CS-878 Intelligent Systems

Lecture 2
Introduction to Knowledge-Base Intelligent Systems

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Introduction to Knowledge-Base Intelligent Systems

Ch - 1 [Michael Negnevitsky]

Slides taken from *Michael Negnevitsky, "Artificial Intelligence"*, 2nd edition.

Outline

- Intelligent machines, or what machines can do
- The history of artificial intelligence or from the “Dark Ages” to knowledge-based systems
- Summary

Intelligent machines, or what machines can do

- Philosophers have been trying for over 200 years to understand and resolve two *Big Questions* of the Universe:
  - **How does a human mind work?**, and
  - **Can non-humans have minds?**
  - These questions are still unanswered.

- Definitions:-
  - Intelligence is their ability to understand and learn things.
  - Intelligence is the ability to think and understand instead of doing things by instinct or automatically.

  (Essential English Dictionary, Collins, London, 1990)

- In order to think, *someone* or *something* has to have a brain, or an organ that enables *someone* or *something* to learn and understand things, to solve problems and to make decisions.
    - So we can define intelligence as **the ability to learn and understand, to solve problems and to make decisions**.

- The goal of **Artificial Intelligence (AI)** as a science is to make machines do things that would require intelligence if done by humans. therefore, the answer to the question *Can Machines Think?* was vitally important to the discipline.

- The answer is not a simple *"Yes"* or *"No"*.

- Some people are smarter in some ways than others, sometimes we make very intelligent decisions but sometimes we also make very silly mistakes.
  - Some of us deal with complex mathematical and engineering problems that are moronic in philosophy and history.
  - Some people are good at making money, while others are better at spending it.

- As humans, we all have the ability to learn and understand, to solve problems and to make decisions; however, our abilities are not equal and lie in different areas.
  - Therefor, we should expect if machines can think, some of them might be smarter than others in some ways.

- One of the most significant papers on machine intelligence, *“Computing Machinery and Intelligence”*, was written by British mathematician **Alan Turing** over fifty years ago.

- However, it still stands up well under the test of time, and the Turing’s approach remains universal.
    - He asked:
        - **Is there thought without experience?**
        - **Is there mind without communication?**
        - **Is there language without living?**
        - **Is there intelligence without life?**

- All these questions, as you can see, are just variations on the fundamental question of artificial intelligence, ***Can machines think?***

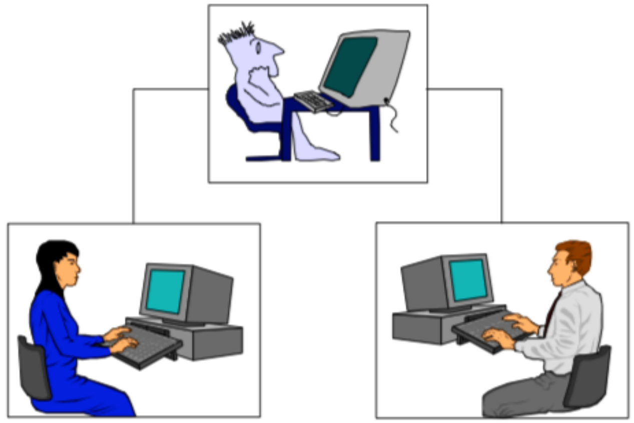
Turing Imitation Game

- Turing did not provide definitions of machines and thinking, he just avoided semantic arguments by inventing a game, the **Turing Imitation Game.**

- The imitation game originally included two phases:-

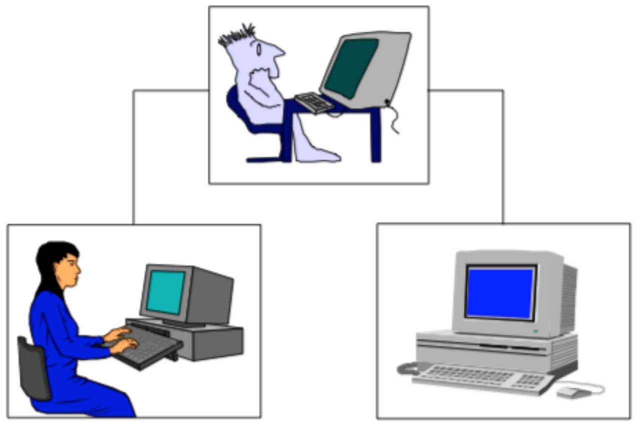
Turing Imitation Game—Phase 1

- In the first phase, the interrogator, a man and a woman are each placed in separate rooms. The interrogator's objective is to work out who is the man and who is the woman by questioning them. The man should attempt to deceive the interrogator that *he* is the woman, while the woman has to convince the interrogator that *she* is the woman.



