Visual and Semantic Features that Predict Object Memory

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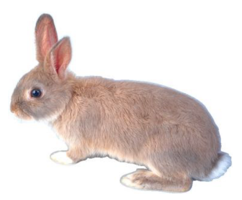
The Electric Dinosaur

Introduction



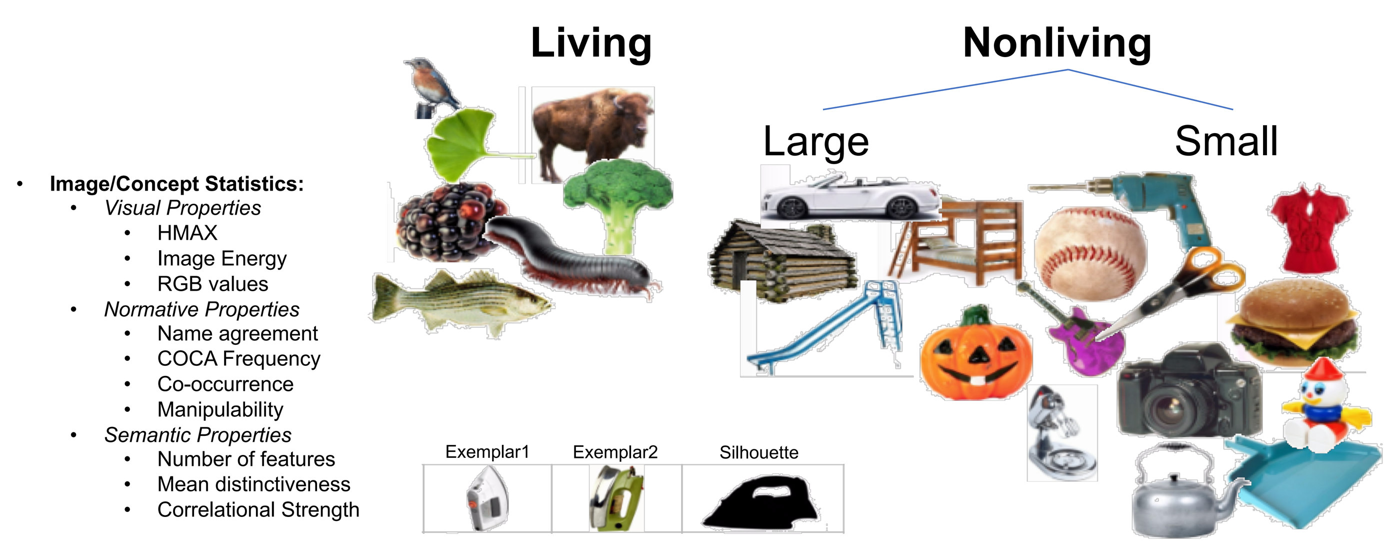
How do we remember what we see? Are visual properties of objects informative or helpful in later retrieval? What semantic properties are necessary to remember an object?

Retrieval of a visual stimulus relies both on visual and semantic information. Here, we reliably show that a collection of semantic and visual features, attributes, and properties predict memorability of objects.

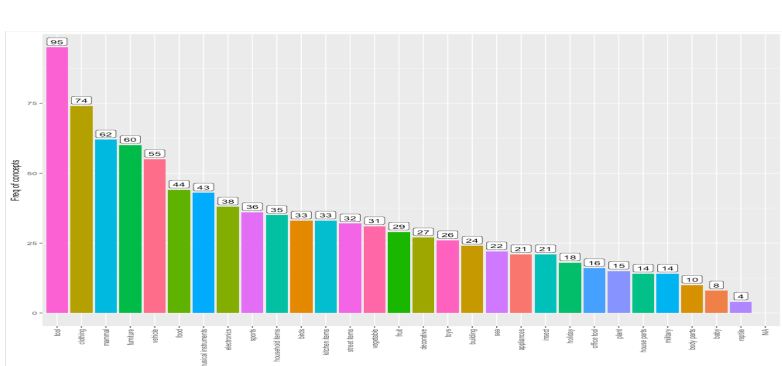
In order to answer the above questions, we collected data from two populations based on: a feature norming study and a memory study, both on Amazon Mechanical Turk (AMT).

