Using Correspondence Theory of Semantic Information to Understand Neural Representational Similarity

Wojciech Mamak

PhD Candidate
Section of Logic and Cognitive Science,
Polish Academy of Sciences

6th Conference
Frontiers in Philosophy of Information and Computing,
Warsaw-Cracow, 16th-17th Dec 2021

Quick overview

1. Intro: informational explanations in cognitive science
2. Information as correspondence - Correspondence Theory of Semantic Information (CTSI)
    a. Swoyer’s surrogative inference
    b. Barwise and Seligman’s formalization of information-flow
3. Representational Similarity Analysis (RSA) in neuroscience
4. Does it fit?
5. Closing remarks

Why bother?

- Dretske's (1981) recipe for naturalistic theory of representation - start with understanding information
    - "Information is a rung on a ladder that gets one to representation. Representation is information, or representation is information plus some other ingredient" (Sprevak 2020: 591)
- Traditionally and still most commonly interpreted as Shannonian information.
- Run-of-the-mill working view in neuroscience: information is assumed to be correlational yet semantic (operationalized as selective responding to a particular set of stimuli).
- The ongoing philosophical quest for content
    - Teleosemantic theories [Neander 2004 & 2012; Cao 2012]
- Purported possibility of readout and prediction ('mindreading') [Ritchie et al, 2019; Poldrack 2018]
- Rathkopf's 'What kind of information is brain information? [2020a]
    - how objective it is if it receiver-relative [2020b]
- Applications in neural representation theory (Bechtel 2016, Thomson & Piccinini 2018)

CTSI (Miłkowski 2021)

- Theoretical landscape is competitive: Shannonian, algorithmic, teleosemantic, transmission, effective etc.
  - Not clear which one(s) is/are in play in empirical practice (in psychology, cognitive science, biology, robotics, etc.)
- Contrary to received views, CTSI is not primarily reliant on correlation, covariation, causation, natural laws, or logical inference
- Formalizes a somewhat paradoxical aspect of information-as-similarity that is omnipresent in common usage but theoretically unanalyzed
- Recipe: take Tarskian correspondence with structural similarity *and shake vigorously*
  - Information is true iff corresponds to what it is about,
  - Structural similarity is a crucial resemblance between the structure of representation vehicles and representation targets that affords representation vehicles' their content
- CTSI - in search for measurement.
  - Representational geometry has some ideas (different yardsticks for distance)
  - The gist: retainment of some properties (e.g. clustering of objects of same category)

Swoyer's surrogative inference (1991)

- Licensed by similarity between A and B
- Allows to draw inferences about B when only A is available
- A carries information about B - similarity is conceptualized as an *information-flow*
- Relations are preserved and counter-preserved

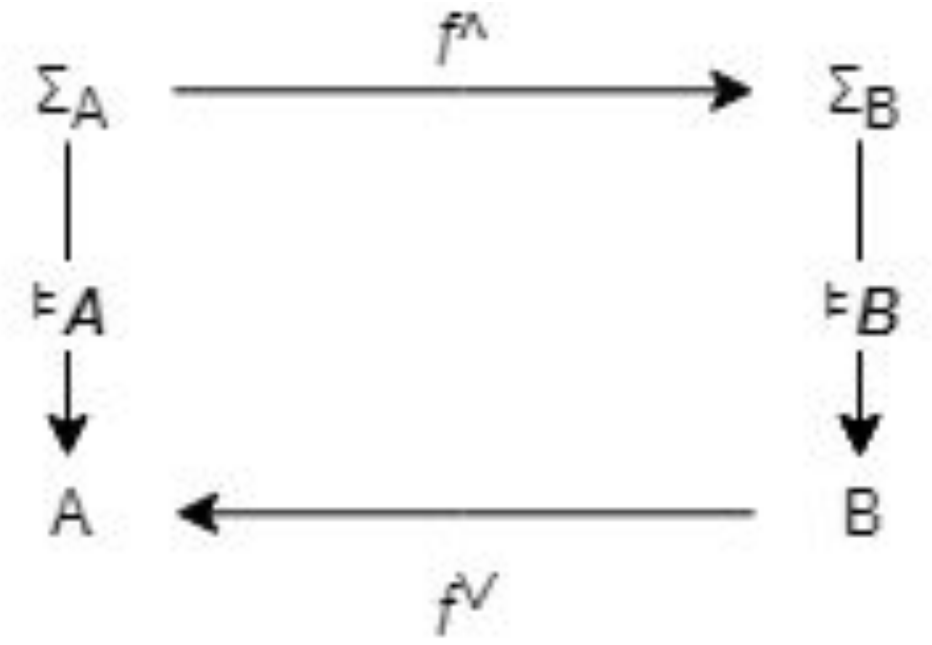
- *CTSI:* $r\text{-}sim\,(A, B) \equiv [r(A) \twoheadrightarrow r(B)]$
    - Note: unidirectionality (implication instead of a biconditional)

