

Computer Intensive Statistics

Individual HWA2: Bootstrap and Simulation-Based Methods

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1. (1p) Let X_1, \dots, X_n be a random sample from a distribution with mean μ and variance σ^2 . The central limit theorem implies that the distribution function of

$$Z = \sqrt{n}(\bar{X} - \mu)$$

converges to the distribution function of $N(0, \sigma^2)$. Let $g(\cdot)$ be a differentiable function. We are interesting in approximating the distribution of

$$\sqrt{n}(g(\bar{X}) - g(\mu)).$$

Is bootstrap a valid approach to approximate it? Motivate your answer.

2. (2p) In the EM algorithm, if $\theta^{(t)}$ maximizes $Q(\theta | \theta^{(t-1)})$ as a function of θ , then the observed likelihood increases, i.e.,

$$\log g(y | \theta^{(t)}) \geq \log g(y | \theta^{(t-1)}).$$

Suppose that $\theta^{(t)}$ does not maximizes $Q(\theta | \theta^{(t-1)})$, but we have $Q(\theta^{(t)} | \theta^{(t-1)}) > Q(\theta^{(t-1)} | \theta^{(t-1)})$. Does the observed likelihood still increase? Is the EM algorithm still self-consistent, in the sense that the MLE is one of the local maxima in this algorithm?

3. (1p) Suppose that the complete data is $X = (Y, Z)$, but we only observe Y . To approximate

$$Q(\theta | \hat{\theta}^{(t-1)}) = E[\log f(x | \theta) | y, \hat{\theta}^{(t-1)}]$$

in the MCEM algorithm, our textbook generates z from $f(y, z | \hat{\theta}^{(t-1)})$. Is $Q(\theta | \hat{\theta}^{(t-1)})$ correctly approximated using such generated z ?

4. (1p) Consider the following parametric logistic model:

$$Y_i \sim \text{Bernoulli}\left(\frac{\exp(\beta_0 + \beta_1 V_i + \beta_2 Z_i)}{1 + \exp(\beta_0 + \beta_1 V_i + \beta_2 Z_i)}\right), \quad i = 1, \dots, n.$$

We observe (Y_i, V_i, X_i) , where $X_i = Z_i + \epsilon_i$ with $\epsilon_i \sim N(0, 0.25)$. A sample of size 1000 is observed. You can obtain the data set **SIMEXlogit** on Studium. Find the estimate of β_0 , β_1 , and β_2 .