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

Consider a vector $\theta = (\theta_1, ..., \theta_n)$ in which each component represents the mean of a distinct Poisson process. The purpose of this paper is to discuss the task of conducting likelihood-based inference for a real-valued parameter of interest $\psi = \tau(\theta)$. In particular, we will examine the utility of the integrated likelihood function as a tool for obtaining interval and point estimates for ψ, using the performance of the more easily calculated profile likelihood as a benchmark.

We may obtain a sample of values from each Poisson process through repeated measurements of the number of events it generates over a fixed period of time. Suppose we have done so, and let X_{ij} represent the jth count from the ith sample, so that $X_{ij} \sim \text{Poisson}(\theta_i)$ for $i = 1, ..., n$ and $j = 1, ..., m_i$. The probability mass function (pmf) for a single observation $X_{ij} = x_{ij}$ is

$$p(x_{ij};\, \theta_i) = \frac{e^{-\theta_i}\theta_i^{x_{ij}}}{x_{ij}!}, \;\; x_{ij} = 0, 1, 2, ...; \;\; \theta_i > 0. \tag{1}$$

Denote the sample of counts from the ith process by the vector $X_{i\bullet} = (X_{i1}, ..., X_{im_i})$, its associated mean by $\bar{X}_{i\bullet} = \frac{1}{m_i}\sum_{j=1}^{m_i} X_{ij}$, and assume that all of the counts both within and between samples are measured independently. The likelihood function for an individual component θ_i based on the data $X_{i\bullet} = x_{i\bullet}$ is then equal to the product of the individual probabilities of the observed counts, i.e.

$$
\begin{aligned}
L(\theta_i; x_{i\bullet}) &= \prod_{j=1}^{m_i} p(x_{ij}; \theta_i) \\
&= \prod_{j=1}^{m_i} \frac{e^{-\theta_i}\theta_i^{x_{ij}}}{x_{ij}!} \\
&= \left(\prod_{j=1}^{m_i} e^{-\theta_i}\right)\left(\prod_{j=1}^{m_i} \theta_i^{x_{ij}}\right)\left(\prod_{j=1}^{m_i} x_{ij}!\right)^{-1} \\
&= \left(e^{-\sum_{j=1}^{m_i}\theta_i}\right)\left(\theta_i^{\sum_{j=1}^{m_i} x_{ij}}\right)\left(\prod_{j=1}^{m_i} x_{ij}!\right)^{-1} \\
&= e^{-m_i\theta_i}\theta_i^{m_i\bar{x}_{i\bullet}}\left(\prod_{j=1}^{m_i} x_{ij}!\right)^{-1}.
\end{aligned}
\tag{2}
$$

Since L is only useful to the extent that it informs our understanding of the value of θ_i, we are free to replace it with any other function differing from it by just a (nonzero) multiplicative term that is constant with respect to θ_i, provided that the result still satisfies the necessary regularity conditions, as this will not change any conclusions regarding θ_i that we draw from it. Hence, we may safely discard the term in parentheses on the final line of Equation 2 as it does not depend on θ_i and instead simply write

$$
L(\theta_i; x_{i\bullet}) = e^{-m_i\theta_i}\theta_i^{m_i\bar{x}_{i\bullet}}. \tag{3}
$$

It will generally be more convenient to work with the log-likelihood function, which is given by

$$
\begin{aligned}
\ell(\theta_i; x_{i\bullet}) &= \log L(\theta_i; x_{i\bullet}) \\
&= \log\left(e^{-m_i\theta_i}\theta_i^{m_i\bar{x}_{i\bullet}}\right) \\
&= -m_i\theta_i + m_i\bar{x}_{i\bullet}\log\theta_i \\
&= m_i(\bar{x}_{i\bullet}\log\theta_i - \theta_i).
\end{aligned}
\tag{4}
$$

The sum of the log-likelihood functions for each component of θ then forms the basis of the log-likelihood function for θ itself:

$$\begin{aligned}
\ell(\theta; x_{1\bullet}, ..., x_{n\bullet}) &= \log L(\theta; x_{1\bullet}, ..., x_{n\bullet}) \\
&= \log\left(\prod_{i=1}^{n} L(\theta_i; x_{i\bullet})\right) \\
&= \sum_{i=1}^{n} \log L(\theta_i; x_{i\bullet}) \\
&= \sum_{i=1}^{n} \ell(\theta_i; x_{i\bullet}) \\
&= \sum_{i=1}^{n} m_i(\bar{x}_{i\bullet} \log\theta_i - \theta_i).
\end{aligned} \tag{5}$$

We can derive the maximum likelihood estimate (MLE) for θ_i by differentiating Equation 4 with respect to θ_i, setting the result equal to 0, and solving for θ_i. This gives the nice result that the MLE is simply equal to the mean of the sample of data $X_{i\bullet}$. That is,

$$\hat{\theta}_i = \bar{X}_{i\bullet}. \tag{6}$$

Similarly, the MLE for the full parameter θ is just the vector of MLEs for its individual components:

$$\hat{\theta} \equiv (\hat{\theta}_1, ..., \hat{\theta}_n) = (\bar{X}_{1\bullet}, ..., \bar{X}_{n\bullet}). \tag{7}$$

2 Pseudolikelihoods

Let $\Theta \subseteq \mathbb{R}_+^n$ represent the space of possible values for θ and suppose we have a real-valued *parameter of interest* $\psi = \tau(\theta)$, where $\tau : \Theta \to \Psi$ is a known function with at least two continuous derivatives. Though it is not strictly necessary, in order to align with the tendency of researchers to focus on one-dimensional summaries of vector quantities we will assume for our purposes that ψ is a scalar, i.e. $\Psi \subseteq \mathbb{R}$.

