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Traffic Flow Prediction on Road Transportation Network

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ABSTRACT—Traffic flow prediction has gained more and more attention with the rapid deployment of intelligent transportation systems (ITSs). The aim of traffic flow prediction is to provide such traffic flow information in data as well as in graphical form more meticulously. Moreover, this experiment demonstrate that the proposed method for traffic flow prediction has superior performance. In the existing systems the data are not expressed accurately. The main objective is to find a line that minimizes the prediction errors with all the data sets. Therefore, using three Machine Learning models such as LSTM, GRU and SAEs which provides the traffic flow prediction data. These data set when compared, the model SAEs shows the predicted result more meticulously.

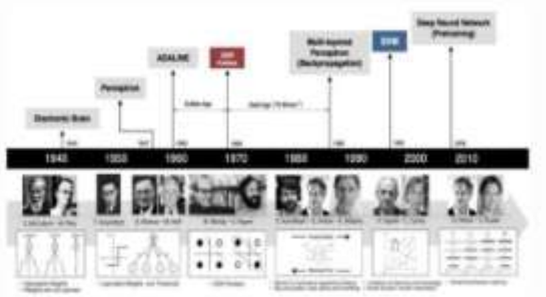
Keywords—Prediction, LSTM, GRU,SAE.

I. INTRODUCTION

A. Background History

To overcome the problems associated with historical, and time series ,to develop a traffic flow prediction model by using machine learning approaches such that SVM and ANN by using these algorithms, developed a UML based prediction system through these users can have interaction with the system and collect the information about current situation of traffic as well as also can check the traffic flow from 1 to next 24 hours of a days with the time interval of 1hour data, this system shows the predicted data from 1 to next 24 hours. in this way they may know the weather effects and conditions of the roads that how much traffic will be on which road in the next 24 hours, they can also see accidentals records of number of vehicle's and how much chances can be occur for accidents on which road so our system may help them to make their planes that which route or road they should select to make their travel easy.

There are several theories and approaches proposed for traffic flow forecasting, which can be divided into two categories. The first category is time series analysis methods, including Kalman filtering (KF) models, the autoregressive integrated moving average, seasonal auto-regressive integrated moving average etc. ANNs can deal with complex non-linear data, so it is widely used in traffic flow forecasting. However, the training ANN model requires a large amount of raw data. The prediction accuracy of ANNs is limited by the sample size.



Development of ML and DL

B. Problem Statement

Existing traffic flow prediction methods mainly use shallow traffic prediction models and are still unsatisfying for many real-world applications. This situation inspires us to rethink the traffic flow prediction problem based on Machine Learning models with dataset. In the current decades, traffic data have been generating exponentially, and we have moved towards the big data concepts for transportation. Traffic flow prediction heavily depends on historical and real-time traffic data collected from various sensor sources Inductive loops, radars, cameras, Mobile Global Positioning System, Crowd sourcing,Social media,etc.

C.Scope

To help road users to make better travel decisions, alleviate traffic congestion, reduce carbon emissions, and improve traffic operation efficiency. Traffic flow prediction has gained more and more attention with the rapid development and deployment of intelligent transportation systems (ITSs). It is regarded as a critical element for the successful deployment of ITS subsystems, particularly advanced traveller information systems, advanced traffic management systems, advanced public transportation systems, and commercial vehicle operations Shallow traffic prediction models and are still unsatisfying for many real world applications. This situation inspires us to rethink the traffic flow prediction problem based on Machine Learning with dataset.

II.EXISTING AND PRPOSED SYSTEM

A.Existing System

By using two existing prediction algorithms, those are ANN and SVM. To utilize these models for our system to give the best prediction result on the developed system. The public can take many benefits by using this system because the users can know what the situation of traffic flow on the current situation is and they can also check what will be the flow of traffic on the right after one hour of the situation.

