train.csv - Input features and target fare_amount values for the training set (about 55M rows). test.csv - Input features for the test set (about 10K rows). Your goal is to predict fare_amount for each row.

In [1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

In [8]:
```
train_df=pd.read_csv(r"F:\Simplilearn_AI_MACHINE LEARNING\Projects\Uber Fare Prediction\train.csv",nrows=200)
test_df=pd.read_csv(r"F:\Simplilearn_AI_MACHINE LEARNING\Projects\Uber Fare Prediction\test.csv")
print (train_df.shape)
print (train_df.columns)
print (test_df.shape)
print (test_df.columns)
```

```
(200, 8)
Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'passenger_count'],
      dtype='object')
(9914, 7)
Index(['key', 'pickup_datetime', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'passenger_count'],
      dtype='object')
```

In [9]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 8 columns):
key                  200 non-null object
fare_amount          200 non-null float64
pickup_datetime      200 non-null object
pickup_longitude     200 non-null float64
pickup_latitude      200 non-null float64
dropoff_longitude    200 non-null float64
dropoff_latitude     200 non-null float64
passenger_count      200 non-null int64
dtypes: float64(5), int64(1), object(2)
memory usage: 12.6+ KB
```

here we can see there are 8columns in which 6 numerics and 2 are object.

Lets change the type of pickup_datetime from object to DateTime

In [10]:
```
train_df["pickup_datetime"]=pd.to_datetime(train_df['pickup_datetime'])
```

In [11]:
```
train_df.head()
```

Out[11]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_l
0	2009-06-15 17:26:21.0000001	4.5	2009-06-15 17:26:21+00:00	-73.844311	40.721319	-7
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16+00:00	-74.016048	40.711303	-7
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00+00:00	-73.982738	40.761270	-7
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42+00:00	-73.987130	40.733143	-7
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00+00:00	-73.968095	40.768008	-7

As this is Taxi fare data and we know there are many factors which affect the price of taxi like

1. Travelled distance
2. Time of Travel
3. Demand and Availability of Taxi
4. Some special places are more costlier like Airport or other places where there might be toll

In [12]:
```
#Lets see the statisitics of our data
```

In [13]:
```
train_df.describe()
```

Out[13]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passe
count	200.000000	200.000000	200.000000	200.000000	200.000000	
mean	11.088250	-72.129763	39.730607	-72.128149	39.731270	
std	8.691217	11.579020	6.377990	11.578776	6.378135	
min	3.300000	-74.035839	0.000000	-74.035839	0.000000	
25%	5.700000	-73.994132	40.733160	-73.992982	40.731490	
50%	8.500000	-73.982926	40.748692	-73.981733	40.751558	
75%	12.600000	-73.970148	40.763612	-73.969754	40.764677	
max	58.000000	0.000000	40.828531	0.000000	40.868610	

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 [14]:
```
#Lets check if there is any null value
train_df.isnull().sum()
```

Out[14]:
```
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
```

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

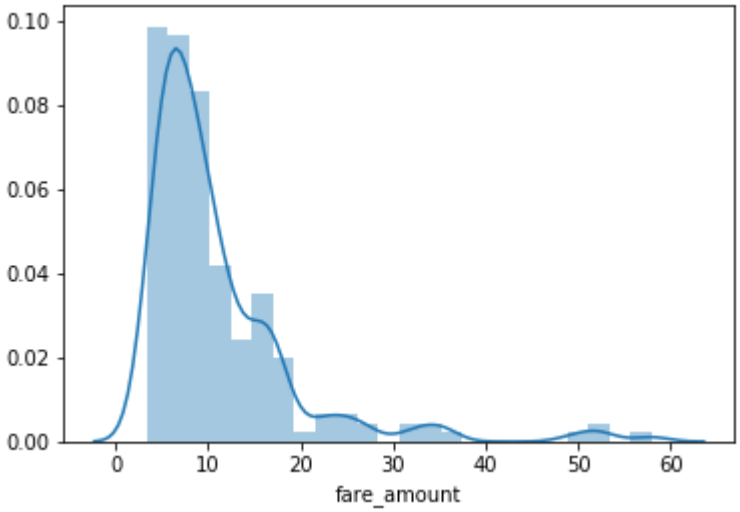
In [9]:
```
train_df.dropna(inplace=True)
print(train_df.isnull().sum())
```

