Indian Institute of Information Technology Vadodara(IIITV)
CS362 Artificial Intelligence Laboratory Report

[1] Bhatt Krutarth(201951041)
[2] Bhimani Yash(201951042)
[3] Rakshilkumar Modi(201951124)
[4] Zala Indravijaysinh(201951182)

I. INTRODUCTION

In this lab report we have given an overview of the experiments, observation and results while performing 4 experiments. We have chosen experiment:

- Week0:To be able to model a given problem in terms of state space search problem and solve the same using BFS/ DFS
- Week1 :To design a graph search agent and understand the use of a hash table, queue in state space search.
- Week3 : Non-deterministic Search - Simulated Annealing
- Week5: Game Playing Agent
- Week6: Understanding Bayesian Network
- Week10: Basics of data structure needed for state-space search tasks and use of random numbers required for MDP and RL
- Week11: Understanding Exploitation - Exploration in simple n-arm bandit reinforcement learning task, epsilon-greedy algorithm
- Week13:To understand the design of type-1 (Mamdani) Fuzzy expert system

We have performed the experiments on jupyter notebook for Python Code and RStudio for R. At the end of this report the GitHub repository link is also added.

II. WEEK 0

To be able to model a given problem in terms of state space search problem and solve the same using BFS/ DFS

A. In the rabbit leap problem, three east-bound rabbits stand in a line blocked by three west-bound rabbits. They are crossing a stream with stones placed in the east west direction in a line. There is one empty stone between them. The rabbits can only move forward one or two steps. They can jump over one rabbit if the need arises, but not more than that. Are they smart enough to cross each other without having to step into the water?

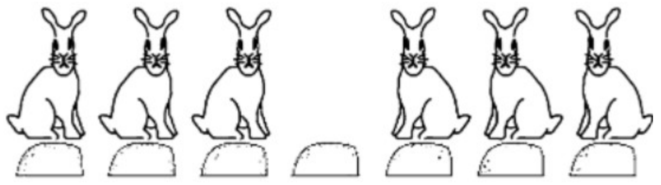


Fig. 1. Rabbit Leap Problem

In this problem the start state is the state shown in Fig 1. Our goal is to make the configuration in such a way that east-bound rabbits can to west side while the west-bound rabbit can go to east side, while maintaining the given conditions in the problem. One such solution can be: Let Configuration be A,B,C,S,D,E,F(Here S represents space), Move D to S , then A,B,C,D,S,E,F. After this step move C to S so the configuration will be A,B,S,D,C,E,F. After this step move B to S so the configuration will be A,S,B,D,C,E,F , then move D to S, so configuration will be A,D,B,S,C,E,F. After this step move E to S, A,D,B,E,C,S,F. then move F to S, A,D,B,E,C,F,S, then move C to S A,D,B,E,S,F,C, then B to S A,D,S,E,B,F,C. similarly after continuing this process we can reach to position D,E,F,S,A,B,C which is our goal state. *Resources:* Aesthetics of Problem Solving

B. The missionaries and cannibals problem is usually stated as follows. Three missionaries and three cannibals are on one side of a river, along with a boat that can hold one or two people. Find a way to get everyone to the other side without ever leaving a group of missionaries in one place outnumbered by the cannibals in that place. This problem is famous in AI because it was the subject of the first paper that approached problem-formulation from an analytical viewpoint.

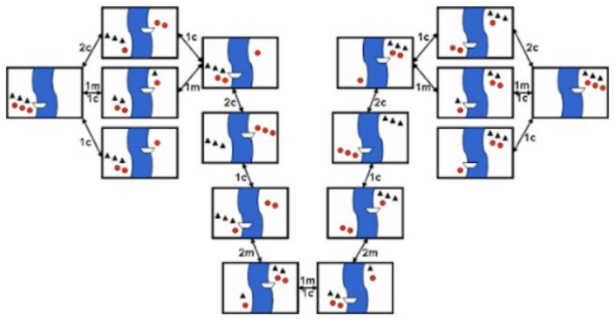


Fig. 2. Rabbit Leap Problem

For solving this, we use a 3-tuple (m, c, b) to represent the state of one side of the river, since the other side can be easily inferred. Here, m stands for the number of missionaries, c, the number of cannibals, and b, whether the boat is at this side of the river. Initially, we have the state (3, 3, 1) and the goal state should be (0, 0, 0). Here, Actions are taken as

1m — one missionary crosses the river
1c — one cannibal crosses the river
2m —- two missionaries cross the river
2c — two cannibals cross the river
1m, 1c — one missionary and one cannibal cross the river

Resources: Missionaries-Cannibals

1) Model the problem as a state space search problem. How large is the search space: A state space is the set of all possible configurations of a system. It is a useful abstraction for reasoning about the behavior of a given system. The state space can be represented as a graph in which the vertices are states and the directed edges between them are actions. The approach for solving both the problem is explained above

2) Solve the problem using BFS. The optimal solution is the one with the fewest number of steps. Is the solution that you have acquired an optimal one? The program should print out the solution by listing a sequence of steps needed to reach the goal state from the initial state. : For implementing BFS we use Queue data structure that works on first in, first out. BFS explores all nodes at one level before proceeding to next level.So BFS find solution in optimal time.

In neither of the solution BFS is optimal. In Rabbit leap problem total number of states are 44 state while in case of missionary and cannibal problem total number of state received is 22.For further explanation look for code in GitHub repository.

3) Solve the problem using DFS. The program should print out the solution by listing a sequence of steps needed to reach the goal state from the initial state: In both the cases DFS gives optimal solution. In Rabbit leap problem total number of states are 23 state while in case of missionary and cannibal problem total number of state received is 20.For further explanation look for code in GitHub repository.

4) Compare solutions found from BFS and DFS. Comment on solutions. Also compare the time and space complexities of both.: Comparison of solution BFS and DFS

1) DFS provides optimal solution than BFS by exploring less state.
2) Solution depends on which how you are describing next possible state.

In case of Missionary Cannibal problem branching factor = 5 while in case of Rabbit leap problem branching factor = 4
DFS
So Time complexity = $\mathbf{O(b^d)}$
Space complexity = O(bd)

For BFS
Time complexity = $\mathbf{O(b^d)}$
Space Complexity = $\mathbf{O(b^d)}$

Here b is the branching factor and d is depth

III. WEEK 1

To design a graph search agent and understand the use of a hash table, queue in state space search.

A. Write a pseudocode for a graph search agent. Represent the agent in the form of a flow chart. Clearly mention all the implementation details with reasons

Answer:

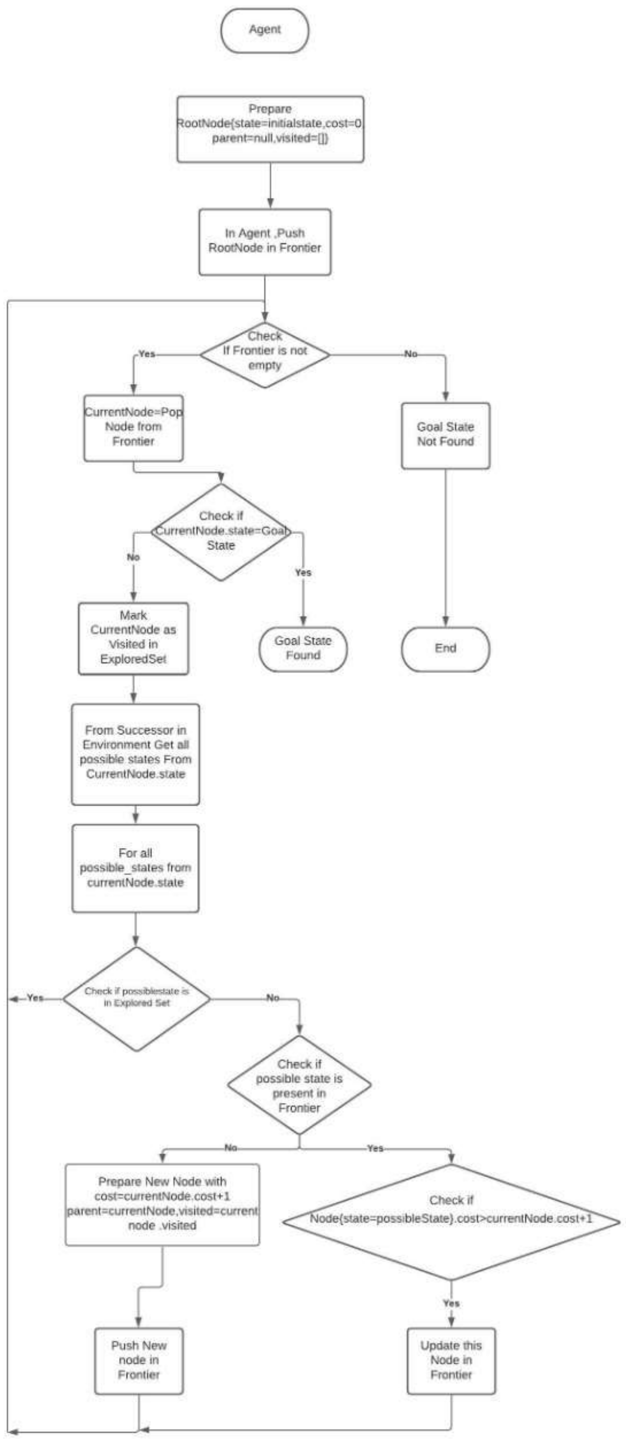

Agent
Prepare RootNode{state=initialstate,cost=0, parent=null,visited=[]}
In Agent ,Push RootNode in Frontier
Check If Frontier is not empty
Yes
No
CurrentNode=Pop Node from Frontier
Goal State Not Found
Check if CurrentNode.state=Goal State
No
Yes
Mark CurrentNode as Visited in ExploredSet
Goal State Found
End
From Successor in Environment Get all possible states From CurrentNode.state
For all possible_states from currentNode.state
Check if possiblestate is in Explored Set
Yes
No
Check if possible state is present in Frontier
No
Yes
Prepare New Node with cost=currentNode.cost+1 parent=currentNode,visited=current node .visited
Check if Node{state=possibleState}.cost>currentNode.cost+1
Yes
Push New node in Frontier
Update this Node in Frontier

