Research Article

Time-Driven Scheduling Based on Reinforcement Learning for Reasoning Tasks in Vehicle Edge Computing

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Received 19 October 2021; Revised 13 January 2022; Accepted 22 January 2022; Published 23 February 2022

Academic Editor: Chi-Hua Chen

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Significant challenges for reasoning tasks scheduling remain, including the selection of an optimal tasks-servers solution from the possible numerous combinations, due to the heterogeneous resources in edge environments and the complicated data dependencies in reasoning tasks. In this study, a time-driven scheduling strategy based on reinforcement learning (RL) for reasoning tasks in vehicle edge computing is designed. Firstly, the reasoning process of vehicle applications is abstracted as a model based on directed acyclic graphs. Secondly, the execution order of subtasks is defined according to the priority evaluation method. Finally, the optimal tasks-servers scheduling solution is chosen by Deep Q-learning (DQN). The extensive simulation experiments show that the proposed scheduling strategy can effectively reduce the completion delay of reasoning tasks. It performs better in algorithm convergence and runtime compared with the classic algorithms.

1. Introduction

In recent years, Internet of Vehicles (IoV) has become a research hotspot for the Intelligent Transportation System (ITS) [1]. The autonomous driving of IoV not only improves the driving safety, but also solves the problem of traffic inefficiency and lane congestion. It is a challenge for the autonomous driving to complete the target application under strict time constraint and restricted computing resources. The current work for autonomous driving mostly focuses on how to design the specific functions, such as traffic recognition, into reasoning tasks [2, 3]. Less attention is paid to how to schedule these reasoning tasks of autonomous driving to the appropriate computing nodes with low latency. Fortunately, IoV in Mobile Edge Computing (MEC) could schedule the real-time tasks from vehicles to the Road Side Units (RSU) with powerful computing resources, alleviating the task execution delay. Besides, a reasonable scheduling for reasoning tasks in MEC can effectively reduce both the execution latency of tasks and the workload of vehicles [4–11]. However, due to the heterogeneous resources in edge environments and the complicated data dependencies in reasoning tasks, significant challenges for reasoning tasks scheduling remain, including the selection of an optimal tasks-servers solution from the possible numerous combinations.

Existing studies are mainly done subject to task scheduling and task coordination through heuristic algorithms [12–15], such as Particle Swarm Optimization (PSO), Colony Algorithm (CA), and Genetic Algorithm (GA). Although these works could obtain the feasible solutions while satisfying different constraints, they fail to predict the deviation between the feasible and optimal solutions in advance, which makes their solutions easily fall into the local optimum. Several studies have been devoted to task scheduling using reinforcement learning (RL) algorithm [16–26], which can not only correct the deviation between the feasible and optimal solutions, but also accelerate the convergence of perfect results. Specifically, Lin et al. [23] proposed a time-driven scheduling strategy based on Q-learning algorithm for reasoning tasks of autonomous driving in IoV. The experimental results demonstrated that the performance of RL algorithms based on simulated annealing was better than other classic algorithms. This work...
is instructive for our work. Zhao et al. [20] put forward a distribution scheduling algorithm based on DQN to achieve the best balance between latency, computational rate, and energy consumption, for an edge access network of IoV. They prioritized the tasks of different vehicles according to the analytic hierarchy process (AHP). The experimental results showed that the average task processing delay of the proposed method could effectively improve the task offload efficiency. However, the priority between tasks has not been scientifically calculated and weighted, but only evaluated by experts based on their experience. The current work [27, 28] for priority evaluation is mostly subjective by experts. There are great achievements in multivehicle task collaborative scheduling [5, 7, 11, 20]. However, the time-driven scheduling for single-vehicle reasoning tasks with data dependencies is still an open issue.

In response to this issue, two research questions are considered: (1) how to design a model for the reasoning tasks with data dependencies to evaluate the latency caused by task execution and data transmission? (2) How to develop an efficient and reliable scheduling strategy to reduce the latency during vehicle driving? To solve the above questions, we design time-driven scheduling based on RL for reasoning tasks in vehicle edge computing, which considers the differences of heterogeneous real-time reasoning tasks and optimizes the completion latency of reasoning tasks.