```
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 [15]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [16]:
```
sns.distplot(train_df['fare_amount'])
```

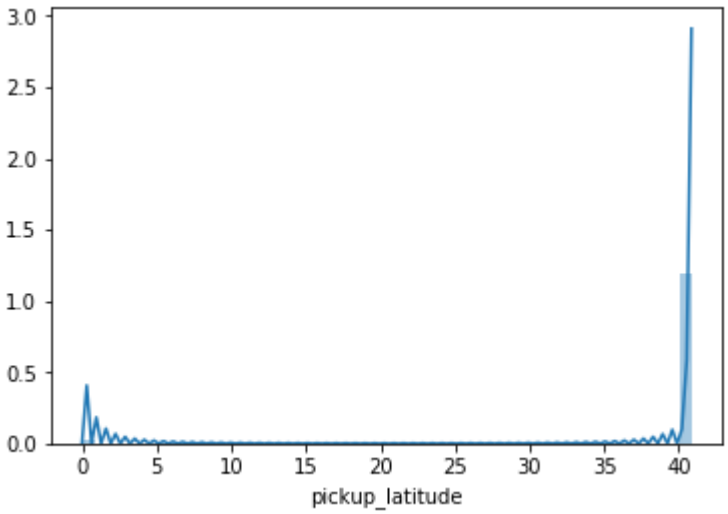
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0xb7b09e8>



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

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

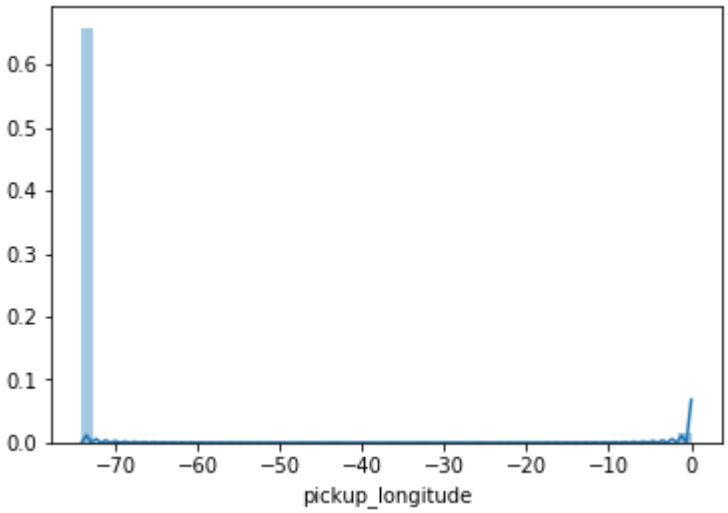
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0xbbef908>



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 [19]:
```
sns.distplot(train_df['pickup_longitude'])
```

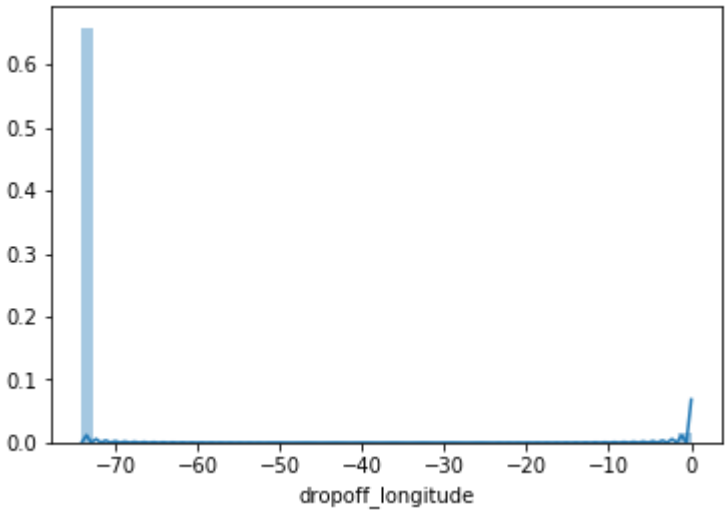
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0xbcc44a8>



