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COMBINING LIKELIHOOD AND SIGNIFICANCE FUNCTIONS

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Abstract: The need to combine likelihood information is common in analyses of complex models and in meta-analyses, where information is combined from several studies. We work to first order, and show that full accuracy when combining scalar or vector parameter information is available from an asymptotic analysis of the score variables. Then we use this approach to combine p-values for scalar parameters of interest.

Key words and phrases: Composite likelihood, meta-analysis, p-value functions.

1. Introduction

Statistical models presented in the form of a family of densities $\{f(y;\theta); y \in \mathbb{R}^d, \theta \in \Theta \subset \mathbb{R}^p\}$ are usually analyzed using the likelihood function $L(\theta) \propto f(y;\theta)$, or equivalently the log-likelihood function $\ell(\theta) = \log\{L(\theta)\}$. Evaluated at the observed data, this provides all data-dependent information required for a standard Bayesian analysis, and almost all data-dependent information required for frequentist-based analysis. In the latter case as described in Fraser and Reid (1993), a full third-order inference also requires sample-space derivatives of the log-likelihood function.

However, in some modeling situations, the full joint density, and hence the likelihood function, may not be available. In such cases, workarounds have been developed using, for example, marginal models for single coordinates or pairs of coordinates. Other variants include pseudo-likelihood or composite likelihood functions, as studied in Lindsay (1988) and reviewed in Varin, Reid and Firth (2011). For example, the composite pairwise log-likelihood function is

$$\ell_{\text{pair}}(\theta) = \sum_{r<s} \log\{f_2(y_r, y_s; \theta)\},$$

where $f_2(y_r, y_s; \theta)$ is the marginal model for a pair of components (y_r, y_s), obtained by marginalizing the joint density $f(y;\theta)$. If we consider what is called the independence likelihood, we have $\ell_{\text{ind}}(\theta) = \Sigma_r \log\{f_1(y_r;\theta)\}$.

Our approach is to assume that the model is sufficiently smooth that the usual asymptotic theory for composite likelihood inference applies; see, for example, the summary in Varin, Reid and Firth (2011, Sec. 2.3). In particular, we assume that the likelihood components have the property that their score functions are asymptotically normal, with finite variances and covariances. This can arise if we have a fixed number of components, each constructed from an underlying sample of size n. It can also occur if we have an increasing number of components with appropriate short-range dependence, such that information accumulates at a rate proportional to the number of components. The latter can arise, for example, in a time series or spatial setting in which the correlations decrease with distance.

We denote an arbitrary composite log-likelihood function by $\sum_{i=1}^{m} \ell_i(\theta)$; for the pairwise log-likelihood function above, we have $m = d(d-1)/2$. We let θ_0 be some trial or reference value of the parameter, and then examine the first derivative of the model about θ_0; we see that to first order the model has a simple linear regression form that is invariant to the starting point. In practice, the starting value could be any consistent estimate, such as that obtained by maximizing the unadjusted composite likelihood function.

We assume that each component log-likelihood function admits an expansion of the form

$$\ell_i(\theta) = a + (\theta-\theta_0)^{\mathrm{T}} s_i - \frac{1}{2}(\theta-\theta_0)^T \jmath_i(\theta-\theta_0) + o(||\theta-\theta_0||), \tag{1.1}$$

where $s_i = s_i(\theta_0) = (\partial/\partial\theta)\ell_i(\theta)|_{\theta_0}$ is the component score variable and $\jmath_i = \jmath_i(\theta_0)$ is the corresponding negative second derivative. The Bartlett identities hold for each component log-likelihood function:

$$E(s_i;\theta_0) = 0, \quad \mathrm{var}(s_i;\theta_0) = E(\jmath_i;\theta_0) = v_{ii}, \tag{1.2}$$

where v_{ii} is the $p \times p$ expected Fisher information matrix from the ith component. We also have the moment relations (Cox and Hinkley (1974)),

$$E(s_i;\theta) = v_{ii}(\theta-\theta_0) + o(||\theta-\theta_0||), \quad \mathrm{var}(s_i;\theta) = v_{ii} + o(||\theta-\theta_0||). \tag{1.3}$$

Then we stack the m score vectors $s = (s_1^{\mathrm{T}}, \ldots, s_m^{\mathrm{T}})^{\mathrm{T}}$, and write

$$E(s;\theta) \doteq V(\theta-\theta_0), \quad \mathrm{var}(s;\theta) \doteq W, \tag{1.4}$$

where $V = (v_{11}, \ldots, v_{mm})^{\mathrm{T}}$ is an $mp \times p$ matrix of stacked information matrices v_{ii}, and W is an $mp \times mp$ matrix with v_{ii} on the diagonal and off-diagonal matrix elements $v_{ij} = \mathrm{cov}(s_i, s_j)$. Expression (1.4) enables us to construct the optimally weighted score vector using Gauss–Markov theory, as described in the next section. Because the error of the approximation is $o(||\theta-\theta_0||)$, the mean and variance results (1.2) and (1.3), respectively, are valid for any θ_0 within moderate deviations of the true value.

