Q learning

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Reinforcement Learning (Model-Free)

- Off-Policy vs On-Policy
  - Function that maps states to actions
  - Probability of an action given a state

$$\pi : S \rightarrow A$$

- MDP?
  - A set of states
  - A transition model **Q(state,action) = R(state, action) + g*max[Q(next_s, all_actions)]**
  - A reward function
  - Acquire optimal policy [after convergence]
  - Off-Policy: Must actually try actions and states out to learn !

$$a = \pi(s)$$

- Value iteration
  - Utility value [Q value]= Q(s,a) for every action at every state
  - Utility of state *s?*
    - maxQ value over all possible actions at that state
  - Utilities of actions?
    - Progressively improve utilities of actions

$$a_t = \pi(s_t) = argmax_a Q(s_t, a)$$

Q learning

- Q learning implementation using Q-Table
  - Specifies the value of each action for each possible state
  - Helps map from values received from the environment to Q-Table indices.
- There are 4 possible actions: [up, down, left, right]
- Objective: To move from starting position to the green goal position
- Search Policy
  - e-Greedy; the robot chooses its next action as the best action it knows at the time
  - Look at the Q-Value for each action at the current state
- **DEMO TIME** (10x10 GridWorld)(https://github.com/aalind0/RL-Game-Bot)
  - Act randomly in search of reward
  - Remember the reward we get for being in state and taking Act randomly in search of a reward
  - The reward for the previous state and action is a combination of the current immediate reward of moving forward and also the best possible reward of any action from the current state, the future reward.
  - Prefer paths which result in positive rewards and avoid negative ones

The Q-Learning Algorithm

- Parameters
- Initialize
- For each World.iteration:
  - Select rand initial state
  - While not at Goal:
    - Select 1 among all actions at curr_state
    - Valid action? Consider transitioning to next state
    - Get maxQ value for this next state based on all possible actions
    - Compute Q(s,action) and update
    - Set the next state as the curr_state
  - End
- End

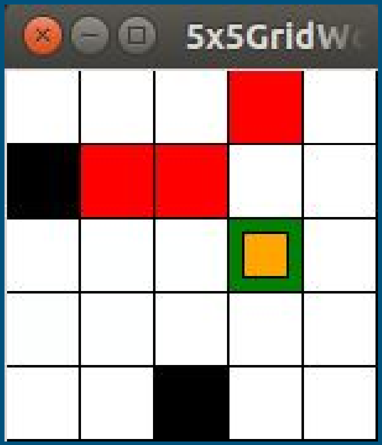
Learning Rate
Vs
Discount Factor

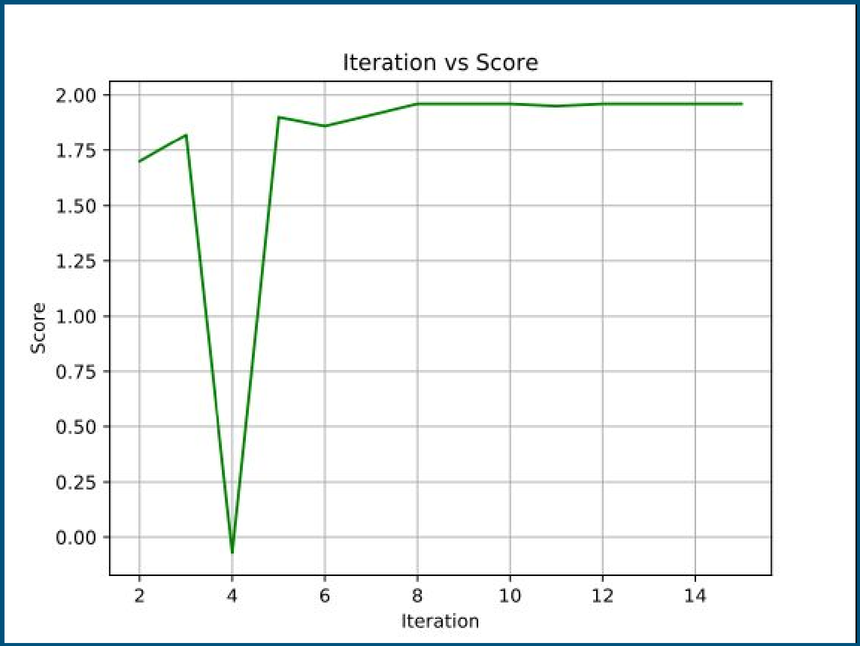
Q Learning Simulation Runs (Grid World)

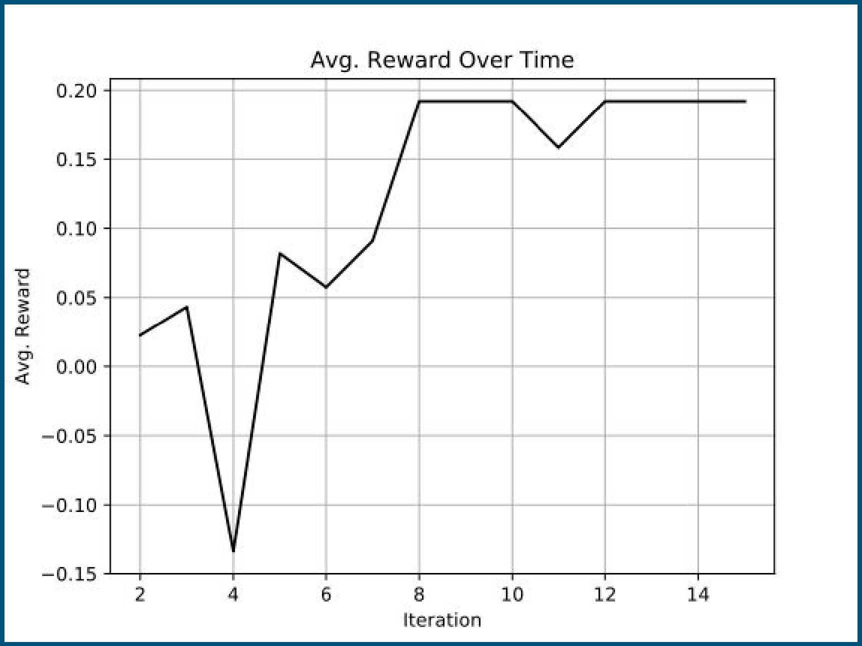
- Discount Factor (Gamma): **0.3**
- Initial Score, alpha : **1.0**
- Walk Reward : **- 0.01**
- Red Square (you die, you restart) : **-1.0**
- *Goal Square* : **+ 1.0**
- Actions: LEFT, DOWN, RIGHT, UP
- Policy ?
  - Explore environment ? random actions
  - Use Greedy Policy to evaluate states
  - Update gather information, [progressively reduce randomness]
- Highest Reward = Action to take
  - Take random action uniformly
  - If enough World iterations are completed, each action will be tried an infinite number of times, thus ensuring optimal actions to be discovered

