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MASTERS THESIS

Large scale real-time traffic flow
prediction using SCATS volume data

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*A thesis submitted in fulfilment of the requirements
for the degree of Master of Science in Computer Science*

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Declaration of Authorship

I , Rabindra Kumar PANDA, certify that

- this thesis does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person where due reference is not made in the text.
- the thesis is approximately 20000 words in length (excluding text in images, table, bibliographies and appendices).

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Date:

Abstract

In this thesis we apply extend an LSTM model for the application of short term traffic flow prediction. We analyse it using the SCATS volume data and suggest improvements.

Acknowledgements

I am deeply indebted to the following people for their invaluable support and comments without which I would not have been able to complete this work. . .

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Abbreviations

| | |
|--------------|---|
| ARIMA | A uto R egressive I ntegrated M oving A verage |
| LSTM | L ong T erm S hort M emory |
| RNN | R ecurrent N eural N etwork |
| SCATS | S ydney C oordinated A daptive T raffic S ystems |

Dedicated to my parents

Chapter 1

Introduction

“As a reader I loathe introductions...Introductions inhibit pleasure, they kill the joy of anticipation, they frustrate curiosity.”

Harper Lee, *To Kill a Mockingbird* (1960)

Road traffic congestion is a serious global issue, resulting in significant wastage of resources. While improving and extending the road infrastructure has reduced the issue to some extent, this is time consuming and limited in capacity. Thus in last few decades, for better planning and control of road traffic, adaptive traffic control systems have been deployed around the world. Still the role of adaptive control systems is not fully realised without predictive capabilities in the short term, without which the adaptive traffic control systems only react to events at the real time. While this is the desired objective, the performance of these systems could be significantly improved by making them proactive (Smith and Demetsky [153]). Short term traffic flow prediction is not only helpful for these advanced traffic control systems, it is also useful for advanced traveller information systems.

1.1 Background

Predicting the future has always been a fascinating topic throughout the history of mankind. Instances of predicting the future through unconventional means have been mentioned in various forms of literature such as mythologies, fantasy, science fiction etc. Even today, while the means of prediction have changed, we still try to predict almost everything in our day to day lives - from election polls to sports outcomes to financial results.

In the context of road traffic, prediction has always been a difficult task, merely due to the dynamic and complex nature of traffic. A lot of research has gone into short term traffic prediction. Various methods have been proposed in last few decades to provide more accurate predictions, yet none of those methods has been claimed to become the best.

1.2 Objectives and scope

Research objective is to propose a new model that can use the large amount of available traffic data to predict the traffic in the short term. More importantly this research tries to answer the following questions -

- How can we use the large amount of traffic data available for predicting short term traffic flow?
- Can the proposed deep learning models have better accuracy than exiting models?

Research scope - The scope of this research is to predict traffic volume in the short term. The use of the phrase 'short term' implies that we are only interested in the prediction within a very short horizon which typically ranges between few seconds to few hours in practice. The traffic parameters that are of usually of interest to be predicted are volume, time, speed and density. The scope of this research is limited to the prediction of only traffic volume. While doing so, we are only taking the past data into consideration and not taking the non-recurrent phenomena such as traffic accidents, weather or public events into consideration.

1.3 Thesis outline

Chapters – This thesis is divided into six chapters.

- Chapter 1: Introduction - In this chapter we present the background and research context, research objectives and scope.
- Chapter 2: Traffic Prediction: Literature Review - In this chapter we provide a reasonably thorough review of existing literature on short term traffic prediction.
- Chapter 3: SCATS Traffic Volume Data - In this chapter we provide the description of the traffic volume data collected by VicRoads using the SCATS systems.

Methods to deal with missing data are presented in this chapter. Finally we present some exploratory data analysis on the traffic data.

- Chapter 4: A Deep LSTM Network for Short Term Traffic Prediction - In this chapter we propose a long short term memory (LSTM) neural network model for short term traffic prediction.
- Chapter 5: Evaluation of the Model - In this chapter we evaluate the model.
- Chapter 6: Conclusions and Future Directions - In this chapter we conclude our thesis and provide inputs for future work.

Chapter 2

Traffic Prediction: Literature Review

“There is no way that we can predict the weather six months ahead beyond giving the seasonal average”

Stephen Hawking, *Black Holes and Baby Universes* (1993)

2.1 Introduction

In this chapter we provide a reasonably complete review of existing literature on short term traffic flow prediction. Research on short term traffic prediction has been going on since 1979, Ahmed and Cook [5]. After more than three decades of research, short term traffic flow prediction is still an interesting research subject for many professionals around the world. The simplest reason being the complex non-linear nature of traffic data and the effects of non-recurrent events (weather, public events, accidents etc.) on it. Critical reviews of existing literature on short term traffic flow have been presented in detail by Smith and Demetsky [153], Vlahogianni et al. [188], Van Lint and Van Hinsbergen [182] and Vlahogianni et al. [193]. The use of the phrase ‘short term’ limits the scope of traffic prediction in terms of the prediction horizon which usually varies between few seconds to few hours depending upon the approach and application.

The traffic parameter that are predicted can be - flow(number of vehicles per hour), time(minutes to travel between two points), speed(mean speed in km/hour) and density(number of vehicles per km).

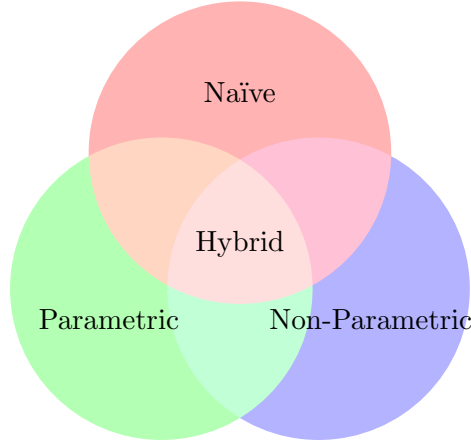


FIGURE 2.1: Methods used for short term traffic prediction

Selecting the right model for short term traffic prediction is a challenging task. A number of models have been suggested and yet there is no one-fits-all model. The various methods that have been suggested for short term traffic prediction can be categorised into four groups - naïve, parametric, non-parametric and hybrid as shown in figure 2.1.

2.2 Naïve methods

These methods, while called as naive are sometimes used in practice because of the simplicity of the method and the ease of implementation. In most cases these methods are used as baselines for comparison while creating more advanced methods. The simplest naive approach in short term prediction would be to take the last observed value and this involves no computational effort.

Instantaneous Travel Time(ITT) assumes that the traffic conditions will remain constant indefinitely.

Historical averages uses the average of past observed values.

2.3 Parametric models

In parametric models, we estimate the parameters from the training dataset to determine the function that classifies new unseen data. The number of parameters are fixed. The advantage of parametric models are that these perform quite well in situations where the large amount of data is not available. Some of the typical examples of parametric models include Linear and nonlinear regression, ARIMA models, Kalman filter, Linear SVM etc.

2.3.1 Classical regression

In machine learning and statistical applications, the use of linear models are predominant. These models are also important in time series domains such as traffic flow prediction. The primary idea behind the regression is to express the output variable as a linear combination of input vectors. We can express the linear regression in time series as an output influenced by a collection of inputs, where the inputs could possibly be an independent series

$$x_t = \beta_1 z_{t1} + \beta_2 z_{t2} + \dots + \beta_q z_{tq} + w_t \quad (2.1)$$

where $\beta_1, \beta_2, \dots, \beta_q$ are unknown regression coefficients and w_t is a random error.

