smartcab

November 7, 2017

1 Machine Learning Engineer Nanodegree

1.1 Reinforcement Learning

1.2 Project: Train a Smartcab to Drive

Welcome to the fourth project of the Machine Learning Engineer Nanodegree! In this notebook, template code has already been provided for you to aid in your analysis of the *Smartcab* and your implemented learning algorithm. You will not need to modify the included code beyond what is requested. There will be questions that you must answer which relate to the project and the visualizations provided in the notebook. Each section where you will answer a question is preceded by a **'Question X'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide in `agent.py`.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. In addition, Markdown cells can be edited by typically double-clicking the cell to enter edit mode.

1.3 Getting Started

In this project, you will work towards constructing an optimized Q-Learning driving agent that will navigate a *Smartcab* through its environment towards a goal. Since the *Smartcab* is expected to drive passengers from one location to another, the driving agent will be evaluated on two very important metrics: **Safety** and **Reliability**. A driving agent that gets the *Smartcab* to its destination while running red lights or narrowly avoiding accidents would be considered **unsafe**. Similarly, a driving agent that frequently fails to reach the destination in time would be considered **unreliable**. Maximizing the driving agent's **safety** and **reliability** would ensure that *Smartcabs* have a permanent place in the transportation industry.

Safety and **Reliability** are measured using a letter-grade system as follows:

Grade	Safety	Reliability
A+	Agent commits no traffic violations,and always chooses the correct action.	Agent reaches the destination in timefor 100% of trips.
A	Agent commits few minor traffic violations,such as failing to move on a green light.	Agent reaches the destination on timefor at least 90% of trips.
B	Agent commits frequent minor traffic violations,such as failing to move on a green light.	Agent reaches the destination on timefor at least 80% of trips.
C	Agent commits at least one major traffic violation, such as driving through a red light.	Agent reaches the destination on timefor at least 70% of trips.

Grade	Safety	Reliability
D	Agent causes at least one minor accident, such as turning left on green with oncoming traffic.	Agent reaches the destination on timefor at least 60% of trips.
F	Agent causes at least one major acci-dent,such as driving through a red light with cross-traffic.	Agent fails to reach the destination on timefor at least 60% of trips.

To assist evaluating these important metrics, you will need to load visualization code that will be used later on in the project. Run the code cell below to import this code which is required for your analysis.

```
In [2]: # Import the visualization code
        import visuals as vs

        # Pretty display for notebooks
        %matplotlib inline
```

1.3.1 Understand the World

Before starting to work on implementing your driving agent, it's necessary to first understand the world (environment) which the *Smartcab* and driving agent work in. One of the major components to building a self-learning agent is understanding the characteristics about the agent, which includes how the agent operates. To begin, simply run the `agent.py` agent code exactly how it is -- no need to make any additions whatsoever. Let the resulting simulation run for some time to see the various working components. Note that in the visual simulation (if enabled), the **white vehicle** is the *Smartcab*.

1.3.2 Question 1

In a few sentences, describe what you observe during the simulation when running the default `agent.py` agent code. Some things you could consider: - *Does the Smartcab move at all during the simulation? - What kind of rewards is the driving agent receiving? - How does the light changing color affect the rewards?*

Hint: From the `/smartcab/` top-level directory (where this notebook is located), run the command

```
'python smartcab/agent.py'
```

Answer:

The smartcab does not move during the simulation for the trials: 1, 2.

The green rewards or positive rewards received by the agent happens when the smartcab is idle. The other types of rewards are:

- Agent idled at red light (positive)
- There was a green light with no oncoming traffic (negative)

The green light indicates a positive reward and red light indicates a negative reward.

1.3.3 Understand the Code

In addition to understanding the world, it is also necessary to understand the code itself that governs how the world, simulation, and so on operate. Attempting to create a driving agent would be difficult without having at least explored the *"hidden"* devices that make everything work. In the `/smartcab/` top-level directory, there are two folders: `/logs/` (which will be used later) and `/smartcab/`. Open the `/smartcab/` folder and explore each Python file included, then answer the following question.

