# Uber Fare Prediction

## Import Libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import datetime as dt
import geopy.distance
import seaborn as sns
from statsmodels.formula.api import ols
import statsmodels.api as sm
import statsmodels.stats.api as sms
import statsmodels.formula.api as smf
import scipy.stats as stats



from math import *
```

## Data Understanding

In [2]:

```
df = pd.read_csv("/Users/kunjiv/Uber_fares_prediction/Data/uber.csv")
```

In [3]:

```
df.info()
```

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

In [4]:

```
df.head()
```

Out[4]:

| | Unnamed: 0 | key | fare_amount | pickup_datetime | pickup_longitude | pickup_latitud |
|---|---|---|---|---|---|---|
| 0 | 24238194 | 2015-05-07 19:52:06.0000003 | 7.5 | 2015-05-07 19:52:06 UTC | -73.999817 | 40.73835 |
| 1 | 27835199 | 2009-07-17 20:04:56.0000002 | 7.7 | 2009-07-17 20:04:56 UTC | -73.994355 | 40.72822 |
| 2 | 44984355 | 2009-08-24 21:45:00.00000061 | 12.9 | 2009-08-24 21:45:00 UTC | -74.005043 | 40.74077 |
| 3 | 25894730 | 2009-06-26 08:22:21.0000001 | 5.3 | 2009-06-26 08:22:21 UTC | -73.976124 | 40.79084 |
| 4 | 17610152 | 2014-08-28 17:47:00.000000188 | 16.0 | 2014-08-28 17:47:00 UTC | -73.925023 | 40.74408 |

In [5]:

```
# dropping the column unnamed which is of no significance.
df= df.drop(['Unnamed: 0'],axis=1)
```

The dataset contains the following fields:

- key - a unique identifier for each trip
- fare_amount - the cost of each trip in usd
- pickup_datetime - date and time when the meter was engaged
- passenger_count - the number of passengers in the vehicle (driver entered value)
- pickup_longitude - the longitude where the meter was engaged
- pickup_latitude - the latitude where the meter was engaged
- dropoff_longitude - the longitude where the meter was disengaged
- dropoff_latitude - the latitude where the meter was disengaged

In [6]:

```
#Finding the count of null values in dataset
df.isna().sum()
```

Out[6]:

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

In [7]:

```
#Dropping the null values
df = df.dropna()
```

In [8]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 199999 entries, 0 to 199999
Data columns (total 8 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   key                199999 non-null  object 
 1   fare_amount        199999 non-null  float64
 2   pickup_datetime    199999 non-null  object 
 3   pickup_longitude   199999 non-null  float64
 4   pickup_latitude    199999 non-null  float64
 5   dropoff_longitude  199999 non-null  float64
 6   dropoff_latitude   199999 non-null  float64
 7   passenger_count    199999 non-null  int64  
dtypes: float64(5), int64(1), object(2)
memory usage: 13.7+ MB
```

In [9]:

```
df['key']
```

Out[9]:

```
0           2015-05-07 19:52:06.0000003
1           2009-07-17 20:04:56.0000002
2          2009-08-24 21:45:00.00000061
3           2009-06-26 08:22:21.0000001
4         2014-08-28 17:47:00.000000188
                      ...              
199995     2012-10-28 10:49:00.00000053
199996      2014-03-14 01:09:00.0000008
199997     2009-06-29 00:42:00.00000078
199998      2015-05-20 14:56:25.0000004
199999     2010-05-15 04:08:00.00000076
Name: key, Length: 199999, dtype: object
```

In [10]:

```
#Splitting the 'key' column which has pickup date and time and dropping column 'key
df[['pickup_date','pickup_time']] = df['key'].str.split(" ", expand= True)
df= df.drop(['key'],axis=1)
```

In [11]:

```
df.pickup_datetime=pd.to_datetime(df.pickup_datetime)
```

In [12]:

```
df['year'] = df.pickup_datetime.dt.year
df['month'] = df.pickup_datetime.dt.month
df['weekday'] = df.pickup_datetime.dt.weekday
df['hour'] = df.pickup_datetime.dt.hour
```

Here we are going to use Heversine formula to calculate the distance between two points and journey, using the longitude and latitude values.¶

In [13]:

```
# function to calculate the travel distance from the longitudes and latitudes
def distance_transform(longitude1, latitude1, longitude2, latitude2):
    travel_dist = []

    for pos in range(len(longitude1)):
        long1,lati1,long2,lati2 = map(radians,[longitude1[pos],latitude1[pos],longit
        dist_long = long2 - long1
        dist_lati = lati2 - lati1
        a = sin(dist_lati/2)**2 + cos(lati1) * cos(lati2) * sin(dist_long/2)**2
        c = 2 * asin(sqrt(a))*6371
        travel_dist.append(c)

    return travel_dist
```

In [14]:

```
df['Distance'] = distance_transform(df['pickup_longitude'].to_numpy(),
                                                df['pickup_latitude'].to_numpy(),
                                                df['dropoff_longitude'].to_numpy(),
                                                df['dropoff_latitude'].to_numpy()
                                              )
```

In [15]:

```
df['Distance'].sort_values().tail(10)
```

Out[15]:

```
40290      8671.705316
11530      8674.803956
78118      8680.851746
145538     8680.863938
165324     8681.105930
140620     8708.233063
34594      8776.106279
65591      8782.898606
139447    10321.507661
75851     16409.239135
Name: Distance, dtype: float64
```

In [16]:

```
df['Distance'].sort_values().head(10)
```

Out[16]:

```
173663    0.0
166921    0.0
40725     0.0
158150    0.0
9198      0.0
144936    0.0
121081    0.0
3952      0.0
192614    0.0
173704    0.0
Name: Distance, dtype: float64
```

In [17]:

```
df.describe()
```

Out[17]:

| | fare_amount | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | pass |
|---|---|---|---|---|---|---|
| **count** | 199999.000000 | 199999.000000 | 199999.000000 | 199999.000000 | 199999.000000 | 19 |
| **mean** | 11.359892 | -72.527631 | 39.935881 | -72.525292 | 39.923890 | |
| **std** | 9.901760 | 11.437815 | 7.720558 | 13.117408 | 6.794829 | |
| **min** | -52.000000 | -1340.648410 | -74.015515 | -3356.666300 | -881.985513 | |
| **25%** | 6.000000 | -73.992065 | 40.734796 | -73.991407 | 40.733823 | |
| **50%** | 8.500000 | -73.981823 | 40.752592 | -73.980093 | 40.753042 | |
| **75%** | 12.500000 | -73.967154 | 40.767158 | -73.963658 | 40.768001 | |
| **max** | 499.000000 | 57.418457 | 1644.421482 | 1153.572603 | 872.697628 | |

From the above it is observed that the minimum value of distance is 0

In [18]:

```
df.loc[(df.Distance == 0)]
```

Out[18]:

| | fare_amount | pickup_datetime | pickup_longitude | pickup_latitude | dropoff_longitude | drop |
|---|---|---|---|---|---|---|
| **5** | 4.9 | 2011-02-12 02:27:09+00:00 | -73.969019 | 40.755910 | -73.969019 | |
| **7** | 2.5 | 2012-12-11 13:52:00+00:00 | 0.000000 | 0.000000 | 0.000000 | |
| **11** | 8.5 | 2011-05-23 22:15:00+00:00 | 0.000000 | 0.000000 | 0.000000 | |
| **48** | 56.8 | 2013-01-03 22:24:41+00:00 | -73.993498 | 40.764686 | -73.993498 | |
| **65** | 6.0 | 2014-05-05 19:27:00+00:00 | 0.000000 | 0.000000 | 0.000000 | |
| **...** | ... | ... | ... | ... | ... | |
| **199880** | 6.5 | 2014-02-22 06:45:46+00:00 | 0.000000 | 0.000000 | 0.000000 | |
| **199883** | 12.5 | 2012-09-10 17:39:00+00:00 | 0.000000 | 0.000000 | 0.000000 | |
| **199917** | 4.5 | 2013-06-24 22:17:43+00:00 | -73.793768 | 40.656939 | -73.793768 | |
| **199932** | 24.9 | 2011-03-22 13:59:00+00:00 | -73.974618 | 40.756295 | -73.974618 | |
| **199963** | 39.0 | 2012-09-22 07:46:01+00:00 | 0.000000 | 0.000000 | 0.000000 | |

5632 rows × 14 columns

There are 5632 rows with distance 0

In [19]:

```
df.loc[(df.Distance >= 130)]
```

Out[19]:

| | fare_amount | pickup_datetime | pickup_longitude | pickup_latitude | dropoff_longitude | drop |
|---|---|---|---|---|---|---|
| **346** | 15.5 | 2015-03-05 19:15:07+00:00 | 0.000000 | 0.000000 | -73.979805 | |
| **1067** | 52.0 | 2014-02-02 22:27:00+00:00 | -73.781095 | 40.645015 | 0.000000 | |
| **1526** | 2.5 | 2014-05-12 12:00:15+00:00 | -74.001849 | 40.715156 | 0.000000 | |
| **1945** | 7.0 | 2013-02-10 16:18:00+00:00 | -0.131667 | 40.757063 | -73.991593 | |
| **2167** | 5.7 | 2012-07-21 12:16:00+00:00 | -1.216667 | 40.748597 | -74.004822 | |
| **...** | ... | ... | ... | ... | ... | |
| **198567** | 23.5 | 2013-10-21 01:28:00+00:00 | -73.968115 | 40.801455 | 0.000000 | |
| **198665** | 20.1 | 2012-06-26 21:29:00+00:00 | -0.116667 | 40.729775 | 0.000000 | |
| **199403** | 7.0 | 2013-01-20 17:58:29+00:00 | -67.370360 | 39.999790 | -73.971058 | |
| **199641** | 8.1 | 2012-06-22 12:36:00+00:00 | -74.000143 | 40.742877 | -7.995197 | |
| **199936** | 4.1 | 2012-07-21 16:19:00+00:00 | -736.400000 | 40.774307 | -73.982215 | |

