In [1]:
```
#Loading necessary libraries
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from fancyimpute import KNN
from scipy import stats
from sklearn.metrics import r2_score
%matplotlib inline
```

```
Using TensorFlow backend.
```

In [2]:
```
#Setting working directory
os.chdir(r"E:\edWisor\Project2\Cab Rental\train_cab")
os.getcwd()
```

Out[2]:
```
'E:\\edWisor\\Project2\\Cab Rental\\train_cab'
```

In [3]:
```
#Loading data
cab_train = pd.read_csv('train_cab.csv')
cab_test = pd.read_csv('test.csv')
```

## Understanding the data and Exploratory Data Analysis

To know the basic understanding of the dataset such as shape, data types, uniques values, missing value analysis, to understand the basic statistics of each variable and all the pre-processing techniques.

In [4]:
```
#Shape of the data
print(cab_train.shape) #(16067,7)
print(cab_test.shape) #(9914,6)
```

```
(16067, 7)
(9914, 6)
```

In [5]:
```
#First five rows of our train data
cab_train.head()
```

Out[5]:

| | fare_amount | pickup_datetime | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_la |
|---|---|---|---|---|---|---|
| **0** | 4.5 | 2009-06-15 17:26:21 UTC | -73.844311 | 40.721319 | -73.841610 | 40.7 |
| **1** | 16.9 | 2010-01-05 16:52:16 UTC | -74.016048 | 40.711303 | -73.979268 | 40.7 |
| **2** | 5.7 | 2011-08-18 00:35:00 UTC | -73.982738 | 40.761270 | -73.991242 | 40.7 |
| **3** | 7.7 | 2012-04-21 04:30:42 UTC | -73.987130 | 40.733143 | -73.991567 | 40.7 |
| **4** | 5.3 | 2010-03-09 07:51:00 UTC | -73.968095 | 40.768008 | -73.956655 | 40.7 |

In [6]:
```
#First five rows of our test data
cab_test.head()
```

Out[6]:

| | pickup_datetime | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | passen |
|---|---|---|---|---|---|---|
| **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 | |

In [7]:
```
#Number of Unique values in train data
cab_train.nunique()
```

Out[7]:
```
fare_amount            468
pickup_datetime      16021
pickup_longitude     13789
pickup_latitude      14241
dropoff_longitude    13887
dropoff_latitude     14263
passenger_count         27
dtype: int64
```

In [8]:
```
#To find the missing values in our dataset
cab_train.isna().sum()
```

Out[8]:
```
fare_amount          24
pickup_datetime       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude     0
dropoff_latitude      0
passenger_count      55
dtype: int64
```

In [9]:
```
#To know the data types in train dataset
cab_train.dtypes

#Fare_amount should be float
#pickup_datetime should be a date type
#passenger_count should be an integer type
```

Out[9]:
```
fare_amount           object
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count      float64
dtype: object
```

In [10]:
```
#To know the data types in test dataset
cab_test.dtypes

#pickup_datetime should be a date type
```

Out[10]:
```
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

A few observations from the datasets

- `pickup_datetime` should be converted to date type using pandas
- `passenger_count` should be an int type and any data point less than 1 and greater than 6 can be removed/imputed
- `fare_amount` should be a float type and any data point less than 0 can be removed/imputed
- `pickup_latitude` and `dropoff_latitude` should have values in between -90 to +90 degrees and data point beyond these values can be removed
- `pickup_longitude` and `dropoff_longitude` should have values in between -180 to +180 degrees and data point beyond these values can be removed
- By using the co-ordinates of latitude and longitude, we can find the distance between pickup and drop locations
- After the above steps, we'll try to drop a few variables and data types are to properly converted

In [11]:
```
#Convert the data types
cab_train['fare_amount'] = pd.to_numeric(cab_train['fare_amount'] , errors = 'coerce')
#By using errors parameter with corece value, we can replace non-numeric values with NaN values
```

To convert the `pickup_datetime` to datetime format and to separate year,month and date etc. While trying to convert `pickup_datetime` it was found that value at index# 1327 is 43, which is to be dropped.

In [12]:
```
np.where(cab_train['pickup_datetime'] == '43')
cab_train.iloc[1327,:]
cab_train = cab_train.drop(cab_train.index[1327])
```

In [13]:
```
#To convert the pickup_datetime to datetime format and separating year,month and date etc.
cab_train['pickup_datetime'] = pd.to_datetime(cab_train['pickup_datetime'], format = "%Y-%m-%d %H:%M:%S UTC")
```

In [14]:
```
#To check the data types
cab_train.dtypes
```

Out[14]:
```
fare_amount                 float64
pickup_datetime      datetime64[ns]
pickup_longitude            float64
pickup_latitude             float64
dropoff_longitude           float64
dropoff_latitude            float64
passenger_count             float64
dtype: object
```

In [15]:
```
#Creating new features such as year, month, date etc. based on the timestamp
cab_train['year'] = cab_train['pickup_datetime'].dt.year
cab_train['Month'] = cab_train['pickup_datetime'].dt.month
cab_train['Date'] = cab_train['pickup_datetime'].dt.day
cab_train['Day'] = cab_train['pickup_datetime'].dt.dayofweek
cab_train['Hour'] = cab_train['pickup_datetime'].dt.hour
```

In [16]:
```
#To check top 5 rows of the data
cab_train.head()
```

Out[16]:

| | fare_amount | pickup_datetime | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_la |
|---|---|---|---|---|---|---|
| **0** | 4.5 | 2009-06-15 17:26:21 | -73.844311 | 40.721319 | -73.841610 | 40.7 |
| **1** | 16.9 | 2010-01-05 16:52:16 | -74.016048 | 40.711303 | -73.979268 | 40.7 |
| **2** | 5.7 | 2011-08-18 00:35:00 | -73.982738 | 40.761270 | -73.991242 | 40.7 |
| **3** | 7.7 | 2012-04-21 04:30:42 | -73.987130 | 40.733143 | -73.991567 | 40.7 |
| **4** | 5.3 | 2010-03-09 07:51:00 | -73.968095 | 40.768008 | -73.956655 | 40.7 |

In [17]:
```
#To convert the pickup_datetime for test data to datetime format and separatin
g year,month and date etc.
cab_test['pickup_datetime'] = pd.to_datetime(cab_test['pickup_datetime'], form
at = "%Y-%m-%d %H:%M:%S UTC")
```

In [18]:
```
#Creating new features such as year, month and date etc based on datetime for
 test data
cab_test['year'] = cab_test['pickup_datetime'].dt.year
cab_test['Month'] = cab_test['pickup_datetime'].dt.month
cab_test['Date'] = cab_test['pickup_datetime'].dt.day
cab_test['Day'] = cab_test['pickup_datetime'].dt.dayofweek
cab_test['Hour'] = cab_test['pickup_datetime'].dt.hour
```

- As of now `pickup_datetime` in `cab_train` dataset is cleaned and now let's check with the `passenger_count`
- Any data point with values < 1 and > 6 in `passenger_count` are to be removed

In [19]:
```
#Let's remove the values in passenger_count variable with the values < 1 and >
6
cab_train = cab_train.drop(cab_train[cab_train['passenger_count'] < 1].index ,
axis = 0)
cab_train = cab_train.drop(cab_train[cab_train['passenger_count'] > 6].index ,
axis = 0)
```

In [20]:
```
#To check if any missing values in passenger_count and delete them if they are
less in number(55 we found)
cab_train['passenger_count'].isnull().sum()
#To remove missing values or null values from passenger_count variable
cab_train = cab_train.drop(cab_train[cab_train['passenger_count'].isnull()].in
dex , axis = 0)
cab_train['passenger_count'].isnull().sum()
```

Out[20]: 0

In [21]:
```
#Let's remove the values in passenger_count variable with the values < 1 and >
6 in test data also and found no null values
cab_test = cab_test.drop(cab_test[cab_test['passenger_count'] < 1].index , axi
s = 0)
cab_test = cab_test.drop(cab_test[cab_test['passenger_count'] > 6].index , axi
s = 0)
```

In [22]:
```
#Let's check for the fair_amount variable and any negative values should be re
moved/imputed
cab_train = cab_train.drop(cab_train[cab_train['fare_amount'] < 0].index, axis
= 0)
```

In [23]:
```
#We found that we have 24 missing values in fare_amount variable. As this is a
less number, we can remove them
cab_train.isnull().sum()
cab_train = cab_train.drop(cab_train[cab_train['fare_amount'].isnull()].index,
axis = 0)
```

By using the the four variables, `pickup_longitude` , `pickup_latitude` , `dropoff_longitude` , `dropoff_latitude` let's try to find the distance travelled. The usual procedure is to find with Haversine's formula, but let us try with different methods.

In [24]:
```
# We have found one value in pickup_latitude > 90, (401...) so let's drop that
observation

cab_train = cab_train.drop(cab_train[cab_train['pickup_latitude'] > 90].index,
axis = 0)
```

In [25]:
```
#To find the distance travelled using latitudes and longitudes
from geopy.distance import geodesic

def distance_conversion(x):
    origin_lat = x[0]
    origin_long = x[1]
    dest_lat = x[2]
    dest_long = x[3]
    origin = [origin_lat,origin_long]
    dest = [dest_lat,dest_long]
    distance = geodesic(origin, dest).kilometers
    return distance

#distance_conversion(40.721319,-73.844311,40.712278,-73.841610)
#distance_conversion(40.711303,-74.016048,40.782004,-73.979268)

#Let's create a variable "distance_travelled" and try to find it's values usin
g the above function in both the datasets

cab_train['distance_travelled'] = cab_train[['pickup_latitude','pickup_longitu
de','dropoff_latitude','dropoff_longitude']].apply(distance_conversion,axis=1)
cab_test['distance_travelled'] = cab_test[['pickup_latitude','pickup_longitud
e','dropoff_latitude','dropoff_longitude']].apply(distance_conversion,axis=1)
```

In [26]:
```
#To check a few observations after removing the variables
cab_train.head()
cab_test.head()
```

Out[26]:

| | pickup_datetime | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | passen |
|---|---|---|---|---|---|---|
| **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 [27]:
```
#To check the variable distance_travelled whose values are zero and found that 454 observations have value as 0
#This will list out the indexes with distance_travelled = 0
#cab_train[cab_train['distance_travelled'] == 0].index

#Let's replace zeros with NAN values and try to impute them
cab_train.loc[cab_train['distance_travelled'] == 0,'distance_travelled'] = np.nan
cab_test.loc[cab_test['distance_travelled'] == 0,'distance_travelled'] = np.nan
cab_train.isna().sum().sum()
```

Out[27]: 454

Let us drop a few variables for which we don't need them as the necessary information from those variables has been extracted

In [28]:
```
#Dropping the 5 variables as mentioned above
var_to_drop = ['pickup_datetime','pickup_longitude', 'pickup_latitude','dropoff_longitude','dropoff_latitude']
cab_train = cab_train.drop(var_to_drop, axis = 1)
cab_test = cab_test.drop(var_to_drop, axis = 1)
```

In [29]:
```
#Let's convert a few variables to the required data types in both train and test data
cab_train['passenger_count'] = cab_train['passenger_count'].astype('int64')
cab_train['Month'] = cab_train['Month'].astype('category')
cab_train['Day'] = cab_train['Day'].astype('category')

