## gps data mapping

## Barbara E. Mottey

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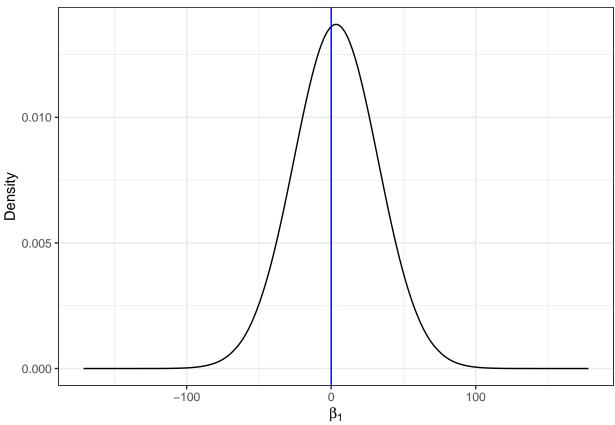
```
dat <- readRDS('C:/Users/sympl/Documents/UMass/msthesis/Data/completedata.rds')
to_factors <- c("fuel_bin", "gender", "residence", "wealth", "education", "marital_s", "region")
dat %<>% mutate_at(to_factors, funs(factor(.)))
```

## LMER in INLA

##

```
formula = c_weight~1+fuel_bin+w_age+bmi+gender+residence+wealth+education+marital_s+ f(region, model =
result<-inla(formula, family = "gaussian", data=dat, control.predictor = list(compute = TRUE))
summary(result)
##
## Call:
      "inla(formula = formula, family = \"gaussian\", data = dat,
      control.predictor = list(compute = TRUE))"
## Time used:
       Pre = 4.7, Running = 3.08, Post = 1.96, Total = 9.74
##
## Fixed effects:
##
                             sd 0.025quant 0.5quant 0.975quant
                   mean
                                                                    mode kld
## (Intercept) 3022.195 139.400
                                  2748.505 3022.191
                                                      3295.657 3022.195
## fuel bin1
                         29.115
                                              3.325
                                                                   3.325
                  3.325
                                   -53.836
                                                         60.439
                                                                           0
                          3.968
                                              4.644
                                                         12.429
                                                                   4.644
## w_age
                  4.644
                                    -3.148
                                                                           0
## bmi
                  1.512
                          2.237
                                    -2.880
                                              1.512
                                                         5.899
                                                                   1.512
                                                                           0
## gender2
                -41.312 27.077
                                   -94.474 -41.312
                                                         11.806
                                                                 -41.312
                                                                           0
## residence2
                14.553 27.455
                                   -39.351
                                             14.552
                                                         68.411
                                                                 14.553
                                                                           0
## wealth2
                  5.296 29.059
                                   -51.756
                                              5.295
                                                         62.300
                                                                   5.296
                                                                           0
## wealth3
                 11.417 28.611
                                   -44.756
                                                         67.544
                                                                  11.417
                                             11.417
                                                                           0
## wealth4
                 -8.900 28.446
                                   -64.748
                                             -8.901
                                                         46.902
                                                                  -8.900
                                                                           0
                                   -54.755
                                                                  1.335
## wealth5
                  1.335 28.569
                                              1.334
                                                         57.378
                 -9.125 28.749
                                   -65.568
                                             -9.125
                                                         47.272
                                                                  -9.125
## education1
                                                                           0
## education2
                 -0.927 27.388
                                   -54.698
                                             -0.927
                                                         52.800
                                                                  -0.927
                                                                           0
                                                         61.253
                                                                  1.081
## education3
                  1.081 30.673
                                   -59.141
                                             1.080
                                                                           0
                                   -47.581
                                                                  10.293
## marital s1
                 10.293 29.477
                                             10.292
                                                         68.119
##
## Random effects:
##
    Name
              Model
##
       region IID model
```

```
## Model hyperparameters:
##
                                                           sd 0.025quant 0.5quant
                                                mean
## Precision for the Gaussian observations
                                                0.00
                                                                    0.00
## Precision for region
                                           852364.70 1327.62 850056.28 852192.26
                                           0.975quant
                                                           mode
## Precision for the Gaussian observations
                                                 0.00
                                                            0.00
## Precision for region
                                            855440.41 851593.50
## Expected number of effective parameters(stdev): 5.01(0.00)
## Number of equivalent replicates : 591.08
## Marginal log-Likelihood: -24438.84
## Posterior marginals for the linear predictor and
## the fitted values are computed
## plot of posterior distribution for b1
marginal <- inla.smarginal(result$marginals.fixed$fuel_bin1) #posterior distn of b1 is stored here
marginal <- data.frame(marginal)</pre>
ggplot(marginal, aes(x = x, y = y)) + geom_line() + labs(x = expression(beta[1]), y = "Density") +
 geom_vline(xintercept = 0, col = "blue") + theme_bw()
```



```
#2014 contains 1310 entries
d <- dat %>% filter(year_cmc=="2014") %>% group_by( cluster.no) %>%
summarize(meanbw = mean(c_weight)) #394 unique clusters
```

## `summarise()` ungrouping output (override with `.groups` argument)

```
#head(d)
#newdata %>% filter(year_cmc=="2014") %>% group_by(cluster.no) %>% summarise(meanbw = mean(c_weight)) #
#unique(d$cluster.no)

#table(dat$fuel_bin[dat$fuel_bin == 0])

##GPS coordinates

#gc<-read.csv("GPS/GHGC72FL.csv")

ge.shp<-readOGR("C:/Users/sympl/Documents/UMass/msthesis/GPS/GHGE71FL/GHGE71FL.shp")

## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\sympl\Documents\UMass\msthesis\GPS\GHGE71FL\GHGE71FL.shp", layer: "GHGE71FL"

## with 427 features
## It has 20 fields
gt<-ge.shp@data
#*summary(gt$ALT_GPS)

plot(ge.shp, pch=".", col="red")</pre>
```



#merge with geo data

 $\#ge.shp@data\$meanbw \leftarrow extract(d, ge.shp@data[, c("DHSCLUST")])$