Bike Demand Forecasting

Bike-sharing system are meant to rent the bicycle and return to the different place for the bike sharing purpose in Washington DC.
The dataset contains rental data spanning for 2 years. The aim is to predict the total count of bikes rented during each hour covered by the test set, using only information available prior to the rental period.

Data Fields

dteday : date

season : season (1:winter, 2:spring, 3:summer, 4:fall)

yr : year (0: 2011, 1:2012)

mnth : month (1 to 12)

hr : hour (0 to 23)

holiday : weather day is holiday or not (extracted from [Web Link])

weekday : day of the week

workingday : if day is neither weekend nor holiday is 1, otherwise is 0.

temp : Normalized temperature in Celsius. The values are derived via (t-t_min)/(t_max-t_min), t_min=-8, t_max=+39 (only in hourly scale)

atemp: Normalized feeling temperature in Celsius. The values are derived via (t-t_min)/(t_max-t_min), t_min=-16, t_max=+50 (only in hourly scale)

hum: Normalized humidity. The values are divided to 100 (max)

windspeed: Normalized wind speed. The values are divided to 67 (max)

casual: count of casual users

registered: count of registered users

count: count of total rental bikes including both casual and registere

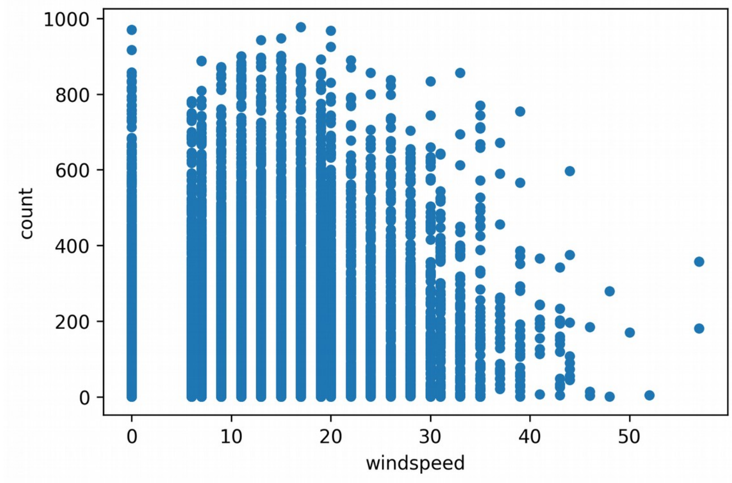
Approach

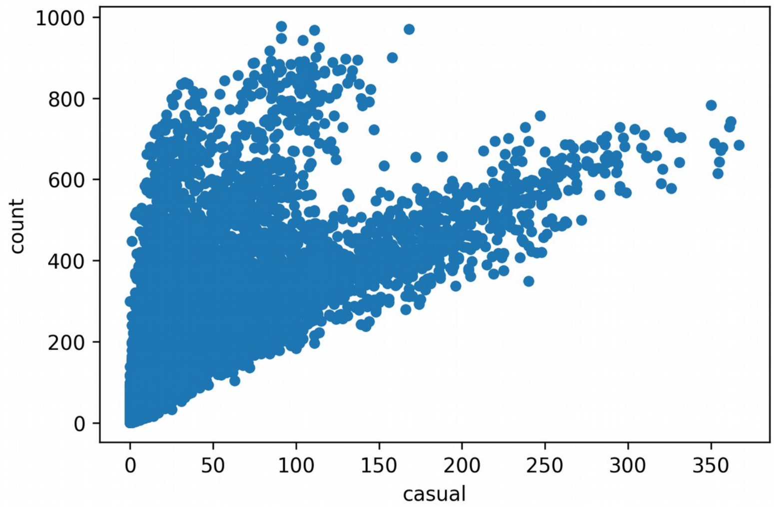
Python is used for data proceesing and Visualization.

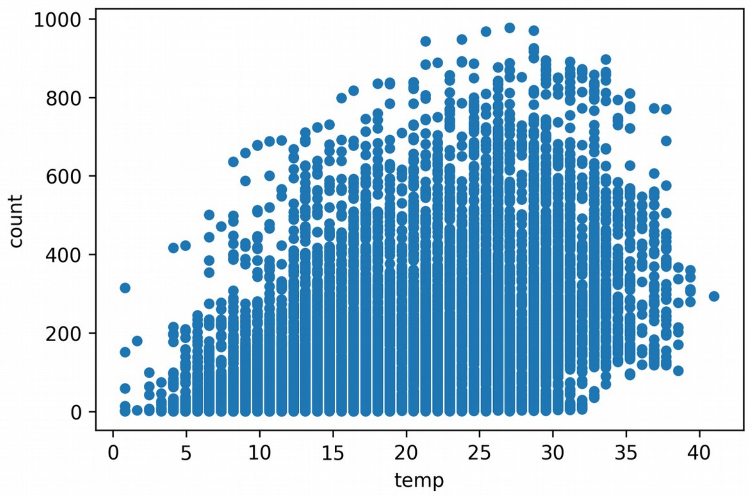
A LSTM, Bi- directional LSTM and a encoder- decoder model have been developed and compared the results.

