Department of Computing and Information Systems
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Masters Thesis

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

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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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Abstract

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. 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. A lot of research has gone into proposing short term traffic prediction models, yet none of those models can be claimed to be perfect due to the nature of traffic data and the variable factors that affect it.

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

Symbols

y	Scalar value
$\mathbf{x}$	Vector
$\mathbf{M}$	Matrix
Σ	Covariance matrix

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 adapative 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 [151]). 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 unconventinal 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 reserch subject for many professionals around the world. The simplest reseaon 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 [151], Vlahogianni et al. [186], Van Lint and Van Hinsbergen [180] and Vlahogianni et al. [191]. 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).

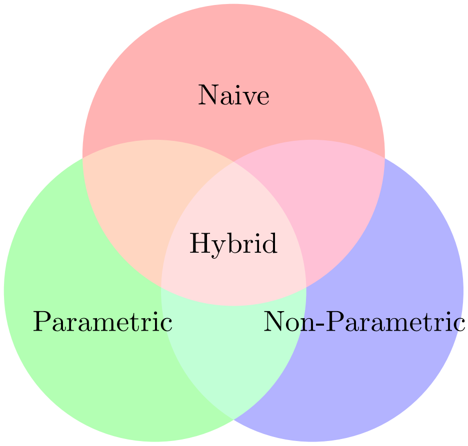

Figure 2.1: Methods used for short term traffic prediction

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 - naive, parametric, non-parametric and hybrid as shown in figure 2.1.

2.2 Naive 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 advances methods. The simplest naive approach in short term prediction would be to take the last observed value and this involves no computational effort.

Instanteneous Travel Time(ITT) assumes that the traffic conditions will remain constant indefinitly.

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 Linear and nonlinear 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 ouput influenced by a collection of inputs, where the inputs could possibly be an independent series

$$x_t = \beta_1 z_{t1} + \beta_2 z_{t2} + ... + \beta_q z_{tq} + w_t \tag{2.1}$$

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

Högberg [81] used non-liner 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 to Tong [168], Brockwell and Davis [19] and Box et al. [17].

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 $x_{t-1}, x_{t-2}, ..., x_{t-p}$, where p is the number of steps into the past. We can express an autoregressive model of order p as below

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + ... + \alpha_p x_{t-p} + w_t \tag{2.2}$$

where x_t is stationary and $\alpha_1, \alpha_2, ..., \alpha_p$ are constants. We have added the term w_t as a Guassian white noise.

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 resonable fit for the short term prediction task.

Nihan and Holmesland [136] used the Box-Jenkins technique on monthly data collected on a freeway segment from 1968 to 1976.

Kumar and Vanajakshi [111] used a seasonal ARIMA in a context of limited data for short term traffic prediction.

The major defficiency of tha 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 are also have the inability to perform will with missing data as pointed out by Smith and Demetsky [151].

2.3.3 Kalman filter

Okutani and Stephanedes [138] used Kalman filtering in traffic prediction in an urabn network and extended it for freeways.

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

2.3.4 Other parametric models

2.4 Non-Parametric models

In nonparamtric models the parameters are not fixed, and vary with the amount of data available. Usually more data is required for this 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 regrssion 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 [124], Rosenblatt [146]) 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

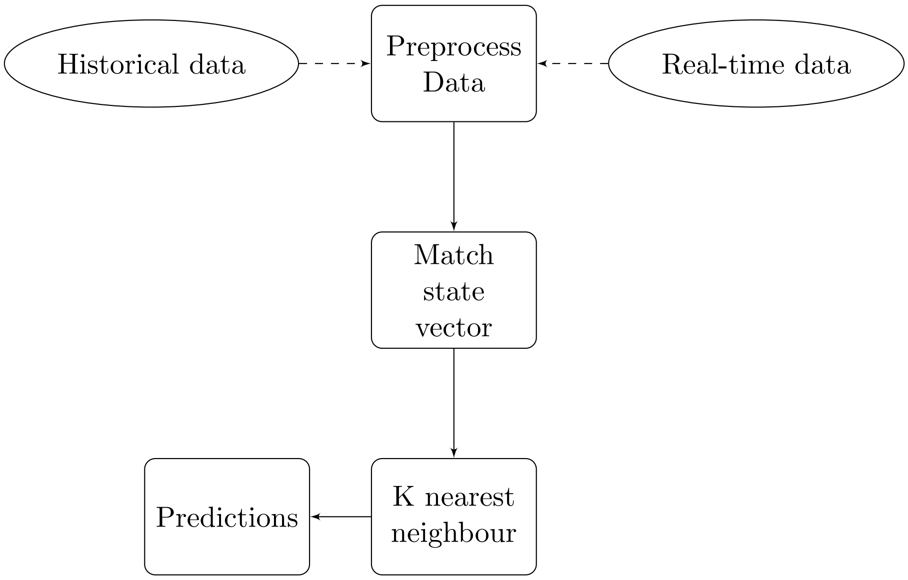

FIGURE 2.2: K nearest neighbour process flow

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 connnected by edges with weights. We can say that the nodes represent the biological neurons and the edges represent the synapses. The conections among the nodes can be cyclic or acyclic. The former is known as a feedforward neural network and the later as a recurrent network.

