Machine Learning Engineer Nanodegree

Capstone Proposal

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Proposal

Domain Background

The project involves writing the learning system to enable a virtual robot to automatically traverse several mazes.

The Micromouse is an event that began in the
1970's and has since become a worldwide event attracting roboticists and and robots enthusiast from all parts of the world.

Also there has been ongoing research into robot automation and in particular automatic maze traversal using various underlying algorithms.[1][2][3]

This past research is relevant because it offers proven techniques that serve as the useful body of work regarding how machine learning has helped to produce solutions to tough robot automation problems that have applications from consumer electronics, to medicine, to safety and security. For example, the underlying technology described here can be applied to urban rescue robots such as what is described in [4]

Why This Problem Should Be Addressed

As the concepts of robot automation embody themselves in an ever greater variety of applications, there is a need to explore various alternative solutions to this particular problem.

My Personal Motivation

From a personal perspective, I believe that machine learning based robot automation has applications in other fields. I believe that working on this will give me deeper insight into how machine learning can be applied to this problem that will help me to apply this solution to new and challenging problems I may encounter in the future.

Problem Statement

Simply put, the problem is to develop the “brain” of a robot that takes as input only the number of free squares to its left, front, and right sides given to it by three sensors, and automatically traverse a maze to any one of the maze’s four goal squares.

The robot will always begin at location (0,0) (shown in red in the diagrams in Datasets) facing upwards (`self.heading=='up'`). The other constraint on the problem is that the robot is only allowed to make the following movements once per time step:

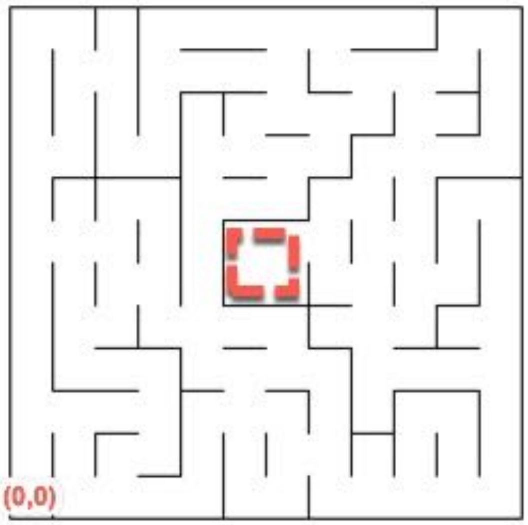
- It can rotate either –90, 0, or 90 degrees
- It can move no more than 3 squares

The robot successfully traverses the maze when it has entered anyone of the four squares in the center of the maze. These will be called the *goal squares* (shown below in red in the diagrams in Datasets) in this proposal.

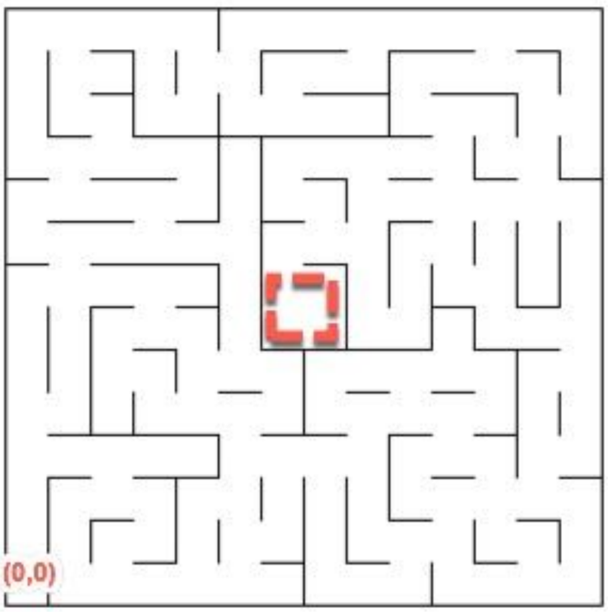
There is an overall time step limitation: The robot gets a total of 1000 time steps to traverse the maze. As is described in Metrics, it will perform two runs that must total no greater than 1000 time steps.

