Route-Oriented Participants Recruitment in Collaborative Crowdsensing

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Abstract. Route-oriented participants recruitment is a critical problem in collaborative crowdsensing, where task publisher uses monetary reward to motivate private cars collecting data along their routes. For map producers, route-oriented crowdsensing scheme helps them achieve maximum roads coverage with a limited budget, by selecting appropriate participants from a group of candidates.

Focused on route-oriented participants recruitment problem, this paper first formalizes the road network and vehicle route model. Each vehicle's route is mapped to a coverage rate on the road set. The recruitment problem therefore transforms to a combinatorial optimization problem, which has proved to be NP-hard. To find a solution, we proposed an approximation algorithm, which leverages submodularity to reduce computation complexity and has a worst performance guarantee. Finally we evaluate the performance of proposed algorithm on real road and trajectory data in Beijing, China.

Keywords: Participants recruitment · Collaborative crowdsensing
Vehicle trajectory · Approximate algorithm

1 Introduction

The rise of big data, the method of collecting data is of great importance. Being intellectualized and networked, smart vehicles are able to sense and communicate in urban area. Their intrinsic mobility can be leveraged to dynamically collect urban data in different time and areas [1]. A promising data service is collecting data for HD (High Definition) map [2], which built from environmental data of multiple sensors. The map producers, such as Here, TomTom and Baidu, need lidar/camera/IMU data to build a live map for autonomous driving [3]. The huge volume of information, as well as fast updating frequency to build a "live" map, challenges map producers because their own devices undoubtedly could

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not meet these requirements. Some researchers therefore proposed crowdsensing in which private cars are incentivized to accomplish a sensing task and upload data to map producer. The incentives could be either real or virtual money.

In real scenario, each private car has its own short-term route which includes a sequence of road segments and sensing cost. For a budget-constrained task publisher, participants recruitment turns into a combinatorial optimization problem. Hence, how to select appropriate participants to maximize road coverage with limited budget is a critical problem for HD map crowdsensing. Concentrated on this problem, this paper has following three contributions.

Problem Formalization of Route-Oriented Participants Recruitment. The problem is route-oriented because road coverage rate is considered as a major indicator in this paper. We first formalize urban road networks as a graph, the road segments are represented by edges in the graph. Then fine-grained trajectory of vehicle is simplified into route, a sequence of edges in graph. With each route has its unique coverage rate on graph, the task publisher selects participants that maximize road coverage within a given budget.

Approximation Algorithm Using Submodularity. The formalized problem is NP-hard, which has no polynomial solution unless $NP = P$. We look for a greedy algorithm guaranteeing lower bound with a ratio of $(1 - 1/e)$. Specifically, we observe and prove that the coverage rate function is submodular, which enables us to employ the property in submodular optimization.

Performance Evaluation by Real Data. To validate effectiveness of proposed algorithm, real road networks and vehicle trajectories in Beijing are used. Selected major roads in Beijing urban area are extracted. Taxi trajectories are partitioned into sequence of road segments. Preprocessed data are fed into our proposed algorithm and two other algorithms, including *naive selection* and *pureGreedy selection*. The results are compared and analyzed to demonstrate effectiveness of approximation algorithm.

The rest of this paper is organized as follows: Sect. 2 describes basic scenario and definitions of participants recruitment. Section 3 presents our proposed approximation algorithm. Section 4 presents simulation results and analysis. We delay our discussion of related work until Sect. 5, in order not to interrupt reader's mind. The paper ends, in Sect. 6, with some conclusions and future works on route-oriented crowdsensing problem.

2 Preliminaries

This section describes the scenario of participants recruitment and frequently used notations.

2.1 Scenario Description

The task publisher on the cloud publishes task among candidate vehicles. Then candidate vehicles report their short-term route to task publisher, who decides to choose appropriate participants at last. The communication between task publisher and vehicles is supported by cellular network. Figure 1 is a description of route-oriented participants recruitment.

