CSC 411: ARTIFICIAL INTELLIGENCE

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MODULE 1 INTRODUCTION TO AI

UNIT 1 WHAT IS ARTIFICIAL INTELLIGENT (AI)?

CONTENTS

1.0 INTRODUCTION

This unit introduces you to Artificial Intelligence and the different faculties involve in it. It also examines different ways of approaching AI.

2.0 OBJECTIVES

At the end of this unit, you should be able to:

- state the definition of Artificial Intelligence
- list the different faculties involved with intelligent behavior
- explain the different ways of approaching AI
- look at some example systems that use AI
- describe the history of AI.

3.0 MAIN CONTENT

3.1 Definition of AI

What is AI?
Artificial Intelligence is a branch of *Science* which deals with helping machines find solutions to complex problems in a more human-like fashion. This generally involves borrowing characteristics from human intelligence, and applying them as algorithms in a computer friendly way. A more or less flexible or efficient approach can be taken depending on the requirements established, which influences how artificial the intelligent behaviour appears.

AI is generally associated with *Computer Science*, but it has many important links with other fields such as *Mathematics*, *Psychology*, *Cognition*, *Biology* and *Philosophy*, among many others. Our ability to combine knowledge from all these fields will ultimately benefit our progress in the quest of creating an intelligent artificial being
It is also concerned with the design of intelligence in an artificial device. The term was coined by McCarthy in 1956. There are two ideas in the definition.

1. Intelligence
2. Artificial device

What is intelligence?

- Is it that which characterize humans? Or is there an absolute standard of judgment?
- Accordingly there are two possibilities:
- A system with intelligence is expected to behave as intelligently as a human
- A system with intelligence is expected to behave in the best possible manner
- Secondly what type of behavior are we talking about?
- Are we looking at the thought process or reasoning ability of the system?
- Or are we only interested in the final manifestations of the system in terms of its actions?

Given this scenario different interpretations have been used by different researchers as defining the scope and view of Artificial Intelligence.

1. One view is that artificial intelligence is about designing systems that are as intelligent as humans. This view involves trying to

understand human thought and an effort to build machines that emulate the human thought process. This view is the cognitive science approach to AI.

2. The second approach is best embodied by the concept of the Turing Test. Turing held that in future computers can be programmed to acquire abilities rivaling human intelligence. As part of his argument Turing put forward the idea of an 'imitation game', in which a human being and a computer would be interrogated under conditions where the interrogator would not know which was which, the communication being entirely by textual messages. Turing argued that if the interrogator could not distinguish them by questioning, then it would be unreasonable not to call the computer intelligent. Turing's 'imitation game' is now usually called 'the Turing test' for intelligence.

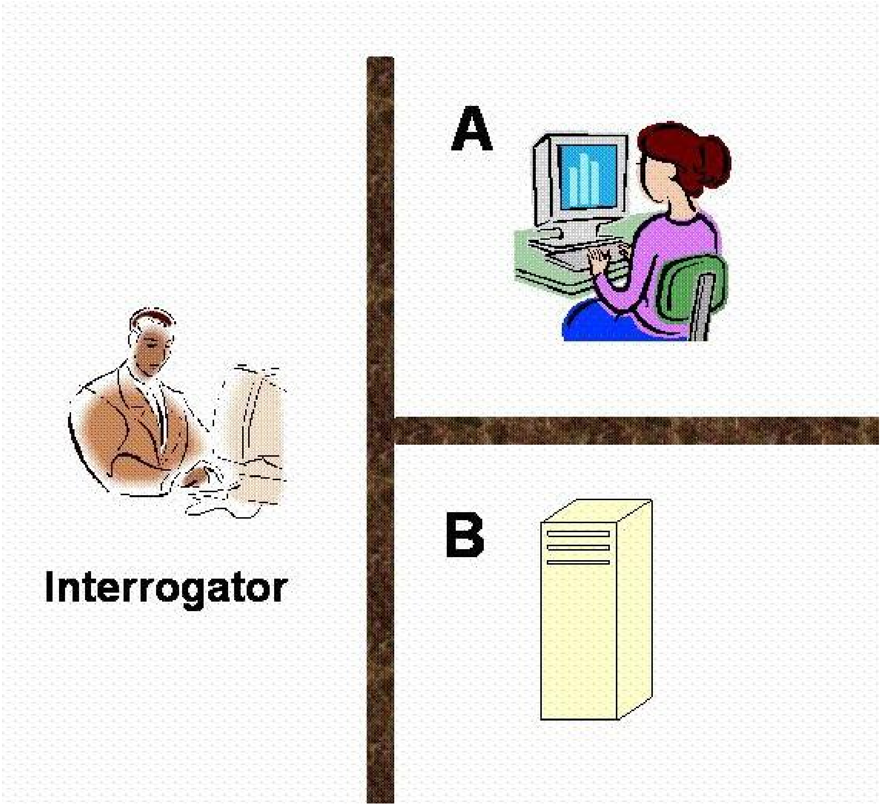


Figure 1: Turing Test

Turing Test

Consider the following setting. There are two rooms, A and B. One of the rooms contains a computer. The other contains a human. The interrogator is outside and does not know which one is a computer. He can ask questions through a teletype and receives answers from both A and B. The interrogator needs to identify whether A or B are humans. To pass the Turing test, the machine has to fool the interrogator into believing that it is human. For more details on the Turing test visit the site http://cogsci.ucsd.edu/~asaygin/tt/ttest.html

3. Logic and laws of thought deals with studies of ideal or rational thought process and inference. The emphasis in this case is on the inferencing mechanism, and its properties. That is how the system arrives at a conclusion, or the reasoning behind its selection of actions is very important in this point of view. The soundness and completeness of the inference mechanisms are important here.

4. The fourth view of AI is that it is the study of rational agents. This view deals with building machines that act rationally. The focus is on how the system acts and performs, and not so much on the reasoning process. A rational agent is one that acts rationally, that is, is in the best possible manner.

3.1.2 Typical AI problems

While studying the typical range of tasks that we might expect an "intelligent entity" to perform, we need to consider both "common-place" tasks as well as expert tasks.
Examples of common-place tasks include

- *Recognizing* people, objects.
- Communicating (through *natural language*).
- *Navigating* around obstacles on the streets

These tasks are done matter of firstly and routinely by people and some other animals.

Expert tasks include:

- Medical diagnosis.
- Mathematical problem solving
- Playing games like chess

These tasks cannot be done by all people, and can only be performed by skilled specialists.

Now, which of these tasks are easy and which ones are hard? Clearly tasks of the first type are easy for humans to perform, and almost all are able to master them. The second range of tasks requires skill development and/or intelligence and only some specialists can perform them well. However, when we look at what computer systems have been able to achieve to date, we see that their achievements include performing sophisticated tasks like medical diagnosis, performing symbolic integration, proving theorems and playing chess.

On the other hand it has proved to be very hard to make computer systems perform many routine tasks that all humans and a lot of animals can do. Examples of such tasks include navigating our way without running into things, catching prey and avoiding predators. Humans and animals are also capable of interpreting complex sensory information. We are able to recognize objects and people from the visual image that we receive. We are also able to perform complex social functions.

Intelligent behaviour. This discussion brings us back to the question of what constitutes intelligent behaviour. Some of these tasks and applications are:

- Perception involving image recognition and computer vision
- Reasoning
- Learning
- Understanding language involving natural language processing, speech processing
- Solving problems
- Robotics

3.1.3 Practical Impact of AI

AI components are embedded in numerous devices e.g. in copy machines for automatic correction of operation for copy quality improvement. AI systems are in everyday use for identifying credit card fraud, for advising doctors, for recognizing speech and in helping complex planning tasks. Then there are intelligent tutoring systems that provide students with personalized attention

Thus AI has increased understanding of the nature of intelligence and found many applications. It has helped in the understanding of human reasoning, and of the nature of intelligence. It will also help you understand the complexity of modeling human reasoning.

You can now look at a few famous AI systems.

1. ALVINN

Autonomous Land Vehicle in a Neural Network

In 1989, Dean Pomerleau at CMU created ALVINN. This is a system which learns to control vehicles by watching a person drive. It contains a neural network whose input is a 30x32 unit two dimensional camera image. The output layer is a representation of the direction the vehicle should travel.

The system drove a car from the East Coast of USA to the west coast, a total of about 2850 miles. Out of this about 50 miles were driven by a human being and the rest solely by the system.

2. Deep Blue

In 1997, the Deep Blue chess program created by IBM, beat the current world chess champion, Gary Kasparov.

3. Machine translation

A system capable of translations between people speaking different languages will be a remarkable achievement of enormous economic and cultural benefit. Machine translation is one of the important fields of endeavour in AI. While some translating systems have been developed, there is a lot of scope for improvement in translation quality.

4. Autonomous agents

In space exploration, robotic space probes autonomously monitor their surroundings, make decisions and act to achieve their goals.
NASA's Mars rovers successfully completed their primary three-month missions in April, 2004. The Spirit rover had been exploring a range of Martian hills that took two months to reach. It is finding curiously eroded rocks that may be new pieces to the puzzle of the region's past. Spirit's twin, Opportunity, had been examining exposed rock layers inside a crater.

5. Internet Agents

The explosive growth of the internet has also led to growing interest in internet agents to monitor users' tasks, seek needed information, and to learn which information is most useful

3.1.4 Approaches to AI

Strong AI _ aims to build machines that can truly reason and solve problems. These machines should be self aware and their overall intellectual ability needs to be indistinguishable from that of a human being. Excessive optimism in the 1950s and 1960s concerning strong AI has given way to an appreciation of the extreme difficulty of the problem. Strong AI maintains that suitably programmed machines are capable of cognitive mental states.

Weak AI deals with the creation of some form of computer-based artificial intelligence that cannot truly reason and solve problems, but can act as if it were intelligent. Weak AI holds that suitably programmed machines can simulate human cognition.

Applied AI aims to produce commercially viable "smart" systems such as, security system that is able to recognise the faces of people who are permitted to enter a particular building. Applied AI has already enjoyed considerable success.

Cognitive AI: computers are used to test theories about how the human mind works--for example, theories about how we recognise faces and other objects, or about how we solve abstract problems.

3.1.5 Limits of AI Today

Today's successful AI systems operate in well-defined domains and employ narrow, specialized knowledge. Common sense knowledge is needed to function in complex, open-ended worlds. Such a system also needs to understand unconstrained natural language. However these capabilities are not yet fully present in today's intelligent systems.

✓ What can AI systems do?

Today's AI systems have been able to achieve limited success in some of these tasks.

- In Computer vision, the systems are capable of face recognition
- In Robotics, we have been able to make vehicles that are mostly autonomous
- In Natural language processing, we have systems that are capable of simple machine translation
- Today's Expert systems can carry out medical diagnosis in a narrow domain

- Speech understanding systems are capable of recognizing several thousand words continuous speech
- Planning and scheduling systems had been employed in scheduling experiments with the Hubble Telescope
- The Learning systems are capable of doing text categorization into about a 1000 topics
- In Games, AI systems can play at the Grand Master level in chess (world champion), checkers, etc.

✓ What can AI systems NOT do yet?

- Understand natural language robustly (e.g., read and understand articles in a newspaper)
- Surf the web
- Interpret an arbitrary visual scene
- Learn a natural language
- Construct plans in dynamic real-time domains
- Exhibit true autonomy and intelligence

3.2 AI History

Intellectual roots of AI date back to the early studies of the nature of knowledge and reasoning. The dream of making a computer imitate humans also has a very early history.

The concept of intelligent machines is found in Greek mythology. There is a story in the 8^{th} century A.D about Pygmalion Olio, the legendary king of Cyprus. He fell in love with an ivory statue he made to represent his ideal woman. The king prayed to the goddess Aphrodite, and the goddess miraculously brought the statue to life. Other myths involve human-like artifacts. As a present from Zeus to Europa, Hephaestus created Talos, a huge robot. Talos was made of bronze and his duty was to patrol the beaches of Crete.

Aristotle (384-322 BC) developed an informal system of syllogistic logic, which is the basis of the first formal deductive reasoning system.

Early in the 17^{th} century, Descartes proposed that bodies of animals are nothing more than complex machines.

Pascal in 1642 made the first mechanical digital calculating machine.

In the 19^{th} century, George Boole developed a binary algebra representing (some) "laws of thought."

Charles Babbage & Ada Byron worked on programmable mechanical calculating machines.

In the late 19th century and early 20th century, mathematical philosophers like Gottlob Frege, Bertram Russell, Alfred North Whitehead, and Kurt Gödel built on Boole's initial logic concepts to develop mathematical representations of logic problems.

The advent of electronic computers provided a revolutionary advance in the ability to study intelligence.

In 1943 McCulloch & Pitts developed a Boolean circuit model of brain. They wrote the paper “A Logical Calculus of Ideas Immanent in Nervous Activity”, which explained how it is possible for neural networks to compute.

Marvin Minsky and Dean Edmonds built the SNARC in 1951, which is the first randomly wired neural network learning machine (SNARC stands for Stochastic Neural-Analog Reinforcement Computer).It was a neural network computer that used 3000 vacuum tubes and a network with 40 neurons.

In 1950 Turing wrote an article on “Computing Machinery and Intelligence” which articulated a complete vision of AI. For more on Alan Turing see the site http://www.turing.org.uk/turing/ . Turing’s paper talked of many things, of solving problems by searching through the space of possible solutions, guided by heuristics. He illustrated his ideas on machine intelligence by reference to chess. He even propounded the possibility of letting the machine alter its own instructions so that machines can learn from experience.

In 1956 a famous conference took place in Dartmouth. The conference brought together the founding fathers of artificial intelligence for the first time. In this meeting the term “Artificial Intelligence” was adopted.

Between 1952 and 1956, Samuel had developed several programs for playing checkers. In 1956, Newell & Simon’s Logic Theorist was published. It is considered by many to be the first AI program. In 1959, Gelernter developed a Geometry Engine. In 1961 James Slagle (PhD dissertation, MIT) wrote a symbolic integration program SAINT. It was written in LISP and solved calculus problems at the college freshman level. In 1963, Thomas Evan's program Analogy was developed which could solve IQ test type analogy problems.

In 1963, Edward A. Feigenbaum & Julian Feldman published Computers and Thought, the first collection of articles about artificial intelligence.

In 1965, J. Allen Robinson invented a mechanical proof procedure, the **Resolution Method**, which allowed programs to work efficiently with formal logic as a representation language. In 1967, the Dendral program (Feigenbaum, Lederberg, Buchanan, Sutherland at Stanford) was demonstrated which could **interpret mass spectra on organic chemical compounds**. This was the first successful knowledge-based program for scientific reasoning. In 1969 the SRI robot, Shakey, demonstrated combining locomotion, perception and problem solving.
The years from 1969 to 1979 marked the early development of **knowledge-based systems**

In 1974, MYCIN demonstrated the power of rule-based systems for knowledge representation and inference in medical diagnosis and therapy. Knowledge representation schemes were developed. These included frames developed by Minski. Logic based languages like Prolog and Planner were developed.

We will now mention a few of the AI systems that were developed over the years.

The Meta-Dendral learning program produced new results in chemistry (rules of mass spectrometry)

In the 1980s, Lisp Machines developed and marketed.

Around 1985, neural networks return to popularity.

In 1988, there was a resurgence of probabilistic and decision-theoretic methods.

The early AI systems used general systems, little knowledge. AI researchers realized that specialized knowledge is required for rich tasks to focus reasoning.

The 1990's saw major advances in all areas of AI including the following:

- Machine learning, data mining
- Intelligent tutoring,
- Case-based reasoning,
- Multi-agent planning, scheduling,

- Uncertain reasoning,
- Natural language understanding and translation,
- Vision, virtual reality, games, and other topics.

Rod Brooks' COG Project at MIT, with numerous collaborators, made significant progress in building a humanoid robot.

The first official Robo-Cup soccer match featuring table-top matches with 40 teams of interacting robots was held in 1997. For details, see the site http://murray.newcastle.edu.au/users/students/2002/c3012299/bg.html

In the late 90s, Web crawlers and other AI-based information extraction programs become essential in widespread use of the world-wide-web.

Interactive robot pets ("smart toys") become commercially available, realizing the vision of the 18th century novelty toy makers.

In 2000, the Nomad robot explores remote regions of Antarctica looking for meteorite samples.

AI in the news
http://www.aaai.org/AITopics/html/current.html

4.0 CONCLUSION

Artificial intelligence (AI) is the intelligence of machines and the branch of computer science that aims to create it. AI textbooks define the field as "the study and design of intelligent agents" where an intelligent agent is a system that perceives its environment and takes actions that maximize its chances of success. John McCarthy, who coined the term in 1956, defines it as "the science and engineering of making intelligent machines."

The field was founded on the claim that a central property of humans, intelligence—the sapience of *Homo sapiens*—can be so precisely described that it can be simulated by a machine. This raises philosophical issues about the nature of the mind and the ethics of creating artificial beings, issues which have been addressed by myth, fiction and philosophy since antiquity. Artificial intelligence has been the subject of optimism, but has also suffered setbacks and, today, has become an essential part of the technology industry, providing the heavy lifting for many of the most difficult problems in computer science.

5.0 SUMMARY

In this unit, you have learnt that:

- Artificial Intelligence is a branch of *Science* which deals with helping machines find solutions to complex problems in a more human-like fashion
- Typical AI problems
- AI History
- Limits of AI Today

UNIT 2 INTRODUCTION TO INTELLIGENT AGENTS

CONTENTS

1.0 INTRODUCTION

This unit introduces you to Intelligence Agents (IA), how it interacts with the environment and Agent architectures. IA is an autonomous entity which observes and acts upon an environment . It may use knowledge to achieve their goals. They may be very simple or very complex.

2.0 OBJECTIVES

At the end of this unit, you should be able to:

- explain what an agent is and how it interacts with the environment.

- identify the percepts available to the agent and the actions that the agent can execute, if given a problem situation
- measure the performance used to evaluate an agent
- list based agents
- identify the characteristics of the environment.

3.0 MAIN CONTENT

3.1 Introduction to Agent

An agent perceives its environment through sensors. The complete set of inputs at a given time is called a percept. The current percept or a sequence of percepts can influence the actions of an agent. The agent can change the environment through actuators or effectors. An operation involving an Effector is called an action. Actions can be grouped into action sequences. The agent can have goals which it tries to achieve.

Thus, an agent can be looked upon as a system that implements a mapping from percept sequences to actions.

A performance measure has to be used in order to evaluate an agent.
An autonomous agent decides autonomously which action to take in the current situation to maximize progress towards its goals.

3.1.1 Agent Performance

An agent function implements a mapping from perception history to action. The behaviour and performance of intelligent agents have to be evaluated in terms of the agent function.

The ideal mapping specifies which actions an agent ought to take at any point in time.

The performance measure is a subjective measure to characterize how successful an agent is. The success can be measured in various ways. It can be measured in terms of speed or efficiency of the agent. It can be measured by the accuracy or the quality of the solutions achieved by the agent. It can also be measured by power usage, money, etc.

3.1.2 Examples of Agents

1. **Humans can be looked upon as agents.** They have eyes, ears, skin, taste buds, etc. for sensors; and hands, fingers, legs, mouth for effectors.

2. **Robots are agents.** Robots may have camera, sonar, infrared, bumper, etc. for sensors. They can have grippers, wheels, lights, speakers, etc. for actuators. Some examples of robots are Xavier from CMU, COG from MIT, etc.

Xavier Robot (CMU)

Figure 2: Xavier Robot (CMU)

Then we have the AIBO entertainment robot from SONY.

Aibo from SONY

Figure 3: Aibo from SONY

3. We also have software agents or softbots that have some functions as sensors and some functions as actuators. Askjeeves.com is an example of a softbot.
4. Expert systems like the Cardiologist are an agent.
5. Autonomous spacecrafts.
6. Intelligent buildings.

3.1.3 Agent Faculties

The fundamental faculties of intelligence are

- Acting
- Sensing
- Understanding, reasoning, learning

Blind action is not a characterization of intelligence. In order to act intelligently, one must sense. Understanding is essential to interpret the sensory percepts and decide on an action. Many robotic agents stress sensing and acting, and do not have understanding.

3.1.4 Intelligent Agents

An Intelligent Agent must sense, must act, must be autonomous (to some extent). It also must be rational.

AI is about building rational agents. An agent is something that perceives and acts.

A rational agent always does the right thing.

1. What are the functionalities (goals)?
2. What are the components?
3. How do we build them?

3.1.5 Rationality

Perfect Rationality assumes that the rational agent knows all and will take the action that maximizes her utility. Human beings do not satisfy this definition of rationality.

Rational Action is the action that maximizes the expected value of the performance measure given the percept sequence to date.

However, a rational agent is not omniscient. It does not know the actual outcome of its actions, and it may not know certain aspects of its environment. Therefore rationality must take into account the limitations of the agent. The agent has too select the best action to the best of its knowledge depending on its percept sequence, its background knowledge and its feasible actions. An agent also has to deal with the expected outcome of the actions where the action effects are not deterministic.

3.1.6 Bounded Rationality

"Because of the limitations of the human mind, humans must use approximate methods to handle many tasks." Herbert Simon, 1972
Evolution did not give rise to optimal agents, but to agents which are in some senses locally optimal at best. In 1957, Simon proposed the notion of Bounded Rationality: that property of an agent that behaves in a manner that is nearly optimal with respect to its goals as its resources will allow.

Under these promises an intelligent agent will be expected to act optimally to the best of its abilities and its resource constraints.

3.2 Agent Environment

Environments in which agents operate can be defined in different ways. It is helpful to view the following definitions as referring to the way the environment appears from the point of view of the agent itself.

3.2.1 Observability

In terms of observability, an environment can be characterized as fully observable or partially observable.

In a fully observable environment, the entire environment relevant to the action being considered is observable. In such environments, the agent does not need to keep track of the changes in the environment. A chess playing system is an example of a system that operates in a fully observable environment.

In a partially observable environment, the relevant features of the environment are only partially observable. A bridge playing program is an example of a system operating in a partially observable environment.

3.2.2 Determinism

In deterministic environments, the next state of the environment is completely described by the current state and the agent's action. Image analysis

If an element of interference or uncertainty occurs then the environment is stochastic. Note that a deterministic yet partially observable environment will *appear* to be stochastic to the agent. Ludo

If the environment state is wholly determined by the preceding state and the actions of *multiple* agents, then the environment is said to be strategic. Example: Chess

3.2.3 Episodicity

An episodic environment means that subsequent episodes do not depend on what actions occurred in previous episodes.

In a sequential environment, the agent engages in a series of connected episodes.

3.2.4 Dynamism

Static Environment: does not change from one state to the next while the agent is considering its course of action. The only changes to the environment are those caused by the agent itself.

- A static environment does not change while the agent is thinking.
- The passage of time as an agent deliberates is irrelevant.
- The agent doesn't need to observe the world during deliberation.

