FINAL_exploration_template

September 4, 2019

1 Ford GoBike Bike Sharing Data Exploration

1.1 by Kai-Sheng Wang

1.2 Preliminary Wrangling

This document explores a dataset which contains user information, time and other attributes for more than 2 million bike sharing rides from May 2018 to April 2019.

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sb
        import math
        import warnings

        %matplotlib inline
```

- Import packages and set plot to be embedded inline

```
In [2]: df_201805 = pd.read_csv('trip_data_files/201805-fordgobike-tripdata.csv')
        df_201806 = pd.read_csv('trip_data_files/201806-fordgobike-tripdata.csv')
        df_201807 = pd.read_csv('trip_data_files/201807-fordgobike-tripdata.csv')
        df_201808 = pd.read_csv('trip_data_files/201808-fordgobike-tripdata.csv')
        df_201809 = pd.read_csv('trip_data_files/201809-fordgobike-tripdata.csv')
        df_201810 = pd.read_csv('trip_data_files/201810-fordgobike-tripdata.csv')
        df_201811 = pd.read_csv('trip_data_files/201811-fordgobike-tripdata.csv')
        df_201812 = pd.read_csv('trip_data_files/201812-fordgobike-tripdata.csv')
        df_201901 = pd.read_csv('trip_data_files/201901-fordgobike-tripdata.csv')
        df_201902 = pd.read_csv('trip_data_files/201902-fordgobike-tripdata.csv')
        df_201903 = pd.read_csv('trip_data_files/201903-fordgobike-tripdata.csv')
        df_201904 = pd.read_csv('trip_data_files/201904-fordgobike-tripdata.csv')
```

```
In [3]: frames = [df_201805, df_201806, df_201807, df_201808,
                  df_201809, df_201810, df_201811, df_201812,
                  df_201901, df_201902, df_201903, df_201904]

        df = pd.concat(frames, ignore_index=True)
```

- Load the files and merge the datasets into a dataframe

1.2.1 Clean Data

```
In [4]: df_clean = df.copy()
```

```
In [5]: df_clean.shape
```

```
Out[5]: (2290554, 16)
```

```
In [6]: df_clean.sample(5)
```

```
Out[6]:          duration_sec                start_time                 end_time  \
        241168            459  2018-06-21 18:22:26.5030  2018-06-21 18:30:06.2550
        1810135          2108  2019-03-29 18:49:58.9830  2019-03-29 19:25:07.9800
        250028            562  2018-06-20 16:48:48.6490  2018-06-20 16:58:11.2440
        663694            475  2018-08-17 08:37:07.0460  2018-08-17 08:45:02.3120
        657692            420  2018-08-18 09:03:51.0140  2018-08-18 09:10:51.2730

                 start_station_id                            start_station_name  \
        241168               37.0                             2nd St at Folsom St
        1810135              30.0  San Francisco Caltrain (Townsend St at 4th St)
        250028               59.0                       S Van Ness Ave at Market St
        663694               98.0                          Valencia St at 16th St
        657692              279.0                         Santa Clara St at 7th St

                 start_station_latitude  start_station_longitude  end_station_id  \
        241168                37.785000              -122.395936            67.0
        1810135               37.776598              -122.395282             6.0
        250028                37.774814              -122.418954           125.0
        663694                37.765052              -122.421866           350.0
        657692                37.339146              -121.884105           317.0

                                                 end_station_name  \
        241168   San Francisco Caltrain Station 2  (Townsend St...
        1810135                     The Embarcadero at Sansome St
        250028                               20th St at Bryant St
        663694                               8th St at Brannan St
        657692                          San Salvador St at 9th St

                 end_station_latitude  end_station_longitude  bike_id   user_type  \
        241168              37.776639            -122.395526     3369  Subscriber
        1810135             37.804770            -122.403234     2890  Subscriber
        250028              37.759200            -122.409851     1876  Subscriber
        663694              37.771431            -122.405787     3650  Subscriber
        657692              37.333955            -121.877349     2547  Subscriber

                 member_birth_year member_gender bike_share_for_all_trip
        241168              1981.0          Male                      No
        1810135             1962.0        Female                      No
        250028              1981.0        Female                      No
```

```
663694              1986.0        Female                       No
657692              1993.0        Female                      Yes
```

- Create a copy for data cleaning
- Check the dataset and name and value of the columns

Missing Values

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

Out[7]:
```
0
```

- No duplicated entries found

In [8]:
```
df_clean.start_station_id.isnull().sum()
```

Out[8]:
```
12501
```

In [9]:
```
df_clean[df_clean.start_station_id.isnull()].sample(5)
```

Out[9]:
```
         duration_sec               start_time                 end_time  \
376449            740  2018-07-31 18:32:13.6390  2018-07-31 18:44:33.8530
1407807           757  2018-12-04 08:03:12.4840  2018-12-04 08:15:50.4450
712907            195  2018-08-09 11:56:29.9610  2018-08-09 11:59:44.9810
1180901           454  2018-11-25 13:21:10.4550  2018-11-25 13:28:45.1550
1069064           311  2018-10-13 15:38:24.5690  2018-10-13 15:43:36.2290

         start_station_id start_station_name  start_station_latitude  \
376449                NaN                NaN                   37.39
1407807               NaN                NaN                   37.41
712907                NaN                NaN                   37.41
1180901               NaN                NaN                   37.40
1069064               NaN                NaN                   37.41

         start_station_longitude  end_station_id end_station_name  \
376449                   -121.93             NaN              NaN
1407807                  -121.95             NaN              NaN
712907                   -121.96             NaN              NaN
1180901                  -121.93             NaN              NaN
1069064                  -121.94             NaN              NaN

         end_station_latitude  end_station_longitude  bike_id   user_type  \
376449                  37.40                -121.92     4128  Subscriber
1407807                 37.41                -121.93     4121    Customer
712907                  37.41                -121.96     4077    Customer
1180901                 37.40                -121.94     4081    Customer
1069064                 37.41                -121.94     4289    Customer

         member_birth_year member_gender bike_share_for_all_trip
```

```
376449                1991.0          Male                         No
1407807               1969.0          Male                         No
712907                1962.0          Male                         No
1180901               1993.0          Male                         No
1069064               1984.0          Male                         No
```

In [10]:
```
df_clean[df_clean.start_station_id.isnull()].start_station_latitude.unique()
```

Out[10]:
```
array([ 37.4 ,  37.41,  37.42,  37.37,  37.39,  37.38,  37.43,  45.51,
        37.34,  37.33,  37.35,  44.95,  37.36,  40.66,  37.45,  37.32,
        45.5 ,  37.44])
```

In [11]:
```
df_clean[df_clean.start_station_id.isnull()].start_station_longitude.unique()
```

Out[11]:
```
array([-121.94, -121.96, -121.93, -121.92, -121.95, -121.97,  -73.57,
       -121.89, -121.91, -121.98,  -93.22, -121.9 ,  -74.01, -121.84,
       -121.86, -121.88, -121.99, -121.87, -121.83])
```

In [12]:
```
df_clean = df_clean[pd.notnull(df_clean['start_station_id'])]
```

- 12,501 entries with null value in 'start_station_id'
- Of the 12,501 entries with null value in 'start_station_id', the number of latitudes and longitudes seems to be too low for combination of coodinates and the values too identical
- As travel distance is a key variable to the analysis, the rows without information about start and end locations are removed

In [13]:
```
df_clean.member_birth_year.isnull().sum()
```

Out[13]:
```
116947
```

In [14]:
```
df_clean.member_gender.isnull().sum()
```

Out[14]:
```
116741
```

In [15]:
```
df_clean = df_clean[pd.notnull(df_clean['member_birth_year'])]
df_clean = df_clean[pd.notnull(df_clean['member_gender'])]
```

- Entries with null value in 'member_birth_year' and 'member_gender' both account for about 5% of the entire data
- Although 5% is substantial, rows with null value in these two columns are removed as gender and age are both key variables to the analysis

Convert data type

In [16]:
```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2161106 entries, 1 to 2290553
Data columns (total 16 columns):
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
dtypes: float64(7), int64(2), object(7)
memory usage: 280.3+ MB
```

```
In [17]: df_clean['start_time'] = pd.to_datetime(df['start_time'])
         df_clean['end_time'] = pd.to_datetime(df['end_time'])
```

- Convert two time-relevant variables 'start_time' and 'end_time' to datetime data type

1.2.2 What is the structure of your dataset?

The original datasets contain the information about 2,290,554 bike rides with 16 columns. There are 2,161,106 rides left after initial data cleaning. 2 time-relevant variables ('start_time', 'end_time') are converted to datetime data type. The latitude and longitude coordinates of both start and end locations are provided. One numeric variable ('member_birth_year') and two categorical variables ('user_type', 'member_gender') about the users are also available.

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

I'm interested in finding out how the bike sharing service is used, especially if any pattern exists, and whether a user's gender, age and user type determine how he or she uses the service.

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

I suppose time variables will play an essential role in how the service is used. Specifically, month of year (seasons), day of week and hour of day need to be created as a new variable to examine user behavior more closely. Additionally, user's profile should also be a strong predictor.

1.3 Univariate Exploration

```
In [18]: base_color = sb.color_palette()[0]
         alt_color = sb.color_palette()[1]
```

In [19]:
```
df_clean['member_age'] = 2019 - df_clean['member_birth_year']
```

- A new variable 'member_age' (user's age) created

In [20]:
```
df_clean['member_age'].describe().apply(lambda x: format(x, 'f'))
```

Out[20]:
```
count    2161106.000000
mean          35.035114
std           10.252398
min           18.000000
25%           28.000000
50%           33.000000
75%           40.000000
max          141.000000
Name: member_age, dtype: object
```

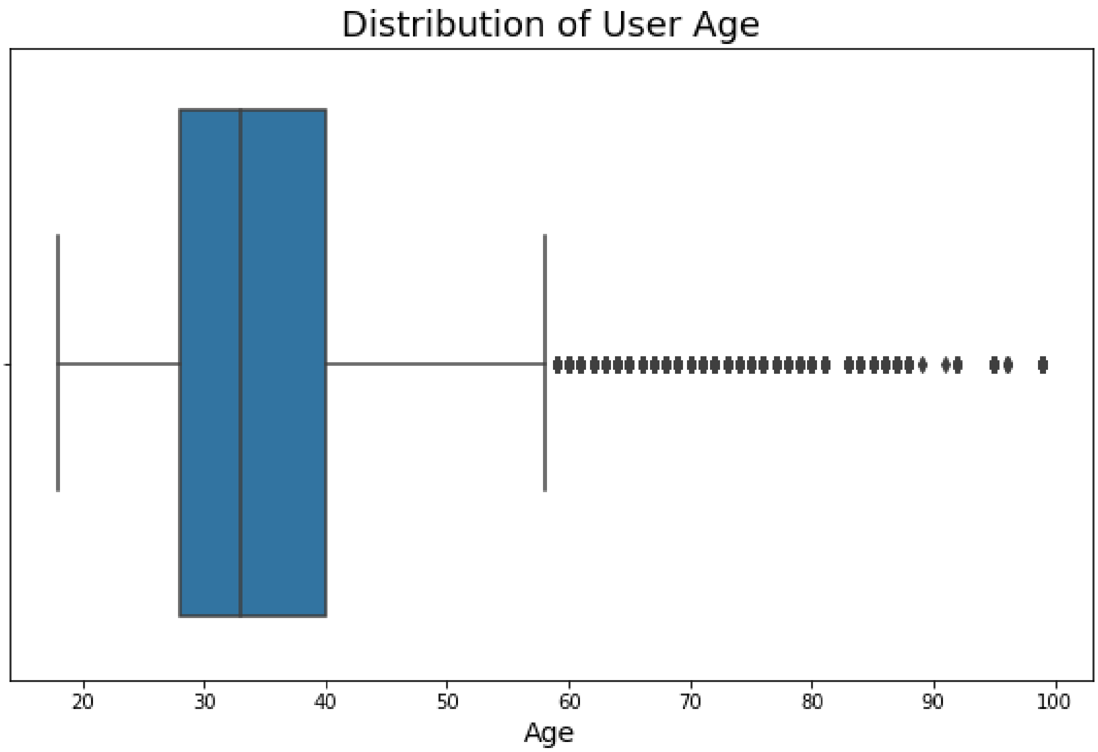
In [21]:
```
df_clean = df_clean.query('member_age <= 100')
```

- Maximum value of age is 141, which is very unlikely. Entries with users more than 100 years of age removed

In [22]:
```
df_clean['member_age'].describe().apply(lambda x: format(x, 'f'))
```

Out[22]:
```
count    2160036.000000
mean          34.994026
std           10.086741
min           18.000000
25%           28.000000
50%           33.000000
75%           40.000000
max           99.000000
Name: member_age, dtype: object
```

In [23]:
```
plt.figure(figsize=(10, 6))
sb.boxplot(data=df_clean, x='member_age', color=base_color)
plt.title("Distribution of User Age", fontsize=18)
plt.xlabel("Age", fontsize=14);
```

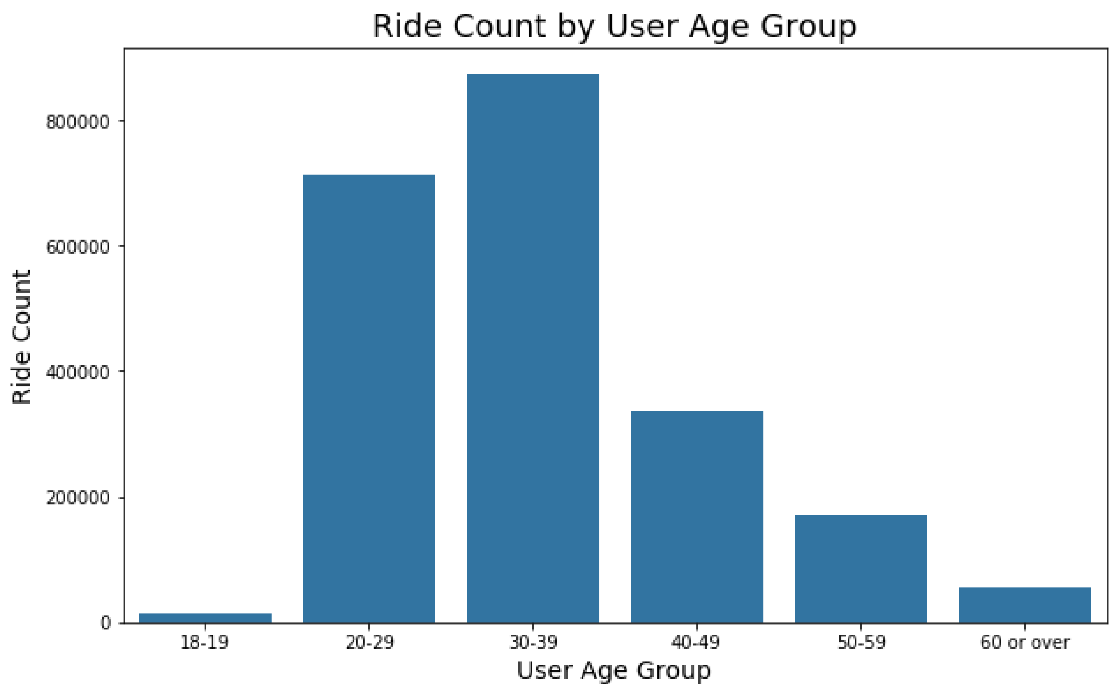


- The service users are mostly between 28 to 40 years of age

```
In [24]: df_clean['member_age_group'] = df_clean['member_age'].apply(lambda x: '18-19' if 18<=x<
                                                                     else '20-29' if 20<=x<30
                                                                     else '30-39' if 30<=x<40
                                                                     else '40-49' if 40<=x<50
                                                                     else '50-59' if 50<=x<60
                                                                     else '60 or over')
```

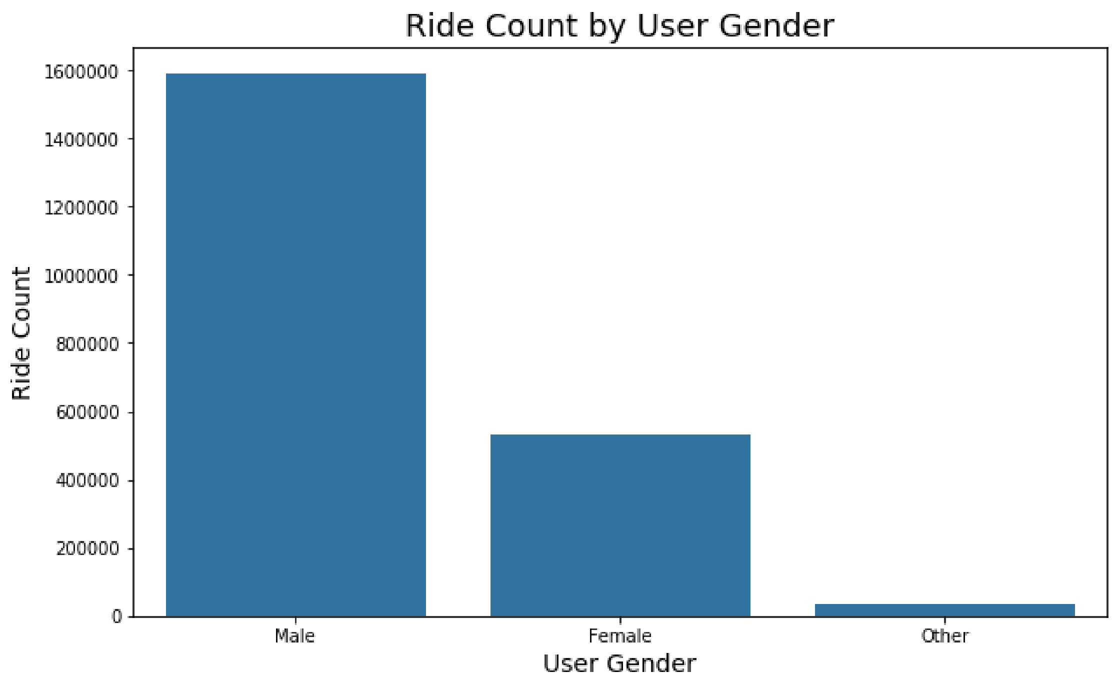
- A new variable 'member_age_group' (users divided into six age groups) created

