On Participant Selection for Minimum Cost Participatory Urban Sensing with Guaranteed Quality of Information

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Abstract. Exploring vehicles to conduct participatory urban sensing has become an economic and efficient sensing paradigm to pursue the smart city vision. Intuitively, having more vehicles participate in one sensing task, higher quality-of-information (QoI) can be achieved. However, more participation also implies a higher sensing cost, which include the cost pay to participated vehicles and 3G traffic cost. This paper introduces an interesting problem on how to select an appropriate set of vehicles to minimize the sensing cost while guaranteeing the required QoI. In this paper, we define a new QoI metric called coverage ratio satisfaction (CRS) with the consideration of coverage from both temporary and spatial aspects. Based on the CRS definition, we formulate the minimum cost CRS guaranteeing problem as an integer linear problem and propose a participant selection strategy called Vehicles Participant Selection (VPS). The high efficiency of VPS is extensively validated by real trace based experiments.

Keywords: Vehicular sensor network · Quality-of-Information · Coverage Ratio Satisfaction · Vehicles Participant Selection

1 Introduction

Participatory sensing is first proposed in [1], which introduces the idea of collecting and sharing environment sensory data via smartphones. As one representative participatory sensing paradigm, vehicular sensor networks (VSNs) that explores moving vehicles are regarded as a promising city sensing solution and therefore have received much attention in the literature. VSNs can be used to obtain various urban life related information (e.g., air quality, noise level, temperature, etc.) using vehicle-equipped sensors. With the rapid development in vehicular networks and cellular communications, these sensory data can be collected at a central server for further data analysis to promote the urban life quality. Unlike traditional sensor networks, VSNs do not have strong energy, storage, processing and communication constraints. In addition, they are applicable to a wide range of data collection thanks to the node mobility.

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In this paper, we consider an application scenario shown in Fig. 1, where a set of vehicles randomly move in a urban area. Each vehicle is equipped with various sensors for data collection and a cellular communication module. Therefore, a vehicle can upload the collected data in real time. In order to ensure high quality-of-information (QoI), we shall ensure each sub-region is covered by a fixed amount of vehicles. Intuitively, more participants implies a higher QoI. However, this is at the expense of higher cost. For a task with given QoI requirement, there is no need to arbitrarily hire a large set of participants.

Our objective is to find a subset of participant vehicles whose coverage can best satisfy CRS metrics requirement of task in both temporal and spatial dimensions, and minimize the cost. The cost of task include two parts. One is the cost of selected vehicles, when a vehicle join the system, it will requires a reward, only satisfied, it will executes data collection task. The other is 3G network traffic costs, the more sensed data upload to server, the higher cost will cause.

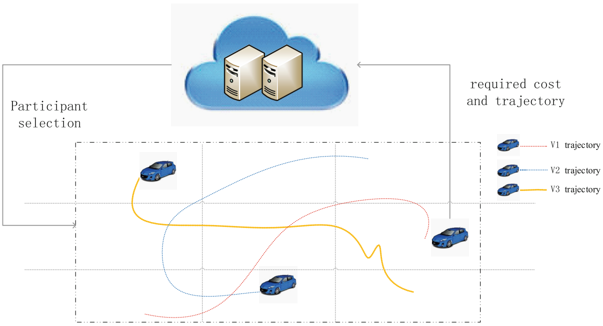

Fig. 1. The application scenario, the role of all vehicles are divided into three categories, The target area is divided into many sub-regions

The main contributions of the paper are as follows:

- We introduce the CRS metrics in terms of vehicular coverage, which is used to ensure each sub-region covered by amount of vehicles in each time slot, it can ensure the quality of monitoring task.
- Assuming knowing each users moving trajectory in advance, even though this assumption may not be realistic, the obtained solutions can be used to show potential data collection cost savings that can be brought by using collaborative sensing in the VSN, and can also serve as a benchmark for performance evaluation.
- We propose a participant selection strategy called VPS. The selected vehicles are selected based on a greedy algorithm that explicitly considers CRS metrics, and minimize the cost of the task.

The rest of the paper is organized as follows: In Sect. 2, we introduce the related research activities. Section 3 gives the system model and then formally defines the problem. In Sect. 4, we describe the details of our strategy. Evaluation results are presented in Sect. 5. The paper is concluded in Sect. 6.

