

GeoModels Tutorial: analysis of (large) spatio-temporal data using Gaussian random fields

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Introduction

In this tutorial we show how to analyze geo-referenced spatio temporal data using Gaussian random fields (RFs) with the R package **GeoModels** (Bevilacqua and Morales-Oñate, 2018) when the number of space-time location is relatively large.

We first load the R libraries needed for the analysis and set the name of the model in the **GeoModels** package:

```
rm(list=ls())
require(devtools)
install_github("vmoprojs/GeoModels-OCL")
require(GeoModels)
require(fields)
model="Gaussian" # model name in the GeoModels package
set.seed(12)
```

Simulation of a space-time Gaussian random field

Let us consider a space-time Gaussian RF $Z = \{Z(\mathbf{s}, t), \mathbf{s} \in S, t \in B\}$, where \mathbf{s} represents a location in the domain S and t represents a temporal instant the domain B . We assume that Z is stationary with zero mean, unit variance and correlation function given by $\rho(\mathbf{h}, u) = \text{cor}(Z(\mathbf{s} + \mathbf{h}, t + u), Z(\mathbf{s}, t))$.

Then we consider the RF $Y = \{Y(\mathbf{s}, t), \mathbf{s} \in S, t \in T\}$ defined by the location and scale transformation:

$$Y(\mathbf{s}, t) = \mu(\mathbf{s}, t) + \sigma Z(\mathbf{s}, t) \quad (1)$$

where $\mu(\mathbf{s}, t) = X(\mathbf{s}, t)^T \boldsymbol{\beta}$ and $X(\mathbf{s}, t)$ is a k -dimensional vector of covariates and $\boldsymbol{\beta} = (\beta_1, \dots, \beta_k)^T$ is a k -dimensional vector of (unknown) parameters (in this tutorial we fix $k = 2$). Then $\mathbb{E}(Y(\mathbf{s}, t)) = X(\mathbf{s}, t)^T \boldsymbol{\beta}$, $\text{var}(Y(\mathbf{s}, t)) = \sigma^2$ and $\text{cov}(Y(\mathbf{s} + \mathbf{h}, t + u), Y(\mathbf{s}, t)) = \sigma^2 \rho(\mathbf{h}, u)$.

Suppose we want to simulate a realization of Y at $t_1 = 1, t_2 = 2, \dots, t_T = 25$, $T = 25$ temporal instants and $N = 400$ spatial locations uniformly distributed in the unit square. The total number of space-time locations is given by $NT = 10000$.

We first set the temporal instants and then the spatial coordinates with associated covariates.

```

coordt=1:25      # number of temporal instants
T=length(coordt)
NN=400           # number of spatial locations
x = runif(NN, 0, 1); y = runif(NN, 0, 1)
coords=cbind(x,y)
X=cbind(rep(1,NN*T),runif(NN*T))

```

We then specify the mean, variance and nugget parameters

```

mean = 0.5; mean1= -0.25
sill=2; nugget=0

```

where `mean`, `mean1` and `sill` are respectively β_1 , β_2 and σ^2 .

A possible approach to simulate a large (exact) realization from a Gaussian space-time RF is to consider a compactly supported correlation space-time correlation function combined with cholesky decomposition algorithms for sparse matrices.

In this tutorial we assume a simple spatially isotropic and symmetric in time separable Wendland model

$$\rho((\mathbf{h}, u); \alpha_s, \alpha_t, \mu_s, \mu_t) = \left(1 - \frac{\|\mathbf{h}\|}{\alpha_s}\right)_+^{\mu_s} \left(1 - \frac{|u|}{\alpha_t}\right)_+^{\mu_t} \quad (2)$$

Then we set the name of the correlation model and the associated parameters:

```

corrmodel="Wend0_Wend0";
scale_s=0.2; scale_t=2

```

where `scale_s` and `scale_t` corresponds to α_s and α_t , the compact supports of the correlation model. We are now ready to simulate the space time Gaussian RF using the function `GeoSim`:

```

param= list(nugget=0,mean=mean,mean1=mean1, scale_t=scale_t,
            scale_s=scale_s,sill=sill,power2_s=4,power2_t=4)
ss1 = GeoSim(coordx=coords, coordt=coordt, corrmodel=corrmodel,X=X,
            sparse=TRUE, model=model,param=param)$data

