the past 4 plots in 4 quarters to gain more insights

In [76]:
```
plot_relations(combined_data,'age_group','user_type')
```





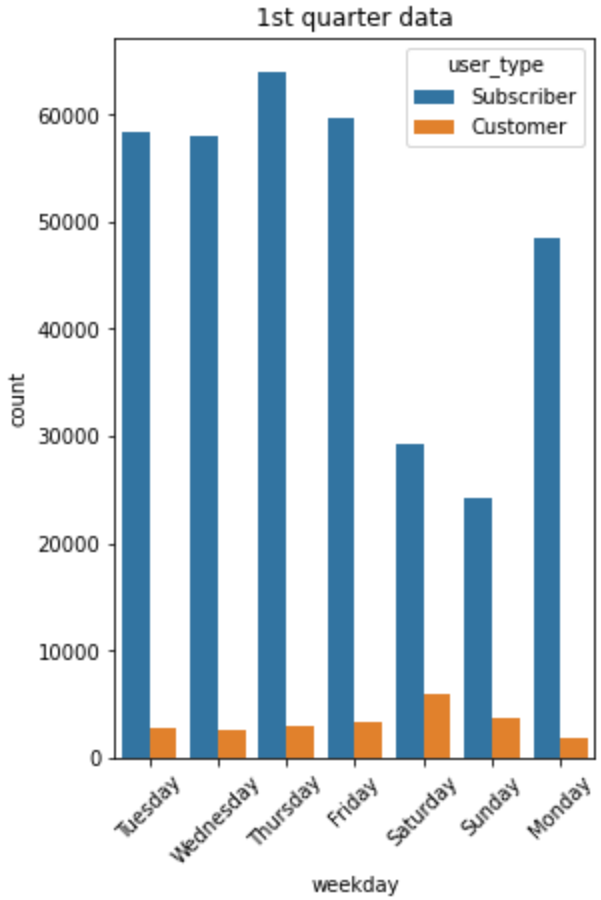


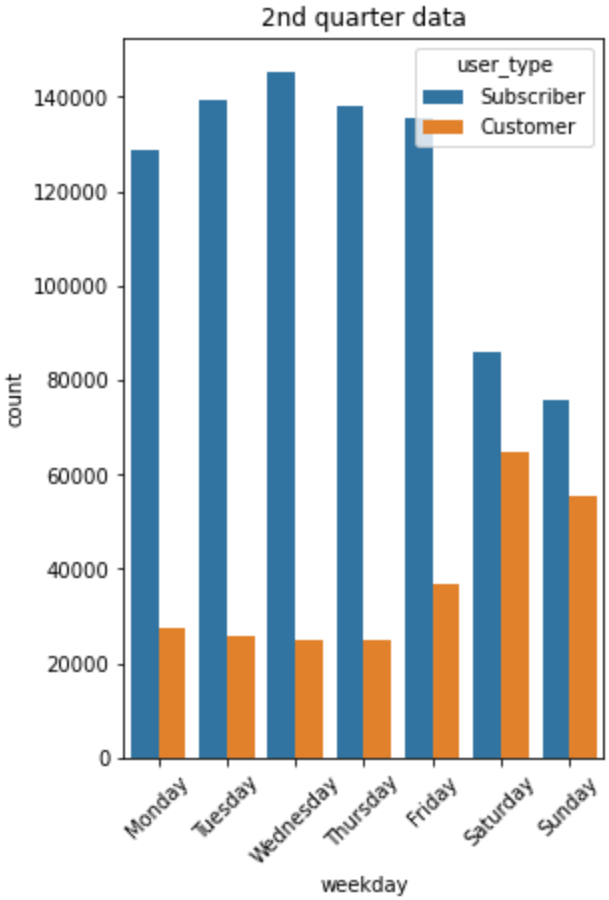


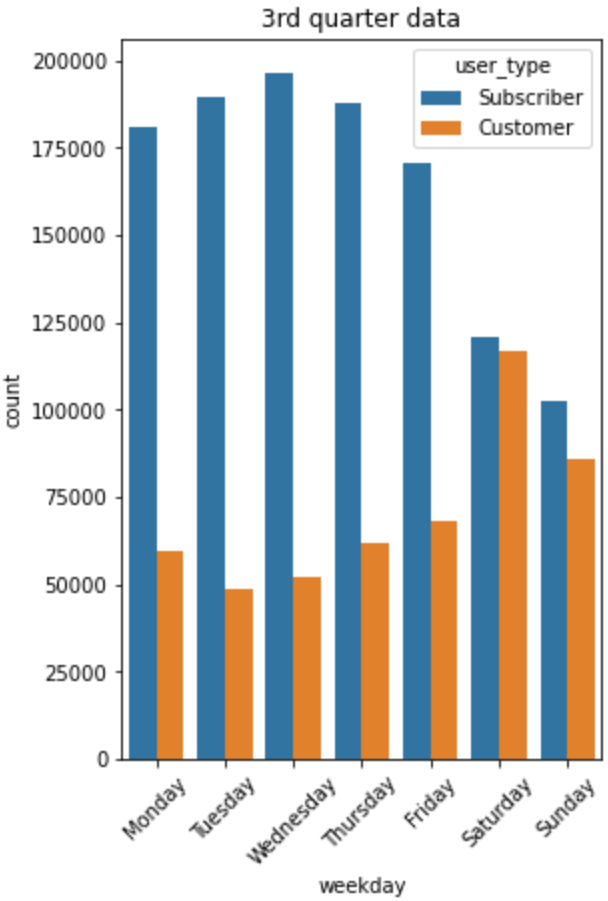
we can see from plots over the 4 seasons that our riders are mostly adults whether it is a subscriber or a customer

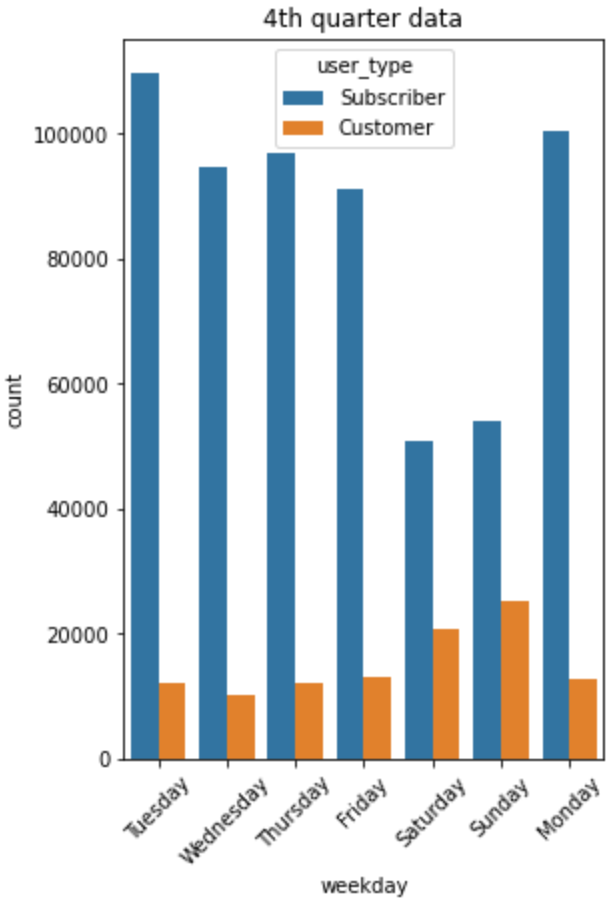
In [77]:

```
plot_relations(combined_data,'weekday','user_type')
```









This plot on the other hand is really usefull it tells us that there is a spike in customers during the weekends and during the warm weather, we can see clearly the effect of the summer on our customers compared to the winter,

this is crucial in chossing the timing of your marketing campain

In [105…

```
#more statistaclly answer on the increase in the summer

#winter ratio
total_count,u,user_type,user_type_count=data_Q1.loc[(data_Q1.weekday == 'Saturday')|(data_
#ratio of customers to Subscribers in weekends of the winter
winter_ratio=round(((total_count-user_type_count)/total_count )*100)

#summer ratio
total_count,u,user_type,user_type_count=data_Q3.loc[(data_Q3.weekday == 'Saturday')|(data_
#ratio of customers to Subscribers in weekends of the winter
summer_ratio=round(((total_count-user_type_count)/total_count )*100)

print('winter customer riders in weekends are %d percent from total customers while summe
      %(winter_ratio,summer_ratio))
```

```
winter customer riders in weekends are 15 percent from total customers while summer custom
er riders are at 48 percent
```

we see that increase in weekends specially in the summer more clearly now, so in this phase of analysis we have reached an idea to seperate subscribers from customers and to identify the behavior of each of them, for example how they are diffrent in age, average ride length and when do they ride their bikes in the next phase we will see our conclusion presented clearly with our recommendations

Share Phase

Following the steps of the data analysis process: Ask, Prepare , Process , Analyze, **Share**, and Act.

