NYC taxi trip

November 20, 2021

1 Course 5: Ensemble Learning

1.1 Project: Building Basic predictive models over the NYC Taxi Trip dataset.

1.1.1 Load libraries

[1]:
```
%matplotlib inline
import numpy as np
import pandas as pd
from datetime import timedelta
import datetime as dt
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn import metrics
from sklearn.model_selection import train_test_split, GridSearchCV
from haversine import haversine
import statsmodels.api as sm
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings; warnings.simplefilter('ignore')
import warnings
warnings.filterwarnings('ignore')
```

1.1.2 Import dataset

[2]:
```
data=pd.read_csv("Project.csv")
```

1.1.3 Data Exploration

[3]:
```
data.head()
```

[3]:
```
          id  vendor_id      pickup_datetime     dropoff_datetime  \
0  id1080784          2  2016-02-29 16:40:21  2016-02-29 16:47:01
1  id0889885          1  2016-03-11 23:35:37  2016-03-11 23:53:57
2  id0857912          2  2016-02-21 17:59:33  2016-02-21 18:26:48
```

```
3  id3744273          2  2016-01-05 09:44:31  2016-01-05 10:03:32
4  id0232939          1  2016-02-17 06:42:23  2016-02-17 06:56:31

   passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
0                1        -73.953918        40.778873         -73.963875
1                2        -73.988312        40.731743         -73.994751
2                2        -73.997314        40.721458         -73.948029
3                6        -73.961670        40.759720         -73.956779
4                1        -74.017120        40.708469         -73.988182

   dropoff_latitude store_and_fwd_flag  trip_duration
0         40.771164                  N            400
1         40.694931                  N           1100
2         40.774918                  N           1635
3         40.780628                  N           1141
4         40.740631                  N            848
```

1.1.4 Feature details:

- id - a unique identifier for each trip
- vendor_id - a code indicating the provider associated with the trip record
- pickup_datetime - date and time when the meter was engaged
- dropoff_datetime - date and time when the meter was disengaged
- passenger_count - the number of passengers in the vehicle (driver entered value)
- pickup_longitude - the longitude where the meter was engaged
- pickup_latitude - the latitude where the meter was engaged
- dropoff_longitude - the longitude where the meter was disengaged
- dropoff_latitude - the latitude where the meter was disengaged
- store_and_fwd_flag - This flag indicates whether the trip record was held in vehicle memory before sending to the vendor because the vehicle did not have a connection to the server - Y=store and forward; N=not a store and forward trip.

1.1.5 Label details:

- trip_duration - duration of the trip in seconds

[4]:
```
data.shape
```

[4]:
```
(729322, 11)
```

[5]:
```
data.isnull().sum()
```

[5]:
```
id                    0
vendor_id             0
pickup_datetime       0
dropoff_datetime      0
passenger_count       0
pickup_longitude      0
```

```
pickup_latitude       0
dropoff_longitude     0
dropoff_latitude      0
store_and_fwd_flag    0
trip_duration         0
dtype: int64
```

1.1.6 Result:

There are no null values in the dataset

[6]:
```
data.dtypes
```

[6]:
```
id                     object
vendor_id               int64
pickup_datetime        object
dropoff_datetime       object
passenger_count         int64
pickup_longitude      float64
pickup_latitude       float64
dropoff_longitude     float64
dropoff_latitude      float64
store_and_fwd_flag     object
trip_duration           int64
dtype: object
```

[7]:
```
data['pickup_datetime'] = pd.to_datetime(data['pickup_datetime'])
data['dropoff_datetime'] = pd.to_datetime(data['dropoff_datetime'])
```

1.1.7 calculate and assign new columns with week_day, month, pickup hour

[8]:
```
data['weekday'] = data.pickup_datetime.dt.day_name()
data['month'] = data.pickup_datetime.dt.month
data['weekday_num'] = data.pickup_datetime.dt.weekday
data['pick_up_hour'] = data.pickup_datetime.dt.hour
```

[9]:
```
data.head()
```

[9]:
```
          id  vendor_id     pickup_datetime    dropoff_datetime  \
0  id1080784          2 2016-02-29 16:40:21 2016-02-29 16:47:01
1  id0889885          1 2016-03-11 23:35:37 2016-03-11 23:53:57
2  id0857912          2 2016-02-21 17:59:33 2016-02-21 18:26:48
3  id3744273          2 2016-01-05 09:44:31 2016-01-05 10:03:32
4  id0232939          1 2016-02-17 06:42:23 2016-02-17 06:56:31

   passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
0                1        -73.953918        40.778873         -73.963875
1                2        -73.988312        40.731743         -73.994751
2                2        -73.997314        40.721458         -73.948029
```

```
3                6       -73.961670       40.759720         -73.956779
4                1       -74.017120       40.708469         -73.988182

   dropoff_latitude store_and_fwd_flag  trip_duration    weekday  month  \
0         40.771164                  N            400     Monday      2
1         40.694931                  N           1100     Friday      3
2         40.774918                  N           1635     Sunday      2
3         40.780628                  N           1141    Tuesday      1
4         40.740631                  N            848  Wednesday      2

   weekday_num  pick_up_hour
0            0            16
1            4            23
2            6            17
3            1             9
4            2             6
```

[10]:
```
from haversine import haversine
```

1.1.8 calculate distance between pickup and dropoff coordinates using haversine formula

[11]:
```
def calc_distance(data):
    pickup = (data['pickup_latitude'], data['pickup_longitude'])
    drop = (data['dropoff_latitude'], data['dropoff_longitude'])
    return haversine(pickup, drop)
```

1.1.9 calculate distance and assign new column to dataframe

[12]:
```
data['Distance'] = data.apply(lambda x: calc_distance(x), axis = 1)
```

1.1.10 calculate speed in km/hr

[13]:
```
data['speed'] = (data.Distance/(data.trip_duration/3600))
```

[14]:
```
data.dtypes.reset_index()
```

[14]:
```
                index               0
0                  id          object
1           vendor_id           int64
2     pickup_datetime  datetime64[ns]
3    dropoff_datetime  datetime64[ns]
4     passenger_count           int64
5    pickup_longitude         float64
6     pickup_latitude         float64
7   dropoff_longitude         float64
8    dropoff_latitude         float64
```

```
9   store_and_fwd_flag         object
10        trip_duration         int64
11              weekday        object
12                month         int64
13          weekday_num         int64
14         pick_up_hour         int64
15             Distance       float64
16                speed       float64
```

1.1.11 Dummify all the categorical features like "store_and_fwd_flag, vendor_id, month, weekday_num, pickup_hour, passenger_count"

[15]:

```
dummy = pd.get_dummies(data.store_and_fwd_flag, prefix='flag')
dummy.drop(dummy.columns[0], axis=1, inplace=True) #avoid dummy trap
data = pd.concat([data,dummy], axis = 1)

dummy = pd.get_dummies(data.vendor_id, prefix='vendor_id')
dummy.drop(dummy.columns[0], axis=1, inplace=True)
data = pd.concat([data,dummy], axis = 1)

dummy = pd.get_dummies(data.month, prefix='month')
dummy.drop(dummy.columns[0], axis=1, inplace=True)
data = pd.concat([data,dummy], axis = 1)

dummy = pd.get_dummies(data.weekday_num, prefix='weekday_num')
dummy.drop(dummy.columns[0], axis=1, inplace=True)
data = pd.concat([data,dummy], axis = 1)

dummy = pd.get_dummies(data.pick_up_hour, prefix='pickup_hour')
dummy.drop(dummy.columns[0], axis=1, inplace=True)
data = pd.concat([data,dummy], axis = 1)

dummy = pd.get_dummies(data.passenger_count, prefix='passenger_count')
dummy.drop(dummy.columns[0], axis=1, inplace=True)
data = pd.concat([data,dummy], axis = 1)
```

[16]:

```
data.head()
```

[16]:

```
          id  vendor_id     pickup_datetime    dropoff_datetime  \
0  id1080784          2 2016-02-29 16:40:21 2016-02-29 16:47:01
1  id0889885          1 2016-03-11 23:35:37 2016-03-11 23:53:57
2  id0857912          2 2016-02-21 17:59:33 2016-02-21 18:26:48
3  id3744273          2 2016-01-05 09:44:31 2016-01-05 10:03:32
4  id0232939          1 2016-02-17 06:42:23 2016-02-17 06:56:31

   passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
0                1        -73.953918        40.778873         -73.963875
```

```
1                2        -73.988312        40.731743        -73.994751
2                2        -73.997314        40.721458        -73.948029
3                6        -73.961670        40.759720        -73.956779
4                1        -74.017120        40.708469        -73.988182

   dropoff_latitude store_and_fwd_flag  …  pickup_hour_22 pickup_hour_23  \
0         40.771164                  N  …               0              0
1         40.694931                  N  …               0              1
2         40.774918                  N  …               0              0
3         40.780628                  N  …               0              0
4         40.740631                  N  …               0              0

   passenger_count_1  passenger_count_2  passenger_count_3  passenger_count_4  \
0                  1                  0                  0                  0
1                  0                  1                  0                  0
2                  0                  1                  0                  0
3                  0                  0                  0                  0
4                  1                  0                  0                  0

   passenger_count_5  passenger_count_6  passenger_count_7  passenger_count_9
0                  0                  0                  0                  0
1                  0                  0                  0                  0
2                  0                  0                  0                  0
3                  0                  1                  0                  0
4                  0                  0                  0                  0

[5 rows x 61 columns]
```

[17]:

```
data.columns
```

[17]:

```
Index(['id', 'vendor_id', 'pickup_datetime', 'dropoff_datetime',
       'passenger_count', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'store_and_fwd_flag',
       'trip_duration', 'weekday', 'month', 'weekday_num', 'pick_up_hour',
       'Distance', 'speed', 'flag_Y', 'vendor_id_2', 'month_2', 'month_3',
       'month_4', 'month_5', 'month_6', 'weekday_num_1', 'weekday_num_2',
       'weekday_num_3', 'weekday_num_4', 'weekday_num_5', 'weekday_num_6',
       'pickup_hour_1', 'pickup_hour_2', 'pickup_hour_3', 'pickup_hour_4',
       'pickup_hour_5', 'pickup_hour_6', 'pickup_hour_7', 'pickup_hour_8',
       'pickup_hour_9', 'pickup_hour_10', 'pickup_hour_11', 'pickup_hour_12',
       'pickup_hour_13', 'pickup_hour_14', 'pickup_hour_15', 'pickup_hour_16',
       'pickup_hour_17', 'pickup_hour_18', 'pickup_hour_19', 'pickup_hour_20',
       'pickup_hour_21', 'pickup_hour_22', 'pickup_hour_23',
       'passenger_count_1', 'passenger_count_2', 'passenger_count_3',
       'passenger_count_4', 'passenger_count_5', 'passenger_count_6',
       'passenger_count_7', 'passenger_count_9'],
      dtype='object')
```

1.1.12 Univariate analysis

1.1.13 Passenger count

1.1.14 New York City Taxi Passenger Limit says:

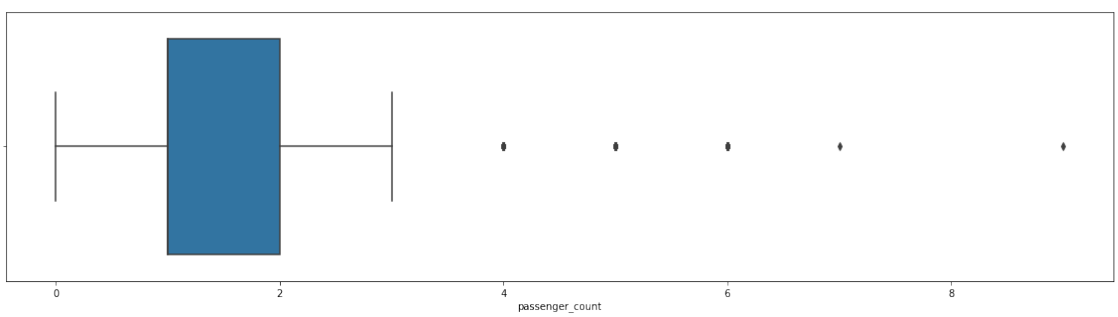
- A maximum of 4 passengers can ride in traditional cabs, there are also 5 passenger cabs that look more like minivans.
- A child under 7 is allowed to sit on a passenger's lap in the rear seat in addition to the passenger limit.

So, in total we can assume that maximum 6 passenger can board the new york taxi i.e. 5 adult + 1 minor

[18]:
```
data.passenger_count.value_counts()
```

[18]:
```
1    517415
2    105097
5     38926
3     29692
6     24107
4     14050
0        33
7         1
9         1
Name: passenger_count, dtype: int64
```

[19]:
```
plt.figure(figsize = (20,5))
sns.boxplot(data.passenger_count)
plt.show()
```



1.1.15 Observation

- Most of the trips are either 1 or 2
- There are 0 passenger count
- Few trips consisted of even 7, 8 or 9 passengers. Clear outliers and pointers to data inconsistency

1.1.16 Idea:

Passenger count is a driver entered value. Since the trip is not possible without passengers. So the driver forgot to enter the value for the trips with 0 passenger count. Lets analyze the passenger count distribution further to make it consistent for further analysis

[20]:
```
data['passenger_count'].describe()
```

[20]:
```
count    729322.000000
mean          1.662055
std           1.312446
min           0.000000
25%           1.000000
50%           1.000000
75%           2.000000
max           9.000000
Name: passenger_count, dtype: float64
```

As per above details. Mean median and mode are all approx equal to 1. So we would replace the 0 passenger count with 1.

[21]:
```
data['passenger_count'] = data.passenger_count.map(lambda x: 1 if x == 0 else x)
```

Also, we will remove the records with passenger count > 7, 8 or 9 as they are extreme values and looks very odd to be ocupied in a taxi.

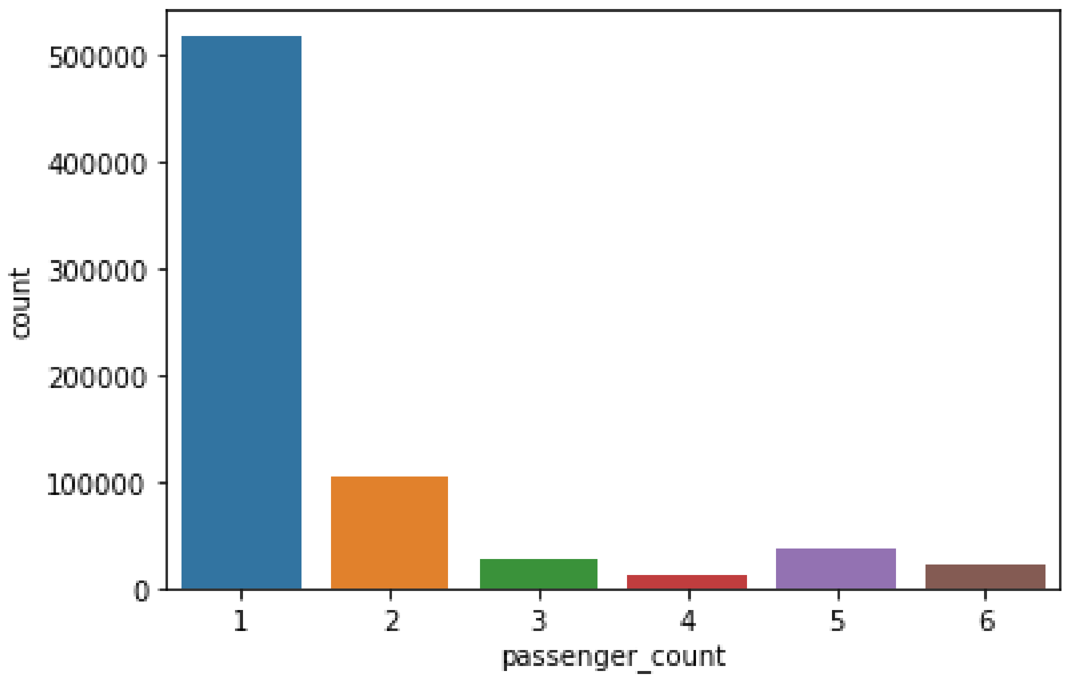
[22]:
```
data = data[data.passenger_count <= 6]
```

[23]:
```
data.passenger_count.value_counts()
```

[23]:
```
1    517448
2    105097
5     38926
3     29692
6     24107
4     14050
Name: passenger_count, dtype: int64
```

1.1.17 Data is consistent.

[24]:
```
sns.countplot(data.passenger_count)
plt.show()
```

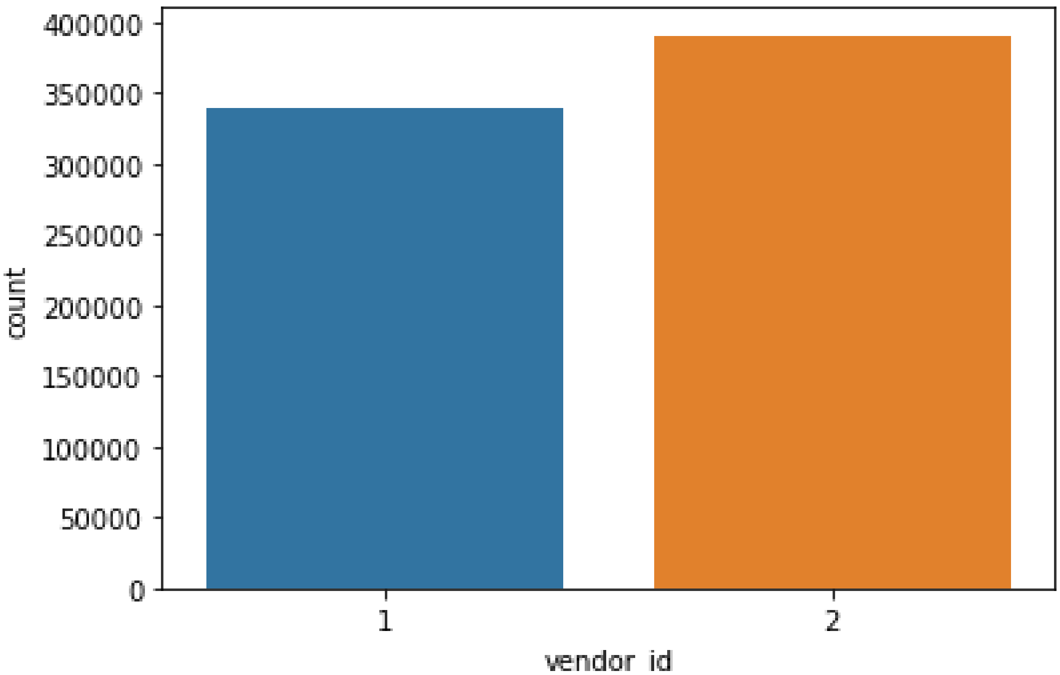


1.1.18 Observation

- Most of the trips was taken by single passenger and that is inline with our day to day observations

1.1.19 Vendor

[25]:
```
sns.countplot(data.vendor_id)
plt.show()
```



1.1.20 Observation

- Vendor 2 is evidently more famous among the population as per the above graph. It has more number of trips as compared to vendor 1
- Vendor 2 has greater market share than vendor 1

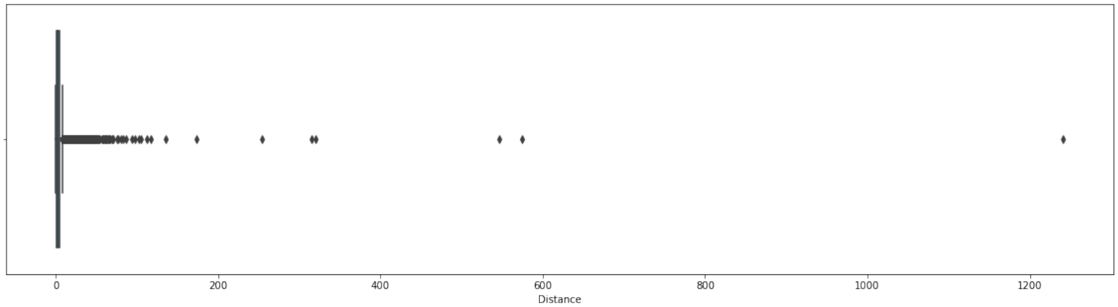
1.1.21 Distance

Distribution of distance at different rides

[26]:
```
data['Distance'].describe()
```

[26]:
```
count    729320.000000
mean          3.441153
std           4.353140
min           0.000000
25%           1.232700
50%           2.095678
75%           3.876491
max        1240.910391
Name: Distance, dtype: float64
```

[27]:
```
plt.figure(figsize = (20,5))
sns.boxplot(data.Distance)
plt.show()
```



1.1.22 Findings

- There are trips where more than 100km distance
- Some of the trips whosee distance value is 0km

1.1.23 Observations

- mean distance travelled is approx 3.5 kms.
- standard deviation of 4.3 which shows that most of the trips are limited to the range of 1-10 kms.

