

Bayesian Inference for High Dimensional Dynamic Spatio-Temporal Models

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ABSTRACT

Spatio-temporal processes are geographically represented, i.e. in space, either by being a point, a field or a map and also they vary in time. We would like to make inference on the spatial and temporal change of certain phenomena which for instance could be the air pollution increasing or decreasing in time and ranging in a city or a country. In this era high dimensional datasets can be available, where measurements are observed daily or even hourly at more than one hundred weather stations or locations along with many predictors. Therefore, what we would like to infer is high dimensional and the analysis is difficult to come through due to high complexity of calculations or efficiency from a computational aspect.

The first reduced dimension *Dynamic Spatio Temporal Model* (DSTM) was introduced by Wikle and Cressie (1999) to jointly describe the spatial and temporal evolution of a function observed subject to noise. A basic state space model is adopted for the discrete temporal variation, while a continuous autoregressive structure describes the continuous spatial evolution.

Application of Wikle and Cressie's DTSM relies upon the pre-selection of a suitable reduced set of basis functions and this can present a challenge in practice. In this poster we propose an offline estimation method for high dimensional spatio-temporal data based upon DTSM which attempt to resolve this issue allowing the basis to adapt to the observed data. Specifically, we present a wavelet decomposition for the spatial evolution but where one would typically expect parsimony. This believed parsimony can be achieved by placing a Spike and Slab prior distribution on the wavelet coefficients. The aim of using the Spike and Slab prior, is to filter wavelet coefficients with low contribution, and thus achieve the dimension reduction with significant computation savings.

We then propose a Hierarchical Bayesian State Space model, for the estimation of which we offer an appropriate Forward Filtering Backward Sampling algorithm which includes Metropolis-Hastings steps for the spatial covariance inference. The proposed methodology is illustrated using simulated data for which an appropriate simulation algorithm is introduced.

References

Wikle, C. K. and Cressie, N. (1999). A dimension-reduced approach to space-time kalman filtering, *Biometrika*, **86** (4): 815–829.