Goal:
Maximize
Sum of Rewards

5x5 Grid World







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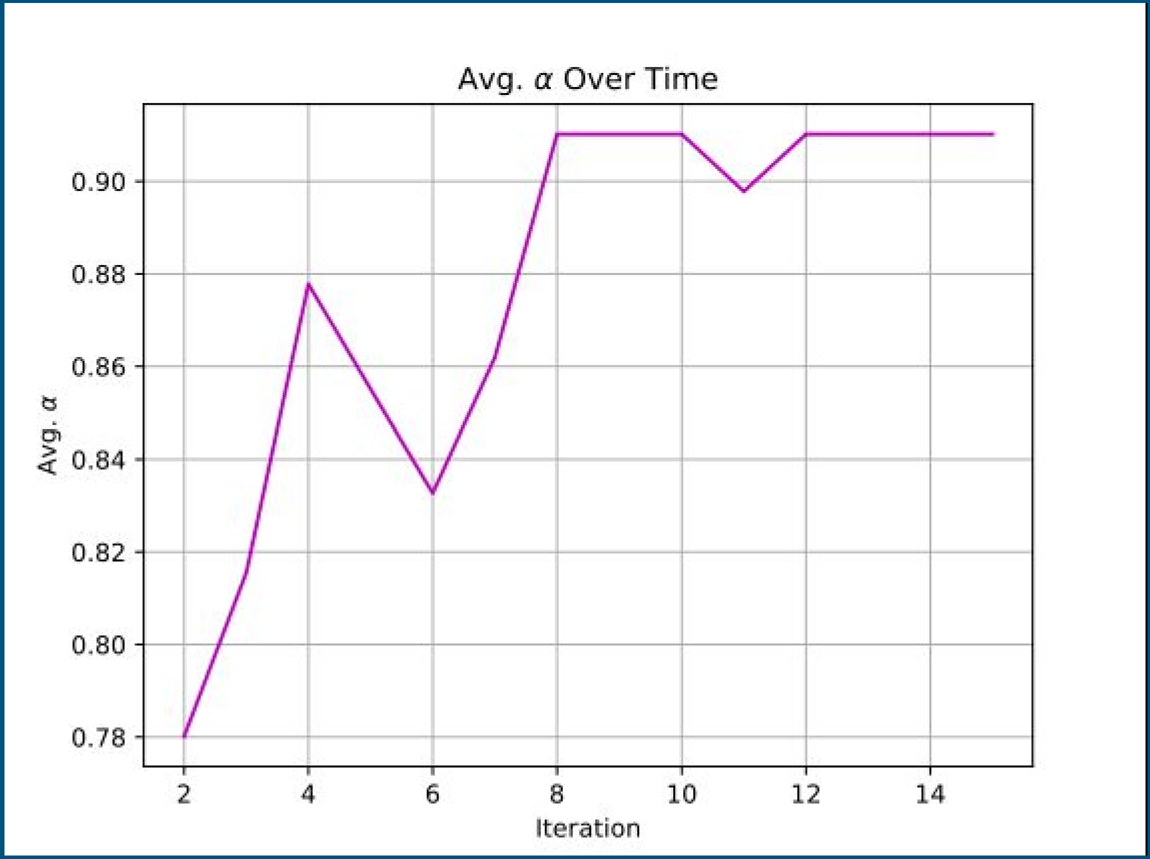
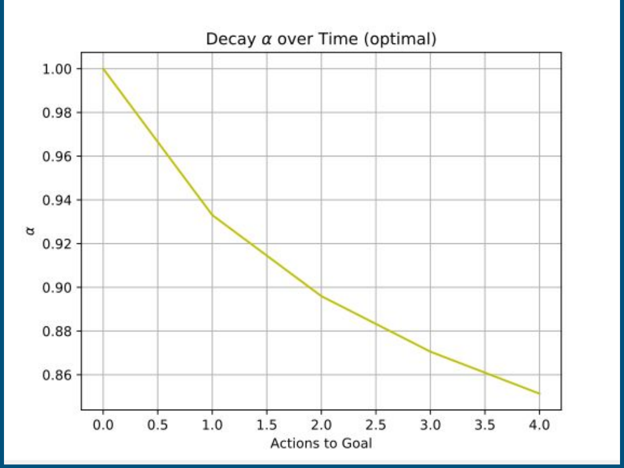
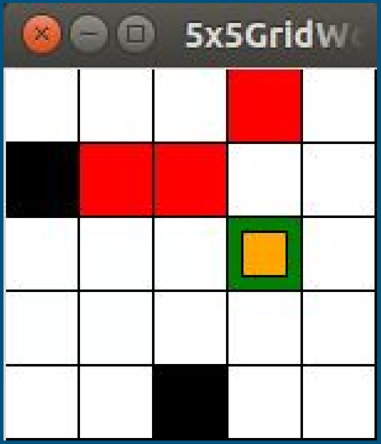
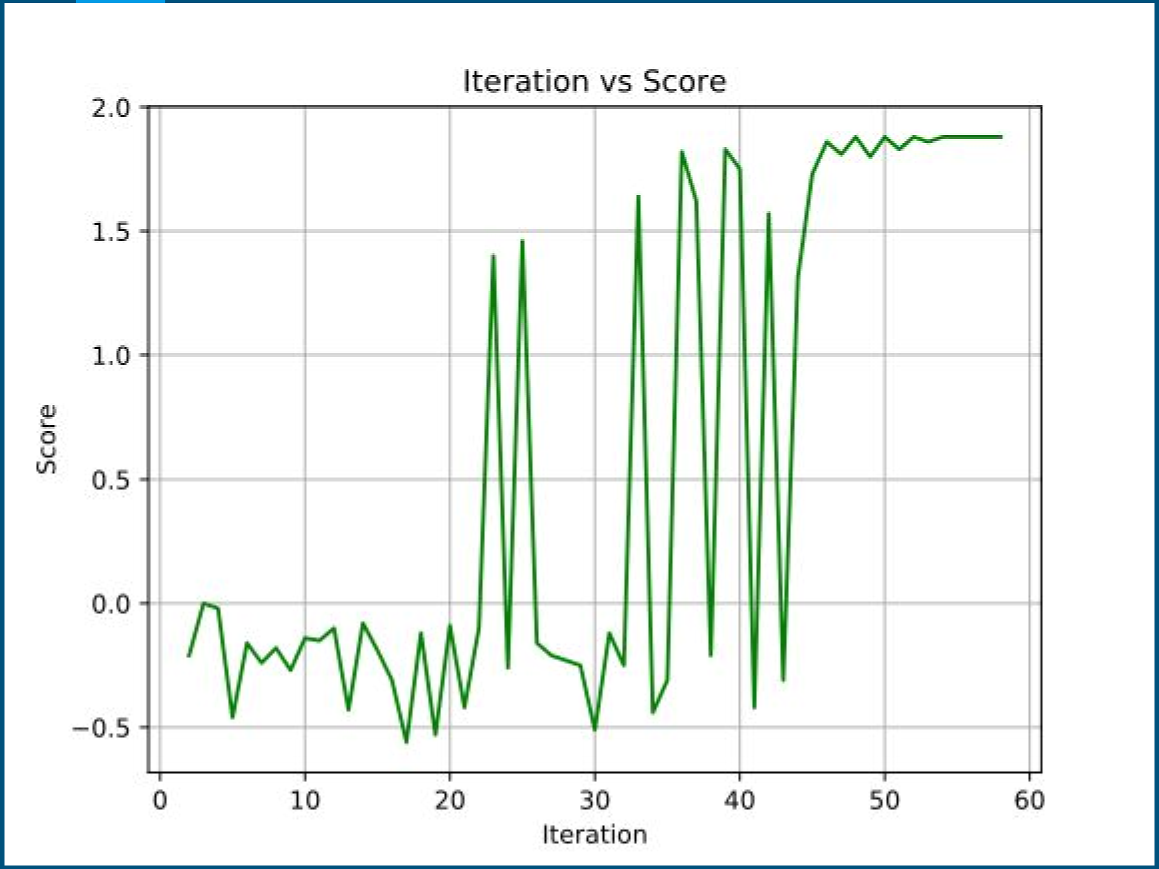
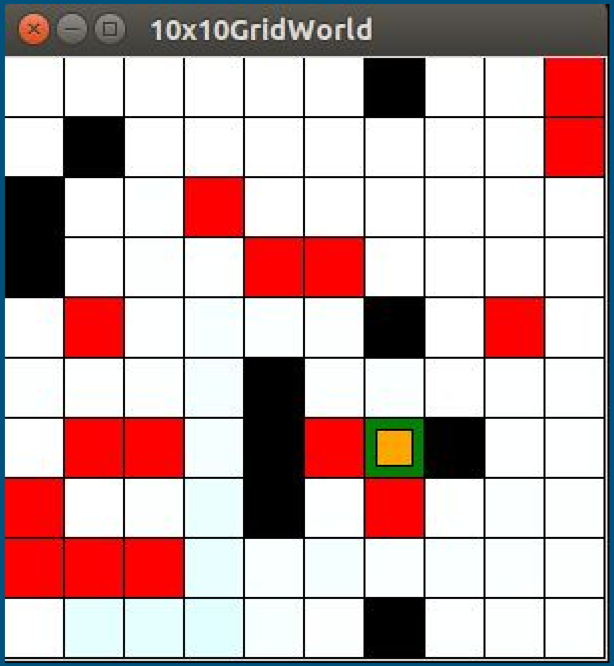