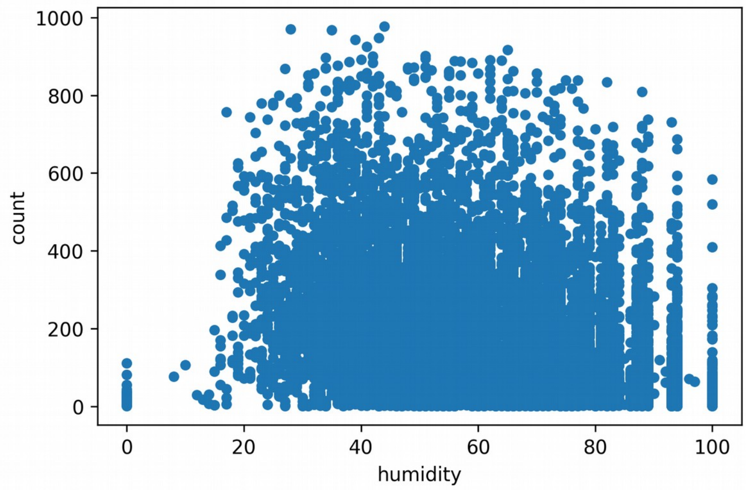
Data Preprocessing

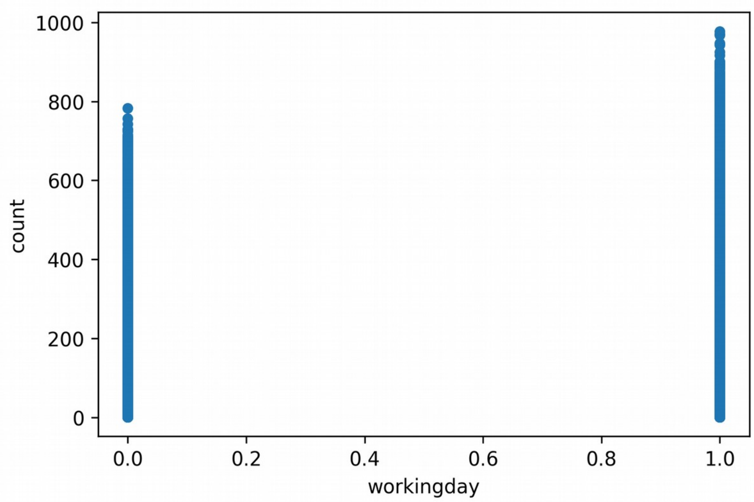
below are some of the distribution of independent variables with respect to the target variable(count).

