ARTIFICIAL INTELLIGENCE: Final project assignment

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An AI-powered solution to control the traffic flux in an intersection.

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# Executive summary

## The problem

This project is designed to **efficiently control the traffic flux in an intersection by operating three traffic lights.** Using sensors in each of the streets that conform the intersection – west, north and east – we can detect if the traffic flux level on each of them is either high or low, giving us a total of eight different possible states. Through an analysis of historical data gathered for roughly 48 hours, we deduce that turning on and off each of the green lights affects the traffic flux of each road, so it follows that **there must be an optimal choice for which light to turn green on each case.**

## The solution

These optimal choices are what we strived, and managed, to find through modelling an automaton to control this problem with a **Markov decision process** (MDP). This MDP receives the probability of each transition via transition tables obtained by previously processed historical data and **tells the automaton** **which action to take given one of the eight states**, namely, the optimal policy for it.

## The value and importance of our solution

**Our automaton provides a solution that a human is unable to.** When deciding on which traffic light to turn green, a human may be tempted to simply turn on the most crowded direction’s corresponding green light, but this isn’t always the best choice – as proved by the historical data, there is even a chance that turning a green light on may increase the traffic flux of that direction rather than decrease it.

Artificial Intelligence is undoubtedly the best approach to this problem, free from human error, learning from data gathered in the past and therefore always making the optimal decision.

# Objectives

Our goal when developing this project was to **find the best course of action** (optimal policy) given the state of the traffic flux and have our controller apply it until we reach a low traffic level on every direction of the intersection (our goal state).

The objective was also to make this solution **easily adjustable** to any other intersection, not just this one, which is why we converted each state and action to a number and defined modifiable constants for every number particular to our problem.

# Formal description of the AI model

A Markov decision process consists of four basic elements: states, actions, transitions and rewards.

## States

We have three different directions: west, north and east. Each of these directions can be in a state of high or low traffic flux. This leaves us with a total of 23 possible states:

|  |  |  |  |
| --- | --- | --- | --- |
| **Low, Low, Low** | Low, Low, High | Low, High, Low | Low, High, High |
| High, Low, Low | High, Low, High | High, High, Low | High, High, High |

Where the first traffic level corresponds to the west road, the second one is the north road and the third one is the east road.

State *Low, Low, Low* constitutes our goal state, that is, it is the state we wish to be in and where our AI will stop execution.

## Actions

The MDP may take one of three actions:

|  |  |  |
| --- | --- | --- |
| Turn on the **west** green light | Turn on the **north** green light | Turn on the **east** green light |

## Transitions

A priori, it may seem like we have a total of 8 \* 3 \* 8 = 192 possible transitions from every state to every other state. However, some of these transitions do not appear on our historical data and therefore have probability 0 of happening. These are impossible transitions, such as starting at *Low, Low, Low* and going to any other state. Eliminating these 123 impossible transitions, we end up with a total of 69 possible transitions.

The probability of every transition is easily accessible by just using the data stored in the 3-dimensional array *T*. Its usage is explained in the source code.

## Rewards

For the reward function, we will use the cost of each action. Since they are traffic lights and we gather the data every 20 seconds, we consider the cost to be uniform and equal to the amount of time (in seconds) that we will be committed to this decision until we receive a new state and the MDP can make a choice again.

|  |  |  |
| --- | --- | --- |
| **Cost of WEST** | **Cost of NORTH** | **Cost of EAST** |
| 20 | 20 | 20 |

## Graphical representation



# Methodology

In order to design this MDP and find the optimal policies, we followed the usual steps:

1. An analysis of the problem and identified which states, actions, transitions and rewards we needed.
2. Formal definitions of each of these elements.
3. Definition of the Bellman equations in order to update the expected value of each of the states.
4. Value iteration to find the convergent expected value of every state.
5. Finding which policy was optimal for each of them.

The dimensions of this problem were too big to manually design this automaton, so we used a Python program to help us manage this data. The development of this code is detailed in its own section.

# Resources used

We chose to use Python to write the code that assisted us in designing the MDP because of its easy portability and versatility. Additionally, we used the library *difflib* to make our automaton immune to human errors when transcribing the historical data fed to it.

In order to graphically represent the MDP as an automaton, we used the free Java-based software *JFLAP*.

On a more theoretical note, we used concepts from the book *Artificial Intelligence: A Modern Approach* by Stuart J. Russell and Peter Norvig.

# Development

To start with, we had to **analyze the problem** to determine the way we wanted to approach and model it. We quickly identified the historical data provided to us as a way to determine which transitions happened on each state and with what frequency, so we had found the source for our probability table.

In order to **extract probabilities from the historical data**, we coded an algorithm that reads each of the lines, parses them in a state-action-new state scheme, translates this into a three-digit code identifying them and adds one more instance of this transition to a **3-dimensional array where we will store the probability** (assigned using the rule of equally likely events). The code translation is more than direct string comparison, as we assumed that some problems may arise with a stiff method like that and the algorithm would collapse due to typographical errors, data corruption or invisible characters appearing when converting data, so we used the function *difflib.get\_close\_matches()* for a **more refined and flexible way of identifying each state** with its numerical code.

Once the probabilities are found, we **found the Bellman equations in order to find the expected value** of each of the states. To do this, we developed the **function *bellman()*,** which takes the current state and previous values as arguments (and the array of possible states and actions, but this is to generalize the problem as stated in the previous section on the objectives of this project) and outputs the next expected value of the given current state, with a precision of six decimal places.