#Convert in test data
cab_test['Month'] = cab_test['Month'].astype('category')
cab_test['Day'] = cab_test['Day'].astype('category')
```

In [30]:
```
#Imputing the missing values
#Actual value = 5.037
#Mean Value = 15.12
#Median Value = 2.196
#KNN value = 4.790
#cab_data['distance_travelled'].iloc[52] = np.nan
#cab_data['distance_travelled'].iloc[52] = cab_data['distance_travelled'].mean
()
#cab_data['distance_travelled'].iloc[52] = cab_data['distance_travelled'].medi
an()

#Imputing with KNN method
cab_train = pd.DataFrame(KNN(k = 3).fit_transform(cab_train), columns = cab_tr
ain.columns)
cab_test = pd.DataFrame(KNN(k = 3).fit_transform(cab_test), columns = cab_test
.columns)
```

```
Imputing row 1/15905 with 0 missing, elapsed time: 79.311
Imputing row 101/15905 with 0 missing, elapsed time: 79.313
Imputing row 201/15905 with 0 missing, elapsed time: 79.314
Imputing row 301/15905 with 0 missing, elapsed time: 79.316
Imputing row 401/15905 with 0 missing, elapsed time: 79.319
Imputing row 501/15905 with 0 missing, elapsed time: 79.320
Imputing row 601/15905 with 0 missing, elapsed time: 79.322
Imputing row 701/15905 with 0 missing, elapsed time: 79.324
Imputing row 801/15905 with 0 missing, elapsed time: 79.326
Imputing row 901/15905 with 0 missing, elapsed time: 79.328
Imputing row 1001/15905 with 0 missing, elapsed time: 79.330
Imputing row 1101/15905 with 0 missing, elapsed time: 79.332
Imputing row 1201/15905 with 1 missing, elapsed time: 79.333
Imputing row 1301/15905 with 0 missing, elapsed time: 79.336
Imputing row 1401/15905 with 0 missing, elapsed time: 79.338
Imputing row 1501/15905 with 0 missing, elapsed time: 79.340
Imputing row 1601/15905 with 0 missing, elapsed time: 79.343
Imputing row 1701/15905 with 1 missing, elapsed time: 79.345
Imputing row 1801/15905 with 0 missing, elapsed time: 79.347
Imputing row 1901/15905 with 0 missing, elapsed time: 79.349
Imputing row 2001/15905 with 0 missing, elapsed time: 79.350
Imputing row 2101/15905 with 0 missing, elapsed time: 79.352
Imputing row 2201/15905 with 0 missing, elapsed time: 79.353
Imputing row 2301/15905 with 0 missing, elapsed time: 79.355
Imputing row 2401/15905 with 0 missing, elapsed time: 79.356
Imputing row 2501/15905 with 0 missing, elapsed time: 79.360
Imputing row 2601/15905 with 0 missing, elapsed time: 79.361
Imputing row 2701/15905 with 0 missing, elapsed time: 79.363
Imputing row 2801/15905 with 0 missing, elapsed time: 79.365
Imputing row 2901/15905 with 0 missing, elapsed time: 79.367
Imputing row 3001/15905 with 0 missing, elapsed time: 79.368
Imputing row 3101/15905 with 0 missing, elapsed time: 79.370
Imputing row 3201/15905 with 0 missing, elapsed time: 79.371
Imputing row 3301/15905 with 0 missing, elapsed time: 79.373
Imputing row 3401/15905 with 0 missing, elapsed time: 79.376
Imputing row 3501/15905 with 0 missing, elapsed time: 79.378
Imputing row 3601/15905 with 0 missing, elapsed time: 79.379
Imputing row 3701/15905 with 0 missing, elapsed time: 79.381
Imputing row 3801/15905 with 0 missing, elapsed time: 79.383
Imputing row 3901/15905 with 0 missing, elapsed time: 79.385
Imputing row 4001/15905 with 0 missing, elapsed time: 79.387
Imputing row 4101/15905 with 0 missing, elapsed time: 79.388
Imputing row 4201/15905 with 0 missing, elapsed time: 79.391
Imputing row 4301/15905 with 0 missing, elapsed time: 79.393
Imputing row 4401/15905 with 0 missing, elapsed time: 79.395
Imputing row 4501/15905 with 0 missing, elapsed time: 79.397
Imputing row 4601/15905 with 0 missing, elapsed time: 79.399
Imputing row 4701/15905 with 0 missing, elapsed time: 79.401
Imputing row 4801/15905 with 0 missing, elapsed time: 79.404
Imputing row 4901/15905 with 0 missing, elapsed time: 79.406
Imputing row 5001/15905 with 0 missing, elapsed time: 79.409
Imputing row 5101/15905 with 0 missing, elapsed time: 79.410
Imputing row 5201/15905 with 0 missing, elapsed time: 79.412
Imputing row 5301/15905 with 0 missing, elapsed time: 79.413
Imputing row 5401/15905 with 0 missing, elapsed time: 79.415
Imputing row 5501/15905 with 0 missing, elapsed time: 79.417
Imputing row 5601/15905 with 0 missing, elapsed time: 79.419
```

```
Imputing row 5701/15905 with 0 missing, elapsed time: 79.421
Imputing row 5801/15905 with 0 missing, elapsed time: 79.423
Imputing row 5901/15905 with 1 missing, elapsed time: 79.425
Imputing row 6001/15905 with 0 missing, elapsed time: 79.427
Imputing row 6101/15905 with 0 missing, elapsed time: 79.429
Imputing row 6201/15905 with 0 missing, elapsed time: 79.430
Imputing row 6301/15905 with 0 missing, elapsed time: 79.432
Imputing row 6401/15905 with 0 missing, elapsed time: 79.434
Imputing row 6501/15905 with 0 missing, elapsed time: 79.436
Imputing row 6601/15905 with 0 missing, elapsed time: 79.438
Imputing row 6701/15905 with 0 missing, elapsed time: 79.440
Imputing row 6801/15905 with 0 missing, elapsed time: 79.442
Imputing row 6901/15905 with 0 missing, elapsed time: 79.443
Imputing row 7001/15905 with 0 missing, elapsed time: 79.445
Imputing row 7101/15905 with 0 missing, elapsed time: 79.446
Imputing row 7201/15905 with 0 missing, elapsed time: 79.448
Imputing row 7301/15905 with 0 missing, elapsed time: 79.450
Imputing row 7401/15905 with 0 missing, elapsed time: 79.452
Imputing row 7501/15905 with 0 missing, elapsed time: 79.453
Imputing row 7601/15905 with 0 missing, elapsed time: 79.456
Imputing row 7701/15905 with 0 missing, elapsed time: 79.458
Imputing row 7801/15905 with 0 missing, elapsed time: 79.459
Imputing row 7901/15905 with 0 missing, elapsed time: 79.461
Imputing row 8001/15905 with 0 missing, elapsed time: 79.462
Imputing row 8101/15905 with 0 missing, elapsed time: 79.465
Imputing row 8201/15905 with 0 missing, elapsed time: 79.466
Imputing row 8301/15905 with 0 missing, elapsed time: 79.468
Imputing row 8401/15905 with 0 missing, elapsed time: 79.470
Imputing row 8501/15905 with 0 missing, elapsed time: 79.473
Imputing row 8601/15905 with 0 missing, elapsed time: 79.475
Imputing row 8701/15905 with 0 missing, elapsed time: 79.477
Imputing row 8801/15905 with 0 missing, elapsed time: 79.479
Imputing row 8901/15905 with 0 missing, elapsed time: 79.481
Imputing row 9001/15905 with 0 missing, elapsed time: 79.482
Imputing row 9101/15905 with 0 missing, elapsed time: 79.484
Imputing row 9201/15905 with 0 missing, elapsed time: 79.485
Imputing row 9301/15905 with 0 missing, elapsed time: 79.488
Imputing row 9401/15905 with 0 missing, elapsed time: 79.489
Imputing row 9501/15905 with 0 missing, elapsed time: 79.491
Imputing row 9601/15905 with 0 missing, elapsed time: 79.493
Imputing row 9701/15905 with 0 missing, elapsed time: 79.495
Imputing row 9801/15905 with 0 missing, elapsed time: 79.497
Imputing row 9901/15905 with 0 missing, elapsed time: 79.502
Imputing row 10001/15905 with 0 missing, elapsed time: 79.504
Imputing row 10101/15905 with 0 missing, elapsed time: 79.505
Imputing row 10201/15905 with 0 missing, elapsed time: 79.508
Imputing row 10301/15905 with 0 missing, elapsed time: 79.510
Imputing row 10401/15905 with 0 missing, elapsed time: 79.512
Imputing row 10501/15905 with 0 missing, elapsed time: 79.514
Imputing row 10601/15905 with 0 missing, elapsed time: 79.517
Imputing row 10701/15905 with 0 missing, elapsed time: 79.519
Imputing row 10801/15905 with 0 missing, elapsed time: 79.522
Imputing row 10901/15905 with 0 missing, elapsed time: 79.525
Imputing row 11001/15905 with 0 missing, elapsed time: 79.528
Imputing row 11101/15905 with 0 missing, elapsed time: 79.531
Imputing row 11201/15905 with 0 missing, elapsed time: 79.533
Imputing row 11301/15905 with 0 missing, elapsed time: 79.537
```

```
Imputing row 11401/15905 with 0 missing, elapsed time: 79.540
Imputing row 11501/15905 with 0 missing, elapsed time: 79.544
Imputing row 11601/15905 with 0 missing, elapsed time: 79.546
Imputing row 11701/15905 with 0 missing, elapsed time: 79.550
Imputing row 11801/15905 with 0 missing, elapsed time: 79.552
Imputing row 11901/15905 with 0 missing, elapsed time: 79.554
Imputing row 12001/15905 with 0 missing, elapsed time: 79.557
Imputing row 12101/15905 with 0 missing, elapsed time: 79.561
Imputing row 12201/15905 with 0 missing, elapsed time: 79.564
Imputing row 12301/15905 with 0 missing, elapsed time: 79.566
Imputing row 12401/15905 with 0 missing, elapsed time: 79.568
Imputing row 12501/15905 with 0 missing, elapsed time: 79.571
Imputing row 12601/15905 with 0 missing, elapsed time: 79.573
Imputing row 12701/15905 with 0 missing, elapsed time: 79.576
Imputing row 12801/15905 with 0 missing, elapsed time: 79.578
Imputing row 12901/15905 with 1 missing, elapsed time: 79.582
Imputing row 13001/15905 with 0 missing, elapsed time: 79.585
Imputing row 13101/15905 with 0 missing, elapsed time: 79.587
Imputing row 13201/15905 with 0 missing, elapsed time: 79.589
Imputing row 13301/15905 with 0 missing, elapsed time: 79.594
Imputing row 13401/15905 with 0 missing, elapsed time: 79.597
Imputing row 13501/15905 with 0 missing, elapsed time: 79.600
Imputing row 13601/15905 with 0 missing, elapsed time: 79.602
Imputing row 13701/15905 with 0 missing, elapsed time: 79.607
Imputing row 13801/15905 with 1 missing, elapsed time: 79.613
Imputing row 13901/15905 with 1 missing, elapsed time: 79.620
Imputing row 14001/15905 with 0 missing, elapsed time: 79.624
Imputing row 14101/15905 with 0 missing, elapsed time: 79.629
Imputing row 14201/15905 with 0 missing, elapsed time: 79.632
Imputing row 14301/15905 with 0 missing, elapsed time: 79.634
Imputing row 14401/15905 with 0 missing, elapsed time: 79.636
Imputing row 14501/15905 with 0 missing, elapsed time: 79.638
Imputing row 14601/15905 with 0 missing, elapsed time: 79.641
Imputing row 14701/15905 with 0 missing, elapsed time: 79.643
Imputing row 14801/15905 with 0 missing, elapsed time: 79.650
Imputing row 14901/15905 with 0 missing, elapsed time: 79.654
Imputing row 15001/15905 with 0 missing, elapsed time: 79.655
Imputing row 15101/15905 with 0 missing, elapsed time: 79.657
Imputing row 15201/15905 with 0 missing, elapsed time: 79.659
Imputing row 15301/15905 with 0 missing, elapsed time: 79.662
Imputing row 15401/15905 with 0 missing, elapsed time: 79.665
Imputing row 15501/15905 with 0 missing, elapsed time: 79.668
Imputing row 15601/15905 with 0 missing, elapsed time: 79.671
Imputing row 15701/15905 with 0 missing, elapsed time: 79.672
Imputing row 15801/15905 with 0 missing, elapsed time: 79.675
Imputing row 15901/15905 with 0 missing, elapsed time: 79.678
Imputing row 1/9914 with 0 missing, elapsed time: 28.939
Imputing row 101/9914 with 0 missing, elapsed time: 28.940
Imputing row 201/9914 with 0 missing, elapsed time: 28.941
Imputing row 301/9914 with 0 missing, elapsed time: 28.942
Imputing row 401/9914 with 0 missing, elapsed time: 28.944
Imputing row 501/9914 with 0 missing, elapsed time: 28.945
Imputing row 601/9914 with 0 missing, elapsed time: 28.946
Imputing row 701/9914 with 0 missing, elapsed time: 28.947
Imputing row 801/9914 with 0 missing, elapsed time: 28.949
Imputing row 901/9914 with 0 missing, elapsed time: 28.951
Imputing row 1001/9914 with 0 missing, elapsed time: 28.952
```

