1. Exploratory Data Analysis

In [1]:

```
# Importing libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder

from sklearn.model_selection import train_test_split

from sklearn.neighbors import KNeighborsRegressor as KNN
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
#Importing the dataset

df = pd.read_csv('nyc_taxi_trip_duration.csv')
```

Let's check the data files! According to the data description we should find the following columns:

- **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)
- **trip_duration** - (target) duration of the trip in seconds

Here, we have 2 variables dropoff_datetime and store_and_fwd_flag which are not available before the trip starts and hence will not be used as features to the model.

In [3]:

```
print("No. of rows: ", df.shape[0])
print("No. of columns: ", df.shape[1])
```

```
No. of rows:  729322
No. of columns:  11
```

In [4]:

```
df.head()
```

Out[4]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitu
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.9539
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.9883
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.9973
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.9616
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.0171

In [5]:

```
df.tail()
```

Out[5]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_lo
729317	id3905982	2	2016-05-21 13:29:38	2016-05-21 13:34:34	2	-73
729318	id0102861	1	2016-02-22 00:43:11	2016-02-22 00:48:26	1	-73
729319	id0439699	1	2016-04-15 18:56:48	2016-04-15 19:08:01	1	-73
729320	id2078912	1	2016-06-19 09:50:47	2016-06-19 09:58:14	1	-74
729321	id1053441	2	2016-01-01 17:24:16	2016-01-01 17:44:40	4	-74

In [6]:

```
#Missing values
print(df.isnull().sum())
```

```
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
```

In [7]:

```
# checking the datatype of all features in the dataset
df.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
```

Categorical variables:

id, pickup_datetime, dropoff_datetime, store_and_fwd_flag

Continuous variables:

vendor_id, passenger_count, pickup_longitude, pickup_latitude dropoff_longitude, dropoff_latitude

Target Exploration: trip_duratation

Here the trip_duration is a continuos variable, which determines that the problem is a regression problem.

understanding categorical variable

In [8]:

```
#Transforming pick_up and drop_off date time into a datetime object
df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'], format= '%Y-%m-%d %H:%M:%S
df['dropoff_datetime'] = pd.to_datetime(df['dropoff_datetime'], format='%Y-%m-%d %H:%M:%
```

In [9]:

```
#Transforming vendor_id and store_and_fwd to categorical data type
df['vendor_id'] = df['vendor_id'].astype('category')
df['store_and_fwd_flag'] = df['store_and_fwd_flag'].astype('category')
```

In [10]:

```
# Converting yes/no flag to 1 and 0 and transforming it into categorical data type
df['store_and_fwd_flag'] = 1 * (df.store_and_fwd_flag.values == 'Y')
df['store_and_fwd_flag'] = df['store_and_fwd_flag'].astype('category')
```

In [11]:

```
#Checking the data types again
df.dtypes
```

Out[11]:

```
id                              object
vendor_id                     category
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            category
trip_duration                    int64
dtype: object
```

In [12]:

```
df['check_trip_duration'] = (df['dropoff_datetime'] - df['pickup_datetime']).map(lambda

duration_difference = df[np.abs(df['check_trip_duration'].values  - df['trip_duration'].
duration_difference.shape
```

Out[12]:

```
(0, 12)
```

This implies that there is no inconsistency in data wrt the drop location and trip duration

In [13]:

```
print("Startdate: ", df['pickup_datetime'].min())
print("Enddate: ", df['pickup_datetime'].max())
```

```
Startdate:  2016-01-01 00:01:14
Enddate:  2016-06-30 23:59:37
```

The trip duration data is collected from the time period of first 6 months from the year 2016

In [14]:

```
# extracting more features from the datetime variable
# For pick_up
df['pickup_day']=df['pickup_datetime'].dt.day
df['pickup_hour'] = df['pickup_datetime'].dt.hour
df['pickup_weekday'] = df['pickup_datetime'].dt.weekday
# for Drop_off
df['dropoff_day'] = df['dropoff_datetime'].dt.day
df['dropoff_hour'] = df['dropoff_datetime'].dt.hour
df['dropoff_weekday'] = df['dropoff_datetime'].dt.weekday
```

In [15]:

```
df.head()
```

Out[15]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitu
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.9539
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.9883
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.9973
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.9616
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.0171

