NYC Taxi Trip Duration Project

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

You are provided with the NYC Taxi Trip Dataset. This dataset contains information about the taxi trips that took place in different parts of New York City and how much time did that trip take to complete.

In this project, the following are the tasks you must complete and submitted.

1. Choose the most suitable evaluation metric and state why you chose it.
2. Build a benchmark model for the given dataset.
3. Build a K-Nearest neighbours' model for the given dataset and find the best value of K.
4. Build a Linear model for the given dataset with regularisation. Attempt to interpret the variable coefficients of the Linear Model.
5. Build a Decision tree model for the given dataset. Attempt to interpret the variable importance.
6. Plot the following Bar plots:
   A. train score of all the above models.
   B. test (not validation!) score of all the above models.
   C. Attempt to explain the observations from the plots (optional)

In [1]:
```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")
sns.set()
```

Reading the csv file

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

Checking the shape of dataset

In [3]:
```
data.shape
```

Out[3]:
```
(729322, 11)
```

Checking first few rows of dataset

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

Out[4]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	drc
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.953918	40.778873	
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.988312	40.731743	
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.997314	40.721458	
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.961670	40.759720	
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.017120	40.708469	

Checking if all id values are unique

In [5]:

```
if data.id.nunique() == data.shape[0]:
    print("All id values are unique")
```

```
All id values are unique
```

Checking for missing values

In [6]:

```
data.isnull().sum()
```

Out[6]:

```
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
```

Checking data types of the different features

In [7]:

```
data.dtypes
```

Out[7]:

```
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
```

Correcting the datatypes

In [8]:

```
# pick-up datetime and dropoff_datetime should be datetime objects
data['pickup_datetime'] = pd.to_datetime(data['pickup_datetime'])
data['dropoff_datetime'] = pd.to_datetime(data['dropoff_datetime'])
```

In [9]:
```
data.dtypes
```

Out[9]:
```
id                            object
vendor_id                      int64
pickup_datetime       datetime64[ns]
dropoff_datetime      datetime64[ns]
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
```

Checking if the trip_duration matches with the difference of dropoff time and pickup time

In [10]:
```
duration_diff = (data['trip_duration'] - ((data['dropoff_datetime'] - data['pickup_datetir
duration_diff
```

Out[10]:
```
0.0
```

- The trip_duration is consistent with the pickup time and dropoff time.

Creating pickup day of month, pickup day of week, and pickup hour features as these could be helpul for further analysis

In [11]:
```
data['pickup_day'] = data.pickup_datetime.dt.day
data['pickup_dayow'] = data.pickup_datetime.dt.strftime('%A')
data['pickup_dow'] = data.pickup_datetime.dt.dayofweek
```

In [12]:
```
data['pickup_hour'] = data.pickup_datetime.dt.hour
```

In [13]:
```
data.head()
```

Out[13]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	drc
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.953918	40.778873	
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.988312	40.731743	
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.997314	40.721458	
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.961670	40.759720	
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.017120	40.708469	

Shuffling and creating train and test data set

In [14]:
```
from sklearn.utils import shuffle

# Shuffling the Dataset
data = shuffle(data, random_state = 42)
```

```
#creating 4 divisions
div = int(data.shape[0]/4)

# 3 parts to train set and 1 part to test set
train = data[:(3*div+1)]
test = data[3*div+1:]
```

In [15]:

```
train.shape
```

Out[15]:

```
(546991, 15)
```

In [16]:

```
test.shape
```

Out[16]:

```
(182331, 15)
```

EDA

The EDA will be carried out on the training data set only to avoid any data leakage to the test dataset.

Univariate Analysis

Getting an overview of the continuous data

In [17]:

```
train.describe()
```

Out[17]:

	vendor_id	passenger_count	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	trip_(
count	546991.000000	546991.000000	546991.000000	546991.000000	546991.000000	546991.000000	5.469
mean	1.535572	1.664185	-73.973443	40.750949	-73.973383	40.751765	9.506
std	0.498733	1.314420	0.042147	0.034114	0.041840	0.035733	4.055
min	1.000000	0.000000	-79.569733	34.712234	-80.355431	32.181141	1.000
25%	1.000000	1.000000	-73.991852	40.737339	-73.991341	40.735851	3.970
50%	2.000000	1.000000	-73.981720	40.754086	-73.979767	40.754517	6.630
75%	2.000000	2.000000	-73.967346	40.768326	-73.963028	40.769741	1.076
max	2.000000	6.000000	-65.897385	51.881084	-65.897385	43.911762	1.939

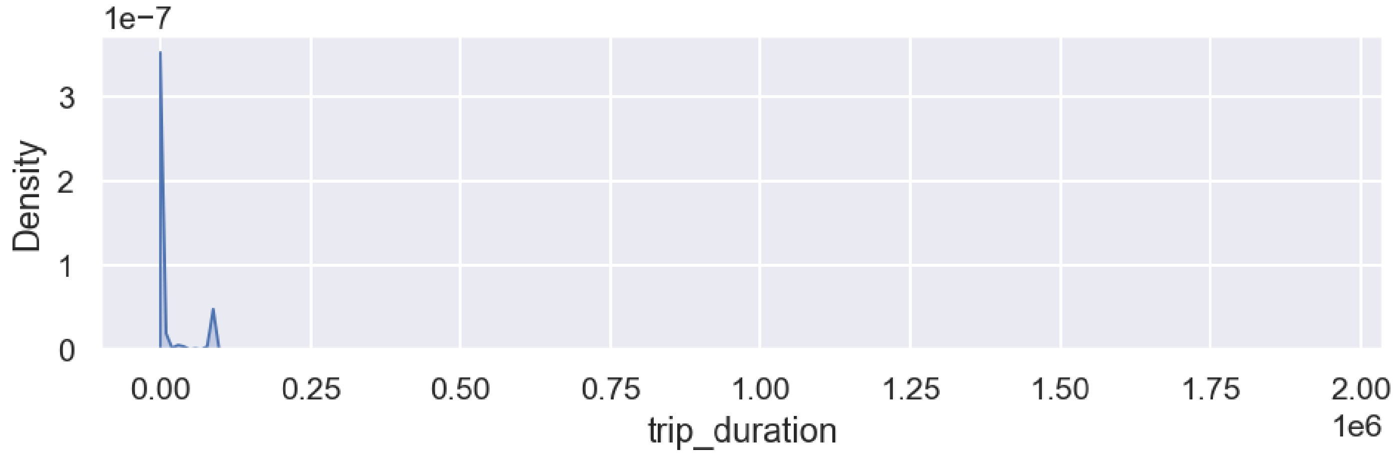
- The trip duration has a very wide range and thus might contain outliers. Needs to be checked further.

In [18]:

```
# setting image resolution
plt.figure(figsize = (8,2) , dpi = 140)

# Plotting histogram and descriptive summary
sns.kdeplot(train['trip_duration'], shade = True)
```

Out[18]:

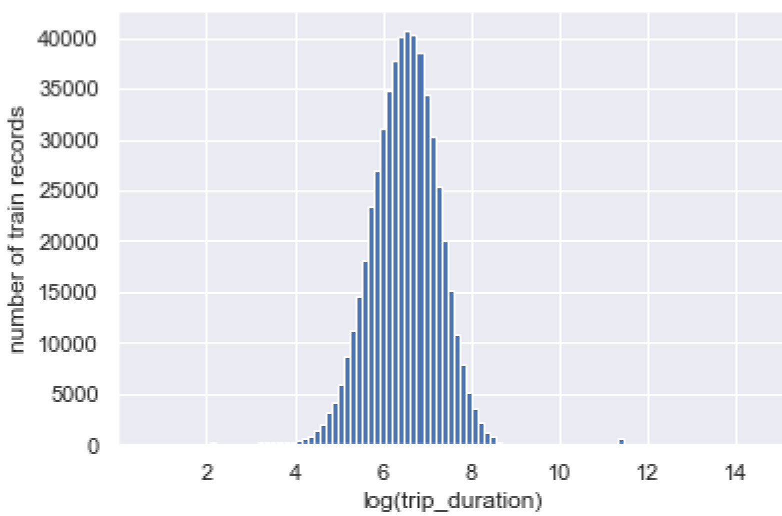
```
<AxesSubplot:xlabel='trip_duration', ylabel='Density'>
```



Because of the presense of outliers, log of trip_duration would be helpful in understanding the distribution.

In [19]:

```
log_trip_duration = np.log(train['trip_duration'] + 1)
plt.hist(log_trip_duration.values, bins=100)
plt.xlabel('log(trip_duration)')
plt.ylabel('number of train records')
plt.show()
```



In [20]:

```
(train['trip_duration']/3600).describe()  # Trip duration in hours
```

Out[20]:

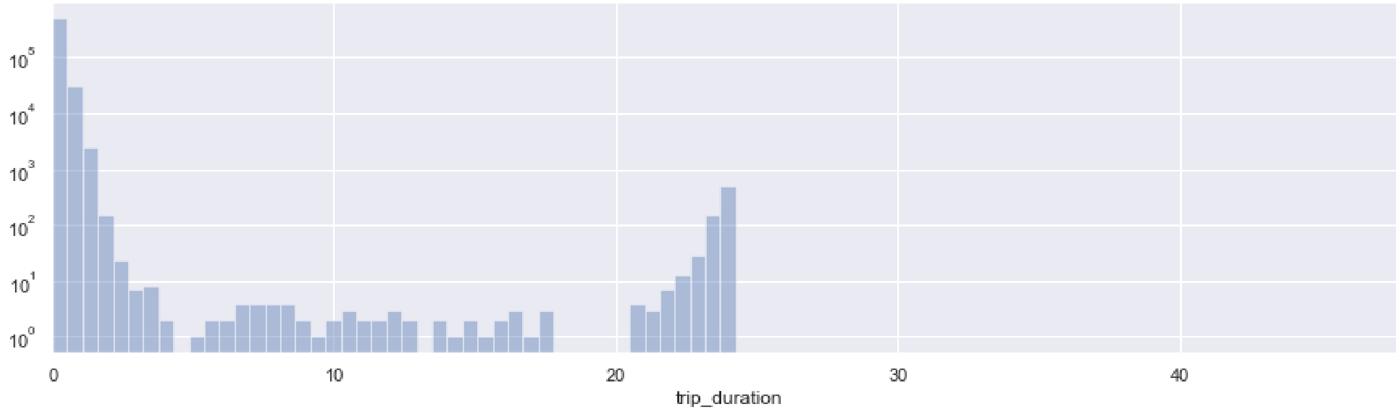
```
count    546991.000000
mean          0.264058
std           1.126499
min           0.000278
25%           0.110278
50%           0.184167
75%           0.298889
max         538.815556
Name: trip_duration, dtype: float64
```

In [21]:

```
fig, ax = plt.subplots(figsize = (15,4), ncols=1, nrows=1)
ax.set_xlim(0,48)
sns.distplot(train['trip_duration']/3600,ax=ax,bins=1000,kde=False, hist_kws={'log':True})
```

