

RESEARCH INSTITUTE  
NATURE AND FOREST



Flanders  
State of  
the Art

# Random intercept models with INLA

Thierry Onkelinx

# Concept of the workshop

- ▶ 5 generic challenges
- ▶ everybody tries to tackle the challenge with own data
- ▶ stuck? ask your neighbour for help
- ▶ still stuck? ask me

slides, code, data and HackMD:

<https://inbo.github.io/tutorials/tutorials/r-inla>



**Flanders**  
State of the Art



RESEARCH INSTITUTE  
NATURE AND FOREST

# Fixed effect model

# Challenge 1

- 1 fit fixed effect model
- 2 extract *WAIC* from the model
- 3 display fixed effect parameters in a table



## Prepare data

```
cars <- data.frame(  
  fuel_consumption = 3.785411784 / 0.01609344 / mtcars$mpg, # liter / 100 km  
  cc = mtcars$disp * 2.54 ^ 3, # engine displacement in cm³  
  gearbox = factor(mtcars$am, levels = 0:1, labels = c("auto", "manual"))  
)  
summary(cars)
```

```
## fuel_consumption      cc      gearbox  
## Min.   : 6.938   Min.   :1165   auto :19  
## 1st Qu.:10.316   1st Qu.:1980   manual:13  
## Median :12.251   Median :3217  
## Mean   :12.755   Mean   :3781  
## 3rd Qu.:15.250   3rd Qu.:5342  
## Max.   :22.617   Max.   :7735
```



# Solution 1

```
library(INLA, quietly = TRUE)
```

```
##  
## Attaching package: 'Matrix'  
  
## The following object is masked from 'package:tidyr':  
##  
##      expand  
  
## This is INLA_18.07.12 built 2019-01-21 15:20:52 UTC.  
## See www.r-inla.org/contact-us for how to get help.  
## To enable PARDISO sparse library; see inla.pardiso()
```

```
model <- inla(fuel_consumption ~ cc * gearbox, data = cars,  
             control.compute = list(waic = TRUE))  
model$waic$waic
```

```
## [1] 140.4934
```



# Parameters

Table: model parameters

|                  | mean     | lcl      | ucl     |
|------------------|----------|----------|---------|
| (Intercept)      | 6.96863  | 4.46417  | 9.47100 |
| cc               | 0.00157  | 0.00108  | 0.00207 |
| gearboxmanual    | -0.92728 | -4.18081 | 2.32436 |
| cc:gearboxmanual | 0.00023  | -0.00068 | 0.00114 |



## Scaling

- ▶ based on mean and standard deviation (standardise)

```
cars$cc_std <- scale(cars$cc)
attr(cars$cc_std, "scaled:center") # reference (cc)
```

```
## [1] 3780.854
```

```
attr(cars$cc_std, "scaled:scale") # scale (cc)
```

```
## [1] 2030.991
```

```
model_std <- inla(fuel_consumption ~ cc_std * gearbox, data = cars,
  control.compute = list(waic = TRUE))
```

- ▶ based on carefully picked values

```
cars$liter <- cars$cc / 1000
cars$liter_c <- cars$liter - 4 # reference = 4 liter = 4000 cc
model_liter <- inla(fuel_consumption ~ liter_c * gearbox, data = cars,
  control.compute = list(waic = TRUE))
```





## Effect on parameters

Table: model parameters for different scaling

| parameter        | mean     | mean_std | mean_liter |
|------------------|----------|----------|------------|
| (Intercept)      | 6.96863  | 12.91607 | 13.26043   |
| cc               | 0.00157  | 3.19316  | 1.57248    |
| gearboxmanual    | -0.92728 | -0.07157 | -0.02142   |
| cc:gearboxmanual | 0.00023  | 0.46172  | 0.22717    |

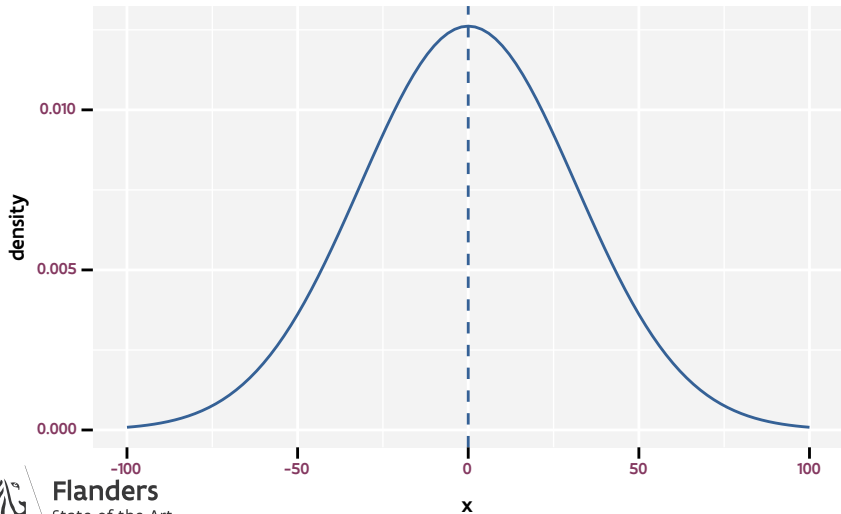
## Challenge 2

- 1 what is the default prior for a fixed effect (`?control.fixed`)
- 2 use a custom prior for a fixed effect (`?inla`)
- 3 specify two linear combinations [r-inla.org](http://r-inla.org), FAQ 17

