Part_I_exploration

September 7, 2022

1 Part I - (Dataset Exploration Title)

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1.2 Introduction

Introduce the dataset: The dataset, 201902-fordgobike-tripdata.csv, is downloaded from Ford GoBike and licensed by Ford GoBike. This dataset includes 519,700 trips with 15 features such as locations, time, and user attributes. There are start and end stations. I noticed that most trips happen on the same stations, so I subset the dataset by choosing top 8 trips start stations with the most trips

1.3 Preliminary Wrangling

```
In [83]: # import all packages and set plots to be embedded inline
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sb
         import calendar
         import math
         import time

         %matplotlib inline
```

Load in your dataset and describe its properties through the questions below. Try and motivate your exploration goals through this section.

```
In [84]: # Import Ford GoBike csv file into jupyter notebook
         df = pd.read_csv('201902-fordgobike-tripdata.csv')
         df.head()
```

```
Out[84]:    duration_sec                start_time                  end_time  \
         0         52185  2019-02-28 17:32:10.1450  2019-03-01 08:01:55.9750
         1         42521  2019-02-28 18:53:21.7890  2019-03-01 06:42:03.0560
         2         61854  2019-02-28 12:13:13.2180  2019-03-01 05:24:08.1460
         3         36490  2019-02-28 17:54:26.0100  2019-03-01 04:02:36.8420
         4          1585  2019-02-28 23:54:18.5490  2019-03-01 00:20:44.0740
```

```
   start_station_id                                  start_station_name  \
0              21.0  Montgomery St BART Station (Market St at 2nd St)   
1              23.0                 The Embarcadero at Steuart St   
2              86.0                       Market St at Dolores St   
3             375.0                       Grove St at Masonic Ave   
4               7.0                           Frank H Ogawa Plaza   

   start_station_latitude  start_station_longitude  end_station_id  \
0               37.789625              -122.400811            13.0   
1               37.791464              -122.391034            81.0   
2               37.769305              -122.426826             3.0   
3               37.774836              -122.446546            70.0   
4               37.804562              -122.271738           222.0   

                               end_station_name  end_station_latitude  \
0                Commercial St at Montgomery St             37.794231   
1                            Berry St at 4th St             37.775880   
2  Powell St BART Station (Market St at 4th St)             37.786375   
3                        Central Ave at Fell St             37.773311   
4                         10th Ave at E 15th St             37.792714   

   end_station_longitude  bike_id   user_type  member_birth_year  \
0            -122.402923     4902    Customer             1984.0   
1            -122.393170     2535    Customer                NaN   
2            -122.404904     5905    Customer             1972.0   
3            -122.444293     6638  Subscriber             1989.0   
4            -122.248780     4898  Subscriber             1974.0   

  member_gender bike_share_for_all_trip  
0          Male                      No  
1           NaN                      No  
2          Male                      No  
3         Other                      No  
4          Male                     Yes  
```

In [85]:
```
df.shape
```

Out[85]:
```
(183412, 16)
```

In [86]:
```
df.describe()
```

Out[86]:
```
         duration_sec  start_station_id  start_station_latitude  \
count  183412.000000     183215.000000           183412.000000   
mean      726.078435        138.590427               37.771223   
std      1794.389780        111.778864                0.099581   
min        61.000000          3.000000               37.317298   
25%       325.000000         47.000000               37.770083   
50%       514.000000        104.000000               37.780760   
```

```
75%       796.000000        239.000000               37.797280
max     85444.000000        398.000000               37.880222

       start_station_longitude  end_station_id  end_station_latitude  \
count            183412.000000   183215.000000         183412.000000
mean               -122.352664      136.249123             37.771427
std                   0.117097      111.515131              0.099490
min                -122.453704        3.000000             37.317298
25%                -122.412408       44.000000             37.770407
50%                -122.398285      100.000000             37.781010
75%                -122.286533      235.000000             37.797320
max                -121.874119      398.000000             37.880222

       end_station_longitude        bike_id  member_birth_year
count          183412.000000  183412.000000      175147.000000
mean             -122.352250    4472.906375        1984.806437
std                 0.116673    1664.383394          10.116689
min              -122.453704      11.000000        1878.000000
25%              -122.411726    3777.000000        1980.000000
50%              -122.398279    4958.000000        1987.000000
75%              -122.288045    5502.000000        1992.000000
max              -121.874119    6645.000000        2001.000000
```

In [87]:
```
df.info(0)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183412 entries, 0 to 183411
Data columns (total 16 columns):
duration_sec               183412 non-null int64
start_time                 183412 non-null object
end_time                   183412 non-null object
start_station_id           183215 non-null float64
start_station_name         183215 non-null object
start_station_latitude     183412 non-null float64
start_station_longitude    183412 non-null float64
end_station_id             183215 non-null float64
end_station_name           183215 non-null object
end_station_latitude       183412 non-null float64
end_station_longitude      183412 non-null float64
bike_id                    183412 non-null int64
user_type                  183412 non-null object
member_birth_year          175147 non-null float64
member_gender              175147 non-null object
bike_share_for_all_trip    183412 non-null object
dtypes: float64(7), int64(2), object(7)
memory usage: 22.4+ MB
```

1.3.1 What is the structure of your dataset?

The datasets consists of 183412 trips and 16 features

1.3.2 What is/are the main feature(s) of interest in your dataset?

The Trip duration might be the main feature of interest of this dataset, as it's for sure affect the revenue of the company, that's why I will study on this analysis the effect of other factors like user_type, trip start and end times, gender and age on the trip duration.

1.3.3 What features in the dataset do you think will help support your investigation into your feature(s) of interest?

- user_type
- trip_duration
- end_station_name
- start_station_name
- start_time
- Gender and Age

In [88]:
```
# checking for the null values
df.isnull().sum()
```

Out[88]:
```
duration_sec                  0
start_time                    0
end_time                      0
start_station_id            197
start_station_name          197
start_station_latitude        0
start_station_longitude       0
end_station_id              197
end_station_name            197
end_station_latitude          0
end_station_longitude         0
bike_id                       0
user_type                     0
member_birth_year          8265
member_gender              8265
bike_share_for_all_trip       0
dtype: int64
```

In [89]:
```
# Percentage of missing data
((df.isnull() | df.isna()).sum() * 100 / df.index.size).round(2)
```

Out[89]:
```
duration_sec               0.00
start_time                 0.00
end_time                   0.00
start_station_id           0.11
```

```
start_station_name         0.11
start_station_latitude     0.00
start_station_longitude    0.00
end_station_id             0.11
end_station_name           0.11
end_station_latitude       0.00
end_station_longitude      0.00
bike_id                    0.00
user_type                  0.00
member_birth_year          4.51
member_gender              4.51
bike_share_for_all_trip    0.00
dtype: float64
```

In [90]:
```
# Since the we have that 4.51% is the highest record of missing values, it is better to
df.dropna(axis = 0, inplace = True)
```

In [91]:
```
# Check the null values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 174952 entries, 0 to 183411
Data columns (total 16 columns):
duration_sec               174952 non-null int64
start_time                 174952 non-null object
end_time                   174952 non-null object
start_station_id           174952 non-null float64
start_station_name         174952 non-null object
start_station_latitude     174952 non-null float64
start_station_longitude    174952 non-null float64
end_station_id             174952 non-null float64
end_station_name           174952 non-null object
end_station_latitude       174952 non-null float64
end_station_longitude      174952 non-null float64
bike_id                    174952 non-null int64
user_type                  174952 non-null object
member_birth_year          174952 non-null float64
member_gender              174952 non-null object
bike_share_for_all_trip    174952 non-null object
dtypes: float64(7), int64(2), object(7)
memory usage: 22.7+ MB
```

In [92]:
```
# Check unique values
df.nunique()
```

Out[92]:
```
duration_sec                 4429
start_time                 174941
end_time                   174939
```

```
start_station_id              329
start_station_name            329
start_station_latitude        329
start_station_longitude       329
end_station_id                329
end_station_name              329
end_station_latitude          329
end_station_longitude         329
bike_id                      4607
user_type                       2
member_birth_year              75
member_gender                   3
bike_share_for_all_trip         2
dtype: int64
```

In [93]:
```
# Check for duplicated values
df.duplicated().sum()
```

Out[93]:
```
0
```

In [94]:
```
# Check the datetypes
df.dtypes
```

Out[94]:
```
duration_sec                 int64
start_time                  object
end_time                    object
start_station_id           float64
start_station_name          object
start_station_latitude     float64
start_station_longitude    float64
end_station_id             float64
end_station_name            object
end_station_latitude       float64
end_station_longitude      float64
bike_id                      int64
user_type                   object
member_birth_year          float64
member_gender               object
bike_share_for_all_trip     object
dtype: object
```

In [95]:
```
# columns start_time and end_time should be in the dtaetime format
# columns user_type and bike_share_for_all_trip should be in categorical datatype and n
# start_station_id, end_station_id and bike_id should be object data type not numerical
df.start_time = pd.to_datetime(df.start_time)
df.end_time = pd.to_datetime(df.end_time)
df['user_type'] = df['user_type'].astype('category')
df['bike_share_for_all_trip'] = df['bike_share_for_all_trip'].astype('category')
df['start_station_id'] = df['start_station_id'].astype('object')
```

```
df['end_station_id'] = df['end_station_id'].astype('object')
df['bike_id'] = df['bike_id'].astype('object')
```