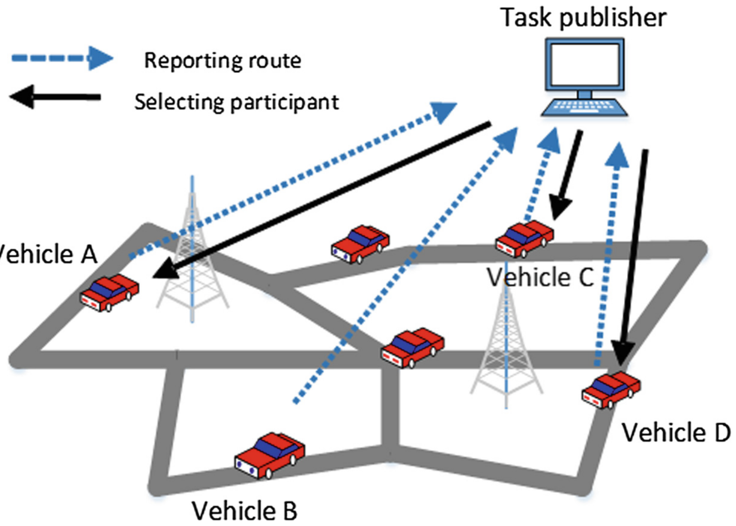

Fig. 1. A description of route-oriented participants recruitment. Task publisher and vehicles communicates by cellular network.

2.2 Models and Measurement

We consider the scenario where task publisher distributes the sensing task to candidate vehicles on the urban road networks.

Definition 1-Road Networks: The road network is modeled as a graph $G = (V, E)$, where the intersections are denoted as vertex V and road segments are denoted as edge E. The set of roads is denoted by $E = \{e_1, e_2, ..., e_m\}$, where m is the number of road segments need to sense.

Definition 2-Participant's Route: A participant p_i's route r_i is a sequence of segments pertaining to one trip. Each segment in r_i is an edge $e \in E$, with an arriving time stamp $e.t_1$ and a leaving time stamp $e.t_2$, *i.e.* $r : e_1 \rightarrow e_2 \rightarrow ... \rightarrow e_k$, where $0 < e_k.t_2 - e_1.t_1 \leq \triangle T$. $\triangle T$ defines the maximum prediction time of participant's route. Participants need to report short-term route prediction to task publisher, larger $\triangle T$ renders lower prediction accuracy due to uncertainty in real transport environment.

Definition 3-Dependent Coverage: A dependent coverage of p_i on road networks E is $C_{p_i}^{dep(P_{i-1})}(E) = \{r_i \cap (E - C_{p_{i-1}}^{dep(P_{i-2})}(E))\}$, when $P_{i-1} = \{p_1, p_2, ..., p_{i-1}\}$ has sequentially made their coverage. As the name suggested,

$C_{p_i}^{dep(P_{i-1})}(E)$ is not only related to the length of r_i, but also depending on $C_{p_{i-1}}^{dep(P_{i-2})}(E)$ which is resulted from $i-1$ previously selected participants.

By definition, for any p_i, if $P_1 \subseteq P_2 \subseteq P$, below equation always stands:

$$C_{p_i}^{dep(P_2)}(E) = C_{p_i}^{dep(P_1)}(E) \cap C_{p_i}^{dep(P_2 \backslash P_1)}(E) \quad (1)$$

Thus,

$$\|C_{p_i}^{dep(P_2)}(E)\| \leq \|C_{p_i}^{dep(P_1)}(E)\| \quad (2)$$

Definition 4-Global Coverage Rate: Given a road networks' edge set E and a group of participants P, with each participant's r_i is consisted of a series of edges, the global coverage rate is $\|C_P^{global}(E)\|$, i.e. the ratio of all covered edges' length to the total E's length. For example, if there are 2 candidate participants $P = \{p_1, p_2\}$, with $r_1 = \{e_1, e_2\}$ and $r_2 = \{e_2, e_3\}$ respectively. We also assume $E = \{e_1, e_2, e_3, e_4\}$. The global coverage rate of p on E is $\|C_P^{global}(E)\| = (|e_1| + |e_2| + |e_3|)/(|e_1| + |e_2| + |e_3| + |e_4|)$.

3 Participants Recruitment with Budget Constraint

In this section, we describe the maximum global coverage with the budget constraint and present the corresponding algorithm to address it.