445 rows × 14 columns

In [20]:

```
df= df.loc[(df.Distance >0)]
print("Remaining observastions in the dataset:", df.shape)
```

```
Remaining observastions in the dataset: (194367, 14)
```

In [21]:

```
df= df.loc[(df.Distance <=130)]
```

In [22]:

```
#dropping pickup_datetime
df= df.drop(['pickup_datetime'],axis=1)
```

In [23]:

```
df.describe()
```

Out[23]:

| | fare_amount | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | pass |
|---|---|---|---|---|---|---|
| **count** | 193922.000000 | 193922.000000 | 193922.000000 | 193922.000000 | 193922.000000 | 19 |
| **mean** | 11.345620 | -73.910614 | 40.690371 | -73.909656 | 40.688792 | |
| **std** | 9.736012 | 2.684739 | 2.753459 | 2.684822 | 2.629362 | |
| **min** | -52.000000 | -75.419276 | -74.015515 | -75.423067 | -74.015750 | |
| **25%** | 6.000000 | -73.992279 | 40.736439 | -73.991600 | 40.735304 | |
| **50%** | 8.500000 | -73.982128 | 40.753292 | -73.980567 | 40.753737 | |
| **75%** | 12.500000 | -73.968453 | 40.767532 | -73.965510 | 40.768327 | |
| **max** | 499.000000 | 40.808425 | 401.066667 | 40.831932 | 45.031598 | |

# Removing outliers

We can see the min value of fare_amount is -52 which might be wrong and also for the min value of passenger count is 0 and maximum value is 208

In [24]:

```
df = df.loc[(df.fare_amount > 0)]
```

In [25]:

```
df.shape
```

Out[25]:

```
(193904, 13)
```

In [26]:

```
df=df[df['passenger_count']<=8]
```

In [27]:

```
df=df[df['passenger_count']>0]
```

In [28]:

```
df.shape
```

Out[28]:

```
(193218, 13)
```

Trips with travel distance less than or equal to 0, and more than 130Kms

In [29]:

```
df.describe()
```

Out[29]:

| | fare_amount | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | pass |
|---|---|---|---|---|---|---|
| **count** | 193218.000000 | 193218.000000 | 193218.000000 | 193218.000000 | 193218.000000 | 19 |
| **mean** | 11.355174 | -73.910373 | 40.690147 | -73.909417 | 40.688560 | |
| **std** | 9.741024 | 2.689622 | 2.758468 | 2.689706 | 2.634144 | |
| **min** | 0.010000 | -75.419276 | -74.015515 | -75.423067 | -74.015750 | |
| **25%** | 6.000000 | -73.992279 | 40.736434 | -73.991600 | 40.735305 | |
| **50%** | 8.500000 | -73.982130 | 40.753282 | -73.980568 | 40.753733 | |
| **75%** | 12.500000 | -73.968458 | 40.767528 | -73.965512 | 40.768322 | |
| **max** | 499.000000 | 40.808425 | 401.066667 | 40.831932 | 45.031598 | |

In [30]:

```
df.isnull().sum()
```

Out[30]:

```
fare_amount          0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
pickup_date          0
pickup_time          0
year                 0
month                0
weekday              0
hour                 0
Distance             0
dtype: int64
```

In [31]:

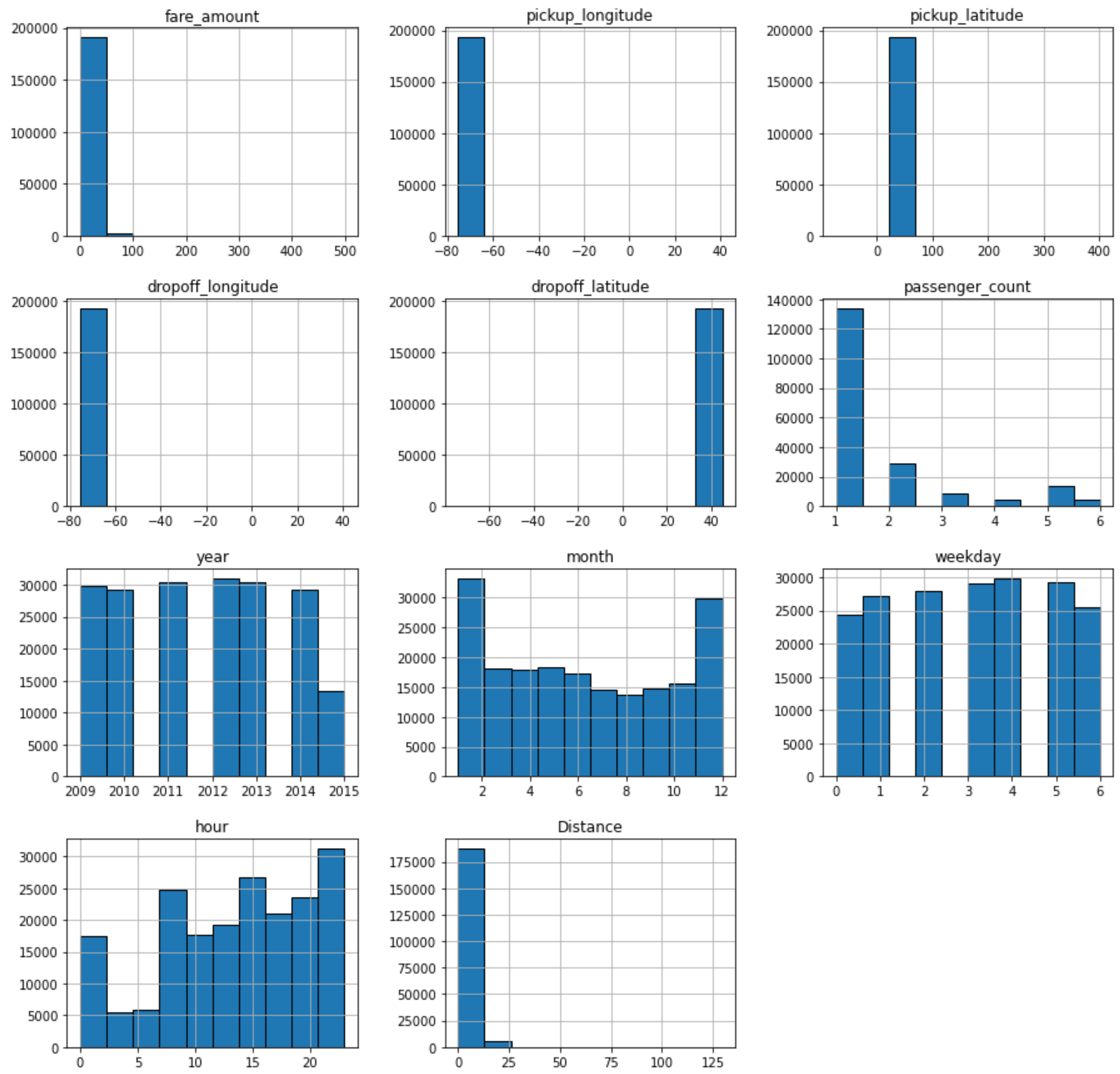
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 193218 entries, 0 to 199999
Data columns (total 13 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   fare_amount        193218 non-null  float64
 1   pickup_longitude   193218 non-null  float64
 2   pickup_latitude    193218 non-null  float64
 3   dropoff_longitude  193218 non-null  float64
 4   dropoff_latitude   193218 non-null  float64
 5   passenger_count    193218 non-null  int64  
 6   pickup_date        193218 non-null  object 
 7   pickup_time        193218 non-null  object 
 8   year               193218 non-null  int64  
 9   month              193218 non-null  int64  
 10  weekday            193218 non-null  int64  
 11  hour               193218 non-null  int64  
 12  Distance           193218 non-null  float64
dtypes: float64(6), int64(5), object(2)
memory usage: 20.6+ MB
```

## Distribution visualization

In [32]:

```
df.hist(figsize=(15,15), edgecolor = 'black');
```



Only month,hour follows a normal distribution

In [33]:

```
df.nunique().sort_values()
```

Out[33]:

```
passenger_count          6
year                     7
weekday                  7
month                   12
hour                    24
fare_amount           1198
pickup_date           2372
pickup_longitude     70372
dropoff_longitude    76151
pickup_latitude      83144
dropoff_latitude     89839
pickup_time         167796
Distance            193209
dtype: int64
```

passenger_count,week_day and month are categorical

# Correlation Visualization

Correlation is a statistic that measures the degree to which two variables move with each other. A correlation coefficient near 1 indicates the strong relationship between them; a weak correlation indicates the extent to which one variable increases as the other decreases. Correlation among multiple variables can be represented in the form of a matrix. This allows us to see which variables are correlated.

In [34]:

```
corr = df.corr()
```

In [35]:

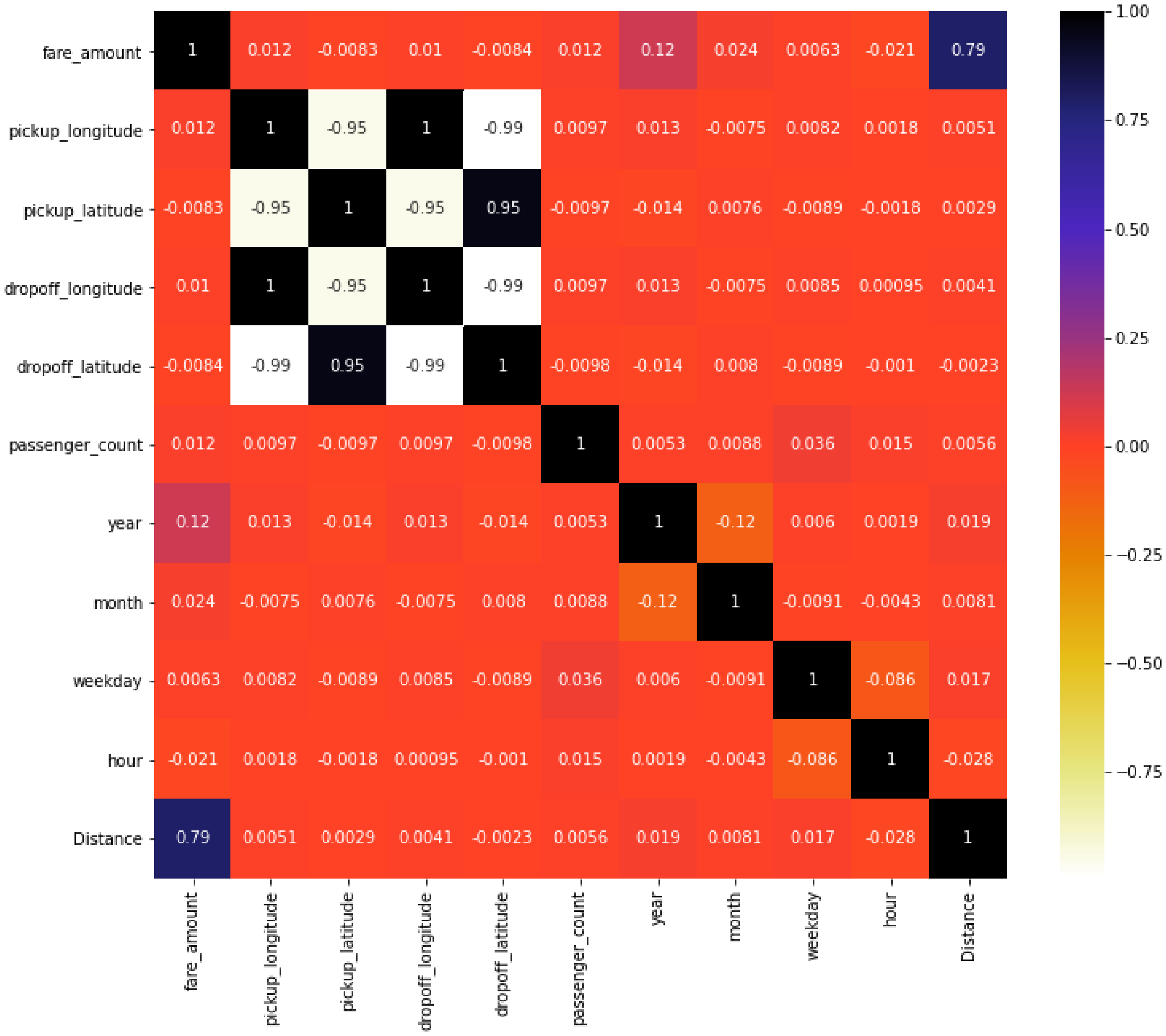
```
corr
```

Out[35]:

| | fare_amount | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitu |
|---|---|---|---|---|---|
| **fare_amount** | 1.000000 | 0.011723 | -0.008344 | 0.010239 | -0.0083 |
| **pickup_longitude** | 0.011723 | 1.000000 | -0.949081 | 0.999875 | -0.9939 |
| **pickup_latitude** | -0.008344 | -0.949081 | 1.000000 | -0.949085 | 0.9547 |
| **dropoff_longitude** | 0.010239 | 0.999875 | -0.949085 | 1.000000 | -0.9939 |
| **dropoff_latitude** | -0.008350 | -0.993961 | 0.954748 | -0.993947 | 1.0000 |
| **passenger_count** | 0.011902 | 0.009664 | -0.009741 | 0.009662 | -0.0097 |
| **year** | 0.120447 | 0.013431 | -0.013684 | 0.013327 | -0.0143 |
| **month** | 0.024138 | -0.007502 | 0.007627 | -0.007469 | 0.0080 |
| **weekday** | 0.006285 | 0.008242 | -0.008919 | 0.008530 | -0.0089 |
| **hour** | -0.020726 | 0.001838 | -0.001821 | 0.000946 | -0.0010 |
| **Distance** | 0.790204 | 0.005115 | 0.002948 | 0.004087 | -0.0022 |

In [36]:

```
plt.figure(figsize=(12,10))
sns.heatmap(corr, annot=True, cmap=plt.cm.CMRmap_r)
plt.show()
```




In [37]:

```
# with the following function we can select highly correlated features
# it will remove the first feature that is correlated with anything other feature

def correlation(dataset, threshold):
    col_corr = set()# Set of all the names of correlated columns
    vals =set()
    corr_matrix = df.corr()
    for i in range(0,len(corr_matrix.columns)):
        for j in range(0,i):
            if abs(corr_matrix.iloc[i, j]) > threshold:
                colname = corr_matrix.columns[i]  # getting the name of column
                col_corr.add(colname)
    return col_corr
```

In [38]:

```
corr_features = correlation(df, 0.7)
```

In [39]:

```
corr_features
```

Out[39]:

```
{'Distance', 'dropoff_latitude', 'dropoff_longitude', 'pickup_latitud
e'}
```

In [40]:

```
features = []
correlations = []
corr_matrix = df.corr()
for idx, correlation in corr_matrix['fare_amount'].T.iteritems():
    if correlation >= .30 and idx != 'fare_amount':
        features.append(idx)
        correlations.append(correlation)
corr_price_df = pd.DataFrame({'Correlations':correlations, 'Features': features}).sc
```

In [41]:

```
display("correlation with fare amount",corr_price_df)
```

```
'correlation with fare amount'
```

| | Correlations | Features |
|---|---|---|
| **0** | 0.790204 | Distance |

In [42]:

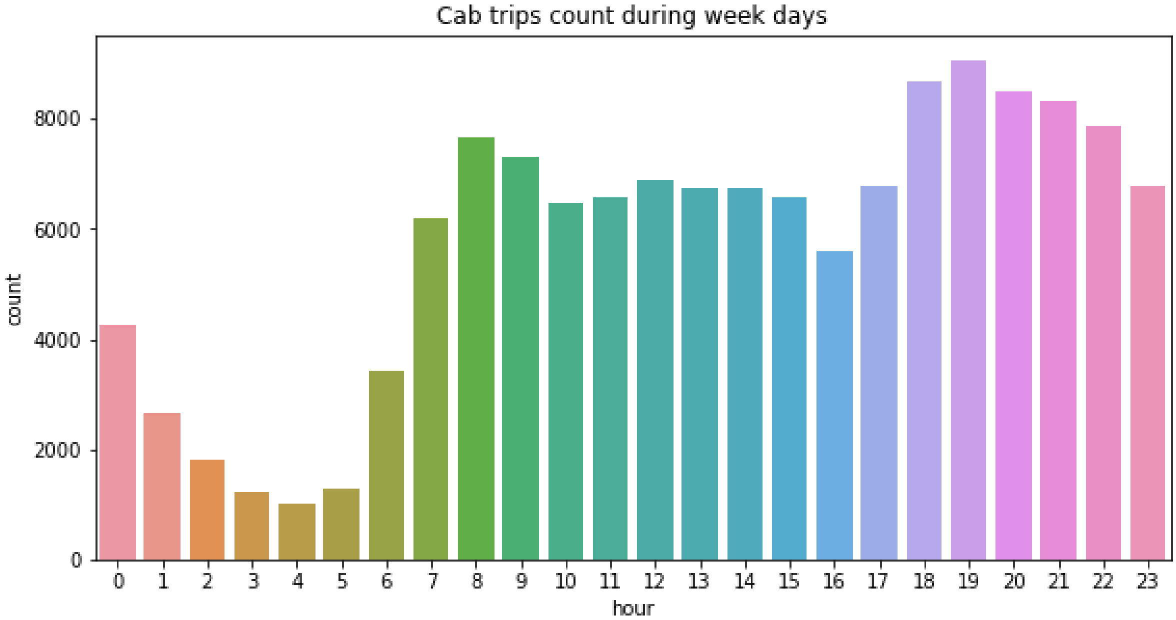
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 193218 entries, 0 to 199999
Data columns (total 13 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   fare_amount        193218 non-null  float64
 1   pickup_longitude   193218 non-null  float64
 2   pickup_latitude    193218 non-null  float64
 3   dropoff_longitude  193218 non-null  float64
 4   dropoff_latitude   193218 non-null  float64
 5   passenger_count    193218 non-null  int64  
 6   pickup_date        193218 non-null  object 
 7   pickup_time        193218 non-null  object 
 8   year               193218 non-null  int64  
 9   month              193218 non-null  int64  
 10  weekday            193218 non-null  int64  
 11  hour               193218 non-null  int64  
 12  Distance           193218 non-null  float64
dtypes: float64(6), int64(5), object(2)
memory usage: 20.6+ MB
```

To find the peak hours during weekdays.

