

formula_algorithms

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The Posterior Distribution of the Parameters Θ

- Assumption:

$$Y_i(t+6) = \beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,i}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t) + \epsilon_i(t)$$

$$f(\mathbf{B} \mid \boldsymbol{\beta}, \boldsymbol{\Sigma}) = \prod_{i=1}^n \left\{ (2\pi)^{-5/2} |\boldsymbol{\Sigma}|^{-1/2} \exp\left\{-\frac{1}{2}(\boldsymbol{\beta}_i - \boldsymbol{\beta})' \boldsymbol{\Sigma}^{-1}(\boldsymbol{\beta}_i - \boldsymbol{\beta})\right\} \right\}$$

$$P(\sigma^2) \propto \frac{1}{\sigma^2}; \quad P(\boldsymbol{\beta}) \propto 1; \quad P(\boldsymbol{\Sigma}^{-1}) \propto |\boldsymbol{\Sigma}|^{-(d+1)} \exp\left(-\frac{1}{2}\boldsymbol{\Sigma}^{-1}\right)$$

- Let's denote:

$$\eta_i(t) = \beta_{0,i} + \beta_{1,i}Y_i(t) + \beta_{2,i}\Delta_{i,1}(t) + \beta_{3,i}\Delta_{i,2}(t) + \beta_{4,i}\Delta_{i,3}(t)$$

- Distribution of $\epsilon_i(t)$:

$$\epsilon_i(t) \sim N(0, \sigma^2)$$

- Distribution of $Y_i(t+6)$

$$Y_i(t+6) \sim N(\eta_i(t), \sigma^2)$$

- pdf for $Y_i(t+6)$:

$$f(Y_i(t+6) \mid \boldsymbol{\beta}_i, \boldsymbol{\beta}, \sigma^2, \boldsymbol{\Sigma}) = -\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{1}{2\sigma^2}[Y_i(t+6) - \eta_i(t)]^2\right\}$$

- pdf for Y : ($t_{i(n)}$ is the time of the last record for hurricane i)

$$f(Y \mid \mathbf{B}, \boldsymbol{\beta}, \sigma^2, \boldsymbol{\Sigma}) = \prod_{i=1}^n \prod_{t=0}^{t_{i(n)}-6} -\frac{1}{\sqrt{2\pi\sigma}} \exp\left\{-\frac{1}{2\sigma^2}[Y_i(t+6) - \eta_i(t)]^2\right\}$$

- posterior distribution of the parameters θ :

$$P(\Theta | Y) \propto f(Y|\Theta)P(\Theta) = f(Y | \mathbf{B}, \beta, \sigma^2, \Sigma)f(\mathbf{B} | \beta, \Sigma)P(\beta)P(\sigma^2)P(\Sigma^{-1})$$

- for efficient computation, we take logarithm:

$$\begin{aligned} \log P(\Theta | Y) \propto & \sum_{i=1}^n \sum_{t=0}^{t_{i(n)}-6} \{ \log(-\sqrt{2\pi}\sigma) - \frac{1}{2\sigma^2} [Y_i(t+6) - \eta_i(t)]^2 \} \\ & + \sum_{i=1}^n \{ -\frac{1}{2} (\beta_i - \beta)' \Sigma^{-1} (\beta_i - \beta) \} \\ & - \log(\sigma^2) - (d+1) \log(|\Sigma|) - \frac{1}{2} \text{trace}(\Sigma^{-1}) \end{aligned}$$

a MCMC algorithm to generate the posterior distribution of Θ

Data Preparation

```
library(tidyverse)
library(lubridate)

correct.year = function(date) {
  date$year = date$year - 100
  return(date)
}

raw = read_csv("data/hurricane703.csv") %>%
  janitor::clean_names() %>%
  select(-nature, -season, -month) %>%
  mutate(
    time = gsub("[()]", "", time),
    time = as.POSIXlt(parse_datetime(time, "%y-%m-%d %H:%M:%S")),
    time = as.POSIXct(correct.year(time))
  ) %>%
  filter(hour(time) %in% c(0, 6, 12, 18),
         minute(time) == 0,
         second(time) == 0)

placeholder = data.frame(id = "placeholder",
                          time = parse_datetime("00-01-01 00:00:00", "%y-%m-%d %H:%M:%S"),
                          latitude = 0,
                          longitude = 0,
                          wind_kt = 0)

dt = bind_cols(rbind(raw, placeholder),
               rbind(placeholder, raw),
               .name_repair = "unique")

dt = dt[2:(nrow(dt)-1),]

dt = dt %>%
```

```

filter(id...1 == id...6,
       time...7 + 6*60*60 == time...2) %>%
mutate(
  d_lat = latitude...3 - latitude...8,
  d_log = longitude...4 - longitude...9,
  d_wkt = wind_kt...5 - wind_kt...10
) %>%
select(id = id...1, wkt_new = wind_kt...5, wkt_cur = wind_kt...10, d_lat, d_log, d_wkt)

hc = distinct(dt, id) %>% add_rownames("i")

dt = dt %>% left_join(hc)

head(dt)

```

```

## # A tibble: 6 x 7
##   id      wkt_new wkt_cur d_lat  d_log d_wkt i
##   <chr>      <dbl>   <dbl> <dbl>  <dbl> <dbl> <chr>
## 1 ABLE.1950      40      35 0.600 -0.800    5 1
## 2 ABLE.1950      45      40 0.5    -1.10    5 1
## 3 ABLE.1950      50      45 0.800 -1.20    5 1
## 4 ABLE.1950      50      50 1      -1.40    0 1
## 5 ABLE.1950      50      50 0.700 -1.10    0 1
## 6 ABLE.1950      55      50 0.600 -1.10    5 1

```