```

Note that the option `sparse=TRUE` allows to consider algorithms for sparse matrices when performing Cholesky decomposition, as described in the package `spam` (Gerber et al. (2017)). Informations about the sparsity of the covariance matrix can be obtained though the function `GeoCovmatrix` with the following code

```
cc = GeoCovmatrix(coordx=coords, coordt=coordt, corrmodel=corrmodel, X=X,
                  sparse=TRUE, model=model, param=param)
is.spam(cc$covmatrix)
[1] TRUE
cc$nozero
[1] 0.0210392
```

This means that (approximatively) 98% of the covariance matrix are zeros *i.e* the matrix is highly sparsed.

Estimation of a Gaussian space-time random field

Given a space-time realization $\{Y(\mathbf{s}_i, t_l), \quad l = 1 \dots T, i = 1, \dots N\}$, let $f_Y(y_{il}, y_{jk})$ the Gaussian density of a pair of observations $Y(\mathbf{s}_i, t_l)$ and $Y(\mathbf{s}_j, t_k)$. Then, the pairwise likelihood function is defined as (Bevilacqua et al. (2012); Bevilacqua and Gaetan (2015)):

$$pl(\boldsymbol{\theta}) = \sum_{i,j,l,k \in D} \log(f_Y(y_{il}, y_{jk})) w_{ijkl} \quad (3)$$

where

$$D = \begin{cases} l = 1 \dots T, & i = 1, \dots, N, & k = l, \dots, T \\ j = i + 1, \dots, N & \text{if } l = k \\ j = 1, \dots, N & \text{if } l > k \end{cases}.$$

and w_{ijkl} are non-negative weights, not depending on $\boldsymbol{\theta}$, specified as:

$$w_{ijkl} = \begin{cases} 1 & \|\mathbf{s}_i - \mathbf{s}_j\| < d_s, |t_l - t_k| < d_t \\ 0 & \text{otherwise} \end{cases}. \quad (4)$$

and in this case $\boldsymbol{\theta} = (\mu, \sigma^2, \alpha_s, \alpha_t)^T$. The pairwise likelihood estimator $\hat{\boldsymbol{\theta}}_{pl}$ is obtained maximizing (3) with respect to $\boldsymbol{\theta}$. In the `GeoModels` package we can choose the fixed parameters and the parameters that must be estimated. Pairwise likelihood estimation is performed with the function `GeoFit`:

```
## estimation with pairwise likelihood
start=list(mean=mean, mean1=mean1, scale_s=scale_s, scale_t=scale_t, sill=sill)
fixed=list(nugget=nugget, power2_s=4, power2_t=4)
```

```
fit = GeoFit(data=ss1, coordx=coords, coordt=coordt, corrmodel=corrmodel,
             maxdist=0.04, maxtime=1, X=X, GPU=0, local=c(1,1),
             start=start, fixed=fixed, model=model)
```

Note that the option `maxdist=0.04` and `maxtime=1` set the (arbitrary) compact supports of the weight function (4) i.e. $d_s = 0.04$ and $d_t = 1$. A suitable choice of the weights allows to improve both the statistical and computational efficiency (Bevilacqua and Gaetan (2015))

The option `GPU=0, local=c(1,1)` allows to speed up time performance. The first parameter (`GPU=0`) sets the computing device. You can call the available devices in your computer through `DeviceInfo()` and choose the associated number. The second argument (`local=c(1,1)`) lets you set the number of local work-items of the OpenCL setup.

