COMPARING THE APPROXIMATIONS FOR THE GENERALIZED LOG LIKELIHOOD RATIO OF A MULTINOMIAL DISTRIBUTION

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1. Introduction and statement of the results

We recall some results from [2]. Assume given real numbers

$$a_1 < a_2 < \cdots < a_N$$

and a discrete probability distribution

$$P : \{a_1, \ldots, a_N\} \to \mathbb{R} : a_i \mapsto p_i\,.$$

Assume a sample taken from $\{a_1, \ldots, a_N\}$ according to P has sample distribution $(\hat{p}_i)_{i=1,\ldots,N}$. We want to compute the corresponding MLE for the true distribution $(p_i)_{i=1,\ldots,N}$, subject to the condition that the latter's expectation value is s. I.e. $\sum_i p_i a_i = s$.

For simplicity we will assume

$$a_1 < s < a_N, \forall i : \hat{p}_i \neq 0\,. \tag{1.1}$$

Proposition 1.1. *The ML distribution is unique. It is given by*

$$p_i = \frac{\hat{p}_i}{1 + \theta(a_i - s)} \tag{1.2}$$

where θ is the unique root of the equation

$$\sum_i \frac{\hat{p}_i(a_i - s)}{1 + \theta(a_i - s)} = 0 \tag{1.3}$$

in the interval $[-1/(a_N - s), 1/(s - a_1)]$.

Let $\mu = \sum_i p_i a_i$ and let $\mathrm{LLR}_{\mathrm{exact}}$ be the generalized log-likelihood ratio [4] for $\mu = s_0$ versus $\mu = s_1$, *divided by the sample size.* If $(\theta_i)_{i=1,2}$ are the solutions to (1.3) for $s = s_i$ then by (1.2) we have

$$\boxed{\mathrm{LLR}_{\mathrm{exact}} = \sum_i \hat{p}_i \log\left(\frac{1 + \theta_0(a_i - s_0)}{1 + \theta_1(a_i - s_1)}\right)}$$

Computing $\mathrm{LLR}_{\mathrm{exact}}$ requires numerically solving the rational equation (1.3) *twice.* This is trivial to do numerically and indeed this is how it is done in Fishtest [5]. Nonetheless to fortify our intuition it is useful to have more manageable approximations to $\mathrm{LLR}_{\mathrm{exact}}$. One such approximation was given in [2, Proposition 2.1].

$$\boxed{\mathrm{LLR}_{\mathrm{alt}} = \frac{1}{2} \log\left(\frac{\sum_i \hat{p}_i(s_0 - a_i)^2}{\sum_i \hat{p}_i(s_1 - a_i)^2}\right)}$$

Another, even simpler approximation, was given in [1, (2.1)]:

$$\boxed{\mathrm{LLR}_{\mathrm{alt2}} = \frac{1}{2}\frac{(s_1-s_0)(2\hat{\mu}-s_0-s_1)}{\hat{\sigma}^2}}$$

where $\hat{\mu}$ and $\hat{\sigma}^2$ are respectively the sample mean and variance. In other words

$$\hat{\mu} = \sum_i \hat{p}_i a_i\,, \qquad \hat{\sigma}^2 = \sum_i \hat{p}_i (a_i - \hat{\mu})^2\,.$$

Put $\Delta := (s_1 - s_0)/\hat{\sigma}$. In this note we relate $\mathrm{LLR}_{\mathrm{exact}}$, $\mathrm{LLR}_{\mathrm{alt}}$ and $\mathrm{LLR}_{\mathrm{alt2}}$ by providing a power series expression in Δ for them, truncated at Δ^4.

Remark 1.2. It can be seen from the data in Example 1.6 below that Δ is typically quite small. Moreover it follows from [3] that the expected duration d of an SPRT test with reasonable resolution is $\sim 1/\Delta^2$. Or, by inverting this, $\Delta \sim 1/\sqrt{d}$.

