Bernoulli candidate sets that are functions of the unkown parameters masked data

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1/22/2022

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[section] [theorem]

0.0.1 Choices for p_1, \ldots, p_m that are functions of θ and other observables

In many cases, the failure rate increases as the lifetime of the system increases. Thus, a reasonable choice for p_i may be of the form

$$p_j(s) = 1 - \exp(-\beta_j s),$$

which is the cdf of an exponential distribution with rate parameter β_j . As $s \to \infty$, $p_j(s) \to 1$.

$$f(x_1, \dots, x_m, s | \theta) = \frac{f(s | \theta)}{\sum_{j=1}^m h_j(s | \theta_j)} \sum_{k=1}^m \left\{ h_k(s | \theta_k) \prod_{j=1}^m (1 - \exp(-\beta_j s))^{x_j} \exp(-\beta_j s)^{1-x_j} \right\}.$$
(1)

A possibly more interesting choice is, say, $p_j(s|\theta_j) = F_j(s|\theta_j)$, the cdf of X_j , so that a random sample X_1, \ldots, X_m stores more information about θ .

A potentially even more interesting choice is given by

$$p_i(s|\theta_i) = f_{K|S}(j|s,\theta).$$

0.0.1.0.1 Estimating p Under the maximum entropy model, p has a straightforward method of moments estimator given by

$$\hat{p} = \frac{\overline{|C|} - 1}{m - 1},$$

where $\overline{|C|} = \sum_{i=1}^{n} |C_i|/n$.

Proof.

$$E(|C|) = E\left(\sum_{j=1}^{m} 1_{\{j=k\}} + 1_{\{j\neq k\}} X_j\right)$$
$$= 1 + E\left(\sum_{\substack{j=1\\j\neq k}} X_j\right).$$

Since X_1,\ldots,X_m are independent, this simplifies to

$$E(|C|) = 1 + \sum_{\substack{j=1\\j \neq k}}^{m} E(X_j)$$

$$= 1 + \sum_{\substack{j=1\\j \neq k}}^{m} p$$

$$= 1 + (m-1)p.$$

We may estimate E(|C|) with the sample average $\overline{|C|} = \sum_{i=1}^{n} |C_i|/n$ and we may estimate p with \hat{p} ,

$$\overline{|C|} = 1 + (m-1)\hat{p}.$$

Solving for \hat{p} , we obtain the result

$$\hat{p} = \frac{\overline{|C|} - 1}{m - 1}.$$

Under different models, where p_1, \ldots, p_m are functions or not all the same constant value, the likelihood approach may be used to estimate them.