Introduction to Bayesian linear regression with brms

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[mention installation]

Random variables

- We have a question about the world, so we collect data (sample from a population).
  - y $= (y_1, y_2, y_3, y_4, ..., y_n)$
- We want to know how the data (the sample) was generated.
- In probability theory, data is generated by a random variable Y.

Random variables

- Y is uncertain.
    - We can describe Y as a probability distribution, expressed by a set of parameters $\Theta = (\theta_1, ..., \theta_n)$.
- Probability distributions:
    - $Normal(\mu, \sigma)$,
    - $Binomial(n, p)$,
    - ...

Random variables

$$vot_i \sim Normal(\mu, \sigma)$$

$$voiced_i \sim Bernoulli(p)$$

$$DoubleDative_i \sim Poisson(\lambda)$$

Frequentist vs Bayesian view

- Parameters: μ, σ, p, λ, ...
- Frequentist view:
  - The parameters are **fixed** (they are unknown but certain).
  - They take on a specific value.
- Bayesian view:
  - The parameters are **random variables** (they are unkown and uncertain).
  - We describe each parameter as a probability distribution, expressed by a set of **hyperparameters**.

Continous random variable

$$vot_i \sim Normal(\mu, \sigma)$$

$$\mu \sim Normal(\mu_1, \sigma_1)$$

$$\sigma \sim HalfCauchy(x_0, \gamma)$$

Bayes' Theorem

$$P(\theta \mid d) = \frac{P(d \mid \theta)\, P(\theta)}{P(d)}$$

Bayes' Theorem

$$posterior\ probability = \frac{likelihood \times prior}{marginal\ likelihood}$$

Priors

- We can incorporate previous knowledge about the hyperparameters as **priors** (prior distributions).
- Priors are chosen based on expert knowledge, previous studies, pilot data…
    - Priors must **not** be chosen based on the data to be analysed.

Priors

- Informative and weakly informative priors.
- Uninformative or diffuse priors.
    - Uniform distribution.
- Regularising priors.

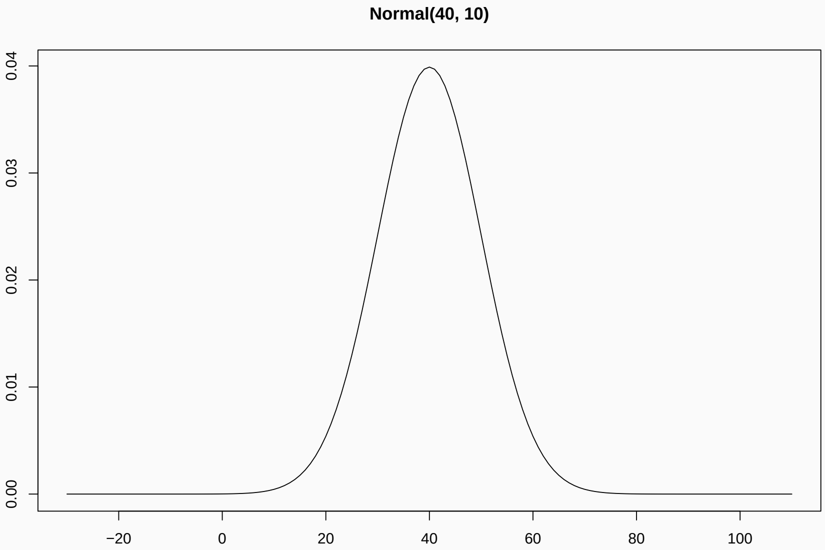
Normal prior

[empirical rule]

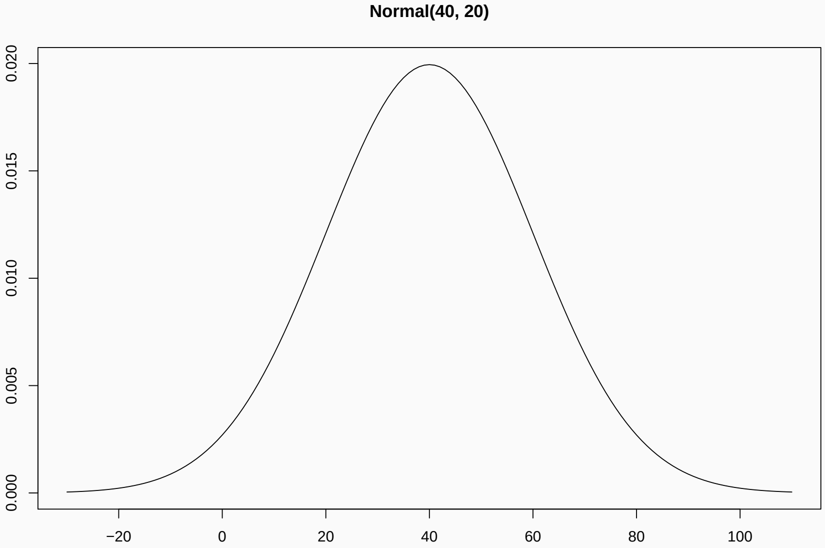
Italian VOT

- Previous literature on VOT in Italian (Esposito, 2002; Stevens & Hajek, 2010) report VOT values for voiceless stops in the range of 20–60 ms.
    - We can express this knowledge with the prior $Normal(40, 10)$.
    - This is a somewhat strongly informative prior.

