AI and Neural Networks (Assignment –I)

Submitted in partial fulfilment of the requirements for the degree of

Master of Technology in Information Technology

by

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AI and Neural Networks

CERTIFICATE

This is to certify that the Assignment-I entitled AI and Neural Networks, subject code: MT22 submitted by Vijayananda D Mohire having Roll Number 921DMTE0113 for the partial fulfilment of the requirements of Master of Technology in Information Technology degree of Karnataka State Open University, Mysore, embodies the bonafide work done by him under my supervision.

Place: _______________ Signature of the Internal Supervisor

Name

Date: _______________ Designation

For Evaluation

Question Number	Maximum Marks	Marks awarded	Comments, if any
1	1		
2	1		
3	1		
4	1		
5	1		
6	1		
7	1		
8	1		
9	1		
10	1		
TOTAL	10		

Evaluator's Name and Signature Date

Preface

This document has been prepared specially for the assignments of M.Tech – IT II Semester. This is mainly intended for evaluation of assignment of the academic M.Tech – IT, II semester. I have made a sincere attempt to gather and study the best answers to the assignment questions and have attempted the responses to the questions. I am confident that the evaluator's will find this submission informative and evaluate based on the provide content.

For clarity and ease of use there is a Table of contents and Evaluators section to make easier navigation and recording of the marks. Evaluator's are welcome to provide the necessary comments against each response; suitable space has been provided at the end of each response.

I am grateful to the Infysys academy, Koramangala, Bangalore in making this a big success. Many thanks for the timely help and attention in making this possible within specified timeframe. Special thanks to Mr. Vivek and Mr. Prakash for their timely help and guidance.

Candidate's Name and Signature   Date

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AI AND NEURAL NETWORKS

RESPONSE TO ASSIGNMENT - I

Question 1 What are the issues in knowledge representation?

Answer 1

Even beyond conversational context, understanding human language requires access to the whole range of human knowledge. Even when speaking with a child, one assumes a great deal of "common sense" knowledge that computers are, as yet, sorely lacking in. The problem of language understanding at this point merges with the general problem of knowledge representation and use.

Real applications of natural language technology for human computer interfaces require a very limited scope so that the computer can get by with limited language skills and can have enough knowledge about the domain to be useful. However, it is difficult to keep people completely within the language and knowledge boundaries of the system. This is why the use of natural language interfaces is still limited.

Some issues that arise in knowledge representation from an AI perspective are:

- How do people represent knowledge?
- What is the nature of knowledge and how do we represent it?
- Should a representation scheme deal with a particular domain or should it be general purpose?
- How expressive is a representation scheme or formal language?
- Should the scheme be declarative or procedural?

There has been very little top-down discussion of the knowledge representation (KR) issues and research in this area is a well aged quillwork. There are well known problems such as "spreading activation" (this is a problem in navigating a network of nodes), "subsumption" (this is concerned with selective inheritance; e.g. an ATV can be thought of as a specialization of a car but it inherits only particular characteristics) and "classification." For example a tomato could be classified both as a fruit and a vegetable.

In the field of artificial intelligence, problem solving can be simplified by an appropriate choice of knowledge representation. Representing knowledge in some ways makes certain problems easier to solve. For example, it is easier to divide numbers represented in Hindu-Arabic numerals than numbers represented as Roman numerals.

Another class of issues are based on Methodology used: Division into analytical and heuristic systems can be also seen in knowledge engineering methodologies.

- Analytical: rule based systems, semantic nets, frames, logic programming, ontologies, etc.
- Heuristic: statistical pattern recognition, neural networks, statistical machine learning, etc.

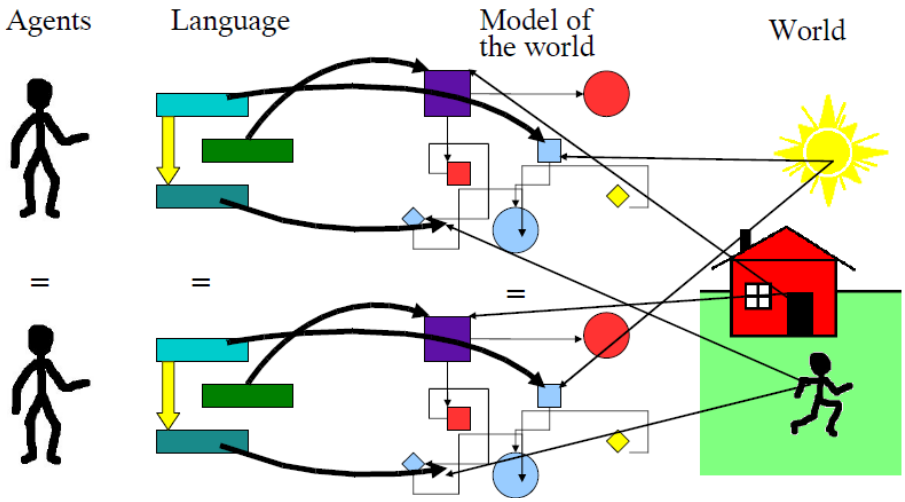


Figure 1 Traditional approach

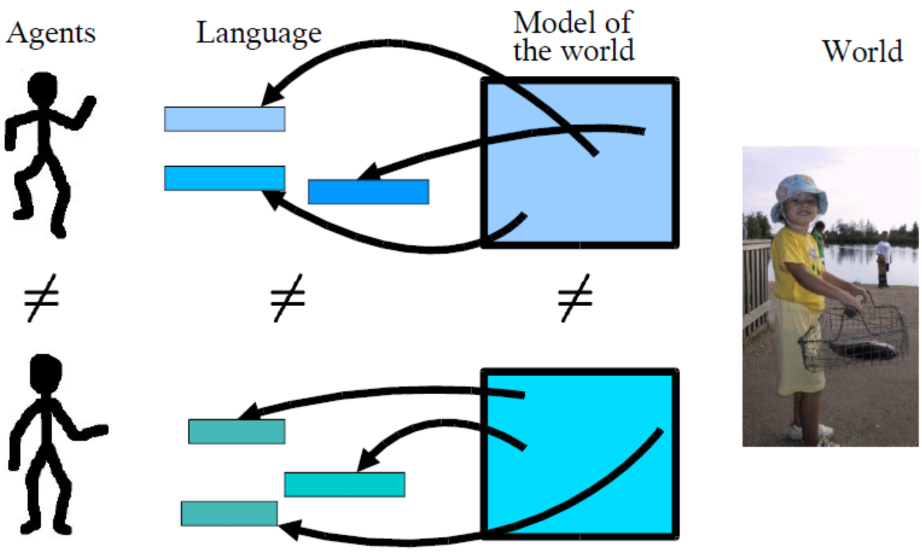


Figure 2 Emergentist approach

Problems of purely analytical approaches

- There is a need for methods that would be more successful as building blocks for knowledge engineering and natural language processing systems as the ones traditionally used
- Two kinds of problems of analytical / logic based formalisms (including Semantic Web and ontologies): one quantitative and many qualitative

