Summary

- Structured representations are important
  - Abstract
  - Recursive
  - Generative

- New primitive concepts can be learned
  - Learning the most parsimonious theory

- How to combine structured representations and statistical inference?
  - Statistical parsing in language
  - Statistical grammar induction
  - Probabilistic inferences about kin relations.
  - Statistical learning of relational concepts and theories.
Outline for today

• The debate about structure in people’s mental representations of concepts
  – Hierarchies or hidden units?
  – Logical relations or hidden units?
  – Definitions or prototypes?

• Probabilistic inference
Semantic networks
(Quillian, 1968)

Why semantic networks?

• Economical encoding of information.
  (a big deal in 1968.)

• Supports generalization.
  – If you learn that a draxel is a bird, you can expect that a draxel has wings, can fly, and has feathers.
Inferring mental structure through reaction times (Collins & Quillian, 1969)

General finding: the more of the hierarchy a relation spans, the longer it takes to verify.

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Reaction time data

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“Cleaned up” reaction time data

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Reaction time data

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Problems

• Typicality effects.
  – “robin is a bird” faster than “chicken is a bird”.

• Violations of hierarchy for atypical items.
  – “chicken is an animal” faster than “chicken is a bird.”

• Rosch: Graded prototype representations more important than all-or-none “is a” relations.
Problems

• Typicality effects.
  – “robin is a bird” faster than “chicken is a bird”.

• Violations of hierarchy for atypical items.
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• But do these problems require us to give up on “is a” hierarchies?
Possible solutions

• We have multiple trees, a default and some alternative hypotheses.
  – In default tree: chicken falls under bird.
  – In alternative tree: chicken falls under animal.
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• The word “bird” maps onto two nodes, one referring just to typical birds and the other to all birds.

• Deny that prototype effects are diagnostic of core representations.
• Prototype ratings and reaction time effects for clearly definitional concepts shows that these data are not diagnostic of conceptual structure.

Why not give up on a definitional core for concepts?

• Reasoning, e.g., “Consider a new person, Boris.”
  – Is the mother of Boris’s father his grandmother?
  – Is the mother of Boris’s sister his mother?
  – Is Boris’s uncle his grandfather?
  – Is the son of Boris’s sister his son?

• Compositionality in concepts and language
  – e.g., Greatgrandmother = mother of a grandparent.
  – “Colorless green idea”
  – “Big”
Why not give up on a definitional core for concepts?

- Even without definitions, need a distinction between typicality and degree of membership.
  - At some level we know for certain that chickens are birds. (Consider a bet....)
  - Some categories really are graded in their membership:
    - green or blue?
    - cup or bowl?

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Other problems for all-or-none semantic relations

• Graded generalization
  – Which is a stronger inference?

  Canaries have sesamoid bones.
  All birds have sesamoid bones.
  Chickens have sesamoid bones.
  All birds have sesamoid bones.

  – More of a problem, as generalization is the main function that “is a” hierarchies are supposed to fulfill.

• Others?
An alternative architecture

• Semantic networks are symbolic:
  – encode discrete, localized bits of knowledge.

• Neural networks are subsymbolic:
  – inspired by long-term memory in the brain (synaptic plasticity).
  – graded representations that can approximate symbolic models, e.g., “is a” hierarchies, while still capturing prototypicality.
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Training set

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Learned distributed representation

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Generalization test

• Train on one fact for new object:
  – Draxel ISA bird

• Network then believes that a Draxel has other properties in common to most other birds . . .
  – can fly, has wings, has feathers.

• . . . but not properties distinctive to individual birds (e.g., is red or is yellow).
Hierarchical structure in conceptual development

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Development of hierarchy in network

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Problems

• Collapses typicality and graded membership.
  - *Chicken* activates the *Bird* unit less than *Canary* does.
  - But recall:
    - At some level we know for certain that chickens are birds.
    - Some categories really are graded in their membership:

Image removed due to copyright considerations. cup or bowl?
Problems

• Requires special care in training.
  – Lots of training data, must be randomly interleaved throughout training.
  – Potential for “catastrophic interference” when learning a new fact, without freezing weights.
  – As knowledge base grows, need to add hidden units (to preserve bottleneck ratio for good generalization).
  – When learning a novel proposition, “blickets may queem”, some controller needs to specify that blicket initializes a new input node, queem a new output node, and may a new relation ndoe.
Problems

• Doesn't know certain obvious things unless explicitly trained:
  – “A bird is a bird”: we don't have to check that fact the same way we check “a bird is an animal”.
  – “A blicket is a blicket”.
  – If these are living things, they are either plants or animals. If animal, they are some kind of animal -- not “just” an animal.
  (i.e., Must initialize an unlabeled node under animal, which is then a candidate word meaning.)
Fodor and Pylyshyn: What’s missing from connectionism?

• Systematicity
  – The thoughts a cognitive system is capable of are not a random collection (like the phrases in a tourist’s foreign language-phrasebook) but a systematic set (like the sentences that can be produced by a fluent speaker of a language).
  – If it can think *Sandy loves Kim*, then it can entertain the thought *Kim loves Sandy.*
Learning family relationships
(Hinton, 1986)

• Tree structure generates relations:

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Learning family relationships
(Hinton, 1986)

• Network architecture:

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Learning family relationships
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• 112 possible facts of the form:
  \(<\text{person1, relation, person2}>\)
  \(<\text{Christopher, father-of, Victoria}>\),
  \(<\text{Colin, son-of, Victoria}>\),
  \(<\text{Jennifer, aunt-of, Colin}>\) . . .

• Trained on 108 examples, network usually generalizes well to the other 4.
  – Doesn’t work with less training.
Learning family relationships  
(Hinton, 1986)

• Does this really count as systematicity?
  – With so much training required, and so little generalization ability?
  – Every time you learn about a new person, still need an external controller to add that person to both the input layer and output layer. That’s the real source of systematicity.
Linear Relational Embedding

- Minor improvement, from 4 to 8 or 12 generalization trials.
Learning family relationships
(Hinton, 1986)

• Problem: Consider a new person, Boris.
  – Is the mother of Boris’s father his grandmother?
  – Is the mother of Boris’s sister his mother?
  – Is Boris’s uncle his grandfather?
  – Is the son of Boris’s sister his son?
A Big open question

- How to integrate abstract knowledge with probabilistic (or typicality-based) reasoning?
  - Is the son of Boris’s sister his son? *(Note: Boris and his family were stranded on a desert island when he was a young boy.)*
  - Is Boris’s son his wife’s son?
  - Boris has five aunts. How many cousins does he have?
A challenge for either approach

• “Because Sarah loves him, John hates Bill.”
  – Who does “him” refer to?
  – How to represent this thought?
• Two hypotheses:
  \[
  \text{cause(loves(Sarah,Bill), hates(John,Bill))} \\
  \text{cause(loves(Sarah,John), hates(John,Bill))}
  \]

• Why prefer the first?
  – Inference rules:
    \[
    \text{implies(and(cause(x,y), cause(y,z)), cause(x,z))} \\
    \text{implies(cause(and(x,y),z), cause(x,z))}
    \]
  – Beliefs with high probability:
    \[
    \text{cause(and(loves(x,y), loves(y,z), not(loves(y,x))), jealous(x,z))} \\
    \text{cause(jealous(x,y), hates(x,y))}
    \]
  – First hypothesis would be true if:
    \[
    \text{loves(John,Sarah)} \\
    \text{not(loves(Sarah,John))}
    \]
  – No such simple explanation for second hypothesis.
So...

... why do we keep having this debate: rules/symbols vs. prototypes/connections?

Other cases:
  – Language acquisition and processing, e.g. past tense
  – Schemas and scripts for events and actions
  – Visual object recognition and scene perception
So...

... why do we keep having this debate: rules/symbols vs. prototypes/connections?

... and why do none of the standard approaches seem to be satisfying?
So...

The real problem: a spurious contest between logic and probability.

– Neither logic nor probability on its own is sufficient to account for human cognition:
  • Generativity
  • Systematicity
  • Recursion and abstraction
  • Flexibility
  • Effective under great uncertainty (e.g., sparse data)

– What we really need is to understand how logic and probability can work together.
So...

The real problem: a spurious contest between logic and probability.

- A confusion between knowledge representations and inference processes:
  Gradedness or fuzziness doesn’t necessarily mean that the knowledge representations lack structure or rules -- merely that the inference processes incorporate uncertainty.

- Probabilistic inference over structured representations is what we need.