Kognitionspsychologie II: Session 9
Knowing

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Die Fakultät für Psychologie der Universität Basel lädt Sie ein!

DIENSTAG, 9. MAI 2023, 17:00

INFORMATIONSVERANSTALTUNG

ZUM MASTERSTUDIUM IN SOZIAL-, WIRTSCHAFTS- UND ENTSCHEIDUNGSPSYCHOLOGIE

17:00 Uhr
FAKULTÄT FÜR PSYCHOLOGIE
MISSIONSSTRASSE 62A
HÖRSAAL 00.006

DIENSTAG, 9. MAI 2023, 17:30

PSYCHOLOGIE IN DER PRAXIS

ABSOLVENTEN/INNEN DER MASTERVERTIEFUNGSRICHTUNG SOZIAL-, WIRTSCHAFTS- UND ENTSCHEIDUNGSPSYCHOLOGIE BERICHTEN VON IHREN BERUFSERFAHRUNGEN NACH DEM STUDIUM

MIT ANSCHLIESSENDEM APÉRO

17:30 Uhr
FAKULTÄT FÜR PSYCHOLOGIE
MISSIONSSTRASSE 62A
HÖRSAAL 00.006

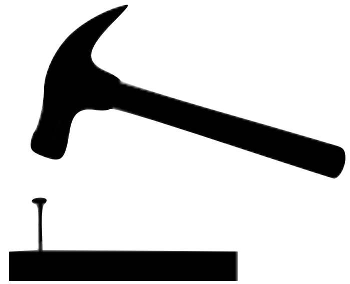
Learning Objectives for Session 7

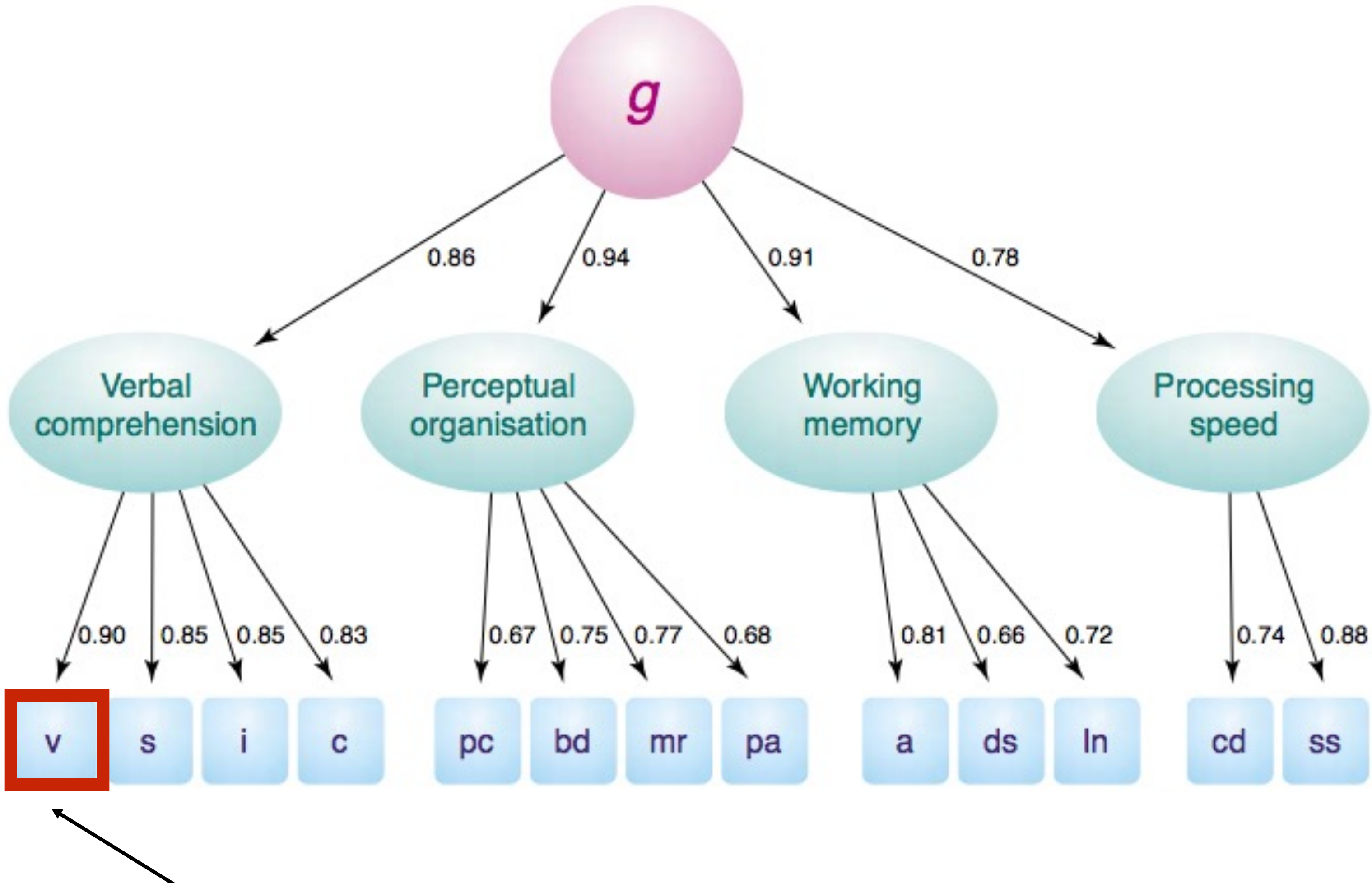
- Be able to discuss different types of human knowledge and the cognitive systems that implement it…
- Discuss the **adaptive significance** of different types of knowledge representations
- Discuss advantages and limits of **comparative approaches** to understand knowledge representation
- Be aware of general **developmental patterns** in the acquisition of knowledge
- Be able to identify central features of **cognitive and neural model**(s) of semantic cognition

Where did you park your bike/car?

What is the capital of France?