Out[21]:

```
<AxesSubplot:xlabel='trip_duration'>
```

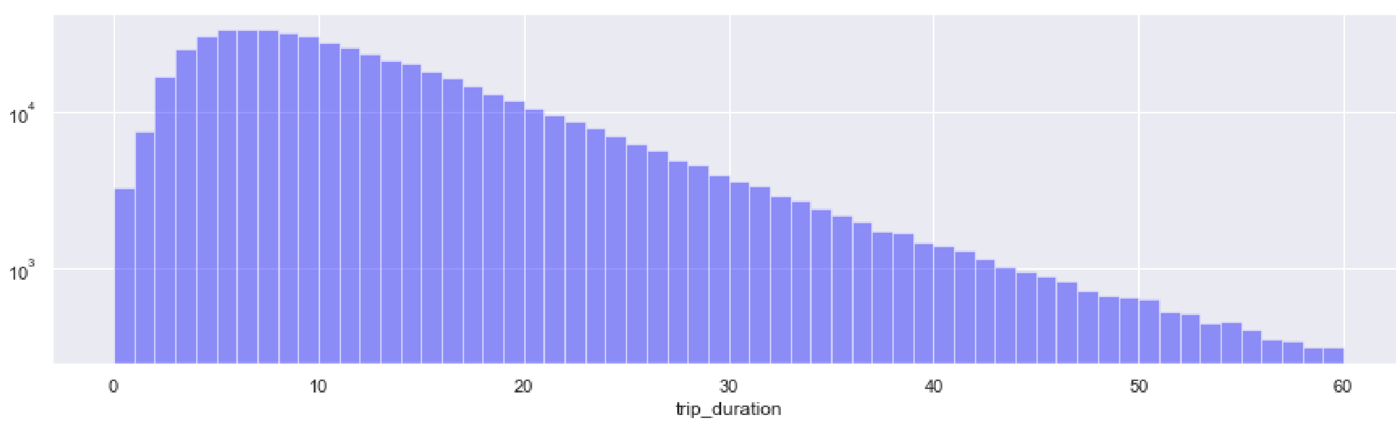


- We can see that most of the trips are withing the 24 hour duration, and the no. of trips increase with duration of about 24 hours, maybe because the meter resets at midnight, and maybe the drivers forget to reset their meters.
- We will restrict the trip duration to less than 22 hours for the reason stated above.
- There are a large number of trips with duration less than an hour. It would be good to have a deeper look at it.

In [22]:
```
train = train[train['trip_duration'] < (3600*22)]
```

In [23]:
```
fig, ax = plt.subplots(figsize = (15,4), ncols=1, nrows=1)
hour_data = train[train['trip_duration'] < 3600]
sns.distplot(hour_data['trip_duration']/60,ax=ax,bins=60,kde=False, hist_kws={'log':True},
```

Out[23]:
```
<AxesSubplot:xlabel='trip_duration'>
```



- We can see that there are a number of trips with duration less than 60 seconds, which is highly improbable in real life. So, we'll remove those trips with trip_duration less than 60.

In [24]:
```
(train['trip_duration'] < 60).value_counts()
```

Out[24]:
```
False    543102
True       3210
Name: trip_duration, dtype: int64
```

In [25]:
```
train = train[train['trip_duration'] > 60]
```

In [26]:
```
train.shape
```

Out[26]: (543027, 15)

Checking the range for pickup and dropoff times

In [27]:
```
train['pickup_datetime'].min()
```

Out[27]: Timestamp('2016-01-01 00:01:14')

In [28]:
```
train['pickup_datetime'].max()
```

Out[28]: Timestamp('2016-06-30 23:59:37')

In [29]:
```
train['dropoff_datetime'].min()
```

Out[29]: Timestamp('2016-01-01 00:05:54')

In [30]:
```
train['dropoff_datetime'].max()
```

Out[30]: Timestamp('2016-07-01 00:46:37')

- The data is for a period of six months. The day of the month, and the day of the week might provide us some insights to predict the trip duration.

Checking values of store and fwd flag

In [31]:
```
train.store_and_fwd_flag.value_counts()
```

Out[31]:
```
N    540050
Y      2977
Name: store_and_fwd_flag, dtype: int64
```

In [32]:
```
# This feature could provide some insights at the later stage, so we can convert it into a
train['store_and_fwd_flag'] = 1 * (train.store_and_fwd_flag.values == 'Y')
```

In [33]:
```
train.store_and_fwd_flag.value_counts(normalize = True)
```

Out[33]:
```
0    0.994518
1    0.005482
Name: store_and_fwd_flag, dtype: float64
```

In [34]:
```
# Analysing Vendor Id
train['vendor_id'].value_counts(normalize=True)
```

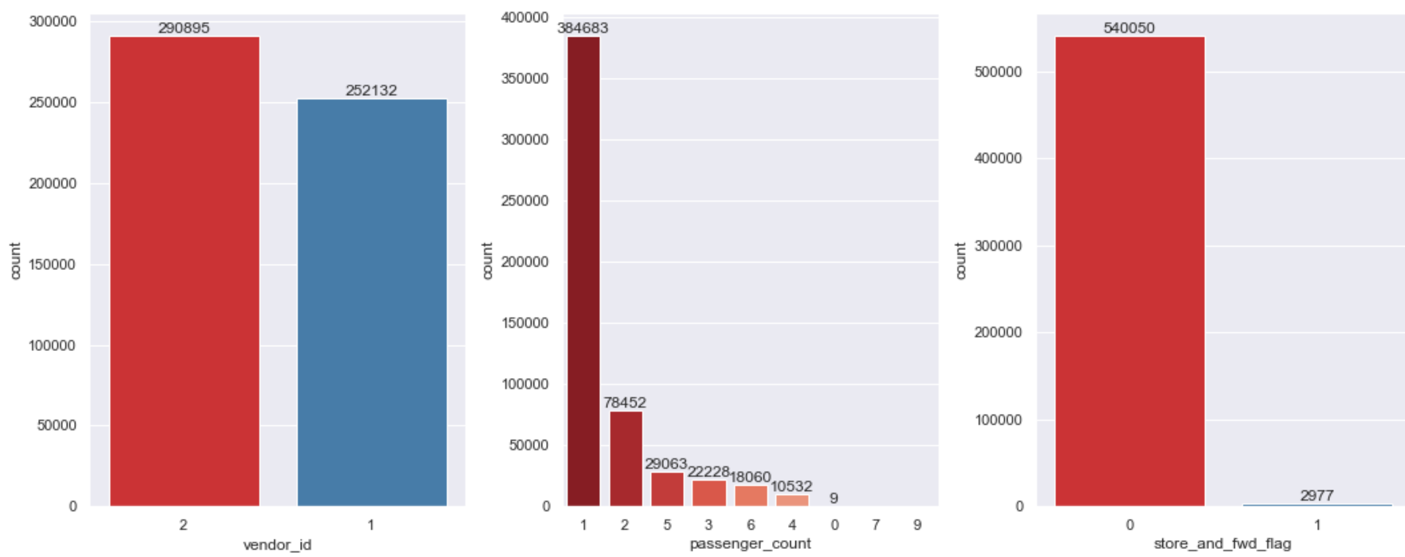
Out[34]:
```
2    0.535692
1    0.464308
Name: vendor_id, dtype: float64
```

In [35]:
```
# Analysing passenger counts
train['passenger_count'].value_counts()
```

Out[35]:
```
1    384683
2     78452
5     29063
3     22228
```

```
6      18060
4      10532
0          9
Name: passenger_count, dtype: int64
```

In [36]:
```
# Plotting vendor id, passenger counts, and store and fwd flag

fig, (ax1,ax2,ax3) = plt.subplots(1,3, figsize = (15,6))

sns.countplot(x="vendor_id", data=train, palette="Set1", ax = ax1, order = data['vendor_ic
sns.countplot(x="passenger_count", data=train, palette="Reds_r", ax = ax2, order = data['p
sns.countplot(x="store_and_fwd_flag", data=train, palette="Set1", ax = ax3)

ax1.bar_label(container=ax1.containers[0])
ax2.bar_label(container=ax2.containers[0])
ax3.bar_label(container=ax3.containers[0])

fig.tight_layout()
```



- Vendor 2 has more number of trips compared to vendor 1.
- Most of the trips have 1 passengers.
- We can see that there are a few rides with the passenger_count as zero. We need to remove these from our training set.

In [37]:
```
train = train[train['passenger_count'] != 0]
```

In [38]:
```
train.shape
```

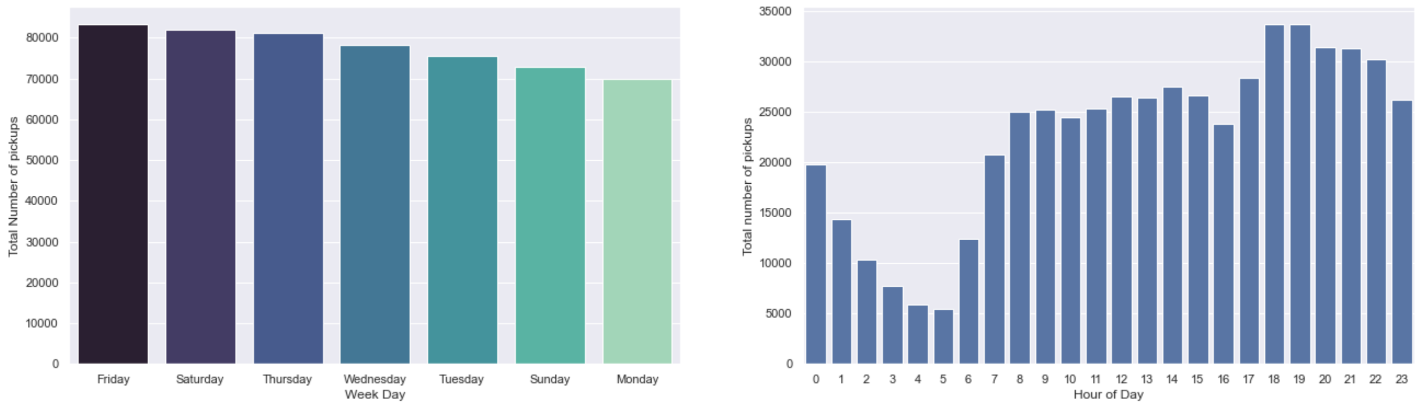
Out[38]:
```
(543018, 15)
```

In [39]:
```
plt.figure(figsize=(22, 6))

# Plotting pickups by day of week
plt.subplot(121)
sns.countplot(train['pickup_dayow'], order = train['pickup_dayow'].value_counts().index, p
plt.xlabel('Week Day')
plt.ylabel('Total Number of pickups')

# Plotting pickups by hour of day
plt.subplot(122)
sns.countplot(train['pickup_hour'], color = 'b')
```

```
plt.xlabel('Hour of Day')
plt.ylabel('Total number of pickups')
```

Out[39]:

```
Text(0, 0.5, 'Total number of pickups')
```



- We can see that the least number of pickups happen on Mondays while Fridays have the highest number of pickups.
- Early morning pickups are low, and pickups are more after 08:00 AM which can be considered as the start of work hours.

