

# Introduction to Bayesian linear regression with brms — Part II: Bayesian Inference

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# Road map

1. Statistical inference.

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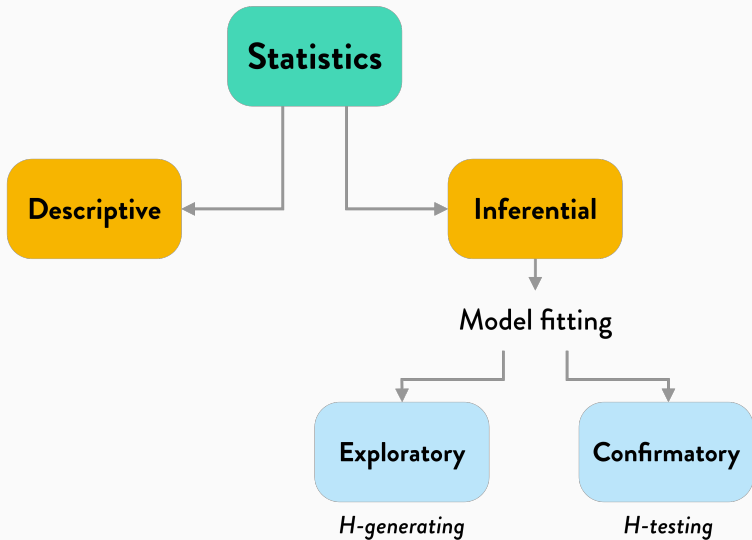
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  - 3.3 Bayes factors.

# STATISTICAL INFERENCE





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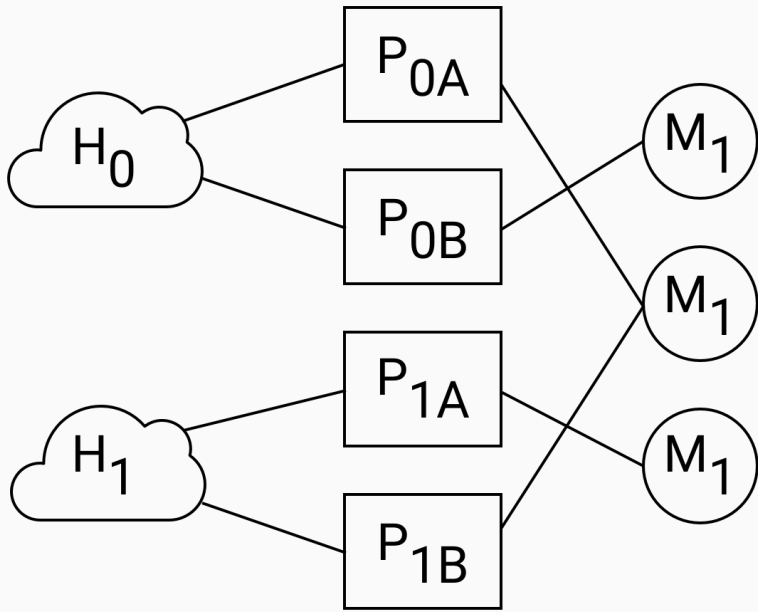
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- We test  $H$  against empirical data (**hypothesis testing**).
  - It is important to decide in advance the details of the analysis.
  - Even when you think you are not making decisions, the model is.
- Inference is ultimately a **long-term endeavour** (via accumulation of knowledge).

# Hypothesis testing





# FREQUENTIST INFERENCE

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  - lme4 package.
  - **Null Hypothesis Significance Testing.**

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  - Should be as low as possible.

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- No degrees of significance.
- “Significance” is a concept that makes sense only within frequentist statistics (NHST).

## (Frequentist) confidence intervals

<https://rpsychologist.com/d3/ci/>

# BAYESIAN INFERENCE

Bayesian statistics is based on the Bayesian interpretation of the **Bayes theorem**.

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

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# Bayesian inference

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- Strength of evidence.
- Capitalise on previous knowledge.

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  - The posterior is **not compatible with H**.

