In [1]:
```python
import numpy as np
import pandas as pd
```

In [2]:
```python
data=pd.read_csv(r"uber.csv")
# test_df=pd.read_csv(r"test.csv")
print (data.shape)
print (data.columns)
```

```
(200000, 9)
Index(['Unnamed: 0', 'key', 'fare_amount', 'pickup_datetime',
       'pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
       'dropoff_latitude', 'passenger_count'],
      dtype='object')
```

In [3]:
```python
data_x = data.iloc[:,0:-1].values
data_y = data.iloc[:,-1].values
print(data_y)
```

```
[1 1 1 ... 2 1 1]
```

In [5]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   Unnamed: 0         200000 non-null  int64  
 1   key                200000 non-null  object 
 2   fare_amount        200000 non-null  float64
 3   pickup_datetime    200000 non-null  object 
 4   pickup_longitude   200000 non-null  float64
 5   pickup_latitude    200000 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    200000 non-null  int64  
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB
```

In [6]:
```python
data["pickup_datetime"]=pd.to_datetime(data['pickup_datetime'])

```

In [7]:
```python
data.head()
```

Out[7]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_lat
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.73
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.72
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.74
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.79
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.74

As this is Taxi fare data and

we know there are many factors which affect the price of taxi like Travelled distance Time of Travel Demand and Availability of Taxi Some special places are more costlier like Airport or other places where there might be toll

In [8]:
```python
data.describe()
```

Out[8]:

	Unnamed: 0	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	drc
count	2.000000e+05	200000.000000	200000.000000	200000.000000	199999.000000	1!
mean	2.771250e+07	11.359955	-72.527638	39.935885	-72.525292	
std	1.601382e+07	9.901776	11.437787	7.720539	13.117408	
min	1.000000e+00	-52.000000	-1340.648410	-74.015515	-3356.666300	
25%	1.382535e+07	6.000000	-73.992065	40.734796	-73.991407	
50%	2.774550e+07	8.500000	-73.981823	40.752592	-73.980093	
75%	4.155530e+07	12.500000	-73.967154	40.767158	-73.963658	
max	5.542357e+07	499.000000	57.418457	1644.421482	1153.572603	

Here first thing which we can see is minimum value of fare is negative which is -62 which is not the valid value, so we need to remove the fare which are negative values. Secondly, passenger_count minimum value is 0 and maximum value is 208 which impossible, so we need to remove them as well, for safer side we can think that a taxi can have maximum 7 people.

In [9]:

```python
#Lets check if there is any null value
data.isnull().sum()
```

Out[9]:

```
Unnamed: 0           0
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

Here we can see there are 14 null values in drop_off latitude and longitude. as removing 14 to 28 rows from our huge dataset will not affect our analysis so, lets remove the rows having null values

In [12]:

```python
data.dropna(inplace=True)
print(data.isnull().sum())
```

```
Unnamed: 0           0
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```

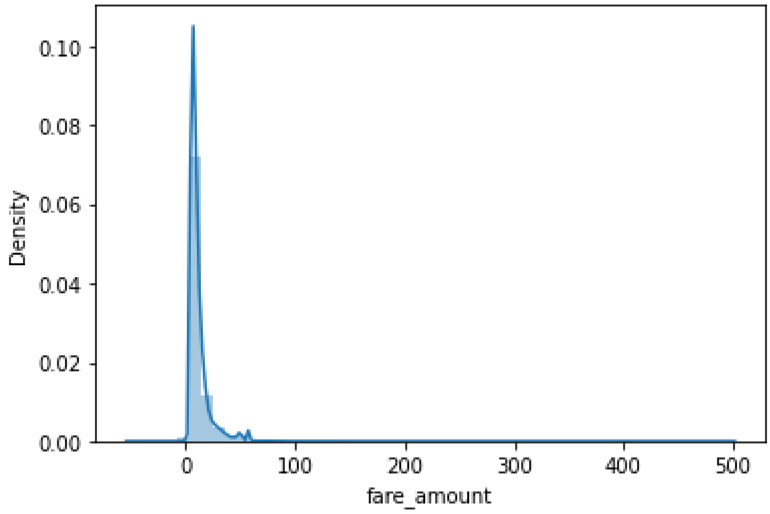
In [13]:

```python
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [15]:
```
sns.distplot(data['fare_amount'])
```

```
c:\users\kedar\appdata\local\programs\python\python39\lib\site-packages\se
aborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated fun
ction and will be removed in a future version. Please adapt your code to u
se either `displot` (a figure-level function with similar flexibility) or
`histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[15]: <AxesSubplot:xlabel='fare_amount', ylabel='Density'>

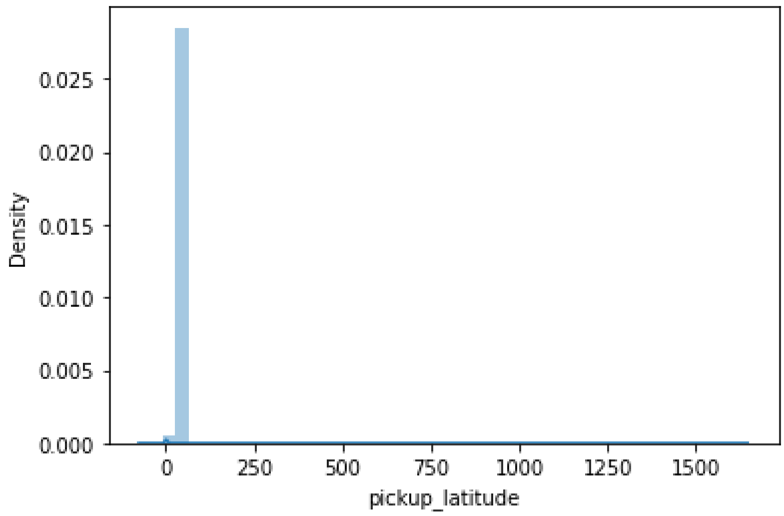


In distribution plot also it can be seen that there are some values which are negative fare

In [18]:
```
sns.distplot(data['pickup_latitude'])
```

```
c:\users\kedar\appdata\local\programs\python\python39\lib\site-packages\se
aborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated fun
ction and will be removed in a future version. Please adapt your code to u
se either `displot` (a figure-level function with similar flexibility) or
`histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[18]: <AxesSubplot:xlabel='pickup_latitude', ylabel='Density'>

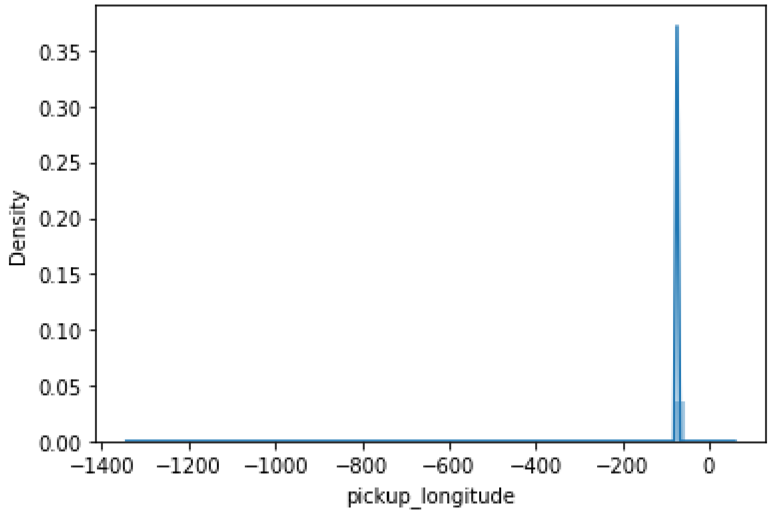


Here we can see minimum value is going to be less than even -3000 which is not correct value and also on positive side also going more than 2000