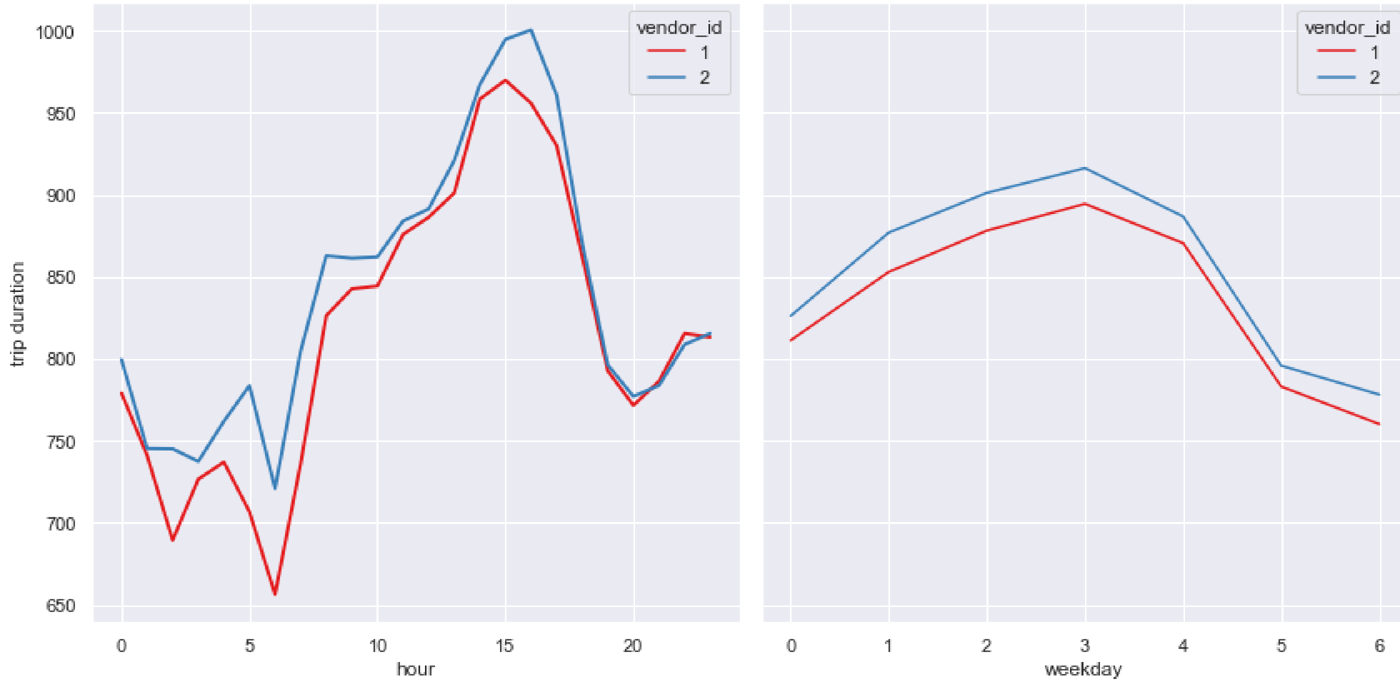
Bivariate and multivariate analysis

In [40]:

```
grouped_data1 = train.groupby(['pickup_hour', 'vendor_id'])['trip_duration'].mean().reset_
grouped_data2 = train.groupby(['pickup_dow', 'vendor_id'])['trip_duration'].mean().reset_i
```

In [41]:

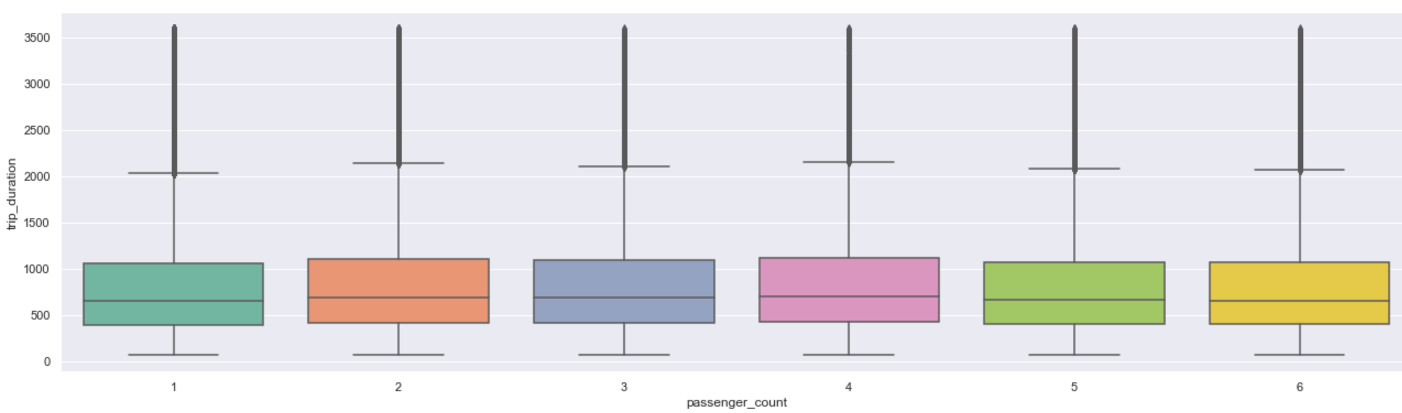
```
fig, ax = plt.subplots(ncols=2, figsize = (12,6), sharey=True)
sns.lineplot(data = grouped_data1, x = 'pickup_hour', y = 'trip_duration', hue = 'vendor_i
sns.lineplot(data = grouped_data2, x = 'pickup_dow', y = 'trip_duration', hue = 'vendor_id

ax[0].set_xlabel('hour')
ax[1].set_xlabel('weekday')
ax[0].set_ylabel('trip duration')

fig.tight_layout()
```



- Trip durations are definitely shorter for late night and early morning hours that can be attributed to low traffic density
- It follows a similar pattern when compared to number of pickups indicating a correlation between number of pickups and trip duration
- Trip durations are particularly low on Saturday(5) and Sunday(6).
- Trip durations for vendor 2 are on an average higher than trip durations for vendor 1 on all days.

In [128…

```
train.passenger_count.value_counts()
plt.figure(figsize=(22, 6))
train_sub = train[train['trip_duration'] < 3600]
sns.boxplot(x="passenger_count", y="trip_duration", data=train_sub, palette = 'Set2')
plt.show()
```



- The boxplot clearly shows that there is not much of a difference in distribution for the most frequently occuring passenger count values.

In [42]:

```
train[['pickup_longitude','pickup_latitude']].describe()
```

Out[42]:

	pickup_longitude	pickup_latitude
count	543018.000000	543018.000000
mean	-73.973567	40.750996

	pickup_longitude	pickup_latitude
std	0.041523	0.033848
min	-79.569733	34.712234
25%	-73.991859	40.737400
50%	-73.981735	40.754116
75%	-73.967438	40.768330
max	-65.897385	51.881084

- We have outliers in latitude and longitude as well.

In [43]:

```
xlong = train['pickup_longitude'].mean()
x_sd = train['pickup_longitude'].std()
ylat = train['pickup_latitude'].mean()
y_sd = train['pickup_latitude'].std()
```

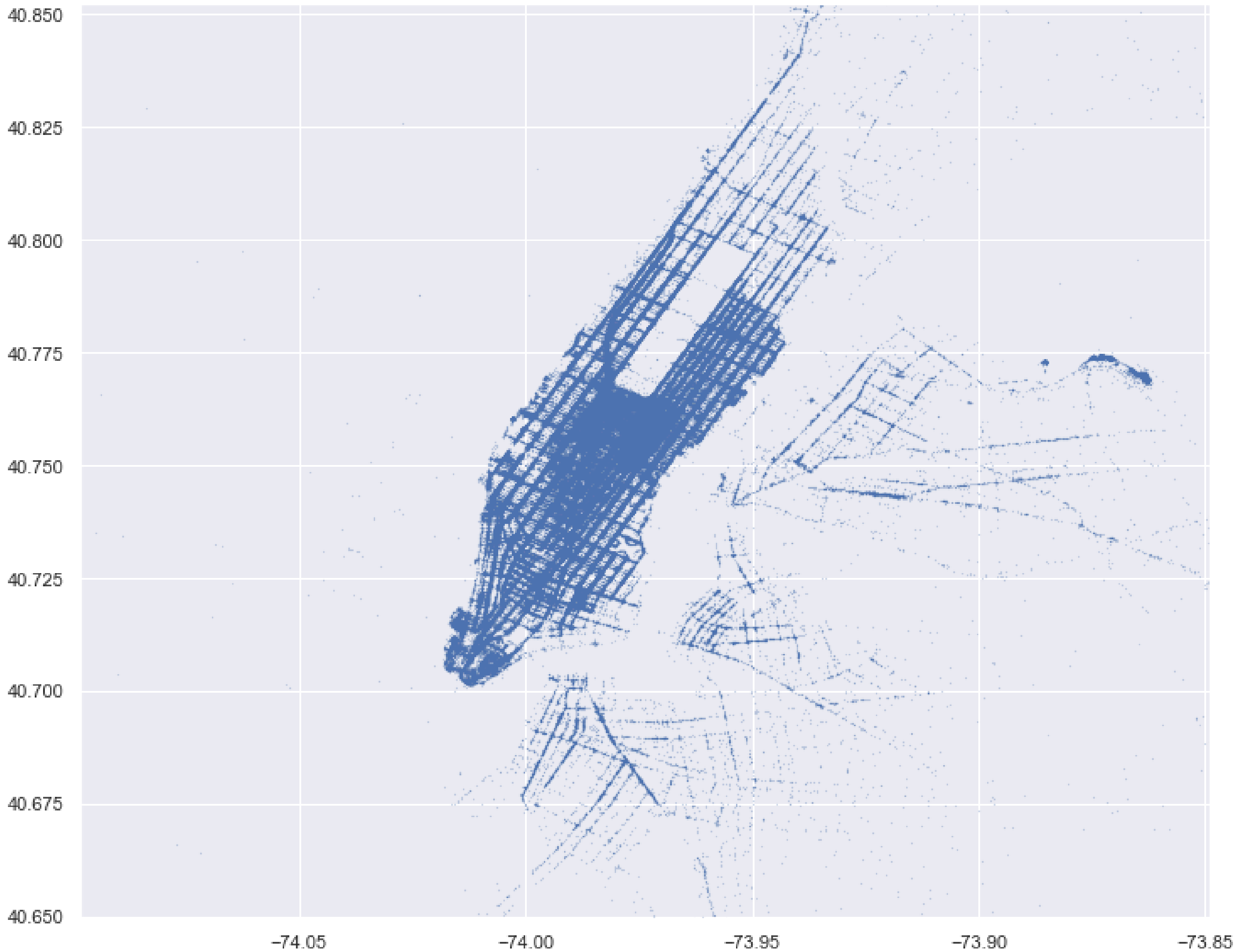
- We'll take points only within the +/- 3 sigma range to visualise the coordinates as this will eliminate the outliers.

