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A Review on Regression Models for Predicting Network Wide Traffic Speeds for Intelligent Traffic Systems

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Abstract:- Off late, statistical and evolutionary algorithms are being extensively used for smart traffic systems whose sub-section is Intelligent Transportation Systems (ITS). For that purpose, different methods are being explored to estimate or forecast the traffic volume in a geographic are under different prevailing conditions so as to monitor and control massive traffic volumes, which has become a serious challenges in urban and even semi-urban areas worldwide. The prediction or forecasting problem is challenging since the nature of the data is extremely random and uncorrelated. A clear functional relationship in terms of correlation or regression analysis is seldom preset. Hence conventional statistical algorithms are being explored in the pretest which an adapt parameters as per the changing statistical properties of the fed data. This paper presents a comprehensive review on the need for evolutionary statistical algorithms for traffic forecasting problems and also cites the salient points of the existing literature. Moreover a comprehensive review of existing statistical algorithms used hitherto, are also cited. Finally the performance metrics are explained to evaluate the performance of such algorithms. This comprehensive review is expected to serve as a baseline for further research in the domain.

Keywords: Smart Traffic Monitoring, Intelligent Traffic systems (ITS), Evolutionary Statistical Methods, Performance Metrics.

I. Introduction

As population explosion and mass exodus of large chunks of population towards urban and semi-urban areas have become prevalent throughout the world, the necessity for automated and smart traffic monitoring systems have also increased. Traffic volume or throughput serves as a crucial indicator in highway performance and transportation operation analysis. Highly- granular traffic volume provides key information in identifying congested roadways, assisting traffic re-distribution, and implementing accident prevention strategies. Furthermore, it is the dis-aggregated source for calculating annual average daily traffic (AADT). AADT at the network level offers a measure of overall utilization of highway facility, implies the level of service of roads, and can be used for highway planning, trend studies, and project prioritization currently, traffic count (volume) is mainly obtained from sensors such as inductive loop detectors, radar detectors and/or continuous counting stations (CCS). Yet installing sensors with a large network coverage can be impractical and expensive given budget constraint, especially in rural areas. As a result, how to spatially estimate/predict traffic volume to substitute massive sensor deployment has been an intriguing topic over the past decade. Some typical applications can be:

1) Route Optimization & Navigation.
2) Smart Parking.
3) Lighting.
4) Accident Detection.
5) Road Anomalies.
6) Infrastructure Management.

II. Existing Evolutionary Statistical Models

Due to the need of large data sets to be analyzed, it is necessary to use computational tools which are fast, accurate and can handle copious amounts of data. Evolutionary statistical algorithms are a set of such algorithms which show the aforesaid characteristics.

Evolutionary Statistical algorithms try to mimic the human attributes of thinking which are:

1) Parallel data processing
2) Self-Organization
3) Learning from experiences

Some of the commonly used techniques are discussed below:

1) Statistical Regression: These techniques are based on the time series approach based on the fitting problem that accurately fits the data set at hand. The approach generally uses the auto-regressive models and means statistical measures. They can be further classified as:

a) Linear
b) Non-Linear

Mathematically:

Let the time series data set be expressed as:

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$$Y = \{Y1, Y2 \ldots \ldots \ldots \ldots \ldots \ldots .. Yt) \quad (1)$$

Here,
Y represents the data set
t represents the number of samples
Let the lags in the data be expressed as the consecutive differences.
The first lag is given by:

$$\Delta Y_1 = Y_{t-1} \quad (2)$$

Similarly, the j^{th} lag is given by:

$$\Delta Y_j = Y_{t-j} \quad (3)$$

2) Correlation based fitting of time series data: The correlation based approaches try to fit the data based on the correlation among the individual lags. Mathematically it can be given by:

$$A_t = corr(Y_t, Y_{t-1}) \quad (4)$$

Here,
Corr represents the auto-correlation (which is also called the serial correlation)
Y_t is the t^{th} lagged value
Y_{t-1} is the $(t-1)^{st}$ lagged value
The mathematical expression for the correlation is given by

$$corr(Y_t, Y_{t-1}) = \frac{conv(Y_t, Y_{t-1})}{\sqrt{varY_t, varY_{t-1}}} \quad (5)$$