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

In [20]:
```
sns.distplot(train_df['dropoff_longitude'])
```

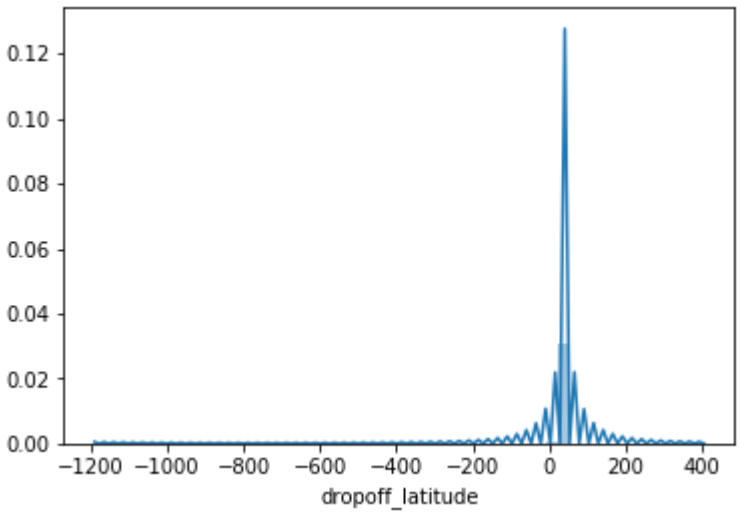
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0xbd88470>



In [15]:
```
#Similarly here also same issue
```

In [16]:
```
sns.distplot(train_df['dropoff_latitude'])
```

Out[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2de7ac0eb70>
```



In [17]:
```
#here also we have noisy data as given value of dropoff_latitude and longitude
are excedding
```

In [18]:
```
#lets look min and max value in test dataset of latitude and longitude
```

In [21]:
```
print("drop_off latitude min value",test_df["dropoff_latitude"].min())
print("drop_off latitude max value",test_df["dropoff_latitude"].max())
print("drop_off longitude min value", test_df["dropoff_longitude"].min())
print("drop_off longitude max value",test_df["dropoff_longitude"].max())
print("pickup latitude min value",test_df["pickup_latitude"].min())
print("pickup latitude max value",test_df["pickup_latitude"].max())
print("pickup longitude min value",test_df["pickup_longitude"].min())
print("pickup longitude max value",test_df["pickup_longitude"].max())
```

```
drop_off latitude min value 40.568973
drop_off latitude max value 41.696683
drop_off longitude min value -74.263242
drop_off longitude max value -72.990963
pickup latitude min value 40.573143
pickup latitude max value 41.709555
pickup longitude min value -74.252193
pickup longitude max value -72.986532
```

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 [22]:
```
min_longitude=-74.263242,
min_latitude=40.573143,
max_longitude=-72.986532,
max_latitude=41.709555
```

In [21]:
```
#lets drop all the values which are not coming in above boundary, as those are noisy data
```

In [23]:
```
tempdf=train_df[(train_df["dropoff_latitude"]<min_latitude) | (train_df["pickup_latitude"]<min_latitude) | (train_df["dropoff_longitude"]<min_longitude) | (train_df["pickup_longitude"]<min_longitude) | (train_df["dropoff_latitude"]>max_latitude) | (train_df["pickup_latitude"]>max_latitude) | (train_df["dropoff_longitude"]>max_longitude) | (train_df["pickup_longitude"]>max_longitude) ]
print("before droping",train_df.shape)
train_df.drop(tempdf.index,inplace=True)
print("after droping",train_df.shape)
```