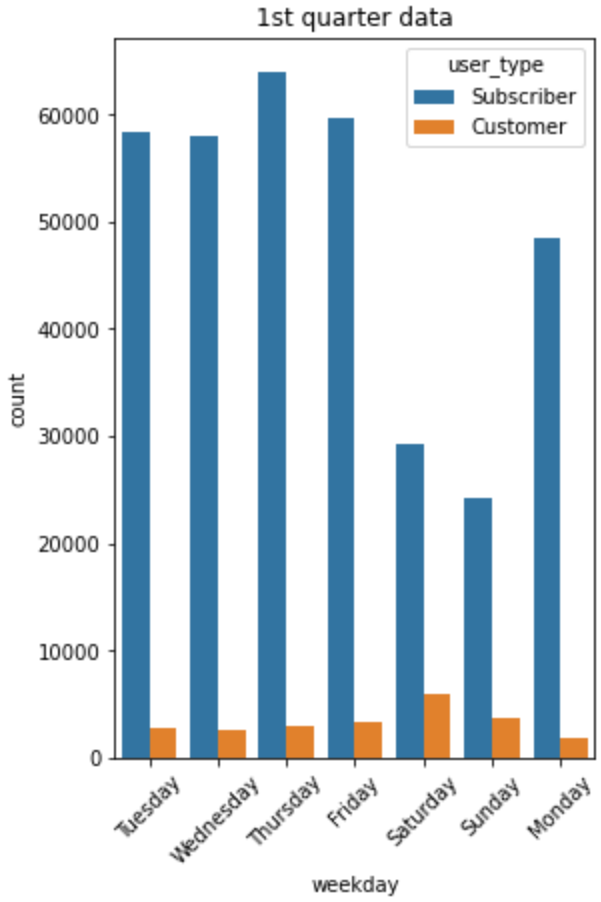
Now we present our finding to our skateholders, we choose our data visualization and combine them with our statistical calculations, we inform them with our recommendations based on our findings, this is where we normally use tableau, power bi or powerpoint

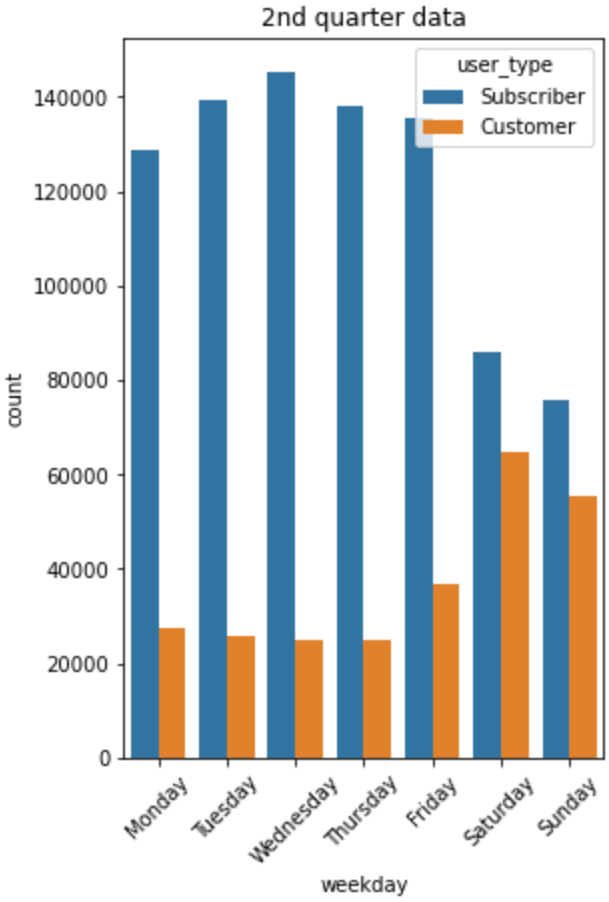
to keep in mind our business question "How do annual members and casual riders use Cyclistic bikes differently?"

