COMP9900 Assignment 2

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1 Introduction

Resources are scarce, finite, and difficult to produce. Whether it be human labour, or building materials for a construction project; these resources have extremely long supply chains for manipulating raw materials to useful assets. When the production of resources is so costly, we must endeavour to make the best use of them as possible; that is to say, we must strive to be as efficient as possible with the resources at hand.

For decades we have taken for granted the production of electricity; powering our buildings, hospitals and our economy. Our growth as a society, and even as a species, hinges on our access to power. The more we have, the more we can grow. It is often the fundamental unit underpinning all other manufacturing – everything needs energy to be produced and that more often than not comes in the form of power.

It is only recently in human history that a single individual has been able to change the world. Millenia would pass with no real technological advancement, where no single person could make a real difference to the state of the world. Hunter Gatherer's would hunt and gather, and hunt and gather and so on, without having the luxury of time to spend improving their situation. As we settled and began our ventures into agriculture, we enabled people to have more time. Using this time, we have taken leaps and bounds on the historical scale, towards human betterment. But it all started with allowing people to have more time. Never before has our time meant so much, both, to the individual and to society as a whole. Many hands make light work, as the saying goes.

To be successful in our drive towards human well being we must be highly efficient in in how we use our resources, especially time and power. This will allow us to reach higher states on the Kardeshev scale[1], becoming perhaps the first interplanetary species.

Our advancement has yielded a plethora of new technologies in our quest for growth and progress. The rise of Artificial Intelligence offers significant promise in many areas of life; optimisation

[1] https://en.wikipedia.org/wiki/Kardashev_scale

problems, image recognition, natural language processing and automation are among the most mainstream of applications. This report aims to focus on the first of these, optimisation problems, as applied to power consumption and productivity in buildings. A probabilistic graphical model will be used to toggle lights on and off with the aim of minimising the overall cost, both in terms of electricity and in lost productivity.

First we will discuss the methodology and assumptions of the approach taken. Then the algorithms used will be presented, followed by a brief description of their running time complexity.

2 Approach

When considering this problem, the cost specification should be front of mind. Given that the cost of electricity is approximately $0.04\frac{\$}{min \cdot room}$ and the cost of lost productivity is $0.16\frac{\$}{min \cdot person}$ its clear that time is considered a more valuable resource.

In the best case scenario (apart from the case where no one comes to work that day), all people will be in one room and the model will toggle all of the other lights off. Assuming the cost is constant, we can calculate the total cost for one day, where one day is defined as being 10 hours long, as follows:

$$cost = elec.cost\ per\ minute \times number\ of\ minutes\ in\ a\ day \times number\ of\ rooms\ being\ lit$$

$$cost = 0.04 * 600 * 1$$

$$cost = \$24$$

In the worst case scenario, the algorithm gets the toggle wrong and the people are left in the dark, and all of the other lights remain on. Here our cost becomes:

$$cost = number\ of\ minutes\ in\ a\ day \times (elec.cost\ per\ minute \times number\ of\ rooms\ being\ lit$$
$$+ productivity\ cost\ per\ minute \times number\ of\ people\ affected)$$

Assuming there are 20 or so people as per the specification, we have;

$$cost = 600 \cdot (0.04 * 34 + 0.16 * 20)$$

$$cost = \$2{,}736$$

Clearly these are the extreme cases. However, what this illustrates is that peoples productivity loss is the controlling factor of the cost. Knowing that there are strictly 35 total rooms, and a variable quantity of people, its important to the optimisation problem that we minimise the effects of lost productivity.

2.1 Methodology and Assumptions

Pragmatism is central to the approach taken. As specified in the project brief there are a number of unreliable sensors, and any of sensors can fail at any time. Given this, and with consideration to the worst case scenario analysis above, it was decided to use a Bayesian network that has disconnected trees within it. These can be thought of sub-networks. Each network is primarily focussed on predicting the presence or absence of people in a small subset of rooms, often only one. All other rooms are toggled on to minimise potential loss of productivity. The network structure can be viewed in the implementation file.

Each sensor, except for the robots, is the parent to one or more rooms. Extending the sensors to rooms further than their immediate location and adjacent rooms reduces the confidence of the model and risks incurring significant cost. The main idea is, unless the model is very confident about a particular room, we will leave the lights on.

Two approaches were tried to simplify the problem for the door sensors. The incoming sensor data reports an integer number of people passing through the door. The first approach was to strictly binarise the data – 0 detections maps to False, and more than 0 detections maps to True, where True and False indicate the presence of a person in a room. On the training data, this approach is reasonably accurate, with the worse performing prediction accuracy being 71.5%. and the best being 93.5%.

The alternate approach was to map odd, even and no detections to three different classes. The idea here was to try and capture the behaviour of someone walking into then out of a room (even case), or one person walking through one room to another. Its performance was comparable to the binary method, hence the binary approach was taken as it has a smaller outcome space which reduces computation.

For some locations, we can expand the network. A good example of this is the room 25, 26 and 27 cluster. There are two sensors, door sensor 3 and reliable sensor 3, in adjacent rooms, 25 and

26. Door sensors are worse predictors than the motion detectors, it proves beneficial to add the reliable sensor 3 as a parent to room 26's network.

The prediction is done from a simple MPE query lookup, where the largest value is taken. This was chosen as run time was an important consideration, and being able to use a lookup table is very efficient – especially when the network is small. The exception to this is when there exists a faulty sensor. In this case, we check all valid combinations of the parent variables, using what evidence is available, and select the most probable.

There is one exception to this approach; how the robot sensors are handled. The specification does not state that the robots have any error. There for it has been assumed that if there is any detection, we should leave the lights on, otherwise toggle them off.

3 Complexity Analysis

As the prediction is an MPE lookup, it runs in $O(1)$. However, it needs to run for every room, therefore it is linear in the number of rooms, giving $O(r)$. In the event that all of the sensors for a room fail, the outcome space for all sensors will need to be generated, finally giving $O(o_s r)$. One could include an additional factor for the simulation, but this has been omitted.

The construction and calculation of the Bayesian network is as discussed in assignment 1. I will repeat the explanation below:

> *Computing the probability tables runs in $O(O_{S_q} \prod_i^P O_{S_i}!)$ where O_{S_q} is the outcome space of the query variable and O_{S_i} is the outcome space i of a parent P. This illustrates why it is crucial to have sparse graphs, where each node is has as few parents as possible. Keeping outcome spaces small is also highly advantageous. Thus, learning the Bayes Net $O(V O_{S_q} \prod_i^P O_{S_i}!)$, where V […] the number of vertices in the the network.*