The object `fit` include informations about the pairwise likelihood estimation

```
fit
#####
Maximum Composite-Likelihood Fitting of Gaussian Random Fields
Setting: Marginal Composite-Likelihood
Model associated to the likelihood objects: Gaussian
Type of the likelihood objects: Pairwise
Covariance model: Wend0_Wend0
Number of spatial coordinates: 400
Number of dependent temporal realisations: 25
Type of the random field: univariate
Number of estimated parameters: 5
Type of convergence: Successful
Maximum log-Composite-Likelihood value: -144544.23
Estimated parameters:
      mean    mean1  scale_s  scale_t    sill
0.5556   -0.2681   0.1983   2.0416   1.9484
#####
```

Checking model assumptions

Given the estimation of the mean regression and sill parameters, the estimated residuals

$$\widehat{Z(s_i, t_l)} = \frac{Y(s_i, t_l) - X(s_i, t_l)^T \widehat{\beta}}{(\widehat{\sigma^2})^{\frac{1}{2}}} \quad i = 1, \dots, N \quad l = 1, \dots, T$$

can be viewed as a realization of a zero mean stationary Gaussian RF with correlation function $\rho(\mathbf{h}, u)$. The residuals can be computed using the `GeoResiduals` function:

```
res=GeoResiduals(fit) # computing residuals
```

Then the marginal distribution assumption on the residuals can be graphically checked for instance with a qq-plot (Figure 1, left part):

```
### checking model assumptions: marginal distribution
qqnorm(unlist(res$data))
abline(0,1)
```

The correlation model assumption can be checked comparing the empirical and the estimated space-time semivariogram functions using the `GeoVariogram` and `GeoCovariogram` functions (Figure 1, right part):

```
### checking model assumptions: ST semi-variogram model
vario = GeoVariogram(data=res$data, coordx_dyn=coordx_dyn, coordt=coordt,
                     maxdist=0.6, maxtime=4)
GeoCovariogram(res, vario=vario, fix.lagt=1, fix.lags=1, show.vario=TRUE, pch=20)
```

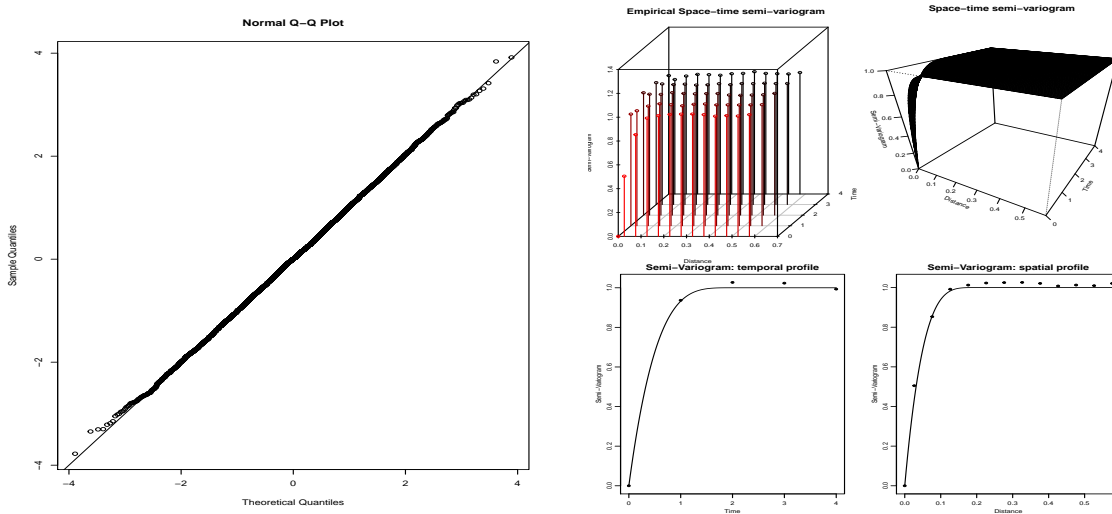


Figure 1: Left: QQ-plot for the residuals of the space-time Gaussian RF. Right: space-time empirical vs estimated semi-variogram function for the residuals

Prediction of space-time Gaussian random fields

For a given space time location (s_0, t_0) with associated covariates $X(s_0, t_0)$, the optimal prediction of Gaussian RF is computed as:

$$\hat{Y}(s_0, t_0) = X(s_0, t_0)^T \hat{\beta} + \sum_{l=1}^T \sum_{i=1}^N \lambda_{l,i} [Y(s_i, t_l) - X(s_i, t_l)^T \hat{\beta}] \quad (5)$$

where the vector of weights $\lambda = (\lambda_{1,1}, \dots, \lambda_{T,N})'$ is given by $\lambda = R^{-1}c$ and

- $c = (\text{cor}(Y(s_0, t_0), Y(s_1, t_1)), \dots, \text{cor}(Y(s_0, t_0), Y(s_N, t_T)))^T$.
- $R = [[\text{cor}(Y(s_i, t_l), Y(s_j, t_k))]_{l,k=1}^T]_{i,j=1}^N$ is the correlation matrix.