A Dynamic Environment changes over time independent of the actions of the agent -- and thus if an agent does not respond in a timely manner, this counts as a choice to do nothing

3.2.5 Continuity

If the number of distinct percepts and actions is limited, the environment is discrete, otherwise it is continuous.

3.2.6 Presence of Other agents

Single agent/ Multi-agent

A multi-agent environment has other agents. If the environment contains other intelligent agents, the agent needs to be concerned about strategic, game-theoretic aspects of the environment (for either cooperative *or* competitive agents)

Most engineering environments do not have multi-agent properties, whereas most social and economic systems get their complexity from the interactions of (more or less) rational agents.

3.3 Agent architectures

3.3.1 Table Based Agent

In table based agent the action is looked up from a table based on information about the agent's percepts. A table is simple way to specify a mapping from percepts to actions. The mapping is implicitly defined by a program. The mapping may be implemented by a rule based system, by a neural network or by a procedure.

There are several disadvantages to a table based system. The tables may become very large. Learning a table may take a very long time, especially if the table is large. Such systems usually have little autonomy, as all actions are pre-determined.

3.3.2 Percept based agent or reflex agent

In percept based agents,

1. information comes from sensors - percepts
2. changes the agents current state of the world
3. triggers actions through the effectors

Such agents are called reactive agents or stimulus-response agents. Reactive agents have no notion of history. The current state is as the sensors see it right now. The action is based on the current percepts only.

The following are some of the characteristics of percept-based agents.

- Efficient
- No internal representation for reasoning, inference.
- No strategic planning, learning.
- Percept-based agents are not good for multiple, opposing, goals.

3.3.3 Subsumption Architecture

We will now briefly describe the subsumption architecture (Rodney Brooks, 1986). This architecture is based on reactive systems. Brooks notes that in lower animals there is no deliberation and the actions are based on sensory inputs. But even lower animals are capable of many complex tasks. His argument is to follow the evolutionary path and build simple agents for complex worlds.

The main features of Brooks' architecture are.

- There is no explicit knowledge representation
- Behaviour is distributed, not centralized
- Response to stimuli is reflexive
- The design is bottom up, and complex behaviours are fashioned from the combination of simpler underlying ones.
- Individual agents are simple

The Subsumption Architecture built in layers. There are different layers of behaviour. The higher layers can override lower layers. Each activity is modeled by a finite state machine.

The subsumption architecture can be illustrated by Brooks' Mobile Robot example.

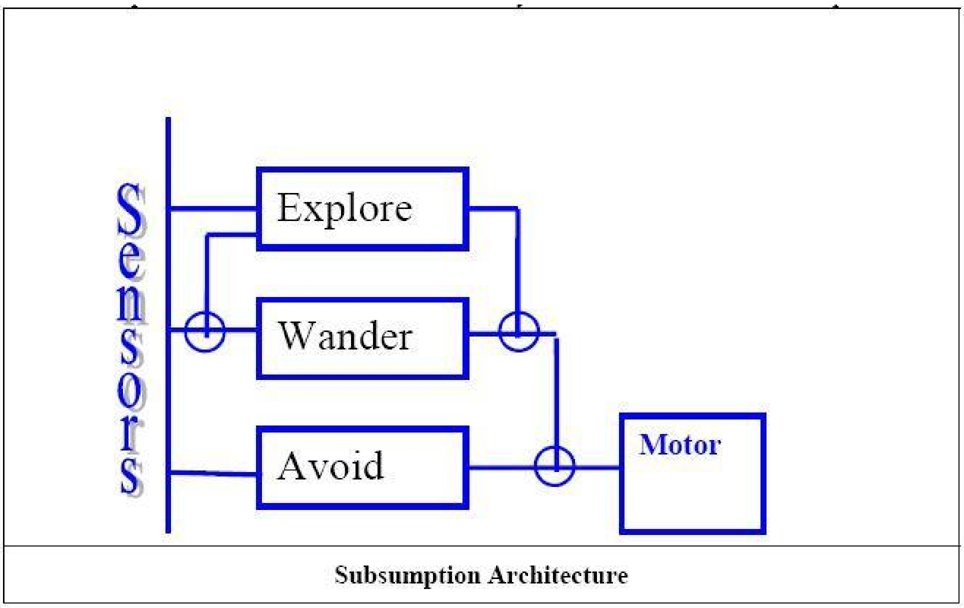


Figure 4: Subsumption Architecture

The system is built in three layers.

1. **Layer 0:** Avoid Obstacles
2. **Layer1:** Wander behaviour
3. **Layer 2:** Exploration behavior

Layer 0 (Avoid Obstacles) has the following capabilities:

- **Sonar:** generate sonar scan
- **Collide:** send HALT message to forward
- **Feel force:** signal sent to run-away, turn

Layer1 (Wander behaviour)

- Generates a random heading
- Avoid reads repulsive force, generates new heading, feeds to turn and forward

Layer 2 (Exploration behaviour)

- Whenlook notices idle time and looks for an interesting place.
- Pathplan sends new direction to avoid.
- Integrate monitors path and sends them to the path plan.

3.3.4 State-Based Agent or Model-Based Reflex Agent

State based agents differ from percept based agents in that such agents maintain some sort of state based on the percept sequence received so far. The state is updated regularly based on what the agent senses, and the agent's actions. Keeping track of the state requires that the agent has knowledge about how the world evolves, and how the agent's actions affect the world.

Thus a state based agent works as follows:

- information comes from sensors – percepts
- based on this, the agent changes the current state of the world
- based on state of the world and knowledge (memory), it triggers actions through the effectors

3.3.5 Goal-based Agent

The goal based agent has some goal which forms a basis of its actions.
Such agents work as follows:

- information comes from sensors - percepts
- changes the agents current state of the world
- based on state of the world and knowledge (memory) and goals/intentions, it chooses actions and does them through the effectors.

Goal formulation based on the current situation is a way of solving many problems and search is a universal problem solving mechanism in AI. The sequence of steps required to solve a problem is not known a priori and must be determined by a systematic exploration of the alternatives.

3.3.6 Utility-based Agent

Utility based agents provide a more general agent framework. In case that the agent has multiple goals, this framework can accommodate different preferences for the different goals.
Such systems are characterized by a utility function that maps a state or a sequence of states to a real valued utility. The agent acts so as to maximize expected utility.

3.3.7 Learning Agent

Learning allows an agent to operate in initially unknown environments. The learning element modifies the performance element. Learning is required for true autonomy

4.0 CONCLUSION

In conclusion, an intelligent agent (IA) is an autonomous entity which observes and acts upon an environment . Intelligent agents may also learn or use knowledge to achieve their goals. They may be very simple or very complex: a reflex machine such as a thermostat is an intelligent agent, as is a human being, as is a community of human beings working together towards a goal.

5.0 SUMMARY

In this unit, you have learnt that:

- AI is a truly fascinating field. It deals with exciting but hard problems. A goal of AI is to build intelligent agents that act so as to optimize performance.
- An agent perceives and acts in an environment that has architecture, and is implemented by an agent program.
- An ideal agent always chooses the action which maximizes its expected performance, given its percept sequence so far.
- An autonomous agent uses its own experience rather than built-in knowledge of the environment by the designer.
- An agent program maps from percept to action and updates its internal state.
- Reflex agents respond immediately to percepts.
- Goal-based agents act in order to achieve their goal(s).
- Utility-based agents maximize their own utility function.
- Representing knowledge is important for successful agent design.

- The most challenging environments are partially observable, stochastic, sequential, dynamic, and continuous, and contain multiple intelligent agents.

MODULE 2 SEARCH IN ARTIFICIAL INTELLIGENCE

UNIT 1 INTRODUCTION TO STATE SPACE SEARCH

CONTENTS

1.0 INTRODUCTION

In computer science, a search algorithm, broadly speaking, is an algorithm for finding an item with specified properties among a collection of items. The items may be stored individually as records in a database; or may be elements of a search space defined by a mathematical formula or procedure, such as the roots of an equation with integer variables; or a combination of the two, such as the Hamiltonian circuits of a graph.

Specifically, Searching falls under Artificial Intelligence (AI). A major goal of AI is to give computers the ability to think, or in other words, mimic human behavior. The problem is, unfortunately, computers don't function in the same way our minds do. They require a series of *well-reasoned out* steps before finding a solution. Your goal, then, is to take a complicated task and convert it into simpler steps that your computer can handle. That conversion from something complex to something simple is what this unit is primarily about. Learning how to use two search algorithms is just a welcome side-effect. This unit will explain the background for AI search and some of the AI search techniques.

2.0 OBJECTIVES

After the end of this unit, you should be able to:

- describe the state space representation
- describe some algorithms
- formulate, when given a problem description, the terms of a state space search problem
- analyse the properties of some algorithms
- analyse a given problem and identify the most suitable search strategy for the problem
- solve some simple problems.

3.0 MAIN CONTENT

3.1 State Space Search

Let us begin by introducing certain terms.

An initial state is the description of the starting configuration of the agent.

An action or an operator takes the agent from one state to another state which is called a successor state. A state can have a number of successor states.

A plan is a sequence of actions. The cost of a plan is referred to as the path cost. The path cost is a positive number, and a common path cost may be the sum of the costs of the steps in the path. The goal state is the partial description of the solution

3.1.1 Goal Directed Agent

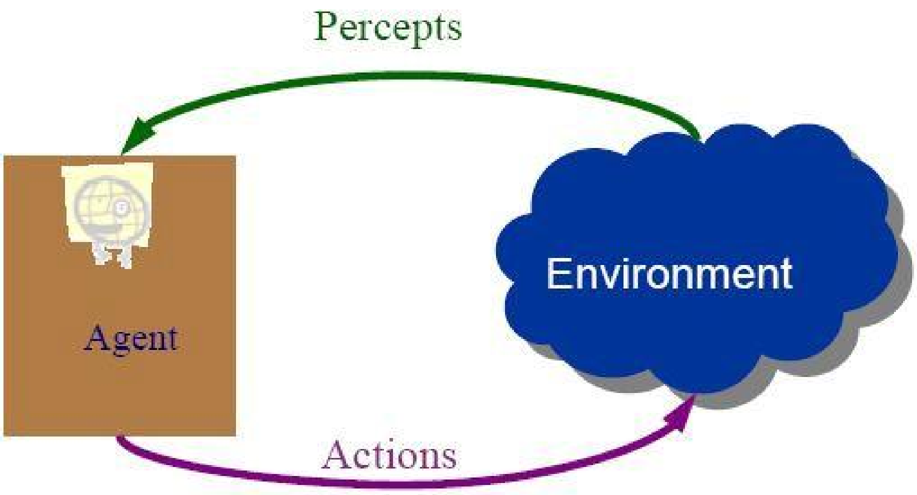


Figure 1: Goal Directed Agent

We have earlier discussed about an intelligent agent. In this unit we will study a type of intelligent agent which we will call a goal directed agent. A goal directed agent needs to achieve certain goals. Such an agent selects its actions based on the goal it has. Many problems can be represented as a set of states and a set of rules of how one state is transformed to another. Each state is an abstract representation of the agent's environment. It is an abstraction that denotes a configuration of the agent.

Let us look at a few examples of goal directed agents.

1. 15-puzzle: The goal of an agent working on a 15-puzzle problem may be to reach a configuration which satisfies the condition that the top row has the tiles 1, 2 and 3. The details of this problem will be described later.

2. The goal of an agent may be to navigate a maze and reach the HOME position.

The agent must choose a sequence of actions to achieve the desired goal.

3.1.2 State Space Search Notations

Now let us look at the concept of a search problem.

Problem formulation means choosing a relevant **set of states** to consider, and a feasible **set of operators** for moving from one state to another.

Search is the process of considering various possible sequences of operators applied to the initial state, and finding out a sequence which culminates in a goal state.

3.2 Problem Space

What is problem space?

A problem space is a set of states and a set of operators. The operators map from one state to another state. There will be one or more states that can be called initial states, one or more states which we need to reach what are known as goal states and there will be states in between initial states and goal states known as intermediate states. So what is the solution? The solution to the given problem is nothing but a sequence of operators that map an initial state to a goal state. This sequence forms a solution path. What is the best solution? Obviously the shortest path from the initial state to the goal state is the best one. Shortest path has only a few operations compared to all other possible solution paths. Solution path forms a tree structure where each node is a state. So searching is nothing but exploring the tree from the root node.

3.2.1 Search Problem

We are now ready to formally describe a search problem.

A search problem consists of the following:

- S: the full set of states
- s_0 : the initial state
- $A:S \rightarrow S$ is a set of operators
- G is the set of final states. Note that $G \subseteq S$

These are schematically depicted in Figure 2.

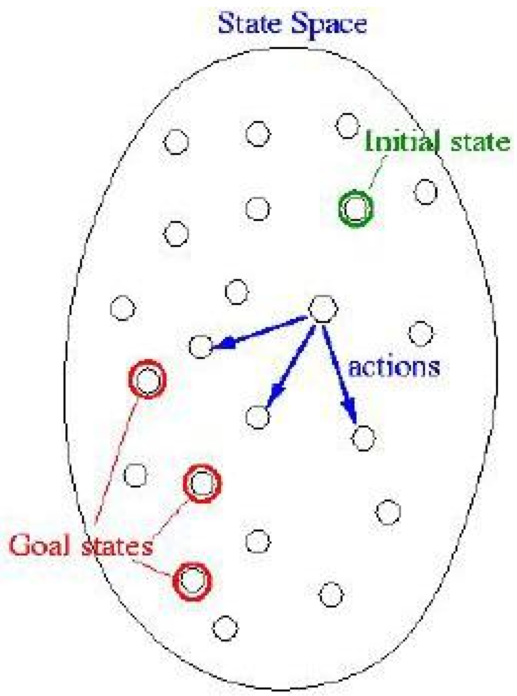


Figure 2

The search problem is to find a sequence of actions which transforms the agent from the initial state to a goal state g∈G. A search problem is represented by a 4-tuple {S, s_0, A, G}.

S: set of states
$s_0 \in$ S: initial state
A: SìI S operators/ actions that transform one state to another state
G: goal, a set of states. G ⊆ S

This sequence of actions is called a solution plan. It is a path from the initial state to a goal state. A *plan* P is a sequence of actions.

P = {a_0, a_1, a_N} which leads to traversing a number of states {s_0, s_1, $Sn+_1$ ∈G}. A sequence of states is called a path. The cost of a path is a positive number. In many cases the path cost is computed by taking the sum of the costs of each action.

Representation of search problems
A search problem is represented using a directed graph.

- The states are represented as nodes.
- The allowed actions are represented as arcs.

Searching process

The generic searching process can be very simply described in terms of the following steps:

Do until a solution is found or the state space is exhausted.

1. Check the current state

2. Execute allowable actions to find the successor states.

3. Pick one of the new states.

4. Check if the new state is a solution state

If it is not, the new state becomes the current state and the process is repeated

3.3 Examples

3.3.1 Illustration of a search process

We will now illustrate the searching process with the help of an example. Consider the problem depicted in Figure 3.

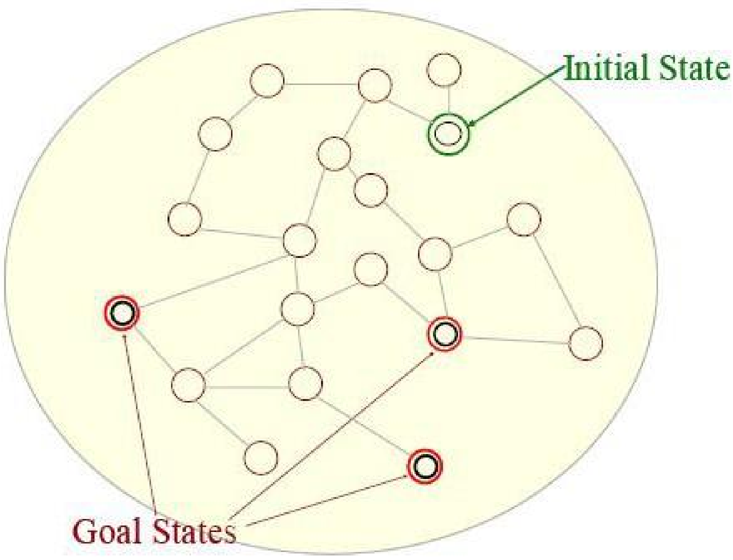


Figure 3

s_0 is the initial state.

The successor states are the adjacent states in the graph.

There are three goal states.

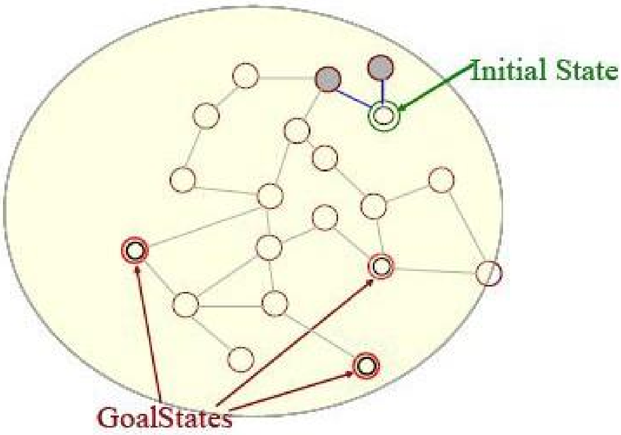


Figure 4

The two successor states of the initial state are generated.

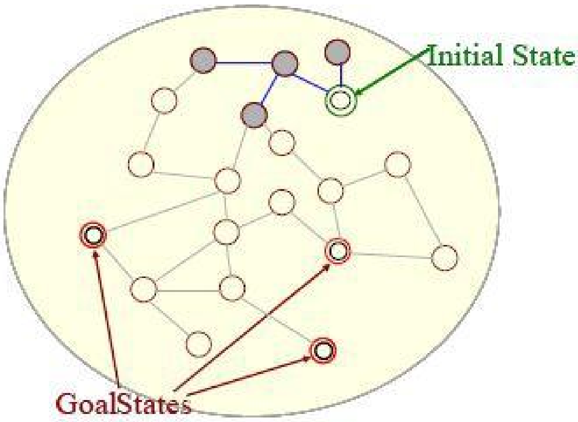


Figure 5

The successors of these states are picked and their successors are generated.

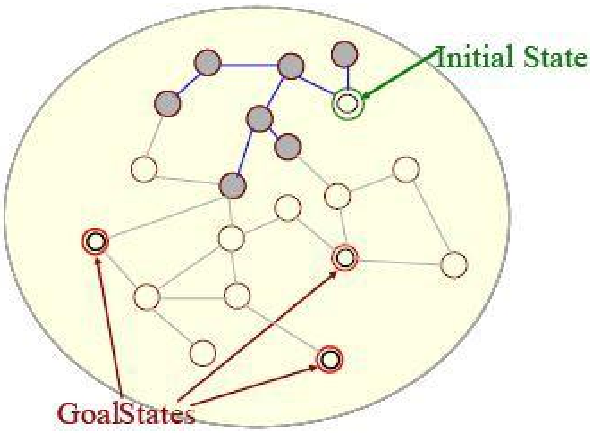


Figure 6

Successors of all these states are generated.

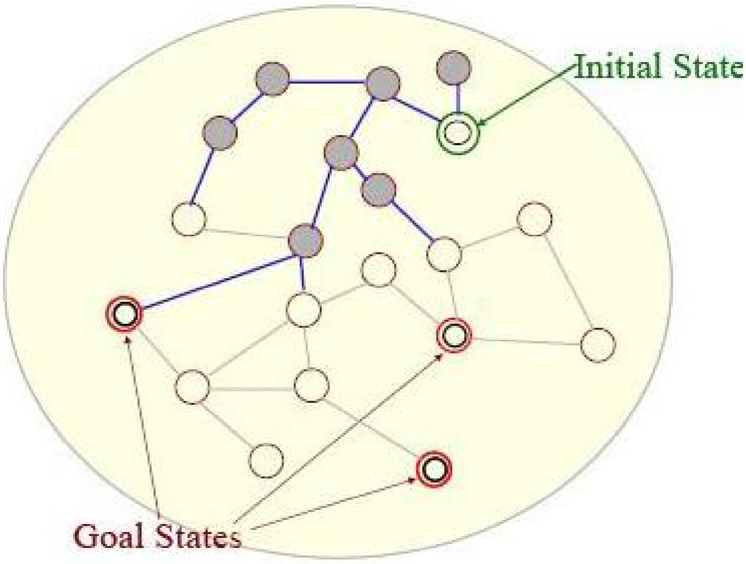


Figure 7

The successors are generated.

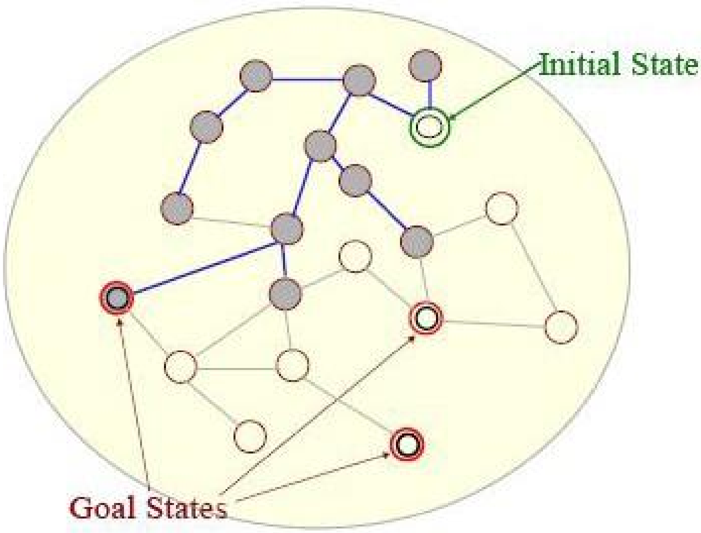


Figure 8

A goal state has been found.

The above example illustrates how we can start from a given state and follow the successors, and be able to find solution paths that lead to a goal state. The grey nodes define the search tree. Usually the search tree is extended one node at a time. The order in which the search tree is extended depends on the search strategy.

We will now illustrate state space search with one more example – the pegs and disks problem. We will illustrate a solution sequence which when applied to the initial state takes us to a goal state.

3.3.2 Example problem: Pegs and Disks problem

Consider the following problem. We have 3 pegs and 3 disks.

Operators: one may move the topmost disk on any needle to the topmost position to any other needle.

In the goal state all the pegs are in the needle B as shown in the figure below.

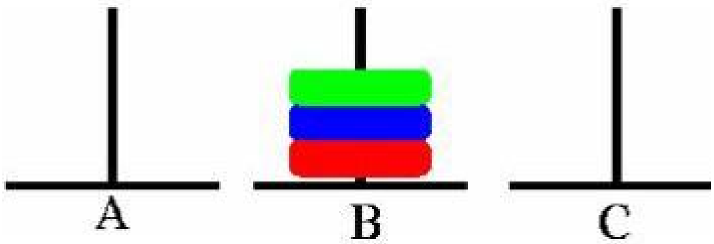


Figure 9

The initial state is illustrated below.

