Understanding the Semantic Structure of Human fMRI Brain Recordings With Formal Concept Analysis

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Sektion Theoretische Sensomotorik
Section Computational Sensomotorics

Cognitive NeuroImaging

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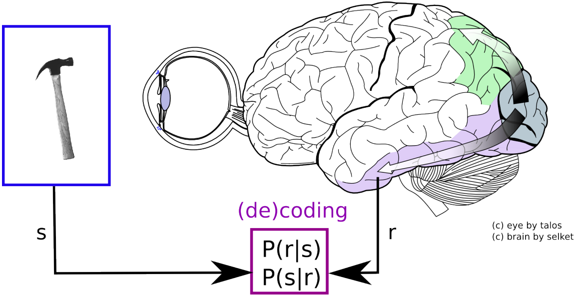
Outline

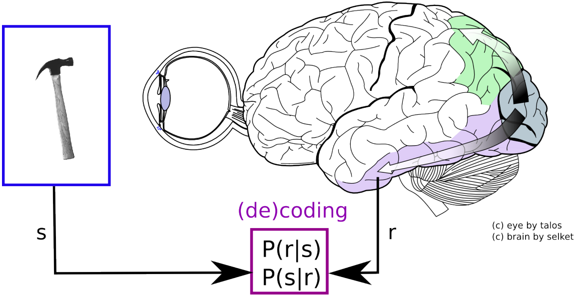
Motivation: neural (de)coding



Neural code, $P(r|s)$:

- Activation pattern of a population of neurons (codewords).
- Represents sensory information items, e.g. presence/absence of stimuli.

Motivation: neural (de)coding



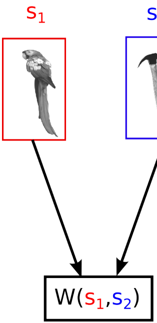
Neural code, $P(r|s)$:

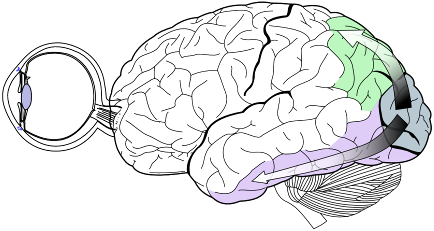
- Activation pattern of a population of neurons (codewords).
- Represents sensory information items, e.g. presence/absence of stimuli.

Neural decoding, $P(s|r)$:

- Reconstruct information item from activation pattern.
- Often classification semantics: stimuli either *same* or *different*
- Quality measures: classification rates, mutual information etc.
- Well explored approach, e.g. [Barlow 1972, Qurioga et al. 2007].

Beyond classification: relational representations

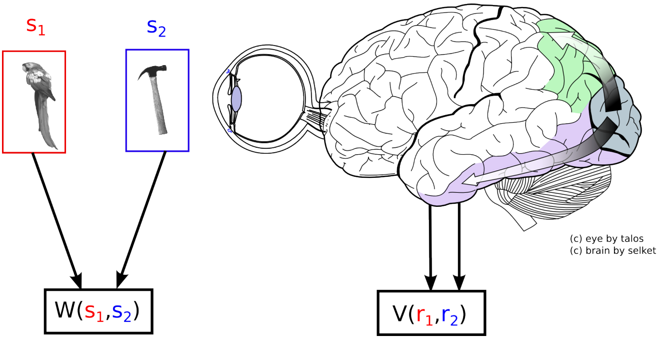




(c) eye by talos
(c) brain by selket

- Stimuli s_1, s_2
- $W(s_1, s_2)$: *perceived* relationship btw. s_1,s_2, e.g. similarity

Beyond classification: relational representations



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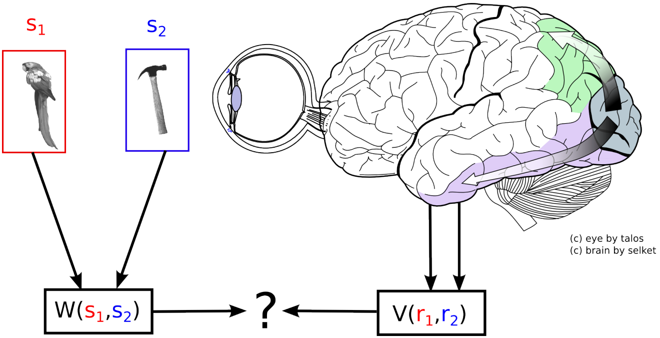
Beyond classification: relational representations



