## **Earthquake Forecasting**

## **Dissertation Project 2**

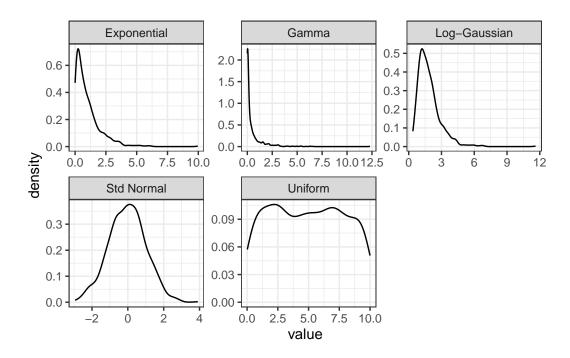
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```
require(ETAS.inlabru)
2 require(ggplot2)
3 require(dplyr)
4 require(magrittr)
5 require(tidyquant)
6 require(rnaturalearth)
7 require(terra)
8 require(sf)
9 require(ggspatial)
   require(rnaturalearthdata)
   require(lubridate)
11
   # Increase/decrease num.cores if you have more/fewer cores on your computer.
14 # future::multisession works on both Windows, MacOS, and Linux
15 num.cores <- 1</pre>
16 future::plan(future::multisession, workers = num.cores)
   INLA::inla.setOption(num.threads = num.cores)
18 # To deactivate parallelism, run
# future::plan(future::sequential)
20 # INLA::inla.setOption(num.threads = 1)
Copula transformation of the priors
1 # set copula transformations list
2 link.f <- list(</pre>
   mu = (x) gamma_t(x, 0.3, 0.6),
    K = (x) unif_t(x, 0, 10),
    alpha = (x) unif_t(x, 0, 10),
    c_= (x) unif_t(x, 0, 10),
```

```
p = (x) unif_t(x, 1, 10)
   # set inverse copula transformations list
10
   inv.link.f <- list(</pre>
     mu = \langle (x) inv_gamma_t(x, 0.3, 0.6),
     K = (x) inv_unif_t(x, 0, 10),
13
    alpha = (x) inv_unif_t(x, 0, 10),
    c_{-} = (x) inv_{unif_t}(x, 0, 10),
    p = (x) inv_unif_t(x, 1, 10)
   )
17
# obtain sample from standard normal distribution
2 X <- rnorm(1000)
3 # apply copula transformations
4 gamma.X <- gamma_t(X, .3, .6)</pre>
  unif.X <- unif_t(X, 0, 10)
   exp.X \leftarrow exp_t(X, 1)
   loggaus.X <- loggaus_t(X, .5, .5)</pre>
   # build data.frame for plotting
   df.to.plot <- rbind(</pre>
     data.frame(
       value = X,
       distribution = "Std Normal"
13
     ),
14
     data.frame(
15
       value = gamma.X,
       distribution = "Gamma"
17
     ),
     data.frame(
       value = unif.X,
       distribution = "Uniform"
     ),
22
     data.frame(
23
       value = exp.X,
^{24}
       distribution = "Exponential"
     ),
     data.frame(
27
       value = loggaus.X,
28
       distribution = "Log-Gaussian"
29
```

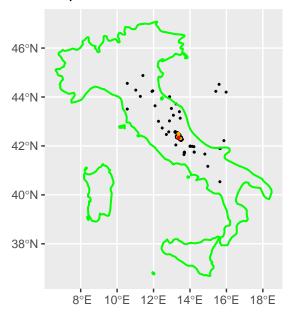
```
30  )
31  )
32  # plot them
33  ggplot(df.to.plot, aes(value)) +
34   geom_density() +
35   theme_bw() +
36   facet_wrap(facets = ~ distribution, scales = "free")
```



## Italy

