### inla v2

#### data

```
dat <- readRDS('C:/Users/sympl/Documents/UMass/msthesis/Data/2014data.rds')</pre>
#dd<- readRDS('C:/Users/sympl/Documents/UMass/msthesis/Data/regiondata.rds')
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
bound<-readOGR("C:/Users/sympl/Documents/UMass/msthesis/GPS/sdr_subnational_boundaries_2021-03-05/shps/
## OGR data source with driver: ESRI Shapefile
\verb| ## Source: "C:\Users\sympl\Documents\UMass\msthesis\GPS\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_subnational\_boundaries\_2021-03-05\shps\sdr\_sub
## with 10 features
## It has 27 fields
# district boundary
dist<-readOGR("C:/Users/sympl/Documents/UMass/msthesis/GPS/Ghana_District_CORRECT/Ghana_districts_corre
## Warning in OGRSpatialRef(dsn, layer, morphFromESRI = morphFromESRI, dumpSRS
## = dumpSRS, : Discarded ellps War Office in Proj4 definition: +proj=tmerc
## +lat_0=4.666666666666667 +lon_0=-1 +k=0.99975 +x_0=274319.739163358 +y_0=0
## +a=6378300 +rf=296 +to_meter=0.304799710181509 +no_defs
## Warning in OGRSpatialRef(dsn, layer, morphFromESRI = morphFromESRI,
## dumpSRS = dumpSRS, : Discarded datum Accra in Proj4 definition: +proj=tmerc
## +lat_0=4.666666666666667 +lon_0=-1 +k=0.99975 +x_0=274319.739163358 +y_0=0
## +a=6378300 +rf=296 +to_meter=0.304799710181509 +no_defs
## Warning in showSRID(wkt2, "PROJ"): Discarded ellps War Office in Proj4
## definition: +proj=tmerc +lat_0=4.6666666666667 +lon_0=-1 +k=0.99975
## +x_0=274319.739163358 +y_0=0 +a=6378300 +rf=296 +to_meter=0.304799710181509
## +no_defs +type=crs
## Warning in showSRID(wkt2, "PROJ"): Discarded datum Accra in Proj4 definition
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\sympl\Documents\UMass\msthesis\GPS\Ghana_District_CORRECT\Ghana_districts_correct.
## with 110 features
## It has 18 fields
```

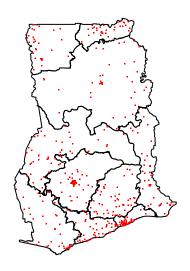
```
dist2<- readOGR("C:/Users/sympl/Documents/UMass/msthesis/GPS/gadm36_GHA_shp/gadm36_GHA_2.shp")

## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\sympl\Documents\UMass\msthesis\GPS\gadm36_GHA_shp\gadm36_GHA_2.shp", layer: "gadm3
## with 137 features
## It has 13 fields

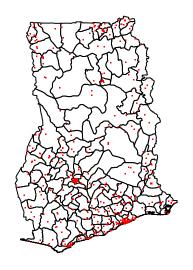
dist3<- readOGR("C:/Users/sympl/Documents/UMass/msthesis/GPS/Ghana_Dist_DHS_Join/GPS_Points_Districts.si

## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\sympl\Documents\UMass\msthesis\GPS\Ghana_Dist_DHS_Join\GPS_Points_Districts.shp",
## with 427 features
## It has 41 fields
## Integer64 fields read as strings: OBJECTID Join_Count TARGET_FID Index Household

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



```
plot(dist2) #from LA
points(ge.shp, pch=".", col="red")
```



#### nb

```
library(spdep)

## Loading required package: spData

## Loading required package: sf

## Linking to GEOS 3.8.0, GDAL 3.0.4, PROJ 6.3.1

nb <- poly2nb(bound, row.names = bound@data$REGCODE) #for calculating neighbors

nb2INLA("map.adj", nb)

g <- inla.read.graph(filename = "map.adj")

##define stuctured and unstructured spatial re vectors
bound$re_u <- 1:nrow(bound@data)
bound$re_v <- 1:nrow(bound@data)

trial<-dat
trial$region<- as.numeric(trial$region)
trial<-trial %>% right_join(bound@data, by= c("region"="REGCODE"))
```

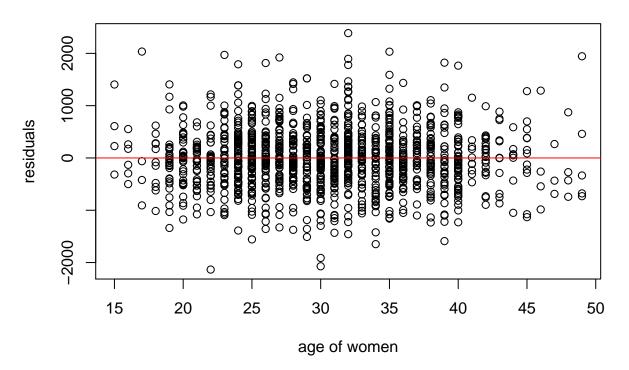
### fitting iid random effect

