NiSpace

Neuroimaging Spatial Colocalization Environment

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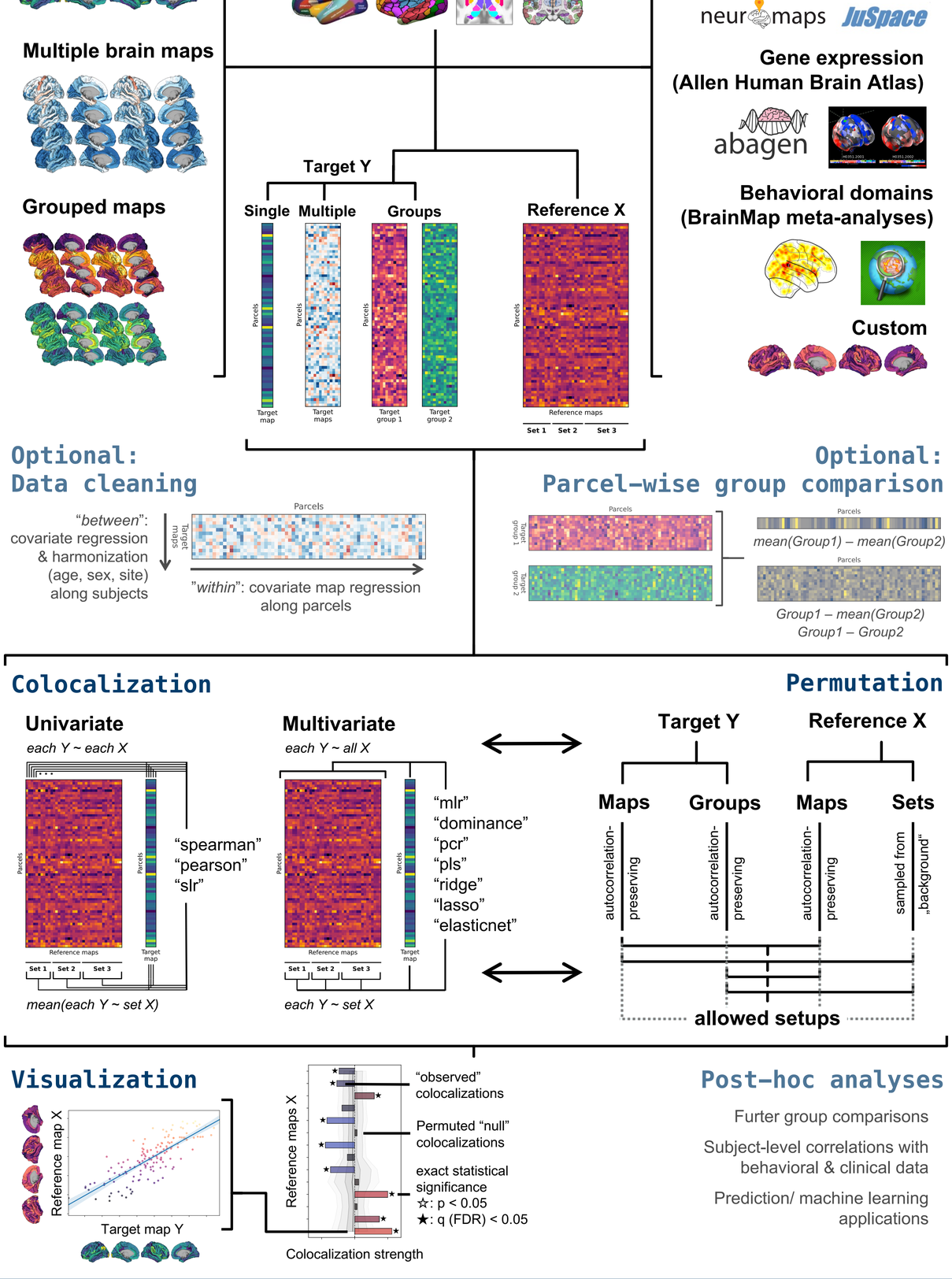
Introduction

- Most neuroimaging research focuses on **brain-regional effect estimates** as outcomes of interest.
- **Spatial patterns across the whole brain, cortex, or subcortex** may convey important information missed by regionally constrained analysis approaches.
- These patterns are found in any given brain map, from **individual neurodevelopment** over time [1] to effect size maps reflecting **case-control differences** on the **individual** [2] or **group level** [3].
- By testing a **target brain map** for its **colocalization** with **reference atlases** of known biological or functional entities (e.g., neurotransmitters, gene expression, or meta-analytic maps of cognitive functions), one can derive **interpretable inferences from in-vivo human neuroimaging data** [1–5].
- **NiSpace** is **a user-friendly API-focused toolbox** integrated in the **Python** neuroimaging ecosystem that allows for **fast, flexible, and easily scalable colocalization analysis**.
- **NiSpace aims to provide high-level tools and workflows** for both novice and experienced users, starting with preprocessed **volumetric and surface** neuroimaging data, over **data cleaning and harmonization**, as well as **several statistics** and different **permutation procedures**, to results **visualization**.
- **NiSpace applies and advances methods provided or introduced by other related toolboxes**, e.g.: JuSpace [2], neuromaps [4], ENIGMA toolbox [5], BrainSpace [6], BrainSMASH [7], MENGA [8], Virtual Histology [9], or GCEA [10].
- **NiSpace integrates prior approaches into a unified framework**, allowing for combinations of, e.g., subject- and group-level analyses, uni- and multivariate methods, or autocorrelation-preserving group, map, and set permutations.
- The **Python API is under development**; a **GUI will be available in the future**.

