es1

2024-01-13

Load libraries

```r
shhh = function(lib_name){ # It's a library, so shhh!
  suppressWarnings(suppressMessages(require(lib_name, character.only = TRUE)))
}
shhh("tidyverse")
shhh("ACutils")
shhh("mvtnorm")
shhh("salso")
shhh("FGM")
shhh("gmp")
shhh("mcclust")
shhh("mcclust.ext")
shhh("logr")
shhh("tidygraph")
shhh("ggraph")
shhh("igraph")
shhh("Rcpp")
shhh("RcppArmadillo")
shhh("RcppEigen")

## Load custom functions
source("functions/utility_functions.R");
source("functions/bulky_functions.R");
source("functions/data_generation.R")
sourceCpp("functions/wade.cpp")
Rcpp::sourceCpp('functions/UpdateParamsGSL.cpp')

library('RcppGSL')
library(fda)
library(tidyverse)
library(coda)
library(lattice)
```

Goal

Smoothing di dati funzionali simulati, con grafo e partizione tenuti fissi.

Simulated data

Simuliamo i dati in sim_data.R con p=40 basi e 3 cluster di dimensioni [13, 13, 14]. Grafo e matrice di precisione sono generati attraverso la funzione Generate_BlockDiagonal.

```r
# Import simulated data
BaseMat = as.matrix(read_csv('simulated_data/BaseMat.csv'))        # matrix Phi, dim = 200 x 40
y_hat_true = as.matrix(read_csv('simulated_data/y_hat_true.csv'))  # y true, dim = 300 x 200
beta_true = as.matrix(read_csv('simulated_data/beta_true.csv'))    # beta, dim = 300 x 40
mu_true = as.matrix(read_csv('simulated_data/mu_true.csv'))        # mu true, dim = 40 x 1

# object containing the true graph G, the true precision matrix K
simKG <- readRDS("simulated_data/simKG.rds")

n <- dim(y_hat_true)[1]  # n=300
r <- dim(y_hat_true)[2]  # r=200
p <- dim(BaseMat)[2]     # p=40
```

Initialization

```r
# Define the starting Beta matrix
Beta = matrix(rnorm(n = p*n), nrow = p, ncol = n)

# Define the starting value of mu
mu = rnorm(n=p)

# Fix tau_eps (squared)
tau_eps = 100

# Define the starting precision matrix K and graph G: in this case we start
# from the true K and true G and we will not update them
K = simKG$Prec
G = simKG$Graph

# Define the true partition with which we have generated data
rho = c(13,13,14)
z = c(rep(1,13), rep(2,13), rep(3,14))

# Compute quantities for function UpdateParamGSL
tbase_base = t(BaseMat)%*%BaseMat            # p x p (phi_t * phi)
tbase_data = t(BaseMat)%*%t(y_hat_true)      # p x n (phi_t * Y_t)
Sdata = sum(diag(y_hat_true%*%t(y_hat_true))) # initialize phi*beta = 0

# Set True binary flag used to update values
Update_Beta <- TRUE
Update_Mu <- TRUE
Update_Tau <- TRUE

# Define hyperparameters values
a_tau_eps <- 2000
b_tau_eps <- 2
```

```r
sigma_mu <- 100

# Define variance of the Beta
beta_sig2 = 0.2

# Compute graph density
graph_density = sum(G) / (p*(p-1))

# Set the number of iterations and burn-in
niter <- 10000
burn_in <- 1000


# Create a list for chains to save the values of each iteration
chains <- list(
  Beta = vector("list", length = niter),
  mu = vector("list", length = niter),
  tau_eps = vector("list", length = niter),
  K = vector("list", length = niter),
  G = vector("list", length = niter),
  z = vector("list", length = niter),
  rho = vector("list", length = niter),
  time = vector("list", length = niter)
)


# Initialization of the chains
chains$Beta[[1]] <- Beta
chains$mu[[1]] <- mu
chains$tau_eps[[1]] <- tau_eps
chains$K[[1]] <- K
chains$G[[1]] <- G
chains$z[[1]] <- z
chains$rho[[1]] <- rho
chains$time <- 0          # execution time

# initialization of parameters for set_options
sigma <-0.5               # parameter of the prior of the partition
theta <-1                 # parameter of the prior of the partition
weights_a <- rep(1,p-1)   # starting weights
weights_d <- rep(1,p-1)   # starting weights
total_weights <- 0        # sum of weights
total_K <- K
total_graphs <- G
graph_start <- NULL
```

