An overview of recent updates to the metafor package

Society for Research Synthesis Methodology
2023 Annual Conference
Paris, France
July 5-7, 2023

Wolfgang Viechtbauer
Maastricht University

2023-06-06

Overview

- present some recent updates to the `metafor` package
  - `rma.glmm()` for binomial-normal models with RRs/RDs
  - `rma.uni()` for fitting location-scale models
  - `vif()` for variance inflation factors (and assessing their size)
  - `vcalc()` for constructing var-cov matrices of dependent ESs
  - `robust()` for cluster-robust inferences (robust variance estimation) inferfacing with the `clubSandwich` package
  - `selmodel()` for fitting (even more) selection models
  - `matreg()` for fitting regression models based on correlation/covariance matrices and how this can be used in combination with a multivariate model fitted with `rma.mv()`
  - the `metadat` package for meta-analysis datasets

Random-Effects Models

```
# load the metafor package
library(metafor)

# look at the BCG dataset (Colditz et al., 1994)
dat.bcg
```

trial	author	year	tpos	tneg	cpos	cneg	ablat	alloc
1	Aronson	1948	4	119	11	128	44	random
2	Ferguson & Simes	1949	6	300	29	274	55	random
3	Rosenthal et al	1960	3	228	11	209	42	random
4	Hart & Sutherland	1977	62	13536	248	12619	52	random
5	Frimodt-Moller et al	1973	33	5036	47	5761	13	alternate
6	Stein & Aronson	1953	180	1361	372	1079	44	alternate
7	Vandiviere et al	1973	8	2537	10	619	19	random
8	TPT Madras	1980	505	87886	499	87892	13	random
9	Coetzee & Berjak	1968	29	7470	45	7232	27	random
10	Rosenthal et al	1961	17	1699	65	1600	42	systematic
11	Comstock et al	1974	186	50448	141	27197	18	systematic
12	Comstock & Webster	1969	5	2493	3	2338	33	systematic
13	Comstock et al	1976	27	16886	29	17825	33	systematic

Random-Effects Models

```
# calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg,
                            ci=cpos, di=cneg, data=dat.bcg)
dat
```

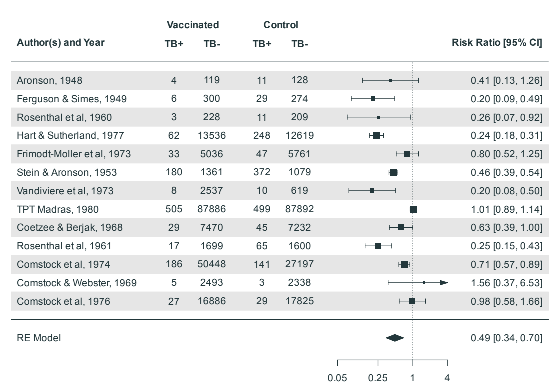
trial	author	year	...	yi	vi
1	Aronson	1948	...	-0.8893	0.3256
2	Ferguson & Simes	1949	...	-1.5854	0.1946
3	Rosenthal et al	1960	...	-1.3481	0.4154
4	Hart & Sutherland	1977	...	-1.4416	0.0200
5	Frimodt-Moller et al	1973	...	-0.2175	0.0512
6	Stein & Aronson	1953	...	-0.7861	0.0069
7	Vandiviere et al	1973	...	-1.6209	0.2230
8	TPT Madras	1980	...	0.0120	0.0040
9	Coetzee & Berjak	1968	...	-0.4694	0.0564
10	Rosenthal et al	1961	...	-1.3713	0.0730
11	Comstock et al	1974	...	-0.3394	0.0124
12	Comstock & Webster	1969	...	0.4459	0.5325
13	Comstock et al	1976	...	-0.0173	0.0714

Random-Effects Models

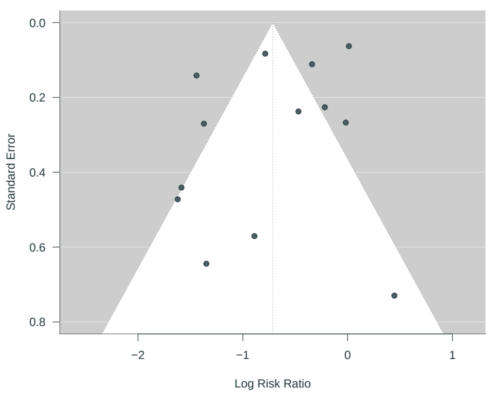
```
# fit a random-effects model (log risk ratios and variances as input)
res <- rma(yi, vi, data=dat)
res
```

```
## Random-Effects Model (k = 13; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0.3132 (SE = 0.1664)
## tau (square root of estimated tau^2 value):      0.5597
## I^2 (total heterogeneity / total variability):   92.22%
## H^2 (total variability / sampling variability):  12.86
##
## Test for Heterogeneity:
## Q(df = 12) = 152.2330, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb    ci.ub
##  -0.7145  0.1798  -3.9744  <.0001  -1.0669  -0.3622
```


