

PRACTICAL 1 - LINEAR (MIXED) MODELS

In this practical we are going to fit linear (mixed) models in inlabru. We are going to to:

- Fit a **simple linear regression**
- Fit a **linear regression with discrete covariates and interactions**
- Fit a linear mixed model.

In all cases we are first going to simulate our data. We then fit the data and explore the results.

Note

You can download the R-script of this practical by clicking the button below:

Start by loading useful libraries:

```
library(dplyr)
library(INLA)
library(ggplot2)
library(patchwork)
library(inlabru)
# load some libraries to generate nice plots
library(scico)
```

1 Simple linear regression

We consider a simple linear regression model with Gaussian observations

$$y_i \sim \mathcal{N}(\mu_i, \sigma^2), \quad i = 1, \dots, N$$

where σ^2 is the observation error, and the mean parameter μ_i is linked to the **linear predictor** (η_i) through an identity function:

$$\eta_i = \mu_i = \beta_0 + \beta_1 x_i.$$

Here $\mathbf{x} = (x_1, \dots, x_N)$ is a continuous covariate and β_0, β_1 are parameters to be estimated.

To finalize the Bayesian model we assign prior distribution as $\tau = 1/\sigma^2 \sim \text{Gamma}(a, b)$ and $\beta_0, \beta_1 \sim \mathcal{N}(0, 1/\tau_\beta)$ (we will use the default prior settings in INLA for now).

Question

What is the dimension of the hyperparameter vector and latent Gaussian field?

Answer

The hyperparameter vector has dimension 1, $\boldsymbol{\theta} = (\tau)$ while the latent Gaussian field $\mathbf{u} = (\beta_0, \beta_1)$ has dimension 2, 0 mean, and sparse precision matrix:

$$Q = \begin{bmatrix} \tau_{\beta_0} & 0 \\ 0 & \tau_{\beta_1} \end{bmatrix}$$

Note that, since β_0 and β_1 are fixed effects, the precision parameters τ_{β_0} and τ_{β_1} are fixed.

i Note

We can write the linear predictor vector $\boldsymbol{\eta} = (\eta_1, \dots, \eta_N)$ as

$$\boldsymbol{\eta} = \mathbf{A}\mathbf{u} = \mathbf{A}_1\mathbf{u}_1 + \mathbf{A}_2\mathbf{u}_2 = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \beta_0 + \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} \beta_1$$

Our linear predictor consists then of two components: an intercept and a slope.

1 Simulate example data

We fix the model parameters β_0, β_1 and the hyperparameter τ_y to a given value and simulate the data accordingly using the code below. The simulated response and covariate data are then saved in a `data.frame` object.

```
# set seed for reproducibility
set.seed(1234)

# Fix the model parameters
beta = c(2,0.5)
sd_error = 0.1

# simulate the data
n = 100
x = rnorm(n)
y = beta[1] + beta[2] * x + rnorm(n, sd = sd_error)

# create the data frame object
df = data.frame(y = y, x = x)
```

1 Fitting a linear regression model with `inlabru`

Step1: Defining model components

The first step is to define the two model components: The intercept and the linear covariate effect.

Task

Define an object called `cmp` that includes and (i) intercept `beta_0` and (ii) a covariate `x` linear effect `beta_1`.

Take hint

The `cmp` object is here used to define model components. We can give them any useful names we like, in this case, `beta_0` and `beta_1`. You can remove the automatic intercept construction by adding a `-1` in the components

[Click here to see the solution](#)

```
cmp = ~ -1 + beta_0(1) + beta_1(x, model = "linear")
```

i Note

Note that we have excluded the default Intercept term in the model by typing `-1` in the model components. However, `inlabru` has automatic intercept that can be called by typing `Intercept()`, which is one of `inlabru` special names and it is used to define a global intercept, e.g.

```
cmp = ~ Intercept(1) + beta_1(x, model = "linear")
```

Step 2: Build the observation model

The next step is to construct the observation model by defining the model likelihood. The most important inputs here are the formula, the family and the data.

Task

Define a linear predictor `eta` using the component labels you have defined on the previous task.

Take hint

The `eta` object defines how the components should be combined in order to define the model predictor.

[Click here to see the solution](#)

```
eta = y ~ beta_0 + beta_1
```

The likelihood for the observational model is defined using the `bru_obs()` function.

Task

Define the observational model likelihood in an object called `lik` using the `bru_obs()` function.

Take hint

The `bru_obs` is expecting three arguments:

- The linear predictor `eta` we defined in the previous task
- The data likelihood (this can be specified by setting `family = "gaussian"`)
- The data set `df`

[Click here to see the solution](#)

```
lik = bru_obs(formula = eta,
              family = "gaussian",
              data = df)
```

Step 3: Fit the model

We fit the model using the `bru()` functions which takes as input the components and the observation model:

```
fit.lm = bru(cmp, lik)
```

Step 5: Extract results

There are several ways to extract and examine the results of a fitted `inlabru` object.