This reduced dimension of Ψ relative to Θ implies the existence of a *nuisance parameter* $\lambda \in \Lambda \subseteq \mathbb{R}^{n-1}$. As its name suggests, λ tends to obfuscate or outright preclude inference regarding ψ and typically must be eliminated from the likelihood before proceeding. The product of this elimination is called a *pseudolikelihood function.* Any function of the data and ψ alone could theoretically be considered a pseudolikelihood, though course in practice some are more useful than others.

If we let $\Theta_\psi = \{\theta \in \Theta :\ \tau(\theta) = \psi\}$, then associated with each $\psi \in \Psi$ is the set of likelihood values $\mathcal{L}_\psi = \{L(\theta) :\ \theta \in \Theta_\psi\}$. For a given value of ψ, there may exist multiple corresponding values of λ.

We can construct pseudolikelihoods for ψ through clever choices by which to summarize $\mathcal{L}_\psi$ over all possible values of λ. Among the most popular methods of summary are profiling (i.e. maximization), conditioning, and integration, each with respect to the nuisance parameter. These summaries do come at a cost, however; eliminating a model's nuisance parameter from its likelihood almost always sacrifices some information about its parameter of interest as well. One measure of a good pseudolikelihood, therefore, is the balance it strikes between the amount of information it retains about ψ and the ease with which it can be computed.

2.1 The Profile Likelihood

The most straightforward method we can use to construct a pseudolikelihood (or equivalently, a pseudo-log-likelihood) function for ψ is usually to find the maximum of $\ell(\theta)$ over all possible of values of θ for each value of ψ. This yields what is known as the *profile* log-likelihood function, formally defined as

$$\ell_p(\psi) = \sup_{\theta \in \Theta:\ \tau(\theta) = \psi} \ell(\theta), \ \ \psi \in \Psi. \tag{8}$$

In the case where an explicit nuisance parameter λ exists so that θ may be written as $\theta = (\psi, \lambda)$, Equation 8 is equivalent to replacing λ with $\hat{\lambda}_\psi$, its conditional MLE given ψ:

$$\ell_p(\psi) = \ell(\psi, \hat{\lambda}_\psi). \tag{9}$$

Historically, the efficiency with which the profile is capable of producing accurate estimates of ψ relative to its ease of computation has made it the method of choice for statisticians when performing likelihood-based inference regarding a parameter of interest. Examples of profile-based statistics are the MLE for ψ, i.e.,

$$\hat{\psi} = \underset{\psi \in \Psi}{\arg\sup}\, \ell_p(\psi), \tag{10}$$

and the signed likelihood ratio statistic for ψ, given by

$$R_\psi = \text{sgn}(\hat{\psi} - \psi)(2(\ell_p(\hat{\psi}) - \ell_p(\psi)))^{\frac{1}{2}}. \tag{11}$$

2.2 The Integrated Likelihood

The *integrated likelihood* for ψ seeks to summarize $\mathcal{L}_\psi$ by its average value with respect to some weight function π over the space Θ_ψ. From a theoretical standpoint, this is preferable to the maximization procedure found in the profile likelihood as it naturally incorporates our uncertainty regarding the nuisance parameter's true value into the resulting pseudo-likelihood. The general form of an integrated likelihood function is given

$$\bar{L}(\psi) = \int_{\Theta_\psi} L(\theta)\pi(\theta; \psi) d\theta. \tag{12}$$

It is up to the researcher to choose the weight function $\pi(\cdot; \psi)$, which plays an important role in the properties of the resulting integrated likelihood. Severini (2007) developed a method for re-parameterizing λ that makes the integrated likelihood relatively insensitive to the exact weight function chosen. Using this new parameterization, we have great flexibility in choosing our weight function; as long as it does not depend on the parameter of interest, the integrated likelihood that is produced will enjoy many desirable frequency properties.

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 Estimating the Weighted Sum of Poisson Means

Consider the weighted sum

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

where each w_i is a known constant greater than zero. Suppose we take for our parameter of interest the expected value of this weighted sum, so that

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

4.1 Examples

5 Zero-Inflated Poisson Regression

A sample of count data is called *zero-inflated* when it contains an excess amount of zero-valued observations. A common tactic to account for this excess is to model the data using a mixture of two distributions. The first is a simple Bernoulli process that generates zeros and the other is one that generates counts, some of which may also be zeros. When this count-generating process is governed by a Poisson distribution, we call the resulting mixture a zero-inflated Poisson (ZIP) model.

Let $X \sim \text{Poisson}(\mu)$ and

References