Semantics

Ontogeny	Mechanism
Phylogeny	 Adaptive Significance

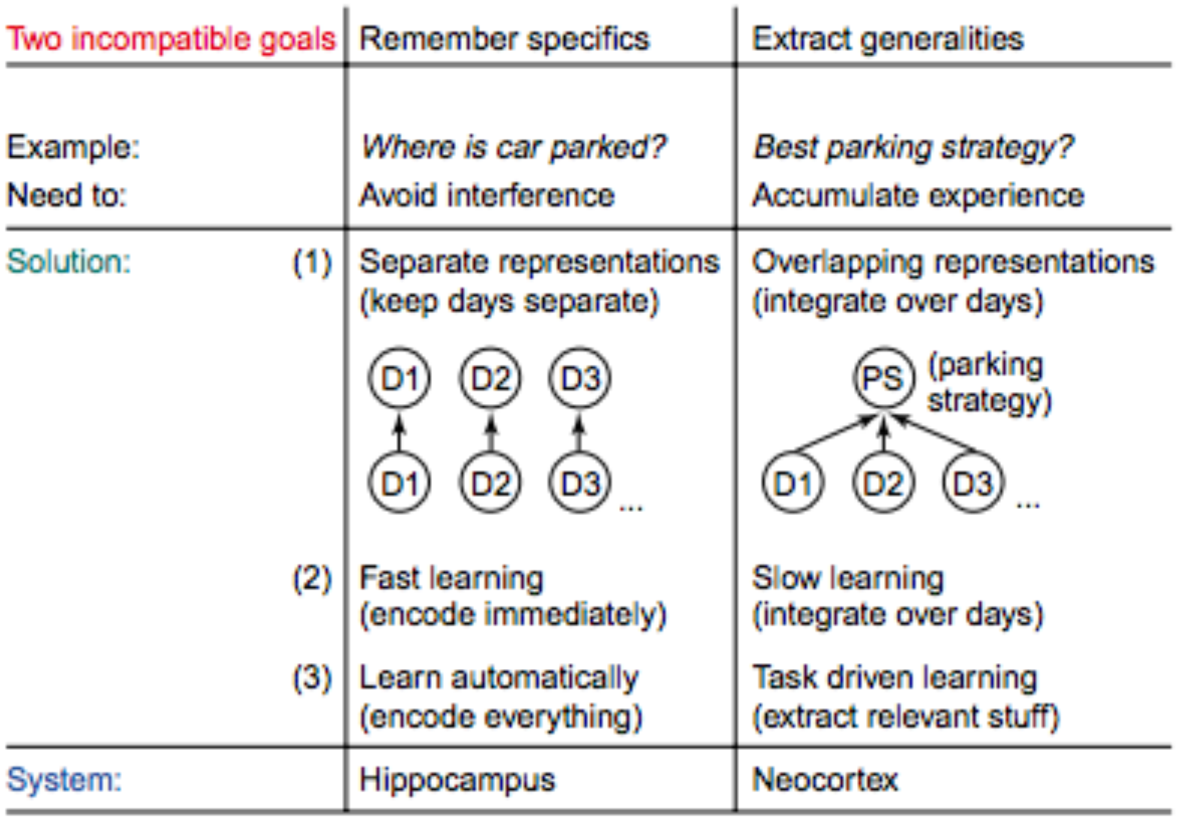


Declarative, verbal knowledge (as measured by a vocabulary test) is one of the best correlates of ***g***…

Deary, I. J. (2001). Human intelligence differences: A recent history. ***Trends in Cognitive Sciences, 5***(3), 127–130.

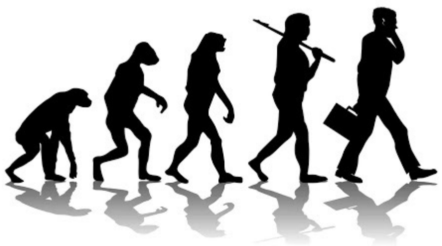
Different types of knowledge systems fulfil different goals

"The complementary learning systems framework is based on the logic of tradeoffs between mutually incompatible computational goals. The central tradeoff behind our framework involves two basic types of learning that an organism must engage in – learning about specifics versus generalities – which require conflicting neural architectures"

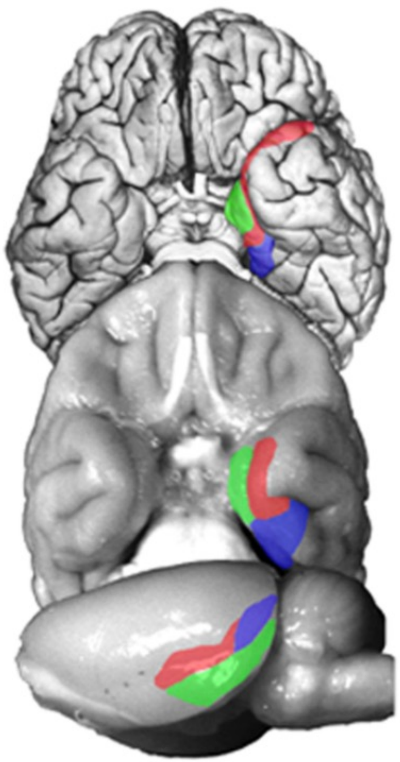


O'Reilly, R.C. & Norman, K.A. (2002). Hippocampal and neocortical contributions to memory: Advances in the complementary learning systems framework. ***Trends in Cognitive Sciences, 6***, 505-510.

Semantics

Ontogeny	Mechanism
 Phylogeny	Adaptive Significance

Opportunities and challenges of comparative approaches



"(…) during the 1960s and early 1970s, the development of an animal model of human memory and human memory impairment was challenged by the fact that animals could use nondeclarative memory to solve some memory tasks that humans typically approached using declarative memory. It therefore became important to understand under what conditions this occurs and to identify what kind of memory is used in each case."

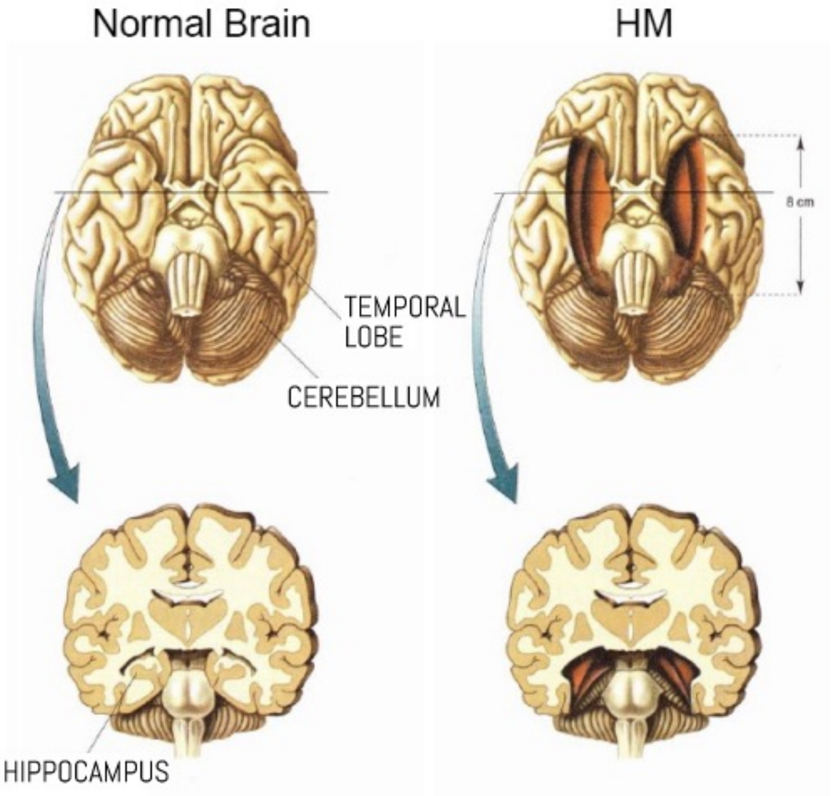
"For example, monkeys learn visual discrimination tasks gradually over many trials in a fashion that is now referred to as habit learning. In the monkey, this kind of learning depends on the basal ganglia rather than the medial temporal lobe. By contrast, humans learn the same task by directly memorizing the stimulus material."

