QUANTIFYING CONCEPTUAL FLEXIBILITY IN A COMPOSITIONAL NETWORK MODEL

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MOTIVATION

Concepts (e.g. CHOCOLATE) can be instantiated in many different forms (e.g., bar, truffle), and our **conceptual system must be flexible** enough to capture this variation.

We use graph-theoretical network models to capture the within-concept statistics that reflect **how properties correlate with each other across instances of a concept**. In these networks, properties are represented as nodes and their associations as edges.

Whereas traditional models[1] define concepts as static structures, we aim to model concepts in a way that can **accommodate the variation of conceptual information** across instances.

BUILDING NETWORKS

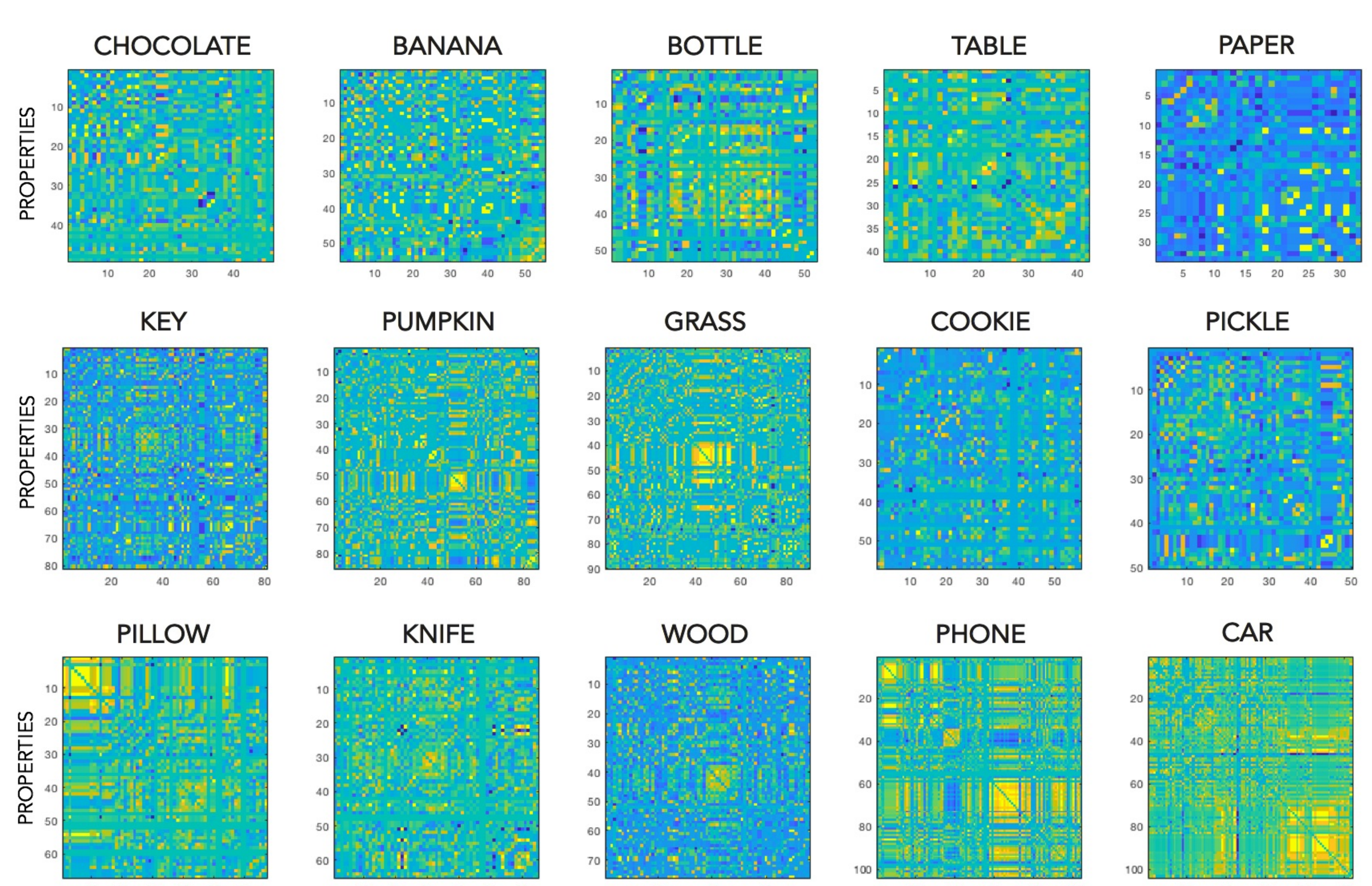
Data Set 1 (5 concepts)
CHOCOLATE, BANANA, BOTTLE, TABLE, PAPER

