Abstract

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```
library(sp)
library(ggplot2)
library(dplyr)

##
## Attaching package:  'dplyr'
##
## The following objects are masked from 'package:stats':
##
##    filter, lag
##
## The following objects are masked from 'package:base':
##
##    intersect, setdiff, setequal, union
```

```r
library(FRK)
#      devtools::load_all("~/Wollongong/pkgs/FRK",
#                                export_all = FALSE)
opts_FRK$set("progress",FALSE)
opts_FRK$set("parallel",0L)
```

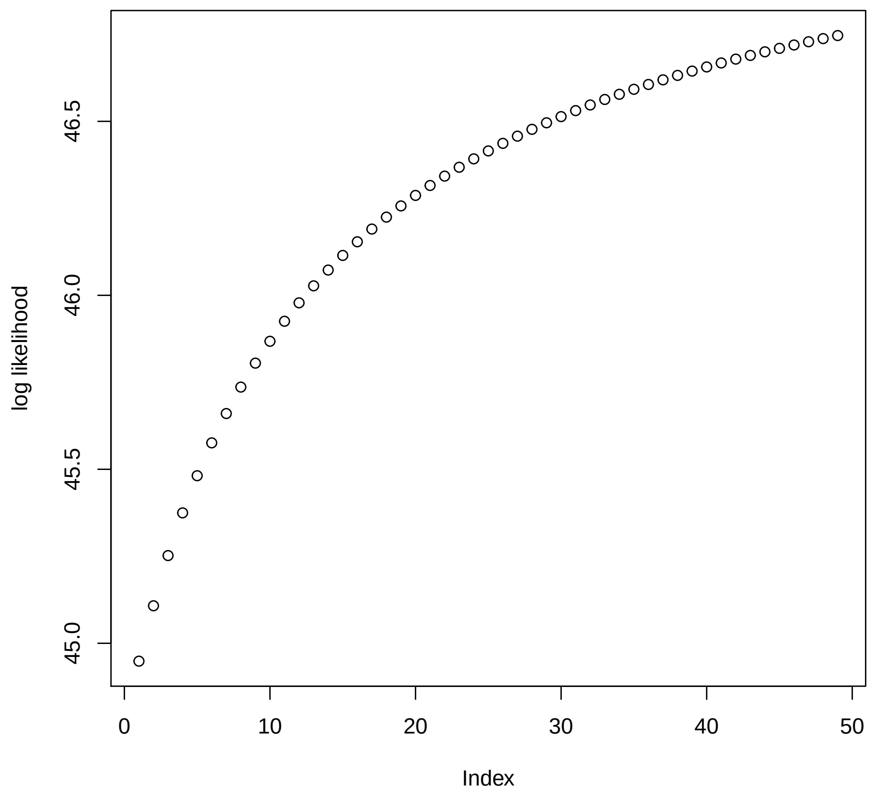
```r
## Load data
set.seed(1)
sim_process <- data.frame(x = seq(0.005,0.995,by=0.01)) %>%
               mutate(y=0,proc = sin(x*10) + 0.3*rnorm(length(x)))

sim_data <- sample_n(sim_process,50) %>%
            mutate(z = proc + 0.1*rnorm(length(x)), std = 0.1)
coordinates(sim_data) = ~x + y# change into an sp object
```

```r
## Prediction (BAU) grid
grid_BAUs <- auto_BAUs(manifold=real_line(),data=sim_data,cellsize = c(0.01),type="grid")

## Warning in points2grid(.):  cell size from constant coordinate 2
possibly taken from other coordinate

grid_BAUs$fs = 1
```

```r
## Set up SRE model
G <- auto_basis(m = real_line(),data=sim_data,
                nres = 2,
                regular=6,
                type = "bisquare",
                subsamp = 20000)

## [1] "Number of basis at resolution 1 = 6"
## [1] "Number of basis at resolution 2 = 12"
```

```r
f <- z ~ 1
S <- SRE(f,list(sim_data),G,
         grid_BAUs,
         est_error = FALSE)

## [1] "Binned data in 0.0649999999999999 seconds"
```

```
S <- SRE.fit(S,n_EM = 50,tol = 1e-5,print_lik=TRUE)