Höberg [81] used non-linear regression for traffic prediction.

2.3.2 ARIMA

ARIMA(Auto Regressive Integrated Moving Average) is a class of parametric regression models. In this section we will introduce ARIMA and related methods such as exponential smoothing and moving averages. For an in depth understanding of these models the reader is encouraged to refer to Tong [170], Brockwell and Davis [19] and Box et al. [17]. It is important to understand that ARIMA modelling works only with stationary time series data. A stationary time series is one whose properties do not depend on the time it is being observed. Trends and seasonality affect time series and hence make it non-stationary. Although this seems as a big restriction, in short term traffic prediction, ARIMA models have been very successful. Two basic models constitute ARIMA models - AR(autoregressive) and MA(moving average).

The main idea behind autoregressive models is that past values affect the present value, i.e. x_t can be expressed as a function of past p values $x_{t-1}, x_{t-2}, \dots, x_{t-p}$, where p is the number of steps into the past. We can express an autoregressive model of order p as below

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots + \phi_p x_{t-p} + w_t \quad (2.2)$$

where x_t is stationary and $\phi_1, \phi_2, \dots, \phi_p$ are constant parameters that are to be chosen. We have added the term w_t as a Gaussian white noise with zero mean and variance σ_w^2 .

In the MA model, the current value is dependent on the last q one-step forecast errors $e_{t-1}, e_{t-2}, \dots, e_{t-q}$ and the white noise w_t . The expression for moving average is

$$x_t = -\theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} + w_t \quad (2.3)$$

$\theta_1, \theta_2, \dots, \theta_q$ are the parameters to be chosen.

Now proceeding to an ARMA (autoregressive moving average) model, we define an ARMA(p,q) model where the present value x_t is dependent on p past recent values and q past recent forecast errors and a white noise w_t .

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots + \phi_p x_{t-p} - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} + w_t \quad (2.4)$$

When q is 0, the model becomes an autoregressive model of order p , AR(p) and when p is 0 the model is a moving average of order q , MA(q). We can rewrite 2.4 by using the backshift operator B^α , which is defined as $B^\alpha z_t = z_{t-\alpha}$,

$$\phi(B)x_t = \theta(B)e_t \quad (2.5)$$

where

$$\phi(z) = 1 - \phi_1 z - \dots - \phi_p z^p \quad (2.6)$$

$$\theta(z) = 1 - \theta_1 z - \dots - \theta_q z^q \quad (2.7)$$

In practice, most time series data are non-stationary and so several approaches, for instance by differencing, are taken to make it stationary before applying the ARMA(p,q) model. By combining differencing with autoregressive and moving average we obtain the ARIMA model defined as below

$$x'_t = \phi_1 x'_{t-1} + \phi_2 x'_{t-2} + \dots + \phi_p x'_{t-p} - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} + w_t \quad (2.8)$$

where x'_t is the differenced series. Formally the model is denoted as ARIMA(p,d,q) where p is the order of autoregressive part, d is the degree of differencing and q is the order of moving average. This is also known as a non-seasonal ARIMA model.

The common method used to determine the parameters in an ARIMA(p,d,q) model is known as the Box-Jenkins approach (Box et al. [17]) which is three stage procedure. The three stages are identification, estimation and diagnostic checking. At the identification stage, the values p , d and q are determined by observing the autocorrelation and partial

autocorrelation functions of the time series and its differences. At the estimation stage, the maximum likelihood estimates are determined for each model parameter. Finally in the diagnostics stage, the residuals are analysed and model comparisons are done. If the model fits well then the standardised residuals behave as an i.i.d. with mean zero and variance one.

Ahmed and Cook [5] used Box-Jenkins method for short-term traffic forecast. The input data used was 166 sets of time series traffic data collected by freeway traffic surveillance systems in three locations - Los Angeles, Minneapolis and Detroit. The authors concluded an ARIMA(0,1,3) model as a reasonable fit for the short term prediction task.

Nihan and Holmesland [138] used the Box-Jenkins technique on monthly data collected on a freeway segment from 1968 to 1976.

Kumar and Vanajakshi [112] used a seasonal ARIMA in a context of limited data for short term traffic prediction.

The major deficiency of the ARIMA models is that they do not take the extremes into consideration and focus on the means. This is in contrast to the nature of the traffic data. ARIMA models also have the inability to perform well with missing data as pointed out by Smith and Demetsky [153].

2.3.3 Exponential smoothing

In exponential smoothing method the forecast is the weighted average of past observations, while the weights decrease exponentially for older observations. For time series data with no trends and seasons single exponential smoothing is usually used.

2.3.4 Kalman filter

Okutani and Stephanedes [140] used Kalman filtering in traffic prediction in an urban network and extended it for freeways.

The main advantage of Kalman filtering is the state variable is updated continuously.

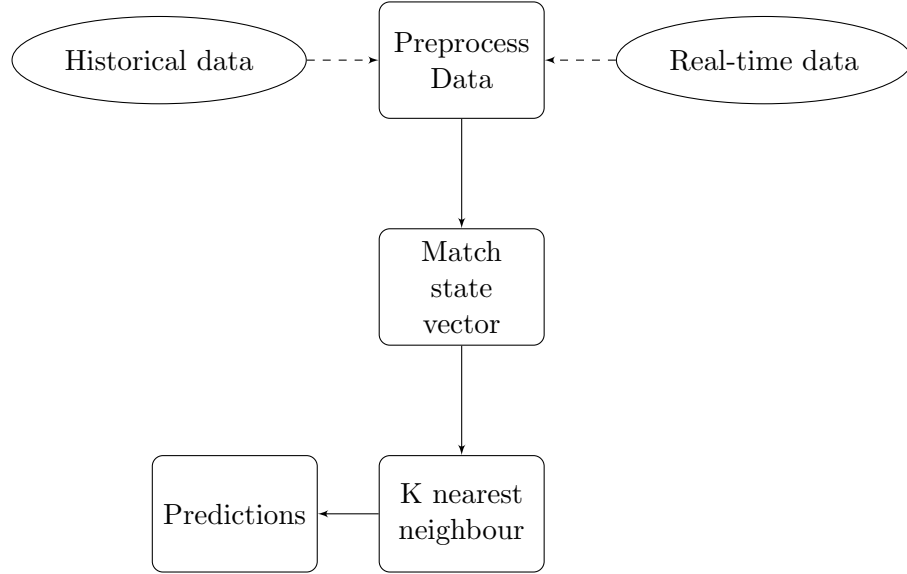


FIGURE 2.2: K nearest neighbour process flow

2.3.5 Other parametric models

2.4 Non-Parametric models

In nonparametric models the parameters are not fixed, and vary with the amount of data available. Usually more data is required for these models than parametric models. The advantage of these models is that they can model the complex non-linear data better. Some of the widely used non-parametric models are - k-Nearest Neighbour, Non-parametric regression and Neural Networks

2.4.1 K-nearest neighbour

The basic process of the k-nearest neighbour algorithm is described in figure 2.2.

2.4.2 Fuzzy logic

2.4.3 Bayesian networks

2.4.4 Neural networks

Artificial Neural Networks(ANN) were mathematical models (McCulloch and Pitts [125], Rosenblatt [148]) designed to provide a representation of how the human brain works. It is obvious now that these mathematical models bear little resemblance to the structure

of brain, yet they have been hugely successful. Because they were initially inspired by the biological brain, the term neural is associated with such kind of mathematical models. A basic artificial neural network consists of a set of nodes connected by edges with weights. We can say that the nodes represent the biological neurons and the edges represent the synapses. The connections among the nodes can be cyclic or acyclic. The former is known as a feedforward neural network and the later as a recurrent network. We describe about these neural networks in more details in chapter 4.