Forest Plot



Funnel Plot

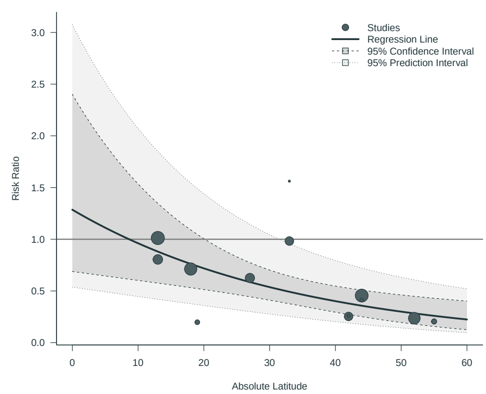


Mixed-Effects Meta-Regression Models

```
# fit a mixed-effects meta-regression model with absolute latitude as
# moderator (and using the Knapp & Hartung adjustment for tests/CIs)
res <- rma(yi, vi, mods = ~ ablat, data=dat, test="knha")
res
```

```
## Mixed-Effects Model (k = 13; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):     0.0764 (SE = 0.0591)
## tau (square root of estimated tau^2 value):             0.2763
## I^2 (residual heterogeneity / unaccounted variability): 68.39%
## H^2 (unaccounted variability / sampling variability):   3.16
## R^2 (amount of heterogeneity accounted for):            75.62%
##
## Test for Residual Heterogeneity:
## QE(df = 11) = 30.7331, p-val = 0.0012
##
## Test of Moderators (coefficient 2):
## F(df1 = 1, df2 = 11) = 12.5905, p-val = 0.0046
##
## Model Results:
##
##          estimate      se     tval  df    pval    ci.lb    ci.ub
## intrcpt    0.2515  0.2839   0.8857  11  0.3948  -0.3735   0.8764
## ablat     -0.0291  0.0082  -3.5483  11  0.0046  -0.0472  -0.0111
```


Bubble Plot



Standard Random-Effects Model with RRs

```
# fit a standard random-effects model (using ML estimation)
rma(yi, vi, data=dat, method="ML")
```

```
## Random-Effects Model (k = 13; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.2800 (SE = 0.1443)
## tau (square root of estimated tau^2 value):      0.5292
## I^2 (total heterogeneity / total variability):   91.38%
## H^2 (total variability / sampling variability):  11.60
##
## Test for Heterogeneity:
## Q(df = 12) = 152.2330, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb    ci.ub
##  -0.7112  0.1719  -4.1374  <.0001  -1.0481  -0.3743
```


Binomial-Normal Model with RRs

```
# fit a binomial-normal model using a log (not logit!) link
rma.glmm(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat)
```

```
## Random-Effects Model (k = 13; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.2711
## tau (square root of estimated tau^2 value):      0.5207
## I^2 (total heterogeneity / total variability):   91.12%
## H^2 (total variability / sampling variability):  11.26
##
## Tests for Heterogeneity:
## Wld(df = 12) = 152.2330, p-val < .0001
## LRT(df = 12) = 166.3203, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb    ci.ub
##  -0.7139  0.1691  -4.2223  <.0001  -1.0453  -0.3825
```


Binomial-Normal Model with RRs

```
# cross-check results using GLMMadaptive (instead of lme4)
rma.glmm(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat,
         control=list(package="GLMMadaptive"))
```

```
## Random-Effects Model (k = 13; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.2710
## tau (square root of estimated tau^2 value):      0.5206
## I^2 (total heterogeneity / total variability):   91.12%
## H^2 (total variability / sampling variability):  11.26
##
## Tests for Heterogeneity:
## Wld(df = 12) = 152.2330, p-val < .0001
## LRT(df = 12) = 166.3203, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb    ci.ub
##  -0.7138  0.1690  -4.2225  <.0001  -1.0451  -0.3825
```