2. First-order Combination of Component Log-likelihood Functions

We express (1.4) to first order using the regression model,

$$s = V(\theta - \theta_0) + e, \tag{2.1}$$

where $e \sim N(0, W)$. From this approximation, we obtain the log-likelihood function

$$\begin{aligned} \ell^*(\theta) &= a - \frac{1}{2}\{s - V(\theta-\theta_0)\}^{\mathrm{T}} W^{-1}\{s - V(\theta - \theta_0)\}, \\ &= a - \frac{1}{2}(\theta-\theta_0)^{\mathrm{T}} V^{\mathrm{T}} W^{-1} V(\theta-\theta_0) + (\theta-\theta_0)^{\mathrm{T}} V^{\mathrm{T}} W^{-1} s, \end{aligned} \tag{2.2}$$

with score function $s^*(\theta) = V^T W^{-1}\{s - V(\theta-\theta_0)\}$, which has expected value zero and variance $V^T W^{-1} V$. This log-likelihood function is maximized at

$$\hat{\theta}^* = \theta_0 + (V^{\mathrm{T}} W^{-1} V)^{-1} V^{\mathrm{T}} W^{-1} s,$$

which has expected value θ and variance $(V^{\mathrm{T}} W^{-1} V)^{-1} = \bar{W}$, say. Then we can equivalently write

$$\ell^*(\theta) = a - \frac{1}{2}(\theta-\hat{\theta}^*)^{\mathrm{T}} V^{\mathrm{T}} W^{-1} V(\theta - \hat{\theta}^*) = c - \frac{1}{2}(\theta-\hat{\theta}^*)^{\mathrm{T}} \overline{W}^{-1}(\theta-\hat{\theta}^*), \tag{2.3}$$

which makes the location form of the log-likelihood more transparent.

If θ is a scalar parameter then from (2.2)

$$\begin{aligned} \ell^*(\theta) &= a - \frac{1}{2} V^{\mathrm{T}} W^{-1} V(\theta-\theta_0)^2 + V^{\mathrm{T}} W^{-1} s(\theta-\theta_0) & (2.4) \\ &\doteq V^{\mathrm{T}} W^{-1} \underline{\ell}(\theta), & (2.5) \end{aligned}$$

where $\underline{\ell}(\theta)$ is the vector of components $\ell_i(\theta)$, equivalent to first order to $a - (1/2)\{s_i - v_{ii}(\theta-\theta_0)\}^2 v_{ii}^{-1}$.

In (2.5), we have an optimally weighted combination of component log-likelihood functions, that agrees with (2.4) or (2.3) up to quadratic terms. However this is usually different in finite samples, because the individual component log-likelihood functions are not constrained to be quadratic.

The linear combination (2.5) is not, in general, available for the vector parameter case as different combinations of components are needed for the different coordinates of the parameter, as indicated by the different rows in the matrix V^{T} in (2.3).

Lindsay (1988) studied the choice of weights for a scalar composite likelihood function by seeking an optimally weighted combination of score functions $\partial\ell_i(\theta)/\partial\theta$ (in his notation, $S_i(\theta)$), where the optimal weights depend on θ. Our approach is to work within moderate deviations of a reference parameter value. Then we use the first-order model for the observed variables s_i, leading directly to a first-order log-likelihood function.

This is closely related to indirect inference, which is widely used in econometrics. For this, a set of estimating functions $\{g_1(\theta),\dots,g_K(\theta)\}$ is available, and the goal is to estimate θ based on an optimal combination of these functions. Combining estimating functions into a quadratic form is explored in Jiang and Turnbull (2004), who refer to the result as an indirect log-likelihood function. In indirect inference the model for the data is often specified by a series of dynamic equations. In such cases it is feasible to simulate from the true model, but not to write down the true log-likelihood function. Estimation of the model parameters proceeds by matching the simulated data to the indirect log-likelihood function. In the present setting, we are instead concerned with optimal combinations of given components, where we assume that each component is a genuine log-likelihood function that satisfies (1.3) and (1.2).

For a scalar or vector parameter of interest ψ of dimension r, with nuisance parameter λ such that $\theta = (\psi^{\mathrm{T}},\lambda^{\mathrm{T}})^{\mathrm{T}}$, we have from (2.3) that the first-order log-likelihood function for the component ψ is

$$\ell^*(\psi) = c - \frac{1}{2}(\psi-\hat{\psi}^*)^{\mathrm{T}}\overline{W}^{\psi\psi}(\psi-\hat{\psi}^*), \tag{2.6}$$

where $\overline{W}^{\psi\psi}$ is the $\psi\psi$ submatrix of $\bar{W}^{-1}$ and $\hat{\psi}^* = \psi(\hat{\theta}^*)$ is the relevant component of $\hat{\theta}^*$. Pace, Salvan and Sartori (2016) consider using profile log-likelihood components for scalar parameters of interest.

3. Illustrations

The first illustrations use latent independent normal variables, because these capture the essential elements and make the role of correlation in the re-weighting clear. The basic underlying densities are assumed to be independent responses x from a $N(\theta,1)$ distribution, with corresponding log-likelihood function $-\theta^2/2+\theta x$; here we take $\theta_0=0$.

