On Multi-Modality Data Integration

From the Perspective of Representational Geometry in Abstraction Coding

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Outline

- Background: Representational Geometry
- Practice on Data Integration, e.g. M/EEG-fMRI Fusion
- Operation: Prior Constraints (Mental Intuitions)

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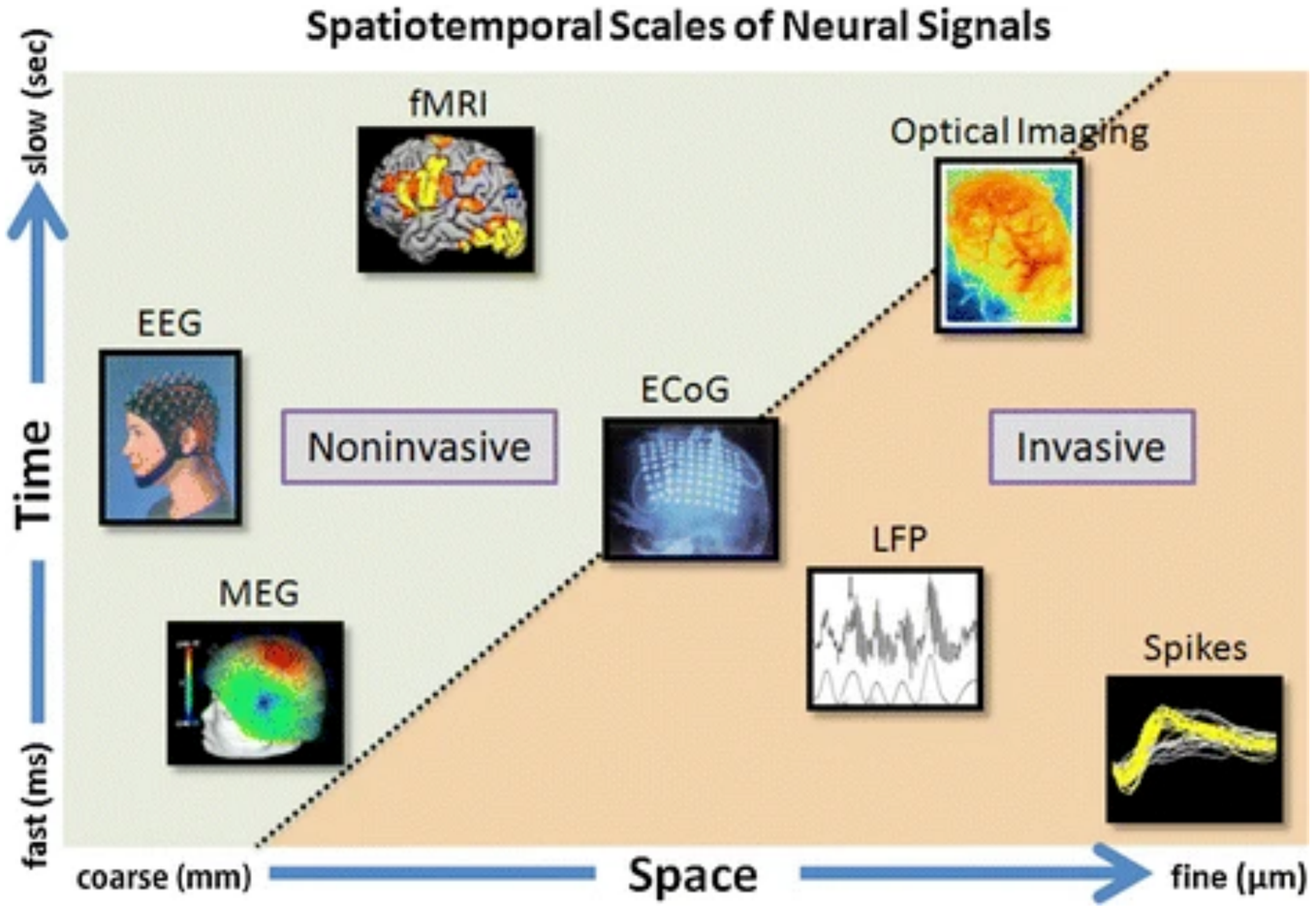
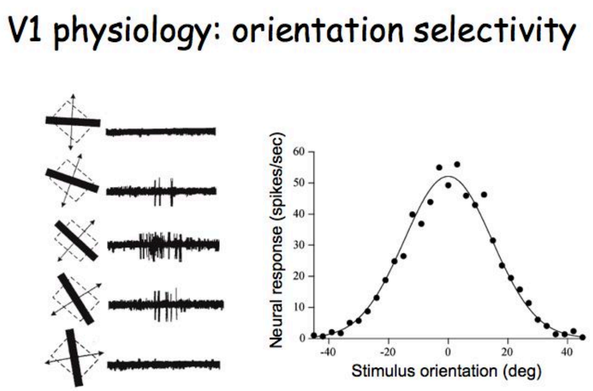
What is neural data?

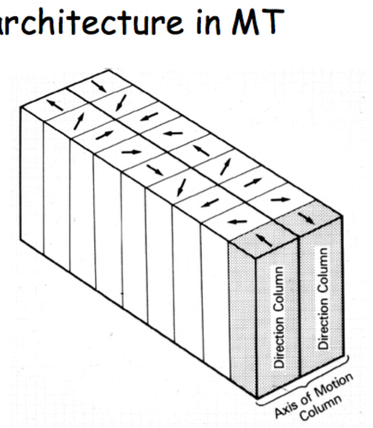


Neural Tuning

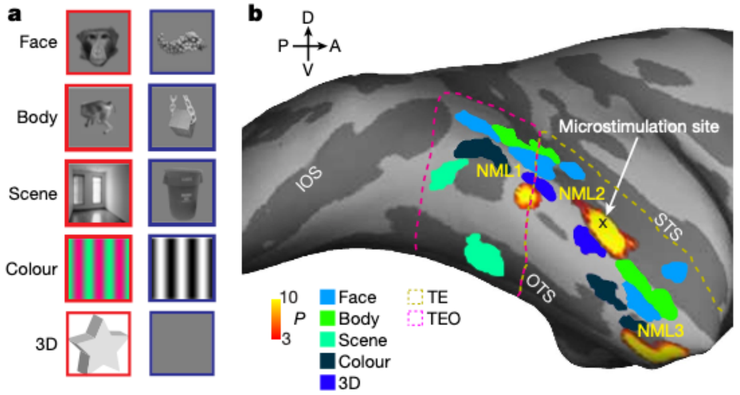
boolean logic based on all-or-none action potentials

- Neural selectivity (functional specialization), very successful in V1 and is being extended to higher-level cortical representations
- First-order isomorphism from stimulus property to neural activity, ideal for characterizing strong dependencies
- Trade off in detracting from non-stimulus-related influences, such as contexts, internal mental forces, etc.

