

# Model Assessment and Comparisons

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1

- First two stages:
  - 1 Construct a reasonable probability model;
  - 2 Compute the posterior distribution of model parameters – typically by drawing samples from it.
- Third stage: Checking the quality of the model's fit. This is crucial – Prior-to-Posterior inferences involve the whole structure (with hierarchies) of the Bayesian model and can produce spurious inference if the model is poor.
- **Sensitivity Analysis**: How much do posterior inferences change when other probability models are used in place of the present model?

2

## Three critical questions

- Do the inferences from the model make sense?
- Is the model consistent with the data?
- How can we compare and, perhaps, "rank" different plausible models in their order of preference with respect to a given data set?

3

## Replicating data sets using the posterior predictive distribution

- Let  $\mathbf{y} = (y_1, y_2, \dots, y_n)'$  be the observed data and  $\theta$  be the collection of *all* parameters (including all hyperparameters) for a model  $p(\theta) \times p(\mathbf{y} | \theta)$ .
- Let  $\mathbf{y}_{rep} = (y_{rep,1}, y_{rep,2}, \dots, y_{rep,n})'$  be the *replicated data* that we *would* see if the experiment that produced  $\mathbf{y}$  today were replicated with the same model and the same value of  $\theta$  that produced the observed data.
- Replicated data  $\mathbf{y}_{rep}$ , like predictions  $\tilde{\mathbf{y}}$ , has two components of uncertainty:
  - 1 The fundamental variability of the model, represented by the posited variability in the data;
  - 2 The posterior uncertainty in the estimation of  $\theta$

4

- The distribution of  $\mathbf{y}_{rep}$  is the posterior predictive distribution:

$$p(\mathbf{y}_{rep} | \mathbf{y}) = \int p(\mathbf{y}_{rep} | \theta) p(\theta | \mathbf{y}) d\theta$$

- We do not evaluate the above integral, but sample from  $p(\mathbf{y}_{rep} | \mathbf{y})$ :
  - 1 Draw  $\theta^{(j)} \sim p(\theta | \mathbf{y})$ ,  $j = 1, 2, \dots, M$
  - 2 Draw  $\mathbf{y}_{rep}^{(j)} \sim p(\mathbf{y}_{rep} | \theta^{(j)})$ ,  $j = 1, 2, \dots, M$ .

5

Usually full inferential output for Bayesian inference comprises a table comprising *both* samples from the posterior distribution of  $\theta$  *and* the posterior predictive distribution of replicated data sets.

Sample	$\theta_1$	$\theta_2$	...	$\theta_p$	$y_{rep,1}$	$y_{rep,2}$	...	$y_{rep,n}$
1	$\theta_1^{(1)}$	$\theta_2^{(1)}$	...	$\theta_p^{(1)}$	$y_{rep,1}^{(1)}$	$y_{rep,2}^{(1)}$	...	$y_{rep,n}^{(1)}$
2	$\theta_1^{(2)}$	$\theta_2^{(2)}$	...	$\theta_p^{(2)}$	$y_{rep,1}^{(2)}$	$y_{rep,2}^{(2)}$	...	$y_{rep,n}^{(2)}$
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
M	$\theta_1^{(M)}$	$\theta_2^{(M)}$	...	$\theta_p^{(M)}$	$y_{rep,1}^{(M)}$	$y_{rep,2}^{(M)}$	...	$y_{rep,n}^{(M)}$

6

## Example: linear regression model

- Recall the Bayesian linear regression model with non-informative priors:

$$y_i | \mu_i, \sigma^2 \stackrel{\text{ind}}{\sim} N(\mu_i, \sigma^2); \quad i = 1, 2, \dots, n;$$

$$\mu_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip} = \mathbf{x}'_i \boldsymbol{\beta}; \quad \boldsymbol{\beta} = (\beta_0, \beta_1, \dots, \beta_p);$$

$$\boldsymbol{\beta}, \sigma^2 \sim p(\boldsymbol{\beta}, \sigma^2) = \frac{1}{\sigma^2}.$$

- Unknown parameters include the regression parameters and the variance, i.e.  $\boldsymbol{\theta} = \{\boldsymbol{\beta}, \sigma^2\}$ .
- Obtain posterior samples:  $\boldsymbol{\theta}^{(j)} = \{\boldsymbol{\beta}^{(j)}, \sigma^{2(j)}\}$ ,  $j = 1, \dots, M$ .

- For each sampled parameter vector  $\boldsymbol{\theta}^{(j)} = \{\boldsymbol{\beta}^{(j)}, \sigma^{2(j)}\}$ , we replicate  $n$  data points:

$$y_{rep,i}^{(j)} \sim N(\mathbf{x}'_i \boldsymbol{\beta}^{(j)}, \sigma^{2(j)}), \quad j = 1, \dots, M \quad \text{and} \quad i = 1, \dots, n.$$

- $\mathbf{y}_{rep}^{(j)} = (y_{rep,1}^{(j)}, y_{rep,2}^{(j)}, \dots, y_{rep,n}^{(j)})'$  is the  $j$ -th sample from the posterior predictive distribution  $p(\mathbf{y}_{rep} | \mathbf{y})$ .

- Remark:** The number of posterior samples,  $M$ , represents post-convergence (i.e. after burn-in) posterior samples. There is no need to consider pre-convergence samples for drawing the posterior predictive samples.