Gibbs sampler

```r
for(s in 2:niter) {

  fit = UpdateParamsGSL(
    chains$Beta[[s-1]],
    chains$mu[[s-1]],
    chains$tau_eps[[s-1]],
    chains$K[[s-1]],
    tbase_base,
    tbase_data,
    Sdata,
    a_tau_eps,
    b_tau_eps,
    sigma_mu,
    r,
    Update_Beta,
    Update_Mu,
    Update_Tau
    )

  # Save Beta
  chains$Beta[[s]] <- fit$Beta

  # Save mu
  chains$mu[[s]] <- fit$mu

  # Save tau
  chains$tau_eps[[s]] <- fit$tau_eps

  # Set options for a single iteration of the Gibbs_sampler
  options = set_options(
    sigma_prior_0=sigma,
    sigma_prior_parameters=list("a"=1,"b"=1,"c"=1,"d"=1),
    theta_prior_0=theta,
    theta_prior_parameters=list("c"=1,"d"=1),
    rho0=chains$rho[[s-1]],
    weights_a0=weights_a,
    weights_d0=weights_d,
    total_weights0=total_weights,
    total_K0 = total_K,
    total_graphs0 = total_graphs,
    graph = graph_start,
    alpha_target=0.234,
    beta_mu=graph_density,   # expected value beta distr of the graph
    beta_sig2=beta_sig2,     # var beta distr del grafo, fra 0 e 0.25
    d=3,                     # param della G wishart (default 3)
    alpha_add=0.5,
    adaptation_step=1/(p*1000),
    update_sigma_prior=FALSE,
    update_theta_prior=FALSE,
    update_weights=FALSE,
    update_partition=FALSE,
    update_graph=FALSE,
    perform_shuffle=FALSE
    )

  # Run an iteration of the Gibbs Sampler
  res <- Gibbs_sampler(
    data = t(fit$Beta - fit$mu),
    niter = 1, # niter finali, già tolto il burn in
    nburn = 0,
    thin = 1,
    options = options,
    seed = 123456,
    print = FALSE
  )

  z = do.call(rbind, lapply(res$rho, rho_to_z))

  # Save rho
  chains$rho[[s]] <- res$rho[[1]]

  # Save K
  chains$K[[s]] <- res$K [[1]]

  # Save G
  chains$G[[s]] <- res$G [[1]]

  # Save z
  chains$z[[s]] <- z

  # Save times for each K
  chains$time[[s]] <- res$execution_time

  # Update quantities for the next iteration
  weights_a <- res$weights_a[[1]]
  weights_d <- res$weights_d[[1]]
  total_weights <- res$total_weights
  total_K <- res$total_K[[1]]
  total_graphs <- res$total_graphs[[1]]
  graph_start = res$bdgraph_start
}
```

