Inference on multiverse meta-analysis

A multivariate permutation testing approach

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Contents I

Multiverse

Multiverse (Steegen et al., 2016)

- Real-world data analysis involve **several choices at each step**
- There are **many plausible alternatives** to the chosen analysis
- The **impact of alternatives** is often neglected or strongly underrated

Inference on multiverse

- The increase in complexity after taking into account scenarios is usually handled only descriptively
- The specification curve (Simonsohn et al., 2020) is the only inferential method but is limited to standard linear models

> **Note**
>
> There is a lack of a general and valid inferential framework for multiverse analysis

PIMA (Girardi et al., 2024)

PSYCHOMETRIKA
https://doi.org/10.1007/s11336-024-09973-6

Psychometric Society

Check for updates

POST-SELECTION INFERENCE IN MULTIVERSE ANALYSIS (PIMA): AN INFERENTIAL FRAMEWORK BASED ON THE SIGN FLIPPING SCORE TEST

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PIMA

- Use a multivariate extension of the sign-flip score test (Hemerik et al., 2020)
- Works on generalized linear models (and meta-analysis)
- Controls the family-wise error rate
- Provides an overall multiverse p-value and corrected p-values for each included scenario

Multiverse meta-analysis

Meta-analysis

We can define a (random-effects) meta-analysis model as:

$$y_i = \mu_\theta + \delta_i + \epsilon_i$$

$$\delta_i \sim \mathcal{N}(0, \tau^2)$$

$$\epsilon_i \sim \mathcal{N}(0, \sigma^2_{\epsilon_i})$$

Where μ_θ is the average true effect, δ_i is the random-effect of the study i ($\theta_i = \mu_\theta + \delta_i$) and ϵ_i is the sampling error of the study i. When $\tau^2 = 0$ we have an equal-effects (or fixed-effect) model.

Meta-analysis many choices

Meta-analysis is a prototypical case of multiverse analysis:

- Should the study x be excluded for theoretical or statistical (e.g., outliers) reasons?
- Should we use an equal or random-effects model?
- Which value should take the pre-post missing correlation?
- ...

Multiverse meta-analysis example

We collected k randomized controlled trials on the effectiveness of short-term memory training. The authors used multiple memory measures that are safe to combine.

- pre-post correlations are missing
- correlations between outcomes are missing
- we have n outliers
- we have n papers that we are not sure to include
- we could run an equal or random-effects model
- ...

Multiverse meta-analysis example

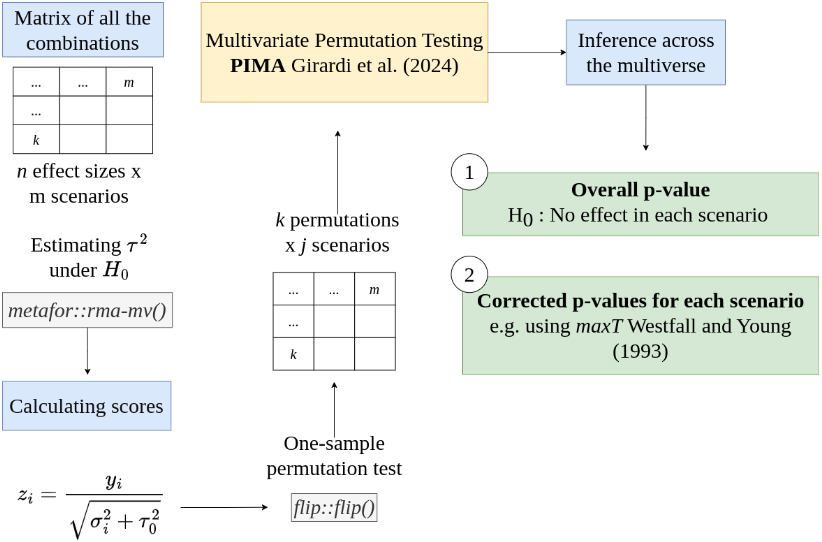
Even for the relatively simple previous example, we could have:

- pre-post $\rho \rightarrow$5 values
- outcomes $\rho \rightarrow$5 values
- 5 outliers
- 3 papers including/not including
- 2 equal vs random-effects

With all combinations, we have 750 **PLAUSIBLE** models with the same datasets.