```
In [25]: groups = ['18-19', '20-29', '30-39', '40-49', '50-59', '60 or over']
         plt.figure(figsize=(10, 6))
         sb.countplot(data=df_clean, x='member_age_group', color=base_color, order=groups)
         plt.title("Ride Count by User Age Group", fontsize=18)
         plt.xlabel("User Age Group", fontsize=14)
         plt.ylabel("Ride Count", fontsize=14);
```



- '30-39' is the largest user group, followed by '20-29' and '40-49'

In [26]:
```
plt.figure(figsize=(10, 6))
sb.countplot(data=df_clean, x='member_gender', color=base_color)
plt.title("Ride Count by User Gender", fontsize=18)
plt.xlabel("User Gender", fontsize=14)
plt.ylabel("Ride Count", fontsize=14);
```



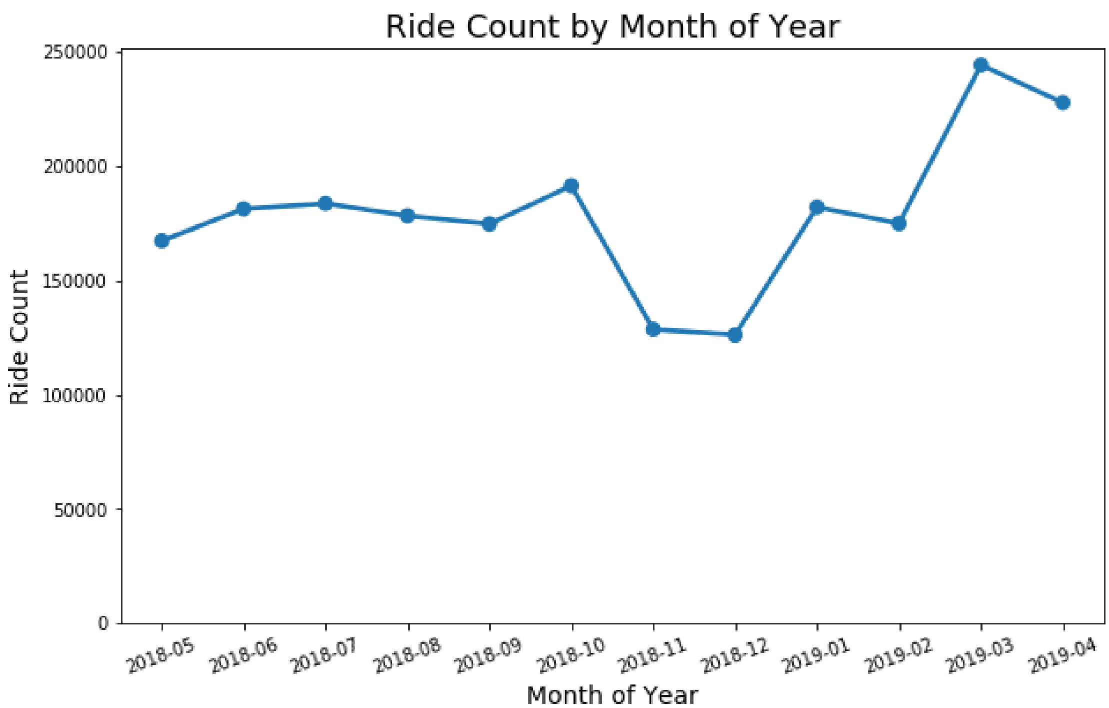
- The ride count by male user group is more than two times larger than the female user group

```
In [27]: df_clean['start_time_year_month'] = df_clean['start_time'].map(lambda x: x.strftime('%Y
         df_clean['end_time_year_month'] = df_clean['end_time'].map(lambda x: x.strftime('%Y-%m'
```

- Two new variables 'start_time_year_month', 'end_time_year_month' (time variables in 'yyyy-mm' format) created

```
In [28]: df_count_month = df_clean.groupby(['start_time_year_month']).size().reset_index()
```

```
In [29]: plt.figure(figsize=(10, 6))
         ax = sb.pointplot(data=df_count_month, x='start_time_year_month', y=0)
         plt.title('Ride Count by Month of Year', fontsize=18)
         plt.xlabel('Month of Year', fontsize=14)
         plt.ylabel('Ride Count', fontsize=14)
         plt.ylim(0,)
         plt.xticks(rotation=20);
```



- Significant decline of use in cold months (November and December, 2018)
- There is a big jump of ride count in March 2019. The count drops slightly in the following month, but still fairly higher than the counts in 2018

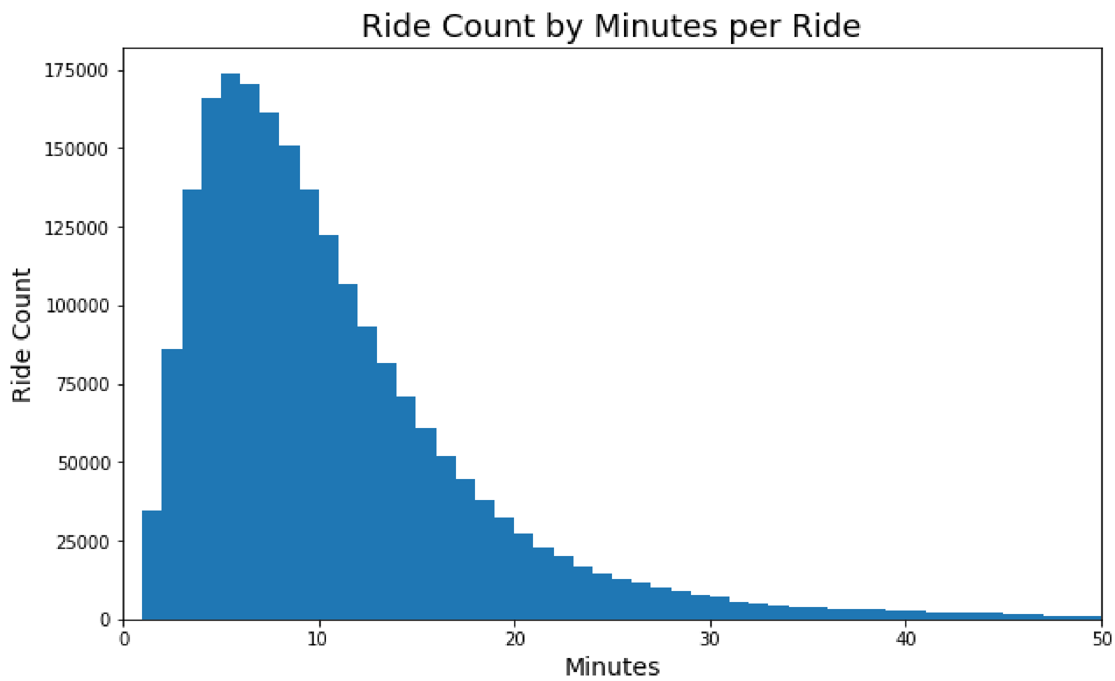
```
In [30]: df_clean['duration_min'] = df_clean['duration_sec']/60
```

- A new variable 'duration_min' (duration of ride in minutes) created

```
In [31]: df_clean['duration_min'].describe().apply(lambda x: format(x, 'f'))
```

```
Out[31]: count    2160036.000000
         mean          12.793658
         std           30.998642
         min            1.016667
         25%            5.666667
         50%            9.000000
         75%           14.016667
         max         1438.016667
         Name: duration_min, dtype: object
```

```
In [32]: plt.figure(figsize=(10, 6))
         bin_edges = np.arange(0, df_clean['duration_min'].max()+1, 1)
         plt.hist(data=df_clean, x='duration_min', color=base_color, bins=bin_edges)
         plt.xlim(0, 50)
         plt.title("Ride Count by Minutes per Ride", fontsize=18)
         plt.xlabel("Minutes", fontsize=14)
         plt.ylabel("Ride Count", fontsize=14);
```



- 75% of the rides takes less than 15 minutes
- Most rides take around 5 minutes

```
In [33]: def coordinates_distance(start, end):
             lat1, lon1 = start
             lat2, lon2 = end
             radius = 6371

             dlat = math.radians(lat2 - lat1)
             dlon = math.radians(lon2 - lon1)
             a = (math.sin(dlat/2)*math.sin(dlat/2)+math.cos(math.radians(lat1))*math.cos(math.r
             c = 2*math.atan2(math.sqrt(a), math.sqrt(1-a))
             d = radius * c

             return d
```

```
In [34]: df_clean['distance'] = df_clean.apply(lambda x: coordinates_distance((x['start_station_
```

- A new variable 'distance' (distance between start and end coordinates in kilometer) created
- Source: https://stackoverflow.com/questions/33029396/using-pandas-to-calculate-distance-between-coordinates-from-imported-csv

```
In [35]: df_clean['distance'].describe().apply(lambda x: format(x, 'f'))
```

```
Out[35]: count    2160036.000000
         mean           1.756792
```

```
std             37.957869
min              0.000000
25%              0.885573
50%              1.405521
75%              2.159999
max          12798.346860
Name: distance, dtype: object
```

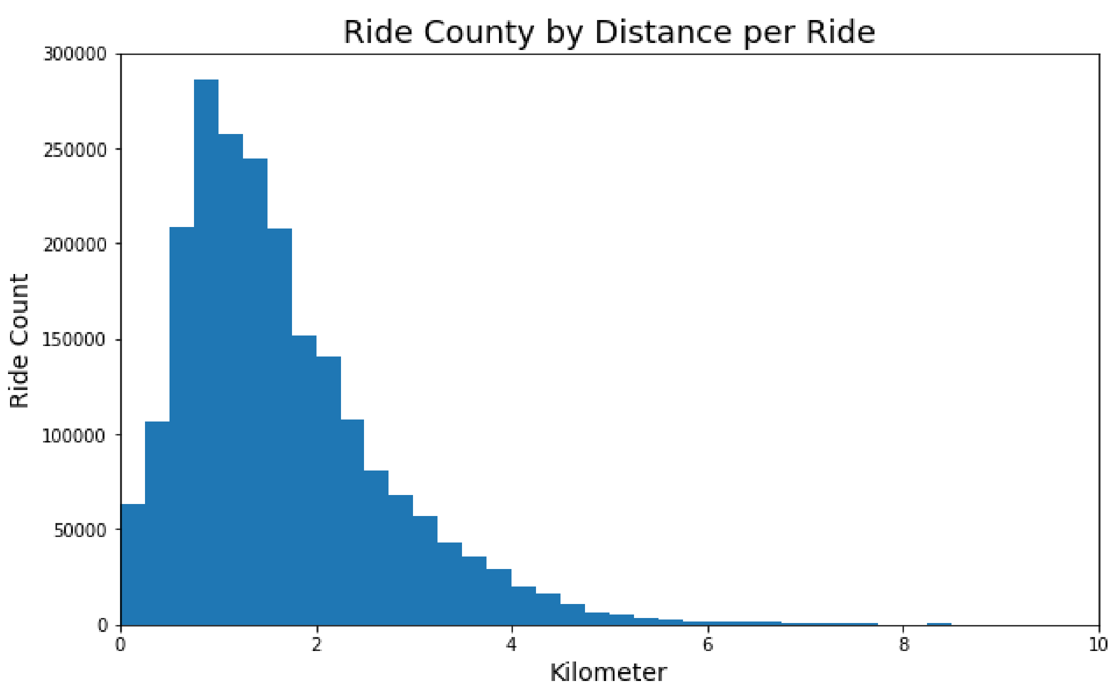
In [36]:
```python
df_clean[df_clean['distance'] > 50].shape
```

Out[36]:
```
(21, 22)
```

In [37]:
```python
df_clean = df_clean[df_clean['distance'] <= 50]
```

- 21 entries with travel distance more than 50 kilometer are found
- As the number of entries is relative small and such travel distance is not of the interest of this analysis, these entries are removed

In [38]:
```python
plt.figure(figsize=(10, 6))
bin_edges = np.arange(0, df_clean['distance'].max()+0.25, 0.25)
plt.hist(data=df_clean, x='distance', color=base_color, bins=bin_edges)
plt.xlim(0, 10)
plt.title("Ride County by Distance per Ride", fontsize=18)
plt.xlabel("Kilometer", fontsize=14)
plt.ylabel("Ride Count", fontsize=14);
```

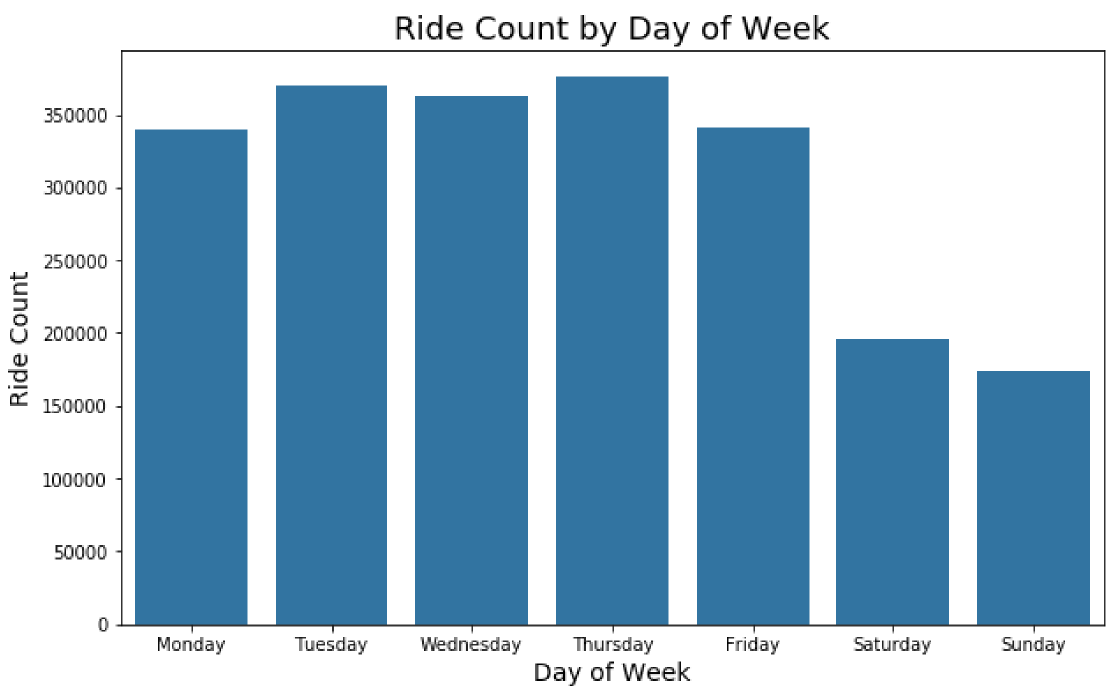


- More than 75% of the ride distance is less than 3 kilometer
- Most frequent ride distance is around 1 kilometer

In [39]:
```
df_clean['start_time_weekday'] = df_clean['start_time'].dt.weekday_name
df_clean['end_time_weekday'] = df_clean['end_time'].dt.weekday_name
```

- Two new variables 'start_time_weekday', 'end_time_weekday' (time variables in day of week format) created

In [40]:
```
weekday_index = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'S
plt.figure(figsize=(10, 6))
sb.countplot(data=df_clean, x='start_time_weekday', color=base_color, order=weekday_ind
plt.title("Ride Count by Day of Week", fontsize=18)
plt.xlabel("Day of Week", fontsize=14)
plt.ylabel("Ride Count", fontsize=14);
```

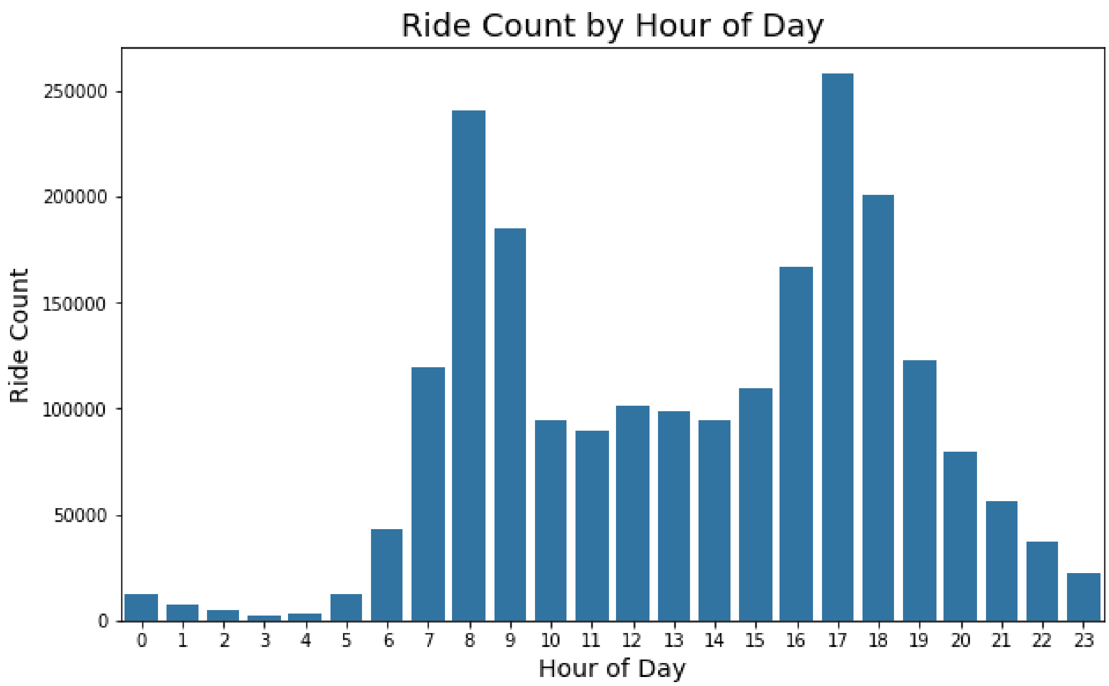


- The highest demand for the service is on Tuesday and Thursday
- The service is used significantly less on weekends

In [41]:
```
df_clean['start_time_hour'] = df_clean['start_time'].dt.hour
df_clean['end_time_hour'] = df_clean['end_time'].dt.hour
```

- Two new variables 'start_time_hour', 'end_time_hour' (time variables in hour of day format) created

In [42]:
```
plt.figure(figsize=(10, 6))
sb.countplot(data=df_clean, x='start_time_hour', color=base_color)
plt.title("Ride Count by Hour of Day", fontsize=18)
plt.xlabel("Hour of Day", fontsize=14)
plt.ylabel("Ride Count", fontsize=14);
```



- There are two daily peak hours for the serivice: 8-9 a.m. and 4-6 p.m.

In [43]:
```
df_start_station = df_clean.groupby('start_station_name').size()
df_start_station.sort_values(ascending=False).head(10)
```

Out[43]:
```
start_station_name
San Francisco Caltrain Station 2  (Townsend St at 4th St)    44685
Market St at 10th St                                         41392
San Francisco Ferry Building (Harry Bridges Plaza)           38241
Berry St at 4th St                                           37137
San Francisco Caltrain (Townsend St at 4th St)               36147
Montgomery St BART Station (Market St at 2nd St)             35812
Powell St BART Station (Market St at 4th St)                 34557
The Embarcadero at Sansome St                                31489
Steuart St at Market St                                      31140
Howard St at Beale St                                        29288
dtype: int64
```

In [44]:
```
df_end_station = df_clean.groupby('end_station_name').size()
df_end_station.sort_values(ascending=False).head(10)
```