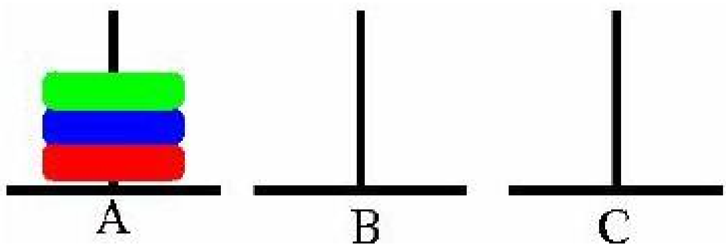


Figure 10

Now we will describe a sequence of actions that can be applied on the initial state.

Step 1: Move A → C

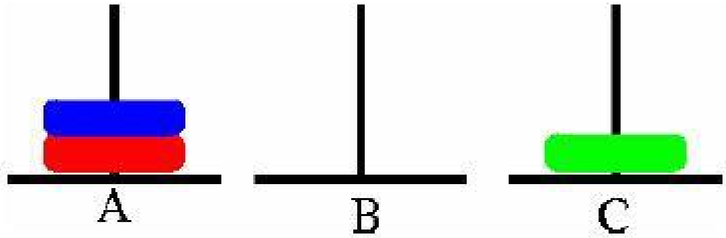


Figure 11

Step 2: Move A → B

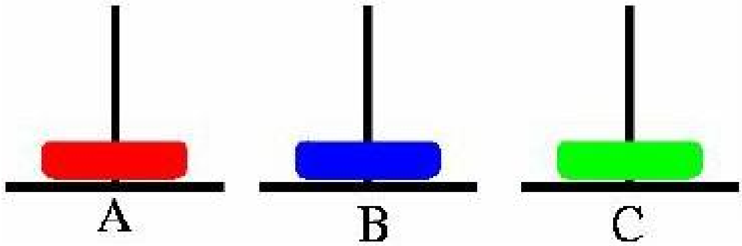


Figure 12

Step 3: Move A → C

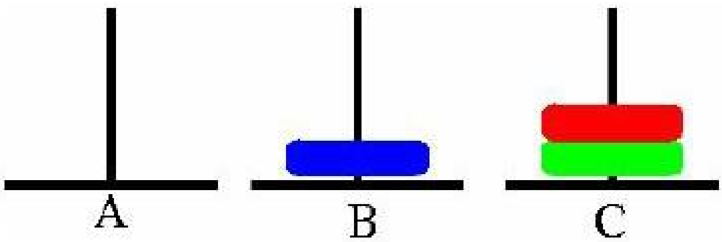


Figure 13

Step 4: Move B→ A

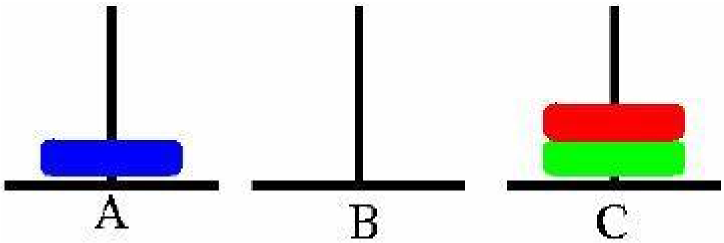


Figure 14

Step 5: Move C → B

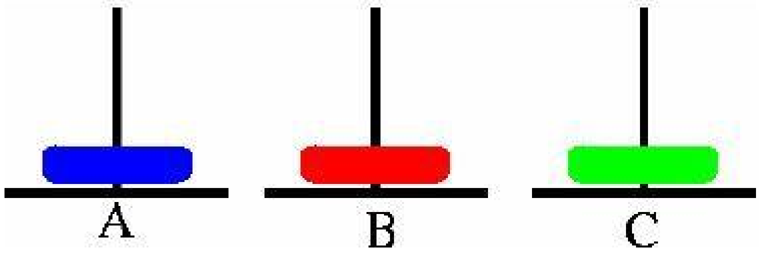


Figure 15

Step 6: Move A → B

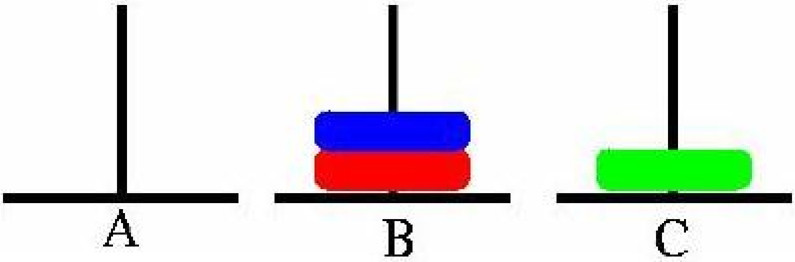


Figure 16

Step 7: Move C→ B

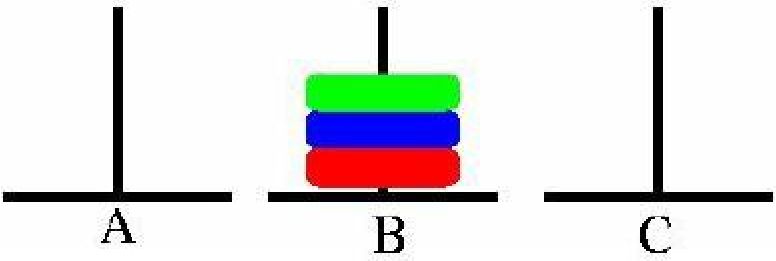


Figure 17

We will now look at another search problem – the 8-queens problem, which can be generalized to the N-queens problem.

3.3.3 Queens Problem

The problem is to place 8 queens on a chessboard so that no two queens are in the same row, column or diagonal.

The picture below on the left shows a solution of the 8-queens problem. The picture on the right is not a correct solution, because some of the queens are attacking each other.

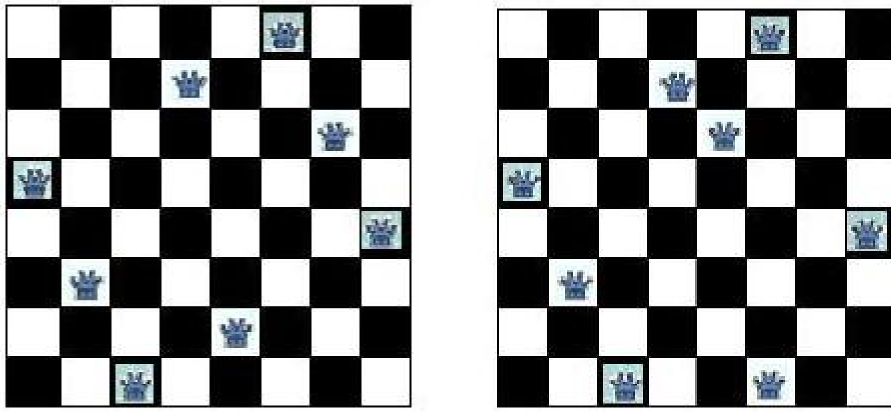


Figure 18: Queens Problem

How do we formulate this in terms of a state space search problem? The problem formulation involves deciding the representation of the states, selecting the initial state representation, the description of the operators, and the successor states. We will now show that we can formulate the search problem in several different ways for this problem.

N queens problem formulation 1

- **States:** Any arrangement of 0 to 8 queens on the board
- **Initial state:** 0 queens on the board
- **Successor function:** Add a queen in any square
- **Goal test:** 8 queens on the board, none are attacked

The initial state has 64 successors. Each of the states at the next level has 63 successors, and so on. We can restrict the search tree somewhat by considering only those successors where no queen is attacking each other. To do that, we have to check the new queen against all existing queens on the board. The solutions are found at a depth of 8.

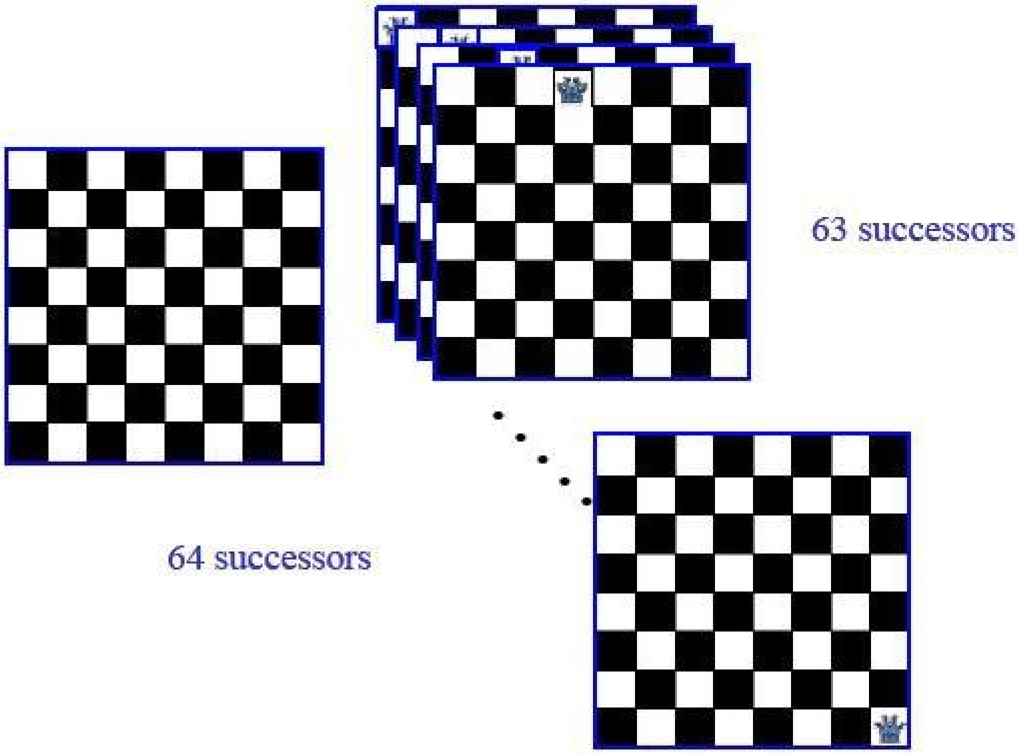


Figure 19

N queens problem formulation 2

- **States:** Any arrangement of 8 queens on the board
- **Initial state:** All queens are at column 1
- **Successor function:** Change the position of any one queen
- **Goal test:** 8 queens on the board, none are attacked

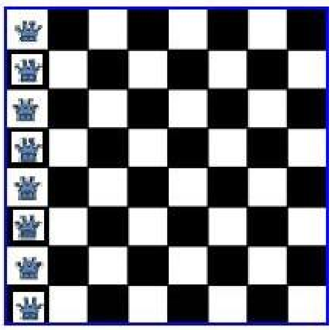


Figure 20

If we consider moving the queen at column 1, it may move to any of the seven remaining columns.

N queens problem formulation 3

- **States:** Any arrangement of k queens in the first k rows such that none are attacked
- **Initial state:** 0 queens on the board
- **Successor function:** Add a queen to the (k+1) th row so that none are attacked.
- **Goal test :** 8 queens on the board, none are attacked

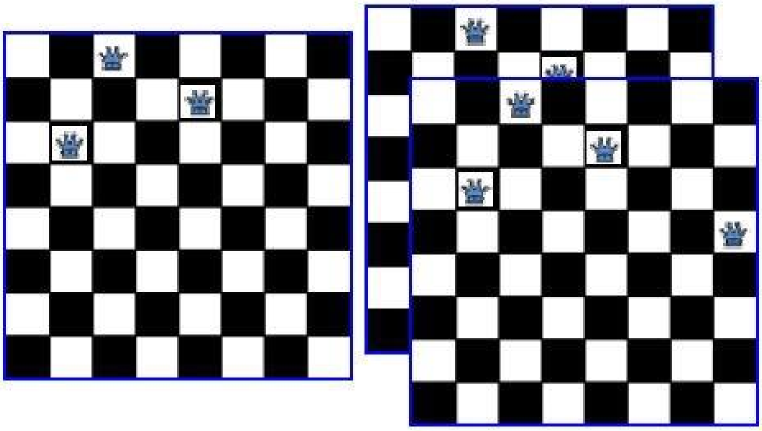


Figure 21

We will now take up yet another search problem, the 8 puzzle.

3.3.4 Problem Definition - Example, 8 puzzle

5	4	
6	1	8
7	3	2

Initial State

1	4	7
2	5	8
3	6	

Goal State

Figure 22

In the 8-puzzle problem we have a 3×3 square board and 8 numbered tiles. The board has one blank position. Bocks can be slid to adjacent blank positions. We can alternatively and equivalently look upon this as the movement of the blank position up, down, left or right. The objective of this puzzle is to move the tiles starting from an initial position and arrive at a given goal configuration.

The 15-puzzle problems is similar to the 8-puzzle. It has a 4×4 square board and 15 numbered tiles

The state space representation for this problem is summarized below:
States: A state is a description of each of the eight tiles in each location that it can occupy.

Operators/Action: The blank moves left, right, up or down

Goal Test: The current state matches a certain state (e.g. one of the ones shown on previous slide)

Path Cost: Each move of the blank costs 1

A small portion of the state space of 8-puzzle is shown below. Note that we do not need to generate all the states before the search begins. The states can be generated when required.

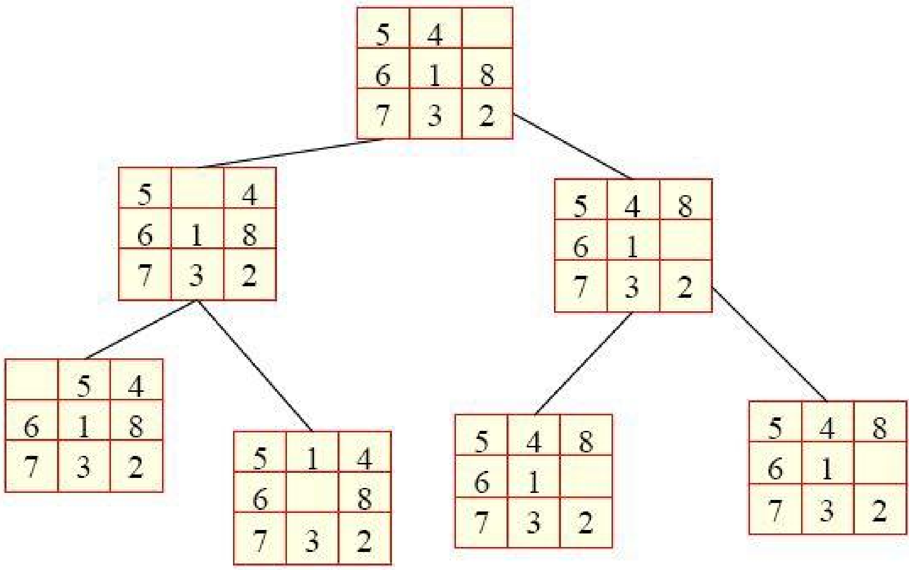


Figure 23

8-puzzle partial state space

3.4 Types of AI Search Techniques

Solution can be found with less information or with more information. It all depends on the problem we need to solve. Usually when we have more information it will be easy to solve the problem. The following are the types of AI search namely: Uninformed Search, List search, Tree search , Graph search, SQL search, Tradeoff Based search, Informed search, Adversarial search. This module will only deal with uninformed search, informed search and Tree search.

4.0 CONCLUSION

State space search is a process used in the field of computer science, including artificial intelligence (AI), in which successive configurations or *states* of an instance are considered, with the goal of finding a *goal state* with a desired property.

Problems are often modelled as a state space, a set of *states* that a problem can be in. The set of states forms a graph where two states are connected if there is an *operation* that can be performed to transform the first state into the second.

State space search often differs from traditional computer science search methods because the state space is *implicit*: the typical state space graph is much too large to generate and store in memory. Instead, nodes are generated as they are explored, and typically discarded thereafter. A solution to a combinatorial search instance may consist of the goal state itself, or of a path from some *initial state* to the goal state.

5.0 SUMMARY

In this unit, you have learnt that:

- State space search is a process used in the field of computer science, including artificial intelligence (AI), in which successive configurations or *states* of an instance are considered, with the goal of finding a *goal state* with a desired property
- The search problem _ is to find a sequence of actions which transforms the agent from the initial state to a goal state $g \in G$. A search problem is represented by a 4-tuple $\{S, s_0, A, G\}$.
- Solution can be found with less information or with more information. It all depends on the problem we need to solve

UNIT 2 UNINFORMED SEARCH OR BRUTE FORCE SEARCH

CONTENTS

1.0 INTRODUCTION

In computer science, uninform-cost search (UCS) is a tree search algorithm used for traversing or searching a weighted tree, tree structure, or graph. The search begins at the root node. The search continues by visiting the next node which has the least total cost from the root. Nodes are visited in this manner until a goal state is reached.

Typically, the search algorithm involves expanding nodes by adding all unexpanded neighbouring nodes that are connected by directed paths to a priority queue. In the queue, each node is associated with its total path cost from the root, where the least-cost paths are given highest priority. The node at the head of the queue is subsequently expanded, adding the next set of connected nodes with the total path cost from the root to the respective node. The uniform-cost search is complete and optimal if the cost of each step exceeds some positive bound ε.

2.0 OBJECTIVES

At the end of this unit, you should be able to:

- explain uninformed search
- list two types of uninformed search
- describe depth first and breadth first search
- solve simple problems on uninformed search.

3.0 MAIN CONTENT

3.1 Uninformed Search

Sometimes we may not get much relevant information to solve a problem. Suppose we lost our car key and we are not able to recall where we left, we have to search for the key with some information such as in which places we used to place it. It may be our pant pocket or may be the table drawer. If it is not there then we have to search the whole house to get it. The best solution would be to search in the places from the table to the wardrobe. Here we need to search blindly with fewer clues. This type of search is called uninformed search or blind search. There are two popular AI search techniques in this category: breadth first search and depth first search.

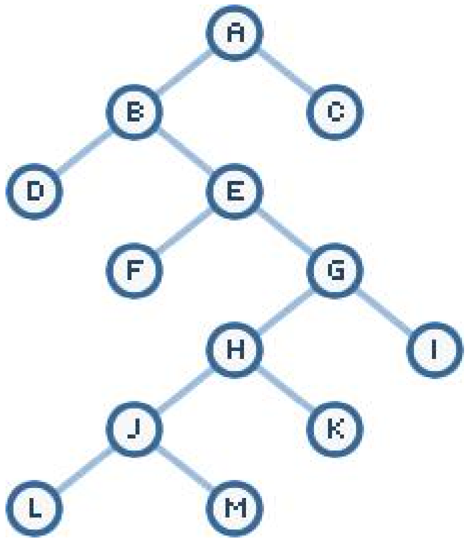
3.2 Depth First and Breadth First Search

If you want to go from Point A to Point B, you are employing some kind of search. For a direction finder, going from Point A to Point B literally means finding a path between where you are now and your intended destination. For a chess game, Point A to Point B might be two points between its current position and its position 5 moves from now. For a genome sequence, Points A and B could be a link between two DNA sequences.

As you can tell, going from Point A to Point B is different for every situation. If there is a vast amount of interconnected data, and you are trying to find a relation between few such pieces of data, you would use search. In this unit, you will learn about two forms of searching, depth first and breadth first.

Our Search Representation

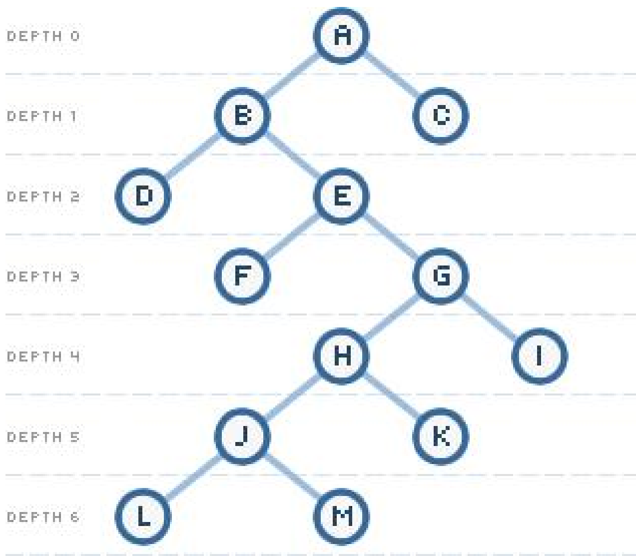
Lets you learn how we humans could solve a search problem. First, we need a representation of how our search problem will exist. The following is an example of our search tree. It is a series of interconnected nodes that we will be searching through:



In our above graph, the path connections are not two-way. All paths go only from top to bottom. In other words, A has a path to B and C, but B and C do not have a path to A. It is basically like a one-way street.

Each lettered circle in our graph is a node. A node can be connected to other via our edge/path, and those nodes that are connected to be called neighbors. B and C are neighbors of A. E and D are neighbors of B, and B is not a neighbor of D or E because B cannot be reached using either D or E.

Our search graph also contains depth:

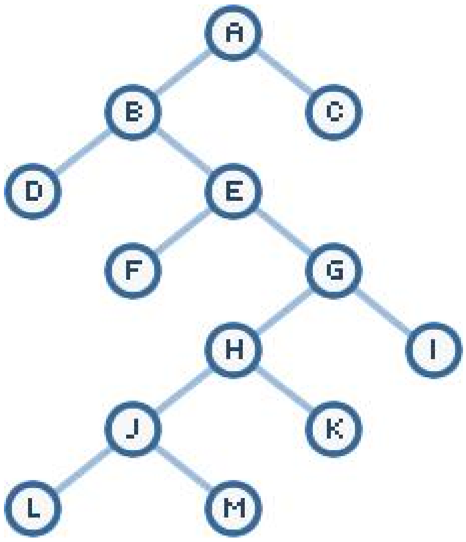


We now have a way of describing location in our graph. We know how the various nodes (the lettered circles) are related to each other (neighbors), and we have a way of characterizing the depth each belongs in. Knowing this information isn't directly relevant in creating our search algorithm, but they do help us to better understand the problem.

3.2.1 Depth First Search

Depth first search works by taking a node, checking its neighbors, expanding the first node it finds among the neighbors, checking if that expanded node is our destination, and if not, continue exploring more nodes.

The above explanation is probably confusing if this is your first exposure to depth first search. I hope the following demonstration will help you more. Using our same search tree, let's find a path between nodes A and F:



Step 0

let’s start with our root/goal node:

I will be using two lists to keep track of what we are doing - an Open list and a Closed List. An Open list keeps track of what you need to do, and the Closed List keeps track of what you have already done. Right now, we only have our starting point, node A. We haven't done anything to it yet, so let's add it to our Open list.