In [44]:

```
fig, ax = plt.subplots(ncols=1, nrows=1,figsize=(12,10))
plt.ylim(ylat - 3*y_sd, ylat + 3*y_sd)
plt.xlim(xlong - 3*x_sd, xlong + 3*x_sd)
ax.scatter(train['pickup_longitude'],train['pickup_latitude'], s=0.01, alpha=1)
```

Out[44]:

```
<matplotlib.collections.PathCollection at 0x23d4560c370>
```



In [45]:
```
train1 = train.loc[(train.pickup_latitude > 40.6) & (train.pickup_latitude < 40.9)]
train1 = train.loc[(train.pickup_longitude > -74.05) & (train.pickup_longitude < -73.7)]
test1 = test.loc[(test.pickup_latitude > 40.6) & (test.pickup_latitude < 40.9)]
test1 = test.loc[(test.pickup_longitude > -74.05) & (test.pickup_longitude < -73.7)]
```

Clustering the pickup locations

In [46]:
```
import geopandas as gpd
from shapely.geometry import Point, Polygon
```

In [47]:
```
geometry = [Point(xy) for xy in zip(train1['pickup_longitude'], train1['pickup_latitude'])
geometry[:3]
```

Out[47]:
```
[<shapely.geometry.point.Point at 0x23d491c80d0>,
 <shapely.geometry.point.Point at 0x23d4563bca0>,
 <shapely.geometry.point.Point at 0x23d4563bcd0>]
```

In [48]:
```
geo_df = gpd.GeoDataFrame(train1, crs = {'init': 'epsg:4326'}, geometry = geometry)
geo_df.head()
```

Out[48]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitud
469114	id2380741	2	2016-05-21 10:40:14	2016-05-21 10:51:11	1	-73.981796	40.76203

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitud
694852	id3946961	2	2016-01-08 18:49:27	2016-01-08 18:52:42	5	-73.980965	40.74767
696324	id0833913	1	2016-05-22 00:54:10	2016-05-22 01:08:10	1	-73.951065	40.78272
356496	id1336849	1	2016-06-11 10:32:12	2016-06-11 10:38:50	1	-73.987625	40.76279
645318	id1610858	1	2016-04-03 10:45:51	2016-04-03 10:57:13	3	-73.964333	40.79250

In [49]:

```
from sklearn.cluster import KMeans
k_means = KMeans(n_clusters = 50)
df_pick = train1[['pickup_longitude', 'pickup_latitude']]
df_drop = train1[['dropoff_longitude','dropoff_latitude']]

k_means.fit(df_pick)
```

Out[49]:

```
▾        KMeans
KMeans(n_clusters=50)
```

In [50]:

```
clust_pick = k_means.labels_
train1['label_pick'] = clust_pick.tolist()
train1['label_drop'] = k_means.predict(df_drop)

centroid_pickups = pd.DataFrame(k_means.cluster_centers_, columns = ['centroid_pick_long',
centroid_dropoff = pd.DataFrame(k_means.cluster_centers_, columns = ['centroid_drop_long',

centroid_pickups.shape
centroid_pickups['label_pick'] = centroid_pickups.index
centroid_dropoff['label_drop'] = centroid_dropoff.index

train1 = pd.merge(train1, centroid_pickups, how='left', on=['label_pick'])
train1 = pd.merge(train1, centroid_dropoff, how='left', on=['label_drop'])
train1.head()
```

Out[50]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	drc
0	id2380741	2	2016-05-21 10:40:14	2016-05-21 10:51:11	1	-73.981796	40.762035	
1	id3946961	2	2016-01-08 18:49:27	2016-01-08 18:52:42	5	-73.980965	40.747677	
2	id0833913	1	2016-05-22 00:54:10	2016-05-22 01:08:10	1	-73.951065	40.782722	
3	id1336849	1	2016-06-11 10:32:12	2016-06-11 10:38:50	1	-73.987625	40.762791	

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitude	drc
4	id1610858	1	2016-04-03 10:45:51	2016-04-03 10:57:13	3	-73.964333	40.792503	

5 rows × 22 columns

In [51]:

```
summary_avg_time = pd.DataFrame(train1.groupby('label_pick')['trip_duration'].mean())
summary_avg_time.reset_index(inplace = True)
summary_pref_clus = pd.DataFrame(train1.groupby(['label_pick', 'label_drop'])['id'].count
summary_pref_clus = summary_pref_clus.reset_index()
summary_pref_clus = summary_pref_clus.loc[summary_pref_clus.groupby('label_pick')['id'].ic
summary =pd.merge(summary_avg_time, summary_pref_clus, how = 'left', on = 'label_pick')
summary = summary.rename(columns={'trip_duration':'avg_triptime'})
summary.head()
```

Out[51]:

	label_pick	avg_triptime	label_drop	id
0	0	817.360420	22	2001
1	1	2594.393606	38	236
2	2	707.563587	14	1282
3	3	1930.848292	38	378
4	4	815.173536	12	1019

In [52]:

```
# Summary of distribution of data over 50 clusters
summary_full_data = pd.DataFrame(train1.groupby('label_pick')['id'].count())
summary_full_data['id'].describe()
```

Out[52]:

```
count        50.000000
mean      10858.040000
std        7658.432426
min           8.000000
25%        2995.000000
50%       12339.500000
75%       16545.250000
max       26180.000000
Name: id, dtype: float64
```

In [53]:

```
def clusters_map(clus_data, full_data, tile = 'OpenStreetMap', sig = 0, zoom = 12, circle
    """ function to plot clusters on map"""
    map_1 = folium.Map(location=[40.767937, -73.982155], zoom_start=zoom,tiles= tile) # 'M
    summary_full_data = pd.DataFrame(full_data.groupby('label_pick')['id'].count())
    summary_full_data.reset_index(inplace = True)
    if sig == 1:
        summary_full_data = summary_full_data.loc[summary_full_data['id']>11500]
    sig_cluster = summary_full_data['label_pick'].tolist()
    clus_summary = summary

    for i in sig_cluster:
        pick_long = clus_data.loc[clus_data.index ==i]['centroid_pick_long'].values[0]
        pick_lat = clus_data.loc[clus_data.index ==i]['centroid_pick_lat'].values[0]
        clus_no = clus_data.loc[clus_data.index ==i]['label_pick'].values[0]
        most_visited_clus = clus_summary.loc[clus_summary['label_pick']==i]['label_drop'].
        avg_triptime = clus_summary.loc[clus_summary['label_pick']==i]['avg_triptime'].val
        pop = 'cluster = '+str(clus_no)+' & most visited cluster = ' +str(most_visited_clu
        if circle == 1:
            folium.CircleMarker(location=[pick_lat, pick_long], radius=radius_,
```

```
                        color='#F08080',
                        fill_color='#3186cc', popup=pop).add_to(map_1)
            folium.Marker([pick_lat, pick_long], popup=pop).add_to(map_1)
    return map_1
```

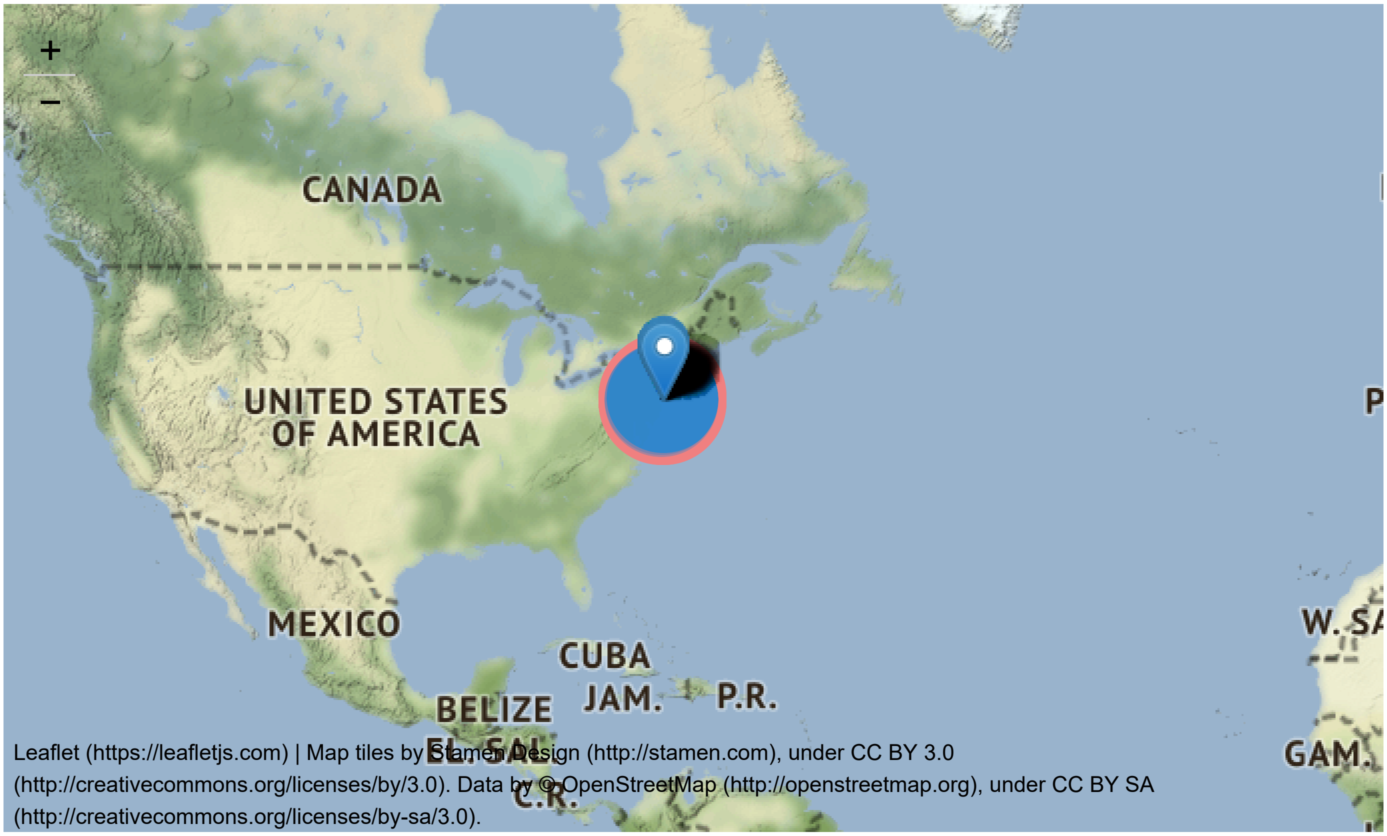
In [54]:

```
import folium
```

In [55]:

```
clus_map = clusters_map(centroid_pickups, train1, sig =0, zoom =12, circle =1, tile = 'Sta
clus_map
```