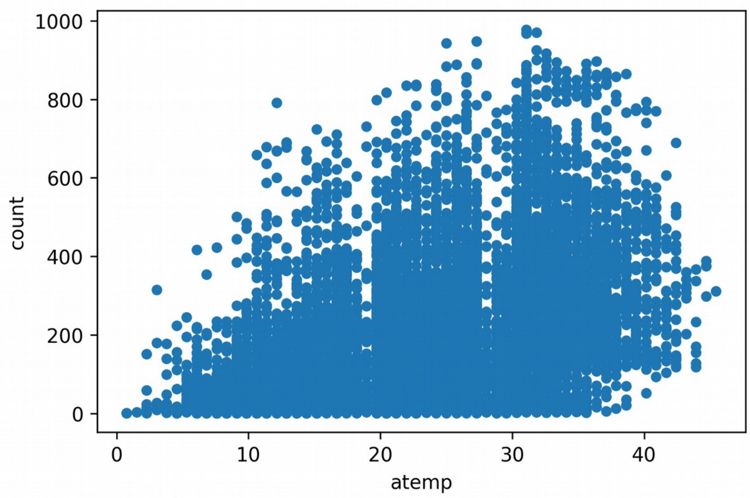

count
1000
800
600
400
200
0
0
10
20
30
40
50
windspeed

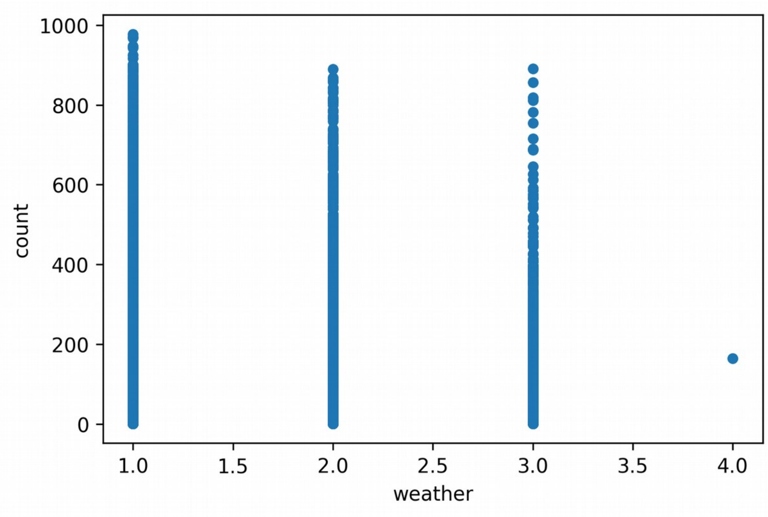

count
1000
800
600
400
200
0
0
50
100
150
200
250
300
350
casual

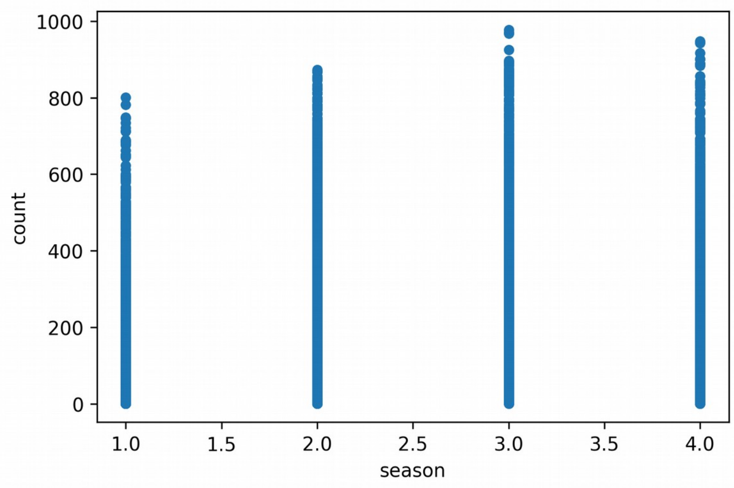

count
1000
800
600
400
200
0
0
5
10
15
20
25
30
35
40
temp


count
1000
800
600
400
200
0
0
20
40
60
80
100
humidity


count
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
workingday


count
1000
800
600
400
200
0
0
10
20
30
40
atemp

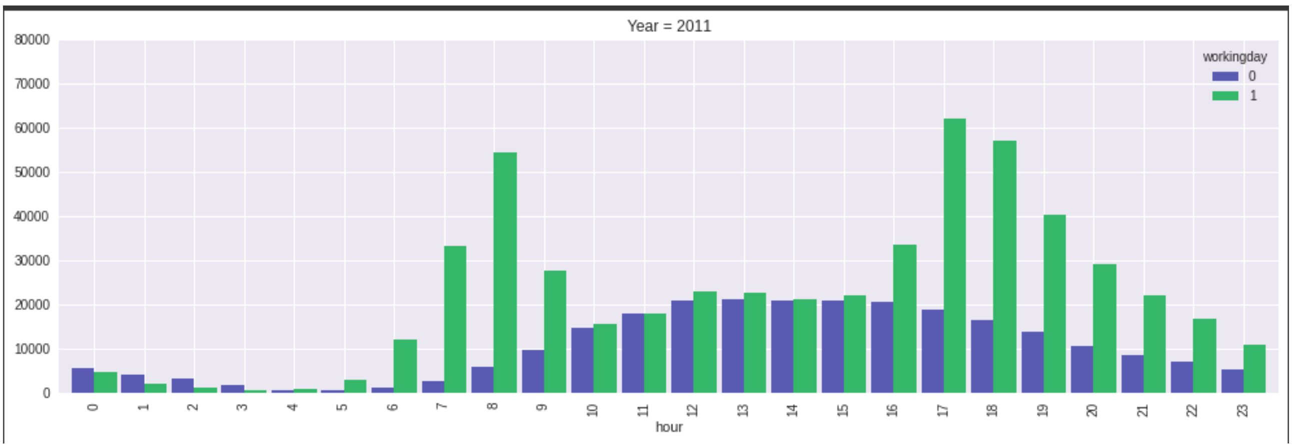


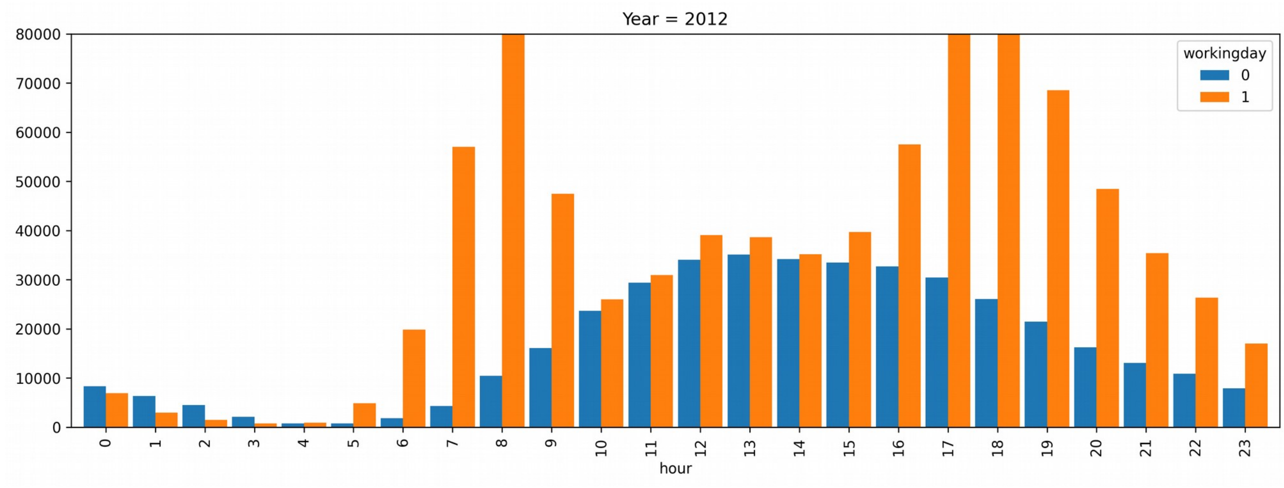


Year Wise Distribution:

A bar plot which shows year wise counts for each hour in a day. From the below plot the following observations have been made.

1) More cycles are rented in the second half of the day.
2) 2012 more cycles are rented compared to 2011.
3) More cycles are rented on Working day than Weekend.

