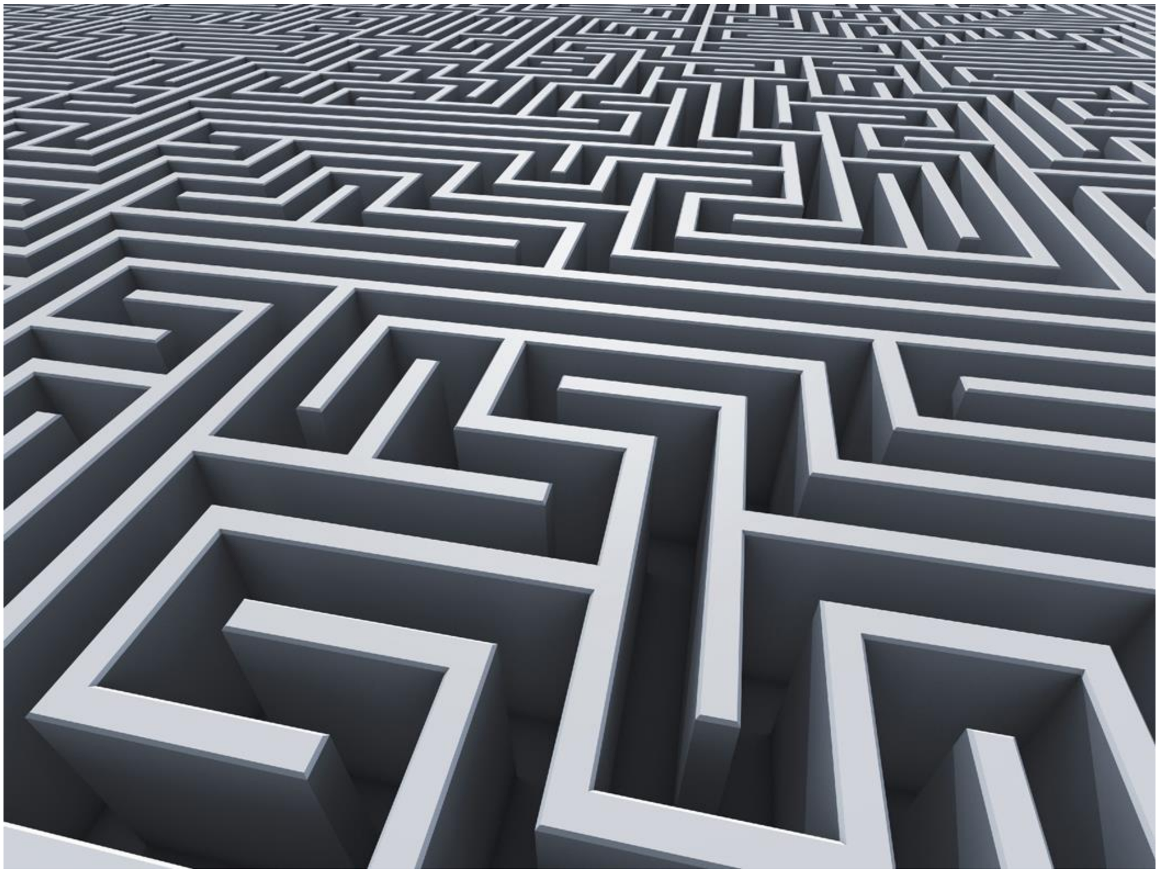

Plot and Navigate a virtual maze

CAPSTONE PROJECT

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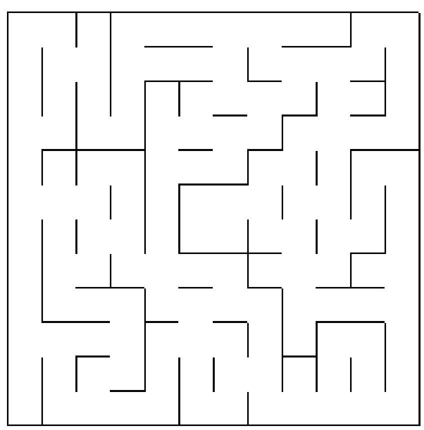
Definition

PROJECT OVERVIEW

This project takes inspiration from Micromouse competitions in which mouse is tasked with plotting a path through a virtual maze to its center. In the first run, the mouse can explore the virtual maze with little penalty but in second run it must reach the center of virtual maze as quickly as possible. Though the mouse is allowed 1000 moves to reach the center but its objective is to reach the center twice as quickly as possible because a score is summed up for both the trial based on the number of moves and the mouse with the lowest score is better than the mouse with higher score. Typical virtual maze would look like the following: -



PROBLEM STATEMENT

The input to the problem is a virtual maze and it can be of dimensions 12x12, 14x14 or 16x16. The maze is enclosed from all sides with boundaries. Each cell within the maze also has boundaries. The mouse starts from cell (0,0) and facing upwards. The mouse can sense the number of blocks that are available to walk in front, left and right direction. In one move, the mouse can only move up to three moves and in the forward, right and left direction. The mouse can choose to not move at all but it can rotate if it is required. The mouse has two trial runs. At the beginning, the mouse does not have any knowledge of the virtual maze hence it should explore the maze in the first trial run. If it has reached the center, the mouse is given choice to end the trial run and start the second run. In this run, it tries to reach the center as quickly as possible. The maximum number of allowed moves is 1000 for the two runs.