Here,
Conv represents convolution given by:

$$conv\{x(t), h(t)\} = \int_{t=1}^{\infty} x(\vartheta)h(t-\vartheta)d\vartheta \quad (6)$$

Here,
ϑ is a dummy shifting variable for the entire span of the time series data
t represents time
Y_t is the t^{th} lagged value
Y_{t-1} is the $(t-1)^{st}$ lagged value
X is function 1
H is function 2
Var represents the variance given by:

$$var(X) = X_i - E(X) \quad (7)$$

Here,
Xi is the random variable sample
E represents the expectation or mean of the random variable X

3) Finite Distribution Lag Model (FDL): This model tries to design a finite distribution model comprising of lags fitted to some distribution such as the normal or lognormal distributions. Mathematically:

$$Y_t = \alpha_t + \delta_1 z_1 + \cdots \ldots \ldots \ldots \ldots . \delta_t z_t + \mu_t \quad (8)$$

Here,
Y_t is the time series data set
α_t is a time dependent variable
δ_1 is a time-varying co-efficient
z is the variable (time variable)
t is the time index
μ_t is the time dependent combination-coefficient

4) Artificial Neural Networks (ANN): In this approach, the time series data is fed to a neural network resembling the working of the human based brain architecture with a self-organizing memory technique.

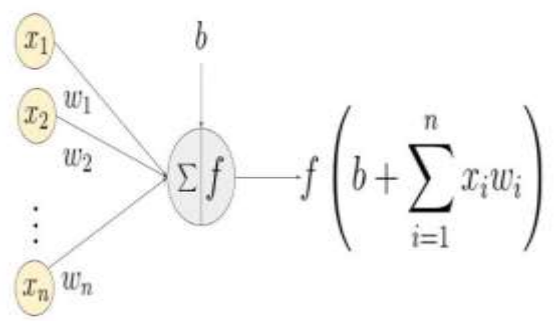

Fig.1 Mathematical Model of Neural Network

The approach uses the ANN and works by training and testing the datasets required for the same. The general rule of the thumb is that 70% of the data is used for training and 30% is used for testing. The neural network can work on the fundamental properties or attributes of the human brain i.e. parallel structure and adaptive self-organizing learning ability. Mathematically, the neural network is governed by the following expression:

$$Y = f(\sum_{i=1}^{n} X_i . W_i \;+\; \theta_i) \quad (9)$$

Here,
X_i represents the parallel data streams
W_i represents the weights
θ represents the bias
f represents the activation function

The second point is critically important owing to the fact that the data in time series problems such as sales forecasting may follow a highly non-correlative pattern and pattern recognition in such a data set can be difficult. Mathematically:

$$x = f(t) \quad (10)$$

Here,
x is the function
t is the time variable.
The relation f is often difficult to find being highly random in nature.
The neural network tries to find the relation f given the data set (D) for a functional dependence of x(t).
The data is fed to the neural network as training data and then the neural network is tested on the grounds of future data prediction. The actual outputs (targets) are then compared with the predicted data (output) to find the errors in prediction. Such a training-testing rule is associated for neural network. The conceptual mathematical architecture for neural networks is shown in the figure below where the input data is x and fed to the neural network.

III. Previous Work

This section highlights the existing work in the domain, along with its salient features:

Xu et al. [7] proposed an attentive graph neural process (AGNP) method for network-level short-term traffic speed prediction and imputation, simultaneously considering reliability. Firstly, the Gaussian process (GP) is used to model the observed traffic speed state. Such a stochastic process is further learned by the proposed AGNP method, which is utilized for inferring the congestion state on the remaining unobserved road segments. Data from a transportation network in Anhui Province, China, is used to conduct three experiments with increasing missing data ratio for model testing. Based on comparisons against other machine learning models, the results show that the proposed AGNP model can impute traffic networks and predict traffic speed with high-level performance. With the probabilistic confidence provided by the AGNP, reliability analysis is conducted both numerically and visually to show that the predicted distributions are beneficial to guide traffic control strategies and travel plans.
Sharma et al. [8] proposed an approach, called STGGAN, for real-time traffic-speed estimation using two different actual traffic datasets: PeMSD4 and PeMSD8. The experimental results validate the prediction accuracy values of 96.67% and 98.75% for the PeMSD4 and PeMSD8 datasets, respectively. The computation of mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) also shows a progressive decline in these error values with increasing iteration count, demonstrating the success of the suggested technique. To confirm the feasibility, reliability, and applicability of the suggested STGGAN technique, we also perform a comparison analysis, including several statistical, analytical, and machine-learning- and deep-learning-based approaches. Our work contributes significantly to the field of traffic-speed estimation by considering the structure and characteristics of road networks through the implementation of DGNNs. The proposed technique trains a neural network to accurately predict traffic flow using data from the entire road network. Additionally, we extend DGNNs by incorporating Gated Graph Attention Network (GGAN) blocks, enabling the modification of the input and output to sequential graphs. The prediction accuracy of the proposed model based on DGNNs is thoroughly evaluated through extensive tests on real-world datasets, providing a comprehensive comparison with existing state-of-the-art models for traffic-flow forecasting.

Qaddoura et al. [9] showed that Drivers always try to plan their trips over the road network by avoiding highly congested areas. Several research studies have considered image processing techniques and vehicular network technologies to predict the level of traffic congestion over pre-determined road scenarios. In this paper, we aim to use big data and machine learning regression techniques to provide the driver ahead of time with the expected level of traffic congestion on the investigated road scenarios. Three basic regression techniques have been experimentally tested over some main roads in Amman, Jordan. Fast and correct traffic characteristics have been predicted on the investigated road scenarios, such as positions, speed, and locations of each vehicle. After that, the best regression technique has been used to predict the level of traffic congestion on the traversed road network during future periods. These predictions are also reported to the moving traffic to be considered in the route options of each moving vehicle.

Zhang et al. [10] proposed a multimodal context-based graph convolutional neural network (MCGCN) model to fuse context data into traffic speed prediction, including spatial and temporal contexts. The proposed model comprises three modules, ie (a) hierarchical spatial embedding to learn spatial representations by organizing spatial contexts from different dimensions, (b) multivariate temporal modeling to learn temporal representations by capturing dependencies of multivariate temporal contexts and (c) attention-based multimodal fusion to integrate traffic speed with the spatial and temporal context representations for multi-step speed prediction. We conduct extensive experiments in Singapore. Compared to the baseline model (spatial-temporal graph convolutional network, STGCN), our results demonstrate the importance of multimodal contexts with the mean-absolute-error improvement of 0.29 km/h, 0.45 km/h and 0.89 km/h in 30-min, 60-min and 120-min speed prediction, respectively. We also explore how different contexts affect traffic speed forecasting, providing references for stakeholders to understand the relationship between context information and transportation systems.

Gao et al. [11] proposed that accurate traffic speed forecasting not only can help traffic management departments make better judgments and improve the efficacy of road monitoring but also can help drivers plan their driving routes and arrive safely and smoothly at their destination. This paper focuses on the lack of traffic speed data and proposes a method for traffic speed forecasting based on the multitemporal traffic flow volume of the previous and later moment states. First, according to traffic flow volume data, the different traffic patterns of previous and later moment states were extracted. Second, the performance of five forecasting models, namely, long short-term memory (LSTM), backpropagation (BP), classification and regression trees, k-nearest neighbor, and support vector regression, were compared. Finally, the model with the best prediction results was used to conduct sensitivity analysis experiments for different traffic patterns. Through a real-data case study, we found that the LSTM model has the highest prediction accuracy compared to other models in both time and space. This traffic pattern "previous = 3 and later = 3" can forecast traffic speed more accurately, and its forecasting ability is robust across a range of scenarios.