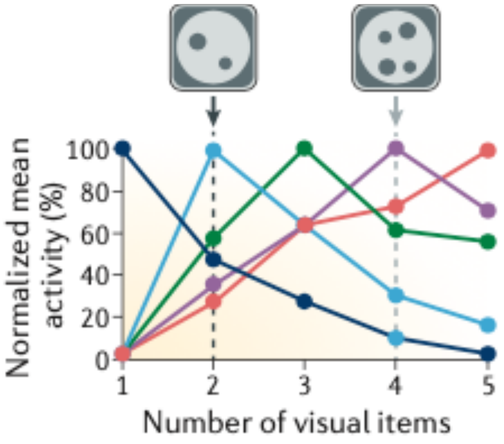




Hubel & Wissel 1968, adapted from David Heeger's Perception Course



Bao & Tsao 2019

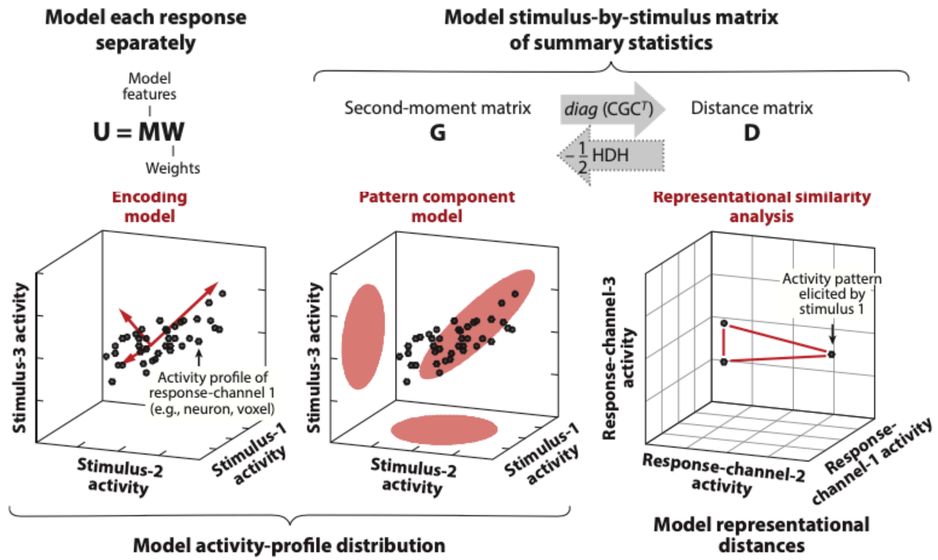


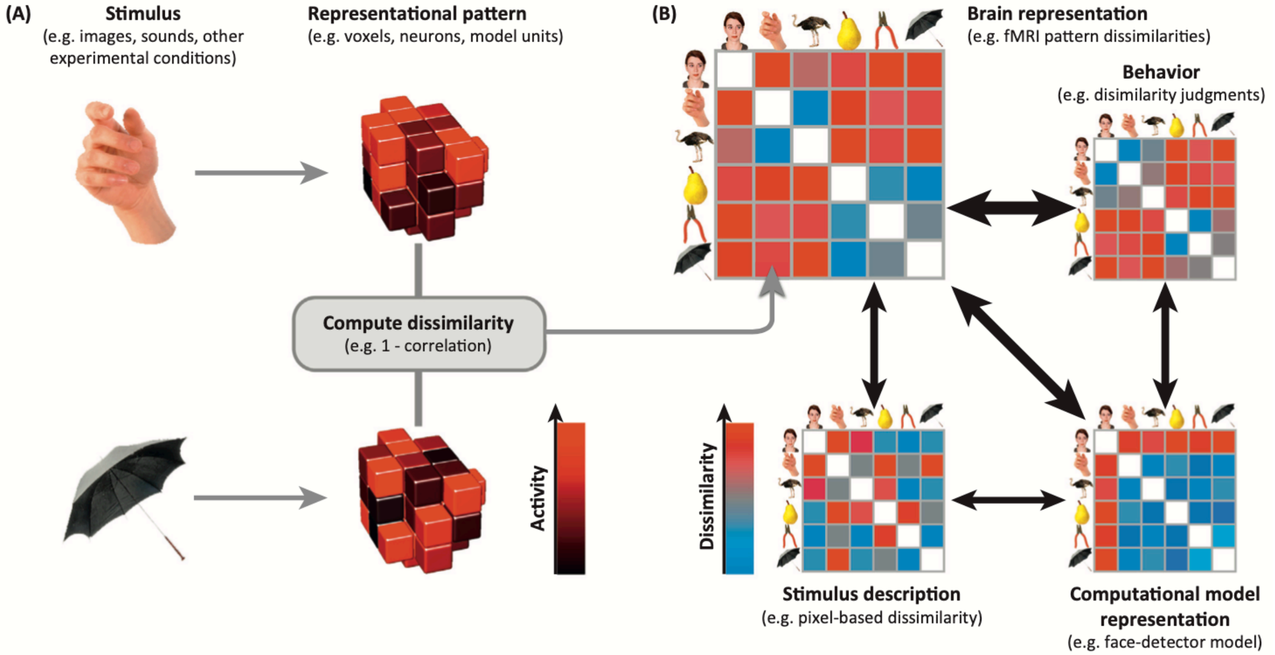
Neider & Dehaene 2009

Representational Geometry

Richer representational space of "neuronal activity states" leads to non-Boolean logic

- Complementary to neural tuning, representational geometry captures all possible interactions among neuronal responses both linearly and non-linearly
- Second-order isomorphism abstracting from neural responses, providing sufficient statistic invariant to permutations of the neurons
- Might be a fundamental computational entity in the nervous system?

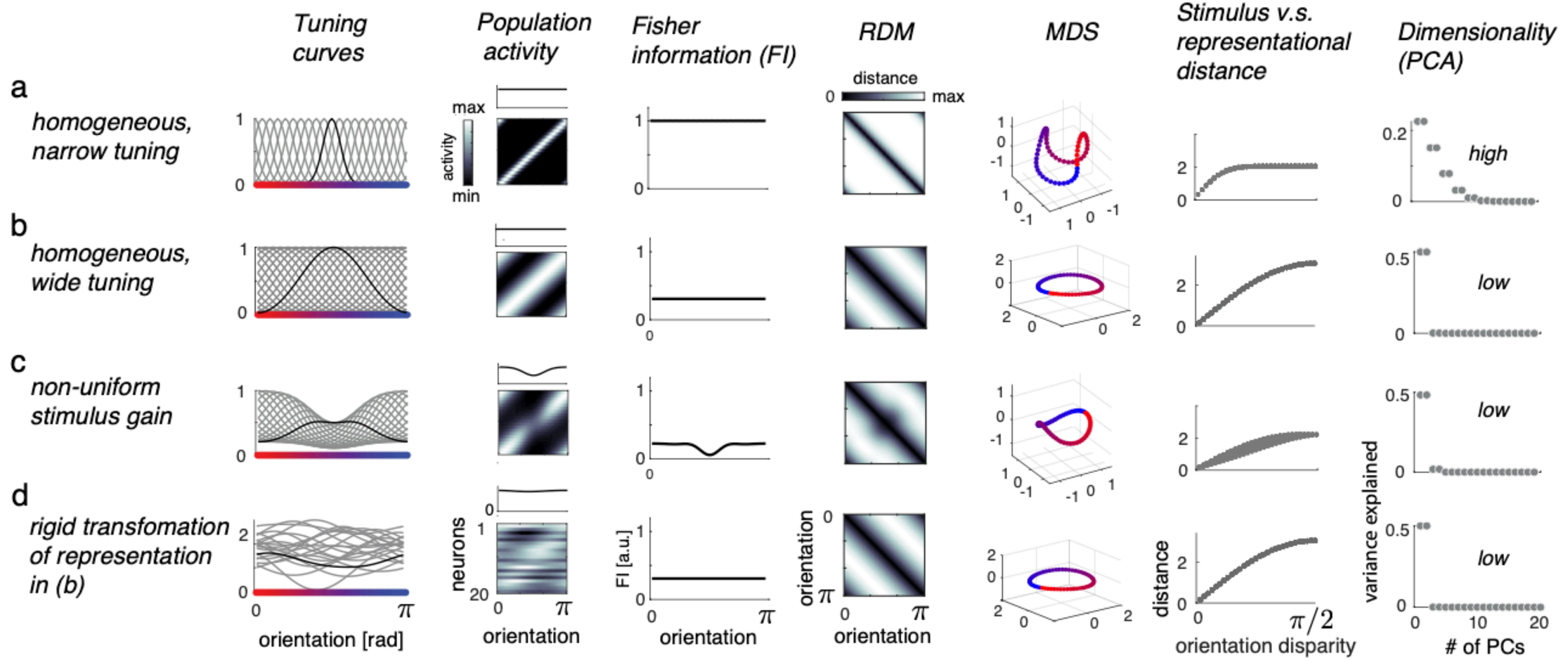




Kriegeskorte, et.al., 2013 & 2019

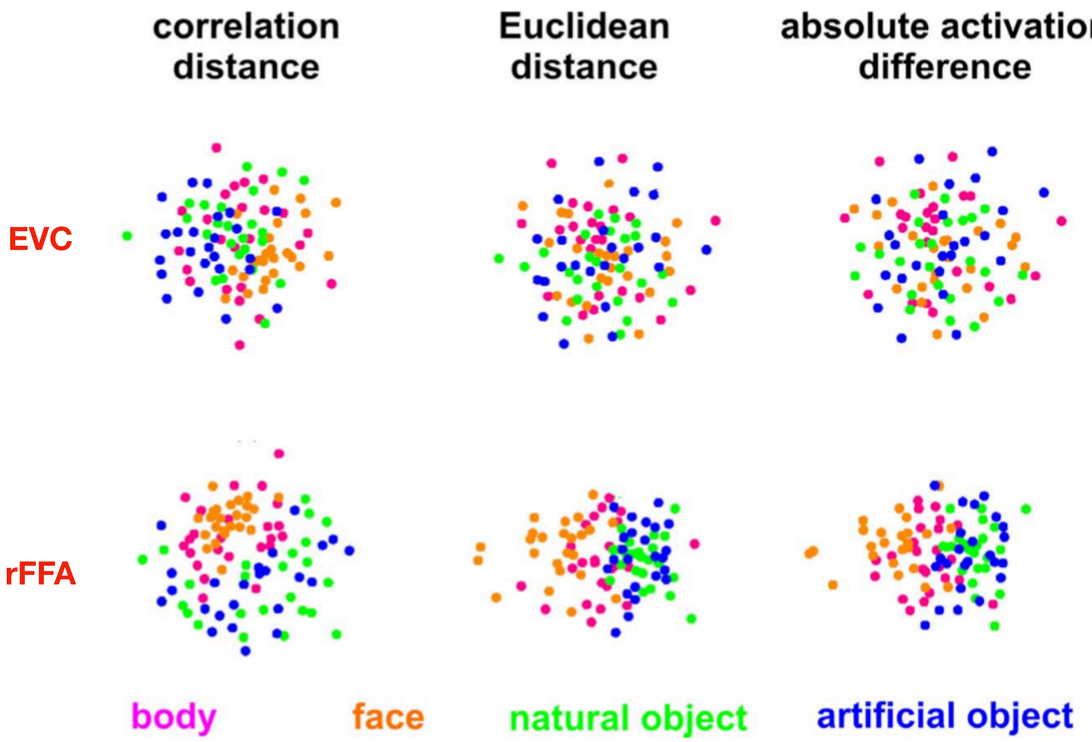
Neural Tuning & Representational Geometry