Let ν, κ be respectively the skewness [7] and the excess kurtosis [6] for the sample distribution. Thus

$$\nu = \frac{\hat{\mu}_3}{\hat{\sigma}^3}\,, \qquad \kappa = \frac{\hat{\mu}_4}{\hat{\sigma}^4} - 3$$

where $\hat{\mu}_3$, $\hat{\mu}_4$ are the third and fourth central sample moments. In other words

$$\hat{\mu}_3 = \sum_i \hat{p}_i (a_i - \hat{\mu})^3\,, \qquad \hat{\mu}_4 = \sum_i \hat{p}_i (a_i - \hat{\mu})^4\,.$$

Let h be the relative position of $\hat{\mu}$ with respect to the interval $[s_0, s_1]$, with $h = 1$ corresponding to $\hat{\mu} = s_1$ and $h = -1$ corresponding to $\hat{\mu} = s_0$. Formally

$$h = \frac{2\hat{\mu} - s_0 - s_1}{s_1 - s_0}\,.$$

Remark 1.3. In an SPRT test of $\mu = s_0$ versus $\mu = s_1$ we do not expect $\hat{\mu}$ to straddle very far outside the interval $[s_0, s_1]$ as otherwise the test would end. So $h = O(1)$.

Proposition 1.4. *With the above definitions we have the following formulas*

$$\boxed{\mathrm{LLR}_{\mathrm{alt2}} = \frac{1}{2}h\Delta^2} \tag{1.4}$$

$$\boxed{\mathrm{LLR}_{\mathrm{alt}} = \frac{1}{2}h\Delta^2 - \frac{1}{8}(h^3+h)\Delta^4 + \cdots} \tag{1.5}$$

$$\boxed{\mathrm{LLR}_{\mathrm{exact}} = \frac{1}{2}h\Delta^2 + \frac{1}{12}\nu(3h^2+1)\Delta^3 + \frac{1}{8}(2\nu^2-\kappa-1)(h^3+h)\Delta^4 + \cdots} \tag{1.6}$$

Corollary 1.5. *One has*

$$\boxed{\mathrm{LLR}_{\mathrm{alt}} - \mathrm{LLR}_{\mathrm{alt2}} \cong -\frac{1}{8}(h^3+h)\Delta^4} \tag{1.7}$$

$$\boxed{\mathrm{LLR}_{\mathrm{exact}} - \mathrm{LLR}_{\mathrm{alt}} \cong \frac{1}{12}\nu(3h^2+1)\Delta^3 + \frac{1}{8}(2\nu^2-\kappa)(h^3+h)\Delta^4} \tag{1.8}$$

Example 1.6. To get a feel for the sizes of the quantities appearing in the above formulas we compute them for some pentanomial data taken from Fishtest [5]. We have $s_i = 1/(1 + 10^{-e_i/400})$ where e_0, e_1 are the Elo bounds, given in the first two columns. The column labeled "approx" gives the approximation to $\mathrm{LLR}_{\mathrm{exact}}$ obtained via the formula (1.8).

e_0	e_1	pent. freqs	size	Δ	h	ν	κ	exact	alt	rel. err.	approx	rel. err.	err. ratio
-0.50	1.50	[729, 5234, 10174, 5154, 898]	22189	0.0132	1.520	0.0463	-0.1717	2.93696	2.93533	-5.6e-04	2.93696	2.8e-07	-1990.0
-0.50	1.50	[441, 3213, 7170, 3164, 399]	14387	0.0140	-2.106	-0.0144	0.0065	-2.96711	-2.96644	-2.3e-04	-2.96711	3.0e-07	-762.5
-0.50	1.50	[1746, 11875, 23034, 11679, 1820]	50154	0.0133	-0.666	0.0154	-0.1731	-2.93641	-2.93673	1.1e-04	-2.93641	-1.7e-08	-6266.1
-0.50	1.50	[550, 3237, 6268, 3224, 478]	13757	0.0131	-2.483	-0.0245	-0.1821	-2.94598	-2.94457	-4.8e-04	-2.94598	5.4e-07	-888.4
0.25	1.75	[504, 6686, 20525, 6609, 557]	34881	0.0122	-1.141	0.0244	0.4324	-2.94903	-2.94977	2.5e-04	-2.94903	-5.6e-08	-4487.4
-1.50	0.50	[271, 2151, 4827, 2241, 299]	9789	0.0139	3.091	0.0028	-0.0289	2.94174	2.94151	-7.7e-05	2.94174	5.6e-07	-137.5

