A Comparative Study Of Road Traffic Forecasting Models

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Abstract

In the context of Intelligent Transport Systems (ITS), the behaviour of road traffic has been the subject of many theoretical and experimental researches. In the last decade, road prediction is placed as the first line of research in this field. The problem has been solved with a variety of models to assist the traffic control, this includes, improving the efficiency of transport, guidance in the road, and smart coordination signals. This paper tries to synthesize the carried out, on three main approaches, namely based on statistical methods, time series and deep learning.A comparatives synthesis in terms quantitative and qualitative index of is provided in order to evaluate the performance and potential of the three forecasting approaches.

Keywords: Intelligent Transportation System, Traffic Forecasting, Artificial Neural Network, Deep Learning.

1 Introduction

Recent years have been marked by an exponential growth in the volume of road traffic. Intelligent Traffic Management systems (ITS) have been deployed in the face of social, economic and ecological challenges, for this purpose, an industrial and scientific partnership have been set up with the aim of improving the fluidity of road traffic. Furthermore, data collection and access to information techniques has been considerably expended, many researches aim to develop decision support tools in different contexts for this domain, including intelligent guidance, intelligent traffic control, or the construction of new roads as shown in Figure1.

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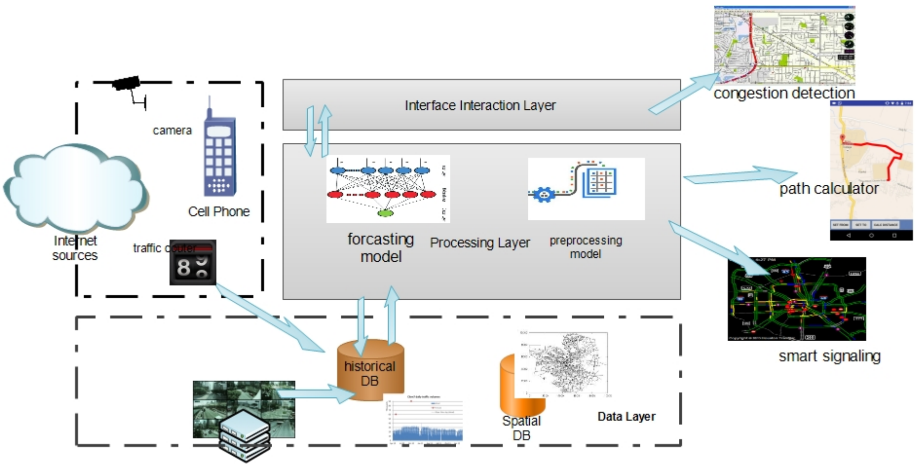

Figure 1: Scope of Road traffic Prediction

The accuracy of prediction has been improved recently by the development of data sciences and machine learning (ML). Research in this field is moving towards the development of models capable of predicting road traffic under normal and abnormal conditions. The approaches adopted depend on the need for the prediction, the exact context and the field of application. Considerable effort, had begun research with classical models, such as the historical average, the Kalman filter proposed by [16] or K-NN. The development of modern statistical theory and machine learning methods have accelerated the pace of research on a variety of approaches, which usually revolved around classification and regression methods.The main goal of the present paper is to synthesize the traffic forecasting models on three main approaches, namely based on statistical methods, time series and deep learning. A quantitative and qualitative comparison is provided in order to evaluate the performance and potential of the three forecasting approaches. This paper is organized into three sections, the first is an introduction, the second contains a review of the literature of approaches adopted in road prediction and the third concludes techniques giving satisfactory results in this domain.

2 Approaches adopted in the prediction of road traffic

Traffic forecasting methods in this context are based on modelling of road traffic data, for prediction methods based on machine learning, early works were boosted in the 2000s by statistical approaches, and continue to evolve using deep learning methods. Formally, the objective is to develop a method that can predict the average speed of flow at a point on the road network in the future, by using a data history. Many techniques have been proposed, and they would not be possible to make an exhaustive state of the art from previous works. An overview of the literature, allowed to synthesize the methods in three categories, Statistical approaches, Time Series approaches and Deep Learning approaches.