Ventral view of a human brain (Top), ventral view of a monkey brain (Middle), and lateral view of a rat brain (Bottom). The major cortical components of the medial temporal lobe are highlighted [perirhinal cortex (red), parahippocampal/postrhinal (blue), and entorhinal cortex (green)].

The organization of the medial temporal lobe is highly conserved across species (rat, monkey, human). However, because of different strategies - it took decades to uncover many of similarities in the role of these structures for memory.

Clark, R. E., & Squire, L. R. (2013). Similarity in form and function of the hippocampus in rodents, monkeys, and humans. Proceedings of the National Academy of Sciences, 110, 10365–10370. http://doi.org/10.1073/pnas.1301225110

Opportunities and challenges of comparative approaches



Patient H.M. had a history of epileptic seizures and underwent an experimental surgical intervention that involved resecting the medial aspect of the temporal lobe bilaterally (Scoville & Milner, 1957). The lesion was bilaterally symmetrical and included large portions of the temporal cortex. The surgery reduced the frequency/severity of seizures but left H.M. with profound amnesia.

A few conclusions were drawn from H.M.'s case (and similar ones):

1. Memory is a distinct cerebral ability that is separate from other cognitive functions, such as perception, intelligence, personality, and motivation.
2. Short-term memory and long-term memory are distinct functions: H.M. had severely impaired long-term memory, however, he could maintain and use information for a short time in immediate memory (and working memory) so long as the material could be effectively rehearsed. With distraction, the information was lost.
3. Medial temporal lobe structures are not the ultimate repository of long-term memory because H.M.'s memory for remote events remained largely intact.

Clark, R. E., & Squire, L. R. (2013). Similarity in form and function of the hippocampus in rodents, monkeys, and humans. Proceedings of the National Academy of Sciences, 110, 10365–10370. http://doi.org/10.1073/pnas.1301225110

Semantics

Ontogeny 	Mechanism
Phylogeny	Adaptive Significance

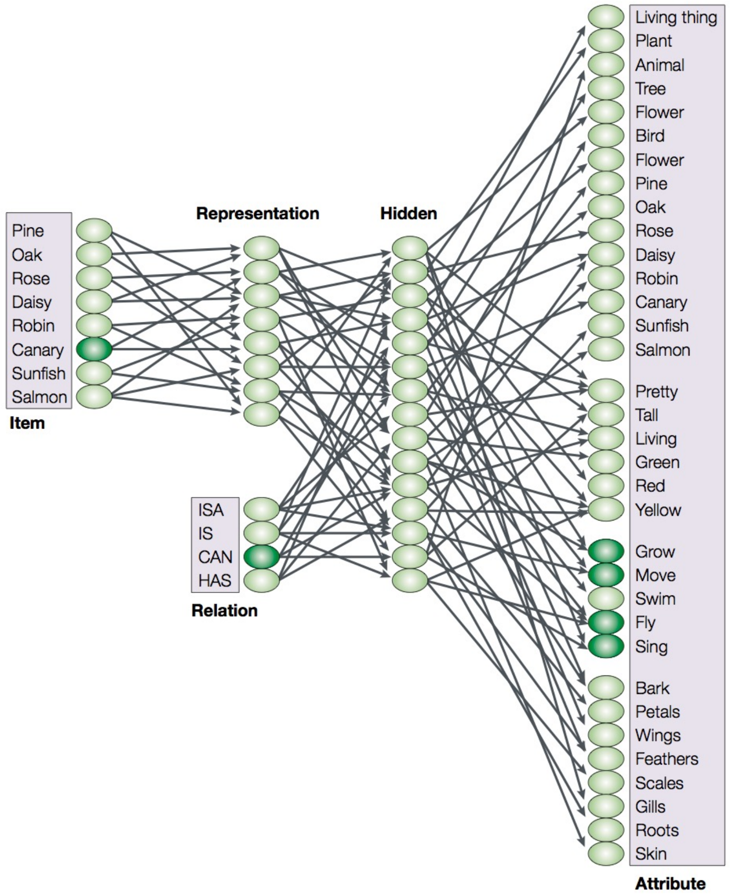
Acquiring Semantic Representations

“it is well-established that early categorization abilities become refined over the developmental trajectory. Researchers have identified a global-to-basic shift in early categorical thinking, such that preverbal infants discriminate between global-level categories (i.e., dogs, cats, chairs, tables, etc.) before basic-level categories (i.e., different breeds of cats and dogs). (…) There is evidence to suggest that infants also use dynamic, causal, and functional information to guide their object categorization and discrimination.”

Poulin-Dubois, D. & Pauen, S. (2017). The development of object categories: What, when, and how? In. H. Cohen & C. Lefebvre (Eds.), Handbook of Categorization in Cognitive Science (2nd Ed., pp. 653–708). Elsevier. doi:10.1016/b978-0-08-101107-2.00027-0

Acquiring Semantic Representations

Distributed Networks



The network is used to simulate learning propositions about concepts. The entire set of units used in the network is shown. Inputs are presented on the left, and activation propagates from left to right. Where connections are indicated, every unit in the pool on the left (sending) side projects to every unit on the right (receiving) side. An input consists of a concept–relation pair; the input 'canary CAN' is represented by darkening the active input units. The network is trained to turn on all those output units that represent correct completions of the input pattern. In this case, the correct units to activate are 'grow', 'move', 'fly' and 'sing'.

Connectionist models aim to provide an explanation for how concepts and categories are acquired in a graded fashion from experience.

Connectionist model

A form of computational model used to understand cognitive processes by simulating the flow of activation among simple, neuron-like processing units through weighted, synapse-like connections.