- Open List: A
- Closed List: <empty>

Step 1

Now, let's explore the neighbors of our A node. To put another way, let's take the first item from our Open list and explore its neighbors:

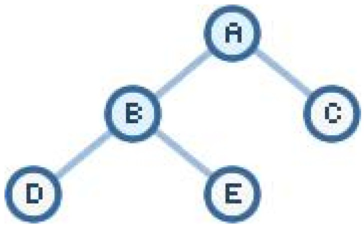
Node A's neighbors are the B and C nodes. Because we are now done with our A node, we can remove it from our Open list and add it to our Closed List. You aren't done with this step though. You now have two new nodes B and C that need exploring. Add those two nodes to our Open list.

Our current Open and Closed Lists contain the following data:

- Open List: B, C
- Closed List: A

Step 2

Our Open list contains two items. For depth first search and breadth first search, you always explore the first item from our Open list. The first item in our Open list is the B node. B is not our destination, so let's explore its neighbors:



Because I have now expanded B, I am going to remove it from the Open list and add it to the Closed List. Our new nodes are D and E, and we add these nodes to the *beginning* of our Open list:

- Open List: D, E, C
- Closed List: A, B

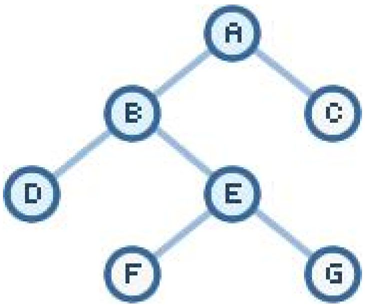
Step 3

You should start to see a pattern forming. Because D is at the beginning of our Open List, we expand it. D isn't our destination, and it does not contain any neighbors. All you do in this step is remove D from our Open List and add it to our Closed List:

- Open List: E, C
- Closed List: A, B, D

Step 4

We now expand the E node from our Open list. E is not our destination, so we explore its neighbors and find out that it contains the neighbors F and G. Remember, F is our target, but we don't stop here though. Despite F being on our path, we only end when we are about to *expand* our target Node - F in this case:

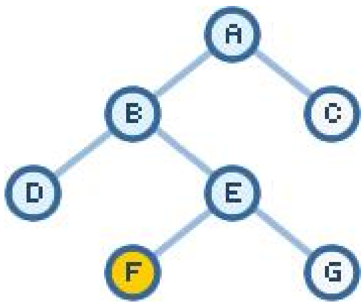


Our Open list will have the E node removed and the F and G nodes added. The removed E node will be added to our Closed List:

- Open List: F, G, C
- Closed List: A, B, D, E

Step 5

We now expand the F node. Since it is our intended destination, we stop:



We remove F from our Open list and add it to our Closed List. Since we are at our destination, there is no need to expand F in order to find its neighbors. Our final Open and Closed Lists contain the following data:

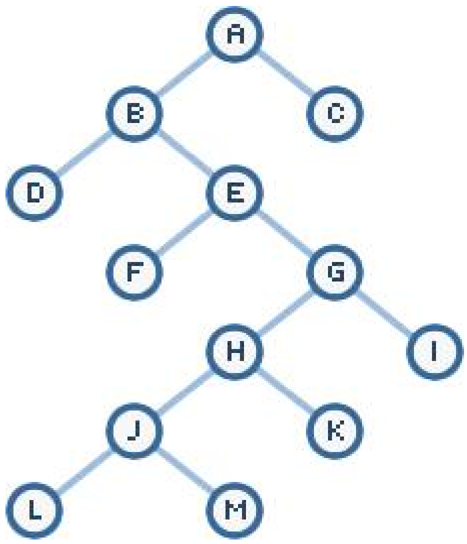
- Open List: G, C
- Closed List: A, B, D, E, F

The final path taken by our depth first search method is what the final value of our Closed List is: A, B, D, E, F. Towards the end of this tutorial, I will analyze these results in greater detail so that you have a better understanding of this search method.

3.2.2 Breadth First Search

The reason I cover both depth and breadth first search methods in the same unit is because they are both similar. In depth first search, newly explored nodes were added to the beginning of your Open list. In breadth first search, newly explored nodes are added to the end of your Open list.

Let's see how that change will affect our results. For reference, here is our original search tree:



Let's try to find a path between nodes A and E.

Step 0

let’s start with our root/goal node:

Like before, I will continue to employ the Open and Closed Lists to keep track of what needs to be done:

- Open List: A
- Closed List: <empty>

Step 1

Now, let's explore the neighbours of our A node. So far, we are following in depth first's footsteps:

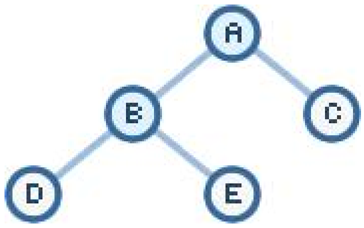
We remove A from our Open list and add A to our Closed List. A's neighbours, the B and C nodes, are added to our Open list. They are added to the end of our Open list, but since our Open list was empty (after removing A), it's hard to show that in this step.

Our current Open and Closed Lists contain the following data:

- Open List: B, C
- Closed List: A

Step 2

Here is where things start to diverge from our depth first search method. We take a look the B node because it appears first in our Open List. Because B isn't our intended destination, we explore its neighbours:

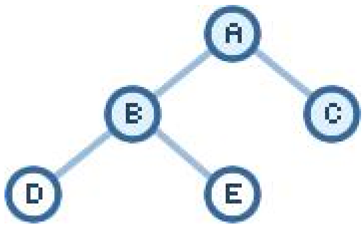


B is now moved to our Closed List, but the neighbours of B, nodes D and E are added to the *end* of our Open list:

- Open List: C, D, E
- Closed List: A, B

Step 3

We now expand our C node:



Since C has no neighbours, all we do is remove C from our Closed List and move on:

- Open List: D, E
- Closed List: A, B, C

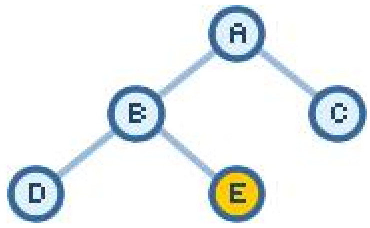
Step 4

Similar to Step 3, we expand node D. Since it isn't our destination, and it too does not have any neighbours, we simply remove D from our to Open list, add D to our Closed List, and continue on:

- Open List: E
- Closed List: A, B, C, D

Step 5

Because our Open list only has one item, we have no choice but to take a look at node E. Since node E is our destination, we can stop here:



Our final versions of the Open and Closed Lists contain the following data:

- Open List: <empty>
- Closed List: A, B, C, D, E

Traveling from A to E takes you through B, C, and D using breadth first search

4.0 CONCLUSION

1. Uninformed search strategies -Also known as "blind search," uninformed search strategies use no information about the likely "direction" of the goal node(s).
2. Uninformed search major methods are Breadth-first and depth-first

5.0 SUMMARY

In this unit, you learnt that:

- Uninformed strategies use only the information available in the problem definition.
- Some such strategies considered :

- Breadth-first search
- Tree Search
- Depth-first search

UNIT 3 INFORMED SEARCH OR HEURISTIC SEARCH

CONTENTS

1.0 INTRODUCTION

We have seen that uninformed search methods that systematically explore the state space and find the goal. They are inefficient in most cases. Informed search methods use problem specific knowledge, and may be more efficient. Informed Search will be able to unravel the factoring an effective way if we now have relevant information, clues or hints. The clues that assist solve the factor constitute heuristic information. Informed search could also be known as heuristic search.

According to George Polya *heuristic* is the study of the methods and rules of discovery and invention. In state space search, *heuristic* define the rules for choosing branches in a state space that are most likely to lead to an acceptable solution. There are two cases in AI searches when heuristics are needed:

- The problem has no exact solution. For example, in medical diagnosis doctors use heuristic to choose the most likely diagnoses given a set of symptoms.
- The problem has an exact solution but is too complex to allow for a *brute force* solution.

Key Point: Heuristics are fallible. Because they rely on limited information, they may lead to a suboptimal solution or to a dead end.

2.0 OBJECTIVES

At the end of this unit, you should be able to:

- explain informed search
- mention other names of informed search
- describe best-first search
- describe greedy search
- solve simple problems on informed search.

3.0 MAIN CONTENT

3.1 What is Heuristic?

Heuristic search methods explore the search space "intelligently". That is, evaluating possibilities without having to investigate every single possibility.

Heuristic search is an AI search technique that employs heuristic for its moves. *Heuristic* is a rule of thumb that probably leads to a solution. Heuristic play a major role in search strategies because of exponential nature of the most problems. Heuristics help to reduce the number of alternatives from an exponential number to a polynomial number. In Artificial Intelligence, heuristic search has a general meaning, and a more specialized technical meaning. In a general sense, the term heuristic is used for any advice that is often effective, but is not guaranteed to work in every case.

Heuristic means “rule of thumb”. To quote Judea Pearl, “Heuristics are criteria, methods or principles for deciding which among several alternative courses of action promises to be the most effective in order to achieve some goal”. In heuristic search or informed search, heuristics are used to identify the most promising search path.

3.1.1 Examples of Heuristic Function

A heuristic function at a node n is an estimate of the optimum cost from the current node to a goal. It is denoted by *h (n)*.
H (n) = estimated cost of the cheapest path from node n to a goal node

Example 1: We want a path from Kolkata to Guwahati Heuristic for Guwahati may be straight-line distance between Kolkata and Guwahati
h(Kolkata) = euclideanDistance(Kolkata, Guwahati)

Example 2: 8-puzzle: Misplaced Tiles Heuristics is the number of tiles out of place.

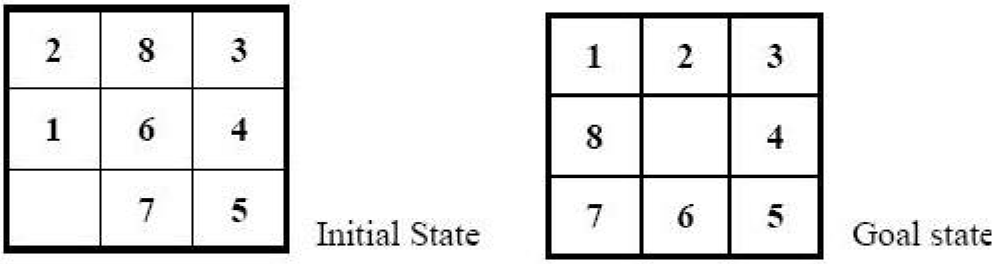


Figure 1: 8 puzzle

The first picture shows the current state *n*, and the second picture the goal state.

h(n) = 5 because the tiles 2, 8, 1, 6 and 7 are out of place.

Manhattan Distance Heuristic: Another heuristic for 8-puzzle is the Manhattan distance heuristic. This heuristic sums the distance that the tiles are out of place. The distance of a tile is measured by the sum of the differences in the x-positions and the y-positions.

For the above example, using the Manhattan distance heuristic,
$h(n) = 1 + 1 + 0 + 0 + 0 + 1 + 1 + 2 = 6$

We will now study a heuristic search algorithm best-first search.

3.2 Best-First Search

Best-first search is a search algorithm which explores a graph by expanding the most promising node chosen according to a specified rule.

Judea Pearl described best-first search as estimating the promise of node *n* by a "heuristic evaluation function *f*(*n*) which, in general, may depend on the description of *n*, the description of the goal, the information gathered by the search up to that point, and most important, on any extra knowledge about the problem domain.

Uniform Cost Search is a special case of the best first search algorithm. The algorithm maintains a priority queue of nodes to be explored. A cost function f(n) is applied to each node. The nodes are put in OPEN in the order of their f values. Nodes with smaller f(n) values are expanded earlier. The generic best first search algorithm is outlined below.

Best First Search
Let *fringe* be a priority queue containing the initial state Loop if *fringe* is empty return failure Node il7remove-first (fringe) if Node is a goal then return the path from initial state to Node else generate all successors of Node, and put the newly generated nodes into fringe according to their f values End Loop

We will now consider different ways of defining the function f. This leads to different search algorithms.

3.2.1 Greedy Search

In greedy search, the idea is to expand the node with the smallest estimated cost to reach the goal.

We use a heuristic function
f(n) = h(n)
h(n) estimates the distance remaining to a goal.

A greedy algorithm is any algorithm that follows the problem solving heuristic of making the locally optimal choice at each stage with the hope of finding the global optimum. In general, greedy algorithms are used for optimization problems.

Greedy algorithms often perform very well. They tend to find good solutions quickly, although not always optimal ones.

The resulting algorithm is not optimal. The algorithm is also incomplete, and it may fail to find a solution even if one exists. This can be seen by running greedy search on the following example. A good heuristic for the route-finding problem would be straight-line distance to the goal.

S is the starting state, G is the goal state.

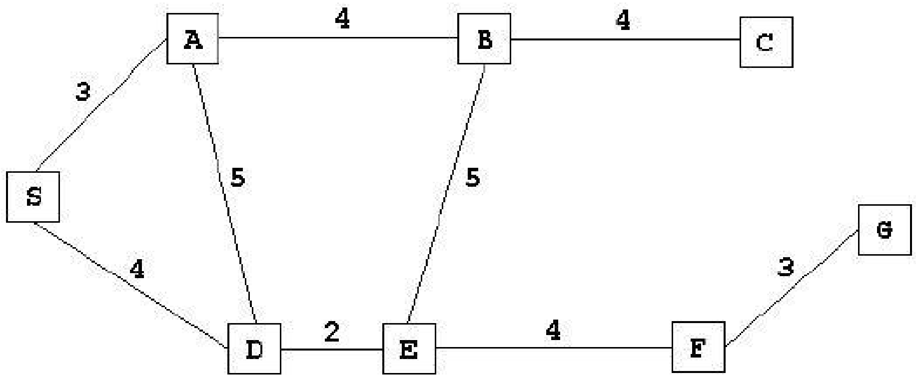


Figure 2 is an example of a route finding problem.

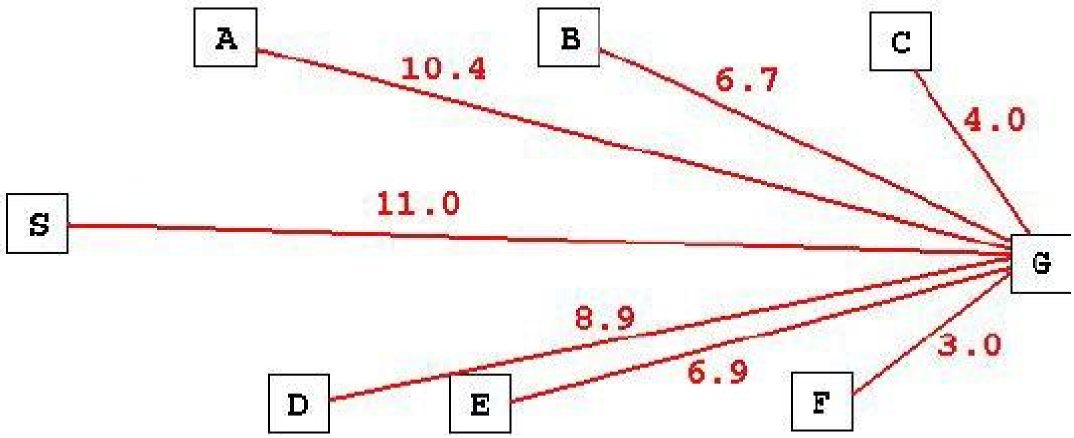
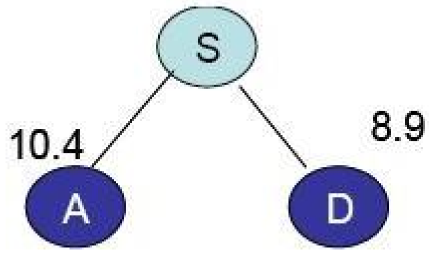


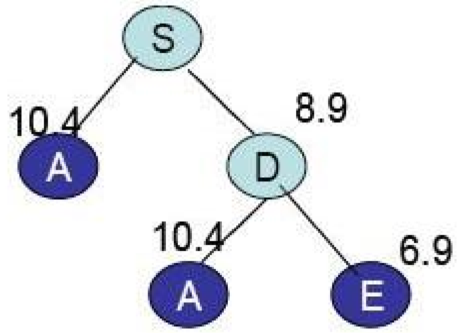
Figure 3 -The straight line distance heuristic estimates for the nodes.

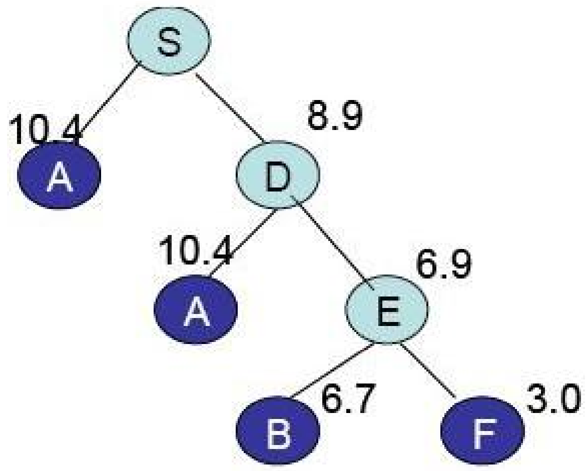
Let us run the greedy search algorithm for the graph given in Figure 2. The straight line distance heuristic estimates for the nodes are shown in Figure 3.

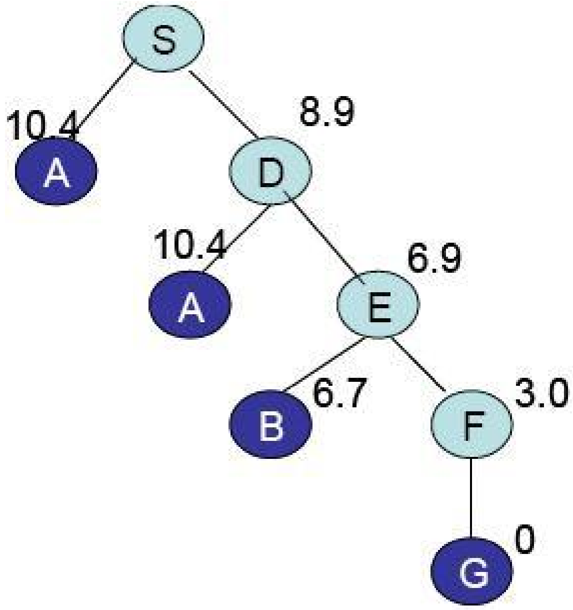
Step 1: S is expanded. Its children are A and D.



Step 2: D has smaller cost and is expanded next.







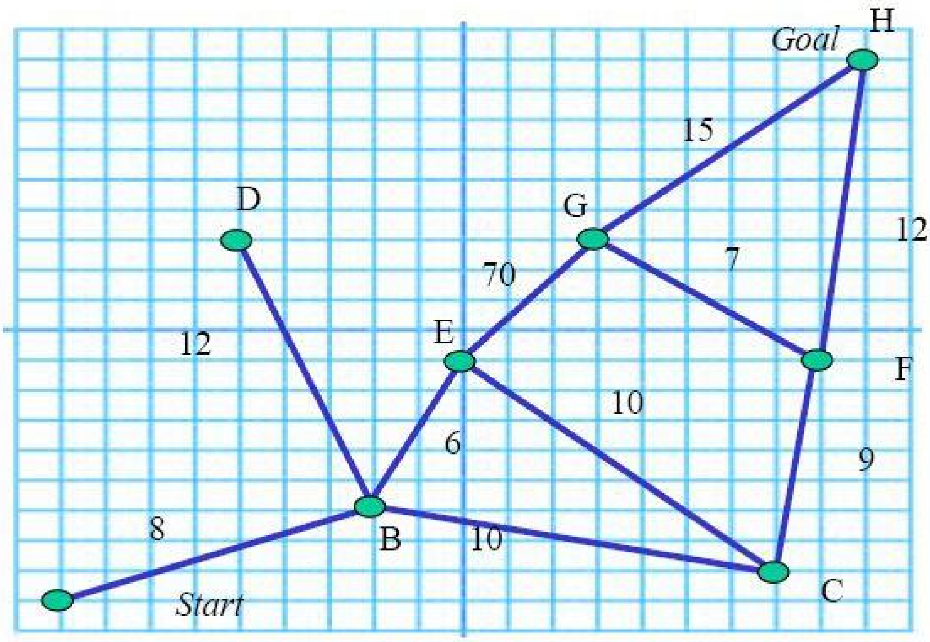


Figure 4

Greedy Best-First Search illustrated

We will run greedy best first search on the problem in Figure 2. We use the straight line heuristic. *h(n)* is taken to be the straight line distance from *n* to the goal position.

The nodes will be expanded m the following order:

A
B
E
G
H

The path obtained is A-B-E-G-H and its cost is 99
Clearly this is not an optimum path. The path A-B-C-F-H has a cost of 39.

3.2.2 A* Search

We w-ill next consider the famous A+ algorithm. This algorithm. was given by Hart, Nilsson & Rafael in 1968.

A+ is a best first search algorithm ,vith
f(n) = g(n) + h(n)
where
g(n) = sum of edge costs from start to n
h(n) = estimate oflowest cost path from n to goal

f(n) = actual distance so far + estimated distance remammg

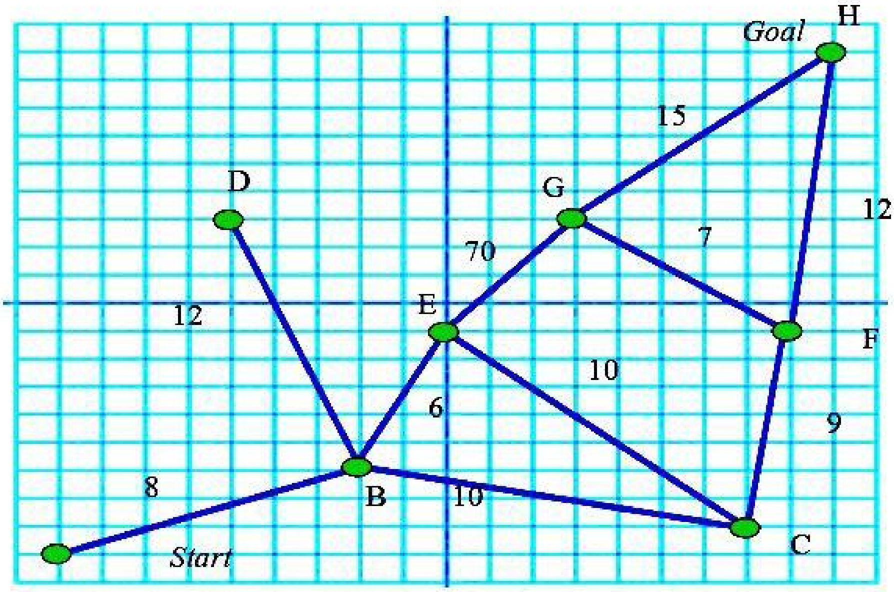
h(n) is said to be admissible if it underestimates the cost of any solution that can be reached from *n*. If *C*(n)* is the cost of the cheapest solution path from *n* to a goal node, and ifh is admissible,
h(n) <= C(n)*.
We can prove that if *h(n)* is admissible, then the search ,vill find an optimal solution.