Useful plots: 1. Plot smoothed curves

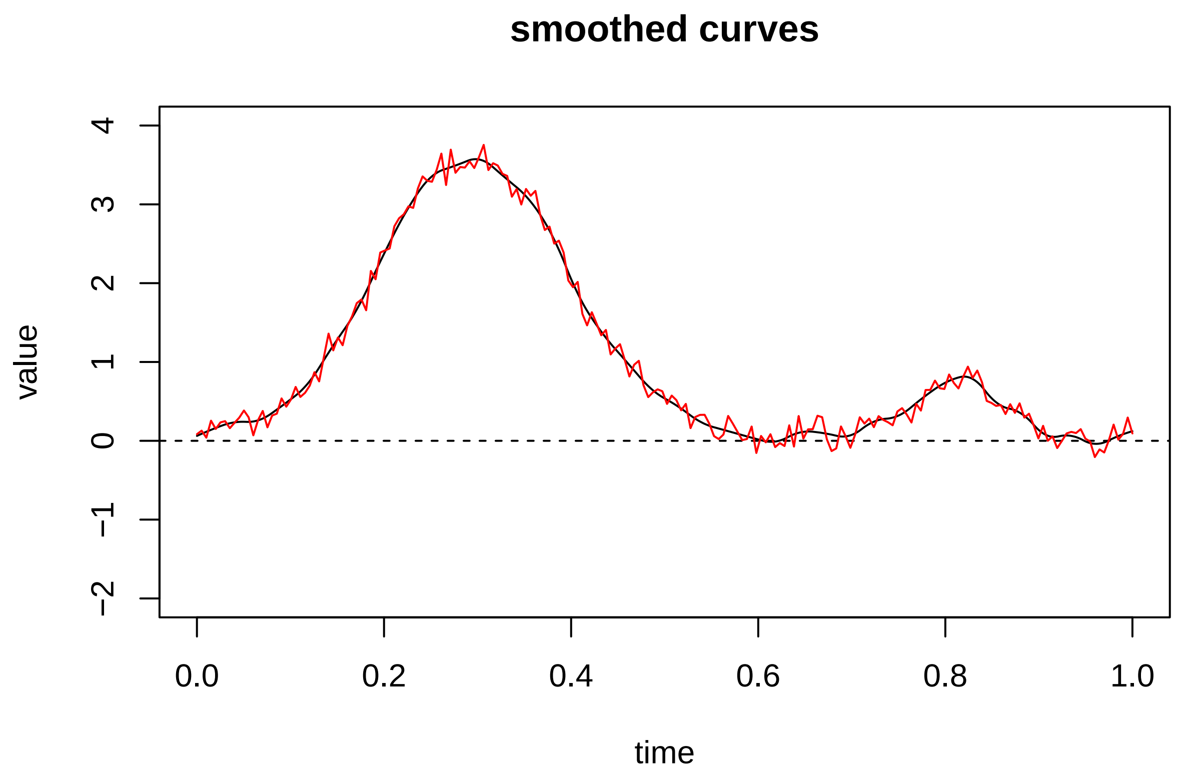
```r
# Compute the mean of Beta in order to have data_post
sum_Beta <- matrix(0, p, n)
for(i in (burn_in+1):niter){
  sum_Beta <- sum_Beta + chains$Beta[[i]]
}
mean_Beta <- sum_Beta/(niter-burn_in)
data_post <- BaseMat %*% mean_Beta

# Compute the x value, create the basis and the functional object
x <- seq(0, 1, length.out=r)
basis <- create.bspline.basis(rangeval=range(x), nbasis=40, norder=3)
data.fd <- Data2fd(y = data_post, argvals = x, basisobj = basis)
```

```r
# Plot smoothed curves
plot.fd(data.fd[1,], main="smoothed curves", ylim=c(-2,4))
```