Quantitative problem

- The efforts required to collect explicit knowledge representation in many domains requires considerable amount of human work
- This conclusion can be made based on numerous examples of development of expert systems and natural language processing applications

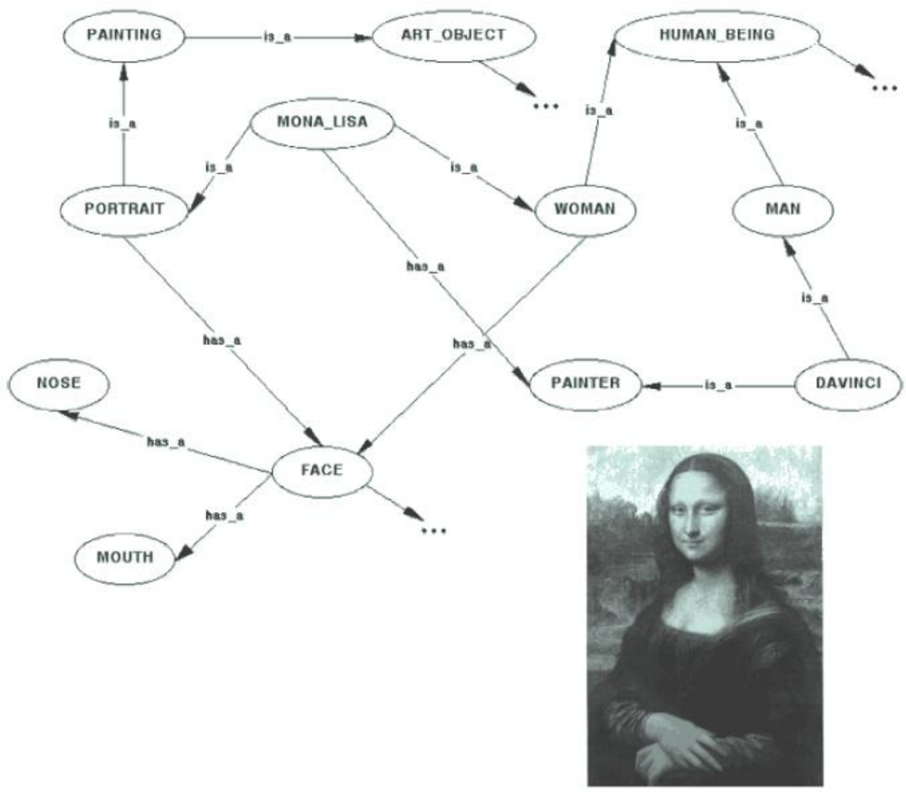


Figure 3 Quantitative approach: Involves huge data collection

Qualitative problems

- Even if the knowledge acquisition problem were solved with machine learning techniques, much more burning qualitative problems remain
- In traditional AI systems, the symbolic representations are not grounded: the semantics are, at best, very shallow (this is an intentional

contradiction with the terminology commonly used)

- Real knowledge is grounded in experience and requires access to the pattern recognition processes that are probabilistic in nature

We tend to perceive the world as a collection of objects, their qualities and relationships. However, the perceptual input is a continuous flow of patterns (fig 4).

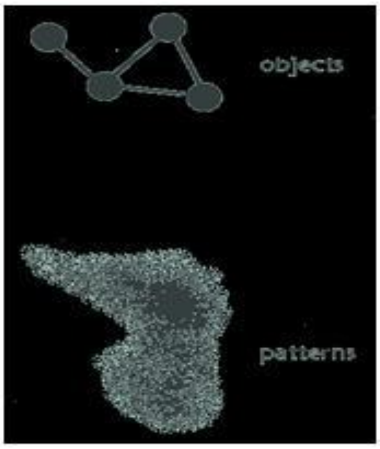


Figure 4 Qualitative problem

The process in which the patterns are interpreted as objects is far from straightforward. The conceptualizations that we use are an emergent result of complex interactions between people and the world. This includes biological, psychological, cognitive, social, etc, aspects.

- Interpretation of words/symbols for human beings is always subjective to some degree.
- When suitably high agreement is reached, one can name it as the state of intersubjectivity.
- Intersubjectivity is, however, always a matter of degree and thus real objectivity in a strict sense cannot be reached.
- Traditional AI representations do not have proper means for dealing with this issue at all.
- Conceptualisation is formed in an iterative process in which a large number of interacting elements influence each other with no central control.
- Efforts of harmonisation or standardization can be successful only to some degree. The higher the degree, the higher the costs.
- The costs include both development costs and implementation (learning) costs.

Few more issues as identified by AI authors Rich and Knight are:

- Are any attributes of objects so basic that they occur in almost every problem domain? If there are, we need to make sure that they are handled appropriately in each of the mechanisms we propose.
- Is there any important relationship that exists among attributes of objects?
- At what level should knowledge be represented? Is there a good set of primitives into which all knowledge can be broken down? Is it helpful to use such primitives?
- How should sets of objects be represented?
- Given a large amount of knowledge stored in a database, how can relevant parts be accessed when they are needed?

Evaluator's Comments if any:

Question 2 What is Expert System?

Answer 2

An expert system is a software system that attempts to reproduce the performance of one or more human experts, most commonly in a specific problem domain, and is a traditional application and/or subfield of AI. A wide variety of methods can be used to simulate the performance of the expert, few important ones that are common to all such systems are:

1) The creation of a so-called "knowledgebase" which uses some knowledge representation formalism to capture the subject matter experts (SME) knowledge.

2) A process of gathering that knowledge from the SME and codifying it accordingly to the formalism, which is called knowledge engineering. Expert systems may or may not have learning components but a third common element is that once a system is developed it is proven by being placed in the same real world problem solving situation as the human SME, typically as an aid to human workers or a supplement to some information system.