Data Set 2 (10 concepts)
KEY, PUMPKIN, GRASS, COOKIE, PICKLE, PILLOW, KNIFE, WOOD, PHONE, CAR

For each data set:

1. Construct a **set of properties** with which to define concepts. *(n=66; 60)*
   BLACK, BLUE, SWEET, SOUR, SMOOTH, ROUGH, HAS-BATTERIES
2. For each concept, **define various sub-kinds**. *(n=66; 60)*
   WHITE CHOCOLATE, ROTTEN PUMPKIN, CHEESE KNIFE, SUGAR COOKIE
3. Measure **property strengths for each subkind** for each concept. *(n=198; 108)*
   "Which properties are true of WHITE CHOCOLATE?"
4. Create **network models** for each concept by calculating within-concept property correlations across sub-kinds.

Concept networks contain within-concept property covariation information for properties that are true of at least one of that concept's sub-kinds



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1. *Tyler, Moss, Durrant-Peatfield, & Levy (2000). Brain and Language.*
2. *Medaglia, Huang, Karuza, Thompson-Schill, Ribeiro, & Bassett (2018). Nature Human Behavior.*
3. *Hoffman, Lambon Ralph, Rogers (2013). Behavior Research Methods.*

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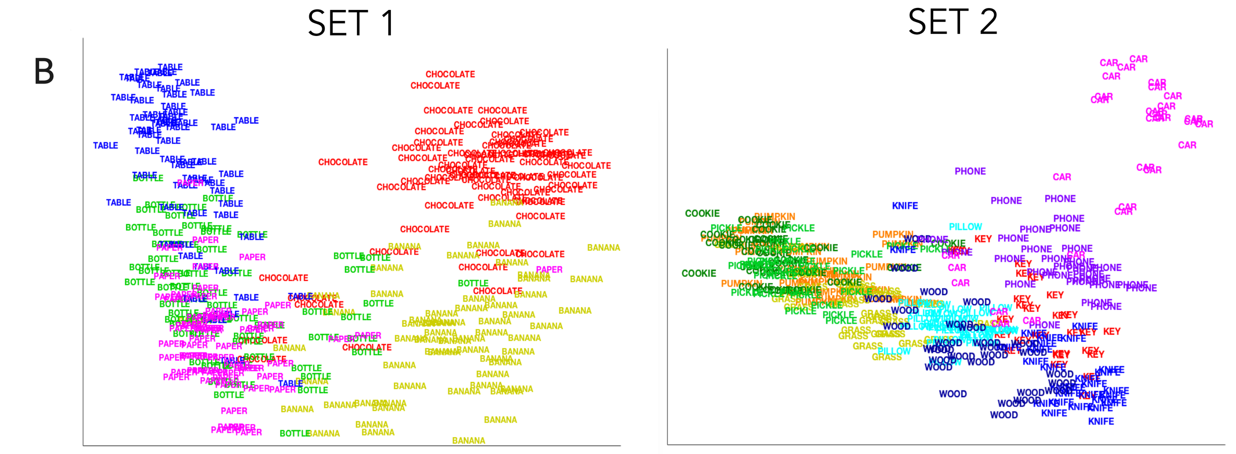
NETWORKS ARE CONCEPT-SPECIFIC

In order to extract concept-specific measures of flexibility, we first need to ensure that our *networks* are concept-specific.



A: Example images used to generate test data in classification analysis. Participants (n=60; 30) made property judgments on images of conceptual exemplars.