```
Out[44]: end_station_name
         San Francisco Caltrain Station 2  (Townsend St at 4th St)    60554
         San Francisco Ferry Building (Harry Bridges Plaza)           44864
         Market St at 10th St                                         41858
         San Francisco Caltrain (Townsend St at 4th St)               41021
         Montgomery St BART Station (Market St at 2nd St)             40980
         Powell St BART Station (Market St at 4th St)                 36099
         Berry St at 4th St                                           35904
         The Embarcadero at Sansome St                                35622
         Steuart St at Market St                                      31662
         Powell St BART Station (Market St at 5th St)                 29060
         dtype: int64
```

```
In [45]: set(list(df_end_station.sort_values(ascending=False).head(10).index)).intersection(list
```

```
Out[45]: {'Berry St at 4th St',
          'Market St at 10th St',
          'Montgomery St BART Station (Market St at 2nd St)',
          'Powell St BART Station (Market St at 4th St)',
          'San Francisco Caltrain (Townsend St at 4th St)',
          'San Francisco Caltrain Station 2  (Townsend St at 4th St)',
          'San Francisco Ferry Building (Harry Bridges Plaza)',
          'Steuart St at Market St',
          'The Embarcadero at Sansome St'}
```

- 9 bike stations are both in top10 start and destination stations
- San Francisco Caltrain Station 2 (Townsend St at 4th St) is both top1 start and destination station, but a lot more as destination (60,554) than start (44,685) station
- Howard St at Beale St is only in the top10 'start_station' list while Powell St BART Station (Market St at 5th St) in only in the top10 'end_station' list

1.3.1 Discuss the distribution(s) of your variable(s) of interest. Were there any unusual points? Did you need to perform any transformations?

- As expected, time variable plays an important in service user behavior. Findings from the creation of new time variables are:
  - The service seems to be getting more popular over time. More data are needed to confirm it
  - The service is used less in cold months
  - The service is used more during the week than on weekend
  - The service is used more between 8-9 a.m. and 4-6 p.m.
- The most frequent service users are male, 28 to 40 years of age
- Many of the Top10 busy bike stations are at Caltrain and BART stations or at ferry building

1.3.2 Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

- Two time-relevant variables 'start_time' and 'end_time' are converted to datetime data type

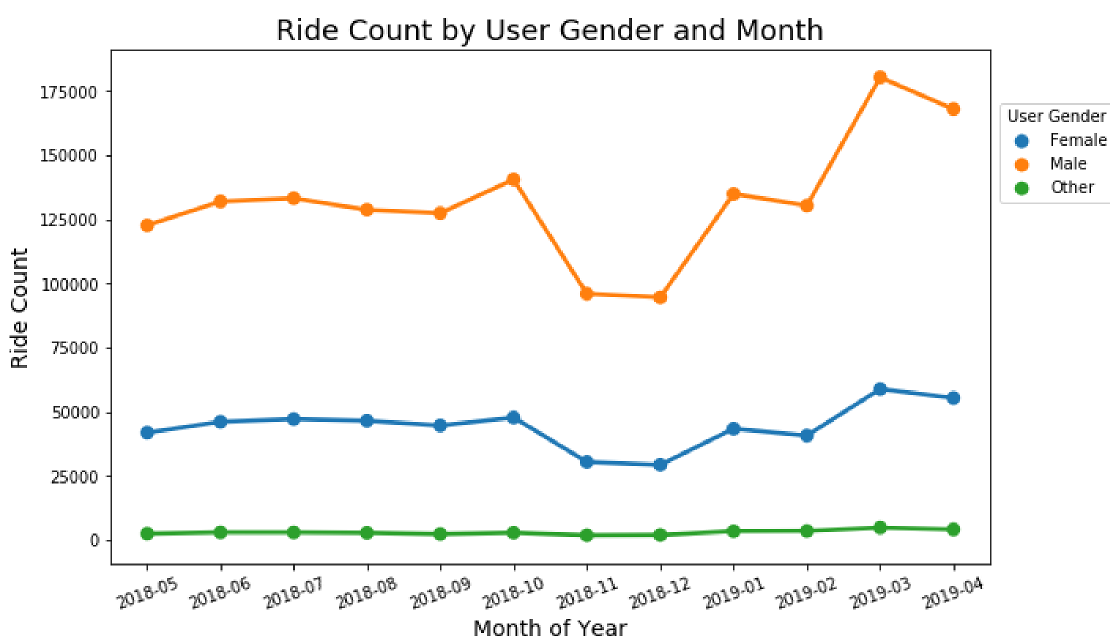
- 12,501 entries were found with null value in 'start_station_id'. Of these 12,501 entries, the number of latitudes and longitudes seems to be too low for combination of coodinates and the values too identical. As travel distance is a key variable to the analysis, the entries without information about start and end locations are removed
- 116,947 entries in 'member_birth_year' and 116,741 entries in 'member_gender' were found with null value. As both user's age and gender are essential to the analysis, the rows with missing data are removed
- Entries with user's age over 100 years are removed, as users of such age are very unlikely
- Entries with travel distance more than 50 kilometer are removed, as the size is small and such distance doesn't fit the purpose of this analysis

1.4 Bivariate Exploration

Gender

In [46]:
```
df_gender_count_month = df_clean.groupby(['start_time_year_month', 'member_gender']).si
```

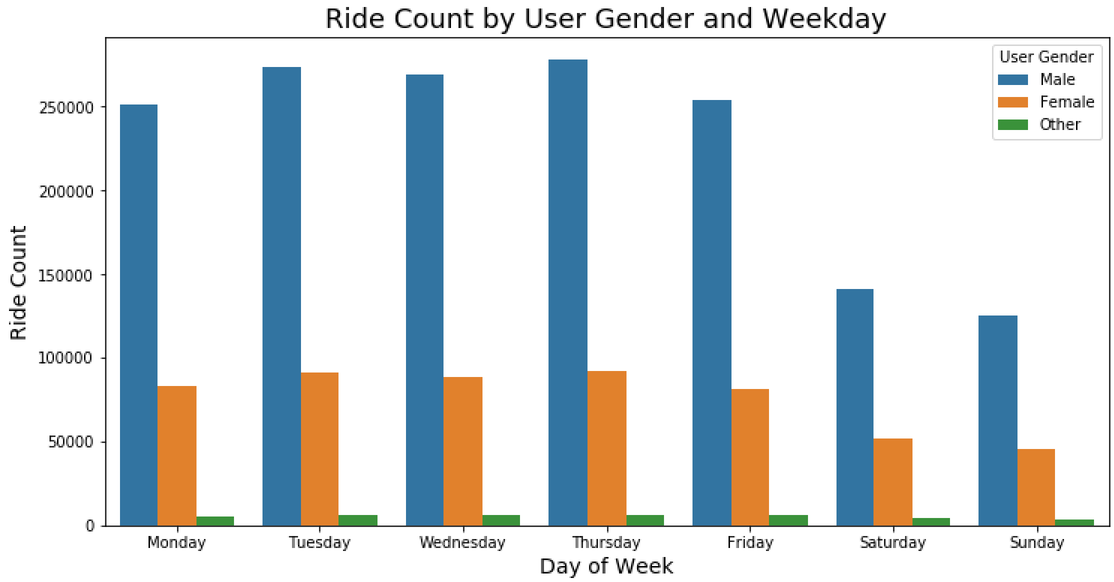
In [47]:
```
plt.figure(figsize=(10, 6))
#colors = {'Subscriber':base_color, 'Customer':alt_color}
ax = sb.pointplot(data=df_gender_count_month, x='start_time_year_month', y=0, hue='memb
plt.title('Ride Count by User Gender and Month', fontsize=18)
plt.xlabel('Month of Year', fontsize=14)
plt.ylabel('Ride Count', fontsize=14)
plt.xticks(rotation=20)
ax.legend(loc='right', bbox_to_anchor=(1.15, 0.8), title='User Gender');
```



- The ride count trend for the male user group resembles that of overall trend

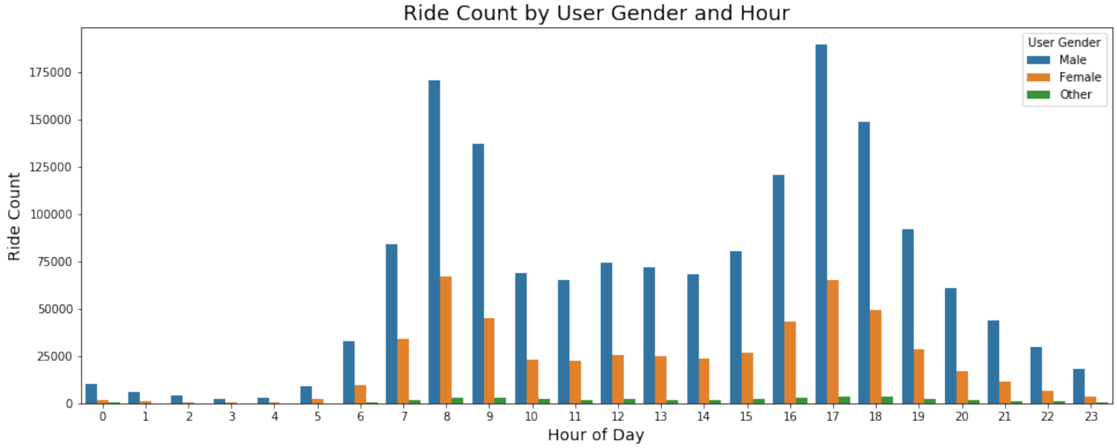
- The decline of rides by the female user group in cold months is not as significant as that of the male user group

```
In [48]: weekday_index = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'S
         plt.figure(figsize=(12, 6))
         ax = sb.countplot(data=df_clean, x='start_time_weekday', hue='member_gender', order=wee
         ax.legend(title='User Gender')
         plt.title('Ride Count by User Gender and Weekday', fontsize=18)
         plt.xlabel('Day of Week', fontsize=14)
         plt.ylabel('Ride Count', fontsize=14);
```



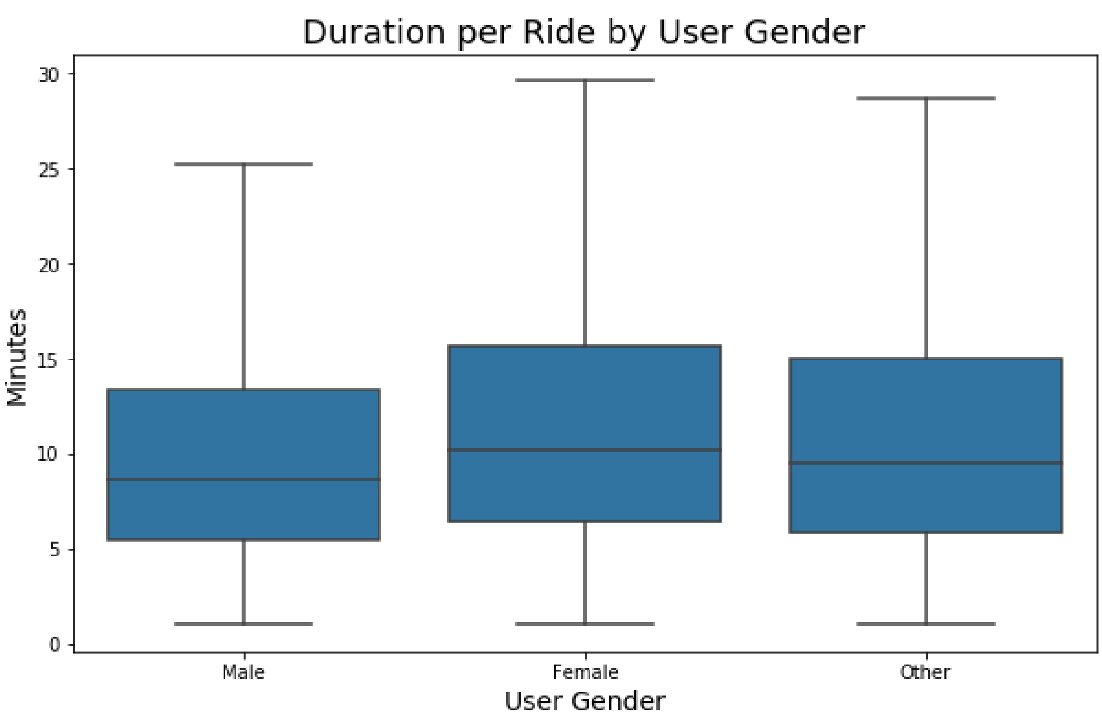
- Both male and female user groups use the service more frequently during the week

```
In [49]: plt.figure(figsize=(16, 6))
         ax = sb.countplot(data=df_clean, x='start_time_hour', hue='member_gender')
         ax.legend(title='User Gender')
         plt.title('Ride Count by User Gender and Hour', fontsize=18)
         plt.xlabel('Hour of Day', fontsize=14)
         plt.ylabel('Ride Count', fontsize=14);
```



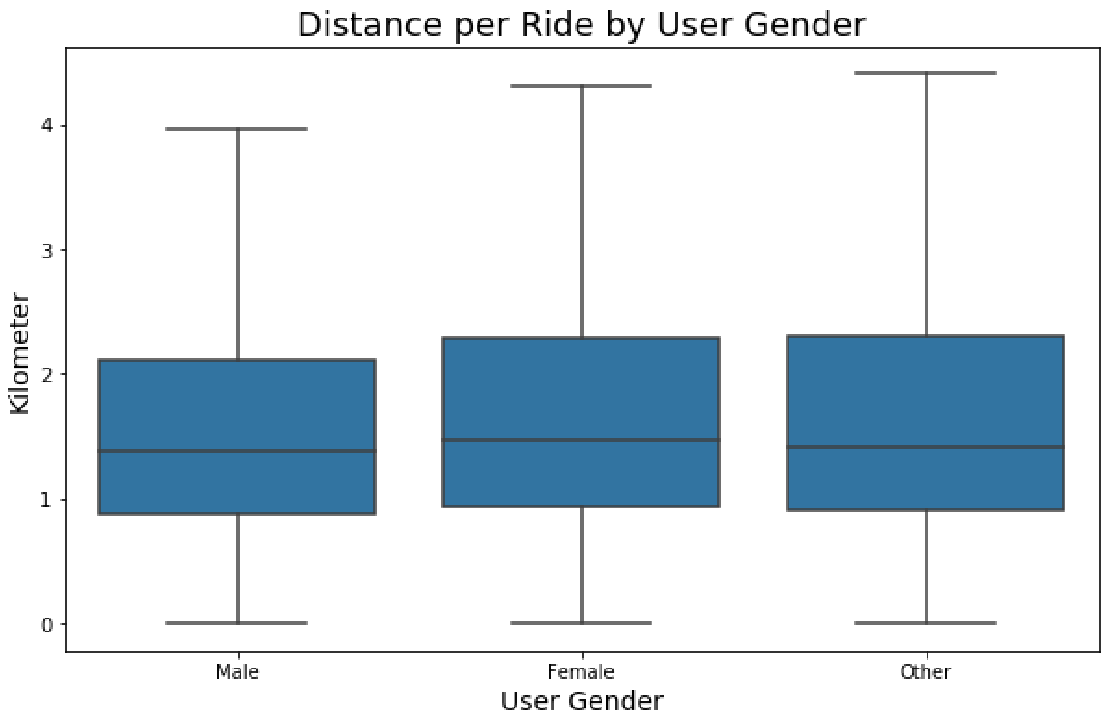
- 8-9 a.m. and 4-6 p.m. are peak hours for both male and female user groups

In [50]:
```
plt.figure(figsize=(10,6))
sb.boxplot(data=df_clean, x='member_gender', y='duration_min', color=base_color, showfl
plt.title('Duration per Ride by User Gender', fontsize=18)
plt.xlabel('User Gender', fontsize=14)
plt.ylabel('Minutes', fontsize=14);
```



- Overall duration per ride for the female user group is longer than their male counterparts

```
In [51]: plt.figure(figsize=(10,6))
         sb.boxplot(data=df_clean, x='member_gender', y='distance', color=base_color, showfliers
         plt.title('Distance per Ride by User Gender', fontsize=18)
         plt.xlabel('User Gender', fontsize=14)
         plt.ylabel('Kilometer', fontsize=14);
```



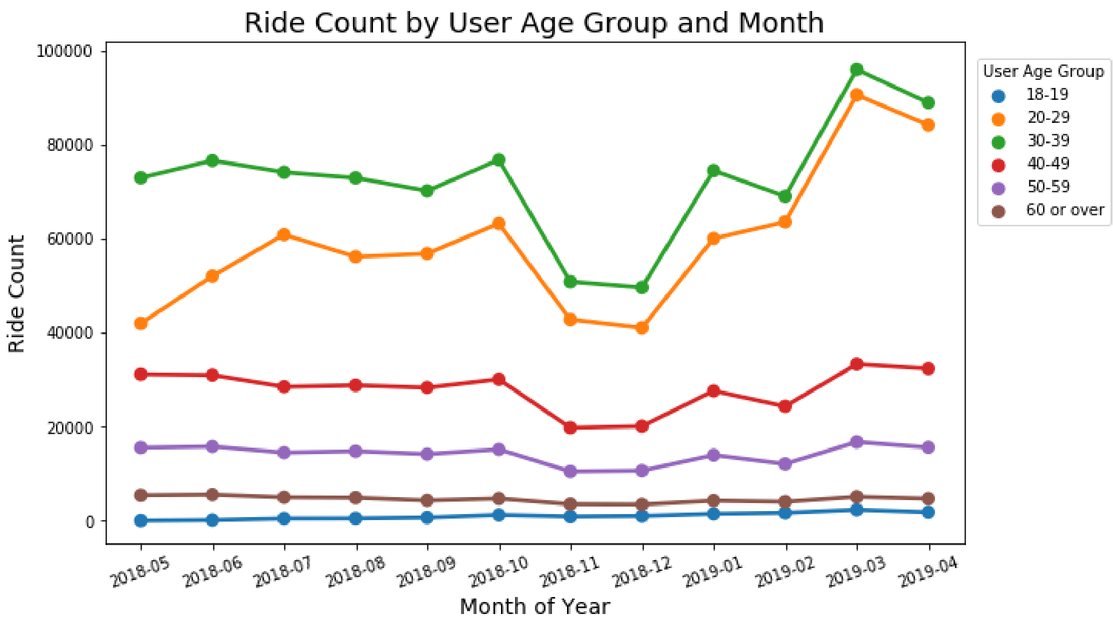
- Overall distance per ride for the female user group is slightly longer than their male counterparts

Summary - Female users use the service less in cold months, but not as less as male users - Overall duration per ride for the female user group is longer - Overall distance per ride for the female user group is also slightly longer

Age Group