1.3.4 Question 2

- *In the* `agent.py`* Python file, choose three flags that can be set and explain how they change the simulation.*
- *In the* `environment.py`* Python file, what Environment class function is called when an agent performs an action?*
- *In the* `simulator.py`* Python file, what is the difference between the *`'render_text()'`* function and the *`'render()'`* function?*
- *In the* `planner.py`* Python file, will the *`'next_waypoint()`* function consider the North-South or East-West direction first?*

Answer:

3 factors - Learning flag: which determines whether the agent is supposed to use Q-learning for maximising the output. - Epsilon: The exploration rate which is determined by a greedy algorithm that randomly assigns a state to the smartcab and learns from the environment - Alpha: Learning factor that determines the rate at which learning must be conducted. It is the rate at which smartcab learns each states based on the environment and applies to the exploration rate.

environment.py - The environment class called is Environment()

simulator.py - render_text outputs text based on a non-GUI simulation and outputs to the console. - render outputs contents based on a Pygame which is a GUI based simulation.

planner.py - next_waypoint considers how close the points are and how farther the points are in the x and y directions. Based on the coordinate directions or the North-South or East-West directions, the planner decides whether to move right, left or forward. The code of the planner considers the alignment of the East-West with x coordinates first compared to the alignment of the North-South with y coordinates.

1.4 Implement a Basic Driving Agent

The first step to creating an optimized Q-Learning driving agent is getting the agent to actually take valid actions. In this case, a valid action is one of `None`, (do nothing) `'left'` (turn left), `right'` (turn right), or `'forward'` (go forward). For your first implementation, navigate to the `'choose_action()'` agent function and make the driving agent randomly choose one of these actions. Note that you have access to several class variables that will help you write this functionality, such as `'self.learning'` and `'self.valid_actions'`. Once implemented, run the agent file and simulation briefly to confirm that your driving agent is taking a random action each time step.

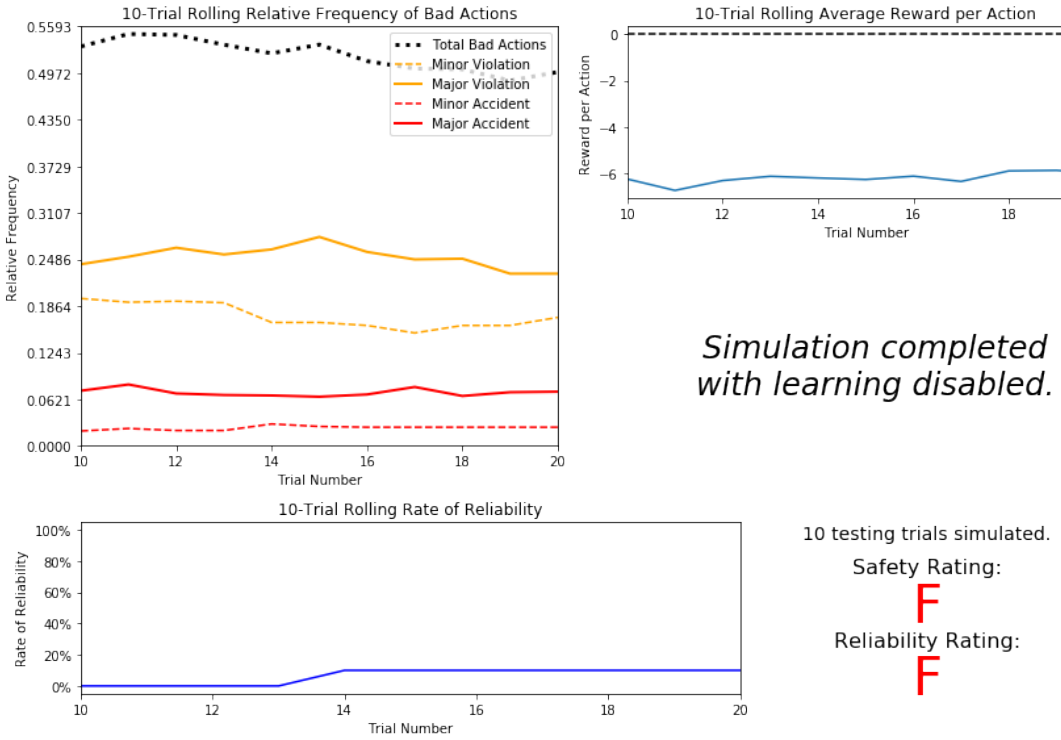
1.4.1 Basic Agent Simulation Results

To obtain results from the initial simulation, you will need to adjust following flags: - `'enforce_deadline'` - Set this to `True` to force the driving agent to capture whether it reaches the destination in time. - `'update_delay'` - Set this to a small value (such as `0.01`) to reduce the time between steps in each trial. - `'log_metrics'` - Set this to `True` to log the simluation results as a `.csv` file in `/logs/`. - `'n_test'` - Set this to `'10'` to perform 10 testing trials.