Location-Scale Models for Meta-Analysis

```r
# data from 48 studies examining the effectiveness of 'writing-to-learn'
# interventions on academic achievement (Bangert-Drowns et al., 2004)
dat <- dat.bangertdrowns2004

# look at a subset of the data
dat[c(1:6,46:48),c(1:3,13:16)]
```

id	author	year	...	subject	ni	yi	vi
1	Ashworth	1992	...	Sci	60	0.650	0.070
2	Ayers	1993	...	Sci	34	-0.750	0.126
3	Baisch	1990	...	Math	95	-0.210	0.042
4	Baker	1994	...	Math	209	-0.040	0.019
5	Bauman	1992	...	Math	182	0.230	0.022
6	Becker	1996	...	Soc	462	0.030	0.009
...							
46	Willey	1988	...	Sci	51	1.460	0.099
47	Willey	1988	...	Soc	46	0.040	0.087
48	Youngberg	1989	...	Math	56	0.250	0.072

Location-Scale Models for Meta-Analysis

```r
# fit a meta-analytic location-scale model
res <- rma(yi, vi, mods = ~ subject + ni, scale = ~ subject + ni, data=dat)
res
```

```
## Location-Scale Model (k = 48; tau^2 estimator: REML)
##
## Test of Location Coefficients (coefficients 2:4):
## QM(df = 3) = 10.1043, p-val = 0.0177
##
## Model Results (Location):
##
##             estimate      se     zval    pval    ci.lb    ci.ub
## intrcpt       0.3443  0.0673   5.1179  <.0001   0.2124   0.4761
## subjectSci   -0.0798  0.2040  -0.3912  0.6957  -0.4796   0.3200
## subjectSoc   -0.1087  0.0829  -1.3121  0.1895  -0.2711   0.0537
## ni           -0.0006  0.0002  -2.8836  0.0039  -0.0010  -0.0002
##
## Test of Scale Coefficients (coefficients 2:4):
## QM(df = 3) = 8.1094, p-val = 0.0438
##
## Model Results (Scale):
##
##             estimate      se     zval    pval    ci.lb    ci.ub
## intrcpt      -3.1022  0.9911  -3.1302  0.0017  -5.0447  -1.1598
## subjectSci    2.2330  1.0474   2.1319  0.0330   0.1801   4.2860
## subjectSoc    0.4011  1.4021   0.2861  0.7748  -2.3470   3.1492
## ni           -0.0054  0.0057  -0.9506  0.3418  -0.0165   0.0057
```


Location-Scale Models for Meta-Analysis

```r
# predicted value of tau^2 for Math, Sci, and Soc when ni=120 (~ mean n)
Xnew <- cbind(c(0,1,0),c(0,0,1),120)
pred <- predict(res, newscale=Xnew, transf=exp, digits=3)
pred$slab <- c("Math", "Sci", "Soc")
pred
```

```
##       pred ci.lb ci.ub
## Math 0.024 0.005 0.103
## Sci  0.220 0.051 0.942
## Soc  0.035 0.004 0.353
```

```r
# predicted value of E(SMD) for Math, Sci, and Soc when ni=120 (~ mean n)
pred <- predict(res, newmods=Xnew, newscale=Xnew, digits=2)
pred$slab <- c("Math", "Sci", "Soc")
pred
```

```
##      pred   se ci.lb ci.ub pi.lb pi.ub
## Math 0.27 0.05  0.17  0.37 -0.04  0.59
## Sci  0.19 0.20 -0.19  0.58 -0.80  1.19
## Soc  0.17 0.08  0.01  0.32 -0.23  0.56
```


Variance Inflation Factors for Meta-Analysis

```r
# look at a subset of the data
dat[c(1:6,46:48),c(1:3,5,9:11,13,15:16)]
```

id	author	year	length	info	pers	imag	subject	yi	vi
1	Ashworth	1992	15	1	1	0	Sci	0.650	0.070
2	Ayers	1993	10	1	1	1	Sci	-0.750	0.126
3	Baisch	1990	2	1	1	0	Math	-0.210	0.042
4	Baker	1994	9	1	0	0	Math	-0.040	0.019
5	Bauman	1992	14	1	1	0	Math	0.230	0.022
6	Becker	1996	1	0	1	0	Soc	0.030	0.009
...									
46	Willey	1988	15	1	1	0	Sci	1.460	0.099
47	Willey	1988	15	1	1	0	Soc	0.040	0.087
48	Youngberg	1989	15	1	0	0	Math	0.250	0.072

