Final Version 1

September 25, 2018

In [77]:
```
# LOADING MODULES

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
%matplotlib inline

from pydoc import help
from scipy.stats.stats import pearsonr

from sklearn import datasets, linear_model
from sklearn import svm
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb

from sklearn.metrics import mean_squared_error, r2_score

from sklearn.cross_validation import cross_val_score, cross_val_predict
from sklearn import metrics

from datetime import datetime
from datetime import timedelta
import datetime as dt
import calendar

import math
```

In [2]:
```
# !conda install -c conda-forge haversine
# y
```

In [3]:
```
# !conda install -c conda-forge/label/gcc7 haversine
```

In [4]:
```
# READING TRAINING DATA
```

```
        train = pd.read_csv('./train.csv', nrows = 1000000)
        train.columns
```

```
Out[4]: Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
               'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
               'passenger_count'],
              dtype='object')
```

```
In [5]: # CHECK FOR NULL ENTRIES
        train[pd.isnull(train)].sum()
```

```
Out[5]: key                  0.0
        fare_amount          0.0
        pickup_datetime      0.0
        pickup_longitude     0.0
        pickup_latitude      0.0
        dropoff_longitude    0.0
        dropoff_latitude     0.0
        passenger_count      0.0
        dtype: float64
```

```
In [6]: # EXTRACT DATA FROM PICKUP_DATETIME FEATURE IN THE DATASET

        train['pickup_datetime'] = pd.to_datetime(train['pickup_datetime'], format = '%Y-%m-%d

        #train['pickup_date']= train['pickup_datetime'].dt.date

        train['pickup_hour']=train['pickup_datetime'].dt.hour
        train['pickup_day']=train['pickup_datetime'].dt.day
        train['pickup_month']=train['pickup_datetime'].dt.month
        train['pickup_year']=train['pickup_datetime'].dt.year
        train['pickup_day_of_week']=train['pickup_datetime'].apply(lambda x:calendar.day_name[
```

```
In [7]: print (train.shape)
        print (train.columns)
```

```
(1000000, 13)
Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'passenger_count', 'pickup_hour', 'pickup_day', 'pickup_day_of_week',
       'pickup_month', 'pickup_year'],
      dtype='object')
```

```
In [8]: # REMOVING ENTRIES WITH -VE FARE AMOUNT

        train=train.loc[train['fare_amount']>=0]

        print (train.shape)
```

```
(999962, 13)
```

TRUNCATING THE LONGITUDE AND LATTITUDE COORDINATES BASED ON THAT OF NEW YORK Used the below link to obtain the Boundary Co-ordinates of New York https://www.mapdevelopers.com/geocode_bounding_box.php

The boundaries of New York are:
North Latitude: 40.917577
South Latitude: 40.477399
East Longitude: -73.700272
West Longitude: -74.259090

Used the above to build a boundary by for the allowed Drop_off and Pick_up Longitude, Latittudes.

This method of data cleaning did not produce substantial results. On analysing the possible reasons for the bad behaviour of the model, I felt that the narrow possible values for the Longitude and Lattitude could be a reason. To verify the same, I checked the boundaries of the Longitudes and Lattitudes on the Test Data and found that a lot of samples had coordinates outside the above used boundary.

Inorder to cater to this issue, I used the Test Data to obtain the boundaries on the Lattitude and Longitude.

Which came out to be
North Latitude: 41.709555
South Latitude: 40.573143
East Longitude: -72.986532
West Longitude: -74.263242

Created the Boundary using the below values as Test Data contained co-ordinates a bit outside the boundaries specified by the link above.

```
In [9]: #Before we  ahead and identify outlier location, let us read the test data and see wha
        test =  pd.read_csv('./test.csv')

        print("Longitude Boundary in test data")
        print (min(test.pickup_longitude.min(), test.dropoff_longitude.min()),max(test.pickup_l

        print("Latitude Boundary in test data")
        print (min(test.pickup_latitude.min(), test.pickup_latitude.min()),max(test.pickup_lati
```

```
Longitude Boundary in test data
-74.263242 -72.986532
Latitude Boundary in test data
40.573143 41.709555
```

```
In [10]: # boundary={'min_lng':-74.263242,
         #           'min_lat':40.573143,
         #           'max_lng':-72.986532,
         #           'max_lat':41.709555}

         boundary={'north_lat':41.709555,
                   'south_lat':40.573143,
                   'east_long':-72.986532,
                   'west_long':-74.263242}
```

```
In [11]: # train[(train.pickup_latitude==0) | (train.pickup_longitude)==0 | (train.dropoff_lat

In [12]: train.loc[~((train.pickup_longitude >= boundary['west_long'] ) & (train.pickup_longitu
                     (train.pickup_latitude >= boundary['south_lat']) & (train.pickup_latitude
                     (train.dropoff_longitude >= boundary['west_long']) & (train.dropoff_longi
                     (train.dropoff_latitude >=boundary['south_lat']) & (train.dropoff_latitude
         train.loc[((train.pickup_longitude >= boundary['west_long'] ) & (train.pickup_longitu
                     (train.pickup_latitude >= boundary['south_lat']) & (train.pickup_latitude
                     (train.dropoff_longitude >= boundary['west_long']) & (train.dropoff_longi
                     (train.dropoff_latitude >=boundary['south_lat']) & (train.dropoff_latitude

         # print("Outlier vs Non Outlier Counts")
         # print(train['is_outlier_loc'].value_counts())

         train=train.loc[train['is_outlier_loc']==0]
         train.drop(['is_outlier_loc'],axis=1,inplace=True)
         print (train.shape)

(978799, 13)

In [13]: # CALCULATING HAVERSIAN DISTANCE

         def haversian_distance(lat1, lat2, lon1,lon2):
             p = 0.017453292519943295 # Pi/180
             a = 0.5 - np.cos((lat2 - lat1) * p)/2 + np.cos(lat1 * p) * np.cos(lat2 * p) * (1 -
             return 0.6213712 * 12742 * np.arcsin(np.sqrt(a))

         train['hav_distance'] = train.apply(lambda row:haversian_distance(row['pickup_latitude

In [14]: # CALCULATING EUCLEDIAN DISTANCE

         train['euc_distance'] = 69 * np.sqrt((np.array(train.dropoff_longitude) - np.array(tra

In [15]: print (train.columns)

Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'passenger_count', 'pickup_hour', 'pickup_day', 'pickup_day_of_week',
       'pickup_month', 'pickup_year', 'hav_distance', 'euc_distance'],
      dtype='object')
```

WEATHER DATA Used the below link for reference to obtain a part of New York Weather Data for the period that The Taxi Fare Dataset spans over.

https://sdaulton.github.io/TaxiPrediction/

The dataset set used is https://raw.githubusercontent.com/sdaulton/TaxiPrediction/master/data/nyc-weather-data.csv

This dataset covers Daily Summary of Weather of New York From Jan 1st 2009 to Nov 11th 2015.

In [16]:
```
# EXTRACTING FEATURES FROM THE WEATHER DATASET

weather=pd.read_csv("./Weather_Data.csv")

# Replacing Values with -9999 with 0 as they indicate Missing Data
weather.loc[weather.SNWD <= -9999, 'SNWD'] = 0
weather.loc[weather.SNOW <= -9999, 'SNOW'] = 0
weather.loc[weather.AWND <= -9999, 'AWND'] = 0

#Extracting the Year, Month, Day with the same Column Name as that of the Existing Da
weather['pickup_year'] = (weather['DATE']/10000).apply(math.floor)
weather['pickup_month'] = ((weather['DATE'].mod(10000))/100).apply(math.floor)
weather['pickup_day'] = weather['DATE'].mod(100)
weather = weather[['pickup_year','pickup_month','pickup_day','PRCP','SNWD','SNOW','TM

# weather['PRCP'] = weather['PRCP'] / 10.
# weather['TMAX'] = weather['TMAX'] / 10.
# weather['TMIN'] = weather['TMIN'] / 10.
# weather['AWND'] = weather['AWND'] / 10. * 3.6
weather.columns = ['pickup_year','pickup_month','pickup_day','precipitation','snow_de
```

In [17]:
```
# MERGING EXISTING DATA WITH WEATHER DATA TO GENERATE NEW FEATURES

train_new = pd.merge(train, weather, how='left', on=['pickup_year','pickup_month','pi

print (train_new.columns)
```

```
Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'passenger_count', 'pickup_hour', 'pickup_day', 'pickup_day_of_week',
       'pickup_month', 'pickup_year', 'hav_distance', 'euc_distance',
       'precipitation', 'snow_depth', 'snowfall', 'max_temp', 'min_temp',
       'avg_wind'],
      dtype='object')
```

In [18]:
```
# CHECKING FOR NULL VALUES

train_new[pd.isnull(train_new)].sum()
print (train_new.dtypes)
```

```
key                           object
fare_amount                  float64
pickup_datetime       datetime64[ns]
pickup_longitude             float64
pickup_latitude              float64
dropoff_longitude            float64
dropoff_latitude             float64
passenger_count                int64
```

```
pickup_hour                    int64
pickup_day                     int64
pickup_day_of_week            object
pickup_month                   int64
pickup_year                    int64
hav_distance                 float64
euc_distance                 float64
precipitation                  int64
snow_depth                     int64
snowfall                       int64
max_temp                       int64
min_temp                       int64
avg_wind                       int64
dtype: object
```

```
In [19]: # FINAL TRAIN DATA SET THAT WILL BE USED FOR TRAINING AND VALIDATION

         train = train_new
         print (train.columns)
         print (train.shape)
         print (train.dtypes)
```

```
Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'passenger_count', 'pickup_hour', 'pickup_day', 'pickup_day_of_week',
       'pickup_month', 'pickup_year', 'hav_distance', 'euc_distance',
       'precipitation', 'snow_depth', 'snowfall', 'max_temp', 'min_temp',
       'avg_wind'],
      dtype='object')
(978799, 21)
key                           object
fare_amount                  float64
pickup_datetime       datetime64[ns]
pickup_longitude             float64
pickup_latitude              float64
dropoff_longitude            float64
dropoff_latitude             float64
passenger_count                int64
pickup_hour                    int64
pickup_day                     int64
pickup_day_of_week            object
pickup_month                   int64
pickup_year                    int64
hav_distance                 float64
euc_distance                 float64
precipitation                  int64
snow_depth                     int64
```

```
snowfall                       int64
max_temp                       int64
min_temp                       int64
avg_wind                       int64
dtype: object
```

