

# Higher-Order Likelihood Inference in Meta-Analysis Using R

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# Outline

- Traditional meta-analysis and random-effects models
- First-order likelihood inference
- Higher-order asymptotics
  - second-order adjustment of the likelihood ratio statistic
  - meta-analysis and meta-regression problems
- R package `metaLik`
- Example
- Concluding remarks and open problems

# Meta-analysis

- The process of combining and analyzing the results from  $K$  separate studies about the same issue of interest
- Aim: providing an overall estimation of a true effect  $\beta$
- Typical in medical and epidemiological investigation
- Recent applications involve different areas of research, such as sociology, behavioral sciences, economics

Roberts (2005); Sutton & Higgins (2008)

# Linear mixed-effects model for meta-analysis

- $Y_i$ : measure of  $\beta$  from the  $i$ -th study (e.g., log-odds ratio)
- $\sigma_i^2$ : within-study variance of the estimator of  $\beta$
- Assumption: sample size of each study large enough to judge  $\sigma_i^2$  as known,  $\sigma_i^2 = \hat{\sigma}_i^2$
- Common meta-analysis model: **linear random-effects model**

$$Y_i = \beta_i + e_i, \quad e_i \sim N(0, \hat{\sigma}_i^2)$$

with

$$\beta_i = \beta + \varepsilon_i, \quad \varepsilon_i \sim N(0, \tau^2)$$

- $e_i$  and  $\varepsilon_i$  independent; marginally,  $Y_i \sim N(\beta, \hat{\sigma}_i^2 + \tau^2)$
- $\tau^2$ : variance component accounting for **between-study heterogeneity**

# Meta-regression

- Extension of meta-analysis to include study-specific covariates
- Way of explaining **sources of between-study heterogeneity**
- $X_i$ : vector of  $p$  covariates available at the aggregated meta-analysis level for study  $i$ , including the first value equal to one
- Meta-regression model

$$Y_i \sim N(X_i^\top \underline{\beta}, \hat{\sigma}_i^2 + \tau^2),$$

with  $\underline{\beta}$  the fixed-effects  $p$ -dimensional vector

Thompson & Higgins (2002); Knapp & Hartung (2003)

- If  $X_i$  equal to one,  $i = 1, \dots, K$ , the meta-regression model coincides with the meta-analysis model.

## Standard approach to meta-analysis

- DerSimonian and Laird's (1986) approach
- Estimate of  $\beta$  as a weighted mean of  $Y_i$

$$\hat{\beta}_{DL} = \frac{\sum_{i=1}^K Y_i / (\hat{\sigma}_i^2 + \hat{\tau}^2)}{\sum_{i=1}^K 1 / (\hat{\sigma}_i^2 + \hat{\tau}^2)},$$

with  $\hat{\tau}^2 = t$  (for  $t > 0$ ), where

$$t = \frac{\hat{q} - (K - 1)}{\sum_{i=1}^K \hat{\sigma}_i^{-2} - \sum_{i=1}^K \hat{\sigma}_i^{-4} / \sum_{i=1}^K \hat{\sigma}_i^{-2}}$$

and  $\hat{\tau}^2 = 0$  otherwise. It is a biased estimate of  $\tau^2$ .

- $\text{var}(\hat{\beta}_{DL}) = 1 / \sum_{i=1}^K (\hat{\sigma}_i^2 + \hat{\tau}^2)^{-1}$
- Normal approximation of the distribution of the  $\beta$  estimator
- The method does not account for the uncertainty in estimating  $\tau^2$  → unreliable inferential conclusions
- Straightforward extension to meta-regression

## First-order likelihood inference

- Whole parameter vector  $\psi = (\theta, \lambda)^\top$ 
  - **scalar interest component  $\theta$** : one component of the fixed-effects vector  $\underline{\beta}$
  - **nuisance component  $\lambda$** : remaining elements of  $\underline{\beta}$  plus  $\tau^2$
- For scalar  $\theta$ , inference can rely on the **signed profile log-likelihood ratio**

$$r_P(\theta) = \text{sign}(\hat{\theta} - \theta) \sqrt{2\{\ell_P(\hat{\psi}) - \ell_P(\tilde{\psi})\}},$$