```
# set up parameters for selection
13
   start.date <- as.POSIXct("2009-01-01T00:00:00",
14
                             format = "%Y-%m-%dT%H:%M:%OS")
   end.date <- as.POSIXct("2010-01-01T00:00:00", format = "%Y-%m-%dT%H:%M:%DS")
16
   min.longitude <- 10.5
   max.longitude <- 16</pre>
   min.latitude <- 40.5
   max.latitude <- 45
   MO < -2.5
   # set up conditions for selection
   aquila.sel <- (horus$time_date >= start.date) &
     (horus$time_date < end.date) &</pre>
25
     (horus$lon >= min.longitude) &
     (horus$lon <= max.longitude) &
     (horus$lat >= min.latitude) &
28
     (horus$lat <= max.latitude) &</pre>
     (horus$M >= M0)
32 # select
   aquila <- horus[aquila.sel, ]
   italy.map <- ne_countries(country = 'Italy', returnclass = "sf",</pre>
                              scale = 'medium')
   aquila.sf <- st_as_sf(aquila,
                         coords = c("lon", "lat"),
                         crs = st_crs('EPSG:4326'))
   ggplot() +
     geom_sf(data = aquila.sf[aquila$M > 3,], size = 0.4) +
     geom_sf(data = italy.map, fill = alpha("lightgrey", 0), colour = 'green',
             linewidth = 0.7) +
10
     geom_sf(data = aquila.sf[aquila$M > 5,], size = 0.5, colour = 'orange') +
     geom_sf(data = aquila.sf[aquila$M > 6,], size = 0.6, colour = 'red') +
12
     ggtitle("Map of event locations")
13
```

## Map of event locations



```
ggplot(aquila, aes(time_date, M)) +
geom_point() +
theme_bw()
```

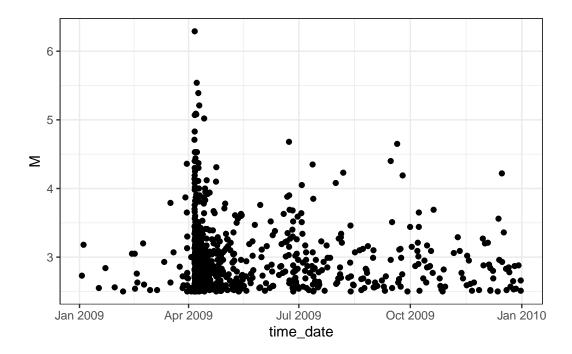


Figure 1: L'Aquila seismic sequence, times versus magnitudes

```
# set up data.frame for model fitting
aquila.bru <- data.frame(
    ts = as.numeric(
    difftime(aquila$time_date, start.date, units = "days")
),
magnitudes = aquila$M,
idx.p = 1 : nrow(aquila)
)

# set up list of initial values
th.init <- list(
    th.mu = inv.link.f$mu(0.5),
    th.K = inv.link.f$K(0.1),
    th.alpha = inv.link.f$alpha(1),
    th.c = inv.link.f$c_(0.1),
    th.p = inv.link.f$p(1.1)
</pre>
```

```
1 # set starting and time of the time interval used for model fitting.
2 # In this case, we use the interval covered by the data.
3 T1 <- 0
4 T2 <- \max(\text{aquila.bru\$ts}) + 0.2 # Use \max(\ldots, na.rm = TRUE) if there may
  # still be NAs here
   # set up list of bru options
pru.opt.list <- list(</pre>
    bru_verbose = 3, # type of visual output
    bru_max_iter = 70, # maximum number of iterations
     # bru_method = list(max_step = 0.5),
     bru_initial = th.init # parameters' initial values
   )
  ETAS <- function(data = aquila.bru, m0 = M0, t1 = T1, t2 = T2,
                     ncore = num.cores, Link.f = link.f,
2
                     Bru.opt.list = bru.opt.list, n.samp = 1000,
3
                     max.batch = 1000, mag = 4.5, n.breaks = 100,
                     t.end.tri.post = 5, t.end.tri.prior = 10,
                     t.end.omori.post = 5, t.end.omori.prior = 5){
       # maximum likelihood estimator for beta
       beta.p <- 1 / (mean(data$magnitudes) - m0)</pre>
10
       # fit the model
11
       model.fit <- Temporal.ETAS(</pre>
12
         total.data = data,
         MO = mO,
         T1 = t1,
15
         T2 = t2.
16
         link.functions = Link.f,
17
         coef.t. = 1,
         delta.t. = 0.1,
19
         N.max. = 5,
         bru.opt = Bru.opt.list
       )
23
        # create input list to explore model output
24
       input_list <- list(</pre>
         model.fit = model.fit,
26
         link.functions = Link.f
27
```

