Short-term Traffic Flow Forecasting with Seasonal Vector Auto-Regressive Moving Average Model

Mai, Tiep
Trinity College Dublin
Dublin, Ireland
E-mail: maik@tcd.ie

Wilson, Simon
Trinity College Dublin
Dublin, Ireland
E-mail: swilson@tcd.ie

1. Short-term traffic flow forecasting

Nowadays, there is an emerging use of Intelligent Transportation Systems, ITS, which refers to a combination of communication technologies to optimize the capacity of a transportation network. In the ITS environment, a large quantity of dynamic real-time information is obtained from various points such as vehicle detectors, sensors and cameras, etc; then, the traffic system manages the network by analyzing the dynamic information. One of the most important tasks of ITS is forecasting the traffic network, the process of predicting future traffic conditions based on observations in the past.

Most of traffic forecasting models are 'univariate' in terms of number of locations, i.e. the spatial correlation of several locations is not considered. This issue is due to the increased model complexity and the real time requirement of applications. Furthermore, most work follows a frequentist approach.

In this study, we use a k-dimension Seasonal Vector Auto-Regressive Moving Average (SVARMA) of additive form and compare with a univariate model. We adopt Bayesian approach and implement MCMC sampling to realize parameter estimation and prediction.

2. SVARMA

We use a VARMA of additive form with a seasonality effect.

(1) $\Phi(B)(Y_t - \beta) = \Theta(B)E_t$

with

$$\Phi(B) = I - \sum_{i=1}^{p} \phi_i B^i$$

$$\Theta(B) = I + \sum_{i=1}^{q} \theta_i B^i$$

where B is the backshift operator i.e. $B.Y_t = Y_{t-1}$; Y_t, β are $k \times 1$ vectors and $E_t \sim N(0, \Sigma_e)$. Each element of ϕ or θ is a $k \times k$ matrix.

Let $\mathcal{IP}$ be a set of integers. If $i \notin \mathcal{IP}$ then $\phi_i = 0$; otherwise, we have $\phi_i \neq 0$ and its corresponding $\mathcal{SP}_i$. Notice that $p = max(\mathcal{IP})$. Similarly, there is $\mathcal{IT}$ for the MA coefficients. So, for the VARMA model with season period 10, we can set $\mathcal{IP} = (1, 10, 20)$.

VARMA accounts for spatial-temporal dependency, for example, $Y_{t,i}$ and $Y_{t-1,j}$ between 2 sites i and j. This dependency is defined by the matrix ϕ_i which can be a full matrix. However, using the full matrix is computationally costly. Hence, we try to reduce the dimension and computational cost by adding neighbour information, as in GMRF. We use matrix $\mathcal{SP}_i$ to denote the dependency; $\mathcal{SP}_i(j,l) = 1$ iff $\phi_i(j,l) \neq 0$; otherwise, $\mathcal{SP}_i(j,l) = 0$. The matrix $\mathcal{ST}_i$ is for θ_i dependency. In a traffic network, the model with first order dependency may be used, i.e. the traffic flow of each junction only depends on its neighbour flows.

REFERENCES (RÉFERENCES)

Box, G. E. P. and G. M. Jenkins (1994). *Time Series Analysis: Forecasting and Control* (3rd ed.). Upper Saddle River, NJ, USA: Prentice Hall PTR.

Chib, S. and E. Greenberg (1994). Bayes inference in regression models with arma (p, q) errors. *Journal of Econometrics 64*(1-2), 183 – 206.

Ghosh, B., B. Basu, and M. O'Mahony (2007). Bayesian time-series model for short-term traffic flow forecasting. *Journal of Transportation Engineering 133*(3), 180–189.

Prado, R. and M. West (2010). *Time Series: Modeling, Computation, and Inference*. Chapman & Hall.

Queen, C. and C. Albers (2009, June). Intervention and causality: Forecasting traffic flows using a dynamic bayesian network. *Journal of the American Statistical Association 104*(486), 669–681.

Ravishanker, N. and B. K. Ray (1997). Bayesian analysis of vector arma models using gibbs sampling. *Journal of Forecasting 16*(3), 177–194.

Vlahogianni, E. I., J. C. Golias, and M. G. Karlaftis (2004). Short-term traffic forecasting: Overview of objectives and methods. *Transport Reviews: A Transnational Transdisciplinary Journal 24*(5), 533 – 557.

Yozgatligil, C. and W. W. S. Wei (2009). Representation of multiplicative seasonal vector autoregressive moving average models. *The American Statistician 63*(4), 328–334.