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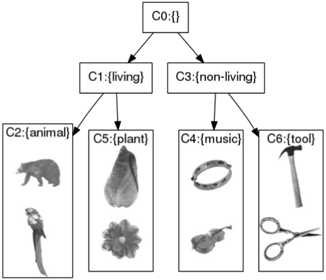
Question 1: How are *perceived* relationships between represented information items reflected in the neural code?

Explicit relationships: taxonomies, partial orders

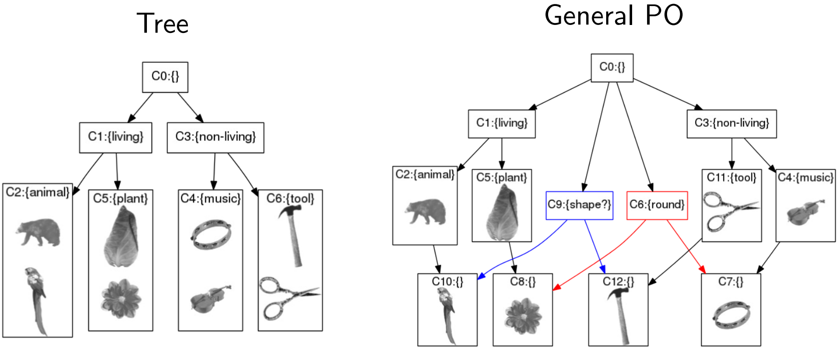


Conceptual/hierarchical organization:

- Related items are 'close', relationship explicit
- Evidence for neural representation

  [Kiani et al. 2007, Kriegeskorte et al. 2008, Naselaris et al. 2012, Endres et al. 2010]
- Often tree-structured

Explicit relationships: more general partial orders

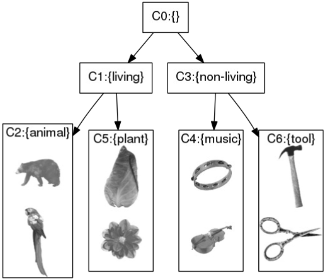


Trees may be too restrictive:

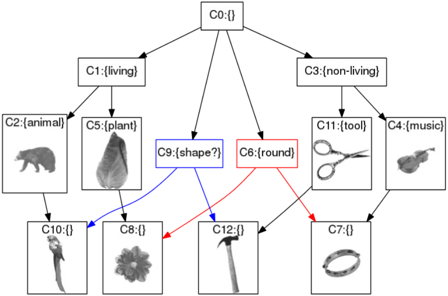
- Stimuli are also related by shape properties
- Trees cannot represent this (either 'round' or 'plant'?)
- More general partial orders could be appropriate.

Explicit relationships: more general partial orders

Tree



General PO



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⇒ analysis should be data-driven !

Explicit relationships: more general partial orders

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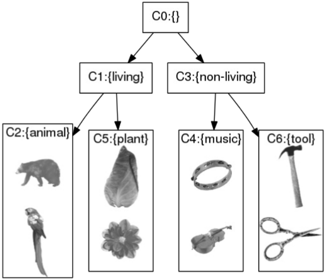

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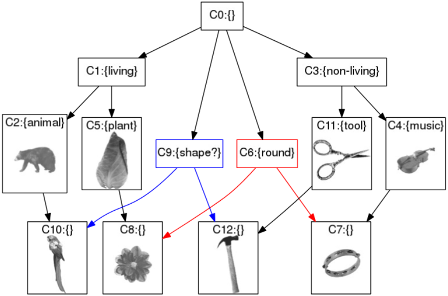


Trees may be too restrictive:

- Stimuli are also related by shape properties
- Trees cannot represent this (either 'round' or 'plant'?)
- More general partial orders could be appropriate.