An example of a typical Expert system is provided in following section.

In this example, we illustrate the reasoning process involved in an expert system for a weather forecasting problem with special emphasis to its architecture. An expert system consists of a **knowledge base**, **database** and an **inference engine** for interpreting the database using the knowledge supplied in the knowledge base. The reasoning process of a typical illustrative expert system is described in Fig. 5. PR 1 in Fig. 5 represents i-th production rule.

The inference engine attempts to match the antecedent clauses (IF parts) of the rules with the data stored in the database. When all the antecedent clauses of a rule are available in the database, the rule is fired, resulting in new inferences. The resulting inferences are added to the database for activating subsequent firing of other rules. In order to keep limited data in the database, a few rules that contain an explicit consequent (THEN) clause to delete specific data from the databases are employed in the knowledge base. On firing of such rules, the unwanted data clauses as suggested by the rule are deleted from the database. Here PR1 fires as both of its antecedent clauses are present in the database. On firing of PR1, the consequent clause "it-will-rain" will be added to the database for subsequent firing of PR2.

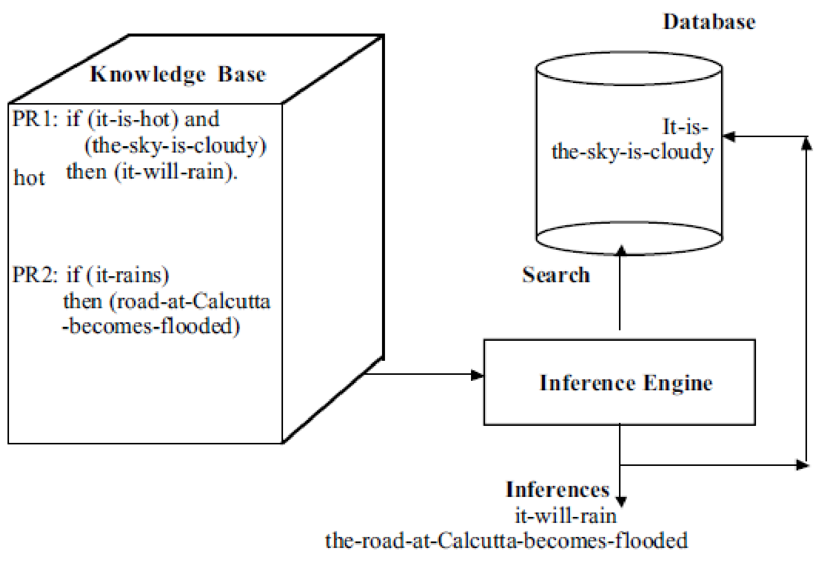


Figure 5 Illustrative architecture of an expert system

Evaluator's Comments if any:

Question 3 What do you understand by forward Vs backward reasoning?

Answer 3

Most of the common classical reasoning problems of AI can be solved by any of the following two techniques called i) forward and ii) backward reasoning.

In a forward reasoning problem such as 4-puzzle games or the water-jug problem, where the goal state is known, the problem solver has to identify the states by which the goal can be reached. Such class of problems are generally solved by expanding states from the known starting states with the help of a domain-specific knowledge base. The generation of states from their predecessor states may be continued until the goal is reached.

On the other hand, consider the problem of system diagnosis or driving a car from an unknown place to home. Here, the problems can be easily solved by employing backward reasoning, since the neighbouring states of the goal node are known better than the neighbouring states of the starting states. For example, in diagnosis problems, the measurement points are known better than the cause of defects, while for the driving problem, the roads close to home are known better than the roads close to the unknown starting location of driving. It is thus clear that, whatever is the class of problems, system states from starting state to goal or vice versa is to be identified, which requires expanding one state to one or more states. If there is no knowledge to identify the right offspring state from a given state, then many possible offspring states are generated from a known state. This enhances the search-space for the goal. When the distance (in arc length) between the starting state and goal state is long, determining the intermediate states and the optimal path (minimum arc length path) between the starting and the goal state becomes a complex problem.

Given a set of rules like explained above, there are essentially two ways we can use them to generate new knowledge:

1. Forward chaining: starts with the facts, and sees what rules apply (and hence what should be done) given the facts. This is data driven.
2. Backward chaining: starts with something to find out, and looks for rules that will help in answering it. This is goal driven.

Forward chaining:

In a forward chaining system (Refer fig 6):

- Facts are held in a working memory
- Condition-action rules represent actions to take when specified facts occur in working memory.
- Typically the actions involve adding or deleting facts from working memory.
- Collect the rule whose condition matches a fact in WM. Do actions indicated by the rule (add facts to WM or delete facts from WM)
- If more than one rule matches Use conflict resolution strategy to eliminate all but one
- Repeat Until problem is solved or no condition match

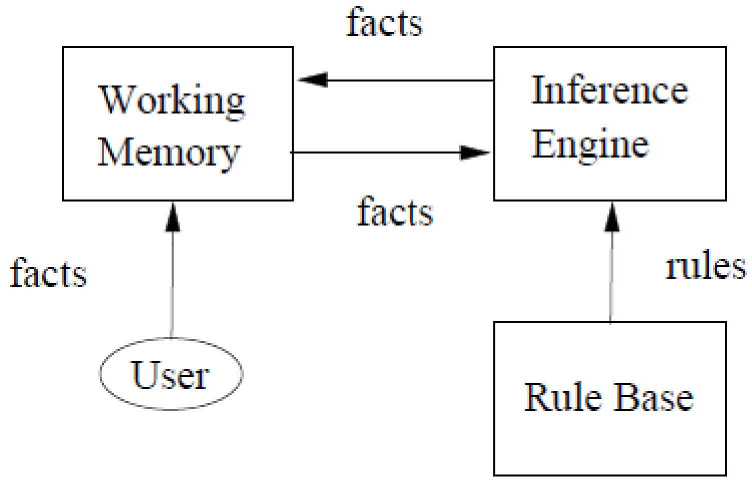


Figure 6 Rule based system

```
R1: IF hot AND smoky THEN ADD fire
R2: IF alarm_beeps THEN ADD smoky
R3: If fire THEN ADD switch_on_sprinklers

F1: alarm_beeps    [Given]
F2: hot            [Given]

F3: smoky                   [from F1 by R2]
F4: fire                    [from F2, F4 by R1]
F5: switch_on_sprinklers    [from F4 by R3]
```

Figure 7 A typical Forward Chaining example

Backward chaining:

- Same rules/facts may be processed differently, using backward chaining interpreter

- Backward chaining means reasoning from goals back to facts. The idea is that this focuses the search.
- Uses checking hypothesis: Should I switch the sprinklers on?
- To prove goal G: If G is in the initial facts, it is proven.
- Otherwise, find a rule which can be used to conclude G, and try to prove each of that rule's conditions.