Fig. 3. Flow Chart of graph search agent

The $8Puzzle$ has a matrix of 3X3 in which numbers from 1 to 8 are arranged randomly with an empty space . In the given figure the start state is [[7,2,4][5,0,6][8,3,1]] where 0 is represented as the blank space , we need to reach the final state [[0,1,2][3,4,5][6,7,8]] by moving the tiles

In case of $8Puzzle$ the Start and Goal state are as follows:.

Algorithm 1 Graph Search Algorithm

```
Set environment for search by initializing start state, Goal
state,hash map for explored nodes and Frontier queue
Initialize with the initial values of rootnode = start
state,cost =0,parents,visited [] = in frontier
while Frontier is not empty do
    pop a element from frontier
    if CurrentNode.state = Goalstate then
        Goal state reached
    else
        mark this state as Explored node in ExploredSet.
        $possiblestate \leftarrow currentstate$
        for every state do
            if state not explored then
                if state present in frontier then
                    if new cost ¡ previous cost then
                        Update the cost, parent, visited
                    end if
                else
                    newNode with parent = currentNode
                    cost = currentNode.cost+1
                    visited = currentN-
ode.visited+currentNode
                end if
                If Goal not found, path not found
            end if
        end for
    end if
end while
```

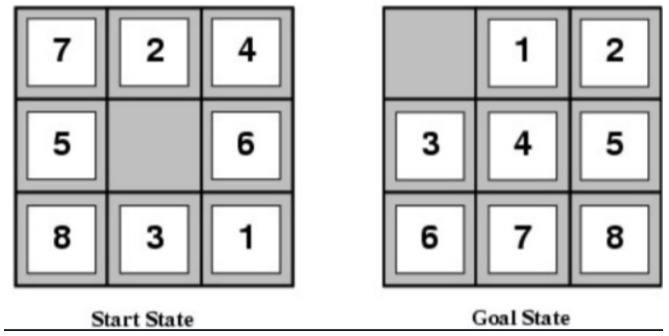


Fig. 4. Start state and Goal state of 8-Puzzle problem

B. Write a collection of functions imitating the environment for 8-Puzzle.

Answer: Environment for 8 puzzle includes current state visited state , path traversed to reach the current node and cost for reaching to the goal state *Function*
check(): If the current state is goal state
validate(): check if it is possible to move futhur or not
getnext():return next possible state

C. Describe what is Iterative Deepening Search ?

Answer: Iterative deepening search is search strategy used with depth first search(DFS).It does a series of depth first searches with increasing depth bounds(in every cycle it perfoms DFS with bound incremented by one) same way as that breadth first search(BFS), but the only difference is that BFS stores all nodes in memory, while iterative-deepening does it by repeating the previous layers, thereby saving memory at the cost of more time.Therefore memory requirements grows linearly with depth.The time complexity of iterative deepening is same as dfs i.e. $\mathbf{O(b^d)}$ where b is the branching factor and d is the depth . The space complexity is **O(bd)**.

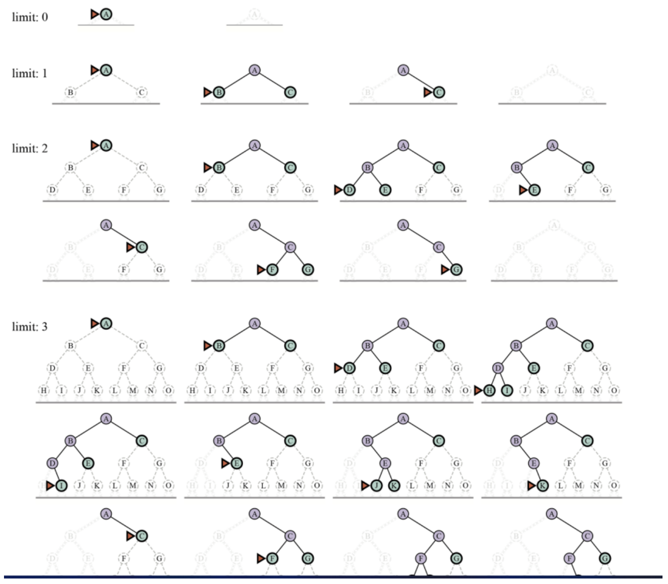


Fig. 5. Iterative Deepening Search

D. Considering the cost associated with every move to be the same (uniform cost), write a function which can backtrack and produce the path taken to reach the goal state from the source/ initial state

Answer:
Please refer to the code for given in github repository

E. Generate Puzzle-8 instances with the goal state at depth "d".

Answer:
For generating puzzle 8 instances with goal state at depth "d". We have to explore each possible states from initial function in order to reach the goal state. For implementation refer to the code

F. Prepare a table indicating the memory and time requirements to solve Puzzle-8 instances (depth "d") using your graph search agent.

Answer:

Depth	Space	time
1	12288	0.002992868423
2	16384	0.0059845
3	24576	0.01897954
4	98304	0.0446937084
5	98304	0.097214698
6	163840	0.1397825428
7	233472	0.2627568244
8	360448	0.345679283

TABLE I
LATITUDE AND LONGITUDE OF THE PLACES OF RAJASTHAN.

IV. WEEK 3

Non-deterministic Search — Simulated Annealing

A. Travelling Salesman Problem (TSP) is a hard problem, and is simple to state. Given a graph in which the nodes are locations of cities, and edges are labelled with the cost of travelling between cities, find a cycle containing each city exactly once, such that the total cost of the tour is as low as possible.

Answer: Travelling Salesman Problem is popularly known as TSP problem. In this problems like "Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city?" arises. It is an NP-hard problem in combinatorial optimization Solution to Travelling salesman problem:

1) Dynamic Programming(DP): The dynamic programming or DP method guarantees to find the best answer to TSP. However, its time complexity would exponentially increase with the number of cities. The time complexity with the DP method asymptotically equals N^2 x 2^N where N is the number of cities

2) Based on Euclidean distance: Let,
No. of cites = N
Total no of states = N!
here a city(i) is assumed to be present in x-y plane have coordinates = (x_i, y_i).
$D_{i,j}$ = Distance matrix of N x N which has the Euclidean distance between each city. Here a city is chosen through random permutation. Here we have to minimize the distance between cities and also find minimum distance between the origin and destination using the given equation :

$$min.f(n) = \sum_{i=1}^{N-1} d(x_i, x_{i+1}) + d(x_n, x_1) \qquad (1)$$

3) Using Simulated Annealing: Here we apply stimulated annealing approach to solve tsp,as it provides an optimal global solution to the given problem.The fundamental idea is to accept moves resulting in solutions of worse quality than the current solution in order to escape from local Minima. The probability of accepting such a move is decreased during the search through parameter temperature. SA algorithm starts with an initial solution x , and candidate solution y is then generated (either randomly or using some pre-specified rule) from the neighbourhood of x. The Metropolis acceptance criterion, which models how a thermodynamic system moves from one state to another state in which the energy is being minimized, is used to decide whether to accept y or not. The candidate solution y is accepted as the current solution x based on the acceptance probability:

$$p = \begin{cases} 1 & if(f(y) \leq f(x)) \\ e^{-(f(y)-f(x))/t} & otherwise \end{cases} \tag{2}$$

Here t is the controlling parameter which plays an important role in computing the probability.Initially the t value is high and the process moves further in order to get the minimum cost we keep on decreasing the t by 0.1 after every iteration.

B. For the state of Rajasthan, find out at least twenty important tourist locations. Suppose your relatives are about to visit you next week. Use Simulated Annealing to plan a cost effective tour of Rajasthan. It is reasonable to assume that the cost of travelling between two locations is proportional to the distance between them.