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, Kohnen 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 raod 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.

3.2.1 Handling missing data

3.3 Exploratory analysis

Figure 3.1 shows the daily, weekly, monthly and yearly average traffic volume at a site location.

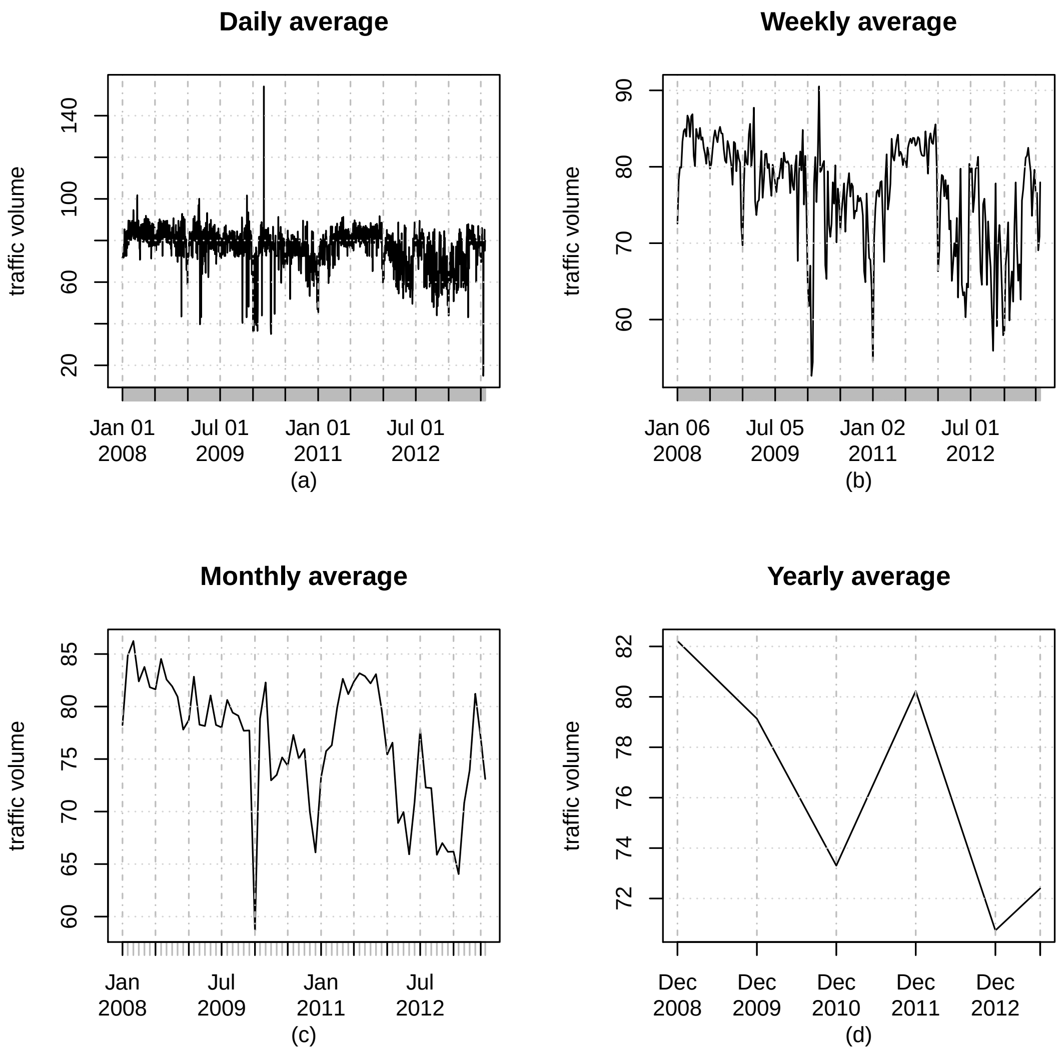

Figure 3.1: (a) daily, (b) weekly, (c) monthly and (d) yearly average of traffic volume (15 mins interval) at a site location from the period 01/01/2008 to 26/07/2013

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 bried 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 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 knowldge base systems, where computers reason about real world concepts, that were defined in hard-coded formal langauges, using logical inference rules. These systems led to little success. The difficulties faced in the knwoledge based appproach made us built computers to learn automatically from data, an approach we know as machine learning.

