COGS 200: Introduction to Cognitive Systems

Bob Woodham

Department of Computer Science
University of British Columbia

Lecture Notes 2014/2015 Term 1

14W1: September–December, 2014

Review: Knowledge Representation (KR)

Questions Bob posed for any KR scheme:

1. What "language" is being used?
2. What knowledge is represented explicitly by a given set of expressions in the language?
3. What inference mechanism is available to make explicit knowledge which is implicit in the given set of expressions?

Questions Laurie and Chris added to the discussion:

4. How is the knowledge represented?
5. How is inference done?

Review: Knowledge Representation (KR)

Questions Bob posed for any KR scheme:

1. What “language” is being used?
2. What knowledge is represented explicitly by a given set of expressions in the language?
3. What inference mechanism is available to make explicit knowledge which is implicit in the given set of expressions?

Questions Laurie and Chris added to the discussion:

4. How is the knowledge represented?
5. How is inference done?

Review: Knowledge Representation (KR)

Questions Bob posed for any KR scheme:

1. What "language" is being used?
2. What knowledge is represented explicitly by a given set of expressions in the language?
3. What inference mechanism is available to make explicit knowledge which is implicit in the given set of expressions?

Questions Laurie and Chris added to the discussion:

4. How is the knowledge represented? (in the brain)
5. How is inference done? (in the brain)

Review (cont'd): Knowledge Representation (KR)

Chris quote, October 28, 2014,

> *"COGS stumbles over what we mean by model"*

1. Competence versus Performance
2. Description versus Explanation
3. Psychological Reality
4. Marr's three levels (September 11, 2014, lecture)

Knowledge Representation in Machine Learning

1. Knowledge is represented in the form of probability distributions
2. Inference is done by numerical computation (to combine/update probability distributions into new probability distributions)
3. Bayes' theorem plays a central role in statistical inference

Bayes' Theorem (aka Bayes' Rule)

Let H be the hypothesis (i.e., belief) and let E be the evidence

likelihood

prior probability

$$P(H \mid E) = P(H)\,\frac{P(E \mid H)}{P(E)}$$

posterior probability

unconditional probability
(marginal likelihood)

Assignment 3 Question 8

Let H be the hypothesis that the student originally transferred from the Wednesday lab is male

Let E be the evidence that the student subsequently selected from the Monday lab is male

P(H) is calculated based on information stated in the problem

P(H|E) is calculated using Bayes' theorem

Interpretation: Evidence, E, updates the probability of the hypothesis, H, from P(H) to P(H|E)

“Big Data”

Corpora (from which probability distributions can be estimated)

Approach	Example
Structured	Cyc NTT’s ALT-JE
Semi-structured	Wikipedia
Unstructured	Google (the entire WWW)

Representation of Linguistic Knowledge

Two "ways" to represent linguistic knowledge

1. Generative approach (linguistic knowledge in the mind)
   - There is a grammar
   - Language is the set of strings generated by the grammar
   - A speaker's knowledge of language consists of that grammar
2. Exemplar approach (linguistic knowledge from input)
   - Creates utterances by re-using pieces (of any size) previously recorded

Generative view: Representation of linguistic knowledge is **NOT** a surrogate (for world knowledge). You **DO** have language in your head. What is in your head **IS** language

Representation of Linguistic Knowledge

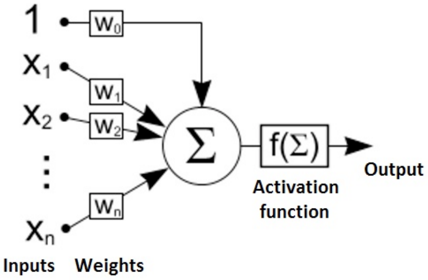
Generative Grammar

- Phrase structure, transformations
- Smallest, independent
- Phrase structure rules, transformations
- Generate linguistic experience
- Corpus: intuitive judgments
- "Goodness" = intuition

Exemplar Theory

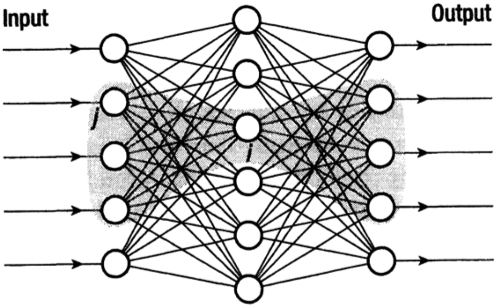
- Well-formed linguistic representation
- Subtrees, any size
- De-composing, composing operations
- Record/re-use all linguistic experience
- Corpus: linguistic input
- "Goodness" = probability

Connectionism: McCulloch–Pitts Neuron



Aside: As a (potential) hardware computing element, the McCulloch–Pitts neuron is “universal” in that it can be used to implement Boolean operations AND, OR and NOT

Connectionism: Neural Network



This example is a fully connected, three layer, feed forward neural network with five input nodes, five output nodes and six middle layer (i.e., hidden) nodes

Features of Connectionist Representation

1. Distributed: Each of the representations generated is composed from several computationally independent parts of the system
2. Overlapping: The different representations generated are composed from overlapping parts
3. Holographic: Any part of any given representation carries information about every part of the content represented by it
4. Learning: If a given neural network can perform a task then it can be trained to perform that task automatically (from examples)

Challenges to Connectionist Representation

1. There is no "universal" connectionist architecture. That is, there is no neural network that is capable of simulating the behaviour of any other neural network
2. For an arbitrary Turing computable task, one can not determine if there exists a neural network capable of performing that task
3. The number of training examples and the number of iterations required for back propagation to converge do not scale well with the size (i.e., with the number of nodes) of a fully connected neural network, even for tasks that the network can perform
4. Successful deployment of neural networks remains an art, involving restrictions on the number of nodes in one or more of the hidden layers and restrictions on the degree of connectivity between nodes in one layer to the next