

Introduction to Bayesian statistics

Part 2 — Application

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⌚ <https://github.com/jorgetendeiro/GSMS-2020>

Worked-out example

I will illustrate Bayesian analyses by means of an example.

General Bayesian workflow:

- ▶ Process data, descriptives.
- ▶ Build Bayesian models.
- ▶ Assess models through *prior* predictive checks.
- ▶ Fit the models to the data.
- ▶ MCMC diagnostics.
- ▶ Assess model fit through *posterior* predictive checks.
- ▶ Model comparison, summarize, report inferences.

Running example

Theory of mind in remitted bipolar disorder

Paper:

Espinós, U., Fernández-Abascal, E. G., & Ovejero, M. (2019). *Theory of mind in remitted bipolar disorder: Interpersonal accuracy in recognition of dynamic nonverbal signals*. PLoS ONE, 14(9), e0222112. doi: 10.1371/journal.pone.0222112.

Data:

[https://www.kaggle.com/mercheovejero/
theory-of-mind-in-remitted-bipolar-disorder](https://www.kaggle.com/mercheovejero/theory-of-mind-in-remitted-bipolar-disorder)

Study

Goal:

Examine interpersonal accuracy (IPA) in remitted patients with bipolar disorder (BD).

Groups:

- ▶ BD I
- ▶ BD II
- ▶ Unipolar depression (UD)
- ▶ Control

Dependent variable:

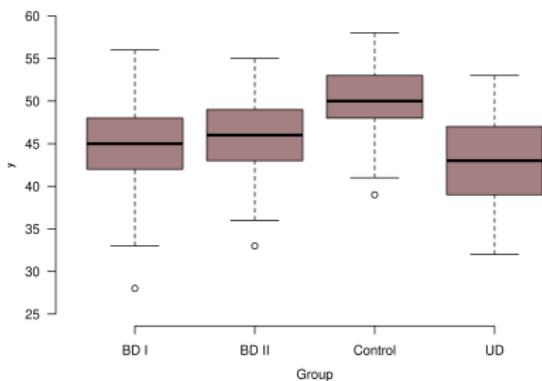
Number-correct score on the MiniPONS test to assess IPA.

Analysis:

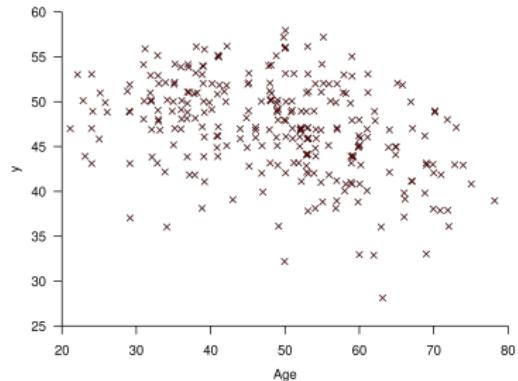
ANCOVA model, with Age as covariate.

Descriptives

Group	<i>n</i>	mean	SD
BD I	70	45.1	4.9
BD II	49	45.7	4.7
Control	119	50.2	3.7
UD	39	42.7	5.0



Group	<i>n</i>	mean	SD
BD I	70	44.5	11.5
BD II	49	49.9	11.5
Control	119	46.1	10.8
UD	39	62.9	9.7



Build Bayesian models

Model	Formula	Obs.
\mathcal{M}_1	$y \sim 1$	baseline
\mathcal{M}_2	$y \sim \text{Age}$	simple regression
\mathcal{M}_3	$y \sim \text{Group}$	ANOVA
\mathcal{M}_4	$y \sim \text{Group} + \text{Age}$	ANCOVA
\mathcal{M}_5	$y \sim \text{Group} + \text{Age} + \text{Group} \times \text{Age}$	Heterog. slopes ANCOVA
\mathcal{M}_6	$y \sim \text{Group} + \text{Age}$	constrained ANCOVA $(\mu_{\text{Control}} = \mu_{UD})$

Espinós et al. (2019) focused on the ANCOVA model, \mathcal{M}_4 .

Here we will also consider the other models and compare them.

Basic Stan code for all models

```
data {  
    int<lower=0> N;      // sample size  
    int<lower=0> K;      // number of predictors  
    matrix[N, K+1] x;   // predictor matrix (incl. intercept)  
    vector[N] y;        // outcome variable  
}  
  
parameters {  
    vector[K+1] beta;    // intercept + reg. coeffs.  
    real<lower=0> sigma; // SD residuals  
}  
  
model {  
    beta ~ normal(0, 10);           // Prior reg. coeffs.  
    sigma ~ cauchy(0, 1);          // Prior sigma  
    y     ~ normal(x * beta, sigma); // Likelihood  
}
```

Assess models through
prior predictive checks

Prior predictive checks

Ask yourself:

What type of data can my model generate, *before I fit it to my own data?*

Answer:

Perform prior predictive checks.

What's that?

Look at data generated from your model (i.e., likelihood + priors).
→ Akin to test-driving a car before buying it.

What am I looking for?

A model that is flexible enough, but not too wild.

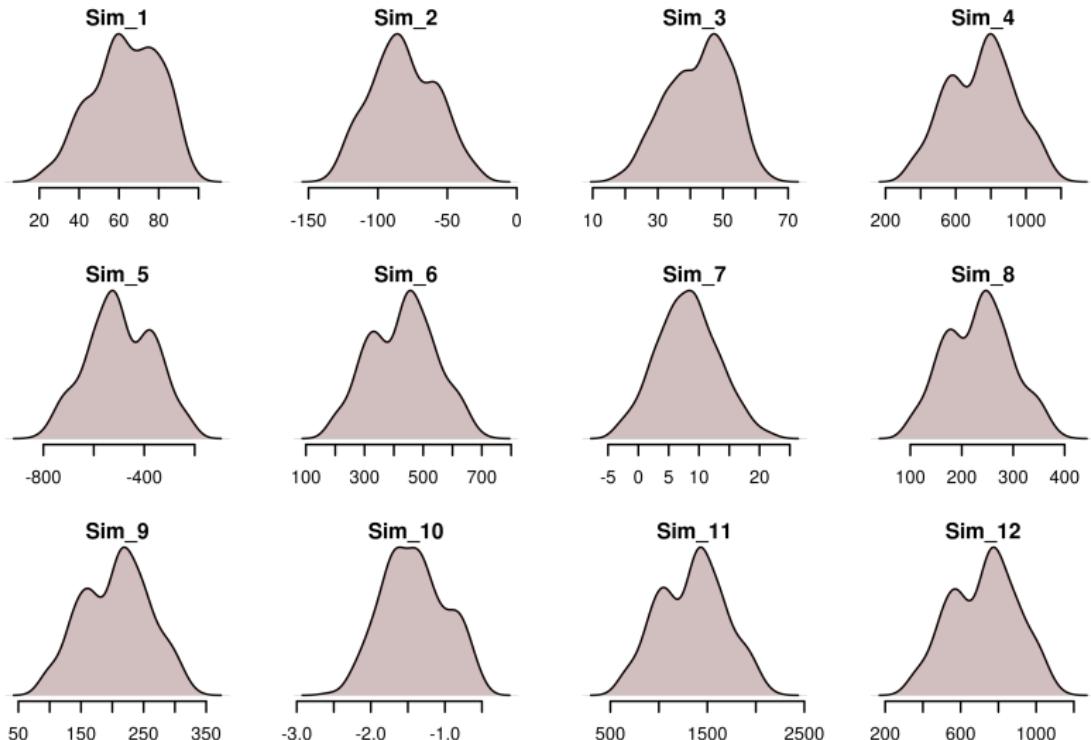
ANCOVA model

```
model {  
    beta ~ normal(0, 10);           // Prior reg. coeffs.  
    sigma ~ cauchy(0, 1);          // Prior sigma  
    y     ~ normal(x * beta, sigma); // Likelihood  
}
```