Stimuli

CabezaLab Image Database



Number of objects in our database across 29 different categories

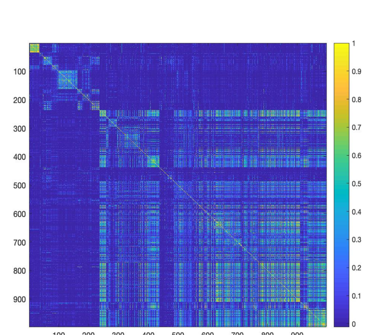


The CabezaLab Image Database consists of approximately 1000 objects from 29 different categories. Roughly 1/5 of them are living objects and 4/5 nonliving objects.

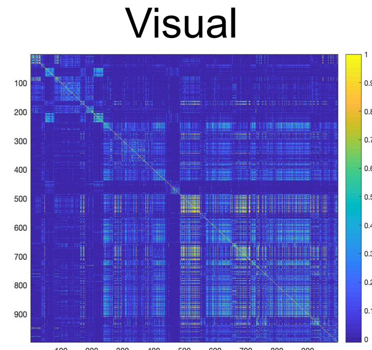
Visual and Semantic Features

We propose to evaluate memory not just based on an item's individual features, but also the relationship between items based on those features.

Visually, this describes how similar objects may have similar colors (**RGB**), luminance (**image energy, QHF**), or visual complexity (**JPEG Size**).
Semantically, this describes how similar objects may be in the same category, appear to have similar visual features, or do the same things.



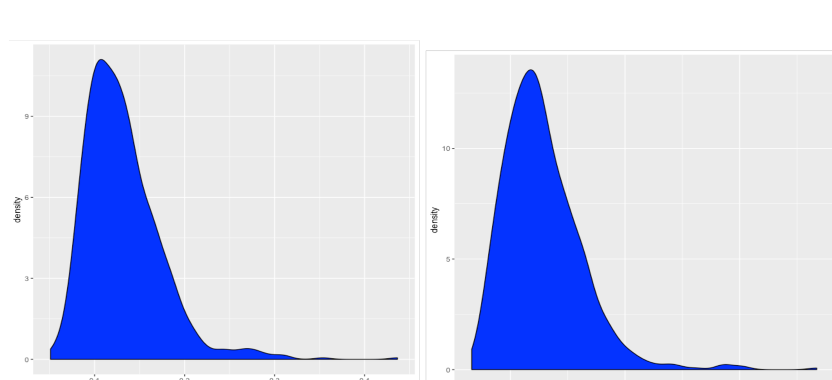
Visual



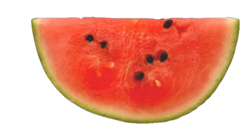
Semantic

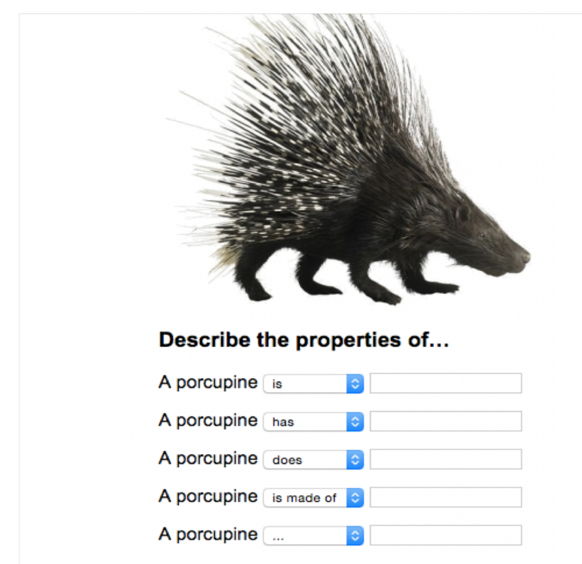
The **Conceptual Structure Account (CSA)** provides a means of formalizing these relationships with two useful measures.

Mean Distinctiveness: concept based statistic that measures the shared relative to distinct features.
Correlational Strength: average of all significant pairwise correlations between a target feature and all other features for a concept.