A large number of real world problems could eaily be tackled using machine leraning. However for the machine learning algorithms to perorm well they need to be provided with proper representaion 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 representaions as well. Autoencodes are such types of algorithms. Again the problem with representation learing 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 Deep feedforward 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 f nodes in the input layer, 3 nodes in hidden layer 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.

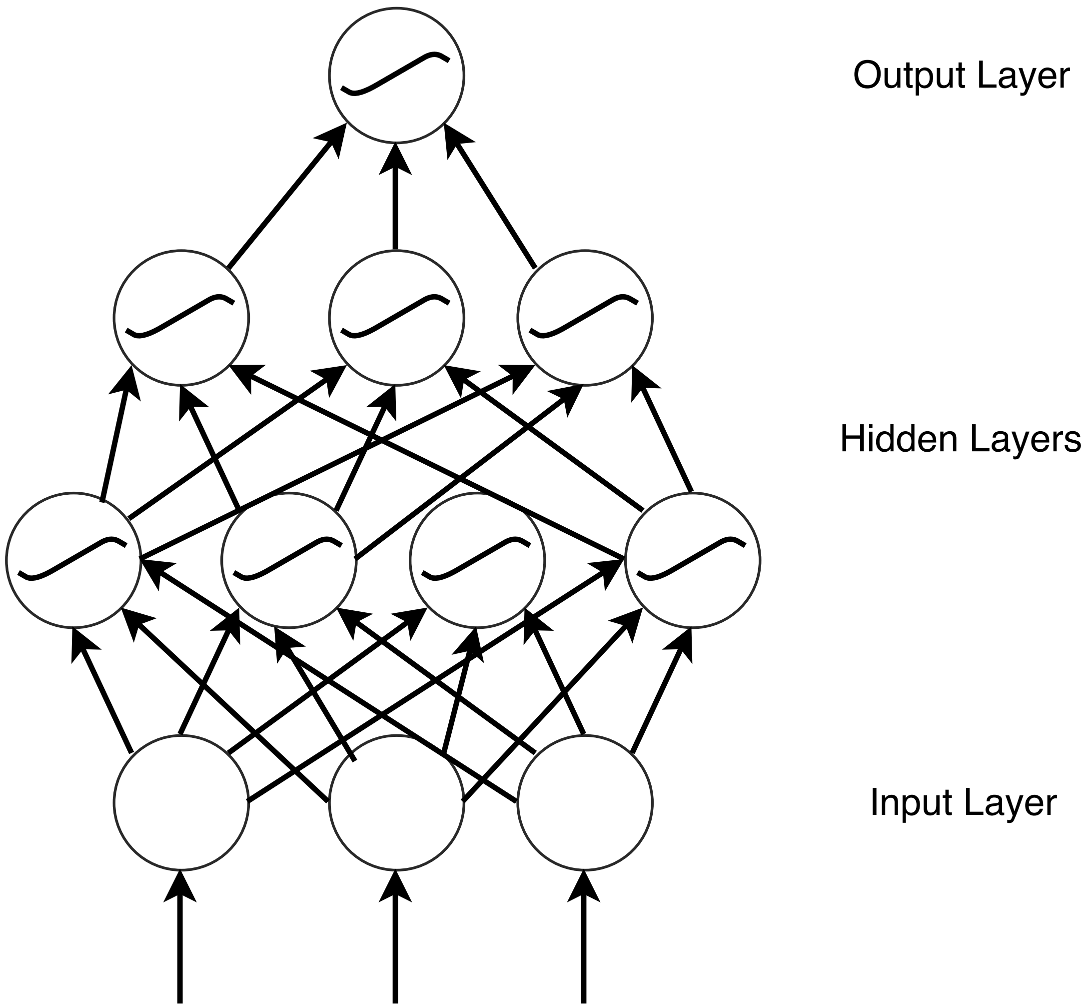

FIGURE 4.1: A feedforward neural netwrok with two hidden layers, this network is also known as a multilayer perceptron. The S-shaped curves denote the sigmoidal function.

4.3 Deep recurrent 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 trvial 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

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 ratain 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 4.2. 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 Momory(LSTM) to address this problem.