The algorithm A+ is outlined below:

```
Algorithm A*
OPEN = nodes on frontier.      CLOSED = expanded nodes.
OPEN= {<s, nil>}
while OPEN is not empty
    remove from OPEN the node <n,p> with minimumf(n)
    place <n,p> on CLOSED
    if n is a goal node,
          return success (pathp)
    for each edge connecting n & m w-ith cost c
       if <m, q> is on CLOSED and {pie} is cheaper than q
           then remove n from CLOSED,
                 put <m,{pie}> on OPEN
       else if <m,q> is on OPEN and {pie} is cheaper than q
           then replace q v.cith {pie}
       else if m is not on OPEN
            then put <m,{ple}> on OPEN
```

return failure

3.2.1 A* illustrated



The heuristic function used is straight line distance. The order of nodes expanded, and the status of Fringe is shown in the following table.

Steps	Fringe	Node expanded	Comments
1	A		
2	B(26.6)	A	
3	E(27.5), C(35.1), D(35.2)	B	
4	C(35.1), D(35.2), ~~C(41.2)~~ G(92.5)	E	C is not inserted as there is another C with lower cost.
5	D(35.2), F(37), G(92.5)	C	
6	F(37), G(92.5)	D	
7	H(39), G(42.5)	F	G is replaced with a lower cost node
8	G(42.5)	H	Goal test successful.

The path returned is A-B-C-F-H.
The path cost is 39. This is an optimal path.

3.2.2 A* search: properties

The algorithm A* is admissible. This means that provided a solution exists, the first solution found by A* is an optimal solution. A* is admissible under the following conditions:

- In the state space graph
    - Every node has a finite number of successors
    - Every arc in the graph has a cost greater than some $\varepsilon > 0$
- Heuristic function: for every node n, $h(n) \leq h^*(n)$

A* is also complete under the above conditions.

A* is optimally efficient for a given heuristic – of the optimal search algorithms that expand search paths from the root node, it can be shown that no other optimal algorithr will expand fewer nodes and find a solution

However, the number of nodes searched still exponential in the worst case.

Unfortunately, estimates are usually not good enough for A* to avoid having to expand an exponential number of nodes to find the optimal solution. In addition, A* must keep all nodes it is considering in memory.

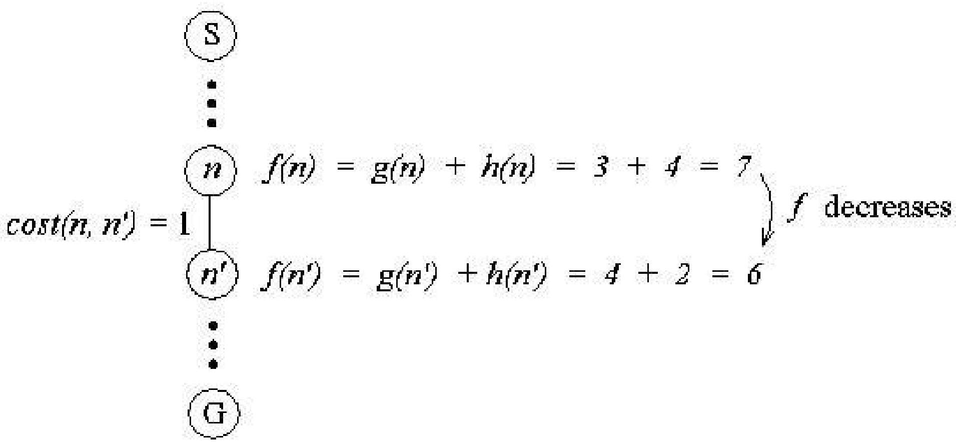
A* is still much more efficient than uninformed methods.

It is always better to use a heuristic function with higher values as long as it does not overestimate.

A heuristic is consistent if:

$h(n) <= cost(n, n') + h(n')$

For example, the heuristic shown below is inconsistent, because h(n) = 4, but $cost(n, n') + h(n') = 1 + 2 = 3$, which is less than 4. This makes the value of f decrease from node n to node n':



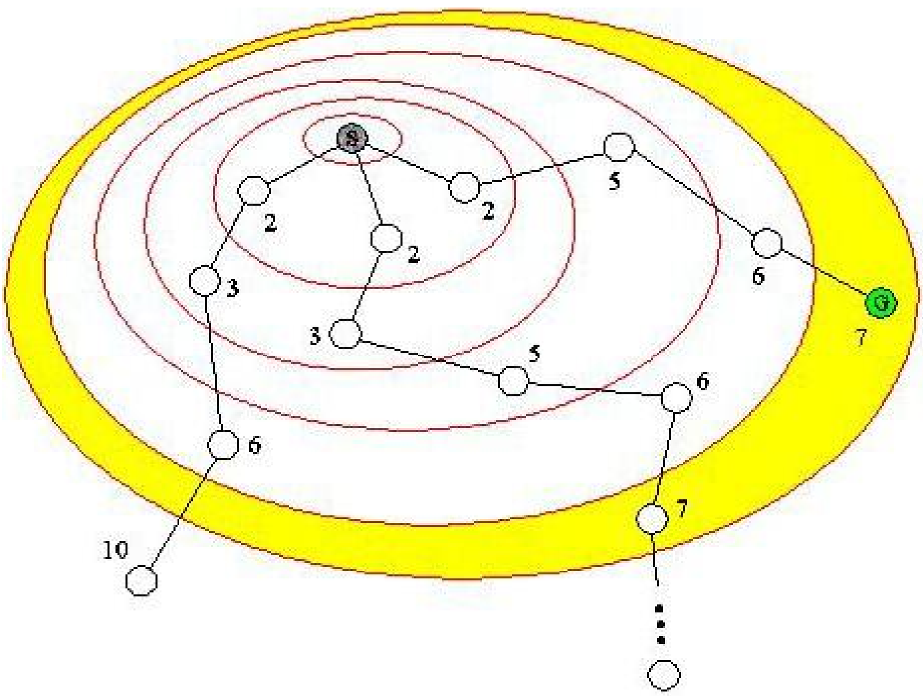
If a heuristic h is consistent, the f values along any path will be nondecreasing:

$f(n')$ = estimated distance from start to goal through n'
= actual distance from start to n + step cost from n to n' + estimated distance from n' to goal
= $g(n) + cost(n, n') + h(n')$
$\geq g(n) + h(n)$ because $cost(n, n') + h(n') \geq h(n)$ by consistency
= $f(n)$

Therefore $f(n') \geq f(n)$, so f never decreases along a path.

If a heuristic h is inconsistent, we can tweak the f values so that they behave as if h were consistent, using the **pathmax equation**:
$f(n') = \max(f(n), g(n') + h(n'))$

This ensures that the f values never decrease along a path from the start to a goal.
Given nondecreasing values of f, we can think of A* as searching outward from the start node through successive **contours** of nodes, where all of the nodes in a contour have the same f value:



For any contour, A* examines all of the nodes in the contour before looking at any contours further out. If a solution exists, the goal node in the closest contour to the start node will be found first.

We will now prove the admissibility of A*.

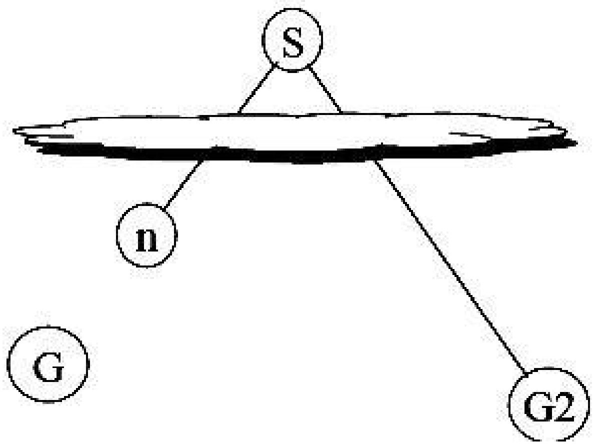
3.2.3 Proof of Admissibility of A*

We will show that A* is admissible if it uses a monotone heuristic.

A monotone heuristic is such that along any path the f-cost never decreases.
But if this property does not hold for a given heuristic function, we can make the f value monotone by making use of the following trick (m is a child of n)
$f(m) = max\ (f(n),\ g(m) + h(m))$

- Let G be an optimal goal state
- C* is the optimal path cost.
- G2 is a suboptimal goal state: g(G2) > C*

Suppose A* has selected G2 from OPEN for expansion.



Consider a node n on OPEN on an optimal path to G. Thus $C^* \geq f(n)$
Since n is not chosen for expansion over G2, $f(n) \geq f(G2)$
G2 is a goal state. $f(G2) = g(G2)$
Hence $C^* \geq g(G2)$.
This is a contradiction. Thus A* could not have selected G2 for expansion before reaching the goal by an optimal path.

3.2.4 Proof of Completeness of A*

Let G be an optimal goal state.
A* cannot reach a goal state only if there are infinitely many nodes where $f(n) \leq C^*$.
This can only happen if either happens:

- o There is a node with infinite branching factor. The first condition takes care of this.
- o There is a path with finite cost but infinitely many nodes. But we assumed that Every arc in the graph has a cost greater than some $\varepsilon > 0$. Thus if there are infinitely many nodes on a path $g(n) > f^*$, the cost of that path will be infinite.

Lemma: A* expands nodes in increasing order of their f values.

A* is thus **complete** and **optimal**, assuming an admissible and consistent heuristic function (or using the pathmax equation to simulate consistency).
A* is also **optimally efficient**, meaning that it expands only the minimal number of nodes needed to ensure optimality and completeness.

3.2.4 Performance Analysis of A*

Model the search space by a uniform b-ary tree with a unique start state s, and a goal state, g at a distance N from s.
The number of nodes expanded by A* is exponential in N unless the heuristic estimate is logarithmically accurate
$|h(n) - h^*(n)| \leq O(\log h^*(n))$

In practice most heuristics have proportional error.

It becomes often difficult to use A* as the OPEN queue grows very large.
A solution is to use algorithms that work with less memory.

3.2.5 Properties of Heuristics

Dominance:
h2 is said to dominate h1 iff $h2(n) \geq h1(n)$ for any node n.
A* will expand fewer nodes on average using h2 than h1.

Proof:

Every node for which $f(n) < C^*$ will be expanded. Thus n is expanded whenever

$$h(n) < f^* - g(n)$$

Since $h2(n) \geq h1(n)$ any node expanded using h2 will be expanded using h1.

3.2.6 Using multiple heuristics

Suppose you have identified a number of non-overestimating heuristics for a problem:
$h1(n), h2(n), \ldots, hk(n)$

Then
$max\ (h1(n), h2(n), \ldots, hk(n))$
is a more powerful non-overestimating heuristic. This follows from the property of dominance

3.3 Beam Search

In computer science, beam search is a heuristic search algorithm that explores a graph by expanding the most promising node in a limited set. Beam search is an optimization of best-first search that reduces its memory requirements. Best-first search is a graph search which orders all partial solutions (states) according to some heuristic which attempts to predict how close a partial solution is to a complete solution (goal state). In beam search, only a predetermined number of best partial solutions are kept as candidates.

Beam search uses breadth-first search to build its search tree. At each level of the tree, it generates all successors of the states at the current level, sorting them in increasing order of heuristic cost.http://en.wikipedia.org/wiki/Beam_search - cite_note-1 However, it only stores a predetermined number of states at each level (called the beam width). The greater the beam width, the fewer states are pruned. With an infinite beam width, no states are pruned and beam search is identical to breadth-first search. The beam width bounds the memory required to perform the search. Since a goal state could potentially be pruned, beam search sacrifices completeness (the guarantee that an algorithm will terminate with a solution, if one exists) and optimality (the guarantee that it will find the best solution).

The beam width can either be fixed or variable. One approach that uses a variable beam width starts with the width at a minimum. If no solution is found, the beam is widened and the procedure is repeated.

3.3.1 Name and Uses

The term "beam search" was coined by Raj Reddy, Carnegie Mellon University, 1976.

A beam search is most often used to maintain tractability in large systems with insufficient amount of memory to store the entire search tree. For example, it is used in many machine translation systems. To select the best translation, each part is processed, and many different ways of translating the words appear. The top best translations according to their sentence structures are kept and the rest are discarded. The translator then evaluates the translations according to a given criteria, choosing the translation which best keeps the goals. The first use of a beam search was in the Harpy Speech Recognition System, CMU 1976.

3.3.2 Extensions

Beam search has been made complete by combining it with depth-first search, resulting in Beam Stack Search and Depth-First Beam Search, and limited discrepancy search, resulting in Beam Search Using Limited Discrepancy Backtrackinghttp://en.wikipedia.org/wiki/Beam_search - cite_note-furcy-3 (BULB). The resulting search algorithms are anytime algorithms that find good but likely sub-optimal solutions quickly, like beam search, then backtrack and continue to find improved solutions until convergence to an optimal solution.

3.4 Hill climbing

In computer science, hill climbing is a mathematical optimization technique which belongs to the family of local search. It is an iterative algorithm that starts with an arbitrary solution to a problem, then attempts to find a better solution by incrementally changing a single element of the solution. If the change produces a better solution, an incremental change is made to the new solution, repeating until no further improvements can be found.

For example, hill climbing can be applied to the travelling salesman problem. It is easy to find an initial solution that visits all the cities but will be very poor compared to the optimal solution. The algorithm starts with such a solution and makes small improvements to it, such as switching the order in which two cities are visited. Eventually, a much shorter route is likely to be obtained.

Hill climbing is good for finding a local optimum (a solution that cannot be improved by considering a neighbouring configuration) but it is not guaranteed to find the best possible solution (the global optimum) out of all possible solutions (the search space). The characteristic that only local optima are guaranteed can be cured by using restarts (repeated local search), or more complex schemes based on iterations, like iterated local search, on memory, like reactive search optimization and tabu search, on memory-less stochastic modifications, like simulated annealing.

The relative simplicity of the algorithm makes it a popular first choice amongst optimizing algorithms. It is used widely in artificial intelligence, for reaching a goal state from a starting node. Choice of next node and starting node can be varied to give a list of related algorithms. Although more advanced algorithms such as simulated annealing or tabu search may give better results, in some situations hill climbing works just as well. Hill climbing can often produce a better result than other algorithms when the amount of time available to perform a search is limited, such as with real-time systems. It is an anytime algorithm: it can return a valid solution even if it's interrupted at any time before it ends.

3.4.1 Mathematical description

Hill climbing attempts to maximize (or minimize) a target function $f(\mathbf{x})$, where $\mathbf{x}$ is a vector of continuous and/or discrete values. At each iteration, hill climbing will adjust a single element in $\mathbf{x}$ and determine whether the change improves the value of $f(\mathbf{x})$. (Note that this differs from gradient descent methods, which adjust all of the values in $\mathbf{x}$ at each iteration according to the gradient of the hill.) With hill climbing, any change that improves $f(\mathbf{x})$ is accepted, and the process continues until no change can be found to improve the value of $f(\mathbf{x})$. $\mathbf{x}$ is then said to be "locally optimal".

In discrete vector spaces, each possible value for $\mathbf{x}$ may be visualized as a vertex in a graph. Hill climbing will follow the graph from vertex to vertex, always locally increasing (or decreasing) the value of $f(\mathbf{x})$, until a local maximum (or local minimum) x_m is reached.

3.4.2 Variants

In simple hill climbing, the first closer node is chosen, whereas in steepest ascent hill climbing all successors are compared and the closest to the solution is chosen. Both forms fail if there is no closer node, which may happen if there are local maxima in the search space which are not solutions. Steepest ascent hill climbing is similar to best-first search, which tries all possible extensions of the current path instead of only one.

Stochastic hill climbing does not examine all neighbours before deciding how to move. Rather, it selects a neighbour at random, and decides (based on the amount of improvement in that neighbour) whether to move to that neighbour or to examine another.

Random-restart hill climbing is a meta-algorithm built on top of the hill climbing algorithm. It is also known as Shotgun hill climbing. It iteratively does hill-climbing, each time with a random initial condition x_0. The best x_m is kept: if a new run of hill climbing produces a better x_m than the stored state, it replaces the stored state.

Random-restart hill climbing is a surprisingly effective algorithm in many cases. It turns out that it is often better to spend CPU time exploring the space, than carefully optimizing from an initial condition.

4.0 CONCLUSION

Informed search strategies -Also known as "heuristic search," informed search strategies use information about the domain to (try to) (usually) head in the general direction of the goal node(s)

-Informed search methods: Hill climbing, best-first, greedy search, beam search, A, A*

5.0 SUMMARY

In this unit, you learnt that:

- Heuristic search is an AI search technique that employs heuristic for its moves.
- Best-first search is a search algorithm which explores a graph by expanding the most promising node chosen according to a specified rule.
- A greedy algorithm is any algorithm that follows the problem solving heuristic of making the locally optimal choice at each stage with the hope of finding the global optimum
- Beam search is a heuristic search algorithm that explores a graph by expanding the most promising node in a limited set
- Hill climbing is a mathematical optimization technique which belongs to the family of local search.

UNIT 3 NATURAL LANGUAGE PROCESSING

CONTENTS

1.0 INTRODUCTION

Natural language processing (NLP) is a field of computer science and linguistics concerned with the interactions between computers and human (natural) languages; it began as a branch of artificial intelligence. In theory, natural language processing is a very attractive method of human–computer interaction. Natural language understanding is sometimes referred to as an AI-complete problem because it seems to require extensive knowledge about the outside world and the ability to manipulate it.

An automated online assistant providing customer service on a web page is an example of an application where natural language processing is a major comp1nt.

2.0 OBJECTIVES

At the end of this unit, you should be able to:

- describe the history of natural language processing
- list major tasks in NLP
- mention different types of evaluation of NPL.

3.0 MAIN CONTENT

3.1 History of natural language processing

The history of NLP generally starts in the 1950s, although work can be found from earlier periods. In 1950, Alan Turing published his famous article "Computing Machinery and Intelligence" which proposed what is now called the Turing test as a criterion of intelligence. This criterion depends on the ability of a computer program to impersonate a human in a real-time written conversation with a human judge, sufficiently well that the judge is unable to distinguish reliably — on the basis of the conversational content alone — between the program and a real human. The Georgetown experiment in 1954 involved fully automatic translation of more than sixty Russian sentences into English. The authors claimed that within three or five years, machine translation would be a solved problem. However, real progress was much slower, and after the ALPAC report in 1966, which found that ten years long research had failed to fulfill the expectations, funding for machine translation was dramatically reduced. Little further research in machine translation was conducted until the late 1980s, when the first statistical machine translation systems were developed.

Some notably successful NLP systems developed in the 1960s were SHRDLU, a natural language system working in restricted "blocks worlds" with restricted vocabularies, and ELIZA, a simulation of a Rogerian psychotherapist, written by Joseph Weizenbaum between 1964 to 1966. Using almost no information about human thought or emotion, ELIZA sometimes provided a startlingly human-like interaction. When the "patient" exceeded the very small knowledge base, ELIZA might provide a generic response, for example, responding to "My head hurts" with "Why do you say your head hurts?”

During the 70's many programmers began to write 'conceptual ontologies', which structured real-world information into computer-understandable data. Examples are MARGIE (Schank, 1975), SAM (Cullingford, 1978), PAM (Wilensky, 1978), TaleSpin (Meehan, 1976), QUALM (Lehnert, 1977), Politics (Carbonell, 1979), and Plot Units (Lehnert 1981). During this time, many chatterbots were written including PARRY, Racter, and Jabberwacky.

Up to the 1980s, most NLP systems were based on complex sets of hand-written rules. Starting in the late 1980s, however, there was a revolution in NLP with the introduction of machine learning algorithms for language processing. This was due both to the steady increase in computational power resulting from Moore's Law and the gradual lessening of the dominance of Chomskyan theories of linguistics (e.g. transformational grammar), whose theoretical underpinnings discouraged the sort of corpus linguistics that underlies the machine-learning approach to language processing. Some of the earliest-used machine learning algorithms, such as decision trees, produced systems of hard if-then rules similar to existing hand-written rules. Increasingly, however, research has focused on statistical models, which make soft, probabilistic decisions based on attaching real-valued weights to the features making up the input data. Such models are generally more robust when given unfamiliar input, especially input that contains errors (as is very common for real-world data), and produce more reliable results when integrated into a larger system comprising multiple subtasks.

Many of the notable early successes occurred in the field of machine translation, due especially to work at IBM Research, where successively more complicated statistical models were developed. These systems were able to take advantage of existing multilingual textual corpora that had been produced by the Parliament of Canada and the European Union as a result of laws calling for the translation of all governmental proceedings into all official languages of the corresponding systems of government. However, most other systems depended on corpora specifically developed for the tasks implemented by these systems, which was (and often continues to be) a major limitation in the success of these systems. As a result, a great deal of research has gone into methods of more effectively learning from limited amounts of data.

Recent research has increasingly focused on unsupervised and semi-supervised learning algorithms. Such algorithms are able to learn from data that has not been hand-annotated with the desired answers, or using a combination of annotated and non-annotated data. Generally, this task is much more difficult than supervised learning, and typically produces less accurate results for a given amount of input data. However, there is an enormous amount of non-annotated data available (including, among other things, the entire content of the World Wide Web), which can often make up for the inferior results.

3.2 NLP Using Machine Learning

As described above, modern approaches to natural language processing (NLP) are grounded in machine learning. The paradigm of machine learning is different from that of most prior attempts at language processing. Prior implementations of language-processing tasks typically involved the direct hand coding of large sets of rules. The machine-learning paradigm calls instead for using general learning algorithms — often, although not always, grounded in statistical inference — to automatically learn such rules through the analysis of large corpora of typical real-world examples. A corpus (plural, "corpora") is a set of documents (or sometimes, individual sentences) that have been hand-annotated with the correct values to be learned.

As an example, consider the task of part of speech tagging, i.e. determining the correct part of speech of each word in a given sentence, typically one that has never been seen before. A typical machine-learning-based implementation of a part of speech tagger proceeds in two steps, a training step and an evaluation step. The first step — the training step — makes use of a corpus of training data, which consists of a large number of sentences, each of which has the correct part of speech attached to each word. (An example of such a corpus in common use is the Penn Treebank. This includes (among other things) a set of 500 texts from the Brown Corpus, containing examples of various genres of text, and 2500 articles from the Wall Street Journal.) This corpus is analyzed and a learning model is generated from it, consisting of automatically created rules for determining the part of speech for a word in a sentence, typically based on the nature of the word in question, the nature of surrounding words, and the most likely part of speech for those surrounding words. The model that is generated is typically the best model that can be found that simultaneously meets two conflicting objectives: To perform as well as possible on the training data, and to be as simple as possible (so that the model avoids over fitting the training data, i.e. so that it generalizes as well as possible to new data rather than only succeeding on sentences that have already been seen). In the second step (the evaluation step), the model that has been learned is used to process new sentences. An important part of the development of any learning algorithm is testing the model that has been learned on new, previously unseen data. It is critical that the data used for testing is not the same as the data used for training; otherwise, the testing accuracy will be unrealistically high.

