

# INFO8006: Project 3 - Report

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December 13, 2020

## 1 Bayes filter

- a. The observable evidence variables at time  $t$  are defined in this way for the ghost  $i$  :

$$NoisyDistance(i) = ManhattanDistance(ghost(i), Pacman) + Binom(n, p) - n * p$$

where:

- $NoisyDistance(i)$  corresponds to the observable evidence variable which is tracking the ghost  $i$  at time  $t$ .
  - $ManhattanDistance(ghost(i), Pacman)$  corresponds to the Manhattan distance between the ghost  $i$  and Pacman at time  $t$ .
  - $Binom(n, p)$  corresponds to a random variable following a binomial distribution with the given parameters  $n$  and  $p$ ,  $p = \frac{1}{2}$ , and  $n = \left\lceil \frac{sensor\_var}{p(1-p)} \right\rceil = \lceil 4 * sensor\_var \rceil$  with  $sensor\_var$  being the variance of the rusty sensor.
- b. The transition model  $P_a(X_t|X_{t-1}, g)$ , with  $a$  being a legal action taken in the state  $X_{t-1}$  and  $g$  being the type of ghost  $\in \{\text{confused, afraid, scared}\}$  is :

$$P_a(X_t|X_{t-1}, g) = \frac{\alpha(X_t, X_{t-1}, g)}{\sum_a \alpha(X_{t-1_a}, X_{t-1}, g)}$$

$$\text{with } \alpha(X_t, X_{t-1}, g) = \begin{cases} 8 & \text{if } g = \text{scared and } d(X_t, P) \geq d(X_{t-1}, P) \\ 2 & \text{if } g = \text{afraid and } d(X_t, P) \geq d(X_{t-1}, P) \\ 1 & \text{else} \end{cases}$$

where :

- $d(X_t, P)$  is the Manhattan distance between Pacman and the ghost at time  $t$ .
- $X_{t-1_a}$  is the state reached from the state  $X_{t-1}$  by performing the action  $a$ .

## 2 Implementation

- a. *Leave empty.*

## 3 Experiment

- a. The entropy of the probability distribution of Pacman's belief state is a measure which can summarize this belief state. The lower the computed entropy is, the better the belief state of Pacman is concentrated in cells of the maze. We chose to compute this entropy using logarithmic base 2 and using the `entropy` function from the `scipy.stats` library.

- b. To measure the quality of the belief state, we chose to take the sum of the Manhattan distances between each cell and the real position of the ghost weighted by the corresponding probability of the Pacman belief state :

$$Quality = \sum_{x,y} PacmanBeliefState(x,y) * ManhattanDistance((x,y), GhostPosition)$$

where:

- $PacmanBeliefState(x, y)$  corresponds to the probability given by Pacman's belief state about the cell with coordinates  $(x, y)$  in the maze.
- $ManhattanDistance((x,y), GhostPosition)$  corresponds to the Manhattan distance between the cell with coordinates  $(x, y)$  in the maze and the position of the ghost (in the real state of the game).

The lower is this quality measurement, the closer Pacman's belief state is from the real state of the game.

- c. We did our measurements on the two provided layouts using a mean based on 10 different runs of our filter with different seeds to ease reproducibility of our experiments. These measurements have been taken after 100 iterations to be sure that they had converged. These measures can be observed on Figures 1 and 2.

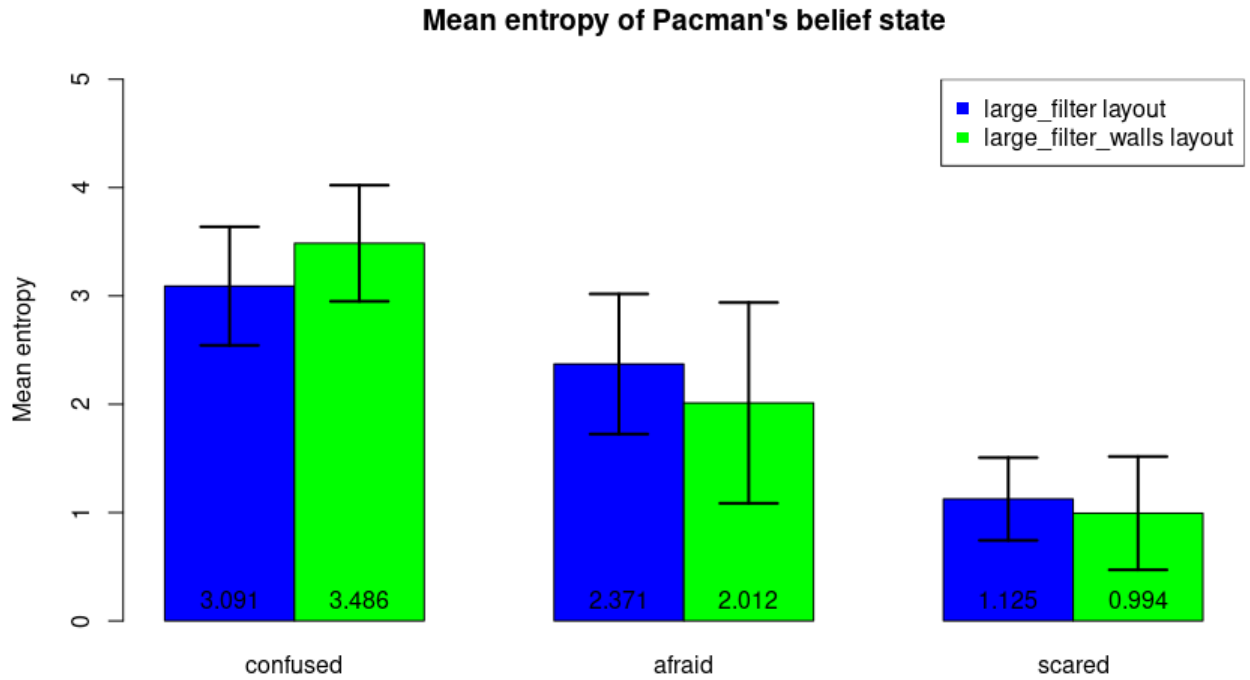


Figure 1: Mean entropy of Pacman's belief state over 10 different runs.