METRICS

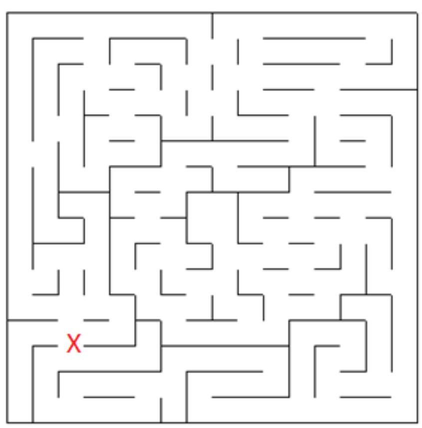
The scores for the each simulation for the mouse is equal to the sum of one thirtieth of the first trial run moves and number of second trial run moves. The aim of this simulation is to reduce number of moves taken to reach the center twice.

Analysis

DATA EXPLORATION

In the first trial run, the mouse explores the virtual maze randomly but giving priority to reaching to the center of the virtual maze because that is the objective of the mouse. The mouse receives signals from three sides i.e. left, front and right. Based on the signals, the mouse creates a maze in its memory by memorizing the barriers and the free movements possible in all four directions. The information is store in *self.Q* dictionary and key of the dictionary is state of the maze or each cell number identified by (x,y) starting from right and bottom corner. The value of the state is dictionary which contains the *0,1,2,3* as keys. 0 denotes if the left direction. If there is *1* as value for the key *0*, it would mean that for the cell in the maze, there is no barrier in the left side of the maze. Similarly, *1* denotes the up direction, *2* denote right direction, *3* denote bottom direction. *1* as value to these keys would mean that there is no barrier in that direction. There is another key *utility* which denotes the utility of the cell (or the state) of the maze

In each move, the mouse moves randomly in the direction of the free movement but it gives preference to the direction of the center of the maze because it must reach there before it can start second run. Once the mouse has reached the center of the maze in the first trial run, the mouse explores the maze randomly till it has explored a fixed percentage of the maze. After that it stops doing it and sends a reset signal to the system. The characteristics of maze becomes very important for the mouse so that he can explore it fully. Consider the following maze 3. It has 16 cells square



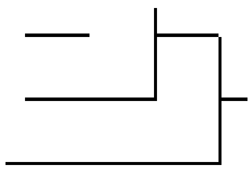
The mouse prefers going in the direction of center. Considered the cell marked with x. At the cell the mouse would prefer to go upward than downwards because of the mouse gives higher priority to move in that direction. If the mouse sets of the journey in the top direction than he might take a longer time to reach to the center because that path can take him in wrong direction. If the mouse moves down which is less likely the mouse will reach the center quickly. These decisions can make or break the mouse trial run in the maze.

Before the beginning of the second run, the mouse implements Q-learning algorithm for value iteration to find the utility of each state given 500 is the reward of reaching the center of the maze and for each cell movement there is a reward of -1. The value iteration algorithm updates utility of each state to find the best policy to reach the center of the maze. The mouse may not have explore the maze fully so the algorithm uses the best of the available data to get the best route to the center.

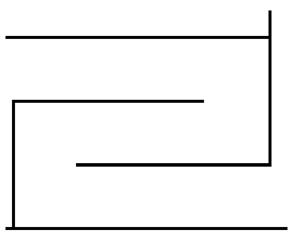
For this maze, the best metric which I have received is 48.

EXPLORATORY VISUALIZATION

In this maze, there are many dead-ends which the mouse might traverse. The mouse might have to travel to the end to realize that he has reached in one. This adds to the number of steps to the trail run. It is not possible for mouse to find out if it is inside them till he goes through them. These dead-ends can be just one cell or many cells.



The best cells are those which do not have many options to decide. In these cells, the mouse will move the most quickly. Here is the example of the cell in which the mouse will move the fastest.



ALGORITHMS AND TECHNIQUES

The mouse uses reinforcement learning algorithm to perform in the second run. The reinforcement learning algorithm works by identifying states in a problem and finding an optimal transition policy between states such that maximum benefits are achieved from the system. The problem in this simulation is reducing number of moves for the mouse. For this problem, it is assumed that every movement penalizes the mouse by 1 unit. Assuming that the reward at the center of maze is 500 units, the mouse has to reduce the number of steps to gets the maximum number of units as rewards. The algorithm implements this by assigning *utility* of the center of the maze to 500 and rest of the blocks to 0. In each cycle and for each cell, the algorithm looks for utility of state (o*r next_state)* adjacent to the current *state* and if the utility is greater, it changes the utility of the *current* state to utility of the *next_state – 1* . The algorithm then iterates it to *maze_dimension**maze_dimension* time so that benefits reach all cells. Intuitively this means that if it takes one step to reach *next_state* then the utility of the current state should be one less than utility of the *next_state.* If we start from center which has 500 utility, we can get to know the utility of correct utility of each next to it and then further in *maze_dimension**maze_dimension* times.

In order to implement the above algorithm, the mouse has to create transition model (Q-learning model). In the first trial run, the mouse creates that by randomly running around the maze. Before the second run, the mouse calculates the optimal policy of each state based on transition models.

At the beginning, the mouse then starts from cell (0,0) and keeps on moving in the direction which increases its utility. If there is a chance to move in multiple steps because the utility is increasing in the direction, the mouse takes multiple steps in that direction. There are other techniques which mouse use. The first one is weighted random exploration. In the first run, the mouse has upto 3 directions to go based on the free movement available to the mouse. The mouse gives weight to each direction because if it can lead to the center of the maze. The weight vectors are modelled by variables high, medium and low. A random number is generated and based on the ranges from normalized vectors, the mouse will move in that directions. This technique is not perfect but it gives better results than complete random walk in the maze. Second technique is the second trial run. The mouse choose to take upto 3 steps based on the optimum policy. The mouse starts off with 1 step and if there is no other barrier in the direction of movement, he takes two steps or three steps. This reduces number of steps taken to move forward.