Italian VOT



Italian VOT



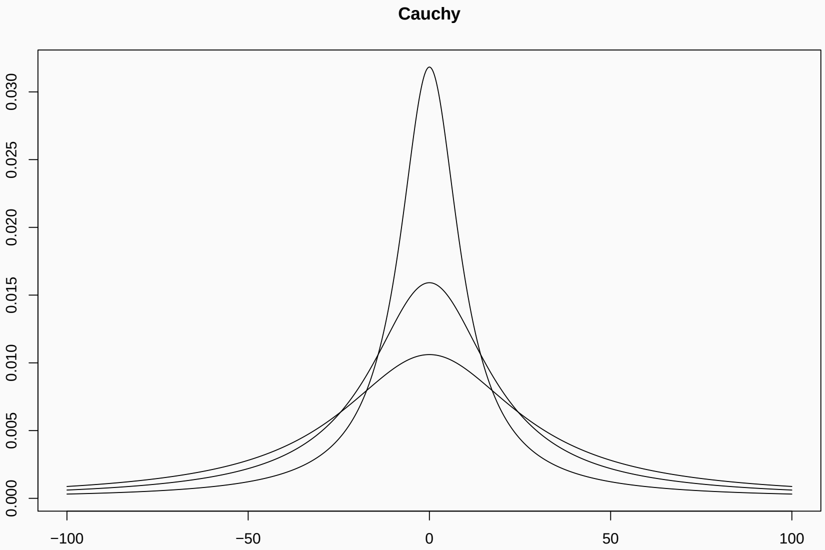
Italian VOT

$$vot_i \sim Normal(\mu, \sigma)$$

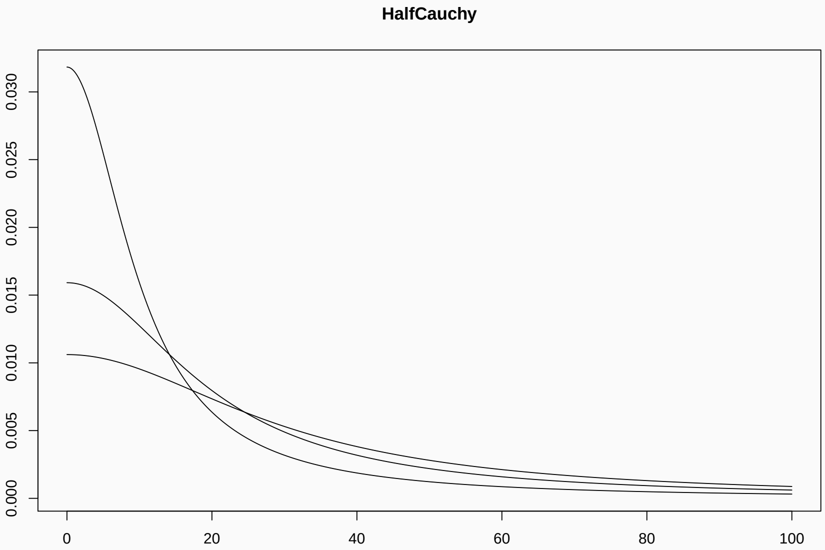
$$\mu \sim Normal(40, 10)$$

$$\sigma \sim HalfCauchy(x_0, \gamma)$$

Cauchy prior



Cauchy prior



Italian VOT

$$vot_i \sim Normal(\mu, \sigma)$$

$$\mu \sim Normal(40, 10)$$

$$\sigma \sim HalfCauchy(0, 10)$$

Italian VOT

- We have a model which incorporates (some of) our knowledge about VOT (through the priors for μ and σ).
- Now we want to obtain the **posterior distributions** of μ and σ.
    - The posterior distribution is the prior distribution *conditioned* on the data.
- **brms** R package: Bayesian Regression Models using Stan (Bürkner, 2018).

