

Motivation: Model selection for large data

- Bigger data sets and more complex models
- We still need to evaluate and compare models
- $\overline{\text{elpd}}_M$ quantifies how model M *generalizes* to unseen data \tilde{y}_i

$$\overline{\text{elpd}}_M = \int \log p_M(\tilde{y}_i | y) p_t(\tilde{y}_i) d\tilde{y}_i,$$

True data generating process

Posterior predictive distribution

Expected log predictive density

Leave-one-out cross-validation

- Basic idea: Hold out observation i and predict y_i based on y_{-i}
- Estimate elpd_M using leave-one-out cross-validation (loo)

$$\overline{\text{elpd}}_{\text{loo}} = \frac{1}{n} \sum_{i=1}^n \log p_M(y_i | y_{-i}) = \frac{1}{n} \sum_{i=1}^n \log \int p_M(y_i | \theta) p_M(\theta | y_{-i}) d\theta$$

- Desirable properties
 - + almost unbiased for large n
 - + straight-forward handling of hierarchical structures
- Two major problems
 - Need to fit the model n times
 - Need to evaluate predictive densities n times

Our contributions: Method

$$\overline{\text{elpd}}_{\text{loo}} = \frac{1}{n} \sum_{i=1}^n \log p_M(y_i | y_{-i})$$

- We propose a fast approximation for $\overline{\text{elpd}}_{\text{loo}}$
 - ① Approximate full data posterior $q_M(\theta|y)$ using Variational Bayes/Laplace
 - ② Compute $p_M(y_i|y_{-i})$ using importance sampling with q_M as proposal
 - ③ Subsample the sum over n using the Hansen-Hurwitz estimator
- Solves both problems with leave-one-out CV
 - ① Only need to fit the model once on the full data set
 - ② Predictive distributions $p_M(y_i|y_{-i})$ are only needed for a small subset

Our contributions: Results

- Theoretical results (under regularity conditions)

$$\widehat{\text{elpd}}_{\text{loo}} \xrightarrow{P} \overline{\text{elpd}}_{\text{loo}} \quad \text{for } n \rightarrow \infty$$

- Extensive empirical results

① Variational Bayes, Laplace approx., MCMC

② Bayesian linear regression

③ Hierarchical models

- For more details, come see us at poster #231
- Thank you for listening!