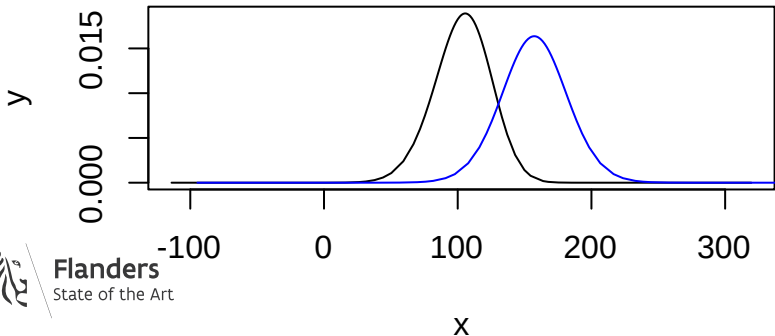


## Default prior for fixed effect

- ▶  $\mu = 0$
- ▶  $\tau = 0.001 \Rightarrow \sigma^2 = 1/\tau = 1000 \Rightarrow \sigma = 31.63$

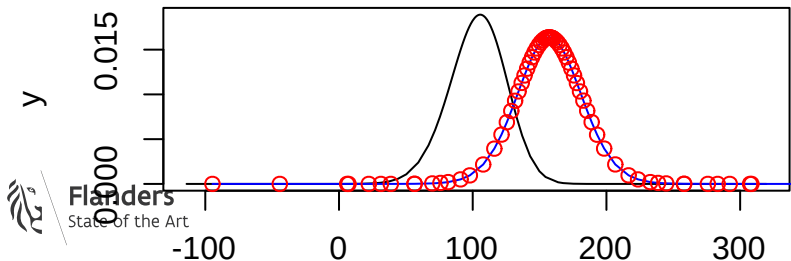


```
cars$extreme <- cars$liter / 100
model_extreme <- inla(fuel_consumption ~ extreme * gearbox, data = cars)
z <- model_liter$marginals.fixed$liter_c
z[, "x"] <- z[, "x"] * 100
z[, "y"] <- z[, "y"] / 100
plot(model_extreme$marginals.fixed$extreme, type = "l")
lines(z, col = "blue")
```



## Change fixed effect prior

```
model_extreme2 <- inla(fuel_consumption ~ extreme * gearbox, data = cars,  
  control.fixed = list(  
    mean = c(extreme = 100),  
    prec = c(extreme = 1e-7, "extreme:gearboxmanual" = 1e-7)))  
plot(model_extreme$marginals.fixed$extreme, type = "l")  
lines(z, col = "blue")  
points(model_extreme2$marginals.fixed$extreme, col = "red")
```



## Linear combinations with fixed effects

```
combinations <- expand.grid(liter = pretty(cars$liter),  
                           gearbox = unique(cars$gearbox)) %>%  
  mutate(liter_c = liter - 4)  
model.matrix(~ liter_c * gearbox, combinations) %>%  
  as.data.frame() %>%  
  inla.make.lincombs() %>%  
  setNames(paste(combinations$gearbox, combinations$liter, sep = ":")) -> lc  
model_lc <- inla(fuel_consumption ~ liter_c * gearbox, data = cars,  
               lincomb = lc, control.compute = list(waic = TRUE))
```



```
model_lc$summary.lincomb #see ?control.inla
```

```
## data frame with 0 columns and 0 rows
```

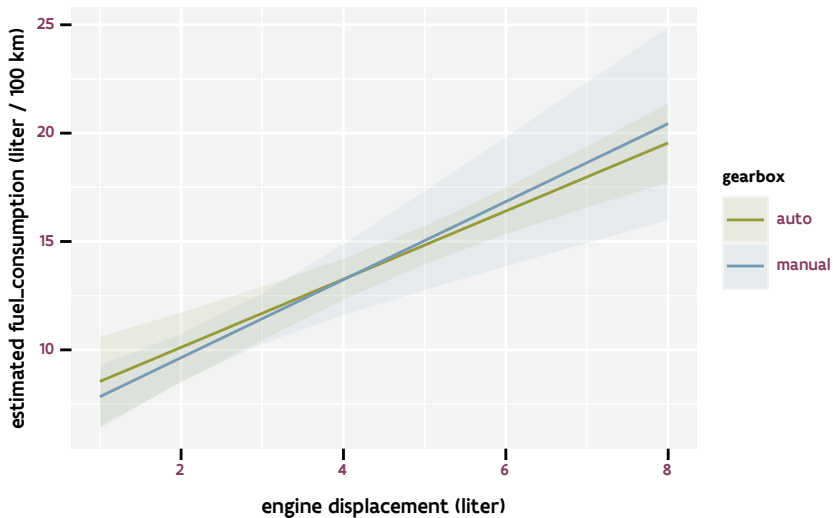
```
model_lc$summary.lincomb.derived
```