Swoyer, C. [1991]: 'Structural Representation and Surrogative Reasoning', *Synthese*, **87**, pp. 449–508.

Barwise and Seligman's (1997) logic of information flow

Infomorphism is a pair of *f* functions $<f^{\wedge}, f^{\vee}>$. For two classifications, $\boldsymbol{A} = <A, \Sigma_{A}, \models_{A}>$ and $\boldsymbol{B} = <B, \Sigma_{B}, \models_{B}>$ an informophism *f* obtains if and only if $f^{\vee}(b) \models_{A} a \equiv b \models_{B} f^{\wedge}(a)$ for all tokens *b* of *B* and all types *a* of *A* (1997:28)

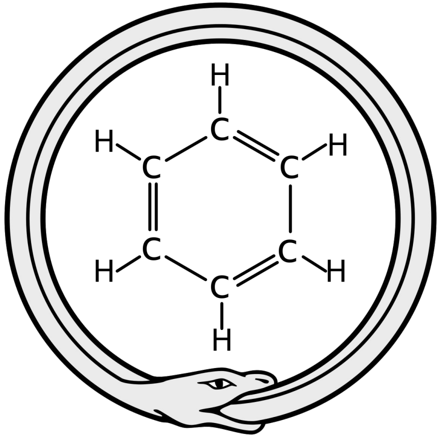
This definition is weakened for practical reasons (e.g. gradability) into the relation of **infocorrespondence** defined over fuzzy sets.

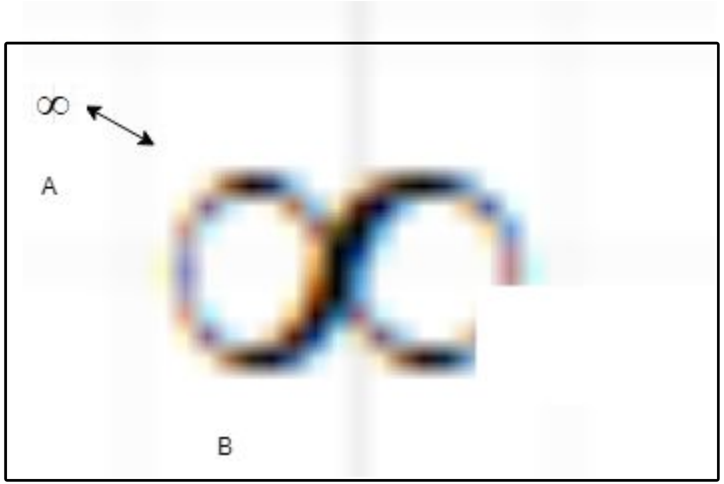


Barwise, J. and Seligman, J. [1997]: 'Information Flow: The Logic of Distributed Systems', Cambridge; NY: Cambridge U. Press.

Extraordinary examples!

- The dictator's doppelganger!
- The cyclical snake!
- Even infinity itself!