Many different classes of machine learning algorithms have been applied to NLP tasks. In common to all of these algorithms is that they take as input a large set of "features" that are generated from the input data. As an example, for a part-of-speech tagger, typical features might be the identity of the word being processed, the identity of the words immediately to the left and right, the part-of-speech tag of the word to the left, and whether the word being considered or its immediate neighbors are content words or function words. The algorithms differ, however, in the nature of the rules generated. Some of the earliest-used algorithms, such as decision trees, produced systems of hard if-then rules similar to the systems of hand-written rules that were then common. Increasingly, however, research has focused on statistical models, which make soft, probabilistic decisions based on attaching real-valued weights to each input feature. Such models have the advantage that they can express the relative certainty of many different possible answers rather than only one, producing more reliable results when such a model is included as a component of a larger system. In addition, models that make soft decisions are generally more robust when given unfamiliar input, especially input that contains errors (as is very common for real-world data).

Systems based on machine-learning algorithms have many advantages over hand-produced rules:

- The learning procedures used during machine learning automatically focus on the most common cases, whereas when writing rules by hand it is often not obvious at all where the effort should be directed.
- Automatic learning procedures can make use of statistical inference algorithms to produce models that are robust to unfamiliar input (e.g. containing words or structures that have not been seen before) and to erroneous input (e.g. with misspelled words or words accidentally omitted). Generally, handling such input gracefully with hand-written rules — or more generally, creating systems of hand-written rules that make soft decisions — is extremely difficult and error-prone.
- Systems based on automatically learning the rules can be made more accurate simply by supplying more input data. However, systems based on hand-written rules can only be made more accurate by increasing the complexity of the rules, which is a much more difficult task. In particular, there is a limit to the complexity of systems based on hand-crafted rules, beyond which the systems become more and more unmanageable. However, creating more data to input to machine-learning systems simply requires a corresponding increase in the number of man-hours worked, generally without significant increases in the complexity of the annotation process.

3.3 Major tasks in NLP

The following is a list of some of the most commonly researched tasks in NLP. Note that some of these tasks have direct real-world applications, while others more commonly serve as subtasks that are used to aid in solving larger tasks. What distinguishes these tasks from other potential and actual NLP tasks is not only the volume of research devoted to them but the fact that for each one there is typically a well-defined problem setting, a standard metric for evaluating the task, standard corpora on which the task can be evaluated, and competitions devoted to the specific task.

- **Automatic summarization:** Produce a readable summary of a chunk of text. Often used to provide summaries of text of a known type, such as articles in the financial section of a newspaper.
- **Co reference resolution:** Given a sentence or larger chunk of text, determine which words ("mentions") refer to the same objects ("entities"). Anaphora resolution is a specific example of this task, and is specifically concerned with matching up pronouns with the nouns or names that they refer to. The more general task of co reference resolution also includes identify so-called "bridging relationships" involving referring expressions. For example, in a sentence such as "He entered John's house through the front door", "the front door" is a referring expression and the bridging relationship to be identified is the fact that the door being referred to is the front door of John's house (rather than of some other structure that might also be referred to).
- **Discourse analysis:** This rubric includes a number of related tasks. One task is identifying the discourse structure of connected text, i.e. the nature of the discourse relationships between sentences (e.g. elaboration, explanation, contrast). Another possible task is recognizing and classifying the speech acts in a chunk of text (e.g. yes-no question, content question, statement, assertion, etc.).
- **Machine translation:** Automatically translate text from one human language to another. This is one of the most difficult problems, and is a member of a class of problems colloquially termed "AI-complete", i.e. requiring all of the different types of knowledge that humans possess (grammar, semantics, facts about the real world, etc.) in order to solve properly.
- **Morphological segmentation:** Separate words into individual morphemes and identify the class of the morphemes. The difficulty of this task depends greatly on the complexity of the morphology (i.e. the structure of words) of the language being considered. English has fairly simple morphology, especially inflectional morphology, and thus it is often possible to ignore this task entirely and simply model all possible forms of a word (e.g. "open, opens, opened, and opening") as separate words. In languages such as Turkish, however, such an approach is not possible, as each dictionary entry has thousands of possible word forms.

- **Named entity recognition (NER):** Given a stream of text, determine which items in the text map to proper names, such as people or places, and what the type of each such name is (e.g. person, location, organization). Note that, although capitalization can aid in recognizing named entities in languages such as English, this information cannot aid in determining the type of named entity, and in any case is often inaccurate or insufficient. For example, the first word of a sentence is also capitalized, and named entities often span several words, only some of which are capitalized. Furthermore, many other languages in non-Western scripts (e.g. Chinese or Arabic) do not have any capitalization at all, and even languages with capitalization may not consistently use it to distinguish names. For example, German capitalizes all nouns, regardless of whether they refer to names, and French and Spanish do not capitalize names that serve as adjectives.
- **Natural language generation:** Convert information from computer databases into readable human language.
- **Natural language understanding:** Convert chunks of text into more formal representations such as first-order logic structures that are easier for computer programs to manipulate. Natural language understanding involves the identification of the intended semantic from the multiple possible semantics which can be derived from a natural language expression which usually takes the form of organized notations of natural languages concepts. Introduction and creation of language metamodel and ontology are efficient however empirical solutions. An explicit formalization of natural languages semantics without confusions with implicit assumptions such as closed world assumption (CWA) vs. open world assumption, or subjective Yes/No vs. objective True/False is expected for the construction of a basis of semantics formalization.
- **Optical character recognition (OCR):** Given an image representing printed text, determine the corresponding text.
- **Part-of-speech tagging:** Given a sentence, determine the part of speech for each word. Many words, especially common ones, can serve as multiple parts of speech. For example, "book" can be a noun ("the book on the table") or verb ("to book a flight"); "set" can be a noun, verb or adjective; and "out" can be any of at least five different parts of speech. Note that some languages have more such ambiguity than others. Languages with little inflectional morphology, such as English are particularly prone to such ambiguity. Chinese is prone to such ambiguity because it is a tonal language during verbalization. Such inflection is not readily conveyed via the entities employed within the orthography to convey intended meaning.

- **Parsing:** Determine the parse tree (grammatical analysis) of a given sentence. The grammar for natural languages is ambiguous and typical sentences have multiple possible analyses. In fact, perhaps surprisingly, for a typical sentence there may be thousands of potential parses (most of which will seem completely nonsensical to a human).
- **Question answering:** Given a human-language question, determine its answer. Typical questions have a specific right answer (such as "What is the capital of Canada?"), but sometimes open-ended questions are also considered (such as "What is the meaning of life?").
- **Relationship extraction:** Given a chunk of text, identify the relationships among named entities (e.g. who is the wife of whom).
- **Sentence breaking (also known as sentence boundary disambiguation):** Given a chunk of text, find the sentence boundaries. Sentence boundaries are often marked by periods or other punctuation marks, but these same characters can serve other purposes (e.g. marking abbreviations).
- **Sentiment analysis:** Extract subjective information usually from a set of documents, often using online reviews to determine "polarity" about specific objects. It is especially useful for identifying trends of public opinion in the social media, for the purpose of marketing.
- **Speech recognition:** Given a sound clip of a person or people speaking, determine the textual representation of the speech. This is the opposite of text to speech and is one of the extremely difficult problems colloquially termed "AI-complete" (see above). In natural speech there are hardly any pauses between successive words, and thus speech segmentation is a necessary subtask of speech recognition (see below). Note also that in most spoken languages, the sounds representing successive letters blend into each other in a process termed coarticulation, so the conversion of the analog signal to discrete characters can be a very difficult process.
- **Speech segmentation:** Given a sound clip of a person or people speaking, separate it into words. A subtask of speech recognition and typically grouped with it.
- Topic segmentation and recognition: Given a chunk of text, separate it into segments each of which is devoted to a topic, and identify the topic of the segment.
- **Word segmentation:** Separate a chunk of continuous text into separate words. For a language like English, this is fairly trivial, since words are usually separated by spaces. However, some written languages like Chinese, Japanese and Thai do not mark

word boundaries in such a fashion, and in those languages text segmentation is a significant task requiring knowledge of the vocabulary and morphology of words in the language.

- **Word sense disambiguation:** Many words have more than one meaning; we have to select the meaning which makes the most sense in context. For this problem, we are typically given a list of words and associated word senses, e.g. from a dictionary or from an online resource such as WordNet.

In some cases, sets of related tasks are grouped into subfields of NLP that are often considered separately from NLP as a whole. Examples include:

- **Information retrieval (IR):** This is concerned with storing, searching and retrieving information. It is a separate field within computer science (closer to databases), but IR relies on some NLP methods (for example, stemming). Some current research and applications seek to bridge the gap between IR and NLP.
- **Information extraction (IE):** This is concerned in general with the extraction of semantic information from text. This covers tasks such as named entity recognition, coreference resolution, relationship extraction, etc.
- **Speech processing:** This covers speech recognition, text-to-speech and related tasks.

Other tasks include:

- Stemming
- Text simplification
- Text-to-speech
- Text-proofing
- Natural language search
- Query expansion
- Truecasing

3.4 Statistical Natural Language Processing

Statistical natural-language processing uses stochastic, probabilistic and statistical methods to resolve some of the difficulties discussed above, especially those which arise because longer sentences are highly ambiguous when processed with realistic grammars, yielding thousands or millions of possible analyses. Methods for disambiguation often involve the use of corpora and Markov models. Statistical NLP comprises all quantitative approaches to automated language processing, including probabilistic modeling, information theory, and linear algebra. The technology for statistical NLP comes mainly from machine learning and data mining, both of which are fields of artificial intelligence that involve learning from data.

3.5 Evaluation of natural language processing

3.5.1 Objectives

The goal of NLP evaluation is to measure one or more qualities of an algorithm or a system, in order to determine whether (or to what extent) the system answers the goals of its designers, or meets the needs of its users. Research in NLP evaluation has received considerable attention, because the definition of proper evaluation criteria is one way to specify precisely an NLP problem, going thus beyond the vagueness of tasks defined only as language understanding or language generation. A precise set of evaluation criteria, which includes mainly evaluation data and evaluation metrics, enables several teams to compare their solutions to a given NLP problem.

3.5.2 Short history of evaluation in NLP

The first evaluation campaign on written texts seems to be a campaign dedicated to message understanding in 1987 (Pallet 1998). Then, the Parseval/GEIG project compared phrase-structure grammars (Black 1991). A series of campaigns within Tipster project were realized on tasks like summarization, translation and searching (Hirschman 1998). In 1994, in Germany, the Morpholympics compared German taggers. Then, the Senseval and Romanseval campaigns were conducted with the objectives of semantic disambiguation. In 1996, the Sparkle campaign compared syntactic parsers in four different languages (English, French, German and Italian). In France, the Grace project compared a set of 21 taggers for French in 1997 (Adda 1999). In 2004, during the Technolangue/Easy project, 13 parsers for French were compared. Large-scale evaluation of dependency parsers were performed in the context of the CoNLL shared tasks in 2006 and 2007. In Italy, the EVALITA campaign was conducted in 2007 and 2009 to compare various NLP and speech tools for Italian; the 2011 campaign is in full progress - EVALITA web site. In France, within the ANR-Passage project (end of 2007), 10 parsers for French were compared - passage web site.

3.5.3 Different types of evaluation

Depending on the evaluation procedures, a number of distinctions are traditionally made in NLP evaluation:

- Intrinsic vs. extrinsic evaluation

Intrinsic evaluation considers an isolated NLP system and characterizes its performance mainly with respect to a gold standard result, pre-defined by the evaluators. Extrinsic evaluation, also called evaluation in use considers the NLP system in a more complex setting, either as an embedded system or serving a precise function for a human user. The extrinsic performance of the system is then characterized in terms of its utility with respect to the overall task of the complex system or the human user. For example, consider a syntactic parser that is based on the output of some new part of speech (POS) tagger. An intrinsic evaluation would run the POS tagger on some labelled data, and compare the system output of the POS tagger to the gold standard (correct) output. An extrinsic evaluation would run the parser with some other POS tagger, and then with the new POS tagger, and compare the parsing accuracy.

- Black-box vs. glass-box evaluation

Black-box evaluation requires one to run an NLP system on a given data set and to measure a number of parameters related to the quality of the process (speed, reliability, resource consumption) and, most importantly, to the quality of the result (e.g. the accuracy of data annotation or the fidelity of a translation). Glass-box evaluation looks at the design of the system, the algorithms that are implemented, the linguistic resources it uses (e.g. vocabulary size), etc. Given the complexity of NLP problems, it is often difficult to predict performance only on the basis of glass-box evaluation, but this type of evaluation is more informative with respect to error analysis or future developments of a system.

- Automatic vs. manual evaluation

In many cases, automatic procedures can be defined to evaluate an NLP system by comparing its output with the gold standard (or desired) one. Although the cost of producing the gold standard can be quite high, automatic evaluation can be repeated as often as needed without much additional costs (on the same input data). However, for many NLP problems, the definition of a gold standard is a complex task, and can prove impossible when inter-annotator agreement is insufficient. Manual evaluation is performed by human judges, which are instructed to estimate the quality of a system, or most often of a sample of its output, based on a number of criteria. Although, thanks to their linguistic competence, human judges can be considered as the reference for a number of language processing tasks, there is also considerable variation across their ratings. This is why automatic evaluation is sometimes referred to as objective evaluation, while the human kind appears to be more subjective.

3.5.4 Shared tasks (Campaigns)

- BioCreative
- Message Understanding Conference
- Technolangue/Easy
- Text Retrieval Conference
- Evaluation exercises on Semantic Evaluation (SemEval)

4.0 CONCLUSION

Systems based on machine-learning algorithms have many advantages over hand-produced rules.

5.0 SUMMARY

In this unit, you learnt:

- NLP using machine learning
- History of natural language processing
- Major tasks in NLP
- Statistical Natural Language Processing
- Evaluation of natural language processing

MODULE 4 ARTIFICIAL INTELLIGENCE AND ITS APPLICATIONS

UNIT 1 EXPERT SYSTEM

CONTENTS

1.0 INTRODUCTION

Expert system is a computer program that uses artificial intelligence to solve problems within a specialized domain that ordinarily requires human expertise. The first expert system was developed in 1965 by Edward Feigenbaum and Joshua Lederberg of Stanford University in California, U.S. Dendral, as their expert system was later known, was designed to analyze chemical compounds. Expert systems now have commercial applications in fields as diverse as medical diagnosis, petroleum engineering, financial investing make financial forecasts and schedule routes for delivery vehicles.

2.0 OBJECTIVES

At the end of this unit, you should be able to:

- explain an expert system
- distinction between expert systems and traditional problem solving programs
- explain the term "knowledge base".

3.0 MAIN CONTENT

3.1 What is an Expert System?

It is a computer application that performs a task that would otherwise be performed by a human expert. Some expert systems are designed to take the place of human experts, while others are designed to aid them.

To design an expert system, one needs a *knowledge engineer,* an individual who studies how human experts make decisions and translates the rules into terms that a computer can understand. In order to accomplish feats of apparent intelligence, an expert system relies on two components: a knowledge base and an inference engine.

3.1.1 Comparison to problem-solving systems

The principal distinction between expert systems and traditional problem solving.

Programs are the way in which the problem related expertise is coded. In traditional applications, problem-related expertise is encoded in both program and data structures. In the expert system approach all of the problem expertise is encoded mostly in data structures.

In an example related to tax advice, the traditional approach has data structures that describe the taxpayer and tax tables, and a program that contains rules (encoding expert knowledge) that relate information about the taxpayer to tax table choices. In contrast, in the expert system approach, the latter information is also encoded in data structures. The collective data structures are called the knowledge base . The program (inference engine) of an expert system is relatively independent of the problem domain (taxes) and processes the rules without regard to the problem area they describe.

This organization has several benefits:

- New rules can be added to the knowledge base or altered without needing to rebuild the program. This allows changes to be made rapidly to a system (e.g., after it has been shipped to its customers, to accommodate very recent changes in state or federal tax codes).
- Rules are arguably easier for (non-programmer) domain experts to create and modify than writing code. Commercial rule engines typically come with editors that allow rule creation/modification through a graphical user interface, which also performs actions such as consistency and redundancy checks.

Modern rule engines allow a hybrid approach: some allow rules to be "compiled" into a form that is more efficiently machine-executable. Also, for efficiency concerns, rule engines allow rules to be defined more expressively and concisely by allowing software developers to create functions in a traditional programming language such as Java, which can then be invoked from either the condition or the action of a rule. Such functions may incorporate domain-specific (but reusable) logic.

3.2 Knowledge Base

A knowledge base (abbreviated KB, kb or Δ) is a special kind of database for knowledge management, providing the means for the computerized collection, organization, and retrieval of knowledge. Also, it is a collection of data representing related experiences which their results is related to their problems and solutions.

Facts for a knowledge base must be acquired from human experts through interviews and observations. This knowledge is then usually represented in the form of “if-then” rules (production rules): “If some condition is true then the following inference can be made (or some action taken).” The knowledge base of a major expert system includes thousands of rules. A probability factor is often attached to the conclusion of each production rule, because the conclusion is not a certainty. For example, a system for the diagnosis of eye diseases might indicate, based on information supplied to it, a 90 percent probability that a person has glaucoma, and it might also list conclusions with lower probabilities. An expert system may display the sequence of rules through which it arrived at its conclusion; tracing this flow helps the user to appraise the credibility of its recommendation and is useful as a learning tool for students.

Human experts frequently employ heuristic rules, or “rules of thumb,” in addition to simple production rules. For example, a credit manager might know that an applicant with a poor credit history, but a clean record since acquiring a new job, might actually be a good credit risk. Expert systems have incorporated such heuristic rules and increasingly have the ability to learn from experience. Nevertheless, expert systems remain supplements, rather than replacements, for human experts.

3.2.1 Types Of Knowledge Base

Knowledge bases are essentially closed or open information repositories and can be categorized under two main headings:

- Machine-readable knowledge bases store knowledge in a computer-readable form, usually for the purpose of having automated deductive reasoning applied to them. They contain a set of data, often in the form of rules that describe the knowledge in a logically consistent manner. An ontology can define the structure of stored data - what types of entities are recorded and what their relationships are. Logical operators, such as *And* (conjunction), *Or* (disjunction), *material implication* and *negation* may be used to build it up from simpler pieces of information. Consequently, classical deduction can be used to reason about the knowledge in the knowledge base. Some machine-readable knowledge bases are used with artificial intelligence, for example as part of an expert system that focuses on a domain like prescription drugs or customs law. Such knowledge bases are also used by the semantic web.
- Human-readable knowledge bases are designed to allow people to retrieve and use the knowledge they contain. They are commonly used to complement a help desk or for sharing information among employees within an organization. They might store troubleshooting information, articles, white papers, user manuals, knowledge tags, or answers to frequently asked questions. Typically, a search engine is used to locate information in the system, or users may browse through a classification scheme.

A text based system that can include groups of documents including hyperlinks between them is known as Hypertext Systems. Hypertext systems support the decision process by relieving the user of the significant effort it takes to relate and remember things." Knowledge bases can exist on both computers and mobile phones in a hypertext format. Knowledge base analysis and design (also known as KBAD) is an approach that allows people to conduct analysis and design in a way that result in a knowledge base, which can later be used to make informative decisions. This approach was first implemented by Dr. Steven H. Dam

3.3 Inference Engine

In computer science, and specifically the branches of knowledge engineering and artificial intelligence, an inference engine is a computer program that tries to derive answers from a knowledge base. It is the "brain" that expert systems use to reason about the information in the knowledge base for the ultimate purpose of formulating new conclusions. Inference engines are considered to be a special case of reasoning engines, which can use more general methods of reasoning.

3.3.1 Architecture

The separation of inference engines as a distinct software component stems from the typical production system architecture. This architecture relies on a data store:

1. An interpreter. The interpreter executes the chosen agenda items by applying the corresponding base rules.
2. A scheduler. The scheduler maintains control over the agenda by estimating the effects of applying inference rules in light of item priorities or other criteria on the agenda.
3. A consistency enforcer. The consistency enforcer attempts to maintain a consistent representation of the emerging solution

3.3.2 The Recognize-Act Cycle

The inference engine can be described as a form of finite state machine with a cycle consisting of three action states: *match rules*, *select rules*, and *execute rules*. Rules are represented in the system by a notation called predicate logic.

In the first state, match rules, the inference engine finds all of the rules that are satisfied by the current contents of the data store. When rules are in the typical *condition-action* form, this means testing the conditions against the working memory. The rule matching that are found are all candidates for execution: they are collectively referred to as the *conflict set*. Note that the same rule may appear several times in the conflict set

if it matches different subsets of data items. The pair of a rule and a subset of matching data items are called an *instantiation* of the rule.
In many applications, where large volumes of data are concerned and/or when performance time considerations are critical, the computation of the conflict set is a non-trivial problem.

3.3.3 Data-Driven Computation versus Procedural Control

The inference engine control is based on the frequent re - evaluation of the data store states, not on any static control structure of the program. The computation is often qualified as *data-driven* or *pattern-directed* in contrast to the more traditional procedural control. Rules can communicate with one another only by way of the data, whereas in traditional programming languages procedures and functions explicitly call one another. Unlike instructions, rules are not executed sequentially and it is not always possible to determine through inspection of a set of rules which rule will be executed first or cause the inference engine to terminate.

In contrast to a procedural computation, in which knowledge about the problem domain is mixed in with instructions about the flow of control—although object-oriented programming languages mitigate this entanglement—the inference engine model allows a more complete separation of the knowledge (in the rules) from the control (the inference engine).

3.3.4 Inference Rules

An inference rule is a conditional statement with two parts namely; if clause and a then clause.

This rule is what gives expert systems the ability to find solutions to diagnostic and prescriptive problems. An example of an inference rule is:

If the restaurant choice includes French and the occasion is romantic,
Then the restaurant choice is definitely Paul Bocuse.

An expert system's rule base is made up of many such inference rules. They are entered as separate rules and it is the inference engine that uses them together to draw conclusions. Because each rule is a unit, rules may be deleted or added without affecting other rules - though it should affect which conclusions are reached. One advantage of inference rules over traditional programming is that inference rules use reasoning which more closely resembles human reasoning.

Thus, when a conclusion is drawn, it is possible to understand how this conclusion was reached. Furthermore, because the expert system uses knowledge in a form similar to the that of the expert, it may be easier to retrieve this information directly from the expert.

3.3.5 Chaining

Two methods of reasoning when using inference rules are forward chaining and backward chaining.

