Vision in Human and Machine

Part 4
Perceptual Feature Learning

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Contents

Motivation

- Identification
  - Decision about unique identity
  - Generalization across invariances
  - Well-defined static process
- Categorization
  - Generalization across members of a class of objects with different shapes
  - Categories are subject to rapid dynamical shifts
  - Conceptual knowledge
- Learning is crucial for both processes
  - Investigate learning mechanisms to understand the representations in the brain

Learning and Representation

- Learning dynamics and performance heavily depends on representation
- Example: View-based object recognition
- Tarr et al investigated the learning of „novel" objects to refuse Biederman's recognition-by-components hypothesis
- Only recognition of well-known objects is viewpoint invariant

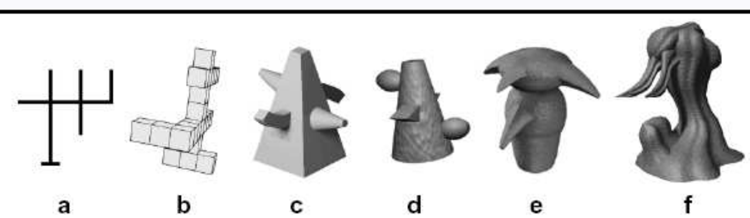
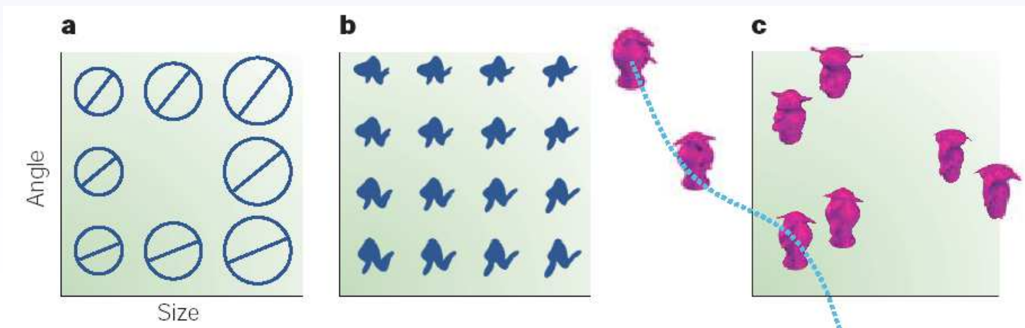


Figure 1. The evolution of the novel stimulus in our lab.

Features and Feature Spaces

- Assumption: Objects and categories are represented in a multidimensional ordered psychological space
- Features can be set apriori (color, texture, etc.) or by multidimensional scaling
- Categorization is performed based on metrical information in the feature space



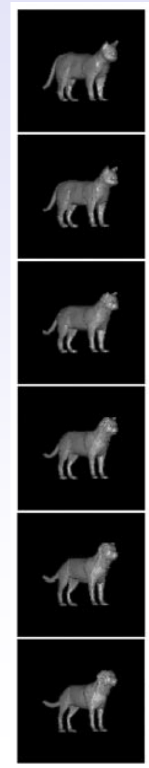
Perceptual Learning

- Acquired change to a perceptual system to improve its ability to respond to the environment
- Perceptual learning modifies the perception of features:
  - *Attentional weighting:* Feature relevance
  - *Imprinting:* Introduce new specialized features
  - *Differentiation:* Separate previously indistiguishable features
  - *Unitization:* Merge separate features into one
- Takes place on an intermediate time-scale
  - But effects can be quite long-lasting
  - Immediate transfer to new learning tasks
- Generally assumed to modify early stages of cognition: Prior to high-level reasoning
  - Can be proved only in experiments with high time resolution
    - Color processing before after-images occur (Goldstone 1995)
    - Silhouettes of familiarized objects influence recognition before figure-ground segmentation is completed (Peterson & Gibson 1994)

Attentional Weighting

- Saliency of features can be modified depending on prediction of experimental categories
- „Latent inhibition": Features that are originally varied independent of reward are later more difficult to associate with reward
- Categorical Perception: People are better able to distinguish between physically different stimuli when the stimuli come from different (acquired) categories than when they come from the same category
- Dimensions are sensitized at the category boundary