brms

- Stan (Stan Development Team, 2017).
  - Statistical programming language written in C++ for fitting Bayesian models (calculate posterior distributions).
  - Calculation can be complex and/or impossible, so we take many samples from the data and from the possible parameter values to find the posterior distributions of the hyperparameters.
  - Markov Chain Monte Carlo (MCMC) sampling using the No-U-Turn sampler (NUTS).
- brms is an interface between R and Stan.
- `brm()` function from brms.
  - lme4 syntax (`y ~ x + (1|w)`).
  - Creates a Stan model, which is compiled and run.

brms

```
library(brms)

vot1 <- brm(
  <model_formula>,
  <family>,
  <prior>,
  <data>,
  chains = 4,
  iter = 2000
)
```

brms

```
library(brms)

vot1 <- brm(
  vot ~ 1,
  family = gaussian(),
  <prior>,
  data = ita_egg,
  chains = 4,
  iter = 2000
)
```

Get prior

```
get_prior(
  vot ~ 1,
  family = gaussian(),
  data = ita_egg
)
```

```
##                  prior     class coef group resp dpa
## 1 student_t(3, 19, 14) Intercept
## 2  student_t(3, 0, 14)     sigma
```

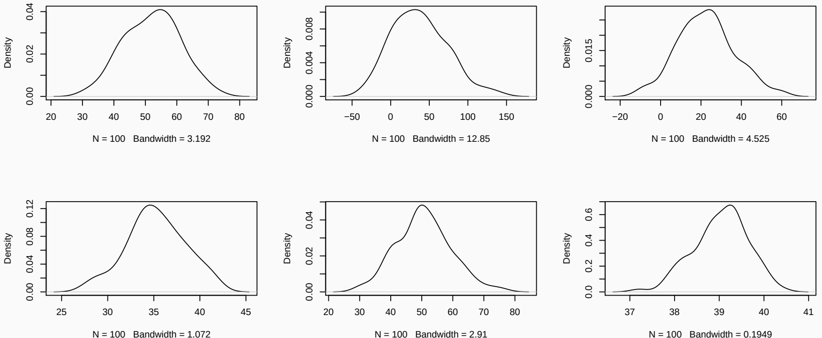
Set prior

Prior predictive checks

```r
nsim <- 1000
nobs <- 100

y <- matrix(rep(NA, nsim * nobs), ncol = nobs)

mu <- rnorm(nsim, 40, 10)
sigma <- rhcauchy(nsim, 10)

for (i in 1:nsim) {
  y[i,] <- rnorm(nobs, mean = mu[i], sd = sigma[i])
}
```

Prior predictive checks

```r
op <- par(mfrow = c(3, 3))
rand_sample <- sample(1:nsim, 9)

for (i in rand_sample) {
  plot(density(y[i,]), main = "")
}
```



Run the model

```r
vot1 <- brm(
  vot ~ 1,
  family = gaussian(),
  prior = priors,
  data = ita_egg,
  chains = 4,
  iter = 2000,
  file = "./cache/vot1"
)
```

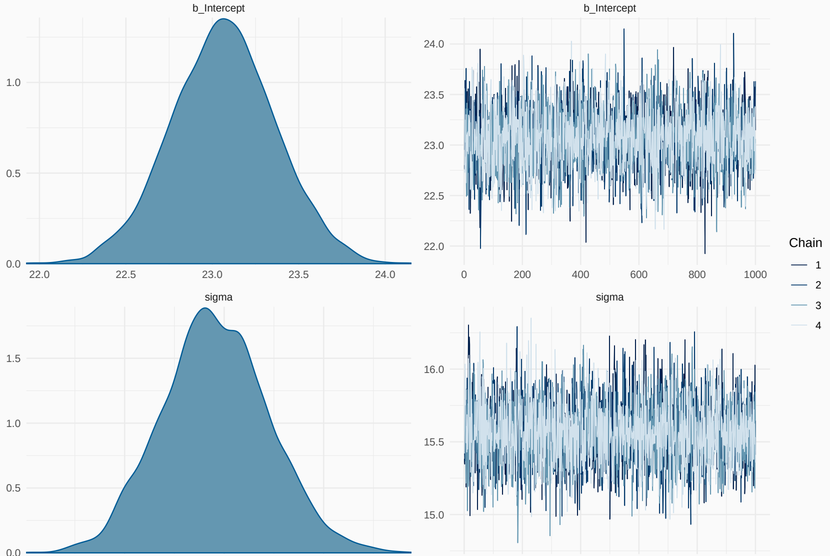
Model summary

```
vot1
```

```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: vot ~ 1
##    Data: ita_egg (Number of observations: 2624)
## Samples: 4 chains, each with iter = 2000; warmup =
##          total post-warmup samples = 4000
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI Rhat
## Intercept    23.06      0.30    22.47    23.65 1.00
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat
```

