Meta-analysis in R - using the metafor package

James Uanhoro

Alternatives to the `metafor` package

The `metafor` package seems to be one of the more comprehensive packages for meta-analysis in *R*. Some commonly used alternatives:

- meta: Supposed to be user-friendly
- metaSEM: For meta-analysis using structural equation modeling
- MAVIS: GUI-based comprehensive option for meta-analysis.

```
# How to use the MAVIS package:
if (!require(MAVIS)) {
  install.packages("MAVIS", repos = "https://cloud.r-project.org")
  library(MAVIS)
}
startmavis()
```

Recent journal article on options for meta-analysis in *R*:

Polanin, J. R., Hennessy, E. A., & Tanner-Smith, E. E. (2017). A Review of Meta-Analysis Packages in R. *Journal of Educational and Behavioral Statistics, 42*(2), 206–242. https://doi.org/10.3102/1076998616674315

Using `metafor`

Guide to using `metafor`: https://cran.r-project.org/web/packages/metafor/vignettes/metafor_diagram.pdf

1. Read data
2. Calculate effect size (optional)
3. Conduct meta-analysis (including *moderation*)
4. Print results, fitted values, residuals diagnostics, publication bias, inference, plots, …

Demo

Load required packages

```
repo <- "https://cloud.r-project.org"
sapply(c("metafor", "lattice"), function(package_name) {
  if (!require(package_name, character.only = TRUE)) {
    install.packages(package_name, repos = repo)
    library(package_name, character.only = TRUE)
  }
})
```

```
## $metafor
## NULL
##
## $lattice
## NULL
```

Load dataset

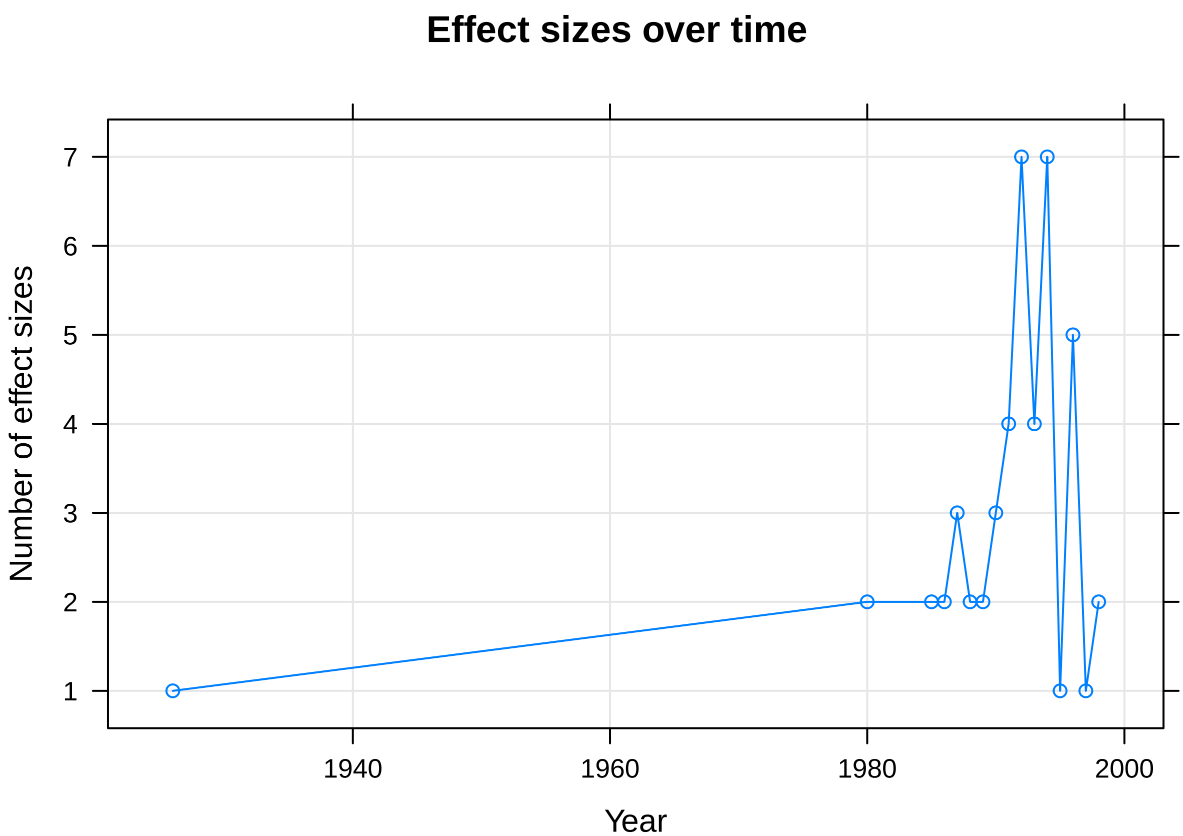
```r
data <- dat.bangertdrowns2004
head(data)
```

```
##   id   author year grade length minutes wic feedback info pers imag meta
## 1  1 Ashworth 1992     4     15      NA   1        1    1    1    0    1
## 2  2    Ayers 1993     2     10      NA   1       NA    1    1    1    0
## 3  3   Baisch 1990     2      2      NA   1        0    1    1    0    1
## 4  4    Baker 1994     4      9      10   1        1    1    0    0    0
## 5  5   Bauman 1992     1     14      10   1        1    1    1    0    1
## 6  6   Becker 1996     4      1      20   1        0    0    1    0    0
##          subject  ni     yi    vi
## 1        Nursing  60  0.650 0.070
## 2 Earth Science  34 -0.750 0.126
## 3           Math  95 -0.210 0.042
## 4        Algebra 209 -0.040 0.019
## 5           Math 182  0.230 0.022
## 6     Literature 462  0.030 0.009
```