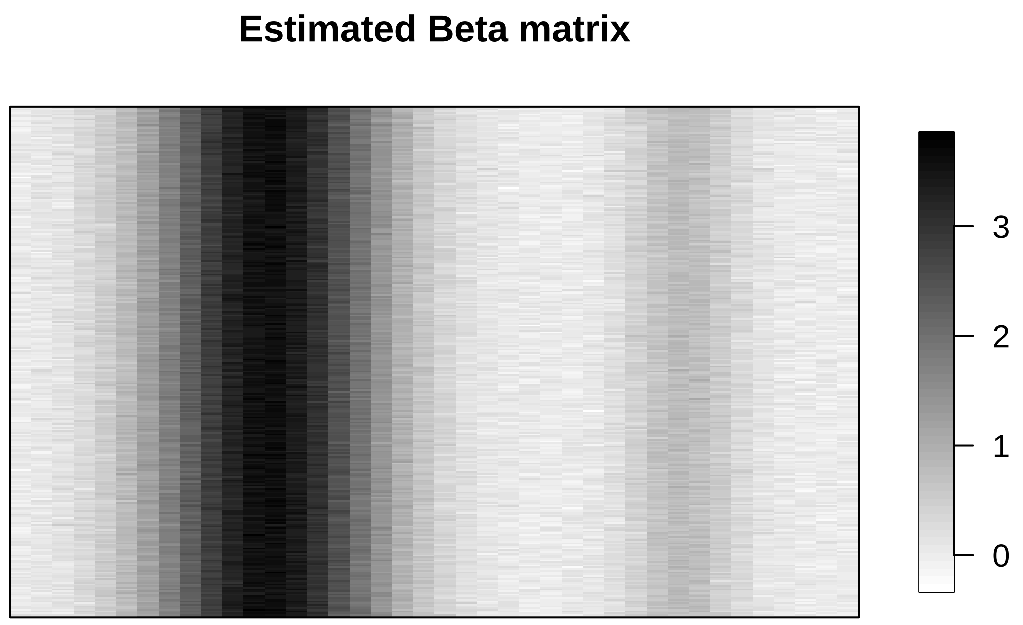
```
## [1] "done"
```

```r
# plot(x, data_post[,1], type='l', ylim=c(-2,4))
lines(x,y_hat_true[1,], main="smoothed curves", col='red')
```



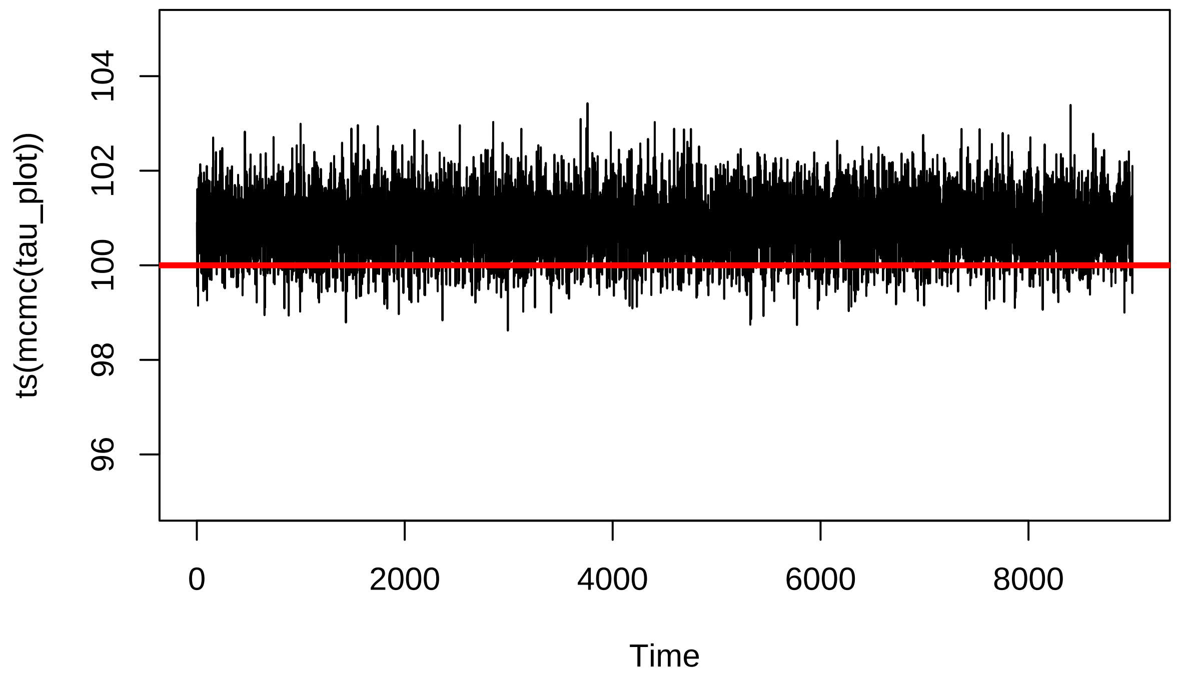
Useful plots: 2. Plot of the final Beta matrix

```r
ACutils::ACheatmap(
  chains$Beta[[niter]],
  use_x11_device = F,
  horizontal = F,
  main = "Estimated Beta matrix",
  center_value = NULL,
  col.upper = "black",
  col.center = "grey50",
  col.lower = "white"
)
```

