SOS LASSO: A new method for finding distributed representations in fMRI data.

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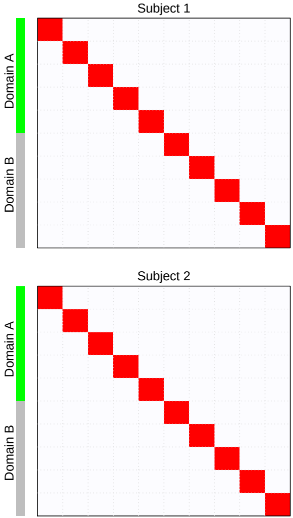
- Importantly, each exists to address different questions, makes different assumptions about for the most relevant neural activity is encoded.

A small glimpse of the problem



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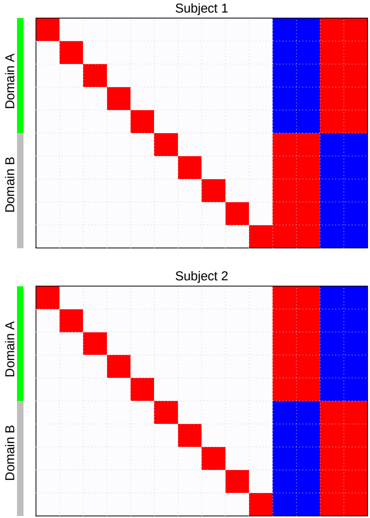

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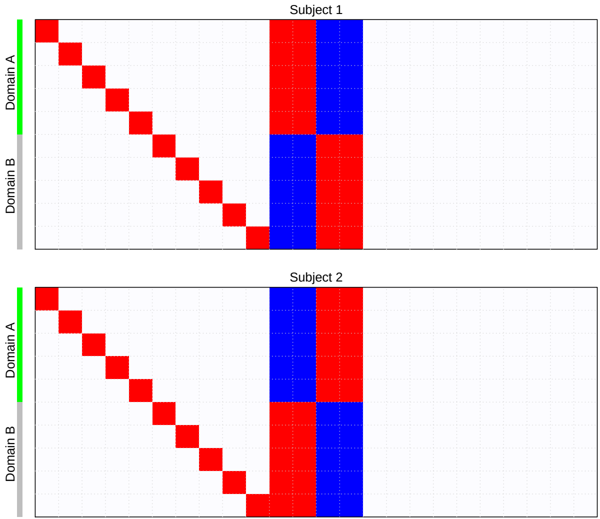

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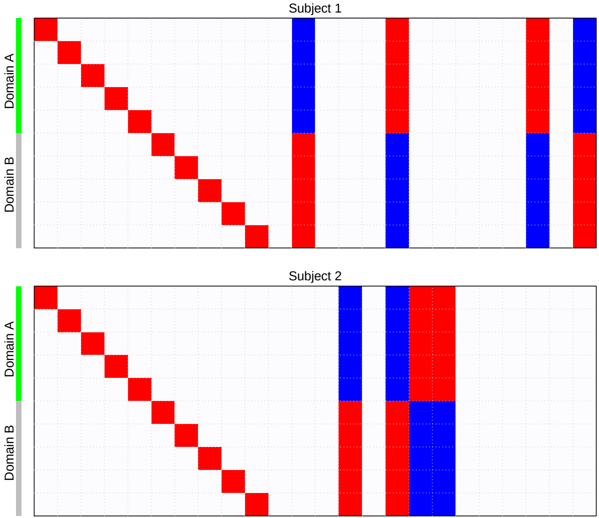

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PDP theory is one of the only mechanistic accounts of cognition that makes explicit predictions about **how** our mental representation are actually encoded by the brain.

PDP theory predicts that representations are **distributed**.

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3. The functional model architecture may not map transparently onto anatomical structure in the brain.
4. The network of interest in any given study co-exists in the brain with many other networks, all subserving other functions that may not be of interest.

What do distributed representations buy us?

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5. Distributed representations can be highly efficient.[6]

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How can we find distributed representations?

The goal: To find a method whose assumptions about the how information is encoded in the brain is sufficiently loose so that individual differences do not wipe out the signal, but sufficiently constrained so that the results are interpretable.