3.1 Problem Formalization

In practical scenarios, the budget of task publisher for rewarding participants is limited. Additionally, each participant has unique cost and coverage conditions, making it difficult for participants selection. Considering the set of candidate participants $P = \{p_1, p_2, ..., p_n\}$ is associated with cost set $D = \{d_1, d_2, ..., d_n\}$. That is, each p_i has a cost d_i. The total cost of selecting participants should not exceed a given budget B.

Definition 5-Maximum Coverage Rate with Budget Constraint: Given an edge set $E = \{e_1, e_2, ..., e_m\}$ and a potential participant set $P = \{p_1, p_2, ..., p_n\}$, with the corresponding cost set $D = \{d_1, d_2, ...d_n\}$. Costs are additive and illustrated by $d(P) = \sum d(p_i) = \sum_{i=1}^{n} d_i$. The maximum global coverage rate under budget constraint B asks for a subset $P' \subseteq P$, such that the total cost of P' is no more than B, i.e., $d(P') = \sum_{p_j \in P'} d_j \leq B$, and the global coverage rate $\|C_{P'}^{global}(E)\|$ is maximized.

Formally, this optimizing problem is given by:

$$\max_{P' \subseteq P} C_{P'}^{global}(E) \;\; \text{s.t.} \;\; d(P') \leq B \quad (3)$$

3.2 Leveraging Submodularity

To solve the given problem, we prove that the set function of the global coverage rate is nondecreasing submodular, so that we could employ the property in submodular optimization.

Definition 6-Submodularity: Given a finite set E, a real-valued function $f(\cdot)$ on the subsets of E is submodular if:

$$f(A) + f(B) \geq f(A \cap B) + f(A \cup B)\ \forall A, B \subseteq E \tag{4}$$

It is convenient to use an incremental style of above inequality. If the function satisfied the *diminish returns* rule for all element x and all pairs $A \subseteq B$, denoted as:

$$f(A \cup \{x\}) - f(A) \geq f(B \cup \{x\}) - f(B) \tag{5}$$

Then, $f(\cdot)$ is said to be nondecreasing if $f(A) \leq f(B)$ for all $A \subseteq B \subseteq E$. Based on the given preliminaries, we obtained the following lemma and further give its proof.

Lemma 1: Given edge set E and a participants set $P'(P' \subseteq P)$, the set function of the global coverage rate $\|C_{P'}^{global}(E)\|$ is nondecreasing submodular.

Proof: It is straight forward that $\|C_{\emptyset}^{global}(E)\| = 0$ because not a single participant has been selected to cover. Consider P''s two arbitrary subsets P_1'' and P_2'', $P_1'' \subseteq P_2'' \subseteq P'$, we have $\|C_{P_1''}^{global}(E)\| \leq \|C_{P_2''}^{global}(E)\|$ since a route set $r_{P_1''}$ always has bigger(at least equal when $P_1'' = P_2''$) global coverage rate than $r_{P_2''}$.

Then we consider any candidate participant $p_x \in P - P'$ and edge set E, when P_1'', P_2'' has been selected. Note that $P_1'' \subseteq P_2'' \subset P$. By Eq. (3), it holds:

$$\|C_{p_x}^{dep(P_2'')}(E)\| \leq \|C_{p_x}^{dep(P_1'')}(E)\| \tag{6}$$

It also holds that:

$$\|C_{P_1''\cup\{p_x\}}^{global}(E)\| - \|C_{P_1''}^{global}(E)\| = \|C_{p_x}^{dep(P_1'')}(E)\| \tag{7}$$

$$\|C_{P_2''\cup\{p_x\}}^{global}(E)\| - \|C_{P_2''}^{global}(E)\| = \|C_{p_x}^{dep(P_2'')}(E)\| \tag{8}$$

Combining (6), (7), (8) we have:

$$\begin{aligned}\|C_{P_1''\cup\{x\}}^{global}(E)\| - \|C_{P_1''}^{global}(E)\| \geq \\ \|C_{P_2''\cup\{x\}}^{global}(E)\| - \|C_{P_2''}^{global}(E)\|\end{aligned} \tag{9}$$

It is satisfied with the *diminish returns* rule (6) in which the difference from adding an new element to a set P'' is at least as large as that from adding the same element to a superset P' of P'', therefore $\|C_{P}^{global}(E)\|$ is nondecreasing submodular with $\|C_{\emptyset}^{global}(E)\| = 0$.