[28]:
```
print("There are {} trip records with 0 km distance".format(data.Distance[data.
↪Distance == 0 ].count()))
```

```
There are 2900 trip records with 0 km distance
```

[29]:
```
data[data.Distance==0].head()
```

[29]:
```
             id  vendor_id     pickup_datetime    dropoff_datetime  \
263   id3155891          2 2016-06-28 11:21:00 2016-06-28 11:25:00
327   id0786923          2 2016-03-26 13:34:38 2016-03-26 13:37:17
795   id2323213          2 2016-06-13 16:49:52 2016-06-13 17:04:49
1176  id3235868          1 2016-02-29 21:39:52 2016-02-29 21:44:08
1257  id1865738          2 2016-03-13 11:38:36 2016-03-13 12:00:46

      passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
263                 2        -73.996422        40.298828         -73.996422
327                 1        -73.996323        40.753460         -73.996323
795                 5        -73.967171        40.763500         -73.967171
1176                1        -73.995232        40.744038         -73.995232
1257                2        -73.912781        40.804428         -73.912781

      dropoff_latitude store_and_fwd_flag  …  pickup_hour_22 pickup_hour_23  \
263          40.298828                  N  …               0              0
327          40.753460                  N  …               0              0
795          40.763500                  N  …               0              0
```

```
1176        40.744038                   N  …              0              0
1257        40.804428                   N  …              0              0

      passenger_count_1  passenger_count_2  passenger_count_3  \
263                   0                  1                  0
327                   1                  0                  0
795                   0                  0                  0
1176                  1                  0                  0
1257                  0                  1                  0

      passenger_count_4  passenger_count_5  passenger_count_6  \
263                   0                  0                  0
327                   0                  0                  0
795                   0                  1                  0
1176                  0                  0                  0
1257                  0                  0                  0

      passenger_count_7  passenger_count_9
263                   0                  0
327                   0                  0
795                   0                  0
1176                  0                  0
1257                  0                  0

[5 rows x 61 columns]
```

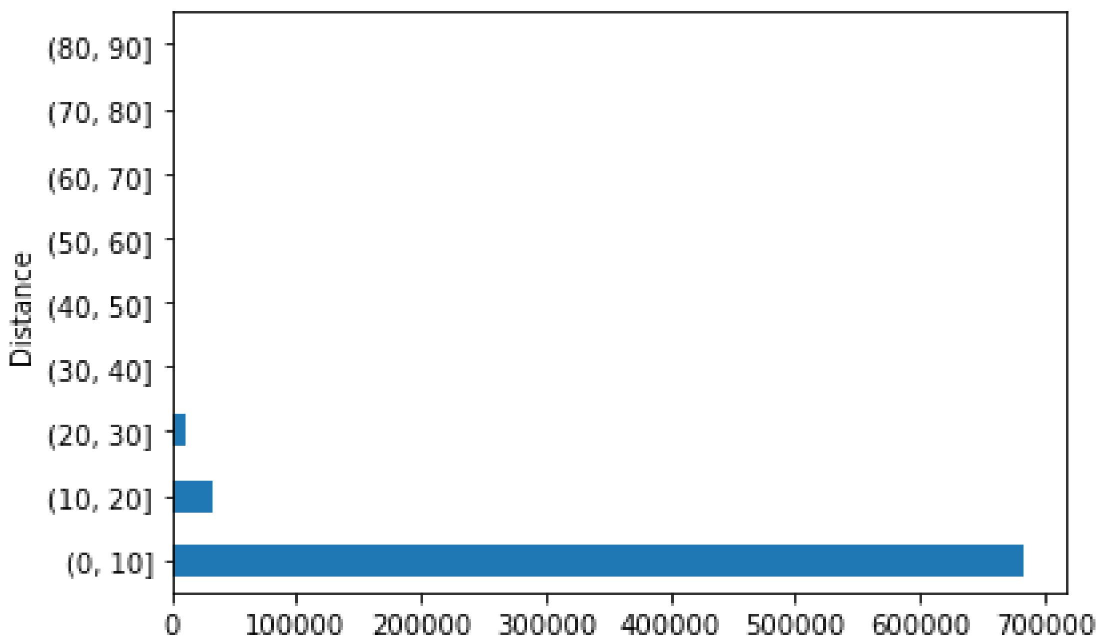
1.1.24 Observation

Around 3K trip record with distance equal to 0. Below are some possible explanation for such records.

1) Customer changed mind and cancelled the journey just after accepting it.
2) Software didn't recorded dropoff location properly due to which dropoff location is the same as the pickup location.
3) Issue with GPS tracker while the journey is being finished.
4) Driver cancelled the trip just after accepting it due to some reason. So the trip couldn't start
5) Or some other issue with the software itself which a technical guy can explain

There is some serious inconsistencies in the data where drop off location is same as the pickup location. Imputing the distance values is not possible by considering a correlation with the duration, then the dropoff_location coordinates would not be inline with the distance otherwise.

[30]:
```
data.Distance.groupby(pd.cut(data.Distance, np.arange(0,100,10))).count().
 ↪plot(kind='barh')
plt.show()
```



1.1.25 Observation

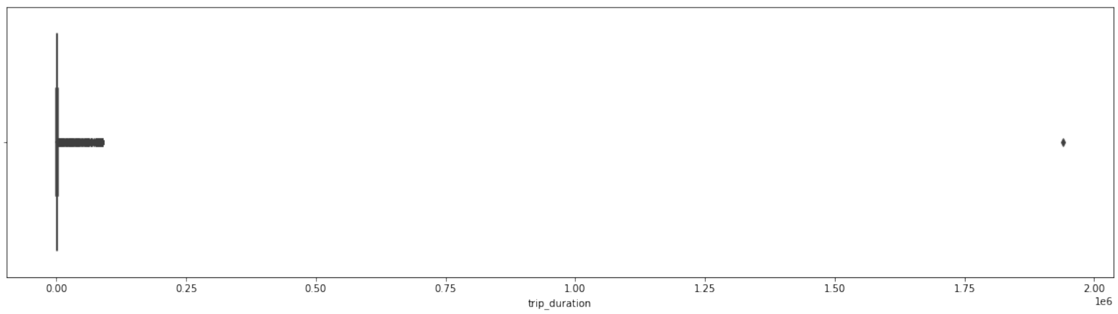
- Most of the rides are completed between 1-10 Kms with some of the rides with distances between 10-30 kms.
- Other slabs bar are not visible because the number of trips are very less as compared to these slabs

1.1.26 Trip Duration

[31]:
```
data.trip_duration.describe()
```

[31]:
```
count    7.293200e+05
mean     9.522310e+02
std      3.864631e+03
min      1.000000e+00
25%      3.970000e+02
50%      6.630000e+02
75%      1.075000e+03
max      1.939736e+06
Name: trip_duration, dtype: float64
```

[32]:
```
plt.figure(figsize = (20,5))
sns.boxplot(data.trip_duration)
plt.show()
```



1.1.27 Observation

- Most of the trips are from 400 seconds to 1075 seconds
- There are outliers which are to be removed.
- Mean and median are not same and mean is greater than median which means the data is right-skewed.
- There are some durations with as low as 1 second. which points towards trips with 0 km distance.

[33]:
```
data.trip_duration.groupby(pd.cut(data.trip_duration, np.arange(1,max(data.
↪trip_duration),3600))).count()
```

[33]:
```
trip_duration
(1, 3601]              723251
(3601, 7201]             4964
(7201, 10801]              61
(10801, 14401]             15
(14401, 18001]              2
                        …
(1918801, 1922401]          0
(1922401, 1926001]          0
(1926001, 1929601]          0
(1929601, 1933201]          0
(1933201, 1936801]          0
Name: trip_duration, Length: 538, dtype: int64
```

1.1.28 Observation

- Most of the trips occurs within 1 hour with some good numbers of trips duration going above 1 hour.
- There are trips with ore than 24 hours of travel duration i.e. 86400 seconds which might have occured for the outstation travels.

[34]:
```
data[data.trip_duration > 86400]
```

[34]:
```
                id  vendor_id     pickup_datetime    dropoff_datetime  \
21813  id1864733          1 2016-01-05 00:19:42 2016-01-27 11:08:38

       passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
21813                1         -73.78965        40.643559          -73.95681

       dropoff_latitude store_and_fwd_flag  …  pickup_hour_22  \
21813         40.773087                  N  …               0

      pickup_hour_23  passenger_count_1  passenger_count_2  passenger_count_3  \
21813              0                  1                  0                  0

       passenger_count_4  passenger_count_5  passenger_count_6  \
21813                  0                  0                  0

       passenger_count_7  passenger_count_9
21813                  0                  0

[1 rows x 61 columns]
```

1.1.29 Observation

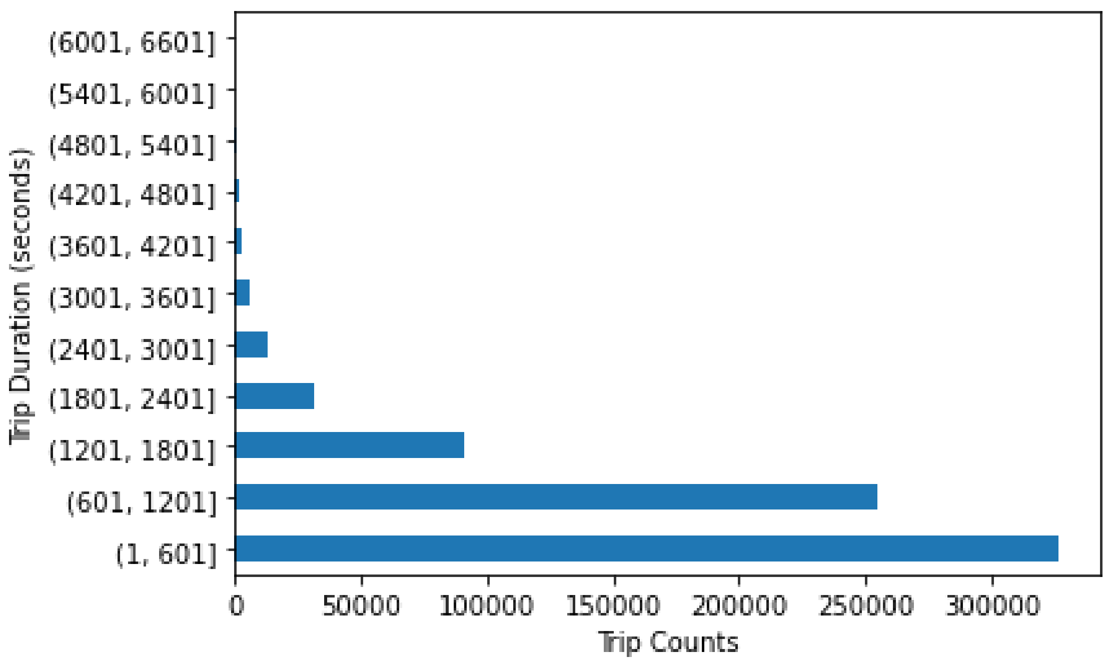
- One trip ran for more than 20 days.
- This trip is taken by vendor 1 which they might allow longer trip
- The trip taken on Tuesday in the first month with the distance of 20kms.

They fail for correct predictions and they bring inconsistency in the algorithm

[35]:
```
data = data[data.trip_duration <= 86400]
```

Visualizing the number of trips taken in slabs of 0-10, 20-30 … minutes respectively

[36]:
```
data.trip_duration.groupby(pd.cut(data.trip_duration, np.arange(1,7200,600))).
 ↪count().plot(kind='barh')
plt.xlabel('Trip Counts')
plt.ylabel('Trip Duration (seconds)')
plt.show()
```



1.1.30 Obseravtion

- Most of the trips took 0 - 30 mins to complete

1.1.31 Speed

Speed is a function of distance and time. Let's visualize speed in different trips. Maximum speed limit in NYC is as follows:

25 mph in urban area i.e. 40 km/hr

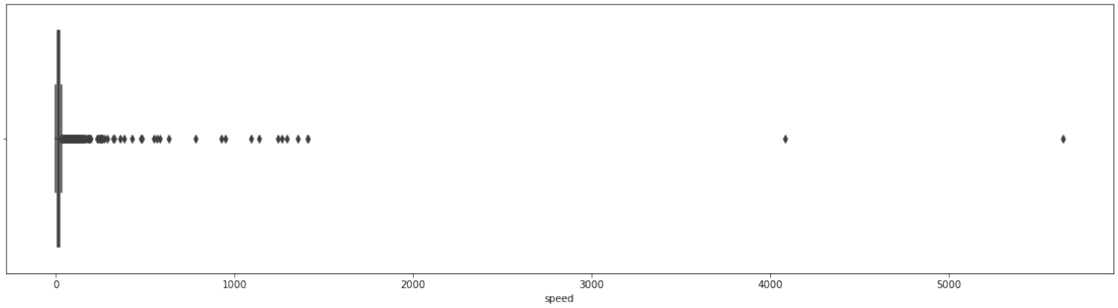
65 mph on controlled state highways i.e. approx 104 km/hr

[37]:
```
data['speed'].describe()
```

[37]:
```
count    729319.000000
mean         14.421527
std          12.341036
min           0.000000
25%           9.124341
50%          12.796887
75%          17.844052
max        5640.501776
Name: speed, dtype: float64
```

[38]:
```
plt.figure(figsize = (20,5))
sns.boxplot(data.speed)
```

```
plt.show()
```

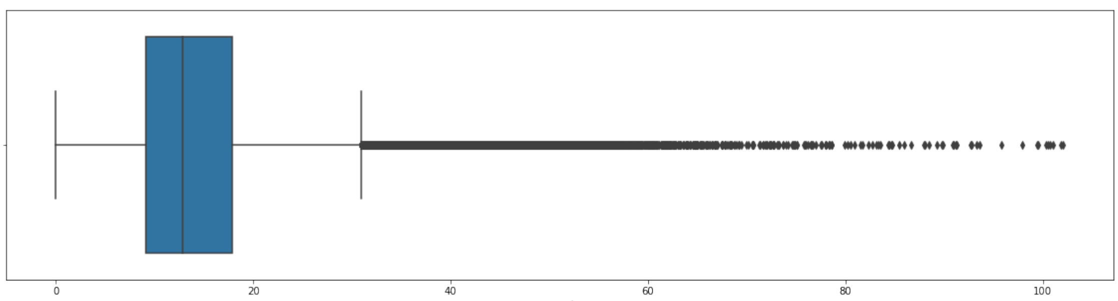


1.1.32 Observations

- Most of the trips are above 104km/hr. These are the outliers
- The maximun speed is 104km/hr on controlles state highways

Removing the speed which are greater than 104km/hr

[39]:
```
data = data[data.speed <= 104]
plt.figure(figsize = (20,5))
sns.boxplot(data.speed)
plt.show()
```

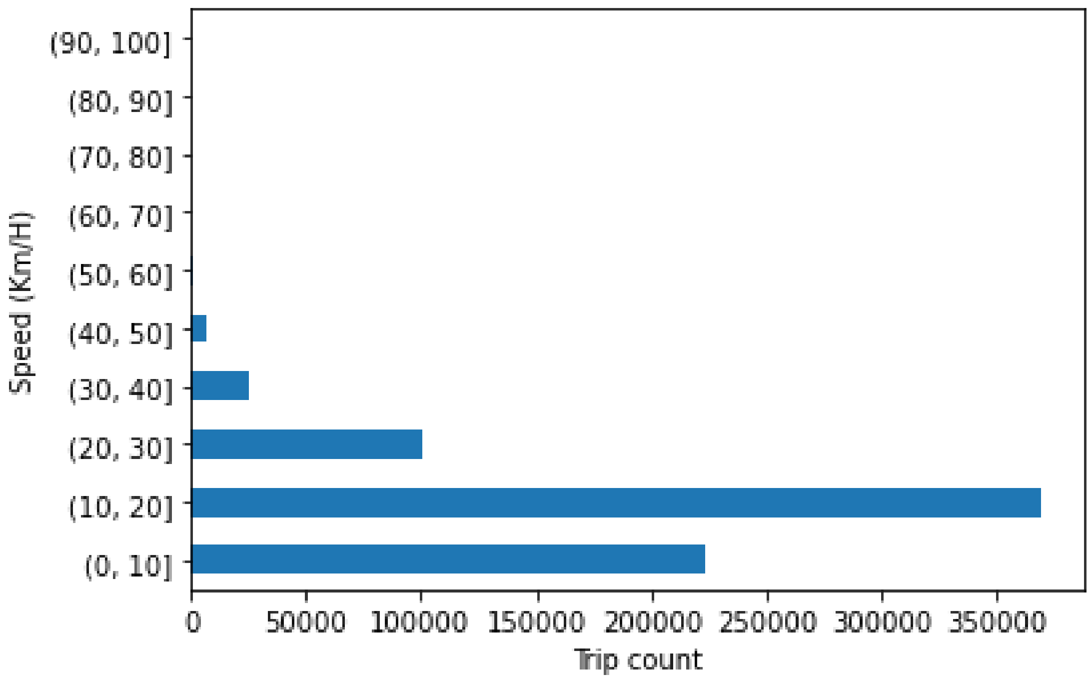


1.1.33 Observations

- Trips over 30 km/hr are being considered as outliers but we cannot ignore them because they are well under the highest speed limit of 104 km/h on state controlled highways.
- Mostly trips are done at a speed range of 10-20 km/hr with an average speed of around 14 km/hr.