Ma et al. [12] proposed that Short-term traffic speed prediction is fundamental to intelligent transportation systems (ITS), and the accuracy of the model largely determines the performance of real-time traffic control and management. In this study, a short-term traffic speed prediction method based on the spatial-temporal analysis of traffic flow and a combined deep-learning model, and a hybrid spatial-temporal feature selection algorithm (STFSA) of a convolutional neural network–gated recurrent unit (CNN-GRU)) is initially developed. Specifically, the STFSA is firstly employed to reconstruct the spatial-temporal matrix of traffic speed based on temporal continuity and spatial characteristics, and then this matrix is considered as the input feature of the prediction model. After this, the nonlinear fitting ability of the CNN is adopted to extract deep features from the convolutional and pooling layers for model training. Finally, by combining the timing and long-range dependence of the captured data with the forward GRU and the reverse GRU, the accuracy of the prediction result is further improved. The validity of the proposed model can be verified by comparing the prediction results with the actual traffic data. Accordingly, in the case study, the performance is compared with various benchmark methods under the same prediction scenario, verifying the superiority of the proposed model.

Xu et al. [13] proposed that accurate traffic speed prediction is crucial for the guidance and management of urban traffic, which at the same time requires a model with a satisfactory computational burden and memory space in applications. In this paper, we propose a factorized Spatial-Temporal Tensor Graph Convolutional Network for traffic speed prediction. Traffic networks are modeled and unified into a graph tensor that integrates spatial and temporal information simultaneously. We extend graph convolution into tensor space and propose a tensor graph convolution network to extract more discriminating features from spatial-temporal graph data. We further introduce Tucker decomposition and derive a factorized tensor convolution to reduce the computational burden, which performs separate filtering in small-scale space, time, and feature modes. Besides, we can benefit from noise suppression of traffic data when discarding those trivial components in the process of tensor decomposition. Extensive experiments on the three real-world datasets demonstrate that our method is more effective than traditional prediction methods, and achieves state-of-the-art performance.

Xu et la. [14] proposed a model in which the temporal and spatial factors are taken into account. Gate Recurrent Unit (GRU) and Gated Linear Units (GLU) are used to learn the short-term temporal features of traffic data, and Graph Convolutional Network (GCN) is used to learn the spatial features of traffic data. In order to fully learn short-term feature changes, a multi time step perception layer is proposed. A new network GCGRU is proposed to learn the long-term features of traffic data. As the sensor will be affected by urban canyon, weather, and other factors, there will be missing value and noise in the collected data. We created a short-term trend based missing value filling up algorithm to fill in missing values and use Singular Spectrum Analysis (SSA) algorithm to eliminate noise of training data set. In order to reduce the process of adjusting parameters manually in the model training process, we propose k-block search method based on fuzzy extreme points. Finally, the model is compared with the existing traffic forecasting models, and the analysis results show that our model has advantages in many indicators.

Zhang et al. [15] proposed that traffic speed prediction is a crucial and challenging task for intelligent transportation systems. The prediction task can be accomplished via graph neural networks with structured data, but accurate traffic speed prediction is challenging due to the complexity of traffic systems and the constantly dynamic changing nature. To address these issues, a novel evolution temporal graph convolutional network (ETGCN) model is proposed in this paper. The ETGCN model first fuses multiple graph structures, and utilizes graph convolutional network (GCN) to model spatial correlation. Then, the spatial–temporal dependence and their dynamical changes are learned simultaneously to predict traffic speed on a road network graph. Especially, a similarity-based attention method is proposed to fuse multiple graph adjacency matrices. Then, the gated recurrent unit is combined with GCN to capture spatial–temporal correlations and their changing status, simultaneously. Extensive experiments on two large-scale datasets show that our methods provide more accurate prediction results than the existing state-of-the-art methods in every prediction horizon.