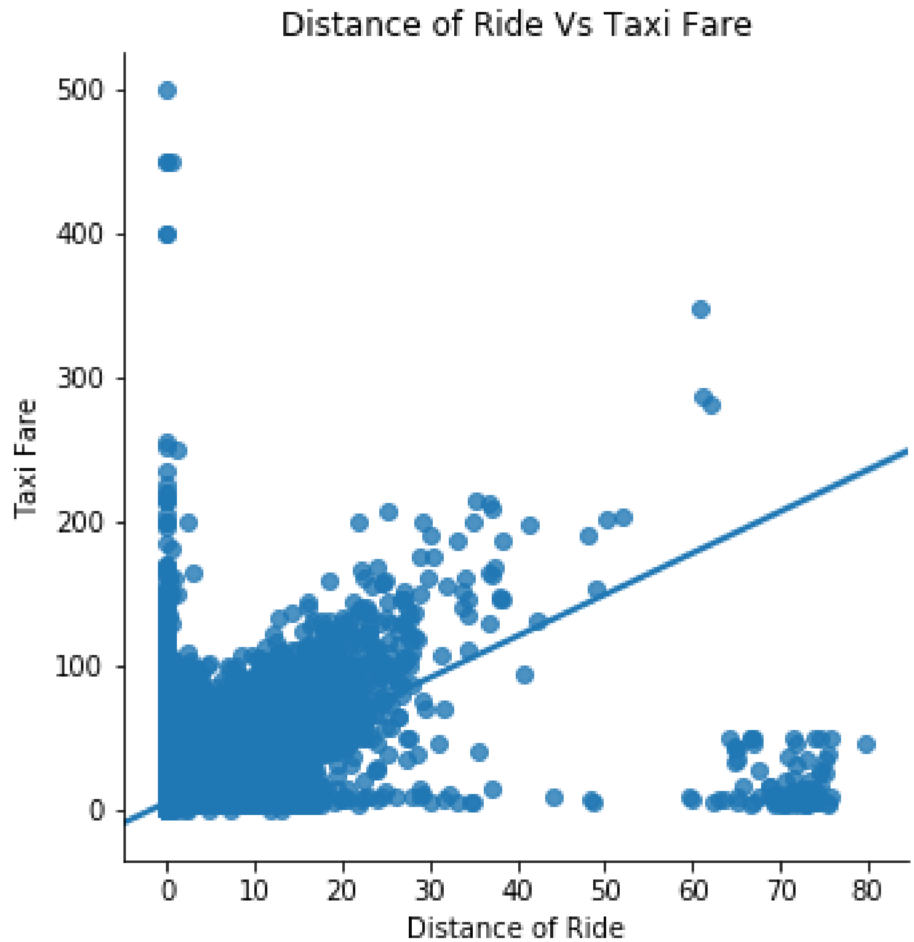
PEARSON CORRELATION

```
In [20]: print ("Corr between Eucledian Distance and Fare Amount")
         corr = pearsonr(train.fare_amount, train.euc_distance)
         print (corr)
```

```
Corr between Eucledian Distance and Fare Amount
(0.8257585563383683, 0.0)
```

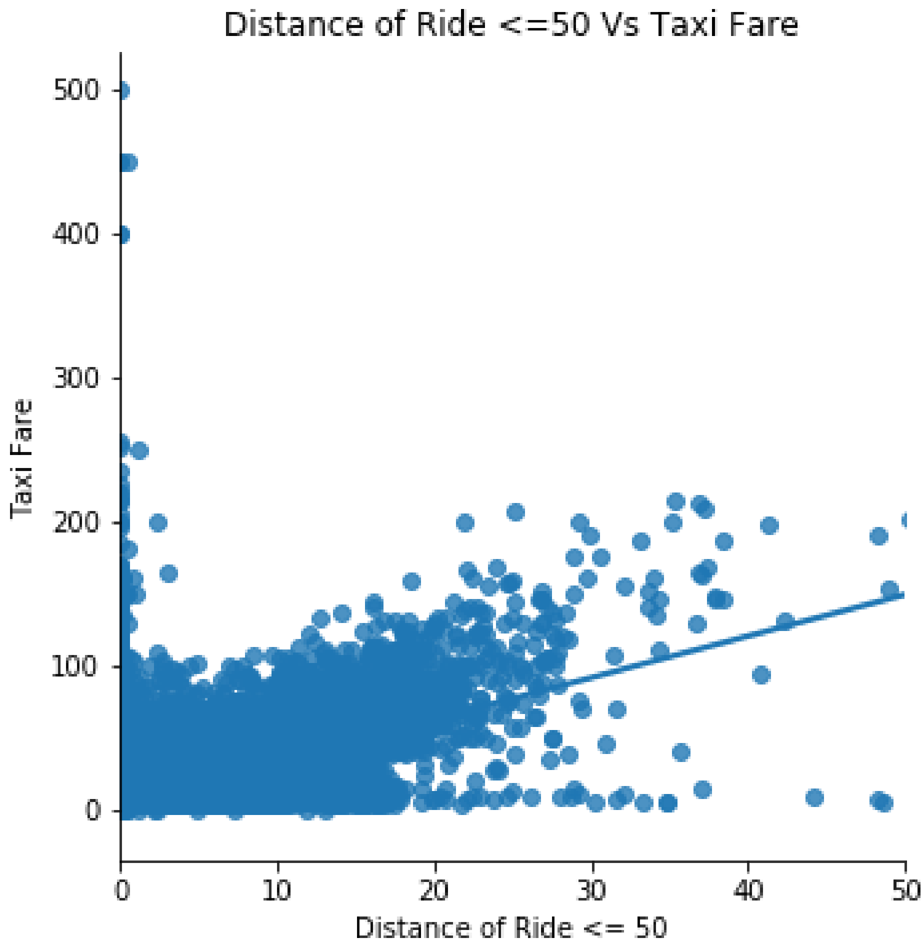
```
In [120]: # Scatter Plot Between Eucledian Distance and Fare Amount

          sns.lmplot(x='euc_distance', y='fare_amount', data=train)

          plt.title('Distance of Ride Vs Taxi Fare')
          # Set x-axis label
          plt.xlabel('Distance of Ride')
          # Set y-axis label
          plt.ylabel('Taxi Fare')
```

```
Out[120]: Text(3.8,0.5,'Taxi Fare')
```



In [122]:
```
# Scatter Plot Between Eucledian Distance <=50 and Fare Amount

lm = sns.lmplot(x='euc_distance', y='fare_amount', data=train)

lm.set(xlim=(0, 50))
plt.title('Distance of Ride <=50 Vs Taxi Fare')
# Set x-axis label
plt.xlabel('Distance of Ride <= 50')
# Set y-axis label
plt.ylabel('Taxi Fare')
```

Out[122]: Text(3.8,0.5,'Taxi Fare')

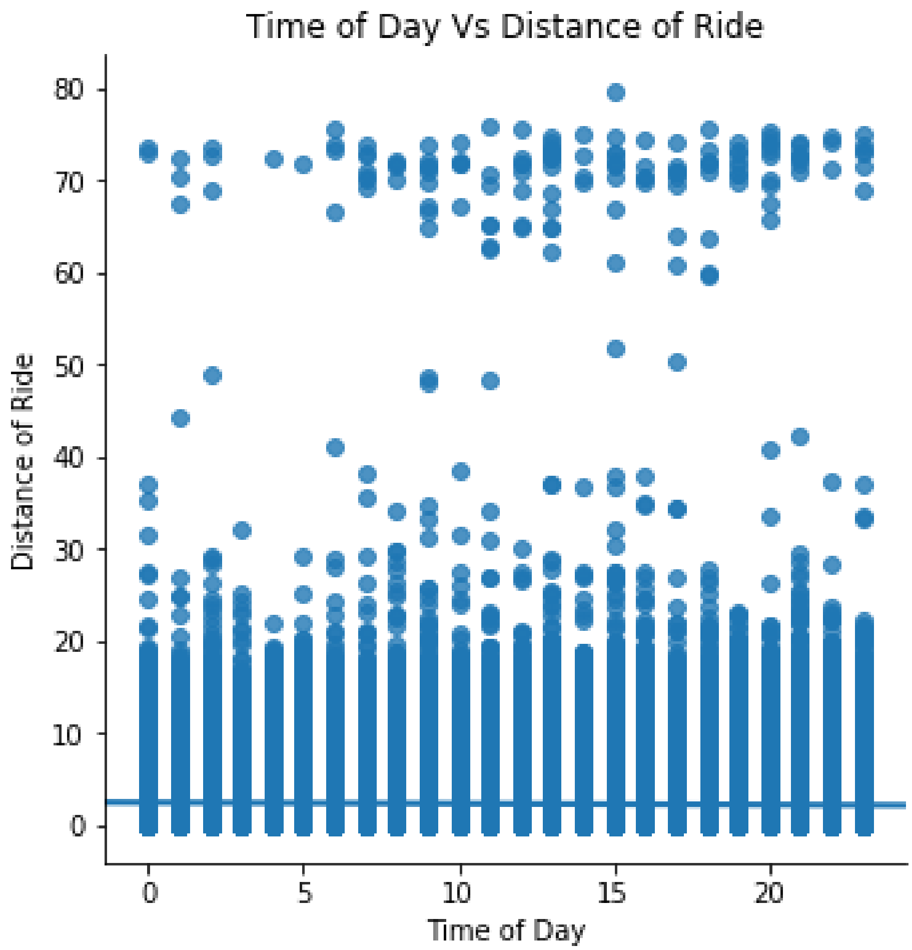



```
In [22]: # pickup_hour is distributed from 0-23 for each hour
         print ("Corr between Time of the Day and Eucledian Distance")
         corr = pearsonr(train.euc_distance, train.pickup_hour)
         print (corr)
```

```
Corr between Time of the Day and Eucledian Distance
(-0.030505480979840977, 3.470537802458462e-200)
```

```
In [105]: # Scatter Plot Between Eucledian Distance and Time of the Day

          sns.lmplot(x='pickup_hour', y='euc_distance', data=train)

          plt.title('Time of Day Vs Distance of Ride')
          # Set x-axis label
          plt.xlabel('Time of Day')
          # Set y-axis label
          plt.ylabel('Distance of Ride')
```

Out[105]: Text(10.05,0.5,'Distance of Ride')

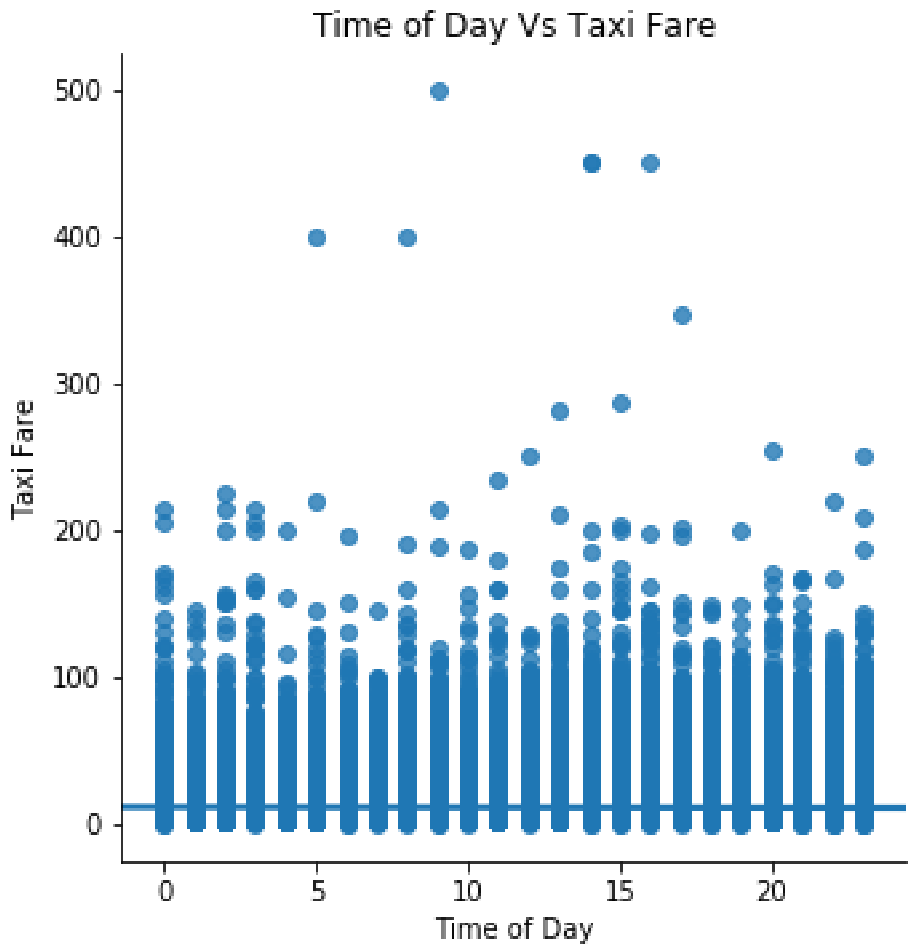


In [24]:
```
print ("Corr between Time of the Day and Fare Amount")
corr = pearsonr(train.fare_amount, train.pickup_hour)
print (corr)
```

```
Corr between Time of the Day and Fare Amount
(-0.01927381911008901, 4.469411432095102e-81)
```