2 Related Works

In this section, we discuss the related works on participatory sensing, which collected data using smartphones, and Vehicular Sensor Network.

2.1 Participatory Sensing

Participatory sensing using smartphones is a promosing method to enable the recently emerging software-defined sensing paradigm [2] as the sensing functions on smartphones can be freely customized according to the sensing needs. Many systems are designed to support data collected task with budget constraints. For Example, Z. Song et al. [3] was to find a subset of participants whose sensory data collection could best satisfy QoI requirements of multiple concurrent tasks in both temporal and spatial dimensions, with a constrained task budget. H. Xiong et al. [4] aimed to maximize the coverage quality of the sensing task while satisfying the incentive budget constraint. The object of this work is different from above works, and the definition of QoI is diffrent, too.

One of the most problem of participatory sensing with smartphones is energy constrain. In [5], Sheng et al. proposed to leverage cloud-assisted collaborative sensing to reduce sensing energy consumption for mobile phone sensing applications. In [6], Zhao et al. presented a novel fair energy-efficient allocation framework whose objective was characterized by min-max aggregate sensing time. In [7], Wang et al. proposed effSense - a novel energy-efficient and cost-effective data uploading framework leveraging the delay-tolerant mechanisms. In VSN, we will not consider the energy constrain.

2.2 Vehicular Sensor Network

Delay Tolerant Network has been widely studied [8–10], and Vehicular Sensor Network is a hot topic in it. There are a number of papers that studied monitoring task in Vehicular Sensor Network [11,12]. In [11], Devarakonda et al. presented a vehicular-based mobile approach for measuring fine-grained air quality in real-time. In [12], The objective of traffic monitoring was to achieve the traffic condition precisely and efficiently. In [13], the authors developed an efficient data collection algorithm capable of providing data redundancy elimination under network capacity constraints. In [14], Li et al. proposed a novel approach for mobile users to collect the network-wide data. In [15], Palazzi et al. presented a solution, based on vehicular sensor networks, for gathering data from a certain geographic area while satisfying with a specific delay bound. Though there are so many works have done in VSN, our work will solve the problem that select an appropriate set of vehicles to minimize the sensing cost from a different angle.

3 System Design

In this section, we introduce the system model used throughout this paper, including the system model related notations and the Coverage Ratio Satisfaction metrics.

3.1 System Model

In order to ensure the quality of monitoring task, we need to select a set of vehicles to participant in the task, which can satisfy CRS metrics requirement of task, while minimize the cost. We assume there exists a central server, a set of vehicles moving in Region $\mathcal{R}$ during time slot $\mathcal{T}$. The central server is used to select the vehicles based on our strategy and collect data. There are m participant vehicles denoted as $\mathcal{M} = \{V_1, V_2, ..., V_m\}$. We divide the target region into r sub-region, they are denoted as $\mathcal{R} = \{R_1, R_2, ..., R_r\}$. We divides the entire sensing period into a set of time slots and they are denoted as $\mathcal{T} = \{T_1, T_2, ..., T_t\}$. e_i^q denotes required cost by participant i for task q. On each virtual cube that is composed of a 2-D area and within a certain time slot, in order to ensure the quality of data collection in the task q, each sub-region should be covered by a certain number of vehicles in each time slot, the required amount of vehicles can be denoted as d_{rt}^q, $\forall r \in \mathcal{R}$, $\forall t \in \mathcal{T}$, which is given by the task publisher as a requirement. Only in each sub-region, the coverage are satisfied in each time slot, it means that the set of selected vehicles satisfy the requirement.

3.2 Coverage Ratio Satisfaction Metrics

In order to ensure the quality of information of data collection, we should make sure that each sub-region should be covered by a manageable number of vehicles. But how to estimate whether the quality of information of collected is good or not? In this section, we will solve this problem.