Abdelraouf, et al. [16] proposed an attention-based multi-encoder-decoder (Att-MED) model is proposed to predict traffic speed. The model uses convolutional-LSTMs to capture the spatiotemporal relationship of multiple input sequences, namely short-term, daily and weekly traffic patterns. The model also employs an LSTM to model the output predictions sequentially. Furthermore, attention mechanism is used to weigh the contribution of each traffic sequence towards the output predictions. The proposed network architecture, when trained end-to-end, results in a superior prediction accuracy compared to baseline models. In addition to contributing towards performance, the attention mechanism creates weight values, which when visualized, provide insights into the decision-making process of the neural network, and consequently produce explainable outputs. Att-MED's extracted attention weights highlight the contribution of daily and weekly periodic input towards speed prediction.

IV. Proposed Model and Performance Metrics

The proposed approach is the Neuro-Fuzzy or ANFIS model for predicting traffic speeds.

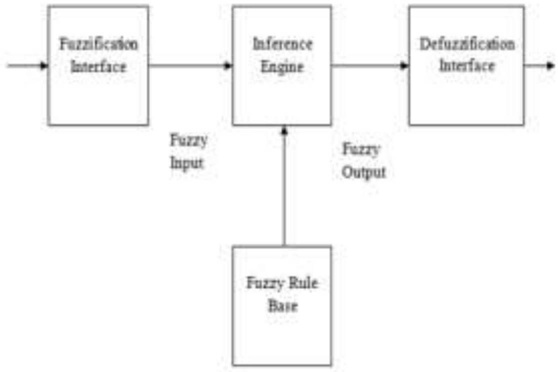

Fig.2 The Fuzzy Logic Architecture

The ANFIS model integrates the fuzzy logic-based Takagi-Sugeno fuzzy inference system with the adaptive learning mechanism of neural networks [17]. It consists of multiple layers that perform fuzzification, rule application, normalization, and defuzzification. The key idea is to map input variables (e.g., time of day, weather, vehicle count) to output traffic speeds through a system of fuzzy rules, while automatically tuning the membership functions using a gradient descent or hybrid learning algorithm. This structure allows ANFIS to model nonlinearity and uncertainty in traffic patterns more effectively than conventional models [18].

Traffic flow is inherently stochastic and influenced by a multitude of interacting factors such as road geometry, signal timings, weather conditions, and driver behavior. ANFIS is particularly suited to such environments because it can learn from imprecise, noisy, and partially observed data, which are common in real-world traffic monitoring systems. Moreover, the model offers a transparent rule-based structure that enhances interpretability, which is essential for transport authorities and system operators who need to understand the underlying logic of predictions [19].

A typical ANFIS model for traffic speed prediction uses input variables such as time intervals, day of the week, traffic volume, occupancy, weather data, and even GPS-based location information. The model structure includes [20]:

1. Input layer: Raw traffic features
2. Fuzzification layer: Membership functions (e.g., “low volume”, “high congestion”)
3. Rule layer: If-Then fuzzy rules
4. Normalization layer: Weights of rules
5. Output layer: Crisp predicted speed

The training process involves adjusting membership function parameters and rule weights to minimize the prediction error using historical traffic speed data.

The training is stopped based on the mean square error or mse given by [21]:

$$mse = \frac{\sum_{i=1}^{n} e_i^2}{n} \tag{11}$$

The final computation of the performance metric is the mean absolute percentage error given by:

$$MAPE = \frac{100}{M} \sum_{i=1}^{N} \frac{E-E_i|}{i} \tag{12}$$

Here,
n is the number of errors
i is the iteration number
E is the actual value
E_i is the predicted value

V. Conclusion

It can be concluded from previous discussions that smart and intelligent traffic systems are extremely important for handling the large volumes of traffic emanating from semi-urban and urban environments worldwide due to mass exodus of populations. While several applications of smart and intelligent traffic monitoring may be considered such as Route Optimization & Navigation, Smart Parking, Lighting, Accident Detection, Road Anomalies and Infrastructure Management etc., one of the key attributes to be computed is the network wide traffic volume. This paper presents a systematic review on the existing statistical techniques employed off late for the prediction of network wide traffic volume along with salient points of previous work. The paper presents a foundation on the development of effective and accurate prediction models for the traffic volumes pertaining to intelligent traffic and transportation systems.

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