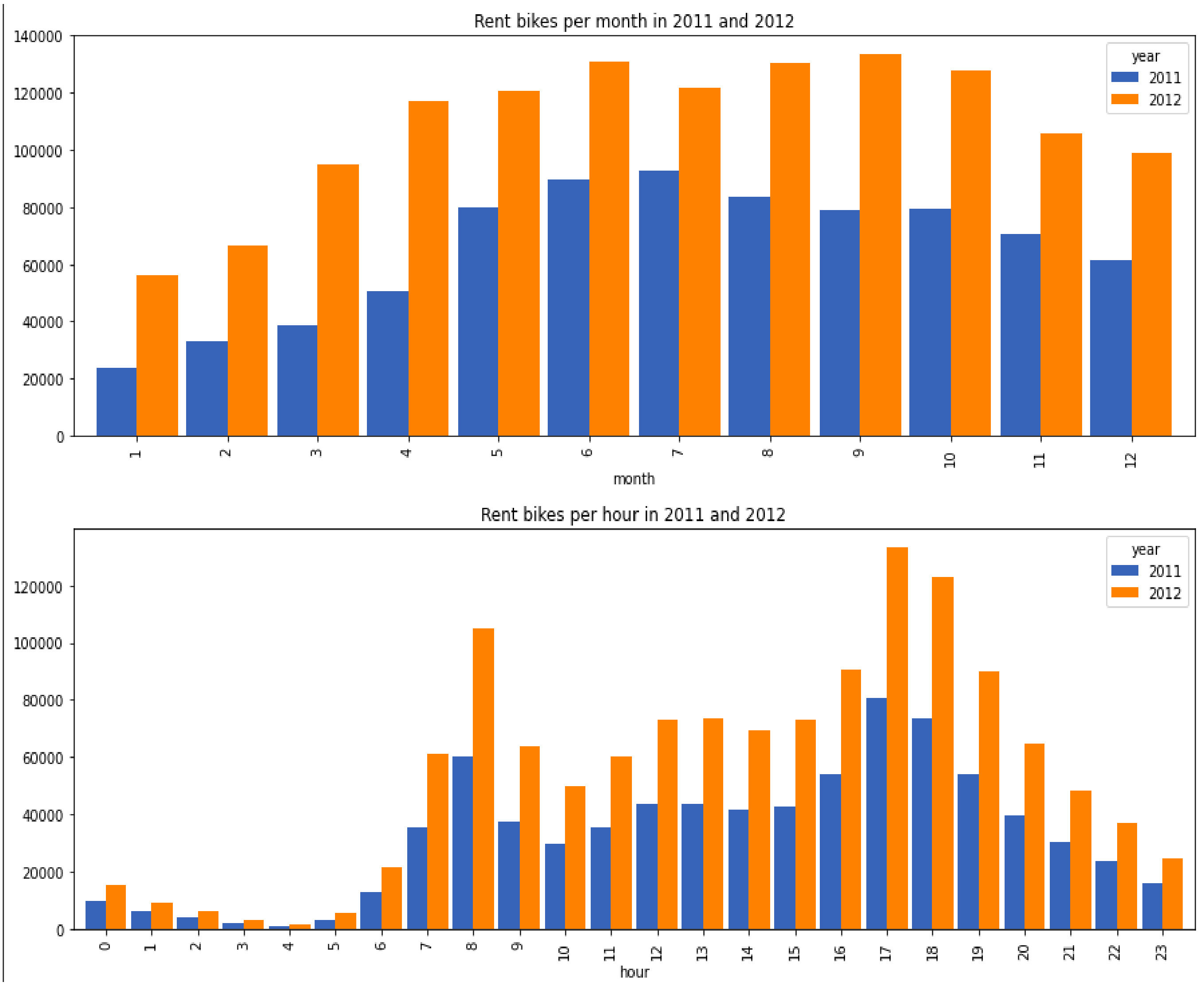


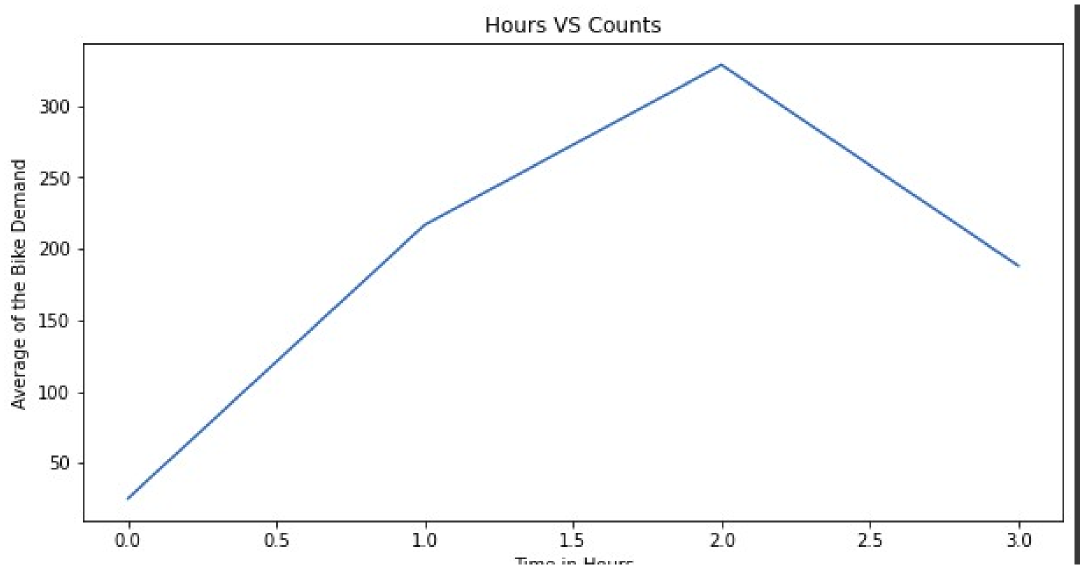


Month and Hour wise Distribution:

The below bar plots shows month and Hour wise counts of bike rents for each year 2011 and 2012. From the below plot the following observations have been made.

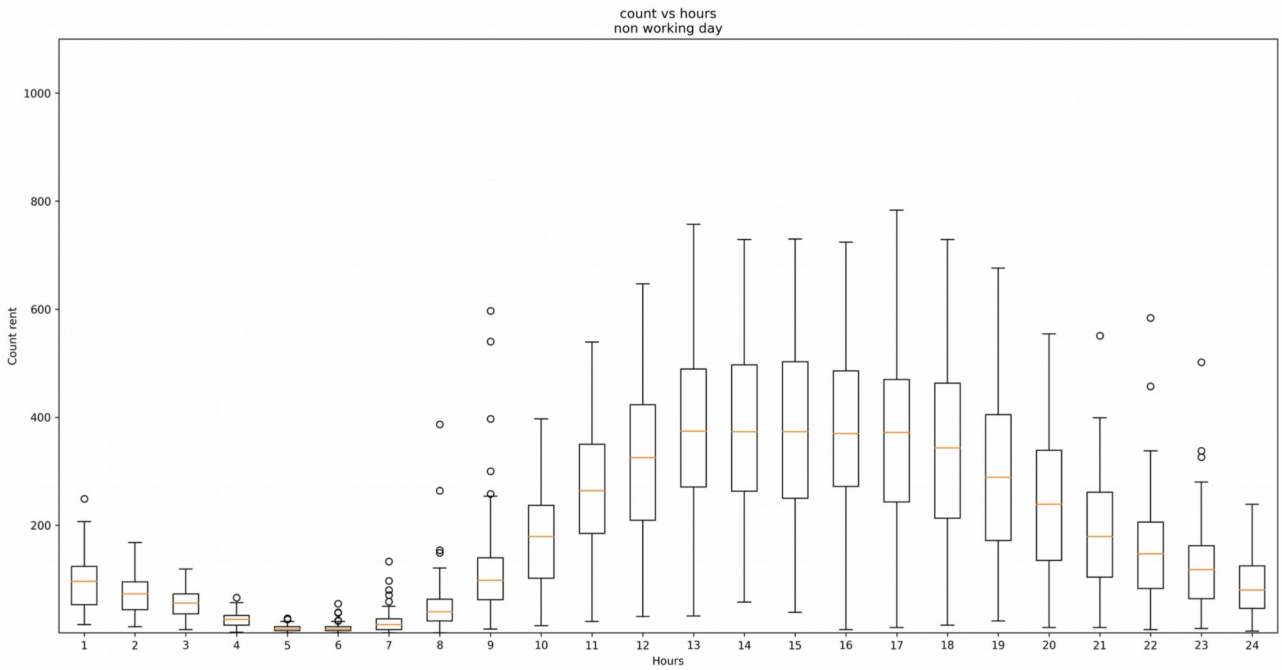
1) More bikes are rented in September Month
2) More bikes are rented in the duration of 5 to 6pm