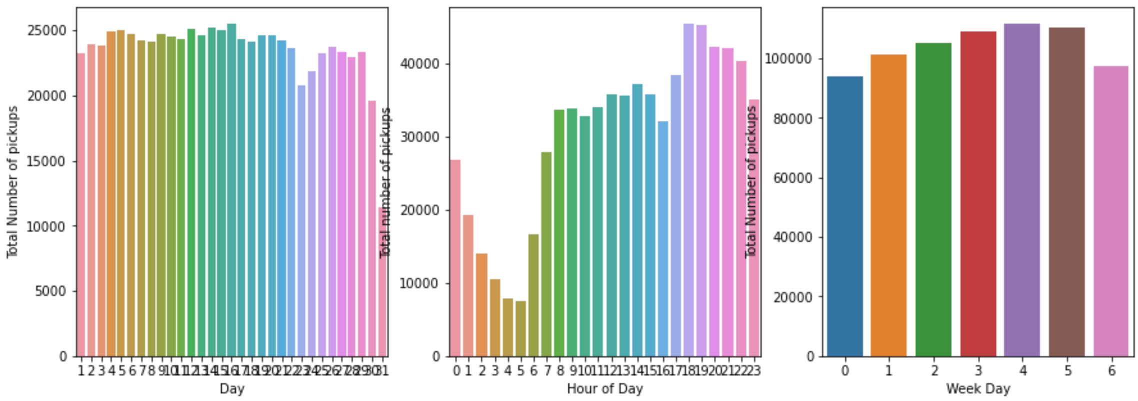
Univariate Visualization

In [16]:

```
# Datetime features
plt.figure(figsize=(20, 5))

# Passenger Count
plt.subplot(141)
sns.countplot(df['pickup_day'])
plt.xlabel('Day')
plt.ylabel('Total Number of pickups')

# vendor_id
plt.subplot(142)
sns.countplot(df['pickup_hour'])
plt.xlabel('Hour of Day')
plt.ylabel('Total number of pickups')

# Passenger Count
plt.subplot(143)
sns.countplot(df['pickup_weekday'])
plt.xlabel('Week Day')
plt.ylabel('Total Number of pickups')
```

Out[16]:

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



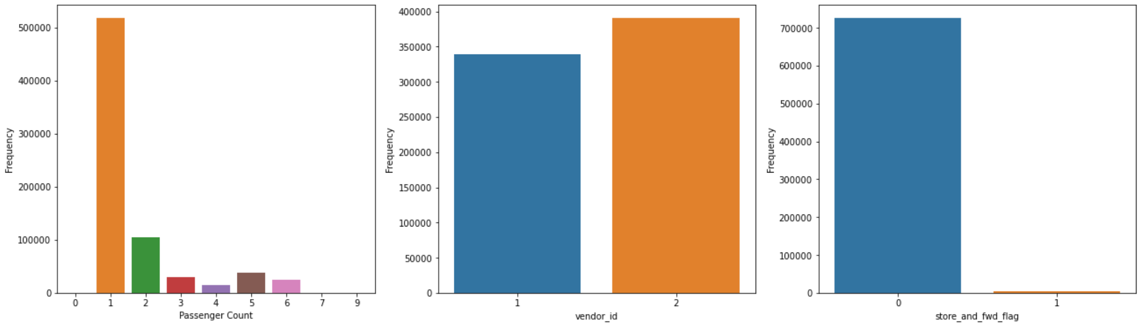
- Trips are very low in early morning, while very high in the late evening hour in the day.
- Trip is on peak on Thursday(4).
- Trips are very low in early morning, while very high in the late evening hour in the day.

In [17]:

```
# Binary Features
plt.figure(figsize=(22, 6))
#fig, axs = plt.subplot(ncols=2)

# Passenger Count
plt.subplot(131)
sns.countplot(df['passenger_count'])
plt.xlabel('Passenger Count')
plt.ylabel('Frequency')


# vendor_id
plt.subplot(132)
sns.countplot(df['vendor_id'])
plt.xlabel('vendor_id')
plt.ylabel('Frequency')

# store_and_fwd_flag
plt.subplot(133)
sns.countplot(df['store_and_fwd_flag'])
plt.xlabel('store_and_fwd_flag')
plt.ylabel('Frequency')
```

Out[17]:

```
Text(0, 0.5, 'Frequency')
```



- Most of the trips involve only 1 passenger.
- Vendor 2 has more trips, compared to vendor 1.
- The value with 1 is very low in the store_and_fwd_flag variable. This suggests that almost no storing took place.

Feature engineering for passenger_count

In [18]:

```
df['passenger_count'].value_counts()
```

Out[18]:

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

Here as we can see that 0 and 9 are very less in number so we will remove it.