BENCHMARK:

In a 16x16 maze, the optimum number of steps will be 30-50 steps or more. It is because it will take around 20-30 steps to reach the center in second trial and then 300-600 steps (equivalent 10-20 steps) to explore the mouse in first trial. If the mouse takes a wrong decision at crucial junctions, then he may not even reach the center of maze in 1000 steps because it travels randomly.

Methodology

DATA PREPROCESSING

The sensors data from the mouse is preprocessed before storing in the memory. The sensors give information about the number of cells which are available to move in front, left and right directions. The mouse only extracts the information that if there is a barrier in these three direction for each cell. It then creates an image of the cell with barrier information in four directions. It has been implemented in the following code.

```
        ######### This section helps you to pre-process information  from the sensors and convert it to barrier information

        if sensors[0]>0:
            anticlockwise=1
        else:
            anticlockwise=0
        if sensors[1]>0:
            straight = 1
        else:
            straight = 0
        if sensors[2]>0:
            clockwise=1
        else:
            clockwise=0

        ###### Based on the direction of the movement, the sensor information should be rotated to ge the exact map of the maze
        if (location_tuple in self.Q):
            a=1
        else:
            if self.heading ==1:
                self.Q[location_tuple]= {0:anticlockwise, 1:straight, 2:clockwise, 3:1}
            elif self.heading == 2:
                self.Q[location_tuple]= {0:1, 1:anticlockwise, 2:straight, 3:clockwise}
            elif self.heading == 3:
                self.Q[location_tuple] = {0:clockwise, 1:1, 2:anticlockwise, 3:straight}
            else:
                self.Q[location_tuple] = {0:straight, 1:clockwise, 2:1, 3:anticlockwise}
```

IMPLEMENTATION

There is one major algorithm in the implementation. The mouse takes decisions using two techniques which is of interests here.

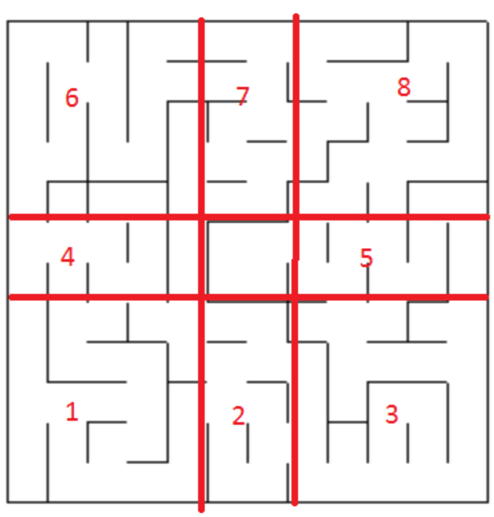
The algorithm for the implementation is value iteration on utility functions for the Q-learning models. For each state, the algorithm looks for states which is next to the current and does not have a barrier in the middle. For these *next_state*, if the utility is two more than the current state, then the current state's utility is increased to one minus the utility of the *next_state*. This algorithm is run on each state maze_dim * maze_dim times. There was no complication running the algorithm because there is no trial and error in this algorithm. It is a standard algorithm and works pretty fine.

```
for z in range(self.maze_dim*self.maze_dim):
    for i in range(self.maze_dim):
        for y in range(self.maze_dim):
            state= (i,y)
            if state in self.Q:
                if (self.Q[state][0] > 0):
                    state_next=(i-1,y)
                    if (state_next in self.Q):
                        if (self.Q[state]['utility'] <self.Q[state_next]['utility']-1) and self.Q[state_next]
['utility']>0:
                            self.Q[state]['utility'] =self.Q[state_next]['utility']-1
                if (self.Q[state][1] > 0):
                    state_next=(i,y+1)
                    if state_next in self.Q:
                        if (self.Q[state]['utility'] <self.Q[state_next]['utility']-1) and self.Q[state_next]
['utility']>0:
                            self.Q[state]['utility'] =self.Q[state_next]['utility']-1
                if (self.Q[state][2] > 0):
                    state_next=(i+1,y)
                    if state_next in self.Q:
                        if (self.Q[state]['utility'] <self.Q[state_next]['utility']-1) and self.Q[state_next]
['utility']>0:
                            self.Q[state]['utility'] =self.Q[state_next]['utility']-1
                if (self.Q[state][3] > 0):
                    state_next=(i,y-1)
                    if state_next in self.Q:
                        if (self.Q[state]['utility'] <self.Q[state_next]['utility']-1)  and self.Q[state_next]
['utility']>0:
                            self.Q[state]['utility'] =self.Q[state_next]['utility']-1
```

.

The first process happens in the first trial run. In that run, the mouse takes decision about the direction to move. It is based on the weights of the direction and probability generated by random function. The weights are higher to move it in towards the center of the maze. Hence the maze is divided into 8 blocks and each block have preference directions towards the center of the maze. Based on the output of random function, the mouse moves and it is more probable towards the center.

The blocks are divided as shown below.



In block 1, moving up and right is preferred over moving down and moving right. The weights are given by *high* and *low*. The same kind of interpretation is applied to blocks 3, 6 and 8. In block 2, the direction up is *high* , the direction left and right is *medium* and the down is *low*. Same kind of logic can be applied to 2, 4, 5, and 7.

