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How hospitals response to disasters; a conceptual deep reinforcement learning approach

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Abstract

During a disaster the requests for using ambulance services increases. Efficient assignment of the ambulances leads to lowering the patients' travel time. Simulating these environments is very complex and needs a solid framework. This paper uses a Deep Reinforcement Learning approach to better schedule ambulance dispatch problem during those disasters. The concept of a call and assignment of ambulances are illustrated and the elements of states, rewards, and actions in the formulations are described. The algorithm steps for solving this problem are also presented. This paper can help disaster planners to have a better idea for better scheduling ambulances.

Introduction

In the disaster situation there is a need for public health service to transfer the patients facing an emergency situation. In the disaster situation, resources should be allocated differently and new policies should be used [1]. Sample of these situation is hospital responses to Covid-19 surge of the patients where hospital allocation needs a special allocation [2]. Another example is hospitals facing with cyber-attacks where the patients should be transferred to another healthcare until full recovery of the hospital [3]. These planning totally can improve regional capacity of the hospitals in response to disaster situation [4]. During the Covid-19 fever and cough increased and the request for ambulances increased. In this situation the pickup time of the patients are very important to serve patients efficiently.

Therefore, the problem of dispatching the ambulances plays a significant role in managing this situation. Previous researchers tried to address this problem. For example, some of them used a Multi-Agent Q-Network framework by reformulating the ambulance dispatch problem with a multi-agent reinforcement learning framework and designing a simulator to control ambulance status and produce patient's request [5].

In this paper we aim to provide a deep reinforcement learning approach using a deep q-learning framework to find the optimal planning of the ambulances. In other words, this research aims to lower the patients' pickup time by a deep reinforcement learning approach.

Method and materials

Deep reinforcement learning is an approach to dynamically optimize the problem while the agents try to take actions to maximize the rewards and minimize the costs and is used in different fields [6]. We use the method implemented in Investigating lake drought prevention using a DRL-based method which is illustrated in the next sessions [7]. In each time step, the agent uses a reward-maximization policy to lower the penalties. Figure1 shows the general framework for deep reinforcement learning (DRL) which is used in a variety of fields. This framework uses a trial-and-error approach to finding the strategies that maximize the objective function value. Figure 2 shows the component of a conceptual dispatching problem in which a Covid-19 patient calls 911 and requests an ambulance. Then agent in the ambulance station assesses the situation and assigns the ambulance to the patient and then transfers them to the hospital and returns to the ambulance center. In this network, the patients calling have several elements in their data structure including geographic status and urgency level of the calls. When a patient requests an ambulance 911 center should decide to assign which ambulance. The ambulance entity has information like geographic status and status which shows if the ambulance is free or not.

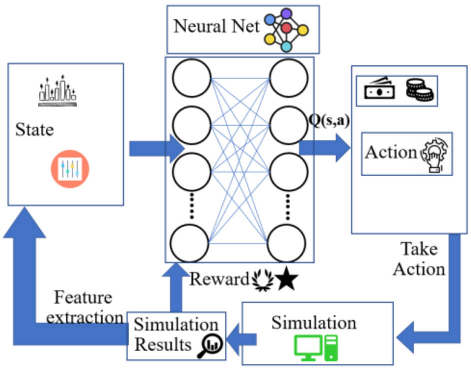

Figure 1. ……………..

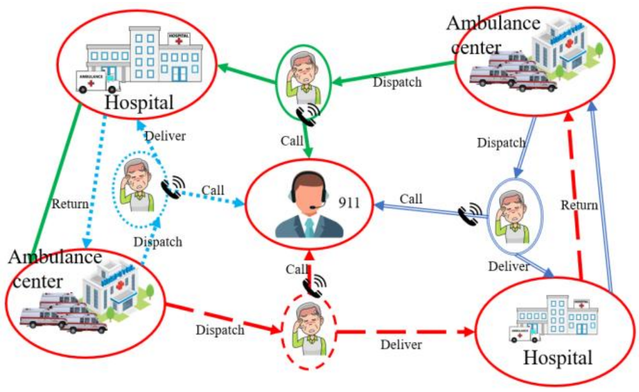

Figure 2. ……………..

