

An introduction to the DLM and GDLM.1.0 package

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Outline

- Introduction
- An Implementation of DLM to Ozone Study
- Results and Conclusions for the Ozone Study
- Prior Settings for the Hyperparameters by the Discount Factors
- GDLM.1.0 Package and Example 1 in Its DEMO
- Lab Exercises

Introduction

- Space-time field: underlying process varies in space and time
 - spatio-temporal (ST) data: dependence structures between pollutants, temporally and spatially.
- Probs:
 - non-stationary process: correlations? heterogeneity?
 - parameter uncertainty
 - curse of dimensionality
 - computational inefficiency

Space-Time (ST) Process

- Space-Time (ST) modelling:

$$\begin{aligned}Z(s_i, t) &= Y(s_i, t) + \epsilon(s_i, t) \\ Y(s_i, t) &= \mu(s_i, t) + \omega(s_i, t),\end{aligned}$$

where $\epsilon \sim WN(0, \cdot)$, ω : mean 0, ST process, $s_i \in D$,
 $i = 1, \dots, n$ & $t = 1, \dots, T$.

- Definitions:
 - stationary? non-stationary?
 - isotropic? anisotropic?
 - separable? non-separable?

DLM Theory

- DLM:

$$\begin{aligned} Y_t &= F_t' x_t + \nu_t \\ x_t &= G_t x_{t-1} + \omega_t, \end{aligned}$$

where $\nu_t \sim N[0, V_t]$, $\omega_t \sim N[0, W_t]$, for $t = 1, \dots, T$.

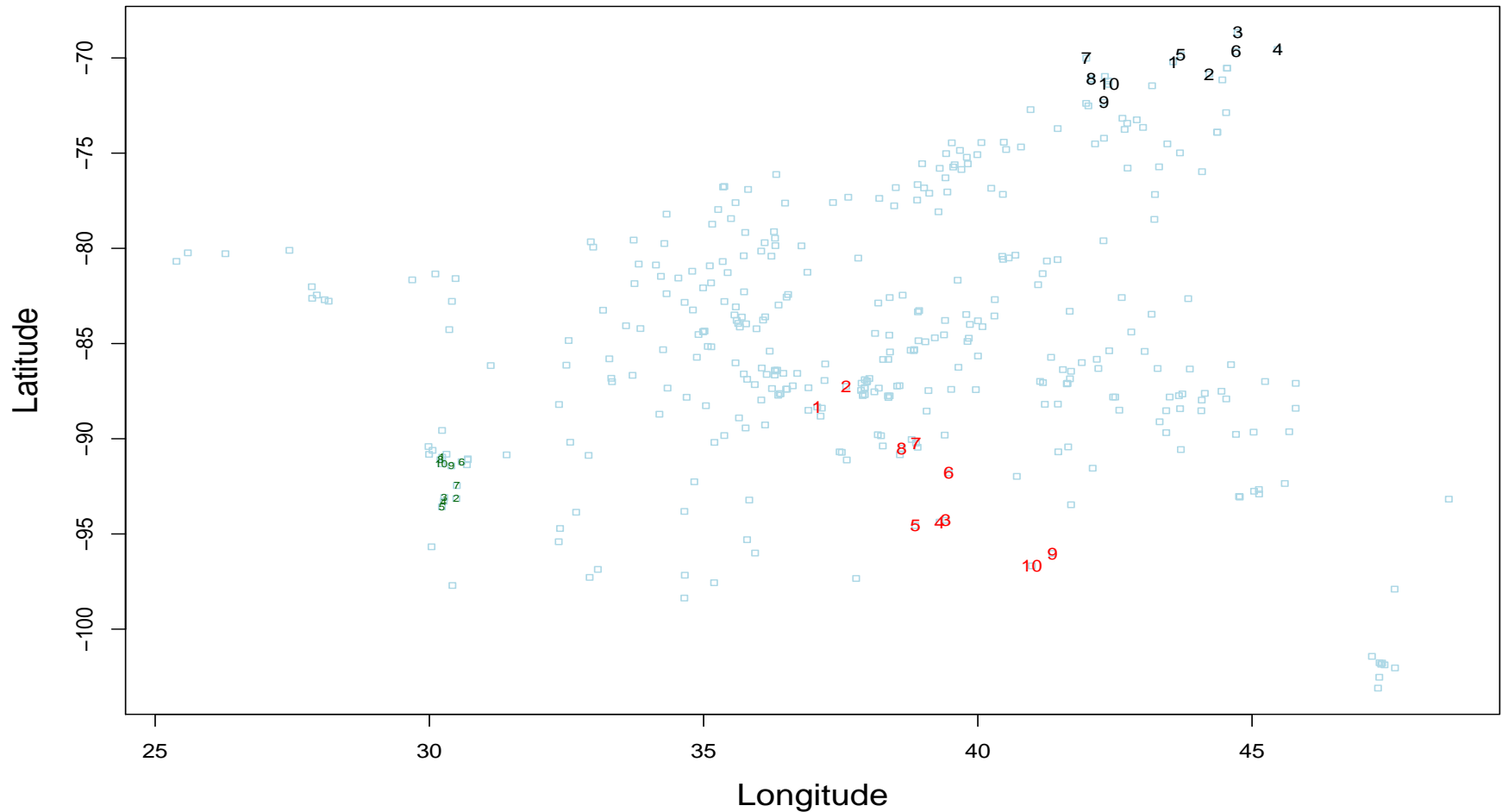
- Initial information: $(x_0 | D_0) \sim N[m_0, C_0]$.

