Ubiquitous Sensor Data Collection with Mobile Users

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***Abstract*—With the advancement of mobile technology, mobile sensing becomes increasingly popular for applications in environmental protection, traffic monitoring, and health care. Apart from sensing, mobile phones have also been suggested to facilitate data collection from wireless sensors in their surroundings. The idea is to use smart phones to collect data from wireless sensors through short range communication, including Bluetooth and Near Field Communication (NFC). In this work, we consider how to optimize this data collection provided by mobile users along their walks in real-time. We formalize the problem as the *Sensor Collection Decision* (SCD) problem and consider several variations of the problem. In practice, SCD is an *online* problem in which collection decisions must be taken in real-time, given no pre-knowledge on the user mobility and the sensor locations. We prove that a greedy strategy achieves a competitive ratio of $\frac{1}{3}$, compared to the optimal offline solution. We conducted a variety of numerical simulations using actual mobility trace data which demonstrate that our proposed algorithms are near optimal in practice.**

***Index Terms*—Sensor networks, mobile data collection**

I. Introduction

Wireless sensor applications have become increasingly popular in many domains, including environmental protection, traffic monitoring, health care, security and safety [1]. Traditional wireless sensor networks (WSNs) are composed of number of stationary wireless sensors. With the advancement of mobile technology, mobile sensing becomes a reality supported by the advanced features of smart phones. Smart phones operate like mini computers nowadays and many of them are equipped with sensing capabilities such as microphone, camera, and GPS. Mobile sensing applications have been developed which encourage mobile users to participate in different sensing activities [2], [3].

Apart from mobile sensing, mobile phones have recently been explored to facilitate ubiquitous data collection from wireless sensors [4], [5]. The idea is to collect data from wireless sensors through short range communication, such as Bluetooth and Near Field Communication (NFC), on the mobile phones. One advantage of this approach is that it does not require densely deployed sensor networks. Mobile phones can collect data directly from the nearby sensors, which can save energy from long multihop communication. GreenOrbs [6] is one of the applications that allows forest rangers to collect scientific data, including temperature, humidity, concentration of carbon dioxide, using their mobile devices.

Nevertheless, there are many challenges in ubiquitous data collection from mobile users. First, the mobile users are moving freely in the sensing field. The contact between mobile users and wireless sensors are unpredictable. The length of contact time can be short depending on the moving speed of the users. It is necessary for the mobile users to decide on what sensing data to be collected in real-time to maximize the reward gained. In addition, the wireless channel is shared among the wireless sensors and mobile users in the same vicinity. The wireless network capacity is limited for collecting large amount of sensing data. Since the mobile users only pass by the wireless sensors occasionally, the sensing data are cached in the buffers of the sensors waiting for collection. In many cases, the limited contact time and network capacity are not sufficient for the mobile users to collect all the available sensing data.

In this paper, we propose an online algorithm to optimize the reward in ubiquitous data collection. The algorithm allows individual mobile users to determine when and what data to be collected from their surrounding sensors in real-time. Our algorithm does not require any pre-knowledge of the sensor locations in the field or user mobility pattern. We measure the reward of sensing data according to the value of information that the data carried. The value of information can be determined by the importance of the sensing data and the quality of the sensors [7], [8]. Given the reward of data from the sensors, our focus is on scheduling data collection to maximize the total reward for the mobile user. Our online algorithm makes real-time decisions based on the available network capacity, value density and collection urgency of the data. We also design and implement a data collection protocol for this online algorithm. We evaluate the performance of our proposed solution through both theoretical analysis and experimental simulations using OMNeT++ [9] and mobility traces collected by GPS [10].

II. Related Work

Data collection have been widely studied for wireless sensor networks. Most of the traditional WSNs considered a number of wireless sensors forwarding their sensing data to a stationary sink [11], [12]. Recently, mobile elements (MEs) have been suggested for data collection in WSNs. The *data mules* architecture has been proposed to collect sensing data using moving entities. Similarly, S. Basagni et al. [13] proposed a heuristic algorithm to determine the routes of the mobile sinks and demonstrated the improved network lifetime. Gu et al. [14] also proposed a partitioning-based algorithm to schedule the movement of mobile elements, which minimizes the required moving speed and eliminates buffer overflow. Xu et al. [15] further studied delay tolerant event collection with mobile sink considering the spatial-temporal correlation of events in the sensing field. Nevertheless, the above work focuses on scheduling the movement of mobile elements, which are different from mobile users walking freely without any control in our work.