```
Imputing row 1101/9914 with 0 missing, elapsed time: 28.953
Imputing row 1201/9914 with 0 missing, elapsed time: 28.955
Imputing row 1301/9914 with 0 missing, elapsed time: 28.956
Imputing row 1401/9914 with 0 missing, elapsed time: 28.956
Imputing row 1501/9914 with 0 missing, elapsed time: 28.958
Imputing row 1601/9914 with 0 missing, elapsed time: 28.958
Imputing row 1701/9914 with 0 missing, elapsed time: 28.959
Imputing row 1801/9914 with 0 missing, elapsed time: 28.960
Imputing row 1901/9914 with 0 missing, elapsed time: 28.962
Imputing row 2001/9914 with 0 missing, elapsed time: 28.962
Imputing row 2101/9914 with 0 missing, elapsed time: 28.963
Imputing row 2201/9914 with 0 missing, elapsed time: 28.965
Imputing row 2301/9914 with 0 missing, elapsed time: 28.967
Imputing row 2401/9914 with 0 missing, elapsed time: 28.968
Imputing row 2501/9914 with 0 missing, elapsed time: 28.969
Imputing row 2601/9914 with 0 missing, elapsed time: 28.969
Imputing row 2701/9914 with 0 missing, elapsed time: 28.972
Imputing row 2801/9914 with 0 missing, elapsed time: 28.973
Imputing row 2901/9914 with 0 missing, elapsed time: 28.973
Imputing row 3001/9914 with 0 missing, elapsed time: 28.975
Imputing row 3101/9914 with 0 missing, elapsed time: 28.976
Imputing row 3201/9914 with 0 missing, elapsed time: 28.976
Imputing row 3301/9914 with 0 missing, elapsed time: 28.977
Imputing row 3401/9914 with 0 missing, elapsed time: 28.978
Imputing row 3501/9914 with 0 missing, elapsed time: 28.979
Imputing row 3601/9914 with 0 missing, elapsed time: 28.979
Imputing row 3701/9914 with 0 missing, elapsed time: 28.980
Imputing row 3801/9914 with 0 missing, elapsed time: 28.981
Imputing row 3901/9914 with 0 missing, elapsed time: 28.981
Imputing row 4001/9914 with 0 missing, elapsed time: 28.982
Imputing row 4101/9914 with 0 missing, elapsed time: 28.982
Imputing row 4201/9914 with 0 missing, elapsed time: 28.983
Imputing row 4301/9914 with 0 missing, elapsed time: 28.984
Imputing row 4401/9914 with 0 missing, elapsed time: 28.984
Imputing row 4501/9914 with 0 missing, elapsed time: 28.985
Imputing row 4601/9914 with 0 missing, elapsed time: 28.986
Imputing row 4701/9914 with 0 missing, elapsed time: 28.987
Imputing row 4801/9914 with 0 missing, elapsed time: 28.988
Imputing row 4901/9914 with 0 missing, elapsed time: 28.989
Imputing row 5001/9914 with 0 missing, elapsed time: 28.990
Imputing row 5101/9914 with 0 missing, elapsed time: 28.990
Imputing row 5201/9914 with 0 missing, elapsed time: 28.991
Imputing row 5301/9914 with 0 missing, elapsed time: 28.992
Imputing row 5401/9914 with 0 missing, elapsed time: 28.992
Imputing row 5501/9914 with 0 missing, elapsed time: 28.994
Imputing row 5601/9914 with 0 missing, elapsed time: 28.995
Imputing row 5701/9914 with 0 missing, elapsed time: 28.997
Imputing row 5801/9914 with 0 missing, elapsed time: 28.998
Imputing row 5901/9914 with 0 missing, elapsed time: 28.998
Imputing row 6001/9914 with 0 missing, elapsed time: 28.999
Imputing row 6101/9914 with 0 missing, elapsed time: 28.999
Imputing row 6201/9914 with 0 missing, elapsed time: 29.000
Imputing row 6301/9914 with 0 missing, elapsed time: 29.001
Imputing row 6401/9914 with 0 missing, elapsed time: 29.003
Imputing row 6501/9914 with 0 missing, elapsed time: 29.004
Imputing row 6601/9914 with 0 missing, elapsed time: 29.006
Imputing row 6701/9914 with 0 missing, elapsed time: 29.007
```

```
Imputing row 6801/9914 with 0 missing, elapsed time: 29.007
Imputing row 6901/9914 with 0 missing, elapsed time: 29.009
Imputing row 7001/9914 with 0 missing, elapsed time: 29.011
Imputing row 7101/9914 with 0 missing, elapsed time: 29.011
Imputing row 7201/9914 with 0 missing, elapsed time: 29.013
Imputing row 7301/9914 with 0 missing, elapsed time: 29.013
Imputing row 7401/9914 with 0 missing, elapsed time: 29.014
Imputing row 7501/9914 with 0 missing, elapsed time: 29.015
Imputing row 7601/9914 with 0 missing, elapsed time: 29.016
Imputing row 7701/9914 with 0 missing, elapsed time: 29.018
Imputing row 7801/9914 with 0 missing, elapsed time: 29.018
Imputing row 7901/9914 with 0 missing, elapsed time: 29.020
Imputing row 8001/9914 with 0 missing, elapsed time: 29.022
Imputing row 8101/9914 with 0 missing, elapsed time: 29.023
Imputing row 8201/9914 with 0 missing, elapsed time: 29.024
Imputing row 8301/9914 with 0 missing, elapsed time: 29.025
Imputing row 8401/9914 with 0 missing, elapsed time: 29.027
Imputing row 8501/9914 with 0 missing, elapsed time: 29.028
Imputing row 8601/9914 with 0 missing, elapsed time: 29.029
Imputing row 8701/9914 with 0 missing, elapsed time: 29.030
Imputing row 8801/9914 with 0 missing, elapsed time: 29.031
Imputing row 8901/9914 with 0 missing, elapsed time: 29.033
Imputing row 9001/9914 with 0 missing, elapsed time: 29.033
Imputing row 9101/9914 with 0 missing, elapsed time: 29.035
Imputing row 9201/9914 with 0 missing, elapsed time: 29.036
Imputing row 9301/9914 with 0 missing, elapsed time: 29.037
Imputing row 9401/9914 with 0 missing, elapsed time: 29.038
Imputing row 9501/9914 with 1 missing, elapsed time: 29.040
Imputing row 9601/9914 with 0 missing, elapsed time: 29.041
Imputing row 9701/9914 with 0 missing, elapsed time: 29.042
Imputing row 9801/9914 with 0 missing, elapsed time: 29.042
Imputing row 9901/9914 with 0 missing, elapsed time: 29.044
```

In [31]:

```
#To verify if we have any null values after KNN imputation
print(cab_train.isnull().sum().sum())
print(cab_train.shape)
```

```
0
(15905, 8)
```

In [32]:

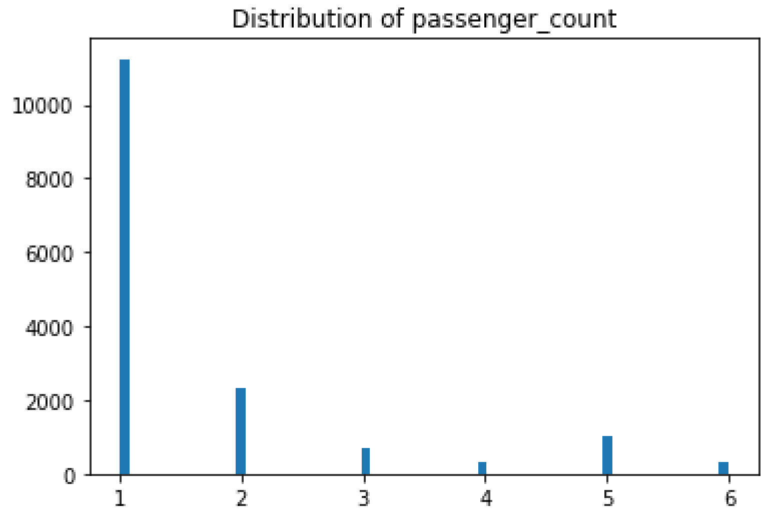
```
cab_train.dtypes

#Dividing categorical and continuous variables

cont_var = ['passenger_count','year','Date','Hour','fare_amount','distance_tra
velled']
cat_var = ['Month','Day']