In [96]:
```
# Corfim the changes made on the dtatype
df.dtypes
```

Out[96]:
```
duration_sec                        int64
start_time                 datetime64[ns]
end_time                   datetime64[ns]
start_station_id                   object
start_station_name                 object
start_station_latitude            float64
start_station_longitude           float64
end_station_id                     object
end_station_name                   object
end_station_latitude              float64
end_station_longitude             float64
bike_id                            object
user_type                        category
member_birth_year                 float64
member_gender                      object
bike_share_for_all_trip          category
dtype: object
```

In [99]:
```
# Extract start_time_month and dayofweek, information from the start_time
df['start_time_dayofweek']= df['start_time'].dt.strftime('%a')
df['start_time_month'] = df['start_time'].dt.strftime('%B')
```

In [100]:
```
# day categories in order
weekday = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']
# change type to ordered categorical
df['start_time_dayofweek']  =  pd.Categorical(df['start_time_dayofweek'], categories=w

# check counts and order (not required)
df['start_time_dayofweek'].value_counts().sort_index()
```

Out[100]:
```
Mon    25641
Tue    30584
Wed    28426
Thu    33712
Fri    27663
Sat    14414
Sun    14512
Name: start_time_dayofweek, dtype: int64
```

In [101]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 174952 entries, 0 to 183411
```

```
Data columns (total 18 columns):
duration_sec               174952 non-null int64
start_time                 174952 non-null datetime64[ns]
end_time                   174952 non-null datetime64[ns]
start_station_id           174952 non-null object
start_station_name         174952 non-null object
start_station_latitude     174952 non-null float64
start_station_longitude    174952 non-null float64
end_station_id             174952 non-null object
end_station_name           174952 non-null object
end_station_latitude       174952 non-null float64
end_station_longitude      174952 non-null float64
bike_id                    174952 non-null object
user_type                  174952 non-null category
member_birth_year          174952 non-null float64
member_gender              174952 non-null object
bike_share_for_all_trip    174952 non-null category
start_time_dayofweek       174952 non-null category
start_time_month           174952 non-null object
dtypes: category(3), datetime64[ns](2), float64(5), int64(1), object(7)
memory usage: 21.9+ MB
```

In [102]:
```
# let's change the duration_sec to duration_min to make it more compact
df['duration_min'] = df['duration_sec'] / 60
```

In [103]:
```
df.duration_min.describe()
```

Out[103]:
```
count    174952.000000
mean         11.733379
std          27.370082
min           1.016667
25%           5.383333
50%           8.500000
75%          13.150000
max        1409.133333
Name: duration_min, dtype: float64
```

In [104]:
```
# Looks like for at least 75% of the data are less than one hour, so end_time_hour wil
# Extract Start_time_hourfrom start_time information
df['start_time_hour']= df['start_time'].dt.hour
```

In [105]:
```
# checking the unique values of the start_time_month
df['start_time_month'].unique()
```

Out[105]:
```
array(['February'], dtype=object)
```

In [106]:
```
# create a new column member_age which is easier to relate with that the birth year th
# since the data set is 2019, we will be subtracting the birth year from 2019
df['member_age'] = 2019 - df['member_birth_year']
df['member_age'].head(2)
```

```
Out[106]: 0    35.0
          2    47.0
          Name: member_age, dtype: float64
```

```
In [107]: # Changing the dtype of both member_birth_year and member_age from float to int datatyp
          df['member_age'] = df['member_age'].astype(int)
          df['member_birth_year'] = df['member_birth_year'].astype(int)
```

```
In [108]: print(df['member_age'].head(2))
          print(df['member_birth_year'].head(2))
```

```
0    35
2    47
Name: member_age, dtype: int64
0    1984
2    1972
Name: member_birth_year, dtype: int64
```

```
In [109]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 174952 entries, 0 to 183411
Data columns (total 21 columns):
duration_sec               174952 non-null int64
start_time                 174952 non-null datetime64[ns]
end_time                   174952 non-null datetime64[ns]
start_station_id           174952 non-null object
start_station_name         174952 non-null object
start_station_latitude     174952 non-null float64
start_station_longitude    174952 non-null float64
end_station_id             174952 non-null object
end_station_name           174952 non-null object
end_station_latitude       174952 non-null float64
end_station_longitude      174952 non-null float64
bike_id                    174952 non-null object
user_type                  174952 non-null category
member_birth_year          174952 non-null int64
member_gender              174952 non-null object
bike_share_for_all_trip    174952 non-null category
start_time_dayofweek       174952 non-null category
start_time_month           174952 non-null object
duration_min               174952 non-null float64
start_time_hour            174952 non-null int64
member_age                 174952 non-null int64
dtypes: category(3), datetime64[ns](2), float64(5), int64(4), object(7)
memory usage: 25.9+ MB
```

In [110]:
```
quatile_range = list(np.arange(0.1, 1, 0.05))
df['duration_min'].quantile(quatile_range)
```

Out[110]:
```
0.10     3.550000
0.15     4.200000
0.20     4.800000
0.25     5.383333
0.30     5.950000
0.35     6.550000
0.40     7.183333
0.45     7.816667
0.50     8.500000
0.55     9.250000
0.60    10.050000
0.65    10.950000
0.70    11.966667
0.75    13.150000
0.80    14.616667
0.85    16.500000
0.90    19.350000
0.95    25.516667
Name: duration_min, dtype: float64
```

In [111]:
```
# We remove outliers row
df = df[df['duration_min'] <= df['duration_min'].quantile(0.99)]
```

In [112]:
```
df.describe()
```

Out[112]:
```
         duration_sec  start_station_latitude  start_station_longitude  \
count  173204.000000           173204.000000            173204.000000
mean      612.726138               37.771176              -122.351553
std       425.821242                0.100544                 0.117839
min        61.000000               37.317298              -122.453704
25%       321.000000               37.770407              -122.411901
50%       506.000000               37.780760              -122.398279
75%       777.000000               37.797320              -122.283093
max      3176.000000               37.880222              -121.874119

       end_station_latitude  end_station_longitude  member_birth_year  \
count         173204.000000          173204.000000      173204.000000
mean              37.771362            -122.351117        1984.808665
std                0.100439               0.117387          10.112763
min               37.317298            -122.453704        1878.000000
25%               37.770407            -122.411647        1980.000000
50%               37.781010            -122.397405        1987.000000
75%               37.797673            -122.285171        1992.000000
max               37.880222            -121.874119        2001.000000

         duration_min  start_time_hour     member_age
```

```
count  173204.000000    173204.000000  173204.000000
mean       10.212102        13.454822      34.191335
std         7.097021         4.739169      10.112763
min         1.016667         0.000000      18.000000
25%         5.350000         9.000000      27.000000
50%         8.433333        14.000000      32.000000
75%        12.950000        17.000000      39.000000
max        52.933333        23.000000     141.000000
```

In [113]:
```python
# copy the data set
df_clean = df.copy()
df_clean.to_csv('clean_ford_data.csv')
```

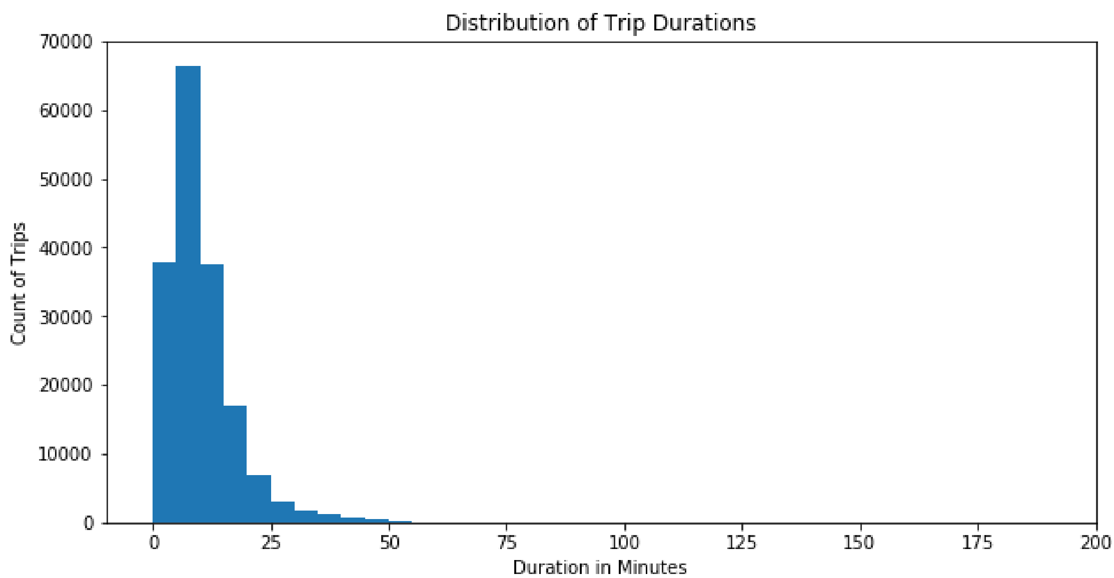
In [114]:
```python
df.describe()
```

Out[114]:
```
         duration_sec  start_station_latitude  start_station_longitude  \
count  173204.000000           173204.000000            173204.000000
mean      612.726138               37.771176              -122.351553
std       425.821242                0.100544                 0.117839
min        61.000000               37.317298              -122.453704
25%       321.000000               37.770407              -122.411901
50%       506.000000               37.780760              -122.398279
75%       777.000000               37.797320              -122.283093
max      3176.000000               37.880222              -121.874119