|             | ID | mean      | sd        | 0.025quant | 0.5quant  | 0.975quant | mode      | kld |
|-------------|----|-----------|-----------|------------|-----------|------------|-----------|-----|
| ## manual:1 | 1  | 7.840054  | 0.7453199 | 6.366800   | 7.840029  | 9.312251   | 7.840050  | 0   |
| ## manual:2 | 2  | 9.639706  | 0.5482119 | 8.556069   | 9.639688  | 10.722562  | 9.639704  | 0   |
| ## manual:3 | 3  | 11.439357 | 0.5870562 | 10.278942  | 11.439339 | 12.598931  | 11.439358 | 0   |
| ## manual:4 | 4  | 13.239009 | 0.8293357 | 11.599689  | 13.238984 | 14.877135  | 13.239013 | 0   |
| ## manual:5 | 5  | 15.038660 | 1.1532669 | 12.759036  | 15.038626 | 17.316623  | 15.038667 | 0   |
| ## manual:6 | 6  | 16.838312 | 1.5070884 | 13.859298  | 16.838267 | 19.815153  | 16.838321 | 0   |
| ## manual:7 | 7  | 18.637964 | 1.8739451 | 14.933794  | 18.637908 | 22.339430  | 18.637976 | 0   |
| ## manual:8 | 8  | 20.437615 | 2.2474629 | 15.995123  | 20.437549 | 24.876865  | 20.437630 | 0   |
| ## auto:1   | 9  | 8.542993  | 1.0370579 | 6.493097   | 8.542950  | 10.591464  | 8.542964  | 0   |
| ## auto:2   | 10 | 10.115472 | 0.8175051 | 8.499552   | 10.115439 | 11.730265  | 10.115451 | 0   |
| ## auto:3   | 11 | 11.687951 | 0.6213738 | 10.459711  | 11.687927 | 12.915329  | 11.687938 | 0   |
| ## auto:4   | 12 | 13.260430 | 0.4783945 | 12.314805  | 13.260413 | 14.205381  | 13.260424 | 0   |
| ## auto:5   | 13 | 14.832909 | 0.4433763 | 13.956495  | 14.832895 | 15.708684  | 14.832911 | 0   |
| ## auto:6   | 14 | 16.405387 | 0.5378374 | 15.342246  | 16.405374 | 17.467741  | 16.405398 | 0   |
| ## auto:7   | 15 | 17.977866 | 0.7119837 | 16.570485  | 17.977850 | 19.384194  | 17.977884 | 0   |
| ## auto:8   | 16 | 19.550345 | 0.9217037 | 17.728407  | 19.550325 | 21.370915  | 19.550371 | 0   |



**Flanders**  
State of the Art

## Plot linear combinations







RESEARCH INSTITUTE  
NATURE AND FOREST

Flanders  
State of  
the Art

# Random intercept model ('iid')

## Challenge 3

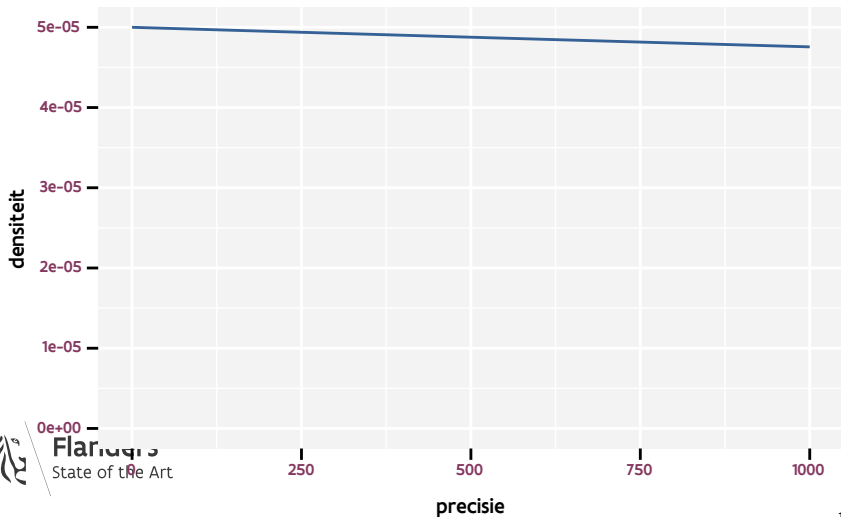
- 1 fit a model with one or more random intercepts (`model = 'iid'`)
- 2 what is the default prior for 'iid' (`inla.doc('iid')`)
- 3 calculate  $\sigma$  for the random intercept
- 4 display the BLUP the random intercept



## Default prior

$$\log \tau \sim \text{logGamma}(1, 0.00005)$$

$$\tau \sim \text{Gamma}(1, 0.00005)$$



## $\sigma$ random intercept

```
read.delim("ButterfliesNEggs_V4.txt") %>%
  mutate(TreeHeight = TreeHeight / 100 - 1,
         Distance2Edge = Distance2Edge / 10 - 1,
         SmallOakAbundance = SmallOakAbundance / 10 - 0.2) -> butterfly
model <- inla(NEggs ~ NLowBranches + TreeHeight + SmallOakAbundance +
             f(Area, model = "iid"), family = "poisson", data = butterfly)
model$summary.hyperpar
```

```
##              mean          sd 0.025quant 0.5quant 0.975quant      mode
## Precision for Area 1.154638 0.6190456  0.3574407 1.023218  2.714477 0.7995142
```

```
to_sigma <- function(tau){sqrt(1/tau)}
model$marginals.hyperpar$`Precision for Area` %>%
  inla.tmarginal(fun = to_sigma) %>%
  inla.zmarginal()
```

```
## Mean          1.02743
## Stdev         0.272553
## Quantile 0.025 0.607468
## Quantile 0.25  0.83313
## Quantile 0.5   0.98818
## Quantile 0.75  1.17742
## Quantile 0.975 1.67119
```