Some studies have been conducted for mobile elements without any fixed trajectory. Lee et al. [16] proposed a routing scheme that exploits the mobility pattern of the mobile sinks to minimize energy consumption and network congestion. Similarly, Kusy et al. [17] proposed an algorithm to predict the mobility pattern of the mobile sinks from the training data to improve reliability in data collection. Recently, ubiquitous data collection with mobile users has been studied for mobile users to collect data from wireless sensors networks. Li et al. [4] proposed a ubiquitous data collection scheme that can efficiently form a new data collection tree by locally modifying the previously constructed data collection tree. However, none of the above work has considered the reward or value collected from the sensing data.

Sadagopan et al. [18] have explored the problem of maximizing the data collected from an energy-limited wireless sensor network. It aims at collecting the maximum amount of data possible from the sensors at a sink node considering the remaining energy constraints in the sensors. Quality of Information (QoI) has also been suggested as a multi-dimensional metric to characterize the value of data captured by the sensor network and the information derived from processing these data [8]. Charbiwala et al. [19] further explored a centralized sensor rate selection mechanism to maximize QoI for event detection. Similar to the above work, we target to maximize the value collected from the sensing data. Nevertheless, we focus on ubiquitous data collection for mobile users, which has to tackle the challenges of data collection with random mobility and limited contact time.

III. Problem Formulation

We consider a mobile user moving in a sensor field to collect data from its surrounding wireless sensors. As the mobile user moves along its path, new sensors will steadily come within range (either directly or indirectly via the data collection tree). The data from the wireless sensors may result in different levels of *reward* according to the importance and value of the carried information [7]. The mobile user does not know whether the data that is available from the current sensors is more or less valuable than data that may come available from sensors that are somewhat further along the path. The mobile must explicitly poll the sensors at a given time to see what new data is available. There are a number of costs associated with polling the sensors; the sensors must transmit and potentially the data collection tree may be changed so it is best to only poll intermittently. When polling is done, the mobile user will receive information about what data items are currently available for collection from the sensors that are within range. The mobile user faces two problems that must be decided in an online fashion: (1) at what times t to poll the sensors for new data, we shall refer to this as the *Polling Rate (PR)* problem, and (2) which available data should be collected so as to stay within its capacity and maximize the reward of the data received, which we refer to as the *Sensor Collection Decision (SCD)* problem. In this work, we concentrate on the SCD problem and do not make specific assumptions about the location of the sensors and the distribution of the data items (and their rewards), so just employ a simple constant rate polling algorithm.

Suppose the mobile user j decides to poll the sensors that are within range at some time t to see what data items are currently available. If a sensor detects a polling request from mobile user j (directly or indirectly), it sends a short message to inform j of the data items it has and their values. The mobile user receives information about each data item d_i in the form of a tuple $(i, l_i, r_i, c, t_l, t_r)$, where i is the index of the data item (assumed to be a unique identifier), $l_i > 0$ is the length of the data (in packets), $r_i \geq 0$ is the reward value per packet, $c > 0$ is transmission capacity required (in bytes) for j to receive a packet of d_i, and d_i is available to be retrieved in the window $[t_l, t_r]$. The mobile user must decide whether or not to receive d_i during the interval of its availability. We assume that the network is capacity limited so that the mobile user does not have the capacity to receive all data items. It is possible that d_i will be available again at a later time, depending on the path of j, but this is not assured. We adopt a simple model of the network capacity; we assume that mobile user j has C_j units of network capacity during each timeslot. If j is presented with the opportunity $(i, l_i, r_i, c, t_l, t_r)$, it must decide whether to collect (some or all of) the data within the time window $[t_l, t_r]$ and not exceed its collection capacity in each timeslot. We wish to find a collection strategy for one or more mobile users that maximizes their reward. We note that there are several important natural variations on this problem:

- *Fractional vs. whole data*: Can data be received partially for fractional reward? For example, if data item d_i has length l_i packets, does receiving $m < l_i$ packets of data produce mr_i reward? This variation reflects that a sensor's data may have partial value even if not all of the data item is collected.
- *Interruptible data transmission*: Is it possible to interrupt the transmission of d_i and continue it at a later time? If so,

it may be advantageous to the collector to stop receiving a data item temporarily in order to collect other newly available valuable data with the possibility to collect the remaining portion of d_i later.

