MAX PLANCK INSTITUTE FOR SOFTWARE SYSTEMS

PRINCETON UNIVERSITY

Machine Learning Department

Computational Biology Department

Neuroscience Institute

Carnegie Mellon University

Same Cause; Different Effects in the Brain

Mariya Toneva* — Princeton, MPI-SWS
Jennifer Williams* — CMU
Anand Bollu — CMU
Christoph Dann — Google
Leila Wehbe — CMU

Summary

Background: To map information processing in the brain, researchers use encoding models to evaluate if stimulus properties predict brain data.

Gap in the field: Naturalistic stimuli make it difficult to infer what stimulus properties affect each brain zone because the stimuli are multivariate and often high-dimensional.

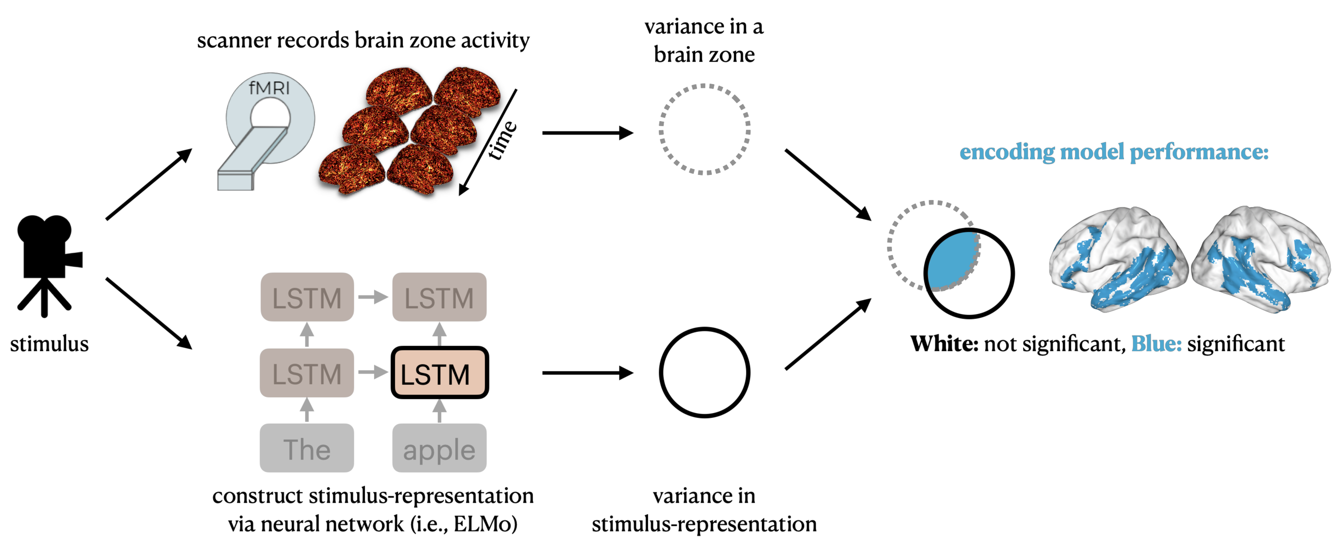
Main contribution: Enable researchers to infer if a stimulus affects two brain zones in the same way by proposing an inference framework that includes two new metrics.

Validation:

Simulations show that the proposed metrics provide new insights beyond current brain mapping techniques.

Consistent inferences across 2 naturalistic fMRI datasets, acquired from different subjects, labs, and stimuli.

Motivation



Encoding model:

$$Y_i = g_i(X) + \epsilon_i$$

$Y_i \in \mathbb{R}$ observation in zone i

$X \in \mathbb{R}^d$ stimulus-representation

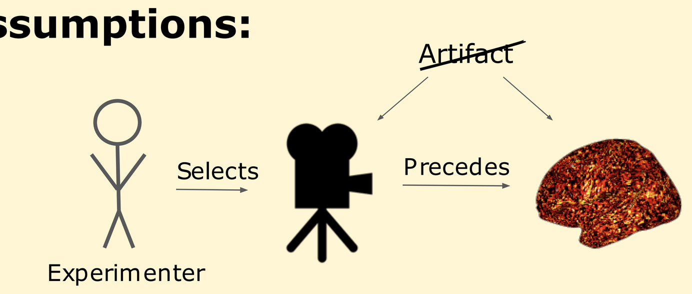
$g_i(X) = \langle X, \theta_i \rangle$ stimulus effect