The main contributions of this paper are concluded as follows:

(1) A latency model is designed for reasoning tasks with data dependencies, which considers the latency caused by task execution and data transmission.

(2) The scheduling for reasoning tasks in MEC is defined as a Markov Decision Process (MDP), which models the scheduling strategy for a reasoning task as the state, the resource allocation decision for each subtask as the action, and the completion latency of a reasoning task as the reward.

(3) A time-driven scheduling strategy based on DQN is designed to explore an optimal tasks-servers solution from the possible numerous combinations in vehicle edge computing.

The remaining part of the paper proceeds as follows. We review the related work in Section 2. Section 3 introduces the problem definitions of reasoning tasks scheduling. Section 4 describes the proposed reasoning tasks scheduling strategy in detail. Section 5 conducts the comparative experiments and analyzes the performance of the proposed strategy. Finally, Section 6 summarizes the work of this paper and looks forwards to the future research directions.

2. Related Work

Task scheduling in MEC has been extensively studied [4–10]. In general, task scheduling approaches mainly include the methods based on heuristic algorithms [12–15] and reinforcement learning [16–26].

2.1. Methods Based on Heuristic Algorithms. Xie et al. [12] proposed a novel Directional and Non-local-Convergent Particle Swarm Optimization (DNCPSO) to address workflow scheduling in cloud-edge environment, which could significantly reduce the execution time and energy consumption by optimally distributing tasks between mobile devices and servers. Lin et al. [15] proposed a linear-time rescheduling algorithm for the task migration in MCC environment. The algorithm started from a minimal-delay scheduling solution and subsequently performed energy reduction by migrating tasks among the local cores and the cloud.

The methods based on heuristic algorithms can easily fall into the local optimal solution, which usually fails to get a good result. Moreover, the time required to process reasoning tasks of IoV is usually strict. The methods based on heuristic algorithms are not suitable for such problem due to their long algorithm execution time.

2.2. Methods Based on Reinforcement Learning. To adapt the scheduling strategies for dynamic scenarios, Deep Reinforcement Learning (DRL) has been widely applied to the task scheduling problems in MEC systems in recent years. Chen et al. [16] designed a double DQN-based computation scheduling policy for a virtual MEC system. Numerical experiments showed that their proposed policy could achieve a significant improvement in computation scheduling performance. Xiong et al. [17] proposed an improved DQN algorithm to minimize the long-term weighted sum of average completion time of jobs and average number of requested resources in IoT edge computing system. Simulation results showed that the proposed algorithm has a better performance than the original DQN algorithm. Wang et al. [18] proposed a new DRL-based scheduling framework to address the challenges of task dependency and adapting to dynamic scenarios in the MEC system. The proposed DRL solution could automatically discover the common patterns behind various applications so as to infer an optimal scheduling policy in different scenarios. Bajpai et al. [21, 26] proposed four deep and RL-based scheduling approaches to automate the process of scheduling large-scale workloads onto cloud computing resources, while reducing both the resource consumption and task waiting time. These approaches derived an appropriate task scheduling mechanism that could minimize both tasks’ execution delay and cloud resources utilization. Qi et al. [22] firstly proposed a multitask DRL approach for scalable parallel task scheduling (MDTS) in IoV. For avoiding the curse of dimensionality when coping with complex parallel computing environments and jobs with diverse properties, they extended the action selection in DRL to a multitask decision, where the output branches of
multitask learning were fine-matched to parallel scheduling tasks. Huang et al. [24] proposed a DRL-based Online Offloading (DROO) framework to optimally adapt task scheduling decisions and wireless resource allocations to the time-varying wireless channel conditions in a wireless powered MEC network. Numerical results showed that the proposed framework could achieve near-optimal performance while significantly decreasing the computation time.

RL-based methods mostly assume that the scheduling problem is a learning task. Through preliminary training, an effective scheduling policy for the task can be quickly formed by a reasonable designed RL algorithm. Note that current work for IoV mostly focuses on multivehicle collaborative scheduling, but the time-driven scheduling for single-vehicle reasoning tasks with data dependencies is still an open issue.

3. Problem definition

Table 1 shows the notations used in this paper.