Example 1 (Independent components). Consider component variables $y_1 = x_1$ and $y_2 = x_2$. The $m=2$ component log-likelihood functions are $\ell_i(\theta;y_i) = -\theta^2/2+y_i\theta$, giving $s_i=y_i$, $V=(1,1)^{\mathrm{T}}$, and $W=\mathrm{diag}(1,1)$. Thus $\ell^*(\theta) = \ell_1(\theta)+\ell_2(\theta)$ is the independence log-likelihood function, as expected.

Example 2 (Dependent and exchangeable components). Consider $y_1 = x_1 + x_2$ and $y_2 = x_1 + x_3$. The component log-likelihood functions are $\ell_i(\theta) = -\theta^2 + \theta y_i$, giving $s_i = y_i$,

$$V = (2,2)^{\mathrm{T}}, \quad W = \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix}, \quad V^{\mathrm{T}} W^{-1} = \left(\frac{2}{3}, \frac{2}{3}\right), \tag{3.1}$$

and the combined first-order log-likelihood function

$$\ell^*(\theta) = \left(\frac{2}{3}, \frac{2}{3}\right)^{\mathrm{T}} \underline{\ell}(\theta) = -\frac{4}{3}\theta^2 + \frac{2}{3}\theta(y_1 + y_2). \tag{3.2}$$

In contrast, the unadjusted composite log-likelihood function obtained by summing the marginal log-likelihood functions is

$$\ell_{UCL}(\theta) = -2\theta^2 + \theta(y_1 + y_2).$$

Here the score variable is $y_1 + y_2$, which has variance 6 and second derivative 4. In this case the second Bartlett identity does not hold, and $\ell_{UCL}(\theta)$ is not a proper log-likelihood. We can recover the Bartlett identity by rescaling: $\ell_{ACL} = a\ell_{UCL} = -2a\theta^2 + \theta a(y_1 + y_2)$. This has negative second derivative $4a$ and score variance $6a^2$, which are equal when $a = 2/3$. In addition the adjusted composite log-likelihood is

$$\ell_{ACL}(\theta) = \frac{2}{3}\ell_{UCL}(\theta) = -\frac{4}{3}\theta^2 + \frac{2}{3}\theta(y_1 + y_2),$$

which agrees with $\ell^*(\theta)$. The next example shows that this agreement does not hold in general.

Example 3 (Dependent, but not exchangeable components). Now let $y_1 = x_1$ and $y_2 = x_1 + x_3$. The individual log-likelihood functions are $\ell_1(\theta) = -\theta^2/2 + \theta y_1$ and $\ell_2(\theta) = -\theta^2 + \theta y_2$, with $s_1 = y_1$ and $s_2 = y_2$. Then, we have $V^{\mathrm{T}} = (1,2)$, the off-diagonal elements of W are equal to one, and $V^{\mathrm{T}} W^{-1} = (0,1)$. This leads to

$$\ell^*(\theta) = -\theta^2 + \theta y_2, \tag{3.3}$$

with maximum likelihood estimate $\hat{\theta}^* = y_2/2$, which has variance $1/2$. This log-likelihood function reflects the fact that $y_2 = x_1 + x_3$ provides all information about θ.

In contrast, the unadjusted composite log-likelihood function is $\ell_{UCL}(\theta) = -(3/2)\theta^2 + \theta(y_1 + y_2)$, with associated maximum likelihood estimate $\hat{\theta}_{UCL} = (y_1 + y_2)/3$. The rescaling factor to recover the Bartlett identity is $a = 3/5$, giving the adjusted composite log-likelihood function

$$\ell_{ACL}(\theta) = \frac{3}{5}\ell_{UCL}(\theta) = -\frac{9}{10}\theta^2 + \frac{3}{5}\theta(y_1 + y_2),$$

which is again maximized at $(y_1 + y_2)/3$. Although the second Bartlett identity is satisfied, the adjusted composite log-likelihood function leads to the same inefficient estimate of θ as that of the unadjusted version. For further discussion on this point, see Freedman (2006).

An asymptotic version of these two illustrations is obtained by having n replications of y_1 and y_2, or equivalently, by assuming x_1, x_2, and x_3 have variances $1/n$ instead of 1.

Example 4 (Bivariate normal). Suppose we have n pairs (y_{i1}, y_{i2}) independently distributed as bivariate normal with mean vector (θ, θ) and known covariance matrix. The sufficient statistic is the pair of sample means $(\bar{y}_{.1}, \bar{y}_{.2})$, and the component log-likelihood functions are taken as those from the marginal densities of $\bar{y}_{.1}$ and $\bar{y}_{.2}$, such that $\ell_1(\theta) = -n(\bar{y}_{.1} - \theta)^2/(2\sigma_1^2)$ and $\ell_2(\theta) = -n(\bar{y}_{.2} - \theta)^2/(2\sigma_2^2)$. The score components s_1 and s_2 are, respectively, $n(\bar{y}_{.1} - \theta)/\sigma_1^2$ and $n(\bar{y}_{.2} - \theta)/\sigma_2^2$, with variance–covariance matrix