Optionally, you may disable to the visual simulation (which can make the trials go faster) by setting the `'display'` flag to `False`. Flags that have been set here should be returned to their default setting when debugging. It is important that you understand what each flag does and how it affects the simulation!

Once you have successfully completed the initial simulation (there should have been 20 training trials and 10 testing trials), run the code cell below to visualize the results. Note that log files are overwritten when identical simulations are run, so be careful with what log file is being loaded! Run the agent.py file after setting the flags from projects/smartcab folder instead of projects/smartcab/smartcab.

```
In [5]: # Load the 'sim_no-learning' log file from the initial simulation results
        vs.plot_trials('sim_no-learning.csv')
```



1.4.2 Question 3

Using the visualization above that was produced from your initial simulation, provide an analysis and make several observations about the driving agent. Be sure that you are making at least one observation about each panel present in the visualization. Some things you could consider: - *How frequently is the driving agent making bad decisions? How many of those bad decisions cause accidents? - Given that the agent is driving randomly, does the rate of reliability make sense? - What kind of rewards is the agent receiving for its actions? Do the rewards suggest it has been penalized heavily? - As the number of trials increases, does the outcome of results change significantly? - Would this Smartcab be considered safe and/or reliable for its passengers? Why or why not?*

Answer:

- The driving agent makes bad decisions very frequently. The bad decisions occur at a probability of about 0.4972 considering all the actions taken by the basic smartcab. The minor and major accidents occur at a probability of about 0.09.
- The rate of reliability in this case makes sense because the driving agent is not learning and is rated 'F'.
- The rewards do suggest that the driving agent has been penalised heavily. The kind of rewards are:
  - "Agent properly idled at a red light" which is positive reward,
  - "Agent idled at a green light with no oncoming traffic" which is negative reward,

  - "Agent followed the waypoint forward", which is a positive reward,
  - "Agent attempted driving left through traffic and cause a minor accident", a negative reward,
  - "Agent attempted driving forward through a red light, a negative reward,
  - "Agent drove left instead of right", a negative reward,
  - "Agent attempted driving left through a red light", a negative reward

The rewards accumulated by the smartcab are mostly negative rewards. The reward values of -335 and -197 in trial numbers: 2 and 8 suggest that the driver has been penalized heavily.

- One random trial has a success factor registered as 1, but an increasing the number of trials do not have much effect on the outcome, as there is not learning happening in the Q-learning driving agent.
- The smartcab is not considered safe due to a grade of 'F' because it creates minor and major traffic violations and also causes accidents. The smartcab is not considered reliable because the success ratio is 0 for 19 trials and due to most of the decisions registered to be bad and it is highly unlikely that the reliability will show a grade above 'F'.

1.5 Inform the Driving Agent

The second step to creating an optimized Q-learning driving agent is defining a set of states that the agent can occupy in the environment. Depending on the input, sensory data, and additional variables available to the driving agent, a set of states can be defined for the agent so that it can eventually *learn* what action it should take when occupying a state. The condition of `'if state then action'` for each state is called a **policy**, and is ultimately what the driving agent is expected to learn. Without defining states, the driving agent would never understand which action is most optimal -- or even what environmental variables and conditions it cares about!

1.5.1 Identify States

Inspecting the `'build_state()'` agent function shows that the driving agent is given the following data from the environment: - `'waypoint'`, which is the direction the *Smartcab* should drive leading to the destination, relative to the *Smartcab*'s heading. - `'inputs'`, which is the sensor data from the *Smartcab*. It includes - `'light'`, the color of the light. - `'left'`, the intended direction of travel for a vehicle to the *Smartcab*'s left. Returns `None` if no vehicle is present. - `'right'`, the intended direction of travel for a vehicle to the *Smartcab*'s right. Returns `None` if no vehicle is present. - `'oncoming'`, the intended direction of travel for a vehicle across the intersection from the *Smartcab*. Returns `None` if no vehicle is present. - `'deadline'`, which is the number of actions remaining for the *Smartcab* to reach the destination before running out of time.

1.5.2 Question 4

*Which features available to the agent are most relevant for learning both **safety** and **efficiency**? Why are these features appropriate for modeling the* Smartcab* in the environment? If you did not choose some features, why are those features* not *appropriate? Please note that whatever features you eventually*

choose for your agent's state, must be argued for here. That is: your code in agent.py should reflect the features chosen in this answer.