Several variations of artificial neural networks have been used in short term traffic prediction. Some well known examples include - *Multilayer perceptrons*, *Radial basis function networks*, *Kohonen maps* and *Hopfield networks*.

2.4.5 Other nonparametric models

2.5 Hybrid Methods

2.6 Comparisons

Chapter 3

SCATS Volume Data

“There is no order in the world around us, we must adapt ourselves to the requirements of chaos instead.”

Kurt Vonnegut, *Breakfast of Champions* (1973)

3.1 Introduction

SCATS(Sydney Coordinated Adaptive Traffic System) is an adaptive traffic control system. It was developed by the Department of Main Roads in the 1970's. SCATS operates in real-time by adjusting signal timings in response to changes in traffic demand and road capacity. All major and minor cities in Australia and New Zealand use SCATS. Few other cities around the world such as Hong Kong, Kuala Lumpur, Sanghai and Singapore also have adopted SCATS over other adaptive traffic control system. In Melbourne and surrounding cities, SCATS controls more than 3,900 sets of traffic signals

There are three main parameters that SCATS user to achieve traffic signal coordination:

- Cycle time: The total time of all signal sequences in a cycle
- Phase split: The proportion of the cycle time allocated to each phase
- Offset: The time relationship between the starting and finishing of the green phases of succesive sets of signals within a coordinated system

The desicion making of the SCATS system occurs at two levels - *strategic* and *tactical*.

3.2 Volume data

Traffic loop detectors are embedded in the road pavement and located in each lane near the stop line at traffic intersections. These detectors collect traffic volume and the time it takes a vehicle to clear the loop. In this research we used the data collected from sensors at 1084 homogeneous links (a road segment where the volume for all traffic along that link is collected). Traffic volume was collected for every 15 minutes interval from 01/01/2008 to 25/07/2013, a total of 195168 observations.

3.2.1 Handling missing data

One of the major difficulties with traffic sensor data is missing data, that can be caused by several factors.

3.3 Exploratory analysis

In this section, we will perform exploratory analysis on the traffic volume data at a homogeneous segment. For this purpose we will use both the south and north bound traffic data at Nicholson street (north of Melbourne's CBD) between Gertrude street and Victoria Parade during the period 01/01/2008 to 25/07/2013.

Figure 3.1 shows the daily, weekly, monthly and yearly average traffic volume at a site location. Figure 3.2 shows how a typical day of the week on average looks like at a homogeneous link.

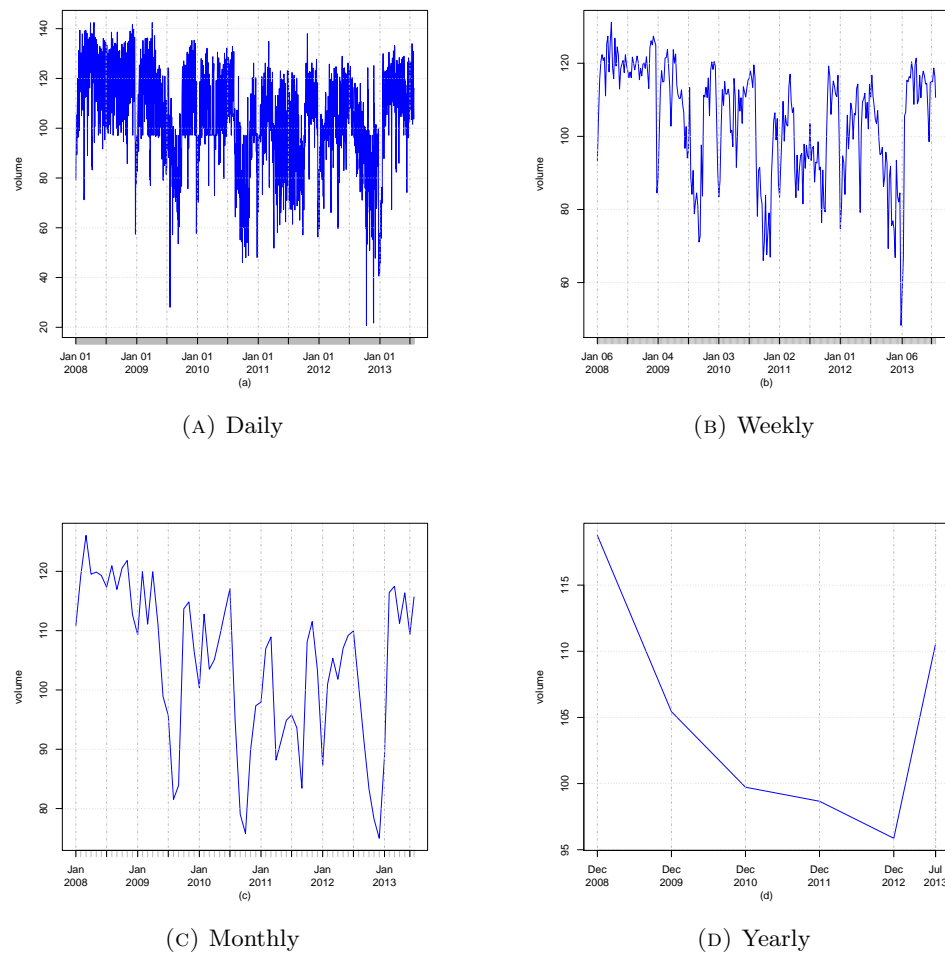
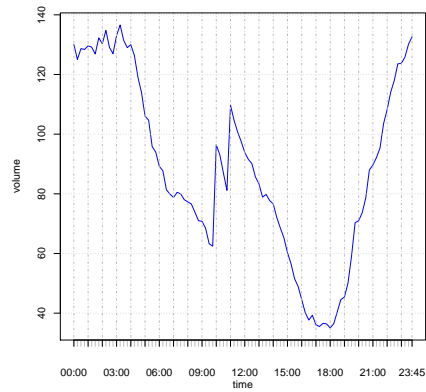
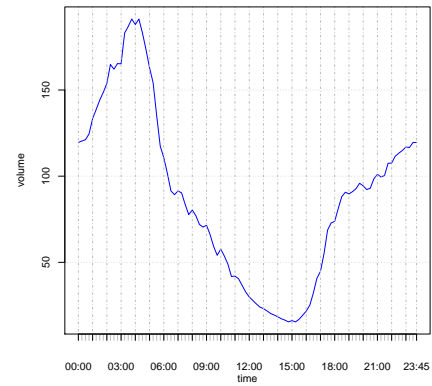


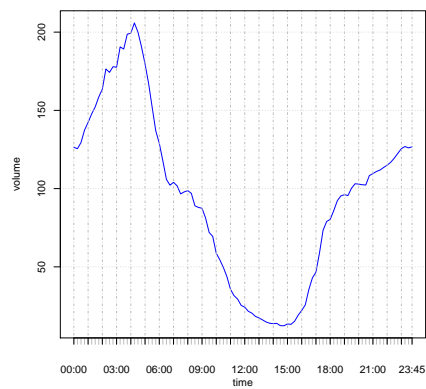
FIGURE 3.1: (a) daily, (b) weekly, (c) monthly and (d) yearly average of traffic volume (15 mins interval) at a site location from the period 01/01/2008 to 26/07/2013