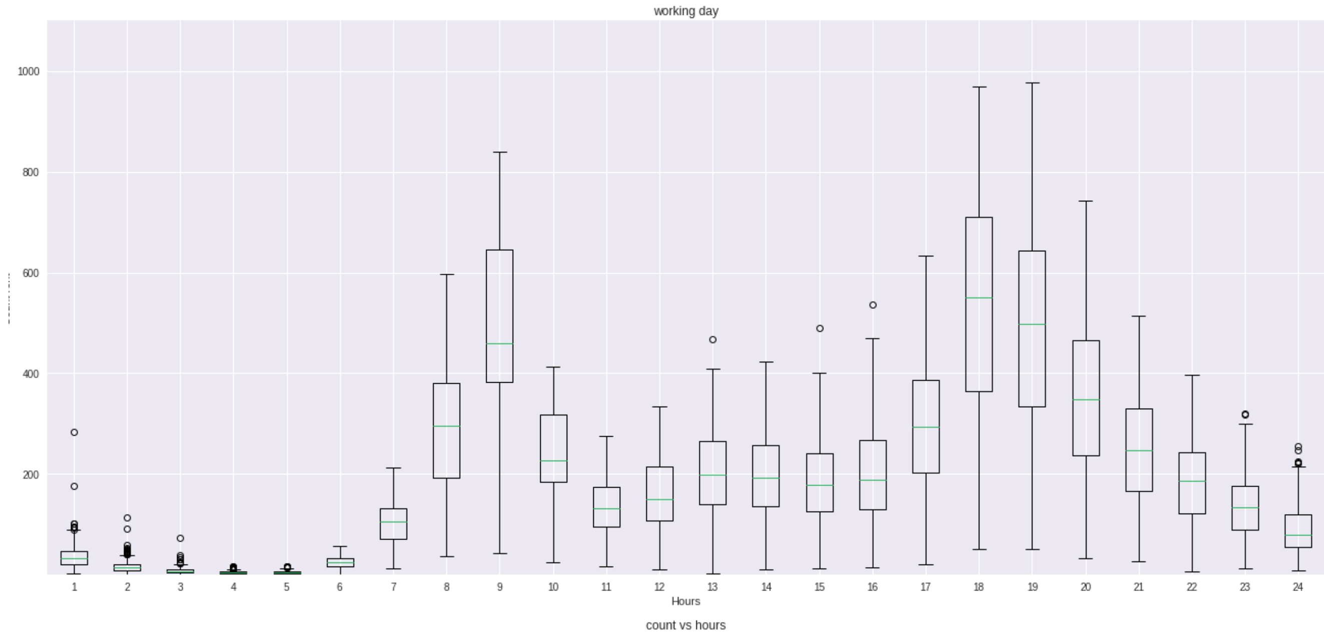




Non-Working/Working day Vs Hour :

From the below fig, we can interpret that the cycles are rented mostly on working days during 5 PM to 6 PM and during non-working days, it is around
1 PM to 5 PM.





Model Development & Comparison:

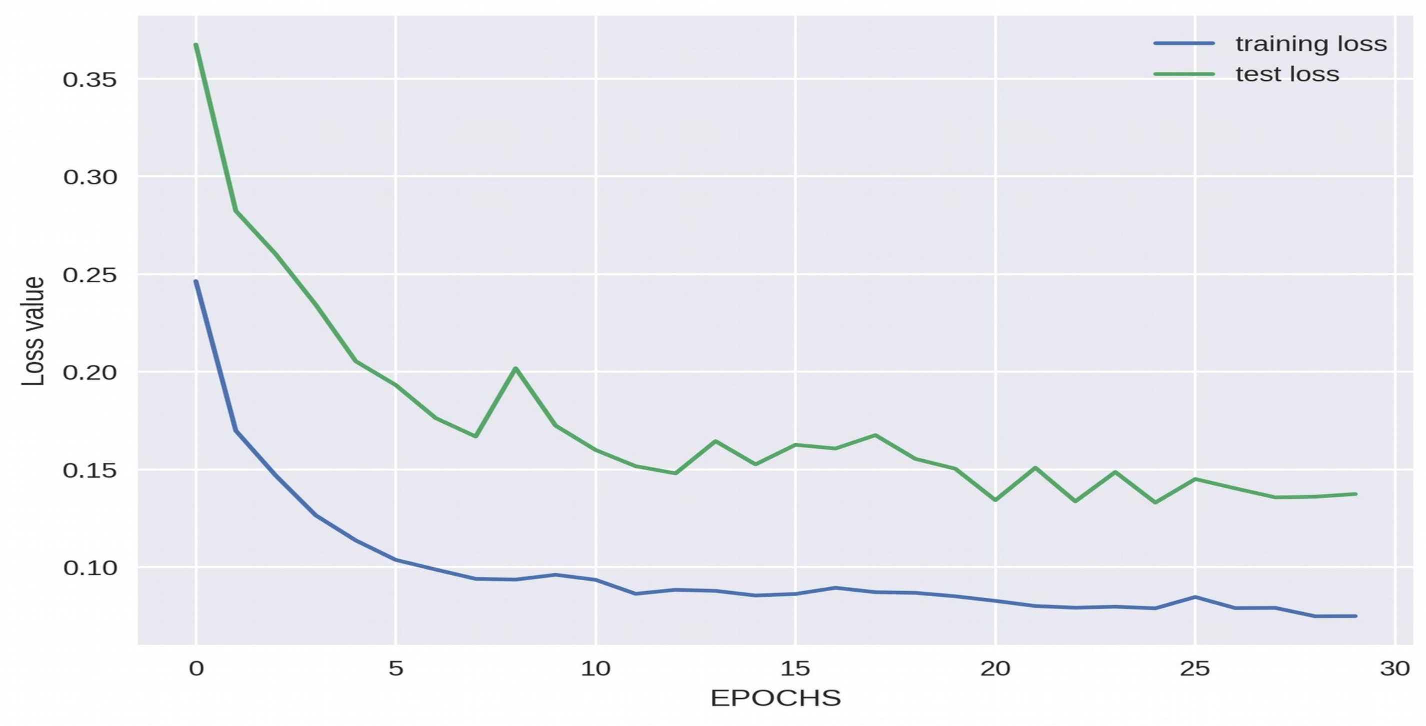
As part of model development, Standardization of features have been done and trained 3 deep learning models(LSTM, bi-directional LSTM, Encoder- decoder model) each with 30 epocs for forecasting the demand of bikes and the performance is recorded.

