Trial-Level RSA – an Enhanced Approach to Representational Similarity Analysis

Mnemology Lab

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1. Neural representations

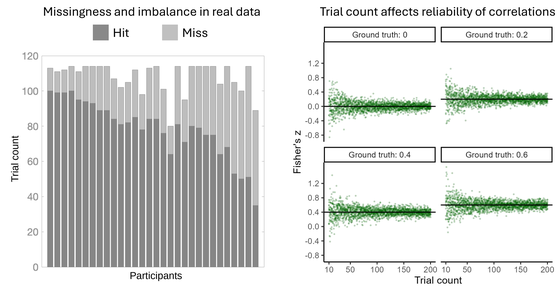
- Neural representation refers to brain activity that stands in for one's cognitive experience (e.g., perception, memory).
- Hypothetical study:

Task	Stimulus	Participant	
		Highschooler Hank	Zoologist Zoe
Name		"Camel"	"Bactrian Camel"
		"steals fries"	"Gull"
Categorize		"domestic"	"domestic"
		zzZ	"wild"

- Factors influencing Zoologist Zoe's representation of
  - a) **Subject-level**: her expert-level knowledge of animals
  - b) **Condition-level**: naming the animal vs. categorizing
  - c) **Stimulus-level**: uniquely distinctive features of the target
  - d) **Trial-level**: mental state (focused) and physiology (awake)

$$\text{ } = \text{ } + \text{} \sim N(0, \sigma_{ijk}^2),\ \sigma_{ijk} = \sigma_{subj,i} + \sigma_{cond,j} + \sigma_{stim,k} + \sigma_{trial}$$

- Representational similarity analysis (RSA) has been the principal method used to study neural representations.[1]
- However, classic RSA or **cRSA** is limited in that
  - it does not capture the multi-level variance in the data, and
  - it has limited flexibility in what questions can be addressed.
- E.g., uncaptured variance due to variable trial counts

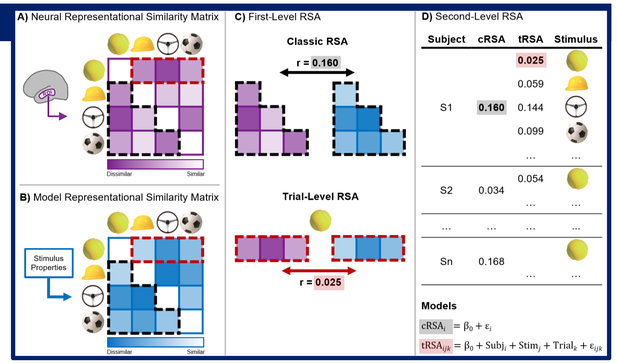


3. Trial-level RSA procedures

First, representational similarity matrices (RSMs) are built based on neural activity and the hypothesis/model.

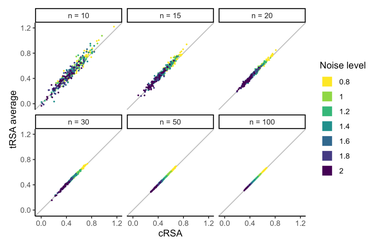
In **cRSA**, the entireties of RSMs are compared, producing a single statistic (e.g., *r*) for each subject/condition. These values are tested at the group level (e.g., 1-sample t-test).

We propose **tRSA**, where RSMs are compared row-wise. This way, **tRSA** estimates the **representational strength** in each trial (e.g.,).[2] Then, these trial-level estimates are modeled in a mixed-effects framework, with *Subjects* and *Stimuli* modeled as random effects, to capture the multi-level variance structure in the data.[3-4]

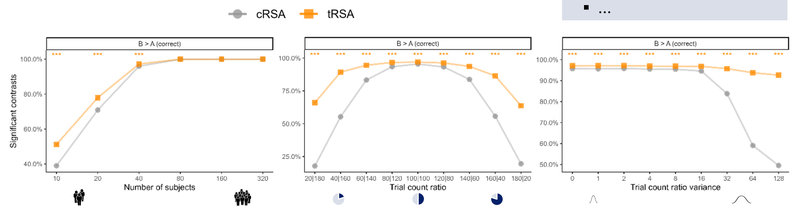


4. Comparing tRSA to cRSA in simulations

Estimating *overall representation*: **tRSA** is highly similar to **cRSA** at each sample size and noise level.



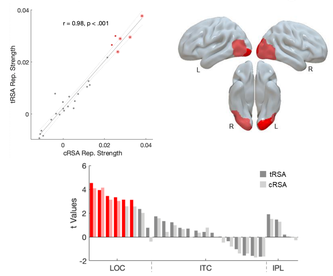
Testing condition differences: **tRSA** displays reliable specificity (not shown) and improved sensitivity over **cRSA** in a wide range of cases.



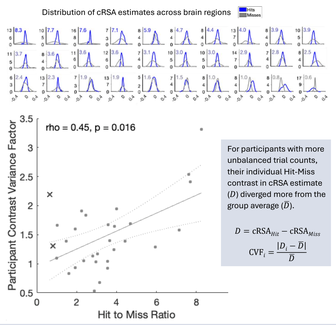
Base setting:
- 40 subjects
- 200 stimuli
- 2 conditions (B > A)
- …

5. Comparing tRSA to cRSA using real fMRI data

Estimating *overall representation*, numerical estimates are highly similar, while **tRSA** identified a few more *representational* brain regions.



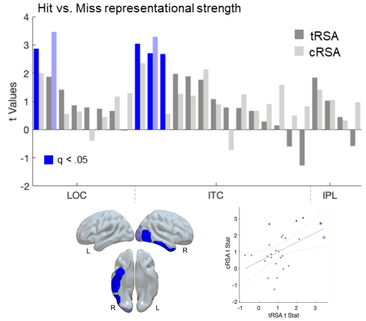
cRSA estimates were largely affected by trial count imbalance.



For participants with more unbalanced trial counts, their individual Hit-Miss contrast in cRSA estimate (D) diverged more from the group average ($\bar{D}$).

$$D = cRSA_{Hit} - cRSA_{Miss}$$
$$CVF_i = \frac{|D_i - \bar{D}|}{\bar{D}}$$

tRSA demonstrated enhanced sensitivity to condition differences in representation.

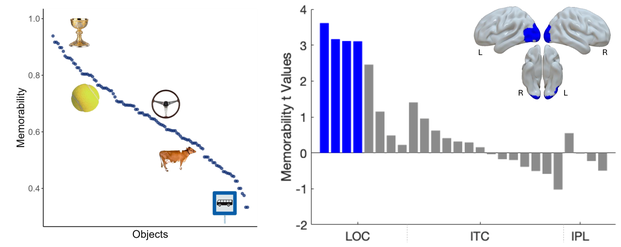


Take-home messages

- **tRSA** produces highly similar estimates as cRSA for overall representation strength.
- **tRSA** shows enhancements in *specificity*, *sensitivity*, and *robustness in edge cases*.
- **tRSA** enables novel analyses of behavior and representations.

6. Item-level representational strengths

- **tRSA** allows us to test how representations vary with trial- or item-level properties, especially continuous variables.
- Memorability refers to the likelihood for anyone to remember a stimulus and is considered an intrinsic property of that stimulus.[5]
- Item-level memorability predicted the strength of the items' visual representations in four regions in the lateral occipital cortex (LOC).



- With trial-level measures of representational strength, we can also analyze inter-regional interactions in terms of representations, such as *representational connectivity*. See Huang et al. (2024).[6]

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