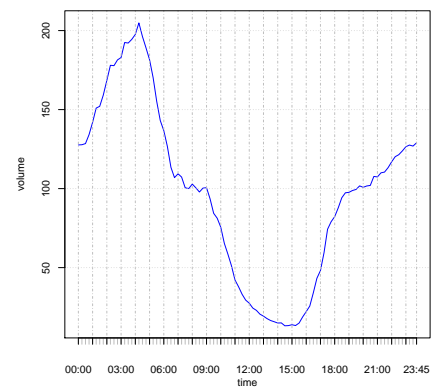
(A) Monday



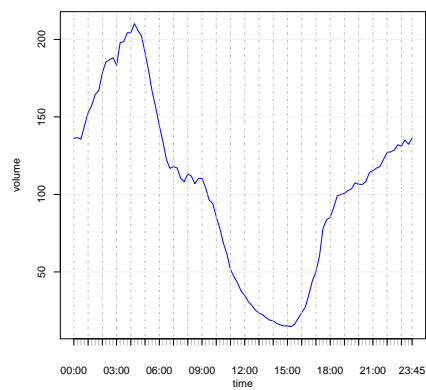
(B) Tuesday



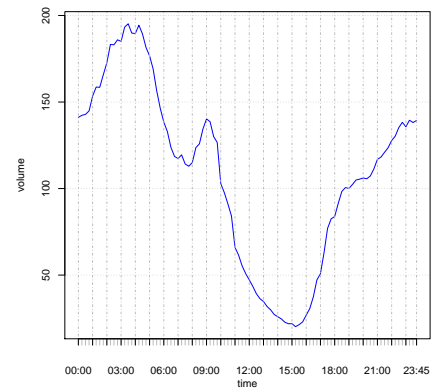
(C) Wednesday



(D) Thursday



(E) Friday



(F) Saturday

FIGURE 3.2: Average traffic grouped by every day of the week.

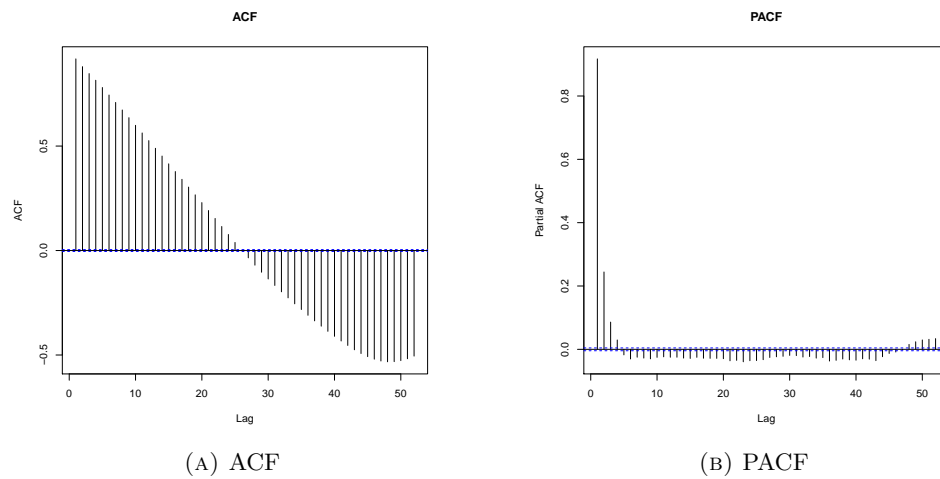


FIGURE 3.3: Plots of the autocorrelation and partial autocorrelation functions

Chapter 4

A Deep LSTM Network for Short Term Traffic Prediction

“I am a brain, Watson. The rest of me is a mere appendix.”

Arthur Conan Doyle, *The Adventure of the Mazarin Stone* (1921)

In section 2.4.4, we presented a brief introduction to artificial neural networks and reviewed existing literature in short term traffic prediction that used various types of neural networks. In the following sections we present a brief overview of deep learning. We then describe deep feedforward networks, deep recurrent networks with emphasis on the Long Short Term Memory (LSTM) networks which are a redesigned version of recurrent networks. Later we present how we can use these kind of networks for short term traffic prediction.

4.1 Introduction

Today we live in a world where almost every interaction of ours with the external world uses some form of computing. Computers have become an inseparable part of human lives. In the earlier days when computers were built, people began to ponder whether they could achieve human level of intelligence. Even though at that point the answers seemed optimistic, it has taken quite some time and understanding on our part to make significant achievements in the field of artificial intelligence. One of the approaches was to use knowledge base systems, where computers reason about real world concepts, that were defined in hard-coded formal languages, using logical inference rules. These systems led to little success. The difficulties faced in the knowledge based approach

made us build computers to learn automatically from data, an approach we know as machine learning.

A large number of real world problems could easily be tackled using machine learning. However for the machine learning algorithms to perform well they need to be provided with proper representation of data. For example, in a problem where we would like to detect humans in images, it is difficult to represent various shapes of human body in terms of raw pixels. Finding a proper representation from data is a challenge and sometimes become very difficult. A class of machine learning algorithms called representation learning, tackles this problem by learning the representations as well. Autoencoders are such types of algorithms. Again the problem with representation learning is that it is not easy to find the representations due to the presence of various factors of influence (Bengio et al. [10]). Deep learning solves this problem in representation learning by taking a layered approach by expressing representations in terms of simpler representations. The mapping from the input to output is done through a series of hidden layers, where each layer is an abstraction on the previous layer. The depth of the model can be viewed as the depth of the computational graph, i.e. the number of sequential instructions that need to be executed to map an input to output.

4.2 Feedforward neural networks

Deep feedforward networks are the most important deep learning models. The main goal of a deep feedforward network is to approximate a function f^* that maps an input \mathbf{x} to an output y . As the name implies, the information in these models flow in the forward direction. These are the basis of several models used in commercial applications such as the convolutional networks, which are extensions of the feedforward networks, have been very successful in image recognition. With the addition of feedback connections to feedforward networks, recurrent networks are created. Feedforward networks consist of a chain of layers, which is simply done by composing functions for instance we can compose three functions as to map an input \mathbf{x} to an output y , $y = f(\mathbf{x}) = f^3(f^2(f^1))$. Function f^2 acts as the hidden layer that maps the output from the input layer f^1 to the input of the output layer f^3 .

The diagram 4.1 illustrates a simple feedforward neural network with 3 nodes in the input layer, 3 and 4 nodes in two hidden layers and a single node output layer. Information propagates from the input layer through the hidden layer to the output layer, known as the forward pass of the network. This kind of feedforward network is called a multilayer perceptron. Multilayer perceptrons are good at classification.