- Forward-filtering-backward-sampling (FFBS):

- for $t \geq 1$, $(x_{t-1} | y_{1:t-1}, \theta) \rightarrow (x_t | y_{1:t-1}, \theta) \rightarrow (y_t | y_{1:t-1}, \theta) \rightarrow (x_t | y_{1:t}, \theta)$;
- for $0 \leq k \leq T - 1$, $(x_{T-k} | y_{1:T}, \theta)$.

Ozone Study: AIRS Dataset

Figure 1. Ozone Study: AIRS dataset in the USA.



Ozone Study: EDA

- Explanatory Data Analysis of Ozone:
 - measured in *ppb*
 - May 14 - Sept. 11, 1995 (120 days)
 - 375 monitoring stations
 - 3 Clusters of sites are chosen:
 - 24-, 12- hour cycles: periodicity v.s. spectrum
 - $\sqrt{\text{Ozone}}$: normality assumption

Ozone Study: DLM setting

- DLM form I:

$$\mathbf{Y}_t = \mathbf{1}'_n \beta_t + S_{1t}(a_1) \alpha_{1t} + S_{2t}(a_2) \alpha_{2t} + \nu_t$$

$$\beta_t = \beta_{t-1} + \omega_t^\beta$$

$$\alpha_{jt} = \alpha_{j,t-1} + \omega_t^{\alpha_j},$$

where $S_{jt}(a_j) = \cos(\pi t j / 12) + a_j \sin(\pi t j / 12)$, $j = 1, 2$;
 $\nu_t \sim N[0, \sigma^2 V_\lambda]$; $\omega_t^\beta \sim N[0, \sigma^2 \tau_y^2]$, $\omega_t^{\alpha_j} \sim N[0, \sigma^2 \tau_j^2 V_{\lambda_j}]$,
 $j = 1, 2$; $V_\lambda = \exp(-V/\lambda)$.

Ozone Study: DLM setting (Cont'd)

- DLM form II:

$$\begin{aligned} \mathbf{Y}_t &= \mathbf{F}'_t \mathbf{x}_t + \nu_t \\ \mathbf{x}_t &= \mathbf{x}_{t-1} + \omega_t, \end{aligned}$$

where $x'_t = (\beta_t, \alpha'_{1t}, \alpha'_{2t})'$; $\omega_t \sim N[0, \sigma^2 W]$,
 $W = \text{block diag} \{ \tau_y^2, \tau_1^2, V_{\lambda_1}, \tau_2^2, V_{\lambda_2} \}$.

- Initial information: $(x_0 | D_0, \theta) \sim N[m_0, \sigma^2 C_0]$.
- Advantages: It
 - reflects the time-dependent structure of data;
 - captures the spatial interaction structure of sites;
 - captures the periodicities of data.