#To take a copy of cab_train dataset
cab_data = cab_train.copy()
```

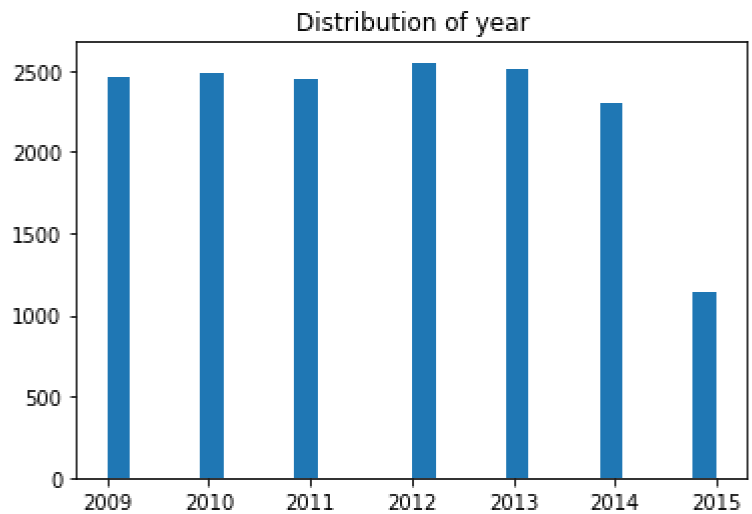
Now our `cab_train` dataset is a cleaned one with no missing values. Let's take a copy of `cab_train` as `cab_data` with dimensions (15905,8) and let's work on it for further steps.

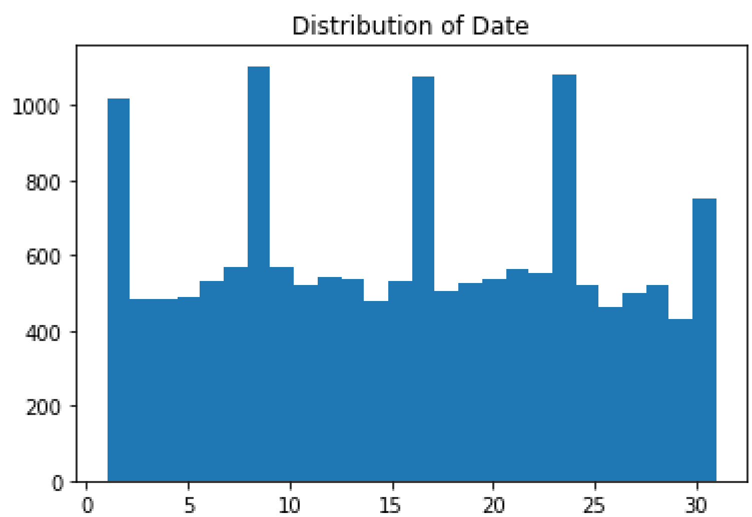
# Univariate and Bivariate Analysis

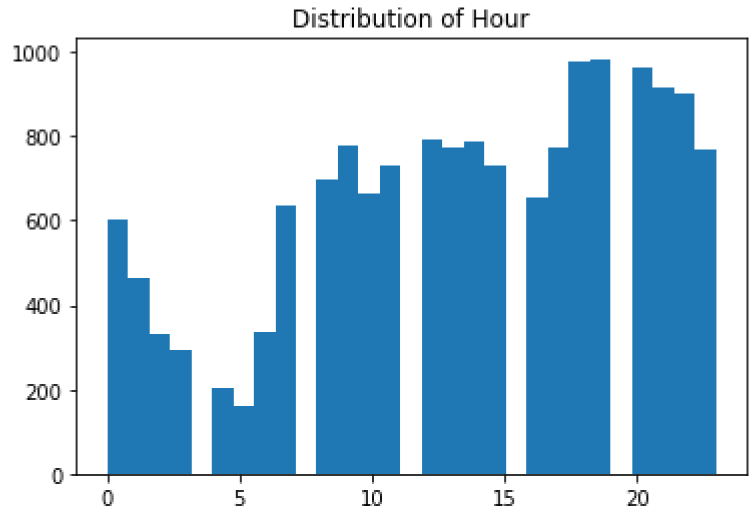
- Let us visualize the distribution of variables in our train dataset
- We will use histograms for continuous variables and barplots for the categorical variables

In [33]:
```
#For continuous variables
for i in cont_var[:4]:
    plt.hist(cab_train[i].dropna(),bins = 'auto')
    plt.title("Distribution of " + str(i))
    plt.show()
```


Distribution of passenger_count
10000
8000
6000
4000
2000
0
1
2
3
4
5
6


Distribution of year
2500
2000
1500
1000
500
0
2009
2010
2011
2012
2013
2014
2015

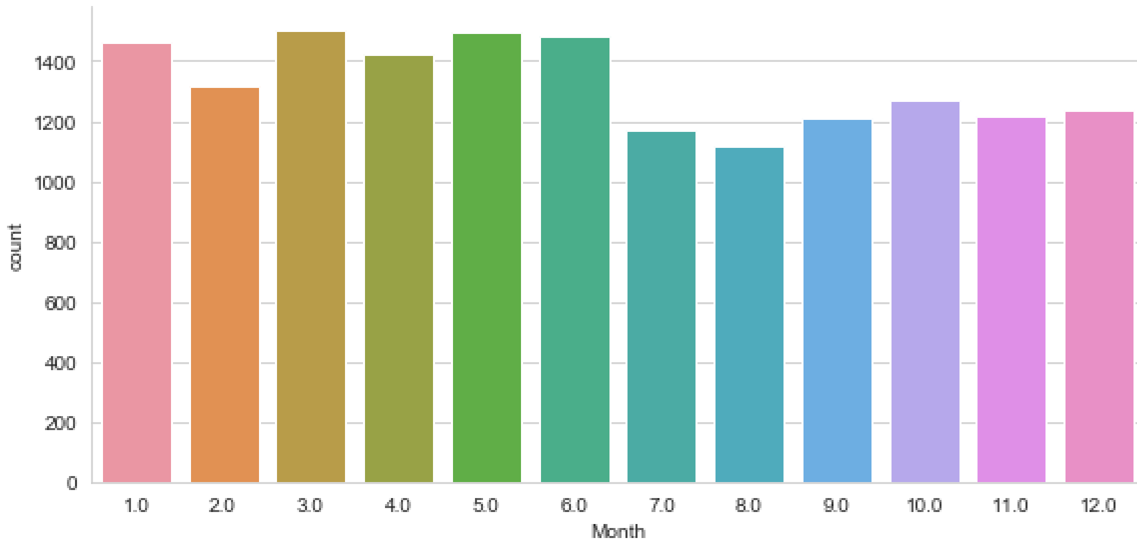

Distribution of Date
1000
800
600
400
200
0
0
5
10
15
20
25
30

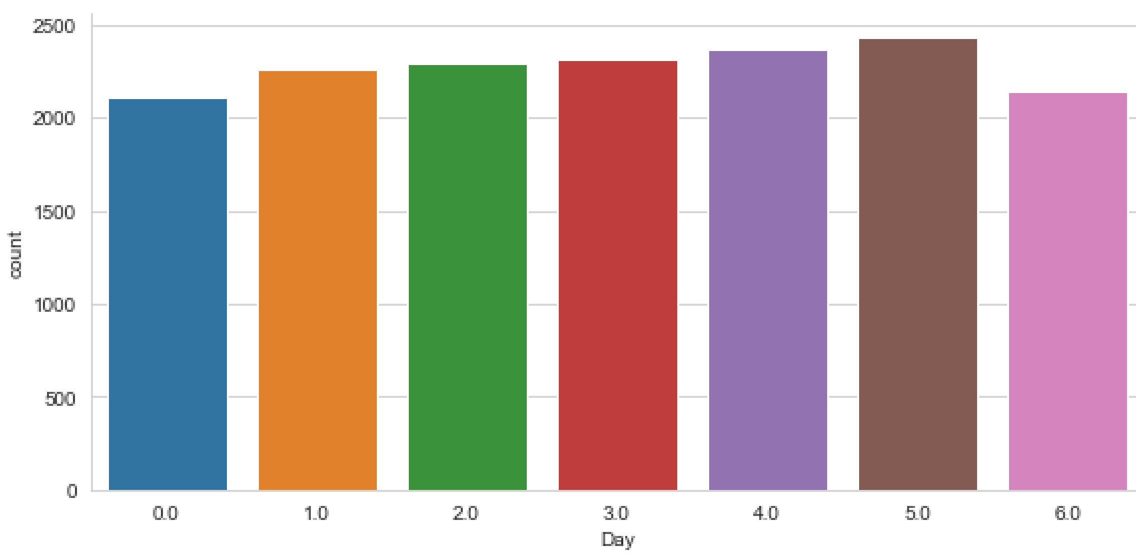

Distribution of Hour
1000
800
600
400
200
0
0
5
10
15
20

In [34]:
```
#Check the distribution of the Categorical variables
sns.set_style("whitegrid")
sns.factorplot(data=cab_data, x='Month', kind= 'count',size=4,aspect=2)
sns.factorplot(data=cab_data, x='Day', kind= 'count',size=4,aspect=2)
```