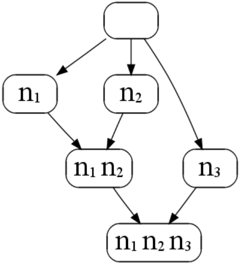
⇒ analysis should be data-driven !

Question 2: Is the neural code 'explicit' ?

Example: structure of a binary neural code

Assume a binary (or binarized) neural code. Neurons either fire or they do not fire.

activity pattern	neuron		
	n_1	n_2	n_3
p_1			
p_2	×		
p_3		×	
p_4			×
p_5	×	×	
p_6	×	×	×



Ordering example: $p_5 \leq p_2 \Leftrightarrow \{n_1, n_2\} \supseteq \{n_1\}$ [Földiák 2003]

Outline

1. Motivation
2. Formal concept analysis
   - Formal context, concepts and concept ordering
3. Human fMRI results
   - Experimental design
   - Feature extraction
   - Validation: similarity comparison

Formal concept analysis

Prerequisites for the application of FCA:
A (binary) relationship between

- *formal objects*, here: stimulus images
- *formal attributes*, here: BOLD responses from IT or V1 neurons

This relationship is called the *formal context*.

A formal context represented as an incidence table:

Stimulus	n_1	n_2	n_3
	×	×	
		×	
	×		
			×

Note: binary attributes for simplicity but conceptual scaling is possible.

Formal concepts

A **formal concept** is a maximal filled rectangle in the formal context, comprised of an **extent** (stimuli) and and **intent** (neurons/voxels).

Stimulus	n_1	n_2	n_3
	×	×	
		×	
	×		
			×

Stimulus	n_1	n_2	n_3
	×	×	
		×	
	×		
			×

Definition (Formal concept)

A *formal concept* $C = (A, B)$ is a subset of formal objects A, the *extent*, and a subset of formal attributes B, the *intent*, such that

- all objects in the extent A have all attributes in the intent B, and
- all attributes in the intent B share all objects in the extent A.

Concept order and lattice diagram

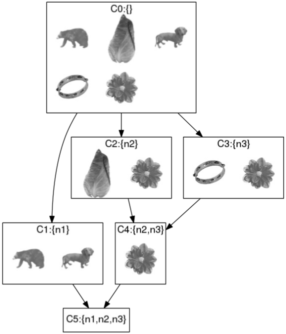
Definition (Concept order)

Let $C_1 = (A_1, B_1)$ and $C_2 = (A_2, B_2)$ be concepts of a context. Then

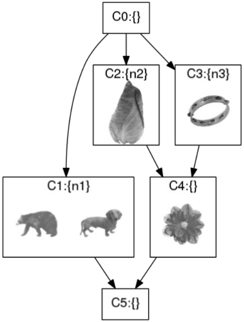
$$C_1 \leq C_2 \leftrightarrow A_1 \subseteq A_2 \leftrightarrow B_1 \supseteq B_2$$

This is a partial order $\Rightarrow$ DAG, Hasse diagram.

Full labeling



Reduced labeling



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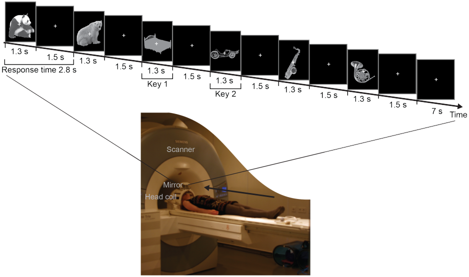
Experimental design



- Target detection task:
- silhouette or intact image
- indicated by keypress
- 48 sessions

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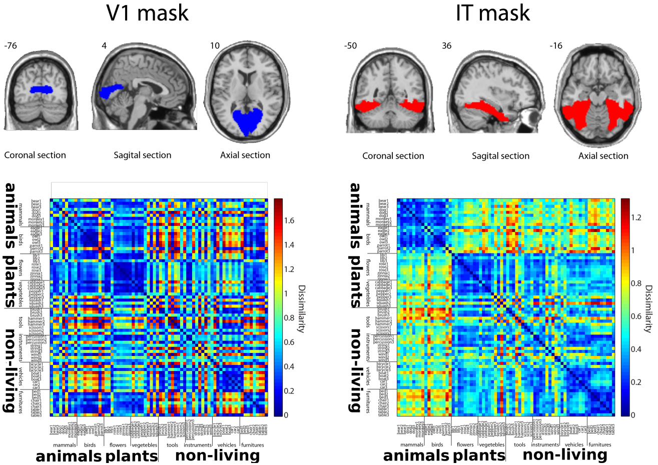
- 72 grayscale photographs as stimuli, animate and inanimate.
- **Animate**: mammals, birds, vegetables, flowers.
- **Inanimate**: furniture, vehicles, tools, musical instruments.
- Luminance equalized, size along main diagonal equalized.

