ADVANCED BAYESIAN MODELING

WAIC: A More Bayesian Approach?

Scores Reconsidered

Bayesian methods for predicting \tilde{y} don't use a "plug-in" estimate, as in

$$p(\tilde{y} \mid \hat{\theta})$$

but rather use a posterior predictive density

$$p_{\mathsf{post}}(\tilde{y}) = \int p(\tilde{y} \mid \theta) \, p(\theta \mid y) \, d\theta$$

Suggests a different way to define the score for a Bayesian model:

$$\log p_{\mathsf{post}}(\tilde{y})$$

May seem reasonable to just substitute data y for \tilde{y} and then add a correction, as for DIC (or AIC).

BDA3 recommends something slightly different:

Consider this expected log pointwise predictive density

elppd =
$$\sum_{i=1}^{n} E_{f_i} (\log p_{post}(\tilde{y}_i))$$

totaled over n separate individual predictions of \tilde{y}_i .

Here, f_i is the "true" density of \tilde{y}_i .

When \tilde{y}_i is a replication of observation y_i , elppd can be estimated by substitution:

$$lppd = \sum_{i=1}^{n} log \ p_{post}(y_i)$$

Since the same data y is being used twice (for the posterior and for substitution), this will tend to overestimate elppd.

Needs a correction ...

WAIC

In BDA3, the Watanabe-Akaike Information Criterion (WAIC) is

WAIC =
$$-2 \text{ lppd} + 2p_{\text{WAIC}}$$

where effective number of parameters p_{WAIC} could be

$$p_{\text{WAIC1}} = 2 \sum_{i=1}^{n} \left(\log \left(\mathbb{E}_{\mathsf{post}} p(y_i \mid \theta) \right) - \mathbb{E}_{\mathsf{post}} \left(\log p(y_i \mid \theta) \right) \right)$$

$$p_{\text{WAIC2}} = \sum_{i=1}^{n} \operatorname{var}_{\mathsf{post}} (\log p(y_i \mid \theta))$$

BDA3 recommends second form.

2

Notes:

- ▶ Smaller values of WAIC are preferred (as with AIC or DIC).
- $holdsymbol{p_{WAIC1}}$ and p_{WAIC2} can be approximated using a posterior Monte Carlo sample: Replace posterior means and variances with sample means and variances.
- ► WAIC can estimate elppd:

$$\widehat{\text{elppd}}_{\text{WAIC}} = -\frac{1}{2} \text{WAIC} = \text{lppd} - p_{\text{WAIC}}$$