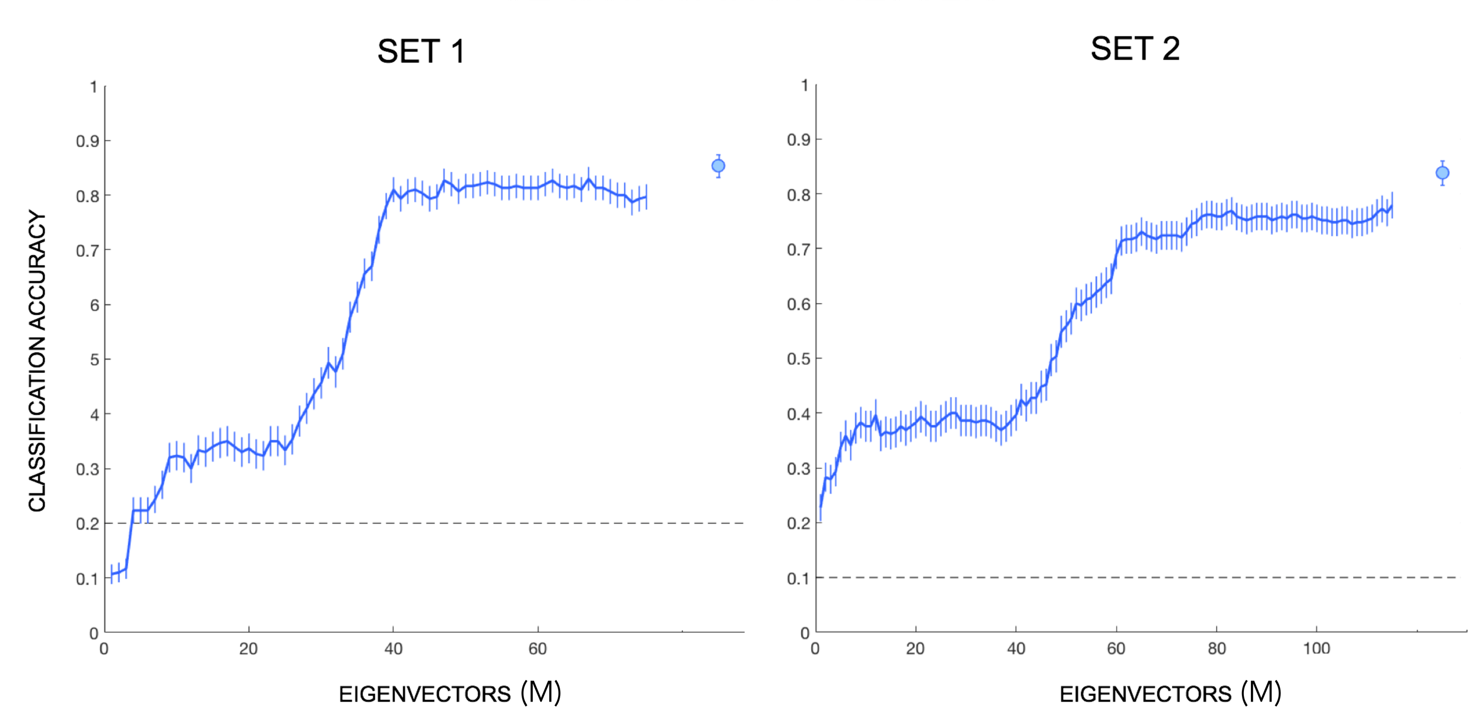
B: MDS plots of the similarity space of test vectors. East test datum is a property vector. Set 1: 60 vectors per concept. Set 2: 30 exemplars per concept.

Our goal was to use our network models to classify each of our exemplars as the correct concept

METHOD: We performed eigendecomposition on each concept network to assess the extent to which a test vector is expected given an underlying network structure (e.g., Medaglia et al., 2018). For each network, we sort the eigenvectors by eigenvalue. *M* is the number of ordered eigenvectors to include in analysis. For each eigenvector *v*, we find the dot product with test vector *x*, which gives us the projection of *x* on that dimension in the network's eigenspace. We can include all eigenvectors in *M* by taking the sum of squares of the dot products for each eigenvector, resulting in an "alignment" value ($\tilde{x}$). The concept network that resulted in the highest alignment value for that test vector was taken as the "guess" of the classifier.

