

Model `rgeneric`

This is a class of generic models allows the user to define latent model-component in R, for cases where the requested model is not yet implemented in INLA, and do the Bayesian inference using INLA. It will run slower as the model properties has to be evaluated in R within a C-program.

Defining a latent model in R

The use of this feature, is in short the following. First we pass our definition of the model `rmodel`, to define a `inla-rgeneric` object,

```
model = inla.rgeneric.define(rmodel, debug, R.init, <args>)
```

Here, `rmodel` is model definition encoded as an R-function, `debug` is a logical parameter if debug information should be printed, `R.init` is a R-file which is `sourced` or `loaded` before the model is defined, and `<args>` are further parameters to the model (like dimension, prior-settings, etc). Then the model can used as

```
y ~ ... + f(i, model=model)
```

Example: the AR1 model

The `rmodel` needs to follow some rules to provide the required features. As an example, we will show how to implement the AR1-model, see `inla.doc("ar1")`. This model is defined as¹

$$x_1 \sim \mathcal{N}(0, \tau)$$

and

$$x_t \mid x_1, \dots, x_{t-1} \sim \mathcal{N}(\rho x_{t-1}, \tau_I), \quad t = 2, \dots, n.$$

The scale-parameter is the marginal precision τ , but the joint density is more naturally expressed using the innovation precision $\tau_I = \tau/(1 - \rho^2)$. The joint density of x is Gaussian

$$\pi(x \mid \rho, \tau) = \left(\frac{1}{\sqrt{2\pi}} \right)^n \tau_I^{n/2} (1 - \rho^2)^{1/2} \exp \left(-\frac{\tau_I}{2} x^T R x \right)$$

where the precision-matrix is

$$Q = \tau_I R = \tau_I \begin{bmatrix} 1 & -\rho & & & & \\ -\rho & 1 + \rho^2 & -\rho & & & \\ & -\rho & 1 + \rho^2 & -\rho & & \\ & & \ddots & \ddots & \ddots & \\ & & & -\rho & 1 + \rho^2 & -\rho \\ & & & & -\rho & 1 \end{bmatrix}$$

There are two (hyper-)parameters for this model, it is the marginal precision τ and the lag-one correlation ρ . We reparameterise these as

$$\tau = \exp(\theta_1)$$

and

$$\rho = 2 \frac{\exp(\theta_2)}{1 + \exp(\theta_2)} - 1$$

¹The second argument in $\mathcal{N}(,)$ is the precision not the covariance.

It is required that the parameters $\theta = (\theta_1, \theta_2)$ have support on \Re and the priors for τ and ρ are given as the corresponding priors for θ_1 and θ_2 . Note that INLA only provide the marginal posteriors for θ , but you can use `inla.tmarginal` to convert it to the appropriate marginals for ρ and τ .

We assign a (Gamma) $\Gamma(\cdot; a, b)$ prior (with mean a/b and variance a/b^2) for τ and a Gaussian prior $\mathcal{N}(\mu, \kappa)$ for θ_2 , so the joint prior for θ becomes

$$\pi(\theta) = \Gamma(\exp(\theta_1); a, b) \exp(\theta_1) \times \mathcal{N}(\theta_2; \mu, \kappa).$$

We will use $a = b = 1$, $\mu = 0$ and $\kappa = 1$.

In order to define the AR1-model, we need to make functions that returns

- the precision matrix $Q(\theta)$,
- the graph,
- the initial values of θ ,
- the log-normalising constant, and
- the log-prior

which except for the graph, depends on the current value of θ . We need to wrap this into a common function, which process the request from the C-program. The list of commands and its names

```
cmd = c("Q", "graph", "mu", "initial", "log.norm.const",
        "log.prior", "quit"),
```

are fixed. The skeleton-function for defining a model is

```
'inla.rgeneric.ar1.model' = function(
  cmd = c("graph", "Q", "mu", "initial", "log.norm.const",
          "log.prior", "quit"),
  theta = NULL,
  args = NULL)
{
  graph = function(n, theta){ <to be completed> }
  Q = function(n, theta) { <to be completed> }
  mu = function(n, theta) { <to be completed> }
  log.norm.const = function(n, theta) { <to be completed> }
  log.prior = function(n, theta) { <to be completed> }
  initial = function(n, theta) { <to be completed> }
  quit = function(n, theta) { <to be completed> }

  cmd = match.arg(cmd)
  val = do.call(cmd, args = list(n = as.integer(args$n), theta = theta))
  return (val)
}
```