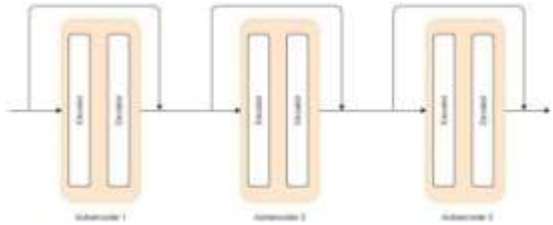
Manual controlling - as the name suggests requires manpower to control traffic. The traffic police are allotted for a required area to control traffic. The traffic police carry signboard, sign light and whistle to control the traffic. **Automatic traffic**- light is controlled by timers and electrical sensors. In traffic constant numerical value loaded in the timer. The lights are automatically getting ON and OFF based on the timer value.

Electronic sensors- is another advanced method is placing some loop detectors or proximity sensors on the road. This sensor gives data about the traffic on the road. According to the sensor data the traffic signals are controlled.

B.Proposed System

The project is to predict the traffic flow in a lane at any given time. To do so, a reliable dataset has to be used. The PeMS 5min-interval traffic flow dataset. This dataset is split into train.csv and test.csv as training and testing dataset. Python file data.py is used to preprocess the data. The number of vehicles is scaled from 0 to 1 and further transformation are done from -1 to 1 in MinMaxScaler thus, the data is now properly made into something that the machine can easily understand.

A SAE model is introduced. The SAE model is a stack of autoencoders, which is a famous deep learning model. It uses autoencoders as building blocks to create a deep network. Some datasets have a complex relationship within the features. Thus, using only one Autoencoder is not sufficient. A single Autoencoder might be unable to reduce the dimensionality of the input features. The stacked autoencoders are, as the name suggests, multiple encoders stacked on top of one another. A stacked autoencoder with three encoders stacked on top of each other is shown in the following figure.



Autoencoder

III.LITEARTURE REVIEW

Review of literature is important in any research work. Many researchers have carried out research work in the area of road accidents. Some of them have analyzed accident data in different ways. Some of them Identification of Black spot zone. Some of them have developed accident models for forecasting future accident trends.

Traffic flow prediction has been discussed several times with different machine learning approaches. Review of different researchers and the methodologies which have been used for prediction. Many algorithms show the excellent results on the given data sets. Those data sets have collected from different sources.

To get accurate information about current and future traffic flow there are many applications such as vehicle navigation devices, congestion management, vehicle routing, and much more application have been introduced to guide the public on the road but the problem is to get realtime data on the spot and helps the users to plan their routs according to the situations on the road but the main problem to get information about traffic flow which are not well equipped with traffic sensors and many other factors that effect to get data such as accidents, public events, and bad weather conditions.

Generally, there are two ways of traffic flow prediction, such as Short Term and Long Term Traffic Flow Prediction probably long term algorithms maybe cannot provide accurate prediction results because this mechanisms predict on hourly basis such as 12 hours or 24 hours data results, as well as short term mechanisms, provide more good results because they give results in terms of minutes such as a 5 to 15 minutes or 30 to 50 minutes so in this way, the short term time interval can give more accurate prediction values.so our model has been trained within a maximum time interval of 1 hour to give prediction results.

Single model has its own advantages and disadvantages to predict short-term traffic flow. To integrate the advantages of two or more models, hybrid prediction methods are developed. The hybrid methods can be divided into the modified hybrid model and the weighted hybrid model. Chen et al. and Du et al. both proposed the modified hybrid methods on the basis of which traffic flow data are divided into two parts. Moreover, the neural network and the Markov model were utilized to predict these two parts, and the final predicted value was obtained by summing the predicted values of these two parts.

Over the past decades, numerous studies have been conducted regarding lane changes. Most lane changing models are applicable to a variety of traffic and transportation research, including transportation planning and trafficmanagement policy development. Recently, lane change research has primarily focused on vehicle control. As described above, it is necessary to integrate both aspects to implement an improved autonomous lane change system. In this section. Traffic flow prediction has been long regarded as a key functional component in ITSs. Over the past few decades, a number of traffic flow prediction models have been developed to assist in traffic management and control for improving transportation efficiency ranging from route guidance and vehicle Traffic flow prediction has been long regarded as a key functional component in ITSs. Over the past few decades, a number of traffic flow prediction models have been developed to assist in traffic management and control for improving transportation efficiency ranging from route guidance and vehicle.