Answer: Here we have taken twenty different places of Rajasthan and for calculating the distance, we first gathered there latitude and longitude for calculating the distance between the place. The gathered latitude and longitude of each place is shown in the table given below:

Sr.no	City	Latitude(N°)	Longitude(E°)
1	Udaipur	24.6	73.1
2	Jaisalmer	26.9	70.9
3	Ganganagar	29.9	73.8
4	Ajmer	26.4	74.6
5	Jaipur	26.9	75.7
6	Chittaurgarh	24.8	74.6
7	Alwar	27.5	76.6
8	Jodhpur	26.2	73.0
9	Dungarpur	23.8	73.7
10	Ranthambore	26.0	76.5
11	Pushkar	26.4	74.5
12	Kota	25.2	75.8
13	Bundi	25.4	75.6
14	Pali	25.7	73.3
15	Kumbalgarh	25.1	73.5
16	Bikaner	28.0	73.3
17	Abu	24.5	72.7
18	Ranakpur	25.1	73.4
19	Nathdwara	24.9	73.8
20	Fatehpur	25.9	80.7

TABLE II
LATITUDE AND LONGITUDE OF THE PLACES OF RAJASTHAN.

The distance between two places from given latitude and longitude can be found using Haversine-formula:
Resources: Harversine Formula

$$d = 2r\sin^{-1}\sqrt{sin^2(\frac{N_2-N_1}{2}) + cos(N_2)cos(N_1)sin^2(\frac{E_2-E_1}{2})} \tag{3}$$

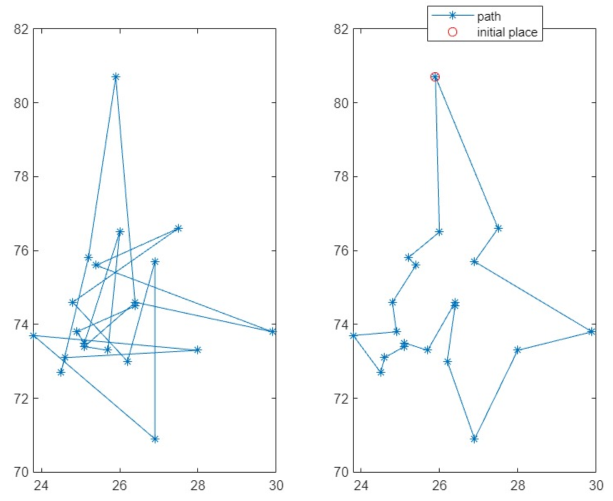
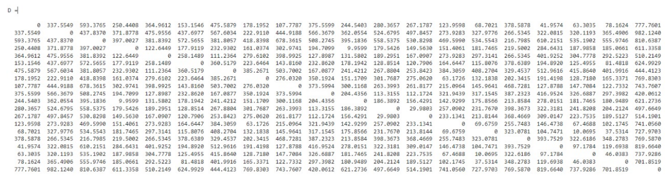


Fig. 6. Graphs showing difference between Initial travelling without simulated annealing and travelling with simulated annealing

After finding the distances from the Haversine-Formula we obtain distance between every cities



```
D =

        0  337.5549  593.3765  250.4408  364.9612  153.1546  475.5879  178.1952  107.7787  375.5599  244.5403  280.3657  267.1787  123.9598   68.7021  378.5878   41.9574   63.3035   78.1624  777.7601
 337.5549         0  437.8370  371.8778  475.9556  437.6977  567.6034  222.9110  444.9188  566.3679  362.0554  524.6795  497.8457  273.9283  327.9776  266.5345  322.0815  320.1193  365.4906  982.1240
 593.3765  437.8370         0  397.0027  381.8392  572.5655  381.8057  418.8398  678.3615  508.2745  395.1836  558.5375  530.8298  469.5990  534.5543  216.7985  610.2151  535.1902  555.9746  810.6387
 250.4408  371.8778  397.0027         0  122.6449  177.9119  232.9302  161.0374  302.9741  194.7099    9.9599  179.5426  149.5630  151.4061  181.7465  219.5002  284.6431  187.9858  185.0661  611.3358
 364.9612  475.9556  381.8392  122.6449         0  258.1489  111.2364  279.6102  398.9925  127.8987  131.5802  189.2951  167.0907  273.9283  297.3141  266.5345  401.9252  304.7778  292.5223  510.2149
 153.1546  437.6977  572.5655  177.9119  258.1489         0  360.5179  223.6464  143.8160  232.8620  178.1942  128.8514  120.7906  164.6447  115.8076  378.6389  194.8920  125.4955   81.4818  624.9929
 475.5879  567.6034  381.8057  232.9302  111.2364  360.5179         0  385.2671  503.7002  167.0877  241.4212  267.8804  253.8423  384.3059  408.2704  329.4537  512.9616  415.8640  401.9916  444.4123
 178.1952  222.9110  418.8398  161.0374  279.6102  223.6464  385.2671         0  276.0320  350.1924  151.1709  301.7687  275.0620   63.1726  132.1838  202.3415  191.4198  128.7180  165.3371  769.8303
 107.7787  444.9188  678.3615  302.9741  398.9925  143.8160  503.7002  276.0320         0  373.5994  300.1168  263.3993  261.8177  215.0964  145.9641  468.7281  127.8788  147.7084  122.7332  743.7607
 375.5599  566.3679  508.2745  194.7099  127.8987  232.8620  167.0877  350.1924  373.5994         0  204.4356  113.3155  112.1724  321.9439  317.1545  387.2323  416.9524  326.6887  297.3982  420.0612
 244.5403  362.0554  395.1836    9.9599  131.5802  178.1942  241.4212  151.1709  300.1168  204.4356         0  186.3892  156.4291  142.9299  175.8566  213.8584  278.0151  181.7465  180.9489  621.2736
 280.3657  524.6795  558.5375  179.5426  189.2951  128.8514  267.8804  301.7687  263.3993  113.3155  186.3892         0   29.9803  257.0902  231.7670  398.3673  322.3181  241.8208  204.2124  497.6649
 267.1787  497.8457  530.8298  149.5630  167.0907  120.7906  253.8423  275.0620  261.8177  112.1724  156.4291   29.9803         0  233.1341  213.8144  368.4669  309.0147  223.7535  189.5127  514.1901
 123.9598  273.9283  469.5990  151.4061  273.9283  164.6447  384.3059   63.1726  215.0964  321.9439  142.9299  257.0902  233.1341         0   69.6759  255.7483  146.4738   67.4688  102.1745  741.0560
  68.7021  327.9776  534.5543  181.7465  297.3141  115.8076  408.2704  132.1838  145.9641  317.1545  175.8566  231.7670  213.8144   69.6759         0  323.0781  104.7471   10.0695   37.5314  727.9703
 378.5878  266.5345  216.7985  219.5002  266.5345  378.6389  329.4537  202.3415  468.7281  387.2323  213.8584  398.3673  368.4669  255.7483  323.0781         0  393.7529  322.6186  348.2783  769.5870
  41.9574  322.0815  610.2151  284.6431  401.9252  194.8920  512.9616  191.4198  127.8788  416.9524  278.0151  322.3181  309.0147  146.4738  104.7471  393.7529         0   97.1784  119.6938  819.6640
  63.3035  320.1193  535.1902  187.9858  304.7778  125.4955  415.8640  128.7180  147.7084  326.6887  181.7465  241.8208  223.7535   67.4688   10.0695  322.6186   97.1784         0   46.0383  737.9286
  78.1624  365.4906  555.9746  185.0661  292.5223   81.4818  401.9916  165.3371  122.7332  297.3982  180.9489  204.2124  189.5127  102.1745   37.5314  348.2783  119.6938   46.0383         0  701.8519
 777.7601  982.1240  810.6387  611.3358  510.2149  624.9929  444.4123  769.8303  743.7607  420.0612  621.2736  497.6649  514.1901  741.0560  727.9703  769.5870  819.6640  737.9286  701.8519         0
```

Fig. 7. Distance matrix cities

Total distance cost = 3033.9 **kms**.
Places traversed in the following manner :
Fatehpur,Alwar,Jaipur,Ganganagar,Bikaner,Jaisalmer,Jodhpur,Nathwara, Chittaurgarh,Bundi,Kota,Ranthambore.

C. An interesting problem domain with TSP instances: VLSI: http://www.math.uwaterloo.ca/tsp/vlsi/index.html#XQF131 (Attempt at least five problems from the above list and compare your results.)