       end_station_latitude  end_station_longitude  member_birth_year  \
count         173204.000000          173204.000000      173204.000000
mean              37.771362            -122.351117        1984.808665
std                0.100439               0.117387          10.112763
min               37.317298            -122.453704        1878.000000
25%               37.770407            -122.411647        1980.000000
50%               37.781010            -122.397405        1987.000000
75%               37.797673            -122.285171        1992.000000
max               37.880222            -121.874119        2001.000000

         duration_min  start_time_hour     member_age
count  173204.000000    173204.000000  173204.000000
mean       10.212102        13.454822      34.191335
std         7.097021         4.739169      10.112763
min         1.016667         0.000000      18.000000
25%         5.350000         9.000000      27.000000
50%         8.433333        14.000000      32.000000
75%        12.950000        17.000000      39.000000
max        52.933333        23.000000     141.000000
```

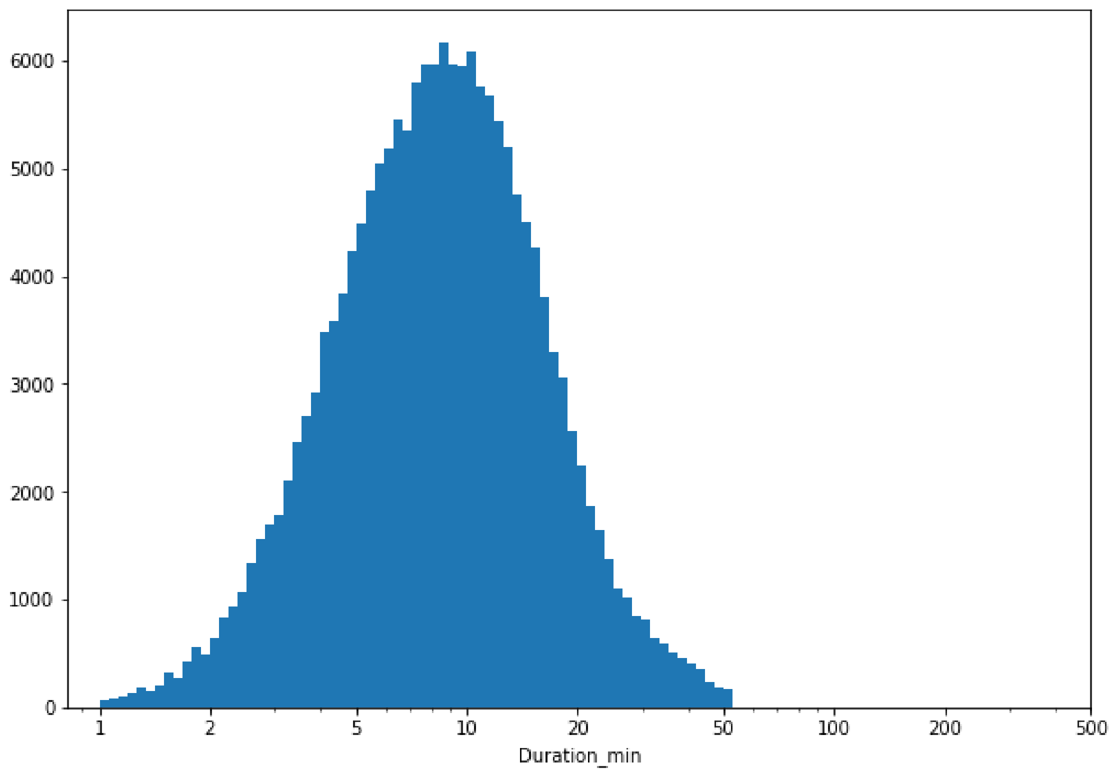
1.4 Univariate Exploration

duration_min

In [115]:
```python
# plotting the duration_min data on a normal scale
binsize = 5
bins = np.arange(0, df['duration_min'].max()+binsize, binsize)

plt.figure(figsize=[10, 5])
plt.hist(data = df, x = 'duration_min', bins = bins)
plt.title('Distribution of Trip Durations')
plt.xlabel('Duration in Minutes')
plt.ylabel('Count of Trips')
plt.axis([-10, 200, 0, 70000])
plt.show()
```

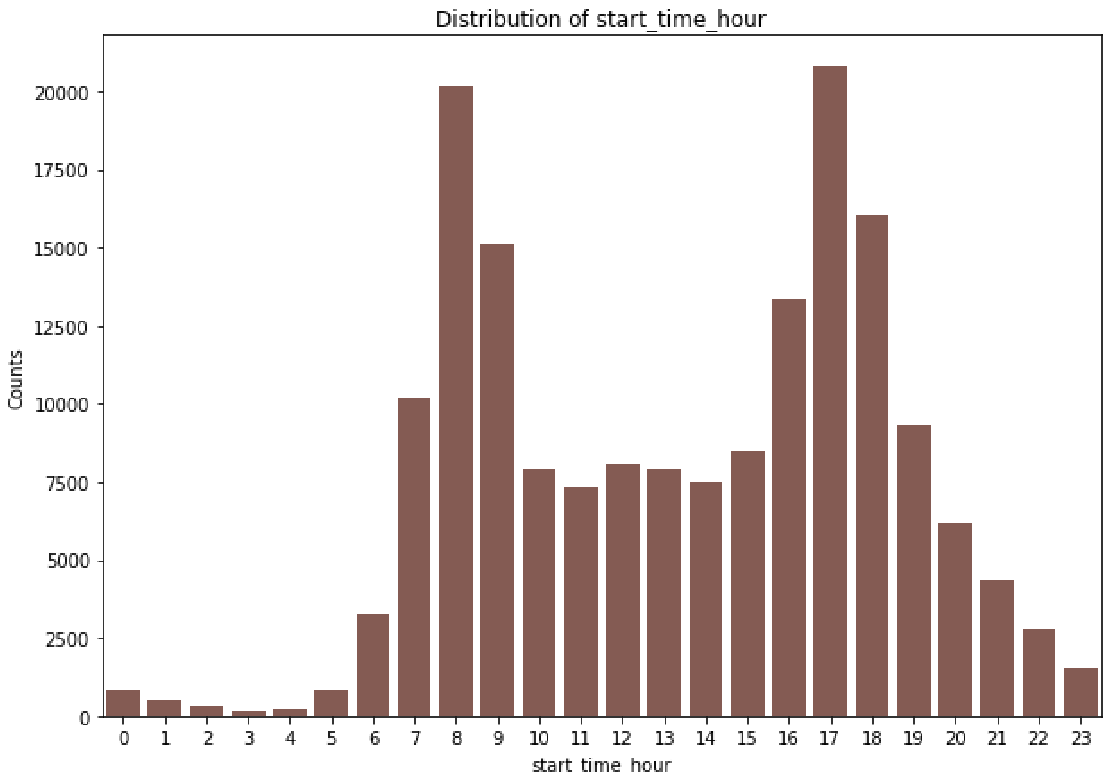


In [116]:
```python
log_binsize = 0.025
bins = 10 ** np.arange(0, np.log10(df['duration_min'].max())+log_binsize, log_binsize)

plt.figure(figsize=[10, 7]);
plt.hist(data = df, x = 'duration_min', bins = bins);
plt.xscale('log');
plt.xticks([1, 2, 5, 10, 20, 50, 100, 200, 500], [1, 2, 5, 10, 20, 50, 100, 200, 500])
plt.xlabel('Duration_min');
```



In [117]:
```
# Functions to avoid repetition of codes
def countplot(data, x, color, order = None):
    plt.figure(figsize=[10, 7])
    base_color = sb.color_palette()[color]
    if order:
        order = df[x].value_counts().index
    sb.countplot(data = data, x = x, color = base_color, order = order)
    plt.title('Distribution of ' + x)
    plt.xlabel(x)
    plt.ylabel('Counts');