The code for the weight vectors is show below.

```
action_taken=0
high = 1.2
medium = 1.1
low = 1
weight_vector_block_1=dict()
weight_vector_block_1[0]={0:low, 1:low, 2:high, 3:high}
weight_vector_block_1[1]={0:low, 1:high, 2:high, 3:low}
weight_vector_block_1[2]={0:high, 1:high, 2:low, 3:low}
weight_vector_block_1[3]={0:high, 1:low, 2:low, 3:high}
weight_vector_block_2 = dict()
weight_vector_block_2[0]={0:low, 1:medium, 2:high, 3:medium}
weight_vector_block_2[1]={0:medium, 1:high, 2:medium, 3:low}
weight_vector_block_2[2]={0:high, 1:medium, 2:low, 3:medium}
weight_vector_block_2[3]={0:medium, 1:low, 2:medium, 3:high}
weight_vector_block_3 = dict()
weight_vector_block_3[0]={0:low, 1:high, 2:high, 3:low}
weight_vector_block_3[1]={0:high, 1:high, 2:low, 3:low}
weight_vector_block_3[2]={0:high, 1:low, 2:low, 3:high}
weight_vector_block_3[3]={0:low, 1:low, 2:high, 3:high}
weight_vector_block_4 = dict()
weight_vector_block_4[0]={0:medium, 1:low, 2:medium, 3:high}
weight_vector_block_4[1]={0:low, 1:medium, 2:high, 3:medium}
weight_vector_block_4[2]={0:medium, 1:high, 2:medium, 3:low}
weight_vector_block_4[3]={0:high, 1:medium, 2:low, 3:medium}
weight_vector_block_5 = dict()
weight_vector_block_5[0]={0:medium, 1:high, 2:medium, 3:low}
weight_vector_block_5[1]={0:high, 1:medium, 2:low, 3:medium}
weight_vector_block_5[2]={0:medium, 1:low, 2:medium, 3:high}
weight_vector_block_5[3]={0:low, 1:medium, 2:high, 3:medium}
weight_vector_block_6 = dict()
weight_vector_block_6[0]={0:high, 1:low, 2:low, 3:high}
weight_vector_block_6[1]={0:low, 1:low, 2:high, 3:high}
weight_vector_block_6[2]={0:low, 1:high, 2:high, 3:low}
weight_vector_block_6[3]={0:high, 1:high, 2:low, 3:low}
weight_vector_block_7 = dict()
weight_vector_block_7[0]={0:high, 1:medium, 2:low, 3:medium}
weight_vector_block_7[1]={0:medium, 1:low, 2:medium, 3:high}
weight_vector_block_7[2]={0:low, 1:medium, 2:high, 3:medium}
weight_vector_block_7[3]={0:medium, 1:high, 2:medium , 3:low}
weight_vector_block_8 = dict()
weight_vector_block_8[0]={0:high, 1:high, 2:low, 3:low}
weight_vector_block_8[1]={0:high, 1:low, 2:low, 3:high}
weight_vector_block_8[2]={0:low, 1:low, 2:high, 3:high}
weight_vector_block_8[3]={0:low, 1:high, 2:high, 3:low}
```

In the second run, to the optimize the number of moves, the mouse should move in multiple steps if the maze allows and takes you towards the center of the maze. The mouse first finds the right policy on the cell which he is standing. He then checks for cells in the direction of its movement to find out if he should take 1, 2 3 steps and improve the utility of the state.

```
    else:
        if (self.location[0]-2,self.location[1]) in self.Q and self.Q[self.location[0]-1,self.location[1]][max_var]>0:
            if self.Q[self.location[0]-2,self.location[1]][max_var]>0 and self.Q[self.location[0]-2,self.location[1]]['utility'] > max_utility:
                max_utility_2= self.Q[self.location[0]-2,self.location[1]]['utility']
                if (self.location[0]-3,self.location[1]) in self.Q:
                    if self.Q[self.location[0]-3,self.location[1]][max_var]>0 and self.Q[self.location[0]-3,self.location[1]][max_var] > max_utility_2:
                        self.location[0]=self.location[0]-3
                        movement=3
                    else:
                        self.location[0]=self.location[0]-2
                        movement=2
                else:
                    self.location[0]=self.location[0]-2
                    movement=2
            else:
                self.location[0]=self.location[0]-1
                movement=1
        else:
            self.location[0]=self.location[0]-1
            movement=1
elif max_var==1:
    if self.heading == 3:
        movement = 0
    else:
        if (self.location[0],self.location[1]+2) in self.Q and self.Q[self.location[0],self.location[1]+1][max_var]
```

REFINEMENT

There was no refinement of algorithm required because the algorithm is a standard reinforcement algorithm.

Results

MODEL EVALUATION AND VALIDATION

The mouse simulation is perfect to understand the power of value iteration algorithm in Q-Learning. The mouse develops a model of the maze and then performs the value iteration to find the best policy to reach the center of the maze. The value iteration guarantees the shortest possible time to reach the center of the maze. The second trial run is very important because every step adds directly the final score. The first run is where the mouse can use different strategies to explore the maze. There can be many different strategies for exploring and they may have different impact on the result.