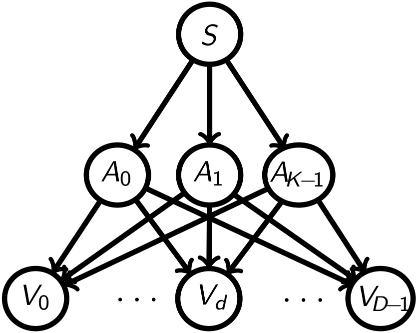
D. Endres, R. Adam, M.A. Giese, U. Noppeney, *Understanding the Semantic Structure of Human fMRI Brain Recordings With Formal Concept Analysis.*, In *ICFCA 2012, 10th International Conference on Formal Concept Analysis, LNAI 7278, Springer*, pages 96-111, 2012.

Regions of interest: IT vs. V1



- Dissimilarity measure: $1 - \rho$, ρ: Pearson corr. coeff.
- Blue: similar, red: dissimilar.

Feature extraction with hierarchical Bayesian classifier

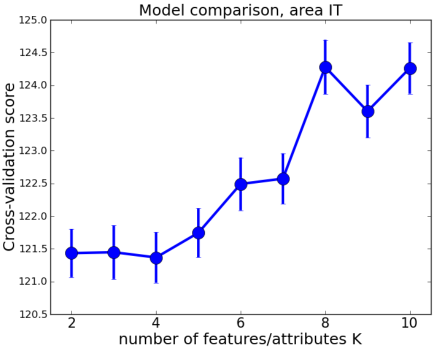


- S: stimulus label
- A_k: binary attributes
- V_d: voxel activations
- $p(A_k|S) \sim \mathrm{Ber}(p_{s,k})$
- $V_d = \sum_k \vec{f}_k A_k$
- $\vec{f}_k > 0$, gamma priors.
- Learning with simulated annealing and VBEM.

- Positivity of $\vec{f}_k$: more attributes $\Rightarrow$ more brain activity.
- Thresholded $p(A_k|S) \Rightarrow$ formal context.
- Pre-selection of 100 *most informative* voxels from each ROI.

Model selection

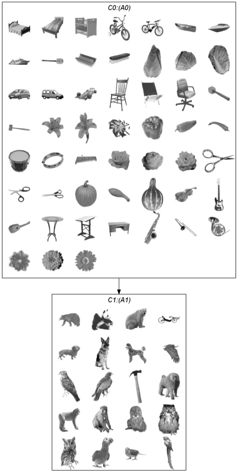
- 12-fold cross-validation.
- Held-out data always 4 complete sessions.
- Cross-validation score: joint log-density of voxels and stimulus labels.



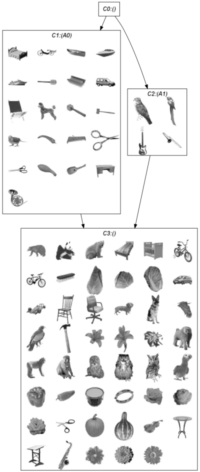
$\Rightarrow \approx$ 8 attributes are sufficient.

