UCS1504 – Artificial Intelligence

Answer Key – CAT3

1. Advantage of Bayesian Networks
   Reduces the no. of connectives between states in DAG, Joint probability value of conditional statements
2. Four techniques suitable for uncertain reasoning
   Probability approach, Fuzzy reasoning, Certainty factor, Dempster shafer theory
3. (b)The Entropy of a node typically decreases as we go down a decision tree
4. Unsupervised learning
5. Supervised: samples with label, Classification, Regression and Prediction problems
   Semi-supervised: Partial samples with label, Classification, Regression and Prediction problems
6. Robot navigation - grasping objects
   Manufacturing sector
   Healthcare domain

7. Reinforcement Learning (RL) and Markov Decision Process

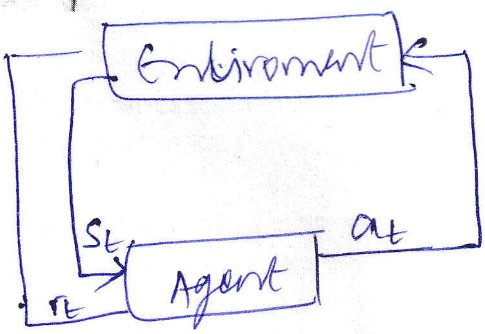
RL: learning with realtime environment, dynamic, reward & punishment.

MDP: sequential decision problems with states, actions, rewards & transition model.

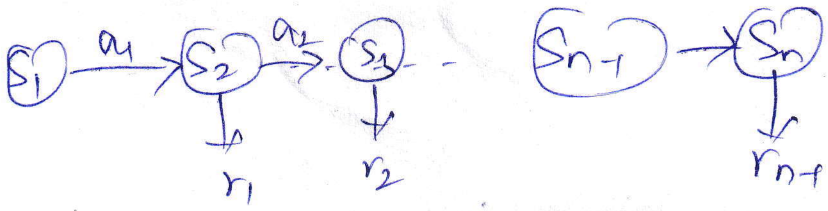
RL-MDP: MDP can be used for RL implementation. components of RL-MDP can be mapped each other to find the next action

s_t, a_t, r_t process iterates.

RL:



MDP:



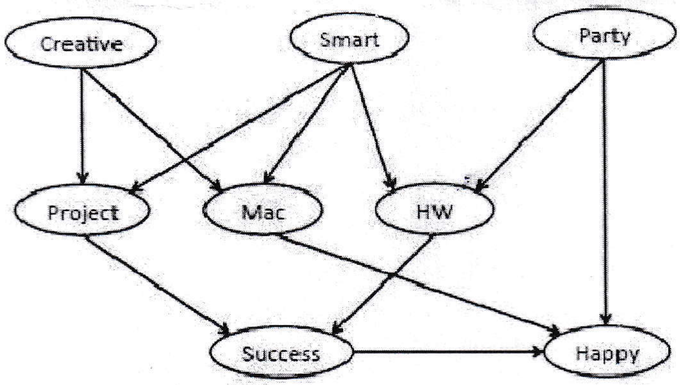
Total reward } r_1 to r_{n-1}

The basic reinforcement learning model consists of:

- a set of environment states S;
- a set of actions A; and
- a set of scalar "rewards" in R

- Sequential decision problem
- A finite set of states $s \in \mathcal{S}$
- A finite set of actions $a \in \mathcal{A}$
- Transition model $T(s'|s, a)$ or $T(s, a, s')$
- Reward function $r(s, a)$
- Observe and act in discrete time steps.

8. Bayesian Network



9. "Malaria" is conditionally independent of "Aches" in the given network
   Exotic trip-Malaria-Jaundice
   Exotic trip-(Malaria & Flu)-Fever-Jaundice
   The above paths are not connected to Aches as per D-separation rule.
   Therefore both are independent.

10. Supervised, unsupervised, reinforcement, semi supervised and evolutionary learning
Any three types learning with diagram, explanation and its applications.