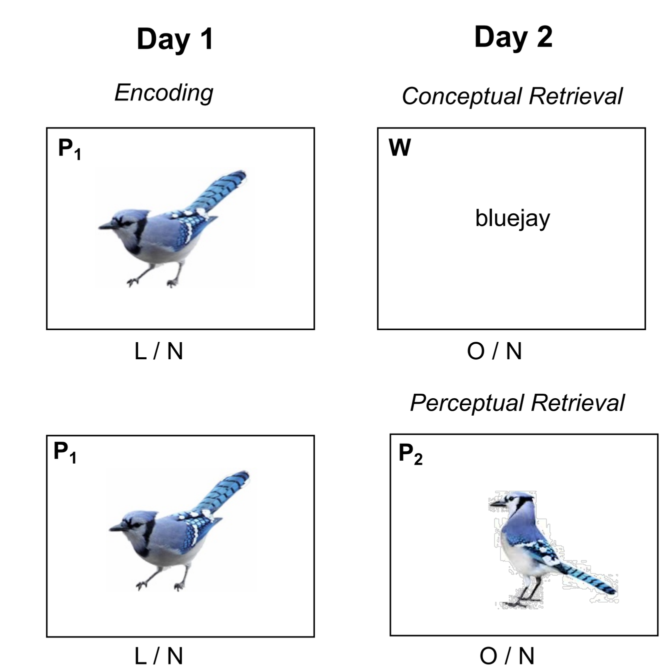


Methods



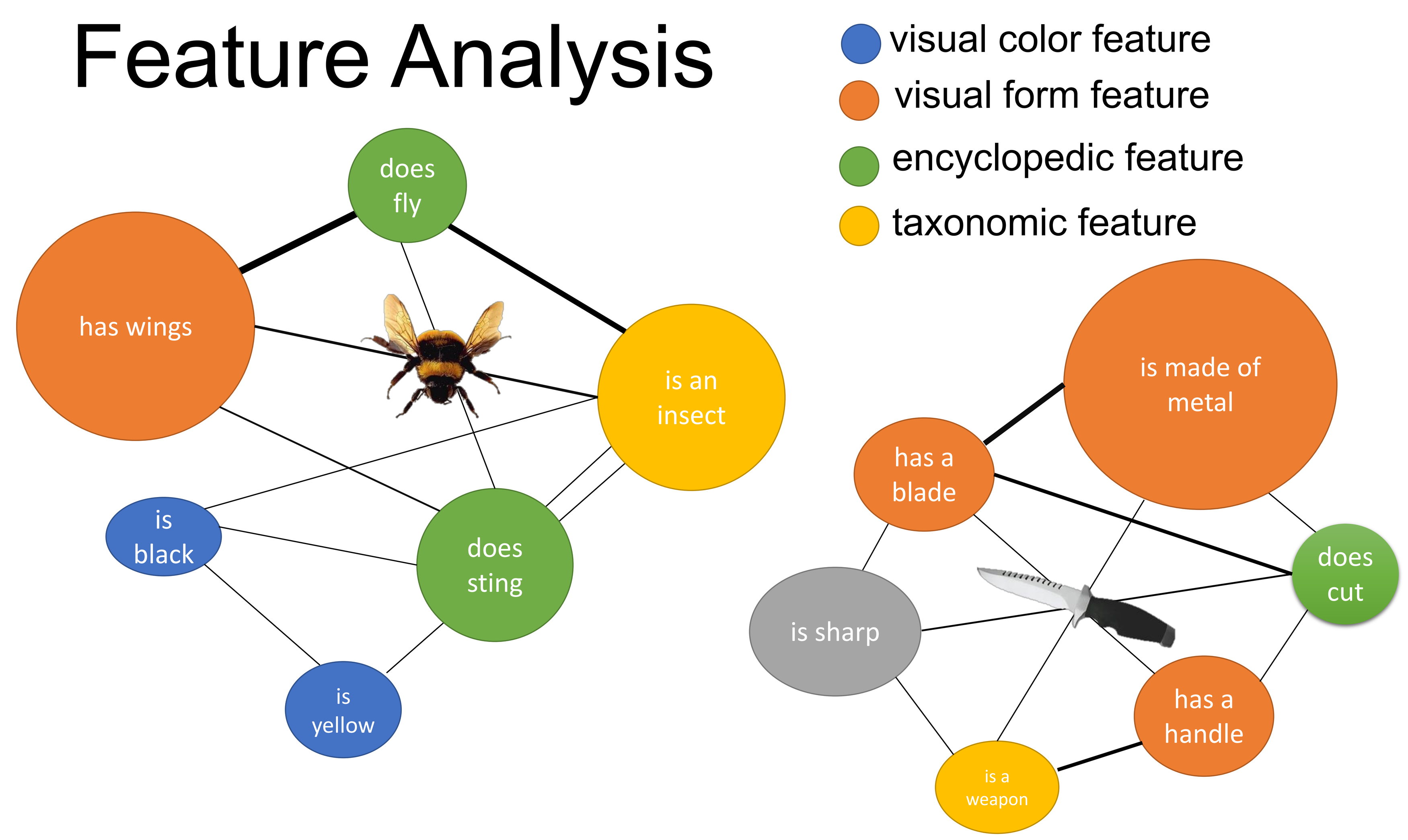


Feature Norming: AMT workers were presented with various objects and required to provide a minimum of five features.



Memory Task: In a separate study, AMT workers were shown objects during encoding. 24 hours later, workers were either presented with a perceptual task (old/new judgement of same or exemplar images) or a conceptual task (old/new judgement of words).

Feature Analysis



Living things tend to have features that co-occur with each other more frequently than non-living things, which tend to have more distinct as opposed to shared features.

- size of circle proportionate to production frequency
- size of connection proportional to correlation of features