```
C:\Users\abhis\Anaconda3\lib\site-packages\seaborn\categorical.py:3666: UserW
arning: The `factorplot` function has been renamed to `catplot`. The original
name will be removed in a future release. Please update your code. Note that
the default `kind` in `factorplot` (`'point'`) has changed `'strip'` in `catp
lot`.
  warnings.warn(msg)
C:\Users\abhis\Anaconda3\lib\site-packages\seaborn\categorical.py:3672: UserW
arning: The `size` paramter has been renamed to `height`; please update your
code.
  warnings.warn(msg, UserWarning)
```

Out[34]: <seaborn.axisgrid.FacetGrid at 0x11a819ca908>



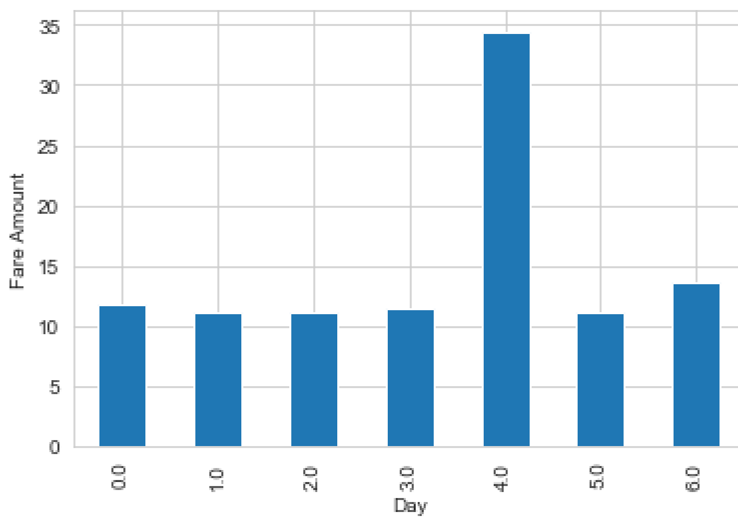



From the above plots, we can have a few quick insights.

- Demand of cabs is high on 6th and 5th days in a week and least on 1st day of the week
- Demand of cabs is high in the month of May, March and June respectively and least demand in August
- Cabs are high in demand during evening hours and least demand during early hours of the day
- Single travelled passenger's prefer cabs than with a group of 4/5

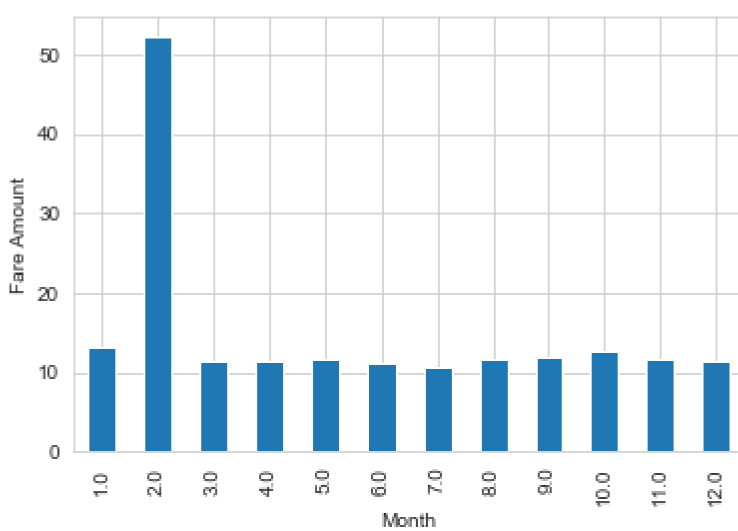
In [35]:
```
# Grouping the data using Day against our target variable and plotting bar plo
t
cab_data.groupby('Day').mean()['fare_amount'].plot.bar()
plt.ylabel('Fare Amount')
```

Out[35]: Text(0, 0.5, 'Fare Amount')



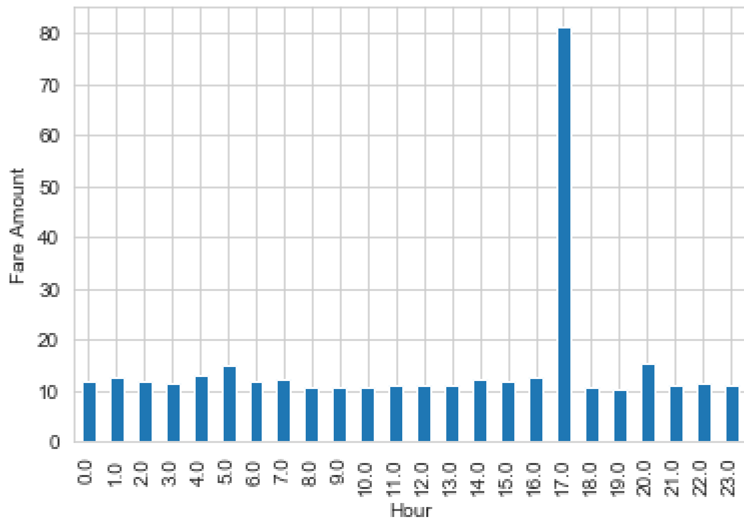

In [36]:
```
# Grouping the data using Month against our target variable and plotting bar p
lot
cab_data.groupby('Month').mean()['fare_amount'].plot.bar()
plt.ylabel('Fare Amount')
```

Out[36]: Text(0, 0.5, 'Fare Amount')



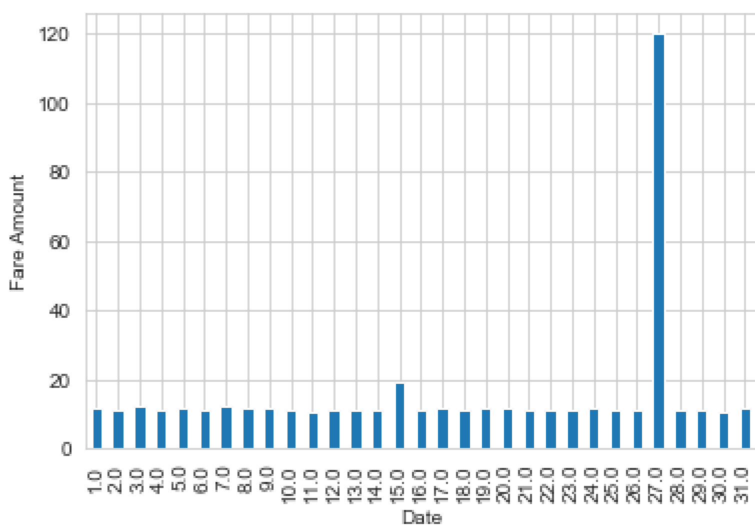
In [37]:
```
# Grouping the data using Hour against our target variable and plotting bar pl
ot
cab_data.groupby('Hour').mean()['fare_amount'].plot.bar()
plt.ylabel('Fare Amount')
```

Out[37]: Text(0, 0.5, 'Fare Amount')




In [38]:
```
# Grouping the data using Date against our target variable and plotting bar pl
ot
cab_data.groupby('Date').mean()['fare_amount'].plot.bar()
plt.ylabel('Fare Amount')
```

Out[38]: Text(0, 0.5, 'Fare Amount')



From the above plots, we can have a few quick insights.

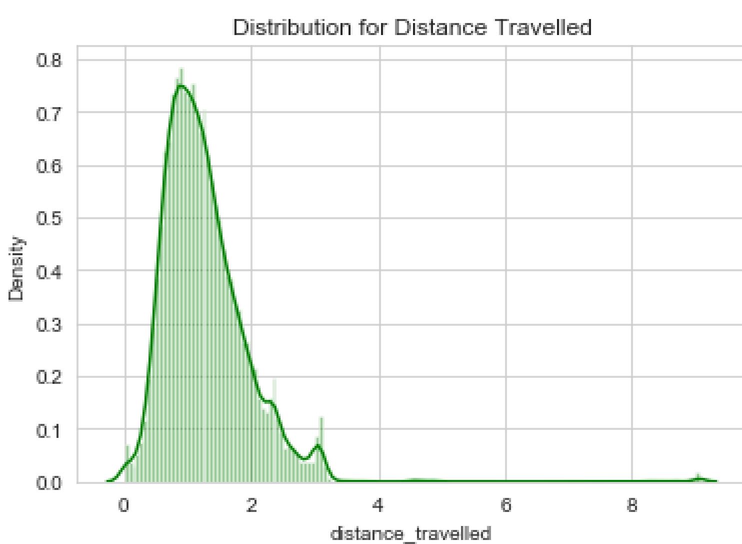
- The average fare amount is higher on the 5th day of the week
- The average fare amount is higher in the month of February
- Fair amounts are higher between 6 P.M.- 7 P.M. and least at5 A.M.
- Average fare price is highest on 27th of every month
- The average fare amount is higher at 5 P.M.

# Feature Scaling

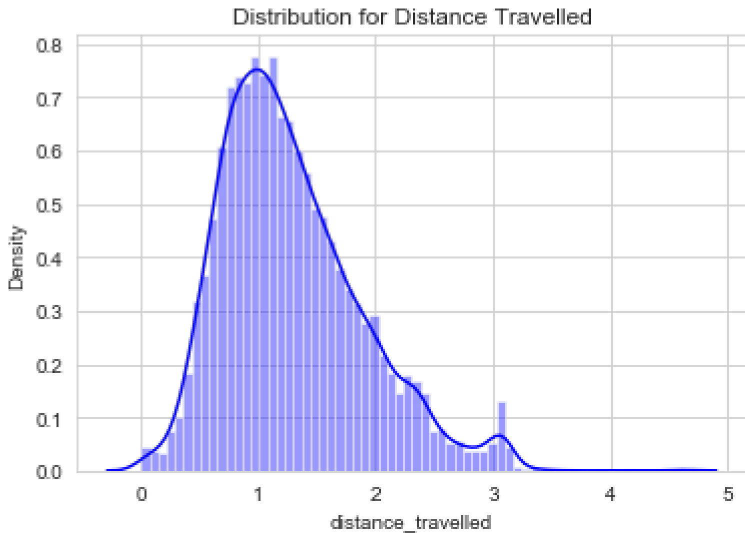
Let's scale our variables distance_travelled and passenger_count in both train and test datasets

In [39]:
```
#The data is right skewed in distance_travelled and hence we'll apply log on t
hat variable
cab_data['distance_travelled'] = np.log1p(cab_data['distance_travelled'])
#To apply normalisation on passenger count
norm_var = ['passenger_count']

for i in norm_var:
    cab_data[i] = (cab_data[i] - cab_data[i].min()) / (cab_data[i].max() - cab
_data[i].min())#Normalization formula

#To apply normalisation on passenger count for Test dataset
cab_test['distance_travelled'] = np.log1p(cab_test['distance_travelled'])
for i in norm_var:
    cab_test[i] = (cab_test[i] - cab_test[i].min()) / (cab_test[i].max() - cab
_test[i].min())#Normalization formula
```

In [40]:
```
#Distribution of distance_travelled
sns.distplot(cab_data['distance_travelled'],bins='auto',color='green')
plt.title("Distribution for Distance Travelled")
plt.ylabel("Density")
plt.show()
```



In [41]:
```
#To check the distribution of distance_travelled in the test data
sns.distplot(cab_test['distance_travelled'],bins='auto',color='blue')
plt.title("Distribution for Distance Travelled")
plt.ylabel("Density")
plt.show()
```



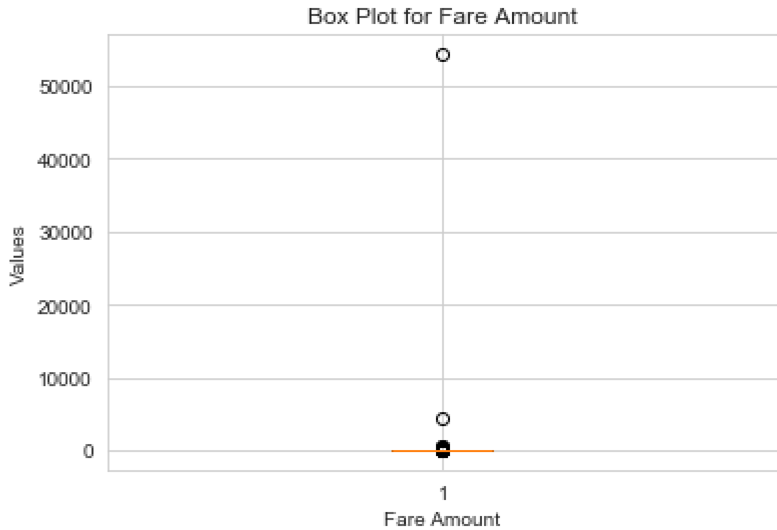

In [42]:
```
#To know the shapes of the train and test data
print(cab_data.shape)
print(cab_test.shape)
```

```
(15905, 8)
(9914, 7)
```

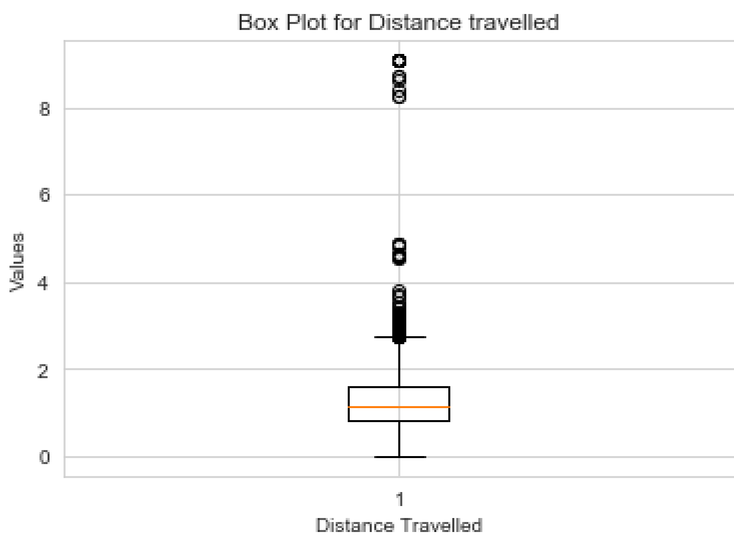
# Outlier Analysis

Outliers are to be detected by using box plot and those values are to be replaced or imputed by using various techniques such as mean, median or KNN method.

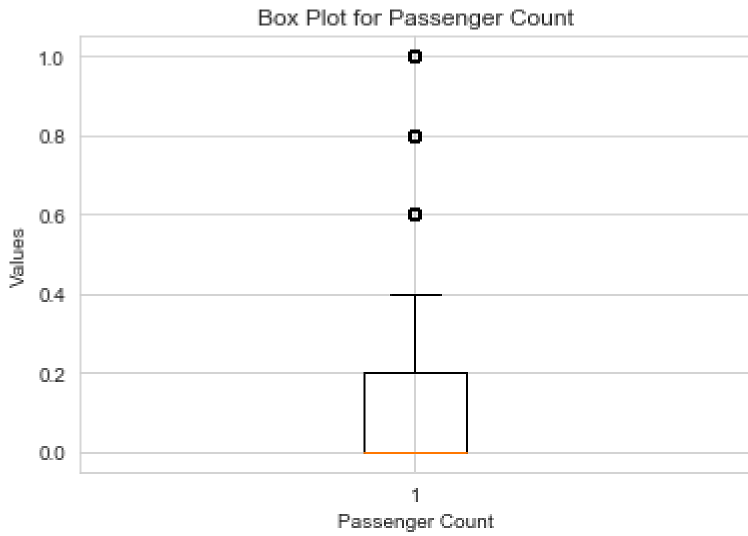
In [43]:
```
#Box plot for Fare Amount
plt.boxplot(cab_data['fare_amount'])
plt.xlabel("Fare Amount")
plt.ylabel("Values")
plt.title("Box Plot for Fare Amount")
plt.show()
```




In [44]:
```
#Box plot for Fare Amount
plt.boxplot(cab_data['distance_travelled'])
plt.xlabel("Distance Travelled")
plt.ylabel("Values")
plt.title("Box Plot for Distance travelled")
plt.show()
```



In [45]:
```
#Box plot for Fare Amount
plt.boxplot(cab_data['passenger_count'])
plt.xlabel("Passenger Count")
plt.ylabel("Values")
plt.title("Box Plot for Passenger Count")
plt.show()
```




It is found that we have a few outliers in passenger_count, fare_amount and distance_travelled

In [46]:
```
#List with variables with outliers
outliers = ['passenger_count', 'distance_travelled', 'fare_amount']