```
)
28
29
        # get marginal posterior information
        post.list <- get_posterior_param(input.list = input_list)</pre>
        # plot marginal posteriors
33
        postplot <- post.list$post.plot</pre>
34
35
        # posterior sampling
36
        post.samp <- post_sampling(</pre>
37
          input.list = input_list,
          n.samp = n.samp,
          max.batch = max.batch,
          ncore = num.cores
41
42
43
        # taking the averages of the posterior parameter estimates
44
        post.par <- apply(post.samp, 2, mean)</pre>
45
        # pair plot
        pair.plot <- post_pairs_plot(</pre>
48
          post.samp = post.samp,
49
          input.list = NULL,
50
          n.samp = NULL,
          max.batch = max.batch
52
        pairplot <- pair.plot$pair.plot</pre>
        # set additional elements of the list
56
        input_list$T12 <- c(t1, t2)
57
        input_list$MO <- mO</pre>
58
        input_list$catalog.bru <- data</pre>
        # posterior number of events
        N.post <- get_posterior_N(input.list = input_list)</pre>
        Npostplot <- N.post$post.plot</pre>
63
        Npostmean <- N.post$post.df[which.max(N.post$post.df$mean), 1]</pre>
64
65
        # number of large events
66
        large_events <- data[data$magnitudes >= mag,]
67
        Nlarge <- nrow(large_events)</pre>
```

```
69
         # mean absolute distance of the differences in magnitudes
70
         diff mag <- diff(data$magnitudes)</pre>
71
         abs dist mag <- mean(abs(diff mag))
72
73
         # mean absolute distance of the inter-arrival time
74
         interarrival <- diff(data$ts)</pre>
75
         abs_dist_int <- mean(abs(interarrival))</pre>
76
         # check if overdispersion occurs
78
         m_int_time <- mean(interarrival)</pre>
79
         v_int_time <- var(interarrival)</pre>
80
         overdisp <- m_int_time ^ 2 < v_int_time</pre>
81
         # triggering function plots
         # posterior
84
         triplotpost <- triggering_fun_plot(</pre>
85
           input.list = input list,
86
           post.samp = post.samp,
87
           n.samp = NULL, magnitude = mag,
88
           t.end = t.end.tri.post, n.breaks = n.breaks
         )
         # prior
92
         triplotprior <- triggering_fun_plot_prior(input.list = input_list,</pre>
93
                                      magnitude = mag, n.samp = n.samp,
94
                                      t.end = t.end.tri.prior)
95
         # omori plots
         # posterior
         omoripost <- omori_plot_posterior(input.list = input_list,</pre>
99
                                post.samp = post.samp,
100
                                n.samp = NULL, t.end = t.end.omori.post)
101
102
         # prior
103
         omoriprior <- omori_plot_prior(input.list = input_list,</pre>
104
                                           n.samp = n.samp,
                                            t.end = t.end.omori.prior)
106
107
         # returns the whole environment
108
         envir <- as.list(environment())</pre>
109
         return(tibble::lst(envir))
110
```

```
111 }
112 etas <- ETAS()
 Start creating grid...
 Finished creating grid, time 4.643445
 Effect of mis-specifying parameters
   # # set copula transformations list
   # link.f1 <- list(
   # mu = (x) gamma_t(x, 0.3, 0.6),
        K = \langle (x) \ unif_t(x, 0, 10),
        alpha = \langle (x) unif_t(x, 0, 10),
       c_{-} = \langle (x) \ unif_{-}t(x, 0, 10),
 7 # p = (x) unif_t(x, 1, 10)
   # )
 Synthetic catalogues generation
    mult.synth.ETAS <- function(t1 = NULL, t2 = NULL, n.cat = 1000,
                           ht = etas$envir$data[which.max(
                               etas$envir$data$magnitudes), ]){
 4
        # inherits the environment from function `ETAS`
        envir <- etas$envir</pre>
        # updates environments if specified by users
        envir$t1 <- ifelse(!is.null(t1), t1, envir$t1)</pre>
        envir$t2 <- ifelse(!is.null(t2), t2, envir$t2)</pre>
10
11
        # Function to generate a synthetic catalogue
12
        synth.gen <- function(i){</pre>
13
             iteration <- i
14
             synth <- generate_temporal_ETAS_synthetic(</pre>
                          theta = envir$post.par %>% as.list,
                          beta.p = envir$beta.p,
17
                          MO = envir$mO, T1 = envir$t1,
18
                          T2 = envir$t2, Ht = ht, ncore = num.cores)
19
             return(synth)
20
        }
21
```

22