At first, we should know the task publisher's demand of vehicles to cover the sub-regions, we use $\mathcal{D}^q$ matrix to denote it, and d_{rt}^q,$\forall r \in \mathcal{R}$, $\forall t \in \mathcal{T}$ means the requirement amount of vehicles that cover sub-region r within time slot t for task q. Before the start of the task, each participant vehicle upload its trajectory to the central server, so we can know each vehicle's coverage and let matrix C_i^q denote the vehicle i's coverage, c_{irt}^q,$\forall i \in \mathcal{M}$, $\forall r \in \mathcal{R}$, $\forall t \in \mathcal{T}$, means vehicle i whether cover the sub-region r within a certain time slot t, where

$$c_{irt}^q = \begin{cases} 0, & \text{vehicle } i \text{ cannot cover sub-region } r \text{ within time slot } t \\ 1, & \text{otherwise} \end{cases} \tag{1}$$

When a set of vehicles are selected as SVs for task q, the subset is denoted as $\mathcal{S}$, then we let $c_{rt}^q(\mathcal{S})$, $\forall r \in \mathcal{R}$, $\forall t \in \mathcal{T}$ denote the set $\mathcal{S}$'s coverage for task q on a certain sub-region l, within a certain time slot t.

If a participant vehicle i is selected into $\mathcal{S}$, the subset's coverage will change. If the value of $c_{rt}^q(\mathcal{S})$, has reached the d_{rt}^q, it will not change. When the value of $c_{rt}^q(\mathcal{S})$ is smaller than d_{rt}^q, then the its value will increased by 1, it means that $c_{rt}^q(\mathcal{S}) \leq d_{rt}^q$.

Now that many vehicles have selected into $\mathcal{S}$, how to calculate the set $\mathcal{S}$'s coverage $C^q(\mathcal{S})$? Because the coverage is related to each vehicle, then the coverage in sub-region r within time slot t can be calculated as follows,

$$c_{rt}^q(\mathcal{S}) = \sum_{i \in \mathcal{S}} c_{irt}^q \tag{2}$$

And in the larger sense, the coverage of $\mathcal{S}$ can be calculated

$$C^q(\mathcal{S}) = \sum_{i \in \mathcal{S}} C_i^q \tag{3}$$

To best understand the Coverage Ratio Satisfaction Metrics, $\mathcal{P}_{rt}^q$ is denoted as the coverage ratio in sub-region r in time slot t for the task q.

$$\mathcal{P}_{rt}^q(\mathcal{S}) = \frac{c_{rt}^q(\mathcal{S})}{d_{rt}^q} \tag{4}$$

As we know, the $c_{rt}^q(\mathcal{S}) \le d_{rt}^q$ and they are all nonnegative number, so the range of $\mathcal{P}_{rt}^q$ is from 0 to 1.

Proposition 1. *Given $\mathcal{S}_1 \subset \mathcal{S}_2$, we have*

$$\mathcal{P}_{rt}^q(\mathcal{S}_1) \le \mathcal{P}_{rt}^q(\mathcal{S}_2)$$

Proof.

$$\mathcal{P}_{rt}^q(S_2) - \mathcal{P}_{rt}^q(\mathcal{S}_1) = \frac{c_{rt}^q(\mathcal{S}_2)}{d_{rt}^q} - \frac{c_{rt}^q(\mathcal{S}_1)}{d_{rt}^q}$$

$$= \frac{c_{rt}^q(\mathcal{S}_2) - c_{rt}^q(\mathcal{S}_1)}{d_{rt}^q}$$

As $\mathcal{S}_1 \subset \mathcal{S}_2$, From (2) we know that,

$$c_{rt}^q(\mathcal{S}_2) = c_{rt}^q(\mathcal{S}_1) + c_{rt}^q(\mathcal{S}_2 - \mathcal{S}_1)$$

As $c_{rt}^q(\mathcal{S}_2 - \mathcal{S}_1)$ must be nonnegative number, so

$$\mathcal{P}_{rt}^q(\mathcal{S}_2) - \mathcal{P}_{rt}^q(\mathcal{S}_1) \ge 0$$

Therefore the proposition is correct.

From proposition 1, we know that if a vehicle is selected as SV, the increasing of coverage is negative. Then if the coverage is not satisfy the requirement, we need select more vehicles to sense. The ϑ_{rt}^q is the coverage ratio that should be satisfied in the sub-region r within time slot t, it is given by the task publisher. In order to better understand whether the requirement coverage is satisfied, we define the Coverage Ratio Satisfaction metrics as follows

- **Definition**: If $\mathcal{P}_{rt}^q(\mathcal{S}) \ge \vartheta_{rt}^q$, $\forall r \in \mathcal{R}$, $\forall t \in \mathcal{T}$ is satisfied, the set $\mathcal{S}$ satisfy the Coverage Ratio Satisfaction(CRS) metrics.