Kriging can be performed using the `GeoKrig` function. We need just to specify the spatial location and temporal instants to predict.

In this example we consider a spatial regular grid and one temporal instant:

```
xx=seq(0,1,0.03)
loc_to_pred=as.matrix(expand.grid(xx,xx))      # locations to predict
n_loc=nrow(loc_to_pred)
times=c(2)                                     #time to predict
```

Moreover we need to specify the associated covariates:

```
Xloc=cbind(rep(1,n_loc),runif(n_loc))
```

Then the optimal linear prediction (5), using the estimated parameters, can be performed using the `GeoKrig` function:

```
param_est=as.list(c(fit$param,fixed))
pr = GeoKrig(data=ss1,coordx=coords, coordt=coordt, corrmodel=corrmodel,
             X=X,Xloc=Xloc,sparse=TRUE,
             model=model,mse=TRUE,loc=loc_to_pred,
             time=times,param=param_est)
```

A kriging map for the temporal instant $t = 2$ with associate mean square error (Figure 2) can be obtained with the following code:

```
par(mfrow=c(1,3))
colour <- rainbow(100)
## observed data at time 2
quilt.plot(coords[,1],coords[,2],ss1[2,],col=colour,main="Time=2")
```

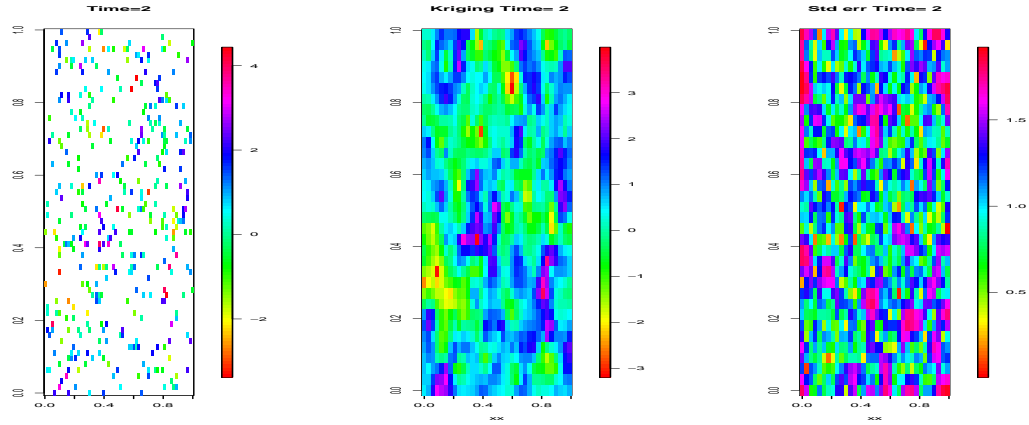


Figure 2: From left to right: observed spatial data at time $t = 2$, associated kriging map and mean square error map.

```
## kriging map at time 2
image.plot(xx, xx, matrix(pr$pred,ncol=length(xx)),col=colour,
           main = paste("Kriging-Time=" , 2),ylab="")
## MSE kriging map at time 2
image.plot(xx, xx, matrix(pr$mse,ncol=length(xx)),col=colour,
           main = paste("Stderr-Time=" , 2),ylab="")
```

References

- Bevilacqua, M. and C. Gaetan (2015). Comparing composite likelihood methods based on pairs for spatial Gaussian random fields. *Statistics and Computing* 25, 877–892.
- Bevilacqua, M., C. Gaetan, J. Mateu, and E. Porcu (2012). Estimating space and space-time covariance functions for large data sets: a weighted composite likelihood approach. *Journal of the American Statistical Association* 107, 268–280.
- Bevilacqua, M. and V. Morales-Oñate (2018). *GeoModels: A Package for Geostatistical Gaussian and non Gaussian Data Analysis*. R package version 1.0.3-4.
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