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

Stefano Coretta 18/01/2020

1. Statistical inference.

- 1. Statistical inference.
- 2. Frequentist inference.

- 1. Statistical inference.
- 2. Frequentist inference.
- 3. Bayesian inference:

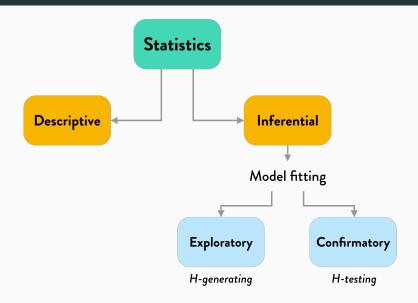
- 1. Statistical inference.
- 2. Frequentist inference.
- 3. Bayesian inference:
 - 3.1 Posterior distributions.

- 1. Statistical inference.
- 2. Frequentist inference.
- 3. Bayesian inference:
 - 3.1 Posterior distributions.
 - 3.2 ROPE.

- 1. Statistical inference.
- 2. Frequentist inference.
- 3. Bayesian inference:
 - 3.1 Posterior distributions.
 - 3.2 ROPE.
 - 3.3 Bayes factors.

STATISTICAL INFERENCE

Statistics



4

We want to know two (interrelated) things:

• Is there evidence for the hypothesis H?

We want to know two (interrelated) things:

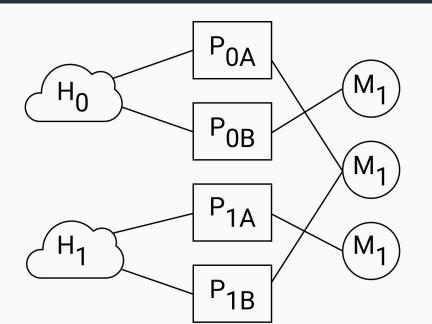
- Is there evidence for the hypothesis H?
- What is the strength of the evidence?

• We test H against empirical data (hypothesis testing).

- · We test H against empirical data (hypothesis testing).
 - It is important to decide in advance the details of the analysis.

- · 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.

- · 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).



FREQUENTIST INFERENCE

• Frequentist statistics is based on the frequentist interpretation of probability.

- Frequentist statistics is based on the frequentist interpretation of probability.
- Frequentist probability of an event is the relative frequency of occurrence of an event within an infinite set of imagined repetitions of that event.

- Frequentist statistics is based on the frequentist interpretation of probability.
- Frequentist probability of an event is the relative frequency of occurrence of an event within an infinite set of imagined repetitions of that event.
- Most of modern science is based on frequentism.

- Frequentist statistics is based on the frequentist interpretation of probability.
- Frequentist probability of an event is the relative frequency of occurrence of an event within an infinite set of imagined repetitions of that event.
- Most of modern science is based on frequentism.
 - lme4 package.

- Frequentist statistics is based on the frequentist interpretation of probability.
- Frequentist probability of an event is the relative frequency of occurrence of an event within an infinite set of imagined repetitions of that event.
- · Most of modern science is based on frequentism.
 - · lme4 package.
 - · Null Hypothesis Significance Testing.

· NHST is based on falsification.

- · NHST is based on falsification.
 - \cdot Rejection of the Null Hypothesis (H_0) .

- · NHST is based on falsification.
 - \cdot Rejection of the Null Hypothesis (H_0) .
 - No direct "support/evidence" for hypotheses.

- · NHST is based on falsification.
 - \cdot Rejection of the Null Hypothesis (H_0) .
 - · No direct "support/evidence" for hypotheses.
- P-value (between 0 and 1).

- · NHST is based on falsification.
 - · Rejection of the Null Hypothesis (H_0) .
 - · No direct "support/evidence" for hypotheses.
- P-value (between 0 and 1).
 - Probability of obtaining an estimate as extreme or more extreme, assuming ${\cal H}_0$ is true.

- · NHST is based on falsification.
 - · Rejection of the Null Hypothesis (H_0) .
 - · No direct "support/evidence" for hypotheses.
- P-value (between 0 and 1).
 - Probability of obtaining an estimate as extreme or more extreme, assuming ${\cal H}_0$ is true.
 - · Should be as low as possible.

· Significance is dichotomous.

- Significance is dichotomous.
 - + $p<\alpha$ = "significant".