In [19]:

```
df=df[df['passenger_count']!=0]
df=df[df['passenger_count']<=6]
```

In [20]:

```
# checking
df['passenger_count'].value_counts()
```

Out[20]:

```
1    517415
2    105097
5     38926
3     29692
6     24107
4     14050
Name: passenger_count, dtype: int64
```

In [21]:

```
#Getting the summary of the trip_duration dataset
df['trip_duration'].describe()/3600 # Trip duration in hours
```

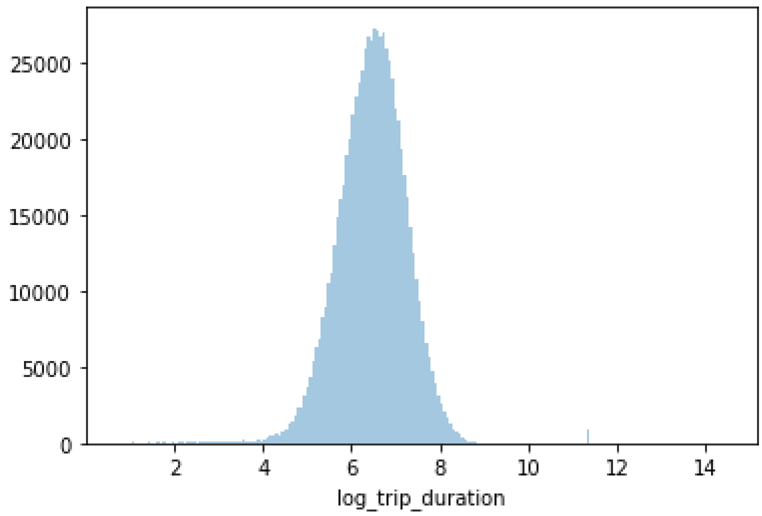
Out[21]:

```
count    202.579722
mean       0.264515
std        1.073531
min        0.000278
25%        0.110278
50%        0.184167
75%        0.298611
max      538.815556
Name: trip_duration, dtype: float64
```

There is a trip with maximum duration of 538 hours. This is a huge outlier and might create problems at the prediction stage. One idea is to log transform this feature.

In [22]:

```
df['log_trip_duration'] = np.log(df['trip_duration'].values + 1)
sns.distplot(df['log_trip_duration'], kde = False, bins = 200)
plt.show()
```



We find:

1. The majority of rides follow a rather smooth distribution that looks almost log-normal with a peak just around exp(6.5) i.e. about 17 minutes.
2. There are several suspiciously short rides with less than 10 seconds duration.
3. As discussed earlier, there are a few huge outliers near 12.

In [23]:

```
df.head()
```

Out[23]:

	id	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	pickup_longitu
0	id1080784	2	2016-02-29 16:40:21	2016-02-29 16:47:01	1	-73.9539
1	id0889885	1	2016-03-11 23:35:37	2016-03-11 23:53:57	2	-73.9883
2	id0857912	2	2016-02-21 17:59:33	2016-02-21 18:26:48	2	-73.9973
3	id3744273	2	2016-01-05 09:44:31	2016-01-05 10:03:32	6	-73.9616
4	id0232939	1	2016-02-17 06:42:23	2016-02-17 06:56:31	1	-74.0171

In [24]:

```
df.shape
```

Out[24]:

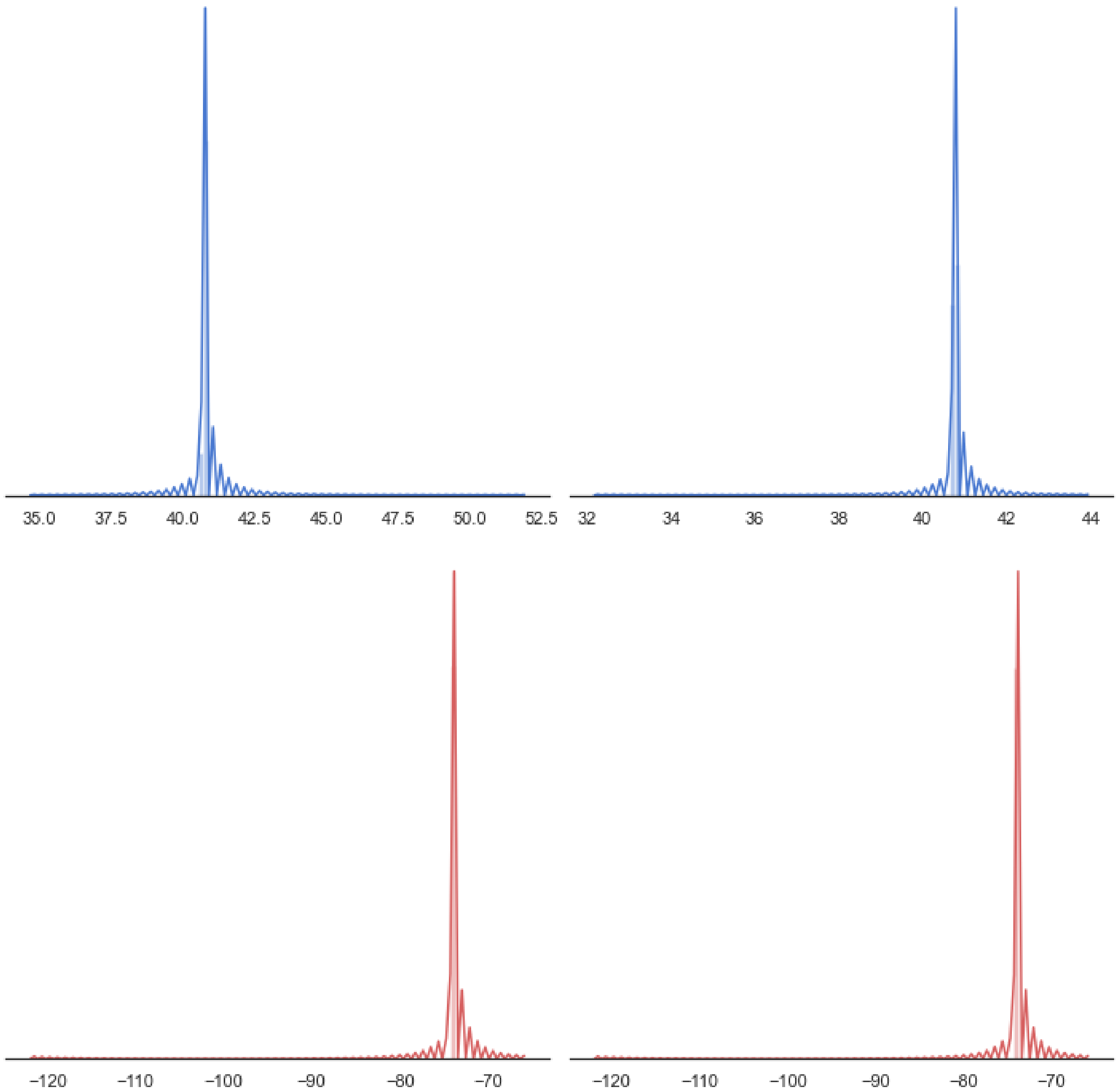
```
(729287, 19)
```

Lattitude & Longitude

Lets look at the geospatial or location features to check consistency. They should not vary much as we are only considering trips within New York city.

In [25]:

```
sns.set(style="white", palette="muted", color_codes=True)
f, axes = plt.subplots(2,2,figsize=(10, 10), sharex=False, sharey = False)
sns.despine(left=True)
sns.distplot(df['pickup_latitude'].values, label = 'pickup_latitude',color="b",bins = 10
sns.distplot(df['pickup_longitude'].values, label = 'pickup_longitude',color="r",bins =1
sns.distplot(df['dropoff_latitude'].values, label = 'dropoff_latitude',color="b",bins =1
sns.distplot(df['dropoff_longitude'].values, label = 'dropoff_longitude',color="r",bins
plt.setp(axes, yticks=[])
plt.tight_layout()
plt.show()
```