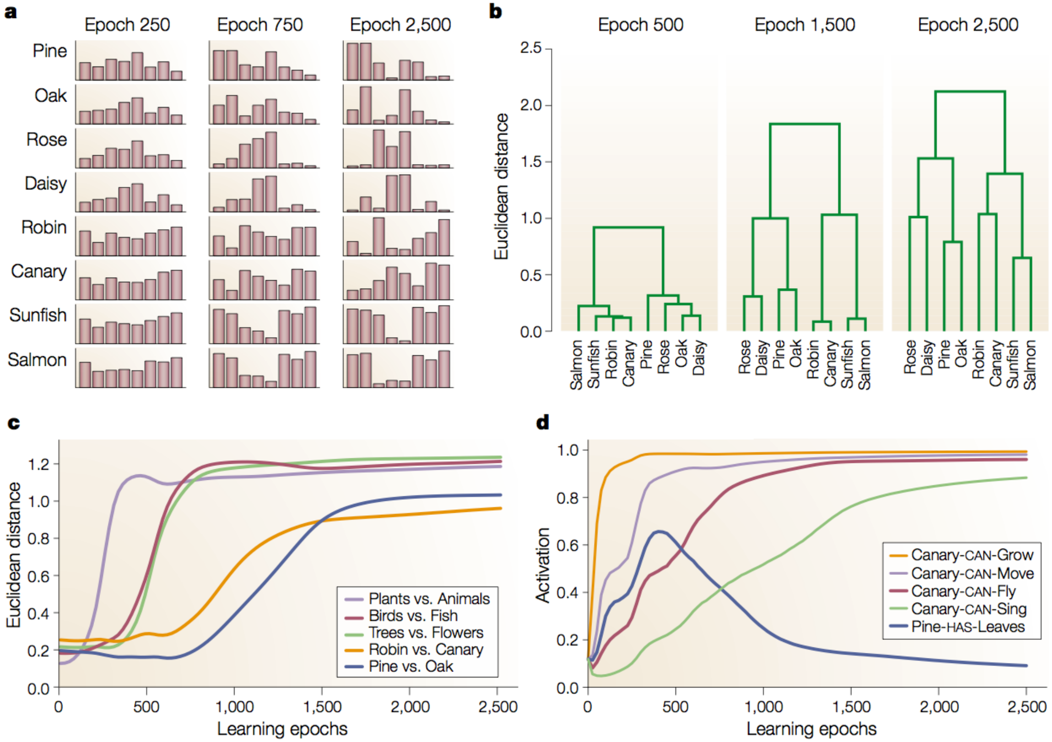
Backward Progagation

Backpropagation is a method used in artificial neural networks to calculate a gradient that is needed in the calculation of the weights to be used in the network. Backpropagation is shorthand for "the backward propagation of errors," since an error is computed at the output and distributed backwards throughout the network's layers. It is commonly used to train deep neural networks. https://en.wikipedia.org/wiki/Backpropagation

McClelland, J. L. & Rogers, T. T. (2003). The parallel distributed processing approach to semantic cognition. ***Nature Reviews Neuroscience, 4,*** 310-322.

Acquiring Semantic Representations

Distributed Networks



a | Patterns of activation in the feedforward network representing the eight objects (e.g., pine, oak, salmon) at three points in the learning process (epochs 250, 750, 2,500).

b | A hierarchical clustering analysis was used to visualize the similarity structure in the patterns of activation. Early in learning, the patterns are relatively undifferentiated; the first difference to appear is between plants and animals. Later, the individual concepts are differentiated, but a hierarchical organization remains showing a clear differentiation at both the superordinate (plant–animal) and intermediate (bird–fish/tree–flower) levels.

c | Pairwise distances between representations of groups of concepts or individual concepts, illustrating the continuous but stage-like character of progressive differentiation.

d | The network's performance in activating various properties of some objects indicating that correct performance is acquired in a general-to-specific manner, and tracks the differentiation of concepts shown in c. Note the activation of 'leaves' when the network is probed with 'pine-HAS'. This shows an inverted 'U'-shaped developmental course, capturing the 'illusory correlations' or incorrect attributions of typical properties.

The toy example suggests that learning of concepts can be acquired over time through learning of features. Crucially, it leads to interesting developmental patterns (global-to-basic) and errors (over-generalization). One should, however, note that learning by supervised learning with explicit, external feedback as in this example is not very plausible…

McClelland, J. L. & Rogers, T. T. (2003). The parallel distributed processing approach to semantic cognition. ***Nature Reviews Neuroscience, 4,*** 310-322.

Acquiring Semantic Representations

Modern large language models (LLM) use self-supervised learning to predict the next token in a sentence, given the surrounding context.