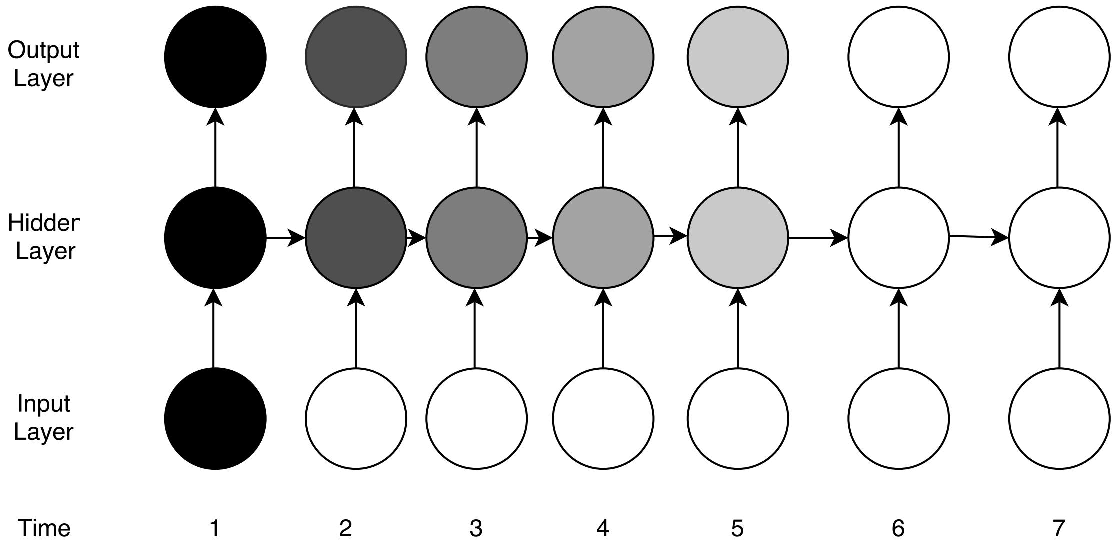

FIGURE 4.2: The problem of vanishing gradient in recurrent neural networks. The sensitivity, as indicated by the shading, gradually diminishes with time

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, output and forget gates) that perform the read, write and reset operations. The units allow the LSTM to store information for a long time and thus addresses the problem of vanishing gradient. A basic LSTM block with one memory cell is depicted in the figure 4.3