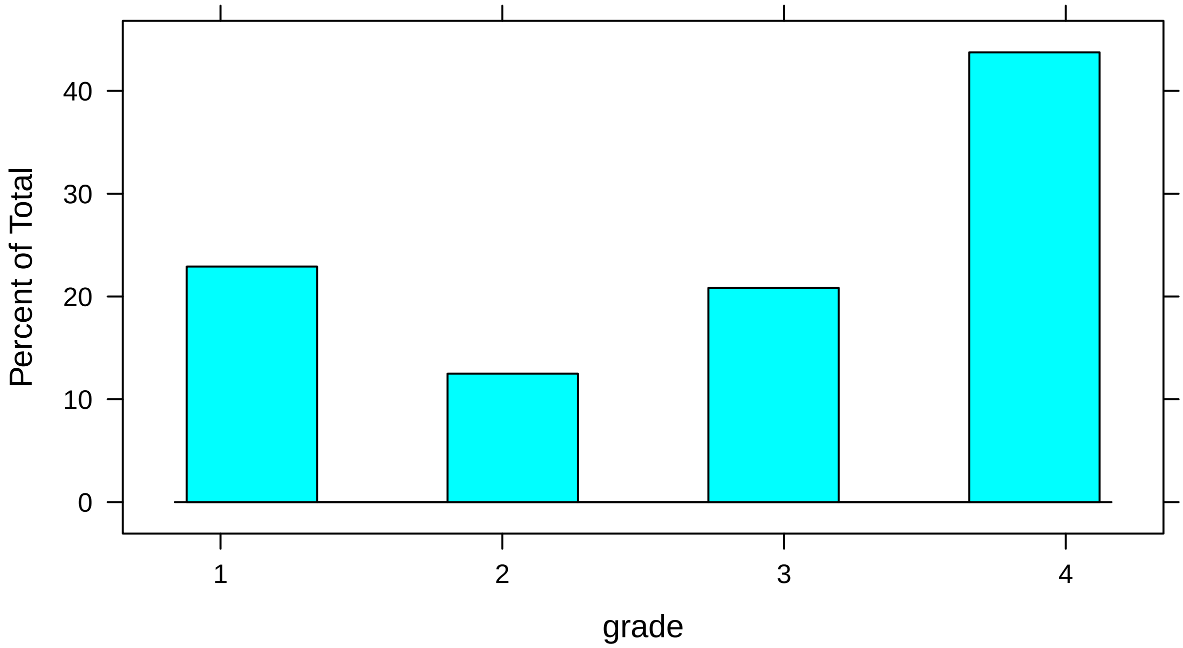
```r
# Run ?dat.bangertdrowns2004 to see what the dataset represents
```