$$W = n\begin{pmatrix} \dfrac{1}{\sigma_1^2} & \dfrac{\rho}{(\sigma_1\sigma_2)} \\ \dfrac{\rho}{(\sigma_1\sigma_2)} & \dfrac{1}{\sigma_2^2} \end{pmatrix}, \tag{3.4}$$

giving

$$V^{\mathrm{T}}W^{-1} = (1-\rho^2)^{-1}\left(1 - \frac{\rho\sigma_1}{\sigma_2}, 1 - \frac{\rho\sigma_2}{\sigma_1}\right),$$

leading to

$$\ell^*(\theta) = -\frac{n}{2(1-\rho^2)}\left\{\left(\frac{\bar{y}_{.1} - \theta}{\sigma_1}\right)^2 (1 - \rho\frac{\sigma_1}{\sigma_2}) + \left(\frac{\bar{y}_{.2} - \theta}{\sigma_2}\right)^2\left(1 - \rho\frac{\sigma_2}{\sigma_1}\right)\right\}. \tag{3.5}$$

As a function of θ this can be shown to be equivalent to the full log-likelihood function based on the bivariate normal distribution of $(\bar{y}_{.1}, \bar{y}_{.2})$, and the maximum likelihood estimate of θ is a weighted combination of $\bar{y}_{.1}$ and $\bar{y}_{.2}$.

If the parameters in the covariance matrix are also unknown then the reduction by sufficiency is more complicated. In this case the vector version of the combination described in (2.3) is needed.

Example 5 (Two parameters). Suppose that x_i follow a $N(\theta_1, 1)$ distribution, and z_i independently follow a $N(\theta_2, 1)$ distribution. We base our component log-likelihood functions on the densities of the vectors

$$y_1 = \begin{pmatrix} x_1 \\ z_2 + z_3 \end{pmatrix}, \quad y_2 = \begin{pmatrix} x_1 + x_3 \\ z_2 \end{pmatrix},$$

giving the score variables $s_1 = (y_{11}, y_{12})^T$ and $s_2 = (y_{21}, y_{22})^T$. The needed variances and covariances are:

$$V = \begin{pmatrix} 1 & 0 \\ 0 & 2 \\ 2 & 0 \\ 0 & 1 \end{pmatrix}, \quad W = \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 1 \\ 1 & 0 & 2 & 0 \\ 0 & 1 & 0 & 1 \end{pmatrix}, \quad W^{-1} = \begin{pmatrix} 2 & 0 & -1 & 0 \\ 0 & 1 & 0 & -1 \\ -1 & 0 & 1 & 0 \\ 0 & -1 & 0 & 2 \end{pmatrix},$$

and $V^T W^{-1} V = \text{diag}(2, 2)$. This gives

$$\ell^*(\theta_1, \theta_2) = -(\theta_1 - \hat{\theta}_1^*)^2 - (\theta_2 - \hat{\theta}_2^*)^2,$$

where $\hat{\theta}^* = (y_{21}/2, y_{12}/2)^{\mathrm{T}}$. This combines the log-likelihood functions for θ based on s_{12} and s_{21}, as we might reasonably have expected from the presentations with the latent x_i and z_i variables. At the same time, the usual composite log-likelihood function derived from the sum of those for s_1 and s_2 contains additional terms.

Example 6 (Two parameters, without symmetry). Within the structure of the previous example, suppose our component vectors are

$$y_1 = \begin{pmatrix} x_1 \\ z_1 \end{pmatrix}, \quad y_2 = \begin{pmatrix} x_1 + x_2 \\ z_2 \end{pmatrix}.$$

The variances and covariances are again directly available:

$$V = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 2 & 0 \\ 0 & 1 \end{pmatrix}, \quad W = \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 2 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \quad W^{-1} = \begin{pmatrix} 2 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

From Example 3 we have that for inference about θ_1, the weights are (0, 1), and from Example 1 the weights for θ_2 are (1, 1). Clearly these are incompatible. For the direct approach using (2.5), we have $V^T W^{-1} V = \text{diag}(2, 2)$, giving

$$\ell^*(\theta_1, \theta_2) = -(\theta_1 - \hat{\theta}_1^*)^2 - (\theta_2 - \hat{\theta}_2^*)^2,$$

where $\hat{\theta}^* = (y_{21}/2, (y_{12} + y_{22})/2)^{\mathrm{T}}$. This simple sum of component likelihood functions for (θ_1, θ_2) is to be expected, because the measurements for θ_1 are independent of those for θ_2. In addition, all information about θ_1 comes from the first coordinate of y_2, and all the information for θ_2 comes from the second coordinates of both y_1 and y_2.

Example 7 (Time series correlation structure). As a more realistic example, we consider that the underlying model follows a q-dimensional normal distribution with mean zero and with correlations $R_{ss'}(\theta)$ between pairs $(y_s, y_{s'})$. We compare $\ell^*(\theta)$ to the unadjusted composite log-likelihood function created from all possible pairs. In computing the elements of W, each score component s_i corresponds to a pair (s, s') and each s_j corresponds to a pair (t, t'). Thus, W_{ij} depends on up to the fourth moments of the original components of the vector y. Although the construction is tedious, it can be automated.

