A Puzzled AI; Challenging a Computer to Solve Mazes

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Problem Statement

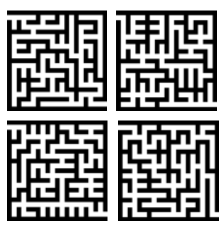
Create a reinforcement learning model that incorporates Monte Carlo methods and can be used to solve mazes

Background

- Reinforcement learning is a widely used machine learning method
- Applications in robotics, transportation, and natural language processing
- Primary components used in episodic evolution:
  - A given **state** of environment
  - A list of possible **actions**
  - A **policy** to connect actions to their **rewards**
- Monte Carlo methods
  - Average returns from sampled sequences
  - Do not require the state to select actions

Dataset

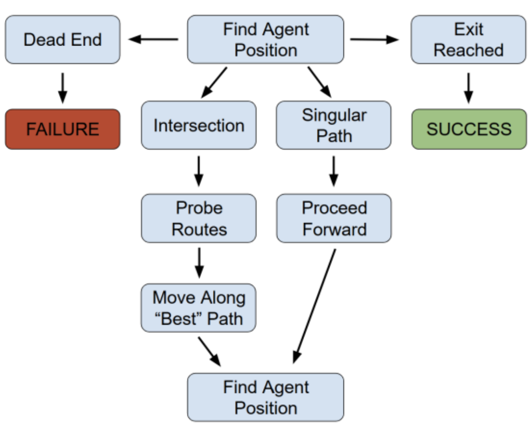
- Mazes were taken from an open-source pool of randomly generated mazes
- Maze imaging was converted into arrays of 21 x 21 pixels
- 1000 mazes used to test algorithm
- All mazes maintained consistent entrance and exit coordinates
- All puzzles were solvable



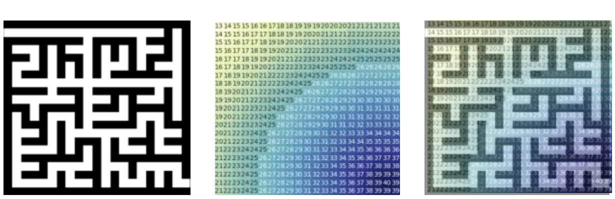
Sample mazes from Kaggle dataset

Reinforcement Learning Model

- Model state determined by position and available paths
- Monte Carlo method of path simulation used at intersections
- Rewards determined by proximity grid and path course
- Path of highest reward selected as the "best" path
- Algorithm proceeds until either a dead end or the exit has been reached



Algorithm decision process for maze navigation



Demonstration of how proximity weights correlate to positions within the maze

Results

- Final model solved **59.0%** of the 1000 mazes (using wandering paths of up to 25 steps)
- Algorithm solved all mazes in **1:16.34** on personal laptop

Conclusions

- Monte Carlo method of averaging proved less effective than pursuing maximum reward
  - Accuracy of 78.6% to 38.6% for maximum seeking and Monte Carlo respectively (15 wandering steps)
  - By the nature of means and random pathing at every intersection, dead ends near intersections cause confounding obstacles
  - Increasing the number of wandering steps allows more successful actions to create a larger impact on the average reward
- Maze solution success directly proportional to the number of wandering steps
- Significantly lower and significantly higher position weight scaling yields lower success than a scale of 40

Future Work

- Expand the concept of traversing a reward distribution to more complicated mazes (e.g. circular mazes, non-standard geometry mazes, mazes with clearings, etc.)
- Generalize the solution method to solve similar problems in other field/puzzles/games
- Test Monte Carlo methods and maximum pursuit against deep learning for the same problem

References

GitHub Repository

LinkedIn Page