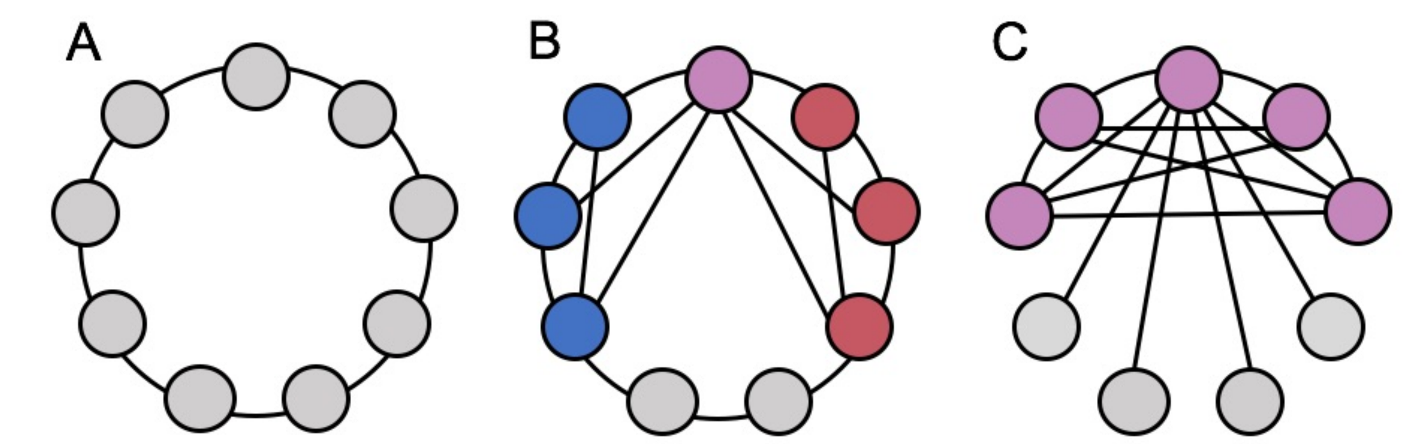
$$\tilde{x} = \sum_{i=1}^{M} (v_i \cdot x)^2$$

CLASSIFICATION RESULTS



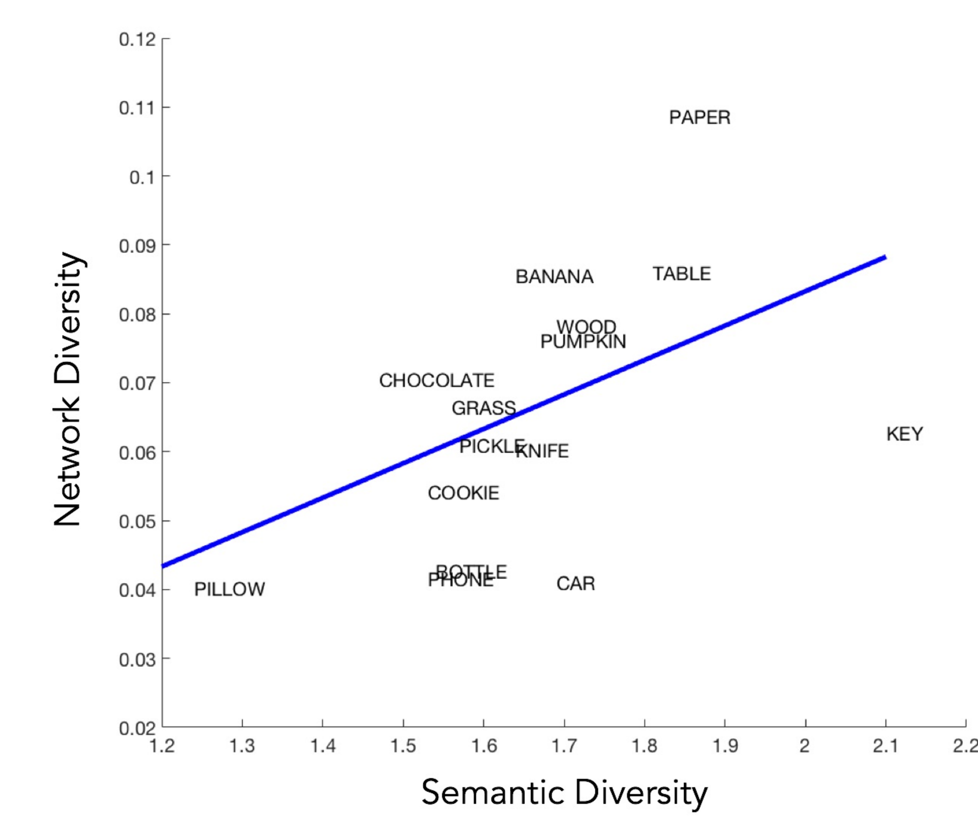
RESULTS: We ran a range of classification analyses using different numbers of eigen-dimensions from our concept networks. Classification was successful using ≥ 7 dimensions in Set 1, and ≥1 dimension in Set 2. Classification performance increased as more dimensions were added, such that performance of the network-models approached performance of vector-based models (single data points).