Visualize data

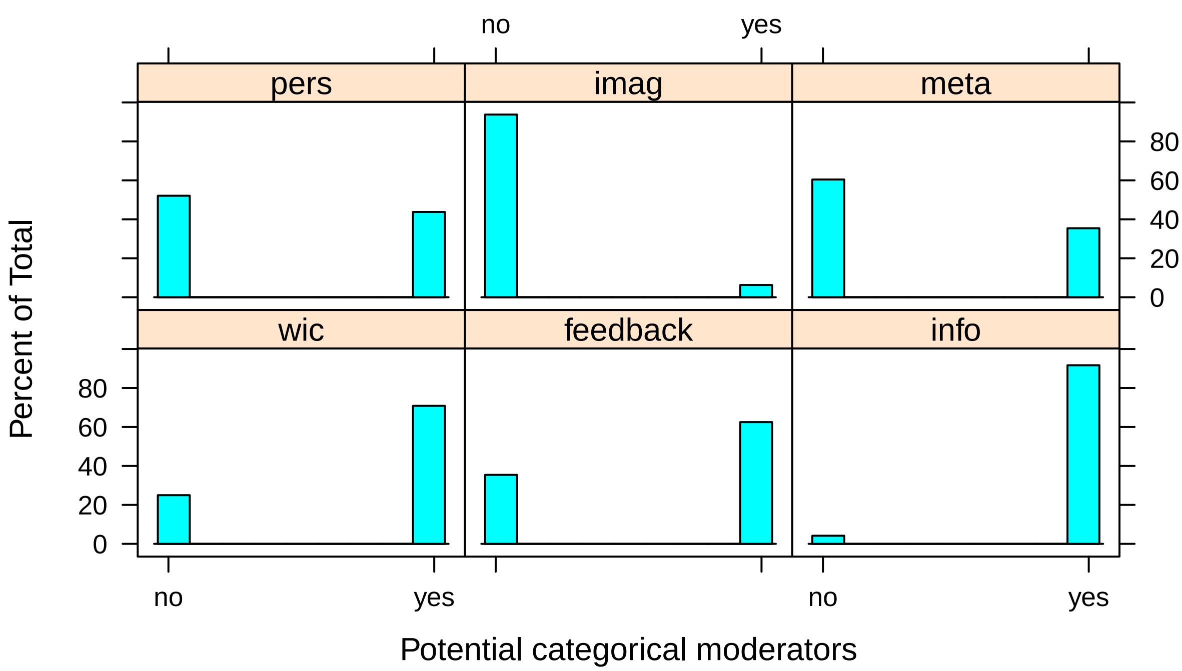
Produced using the `lattice` package

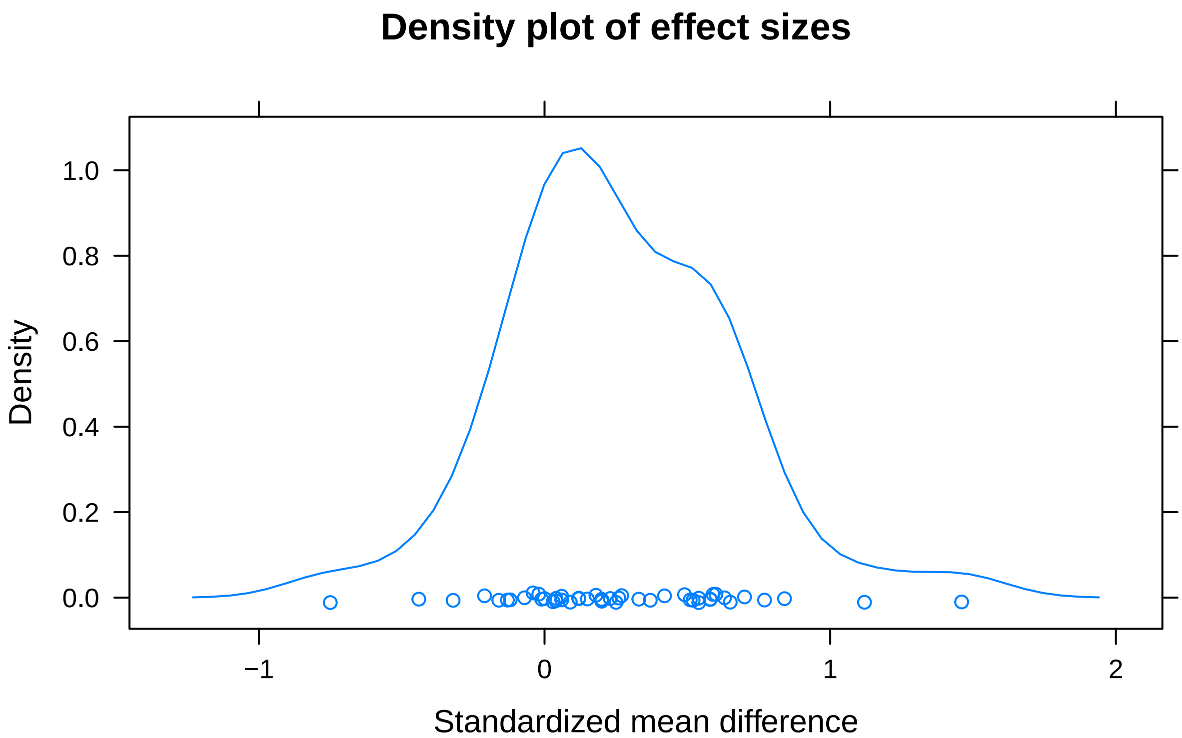


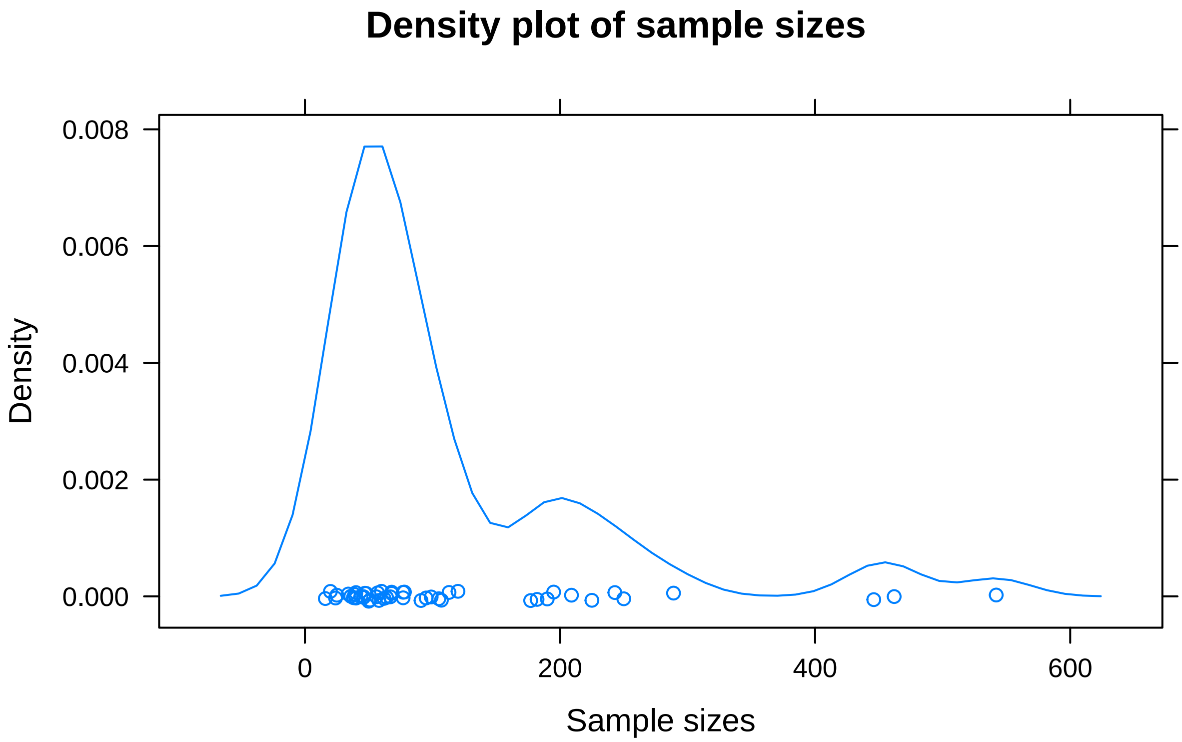
Effect size distribution by grade



Proportions of potential moderators




Density plot of effect sizes
Density
1.0
0.8
0.6
0.4
0.2
0.0
−1
0
1
2
Standardized mean difference


Density plot of sample sizes
Density
0.008
0.006
0.004
0.002
0.000
0
200
400
600
Sample sizes

Conduct meta-analysis

I will conduct a random-effects meta-analysis. Assuming I wanted to conduct a fixed-effects meta-analysis, I would add `method = FE` as one of the arguments to the `rma` function below. The default method of estimation is `REML`.