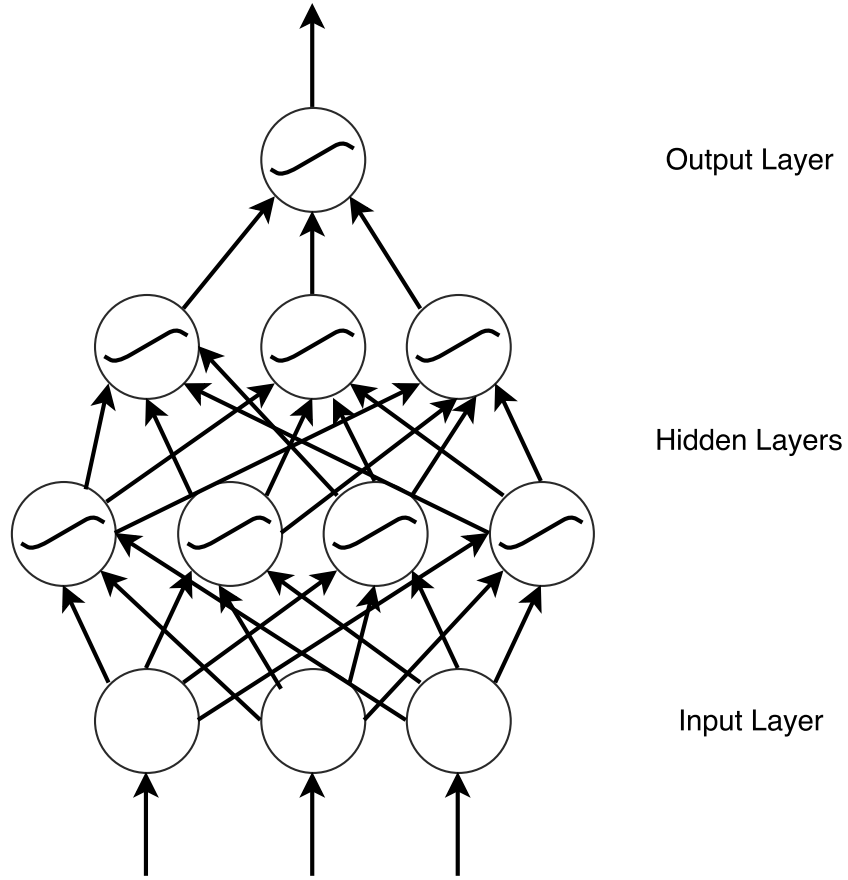


FIGURE 4.1: A feedforward neural network with two hidden layers, this network is also known as a multilayer perceptron. The S-shaped curves denote the sigmoidal function.

Let's consider a simple multilayer perceptron with I nodes in the input layer. For an input vector \mathbf{x} , where length of \mathbf{x} is I . Each node in the hidden layer gets a weighted sum of the units in the input layer. The output of each hidden unit a_h is then applied to an activation function θ_h to produce the activation b_h

$$a_h = \sum_{i=1}^I w_{ih} x_i \quad (4.1)$$

$$b_h = \theta_h(a_h) \quad (4.2)$$

There are several choices for the activation functions with sigmoidal and hyperbolic tan functions are the most common choices. The reason of these choices is nonlinearity of these functions. Recently the recommended activation function for feedforward neural networks is the *rectified linear unit* or ReLU (Nair and Hinton [133]), defined as $f(x) = \max(0, x)$, as they allow faster and efficient training of deep neural network architectures.

The activations flow through the rest of the hidden layers in similar fashion. For instance the l^{th} hidden unit in layer H_l

$$a_h = \sum_{h' \in H_{l-1}} w_{h'h} b_{h'} \quad (4.3)$$

$$b_h = \theta_h(a_h) \quad (4.4)$$

In the output layer, the activation function is applied on the output from the hidden layer to produce the output y . The input a_k to the output unit is given by

$$a_k = \sum_{h \in H_L} w_{hk} b_h \quad (4.5)$$

where L is the number of hidden layers in the network. The number of units in the output layer and the type of activation function are chosen based on the problem task at hand. For binary classification a single unit with logistic sigmoid activation function is primarily used. For classification with $k \geq 2$ classes, k output units are used and the outputs are normalised using the *softmax* function. A very common example of this is the hand-written digits classification, where the output layer consists of 10 units.

4.3 Recurrent neural networks

As mentioned earlier, we can create a recurrent neural network by adding feedback connections to a feedforward network. Several types of recurrent neural networks have been proposed over the years, some of which are - *echo state networks*, *time delay networks*, *jordan networks*. At first the difference between a feedforward and a recurrent network may not be obvious and seem trivial but recurrent networks are very powerful in the sense that they can retain the history and thus forming a memory in their feedback connections.

4.4 Network training using gradient descent

Training neural networks is no different than any other machine learning models with a loss function and gradient descent algorithm. However the difficulty is that the non-linear characteristics of neural networks causes to the loss functions to become non-convex. So the training procedure usually involves small iterative gradient descent algorithm to get

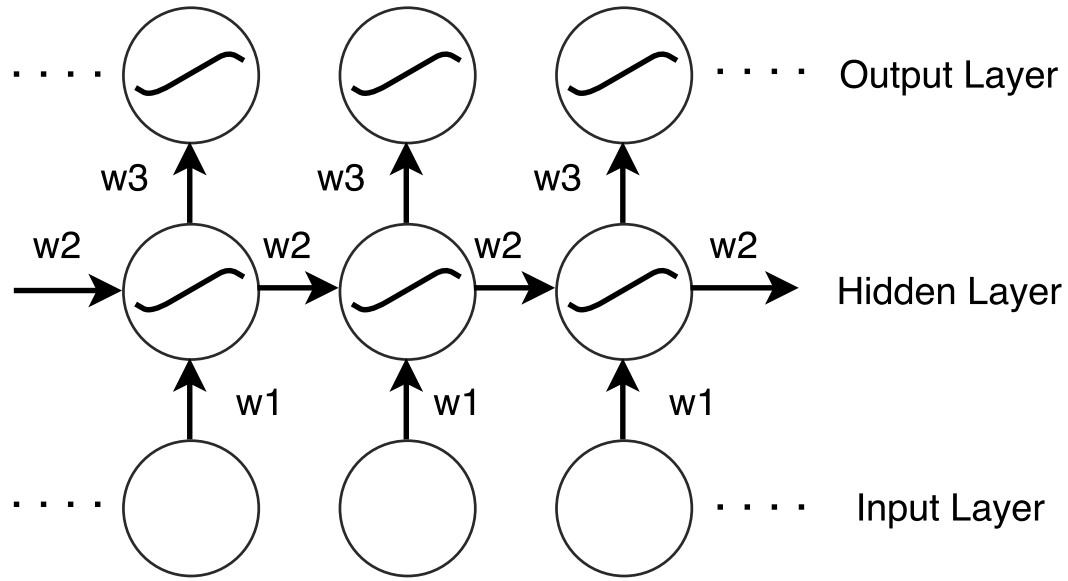


FIGURE 4.2: An unfolded recurrent neural network. w_1 , w_2 and w_3 are weighted connections.

a very low value of the cost function. For feedforward networks the weights are initialised with very small random numbers and the biased may be initilised to zero or very small values as well.

The choice of a cost function is somehow important and usually these are same as the linear models.

4.5 LSTM networks

In previous section we learn that using a recurrent neural networks we can store information in form of activations in the feedback connections. The major disadvantage with recurrent neural networks is their inability to rertain information for a long period of time. This is caused by an effect known as *vanishing gradient problem*(Bengio et al. [11], Hochreiter et al. [78]). The vanishing gradient problem is depicted in the figure 4.3. Number of attempts were made in the 1990's to resolve this issue. Hochreiter and Schmidhuber [79] proposed a redesigned network called Long Short Term Memory(LSTM) to address this problem.