The most natural place to start is to use the `summary()` which gives access to some basic information about model fit and estimates

```
summary(fit.lm)
## inlabru version: 2.13.0.9016
## INLA version: 25.11.22
## Components:
## Latent components:
## beta_0: main = linear(1)
## beta_1: main = linear(x)
## Observation models:
##   Family: 'gaussian'
##   Tag: <No tag>
##   Data class: 'data.frame'
##   Response class: 'numeric'
##   Predictor: y ~ beta_0 + beta_1
##   Additive/Linear: TRUE/TRUE
##   Used components: effects[beta_0, beta_1], latent[]
## Time used:
##   Pre = 0.951, Running = 0.181, Post = 0.0162, Total = 1.15
## Fixed effects:
##           mean    sd 0.025quant 0.5quant 0.975quant  mode kld
## beta_0  2.004 0.01      1.983    2.004      2.024 2.004  0
## beta_1  0.497 0.01      0.477    0.497      0.518 0.497  0
##
## Model hyperparameters:
##                                     mean    sd 0.025quant 0.5quant
## Precision for the Gaussian observations 94.85 13.41      70.43    94.22
##                                     0.975quant  mode
## Precision for the Gaussian observations 122.92 92.96
##
## Marginal log-Likelihood: 63.27
## is computed
## Posterior summaries for the linear predictor and the fitted values are computed
## (Posterior marginals needs also 'control.compute=list(return.marginals.predictor=TRUE)')
```

We can see that both the intercept and slope and the error precision are correctly estimated.

Another way, which gives access to more complicated (and useful) output is to use the `predict()` function.

Below we take the fitted `bru` object and use the `predict()` function to produce predictions for μ given a new set of values for the model covariates or the original values used for the model fit

```
new_data = data.frame(x = c(df$x, runif(10)),
                      y = c(df$y, rep(NA,10)))
pred = predict(fit.lm, new_data, ~ beta_0 + beta_1,
               n.samples = 1000)
```

The `predict()` function generate samples from the fitted model. In this case we set the number of samples to 1000.

2 Plot

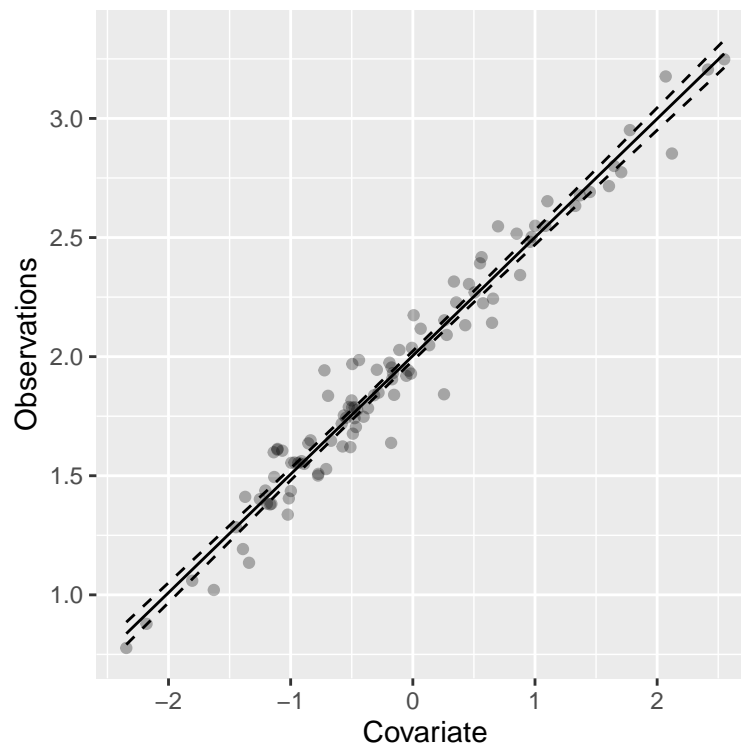


Figure 1: Data and 95% credible intervals

3 R Code

```
pred %>% ggplot() +
  geom_point(aes(x,y), alpha = 0.3) +
  geom_line(aes(x,mean)) +
  geom_line(aes(x, q0.025), linetype = "dashed")+
  geom_line(aes(x, q0.975), linetype = "dashed")+
  xlab("Covariate") + ylab("Observations")
```

Task

Generate predictions for the linear predictor μ when the covariate has value $x_0 = 0.45$.

What is the predicted value for μ ? And what is the uncertainty?

Take hint

You can create a new data frame containing the new observation x_0 and then use the

predict function.

[Click here to see the solution](#)

```
new_data = data.frame(x = 0.45)
pred = predict(fit.lm, new_data, ~ beta_0 + beta_1,
               n.samples = 1000)
```

```
pred
```

```
      x    mean      sd  q0.025    q0.5    q0.975  median sd.mc_std_err
1 0.45 2.22759 0.01158763 2.206017 2.227908 2.249129 2.227908 0.0002438256
mean.mc_std_err
1    0.0003818539
```

You can see the predicted mean and sd by examining the produced pred object. In this case the mean is ca 2.22 with sd ca 0.01. This gives a 95% CI ca [2.20, 2.25].

NOTE Now we have produced a credible interval for the expected mean μ if we want to produce a *prediction* interval for a new observation y we need to add the uncertainty that comes from the likelihood with precision τ_y . To do this we can again use the `predict()` function to compute a 95% prediction interval for y .

```
pred2 = predict(fit.lm, new_data,
               formula = ~ {
                 mu = beta_0 + beta_1
                 sigma = sqrt(1/Precision_for_the_Gaussian_observations)
                 list(q1 = qnorm(0.025, mean = mu, sd = sigma),
                     q2 = qnorm(0.975, mean = mu, sd = sigma))},
               n.samples = 1000)
round(c(pred2$q1$mean, pred2$q2$mean), 2)
```

```
[1] 2.03 2.43
```

Notice that now the interval we obtain is larger.

4 Linear model with interactions