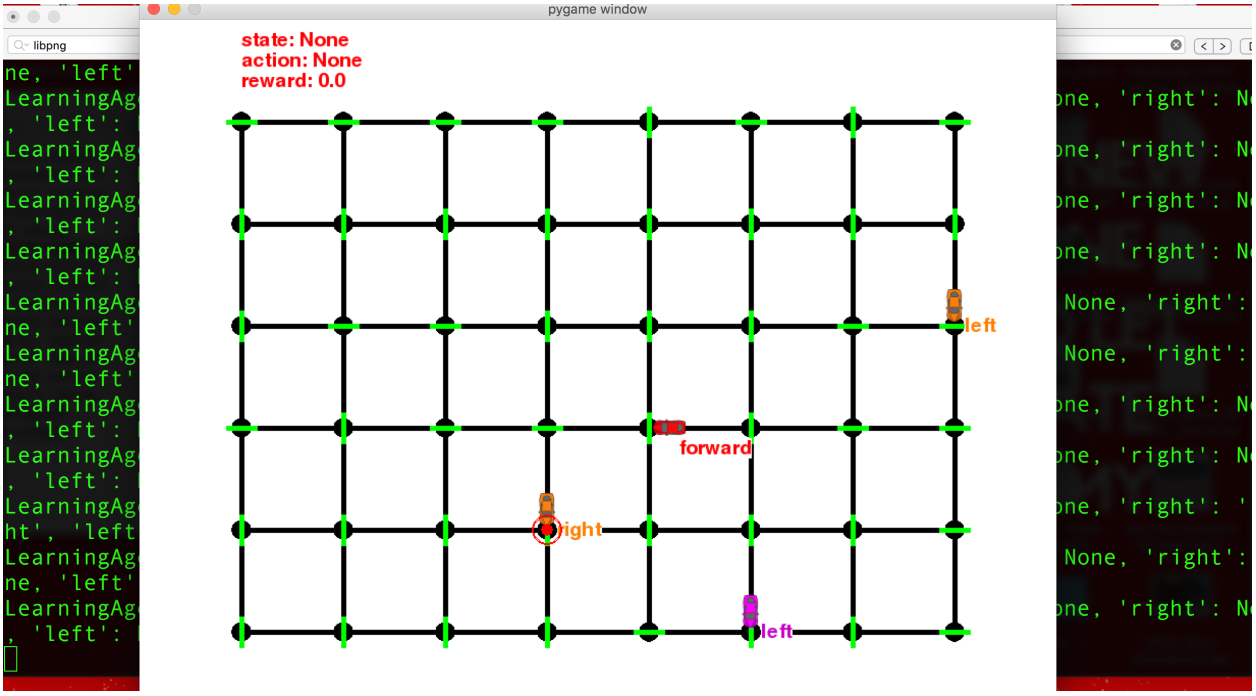
1. ***QUESTION:*** *Observe what you see with the agent's behavior as it takes random actions. Does the **smartcab** eventually make it to the destination? Are there any other interesting observations to note?*
   ANSWER: The agent eventually makes it to the destination as shown in the image below. However, numerous times a car would be close to the destination and never get there. After a while with no agent getting to the destination the destination would just change, which might be a random restart. Also important to note, it looks like cars can go "off screen." If the car is at the far left of the grid and takes a left it will wind up on the right side of the grid. That's something that would need fixing because it doesn't happen like that in the real world, unless we are assuming this is a 2d visualization of a 3d sphere.



Inform the Driving Agent

2. QUESTION: What states have you identified that are appropriate for modeling the smartcab and environment? Why do you believe each of these states to be appropriate for this problem?
   Inputs: If the light is **red** or **green**, if there is **oncoming traffic**, **oncoming traffic from the left** or **oncoming traffic from the right** or **no oncoming traffic**.
   From agent.py: self.next_waypoint
   From environment.py:
   valid_inputs = {'light': TrafficLight.valid_states, 'oncoming': valid_actions, 'left': valid_actions, 'right': valid_actions}
   TrafficLight.valid_states = valid_states = [True, False] #red light green light

These are important for this problem because each of those variables affect what action is possible for the agent to take at each intersection. If these inputs were not included then the other agents would be irrelevant to this algorithm. With these inputs the algorithm must account for a more real world scenario that includes finding the destination while navigating changing variables in the system.

I didn't include the deadline in the state space because I wanted the algorithm to have the same efficiency from beginning to end. If I added a deadline then the algorithm might become less efficient, or exhibit lower performance, towards the end in an effort to find the destination before the deadline. Including the deadline could increase the complexity of the algorithm my adding another dimension to each step that would grow more important as the algorithm steps grew closer to the deadline.