To sample from the prior predictive distribution, do this a few times:

- ▶ Sample beta from its prior $\mathcal{N}(0, 10)$, say β_i .
- ▶ Sample sigma from its prior Cauchy($0, 1$), say σ_i .
- ▶ Sample data from the likelihood $\mathcal{N}(x * \beta_i, \sigma_i)$, say y_i .
- ▶ Plot y_i .

ANCOVA model



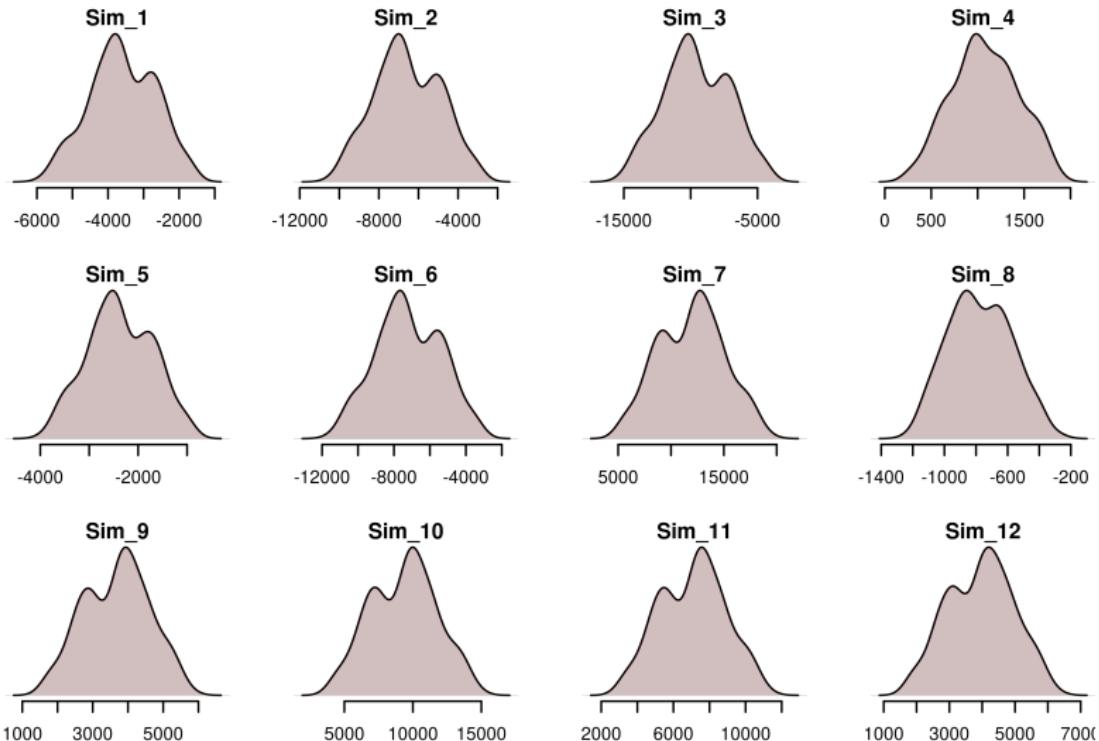
Flexible.

ANCOVA model

What if we broaden the prior on beta?

```
model {  
    beta ~ normal(0, 100);           // Prior reg. coeffs.  
    sigma ~ cauchy(0, 1);           // Prior sigma  
    y     ~ normal(x * beta, sigma); // Likelihood  
}
```

ANCOVA model



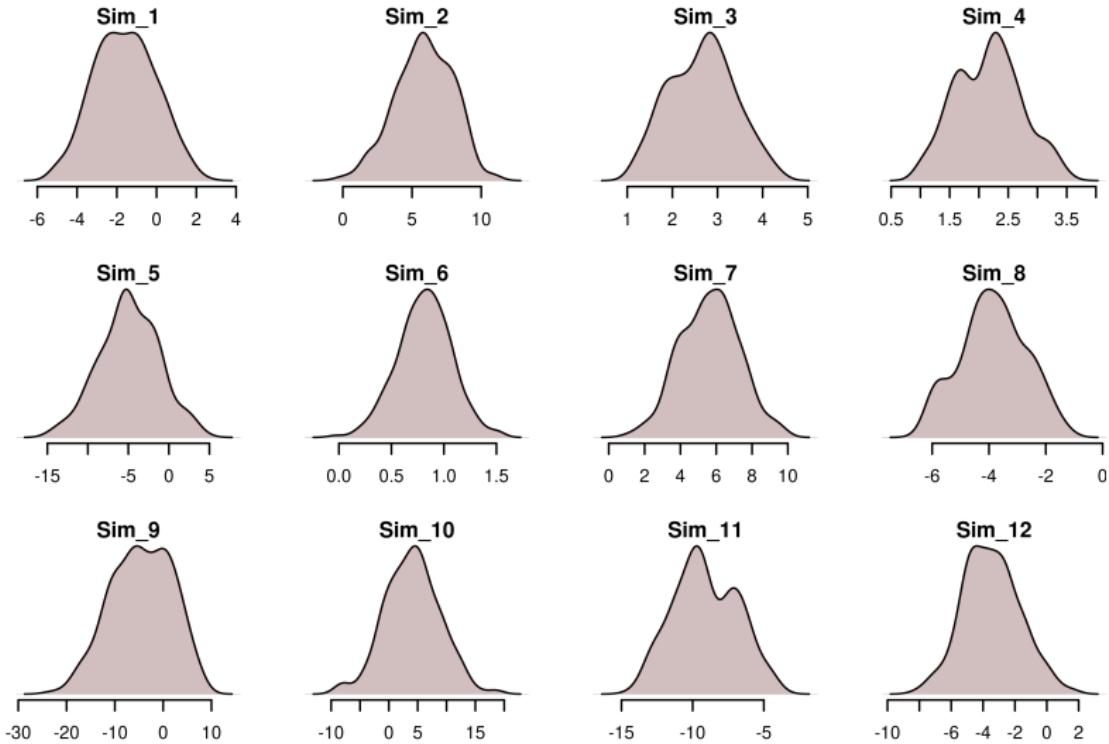
Yikes.