The effect size `measure` used below, `yi`, is a standardized mean difference (`SMD`), and the Knapp and Hartung (2003) adjustment is used to improve the estimation of standard errors (`test = "knha"`).

```
(res.0 <- rma(
  yi = yi, vi = vi, ni = ni, data = data,
  measure = "SMD", test = "knha"
))
```

```
##
## Random-Effects Model (k = 48; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0499 (SE = 0.0197)
## tau (square root of estimated tau^2 value):      0.2235
## I^2 (total heterogeneity / total variability):   58.37%
## H^2 (total variability / sampling variability):  2.40
##
## Test for Heterogeneity:
## Q(df = 47) = 107.1061, p-val < .0001
##
## Model Results:
##
## estimate       se     tval     pval    ci.lb    ci.ub
##   0.2219   0.0495   4.4810   <.0001   0.1223   0.3216      ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The effect of school-based writing-to-learn interventions on academic achievement was 0.2 standard deviations ($SMD = 0.22, 95\%$ CI $[0.12, 0.32]$) and this effect was statistically different from zero, $t(47) = 4.48, p < .001$.

The result from the Q test for heterogeneity suggests that there was unexplained heterogeneity in the estimate calculated above, $Q(47) = 107, p < .001$. Since we performed a random-effects meta-analysis, we modeled this heterogeneity in the τ^2 statistic.

We can use the following syntax to obtain the 95% confidence interval around the estimates of heterogeneity.