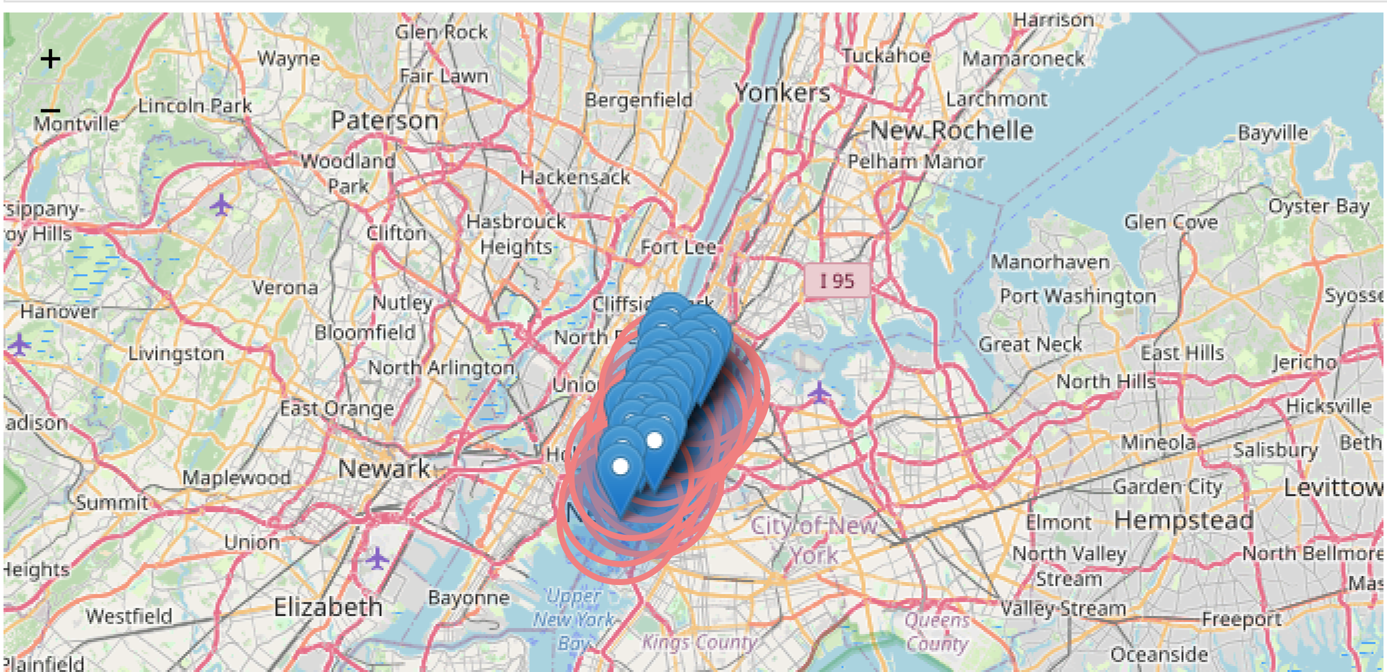
Out[55]:



In [56]:

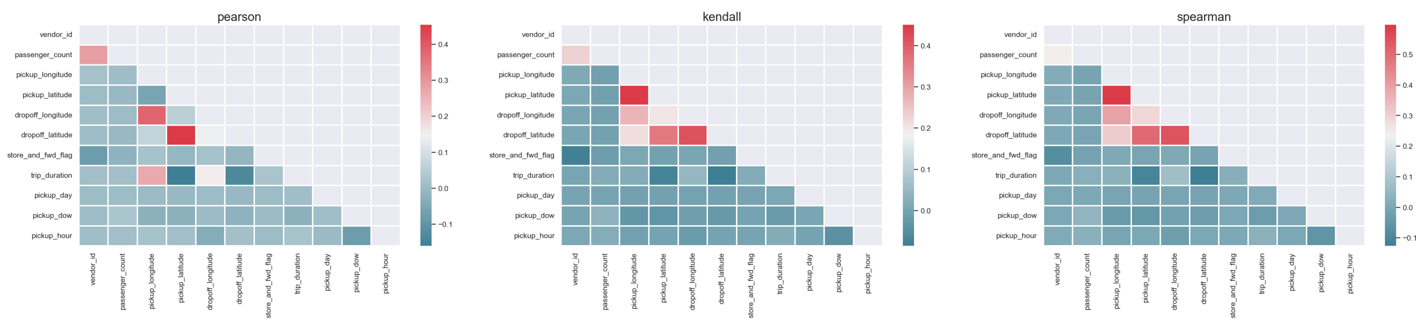
```
# Visualizing top 50% of the clusters
clus_map_sig = clusters_map(centroid_pickups, train1, sig =1, circle =1, zoom = 12)
clus_map_sig
```

Out[56]:



In [57]:

```
# Checking correlation

# plotting heatmap usill all methods for all numerical variables
plt.figure(figsize=(36,6), dpi=140)
for j,i in enumerate(['pearson','kendall','spearman']):
  plt.subplot(1,3,j+1)
  correlation = train.dropna().corr(method=i)
# Generate a mask for the upper triangle
  mask = np.triu(np.ones_like(correlation, dtype=bool))
# Generate a custom diverging colormap
  cmap = sns.diverging_palette(220, 10, as_cmap=True)
  sns.heatmap(correlation, mask = mask, cmap = cmap, linewidth = 2)
  plt.title(i, fontsize=18)
```



- The correlation plot shows that the strongest correlations are between `passenger_count` and `vendor_id`, `dropoff_longitude` and `pickup_longitude`, `dropoff_latitude` and `pickup_latitude`.

Feature Engineering

Knowing the distance between pickup and dropoff could be helpful in predicting the trip duration. This can be calculated using the haversine distance formula that uses the latitude and longitude coordinates to calculate the distance between the two places.

In [58]:

```
def haversine(lat1, lng1, lat2, lng2):
    lat1, lng1, lat2, lng2 = map(np.radians, (lat1, lng1, lat2, lng2))
    AVG_EARTH_RADIUS = 6371  # in km
    lat = lat2 - lat1
    lng = lng2 - lng1
    d = np.sin(lat * 0.5) ** 2 + np.cos(lat1) * np.cos(lat2) * np.sin(lng * 0.5) ** 2
    h = 2 * AVG_EARTH_RADIUS * np.arcsin(np.sqrt(d))
    return h
```

In [59]:

```
train['distance'] = haversine(train.pickup_latitude, train.pickup_longitude,
                                           train.dropoff_latitude, train.dropoff_longitude
test['distance'] = haversine(test.pickup_latitude, test.pickup_longitude,
                                           test.dropoff_latitude, test.dropoff_longitude)
```

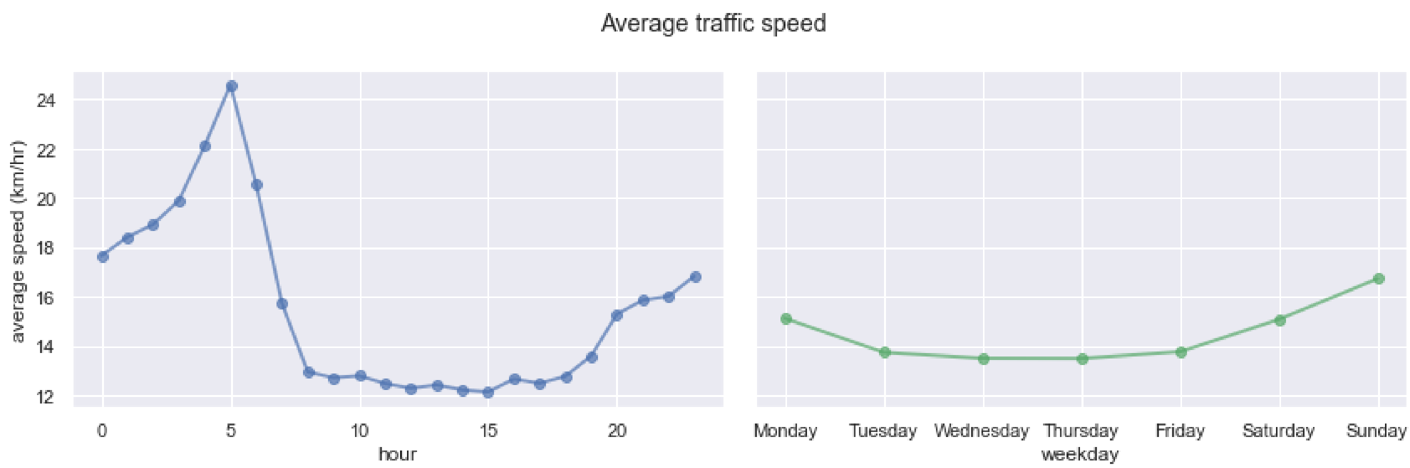
In [60]:

```
train.distance.describe()
```

```
Out[60]: count     543018.000000
mean           3.460875
std            4.398021
min            0.000000
25%            1.247133
50%            2.112514
75%            3.901750
max         1240.908677
Name: distance, dtype: float64
```

```
In [61]: train.loc[:, 'avg_speed_h'] = train['distance'] / (train['trip_duration']/3600)
```

```
In [62]: fig, ax = plt.subplots(figsize = (12,4), ncols=2, sharey=True)
ax[0].plot(train.groupby('pickup_hour').mean()['avg_speed_h'], 'bo-', lw=2, alpha=0.7)
ax[1].plot(train.groupby('pickup_dow').mean()['avg_speed_h'], 'go-', lw=2, alpha=0.7)

ax[0].set_xlabel('hour')
ax[1].set_xlabel('weekday')
ax[1].set_xticks([0,1,2,3,4,5,6], ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',
ax[0].set_ylabel('average speed (km/hr)')
fig.suptitle('Average traffic speed')
fig.tight_layout()
```



- The hours 08:00 to 18:00 seem to be the work hours with more traffic and thus lower traffic speed.
- A new feature named work_hours can be introduced with its value as 1 during the work hours, from Monday to Friday, and 0 otherwise.

```
In [63]: train['work_hours'] = ((train['pickup_hour'] >= 8) & (train['pickup_hour'] < 18) & (train
train.head()
```

Out[63]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitud
469114	id2380741	2	2016-05-21 10:40:14	2016-05-21 10:51:11	1	-73.981796	40.76203
694852	id3946961	2	2016-01-08 18:49:27	2016-01-08 18:52:42	5	-73.980965	40.74767
696324	id0833913	1	2016-05-22 00:54:10	2016-05-22 01:08:10	1	-73.951065	40.78272
356496	id1336849	1	2016-06-11 10:32:12	2016-06-11 10:38:50	1	-73.987625	40.76279
645318	id1610858	1	2016-04-03 10:45:51	2016-04-03 10:57:13	3	-73.964333	40.79250

Evaluation metric

- The most suitable evaluation metric for trip duration would be RMSLE, as it wouldn't be affected by outliers.