```
In [52]: df_age_group_count_month = df_clean.groupby(['start_time_year_month', 'member_age_group
```

```
In [53]: plt.figure(figsize=(10, 6))
         ax = sb.pointplot(data=df_age_group_count_month, x='start_time_year_month', y=0, hue='m
         plt.title('Ride Count by User Age Group and Month', fontsize=18)
         plt.xlabel('Month of Year', fontsize=14)
         plt.ylabel('Ride Count', fontsize=14)
         plt.xticks(rotation=20)
         leg = ax.legend(loc='right', bbox_to_anchor=(1.18, 0.8), title='User Age Group')
```

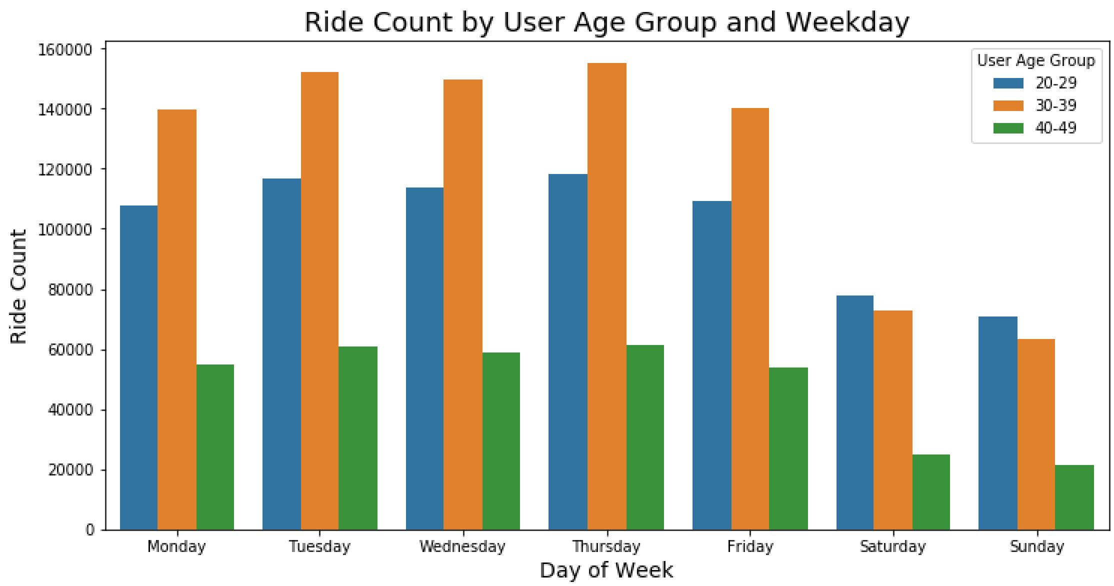


- The '30-39' and '20-29' groups top the ride counts among all groups
- The '20-20' group is closing its gap with the '30-39' group

```
In [54]: selected_age_group = ['20-29', '30-39', '40-49']
         df_selected_age_group = df_clean[df_clean['member_age_group'].isin(selected_age_group)]
```

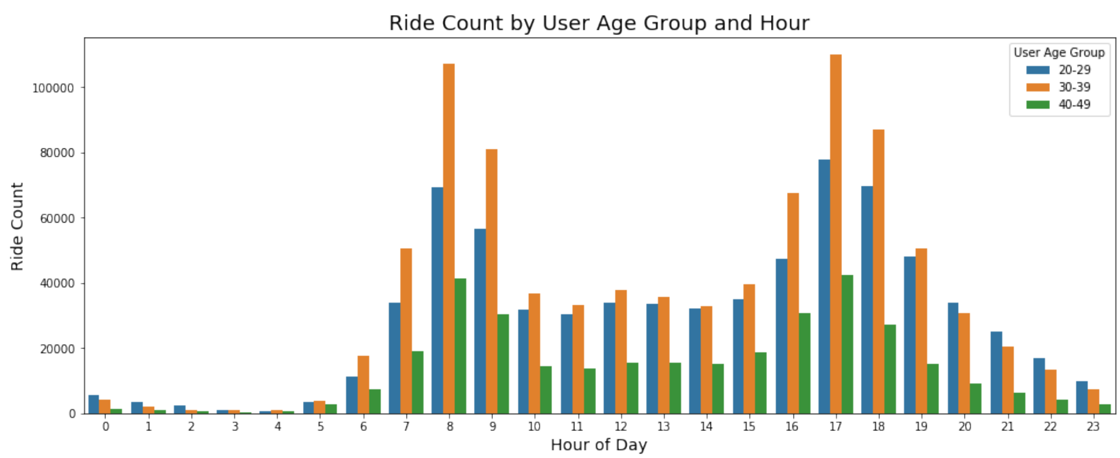
- The top3 age groups are selected for further analysis

```
In [55]: weekday_index = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'S
         plt.figure(figsize=(12, 6))
         ax = sb.countplot(data=df_selected_age_group, x='start_time_weekday', hue='member_age_g
         ax.legend(title='User Age Group')
         plt.title('Ride Count by User Age Group and Weekday', fontsize=18)
         plt.xlabel('Day of Week', fontsize=14)
         plt.ylabel('Ride Count', fontsize=14);
```



- The service is still used more during the week across the three groups
- '30-39' is the largest user group during the week
- However, the '20-29' group uses the service more than other groups on weekends

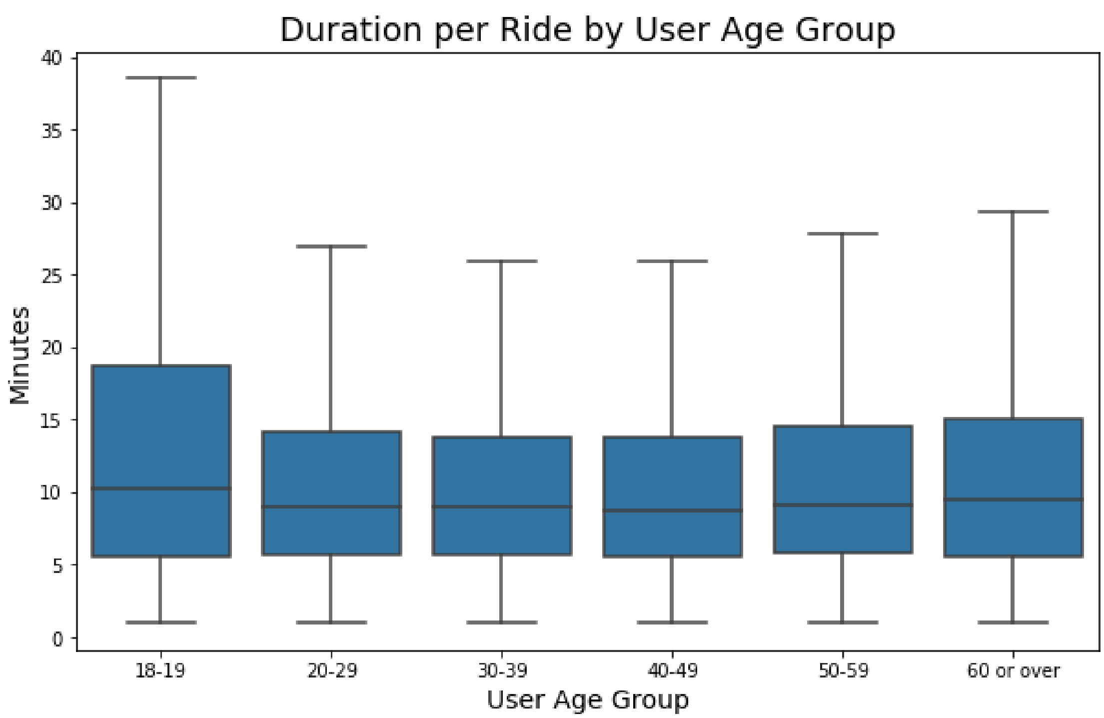
```
In [56]: plt.figure(figsize=(16, 6))
         ax = sb.countplot(data=df_selected_age_group, x='start_time_hour', hue='member_age_grou
         ax.legend(title='User Age Group')
         plt.title('Ride Count by User Age Group and Hour', fontsize=18)
         plt.xlabel('Hour of Day', fontsize=14)
         plt.ylabel('Ride Count', fontsize=14);
```



- 8-9 a.m. and 5-6 p.m. are the peak hours across the three groups, which is the same as the overall trend

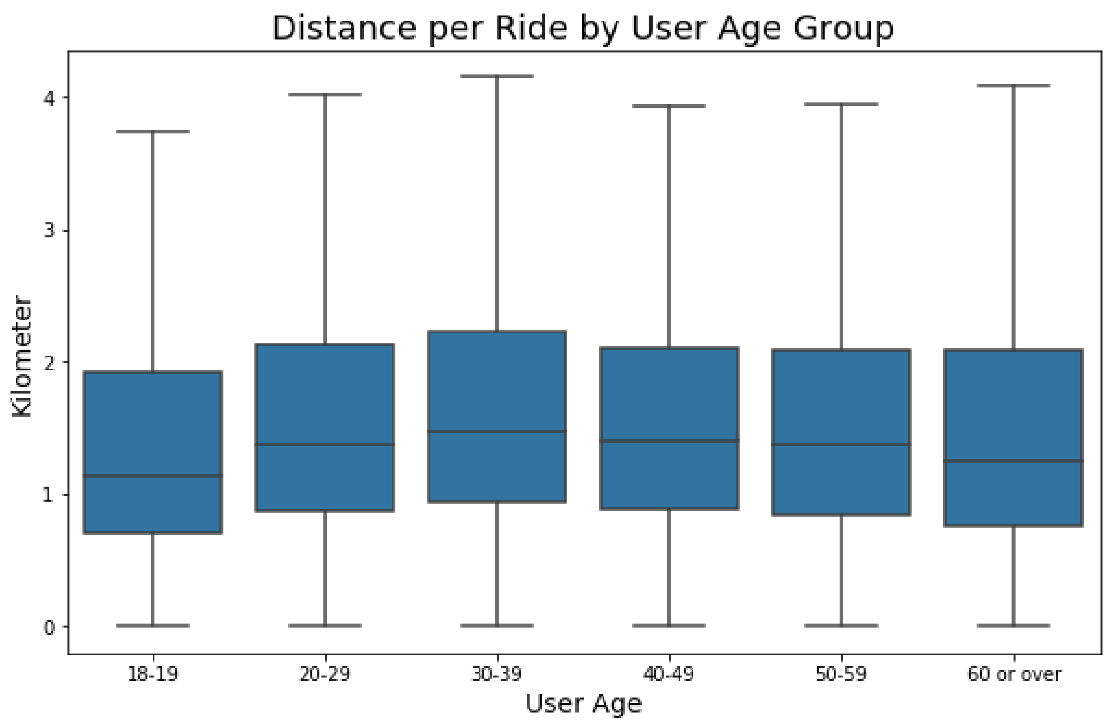
- The '20-29' group uses the service more than other groups from 8 p.m. to 2 a.m.

```
In [57]: age_group = ['18-19', '20-29', '30-39', '40-49', '50-59', '60 or over']
         plt.figure(figsize=(10,6))
         sb.boxplot(data=df_clean, x='member_age_group', y='duration_min', color=base_color, ord
         plt.title('Duration per Ride by User Age Group', fontsize=18)
         plt.xlabel('User Age Group', fontsize=14)
         plt.ylabel('Minutes', fontsize=14);
```



- Both interquartile range box and whiskers for the '18-19' group are longer than other age groups
- Distribution of ride duration for '20-29', '30-39' and '40-49' groups is almost identical

```
In [58]: plt.figure(figsize=(10,6))
         sb.boxplot(data=df_clean, x='member_age_group', y='distance', color=base_color, order=a
         plt.title('Distance per Ride by User Age Group', fontsize=18)
         plt.xlabel('User Age', fontsize=14)
         plt.ylabel('Kilometer', fontsize=14);
```



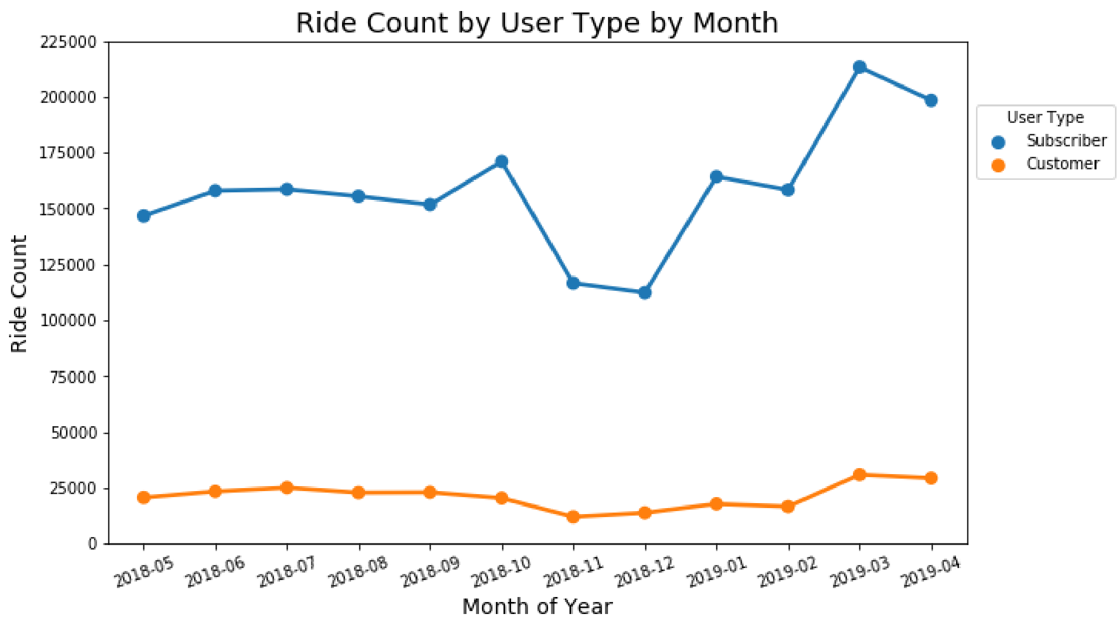
- Overall ride distance for the '30-39' group is slightly longer than other groups

Summary - '20-29', '30-39' and '40-49' are the top3 user groups, with the '30-39' group being the largest - However, the '20-29' group is closing its gap with the '30-39' group - While the '30-39' group is the largest during the week, the '20-29' group uses the service more than other groups on weekends - While the '30-39' group is the largest during the day (6 a.m. to 7 p.m.), the '20-29' group uses the service more than other groups from 8 p.m. to 2 a.m. - Compared to other groups, duration per ride for the '18-19' group is sparesely distributed - Ride distance for the '30-39' group is slightly longer than other groups

User Type

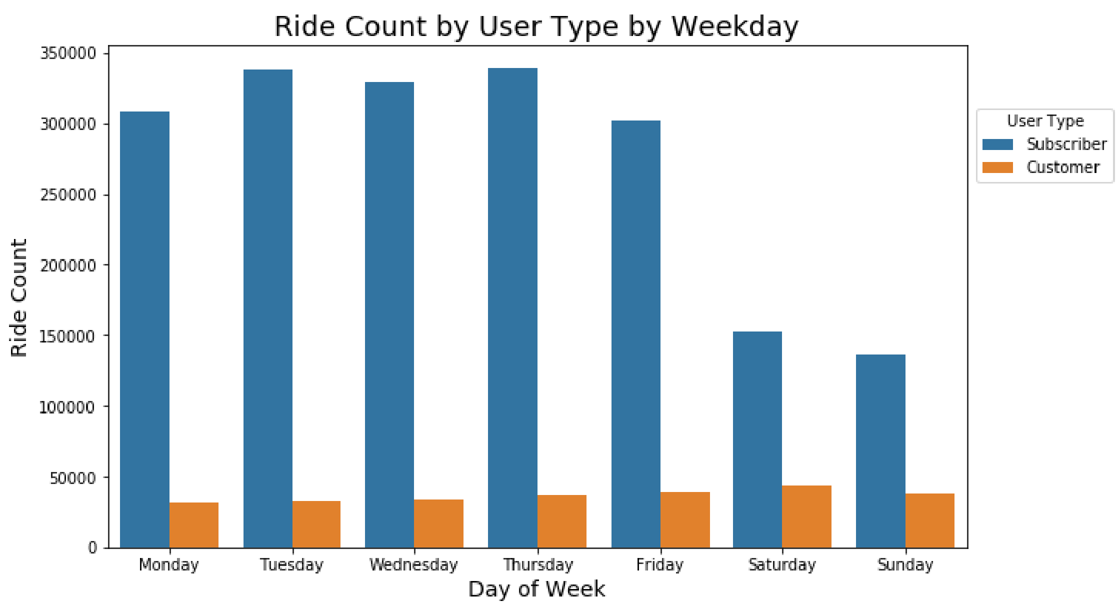
```
In [59]: df_user_type_count_month = df_clean.groupby(['start_time_year_month', 'user_type']).siz
```