Claim: encoding model cannot infer if stim. properties affect 2 brain zones in the same way

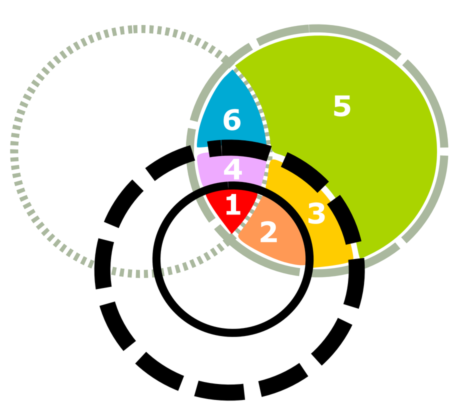
Causal interpretation:

reveals which brain zones affected by stimulus properties captured by stimulus-representation [1]

Assumptions:



1+4 similar effect
2+3 different effect
1 similar effect of stim. properties captured by ELMo
4 similar effect of stim. properties missing from ELMo
2 different effect of stim. properties captured by ELMo
3 different effect of stim. properties missing from ELMo
5 different noise
6 similar noise



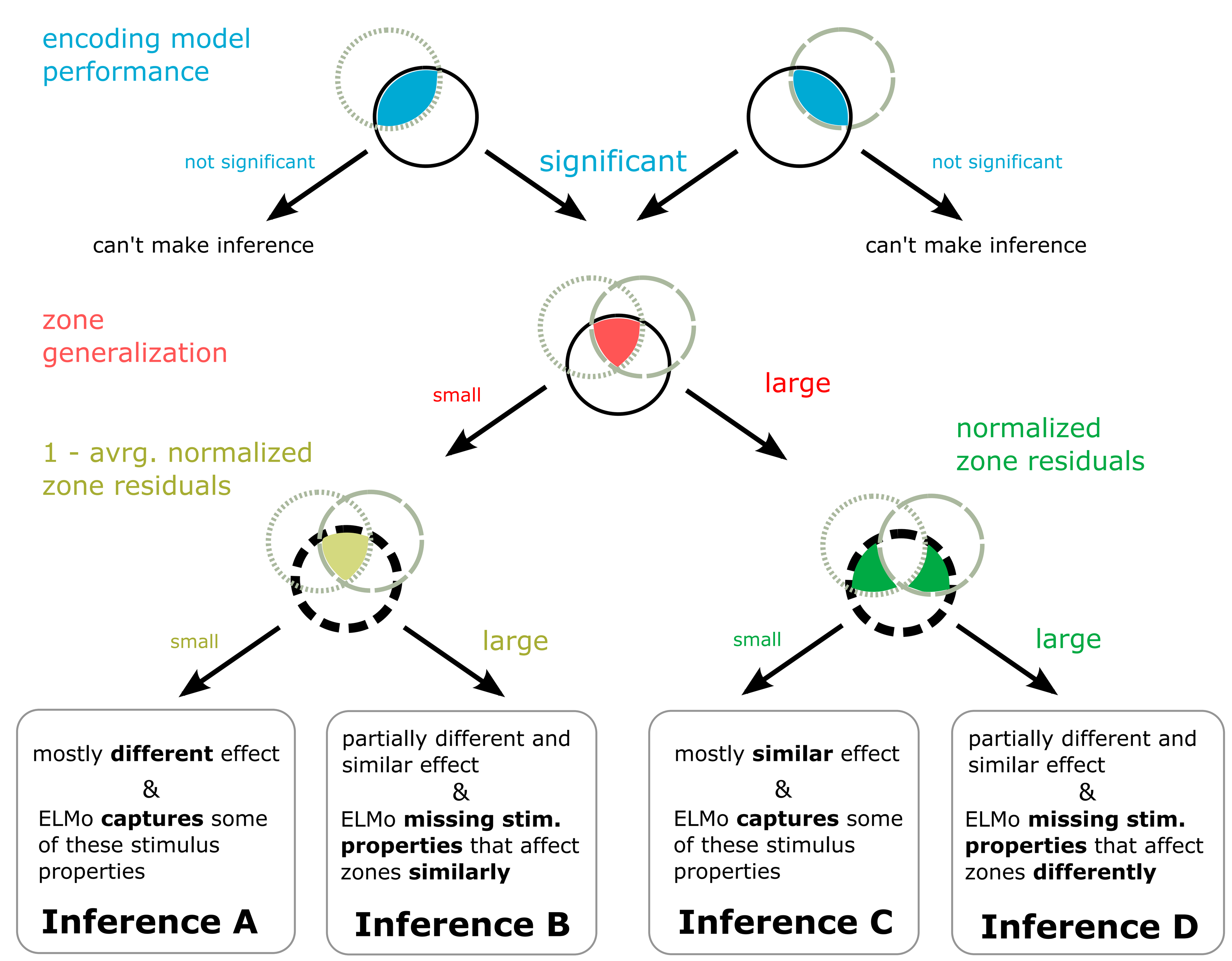
variance in a brain zone; variance in a second brain zone; variance in stimulus representation (e.g. ELMo); variance in stimulus