Datasets and Inputs

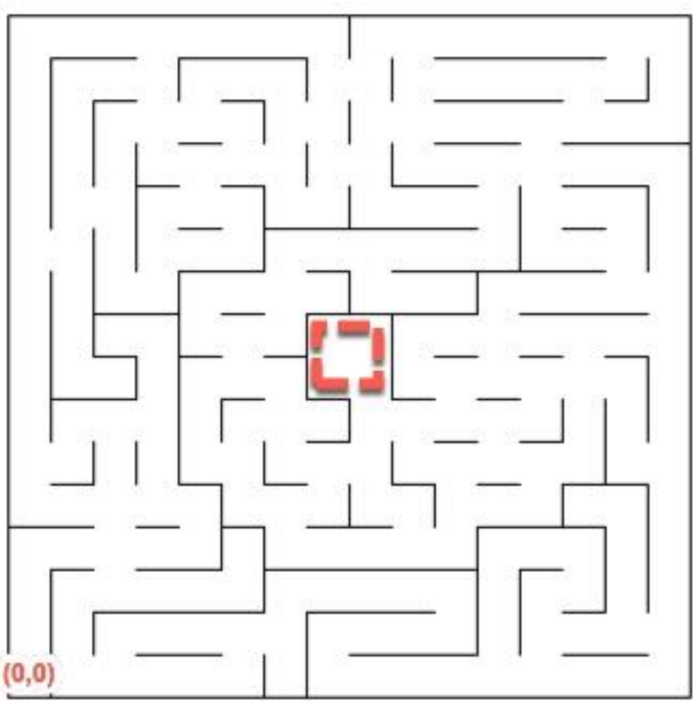
The dataset for this problem is composed of the three mazes depicted below.



(0,0)



(0,0)



(0,0)

As you can see there are three mazes that must be traversed. The overall shape of each maze is a perfect square. The dimensions for the first maze are 12x12, for the second maze are 14x14, and the third maze are 16x16.

Solution Statement

The “brain” of the robot will be a re-enforcement learning (RL) based system that implements the Q-learning algorithm. It will be based on a state space that is large enough to thoroughly cover all possible situations the robot may be in as it traverses the maze without including too many state variables that would explode the state space, which makes it harder for RL based machine to learn the maze.

Benchmark Model

The benchmark model used in this project will be that of a robot that always randomly makes movements on every time step. I will compare the score achieved by the RL-based robot to the score of a robot that always moves based on random decisions.

Evaluation Metrics

The scoring scheme is as follows:

The robot will be scored based on two runs, where in each run the robot starts at square (0,0) with heading “up”:

- In run #1, the score is is the number of time steps it took the robot to explore the maze and eventually move into a goal square divided by 30. Run #1 ends when the robot has reached a goal square.
- In run #2, the score is the number of time steps it took the robot to reach the goal square.

Once it has reached a goal square in run #2, the overall score will be the summation of the score from #1 and run #2.

For example if the robot took 600 steps in run #1 to reach a goal square, and then took 400 steps to reach the goal in run #2, then the overall score would be:

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Overall Score = 1/30 * 600 + 400 = 420
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Project Design

The workflow for this approaching the solution will involve:

- Running the benchmark model and comparing its scores to the final RL-based model
- Choosing a state space for the robot’s Q-learning system
- Choosing a reward calculation methodology that results in a populated state space that based on the Q-learning algorithm drives the robot to a goal square as quickly as possible

- Determine adequate hyper parameters for the Q-learning system
- Setup a training program to adequately train the robot's RL system
- Develop enough diagnostic information to be able to debug issues with the robot while it is training or running the scored test.

Hyper parameters will be determined by running a few experiments with epsilon, and different exploration rate equations

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1. Osmankovic, D & Konjicija, Samim. (2011). Implementation of Q - Learning algorithm for solving maze problem.. 1619–1622. ↩

2. Ahamed Munna, Tanvir. (2013). Maze solving Algorithm for line following robot and derivation of linear path distance from nonlinear path. . ↩

3. Rakshit, Pratyusha & Konar, Amit & Bhowmik, Pavel & Goswami, Indrani & Das, Sanjoy & C. Jain, Lakhmi & Nagar, Atulya. (2013). Realization of an Adaptive Memetic Algorithm Using Differential Evolution and Q-Learning: A Case Study in Multirobot Path Planning. Systems, Man, and Cybernetics: Systems, IEEE Transactions on. 43. 814–831. 10.1109/TSMCA.2012.2226024. ↩

4. Davids, Angela. (2002). Urban Search and Rescue Robots: From Tragedy to Technology.. IEEE Intelligent Systems. 17. 81–83. 10.1109/5254.999224. ↩