2.1 Statistical approaches

Statistical methods are beginning to appear as powerful methods in the field of Machine Learning, starting with classical linear regression techniques such as K-NN, or kernel-based methods (SVM). In the statistics, Machine Learning is a problem of functional approximation or regression, as it proposed by [11], the model tries to find a relation between the future speed and the combination of the speeds observed before the moment of the forecast, this work is based on the unsupervised classification of daily traffic trends and gives inaccurate results in the very short term forecasting, these daily trends are modelled from the calendar measures assumed to be exact, the application of this model does not support missing or incorrect data.
An other methods, aim at modelling the joint density of probability and uses the inference to clean the data, the generative model proposed by [20] is called Multi-Varied Gaussian Trees (MGT), the idea is to characterizing the road traffic and the dependencies between the measured quantities, This computationally complex work, illustrates the power of prediction approaches based on conditional statistical theories including methods derived from Bayesian networks. Kernel-based methods are also one of the most promising approaches in predicting road traffic, the work was initiated by [29] then [15].The performances of these techniques were also demonstrated by [22] exploiting a dataset of Chennei.
SVMs are categorized in the paradigm of supervised learning and implemented frequently in classification and regression analyses, in the case the flow of traffic is affected by many non-linear elements such as weather conditions, accidents or vacation days(see Figure 2).

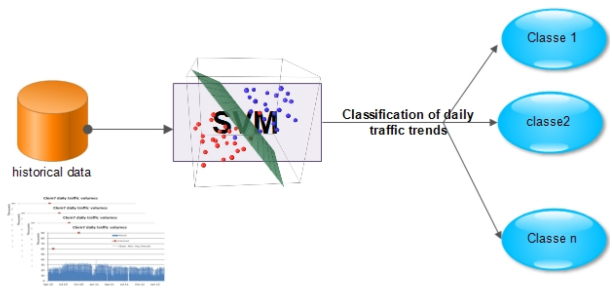

Figure 2: SVM Classification

Another variant LSSVMS (Least Square SVM), proposed by [26], in order to reduce the calculation compared to the use of basic SVMs, by transforming the quadratic programming problem into a problem solving a linear equation.

2.2 Time Series based approaches

Time Series are an important part of the data produced and available on the internet or in specific deployments namely, traffic control centers. ARIMA (Auto Regressive Means Average) or Jinkins-BOX methods have been reported on several studies in road prediction. The work shows that this method is the most adopted in the short term prediction.

