

Evaluation of the validity of ALE meta-analytic contrasts



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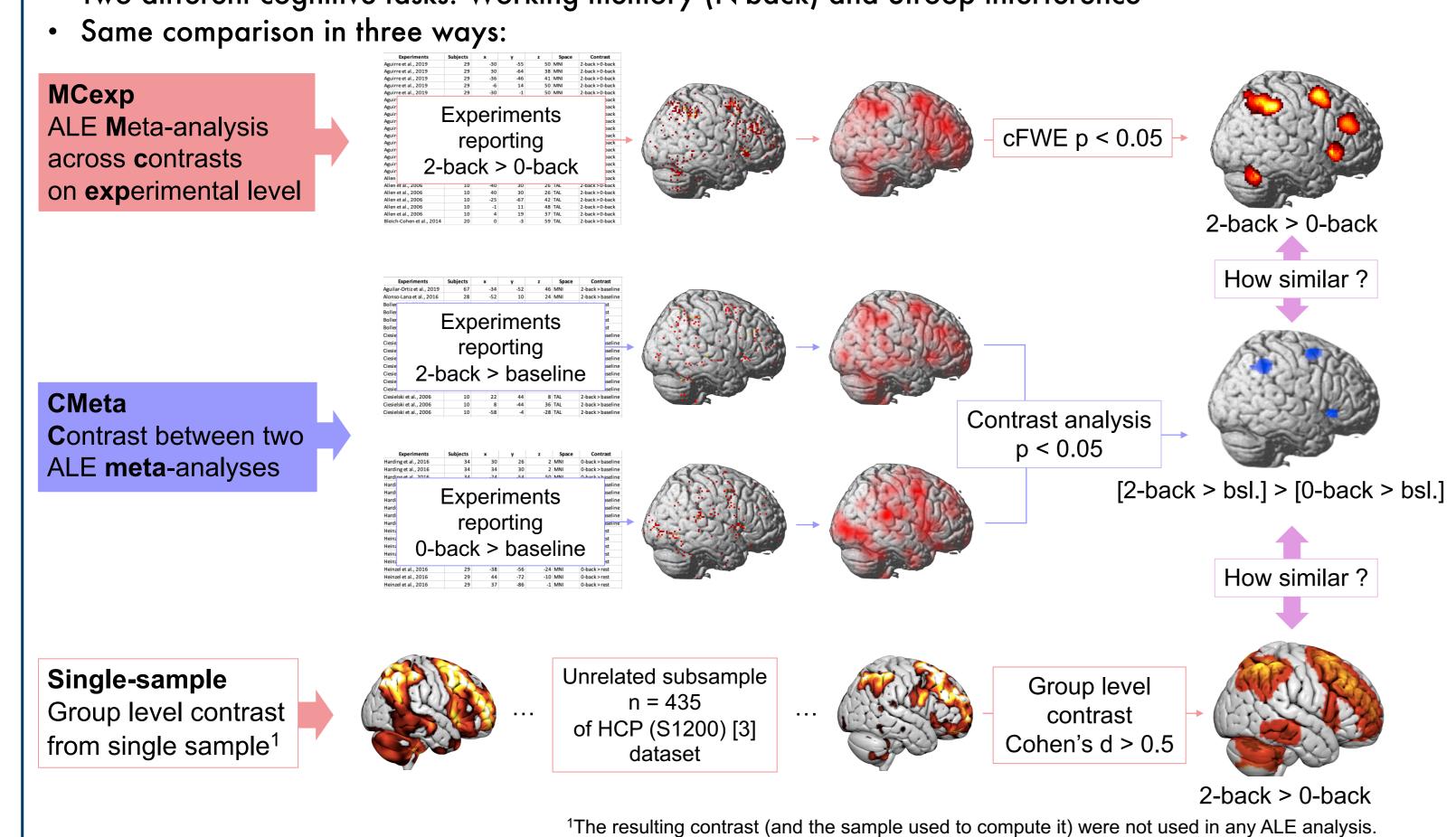


Background

- Activation Likelihood Estimation (ALE) meta-analyses of neuroimaging studies are key to overcome spurious findings, low power, analytical and experimental flexibility in individual fMRI studies
- ALE Meta-analytic contrasts [1] are statistical comparisons between the results of two individual metaanalyses, showing significant stronger convergence of one meta-analysis in comparison to another
 - Use-cases: e.g., dissect larger cognitive concepts (cognitive emotion vs. cognitive action regulation [2]); Testing new hypotheses (not yet investigated/ difficult to investigate in individual studies)
 - However, it remains unclear what exactly meta-analytic contrasts reflect
- AIM: investigate the validity of meta-analytic contrasts