Rules:

R1: IF hot AND smoky THEN fire

R2: IF alarm_beeps THEN smoky

R3: If fire THEN switch_on_sprinklers

Facts:

F1: hot

F2: alarm_beeps

Goal:

Should I switch sprinklers on?

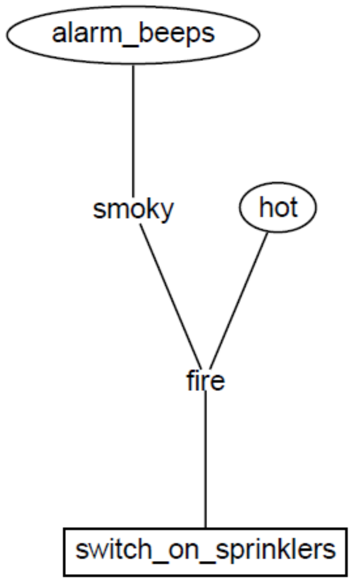


Figure 8 A typical backward chaining example

Evaluator's Comments if any:

Question 4 Describe procedural Vs declarative knowledge?

Answer 4

The knowledge that goes into problem solving can be broadly classified into three categories, viz., compiled knowledge, qualitative knowledge and quantitative knowledge. Knowledge resulting from the experience of experts in a domain, knowledge gathered from handbooks, old records, and standard specifications etc., forms the compiled knowledge. Qualitative knowledge consists of rules of thumb, approximate theories, causal models of processes and common sense. Quantitative knowledge deals with techniques based on mathematical theories, numerical techniques etc. Compiled as well as qualitative knowledge can be further classified into two broad categories, viz., *declarative knowledge* and *procedural knowledge*. Declarative knowledge deals with knowledge on physical properties of the problem domain, whereas procedural knowledge deals with problem-solving techniques.

As per KSOU,

Declarative representation:

- Static representation – knowledge about objects, events etc. and their relationship and states given.
- This necessitates a program to know what to do with the knowledge and how to do it.

Procedural representation:

- Proceedings or control information needed to use the knowledge is embedded in itself (knowledge), like how to find relevant facts...
- This needs an interpreter to follow instructions specified in knowledge.
- Knowledge encoded in some procedures and programs like the parser has its inbuilt nouns, adjectives and verbs and will use them suitably.

Architectures with **declarative** representations *have knowledge in a format that may be manipulated decomposed and analyzed by its reasoners*. A classic example of a declarative representation is *logic*. Advantages of declarative knowledge are:

- The ability to use knowledge in ways that the system designer did not foresee

Architectures with **procedural** representations encode *how to achieve a particular result*. Advantages of procedural knowledge are:

- Possibly faster usage

Often times, whether knowledge is viewed as **declarative** or **procedural** is not an intrinsic property of the knowledge base, but is a function of what is allowed to read from it.

A particular architecture may use both declarative and procedural knowledge at different times, taking advantage of their different advantages. An example of this is Atlantis, which has a low-level. The distinction between declarative and procedural representations is somewhat artificial in that they may easily be interconverted, depending on the type of processing that is done on them.

Evaluator's Comments if any:

Question 5 Write a short note on Best first search?

Answer 5

Best first search depends on the use of heuristic to select most promising paths to the goal node. Unlike hill climbing, however, this algorithm retains all estimates computed for previously generated nodes and makes its selections based on the best among them all. Thus at any point in the search process, best first moves forward from the most promising of all the nodes generated so far. In doing so, it avoids the potential traps encountered in hill climbing.

The algorithm uses an evaluation function *f (n)* for each node to compute estimate of "desirability" and expands most desirable unexpanded node.

- Evaluation function *f (n) = h (n)* (heuristic) = estimate of cost from *n* to *goal.*

E.g., h_{SLD} *(n)* = straight-line distance from *n* to desired goal.

In below example distance from Arad to Bucharest is estimated using the lowest cost. At Arad 3 choices, Sibiu (253), Timisoara (329), Zerind (374). Since Sibiu is least distance it is chosen. At Sibiu distance to Fagaras (176) is least and it is selected. This continues till goal is reached.

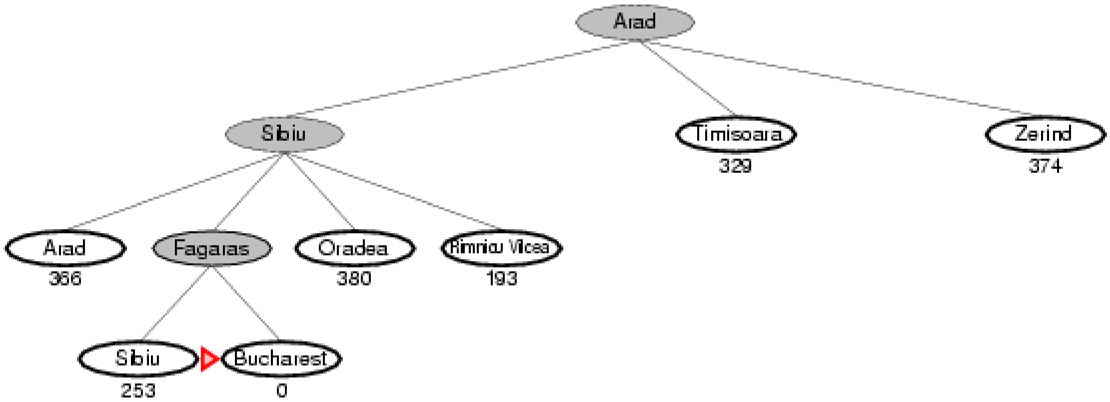


Figure 9 Best first search

Algorithm:

1. Place the starting node s on the queue.
2. If the queue is empty, return failure and stop
3. If the first element on the queue is a goal node return success and stop otherwise.
4. Remove the first element from the queue. Expand it and compute the estimated goal distances for each child. Place the children on the queue and arrange all queue elements in the ascending order corresponding to goal distance from the front of the queue.
5. Return to step 2

Evaluator's Comments if any:

Question 6 Explain with example traveling salesman problem?