In this work we focus on the fractional and interruptible variation of the problem. We note that the whole data case bares some resemblance to the *online weighted secretary problem* [20]; in this problem an employer must decide at what point to hire someone as he or she interviews a series of candidates. In the case of whole sensor data, a particular piece of data d_i may preempt future data that is potentially more valuable so the collector must decide whether to commit to collecting each piece of data in an online fashion.

IV. Proposed Algorithms

A. SCD Algorithms

We propose two related algorithms for the fractional, interruptible variation of the sensor collection decision (SCD) problem based on computing a weight for each data collection opportunity in the current time slot and then using a *knapsack* algorithm to chose the most valuable combination of the weighted data to collect in the time slot.

The data available to be collected during time t is either from a new data item opportunity $(i, l_i, r_i, c, t_l, t_r)$, where $t = t_l$, or or an existing opportunity such that $t \in [t_l, t_r]$. We define the *value density* of a data opportunity as

$$\rho(i, l_i, r_i, c, t_l, t_r) = \frac{r_i}{c}.$$

We will use a simple greedy strategy to chose which collection opportunities the mobile collector should pursue at time t (see Algorithm 1).

Algorithm 1 SCD-Greedy Algorithm

1: O_j: collection opportunities for j at time t;
2: C_j: capacity available at time t;
3: **SCD-Greedy**(O_j**,** C_i)
4: $D_t = \emptyset$: data items to collect;
5: $s = C_j$: remaining capacity available;
6: **while** $O_j \neq \emptyset$ **do**
7:     Choose $o^* = (i^*, l_i^*, r_i^*, c^*, t_l^*, t_r^*) = \operatorname{argmax}_{O_j} \rho(o)$;
8:     $D_t = D_t \cup \{i^*\}$;
9:     $s = s - c^*$;
10:     Update $O_j = \{(i, l_i, r_i, c, t_l, t_r) \in O_j | c \leq s\}$;
11: **end while**
12: **return** D_t;

We also consider a variation of Algorithm 1 in which we consider how urgent it is to collect a data opportunity. We define the *collection urgency* at time t of a data opportunity as

$$\kappa_t(i, l_i, r_i, c, t_l, t_r) = \frac{\min(l_i, t_r - t)}{t_r - t}.$$

We assume that the data locations and values are random and so we expect that there will be fluctuations in the intensity of data opportunities. In particular, in "high" intensity periods in which a lot of data becomes available it may be prudent to collect data is who value density is somewhat lower than other available data but whose collection urgency is greater. The higher value data will likely be collectable in the future. Thus, we will employ a weighting scheme that balances both the value density of the objects collected with their urgency. The function we have chosen is

$$w(i, l_i, r_i, c, t_l, t_r) = \rho(i, l_i, r_i, c, t_l, t_r)^{\kappa_t(i, l_i, r_i, c, t_l, t_r)}.$$

We updated the algorithm to accommodate urgency in data collection (see Algorithm 2).

Algorithm 2 SCD-UrgentGreedy Algorithm

O_j: collection opportunities for j at time t;
C_j: capacity available at time t;
SCD-UrgentGreedy(O_j**,** C_i)
Identical to Algorithm 1, except line 6 is replaced with:
Choose $o^* = (i^*, l_i^*, r_i^*, c^*, t_l^*, t_r^*) = \operatorname{argmax}_{O_j} w(o)$;

B. Distributed Protocol Design

We present the details of the protocol design as follows. The greedy online data collection algorithm can be implemented with a distributed protocol between the mobile users and the wireless sensors. We separate the implementation into two phases, namely tree construction and tree migration. Tree construction is performed when a mobile user j joins the network the first time or moves to a new place that requires exploration from scratch (see Algorithm 3). On the other hand, tree migration is performed when the mobile user moves and requires minor adjustment on the data collection tree (see Algorithm 4).