- $\ell_P(\cdot)$ : profile log-likelihood
- $\hat{\psi} = (\hat{\theta}, \hat{\lambda})^\top$ : MLE, not in closed-form in meta-analysis and meta-regression
- $\tilde{\psi} = (\theta, \hat{\lambda}_\theta)^\top$ : constrained MLE for a fixed  $\theta$
- Under mild regularity conditions,  $r_P(\theta) \xrightarrow{d} N(0, 1)$ , up to an error of order  $O(n^{-1/2})$  Severini (2000)
- **Questionable accuracy**, especially in case of small sample sizes, as in meta-analysis or meta-regression problems

## Higher-order inference

- Aim: improving the accuracy of the first-order asymptotic results

Severini (2000); Reid (2003); Brazzale *et al.* (2007)

- Skovgaard's adjustment

Skovgaard (1996)

$$\bar{r}_P(\theta) = r_P(\theta) + \frac{1}{r_P(\theta)} \log \frac{\bar{u}_P(\theta)}{r_P(\theta)},$$

where

$$\bar{u}_P(\theta) = [S^{-1}q]_{\theta} |\hat{j}|^{1/2} |\hat{i}|^{-1} |S| |\tilde{j}_{\lambda\lambda}|^{-1/2}$$

is a correction term, involving

- $\hat{j}$ : observed information matrix evaluated at  $\hat{\psi}$ ;
- $\hat{i}$ : expected information matrix evaluated at  $\hat{\psi}$ ;
- $\tilde{j}_{\lambda\lambda}$ : subblock of  $j$  corresponding to  $\lambda$ , evaluated at  $\tilde{\psi}$ ;
- $[S^{-1}q]_{\theta}$ : component of the vector  $S^{-1}q$  corresponding to  $\theta$ , where  $S$  and  $q$  are covariances of likelihood quantities.

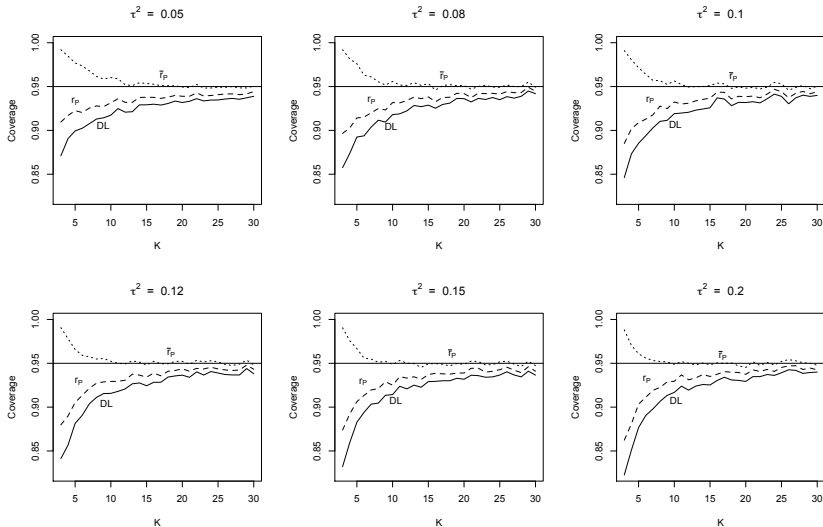


## Skovgaard's statistic $\bar{r}_P(\theta)$ : properties

- $N(0, 1)$  approximation up to an error of order  $O(n^{-1})$
- Third-order accuracy in a full exponential family (unlikely, when  $\hat{\sigma}_i^2 = \hat{\sigma}^2$ )
- Well defined for a wide class of parametric models
- Invariant w.r.t. interest-respecting reparametrizations
- Components  $S$  and  $q$  with a compact form
- Complexity of components  $S$  and  $q$  similar to that of the expected information matrix
- Simulations studies indicate a performance superior to  $r_P(\cdot)$  in terms of accuracy when approximating  $N(0, 1)$ , under different scenarios.

# Simulation study

Empirical coverages of confidence intervals; meta-analysis model with interest on  $\beta = 0.5$ ; 10,000 replications



## metaLik package

- R package for likelihood inference in meta-analysis and meta-regression
- First-order likelihood inference based of the signed profile log-likelihood ratio statistic  $r_P(\cdot)$  and its second-order Skovgaard's (1996) adjustment  $\bar{r}_P(\cdot)$
- Comparison with DerSimonian and Laird's (1986) approach
- Hypothesis testing and confidence intervals for the fixed-effects components
- Extension to heterogeneity component  $\tau^2$  under development