Answer 6

The travelling salesman involves n cities with paths connecting the cities, which begins with some starting city, visits each of the other cities exactly once. He returns to the starting city. A typical tour is depicted in Figure 10

Typically a travelling salesperson will want to cover all the towns in their area using the minimum driving distance.

The objective of a TSP is to find the minimal distance tour. To explore all such tours requires an exponential amount of time. For examples a minimal solution with only 10 cities is tractable, as an attempt to calculate for 20 cities leads to a worst case search of the order of 20! Tours.

Travelling salesperson problems tackle this by first turning the towns and roads into a network.

We have seen that finding a tour that visits every arc (route inspection) depended on earlier work by Euler. Similarly the problem of finding a tour that visits every node (travelling salesperson) was investigated in the 19^{th} Century by the Irish mathematician Sir William Hamilton.

A *Hamiltonian cycle* is a tour which contains every node once.

Consider the Hamiltonian cycles for graph in Figure 11

There are just three essentially different Hamiltonian cycles:

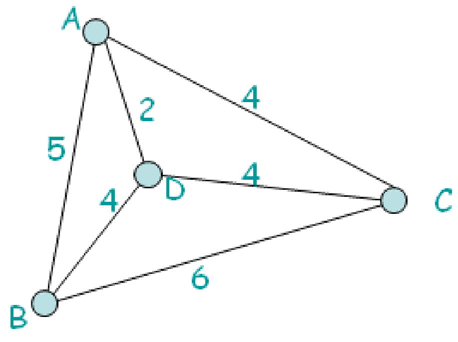


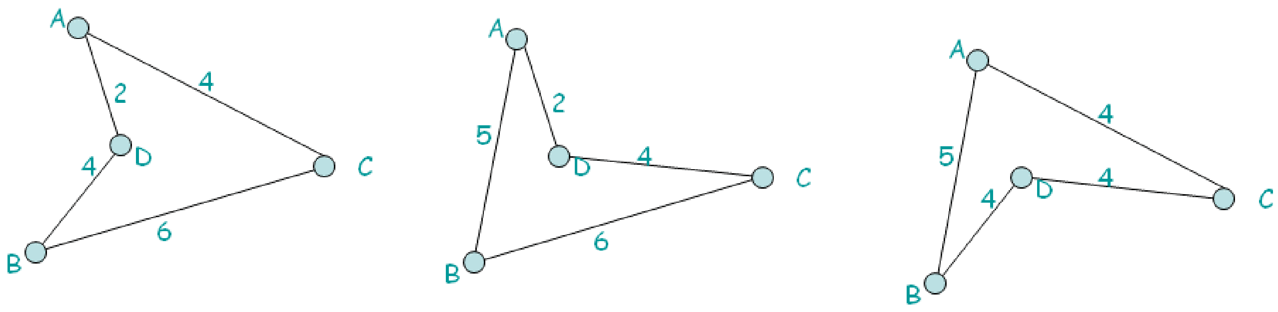
Figure 10 Typical TSP tour

ABCDA with weight 17

ABDCA with weight 17

ACBDA with weight 16

Figure 11 Hamilton cycles



TSP is solved by selecting one of the optimal Hamilton cycles that make use of least weight ACBDA with weight 16.

Evaluator's Comments if any:

Question 7 Describe neural model?

Answer 7

The three classical models for an artificial neuron are described here.

McCulloch-Pitts Model

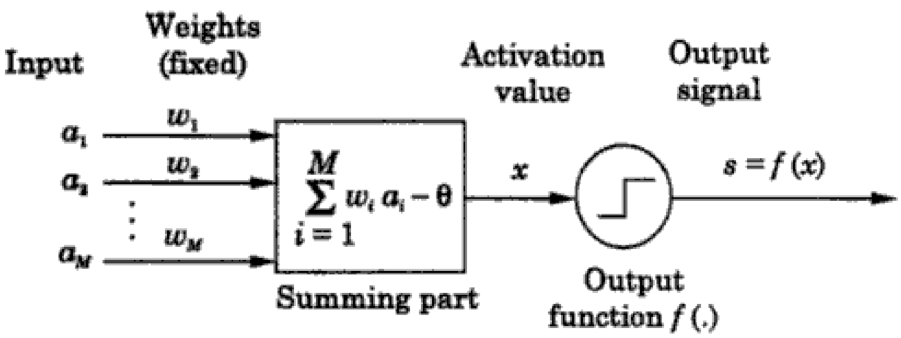


Figure 12 McCulloch-Pitts model of a neuron

In McCulloch-Pitts (MP) model figure 12 the activation (x) is given by a weighted sum of its M input values (a_i) and a bias term (θ). The output signal (s) is typically a nonlinear function f(x) of the activation value x. The following equations describe the operation of an MP model:

Activation: $$x = \sum_{i=1}^{M} w_i a_i - \theta$$

Output signal: $$s = f(x)$$

Three commonly used non linear functions (binary, ramp and sigmoid) are shown in Figure 13, although only the binary function was used in the original MP model.