In [64]:
```
def rmsle(evaluator,X,real):
    sum = 0.0
    predicted = evaluator.predict(X)
    #print("Number predicted less than 0: {}".format(np.where(predicted < 0)[0].shape))

    predicted[predicted < 0] = 0
    for x in range(len(predicted)):
        p = np.log(predicted[x]+1)
        r = np.log(real[x]+1)
        sum = sum + (p-r)**2
    return (sum/len(predicted))**0.5
```

Preparing Test Data

In [65]:
```
test.head()
```

Out[65]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitud
409888	id3315205	1	2016-06-21 22:06:35	2016-06-21 22:19:19	1	-73.981903	40.76569
666838	id0273627	1	2016-01-29 08:50:01	2016-01-29 09:37:45	1	-73.963600	40.77439
421168	id3291472	1	2016-03-30 12:36:29	2016-03-30 12:45:53	1	-73.991081	40.73741
348868	id2444699	1	2016-04-11 05:36:57	2016-04-11 05:44:28	1	-73.962936	40.76647
34687	id2159293	1	2016-01-01 02:52:32	2016-01-01 03:01:51	1	-73.976067	40.75044

In [66]:
```
test['store_and_fwd_flag'] = 1 * (test.store_and_fwd_flag.values == 'Y')
```

In [67]:
```
test['work_hours'] = ((test['pickup_hour'] >= 8) & (test['pickup_hour'] < 18) & (test['pic
```

In [68]:
```
test.loc[:, 'avg_speed_h'] = 1000 * test['distance'] / test['trip_duration']
```

In [69]:
```
test.head()
```

Out[69]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitud
409888	id3315205	1	2016-06-21 22:06:35	2016-06-21 22:19:19	1	-73.981903	40.76569
666838	id0273627	1	2016-01-29 08:50:01	2016-01-29 09:37:45	1	-73.963600	40.77439

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitud
421168	id3291472	1	2016-03-30 12:36:29	2016-03-30 12:45:53	1	-73.991081	40.73741
348868	id2444699	1	2016-04-11 05:36:57	2016-04-11 05:44:28	1	-73.962936	40.76647
34687	id2159293	1	2016-01-01 02:52:32	2016-01-01 03:01:51	1	-73.976067	40.75044

Benchmark Model

In [70]:

```
# storing simple median in a new column in the test set as "simple_median"
test['median_duration'] = train['trip_duration'].median()
test.head()
```

Out[70]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitude	pickup_latitud
409888	id3315205	1	2016-06-21 22:06:35	2016-06-21 22:19:19	1	-73.981903	40.76569
666838	id0273627	1	2016-01-29 08:50:01	2016-01-29 09:37:45	1	-73.963600	40.77439
421168	id3291472	1	2016-03-30 12:36:29	2016-03-30 12:45:53	1	-73.991081	40.73741
348868	id2444699	1	2016-04-11 05:36:57	2016-04-11 05:44:28	1	-73.962936	40.76647
34687	id2159293	1	2016-01-01 02:52:32	2016-01-01 03:01:51	1	-73.976067	40.75044

In [71]:

```
#calculating mean absolute error
from sklearn.metrics import mean_squared_error as MSE

median_rmsle = MSE(np.log(test['trip_duration']+1) , np.log(test['median_duration']+1), sc
median_rmsle
```

Out[71]:

```
0.7965105610441814
```

KNN Model

In [72]:

```
train.dtypes
```

Out[72]:

```
id                             object
vendor_id                       int64
pickup_datetime        datetime64[ns]
dropoff_datetime       datetime64[ns]
passenger_count                 int64
pickup_longitude              float64
pickup_latitude               float64
```

```
dropoff_longitude          float64
dropoff_latitude           float64
store_and_fwd_flag           int32
trip_duration                int64
pickup_day                   int64
pickup_dayow                object
pickup_dow                   int64
pickup_hour                  int64
distance                   float64
avg_speed_h                float64
work_hours                   int32
dtype: object
```

In [73]:
```
# Seperating the object datatypes from the dataframe
data1 = train.select_dtypes(exclude = ['object', 'datetime'])
data1.columns
```

Out[73]:
```
Index(['vendor_id', 'passenger_count', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'store_and_fwd_flag',
       'trip_duration', 'pickup_day', 'pickup_dow', 'pickup_hour', 'distance',
       'avg_speed_h', 'work_hours'],
      dtype='object')
```

Seperating dependent and independent variables

In [74]:
```
#seperating independent and dependent variables
train_x = data1.drop(['trip_duration', 'avg_speed_h'], axis=1)
train_y = data1['trip_duration']
train_x.shape, train_y.shape
```

Out[74]:
```
((543018, 12), (543018,))
```

In [75]:
```
# Seperating the object datatypes from the dataframe
data2 = test.select_dtypes(exclude = ['object', 'datetime'])
test_x = data2.drop(['trip_duration', 'median_duration', 'avg_speed_h'], axis=1)
test_y = data2['trip_duration']
test_x.shape, test_y.shape
```

Out[75]:
```
((182331, 12), (182331,))
```

In [76]:
```
#importing KNN regressor and metric mse

from sklearn.neighbors import KNeighborsRegressor as KNN
from sklearn.metrics import mean_squared_error as mse

from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import cross_val_score
```

In [77]:
```
# Creating instance of KNN
knn = KNN(n_neighbors = 10)

# Fitting the model
cv = ShuffleSplit(n_splits=4, test_size=0.1, random_state=10)
score = cross_val_score(knn, train_x, np.ravel(train_y), cv=cv,scoring=rmsle)
score
```

Out[77]:
```
array([0.44162558, 0.44000236, 0.44092562, 0.44213926])
```

In [78]:
```
score.mean()
```

Out[78]: 0.441173204338767940

In [79]:
```
knn.fit(train_x, train_y)
```

Out[79]:
```
▾ KNeighborsRegressor
KNeighborsRegressor(n_neighbors=10)
```

In [80]:
```
# Predicting over the Train Set and calculating MSE
test_predict = knn.predict(test_x)
k = mse(np.log(test_predict+1), np.log(test_y+1), squared = False)
print('Test RMSLE    ', k )
```

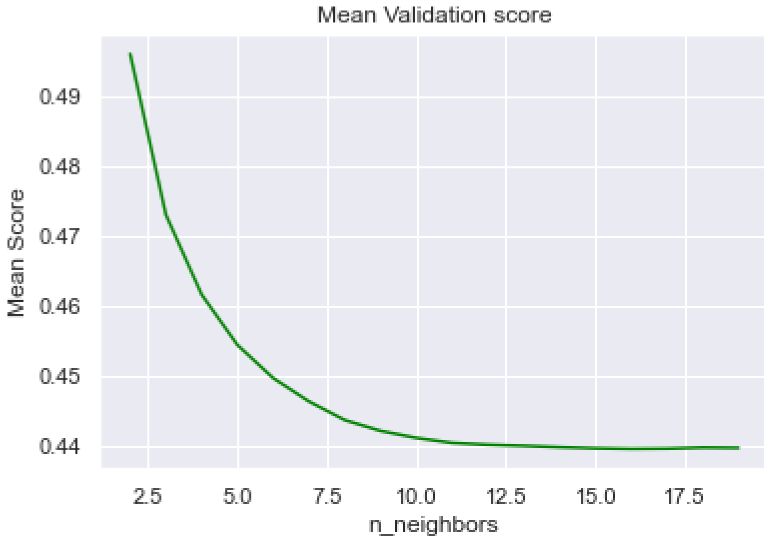
```
Test RMSLE     0.519649027522984
```

In [81]:
```
def Val_score(n_neighbors):
    '''
  takes range of n_neighbors as input
  returns Mean and Standard Deviation for each value of n_neighbors
  '''
    avg = []
    std = []

    for i in n_neighbors:

    # 10 fold cross validation for every value of n_neighbor
      cv = ShuffleSplit(n_splits=4, test_size=0.1, random_state=10)
      score = cross_val_score(KNN(n_neighbors = i), train_x, np.ravel(train_y), cv=cv,scor
    # adding mean to avg list
      avg.append(score.mean())

    # adding standard deviation to std list
      std.append(score.std())

    return avg, std
```

In [82]:
```
n_neighbors = range(1,20)
mean, std = Val_score(n_neighbors)
```

In [83]:
```
plt.plot(n_neighbors[1:20], mean[1:20], color = 'green', label = 'mean' )
plt.xlabel('n_neighbors')
plt.ylabel('Mean Score')
plt.title('Mean Validation score')
```

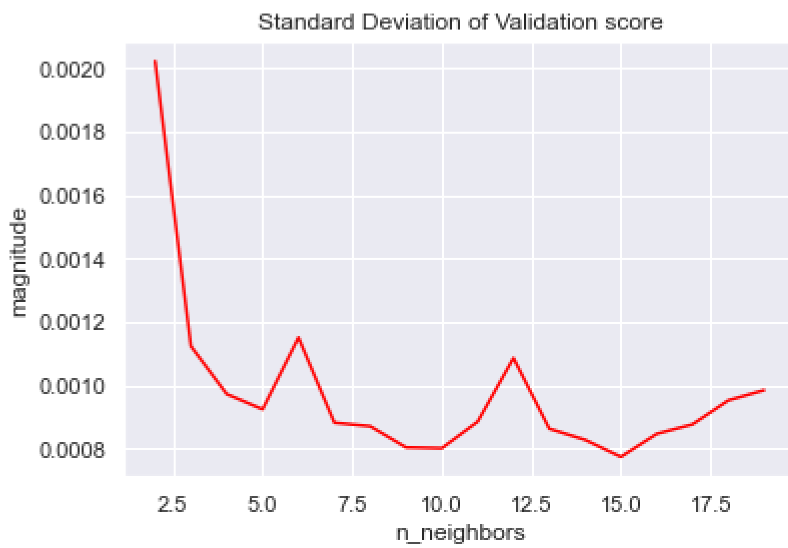
Out[83]:
```
Text(0.5, 1.0, 'Mean Validation score')
```



In [84]:

```
plt.plot(n_neighbors[1:20], std[1:20], color = 'red', label = 'Standard deviation' )
plt.xlabel('n_neighbors')
plt.ylabel('magnitude')
plt.title('Standard Deviation of Validation score')
```

Out[84]: Text(0.5, 1.0, 'Standard Deviation of Validation score')



In [85]:

```
def Elbow(K):
  #initiating empty list
    test_rmsle = []

  #training model for evey value of K
    for i in K:
        #Instance of KNN
        reg = KNN(n_neighbors = i)
        reg.fit(train_x, train_y)
        #Appending mse value to empty list claculated using the predictions
        tmp = reg.predict(test_x)
        tmp = mse(np.log(tmp+1),np.log(test_y+1), squared = False)
        test_rmsle.append(tmp)

    return test_rmsle
```

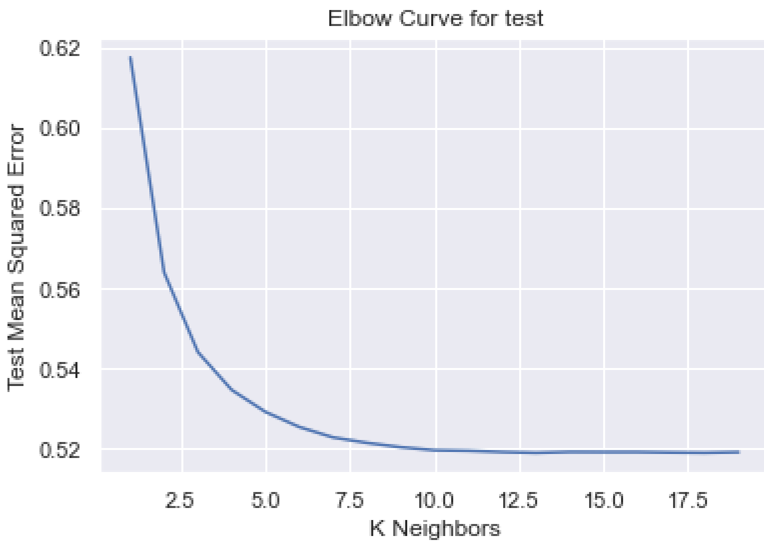
In [86]:

```
#Defining K range
k = range(1,20)
# calling above defined function
```

```
b = Elbow(k)
# plotting the Curves
plt.plot(k, b)
plt.xlabel('K Neighbors')
plt.ylabel('Test Mean Squared Error')
plt.title('Elbow Curve for test')
```

Out[86]:

```
Text(0.5, 1.0, 'Elbow Curve for test')
```



In [87]:

```
# Creating instance of KNN with optimal value of K = 10 as it has low RMSLE for both trai
reg = KNN(n_neighbors = 10)

# Fitting the model
cv = ShuffleSplit(n_splits=4, test_size=0.1, random_state=10)
knn_train_score = cross_val_score(reg, train_x, np.ravel(train_y), cv=cv,scoring=rmsle)
knn_train_score = knn_train_score.mean()
print('Train RMSLE      ', knn_train_score)
reg.fit(train_x, train_y)

# Predicting over the Train Set and calculating F1
test_predict = reg.predict(test_x)
knn_test_score = mse(np.log(test_predict+1), np.log(test_y+1), squared = False)
print('Test RMSLE     ', knn_test_score)
```

```
Train RMSLE      0.44117320433876794
Test RMSLE     0.519649027522984
```