2. Derivations

2.1. The expression for $\mathrm{LLR}_{\mathbf{alt2}}$. This is obvious.

2.2. The expression for $\mathrm{LLR}_{\mathbf{exact}}$. We will use a formula which was derived during the proof of [2, Proposition 2.1]

$$\mathrm{LLR} = \int_{s_0}^{s_1} \theta(s)\, ds \tag{2.1}$$

where $\theta = \theta(s)$ is the root of

$$\sum_i \frac{\hat{p}_i(a_i - s)}{1 + \theta(a_i - s)} = 0 \tag{2.2}$$

in the interval $[-1/(a_N - s), 1/(s - a_1)]$. We will think of the latter condition as "being close to zero". It will be convenient to write

$$\hat{o}_n(s) = \sum_i \hat{p}_i(a_i - s)^n\,.$$

Note

$$\begin{aligned}
\hat{o}_1(s) &= \hat{\mu} - s\\
\hat{o}_2(s) &= \hat{\sigma}^2 + (\hat{\mu} - s)^2\\
\hat{o}_3(s) &= \hat{\mu}_3 + 3\hat{\sigma}^2(\hat{\mu} - s) + (\hat{\mu} - s)^3\\
\hat{o}_4(s) &= \hat{\mu}_4 + 4\hat{\mu}_3(\hat{\mu} - s) + 6\hat{\sigma}^2(\hat{\mu} - s)^2 + (\hat{\mu} - s)^4\,.
\end{aligned}$$

We obtain from (2.2)

$$\hat{o}_1(s) - \theta\hat{o}_2(s) + \theta^2\hat{o}_3(s) - \theta^3\hat{o}_4(s) + \cdots = 0\,.$$

Or

$$\theta = \frac{\hat{o}_1(s)}{\hat{o}_2(s)} + \theta^2\frac{\hat{o}_3(s)}{\hat{o}_2(s)} - \theta^3\frac{\hat{o}_4(s)}{\hat{o}_2(s)} + \cdots$$

This equation can be solved by repeated self substitution, starting with $\theta = 0$. First step:

$$\theta \cong \frac{\hat{o}_1(s)}{\hat{o}_2(s)}\,.$$

Second step:

$$\theta \cong \frac{\hat{o}_1(s)}{\hat{o}_2(s)} + \frac{\hat{o}_3(s)\hat{o}_1(s)^2}{\hat{o}_2(s)^3} - \frac{\hat{o}_4(s)\hat{o}_1(s)^3}{\hat{o}_2(s)^4}\,.$$

Third step (truncating at $\hat{o}_1(s)^3$):

$$\begin{aligned}\theta &\cong \frac{\hat{o}_1(s)}{\hat{o}_2(s)} + \frac{\hat{o}_3(s)\hat{o}_1(s)^2}{\hat{o}_2(s)^3} - \frac{\hat{o}_4(s)\hat{o}_1(s)^3}{\hat{o}_2(s)^4} + 2\frac{\hat{o}_3(s)^2\hat{o}_1(s)^3}{\hat{o}_2(s)^5}\\
&\cong \frac{\hat{\mu}-s}{\hat{\sigma}^2+(\hat{\mu}-s)^2} + \frac{(\hat{\mu}_3+3\hat{\sigma}^2(\hat{\mu}-s))(\hat{\mu}-s)^2}{\hat{\sigma}^6} - \frac{\hat{\mu}_4(\hat{\mu}-s)^3}{\hat{\sigma}^8} + 2\frac{\hat{\mu}_3^2(\hat{\mu}-s)^3}{\hat{\sigma}^{10}}\\
&\cong \frac{\hat{\mu}-s}{\hat{\sigma}^2} - \frac{(\hat{\mu}-s)^3}{\hat{\sigma}^4} + \frac{(\hat{\mu}_3+3\hat{\sigma}^2(\hat{\mu}-s))(\hat{\mu}-s)^2}{\hat{\sigma}^6} - \frac{\hat{\mu}_4(\hat{\mu}-s)^3}{\hat{\sigma}^8} + 2\frac{\hat{\mu}_3^2(\hat{\mu}-s)^3}{\hat{\sigma}^{10}}\\
&= \frac{1}{\hat{\sigma}^2}(\hat{\mu}-s) + \frac{\hat{\mu}_3}{\hat{\sigma}^6}(\hat{\mu}-s)^2 + \left(\frac{2}{\hat{\sigma}^4} - \frac{\hat{\mu}_4}{\hat{\sigma}^8} + \frac{2\hat{\mu}_3^2}{\hat{\sigma}^{10}}\right)(\hat{\mu}-s)^3\,.\end{aligned}$$

