Deviance Information Criterion

PUBH 8442: Bayes Decision Theory and Data Analysis

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BIC and AIC

- Define the *deviance* function for a model with parameters $\theta$:
  \[ D(\theta) = -2 \log p(y \mid \theta) \]

- Recall: Bayesian information criterion
  \[ BIC : D(\hat{\theta}) + p \log n \]
  - $\hat{\theta}$ is the maximum likelihood estimate
  - $p$ is model dimension, $\theta = (\theta_1, \ldots, \theta_p)$,
  - $n$ is sample size, $y = y_1, \ldots, y_n$
  - Motivated by asymptotic approximation of Bayes factor

- Akaike information criterion
  \[ AIC = D(\hat{\theta}) + 2p \]
  - Motivated by asymptotic approximation to Kullback-Leibler divergence
What if choice of $p$ and $n$ is not clear?

This is common in Bayesian hierarchical models.

Example: Consider the multi-level normal model

$$y_{ij} \sim \text{Normal}(\theta_i, \sigma^2) \text{ for } i = 1, \ldots, m \text{ and } j = 1, \ldots, n_i$$

$$\theta_i \sim \text{Normal}(\mu, \tau^2)$$

- If $\theta_i$ are all nearly identical ($\tau^2 \to 0$), model depends only on estimation of $\mu$ ($p \approx 1$)
- If $\theta_i$ are estimated independently ($\tau^2 \to \infty$), $p \approx m$ makes sense.
- The choice of “sample size” is similarly unclear
Define the effective number of parameters by

\[ p_D = E_{\theta | y} D(\theta) - D(\hat{\theta}) \]

where typically \( \hat{\theta} = E_{\theta | y} \theta \).

The “expected” deviance minus the “fitted” deviance

- Higher \( p_D \) implies more over-fitting with estimate \( \hat{\theta} \)
- For a non-hierarchical model, the Bayesian CLT implies \( p \approx p_D \) for large \( n \)
The Deviance information criteria (DIC) is

\[ DIC = E_{\theta | y} D(\theta) + p_D \]

Approximates AIC for a non-hierarchical model
Similar asymptotic justification as AIC
Used for model comparison
  Lower DIC values are better
Can estimate DIC from posterior samples:

\[ DIC = 2\bar{D} - D(\bar{\theta}) \]

where \( \bar{\theta} = \frac{1}{N} \sum_{t=1}^{N} \theta^{(t)} \),

\[ \bar{D} = \frac{1}{N} \sum_{t=1}^{N} -2 \log p(y | \theta^{(t)}) \]
DIC comments

- DIC values are not very informative on their own
  - Used for comparisons

- Includes a “goodness-of-fit” term $\bar{D}$ with a penalty for “complexity” ($p_D$)
  - Like BIC, AIC, and other model selection criteria

- More appropriate for hierarchical models than $AIC$, $BIC$

- $p_D$ can be negative if $D(\bar{\theta})$ is relatively large.
  - Implies Bayesian CLT does not hold and $\bar{\theta}$ is a poor estimate

- Compute in winBUGS and openBUGS: \url{http://www.openbugs.net/Manuals/InferenceMenu.html}
Example: gene testing

- 40 mice are given a given a dose of alcohol, 40 are kept as control
- Expression levels are subsequently measured for 500 genes in liver
- $Y_{ij}^g$ is expression level for gene $i$, mouse $j$, group $g$
- Measurements are normally distributed with variance 1:
  \[ Y_{ij}^g \sim \text{Normal}(\mu_i^g, 1) \]

- Consider the group differences
  \[ Y_i^{\text{diff}} = \bar{Y}_i^{\text{alc}} - \bar{Y}_i^{\text{con}} \sim \text{Normal} \left( \mu_i^{\text{alc}} - \mu_i^{\text{con}}, \frac{1}{20} \right) \]
Example: gene testing

- We are interested in effect of alcohol on each gene $i$:
  
  $$\mu^\text{diff}_i = \mu^\text{alc}_i - \mu^\text{con}_i$$

- Use normal prior for effects:
  
  $$\mu^\text{diff}_i \sim \text{Normal}(0, \tau^2)$$

- Jeffrey’s prior for effect variance:
  
  $$p(\tau^2) \propto \frac{1}{\tau^2}$$

- Full distribution for $y^\text{diff}_i$ s:
  
  $$\frac{1}{\tau^2} \prod_{i=1}^{500} N(\mu^\text{diff}_i | 0, \tau^2) \cdot N(y^\text{diff}_i | \mu^\text{diff}_i, 1/20)$$
Example: gene testing

- Gibbs sample conditionals for $\mu_i^{\text{diff}}$s and $\tau^2$:

$$p(\mu_i^{\text{diff}} \mid \tau^2, y) = \text{Normal} \left( \frac{\tau^2 y_i^{\text{diff}}}{\tau^2 + 1/20}, \frac{(1/20)\tau^2}{\tau^2 + 1/20} \right)$$

$$p(\tau^2 \mid \mu^{\text{diff}}, y) = IG \left( 250, \frac{1}{2} \sum_{i=1}^{500} \mu_i^2 \right)$$