```
confint(res.0, level = .95)
```

```
##
##        estimate   ci.lb   ci.ub
## tau^2    0.0499  0.0274  0.1525
## tau      0.2235  0.1656  0.3905
## I^2(%)  58.3740 43.4940 81.0705
## H^2      2.4023  1.7697  5.2828
```

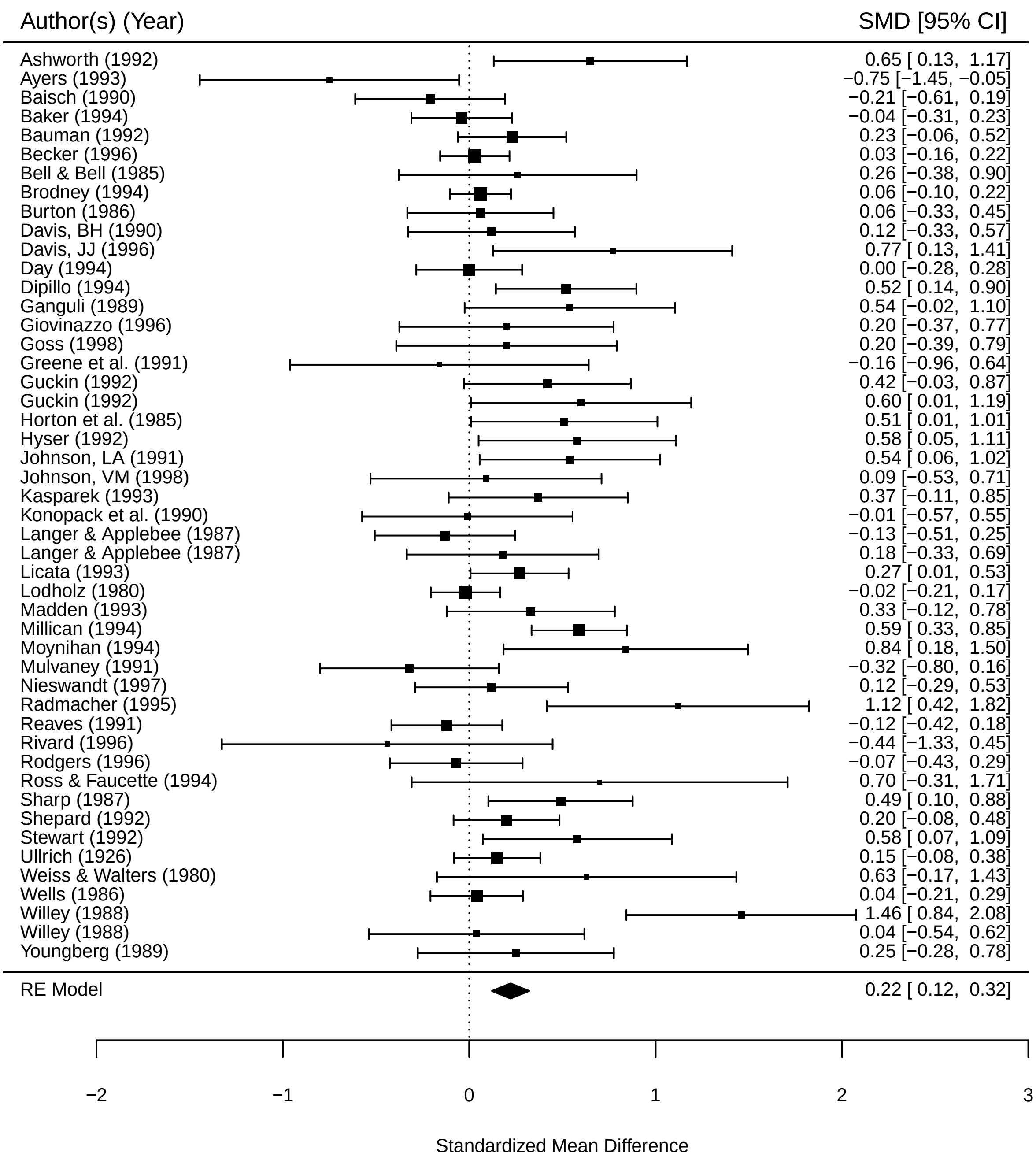
The heterogeneity in our estimate was statistically different from zero, $\tau^2 = .050, 95\%$ CI $[.027, .15]$.

The I^2 statistic estimates how much of the total heterogeneity can be attributed to true heterogeneity in the effects, and this was 58.3%, 95% CI [43.9%, 81.1%]. The confidence intervals for heterogeneity estimates are often large.

Forest plot

We can create a forest plot of the effect sizes in included meta-analysis.

