TRAFFIC FLOW FORECAST USING TIME SERIES ANALYSIS

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Abstract----- Traffic congestion is a thorny issue to many large and medium-sized cities, posing a serious threat to sustainable urban development. Recently,intelligent traffic system (ITS) has emerged as an effective tool to mitigate urban congestion. The key to the ITS lies in the accurate forecast of traffic flow. However, the existing forecast methods of traffic flow cannot adapt to the stochasticity and sheer length of traffic flow time series. To solve the problem, this paper relies on deep learning (DL) to forecast traffic flow through time series analysis. The authors developed a traffic flow forecast model based on the long shortterm memory (LSTM) network. The proposed model was compared with two classic forecast models, namely, the autoregressive integrated moving average (ARIMA) model and the backpropagation neural network (BPNN) model, through long-term traffic flow forecast experiments, using an actual traffic flow time series from OpenITS. The experimental results show that the proposed LSTM network outperformed the classic models in prediction accuracy. Our research discloses the dynamic evolution law of traffic flow, and facilitates the decision-making of traffic management.

Keywords---- Deep Learning, Long Short Term Memory Networks (LSTM), **T**raining set, **T**est set, Tensorflow, Traffic Flow Prediction.

I. INTRODUCTION

A smart nation program is recently raised in many countries which aim to improve living standards of citizens with advanced information and communications technologies. Intelligent transport system is one of those technologies which ensures the success of smart nation program. As we know that information of accurate traffic flow has become a basic part of our daily life and it is strongly needed for individual travelers. The primary goal of traffic stream forecast is to give the data of traffic stream so on the basis of that road users can make wise travel decisions which leads to 1)reduce their travel time; and also helps in 2)reducing traffic flow; and 3)carbon emission. The successful prediction of traffic flow also helps in management and control.

Many methods have been presented for traffic flow forecasting in terms of prediction of speed, density, size and travel time. Examination of new methods in this area mainly focus on methodology part, researchers are coming up with different models to enhance prediction accuracy, robustness and efficiency. As per the literature, researches are being divided into two divisions: parametric displaying and non-parametric demonstrating.

Various parametric techniques are there but the one which is applied in many studies is Auto-Regressive Integrated Moving Average (ARIMA). ARIMA was acquainted in rush hour gridlock expectation with research the stochastic highlights of traffic framework.

As of late, non-parametric AI methods are being used to solve non-linear problems. Applications of Neural Networks are the current interest in traffic research area. The comparison between NN and traditional techniques shows that NN is clearly superior in traffic forecasting. Deep learning, an application of NN, can learn features from large database. Profound learning calculations utilize a gigantic measure of unaided information to consequently extricate complex portrayal. It not just gives complex portrayals of information which are reasonable for Artificial Intelligence assignments yet in addition makes the machines free of human learning which is a definitive objective of AI. In rush hour gridlock stream forecast, profound learning models are of incredible criticalness. Profound learning has favorable circumstances, for example, less computational multifaceted nature and better include extraction. Not many utilizations of profound learning have been applied to anticipate the traffic stream and gave great outcomes.

In this work, we have proposed a profound learning model dependent on Long Short Term Memory Network (LSTM). Experimental results show that LSTM is a promising model in this field.

Objective of our work is to apply deep learning models to predict short term traffic flow.

Rest of this paper composed as pursues. Area II has the presentation of LSTM model and segment III has the trial consequences of our methodology.

II. METHODOLOGY

Dataset Acquisition and Pre-processing

The first step is to collect historical traffic flow data from a specific location, such as a highway or intersection. The data should include variables such as date, time, traffic volume, weather conditions, and other relevant factors that may impact traffic flow. The data is then preprocessed to ensure it is clean and formatted correctly for analysis.

Feature extraction:

Next, relevant features are extracted from the data, such as hourly traffic volume and weather conditions. The data is then split into training and testing sets.

Introduction of LSTM

Long transient memory systems – as a rule called LSTM – are an extraordinary sort of RNN, equipped for adapting long haul conditions. LSTM is unequivocally intended to keep away from the long haul reliance issue. Recollecting data for significant stretches of time is basically their default conduct. LSTM only stores relevant information, one of the best example of this is – Chatpot.

It has following layers; 1) sigmoid; 2) tanh; 3)pre-sigmoid. Sigmoid&tanh layers help in retaining the memory.

LSTM Structure

LSTM have chain like structure. This structure has many connecting lines; each line conveys a whole vector, from one hub to the contributions of others.