Figure 1 gives an example of reasoning tasks scheduling in vehicle edge computing. This example considers autonomous driving reasoning system [2, 3], which consists of applications such as emergency rule inference engine and security operations. The user equipment (UE) makes scheduling decision for those applications according to the data dependency relationship matrix as (3). If \( a_{x,y} = 1 \), it means that subtask \( n_x \) is offloaded to edge node \( m_x \); otherwise, it means that subtask \( n_x \) is executed locally. When the edge node is running normally, the execution latency of the reasoning tasks can be expressed by (4), where \( t_{\text{process}} \) means the processing latency of the reasoning tasks. If there is no available edge node in the edge environment, all subtasks will be executed serially on the vehicle, where \( m \) is set to 0. When the worst scheduling occurs, the completion latency of the reasoning tasks is described as in equation (5):

\[
\begin{align*}
\mathbf{A}_{m,x} = & \begin{cases} 1 & \ldots & a_{1,j} \\ \ldots & \ldots & \ldots \\ 0 & \ldots & a_{m,z} \end{cases} \\
 t_{\text{all}} = t_{\text{process}} + \max \left( t_{\text{transmission}} \right), \\
 t_{\text{worst}} = \sum_{i=0}^{z} i f_{\text{vehicle}}. 
\end{align*}
\]

To make better use of computing resources in different edge environments, we assume that edge nodes should satisfy the following processing principles:

(1) A subtask is processed by only one corresponding edge node, which is formally defined as (6).

(2) After all subtasks are assigned to the corresponding edge nodes, the edge nodes begin to process the subtasks.

(3) The subtasks on different edge nodes without data dependencies can be processed in parallel.

(4) The subtasks on the same edge node are processed according to the data dependencies. Otherwise, they are processed according to their corresponding priorities.

(5) The tolerable delay of the subtasks on the edge node is not greater than the execution latency of the corresponding edge node, which is formally defined as (7):

\[
\begin{align*}
\sum_{j=1}^{z} a_{x,y} & \leq 1, \\
t_{\text{transmission}}^i & \leq t_{\text{vehicle}}^i, \\
t_{\text{RSU}}^i & \leq t_{\text{vehicle}}^i. 
\end{align*}
\]
4. Algorithm Design

In this section, we first describe the priority evaluation for subtasks in a reasoning task, which is employed to determine the order of execution for the subtasks without data dependencies. And then give an overview of our proposed scheduling algorithm. Finally, we introduce the implementation of the scheduling algorithm in detail.

4.1. Priority Evaluation for Each Subtask. It is difficult to estimate the execution time of a reasoning task that defines the execution sequence of subtasks. Fuzzy analytic hierarchy process (FAHP) [27–29] is usually employed to analyze multiobjective problems, which decomposes the problem hierarchically according to its feature and overall goal, forming a bottom-up gradient hierarchy. In this work, FAHP is commonly used to measure the subtask weight, which can determine the order of execution for the subtasks without data dependencies. Each subtask weight is modified by calculating the information entropy of objective factors (i.e., each subtask’s own parameters) [30, 31]. The pseudocode of the priority evaluation for each subtask is described as follows:

\[ p_{i,j} = \begin{cases} 
0, & s_t < s_j, \\
0.5, & s_t = s_j, \\
1, & s_t > s_j, 
\end{cases} \]

\[ R = (r_{i,j})_{n \times n}, \quad r_{i,j} = r_{i,k} - r_{j,k} + 0.5, \]

Table 1: Notations and descriptions.

| Notation | Description |
|----------|-------------|
| A_{m \times n}, c_r, \text{data}_r, t'_d | A reasoning task, a set of subtasks, and the data dependencies between subtasks |
| t'_{\text{process}}, f_{\text{vehicle}}, f_{\text{RSU}}, t'_{\text{transmission}} | Computational scheduling plan for n tasks |
| t'_{\text{vehicle}}, t'_{\text{RSU}} | Task size, computation intensity, tolerable delay of subtask \( n_i \) |
| \text{Local computing capacity and scheduling capacity} | Computation latency in vehicle and RSU |
| \text{Transmission latency of subtasks} | Local computing capacity and scheduling capacity |
| \text{Completion latency of a reasoning task} | Transmission latency of subtasks |
| \text{State, action, and reward of an MDP at time step} \( t \) | State, action, and reward of an MDP at time step \( t \) |
| \alpha, \gamma | Parametrized policy and value function for computation scheduling |

Figure 1: An example of reasoning tasks scheduling in vehicle edge computing.