4.5.1 Architecture

An LSTM network is a set of recurrently connected LSTM blocks, also known as memory blocks, where each memory block has one or more memory cells and three units (input,

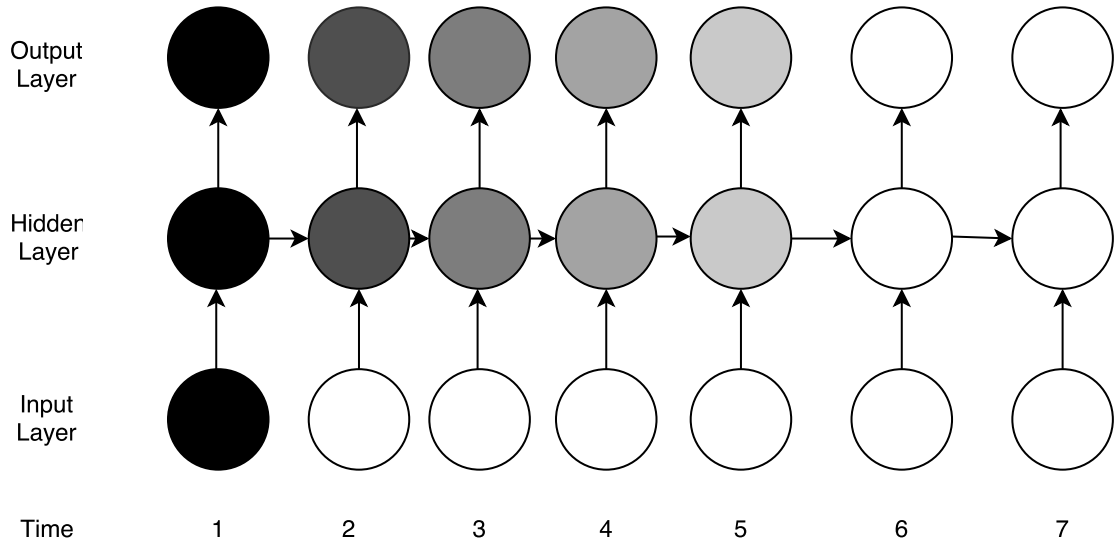


FIGURE 4.3: The problem of vanishing gradient in recurrent neural networks. The sensitivity, as indicated by the shading, gradually diminishes with time

output and forget gates) that perform the read, write and reset operations. A basic LSTM block with one memory cell is depicted in the figure 4.4. The multiplicative units allow the LSTM to store information for a long time and thus addresses the problem of vanishing gradient. An LSTM network is shown in figure 4.5, the hidden layers contains the LSTM blocks.

4.5.2 Training

4.6 A Stacked LSTM network for short term traffic prediction

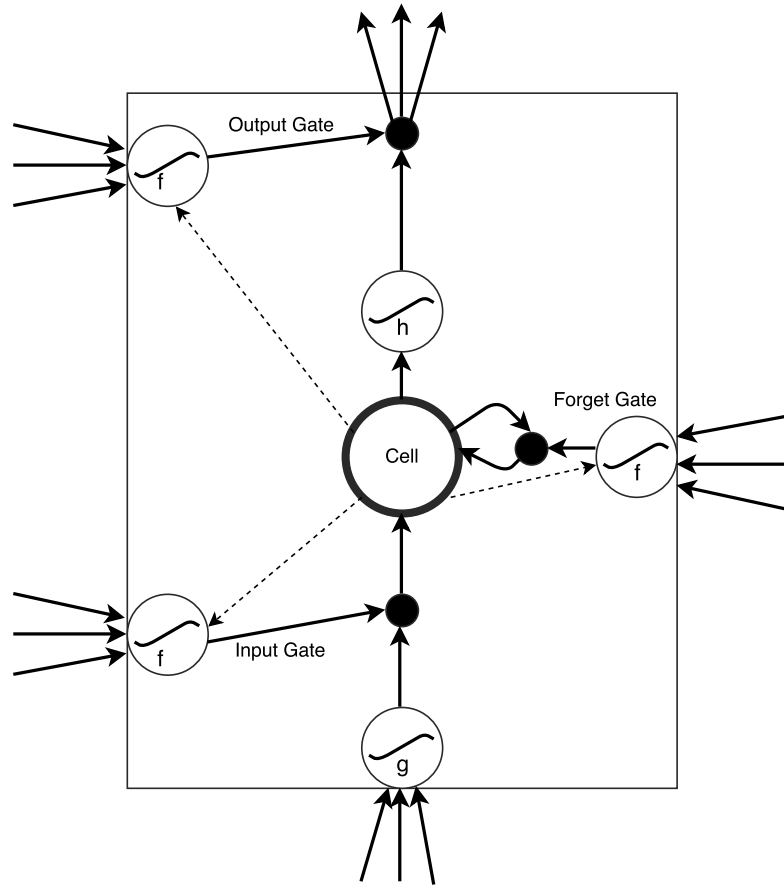


FIGURE 4.4: An LSTM block with one cell. The three units collect activations from both inside and outside of the block. The small black circles represents multiplications by which the gates control the memory cell. The gate activation function is f , usually a logistic sigmoid. The cell input and output functions are g and h , usually \tanh or logistic sigmoid. The dashed lines represent the weighted peephole connections from the cell to the gates. All other connections are not weighted. The only outputs from the block to the rest of the network is from the output gate multiplication.