Answer:

1) **Board 1:** NAME: xqf131 COMMENT : Bonn VLSI data set with 131 points COMMENT : Uni Bonn, Research Institute for Discrete Math COMMENT : Contributed by Andre Rohe TYPE : TSP DIMENSION : 131 $EDGE\_WEIGHT\_TYPE : EUC\_2D$

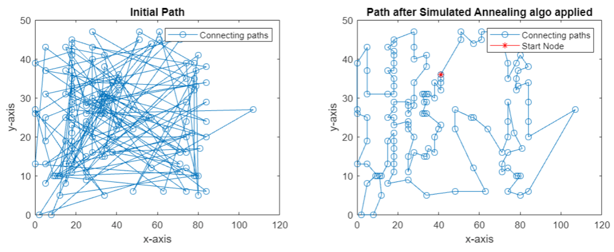


Fig. 8. Graphs showing difference between Initial travelling without simulated annealing and travelling with simulated annealing

*2) **Board 2:*** NAME : xqg237 COMMENT : Bonn VLSI data set with 237 points COMMENT : Uni Bonn, Research Institute for Discrete Math COMMENT : Contributed by Andre Rohe TYPE : TSP DIMENSION : 237 $EDGE\_WEIGHT\_TYPE$: EUC_2D

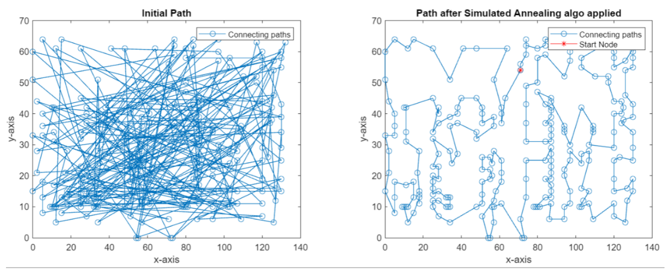


Fig. 9. Graphs showing difference between Initial travelling without simulated annealing and travelling with simulated annealing

*3) **Board 3:*** NAME : pbl395 COMMENT : Bonn VLSI data set with 395 points COMMENT : Uni Bonn, Research Institute for Discrete Math COMMENT : Contributed by Andre Rohe TYPE : TSP DIMENSION : 395 $EDGE\_WEIGHT\_TYPE$: EUC_2D $NODE\_COORD\_SECTION$

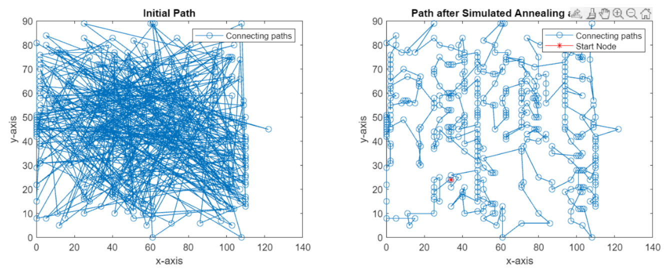


Fig. 10. Graphs showing difference between Initial travelling without simulated annealing and travelling with simulated annealing

*4) **Board 4:*** NAME : bcl380 COMMENT : Bonn VLSI data set with 380 points COMMENT : Uni Bonn, Research Institute for Discrete Math COMMENT : Contributed by Andre Rohe TYPE : TSP DIMENSION : 380 $EDGE\_WEIGHT\_TYPE$: EUC_2D $NODE\_COORD\_SECTION$

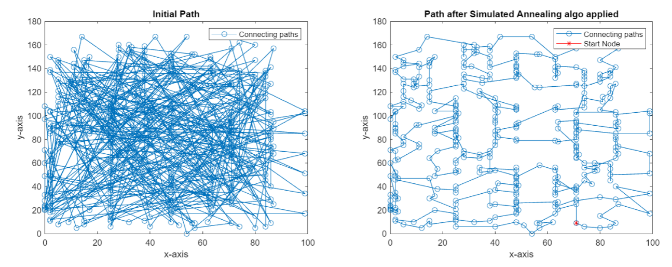


Fig. 11. Graphs showing difference between Initial travelling without simulated annealing and travelling with simulated annealing

*5) **Board 5:*** NAME : pbk411 COMMENT : Bonn VLSI data set with 411 points COMMENT : Uni Bonn, Research Institute for Discrete Math COMMENT : Contributed by Andre Rohe TYPE : TSP DIMENSION : 411 $EDGE\_WEIGHT\_TYPE$: EUC_2D $NODE\_COORD\_SECTION$

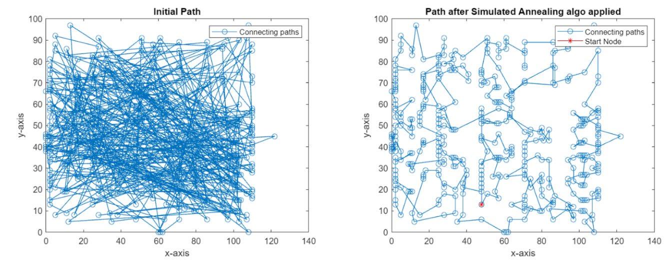


Fig. 12. Graphs showing difference between Initial travelling without simulated annealing and travelling with simulated annealing

V. <u>WEEK 5</u>

Game Playing Agent — Minimax — Alpha-Beta Pruning Systematic adversarial search can lead to savings in terms of pruning of sub-trees resulting in lesser node evaluations

A. What is the size of the game tree for Noughts and Crosses? Sketch the game tree.

<u>Answer:</u> Noughts and crosses(tic-Tac-Toe) is a interesting game which require two players. Each player has to play alternatively. It has 3X3 Empty board which has to filled by 'X' and 'O'. Game continues till either of the player wins or the game draws. Let's suppose Player 1 starts the game so it has 9 choices of filling the box(assuming he will be fill 'X') which we can consider as depth 1, after player 1's chance Player 2 will have to fill 'O' in 8 possible choices. Then again Player1 gets chance to fill out of 7 choices, and this continues till a player wins or the game draws. For wining the game either following conditions must be satisfied:

- A row has same character i.e complete row has Use recurrence to show that under perfect ordering of leaf nodes, the alpha-beta pruning time complexity is O($b^{m/2}$), where b is the effective branching factor and m is the depth of the tree.to be either ('X' or 'O')
- A Column has same character i.e complete column has to be either ('X' or 'O')
- Either of the two diagonals have same character i.e complete diagonal has to be either ('X' or 'O')

So, Total possible states are 9! = 9x8x7x6x5x4x3x2x1 = 362880 states

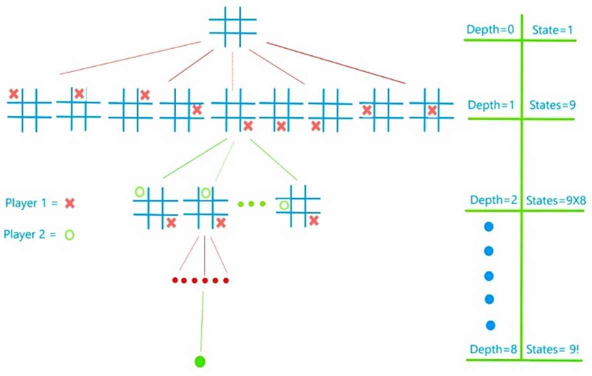


Fig. 13. Tic-Tac-Toe game tree

B. Read about the game of Nim (a player left with no move losing the game). For the initial configuration of the game with three piles of objects as shown in Figure, show that regardless of the strategy of player-1, player-2 will always win. Try to explain the reason with the MINIMAX value backup argument on the game tree.

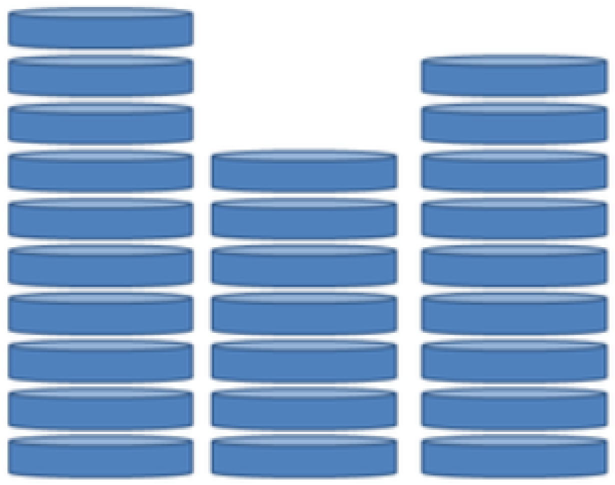


Fig. 14. Hill Climbing with bdla Score

Answer: Game of Nim consists of 'n' piles where each pile contains i number of nims such that

$$1 \leq i \leq n \tag{4}$$

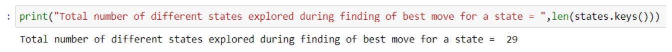
The player to pick the last nim is going to win the game
The winning in the Nim game depends on the two factor:

- One who starts the game
- Initial configuration of game

Here with observation, if initial configuration of the Nims i.e if the XOR sum of the no. of the Nims is non-zero then who starts the game first will definitely lose. Here in the question starting configuration is [7,9,10] whose XOR is $4 \neq 0$, hence even if player 1 has the strategy of winning the game he will definitely lose.

C. Implement MINIMAX and alpha-beta pruning agents. Report on number of evaluated nodes for Noughts and Crosses game tree.

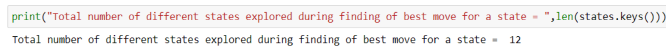
Answer: *number of different states explored during finding of best move for a state in Minimax algorithm:* 29



```
print("Total number of different states explored during finding of best move for a state = ",len(states.keys()))
Total number of different states explored during finding of best move for a state =  29
```

Fig. 15.

number of different states explored during finding of best move for a state in alpha-beta algorithm: 12



```
print("Total number of different states explored during finding of best move for a state = ",len(states.keys()))
Total number of different states explored during finding of best move for a state =  12
```

Fig. 16.

D. Use recurrence to show that under perfect ordering of leaf nodes, the alpha-beta pruning time complexity is $O(b^{m/2})$, where b is the effective branching factor and m is the depth of the tree.

Answer: The time complexity of Minimax algorithm is O(b^m) which can reduced by without checking each node. The technique of reduction in time complexity is called pruning. This involves two threshold parameters alpha and beta, thus this is also called alpha-beta pruning.