In particular, we have

$$\ell_j(\theta; y_s, y_{s'}) = -\frac{1}{2}\log(1 - R_{ss'}^2) - \frac{y_s^2 + y_{s'}^2 - 2y_s y_{s'} R_{ss'}}{2(1 - R_{ss'}^2)}, \tag{3.6}$$

and

$$s_j = \frac{\partial l_j(\theta)}{\partial\theta}\Big|_{\theta=\theta_0} = \frac{R_{ss'}\dot{R}_{ss'}}{1 - R_{ss'}^2} + \frac{y_s y_{s'}\dot{R}_{ss'}}{1 - R_{ss'}^2} - \frac{(y_s^2 + y_{s'}^2 - 2y_s y_{s'} R_{ss'})R_{ss'}\dot{R}_{ss'}}{(1 - R_{ss'}^2)^2}, \tag{3.7}$$

where $R_{ss'} = R_{ss'}(\theta_0)$ and $\dot{R}_{ss'} = (d/d\theta)R_{ss'}(\theta_0)$. From this, we have

$$v_{jj} = \text{var}\{s_j(\theta_0)\} = \frac{\dot{R}_{ss'}^2}{1 - R_{ss'}^2} + \frac{2R_{ss'}^2\dot{R}_{ss'}^2}{(1 - R_{ss'}^2)^2}. \tag{3.8}$$

There is a similar, but lengthy, formula for the covariance elements, that takes into account the pairs (s, s') and (t, t') which have $s' = t'$ and $s' \neq t'$, for example.

For illustration, we chose $R_{ss'}(\theta) = \theta^{|s-s'|}$ if $|s - s'| \leq 2$, and 0 otherwise; only pairs differing by one or two places contribute to $\ell^*(\cdot)$ and to the unadjusted composite likelihood function $\ell_{UCL}(\theta) = 1^{\mathrm{T}}\underline{\ell}(\theta)$. This is a time series version of correlations between near neighbours only. Similar structures are often used in spatial modeling. Figure 1 illustrates $\ell_{UCL}(\theta)$ and $\ell^*(\theta)$ for sample data sets of length 10, and compares them to the true full log-likelihood function. Simulations from this model are summarized in Table 1. In computing the averages of the point estimates and standard error, simulations leading to a maximum on the boundary were removed.

Asymptotic theory is strongly tested in these simulations of a single time series of length 11 or 21. There is some replication because correlations are zero beyond two lags. However, we can see from Table 1 that even the full maximum likelihood estimate has appreciable bias. The covariance matrix is positive-definite only over a restricted range for θ, although the 2×2 submatrices needed for the weighted and unweighted pairwise likelihood calculations do not require a restricted range: both ℓ^* and ℓ_{UCL} can be computed if a full multivariate normal model does not exist. Whether or not there may be another multivariate