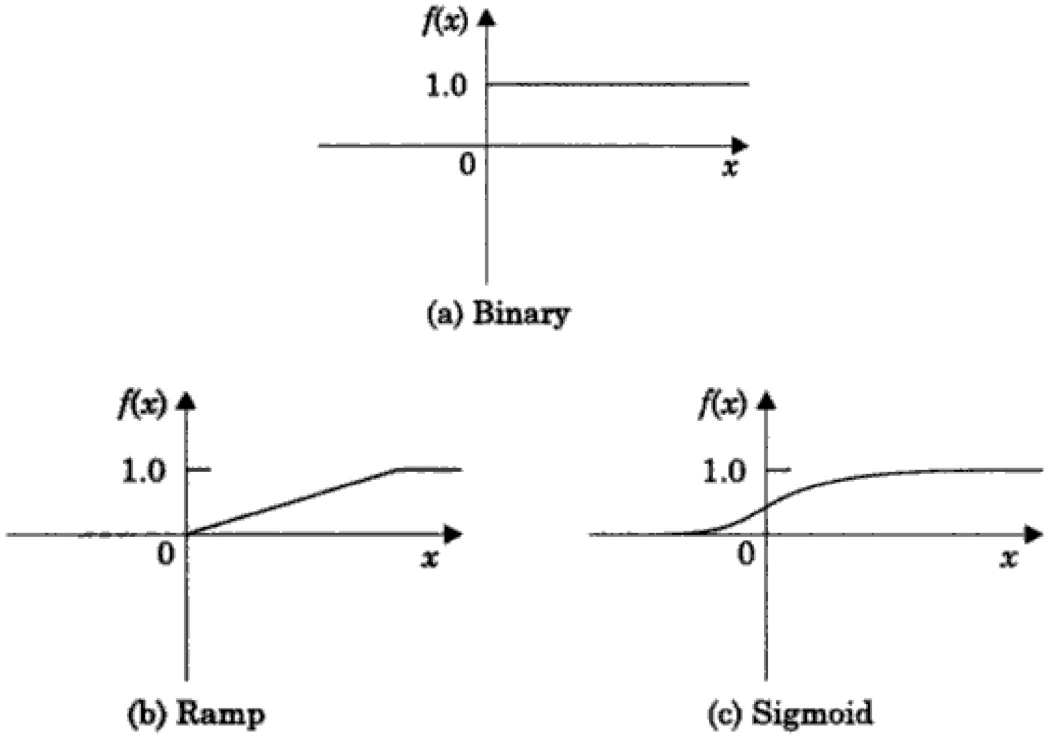


Figure 13 Some non linear functions

Networks consisting of MP neurons with binary (on-off) outputs signals can be configured to perform several logical functions. Figure 14 shows some examples of logic circuits realized using the MP model.

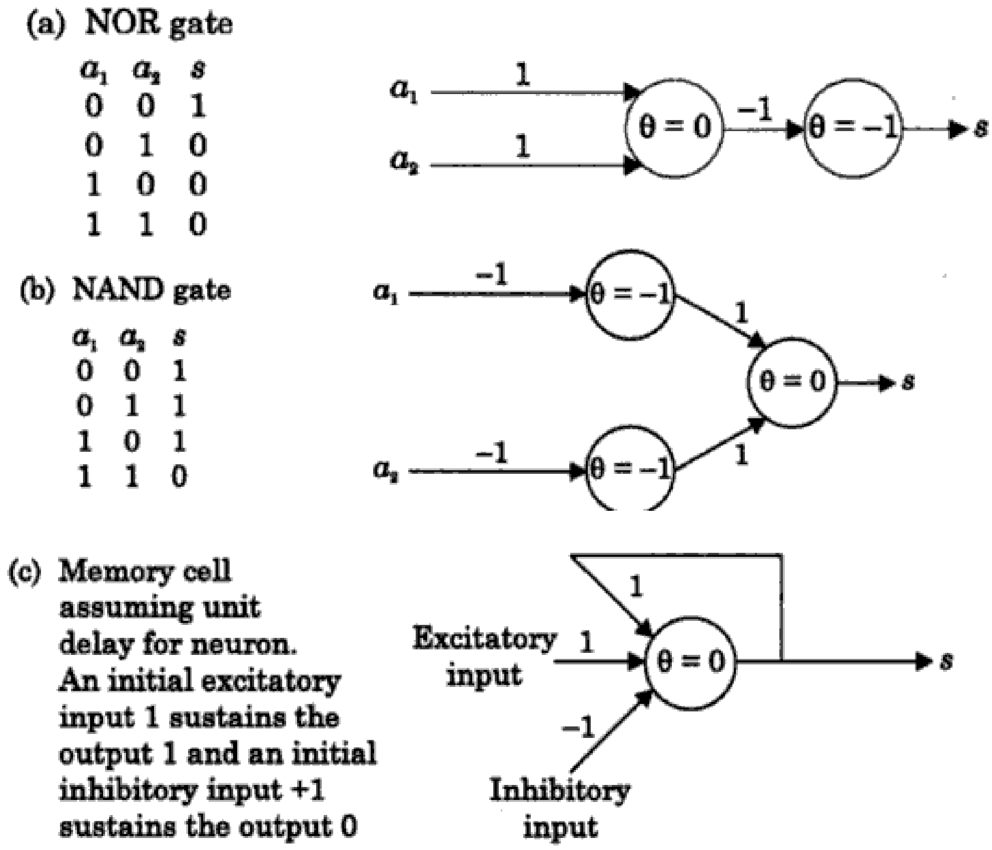


Figure 14 Illustration of some elementary logic networks using MP neurons.

In this model a binary output function is used with the following logic:

$$f(x) = 1, x > 0$$
$$= 0, x \leq 0$$

A single input and a single output MP neuron with proper weight and threshold gives an output a unit time later. This unit delay property of the MP neuron can be used to build sequential digital circuits. With feedback, it is also possible to have a memory cell which can retain the output indefinitely in the absence of any input.

In the MP model the weights are fixed. Hence a network using this model does not have the capability of learning. Moreover, the original model allows only binary outputs states, operating at discrete time steps.

Perceptron:

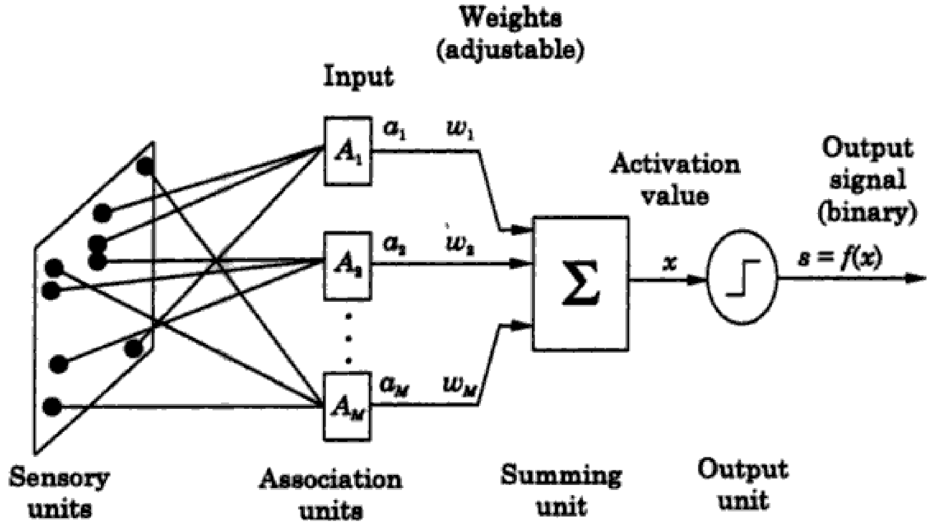


Figure 15 Perceptron model

The Rosenblatt's perceptron model (Figure 15) for an artificial neuron consists of outputs from sensory units to a fixed set of association units, the outputs of which are fed to an MP neuron. The association units perform predetermined manipulations on their inputs. The main deviation from the MP model is that learning (i.e. adjustment of weights) is incorporated in the operation of the unit. The desired or target output (b) is compared with the actual binary output(s), and the error (δ) is used to adjust the weights. The following equations describe the operation of the perceptron model of a neuron.