NETWORK MEASURES

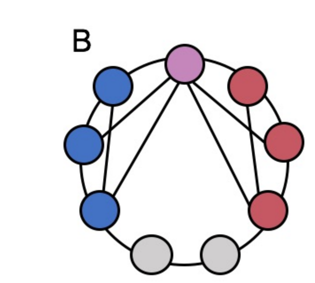


Schematics of network structure. (A) Low-modularity network that contains nodes with equal degree. (B) High-modularity network with nodes in either module 1 (red) or module 2 (blue). One node (purple) participates in both modules; this is a high-diversity node. (C) Network with a strong core-periphery structure; some nodes comprise a densely connected core (purple) and others a weakly connected periphery (grey).

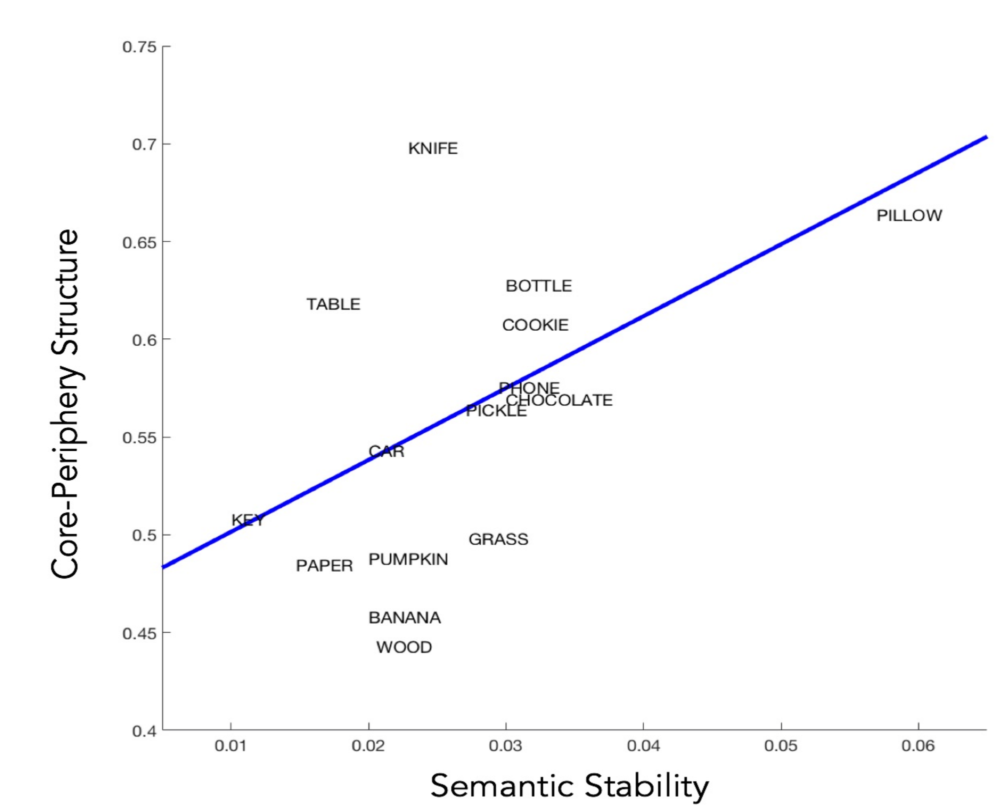
PREDICTING SEMANTIC DIVERSITY



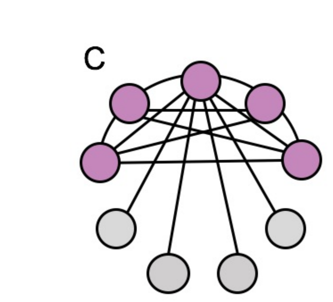
Semantic diversity measures calculated using word co-occurrence statistics (Hoffman et al., 2013) predict mean network diversity across 15 concepts.



PREDICTING SEMANTIC STABILITY



Semantic stability measures calculated using word co-occurrence statistics (Hoffman et al., 2013) predict core-periphery structure across 15 concepts.



CONCLUSION

Concept network models based on within-concept property associations are successful at classifying individual exemplars, revealing that they are concept-specific.

We can extract measures from these concept networks (i.e. diversity coefficients, core-periphery structure) which reliably predict measures associated with conceptual flexibility (i.e., semantic diversity and stability).