Infinity sign taken from Miłkowski (2020),
Others mined from the depths of Google search engine

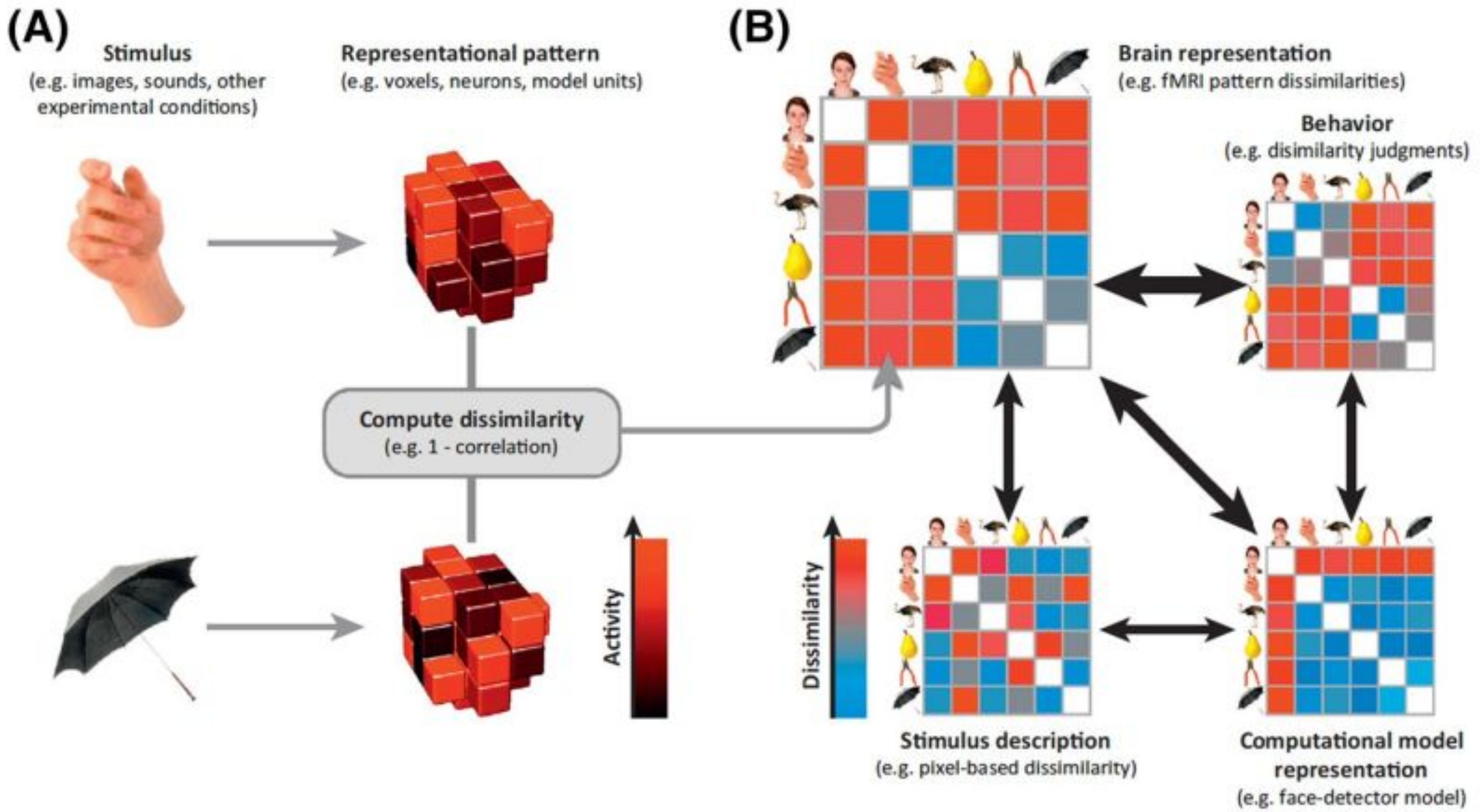
Representational Similarity Analysis (Kriegeskorte 2008)