```
In [60]: plt.figure(figsize=(10, 6))
         user_type = ['Subscriber', 'Customer']
         ax = sb.pointplot(data=df_user_type_count_month, x='start_time_year_month', y=0, hue='u
         plt.title('Ride Count by User Type by Month', fontsize=18)
         plt.xlabel('Month of Year', fontsize=14)
         plt.ylabel('Ride Count', fontsize=14)
         plt.xticks(rotation=20)
         plt.ylim(0,)
         ax.legend(loc='right', bbox_to_anchor=(1.18, 0.8), title='User Type');
```



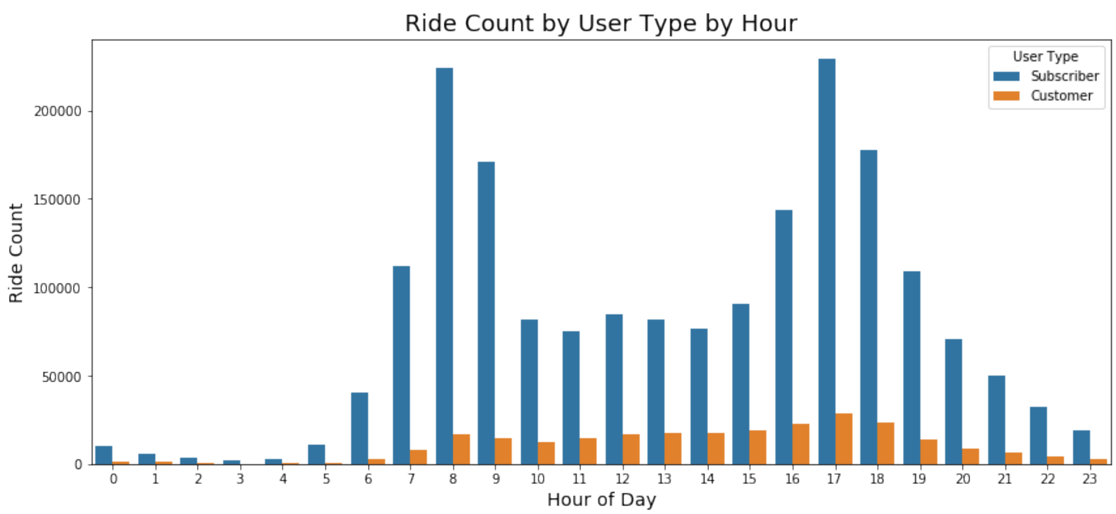
- The subscriber group uses the service a lot more than the customer group

In [61]:
```
weekday_index = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'S
plt.figure(figsize=(10, 6))
ax = sb.countplot(data=df_clean, x='start_time_weekday', hue='user_type', order=weekday
ax.legend(loc='right', bbox_to_anchor=(1.18, 0.8), title='User Type')
plt.title('Ride Count by User Type by Weekday', fontsize=18)
plt.xlabel('Day of Week', fontsize=14)
plt.ylabel('Ride Count', fontsize=14);
```



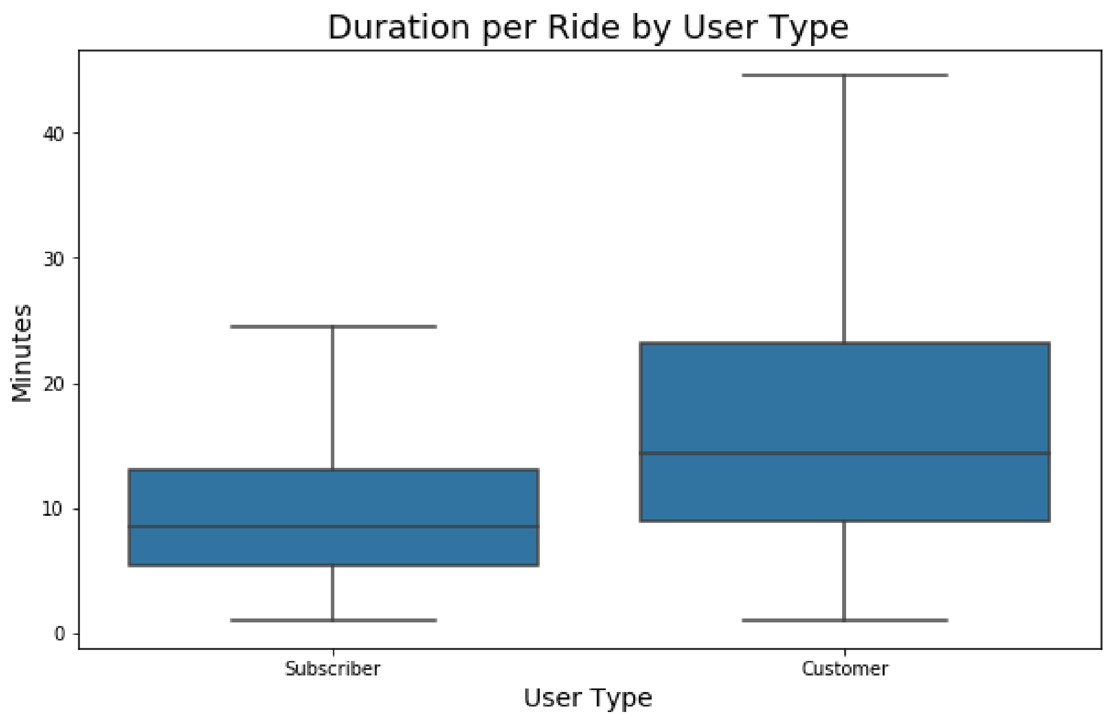
- The subscriber group uses the service more during the week
- The customer group uses the service more on Saturdays

```
In [62]: plt.figure(figsize=(14, 6))
         ax = sb.countplot(data=df_clean, x='start_time_hour', hue='user_type', hue_order=user_t
         ax.legend(title='User Type')
         plt.title('Ride Count by User Type by Hour', fontsize=18)
         plt.xlabel('Hour of Day', fontsize=14)
         plt.ylabel('Ride Count', fontsize=14);
```



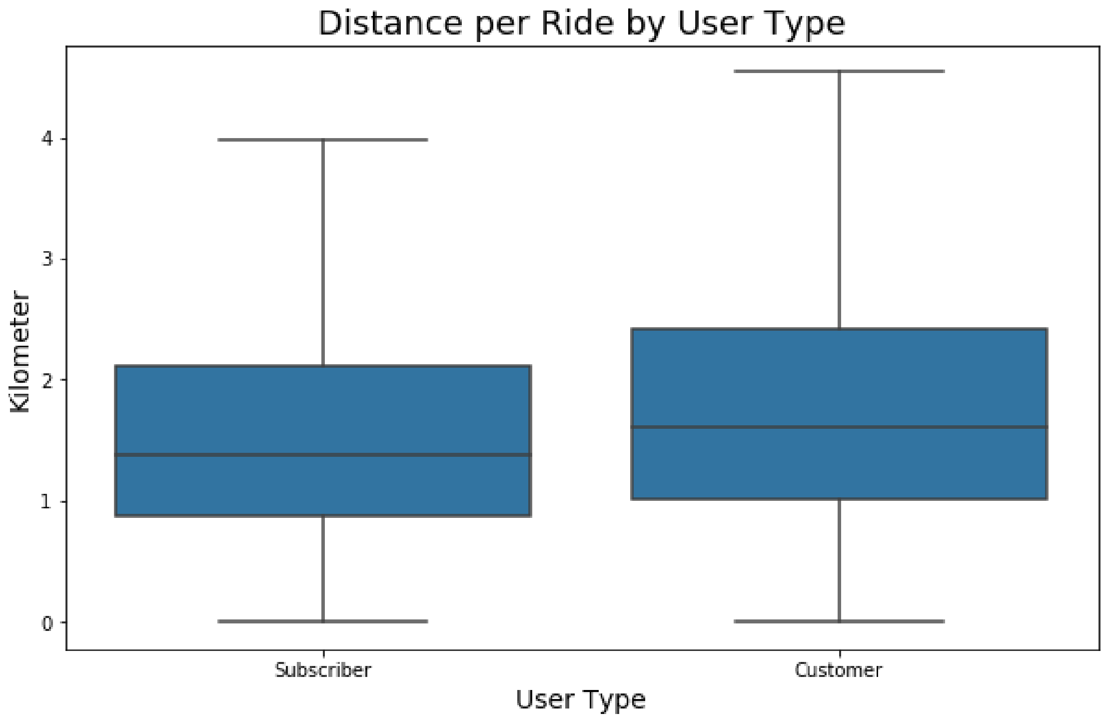
- 8-9 a.m. and 5-6 p.m. are the peak hours for the subscriber group
- The customer group's peak hours are from 4 p.m. and 6 p.m.

```
In [63]: plt.figure(figsize=(10,6))
         sb.boxplot(data=df_clean, x='user_type', y='duration_min', color=base_color, showfliers
         plt.title('Duration per Ride by User Type', fontsize=18)
         plt.xlabel('User Type', fontsize=14)
         plt.ylabel('Minutes', fontsize=14);
```



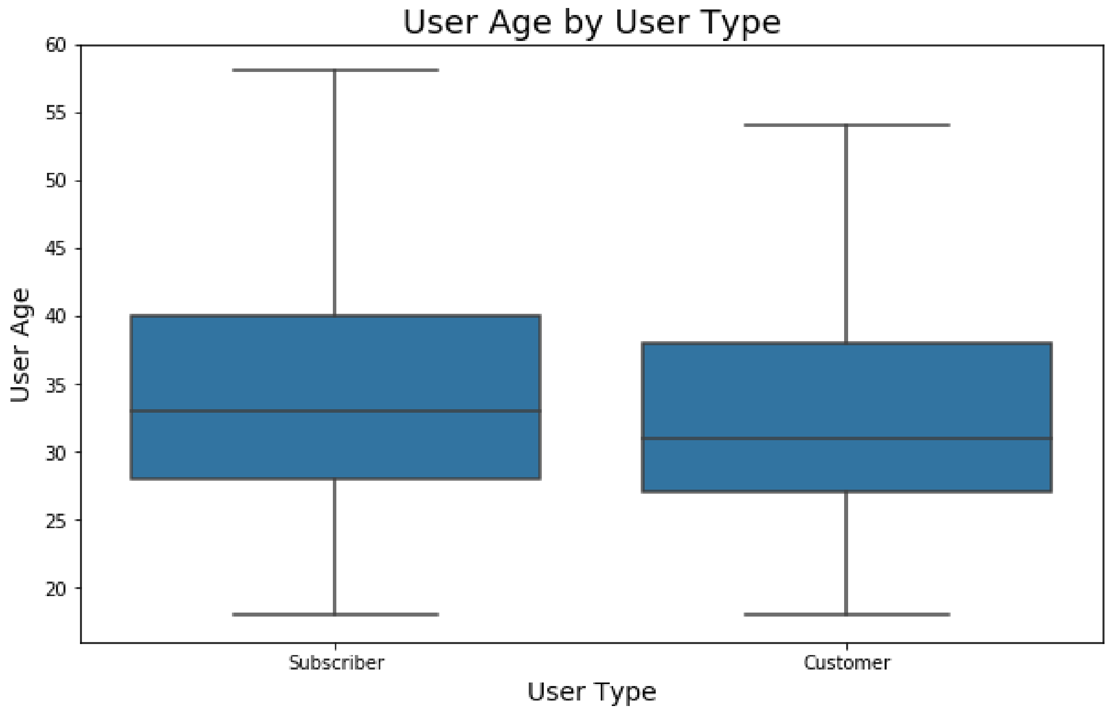
- Overall duration per ride for the customer group is longer than that of the subscriber group
- The duration per ride for the customer group is also more sparsely distributed

```
In [64]: plt.figure(figsize=(10,6))
         sb.boxplot(data=df_clean, x='user_type', y='distance', color=base_color, showfliers=Fal
         plt.title('Distance per Ride by User Type', fontsize=18)
         plt.xlabel('User Type', fontsize=14)
         plt.ylabel('Kilometer', fontsize=14);
```



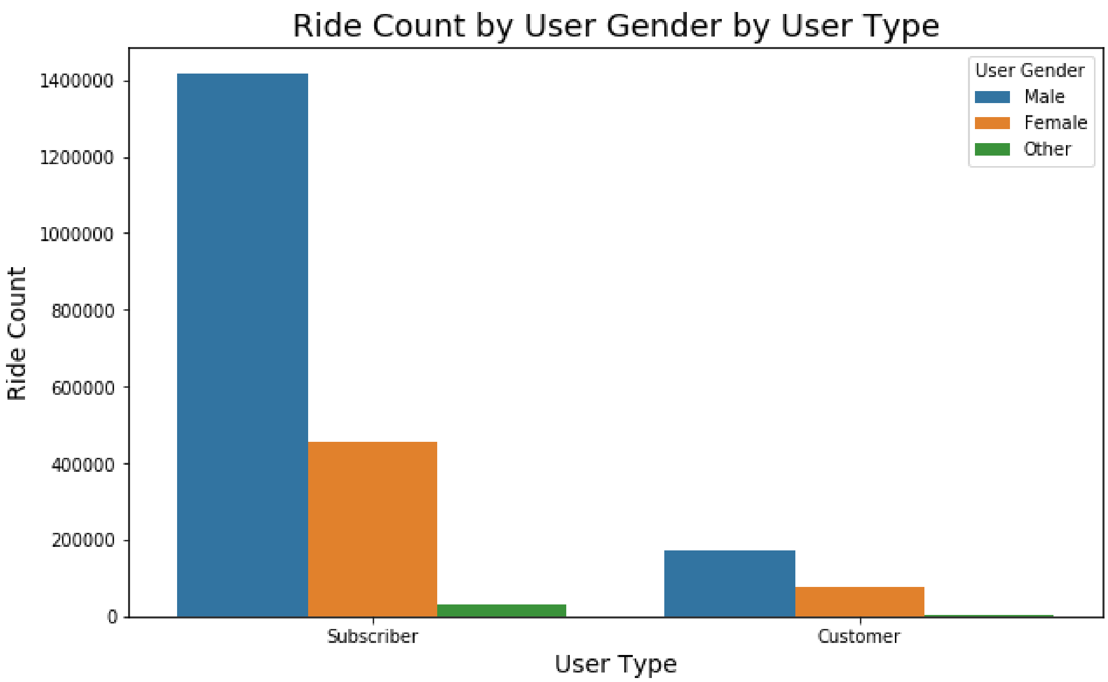
- Distance per ride for the customer group is slightly longer than that of the subscriber group

In [65]:
```
plt.figure(figsize=(10,6))
sb.boxplot(data=df_clean, x='user_type', y='member_age', color=base_color, showfliers=F
plt.title('User Age by User Type', fontsize=18)
plt.xlabel('User Type', fontsize=14)
plt.ylabel('User Age', fontsize=14);
```



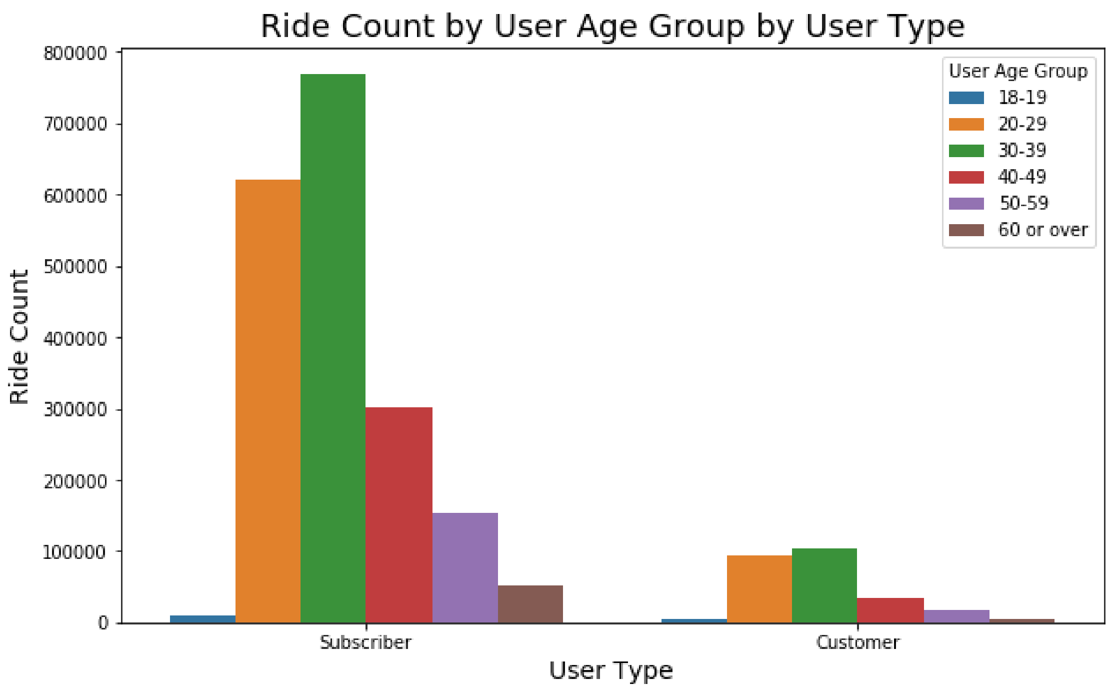
- There seems to be a quite different user behavior between the subscriber and customer group. Therefore, I would like to know more about the profile of the customer group
- The customer group is younger than the subscriber group

In [66]:
```
plt.figure(figsize=(10, 6))
ax = sb.countplot(data=df_clean, x='user_type', hue='member_gender')
ax.legend(title='User Gender')
plt.title('Ride Count by User Gender by User Type', fontsize=18)
plt.xlabel('User Type', fontsize=14)
plt.ylabel('Ride Count', fontsize=14);
```



- The proportion of female users in the customer group is slightly higher than the subscriber group

In [67]:
```
age_group = ['18-19', '20-29', '30-39', '40-49', '50-59', '60 or over']
plt.figure(figsize=(10, 6))
ax = sb.countplot(data=df_clean, x='user_type', hue='member_age_group', hue_order=age_g
ax.legend(title='User Age Group')
plt.title('Ride Count by User Age Group by User Type', fontsize=18)
plt.xlabel('User Type', fontsize=14)
plt.ylabel('Ride Count', fontsize=14);
```

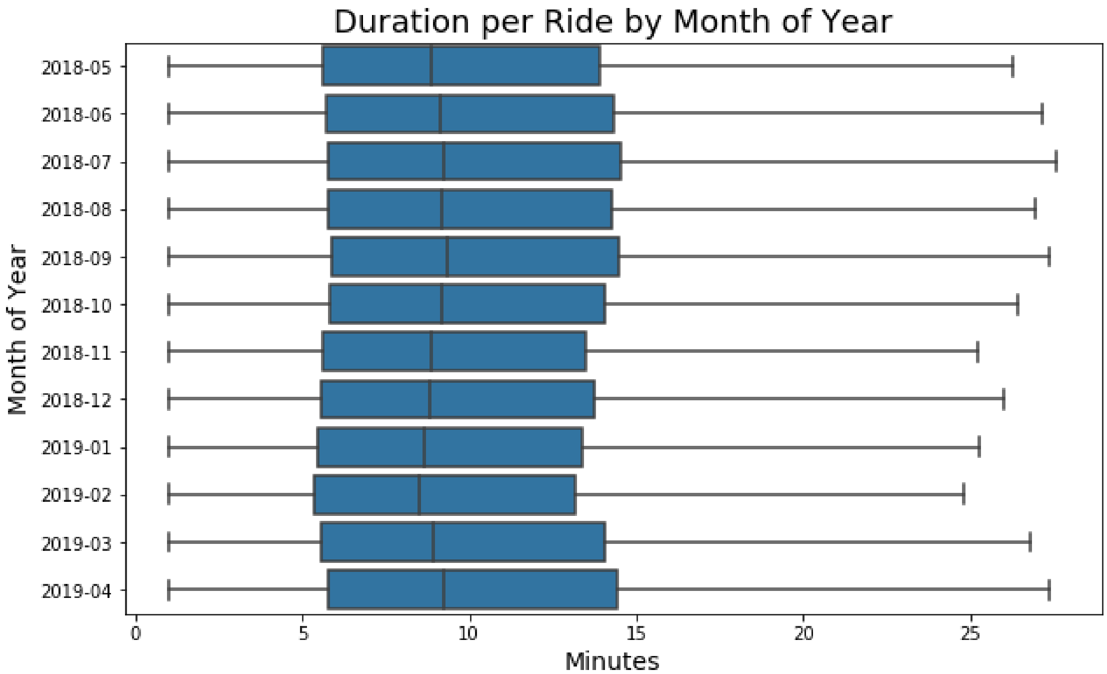


- The proportion of '20-29' group in the customer group is slightly more than the subscriber group

Summary - The majority of the rides in the data is by the subscriber group, and the frequency is much higher than the customer group - The two user type groups have different profile and user behavior: - The subscriber group uses the service more during the week while the customer group more on Saturdays - Both overall duration per ride and overall distance per ride for the customer group are longer than that of the subscriber group - The customer group is younger than the subscriber group. Specifically, the porportion of the '20-29' age group is slightly higher for the customer group - The proportion of female users in the customer group is slightly higher than the subscriber group

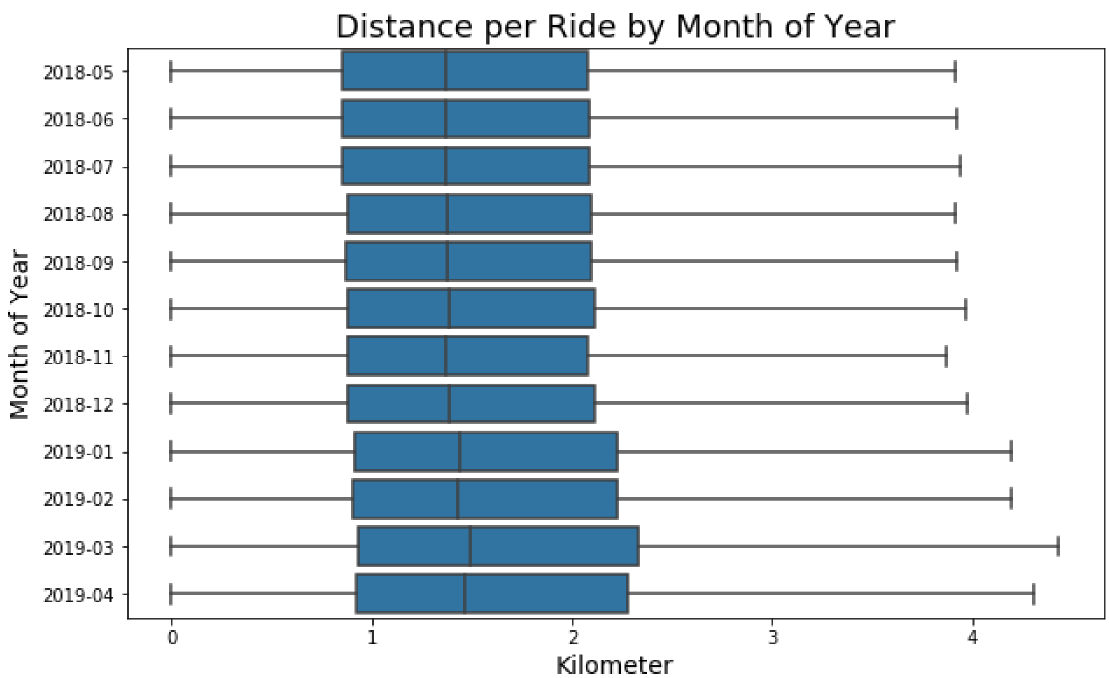
Month by Duration & Distance