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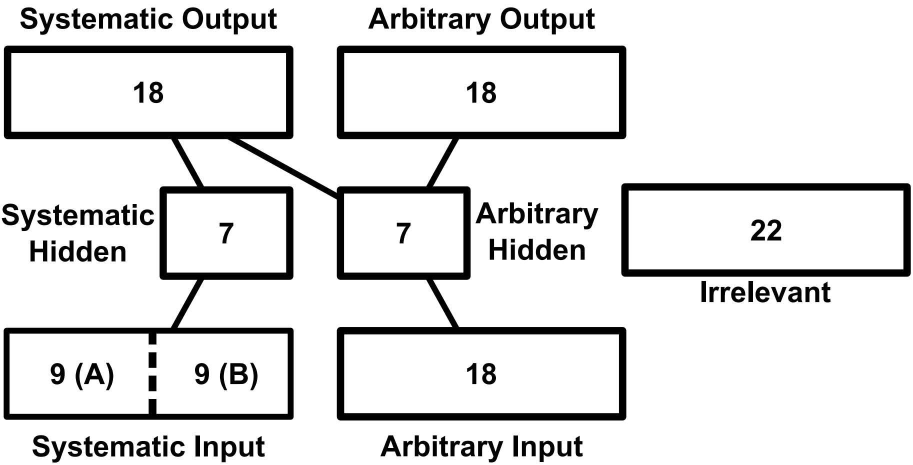
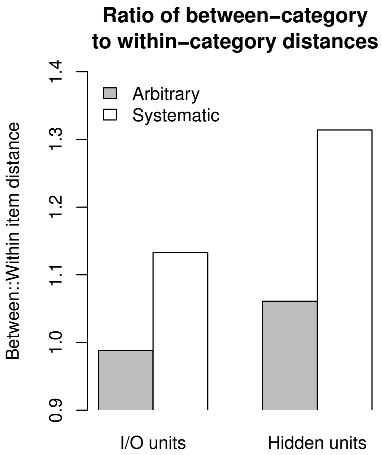
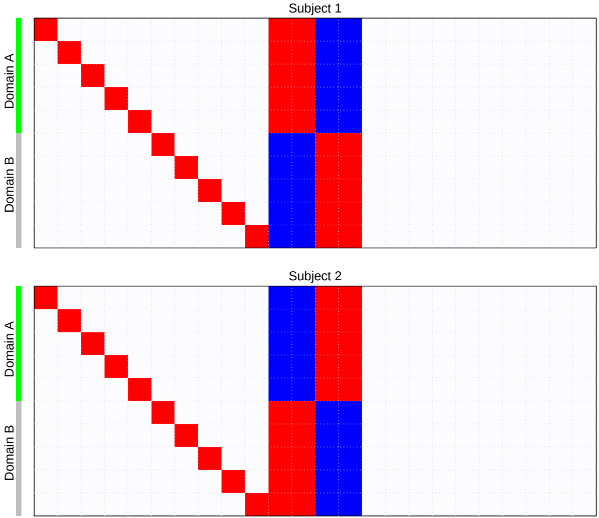
A model to simulate our data