#Loop through the above list of variables
for i in outliers:
    q75,q25 = np.percentile(cab_data[i], [75,25]) #To get 75 and 25 percentile values
    iqr = q75 - q25 #Interquartile region
    #Calculating outerfence and innerfence
    outer = q75 + (iqr*1.5)
    inner = q25 - (iqr*1.5)
# Replacing all the outliers value to NA
cab_data.loc[cab_data[i]< inner,i] = np.nan
cab_data.loc[cab_data[i]> outer,i] = np.nan
```

In [47]:
```
# Imputing missing values with KNN
cab_data = pd.DataFrame(KNN(k = 3).fit_transform(cab_data), columns = cab_data
.columns)
# Checking if there is any missing value
cab_data.isnull().sum().sum()
```

```
Imputing row 1/15905 with 0 missing, elapsed time: 77.164
Imputing row 101/15905 with 0 missing, elapsed time: 77.167
Imputing row 201/15905 with 0 missing, elapsed time: 77.170
Imputing row 301/15905 with 0 missing, elapsed time: 77.173
Imputing row 401/15905 with 1 missing, elapsed time: 77.176
Imputing row 501/15905 with 0 missing, elapsed time: 77.180
Imputing row 601/15905 with 0 missing, elapsed time: 77.184
Imputing row 701/15905 with 0 missing, elapsed time: 77.188
Imputing row 801/15905 with 0 missing, elapsed time: 77.192
Imputing row 901/15905 with 0 missing, elapsed time: 77.194
Imputing row 1001/15905 with 0 missing, elapsed time: 77.198
Imputing row 1101/15905 with 1 missing, elapsed time: 77.201
Imputing row 1201/15905 with 0 missing, elapsed time: 77.204
Imputing row 1301/15905 with 1 missing, elapsed time: 77.207
Imputing row 1401/15905 with 0 missing, elapsed time: 77.210
Imputing row 1501/15905 with 0 missing, elapsed time: 77.213
Imputing row 1601/15905 with 0 missing, elapsed time: 77.216
Imputing row 1701/15905 with 0 missing, elapsed time: 77.220
Imputing row 1801/15905 with 0 missing, elapsed time: 77.222
Imputing row 1901/15905 with 0 missing, elapsed time: 77.225
Imputing row 2001/15905 with 0 missing, elapsed time: 77.228
Imputing row 2101/15905 with 1 missing, elapsed time: 77.232
Imputing row 2201/15905 with 0 missing, elapsed time: 77.236
Imputing row 2301/15905 with 0 missing, elapsed time: 77.238
Imputing row 2401/15905 with 0 missing, elapsed time: 77.242
Imputing row 2501/15905 with 0 missing, elapsed time: 77.244
Imputing row 2601/15905 with 0 missing, elapsed time: 77.248
Imputing row 2701/15905 with 0 missing, elapsed time: 77.250
Imputing row 2801/15905 with 0 missing, elapsed time: 77.253
Imputing row 2901/15905 with 0 missing, elapsed time: 77.256
Imputing row 3001/15905 with 0 missing, elapsed time: 77.259
Imputing row 3101/15905 with 1 missing, elapsed time: 77.261
Imputing row 3201/15905 with 1 missing, elapsed time: 77.264
Imputing row 3301/15905 with 0 missing, elapsed time: 77.268
Imputing row 3401/15905 with 0 missing, elapsed time: 77.271
Imputing row 3501/15905 with 0 missing, elapsed time: 77.274
Imputing row 3601/15905 with 0 missing, elapsed time: 77.277
Imputing row 3701/15905 with 0 missing, elapsed time: 77.280
Imputing row 3801/15905 with 0 missing, elapsed time: 77.282
Imputing row 3901/15905 with 0 missing, elapsed time: 77.285
Imputing row 4001/15905 with 0 missing, elapsed time: 77.288
Imputing row 4101/15905 with 0 missing, elapsed time: 77.290
Imputing row 4201/15905 with 0 missing, elapsed time: 77.294
Imputing row 4301/15905 with 0 missing, elapsed time: 77.298
Imputing row 4401/15905 with 0 missing, elapsed time: 77.301
Imputing row 4501/15905 with 0 missing, elapsed time: 77.305
Imputing row 4601/15905 with 0 missing, elapsed time: 77.309
Imputing row 4701/15905 with 0 missing, elapsed time: 77.312
Imputing row 4801/15905 with 0 missing, elapsed time: 77.316
Imputing row 4901/15905 with 0 missing, elapsed time: 77.319
Imputing row 5001/15905 with 0 missing, elapsed time: 77.321
Imputing row 5101/15905 with 0 missing, elapsed time: 77.325
Imputing row 5201/15905 with 0 missing, elapsed time: 77.328
Imputing row 5301/15905 with 0 missing, elapsed time: 77.330
Imputing row 5401/15905 with 0 missing, elapsed time: 77.333
Imputing row 5501/15905 with 0 missing, elapsed time: 77.336
Imputing row 5601/15905 with 0 missing, elapsed time: 77.339
```

```
Imputing row 5701/15905 with 0 missing, elapsed time: 77.343
Imputing row 5801/15905 with 0 missing, elapsed time: 77.347
Imputing row 5901/15905 with 0 missing, elapsed time: 77.351
Imputing row 6001/15905 with 0 missing, elapsed time: 77.354
Imputing row 6101/15905 with 0 missing, elapsed time: 77.357
Imputing row 6201/15905 with 1 missing, elapsed time: 77.361
Imputing row 6301/15905 with 0 missing, elapsed time: 77.364
Imputing row 6401/15905 with 1 missing, elapsed time: 77.367
Imputing row 6501/15905 with 0 missing, elapsed time: 77.370
Imputing row 6601/15905 with 0 missing, elapsed time: 77.374
Imputing row 6701/15905 with 0 missing, elapsed time: 77.377
Imputing row 6801/15905 with 0 missing, elapsed time: 77.380
Imputing row 6901/15905 with 0 missing, elapsed time: 77.384
Imputing row 7001/15905 with 0 missing, elapsed time: 77.388
Imputing row 7101/15905 with 0 missing, elapsed time: 77.392
Imputing row 7201/15905 with 0 missing, elapsed time: 77.395
Imputing row 7301/15905 with 0 missing, elapsed time: 77.400
Imputing row 7401/15905 with 0 missing, elapsed time: 77.405
Imputing row 7501/15905 with 0 missing, elapsed time: 77.410
Imputing row 7601/15905 with 0 missing, elapsed time: 77.415
Imputing row 7701/15905 with 0 missing, elapsed time: 77.424
Imputing row 7801/15905 with 0 missing, elapsed time: 77.428
Imputing row 7901/15905 with 1 missing, elapsed time: 77.432
Imputing row 8001/15905 with 0 missing, elapsed time: 77.436
Imputing row 8101/15905 with 0 missing, elapsed time: 77.444
Imputing row 8201/15905 with 0 missing, elapsed time: 77.449
Imputing row 8301/15905 with 0 missing, elapsed time: 77.452
Imputing row 8401/15905 with 0 missing, elapsed time: 77.458
Imputing row 8501/15905 with 0 missing, elapsed time: 77.462
Imputing row 8601/15905 with 1 missing, elapsed time: 77.465
Imputing row 8701/15905 with 0 missing, elapsed time: 77.468
Imputing row 8801/15905 with 0 missing, elapsed time: 77.471
Imputing row 8901/15905 with 0 missing, elapsed time: 77.475
Imputing row 9001/15905 with 0 missing, elapsed time: 77.478
Imputing row 9101/15905 with 0 missing, elapsed time: 77.481
Imputing row 9201/15905 with 0 missing, elapsed time: 77.485
Imputing row 9301/15905 with 0 missing, elapsed time: 77.488
Imputing row 9401/15905 with 0 missing, elapsed time: 77.490
Imputing row 9501/15905 with 0 missing, elapsed time: 77.492
Imputing row 9601/15905 with 0 missing, elapsed time: 77.495
Imputing row 9701/15905 with 0 missing, elapsed time: 77.498
Imputing row 9801/15905 with 0 missing, elapsed time: 77.502
Imputing row 9901/15905 with 0 missing, elapsed time: 77.507
Imputing row 10001/15905 with 0 missing, elapsed time: 77.511
Imputing row 10101/15905 with 0 missing, elapsed time: 77.513
Imputing row 10201/15905 with 0 missing, elapsed time: 77.518
Imputing row 10301/15905 with 0 missing, elapsed time: 77.520
Imputing row 10401/15905 with 0 missing, elapsed time: 77.524
Imputing row 10501/15905 with 0 missing, elapsed time: 77.527
Imputing row 10601/15905 with 0 missing, elapsed time: 77.533
Imputing row 10701/15905 with 0 missing, elapsed time: 77.536
Imputing row 10801/15905 with 0 missing, elapsed time: 77.539
Imputing row 10901/15905 with 0 missing, elapsed time: 77.542
Imputing row 11001/15905 with 0 missing, elapsed time: 77.544
Imputing row 11101/15905 with 0 missing, elapsed time: 77.549
Imputing row 11201/15905 with 0 missing, elapsed time: 77.553
Imputing row 11301/15905 with 0 missing, elapsed time: 77.555
```