- · Significance is dichotomous.
 - \cdot $p<\alpha$ = "significant".
 - + $p \geq \alpha$ = "non-significant".

- · Significance is dichotomous.
 - \cdot $p < \alpha$ = "significant".
 - \cdot $p \geq \alpha$ = "non-significant".
- · No degrees of significance.

- · Significance is dichotomous.
 - \cdot p<lpha = "significant".
 - \cdot $p \geq \alpha$ = "non-significant".
- · 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 inference

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

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

• Evidence for any H (even the null).

- Evidence for any H (even the null).
- · Strength of evidence.

- Evidence for any H (even the null).
- · Strength of evidence.
- · Capitalise on previous knowledge.

Three ways of doing hypothesis testing with Bayesian statistics:

Three ways of doing hypothesis testing with Bayesian statistics:

- · Inference from the posterior.
- Inference using a **Region Of Practical Equivalence** (ROPE).

Three ways of doing hypothesis testing with Bayesian statistics:

- · Inference from the posterior.
- Inference using a **Region Of Practical Equivalence** (ROPE).
- · Inference using the Bayes factor.

1. Formulate a **hypothesis**:

- 1. Formulate a **hypothesis**:
 - H: Condition B decreases reaction times relative to Condition
 A.

- 1. Formulate a **hypothesis**:
 - H: Condition B decreases reaction times relative to Condition
 A.
- 2. Choose model specification (including priors).

- 1. Formulate a hypothesis:
 - H: Condition B decreases reaction times relative to Condition
 A.
- 2. Choose model specification (including priors).
- 3. Collect data.

- 1. Formulate a **hypothesis**:
 - H: Condition B decreases reaction times relative to Condition
 A.
- 2. Choose model specification (including priors).
- 3. Collect data.
- 4. Calculate the **posterior** (fit the model):

- 1. Formulate a **hypothesis**:
 - H: Condition B decreases reaction times relative to Condition
 A.
- 2. Choose model specification (including priors).
- 3. Collect data.
- 4. Calculate the **posterior** (fit the model):
 - Condition B 95% CI = [-80, -15] ms.

- 1. Formulate a **hypothesis**:
 - H: Condition B decreases reaction times relative to Condition
 A.
- 2. Choose model specification (including priors).
- 3. Collect data.
- 4. Calculate the **posterior** (fit the model):
 - Condition B 95% CI = [-80, -15] ms.
- 5. Inference:

- 1. Formulate a hypothesis:
 - H: Condition B decreases reaction times relative to Condition
- 2. Choose **model specification** (including priors).
- 3. Collect data.
- 4. Calculate the **posterior** (fit the model):
 - Condition B 95% CI = [-80, -15] ms.
- 5. Inference:
 - The posterior suggests that Condition B decreases reaction times by 15 to 80 ms at 95% confidence.

- 1. Formulate a **hypothesis**:
 - H: Condition B decreases reaction times relative to Condition
- 2. Choose **model specification** (including priors).
- 3. Collect data.
- 4. Calculate the **posterior** (fit the model):
 - Condition B 95% CI = [-80, -15] ms.
- 5. Inference:
 - The posterior suggests that Condition B decreases reaction times by 15 to 80 ms at 95% confidence.
 - The posterior is compatible with H.

1. Formulate a hypothesis:

- 1. Formulate a **hypothesis**:
 - H: Condition B decreases reaction times relative to Condition A by 100 ms.

- 1. Formulate a hypothesis:
 - H: Condition B decreases reaction times relative to Condition A by 100 ms.
- 2. Choose model specification (including priors).

- 1. Formulate a hypothesis:
 - H: Condition B decreases reaction times relative to Condition A by 100 ms.
- 2. Choose model specification (including priors).
- 3. Collect data.

- 1. Formulate a hypothesis:
 - H: Condition B decreases reaction times relative to Condition A by 100 ms.
- 2. Choose model specification (including priors).
- 3. Collect data.
- 4. Calculate the **posterior** (fit the model):

- 1. Formulate a hypothesis:
 - H: Condition B decreases reaction times relative to Condition A by 100 ms.
- 2. Choose model specification (including priors).
- 3. Collect data.
- 4. Calculate the **posterior** (fit the model):
 - Condition B 95% CI = [-80, -15] ms.