Turing Imitation Game—Phase 2

- In the second phase of the game, the man is replaced by a computer programmed to deceive the interrogator as the man did. It would even be programmed to make mistakes and provide fuzzy answers in the way a human would. If the computer can fool the interrogator as often as the man did, we can say this computer has passed the intelligent behaviour test.



Outcome of Turing Test

- The test has two remarkable qualities that make it really universal.
- By maintaining communication between the human and the machine via terminals, the test gives us an objective standard view of intelligence.
- The test itself is quite independent from the details of the experiment. It can be conducted as a two-phase game, or even as a single-phase game when the interrogator needs to choose between the human and the machine from the beginning of the test.

- Turing believed that by the end of 20th century it would be possible to program a digital computer to play the imitation game. Although modern computers still cannot pass the Turing test, it provides a basis for the *verification* and *validation* of knowledge-based systems.

- **A program thought intelligent in some narrow area of expertise is evaluated by comparing its performance with the performance of a human expert.**

- To build an intelligent computer system, we have to capture, organise and use human expert knowledge in some narrow area of expertise.

The History of Artificial Intelligence (AI)

The birth of AI (1943–1956)

- The first work recognised in the field of AI was presented by **Warren McCulloch** and **Walter Pitts** in 1943.
- They proposed a model of an artificial neural network and demonstrated that simple network structure could learn.
- McCullouch, the second “founding father” of AI after Alan Turing, had created the corner stone of neural computing and artificial neural networks (ANN).

- The third founder of AI was **John von Neumann**, the brilliant Hungarian-born mathematician. In 1930, he joined the Princeton University, lecturing in mathematical physics. He was an advisor for the Electronic Numerical Integrator and Calculator (ENIC) project at the University of Pennsylvania and helped to design the **Electronic Discrete Variable Calculator**.

- Another of the first generation researchers was **Claude Shannon**. He graduated from MIT and joined Bell Telephone Laboratories in 1941. Shannon shared Alan Turing's ideas on the positility of machine intelligence. In 1950, he published a paper on chess-playing machines, which pointed out that a typical chess game involved about 10^{120} possible moves (Shannon, 1950).
  - Even if the new von Neumann-type computer could examine one move per microsecond, it would take 3×10^{106} years to make its first move.
  - Thus Shannon demonstrated the need to use heuristics in the search for the solution.

- In 1956, **John McCarthy**, **Martin Minsky** and **Claude Shannon** organised a summer workshop at Dartmouth College. They brought together researchers interested in the study of machine intelligence, artificial neural nets and automata theory. Although there were just ten researchers, this workshop gave birth to a new science called **artificial intelligence.**

The Rise of AI (1956–1960)

- The early works on neural computing and artificial neural networks started by McCulloch and Pitts was continued. Learning methods were improved and **Frank Rosenblatt** proved **perceptron convergence theorem**, demonstrating that his learning algorithm could adjust the connection strengths of a perceptron.

- One of the most ambitious projects of the era was the **General Problem Solver (GPS)**. **Allen Newell** and **Herbert Simon** from the Carnegie Mellon University developed a general-purpose program to simulate human-solving methods.

- Newell and Simon postulated that a problem to be solved could be defined in terms of states. They used the mean-end analysis to determine a difference between the current and desirable or goal state of the problem, and to choose and apply operators to reach the goal state. The set of operators determined the solution plan.

The Technology of Expert Systems (Early 70s—Mid 80s)

- Probably the most important development in the 70s was the realisation that the domain for intelligent machines had to be sufficiently restricted. Previously, AI researchers had believed that clever search algorithms and reasoning tetchniques could be invented to emulate general human-like problem-solving methods. A general-purpose search mechanism could rely on elementary steps to find complete solutions and could use weak knowledge about domain.

- When weak methods failed, researchers finally realised that the only way to deliver practical results was to solve typical cases in narrow areas of expertise, making large reasoning steps.

DENDRAL

- DENDRAL was developed at Stanford University to determine the molecular structure of Martian soil, based on the mass spectral data provided by a mass spectrometer. The project was supported by NASA. Edward Feigenbaum, Bruce Buchanan (a computer scientist) and Joshua Lederber (a Nobel prize winner in genetics) formed a team.

- There was no scientific algorithm for mapping the mass spectrum into its molecular structure. Feigenbaum's job was to incorporate the expertise of Lederberg into a computer program to make it perform at a human expert level. Such programs were later called **expert system**.

- DENDRAL marked a major “paradigm shift” in AI: a shift from general-purpose, knowledge-sparse weak methods to domain-specific, knowledge-intensive techniques.