The following results have been obtained till now with weights *high, medium and low* as 1.2, 1.1 and 1.0 respectively and percentage covered as 70%

Runs	12x12	14x14	16x16
1	33.267	34.867	41.467
2	28.8	52.467	Unable to complete
3	23.67	56.733	45.43
4	23.73	48.767	48.3
5	26.87	Unable to complete	44.8
6	33.167	51.7	40.13
7	36.33	56.267	40.667
8	29.63	50.267	45.833
9	Unable to complete	47.33	50.2
10	28.0	45.233	51.70

Performance of the 12x12 for different *high*, *low* and *medium* configurations are as follows:-

high, medium, low	*(1,1,1)*	(1.1,1.05,1.0)	(1.2,1.1,1.0)	(1.4,1.2,1.0)
1	41	32.067	30.833	Unable to complete
2	Unable to complete	Unable to complete	35.367	42.167
3	24.233	29.733	23.467	Unable to complete
4	28.0	28.833	29.20	41.867
5	29.6	26.80	23.30	51.80

Clearly the best performance for the mouse is when the *high, medium* and *low* are 1.2,1,1 and 1.0.

Performance of the 12x12 for different *percentage_covered* configurations are as follows:-

Percentage	60%	70%	80%	90%
1	33.40	30.267	35.50	Unable to complete
2	40.333	22.233	Unable to complete	34.433
3	38.633	21.90	29.867	37.60
4	26.667	30.50	28.10	37.90
5	24.70	22.533	32.10	32.367

We see the same effect here. As the percentage goes up, chances that mouse is unable to finish exploring higher percentage of maze increases and it decreases the performance.

The mouse requires working on two parameters for better performance. These parameters are incorporated in the techniques discussed above. The first parameter is percentage_covered. This variable decides how much the mouse explores the maze in first trial in percentage before starting second trial. This is very important factor because this factor can drastically increase the number of trials for the mouse if it is very high number. The optimum value is around 70% for this simulation. This factor is very important for the simulation because if it was 100% then we would never be able to complete any challenge. If is less than we will get less than optimum results. With lower values around (50-60%), I have seen the metric taking around 80 to 90 units to finish.

The second parameters are the weights for the direction which the mouse uses to prioritize his movement towards the center of maze. Those are three variables high, medium and low and it gets normalized hence the relative ratios are important to get absolutely probability range. Currently I have assigned the variables high, medium and low to 1.2, 1.1 and 1.0 respectively. The performance with high, medium and low is average 80 when all the values are set to 1. The performance goes down when the weights are increased because there are several crucial cells where the better decision is different from weights of the directions. Wrong decision in those cells have increased the trial time. In some cases, the mouse has not been able to complete the maze at all.

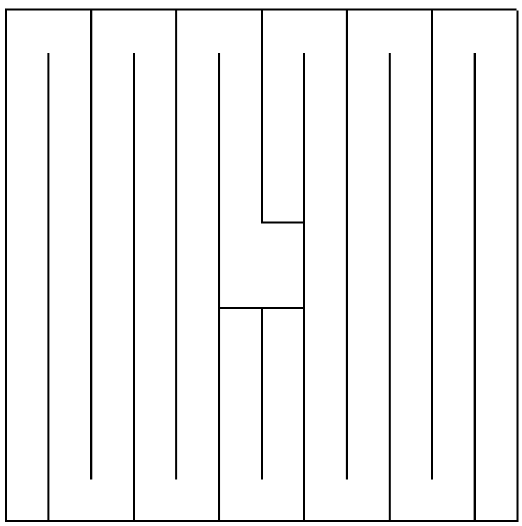
JUSTIFICATIONS

The results justify the model that it is good for the simulation. The results obtained for 16x16 average around 45 units. Based on rough calculations, the optimum number of steps for the maze is around 25-30 steps and the maze requires around 400-600 steps in stage 1. This adds up to the approximately 45 units. There are several things which can be improved in this model but they will add to complexity of the algorithm and may be very specific to one of the problems in the maze. This way the algorithm will overfit to the testing maze.

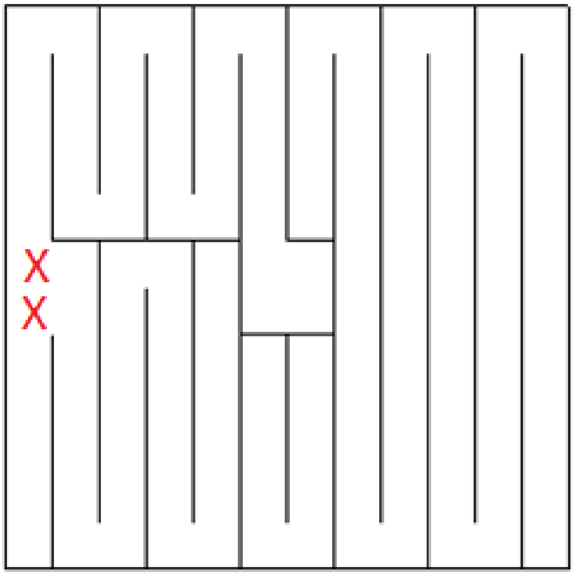
Conclusion

FREE FORM VISUALIZATION

Maze architecture can improve or reduce the performance of the mouse. Consider the following maze. This kind of the maze is easiest to solve because the mouse has only one option to go which is the forward direction. The maze guides the mouse center of the maze. The weight vectors do not provide any guidance because the mouse has only one option which is to move forward.