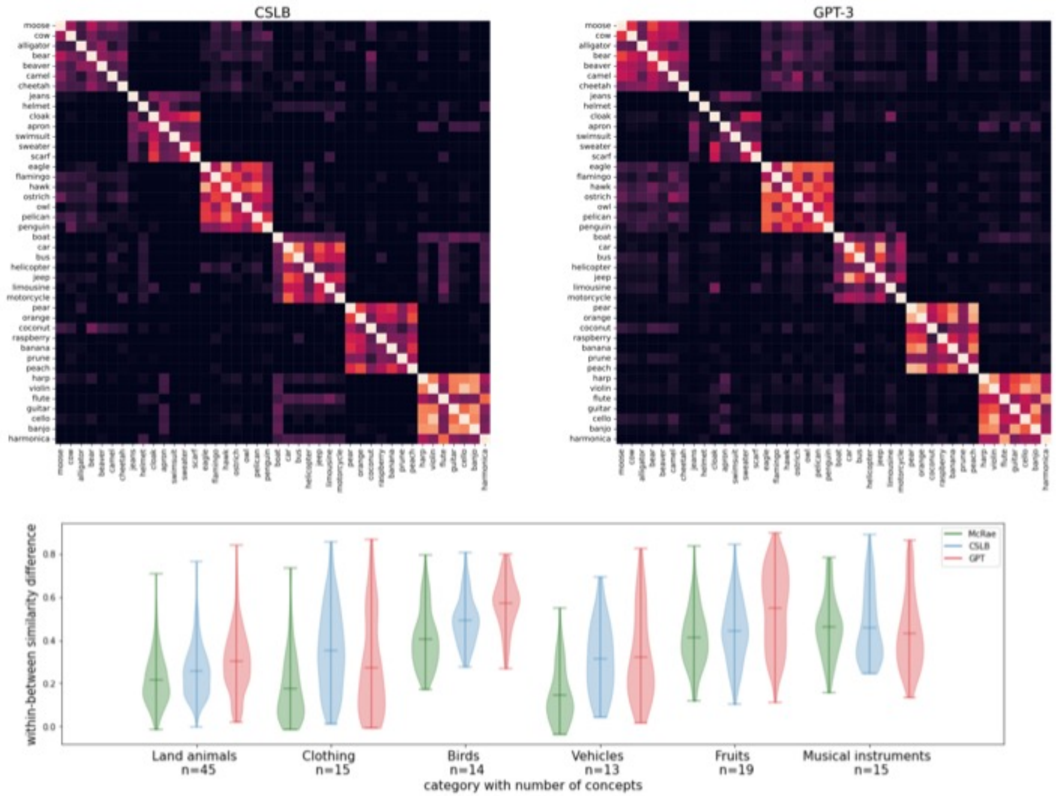


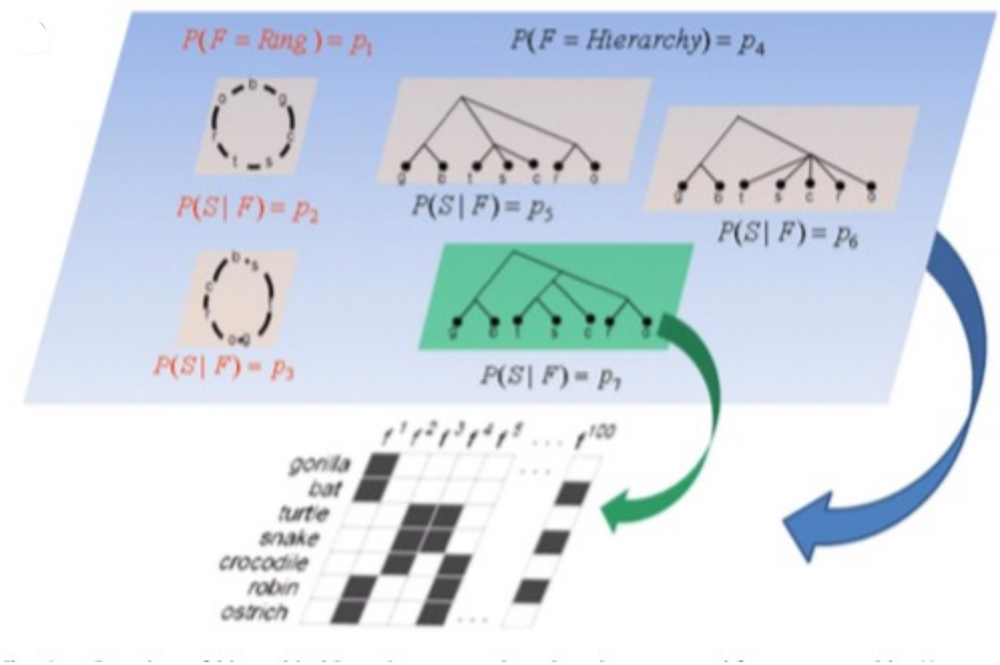
Figure 2: Representational similarity matrices for 6 concepts in the categories land animals, fruits, vehicles, fruits, birds and clothing using the CSLB and GPT-3 feature norms (top) and pairwise cosine similarities per category (bottom).

"Our results demonstrate that recent large language models are indeed able to accurately reflect important aspects of human conceptual knowledge".

Hansen, H., & Hebart, M. N. (2022). Semantic features of object concepts generated with GPT-3 (arXiv:2202.03753). arXiv. http://arxiv.org/abs/2202.03753

Acquiring Semantic Representations

Bayesian learning



Overview of hierarchical Bayesian approach to learning using examples of similarities among a set of animals.

The data at the bottom, in the form of a feature vector for each animal, can potentially be produced by alternative forms (ring, partition, tree, order, hierarchy) that can take on many different structures (defined by nodes and edges in graph). Bayesian inference identifies the specific structure (hierarchy in green) that has maximal probability as determined by the product of the likelihood (how likely it produced the observed data) and prior knowledge (some structures are a priori more likely, for example, because they are simpler).

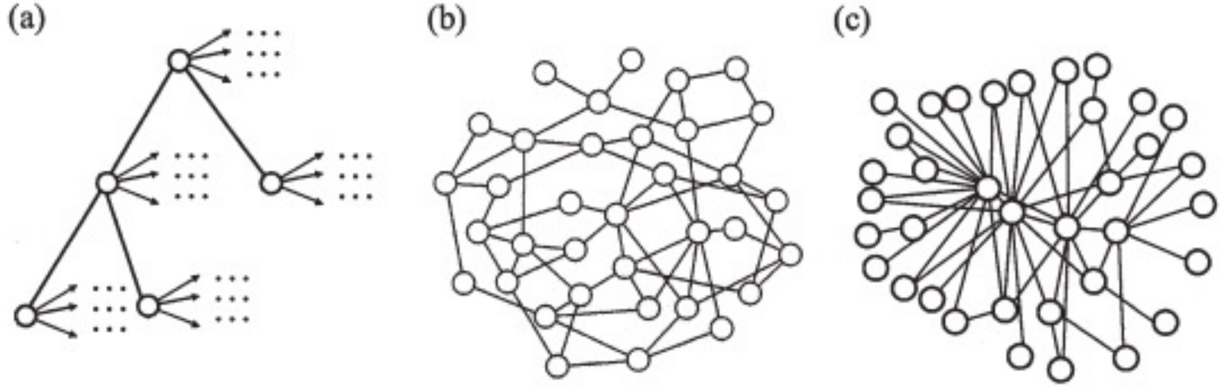
Newer (Bayesian) machine learning approaches suggest cognitive systems go though a process of hypothesis testing, that is, systems compares a number of plausible hypotheses concerning how likely they are given the observed data. These models are so far silent about implementation level of explanation.

Tenenbaum, J. B., Kemp, C., Griffiths, T. L., & Goodman, N. D. (2011). How to grow a mind: Statistics, structure, and abstraction. Science, 331(6022), 1279–1285. http://doi.org/10.1126/science.1192788

Semantics

Ontogeny	Mechanism 
Phylogeny	Adaptive Significance

Cognitive Models of Semantic Representations



Different proposals for network models of semantic representations:

(a) tree-structured hierarchy: Collins and Quillian (1969) proposed that people have and search efficiently inheritance hierarchies to retrieve or verify facts such as "Robins have wings" and showed that reaction times of human subjects matched qualitative predictions of this model (bird vs. robin).