In tree construction, the mobile user j broadcasts to sensors in its k-hop neighbor. Each sensor i replies to j with r_i, l_i, and c. The data collection tree T_j is then constructed. j adds the replies in the format of $o_i = (i, l_i, r_i, c, t_l, t_r)$ to O_j. After collecting all $o_i \in O_j$, the mobile user runs the SCD-Greedy algorithm to make data collection decisions. It then notifies the selected sensors to start data collection.

Algorithm 3 Tree construction with mobile user j

Mobile user j broadcasts to sensors in k hops;
Each sensor i replies to j with $< i, l_i, r_i, c >$;
for each reply from neighboring nodes **do**
    j adds $o_i = (i, l_i, r_i, c, t_l, t_r)$ to O_j;
end for
D_t = SCD-Greedy(O_j, C_i);
send message to nodes in D_t to start data collection;

As j moves, it may lose connection to some sensors in T_j. The hopcount c of some nodes may also change with their distances to j. Tree migration is necessary to update the tree structure to maintain the communication for data collection. This operation can be performed either periodically, or adaptively as the mobile user j loses connectivity with its existing neighboring sensors (in our simulations we use an adaptive approach). In tree migration, mobile user j broadcasts to collect updated information from its neighboring nodes. It removes nodes that are no longer in the tree from O_j. For nodes that are carried forward, j updates their value density.

For instance, a sensor that becomes farther away from the mobile user requires more network capacity to deliver its data through routing. Its value density will decrease with its increased hopcount to the mobile user. Similarly, the length of data l_i and the data retrieval time window $[t_l, t_r]$ may change with the mobility of the mobile user as well. After updating O_j, j re-runs the SCD-Greedy algorithm and notifies the relevant sensors.

Algorithm 4 Tree migration with mobile user j

Mobile user j broadcasts to sensors in k hops;
Each sensor i replies to j with updated o_i;
for each nodes $o_i \in O_j$ with no replies **do**
    remove o_i from O_j;
end for
for each replies of $o_i \in O_j$ with changed o_i **do**
    update the value density
end for
for each replies from nodes $i \notin O_j$ **do**
    add o_i to O_j;
end for
D_t = SCD-Greedy(O_j, C_i);
send message to nodes in D_t for data collection;

V. Performance Analysis

In this section we analyze the performance of Algorithm 1 and develop an Integer Linear Program (ILP) formulation for the offline version of the problem.

A. SCD Competitive Ratio

The algorithms proposed for the SCD problem are *online* algorithms, meaning that they observe the input as a stream, in this case, the newly available data items at time step t and must make a decision on whether to collect each data item or not. Online algorithms are typically analyzed with respect to their *competitive ratio* relative to the optimal offline solution as found by an optimal algorithm that has immediate access to the entire input stream.

Lemma 1: Algorithm 1 achieves a competitive ratio of $\frac{1}{3}$.

Proof: Let S^* be an optimal offline solution to an instance of the SCD problem and let S^{alg} be the online solution found by Algorithm 1. We will consider these solutions as a set of data packets that have been collected; let $S^*(t)$ and $S^{\text{alg}}(t)$ be the packets collected by the respective solutions at time t. We have

$$S^* = (S^* \cap S^{\text{alg}}) \cup (S^* \setminus S^{\text{alg}}).$$

Next, we can write

$$\sum_{S^* \setminus S^{\text{alg}}} \text{reward}(p) = \sum_t \sum_{S^*(t) \setminus S^{\text{alg}}} \text{reward}(p). \tag{1}$$

If a packet $p \in S^*(t) \setminus S^{\text{alg}}$, then it was available at time t to be collected by Algorithm 1, but the algorithm chose not to collect it. Recall that Algorithm 1 proceeds by solving an instance of a knapsack problem for all of the data packet collection opportunities at time t. Let $K^*(t)$ be an optimal solution to this knapsack instance. We note that

$$\sum_{S^*(t) \setminus S^{\text{alg}}} \text{reward}(p) \le \sum_{K^*(t)} \text{reward}(p)$$
$$\le 2 \sum_{S(t)} \text{reward}(p), \tag{2}$$

since the standard greedy knapsack algorithm employed by Algorithm 1 finds a knapsack solution that is at least $\frac{1}{2}$ of optimal. Combining (1) and (2), we have

$$\sum_{S^* \setminus S^{\text{alg}}} \text{reward}(p) \le 2 \sum_t \sum_{S(t)} \text{reward}(p)$$
$$= 2 \sum_S \text{reward}(p).$$