10x10 Grid World





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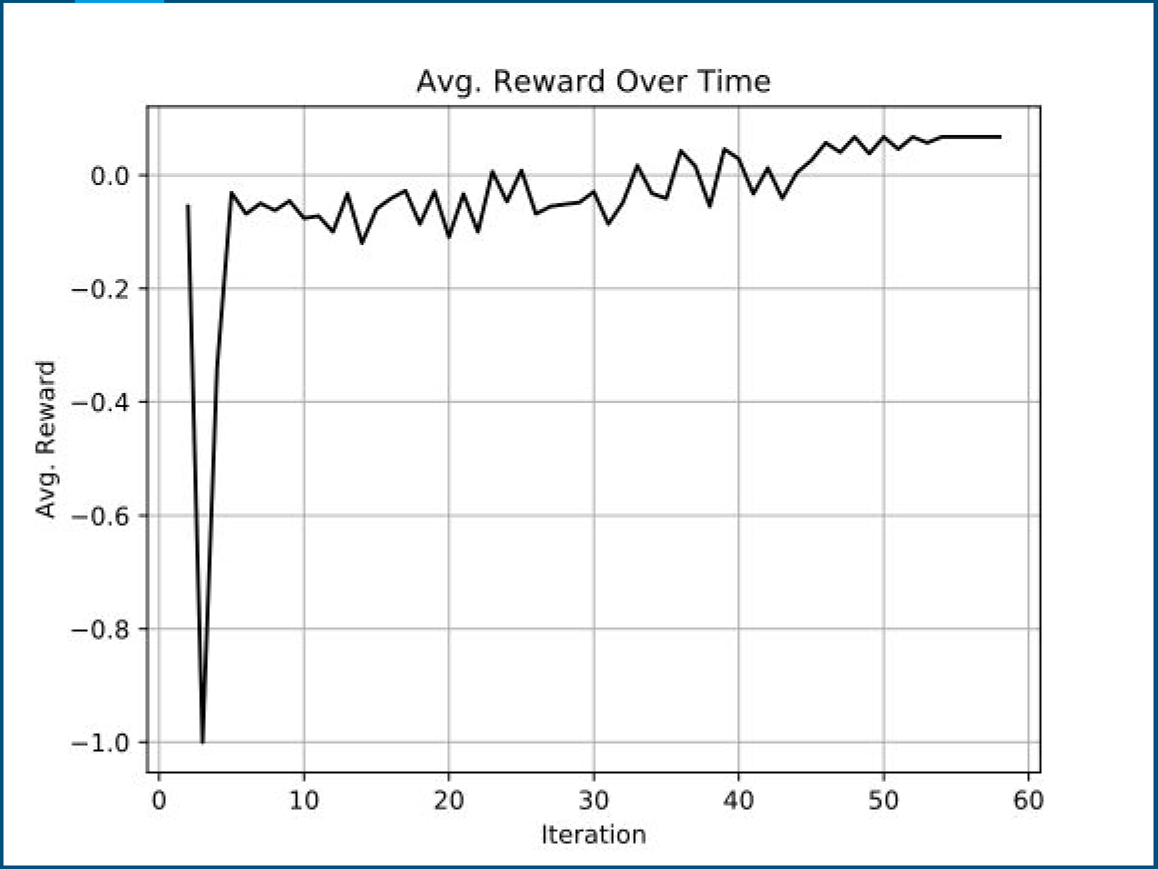