Flanders

State of the Art

# Best Linear Unbiased Predictor (BLUP)

```
glimpse(model$summary.random$Area)
```

```
## Observations: 22
## Variables: 8
## $ ID          <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16,...
## $ mean        <dbl> -0.70876380, 0.89228904, -0.35082396, -0.67654342, -0....
## $ sd          <dbl> 0.5554291, 0.4237639, 0.6676452, 0.8143332, 0.8270883,...
## $ `0.025quant` <dbl> -1.87289647, 0.10071051, -1.76737211, -2.48509876, -2....
## $ `0.5quant`   <dbl> -0.68655883, 0.87658241, -0.31935080, -0.61132373, -0....
## $ `0.975quant` <dbl> 0.3289457, 1.7741420, 0.8840476, 0.7496895, 0.8490009,...
## $ mode        <dbl> -0.64488601, 0.84680983, -0.26408689, -0.50262798, -0....
## $ kld         <dbl> 4.131327e-05, 1.788192e-04, 3.417066e-05, 9.033027e-05...
```



## Challenge 4

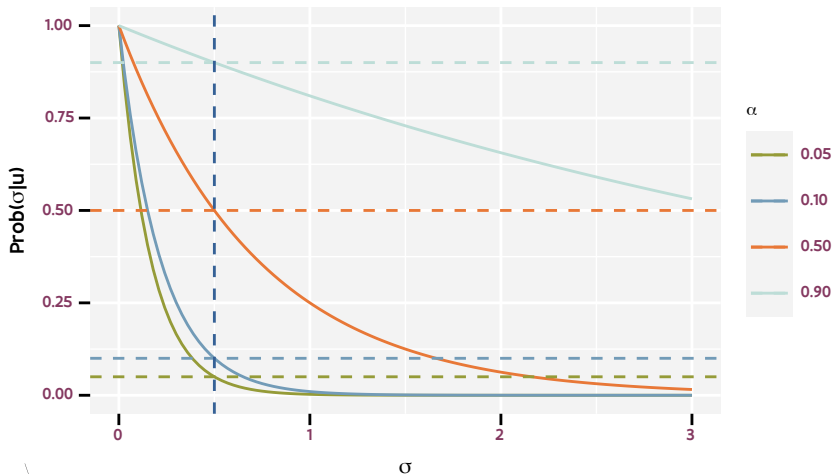
- 1 Think about the relevant magnitude of  $\sigma$  for your random effect
- 2 Use a custom “pc.prec” prior with that  $\sigma$  (`inla.doc("pc.prec")`)



## Penalised Complexity prior

$\text{Prob}(\sigma > u) = \alpha$  met  $u > 0$  en  $0 < \alpha < 1$

$u = 0.5$



**Flanders**  
State of the Art

# inlatools package

<https://inlatools.netlify.com>

```
remotes::install_github("inbo/inlatools")
```

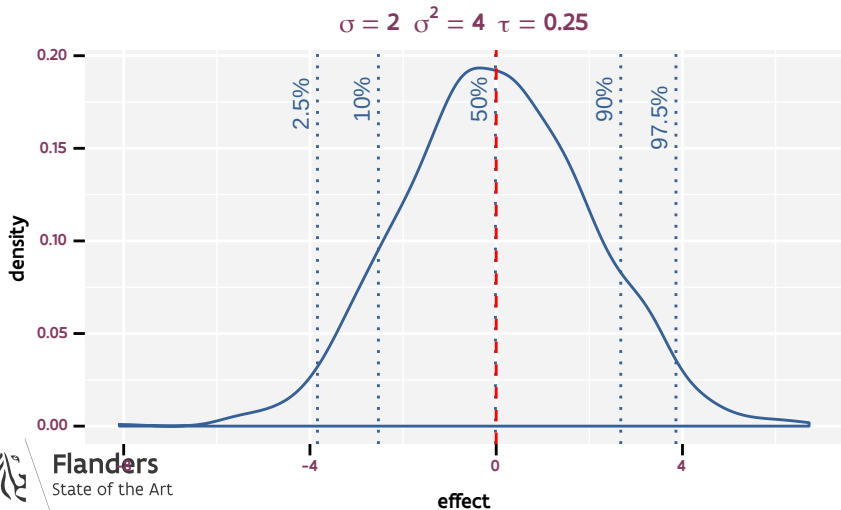
- ▶ assessing  $\sigma$  random intercept
- ▶ assessing  $\sigma$  random walk
- ▶ check dispersion
- ▶ check distribution
- ▶ extract fitted values, observed values, Pearson residuals