- A type of MVPA - multivariate pattern analysis [Haxby 1991]
- First proposed by N. Kriegeskorte in 2008 to compare different representational geometries
- Philosophically analyzed recently by Roskies (2021)
- A two step procedure

RSA - Step One: Constructing the Representational Dissimilarity Matrix (RDM)

- Firstly, patterns of brain activity during different experimental manipulations are encoded as vectors
- Distance metric is used to calculate the distance (Euclidean, angular, etc.) between pairs of vectors.
- These distance measurements comprise a **representational dissimilarity matrix, or RDM**, of the activity in that task.
- The individual entries in an RDM are thus numbers characterizing the dissimilarity of the brain activity patterns across the two conditions, yielding a diagonalized matrix.
- As RDM entries are scalar quantities, they are **content-neutral** and abstract from particularities of their provenance, such as spatial layout

RSA - First step



RSA - Step Two: Meta-Analysis

- In this phase, **second-order comparisons** between different RDMs are performed
- Different measurements over the same experimental conditions
- Allows comparisons between sets of measurements that differ in substantial ways.
- Provides a means of comparing structural relationships embedded in multivariate data to the structural relationships in other datasets
- **It is this second-order comparison between RDMs that makes RSA so versatile**
- Turns out a **lot of structure is retained** throughout representational geometries coming not only from different areas or modes of measurement, but also different subjects or even species