```
# generates catalogues as list of lists
23
        multi.synth.cat.list <- lapply(seq_len(n.cat), \(x)</pre>
24
            synth.gen(x))
26
        # stores catalogues as list of data.frames
27
        multi.synth.cat.list.df <- lapply(multi.synth.cat.list,</pre>
                                             (x) do.call(rbind, x))
30
        # calculates the number of events in each catalogue
31
        Nevents <- unlist(lapply(seq_len(n.cat), \(i) nrow(</pre>
32
            multi.synth.cat.list.df[[i]])))
34
        # sets catalogue identifier
35
        multi.synth.cat.list.df <- lapply(seq_len(n.cat),</pre>
                                             \(x) cbind(
                                                 multi.synth.cat.list.df[[x]],
38
                                                   cat.idx = x,
39
                                                 num_events = Nevents[x]))
40
        # merges catalogues in unique data.frame
42
        multi.synth.cat.df <- do.call(rbind, multi.synth.cat.list.df)</pre>
43
        # returns the whole environment
45
        environ <- as.list(environment())</pre>
46
        return(tibble::lst(environ))
47
48
   mult.synth <- mult.synth.ETAS(ht = NULL)</pre>
Fitting Models on the Synthetic Catalogues
   synth.fit <- function(breaks = c(0, 110, 130, 150, 170, 190, 210),
                           samp.each.class = 1){
2
3
4
        # selecting catalogues
        Nevents <- mult.synth$environ$Nevents</pre>
        classes <- cut(Nevents, breaks = breaks)</pre>
        samp.id <- rep(0, samp.each.class * (classes %>% levels %>% length))
        for(i in classes %>% levels %>% length %>% seq_len){
            samp.id[(samp.each.class * (i - 1) + 1) : (samp.each.class * i)] <-
                sample(which(classes == levels(classes)[i]), samp.each.class)
10
        }
11
12
```

```
# we need to bing the synthetics with the observed catalogue
13
        # for plotting
14
       cat.df.for.plotting <- rbind(</pre>
15
         mult.synth$environ$multi.synth.cat.df[
16
            which(
17
              mult.synth$environ$multi.synth.cat.df$cat.idx %in% samp.id),
            ],
          cbind(mult.synth$environ$envir$data[, c("ts", "magnitudes")],
20
            gen = NA, cat.idx = "observed", num_events = nrow(etas$envir$data)
21
       )
23
24
       # plot them
25
       multi.synth.cat.plot <- ggplot(cat.df.for.plotting,</pre>
                                        aes(ts, magnitudes)) +
          geom\ point(size = 0.5) +
28
          geom_point(
29
            data = mult.synth$environ$ht,
30
            mapping = aes(ts, magnitudes), colour = "black"
          ) +
32
          facet_wrap(facets = vars(cat.idx, num_events),
                     labeller = 'label_both')
35
       # modelling
36
       input <- rep(list(NULL), classes %>% levels %>% length)
37
       post <- rep(list(NULL), classes %>% levels %>% length)
       post.par <- matrix(rep(0, (classes %>% levels %>% length) * 5),
39
                            ncol = 5)
40
       Npost <- rep(list(NULL), classes %>% levels %>% length)
       Npostmean <- rep(0, classes %>% levels %>% length)
       Nlarge <- rep(0, classes %>% levels %>% length)
43
       abs_dist_int <- rep(0, classes %>% levels %>% length)
44
       abs_dist_mag <- rep(0, classes %>% levels %>% length)
45
       overdisp <- rep(0, classes %>% levels %>% length)
46
47
       for(i in classes %>% levels %>% length %>% seq_len){
            multi.synth.etas <- ETAS(data =</pre>
                mult.synth$environ$multi.synth.cat.list.df[[samp.id[i]]],
                                         t1 = mult.synth$environ$envir$t1,
51
                                         t2 = mult.synth$environ$envir$t2)
52
            post[[i]] <- multi.synth.etas$envir$post.list</pre>
53
```