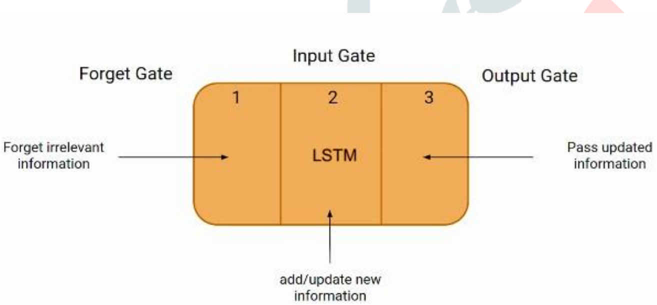

Fig. 1. Structure of LSTM

The way to LSTM is cell indicate, the even line moving direct to the high point of the graph. It is a transport line which conveys all the data that is pertinent to the past information. LSTM has the volume to dismiss and append data to the phone state, attentively controlled by structures called Gates. LSTM has three gates to ensure and control the cell state, which help to let the data through.

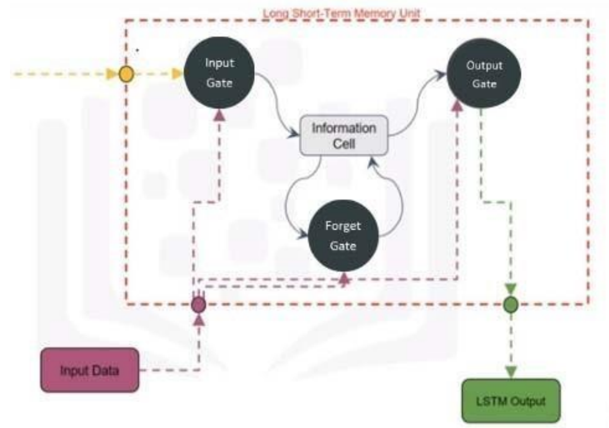

Fig. 2. Gates guarding the cell state

Working Steps of LSTM

The beginning step of LSTM is to delete the data from the cell state which are not useful. This process of removing unuseful knowledge is done by sigmoid layer which is also called as forget gate layer.Considering h and , overlook gate layer yields a number in the radius of 0 and 1 for each number in the phone state . Here, 1 implies that the data will be kept while if there should be an occurrence of 0, it will be discarded.

The condition will resemble-

= (. [,] +) (1)

Successive stage is to select the part of data which will be forwarded at first in the cell state.

1. Input gate layer (a sigmoid layer) will select the node which will be refreshed.
2. There will be a tanh layer which will make a vector of new competitor esteems , which can be added to the cell state.
3. = (. [,] =) (2)
4. = tanh (. [h ,] =)

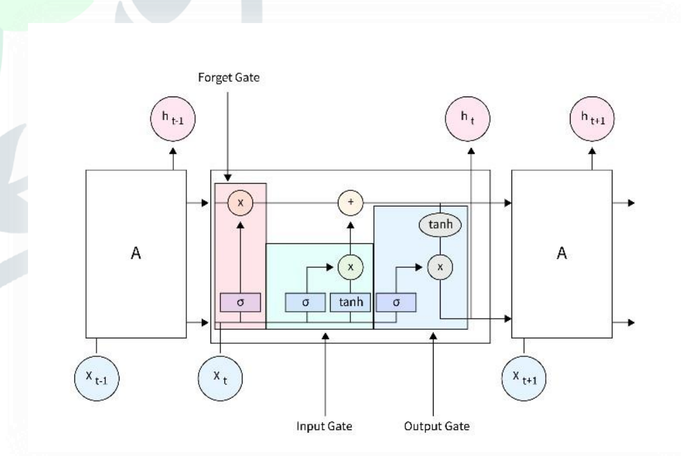

Fig. 3. Working of LSTM

In following stage, we will connect these two to mark an update to the state. Now will be updated to .

- First, the old state will be multiplied by , neglecting the objects we determined to forge first.
- Then we add on * , this is the new applicant values.

= * + * (4)

Finally, it will pass a sigmoid layer which will select which block of the cell state we are proceeding to submit [5]. At that point, it will put the cell state out of tanh and enlarge it by the yield of the sigmoid gate, so it just yield the chunks it chose to.

= (. [,] +) (5) h = * tanh ( ) (6)

The optimization algorithm which we have utilized is Adam Optimizer. Adam is an enhancement calculation which aides in update system loads iterative dependent on preparing information.

We have also used RMSE (Root Mean Square Error) to calculate the loss while training and testing the data. At the end, it tells how the information is near the line of best fit.

The method is:

$$RMSE = \sqrt{\overline{(f-o)^2}}$$

Where-

f = forecasts (expected valued or unknown results)

o = observed values (known results).

The bar above the squared differences is the mean.

III. EXPERIMENTAL RESULTS AND DISCUSSION

Data description

We applied the LSTM model on the data collected from Kaggel. The work of counting vehicles on particular time intervals for the purpose of designing overpass to diverse the traffic flow in particular areas. The data then aggregated into a 5-min interval. Two months data (October 2015 to January 2016) is selected for experiment. Here, we have only analyzed the data to predict traffic flow.