Linear Regression

In [90]:

```
import sklearn
from sklearn.linear_model import LinearRegression as LR
```

In [91]:

```
# Creating instance of Linear Regression
lr = LR(normalize = True)
```

In [92]:

```
lr.fit(train_x,train_y)
```

Out[92]:

```
LinearRegression
LinearRegression(normalize=True)
```

In [93]:
```
cv = ShuffleSplit(n_splits=4, test_size=0.1, random_state=0)
lr_score = cross_val_score(lr, train_x, np.ravel(train_y), cv=cv, scoring=rmsle)
lr_score.mean()
```

Out[93]:
```
0.5433030182199867
```

In [94]:
```
# Predicting over the train set and calculating the error
train_predict = lr.predict(train_x)
train_predict[train_predict<0] = 0

lr_train_score = mse(np.log(train_predict+1), np.log(train_y+1), squared = False)
print("Training RMSLE", lr_train_score)
```

```
Training RMSLE 0.5395718246312002
```

In [95]:
```
# Predicting over the Train Set and calculating F1
test_predict = lr.predict(test_x)
test_predict[test_predict<0] = 0

lr_test_score = mse(np.log(test_predict+1), np.log(test_y+1), squared = False)
print('Test RMSLE     ', lr_test_score)
```

```
Test RMSLE      0.6179021010187421
```

In [96]:
```
reg_data = pd.DataFrame({'coeff': lr.coef_, 'features': train_x.columns})
reg_data
```

Out[96]:

	coeff	features
0	10.348246	vendor_id
1	4.337605	passenger_count
2	471.860923	pickup_longitude
3	-3156.478564	pickup_latitude
4	773.384686	dropoff_longitude
5	110.073430	dropoff_latitude
6	65.911018	store_and_fwd_flag
7	0.670932	pickup_day
8	12.044423	pickup_dow
9	6.992475	pickup_hour
10	99.694782	distance
11	266.542266	work_hours

We can see from the coefficients that the latitudes, longitudes, distance and work_hours affect the trip_duration the most.

In [97]:
```
from sklearn.linear_model import Ridge
```

```
alpha = [0, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20, 25]
```

In [98]:

```
# defining a function which will fit ridge regression model, plot the results, and return
def ridge_regression(train_x, train_y, test_x, test_y, alpha):
    #Fit the model
    ridgereg = Ridge(alpha=alpha,normalize=True)
    ridgereg.fit(train_x,train_y)
    train_y_pred = ridgereg.predict(train_x)
    test_y_pred = ridgereg.predict(test_x)
    train_y_pred[train_y_pred<0] = 0
    test_y_pred[test_y_pred<0] = 0


    #Return the result in pre-defined format
    k1 = mse(np.log(train_y_pred+1), np.log(train_y+1), squared = False)
    ret = [k1]

    k2 = mse(np.log(test_y_pred+1), np.log(test_y+1), squared = False)
    ret.extend([k2])

    ret.extend([ridgereg.intercept_])
    ret.extend(ridgereg.coef_)

    return ret
```

In [99]:

```
ind = ['alpha_%.2g'%alpha[i] for i in range(0,10)]
rmsle_matrix_ridge = pd.DataFrame(index = ind, columns = ['train_rmsle', 'test_rmsle', 'ir
```

In [100…

```
for i in range(10):
    rmsle_matrix_ridge.iloc[i,] = ridge_regression(train_x, train_y, test_x, test_y, alpha
```

In [101…

```
#Set the display format to be scientific for ease of analysis
pd.options.display.float_format = '{:,.5g}'.format
rmsle_matrix_ridge
```

Out[101…

	train_rmsle	test_rmsle	intercept	coef_Var_1	coef_Var_2	coef_Var_3	coef_Var_4	coef_Var_5	coef_V
alpha_0	0.53957	0.6179	2.165e+05	10.348	4.3376	471.86	-3,156.5	773.38	11
alpha_1e-08	0.53957	0.6179	2.165e+05	10.348	4.3376	471.86	-3,156.5	773.38	11
alpha_0.0001	0.53959	0.61792	2.1655e+05	10.347	4.3376	472.44	-3,156	773.44	10
alpha_0.001	0.53975	0.61809	2.1699e+05	10.339	4.3375	477.67	-3,151.5	773.9	10
alpha_0.01	0.54138	0.6198	2.2124e+05	10.256	4.3358	528.41	-3,107.4	778.45	56
alpha_1	0.63811	0.71384	2.7084e+05	6.3815	3.0161	1,481.5	-1,538.5	840.06	-87
alpha_5	0.71733	0.78836	1.3127e+05	2.6802	1.1992	754.56	-597.8	434.3	-44
alpha_10	0.74064	0.81027	77,840	1.5507	0.68291	447.85	-341.2	260.75	-2
alpha_20	0.75583	0.82452	43,032	0.8411	0.36698	246.01	-183.69	144.27	-14
alpha_25	0.75924	0.82775	35,246	0.68445	0.29805	200.7	-149.25	117.88	-11

In [102…

```
#Importing Lasso model from sklearn's linear_model module
from sklearn.linear_model import Lasso
```

In [103…

```
alpha_lasso = [0, 1e-10, 1e-8, 1e-5,1e-4, 1e-3,1e-2, 1, 5, 10]
```

In [104…

```
# defining a function which will fit lasso regression model, plot the results, and return
def lasso_regression(train_x, train_y, test_x, test_y, alpha):
    #Fit the model
    lassoreg = Lasso(alpha=alpha,normalize=True)
    lassoreg.fit(train_x,train_y)
    train_y_pred = lassoreg.predict(train_x)
    test_y_pred = lassoreg.predict(test_x)
    train_y_pred[train_y_pred<0] = 0
    test_y_pred[test_y_pred<0] = 0


    #Return the result in pre-defined format
    k1 = mse(np.log(train_y_pred+1), np.log(train_y+1), squared = False)
    ret = [k1]

    k2 = mse(np.log(test_y_pred+1), np.log(test_y+1), squared = False)
    ret.extend([k2])

    ret.extend([lassoreg.intercept_])
    ret.extend(lassoreg.coef_)

    return ret
```

In [105…

```
rmsle_matrix_lasso = pd.DataFrame(index = ind, columns = ['train_rmsle', 'test_rmsle', 'in
```

In [106…

```
for i in range(10):
    rmsle_matrix_lasso.iloc[i,] = lasso_regression(train_x, train_y, test_x, test_y, alpha
```

In [107…

```
rmsle_matrix_lasso
```

Out[107…

	train_rmsle	test_rmsle	intercept	coef_Var_1	coef_Var_2	coef_Var_3	coef_Var_4	coef_Var_5	coef_V
alpha_0	0.53957	0.6179	2.165e+05	10.348	4.3376	471.86	-3,156.5	773.38	11
alpha_1e-08	0.53957	0.6179	2.165e+05	10.348	4.3376	471.86	-3,156.5	773.38	11
alpha_0.0001	0.53957	0.6179	2.165e+05	10.348	4.3376	471.86	-3,156.5	773.38	11
alpha_0.001	0.53957	0.6179	2.1649e+05	10.336	4.3335	471.86	-3,156.1	773.27	10
alpha_0.01	0.53959	0.61792	2.1641e+05	10.223	4.2963	471.88	-3,152.3	772.22	10
alpha_1	0.53974	0.6181	2.156e+05	9.098	3.9247	472.03	-3,115.1	761.76	70
alpha_5	0.5421	0.62043	1.9629e+05	0	0.023554	437.87	-2,875.1	627.27	
alpha_10	0.77474	0.8422	847.08	0	0	0	-0	0	
alpha_20	0.77474	0.8422	847.08	0	0	0	-0	0	
alpha_25	0.77474	0.8422	847.08	0	0	0	-0	0	

Decision Tree

In [108…

```
from sklearn.tree import DecisionTreeRegressor as DT
```

```
dreg = DT()
```

In [109…

```
dreg = dreg.fit(train_x,np.ravel(train_y))
```

In [110…

```
train_predict = dreg.predict(train_x)

dt_train_score = mse(np.log(train_predict+1), np.log(train_y+1), squared = False)
print('Train RMSLE     ', dt_train_score)
```

```
Train RMSLE     0.0015605166604175274
```

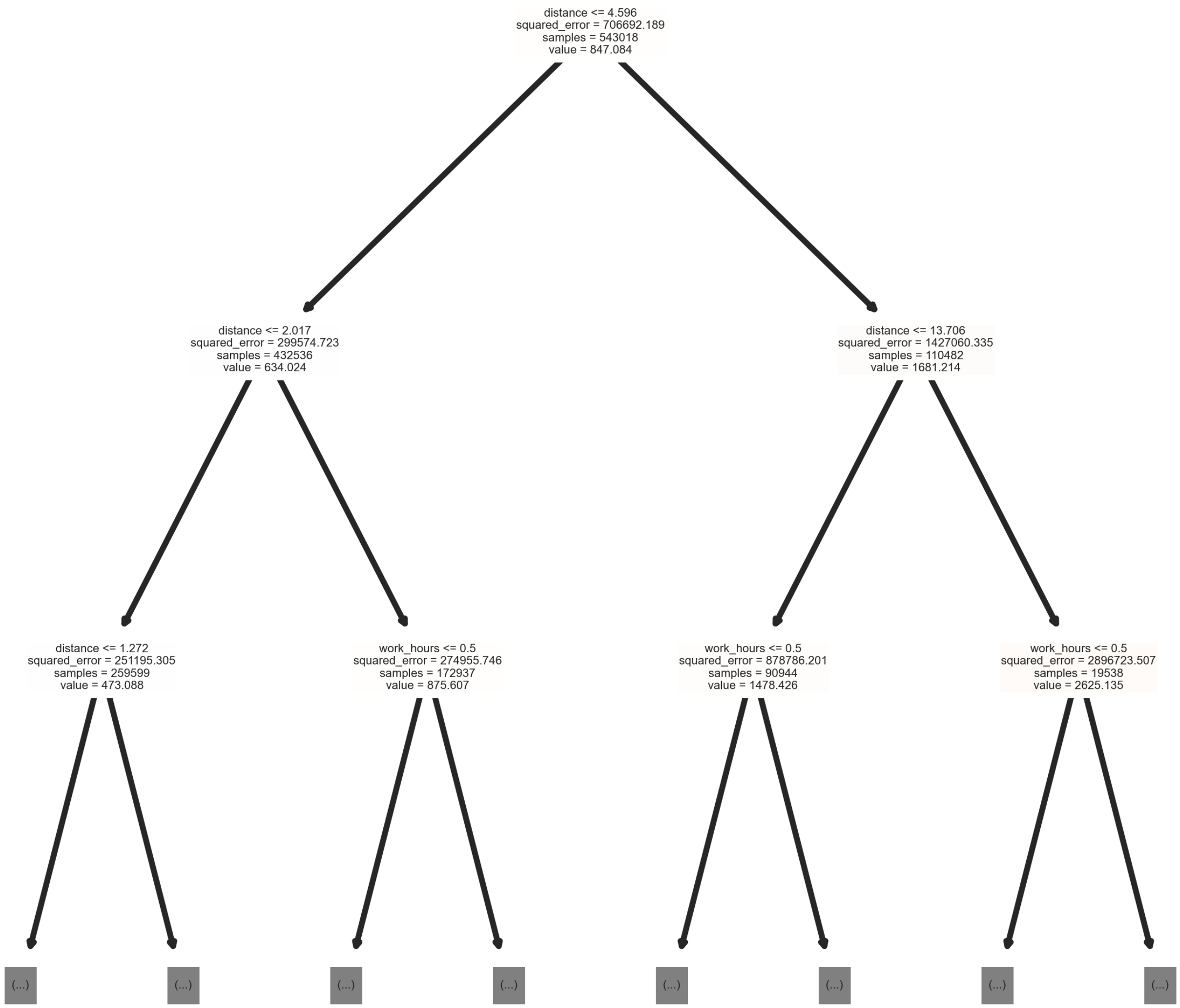
In [111…

```
test_predict = dreg.predict(test_x)

dt_test_score = mse(np.log(test_predict+1), np.log(test_y+1), squared = False)
print('Test RMSLE     ',dt_test_score)
```

```
Test RMSLE     0.568099778720311
```

In [112…

```
from sklearn import tree
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=800)
tree.plot_tree(dreg,
               feature_names = train_x.columns,
               max_depth = 2,
               filled = True);
```



- We can see from the decision tree that the distance and work_hours are the two most important features to predict the trip_duration.