Figure 2: A reasoning task.
### 4.2. Scheduling Algorithm

MDP is a basic model of the RL in this paper. The scheduling algorithm can be simplified according to the MDP property, which means that the next state is only related to the current state as Figure 3. In Figure 3, each state represents a corresponding allocation strategy for real-time vehicle tasks in different edge environment and corresponds to a specific reward. Each action is calculated by the agent (neural network), and it is used to guide the current state to a better direction.

![Figure 3: The MDP model of scheduling algorithm.](image)

The model characteristics of the discussed problem in this paper are described as follows:

(1) **State space:** the number of states for the feasible solutions is not constant. They can change dynamically as the change of the number of subtasks after decomposition and the changed distribution of edge nodes in various time-slots.

(2) **Action space:** the number of optional actions in the action space is equal to the number of subtasks. Action selection means scheduling the corresponding subtasks in current state to the specific edge nodes.

(3) **Reward value:** this work tries to minimize the completion latency of the reasoning task, so the reward value is set to \( r_i = (1/t_{\text{all}}) \).

#### Algorithm 1: Priority evaluation for each subtask.

**Input:** computational complexity \( a_i \), the amount of data \( a_2 \), the tolerable delay \( a_3 \).

**Output:** the priority of subtask \( z \).

1. Sort subtask’s factor according to equation (9) and construct matrix \( P \).
2. For \( i \leftarrow 0 \) to maximum rows of \( P \) do
3. \( r_i = 0 \)
4. For \( j \leftarrow 0 \) to maximum columns of \( P \) do
5. \( r_i = r_i + p_{i,j} \)
6. End for
7. End for
8. \( u_j = 0 \)
9. For \( j \leftarrow 0 \) to maximum columns of \( R \) do
10. Update \( u_j \) via equation (13)
11. End for
12. \( w_i \) are transformed through equation (12) to obtain \( R \)
13. For \( i \leftarrow 0 \) to maximum rows of \( R \) do
14. \( w_i \) via equation (16)
15. End for
16. Calculate the information entropy \( \delta_i \) via equations (14) and (15)
17. \( z = w_{i1} \cdot a_1 + w_{i2} \cdot a_2 + w_{i3} \cdot a_3 \)

\[
\begin{align*}
    r_i & = \sum_{k=1}^{n} r_{i,k}, \quad i = 1, 2, \ldots, \alpha, \\
    r_{ij} & = \frac{r_i - r_j}{2 \cdot \alpha} + 0.5, \quad i = 1, 2, \ldots, \alpha, \\
    w_i & = \frac{\sum_{j=1}^{\alpha} r_{jk}}{\sum_{i=1}^{\alpha} \sum_{j=1}^{\alpha} r_{ij}} = \frac{2}{\alpha^2} \sum_{k=1}^{\alpha} r_{jk}, i = 1, 2, \ldots, \alpha, \\
    Y_{ij} & = \frac{\max(a_i) - a_{i,j}}{\max(a_i) - \min(a_i)}, \\
    \delta_i & = \frac{1}{\ln n} \sum_{j=1}^{\alpha} p_{ij} \ln p_{ij}, \quad 0 \leq \delta_i \leq 1, \\
    g_i & = \frac{1 - \delta_i}{\sum_{i=1}^{n} \delta_i}, \\
    w'_{i} & = \frac{w_i \cdot g_i}{\sum_{i=1}^{n} w_i \cdot g_i}.
\end{align*}
\]
The scheduling strategy is based on the DQN algorithm. It can be abstracted as a function fitting problem when the discrete tangent dimension of the state and action space are high. The pseudocode of our scheduling algorithm is described in Algorithm 2. where $a_k$ and $\gamma$ represent the learning rate and discount factor, respectively. $s'$ is the state after executing the action $a_i$ in the $k_{th}$ iteration. $d$ represents the action of the largest reward in state $s'$, and $R_k$ represents the accumulated reward during the iterations.