```
post.par[i,] <- multi.synth.etas$envir$post.par</pre>
54
            Npost[[i]] <- multi.synth.etas$envir$N.post</pre>
55
            Npostmean[i] <- multi.synth.etas$envir$Npostmean</pre>
            Nlarge[i] <- multi.synth.etas$envir$Nlarge</pre>
            abs_dist_int[i] <- multi.synth.etas$envir$abs_dist_int</pre>
            abs_dist_mag[i] <- multi.synth.etas$envir$abs_dist_mag
59
            overdisp[i] <- multi.synth.etas$envir$overdisp</pre>
60
        }
61
62
        for(i in samp.id %>% length %>% seq_len){
63
            post[[i]]$post.df$Catalogues <-</pre>
            paste('Random Catalogue', i, ':', Nevents[samp.id[i]],
                   'Events')
        }
67
68
        df.true.param <- data.frame(x = etas$envir$post.par,</pre>
69
                              param = names(etas$envir$post.par %>% as.list))
70
71
        # bind marginal posterior data.frames
72
        bind.post.df <- do.call(rbind,</pre>
                                   lapply(samp.id %>% length %>% seq_len,
74
                                          \(i) post[[i]]$post.df))
75
76
        # plot them
77
        post.par.plot <- ggplot(bind.post.df,</pre>
78
                                   aes(x = x, y = y, colour = Catalogues)) +
79
          geom line() +
          facet_wrap(facets = ~ param, scales = "free") +
          xlab("param") +
82
          ylab("pdf") +
83
          geom_vline(
84
            data = df.true.param,
85
            mapping = aes(xintercept = x), linetype = 2
          )
        ##
89
        for(i in samp.id %>% length %>% seq_len){
90
            Npost[[i]]$post.df$Catalogues <-</pre>
91
            paste('Random Catalogue', i, ':', Nevents[samp.id[i]],
92
                   'Events')
93
        }
94
```

```
95
        df.true.N <- data.frame(N = etas$envir$Npostmean, param = 'N')</pre>
96
97
        # bind marginal posterior data.frames
98
        bind.post.N.df <- do.call(rbind,</pre>
                                  lapply(samp.id %>% length %>% seq_len,
                                          \(i) Npost[[i]]$post.df))
102
        # plot them
103
        post.N.plot <- ggplot(bind.post.N.df,</pre>
104
                                aes(x = N, y = mean, colour = Catalogues)) +
105
          geom_line() +
106
          xlab("N") +
107
          ylab("pdf") +
          geom_vline(
             data = df.true.N,
110
             mapping = aes(xintercept = N), linetype = 2
111
          )
112
113
        # returns the whole environment
        environ <- as.list(environment())</pre>
115
        return(tibble::lst(environ))
    }
    mult.synth.fit <- rep(list(NULL), 3)</pre>
118
    mult.synth.fit[[1]] <- synth.fit()</pre>
 Start creating grid...
 Finished creating grid, time
                                  0.2027328
 Start creating grid...
 Finished creating grid, time
                                 0.2167971
 Start creating grid...
 Finished creating grid, time 0.344548
 Start creating grid...
 Finished creating grid, time
                                 0.369961
 Start creating grid...
 Finished creating grid, time
                                 0.79897
 Start creating grid...
 Finished creating grid, time
                                  0.9608929
    mult.synth.fit[[2]] <- synth.fit(breaks =</pre>
                                            c(210, 240, 270, 300, 330, 360, 400))
```