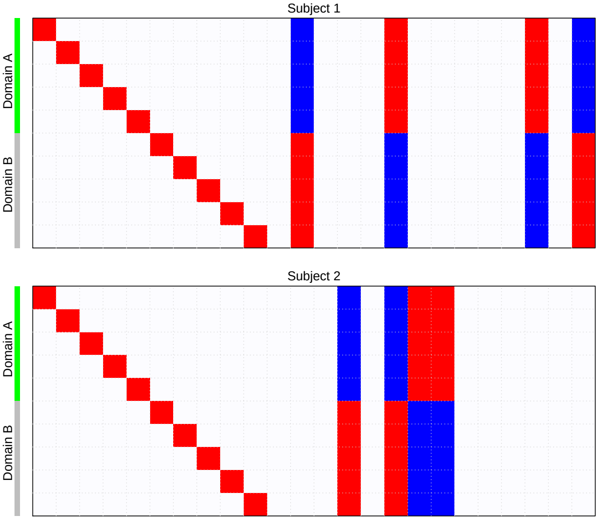
Where information is located



"Localized" distributed representations



"Dispersed" distributed representations



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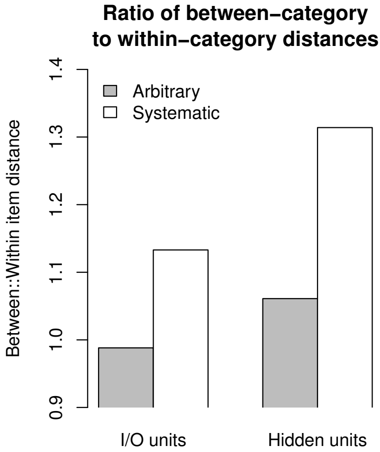
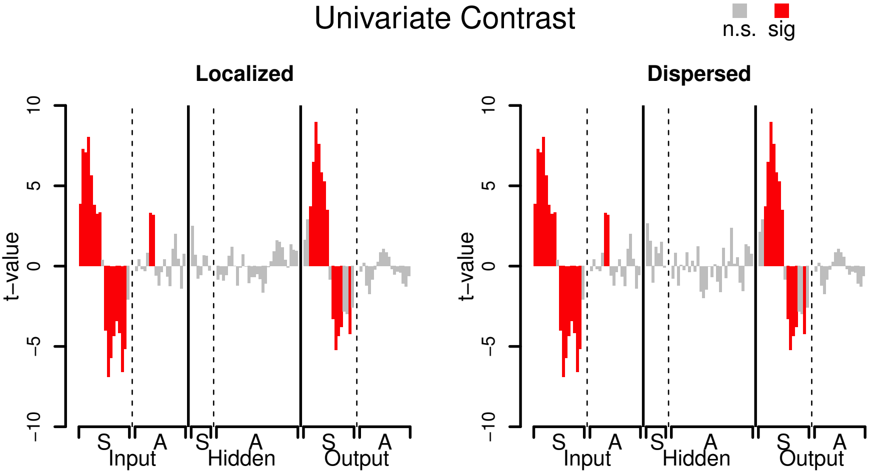
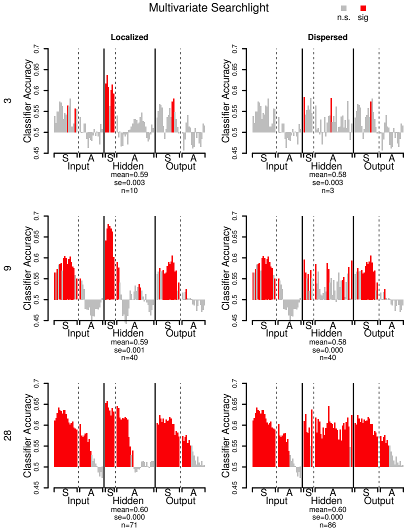


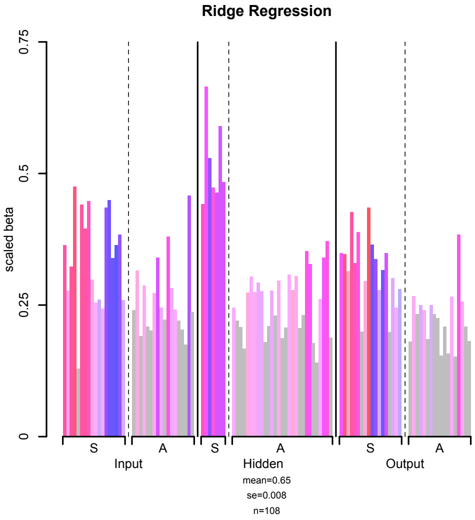
Strong localization assumption, within and across



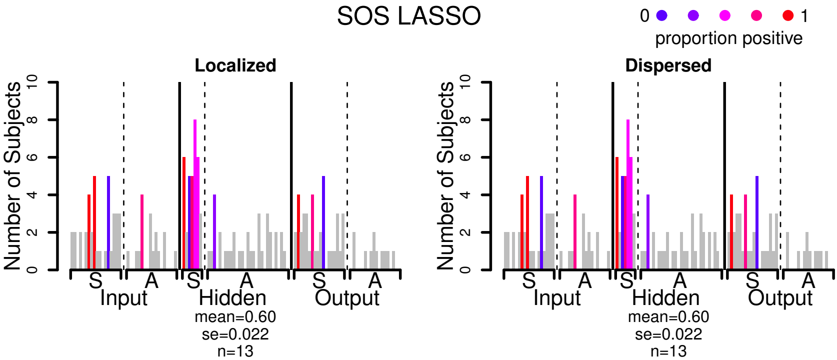
Less strong localization assumptions (but still there)



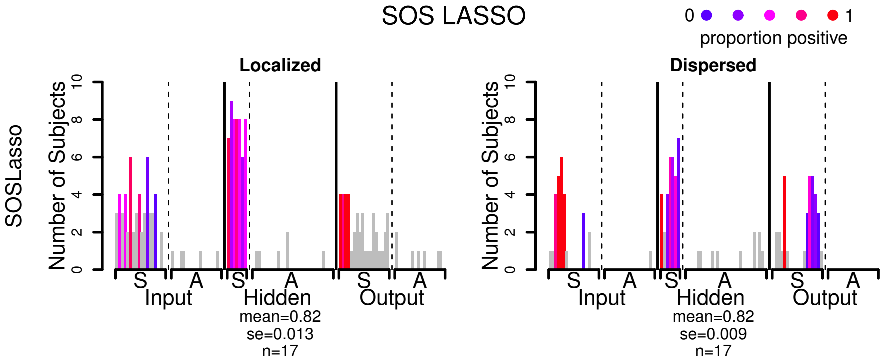
No localization assumption (and no feature selection!)



No localization assumption, with feature selection



Relaxed localization assumption + feature selection



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2. The assumptions that an method makes about how information is encoded has a large effect on what will be found.
3. Different methods provide different levels of information about the signal it does identify.
4. SOS LASSO appears uniquely suited to test hypotheses about distributed representations in the brain.