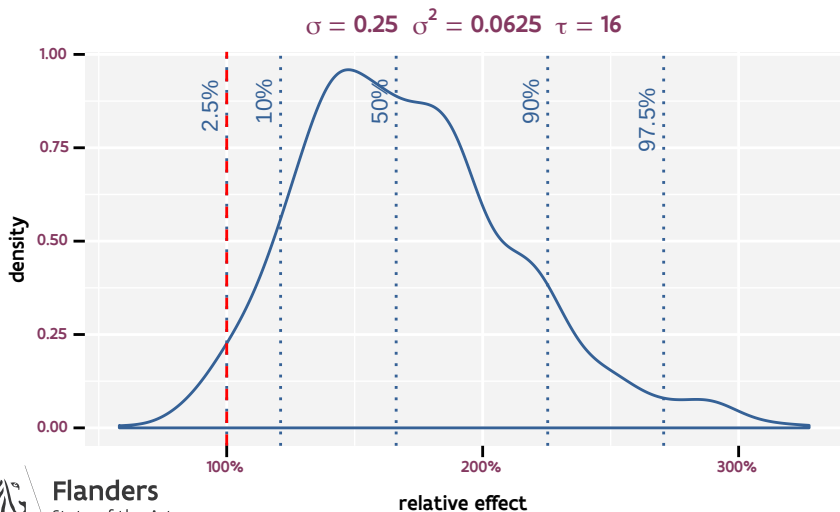
## Assessing $\sigma$ random intercept

```
library(inlatools)  
plot(simulate_iid(sigma = 2))
```



## Assessing $\sigma$ random intercept with link and center

```
plot(simulate_iid(tau = 16), link = "log", center = "bottom")
```



**Flanders**  
State of the Art

## Solution 4

```
model_pc <- inla(NEggs ~ NLowBranches + TreeHeight + SmallOakAbundance +  
  f(Area, model = "iid",  
    hyper = list(  
      theta = list(prior = "pc.prec", param = c(0.1, 0.05))),  
  family = "poisson", data = butterfly)  
model_pc$marginals.hyperpar$`Precision for Area` %>%  
  inla.tmarginal(fun = to_sigma) %>%  
  inla.zmarginal()
```

```
## Mean          0.491791  
## Stdev         0.0881641  
## Quantile 0.025 0.335646  
## Quantile 0.25  0.429468  
## Quantile 0.5   0.48571  
## Quantile 0.75  0.547405  
## Quantile 0.975 0.681398
```



# Check dispersion

```
plot(dispersion_check(model_pc))
```

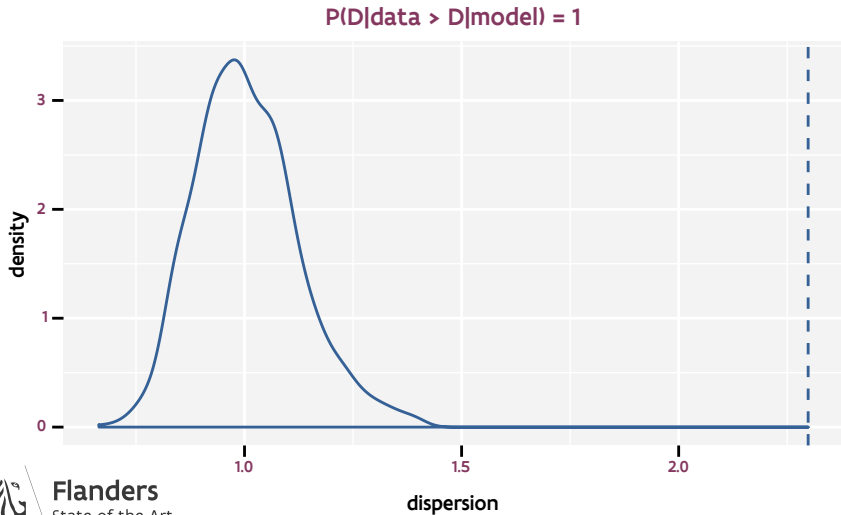
```
## Error in fitted(object): no fitted values in object.  
## Refit the object with 'control.predictor = list(compute = TRUE)'
```

```
model_pc <- inla(NEggs ~ NLowBranches + TreeHeight + SmallOakAbundance +  
  f(Area, model = "iid",  
    hyper = list(  
      theta = list(prior = "pc.prec", param = c(0.1, 0.05))),  
  family = "poisson", data = butterfly,  
  control.predictor = list(compute = TRUE))
```



## Clear overdispersion

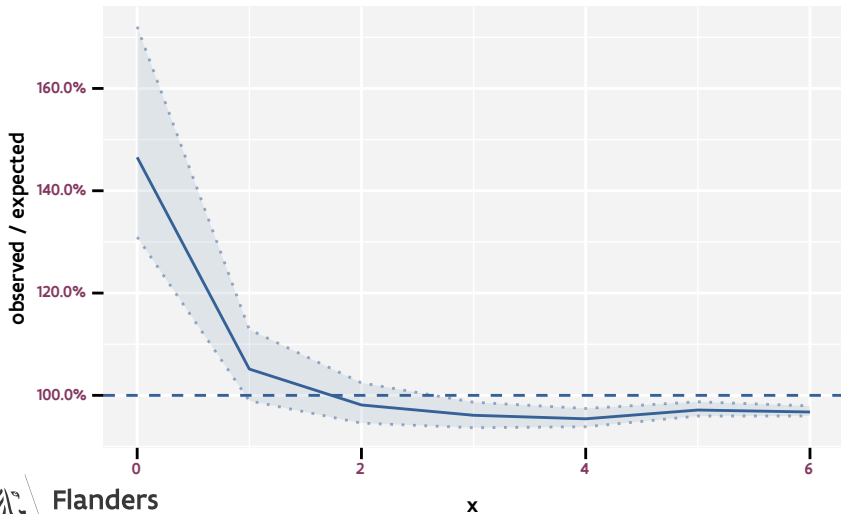
```
plot(dispersion_check(model_pc))
```