Activation: $$x = \sum_{i=1}^{M} w_i a_i - \theta$$

Output signal: $$s = f(x)$$

Error: $$\delta = b - s$$

Weight change: $$\Delta w_i = \eta \delta a_i$$

where η is the learning rate parameter.

There is a perception learning law which gives a step-by-step procedure for adjusting the weights. Whether the weight adjustment converge or not depends on the nature of the desired input-output pairs to be represented by the model. The perceptron convergence theorem enables us to determine whether the given pattern pairs are represent able or not. If the weights values converge, then the corresponding problem is said to be represented by the perceptron network.

Adaline:

Adaptive LINear Element (ADALINE) is a computing model proposed by Widrow and is shown if Fig 15.

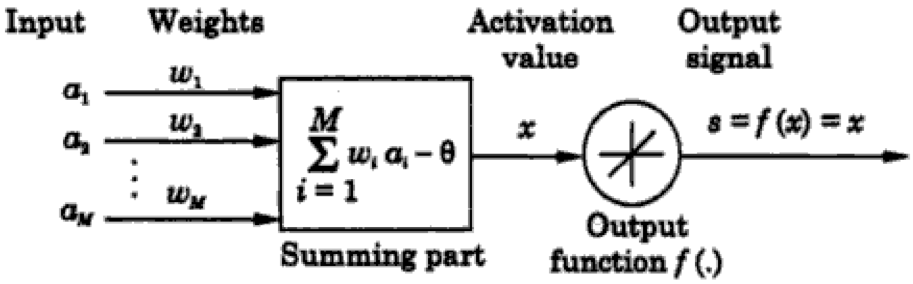


Figure 16 Widrow's Adaline model of a neuron

The main distinction between the Rosenblatt's perceptron model and the Widrow's Adaline model is that, in the Adaline the analog activation value (x) is compared with the target output (b). In other words, the output is a linear function of the activation value(x). The equations that describe the operation of an Adaline are as follows:

Activation: $$x = \sum_{i=1}^{M} w_i a_i - \theta$$

Output signal: $$s = f(x) = x$$

Error: $$\delta = b - s = b - x$$

Weight change: $$\Delta w_i = \eta \delta a_i$$

Where η is the learning rate parameter. This weight update rule minimizes the mean squared error δ^2 , averaged over all inputs. Hence it is called Least Mean Squared(LMS) error learning law. This law is derived using the negative gradient of the error surface in the weight space. Hence it is also known as gradient descent algorithm.

Evaluator's Comments if any:

Question 8 Describe Pattern Recognition problem?

Answer 8

First let's get a brief introduction to Pattern recognition and later define the problem.

Pattern recognition is characteristic to all living organisms. However, different creatures recognize differently. If a human would recognize another human by sight, by voice or by handwriting, a dog may recognize a human or other animal by smell thirty yards away which most humans are incapable of doing. All of these examples are classified as recognition.

The object which is inspected for the "recognition" process is called a pattern. Usually we refer to a pattern as a description of an object which we want to recognize. In this text we are interested in spatial patterns like humans, apples, fingerprints, electrocardiograms or chromosomes. In most cases a pattern recognition problem is a problem of discriminating between different populations. For example we may be interested among a thousand humans to discriminate between four different types: (a) tall and thin (b) tall and fat (c) short and thin (d) short and fat. We thus want to classify each person in one of four populations. The recognition process thus turns into classification. To determine which class the person belongs to, we must first find which features are going to determine this classification. The age of the person is clearly not a feature in this case. A reasonable choice of course is the pair of numbers (height, weight) and we thus perform a feature selection for this particular problem. Getting these measurements is called feature extraction.

Clustering given input data is a major subject in pattern recognition. It consists of dividing the data into clusters and establishing the cluster centers and cluster boundaries. An a priori knowledge of the number of clusters and their approximate locations definitely simplifies our task. We then carry a supervised learning process. If the data is of no known characteristic we obtain an unsupervised learning process.

Pattern recognition problem as defined by KSOU:

In any pattern recognition task we have a set of input patterns and the corresponding output patterns. Depending on the nature of the output patterns and the nature of the task environment, the problem could be identified as one of association or classification or mapping. The given set of input-output pattern pairs form only a few samples of an unknown system. From these samples the pattern recognition model should capture the characteristic of the system. Without looking into the details of the system, let us assume that the input-output patterns are available or given to us. Without loss of generality, let us alone assume that the patterns could be represented as vectors in multidimensional spaces. We first state that the most straightforward pattern recognition problem, namely, the pattern association problem, and discuss its characteristic.

Pattern Association problem: Given a set of input-output pattern pairs(a_1,b_1),(a_2,b_2),…(a_i,b_i),…,(a_l,b_l) where a_l = (a_{l1},a_{l2}, ---,a_{1M}) and b_l = (b_{l1}, b_{l2},…, b_{ln}) are M and N dimensional vectors, respectively, design a neural network to associate each input pattern with the corresponding output pattern.

If a_l, b_l are distinct, then the problem is called heteroassociation. On the other hand, if $b_l = a_l$, then the problem is called autoassociaiton. In the latter case the input and the corresponding output patterns refer to the same point in an N-dimensional space, since M=N and $a_{li} = b_{li}$, I =1,2,…N, l=1,2,…, L.

The problem of storing the association of the input-output pattern pairs(a_l,b_l), l =1,2,…,L, involves determining the weights of a network to accomplish the task. This is the training part. Once stored, the problem of recall involves determining the output pattern for a given input pattern by applying the operations of the network on the input pattern.