```
before droping (200, 8)
after droping (195, 8)
```

In [23]:
```
#lets remove all those rows where fare amount is negative
```

In [24]:
```
print("before droping", train_df.shape)
train_df=train_df[train_df['fare_amount']>0]
print("after droping", train_df.shape)
```

```
before droping (195, 8)
after droping (195, 8)
```

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 [25]:
```
import calendar
train_df['day']=train_df['pickup_datetime'].apply(lambda x:x.day)
train_df['hour']=train_df['pickup_datetime'].apply(lambda x:x.hour)
train_df['weekday']=train_df['pickup_datetime'].apply(lambda x:calendar.day_name[x.weekday()])
train_df['month']=train_df['pickup_datetime'].apply(lambda x:x.month)
train_df['year']=train_df['pickup_datetime'].apply(lambda x:x.year)
```

In [26]:
```
train_df.head()
```

Out[26]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_l
0	2009-06-15 17:26:21.0000001	4.5	2009-06-15 17:26:21+00:00	-73.844311	40.721319	-7
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16+00:00	-74.016048	40.711303	-7
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00+00:00	-73.982738	40.761270	-7
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42+00:00	-73.987130	40.733143	-7
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00+00:00	-73.968095	40.768008	-7

In [27]:
```
#here we can see that week are in monday , tuesday and so on. So we need conve
rt them in numerical for
```

In [28]:
```
train_df.weekday = train_df.weekday.map({'Sunday':0,'Monday':1,'Tuesday':2,'We
dnesday':3,'Thursday':4,'Friday':5,'Saturday':6})
```

In [29]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 195 entries, 0 to 199
Data columns (total 13 columns):
key                  195 non-null object
fare_amount          195 non-null float64
pickup_datetime      195 non-null datetime64[ns, UTC]
pickup_longitude     195 non-null float64
pickup_latitude      195 non-null float64
dropoff_longitude    195 non-null float64
dropoff_latitude     195 non-null float64
passenger_count      195 non-null int64
day                  195 non-null int64
hour                 195 non-null int64
weekday              195 non-null int64
month                195 non-null int64
year                 195 non-null int64
dtypes: datetime64[ns, UTC](1), float64(5), int64(6), object(1)
memory usage: 21.3+ KB
```

In [30]:
```
# we will keep only those rows where number of passangers are less than or equ
al to 8
```

In [31]:
```
train_df=train_df[train_df['passenger_count']<=8]
```

In [32]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 195 entries, 0 to 199
Data columns (total 13 columns):
key                195 non-null object
fare_amount        195 non-null float64
pickup_datetime    195 non-null datetime64[ns, UTC]
pickup_longitude   195 non-null float64
pickup_latitude    195 non-null float64
dropoff_longitude  195 non-null float64
dropoff_latitude   195 non-null float64
passenger_count    195 non-null int64
day                195 non-null int64
hour               195 non-null int64
weekday            195 non-null int64
month              195 non-null int64
year               195 non-null int64
dtypes: datetime64[ns, UTC](1), float64(5), int64(6), object(1)
memory usage: 21.3+ KB
```

In [36]:
```
#here key column and pickup_datetime columns are not needed as we have already
created variables extracted from it
```

In [37]:
```
train_df.drop(["key","pickup_datetime"], axis=1, inplace=True)
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
<ipython-input-37-788d50d2c0eb> in <module>
----> 1 train_df.drop(["key","pickup_datetime"], axis=1, inplace=True)

~\Anaconda3\lib\site-packages\pandas\core\frame.py in drop(self, labels, axi
s, index, columns, level, inplace, errors)
   3938                                           index=index, columns=colum
ns,
   3939                                           level=level, inplace=inpla
ce,
-> 3940                                           errors=errors)
   3941
   3942     @rewrite_axis_style_signature('mapper', [('copy', True),