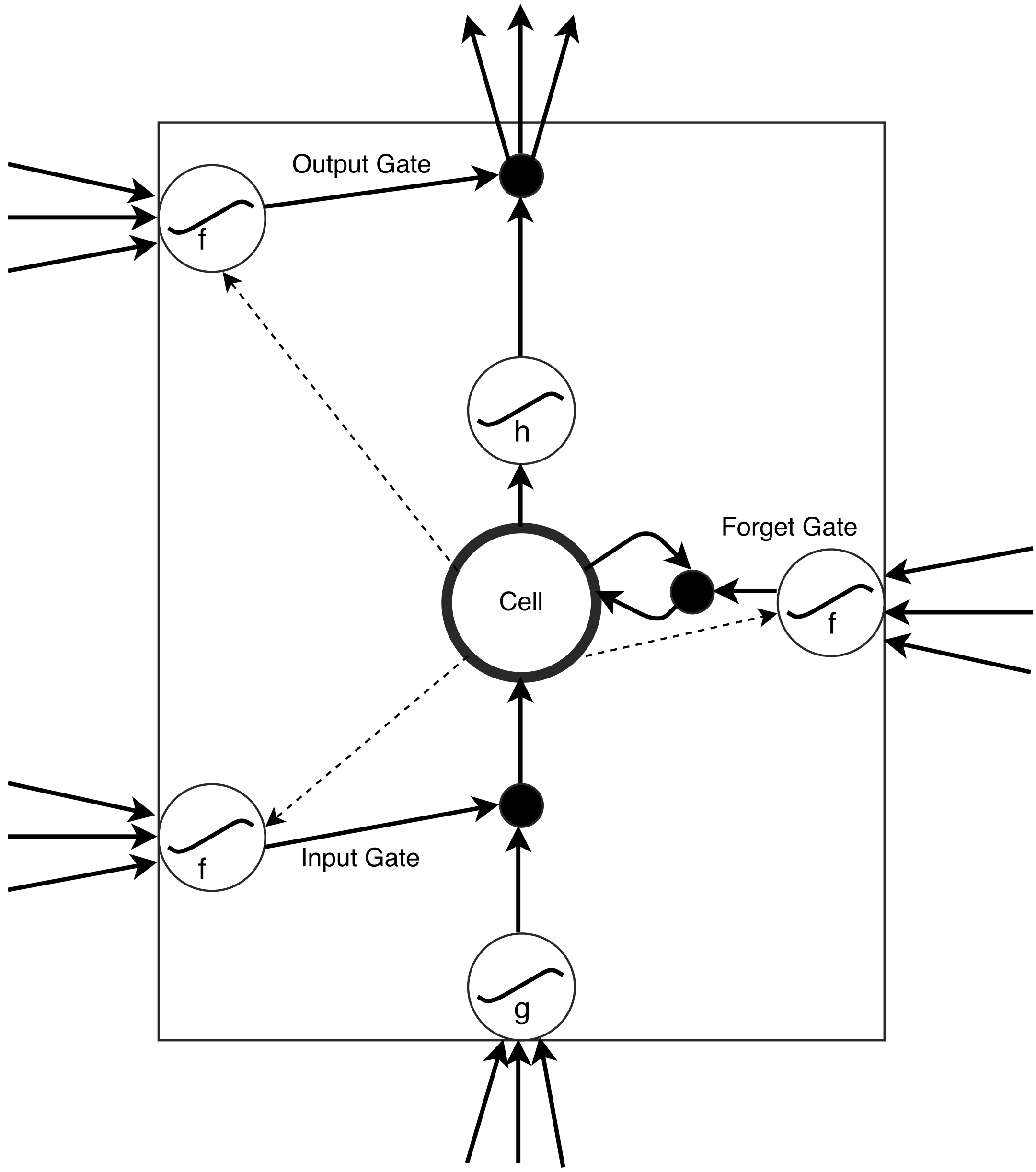

Figure 4.3: An LSTM block with one cell. The three units collect activations from both inside and outside of the block. The small black circles represents mulitipications by which the gates control the memory cell. The gate activation function is f, usually a logistic sigmoid. The cell input and output 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.

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

5.2 Results

The results of the LSTM are shown in the figure 5.1

5.3 Evaluation

Comparision of the LSTM model with the following models

- Exponential smoothing
- ARIMA
- K-Nearest Neighbour
- Backpropagation Neural Network
- Radial Basis Function(RBF) NN model
- Stacked Autoencoders

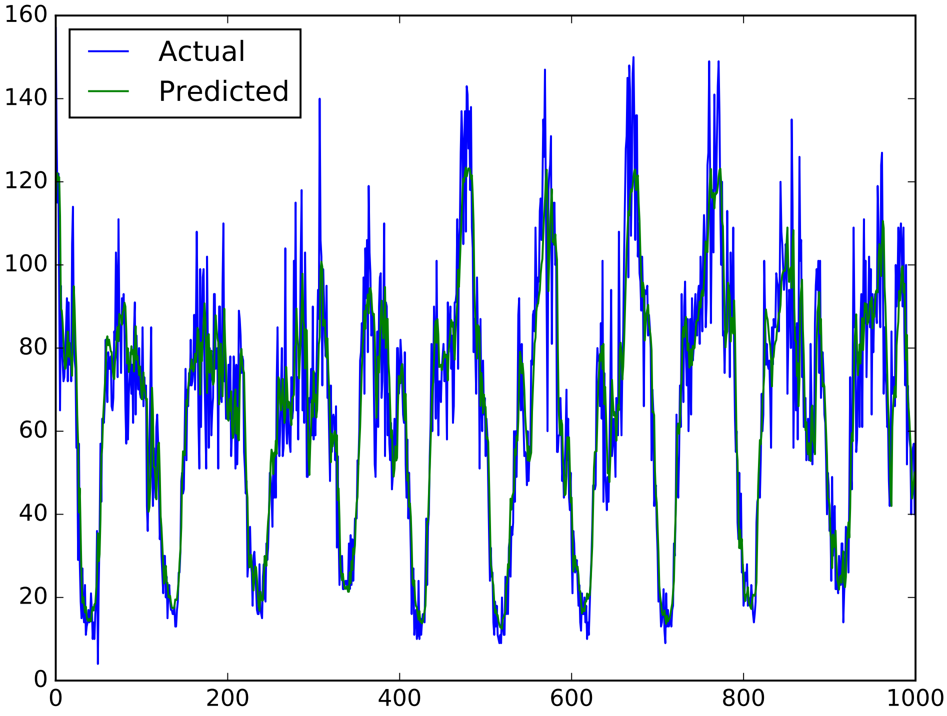

FIGURE 5.1: Long Short Term Memory predictions vs actual test data for 1000 observations.

The accuracy scores are - MAE, MRE and RMSE

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 momory recurrent neural network can be used for this task.

6.2 Future works

Appendix A

Appendix Title Here

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