In order to **find the optimal policy for each of the states, we had to perform the value iteration algorithm** until the values converged, i.e., the last two iterations were identical. This gave us the expected values of all eight states. When plugging these into the Bellman equations, we can find the action that gives us the minimal expected value on each of them, and that action is, by definition, the optimal policy for that state.

# Results

Here, we will explain some questions that may arise with this problem and our proposed solution.

## Question 1

The input data does not include any cases where the starting situation was low traffic level in all three directions. Is this normal? If you had this kind of data, what would happen or what should we have done?

If the starting situation is *Low* in all three directions, that is our goal state. It is logical that no data exists where this was the starting situation. Our AI stops execution when this happens.

Were we to have encountered this kind of data, we would have to interpret is as the most likely states to appear and restart the AI after the traffic is stabilized. Also, we would have to note the most common action among the transitions starting on *LLL* as the worst possible action to take after the traffic is stabilized.

## Question 2

The statement does not say anything about the cost of the actions. What reasonable assumption could we make?

As specified in the section on rewards in the section detailing the formal description of the AI model, we have assumed the cost is uniform, as turning on any of the green lights has equal cost. We have considered a time cost, however, and that is the time that we are committed to each of the decisions that our MDP makes at any given time, 20 seconds.

## Question 3

What are the expected values of the states? Provide the values to six decimal places. The precision must be greater than one thousandth.

The values obtained and stored in the array *value\_iterations* are as follows:

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | *0* | *1* | *2* | *3* | *4* | *5* | *6* | ***7, 8, …, ∞*** |
| *LLL* | **0** | **0** | **0** | **0** | **0** | **0** | **0** | **0** |
| *LLH* | 0 | 20 | 20.771770 | 20.804715 | 20.806184 | 20.806250 | 20.806253 | **20.806254** |
| *LHL* | 0 | 20 | 20.881047 | 20.920119 | 20.921875 | 20.921955 | 20.921958 | **20.921959** |
| *LHH* | 0 | 20 | 20.937962 | 20.981951 | 20.984014 | 20.984111 | 20.984115 | **20.984116** |
| *HLL* | 0 | 20 | 20.785430 | 20.819108 | 20.820604 | 20.820672 | **20.820675** | **20.820675** |
| *HLH* | 0 | 20 | 20.915196 | 20.957076 | 20.958992 | 20.959080 | **20.959084** | **20.959084** |
| *HHL* | 0 | 20 | 20.924303 | 20.965687 | 20.967550 | 20.967634 | **20.967638** | **20.967638** |
| *HHH* | 0 | 20 | 20.937962 | 20.981746 | 20.983763 | 20.983855 | **20.983860** | **20.983860** |

Where the rightmost column is the final expected value of each state. Six to seven iterations were needed for this value to converge, depending on the state, except for the goal state *LLL* which, by definition, has an expected value of 0 on all iterations.

## Question 4

What are the expected values of the states? Provide the values to six decimal places. The precision must be greater than one thousandth.

The optimal policy obtained for each of the eight possible states in this problem as stored in the dictionary *{op}* are as follows:

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **State** | *LLL* | *LLH* | *LHL* | *LHH* | *HLL* | *HLH* | *HHL* | *HHH* |
| **Optimal policy** | Undefined | West | East | North | North | East | East | West |

The optimal policy for the goal state is undefined, as we do not need to take any actions once we arrive to it.

## Question 5

If we had also had incoming traffic from the South and for each direction we had measured traffic at 5 levels instead of 2, what would have changed in the problem?

For starters, we would have had 54 = 624 different possible states, which would have made the problem much more complicated but also our solution more refined thanks to the more detailed information that those five traffic levels would have given us.

The introduction of three more traffic levels (hypothetically: *Low*, *Low-Mid*, *Mid*, *Mid-High*, *High*) could also help us adjust what we consider to be a “good” level of traffic. We could determine that *Low* and *Low-Mid* are both acceptable traffic levels or we could be stricter and only accept *Low*.

Additionally, assuming the involvement of a fourth direction, south, would also give us a fourth traffic light, this would give us a new action to take: turning on the southern green light, and a total of 624 \* 4 \* 624 = 1,557,504 different transitions a priori.

# Conclusions

This project proved to be a very interesting look on how artificial intelligence can be applied to optimize problems in our daily life. We had a lot of freedom to find a solution, which was **both an engaging and a daunting aspect.** Engaging because we had the opportunity to put our abilities and knowledge of artificial intelligence development to the test, but daunting because this was the first time we had to apply it to coding.

We didn’t have any **experience working with CSV files**, so we had to research them and develop a way of processing the historical data. We considered importing the *csv* library, but ultimately decided to code our own algorithm so that we could have more control over it and adjust it perfectly to the type of problem we were facing.

The **amount of data** was also much bigger than what we were used to working with, as were the number of states and, consequentially, the number of transitions, but after a lot of testing and rewriting the code, we learned to manage them.

Initially, we planned to manually identify each of the transitions, but after realizing that there were almost two hundred of them, we realized we had to **find a way to reduce the number** of *if* statements used to identify them. That is when we came up with the code system we ended up using, which restructures the identification problem into three separate identifications rather than a combination of all three. This gave us 8 + 3 + 8 = 19 possible identifications, less than a tenth of the original plan, and fit nicely with the 3-D matrix we intended to use as a probability table.

After that, we simply implemented ways to apply the methods we use to design MDPs and find optimal policies. The main difficulty on this step was our **lack of experience with Python,** accentuated by the fact this was the first time we had to code to solve this kind of problem. We researched multidimensional arrays, the use of *continue*, library usage, file management and string manipulation, all concepts we already knew from working with MATLAB or C/C++, but not Python, which we have been learning this same semester.