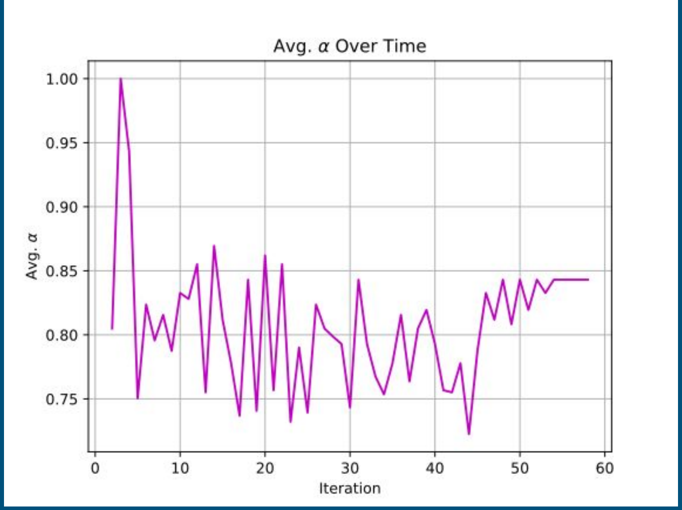

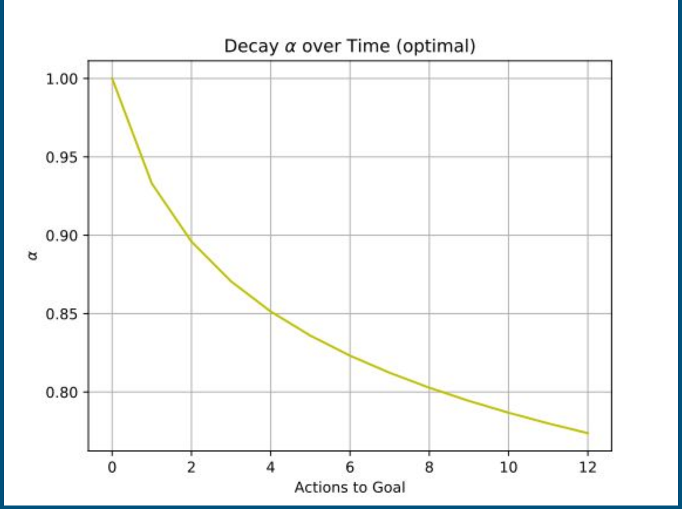

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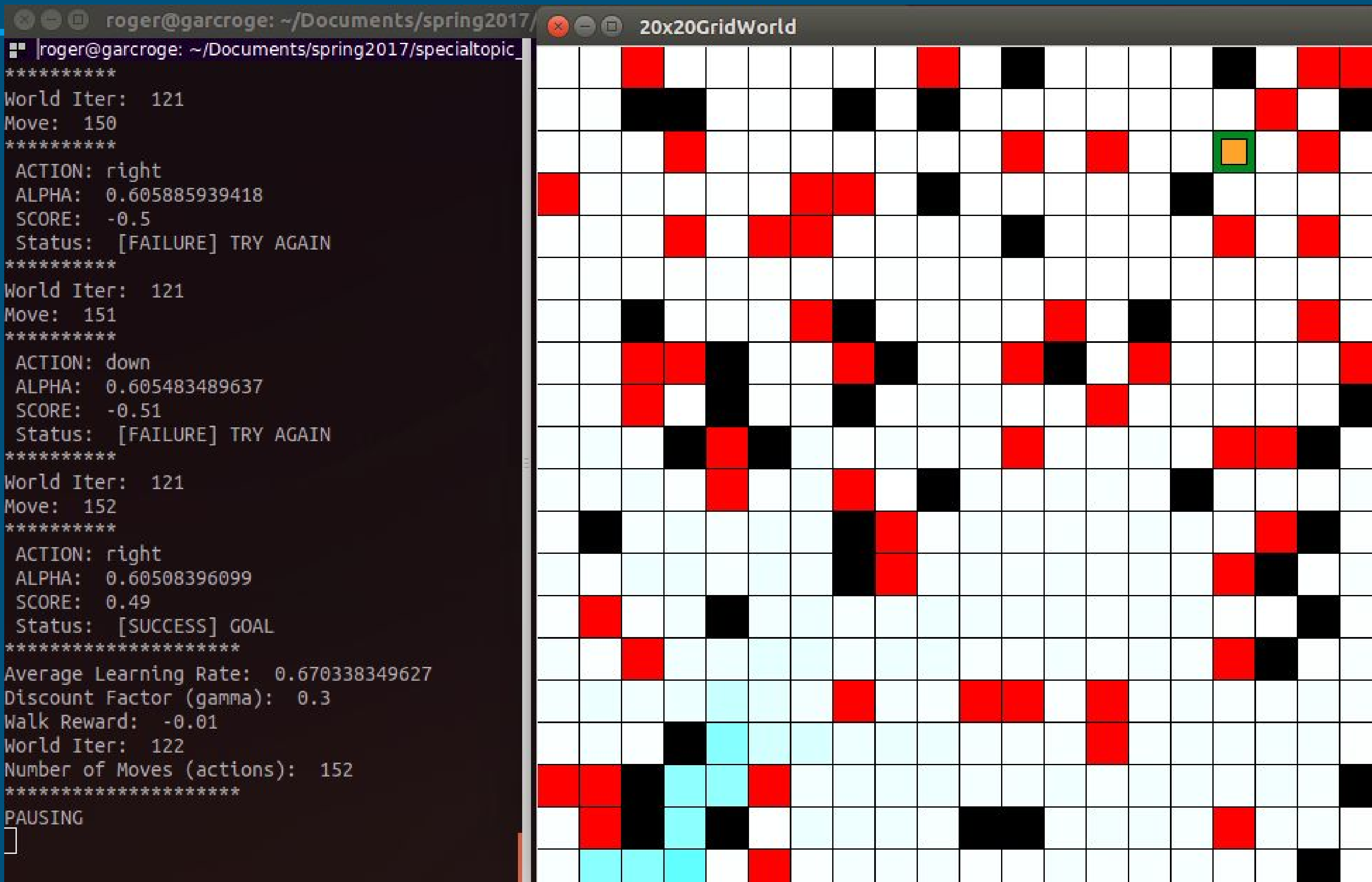

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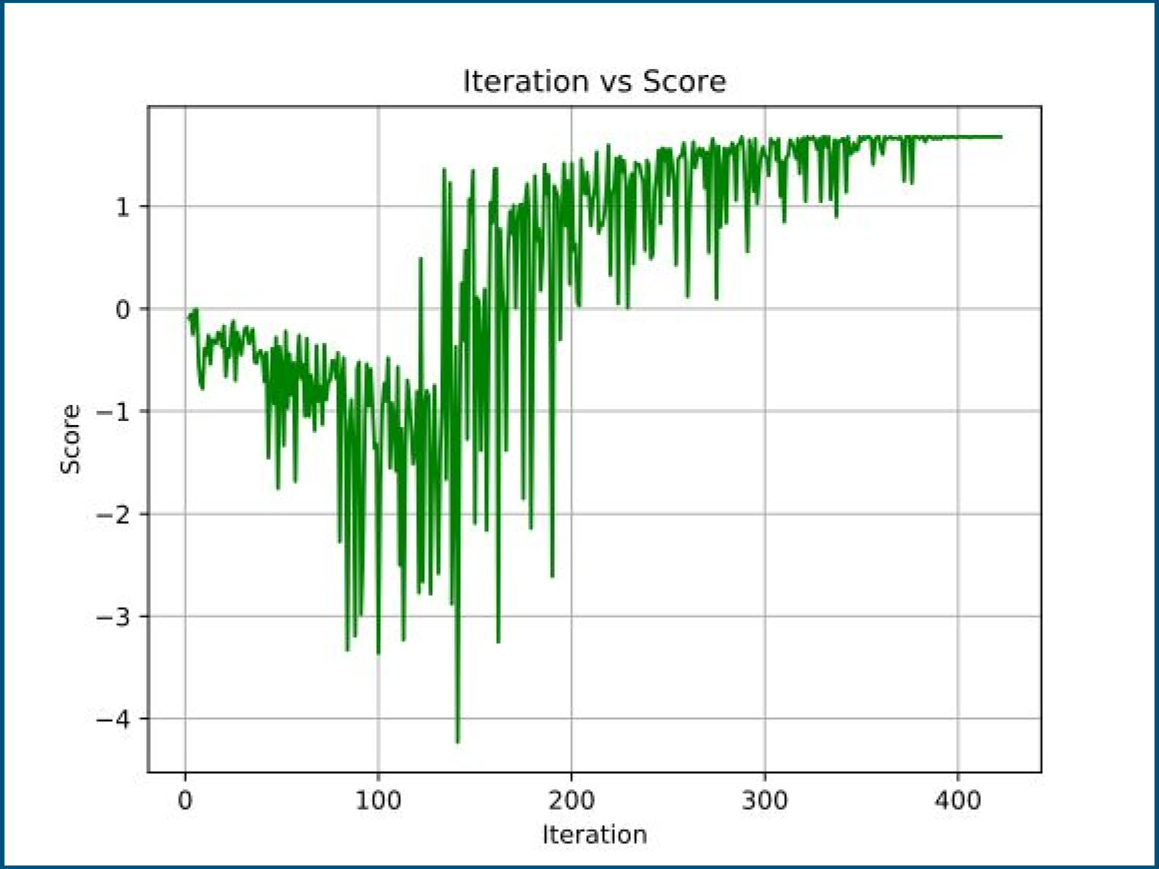

