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Long-term Traffic Flow Forecasting Based on an Artificial Neural Network

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ABSTRACT

There is no doubt that a good knowledge of traffic demand has a direct impact on improving traffic management. Road traffic is strongly correlated with many factors such as day of week, time of day, season and holidays which make it suitable for prediction. In this paper, we develop a neural network model for hourly traffic prediction that makes full use of these temporal characteristics. The proposed algorithm is tested on a real-world case, and the experiment results is presented to evaluate its accuracy.

1 Introduction

Accurate traffic volume prediction plays a significant role in traffic management and control. Estimate the number of vehicles passing per unit time can help traffic managers make the right decisions. Up to now a variety of traffic flow prediction algorithms have been proposed. These methods can be arranged into two categories: parametric approach and non-parametric approach.

Since the early 1980s, a wide range of parametric techniques have been studied such as historical average algorithms, smoothing techniques, linear regression, filtering techniques [1], and autoregressive integrated moving average (ARIMA)[2] family. Later on, researchers began to explore the potential of non-parametric techniques in traffic forecasting, including neural networks [3, 4, 5, 6, 7], support vector machines [8, 9], k-nearest neighbor [10, 11], etc. These methods have gained more attention compared to parametric techniques considering that they can capture the stochastic and nonlinearity of the traffic flow. They are flexible in their use and are generally quite robust.

The rest of the paper is structured as follows. Following this introductory section, a description of the proposed methodology is provided. The dataset for the numerical experiments is introduced in section 3 along with the results and performance evaluation. Finally, concluding remarks are stated in section 4.

2 Methodology

In this section, a description of the Artificial Neural Network structure is presented. Artificial Neural Networks (ANNs) are one of the recent methods employed for traffic forecasting. They have the ability to approximate almost any function due to their properties of self-learning and self-adaptive capabilities.

2.1 Prediction logic with artificial neural network

A neural network consists of a set of interconnected processing elements, called neurons, which are arranged in a series of layers: an input layer, one or more hidden layers and an output layer.

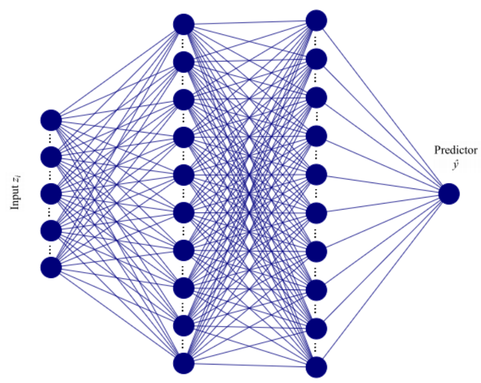

Figure 1: Architecture of a neural network prediction model

There is no connection between neurons in the same layer. However, each neuron in a layer is fully connected to all neurons in the next layer. Those connections are uni-

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directional: information from the inputs pass through the hidden units to eventually reach the output units. This type of architecture is called feedforward neural network (Fig. 1).

Neural networks are able to perform different categories of tasks, including regression. ANN can be trained to model the relationship between a number of input variables and a set of continuous results (target variables).

The inputs z_i reach the neuron through connection links, each with an associated weight w_i. The higher the value of a weight, the stronger the intensity of the incoming signal. When the signals are received, a weighted sum of the inputs plus a bias b, called the net input, is calculated:

$$net_i = \sum_i (w_i z_i) + b_i \quad (1)$$

The output is then determined by applying a transfer function f to the net input. The transfer function can be any differentiable non-linear function.

$$output_i = f(net_i) \quad (2)$$

This output will serve as input to other neurons in the next layer and so on. When the entire network has been executed, the neurons in the output layer become the outputs of the entire network (predicted values).

3 Experiments

In this section, the real-world data used in this study is described and the forecasting model along with the results are presented. The forecasting model is implemented using Python and Keras.

3.1 Data preparation and description

Data on the volume of traffic on hourly basis has been collected from the Melloussa Toll plaza. This traffic represents the number of vehicles passing through the system during each hour of the day. The Toll Lane Controller collects data from the lanes and transmits it to a server where all transaction data are stored.

The Melloussa Toll plaza is one of the major toll highways in Tangier. It is located on a North-South motorway axis that leads directly to The Port of Tangier, Africa's biggest port, allowing the toll plaza to become an important transit point between Morocco and the European continent, with a throughput volume that could approach 900 vehicles per hour during summer peak periods.

Collected data for experiments spans for two years ranging from 2017/01 to 2018/12. The first 80% of the observations was selected to train the forecasting model, while the remaining 20% was treated as the testing dataset.