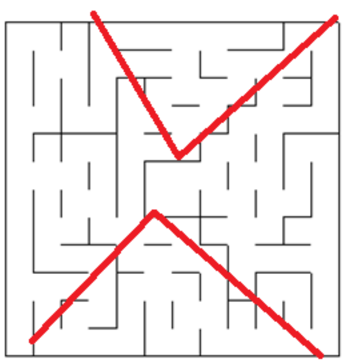


Consider the following maze shown below. There are two places where the weights of direction would increase the chances of the mouse going towards wrong direction and hence wasting the important trial runs.



Most of the time, the maze will have the architecture which will get benefitted from the weights.

Consider the following maze. In this maze, if the mouse is on the right or the left side then any movement towards the center will help the mouse to reach the center as soon as possible.



REFLECTION

The challenge starts with mouse exploring the maze in the first trial. The mouse starts from cell (0,0) and facing upwards. The mouse captures information from the sensors, processes and stores in *self.Q* dictionary with cell number as state name.

```
        if self.learning == True: ############# Trial run 1
            location_tuple = (self.location[0],self.location[1]) ####### intialization function

            ######### This section helps you to pre-process information  from the sensors and convert it to barrier information

            if sensors[0]>0:
                anticlockwise=1
            else:
                anticlockwise=0
            if sensors[1]>0:
                straight = 1
            else:
                straight = 0
            if sensors[2]>0:
                clockwise=1
            else:
                clockwise=0

            ###### Based on the direction of the movement, the sensor information should be rotated to ge the exact map of the maze
            if (location_tuple in self.Q):
                a=1
            else:
                if self.heading ==1:
                    self.Q[location_tuple]= {0:anticlockwise, 1:straight, 2:clockwise, 3:1}
                elif self.heading == 2:
                    self.Q[location_tuple]= {0:1, 1:anticlockwise, 2:straight, 3:clockwise}
                elif self.heading == 3:
                    self.Q[location_tuple] = {0:clockwise, 1:1, 2:anticlockwise, 3:straight}
                else:
                    self.Q[location_tuple] = {0:straight, 1:clockwise, 2:1, 3:anticlockwise}
```

In order to move ahead the mouse chooses his direction based on random probability but giving weight to directions based on the philosophy that it has reach the center as quickly as possible.

```
            high = 1.2 ## Initializing probability variables
            medium = 1.1 ##
            low = 1
            ## Creating a weight vector blocks for each quadrant
            weight_vector_block_1=dict()
            weight_vector_block_1[0]={0:low, 1:low, 2:high, 3:high}
            weight_vector_block_1[1]={0:low, 1:high, 2:high, 3:low}
            weight_vector_block_1[2]={0:high, 1:high, 2:low, 3:low}
            weight_vector_block_1[3]={0:high, 1:low, 2:low, 3:high}
            weight_vector_block_2 = dict()
            weight_vector_block_2[0]={0:low, 1:medium, 2:high, 3:medium}
            weight_vector_block_2[1]={0:medium, 1:high, 2:medium, 3:low}
            weight_vector_block_2[2]={0:high, 1:medium, 2:low, 3:medium}
            weight_vector_block_2[3]={0:medium, 1:low, 2:medium, 3:high}
            weight_vector_block_3 = dict()
            weight_vector_block_3[0]={0:low, 1:high, 2:high, 3:low}
            weight_vector_block_3[1]={0:high, 1:high, 2:low, 3:low}
            weight_vector_block_3[2]={0:high, 1:low, 2:low, 3:high}
            weight_vector_block_3[3]={0:low, 1:low, 2:high, 3:high}
            weight_vector_block_4 = dict()
            weight_vector_block_4[0]={0:medium, 1:low, 2:medium, 3:high}
            weight_vector_block_4[1]={0:low, 1:medium, 2:high, 3:medium}
            weight_vector_block_4[2]={0:medium, 1:high, 2:medium, 3:low}
            weight_vector_block_4[3]={0:high, 1:medium, 2:low, 3:medium}
            weight_vector_block_5 = dict()
            weight_vector_block_5[0]={0:medium, 1:high, 2:medium, 3:low}
            weight_vector_block_5[1]={0:high, 1:medium, 2:low, 3:medium}
            weight_vector_block_5[2]={0:medium, 1:low, 2:medium, 3:high}
            weight_vector_block_5[3]={0:low, 1:medium, 2:high, 3:medium}
            weight_vector_block_6 = dict()
            weight_vector_block_6[0]={0:high, 1:low, 2:low, 3:high}
            weight_vector_block_6[1]={0:low, 1:low, 2:high, 3:high}
            weight_vector_block_6[2]={0:low, 1:high, 2:high, 3:low}
            weight_vector_block_6[3]={0:high, 1:high, 2:low, 3:low}
            weight_vector_block_7 = dict()
            weight_vector_block_7[0]={0:high, 1:medium, 2:low, 3:medium}
            weight_vector_block_7[1]={0:medium, 1:low, 2:medium, 3:high}
            weight_vector_block_7[2]={0:low, 1:medium, 2:high, 3:medium}
            weight_vector_block_7[3]={0:medium, 1:high, 2:medium , 3:low}
            weight_vector_block_8 = dict()
            weight_vector_block_8[0]={0:high, 1:high, 2:low, 3:low}
            weight_vector_block_8[1]={0:high, 1:low, 2:low, 3:high}
            weight_vector_block_8[2]={0:low, 1:low, 2:high, 3:high}
            weight_vector_block_8[3]={0:low, 1:high, 2:high, 3:low}
```

```
            if sensors[0] == 0 and sensors[1]== 0 and sensors[2] == 0:
                rotation = 90
                movement = 0
            else:
                while action_taken == 0:
                    if reached_goal == 0:
                        if (self.location[0] < self.maze_dim/2-1) and self.location[1]< self.maze_dim/2-1:
                            weight_vectors=weight_vector_block_1[self.heading]
                        elif (self.location[0] < self.maze_dim/2+1) and (self.location[0]>=self.maze_dim/2-1) and self.locatic
[1]<self.maze_dim/2-1:
                            weight_vectors = weight_vector_block_2[self.heading]
                        elif (self.location[0]>=self.maze_dim/2+1) and self.location[1]<self.maze_dim/2-1:
                            weight_vectors = weight_vector_block_3[self.heading]
                        elif (self.location[0] < self.maze_dim/2-1) and self.location[1]<self.maze_dim/2+1 and self.location[1
>=self.maze_dim/2-1:
                            weight_vectors = weight_vector_block_4[self.heading]
                        elif (self.location[0] >= self.maze_dim/2+1) and self.location[1]>=self.maze_dim/2-1 and self.location
<self.maze_dim/2+1:
                            weight_vectors = weight_vector_block_5[self.heading]
                        elif (self.location[0] < self.maze_dim/2-1) and self.location[1]>=self.maze_dim/2+1:
                            weight_vectors = weight_vector_block_6[self.heading]
                        elif (self.location[0] < self.maze_dim/2+1) and (self.location[0]>=self.maze_dim/2-1) and self.locatic
[1]>=self.maze_dim/2+1:
                            weight_vectors = weight_vector_block_7[self.heading]
                        elif (self.location[0] >= self.maze_dim/2+1) and self.location[1]>=self.maze_dim/2+1:
                            weight_vectors = weight_vector_block_8[self.heading]
```

```
                        ############# Normalizaing the weight vectors
                        weight_vector_normalized = {0:float(weight_vectors[0])/(weight_vectors[0]+weight_vectors[1]
+weight_vectors[2]), 1:float(weight_vectors[1])/(weight_vectors[0]+weight_vectors[1]+weight_vectors[2]), 2:float(weight_vectors
[2])/(weight_vectors[0]+weight_vectors[1]+weight_vectors[2])}
                        ############## Deciding on action based on randomly generated probability and ignoring 180 movements
                        prob= random.random()
                        if prob < weight_vector_normalized[0]:
                            action =0
                        elif prob < weight_vector_normalized[1]+weight_vector_normalized[0]:
                            action=1
                        else:
                            action =2
```