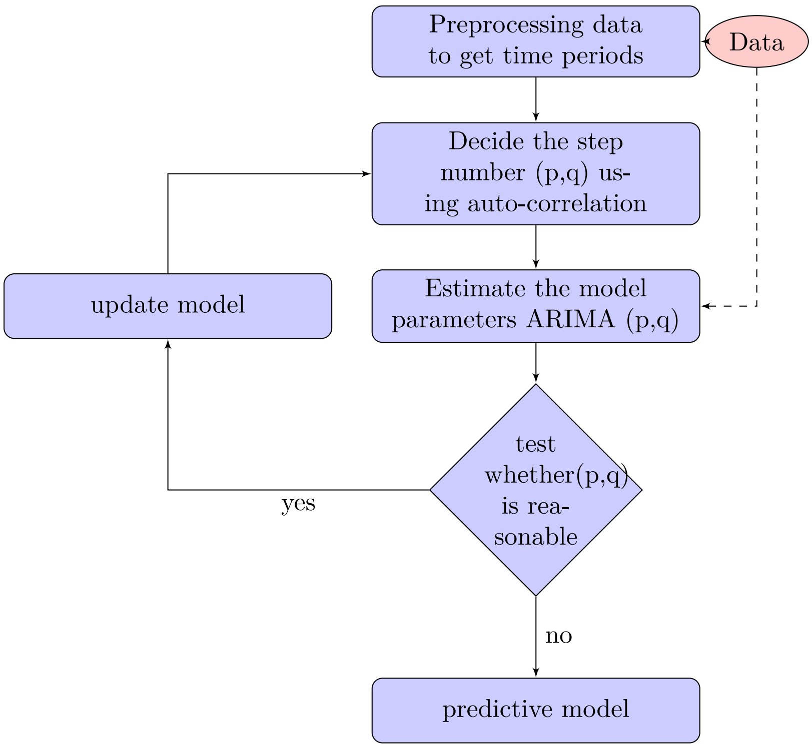

Figure 3: ARIMA Process

The first results [21, 12] show that cloud data availability is a major problem in the application of these methods. Current efforts are trying to define alternatives to out-discard this problem, the work of [7] with the SARIMA model (Seasonal ARIMA) gives conclusive results with a limited input data set, [30] also proposes the Switching ARIMA method to remedy the lack of data. These methods are a bit attractive because of their simplicity and efficiency, nevertheless, the no linearity must be insignificant for autoregressive models to show acceptable performance. The lack of data must be treated also in the time series, the work of [3] illustrate the use auto regressive in a time series completion tasks, by adding special constraints making it possible to model the relation between several series through a graph.

2.3 Deep Learning Approaches

In the past few years, there has been a resurgence in the use of ANN (Artificial Neural Network) for the treatment of predictive tasks which allowed the rebooting of the works in the different contexts, particularly in the field of road traffic management. The return was motivated by the availability of data and the experimental platforms, Neural networks have also evolved, in terms of modelling, the techniques are no longer iterative algorithms as the case of Perceptron, but with a more complex and deep architecture as the case of CNN and RNN.

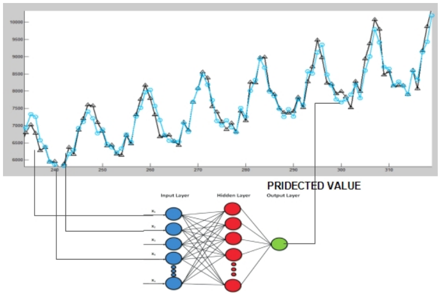

Figure 4: ANN Regression

ANN show their power following the work of [4], [8] and [9], a FNN (Fuzzy Neural Network) is proposed by [5] for prediction in the urban road network using a self-adaptive predictor. Neural Network with deep architectures have been successful in the solving of various learning tasks, including image and speech and recently presented in the context of prediction as the most adopted techniques.
Yisheng et al. proposes a neural network with a SAE (Stacked Auto Encoder) architecture used for learning the generic characteristics of the traffic[27]. This model was trained, with data from a highways control center in California, by using an unsupervised learning algorithm, the results were compared with other classical NN architectures namely the DBNN (Deep Belief Neural Network) proposed by [24] and RBFN (Radial Basis Function Network) and SVM methods as an anther approach. The same set of data is applied in [28] by an architecture of an LSTM (Long Short Term Memory) network, then [25] with the proposal of a model called DeepTrend inspired by the classification of daily traffic trends, in this work, the architecture of the model is deeper and is based on two layers one for extracting daily traffic trends, and one based on an LSTM network for prediction.
Haiyang et al. develops a hybrid model called (SRCN) Spatial Recurve Convolutional Network [14], which combines two architectures, DCNN (Deep Convolutional Neural Network) and LSTM for the prediction of traffic speed in a road network. In this architecture, the DCNN layer has been used to capturing special dependencies of traffic in road network.
The combination of approaches is becoming more adopted in traffic modelling, especially for arterial roads, Spatio-temporal dependencies are modelled efficiency and in a finer way by using hierarchical representations of deep architectures [23].

3 Comparative synthesis for the three approaches

In order to fully evaluate the performance and potential for field implementation of the three forecasting approaches, a performance index system is established in terms of two parts: quantitative and qualitative indexes. The quantitative index consists of Root Mean Square Error (RMSE). The qualitative index refers to the ease of implementing a forecasting model, which is evaluated based on time and effort required for model development, the required expertise, adaptability to changing temporal or spatial behaviour.