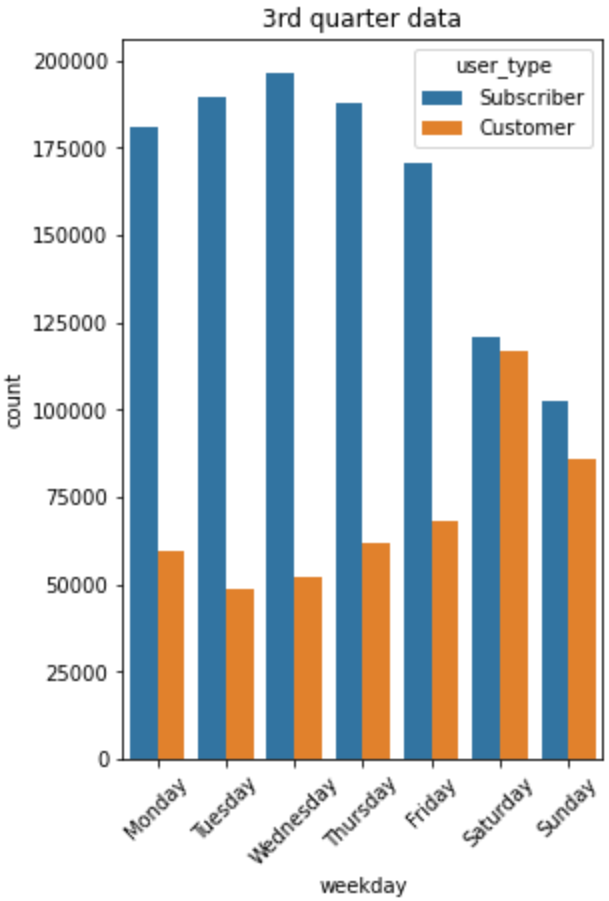
Q1 - How do annual members and casual riders use Cyclistic bikes differently?

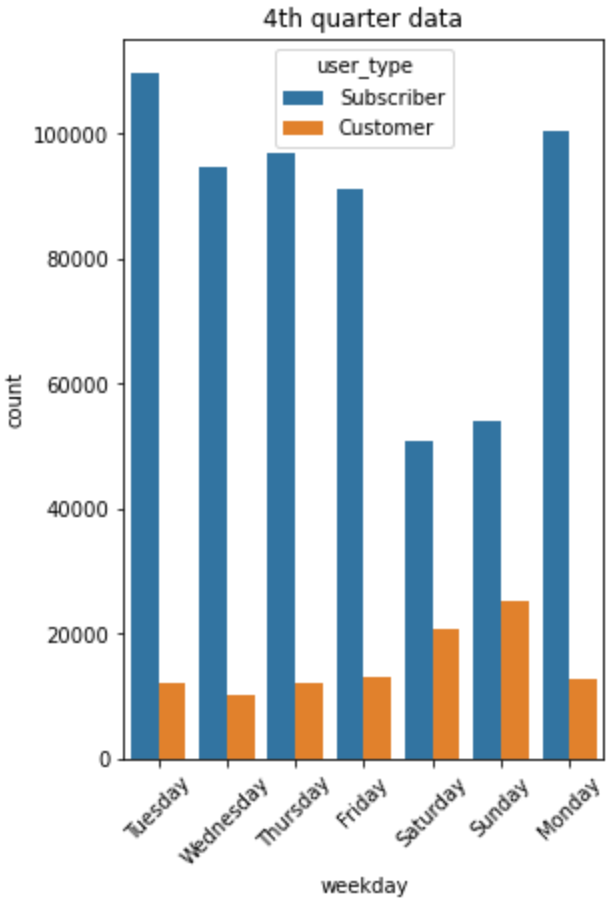
In [113…

```
plot_relations(combined_data,'weekday','user_type')
```









we can see that two important insights here

> **Subscribers** tend to ride bikes through out the week and inore it in the weekends

> **Customers** tend to ride bikes in the weekends not through the week

So we know that subscribers normally uses the bike for daily tasks like comuting to work for example, but customers on the other hand uses the bikes for fun in the weekends rather than daily tasks

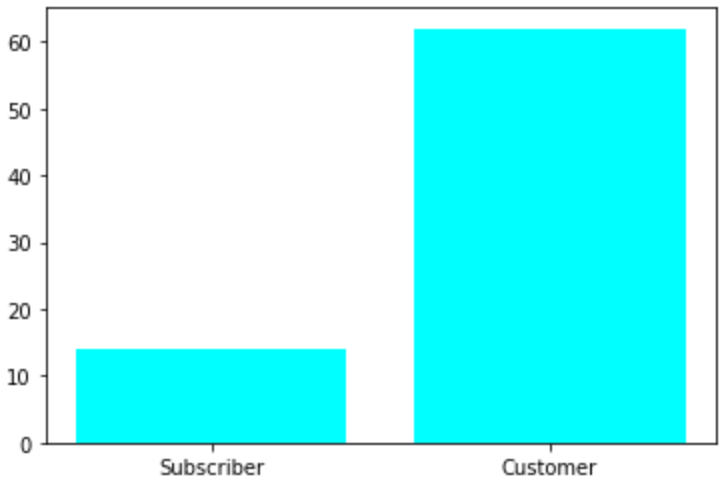
> **Customers** represent nearly 50% of users on weekends in the summer

we see that the number of customers gradually increase as we move into hot weather and reaches nearly 50% of users on weekends