ANCOVA model

What if we shrink the prior on beta?

```
model {  
    beta ~ normal(0, .1);           // Prior reg. coeffs.  
    sigma ~ cauchy(0, 1);          // Prior sigma  
    y     ~ normal(x * beta, sigma); // Likelihood  
}
```

ANCOVA model



Ups.

Fit the models to the data

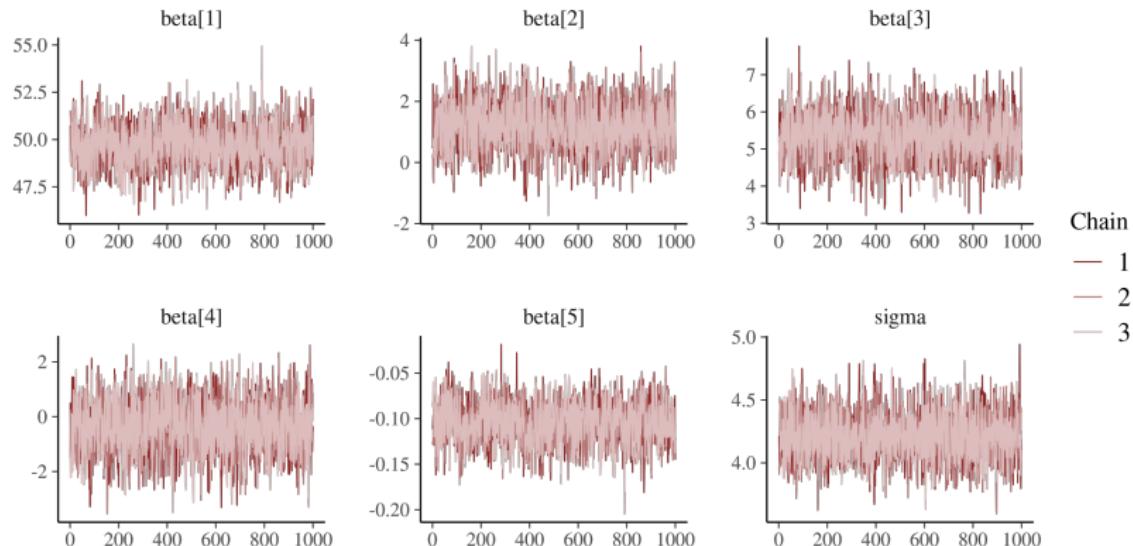
I used R and rstan for the job.

All code is available at:

<https://github.com/jorgetendeiro/GSMS-2020>.

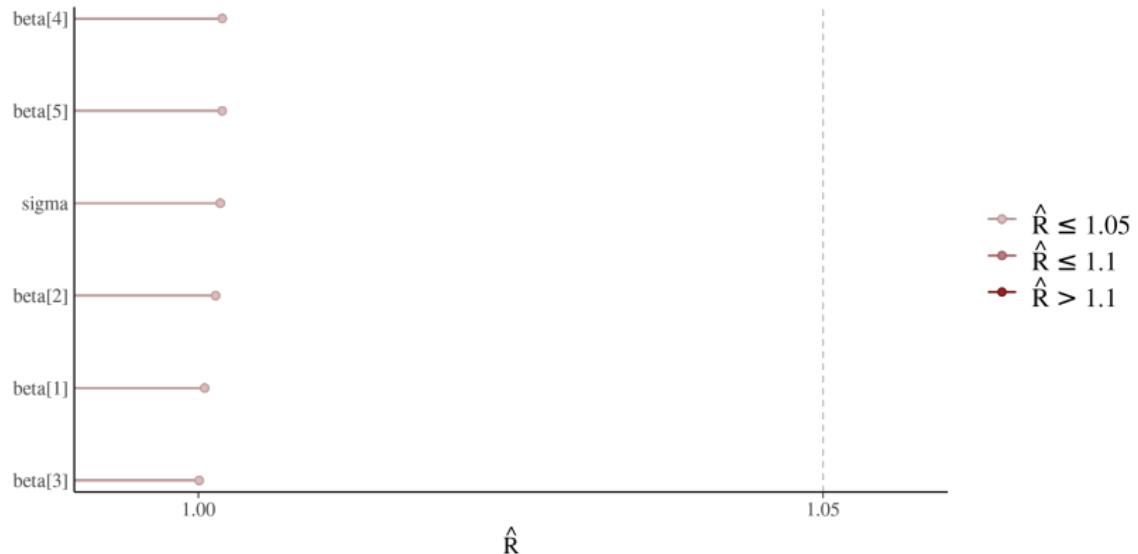
MCMC diagnostics

Trace plot



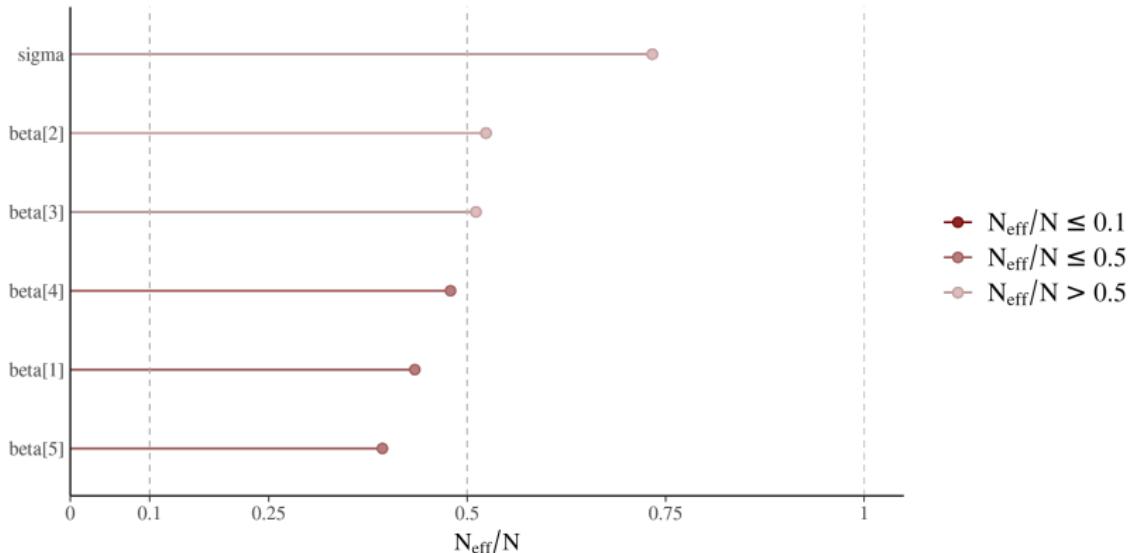
The chains mixed well.