def piechart(x):
    sorted_counts = df[x].value_counts()
    plt.figure(figsize=[10,7])
    plt.pie(sorted_counts, labels = sorted_counts.index, startangle = 90, counterclock
    plt.axis('square')
    plt.title('Pie Chart of ' + x);
```

In [118]:
```
# a bar plot showing the peak start hours
countplot(data = df, x = 'start_time_hour', color = 5)
```



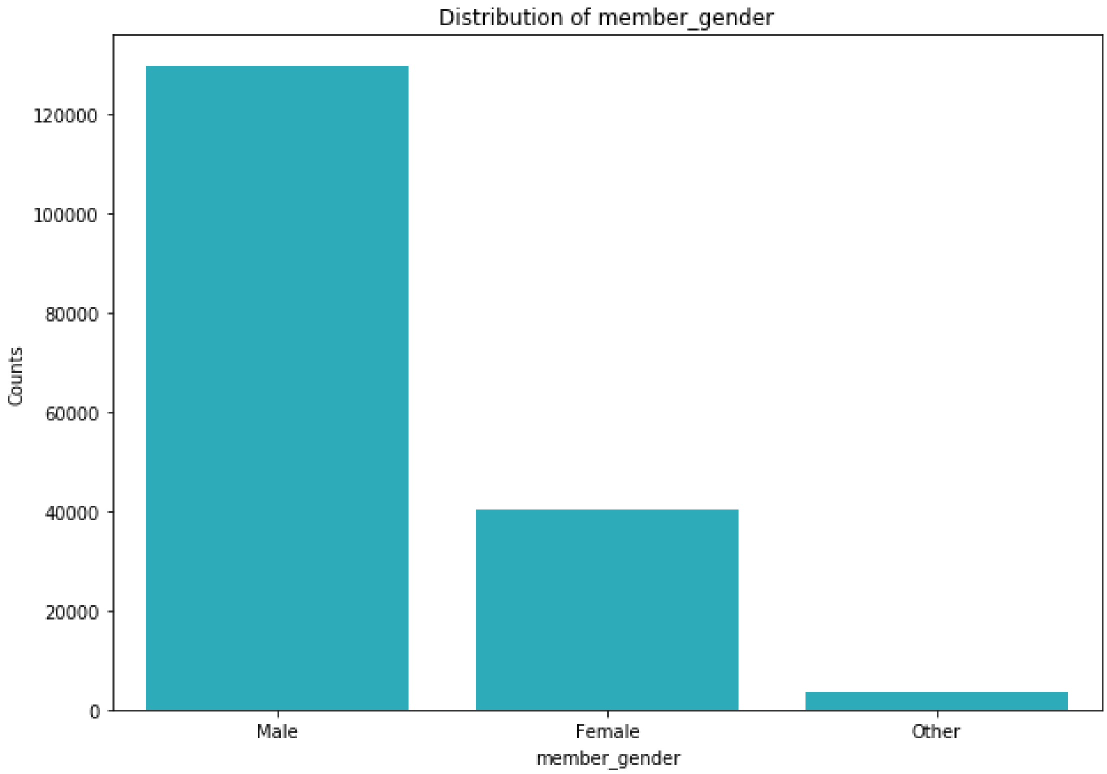
Check for start hours with the peak time

member_gender

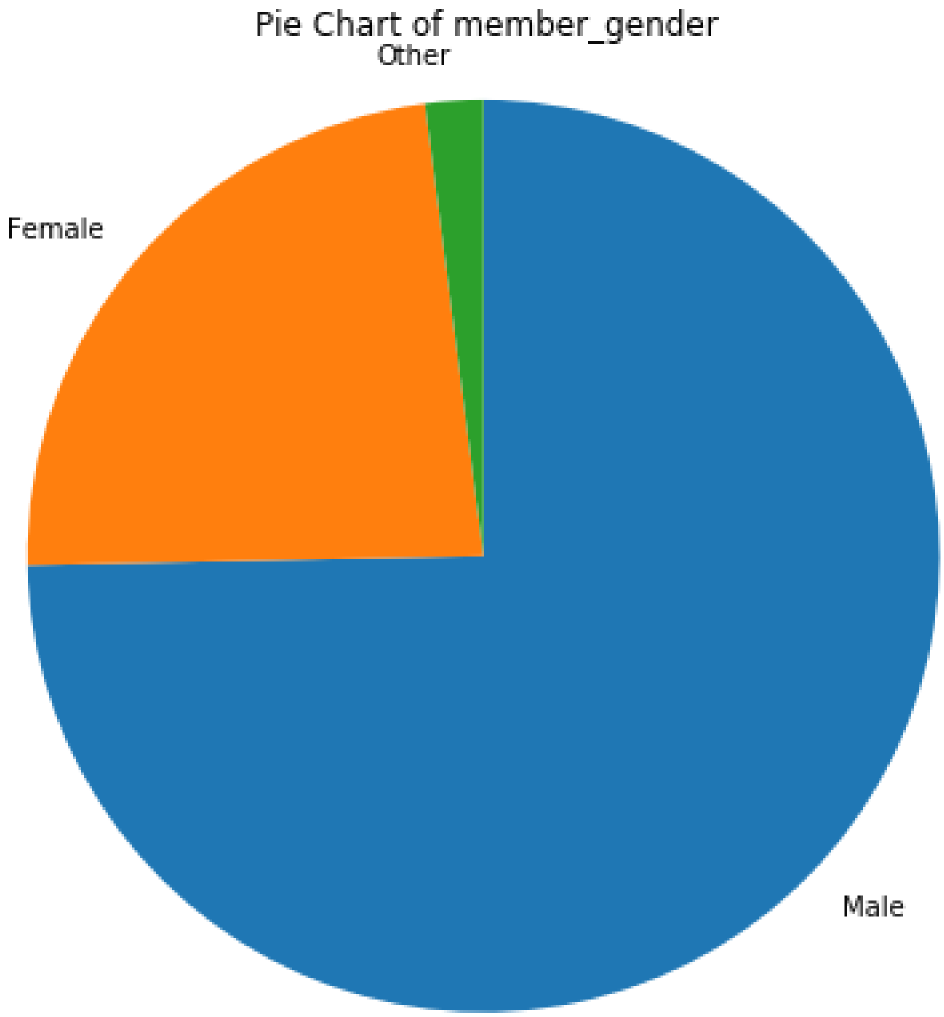
```
In [119]: df['member_gender'].value_counts()
```

```
Out[119]: Male      129347
          Female     40310
          Other       3547
          Name: member_gender, dtype: int64
```

```
In [120]: # Bar plot showing that most Bikers are Male
          countplot(data = df, x = 'member_gender', color=9)
```




```
In [121]: # A pie chart to justify the bar chart that most Bikers are Male
          piechart('member_gender')
```



start and end stations

```
In [122]: df['start_station_name'].value_counts()[1:10]

Out[122]: San Francisco Caltrain Station 2  (Townsend St at 4th St)    3399
          Berry St at 4th St                                          2933
          Montgomery St BART Station (Market St at 2nd St)            2694
          Powell St BART Station (Market St at 4th St)                2570
          San Francisco Caltrain (Townsend St at 4th St)              2565
          San Francisco Ferry Building (Harry Bridges Plaza)          2493
          Howard St at Beale St                                       2211
          Steuart St at Market St                                     2174
          Powell St BART Station (Market St at 5th St)                2098
          Name: start_station_name, dtype: int64
```

In [123]:
```
df['end_station_name'].value_counts()[1:10]
```

Out[123]:
```
Market St at 10th St                                    3697
Montgomery St BART Station (Market St at 2nd St)        3438
San Francisco Ferry Building (Harry Bridges Plaza)      3109
San Francisco Caltrain (Townsend St at 4th St)          2864
Powell St BART Station (Market St at 4th St)            2824
Berry St at 4th St                                      2772
The Embarcadero at Sansome St                           2283
Steuart St at Market St                                 2256
Powell St BART Station (Market St at 5th St)            2122
Name: end_station_name, dtype: int64
```

In [124]:
```
# since most start and end stations have the same frequency, we then add both together
# select top 10
start_stations = df['start_station_name'].value_counts()
end_stations = df['end_station_name'].value_counts()
station_total = start_stations + end_stations
```

In [125]:
```
station_total.head()
```

Out[125]:
```
10th Ave at E 15th St          90
10th St at Fallon St          683
10th St at University Ave     452
11th St at Bryant St         1733
11th St at Natoma St         1634
dtype: int64
```

In [126]:
```
station_total =  pd.DataFrame(station_total, index=None).reset_index().rename(columns=