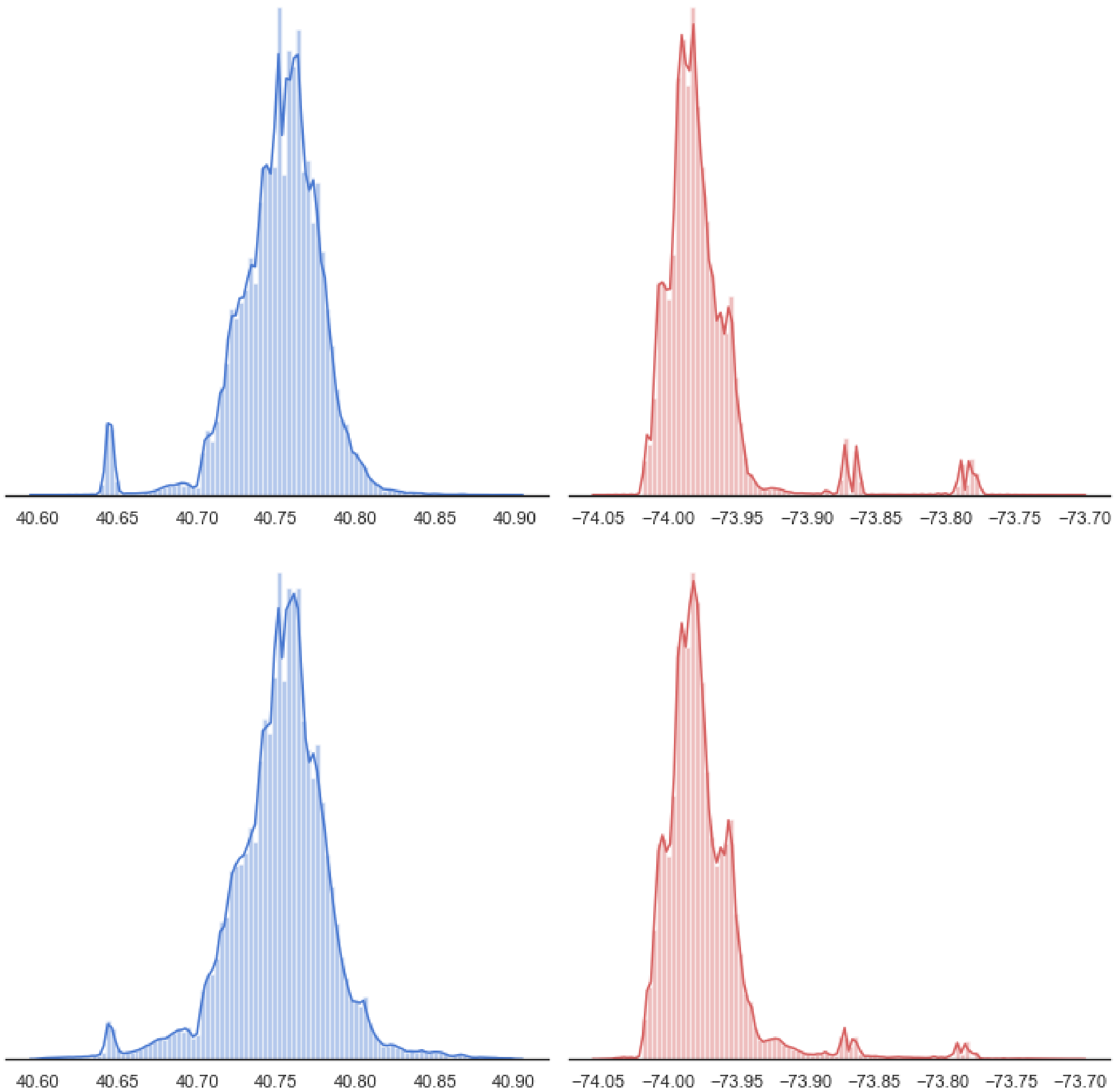


Findings - (Here, red represents pickup and dropoff Longitudes & blue represents pickup & dropoff lattitudes)

1. From the plot above it is clear that pick and drop latitude are centered around 40 to 41, and longitude are situated around -74 to -73.
2. Some extreme co-ordinates has squeezed the plot such that we see a spike here

In [26]:

```
df = df.loc[(df.pickup_latitude > 40.6) & (df.pickup_latitude < 40.9)]
df = df.loc[(df.dropoff_latitude>40.6) & (df.dropoff_latitude < 40.9)]
df = df.loc[(df.dropoff_longitude > -74.05) & (df.dropoff_longitude < -73.7)]
df = df.loc[(df.pickup_longitude > -74.05) & (df.pickup_longitude < -73.7)]
df_data_new = df.copy()
sns.set(style="white", palette="muted", color_codes=True)
f, axes = plt.subplots(2,2,figsize=(10, 10), sharex=False, sharey = False)#
sns.despine(left=True)
sns.distplot(df_data_new['pickup_latitude'].values, label = 'pickup_latitude',color="b",
sns.distplot(df_data_new['pickup_longitude'].values, label = 'pickup_longitude',color="r
sns.distplot(df_data_new['dropoff_latitude'].values, label = 'dropoff_latitude',color="b
sns.distplot(df_data_new['dropoff_longitude'].values, label = 'dropoff_longitude',color=
plt.setp(axes, yticks=[])
plt.tight_layout()

plt.show()
```



- We have a much better view of the distribution of coordinates instead of spikes. And we see that most trips are concentrated between these lat long only with a few significant clusters.
- These clusters are represented by the numerous peaks in the lattitude and longitude histograms