Approach

Two different cognitive tasks: Working memory (N-back) and Stroop interference

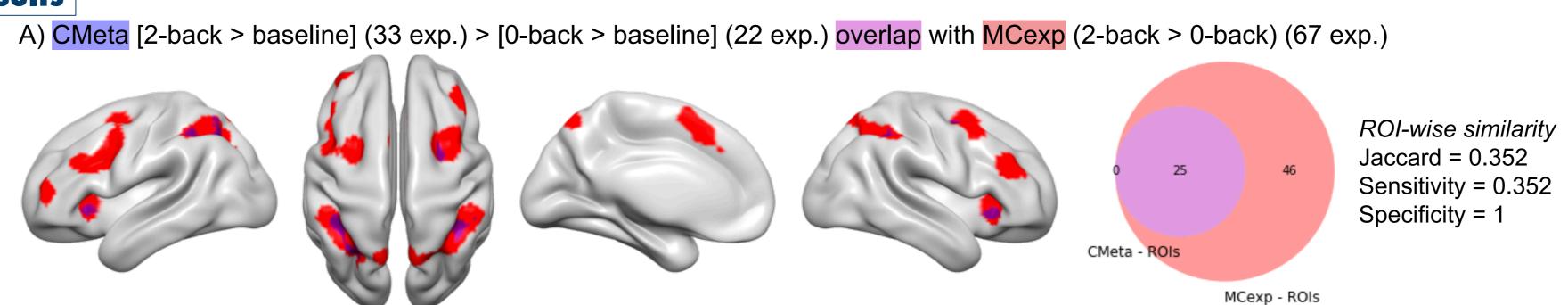


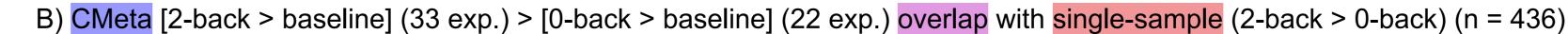
- Same was done for Stroop (incongruent > congruent), however without single-sample comparison.
- Effect of control condition: Comparing CMeta across experiments with high level control condition (CMeta-HLC) with CMeta across experiments with passive baseline condition (CMeta-Base)

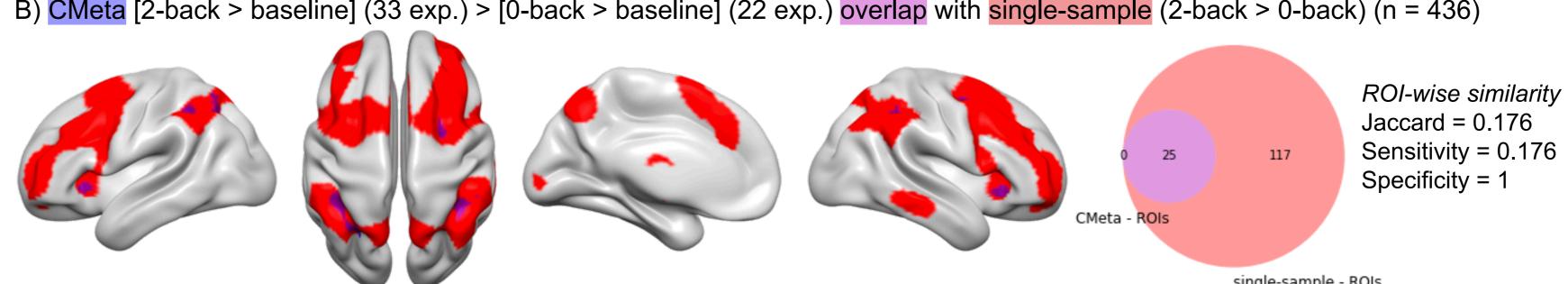
Quantification of similarity as ROI²-wise measure of Jaccard similarity coefficient [4], sensitivity, specificity

$$Jaccard = \frac{ROIs\ A\ \cap\ ROIs\ B}{ROIs\ A\ \cup\ ROIs\ B} \quad Sensitivity = \frac{ROIs\ A\ \cap\ ROIs\ B}{ROIs\ B} \quad Specificity = \frac{NOT(ROIs\ A\ \cup\ ROIs\ B)}{NOT(ROIs\ B)}$$
²defined by Brainnetome Atlas 274 [5] parcellation (246 parcels; Diedrichsen [6] 28 cerebellar regions)

Results







C) CMeta [incongr. > neut./bsl.] (20 exp.) > [congr. > neut./bsl.] (20 exp.) overlap with MCexp (incongr. > congr.) (52 exp.)