Ozone Study: MCMC Sampling

- Fix τ_y^2 , τ_1^2 , λ_1 , τ_2^2 and λ_2 , consider the joint posterior density:

$$p(x_{1:T}, \lambda, \sigma^2, a_1, a_2 | y_{1:T}).$$

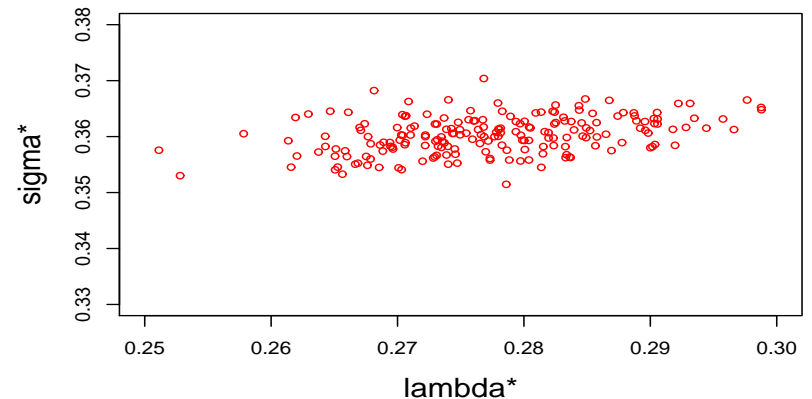
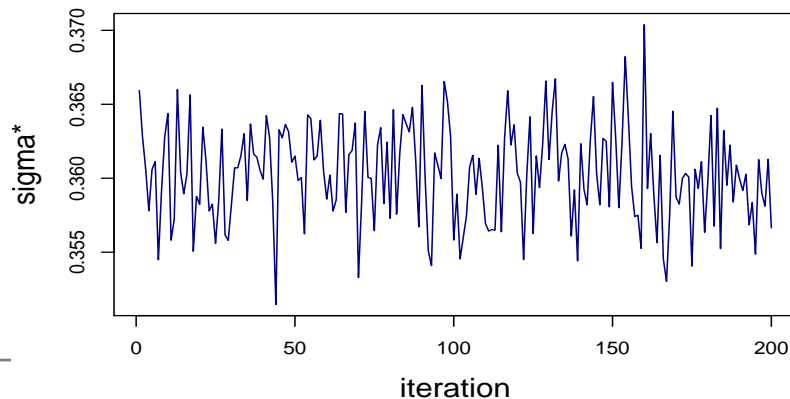
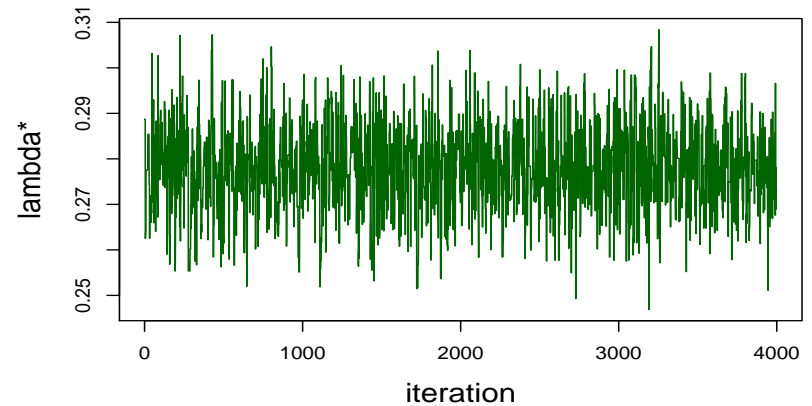
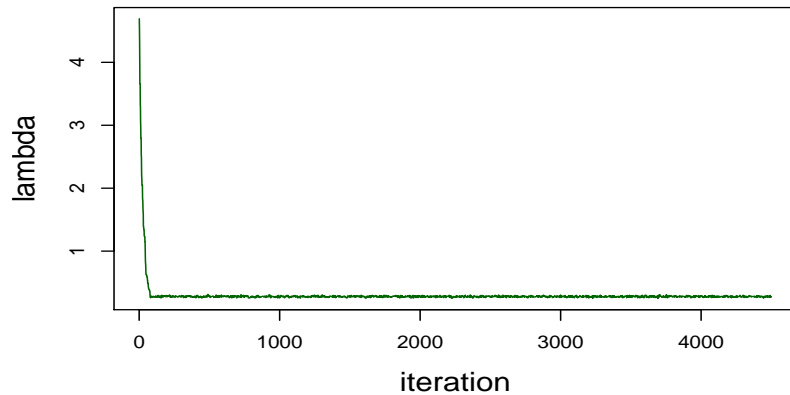
- Sampling each component iteratively until convergence:
 - Sampling from $p(x_{1:T} | \lambda, \sigma^2, y_{1:T})$:
 - $p(\lambda | y_{1:T})$: Metropolis-Hasting algorithm
 - $p(\sigma^2 | \lambda, y_{1:T}) \sim IG$: given $p(\sigma^2) \sim IG$
 - $p(x_{1:T} | \lambda, \sigma^2, y_{1:T})$: FFBS method