Code: github.com/brainML/stim-effect

Inference Framework

Zone generalization: how similarly two zones are affected by stim. properties in the stimulus-representation (area 1)

Zone residuals: capture any stimulus effect that is not shared between two zones (areas 2 & 3)



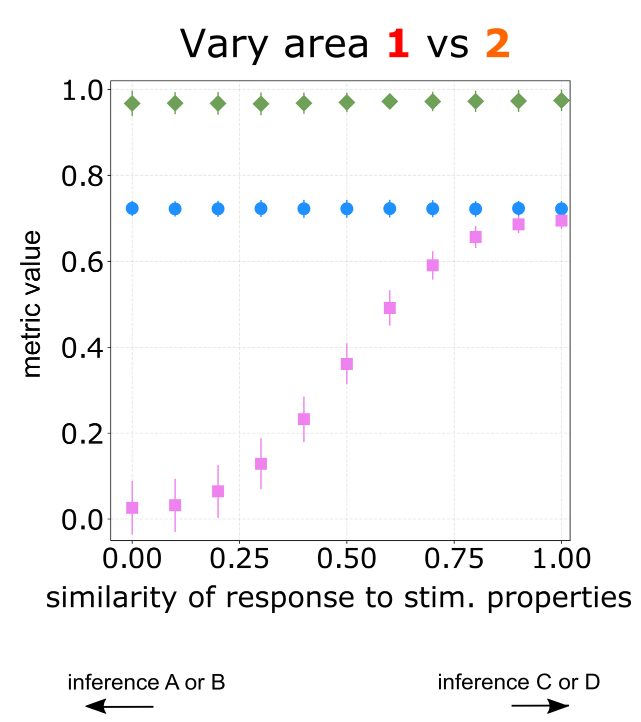
Metrics Implementation & Validation

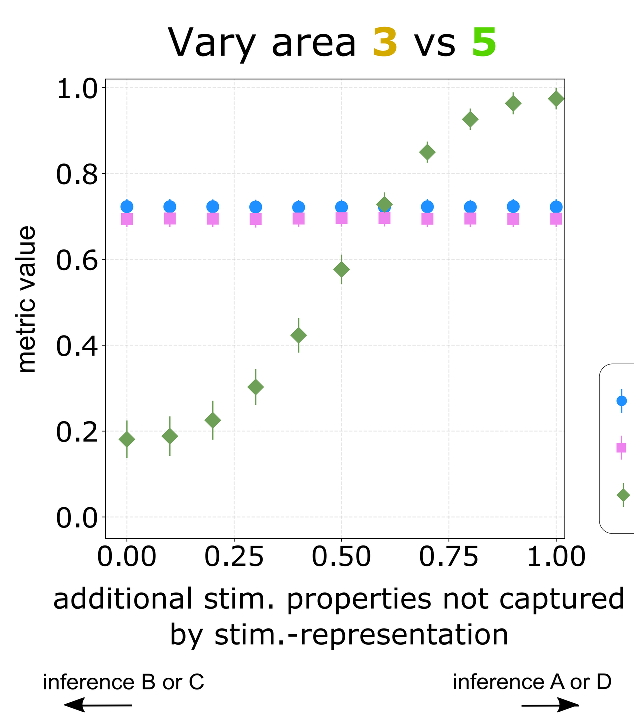
encoding model performance $(\text{zone}_i) = \text{corr}(\widehat{Y}_i, Y_i)$ commonly used, e.g. [2-3]