It follows that

$$\text{reward}(S^*) = \sum_{S^* \cap S^{\text{alg}}} \text{reward}(p) + \sum_{S^* \setminus S^{\text{alg}}} \text{reward}(p)$$
$$\le \text{reward}(S^{\text{alg}}) + \sum_{S^* \setminus S^{\text{alg}}} \text{reward}(p)$$
$$\le 3 \ \text{reward}(S^{\text{alg}}),$$

so $\text{reward}(S^{\text{alg}}) \ge \frac{1}{3}\text{reward}(S^*)$. ■

B. Solving the Offline SCD Problem

In order to obtain optimal solutions for the offline SCD problem, we formulate an ILP. We consider the fractional, interruptible version of the problem, although it is straightforward to modify it for the other variations. In the offline version, we have a set of data collection opportunities $O = \{(i, l_i, r_i, c, t_l, t_r)\}$ within a time interval $[0, T]$, and the objective is to maximize the total reward of all packets collected, subject to the transmission capacity constraint in each timeslot. Let $T_i = \{t : \exists (i, l_i, r_i, c, t_l, t_r) \in O \text{ s.t. } t \in [t_l, t_r]\}$ be the set of times available to collect data item i. We shall assume that opportunities to collect data item i do not overlap and define

$$c_{it} = \begin{cases} c & \text{if } \exists (i, l_i, r_i, c, t_l, t_r) \in O \text{ s.t. } t \in [t_l, t_r] \\ 0 & \text{otherwise.} \end{cases}$$

ILP:
Variables:
$x_{it} \ge 0$: the number of packets of data item d_i collected at time t (integer).
Objective:

$$\max \sum_{i,t} r_i x_{it} \tag{3}$$

Constraints:

$$\sum_t x_{it} \le l_i, \ \forall i \tag{4}$$

$$x_{it} = 0, \ \forall i, t \notin T_i \tag{5}$$

$$\sum_i c_{it} x_{it} \le C_j, \ \forall t \tag{6}$$

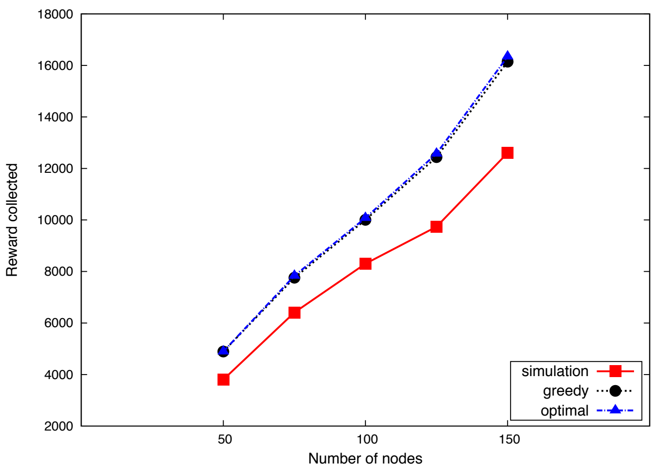

Fig. 1. Reward collected VS. number of sensors.

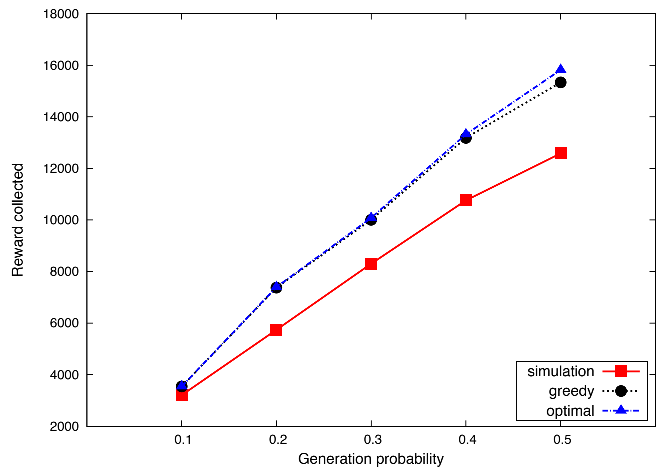

Fig. 2. Reward collected VS. data generation rate.