- We distinguish between the replicated data,  $\mathbf{y}_{rep}$ , and the predictive outcomes,  $\tilde{\mathbf{y}}$ .
- The variable  $\tilde{\mathbf{y}}$  is any *future* observable value of the outcome. For example, in a linear regression model  $\tilde{\mathbf{y}}$  can have its own set of explanatory variables  $\tilde{\mathbf{X}}$ .
- On the other hand,  $\mathbf{y}_{rep}$  *must* have the same explanatory variables  $\mathbf{X}$  as those used in the model for the observed data  $\mathbf{y}$ . In this sense,  $\mathbf{y}_{rep}$  is similar to “predicting the observed data”.

- Lack of fit of the data with respect to the posterior predictive distribution can be measured by the tail-area probability, or  $p$ -value, of a test statistic.

- Recall the classical  $p$ -value for a test statistic  $T(\mathbf{y})$ :

$$p_C = P(T(\mathbf{y}_{rep}) \geq T(\mathbf{y}) | \boldsymbol{\theta}),$$

where the probability is taken over the distribution of  $\mathbf{y}_{rep}$  with  $\boldsymbol{\theta}$  fixed (usually at a value specified by a “null” hypothesis).

- In classical statistics, the test statistic  $T(\mathbf{y})$  does not depend upon model parameters.

- In Bayesian inference, a test statistic *can* be a function of the parameters and the data because the test measure is evaluated over draws from the posterior distribution of the unknown parameters. We call  $T(\mathbf{y}; \boldsymbol{\theta})$  a *test measure*.
- The  $p$ -value is computed using the posterior samples of  $\boldsymbol{\theta}$  and  $\mathbf{y}_{rep}$ .

- Does our model represent our data adequately? Choose a discrepancy measure or *test measure*, say

$$T(\mathbf{y}; \boldsymbol{\theta}) = T(\mathbf{y}; \boldsymbol{\beta}, \sigma^2) = \sum_{i=1}^n \frac{(y_i - \mathbf{E}[y_i | \boldsymbol{\theta}])^2}{\text{var}(y_i | \boldsymbol{\theta})}$$

$$= \sum_{i=1}^n \frac{(y_i - \mathbf{x}'_i \boldsymbol{\beta})^2}{\sigma^2}$$

- Compute  $T(\mathbf{y}, \boldsymbol{\theta}^{(j)})$  and the set of  $T(\mathbf{y}_{rep}^{(j)}, \boldsymbol{\theta}^{(j)})$  and obtain “Bayesian  $p$ -values”:

$$p_B = P(T(\mathbf{y}_{rep}, \boldsymbol{\theta}) > T(\mathbf{y}, \boldsymbol{\theta}) | \mathbf{y})$$

$$= \frac{1}{M} \sum_{j=1}^M 1[T(\mathbf{y}_{rep}^{(j)}, \boldsymbol{\theta}^{(j)}) > T(\mathbf{y}, \boldsymbol{\theta}^{(j)})].$$

- Bayesian  $p$ -values close to 0 or 1 signifies lack of fit of the model with respect to the test measure. On the other hand, values of  $p_B$  close to 0.5 indicate very good fit.
- Estimates of  $p_B$  may be sensitive to choice of the test measure.
- Unlike  $p_C$ , we should not interpret  $p_B$  with regard to “significance levels” of a test. Instead it should be used as a diagnostic to see if the model adequately fits the data.
- Bayesian  $p$ -values are not concerned with “Type-I error” rates. Hence, there is no need to consider adjusting  $p_B$  for multiple comparisons (in case we use several test measures).

### Model comparisons using replicated data

- Compute the posterior predictive mean and variance for each observation:

$$\mu_{rep,i} = E[y_{rep,i} | \mathbf{y}] = \frac{1}{M} \sum_{j=1}^M y_{rep,i}^{(j)}, \quad i = 1, \dots, n;$$

$$\sigma_{rep,i}^2 = \text{var}[y_{rep,i} | \mathbf{y}] = \frac{1}{M} \sum_{j=1}^M (y_{rep,i}^{(j)} - \mu_{rep,i})^2.$$

- Goodness of fit measure  $G$  and expected mean-square predictive error  $P$ :

$$G = \sum_{i=1}^n (y_i - \mu_{rep,i})^2; \quad P = \sum_{i=1}^n \sigma_{rep,i}^2; \quad D = G + P$$

- $D$  is a model comparison metric (lower values better).

### Model comparisons using the DIC

- A general choice for the test measure is the *deviance*:

$$T(\mathbf{y}; \boldsymbol{\theta}) = D(\mathbf{y}; \boldsymbol{\theta}) = -2 \log p(\mathbf{y} | \boldsymbol{\theta}).$$

- A better option for hierarchical models that does not require replicated data (saves computation time):

$$\bar{D}(\mathbf{y}) = E[D(\mathbf{y}; \boldsymbol{\theta}) | \mathbf{y}] = \frac{1}{M} \sum_{j=1}^M D(\mathbf{y}; \boldsymbol{\theta}^{(j)});$$

$$p_D = \bar{D}(\mathbf{y}) - D(\mathbf{y}; \bar{\boldsymbol{\theta}}), \quad \text{where } \bar{\boldsymbol{\theta}} = E[\boldsymbol{\theta} | \mathbf{y}] = \frac{1}{M} \sum_{j=1}^M \boldsymbol{\theta}^{(j)};$$

$$DIC = \bar{D}(\mathbf{y}) + p_D = 2\bar{D}(\mathbf{y}) - D(\mathbf{y}; \bar{\boldsymbol{\theta}}).$$