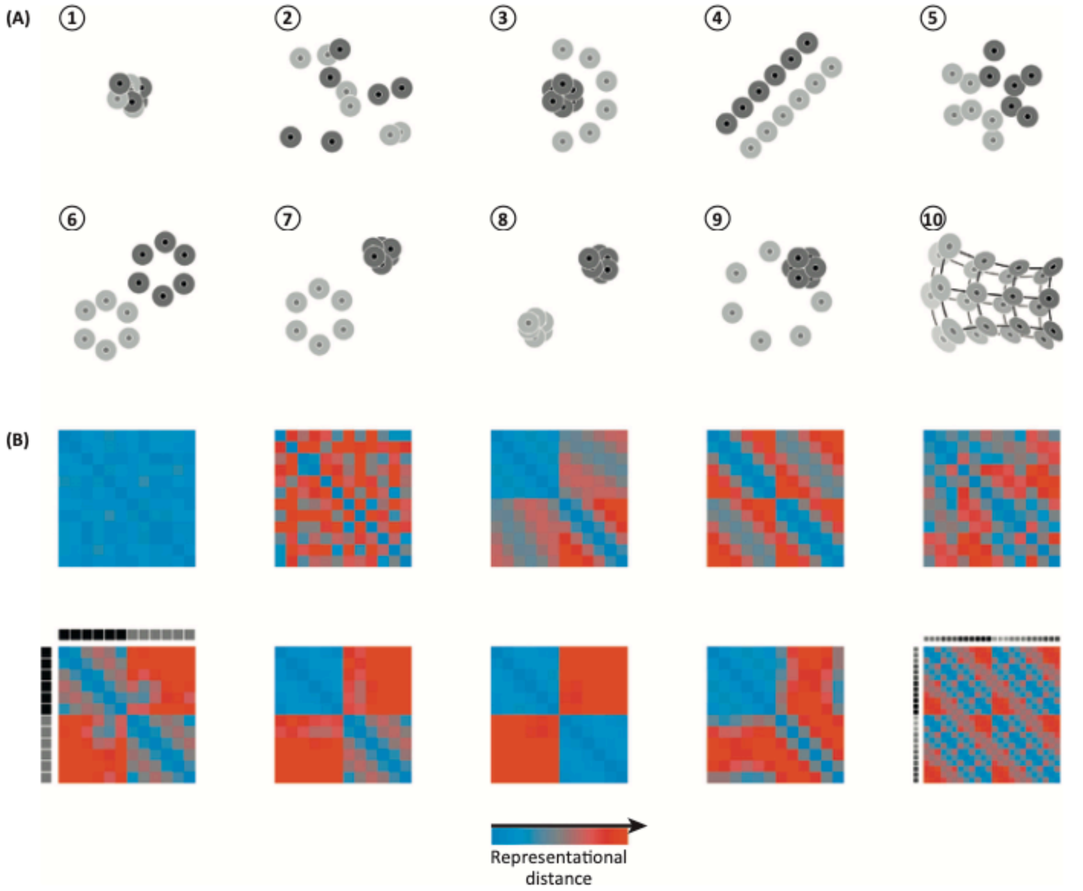
stability vs. flexibility



Kriegeskorte & Wei, 2021

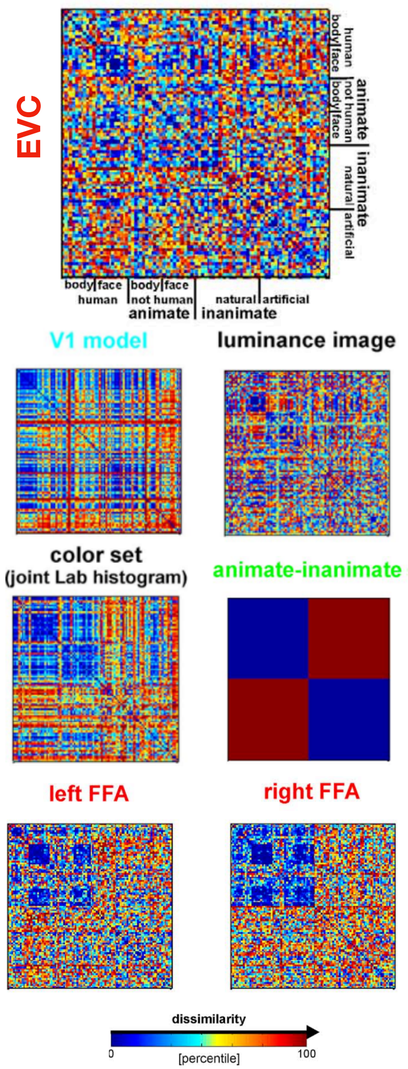
Representational geometries and their reflection in distance matrices

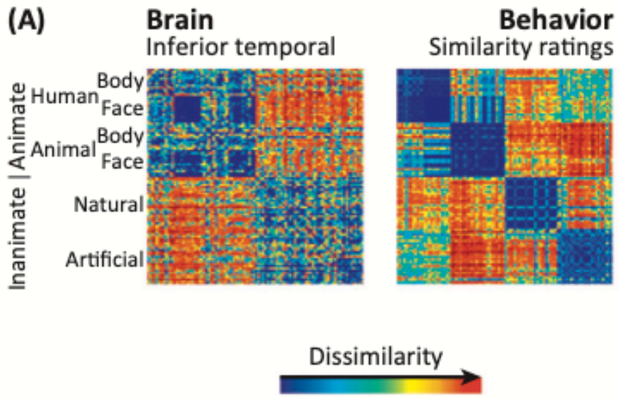


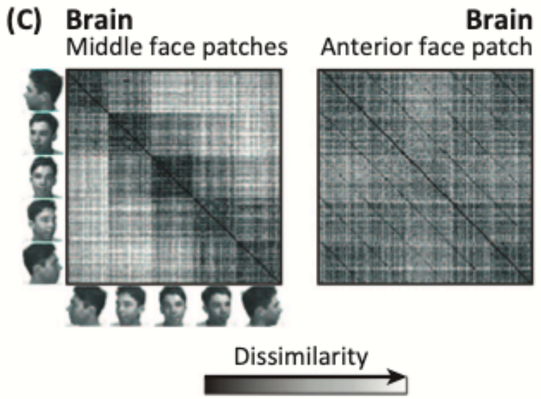


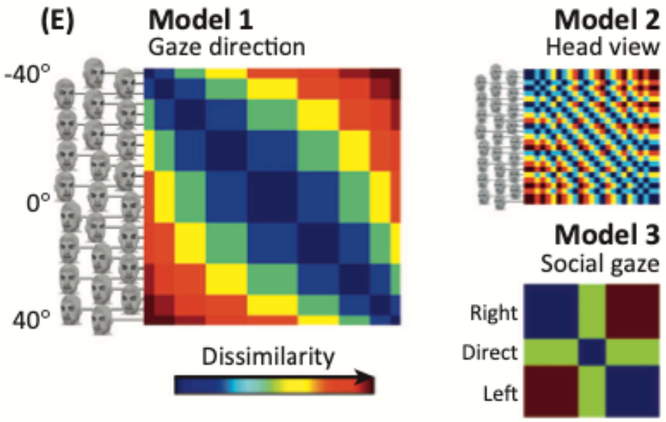
Kriegeskorte, et.al., 2008 & 2013

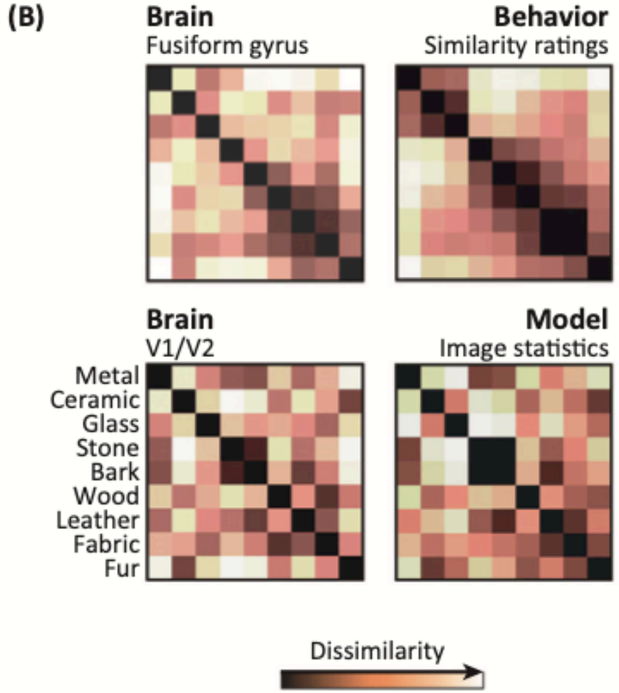
Actual brain representations exhibiting some of the geometric features

