

# Bayesian animal model using Integrated Nested Laplace Approximations

-A wild house sparrow population case study

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Animal model workshop with application to ecology at Oulu  
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- Lecture
  - Motivating cases
  - Animal models
  - Bayesian inference
  - INLA
  - Animal model and INLA
- Computer exercise 1: `AnimalINLA` R package
- Computer exercise 2: R – INLA package

- In the beginning there was  
GMRFLib  
a C library for fast computations for GMRFs.
- GMRFLib became  
INLA  
a C library for fast approximate inference, accessed through  
.ini files
- After much wailing and gnashing of teeth there came  
R — INLA  
which takes R code and writes an appropriate .ini file for the  
INLA C-program to read. (This is why R — INLA is not on  
CRAN).

- Can be downloaded from <http://www.math.ntnu.no/hrue/GMRFLib/R-INLA/> or [www.r-inla.org](http://www.r-inla.org)
- Available from Unix, Windows and Mac

## The R-INLA project

Search this site

The home of the R-INLA project

Contact us, stay updated, get help or report an error

Discussion forum

Download

Examples and tutorials

- Case studies and code from papers
- Tutorials
- Volume I
- Volume II

FAQ

Getting started

Help

Internal use

Models

- Latent models
- Likelihoods
- Priors
- Tools to manipulate models and likelihoods

News

- 1.5 day INLA-course in Oslo, 5-6 November 2014
- 10th Applied Statistics 2013 International conference, Slovenia
- 3-day INLA course in St Andrews, June 2nd-4th
- Bayes 2013: An International Conference on Bayesian Statistics

## Bayesian computing with INLA:

This site provides documentation to the [R-INLA package](#) which solves a large class of statistical models using the [INLA](#) approach.

[Here](#) is a short introduction describing the class of models which can be solved using R-INLA. All [models](#) implemented in R-INLA are described in details, moreover a large series of worked out [examples](#) are provided and we hope that this will help the user to gain familiarity with the library. Recent changes in the code can be [viewed here](#).

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### Recent posts to the discussion group

Google Group

Hjetp


Det oppstod en feil under kommunikasjon med tjeneren.  
Last inn på nytt

### Recent announcements


**Recent Announcements**

[New paper in applied fisheries ecology using INLA/SPDE](#) A new paper entitled: "Applying Bayesian spatio-temporal models to fisheries bycatch in the Canadian Arctic" is now available online on the Canadian Journal of Fisheries and Aquatic Sciences, 10 ...  
Posted 8 Oct 2014 12:18 by Aurelie Godin

[Two INLA courses in Brasil, October 2014](#) First in Belo Horizonte at DCC/UFMG in 13-14 October, second in Manaus during the week of statistics  
Posted 28 Sep 2014 12:38 by Elias Krainski



**INLA short course in Belo Horizonte 18-19 August 2014** See here for details.  
There will also be a talk about the exiting pc-priors... Håvard  
Posted 15 Aug 2014 14:11 by Håvard Rue



**New comparison paper: logit mixed models** A new paper which discuss and

5/21

All functions are provided with a help file which can be viewed  
using `>?inla`

Else, maybe a bit poor/outdated manuals...

# The structure of an R program using INLA

There are essentially three parts to an INLA program:

- 1 The data organization (important!)
- 2 The *formula* -notation inherited from R's native `glm` function
- 3 The call to the INLA program

## Running INLA on a remote machine

It is also possible to run INLA on a remote (Linux) machine.

- It takes some effort to set up (see the FAQ at [r – inla.org](http://r-inla.org))
- But INLA is programmed using OpenMP and can make use of multiple cores
- The option in the `inla` call is `inla.call = "remote"`

We have a 12 core machine with lots of memory that we use for big problems. It works well!



## Model specification the R-INLA package

The INLA framework supports latent GMRF models of the following type

$$y_i \mid \eta_i, \boldsymbol{\theta}_1 \sim \pi(y_i \mid \eta_i, \boldsymbol{\theta}_1) \quad (1)$$

$$\eta_i \mid \boldsymbol{\theta}_2 = \alpha + \sum_k \beta_k(z_{ki})(\boldsymbol{\theta}_2) + \sum_j f^j(u_{ij})(\boldsymbol{\theta}_2) + \epsilon_i(\boldsymbol{\theta}_2) \quad (2)$$

- $\boldsymbol{x} = (\alpha, f^j(), \beta_k, \epsilon_i, )$  ( $\boldsymbol{\eta}$  a linear combination of  $\boldsymbol{x}$ )
- $\{f^j()\} \sim \mathcal{N}(0, Q_f^{-1}(\tau_2))$ :  
non-linear effects of the covariates  $\boldsymbol{u}$  with unknown functions (structured random effects)
- $\beta_k \sim \mathcal{N}(0, \tau_1^{-1})$ :  
linear effect of covariates  $\boldsymbol{z}$  (fixed effects)
- $\epsilon_i$ :  
unstructured random effect of observation  $i$ .
- $\boldsymbol{\theta} = (\boldsymbol{\theta}_1, \boldsymbol{\theta}_2)$ :  
hyperparameters (likelihood and latent field)