Now recomendation based on this would be to start the marketing campain in the summer and to have discounts in the weekends as these days have the most number of customers

In [114…
```
#how long do subscribers ride comparing to customers ?
duration_mean = [round(data_Q1[data_Q1.user_type == 'Subscriber']['duration'].mean()),
            round(data_Q1[data_Q1.user_type == 'Customer']['duration'].mean())]
plt.bar(['Subscriber','Customer'],duration_mean,color='Aqua')
```

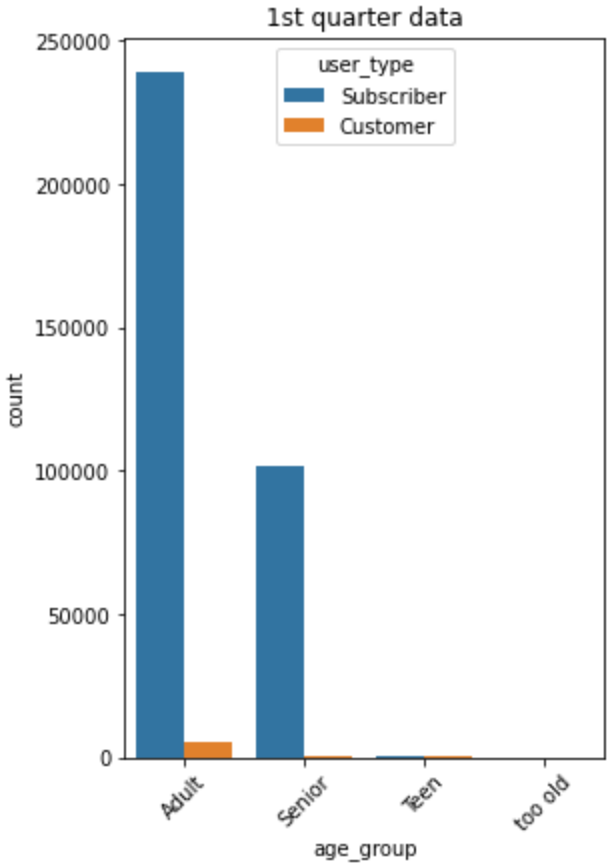
Out[114…
```
<BarContainer object of 2 artists>
```