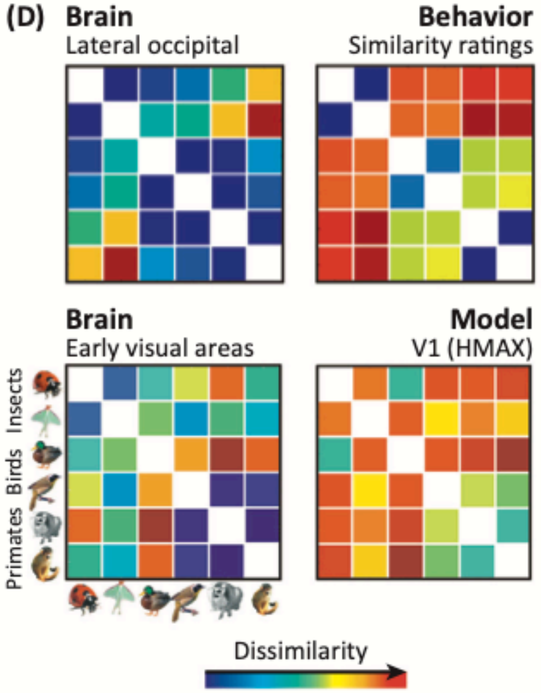


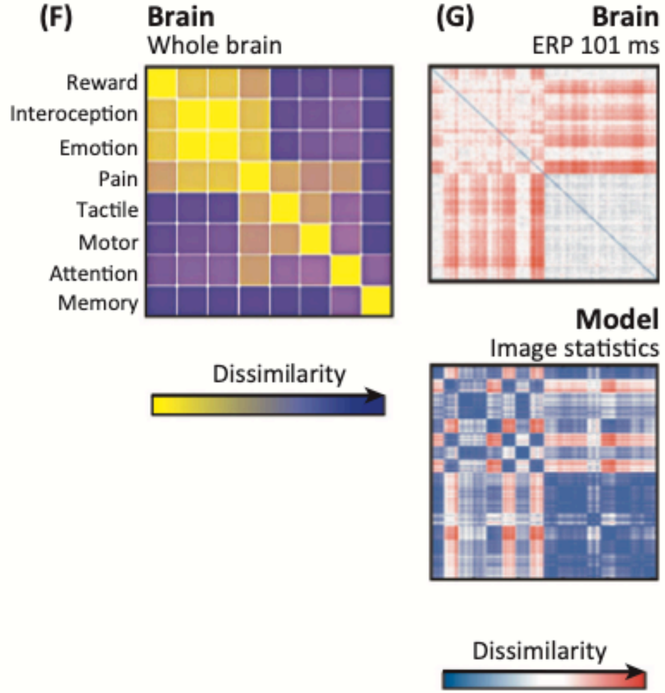






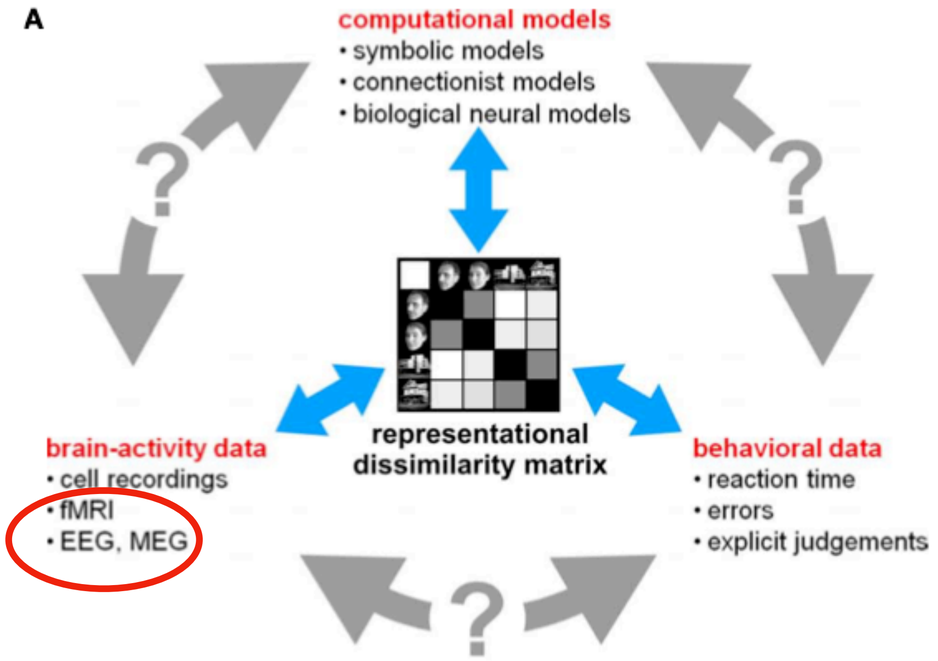


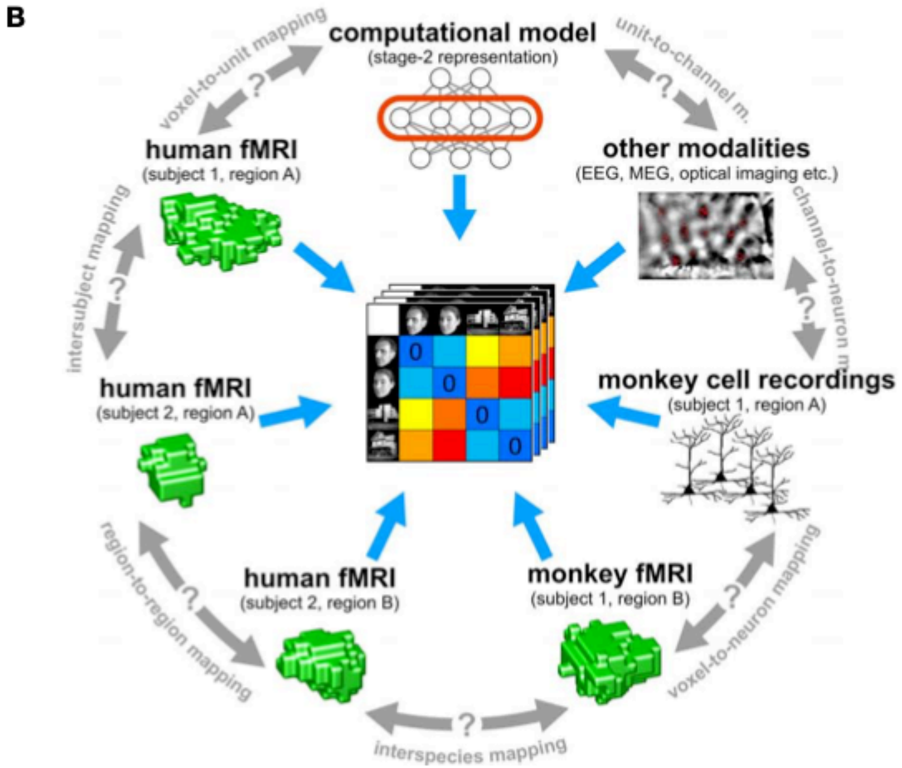




Kriegeskorte, et.al., 2008 & 2013

The representational dissimilarity matrix as a hub that relates different representations