Missing and abnormal data are almost inevitable in practice. Their presence can affect the quality of data and can lead to incorrect results and conclusions. Therefore, missing and abnormal data were removed and repaired by estimating values from historical data.

To fit into the ANN model, the data was arranged in the following format (see Tab. I):

Table 1: Data structure used in the experiment

Year	Month	Day	Hours	Holiday	Traffic
2017	January	Sunday	1	Yes	61
2017	January	Sunday	2	Yes	32
2017	January	Sunday	3	Yes	17
2017	January	Sunday	4	Yes	16
2017	January	Sunday	5	Yes	33
...	...	...	...	...	...
...	...	...	...	...	...
2018	December	Monday	23	No	83
2018	December	Monday	24	No	47

Before being able to model a problem with a machine learning algorithm, it is often necessary to perform a number of transformations on the data, so that the problem can be easily understood and interpreted by the machine learning algorithm.

Therefore, the data, including Hours, Day, Month, and Holiday were converted into binary variables (for example, "Day of Week" feature 2 is transformed to 001000).

3.2 The forecasting model

Artificial neural networks are characterized by two main parameters: the number of hidden layers and the number of neurons per hidden layer.

There is no general method for determining the appropriate values of these parameters. Thus, it is usually necessary to proceed by trial and error in order to find the optimal structure.

In our approach, a three-layer ANN with 100 hidden neurons in each layer was found to achieve the lowest error rates. ReLU(Rectified Linear Unit) was used as the activation function for the hidden layers while the linear function was used for the output layer.

3.3 Model Evaluation

The mean square error (MSE) was used as the indicator of the accuracy of the prediction method, defined as:

$$MSE = \frac{1}{N}(\sum_{i=0}^{n}(f_i - y_i)^2 \quad (3)$$

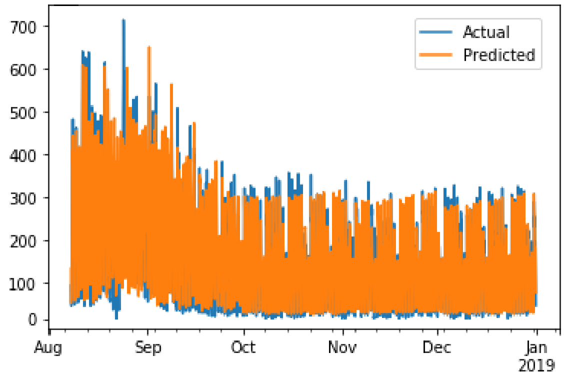
Where,

- N is the number of data points
- f_i is the predicted value (the network's output)
- y_i is the target value for the ith observation

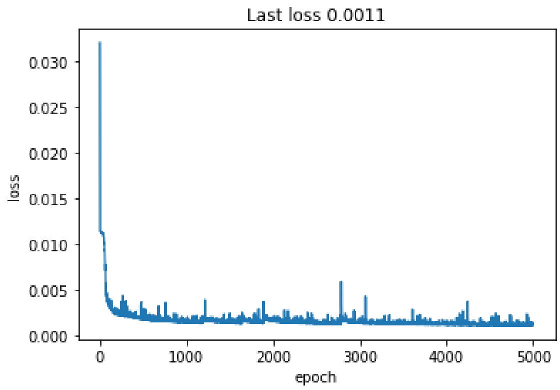
3.4 Forecasting results

As we mentioned earlier, the traffic flow data is divided into two parts: the first part is the training sample and the second part is the testing sample. The training data is used to identify the pattern of data and the test data is used for checking the performance. The forecasting results of the testing data set are shown in Fig. 2.

The error is quantified using Mean Square Error (MSE) and the values obtained for each iteration are shown in Fig. 2(b).