In [106]:
```
# Scatter Plot Between Fare Amount and Time of the Day

sns.lmplot(x='pickup_hour', y='fare_amount', data=train)

plt.title('Time of Day Vs Taxi Fare')
# Set x-axis label
plt.xlabel('Time of Day')
# Set y-axis label
plt.ylabel('Taxi Fare')
```

Out[106]: Text(3.8,0.5,'Taxi Fare')



OTHER INTERESTING PLOTS AND CORRELATIONS BETWEEN CERTAIN FEATURES

In [26]:
```
# Checking the Correlation between Fare Amount and all other Features

print ("Corr between Fare Amount and all other parameters")
print (train.corr('pearson')["fare_amount"])
```

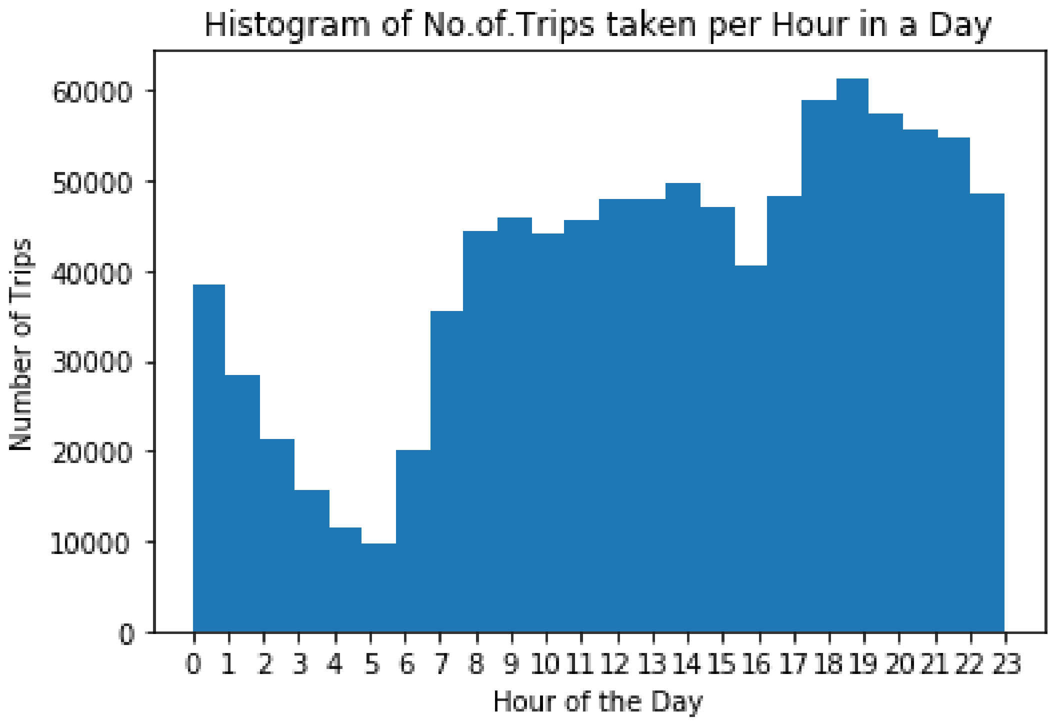
```
Corr between Fare Amount and all other parameters
fare_amount          1.000000
pickup_longitude     0.385422
pickup_latitude     -0.187734
dropoff_longitude    0.302614
dropoff_latitude    -0.152105
passenger_count      0.014255
pickup_hour         -0.019274
```

```
pickup_day           0.001666
pickup_month         0.025464
pickup_year          0.116534
hav_distance         0.817532
euc_distance         0.825759
precipitation       -0.005898
snow_depth           0.003205
snowfall            -0.007590
max_temp             0.010604
min_temp             0.010626
avg_wind            -0.022123
Name: fare_amount, dtype: float64
```

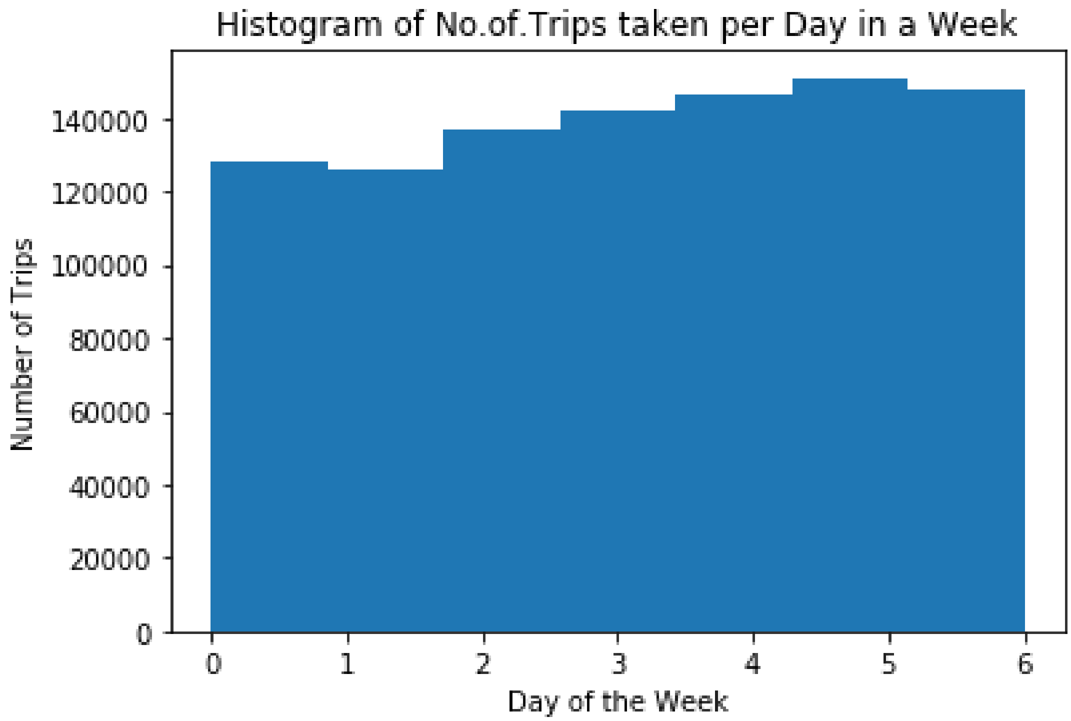
In [27]:
```python
# And, checking the Correlation between Haversian Distance and all other Features

print ("Corr between Haversian Distance and all other parameters")
print (train.corr('pearson')["hav_distance"])
```

```
Corr between Haversian Distance and all other parameters
fare_amount          0.817532
pickup_longitude     0.430822
pickup_latitude     -0.151202
dropoff_longitude    0.339358
dropoff_latitude    -0.124345
passenger_count      0.010201
pickup_hour         -0.030179
pickup_day           0.001794
pickup_month         0.013716
pickup_year          0.019573
hav_distance         1.000000
euc_distance         0.993842
precipitation       -0.009177
snow_depth          -0.006396
snowfall            -0.008801
max_temp             0.019485
min_temp             0.018716
avg_wind            -0.014780
Name: hav_distance, dtype: float64
```

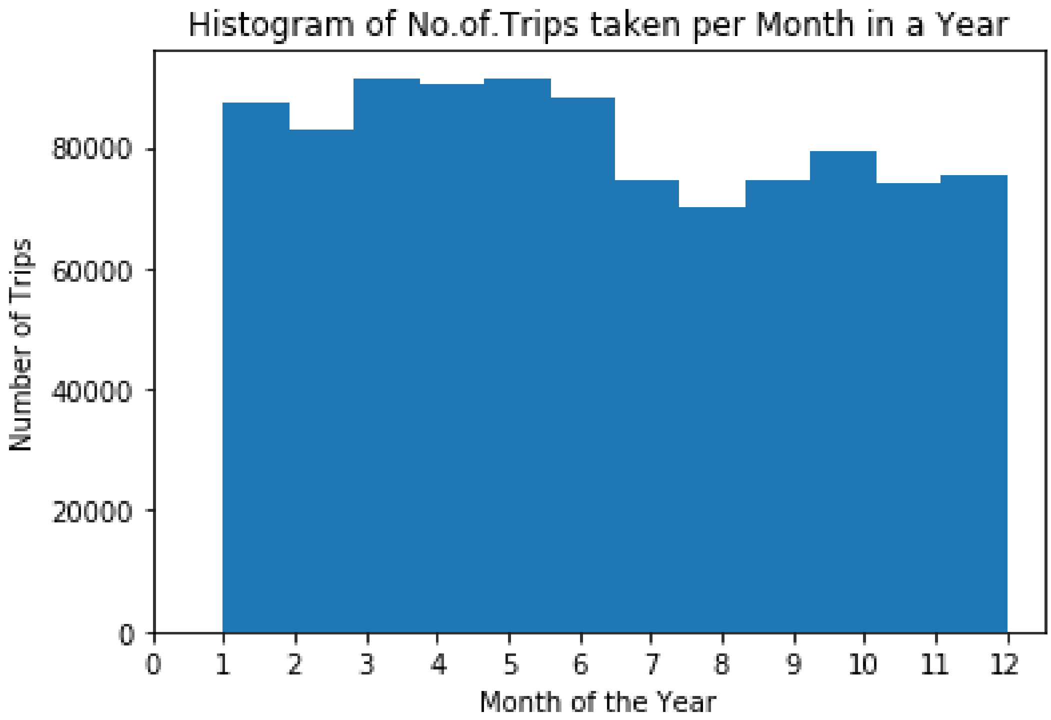
In [32]:
```python
# Histogram of No.of.Trips taken per Hour in a Day

plt.hist(train.pickup_hour, bins=24)
plt.xticks(np.arange(0,24,step=1))
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Trips')
plt.title('Histogram of No.of.Trips taken per Hour in a Day')
plt.show()
```