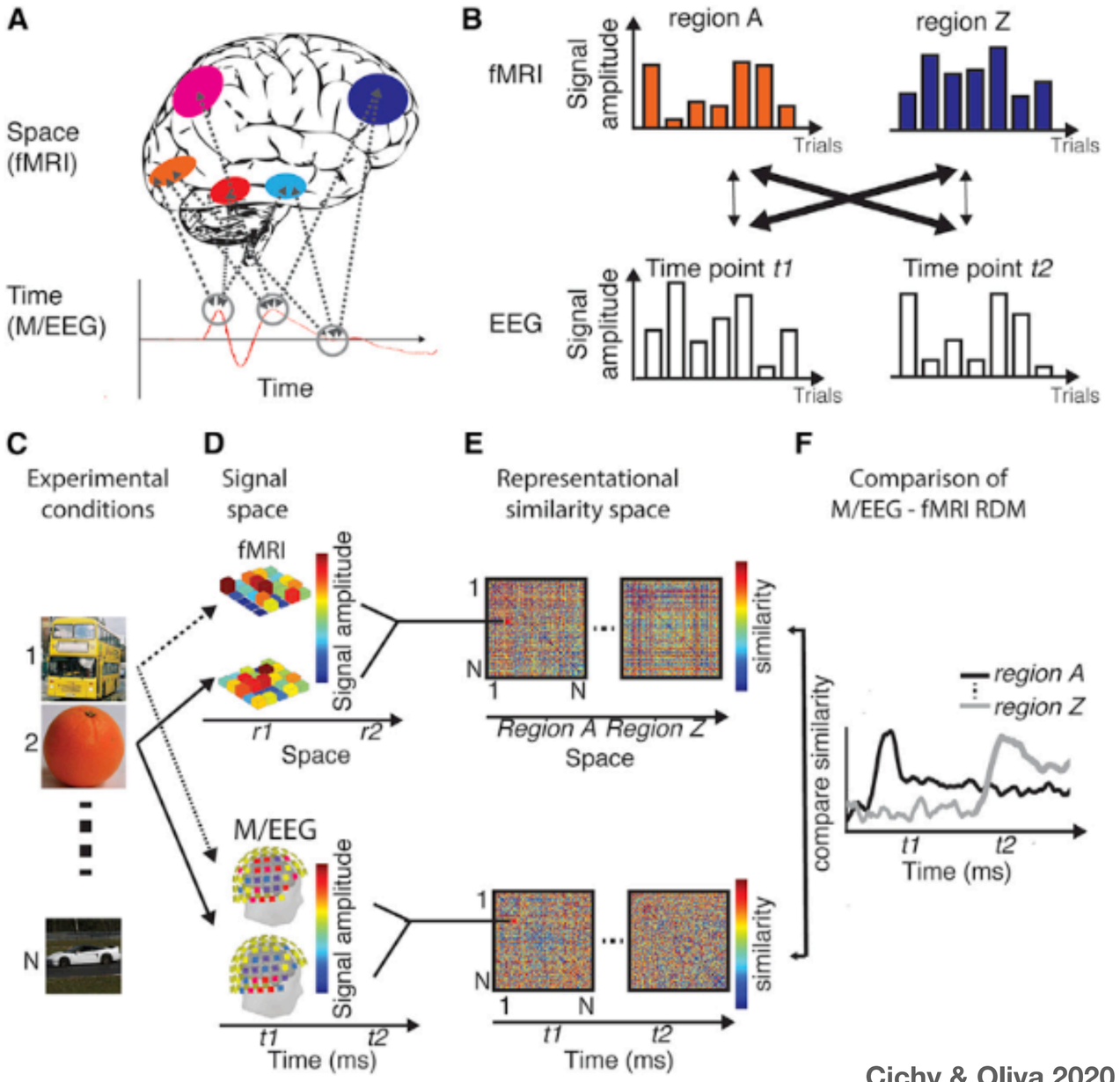
Kriegeskorte, et.al., 2008

M/EEG-fMRI Data Fusion

based on representational geometry model

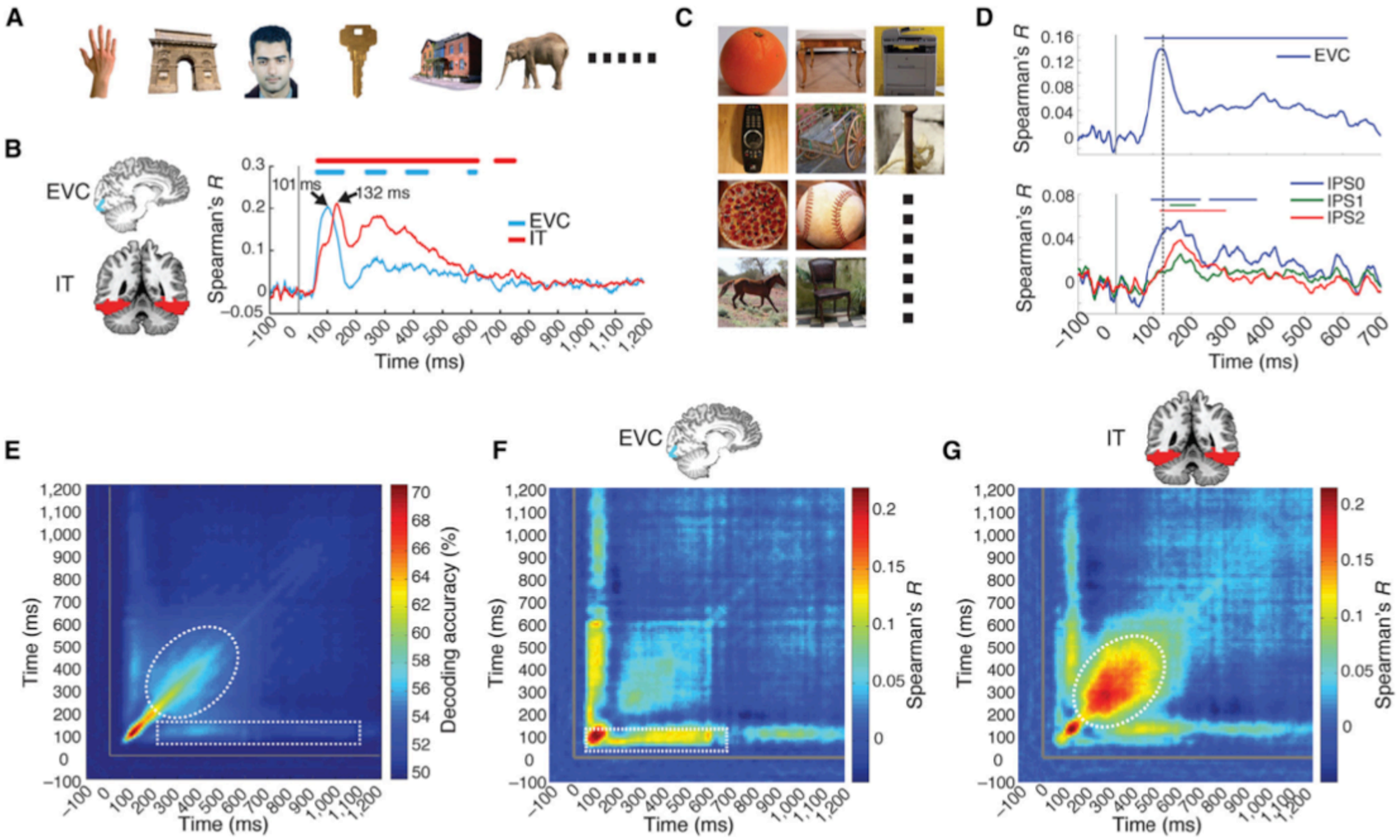
- Connecting incommensurate multivariate measurement spaces such as MEG sensor spaces, fMRI voxel spaces, or model unit spaces for a common abstract similarity space

- Applications on lower and higher-level cognitions, such as visual processing, task context processing, attentional processing, etc