Variance Inflation Factors for Meta-Analysis

```r
# fit a mixed-effects meta-regression model
res <- rma(yi, vi, mods = ~ length + info + pers + imag + subject, data=dat)
res
```

```
## Mixed-Effects Model (k = 44; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):     0.0463 (SE = 0.0216)
## tau (square root of estimated tau^2 value):             0.2151
## R^2 (amount of heterogeneity accounted for):            0.91%
##
## Test of Moderators (coefficients 2:7):
## QM(df = 6) = 8.6287, p-val = 0.1956
##
## Model Results:
##
##             estimate      se     zval    pval    ci.lb   ci.ub
## intrcpt       0.2205  0.2346   0.9400  0.3472  -0.2393  0.6803
## length        0.0152  0.0085   1.7844  0.0744  -0.0015  0.0319
## info         -0.1692  0.2251  -0.7515  0.4523  -0.6104  0.2721
## pers          0.0618  0.1070   0.5778  0.5634  -0.1479  0.2715
## imag          0.0455  0.1998   0.2276  0.8199  -0.3462  0.4372
## subjectSci    0.0525  0.1455   0.3611  0.7180  -0.2326  0.3377
## subjectSoc   -0.1867  0.1164  -1.6038  0.1088  -0.4148  0.0415
```


Variance Inflation Factors for Meta-Analysis

```r
# compute variance inflation factors (VIFs)
vif(res)
```

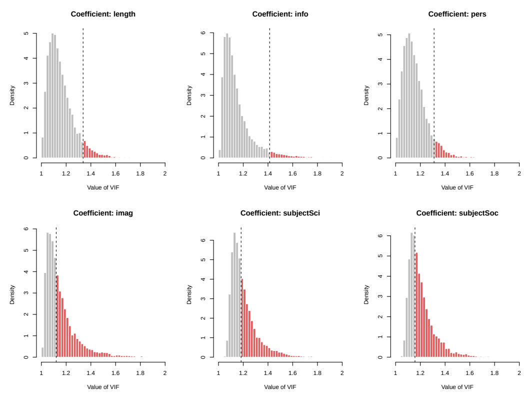
```
## length     info     pers     imag  subjectSci  subjectSoc
## 1.3371   1.4134   1.3109   1.1197      1.1828      1.1566
```

```r
# simulate the distribution of the VIFs under independence
# (by randomly reshuffling the columns of the model matrix)
sav <- vif(res, sim=TRUE, seed=1234)
sav
```

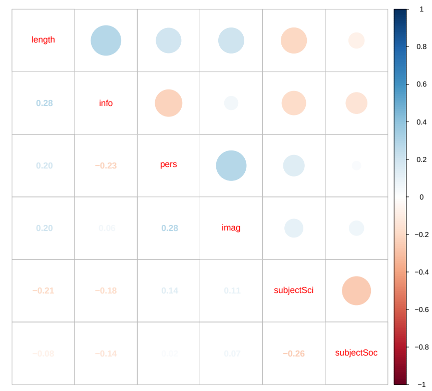
```
##                vif  prop
## length      1.3371  0.93
## info        1.4134  0.95
## pers        1.3109  0.93
## imag        1.1197  0.52
## subjectSci  1.1828  0.55
## subjectSoc  1.1566  0.40
```

```r
# plot the distribution of the VIFs
plot(sav)
```

Variance Inflation Factors for Meta-Analysis



Variance Inflation Factors for Meta-Analysis



Var-Cov Matrix of Dependent Effect Sizes

```
# results from 17 studies on the association between recidivism and
# mental health in delinquent juveniles (Assink & Wibbelink, 2016)
dat <- dat.assink2016

# look at the data for studies 1 and 12
dat[dat$study %in% c(1,12),]
```

study	esid	id	yi	vi	pubstatus	year	deltype
1	1	1	0.9066	0.0740	1	4.5000	general
1	2	2	0.4295	0.0398	1	4.5000	general
1	3	3	0.2679	0.0481	1	4.5000	general
1	4	4	0.2078	0.0239	1	4.5000	general
1	5	5	0.0526	0.0331	1	4.5000	general
1	6	6	-0.0507	0.0886	1	4.5000	general
12	1	63	0.2994	0.0041	0	4.5000	overt
12	2	64	0.2992	0.0042	0	4.5000	general
12	3	65	0.2989	0.0041	0	4.5000	overt
12	4	66	0.2910	0.0042	0	4.5000	overt
12	5	67	0.2170	0.0041	0	4.5000	overt