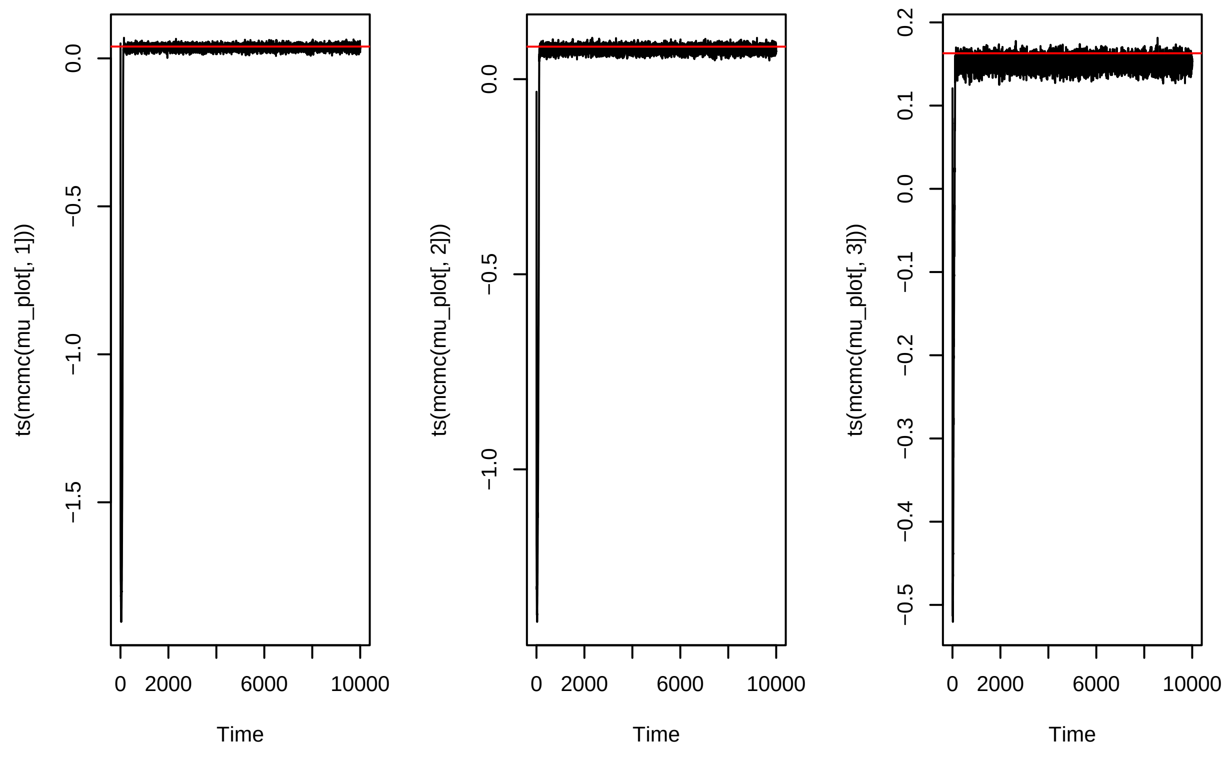


Useful plots: 2. Traceplots (tau_eps, mu, beta)

```r
# tau_eps
tau_plot <- as.vector(chains$tau_eps)
tau_plot <- tau_plot[(burn_in+1):niter]
plot(ts(mcmc(tau_plot)), ylim=c(95,105))
abline(h=tau_eps, col='red', lwd=3)
```