3.3 Approximation Algorithm

Motivated by the submodular property of coverage [4], we proposed an approximation algorithm to address the global coverage rate with guaranteed performance. As shown in Algorithm 1, the algorithm partially uses an enumeration technique, and then employs greedy heuristic to get selection results for maximum global coverage rate with budget constraint.

Algorithm 1 is mainly composed by two components. The first component is in line 2–line 3, which enumerates all subsets $\mathbb{S}_1$ whose cardinality is smaller than k, and has cost less than B. The enumerated subset who has the most global coverage rate is set as H_1, the candidate subset of the first component. Another candidate is generated from the second component from line 4–line 12. This component first enumerates some subsets $\mathbb{S}_2$ whose cardinality $Card(S_2) = k$, and complements these subsets using the greedy algorithm (line 6–line 11).

Algorithm 1. Approximation Algorithm for Maximum Coverage Rate with Budget Constraint Problem

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Input: Edge set $E = \{e_1, e_2, ..., e_m\}$, potential participants set $P = \{p_1, p_2, ..., p_n\}$ and corresponding cost set $D = \{d_1, d_2, ..., d_n\}$, budget B, a predefined integer k.

Output: Participants set $P' \subseteq P$.

1 $H_1 \leftarrow \emptyset$, $H_2 \leftarrow \emptyset$

2 **for** *all* $S_1 \subseteq P$, *such that* $|S_1| < k$, *and* $d(S_1) \leq B$ **do**

3   if $\|C_{S_1}^{global}(E)\| > \|C_{H_1}^{global}(E)\|$ then $H_1 \leftarrow S_1$

4 **for** *all* $S_2 \subseteq P$, *such that* $|S_2| = k$, *and* $d(S_2) \leq B$ **do**

5     $T \leftarrow P \backslash S_2$

6   **Repeat**

7   find p_j that maximize $\|C_{p_j}^{dep(S_2)}(E)\| / d(p_j)$

8   if $d(S_2) + d(p_j) \leq B$ then

9         $S_2 \leftarrow S \cup p_j$

10       $T \leftarrow T \backslash p_j$

11   **Until** $T = \emptyset$

12   if $\|C_{S_2}^{global}(E)\| > \|C_{H_2}^{global}(E)\|$ then $H_2 \leftarrow S_2$

13 if $\|C_{H_1}^{global}(E)\| > \|C_{H_2}^{global}(E)\|$, $P' \leftarrow H_1$, else $P' \leftarrow H_2$.

14 return P'

Theorem 1: For $k \geq 3$, Algorithm 1 has an approximation ratio of $(1 - 1/e)$ for the maximum global coverage rate with budget constraint problem. That is:

$$C_{P'}^{global} \geq \underbrace{(1 - 1/e)}_{\approx 0.632} C_{optimal}^{global}, \quad \text{for} \quad k \geq 3 \tag{10}$$

where $C_{optimal}^{global}$ is the optimal value of the total global coverage rate that can be achieved by any participants set $P' \subseteq P$. See Khuller's work [5] for a detail proof.

The time complexity of Algorithm 1 is $O(l^{k+2})$, where k is an integer that is bigger or equals to 3. This algorithm is polynomial and achieves an approximation guarantee of $(1-1/e)$. Since the complexity of proposed algorithm increases with k, we recommend to set $k = 3$ as usual. To get better performance in coverage rate, a larger k could be set with a price of larger time complexity.

4 Real Data Based Simulation

We evaluate the performance of the proposed algorithm using real road networks and trajectory data from Beijing, China. Then we make a comparison between proposed algorithm and other two algorithms, and finally make an analysis on these results.

4.1 Simulation Data and Settings

Road Networks in Beijing. The road network (V, E) is built from Beijing map [6]. The detailed information of map is trivial, therefore only main roads are solicited in our experiment. Each road has its direction and length, which are important for building road set E.

Taxi Trajectory Data. We extract route from real taxi trajectory data collected by MSRA [7]. The data package includes over 10000 taxicabs' trajectories on several days in November 2013. For each day the data package contains a full-scale GPS during 24 h. Since trajectory is too detailed for use, we simplified the GPS trajectory into route by trajectory-map-matching [8], i.e. transforming GPS trajectory into series of road segments, and tag each segment with arriving/leaving time. Considering the scenario of participants recruitment for HD map sensing, a vehicle could predict its short-term route in $\triangle T$. After defining an initial time t_{init}, we randomly choose a batch of taxi, whose trajectory is in the range of selected urban area and within time $[t_{init}, t_{init} + \triangle T]$.