1.1.34 speed range ditribution

[40]:
```
data.speed.groupby(pd.cut(data.speed, np.arange(0,104,10))).count().plot(kind =␣
 ↪'barh')
plt.xlabel('Trip count')
plt.ylabel('Speed (Km/H)')
plt.show()
```



1.1.35 Observation

It has been proved from this graph that most of the trips were done at a speed range of 10-20 km/hr.

1.1.36 Store_and_fwd_flag

This flag indicates whether the trip record was held in vehicle memory before sending to the vendor because the vehicle did not have a connection to the server - Y=store and forward; N=not a store and forward trip.

[41]:
```
data.flag_Y.value_counts(normalize=True)
```

[41]:
```
0    0.994461
1    0.005539
Name: flag_Y, dtype: float64
```

1.1.37 Observations

- Above result shows that only about 0.5% of the trip details were stored in the vehicle first before sending it to the server.

This might have occured because of the following reasons:

1) Outstation trips didn't had proper connection at the time when trip completes.
2) Temporary loss of signals while the trip was about to finish
3) Inconsistent signal reception over the trip duration.
4) The GPS or mobile device battery was down when the trip finished.

[42]:
```
data.flag_Y.value_counts()
```

[42]:
```
0    725200
1      4039
Name: flag_Y, dtype: int64
```

1.1.38 Observation

- Around 4K trips had to store the flag and then report to the server when the connection was established.

Distribution for the vendors of the offline trip

[43]:
```
data.vendor_id[data.flag_Y == 1].value_counts()
```

[43]:
```
1    4039
Name: vendor_id, dtype: int64
```

1.1.39 Observation

Above result shows that all the offline trips were taken by vendor 1. We already know that vendor 2 has greater market share as compared to vendor 1. So, there can be two reasons for this scenario.

1) Either vendor 1 utilizes advance technology than vendor 2 to store and forward trip details in case of temporary signal loss.
2) Or vendor 1 uses poor infrastructure which often suffers from the server connection instability due to which they have to store the trip info in the vehicle and send it to the server later when the server connection is back.

[44]:
```
data[data.flag_Y == 1]
```

[44]:
```
                id  vendor_id     pickup_datetime    dropoff_datetime  \
378      id1347533          1 2016-05-27 18:09:01 2016-05-27 18:16:30
400      id2733049          1 2016-03-02 20:05:12 2016-03-02 20:52:52
501      id2484490          1 2016-01-21 08:07:13 2016-01-21 08:18:21
644      id2090829          1 2016-01-11 12:10:13 2016-01-11 12:25:41
```

```
1278    id0512889          1 2016-06-10 21:20:14 2016-06-10 21:26:51
…           …        …                  …                  …
728481  id0008273          1 2016-04-08 17:52:56 2016-04-08 18:35:36
728607  id3254730          1 2016-06-03 01:21:11 2016-06-03 01:30:16
729074  id1347803          1 2016-03-17 01:24:10 2016-03-17 01:35:25
729119  id2265972          1 2016-01-07 07:51:18 2016-01-07 07:51:41
729217  id2475363          1 2016-06-17 13:40:15 2016-06-17 13:47:04

        passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
378                   1        -73.976051        40.744671         -73.979721
400                   2        -73.978134        40.757484         -73.998955
501                   1        -73.999771        40.739487         -73.983940
644                   2        -74.013611        40.714310         -73.976601
1278                  1        -73.958183        40.766190         -73.956032
…                   …              …                …                  …
728481                1        -73.969627        40.760384         -73.862061
728607                1        -74.004692        40.751846         -74.004860
729074                1        -73.988808        40.723038         -73.997543
729119                3        -73.782356        40.644211         -73.782364
729217                1        -73.985519        40.747314         -73.974854

        dropoff_latitude store_and_fwd_flag  …  pickup_hour_22  \
378            40.722958                  Y  …               0
400            40.614380                  Y  …               0
501            40.761421                  Y  …               0
644            40.751938                  Y  …               0
1278           40.782814                  Y  …               0
…                  …                …   …             …
728481         40.768559                  Y  …               0
728607         40.735130                  Y  …               0
729074         40.695587                  Y  …               0
729119         40.644211                  Y  …               0
729217         40.755192                  Y  …               0

       pickup_hour_23  passenger_count_1  passenger_count_2  \
378                 0                  1                  0
400                 0                  0                  1
501                 0                  1                  0
644                 0                  0                  1
1278                0                  1                  0
…                 …                …                 …
728481              0                  1                  0
728607              0                  1                  0
729074              0                  1                  0
729119              0                  0                  0
729217              0                  1                  0
```

```
        passenger_count_3  passenger_count_4  passenger_count_5  \
378                     0                  0                  0
400                     0                  0                  0
501                     0                  0                  0
644                     0                  0                  0
1278                    0                  0                  0
…                     …                …                …
728481                  0                  0                  0
728607                  0                  0                  0
729074                  0                  0                  0
729119                  1                  0                  0
729217                  0                  0                  0

        passenger_count_6  passenger_count_7  passenger_count_9
378                     0                  0                  0
400                     0                  0                  0
501                     0                  0                  0
644                     0                  0                  0
1278                    0                  0                  0
…                     …                …                …
728481                  0                  0                  0
728607                  0                  0                  0
729074                  0                  0                  0
729119                  0                  0                  0
729217                  0                  0                  0

[4039 rows x 61 columns]
```

1.1.40 Observation

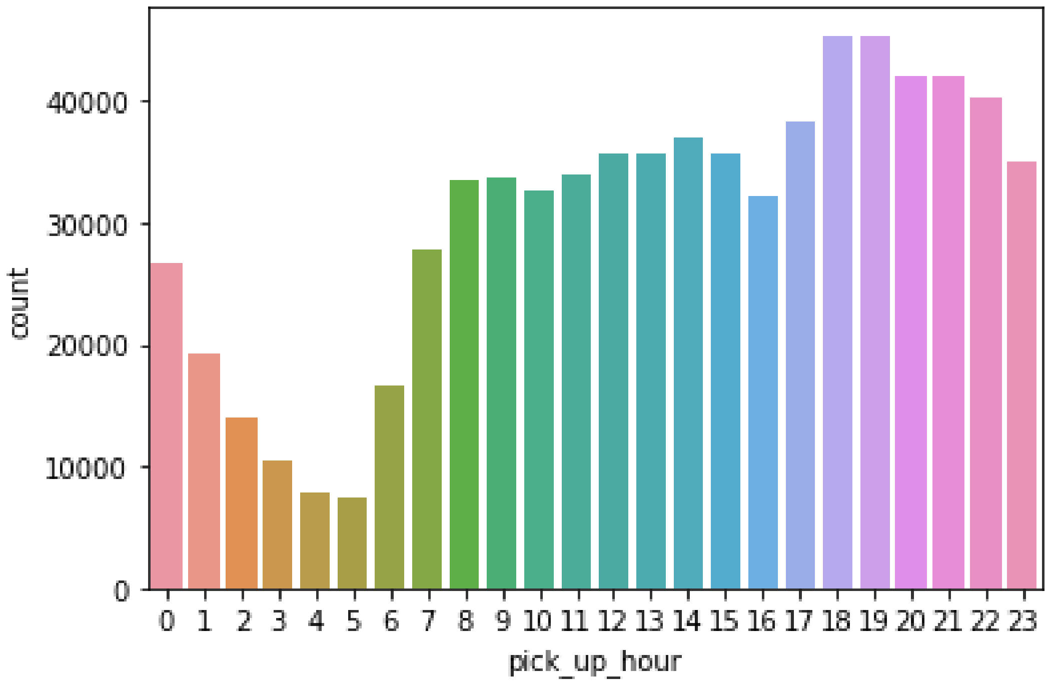
- Some trips are local some cover longer distance
- Almost each day is listed against offline trips.
- Offline trips were taken almost at all hours as per the search result.
- There is no month which appears to be more dominant in the results.
- Even the trip duration covers different scales.

So all in all there doesn't seems to be any relation with either of the metric for the offline

1.1.41 Total Trips per hour

Distribution of the pickups across the 24 hour time scale.

[45]:
```
sns.countplot(data.pick_up_hour)
plt.show()
```



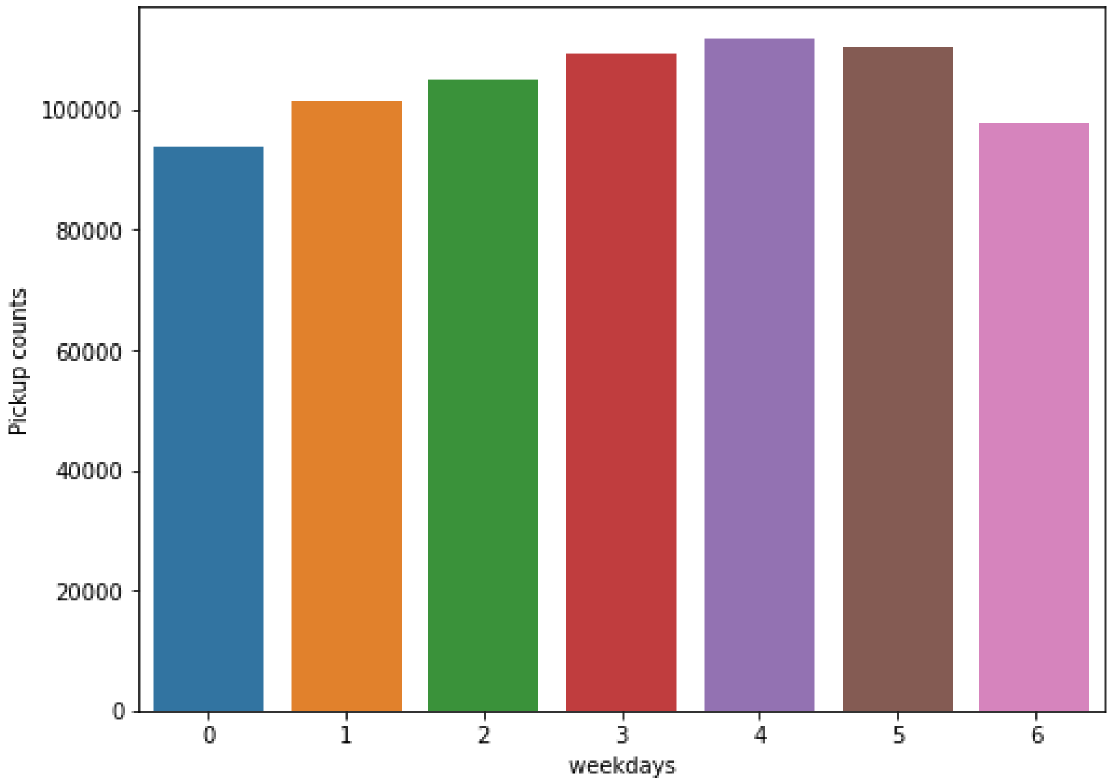
1.1.42 Observation

- Taxi pickups which starts increasing from 6AM in the morning and then declines from late evening i.e. around 7 PM.

1.1.43 Total trips per weekday

Distribution of taxi pickup across the week

[46]:
```
plt.figure(figsize = (8,6))
sns.countplot(data.weekday_num)
plt.xlabel(' weekdays ')
plt.ylabel('Pickup counts')
plt.show()
```

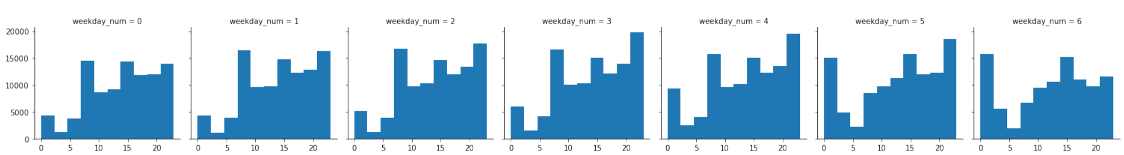


1.1.44 Observation

- Increasing trend of taxi pickups starting from Monday till Friday. The trend starts declining from saturday till monday which is normal where some office going people likes to stay at home for rest on the weekends.

Hourwise pickup pattern across the week

[47]:
```
n = sns.FacetGrid(data, col='weekday_num')
n.map(plt.hist, 'pick_up_hour')
plt.show()
```



1.1.45 Observation

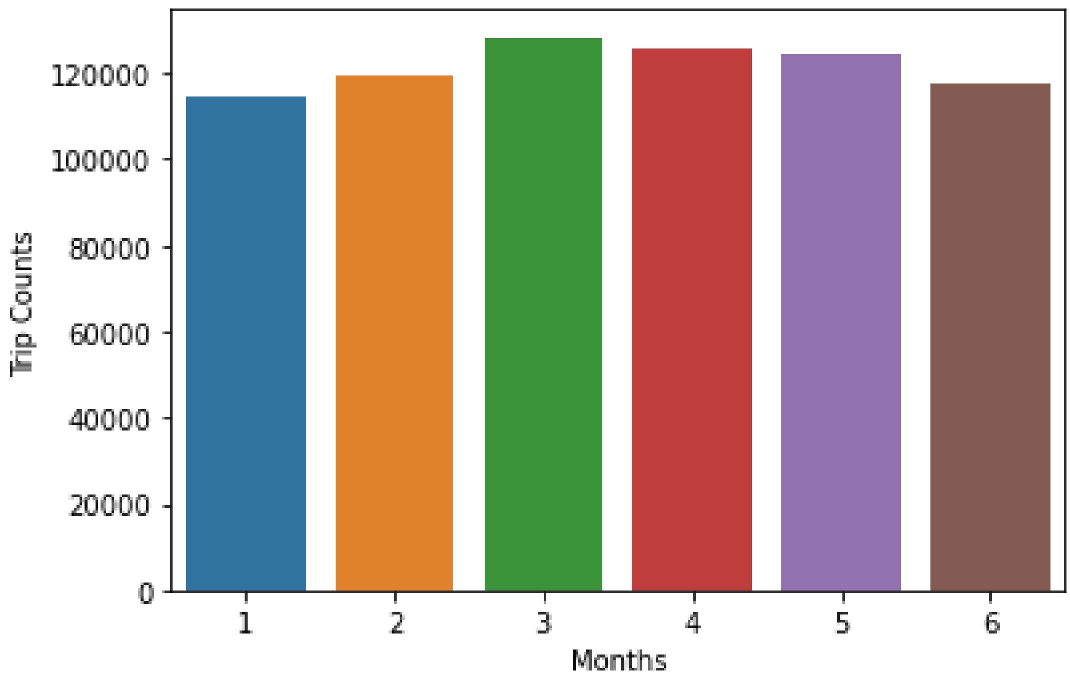
- Taxi pickups increased in the late night hours over the weekend possibly due to more outstation rides or for the late night leisures nearby activities.

- Early morning pickups i.e before 5 AM have increased over the weekend in comparison to the office hours pickups i.e. after 7 AM which have decreased due to obvious reasons.
- Taxi pickups seems to be consistent across the week at 15 Hours i.e. at 3 PM.