VI. Simulations

We simulate our online algorithm in OMNeT++ using 802.15.4 MAC layer (2.4GHz) [9]. The wireless sensors are randomly deployed in a $600m \times 600m$ sensing area. We vary the number of nodes from 50 to 150 in our experiments. This results in an average degree of 5 to 10 for the sensor nodes in the network. We adopt the mobility traces collected by GPS in a state fair at North Carolina, USA [10]. The maximum hopcount is set to five for the mobile user to broadcast its HELLO message. We repeat each experiment with five runs and show the averaged result. We also compare our simulation results with the ideal greedy solution and the optimal solution. The ideal greedy solution shows the results of our online algorithm without considering any packet losses and retransmissions due to network interference. The optimal offline solution is generated by the ILP solver CPLEX. At each time t, a sensor generates a new random data item with independent probability p (Poisson process model).

We considered three experimental scenarios:

- *Scenario* 1: Vary n, the number of randomly deployed sensors, from 50 to 150 nodes with a step size of 25. Fix $p = 0.3$ and $C = 30$kbps.
- *Scenario* 2: Vary p the probability of a sensor randomly generates a new data item in a timeslot, from 0.1 to 0.5 with a step size of 0.1. Fix $n = 100$ and $C = 30$kbps.
- *Scenario* 3: Vary C, the collection bandwidth of the mobile user from 1kbps to 5kbps with a step size of 1kbps. Fix $n = 100$ and $p = 0.3$.

Figure 1 shows the total reward collected by the mobile user varying the number of sensors. The result shows that the mobile user can collect more reward if there are more sensors in the field. It also demonstrates that our greedy algorithm can achieve close to optimal performance in an ideal network without any interference. We also implemented our online algorithm and run it in the simulator OMNeT++. The simulation result is slightly below the idealized greedy and the optimal solutions due to network interference, packet losses and retransmissions.

Next, we evaluate the reward collected by the mobile user varying the data generation probability. Again, Figure 2 shows that our greedy algorithm can achieve close to optimal performance in an ideal network without any interference. Similarly to Figure 1, our simulation result obtains less reward compared with the idealized greedy and optimal solutions. This is because packet losses and retransmissions occur due to interferences in the network.

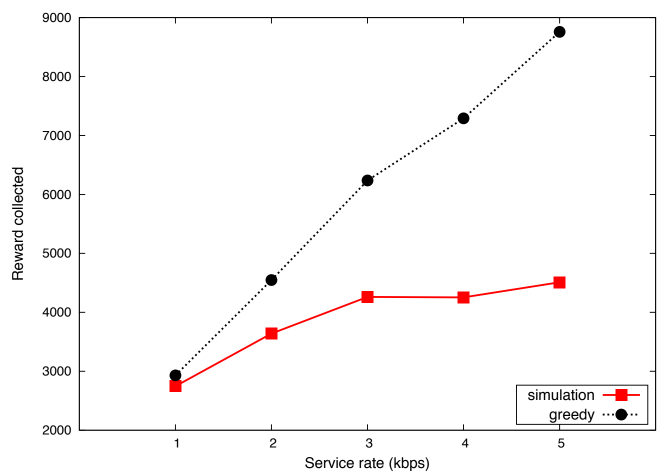

Fig. 3. Reward collected VS. service rate of mobile user.

Finally, we evaluate the reward collected varying the service rate of the mobile user in Figure 3. The results show that both the idealized greedy and the optimal solutions achieve similar performances. It is also interesting to see that both solutions perform the best when the service rate is around 20kbps. On the contrary, the simulation result keeps quite steady at different service rates. We believe that it is due to the limitation of the wireless channel being shared among the nodes in the same vicinity.

VII. Conclusions

In this work we considered the problem of how a mobile user should best collect data from sensors that it can communicate with in order that the most important data is collected. We formalized the problem as the Sensor Collection

Decision Problem (SCD) and proved that the a greedy strategy achieves a $\frac{1}{3}$ competitive ratio for the online problem. We also gave an ILP formulation of SCD which permitted us to compute optimal solutions for offline problem instances. We conducted accurate MAC level simulations using OMNeT++ and showed that the simulation tracked the idealized greedy online algorithm well. For the instances we considered, the online greedy solutions were nearly equal to the optimal offline ILP solutions.

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