4 Problem Formulation and Solution

The goal of this paper is to find a set of participant vehicles that make the cost of task least while ensure the coverage ratio in each sub-region within any time slot, the cost include each participant vehicle's required cost and the spend to upload sensed data. We denote the optimal set of SVs as $\mathcal{S}^*$. We denote

$$x_i^q = \begin{cases} 0, & \text{vehicle i do not select as SV} \\ 1, & \text{otherwise} \end{cases} \tag{5}$$

Hence, the optimization problem is formulated as

$$\text{Minimize}: \quad \sum\nolimits_{i \in \mathcal{M}} x_i^q \cdot (e_i^q + \sum\nolimits_{r \in \mathcal{R}} \sum\nolimits_{t \in \mathcal{T}} c_{irt}^q \cdot p)$$

subject to:

$$\begin{array}{c} x_i^q = \{0, 1\}, \quad \forall i \in \mathcal{M} \\ \mathcal{P}_{rt}^q(\sum\nolimits_{i \in \mathcal{M}} x_i^q) \geq \vartheta_{rt}^q, \quad \forall i \in \mathcal{M}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \end{array} \tag{6}$$

p denotes the cost of each data uploaded to server. If the $x_i^q = 1$, the vehicle i will be selected to the $\mathcal{S}^*$.

Until now, the problem of participant selection is formalized as an optimization problem. the novel optimization problem treats the coverage ratio as constraint for selecting participants and aims at minimizing the cost of the task. But the optimization problem is an NP-hard problem, it is obviously a 0/1 knapsack problem. When the amount of participant vehicles are large enough, we need a heuristic algorithm to compute the suboptimal solution.

4.1 Proposed VPS Strategy

The objective function of (8) fits the basic form of nonlinear knapsack problem, The knapsack problem or rucksack problem is a problem in combinatorial optimization: Given a set of items, each with a mass and a value, determine the number of each item to include in a collection so that the total weight is less than or equal to a given limit and the total value is as large as possible.

The optimization target of the nonlinear knapsack problem is to find a set of vehicles, The decision problem form of the knapsack problem is NP complete, the greedy algorithms are frequently used to provide a suboptimal approximated solution. The central part of our participant selection strategy is also in line with the heuristic greedy algorithm, we need to select the maximum value of units and define this vehicle as "efficient" participant vehicle. Each participant vehicle has the efficiency, so first we need to define how to compute vehicle's efficiency. let $\mathcal{S}^*$ denote the set of participants that were selected in the previous round, then the efficiency $\varphi(\mathcal{S}^*, i)$ of a participant vehicle i in this round can be calculated by

$$\varphi(\mathcal{S}^*, i) = \frac{\sum\limits_{r \in \mathcal{R}} \sum\limits_{t \in \mathcal{T}} (c_{rt}^q(\mathcal{S}^* + i) - c_{rt}^q(\mathcal{S}^*))}{e_i^q} \tag{7}$$

The method how to calculate $\varphi(\mathcal{S}^*, i)$ will be used in the proposed strategy VPS, which select participants by rounds of iterations. The pseudo-code of VPS is given in Algorithm 1, and a detailed description is given as follows.

- *Step 1: Initialization.* At the beginning, we should input the task publisher's requirement coverage matrix $\mathcal{D}^q$, the coverage ration constrain matrix ϑ^q, the participant vehicles coverage matrix $C_i^q, \forall i \in \mathcal{M}$ and each participant vehicle's required cost $e_i^q, \forall i \in \mathcal{M}$. All participant vehicles are divided into two sets, the selected set $\mathcal{A}$ and unselected $\mathcal{B}$. At this step, all participant vehicles are put into $\mathcal{B}$ and the set $\mathcal{A}$ is empty.
- *Step 2: Selection.* In this step, we will select a vehicle from unselected set $\mathcal{B}$ to selected set $\mathcal{A}$. We need to compute each vehicle's efficiency in the set $\mathcal{B}$ and select the most efficiency vehicle to selected set $\mathcal{A}$.
- *Step 3: Looping.* Loop step 2, until the selected vehicles satisfy the CRS metrics. How to judge the selected set whether satisfied, we will show it in the Algorithm 2.