1.1.46 Total trips per month

Distribution of trip across the months

[48]:
```
sns.countplot(data.month)
plt.ylabel('Trip Counts')
plt.xlabel('Months')
plt.show()
```



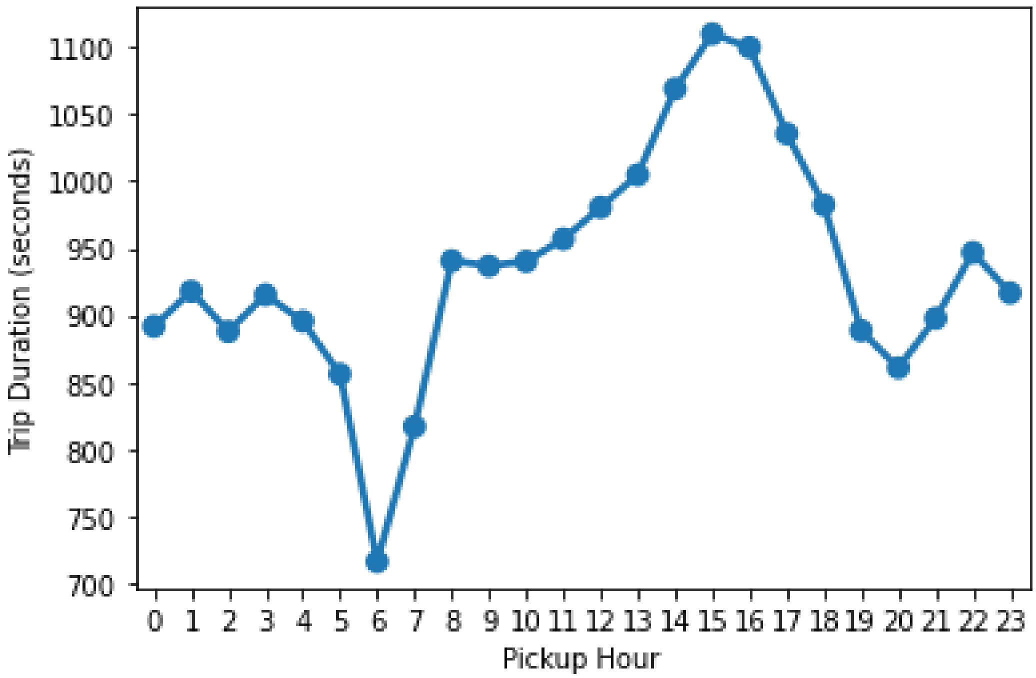
1.1.47 Observation

- There is balance in the trip across months

1.1.48 Bivariate Analysis

1.1.49 Trip duration per hour

[49]:
```
group1 = data.groupby('pick_up_hour').trip_duration.mean()
sns.pointplot(group1.index, group1.values)
plt.ylabel('Trip Duration (seconds)')
plt.xlabel('Pickup Hour')
plt.show()
```

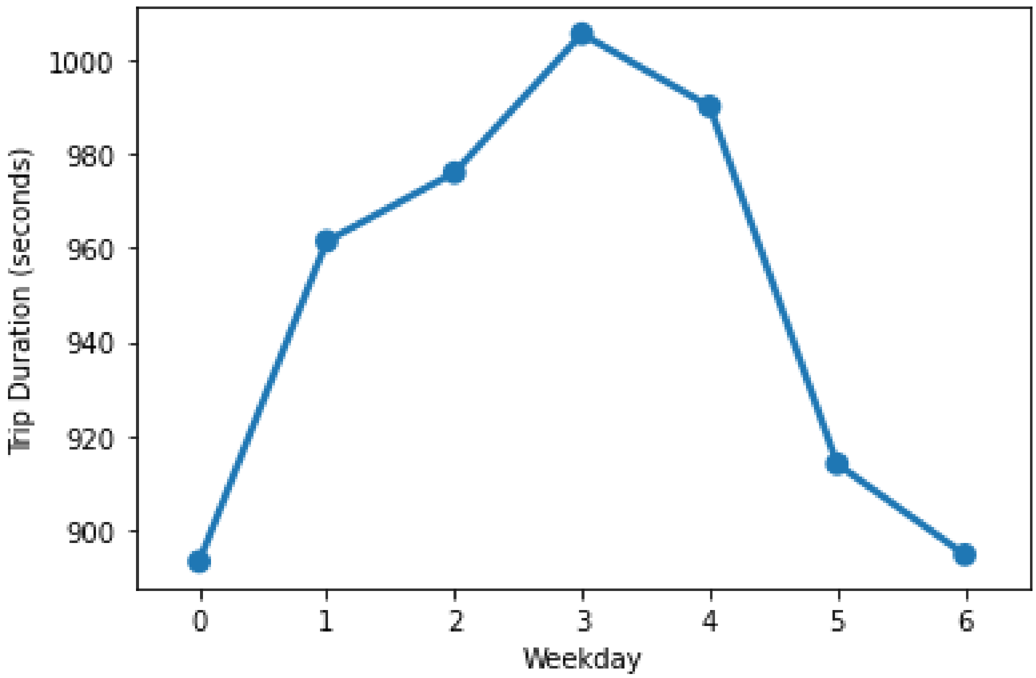


1.1.50 Observation

- Average trip duration is lowest at 6 AM when there is minimal traffic on the roads.
- Average trip duration is generally highest around 3 PM during the busy streets.
- Trip duration on an average is similar during early morning hours i.e. before 6 AM & late evening hours i.e. after 6 PM.

1.1.51 Trip duration per weekday

[50]:
```
group2 = data.groupby('weekday_num').trip_duration.mean()
sns.pointplot(group2.index, group2.values)
plt.ylabel('Trip Duration (seconds)')
plt.xlabel('Weekday')
plt.show()
```

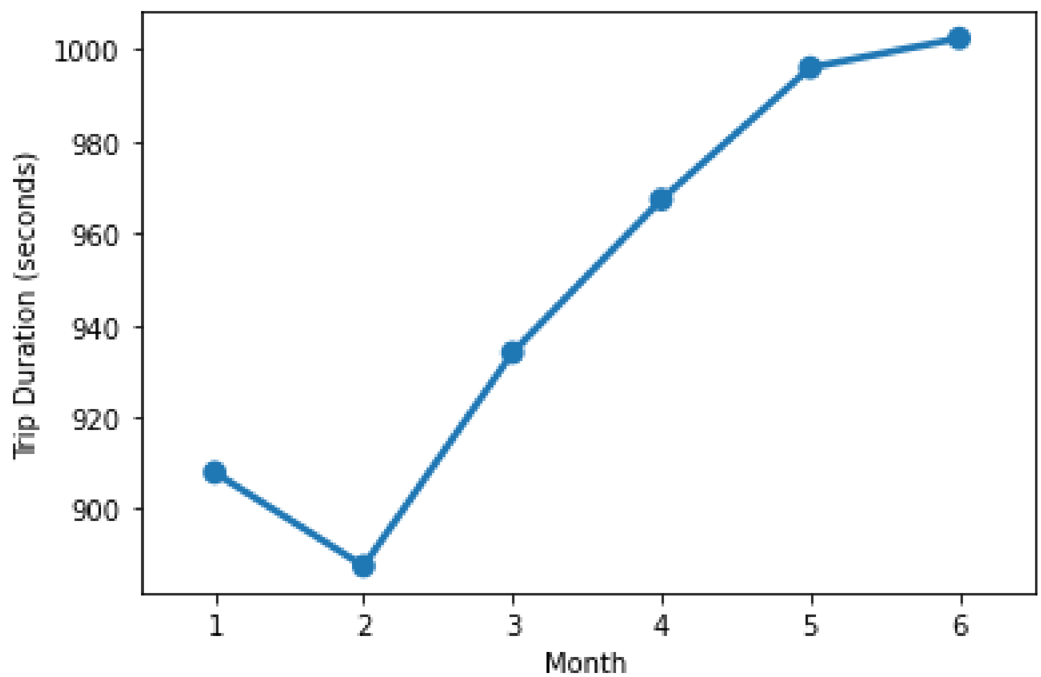


1.1.52 Observation

- Trip duration is almost equally distributed across the week on a scale of 0-1000 minutes with minimal difference in the duration times.
- Trip duration on thursday is longest among all days.

1.1.53 Trip duration per month

[51]:
```
group3 = data.groupby('month').trip_duration.mean()
sns.pointplot(group3.index, group3.values)
plt.ylabel('Trip Duration (seconds)')
plt.xlabel('Month')
plt.show()
```

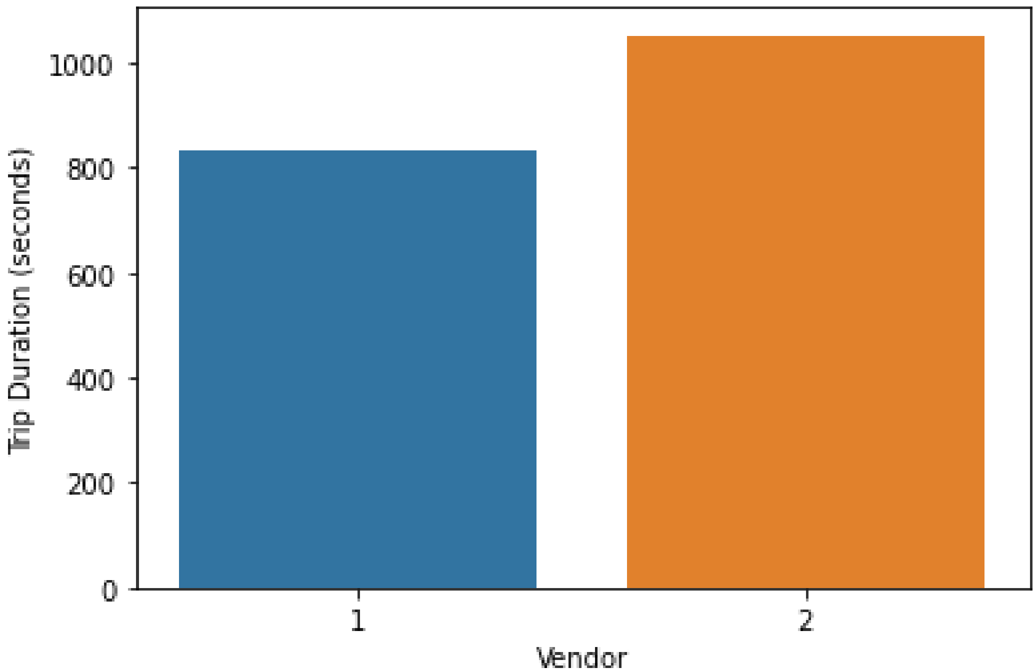


1.1.54 Observation

- Increasing trend in the average trip duration along with each subsequent month.
- The duration difference between each month is not much. It has increased gradually over a period of 6 months.
- It is lowest during february when winters starts declining.
- There might be some seasonal parameters like wind/rain which can be a factor of this gradual increase in trip duration over a period. Like May is generally the rainy season in NYC and which is inline with our visualization. As it generally takes longer on the roads due to traffic jams during rainy season. So natually the trip duration would increase towards April May and June.

1.1.55 Trip Duration per vendor

[52]:
```
group4 = data.groupby('vendor_id').trip_duration.mean()
sns.barplot(group4.index, group4.values)
plt.ylabel('Trip Duration (seconds)')
plt.xlabel('Vendor')
plt.show()
```

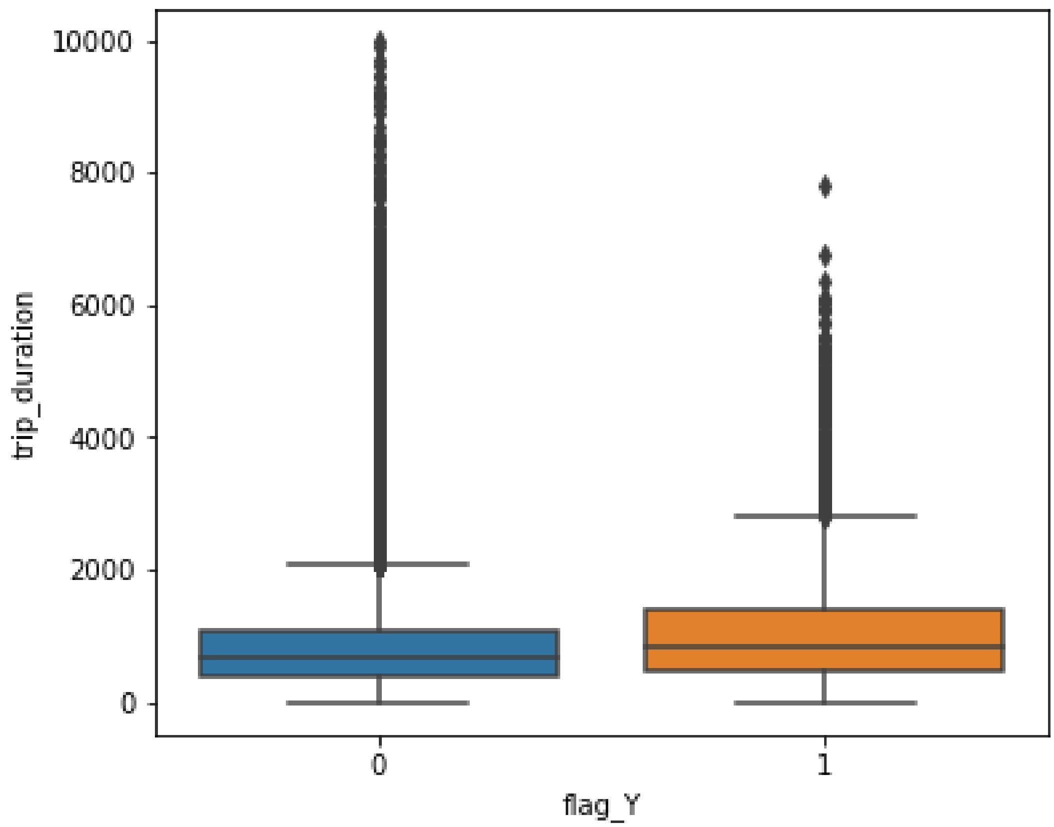


1.1.56 Observation

- Average trip duration for vendor 2 is higher than vendor 1 by approx 200 seconds i.e. atleast 3 minutes per trip.

1.1.57 Trip Duration Vs. flag

[53]:
```
plt.figure(figsize = (6,5))
plot_dur = data.loc[(data.trip_duration < 10000)]
sns.boxplot(x = "flag_Y", y = "trip_duration", data = plot_dur)
plt.show()
```



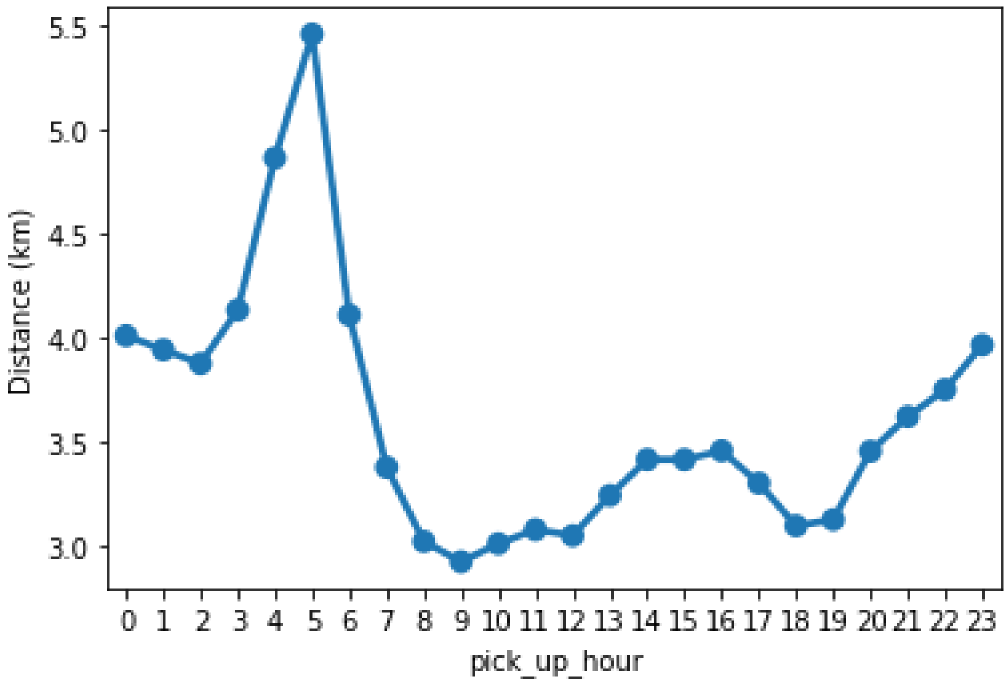
1.1.58 Observation

- Trip durations scale is less for the trips where the flag is set i.e. the trip details are stored before sending it to the server.
- Trip duration outliers are also less for the trips with flag 'Y' as compared the trips with flag 'N'.
- Trip duration is longer for the trips where the flag is not set.
- Inter quartile range of trip duration is more for the trips with the flag 'Y' as compared to the trips with flag 'N' but the median value is almost equal for both.

1.1.59 Distance per hour

Trip distance must be more or less proportional to the trip duration if we ignore general traffic and other stuff on the road.

[54]:
```
group5 = data.groupby('pick_up_hour').Distance.mean()
sns.pointplot(group5.index, group5.values)
plt.ylabel('Distance (km)')
plt.show()
```



1.1.60 Observation

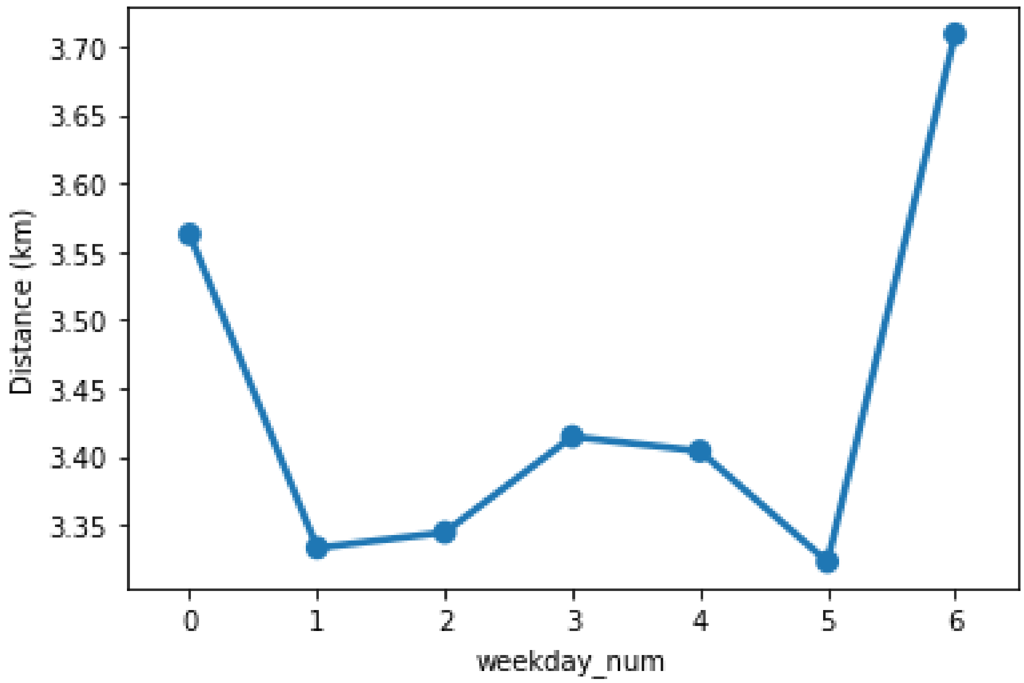
- Trip distance is highest during early morning hours which can account for some things like:

```
1) Outstation trips taken during the weekends.

2) Longer trips towards the city airport which is located in the outskirts of the city.
```

- Trip distance is fairly equal from morning till the evening varying around 3 - 3.5 kms.
- It starts increasing gradually towards the late night hours starting from evening till 5 AM and decrease steeply towards morning.

