gps data mapping

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```
dat <- readRDS('C:/Users/sympl/Documents/UMass/msthesis/Data/completedata.rds')</pre>
to_factors <- c("fuel_bin", "gender", "residence", "wealth", "education", "marital_s", "region")
dat %<>% mutate_at(to_factors, funs(factor(.)))
## Warning: `funs()` is deprecated as of dplyr 0.8.0.
## Please use a list of either functions or lambdas:
##
##
     # Simple named list:
     list(mean = mean, median = median)
##
##
     # Auto named with `tibble::lst()`:
##
     tibble::lst(mean, median)
##
##
##
     # Using lambdas
     list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_warnings()` to see where this warning was generated.
```

LMER in INLA

```
library(INLA)
## Loading required package: Matrix
```

```
##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
## expand, pack, unpack

## Loading required package: parallel

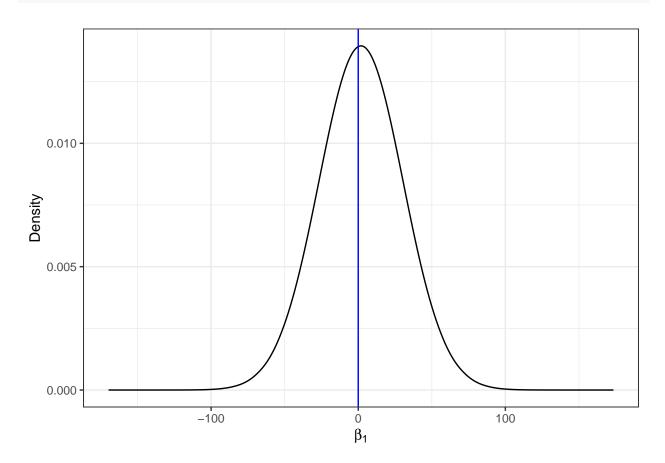
## Loading required package: foreach

##
## Attaching package: 'foreach'
```

```
## The following objects are masked from 'package:purrr':
##
##
       accumulate, when
## This is INLA_21.01.26 built 2021-01-26 11:21:34 UTC.
   - See www.r-inla.org/contact-us for how to get help.
   - Save 379.8Mb of storage running 'inla.prune()'
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 = 4.38, Running = 15.9, Post = 1.94, Total = 22.2
## Fixed effects:
                   mean
                             sd 0.025quant 0.5quant 0.975quant
                                                                    mode kld
## (Intercept) 2994.148 126.412
                                  2745.960 2994.145
                                                       3242.130 2994.148
## fuel_bin1
                  1.882 28.597
                                   -54.264
                                              1.881
                                                         57.981
                                                                   1.882
                                                                           0
## w age
                  5.601
                          3.576
                                    -1.420
                                              5.601
                                                         12.617
                                                                   5.601
                                                                           0
## bmi
                  1.485
                          1.926
                                    -2.295
                                              1.485
                                                          5.263
                                                                   1.485
                                                                           0
## gender2
                -46.128 26.280
                                   -97.724 -46.128
                                                          5.426 - 46.128
                                                                           0
## residence2
                 15.802 26.772
                                   -36.761
                                             15.801
                                                         68.320
                                                                  15.802
                                                                           0
## wealth2
                  6.606 28.530
                                   -49.409
                                              6.605
                                                         62.574
                                                                  6.606
                                                                           0
                                   -41.380
## wealth3
                 13.851 28.131
                                             13.850
                                                         69.036
                                                                  13.851
                                                                           0
## wealth4
                 -8.812 27.855
                                   -63.501
                                             -8.813
                                                         45.832
                                                                  -8.812
## wealth5
                  1.919 28.123
                                   -53.296
                                              1.919
                                                         57.089
                                                                   1.919
                                                                           0
## education1
                 -9.664 28.209
                                   -65.047
                                                         45.673
                                                                  -9.664
                                             -9.664
                                                                           0
## education2
                  0.546 26.680
                                   -51.835
                                              0.545
                                                         52.883
                                                                   0.546
                                                                           0
## education3
                  1.321 30.530
                                   -58.620
                                              1.320
                                                         61.212
                                                                   1.321
                 10.667 29.067
## marital_s1
                                   -46.401
                                             10.666
                                                         67.686
                                                                  10.667
                                                                           0
## Random effects:
    Name
              Model
       region IID model
##
##
## Model hyperparameters:
                                                           sd 0.025quant 0.5quant
                                                 mean
## Precision for the Gaussian observations
                                                 0.00
                                                         0.00
                                                                    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): 5.29(0.00)
## Number of equivalent replicates : 559.52
##
## 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)
ggplot(marginal, aes(x = x, y = y)) + geom_line() + labs(x = expression(beta[1]), y = "Density") +
    geom_vline(xintercept = 0, col = "blue") + theme_bw()</pre>
```



```
#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")</pre>
```

```
## 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 <- \ extract(d, \ ge.shp@data[, \ c("DHSCLUST")])
```