The integral is

$$\int_{s_0}^{s_1}\theta(s)ds = -\frac{1}{2\hat{\sigma}^2}(\hat{\mu}-s)^2 - \frac{\hat{\mu}_3}{3\hat{\sigma}^6}(\hat{\mu}-s)^3 - \frac{1}{4}\left(\frac{2}{\hat{\sigma}^4} - \frac{\hat{\mu}_4}{\hat{\sigma}^8} + \frac{2\hat{\mu}_3^2}{\hat{\sigma}^{10}}\right)(\hat{\mu}-s)^4\Big|_{s_0}^{s_1}\,.$$

Put

$$\begin{aligned}\delta &= s_1 - s_0\\ m &= (s_1+s_0)/2\,.\end{aligned}$$

Then

$$\hat{\mu} = m + h\delta/2\,.$$

We have

$$\begin{aligned}\hat{\mu} - s_0 &= \delta/2 + h\delta/2 = \frac{1}{2}\delta(h+1)\\ \hat{\mu} - s_1 &= -\delta/2 + h\delta/2 = \frac{1}{2}\delta(h-1)\,.\end{aligned}$$

Hence

$$\begin{aligned}(\hat{\mu}-s_0)^2 - (\hat{\mu}-s_1)^2 &= \delta^2 h\\ (\hat{\mu}-s_0)^3 - (\hat{\mu}-s_1)^3 &= \frac{1}{4}\delta^3(3h^2+1)\\ (\hat{\mu}-s_0)^4 - (\hat{\mu}-s_1)^4 &= \frac{1}{2}\delta^4(h^3+h)\,.\end{aligned} \tag{2.3}$$

Substituting yields

$$\int_{s_0}^{s_1}\theta(s)ds = \frac{h\delta^2}{2\hat{\sigma}^2} + \frac{\hat{\mu}_3\delta^3}{12\hat{\sigma}^6}(3h^2+1) + \frac{1}{8}\left(\frac{2}{\hat{\sigma}^4} - \frac{\hat{\mu}_4}{\hat{\sigma}^8} + \frac{2\hat{\mu}_3^2}{\hat{\sigma}^{10}}\right)\delta^4(h^3+h)$$

which is (1.6).

2.3. **The expression for** $\mathrm{LLR}_{\mathbf{alt}}$**.** We have

$$\begin{aligned}
\frac{1}{2}\log\left(\frac{\sum_i \hat{p}_i(s_0-a_i)^2}{\sum_i \hat{p}_i(s_1-a_i)^2}\right) &= \frac{1}{2}\log\left(\frac{\hat{\sigma}^2+(\hat{\mu}-s_0)^2}{\hat{\sigma}^2+(\hat{\mu}-s_1)^2}\right)\\
&= \frac{1}{2}\log\left(\frac{1+\dfrac{(\hat{\mu}-s_0)^2}{\sigma^2}}{1+\dfrac{(\hat{\mu}-s_1)^2}{\hat{\sigma}^2}}\right)\\
&\cong \frac{1}{2}\left(\frac{(\hat{\mu}-s_0)^2}{\hat{\sigma}^2}-\frac{1}{2}\frac{(\hat{\mu}-s_0)^4}{\hat{\sigma}^4}-\frac{(\hat{\mu}-s_1)^2}{\hat{\sigma}^2}+\frac{1}{2}\frac{(\hat{\mu}-s_1)^4}{\hat{\sigma}^4}\right)\\
&= \frac{h\delta^2}{2\hat{\sigma}^2}-\frac{1}{8}\frac{\delta^4}{\hat{\sigma}^4}(h^3+h) \qquad \text{(using (2.3))}\,.
\end{aligned}$$

This is (1.5).

References

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