Integrated Likelihood Inference in Poisson Distributions

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Abstract

The text of your abstract. 200 or fewer words.

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1 Introduction

Suppose the random variables N_i, $i = 1, ..., m$, each have independent Poisson distributions such that $\mathrm{E}(N_i) = \theta_i$ and $\theta = (\theta_1, ..., \theta_m) \in \Theta \subset \mathbb{R}_+^m$. The purpose of this paper is to consider likelihood-based inference for a real-valued parameter of interest $\psi = g(\theta)$, where $g : \Theta \to \Psi$ is a known twice continuously differentiable function.

The log-likelihood function of the model is given by

$$\ell(\theta) = \sum_{i=1}^{m} [N_i \log(\theta_i) - \theta_i]. \tag{1}$$

Note that while ℓ is a function of the full m-dimensional vector parameter θ, ψ is just a scalar. This reduction in dimension induces a nuisance parameter λ in the model that typically must be eliminated from the log-likelihood function before inference regarding ψ can be conducted. The standard procedure for doing so involves choosing some method with which to summarize $\ell(\theta)$ over its possible values while holding ψ fixed in place. In the general case where both ψ and λ are defined implicitly (i.e. ψ isn't just equal to one of the components of θ), this effectively reduces $\ell(\theta)$ to a simple function of ψ alone, having replaced each dimension of θ that depends on λ with a static summary of its range of values. We call this new function a pseudo-log-likelihood function for ψ and denote it as $\ell(\psi)$.

Perhaps the most straightforward method of summarization we can use to construct $\ell(\psi)$ is to maximize $\ell(\theta)$ over all possible of values of θ for a fixed value of ψ. This yields what is known as the *profile* log-likelihood function, formally defined as

$$\ell_p(\psi) = \sup_{\theta \in \Theta \colon g(\theta) = \psi} \ell(\theta). \tag{2}$$

2 Integrated Likelihood Functions

3 Application to Poisson Models

We now turn our attention to the task of using the ZSE parameterization to construct an integrated likelihood that can be used to make inferences regarding a parameter of interest derived from the Poisson model described in the introduction. We will

4 Inference for the Weighted Sum of Poisson Means

5 Examples

Suppose we are interested in estimating the weighted sum of a group of Poisson means corresponding to n independent populations, where n is a known positive integer. Note that the maximum likelihood estimate (MLE) for θ_i is simply $\hat{\theta}_i = x_i$, the observed value of X_i. Consider the weighted sum

$$Y = \sum_{i=1}^{n} w_i X_i,$$

where each w_i is a known constant greater than zero.

The purpose of this paper is to consider likelihood- and pseudolikelihood-based inference for the real-valued parameter of interest

$$\psi \equiv \mathrm{E}(Y) = \sum_{i=1}^{n} w_i \theta_i.$$

In particular, we will analyze the performance of point and inverval estimates for ψ based on the integrated likelihood function and a proposed modification to it. Similar estimates obtained from the profile likelihood will be used as a benchmark.

References