zone generalization $(\text{zone}_i, \text{zone}_j) = \text{corr}(\widehat{Y}_i, Y_j)$ inspired by [4-5]

zone residuals $(\text{zone}_i, \text{zone}_j) = \frac{1}{M^2 - M} \sum_{S,T,S \neq T} \text{corr}(R_{i-j,S}, R_{i-j,T}),$ inspired by [6]

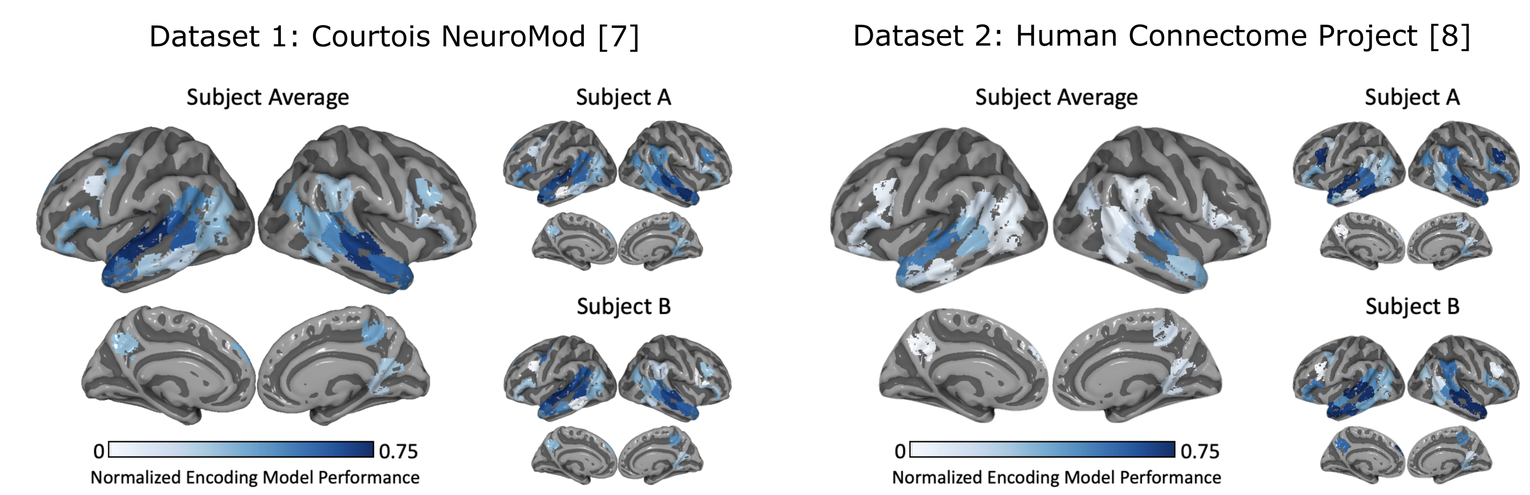
$$R_{i-j,P} = Y_{i,P} - Y_{j,P}\beta_P^{ij}$$



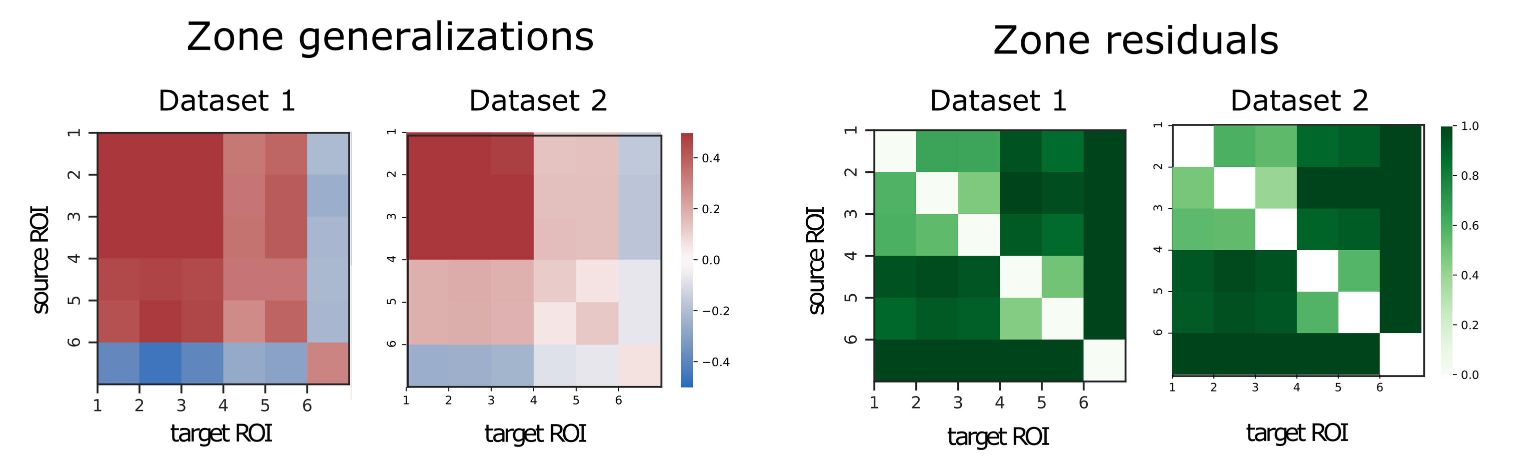


Both types of new metrics needed to make one of the **4 inferences**

Results on 2 fMRI Datasets

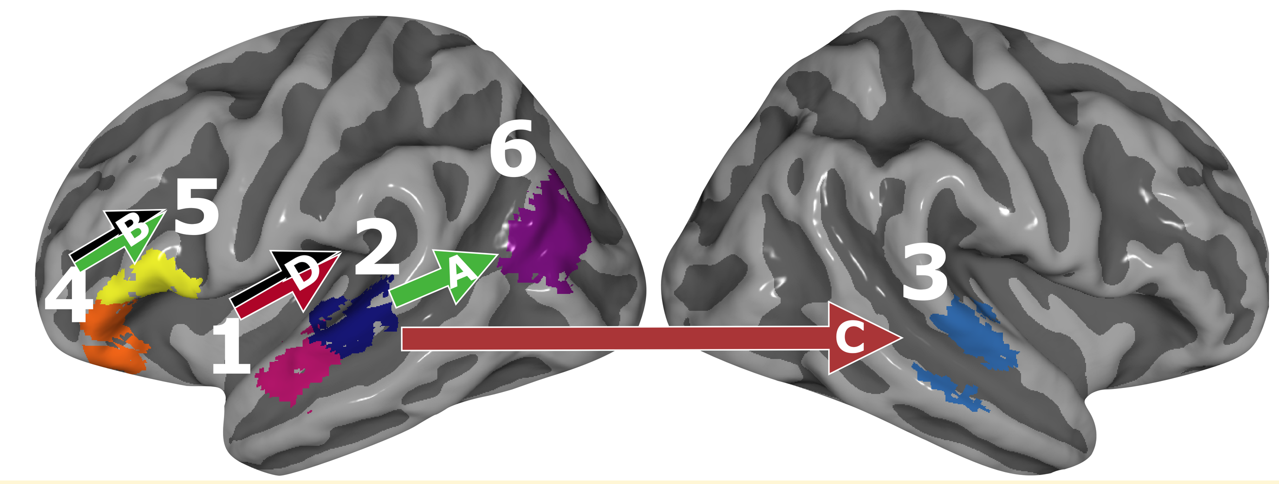


Encoding model performance significant in 34 language regions



Each of the proposed metrics reveals **distinct zone clusters**, that are consistent across datasets

Examples of the 4 types of inferences



Stimulus properties affect brain zones:

- mostly differently **(Inference A)**
- similarly & differently ELMo is missing properties that affect zones similarly **(Inference B)**
- mostly similarly **(Inference C)**
- similarly & differently ELMo is missing properties that affect zones differently **(Inference D)**

References

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