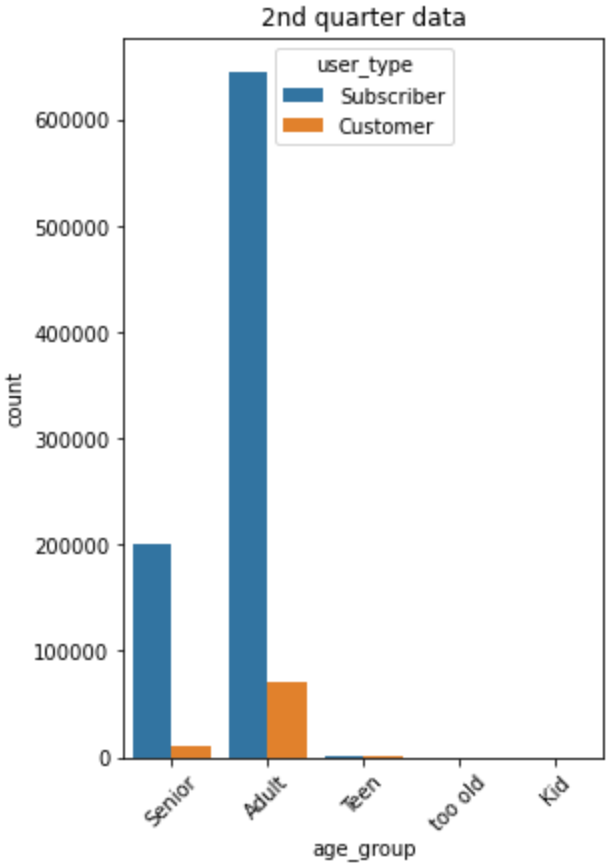


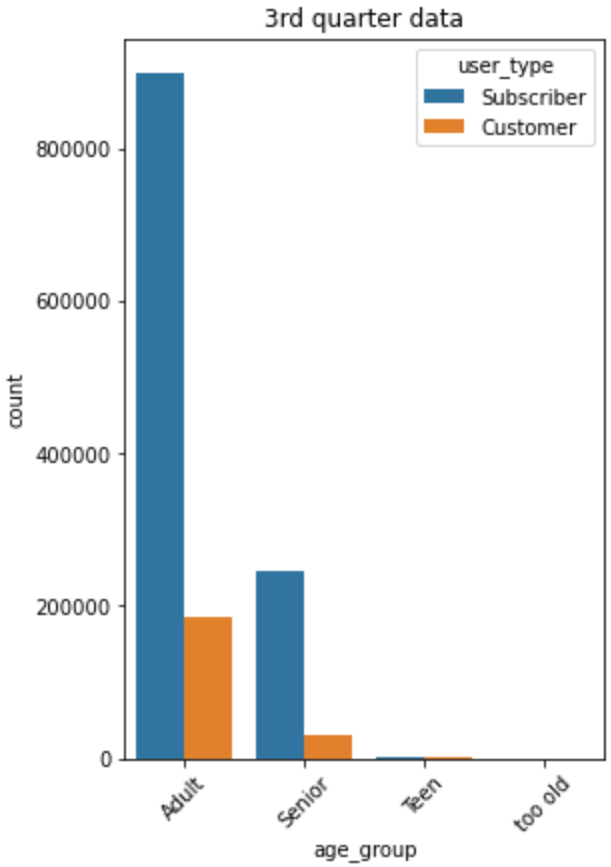
Surperisingly **customers** average trips are **435%** longer than **subscribers** this information will help us shape our discount behaviour for example we can grant a discount coupon if a customer rode the bike over 40 minutes on upgrading to be subscriber that expiers right after the weekend so we garantue that he will most probably active then

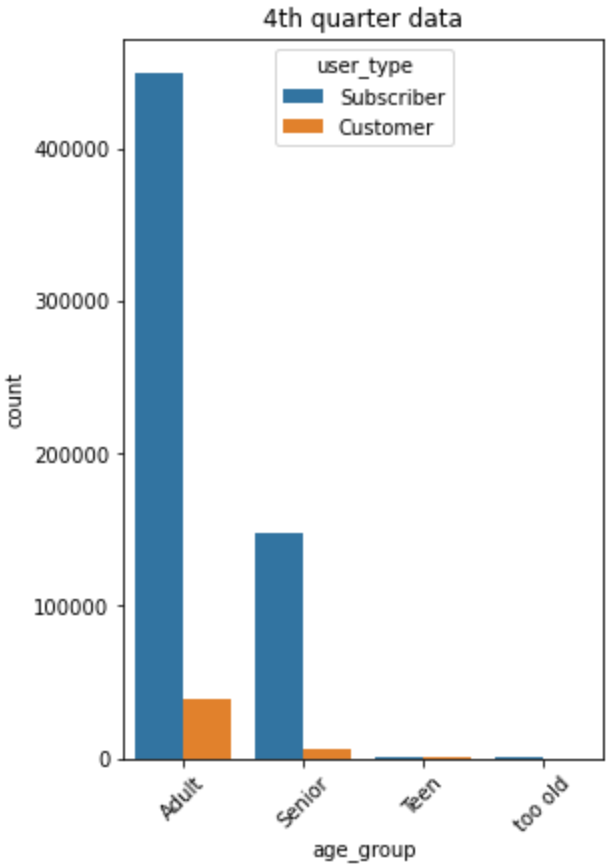
Q2 Which age group has the most annual members ?

In [115…
```
plot_relations(combined_data,'age_group','user_type')
```









we can see that adults hold the majority for our users although it is worth mentioning that the average age for our customers is less than that of our Subscribers, this will help us in the design of the ads and which age group to target

Q3 What do annaual users gain from the membership that casual users do not?

Unfortunately we do not have data to answer that question so we have our limitations even with this large dataset, we are looking for the pricing and how it is diffrent to the customers from the subscriber, how much a subscriber save during a ride, this questions will be a great help to us but since they are missing now would be the time where we reach to our stakeholders for more info and lunch a survay for customers to ask them for opinions about the pricing plans

Recommendations

- Start the marketing campain in the summer
- Discounts in the weekends as these days have the most number of customers
- Have discount coupons when a customer passes a certain duration
- Target adults groups