```r
forest(
  res.0, slab = paste0(data$author, " (", data$year, ")"),
  xlim = c(-2.5, 2.5), cex = .7
)
op <- par(cex = .8, font = 1)
text(-2.5, 50, "Author(s) (Year)", pos = 4)
text(2.9775, 50, "SMD [95% CI]", pos = 2)
```



We can do a lot more with these forest plots, say separation into subgroups based on moderator variables.

Moderation analysis

We can check how study characteristics influence average effect calculated earlier. Let's use the `grade` variable as a moderator. By using `factor(grade)`, we specify that `grade` should be treated as a categorical variable.

```
(res.1 <- rma(
  yi = yi, vi = vi, ni = ni, data = data,
  mods = ~ factor(grade),
  measure = "SMD", test = "knha"
))
```

```
##
## Mixed-Effects Model (k = 48; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):     0.0539 (SE = 0.0216)
## tau (square root of estimated tau^2 value):             0.2322
## I^2 (residual heterogeneity / unaccounted variability): 59.15%
## H^2 (unaccounted variability / sampling variability):   2.45
## R^2 (amount of heterogeneity accounted for):            0.00%
##
## Test for Residual Heterogeneity:
## QE(df = 44) = 102.0036, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## F(df1 = 3, df2 = 44) = 1.8783, p-val = 0.1472
##
## Model Results:
##
##                 estimate      se     tval    pval    ci.lb    ci.ub
## intrcpt           0.2639  0.0925   2.8545  0.0066   0.0776   0.4502  **
## factor(grade)2   -0.3727  0.1756  -2.1226  0.0395  -0.7266  -0.0188   *
## factor(grade)3    0.0248  0.1405   0.1769  0.8604  -0.2583   0.3080
## factor(grade)4   -0.0155  0.1195  -0.1300  0.8972  -0.2563   0.2252
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We would interpret the coefficients the same as we would from a regular regression with coefficients as comparisons to the reference group. However, these are interpreted at the effect size level. The `intrcpt` represents the effect at grade 1, with an effect of 0.26 standard deviations, $SMD = 0.26$, 95% CI $[0.078, 0.45]$, $t(44) = 2.85, p = .007$.

The grade 2 coefficient differed significantly from zero, $b = -0.37, t(44) = -2.12, p = .039$. Hence the effect at second grade was -0.11 standard deviations (0.26 - 0.37). Other grade level effects were not statistically different from the grade 1 effect.

We could modify the syntax as below (adding `-1` when defining the moderators), and this would give us coefficients for the specific grade levels.

```
rma(
  yi = yi, vi = vi, ni = ni, data = data,
  mods = ~ factor(grade) - 1,
  measure = "SMD", test = "knha"
)
```

This would allow us to tell which coefficients were statistically different from zero, not compared to the reference group.