Var-Cov Matrix of Dependent Effect Sizes

```
# construct an approximate var-cov matrix assuming a correlation of 0.7 for
# effect sizes corresponding to the same type of delinquent behavior and a
# correlation of 0.5 for effect sizes corresponding to different types of
# delinquent behavior within studies
V <- vcalc(vi, cluster=study, type=deltype, obs=esid, data=dat, rho=c(0.7,0.5))

# examine the part of V corresponding to study 1
blsplit(V, cluster=dat$study, round, 4)[[1]]
```

```
##        [,1]   [,2]   [,3]   [,4]   [,5]   [,6]
## [1,] 0.0740 0.0380 0.0418 0.0294 0.0346 0.0567
## [2,] 0.0380 0.0398 0.0306 0.0216 0.0254 0.0416
## [3,] 0.0418 0.0306 0.0481 0.0237 0.0279 0.0457
## [4,] 0.0294 0.0216 0.0237 0.0239 0.0197 0.0322
## [5,] 0.0346 0.0254 0.0279 0.0197 0.0331 0.0379
## [6,] 0.0567 0.0416 0.0457 0.0322 0.0379 0.0886
```


Var-Cov Matrix of Dependent Effect Sizes

```
# fit a multilevel random-effects model to the data using this approximate V
# matrix (using a t-distribution for tests/CIs with the 'containment' method
# for computing the degrees of freedom)
res <- rma.mv(yi, V, random = ~ 1 | study/esid, data=dat, test="t", dfs="contain")
res
```

```
## Multivariate Meta-Analysis Model (k = 100; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed      factor
## sigma^2.1  0.0704  0.2654     17     no       study
## sigma^2.2  0.1508  0.3883    100     no  study/esid
##
## Test for Heterogeneity:
## Q(df = 99) = 840.9174, p-val < .0001
##
## Model Results:
##
## estimate      se    tval  df    pval   ci.lb   ci.ub
##   0.3618  0.0933  3.8794  16  0.0013  0.1641  0.5595
```


Cluster-Robust Inference Methods with clubSandwich

```
# use cluster-robust inference methods (i.e., robust variance estimation)
robust(res, cluster=study, clubSandwich=TRUE)
```

```
## Multivariate Meta-Analysis Model (k = 100; method: REML)
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed      factor
## sigma^2.1  0.0704  0.2654     17     no       study
## sigma^2.2  0.1508  0.3883    100     no  study/esid
##
## Test for Heterogeneity:
## Q(df = 99) = 840.9174, p-val < .0001
##
## Number of estimates:   100
## Number of clusters:    17
## Estimates per cluster: 1-22 (mean: 5.88, median: 5)
##
## Model Results:
##
## estimate      se    tval     df    pval   ci.lb   ci.ub
##   0.3618  0.0938  3.8567  14.34  0.0017  0.1611  0.5626
```

Selection Models

```r
# results from 37 studies on the risk of lung cancer in women exposed
# to environmental tobacco smoke (ETS) from their smoking spouse
dat <- dat.hackshaw1998
dat
```

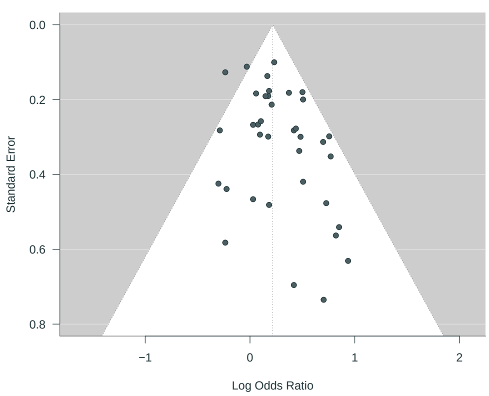
study	author	year	country	yi	vi
1	Garfinkel	1981	USA	0.1655	0.0188
2	Hirayama	1984	Japan	0.3716	0.0330
3	Butler	1988	USA	0.7031	0.5402
4	Cardenas	1997	USA	0.1823	0.0313
5	Chan	1982	Hong Kong	-0.2877	0.0797
6	Correa	1983	USA	0.7275	0.2273
7	Trichopolous	1983	Greece	0.7561	0.0889
8	Buffler	1984	USA	-0.2231	0.1927
...					
35	Zaridze	1995	Russia	0.5068	0.0399
36	Sun	1996	China	0.1484	0.0364
37	Wang	1996	China	0.1044	0.0664

Selection Models

```r
# fit a random-effects model (using ML estimation)
res <- rma(yi, vi, data=dat, method="ML")
res
```

```
## Random-Effects Model (k = 37; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0204 (SE = 0.0165)
## tau (square root of estimated tau^2 value):      0.1427
## I^2 (total heterogeneity / total variability):   27.62%
## H^2 (total variability / sampling variability):  1.38
##
## Test for Heterogeneity:
## Q(df = 36) = 47.4979, p-val = 0.0952
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.2171  0.0486  4.4712  <.0001  0.1219  0.3123
```