Forward chaining starts with the data available and uses the inference rules to extract more data until a desired goal is reached. An inference engine using forward chaining searches the inference rules until it finds one in which the if clause is known to be true . It then concludes the then clause and adds this information to its data. It continues to do this until a goal is reached. Because the data available determines which inference rules are used, this method is also classified as data driven. Backward chaining starts with a list of goals and works backwards to see if there is data which will allow it to conclude any of these goals. An inference engine using backward chaining would search the inference rules until it finds one which has a then clause that matches a desired goal. If the if clause of that inference rule is not known to be true, then it is added to the list of goals. For example, suppose a rule base contains:

(1) IF X is green THEN X is a frog. (Confidence Factor: +1%)
(2) IF X is NOT green THEN X is NOT a frog. (Confidence Factor: +99%)
(3) IF X is a frog THEN X hops. (Confidence Factor: +50%)
(4) IF X is NOT a frog THEN X does NOT hop. (Confidence Factor +50%)

Suppose a goal is to conclude that Fritz hops. Let X = "Fritz". The rule base would be searched and rule (3) would be selected because its conclusion (the then clause) matches the goal. It is not known that Fritz is a frog, so this "if" statement is added to the goal list. The rule base is again searched and this time rule (1) is selected because its then clause matches the new goal just added to the list. This time, the if clause (Fritz is green) is known to be true and the goal that Fritz hops is concluded. Because the list of goals determines which rules are selected and used, this method is called goal driven.

However, note that if we use confidence factors in even a simplistic fashion - for example, by multiplying them together as if they were like soft probabilities - we get a result that is known with a confidence factor of only one-half of 1%. (This is by multiplying 0.5 x 0.01 = 0.005). This is useful, because without confidence factors, we might erroneously conclude with certainty that a sea turtle named Fritz hops just by virtue of being green. In Classical logic or Aristotelian term logic systems, there are no probabilities or confidence factors; all facts are regarded as certain. An ancient example from Aristotle states, "Socrates is a man. All men are mortal. Thus Socrates is mortal."

In real world applications, few facts are known with absolute certainty and the opposite of a given statement may be more likely to be true ("Green things in the pet store are not frogs, with the probability or confidence factor of 99% in my pet store survey"). Thus it is often useful when building such systems to try and prove both the goal and the opposite of a given goal to see which is more likely.

3.4 Certainty Factors

One method of operation of expert systems is through a quasi-probabilistic approach with certainty factors: A human, when reasoning, does not always make statements with 100% confidence: he might venture, "If Fritz is green, then he is probably a frog" (after all, he might be a chameleon). This type of reasoning can be imitated using numeric values called confidences. For example, if it is known that Fritz is green, it might be concluded with 0.85 confidence that he is a frog; or, if it is known that he is a frog, it might be concluded with 0.95 confidence that he hops. These Certainty factor (CF) numbers quantify uncertainty in the degree to which the available evidence supports a hypothesis. They represent a degree of confirmation, and are not probabilities in a Bayesian sense. The CF calculus, developed by Shortliffe & Buchanan, increases or decreases the CF associated with a hypothesis as each new piece of evidence becomes available. It can be mapped to a probability update, although degrees of confirmation are not expected to obey the laws of probability. It is important to note, for example, that evidence for hypothesis H may have nothing to contribute to the degree to which Noth is confirmed or disconfirmed (e.g., although a fever lends some support to a diagnosis of infection, fever does not disconfirm alternative hypotheses) and that the sum of CFs of many competing hypotheses may be greater than one (i.e., many hypotheses may be well confirmed based on available evidence).

The CF approach to a rule-based expert system design does not have a widespread following, in part because of the difficulty of meaningfully assigning CFs a priori. (The above example of green creatures being likely to be frogs is excessively naive.) Alternative approaches to quasi-probabilistic reasoning in expert systems involve fuzzy logic, which has a firmer mathematical foundation. Also, rule-engine shells such as

Drools and Jess do not support probability manipulation: they use an alternative mechanism called salience, which is used to prioritize the order of evaluation of activated rules.

In certain areas, as in the tax-advice scenarios discussed below, probabilistic approaches are not acceptable. For instance, a 95% probability of being correct means a 5% probability of being wrong. The rules that are defined in such systems have no exceptions: they are only a means of achieving software flexibility when external circumstances change frequently. Because rules are stored as data, the core software does not need to be rebuilt each time changes to federal and state tax codes are announced.

3.5 Real-Time Adaption

Industrial processes, data networks, and many other systems change their state and even their structure over time. Real time expert systems are designed to reason over time and change conclusions as the monitored system changes. Most of these systems must respond to constantly changing input data, arriving automatically from other systems such as process control systems or network management systems.

Representation includes features for defining changes in belief of data or conclusions over time. This is necessary because data becomes stale. Approaches to this can include decaying belief functions, or the simpler validity interval that simply lets data and conclusions expire after specified time period, falling to "unknown" until refreshed. An often-cited example (attributed to real time expert system pioneer Robert L. Moore) is a hypothetical expert system that might be used to drive a car. Based on video input, there might be an intermediate conclusion that a stop light is green and a final conclusion that it is OK to drive through the intersection. But that data and the subsequent conclusions have a very limited lifetime. You would not want to be a passenger in a car driven based on data and conclusions that were, say, an hour old.

The inference engine must track the times of each data input and each conclusion, and propagate new information as it arrives. It must ensure that all conclusions are still current. Facilities for periodically scanning data, acquiring data on demand, and filtering noise, become essential parts of the overall system. Facilities to reason within a fixed deadline are important in many of these applications.

An overview of requirements for a real-time expert system shell is given in. Examples of real time expert system applications are given in and.

Several conferences were dedicated to real time expert system applications in the chemical process industries, including.

3.5.1 Ability to Make Relevant Inquiries

An additional skill of an expert system is the ability to give relevant inquiries based on previous input from a human user, in order to give better replies or other actions, as well as working faster, which also pleases an impatient or busy human user - it allows a priori volunteering of information that the user considers important.

Also, the user may choose not to respond to every question, forcing the expert system to function in the presence of partial information.

Commercially viable systems will try to optimize the user experience by presenting options for commonly requested information based on a history of previous queries of the system using technology such as forms, augmented by keyword-based search. The gathered information may be verified by a confirmation step (e.g., to recover from spelling mistakes), and now act as an input into a forward-chaining engine. If confirmatory questions are asked in a subsequent phase, based on the rules activated by the obtained information, they are more likely to be specific and relevant. Such abilities can largely be achieved by control flow structures.

In an expert system, implementing the ability to learn from a stored history of its previous use involves employing technologies considerably different from that of rule engines, and is considerably more challenging from a software-engineering perspective. It can, however, make the difference between commercial success and failure. A large part of the revulsion that users felt towards Microsoft's Office Assistant was due to the extreme naivete of its rules ("It looks like you are typing a letter: would you like help?") and its failure to adapt to the user's level of expertise over time (e.g. a user who regularly uses features such as Styles, Outline view, Table of Contents or cross-references is unlikely to be a beginner who needs help writing a letter).

3.6 Explanation System

Another major distinction between expert systems and traditional systems is illustrated by the following answer given by the system when the user answers a question with another question, "Why", as occurred in the above example. The answer is:

A. I am trying to determine the type of restaurant to suggest. So far Indian is not a likely choice. It is possible that French is a likely choice. If I know that if the diner is a wine drinker, and the preferred wine is French, then there is strong evidence that the restaurant choice should include French.

It is very difficult to implement a general explanation system (answering questions like "Why" and "How") in a traditional computer program. An expert system can generate an explanation by retracing the steps of its reasoning. The response of the expert system to the question "Why" exposes the underlying knowledge structure. It is a rule; a set of antecedent conditions which, if true, allow the assertion of a consequent. The rule references values, and tests them against various constraints or asserts constraints onto them. This, in fact, is a significant part of the knowledge structure. There are values, which may be associated with some organizing entity. For example, the individual diner is an entity with various attributes (values) including whether they drink wine and the kind of wine. There are also rules, which associate the currently known values of some attributes with assertions that can be made about other attributes. It is the orderly processing of these rules that dictates the dialogue itself.

3.7 Knowledge Engineering

The building, maintaining and development of expert systems are known as knowledge engineering. Knowledge engineering is a "discipline that involves integrating knowledge into computer systems in order to solve complex problems normally requiring a high level of human.

There are generally three individuals having an interaction in an expert system. Primary among these is the end-user, the individual who uses the system for its problem solving assistance. In the construction and maintenance of the system there are two other roles: the problem domain expert who builds the system and supplies the knowledge base, and a knowledge engineer who assists the experts in determining the representation of their knowledge, enters this knowledge into an explanation module and who defines the inference technique required to solve the problem. Usually the knowledge engineer will represent the problem solving activity in the form of rules. When these rules are created from domain expertise, the knowledge base stores the rules of the expert system.

3.8 General Types of Problems Solved

Expert systems are most valuable to organizations that have a high-level of know-how experience and expertise that cannot be easily transferred to other members. They are designed to carry the intelligence and information found in the intellect of experts and provide this knowledge to other members of the organization for problem-solving purposes.

Typically, the problems to be solved are of the sort that would normally be tackled by a professional, such as a medical professional in the case of clinical decision support systems. Real experts in the problem domain (which will typically be very narrow, for instance "diagnosing skin conditions in teenagers") are asked to provide "rules of thumb" on how they evaluate the problem — either explicitly with the aid of experienced systems developers, or sometimes implicitly, by getting such experts to evaluate test cases and using computer programs to examine the test data and derive rules from that (in a strictly limited manner). Generally, expert systems are used for problems for which there is no single "correct" solution which can be encoded in a conventional algorithm — one would not write an expert system to find the shortest paths through graphs, or to sort data, as there are simpler ways to do these tasks.

Simple systems use simple true/false logic to evaluate data. More sophisticated systems are capable of performing at least some evaluation, taking into account real-world uncertainties, using such methods as fuzzy logic. Such sophistication is difficult to develop and still highly imperfect.

3.9 Different Types of Expert System are

- Rule-Based expert system
- Frames-Based expert system
- Hybird system
- Model-based expert system
- Ready-made system
- Real-Time expert system

3.10 Examples of Applications

Expert systems are designed to facilitate tasks in the fields of accounting, medicine, process control, financial service, production, human resources among others. Typically, the problem area is complex enough that a more simple traditional algorithm cannot provide a proper solution, The foundation of a successful expert system depends on a series of technical procedures and development that may be designed by technicians and related experts. As such, expert systems do not typically provide a definitive answer, but provide probabilistic recommendations. An example of the application of expert systems in the financial field is expert systems for mortgages. Loan departments are interested in expert systems for mortgages because of the growing cost of labour, which makes the handling and acceptance of relatively small loans less profitable. They also see a possibility for standardised, efficient handling of mortgage loan by applying expert systems, appreciating that for the acceptance of mortgages there are hard and fast rules which do not always exist with other types of loans. Another common application in the financial area for expert systems is in trading recommendations in various marketplaces. These markets involve numerous variables and human emotions which may be impossible to deterministically characterize, thus expert systems based on the rules of thumb from experts and simulation data are used. Expert system of this type can range from ones providing regional retail recommendations, like Wishabi, to ones used to assist monetary decisions by financial institutions and governments. Another 1970s and 1980s application of expert systems, which we today would simply call AI, was in computer games. For example, the computer baseball games Earl Weaver Baseball and Tony La Russa Baseball each had highly detailed simulations of the game strategies of those two baseball managers. When a human played the game against the computer, the computer queried the Earl Weaver or Tony La Russa Expert System for a decision on what strategy to follow. Even those choices where some randomness was part of the natural system (such as when to throw a surprise pitch-out to try to trick a runner trying to steal a base) were decided based on probabilities supplied by Weaver or La Russa. Today we would simply say that "the game's AI provided the opposing manager's strategy."

3.11 Advantages

- Compared to traditional programming techniques, expert-system approaches provide the added flexibility (and hence easier modifiability) with the ability to model rules as data rather than as code. In situations where an organization's IT department is overwhelmed by a software-development backlog, rule-engines, by facilitating turnaround, provide a means that can allow organizations to adapt more readily to changing needs.
- In practice, modern expert-system technology is employed as an adjunct to traditional programming techniques, and this hybrid approach allows the combination of the strengths of both approaches. Thus, rule engines allow control through programs

(and user interfaces) written in a traditional language, and also incorporate necessary functionality such as inter-operability with existing database technology.

3.12 Disadvantages

- The Garbage In, Garbage Out (GIGO) phenomenon: A system that uses expert-system technology provides no guarantee about the quality of the rules on which it operates. All self-designated "experts" are not necessarily so, and one notable challenge in expert system design is in getting a system to recognize the limits to its knowledge.
- Expert systems are notoriously narrow in their domain of knowledge— as an amusing example, a researcher used the "skin disease" expert system to diagnose his rust bucket car as likely to have developed measles — and the systems are thus prone to making errors that humans would easily spot. Additionally, once some of the mystique had worn off, most programmers realized that simple expert systems were essentially just slightly more elaborate versions of the decision logic they had already been using. Therefore, some of the techniques of expert systems can now be found in most complex programs without drawing much recognition.
- An expert system or rule-based approach is not optimal for all problems, and considerable knowledge is required so as to not misapply the systems.
- Ease of rule creation and rule modification can be double-edged. A system can be sabotaged by a non-knowledgeable user who can easily add worthless rules or rules that conflict with existing ones. Reasons for the failure of many systems include the absence of (or neglect to employ diligently) facilities for system audit, detection of possible conflict, and rule lifecycle management (e.g. version control, or thorough testing before deployment). The problems to be addressed here are as much technological as organizational.

An example and a good demonstration of the limitations of an expert system is the Windows operating system troubleshooting software located in the "help" section in the taskbar menu. Obtaining technical operating system support is often difficult for individuals not closely involved with the development of the Operating System. Microsoft has designed their expert system to provide solutions, advice, and suggestions to common errors encountered while using their operating systems.

4.0 CONCLUSION

Expert systems now have commercial applications in fields as diverse as medical diagnosis, petroleum engineering, financial investing make financial forecasts and schedule routes for delivery vehicles.

5.0 SUMMARY

In this unit, you learnt:

- Definition of an Expert System
- Knowledge Base and Types of Knowledge Base
- Inference Engine
- Certainty factors
- Real-time adaption
- Knowledge Engineering
- General types of problems solved
- Different types of expert system

UNIT 2 ROBOTICS

CONTENTS

1.0 INTRODUCTION

Robotics is the branch of technology that deals with the design, construction, operation, structural disposition, manufacture and application of robots. Robotics is related to the sciences of electronics, engineering, mechanics, and software.

2.0 OBJECTIVES

At the end of this unit, you should be able to:

- explain the word robotics
- list 4 types of robotics you know
- describe the history of robotics.

3.0 MAIN CONTENT

3.1 What is a Robot?

The word robotics was derived from the word robot, which was introduced to the public by Czech writer Karel Čapek in his play R.U.R. (Rossum's Universal Robots), which premiered in 1921.

According to the Oxford English Dictionary, the word robotics was first used in print by Isaac Asimov, in his science fiction short story "Liar!", published in May 1941 in Astounding Science Fiction. Asimov was unaware that he was coining the term; since the science and technology of electrical devices is electronics, he assumed robotics already referred to the science and technology of robots. In some of Asimov's other works, he states that the first use of the word robotics was in his short story Runaround (Astounding Science Fiction, March 1942). However, the word robotics appears in "Liar!"

3.1.1 Types of Robots

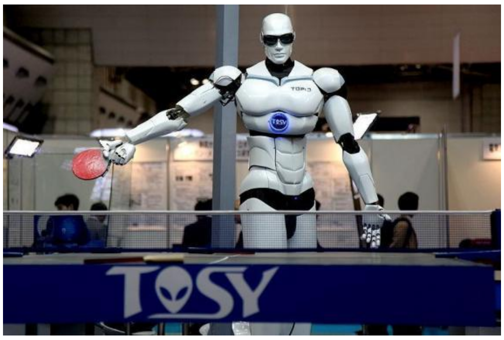


Figure 1: TOPIO, a humanoid robot, played ping pong at Tokyo International Robot Exhibition (IREX)

Figure 2: The Shadow robot hand system

Figure 3: A Pick and Place robot in a factory

3.1.2 History of Robots

Stories of artificial helpers and companions and attempts to create them have a long history.

Figure 4: A scene from Karel Čapek's 1920 play R.U.R. (Rossum's Universal Robots), showing three robots.

The word robot was introduced to the public by the Czech writer Karel Čapek in his play R.U.R. (Rossum's Universal Robots), published in 1920. The play begins in a factory that makes artificial people called robots creatures who can be mistaken for humans – though they are closer to the modern ideas of androids. Karel Čapek himself did not coin the word. He wrote a short letter in reference to an etymology in the Oxford English Dictionary in which he named his brother Josef Čapek as its actual originator.

In 1927 the Maschinenmensch ("machine-human") gynoid humanoid robot (also called "Parody", "Futura", "Robotrix", or the "Maria impersonator") was the first and perhaps the most memorable depiction of a robot ever to appear on film was played by German actress Brigitte Helm) in Fritz Lang's film Metropolis.

In 1942 the science fiction writer Isaac Asimov formulated his Three Laws of Robotics and, in the process of doing so, coined the word "robotics" (see details in "Etymology" section below).

In 1948 Norbert Wiener formulated the principles of cybernetics, the basis of practical robotics.

Fully autonomous robots only appeared in the second half of the 20th century. The first digitally operated and programmable robot, the Unimate, was installed in 1961 to lift hot pieces of metal from a die casting machine and stack them. Commercial and industrial robots are widespread today and used to perform jobs more cheaply, or more accurately and reliably, than humans. They are also employed in jobs which are too dirty, dangerous, or dull to be suitable for humans. Robots are widely used in manufacturing, assembly, packing and packaging, transport, earth and space exploration, surgery, weaponry, laboratory research, safety, and the mass production of consumer and industrial goods.

Date	Significance	Robot Name	Inventor
Third century B.C. and earlier	One of the earliest descriptions of automata appears in the Lie Zi text, on a much earlier encounter between King Mu of Zhou (1023-957 BC) and a mechanical engineer known as Yan Shi, an 'artificer'. The latter allegedly presented the king with a life-size, human-shaped figure of his mechanical handiwork.		Yan Shi
First century A.D. and earlier	Descriptions of more than 100 machines and automata, including a fire engine, a wind organ, a coin-operated machine, and a steam-powered engine, in Pneumatica and Automata by Heron of Alexandria		Ctesibius, Philo of Byzantium, Heron of Alexandria, and others
1206	Created early humanoid automata, programmable automaton band	Robot band, hand-	Al-Jazari

		washing automaton,[11] automated moving peacocks[12]	
1495	Designs for a humanoid robot	Mechanical knight	Leonardo da Vinci
1738	Mechanical duck that was able to eat, flap its wings, and excrete	Digesting Duck	Jacques de Vaucanson
1898	Nikola Tesla demonstrates first radio-controlled vessel.	Teleautomaton	Nikola Tesla
1921	First fictional automatons called "robots" appear in the play R.U.R.	Rossum's Universal Robots	Karel Čapek
1930s	Humanoid robot exhibited at the 1939 and 1940 World's Fairs	Elektro	Westinghouse Electric Corporation
1948	Simple robots exhibiting biological behaviors	Elsie and Elmer	William Grey Walter
1956	First commercial robot, from the Unimation company founded by George Devol and Joseph Engelberger, based on Devol's patents	Unimate	George Devol
1961	First installed industrial robot.	Unimate	George Devol
1963	First palletizing robothttp://www.ask.com/wiki/Robotics - cite_note-14	Palletizer	Fuji Yusoki Kogyo
1973	First industrial robot with six electromechanically driven axes	Famulus	KUKA Robot Group
1975	Programmable universal manipulation arm, a Unimation product	PUMA	Victor Scheinman

3.2 Components

3.2.1 Power source

At present; mostly (lead-acid) batteries are used, but potential power sources could be:

- pneumatic (compressed gases)
- hydraulics (compressed liquids)
- flywheel energy storage
- organic garbage (through anaerobic digestion)
- faeces (human, animal); may be interesting in a military context as faeces of small combat groups may be reused for the energy requirements of the robot assistant (see DEKA's project Slingshot Stirling engine on how the system would operate)
- still unproven energy sources: for example Nuclear fusion, as yet not used in nuclear reactors whereas Nuclear fission is proven (although there are not many robots using it as a power source apart from the Chinese rover tests).
- radioactive source (such as with the proposed Ford car of the '50s); to those proposed in movies such as *Red Planet*

3.2.2 Actuation

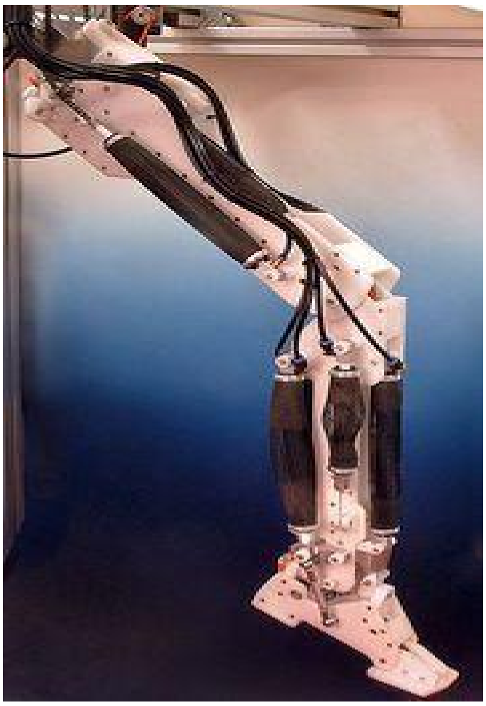


Figure 5: A robotic leg powered by Air Muscles

Actuators are like the "muscles" of a robot, the parts which convert stored energy into movement. By far the most popular actuators are electric motors that spin a wheel or gear, and linear actuators that control industrial robots in factories. But there are some recent advances in alternative types of actuators, powered by electricity, chemicals, or compressed air:

3.2.2.1 Electric motors

The vast majority of robots use electric motors, often brushed and brushless DC motors in portable robots or AC motors in industrial robots and CNC machines.

3.2.2.2 Linear Actuators

Various types of linear actuators move in and out instead of by spinning, particularly when very large forces are needed such as with industrial robotics. They are typically powered by compressed air (pneumatic actuator) or an oil (hydraulic actuator).

3.2.2.3 Series Elastic Actuators

A spring can be designed as part of the motor actuator, to allow improved force control. It has been used in various robots, particularly walking humanoid robots.

3.2.2.4 Air Muscles

Pneumatic artificial muscles, also known as air muscles, are special tubes that contract (typically up to 40%) when air is forced inside it. They have been used for some robot applications.

3.2.2.5 Muscle Wire

Muscle wire, also known as Shape Memory Alloy, Nitinol or Flexinol Wire, is a material that contracts slightly (typically under 5%) when electricity runs through it. They have been used for some small robot applications.

3.2.2.6 Electroactive Polymers

EAPs or EPAMs are a new plastic material that can contract substantially (up to 400%) from electricity, and have been used in facial muscles and arms of humanoid robots, and to allow new robots to float, fly, swim or walk.