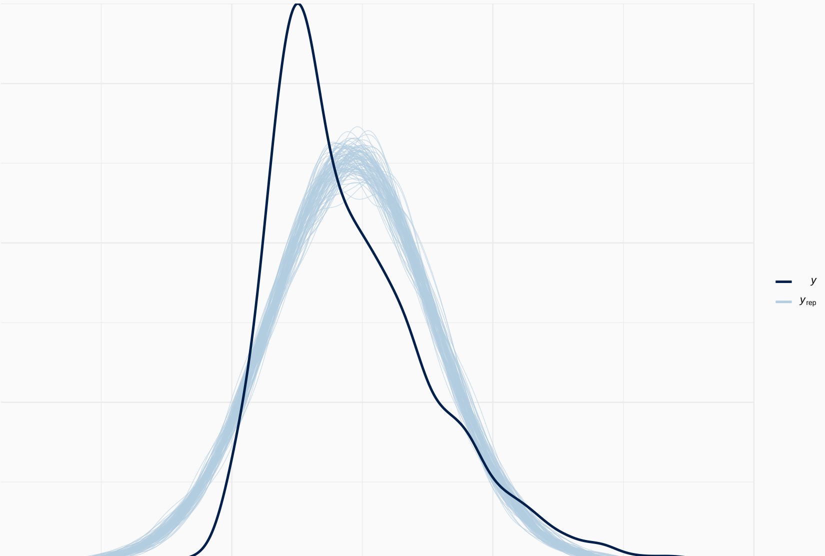
Plot model

```
plot(vot1)
```



Posterior predictive check

```r
pp_check(vot1, nsamples = 100)
```



Adding predictors

$$vot_i \sim Normal(\mu_i, \sigma)$$

$$\mu_i = \alpha + \beta_1 \times coronal_i + \beta_2 \times velar_i$$

$$\alpha \sim Normal(\mu_1, \sigma_1)$$

$$\beta_1 \sim Normal(\mu_2, \sigma_2)$$

$$\beta_2 \sim Normal(\mu_3, \sigma_3)$$

$$\sigma \sim HalfCauchy(x_0, \gamma)$$

Adding predictors

$$vot_i \sim Normal(\mu_i, \sigma)$$

$$\mu_i = \alpha + \beta_1 \times coronal_i + \beta_2 \times velar_i$$

$$\alpha \sim Normal(25, 10)$$

$$\beta_1 \sim Normal(10, 10)$$

$$\beta_2 \sim Normal(20, 10)$$

$$\sigma \sim HalfCauchy(0, 10)$$

Get prior

```
##                      prior     class               coef gro
## 1                                   b
## 2                                   b c1_placecoronal
## 3                                   b   c1_placevelar
## 4 student_t(3, 19, 14) Intercept
## 5  student_t(3, 0, 14)     sigma
```

Set prior

Run the model

```r
vot2 <- brm(
  vot ~ 1 + c1_place,
  family = gaussian(),
  prior = priors,
  data = ita_egg,
  chains = 4,
  iter = 2000,
  file = "./cache/vot2"
)
```

Random effects

```
##                     prior     class              coef
## 1                                 b
## 2                                 b c1_placecoronal
## 3                                 b   c1_placevelar
## 4                  lkj(1)       cor
## 5                                 cor                 sp
## 6  student_t(3, 19, 14) Intercept
## 7   student_t(3, 0, 14)        sd
## 8                                sd                 sp
## 9                                sd c1_placecoronal sp
## 10                               sd   c1_placevelar sp
## 11                               sd       Intercept sp
## 12  student_t(3, 0, 14)     sigma
```

Random effects

Random effects

```
vot3 <- brm(
  vot ~ 1 + c1_place + (1 + c1_place | speaker),
  family = gaussian(),
  prior = priors,
  data = ita_egg,
  chains = 4,
  iter = 2000,
  file = "./cache/vot3"
)
```

References

Bürkner, Paul-Christian. 2018. Advanced Bayesian multilevel modeling with the R package brms. *The R Journal* 10(1). 395–411. doi:10.32614/RJ-2018-017.

Esposito, Anna. 2002. On vowel height and consonantal voicing effects: Data from Italian. *Phonetica* 59(4). 197–231. doi:10.1159/000068347.

Stan Development Team. 2017. Stan: A C++ library for probability and sampling, version 2.14.0. http://mc-stan.org/.

Stevens, Mary & John Hajek. 2010. Post-aspiration in standard Italian: some first cross-regional acoustic evidence. Paper presented at Interspeech, 26-30 September 2010, Makuhari, Chiba, Japan.