R -hat



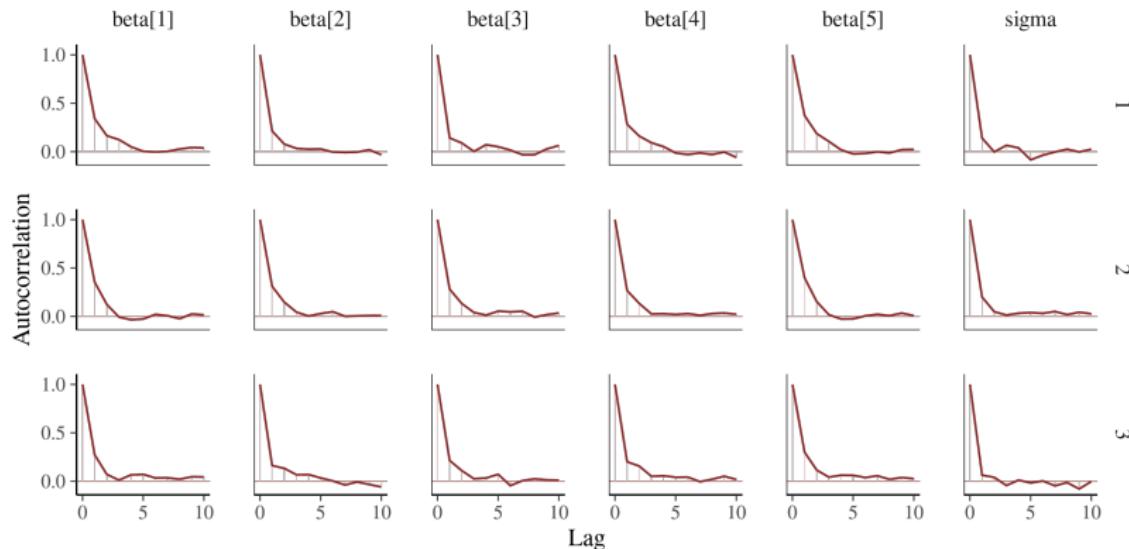
All below, say, 1.05. Good.

Effective sample size



All above, say, 0.1. Good.

Auto-correlation



It approaches 0 rather quickly. Nice.

Assess model fit through
posterior predictive checks

Posterior predictive checks

Ask yourself:

How likely is your fitted model of generating data *like* you collected?

Answer:

Perform posterior predictive checks.

What's that?

Compare observed data to data generated from your *fitted* model.
→ Assess model fit.

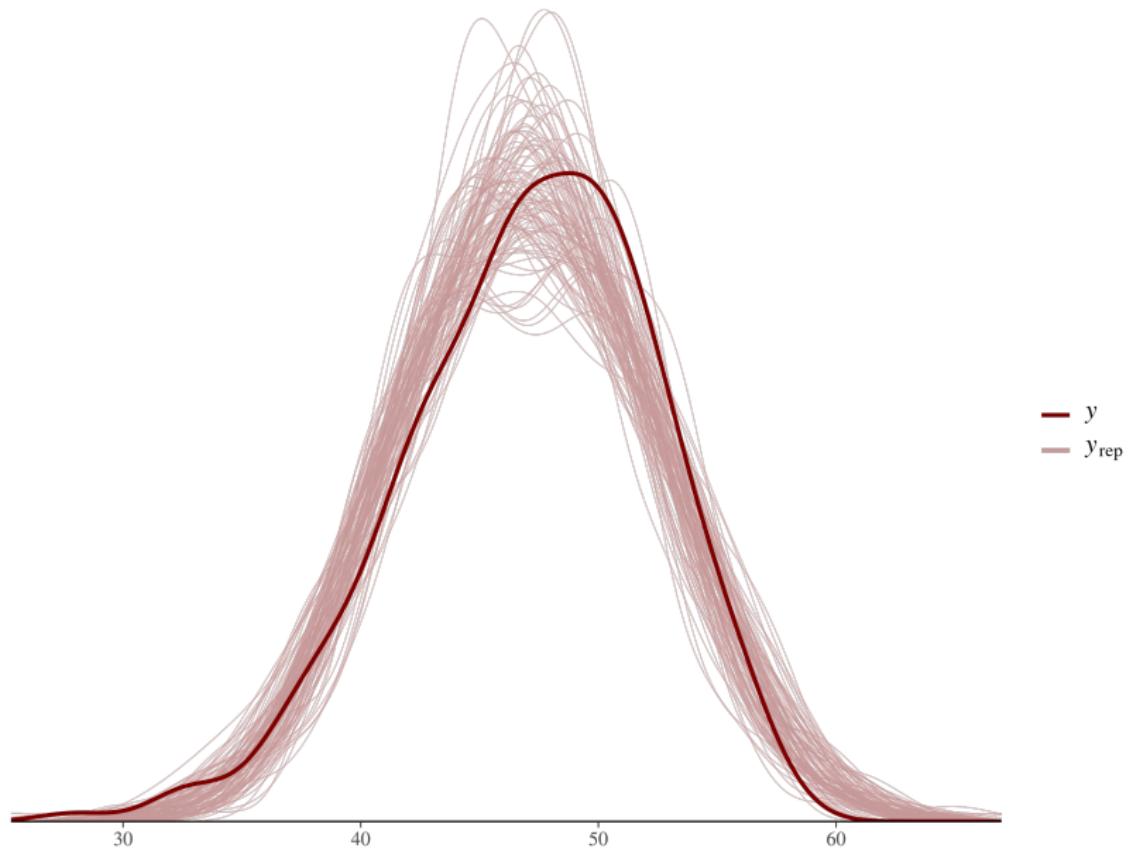
What am I looking for?

Evidence that your data *could have been* generated from the fitted model.

Posterior predictive checks

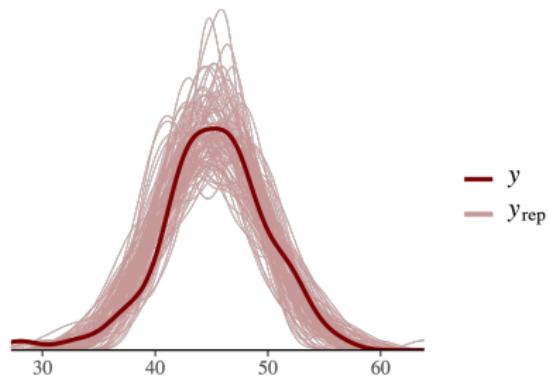
Let's first focus on the ANCOVA model \mathcal{M}_4 .