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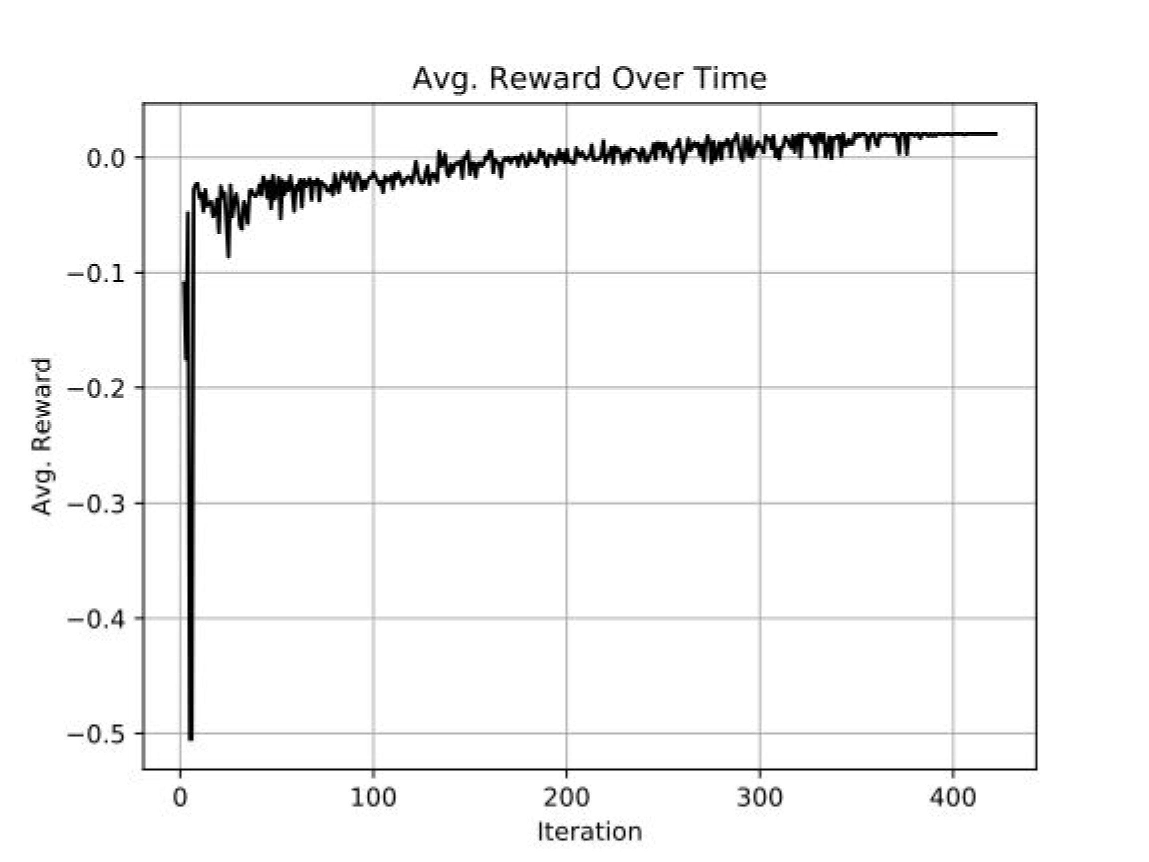
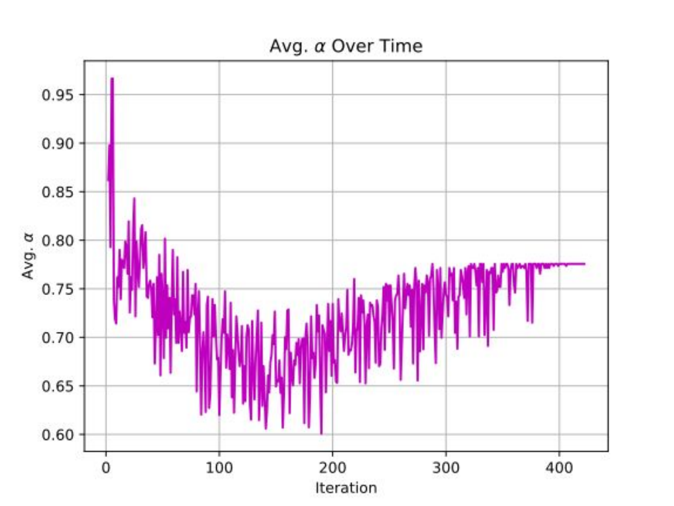
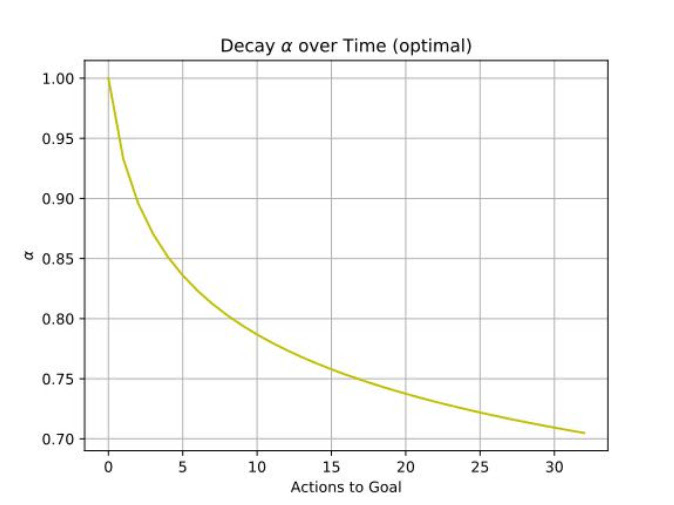
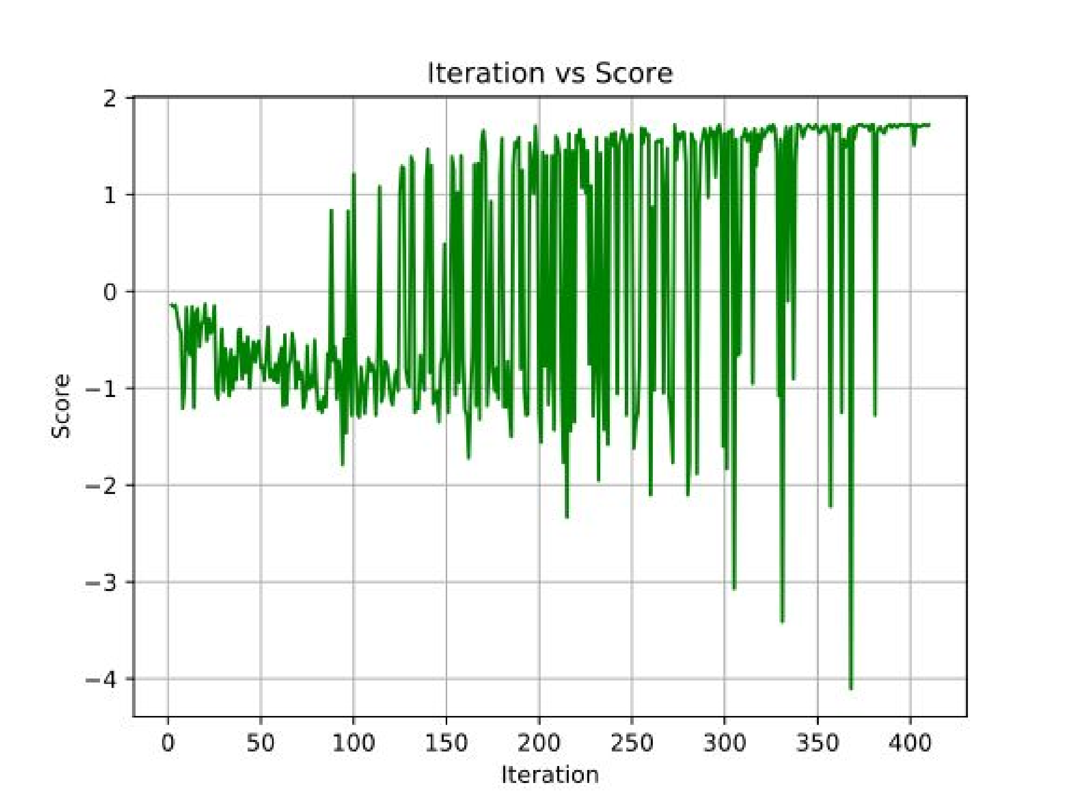
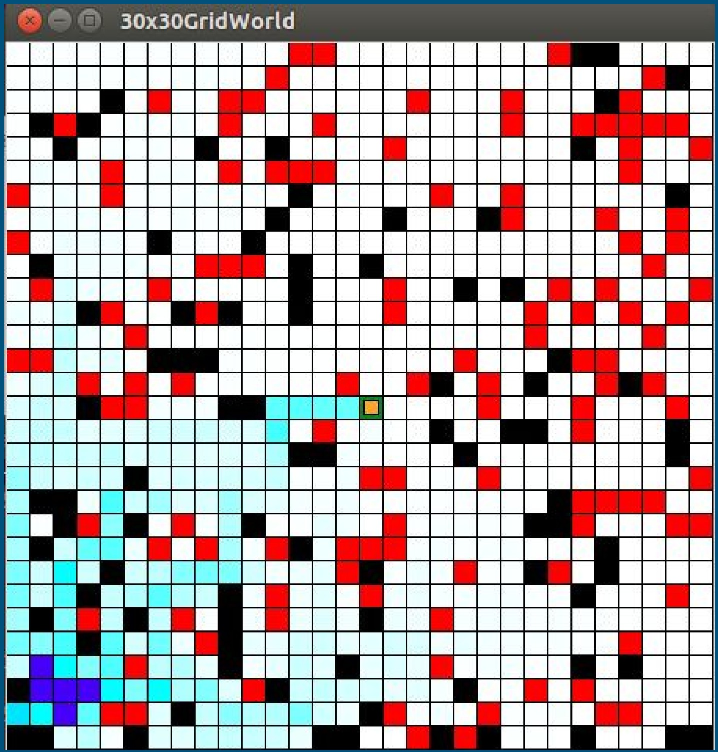