1.1.61 Distance per weekday

[55]:
```
group6 = data.groupby('weekday_num').Distance.mean()
sns.pointplot(group6.index, group6.values)
plt.ylabel('Distance (km)')
plt.show()
```

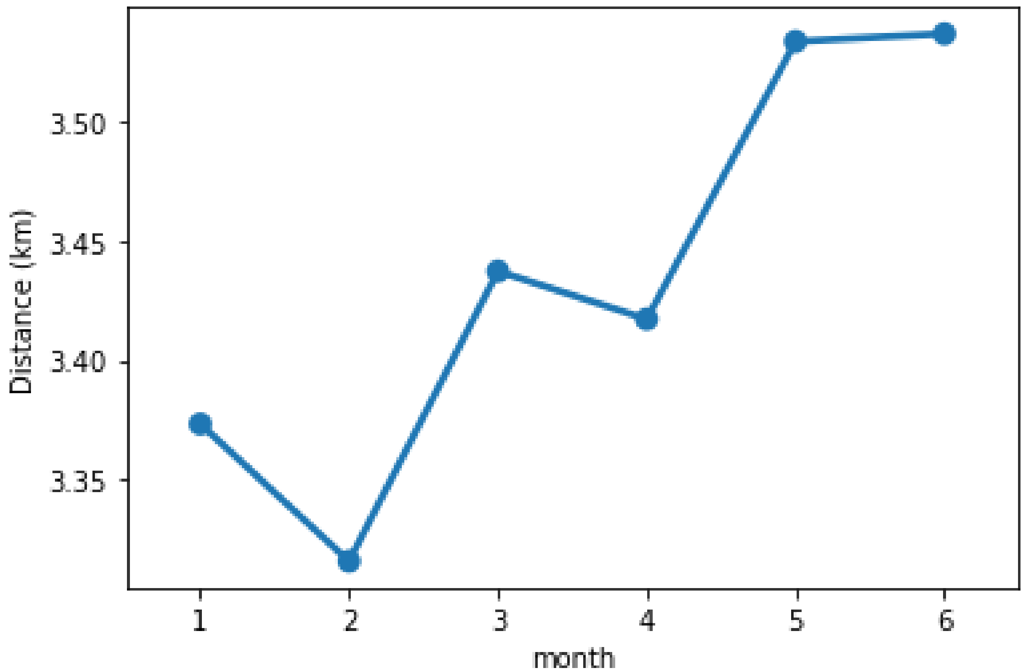


1.1.62 Observation

- Sunday to be in the top may be due to outstation trips or night trips towards the airport.
- Equal distribution with n average distance around 3.5 km/hr

1.1.63 Distance per month

[56]:
```
group7 = data.groupby('month').Distance.mean()
sns.pointplot(group7.index, group7.values)
plt.ylabel('Distance (km)')
plt.show()
```

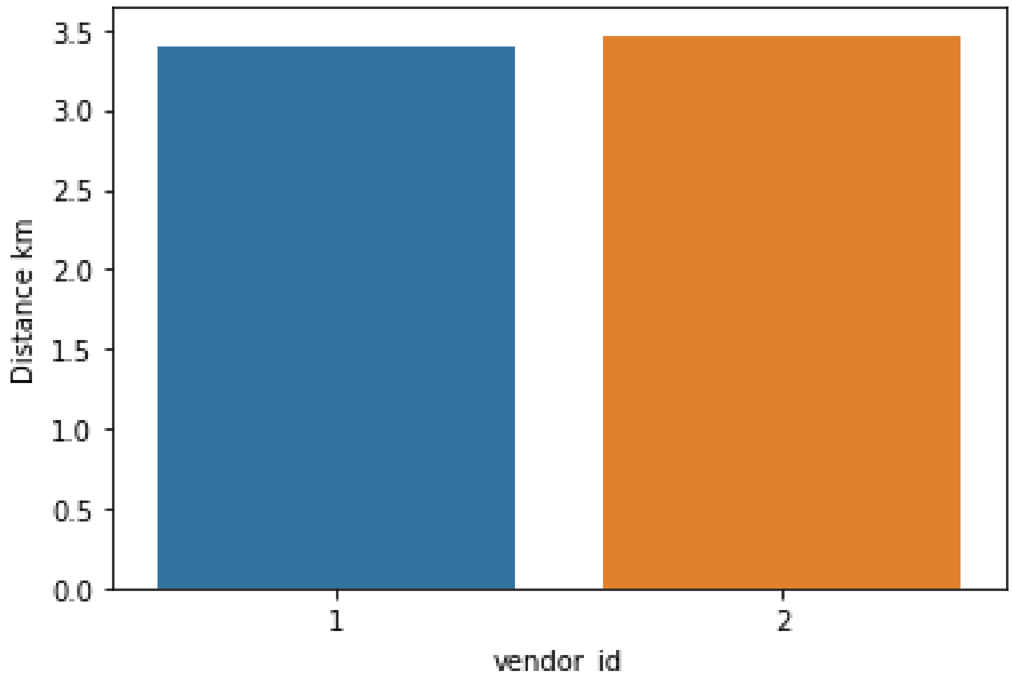


1.1.64 Observation

- The distibution is almost equivalent, varying mostly around 3.5 km/hr with 5th month being the highest in the average distance and 2nd month being the lowest.

1.1.65 Distance per vendor

[57]:
```
group8 = data.groupby('vendor_id').Distance.mean()
sns.barplot(group8.index, group8.values)
plt.ylabel("Distance km")
plt.show()
```

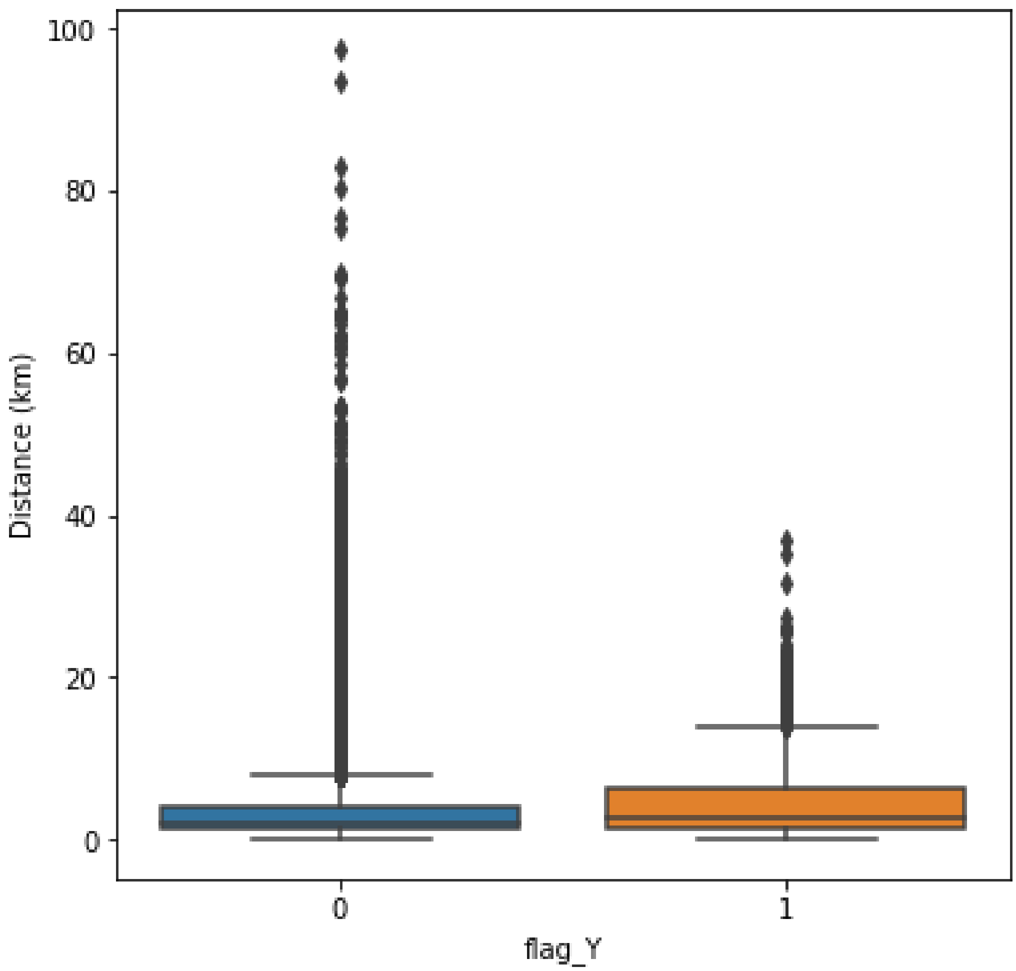


1.1.66 Observation

- Both the vendores are in the same with respect to distance

1.1.67 Distance Vs Flag

[58]:
```
plt.figure(figsize = (6,6))
plot_dist = data.loc[(data.Distance < 100)]
sns.boxplot(x = "flag_Y", y = "Distance", data = plot_dist)
plt.ylabel('Distance (km)')
plt.show()
```

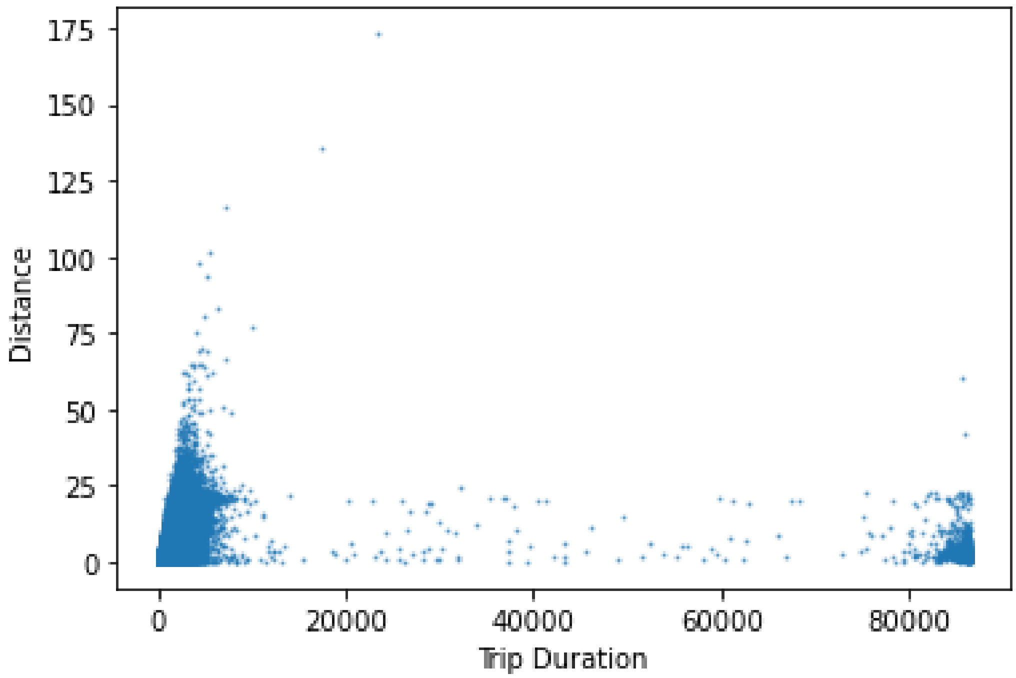


1.1.68 Observation

- Interquartile range of distance is almost twice for Flag 'Y' trips as compared to the Flag 'N' trips
- Median value is much different in both the case as well.
- The range of distance and trip duration for the Flag 'Y' trips is much more limited and confined as compared with the flag 'N' trips and this also resulted in much less number of outliers for Flag 'Y' trips.

1.1.69 Distance Vs. Trip duration

[59]:
```
plt.scatter(data.trip_duration, data.Distance , s=1, alpha=0.5)
plt.ylabel('Distance')
plt.xlabel('Trip Duration')
plt.show()
```

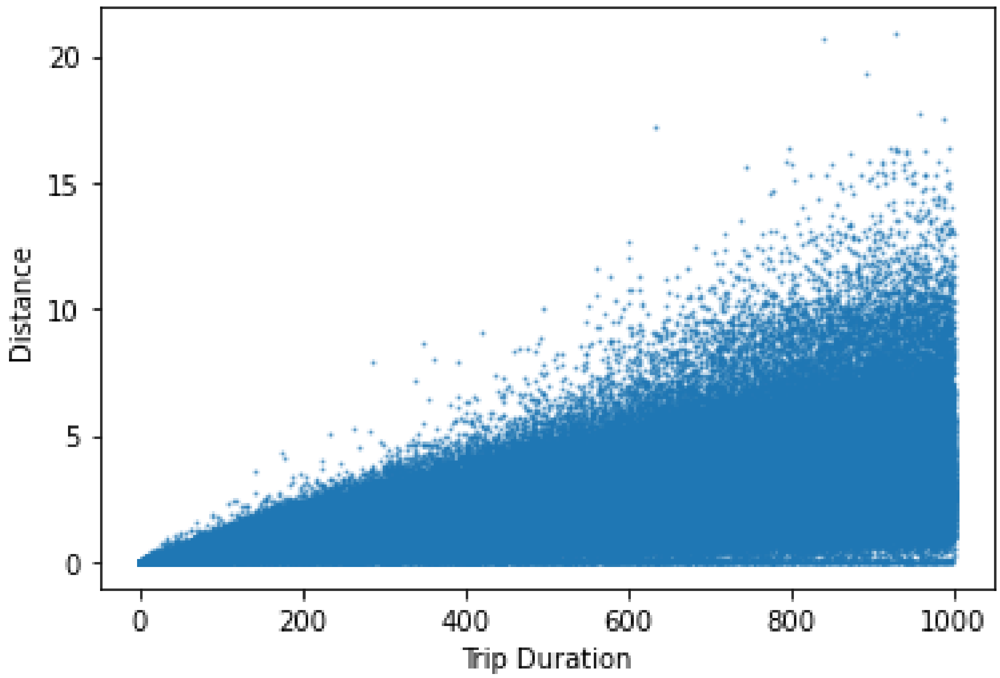


1.1.70 Observation

- There are lots of trips which covered negligible distance but clocked more than 20,000 seconds in terms of the Duration.
- Initially there is some proper correlation between the distance covered and the trip duration in the graph. but later on it all seems uncorrelated.
- There were few trips which covered huge distance of approx 200 kms within very less time frame, which is unlikely and should be treated as outliers.

Graph area where distance is < 50 km and duration is < 1000 seconds

[60]:
```
dur_dist = data.loc[(data.Distance < 50) & (data.trip_duration < 1000),␣
↪['Distance','trip_duration']]
plt.scatter(dur_dist.trip_duration, dur_dist.Distance , s=1, alpha=0.5)
plt.ylabel('Distance')
plt.xlabel('Trip Duration')
plt.show()
```



1.1.71 Observation

- There should have been a linear relationship between the distance covered and trip duration on an average but we can see dense collection of the trips in the lower right corner which showcase many trips with the inconsistent readings.

1.1.72 Idea:

- Remove those trips which covered 0 km distance but clocked more than 1 minute to make our data more consistent for predictive model. Because if the trip was cancelled after booking, than that should not have taken more than a minute time. This is our assumption.

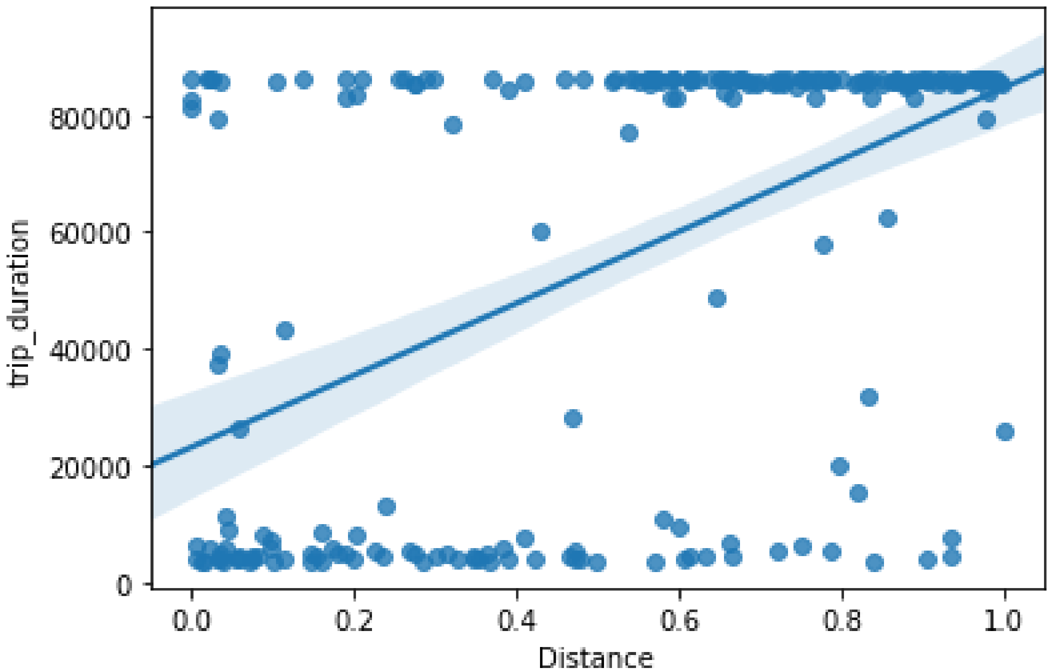
[61]:
```
data = data[~((data.Distance == 0) & (data.trip_duration >= 60))]
```

1.1.73 Observation

- Now, Instead of looking at each and every trip, we should approximate and try to filter those trips which covered less than 1 km distance and but clocked more than an hour.