```
Imputing row 11401/15905 with 0 missing, elapsed time: 77.559
Imputing row 11501/15905 with 0 missing, elapsed time: 77.563
Imputing row 11601/15905 with 0 missing, elapsed time: 77.567
Imputing row 11701/15905 with 0 missing, elapsed time: 77.571
Imputing row 11801/15905 with 1 missing, elapsed time: 77.573
Imputing row 11901/15905 with 0 missing, elapsed time: 77.578
Imputing row 12001/15905 with 0 missing, elapsed time: 77.582
Imputing row 12101/15905 with 0 missing, elapsed time: 77.585
Imputing row 12201/15905 with 0 missing, elapsed time: 77.590
Imputing row 12301/15905 with 0 missing, elapsed time: 77.595
Imputing row 12401/15905 with 0 missing, elapsed time: 77.598
Imputing row 12501/15905 with 0 missing, elapsed time: 77.601
Imputing row 12601/15905 with 0 missing, elapsed time: 77.604
Imputing row 12701/15905 with 0 missing, elapsed time: 77.607
Imputing row 12801/15905 with 0 missing, elapsed time: 77.610
Imputing row 12901/15905 with 0 missing, elapsed time: 77.615
Imputing row 13001/15905 with 0 missing, elapsed time: 77.619
Imputing row 13101/15905 with 0 missing, elapsed time: 77.622
Imputing row 13201/15905 with 1 missing, elapsed time: 77.624
Imputing row 13301/15905 with 0 missing, elapsed time: 77.629
Imputing row 13401/15905 with 0 missing, elapsed time: 77.635
Imputing row 13501/15905 with 0 missing, elapsed time: 77.638
Imputing row 13601/15905 with 0 missing, elapsed time: 77.643
Imputing row 13701/15905 with 0 missing, elapsed time: 77.646
Imputing row 13801/15905 with 0 missing, elapsed time: 77.651
Imputing row 13901/15905 with 1 missing, elapsed time: 77.655
Imputing row 14001/15905 with 0 missing, elapsed time: 77.658
Imputing row 14101/15905 with 0 missing, elapsed time: 77.662
Imputing row 14201/15905 with 0 missing, elapsed time: 77.666
Imputing row 14301/15905 with 0 missing, elapsed time: 77.670
Imputing row 14401/15905 with 0 missing, elapsed time: 77.674
Imputing row 14501/15905 with 0 missing, elapsed time: 77.677
Imputing row 14601/15905 with 0 missing, elapsed time: 77.680
Imputing row 14701/15905 with 0 missing, elapsed time: 77.683
Imputing row 14801/15905 with 0 missing, elapsed time: 77.686
Imputing row 14901/15905 with 0 missing, elapsed time: 77.690
Imputing row 15001/15905 with 0 missing, elapsed time: 77.693
Imputing row 15101/15905 with 0 missing, elapsed time: 77.696
Imputing row 15201/15905 with 0 missing, elapsed time: 77.699
Imputing row 15301/15905 with 0 missing, elapsed time: 77.703
Imputing row 15401/15905 with 0 missing, elapsed time: 77.707
Imputing row 15501/15905 with 1 missing, elapsed time: 77.710
Imputing row 15601/15905 with 0 missing, elapsed time: 77.713
Imputing row 15701/15905 with 0 missing, elapsed time: 77.717
Imputing row 15801/15905 with 0 missing, elapsed time: 77.722
Imputing row 15901/15905 with 0 missing, elapsed time: 77.726
```

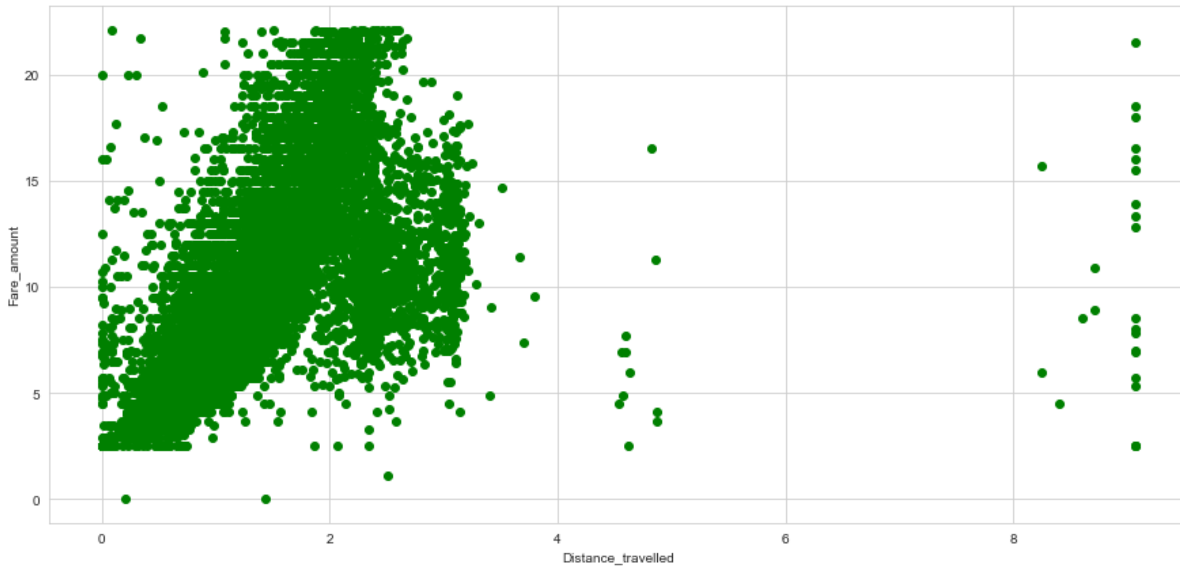
Out[47]: 0

In [48]:

```
#To ensure if the outliers are removed
cab_data.describe()
cab_data.shape
```

Out[48]: (15905, 8)

In [49]:
```
#Relationship between distance_travelled and fare_amount
plt.figure(figsize=(15,7))
plt.scatter(x = cab_data['distance_travelled'],y = cab_data['fare_amount'],c = "g")
plt.xlabel('Distance_travelled')
plt.ylabel('Fare_amount')
plt.show()
```



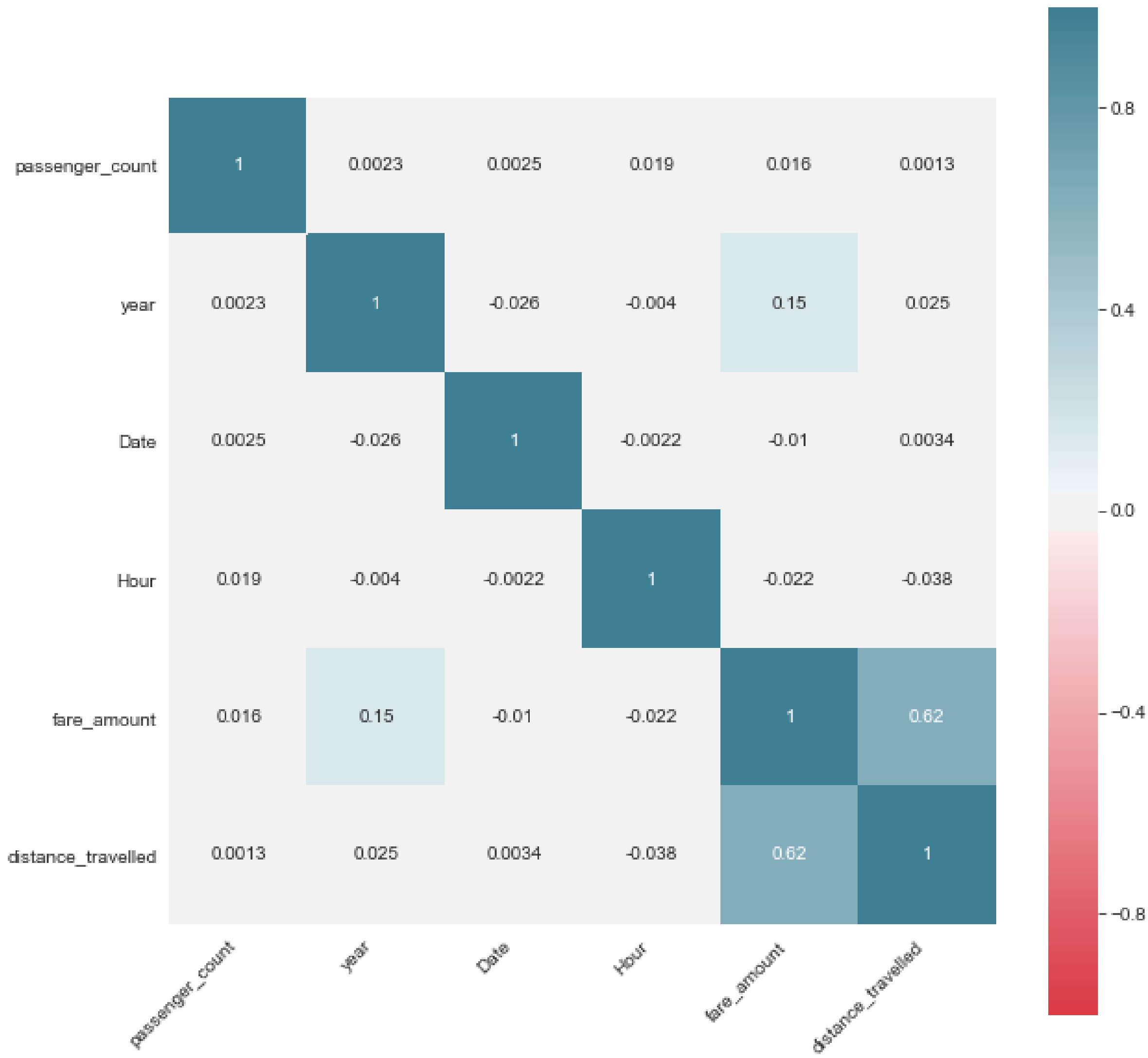

Now `cab_data` is free from missing values, outliers with shape as (15905, 8). Let's proceed for Feature Selection, Feature Scaling and developing ML alogorithms on our training dataset.

## Feature Selection

To check for the multicollinearity for continuous variables by plotting correlation plot and remove the variables with r > 0.8

In [50]:
```
#Correlation analysis for continuous variables
#Let's store all the numeric data into an object
numeric_data = cab_data.loc[:,cont_var]
#Set the measurements of the plot, let's say width = 10 and height = 10
a , k = plt.subplots(figsize=(10,10))
#Correlation matrix
corr_matrix = numeric_data.corr()
#Plotting a correlation graph
ax = sns.heatmap(corr_matrix, vmin=-1, vmax=1, center=0, cmap=sns.diverging_pa
lette(10, 220, n=200),
square=True, annot = True)
ax.set_xticklabels(ax.get_xticklabels(), rotation=45,horizontalalignment='righ
t')
```

Out[50]:
```
[Text(0.5, 0, 'passenger_count'),
 Text(1.5, 0, 'year'),
 Text(2.5, 0, 'Date'),
 Text(3.5, 0, 'Hour'),
 Text(4.5, 0, 'fare_amount'),
 Text(5.5, 0, 'distance_travelled')]
```



In [51]:
```
#Let's create dummy variables for categorical variables
#Get dummy variables for categorical variables
cab_data = pd.get_dummies(cab_data, columns = cat_var)
cab_test = pd.get_dummies(cab_test, columns = cat_var)
print(cab_data.shape)
print(cab_test.shape)
```

```
(15905, 25)
(9914, 24)
```

# Model development

We've performed all the Preprocessing techniques for our data. Our next step is to divide the data into train and test, build a model upon the train data and evaluate on the test data. Then finally choose one ML model to validate on our actual test data and predict the values of `fare_amount`

In [52]:
```
#Splitting into train and test data
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(cab_data.iloc[:,cab_data.colu
mns != 'fare_amount'],
cab_data.iloc[:, 0], test_size = 0.20, random_state = 1)
```

In [53]:
```
#Building the model using linear regression
#Importing the necessary libraries for Linear Regression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
#Build a model on our training dataset
lr_model = LinearRegression().fit(X_train,y_train)
#Predict for the test cases
lr_predictions = lr_model.predict(X_test)
#To create a dataframe for both actual and predicted values
cabdata_lrmodel = pd.DataFrame({"Actual" : y_test, "Predicted" : lr_prediction
s})

#Function to find RMSE
def RMSE(x,y):
    rmse = np.sqrt(mean_squared_error(x,y))
    return rmse

#Function to find MAPE
def MAPE(true,predict):
    mape = np.mean(np.abs((true - predict) / true)) * 100
    return mape

#Calculate RMSE, MAPE and R-Squared value for this model

print("Root Mean Squared error :- " + str(RMSE(y_test,lr_predictions)))
print("R-Squared value :- " + str(r2_score(y_test,lr_predictions)))
print("Mean Absolute Percentage Error :- " + str(MAPE(y_test,lr_predictions)))
```