If the mouse reached the center then mouse is given an option to explore the maze randomly.

```
                    ############# If the mouse has reached the center once then allowing the mouse to explore the maze more
randomly
                    else:
                        action = random.randrange(0,3)
                    if action == 3:
                        rotation= 90
                        movement=0
                        action_taken =1
                    elif sensors[action]>0:
                        if action == 0:
                            rotation = -90
                            movement =1
                        elif action == 1:
                            rotation = 0
                            movement =1
                        else :
                            rotation= 90
                            movement =1
                        action_taken =1
```

If the mouse reaches the center and explores a fixed percentage of the maze then it sends a reset signal.

```
            if self.learning_counter == 1000 or (percentage_covered > 70 and reached_goal==1):
                self.learning= False
                self.heading = 1
                self.location=[0,0]
                if reached_goal ==1:
                    rotation='Reset'
                    movement='Reset'
```

After ending the first trial the mouse performs the value iteration algorithm.

```
                ################# Value iteration algorithm in exectution
                for z in range(self.maze_dim*self.maze_dim):
                    for i in range(self.maze_dim):
                        for y in range(self.maze_dim):
                            state= (i,y)
                            if state in self.Q:
                                if (self.Q[state][0] > 0):
                                    state_next=(i-1,y)
                                    if (state_next in self.Q):
                                        if (self.Q[state]['utility'] <self.Q[state_next]['utility']-1) and self.Q[state_next]['utility']>0:
                                            self.Q[state]['utility'] =self.Q[state_next]['utility']-1
                                if (self.Q[state][1] > 0):
                                    state_next=(i,y+1)
                                    if state_next in self.Q:
                                        if (self.Q[state]['utility'] <self.Q[state_next]['utility']-1) and self.Q[state_next]['utility']>0:
                                            self.Q[state]['utility'] =self.Q[state_next]['utility']-1
                                if (self.Q[state][2] > 0):
                                    state_next=(i+1,y)
                                    if state_next in self.Q:
                                        if (self.Q[state]['utility'] <self.Q[state_next]['utility']-1) and self.Q[state_next]['utility']>0:
                                            self.Q[state]['utility'] =self.Q[state_next]['utility']-1
                                if (self.Q[state][3] > 0):
                                    state_next=(i,y-1)
                                    if state_next in self.Q:
                                        if (self.Q[state]['utility'] <self.Q[state_next]['utility']-1)  and self.Q[state_next]['utility']>0:
                                            self.Q[state]['utility'] =self.Q[state_next]['utility']-1