[62]:
```
duo = data.loc[(data['Distance'] <= 1) & (data['trip_duration'] >=␣
↪3600),['Distance','trip_duration']].reset_index(drop=True)
```

[63]:
```
sns.regplot(duo.Distance, duo.trip_duration)
plt.show()
```



1.1.74 Observations:

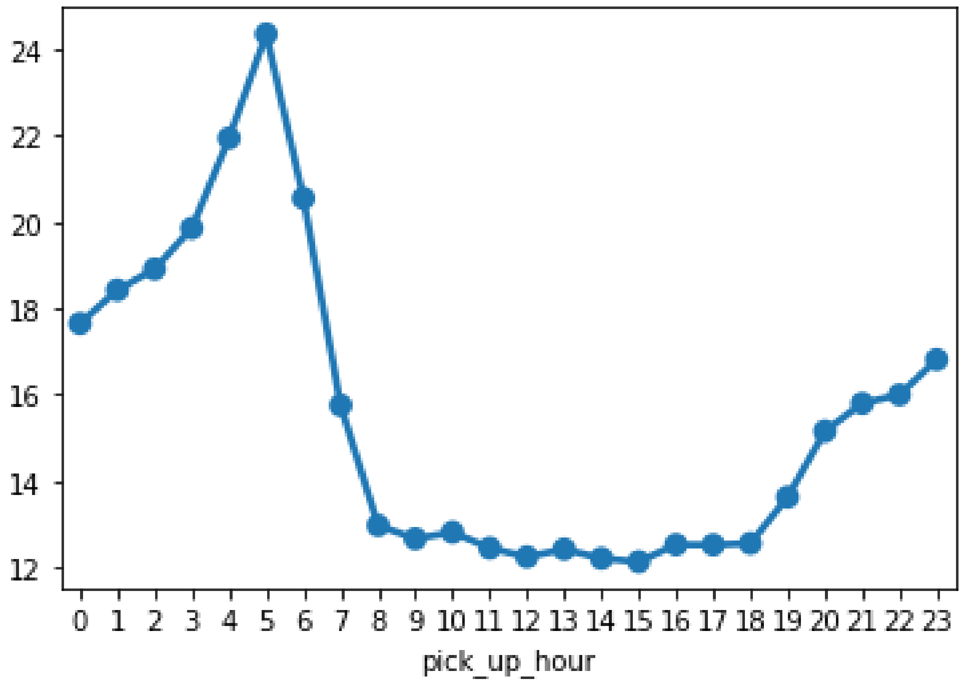
- Though the straight line tries to show some linear relation between the two. But there seems to be negligible correlation between these two metric as seen from the scatter plot where it should have been a linear distribution.
- It is rarely occurs that customer keep sitting in the taxi for more than an hour and it does not travel for even 1 km.

These should be removed to bring in more consistency to our results.

[64]:
```
data = data[~((data['Distance'] <= 1) & (data['trip_duration'] >= 3600))]
```

1.1.75 Average speed per hour

[65]:
```
group9 = data.groupby('pick_up_hour').speed.mean()
sns.pointplot(group9.index, group9.values)
plt.show()
```

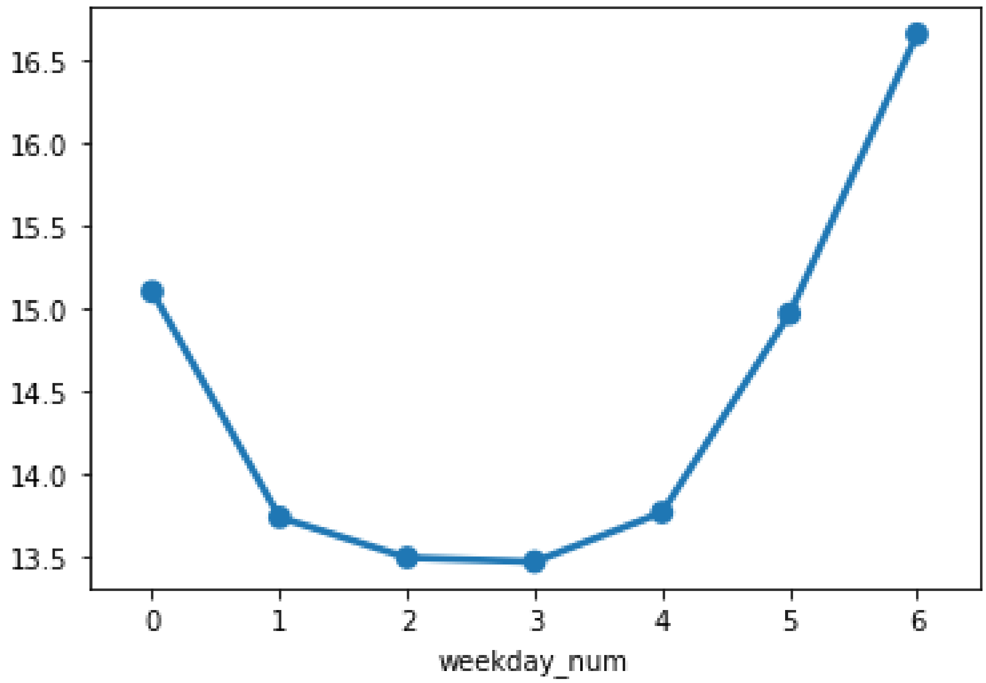


1.1.76 Observation

- The average trend is totally inline with the normal circumstances.
- Average speed tend to increase after late evening and continues to increase gradually till the late early morning hours.
- Average taxi speed is highest at 5 AM in the morning, then it declines steeply as the office hours approaches.
- Average taxi speed is more or less same during the office hours i.e. from 8 AM till 6PM in the evening.

1.1.77 Average speed per weekday

[66]:
```
group10 = data.groupby('weekday_num').speed.mean()
sns.pointplot(group10.index, group10.values)
plt.show()
```

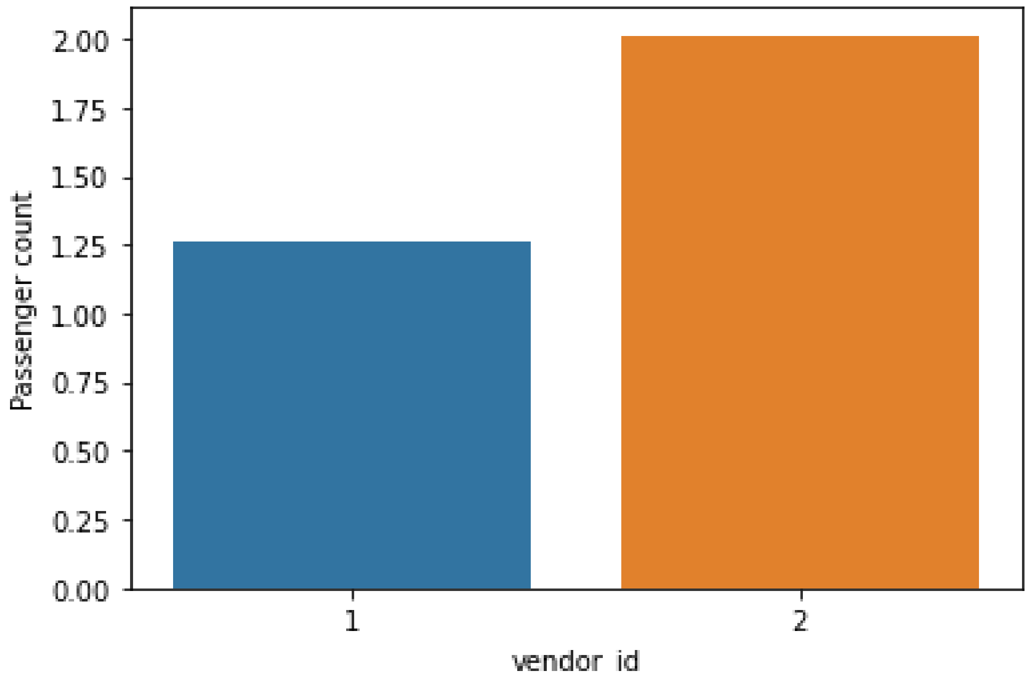


1.1.78 Observations

- Average taxi speed is higher on weekend as compared to the weekdays which is obvious when there is mostly rush of office goers and business owners.
- Even on monday the average taxi speed is shown higher which is quite surprising when it is one of the most busiest day after the weekend. There can be several possibility for such behaviour 1) Lot of customers who come back from outstation in early hours of Monday before 6 AM to attend office on time. 2) Early morning hours customers who come from the airports after vacation to attend office/business on time for the coming week.
- There could be some more reasons as well which only a local must be aware of.

1.1.79 Passenger count per vendor

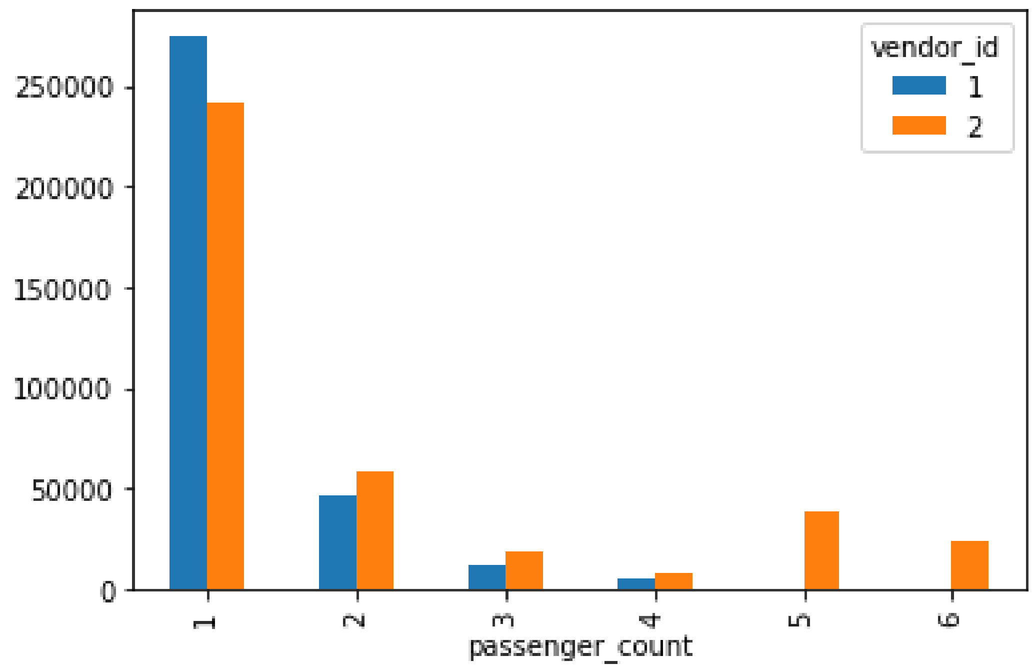
[67]:
```
group9 = data.groupby('vendor_id').passenger_count.mean()
sns.barplot(group9.index, group9.values)
plt.ylabel('Passenger count')
plt.show()
```



1.1.80 Observation

- Vendor 2 trips generally consist of 2 passengers as compared to the vendor 1 with 1 passenger.

[68]:
```
data.groupby('passenger_count').vendor_id.value_counts().
 ↪reset_index(name='count').pivot("passenger_count","vendor_id","count").
 ↪plot(kind='bar')
plt.show()
```



1.1.81 Observation

- Most of the big cars are served by the Vendor 2 including minivans because other than passenger 1, vendor 2 has majority in serving more than 1 passenger count and that explains it greater share of the market.

1.1.82 Map Visualization

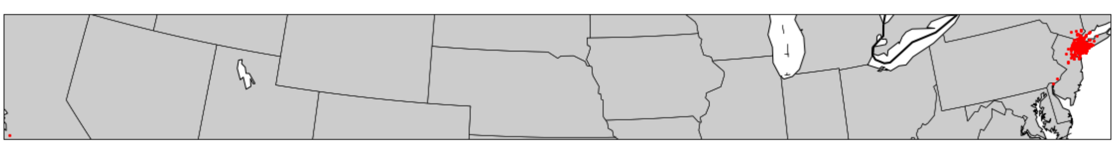
- Visualize the Taxi pickup locations by placing longitude and latitude marker on the MAP of the US. So that we can analyze below questions:
- Are all pickups constrained to NYC and it's surrounding areas?
- Is there any unusual location of the pickup?
- Are the latitude longitude constrained to the land area of the US and nowhere else?

[69]:
```
def map_marker(set):

    from mpl_toolkits.basemap import Basemap
    plt.figure(figsize = (20,20))

    lat_min = data["pickup_latitude"].min() - .2
    lat_max = data["pickup_latitude"].max() + .2
    lon_min = data["pickup_longitude"].min() - .2
    lon_max = data["pickup_longitude"].max() + .2
```

```
    cent_lat = (lat_min + lat_max) / 2
    cent_lon = (lon_min + lon_max) / 2


    map = Basemap(llcrnrlon=lon_min,
                  llcrnrlat=lat_min,
                  urcrnrlon=lon_max,
                  urcrnrlat=lat_max,
                  resolution='l',
                  projection='tmerc',
                  lat_0 = cent_lat,
                  lon_0 = cent_lon)


    map.drawmapboundary()
    map.drawcoastlines()
    map.fillcontinents()
    map.drawcountries(linewidth=2)
    map.drawstates()



    long = np.array(data["pickup_longitude"])
    lat = np.array(data["pickup_latitude"])

    x, y = map(long, lat)
    map.plot(x, y,'ro', markersize=2, alpha=1)

    plt.show()
```

1.1.83 Taxi pickup location

[70]:
```
map_marker(data)
```



1.1.84 Observation

- One unusual pickup from the CA state.
- There are quite a few pickup from the neighbouring state as well. Some are quite far and some very near to the NYC state

CA state pickup

[71]:
```
data[data.pickup_longitude == data.pickup_longitude.min()]
```

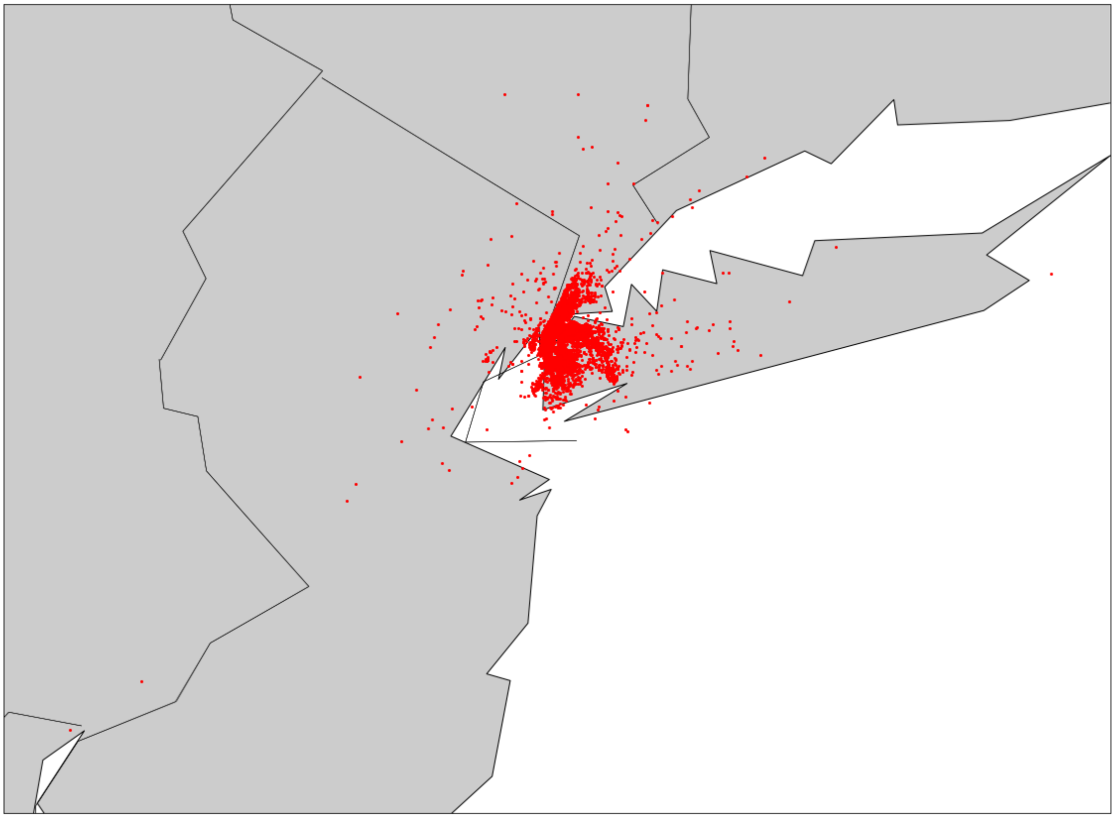
[71]:
```
                id  vendor_id     pickup_datetime    dropoff_datetime  \
421819  id2854272          2 2016-02-26 13:50:19 2016-02-26 13:58:38

        passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
421819                2       -121.933342        37.389381        -121.933304

        dropoff_latitude store_and_fwd_flag  …  pickup_hour_22  \
421819         37.389511                  N  …               0

       pickup_hour_23  passenger_count_1  passenger_count_2  \
421819              0                  0                  1

        passenger_count_3  passenger_count_4  passenger_count_5  \
421819                  0                  0                  0

        passenger_count_6  passenger_count_7  passenger_count_9
421819                  0                  0                  0

[1 rows x 61 columns]
```

1.1.85 Observation

- The trip duration is approx 8 minutes still the distance travelled is just in few meters.
- Moreover the Latitude and Longitude readings are same.
- These are the outliers and should be removed for the consistency of the model

[72]:
```
data = data[data.pickup_longitude != data.pickup_longitude.min()]
```

[73]:
```
map_marker(data)
```



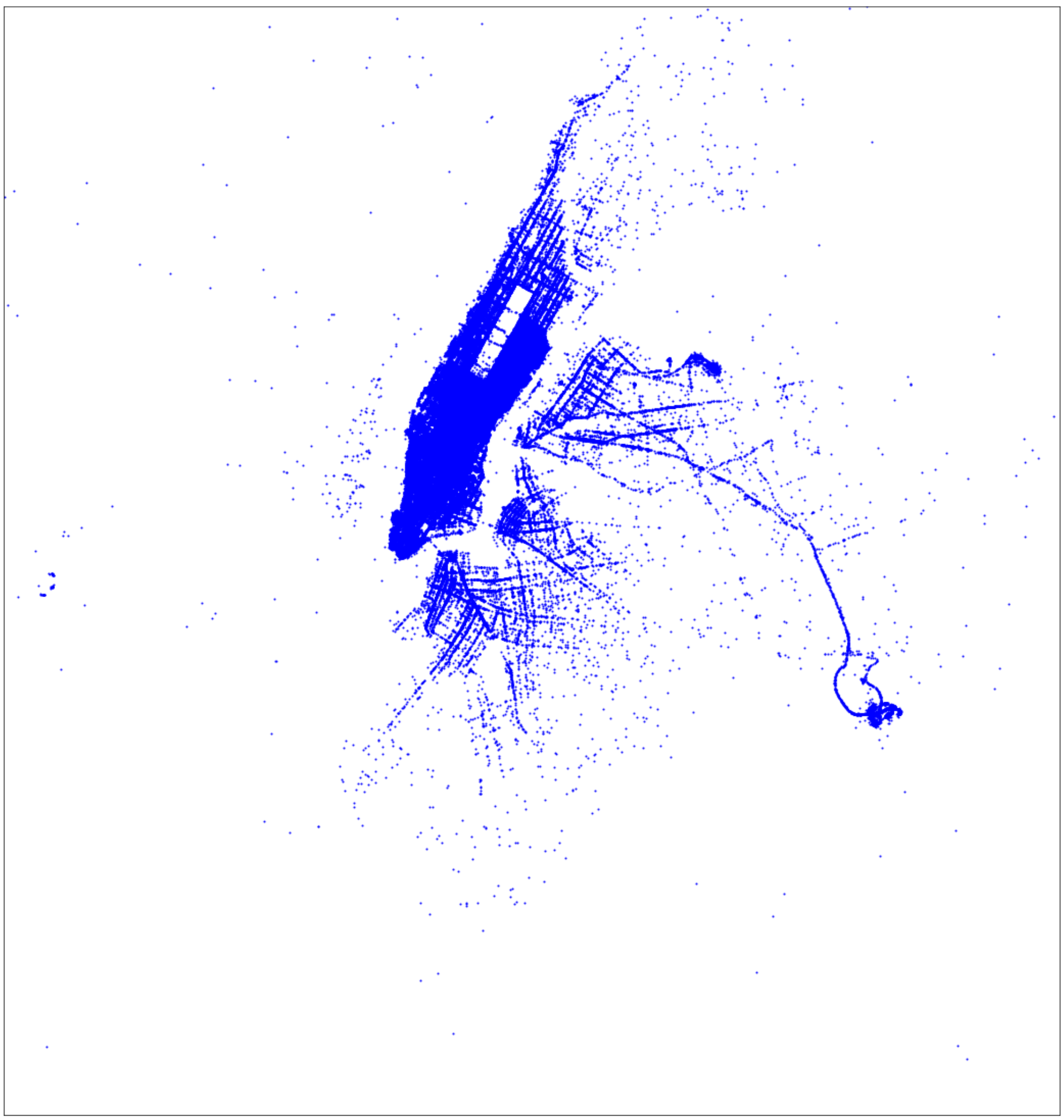
1.1.86 Observation

- There are quite a few pickups being shown off the NYC coast i.e. in the Atlantic ocean.
- Most of the pickups are being shown in and around NYC area.