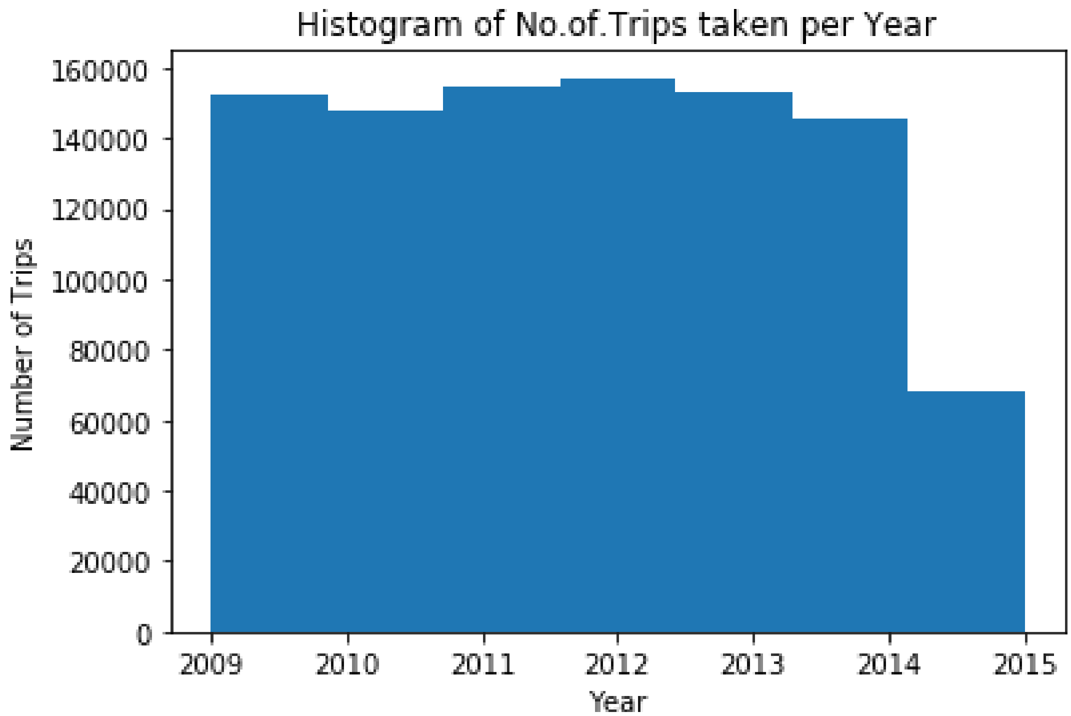

```
In [54]: # Histogram of No.of.Trips taken per Day in a Week

         def encodeDays(day_of_week):
             day_dict={'Sunday':0,'Monday':1,'Tuesday':2,'Wednesday':3,'Thursday':4,'Friday':5
             return day_dict[day_of_week]
         train['pickup_day_of_week']=train['pickup_day_of_week'].apply(lambda x:encodeDays(x))

         plt.hist(train.pickup_day_of_week, bins=7)
         plt.xticks(np.arange(0,7,step=1))
         plt.xlabel('Day of the Week')
         plt.ylabel('Number of Trips')
         plt.title('Histogram of No.of.Trips taken per Day in a Week')
         plt.show()
```



In [35]:
```
# Histogram of No.of.Trips taken per Month in a Year

plt.hist(train.pickup_month, bins=12)
plt.xticks(np.arange(0,13,step=1))
plt.xlabel('Month of the Year')
plt.ylabel('Number of Trips')
plt.title('Histogram of No.of.Trips taken per Month in a Year')
plt.show()
```

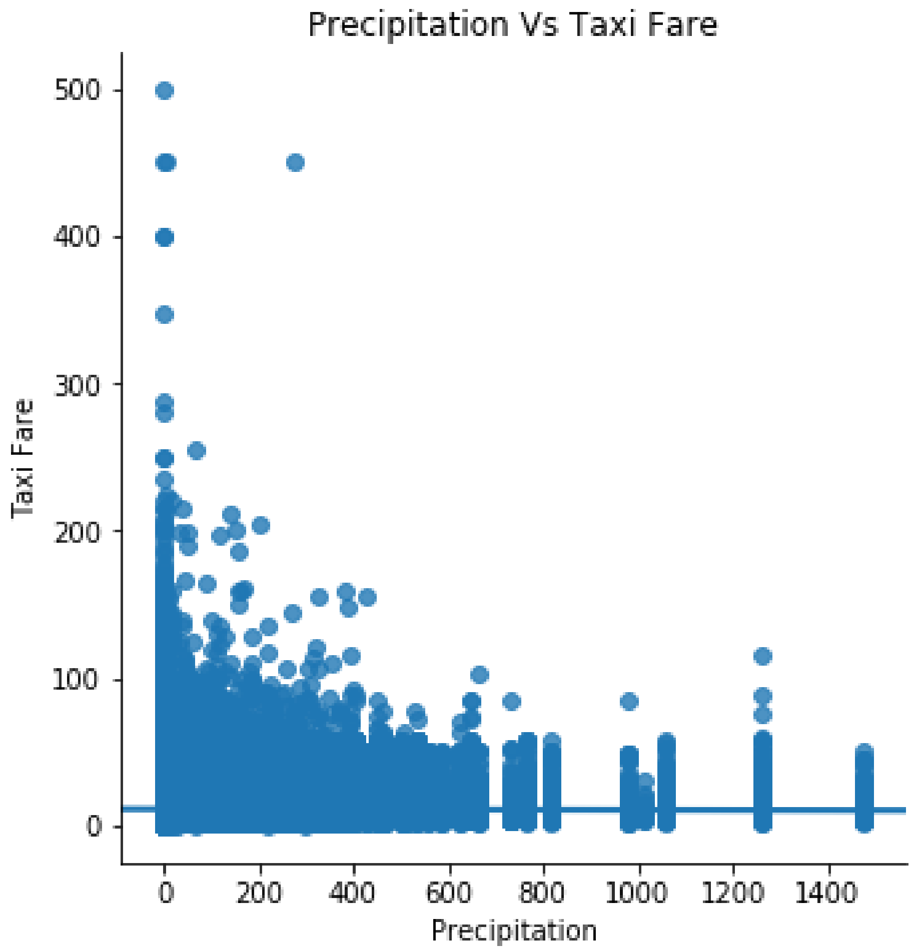



```
In [36]: # Histogram of No.of.Trips taken per Year

         plt.hist(train.pickup_year, bins=8)
         plt.xticks(np.arange(2009,2016,step=1))
         plt.xlabel('Year')
         plt.ylabel('Number of Trips')
         plt.title('Histogram of No.of.Trips taken per Year')
         plt.show()
```

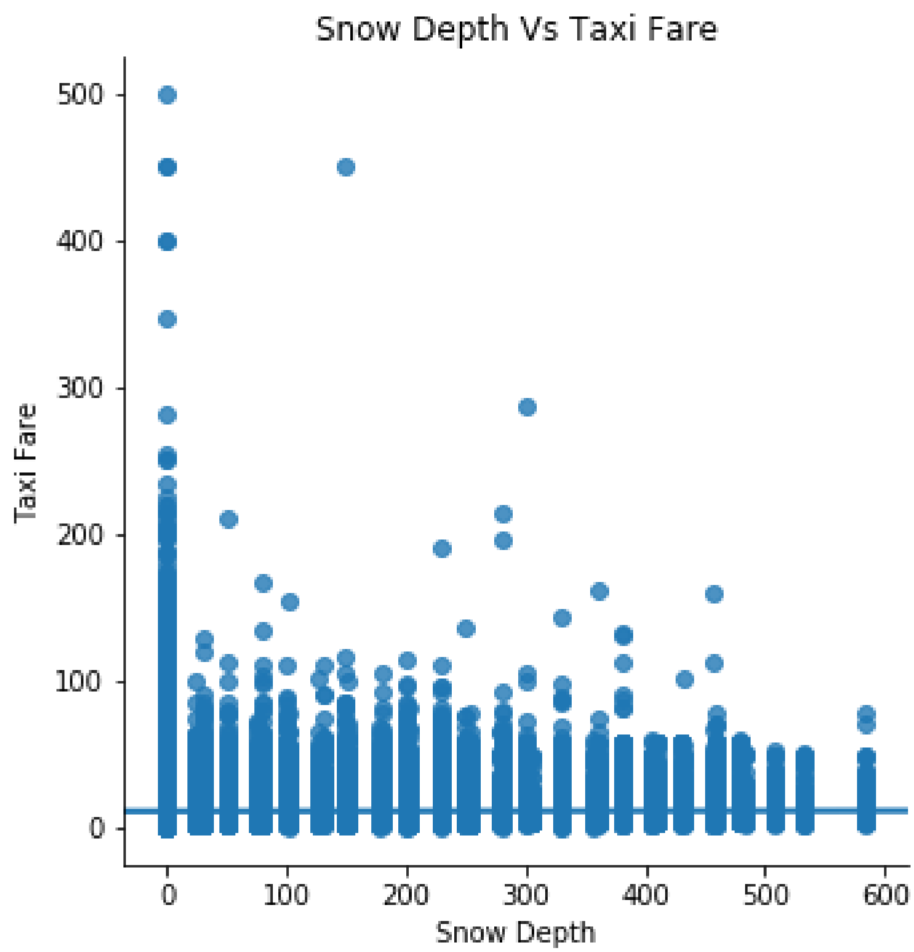


PLOTS BETWEEN FARE AMOUNT AND WEATHER CONDITIONS

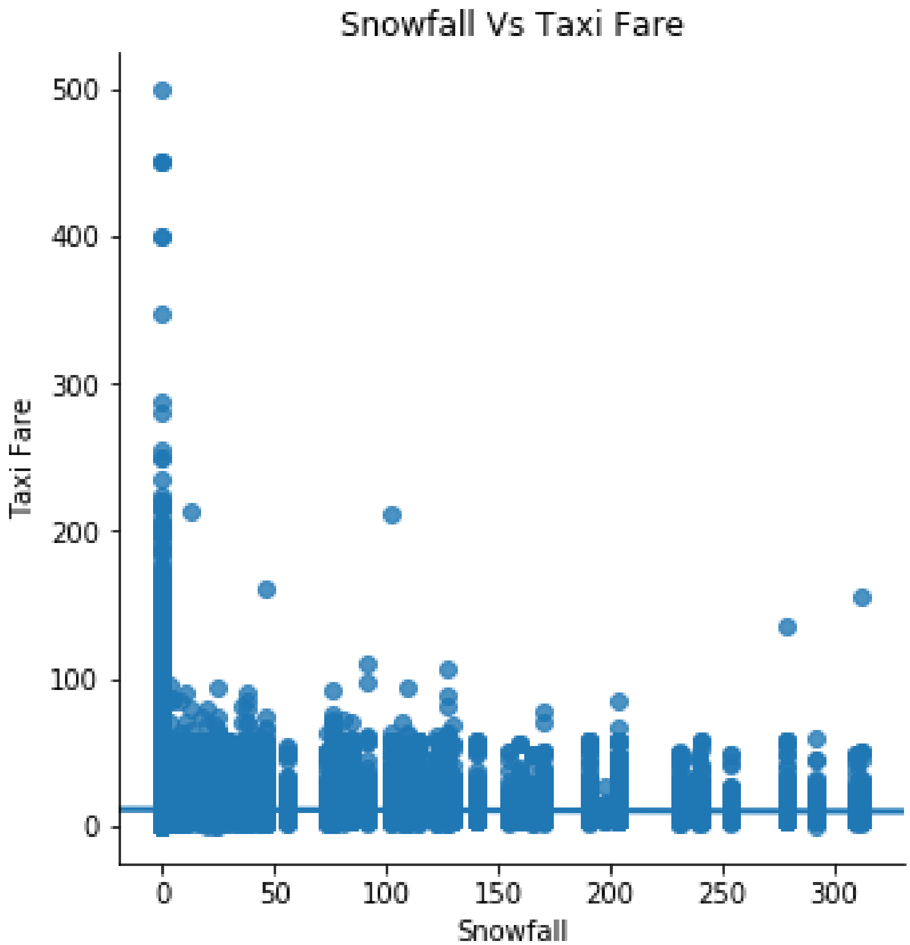
```
In [123]: sns.lmplot(x='precipitation', y='fare_amount', data=train)

          plt.title('Precipitation Vs Taxi Fare')
          # Set x-axis label
          plt.xlabel('Precipitation')
          # Set y-axis label
          plt.ylabel('Taxi Fare')

Out[123]: Text(3.8,0.5,'Taxi Fare')
```



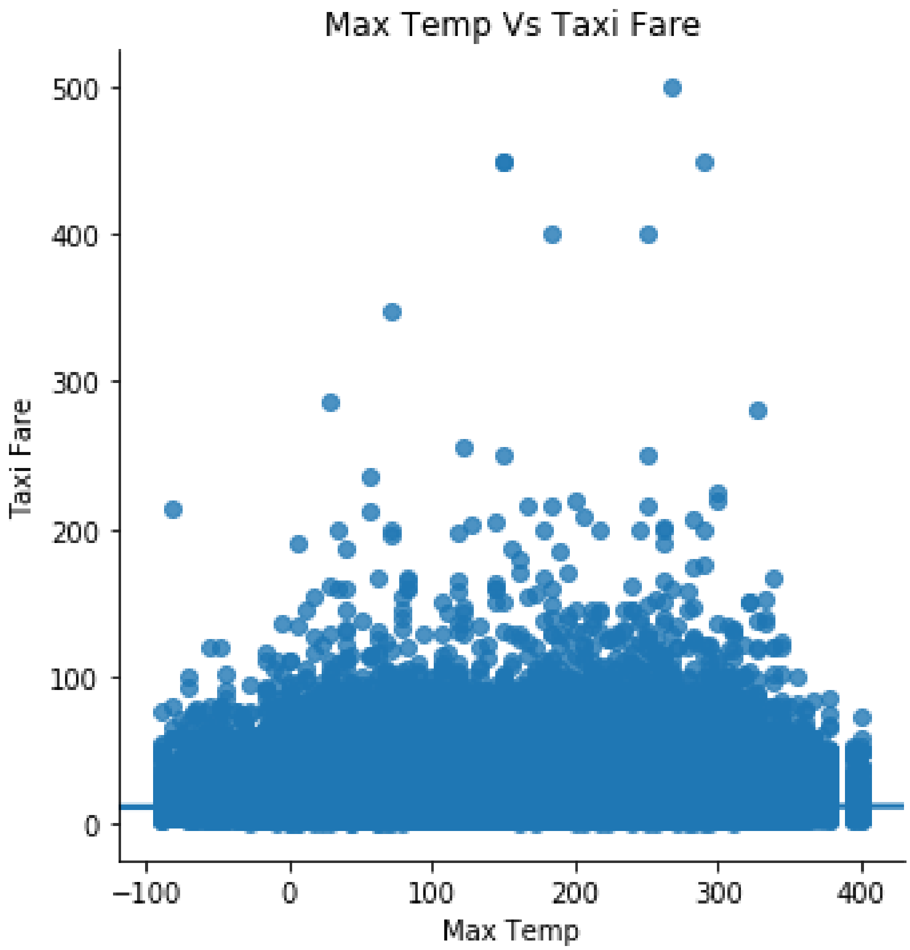

```
In [108]: sns.lmplot(x='snow_depth', y='fare_amount', data=train)

          plt.title('Snow Depth Vs Taxi Fare')
          # Set x-axis label
          plt.xlabel('Snow Depth')
          # Set y-axis label
          plt.ylabel('Taxi Fare')

Out[108]: Text(3.8,0.5,'Taxi Fare')
```




```
In [109]: sns.lmplot(x='snowfall', y='fare_amount',data=train)

          plt.title('Snowfall Vs Taxi Fare')
          # Set x-axis label
          plt.xlabel('Snowfall')
          # Set y-axis label
          plt.ylabel('Taxi Fare')

Out[109]: Text(3.8,0.5,'Taxi Fare')
```

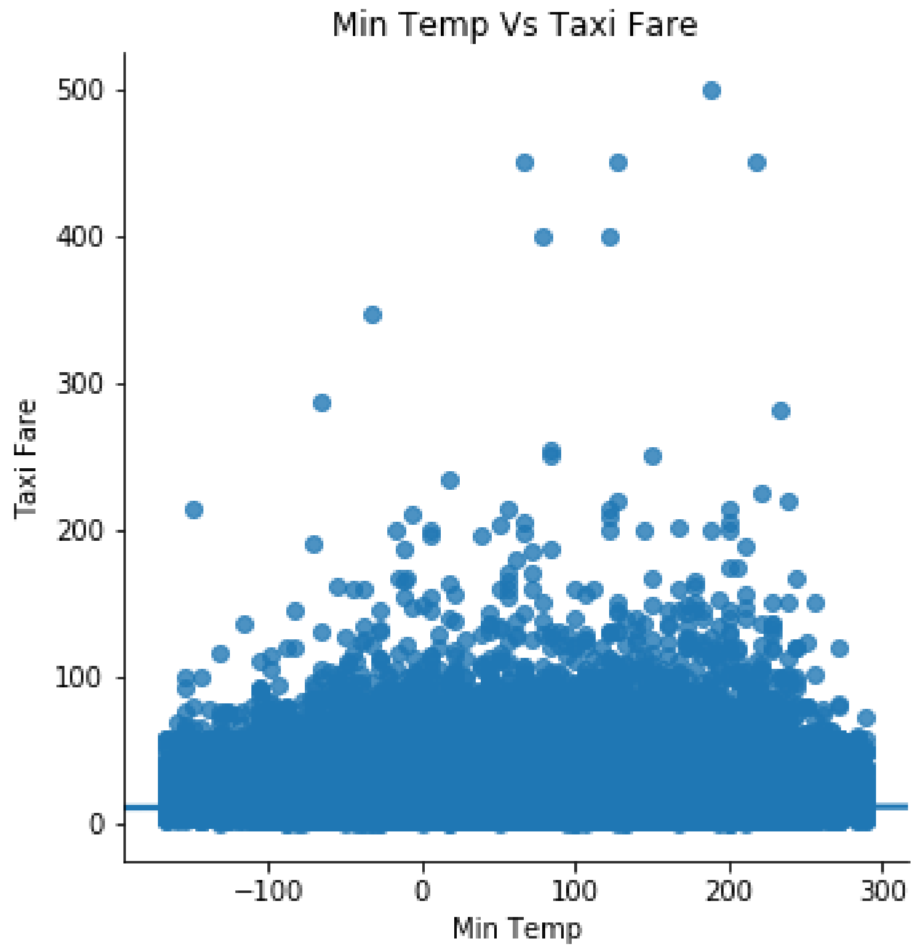



```
In [110]: sns.lmplot(x='max_temp', y='fare_amount',data=train)

          plt.title('Max Temp Vs Taxi Fare')
          # Set x-axis label
          plt.xlabel('Max Temp')
          # Set y-axis label
          plt.ylabel('Taxi Fare')

Out[110]: Text(3.8,0.5,'Taxi Fare')
```

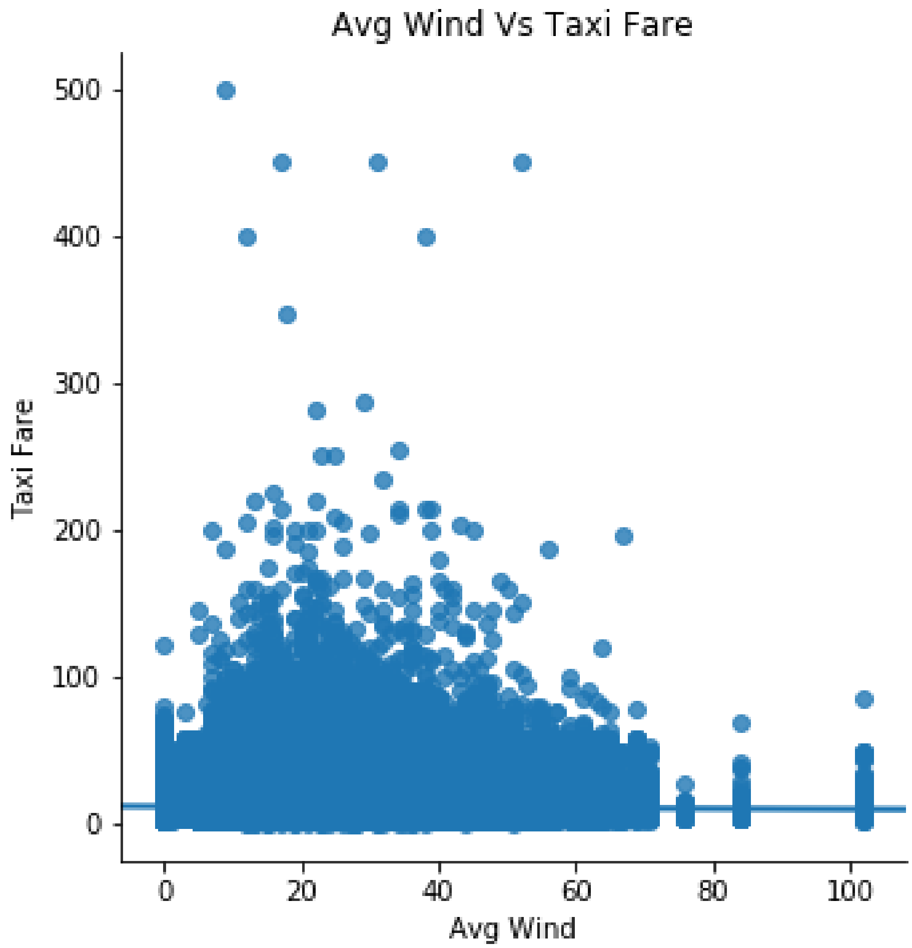


In [111]:
```
sns.lmplot(x='min_temp', y='fare_amount',data=train)

plt.title('Min Temp Vs Taxi Fare')
# Set x-axis label
plt.xlabel('Min Temp')
# Set y-axis label
plt.ylabel('Taxi Fare')
```

Out[111]: Text(3.8,0.5,'Taxi Fare')

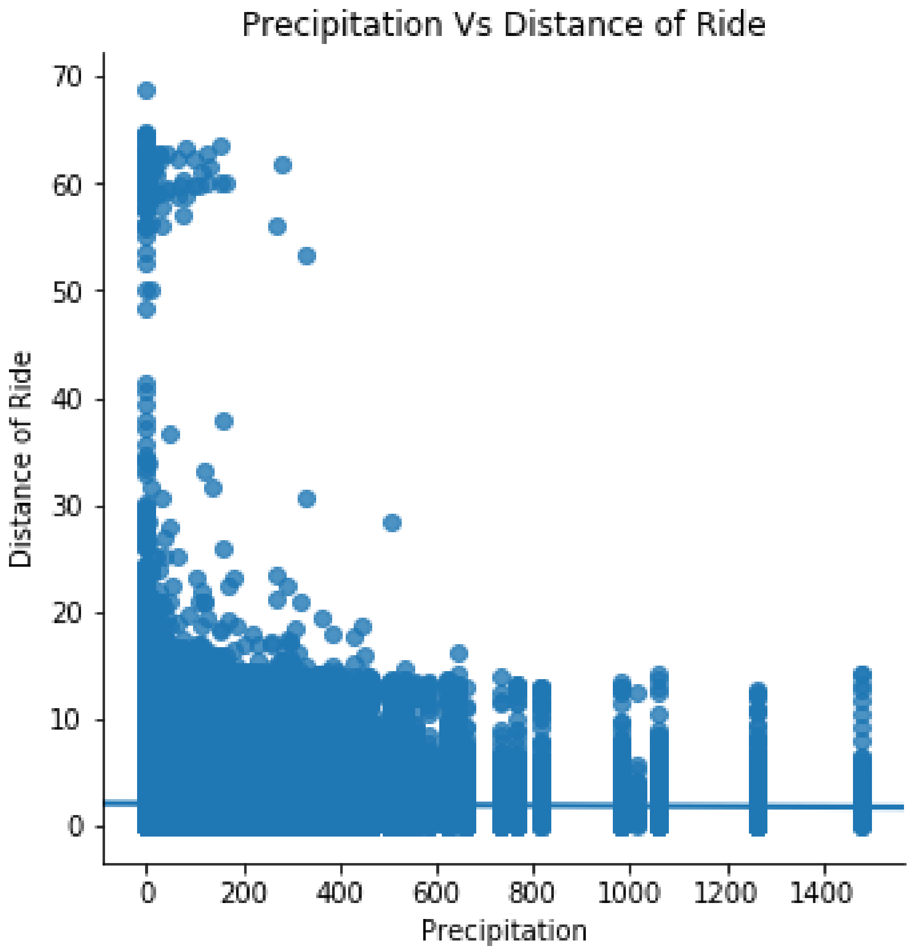



```
In [112]: sns.lmplot(x='avg_wind', y='fare_amount', data=train)

          plt.title('Avg Wind Vs Taxi Fare')
          # Set x-axis label
          plt.xlabel('Avg Wind')
          # Set y-axis label
          plt.ylabel('Taxi Fare')

Out[112]: Text(3.8,0.5,'Taxi Fare')
```



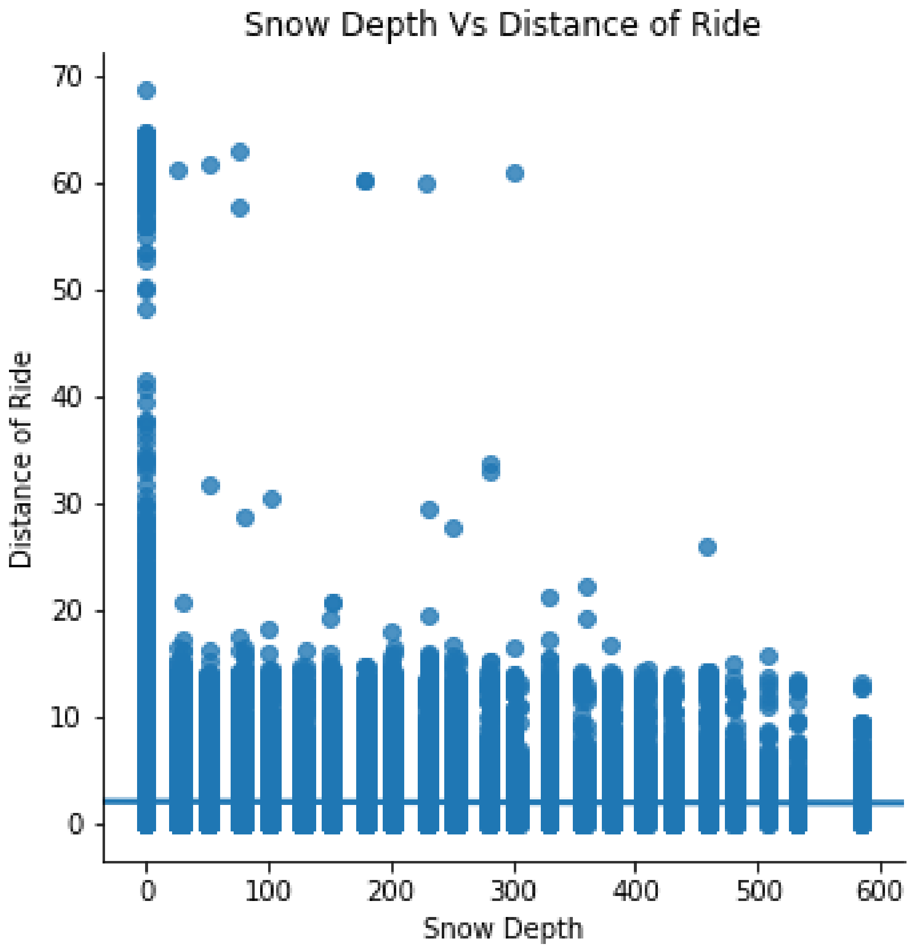
PLOTS BETWEEN TRIP DISTANCE AND WEATHER CONDITIONS

```
In [113]: sns.lmplot(x='precipitation', y='hav_distance', data=train)

          plt.title('Precipitation Vs Distance of Ride')
          # Set x-axis label
          plt.xlabel('Precipitation')
          # Set y-axis label
          plt.ylabel('Distance of Ride')

Out[113]: Text(10.05,0.5,'Distance of Ride')
```

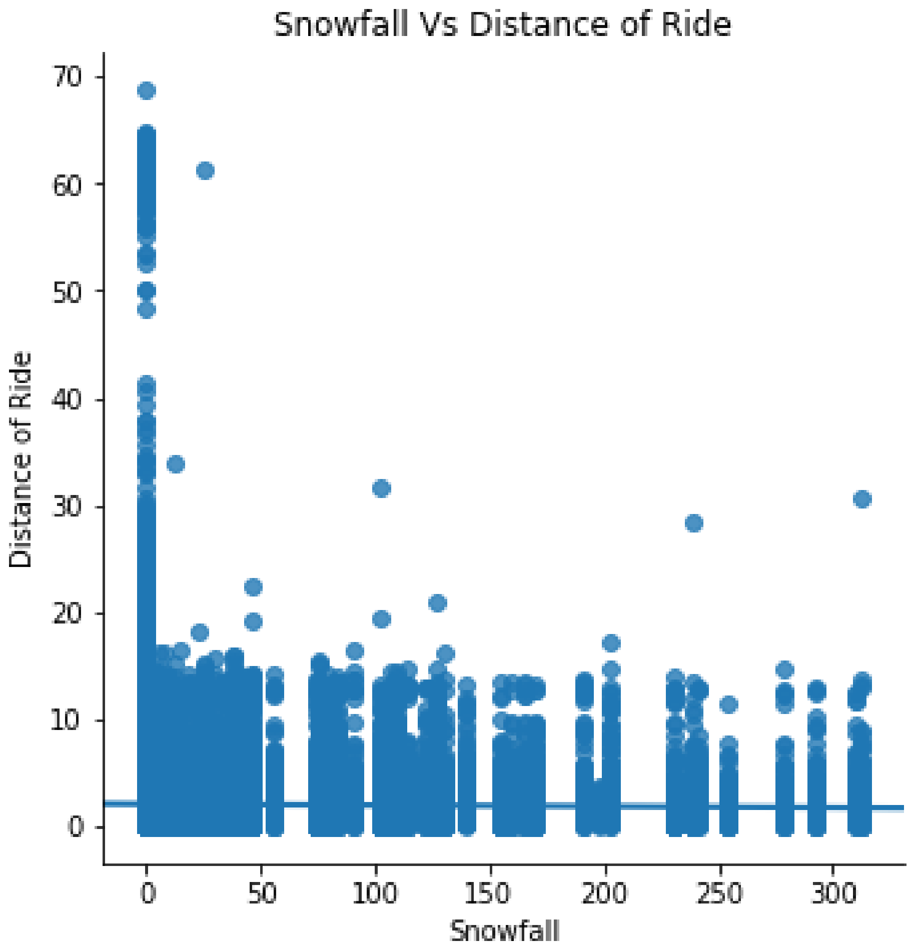


In [114]:
```
sns.lmplot(x='snow_depth', y='hav_distance', data=train)

plt.title('Snow Depth Vs Distance of Ride')
# Set x-axis label
plt.xlabel('Snow Depth')
# Set y-axis label
plt.ylabel('Distance of Ride')
```

Out[114]:
```
Text(10.05,0.5,'Distance of Ride')
```

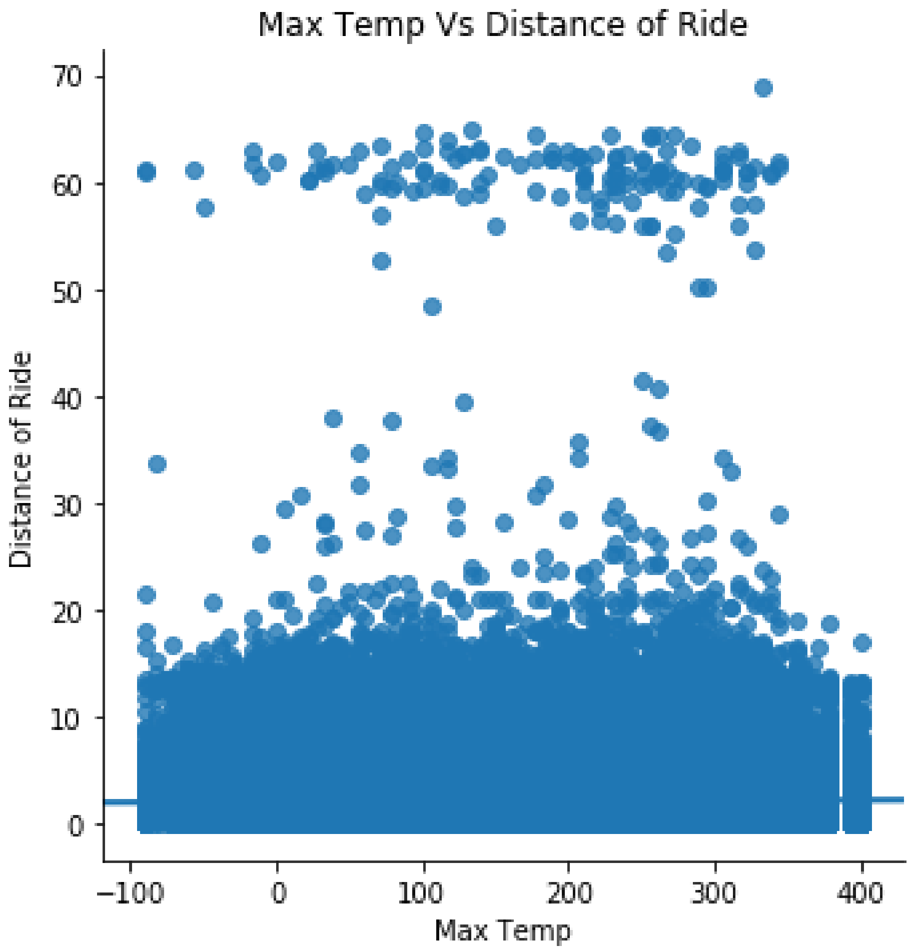



```
In [115]: sns.lmplot(x='snowfall', y='hav_distance',data=train)

          plt.title('Snowfall Vs Distance of Ride')
          # Set x-axis label
          plt.xlabel('Snowfall')
          # Set y-axis label
          plt.ylabel('Distance of Ride')

Out[115]: Text(10.05,0.5,'Distance of Ride')
```



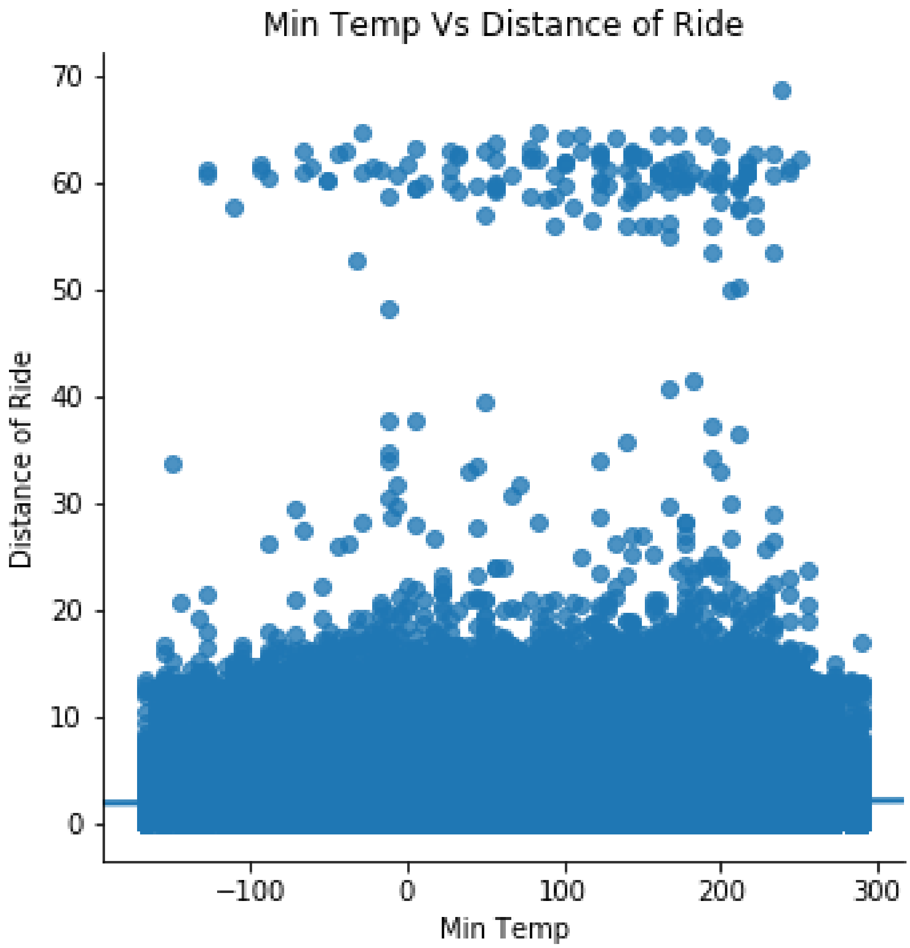
In [119]:
```
sns.lmplot(x='max_temp', y='hav_distance',data=train)

plt.title('Max Temp Vs Distance of Ride')
# Set x-axis label
plt.xlabel('Max Temp')
# Set y-axis label
plt.ylabel('Distance of Ride')
```

Out[119]:
```
Text(10.05,0.5,'Distance of Ride')
```

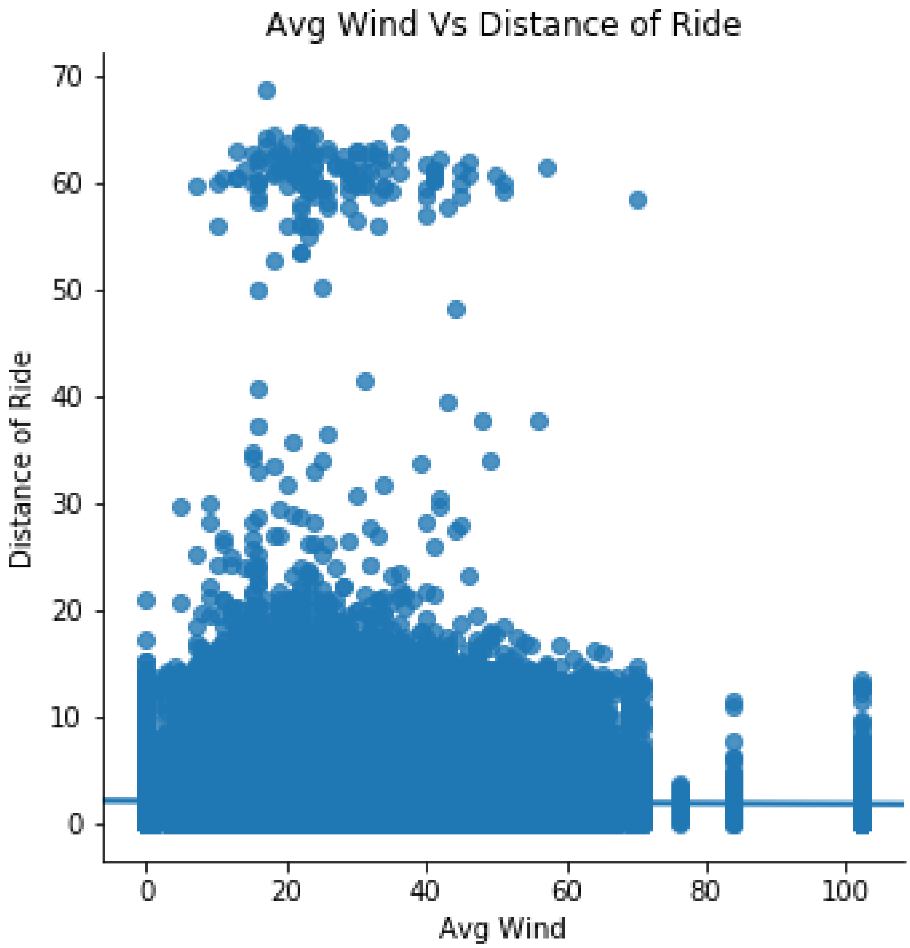


In [117]:
```
sns.lmplot(x='min_temp', y='hav_distance',data=train)

plt.title('Min Temp Vs Distance of Ride')
# Set x-axis label
plt.xlabel('Min Temp')
# Set y-axis label
plt.ylabel('Distance of Ride')
```

Out[117]:
```
Text(10.05,0.5,'Distance of Ride')
```




```
In [118]: sns.lmplot(x='avg_wind', y='hav_distance', data=train)

          plt.title('Avg Wind Vs Distance of Ride')
          # Set x-axis label
          plt.xlabel('Avg Wind')
          # Set y-axis label
          plt.ylabel('Distance of Ride')

Out[118]: Text(10.05,0.5,'Distance of Ride')
```



PROCESSING TEST DATA

```
In [66]: # Pre-Processing Test Data

         test =  pd.read_csv('./test.csv')
         test['pickup_datetime']=pd.to_datetime(test['pickup_datetime'],format='%Y-%m-%d %H:%M

         test['pickup_date']= test['pickup_datetime'].dt.date
         test['pickup_day']=test['pickup_datetime'].dt.day
         test['pickup_hour']=test['pickup_datetime'].dt.hour
         test['pickup_day_of_week']=test['pickup_datetime'].apply(lambda x:calendar.day_name[x
         test['pickup_month']=test['pickup_datetime'].dt.month
         test['pickup_year']=test['pickup_datetime'].dt.year


         test['hav_distance']=test.apply(lambda row:haversian_distance(row['pickup_latitude'],
         test['euc_distance'] = 69 * np.sqrt((np.array(test.dropoff_longitude) - np.array(test
```

In [67]: # Merging with Weather Data to obtain extra Features

```
test_new = pd.merge(test, weather, how='left', on=['pickup_year','pickup_month','picku
print (test_new.columns)
```

```
Index(['key', 'pickup_datetime', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'passenger_count',
       'pickup_date', 'pickup_day', 'pickup_hour', 'pickup_day_of_week',
       'pickup_month', 'pickup_year', 'hav_distance', 'euc_distance',
       'precipitation', 'snow_depth', 'snowfall', 'max_temp', 'min_temp',
       'avg_wind'],
      dtype='object')
```

In [68]: # Checking for NULL Values

```
test_new[pd.isnull(test_new)].sum()
print (test_new.dtypes)
```

```
key                          object
pickup_datetime      datetime64[ns]
pickup_longitude            float64
pickup_latitude             float64
dropoff_longitude           float64
dropoff_latitude            float64
passenger_count               int64
pickup_date                  object
pickup_day                    int64
pickup_hour                   int64
pickup_day_of_week           object
pickup_month                  int64
pickup_year                   int64
hav_distance                float64
euc_distance                float64
precipitation                 int64
snow_depth                    int64
snowfall                      int64
max_temp                      int64
min_temp                      int64
avg_wind                      int64
dtype: object
```

In [69]: # Final Test Set that will be Used For Testing

```
test = test_new
print (test.columns)
print (test.shape)
print (test.dtypes)
```

```
Index(['key', 'pickup_datetime', 'pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'passenger_count',
       'pickup_date', 'pickup_day', 'pickup_hour', 'pickup_day_of_week',
       'pickup_month', 'pickup_year', 'hav_distance', 'euc_distance',
       'precipitation', 'snow_depth', 'snowfall', 'max_temp', 'min_temp',
       'avg_wind'],
      dtype='object')
(9914, 21)
key                           object
pickup_datetime       datetime64[ns]
pickup_longitude             float64
pickup_latitude              float64
dropoff_longitude            float64
dropoff_latitude             float64
passenger_count                int64
pickup_date                   object
pickup_day                     int64
pickup_hour                    int64
pickup_day_of_week            object
pickup_month                   int64
pickup_year                    int64
hav_distance                 float64
euc_distance                 float64
precipitation                  int64
snow_depth                     int64
snowfall                       int64
max_temp                       int64
min_temp                       int64
avg_wind                       int64
dtype: object
```

PREPARING TRAIN AND VALIDATION SET FROM TRAINING DATA

```
In [124]: # Considering all the Features except 'Key', 'pickup_date', 'pickup_day_of_week' and
          traindata = train[train.columns[3:]]
          traindata = traindata[traindata.columns.difference(['pickup_day_of_week'])]
          traindata = traindata[traindata.columns.difference(['pickup_date'])]
          traindata = traindata[traindata.columns.difference(['euc_distance'])]

          # Trainoutput is the Fare Amount column
          trainoutput = train[train.columns[1:2]]

          # Considering 2/3rd of the data for Training and 1/3rd for Validation
          x, y = traindata.shape
          x1 = 2 * int(x / 3)

          traindata_X = traindata[0:x1]
```

```
testdata_X = traindata[x1:x]

traindata_Y = trainoutput[0:x1]
testdata_Y = trainoutput[x1:x]

x, y
print (traindata.columns)
```

```
Index(['avg_wind', 'dropoff_latitude', 'dropoff_longitude', 'hav_distance',
       'max_temp', 'min_temp', 'passenger_count', 'pickup_day', 'pickup_hour',
       'pickup_latitude', 'pickup_longitude', 'pickup_month', 'pickup_year',
       'precipitation', 'snow_depth', 'snowfall'],
      dtype='object')
```

PREPARING TEST DATA

```
In [125]: # Considering all Features except 'Key', 'pickup_date', 'pickup_day_of_week'
          testdata = test[test.columns[2:]]
          testdata = testdata[testdata.columns.difference(['pickup_day_of_week'])]
          testdata = testdata[testdata.columns.difference(['pickup_date'])]
          testdata = testdata[testdata.columns.difference(['euc_distance'])]

          print (testdata.columns)
```

```
Index(['avg_wind', 'dropoff_latitude', 'dropoff_longitude', 'hav_distance',
       'max_temp', 'min_temp', 'passenger_count', 'pickup_day', 'pickup_hour',
       'pickup_latitude', 'pickup_longitude', 'pickup_month', 'pickup_year',
       'precipitation', 'snow_depth', 'snowfall'],
      dtype='object')
```

0.1 PREDICTION MODELS

LINEAR REGRESSION MODEL

```
In [126]: #TRAINING USING LINEAR REGRESSION

          regr = linear_model.LinearRegression()
          regr.fit(traindata_X, traindata_Y)
          testdata_Y_pred_LR = regr.predict(testdata_X)

          # The coefficients
          print('Coefficients: \n', regr.coef_)

          # ERROR METRICS

          # Root Mean Square Error
          rmse = np.sqrt(mean_squared_error(testdata_Y, testdata_Y_pred_LR))
```

```
print("RMSE: %f" % (rmse))

# The Mean Squared Error
print("Mean squared error: %.2f"
      % mean_squared_error(testdata_Y, testdata_Y_pred_LR))

# R2 Score
print('Variance score: %.2f' % r2_score(testdata_Y, testdata_Y_pred_LR))
```

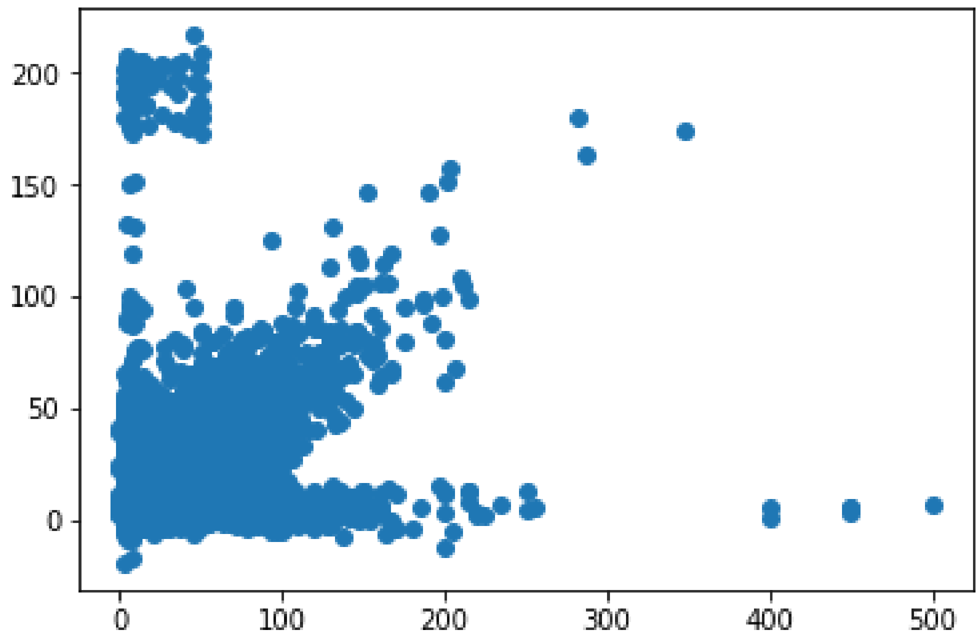
```
Coefficients:
 [[ 1.60929997e-04 -1.36371540e+01  1.07266298e+01  3.16495014e+00
  -1.10849266e-03  4.61756423e-04  3.70720804e-02  1.90155047e-03
   9.94131511e-03 -2.05127099e+01  1.40138653e+01  7.91423303e-02
   5.36076031e-01  2.81981289e-04  1.78000353e-05 -9.99671939e-04]]
RMSE: 5.255454
Mean squared error: 27.62
Variance score: 0.70
```

```
In [127]: # TESTING ON TEST USED USING THE ABOVE MODEL

          actual_testdata_pred_lr = regr.predict(testdata)

          #EXPORTING PREDICTIONS TO CSV

          key = pd.DataFrame(test[test.columns[0:1]])

          key['fare_amount'] = actual_testdata_pred_lr
          key.to_csv('test_predictions_lr.csv')
```

USING K-FOLD CROSS VALIDATION The whole traindata and trainoutput are used here without splitting.
K-Fold does the splitting based on K (Here K=6)

```
In [78]: # USING K-FOLD CROSS VALIDATION

         scores = cross_val_score(regr, traindata, trainoutput, cv=6)
         print ("Cross validated scores:", scores)

         predictions = cross_val_predict(regr, traindata, trainoutput, cv=6)
         plt.scatter(trainoutput, predictions)

         accuracy = metrics.r2_score(trainoutput, predictions)
         print ("Cross-Predicted Accuracy:", accuracy)
```

```
Cross validated scores: [0.67103047 0.67908206 0.70298945 0.71866223 0.70759829 0.71236777]
Cross-Predicted Accuracy: 0.6984046393131362
```




```
In [79]: actual_testdata_pred_lr = regr.predict(testdata)

         #EXPORTING PREDICTIONS TO CSV

         key = pd.DataFrame(test[test.columns[0:1]])

         key['fare_amount'] = actual_testdata_pred_lr
         key.to_csv('test_predictions_lr_cv.csv')
```

DECISION TREE REGRESSOR MODEL

```
In [137]: # TRAINING USING DECISION TREE REGRESSOR MODEL

          dtr = DecisionTreeRegressor().fit(traindata_X, traindata_Y)
          testdata_Y_pred_DTR = dtr.predict(testdata_X)

          # Error Metrics

          # Root Mean Square Error
          rmse = np.sqrt(mean_squared_error(testdata_Y, testdata_Y_pred_DTR))
          print("RMSE: %f" % (rmse))

          # Mean Squared Error
          print("Mean squared error: %.2f"
                % mean_squared_error(testdata_Y, testdata_Y_pred_DTR))
```

```
# R2 Score
print('Variance score: %.2f' % r2_score(testdata_Y, testdata_Y_pred_DTR))
```

```
RMSE: 5.733288
Mean squared error: 32.87
Variance score: 0.64
```

```
In [138]: actual_testdata_pred_dtr = dtr.predict(testdata)

          #EXPORTING PREDICTIONS TO CSV

          key = pd.DataFrame(test[test.columns[0:1]])

          key['fare_amount'] = actual_testdata_pred_dtr
          key.to_csv('test_predictions_dtr.csv')
```

RANDOM FOREST REGRESSOR MODEL

```
In [128]: #TRAINING USING RANDOM FOREST REGRESSOR

          rf = RandomForestRegressor()
          rf.fit(traindata_X, traindata_Y)
          testdata_Y_pred_RFR = rf.predict(testdata_X)

          # Error Metrics

          # Root Mean Square Error
          rmse = np.sqrt(mean_squared_error(testdata_Y, testdata_Y_pred_RFR))
          print("RMSE: %f" % (rmse))

          # Mean Squared Error
          print("Mean squared error: %.2f"
                % mean_squared_error(testdata_Y, testdata_Y_pred_RFR))

          # R2 Score
          print('Variance score: %.2f' % r2_score(testdata_Y, testdata_Y_pred_RFR))
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:4: DataConversionWarning: A colum
  after removing the cwd from sys.path.


RMSE: 3.953216
Mean squared error: 15.63
Variance score: 0.83
```

```
In [129]: actual_testdata_pred_rfr = rf.predict(testdata)
```

```
#EXPORTING PREDICTIONS TO CSV

key = pd.DataFrame(test[test.columns[0:1]])

key['fare_amount'] = actual_testdata_pred_rfr
key.to_csv('test_predictions_rfr.csv')
```

XGB REGRESSOR

```
In [130]: #TRAINING USING XGB REGRESSOR

          xg_reg = xgb.XGBRegressor()
          xg_reg.fit(traindata_X,traindata_Y)
          testdata_Y_pred_XGB = xg_reg.predict(testdata_X)

          # Error Metrics

          # Root Mean Square Error
          rmse = np.sqrt(mean_squared_error(testdata_Y, testdata_Y_pred_XGB))
          print("RMSE: %f" % (rmse))

          # Mean Square Error
          print("Mean squared error: %.2f"
                % mean_squared_error(testdata_Y, testdata_Y_pred_XGB))

          # R2 Score
          print('Variance score: %.2f' % r2_score(testdata_Y, testdata_Y_pred_XGB))
```

```
RMSE: 3.925925
Mean squared error: 15.41
Variance score: 0.83
```

```
In [131]: actual_testdata_pred_xgb = xg_reg.predict(testdata)

          #EXPORTING PREDICTIONS TO CSV

          key = pd.DataFrame(test[test.columns[0:1]])

          key['fare_amount'] = actual_testdata_pred_xgb
          key.to_csv('test_predictions_xgb.csv')
```

XGB WITH HYPERPARAMETERS

```
In [132]: dtrain = xgb.DMatrix(traindata_X, label=traindata_Y)
          dtest = xgb.DMatrix(testdata_X)

          #set parameters for xgboost
```

```
params = {'max_depth':7,
          'eta':1,
          'silent':1,
          'objective':'reg:linear',
          'eval_metric':'rmse',
          'learning_rate':0.1
         }
num_rounds = 50

xb = xgb.train(params, dtrain, num_rounds)

y_pred_xgb = xb.predict(dtest)

rmse = np.sqrt(mean_squared_error(testdata_Y, y_pred_xgb))
print("RMSE: %f" % (rmse))

print("Mean squared error: %.2f"
      % mean_squared_error(testdata_Y, y_pred_xgb))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % r2_score(testdata_Y, y_pred_xgb))
```

```
RMSE: 3.779267
Mean squared error: 14.28
Variance score: 0.84
```

Tried changing the Parameters to check for better performance

```
In [133]: dtrain = xgb.DMatrix(traindata_X, label=traindata_Y)
          dtest = xgb.DMatrix(testdata_X)

          #Set parameters for xgboost
          params = {'max_depth':9,
                    'eta':1,
                    'silent':1,
                    'objective':'reg:linear',
                    'eval_metric':'rmse',
                    'learning_rate':0.1
                   }
          num_rounds = 100

          xb = xgb.train(params, dtrain, num_rounds)

          y_pred_xgb = xb.predict(dtest)

          # Error Metrics

          # Root Mean Square Error
```

```
rmse = np.sqrt(mean_squared_error(testdata_Y, y_pred_xgb))
print("RMSE: %f" % (rmse))

# Mean Squared Error
print("Mean squared error: %.2f"
      % mean_squared_error(testdata_Y, y_pred_xgb))

# R2 Score
print('Variance score: %.2f' % r2_score(testdata_Y, y_pred_xgb))
```

```
RMSE: 3.692071
Mean squared error: 13.63
Variance score: 0.85
```

Tried changing the Parameters again. ##### This gave the best performance among all the previous models.

```
In [134]: dtrain = xgb.DMatrix(traindata_X, label=traindata_Y)
          dtest = xgb.DMatrix(testdata_X)

          #set parameters for xgboost
          params = {'max_depth':10,
                    'eta':1,
                    'silent':1,
                    'objective':'reg:linear',
                    'eval_metric':'rmse',
                    'learning_rate':0.15
                   }
          num_rounds = 100

          xb = xgb.train(params, dtrain, num_rounds)

          y_pred_xgb = xb.predict(dtest)

          # Error Metrics

          # Root Mean Square Error
          rmse = np.sqrt(mean_squared_error(testdata_Y, y_pred_xgb))
          print("RMSE: %f" % (rmse))

          # Mean Squared Error
          print("Mean squared error: %.2f"
                % mean_squared_error(testdata_Y, y_pred_xgb))

          # R2 Score
          print('Variance score: %.2f' % r2_score(testdata_Y, y_pred_xgb))
```

```
RMSE: 3.641732
Mean squared error: 13.26
```

```
Variance score: 0.86
```

```
In [135]: dtest_actual = xgb.DMatrix(testdata)
          actual_testdata_pred_xgb_params = xb.predict(dtest_actual)

          #EXPORTING PREDICTIONS TO CSV

          key = pd.DataFrame(test[test.columns[0:1]])

          key['fare_amount'] = actual_testdata_pred_xgb_params
          key.to_csv('test_predictions_xgb_params.csv')
```

Below Plot shows the importance of each feature towards building the Prediction Model.

```
In [136]: xgb.plot_importance(xb)
          plt.rcParams['figure.figsize'] = [7, 7]
          plt.show()
```