In [20]:
```
sns.distplot(data['pickup_longitude'])
```

```
c:\users\kedar\appdata\local\programs\python\python39\lib\site-packages\se
aborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated fun
ction and will be removed in a future version. Please adapt your code to u
se either `displot` (a figure-level function with similar flexibility) or
`histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[20]: <AxesSubplot:xlabel='pickup_longitude', ylabel='Density'>

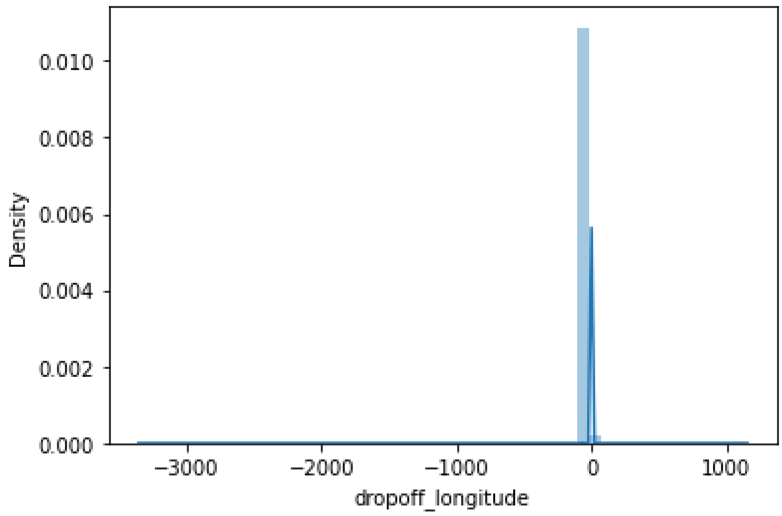


Here also negative and positive values are excedding far behond the real limit.

In [21]:
```
sns.distplot(data['dropoff_longitude'])
```

```
c:\users\kedar\appdata\local\programs\python\python39\lib\site-packages\se
aborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated fun
ction and will be removed in a future version. Please adapt your code to u
se either `displot` (a figure-level function with similar flexibility) or
`histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[21]: <AxesSubplot:xlabel='dropoff_longitude', ylabel='Density'>

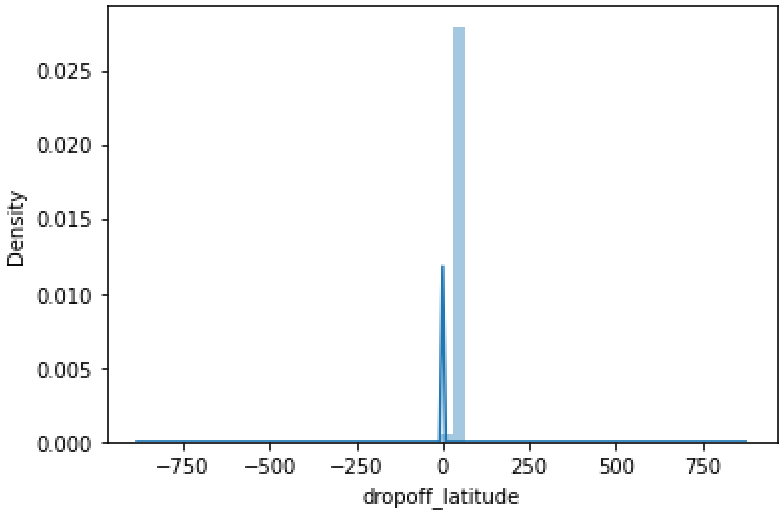


In [23]:

```
#Similarly here also same issue
sns.distplot(data['dropoff_latitude'])
```

```
c:\users\kedar\appdata\local\programs\python\python39\lib\site-packages\se
aborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated fun
ction and will be removed in a future version. Please adapt your code to u
se either `displot` (a figure-level function with similar flexibility) or
`histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[23]: <AxesSubplot:xlabel='dropoff_latitude', ylabel='Density'>



In [24]:

```
print("drop_off latitude min value",data["dropoff_latitude"].min())
print("drop_off latitude max value",data["dropoff_latitude"].max())
print("drop_off longitude min value", data["dropoff_longitude"].min())
print("drop_off longitude max value",data["dropoff_longitude"].max())
print("pickup latitude min value",data["pickup_latitude"].min())
print("pickup latitude max value",data["pickup_latitude"].max())
print("pickup longitude min value",data["pickup_longitude"].min())
print("pickup longitude max value",data["pickup_longitude"].max())
```

