# Aggregated Gaussian

#### Parametrisation

This is shorthand to allow for aggregated Gaussian observations, where we have repeated observations with the same mean and (known scaled) precision. These can be aggregated into an equivalent likelihood reducing the computional effort.

Let  $y = (y_1, ..., y_n)$  be iid observations of a Gaussian with mean  $\mu$  and precisions  $s_i\tau$ , where the  $s_i$ 's are fixed and known scaling parameters (default  $s_i = 1$ ), then

$$f(y|\mu,\tau) = \prod_{i=1}^{n} (2\pi)^{-1/2} (s_i \tau)^{1/2} \exp\left(-\frac{1}{2} (s_i \tau) (y_i - \mu)^2\right)$$
 (1)

$$= (2\pi)^{-n/2} \tau^{n/2} \left( \prod_{i=1}^{n} s_i^{1/2} \right) \exp\left( -\frac{1}{2} \tau \sum_{i=1}^{n} s_i (y_i - \mu)^2 \right)$$
 (2)

$$= (2\pi)^{-n/2} \tau^{n/2} \left( \prod_{i=1}^{n} s_i^{1/2} \right) \exp\left( -\frac{1}{2} m \tau \left[ (\bar{y} - \mu)^2 + v \right] \right)$$
 (3)

where

$$m = \sum_{i=1}^{n} s_i$$

$$\bar{y} = \frac{1}{m} \sum_{i=1}^{n} s_i y_i$$

$$v = \frac{1}{m} \sum_{i=1}^{n} s_i y_i^2 - \bar{y}^2$$

### **Link-function**

The mean  $\mu$  is linked to the linear predictor  $\eta$  by

$$\mu = \eta$$

# Hyperparameters

The hyperparameter is  $\theta$ , where

$$\theta = \log \tau$$

and the prior is defined on  $\theta$ .

# Specification

This family require the response to be an inla.mdata-object, where each row is

$$(v, \frac{1}{2} \sum_{i=1}^{n} \log(s_i), m, n, \bar{y})$$

This object is most easily constructed using the inla.agaussian() function, which gives the object to use directly.

- family="agaussian"
- Required arguments: An inla.mdata-object created with inla.agaussian().

<sup>&</sup>lt;sup>1</sup>It is a list of vectors, so not strictly a "row".

#### Hyperparameter spesification and default values

```
doc The aggregated Gaussian likelihoood
```

```
hyper
```

```
theta
        hyperid 66001
        name log precision
        short.name prec
        initial 4
        fixed FALSE
        prior loggamma
        param 1 5e-05
        to.theta function(x) log(x)
        from.theta function(x) exp(x)
status experimental
survival FALSE
discrete FALSE
link default identity logit loga cauchit log logoffset
pdf agaussian
Example
## plain example, either with all n observations or to aggregate them
n <- 10
y <- rnorm(n)
Y <- inla.agaussian(y)
r <- inla(Y ~ 1,
         data = list(Y = Y),
         family = "agaussian")
rr <- inla(y ~ 1,
          data = data.frame(y),
          family = "gaussian")
print(r$mlik - rr$mlik)
inla.dev.new()
par(mfrow = c(1, 2))
plot(r$internal.marginals.hyperpar[[1]], pch = 19, main = "prec")
lines(rr$internal.marginals.hyperpar[[1]], lwd = 3)
plot(r$marginals.fixed$'(Intercept)', pch = 19, main = "intercept")
lines(rr$marginals.fixed$'(Intercept)', lwd = 3)
```

```
## same example, but with different scalings for the precision for 'yy'
n <- 5
s <- 1:n ## scale the precision
y <- rnorm(n)
yy \leftarrow rnorm(n, sd = sqrt(1/s))
Y <- inla.agaussian(rbind(y, yy),
                   rbind(rep(1, n), s))
r <- inla(Y ~ 1,
         data = list(Y = Y),
         family = "agaussian",
         control.compute = list(cpo = TRUE, dic = TRUE))
rr <- inla(yyy ~ 1,
          data = data.frame(yyy = c(y, yy)),
          scale = c(rep(1, n), s),
          control.compute = list(cpo = TRUE, dic = TRUE),
          family = "gaussian")
print(r$mlik - rr$mlik)
inla.dev.new()
par(mfrow = c(1, 2))
plot(r$internal.marginals.hyperpar[[1]], pch = 19, main = "prec")
lines(rr$internal.marginals.hyperpar[[1]], lwd = 3)
plot(r$marginals.fixed$'(Intercept)', pch = 19, main = "intercept")
lines(rr$marginals.fixed$'(Intercept)', lwd = 3)
## if one want to build the aggrated data for each replication
## at the time, one can do
y.agg <- unlist(inla.agaussian(y))</pre>
yy.agg <- unlist(inla.agaussian(yy, s))</pre>
agg.matrix <- rbind(y.agg, yy.agg)</pre>
Y.agg <- inla.mdata(agg.matrix)
## and then
r.agg <- inla(Y.agg ~ 1,</pre>
             data = list(Y.agg = Y.agg),
             family = "agaussian")
## For further details, see also INLA:::inla.agaussian.test()
```

#### Notes

• Thanks to JW for suggesting this formulation and for providing the details.