## H0 vs H1

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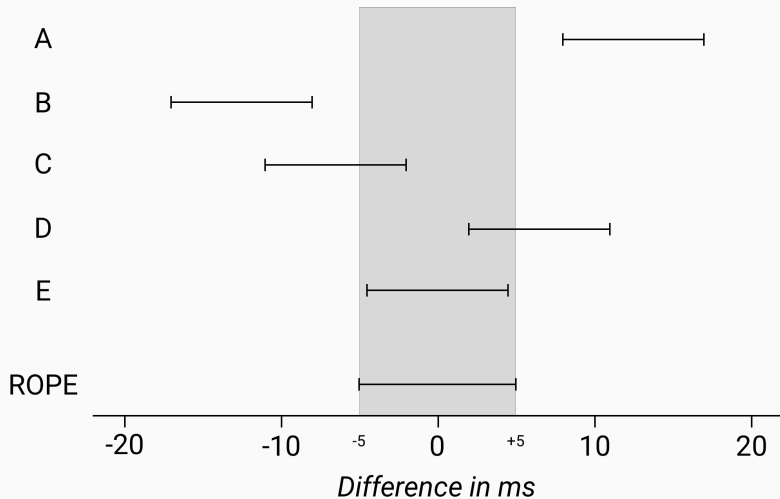
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  - This ROPE has a width of 10 ms.
- Collect data until the 95% CI of  $\beta$  has a width equal to or smaller than the width of the ROPE.
  - Choose a minimal sample size (ideally based on a prospective power analysis).
  - Collect data and check 95% CI. If the width is greater than the ROPE, collect more data and repeat (*sequential testing*).

# Inference with a ROPE



- We focus on the estimate **precision** of  $\beta$ .

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- We focus on the estimate **precision** of  $\beta$ .
- Independent from the value of  $\beta$ .
- Higher precision means greater confidence in the estimated value of  $\beta$ .

The Bayes factor is the ratio of the likelihood of  $H_1$  to the likelihood of  $H_2$ .

$$BF_{12} = \mathcal{L}(H_1) / \mathcal{L}(H_2)$$

# Bayes Factor

BF	$p(M1 D)$	evidence
1–3	0.5–0.75	weak
3–20	0.75–0.95	positive
20–150	0.95–0.99	strong
> 150	> 0.99	very strong

```
priors <- c(  
  prior(normal(0, 500), class = Intercept),  
  prior(cauchy(0, 15), class = sigma),  
  prior(normal(0, 750), class = b, coef = "vowel_o"),  
  prior(normal(0, 750), class = b, coef = "vowel_u"),  
  prior(cauchy(0, 15), class = sd),  
  prior(lkj(2), class = cor)  
)
```

## Bayes Factor

```
f1_3_bf <- brm(  
  f1 ~ 1 + vowel + (1 + vowel | speaker),  
  family = gaussian(),  
  prior = priors,  
  data = f_end,  
  chains = 4,  
  iter = 2000,  
  file = "./cache/f1_3_bf",  
  save_all_pars = TRUE  
)
```

# Bayes Factor

```
priors <- c(  
  prior(normal(0, 500), class = Intercept),  
  prior(cauchy(0, 15), class = sigma),  
  prior(normal(0, 750), class = b, coef = "vowel_o"),  
  prior(normal(0, 750), class = b, coef = "vowel_u"),  
  prior(normal(0, 750), class = b, coef = "c2_placevelar"),  
  prior(cauchy(0, 15), class = sd),  
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)
```

# Bayes Factor

```
f1_3_place <- brm(  
  f1 ~ 1 + vowel + c2_place + (1 + vowel + c2_place | sp  
  family = gaussian(),  
  prior = priors,  
  data = f_end,  
  chains = 4,  
  iter = 2000,  
  file = "./cache/f1_3_place",  
  save_all_pars = TRUE  
)
```

## Bayes Factor

```
bf <- bayes_factor(f1_3_bf, f1_3_place)
```

```
## Iteration: 1
```

```
## Iteration: 2
```

```
## Iteration: 3
```

```
## Iteration: 4
```

```
## Iteration: 5
```

```
## Iteration: 6
```

```
## Iteration: 7
```

```
## Iteration: 8
```

```
## Iteration: 9
```

```
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```

```
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```

```
## Iteration: 3
```

```
## Iteration: 4
```



# Bayes Factor

```
bf
```

```
## Estimated Bayes factor in favor of f1_3_bf over f1_3_place: 0.58852
```

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- Always calculate and report BFs by comparing models with increasingly narrower priors (at least 3-4).
- It's important to run *sensitivity analyses* that assess the influence of the priors on the posterior (not only if you use BFs, but always).

THE END