1.1.87 NYC pickup locations

[74]:
```
plt.figure(figsize=(20,20))
from mpl_toolkits.basemap import Basemap

lat_min = 40.5
lat_max = 40.9
lon_min = -74.2
lon_max = -73.7

cent_lat = (lat_min + lat_max) / 2
cent_lon = (lon_min + lon_max) / 2

map = Basemap(llcrnrlon=lon_min,
              llcrnrlat=lat_min,
              urcrnrlon=lon_max,
```

```
                urcrnrlat=lat_max,
                resolution='l',
                projection='tmerc',
                lat_0 = cent_lat,
                lon_0 = cent_lon)

long = np.array(data["pickup_longitude"])
lat = np.array(data["pickup_latitude"])

x, y = map(long, lat)
map.plot(x, y,'bo', markersize=1, alpha=1)
plt.xticks()
plt.show()
```



1.1.88 Observations

- Most of the taxi pickups were done in the manhattan area as compared to the other areas in NYC.
- A long trail towards the airport shows that the airport is situated quite far from the Manhattan area.
- There must have been some long distance rides towards and from the airport.
- Similarly the average duration for the rides picked-up to or for the airport would have been longer.

1.1.89 NYC drop off location

[75]:
```
plt.figure(figsize=(20,20))

lat_min = 40.5
lat_max = 40.9
lon_min = -74.2
lon_max = -73.7

cent_lat = (lat_min + lat_max) / 2
cent_lon = (lon_min + lon_max) / 2

map = Basemap(llcrnrlon=lon_min,
              llcrnrlat=lat_min,
              urcrnrlon=lon_max,
              urcrnrlat=lat_max,
              resolution='l',
              projection='tmerc',
              lat_0 = cent_lat,
              lon_0 = cent_lon)

long = np.array(data["dropoff_longitude"])
lat = np.array(data["dropoff_latitude"])

x, y = map(long, lat)
map.plot(x, y,'go', markersize=1, alpha=1)
plt.xticks()
plt.show()
```

1.1.90 Observation

- Dropoff's are much more distributed around the NYC area where still most of the dropoff's were done in the Manhattan.

1.1.91 Question:

- Does that mean there were more dropoff's than the pickup's?

1.1.92 Idea:

- Though the dropoffs seems to be larger in number than the pickups. But for each pickup we have a associated dropoffs in the dataset. It's just that the pickups were majorly concentrated in the Manhattan area.

[76]:
```
data
```

[76]:
```
                 id  vendor_id      pickup_datetime     dropoff_datetime  \
0         id1080784          2  2016-02-29 16:40:21  2016-02-29 16:47:01
1         id0889885          1  2016-03-11 23:35:37  2016-03-11 23:53:57
2         id0857912          2  2016-02-21 17:59:33  2016-02-21 18:26:48
3         id3744273          2  2016-01-05 09:44:31  2016-01-05 10:03:32
4         id0232939          1  2016-02-17 06:42:23  2016-02-17 06:56:31
…               …          …                  …                  …
729317    id3905982          2  2016-05-21 13:29:38  2016-05-21 13:34:34
729318    id0102861          1  2016-02-22 00:43:11  2016-02-22 00:48:26
729319    id0439699          1  2016-04-15 18:56:48  2016-04-15 19:08:01
729320    id2078912          1  2016-06-19 09:50:47  2016-06-19 09:58:14
729321    id1053441          2  2016-01-01 17:24:16  2016-01-01 17:44:40

        passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
0                     1        -73.953918        40.778873         -73.963875
1                     2        -73.988312        40.731743         -73.994751
2                     2        -73.997314        40.721458         -73.948029
3                     6        -73.961670        40.759720         -73.956779
4                     1        -74.017120        40.708469         -73.988182
…                   …               …               …                 …
729317                2        -73.965919        40.789780         -73.952637
729318                1        -73.996666        40.737434         -74.001320
729319                1        -73.997849        40.761696         -74.001488
729320                1        -74.006706        40.708244         -74.013550
729321                4        -74.003342        40.743839         -73.945847

        dropoff_latitude store_and_fwd_flag  …  pickup_hour_22  \
0              40.771164                  N  …               0
1              40.694931                  N  …               0
2              40.774918                  N  …               0
3              40.780628                  N  …               0
4              40.740631                  N  …               0
…                    …                  …  …             …
729317         40.789181                  N  …               0
729318         40.731911                  N  …               0
729319         40.741207                  N  …               0
729320         40.713814                  N  …               0
729321         40.712841                  N  …               0

       pickup_hour_23  passenger_count_1  passenger_count_2  \
```

```
0                     0                   1                   0
1                     1                   0                   1
2                     0                   0                   1
3                     0                   0                   0
4                     0                   1                   0
…                   …                 …                 …
729317                0                   0                   1
729318                0                   1                   0
729319                0                   1                   0
729320                0                   1                   0
729321                0                   0                   0

        passenger_count_3  passenger_count_4  passenger_count_5  \
0                       0                  0                  0
1                       0                  0                  0
2                       0                  0                  0
3                       0                  0                  0
4                       0                  0                  0
…                     …                …                …
729317                  0                  0                  0
729318                  0                  0                  0
729319                  0                  0                  0
729320                  0                  0                  0
729321                  0                  1                  0

        passenger_count_6  passenger_count_7  passenger_count_9
0                       0                  0                  0
1                       0                  0                  0
2                       0                  0                  0
3                       1                  0                  0
4                       0                  0                  0
…                     …                …                …
729317                  0                  0                  0
729318                  0                  0                  0
729319                  0                  0                  0
729320                  0                  0                  0
729321                  0                  0                  0

[726928 rows x 61 columns]
```

[77]:
```
data['vendor_id_2'].unique()
```

[77]:
```
array([1, 0], dtype=uint8)
```

[78]:
```
list(zip( range(0,len(data.columns)),data.columns))
```

[78]:
```
[(0, 'id'),
 (1, 'vendor_id'),
 (2, 'pickup_datetime'),
 (3, 'dropoff_datetime'),
 (4, 'passenger_count'),
 (5, 'pickup_longitude'),
 (6, 'pickup_latitude'),
 (7, 'dropoff_longitude'),
 (8, 'dropoff_latitude'),
 (9, 'store_and_fwd_flag'),
 (10, 'trip_duration'),
 (11, 'weekday'),
 (12, 'month'),
 (13, 'weekday_num'),
 (14, 'pick_up_hour'),
 (15, 'Distance'),
 (16, 'speed'),
 (17, 'flag_Y'),
 (18, 'vendor_id_2'),
 (19, 'month_2'),
 (20, 'month_3'),
 (21, 'month_4'),
 (22, 'month_5'),
 (23, 'month_6'),
 (24, 'weekday_num_1'),
 (25, 'weekday_num_2'),
 (26, 'weekday_num_3'),
 (27, 'weekday_num_4'),
 (28, 'weekday_num_5'),
 (29, 'weekday_num_6'),
 (30, 'pickup_hour_1'),
 (31, 'pickup_hour_2'),
 (32, 'pickup_hour_3'),
 (33, 'pickup_hour_4'),
 (34, 'pickup_hour_5'),
 (35, 'pickup_hour_6'),
 (36, 'pickup_hour_7'),
 (37, 'pickup_hour_8'),
 (38, 'pickup_hour_9'),
 (39, 'pickup_hour_10'),
 (40, 'pickup_hour_11'),
 (41, 'pickup_hour_12'),
 (42, 'pickup_hour_13'),
 (43, 'pickup_hour_14'),
 (44, 'pickup_hour_15'),
 (45, 'pickup_hour_16'),
 (46, 'pickup_hour_17'),
```

```
(47, 'pickup_hour_18'),
(48, 'pickup_hour_19'),
(49, 'pickup_hour_20'),
(50, 'pickup_hour_21'),
(51, 'pickup_hour_22'),
(52, 'pickup_hour_23'),
(53, 'passenger_count_1'),
(54, 'passenger_count_2'),
(55, 'passenger_count_3'),
(56, 'passenger_count_4'),
(57, 'passenger_count_5'),
(58, 'passenger_count_6'),
(59, 'passenger_count_7'),
(60, 'passenger_count_9')]
```

1.1.93 Creating Benchmark model

[79]:
```
from sklearn.utils import shuffle

data = shuffle(data, random_state = 42)

div = int(data.shape[0]/4)

train = data.loc[:3*div+1,:]
test = data.loc[3*div+1:]
```

[80]:
```
train.head()
```

[80]:
```
                id  vendor_id      pickup_datetime     dropoff_datetime  \
128974  id0192028          1  2016-01-25 21:24:25  2016-01-25 21:40:20
45334   id3265312          2  2016-01-15 06:36:08  2016-01-15 06:45:36
321158  id0237424          2  2016-01-03 02:05:35  2016-01-03 02:19:08
202673  id0489855          1  2016-02-19 23:04:44  2016-02-19 23:11:22
408616  id3975782          1  2016-06-13 06:32:39  2016-06-13 06:35:05

        passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
128974                1        -74.009605        40.715126         -73.987381
45334                 1        -73.985847        40.763874         -73.952675
321158                5        -74.002525        40.749935         -73.996269
202673                1        -74.003922        40.737373         -74.006622
408616                1        -73.990120        40.757122         -73.979187

        dropoff_latitude store_and_fwd_flag  …  pickup_hour_22  \
128974         40.739616                  N  …               0
45334          40.789043                  N  …               0
321158         40.720226                  N  …               0
202673         40.744141                  N  …               0
```

```
408616          40.756207                  N  …              0

       pickup_hour_23  passenger_count_1  passenger_count_2  \
128974              0                  1                  0
45334               0                  1                  0
321158              0                  0                  0
202673              1                  1                  0
408616              0                  1                  0

        passenger_count_3  passenger_count_4  passenger_count_5  \
128974                  0                  0                  0
45334                   0                  0                  0
321158                  0                  0                  1
202673                  0                  0                  0
408616                  0                  0                  0

        passenger_count_6  passenger_count_7  passenger_count_9
128974                  0                  0                  0
45334                   0                  0                  0
321158                  0                  0                  0
202673                  0                  0                  0
408616                  0                  0                  0

[5 rows x 61 columns]
```

[81]:
```
test.head()
```

[81]:
```
               id  vendor_id     pickup_datetime    dropoff_datetime  \
545197  id0001618          2 2016-04-05 22:58:14 2016-04-05 23:07:08
477367  id1076081          1 2016-02-20 19:28:55 2016-02-20 20:12:09
490112  id2622397          2 2016-04-18 22:56:56 2016-04-18 23:01:19
632259  id0083884          1 2016-03-23 18:29:03 2016-03-23 18:36:27
259210  id3305446          1 2016-06-28 19:41:57 2016-06-28 20:00:53

        passenger_count  pickup_longitude  pickup_latitude  dropoff_longitude  \
545197                1        -73.989052        40.721561         -74.005669
477367                1        -73.993111        40.727898         -73.933746
490112                1        -73.987152        40.756119         -73.978630
632259                2        -73.959091        40.709164         -73.963051
259210                2        -73.995300        40.717667         -73.983711

        dropoff_latitude store_and_fwd_flag  …  pickup_hour_22  \
545197         40.709179                  N  …               1
477367         40.846863                  N  …               0
490112         40.759521                  N  …               1
632259         40.719185                  N  …               0
259210         40.756245                  N  …               0
```

```
        pickup_hour_23  passenger_count_1  passenger_count_2  \
545197               0                  1                  0
477367               0                  1                  0
490112               0                  1                  0
632259               0                  0                  1
259210               0                  0                  1

        passenger_count_3  passenger_count_4  passenger_count_5  \
545197                  0                  0                  0
477367                  0                  0                  0
490112                  0                  0                  0
632259                  0                  0                  0
259210                  0                  0                  0

        passenger_count_6  passenger_count_7  passenger_count_9
545197                  0                  0                  0
477367                  0                  0                  0
490112                  0                  0                  0
632259                  0                  0                  0
259210                  0                  0                  0

[5 rows x 61 columns]
```

1.1.94 Simple mean(Mean of Trip duration)

[82]:
```
test['simple_mean'] = train['trip_duration'].mean()
```

[83]:
```
from sklearn.metrics import mean_squared_error as mse

simple_mean_squared_error = np.sqrt(mse(test['vendor_id'] ,␣
 ↪test['simple_mean']))
simple_mean_squared_error
```

[83]: 925.5461965813723

[84]:
```
simple_mean_squared_error = np.sqrt(mse(test['passenger_count'] ,␣
 ↪test['simple_mean']))
simple_mean_squared_error
```

[84]: 925.4194705751834

[85]:
```
simple_mean_squared_error = np.sqrt(mse(test['Distance'] , test['simple_mean']))
simple_mean_squared_error
```

[85]: 923.6342580520067

[86]:
```
simple_mean_squared_error = np.sqrt(mse(test['speed'] , test['simple_mean']))
simple_mean_squared_error
```

[86]:
```
912.6946471447654
```

1.1.95 Mean trip duration with respect to passenger_count

[87]:
```
out_type = pd.pivot_table(train, values='trip_duration', index =␣
↪['passenger_count'], aggfunc=np.mean)
out_type
```

[87]:
```
                 trip_duration
passenger_count
1                   895.529689
2                   987.054239
3                  1027.874453
4                  1007.166781
5                  1020.668969
6                  1025.422071
```

[88]:
```
test['pc_mean'] = 0

for i in train['passenger_count'].unique():
    test['pc_mean'][test['passenger_count'] == str(i)] =␣
↪train['trip_duration'][train['passenger_count'] == str(i)].mean()
```

calculating root mean squared error

[89]:
```
out_type_error = np.sqrt(mse(test['trip_duration'] , test['pc_mean'] ))
out_type_error
```

[89]:
```
3076.030083379951
```

1.1.96 Mean trip duration with respect to vendor_id

[90]:
```
out_type = pd.pivot_table(train, values='trip_duration', index = ['vendor_id'],␣
↪aggfunc=np.mean)
out_type
```

[90]:
```
           trip_duration
vendor_id
1             826.228271
2            1014.917320
```

[91]:
```
test['vid_mean'] = 0

for i in train['vendor_id'].unique():
```

```
    test['vid_mean'][test['vendor_id'] == str(i)] =␣
↪train['trip_duration'][train['vendor_id'] == str(i)].mean()
```

calculating root mean squared error

```
[92]: out_type_error = np.sqrt(mse(test['trip_duration'] , test['vid_mean'] ))
out_type_error
```

```
[92]: 3076.030083379951
```

1.1.97 Mean trip duration with respect to weekday

```
[93]: out_type = pd.pivot_table(train, values='trip_duration', index = ['weekday'],␣
↪aggfunc=np.mean)
out_type
```

```
[93]:            trip_duration
weekday
Friday          964.447934
Monday          858.861128
Saturday        893.315898
Sunday          896.699168
Thursday        975.070615
Tuesday         927.957861
Wednesday       961.103568
```

```
[94]: test['weekday_mean'] = 0

for i in train['weekday'].unique():
    test['weekday_mean'][test['weekday'] == str(i)] =␣
↪train['trip_duration'][train['weekday'] == str(i)].mean()
```

calculating root mean squared error

```
[95]: out_type_error = np.sqrt(mse(test['trip_duration'] , test['weekday_mean'] ))
out_type_error
```

```
[95]: 2929.6901214074487
```

1.1.98 Mean trip duration with respect to store and forward flag

```
[96]: out_type = pd.pivot_table(train, values='trip_duration', index =␣
↪['store_and_fwd_flag'], aggfunc=np.mean)
out_type
```

```
[96]:                     trip_duration
store_and_fwd_flag
N                      926.220358
Y                     1079.681853
```

[97]:
```
test['sf_mean'] = 0

for i in train['store_and_fwd_flag'].unique():
    test['sf_mean'][test['store_and_fwd_flag'] == str(i)] =␣
↪train['trip_duration'][train['store_and_fwd_flag'] == str(i)].mean()
```

calculating root mean squared error

[98]:
```
out_type_error = np.sqrt(mse(test['trip_duration'] , test['sf_mean'] ))
out_type_error
```

[98]:
```
2929.9902949286056
```

1.1.99 Mean trip duration with respect to month

[99]:
```
out_type = pd.pivot_table(train, values='trip_duration', index = ['month'],␣
↪aggfunc=np.mean)
out_type
```

[99]:

month	trip_duration
1	892.200560
2	889.693945
3	897.695070
4	945.995096
5	970.045297
6	965.979263