Random Forest

In [116…

```
from sklearn.ensemble import RandomForestRegressor as RF
rf = RF()
cv = ShuffleSplit(n_splits=4, test_size=0.1, random_state=0)
rf_score = cross_val_score(rf, train_x, np.ravel(train_y), cv=cv,scoring=rmsle)
rf_score.mean()
```

Out[116… 0.36326167406351806

In [117…

```
rf = rf.fit(train_x,np.ravel(train_y))
```

In [118…

```
train_predict = rf.predict(train_x)

rf_train_score = mse(np.log(train_predict+1), np.log(train_y+1), squared = False)
print('Train RMSLE     ', rf_train_score)
```

```
Train RMSLE     0.15588947391892835
```

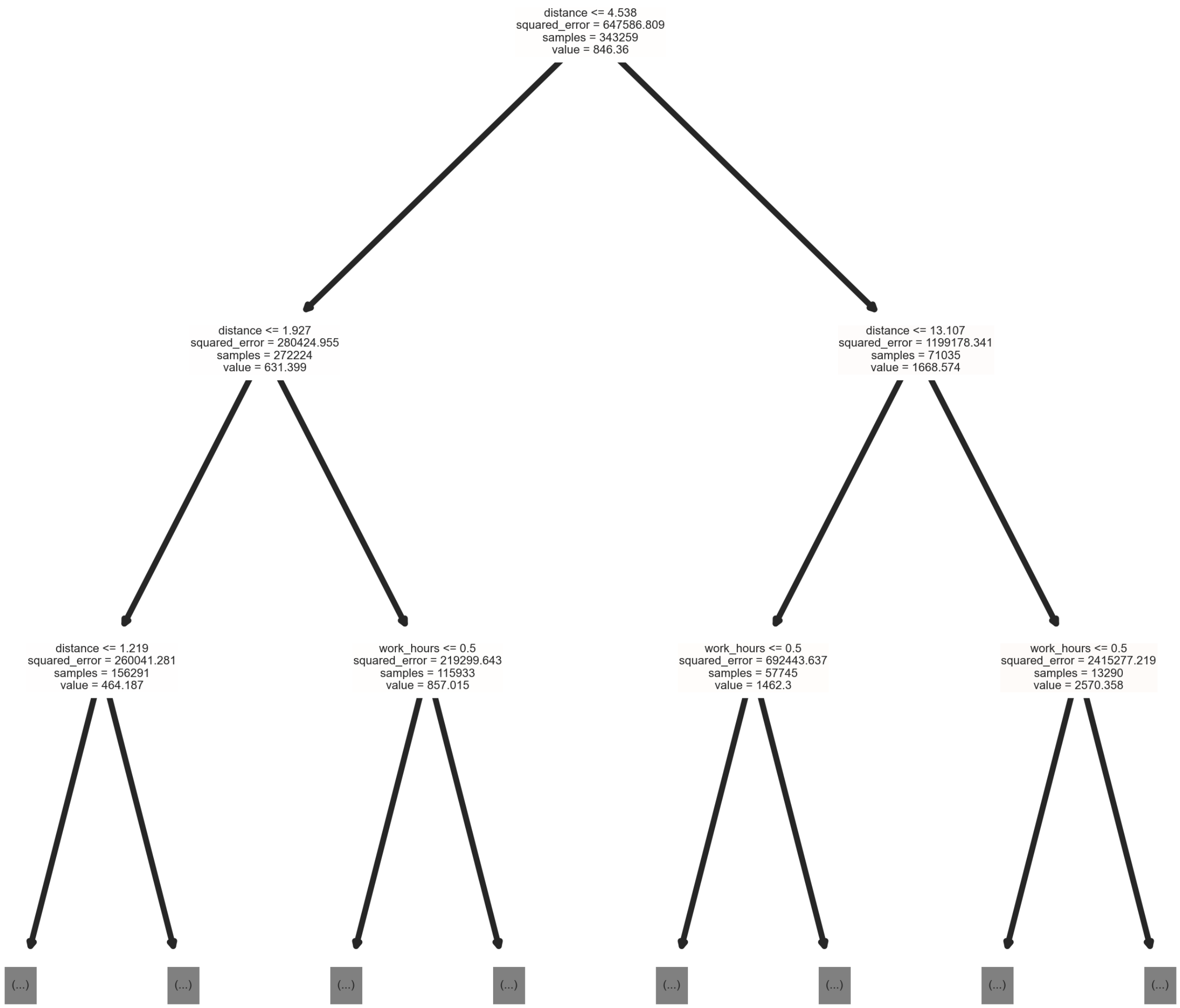
In [119…

```
test_predict = rf.predict(test_x)

rf_test_score = mse(np.log(test_predict+1), np.log(test_y+1), squared = False)
print('Test RMSLE     ',rf_test_score)
```

```
Test RMSLE     0.4803150083992271
```

In [120…

```
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=800)
tree.plot_tree(rf.estimators_[0],
               feature_names = train_x.columns,
               max_depth = 2,
               filled = True);
```



In [121…

```
result = pd.DataFrame(data  = {'Model' : ['KNN', 'Linear Reg', 'Decision Tree', 'Random Fo
                                'train_RMSLE': [knn_train_score, lr_train_score, dt_train_
                               'test_RMSLE': [knn_test_score, lr_test_score, dt_test_scor
result
```

Out[121…

	Model	train_RMSLE	test_RMSLE
0	KNN	0.44117	0.51965
1	Linear Reg	0.53957	0.6179
2	Decision Tree	0.0015605	0.5681
3	Random Forest	0.15589	0.48032

In [122…

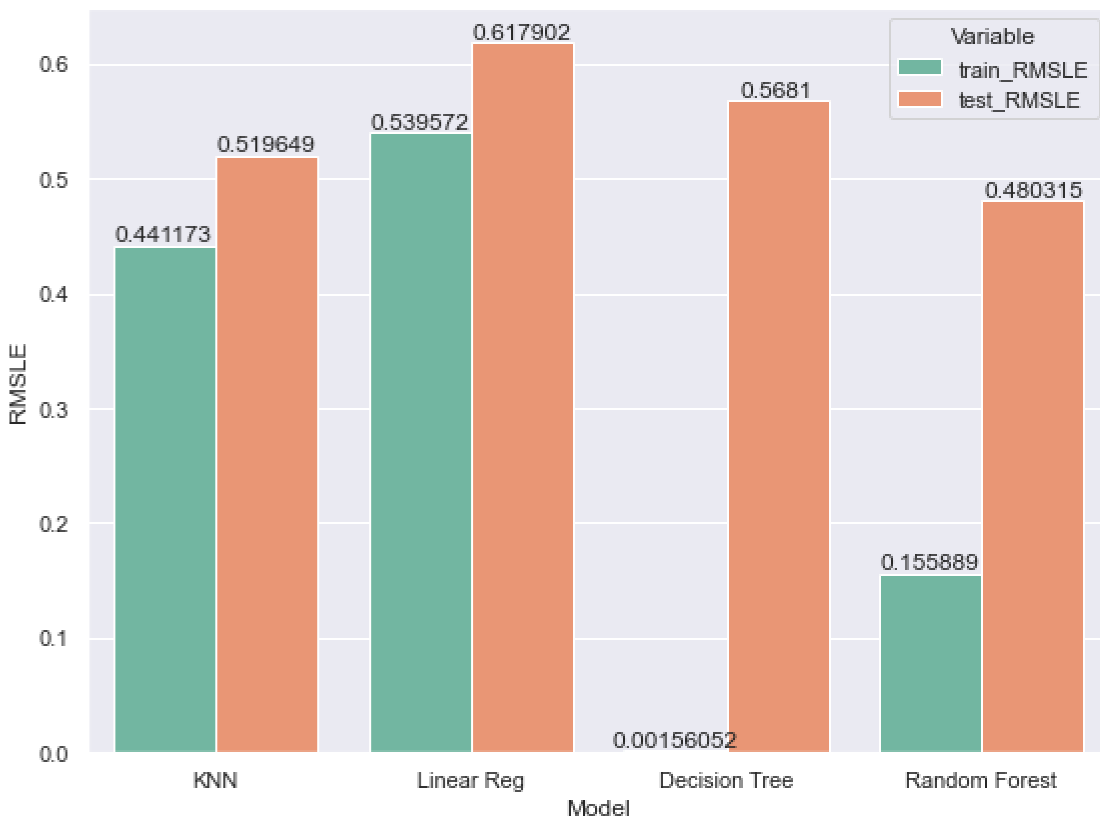
```
tidy = result.melt(id_vars='Model').rename(columns=str.title)
tidy
```

Out[122…

	Model	Variable	Value
0	KNN	train_RMSLE	0.44117
1	Linear Reg	train_RMSLE	0.53957
2	Decision Tree	train_RMSLE	0.0015605
3	Random Forest	train_RMSLE	0.15589
4	KNN	test_RMSLE	0.51965
5	Linear Reg	test_RMSLE	0.6179
6	Decision Tree	test_RMSLE	0.5681
7	Random Forest	test_RMSLE	0.48032

In [123…

```
fig,ax = plt.subplots(figsize = (8,6))
sns.barplot(x = 'Model', y = 'Value', hue = 'Variable', data = tidy, palette = 'Set2')
ax.bar_label(container=ax.containers[0])
ax.bar_label(container=ax.containers[1])
ax.set_ylabel('RMSLE')

fig.tight_layout()
```



- We can see from the results that decision tree model gives the lowest RMSLE for our training data among other models but a higher RMSLE than KNN and Random Forest for the test data. This is because the models overfits to the training data and hence does not perform very well on the test data.
- The best model among the four would be the Random Forest model as it gives very low RMSLE for training data and the lowest RMSLE for the test data.