The input parameters are

cmd What to return

theta The values of the θ -parameters

args User-defined argument(s) from the `inla.rgeneric.define()`-call; all arguments in `<args>` as a list. In this example we use `n` as the user-defined argument and pass it to every function. We then need to pass `n` when we define the model

```
model = inla.rgeneric.define(inla.rgeneric.ar1.model, n = 100)
```

This is just an example, and you may chose to do this differently.

Our next task, is the “fill in the blanks” in this function.

Function graph

This function must return a sparseMatrix, with the non-zero elements of the precision matrix. Only the lower-triangular part of the matrix is used.

```
graph = function(n, theta)
{
  ## return the graph of the model. the values of Q is only interpreted as zero or
  ## non-zero. return a sparse.matrix
  if (FALSE) {
    ## slow and easy: dense-matrices
    G = toeplitz(c(1, 1, rep(0, n-2L)))
    G = inla.as.sparse(G)
  } else {
    ## faster. we only need to define the lower-triangular of G
    i = c(
      ## diagonal
      1L, n, 2L:(n-1L),
      ## off-diagonal
      1L:(n-1L))
    j = c(
      ## diagonal
      1L, n, 2L:(n-1L),
      ## off-diagonal
      2L:n)
    x = 1 ## meaning that all are 1
    G = sparseMatrix(i=i, j=j, x=x, giveCsparse = FALSE)
  }
  return (G)
}
```

Function Q

This function must return the precision matrix $Q(\theta)$, and must be a sparseMatrix. Only the lower-triangular part of the matrix is used. We will make use of the helper function

```
interpret.theta = function(n, theta)
{
  ## internal helper-function to map the parameters from the internal-scale to the
  ## user-scale
  return (list(prec = exp(theta[1L]),
               rho = 2*exp(theta[2L])/(1+exp(theta[2L])) - 1.0))
}
```

to convert from θ_1 to τ , and from θ_2 to ρ . The Q-function can then be implemented as follows.

```
Q = function(n, theta)
{
  ## returns the precision matrix for given parameters
  param = interpret.theta(n, theta)
  if (FALSE) {
    ## slow and easy: dense-matrices
    Q = param$prec/(1-param$rho^2) * toeplitz(c(1+param$rho^2, -param$rho, rep(0, n-2L)))
    Q[1, 1] = Q[n, n] = param$prec/(1-param$rho^2)
    Q = inla.as.sparse(Q)
  } else {
    ## faster. we only need to define the lower-triangular Q!
    i = c(
      ## diagonal
```

```

        1L, n, 2L:(n-1L),
        ## off-diagonal
        1L:(n-1L))
    j = c(
        ## diagonal
        1L, n, 2L:(n-1L),
        ## off-diagonal
        2L:n)
    x = param$prec/(1-param$rho^2) *
        c( ## diagonal
          1L, 1L, rep(1+param$rho^2, n-2L),
          ## off-diagonal
          rep(-param$rho, n-1L))
    Q = sparseMatrix(i=i, j=j, x=x, giveCsparse=FALSE)
  }
  return (Q)
}

```

Function mu

This function must return the mean of the model. Often, the mean is zero, but sometimes it might depend on the hyperparameters as well. If `numeric(0)` is returned, then this is equivalent that the mean is zero. An alternative in this example, would be to return `rep(0,n)`.

```

mu = function(n, theta)
{
  return(numeric(0))
}