Concept lattices, IT vs. V1

Region IT



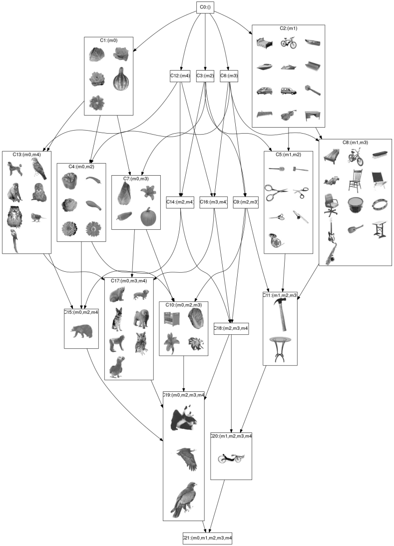
Region V1



- **C1**: animals (18/20)
- **C0**: non-animals (52/52)

- no clear separation

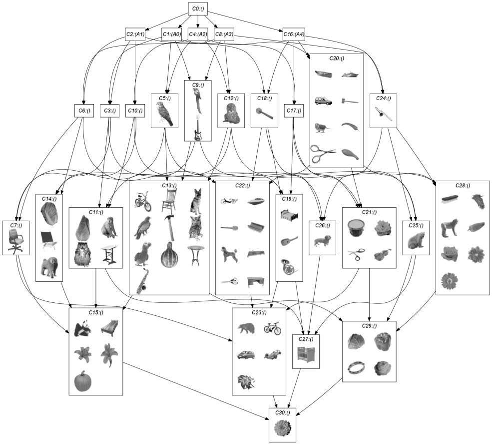
Concept lattice IT



- 5 attributes
- animals (m4): **C13** (7/7), **C15**, **C17** (7/7), **C19** (3/3)
- plants (m0): **C1** (5/5), **C4** (6/6), **C10** (3/4)
- tools, furniture, vehicles: **C2** (12/12), **C5** (13/13), **C5** (7/7), **C11** (2/2)
- **C20** recumbent bicycle. Why?

Concept lattice V1

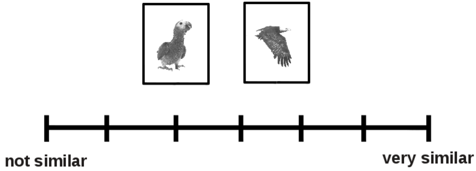
Region V1



- 5 attributes
- no clear high-level concepts
- but: 21 concepts introduce objects
- only 12 do in IT
- $\Rightarrow$ V1 is better classifier.
- Some concept seem to show low-level feature tuning.

Similarity ranking comparison

Subjects rated pairwise similarity btw. stimuli on a 7-point Likert scale:



- Compared subject's pairwise similarity ratings to the (partial) similarity ordering of stimuli induced by attribute sets.
- Contrast model by [Tversky 1977], formalized and extended in [Lengnink 1996]

Shared attributes: sim. ↑

Attributes:					
bird	X	X		X	X
owl	X			X	X
eagle		X			

Separating attributes: sim. ↓

Attributes:					
brush	X	X		X	X
handle					X

Some important properties of similarity

Similarity is not transitive / not metrical:

Similarities are not always comparable:

Comparable:

Incomparable:

Similarity ranking comparison

For stimuli $g_1, g_2, f_1, f_2 \in G$, let

- $\mathrm{sim}(g_1, g_2)$ be the subject's similarity rating, and
- $(g_1, g_2) \geq (f_1, f_2) \Leftrightarrow$ 'g_1 is at least as similar to g_2 as f_1 is to f_2'

We computed the **frequency** μ with which the following conditional holds:

$$\mathrm{sim}(g_1, g_2) \geq \mathrm{sim}(f_1, f_2) \text{ given } (g_1, g_2) \geq (f_1, f_2)$$

Definition (Similarity (partial) ordering)

Let $g_1, g_2, f_1, f_2 \in G$ be stimuli, and denote by
$(g_1, g_2) \geq (f_1, f_2) \Leftrightarrow$ 'g_1 is at least as similar to g_2 as f_1 is to f_2',
then

$$(g_1, g_2) \geq (f_1, f_2) \quad \Leftrightarrow \quad \begin{array}{l} g_1' \cap g_2' \supseteq f_1' \cap f_2',\ g_1' \cap \overline{g_2'} \subseteq f_1' \cap \overline{f_2'} \\ \overline{g_1'} \cap g_2' \subseteq \overline{f_1'} \cap f_2',\ \overline{g_1'} \cap \overline{g_2'} \supseteq \overline{f_1'} \cap \overline{f_2'} \end{array}$$

Similarity ranking comparison

Validation: with stimulus shuffling, i.e. randomizing the stimulus/attribute set assignments.