To determine exact value of a state, we need the exact value of one of its children and bounds on the rest of the children.For determining a bound of state's value, exact value of one of its children must be known.
Let S(k) be the minimum number of states to be considered k ply from a given state for knowing the exact value of the state. Similarly let R(k) be the minimum number of states to be considered k ply from a given state when we need to know a bound on the state's value.Let b be the branching factor. Thus,

$$S(k) = S(k-1) + (b-1)R(k-1) \tag{5}$$

i.e., the exact value of one child and bounds on the rest,and

$$R(k) = S(k-1) \tag{6}$$

i.e., the exact value of one child. The base is S(0) = R(0) = 1. Note, for fig, this gives S(3) = b^2 + b -1 = 11 for b = 3
when we expand the recursive equation, we get:
S(k) = S(k-1)+(b-1)R(k-1)
= (S(k-2)+(b-1)R(k-2)) + (b-1)S(k-2)
= bS(k-2)+ (b-1)R(k-2)
= bS(k-2) + (b-1)S(k-3)
It is obvious that S(k-3)¡S(k-2),so: S(k) ¡ (2b-1)S(k-2) ¡ 2bS(k-2)
That is, the branching factor every two levels is less than 2b, which means the effective branching factor is less than $\sqrt{2b}$.

So, for even k, we derive $S(k) \leq (\sqrt{2b})^k$, which is not too far off the asymptotic upper bound of $(\sqrt{b} + \frac{1}{2})^{\,k+1}$

In effect, alpha-beta pruning can nearly double the depth that a game tree can be searched in comparison to straightforward minimax.

Resources: a-b-analysis

VI. WEEK 6

Understand the graphical models for inference under uncertainty, build Bayesian Network in R, Learn the structure and CPTs from Data, naive Bayes classification with dependency between features.

A. Consider grades earned in each of the courses as random variables and learn the dependencies between courses.

Answer: Using the hill Climbing greedy search function 'hc' of the bnlearn package several different bayesian network based on scores have been generated.

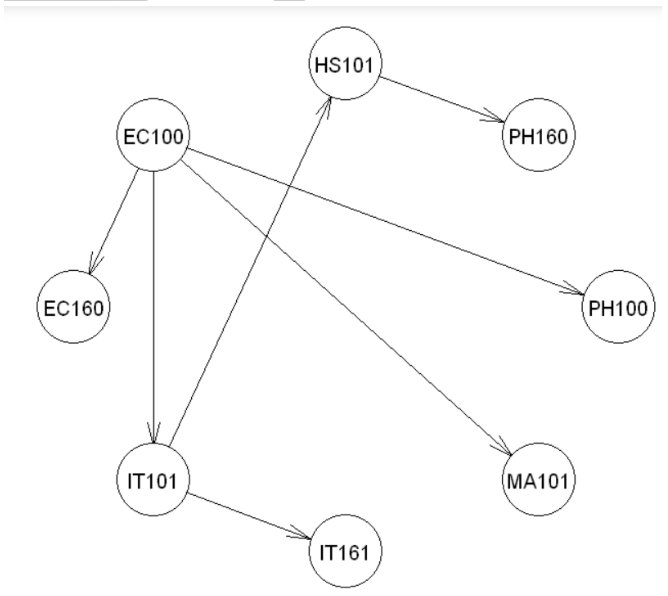


Fig. 17. Hill Climbing with aic Score

1) Using **'aic'** *score:* MODEL: There are 7 dependencies between each subject which can seen from the above fig. using aic score and the dependencies are [EC100][EC160—EC100][IT101—EC100] [MA101—EC100][PH100—EC100][IT161—IT101] [HS101—IT101][PH160—HS101]

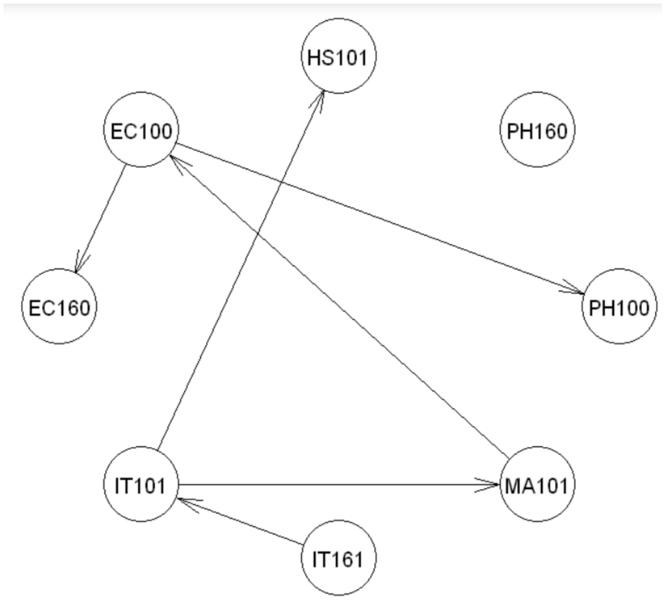


Fig. 18. Hill Climbing with bdla Score

2) Using **'bdla'** *score:* MODEL: There are 6 dependencies between each subject which can seen from the above fig. using bdla score and the dependencies are [IT161][PH160][IT101—IT161][MA101—IT101] [HS101—IT101][EC100—MA101][EC160—EC100] [PH100—EC100].

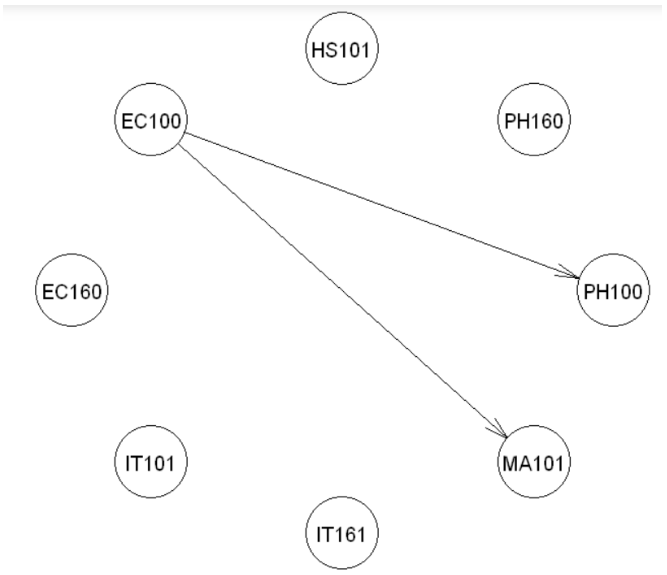


Fig. 19. Hill Climbing with bic Score

3) Using **'bic'** *score:* MODEL: There are 2 dependencies between each subject which can seen from the above fig. using bic score and the dependencies are [EC100][EC160][IT101][IT161][PH160] [HS101][MA101—EC100][PH100—EC100].

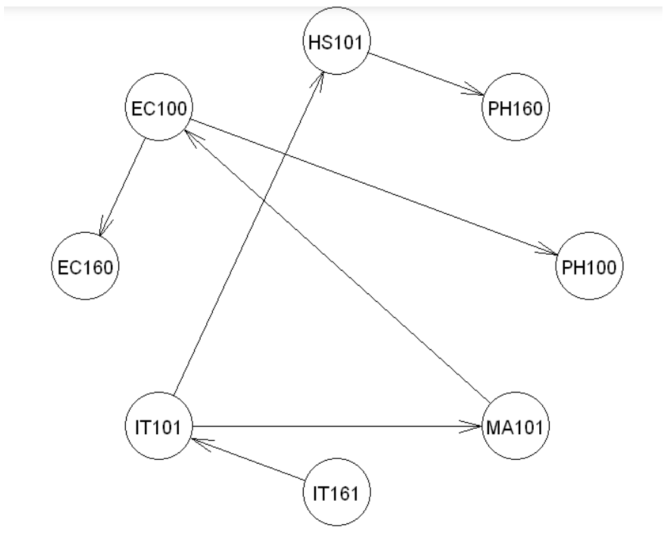


Fig. 20. Hill Climbing with k2 Score

4) Using **’k2’** *score:* MODEL: There are 7 dependencies between each subject which can seen from the above fig. using k2 score and the dependencies are [IT161][IT101—IT161][MA101—IT101][HS101—IT101] [EC100—MA101][PH160—HS101][EC160—EC100] [PH100—EC100]

B. Using the data, learn the CPTs for each course node.

Using hill climbing K2 score the CPTs of each course is plotted below:

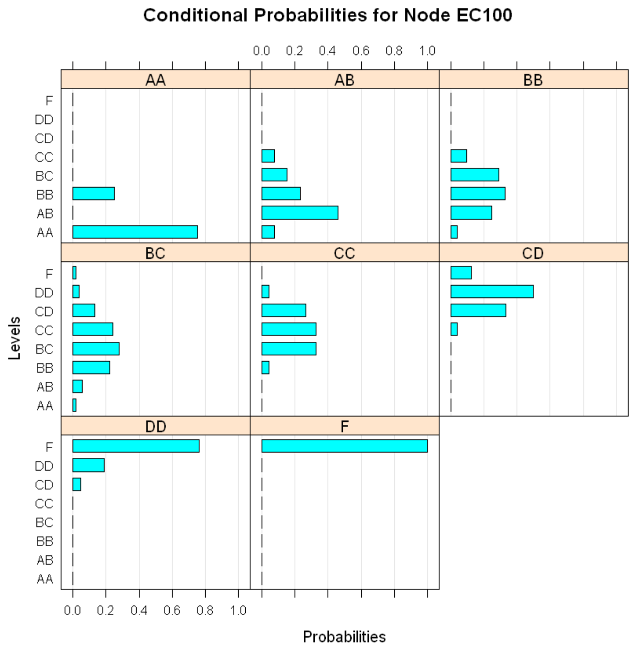


Fig. 21. CPT of EC100

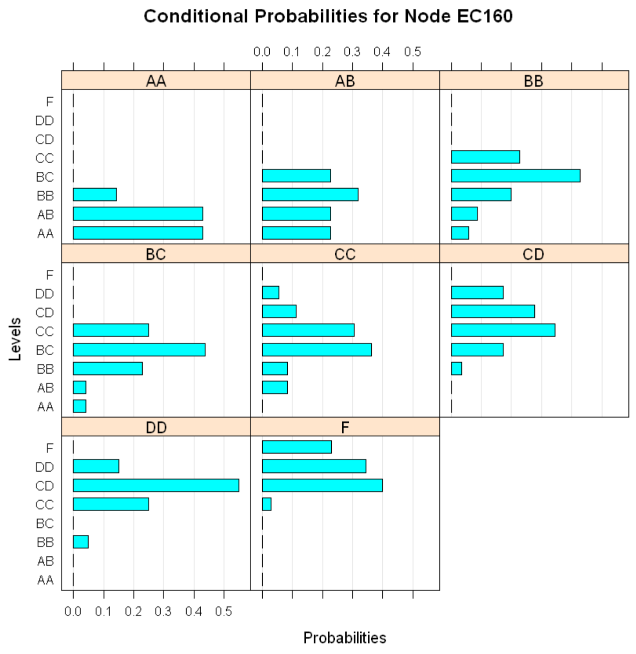


Fig. 22. CPT of EC100

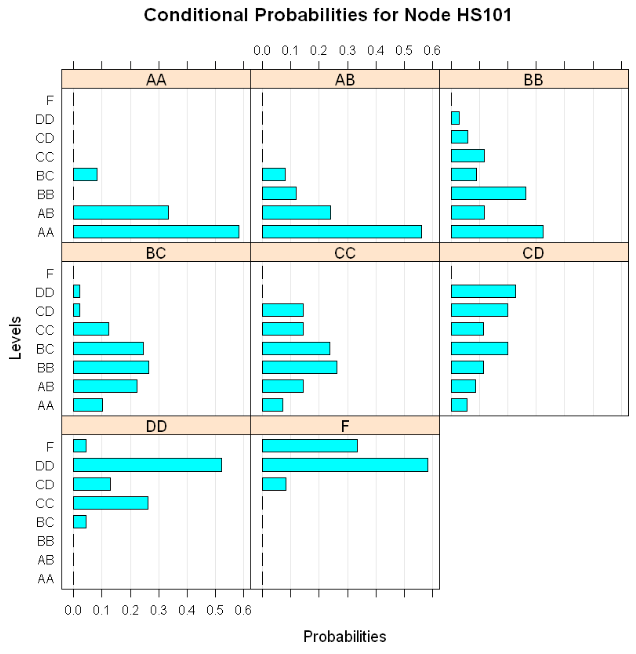


Fig. 23. CPT of EC100

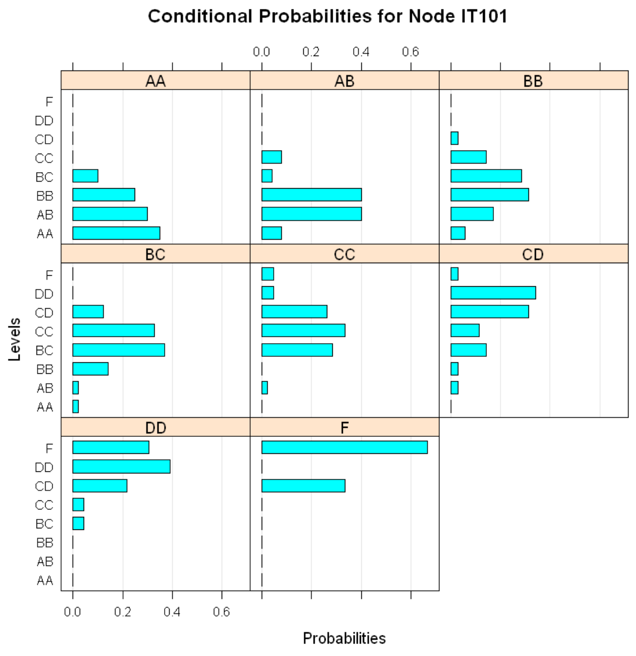


Fig. 24. CPT of EC100

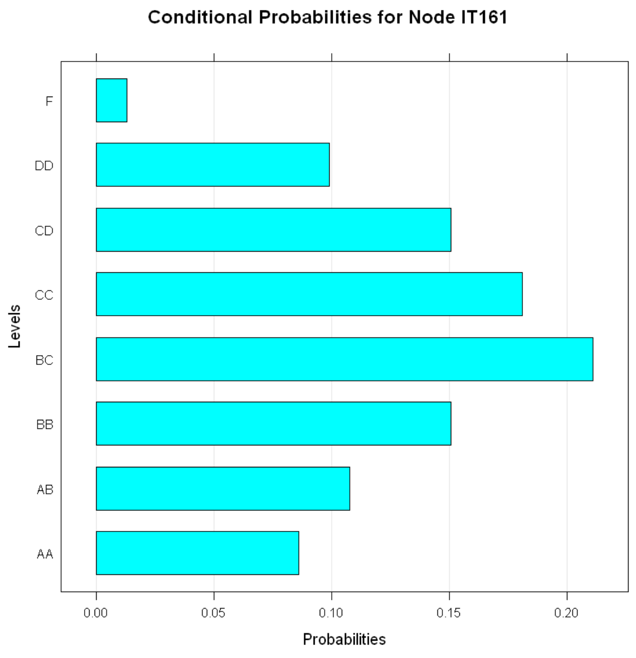


Fig. 25. CPT of EC100

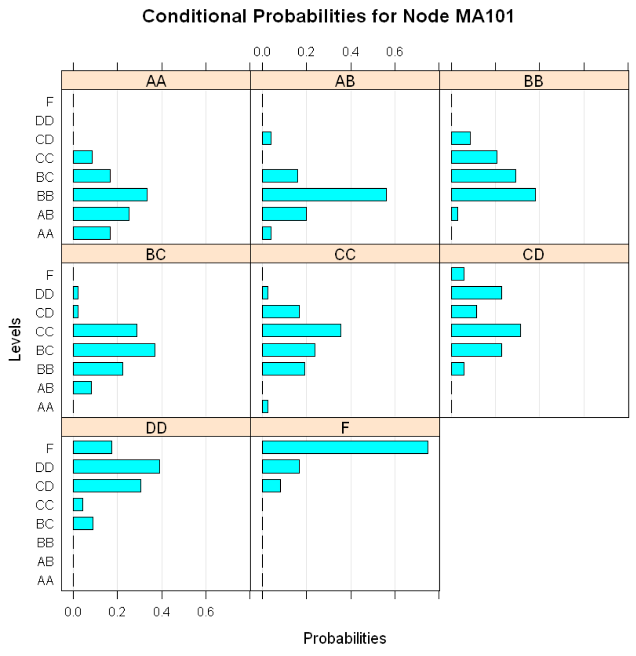


Fig. 26. CPT of EC100

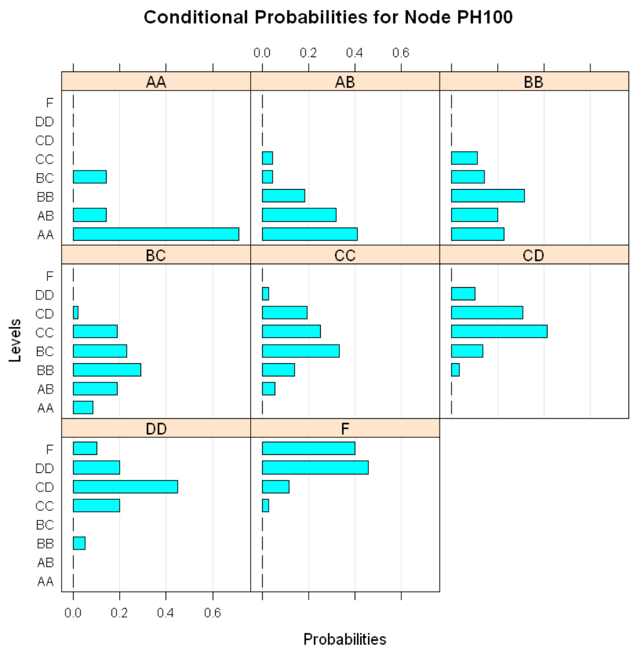


Fig. 27. CPT of EC100

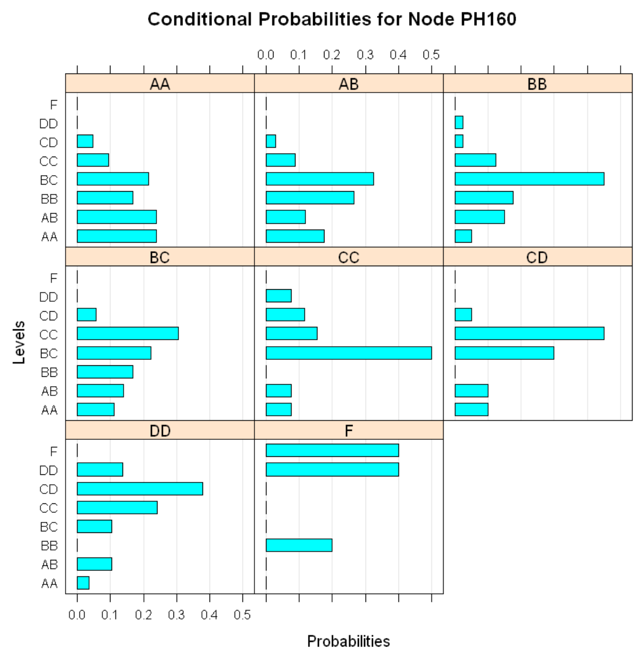


Fig. 28. CPT of EC100

C. *What grade will a student get in PH100 if he arns DD in EC100, CC in IT101 and CD in MA101.Any of this trained model would give the same prediction about the grade*