```
In [68]: plt.figure(figsize=(10, 6))
         sb.boxplot(data=df_clean, x='duration_min', y='start_time_year_month', color=base_color
         plt.title('Duration per Ride by Month of Year', fontsize=18)
         plt.xlabel('Minutes', fontsize=14)
         plt.ylabel('Month of Year', fontsize=14);
```



- Overall duration per ride is shorter in cold months (November 2018 - February 2019)

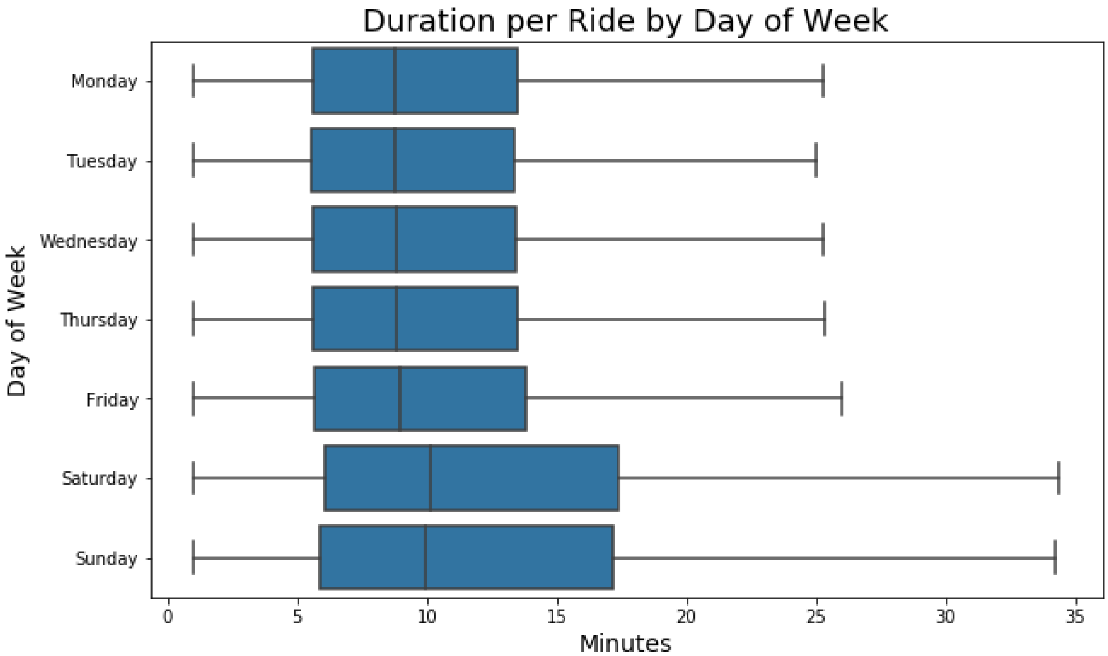
In [69]:
```
plt.figure(figsize=(10, 6))
sb.boxplot(data=df_clean, x='distance', y='start_time_year_month', color=base_color, sh
plt.title('Distance per Ride by Month of Year', fontsize=18)
plt.xlabel('Kilometer', fontsize=14)
plt.ylabel('Month of Year', fontsize=14);
```



- Overall distance per ride didn't drop in cold months
- However, there is a general increase in travel distance since January 2019

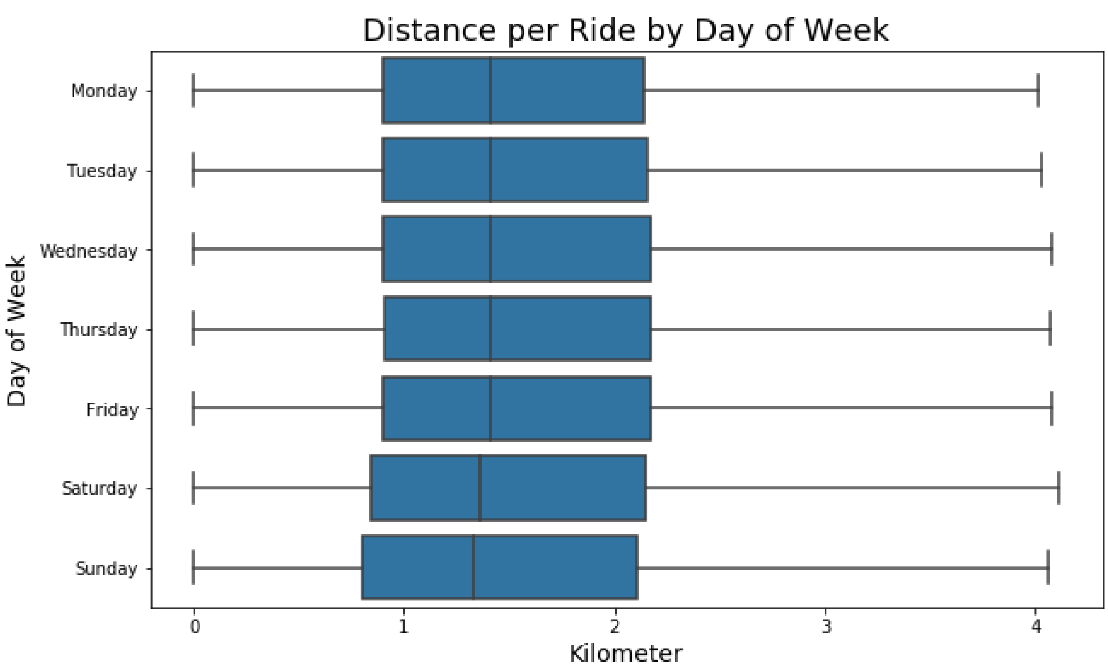
Weekday by Duration & Distance

```
In [70]: plt.figure(figsize=(10, 6))
         sb.boxplot(data=df_clean, x='duration_min', y='start_time_weekday', color=base_color, o
         plt.title('Duration per Ride by Day of Week', fontsize=18)
         plt.xlabel('Minutes', fontsize=14)
         plt.ylabel('Day of Week', fontsize=14);
```



- Over duration per ride is longer on weekends and also more sparsely distributed

In [71]:
```
plt.figure(figsize=(10, 6))
sb.boxplot(data=df_clean, x='distance', y='start_time_weekday', color=base_color, order
plt.title('Distance per Ride by Day of Week', fontsize=18)
plt.xlabel('Kilometer', fontsize=14)
plt.ylabel('Day of Week', fontsize=14);
```

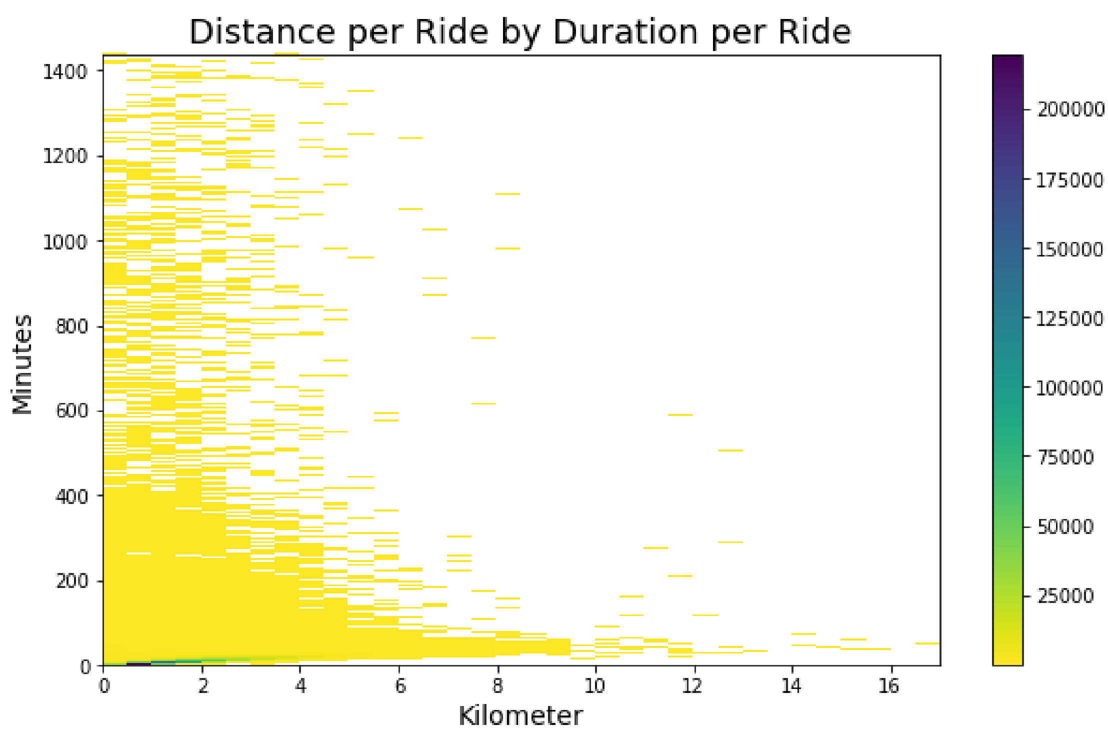


- However, overall distance per ride is slightly shorter on weekends

Summary - The overall duration per ride in cold months is shorter than other months, but no much difference in overall distance per ride - There is a general increase in travel distance since January 2019 - The overall duration per ride is longer on weekends, but the distance is shorter

Duration by Distance

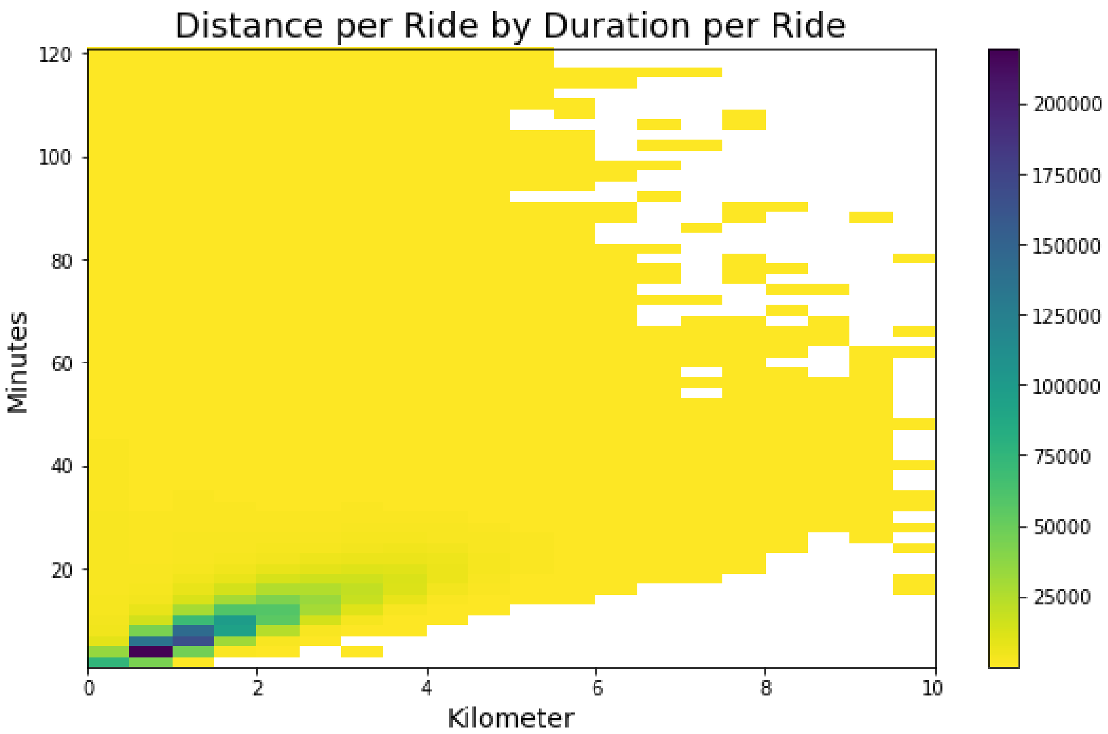
```
In [72]: plt.figure(figsize=(10, 6))
         bins_x = np.arange(0, df_clean['distance'].max()+0.5, 0.5)
         bins_y = np.arange(1, df_clean['duration_min'].max()+2, 2)
         plt.hist2d(data=df_clean, x='distance', y='duration_min', bins=[bins_x, bins_y], cmap='
         plt.colorbar()
         plt.title('Distance per Ride by Duration per Ride', fontsize=18)
         plt.xlabel('Kilometer', fontsize=14)
         plt.ylabel('Minutes', fontsize=14);
```



- An overview of the dataset shows that most travel distance per ride is shorter than 4 kilometer and the duration lasts up to more than 1,400 minutes

```
In [73]: df_min_dis = df_clean[(df_clean['distance'] <= 10) & (df_clean['duration_min'] <= 120)]
```

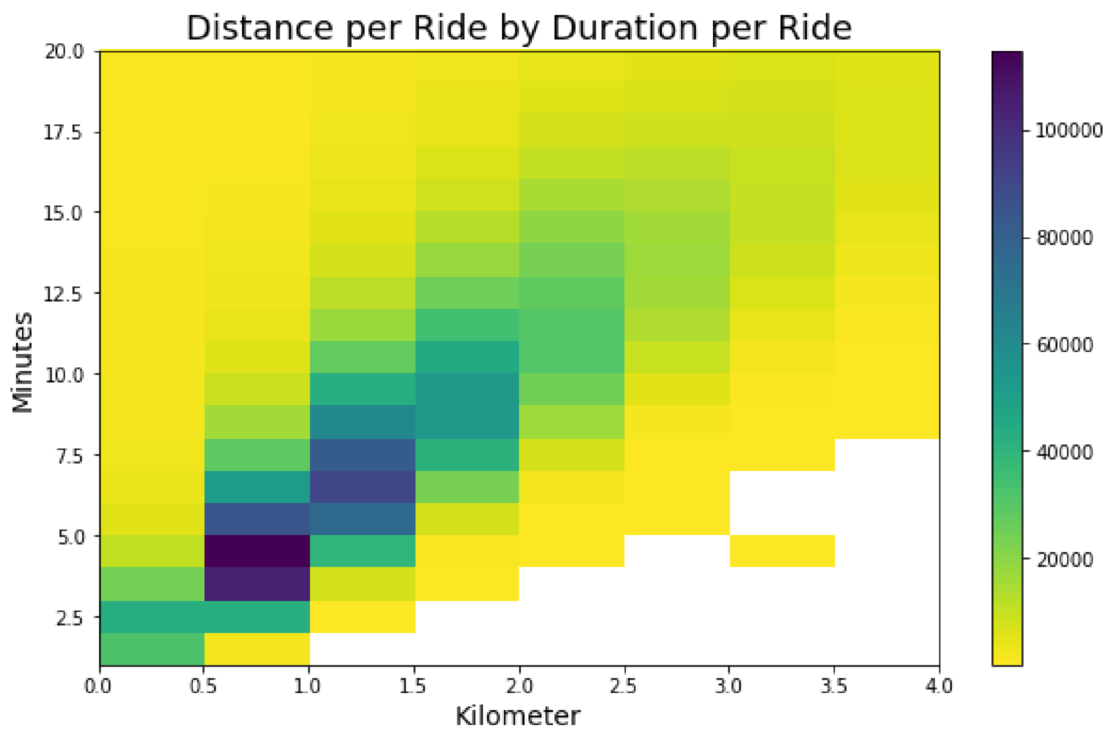
```
In [74]: plt.figure(figsize=(10, 6))
         bins_x = np.arange(0, df_min_dis['distance'].max()+0.5, 0.5)
         bins_y = np.arange(1, df_min_dis['duration_min'].max()+2, 2)
         plt.hist2d(data=df_min_dis, x='distance', y='duration_min', bins=[bins_x, bins_y], cmap
         plt.colorbar()
         plt.title('Distance per Ride by Duration per Ride', fontsize=18)
         plt.xlabel('Kilometer', fontsize=14)
         plt.ylabel('Minutes', fontsize=14);
```



- A closer look shows that the duration per ride is mostly within 20 minutes

