Problem and Objective

You are a cab rental start-up company. You have successfully run the pilot project and now want to launch your cab service across the country. You have collected the historical data from your pilot project and now have a requirement to apply analytics for fare prediction. You need to design a system that predicts the fare amount for a cab ride in the city.

In [1]:

```
#Importing required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
import seaborn as sns
from random import randrange,uniform
from scipy import stats
from sklearn.metrics import r2_score
```

In [2]:

```
# Set working directory
os.chdir("C:/Users/User/Desktop/edwisor/python/")
os.getcwd()
```

Out[2]:

```
'C:\\Users\\User\\Desktop\\edwisor\\python'
```

In [3]:

```
print(os.listdir(os.getcwd()))
```

```
['day.csv', 'practice', 'test.csv', 'test_Predicted.csv', 'train_cab.csv']
```

In [4]:

```
# Load Both Data in .csv format
Train=pd.read_csv("train_cab.csv")
Test=pd.read_csv("test.csv")
```

In [5]:

```
Train.head()
```

Out[5]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropo
0	4.5	2009-06-15 17:26:21 UTC	-73.844311	40.721319	-73.841610	
1	16.9	2010-01-05 16:52:16 UTC	-74.016048	40.711303	-73.979268	
2	5.7	2011-08-18 00:35:00 UTC	-73.982738	40.761270	-73.991242	
3	7.7	2012-04-21 04:30:42 UTC	-73.987130	40.733143	-73.991567	
4	5.3	2010-03-09 07:51:00 UTC	-73.968095	40.768008	-73.956655	

In [6]:

```
Test.head()
```

Out[6]:

	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pas
0	2015-01-27 13:08:24 UTC	-73.973320	40.763805	-73.981430	40.743835	
1	2015-01-27 13:08:24 UTC	-73.986862	40.719383	-73.998886	40.739201	
2	2011-10-08 11:53:44 UTC	-73.982524	40.751260	-73.979654	40.746139	
3	2012-12-01 21:12:12 UTC	-73.981160	40.767807	-73.990448	40.751635	
4	2012-12-01 21:12:12 UTC	-73.966046	40.789775	-73.988565	40.744427	

EXPLORATORY DATA ANALYSIS

In [7]:

```
# To check the data Types of Varaibles

Train.dtypes
```

Out[7]:

```
fare_amount            object
pickup_datetime        object
pickup_longitude      float64
pickup_latitude       float64
dropoff_longitude     float64
dropoff_latitude      float64
passenger_count       float64
dtype: object
```

In [8]:

```
Test.dtypes
```

Out[8]:

```
pickup_datetime        object
pickup_longitude      float64
pickup_latitude       float64
dropoff_longitude     float64
dropoff_latitude      float64
passenger_count         int64
dtype: object
```

In [9]:

```
#Shape of the data
Train.shape
```

Out[9]:

```
(16067, 7)
```

In [10]:

```
Test.shape
```

Out[10]:

```
(9914, 6)
```

Missing Value Analysis

In [11]:

```
#sum of the missing values

Train.isnull().sum()
```

Out[11]:

```
fare_amount          24
pickup_datetime       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude     0
dropoff_latitude      0
passenger_count      55
dtype: int64
```

We observe that there are missing values present in Train data set

In [12]:

```
Test.isnull().sum()
```

Out[12]:

```
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```

we observe that there are No missing values present in Test data set

In [13]:

```
#Create the dataframe of missing percentage
missing_value = pd.DataFrame(Train.isnull().sum())

#Reset the index
missing_value = missing_value.reset_index()

#Rename the variable
missing_value = missing_value.rename(columns = {'index': 'Variables', 0: 'Missing_value
s'})
```

In [14]:

```
#Calculate the new variable - missing value percentage
missing_value['Missing_Value_Percentage'] = (missing_value.Missing_values/len(Train))*1
00

#arrange in descending order
missing_value = missing_value.sort_values('Missing_Value_Percentage', ascending=False).
reset_index(drop=True)
```

In [15]:

```
missing_value
```

Out[15]:

	Variables	Missing_values	Missing_Value_Percentage
0	passenger_count	55	0.342317
1	fare_amount	24	0.149374
2	pickup_datetime	0	0.000000
3	pickup_longitude	0	0.000000
4	pickup_latitude	0	0.000000
5	dropoff_longitude	0	0.000000
6	dropoff_latitude	0	0.000000

In [16]:

```
#From the above code we can observe that the null values available in the given dataset
is less than 10%
#hence can be dropped with out any issues
#Then we have to note that the object datatypes of the columns "fare_amount" and "picku
p_datetime" needs to be converted.
```

In [17]:

```
# changing datatype of pickup_datetime variable from object to datetime
Train['pickup_datetime'] =  pd.to_datetime(Train['pickup_datetime'], format='%Y-%m-%d %
H:%M:%S UTC', errors='coerce')
```

In [18]:

```
print(Train['pickup_datetime'].isnull().sum())
```

1

In [19]:

```
# one value is null in pickup_datetime variable, so drop it.
Train = Train.drop(Train[Train['pickup_datetime'].isnull()].index, axis=0)
```

In [20]:

```
# separate the pickup_datetime column into separate fields like year, month,day, day of
the week, hour etc.
Train['year'] =Train['pickup_datetime'].dt.year
Train['Month'] = Train['pickup_datetime'].dt.month
Train['Date'] = Train['pickup_datetime'].dt.day
Train['Day'] = Train['pickup_datetime'].dt.dayofweek
Train['Hour'] = Train['pickup_datetime'].dt.hour
Train['Minute'] = Train['pickup_datetime'].dt.minute
```

In [21]:

```
Train.dtypes
```

Out[21]:

```
fare_amount                   object
pickup_datetime       datetime64[ns]
pickup_longitude             float64
pickup_latitude              float64
dropoff_longitude            float64
dropoff_latitude             float64
passenger_count              float64
year                           int64
Month                          int64
Date                           int64
Day                            int64
Hour                           int64
Minute                         int64
dtype: object
```

In [22]:

```
Train.shape
```

Out[22]:

```
(16066, 13)
```

In [23]:

```
# checking null values
print(Train['pickup_datetime'].isnull().sum())
print(Train['year'].isnull().sum())
print(Train['Month'].isnull().sum())
print(Train['Date'].isnull().sum())
print(Train['Day'].isnull().sum())
print(Train['Hour'].isnull().sum())
print(Train['Minute'].isnull().sum())
```

```
0
0
0
0
0
0
0
```

In [24]:

```
#similarly on Test data set
Test['pickup_datetime'] =  pd.to_datetime(Test['pickup_datetime'], format='%Y-%m-%d %H:%M:%S UTC',errors="coerce")
```

In [25]:

```
Test['year'] = Test['pickup_datetime'].dt.year
Test['Month'] = Test['pickup_datetime'].dt.month
Test['Date'] = Test['pickup_datetime'].dt.day
Test['Day'] = Test['pickup_datetime'].dt.dayofweek
Test['Hour'] = Test['pickup_datetime'].dt.hour
Test['Minute'] = Test['pickup_datetime'].dt.minute
```

In [26]:

```
Test.dtypes
```

Out[26]:

```
pickup_datetime      datetime64[ns]
pickup_longitude            float64
pickup_latitude             float64
dropoff_longitude           float64
dropoff_latitude            float64
passenger_count               int64
year                          int64
Month                         int64
Date                          int64
Day                           int64
Hour                          int64
Minute                        int64
dtype: object
```

In [27]:

```
Test.shape
```

Out[27]:

```
(9914, 12)
```

In [28]:

```
# Checking the fare_amount variable
#Converting fare_amount variable from object to numeric
Train["fare_amount"]=pd.to_numeric(Train["fare_amount"],errors = "coerce")
```

In [29]:

```
Train.dtypes
```

Out[29]:

```
fare_amount                 float64
pickup_datetime      datetime64[ns]
pickup_longitude            float64
pickup_latitude             float64
dropoff_longitude           float64
dropoff_latitude            float64
passenger_count             float64
year                          int64
Month                         int64
Date                          int64
Day                           int64
Hour                          int64
Minute                        int64
dtype: object
```

In [30]:

```
Train["fare_amount"].sort_values(ascending=False)
```

Out[30]:

```
1015    54343.0
1072     4343.0
607       453.0
980       434.0
1335      180.0
         ...   
1712        NaN
2412        NaN
2458        NaN
8178        NaN
8226        NaN
Name: fare_amount, Length: 16066, dtype: float64
```

In [31]:

```
Train["fare_amount"].describe()
```

Out[31]:

```
count    16041.000000
mean        15.015223
std        430.474362
min         -3.000000
25%          6.000000
50%          8.500000
75%         12.500000
max      54343.000000
Name: fare_amount, dtype: float64
```

In [32]:

```
# We could observe above that there is huge difference in first three values of fare am
ount
# So first two values seems to be outlier in fare_amount, so drop them initially
#Also drop zero and negative values
Train = Train.drop(Train[Train["fare_amount"]>500  ].index, axis=0)
Train = Train.drop(Train[Train["fare_amount"]<=0 ].index, axis=0)
Train = Train.drop(Train[Train["fare_amount"].isnull()].index, axis=0)
```

In [33]:

```
#Working on column "passenger_count"
#any cab can not have more than 6 passengers, so we are dropping rows which includes mo
re than 6 passengers
Train = Train.drop(Train[Train["passenger_count"]> 6 ].index, axis=0)
Train = Train.drop(Train[Train["passenger_count"]==0 ].index, axis=0)
Train = Train.drop(Train[Train["passenger_count"] == 0.12].index, axis=0)
Train = Train.drop(Train[Train["passenger_count"].isnull()].index, axis=0)
```

In [34]:

```
print(Train['passenger_count'].isnull().sum())
```

```
0
```

In [35]:

```
# Working on the columns "pickup_latitude","pickup_longitude","dropoff_latitude" & "dro
poff_longitude"
# As we know that Lattitude ranges from (-90 to 90) and Longitude ranges from (-180 to
 180)
# So, drop the rows which includes values outside the Lattitude and Longitude ranges`
```

In [36]:

```
Train.describe()
```

Out[36]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	p
count	15903.000000	15903.000000	15903.000000	15903.000000	15903.000000	
mean	11.375641	-72.475079	39.921495	-72.465336	39.899371	
std	10.814944	10.538127	6.817244	10.566052	6.186041	
min	0.010000	-74.438233	-74.006893	-74.429332	-74.006377	
25%	6.000000	-73.992143	40.734946	-73.991181	40.734715	
50%	8.500000	-73.981689	40.752640	-73.980157	40.753565	
75%	12.500000	-73.966801	40.767382	-73.963643	40.768027	
max	453.000000	40.766125	401.083332	40.802437	41.366138	

In [37]:

```
# We can see pickup_latitude has outlier
#dropping one value of >90
Train = Train.drop((Train[Train['pickup_latitude']< -90]).index, axis=0)
Train = Train.drop((Train[Train['pickup_latitude']> 90]).index, axis=0)
```

In [38]:

```
Train.isnull().sum()
```

Out[38]:

```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
year                 0
Month                0
Date                 0
Day                  0
Hour                 0
Minute               0
dtype: int64
```

Calculating the distance based on latitude and longitude: we are having the values of latitude and longitude, hence we can calculate the distance travelled by a passenger so that we can have only one input feature instead of four. This helps in reduction of dimensions of input features which helps improving the model accuracy. We will calculate the distance using haversine formula.

In [39]:

```
#As we know that we have given pickup longitute and latitude values and same for drop.
#So we need to calculate the distance Using the haversine formula and we will create a
 new variable called distance
```

In [40]:

```
# function for calculating the distance using haversine formula.
from math import radians, cos, sin, asin, sqrt

def haversine(a):
    lon1=a[0]
    lat1=a[1]
    lon2=a[2]
    lat2=a[3]

    # convert decimal degrees to radians
    lon1, lat1, lon2, lat2 = map(radians, [lon1, lat1, lon2, lat2])

    # haversine formula
    dlon = lon2 - lon1
    dlat = lat2 - lat1
    a = sin(dlat/2)**2 + cos(lat1) * cos(lat2) * sin(dlon/2)**2
    c =  2 * asin(sqrt(a))
    # Radius of earth in kilometers is 6371
    km = 6371* c
    return km
```

In [41]:

```
# Applying the haversine formula on  both Train and Test datasets
Train['distance'] = Train[['pickup_longitude','pickup_latitude','dropoff_longitude','dr
opoff_latitude']].apply(haversine,axis=1)
```

In [42]:

```
Test['distance'] = Test[['pickup_longitude','pickup_latitude','dropoff_longitude','drop
off_latitude']].apply(haversine,axis=1)
```

In [43]:

```
Train.head()
```

Out[43]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropo
0	4.5	2009-06-15 17:26:21	-73.844311	40.721319	-73.841610	
1	16.9	2010-01-05 16:52:16	-74.016048	40.711303	-73.979268	
2	5.7	2011-08-18 00:35:00	-73.982738	40.761270	-73.991242	
3	7.7	2012-04-21 04:30:42	-73.987130	40.733143	-73.991567	
4	5.3	2010-03-09 07:51:00	-73.968095	40.768008	-73.956655	

In [44]:

```
Test.head()
```

Out[44]:

	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pas
0	2015-01-27 13:08:24	-73.973320	40.763805	-73.981430	40.743835	
1	2015-01-27 13:08:24	-73.986862	40.719383	-73.998886	40.739201	
2	2011-10-08 11:53:44	-73.982524	40.751260	-73.979654	40.746139	
3	2012-12-01 21:12:12	-73.981160	40.767807	-73.990448	40.751635	
4	2012-12-01 21:12:12	-73.966046	40.789775	-73.988565	40.744427	

In [45]:

```
#Working on column "Distance"
#Removing outliers
Train["distance"].describe(include="all")
```

Out[45]:

```
count    15902.000000
mean        15.070783
std        311.732401
min          0.000000
25%          1.215750
50%          2.125950
75%          3.851269
max       8667.542104
Name: distance, dtype: float64
```

In [46]:

```
Train["distance"].sort_values(ascending=False).head(50)
```

Out[46]:

```
9147     8667.542104
8647     8667.497512
2397     8667.454421
472      8667.304968
11653    8666.701504
13340    8666.613646
10215    8666.584706
4597     8666.566030
10458    8665.976222
10672    8665.702390
10488    8665.555634
1260     8665.268588
4278     8665.223767
6188     8664.191488
12983    8664.131808
6302     8663.039123
12705    8661.362152
14197    8657.136619
15783    8656.714168
15749    6028.926779
2280     6026.494216
5864     5420.988959
7014     4447.086698
10710     129.950482
14536     129.560455
11619     127.509261
12228     123.561157
5663      101.094619
1684       99.771579
3075       97.985088
9899       97.670590
4487       95.852036
9808       93.925599
7401       92.605848
12349      43.648755
649        39.476975
6308       37.812945
4118       32.602535
7021       29.478280
6677       26.369072
4567       25.735917
8105       24.690884
15023      24.125745
15178      23.814940
14099      23.696200
12433      23.513721
4268       23.196680
3216       23.184092
4299       23.168706
12941      23.114168
Name: distance, dtype: float64
```

In [47]:

```
# And after first 23 values, distance goes down to 129 km, So drop rows which includes
 distance above 130km
# distance can not be 0 km, so drop the rows which includes distance 0 km
Train=Train.drop(Train[Train["distance"]>130].index,axis=0)
Train=Train.drop(Train[Train["distance"]==0].index,axis=0)
```

In [48]:

```
#Since the pickup date time is splitted into different variables like month, year, day
 so on and also distance  variable has been created using pickup and drop longitudes an
d latitudes
#So we will drop pickup date time, pickup and drop longitudes and latitudes variables o
n both Train and Test data.
```

In [49]:

```
cols=["pickup_datetime","pickup_longitude","pickup_latitude","dropoff_longitude","dropo
ff_latitude","Minute"]
Train=Train.drop(cols,axis=1)
```

In [50]:

```
Train.head()
```

Out[50]:

	fare_amount	passenger_count	year	Month	Date	Day	Hour	distance
0	4.5	1.0	2009	6	15	0	17	1.030764
1	16.9	1.0	2010	1	5	1	16	8.450134
2	5.7	2.0	2011	8	18	3	0	1.389525
3	7.7	1.0	2012	4	21	5	4	2.799270
4	5.3	1.0	2010	3	9	1	7	1.999157

In [51]:

```
Test=Test.drop(cols,axis=1)
```

In [52]:

```
Test.head()
```

Out[52]:

	passenger_count	year	Month	Date	Day	Hour	distance
0	1	2015	1	27	1	13	2.323259
1	1	2015	1	27	1	13	2.425353
2	1	2011	10	8	5	11	0.618628
3	1	2012	12	1	5	21	1.961033
4	1	2012	12	1	5	21	5.387301

In [53]:

```
Train.dtypes
```

Out[53]:

```
fare_amount        float64
passenger_count    float64
year                 int64
Month                int64
Date                 int64
Day                  int64
Hour                 int64
distance           float64
dtype: object
```

In [54]:

```
# Converting the all the datatypes of "columns" into desired format
Train["passenger_count"]=Train["passenger_count"].astype("int64")
Train["year"]=Train["year"].astype("int64")
Train["Month"]=Train["Month"].astype("int64")
Train["Date"]=Train["Date"].astype("int64")
Train["Day"]=Train["Day"].astype("int64")
Train["Hour"]=Train["Hour"].astype("int64")
```

In [55]:

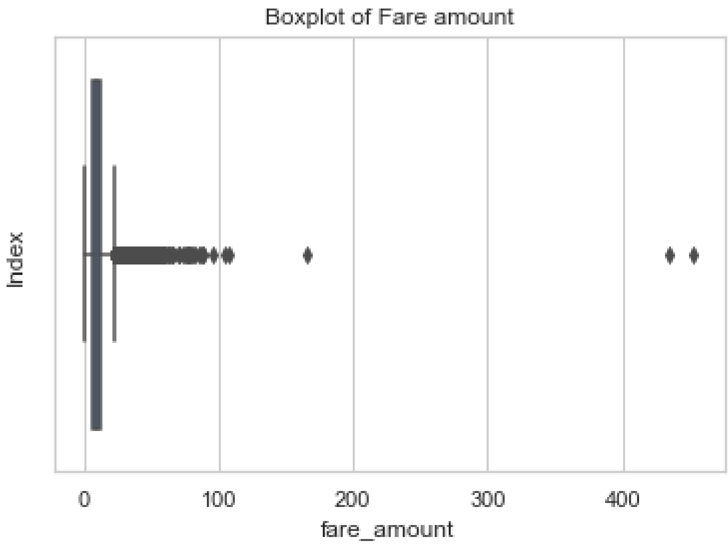
```
#taking copy of the data

train_data_df1 = Train.copy()
test_data_df1 = Test.copy()
```

In [56]:

```
#### boxplot and scatter plot analysis for outlier detection
```

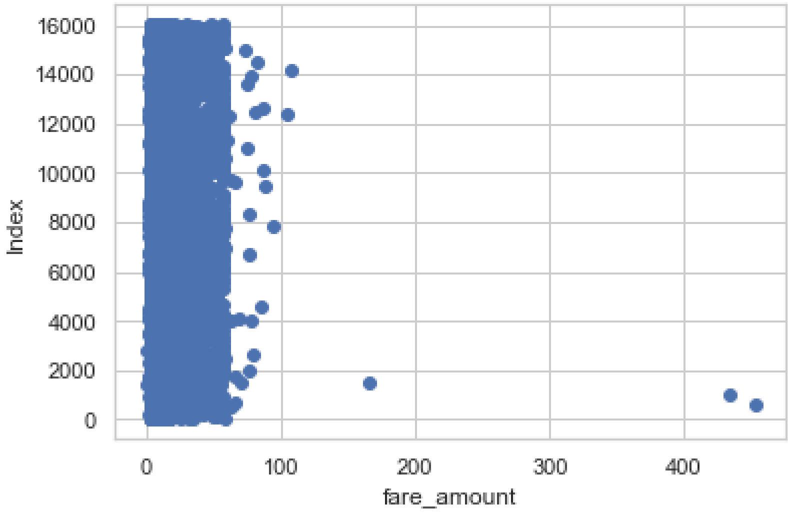
In [57]:

```
# checking boxplot of continous variable- Fare amount
sns.set(style="whitegrid")
sns.boxplot(y =Train['fare_amount'], orient="h")
plt.xlabel('fare_amount')
plt.ylabel('Index')
plt.title("Boxplot of Fare amount")
plt.show()
```



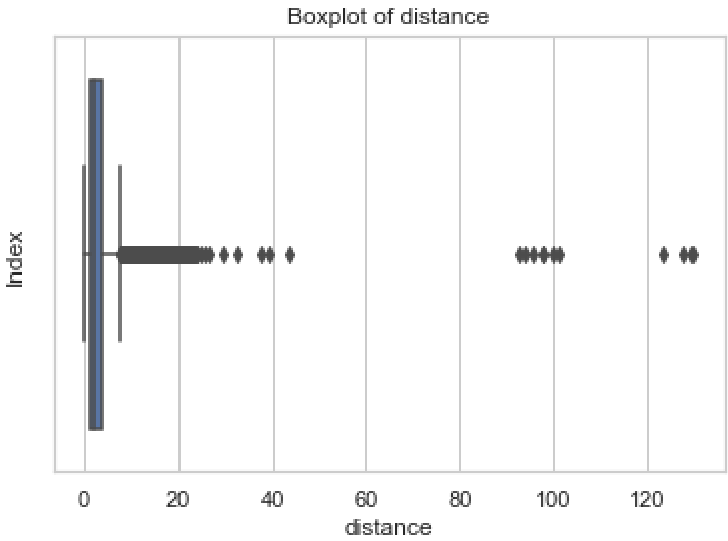
In [58]:

```
# scatter plot of fare amount

plt.scatter(x=Train.fare_amount, y=Train.index)
plt.ylabel('Index')
plt.xlabel('fare_amount')
plt.show()
```



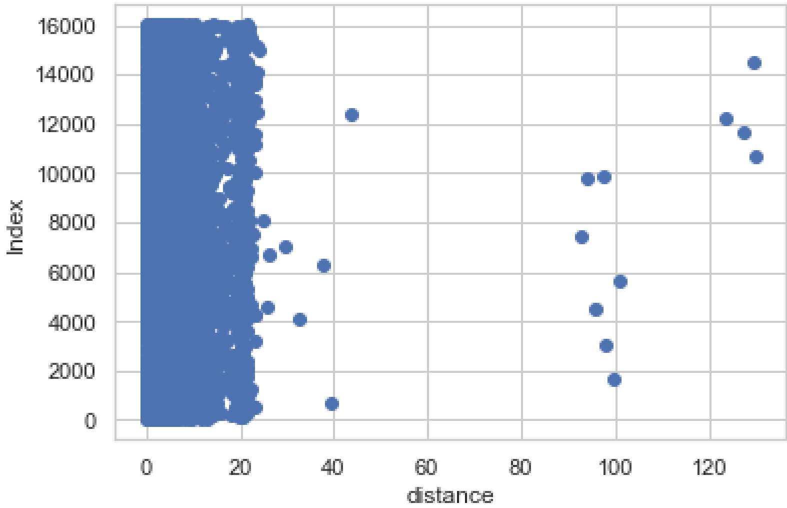
In [59]:

```
# checking boxplot of continous variable - Distance
sns.set(style="whitegrid")
sns.boxplot(y =Train['distance'], orient="h")
plt.xlabel('distance')
plt.ylabel('Index')
plt.title("Boxplot of distance")
plt.show()
```



In [60]:

```
# scatter plot of Distance

plt.scatter(x=Train.distance, y=Train.index)
plt.ylabel('Index')
plt.xlabel('distance')
plt.show()
```



From above scatter plots, it is clear that fare greater than 100 is outlier and distance greater than 30 km is outlier. so, drop the rows which includes fare greater than 100 and distance greater than 30 km

In [61]:

```
Train = Train.drop(Train[Train['fare_amount'] > 100].index, axis=0)
Train = Train.drop(Train[Train['distance'] > 30].index, axis=0)
```

In [62]:

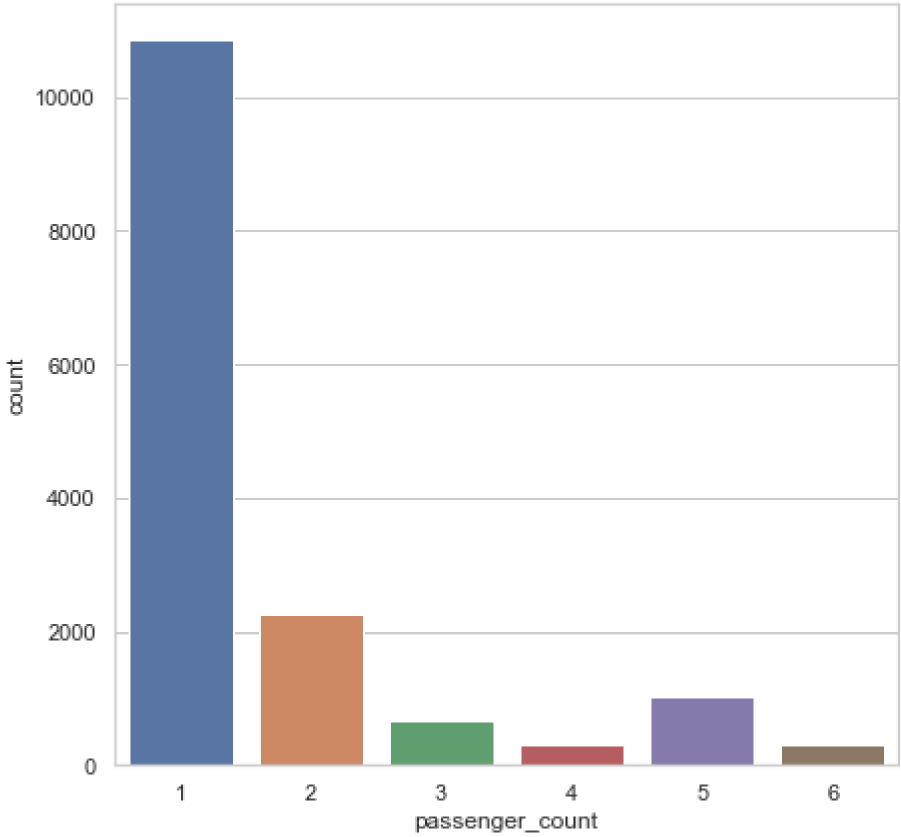
```
# # Visualization of Data
```

In [63]:

```
#passenger count visualization
plt.figure(figsize=(7,7))
sns.countplot(x="passenger_count", data=Train)
```

Out[63]:

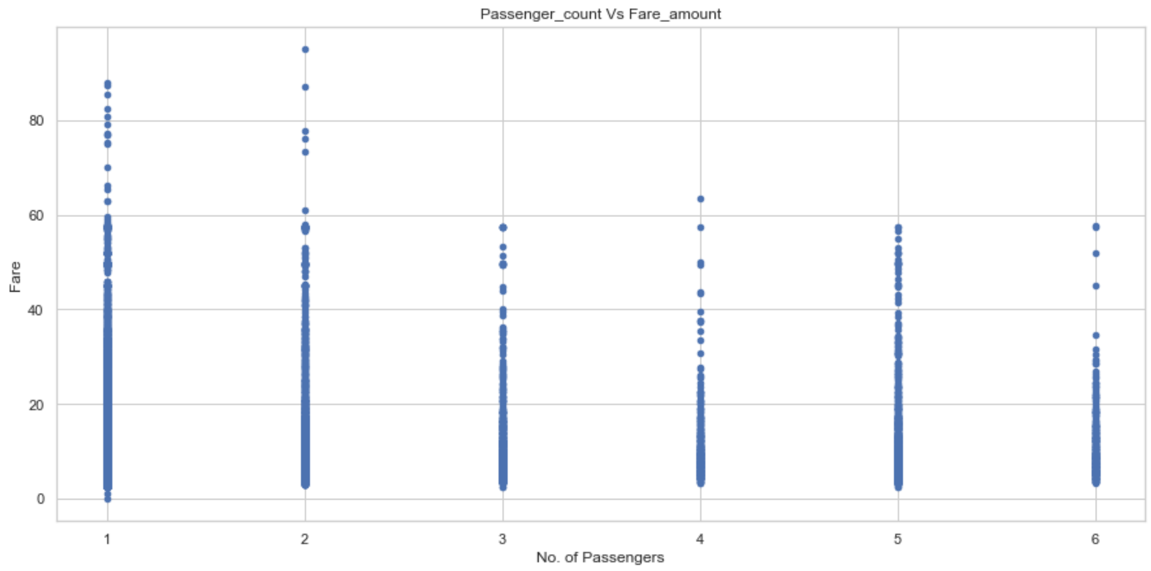
```
<matplotlib.axes._subplots.AxesSubplot at 0x479f75a8c8>
```



From the above graph it can be observe that the most of the rides were availed by one or two passengers at a time.

In [64]:

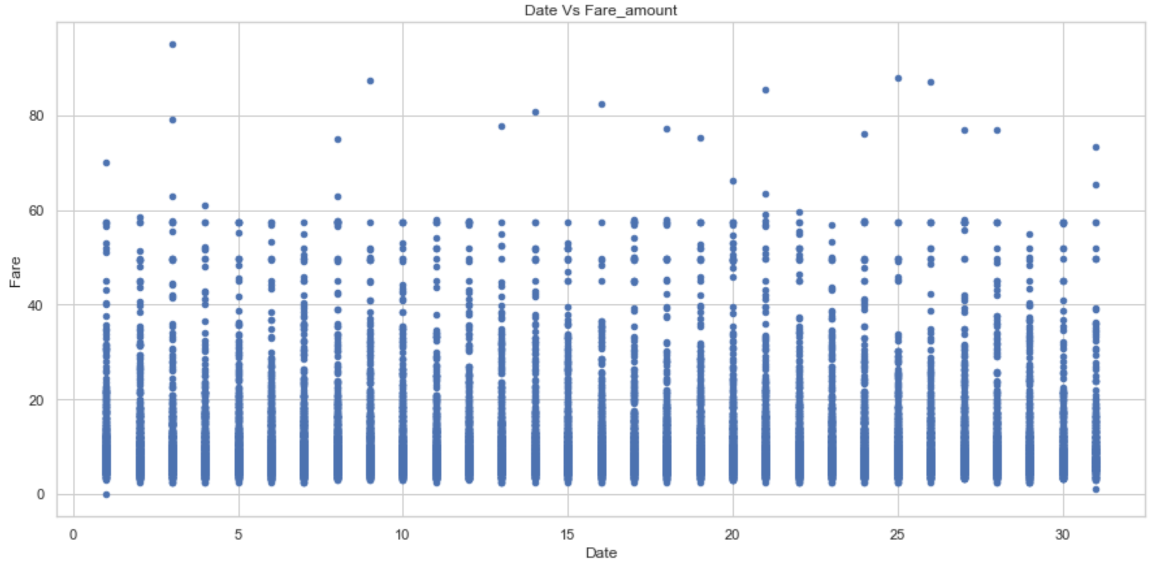
```
#Relationship beetween number of passengers and Fare amount

