Bayesian Inference Session 10

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Summary

1 Bayesian Hypothesis Testing

Bayesian Hypothesis Testing

■ In the Bayesian context, the problem of deciding about which hypothesis to accept is conceptually simple. Typically, one would compare the hypotheses H_1, \ldots, H_k through their respective posterior probabilities, obtained via Bayes theorem as

$$p(H_i|\mathbf{x}) \propto p(\mathbf{x}|H_i)p(H_i).$$

Once again, this setup can be framed as a decision problem. In addition to the posterior probabilities attached to the hypotheses (or states of nature), a loss structure with the possible actions can be incorporated.

In the context of hypothesis testing procedure framed as a decision problem, one would have $\mathcal{A}=\{d_0,d_1\}$, where d_i is to accept $H_i:\theta\in\Theta_i$, (for i=0,1) as the most plausible hypothesis. Under this setting $\Theta=\Theta_0\cup\Theta_1$. In this situation a hypothesis testing procedure can be seen as a decision function $\delta:\Omega\to\{d_0,d_1\}$. Example 1:

$$egin{array}{cccc} \Theta & & & \delta & & & \\ & & d_0 & d_1 & & & \\ H_0 & 0 & a & & & \\ H_1 & b & 0 & & & \end{array}$$

In this sense, the Bayesian testing procedure can be presented as

$$\delta^* = \begin{cases} \mathsf{d}_1 & p(H_0|\mathbf{x}) \leq \frac{b}{a+b} \\ \mathsf{d}_0 & \text{otherwise.} \end{cases}$$

Assuming equal error loss, if $p(H_0|\mathbf{x})>p(H_1|\mathbf{x})$ then H_0 should be accepted as the most plausible hypothesis for θ . In this case, it can be said that H_0 is preferable to H_0 . Otherwise, H_1 is preferred to H_0 .

An alternative way to test hypotheses is by using **Bayes factors**, which are defined as follows:

$$B_{01} = \frac{m_0(\mathbf{y})}{m_1(\mathbf{y})} = \frac{f(\mathbf{y}|\theta_0)}{f(\mathbf{y}|\theta_1)}, \qquad H_0: \theta = \theta_0 \quad \text{vs.} \quad H_1: \theta = \theta_1$$

$$B_{01} = \frac{m_0(\mathbf{y})}{m_1(\mathbf{y})} = \frac{f(\mathbf{y}|\theta_0)}{\int_{\Theta_1} f(\mathbf{y}|\theta)f(\theta)d\theta}, \quad H_0: \theta = \theta_0 \quad \text{vs.} \quad H_1: \theta \in \Theta_1$$

$$B_{01} = \frac{m_0(\mathbf{y})}{m_1(\mathbf{y})} = \frac{\int_{\Theta_0} f(\mathbf{y}|\theta)f(\theta)d\theta}{\int_{\Theta_1} f(\mathbf{y}|\theta)f(\theta)d\theta}, \quad H_0: \theta \in \Theta_0 \quad \text{vs.} \quad H_1: \theta \in \Theta_1$$

The concept of Bayes factors was introduced by Jeffreys (1961). The following table presents some cutoff points that can help interpret the values one would obtain from the Bayes factor.

Cutoff	Interpretation
$B_{01} < 1$	Evidence supporting H_1
$B_{01} \in (1,3)$	Weak evidence in favor of H_0
	(not enough to make a decision)
$B_{01} \in (3,20)$	Strong evidence in favor of H_0
$B_{01} \in (20, 150)$	Solid evidence in favor of $H_{ m 0}$
$B_{01} > 150$	Extreme evidence in favor of ${\cal H}_0$

Caption

Example 1: Let us suppose that one is interested to test

$$H_0: \quad \theta = 1/2 \\ H_1: \quad \theta > 1/2,$$

where θ represents the probability of success in a Bernoulli process. Assuming that $\theta \sim U(0,1)$ and after observing the first six trials (1,1,1,1,1,0) compute B_{01} .

Example 2: One wants to perform inference about λ : the number of goals scored by the visitor team in a local tournament. The hypotheses of interest are

$$H_0: \lambda = 1 \ vs \ H_1: \lambda = 2$$

After observing seven matches, the number of goals scored by the visitor is 3, 1, 0,1,0,0,1.

Example 3: Now the interest is about the number of goals scored by the local team. One wishes to perform the following test:

$$H_0: \lambda \leq 1 \ vs \ H_1: \lambda > 1$$

After observing the games of the first four dates of the season:

Assuming that $\lambda \sim Gamma(0.1, 0.1)$ compute B_{01} .

The Bayes factor can also be used to compare candidate models for \mathbf{y} . Suppose that one has K candidate models, where the iht model has likelihood $f_i(\mathbf{y}|\theta_i)$ and θ_i has density $f(\theta_i)$, for $i=1,\ldots K$. Thus, the Bayes factor is given by:

$$B_{ij} = \frac{m_i(\mathbf{y})}{m_j(\mathbf{y})} = \frac{\int f_i(\mathbf{y}|\theta_i) f_i(\theta_i)}{\int f_j(\mathbf{y}|\theta_j) f_j(\theta_j)}$$

Example 4: More hypothesis testing!

Let $\mathbf{Y}=(Y_1,\ldots,Y_n)$ be a random sample from the $N(\theta,10)$ and assume one wishes to test $H_0:\theta=\theta_0$ versus $H_1:\theta\neq\theta_0$. Supposing $\theta|H_1\sim N(\mu,w)$ compute B_{01} .

The End