```
In [75]: df_min_dis_2 = df_clean[(df_clean['distance'] <= 4) & (df_clean['duration_min'] <= 20)]

In [76]: plt.figure(figsize=(10, 6))
         bins_x = np.arange(0, df_min_dis_2['distance'].max()+0.5, 0.5)
         bins_y = np.arange(1, df_min_dis_2['duration_min'].max()+1, 1)
         plt.hist2d(data=df_min_dis_2, x='distance', y='duration_min', bins=[bins_x, bins_y], cm
         plt.colorbar()
         plt.title('Distance per Ride by Duration per Ride', fontsize=18)
         plt.xlabel('Kilometer', fontsize=14)
         plt.ylabel('Minutes', fontsize=14);
```



- A further closer look shows a linear correlation between distance and duration per ride
- The most frequent rides are about 0.5 to 1 kilometer in distance and 3 to 5 minutes in duration

Summary - Most rides are within 4 kilometer in distance and 20 minutes in duration. There is a linear correlation between distance and duration per ride within this range - The most frequent rides are about 0.5 to 1 kilometer in distance and 3 to 5 minutes in duration

1.4.1 Talk about some of the relationships you observed in this part of the investigation. How did the feature(s) of interest vary with other features in the dataset?

Gender - Female users use the service less in cold months, but not as less as male users - Overall duration per ride for the female user group is longer - Overall distance per ride for the female user group is also slightly longer

Age - '20-29', '30-39' and '40-49' are the top3 user groups, with the '30-39' group being the largest - However, the '20-29' group is closing its gap with the '30-39' group - While the '30-39' group is the largest during the week, the '20-29' group uses the service more than other groups on weekends - While the '30-39' group is the largest during the day, the '20-29' group uses the service more than other groups from 8 p.m. to 2 a.m. - Compared to other groups, duration per ride for the '18-19' group is sparesely distributed - Ride distance for the '30-39' group is slightly longer than other groups

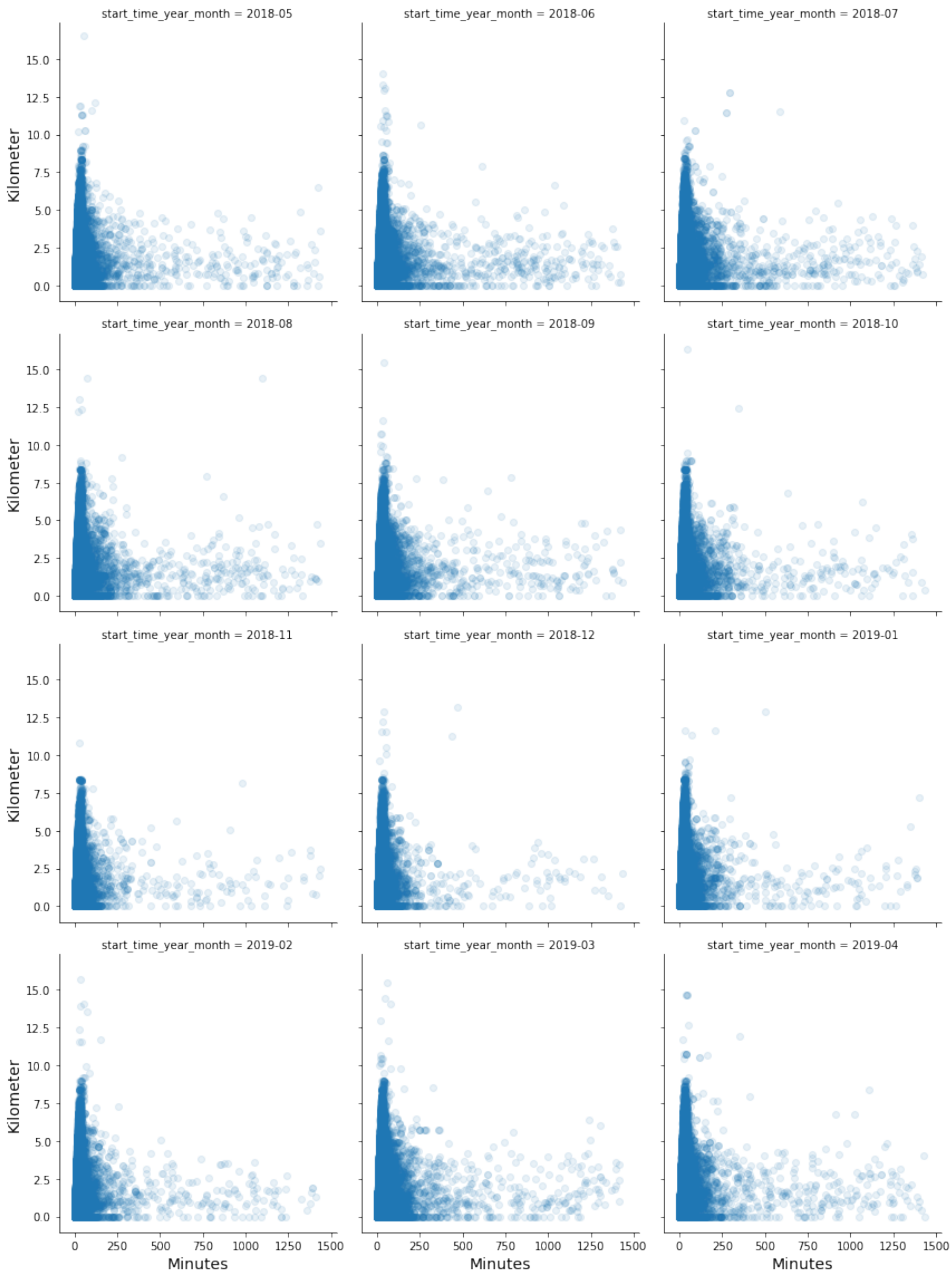
User Type - The majority of the rides in the data is by the subscriber group, and the frequency is much higher than the customer group - The two groups have different profile and user behavior: - The subscriber group uses the service more during the week while the customer group more on Saturdays - Both overall duration per ride and overall distance per ride for the customer group are longer than that of the subscriber group - The customer group is younger than the subscriber group. Specifically, the porportion of the '20-29' group is slightly higher for the customer group - The proportion of female users in the customer group is slightly higher than the subscriber group

Time Variables by Duration and Distance - The overall duration per ride in cold months is shorter than other months, but no much difference in overall distance per ride - There is a general increase in travel distance since January 2019 - The overall duration per ride is longer on weekends, but the distance is shorter

Duration by Distance - Most rides are within 4 kilometer in distance and 20 minutes in duration. There is a positive linear correlation between distance and duration per ride within this range - The most frequent rides are about 0.5 to 1 kilometer in distance and 3 to 5 minutes in duration

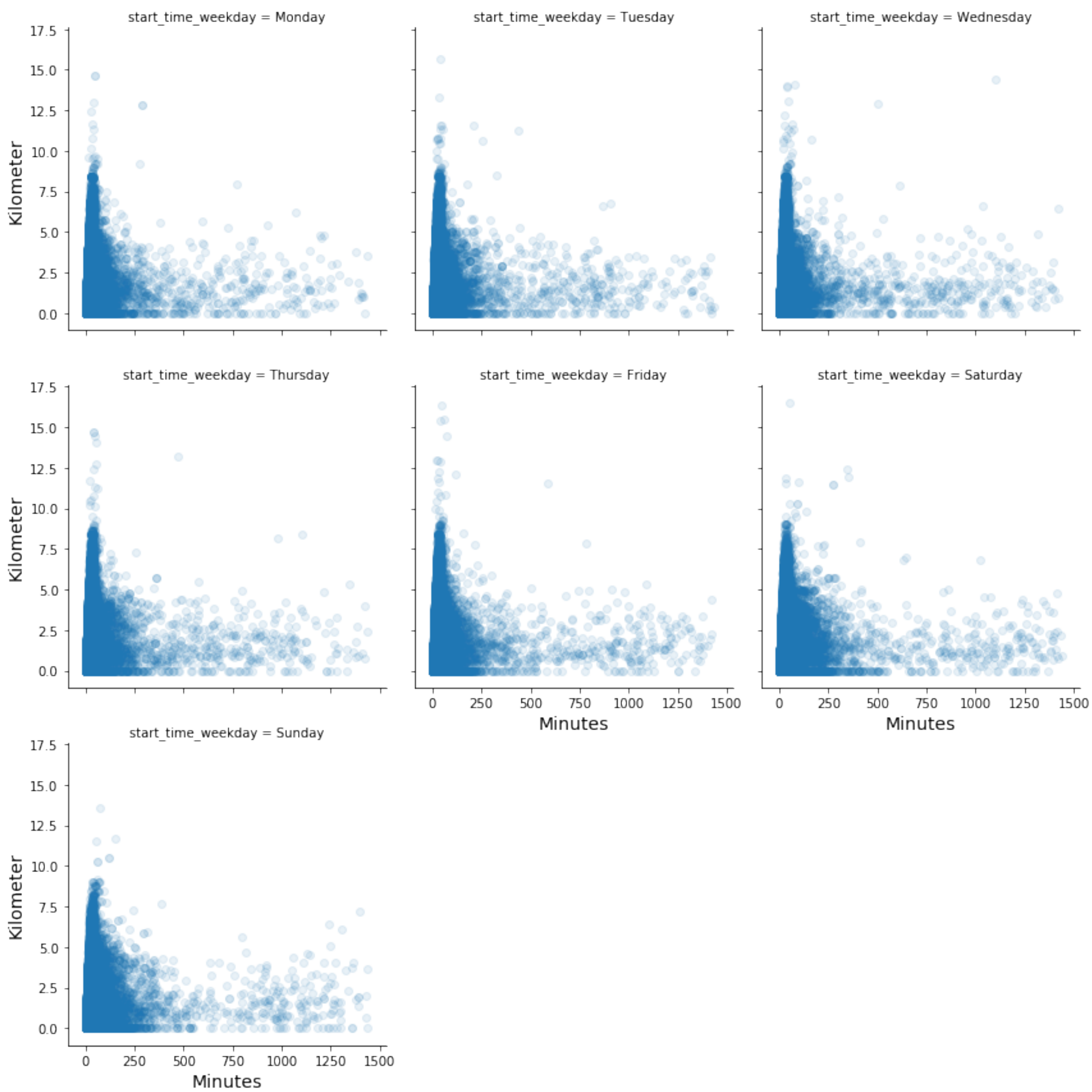
1.5 Multivariate Exploration

```
In [77]: g = sb.FacetGrid(data=df_clean, col='start_time_year_month', col_wrap=3, size=4)
         g.map(plt.scatter, 'duration_min', 'distance', alpha=0.1)
         g.set_xlabels('Minutes', fontsize=14)
         g.set_ylabels('Kilometer', fontsize=14);
```



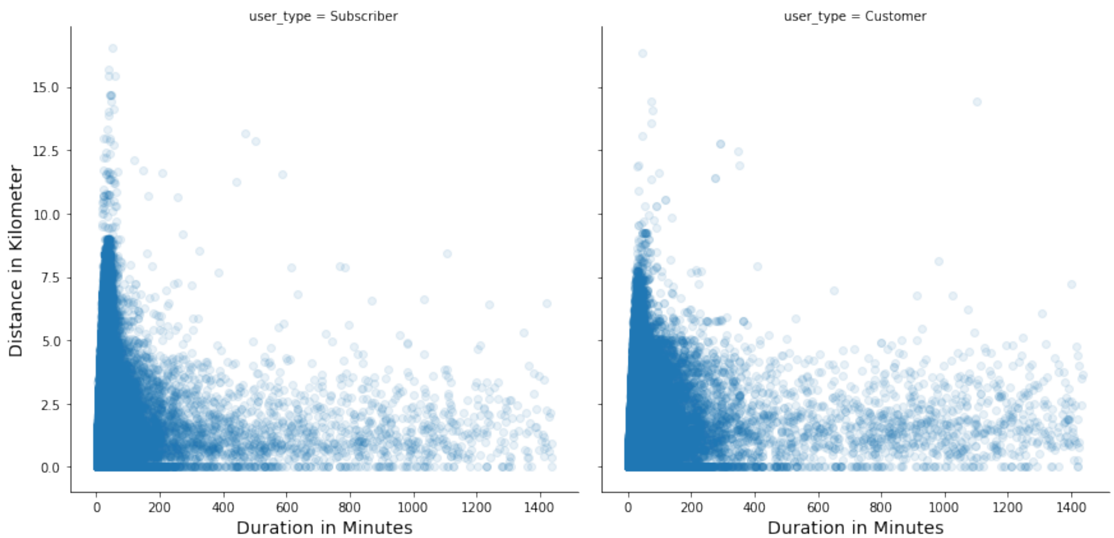
- As observed previously, the duration per ride is shorter in cold months
- Distance per ride is increasing slightly over time