```

Function log.norm.const

This function must return the log of the normalising constant. For the AR1-model the normalising constant is

$$\left(\frac{1}{\sqrt{2\pi}}\right)^n \tau_I^{n/2} (1 - \rho^2)^{1/2}$$

where

$$\tau_I = \tau / (1 - \rho^2).$$

The function can then be implemented as

```

log.norm.const = function(n, theta)
{
  ## return the log(normalising constant) for the model
  param = interpret.theta(n, theta)
  prec.innovation = param$prec / (1.0 - param$rho^2)
  val = n * (- 0.5 * log(2*pi) + 0.5 * log(prec.innovation)) + 0.5 * log(1.0 - param$rho^2)
  return (val)
}

```

Function log.prior

This function must return the (log-)prior of the prior density for θ . For the AR1-model, we have for simplicity chosen this prior

$$\pi(\theta) = \Gamma(\exp(\theta_1); a, b) \exp(\theta_1) \times \mathcal{N}(\theta_2; \mu, \kappa)$$

so we can implement this as with our choices $a = b = 1$, $\mu = 0$ and $\kappa = 1$.

```
log.prior = function(n, theta)
{
  ## return the log-prior for the hyperparameters. the '+theta[1L]' is the log(Jacobian)
  ## for having a gamma prior on the precision and convert it into the prior for the
  ## log(precision).
  param = interpret.theta(n, theta)
  val = (dgamma(param$prec, shape = 1, rate = 1, log=TRUE) + theta[1L] +
        dnorm(theta[2L], mean = 0, sd = 1, log=TRUE))
  return (val)
}
```

Function initial

This function returns the initial values for θ .

```
initial = function(n, theta)
{
  ## return initial values
  ntheta = 2
  return (rep(1, ntheta))
}
```

Function quit

This function is called when all the computations are done and before exit-ing the C-program. Usually, there is nothing in particular to do, but if there is something that should be done, you can do this here.

```
quit = function(n, theta)
{
  return (invisible())
}
```

The complete definition of the AR1-model

For completeness, we include here the complete code for the AR1-model, collecting all the functions already defined. The function is predefined in the INLA-library.

```
'inla.rgeneric.ar1.model' = function(cmd = c("graph", "Q", "mu", "initial",
      "log.norm.const", "log.prior", "quit"),
      theta = NULL, args = NULL)
{
  ## this is an example of the 'rgeneric' model. here we implement
  ## the AR-1 model as described in inla.doc("ar1"), where 'rho' is
  ## the lag-1 correlation and 'prec' is the *marginal* (not
  ## conditional) precision.

  interpret.theta = function(n, theta)
  {
    ## internal helper-function to map the parameters from the internal-scale to the
    ## user-scale
    return (list(prec = exp(theta[1L]),
      rho = 2*exp(theta[2L])/(1+exp(theta[2L])) - 1.0))
  }

  graph = function(n, theta)
  {
    ## return the graph of the model. the values of Q is only interpreted as zero or
```

```

## non-zero. return a sparse.matrix
if (FALSE) {
  ## slow and easy: dense-matrices
  G = toeplitz(c(1, 1, rep(0, n-2L)))
  G = inla.as.sparse(G)
} else {
  ## faster. we only need to define the lower-triangular of G
  i = c(
    ## diagonal
    1L, n, 2L:(n-1L),
    ## off-diagonal
    1L:(n-1L))
  j = c(
    ## diagonal
    1L, n, 2L:(n-1L),
    ## off-diagonal
    2L:n)
  x = 1 ## meaning that all are 1
  G = sparseMatrix(i=i, j=j, x=x, giveCsparse = FALSE)
}
return (G)
}

Q = function(n, theta)
{
  ## returns the precision matrix for given parameters
  param = interpret.theta(n, theta)
  if (FALSE) {
    ## slow and easy: dense-matrices
    Q = param$prec/(1-param$rho^2) * toeplitz(c(1+param$rho^2, -param$rho, rep(0, n-2L)))
    Q[1, 1] = Q[n, n] = param$prec/(1-param$rho^2)
    Q = inla.as.sparse(Q)
  } else {
    ## faster. we only need to define the lower-triangular Q!
    i = c(
      ## diagonal
      1L, n, 2L:(n-1L),
      ## off-diagonal
      1L:(n-1L))
    j = c(
      ## diagonal
      1L, n, 2L:(n-1L),
      ## off-diagonal
      2L:n)
    x = param$prec/(1-param$rho^2) *
      c( ## diagonal
        1L, 1L, rep(1+param$rho^2, n-2L),
        ## off-diagonal
        rep(-param$rho, n-1L))
    Q = sparseMatrix(i=i, j=j, x=x, giveCsparse=FALSE)
  }
  return (Q)
}

mu = function(n, theta)
{
  return(numeric(0))
}