(b) arbitrary, unstructured graph: whereas Collins & Loftus (1975) propose connections are based on personal experience (not logic), and this could better account for effects of specific items (robin vs. ostrich). Associations as underlying mechanism of spreading activation and priming

(c), a scale-free, small-world graph: semantic networks estimated from large linguistic corpi have a small-world structure (most nodes are not neighbours of one another, but can be reached from every other by a small number of steps) and such patterns are compatible with a process of preferential attachment (more highly connected nodes are more likely to acquire new connections; Steyvers & Tenenbaum, 2005)

Steyvers, M., & Tenenbaum, J.B. (2005). Graph theoretic analyses of semantic networks: Small worlds in semantic networks. ***Cognitive Science, 29***, 41-78

Spreading Activation

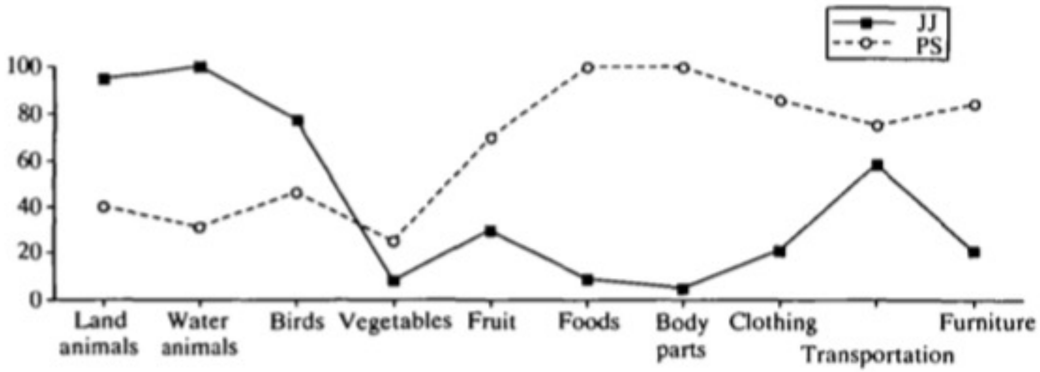
A method for searching associative networks, neural networks, or semantic networks. The search process is initiated by labeling a set of source nodes (e.g. concepts in a semantic network) with weights or "activation" and then iteratively propagating or "spreading" that activation out to other nodes linked to the source nodes. Most often these "weights" are values that decay as activation propagates through the network.

Semantic Priming

Priming is an implicit memory effect in which exposure to one stimulus influences a response to another stimulus. The seminal experiments of Meyer and Schvaneveldt in the early 1970's. Their original work showed that people were faster in deciding that a string of letters is a word when the word followed an associatively or semantically related word. For example, NURSE is recognized more quickly following DOCTOR than following BREAD.

The Neural Basis of Semantic Representations

Category-specific deficits (double dissociations from lesion studies)



Caramazza and colleagues have suggested that evolutionary pressures resulted in specialised (and functionally dissociable) neural circuits dedicated to processing, perceptually and conceptually, different categories of objects (i.e., Domain-Specific hypothesis). The hypothesis suggests specific categories for which rapid and efficient identification could have had survival and reproductive advantages: including 'animals', 'fruit/vegetables', 'conspecifics', and possibly 'tools'.

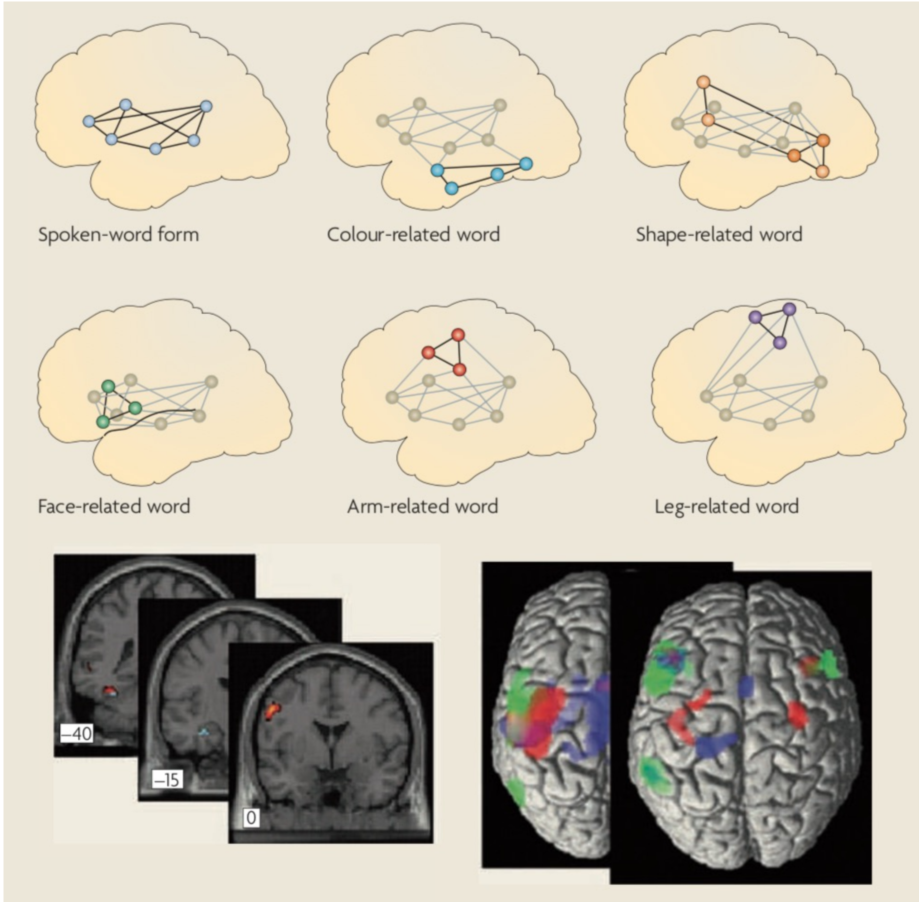
Lesion studies suggest that there are category-specific semantic deficits. More recent models (discussed in the next slides) do not dispute the categorical deficits but suggest these may be related to functional/modality characteristics associated with the categories (e.g., tools -> function and use; animals -> sensory characteristics) rather than category dedicated neural areas.

Hillis, A. E., & Caramazza, A. (1991). Category-specific naming and comprehension impairment: A double dissociation. *Brain*, *114*(5), 2081–2094. http://doi.org/10.1093/brain/114.5.2081

The Neural Basis of Semantic Representations

Category-specific neural activation (neuroimaging)

The figure shows a model of action–perception circuits for spoken words and their meaning. **a**) Word-related circuits are located in the perisylvian language cortex, especially inferior frontal and superior temporal areas, and are strongly lateralized to the dominant left hemisphere. The learned, arbitrary links between the form of words and their meanings are provided by the coupling between these word-related circuits and semantic action–perception circuits (illustrated by different colours in the other brain diagrams). The higher-order assemblies (including both word form- and meaning-related circuits) are specific to the semantic category and store information about the actions and objects that the words are typically used to describe; **b**) Results of event-related functional MRI studies that support this model of semantic circuits.