```
##formula
formula <- c_weight ~ fuel_bin+gender+education+ w_age+ marital_s+wealth+bmi+residence + f(re_v, model
res <- inla(formula, family = "gaussian", data = trial, control.predictor = list(compute = TRUE))
summary(res)
##
## Call:
      "inla(formula = formula, family = \"gaussian\", data = trial,
      control.predictor = list(compute = TRUE))"
##
      Pre = 6.08, Running = 1.9, Post = 2.57, Total = 10.5
##
## Fixed effects:
##
                  mean
                           sd 0.025quant 0.5quant 0.975quant
                                                                 mode kld
## (Intercept) 2599.928 69.569
                                2463.341 2599.926
                                                    2736.401 2599.928
                -5.341 21.811
## fuel_bin1
                                 -48.163
                                           -5.342
                                                      37.445
                                                               -5.341
                                                                        0
## gender2
              -102.996 17.078
                               -136.526 -102.996
                                                     -69.494 -102.996
                                                                        0
## education1
               11.204 21.372
                                 -30.756
                                          11.203
                                                      53.129
                                                               11.204
## education2
              10.220 18.917
                                 -26.921 10.219
                                                      47.330
                                                               10.220
                                                                        0
## education3
                -2.365 26.511
                                 -54.416
                                          -2.366
                                                      49.642
                                                               -2.365
                                                                        0
                 6.167 1.603
                                                      9.312
                                                                6.167
## w_age
                                   3.021
                                          6.167
                                                                        0
## marital_s1
                 0.951 21.623
                                 -41.503
                                           0.951
                                                      43.370
                                                                0.951
## wealth2
                13.386 21.731
                                 -29.279
                                          13.385
                                                      56.016
                                                              13.386
                                                                        0
## wealth3
                48.649 20.730
                                   7.949
                                          48.648
                                                      89.314
                                                               48.649
                                                      10.064 -32.544
## wealth4
               -32.544 21.720
                                 -75.188 -32.545
                                                                        0
## wealth5
                31.149 23.734 -15.450 31.148
                                                      77.709
                                                               31.149
## bmi
                14.513 1.996
                                 10.594 14.513
                                                      18.429
                                                               14.513
                                                                        0
## residence2
                14.917 18.851
                                 -22.093
                                          14.916
                                                      51.896
                                                               14.917
##
## Random effects:
##
    Name
             Model
##
      re_v IID model
##
## Model hyperparameters:
                                          mean
                                                  sd 0.025quant 0.5quant
## Precision for the Gaussian observations 0.00 0.000
                                                          0.000
                                                                    0.00
                                          0.52 0.002
                                                          0.517
                                                                    0.52
## Precision for re_v
                                          0.975quant mode
## Precision for the Gaussian observations
                                               0.000 0.00
## Precision for re_v
                                               0.524 0.52
## Expected number of effective parameters(stdev): 8.96(0.00)
## Number of equivalent replicates : 146.12
##
## Marginal log-Likelihood: -10650.49
## Posterior marginals for the linear predictor and
## the fitted values are computed
```

## plotting residuals

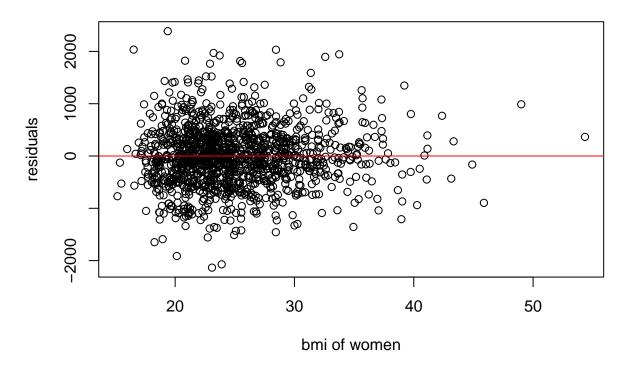
```
#age
residuals= trial$c_weight-res$summary.fitted.values[,1]
plot(trial$w_age,residuals, main= "age against residual", xlab="age of women")
abline(h=0, col="red")
```

## age against residual



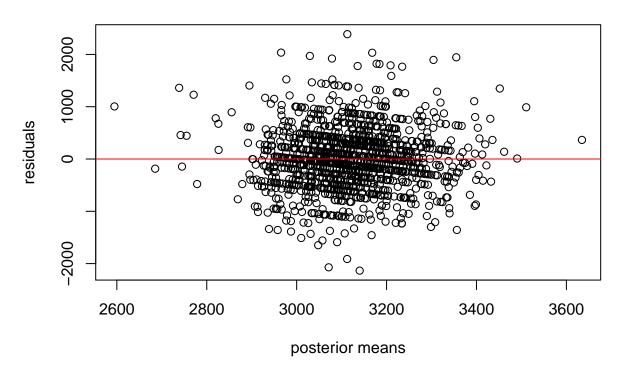
```
#bmi
plot(trial$bmi,residuals, main= "bmi against residual", xlab="bmi of women")
abline(h=0, col="red")
```

# bmi against residual



#posterior
plot(res\$summary.fitted.values[,1],residuals, main= "posterior vs residual", xlab="posterior means")
abline(h=0, col="red")

# posterior vs residual



#priors not sure