Algorithm 1. VPS Algorithm.

Require:

coverage requirement of each task $\mathcal{D}^q$;
area and time division of tasks, $\mathcal{R}$ and $\mathcal{T}$;
participant vehicles, $\mathcal{M}$;
each participant vehicle's required cost, e_i^q;
the location of participant vehicle, $C_i^q, \forall i \in \mathcal{M}$;

Ensure:

Selected participant vehicles, $\mathcal{S}^*$;

set of participant vehicles $\mathcal{B} = \mathcal{M}$, set of selected vehicles $\mathcal{A} = NULL$;
$coverageLeft \leftarrow \mathcal{D}^q$;
$selectedID \leftarrow 0$;
while $!GetRatio(coverageLeft)$ **do** :
  $maxEfficiency \leftarrow 0.0$;
  for vehicle $i \in \mathcal{B}$ **do** :
    compute i's efficiency $\varphi(\mathcal{A}, i)$ in (7);
    if $\varphi(\mathcal{A}, i) > maxEfficiency$
      $selectedID = i$;
      $maxEfficiency = \varphi(\mathcal{A}, i)$;
    end if
  end for
  $\mathcal{A} \leftarrow \mathcal{A} + selectedID$;
  $\mathcal{B} \leftarrow \mathcal{B} + selectedID$;
  $coverageLeft \leftarrow coverageLeft - O^q_{selectedID}$;
end while
return selected participant set $\mathcal{S}^* = \mathcal{A}$;

Algorithm 2. GetRatio Algorithm.

Require:
coverage requirement left of each task, *coverageLeft*;
the required coverage ratio, ϑ;
Ensure:
Judge whether the coverage satisfied the requirement, *true or false*;
for $r \in \mathcal{R}$ **do** :
  for $t \in \mathcal{T}$ **do** :
    if $\mathit{coverageLeft}_{rt}/R^q_{rt} > 1 - \vartheta^q_{rt}$
      return false;
    else
      continue;
    end if
  end for
end for
return true;

5 Performance Evaluation

In this section, we implemented the Vehicular Participant Strategy for the sensing collection task in Vehicular Sensor Network. While the amount of participant vehicles is invariable, we are interested in exploring the relationship between the coverage ratio and the total cost, the relationship between the coverage ratio and the amount of selected vehicles, the relationship between the coverage ratio and the total collected data. While the coverage ratio is invariable, we are interested in exploring the relationship between the amount of the participant vehicles and the total cost, the relationship between the amount of the participant vehicles and the amount of selected vehicles, the relationship between the amount of participant vehicles and the amount of total collected data.

5.1 Simulation Settings

We evaluate the performances of VPS using the real GPS traces collected from 300 taxis in Shanghai on February 1, 2007 [16]. The dataset record the taxis' trajectory, each record item includes many attributes, in this evaluation we only need the four attributes: time, nodeID, longitude and latitude.

We assume there is a data collected task in a region of Shanghai, the region's longitude is from 121.35 to 121.55 and its latitude is from 31.14 to 31.34. We divided the region into 16 sub-regions, and the area of those sub-regions are equal size, we also divide the sensing time into 6 time slot. In order to ensure the quality of the data collected, we also stipulate that each sub-region should be covered by a certain number of vehicles in each time slot.

We refer to the proposed scheme as VPS and to examine the system performance, we will compare it with the theory resolution and another participant selection scheme "DPS" [3]. Comparing with the theory resolution, we can know the error of our strategy "VPS". The scheme "DPS" is a dynamic participant selection strategycompare with it, we can know the advantage of our strategy "VPS".

5.2 Results and Analysis

In this section, we will give a detailed exposition about the relationship between variables and objectives through the experimental data. In order to do the experiment more convenient, we let each sub-region's requirement coverage ratio is same. In Fig.2, the variable coverage ratio range from 0.5 to 1, we know that the amount of selected vehicles is increasing while the coverage ratio is growing, in other words, if we want high coverage, we need more vehicles to sense. Compared with strategy DPS, our strategy need less selected vehicles, and the error between VPS and theory resolution is affordable.

