

MLEND Capstone Project: Training a Smartcab Planner

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1 Definition

1.1 Project Overview

In Project 4 of Udacity’s Machine Learning Engineer Nanodegree, I had to teach a smartcab in grid-like world how to get to a destination on time by obeying traffic rules and following the directions passed by a planner. Without any kind of hard programming, the agent should learn right-of-way rules and to go straight when the planner sent a ”forward” input, for instance.

A natural extension of this project is, instead of relying on an outside planner, coming up with an agent that, given the smartcab’s location and destination, learns how to plan a route. This is the goal of my capstone project.

1.2 Problem Statement

The problem at hand is to program an agent that learns to identify what the next waypoint should be for a smartcab in a grid-like world to reach its destination as fast as possible. I’ll use an 8×6 grid for the project, similar to the one used for the Nanodegree Project 4, but in principle the solution should apply to a grid of any size.

1.3 Metrics

The goal of the planner is to come up with the best possible action for the smartcab at all times. As we will see, it is not hard to write a planner that always comes up with the best next waypoint (not taking into account eventualities such as red lights or traffic jams). I’ll present such a ”perfect planner” in the Benchmark section below. The main metric I’ll use to evaluate my learning agent, then, is the **rate of agreement** with the perfect planner.

However, it is possible that a learning agent will come up with a different action that is just as good, or even better, than a ”perfect planner” would. Therefore, I’ll also keep track of metrics such as the number of steps needed for the planner to reach the deadline (again disconsidering the possibility of red lights or traffic; i.e., the agent will always be able to move), and also, more generally, the number of destinations reached.

Finally, I’ll also keep track of the sum of rewards received by the agent. However, as we’ll see in the Algorithm and Techniques section below, the rewards are just a means to an end: they exist to get the agent to learn the desired behavior, and its accumulation only matters inasmuch as it helps with this goal.

2 Analysis

2.1 Input Space Description

In Project 4 of Udacity’s Machine Learning nanodegree, the world in which the smartcab existed was represented by a graphical 8×6 grid rendered in Pygame. I’ll use an image of that world in the next section, but for now I’ll describe the problem’s input space abstractly.

In the grid-like world of the smartcab, each position is defined by an (i, j) tuple, in which i is the longitude (the position across the East-West axis) and j is the latitude (the position across the North-South axis). In a $m \times n$ grid, $(1, 1)$ represents the northwesternmost position, while (m, n) represents the southeasternmost position.

The goal, then, is that, given a position tuple (i_{cab}, j_{cab}) , a destination tuple (i_{dest}, j_{dest}) , and a heading (described below), the planner should be able to come up with the best next action for the smartcab: forward, right, or left.

The results of an action taken by the smartcab depends on its heading. The heading is a tuple (i_{head}, j_{head}) , whose items represent East-West heading and North-South heading, respectively. The heading tuple must obey the following rules to be valid:

1. The value of a tuple element indicates how the smartcab will move along the element's axis if it moves forward. This value can be either -1, 1, or 0.
2. If the first element of the tuple is non-zero, the second element is zero and vice-versa. (This means the smartcab can only be headed in one direction at a time.)

From these rules we can surmise there are four valid headings: $\{(1, 0), (-1, 0), (0, 1), (0, -1)\}$. These headings indicate the smartcab is turned East, West, South, and North, respectively.

Therefore, if the smartcab is at position (i_{cab}, j_{cab}) and moves forward, at the next step it will be at position $(i_{cab} + i_{head}, j_{cab} + j_{head})$ - with an important exception: the grid world is *toroidal*, which means going "over the border" will bring the smartcab to the other side. If the smartcab is headed East at the eastnorthernmost position $(8, 1)$ in an 8×6 grid, for instance, moving forward will bring it to the westnorthernmost position $(1, 1)$. The more general formula for the smartcab's position at the next step after moving forward is therefore **COMPLETE**

2.2 Exploratory Visualization

2.3 Algorithm and Techniques

2.4 Benchmark

3 Methodology

3.1 Data Preprocessing

3.2 Implementation

3.3 Refinement

4 Results

4.1 Model Evaluation and Validation

4.2 Justification

5 Conclusion

5.1 Free-Form Visualization

5.2 Reflection

Does agent consider if it's easier to turn right or left (or go forward)?

5.3 Improvement

Improvement: put planner and smartcab together to learn how to play around traffic or red lights
Improvement: modify get_distance code to consider modular arithmetics *Modification: what if the grid world is not toroidal?*