In [43]:

```
plt.figure(figsize=(10,5))
plt.title('Cab trips count during week days')
sns.countplot(x='hour', data=df.loc[(df.weekday >= 0) & (df.weekday <=4)])
plt.show()
```

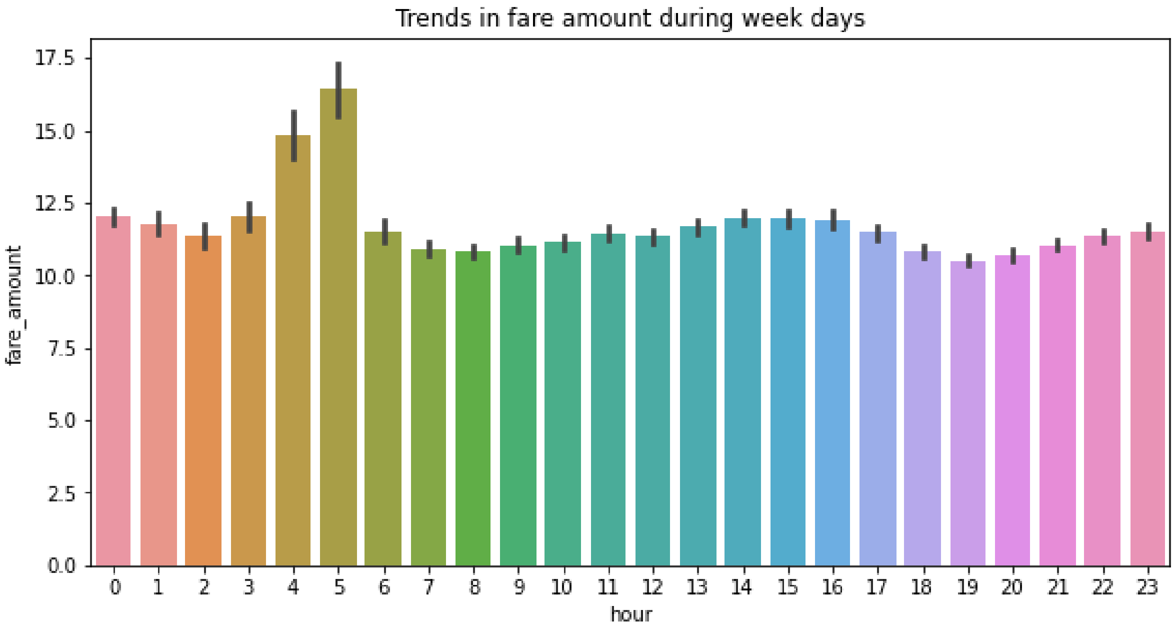



From the above plot we can infer that during weekdays the peak hours with maximum trips are 8am to 9am during the day and 6pm to 8pm during the night.

To find the fare amount during peak hours during week days

In [44]:

```
plt.figure(figsize=(10,5))
plt.title('Trends in fare amount during week days')
sns.barplot(x='hour',y='fare_amount' ,data=df.loc[(df.weekday >= 0) & (df.weekday <=
plt.show()
```

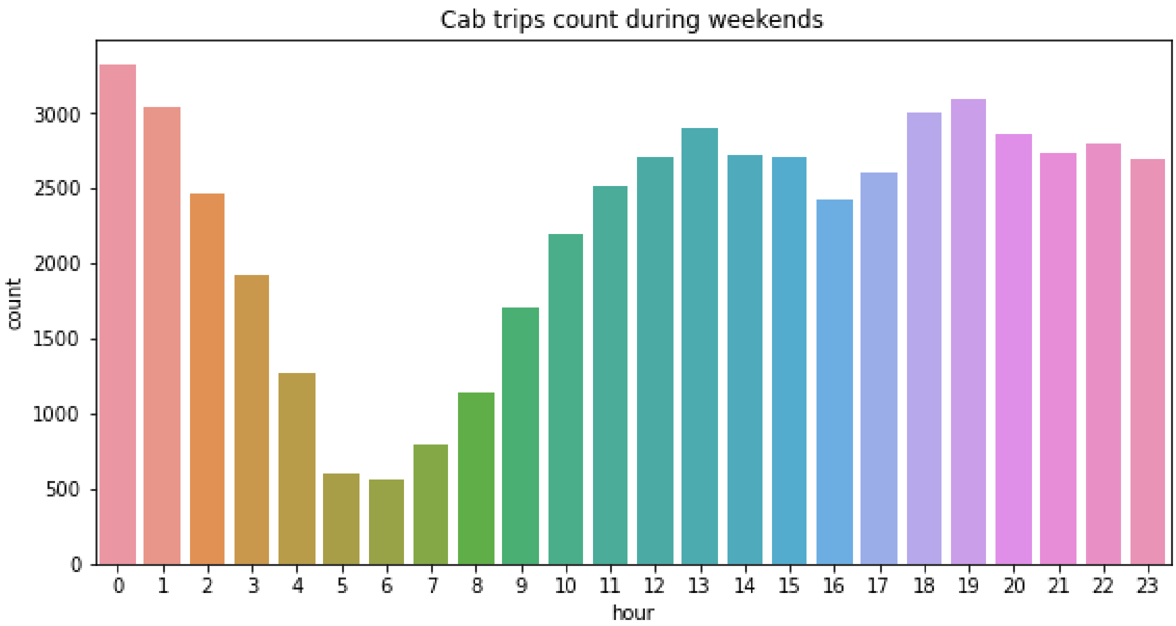


From the above plot it is found that fare price is high only during early morning hours which is not a peak hour else it is uniform.

To find the peak hours during weekends.

In [45]:

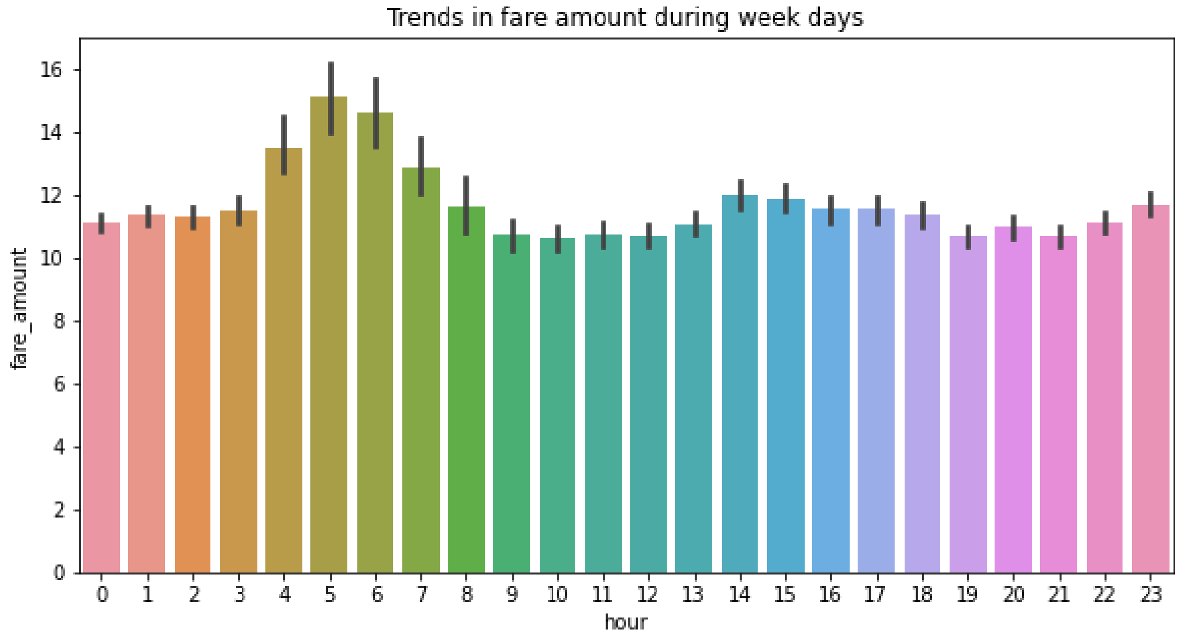
```
plt.figure(figsize=(10,5))
plt.title('Cab trips count during weekends')
sns.countplot(x='hour', data=df.loc[(df.weekday >= 5) & (df.weekday <=6)])
plt.show()
```




To find the fare amount during peak hours during weekends

In [46]:

```
plt.figure(figsize=(10,5))
plt.title('Trends in fare amount during week days')
sns.barplot(x='hour',y='fare_amount' ,data=df.loc[(df.weekday >= 5) & (df.weekday <=
plt.show()
```