```

The output of the algorithm is optimum policy for the mouse to travel to the center in the second trial run. The mouse not only decides the direction but also the number of steps to move in that direction.

```
            ########### THis section is helps to identify the direction of the movement and the number of steps which should be taken.
            for i in range(4):
                if max_utility < utility[i]:
                    max_utility = utility[i]
                    max_var = i
            rotation=rotation_array[self.heading][max_var]
            self.heading=self_heading[self.heading][max_var]
            if max_var==0:############### if the direction decided is going left
                if self.heading == 2: ######### But we are pointing in right
                    movement = 0
                else:
                    if (self.location[0]-2,self.location[1]) in self.Q :  ####### if state next to next_state in the direction of max_var is available.
                        if self.Q[self.location[0]-2,self.location[1]]['utility'] > max_utility and self.Q[self.location[0]-1,self.location[1]][max_var]>0: ### If that state is accesible and has utilty requirements
                            max_utility_2= self.Q[self.location[0]-2,self.location[1]]['utility']
                            if (self.location[0]-3,self.location[1]) in self.Q: ####### If the state is next to next to the next_state direction of max_var.
                                if self.Q[self.location[0]-2,self.location[1]][max_var]>0 and self.Q[self.location[0]-3,self.location[1]]['utility'] > max_utility_2: ## If the state is accesible and has utility requirements
                                    self.location[0]=self.location[0]-3
                                    movement=3
                                else:
                                    self.location[0]=self.location[0]-2
                                    movement=2
                            else:
                                self.location[0]=self.location[0]-2
                                movement=2
                        else:
                            self.location[0]=self.location[0]-1
                            movement=1

                    else:
                        self.location[0]=self.location[0]-1
                        movement=1
```

```
        elif max_var==1: #### If the direction decided is going up
            if self.heading == 3: ####### If point towards down
                movement = 0
            else:
                if (self.location[0],self.location[1]+2) in self.Q :
                    if self.Q[self.location[0],self.location[1]+2]['utility'] > max_utility and self.Q[self.location[0],self.location[1]+1][max_var]>0:
                        max_utility_2= self.Q[self.location[0],self.location[1]+2]['utility']
                        if (self.location[0],self.location[1]+3) in self.Q:
                            if self.Q[self.location[0],self.location[1]+2][max_var]>0 and self.Q[self.location[0],self.location[1]+3]['utility'] > max_utility_2:
                                self.location[1]=self.location[1]+3
                                movement=3
                            else:
                                self.location[1]=self.location[1]+2
                                movement=2
                        else:
                            self.location[1]=self.location[1]+2
                            movement=2
                    else:
                        self.location[1]=self.location[1]+1
                        movement=1
                else:
                    self.location[1]=self.location[1]+1
                    movement=1
```

```
        elif max_var==2: ############ if the direction decided is going right
            if self.heading==0:
                movement = 0 ######### if the mouse point towards left
            else:
                if (self.location[0]+2,self.location[1]) in self.Q :
                    if self.Q[self.location[0]+2,self.location[1]]['utility'] > max_utility and self.Q[self.location[0]+1,self.location[1]][max_var]>0:
                        max_utility_2= self.Q[self.location[0]+2,self.location[1]]['utility']
                        if (self.location[0]+3,self.location[1]) in self.Q:
                            if self.Q[self.location[0]+2,self.location[1]][max_var]>0 and self.Q[self.location[0]+3,self.location[1]]['utility'] > max_utility_2:
                                self.location[0]=self.location[0]+3
                                movement=3
                            else:
                                self.location[0]=self.location[0]+2
                                movement=2
                        else:
                            self.location[0]=self.location[0]+2
                            movement=2
                    else:
                        self.location[0]=self.location[0]+1
                        movement=1
                else:
                    self.location[0]=self.location[0]+1
                    movement=1
```

```
        else: ############## if the direction decided is down
            if self.heading == 1:######## if the mouse is pointing towards up
                movement = 0
            else:
                if (self.location[0],self.location[1]-2) in self.Q :
                    if self.Q[self.location[0],self.location[1]-2]['utility'] > max_utility and self.Q[self.location[0],self.location[1]-1][max_var]>0:
                        max_utility_2= self.Q[self.location[0],self.location[1]-2]['utility']
                        if (self.location[0],self.location[1]-3) in self.Q:
                            if self.Q[self.location[0],self.location[1]-2][max_var]>0 and self.Q[self.location[0],self.location[1]-3]['utility'] > max_utility_2:
                                self.location[1]=self.location[1]-3
                                movement=3
                            else:
                                self.location[1]=self.location[1]-2
                                movement=2
                        else:
                            self.location[1]=self.location[1]-2
                            movement=2
                    else:
                        self.location[1]=self.location[1]-1
                        movement=1
                else:
                    self.location[1]=self.location[1]-1
                    movement=1
```

The most difficult part of the challenge was the value iteration algorithm implementation. Implementing it correctly was tricky since there are lot of conditions associated with the algorithm which should be taken care of while implementing the algorithm. One of the conditions is that the cell adjacent to the current cell should have access to the cell and there should not be a wall between the cell. All these conditions should be met before utility can be updated.

Improvement

This algorithm can be improved too. Now the value iteration algorithm is done choosing the *next_state* as one adjacent state or cell. However, the mouse can jump 3 steps at time hence algorithm should be modified to achieve that. The current implementation tries to do the same thing but in the second trial run when the mouse decides to take a single step or multiple steps. This can be implemented by changing the value iteration algorithm by not only analyzing the adjacent cell for the *utility* value but also the cells which are 2 or 3 steps away from the current cell. This way 2-3 step information will get encoded in *utility* value of each cell.

If the maze was setup in continuous domain. For example, each square has a unit length, walls are 0.1 units thick, and the robot is a circle of diameter 0.4 units. The algorithm will modify slightly to accommodate the dimensions of the maze. Taking the minimum size of 0.1 units, each of the dimensions will have number of unit assigned to it. A single cell will be 10 units and mouse is 4 units a wall is 1 unit. The algorithm must keep track of the units travelled to accommodate the movement of mouse across the maze.