Cichy & Oliva 2020

Application on Investigating Spatiotemporal Dynamics of Visual Processing



Cichy & Oliva 2014 & 2020

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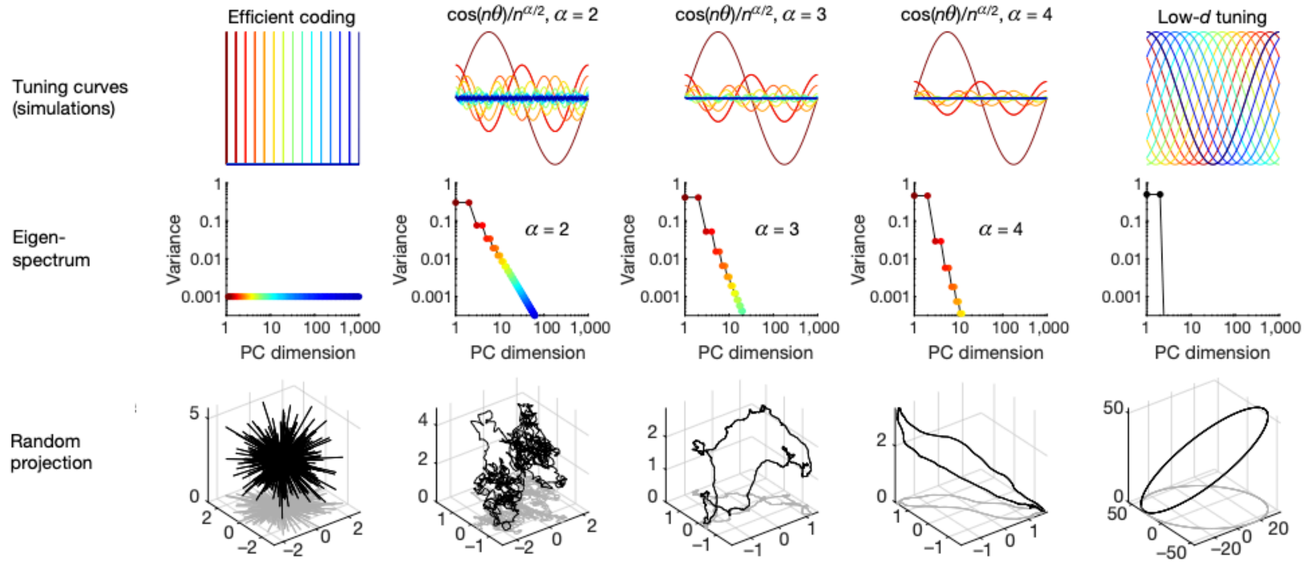
High-Dimensional Space in Sensory Cortex

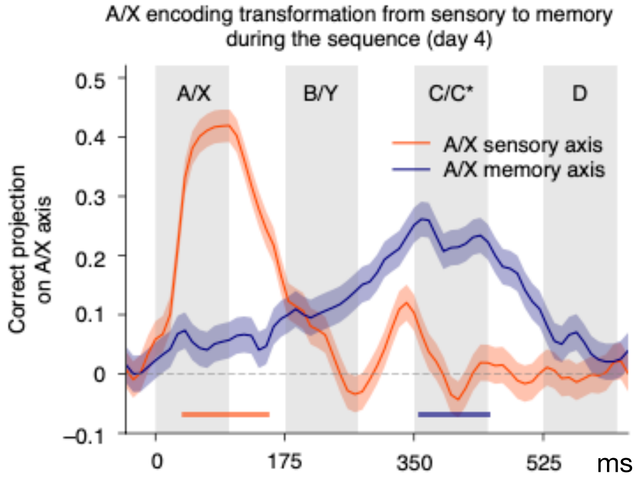
Grounded Principle of Neural Information and Computation

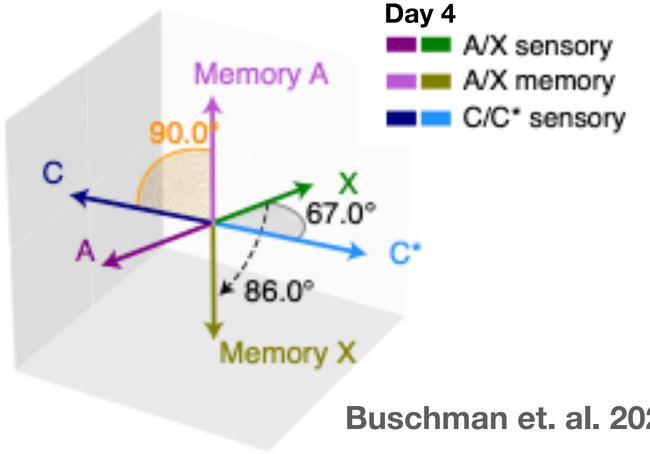
- If the variance spectrum was to decay more slowly then the population code could not be smooth, allowing small changes in input to dominate population activity, and larger power-law exponents for lower-dimensional stimulus ensembles

- Rotational dynamic in auditory cortex efficiently transform orthogonal representations



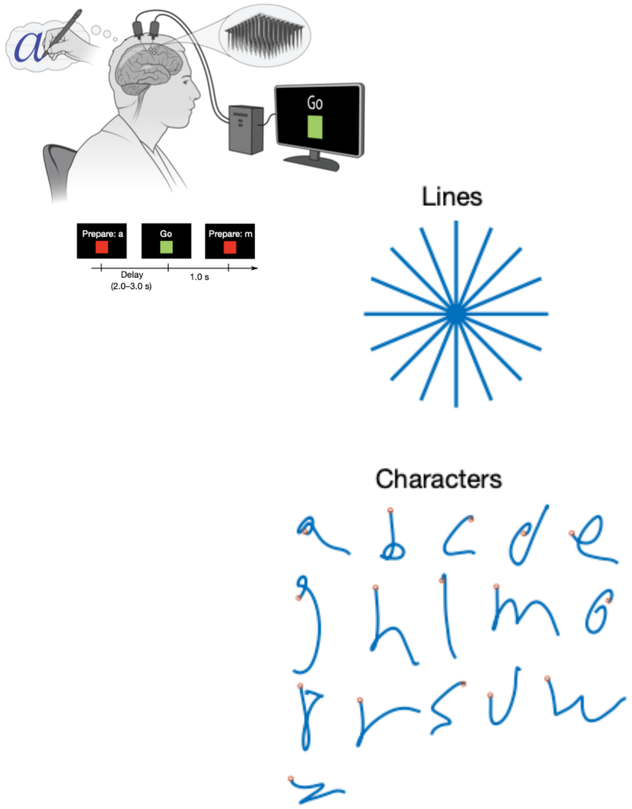
Harris et. al. 2019

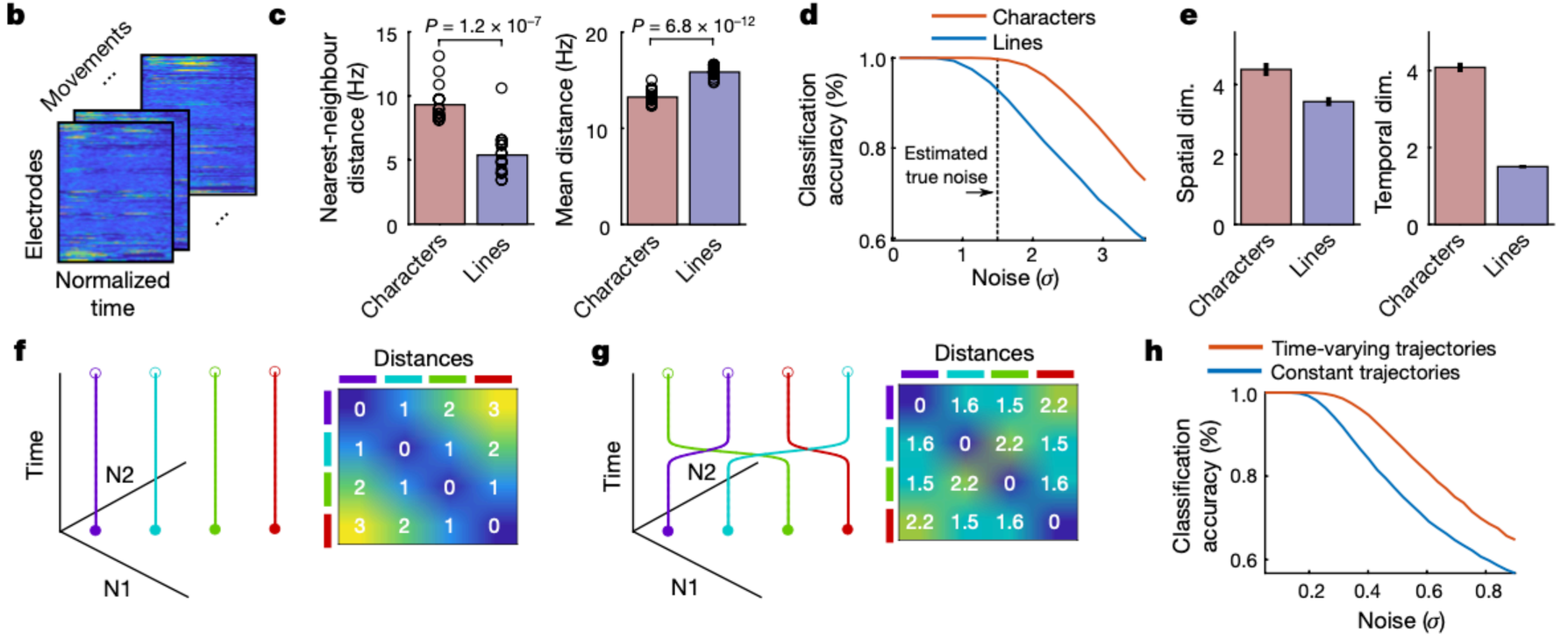




Buschman et. al. 2021

Temporally complex movements may be fundamentally easier to decode than point-to-point movements in motor cortex