RSA - Second step

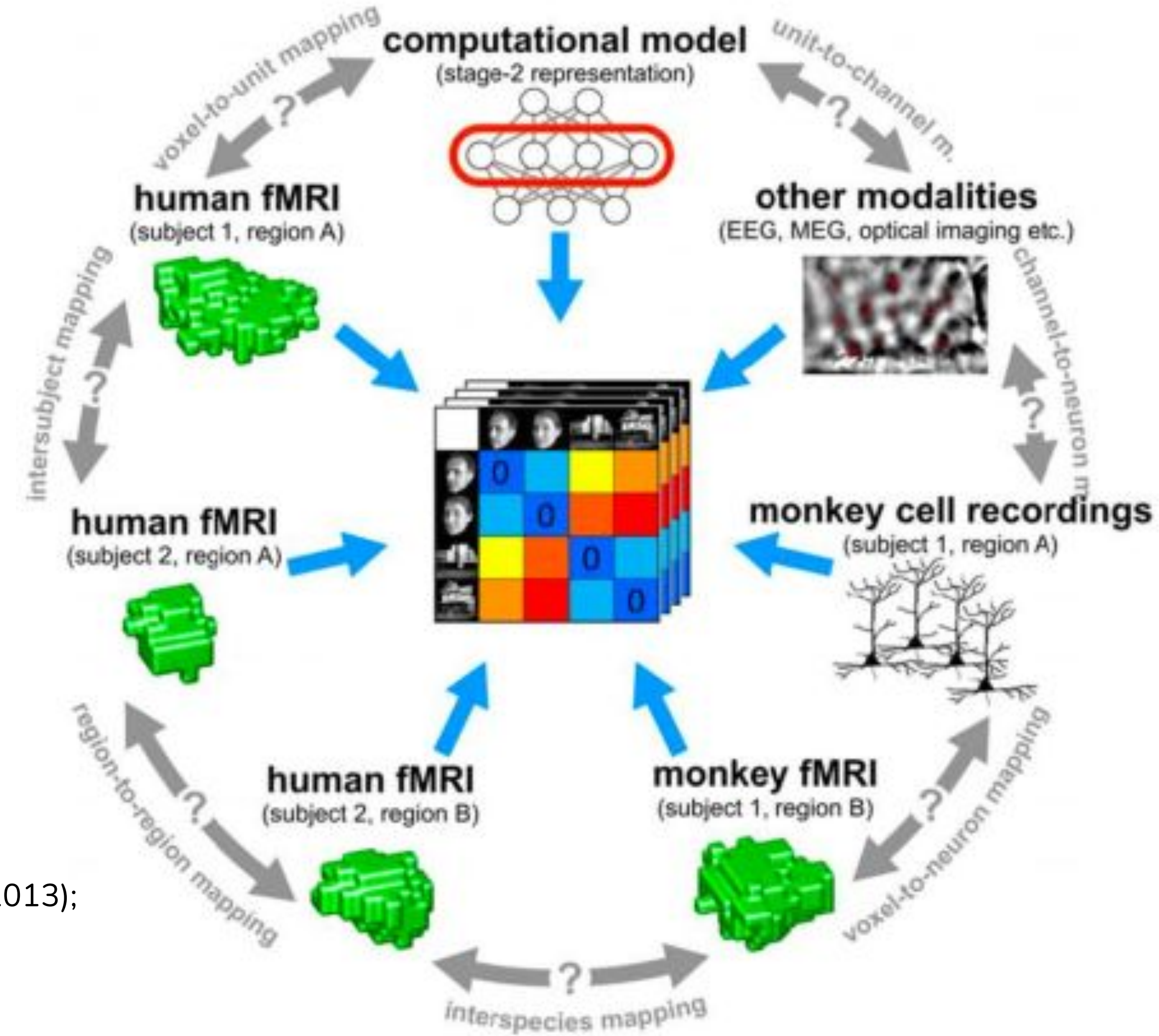
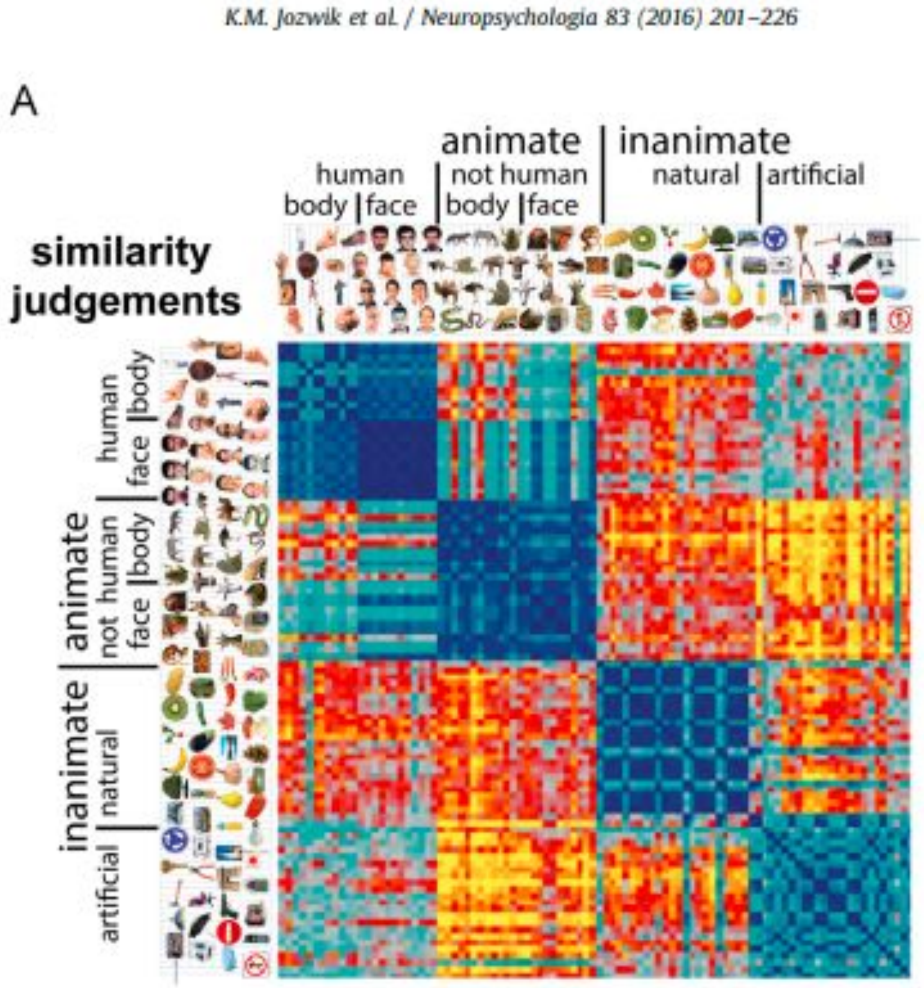


Diagram comes from (Kriegeskorte 2008);
previous slide's from (Kriegeskorte & Kievit 2013);
both adapted from (Roskies 2021)

Retainment of categorical structure in clusters



Structural information in RSA - a lot to like?