station_total.head()
```

Out[126]:

	station	count
0	10th Ave at E 15th St	90
1	10th St at Fallon St	683
2	10th St at University Ave	452
3	11th St at Bryant St	1733
4	11th St at Natoma St	1634

In [127]:
```
top_10 = pd.DataFrame(start_stations.sort_values(ascending=False)[:10],
                     index=None).reset_index().rename(columns={'index':'station', 'sta
```

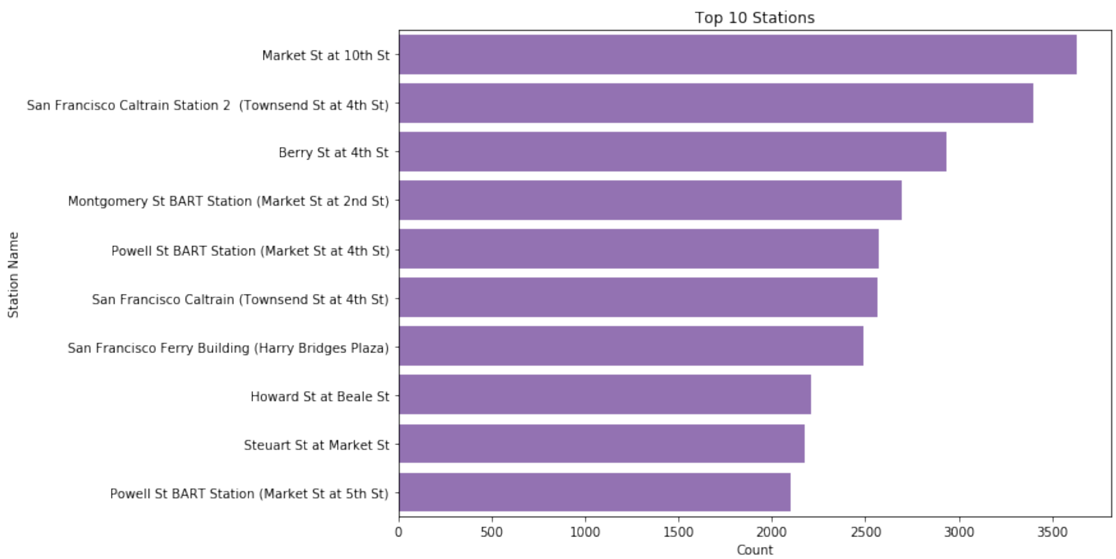
In [128]:
```
top_10
```

Out[128]:

	station	count
0	Market St at 10th St	3634
1	San Francisco Caltrain Station 2 (Townsend St...	3399
2	Berry St at 4th St	2933
3	Montgomery St BART Station (Market St at 2nd St)	2694

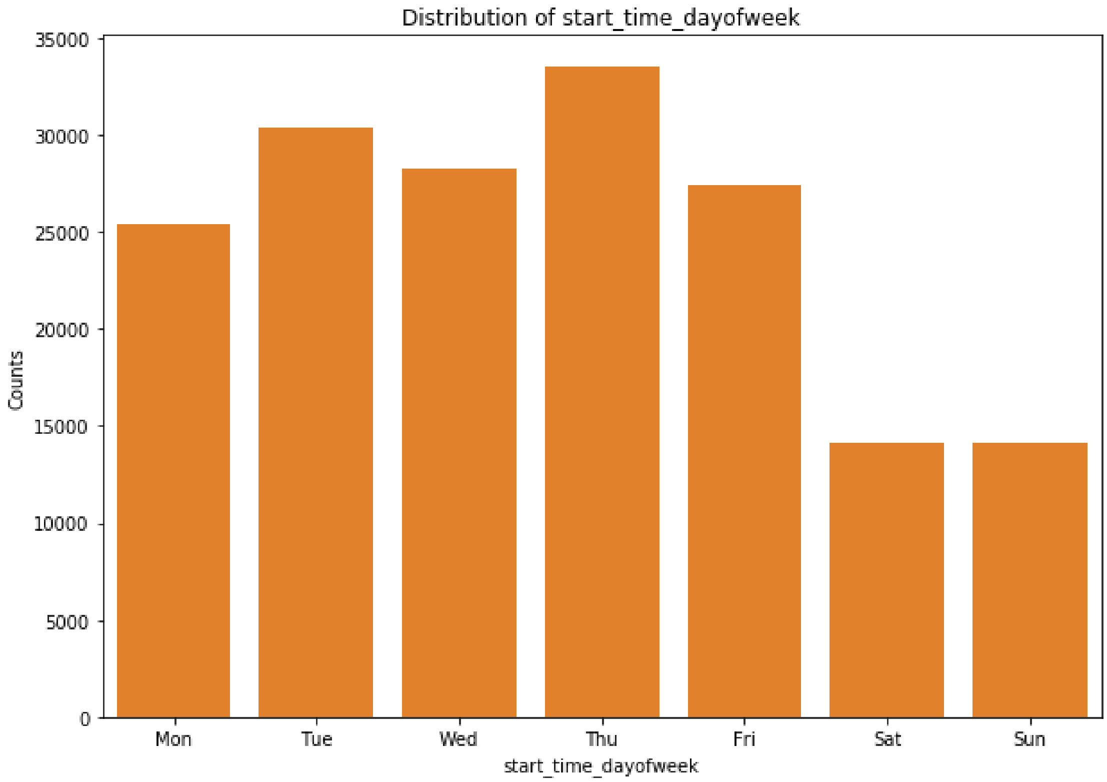
```
4       Powell St BART Station (Market St at 4th St)   2570
5     San Francisco Caltrain (Townsend St at 4th St)   2565
6   San Francisco Ferry Building (Harry Bridges Pl...   2493
7                               Howard St at Beale St   2211
8                             Steuart St at Market St   2174
9       Powell St BART Station (Market St at 5th St)   2098
```

In [129]:
```
# plot the top ten stations
plt.figure(figsize = [10,7])
base_color = sb.color_palette()[4]
sb.barplot(data=top_10, y = 'station', x='count', color=base_color)
plt.title('Top 10 Stations')
plt.xlabel('Count')
plt.ylabel('Station Name')
plt.show();
```



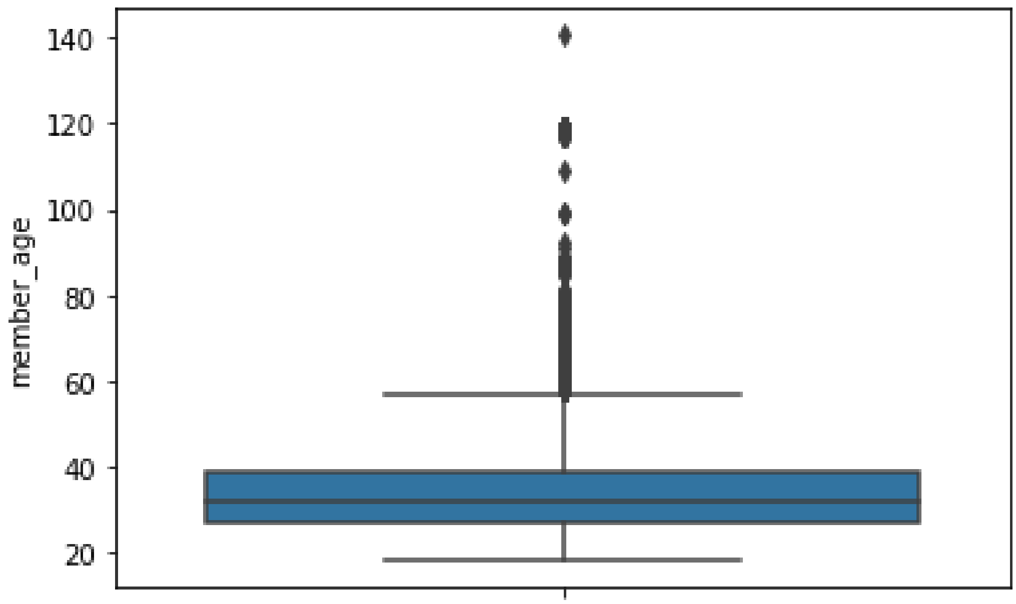
Days of the week

In [130]:
```
# A bar plot to show the counts for days of the week
# Most bikers work during the weekedays
countplot(data = df, x = 'start_time_dayofweek', color = 1)
```

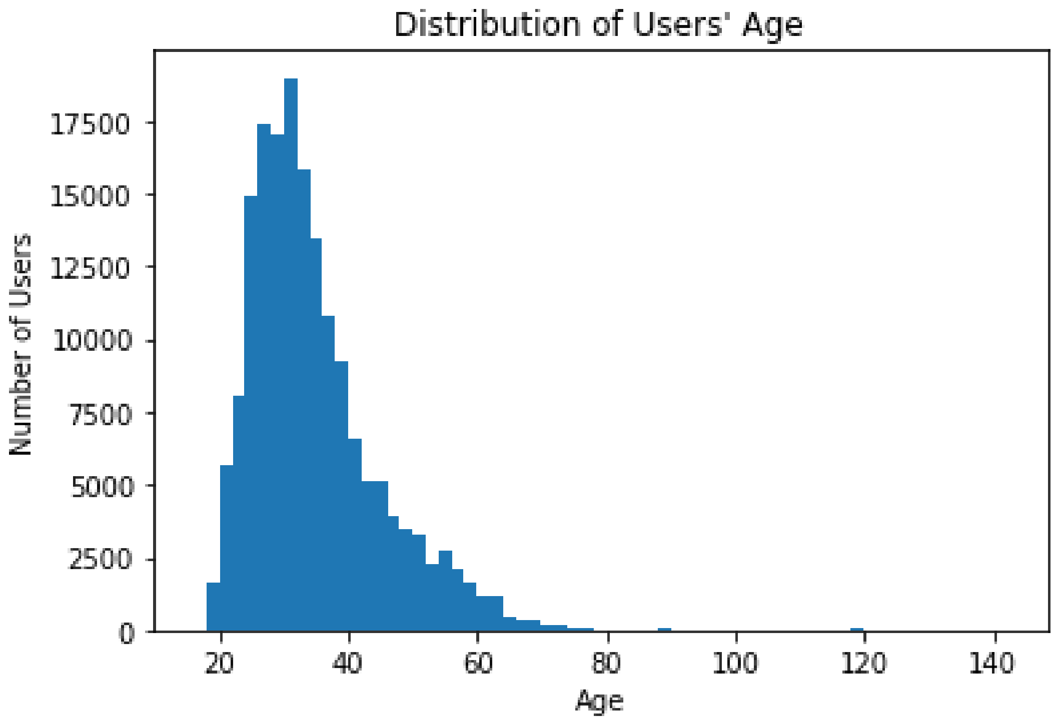


Age