Ozone Study: MCMC Sampling (cont.)

- ● Sampling from $p(a_1, a_2 | x_{1:T}, \lambda, \sigma^2, y_{1:T})$, given $p(a_1, a_2) \sim BN$.
- Interpolation at an unknown site s : Given $\alpha_{t-1}^s, y_{t-1}^s$,
 - Sampling from $p(\alpha_{jt}^s | \alpha_{j,t-1}^s, a_1, a_2, x_t, \lambda, \sigma^2, y_t), j = 1, 2$;
 - Sampling from $p(y_t^s | \alpha_{1t}^s, \alpha_{2t}^s, a_1, a_2, x_t, \lambda, \sigma^2, y_t)$.

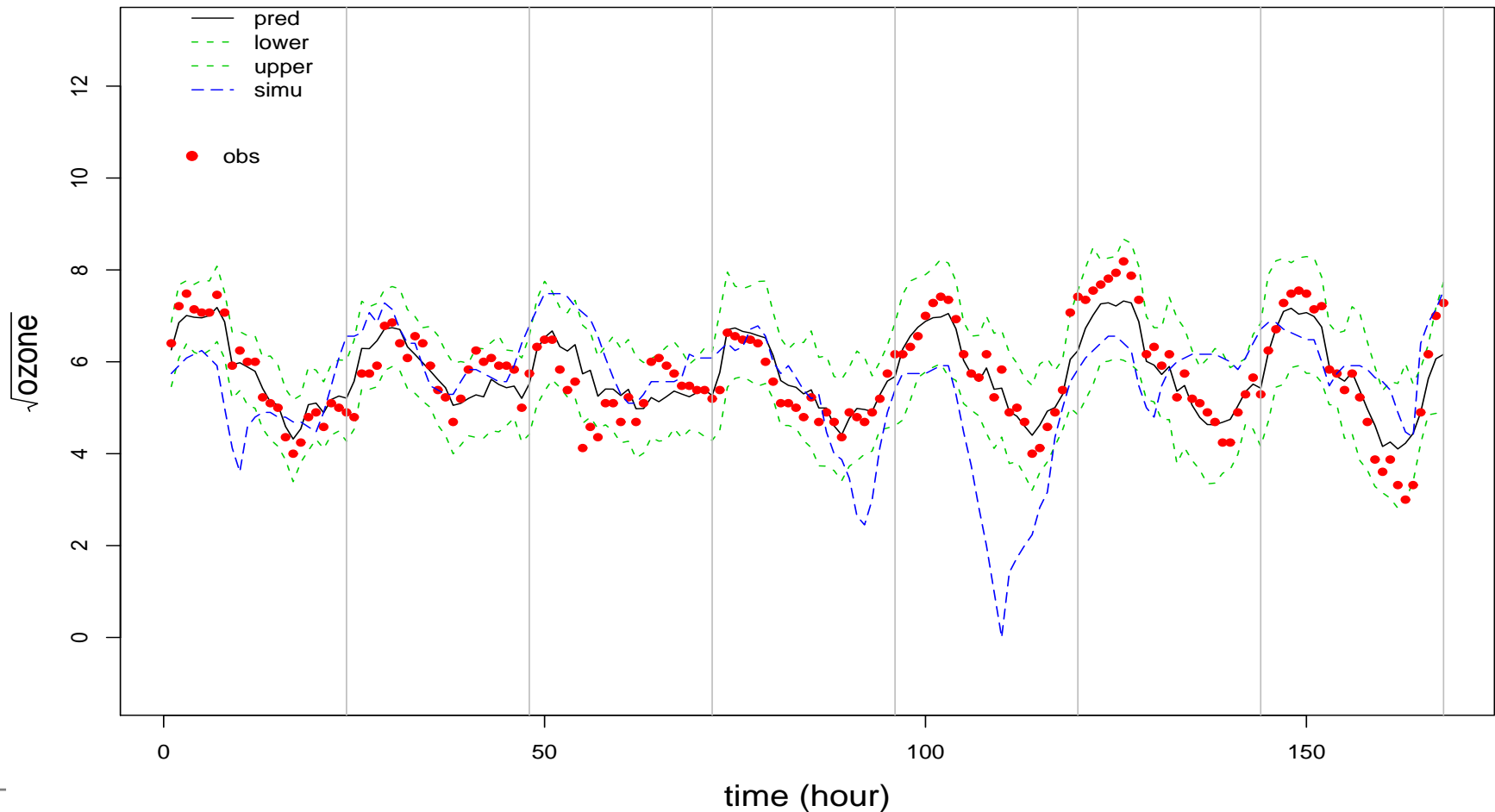
Ozone Study: MCMC Results

Figure 2. Upper panel: (left) λ by M-H ; (right) λ^* after 550 burn in period; Lower panel: (left) σ^{2*} sample from $p(\sigma^2|\lambda, y_{1:T})$; (right) λ^* v.s. σ^{2*} .



Ozone Study: Interpolation

Figure 3. Interpolation result at Center 2 in Cluster 2 sites, 1st week during the study period.



Ozone Study: Model Assessment

- Cross-validation (CV) study:

Site	1	2	3	4	5	6	7	8	9	10
CP(%)	95.6	98.4	97.4	97.2	96.3	96.9	99.3	93.9	96.9	98.6

- Mean Square predicted error (MSPE):

Site	1	2	3	4	5	6	7	8	9	10
MSPE _S ($\times 10^4$)	1.5	8.9	0.6	1.0	0.7	0.5	2.9	1.0	1.3	0.6
MSPE _P ($\times 10^3$)	4.1	1.9	2.8	2.8	2.5	1.9	0.4	4.9	0.3	2.3
Ratio	3.74	4.79	2.12	3.70	2.93	2.55	81.13	2.10	36.96	2.48

Ozone Study: Conclusions

- Major achievements:
 - Develop C programs to solve the computational inefficiency
 - Implement the DLM in modelling conditionally Gaussian space-time fields

Ozone Study: Conclusions (cont.)

- Pros:

- Bayesian hierarchical model + Gaussian framework
- Good performance: better than MAQSIP?

- Cons:

- Isotropic & stationary: Yes? No?
- Computational burden
- Estimating hyperparameters? Trial-and-error?

Prior setting for the hyperparameters

- Discount factor in the first order polynomial model
- Relationship between the discount factors and the hyperparameters
- How to set them?

GDLM.1.0 package

- Developed about one year ago
- Successfully in spatial interpolation in Dou, Le, & Zidek (2007)
- Use C and R codes to fast the computational speed
- Run in Linux, Unix and Windows
- URL: <http://enviro.stat.ubc.ca>
- Probs:
 - Curse of dimensionality
 - Computational burden

GDLM.1.0: one example

- Download the GDLM.1.0.tar.gz or GDLM.1.0.zip
- Install GDLM.1.0
- Run “Example1.txt” in C:/GDLM.1.0/DEMO
- Check the results – you can find some graphs in “Output”

Summary

- DLM and its modelling
- Ozone study using the DLM and GDLM.1.0 package
- Example on using GDLM.1.0 package

Reference

- West & Harrison, 1997
- Huerta, Sanso, & Stroud, 2004
- Dou, Le, & Zidek, 2007

Lab Exercises

- Experiment:
 - split into small teams
 - each team select one set of data
 - each team running GDLM.1.0 using daily, two-days data: record time
 - put your running results on the board

Lab Exercises

- Real data experiment:
 - select one real data set
 - set the DLM in the GDLM.1.0
 - run GDLM.1.0 and check your results