IV.REQUIRMENTS SPECIFICATION

A.Hardware requirements

1. Processor: Intel Pentium 4 or more
2. Ram: 1 GB or more
3. Hard disk: 40 GB hard disk recommended for the primary partition.
4. Device: Tesla K80.

B.Software requirements

1. Python 3.6
2. Tensorflow-gpu 1.5.0
3. Keras 2.1.3
4. Scikit-learn 0.19
5. Dataset: PeMS 5min-interval traffic flow.

V . METHOLOGY

The proposed deep architecture model was applied to the data collected from the Caltrans Performance Measurement System (PeMS) database as a numerical example. The traffic data are collected every 30 s from over 15 000 individual detectors, which are deployed statewide in freeway systems across California.

The collected data are aggregated 5-min interval each for each detector station. The traffic flow data collected in the weekdays of the first three months of the year 2013 were used for the experiments. The data of the first two months were selected as the training set, and the remaining one month's data were selected as the testing set. For freeways with multiple detectors, the traffic data collected by different detectors are aggregated to get the average traffic flow of this freeway. Note that we separately treat two directions of the same freeway among all the freeways, in which three are one-way Long Short Term Memory.

A.Data Collection

The data PeMS 5min-interval traffic flow dataset. This dataset is split into train.csv and test.csv as training and testing dataset. Python file data.py is used to preprocess the data. The process_data() function has three parameters, train, test, and lag. Lag is the number of intervals in a given hour, which is 12. First, incomplete rows of data are filled with 0, which is done using fillna(0). Then, the number of vehicles is scaled from 0 to 1 using the MinMaxScaler function. Further transformation is done by reshaping the values from -1 to 1, since MinMaxScaler requires the range to be from negative to positive. Now, the values are appended into a train list and test list. Further, x_train, y_train, x_test and y_testare defined with the train list for x_train and y_train and test list for x_test and y_test. The data is now properly made into something that the machine can easily understand.

In the existing systems the data are not expressed accurately . The main objective is to find a line that minimizes the prediction errors with all the data sets. Therefore, using three Machine Learning models such as LSTM, GRU and SAEs which provides the traffic flow prediction data. These data set when compared, the model SAEs shows the predicted result more meticulously.

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	A	B	C	D
1	5 Minutes	Lane 1 Flow (Veh/5 Minutes)	# Lane Points	% Observed
2	04-01-2016 00:00	12	1	100
3	04-01-2016 00:05	13	1	100
4	04-01-2016 00:10	11	1	100
5	04-01-2016 00:15	13	1	100
6	04-01-2016 00:20	10	1	100
7	04-01-2016 00:25	10	1	100
8	04-01-2016 00:30	13	1	100
9	04-01-2016 00:35	11	1	100
10	04-01-2016 00:40	10	1	100
11	04-01-2016 00:45	6	1	100
12	04-01-2016 00:50	7	1	100
13	04-01-2016 00:55	6	1	100
14	04-01-2016 01:00	8	1	100
15	04-01-2016 01:05	12	1	100
16	04-01-2016 01:10	7	1	100
17	04-01-2016 01:15	5	1	100
18	04-01-2016 01:20	2	1	100
19	04-01-2016 01:25	6	1	100
20	04-01-2016 01:30	4	1	100
21	04-01-2016 01:35	3	1	100
22	04-01-2016 01:40	5	1	100
23	04-01-2016 01:45	6	1	100
24	04-01-2016 01:50	5	1	100
25	04-01-2016 01:55	6	1	100
26	04-01-2016 02:00	7	1	100

Training Data

	A	B	C	D
31	04-03-2016 02:25	4	1	100
32	04-03-2016 02:30	5	1	100
33	04-03-2016 02:35	4	1	100
34	04-03-2016 02:40	4	1	100
35	04-03-2016 02:45	6	1	100
36	04-03-2016 02:50	1	1	100
37	04-03-2016 02:55	5	1	100
38	04-03-2016 03:00	6	1	100
39	04-03-2016 03:05	3	1	100
40	04-03-2016 03:10	3	1	100
41	04-03-2016 03:15	5	1	100
42	04-03-2016 03:20	4	1	100
43	04-03-2016 03:25	2	1	100
44	04-03-2016 03:30	8	1	100
45	04-03-2016 03:35	8	1	100
46	04-03-2016 03:40	5	1	100
47	04-03-2016 03:45	7	1	100
48	04-03-2016 03:50	10	1	100
49	04-03-2016 03:55	5	1	100
50	04-03-2016 04:00	10	1	100
51	04-03-2016 04:05	8	1	100
52	04-03-2016 04:10	14	1	100
53	04-03-2016 04:15	6	1	100
54	04-03-2016 04:20	18	1	100
55	04-03-2016 04:25	18	1	100
56	04-03-2016 04:30	15	1	100