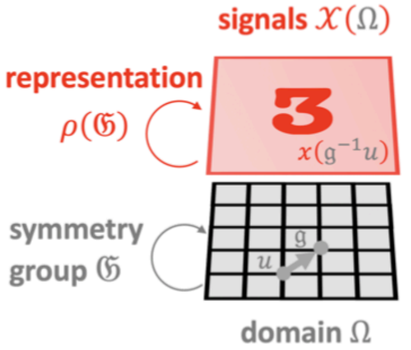


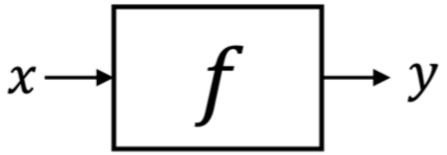
Willett et. al., 2021

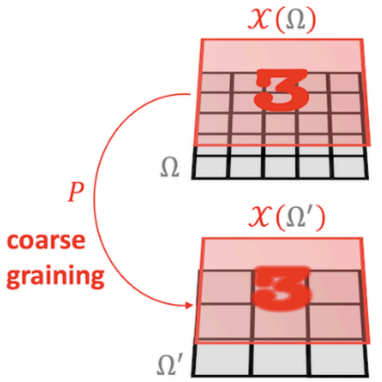
Beyond Representational Geometry

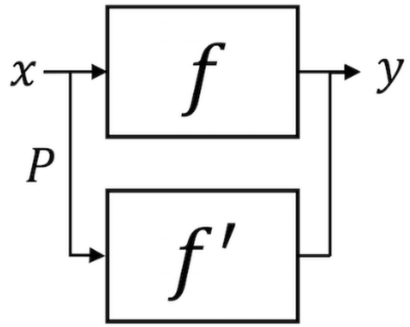
operational algorithms of prior constraints (or mental intuitions)

- geometric priors in CNNs
  - symmetry
  - scale separation
- geometric regularity effect
  - putative human uniqueness