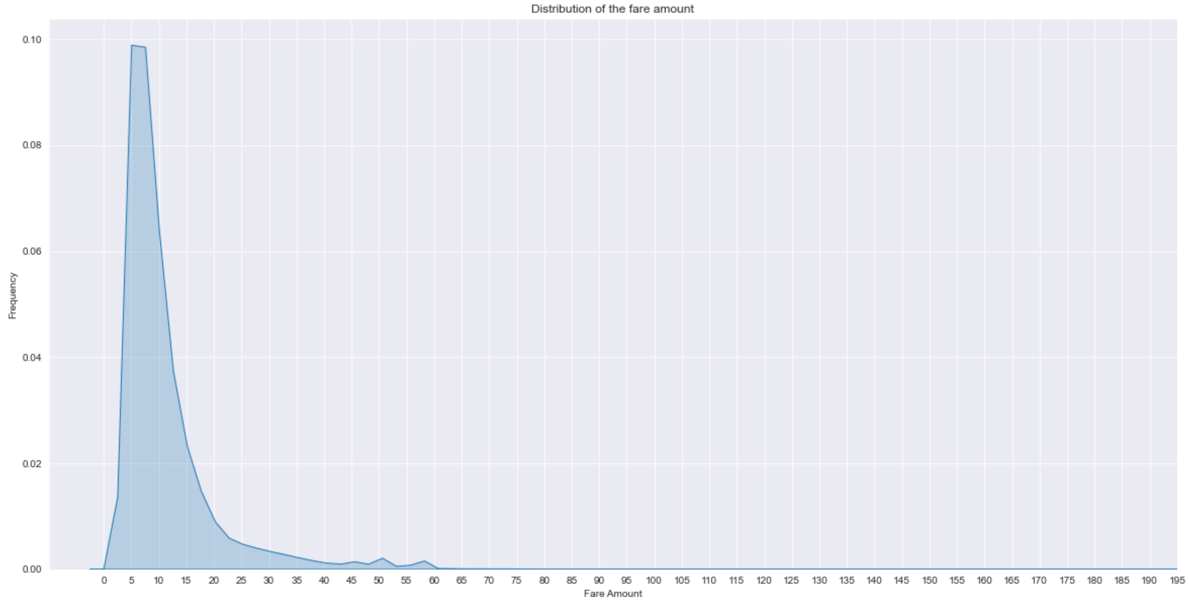



From the above plots we can understand that the fare amount is high only during the non-peak hours.Thus hours is an important predictor.

## Distribution of key numeric variables

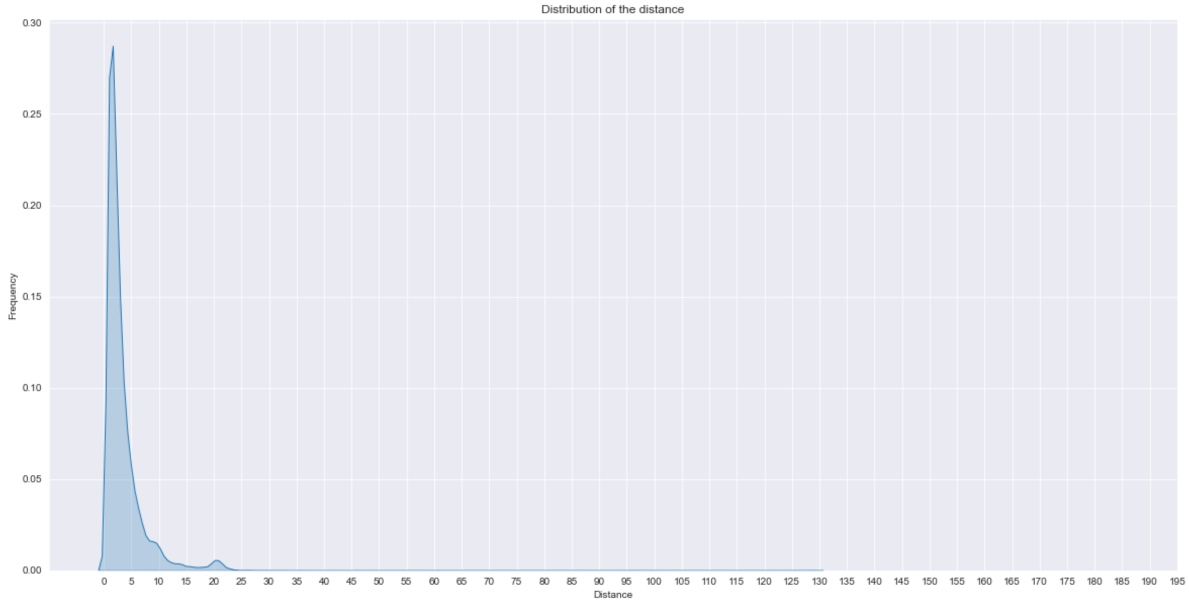
In [47]:

```
plt.figure(figsize=(20,10))
sns.set_style("darkgrid")
plt.title("Distribution of the fare amount")
plt.xlabel("Fare Amount")
plt.ylabel("Frequency")
plt.xlim(-10,20)
plt.xticks(range(0,200,5))

snsplot = sns.kdeplot(df.fare_amount, shade=True)
```



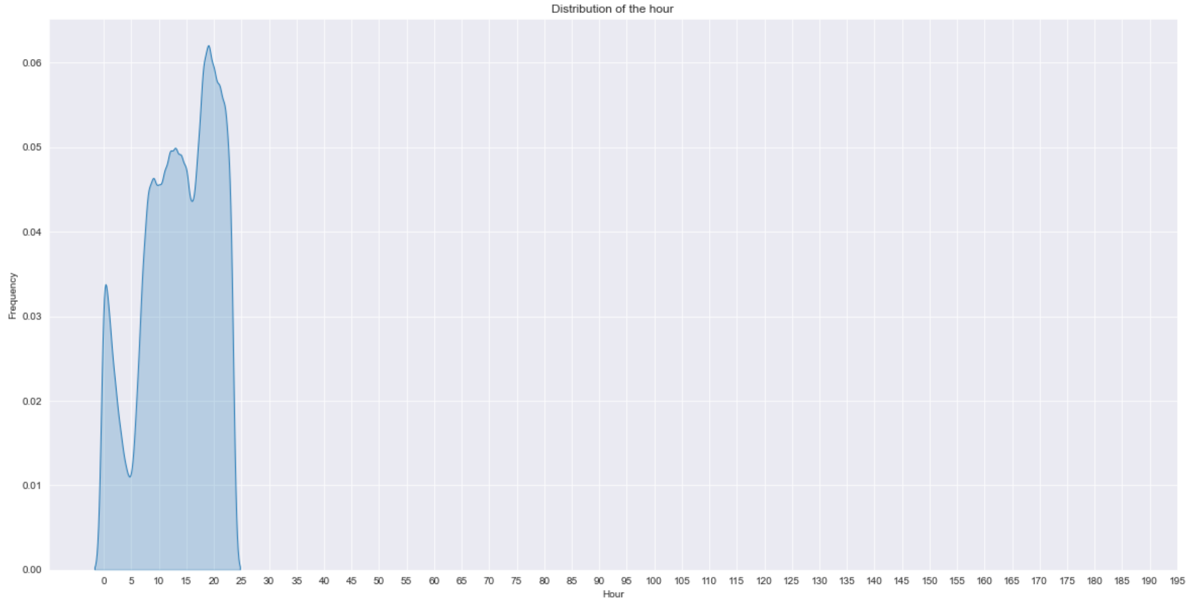

In [48]:

```
plt.figure(figsize=(20,10))
sns.set_style("darkgrid")
plt.title("Distribution of the distance")
plt.xlabel("Distance")
plt.ylabel("Frequency")
plt.xlim(-10,20)
plt.xticks(range(0,200,5))

snsplot = sns.kdeplot(df.Distance, shade=True)
```



In [49]:

```
plt.figure(figsize=(20,10))
sns.set_style("darkgrid")
plt.title("Distribution of the hour")
plt.xlabel("Hour")
plt.ylabel("Frequency")
plt.xlim(-10,20)
plt.xticks(range(0,200,5))

snsplot = sns.kdeplot(df.hour, shade=True)
```




# Categorical Variables

In [50]:

```
#creating dummy variables for month,weekday and passenger count
month_dummies = pd.get_dummies(df['month'], prefix='month', drop_first=True)
weekday_dummies = pd.get_dummies(df['weekday'], prefix='day', drop_first=True)
count_dummies = pd.get_dummies(df['passenger_count'], prefix='count', drop_first=Tru
```

In [51]:

```
df = df.drop(['month','weekday','passenger_count'], axis=1)
```

In [52]:

```
df = pd.concat([df, month_dummies, weekday_dummies, count_dummies], axis=1)
df.head()
```

Out[52]:

| | fare_amount | pickup_longitude | pickup_latitude | dropoff_longitude | dropoff_latitude | pickup_date |
|---|---|---|---|---|---|---|
| **0** | 7.5 | -73.999817 | 40.738354 | -73.999512 | 40.723217 | 2015-05-07 |
| **1** | 7.7 | -73.994355 | 40.728225 | -73.994710 | 40.750325 | 2009-07-17 |
| **2** | 12.9 | -74.005043 | 40.740770 | -73.962565 | 40.772647 | 2009-08-24 |
| **3** | 5.3 | -73.976124 | 40.790844 | -73.965316 | 40.803349 | 2009-06-26 |
| **4** | 16.0 | -73.925023 | 40.744085 | -73.973082 | 40.761247 | 2014-08-28 |