## [1] "Maximum EM iterations reached"
```

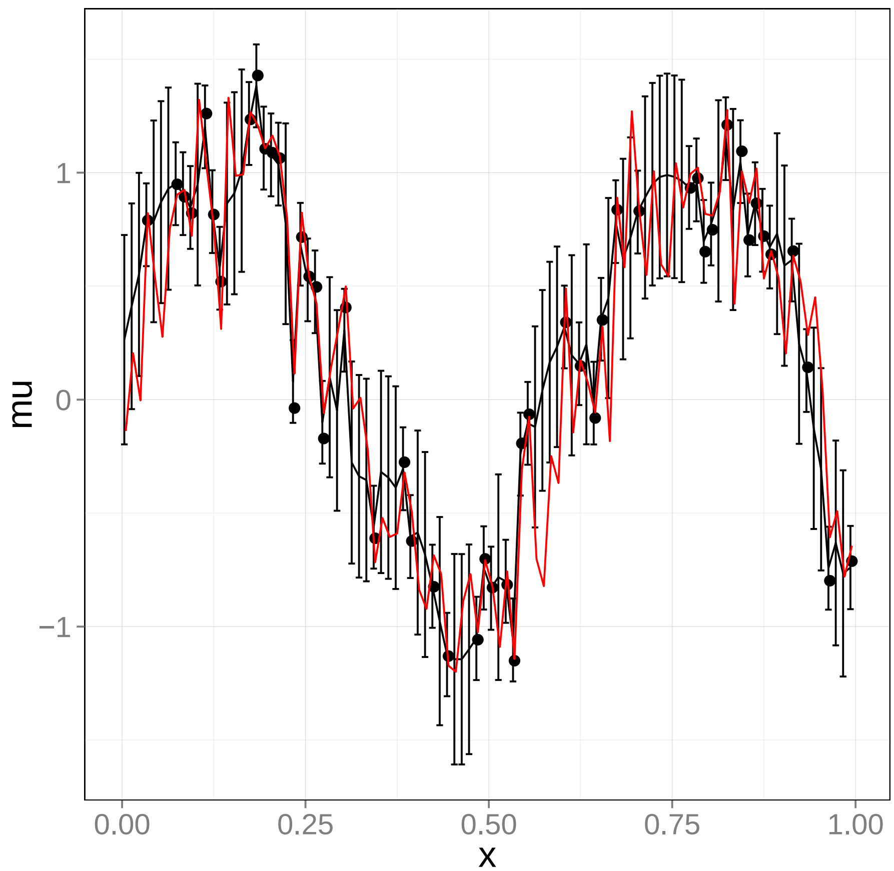



```
## [1] "Warning: Ignoring constants in log-likelihood computation"
```

```
grid_BAUs <- SRE.predict(S,pred_locs = grid_BAUs,use_centroid = TRUE)
```

```
X <- grid_BAUs@data %>%
     filter(x >= 0 & x <= 1)

g1 <- LinePlotTheme() +
          geom_line(data=X,aes(x,y=mu)) +
          geom_errorbar(data=X,aes(x=x,ymax = mu + 2*sqrt(var), ymin= mu - 2*sqrt(var))) +
```

```
          geom_point(data = data.frame(sim_data),aes(x=x,y=z),size=3) +
          geom_line(data=sim_process,aes(x=x,y=proc),col="red")