- The aim of the project was to develop a computer program to attain the level of performance of an experienced human chemist. Using heuristics in the form of high-quality specific rules, rules-of-thumb, the DENDRAL team proved that computers could equal an expert in narrow, well-defined, problem areas.

- The DENDRAL project originated the fundamental idea of expert systems- **knowledge engineering**, which encompassed techniques of capturing, analysing and expressing in rules an expert’s “know-how”.

MYCIN

- MYCIN was a rule-based expert system for the diagnosis of infections blood diseases. It also provided a doctor with therapeutic advice in a convenient, user-friendly manner.

- MYCIN's knowledge consisted of about 450 rules derived from human knowledge in a narrow domain through extensive interviewing of experts.

- The knowledge incorporated in the form of rules was clearly separated from the reasoning mechanism. The system developer could easily maniplete knowledge in the system by inserting or deleting some rules. For example, a domain-dependent version of MYCIN called EMYCIN (Empty MYCIN) was later produced.

PROSPECTOR

- PROSPECTOR was an expert system for mineral exploration developed by the Stanford Research Institute. Nine experts contributed their knowledge and expertise. PROSPECTOR used a combined structure that incorporated rules and a semantic network. PROSPECTOR had over 1000 rules.

- The user, an exploration geologist, was asked to input the characteristics of a suspected deposit: the geologist setting, structures, kinds of rocks and minerals.
    - PROSPECTOR compared these characteristics with models of ore deposits and made an assessment of the suspected mineral deposit. It could also explain the steps it used to reach the conclusion.

- A 1986 survey reported a remarkable number of successful expert system applications in different fields: chemistry, electronics, engineering, geology management, medicine, process control and military science (Waterman, 1986).
    - Although, Waterman found nearly 200 expert systems, most of the applications were in the field of medical diagnosis.

- Seven years later a similar survey reported over 2500 developed expert systems (Durkin, 1994). The new growing area was business and manufacturing, which accounted for about 60% of the applications.

- Expert system technology had clearly matured.

However

- Expert systems are restricted to a very narrow domain of expertise.
  - For example, MYCIN, which was developed for the diagnosis of infections blood diseases, lacks may real knowledge of human physiology. If a patient has more than one disease, we can not rely on MYCIN. In fact, therapy prescribed for the blood diseases might even be harmful because of other disease.

- Expert systems can show the sequence of the rules they applied to reach a solution, but cannot relate accumulated, heuristic knowledge to any deeper understanding of the problem domain.

- Expert systems have difficulty in recognising domain boundaries. When given a task different from the typical problems, an expert system might attempt to solve it and fail in rather unpredictable ways.

- Heuristic rules represent knowledge in the abstract form and lack even basic understanding of the domain area. It makes the task of identifying incorrect, incomplete or inconsistent knowledge difficult.

- Expert systems, especially the first generation, have little or no ability to learn from their experience. Expert systems are built individually and cannot be developed fast. Complex systems can take over 30 person-years to build.

How to make a Machine Learn?

The Rebirth of Neural Networks (mid 80s—onwards)

- In mid 80s, researcher, engineers and experts found that building an expert system required much more than just buying a reasoning system or expert system shell and putting enough rules in it. Disillusions about the applicability of expert system technology even led to people predicting an **AI “winter”** with severely squeezed funding for AI projects. AI researchers decided to have a new look at neural networks.

- By the late sixties, most of the basic ideas and concepts necessary for neural computing had been formulated. However, only in the mid-eighties did the solution emerge. The major reason for the delay was technological: there were no PCs or powerful workstations to model and experiment with artificial neural network.

- In 80s, because of the need of brain-like information processing, as well as the advances in computer technology and progress in neuroscience, the filed of neural networks experienced a dramatic resurgence. Major contributions to both theory and design were made on several fronts.

- Grossberg established a new principle of self-organisation (**adaptive resonance theory**), which provided the basis for a new class of neural networks (Grossberg, 1980).
- Hopfield introduced neural networks with feedback — **Hopfield networks**, which attracted much attention in 80s (Hopfield, 1982).
- Kohonen published a paper on **self-organising maps** (Kohonen, 1982).
- Barto, Sutton and Anderson published their work on **reinforcement learning** and its application in control (Barto et al., 1983).

- But the real breakthrough came in 1986 when the **back-prolongation learning algorithm**, first introduced by Bryson and Ho in 1969 (Bryson & Ho, 1969), was reinvented by Rumerlhart and McCulloch in *Parallel Distributed Processing* (1986).

- Artificial neural networks have come a long way from the early models of McCulloch and Pitts to an interdisciplinary subject with roots in neuroscience, psychology, mathematics and engineering, and will continue to develop in both theory and practical applications.