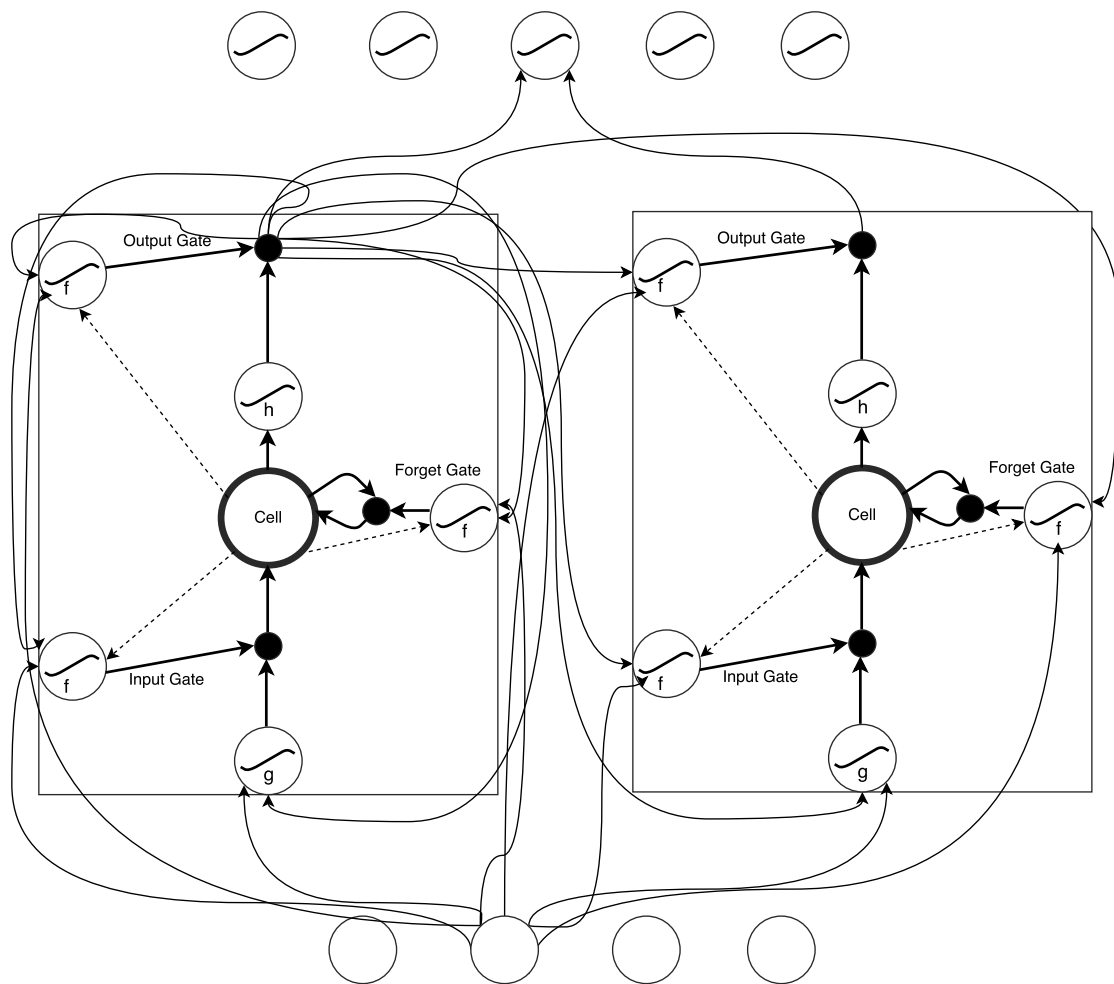


FIGURE 4.5: An LSTM network with one hidden layer with two memory blocks. The input layer consists of four input units and the output layer consists of five output units. Not all connections are shown in the figure. There is only one output from the block.

Chapter 5

Evaluation of the Model

“Science, my boy, is made up of mistakes, but they are mistakes which it is useful to make, because they lead little by little to the truth”

Jules Verne, *Journey to the Centre of the Earth* (1864)

5.1 Experimental setup

We chose a subset of the obtained traffic data for experimentation as shown in the figure [5.1](#). The region boundary of the subnetwork is denoted by the red line.

5.1.1 Training details

We trained our stacked LSTM network([4.6](#))

5.2 Results

For comparison purpose we used the following methods that have been in used predominantly in short term traffic prediction - Naïve, Linear regression, ARIMA, Exponential smoothing and Feedforward neural network. In figure [5.2](#), we present the predictions of these models on test data. The input sequence was set to 96 observations(1 day) and the prediction was done for next 15 minutes(1 step ahead).

The results of the LSTM network are shown in the figure [5.3](#)

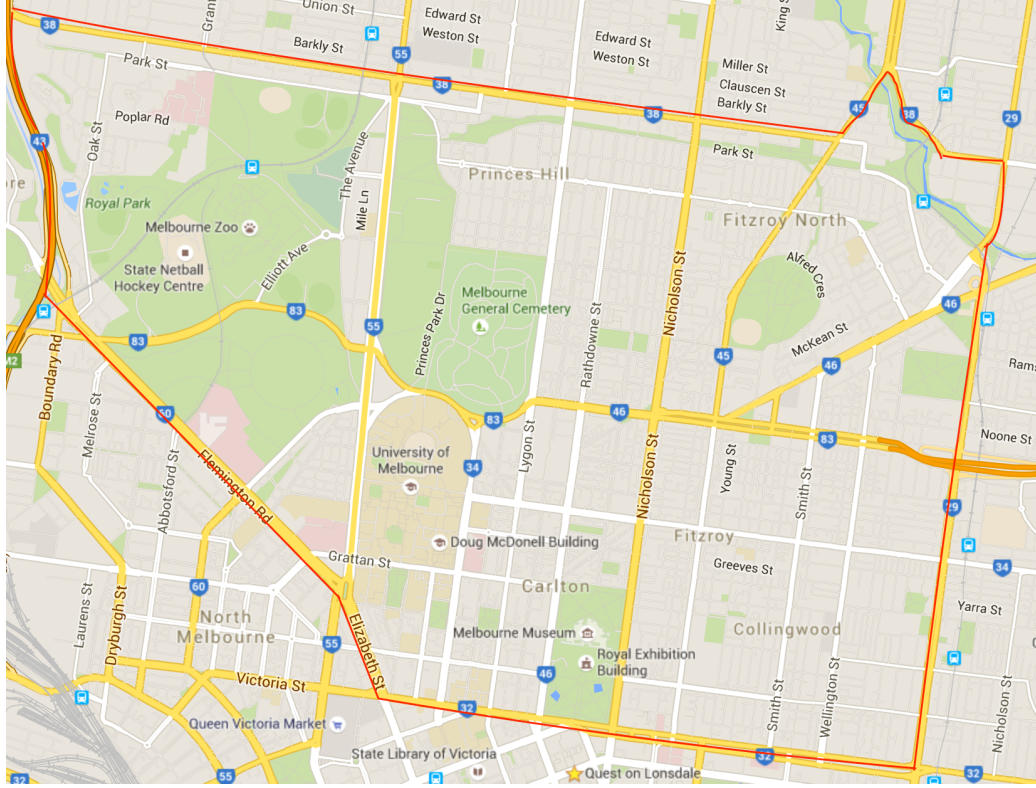


FIGURE 5.1: The traffic region used in this experiment. The boundary is denoted by the red line.

In table 5.1, the performance of the LSTM network along with the compared models are given.

Several accuracy measures exist to evaluate a model. In below sections we describe the accuracy measures and use those to evaluate our proposed model against the benchmark models. For defining the accuracy measures let us denote x_i be the i^{th} observation and \hat{x}_i be the prediction of x_i .

Scale-dependent errors The prediction error is simply given by $e_i = x_i - \hat{x}_i$, which is in the same scale as of the original data. So accuracy measures that depend on e_i are scale dependent and can not be used across multiple series on different scales. The two most used scale-dependent accuracy measures are mean absolute error and root mean squared error defined as below

$$MAE = \text{mean}(|e_i|) \quad (5.1)$$

$$RMSE = \sqrt{\text{mean}(e_i^2)} \quad (5.2)$$

MAE is easy to understand and popular in usage when using a single dataset.

Percentage errors Percentage errors are scale-independent and thus used across multiple datasets on different scales. The percentage error is given by $p_i = 100 * e_i / x_i$. The most commonly used percentage measure is Mean Absolute Percentage Error(MAPE) which is given by the below formula

$$MAPE = mean(|p_i|) \quad (5.3)$$

There are however few shortcomings of the MAPE, for instance when x_i is 0 or very large. Another shortcoming is that they put heavier penalty on negative error values than positive error values.