There are additional elements from moderation analysis.

```r
res.1
```

```
##
## Mixed-Effects Model (k = 48; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):     0.0539 (SE = 0.0216)
## tau (square root of estimated tau^2 value):             0.2322
## I^2 (residual heterogeneity / unaccounted variability): 59.15%
## H^2 (unaccounted variability / sampling variability):   2.45
## R^2 (amount of heterogeneity accounted for):            0.00%
##
## Test for Residual Heterogeneity:
## QE(df = 44) = 102.0036, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4):
## F(df1 = 3, df2 = 44) = 1.8783, p-val = 0.1472
##
## Model Results:
##
##                 estimate      se     tval    pval    ci.lb    ci.ub
## intrcpt           0.2639  0.0925   2.8545  0.0066   0.0776   0.4502  **
## factor(grade)2   -0.3727  0.1756  -2.1226  0.0395  -0.7266  -0.0188   *
## factor(grade)3    0.0248  0.1405   0.1769  0.8604  -0.2583   0.3080
## factor(grade)4   -0.0155  0.1195  -0.1300  0.8972  -0.2563   0.2252
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

It is important to note that there remained some residual heterogeneity, $Q(44) = 102, p < .001$. Additionally, an omnibus test of the moderators suggested that the moderator coefficients were not statistically different from zero, $F(3, 44) = 1.88, p = .15$.

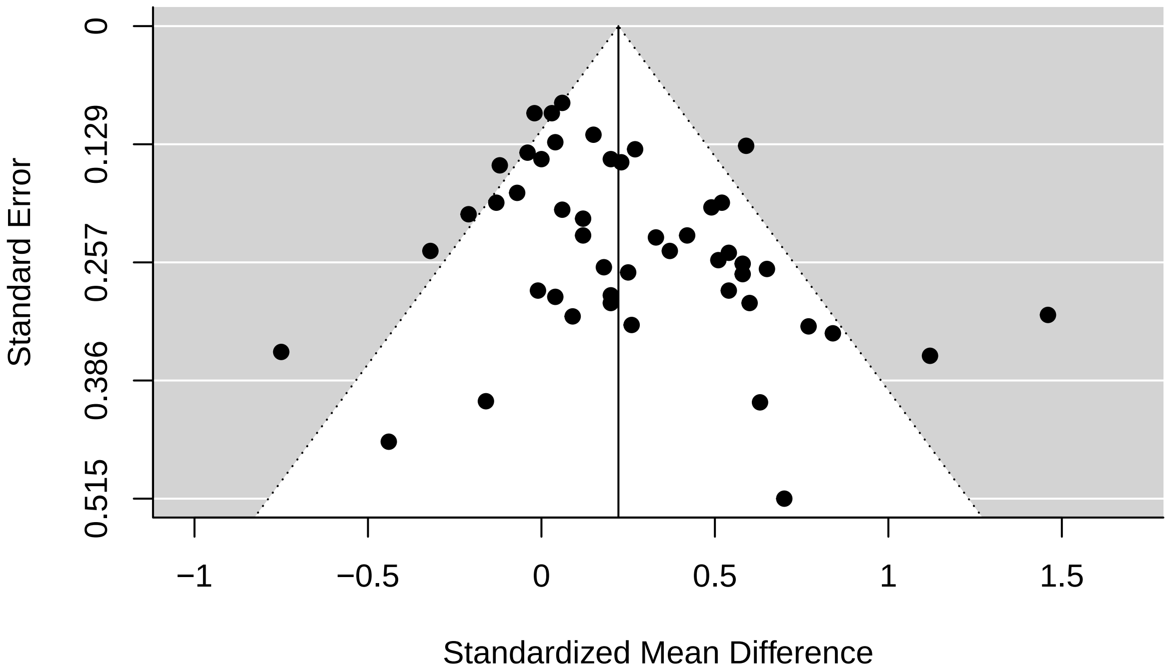
We can also observe the change in τ^2, `metafor` uses this to calculate a pseudo-`R^2` and when this value is negative, it reports 0% as above.

All these pieces of evidence suggest that we were unsuccessful at reducing the heterogeneity in our estimates despite adding a moderator.

Publication bias

We can use something called a funnel plot to check for some types of publication bias. If some types of results have been systematically excluded from the meta-analysis, we might see asymmetry about the center in the plot below.

```r
funnel(res.0)
```



It seems like the plot is light on the left at the lower ends, suggesting some negative results with large uncertainty might be missing from our analysis.

We can conduct a test of asymmetry.

```r
regtest(res.0)
```

```
##
## Regression Test for Funnel Plot Asymmetry
##
## model:     mixed-effects meta-regression model
## predictor: standard error
##
## test for funnel plot asymmetry: t = 2.2533, df = 46, p = 0.0291
```

Since the asymmetry is statistically different from zero ($t(46) = 2.25, p = .029$), this statistical test suggests we have some amount of asymmetry, hence publication bias (towards positive results based on the funnel plot).

References

- Knapp, G., & Hartung, J. (2003). Improved tests for a random effects meta-regression with a single covariate. *Statistics in Medicine, 22*(17), 2693–2710. https://doi.org/10.1002/sim.1482