Exercise 2: A Reactive Agent for the Pickup and Delivery Problem

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1 Problem Representation

1.1 Representation Description

Our state representation design is done by initialising a $N * N$ matrix, N being the number of cities in a topology as shown below. We initialise the diagonal of this matrix (S_{ij} with $i = j$) as having no package and being in city $i = j$. The rest (S_{ij} with $i \neq j$) are initialised as being in city i with a package destined to city j.

$$State = \begin{bmatrix} S_{11} & \dots & S_{1N} \\ \vdots & \ddots & \\ S_{N1} & & S_{NN} \end{bmatrix}$$

Our possible actions are designed by initialising an array of size $(N + 1)$ (considered a $1 * (N + 1)$ matrix), N still being the number of cities in a topology. We fill the first N values of the array with the list of cities in the topology, here the agent does not want to take a delivery and wants to move in city i thanks to action a_i. The final value of the array, a_{N+1}, is the action to take a delivery.

$$action = \begin{bmatrix} \underbrace{a_1 \quad a_2 \quad \dots \quad a_N}_{N \text{ cities}} & \underbrace{a_{N+1}}_{\text{Take Delivery}} \end{bmatrix}$$

Our reward table is designed with three cases. First of all, if the agent does not have a package and refuses to take a delivery, his reward is the negative of the distance to a neighbouring city (equation 1). Secondly, if the agent is looking for a package but no package is available in the city, his reward is also the negative of the distance to a neighbouring city (equation 1). Finally, if the agent does have a package and completes the delivery, his reward is the reward R_{ij} for a task that is transported from city i to city j, defined by the $TaskDistribution$, minus the distance between the destination city j and the previous city i (equation 2). We add an "infinite" negative reward for any other state/action combinations to avoid impossible situations. Note that for equations 1 and 2 we have coefficients $C \in \mathbb{R}$ to be determined during experiments.

$$Reward = -C \cdot Distance \quad (1) \qquad\qquad Reward = R_{task} - C \cdot Distance \quad (2)$$

Our probability transition table is designed as following. We notice that while in a state with no package in the city (S_{ij} with $i = j$), it is impossible to take the "Take Delivery" action (a_{N+1}). Therefore we give this combination a probability $p = 0$. It is also impossible to move to the same city, therefore action a_i while in state S_{ij} ($i \neq j$) is also impossible and therefore takes a probability $p = 0$. The other transition probabilities are obtained from the $TaskDistribution$ class.

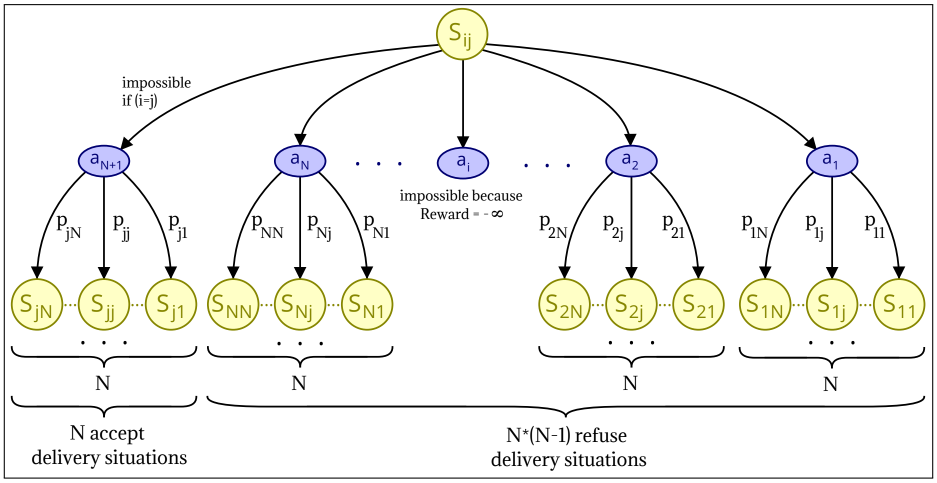


Figure 1: State-Action diagram with Probabilities ($i, j \in \mathbb{N}$ and $< N$, the number of cities in a topology)

1.2 Implementation Details

We created two additional classes for the implementation of our reactive agents: *StateObj* and *ActionObj* that represent the features of states and actions available. To implement the policy we use matrices (2D-array) that first we have initialised and then we have computed them following the algorithm given.