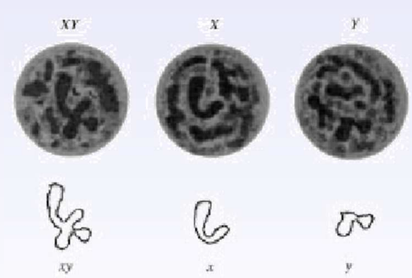
Cat-like



Dog-like

Stimulus Imprinting

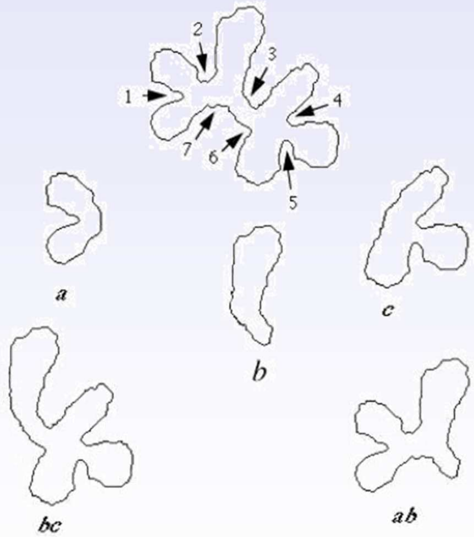
- Categorization performance increases with frequency of stimulus presentation
- This effect is transferred to novel, but similar stimuli
- Whole features can be imprinted
  - If a part was useful for recognition this is directly transferred to a new categorization task
- Topological imprinting
  - A spatial multi-dimensional mapping is created
  - Topographical maps (e.g. SOMs)

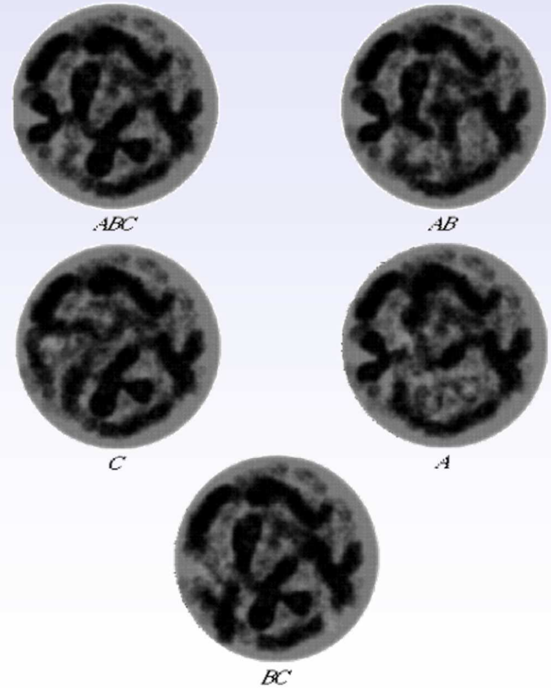


(„Martian cells", Schyns et al 1997)

Schyns & Rodet 1997

- "Martian Cells" as a model for feature learning

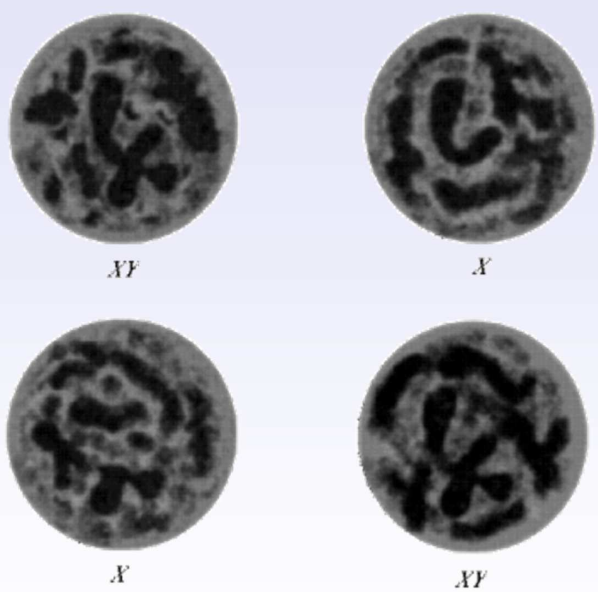




Schyns & Rodet 1997

Group 1 (XY→X)

Group 2 (X→XY)



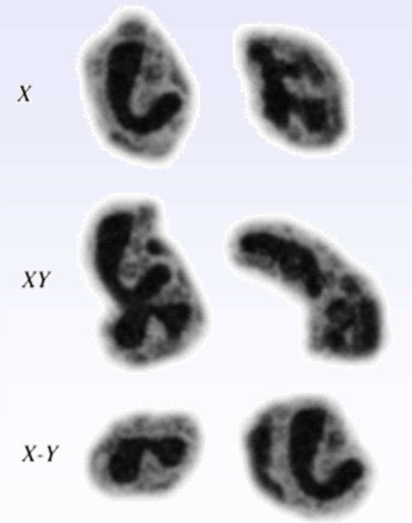
Features (XY,X) ?