```
Root Mean Squared error :- 3.2439912807373465
R-Squared value :- 0.3646367994234325
Mean Absolute Percentage Error :- 26.610288661061137
```

In [54]:
```
#Building the model using Decisison Tree
#Importing necessary libraries for Decision tree
from sklearn.tree import DecisionTreeRegressor
#Build Decision tree model on the train data
dt_model = DecisionTreeRegressor(max_depth = 2).fit(X_train,y_train)
#Predict for the test cases
dt_predict = dt_model.predict(X_test)
#Create a dataframe for actual and predicted values
df_dtmodel = pd.DataFrame({"Actual" : y_test, "Predicted" : dt_predict})
#Calculate RMSE, MAPE and R_squared value for this model

print("RMSE: " + str(RMSE(y_test,dt_predict)))
print("R_Square score: " + str(r2_score(y_test,dt_predict)))
print("Mean Absolute Percentage Error :- " + str(MAPE(y_test,dt_predict)))
```

```
RMSE: 2.630702513439224
R_Square score: 0.5821636871780009
Mean Absolute Percentage Error :- 23.164666577472058
```

In [55]:
```
#Building the model using Randomforest
#Import library for RandomForest
from sklearn.ensemble import RandomForestRegressor
#Build random forest using RandomForestRegressor
ranfor_model = RandomForestRegressor(n_estimators = 300, random_state = 1).fit
(X_train,y_train)
#Perdict for test cases
rf_predictions = ranfor_model.predict(X_test)
#Create data frame for actual and predicted values
df_rf = pd.DataFrame({'Actual': y_test, 'Predicted': rf_predictions})
#Calculate RMSE and R-squared value
print("Root Mean Squared Error: "+str(RMSE(y_test, rf_predictions)))
print("R_square Score: "+str(r2_score(y_test, rf_predictions)))
print("Mean Absolute Percentage Error :- " + str(MAPE(y_test,rf_predictions)))
```

```
Root Mean Squared Error: 2.3478613526491965
R_square Score: 0.6671813955736665
Mean Absolute Percentage Error :- 19.23515165255917
```

In [56]:
```
#Building the model using GradientBoosting
#Import necessary libraries for this ML algorithm
from sklearn.ensemble import GradientBoostingRegressor
#Build GB model on the train data
gb_model = GradientBoostingRegressor().fit(X_train,y_train)
#Predict the test cases
gb_predict = gb_model.predict(X_test)
#Create a dataframe for actual and predicted values
df_gbmodel = pd.DataFrame({"Actual" : y_test, "Predicted" : gb_predict})
#Calculate RMSE and R_squared values
print("RMSE: " + str(RMSE(y_test,dt_predict)))
print("R_Square score: " + str(r2_score(y_test,gb_predict)))
print("Mean Absolute Percentage Error :- " + str(MAPE(y_test,gb_predict)))
```

```
RMSE: 2.630702513439224
R_Square score: 0.6812319510750917
Mean Absolute Percentage Error :- 18.700421380160815
```

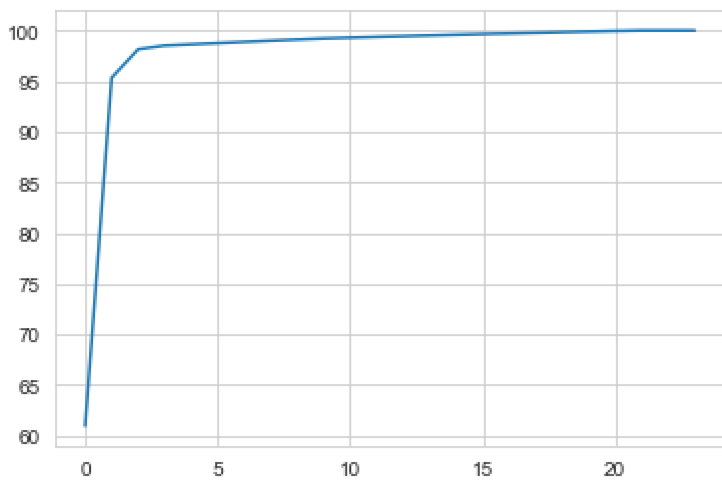
## Dimension Reduction using Pricipal Component Analysis

Principal Component Analysis (PCA) is a dimension-reduction tool that can be used to reduce a large set of variables to a small set that still contains most of the information in the large set.

In [57]:
```
#Get the target variable
target_var = cab_data['fare_amount']
#Get the shape of our cleaned dataset
cab_data.shape #(15451, 25)
#Importing the library for PCA
from sklearn.decomposition import PCA
#Dropping the target variable
cab_data.drop(['fare_amount'], inplace = True, axis =1)
#To check the shape of the data after dropping the target variable
cab_data.shape# (15451, 25)
```

Out[57]:
```
(15905, 24)
```

In [58]:
```
#Converting our data to numpy array
numpy_data = cab_data.values
#Our data without target variable has 133 variables, so number of components = 
24
pca = PCA(n_components = 24)
pca.fit(numpy_data)
#To check the variance that each PC explains
var = pca.explained_variance_ratio_
#Cumulative variance
var_cum = np.cumsum(np.round(var, decimals = 4) * 100)
plt.plot(var_cum)
plt.show()
```




From the above graph, it is clear that approximately after 7 components, there is no variance even if all the rest of the components are considered. So let's select these 7 components as it explains almost 95 percent of data variance.

In [59]:
```
#Selecting the 7 components
pca = PCA(n_components = 7)
#To fit the selected components to the data
pca.fit(numpy_data)
#Splitting into train and test data using train_test_split
X_train1,X_test1,y_train1,y_test1 = train_test_split(numpy_data,target_var,tes
t_size = 0.2)
```

Now by using the above data let's develop the model on our train data

In [60]:
```
#Building the model using linear regression
#Importing the necessary libraries for Linear Regression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
#Build a model on our training dataset
lr_model = LinearRegression().fit(X_train1,y_train1)
#Predict for the test cases
lr_predictions = lr_model.predict(X_test1)
#To create a dataframe for both actual and predicted values
cabdata_lrmodel = pd.DataFrame({"Actual" : y_test1, "Predicted" : lr_predictio
ns})

#Function to find RMSE
def RMSE(x,y):
    rmse = np.sqrt(mean_squared_error(x,y))
    return rmse

#Function to find MAPE
def MAPE(true,predict):
    mape = np.mean(np.abs((true - predict) / true)) * 100
    return mape

#Calculate RMSE, MAPE and R-Squared value for this model

print("Root Mean Squared error :- " + str(RMSE(y_test1,lr_predictions)))
print("R-Squared score :- " + str(r2_score(y_test1,lr_predictions)))
print("Mean Absolute Percentage Error :- " + str(MAPE(y_test1,lr_predictions
)))
```

```
Root Mean Squared error :- 3.181328125797752
R-Squared score :- 0.38830975176005045
Mean Absolute Percentage Error :- inf
```

In [61]:
```
#Building the model using Decisison Tree
#Importing necessary libraries for Decision tree
from sklearn.tree import DecisionTreeRegressor
#Build Decision tree model on the train data
dt_model = DecisionTreeRegressor(max_depth = 2).fit(X_train1,y_train1)
#Predict for the test cases
dt_predict = dt_model.predict(X_test1)
#Create a dataframe for actual and predicted values
df_dtmodel = pd.DataFrame({"Actual" : y_test1, "Predicted" : dt_predict})
#Calculate RMSE, MAPE and R_squared value for this model

print("RMSE: " + str(RMSE(y_test1,dt_predict)))
print("R_Square score: " + str(r2_score(y_test1,dt_predict)))
print("Mean Absolute Percentage Error :- " + str(MAPE(y_test1,dt_predict)))
```

```
RMSE: 2.6366641934454624
R_Square score: 0.5798307460004233
Mean Absolute Percentage Error :- inf
```

In [62]:
```
#Building the model using Randomforest
#Import library for RandomForest
from sklearn.ensemble import RandomForestRegressor
#Build random forest using RandomForestRegressor
rf_model = RandomForestRegressor(n_estimators = 300, random_state = 1).fit(X_t
rain1,y_train1)
#Perdict for test cases
rf_predictions = rf_model.predict(X_test1)
#Create data frame for actual and predicted values
df_rf = pd.DataFrame({'Actual': y_test1, 'Predicted': rf_predictions})
#Calculate RMSE and R-squared value
print("Root Mean Squared Error: "+str(RMSE(y_test1, rf_predictions)))
print("R_square Score: "+str(r2_score(y_test1, rf_predictions)))
print("Mean Absolute Percentage Error :- " + str(MAPE(y_test1,rf_predictions
)))
```

```
Root Mean Squared Error: 2.3083096540441312
R_square Score: 0.6779652316471204
Mean Absolute Percentage Error :- inf
```

In [63]:
```
#Building the model using GradientBoosting
#Import necessary libraries for this ML algorithm
from sklearn.ensemble import GradientBoostingRegressor
#Build GB model on the train data
gb_model = GradientBoostingRegressor().fit(X_train1,y_train1)
#Predict the test cases
gb_predict = gb_model.predict(X_test1)
#Create a dataframe for actual and predicted values
df_gbmodel = pd.DataFrame({"Actual" : y_test1, "Predicted" : gb_predict})
#Calculate RMSE and R_squared values
print("RMSE: " + str(RMSE(y_test1,dt_predict)))
print("R_Square score: " + str(r2_score(y_test1,gb_predict)))
print("Mean Absolute Percentage Error :- " + str(MAPE(y_test1,gb_predict)))
```

```
RMSE: 2.6366641934454624
R_Square score: 0.6898300778943877
Mean Absolute Percentage Error :- inf
```

So we have finally decided that RandomForest has predicted the least RMSE indicating the best fit. So let's predict our cleaned test data using Randomforest Regressor.

In [64]:
```
#Building the model using Randomforest
#Import library for RandomForest
from sklearn.ensemble import RandomForestRegressor
#Build random forest using RandomForestRegressor
rf_predictions_test = rf_model.predict(cab_test)
#Create a new variable to the test dataset
cab_test['Predicted_Fare'] = rf_predictions_test
```

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

Out[65]:

| | passenger_count | year | Date | Hour | distance_travelled | Month_1.0 | Month_2.0 | Month_3.0 | M |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 2015.0 | 27.0 | 13.0 | 1.200263 | 1 | 0 | 0 | |
| **1** | 0.0 | 2015.0 | 27.0 | 13.0 | 1.230751 | 1 | 0 | 0 | |
| **2** | 0.0 | 2011.0 | 8.0 | 11.0 | 0.481303 | 0 | 0 | 0 | |
| **3** | 0.0 | 2012.0 | 1.0 | 21.0 | 1.085078 | 0 | 0 | 0 | |
| **4** | 0.0 | 2012.0 | 1.0 | 21.0 | 1.853612 | 0 | 0 | 0 | |

5 rows × 25 columns

In [66]:
```
cab_test.isna().sum()
```

Out[66]:
```
passenger_count       0
year                  0
Date                  0
Hour                  0
distance_travelled    0
Month_1.0             0
Month_2.0             0
Month_3.0             0
Month_4.0             0
Month_5.0             0
Month_6.0             0
Month_7.0             0
Month_8.0             0
Month_9.0             0
Month_10.0            0
Month_11.0            0
Month_12.0            0
Day_0.0               0
Day_1.0               0
Day_2.0               0
Day_3.0               0
Day_4.0               0
Day_5.0               0
Day_6.0               0
Predicted_Fare        0
dtype: int64
```

In [67]:
```
cab_test.to_csv("Predicted_testdata.csv")
```