Selection Models

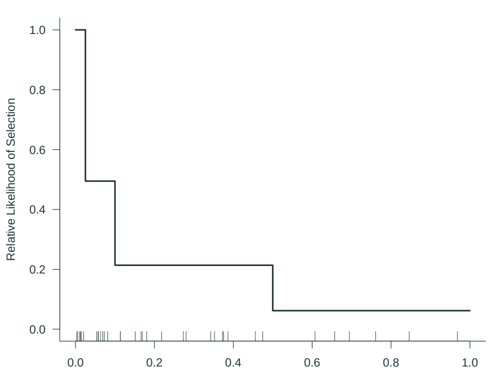


Selection Models

```r
# fit a step function selection model
sel1 <- selmodel(res, type="stepfun", steps=c(.025,.1,.5,1))
sel1
```

```
## Random-Effects Model (k = 37; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0096 (SE = 0.0128)
## tau (square root of estimated tau^2 value):      0.0981
##
## Model Results:
##
## estimate      se    zval    pval    ci.lb   ci.ub
##   0.0020  0.0889  0.0225  0.9821  -0.1723  0.1763
##
## Test for Selection Model Parameters:
## LRT(df = 3) = 6.4020, p-val = 0.0936
##
## Selection Model Results:
##
##                      k  estimate      se      zval    pval   ci.lb   ci.ub
## 0     < p <= 0.025   7    1.0000     ---       ---     ---     ---     ---
## 0.025 < p <= 0.1     8    0.4946  0.3152   -1.6032  0.1089  0.0000  1.1125
## 0.1   < p <= 0.5    16    0.2136  0.1687   -4.6613  <.0001  0.0000  0.5443
## 0.5   < p <= 1       6    0.0618  0.0689  -13.6177  <.0001  0.0000  0.1969
```


Selection Models

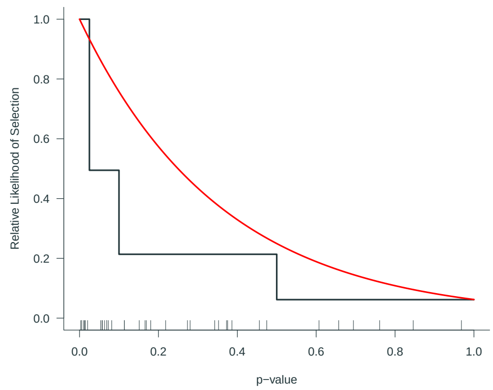


Selection Models

```r
# fit a negative-exponential selection function model
sel2 <- selmodel(res, type="negexp")
sel2
```

```
## Random-Effects Model (k = 37; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0262 (SE = 0.0224)
## tau (square root of estimated tau^2 value):      0.1619
##
## Model Results:
##
## estimate      se    zval    pval    ci.lb   ci.ub
##   0.0049  0.1558  0.0314  0.9750  -0.3004  0.3102
##
## Test for Selection Model Parameters:
## LRT(df = 1) = 4.1277, p-val = 0.0422
##
## Selection Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   2.7768  1.5416  1.8012  0.0717  0.0000  5.7983
```

Selection Models



Selection Models

```
# truncated distribution selection model
sel3 <- selmodel(res, type="trunc")
sel3
```

```
## Random-Effects Model (k = 37; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0268 (SE = 0.0206)
## tau (square root of estimated tau^2 value):      0.1636
##
## Model Results:
##
## estimate      se    zval    pval    ci.lb   ci.ub
##   0.1427  0.0741  1.9267  0.0540  -0.0025  0.2879
##
## Test for Selection Model Parameters:
## LRT(df = 1) = 3.0545, p-val = 0.0805
##
## Selection Model Results:
##
## estimate      se     zval    pval   ci.lb   ci.ub
##   0.3818  0.2236  -2.7652  0.0057  0.0000  0.8200
```


Selection Models

```
# selection model assuming truncation at the minimum effect size estimate
sel4 <- selmodel(res, type="trunc", steps=min(dat$yi))
sel4
```