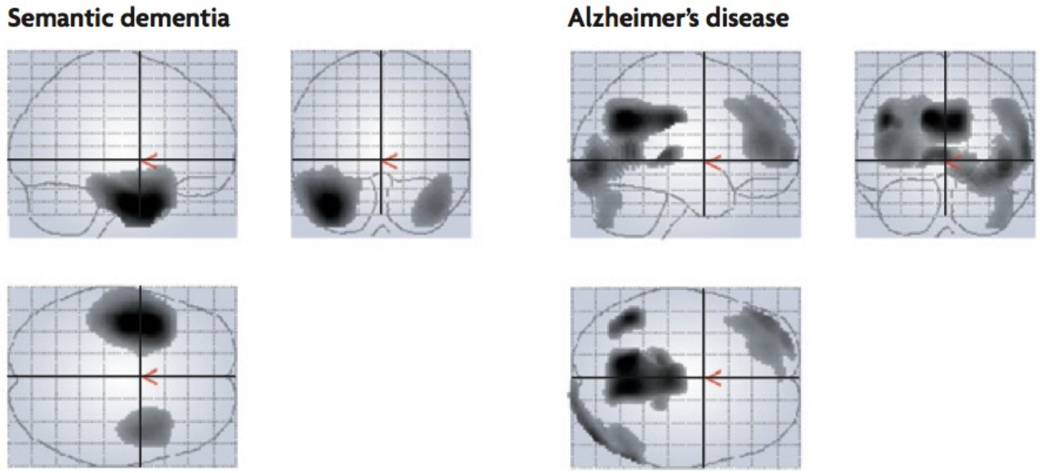


Neuroimaging studies also suggest category-specific neural activation and bolster the idea of a mapping between types of representations and specific neural circuits.

Pulvermüller, F., & Fadiga, L. (2010). Active perception: Sensorimotor circuits as a cortical basis for language. *Nature Reviews Neuroscience*, *11*(5), 351–360. http://doi.org/10.1038/nrn2811

The Neural Basis of Semantic Representations

General (amodal) deficits associated with Semantic Dementia (SD)



Semantic Dementia

A degenerative neuropathological condition that results in the progressive loss of semantic knowledge as revealed through naming, description and non-verbal tests of semantic knowledge, resulting from disease of the anterior and lateral aspects of the temporal lobes.

The are significant differences between semantic dementia and Alzheimer's disease in measures of brain function and semantic memory. The brain areas of reduced metabolism (shown as graded grey areas in the figure above), are widespread in patients with Alzheimer's disease (AD) and include some regions that are implicated in the cortical semantic network. In the AD cases shown, however, there was little evidence of any abnormality in anterior temporal regions, which show substantial and focal hypometabolism in patients with semantic dementia (SD).

The performance of Semantic Dementia patients is significantly more impaired than AD patients on many semantic tasks (e.g., naming, verbal fluency) despite having more localised lesions.

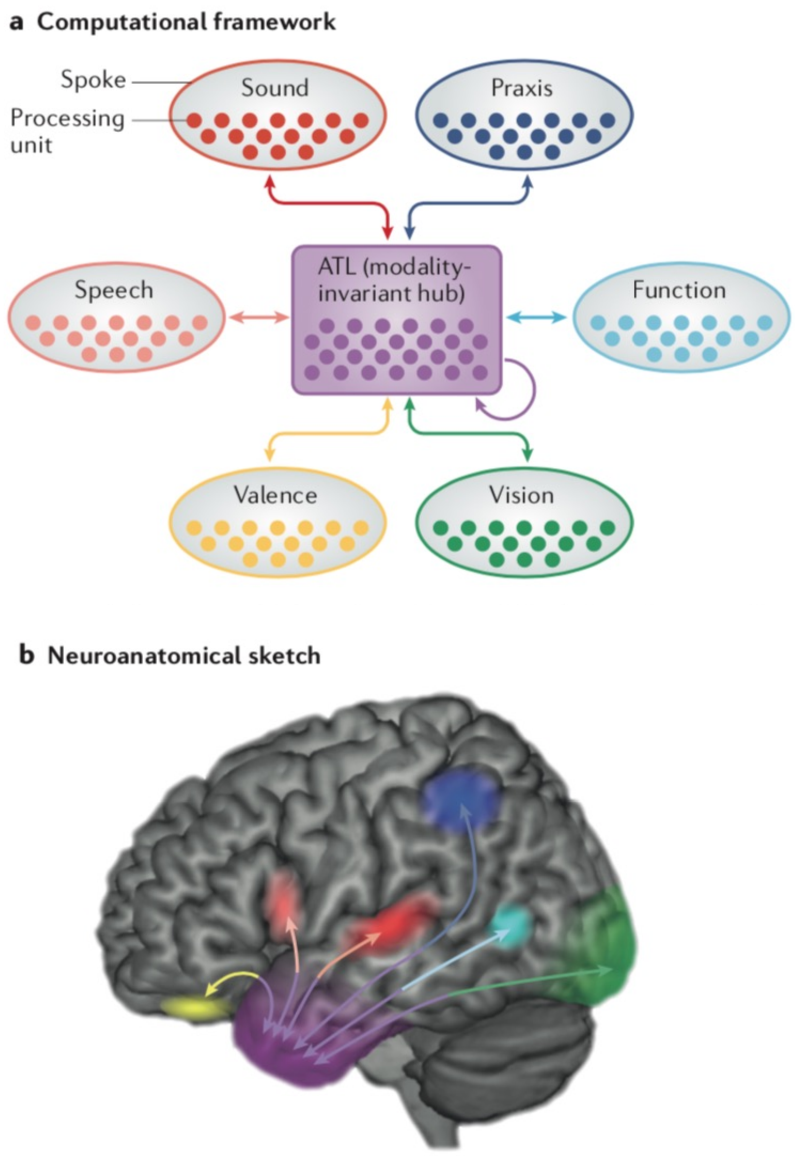
Semantic dementia suggests that there are general (amodal) semantic deficits associated with anterior temporal function.

Patterson, K., Nestor, P. & Rogers, T. T. (2007). Where do you know what you know? The representation of semantic knowledge in the human brain. ***Nature Reviews Neuroscience, 8***, 976-988.