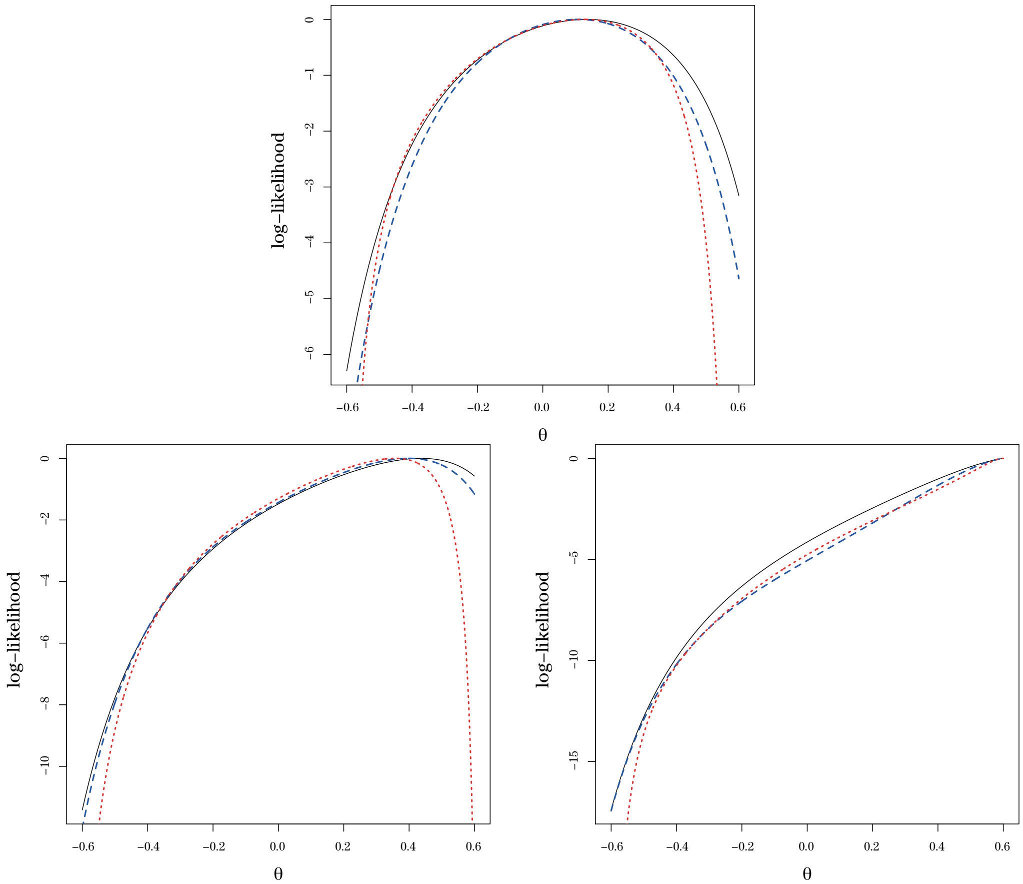

Figure 1. Illustrations of the the proposed combination $\ell^*(\cdot)$ (black, solid), pairwise composite log-likelihood function (blue, dashed), and full log-likelihood function (red, dotted) for three simulations of length 11 from the model $N\{0, R(\theta)\}$. In the third plot, the likelihood functions do not have the approximate quadratic behavior needed for first-order theory.

model compatible with these marginal densities is not clear. This is a limitation of composite likelihood methods from the viewpoint of modeling, but can be an advantage from the viewpoint of robust estimation. Simulations (not shown) suggest that both ℓ^* and the unadjusted composite pairwise likelihood functions give accurate point estimates when the range of θ is expanded to $(-1, 1)$. In Table 2, we show the effect of using incorrect weights when computing ℓ^*. The simulation results do not appear to be very sensitive to changing the point at which the weights are computed.

Table 1. *Example 7.* Averages over 10,000 simulations from the model $N\{0, R(\theta)\}$. We have deleted simulation runs in which the estimates were on the boundary of the parameter space; N^* is the number remaining. The weights in ℓ^* use the true value of θ. The theoretical standard error is based on the second derivative at the maximum.

	true $\theta = 0.2$							
	$q = 11$				$q = 21$			
	estimate	simulation st. err.	theoretical st. err.	N^*	estimate	simulation st. err.	theoretical st. err.	N^*
ℓ	0.149	0.309		9,056	0.182	0.238		9,890
ℓ^*	0.140	0.290	0.288	8,586	0.178	0.230	0.219	9,673
ℓ_{UCL}	0.135	0.278	0.304	8,551	0.172	0.225	0.187	9,604
	true $\theta = 0.4$							
	$q = 11$				$q = 21$			
	estimate	simulation st. err.	theoretical st. err.	N^*	estimate	simulation st. err.	theoretical st. err.	N^*
ℓ	0.314	0.269		8,437	0.366	0.190		9,665
ℓ^*	0.289	0.251	0.270	7,479	0.347	0.188	0.194	8,684
ℓ_{UCL}	0.279	0.246	0.295	7,504	0.340	0.187	0.152	8,658

Table 2. *Example 7.* Simulations from the model $N\{0, R(\theta)\}$; ℓ^* uses weights $W(\theta_0)$ computed at a different value of θ. Simulation size is 10,000.

Weights W and V computed at $\theta_0 = 0.2$			
q	true θ	estimate	standard error
11	0.4	0.289	0.260
21	0.4	0.347	0.192
11	0.3	0.216	0.273
21	0.3	0.264	0.215
11	0.1	0.075	0.294
21	0.1	0.090	0.240
11	0.0	0.002	0.293
21	0.0	0.001	0.238
11	−0.1	−0.078	0.291
21	−0.1	−0.090	0.240

4. Comparison to Composite Likelihood

Composite likelihood inference combines information from different components, often by adding the log-likelihood functions. Care is needed in constructing inference from the resulting function, as the curvature at the maximum does not give an accurate reflection of the precision. Corrections for this in the scalar parameter setting involve either rescaling the composite log-likelihood function or accommodating the dependence among the components in the estimate of the variance of the composite likelihood estimator. In the vector parameter setting, adjustments to the composite log-likelihood function are more complex than a simple rescaling; see Pace, Salvan and Sartori (2011).

This rescaling is not sufficient; the location of the composite log-likelihood function is incorrect to first order, and the resulting confidence intervals are not correctly located to first order. This is corrected by using $\ell^*(\theta)$ from Section 2.

As we are using only first-order log-likelihood functions, it suffices to illustrate this with normal distributions. Suppose $y^{\mathrm{T}} = (y_1, \ldots, y_m)$, where the marginal models for the individual coordinates y_i are normal with mean θv_{ii}, variance v_{ii}, and $\mathrm{cov}(y_i, y_j) = v_{ij}$. These are all elements of the matrix W. The unadjusted composite log-likelihood function is

$$\ell_{UCL}(\theta) = -\frac{1}{2}\theta^2 \Sigma_{i=1}^m v_{ii} + \Sigma_{i=1}^m y_i \theta,$$

with maximum likelihood estimate $\hat{\theta}_{CL} = \Sigma y_i / \Sigma v_{ii}$ and curvature Σv_{ii} at the maximum point. This curvature is not the inverse variance of $\hat{\theta}_{CL}$ as the second Bartlett identity does not hold.