```

```

}

log.norm.const = function(n, theta)
{
  ## return the log(normalising constant) for the model
  param = interpret.theta(n, theta)
  prec.innovation = param$prec / (1.0 - param$rho^2)
  val = n * (- 0.5 * log(2*pi) + 0.5 * log(prec.innovation)) + 0.5 * log(1.0 - param$rho^2)
  return (val)
}

log.prior = function(n, theta)
{
  ## return the log-prior for the hyperparameters. the '+theta[1L]' is the log(Jacobian)
  ## for having a gamma prior on the precision and convert it into the prior for the
  ## log(precision).
  param = interpret.theta(n, theta)
  val = (dgamma(param$prec, shape = 1, rate = 1, log=TRUE) + theta[1L] +
        dnorm(theta[2L], mean = 0, sd = 1, log=TRUE))
  return (val)
}

initial = function(n, theta)
{
  ## return initial values
  ntheta = 2
  return (rep(1, ntheta))
}

quit = function(n, theta)
{
  return (invisible())
}

cmd = match.arg(cmd)
val = do.call(cmd, args = list(n = as.integer(args$n), theta = theta))
return (val)
}

```

Example of usage

```

n = 100
rho=0.9
x = arima.sim(n, model = list(ar = rho)) * sqrt(1-rho^2)
y = x + rnorm(n, sd = 0.1)
model = inla.rgeneric.define(inla.rgeneric.ar1.model, n=n)
formula = y ~ -1 + f(idx, model=model)
r = inla(formula, data = data.frame(y, idx = 1:n), family = "gaussian")

```

Example: the iid-model

The following function defines the iid-model, see `inla.doc("iid")`, which we give without further comments. To run this model in R, you may do `demo(rgeneric)`.

```

'inla.rgeneric.iid.model' = function(cmd = c("graph", "Q", "mu", "initial",
      "log.norm.const", "log.prior", "quit"),

```

```

                                theta = NULL, args = NULL)
{
  ## this is an example of the 'rgeneric' model. here we implement the iid model as described
  ## in inla.doc("iid"), without the scaling-option

  interpret.theta = function(n, theta)
  {
    return (list(prec = exp(theta[1L])))
  }

  graph = function(n, theta)
  {
    G = Diagonal(n, x= rep(1, n))
    return (G)
  }

  Q = function(n, theta)
  {
    prec = interpret.theta(n, theta)$prec
    Q = Diagonal(n, x= rep(prec, n))
    return (Q)
  }

  mu = function(n, theta)
  {
    return(numeric(0))
  }

  log.norm.const = function(n, theta)
  {
    prec = interpret.theta(n, theta)$prec
    val = sum(dnorm(rep(0, n), sd = 1/sqrt(prec), log=TRUE))
    return (val)
  }

  log.prior = function(n, theta)
  {
    prec = interpret.theta(n, theta)$prec
    val = dgamma(prec, shape = 1, rate = 1, log=TRUE) + theta[1L]
    return (val)
  }

  initial = function(n, theta)
  {
    ntheta = 1
    return (rep(1, ntheta))
  }

  quit = function(n, theta)
  {
    return (invisible())
  }

  cmd = match.arg(cmd)
  val = do.call(cmd, args = list(n = as.integer(args$n), theta = theta))
  return (val)
}

```