Distribution of y

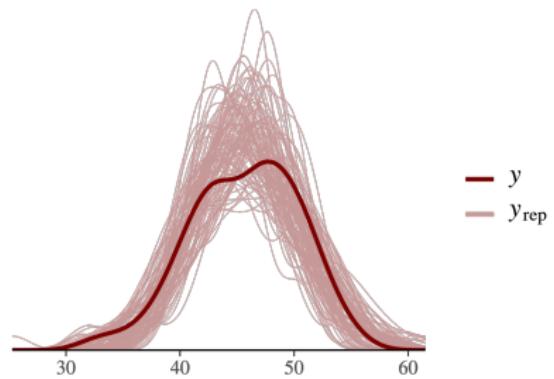


Distribution of y per group

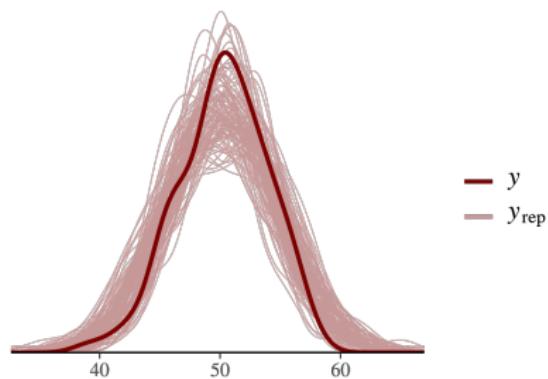
BD I



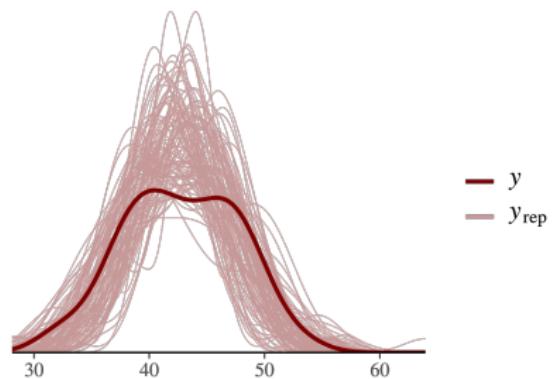
BD II



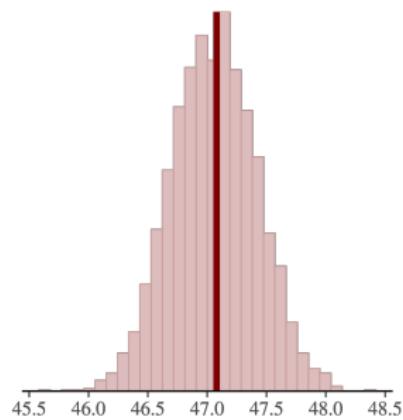
Control



UD

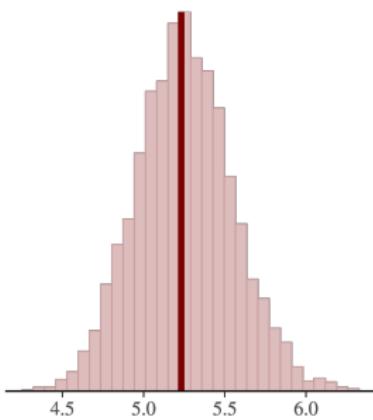


Various statistics of y



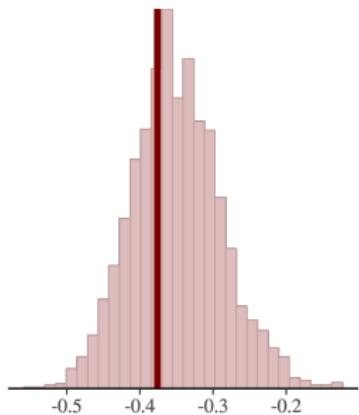
$T = \text{mean}$
 $T(y_{\text{rep}})$

| $T(y)$



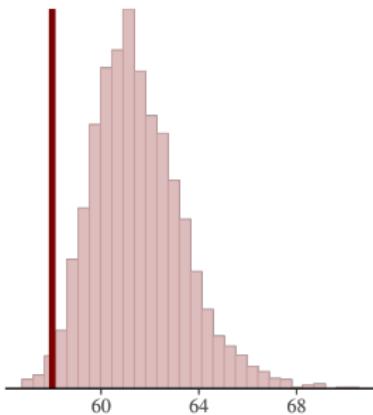
$T = \text{sd}$
 $T(y_{\text{rep}})$

| $T(y)$



$T = \text{cor.y_Age}$
 $T(y_{\text{rep}})$

| $T(y)$



$T = \text{max}$
 $T(y_{\text{rep}})$

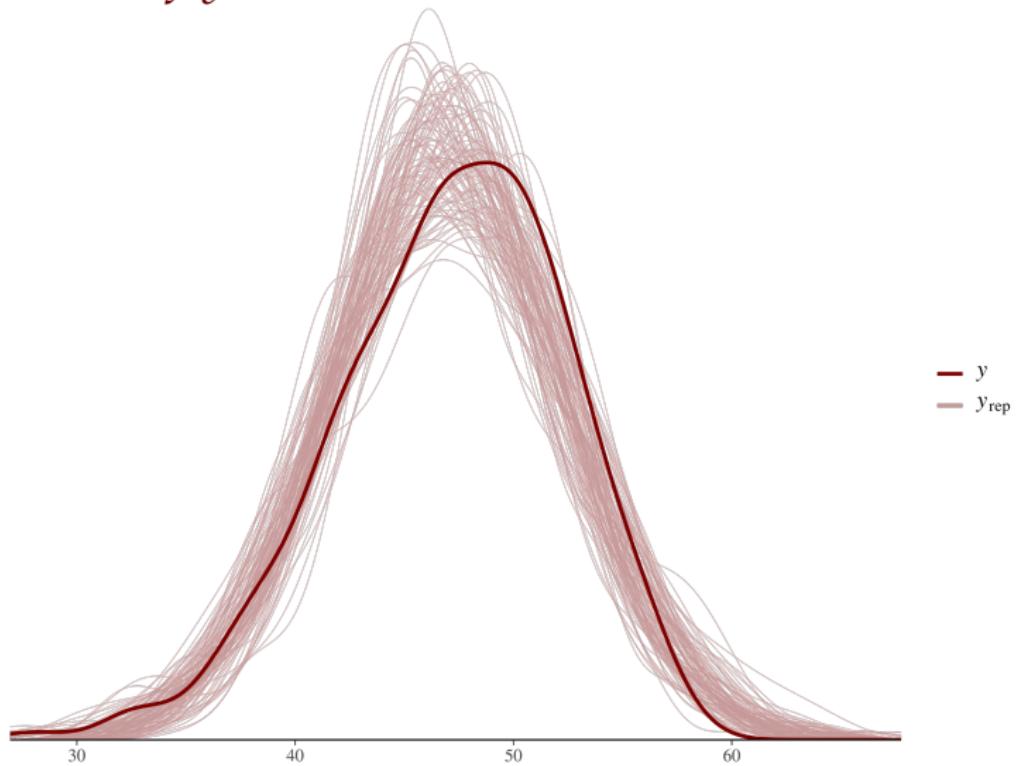
| $T(y)$

Posterior predictive checks

So the ANCOVA model seems to fit the data well.