30x30 Grid World





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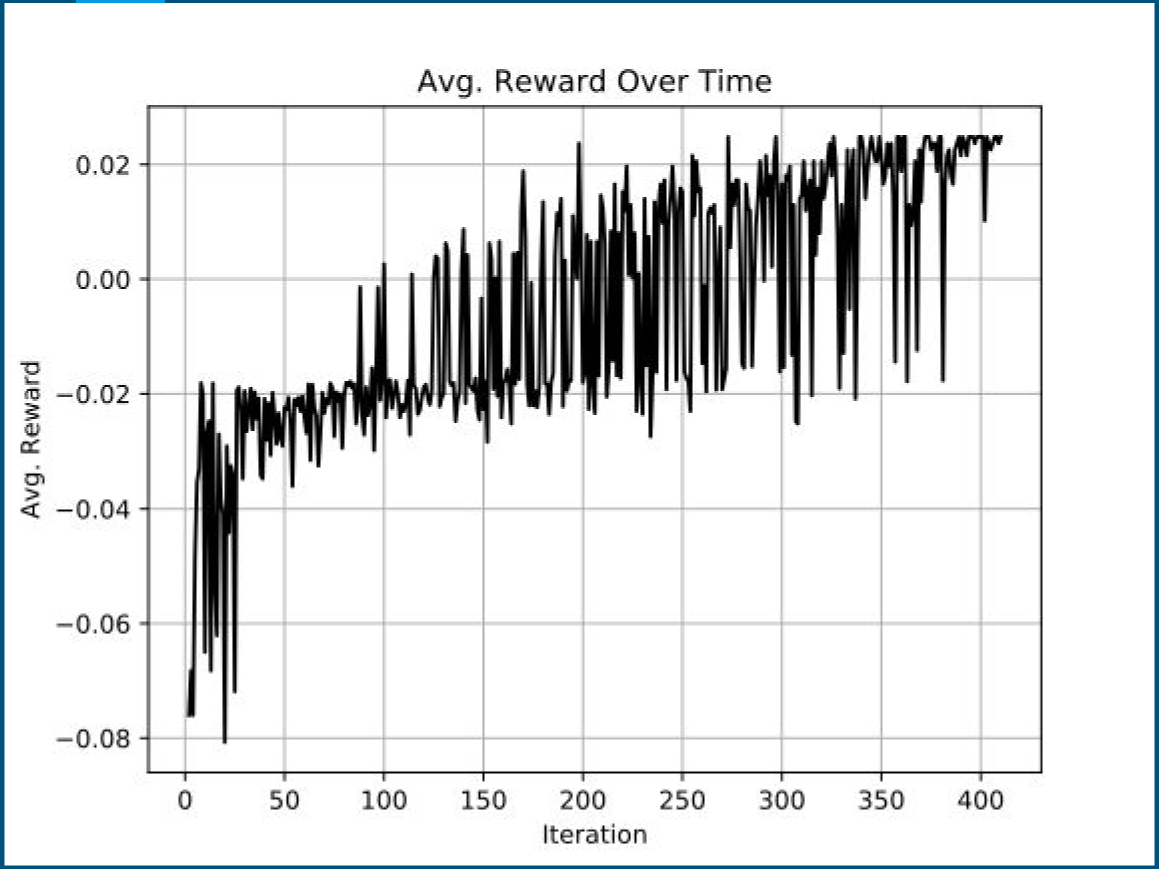
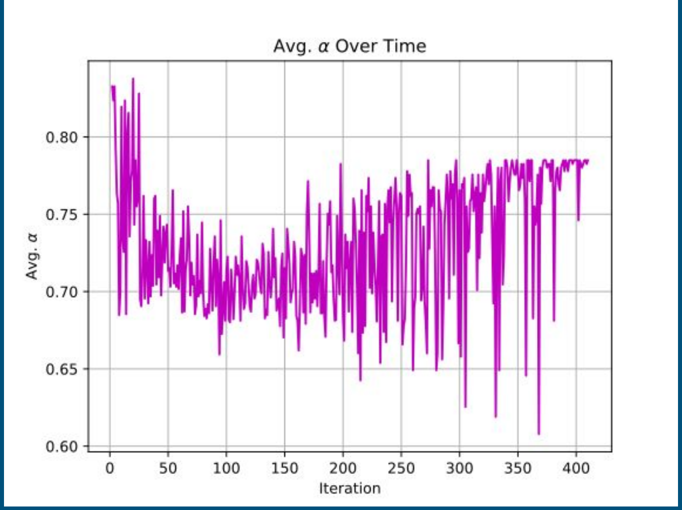
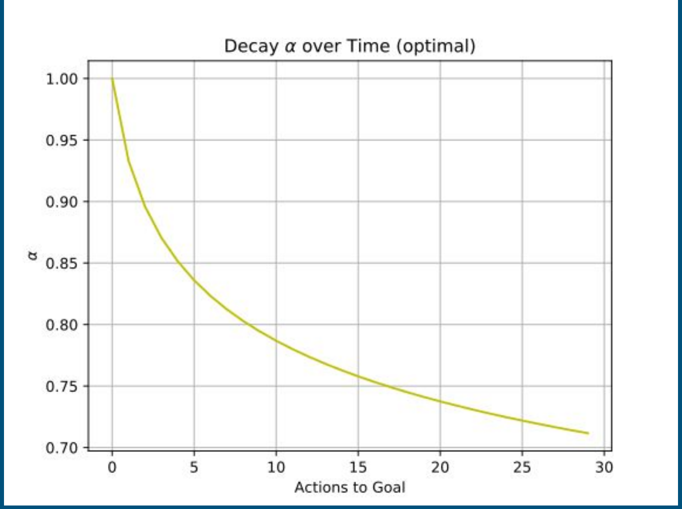
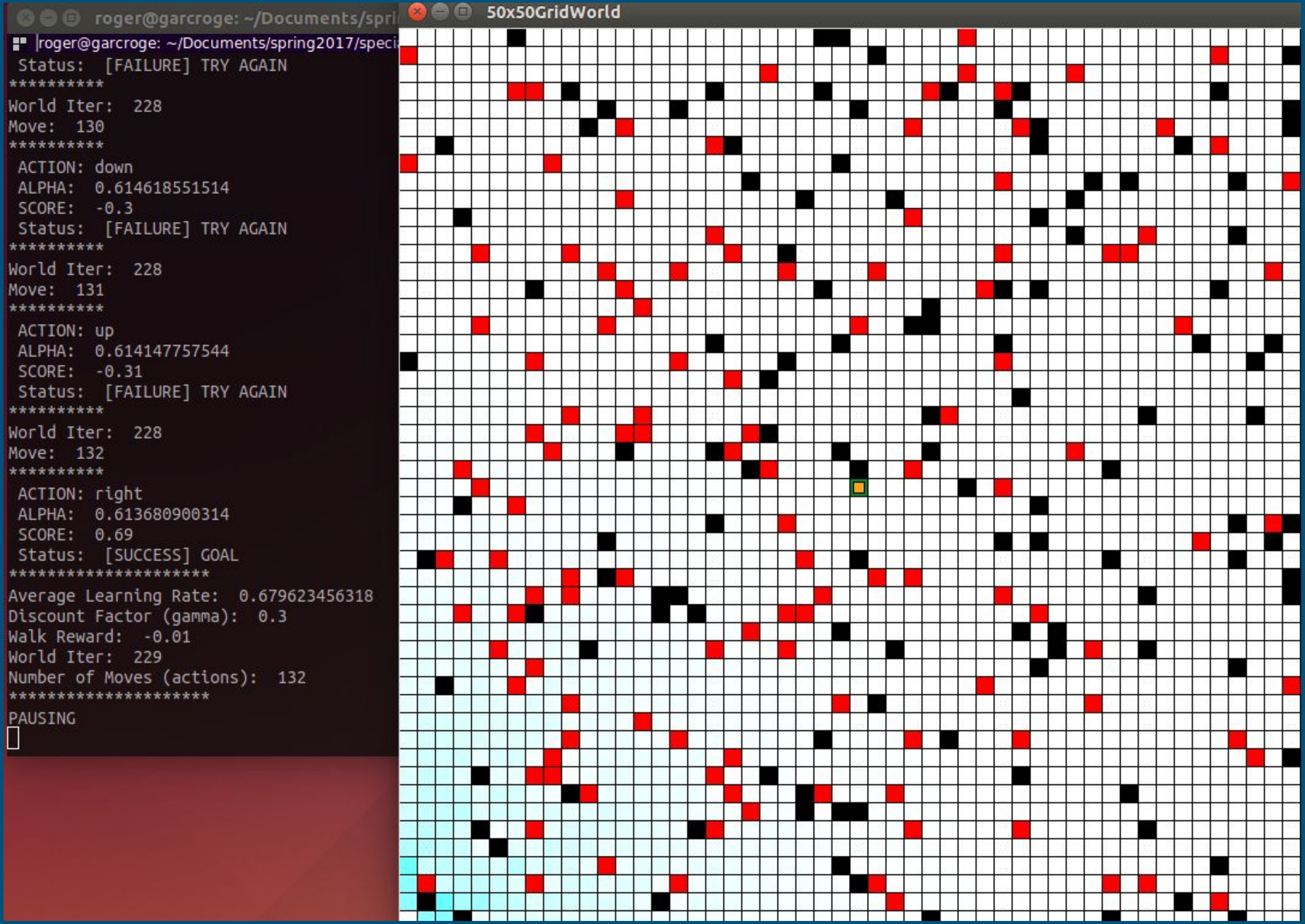