NOTE: You are not allowed to engineer new features for the smartcab.

Answer:

Features

- Waypoint: The waypoint determines the next action to be taken in the sequence of steps within a trial
- Inputs: The inputs are those values that determine the status of the dummy agents. If the input left is of a value of forward, then the dummy agent at the left hand side of the smartcab is heading forward in the traffic zone. If the input right is 'right', then the dummy agent is turning right in the cross roads. Similarly there are inputs for oncoming traffic which may be forward or can turn towards right or left at the crossroads.
- Light: The light is either 'green' or 'red' showing the traffic signal.
- Deadline: The deadline value determines the distance to the destination and at each cross-roads or each step of the evaluation, the L1 distance is evaluated based on the grid point of the destination.

Not chosen - Deadline: the deadline is not chosen because it is not a feature and it is not state variable as deadline varies at each step of the evaluation. Deadline denotes the distance, the safety and reliability parameters are based on the success ratio and best action chosen.

1.5.3 Define a State Space

When defining a set of states that the agent can occupy, it is necessary to consider the *size* of the state space. That is to say, if you expect the driving agent to learn a **policy** for each state, you would need to have an optimal action for *every* state the agent can occupy. If the number of all possible states is very large, it might be the case that the driving agent never learns what to do in some states, which can lead to uninformed decisions. For example, consider a case where the following features are used to define the state of the *Smartcab*:

`('is_raining', 'is_foggy', 'is_red_light', 'turn_left', 'no_traffic', 'previous_turn_left', 'time_of_day')`.

How frequently would the agent occupy a state like `(False, True, True, True, False, False, '3AM')`? Without a near-infinite amount of time for training, it's doubtful the agent would ever learn the proper action!

1.5.4 Question 5

If a state is defined using the features you've selected from ***Question 4****, what would be the size of the state space? Given what you know about the environment and how it is simulated, do you think the driving agent could learn a policy for each possible state within a reasonable number of training trials?*

Hint: Consider the *combinations* of features to calculate the total number of states!

Answer:

The states are: - Waypoint (None, Left, Right, Forward) - Input Light (Green, Red) - Input Left (None, Left, Right, Forward) - Input Right (None, Left, Right, Forward) - Input Oncoming (None, Left, Right, Forward)

If the waypoint is None, no action is taken and hence the learning of the states will be penalised. Hence the total number of states will be:

3 x 2 x 4 x 4 x 4 = 384 states

1.5.5 Update the Driving Agent State

For your second implementation, navigate to the `'build_state()'` agent function. With the justification you've provided in **Question 4**, you will now set the `'state'` variable to a tuple of all the features necessary for Q-Learning. Confirm your driving agent is updating its state by running the agent file and simulation briefly and note whether the state is displaying. If the visual simulation is used, confirm that the updated state corresponds with what is seen in the simulation.

Note: Remember to reset simulation flags to their default setting when making this observation!

Agent state tuple updated. The simulation is running as per before and the states are getting displayed in the PyGames window for each trial.

the final state is chosen to be: (waypoint, input signal light, input left, input right, input oncoming)

The deadline is not chosen because it reduces the choice of best Q-value selection and is not appropriate as deadlines are not representing the actions in terms of what turns or decisions to be made.

1.6 Implement a Q-Learning Driving Agent

The third step to creating an optimized Q-Learning agent is to begin implementing the functionality of Q-Learning itself. The concept of Q-Learning is fairly straightforward: For every state the agent visits, create an entry in the Q-table for all state-action pairs available. Then, when the agent encounters a state and performs an action, update the Q-value associated with that state-action pair based on the reward received and the iterative update rule implemented. Of course, additional benefits come from Q-Learning, such that we can have the agent choose the *best* action for each state based on the Q-values of each state-action pair possible. For this project, you will be implementing a *decaying, ϵ-greedy* Q-learning algorithm with *no* discount factor. Follow the implementation instructions under each **TODO** in the agent functions.

Note that the agent attribute `self.Q` is a dictionary: This is how the Q-table will be formed. Each state will be a key of the `self.Q` dictionary, and each value will then be another dictionary that holds the *action* and *Q-value*. Here is an example:

```
{ 'state-1': {
    'action-1' : Qvalue-1,
    'action-2' : Qvalue-2,
     ...
   },
  'state-2': {
    'action-1' : Qvalue-1,
     ...
   },
   ...
}
```