How does the seemingly worse baseline \mathcal{M}_1 model do?

Distribution of y

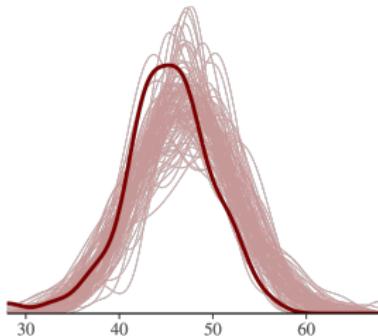


Not that bad!!

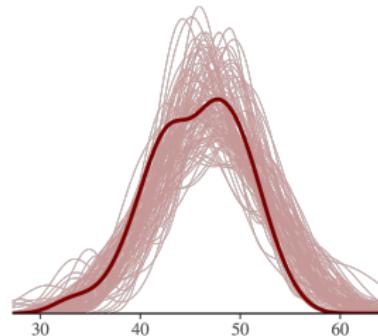
(But only because $y \approx \mathcal{N}(\cdot)$, which need not happen in general).

Distribution of y per group

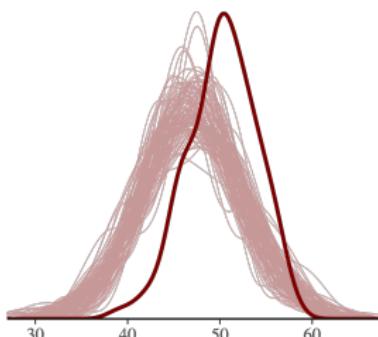
BD I



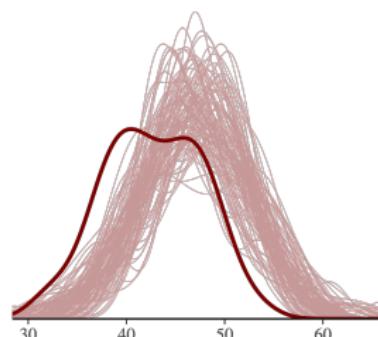
BD II



Control

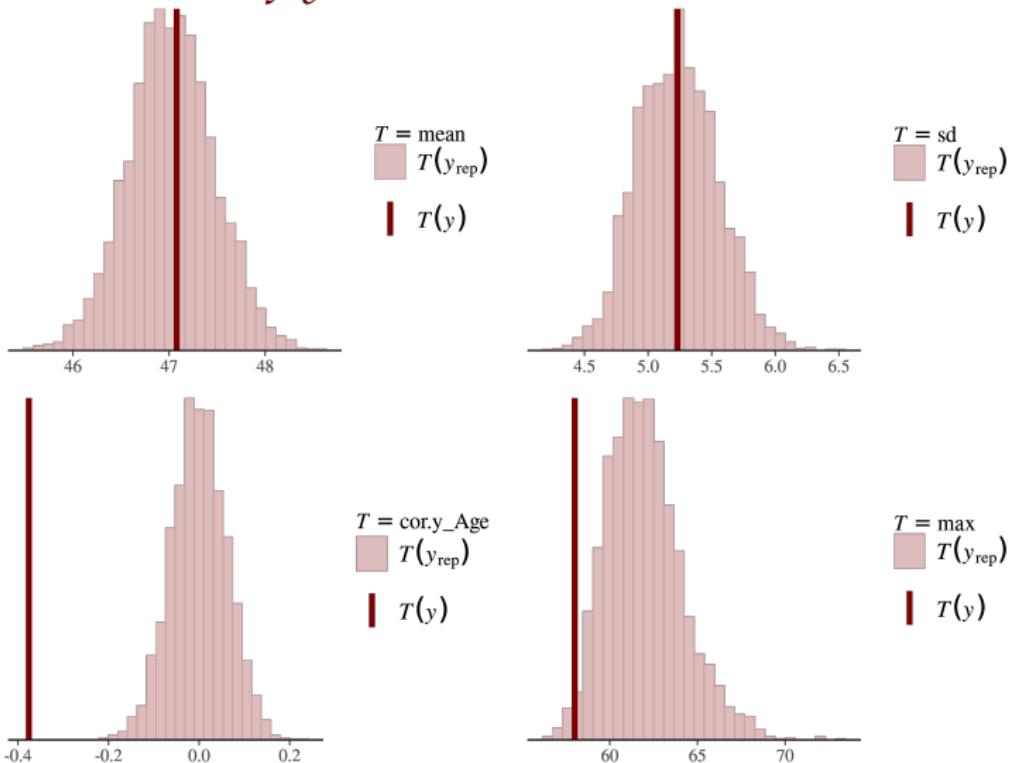


UD



Humm, the Control and UD groups are misspecified.
(Of course, 'Group' was not modelled...)

Various statistics of y



$\text{cor}(y, \text{Age})$ completely missed.
(Of course, 'Age' was not modelled...)

Model comparison

Leave-one-out cross validation (LOO-CV)

Idea:

- ▶ Models are compared based on out-of-sample *expected predictive accuracy*.
- ▶ LOO-CV is efficiently approximated by means of PSIS-LOO (Pareto smoothed importance sampling).

Interpretation:

- ▶ PSIS-LOO essentially provides a means to **rank** models.
- ▶ It doesn't really quantify differences between models.
- ▶ However, as a **rule of thumb**, consider values of *elpd_diff* at least 4 times as large as its SE as noteworthy.

Leave-one-out cross validation (LOO-CV)

Model	elpd_diff	se_diff	looic
$y \sim \text{Group} + \text{Age}$ (ANCOVA)	0.0	0.0	1589.8
$y \sim \text{Group} + \text{Age} + \text{Group} \times \text{Age}$	-2.4	1.2	1594.6
$y \sim \text{Group}$	-11.5	4.2	1612.7
$y \sim \text{Group} + \text{Age}, \mu_{\text{Control}} = \mu_{\text{UD}}$	-18.4	7.1	1626.7
$y \sim \text{Age}$	-38.3	7.9	1666.4
$y \sim 1$	-58.1	8.6	1706.1

- Models are ordered from best to worst.
- Thus, ANCOVA appears to have the best predictive ability.
- Based on the '4SEs' rule of thumb, we discard the last two models.

Bayes factors

I also tried to compare models using Bayes factors.
I have a lot to say about BFs, not all of it is good.