Features (X,Y) ?

Two categories to distinguish:
X and XY

Schyns & Rodet 1997

Sequential presentation	Group 1 (XY→X) (XY, X) ?	Group 2 (X→XY) (X, Y) ?

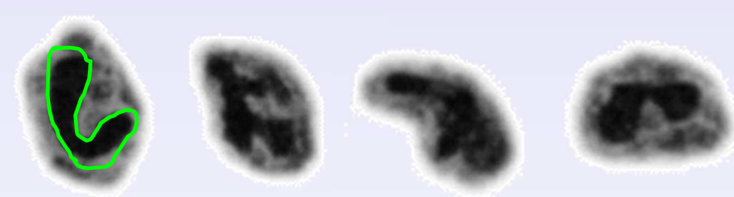


	Group 1 (XY→X) (XY, X) ?	Group 2 (X→XY) (X, Y) ?
X	X: 97% XY: 03%	X: 94% XY: 06%
XY	X: 19% XY: 81%	X: 19% XY: 81%
X-Y	X: 84% XY: 16%	X: 44% XY: 56%

Schyns & Rodet 1997

“What did you see for making your category decision ? – Please lineout”

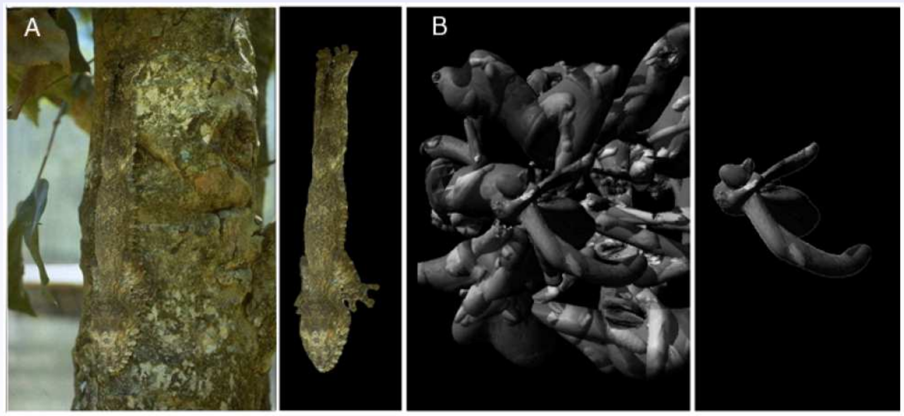
Group 1 (XY→X)
(XY,X) !



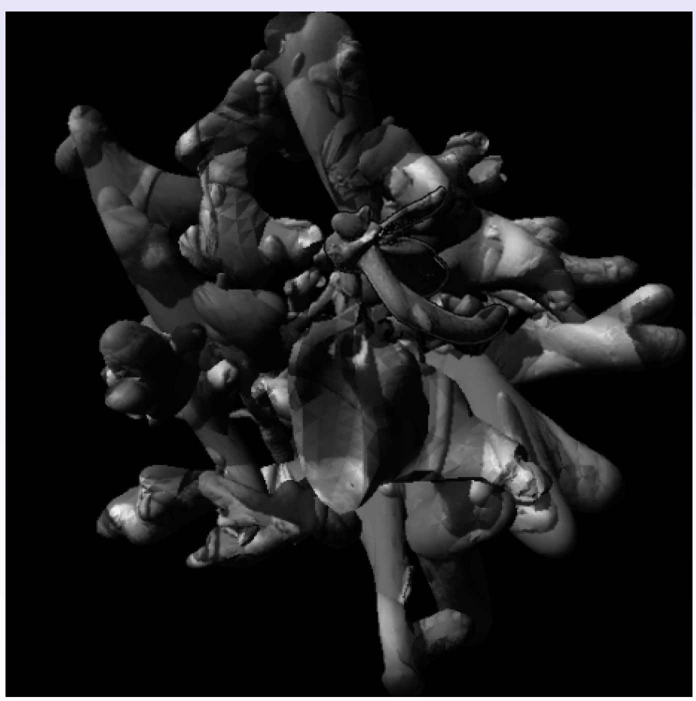
Group 2 (X→XY)
(X,Y) !