```
In [131]: df['member_age'].describe()

Out[131]: count    173204.000000
          mean         34.191335
          std          10.112763
          min          18.000000
          25%          27.000000
          50%          32.000000
          75%          39.000000
          max         141.000000
          Name: member_age, dtype: float64

In [132]: sb.boxplot(data = df, y = 'member_age');
```



In [133]:
```
# This plot shows the age range of the Bikers
binsize = 2
bins = np.arange(16, df['member_age'].max()+binsize, binsize)
plt.hist(data = df, x = 'member_age', bins = bins);
plt.title("Distribution of Users' Age")
plt.xlabel('Age')
plt.ylabel('Number of Users')
plt.show()
```



In [134]:
```
# group the ages into generation
def age_distribution(yob):
    if yob >= 1928 and yob <= 1945:
        return('Post War')
    elif yob >= 1946 and yob <= 1964:
        return('Baby Boomers')
    elif yob >= 1965 and yob <= 1980:
        return('Gen X')
    elif yob >= 1981 and yob <= 1996:
        return('Millenials')
    elif yob >= 1997 and yob <= 2012:
        return('Gen Z')
    else: np.NaN
```

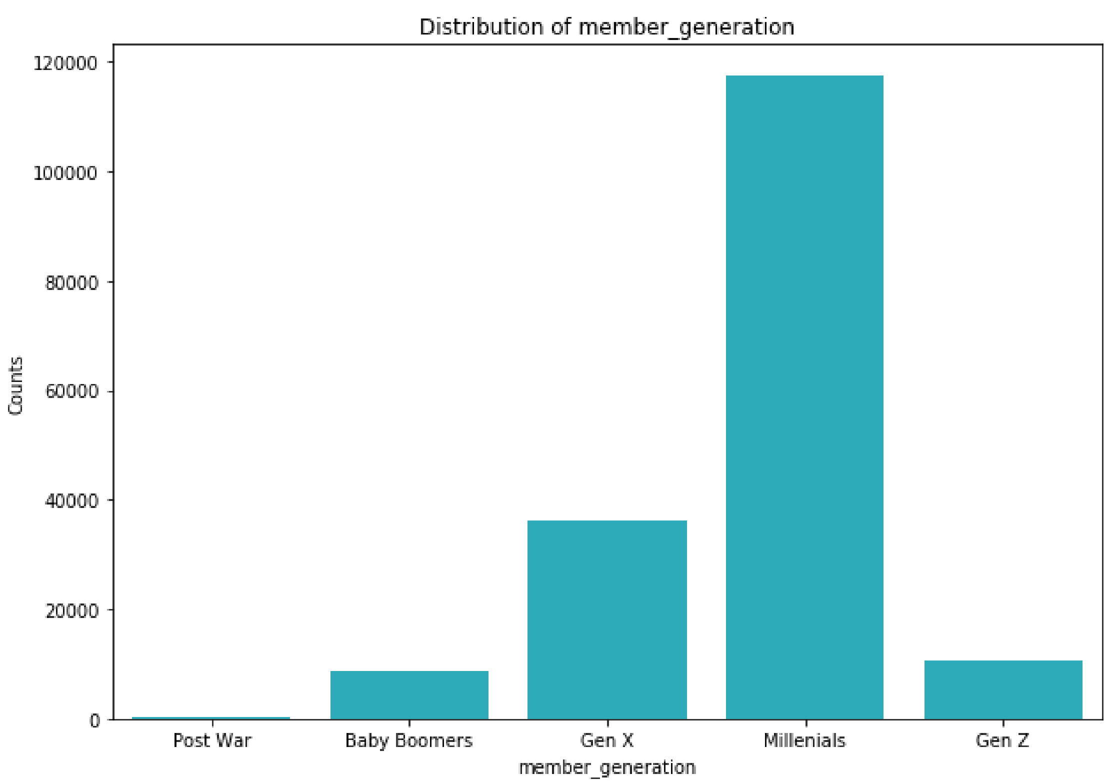
In [135]:
```
# create member generation variables
df['member_generation'] = df['member_birth_year'].apply(age_distribution)

# create generations variable
generations = ['Post War','Baby Boomers', 'Gen X', 'Millenials',  'Gen Z']

# Order member_generation categorically
df['member_generation'] = pd.Categorical(df['member_generation'], categories = generat
```

```
# Counts in order
df['member_generation'].value_counts().sort_index()
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#

/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
```

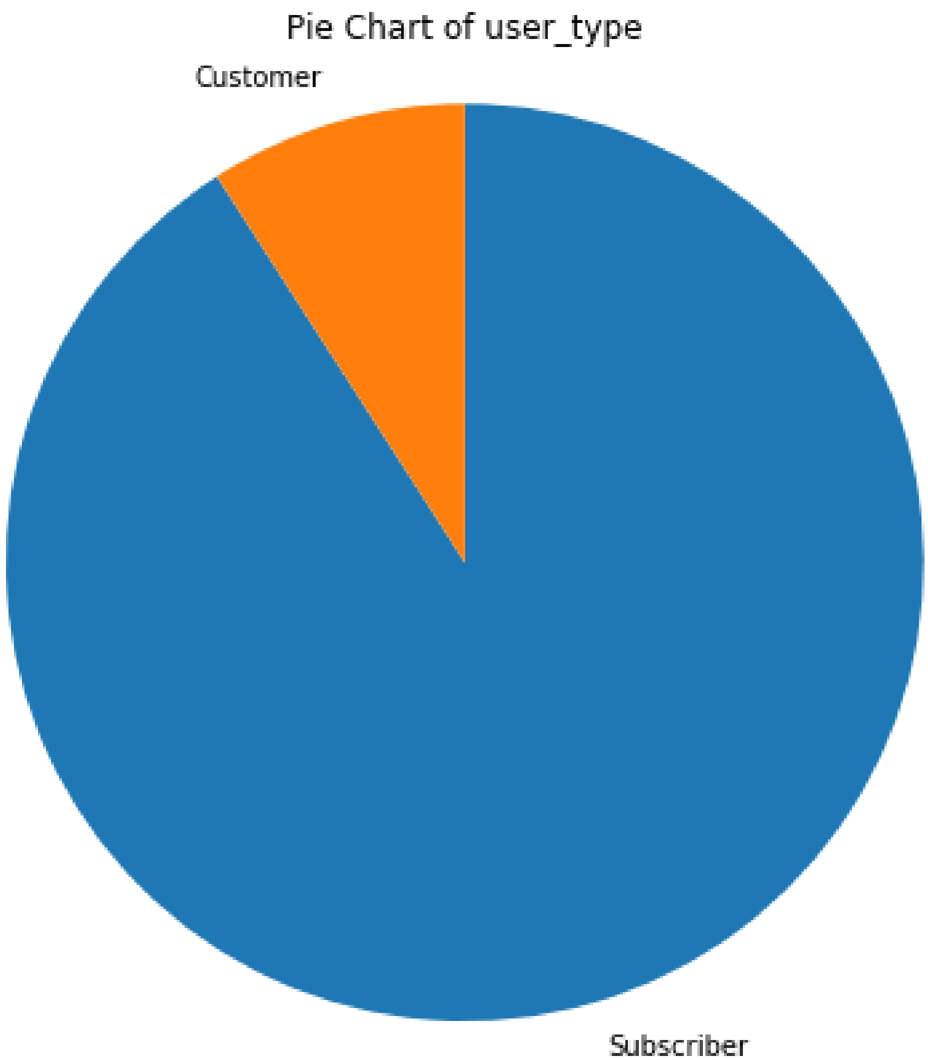
```
Out[135]: Post War           289
          Baby Boomers      8592
          Gen X            36189
          Millenials      117290
          Gen Z            10768
          Name: member_generation, dtype: int64
```

```
In [136]: countplot(data = df, x = 'member_generation', color = 9)
```



Bikers Type