Elements of deep Q-network

In a simple reinforcement learning the goal is to maximize the value function in a sequential decision-making process. But in the deep reinforcement learning approach, a deep neural network approximates the Q-Function and updates the buffer information. In this framework, the loss function is provided in the Equation 1.

$$L(\theta) = \left(\left(r + \gamma \max_{a_t+1} Q(s_{t+1}, a_{t+1}; \theta^{-})\right) - Q(s, a, \theta^{pred})\right)^2 \quad (1)$$

Where parameters $(s_t, a_t, \gamma_t s_{t+1})$ are random parameters which are selected from reply memory. Following algorithm shows psuedocode for solving this problem, where the Q-Values are estimatd by a deep nueral network approximation. In this algorithm and formulas, $Q(s,\theta')$ is the target network while $Q(s,\theta)$ is the current network. using $Q(s,\theta)$ the actions and $Q(s,\theta')$ is evaluated. In this algorithm steps 0-3 is initializatuion, spets 7-12 are experlearning steps, steps 7-12 are experience learning. In this algorithm step 5 and step 7 count episodes and steps respectively.

Algorithm 1: Training of the Deep Reinforcement algorithm

0 Inputs (Memory size, batch size, Episode and step numbers
1 Initialize parameters θ for the simulation
2 Initialize parameters θ' for the simulation
3 Initializing memory
4 **for** each episode:
5 **for** each simulation set:
6 *Actions and simulating */
7 **if** $random() < \varepsilon$ **then:**
8 Select a random action a:
9 **else**:
10 Select $a = max\ Q(s, a; \theta)$:
11 **end**
12 Get short-term reward R and new state s' by simulating action a;
13 Save state transition data (s, a, s', R);
/* Updating Q-network parameters*/
14 Sample batch state transition $\{(s, a, s', R)\}$;
if simulator terminated **then**:
$Q^* = R$
else:
$Q^* = R + \gamma\ max_{a'}\ Q(s', a';\ \theta)$
End
Use equation 1 to perform using gradient descent on the loss $L\ (\theta)$ based on Q^*;
end
End

In this algorithm the states are the times that the ambulances finnish their serices which are treatment or drop offthe patients. The actions are different options that the agent can use to go to the next steps. In other word the actions here are the stations or dispatch areas that ambulance finnish their work and stay for future work. The agent aims to minimize the time and distance between pispatch points and call points. The ambulance moves to the targe location with the specified speed to the location. Rewards in this algorithm is squared diference of the arrival time and dispatch time. In Equation 2, agent tries to get maximum rewards that can get from different actions:

$$R(s, a) = -(T_{Ar} - T_{Dis})^2 \quad (2)$$

Where T_{Ar} is the arrival time of ambulance and T_{Dis} is the dispatch time of the ambulnce. The agent tries to minimize the difference between these times.

Simulation

A reinforcement learning is used to find the optimal solution for this problem. The goal is to minimize the difference time between the request and the arrival time. the calls for ambulances are due to different reasons including accident, hearth attack, Covid-19 related calls. Call requests are time dependant and usually follow the daily traffic patern. The reason is probably due to increase in the accidents in the peak trafic periods. For simulating this problem python packages can be used. The learning part can be implemented using open source package named Pytorch. For the deep reenforcement learning section a neural network can be developed with some hidden layers and layers. The number of actions are equal to the number of the stations. First agent is trained over some episodes with a predifined buffer size and discount factor and learning rate. At the beginning of the simulation, the states, actions, rewards and next states are initialized to let the environment save the experiences for the future learning.

Conclusion

This paper provided a framework for an efficient ambulance dispatching problem using a Q-learning reinforcement algorithm. The elements of this simulation including actions, states, and rewards have been illustrated. The results reduce the time between the ambulance request and ambulance arrival time. The algorithm for solving this problem also has been presented.

Future works can extend this work by adding more realistic constraints to provide insights for hospital managers using a deep reinforcement learning approach. This research can help them plan ambulance scheduling in response to pandemics.

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