(or at least a bit?)

- Correspondence component: representations in the matrices have **satisfaction conditions**, insofar they accurately inform about their targets
- It is **through the second step** that structure is preserved not due to correlational information, nor causal processes (each first-order RDM can, and usually does, follow different causal path)
- The meta-level component that makes RSA so versatile and powerful comes from **format-friendliness** i.e. the internal structural features are the ones that count
- A **structure-preserving relation** holds (retainment of core categorical features), but there is some counter-preservation, too (similarity score is almost never = 1)
- It allows researchers to draw inferences about *semantic* properties from one representational geometry to another (surrogative inference)
- RDMs code gradable properties (from 0-1 range) ↠ according to the infocorrespondence formalization of information flow
    - one RDM is informative of another, actively and successfully used by neuroscientists for prediction of neural data)
- Tentatively, measurement in conceptual geometry can provide quantificational aspect to CTSI

- That being said, off we go to some potential objections and worries (in lieu of firm conclusions, yet)

Some potential objections and open problems

- Received view is that ‘representation’ in this paradigm is understood as a mathematical notion, not in the philosophical (much more restricted) sense
- Unidirectionality of bidirectionality? Symmetric or asymmetric similarity?
- How arbitrary is the correspondence? Issue of too many correspondences (Kotarbińska, Goodman)
  - Pragmatically-decided grounding has to be assumed to limit which types of similarities one is interested in when inferring surrogatively
- Aren’t the similarities spurious?
- Is such neural information explicitly represented *for* the system? Can we compare similarity geometries to cognitive maps (such as place cell grid)?
- What ‘uses’ information? Who is a consumer? Next layer, different voxel, region, personal level operator, or maybe merely an external observer (researcher)?

Selected bibliography

- Barwise, J., & Seligman, J. (1997). *Information flow: The logic of distributed systems*. Cambridge University Press.
- Cao, R. (2012). A teleosemantic approach to information in the brain. *Biology & Philosophy*, *27*(1), 49–71
- Dretske, F. I. (1981). *Knowledge and the Flow of Information*. MIT Press
- Kriegeskorte, N., Mur, M., & Bandettini, P. A. (2008). Representational similarity analysis-connecting the branches of systems neuroscience. *Frontiers in systems neuroscience*, *2*, 4.
- Kriegeskorte, N., & Kievit, R. A. (2013). Representational geometry: Integrating cognition, computation, and the brain. *Trends in cognitive sciences*, *17*(8), 401–412
- Ritchie, J. B., Kaplan, D. M., & Klein, C. (2019). Decoding the brain: Neural representation and the limits of multivariate pattern analysis in cognitive neuroscience. *The British journal for the philosophy of science*, *70*(2), 581–607.
- .Miłkowski, M. (2021). Correspondence Theory of Semantic Information. *The British Journal for the Philosophy of Science*. https://doi.org/10.1086/714804
- Roskies, A. L. (2021). Representational similarity analysis in neuroimaging: Proxy vehicles and provisional representations. *Synthese*, 1–19.
- Sprevak, M. (2020). Two kinds of information processing in cognition. *Review of Philosophy and Psychology*, *11*(3), 591–611.
- Swoyer, C. (1991). Structural representation and surrogative reasoning. *Synthese*, *87*(3), 449–508.

Thank you for your attention!

For follow-up questions, do not hesitate to contact me: wojciech.mamak@gmail.com