- K: number of attributes
- μ: frequency of: $\boxed{\mathrm{sim}(g_1, g_2) \geq \mathrm{sim}(f_1, f_2) \text{ given } (g_1, g_2) \geq (f_1, f_2)}$
- $\mu_0 \pm \sigma_0$: mean and std.dev. of frequency after randomization.
- z, p: normalized z-score and associated p-value.

K	μ	$\mu_0 \pm \sigma_0$	z	p
2	0.680	0.614 ± 0.006	11.907	0.000
3	0.711	0.614 ± 0.007	13.860	0.000
4	0.713	0.615 ± 0.008	11.749	0.000
5	0.755	0.617 ± 0.011	12.085	0.000
6	0.737	0.618 ± 0.013	9.254	0.000
7	0.735	0.619 ± 0.014	8.022	0.000
8	0.812	0.623 ± 0.017	11.007	0.000
9	0.815	0.624 ± 0.016	11.725	0.000
10	0.821	0.631 ± 0.019	10.132	0.000

$\Rightarrow$ for *all* K, μ is significantly above chance.

Conclusion

Question 1: How are relationships between represented information items reflected?
Answer: semantic relationships are represented by set overlaps of active voxels.

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Question 2: Is the neural code 'explicit' ?
Answer: to some degree, because

- *positive* voxel activations correspond to presence of meaningful binary features,
- sub/superordination relationships can be read off directly from the lattice diagrams,
- and similarity is preserved in the attribute structure.

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TODOs:

- Adaptation analysis
- Study individual differences vs. commonalities

Bibliography I

H.B. Barlow. *Single units and sensation: A neuron doctrine for perceptual psychology?*, Perception (1972), **1**(4) 371 – 394.

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D. Endres, P. Földiák and U. Priss *An Application of Formal Concept Analysis to Semantic Neural Decoding.*, Annals of Mathematics and Artificial Intelligence, **57**(3-4), pp. 233-248.

D. Endres, P. Földiák, and U. Priss. *An application of formal concept analysis to neural decoding*. In *Proceedings of the Sixth International Conference on Concept Lattices and Their Applications (CLA2008)*, Olomouc, Czech Republic, 2009. http://sunsite.informatik.rwth-aachen.de/Publications/CEUR-WS/Vol-433/.

D. Endres and P. Földiák, *Interpreting the neural code with formal concept analysis*, Advances in Neural Information Processing Systems 21 (D. Koller, D. Schuurmans, Y. Bengio, and L. Bottou, eds.), 2009, http://books.nips.cc/nips21.html, pp. 425–432.

D. Endres and P. Földiák, *Exact Bayesian bin classification: a fast alternative to bayesian classification and its application to neural response analysis*, Journal of Computational Neuroscience **24** (2008), no. 1, 24–35, DOI: 10.1007/s10827-007-0039-5.

P. Földiák, *Sparse neural representation for semantic indexing*, XIII Conference of the European Society of Cognitive Psychology (ESCOP-2003), 2003, http://www.st-andrews.ac.uk/~pf2/escopill2.pdf.