```
In [137]: # Plot a pie chart to show the user_type
          # It shows that most of the Bikers are Subscriber
          piechart('user_type')
```



Plotting the duration of trips using histogram shows that we need to scale. I apply log scaling to show to the plot which now shos that the duration of most trips are between 6 - 15 mins

The rides across the week clearly shows that Thursday has the highest number of trips. Weekdays semms to be the most significant counts, while weekends (Saturday and Sunday) have the least counts

The start stations and end stations have similar top records which is why it was added together and it was plotted in the graph to show the most top 10 most frequest places in San francisco

The Bikers were splitted generations using their bith year after plotting it was observed that the millenials generation has the highest number i.e Bikers that are born between 1981 and 1996. The generation was gotten using birth_year

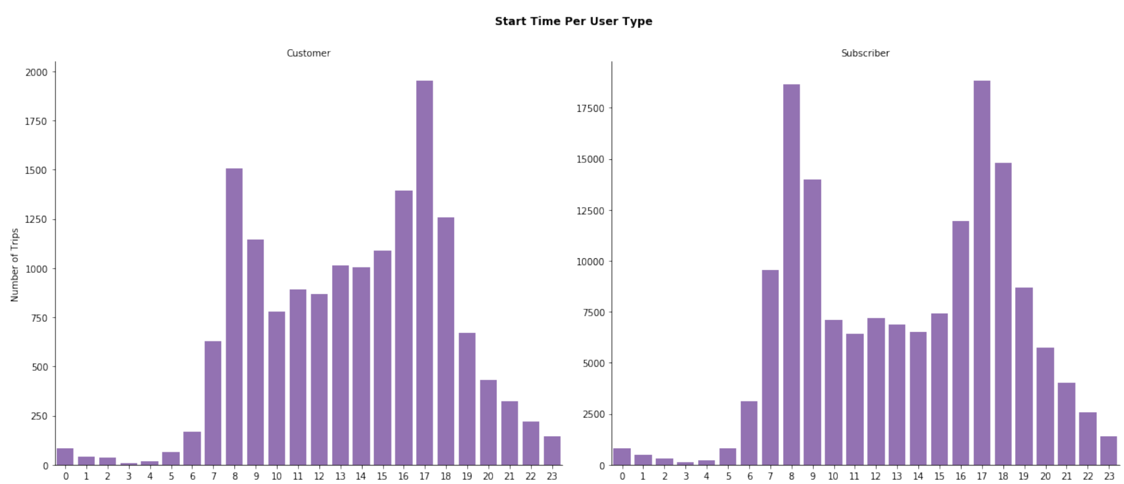
Majority of the Bikers are subscribers, which can be seen from the pie chart

The hour of the day and the day of the week were extracted from the timestamp.

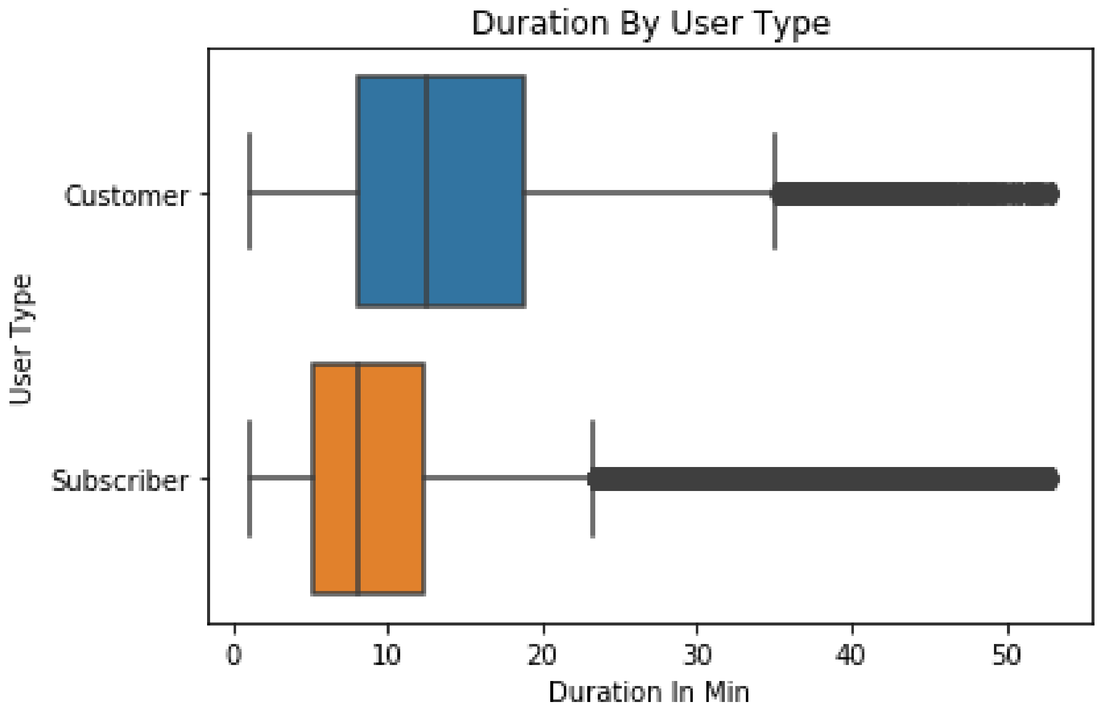
1.5 Bivariate Exploration

In this section, investigate relationships between pairs of variables in your data. Make sure the variables that you cover here have been introduced in some fashion in the previous section (univariate exploration).

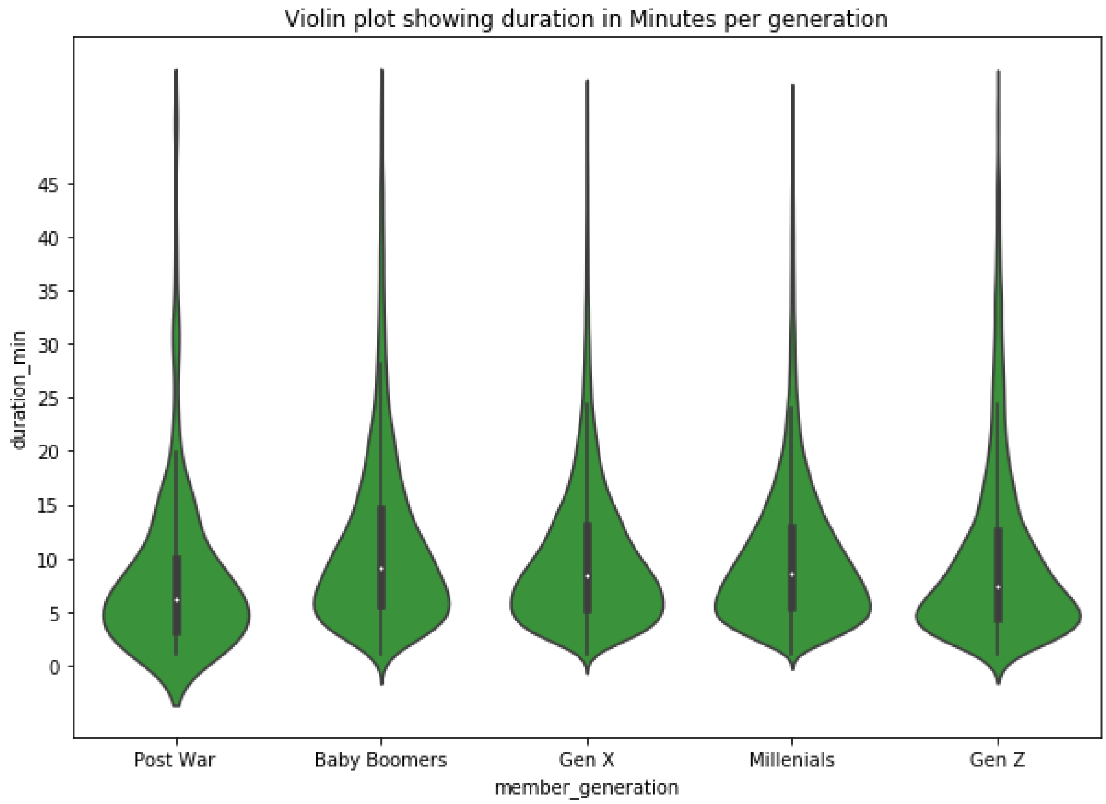
In [138]:
```
# User type per hour
base_color = sb.color_palette()[4]
user_per_hour = sb.factorplot(data=df, x='start_time_hour', col="user_type", kind='cou
                              color = base_color, size=7, aspect=1.2)
user_per_hour.set_axis_labels("hour_of_Day", "Number of Trips")
user_per_hour.set_titles("{col_name}")
user_per_hour.fig.suptitle('Start Time Per User Type', y=1.05, fontsize=12, fontweight
```



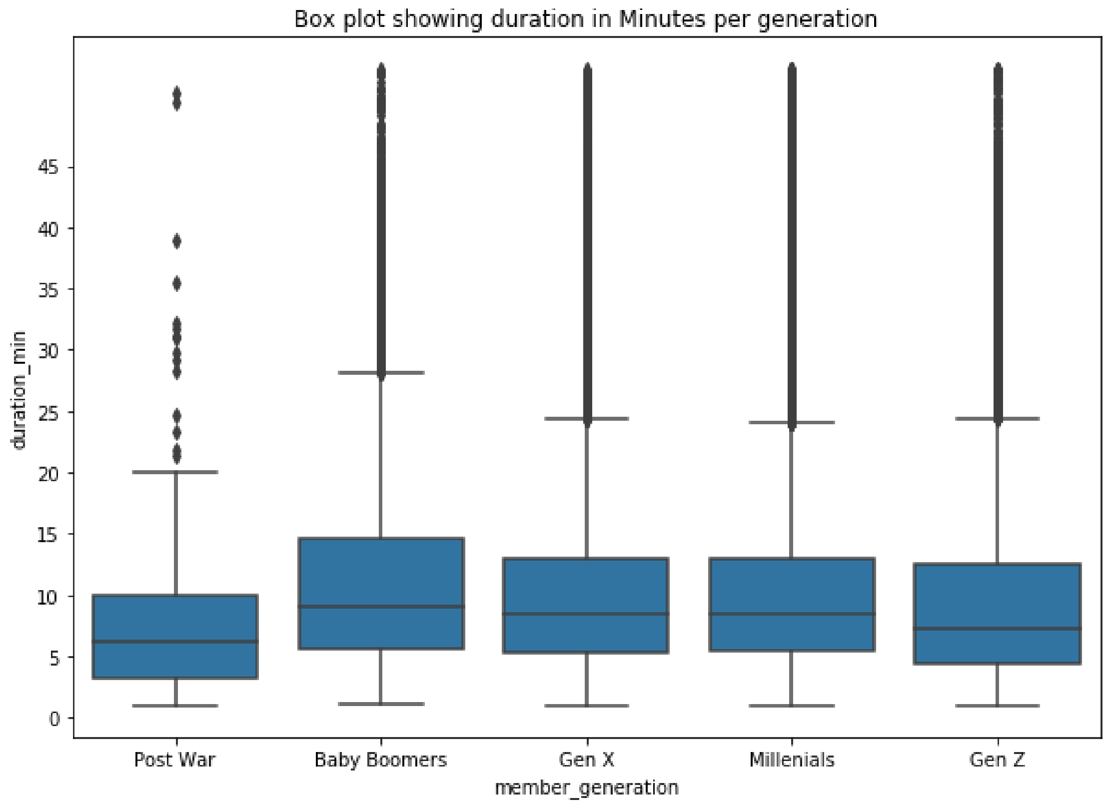
```
In [139]: # Duration of usertypes per minutes
          sb.boxplot(data =df , y='user_type', x='duration_min')
          plt.title('Duration By User Type')
          plt.xlabel('Duration In Min')
          plt.ylabel('User Type');
```




