INLA

- Recently an alternative to McMC has been proposed for certain Bayesian models
- Integrated Nested Laplace approximation (INLA)
- This uses an approximation to the posterior distribution
- Computationally it is fast: uses numerical integration and Gaussian approximation
- No need to do ANY McMC !
- Useful for simpler models

Some Information

- Use R-INLA package
  - Obtainable from www.r-inla.org

SC congenital mortality

- File: SCcongen90_INLA_Rcode.txt
  - Includes the data, inla call, and graphics function
  - Need to import/create polygon maps in R
  - GeoBUGS maps can be exported in SPlus format (as text file: SC_geobugsSPlus.txt)
  - Code below sets up the polygon map:
    - `geobugsSC<-readSplus("SC_geobugsSPlus.txt")`
    - `plot(geobugsSC)`
  - Fillmap function produces the polygon plot:
    - `fillmap(geobugsSC,maintitle1,RE1,n.col=6)`

Some inla code

- library(INLA)
- Need to create a .graph file including the adjacencies and number of neighbors
- There is an **inla** function for this:

```
inla.geobugs2inla(adj,num,graph.file="SC.graph")
```

- Uses the ‘adj’ and ‘num’ vectors from WinBUGS
- this creates a file with the correct structure

Model Code

```
prior.iid = c(1,0.01)
prior.besag = c(1,0.001)
initial.iid = 4
initial.besag = 3

formula1.bym = obs ~ f(region, model = "bym", graph.file =
"SC.graph",
                       param = c(prior.iid, prior.besag),
                       initial = c(initial.iid, initial.besag))
result1 = inla(formula1.bym,family="poisson",
data=SCcongen90,control.compute=list(dic=TRUE,cpo=TRUE,gra
ph=TRUE),E=expe)
```

Formula call

formula1.bym = obs ~ f(region, model = "bym", graph.file = "SC.graph",param = c(prior.iid, prior.besag),

initial = c(initial.iid, initial.besag))

- This call sets up a model formula (like in `glm` in R)
  - In this case th dependent variable 'obs' is related to 'region' with a convolution model with UH and CH components ('iid', and 'Besag')
  - It uses the SC.graph polygons
  - Note that the f(.....) function could be much more general...including linear functions of covariates and even spline functions

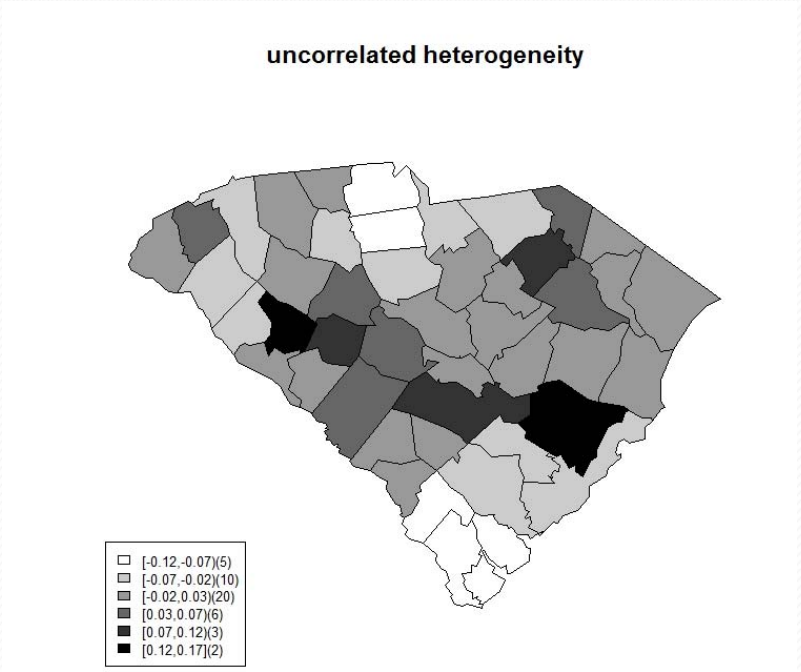
Function examples

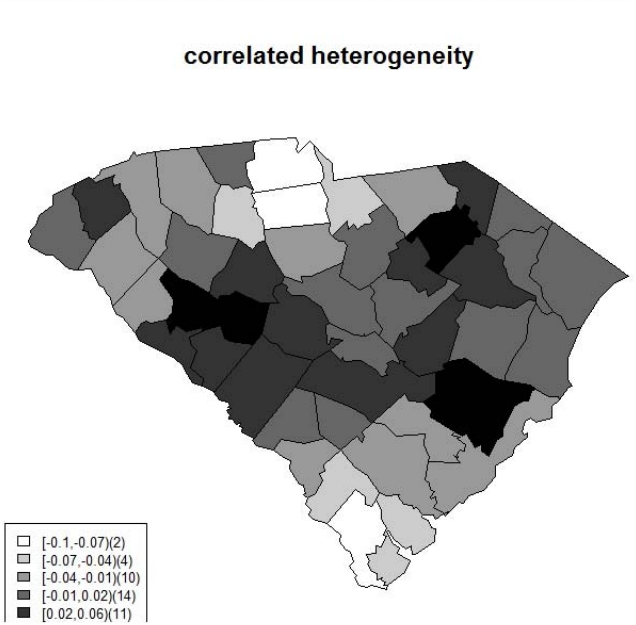
- Example:

inla(obs~1+x+f(ind, model="iid") + f(ind2, weights, model="ar1"))