3.1 The qualitative index

The study of three modelling approaches allows to provide a brief comparison shown in the following table :

Qualitative Index	Statistical Approaches	Time Series Approaches	Deep Learning Approaches
Time and effort required for model development	The methods derived from baysien networks require design of a complex graph. SVM are the most statistical methods used for traffic prediction, the model is described by quadratic programming problem witch is complex to resolve.	As shown in Figure 3, the modelling process is simple but required a completion. for prediction traffic of many points in road network the relation between several series must be modelled in complex graph.	Artificial Neural network in traffic prediction are designed with a complex architecture. Recent works in this context use a combination of several model of Neural Network.
required Skills	Require an experience in statistical theories of Machine Learning and the understand of the kernel functions.	Require experience in statistical theories of time series.	Require experience in ANN (Artificial Neural Network) and Combination of several variants.
Adaptative to change temporal and spatial behaviour	Statistic studies are developed for specific phenomena. The methods based on SVM are less adaptative when the flow of traffic is affected by many other no linear elements such as weather conditions, accidents or vacation days.	Variants of ARIMA proposed in[6] and[29] are designed for specific context. The variables(exogenous inputs)added depend to a particular spatial context.	The data-driven methods are better suited to develop adaptative model, this is the strong point compared to model-driven methods.

The first models described in the first and the second approach, have proved a capacity and simplicity and contributed to the perfection of ITS, however they are considered classic and are developed for a simple contexts by using a limited datasets. It has been observed from complex parametric models that the accuracy of the prediction depends on the characteristics embedded in the spatial-temporal data collected. At this stage, the use of non-parametric methods, based on Neural Networks, are more promising and allow having a good prediction when the architecture is deeper.

3.2 quantitative index

In order to compare the approaches cited above, experiments were carried out on open dataset. The performance of the model has been evaluated by the Root Mean Square Error :

$$\text{RMSE} = \sqrt{(\frac{1}{N})\sum_{i=1}^{n}(t_i - p_i)^2}$$

Where pi = predicted traffic flow; ti = actual traffic flow; N = the number of predictions.
In this experiment, traffic flow data was obtained from Baidu research Open Access dataset [1], A traffic dataset was provided for the 6th ring road, the speed of 15,073 road segments is recorded per minute, then averaged with a 15-minute time. This data was formatted as line delimited, in total there are 88,267,488 rows in the specific time period.We limit our study only for the highway.(See the studied segments explored by QGis tool in Figure 5)

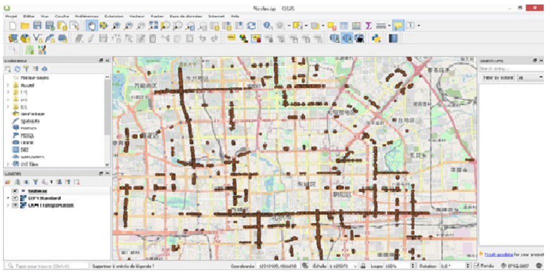

Figure 5: The spatial distribution of studied segments

The result data is formatted as large matrix, then stored in CSV file.The data can be easily manipulated by Python libraries such as Pandas and explored by the elegant library matplotlib
For all models, the experiments were performed under PC (Windows 8 Professional, CPU: Intel Xeon(R) E51650 3.50GHZ, Memory: 8G), which installed TensorFlow TM (Version 1.0.0 CPU) and Python (Version 2.5.3). The Neural Networks model are fit using the efficient Adam version of stochastic gradient descent and optimized using the mean squared error, or 'MSE' loss function with the following parameter settings: Epoch = 50. Batch size = 72. result are obtained as follow :

Models	RMSE
ARIMA	95.140
SVR-LINEAR	102.847
SVR-POLY	101.144
SVR-RBF	101.843
SAE	62.19
LSTM	39.105
SE LSTM	35.458
CNN LSTM	31.585

The results are more conclusive for the architectures using deep learning models, especially for the hybrids architecture(CNN LSTM combination) which justifies the frequent adoption of these techniques in the most of current works.

4 Conclusion

This paper has describing and categorizing the different methods adopted in road traffic forecasting on three approaches; the statistical approaches based on statistical machine learning methods (KNN, SVM), time-series based approaches (ARIMA or box-Jinkins) and deep learning approaches (SAE, LSTM, CNN). A comparative study has been provided in terms of two parts: quantitative and qualitative index.It has been shown that the deep learning methods outperform the tow other approaches and improved by adopting an hybrid models.
The performance and accuracy of these methods were justified in the results and experiments compared to other approaches on the same datasets. It has been found from review, that recent researches are adopting models based on Deep Learning, more precisely, most popular works are currently focusing on the combination of the different architectures such as LSTM, CNN.

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