5 rows × 32 columns

In [53]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 193218 entries, 0 to 199999
Data columns (total 32 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   fare_amount        193218 non-null  float64
 1   pickup_longitude   193218 non-null  float64
 2   pickup_latitude    193218 non-null  float64
 3   dropoff_longitude  193218 non-null  float64
 4   dropoff_latitude   193218 non-null  float64
 5   pickup_date        193218 non-null  object 
 6   pickup_time        193218 non-null  object 
 7   year               193218 non-null  int64  
 8   hour               193218 non-null  int64  
 9   Distance           193218 non-null  float64
 10  month_2            193218 non-null  uint8  
 11  month_3            193218 non-null  uint8  
 12  month_4            193218 non-null  uint8  
 13  month_5            193218 non-null  uint8  
 14  month_6            193218 non-null  uint8  
 15  month_7            193218 non-null  uint8  
 16  month_8            193218 non-null  uint8  
 17  month_9            193218 non-null  uint8  
 18  month_10           193218 non-null  uint8  
 19  month_11           193218 non-null  uint8  
 20  month_12           193218 non-null  uint8  
 21  day_1              193218 non-null  uint8  
 22  day_2              193218 non-null  uint8  
 23  day_3              193218 non-null  uint8  
 24  day_4              193218 non-null  uint8  
 25  day_5              193218 non-null  uint8  
 26  day_6              193218 non-null  uint8  
 27  count_2            193218 non-null  uint8  
 28  count_3            193218 non-null  uint8  
 29  count_4            193218 non-null  uint8  
 30  count_5            193218 non-null  uint8  
 31  count_6            193218 non-null  uint8  
dtypes: float64(6), int64(2), object(2), uint8(22)
memory usage: 20.3+ MB
```

In [54]:

```
df= df.drop(['pickup_date','pickup_time'],axis=1)
```

In [55]:

```
#Dependent variable is 'fare_amount' and independent variables/predictors are the re

#y = pd.DataFrame(df['fare_amount'])
#x = df.drop('fare_amount',axis = 1)
```

In [56]:

```
#x_cols = ['Distance','fare_amount','year','hour']
```

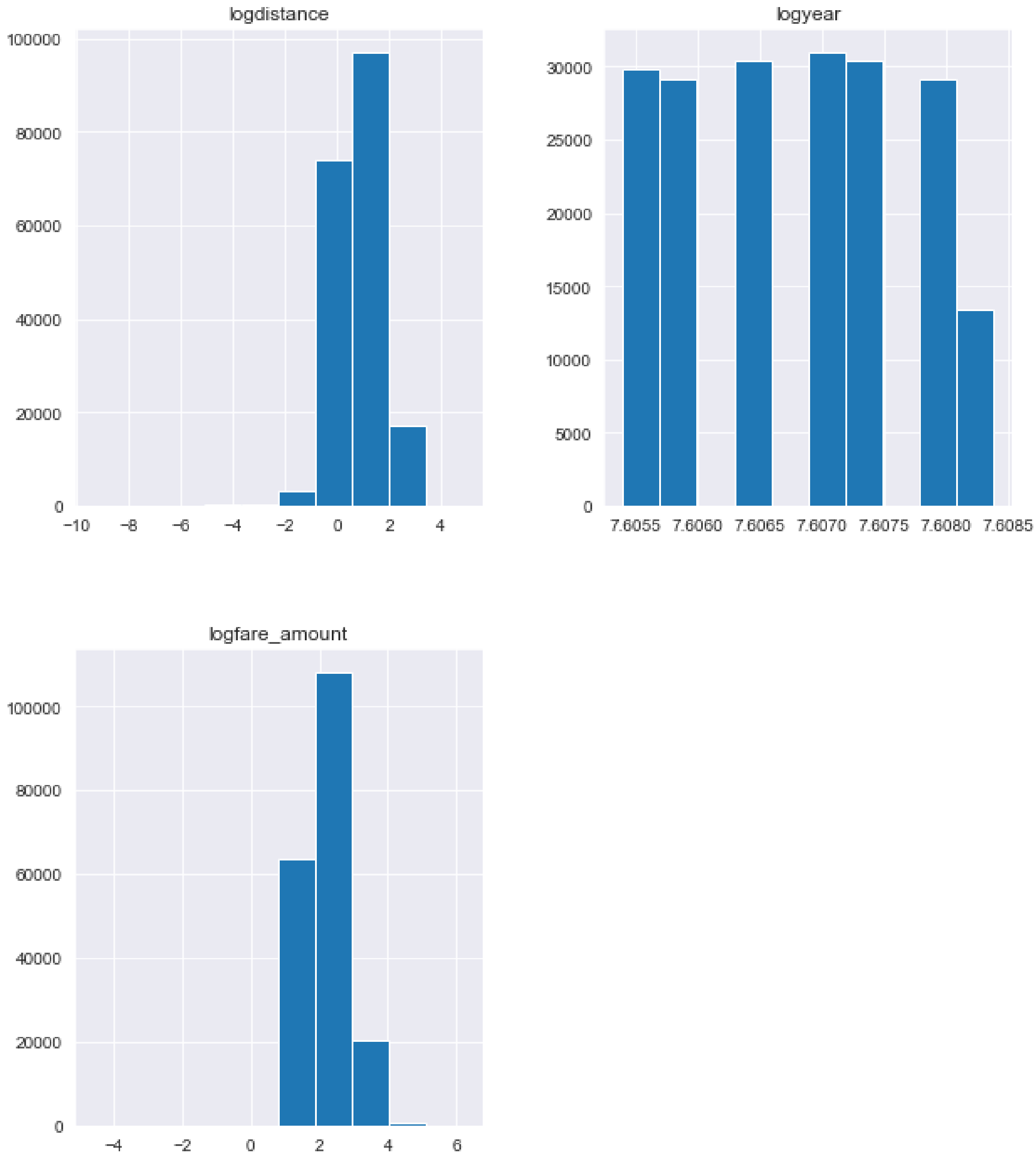
In [57]:

```
#pd.plotting.scatter_matrix(df[x_cols], figsize=(10,12));
```

Log transformation of the non-normal variables -distance,year,fare amount

In [58]:

```
data_log = pd.DataFrame([])
data_log['logdistance'] = np.log(df['Distance'])
data_log['logyear'] =np.log(df['year'])
data_log['logfare_amount'] = np.log(df['fare_amount'])
data_log.hist(figsize  = [10,12]);
```



In [59]:

```
#Dependent variable is 'fare_amount' and independent variables/predictors are the re

y = pd.DataFrame(data_log['logfare_amount'])
x = df.drop(['Distance','fare_amount','year'],axis = 1)
```

In [60]:

```
x = x.join(data_log[['logdistance','logyear']])
```

# MULTIPLE REGRESSION

# Model 1

In [61]:

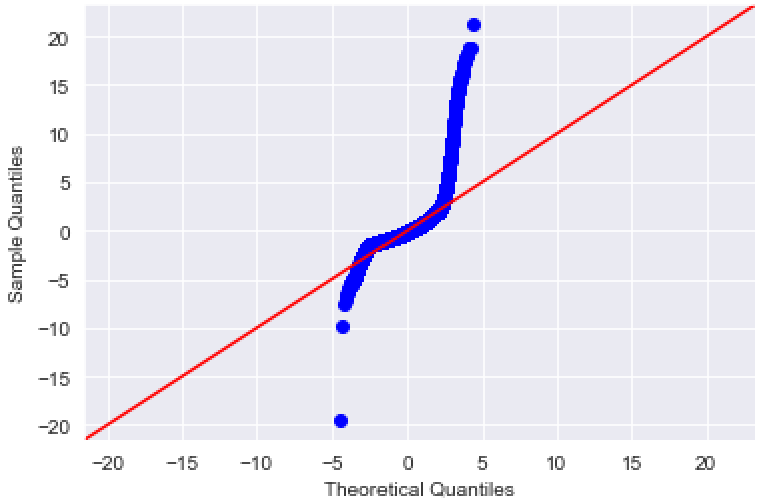
```
# adding the constant term
x = sm.add_constant(x)

# performing the regression
# and fitting the model
model1 = sm.OLS(y, x).fit()

# printing the summary table
print(model1.summary())
```

```
                            OLS Regression Results
==============================================================================
========
Dep. Variable:         logfare_amount   R-squared:
0.614
Model:                            OLS   Adj. R-squared:
0.614
Method:                 Least Squares   F-statistic:
1.058e+04
Date:                Tue, 21 Jun 2022   Prob (F-statistic):
0.00
Time:                        20:46:58   Log-Likelihood:
-83140.
No. Observations:              193218   AIC:
1.663e+05
Df Residuals:                  193188   BIC:
1.666e+05
Df Model:                          29
Covariance Type:            nonrobust
==============================================================================
===============
                        coef    std err          t      P>|t|      [0.
025      0.975]
------------------------------------------------------------------------------
---------------
const              -649.1495      7.062    -91.919      0.000    -662.
991    -635.308
pickup_longitude      0.4261      0.020     21.276      0.000       0.
387       0.465
pickup_latitude      -0.0036      0.001     -3.491      0.000      -0.
006      -0.002
dropoff_longitude    -0.3923      0.020    -19.612      0.000      -0.
431      -0.353
dropoff_latitude      0.0355      0.003     11.434      0.000       0.
029       0.042
hour                 -0.0006      0.000     -4.660      0.000      -0.
001      -0.000
month_2               0.0094      0.004      2.295      0.022       0.
001       0.017
month_3               0.0107      0.004      2.684      0.007       0.
003       0.018
month_4               0.0242      0.004      6.073      0.000       0.
016       0.032
month_5               0.0295      0.004      7.426      0.000       0.
022       0.037
month_6               0.0338      0.004      8.409      0.000       0.
026       0.042
month_7               0.0222      0.004      5.290      0.000       0.
014       0.030
```