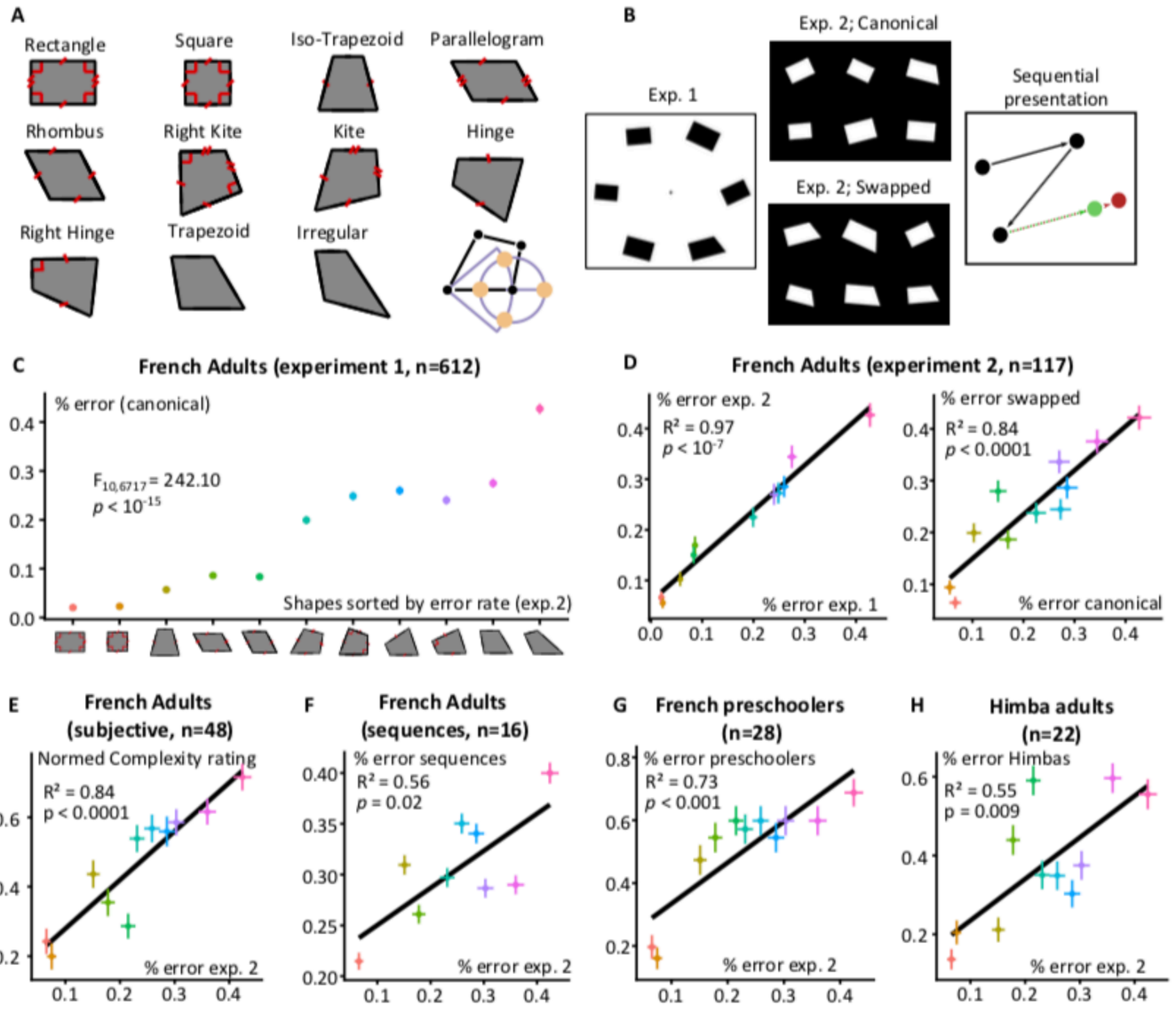


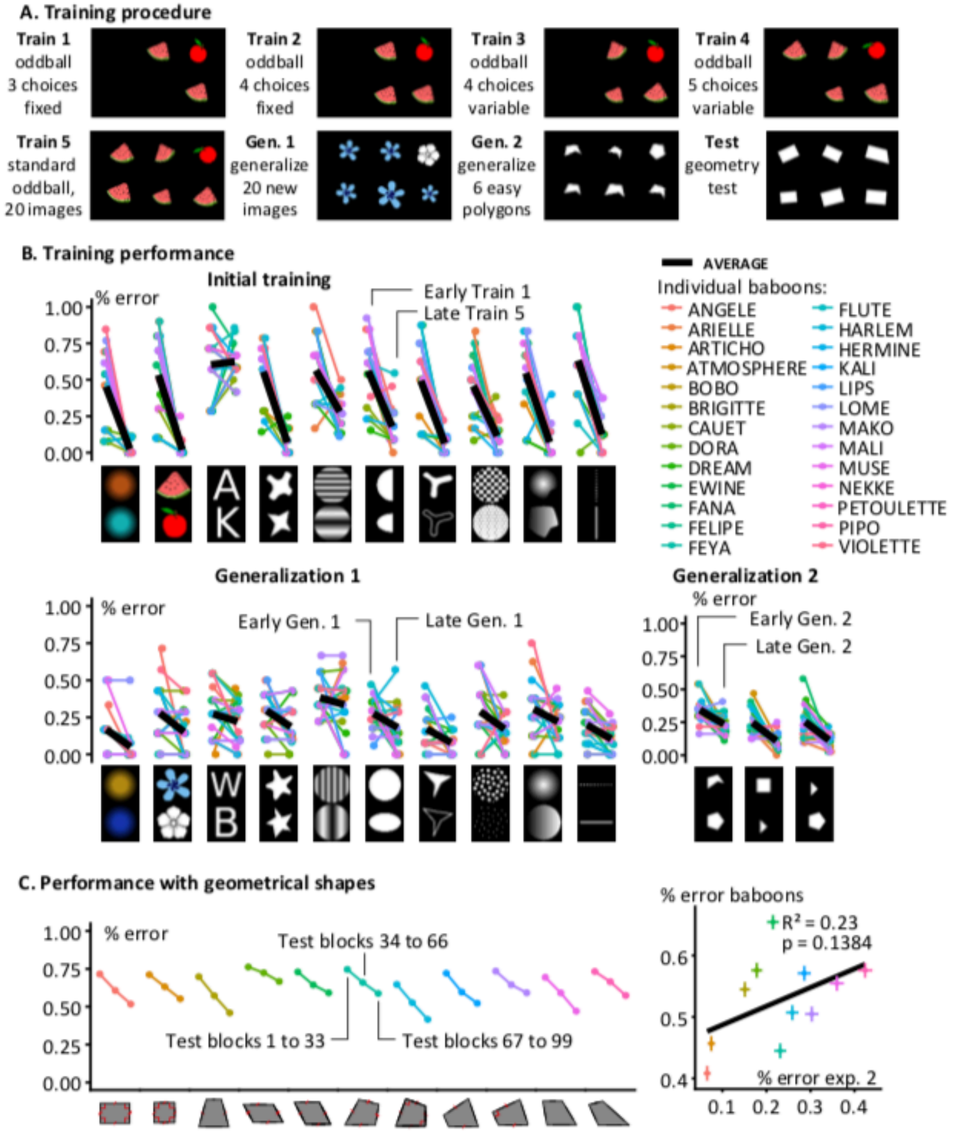




Bronstein et. al., 2021

A signature of human uniqueness in the perception of geometric shapes

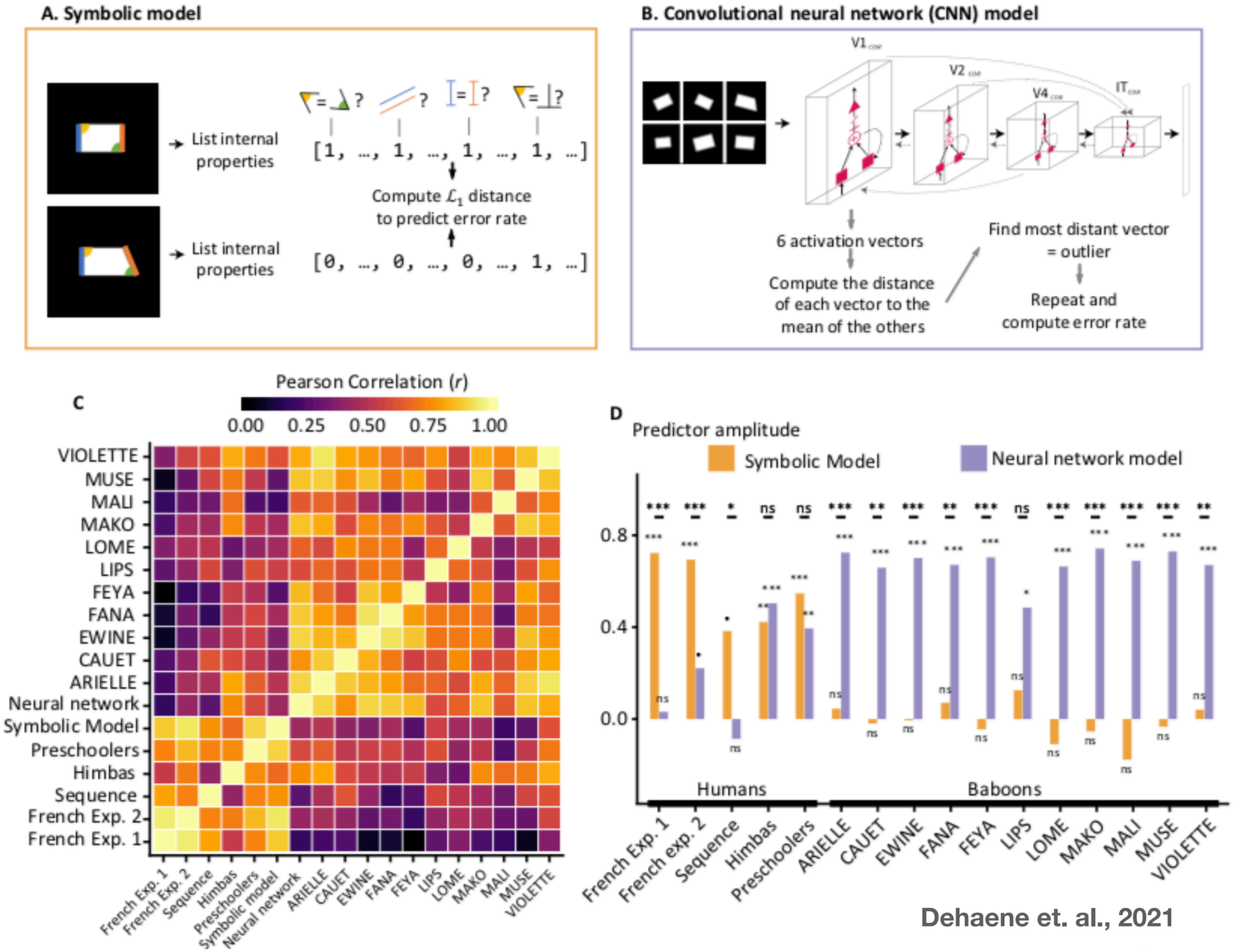




Dehaene et. al., 2021

Baboon behavior was captured by a convolutional neural network, but a **symbolic model** was required to fit human behavior

- Abstraction required symbolic modeling
- Non-symbolic neural networks failed to capture human abstraction behavior
- Modeling human intelligence might require a mechanical combination of symbolic model and neural networks

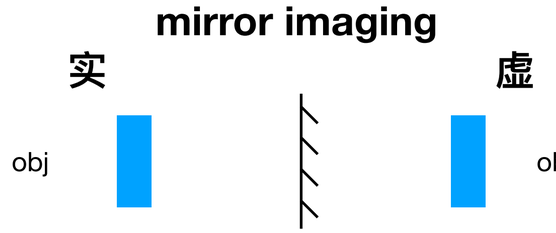


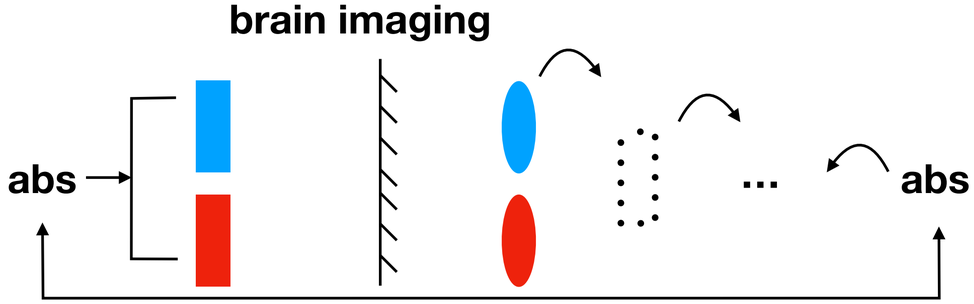
Dehaene et. al., 2021

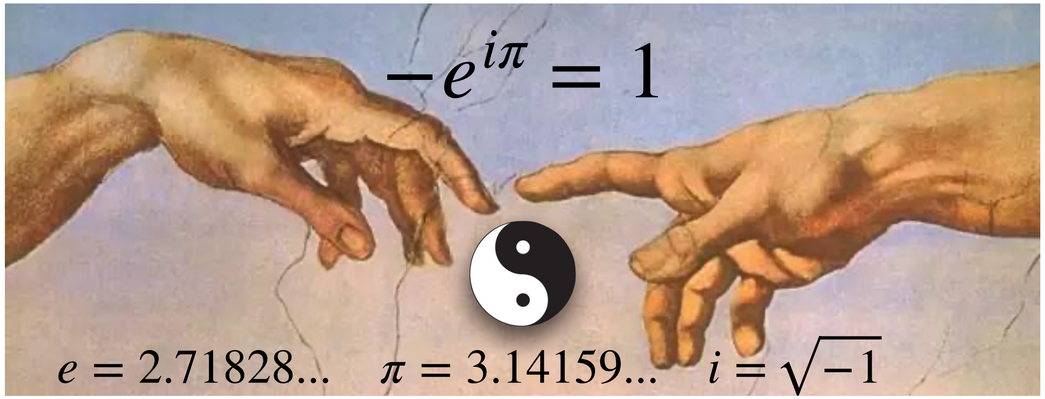
Summary - for further thinking

Shared abstract entities between natural and mental world

- The tuning property of neuronal responses leads to a Boolean algebra, the representational geometry capturing all possible interactions among neuronal responses both linearly and non-linearly, naturally leads to an algebra which is non-Boolean
- Neural information and computation might rely on a combination of Boolean and non-Boolean logic, while the latter might be the grounded principled underlying mechanism.
- Beyond linearity and non-linearity, the operational algorithms of prior constraints (or mental intuitions) in the transformation of representational geometry might be of great interest for future investigations in the convergence of brain science and intelligence technology.







$$e^{ix} = \cos x + i \sin x$$

$$\underrightarrow{x = \pi} \quad e^{i\pi} + 1 = 0 \quad \Longrightarrow 1 = -e^{i\pi} = -\sum_{n=0}^{\infty} \frac{i\pi^n}{n!}$$

$$e = \sum_{n=0}^{\infty} \frac{1}{n!} \qquad \pi = 4\sum_{n=0}^{\infty} \frac{(-1)^n}{2n+1}$$

$$n \in 0, 1, 2, \ldots, N$$