P. Földiák, *Neural Coding: Non-Local but Explicit and Conceptual*, Current Biology, **19**(19):R904-R906, 2009.

Bibliography II

- P. Földiák, D. Xiao, C. Keysers, R. Edwards, and D. I. Perrett, *Rapid serial visual presentation for the determination of neural selectivity in area STSa*, Progress in Brain Research **144** (2004), 107–116.
- Földiák, P.: Sparse coding in the primate cortex. In: Arbib, M.A. (ed.) The Handbook of brain theory and neural networks. MIT Press, Cambridge, MA, 2nd edn. (2002)
- B. Ganter and R. Wille, *Formal concept analysis: Mathematical foundations*, Springer, 1999.
- G. E. Hinton, *Products of experts*, Ninth International Conference on Artificial Neural Networks ICANN 99, ICANN, no. 470, 1999.
- R. Kiani, H. Esteky, K. Mirpour, and K. Tanaka, *Object category structure in response patterns of neuronal population in monkey inferior temporal cortex*, Journal of Neurophysiology **97** (2007), no. 6, 4296–4309.
- N. Kriegeskorte, M. Mur, D.A. Ruff, J. Bodurka, H. Esteky, K. Tanaka, and P.A. Bandettini, *Matching categorical object representations in inferior temporal cortex of man and monkey*, Neuron **60** (2008), no. 6, 1126–41.
- Lengnink, K.: Formalisierungen von Ähnlichkeit aus Sicht der Formalen Begriffsanalyse. Ph.D. thesis, Technische Hochschule Darmstadt, Fachbereich Mathematik (1996)
- Thomas Naselaris, Dustin E. Stansbury, and Jack L. Gallant, *Cortical representation of animate and inanimate objects in complex natural scenes*, Journal of Physiology-Paris (2012), no. 0, –, in press.
- Olshausen, B.A., Field, D.J.: Emergence of simple-cell receptive field properties by learning a sparse code for natural images. Nature 381(6583), 607–609 (1996)

Bibliography III

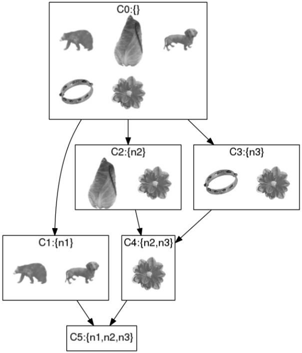
R. Q. Quiroga, L. Reddy, C. Koch, and I. Fried, *Decoding Visual Inputs From Multiple Neurons in the Human Temporal Lobe*, J Neurophysiol **98** (2007), no. 4, 1997–2007.

Tversky, A.: Features of similarity. Psychological Review 84(4), 327–352 (1977)

R. Wille, *Restructuring lattice theory: an approach based on hierarchies of concepts*, Ordered sets (I. Rival, ed.), Reidel, Dordrecht-Boston, 1982, pp. 445–470.

Product-of-experts code

- Each expert represents a constraint [Hinton 1999].
- A stimulus is encoded by stating which constraints it fulfills.
- In FCA, an concept can be specified by stating which other concepts it is subordinate to.



⇒ flower is both in the 'plant' concept and in the 'round' concept.

Familiarity ranking comparison

- Compared stimulus ordering by attribute sets with subject's familiarity ranking
- Ranking on 7-point Likert scale (1-low, 7-high)
- Let $g_1, g_2 \in G$ be two stimuli, and
- $\mathrm{fam}(g)$ the subject's familiarity ranking.

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If the attribute set inclusion order reflects the familiarity ranking, then the conditional

$$\mathrm{fam}(g_1) \geq \mathrm{fam}(g_2) \text{ given } g_1' \subseteq g_2'$$

should be true in (above chance) many instances.

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should be true in (above chance) many instances.
The reason for choosing the direction of the inequality signs is the *sparse and efficient* coding hypothesis: less familiar stimuli are encoded with more neural effort [Olshausen & Field 1996, Földiák 2002].

Familiarity ranking comparison

Validation: with stimulus shuffling, i.e. randomizing the stimulus/attribute set assignments.

- K: number of attributes
- μ: frequency with which conditional holds across all pairs of stimuli.
- $mu_0 \pm \sigma_0$: mean and std.dev. of frequency after randomization.
- z, p: normalized z-score and associated p-value.

K	μ	$\mu_0 \pm \sigma_0$	z	p
2	0.672	0.573 ± 0.023	4.409	0.000
3	0.682	0.572 ± 0.027	4.062	0.000
4	0.630	0.572 ± 0.028	2.077	0.019
5	0.611	0.572 ± 0.034	1.143	0.127
6	0.653	0.572 ± 0.042	1.919	0.027
7	0.685	0.572 ± 0.060	1.901	0.029
8	0.631	0.572 ± 0.051	1.155	0.124
9	0.657	0.572 ± 0.061	1.379	0.084
10	0.635	0.572 ± 0.077	0.816	0.207

$\Rightarrow$ for most K, μ is significantly above chance.