(a) Line plot of ANN forecast vs original values



(b) Model loss

Figure 2: The forecasting results

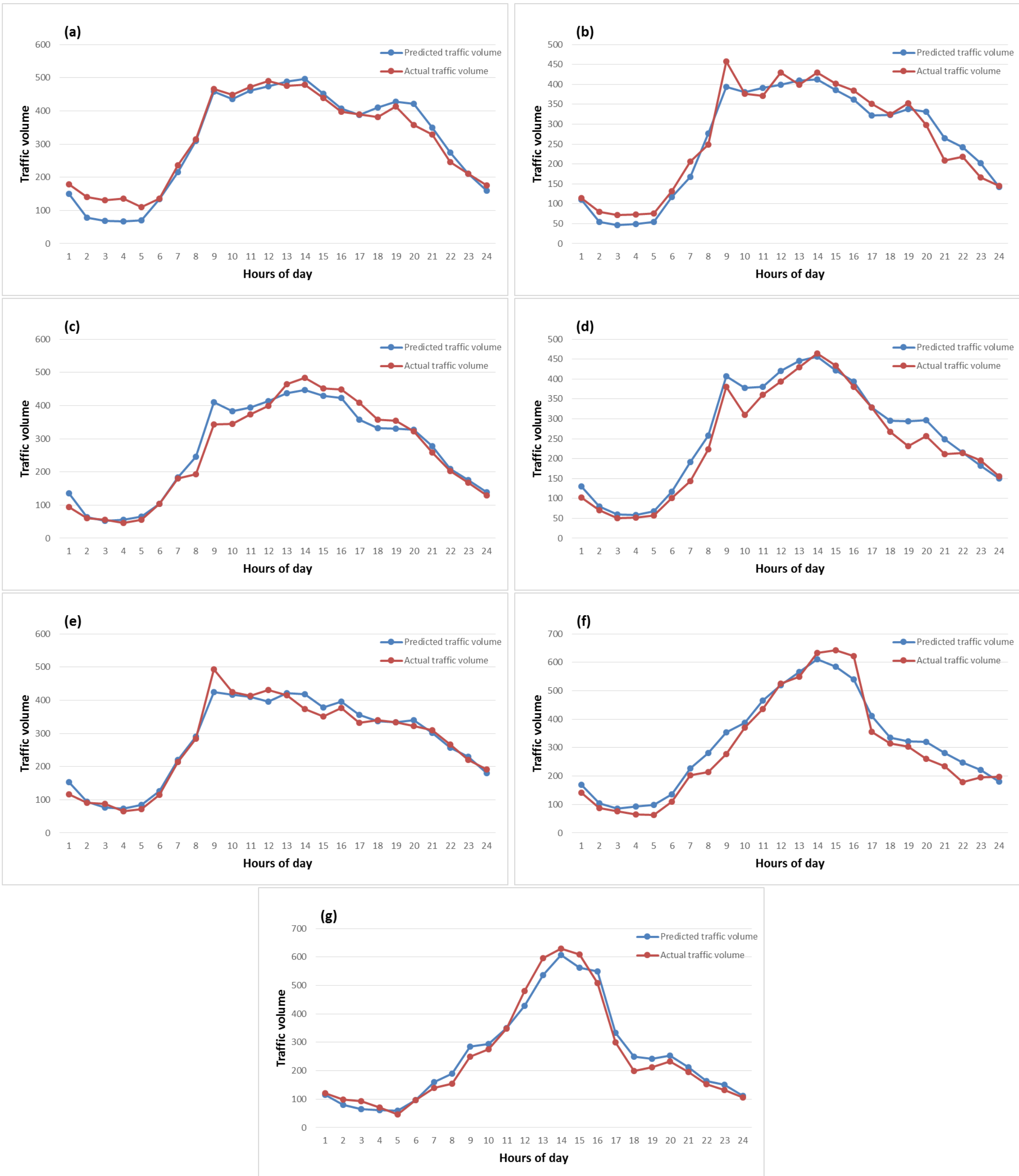


Figure 3: The hourly traffic volumes of different days in a week: (a) Monday, (b) Tuesday, (c) Wednesday, (d) Thursday, (e) Friday, (f) Saturday, and (g) Sunday

From Fig. 2(a), it can be seen that the line graph is divided into two parts: the first part is the one with the highest traffic volume and varying traffic patterns, which corresponds to the month of August. The second part presents the remaining months of the year, which shows a relatively stable traffic patterns. The model perform reasonably well in predicting the second part compared to the first one. This could be explained by the following reasons:

- During this time period, the variations of traffic flow are high. Traffic patterns are not the same comparing day with day, which makes it hard to capture pattern similarities.

- The shifting nature of Eid festivals had a direct impact on the traffic flow pattern. In this particular period, Eid Al-Adha, one of the most important festivities of the year, coincides with the end of the summer holidays and the start of the school year, which help increase the variability in traffic demand.

- The proposed method is trained to learn the behavior and predict future outcomes using historical data. Therefore, a larger training set provides better results. Here in this study, we only have August of 2017 as historical data.

In order to better underline the predictive accuracy of the ANN model, a comparison of estimated and actual traffic values for different times of the day and week is presented in Fig. 3.

We can observe that the ANN model performs well in capturing the data patterns on hourly and daily basis.

The same results has been obtained for the next year (see Fig. 4).