1) LSTM:

The below LSTM architecture is trained with 30 epocs and the loss of 0.075 and validation loss of 0.137 is observed.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_27 (LSTM)               (None, 128)               72192
_________________________________________________________________
dropout_22 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_24 (Dense)             (None, 1)                 129
=================================================================
Total params: 72,321
Trainable params: 72,321
Non-trainable params: 0
```

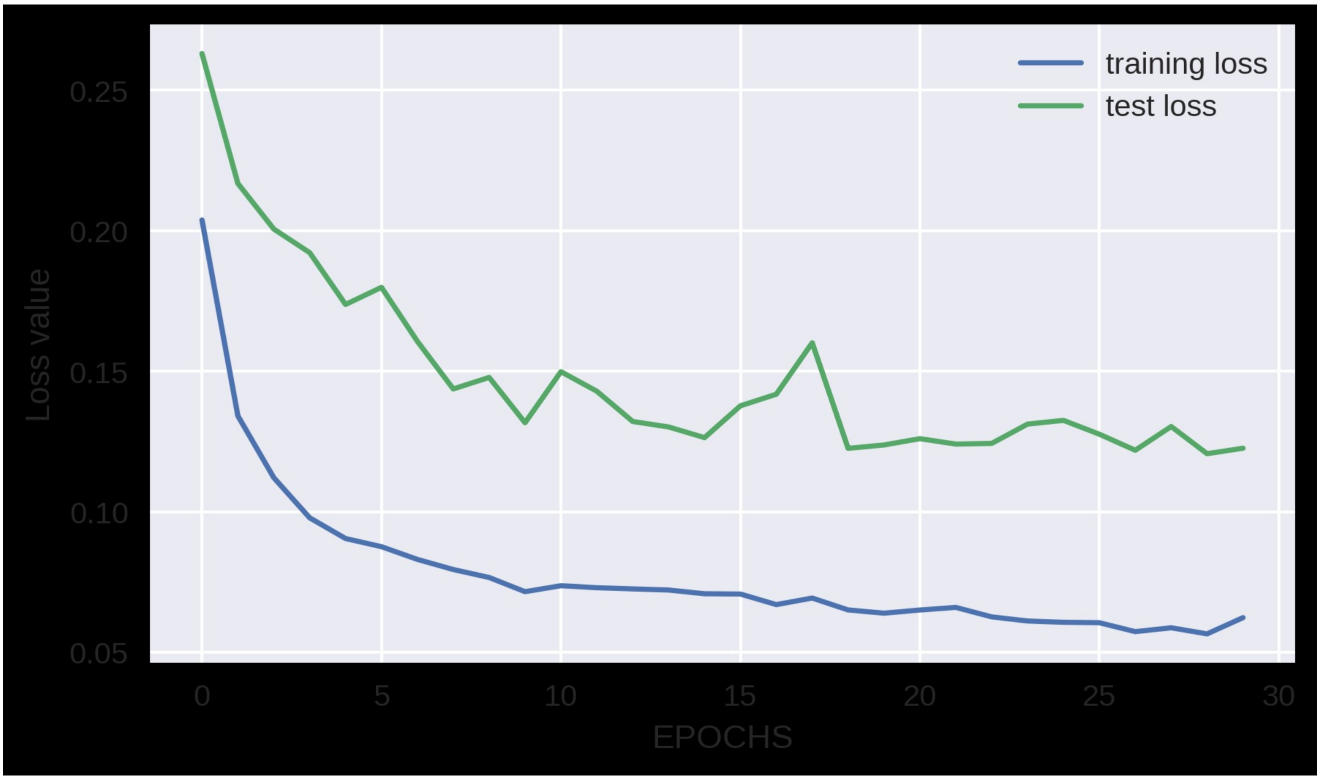
The model convergence during training is plotted below.



2) Bi- directional LSTM:

A Bi- directional LSTM model is trained and the loss of 0.062 and validation loss of 0.122 is observed.

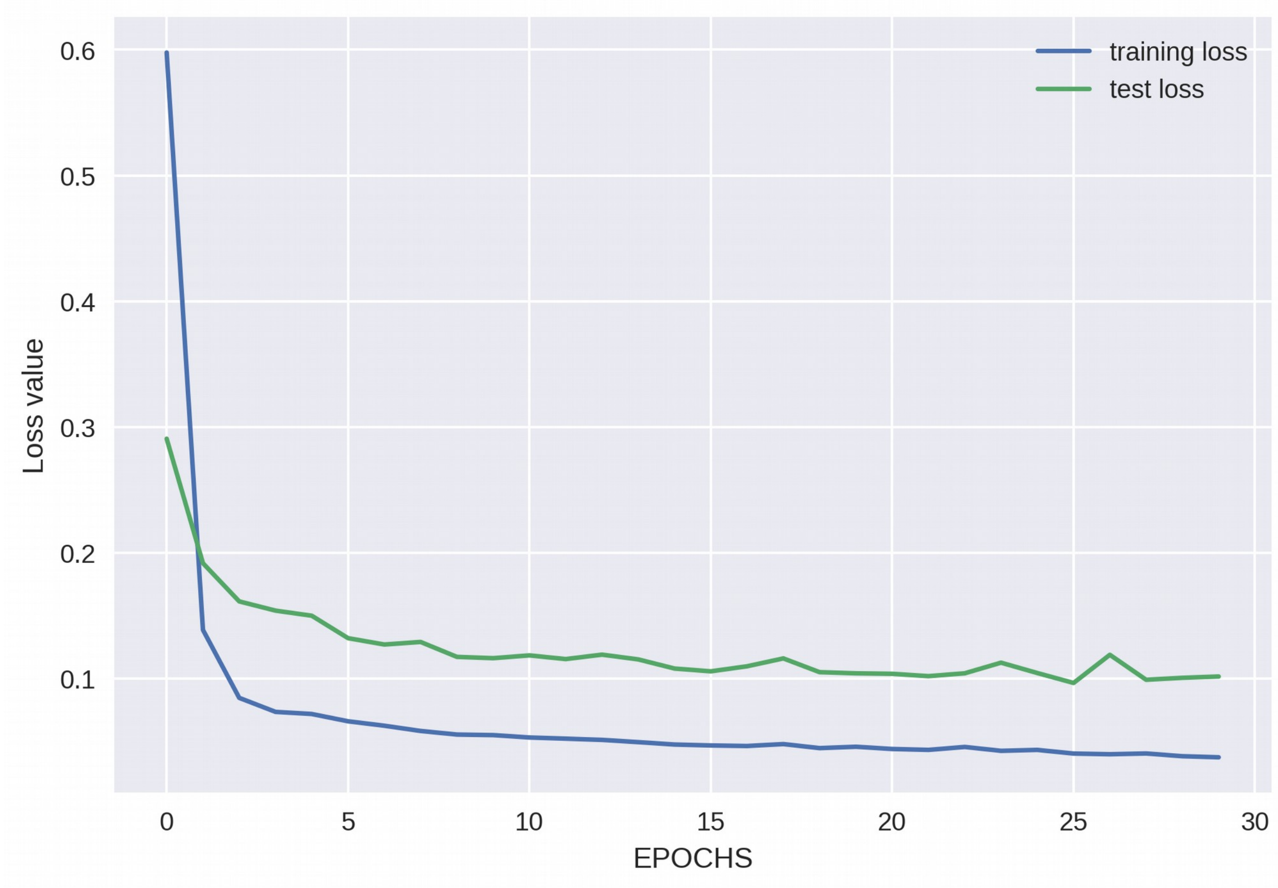
```
Model: "sequential_28"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
bidirectional_14 (Bidirectio (None, 256)               144384    
_________________________________________________________________
dropout_23 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_25 (Dense)             (None, 1)                 257       
