Training a smartcab with q-learning

April 13, 2016

0.1 Implement a basic driving agent

In your report, mention what you see in the agent's behavior. Does it eventually make it to the target location?

When I set the agent to choose a random action, it travels around randomly, disobeying road rules and running through red lights. It eventually does make the destination. I would call this a behaviour highly explorative.

0.2 Identify and update state

Justify why you picked these set of states, and how they model the agent and its environment.

I initially selected a large state space that used all available information. This included - Light color - Car direction at each intersection - Next waypoint - Deadline

This state space has more information than is required for the agent to work sufficiently, so I refined it. Firstly I dropped the deadline as it has the largest impact on the state space size, and then I refined which information that I needed from the intersection traffic. The state space became - Light color - Oncoming car going forward - Oncoming car turning left - Next waypoint

This state space has enough information to model the world, including the give way rules, which I soon found out were not implememnted, and so I refined the state space further to it's canonical form. - Light color - Next waypoint

0.3 Implement Q-Learning

What changes do you notice in the agent's behavior?

I implemented q-learning and made the agent chose the action that correlated with the highest q-value in the state. I notice that the agent would quickly fall into a local minimum of doing the same action, which was either "do nothing" or "turn right". Each of those actions would give a reward of one in all situations.

0.4 Enhance the driving agent

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?

Overall the agent performs very well. The q-values will normally converge to an optimal policy within 5 trials, which will only be disrupted by the randomness built into the action choice. I mitigated this by enforcing no random action will happen after 70% of trials have been run.

I used a number of techniques to enhance the agent from it's previous state.

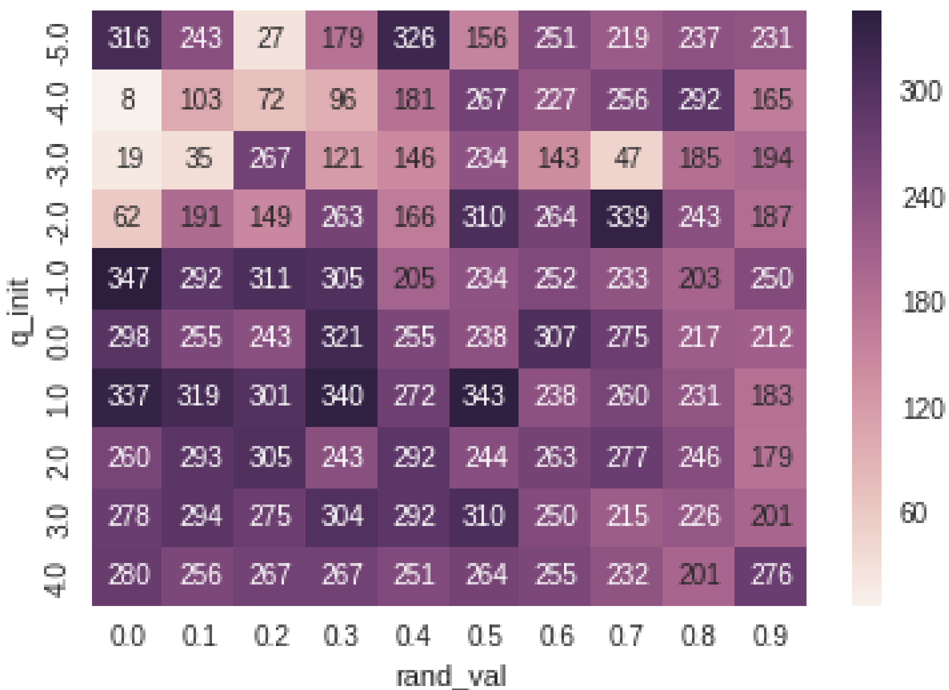
To make the agent explore, I changed the way the state space was initialised. I set all new states to have a high q-value which makes the space highly explorable. I chose this initial value to be 2 after trying lower and higher values.

To make help the agent out of local minimums I added a randomness factor when chosing an action. This had the desired effect and the agent would no longer get stuck choosing the same response over and over. I set the random percentage to 20%

After tring a number of gamma and learing_rates I chose a gamma of 0.2 and learning rate of 0.1.

```
In [13]: import pandas as pd
         import numpy as np
         %matplotlib inline
         import seaborn as sns

         def show_heatmap(filename, columns):
             df = pd.read_csv(filename, header=None)
             df.columns=columns
             df2 = df.pivot(index=columns[0], columns=columns[1], values=columns[2])
             sns.heatmap(df2, annot=True, fmt="d")
         show_heatmap("results.csv", ["q_init", "rand_val", "res"])
```



Variable tuning

In order to enhance the agent, I undertook parameter tuning by iterating over a number of variables. The graph above shows the total rewards after 50 trials varying the following 2 variables; - q_init : the initial value for all q states - rand_val : the chance of choosing a random action.

The plot shows high rewards scores within the ranges -1.0 < q_init =< 1.0 and 0.0 < rand_val =< 0.4. The plot shows especially poor learning when q_init < -1.0 and rand_val < 0.4, which is consistant with the agent getting stuck in a local minimum with no way out.