Learning objects in camouflage

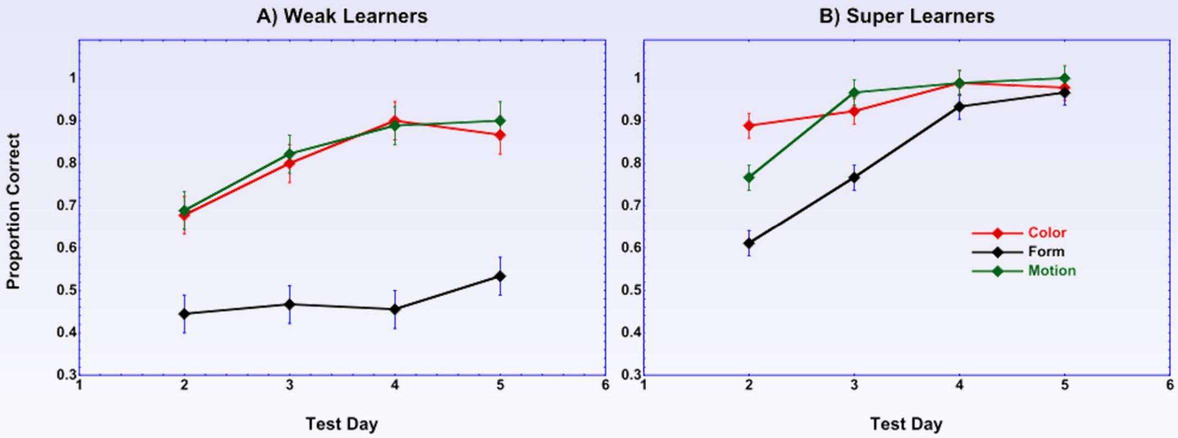
Can humans learn artificial objects without any segmentation cue ?)



Brady & Kersten (2002)



Performance Results



Differentiation vs Unitization

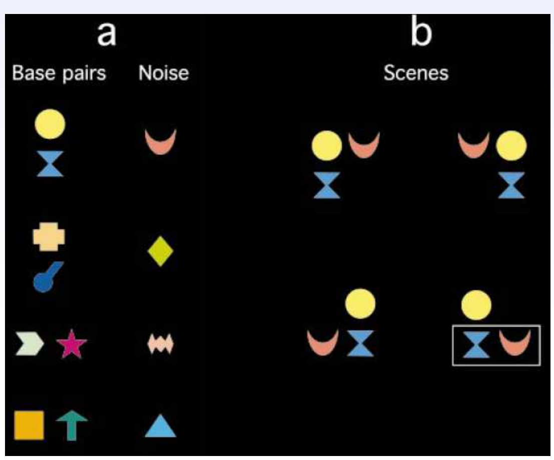
- Differentiation
  - Single feature dimensions can be differentiated
    - Increase neural specificity
    - Recruit more representational resources
  - Categories are substructured
- Unitization
  - Construction of single features out of complex feature combinations
  - Partial features are unitized if they co-occur frequently
- Unitization and differentiation are competing processes

Experiments on unsupervised „imprinting"

- Collection of psychophysical experiments on feature learning by Fiser & Aslin

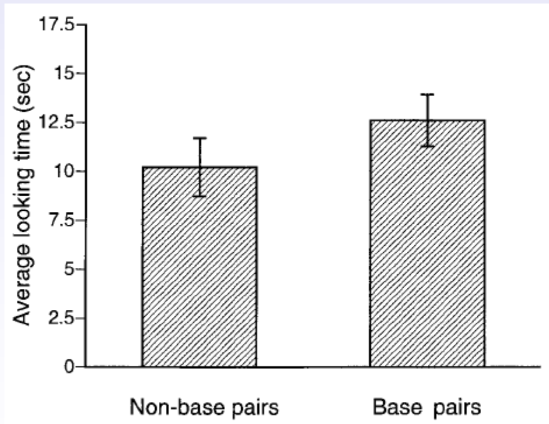
Training phase

- 9 Month old infants
- Training: 4 Base pairs, looming presentation to attract interest, show until habituation threshold is reached



Results

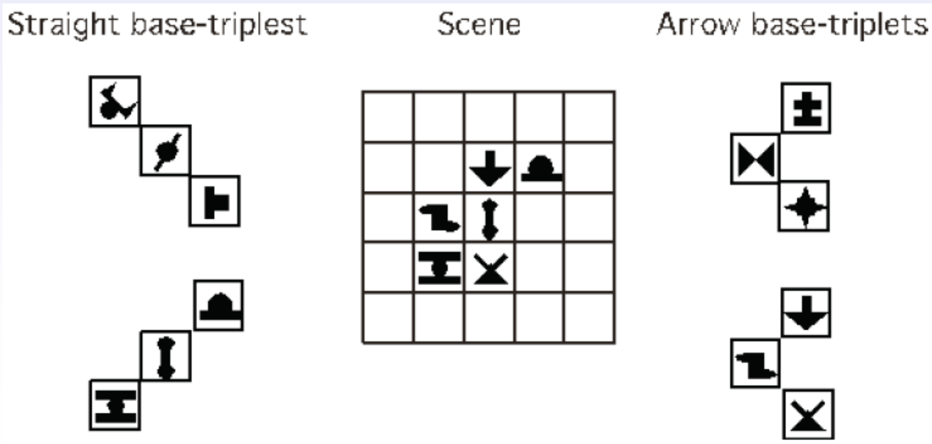
- Looking preference for base pairs is significantly higher



Compositionality and Embedding

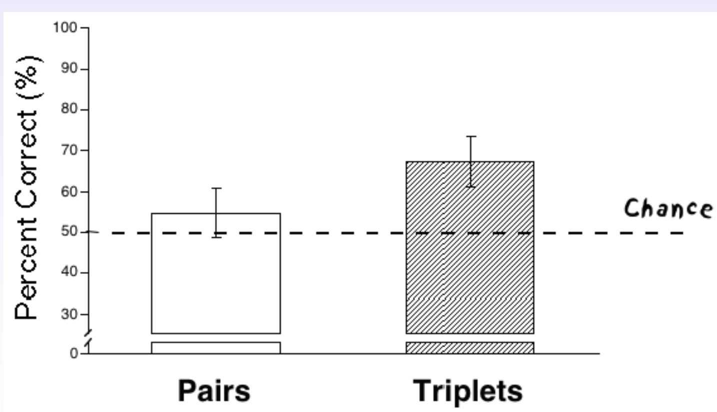
Training phase

- Patterns are composed of 4 base triplets



Key result

- Testing: 2 AFC paradigm, show triplets that are either base triplets or unknown triplets
- Show pairs, that are either parts of the base triplets or unknown



- Result: Embedded part features are not available for the familiarity discrimination

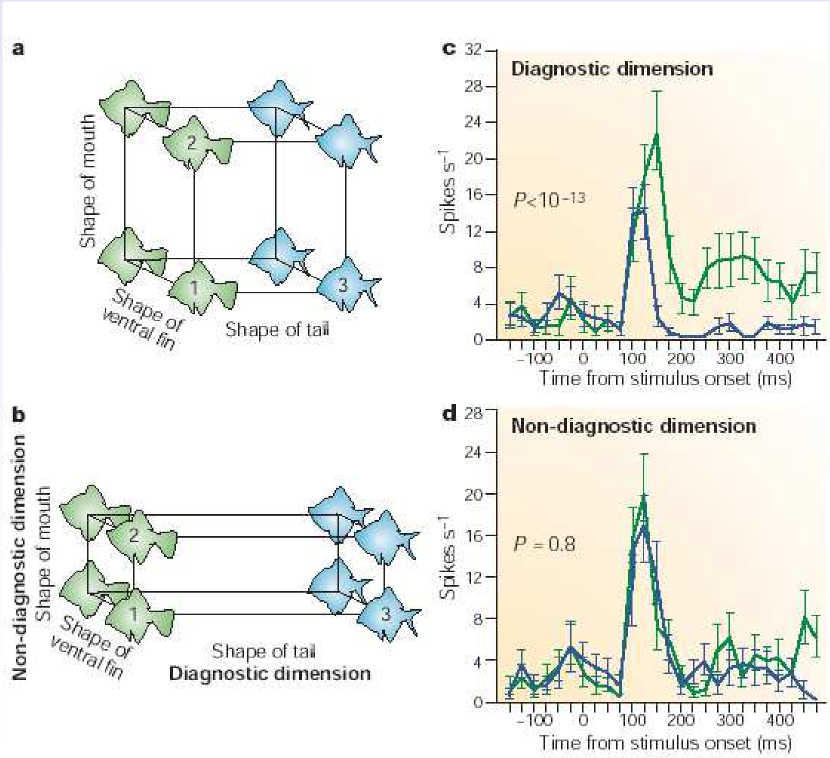
Cross checking

- Does the experimental setup prevent learning of pairs ?
  - If the training scenes are composed of 6 base pairs, learning of pairs is highly significant
- Is learning of triplets and base pairs at the same time difficult ?
  - If 3 base pairs and 2 triplets are used during training, both can be learned

Beer Perception

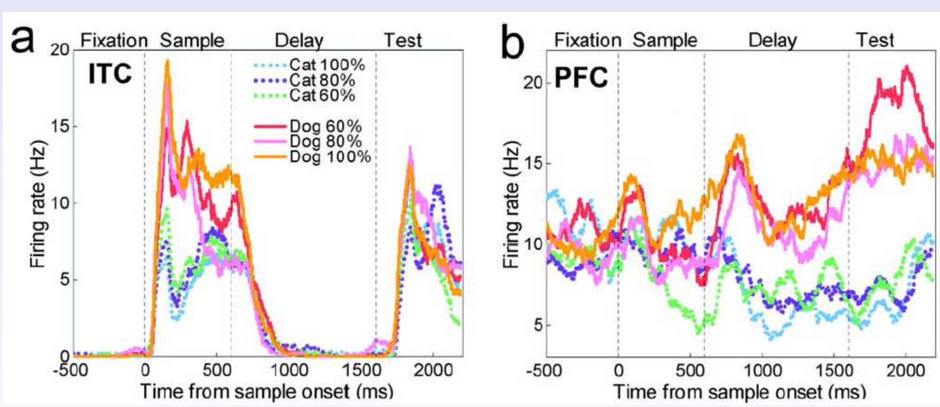
- Experience with tasting beers improves beer classification, while increased experience only with beer-flavor terminology does not (Peron & Allen 1988)
- After two year training on a set of beers, subjects are better than novices on tasting beer discrimination and matching. This does not generalize to novel types of beer. If verbal descriptions are used, generalization to new beers can be observed (Chollet et al 2004)
- Perceptual generalization can be more limited than verbalized cognitive generalization

Feature shaping in Inferotemporal Cortex



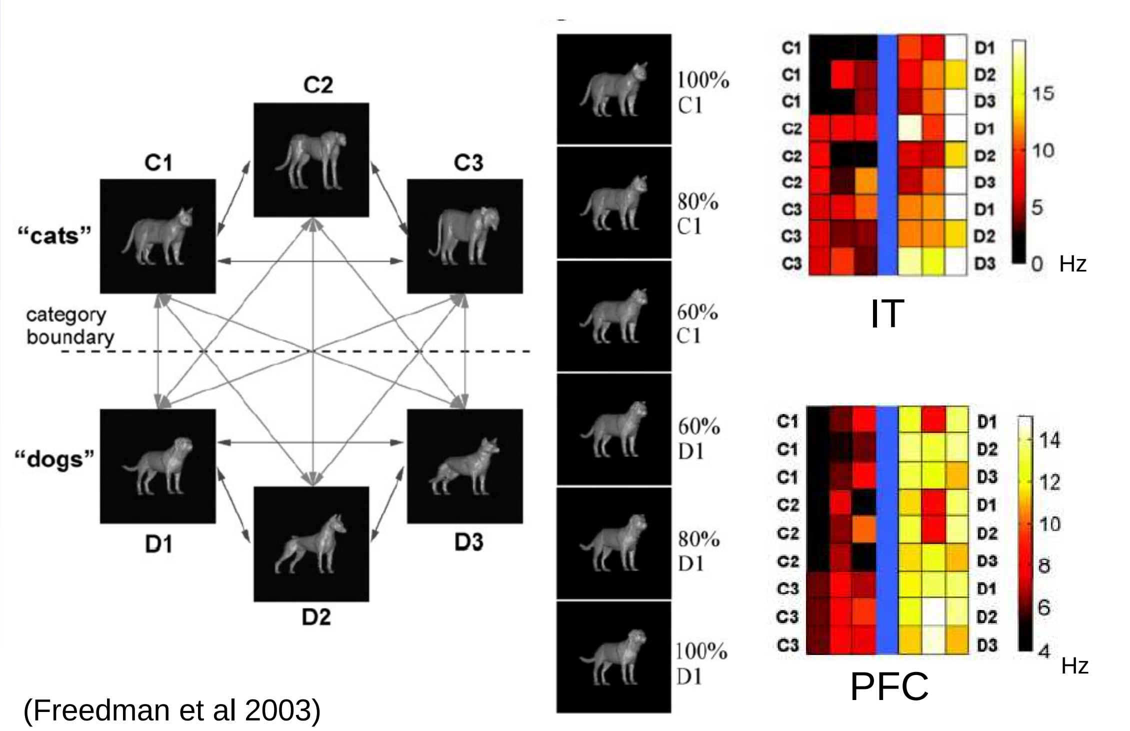
(Sigala & Logothetis 2002)

Categorical Perception in IT and Prefrontal Cortex



(Freedman et al 2003)

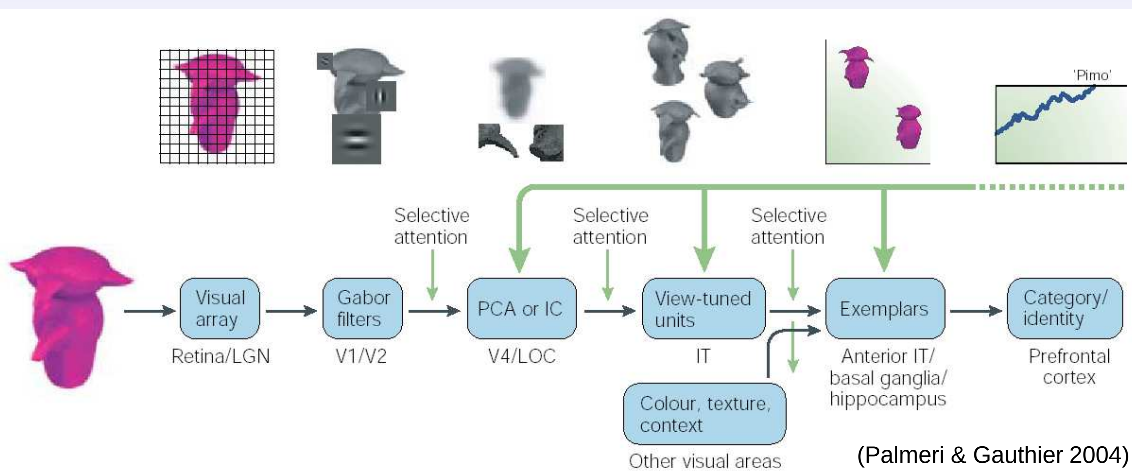
Categorical Perception in IT and PFC



(Freedman et al 2003)

View-based models

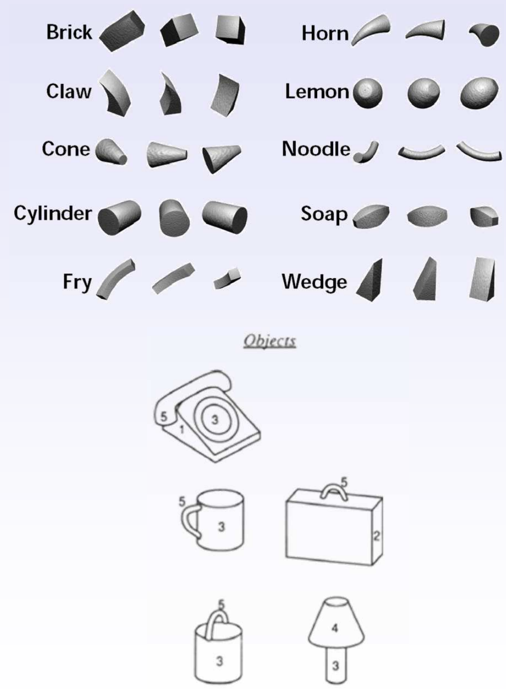
- View-based models favour exemplar-based object representations
- Contrary to recognition-by-components (geons)
- Generalization is the main argument for structural decomposition



(Palmeri & Gauthier 2004)

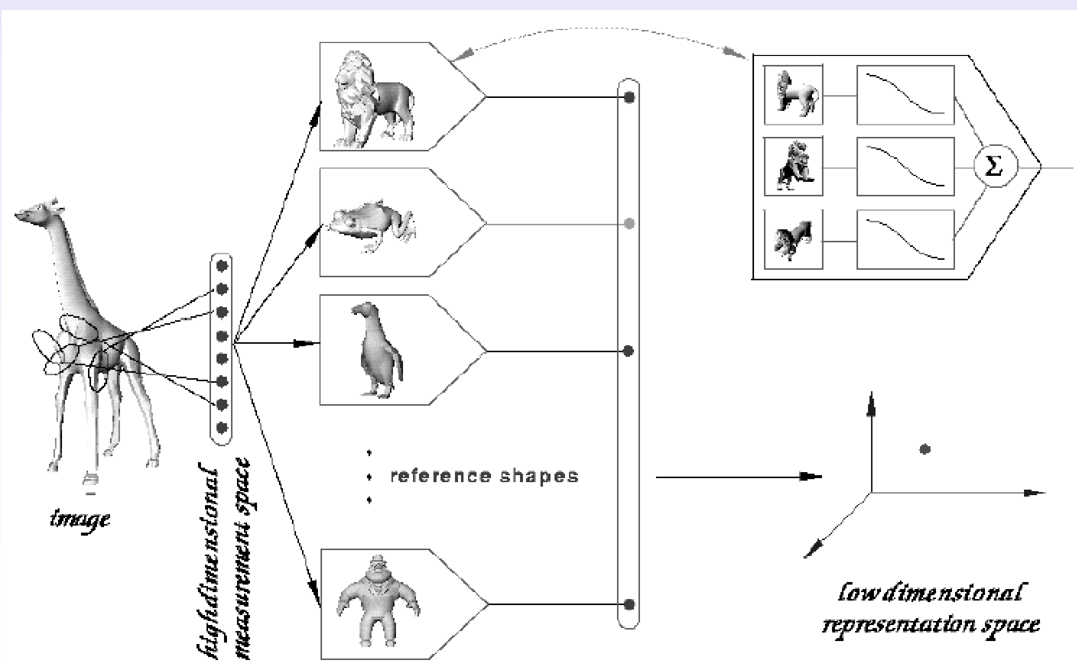
Structuralist vs Appearance Models

- Structuralists claim that recognition and especially categorization is performed by comparison of structural primitives
- But even recognition of single geons is strongly view-point dependent (Tarr et all 1998)
- When novel shapes are learned rather view-dependent than structural generalization behaviour is observed (Tarr, Bülthoff)



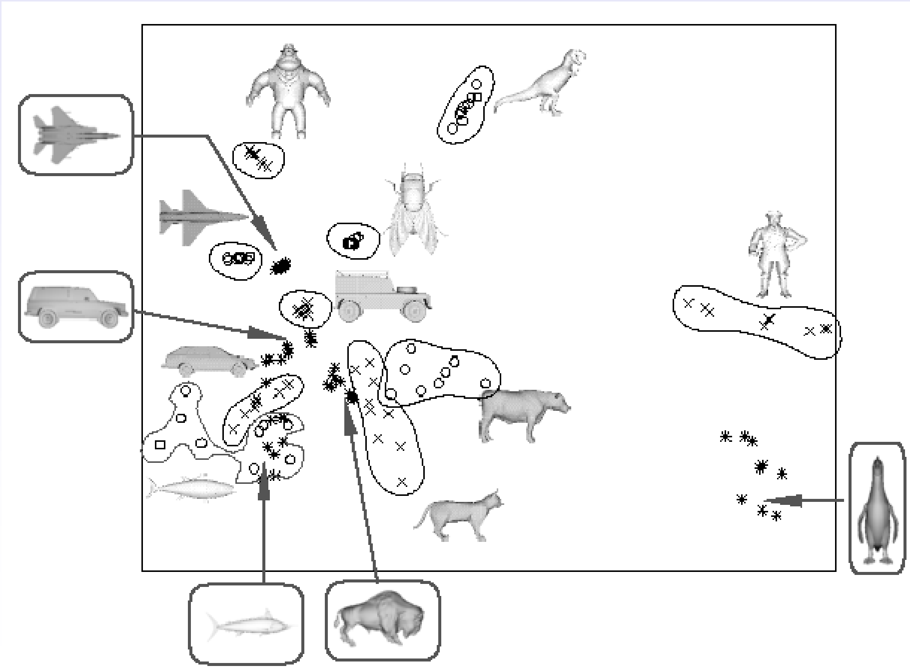
Chorus of Prototypes (Edelman 1999)

- Use distances to prototypes for defining metrics - RBF



Chorus of Prototypes (Edelman 1999)

- Multidimensional scaling of gabor features and orientation



Summary

- Categorization is a highly dynamic process that involves both perceptual (low-level) and cognitive (high-level) processes
- The feature concept can describe categorization processes using multidimensional spaces
- Perceptual learning covers processes that shape features and thus influence perception of categories
- The investigation and modeling of object category learning provides important insight into the nature of object representations