The New Era

Knowledge Engineering or Computing with Words (late 80s—onwards)

- Neural network technology offers more natural interaction with the real world than do systems based on symbolic reasoning. Neural networks can learn, adapt to changes in a problem's environment, establish patterns in situations where rules are not known, and deal with fuzzy or incomplete information. However, they lack explanation facilities and usually act as a black box. The process of training neural networks with current technologies is slow, and frequent retraining can cause serious difficulties.

- Classic expert systems are especially good for closed-system applications with precise inputs and logical outputs. They use expert knowledge in the form of rules and, if required, can interact with the user to establish a particular fact. A major drawback is that human experts cannot always express their knowledge in terms of rules or explain the line of their reasoning. This can prevent the expert system from accumulating the necessary knowledge, and consequently lead to its failure.

- Very important technology dealing with vague, imprecise and uncertain knowledge and data is **fuzzy logic**.

- Human experts do not usually think in probability values, but in such terms as *often*, *generally*, *sometimes*, *occasionally* and *rarely*. Fuzzy logic is concerned with capturing the meaning of words, human reasoning and decision making. Fuzzy logic provides the way to break through the computational bottlenecks of traditional expert systems.

- At the heart of fuzzy logic lies the concept of **linguistic variable**. The values of the linguistic variable are words rather than numbers.

- Fuzzy logic or fuzzy set theory was introduced by Professor Lotfi Zadeh, Berkeley's electrical engineering department chairman, in 1965. It provided a means of competing with words. however, acceptance of fuzzy set theory by the teahnical community was slow and difficult. Part of the problem was the provocative name — "fuzzy" — it seemed to light-hearted to be taken seriously. Eventually, fuzzy theory, ignored in the West, was taken seriously in the East — by the Japanese. It has been used successfully since 1987 in Japanese-designed dishwashers, washing machines, air conditioners, television sets, copiers, and even cars.

Benefits derived from the application of fuzzy logic models in knowledge-based and decision-support systems can be summarised as follows:

- **Improved computational power:** Fuzzy rule-based systems perform faster than conventional expert systems and require fewer rules. A fuzzy expert system merges the rules, making them more powerful. Lotfi Zadeh believes than in few years most expert systems will use fuzzy logic to solve highly non-linear and computational difficult problems.

- **Improved Cognitive Modelling:** Fuzzy systems allow the encoding of knowledge in a form that reflects the way experts think about a complex problem. They usually think in such imprecise terms as *high*, *low*, *fast and slow*, *heavy and light*. In order to build conventional rules, we need to define the crisp boundaries for these terms by breaking down the expertise into fragments. This fragmentation leads to the poor performance of conventional expert systems when they deal with complex problems. In contrast, fuzzy expert systems model imprecise information, capturing expertise similar the way it is represented in the expert mind, and thus improve cognitive modelling of the problem.

- **The ability to represent multiple experts:** Conventional expert systems are built for a narrow domain. It makes the system's performance fully dependent on the right choice of experts. When a more complex expert system is being built or when expertise is not well-defined, ***multiple experts*** might be needed. However, multiple experts seldom reach close agreements; there are often differences in opinions and even conflicts. This is especially true in areas, such as business and management, where no simple solution exists and conflicting views should be taken into account. Fuzzy expert systems can help to represent the expertise of multiple experts when they have opposing view.

- Although fuzzy systems allow expression of expert knowledge in a more natural way, they still depend on the rules extracted from the experts, and thus might be smart or dumb. Some experts can provide very clear fuzzy rules—but some just guess and may even get them wrong. Therefore, all rules must be tested and tuned, which can be prolonged and tedious process. For example, it took Hitachi engineers several years to test and tune only 54 fuzzy rules to guide the Sendal Subway System.

- In recent years, several methods based on neural network technology have been used to search numerical data for fuzzy rules. Adaptive or neural fuzzy systems can find new fuzzy rules, or change and tune existing ones based on the data provided. In other words, data in—rules out, or experience in—common sense out.

Summary

- Expert, neural and fuzzy systems have now matured and been applied to a broad range of different problems, mainly in engineering, medicine, finance, business and management.

- Each technology handles the uncertainty and ambiguity of human knowledge differently, and each technology has found its place in knowledge engineering. They no longer compete; rather they complement each other.

- A synergy of expert systems with fuzzy logic and neural computing improves adaptability, robustness, fault-tolerance and speed of knowledge-based systems. Besides computing with words makes them more “human”. It is now common practice to build intelligenceent systems using existing technologies rather than to propose new ones, and to apply these systems to real-world problems rather than to “toy” problems.