**Algorithm 2:** Scheduling algorithm.

The scheduling strategy is based on the DQN algorithm. It can be abstracted as a function fitting problem when the discrete tangent dimension of the state and action space are high. The pseudocode of our scheduling algorithm is described in Algorithm 2. where $a_k$ and $\gamma$ represent the learning rate and discount factor, respectively. $s'$ is the state after executing the action $a_i$ in the $k_{th}$ iteration. $d$ represents the action of the largest reward in state $s'$, and $R_k$ represents the accumulated reward during the iterations.

4.3. Algorithm Implementation. In various time-slots, reasoning tasks and edge environments can change dynamically. These changes are summarized as follows:

1. The topological structure of reasoning tasks and the number of nodes in edge environments
2. The computational complexity, the datasets between subtasks, and the tolerable delay of subtasks in various environments
3. The transmission latency and execution latency of subtasks

The algorithm implementation will calculate the completion latency of reasoning tasks in edge environments. The pseudocode of the algorithm implementation is described in Algorithm 3. Figure 4 presents the calculation process of execution latency, which includes the following steps.

Step 1: initiate the parameters of Algorithm 3, including the subtask queue $Q$ and the set of predecessor nodes R. Next, a reasoning task is expressed as a specific directed acyclic graph.

Step 2: $Q$ is used to sort the subtasks by the topology of the reasoning task.

Step 3: calculate the task execution time according to the specific strategy derived from Algorithm 2.

5. Simulation Experiment and Analysis

5.1. Experimental Parameter Settings. The simulation experiments are implemented with the Python 3.7 and conducted on a 64-bit Win10 system, which is configured with Inter(R) Core(TM)i7-7700HQ CPU and 16 GB RAM. Our proposed scheduling algorithm is DQN, and Q-learning algorithm [23] and GA-PSO [32] are introduced as the comparison algorithms. Based on the effects of adjusting parameters in many experiments, the corresponding parameters of DQN and Q-learning [23] are set as $\alpha = 0.005$, $\gamma = 0.9$, and $\epsilon = 0.9$. The corresponding parameters of GA-PSO [32] are set as $w_{max} = 0.9$, $w_{min} = 0.4$, $C_{1}^{start} = 0.9$, $C_{1}^{end} = 0.2$, $C_{2}^{start} = 0.9$, and $C_{2}^{end} = 0.4$. In addition, the number of rounds is set as 100 and the number of iterations is set as 1000 for DQN, Q-learning, and GA-PSO, respectively.

All the algorithms try to find the optimal scheduling result with the shortest completion latency of reasoning tasks in edge environments.

UEs have different reasoning tasks with various topologies and task number, and the topological structure of reasoning tasks is shown in Figure 5. The related parameters for the vehicle edge computing environment are set according to the IEEE 802.11p [33], and other parameters are set as Table 2.

5.2. Analysis of Results. Table 3 shows the completion latency of different reasoning tasks in various edge environments with our proposed scheduling algorithm, where $m$ and $n$ denote the number of edge nodes and subtasks in each experiment. Note that $n = 6$ corresponds to the "Topology I," $n = 9$ corresponds to the "Topology II," and $n = 12$ corresponds to the "Topology III" in Figure 5. Each grid in Table 3 corresponds to an experiment with different reasoning tasks with specific topologies and different edge nodes in edge environments. In addition, the execution order of subtasks is
Input: \( m_i, z_i, G_i, A_{z_i \times 3}, B_{m_i \times z_i}, H_{m_i \times z_i} \)

Output: \( t'_{m_i} \)

(1) **Initialization:** set the array \( I \), the subtask queue \( Q \) and the set of predecessor nodes \( R \) to \( \emptyset \)

(2) Use the constraint relationship \( G_i \) to set the array \( I(i) \)

(3) Enqueue the \( i \)th subtask with \( I(i) = 0 \) to \( Q \) and set the number of traversed subtasks \( u = 0 \), the number of subtasks in the current layer \( k \) to the current queue size

(4) while \( Q' = \emptyset \) do

(5) if \( u = k \) then

(6) \( u = 0 \), \( k = \text{size}(Q) \).