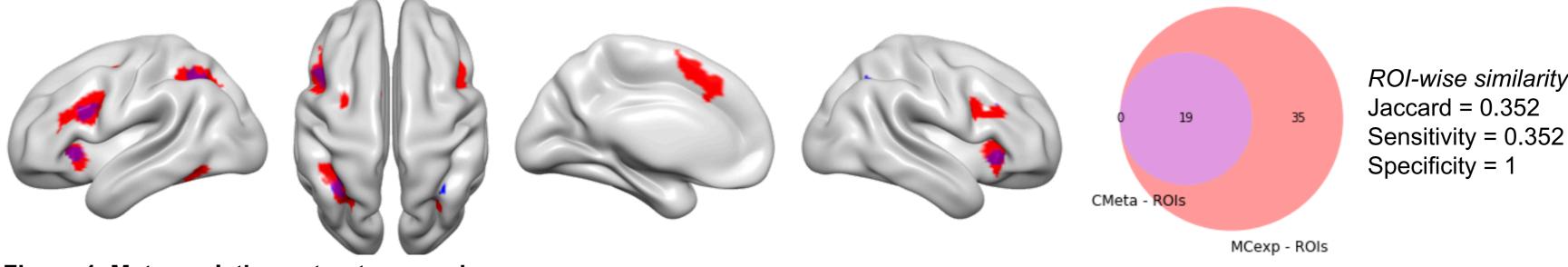
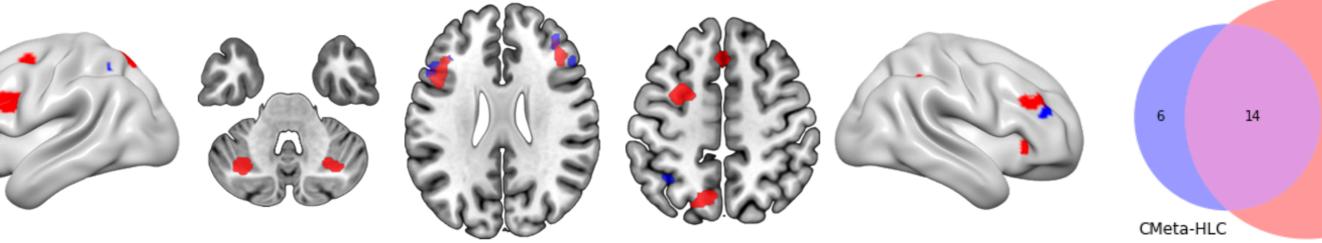


Figure 1. Meta-analytic contrast comparison

CMeta-HLC [2-back > 0-back] (21 exp.) > [1-back > 0-back] (21 exp.) overlap with MCexp (2-back > 1-back) (22 exp.)



(19 exp.) > [1-back > rest] (19 exp.) overlap with MCexp (2-back > 1-back) (22 exp.)

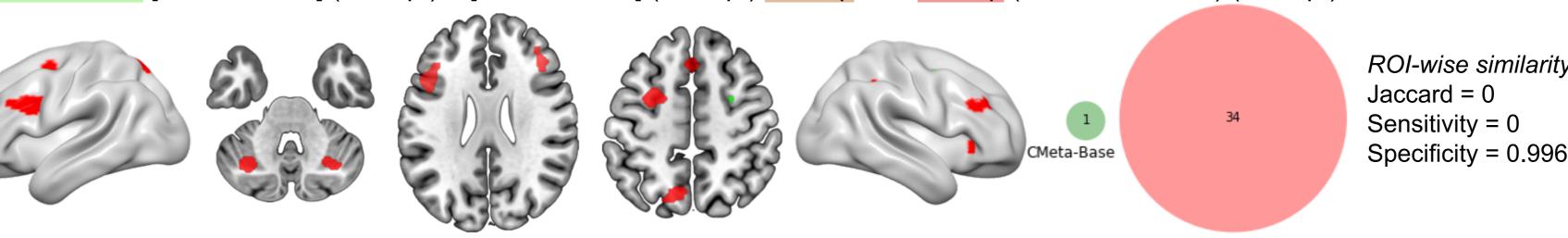


Figure 2. Evaluation of baseline/ contrasting condition

Summary

- Regions showing significantly stronger convergence in the CMeta networks lie perfectly within the network of significant convergence seen in the MCexp for N-back (Fig. 1A) and Stroop (Fig. 1C) (specificity = 1)
- However only 1/3 of regions (sign. in MCexp) seem to be found (in CMeta)
- Comparison of CMeta with single-sample contrast (Fig. 1B) shows similar but overall lower degree of similarity (Jaccard = 0.176, sensitivity = 0.176)
- Low-level baseline conditions (i.e., rest, fixation) seem to be less suitable for meta-analytic contrasts (Fig. 2B)
 - Possibly: large clusters formed in such contrasts → not reliably covered by a few coordinates reported
- Substantial similarity between CMeta-HLC (high level control condition, i.e., 0-back) and MCexp map (Fig. 2A) > eventually better suitability for meta-analytic contrasts

Conclusions – How valid are meta-analytic contrasts?

- High specificity → regions identified in CMeta appear to be highly valid – interpretation: similar as results of MCexp/ single experiments
- Low sensitivity \rightarrow highly conservative \rightarrow absence of expected regions \Rightarrow lack of involvement in the mental processes investigated
- Ideally, inclusion only of experiments contrasting against a high-level control condition

References

ROI-wise similarity

Jaccard = 0.35

Sensitivity = 0.411

Specificity = 0.98

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