Bivariate Relations with Target

In [27]:

```
df.columns
```

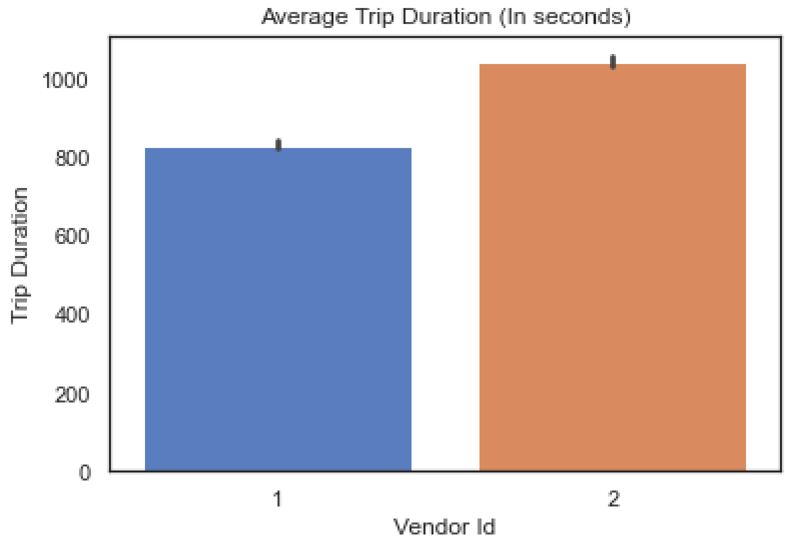
Out[27]:

```
Index(['id', 'vendor_id', 'pickup_datetime', 'dropoff_datetime',
       'passenger_count', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'store_and_fwd_flag',
       'trip_duration', 'check_trip_duration', 'pickup_day', 'pickup_hou
r',
       'pickup_weekday', 'dropoff_day', 'dropoff_hour', 'dropoff_weekday',
       'log_trip_duration'],
      dtype='object')
```

Trip Duration vs Vendor Id

In [28]:

```
sns.barplot(x="vendor_id", y="trip_duration",data=df);
plt.title("Average Trip Duration (In seconds)");
plt.xlabel("Vendor Id");
plt.ylabel("Trip Duration");
```



- The average trip duration of vendor 2 is greater than vendor 1

Correlation Heatmap

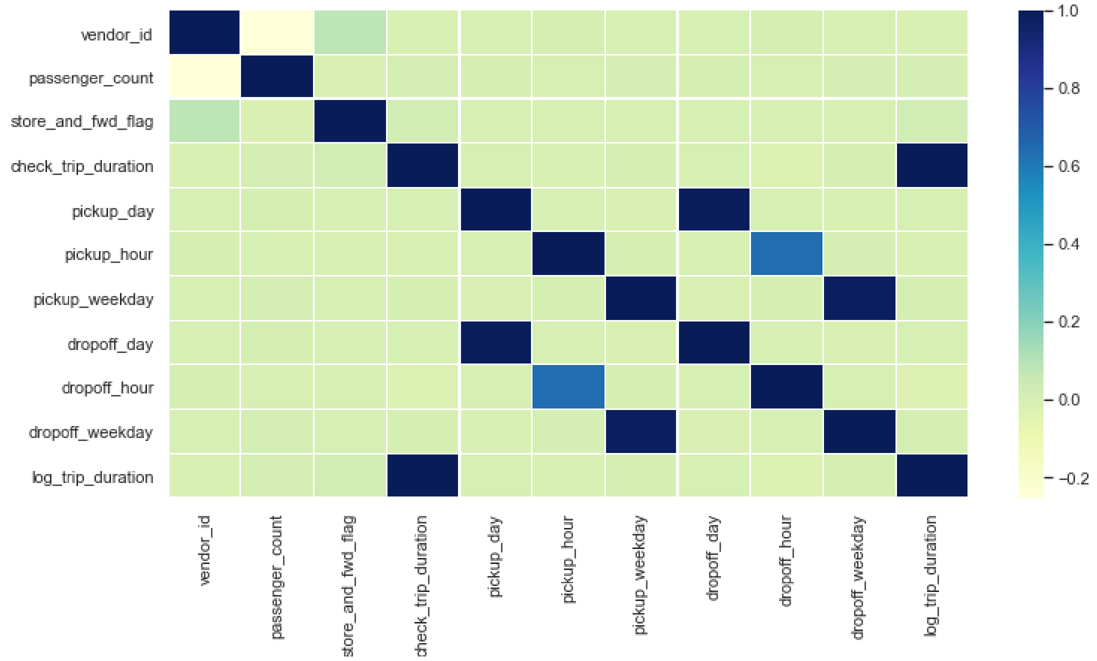
Let us quickly look at the correlation heatmap to check the correlations amongst all features.

In [29]:

```
df1 = df.drop(columns=['id', 'pickup_datetime', 'dropoff_datetime', 'pickup_longitude','
                       'dropoff_longitude','dropoff_latitude','trip_duration'])
```

In [30]:

```
# checking the correlation among all features
plt.figure(figsize=(12, 6))
corr = df1.apply(lambda x: pd.factorize(x)[0]).corr()
#corr = df1.corr()
ax = sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns,
                 linewidths=.2, cmap="YlGnBu")
```



Basic Predictive Modeling

As we know that this is a regression problem then we have to predict discrete value, which is our target-trip_duration.