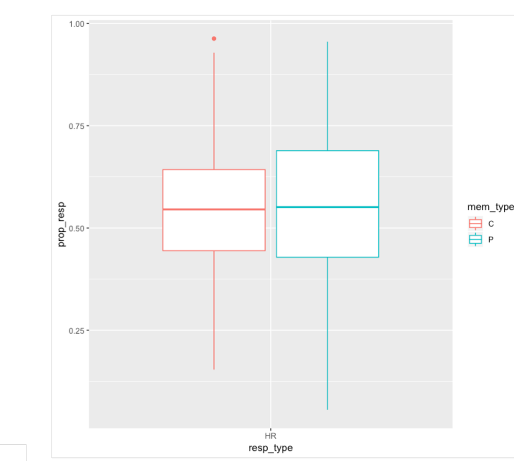
Summary

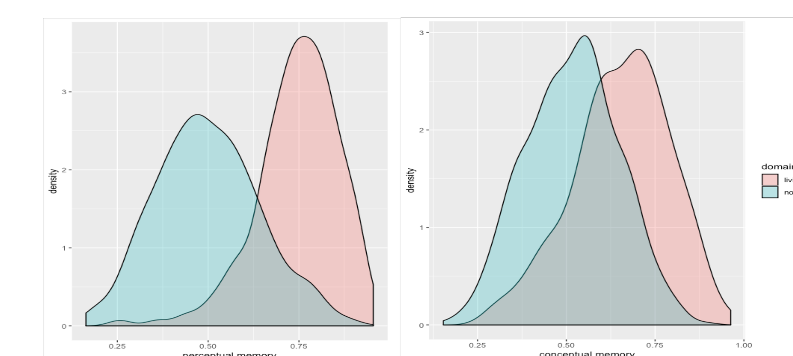
1. Memory for object images is better than memory for object concepts.
2. Visual properties of objects do not predict memory for objects.
3. Semantic properties of objects (mean distinctiveness, correlational strength) predict memory for objects.
4. Critically, the assessment of visual features (by AMT workers) –and not image properties-predicted memory for both tasks.

Overall, these results suggest a strong role for semantic attributes in overall object memorability and provide a new set of property norms that can be used across a wide range of research domains.
www.cabezalab.org/CabezaLabObjects

Memory Results

There is a significant difference between type of memory being tested (conceptual vs. perceptual).