Figure 2 is a sketch map of road networks, which is located in a prosperous block in Haidian district, Beijing. Selected roads are in blue and three road examples are presented in Fig. 2(a) and (b). Additionally, three routes/trajectories are

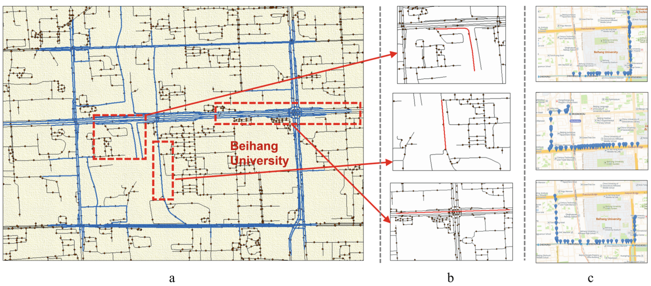

Fig. 2. A sketch map of road networks and routes. a: selected roads are in blue; b: examples of road segment; c: examples of route. (Color figure online)

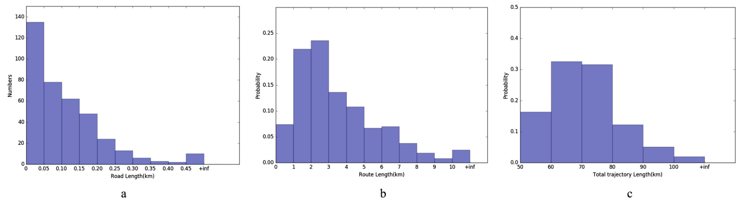

Fig. 3. Statistics of roads and route data.

also presented in Fig. 2(c). To give an insight of simulation configuration, Fig. 3 shows some statistics of road and route data. Note that total trajectory length in Fig. 3(c) is the whole length of all candidates' trajectories.

Participants Cost. Unfortunately, there is no real cost data of participants. As a rule of thumb, each driver has different preference and driving cost. Therefore we generate a cost d_i for each candidate participant with uniform distribution, i.e. $D \sim U[a, b]$. Hence, costs and routes are synthesized to support our simulation.

Overall, simulation settings are illustrated in Table 1.

Table 1. Simulation settings

$[t_{init}, t_{init} + \triangle T]$	$[16, 16.5]$ (30 min)
Road segments number	362
Candidate participants number	$\{5, 10, 15, 20, 25, 30\}$
U(a, b)	$[1, 0]$
Budget	$\{40, 60, 80, 100\}$

4.2 Simulation Results

Our proposed approximation algorithm is named after **boundedGreedy selection** to indicate its bounded performance guarantee. Besides our proposed algorithm, two other algorithms are arranged to make comparison. **Naive selection**. Task publisher randomly chooses participants when participants arrive, until the total cost exceeds budget B. **PureGreedy Selection**. PureGreedy algorithm repeatedly picks participant p_i that has the maximum $\triangle C/d_i$ until the total cost exceeds budget B. It is easy to applied pureGreedy with high efficiency. PureGreedy works fine most time but it could not guarantee the worst performance. This will inevitably deteriorate coverage on urban sensing, where task publisher needs stable and balanced coverage performance. Figure 4 illustrates the comparison of three algorithms. The simulation runs 100 times and results are averaged.

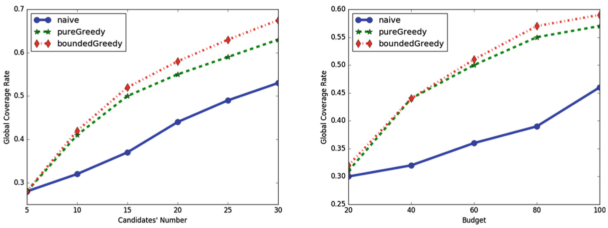

Fig. 4. Comparison of three algorithms on coverage rate. left: impact of candidates' number, budget = 100; right: impact of budget, candidates' number = 20.