  - Would fit a regrssion wiht intercept and x covariayte with 2 other smooth terms in the variable ‘ind’
  - One term is random
  - One term is autoregressive with ‘weights’

Results


uncorrelated heterogeneity
[-0.12,-0.07)(5)
[-0.07,-0.02)(10)
[-0.02,0.03)(20)
[0.03,0.07)(6)
[0.07,0.12)(3)
[0.12,0.17](2)


correlated heterogeneity
[-0.1,-0.07)(2)
[-0.07,-0.04)(4)
[-0.04,-0.01)(10)
[-0.01,0.02)(14)
[0.02,0.06)(11)

Results

RGui

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R Console

```
> edit(sum$region)
   ID          mean        sd 0.025quant      0.5quant 0.975quant          kld
1   0 -0.0267668404 0.1939465 -0.4384379 -0.0217855029  0.3639045 1.683052e-05
2   1  0.0465928465 0.1691089 -0.2818824  0.0380368736  0.4078199 2.784321e-04
3   2 -0.0089925407 0.2165670 -0.4687503 -0.0052716786  0.4335687 2.032231e-07
4   3 -0.0478311814 0.1798571 -0.4332898 -0.0394377249  0.3001325 1.793872e-04
5   4 -0.0076171760 0.1996556 -0.4286395 -0.0049650051  0.4005008 2.531212e-06
6   5  0.0119104143 0.2035690 -0.4064928  0.0091065072  0.4397640 1.252160e-05
7   6 -0.0745912790 0.2173019 -0.5607765 -0.0550124345  0.3261157 1.686384e-04
8   7  0.1682153940 0.1750763 -0.1279590  0.1470248159  0.5544079 5.089286e-04
9   8  0.0059383567 0.1846007 -0.3760298  0.0046639506  0.3908988 4.047376e-05
10  9 -0.0244197175 0.1506935 -0.3403545 -0.0204139943  0.2707318 1.035006e-03
11 10  0.0291659832 0.2139648 -0.4028410  0.0232179377  0.4840997 6.864655e-05
12 11 -0.1047963649 0.2129792 -0.5908793 -0.0797417110  0.2730170 2.626554e-05
13 12 -0.0441207029 0.1911567 -0.4607993 -0.0343384212  0.3280412 3.618038e-05
14 13  0.0138846729 0.1744952 -0.3434244  0.0113985554  0.3779756 5.964914e-05
15 14 -0.0379207991 0.1808017 -0.4290484 -0.0292472697  0.3141130 1.047618e-05
16 15  0.1184766516 0.1935189 -0.2232918  0.0965173952  0.5517373 1.149113e-04
17 16 -0.0111115938 0.2019813 -0.4389249 -0.0078348403  0.3985549 3.653333e-05
18 17 -0.0431224927 0.1829479 -0.4395970 -0.0341703651  0.3111877 2.114600e-04
19 18  0.0207948890 0.2090568 -0.3998356  0.0136883644  0.4694861 2.199251e-05
20 19 -0.0561733507 0.1816439 -0.4564032 -0.0438505766  0.2896614 2.490242e-05
21 20  0.0518826246 0.1576330 -0.2520315  0.0439761713  0.3886850 2.084384e-04
22 21 -0.0011361790 0.1845108 -0.3862615 -0.0002157275  0.3757861 9.089767e-05
23 22 -0.0673081055 0.1567985 -0.4039999 -0.0581559859  0.2276833 6.511608e-04
24 23  0.1265671849 0.1913319 -0.2034969  0.1026088712  0.5578177 9.954015e-05
25 24 -0.0767117739 0.2172256 -0.5640833 -0.0568383117  0.3261126 6.295212e-08
26 25  0.0176694803 0.1896181 -0.3721790  0.0161497570  0.4060684 3.842697e-04
27 26 -0.1165498868 0.2854489 -0.7779722 -0.0798529619  0.3950116 1.601444e-06
28 27  0.0200084839 0.1705127 -0.3241635  0.0164264968  0.3792264 5.432093e-05
29 28 -0.0598726198 0.1887023 -0.4770738 -0.0459079705  0.2963274 5.137703e-05
30 29  0.0225459859 0.1689733 -0.3126575  0.0176102200  0.3810876 6.387411e-05
31 30  0.0209016260 0.1909122 -0.3659577  0.0162264583  0.4254311 2.395508e-05
32 31  0.0678645968 0.1561842 -0.2249785  0.0572953439  0.4049973 4.809744e-04
33 32  0.0162784308 0.2319624 -0.4563526  0.0102355588  0.5138774 5.670126e-06
34 33 -0.0133800628 0.1914250 -0.4196722 -0.0094774267  0.3719414 4.058337e-05
35 34  0.0345366225 0.2018524 -0.3690068  0.0268573015  0.4666643 3.257611e-05
36 35  0.0543137453 0.1708542 -0.2694922  0.0428276840  0.4297424 4.611511e-05
37 36  0.0181836784 0.2459204 -0.4869638  0.0139728148  0.5336667 8.780090e-05
38 37  0.0844144002 0.1578797 -0.2021776  0.0707924450  0.4332806 1.539528e-04
```

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McMC Versus INLA

- McMC is often more flexible
- Easier for complex models with unusual structures
- Deals with missingness easily

- INLA is easy to implement for Gaussian –like models
- Good for flexible spline –like covariate models
- INLA is fast
- INLA can't deal with missing values in covariates