print(g1)
```



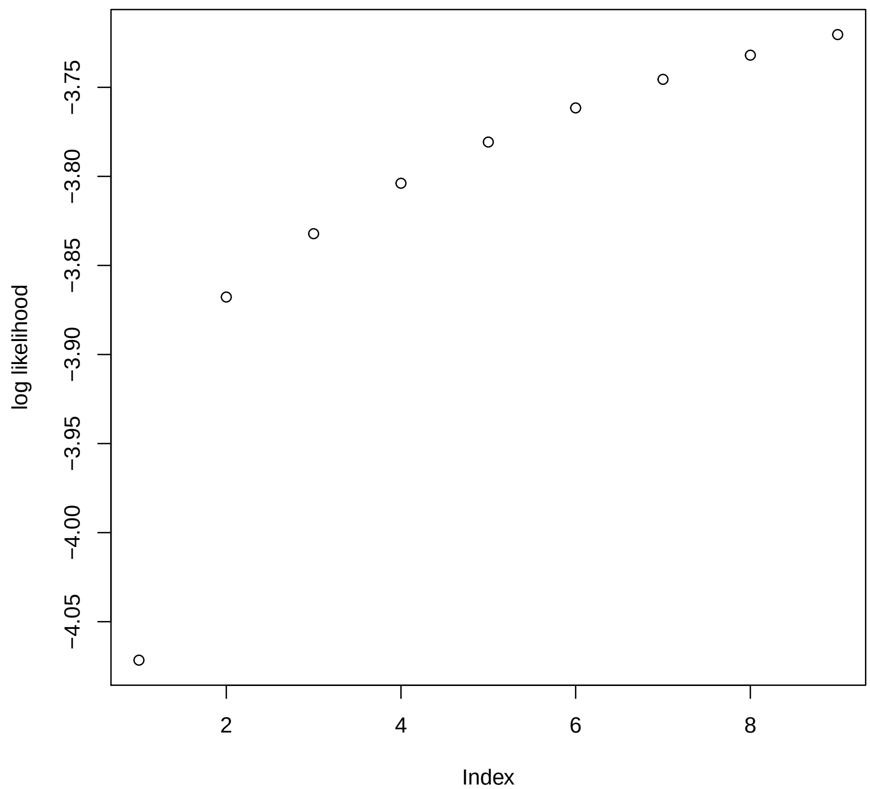
4.4 2D Simple example

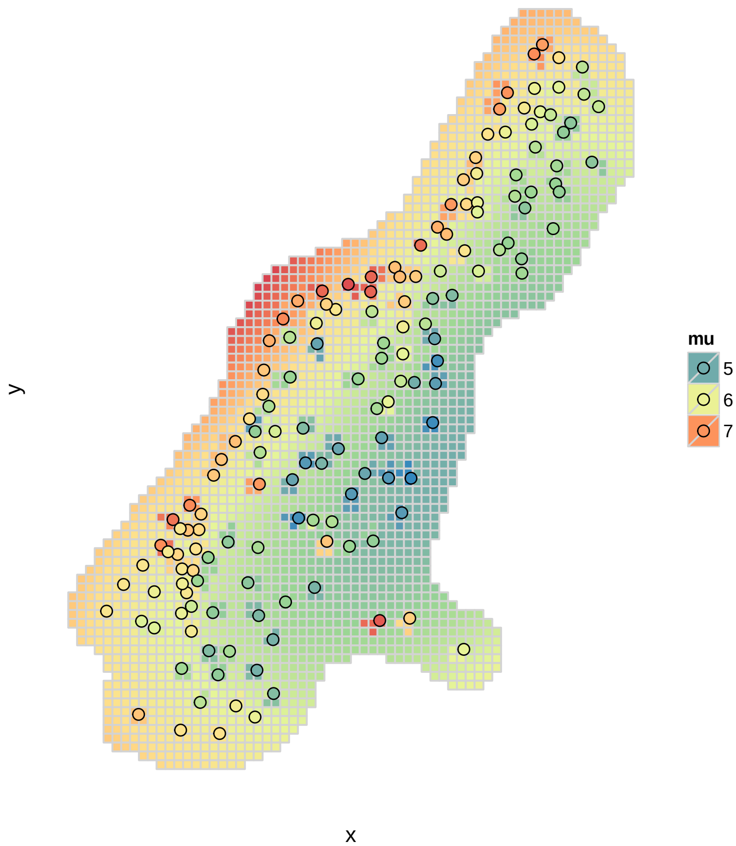
```
library(sp)
library(ggplot2)
library(dplyr)
library(FRK)
#  devtools::load_all("~/Wollongong/pkgs/FRK",
                    # export_all = FALSE)

opts_FRK$set("progress",FALSE)
```

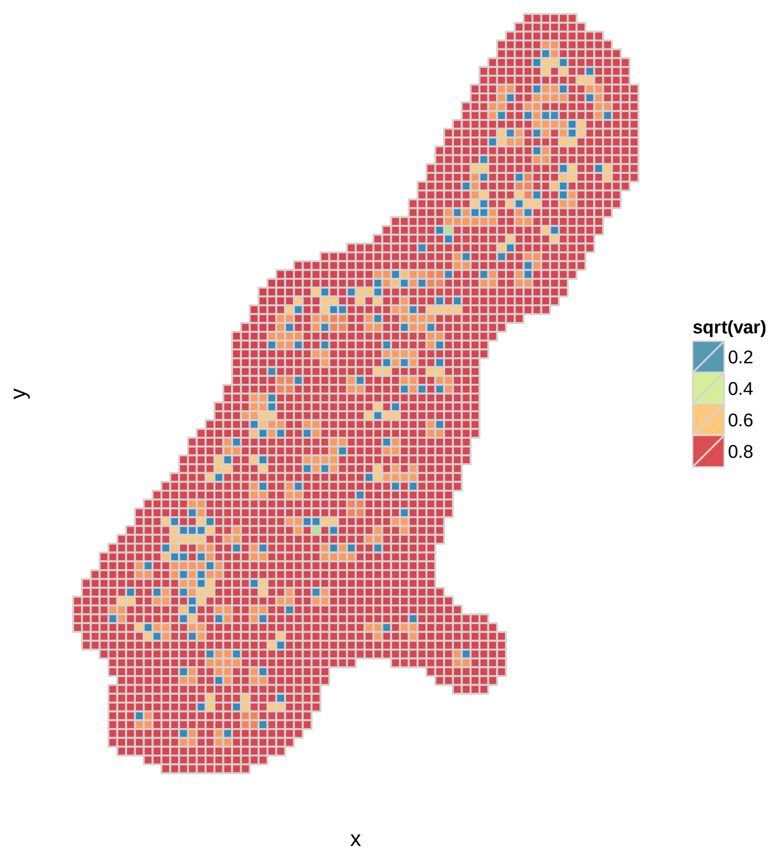
```r
opts_FRK$set("parallel",0L)
set.seed(1)