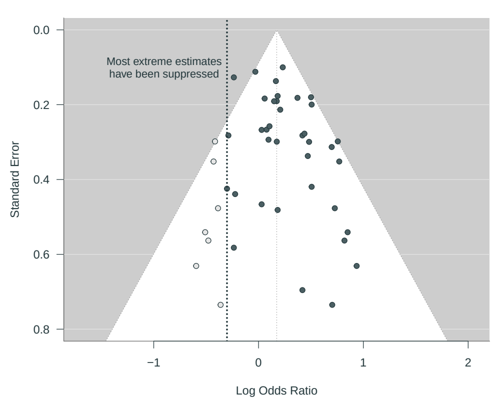
```
## Random-Effects Model (k = 37; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0239 (SE = 0.0186)
## tau (square root of estimated tau^2 value):      0.1547
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.1947  0.0543  3.5835  0.0003  0.0882  0.3012
##
## Test for Selection Model Parameters:
## LRT(df = 1) = 2.1618, p-val = 0.1415
##
## Selection Model Results:
##
## estimate      se     zval    pval   ci.lb   ci.ub
##   0.2700  0.2864  -2.5491  0.0108  0.0000  0.8313
```


Trim and Fill Method

```
# trim and fill method
taf <- trimfill(res)
taf
```

```
## Estimated number of missing studies on the left side: 7 (SE = 4.0402)
##
## Random-Effects Model (k = 44; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0222 (SE = 0.0170)
## tau (square root of estimated tau^2 value):      0.1490
## I^2 (total heterogeneity / total variability):   26.86%
## H^2 (total variability / sampling variability):  1.37
##
## Test for Heterogeneity:
## Q(df = 43) = 60.5603, p-val = 0.0397
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.1736  0.0476  3.6472  0.0003  0.0803  0.2669
```


Trim and Fill Method



Selection Models

```
# force the relative likelihood of selection for effect sizes below the
# minimum effect size estimate to essentially 0 (as assumed by trim and fill)
sel5 <- selmodel(res, type="trunc", steps=min(dat$yi), delta=0.001)
sel5
```

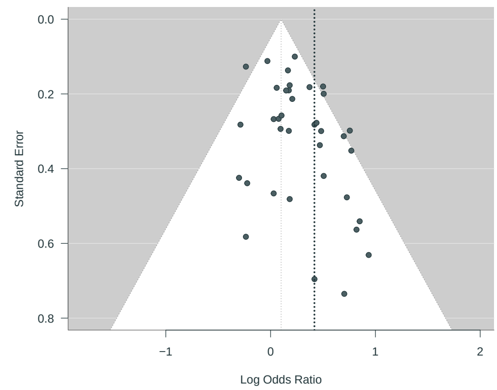
```
## Random-Effects Model (k = 37; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0271 (SE = 0.0219)
## tau (square root of estimated tau^2 value):      0.1647
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.1815  0.0565  3.2123  0.0013  0.0708  0.2923
##
## Test for Selection Model Parameters:
## LRT(df = 0) = 0.0000, p-val = NA
##
## Selection Model Results:
##
## estimate   se  zval  pval  ci.lb  ci.ub
##   0.0010  ---   ---   ---    ---    ---
```

Selection Models

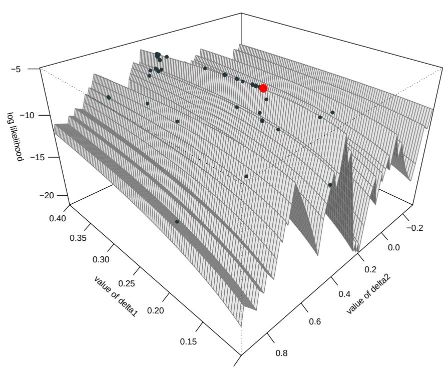
```
# truncated distribution selection model with estimated truncation point
sel6 <- selmodel(res, type="truncest")
sel6
```

```
## Random-Effects Model (k = 37; tau^2 estimator: ML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0049 (SE = 0.0075)
## tau (square root of estimated tau^2 value):      0.0699
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.1002  0.0462  2.1707  0.0300  0.0097  0.1906
##
## Test for Selection Model Parameters:
## LRT(df = 1) = 10.7035, p-val = 0.0011
##
## Selection Model Results:
##
##          estimate      se      zval    pval   ci.lb   ci.ub
## delta.1    0.1957  0.0961   -8.3710  <.0001  0.0074  0.3840
## delta.2    0.4181  0.0006  643.3839  <.0001  0.4168  0.4194
```


Selection Models



Selection Models



Regression Analysis of Multivariate Model Results

```
# results from 17 studies examining overall and disease-free survival in
# neuroblastoma patients with amplified vs normal MYC-N protein levels
dat <- dat.riley2003[1:34,]
dat
```

study	yi	vi	sei	outcome
1	-0.11	0.45	0.67	DFS
1	-0.14	0.66	0.81	OS
2	0.30	0.07	0.26	DFS
2	0.67	0.08	0.29	OS
…				
16	2.95	1.17	1.08	DFS
16	2.75	1.21	1.10	OS
17	5.70	2.99	1.73	DFS
17	5.70	2.99	1.73	OS

```
# construct an approximate var-cov matrix, assuming a correlation
# of 0.8 for the pairs of log hazard ratios within studies
V <- vcalc(vi, cluster=study, type=outcome, rho=0.8, data=dat)
```