```
month_8                  0.0209      0.004      4.889      0.000       0.
013        0.029
month_9                  0.0682      0.004     16.292      0.000       0.
060        0.076
month_10                 0.0715      0.004     17.353      0.000       0.
063        0.080
month_11                 0.0605      0.004     14.471      0.000       0.
052        0.069
month_12                 0.0715      0.004     17.158      0.000       0.
063        0.080
day_1                    0.0165      0.003      5.036      0.000       0.
010        0.023
day_2                    0.0293      0.003      8.980      0.000       0.
023        0.036
day_3                    0.0355      0.003     10.960      0.000       0.
029        0.042
day_4                    0.0294      0.003      9.142      0.000       0.
023        0.036
day_5                   -0.0071      0.003     -2.202      0.028      -0.
013       -0.001
day_6                   -0.0120      0.003     -3.578      0.000      -0.
019       -0.005
count_2                  0.0193      0.002      7.917      0.000       0.
014        0.024
count_3                  0.0159      0.004      3.854      0.000       0.
008        0.024
count_4                  0.0241      0.006      4.108      0.000       0.
013        0.036
count_5                  0.0155      0.003      4.615      0.000       0.
009        0.022
count_6                  0.0120      0.006      2.039      0.041       0.
000        0.024
logdistance              0.4824      0.001    541.508      0.000       0.
481        0.484
logyear                 85.7306      0.928     92.344      0.000      83.
911       87.550
======================================================================
========
Omnibus:                   187477.624   Durbin-Watson:
1.999
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2280
0893.561
Skew:                           4.425   Prob(JB):
0.00
Kurtosis:                      55.477   Cond. No.
1.01e+06
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.01e+06. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

In [62]:

```
import scipy.stats as stats
residuals = model1.resid
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True, )
plt.show;
```




There seems to be multicollinearity.

In [63]:

```
name = ['Jarque-Bera','Prob','Skew', 'Kurtosis']
test = sms.jarque_bera(model1.resid)
list(zip(name, test))
```

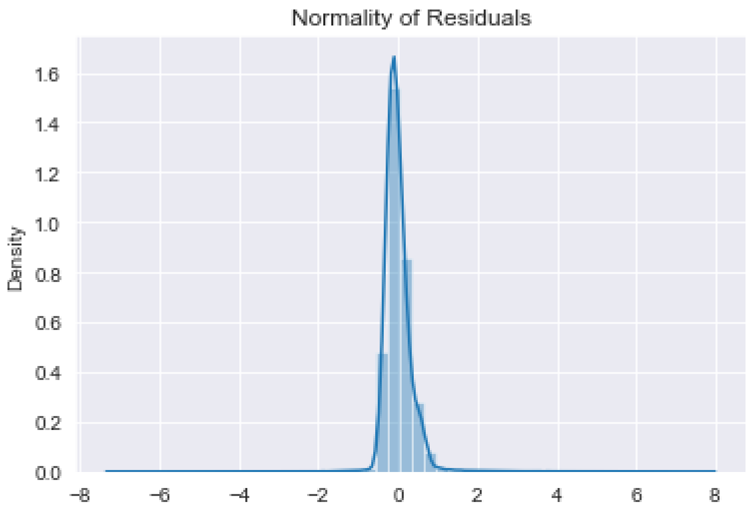
Out[63]:

```
[('Jarque-Bera', 22800893.561292782),
 ('Prob', 0.0),
 ('Skew', 4.4245379759151415),
 ('Kurtosis', 55.47703429483271)]
```

In [64]:

```
#Histogram of Residuals
sns.distplot(model1.resid)
plt.title('Normality of Residuals')
plt.show()
```

```
/Users/kunjiv/opt/anaconda3/envs/learn-env/lib/python3.8/site-package
s/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt yo
ur code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```




## Model 2

Among the correlated variables {'Distance', 'dropoff_latitude', 'dropoff_longitude', 'pickup_latitude'},we may remove 'dropoff_latitude', 'dropoff_longitude', 'pickup_latitude' as distance is calculated from former two variables

In [65]:

```

x = df.drop(['dropoff_latitude', 'dropoff_longitude', 'pickup_latitude'],axis = 1)
```

In [66]:

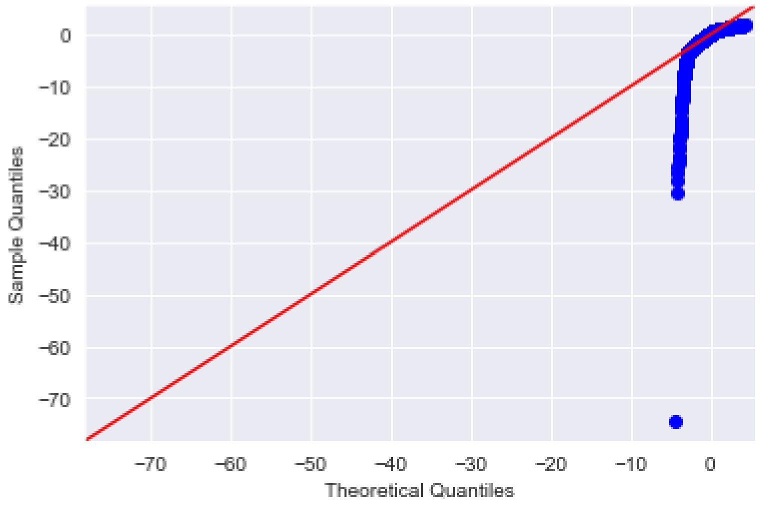
```
# adding the constant term
x = sm.add_constant(x)

# performing the regression
# and fitting the model
model2 = sm.OLS(y, x).fit()

# printing the summary table
print(model2.summary())
```

```
                            OLS Regression Results                            
==============================================================================
========
Dep. Variable:          logfare_amount   R-squared:                       
0.806
Model:                             OLS   Adj. R-squared:                  
0.806
Method:                  Least Squares   F-statistic:                     
2.966e+04
Date:                 Tue, 21 Jun 2022   Prob (F-statistic):              
0.00
Time:                         20:46:59   Log-Likelihood:                  
-16751.
No. Observations:               193218   AIC:                             
3.356e+04
Df Residuals:                   193190   BIC:                             
3.384e+04
Df Model:                           27                                         
Covariance Type:             nonrobust                                         
==============================================================================
==============
                      coef    std err          t      P>|t|      [0.0
25      0.975]
------------------------------------------------------------------------------
--------------
const             -30.5942      0.669    -45.729      0.000     -31.9
05     -29.283
fare_amount         0.0487      0.000    475.481      0.000       0.0
48       0.049
pickup_longitude -7.306e-05      0.000     -0.326      0.744      -0.0
01       0.000
year                0.0160      0.000     48.081      0.000       0.0
15       0.017
hour                0.0002   9.27e-05      1.912      0.056    -4.48e-
06       0.000
Distance            0.0181      0.000     72.947      0.000       0.0
18       0.019
month_2             0.0116      0.003      4.002      0.000       0.0
06       0.017
month_3             0.0108      0.003      3.838      0.000       0.0
05       0.016
month_4             0.0182      0.003      6.445      0.000       0.0
13       0.024
month_5             0.0194      0.003      6.882      0.000       0.0
14       0.025
month_6             0.0200      0.003      7.029      0.000       0.0
14       0.026
month_7             0.0235      0.003      7.883      0.000       0.0
18       0.029
```

```
month_8              0.0157      0.003      5.172      0.000       0.0
10        0.022
month_9              0.0310      0.003     10.451      0.000       0.0
25        0.037
month_10             0.0353      0.003     12.069      0.000       0.0
30        0.041
month_11             0.0323      0.003     10.876      0.000       0.0
26        0.038
month_12             0.0325      0.003     10.983      0.000       0.0
27        0.038
day_1                0.0144      0.002      6.200      0.000       0.0
10        0.019
day_2                0.0185      0.002      7.980      0.000       0.0
14        0.023
day_3                0.0211      0.002      9.203      0.000       0.0
17        0.026
day_4                0.0203      0.002      8.887      0.000       0.0
16        0.025
day_5                0.0196      0.002      8.523      0.000       0.0
15        0.024
day_6                0.0056      0.002      2.379      0.017       0.0
01        0.010
count_2              0.0113      0.002      6.530      0.000       0.0
08        0.015
count_3              0.0140      0.003      4.754      0.000       0.0
08        0.020
count_4              0.0150      0.004      3.603      0.000       0.0
07        0.023
count_5              0.0091      0.002      3.814      0.000       0.0
04        0.014
count_6              0.0130      0.004      3.120      0.002       0.0
05        0.021
======================================================================
========
Omnibus:                   213327.146   Durbin-Watson:
1.997
Prob(Omnibus):                  0.000   Jarque-Bera (JB):        30538
4481.833
Skew:                          -4.686   Prob(JB):
0.00
Kurtosis:                     197.537   Cond. No.
2.24e+06
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 2.24e+06. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