~\Anaconda3\lib\site-packages\pandas\core\generic.py in drop(self, labels, ax
is, index, columns, level, inplace, errors)
   3778         for axis, labels in axes.items():
   3779             if labels is not None:
-> 3780                 obj = obj._drop_axis(labels, axis, level=level, error
s=errors)
   3781
   3782         if inplace:

~\Anaconda3\lib\site-packages\pandas\core\generic.py in _drop_axis(self, labe
ls, axis, level, errors)
   3810                 new_axis = axis.drop(labels, level=level, errors=erro
rs)
   3811             else:
-> 3812                 new_axis = axis.drop(labels, errors=errors)
   3813             result = self.reindex(**{axis_name: new_axis})
   3814

~\Anaconda3\lib\site-packages\pandas\core\indexes\base.py in drop(self, label
s, errors)
   4963             if errors != 'ignore':
   4964                 raise KeyError(
-> 4965                     '{} not found in axis'.format(labels[mask]))
   4966             indexer = indexer[~mask]
   4967         return self.delete(indexer)

KeyError: "['key' 'pickup_datetime'] not found in axis"
```

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 195 entries, 0 to 199
Data columns (total 11 columns):
fare_amount          195 non-null float64
pickup_longitude     195 non-null float64
pickup_latitude      195 non-null float64
dropoff_longitude    195 non-null float64
dropoff_latitude     195 non-null float64
passenger_count      195 non-null int64
day                  195 non-null int64
hour                 195 non-null int64
weekday              195 non-null int64
month                195 non-null int64
year                 195 non-null int64
dtypes: float64(5), int64(6)
memory usage: 18.3 KB
```

lets divide the data set into train and validation test set

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

In [41]:
```
x=train_df.drop("fare_amount", axis=1)
```

In [42]:
```
y=train_df['fare_amount']
```

In [43]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=101)
```

In [44]:
```
x_train.head()
```

Out[44]:

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	day
83	-74.009728	40.705167	-73.970897	40.749307	1	8
120	-73.972018	40.750142	-74.006008	40.736220	5	8
174	-73.944023	40.775959	-73.955048	40.785080	1	27
125	-73.971696	40.763378	-73.962035	40.776598	1	10
4	-73.968095	40.768008	-73.956655	40.783762	1	9

In [45]:
```
x_test.head()
```

Out[45]:

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	day
42	-73.978450	40.762920	-74.008482	40.716502	1	22
167	-73.954598	40.786760	-73.966013	40.768112	1	13
64	-74.003919	40.753019	-73.992368	40.735362	1	7
35	-73.983330	40.738720	-73.933197	40.847225	1	11
127	-73.988492	40.717977	-73.978180	40.737407	1	6

In [46]:
```
x_train.shape
```

Out[46]:
```
(156, 10)
```

In [47]:
```
x_test.shape
```

Out[47]:
```
(39, 10)
```

In [48]:
```
#Lets run the model.
#As we have to build regression model, lets start with linear regression model
```

In [4]:
```
from sklearn.linear_model import LinearRegression
```

In [6]:
```
lrmodel=LinearRegression()
lrmodel.fit(x_train, y_train)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-6-0a2b58c157ac> in <module>
      1 lrmodel=LinearRegression()
----> 2 lrmodel.fit(x_train, y_train)

NameError: name 'x_train' is not defined
```

In [7]:
```
predictedvalues = lrmodel.predict(x_test)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-7-f5b9a00bc32d> in <module>
----> 1 predictedvalues = lrmodel.predict(x_test)

NameError: name 'x_test' is not defined
```

In [52]:
```
#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 9.802436637397324
```

In [55]:
```
#Lets see with Random Forest and calculate its rmse
from sklearn.ensemble import RandomForestRegressor
rfrmodel = RandomForestRegressor(n_estimators=100, random_state=101)
```

In [56]:
```
rfrmodel.fit(x_train,y_train)
rfrmodel_pred= rfrmodel.predict(x_test)
```

In [57]:
```
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  7.666053053158853
```

In [52]:
```
#RandomForest Regressor is giving good value, so we can use it as final model
```