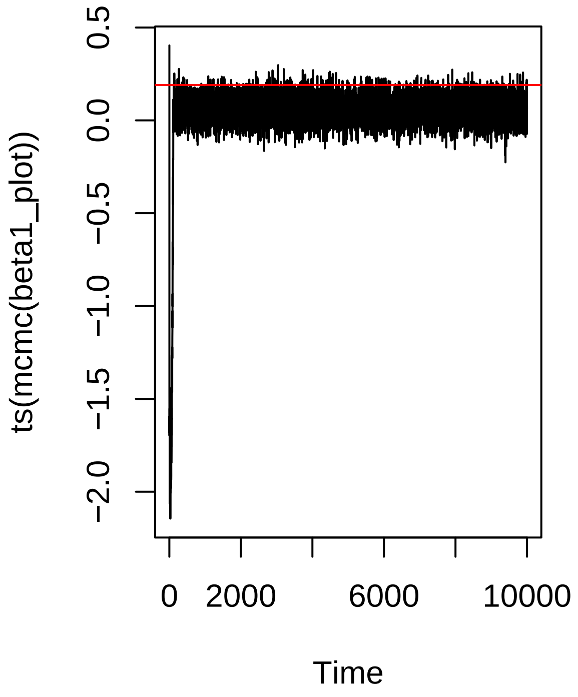
```
# mu
mu_plot <- matrix(0, niter, p)
for(i in 1:niter){
  mu_plot[i, ] <- chains$mu[[i]]
}
par(mfrow=c(1,3))
plot(ts(mcmc(mu_plot[, 1])))
abline(h=mu_true[1], col='red')
plot(ts(mcmc(mu_plot[, 2])))
abline(h=mu_true[2], col='red')
plot(ts(mcmc(mu_plot[, 3])))
abline(h=mu_true[3], col='red')
```



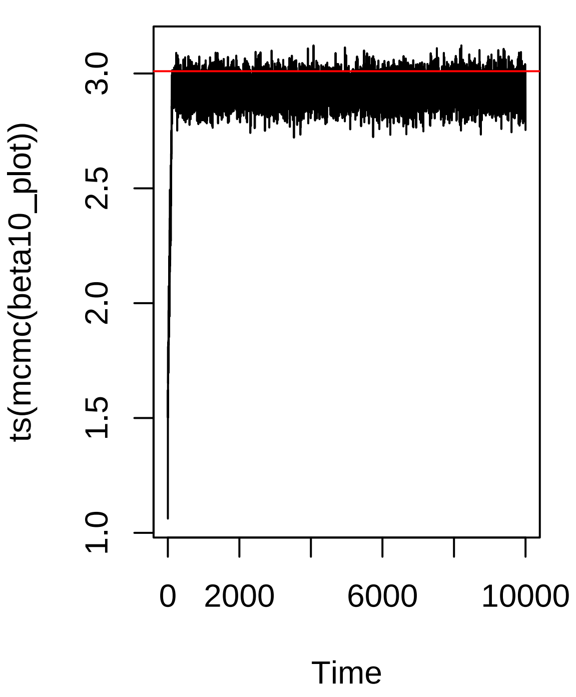
```
# first element of first beta
beta1_plot <- rep(0, niter)
for(i in 1:niter){
  beta1_plot[i] <- chains$Beta[[i]][1,1]
}
# and 10th element of first beta
beta10_plot <- rep(0, niter)
for(i in 1:niter){
  beta10_plot[i] <- chains$Beta[[i]][10,1]
}

par(mfrow=c(1,2))
plot(ts(mcmc(beta1_plot)))
abline(h=beta_true[1,1], col='red')

plot(ts(mcmc(beta10_plot)))
abline(h=beta_true[1,10], col='red')
```



ts(mcmc(beta1_plot))
0.5
0.0
−0.5
−1.0
−1.5
−2.0
0
2000
6000
10000
Time



ts(mcmc(beta10_plot))
3.0
2.5
2.0
1.5
1.0
0
2000
6000
10000
Time