In [67]:

```
import scipy.stats as stats
residuals = model2.resid
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True, )
plt.show;
```




In [68]:

```
name = ['Jarque-Bera','Prob','Skew', 'Kurtosis']
test = sms.jarque_bera(model2.resid)
list(zip(name, test))
```

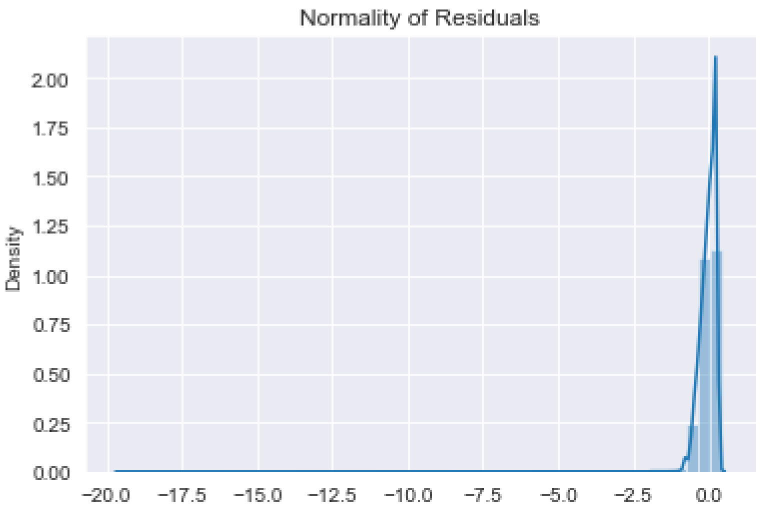
Out[68]:

```
[('Jarque-Bera', 305384481.83292425),
 ('Prob', 0.0),
 ('Skew', -4.68639662711109),
 ('Kurtosis', 197.53682722240424)]
```

In [69]:

```
#Histogram of Residuals
sns.distplot(model2.resid)
plt.title('Normality of Residuals')
plt.show()
```

```
/Users/kunjiv/opt/anaconda3/envs/learn-env/lib/python3.8/site-package
s/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt yo
ur code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```




Even though R2 is 0.806,the model is not satisfying normality so lets look into next model.

# Model 3

In [70]:

```
y = pd.DataFrame(data_log['logfare_amount'])
x = pd.DataFrame(data_log['logdistance'])
x = x.join(df['hour'])
```

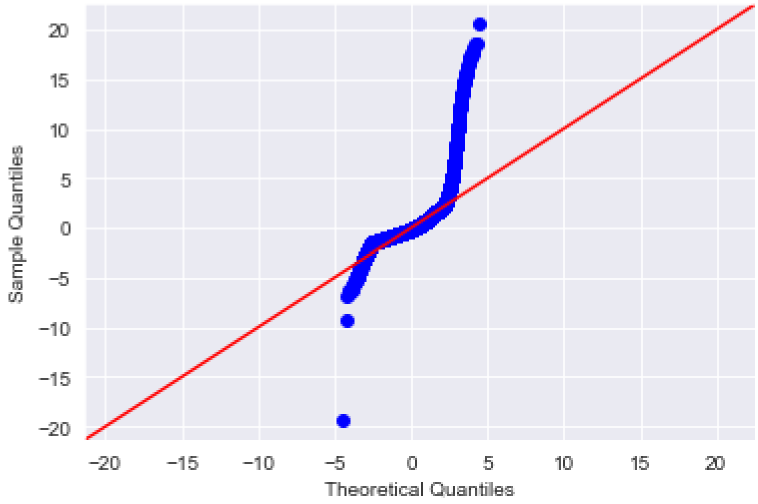
In [71]:

```
# adding the constant term
x = sm.add_constant(x)

# performing the regression
# and fitting the model
model3 = sm.OLS(y, x).fit()

# printing the summary table
print(model3.summary())
```

```
                            OLS Regression Results
==============================================================================
========
Dep. Variable:         logfare_amount   R-squared:
0.593
Model:                            OLS   Adj. R-squared:
0.593
Method:                 Least Squares   F-statistic:
1.409e+05
Date:                Tue, 21 Jun 2022   Prob (F-statistic):
0.00
Time:                        20:47:01   Log-Likelihood:
-88107.
No. Observations:              193218   AIC:
1.762e+05
Df Residuals:                  193215   BIC:
1.763e+05
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
=========
                  coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
---------
const           1.8296      0.002    854.810      0.000       1.825
1.834
logdistance     0.4843      0.001    530.703      0.000       0.483
0.486
hour           -0.0002      0.000     -1.469      0.142      -0.000
6.55e-05
==============================================================================
========
Omnibus:                   178710.333   Durbin-Watson:
1.998
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1854
9336.934
Skew:                           4.126   Prob(JB):
0.00
Kurtosis:                      50.286   Cond. No.
37.6
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

In [72]:

```
import scipy.stats as stats
residuals = model3.resid
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True, )
plt.show;
```




Normality Check (Jarque-Bera Test) The Jarque-Bera (JB) test is a test for normality. This test is usually used for large data sets, because other tests like Q-Q Plots can become unreliable when your sample size is large.

In [73]:

```
name = ['Jarque-Bera','Prob','Skew', 'Kurtosis']
test = sms.jarque_bera(model3.resid)
list(zip(name, test))
```

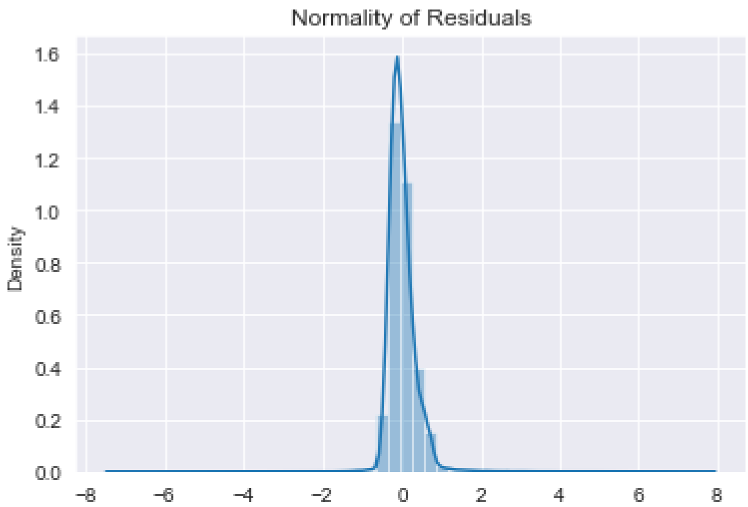
Out[73]:

```
[('Jarque-Bera', 18549336.934067406),
 ('Prob', 0.0),
 ('Skew', 4.125842356489469),
 ('Kurtosis', 50.28594393610232)]
```

In [74]:

```
#Histogram of Residuals
sns.distplot(model3.resid)
plt.title('Normality of Residuals')
plt.show()
```

```
/Users/kunjiv/opt/anaconda3/envs/learn-env/lib/python3.8/site-package
s/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt yo
ur code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```




The QQ plot is not having satifactory linear plot which might be due to skewed data.

# Validating the Model

In [75]:

```
from sklearn.model_selection import train_test_split
```

In [76]:

```
# split data into train subset and test subset for predictor and target variables
# 'test_size' returns the proportion of data to be included in the test set
# set 'random_state' to generate the same dataset each time you run the code
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_st

# check the dimensions of the train & test subset for
# print dimension of predictors train set
print("The shape of X_train is:",x_train.shape)

# print dimension of predictors test set
print("The shape of X_test is:",x_test.shape)

# print dimension of target train set
print("The shape of y_train is:",y_train.shape)

# print dimension of target test set
print("The shape of y_test is:",y_test.shape)
```

```
The shape of X_train is: (154574, 3)
The shape of X_test is: (38644, 3)
The shape of y_train is: (154574, 1)
The shape of y_test is: (38644, 1)
```

In [77]:

```
# Import and initialize the linear regression model class
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
```

In [78]:

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

Out[78]:

```
LinearRegression()
```

In [79]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Out[79]:

```
LinearRegression()
```

In [80]:

```
y_hat_train = linreg.predict(x_train)
y_hat_test = linreg.predict(x_test)
```

In [81]:

```

train_residuals = y_hat_train - y_train
test_residuals = y_hat_test - y_test
```

In [82]:

```
from sklearn.metrics import mean_squared_error

train_mse = mean_squared_error(y_train, y_hat_train)
test_mse = mean_squared_error(y_test, y_hat_test)
print('Train Mean Squarred Error:', train_mse)
print('Test Mean Squarred Error:', test_mse)
```

```
Train Mean Squarred Error: 0.1469148176444233
Test Mean Squarred Error: 0.14109311700096908
```

The Mean Squarred Error for the train and test subsets are similar. This suggests that the model will perform similarly on different data.

Distance,hour are the best fit for a multiple regression model. These features are highly correlated with fare amount, have relatively low multicollinearity, and can together account for more than half of the variability of price. All multiple regression assumptions are satisfied with these features included.