2 Results

2.1 Experiment 1: Discount factor

2.1.1 Setting

To see the influence of the discount factor we created a simulation with multiple agents with different discount factors from $\gamma = 0.1$ to $\gamma = 0.95$, with increments of 0.05 in between. Let's consider Reward per km to determine performance. Over multiple experiments placing the agents in different starting positions with different discount factors and a time of 20'000 clicks at $SimSpeed = 100$ we observe the following. (Note that all of this is done without changing the coefficient defined in part 1.1).

2.1.2 Observations

The best performing agent here has a discount factor of $\gamma = 0.9$ which will now consider our optimal discount factor. The Reward per km reaches a stable 66 as opposed to 63 for the lower performing agents.

2.2 Experiment 2: Coefficient determination

2.2.1 Setting

In our representation the reward follows equations 1 and 2 as described in part 1.1. We modify the coefficient C to different values, run the experiment for 5'000 clicks at $SimSpeed = 100$. We use $C_1 = 1$, $C_2 < 1$, $C_3 > 1$ and $C_4 >> 1$ and observe the following.

2.2.2 Observations

We can clearly see in Figure 2 that the reward per km increases with a high coefficient, and stays the same for values around 1. However the average profit decreases with a higher coefficient. This is because a high coefficient punishes long distances, therefore the agent values shorter journeys with lower rewards over longer journeys with higher rewards (average profit is around 3900 for low C and around 3400 for high C). If we are looking for a long term investment, a high Reward per km is more interesting. We hereby choose a coefficient $C = 70$ to get a Reward per km of around 90.

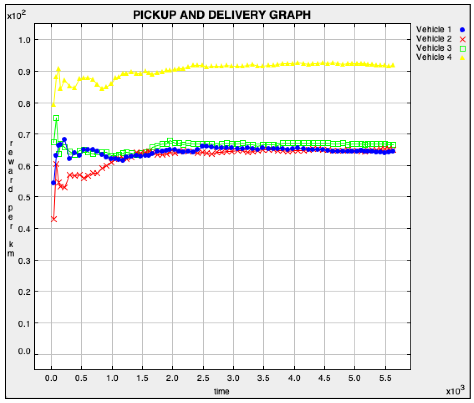


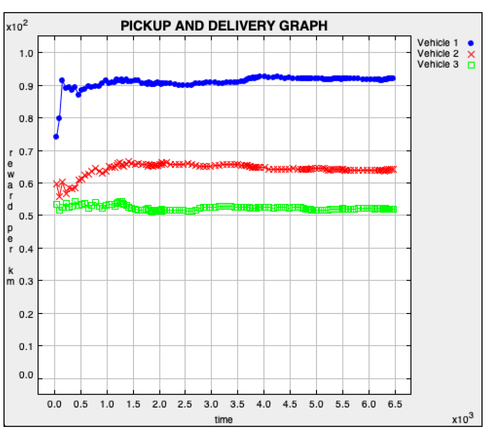
Figure 2: Reward per km as a function of time with vehicle 1 (blue): $C_1 = 1$, vehicle 2 (red): $C_2 < 1$, vehicle 3 (green): $C_3 > 1$ and vehicle 4 (yellow): $C_4 >> 1$

2.3 Experiment 3: Comparisons with dummy agents

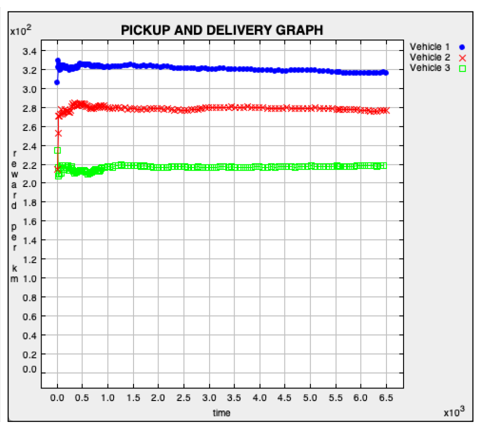
2.3.1 Setting

We use the random agent given, our reactive agent with $\gamma = 0.9$ and $C = 70$, and our dummy agent is a reactive agent with $\gamma = 0.5$ and $C = 1$. We observe the following for two topologies: France (Figure 3a) and England (Figure 3b).

2.3.2 Observations



(a) Topology: France



(b) Topology: England

Figure 3: Reward per km as a function of time with Reactive Agent (blue), Dummy Agent (Red), and Random Agent (green)

In all cases, our agent outperforms the dummy and the random.