## Vaccine data

- $K = 13$  clinical studies on the efficacy of the Bacillus Calmette-Gurin (BCG) vaccine for preventing tuberculosis  
Berkey *et al.* (1995); Knapp & Hartung (2003)
- $y_i$ : logarithm of the risk ratio in the  $i$ -th trial
- $x_i$ : distance of the  $i$ -th study from the equator (latitude), surrogate for the presence of environmental mycobacteria providing a level of natural immunity against tuberculosis
- Meta-regression model

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i, \quad \varepsilon_i \sim N(0, \hat{\sigma}_i^2 + \tau^2)$$

- Inferential interest is mainly on  $\beta_1$
- DerSimonian and Laird's test for  $\beta_1 = 0$ : -2.475  
(p-value=0.013)

## metaLik function

Implements first- and second-order likelihood inference

```
library(metaLik)
data(vaccine)
m <- metaLik(y~latitude, data=vaccine, sigma2=vaccine$sigma2)
m
```

Call:

```
metaLik(formula=y~latitude, data=vaccine, sigma2=vaccine$sigma2)
```

Coefficients:

(Intercept)	latitude	tau <sup>2</sup>
-0.30500	-0.01542	0.16756

Variance/covariance matrix:

	(Intercept)	latitude	tau <sup>2</sup>
(Intercept)	5.020e-02	-1.101e-03	-2.629e-03
latitude	-1.101e-03	4.056e-05	3.600e-05
tau <sup>2</sup>	-2.629e-03	3.600e-05	1.050e-02

Maximized log-likelihood:

```
[1] 1.121
```

## Vaccine data analysis: summary

Adds information about the significance of the parameters

`summary(m)`

Likelihood inference in random effects meta analysis models

Call:

```
metaLik(formula=y~latitude, data=vaccine, sigma2=vaccine$sigma2)
```

```
Est. heterogeneity component tau^2: 0.1676 (std.err. 0.1025)
```

Fixed effects:

	estimate	std.err.	signed logLRT	p-value	Skovgaard	p-value
(Intercept)	-0.3051	0.2241	-1.3380	0.1809	-1.2246	0.2207
latitude	-0.0154	0.0064	-2.1202	0.0340	-1.8163	0.0693

Log-likelihood: 1.1212

## test.metaLik function

Hypothesis testing on a scalar component of the fixed-effects vector, using  $r_P(\cdot)$  and  $\bar{r}_P(\cdot)$

```
##Test on latitude coefficient  
test.metaLik(m, param=2, value=0, alternative='less')
```

Signed profile log-likelihood ratio test for parameter latitude

First-order statistic

r:-2.12, p-value:0.01699

Skovgaard's statistic

rSkov:-1.816, p-value:0.03466

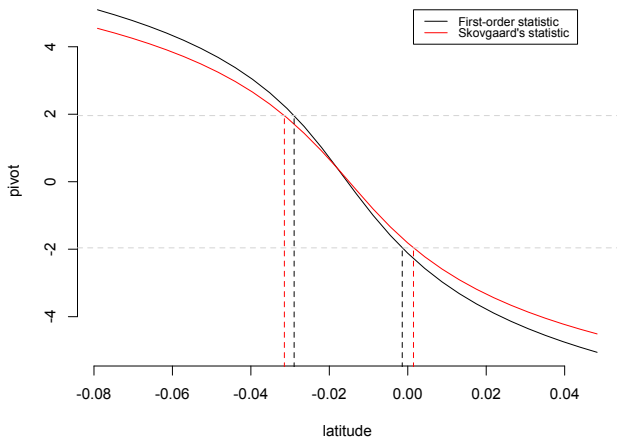
alternative hypothesis: parameter is less than 0

## profile.metaLik function

##95% confidence interval for the latitude coefficient

```
profile.metaLik(m, param=2, level=0.95, plot=TRUE)
```

	2.5%	97.5%
signed logLRT	-0.02897	-0.00141
Skovgaard	-0.03146	0.00146





# Conclusions and open problems

## metaLik:

- likelihood approach for meta-analysis and meta-regression
- inference on a scalar parameter of interest
- signed profile log-likelihood ratio statistic and Skovgaard's second-order statistic

## Higher-order asymptotics:

- advantages over standard meta-analysis techniques
- superior to first-order results in terms of accuracy
- especially for small sample sizes

## Open problems:

- between-study heterogeneity problems
- extension to generalized linear and to nonlinear mixed models
- empirical studies suggest Skovgaard's proposal improves on first-order solutions, but theoretical investigation is needed

Guolo, A. (2011). Higher-order likelihood inference in meta-analysis and meta-regression. *Submitted*.