Scaled errors Hyndman and Koehler [93] proposed scaled errors to be used as an alternative in place of percentage errors. The proposed Mean Absolute Scaled Error(MASE) is defined as

$$MASE = mean(|q_i|) \quad (5.4)$$

where

$$q_i = \frac{e_i}{\frac{1}{T-1} \sum_{t=2}^T |x_t - x_{t-1}|} \quad (5.5)$$

A scaled error is less than one if it is better than the average naïve forecast computed on the training data and vice versa.

| Model | ME | MAE | RMSE | MPE(%) | MAPE(%) | MASE |
|-------------------------------|-------|-------|-------|--------|---------|------|
| 15 minutes | | | | | | |
| Mean Forecast | 10.73 | 48.13 | 48.13 | -63.61 | 98.34 | 1.57 |
| Naive | -0.18 | 15.25 | 15.25 | -5.65 | 21.24 | 0.49 |
| Linear Regression | 9.75 | 50.30 | 50.30 | -62.20 | 97.84 | 1.65 |
| ARIMA | 1.87 | 15.10 | 15.10 | -6.05 | 21.30 | 1.02 |
| Eponential Smoothing | 0.04 | 15.33 | 15.33 | -5.48 | 20.68 | 1.04 |
| Feedforward Neural Network | 5.61 | 19.40 | 19.40 | -5.51 | 24.29 | 1.30 |
| Deep LSTM(single location) | | | | | | |
| Deep LSTM(multiple locations) | | | | | | |
| 30 minutes | | | | | | |
| Mean Forecast | 10.29 | 47.13 | 48.31 | -63.63 | 98.27 | 1.54 |
| Naive | -0.62 | 16.65 | 18.16 | -6.35 | 23.02 | 0.54 |
| Linear Regression | 9.30 | 49.30 | 50.38 | -62.67 | 98.30 | 1.62 |
| ARIMA | 2.42 | 16.56 | 18.02 | -7.18 | 23.67 | 1.12 |
| Eponential Smoothing | -0.61 | 16.66 | 18.08 | -5.74 | 22.20 | 1.13 |
| Feedforward Neural Network | 6.61 | 19.54 | 20.98 | -4.51 | 25.06 | 1.33 |
| Deep LSTM(single location) | | | | | | |
| Deep LSTM(multiple locations) | | | | | | |

TABLE 5.1: Accuracy measures for the evaluted models. The scores are calculated for prediction horizon of 15-minutes(top half) and 30-minutes(bottom half). Mean 15-minutes traffic volume is 104.4

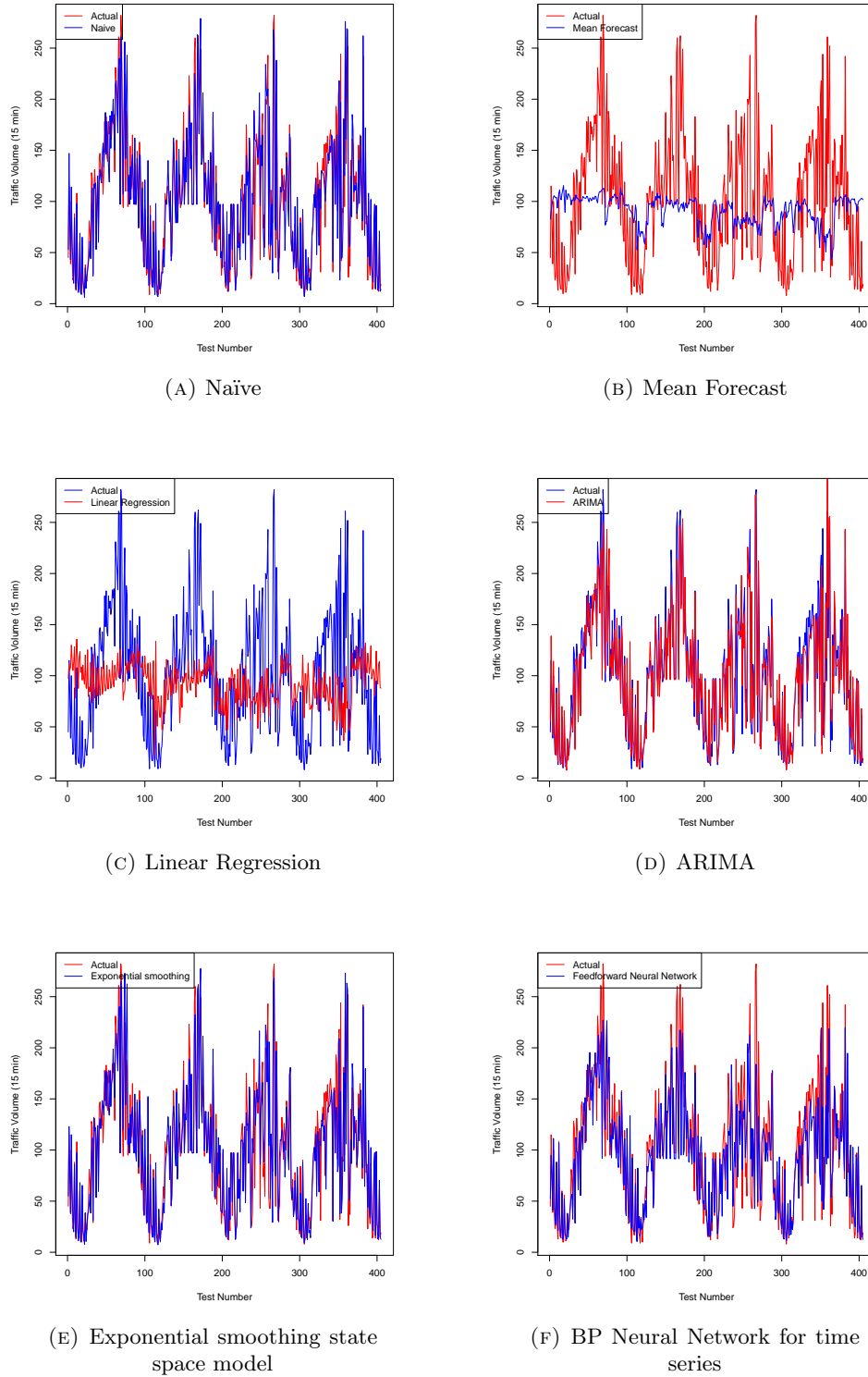


FIGURE 5.2: Actual vs Predictions - linear regression, ARIMA, feed forward neural network one hidden layer and exponential smoothing using state space model. The models were trained on traffic data from one homogeneous road segment. The plots show the actual vs predictions(15 mins) on 400 test examples, for one of those road segment (Nicholson street between Gertrude street and Victoria Parade).

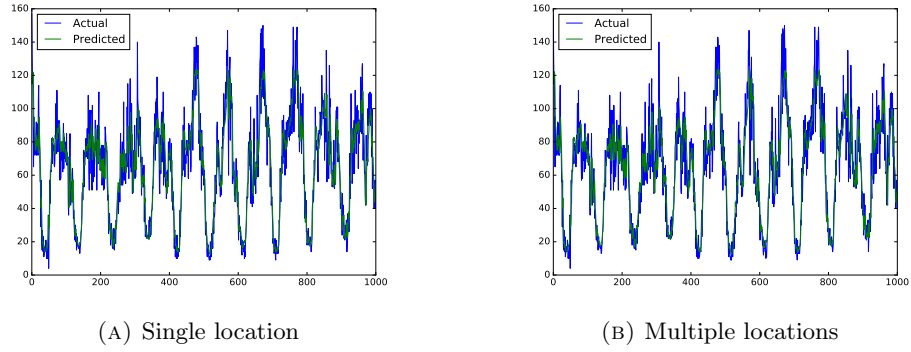


FIGURE 5.3: Actual vs Predictions - The left figure is from the model trained using data from a single homogeneous road segment only. The figure in right is from the model trained on 67 homogeneous road segments in the chosen subnetwork(5.1). Both the plots show the actual vs predictions(15 mins) on 400 test examples, for one of those road segment(Nicholson street between Gertrude street and Victoria Parade).

Chapter 6

Conclusions and Future Directions

“Everything should be made as simple as possible but not simpler.”

Albert Einstein

6.1 Conclusions

In this work, we reviewed the existing literature on short term traffic prediction and proposed how a long short term memory recurrent neural network can be used for this task.

6.2 Future works

Appendix A

Appendix Title Here

Write your Appendix content here.

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