Approach

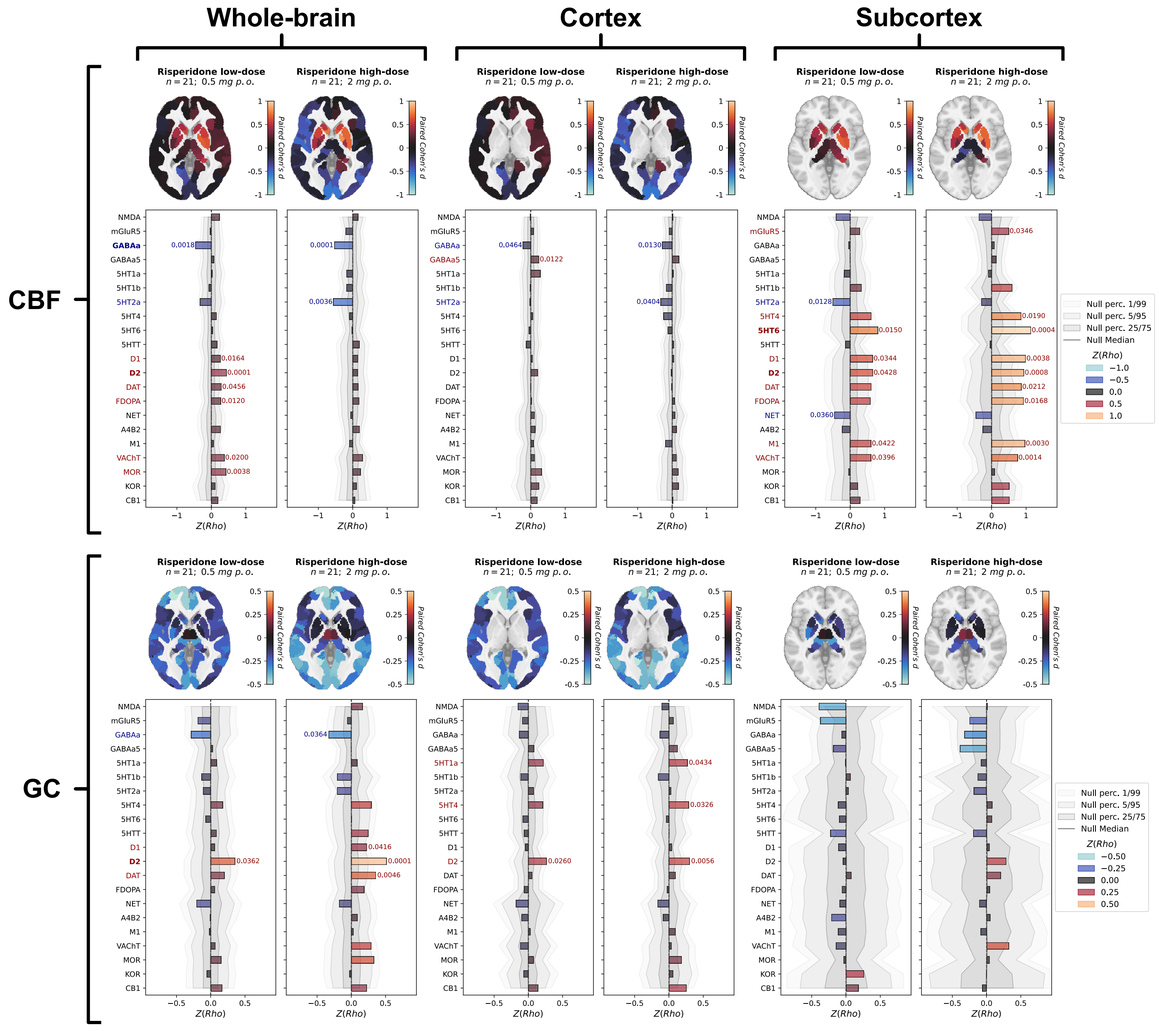


Case studies

Drug challenge – Session permutation

Colocalization between placebo-controlled drug effects on MRI (cerebral blood flow, CBF, and global correlation, GC) and independent neurotransmitter reference maps.