50x50 Grid World



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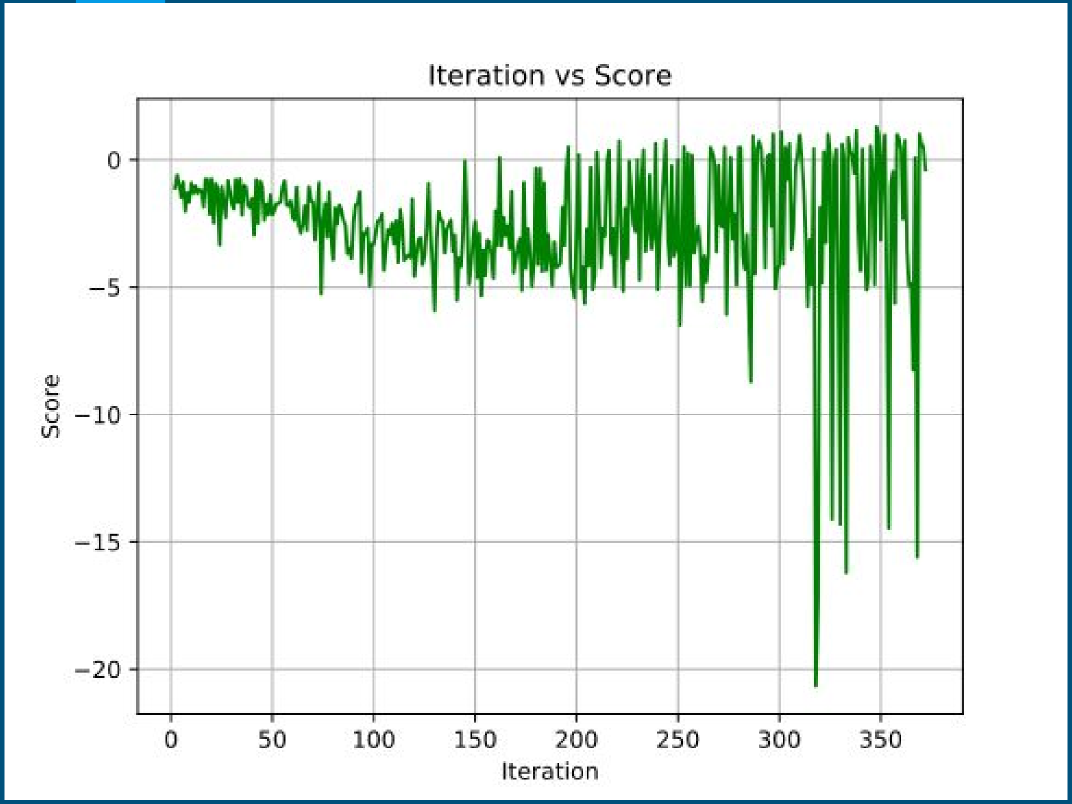