```
drop_off latitude min value -881.9855130000001
drop_off latitude max value 872.6976279999999
drop_off longitude min value -3356.6663
drop_off longitude max value 1153.5726029999998
pickup latitude min value -74.01551500000001
pickup latitude max value 1644.421482
pickup longitude min value -1340.64841
pickup longitude max value 57.418457
```

we can see what is range of latitude and longitude of our test dataset, lets keep the range same in our train set so that even noisy data is remove and we have only the values which belongs to new york

In [25]:

```
min_longitude=-74.263242,
min_latitude=40.573143,
max_longitude=-72.986532,
max_latitude=41.709555
```

In [26]:
```
#lets drop all the values which are not coming in above boundary, as th
```

In [27]:
```
tempdf=data[(data["dropoff_latitude"]<min_latitude) | (data["pickup_lat
print("before droping",data.shape)
data.drop(tempdf.index,inplace=True)
print("after droping",data.shape)
```

```
before droping (199999, 9)
after droping (195732, 9)
```

In [28]:
```
#lets remove all those rows where fare amount is negative
```

In [29]:
```
print("before droping", data.shape)
train_df=data[data['fare_amount']>0]
print("after droping", data.shape)
```

```
before droping (195732, 9)
after droping (195732, 9)
```

On different day and time there would be different price like during eveing price would be more compare to afternoon, during christmas price would be different and similarly on weekends price would be different compare to week days. so lets create some extra features which will take care of all these things

In [30]:
```
import calendar
data['day']=data['pickup_datetime'].apply(lambda x:x.day)
data['hour']=data['pickup_datetime'].apply(lambda x:x.hour)
data['weekday']=data['pickup_datetime'].apply(lambda x:calendar.day_nam
data['month']=data['pickup_datetime'].apply(lambda x:x.month)
data['year']=data['pickup_datetime'].apply(lambda x:x.year)
```

In [31]:
```
data.head()
```

Out[31]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_lat
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.73
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.72
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.74
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.79
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.74

In [ ]:
```
#here we can see that week are in monday , tuesday and so on. So we nee
```

In [32]:
```
data.weekday = data.weekday.map({'Sunday':0,'Monday':1,'Tuesday':2,'Wec
```

In [33]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 195732 entries, 0 to 199999
Data columns (total 14 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         195732 non-null  int64
 1   key                195732 non-null  object
 2   fare_amount        195732 non-null  float64
 3   pickup_datetime    195732 non-null  datetime64[ns, UTC]
 4   pickup_longitude   195732 non-null  float64
 5   pickup_latitude    195732 non-null  float64
 6   dropoff_longitude  195732 non-null  float64
 7   dropoff_latitude   195732 non-null  float64
 8   passenger_count    195732 non-null  int64
 9   day                195732 non-null  int64
 10  hour               195732 non-null  int64
 11  weekday            195732 non-null  int64
 12  month              195732 non-null  int64
 13  year               195732 non-null  int64
dtypes: datetime64[ns, UTC](1), float64(5), int64(7), object(1)
memory usage: 22.4+ MB
```

In [34]:
```
# we will keep only those rows where number of passangers are less thar
```