```
In [140]: base_color = sb.color_palette()[2]
          plt.figure(figsize=(10,7))
          sb.violinplot(data = df, x='member_generation', y= 'duration_min', color = base_color)
          plt.title('Violin plot showing duration in Minutes per generation')
          plt.yticks(np.arange(0, 50, step=5));
```



In [141]:
```
base_color = sb.color_palette()[0]
plt.figure(figsize=(10,7))
sb.boxplot(data = df, x='member_generation', y= 'duration_min', color = base_color)
plt.title('Box plot showing duration in Minutes per generation')
plt.yticks(np.arange(0, 50, step=5));
```



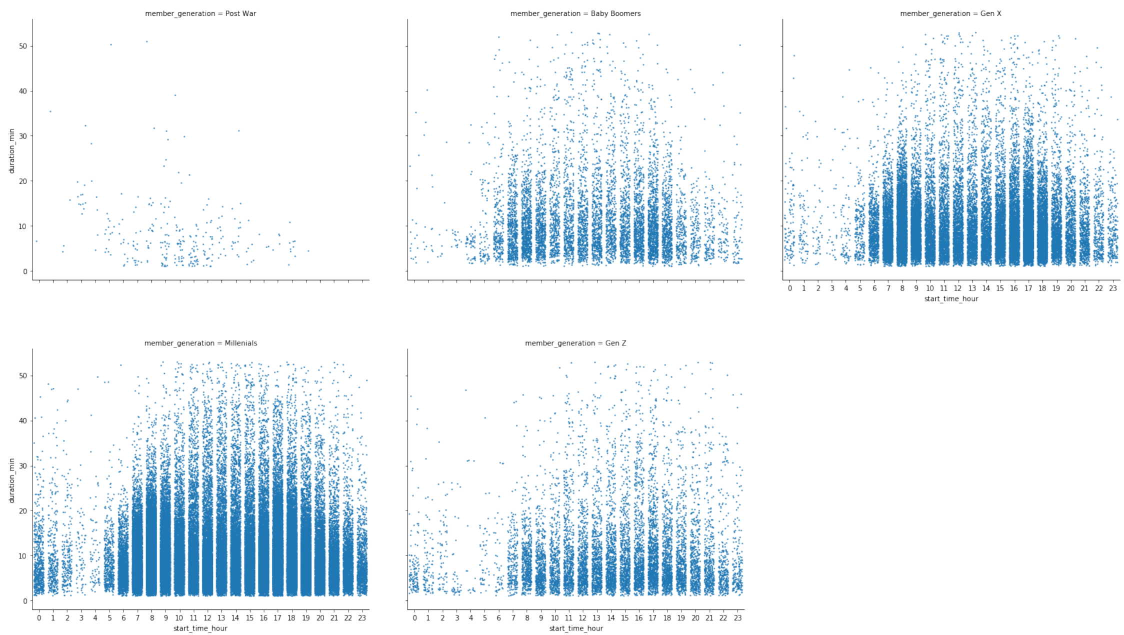
From the factor plot, after splitting the hour per usage into customer and subscribers, it clearly shows that most customers have their start time at 17:00, follwed by 8:00 but subscribers have thier peake hours at 8:00 and 17:00 which clearly shows that some of the importance of Bivariate to Univariate

I found that the duration minutes were different for Customers and Subscribers. Subscribers have their most duration minutes between 7 - 16 minutes while Customers have their most duration between 5 - 12 minutes.

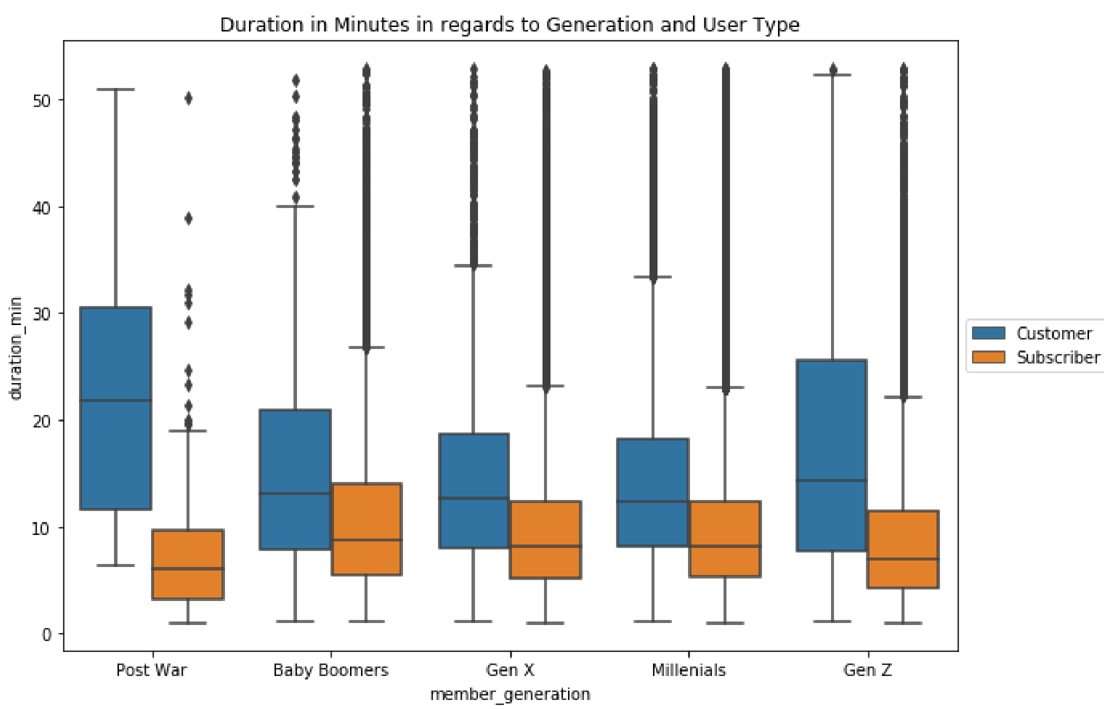
The box plot gives more summary details visibly than the violin plot. From the box plot, it is noticed that the Baby Boomers ride for the longest time compared to the other generations.The Post War generation have the least riding duration and this is likely due to age.

1.6 Multivariate Exploration

In [142]:
```
# This plot compares the start_time_hour and the duration_min in regards to generation
g = sb.FacetGrid(data = df, col = 'member_generation', col_wrap = 3)
g.map(sb.stripplot, 'start_time_hour', 'duration_min', size = 2, jitter = 0.35, order

g.fig.set_size_inches(24, 14)
```



In [143]:
```python
plt.figure(figsize=[10, 7])
sb.boxplot(data = df, x = 'member_generation', y = 'duration_min', hue = 'user_type')
plt.legend(loc = 6, bbox_to_anchor = (1.0, 0.5))
plt.title('Duration in Minutes in regards to Generation and User Type');
```



From the boxplot for duration in Minutes in regards to Generation and User Type shows that it's the post customer usertype that has the least duration minutes and the post war subscribers have the Highest duration in Minutes

1.7 Conclusions

From the data set, 8am and 9pm have the highest number of trips

Customers have the lowest duration minutes while subscribers are the highest

Majority of the Bikers are subscribers, which can be seen from the pie chart

Most bikers falls within the Millenials Generation that is they are born between 1981 and 1996