Implementation

For implementation of our model, we have used Anaconda and Jupyter notebook. Anaconda is the best platform to perform Deep Learning models. Jupyter notebook is a tool within Anaconda, lots of Deep Learning packages are already installed in Jupyter notebook so we don't need to spend time on installation part.

For the traffic prediction model, LSTM is employed on the dataset. It takes the dataset as input, process it and gives output of traffic flow, which is a predicted value. The output shows the result of traffic flow is promising. We have trained our model using linear traffic flow.

To calculate the loss, we have used 'mean_squared_error' and for optimization, we have used 'adam optimizer'.

- Epochs – it is the number of times we feed our data to the network with updated weights, so that it can train itself well.
- Batch-size – it tells us what the interval of iteration is and allows the change rate after particular observation.
- Verbose – it is general programming term for produce lots of logging output.

```
model = Sequential()
model.add(LSTM(units[1], input_shape=(units[0], 1), return_sequences=True))
model.add(LSTM(units[2]))
model.add(Dropout(0.2))
model.add(Dense(units[3], activation='sigmoid'))

return model
```

Fig. 4. code to construct LSTM model

The result of experiment is shown below:

```
Epoch 1/5
 - 41s - loss: 0.0047
Epoch 2/5
 - 41s - loss: 0.0037
Epoch 3/5
 - 40s - loss: 0.0036
Epoch 4/5
 - 40s - loss: 0.0035
Epoch 5/5
 - 37s - loss: 0.0035
```

It shows the loss in training on the dataset we have used is 0.0035 which is very low. The result doesn't show much difference because we have a small amount of data. This result shows that our model is working good on this dataset and also it is good for traffic flow prediction.

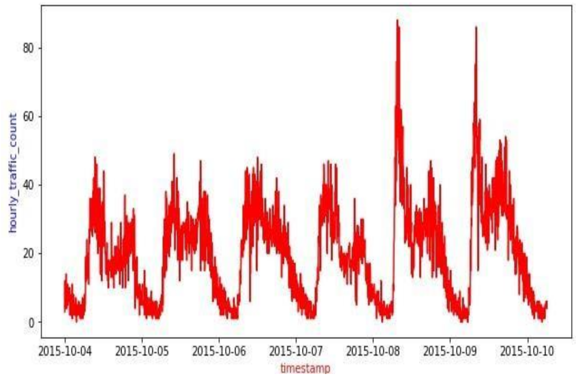

Fig. 5. Graph of Real Traffic Flow.

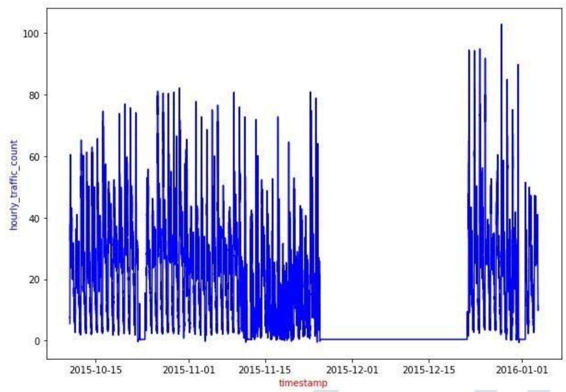

Fig. 6. Graph of Predicted Traffic Flow.

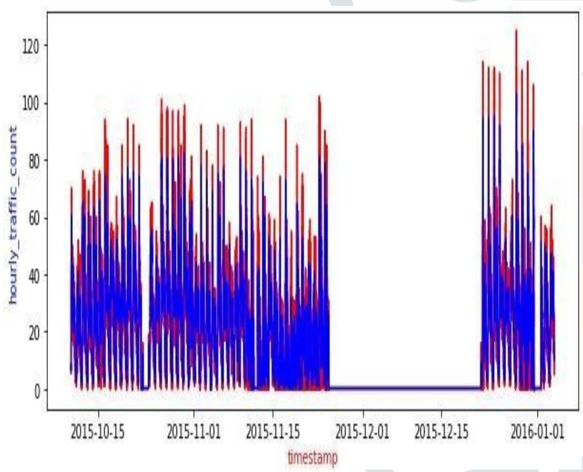

Fig. 7. Comparison Graph of Real and Predicted Traffic Flow.

Experimental results

Metrics presentation of the results of the model is:

TABLE I. EXPERIMENTAL RESULTS

MSE	RMSE	Act_value	Pred_value
0.0035	7.40	26	31

Where MSE is the error of training process and RMSE is the error of testing process. The lower the loss is the higher the accuracy.

IV. CONCLUSION

In this work, we have applied a Deep Learning model LSTM to forecast the short-term traffic flow. LSTM is apt to store long-term dependencies of data sequence. The dataset we have applied on this model has the time interval of 5-minutes. Result shows the applied model gives good results to other models. This model takes the linear-dataset only, so it will be interesting to work on this model and train it on bidirectional dataset.

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