Impact of Participants Number. Figure 4(left) shows *Candidates' number-Global Coverage Rate plot* under a fixed budget $B = 100$. The curves generally show that the global coverage rate increases with the candidates' number. The reason is two-fold: First, when candidates' number n is relatively small ($n \leq 20$) and budget is enough, hiring a new candidate is always feasible and beneficial to coverage rate. Second, when n is big, the budget is not enough to hire all candidates. However, more candidates could lead to more combinations of routes, making it more likely to find a combination with higher coverage rate. Moreover, this figure demonstrates that boundedGreedy outperforms naive and pureGreedy selection. It could be prudently speculated that the performance gain of boundedGreedy is also increasing with candidates' number.

Impact of Participants Budget. Figure 4(right) shows *Budget-Global Coverage Rate plot* under a fixed candidate number $N = 20$. From this facet, boundedGreedy still outperforms other two algorithms. Intuitively, increasing budget is always good so that we could hire more participants. For example, hiring with $B = 60$ gets larger global coverage rate than that when $B = 80$, and hiring with $B = 100$ gets larger coverage rate than $B = 80$. Nonetheless, this effect conforms with *diminish returns* rule that the utility gain $\triangle rate/\triangle budget$ decreases as budget increases.

5 Related Work

Crowdsensing has been a hot topic recent years. The research on this field primarily focus on economic model where each participant is only associated with a cost value and no physical scenario is further considered. Lee [9] designed and evaluated RADP incentive mechanism, where users can sell their sensing data to a service provider with a bid price. The proposed mechanism focuses on minimizing and stabilizing incentive cost while maintaining enough participants. Yang [10] and Duan [11] both proposed a platform-centric model where platform provides a reward shared by participants using Stackelberg game. To protect participants' privacy, Dimitriou [12] and Krontiris presented an auction protocol guaranteeing anonymity of bidders.

Leveraging vehicles for crowdsensing as well as data processing have gained extensive attention. Zhu [13] proposed PUS (Pervasive Urban Sensing) framework and used probe cars to sense traffic density. The authors also designed a compressive sensing algorithm to tackle sparsity of data. Yuan [14] observed that the distribution of probe vehicles is uneven over space and time. He therefore proposed an adaptive and compressive data gathering scheme based on matrix completion theory. Beside data processing, there are some works focused on optimal participants recruitment of crowdsensing. Song [15] aims to select the most appropriate participants with different budget constraints, a multi-task-oriented QoI (Quality of Information) optimization problem is discussed and converted to a nonlinear knapsack problem. Zhang [16] proposed an event-driven QoI-aware participatory sensing framework with energy and budget constraints where the main method is boundary detection. The above works discuss participants recruitment in a grid-based approach, where urban area is partitioned into small squares. The grid-based approach gives researchers convenience to model some urban sensing requirements, such as traffic flow or air quality, but remains coarse and unappeasable if applied to fine-grained sensing tasks.

The fined-grained sensing task usually associates with participants' trajectories. For example, in a HD map sensing task, participant (smart vehicle) may collect 3D environmental data along his trajectories. Hence, HD map sensing task needs an accurate trajectory model, rather than coarse grid-based motion model of potential participants. To address this problem, Zhang [17] considered the optimal quality-aware coverage in mobile crowdsensing networks, where POIs are sensed by passing-by participants. TRACCS [18] is a trajectory-aware coordinated design for urban crowdsourcing. The authors formulated crowd-task scheduling as an optimization problem and developed computationally-efficient heuristic to tackle the problem. Hamid [19] proposed an efficient recruitment scheme for vehicles in urban sensing applications. They utilized trajectories of the candidate participants, and applied a minimal-cover greedy algorithm for recruitment.

6 Conclusion

This paper has discussed route-oriented participants recruitment of collaborative crowdsensing. Task publisher collects candidates' route and selects appropriate participants to sense data along their routes. Given a limited budget, our proposed approximation algorithm could achieve larger global coverage rate than other two algorithms on real data simulation.

In the future, we will consider a more complicated and realistic scenario where participants may drop out the sensing task during task execution. This needs a more vivid model to depict both vehicle's and driver's behavior. Moreover, a remedy algorithm should be considered to reduce the influence of dropping out.

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