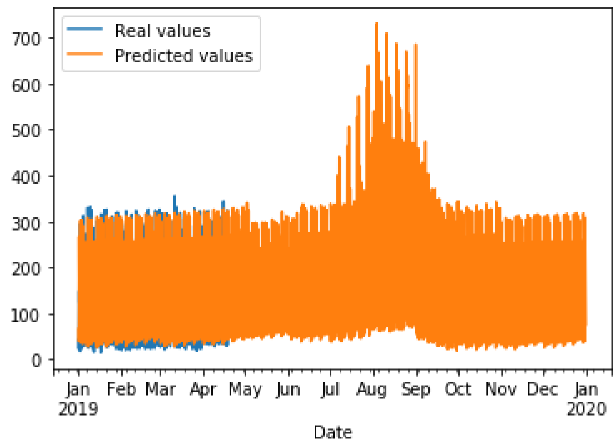


Figure 4: Prediction results of the hourly traffic volume for the first four months of 2019.

On a seasonal basis, the proposed model was able to accurately capture the behaviour of traffic over time as can be seen in Fig. 5. Traffic tends to pick up heavily during the summer months compared to other time of the year.

4 Conclusion

By visually exploring the traffic data, we observe that traffic is affected by a number of temporal features. In this paper, we developed an ANN algorithm for the prediction of hourly traffic volume that model the relationship between the traffic and these temporal features. The suggested model is tested on real world traffic volume, collected from The Melloussa toll plaza and the results showed that the method was able to identify the changes in traffic pattern at different period of time.

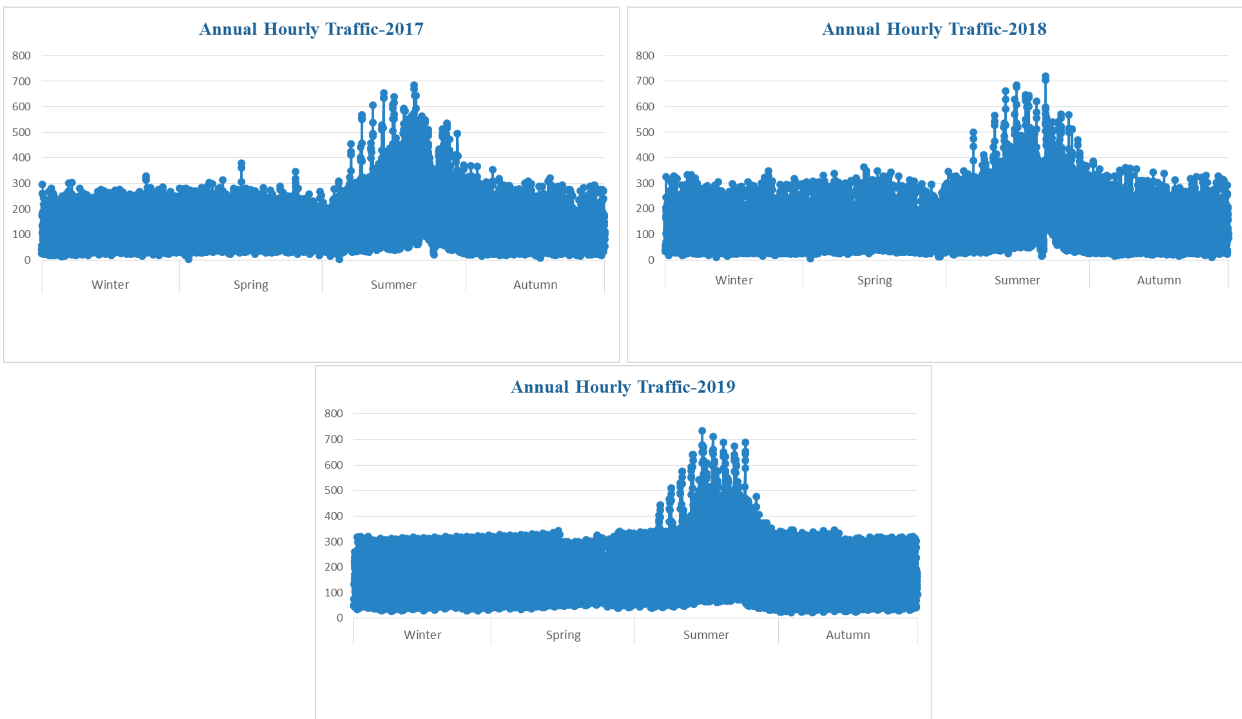


Figure 5: Seasonal variation in traffic flows

Special events are also one of the factors that can greatly affect traffic pattern. Adding this feature to the model is worth studying.

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