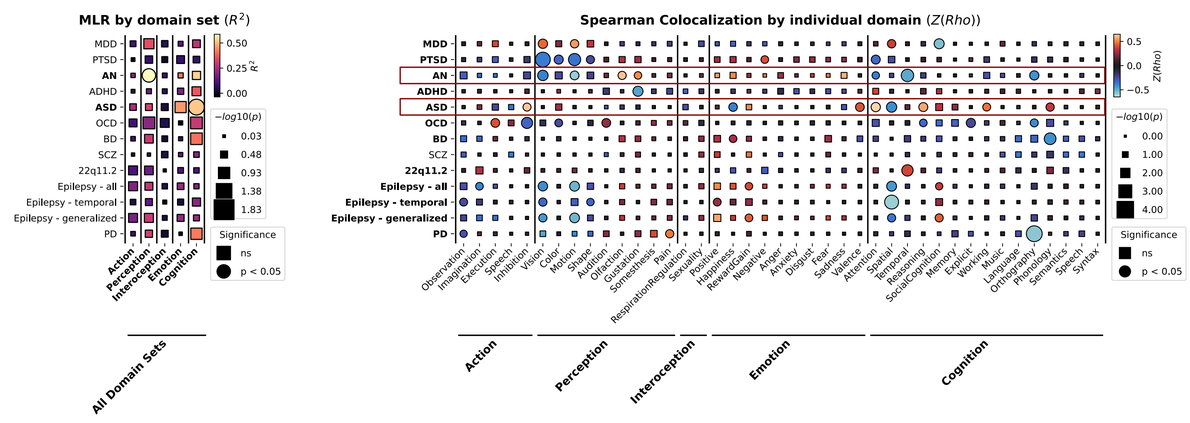
Target: CBF/GC maps [11] | **Reference**: group-average nuclear imaging maps (included in **NiSpace**) | **Parcellation**: Schaefer-200/ Melbourne-S2 | **Processing**: gray matter (GM) regression across parcels | **Comparison**: group level: parcel-wise paired Cohen's *d* | **Colocalization**: Spearman's Rho | **Permutation**: drug vs. placebo labels, shuffled within each subject, retaining constant 50/50 drug/placebo splits.



ENIGMA cortical thickness effect sizes – Map permutation

Colocalization between ENIGMA effect sizes maps and BrainMap behavioral domains in a multilevel analysis: MLR by domain class, followed by individual analyses for each specific domain. AN (anorexia nervosa): perception; ASD: cognition.

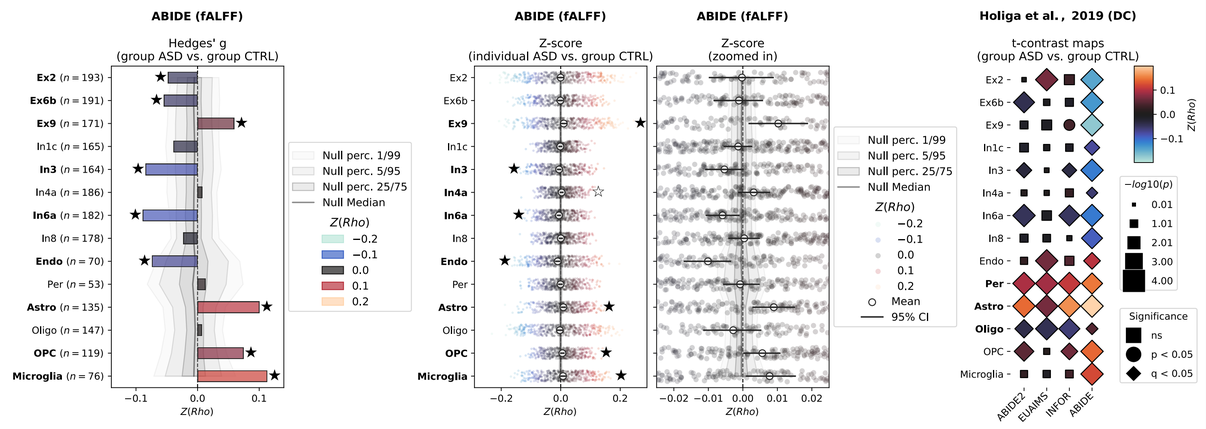
Target: ENIGMA effect size maps [mostly 5] | **Reference**: meta-analytic maps calculated from BrainMap coordinates [15] (included in **NiSpace**) | **Parcellation**: Desikan-Killiany | **Colocalization**: Multivariate regression (MLR); Spearman's Rho | **Permutation**: Spatial autocorrelation-preserving reference null maps ("Moran" method [4,6]).



Autism spectrum disorder (ASD) – Gene ("X")-set enrichment analysis

Colocalization between ASD-related resting-state brain activity/connectivity alterations and brain cell type markers: Consistent colocalization with astrocyte markers.

Target: ABIDE-I fALFF maps [12]; Group level DC t-contrast maps from four ASD cohorts [13] | **Reference**: Cell type marker genes [14] (included in **NiSpace**) | **Parcellation**: Schaefer-200+Melbourne-S2 | **Processing**: GM regression across parcels; age/sex regression & ComBat harmonization across subjects | **Comparison**: group level: parcel-wise Hedges' *g* (left); individual level: parcel-wise Z-scores (center) | **Colocalization**: Spearman's Rho (set-wise signed average) | **Permutation**: gene sets retaining original set sizes, sampled from the full (n ~= 7000) mRNA dataset.



Docs under construction:
nispace.readthedocs.io

Development version:
GitHub.com/LeonDLotter/NiSpace

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