=================================================================
Total params: 144,641
Trainable params: 144,641
Non-trainable params: 0
```



2)Encoder Decoder Model:

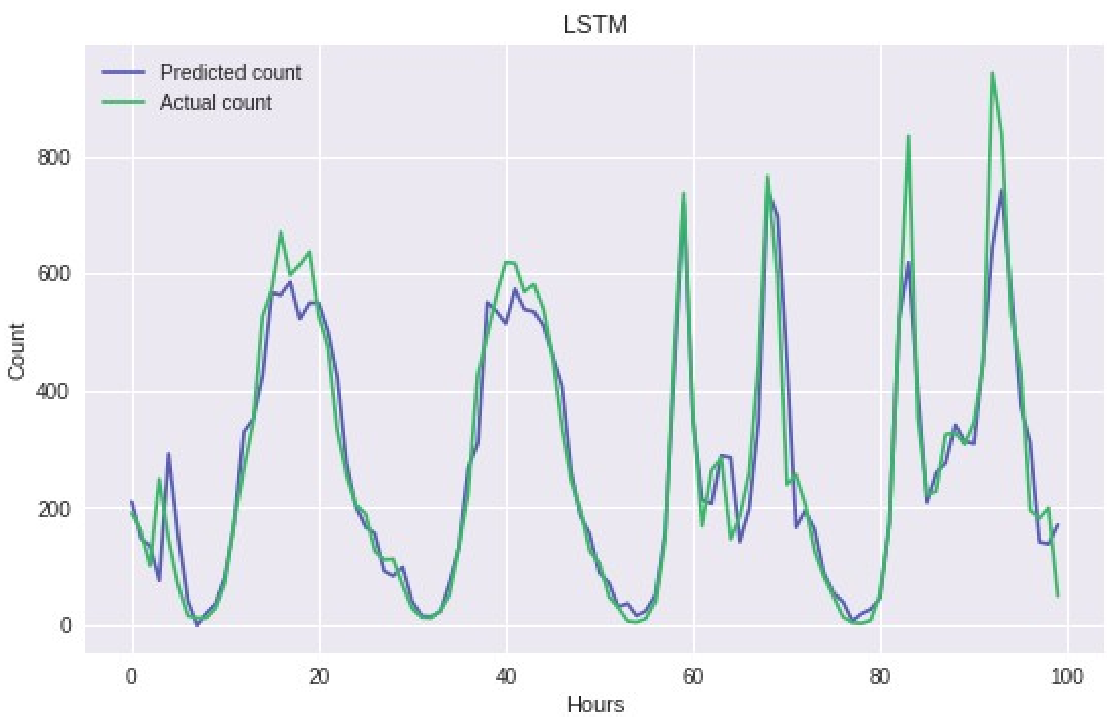
A **Encoder Decoder** model has been trained and the loss of 0.037 and validation loss of 0.105 is observed.

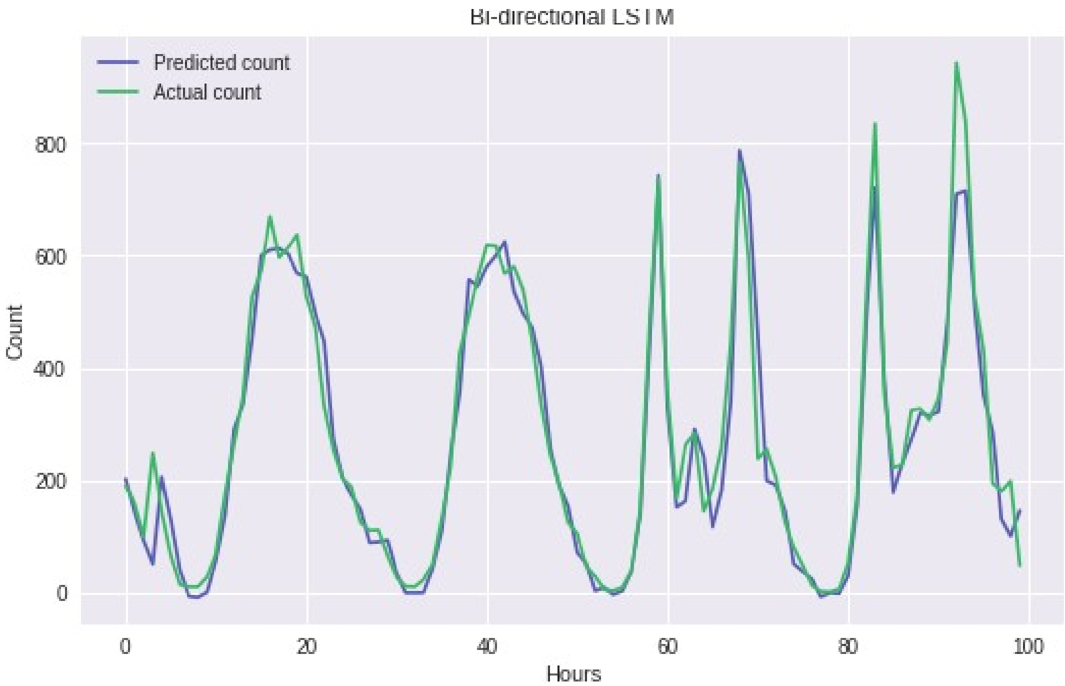
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_29 (LSTM)               (None, 200)               170400
_________________________________________________________________
repeat_vector_1 (RepeatVecto (None, 7, 200)            0
_________________________________________________________________
lstm_30 (LSTM)               (None, 7, 200)            320800
_________________________________________________________________
time_distributed_2 (TimeDist (None, 7, 100)            20100
_________________________________________________________________
time_distributed_3 (TimeDist (None, 7, 1)              101
=================================================================
Total params: 511,401
Trainable params: 511,401
Non-trainable params: 0
_________________________________________________________________
```