The Neural Basis of Semantic Representations: Hub-and-spokes model

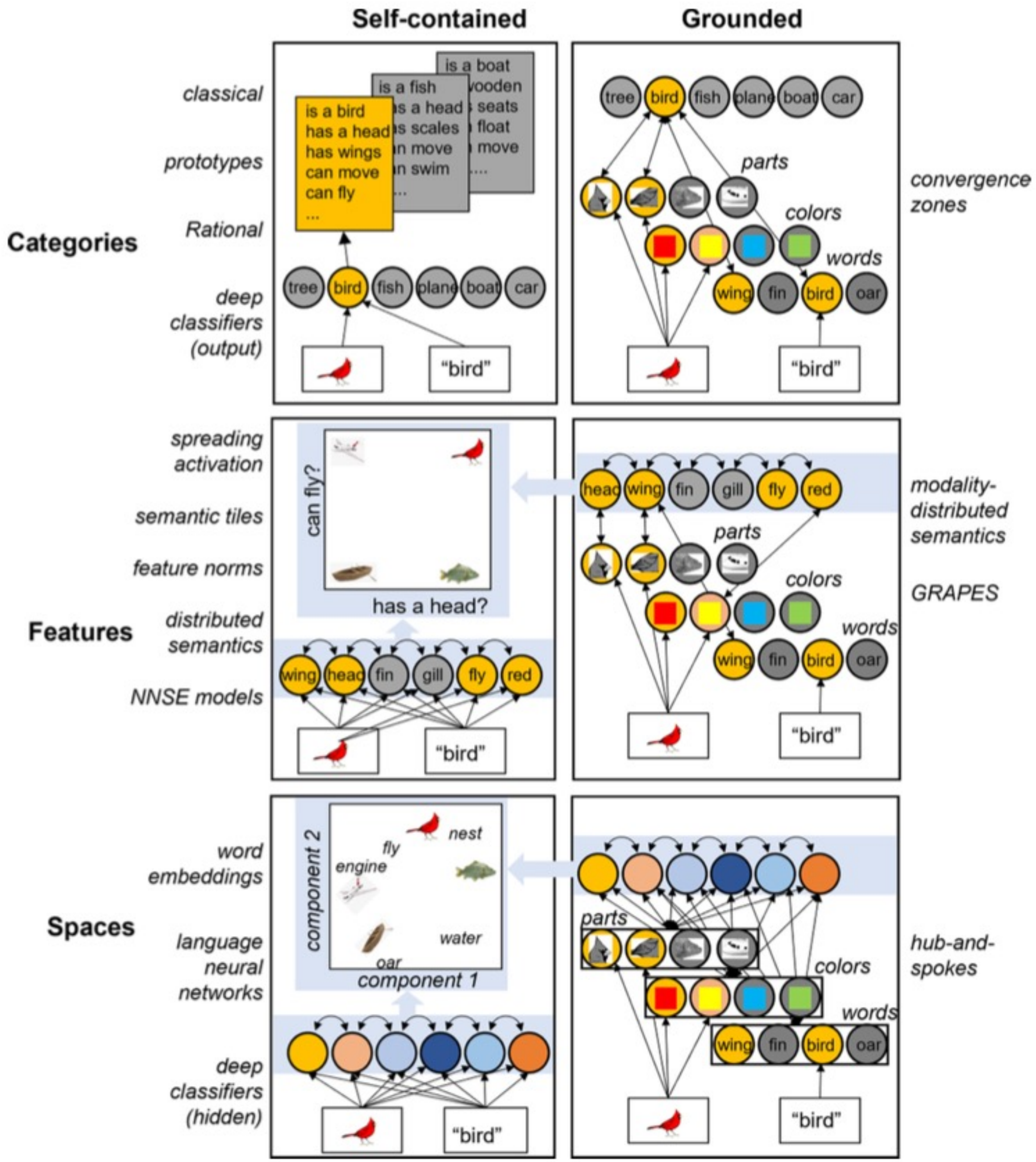
a | Modality-specific sources of information (spokes) are coded across a set of processing units within separate processing layers in the model. Each ‘spoke’ layer is reciprocally connected to a single transmodal ‘hub’. The model is trained to take each of the spokes, in turn, as input and, through the hub, to reproduce the correct information across the other spokes. For example, the model is provided with the visual form of each item as input and is trained to reproduce the sounds, names, valence and other types of information that are associated with each item. The emergent result of this training is that the model forms generalizable semantic representations. The progressive, multimodal semantic impairment of patients with semantic dementia can be mimicked by gradually removing the hub connections.

b | A neuroanatomical sketch of the location of the hub and spokes is presented. The hub is located within the anterior temporal lobe (ATL) region, whereas the modality-specific spokes are distributed across different neocortical regions (the same colour coding is used as for the computational model). Each spoke communicates bidirectionally with the ATL hub through short- and long-range white-matter connections (arrows).



Lambon-Ralph, M. A. L., Jefferies, E., Patterson, K., & Rogers, T. T. (2017). The neural and computational bases of semantic cognition. *Nature Reviews Neuroscience*, *18*(1), 42–55. http://doi.org/10.1038/nrn.2016.150

The Neural Basis of Semantic Representations: Hub-and-spokes model



Computational hypotheses about semantic representation. Three ways in which conceptual structure could be encoded. First, information may be encoded in discrete, independent category representations (top row). On this view, sensory inputs recruit discrete and independent category representations which either encapsulate semantic information within themselves or connect and bind modality-specific surface representations encoding characteristics of category members (top right). Second, semantic information may be distributed across independent and interpretable semantic feature representations, with featural overlap indicating conceptual similarity (middle). Features may independently and intrinsically encode the presence of stipulated semantic features within a concept (middle left) or gain meaning via connection to surface representations that directly encode such information (middle right). Third, semantic information may be encoded by a continuous distributed representation space that expresses conceptual similarities among items even though its dimensions are not independently interpretable (bottom). Semantic information may be self-contained by the distances encoded in such a space (bottom left) or grounded via mappings from the space to modality-specific surface representations of specific properties (bottom right). Black arrows illustrate how information flows through the network given the stimuli shown. Text on either side indicates well-known perspectives in the literature that characterize each view. For feature-based and vector space representations, representational spaces are schematized on a blue background. Blue arrows point to the type of representational similarity structure encoded by the corresponding layers. Abbreviations: GRAPES, grounding representations in action, perception, and emotion systems; NNSE, non-negative sparse embeddings.

Frisby, S. L., Halai, A. D., Cox, C. R., Lambon Ralph, M. A., & Rogers, T. T. (2023). Decoding semantic representations in mind and brain. Trends in Cognitive Sciences, S1364661322003230. https://doi.org/10.1016/j.tics.2022.12.006

Summary

- **Adaptive Significance**: Knowledge (e.g., facts, causal relations) is a hallmark of intellectual performance; the cognitive system is structured such that it allows the pursuit of different (potentially incompatible) goals, suggesting the representation of abstract knowledge may be dissociable from other types of knowledge (procedural, episodic).
- **Comparative approaches:** Comparative approaches are limited in providing a picture of language-dependent, abstract knowledge; nevertheless. animal models helped understand the role of hippocampal function (central for declarative knowledge) as well as other structures (e.g., central for procedural knowledge); overall, suggest that different systems support different types of knowledge.
- **Development:** Evidence for developmental patterns of general-to-specific learning of concepts; current work focuses on answering how computational/learning processes can create complex cognitive representations while accounting for such developmental patterns.
- **Cognitive and neural models:** some disconnect between cognitive and neural models; there is a predominance of network models of semantic knowledge that are largely amodal but are useful to account for spreading activation and priming results from behavioural studies; current neural models, such as the hub-and-spokes model, propose both modality-specific representations (neocortex) and amodal representations (anterior temporal lobe), as well as important role for frontal cortex in cognitive control of knowledge elicitation.