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# The inla function

`inla()`: Performs Bayesian analysis of additive models

```
> result<- inla(  
  formula, # This describes your latent field  
  family ="gaussian", #The likelihood distribution  
  data = dat # A list or dataframe  
  #This is all that is needed for a basic call  
  
  verbose = TRUE, #shows the steps of the process  
  keep = FALSE, #keeps the output)  
  
  #Then there are some "control statements"  
  #that allow you to customise some things  
  control.predictor = list(A = ObservationMatrix)  
  )...
```

# Likelihood functions

- "gaussian" item "gev"
- "binomial"
- "coxph"
- "Exponential"
- "laplace"
- "sn" (Skew Normal)
- "stocvol", "stochvol.nig", "stochvol.t"
- "T"
- "weibull"
- Many others: go to <http://r-inla.org>



# Control statements

The `control.xxx` statements control various parts of the INLA program

- `control.compute`
  - `dic`, `mlik`, `cpo` – Compute measures of fit
- `control.inla`
  - `strategy` and `int.strategy` contain useful advanced features, `dz=1`, `diff.logdens=2.5`, `h=0.01`
- `control.family`
  - `hyper = list(prior = "", param = c(, ), fixed = FALSE)`  
control variance of the likelihood
- `control.mode`
  - `x`,  `$\theta$` , `result`– Gives modes to INLA
  - `restart = TRUE`– Tells INLA to try to improve on the supplied mode

Various other – see help!

## Using different link functions

INLA typically implements the canonical link functions, which, in this case is the logit link. Sometimes, you want other things

- `control.data = list(link = "logit")`
- `control.data = list(link = "probit")`
- `control.data = list(link = "cloglog")`

## formula: specifying the latent field

The latent field is specified using the "standard" R method  
`formula = y ~ 1 + covariate( $\beta$ ) + f(...)`.

- `y` is the name of your data in the data frame
- An intercept is fitted *automatically!* Use `-1` in your formula to avoid it
- The fixed effects (covariates) are taken as i.i.d. normal with a common prior (this can be changed)
- The `f()` function contains the (non-linear) random effect specifications

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## Specifying random effects

Random effects are added to the formula through the function `f(name, model = "...", hyper = ...,)`

`replicate = ..., constr = FALSE, cyclic = FALSE`

- `name`– the name of the random effect. Also refers to the values on the data which are used for various things
- `model`– the latent model. E.g. "iid", "generic0", "rw2", "ar1", etc
- `hyper`– specify the prior on the hyperparameters
- `replicate`– for replicates
- `constr`– Sum to zero constraints?
- `cyclic`– Are you cyclic (RW1, RW2 and AR1)

## formula: specifying the latent field - $f()$

The implemented models are

- `iid`: random effects
- `rw1`, `rw2`, `ar1`: smooth effect of covariates or time effect
- `seasonal`: seasonal effect
- `besag`: spatial effect (CAR model)
- `generic`: user defined precision matrix



## Additional functions of the INLA package

- `summary()`: produces a summary of the main results from a fitted model
- `plot()`: produces some plots from the fitted model
- `$ tab`: all the results/output

# Internal scale-Input/Output

Internal scale:

the precision parameter  $\tau$  is represented as

$$\theta = \log \tau \quad (3)$$

and the prior is defined on  $\theta$ .

## Hyperparameter specification and default values

**hyper**

**theta**

**name** log precision

**short.name** prec

**prior** loggamma

**param** 1 5e-05

**initial** 4

**fixed** FALSE

**to.theta** function(x) log(x)

**from.theta** function(x) exp(x)

## Internal scale-Input/Output

The variances ( $\sigma_a^2$ ) is the inverse of the precision ( $\tau$ )

```
##transform the marginal
marg=inla.tmarginal(function(x) 1/x, model$marginals.hyperp
"Precision for ...")

##Find the expectation and quantiles from transformed margin
inla.emarginal(function(x) x,marg)
inla.qmarginal(c(0.025,0.5,0.975), marg)

##Find DIC
DIC=model$dic$dic
```

## Examples from house sparrow dataset

- Repeated measures-individual random effect
- Non-linear effects
- Maternal effects, covariance
- (Multivariate)

## Computer exercises 2

### Exercises:

- Look at the output from `animal.inla()` - run inla call and formula in R – INLA
- Run with multiple measurements data, find individual random effect, age as RW1 model
- Run different models for maternal effect
  - Look at the summary (plot)
  - Transform the marginals of hyper-parameter to get the variances
  - Take out variables and compare DIC values
  - Find individual breeding values and summary of breeding values (Hint: `model$marginals.random$name[1]`, `model$summary.random$names[1]`)
  - +++