**Flanders**  
State of the Art

## Excess of zeros

```
plot(fast_distribution_check(model_pc))
```



**Flanders**  
State of the Art

## Linear combinations including random intercept

Create a matrix for each random effect

- ▶ 1 row per linear combination
- ▶ 1 column per random effect level

```
Area <- matrix(0, nrow = 3, ncol = 22)
Area[1, 5] <- 1
Area[2, c(3, 4)] <- c(1, -1)
Area[3, ] <- 1 / 22
lc1 <- inla.make.lincombs(NLowBranches = c(2, 0, 1), Area = Area)
names(lc1) <- c("Area 5", "Area 3 - Area 4", "average area")
lc2 <- inla.make.lincombs(NLowBranches = 1)
names(lc2) <- "fixed only"
lc <- c(lc1, lc2)
str(lc, 1)
```

```
## List of 4
## $ Area 5          :List of 2
## $ Area 3 - Area 4:List of 2
## $ average area    :List of 2
## $ fixed only      :List of 1
```



**Flanders**  
State of the Art

```

model_lc <- inla(NEggs ~ NLowBranches + TreeHeight + SmallOakAbundance +
  f(Area, model = "iid",
    hyper = list(
      theta = list(prior = "pc.prec", param = c(0.1, 0.05))),
  family = "poisson", data = butterfly, lincomb = lc)
model_lc$summary.lincomb.derived # estimate are always on the link scale!

```

| ##                 | ID | mean       | sd         | 0.025quant | 0.5quant   | 0.975quant |
|--------------------|----|------------|------------|------------|------------|------------|
| ## Area 5          | 1  | 0.75712122 | 0.47095877 | -0.1984497 | 0.76622380 | 1.6625693  |
| ## Area 3 - Area 4 | 2  | 0.04482048 | 0.58720259 | -1.1049607 | 0.04018034 | 1.2205331  |
| ## average area    | 3  | 0.54350370 | 0.13484111 | 0.2784505  | 0.54317773 | 0.8100311  |
| ## fixed only      | 4  | 0.52613809 | 0.08243795 | 0.3642870  | 0.52613415 | 0.6878707  |
| ##                 |    | mode       | kld        |            |            |            |
| ## Area 5          |    | 0.78398220 | 0          |            |            |            |
| ## Area 3 - Area 4 |    | 0.03151894 | 0          |            |            |            |
| ## average area    |    | 0.54263242 | 0          |            |            |            |
| ## fixed only      |    | 0.52613313 | 0          |            |            |            |





## Back transform to natural scale

```
exp(model_lc$summary.lincomb.derived["average area", 4:6])
```

```
##              0.025quant 0.5quant 0.975quant  
## average area   1.321081 1.721469   2.247978
```

```
inla.tmarginal(exp, model_lc$marginals.lincomb.derived$`average area`) %>%  
  inla.zmarginal()
```

```
## Mean              1.73754  
## Stdev             0.234051  
## Quantile 0.025    1.32279  
## Quantile 0.25     1.57399  
## Quantile 0.5      1.72106  
## Quantile 0.75     1.88237  
## Quantile 0.975    2.24489
```





RESEARCH INSTITUTE  
NATURE AND FOREST

Flanders  
State of  
the Art

# First order random walk model ('rw1')

## Definition

$$\Delta x_i = x_i - x_{i-1} \sim \mathcal{N}(0, \sigma^2)$$

$$x_i \sim \mathcal{N}(x_{i-1}, \sigma^2)$$

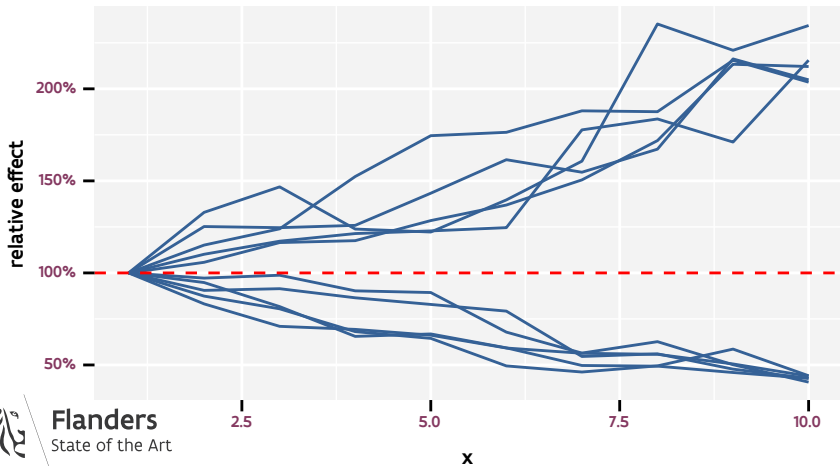
```
inla.doc("rw1")
```

- ▶ Useful in case of non-linear patterns in discrete variables (year, day, ...)
- ▶ Works with discretised continuous variables (e.g. after rounding)