plt.figure(figsize=(15,7))
plt.scatter(x=Train['passenger_count'], y=Train['fare_amount'], s=20) #s means here ,s=
number of dots
plt.xlabel('No. of Passengers')
plt.ylabel('Fare')
plt.title("Passenger_count Vs Fare_amount")
plt.show()
```



From this graph it is observed that the revenue is more from the rides that are availed by one or two passengers at a time

In [65]:

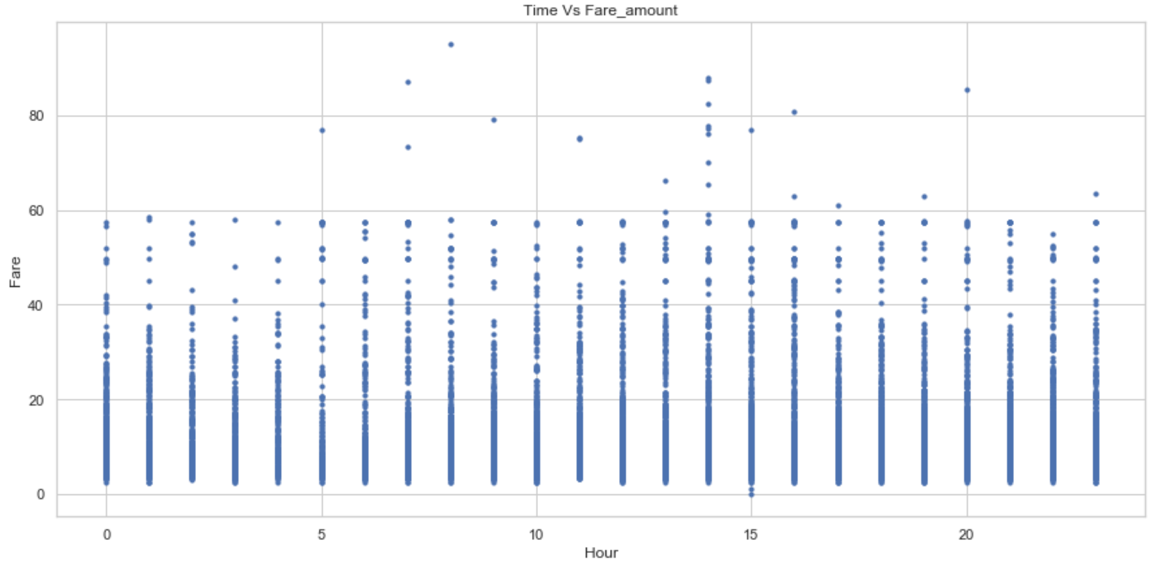
```
#Relationship between date and Fare amount
plt.figure(figsize=(15,7))
plt.scatter(x=Train['Date'], y=Train['fare_amount'], s=20)
plt.xlabel('Date')
plt.ylabel('Fare')
plt.title("Date Vs Fare_amount")
plt.show()
```



From the above graph it is seen that highest fare was charged on 3rd and 24th of the month

In [66]:

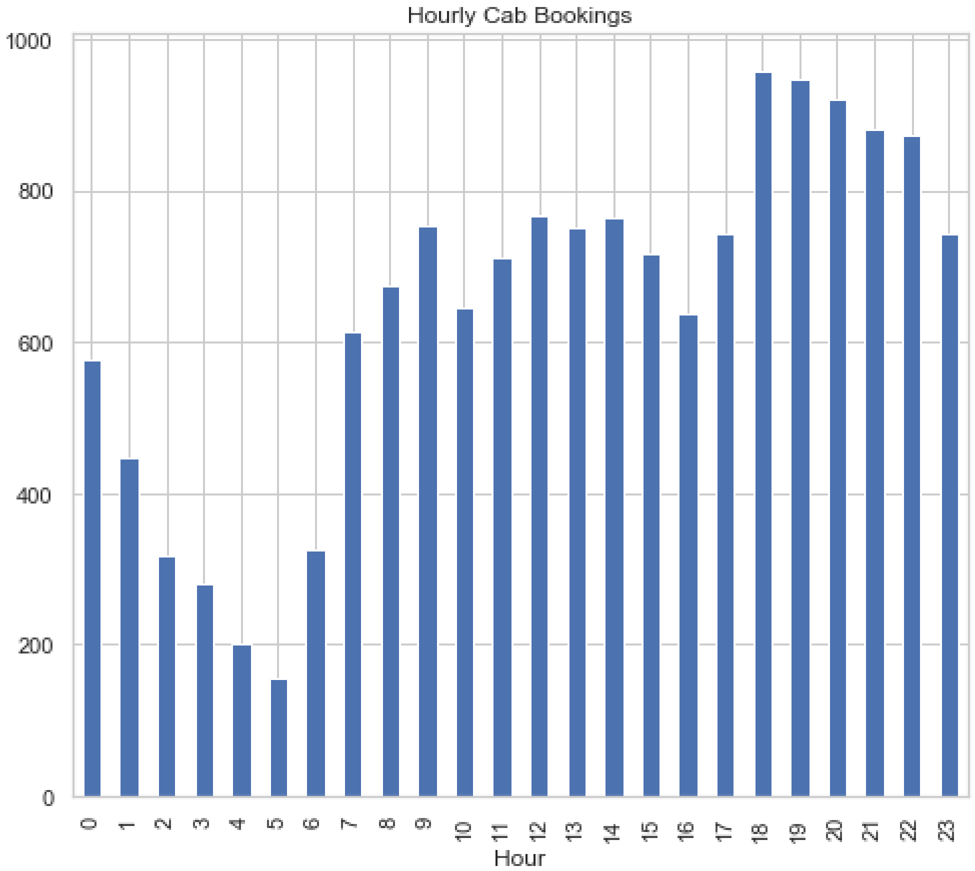
```
#Relationship between Time and Fare amount
plt.figure(figsize=(15,7))
plt.scatter(x=Train['Hour'], y=Train['fare_amount'], s=10)
plt.xlabel('Hour')
plt.ylabel('Fare')
plt.title("Time Vs Fare_amount")
plt.show()
```



The highest fare was 8AM in the morning, 2pm in afternoon and 10PM in the night of a day.

In [67]:

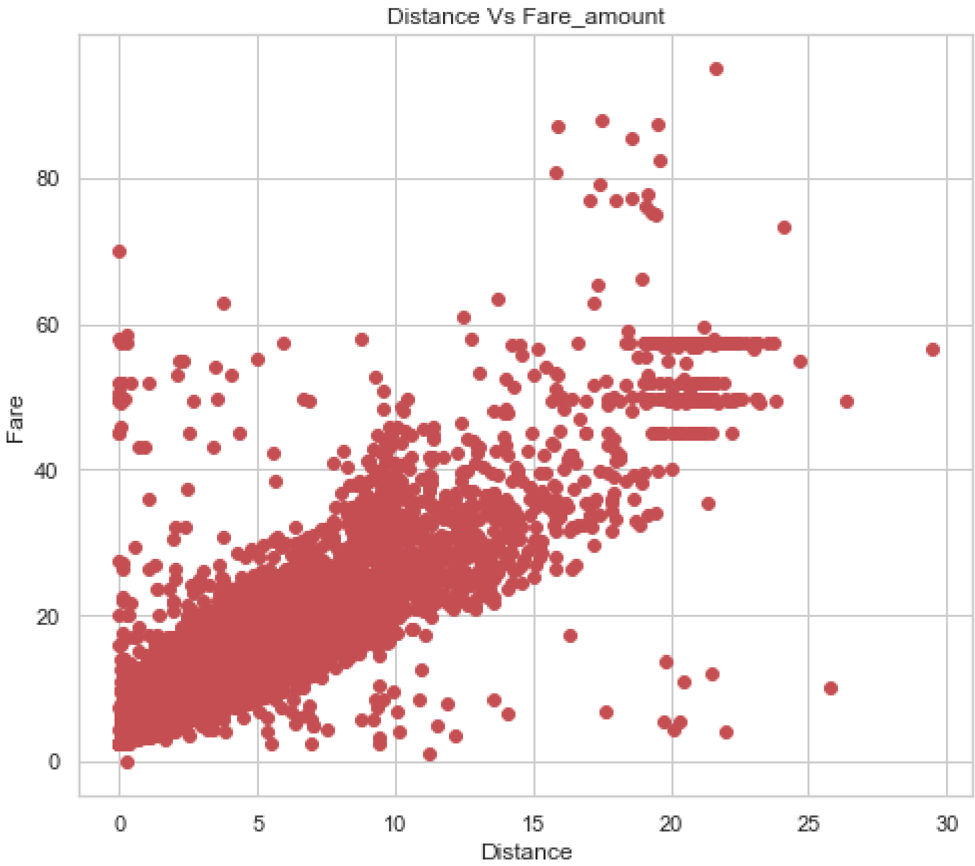
```
#Visualisation for hourly cab bookings
plt.figure(figsize=(8,7))
Train.groupby(Train["Hour"])['Hour'].count().plot(kind="bar")
plt.title("Hourly Cab Bookings")
plt.show()
```



We can confirm that least number of rides were at 5AM and more number of rides were taken at 6PM and 7PM, hence the high number of cars can be arranged at those peak hours.

In [68]:

```
#Relationship between distance and fare amount
plt.figure(figsize=(8,7))
plt.scatter(x = Train['distance'],y = Train['fare_amount'],c = "r")
plt.xlabel('Distance')
plt.ylabel('Fare')
plt.title("Distance Vs Fare_amount")
plt.show()
```



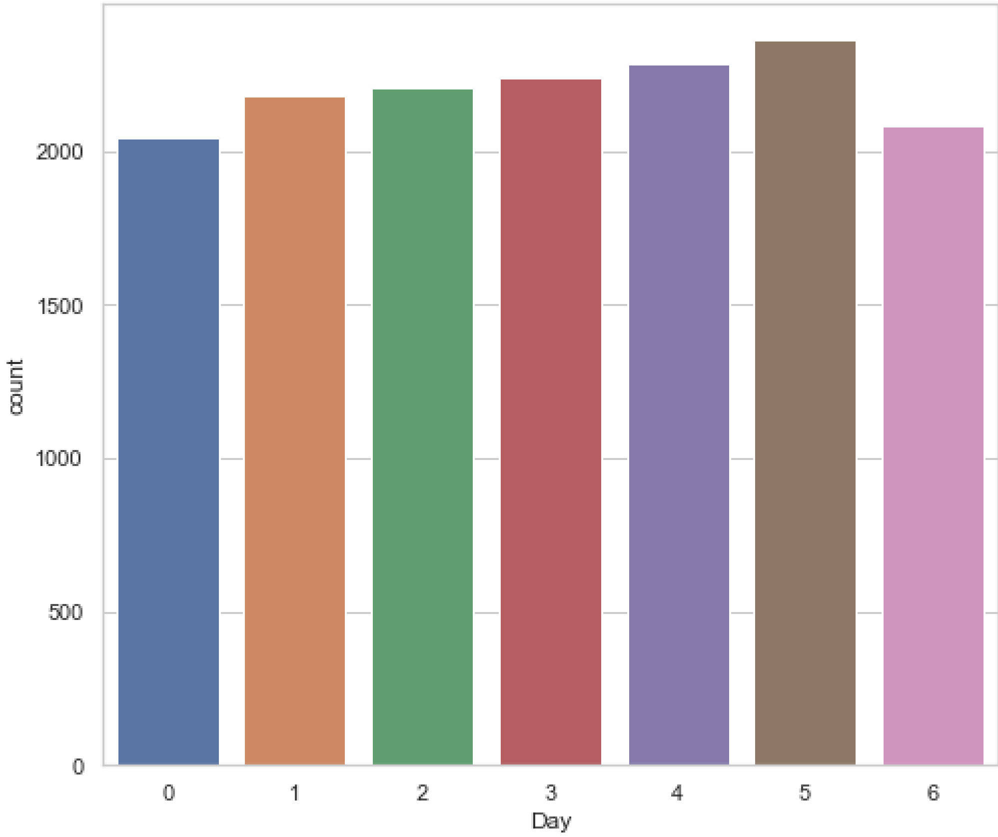
Most no of rides were taken between the distance 0 to 30kms, And also the highest fare being charged with in this limit.

In [69]:

```
#impact of Day on the number of cab rides
plt.figure(figsize=(8,7))
sns.countplot(x="Day", data=Train)
```

Out[69]:

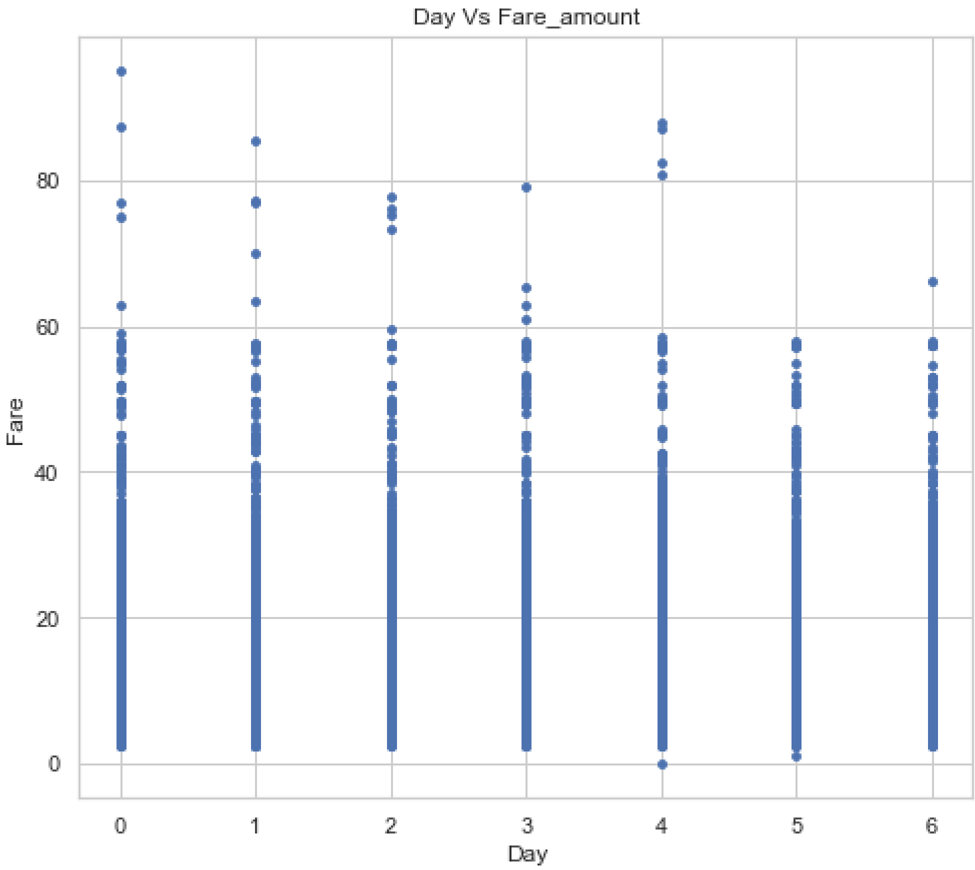
```
<matplotlib.axes._subplots.AxesSubplot at 0x479f717448>
```



We can see that the day is not impacting much on the number of rides

In [70]:

```
#Relationships between day and Fare amount
plt.figure(figsize=(8,7))
plt.scatter(x=Train['Day'], y=Train['fare_amount'], s=15)
plt.xlabel('Day')
plt.ylabel('Fare')
plt.title("Day Vs Fare_amount")
plt.show()
```



The highest fare was charged on Monday, Thursday and Friday.

In [71]:

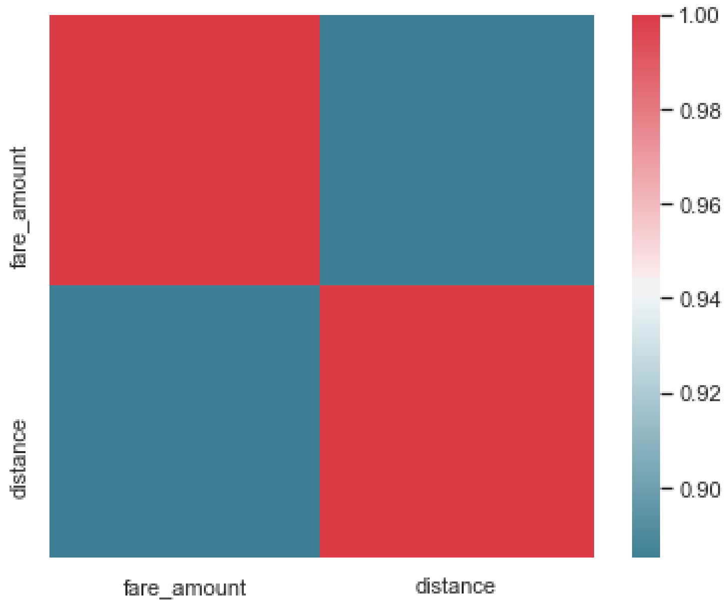
```
#taking copy of the data

train_data_df2 = Train.copy()
test_data_df2 = Test.copy()
```

In [72]:

```
# Correlation Analysis
# generating the heatmap

cnames = ['fare_amount', 'distance']
df_corr = Train.loc[:,cnames]
f, ax = plt.subplots(figsize=(7, 5))

# correlation matrix
corr = df_corr.corr()

sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool), cmap=sns.diverging_palette(2
20, 10, as_cmap=True), square=True, ax=ax)
```

Out[72]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x47a1186188>
```



In [73]:

```
# checking VIF for multicolinerity

from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant

VIF_df = add_constant(Train.iloc[:,1:8])
pd.Series([variance_inflation_factor(VIF_df.values, i)
               for i in range(VIF_df.shape[1])],
              index=VIF_df.columns)
```

Out[73]:

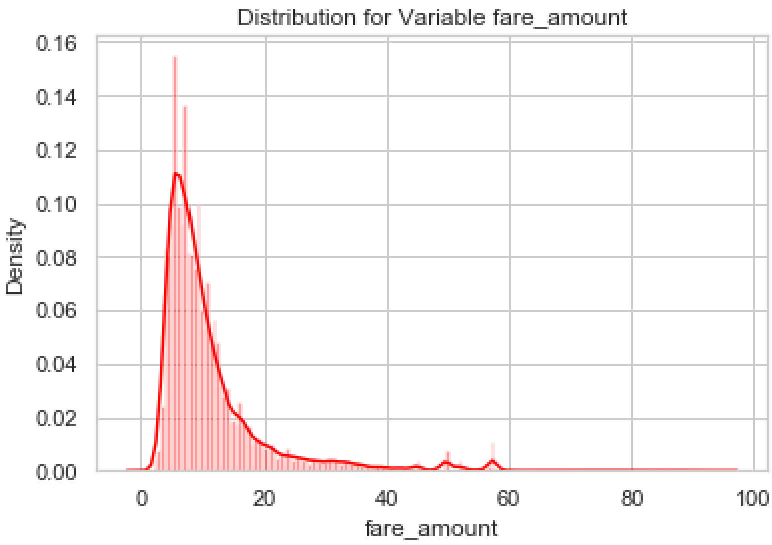
```
const              1.175167e+06
passenger_count    1.002383e+00
year               1.015269e+00
Month              1.015250e+00
Date               1.001272e+00
Day                1.010594e+00
Hour               1.010571e+00
distance           1.003535e+00
dtype: float64
```

From the above VIF values since they are less than 10 for each variable, there is no multicolinerity exists.