Idea:

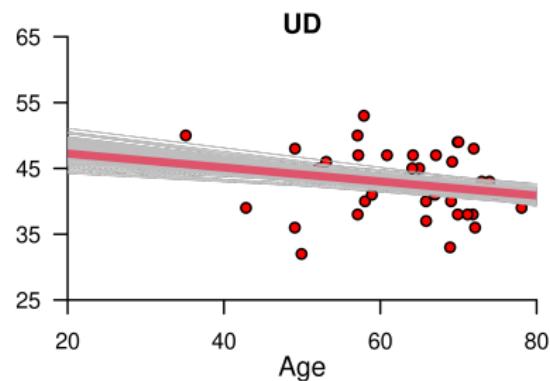
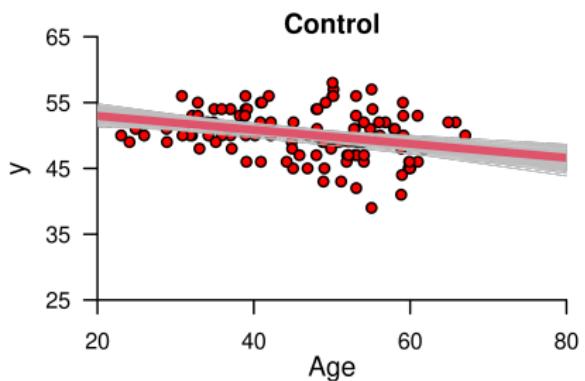
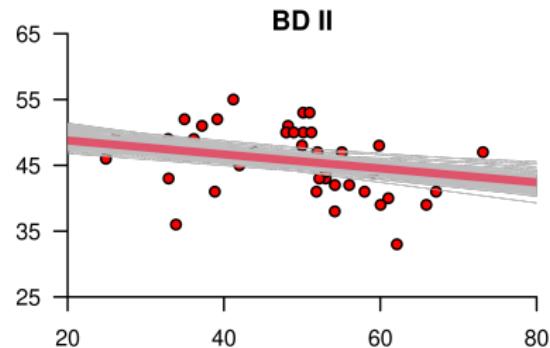
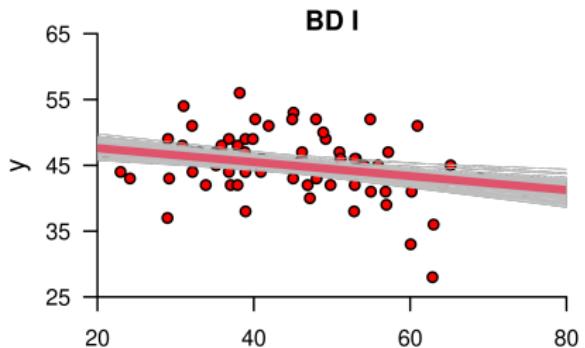
Bayes factors compare the models' predictive ability *for the observed data*. Thus:

Under which model are the observed data more likely?

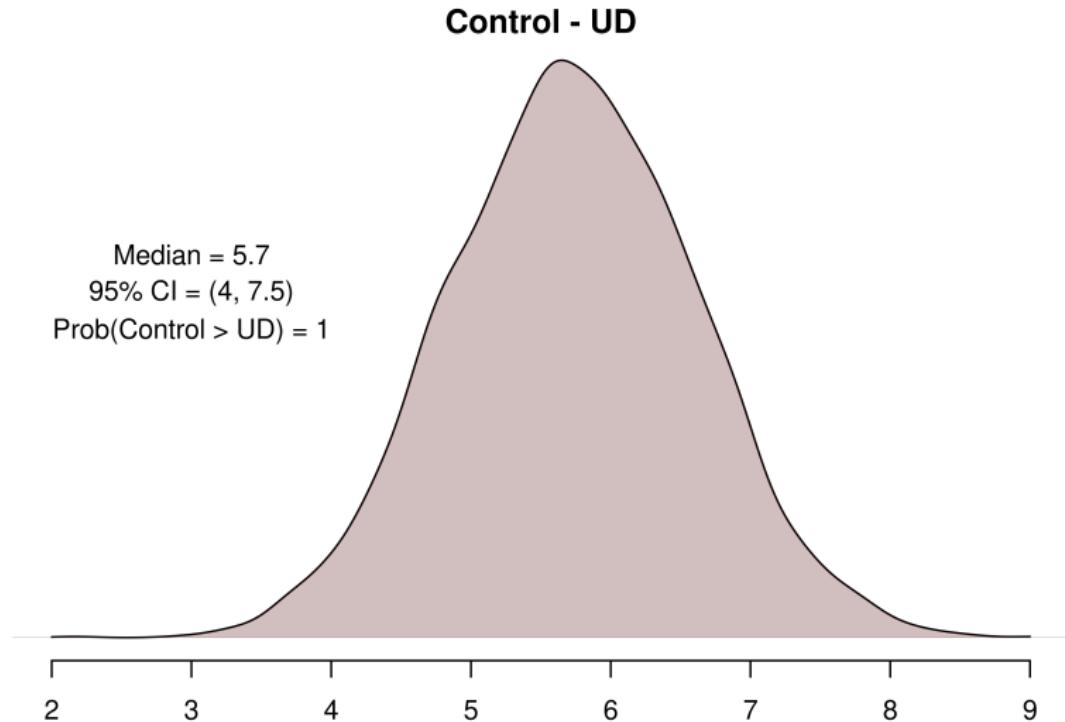
Unfortunately, the results were *tremendously* sensitive to prior specification.
I decided to leave them out.

Summarize and report inferences

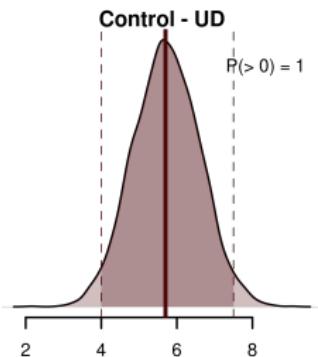
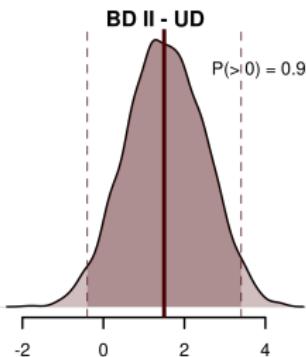
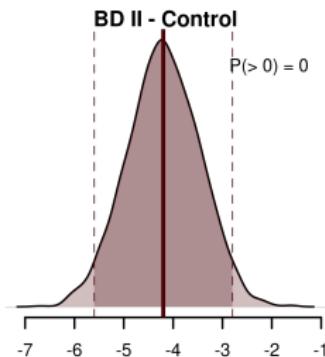
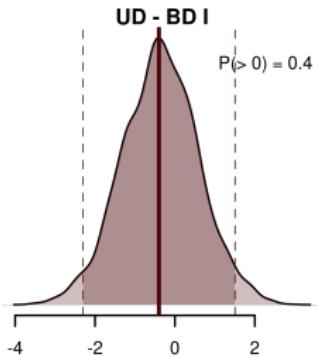
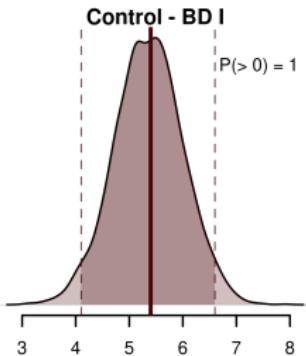
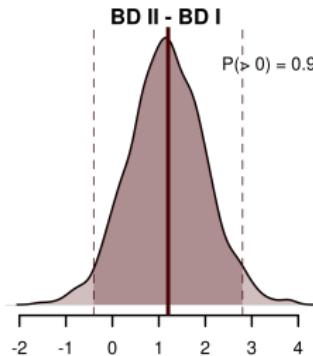
Plots per groups