## Divergent series

```
rw1 <- simulate_rw(sigma = 0.1)
plot(select_divergence(rw1), link = "log")
```

$$\sigma = 0.1 \quad \sigma^2 = 0.01 \quad \tau = 100$$

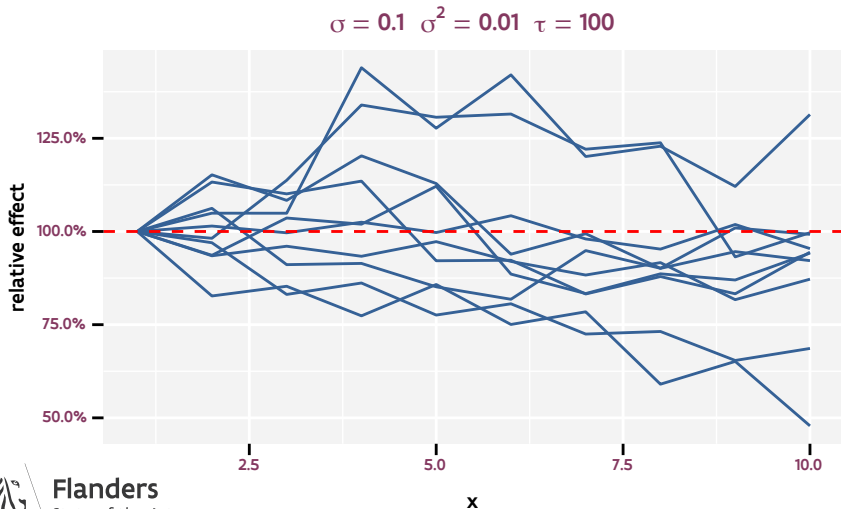


**Flanders**  
State of the Art

x

## Series with frequency change in direction

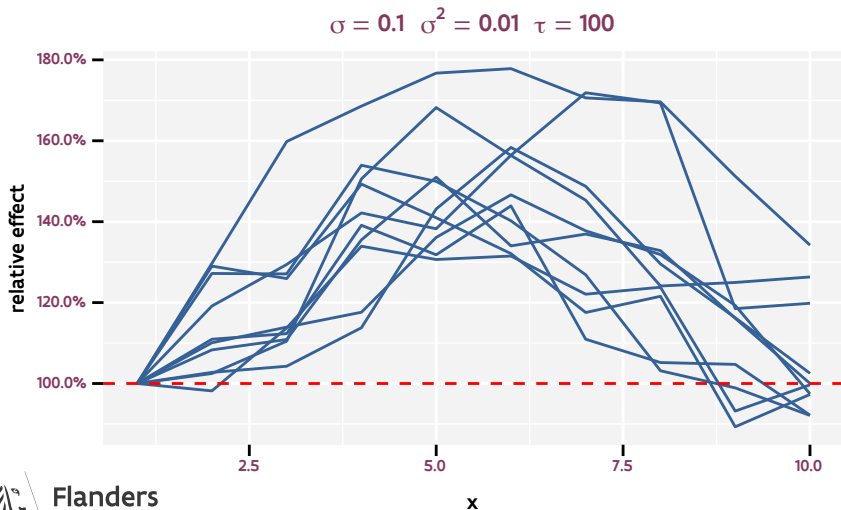
```
plot(select_change(rw1), link = "log")
```



**Flanders**  
State of the Art

## Series with central maximum

```
plot(select_poly(rw1, coefs = c(0, -1)), link = "log")
```



**Flanders**  
State of the Art

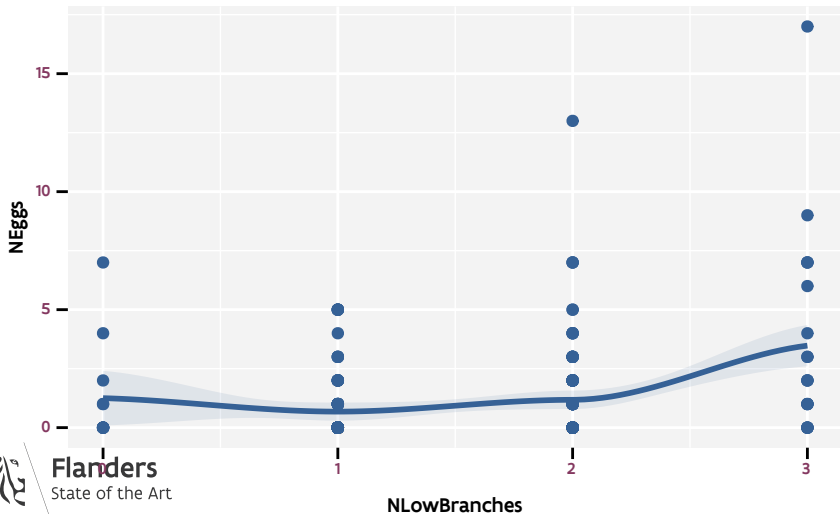
## Challenge 5

- 1 pick a relevant variable for an 'rw1' model
- 2 ponder on a relevant  $\sigma$  for that model
- 3 fit model with 'rw1' component and `pc.prec` prior



## Data exploration NLowBranches

```
ggplot(butterfly, aes(x = NLowBranches, y = NEggs)) +  
  geom_smooth() + geom_point()
```