Answer: We use cpquery method for getting the value that match with given condition. After applying method it is most likely to 'DD' grade in PH100

D. *The last column in the data file indicates whether a student qualifies for an internship program or not. From the given data, take 70 percent data for training and build a naive Bayes classifier (considering that the grades earned in different courses are independent of each other) which takes in the student's performance and returns the qualification status with a probability. Test your classifier on the remaining 30 percent data. Repeat this experiment for 20 random selection of training and testing data. Report results about the accuracy of your classifier.*

Answer: This networks works on splited data which we have use-in for training the model.In the second case, dependencies to exits among courses as well with QP through an direct acyclic graph(DAG).We here use Naive Bayes network from bnclassify. The structure is shown below:

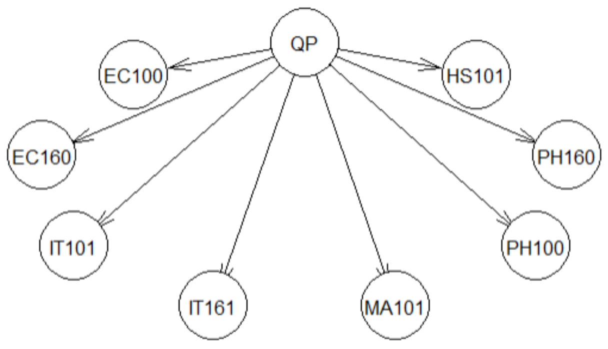


Fig. 29. Naive Bayes Independent data

This network learns on the training dataset that we split before and test it on test data.The Table below shows the accuracy:

Experiment No.	Accuracy
1	0.987013
2	0.974026
3	0.987013
4	0.974026
5	0.987013
6	0.974026
7	0.987013
8	0.9871795
9	0.961039
10	0.9615385
11	0.9871795
12	0.974026
13	0.987013
14	1
15	0.987013
16	0.974026
17	1
18	0.974026
19	0.987013
20	0.974026

TABLE III
ACCURACY ON TEST DATASET ON NAIVE BAYES CLASSIFIER IN INDEPENDENT DATA

E. *Repeat 4, considering that the grades earned in different courses may be dependent.*

Answer:

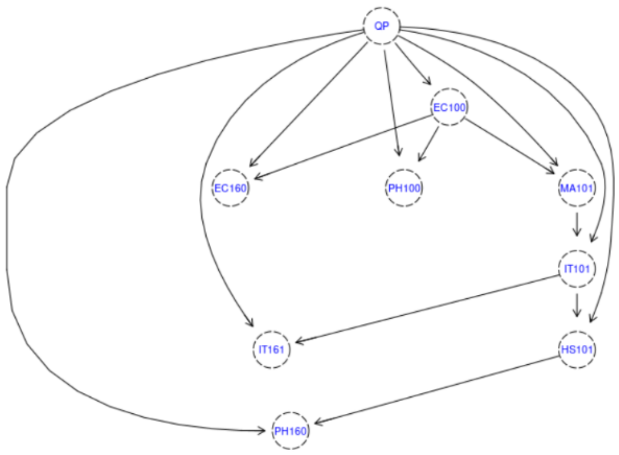


Fig. 30. Naive Bayes dependent data

Experiment No.	Accuracy
1	0.8974359
2	0.961039
3	0.9358974
4	0.974359
5	0.9473684
6	0.9487179
7	0.9480519
8	0.9480519
9	0.974026
10	0.9615385
11	0.9342105
12	0.9358974
13	0.9480519
14	0.9480519
15	0.9487179
16	0.9220779
17	0.8961039
18	0.9615385
19	0.9868421
20	0.9342105

TABLE IV
ACCURACY ON TEST DATASET ON NAIVE BAYES CLASSIFIER IN DEPENDENT DATA

VII. WEEK 10

Basic of data structure needed for state-space search tasks and use of random numbers required for MDP and RL

A. Read the reference on MENACE by Michie and check for its implementations. Pick the one that you like the most and go through the code carefully. Highlight the parts that you feel are crucial. If possible, try to code the MENACE in any programming language of your liking.

Answer: MENACE(Matchbox Educable Noughts and Crosses Engine) is a simple machine learning system(based on trail and error) designed to learn tic-tac-toe. It was developed by Donald Michie in 1961-62. He used a total 304 matchboxes, on which he drew almost all possible states or position of game. Each box contains colored beads, where each blank space is assigned with a different color bead. While playing the game, he decided to have rewards i.e if the MENACE wins then three beads of same color corresponding to the moves are being added by backtracking the moves. If the MENACE loses the game, then MENACE is punished by removing beads of same color corresponding to the moves are being removed using same backtracking method. Here there a province for the game having to be drawn, where single bead of same color corresponding to the move is being added. The MENACE move at the starting of the game is chosen randomly, and according to that further game is carried out. After many games the MENACE based upon rewards received will be trained and will be capable to win against a human. Code for the MENACE is present in the GitHub repository. *Resources:* menace

VIII. WEEK 11

Understanding Exploitation - Exploration in simple n-arm bandit reinforcement learning task, epsilon-greedy algorithm

A. Consider a binary bandit with two rewards 1-success, 0-failure. The bandit returns 1 or 0 for the action that you select, i.e. 1 or 2. The rewards are stochastic (but stationary). Use an epsilon-greedy algorithm discussed in class and decide upon the action to take for maximizing the expected reward. There are two binary bandits named binaryBanditA.m and binaryBanditB.m are waiting for you.

Answer: After using both the rewards(function) binaryBanditA and binaryBanditB here are the observations :

When the probability of rewards was low (for banditA), the expected rewards were 0 at first, but as the number of trials increased, the expected rewards increased as well. However, in the case of banditB, because the reward probability was high (0.8 and 0.9), the expected payouts in the beginning were near to 1, and when the steps were increased, the expected rewards became constant due to the averaging factor.

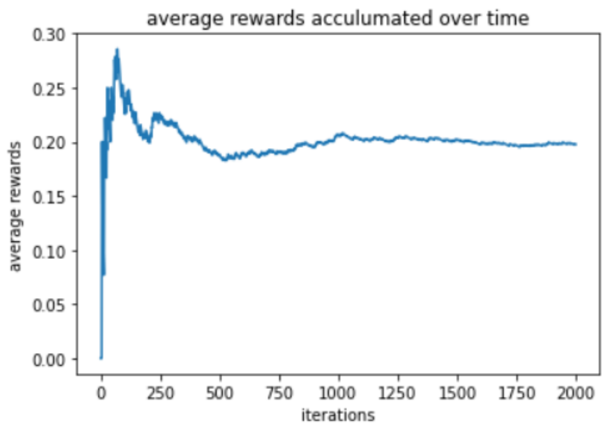


Fig. 31. Expected rewards we get after using banditA

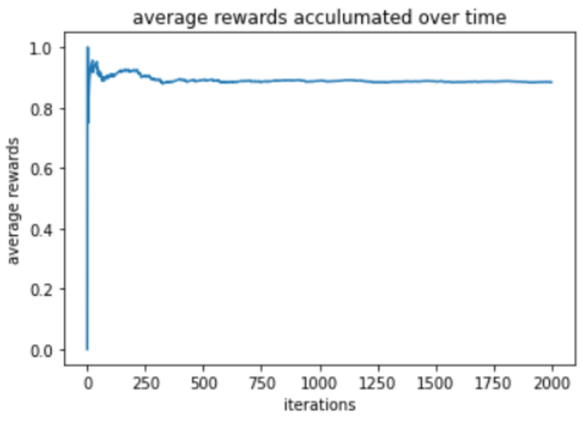


Fig. 32. Expected rewards we get after using banditB

B. Develop a 10-armed bandit in which all ten mean-rewards start out equal and then take independent random walks (by adding a normally distributed increment with mean zero and standard deviation 0.01 to all mean-rewards on each time step). function [value] = $bandit_nonstat(action)$

Answer: The mean-rewards are initially taken as a constant valued array initialised by 1 in the case of a ten-arm bandit. We performed exploration and exploitation based on the Epsilon Greedy Algorithm. We produce a random number between 0 and 1, and if it is greater than epsilon, we perform exploitation, which is based on prior knowledge. Every iteration generates a ten-value array that is normally distributed with a mean of zero and a standard deviation of 0.01. This array is added to the mean array, and this updated array is used every time. For every action a reward is given from this updated mean-rewards array. The rewards given in this case are non-stationary.