As indicated in Example 2, the rescaled version that recovers the second Bartlett identity is

$$\ell_{ACL}(\theta) = \frac{H}{J}\ell_{UCL}(\theta) = -\frac{1}{2}\theta^2 \frac{(\Sigma v_{ii})^2}{\Sigma v_{ij}} + \theta \sum y_i \frac{\Sigma v_{ii}}{\Sigma v_{ij}},$$

where $H = E\{-\ell''_{UCL}(\theta)\} = \Sigma_i v_{ii}$ and $J = \mathrm{var}\{\ell'_{UCL}\theta)\} = \Sigma_{i,j} v_{ij}$; in this context neither H nor J depend on θ. The maximum likelihood estimate from this function is the same, $\hat{\theta}_{UCL}$; however the inverse of the second derivative gives the correct asymptotic variance.

What is less apparent is that the location of the log-likelihood function needs a correction. This is achieved using the weighted version from Section 2:

$$\ell^*(\theta) = -\frac{1}{2}\theta^2 (V^{\mathrm{T}} W^{-1} V) + \theta V^{\mathrm{T}} W^{-1} y,$$

which has maximum likelihood estimate $\hat{\theta}^* = (V^{\mathrm{T}} W^{-1} V)^{-1} V^{\mathrm{T}} W^{-1} y$, with variance $(V^{\mathrm{T}} W^{-1} V)^{-1}$. Note that the linear and quadratic coefficients for θ of $\ell^*(\theta)$ are the same as those of the full log-likelihood function for the model $N(\theta V, W)$. Computating $\ell_{ACL}(\theta)$ and $\ell^*(\theta)$ requires variances and covariances of the score variables.

Writing the uncorrected composite log-likelihood function as $1^{\mathrm{T}} \underline{\ell}(\theta)$, where $\underline{\ell}(\theta)$ is the vector $\{\ell_1(\theta), \ldots, \ell_m(\theta)\}$, with $\ell_i(\theta) = -(1/2) v_{ii} \theta^2 + y_i \theta$, we have $\mathrm{var}(\hat{\theta}_{UCL}) = (1^{\mathrm{T}} W)/(1^{\mathrm{T}} V^2)$, $\mathrm{var}(\hat{\theta}^*) = (V^{\mathrm{T}} W^{-1} V)^{-1}$, and $\mathrm{cov}(\hat{\theta}_{UCL}, \hat{\theta}^*) =$

$(V^{\mathrm{T}}W^{-1}V)^{-1}$, giving

$$\mathrm{var}(\hat{\theta}_{UCL} - \hat{\theta}^*) = \frac{1^{\mathrm{T}}W1}{(1^{\mathrm{T}}V)^2} - \frac{1}{V^{\mathrm{T}}W^{-1}V}$$

and

$$\frac{\mathrm{var}(\hat{\theta}_{UCL})}{\mathrm{var}(\hat{\theta}^*)} = \frac{(1^{\mathrm{T}}V)^2}{(1^{\mathrm{T}}W1)(V^{\mathrm{T}}W^{-1}V)}.$$

5. Combining Significance or p-value Functions

In the case of a scalar parameter, we can directly link the score variable for each component to a standard normal variable, and hence to a p-value. Using the regression formulation given in (2.1) and taking $\theta_0 = 0$ as in Section 3, we obtain

$$s_i - v_{ii}\theta \longrightarrow z_i = v_{ii}^{-1/2}(s_i - v_{ii}\theta) \longrightarrow p_i = \Phi(z_i),$$

where z_i is standard normal, and p_i is the first-order p-value used to assess $\theta = \theta_0$. Similarly, we can make the inverse sequence of transformations

$$p_i \longrightarrow z_i = \Phi^{-1}(p_i) \longrightarrow (s_i - v_{ii}\theta) = (v_{ii})^{1/2} z_i.$$

As we have seen, to first order, the optimal combination is linear in $s_i - v_{ii}\theta$, which allows us to combine the associated p-values:

$$V^{\mathrm{T}}W^{-1}(s - V\theta) = V^{\mathrm{T}}W^{-1}V^{1/2}\Phi^{-1}\{p(\theta; s)\}, \tag{5.1}$$

where $V^{1/2}\Phi^{-1}\{p(\theta; s)\}$ is the vector with coordinates $v_{ii}^{1/2}\Phi^{-1}\{p(\theta; s_i)\}$. We can then convert this to a combined first-order p-value:

$$\tilde{p}(\theta; s) = \Phi[(V^T W^{-1}V)^{-1/2}V^{\mathrm{T}}W^{-1}V^{1/2}\Phi^{-1}\{p(\theta; s)\}]. \tag{5.2}$$