- Initialize $\tau^2 = 1/20$, run 10000 iterations with 2000 burn-in

- Compute

$$D(\mu^{\text{diff}}, \tau^2) = -2 \sum_{i=1}^{500} \log[N(y_i^{\text{diff}} \mid \mu_i^{\text{diff}}, 1/20)]$$

at each iteration.
T=10000
BurnIn = 2000
N=T-BurnIn
draws_tau_2 = rep(0,T)
draws_mu_diff = matrix(nrow = T, ncol = 500)
Ds = rep(0,T)
tau_2 = 1/20  ## initialize
for(t in 1:T){  ##Run gibbs sampler
    mus = rnorm(500, tau_2*y_diffs/(tau_2+0.05),  
      ^I^I^I    sqrt(0.05*tau_2/tau_2+0.05))
tau_2 =1/rgamma(1,250, 0.5*sum(mus^2))
draws_tau_2[t] = tau_2
draws_mu_diff[t,] = mus
Ds[t] = -2*sum(log(dnorm(y_diffs,mus,sqrt(0.05))))
}
Gibbs draws for $\tau^2$: 

Example: gene testing

- Gibbs draws for $\mu_{\text{diff}}$, three genes:

Example: gene testing

- Plot of deviance over Gibbs draws
```r
### compute DIC
mean_mus = colMeans(draws_mu_diff[2001:T,])
D_mean = -2*sum(log(dnorm(y_diffs,mean_mus,sqrt(0.05))))
p_d = mean(Ds[2001:T])-D_mean
DIC = 2*mean(Ds[2001:T])-D_mean
DIC_null = -2*sum(log(dnorm(y_diffs,0,sqrt(0.05))))
```
Example: gene testing

- The deviance for $\hat{\mu}^\text{diff}$, the mean vector over draws, is
  \[ D(\hat{\mu}^\text{diff}) = -422.7 \]

- Thus $p_D = \bar{D} - D(\hat{\mu}^\text{diff}) = 344.9$
- DIC is $DIC = \bar{D} + p_D = 267.1$
- Consider the null model $\mu_i^\text{diff} = 0 \forall i$
  - The effective number of parameters is $p_D = 0$
  - DIC is
    \[ DIC = -2 \sum_{i=1}^{500} \log[N(y_i^\text{diff} | 0, 1/20)] = 1029 \]

- Evidence there are alcohol effects (for at least some genes)
Example: gene testing

Consider a third model, that allows “no effect” for some genes.

$P_1$ is shared probability that $\mu_i^{\text{diff}} \neq 0$ for a given gene:

$$
\mu_i^{\text{diff}} \sim \begin{cases} 
0 \text{ with probability } 1 - P_1 \\
N(0, \tau^2) \text{ with probability } P_1 
\end{cases}
$$

Again, $p(\tau^2) = 1/\tau^2$

Use a uniform prior for $P_1$

$$P_1 \sim \text{Beta}(1, 1)$$

Let $\zeta_i = 1 \{ \mu_i^{\text{diff}} \neq 0 \}$
Gibbs sampling

- Draw from conditional for $(\zeta, \mu^{\text{diff}})$ for each gene $i$:
  - Draw $\zeta_i \in \{0, 1\}$ by
    \[
P(\zeta_i = 1 | y, \tau^2, P_1) = \frac{P_1 N(y_i^{\text{diff}} | 0, \tau^2 + \frac{1}{20})}{P_1 N(y_i^{\text{diff}} | 0, \tau^2 + \frac{1}{20}) + (1 - P_1) N(y_i^{\text{diff}} | 0, \frac{1}{20})}
    \]
  - If $\zeta_i = 0$, set $\mu_i^{\text{diff}} = 0$
  - Otherwise, generate $\mu_i \sim \text{Normal} \left( \frac{\tau^2 y_i^{\text{diff}}}{\tau^2 + 1/20}, \frac{(1/20) \tau^2}{\tau^2 + 1/20} \right)$
  - Draw $\tau^2$ from $P(\tau^2 | \mu^{\text{diff}}, y, \zeta) = \text{IG} \left( \frac{1}{2} \sum \zeta_i, \frac{1}{2} \sum \zeta_i \mu_i^2 \right)$
  - Draw $P_1$ from
    \[
P(P_1 | y, \zeta, \mu, \tau^2) = \text{Beta}(1 + \sum \zeta_i, 1 + 500 - \sum \zeta_i)
    \]
Example: gene testing

Gibbs draws for $P_1$:

- Estimate $\approx 21\%$ of genes show an alcohol effect
Example: gene testing

- Gibbs draws for $\tau^2$: 

![Gibbs draws for $\tau^2$](image)
Example: gene testing

- Gibbs draws for $\mu^{\text{diff}}$, three genes:

- Estimated probability of an effect for the red gene: 0.06
- For the blue gene: 0.12
- For the black gene: 0.99
Example: gene testing

- $p_D$ for the present model is 179.8
- DIC is 106.57
- Suggests this is a good compromise between
  - Null model ($DIC = 1029$)
  - Model with an effect in every gene ($DIC = 267.1$)