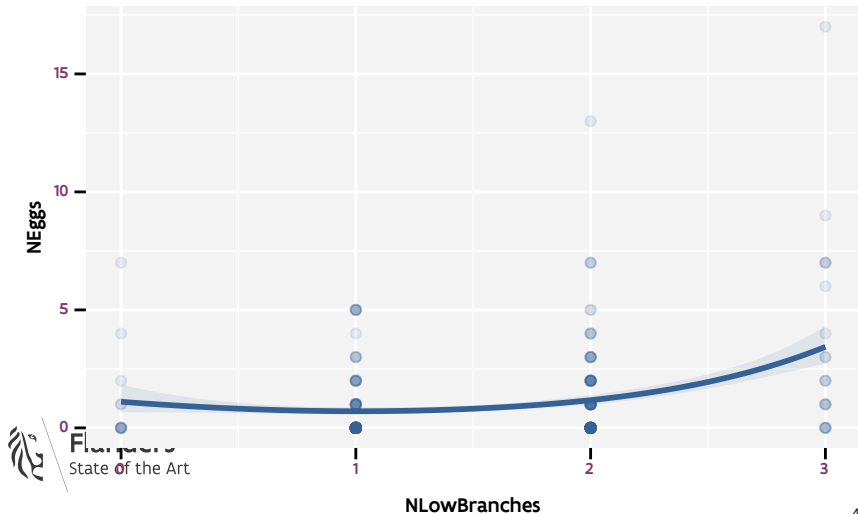
Flanders  
State of the Art

NLowBranches



## Data exploration NLowBranches

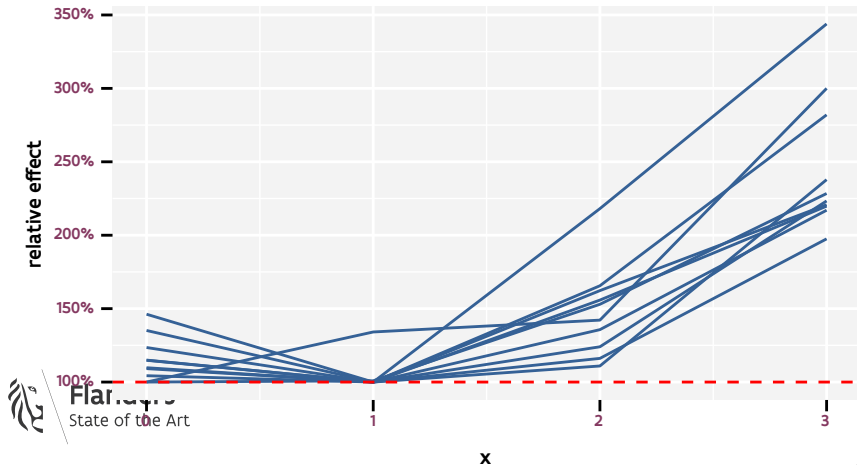
```
ggplot(butterfly, aes(x = NLowBranches, y = NEggs)) +  
  geom_smooth(method = "gam", formula = y ~ s(x, bs = "cs", k = 4),  
    method.args = list(family = poisson)) + geom_point(alpha = 0.1)
```



## Relevant $\sigma$ for prior NLowBranches

```
simulate_rw(sigma = 0.25, start = 0, length = 4) %>%  
  select_poly(coef = c(1, 1)) %>%  
  plot(link = "log", center = "bottom")
```

$$\sigma = 0.25 \quad \sigma^2 = 0.0625 \quad \tau = 16$$

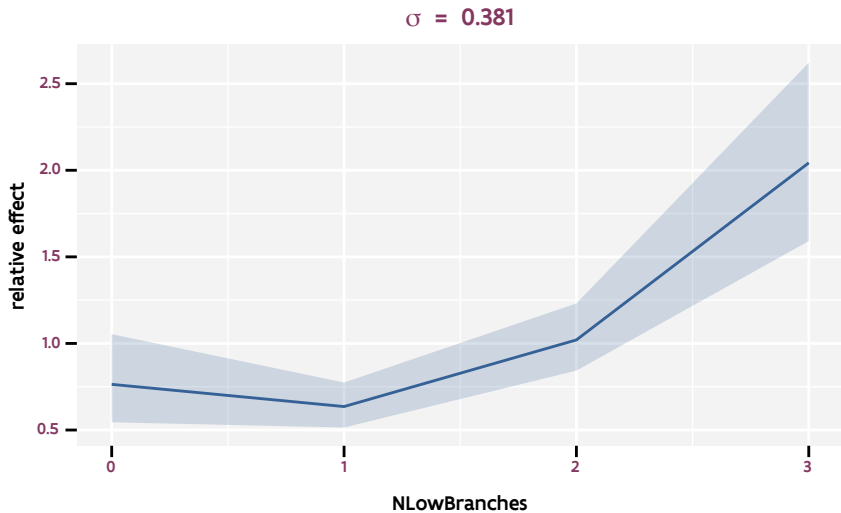


## Solution 5

```
model_rw1 <- inla(NEggs ~ TreeHeight + SmallOakAbundance +  
  f(NLowBranches, model = "rw1",  
    hyper = list(  
      theta = list(prior = "pc.prec", param = c(0.25, 0.05)))) +  
  f(Area, model = "iid",  
    hyper = list(  
      theta = list(prior = "pc.prec", param = c(0.1, 0.05)))),  
  family = "poisson", data = butterfly,  
  control.predictor = list(compute = TRUE))
```



## Non-linear pattern NLowBranches



**Flanders**  
State of the Art