	A	B	C	D
31	04-03-2016 02:25	4	1	100
32	04-03-2016 02:30	5	1	100
33	04-03-2016 02:35	4	1	100
34	04-03-2016 02:40	4	1	100
35	04-03-2016 02:45	6	1	100
36	04-03-2016 02:50	1	1	100
37	04-03-2016 02:55	5	1	100
38	04-03-2016 03:00	6	1	100
39	04-03-2016 03:05	3	1	100
40	04-03-2016 03:10	3	1	100
41	04-03-2016 03:15	5	1	100
42	04-03-2016 03:20	4	1	100
43	04-03-2016 03:25	2	1	100
44	04-03-2016 03:30	8	1	100
45	04-03-2016 03:35	8	1	100
46	04-03-2016 03:40	5	1	100
47	04-03-2016 03:45	7	1	100
48	04-03-2016 03:50	10	1	100
49	04-03-2016 03:55	5	1	100
50	04-03-2016 04:00	10	1	100
51	04-03-2016 04:05	8	1	100
52	04-03-2016 04:10	14	1	100
53	04-03-2016 04:15	6	1	100
54	04-03-2016 04:20	18	1	100
55	04-03-2016 04:25	18	1	100
56	04-03-2016 04:30	15	1	100

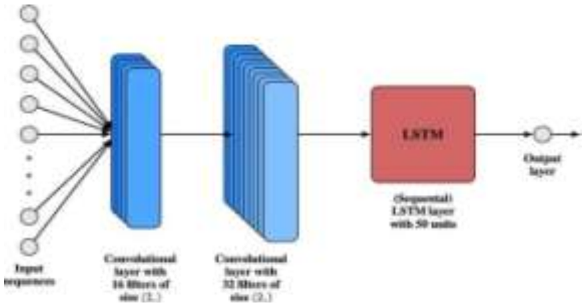
Testing data

VI . MODELS

A. Long Short-Term Memory

Long Short-Term Memory (LSTM) is an artificialrecurrent neural network(RNN) architecture used in the field ofdeep learning.Unlike standardfeedforward neuralnetworks,LSTM has feedback connections. It can process not only single data points (such as images), but also entire sequences of data (such as speech or video). For example, LSTM is applicable to tasks such as unsegmented, connectedhandwriting recognition,speech recognitionand anomaly detection in network traffic or IDSs (intrusion detection systems).

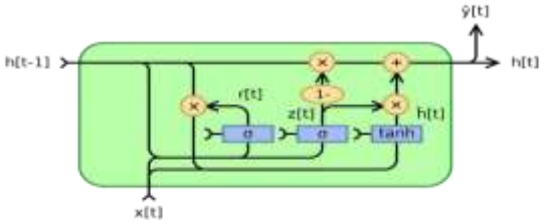
LSTM networks are well-suited toclassifying,processingandmaking predictionsbased ontime seriesdata, since there can be lags of unknown duration between important events in a time series. LSTMs were developed to deal with thevanishing gradient problemthat can be encountered when training traditional RNNs. Relative insensitivity to gap length is an advantage of LSTM over RNNs,hidden Markov modelsand other sequence learning methods in numerous applications.