3. **OPTIONAL:** How many states in total exist for the **smartcab** in this environment? Does this number seem reasonable given that the goal of Q-Learning is to learn and make informed decisions about each state? Why or why not? The total number of states in the smartcab environment is 48x2x4= 384 total states are possible. This seems like a reasonable number of states. Because the addition of a new "feature" or variable that impacts the state will possibly cause the number of possible states to grow exponentially, I would expect a learning algorithm to be able to cope with a very large number of possible states. If the algorithm could not account for multiple features impacting the state, then it seems the user would have to leave out a lot of information that would otherwise be important in order to simplify the problem for the algorithm.

Implement a Q-Learning Driving Agent

4. QUESTION: What changes do you notice in the agent's behavior when compared to the basic driving agent when random actions were always taken? Why is this behavior occurring?

   The agent chooses to act more often by either going forward, left, or right, instead of None. This enabled the agent to experience more possible states before the deadline was reached. Thus, because it explores more states it begins to find the destination more efficiently and over time it began finding the destination much faster. Overall, the agent found the destination more frequently than before.

Improve the Q-Learning Driving Agent

5. QUESTION: Report the different values for the parameters tuned in your basic implementation of Q-Learning. For which set of parameters does the agent perform best? How well does the final driving agent perform?

*to determine how many times the cab reached the destination I printed out the log to a text file by running the python file in terminal using the command 'python agent.py > log.txt, then using search to see how many times "reached destination!" appeared. To determine how many steps were taken overall I searched for "LearningAgent.update():"

epsilon = 0.15
alpha = 0.7
gamma = 0.2
success = 95/100
steps= 1,568
penalties = 208

epsilon = 0.3 ← changed from 0.15
alpha = 0.7
gamma = 0.2
success = 94/100 (decrease success rate)
steps= 1,640 (Increase # of steps)
penalties = 192

epsilon = 0.15
alpha = 0.9 ← changed from 0.7
gamma = 0.2
success = 94/100 (decrease success rate)
steps= 1,534 (decrease # of steps)
penalties = 220

epsilon = 0.15
alpha = 0.9
gamma = 0.8 ← changed from 0.2
success = 81/100 (decrease success rate)
steps= 1,842 (Increase # of steps)
penalties = 461

epsilon = 0.1 ← changed from 0.15
alpha = 0.8 ← changed from 0.7
gamma = 0.1 ← changed from 0.2
success = 97/100 (increase success rate)
steps= 1,572 (decrease # of steps)
penalties = 173

Best Performance
epsilon = 0.05 ← changed from 0.15
alpha = 0.9 ← changed from 0.7
gamma = 0.05 ← changed from 0.2

success = 99/100 **(increase success rate)**
steps= 1,470 **(decrease # of steps)**
penalties = 91

6. QUESTION: Does your agent get close to finding an optimal policy, i.e. reach the destination in the minimum possible time, and not incur any penalties? How would you describe an optimal policy for this problem?

   The agent does use less steps than the other agents and variables tested. It also incurs the least penalties. There are multiple ways to describe the optimal policy, one is the least amount of lefts and rights (turns), another is the least number of mistakes/penalties, another is the highest success rate, and another is the least number of steps taken. However, I personally would prefer the least number of turns.

   Towards the end the agent continues to incur penalties. For penalties incurred when a green light is present, it seems to be a penalty that results from moving away from the destination as opposed to heading into traffic or running a red light. This is better from a safety standpoint than the penalties incurred when the light is red. When the light is red, the agent continues to "run" the red light instead of stopping on some occasions. That is not following policy and is a safety issue that would not be allowed if this algorithm was to be applied in a real world setting.

   Trial 99
   deadline = 19, inputs = {'light': 'green', 'oncoming': None, 'right': None, 'left': None}, action = left, reward = -0.5

   Trial 98 Red light
   deadline = 12, inputs = {'light': 'red', 'oncoming': None, 'right': None, 'left': None}, action = left, reward = -1.0
   deadline = 15, inputs = {'light': 'red', 'oncoming': None, 'right': 'left', 'left': None}, action = right, reward = -0.5
   deadline = 18, inputs = {'light': 'red', 'oncoming': None, 'right': None, 'left': None}, action = forward, reward = -1.0
   deadline = 20, inputs = {'light': 'green', 'oncoming': None, 'right': None, 'left': None}, action = right, reward = -0.5