11. Active RL: policy to be explored,
Passive RL: deriving optimal policy, fixed policy

Algorithm: Policy Iteration (MDP, ϵ)

Input: MDP with S, T, r
Output: π

Initialize $V(s) \in R$ and $\pi(s) \in \mathcal{A}$ arbitrarily for all $s \in S$.
repeat
 ▷ Policy evaluation
 $V(s) \leftarrow$ Solve linear equations
 $$V^{\pi}(s) = r(s, \pi(s)) + \gamma \sum_{s'} T(s, a, s') V^{\pi}(s')$$
 ▷ Policy improvement
 foreach $s \in S$ **do**
  $\pi(s) \leftarrow \arg\max_a [\, r(s, a) + \gamma \sum_{s'} T(s, a, s') V^{\pi}(s') \,]$
 end
until π *is unchanged*

12. Decision tree construction
Formula for Entropy, Information gain

$\text{Entropy}(S) = -P_+ \log_2 P_+ - P_- \log_2 P_-$
$IG(S, F) = \text{Entropy}(S) - \sum \frac{|S_f|}{|S|} \text{Entropy}$

Entropy(S) = — (8/14) * $\log_2$(8/14) — (6/14) * $\log_2$(6/14) = 0.99

Calculation of Information Gain for **Fever**
|S| = 14 For v = YES, $|S_v|$ = 8
Entropy (S_v) = - (6/8) * $\log_2$(6/8) - (2/8) * $\log_2$(2/8) = 0.81
For v = NO, $|S_v|$ = 6
Entropy (S_v) = - (2/6) * $\log_2$(2/6) - (4/6) * $\log_2$(4/6) = 0.91
Expanding the summation in the IG formula:
IG(S, Fever) = Entropy(S) - (|S_{YES}| / |S|) * Entropy(S_{YES}) - (|S_{NO}| / |S|) * Entropy(S_{NO})
IG(S, Fever) = 0.99 - (8/14) * 0.81 - (6/14) * 0.91 = 0.13

IG(S, Cough) = 0.04

IG(S, BreathingIssues) = 0.40

Root node: BreathingIssues (having highest IG value)

Fever: 8 yes (6+2), 6 no (2+4)
Cough: 10 yes (5+5), 4 no (3+1)
BreathingIssues: 8 yes (7+1), 6 no (1+5)

$IG(\text{cough}) = \text{Entropy}(S) - \sum \frac{|S_f|}{S} \text{entropy}(S_f)$
$= 0.99 - \frac{10}{14} \times 1 - \frac{4}{14} \times 0.811$
$= 0.04$

IG (Breathing Issues)

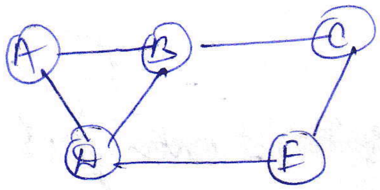
$$= \text{Entropy}(S) - \frac{8}{14}\left[-\frac{7}{8}\log_2 7/8 - \frac{1}{8}\log_2 1/8\right]$$

$$- \frac{6}{14}\left[-\frac{1}{6}\log_2 1/6 - \frac{5}{6}\log_2 5/6\right]$$

$$= 0.99 - \frac{8}{14} \times 0.54 - \frac{6}{14} \times 0.65$$

$$= \boxed{0.40}$$ Root Attribute of the decision tree.

(13)



$$\begin{array}{c|c} & \text{Next State} \\ \text{Current State} & \begin{array}{ccccc} A & B & C & D & E \end{array} \\ \begin{array}{c} A \\ B \\ C \\ D \\ E \end{array} & \left[\begin{array}{ccccc} -5 & 0 & - & 0 & - \\ 0 & -5 & 0 & 0 & - \\ - & 0 & -5 & - & 100 \\ 0 & 0 & - & -5 & 100 \\ - & - & 0 & 0 & -5 \end{array}\right] \end{array}$$

Assume -5 = Same State

path exist between states = 0

nearest state to the goal state = 100 (max value)

no path exist = undefined.

$$0 \leq \gamma \leq 1 \qquad R_t = r_{t+1} + \gamma r_{t+2} + \gamma^3 r_{t+3} + \dots + \gamma^{k-1} r_k$$

$$= \sum_{k=0}^{A} \gamma^k r_{t+k+1}.$$