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Short-term traffic flow prediction using time-varying Vasicek model

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ABSTRACT

This paper provides a two-step approach based on the stochastic differential equations (SDEs) to improve short-term prediction. In the first step of this framework, a Hull-White (HW) model is applied to obtain a baseline prediction model from previous days. Then, the extended Vasicek model (EV) is employed for modeling the difference between observations and baseline predictions (residuals) during an individual day. The parameters of this time-varying model are estimated at each sample using the residuals in a short duration of time before the time point of prediction; so it provides a real time prediction. The extracted model recovers the valuable local variation information during each day. The performance of our method in comparison with other methods improves significantly in terms of root mean squared error (RMSE), mean absolute error (MAE) and mean relative error (MRE) for real data from Tehran's highways and the open-access PeMS database. We also demonstrate that the proposed model is appropriate for imputing the missing data in traffic dataset and it is more efficient than the probabilistic principal component analysis (PPCA) and k-Nearest neighbors (k-NN) methods.

1. Introduction

In response to the rising demand for reliable transportation networks, rapid development in intelligent transportation systems are obtained. Among different aspects in ITSs, short-term traffic flow prediction has attracted significant attention over the last few decades. The short-term information improves traffic management in order to reduce congestion and provide dynamic bandwidth allocation, etc.

In an attempt to deal with this issue, many techniques are deployed for modeling the evolution of the traffic circulation. Some of these methods employ statistical time series analysis methods like autoregressive integrated moving average (ARIMA) model (Levin and Tsao, 1980; Hamed et al., 1995), seasonal ARIMA (SARIMA) model (Williams and Hoel, 2003), autoregressive conditional heteroscedasticity (ARCH) model (Tsekeris and Stathopoulos, 2006), generalized autoregressive conditional heteroscedasticity (GARCH) model (Chen et al., 2011) and their combination. For example, Guo et al. (2014) study SARIMA + GARCH to model traffic flow series and employ the adaptive Kalman filtering approach to implement this SARIMA + GARCH structure. Dong et al. (2014) develop multivariate state space models for network traffic flow prediction and Yang et al. (2004) propose to use a general and flexible state space model and a Kalman filter for prediction. Wang et al. (2014) propose a new Bayesian combination method to overcome the deficiency of the traditional ones (Petridis et al., 2001). Some researchers have used machine learning methods such as support vector regression (SVR) (Castro-Neto

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et al., 2009) and neural network (NN) (Chan et al., 2012; Kumar et al., 2013; Vlahogianni et al., 2005). Qi and Ishak (2014) utilize Hidden Markov Model (HMM) for predicting short-term freeway traffic data during peak periods. K-Nearest neighbor and its extensions (Chang et al., 2012; Guo et al., 2012; Zheng and Su, 2014) are also used. For detailed information on existing models, please refer to the review papers (Vlahogianni et al., 2004; Vlahogianni et al., 2014; Smith et al., 2002; Chen et al., 2012; Karlaftis and Vlahogianni, 2011). Each of these methods have their own benefits and drawbacks, thereby flow prediction is yet an opening and challenging dynamic research area.

The deficiency of these methods is yielded from the non-recurrent events in distinct days which are not predictable using the constructed models based on the historical data. To describe it more precisely, we note that the traffic data is divided into two parts, a large and a small components. The large component is the time-invariant part which is almost similar in different days. The small component is the time-variant trend that is the fluctuation of traffic data in each day and it represents the sudden volatility because of the occurrence of different non-recurrent events in each day (Li et al., 2015). The popular methods construct a model to capture daily similarities or large component in the historical database (training data). When these models are used to forecast the traffic volume for the test days, they only predict the long-term trend and cannot forecast the local trend during each test day, and consequently the inefficiency of the model to predict local variation patterns causes the deviation of predicted data from the observations and finally the residuals show non-Gaussian property in test days with non-recurrent events. To overcome the problem, Chen et al. (2012) proposed to detrend the traffic data by the simple average method before constructing the prediction model. This idea prevents bias of training results and false prediction (Li et al., 2015). Another method to consider these short-term events is proposed by Tahmasbi and Hashemi (2014). They proposed a novel methodology based on the stochastic differential equations which employs the Hull-White model for modeling the urban volume. In this model, the drift part models the long-term trend and the diffusion part models the short-term variation in historical data. Although their methods outperform the others (Tahmasbi and Hashemi, 2014; Chen et al., 2012), the prediction error in the days that have different traffic patterns from the training collection is considerable. This occurs because their models are constructed based on the previous days and they model the short variations of the historical days while in some test days, the short-term trend is different and non-recurrent from the training one. We would note again that this short-term trend in daily residuals are temporary and caused by events. Examples of these events are occurring accidents, holding a football match or a festival in the city and etc. Accordingly, the shortcoming of the popular methods is that they are not adequate for handling a dynamic traffic, since these models heavily depend on the training data and they always do not describe different patterns of change or daily short-term trends in traffic flow within each individual day. To overcome their deficiency, we present a new solution in this paper, i.e., to add a second step beside the historical data modeling to the prediction algorithm. In other words, a more flexible model along with the baseline model is employed to compensate the prediction error of the baseline model before the time point of prediction in a real time mode in each day. Here, the baseline model is referred to the model constructed by the historical data. In this regard, we propose a new application of the extended Vasicek (EV) model along with the baseline model for modeling the short-term trend during the days. In summary, the proposed algorithm is a two-step approach; first, the baseline predictor provides a trend which is predicted according to the several previous days. The next step is employing the time-varying Vasicek model to construct a prediction model for fluctuations during the day using the residuals in a short duration of time before the time point of prediction. These fluctuations were acquired by subtracting the baseline predictions from observations. For the parameter estimation of the time-varying Vasicek, a window containing a few residuals, captured until the time point of prediction, is used. It will be shown in the following that this model has the potential to capture the real time variation of the volumes during the day, which is different from the predicted volatility according to historical data, and eventually improves the traffic prediction. The reason for such improvements is that this model considers the temporal correlation between volumes within a particular day. In other words, if the flow is increased compared to the average predicted volumes using the baseline model, then it will be more probable to have more volumes in the next time scale. Finally, considering daily uncertainty impacts using the EV model results in significant improvements in traffic prediction over the next time step. The results show that the prediction performance of this hybrid model is superior to five different techniques namely ARIMA, ARIMA-GARCH, NN, SVR, random walk (RW) and HW model.

The organization of the paper is as follows. The next section is dedicated to the proposed procedure with detail. Description of the problem with an example is also presented in this section. Power and performance of this procedure are examined through real data in Section 3. For a comparison with the other methods, the performances of five different methods are evaluated in this section. Application to missing data imputation is explained in Section 4. Finally, some conclusions are drawn in section 5.

2. Problem statement and proposed methodology

In this section, first we describe data and criteria that are used for evaluation of the methods. Next, we illustrate the insufficiency of utilizing only baseline prediction models in days with non-recurrent events. Then, we show how to deal with such events by extending the prediction algorithm to two-step algorithm. Please note that amongst the methods for baseline prediction, Tahmasbi and Hashemi (2014) propose a new model which outperforms others in fitting to the traffic data. So, we use their method as the baseline prediction model to capture the baseline trend. Accordingly, we describe Tahmasbi's method and show its deficiency as the baseline prediction method in Section 2.2.