```
Start creating grid...
Finished creating grid, time
                                0.6186411
 Start creating grid...
Finished creating grid, time 0.6089611
 Start creating grid...
Finished creating grid, time
                               0.5968621
 Start creating grid...
Finished creating grid, time 0.6932831
 Start creating grid...
Finished creating grid, time
                               0.8530071
 Start creating grid...
Finished creating grid, time 0.8823462
nult.synth.fit[[3]] <- synth.fit(breaks = c(400, 600, 800, 1600))</pre>
 Start creating grid...
Finished creating grid, time
                               1.390939
 Start creating grid...
Finished creating grid, time 2.207845
 Start creating grid...
Finished creating grid, time 3.399027
Analysis on the Behaviours of the Time-between-Events
   ECDF.interarrival <- function(i){</pre>
       samp.id <- mult.synth.fit[[i]]$environ$samp.id</pre>
       Nevents <- mult.synth$environ$Nevents</pre>
       data.list <- lapply(samp.id %>% length %>% seq_len, \(i) data.frame(
           Time_between_events =
                mult.synth$environ$multi.synth.cat.list.df[[samp.id[i]]]$ts %>%
                    sort %>% diff,
           Num_Events = paste(Nevents[samp.id[i]], '(synthetic)')
11
       )
12
13
       data.list[[length(samp.id) + 1]] <- data.frame(</pre>
14
           Time_between_events = etas$envir$interarrival,
15
           Num_Events = paste(nrow(etas$envir$data), '(observed)'))
16
```

```
data.list[[length(samp.id) + 2]] <- data.frame(</pre>
18
            Time_between_events =
19
                rexp(length(etas$envir$interarrival),
20
                      1 / etas$envir$m_int_time),
            Num_Events = paste(nrow(etas$envir$data),
                                 '(under exponential assumption)'))
23
24
        df <- do.call(rbind, data.list)</pre>
25
26
        ECDF.plot <- ggplot(df, aes(x = Time_between_events,</pre>
27
                                       colour = Num_Events)) +
            stat ecdf() +
            xlab('Time between Events') +
          ylab('Empirical Cumulative Probability')
31
32
        return(ECDF.plot)
33
34
35
   ecdf_interarrival <- lapply(seq_len(3), \(i) ECDF.interarrival(i))</pre>
Forecasting
   ETAS.forecast <- function(){</pre>
        # inherits the environment from function `ETAS`
3
        envir <- etas$envir</pre>
        # express 1 minute in days
        min.in.days <- 1 / (24 * 60)
        # find time of the event with the greatest magnitude
        t.max.mag <- envir$data$ts[which.max(envir$data$magnitudes)]</pre>
        # set starting time of the forecasting period
10
        T1.fore <- t.max.mag + min.in.days</pre>
11
        # set forecast length
12
        fore.length <- 1
        # set end time of the forecasting period
14
        T2.fore <- T1.fore + fore.length
15
        # set known data
16
       Ht.fore <- envir$data[envir$data$ts < T1.fore, ]</pre>
17
18
        # produce forecast
19
```

```
daily.fore <- Temporal.ETAS.forecast(</pre>
20
         post.samp = envir$post.samp, # ETAS parameters posterior samples
21
         n.cat = nrow(envir$post.samp), # number of synthetic catalogues
         beta.p = envir$beta.p, # magnitude distribution parameter
         MO = envir$mO, # cutoff magnitude
         T1 = T1.fore, # forecast starting time
25
         T2 = T2.fore, # forecast end time
26
         Ht = Ht.fore, # known events
27
         ncore = num.cores # number of cores
28
       # find number of events per catalogue
       N.fore <- vapply(</pre>
          seq_len(daily.fore$n.cat),
33
          \(x)  sum(daily.fore$fore.df$cat.idx == x), 0
34
35
       # find number of observed events in the forecasting period
       N.obs <- sum(envir$data$ts >= T1.fore & envir$data$ts <= T2.fore)
37
       # plot the distribution
       histfore <- ggplot() +</pre>
          geom_histogram(aes(x = N.fore, y = after_stat(density)),
40
                         binwidth = 1) +
41
          geom_vline(xintercept = N.obs) +
42
         xlim(100, 500)
44
       return(tibble::lst(N.fore, N.obs, histfore))
45
   }
46
   fore <- ETAS.forecast()</pre>
   # save.image(file = 'Robin_new.RData')
```