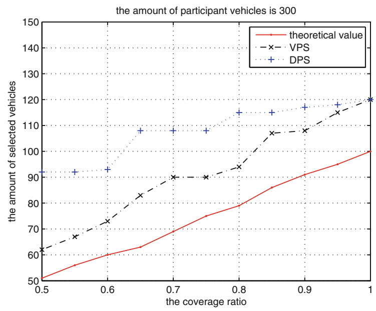

Fig. 2. The amount of selected vehicles vs. coverage ratio

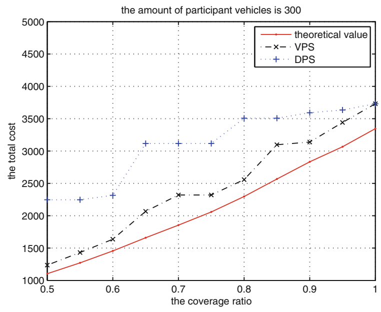

Fig. 3. The total cost vs. coverage ratio

Figure 3 shows the relationship between the coverage ratio and the cost. As the coverage ratio increased, we need pay more to satisfied the requirement. From this figure, We can clearly observe that our strategy is satisfactory, the result of our cost is less than VPS, and slightly higher than the theoretical value. Figure 4 shows that the total amount of collected data increase as the coverage ratio grow.

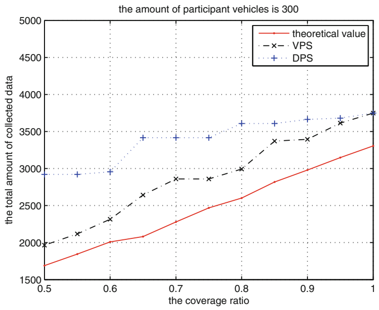

Fig. 4. The total amount of collected data vs. coverage ratio

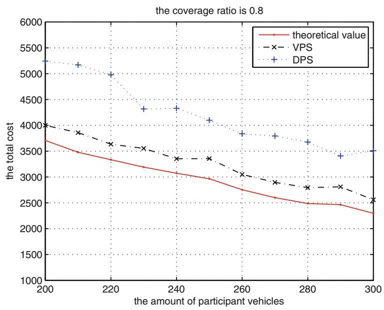

Fig. 5. The total cost vs. the amount of participant vehicles

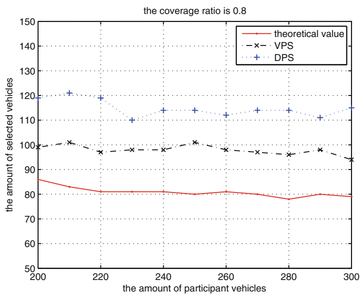

Fig. 6. The amount of selected vehicles vs. the amount of participant vehicles

As we know, if the coverage matrix and the amount of participant vehicles are certain, the coverage ratio can make much of an effect on the total cost, the amount of selected vehicles and the total amount of collected data. Now, we want to know the relationship between the amount of participant vehicles and the total cost, the amount of selected vehicles and the amount of collected data while the coverage matrix and coverage ratio is certain. Figure 5 means that the total cost will decreased while the amount of participant vehicles increased, it is easy to understand, as more vehicles participate in the task, it must be some vehicles require lower cost, so the total cost will decrease. On the other hand, it's very important to let more vehicles participate in the sensing task. Figures 6 and 7 means that as the amount of participant vehicles increased, the amount of selected vehicles and the amount of collected data maintain steady, change in a fixed interval.

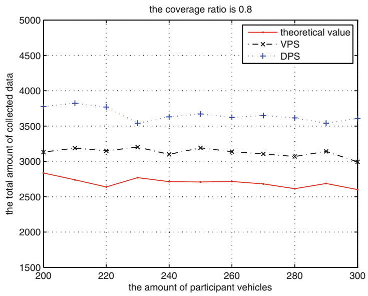

Fig. 7. The total amount of collected data vs. the amount of participant vehicles

6 Conclusion

In this paper, we define a new QoI metric called coverage ratio satisfaction (CRS) with the consideration of coverage from both temporary and spatial aspects. Based on the CRS definition, we formulate the minimum cost CRS guaranteeing problem as an integer linear problem and propose a participant selection strategy called Vehicles Participant Selection (VPS) and experiments show that it is an efficient strategy. We want to let our strategy can serve as a benchmark for performance evaluation. In the future work, we want to let the selection strategy be distributed instead of centralized.

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