3.2.2.7 Piezo Motors

A recent alternative to DC motors are piezo motors or ultrasonic motors. These work on a fundamentally different principle, whereby tiny piezoceramic elements, vibrating many thousands of times per second, cause linear or rotary motion. There are different mechanisms of operation; one type uses the vibration of the piezo elements to walk the motor in a circle or a straight line. Another type uses the piezo elements to cause a nut to vibrate and drive a screw. The advantages of these motors are nanometer resolution, speed, and available force for their size. These motors are already available commercially, and being used on some robots.

3.2.2.8 Elastic Nanotubes

Elastic Nanotubes are a promising artificial muscle technology in early-stage experimental development. The absence of defects in carbon nanotubes enables these filaments to deform elastically by several percent, with energy storage levels of perhaps 13 J/cm3 for metal nanotubes. Human biceps could be replaced with an 8 mm diameter wire of this material. Such compact "muscle" might allow future robots to outrun and out jump humans.

3.3 Sensing

3.3.1 Touch

Current robotic and prosthetic hands receive far less tactile information than the human hand. Recent research has developed a tactile sensor array that mimics the mechanical properties and touch receptors of human fingertips. The sensor array is constructed as a rigid core surrounded by conductive fluid contained by an elastomeric skin. Electrodes are mounted on the surface of the rigid core and are connected to an impedance-measuring device within the core. When the artificial skin touches an object the fluid path around the electrodes is deformed, producing impedance changes that map the forces received from the object. The researchers expect that an important function of such artificial fingertips will be adjusting robotic grip on held objects.

Scientists from several European countries and Israel developed a prosthetic hand in 2009, called SmartHand, which functions like a real one—allowing patients to write with it, type on a keyboard, play piano and perform other fine movements. The prosthesis has sensors which enable the patient to sense real feeling in its fingertips.

3.3.2 Vision

Computer vision is the science and technology of machines that see. As a scientific discipline, computer vision is concerned with the theory behind artificial systems that extract information from images. The image data can take many forms, such as video sequences and views from cameras.

In most practical computer vision applications, the computers are pre-programmed to solve a particular task, but methods based on learning are now becoming increasingly common.

Computer vision systems rely on image sensors which detect electromagnetic radiation which is typically in the form of either visible light or infra-red light. The sensors are designed using solid-state physics. The process by which light propagates and reflects off surfaces is explained using optics. Sophisticated image sensors even require quantum mechanics to provide a complete understanding of the image formation process.

There is a subfield within computer vision where artificial systems are designed to mimic the processing and behavior of biological systems, at different levels of complexity. Also, some of the learning-based methods developed within computer vision have their background in biology.

3.4 Manipulation

Robots which must work in the real world require some way to manipulate objects; pick up, modify, destroy, or otherwise have an effect. Thus the "hands" of a robot are often referred to as end effectors, while the "arm" is referred to as a manipulator. Most robot arms have replaceable effectors, each allowing them to perform some small range of tasks. Some have a fixed manipulator which cannot be replaced, while a few have one very general purpose manipulator, for example a humanoid hand.

For the definitive guide to all forms of robot end-effectors, their design, and usage consult the book "Robot Grippers".

3.4.1 Mechanical Grippers

One of the most common effectors is the gripper. In its simplest manifestation it consists of just two fingers which can open and close to pick up and let go of a range of small objects. Fingers can for example be made of a chain with a metal wire run through it. See Shadow Hand.

3.4.2 Vacuum Grippers

Vacuum grippers are very simple astrictive devices, but can hold very large loads provided the prehension surface is smooth enough to ensure suction.

Pick and place robots for electronic components and for large objects like car windscreens, often use very simple vacuum grippers.

3.4.3 General Purpose Effectors

Some advanced robots are beginning to use fully humanoid hands, like the Shadow Hand, MANUS, and the Schunk hand. These highly dexterous manipulators with as many as 20 degrees of freedom and hundreds of tactile sensors.

3.5 Locomotion

3.5.1 Rolling Robots

Figure 6: Segway in the Robot museum in Nagoya.

For simplicity most mobile robots have four wheels or a number of continuous tracks. Some researchers have tried to create more complex wheeled robots with only one or two wheels. These can have certain advantages such as greater efficiency and reduced parts, as well as allowing a robot to navigate in confined places that a four wheeled robot would not be able to.

3.5.1.1 Two-Wheeled Balancing Robots

Balancing robots generally use a gyroscope to detect how much a robot is falling and then drive the wheels proportionally in the opposite direction, to counter-balance the fall at hundreds of times per second, based on the dynamics of an inverted pendulum. Many different balancing robots have been designed. While the Segway is not commonly thought of as a robot, it can be thought of as a component of a robot, such as NASA's Robonaut that has been mounted on a Segway.

3.5.1.2 One-Wheeled Balancing Robots

A one-wheeled balancing robot is an extension of a two-wheeled balancing robot so that it can move in any 2D direction using a round ball as its only wheel. Several one-wheeled balancing robots have been designed recently, such as Carnegie Mellon University's "Ballbot" that is the approximate height and width of a person, and Tohoku Gakuin University's "BallIP". Because of the long, thin shape and ability to maneuver in tight spaces, they have the potential to function better than other robots in environments with people.

3.5.1.3 Spherical Orb Robots

Several attempts have been made in robots that are completely inside a spherical ball, either by spinning a weight inside the ball, or by rotating the outer shells of the sphere. These have also been referred to as an orb bot or a ball bot.

3.5.1.4 Six-Wheeled Robots

Using six wheels instead of four wheels can give better traction or grip in outdoor terrain such as on rocky dirt or grass.

3.5.1.5 Tracked Robots

Tank tracks provide even more traction than a six-wheeled robot. Tracked wheels behave as if they were made of hundreds of wheels, therefore are very common for outdoor and military robots, where the robot must drive on very rough terrain. However, they are difficult to use indoors such as on carpets and smooth floors. Examples include NASA's Urban Robot "Urbie".

3.5.2 Walking Applied to Robots

Figure 6: iCub robot, designed by the RobotCub Consortium

Walking is a difficult and dynamic problem to solve. Several robots have been made which can walk reliably on two legs; however none have yet been made which are as robust as a human. Many other robots have been built that walk on more than two legs, due to these robots being significantly easier to construct. Hybrids too have been proposed in movies such as I, Robot, where they walk on 2 legs and switch to 4 (arms+legs) when going to a sprint. Typically, robots on 2 legs can walk well on flat floors and can occasionally walk up stairs. None can walk over rocky, uneven terrain. Some of the methods which have been tried are:

3.5.2.1 ZMP Technique

The Zero Moment Point (ZMP) is the algorithm used by robots such as Honda's ASIMO. The robot's onboard computer tries to keep the total inertial forces (the combination of earth's gravity and the acceleration and deceleration of walking), exactly opposed by the floor reaction force (the force of the floor pushing back on the robot's foot). In this way, the two forces cancel out, leaving no moment (force causing the robot to rotate and fall over). However, this is not exactly how a human walks, and the difference is obvious to human observers, some of whom have pointed out that ASIMO walks as if it needs the lavatory. ASIMO's walking algorithm is not static, and some dynamic balancing is used (see below). However, it still requires a smooth surface to walk on.

3.5.2.2 Hopping

Several robots, built in the 1980s by Marc Raibert at the MIT Leg Laboratory, successfully demonstrated very dynamic walking. Initially, a robot with only one leg, and a very small foot, could stay upright simply by hopping. The movement is the same as that of a person on a pogo stick. As the robot falls to one side, it would jump slightly in that direction, in order to catch itself. Soon, the algorithm was generalised to two and four legs. A bipedal robot was demonstrated running and even performing somersaults. A quadruped was also demonstrated which could trot, run, pace, and bound. For a full list of these robots, see the MIT Leg Lab Robots page.

3.5.2 .3 Dynamic Balancing (Controlled Falling)

A more advanced way for a robot to walk is by using a dynamic balancing algorithm, which is potentially more robust than the Zero Moment Point technique, as it constantly monitors the robot's motion, and places the feet in order to maintain stability. This technique was recently demonstrated by Anybots' Dexter Robot,http://www.ask.com/wiki/Robotics - cite_note-64 which is so stable, it can even jump. Another example is the TU Delft Flame.

3.5.2.4 Passive Dynamics

Perhaps the most promising approach utilizes passive dynamics where the momentum of swinging limbs is used for greater efficiency. It has been shown that totally unpowered humanoid mechanisms can walk down a gentle slope, using only gravity to propel them. Using this technique, a robot need only supply a small amount of motor power to walk along a flat surface or a little more to walk up a hill. This technique promises to make walking robots at least ten times more efficient than ZMP walkers, like ASIMO.

3.5.3 Other methods of locomotion

Figure 7: RQ-4 Global Hawk unmanned aerial vehicle

3.5.3.1 Flying

A modern passenger airliner is essentially a flying robot, with two humans to manage it. The autopilot can control the plane for each stage of the journey, including takeoff, normal flight, and even landing. Other flying robots are uninhabited, and are known as unmanned aerial vehicles (UAVs). They can be smaller and lighter without a human pilot onboard, and fly into dangerous territory for military surveillance missions. Some can even fire on targets under command. UAVs are also being developed which can fire on targets automatically, without the need for a command from a human. Other flying robots include cruise missiles, the Entomopter, and the Epson micro helicopter robot. Robots such as the Air Penguin, Air Ray, and Air Jelly have lighter-than-air bodies, propelled by paddles, and guided by sonar.

Figure 8: Two robot snakes. Left **one** has 64 motors (with 2 degrees of freedom per segment), the right one 10.

3.5.3.2 Snaking

Several snake robots have been successfully developed. Mimicking the way real snakes move, these robots can navigate very confined spaces, meaning they may one day be used to search for people trapped in collapsed buildings. The Japanese ACM-R5 snake robot can even navigate both on land and in water.

3.5.3.3 Skating

A small number of skating robots have been developed, one of which is a multi-mode walking and skating device. It has four legs, with unpowered wheels, which can either step or roll. Another robot, Plen, can use a miniature skateboard or rollerskates, and skate across a desktop.

3.5.3.4 Climbing

Several different approaches have been used to develop robots that have the ability to climb vertical surfaces. One approach mimicks the movements of a human climber on a wall with protrusions; adjusting the center of mass and moving each limb in turn to gain leverage. An example of this is Capuchin, built by Stanford University, California. Another approach uses the specialised toe pad method of wall-climbing geckoes, which can run on smooth surfaces such as vertical glass. Examples of this approach include Wallbot and Stickybot. China's "Technology Daily" November 15, 2008 reported New Concept Aircraft (ZHUHAI) Co. Ltd. Dr. Li Hiu Yeung and his research group have recently successfully developed the bionic gecko robot "Speedy Freelander". According to Dr. Li introduction, this gecko robot can rapidly climbing up and down in a variety of building walls, ground and vertical wall fissure or walking upside down on the ceiling, it is able to adapt on smooth glass, rough or sticky dust walls as well as the various surface of metallic materials and also can automatically identify obstacles, circumvent the bypass and flexible and realistic movements. Its flexibility and speed are comparable to the natural gecko. A third approach is to mimick the motion of a snake climbing a pole.

3.5.3.5 Swimming (like a Fish)

It is calculated that when swimming some fish can achieve a propulsive efficiency greater than 90%. Furthermore, they can accelerate and maneuver far better than any man-made boat or submarine, and produce less noise and water disturbance. Therefore, many researchers studying underwater robots would like to copy this type of locomotion. Notable examples are the Essex University Computer Science Robotic Fish, and the Robot Tuna built by the Institute of Field Robotics, to analyze and mathematically model thunniform motion. The Aqua Penguin, designed and built by Festo of Germany, copies the streamlined shape and propulsion by front "flippers" of penguins. Festo have also built the Aqua Ray and Aqua Jelly, which emulate the locomotion of manta ray, and jellyfish, respectively.

3.6 Environmental interaction and navigation

Figure 9: RADAR, GPS, LIDAR, ... are all combined to provide proper navigation and obstacle avoidance

Though a significant percentage of robots in commission today are either human controlled, or operate in a static environment, there is an increasing interest in robots that can operate autonomously in a dynamic environment. These robots require some combination of navigation hardware and software in order to traverse their environment. In particular unforeseen events (e.g. people and other obstacles that are not stationary) can cause problems or collisions. Some highly advanced robots as ASIMO, EveR-1, Meinü robot have particularly good robot navigation hardware and software. Also, self-controlled cars, Ernst Dickmanns' driverless car, and the entries in the DARPA Grand Challenge, are capable of sensing the environment well and subsequently making navigational decisions based on this information. Most of these robots employ a GPS navigation device with waypoints, along with radar, sometimes combined with other sensory data such as LIDAR, video cameras, and inertial guidance systems for better navigation between waypoints.

3.7 Human-Robot Interaction

Figure 10: Kismet can produce a range of facial expressions.

If robots are to work effectively in homes and other non-industrial environments, the way they are instructed to perform their jobs, and especially how they will be told to stop will be of critical importance. The people who interact with them may have little or no training in robotics, and so any interface will need to be extremely intuitive. Science fiction authors also typically assume that robots will eventually be capable of communicating with humans through speech, gestures, and facial expressions, rather than a command-line interface. Although speech would be the most natural way for the human to communicate, it is unnatural for the robot. It will probably be a long time before robots interact as naturally as the fictional C-3PO.

3.7.1 Speech Recognition

Interpreting the continuous flow of sounds coming from a human, in real time, is a difficult task for a computer, mostly because of the great variability of speech. The same word, spoken by the same person may sound different depending on local acoustics, volume, the previous word, whether or not the speaker has a cold, etc.. It becomes even harder when the speaker has a different accent. Nevertheless, great strides have been made in the field since Davis, Biddulph, and Balashek designed the first "voice input system" which recognized "ten digits spoken by a single user with 100% accuracy" in 1952. Currently, the best systems can recognize continuous, natural speech, up to 160 words per minute, with an accuracy of 95%.

3.7.2 Robotic Voice

Other hurdles exist when allowing the robot to use voice for interacting with humans. For social reasons, synthetic voice proves suboptimal as a communication medium, making it necessary to develop the emotional component of robotic voice through various techniques.

3.7.3 Gestures

One can imagine, in the future, explaining to a robot chef how to make a pastry, or asking directions from a robot police officer. In both of these cases, making hand gestures would aid the verbal descriptions. In the first case, the robot would be recognizing gestures made by the human, and perhaps repeating them for confirmation. In the second case, the robot police officer would gesture to indicate "down the road, then turn right". It is likely that gestures will make up a part of the interaction between humans and robots. A great many systems have been developed to recognize human hand gestures.

3.7.4 Facial Expression

Facial expressions can provide rapid feedback on the progress of a dialog between two humans, and soon it may be able to do the same for humans and robots. Robotic faces have been constructed by Hanson Robotics using their elastic polymer called Frubber, allowing a great amount of facial expressions due to the elasticity of the rubber facial coating and imbedded subsurface motors (servos) to produce the facial expressions. The coating and servos are built on a metal skull. A robot should know how to approach a human, judging by their facial expression and body language. Whether the person is happy, frightened, or crazy-looking affects the type of interaction expected of the robot. Likewise, robots like Kismet and the more recent addition, Nexi can produce a range of facial expressions, allowing it to have meaningful social exchanges with humans.

3.7.5 Artificial Emotions

Artificial emotions can also be imbedded and are composed of a sequence of facial expressions and/or gestures. As can be seen from the movie Final Fantasy: The Spirits Within, the programming of these artificial emotions is complex and requires a great amount of human observation. To simplify this programming in the movie, presets were created together with a special software program. This decreased the amount of time needed to make the film. These presets could possibly be transferred for use in real-life robots.

3.7.6 Personality

Many of the robots of science fiction have a personality, something which may or may not be desirable in the commercial robots of the future. Nevertheless, researchers are trying to create robots which appear to have a personality: i.e. they use sounds, facial expressions, and body language to try to convey an internal state, which may be joy, sadness, or fear. One commercial example is Pleo, a toy robot dinosaur, which can exhibit several apparent emotions.

3.8 Control

Figure 11: A robot-manipulated marionette, with complex control systems

The mechanical structure of a robot must be controlled to perform tasks. The control of a robot involves three distinct phases - perception, processing, and action (robotic paradigms). Sensors give information about the environment or the robot itself (e.g. the position of its joints or its end effector). This information is then processed to calculate the appropriate signals to the actuators (motors) which move the mechanical.

The processing phase can range in complexity. At a reactive level, it may translate raw sensor information directly into actuator commands. Sensor fusion may first be used to estimate parameters of interest (e.g. the position of the robot's gripper) from noisy sensor data. An immediate task (such as moving the gripper in a certain direction) is inferred from these estimates. Techniques from control theory convert the task into commands that drive the actuators.

At longer time scales or with more sophisticated tasks, the robot may need to build and reason with a "cognitive" model. Cognitive models try to represent the robot, the world, and how they interact. Pattern recognition and computer vision can be used to track objects. Mapping techniques can be used to build maps of the world. Finally, motion planning and other artificial intelligence techniques may be used to figure out how to act. For example, a planner may figure out how to achieve a task without hitting obstacles, falling over, etc.

3.8.1 Autonomy Levels

Control systems may also have varying levels of autonomy.

Direct interaction is used for haptic or tele-operated devices, and the human has nearly complete control over the robot's motion.

Operator-assist modes have the operator commanding medium-to-high-level tasks, with the robot automatically figuring out how to achieve them.

An autonomous robot may go for extended periods of time without human interaction. Higher levels of autonomy do not necessarily require more complex cognitive capabilities. For example, robots in assembly plants are completely autonomous, but operate in a fixed pattern.

Another classification takes into account the interaction between human control and the machine motions.

Teleoperation. A human controls each movement, each machine actuator change is specified by the operator.

Supervisory. A human specifies general moves or position changes and the machine decides specific movements of its actuators.

Task-level autonomy. The operator specifies only the task and the robot manages itself to complete it.

Full autonomy. The machine will create and complete all its tasks without human interaction.

3.9 Robotics Research

Much of the research in robotics focuses not on specific industrial tasks, but on investigations into new types of robots, alternative ways to think about or design robots, and new ways to manufacture them but other investigations, such as MIT's cyberflora project, are almost wholly academic.

A first particular new innovation in robot design is the opensourcing of robot-projects. To describe the level of advancement of a robot, the term "Generation Robots" can be used. This term is coined by Professor Hans Moravec, Principal Research Scientist at the Carnegie Mellon University Robotics Institute in describing the near future evolution of robot technology. First generation robots, Moravec predicted in 1997, should have an intellectual capacity comparable to perhaps a lizard and should become available by 2010. Because the first generation robot would be incapable of learning, however, Moravec predicts that the second generation robot would be an improvement over the first and become available by 2020, with intelligence maybe comparable to that of a mouse. The third generation robot should have intelligence comparable to that of a monkey. Though fourth generation robots, robots with human intelligence, professor Moravec predicts, would become possible, he does not predict this happening before around 2040 or 2050.

The second is Evolutionary Robots. This is a methodology that uses evolutionary computation to help design robots, especially the body form, or motion and behavior controllers. In a similar way to natural evolution, a large population of robots is allowed to compete in some way, or their ability to perform a task is measured using a fitness function. Those that perform worst are removed from the population, and replaced by a new set, which have new behaviors based on those of the winners. Over time the population improves, and eventually a satisfactory robot may appear. This happens without any direct programming of the robots by the researchers. Researchers use this method both to create better robots, and to explore the nature of evolution. Because the process often requires many generations of robots to be simulated, this technique may be run entirely or mostly in simulation, then tested on real robots once the evolved algorithms are good enough. Currently, there are about 1 million industrial robots toiling around the world, and Japan is the top country having high density of utilizing robots in its manufacturing industry.

3.9.1 Dynamics and Kinematics

The study of motion can be divided into kinematics and dynamics. Direct kinematics refers to the calculation of end effector position, orientation, velocity, and acceleration when the corresponding joint values are known. Inverse kinematics refers to the opposite case in which required joint values are calculated for given end effector values, as done in path planning. Some special aspects of kinematics include handling of redundancy (different possibilities of performing the same movement), collision avoidance, and singularity avoidance. Once all relevant positions, velocities, and accelerations have been calculated using kinematics, methods from the field of dynamics are used to study the effect of forces upon these movements. Direct dynamics refers to the calculation of accelerations in the robot once the applied forces are known. Direct dynamics is used in computer simulations of the robot. Inverse dynamics refers to the calculation of the actuator forces

necessary to create a prescribed end effector acceleration. This information can be used to improve the control algorithms of a robot.
In each area mentioned above, researchers strive to develop new concepts and strategies, improve existing ones, and improve the interaction between these areas. To do this, criteria for "optimal" performance and ways to optimize design, structure, and control of robots must be developed and implemented.

3.10 Education and Training

Figure 12: The SCORBOT-ER 4u - educational robot.

Robots recently became a popular tool in raising interests in computing for middle and high school students. First year computer science courses at several universities were developed which involves the programming of a robot instead of the traditional software engineering based coursework.

3.10.1 Career training

Universities offer Bachelors, Masters and Doctoral degrees in the field of robotics. Select Private Career Colleges and vocational schools offer robotics training to train individuals towards being job ready and employable in the emerging robotics industry.

3.10.2 Certification

The Robotics Certification Standards Alliance (RCSA) is an international robotics certification authority who confers various industry and educational related robotics certifications.

3.11 Employment

Figure 13: A robot technician builds small all-terrain robots. (Courtesy: MobileRobots Inc)

Robotics is an essential component in any modern manufacturing environment. As factories increase their use of robots, the number of robotics related jobs grow and have been observed to be on a steady rise.

3.11.1 Effects on Unemployment

Some analysts, such as Martin Ford, argue that robots and other forms of automation will ultimately result in significant unemployment as machines begin to match and exceed the capability of workers to perform most jobs. At present the negative impact is only on menial and repetitive jobs, and there is actually a positive impact on the number of jobs for highly skilled technicians, engineers, and specialists. However, these highly skilled jobs are not sufficient in number to offset the greater decrease in employment among the general population, causing structural unemployment in which overall (net) unemployment rises.

As robotics and artificial intelligence develop further, some worry even many skilled jobs may be threatened. In conventional economic theory this should merely cause an increase in the productivity of the involved industries, resulting in higher demand for other goods, and hence higher labour demand in these sectors, off-setting whatever negatives are caused. Conventional theory describes the past well but may not describe the future due to shifts in the parameter values that shape the context.

4.0 CONCLUSION

Robotics is an essential component in any modern manufacturing environment. As factories increase their use of robots, the number of robotics related jobs grow and have been observed to be on a steady rise. As robotics and artificial intelligence develop further, some worry even many skilled jobs may be threatened.

5.0 SUMMARY

In this unit, you learnt:

- Robots and Types of Robots
- History of Robots
- Components of Robots
- Robotics research
- Education and training
- Robots and Employment.