(7) end if

(8) The subtask is dequeued, and the task is expressed as \( v, u+1 \)

(9) for \( i \leftarrow 0 \) to \( z_i \) do

(10) if there exists a directed edge of \( v \) to \( i \) then

(11) Add the \( v \)th subtask and its predecessor node set \( R(v) \) to \( R(i) \)

(12) if \( I(i) = 0 \) then

(13) enqueue the \( i \)th subtask to \( Q \)

(14) end if

(15) end if

(16) end for

(17) end while

(18) According to \( B_{m_i \times z_i} \), the subtasks are assigned to edge nodes.

(19) **Initialization:** set the subtask completion list \( O \) to \( \emptyset \), set the remaining execution latency of subtasks \( Y \) by \( C_{m_i \times z_i} \), and set the current running time \( h = 0 \)

(20) while \( O < z_i \) do

(21) Determine the subtask to be assigned to each edge node, which satisfies the direct predecessor set is subset of \( O \)

(22) Find the minimum execution latency \( w \) from the currently executed subtasks in parallel

(23) \( Y(i) = w \), when \( Y(i) = 0 \), add the \( i \)th subtask to \( O \) and set \( h+1 = w \)

(24) end while

(25) return \( h \)

**Algorithm 3:** Algorithm implementation.

**Figure 4:** The calculation process of execution latency.
based on two rules: traditional rule and priority rule. Traditional rule executes the subtasks according to their corresponding topology depths [23] and priority rule executes the ones according to the priority evaluation for each subtask discussed in Section 4.1.

From Table 3, we find that the completion latency of reasoning tasks reduces as the number of edge nodes increases. Under the same circumstances, the priority rule for subtask execution can effectively reduce the completion latency of reasoning tasks compared to the traditional rule. However, the convergence performance of Q-learning will decrease as the topology complexity of reasoning tasks increases. The main reason for the different scheduling results with various algorithms is that the increase in the number of subtasks has brought about the multiplication of the number of solutions in searching space. For GA-PSO, finding the optimal solution mainly relies on randomness and fitness function. Therefore, when the number of feasible solutions in searching space is huge, GA-PSO is easy to fall into the local optimal solution. Q-learning is difficult to build the Q list and converge also due to the huge number of feasible solutions in searching space. However, DQN converts the Q list to the Q value function by neural network, which can solve the problem with a huge number of states (i.e., feasible solutions) and make it easier to converge.

Table 4 shows the average runtime (s) of different algorithms with different seasons in various edge environments. Each grid in Table 4 is the average of the runtime of 100 rounds for different algorithms. From Table 4, we find that the runtime of GA-PSO is relatively stable with different seasons in various edge environments. This is because that the runtime of GA-PSO mainly depends on
the number of particles used in the update process, which is relatively stable even if the edge environments change during the scheduling process. The average runtime of DQN and Q-learning is better than that of GA-PSO, and DQN performs best with different seasoning tasks in various edge environments. This is because the runtime of RL algorithms will decrease as the number of feasible solutions learned increases. In addition, the architecture of the neural network used in DQN is more suitable for reasoning tasks scheduling in vehicle edge computing, compared with the Q list used in Q-learning.

6. Conclusions

This paper proposes a scheduling strategy based on DQN for reasoning tasks in vehicle edge computing, which aims to reduce the completion latency of reasoning tasks. The extensive simulation experiments show that the proposed strategy can achieve the superior performance compared to other classic methods. Our strategy and other classic methods all perform well when the structure of reasoning tasks is simple, while GA-PSO has poor convergence. Specially, our strategy has better performance and convergence than any other classic methods when the structure of reasoning tasks is complex.

In the future, we will improve the scheduling algorithm through optimizing the training efficiency of the neural network to fit the wireless channel fluctuations and radio interference in vehicle edge computing. In addition, we will further consider a multivehicle collaborative scheduling strategy to alleviate uneven resources allocation for multi-vehicle tasks in edge environments.

Data Availability

The data used to support the findings of this study are included within the article.

Disclosure

This work was presented in part at the 2019 IEEE Intl Conf on Parallel and Distributed Processing with Applications (ISPA) with the title "A Time-Driven Workflow Scheduling Strategy for Reasoning Tasks of Autonomous Driving in Edge Environment."

Conflicts of Interest

The authors declare that they have no conflicts of interest.
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