CNN-LSTM forecasting model architecture

B. Gated Recurrent Units

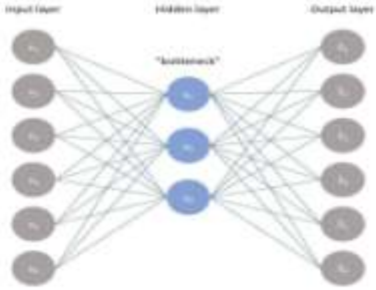
Gated Recurrent Units (GRUs) are a gating mechanism inrecurrent neural networks,introduced in 2014 by Kyunghyun Cho et al. The GRU is like along short-term memory(LSTM) with a forget gate, but has fewer parameters than LSTM, as it lacks an output gate. GRU's performance on certain tasks of polyphonic music modelling, speech signal modelling and natural language processing was found to be similar to that of LSTM. GRUs have been shown to exhibit better performance on certain smaller and less frequent datasets.



Gated Recurrent Unit, fully gated version

C. Stacked Auto Encoders

A stacked autoencoder with three encoders stacked on top of each other. According to the architecture shown in the figure above, the input data is first given to autoencoder 1. The output of the autoencoder 1 and the input of the autoencoder 1 is then given as an input to autoencoder 2. Similarly, the output of autoencoder 2 and the input of autoencoder 2 are given as input to autoencoder 3.


Introduction to Encoder

VII . RESULTS AND DISCUSSION

The proposed deep architecture model was applied to the data collected from the Caltrans Performance Measurement System (PeMS) database as a numerical example. The traffic data are collected every 30 s from over 15 000 individual detectors, which are deployed state wide in freeway systems across California. The collected data are aggregated 5-min interval each for each detector station. The traffic flow data collected in the weekdays of the first three months of the year 2013 were used for the experiments. The data of the first two months were selected as the training set, and the remaining one month's data were selected as the testing set.For freeways with multiple detectors, the traffic data collected by different detectors are aggregated to get the average traffic flow of this freeway. Note that we separately treat two directions of the same freeway among all the freeways, in which three are one way.

```
LSTM
explained_variance_score:0.941900
mape:16.585224%
mae:7.216393
mse:98.054023
rmse:9.902223
r2:0.939638
```

LSTM model

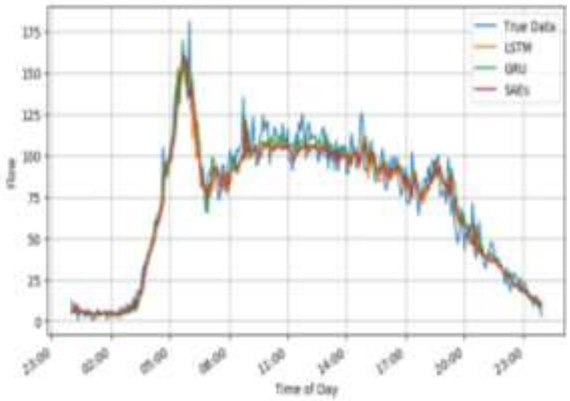
```
GRU
explained_variance_score:0.938862
mape:16.781863%
mae:7.202081
mse:99.315664
rmse:9.965724
r2:0.938862
```

GRU model

```
SAEs
explained_variance_score:0.944269
mape:17.881878%
mae:7.858258
mse:92.077286
rmse:9.595687
r2:0.943318
```

SAEs model

The model has to trained, which the train.py file takes care of. The train_model() function is used to train the LSTM, GRU and SAES model. The model is compiled with three arguments. Loss defines the loss function which calculates loss value. This value will be minimized by the model. The optimizer used is rmsprop, which returns the root-meansquare-value of the kernel. The metrics argument is the list of metrics to be evaluated by the model during training and testing. In this case, it is 'mape', Mean-Absolute-PercentageError. Next, the model is fit with the correct batch size, epochs and a validation split of 5%. Now, the model is saved with '.h5' extension. For the Stacked Auto-Encoders model, since there are hidden models with layers of its own, these hidden layers have to be compiled and fit first, which is done in the train_saes() function, using a for loop. The weights of the hidden layers have to retrieved to train the model, which is done in the 74th line. The main() function defines the argument to be passed to train a specific model.



B . Future work

For future work, it would be interesting to investigate other deep learning algorithms for traffic flow prediction and to apply these algorithms on different public open traffic data sets to examine their effectiveness. Furthermore, the prediction layer in our paper has been just a logistic regression. Extending it to more powerful predictors may make further performance improvement.

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