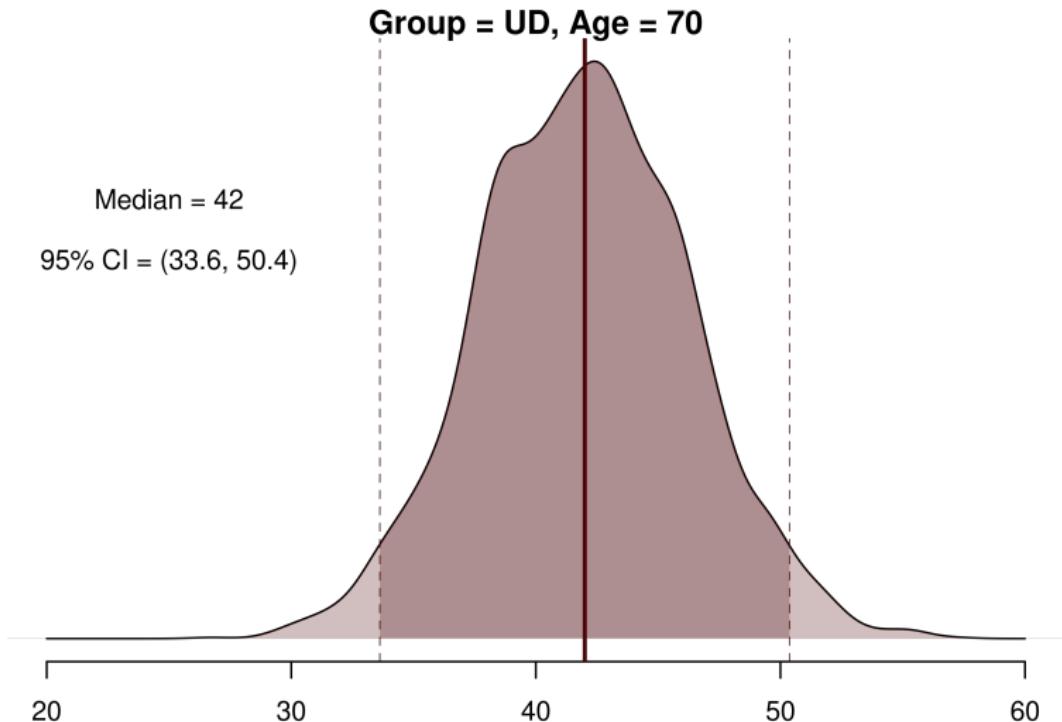
Contrast: $\mu_{Control} - \mu_{UD} = 0$



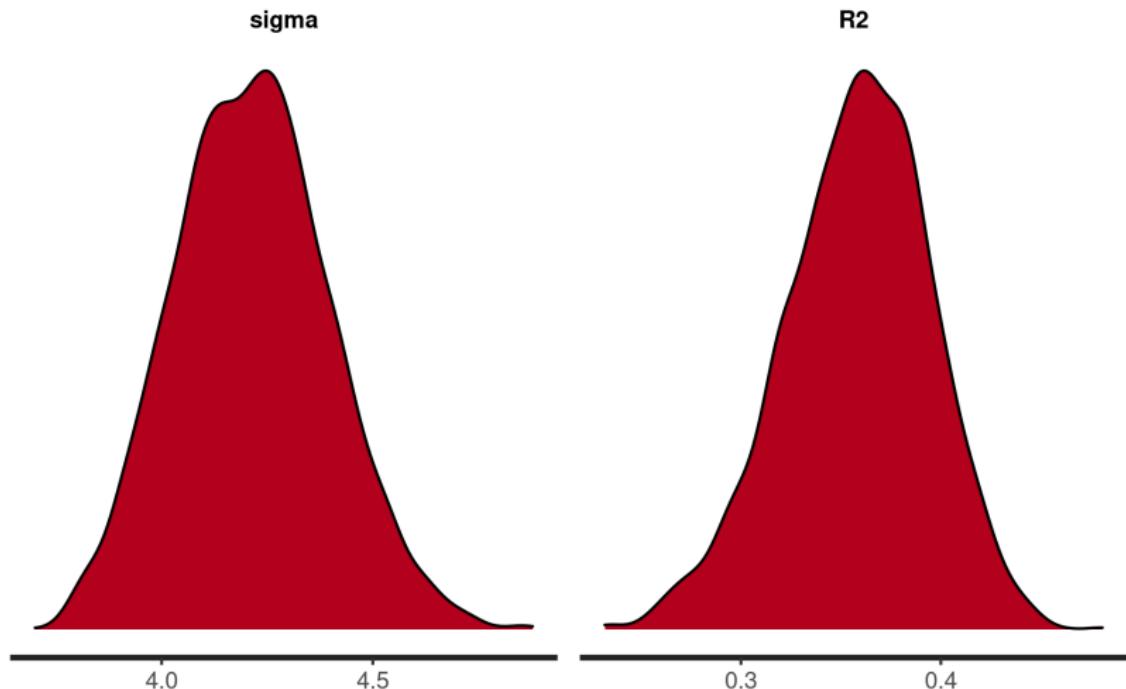
All pairwise contrasts



Prediction for one subject



Posterior dists. σ , R^2



Summary

	Mean	SD	2.5%	97.5%
beta[1]	49.73	1.14	47.46	51.94
beta[2]	1.17	0.81	-0.40	2.79
beta[3]	5.36	0.64	4.08	6.61
beta[4]	-0.36	0.95	-2.27	1.51
beta[5]	-0.11	0.02	-0.15	-0.06
sigma	4.21	0.18	3.88	4.58
R2	0.36	0.04	0.28	0.42

Conclusion

Bayesian modelling is *very* flexible:

- ▶ Checking model fit is very *intuitive* and *visual*.
- ▶ It is not *that* difficult to adapt the model, if needed be.
- ▶ It is possible to perform *any* inference that is a functional form of the data or model parameters.
- ▶ It is possible to compare models, for various predictive criteria.
- ▶ No statistical significance required.
- ▶ All outcomes are *stochastic*:
You get to report the *uncertainty* in your results.
- ▶ The sky is the limit:
The types of models available are nearly endless.

Now **you** give it a go!