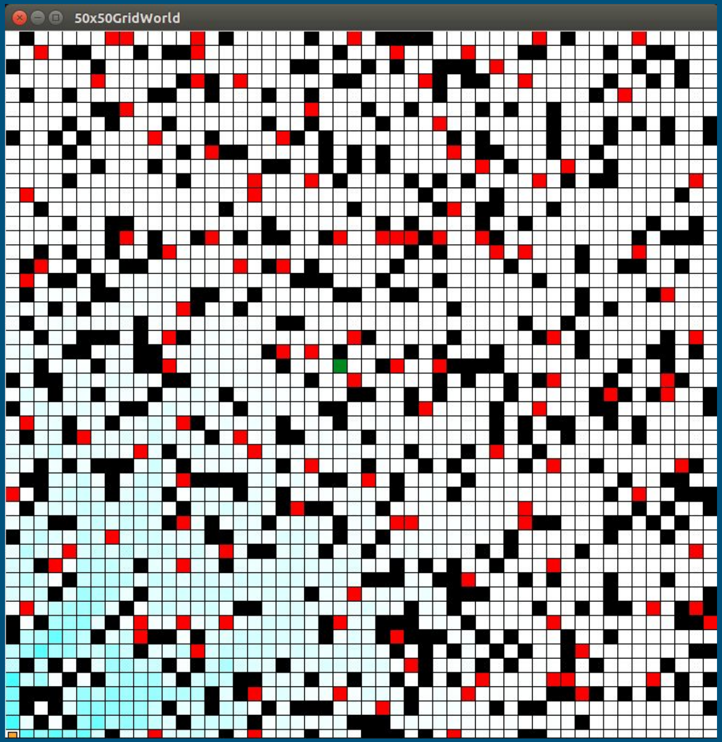

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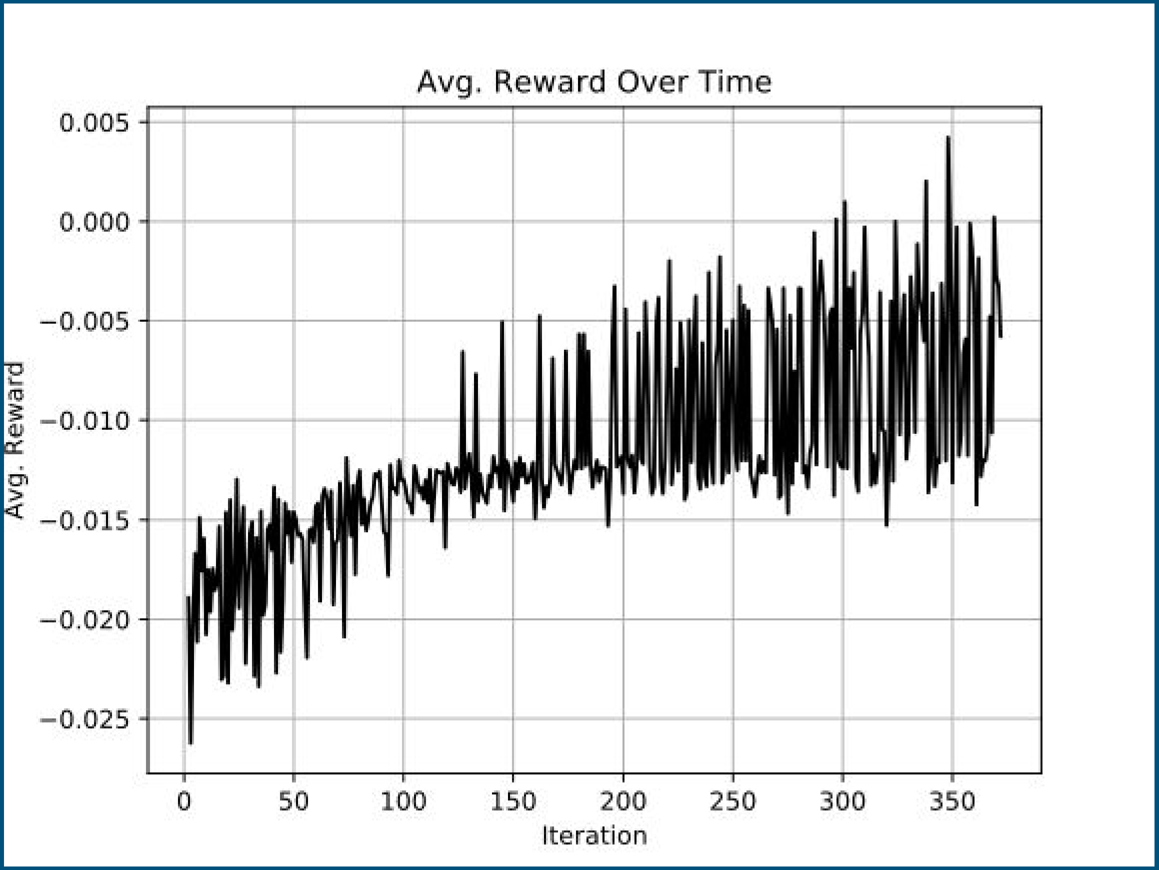

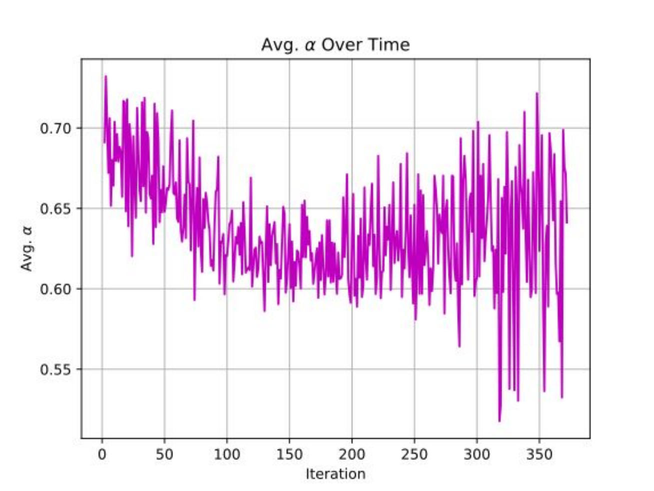

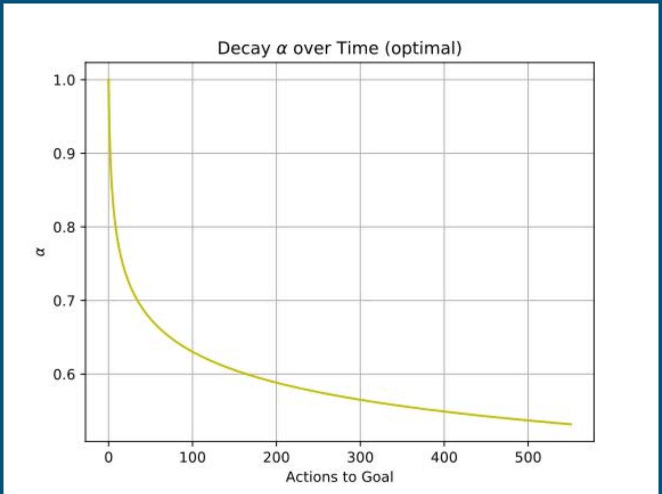

Conclusion

- Updating policy *always* even when exploring far from Goal
- Greedy Policy used (with exploration)
  - e-soft
  - Softmax (rank or weight)
- Future work
  - Explore tradeoff between policies, to produce best results overall
  - Impact of policy to learning
  - On-Policy vs Off-Policy
- References

  - http://mnemstudio.org/path-finding-q-learning-tutorial.htm
  - https://github.com/aalind0/RL-Game-Bot
  - http://mbb-team.github.io/VBA-toolbox/wiki/Fast-demo-Q-learning-model/
  - http://www.cse.unsw.edu.au/~cs9417ml/RL1/tdlearning.html#aselection