PIMA on meta-analysis

General Workflow



Fast meta-analysis using permutations

Follmann & Proschan (1999) proposed a standard permutation test by re-computing τ^2 and μ_θ after each permutation.

We proposed a faster approach, especially for multiverse analysis with several scenarios.

1. Estimating τ^2 when $H_0 : \mu_\theta = 0$ maximizing the log-likelihood fixing $\mu_\theta = 0$
2. Calculating observed scores as $z_i = \frac{y_i}{\sqrt{v_i + \tau_0^2}}$
3. Doing B permutations flipping the sign of scores z_i
4. Repeat for each scenario of the multiverse

A simulated example

Simulating a multiverse analysis

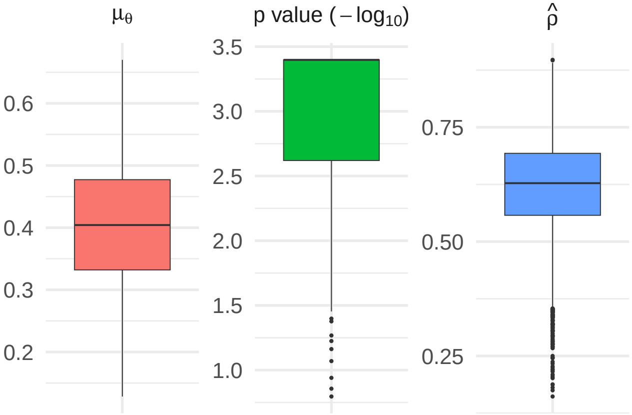
We simulated a meta-analysis with $k = 30$ and $m = 162$ sampling from a multivariate normal distribution.

We can describe a multiverse meta-analysis reporting summary statistics of the m estimated μ_θ and the correlation between scenarios.

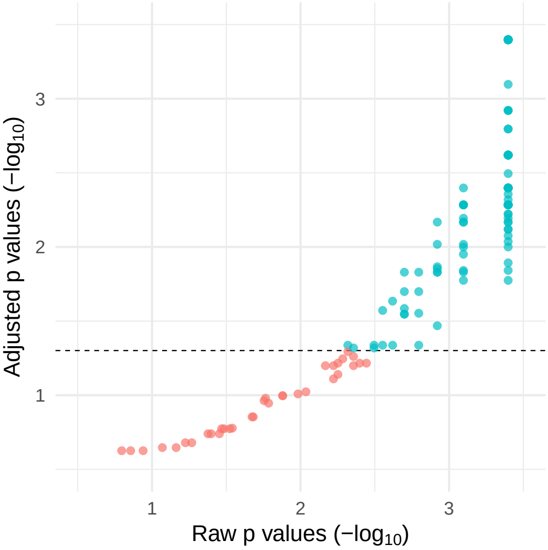
Overall inference

The multiverse is a associated with an **overall p-value** < 0.001, an **average effect of** 0.403 **(**$SD = 0.112$**)** and an **average correlation of** 0.620 **(**$SD = 0.102$**)**

Simulating a multiverse analysis



Impact of multiplicity correction



(valid) Post-hoc selective inference

Legal P-Hacking :)

After the overall test and p values correction, the survived scenarios (the blue dots) can be selectively commented, without inflating the type-1 error.

Guidelines for multiverse meta-analysis

Guidelines for multiverse meta-analysis

1. Multiverse meta-analysis must contain only **PLAUSIBLE** models. Including implausible models (e.g., assuming a pre-post correlation of 0.95) reduces the statistical power.
2. As with any other inferential test, multiverse analysis should be **PLANNED** otherwise no control of type-1 error.
3. Like in standard meta-analysis, the quality of the conclusions is related to the input data and the choice of multiverse scenarios.

Future steps

Future steps

- extending to multilevel and multivariate meta-analysis (the permutation approach is not straightforward)
- create an R package for multiverse meta-analyses with ad-hoc functions to analyze, report, and visualize the results
- create a data simulation framework for simulating a plausible multiverse for power and design analysis

References

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