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
```

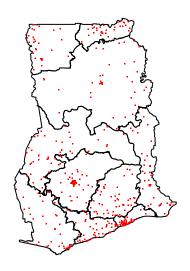
```
dist2<- readOGR("C:/Users/sympl/Documents/UMass/msthesis/GPS/gadm36_GHA_shp/gadm36_GHA_2.shp")

## 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

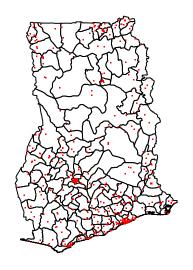
dist3<- readOGR("C:/Users/sympl/Documents/UMass/msthesis/GPS/Ghana_Dist_DHS_Join/GPS_Points_Districts.si

## 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"))
```

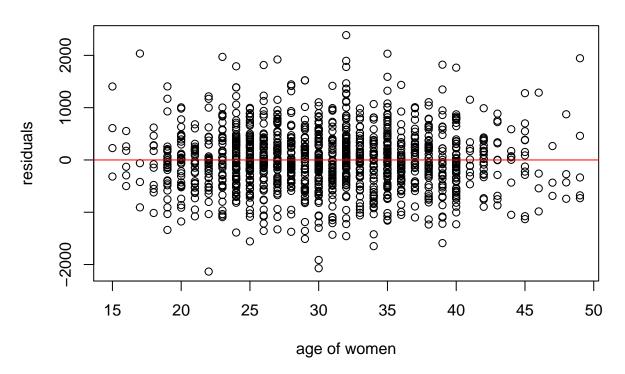
fitting iid random effect

```
##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 = 3.08, Running = 1.48, Post = 1.04, Total = 5.6
##
## Fixed effects:
##
                  mean
                            sd 0.025quant 0.5quant 0.975quant
                                                                 mode kld
## (Intercept) 2599.682 69.199
                                2463.822 2599.680
                                                    2735.429 2599.682
                -5.315 21.769
## fuel_bin1
                                 -48.054
                                           -5.315
                                                      37.389
                                                               -5.315
                                                                        0
## gender2
              -103.282 17.023
                                -136.703 -103.283
                                                     -69.889 -103.282
                                                                        0
## education1
                11.251 21.314
                                 -30.595
                                          11.251
                                                      53.063
                                                               11.251
## education2
              10.229 18.874
                                 -26.827
                                           10.228
                                                      47.253
                                                               10.229
                                                                        0
## education3
                -2.386 26.490
                                 -54.394
                                          -2.387
                                                      49.579
                                                               -2.386
                                                                        0
                                                      9.299
                                                                6.169
                                                                        0
## w_age
                 6.169 1.595
                                   3.037
                                          6.169
## marital_s1
                 0.947 21.572
                                 -41.406
                                           0.946
                                                      43.263
                                                                0.947
                13.454 21.673
## wealth2
                                 -29.098 13.453
                                                      55.971
                                                               13.454
                                                                        0
## wealth3
                48.840 20.685
                                   8.229
                                          48.840
                                                     89.418
                                                               48.840
                                                                        0
                                                      9.935 -32.590
## wealth4
               -32.590 21.678
                                 -75.151 -32.591
                                                                        0
## wealth5
                31.310 23.696 -15.213 31.309
                                                      77.794
                                                               31.310
                14.521 1.980
## bmi
                                 10.633 14.521
                                                      18.405
                                                               14.521
                                                                        0
## residence2
                15.009 18.799
                                 -21.901 15.008
                                                      51.887
                                                               15.009
##
## 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): 8.98(0.005)
## Number of equivalent replicates : 145.81
##
## Marginal log-Likelihood: -10650.49
## Posterior marginals for the linear predictor and
## the fitted values are computed
```

plotting residuals

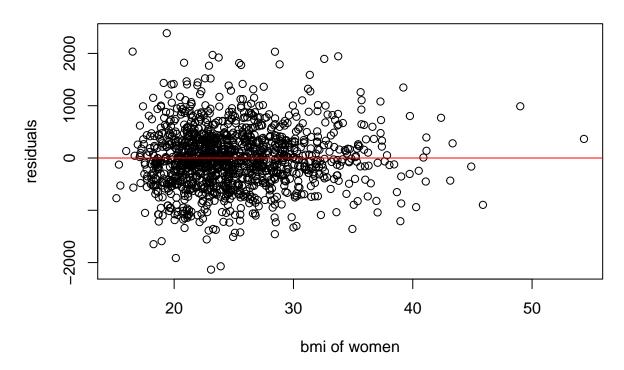
```
#age
residuals= trial$c_weight-res$summary.fitted.values[,1]
plot(trial$w_age,residuals, main= "age against residual", xlab="age of women")
abline(h=0, col="red")
```

age against residual



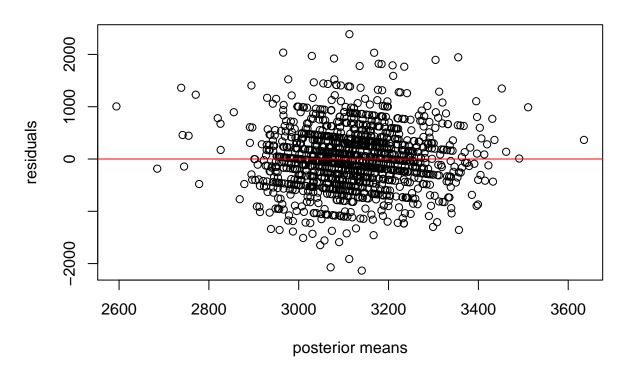
```
#bmi
plot(trial$bmi,residuals, main= "bmi against residual", xlab="bmi of women")
abline(h=0, col="red")
```

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

```
dd <- trial %>% group_by(region) %>%
  summarize(meanbw = mean(c_weight))
## `summarise()` ungrouping output (override with `.groups` argument)
#how to interpret
moran.test(dd$meanbw, nb2listw(nb), 10)
##
##
    Moran I test under randomisation
##
## data: dd$meanbw
## weights: nb2listw(nb)
## Moran I statistic standard deviate = 2.4512, p-value = 0.007119
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic
                           Expectation
                                                Variance
          0.33609153
                           -0.11111111
                                              0.03328468
##
```