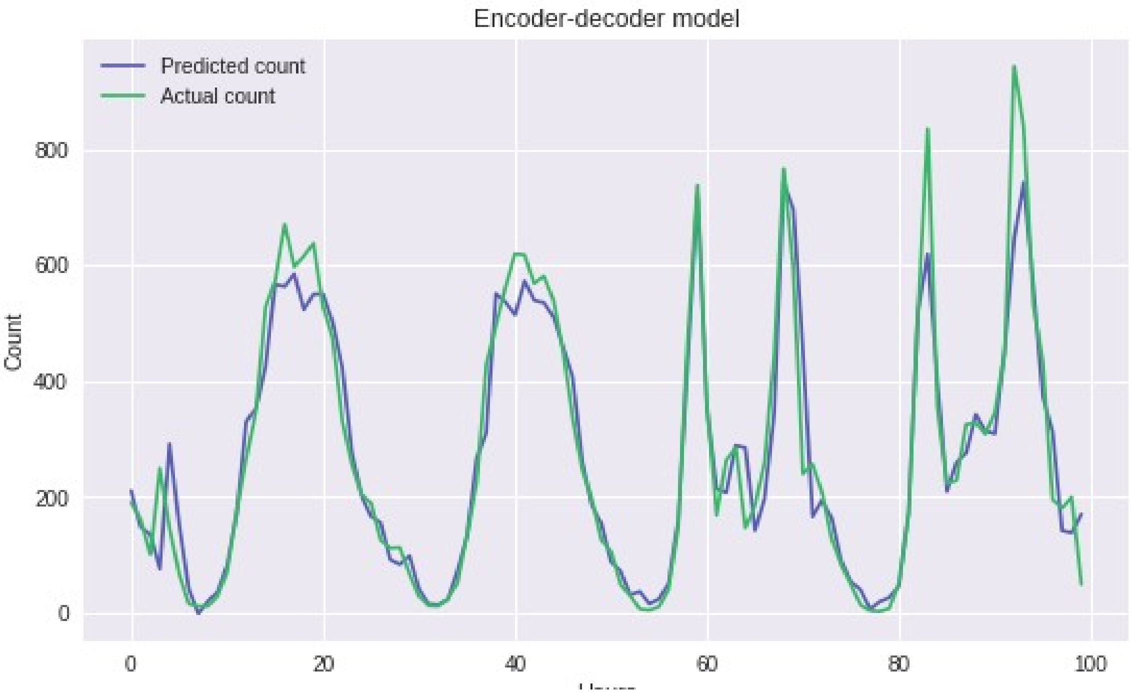
Model Prediction:

Below images represent the Model Predictions vs Actual Values.





Bi-directional LSTM
Predicted count
Actual count
Count
Hours
0
200
400
600
800
0
20
40
60
80
100



Encoder-decoder model
Predicted count
Actual count
Count
0
200
400
600
800
0
20
40
60
80
100