## Get data
data(meuse)
meuse$fs <- 1
coordinates(meuse) = ~x+y # change into an sp object

# Generate observations with large spatial support
data(meuse.grid)
gridded(meuse.grid) = ~x + y

HexPts2 <- spsample(meuse.grid,
                    type = "hexagonal",
                    cellsize = 100)
HexPols2 <- HexPoints2SpatialPolygons(HexPts2)
HexPols_df2 <- SpatialPolygonsDataFrame(HexPols2,
                                        over(HexPols2,meuse) %>%
                                            select(zinc)) %>%
    subset(!is.na(zinc))

if(require(INLA)) { ## Need INLA from here on

        # Generate BAUs
        HexPols_df <- auto_BAUs(manifold = plane(),cellsize = c(50,50),type = "grid",data =
        HexPols_df$fs <- 1

        ## Generate basis functions
        G <- auto_basis(m = plane(),data=meuse,nres = 2,
                        prune=10,type = "Gaussian")

        ## Setup SRE model
        f <- log(zinc) ~ 1
        S <- SRE(f,list(meuse,HexPols_df2),BAUs = HexPols_df, G,est_error=T)
        S <- SRE.fit(S,n_EM = 10,print_lik=TRUE)

        ## Point predict
        HexPols_df <- SRE.predict(S,use_centroid = TRUE)

        X <- SpatialPolygonsDataFrame_to_df(sp_polys = HexPols_df,
                                            vars = c("mu","var"))

        g1 <- EmptyTheme() +
            geom_polygon(data=X,aes(x,y,fill=mu,group=id),
                         colour="light grey") +
```

```
            scale_fill_distiller(palette="Spectral",trans="reverse") +
            geom_point(data=data.frame(meuse),
                       aes(x,y,fill=log(zinc)),
                       colour="black",
                       pch=21, size=3) +
            coord_fixed()

        g2 <- EmptyTheme() +
            geom_polygon(data=X,aes(x,y,fill=sqrt(var),group=id),
                         colour="light grey") +
            scale_fill_distiller(palette="Spectral",trans="reverse") +
            #geom_point(data=data.frame(meuse),
            #           aes(x,y),colour="black",pch=21, size=3) +
            coord_fixed()

        print(g1)
        print(g2)
}

## Loading required package:  INLA
## Loading required package:  Matrix
##
## Attaching package:  'Matrix'
##
## The following objects are masked from 'package:base':
##
##    crossprod, tcrossprod
##
## Loading required package:  splines
## Loading required package:  splancs
##
## Spatial Point Pattern Analysis Code in S-Plus
##
##  Version 2 - Spatial and Space-Time analysis

## [1] "Number of basis at resolution 1 = 1"
## [1] "Number of basis at resolution 2 = 4"
## [1] "Binned data in 1.132 seconds"

## Warning in est_obs_error(data_proc, variogram.formula = f):  Not
accounting for multiple data in the same grid box during variogram
estimation.
##                 Need to see how to do this with gstat

## [1] "sigma2e estimate = 0.031397973693542"
## Called from: .local(data_sp, sp_pols, av_var)
## debug: new_sp_pts
```

```
## Warning in est_obs_error(data_proc, variogram.formula = f):  Not
accounting for multiple data in the same grid box during variogram
estimation.
##                  Need to see how to do this with gstat

## [1] "sigma2e estimate = 0.00973076660686084"
## [1] "Averaging over polygons"
## [1] "Maximum EM iterations reached"
## [1] "Warning: Ignoring constants in log-likelihood computation"

## Joining by:  "id"
```




y
x
mu
5
6
7



4.5 Modifying the distance measure - a 1D space-time example

5 Global prediction of global mid-tropospheric CO2

6 Global prediction of sea-surface temperatures using Hadoop

7 Conclusion