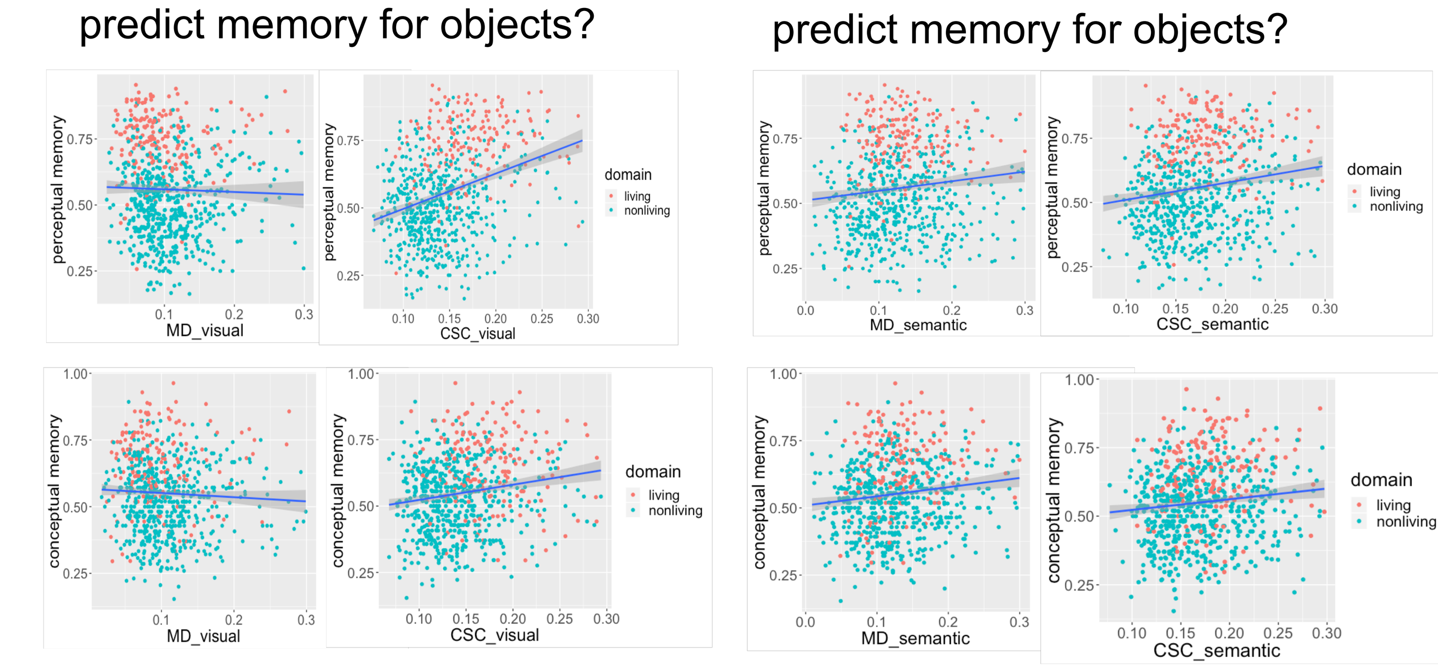




Memory is better for living than non-living items and better in the perceptual task than the conceptual task.

In order to address our principle question—*what properties are useful to remember an object?*—we first perform correlations to assess the strength of each visual or semantic measure.

Do visual features predict memory for objects? Do semantic features predict memory for objects?



Next, we combine these features into a formal regression model, and allow individual image properties to compete to predict memory performance across items.

$$PW = \beta x_{rgb} + \beta x_{QHF} + \beta x_{JPEG} + \beta x_{energy} + \beta x_{PNWS} + \beta x_{CS\_visual} + \beta x_{CS\_ency} + \beta x_{MD\_visual} + \beta x_{MD\_ency}$$
$$PP = \beta x_{rgb} + \beta x_{QHF} + \beta x_{JPEG} + \beta x_{energy} + \beta x_{PNWS} + \beta x_{CS\_visual} + \beta x_{CS\_ency} + \beta x_{MD\_visual} + \beta x_{MD\_ency}$$