Regression Analysis of Multivariate Model Results

```
# fit a bivariate model to the data
res <- rma.mv(yi, V, mods = ~ outcome - 1, random = ~ outcome | study,
              struct="UN", data=dat)
res
```

```
## Multivariate Meta-Analysis Model (k = 34; method: REML)
##
## Variance Components:
##
## outer factor: study   (nlvls = 17)
## inner factor: outcome (nlvls = 2)
##
##             estim    sqrt  k.lvl  fixed  level
## tau^2.1    0.2919  0.5403     17     no    DFS
## tau^2.2    0.3112  0.5578     17     no     OS
##
## Model Results:
##
##             estimate      se    zval    pval   ci.lb   ci.ub
## outcomeDFS    1.3011  0.1915  6.7955  <.0001  0.9258  1.6763
## outcomeOS     1.4699  0.2040  7.2066  <.0001  1.0702  1.8697
```


Regression Analysis of Multivariate Model Results

```
# cross-check results using cluster-robust inference methods
robust(res, cluster=study, clubSandwich=TRUE)
```

```
## Multivariate Meta-Analysis Model (k = 34; method: REML)
##
## Variance Components:
##
## outer factor: study   (nlvls = 17)
## inner factor: outcome (nlvls = 2)
##
##             estim    sqrt  k.lvl  fixed  level
## tau^2.1    0.2919  0.5403     17     no    DFS
## tau^2.2    0.3112  0.5578     17     no     OS
##
## Model Results:
##
##             estimate      se    tval     df    pval   ci.lb   ci.ub
## outcomeDFS    1.3011  0.1918  6.7835  13.90  <.0001  0.8894  1.7127
## outcomeOS     1.4699  0.2037  7.2179  13.62  <.0001  1.0320  1.9079
```

Regression Analysis of Multivariate Model Results

```
# var-cov matrix of the random effects
res$G
```

```
##           DFS        OS
## DFS 0.2919139 0.2190741
## OS  0.2190741 0.3111915
```

```
# fit a regression model based on this var-cov matrix, predicting the overall
# survival log hazard ratio from the disease-free survival log hazard ratio
matreg(y=2, x=1, R=res$G, cov=TRUE, means=coef(res), n=res$g.levels.comb.k)
```

```
##          estimate      se    tval  df    pval    ci.lb   ci.ub
## intrcpt    0.4935  0.2568  1.9218  15  0.0738  -0.0538  1.0409
## DFS        0.7505  0.1831  4.0990  15  0.0009   0.3602  1.1407
```


Regression Analysis of Multivariate Model Results

```
# fit the bivariate model again, but now also obtain the var-cov matrix of the
# estimates in res$G
res <- rma.mv(yi, V, mods = ~ outcome - 1, random = ~ outcome | study,
              struct="UN", data=dat, cvvc="varcov")

# var-cov matrix of the estimates in the G matrix
res$vvc
```

```
##            tau^2.1        cov    tau^2.2
## tau^2.1 0.04023357 0.03244148 0.02677589
## cov     0.03244148 0.03714984 0.04062991
## tau^2.2 0.02677589 0.04062991 0.06321372
```

```
# now use res$vvc as the var-cov matrix of the estimates in res$G
matreg(y=2, x=1, R=res$G, cov=TRUE, means=coef(res), V=res$vvc)
```

```
##          estimate      se    zval    pval    ci.lb   ci.ub
## intrcpt    0.4935  0.4699  1.0502  0.2936  -0.4275  1.4146
## DFS        0.7505  0.3612  2.0778  0.0377   0.0426  1.4584
```


The metadat Package

- the `metafor` package used to contain around 60 datasets
- moved to a separate data package called `metadat`
- also contains additional contributed datasets (now 87)
- useful for teaching purposes, illustrating/testing meta-analytic methods, and validating published analyses
- instructions for contributing additional datasets: https://wviechtb.github.io/metadat/
- the `datsearch()` function can help to find datasets

Thank You for Your Attention!

Questions, Comments, Suggestions?

wolfgang.viechtbauer@maastrichtuniversity.nl

https://www.wvbauer.com

https://www.metafor-project.org

@wviechtb @wviechtb