- 1. Formulate a hypothesis:
 - H: Condition B decreases reaction times relative to Condition A by 100 ms.
- 2. Choose **model specification** (including priors).
- 3. Collect data.
- 4. Calculate the **posterior** (fit the model):
 - Condition B 95% CI = [-80, -15] ms.
- 5. Inference:

- 1. Formulate a hypothesis:
 - H: Condition B decreases reaction times relative to Condition A by 100 ms.
- 2. Choose **model specification** (including priors).
- 3. Collect data.
- 4. Calculate the **posterior** (fit the model):
 - Condition B 95% CI = [-80, -15] ms.
- 5. Inference:
 - The posterior suggests that Condition B decreases reaction times by 15 to 80 ms at 95% confidence.

- 1. Formulate a hypothesis:
 - H: Condition B decreases reaction times relative to Condition A by 100 ms.
- 2. Choose model specification (including priors).
- 3. Collect data.
- 4. Calculate the **posterior** (fit the model):
 - Condition B 95% CI = [-80, -15] ms.
- 5. Inference:
 - The posterior suggests that Condition B decreases reaction times by 15 to 80 ms at 95% confidence.
 - The posterior is not compatible with H.

H₀ vs H₁

H1 states that Condition B increases reaction times
 (alternative hypothesis), while H0 states that Condition B does
 not increase reaction times (null hypothesis, null effect).

H0 vs H1

- H1 states that Condition B increases reaction times
 (alternative hypothesis), while H0 states that Condition B does
 not increase reaction times (null hypothesis, null effect).
 - $\cdot H_1: \beta > 0$

H₀ vs H₁

- H1 states that Condition B increases reaction times
 (alternative hypothesis), while H0 states that Condition B does not increase reaction times (null hypothesis, null effect).
 - $\cdot H_1: \beta > 0$
 - $\cdot H_0: \beta = 0$

Region Of Practical Equivalence (ROPE):

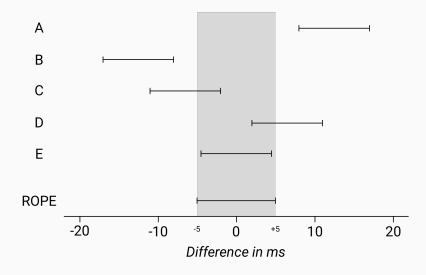
- Define a region around $\beta=0$ that practically corresponds to a null effect.

- Define a region around $\beta=0$ that practically corresponds to a null effect.
 - For example: [-5, +5] ms ($-5 \ge \beta \le +5$ = null effect).

- Define a region around $\beta=0$ that practically corresponds to a null effect.
 - For example: [-5, +5] ms ($-5 \ge \beta \le +5$ = null effect).
 - · This ROPE has a width of 10 ms.

- Define a region around $\beta=0$ that practically corresponds to a null effect.
 - For example: [-5, +5] ms ($-5 \ge \beta \le +5$ = null effect).
 - · This ROPE has a width of 10 ms.
- Choose a minimal sample size (ideally based on a prospective power analysis).

- Define a region around $\beta=0$ that practically corresponds to a null effect.
 - For example: [-5, +5] ms ($-5 \ge \beta \le +5$ = null effect).
 - · This ROPE has a width of 10 ms.
- Choose a minimal sample size (ideally based on a prospective power analysis).
- Collect data until the 95% CI of β has a width equal to or smaller than the width of the ROPE.



- We focus on the estimate **precision** of β .

- We focus on the estimate **precision** of β .
- · Independent from the value of β .

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

Bayes Factor

The Bayes factor is the ratio of the likelihood of H1 to the likelihood of H2.

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

Bayes Factor

p(M1 D)	evidence
0.5-0.75	weak
0.75-0.95	positive
0.95-0.99	strong
> 0.99	very strong
	0.5-0.75 0.75-0.95 0.95-0.99

Bayes Factor

```
priors <- c(
  prior(normal(40, 10), class = Intercept),
  prior(cauchy(0, 10), class = sigma),
  prior(normal(10, 10), class = b, coef = "c1_placecoronal"),
  prior(normal(20, 10), class = b, coef = "c1_placevelar"),
  prior(normal(0, 25), class = sd),
  prior(lkj(2), class = cor)
)</pre>
```