```
In [78]: g = sb.FacetGrid(data=df_clean, col='start_time_weekday', col_order=weekday_index, col_
         g.map(plt.scatter, 'duration_min', 'distance', alpha=0.1)
         g.set_xlabels('Minutes', fontsize=14)
         g.set_ylabels('Kilometer', fontsize=14);
```



- For the same distance travelled, the duration per ride is longer and the distribution wider on Saturday

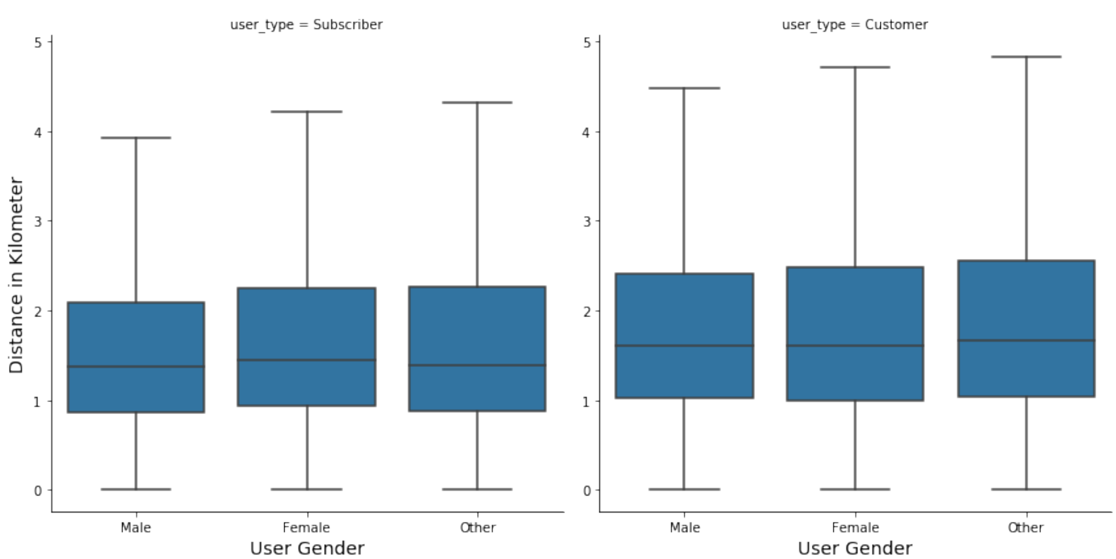
```
In [79]: g = sb.FacetGrid(data=df_clean, col='user_type', col_wrap=3, size=6)
         g.map(plt.scatter, 'duration_min', 'distance', alpha=0.1)
         g.set_xlabels('Duration in Minutes', fontsize=14)
         g.set_ylabels('Distance in Kilometer', fontsize=14);
```



- Even though the number of rides by the customer group in the data is substianlly fewer than the subscriber group, it is clear that the duration per ride for the customer group is significantly longer

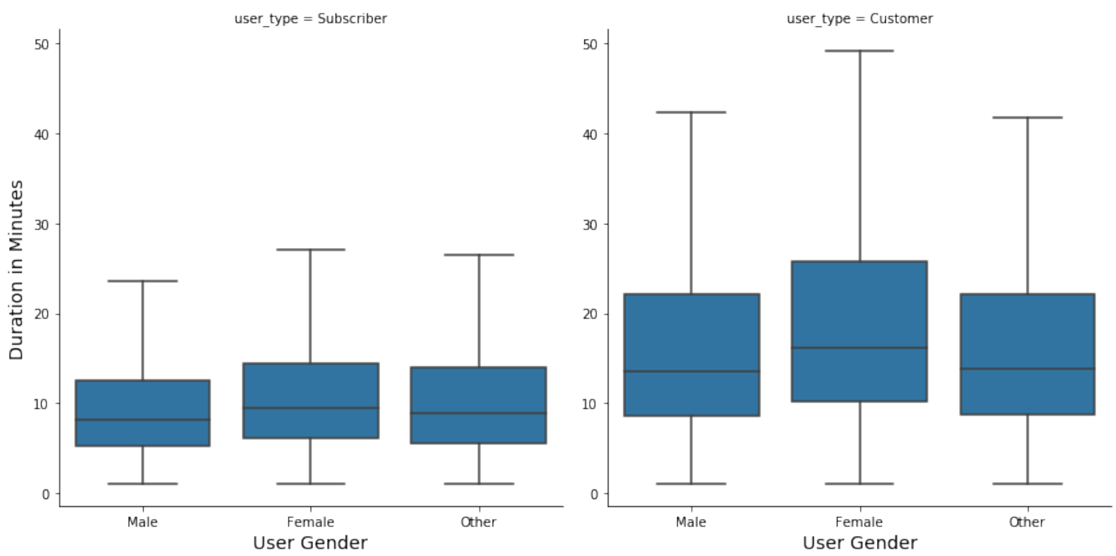
In [80]:
```
warnings.filterwarnings("ignore")
```

In [81]:
```
g = sb.FacetGrid(data=df_clean, col='user_type', size=6)
g.map(sb.boxplot, 'member_gender', 'distance', showfliers=False)
g.set_xlabels('User Gender', fontsize=14)
g.set_ylabels('Distance in Kilometer', fontsize=14);
```



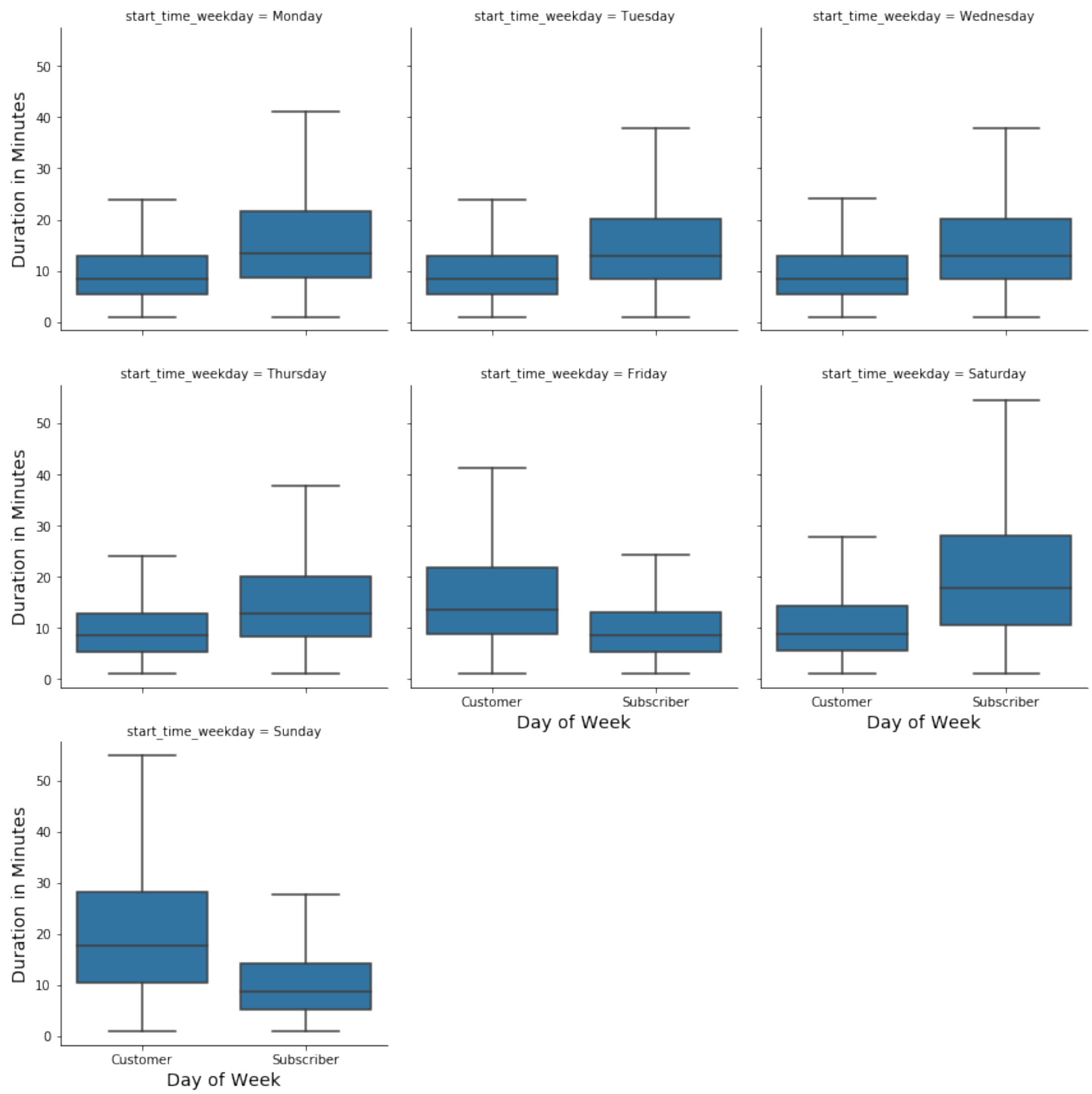
- There is a slight increase in distance per ride across all gender groups in the customer group

In [82]:
```
g = sb.FacetGrid(data=df_clean, col='user_type', size=6)
g.map(sb.boxplot, 'member_gender', 'duration_min', showfliers=False)
g.set_xlabels('User Gender', fontsize=14)
g.set_ylabels('Duration in Minutes', fontsize=14);
```



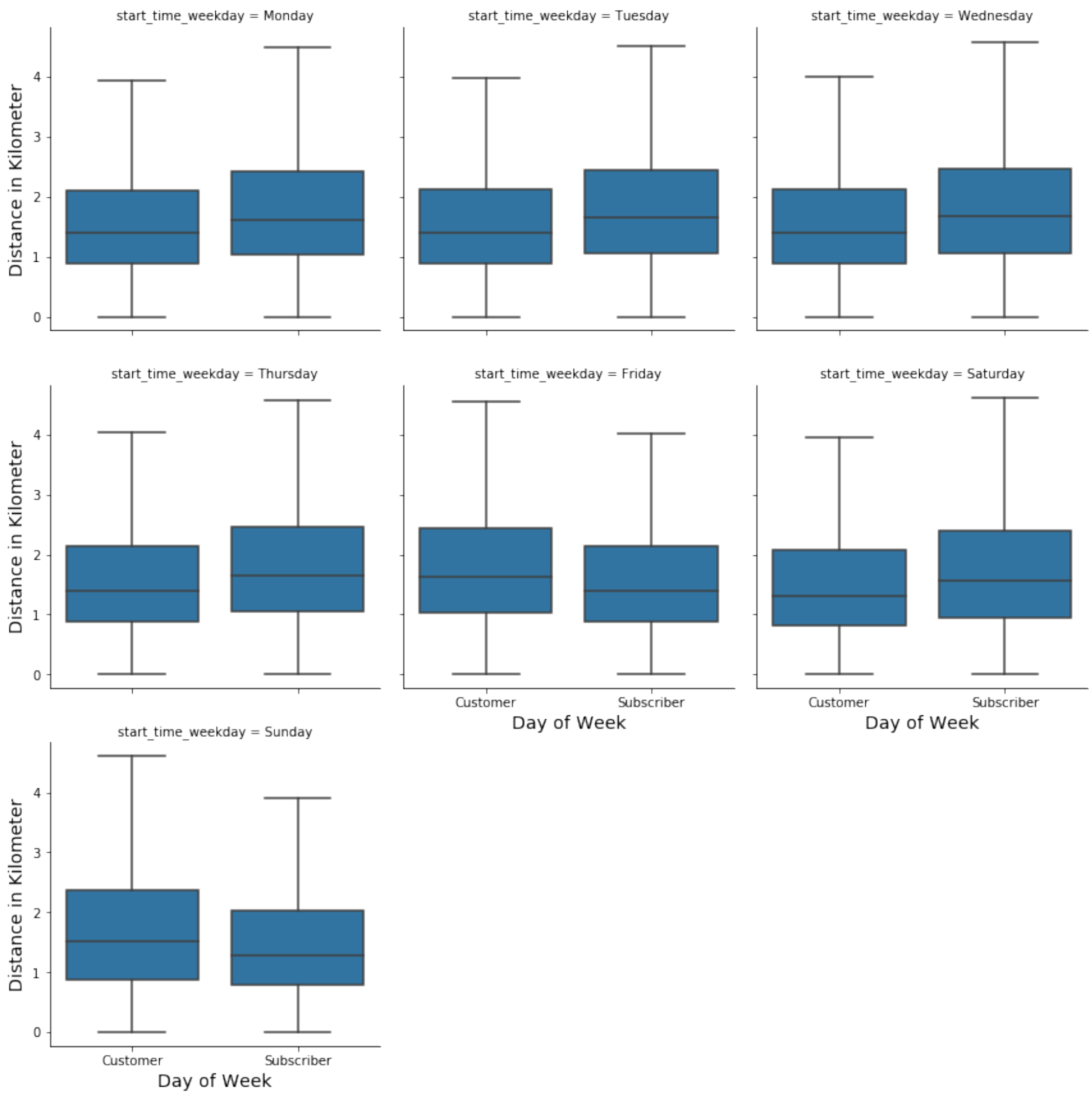
- Duration per ride is significantly longer for all gender groups in the customer group, especially the female user group
- The interquartile range box for the subscriber group is significantly smaller

In [83]:
```
g = sb.FacetGrid(data=df_clean, col='start_time_weekday', col_order=weekday_index, col_
g.map(sb.boxplot, 'user_type', 'duration_min', showfliers=False)
g.set_xlabels('Day of Week', fontsize=14)
g.set_ylabels('Duration in Minutes', fontsize=14);
```



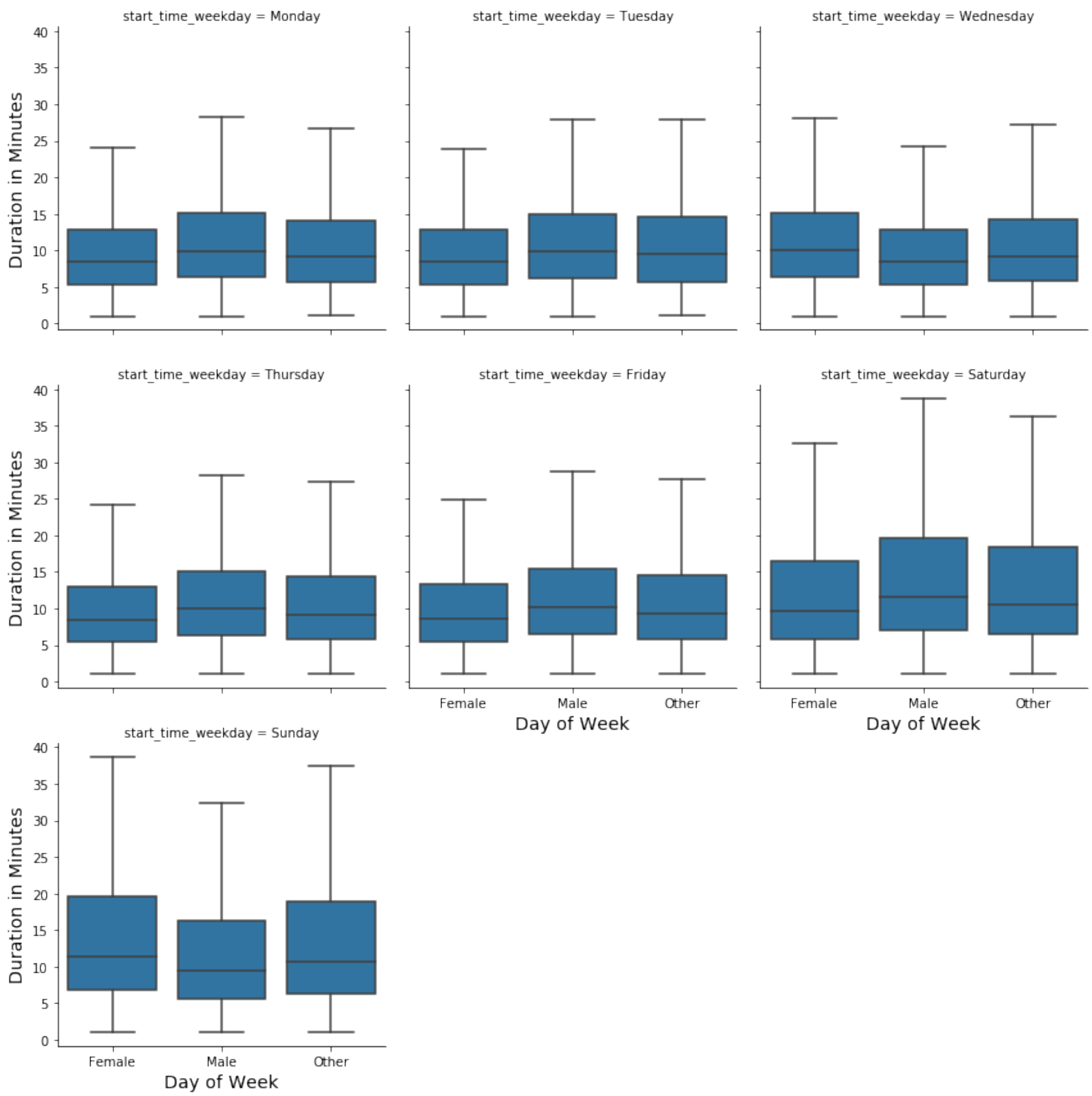
- While the overall duration per ride for the customer group is longer, it is only true for Friday and Sunday
- Distribution of duration per ride is identical from Monday to Thursday for both customer and subscriber group

```
In [84]: g = sb.FacetGrid(data=df_clean, col='start_time_weekday', col_order=weekday_index, col_
         g.map(sb.boxplot, 'user_type', 'distance', showfliers=False)
         g.set_xlabels('Day of Week', fontsize=14)
         g.set_ylabels('Distance in Kilometer', fontsize=14);
```



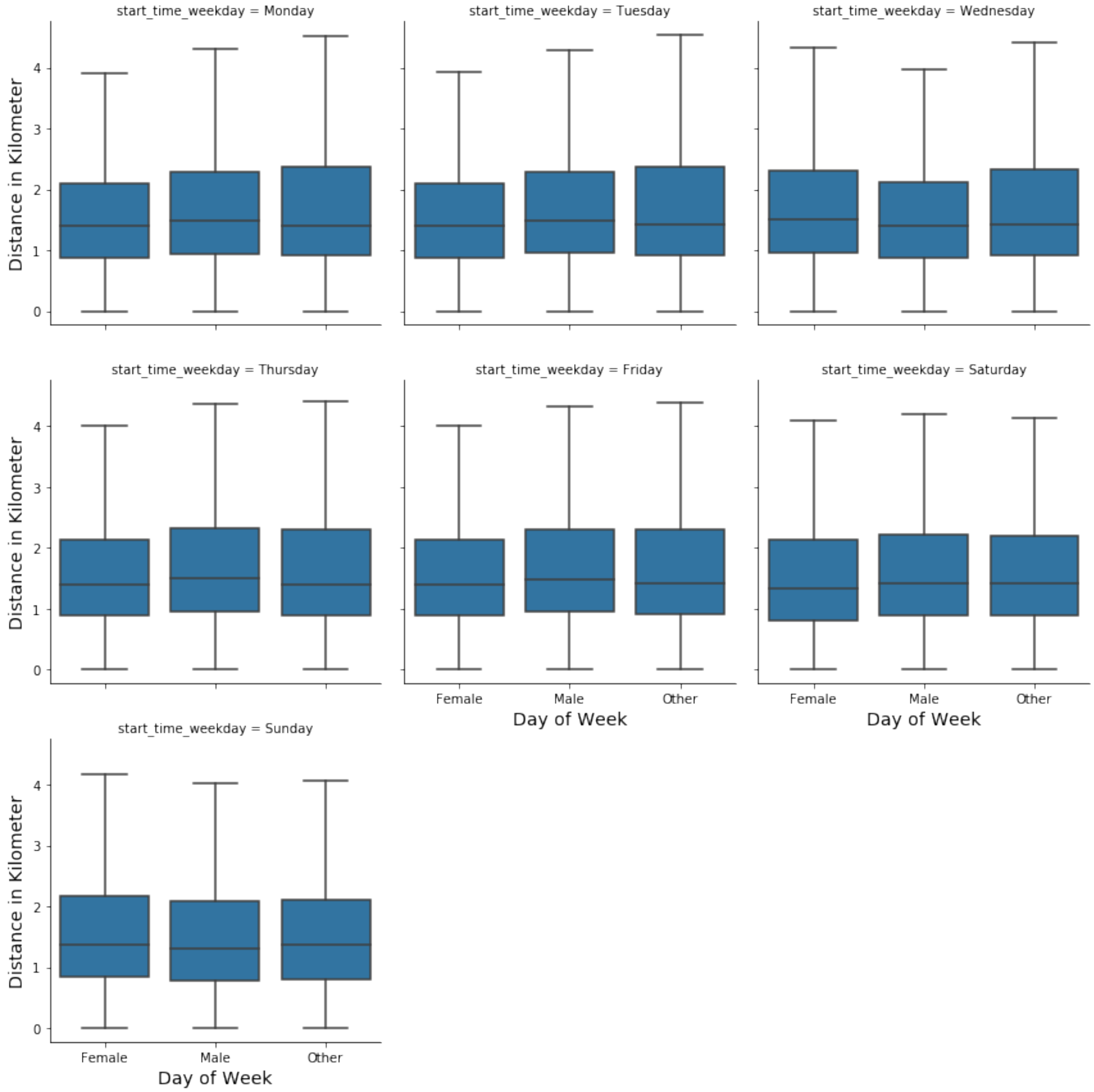
- Similar pattern also found in distance: while the overall distance per ride for the customer group is longer, it is only true for Friday and Sunday
- Distribution of distance per ride is also identical from Monday to Thursday for both customer and subscriber group

```
In [85]: g = sb.FacetGrid(data=df_clean, col='start_time_weekday', col_order=weekday_index, col_
         g.map(sb.boxplot, 'member_gender', 'duration_min', showfliers=False)
         g.set_xlabels('Day of Week', fontsize=14)
         g.set_ylabels('Duration in Minutes', fontsize=14);
```



- Although the overall duration per ride for the female user group is longer, no particular pattern is identified when the data are illustrated by day of week
- Interquartile range box and whiskers are both longer on weekends

```
In [86]: g = sb.FacetGrid(data=df_clean, col='start_time_weekday', col_order=weekday_index, col_
         g.map(sb.boxplot, 'member_gender', 'distance', showfliers=False)
         g.set_xlabels('Day of Week', fontsize=14)
         g.set_ylabels('Distance in Kilometer', fontsize=14);
```



- No particular pattern of distance per ride found for all gender groups by days of week

1.5.1 Talk about some of the relationships you observed in this part of the investigation. Were there features that strengthened each other in terms of looking at your feature(s) of interest?

Multivariate exploration confirms the findings in previous analysis, and also provides additional information in some cases:

- As observed in the previous analysis, the duration per ride in cold months is shorter, but there is no much change to the distance per ride
- The scatterplot clearly shows that the duration per ride for the customer group is significantly longer and it is true across different user gender groups. Features of the customer group inclide:

- Younger than the subscriber group, specifically the porportion of the '20-29' group is higher
- The porportion of the female user group is also higher

- The distribution range of duration per ride for the subscriber group is significantly shorter

1.5.2 Were there any interesting or surprising interactions between features?

- While the overall duration per ride for the customer group is longer than the subscriber, it is only true for Friday and Sunday
- Similar pattern also found in distance: while the overall distance per ride for the customer group is longer than the subscriber group, it is only true for Friday and Sunday
- Although the overall duration per ride for the female user group is longer, no particular pattern is identified when the data are illustrated by day of week