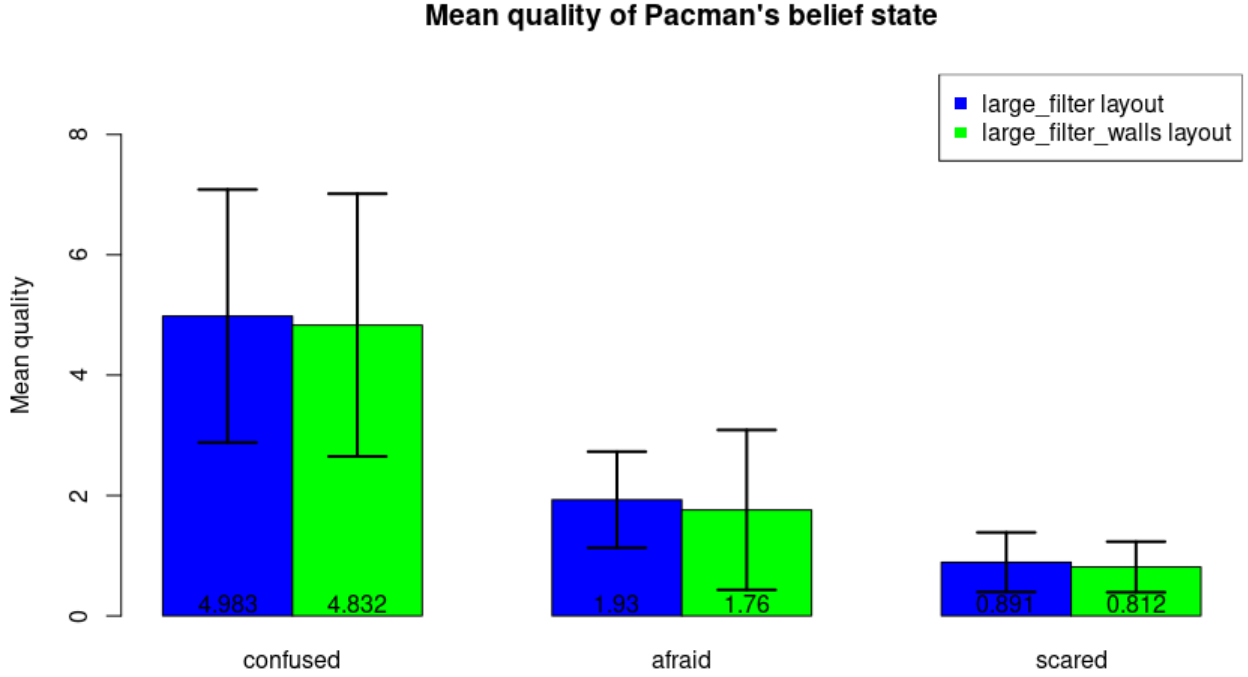


Figure 2: Mean quality of Pacman's belief state over 10 different runs.

- d. We can see, by using our measures and the model itself, that the values of Pacman's belief state are more concentrated in the maze with the scared than with the afraid which gives itself more concentrated values than with the confused ghost. It is because the probability to escape from Pacman is higher with the scared ghost than with the afraid ghost which has itself a higher probability than the confused one. Thus, they are reaching a corner of the maze and the probabilities representing Pacman's belief state are more concentrated in the maze : the entropy is lower. Moreover, we can see that, for the same reasons, the quality of Pacman's belief state is better with the afraid ghost than with the scared ghost which is itself of better quality than with the confused one. It can seem intuitive that with a more concentrated belief state (lower entropy), the belief state of Pacman is of better quality. In general, in the **large\_filter** layout, Pacman's belief state has a greater entropy and quality than in the **large\_filter\_walls** because, in this first layout, there are less walls than in the second layout. Indeed, walls are decreasing the Pacman's belief state entropy and so improving its quality.

- e. Reducing the variance of the sensor will reduce the noise in the distances between the ghosts and Pacman obtained from the sensor. This can be verified in a more mathematical way. We know that the noise is given by:

$$\text{noise} = \text{Binom}(n, p) - n * p$$

where  $n = \frac{\text{sensor\_variance}}{p^2}$  and  $p = 0.5$ . Thus, increasing the sensor\_variance will lead to bigger values for the noise. While reducing the sensor\_variance will lead to smaller values for the noise. So, the entropy of Pacman's belief state will be lower with a low sensor\_variance and of better quality.

- f. For each remaining ghost, we could only consider the cell which has the highest probability<sup>1</sup> of containing the ghost. Then, we compute the least cost path between Pacman and this cell recursively starting from

<sup>1</sup>If there are multiple cells that have the same highest probability of containing the ghost, we keep the one which is the closest to Pacman.

this cell, we play the first move of this path, and repeat this process at each iteration. Note that when we start to chase one ghost, we will keep chasing it until we ate it in order to save time. This will force Pacman to kill all the ghosts in a minimal number of moves which will increase the score of Pacman at the end of the game.

g. *Leave empty.*