So the evalutation metric for this model is - Root Mean Squared Error(RMSE)

RMSE is a very simple metric to be used for evaluation. Since, we will be comparing our models and we will create a benchmark model as a baseline, RMSE will easy to compare these different models. Lower, the value of RMSE, better the model. It will help in getting the elbow curve.

Benchmark model

Segregating variables: Independent and Dependent Variables

In [31]:

```
#seperating independent and dependent variables
X = df1.drop('log_trip_duration', axis=1)
y = df1['log_trip_duration']
```

Scaling the data (Using MinMax Scaler)

In [32]:

```
#Importing MinMax Scaler
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
x_scaled = scaler.fit_transform(X)
X = pd.DataFrame(x_scaled, columns=X.columns)
```

In [33]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=4
```

In [34]:

```
# creating train and test out of dataset for benchmark model
train = pd.concat([X_train, y_train], axis=1, join="inner")
test = pd.concat([X_test, y_test], axis=1, join="inner")
```

In [35]:

```
train.head()
```

Out[35]:

	vendor_id	passenger_count	store_and_fwd_flag	check_trip_duration	pickup_day	p
515261	0.0	0.0	0.0	0.000792	0.266667	
564538	1.0	0.0	0.0	0.000720	0.700000	
449767	1.0	0.0	0.0	0.000669	0.433333	
554996	1.0	0.0	0.0	0.000032	0.433333	
403942	0.0	0.0	1.0	0.001076	0.900000	

In [36]:

```
test.head()
```

Out[36]:

	vendor_id	passenger_count	store_and_fwd_flag	check_trip_duration	pickup_day	p
715403	1.0	0.0	0.0	0.000372	0.333333	
662439	0.0	0.0	0.0	0.000469	0.866667	
631617	0.0	0.0	0.0	0.000041	0.833333	
383387	1.0	0.0	0.0	0.000777	0.833333	
429837	1.0	0.0	0.0	0.000588	0.633333	

In [37]:

```
# storing simple mean in a new column in the test set as "simple_mean"
test['simple_mean'] = train['log_trip_duration'].mean()
```

In [38]:

```
#importing the library
from sklearn.metrics import mean_squared_error as MSE
from math import sqrt

#calculating root mean squared error
error = sqrt(MSE(test['log_trip_duration'] , test['simple_mean']))
error
```

Out[38]:

```
0.7871127279815822
```

In [39]:

```
trip_store = pd.pivot_table(train, values='log_trip_duration', index =['store_and_fwd_fl
trip_store
```

Out[39]:

	log_trip_duration
store_and_fwd_flag	
0.0	6.462442
1.0	6.464510

In [40]:

```
# initializing new column to zero
test['trip_store_mean'] = 0

# For every unique entry in Outlet_Identifier
for i in train['store_and_fwd_flag'].unique():
  # Assign the mean value corresponding to unique entry
  test['trip_store_mean'][test['store_and_fwd_flag'] == i] = train['log_trip_duration'][
```

In [41]:

```
#calculating root mean squared error
error = sqrt(MSE(test['log_trip_duration'] , test['trip_store_mean']))
error
```

Out[41]:

```
0.7871117102087578
```

As after the Calculation, The Error value as : **0.7871** for our **Benchmark Model**

KNN Model

In [*]:

```
# Creating instance of KNN
knn = KNN(n_neighbors=5)

# Fitting the model
knn.fit(X_train, y_train)

# Predicting over the Train Set and calculating RMSE
y_pred = knn.predict(X_test)

error = sqrt(MSE(y_test, y_pred))

print("Test RMSE: ", error)
```

Elbow curve to determine the best value of k

In [49]:

```
def Elbow(k):
  test = []
#training model for evey value of K
  for i in k:
    #Instance of KNN
    reg = KNN(n_neighbors=i)
    reg.fit(X_train, y_train)
    #Appending RMSE value to empty list claculated using the predictions
    tmp_pred = reg.predict(X_test)
    temp_error = sqrt(MSE(tmp_pred, y_test))
    test.append(temp_error)

  return test
```

In [50]:

```
#Defining K range
k = range(1, 10)
```

In [*]:

```
# calling above defined function
test = Elbow(k)
```

In [*]:

```
# plotting the curve
plt.plot(k, test)
plt.xlabel('K Neighbors')
plt.ylabel('RMSE')
plt.title('Elbow curve for test')
```

Test Score

In [ ]:

```
# Creating instance of KNN again at the value of n_neighbours=6
knn = KNN(n_neighbors=4)

# Fitting the model
knn.fit(X_train, y_train)

# Predicting over the Test Set and calculating RMSE
y_pred = knn.predict(X_test)

error = sqrt(MSE(y_test, y_pred))

print("Test RMSE: ", error)
```

Train Score

In [ ]:

```
# Predicting over the Train Set and calculating RMSE
y_pred = knn.predict(X_train)

knn_train_rmse = sqrt(MSE(y_train, y_pred))

print("Train RMSE: ", knn_train_rmse)
```

Linear Model

In [42]:

```
lr = LinearRegression()
lr.fit(X_train, y_train)
```

Out[42]:

```
LinearRegression()
```

Test Score

In [43]:

```
y_pred = lr.predict(X_test)

lm_test_rmse = sqrt(MSE(y_test, y_pred))
print("RMSE of linear regressor model: ", lm_test_rmse)
```

```
RMSE of linear regressor model:  0.7345971909495087
```

Train Score

In [44]:

```
y_pred = lr.predict(X_train)

lm_train_rmse = sqrt(MSE(y_train, y_pred))

print("RMSE of linear regressor model: ", lm_train_rmse)
```

```
RMSE of linear regressor model:  0.749042155992732
```

Decision tree model

In [45]:

```
dtr = DecisionTreeRegressor(random_state=42)
dtr.fit(X_train, y_train)
```

Out[45]:

```
DecisionTreeRegressor(random_state=42)
```

Test Score

In [46]:

```
y_pred = dtr.predict(X_test)

dtr_test_rmse = sqrt(MSE(y_test, y_pred))
print("RMSE of decision tree regressor model: ", dtr_test_rmse)
```

```
RMSE of decision tree regressor model:  0.0004080035098783167
```

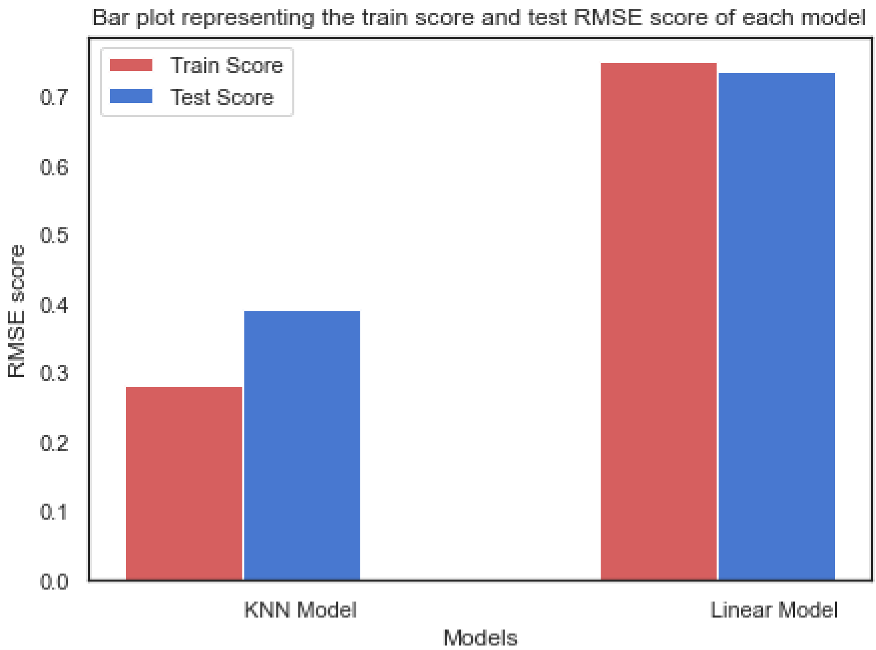
In [47]:

```
y_pred = dtr.predict(X_train)

dtr_train_rmse = sqrt(MSE(y_train, y_pred))

print("RMSE of decision tree regressor model: ", dtr_train_rmse)
```

```
RMSE of decision tree regressor model:  2.911523031894004e-14
```

In [48]:

```
# Declaring the figure or the plot (y, x) or (width, height)
plt.figure(figsize=[7, 5])

train_scores = [0.2809, 0.7490 ]
test_scores = [0.3913, 0.7345]

# Passing the parameters to the bar function
# Using X now to align the bars side by side
X = np.arange(len(train_scores))


# Passing the parameters to the bar function, this is the main function which creates th
# Using X now to align the bars side by side
plt.bar(X, train_scores, color = 'r', width = 0.25)
plt.bar(X + 0.25, test_scores, color = 'b', width = 0.25)

# Creating the legend of the bars in the plot
plt.legend(['Train Score', 'Test Score'])

labels = ['KNN Model', 'Linear Model']

# Overiding the x axis with the country names
plt.xticks([i + 0.25 for i in range(2)], labels)

# Giving the tilte for the plot
plt.title("Bar plot representing the train score and test RMSE score of each model")
# Namimg the x and y axis
plt.xlabel('Models')
plt.ylabel('RMSE score')


# Displaying the bar plot
plt.show()
```



In [ ]:

```

```