In [35]:
```
data=data[data['passenger_count']<=8]
```

In [36]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 195731 entries, 0 to 199999
Data columns (total 14 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         195731 non-null  int64
 1   key                195731 non-null  object
 2   fare_amount        195731 non-null  float64
 3   pickup_datetime    195731 non-null  datetime64[ns, UTC]
 4   pickup_longitude   195731 non-null  float64
 5   pickup_latitude    195731 non-null  float64
 6   dropoff_longitude  195731 non-null  float64
 7   dropoff_latitude   195731 non-null  float64
 8   passenger_count    195731 non-null  int64
 9   day                195731 non-null  int64
 10  hour               195731 non-null  int64
 11  weekday            195731 non-null  int64
 12  month              195731 non-null  int64
 13  year               195731 non-null  int64
dtypes: datetime64[ns, UTC](1), float64(5), int64(7), object(1)
memory usage: 22.4+ MB
```

In [37]:
```
#here key column and pickup_datetime columns are not needed as we have
```

In [38]:
```
data.drop(["key","pickup_datetime"], axis=1, inplace=True)
```

In [39]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 195731 entries, 0 to 199999
Data columns (total 12 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         195731 non-null  int64
 1   fare_amount        195731 non-null  float64
 2   pickup_longitude   195731 non-null  float64
 3   pickup_latitude    195731 non-null  float64
 4   dropoff_longitude  195731 non-null  float64
 5   dropoff_latitude   195731 non-null  float64
 6   passenger_count    195731 non-null  int64
 7   day                195731 non-null  int64
 8   hour               195731 non-null  int64
 9   weekday            195731 non-null  int64
 10  month              195731 non-null  int64
 11  year               195731 non-null  int64
dtypes: float64(5), int64(7)
memory usage: 19.4 MB
```

lets divide the data set into train and validation test set

In [40]:
```
from sklearn.model_selection import train_test_split
```

In [54]:
```
x=data.drop("fare_amount", axis=1)
```

In [55]:
```
y=data['fare_amount']
```

In [56]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,ranc
```

In [57]:
```
x_train.head()
```

Out[57]:

	Unnamed: 0	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pas
7570	51992033	-73.991973	40.742657	-73.991358	40.750086	
155037	10241908	-73.964111	40.807957	-73.966688	40.803299	
67010	48963133	-73.987658	40.700823	-73.985670	40.770540	
155236	30446807	-73.999577	40.726656	-74.007562	40.713286	
187226	40739497	-73.983377	40.738938	-73.978432	40.745286	

In [58]:
```
x_test.head()
```

Out[58]:

	Unnamed: 0	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pas
51869	5536882	-73.953347	40.767932	-73.990867	40.751295	
44724	35054768	-73.137393	41.366138	-73.137393	41.366138	
47705	15258057	-74.009707	40.712480	-73.962757	40.758977	
17345	34739111	-74.016055	40.715077	-74.008840	40.711375	
179351	53446498	-73.950474	40.784003	-73.971086	40.748328	

In [59]:
```
x_train.shape
```

Out[59]: (156584, 11)

In [60]:
```
x_test.shape
```

Out[60]: (39147, 11)

In [61]:
```

#Lets run the model.
#As we have to build regression model, lets start with linear regressic
```

In [62]:
```
from sklearn.linear_model import LinearRegression
```

In [63]:
```
lrmodel=LinearRegression()
lrmodel.fit(x_train, y_train)
```

Out[63]: LinearRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [64]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=F
```

Out[64]: LinearRegression(n_jobs=1, normalize=False)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [65]:
```
predictedvalues = lrmodel.predict(x_test)
```

In [66]:

```
#Lets calculate rmse for Linear Regression model
from sklearn.metrics import mean_squared_error
lrmodelrmse = np.sqrt(mean_squared_error(predictedvalues, y_test))
print("RMSE value for Linear regression is", lrmodelrmse)
```

```
RMSE value for Linear regression is 8.363019859396488
```

In [71]:

```
#Lets see with Random Forest and calculate its rmse
from sklearn.ensemble import RandomForestRegressor
# rfrmodel = RandomForestRegressor(n_estimators=100, random_state=101)
rfrmodel = RandomForestRegressor(n_estimators=50, random_state=101)
```

In [72]:

```
rfrmodel.fit(x_train,y_train)
```

Out[72]:

```
RandomForestRegressor(n_estimators=50, random_state=101)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [74]:

```
rfrmodel_pred= rfrmodel.predict(x_test)
```

In [75]:

```
rfrmodel_rmse=np.sqrt(mean_squared_error(rfrmodel_pred, y_test))
print("RMSE value for Random forest regression is ",rfrmodel_rmse)
```

```
RMSE value for Random forest regression is  3.9973617568779463
```

In [76]:

```
#RandomForest Regressor is giving good value, so we can use it as final
```