[100]:
```
test['month_mean'] = 0

for i in train['month'].unique():
    test['month_mean'][test['month'] == str(i)] =␣
↪train['trip_duration'][train['month'] == str(i)].mean()
```

calculating root mean squared error

[101]:
```
out_type_error = np.sqrt(mse(test['trip_duration'] , test['month_mean'] ))
out_type_error
```

[101]:
```
3076.030083379951
```

1.1.100 Mean trip_duration with respect to both vendor_id and passenger_count

[102]:
```
combo = pd.pivot_table(train, values = 'trip_duration', index =␣
↪['vendor_id','passenger_count'], aggfunc = np.mean)
combo
```

[102]:
```
                                trip_duration
vendor_id passenger_count
```

```
1         1                    801.184459
          2                    928.335185
          3                    941.943985
          4                    992.639560
          5                    729.444444
          6                   1157.869565
2         1                   1003.377783
          2                   1032.407864
          3                   1082.023648
          4                   1017.458544
          5                   1022.167429
          6                   1025.022557
```

[103]:
```
test['Super_mean'] = 0

s2 = 'vendor_id'
s1 = 'passenger_count'

for i in test[s1].unique():
    for j in test[s2].unique():
        test['Super_mean'][(test[s1] == i) & (test[s2]==str(j))] =␣
↪train['trip_duration'][(train[s1] == i) & (train[s2]==str(j))].mean()
```

calculating root mean squared error

[104]:
```
super_mean_squared_error = np.sqrt(mse(test['trip_duration'] ,␣
↪test['Super_mean'] ))
super_mean_squared_error
```

[104]:
```
3076.030083379951
```

1.1.101 Mean trip_duration with respect to both weekday and store and forward flag

[105]:
```
combo = pd.pivot_table(train, values = 'trip_duration', index =␣
↪['weekday','store_and_fwd_flag'], aggfunc = np.mean)
combo
```

[105]:
```
                             trip_duration
weekday   store_and_fwd_flag
Friday    N                     963.296795
          Y                    1154.807512
Monday    N                     857.405713
          Y                    1111.829412
Saturday  N                     893.502314
          Y                     853.533742
Sunday    N                     896.497868
          Y                     934.870370
Thursday  N                     973.458200
```

```
          Y                          1246.794118
Tuesday   N                           927.067631
          Y                          1081.572973
Wednesday N                           960.261480
          Y                          1101.974747
```

[106]:
```
test['Super_mean'] = 0
s2 = 'weekday'
s1 = 'store_and_fwd_flag'

for i in test[s1].unique():
    for j in test[s2].unique():
        test['Super_mean'][((test[s1] == str(i)) & (test[s2]==str(j)))] =␣
 ↪train['trip_duration'][(train[s1] == str(i)) & (train[s2]==str(j))].mean()
```

calculating root mean squared error

[107]:
```
super_mean_squared_error = np.sqrt(mse(test['trip_duration'] ,␣
 ↪test['Super_mean'] ))
super_mean_squared_error
```

[107]:
```
2929.664784026928
```

1.1.102 Mean trip_duration with respect to both weekday and month

[108]:
```
combo = pd.pivot_table(train, values = 'trip_duration', index =␣
 ↪['weekday','month'], aggfunc = np.mean)
combo
```

[108]:
```
                 trip_duration
weekday   month
Friday    1         920.578811
          2         908.180140
          3         886.245230
          4        1024.302175
          5        1036.493422
          6        1010.064229
Monday    1         842.743100
          2         880.982032
          3         832.726255
          4         823.643323
          5         896.371409
          6         862.428828
Saturday  1         873.565194
          2         840.543251
          3         823.821033
          4         928.823456
          5         892.395547
```

```
          6         999.799847
Sunday    1         901.544301
          2         884.134039
          3         921.731936
          4         898.260967
          5         877.009423
          6         902.123693
Thursday  1         887.360187
          2         916.590473
          3         962.810317
          4         994.794881
          5        1076.014466
          6        1007.850000
Tuesday   1         955.030612
          2         875.893162
          3         887.527432
          4         927.173452
          5         986.239348
          6         933.111341
Wednesday 1         853.885901
          2         922.316157
          3         945.552758
          4         986.426429
          5        1044.123906
          6        1004.040353
```

[109]:
```
test['Super_mean'] = 0
s2 = 'weekday'
s1 = 'month'

for i in test[s1].unique():
    for j in test[s2].unique():
        test['Super_mean'][(test[s1] == i) & (test[s2]==str(j))] =␣
 ↪train['trip_duration'][(train[s1] == i) & (train[s2]==str(j))].mean()
```

calculating mean absolute error

[110]:
```
super_mean_squared_error = np.sqrt(mse(test['trip_duration'] ,␣
 ↪test['Super_mean'] ))
super_mean_squared_error
```

[110]: 2929.471119515208

Segregating dependent and independent variable

[111]:
```
y = data.iloc[:,10]
X = data.iloc[:,range(15,60)]
X.shape, y.shape
```

[111]: ((726928, 45), (726928,))

Idea:

- Duration variable assigned to Y because that is the dependent variable.
- Features such as id, timestamp and weekday were not assigned to X array because they are of type object. And we need an array of float data type.

1.1.103 Modelling

1.1.104 Multiple Linear Regression

Model Training

[112]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, random_state=56)
```

[113]:
```
regressor = LinearRegression()
regressor.fit(X_train,y_train)
```

[113]: LinearRegression()

Model Predictions

[114]:
```
y_pred = regressor.predict(X_test)
```

Model evaluation We will evaluate our model's accuracy through two suggested metrics for the regression models. i.e. RMSE and variance score. Where RMSE of 0 and variance of 1 is considered as the best score for a prediction model.

[115]:
```
print('RMSE score for the Multiple LR is : {}'.format(np.sqrt(metrics.
 ↪mean_squared_error(y_test,y_pred))))
print('Variance score for the Multiple LR is : %.2f' % regressor.score(X_test,␣
 ↪y_test))
print("\n")
```

```
RMSE score for the Multiple LR is : 2686.2099778243733
Variance score for the Multiple LR is : 0.07
```

1.1.105 Observations

- Very poor Root mean squared value.
- And the low variance score which is also bad.

1.1.106 Lasso Regularization

[116]:
```
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=1.5)
```

[117]:
```
lasso = Lasso(alpha=1.5)
lasso.fit(X_train,y_train)
```

[117]:
```
Lasso(alpha=1.5)
```

Model Predictions

[118]:
```
y_pred_lasso = lasso.predict(X_test)
```

Model Evaluation

[119]:
```
print('RMSE score for the Lasso Regression is : {}'.format(np.sqrt(metrics.
 ↪mean_squared_error(y_test,y_pred_lasso))))
print('Variance score for the Lasso Regression is : %.2f' % lasso.score(X_test,␣
 ↪y_test))
print("\n")
```

```
RMSE score for the Lasso Regression is : 2686.3901377863476
Variance score for the Lasso Regression is : 0.07
```

1.1.107 Observation:

- Linear Regression with regularization also gives the same result

Let's find the solution

[120]:
```
X_train.shape
```

[120]:
```
(545196, 45)
```

Linear correlation of each feature with the target variable

[121]:
```
from scipy.stats import pearsonr
df1 = pd.DataFrame(np.concatenate((X_train,y_train.values.
 ↪reshape(len(y_train),1)),axis=1))
df1.columns = df1.columns.astype(str)

features = df1.iloc[:,:45].columns.tolist()
target = df1.iloc[:,45].name

correlations = {}
for f in features:
    data_temp = df1[[f,target]]
    x1 = data_temp[f].values
    x2 = data_temp[target].values
    key = f + ' vs ' + target
    correlations[key] = pearsonr(x1,x2)[0]

data_correlations = pd.DataFrame(correlations, index=['Value']).T
```

```python
data_correlations.loc[data_correlations['Value'].abs().
↪sort_values(ascending=False).index]
```

[121]:

	Value
0 vs 45	0.183363
1 vs 45	-0.047699
3 vs 45	0.033454
38 vs 45	-0.016628
30 vs 45	0.012806
20 vs 45	-0.011687
29 vs 45	0.011529
42 vs 45	0.010868
28 vs 45	0.009694
11 vs 45	0.009582
21 vs 45	-0.008523
4 vs 45	-0.008501
14 vs 45	-0.008279
8 vs 45	0.007978
7 vs 45	0.007456
43 vs 45	0.006981
34 vs 45	-0.006810
39 vs 45	0.006795
31 vs 45	0.006622
33 vs 45	-0.005630
12 vs 45	0.005285
13 vs 45	-0.004805
15 vs 45	-0.004559
40 vs 45	0.004501
27 vs 45	0.004479
41 vs 45	0.004318
35 vs 45	-0.004277
2 vs 45	0.004133
37 vs 45	-0.003539
10 vs 45	0.003096
16 vs 45	-0.003029
19 vs 45	-0.002782
26 vs 45	0.002613
17 vs 45	-0.002461
18 vs 45	-0.002360
5 vs 45	-0.002240
32 vs 45	0.002133
6 vs 45	0.001728
9 vs 45	0.001611
22 vs 45	-0.001361
24 vs 45	0.000419
23 vs 45	-0.000351
36 vs 45	0.000140

```
25 vs 45 -0.000131
44 vs 45       NaN
```

1.1.108 Observations¶

- None of the feature is linearly correlated with the target variable "45". That is why it is not a good model for the prediction of the trip duration.

1.1.109 KNN Model

[122]:
```python
y = data.iloc[:,10]
X = data.iloc[:,range(15,60)]
X.shape, y.shape
```

[122]:
```
((726928, 45), (726928,))
```

[123]:
```python
X.shape, y.shape
```

[123]:
```
((726928, 45), (726928,))
```

Importing MinMax Scaler

[124]:
```python
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
```

[125]:
```python
X = pd.DataFrame(X_scaled)
```

[126]:
```python
X.head()
```

[126]:
```
          0         1    2    3    4    5    6    7    8    9  ...   35   36  \
0  0.019101  0.122096  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  1.0  0.0
1  0.022852  0.245603  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
2  0.019334  0.145168  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
3  0.004543  0.069686  0.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
4  0.005354  0.223879  0.0  0.0  0.0  0.0  0.0  0.0  1.0  0.0  ...  0.0  0.0

    37   38   39   40   41   42   43   44
0  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0
1  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0
2  0.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0
3  1.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0
4  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0

[5 rows x 45 columns]
```

Importing Train test split

[127]:
```python
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y, random_state = 56)
```

[128]:
```python
from sklearn.neighbors import KNeighborsRegressor as KNN
```

Creating instance of KNN

[129]:
```python
reg = KNN(n_neighbors = 2)
```

Fitting the model

[130]:
```python
reg.fit(X_train, y_train)
```

[130]:
```
KNeighborsRegressor(n_neighbors=2)
```

Predicting over the Train Set and calculating root mean squared log error and variance score

[131]:
```python
y_pred_KNN = reg.predict(X_test)

print('RMSE score for the KNN is : {}'.format(np.sqrt(metrics.
 ↪mean_squared_error(y_test,y_pred_KNN))))
print('Variance score for the KNN is : %.2f' % reg.score(X_test, y_test))
print("\n")
```

```
RMSE score for the KNN is : 2708.4652245101393
Variance score for the KNN is : 0.05
```

1.1.110 Random Forest Regressor

Model Training

Create instance of Random forest

[132]:
```python
regressor_rfraw = RandomForestRegressor(n_jobs=-1)
```

Fitting the model

[133]:
```python
regressor_rfraw.fit(X_train,y_train)
```

[133]:
```
RandomForestRegressor(n_jobs=-1)
```

Model Prediction

[134]:
```python
y_pred_rfraw = regressor_rfraw.predict(X_test)
```

Model Evaluation

[135]:
```python
print('RMSE score for the RF regressor is : {}'.format(np.sqrt(metrics.
 ↪mean_squared_error(y_test,y_pred_rfraw))))
print('RMSLE score for the RF regressor is : {}'.format(np.sqrt(metrics.
 ↪mean_squared_log_error(y_test,y_pred_rfraw))))
```

```
print('Variance score for the RF regressor is : %.2f' % regressor_rfraw.
 ↪score(X_test, y_test))
```

```
RMSE score for the RF regressor is : 94.94325945795734
RMSLE score for the RF regressor is : 0.031724547422723876
Variance score for the RF regressor is : 1.00
```

Interesting find

- There is approx 200% improvement on the RMSE score for the Random forest regressor over the Linear regressor.
- Even the variance score is approx 1 which is a good score.

1.1.111 XGBoost Regressor

Model training

Create instance of XGBoost Regressor

[136]:
```
regressor_xgbraw = XGBRegressor(n_jobs=-1)
```

Fitting the model

[137]:
```
regressor_xgbraw.fit(X_train,y_train)
```

[137]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.300000012,
             max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=-1,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

Model Prediction

[138]:
```
y_pred_xgbraw = regressor_xgbraw.predict(X_test)
```

Model Evaluation

[139]:
```
print('RMSE score for the XGBoost regressor is : {}'.format(np.sqrt(metrics.
 ↪mean_squared_error(y_test,y_pred_xgbraw))))
print('Variance score for the XGBoost regressor is : %.2f' % regressor_xgbraw.
 ↪score(X_test, y_test))
```

```
RMSE score for the XGBoost regressor is : 145.13960553222913
Variance score for the XGBoost regressor is : 1.00
```

1.1.112 Observations

- There is a significant improvement in the RMSE score for the tuned XGBoost regressor over the Random forest regressor when trained on the given features.

Comparing test results for the XGBoost and RF regressor

[140]:
```
print("Total sum of difference between the actual and the predicted values for␣
↪the RF regressor is : %d"%np.abs(np.sum(np.subtract(y_test,y_pred_rfraw))))
print("Total sum of difference between the actual and the predicted values for␣
↪the tuned XGB regressor is : %d"%np.abs(np.sum(np.
↪subtract(y_test,y_pred_xgbraw))))
```

```
Total sum of difference between the actual and the predicted values for the RF
regressor is : 112305
Total sum of difference between the actual and the predicted values for the
tuned XGB regressor is : 88273
```

1.1.113 Averaging

[141]:
```
from statistics import mean
final_pred = np.array([])
for i in range(0,len(X_test)):
    final_pred = np.append(final_pred, np.
↪mean([y_pred_lasso[i],y_pred_rfraw[i],y_pred_xgbraw[i],y_pred_KNN[i]]))
```

[142]:
```
from sklearn.metrics import r2_score
r2_score(y_test, final_pred)
```

[142]:
```
0.7738766410788914
```

[143]:
```
r2_score(y_test, y_pred_lasso), r2_score(y_test,y_pred_rfraw), r2_score(y_test,␣
↪y_pred_xgbraw), r2_score(y_test, y_pred_KNN)
```

[143]:
```
(0.06919759159294825,
 0.9988373537265591,
 0.9972829901912323,
 0.05383722596395535)
```

1.1.114 Weighted Averaging

[144]:
```
from statistics import mean
final_pred = np.array([])
for i in range(0,len(X_test)):
    final_pred = np.append(final_pred, np.mean([y_pred_lasso[i], y_pred_KNN[i],␣
↪y_pred_rfraw[i],y_pred_rfraw[i],y_pred_xgbraw[i],y_pred_xgbraw[i]]))
```

[145]:
```
r2_score(y_test, final_pred)
```

[145]:
```
0.8981685556315506
```

[146]:
```
r2_score(y_test, y_pred_lasso), r2_score(y_test,y_pred_rfraw), r2_score(y_test,␣
↪y_pred_xgbraw), r2_score(y_test, y_pred_KNN)
```

[146]:
```
(0.06919759159294825,
 0.9988373537265591,
 0.9972829901912323,
 0.05383722596395535)
```

1.1.115 Rank averaging

[147]:
```python
m1_score= lasso.score(X_test, y_test)
m2_score= reg.score(X_test,y_test)
m3_score= regressor_rfraw.score(X_test, y_test)
m4_score= regressor_xgbraw.score(X_test, y_test)

m1_score, m2_score, m3_score, m4_score
```

[147]:
```
(-0.024331240775971263,
 0.05383722596395535,
 0.9988373537265591,
 0.9972829901912323)
```

[148]:
```python
index_ = [1,2,3,4]
valid_r2 = [m1_score,m2_score,m3_score,m4_score]

rank_eval = pd.DataFrame({
    'score':valid_r2
}, index = index_)
rank_eval
```

[148]:
```
      score
1 -0.024331
2  0.053837
3  0.998837
4  0.997283
```

[149]:
```python
sorted_rank = rank_eval.sort_values('score')
sorted_rank
```

[149]:
```
      score
1 -0.024331
2  0.053837
4  0.997283
3  0.998837
```

[150]:
```python
sorted_rank['rank'] = [i for i in range(1,5)]
sorted_rank
```

[150]:
```
      score  rank
1 -0.024331     1
2  0.053837     2
```

```
4  0.997283     3
3  0.998837     4
```

[151]:
```
sorted_rank['weight'] = sorted_rank['rank']/sorted_rank['rank'].sum()
sorted_rank
```

[151]:

	score	rank	weight
1	-0.024331	1	0.1
2	0.053837	2	0.2
4	0.997283	3	0.3
3	0.998837	4	0.4

[152]:
```
wt_pred1 = y_pred_lasso * float(sorted_rank.loc[[1],['weight']].values)
wt_pred2 = y_pred_KNN * float(sorted_rank.loc[[2],['weight']].values)
wt_pred3 = y_pred_rfraw * float(sorted_rank.loc[[3],['weight']].values)
wt_pred4 = y_pred_xgbraw * float(sorted_rank.loc[[4],['weight']].values)
ranked_prediction = wt_pred1 + wt_pred2 + wt_pred3 + wt_pred4
ranked_prediction
```

[152]:
```
array([ 517.05106882, 1254.47505352, 1619.71622265, …,  173.43989475,
        953.23590537,  516.72151533])
```

[153]:
```
r2_score(y_test, ranked_prediction)
```

[153]:
```
0.9163963208953789
```

2 Result:

- By using Averaging technique combined all the models linear regression with lasso regularization, KNN, Random forest, XGBoost regressor predicting the final predictions.
- In all the techniques, can see that random forest regressor and XGBoost regressor has scored 0.99 respectively.
- Performed averaging, weighted averaging, ranked averaging and obtained the predictions.
- The ranked averaging has scored 0.91, weighted averaging has scored 0.89 and averaging has scored 0.77.
- The ranked averaging performed better than other averaging techniques