Example 2 continued (Dependent and exchangeable components). The composite score variable relative to the nominal parameter value $\theta_0 = 0$ is

$$V^{\mathrm{T}}W^{-1}s = \frac{2}{3}(y_1 + y_2),$$

which is the score variable from the proposed log-likelihood function $\ell^*(\theta)$. The relevant quantile is

$$z = \left(\frac{8}{3}\right)^{-1/2}\left\{\frac{2}{3}(y_1 + y_2) - \frac{8}{3}\theta\right\},$$

which has a standard normal distribution that is exact in this case. The corresponding composite p-value function is then

$$\tilde{p}(\theta; s) = \Phi(z).$$

Example 3 continued (Dependent, but not exchangeable components). The combined score variable for $\theta_0 = 0$ is $V^{\mathrm{T}}W^{-1}s = y_2$, which is the score variable from $\ell^*(\theta)$. The corresponding quantile is $z = 2^{-1/2}(y_2 - 2\theta)$, and the corresponding composite p-value function is

$$\tilde{p}(\theta; s) = \Phi(z) = \Phi\{2^{-1/2}(y_2 - 2\theta)\},$$

which agrees with the general observation that y_2 provides full information on the parameter θ.

Example 8 (Combining three p-values). Suppose three investigations of a common scalar parameter θ yield the following p-values for assessing a null value θ_0: $1.15\%, 3.01\%$, and 2.31%. To combine these, we need the measure of precision provided by the information, or the variance of the score, for each component, say, $v_{11} = 3.0, v_{22} = 6.0$, and $v_{33} = 9.0$. The corresponding z-values and score values s are

$$\begin{aligned} z_1 &= \Phi^{-1}(0.0115) = -2.273 \quad s_1 - 3\theta_0 = 3^{1/2}(-2.273) = -3.938, \\ z_2 &= \Phi^{-1}(0.0301) = -1.879 \quad s_2 - 6\theta_0 = 6^{1/2}(-1.879) = -4.603, \\ z_3 &= \Phi^{-1}(0.0231) = -1.994 \quad s_3 - 9\theta_0 = 9^{1/2}(-1.994) = -5.981. \end{aligned} \tag{5.3}$$

First, suppose for simplicity that the investigations are independent, such that $W = \mathrm{diag}(V)$ and $V^T W^{-1} = (1, 1, 1)$ and that we add the scores. This gives the combined score -14.522. Then, standardizing by the root of the combined information $18^{1/2} = 4.243$, we obtain $\tilde{p} = \Phi(-3.423) = 0.00031$.

To examine the effect of dependence between the scores, we consider a cross-correlation matrix of the form

$$R = \begin{pmatrix} 1 & \rho & \rho \\ \rho & 1 & \rho \\ \rho & \rho & 1 \end{pmatrix},$$

with a corresponding covariance matrix W with entries $3, 6$, and 9 on the diagonal, and appropriate covariances otherwise. To illustrate a low level of correlation, we take $\rho = 0.2$. The coefficients for combining the scores s_i in array (17) are given in the following array:

$$\begin{aligned} V^T W^{-1} = (3, 6, 9) &\begin{pmatrix} 3.000 & 0.848 & 1.039 \\ 0.848 & 6.000 & 1.470 \\ 1.039 & 1.470 & 9.000 \end{pmatrix}^{-1} \\ &= (0.510, 0.726, 0.822). \end{aligned}$$

The resulting z- and p-value are -2.81 and $\tilde{p} = 0.0025$, respectively, which are an order of magnitude larger than those obtained when assuming independence.

The combined p-value increases with ρ; for example, if $\rho = 0.8$, the combined p-value is 0.075.

Fisher's combined p-value, obtained by referring $-2\Sigma \log p_i$ to a χ^2_6 distribution, is 0.0006. This is independent of the value of ρ, because Fisher's method assumes that the p-values are independent. The Bonferroni p-value is $3 \min(p_i) = 0.0345$, which, although valid under dependence, is known to be conservative.

Many modern treatments of meta-analysis concentrate instead on combining the effect estimates, typically weighted by inverse variances. Our approach is similar, although we work in the space of score functions. More specifically, we combine the estimates $\hat{\theta}_i = -v_{ii}^{-1/2} z_i$ with the weights v_{ii}. Under independence, the combined estimate of θ is 0.807 with a standard error of 0.236, leading to the same p-value 0.0003 under independence. Similarly weighted linear combinations of $\hat{\theta}_i$ that incorporate correlation give the same p-values as above. The combination of point estimates here is analogous to a random-effects meta-analysis, except that we assume that the within-study and between-study variances are known. Here ρ plays the role of the between-study correlation. Of course, in more practical applications of meta-analysis both the within-study and the between-study variances must be estimated.

6. Conclusion

In this study, we use likelihood asymptotics to construct a fully first-order accurate log-likelihood function for a composite likelihood context. This requires the covariance matrix of the score variables, which is also needed for inference based on the composite likelihood function.

The advantage of the first-order approach is that it expresses each component log-likelihood function as equivalent to that from a normal model with an unknown mean and a known variance. This, in turn, provides a straightforward way to describe the optimal combination. We achieve this using a linear combination of the score variables, which can be converted both from p-values (for components) and to p-values (for the combination), yielding a procedure for meta-analysis.

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