The recalled output pattern depends on the nature of the input and the design of the network. If the input pattern is the same as one of those used in the training, then the recalled output pattern is the same as the associated pattern in the training. If the input pattern is a noisy version of the trained input pattern, then the pattern may not be identical to any of the patterns used in training the network. Let the input pattern is $\hat{a} = al + \varepsilon$, where ε is a (small amplitude) noise vector. Let us assume that $\hat{a}$ is closer(according to some distance measure) to a_l than any other a_k, $k \neq l$. If the output of the network for this input â is still b_l, then the network is designed to exhibit an accretive behavior. On the other hand, if the network produces an output $\hat{b} = b_l+\delta$, such that $|\delta| \to 0$ as $|\varepsilon| \to 0$, then the network is designed to exhibit an interpolative behaviour. Depending on the interpretation of the problem, several pattern recognition tasks can be viewed as variants of the pattern association problem.

Evaluator's Comments if any:

Question 9 Define simulated annealing?

Answer 9

In metallurgy, **annealing** is the process used to temper or harden metals and glass by heating them to a high temperature and then gradually cooling them, thus allowing the material to coalesce into a low-energy crystalline state. The structural properties of a solid depend on the rate of cooling after the solid has been heated beyond its melting point. If the solid is cooled slowly, large crystals can be formed that are beneficial to the composition of the solid. If the solid is cooled in a less controlled way, the result is a fragile solid with undesirable properties. Annealing is to shake up the object at higher temperatures so that the loose bonding of the molecules at that temperature can be used to our advantage to give shape and reach the proper desired goal state. In IT this has an analogous use to reach the desired best solution.

To understand simulated annealing, let's consider **gradient descent** (i.e., minimizing cost) and imagine the task of getting a ping-pong ball into the deepest crevice in a bumpy surface. If we just let the ball roll, it will come to rest at a local minimum. If we shake the surface, we can bounce the ball out of the local minimum. The trick is to shake just hard enough to bounce the ball out of local minima, but not hard enough to dislodge it from the global minimum. The simulated annealing solution is to start by shaking hard (i.e., at a high temperature) and then gradually reduce the intensity of the shaking (i.e., lower the temperature).

The innermost loop of the simulated-annealing algorithm (Figure 17) is quite similar to hill climbing. Instead of picking the *best* move, however, it picks a ***random*** move. If the move improves the situation, it is always accepted. Otherwise, the algorithm accepts the move with some probability less than 1. The probability decreases exponentially with the "badness" of the move-the amount ΔE by which the evaluation is worsened. The probability also decreases as the "temperature" T goes down: "bad moves are more likely to be allowed at the start when temperature is high, and they become more unlikely as T decreases. One can prove that if the schedule lowers T slowly enough, the algorithm will find a global optimum with probability approaching 1.

Simulated annealing was first used extensively to solve VLSI layout problems in the early 1980s. It has been applied widely to factory scheduling and other large-scale optimization tasks.

```
function SIMULATED-ANNEALING(problem, schedule) returns a solution state
   inputs: problem, a problem
           schedule, a mapping from time to "temperature"
   local variables: current, a node
                    next, a node
                    T, a "temperature" controlling the probability of downward steps

   current ← MAKE-NODE(INITIAL-STATE[problem])
   for t ← 1 to ∞ do
      T ← schedule[t]
      if T = 0 then return current
      next ← a randomly selected successor of current
      ΔE ← VALUE[next] – VALUE[current]
      if ΔE > 0 then current ← next
      else current ← next only with probability e^(ΔE/T)
```

Figure 17 Simulated annealing search algorithm

A version of stochastic hill climbing where some downhill moves are allowed. Downhill moves are accepted readily early in the annealing schedule and then less often as time goes on. The Schedule input determines the value T as a function of time.

Evaluator's Comments if any:

Question 10 What is Boltzmann machine?

Answer 10

A Boltzmann machine (BM) is the name given to a type of simulated stochastic recurrent neural network by Geofferey Hinton and Terry Sejnowski.

Boltzmann machines can be seen as the stochastic, generative counterpart of Hopfield nets. They were one of the first examples of a neural network capable of learning internal representations, and are able to represent and solve difficult combinatoric problems. However, due to a number of issues discussed below, BM with un constrained connectivity has not proven useful for practical problems in machine learning or inference. They are still theoretically intriguing, however, due to the locality and hebbian nature of their training algorithm, as well as their parallelism and the resemblance of their dynamics to simple physical processes. If the connectivity is constrained, the learning can be made efficient enough to be useful for practical problems.

The BM is important because it is one of the first neural networks to demonstrate learning of latent variables. BM learning was at first slow to simulate, but the contrastive divergence algorithm of Geoff Hinton (year 2000) allows models such as BM to be trained much faster.

Structure of BM:

A BM like a Hopfield network, is a network of units with an "energy" defined for the network. It also has binary units, but unlike Hopfield nets, BM units are stochastic. The global energy, E, in a BM is identical in form to that of a Hopfield network:

$E = -\sum w_{ij}\, s_i\, s_j + \sum \theta_i\, s_i$

where

$i < j$

w_{ij} is the connection strength between unit j and unit i.

s_i is the state of unit i

θ_i is the threshold of unit i.

The connections in a BM have two restrictions:

- No unit has a connection with itself.
- All connections are symmetric

Thus the difference in the global energy that results from a single unit I being 0 versus 1, written ΔE_i is given by:

$\Delta E_i = \Sigma\ w_{ij}\ s_j - \theta_i$

A BM is made up of stochastic units. The probability, Pi of the ith unit being on is given by:

$Pi = 1\ /\ (1 + \exp(-1/T\ \Delta E_i)$

Where the scalar T is referred to as the temperature of the system.

The network is run by repeatedly choosing a unit and setting its state according to the above formula. After running for long enough at a certain temperature, the probability of a global state of the network will depend only upon the global state's energy, according to a Boltzmann distribution. This means that log-probabilities of global state become linear in their energies.

This relationship is true when the machine is at "thermal equilibrium", meaning that the probability distribution of global states has converged. If we start running the network from a high temperature, and gradually decrease it until we reach a thermal equilibrium at a low temperature, we are guaranteed to converge to a distribution where the energy level fluctuates around the global minimum. This process is simulated annealing.

Evaluator's Comments if any: