Rule-Based AI

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Outline

• Background

• Early attempts

• Expert systems

• Conclusions
Rules

• If X then Y
  • If it is a federal holiday, then there are no classes.

• All X are Y
  • Baseballs are round

• To do X, one must first do Y
  • Requesting leave requires submitting a form
Inference

Rules and facts
• If something is round, then it can roll away.
• A baseball is round.

Conclusion
• A baseball can roll away.
Components of a rule-based AI

- Facts+Rules
- Inference engine
- Working memory
- User interface
Tools of the trade

**Prolog**

```
roll_away(X) :- shape(X, round).
shape(baseball, round).
?- roll_away(baseball)
```
Early attempts

• 1959: Checkers
  • Arthur Samuel
• 1959: GPS
  • General Problem Solver
• 1961: SAINT
  • Symbolic Automatic Integrator
• 1962: ANALOGY
  • A is to B as C is to ?
• 1964: STUDENT
  • If the number of customers Tom gets is twice the square of 20% of the number of advertisements he runs, and the number of advertisements is 45, then what is the number of customers Tom gets?
The rise of Good old-fashioned AI (GOFAI)

“at the end of the century [i.e., by 2000], the use of words and general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted”
   - Alan Turing, 1950

“within a generation ... the problem of creating 'artificial intelligence' will substantially be solved.”
   - Marvin Minsky, 1967

“In from three to eight years we will have a machine with the general intelligence of an average human being.”
   - Marvin Minsky, 1970
The 1st AI winter: 1974-1980

1973 “Controversy” debate following the Lighthill Report
Expert systems

Dendral

MYCIN

XCON
Japan’s “Fifth Generation Computer Systems”

• The next step in computing
  • Vacuum tubes → transistors → integrated circuits → microprocessors → parallelism

• Began 1982, lasted 10 years

• $400 million effort

• Failure or ahead of it’s time?

Parallel Interface Machine (PIM)
The 2\textsuperscript{nd} AI Winter: 1987-1993

- Commercialization slowed
- LISP machines underperformed
- Fifth Generation project ended

<table>
<thead>
<tr>
<th>Company/Headquarters</th>
<th>Description</th>
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<tr>
<td>Teknowledge, Palo Alto, Calif.</td>
<td>Four quarters of losses; 60 workers of 200 laid off, 1987 sales: $2 million.</td>
</tr>
<tr>
<td>Inference*, Los Angeles</td>
<td>Losses; 30 workers of 130 laid off, 1987 sales: $12 million.</td>
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Expert system limitations

• They cannot learn (easily)

• Restricted by the size of the knowledgebase

• Expensive to maintain

• Lack understanding of what human expertise really is

• Not possible to explicitly define some rules
A difficult task for rule-based AI

Recognize sunglasses if:
• pixel at 100,150 is pink
• pixel below is pink
• pixel to right is black
• ...

![Image of a dog wearing sunglasses and a scarf, with a pink background.](image-url)
The context problem

Winograd Schema Challenge

The city councilmen refused the demonstrators a permit because they feared violence.

The city councilmen refused the demonstrators a permit because they advocated violence.
Ongoing effort: Cyc

- Started by Doug Lenat in 1984
- An attempt to solve the “common sense problem”
- 25 million common sense rules
  - 1000 persons-years to build
- Just recently started to commercialize
Rule-based AI vs neural networks
Advantages of rule-based AI

• Computationally inexpensive

• Explainable

• Well-suited for symbol manipulation and reasoning
Current trends

DNC: Differentiable Neural Computer, 2016

1988
Suggested reading

Why AI is Harder Than We Think

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Abstract

Since its beginning in the 1950s, the field of artificial intelligence has cycled several times between periods of optimistic predictions and massive investment (“AI spring”) and periods of disappointment, loss of confidence, and reduced funding (“AI winter”). Even with today’s seemingly fast pace of AI breakthroughs, the development of long-promised technologies such as self-driving cars, housekeeping robots, and conversational companions has turned out to be much harder than many people expected. One reason for these repeating cycles is our limited understanding of the nature and complexity of intelligence itself. In this paper I describe four fallacies in common assumptions made by AI researchers, which can lead to overconfident predictions about the field. I conclude by discussing the open questions spurred by these fallacies, including the age-old challenge of imbuing machines with humanlike common sense.

The Myth of Artificial Intelligence

Why Computers Can’t Think the Way We Do

Erik J. Larson
Questions?

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