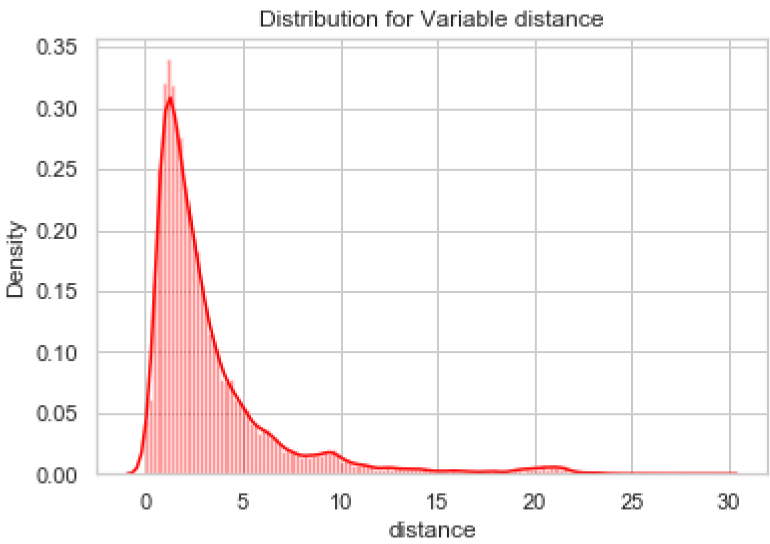
In [74]:

```
#Normality check

for i in ['fare_amount', 'distance']:
    print(i)
    sns.distplot(Train[i],bins='auto',color='red')
    plt.title("Distribution for Variable "+i)
    plt.ylabel("Density")
    plt.show()
```

```
fare_amount
```




```
distance
```



From the above graph we observe that the distribution of "fare_amount" and "distance" are skewed. So to get right predictions we transform these values of two columns using logarithmic function.

In [75]:

```
#since the skewness of fare amount variable is high,we apply log transform to reduce th
e skewness
Train['fare_amount'] = np.log1p(Train['fare_amount'])
```

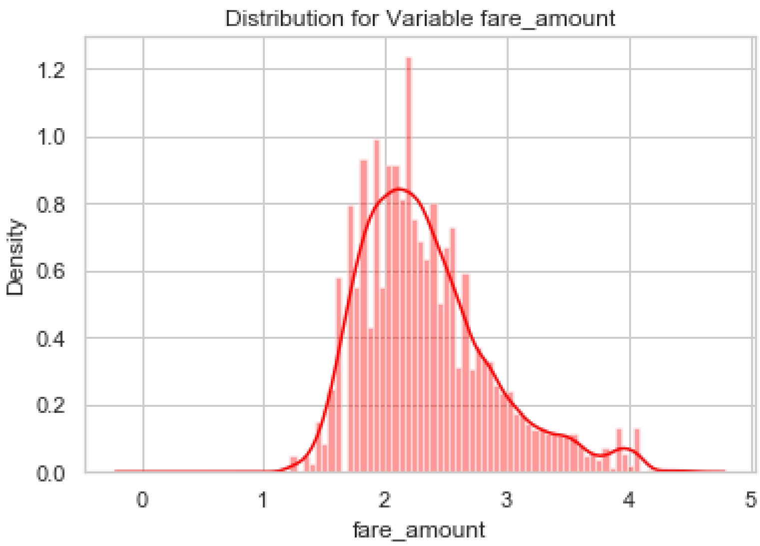
In [76]:

```
#since the skewness of distance variable is high, we apply log transform to reduce the
 skewness
Train['distance'] = np.log1p(Train['distance'])
```

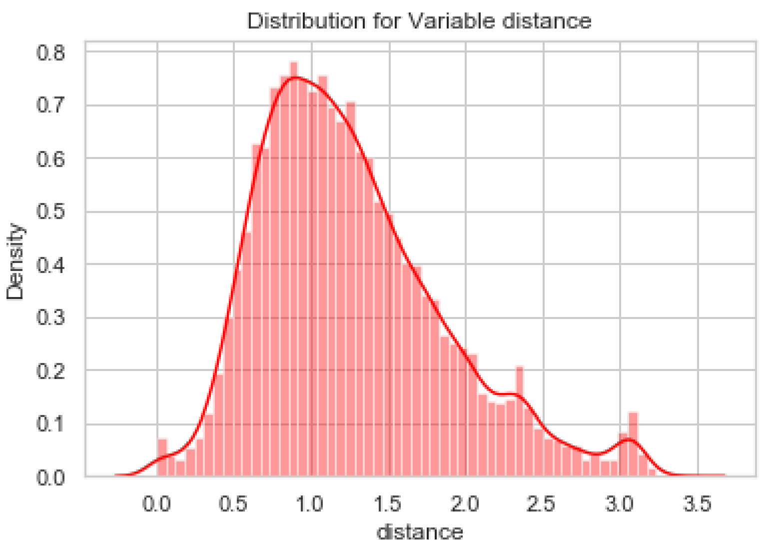
In [77]:

```
#Re-checking the Normality after log transformartion

for i in ['fare_amount', 'distance']:
    print(i)
    sns.distplot(Train[i],bins='auto',color='red')
    plt.title("Distribution for Variable "+i)
    plt.ylabel("Density")
    plt.show()
```

fare_amount



distance



From the above graph we observe that the distribution of "fare_amount" and "distance" are not skewed and hence they are ready for the Training of a model.

In [78]:

```
Train.head()
```

Out[78]:

	fare_amount	passenger_count	year	Month	Date	Day	Hour	distance
0	1.704748	1	2009	6	15	0	17	0.708412
1	2.884801	1	2010	1	5	1	16	2.246029
2	1.902108	2	2011	8	18	3	0	0.871095
3	2.163323	1	2012	4	21	5	4	1.334809
4	1.840550	1	2010	3	9	1	7	1.098331

In [79]:

```
Test.head()
```

Out[79]:

	passenger_count	year	Month	Date	Day	Hour	distance
0	1	2015	1	27	1	13	2.323259
1	1	2015	1	27	1	13	2.425353
2	1	2011	10	8	5	11	0.618628
3	1	2012	12	1	5	21	1.961033
4	1	2012	12	1	5	21	5.387301

Models Development

In [80]:

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn.model_selection import GridSearchCV
```

In [81]:

```
X=np.array(Train.iloc[:,1:])
y=np.array(Train.iloc[:,0])
```

In [82]:

```
# split train data into train and test

X_Train,X_Test,y_Train,y_Test=train_test_split(X,y,test_size=0.2,random_state=1)
```

In [83]:

```
#define the Error Metrics.

def MAPE(y_actual, y_predicted):
    MAPE = np.mean(np.abs(y_actual-y_predicted)/y_actual)*100
    return MAPE
```

Linear Regression Model

In [84]:

```
# Build model on train data
LR = LinearRegression().fit(X_Train , y_Train)
```

In [85]:

```
#Predict the model on Train data
pred_train_LR = LR.predict(X_Train)
```

In [86]:

```
#Predict the model on Test data
pred_test_LR = LR.predict(X_Test)
```

In [87]:

```
#MAPE
LRMape = MAPE(y_Train, pred_train_LR)
```

In [88]:

```
##calculate RMSE for Test data
RMSE_test_LR = np.sqrt(mean_squared_error(y_Test, pred_test_LR))
```

In [89]:

```
##calculate RMSE for Train data
RMSE_train_LR= np.sqrt(mean_squared_error(y_Train, pred_train_LR))
```

In [90]:

```
##calculate R^2 on train data
r2_train_LR = r2_score(y_Train, pred_train_LR)

##calculate R^2 on test data
r2_test_LR = r2_score(y_Test, pred_test_LR)
```

In [91]:

```
print("MAPE = "+str(LRMape))
print("RMSE on train data = "+str(RMSE_train_LR))
print("RMSE on test data = "+str(RMSE_test_LR))
print("r2 score on train data = "+str(r2_train_LR))
print("r2 score on test data = "+str(r2_test_LR))
```

```
MAPE = 7.385880554349929
RMSE on train data = 0.2572334751441916
RMSE on test data = 0.23494167589601445
r2 score on train data = 0.7757819647958124
r2 score on test data = 0.8100377286623632
```

Decision Tree Model

In [92]:

```
#Train the data using Decision Tree model
DT = DecisionTreeRegressor(max_depth = 2).fit(X_Train, y_Train)
#Predict the model on Train data and test data
pred_train_DT = DT.predict(X_Train)
pred_test_DT = DT.predict(X_Test)
```

In [93]:

```
#MAPE
DTMape = MAPE(y_Train, pred_train_DT)
```

In [94]:

```
##calculate RMSE for Test data
RMSE_test_DT = np.sqrt(mean_squared_error(y_Test, pred_test_DT))
##calculate RMSE for Train data
RMSE_train_DT = np.sqrt(mean_squared_error(y_Train, pred_train_DT))
```

In [95]:

```
##calculate R^2 on train data
r2_train_DT = r2_score(y_Train, pred_train_DT)

##calculate R^2 on test data
r2_test_DT = r2_score(y_Test, pred_test_DT)
```

In [96]:

```
print("MAPE = "+str(DTMape))
print("RMSE on train data = "+str(RMSE_train_DT))
print("RMSE on test data = "+str(RMSE_test_DT))
print("r2 score on train data = "+str(r2_train_DT))
print("r2 score on test data = "+str(r2_test_DT))
```

```
MAPE = 9.415292382085193
RMSE on train data = 0.2914690450301004
RMSE on test data = 0.28143013485925555
r2 score on train data = 0.7121273214557522
r2 score on test data = 0.727423490035964
```

Random Forest Regressor Model

In [97]:

```
#Train the data using Random Forest model
RF = RandomForestRegressor(n_estimators = 100).fit(X_Train, y_Train)
#Predict the model on Train data and test data
pred_train_RF = RF.predict(X_Train)
pred_test_RF = RF.predict(X_Test)
```

In [98]:

```
#MAPE
RFMape = MAPE(y_Train, pred_train_RF)
```

In [99]:

```
##calculate RMSE for Test data
RMSE_test_RF = np.sqrt(mean_squared_error(y_Test, pred_test_RF))
##calculate RMSE for Train data
RMSE_train_RF = np.sqrt(mean_squared_error(y_Train, pred_train_RF))
```

In [100]:

```
# calculate R^2 on train dataset
r2_train_RF = r2_score(y_Train, pred_train_RF)

# calculate R^2 on test dataset
r2_test_RF = r2_score(y_Test, pred_test_RF)
```

In [101]:

```
print("MAPE = "+str(RFMape))
print("RMSE on train data = "+str(RMSE_train_RF))
print("RMSE on test data = "+str(RMSE_test_RF))
print("r2 score on train data = "+str(r2_train_RF))
print("r2 score on test data = "+str(r2_test_RF))
```

```
MAPE = 2.77704332883657 57
RMSE on train data = 0.09222857911192858
RMSE on test data = 0.2390542691604747
r2 score on train data = 0.971176507105449
r2 score on test data = 0.8033290403440289
```

Upon observing the values, we choose Random forest as best model and apply Hyper parameter Tuning for optimizing the results

Applying Hyper-parameter Tuning for optimizing the results

There are 2 ways to apply hyper-parameter tuning

1. RandomizedSearchCV

2. GridSearchCV

RandomizedSearchCV on Random Forest Model

In [102]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split,RandomizedSearchCV
model_rrf = RandomForestRegressor(random_state = 42)
n_estimator = list(range(1,20,2))
depth = list(range(1,100,2))
```

In [103]:

```
# Create the random grid
rand_grid = {'n_estimators': n_estimator,
               'max_depth': depth}

randomcv_rf = RandomizedSearchCV(model_rrf, param_distributions = rand_grid, n_iter = 5
, cv = 5, random_state=0)
randomcv_rf = randomcv_rf.fit(X_Train,y_Train)
predictions_RRF = randomcv_rf.predict(X_Test)

view_best_params_RRF = randomcv_rf.best_params_

best_model = randomcv_rf.best_estimator_
predictions_RRF = best_model.predict(X_Test)
```

In [104]:

```
#R^2 score
RRF_r2 = r2_score(y_Test, predictions_RRF)
#Calculating RMSE
RRF_rmse = np.sqrt(mean_squared_error(y_Test,predictions_RRF))

print('Randomized Search CV Random Forest Regressor Model Performance:')
print('Best Parameters = ',view_best_params_RRF)
print('R-squared = {:0.2}.'.format(RRF_r2))
print('RMSE = ',RRF_rmse)
```

```
Randomized Search CV Random Forest Regressor Model Performance:
Best Parameters =  {'n_estimators': 15, 'max_depth': 9}
R-squared = 0.81.
RMSE =  0.23635853653501906
```

Grid Search CV for random Forest model

In [105]:

```
from sklearn.model_selection import GridSearchCV
## Grid Search CV for random Forest model
regr = RandomForestRegressor(random_state = 0)
n_estimator = list(range(11,20,1))
depth = list(range(5,15,2))

# Create the grid
grid_search = {'n_estimators': n_estimator,
               'max_depth': depth}

## Grid Search Cross-Validation with 5 fold CV
gridcv_rf = GridSearchCV(regr, param_grid = grid_search, cv = 5)
gridcv_rf = gridcv_rf.fit(X_Train,y_Train)
view_best_params_GRF = gridcv_rf.best_params_

best_estimator_GRF = gridcv_rf.best_estimator_

#Apply model on test data
predictions_grf = best_estimator_GRF.predict(X_Test)
```

In [106]:

```
#R^2 score
grf_r2 = r2_score(y_Test, predictions_grf)
#Calculate RMSE
grf_rmse = np.sqrt(mean_squared_error(y_Test,predictions_grf))

print('Grid Search CV Random Forest Regressor Model Performance:')
print('Best Parameters = ',view_best_params_GRF)
print('R-squared = {:0.2}.'.format(grf_r2))
print('RMSE = ',(grf_rmse))
```

```
Grid Search CV Random Forest Regressor Model Performance:
Best Parameters =  {'max_depth': 7, 'n_estimators': 18}
R-squared = 0.81.
RMSE =  0.23449124746285915
```

Observations: Grid Search CV Random Forest Regressor Model shows better results. Hence we choose that Model to predict the values for the "Test.csv"

Selection of the model: Random Forest Regressor Model

In [107]:

```
train = train_data_df2.copy()
```

In [108]:

```
X = train.drop('fare_amount', axis=1).values
y = train['fare_amount'].values
```

In [109]:

```
## Grid Search CV for random Forest model
regr = RandomForestRegressor(random_state = 0)
n_estimator = list(range(11,20,1))
depth = list(range(5,15,2))

# Create the grid
grid_search = {'n_estimators': n_estimator,
               'max_depth': depth}

## Grid Search Cross-Validation with 5 fold CV
gridcv_rf = GridSearchCV(regr, param_grid = grid_search, cv = 5)
gridcv_rf = gridcv_rf.fit(X,y)
view_best_params_GRF = gridcv_rf.best_params_
best_estimator_GRF = gridcv_rf.best_estimator_

predictions_GRF_test = best_estimator_GRF.predict(Test)

print('Grid Search CV Random Forest Regressor Model Performance:')
print('Best Parameters = ',view_best_params_GRF)
print('R-squared = {:0.2}.'.format(grf_r2))
print('RMSE = ',(grf_rmse))
```

```
Grid Search CV Random Forest Regressor Model Performance:
Best Parameters =  {'max_depth': 7, 'n_estimators': 19}
R-squared = 0.81.
RMSE =  0.23449124746285915
```

In [110]:

```
# # Creating the target label on the "Test"(Test.csv)
```

In [111]:

```
predictions_GRF_test
Test['Predicted_fare'] = predictions_GRF_test
```

In [112]:

```
predictions_GRF_test
```

Out[112]:

```
array([ 9.94773355, 10.27565781,  4.95221369, ..., 46.61877211,
       23.01274936,  6.14832956])
```

In [113]:

```
Test.head()
```

Out[113]:

	passenger_count	year	Month	Date	Day	Hour	distance	Predicted_fare
0	1	2015	1	27	1	13	2.323259	9.947734
1	1	2015	1	27	1	13	2.425353	10.275658
2	1	2011	10	8	5	11	0.618628	4.952214
3	1	2012	12	1	5	21	1.961033	8.124924
4	1	2012	12	1	5	21	5.387301	15.083241

In [114]:

```
Test.describe()
```

Out[114]:

	passenger_count	year	Month	Date	Day	Hour
count	9914.000000	9914.000000	9914.000000	9914.000000	9914.000000	9914.000000
mean	1.671273	2011.815816	6.857979	16.194170	2.852834	13.467420
std	1.278747	1.803347	3.353272	8.838482	1.994451	6.868584
min	1.000000	2009.000000	1.000000	1.000000	0.000000	0.000000
25%	1.000000	2010.000000	4.000000	9.000000	1.000000	8.000000
50%	1.000000	2012.000000	7.000000	16.000000	3.000000	15.000000
75%	2.000000	2014.000000	10.000000	25.000000	5.000000	19.000000
max	6.000000	2015.000000	12.000000	31.000000	6.000000	23.000000

In [115]:

```
# Writing the whole dataframe into "test_Predicted.csv"
Test.to_csv('test_Predicted.csv')
```