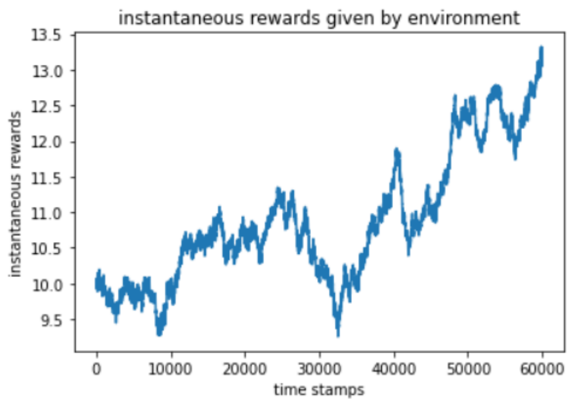


Fig. 33. Expected rewards we get when rewards are non stationary (averaging method)

We can see that because all the rewards were initially equal to 0, we obtain a constant reward of say 1, but as the steps increase, it affects the rewarding policy of every action, and therefore the expected rewards started increasing at a very high non-zero rate.

C. The 10-armed bandit that you developed is difficult to crack with a standard epsilon-greedy algorithm since the rewards are non-stationary. We did discuss how to track non-stationary rewards in class. Write a modified epsilon-greedy agent and show whether it is able to latch onto correct actions or not. (Try at least 10000 time steps before commenting on results)

Answer: The main difference between this problem and Problem 2 is that in Problem 2, an average method was used to update the action reward estimation, but in this problem, more weight is given to current earned reward by using the alpha parameter.

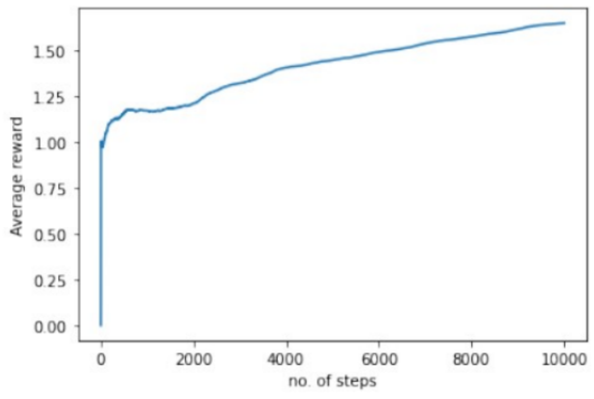


Fig. 34. Expected rewards we get when rewards are non stationary (averaging method)

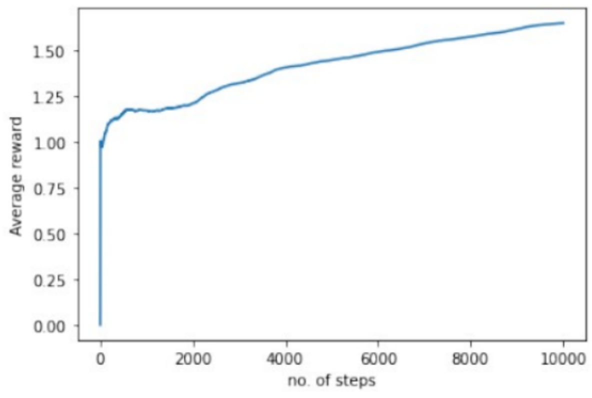


Fig. 39: Expected rewards we get when rewards are non stationary (averaging method)

Load Dirtiness/ Load Volume vd md ld
nd

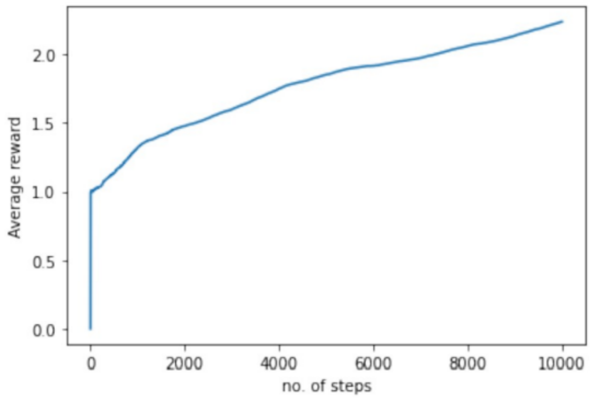


Fig. 35. Expected rewards we get when rewards are non stationary (non averaging method)

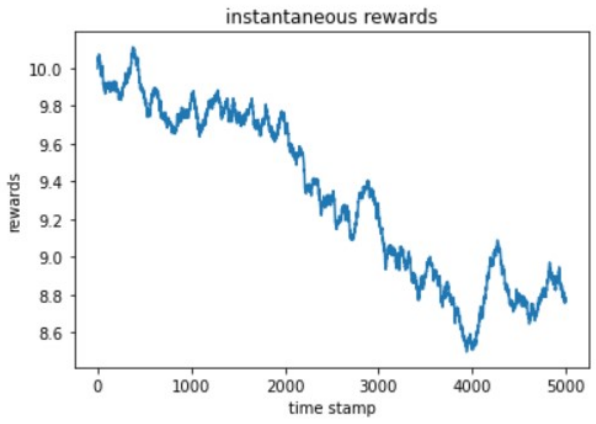


Fig. 36. Instantous reward

The expected rewards were substantially higher than in case 2, and the slope of the graph was much steeper than that in case 1.

Resource: n-bandit Problem

IX. WEEK 13

To understand the design of type-1 (Mamdani) Fuzzy expert system

In this laboratory, we will try to identify the appropriate time needed to wash the load of clothes, given the dirtiness and the volume of the load. This is a simplified design, in practice a lot more variables are involved including: water level, amount of detergent to be dispensed, and temperature of water (recent development) and variables that you and I may imagine in future.

A simple rule-base for the washing machine time problem is given below for reference.

A. The rule table consists of 12 rules.

If load volume is medium load
And load dirtiness is lightly dirty
Then washing time is medium time

Answer: ;We examine a simple two-input one-output problem that includes total 12 rules using Mamdami-style fuzzy inference process
input : x and y (Load Dirtiness and Load Volume) with linguistic values A1,A2,A3,A4 (very dirty,medium dirty,low dirty,not dirty) and B1,B2,B3 (full load,medium load,low load) respectively
Output: z (time needed) with linguistic values C1,C2,C3, and C4 (very long time,long time,medium time and little time).
Let's define membership functions for all input linguistic value (i.e., for A1) membership function for Load Dirtiness
$\mu_{A1(x)} = (x60)/40, 60 \leq$ x $\leq$ 100
$\mu_{A2(x)} = (65 - x)/15, 50 \leq$ x $\leq$ 65
$\mu_{A3(x)} = (35 - x)/15, 20 \leq$ x $\leq$35
$\mu_{A4(x)} = (5 - x)/5, 0 \leq$ x $\leq$ 5
membership function for Load Volume
$\mu_{B1(x)} = (x50)/50, 50 \leq$ x $\leq$ 100
$\mu_{B2(x)} = (100 - x)/50, 50 \leq$ x $\leq$ 100
$\mu_{B3(x)} = (50 - x)/50, 0 \leq$ x $\leq$50

Step 1: Fuzzification

1) Take the crisp inputs, x1 and y1 (Load Dirtiness and Load Volume)
2) Determine the degree to which these inputs belong to each of the appropriate fuzzy sets.

Step 2: Rule Evaluation

Take the fuzzified inputs, and apply them to the antecedents of the fuzzy rules. If a given fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent evaluation. This number (the truth value) is then applied to the consequent membership function. For example, the entry in the second row and the third column of the table specifies the rule:
If load volume (y) is medium load (B1)
AND load dirtiness (x) is low dirty (A3) Then washing time is medium time and for x1 = 91, y1 = 79

$$\mu_{A3 \cap B1}(x) = min[\mu_{A3}, \mu_{B1}] = min(0, 0.58) = 0 \qquad (7)$$

OR

$$\mu_{A3 \cap B1}(x) = prod[\mu_{A3}, \mu_{B1}] = \mu_{A3} x \mu_{B1} = 0x0.58 = 0 \qquad (8)$$

The result of the antecedent evaluation can be applied to the membership function of the consequent. In other words, the consequent membership function is clipped or scaled to the level of the truth value of the rule antecedent

Step 3 Aggregation of the rule outputs the membership functions of all rule consequent previously clipped or scaled and combine them into a single fuzzy set.

Step 4 Defuzzification Centroid Technique: Here we find the centroid of the found model using the below formula:

$$COG = \frac{\int_a^b uA(x)x \, \mathrm{d}x}{\int_a^b uA(x) \, \mathrm{d}x} \tag{9}$$

Resources: Fuzzy Expert system

X. Link for Laboratory code

The complete codes for different Laboratories is given below: GitHub