Social Coalition-Aware Task Assignment in Flying Internet of Things

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Abstract. In this paper, we propose a social coalition-aware framework for task assignment in Flying Internet of Things (Flying IoT), where the intelligent unmanned aerial vehicles (UAVs), as a rising form of new IoT devices, can execute diverse tasks in a self-organized way. In this respect, the Social IoT (SIoT) paradigm promises to enable smart objects to autonomously work socially with surround objects, and thus build the social networks of objects without human intervention. The proposed framework aims at exploiting the extracted social attributes of drones for improving the efficiency of task coordination in a multi-hop delivery way. To measure the collaborative effect, a social-aware coalition game is formulated, and then we adopt the Shapley value to capture the relative importance of coalition members. The member with highest value will be elected as a leader for each coalition. Simulation results demonstrate that the proposed scheme can notably enhance the efficiency of task diffusion process compared to other benchmarks.

Keywords: Flying IoT · Social IoT · Task assignment · Game theory · Shapley value

1 Introduction

Internet of Things (IoT) promises to revolutionize humans' daily life by interconnect any possible smart objects, which can embrace some form of intelligence by providing a rich set of useful information to be gathered by heterogeneous objects [1]. However, the densification and heterogeneity of IoT devices have brought challenges to the scalability of IoT network architecture [2]. The unmanned aerial vehicle (UAV), as an emerging form of new smart devices, can collaboratively execute some dangerous tasks, such as environment sensing and emergency communication in disaster rescue [3]. However, it is impractical that

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all UAVs can directly communicate with ground controllers due to the limited power, which poses a challenge to the task implement [4]. Assume that intelligent UAVs can self-organize their decision making to free ground controllers from the tedious task of centralized control, the so-called Flying IoT are potential to play a crucial part in both civilian and military fields [5]. For better co-ordination and smoother task execution, drones need to collaborate on one mission. In this scenario, UAVs can be divided into several coalitions based on diverse mission types. In general, one UAV who communicates well with the ground controller can be elected as the coalition leader to guide the task implementation by broadcast task to its coalition members [4]. However, except for physical condition, some valuable social attributes should also be considered for UAVs to determine the importance in a coalition. In this respect, drones can establish social ties and collaborate socially with their surrounding drones, even though their owners have not established any relation on a social network, which conforms to the concept of Social Internet of Things (SIoT) [6]. According to the paradigm of SIoT, the UAVs can build the social networks among objects rather than participate in their owners' social networks, which inspires us to leverage the social context to improve the efficiency of task coordination.

Due to the dynamics of large-scale UAV networks, it is challenging to dynamically select a suitable sets of coalition leaders by accurately measuring their importance [4]. Game theory as a powerful mathematical tool, can analyze the users' rational behavior in wireless communications [7]. As one the most common characteristic function in cooperative game, the Shapley value plays an important role in value or cost-sharing game theoretic applications [8]. Due to its inherent ability to measure the contribution of the single players, the Shapley-value has been well applied into network and social-aware networking analysis [9–11]. The authors in [9] investigated the computation of Shapley value in the network centrality. In [10], the Shapley-value was used to enhance the networking Navigability in SIoT by measuring the influence of neighbor nodes. In [11], the authors adopted the Shapley-value to select the cluster head for each social community, and the selected seed user can improve the local offloading through multi-hop device-to-device (D2D) transmission. However, few work study how to utilize the Shapley-value to guide the task assignment in UAV networks.

To the best of our knowledge, the idea of leveraging social attributes to improve the task diffusion efficiency in Flying IoT has not been investigated yet. In this paper we intend to fill this gap, by designing a social coalition-aware task assignment method. The main contribution is the proposed novel social-aware scheme, which can select a set of suitable coalition leaders that can improve the efficiency of task coordination. In general, the proposed scheme aims to optimize the task diffusion speed through multi-hop delivery. To measure the collaborative effect of coalition leader, a social-aware coalition game is formulated. For this game, we adopt the Shapley value to capture the collaborative effect of one coalition member on the effectiveness of task diffusion.

The rest of this paper is organized as follows. In Sect. 2, we depict the social coalition-aware communication model with the framework of three different graph models and the optimization problem is formulated. In Sect. 3, the

Shapley value is adopted to measure the collaborative effect of coalition leader. The simulation results are conducted in Sect. 4 while conclusions are drawn in Sect. 5.

2 System Model and Problem Formulation

As shown in Fig. 1, we consider a multi-UAV networks with N UAVs and one ground controller. The sets of UAVs are denoted as $U = \{u_i\}_{i=1}^{N}$. Each UAV belongs to a coalition corresponding to a type of mission. Each UAV can directly receive the real-time task from a ground controller or from a coalition leader in a multi-hop delivery way. In this scenario, a UAV can directly deliver a B bits of data to the surrounding UAV, within one time slot t. We further assume that the span of each time slot is T seconds. Similar to assumption in [11], we focuses on delay-tolerant services, and thus the potential delay caused by multi-hop delivery can be ignored. Meanwhile, each drones is equipped with two antennas for transmit the mission information and control information, respectively [12]. The set of available service channel is denoted by $SC = \{sc_l\}_{l=1}^{L}$.

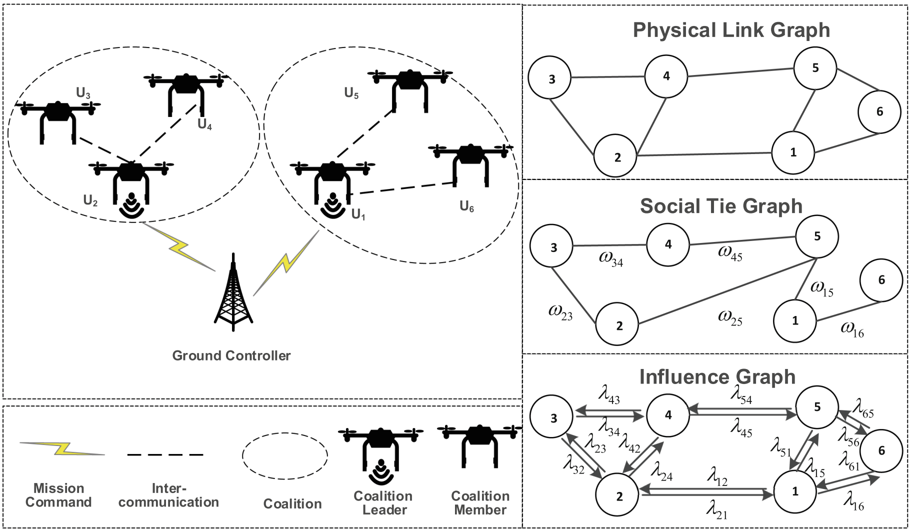

Fig. 1. The system model of coalition-based Flying IoT and its abstracted graph models.

Considering the dynamic 3D Cartesian coordinate model, the coordinate of u_i is denoted by $c_i = (x_i, y_i, z_i)$, and the distance between u_i and u_j can be represented as $d_{ij} = \|c_i - c_j\|$. Similar to the cooperative direct transmission in [12], the one-hop transmission rate for the link between u_i and u_j in channel sc_l is given by

$$R(i,j,l) = \frac{W}{2I_i(l)} \log_2(1 + \gamma_{i,j}) \tag{1}$$

where W is the normalized bandwidth block, $I_i(l)$ represents the sets of UAVs which select channel sc_l within the interference range, $\gamma_{i,j}$ represents the signal-to-noise ratio (SNR), and the channels between drones are dominated by line of sight (LoS) links [12]. Similar to [13], we further assume the fading process is constant within each time slot, and thus the data rate is constant during the time span of each one-hop link.

By establishing one-hop link among UAVs, we first introduce a physical link graph $G_p(U, E_p)$, where U represents the set of vertices (UAVs), and E_p represents the set of edges (available links). The edges can be constructed by satisfying the condition $E_p = \{(i,j)|B/R(i,j,l) \leq T\}$, which indicates that available link exists when u_i can entirely deliver the data packet to u_j within a given time slot. Considering that UAVs collaborate on different tasks, we assume that all the N UAVs form K coalitions. Let $C = \{c_k\}_{k=1}^{K}$ denotes the coalition set, where c_k denotes the set of UAVs in coalition k, and thus $\cup_{k=1}^{K} c_k = U$. In this paper, we assume that there exists no overlay part between any two coalitions.

In this paper, we innovatively consider the impact of social attributes on the performance of UAV task assignment. The context information such as position and mission target needs to be exchanged among drones to ensure the completion of various tasks. Through the interaction, the social ties can be built among UAVs. According to the SIoT paradigm [6], we consider the following types of social ties between two UAVs: the Ownership Object Relationship (OOR) determines whether two objects belongs to the same owner, the CoLocation Object Relationship (CLOR) measures the degree of location proximity; the Co-target Object Relationship (CTOR) is created when two objects collaborate to execute the same task; the Social Object Relationship (SOR) is established to measure the contact interval, such as contact frequency. For simplicity, we assume that the weighted social tie between two UAV i and j is denoted as $\omega_{i,j}$. Given the social ties between any two UAVs, we further construct a social tie graph $G_s(U, E_s, w_s)$, where $E_s = \{(i,j)|w_{i,j} > 0\}$ denotes the set of edges determine whether social tie exists between two UAVs.

Intuitively, in each coalition, the member has the highest centrality in both physical and social domains can be elected as coalition leader, which can accelerate the diffusion speed of task by broadcasting. In this paper, we consider K task data packets corresponding to K coalitions, and one coalition leader corresponding to one coalition. The ground controller first releases different tasks to each coalition leader. For a given coalition and its associated task, other UAVs in other coalitions can help to forward the task by multi-hop delivery. Hence, the successful delivery of task is influenced by both the social tie and physical condition between any two UAVs.

Next, we want to measure the influence according to both social tie graph and physical link graph. For instance, if $u_i \in c_k$ have to deliver the task information to another coalition member and the shortest multi-hop path containing $u_j \in c_{k'}$, there must exist a one-hop link passing u_j. Hence, the *directed influence* $\lambda_{i,j}$ is defined as the preference of $u_i \in c_k$ delivering task to its neighbor u_j, as follows:

$$\lambda_{i,j} = \sum_{u_{i'} \in c_k \setminus \{u_i\}, u_j \in SP_{i,i'}} \frac{\omega_{i,i'}}{|SP_{i,i'}|} \tag{2}$$

where $|SP_{i,i'}|$ denotes the number of UAVs within the shortest multi-hop path in $G_p(U, E_p)$.

Given the directed influence between any two UAVs, we further depict the influence graph $G_i(U, E_i, \lambda_i)$ to model the global influence. We aim to maximize the expected number of UAVs receiving the real-time task through multihop delivery by selecting suitable coalition leader for each coalition based on the influence graph. Let ρ_t be the UAVs set that have received task until time slot t, and $\Lambda = \{\rho_0, \rho_1, ...\rho_t\}$ represents the task diffusion process.

To accurately model the influence, we denote $\mathcal{N}_i$ as the one-hop neighbor set of u_i, and d_{ij}^s as the sum distance of shortest path between u_i and u_j. Next, we further define $\mathcal{N}_i^m = \{u_j | d_{ij}^s < d_{th}, u_j \in G_p\}$ as the multi-hop neighbor, whose distance from u_i is less than a given threshold. Next, we redefine the *undirected influence* based on closer neighbor set.

Definition 1. *The undirected influence of ρ_t on $u_i \in U \setminus \rho_t$ is defined as the expected number of UAVs on the multi-hop neighbor set $\mathcal{N}_i^m$ that will successfully receive the task data packet from the UAVs in ρ_t, which is expressed as*

$$\lambda_u(i, \rho_t) = \sum_{u_{i'} \in N_i^m} \left(1 - \prod_{u_j \in N_{i'}^m \cap \rho_t} (1 - \lambda_{i,j})\right) \tag{3}$$

If $u_k \in \rho_t$ delivers the data packet to any UAV in the close neighbor set of u_i, we can say that u_k has an influence on u_i. If only u_k in ρ_t can affect u_i, the u_k is considered to has an *exclusive influence* on u_i, which is given by

$$\begin{aligned}
\lambda_u(i, k) &= \lambda_u(i, \rho_t) - \lambda_u(i, \rho_t \setminus u_k) \\
&= \sum_{u_{i'} \in N_i^m} \left(1 - \prod_{u_j \in N_{i'}^m \cap \rho_t} (1 - \lambda_{i,j})\right) - \sum_{u_{i'} \in N_i^m} \left(1 - \prod_{u_j \in N_{i'}^m \cap \rho_t \setminus u_k} (1 - \lambda_{i,j})\right) \\
&= \sum_{u_{i'} \in N_i^m} \left(\prod_{u_j \in N_{i'}^m \cap \rho_t \setminus u_k} (1 - \lambda_{i,j}) - \prod_{u_j \in N_{i'}^m \cap \rho_t} (1 - \lambda_{i,j})\right) \\
&= \sum_{u_{i'} \in N_i^m} \left((1 - \prod_{u_j \in N_{i'}^m \cap \rho_t} (1 - \lambda_{i,j})) \prod_{u_j \in N_{i'}^m \cap \rho_t \setminus u_k} (1 - \lambda_{i,j})\right)
\end{aligned} \tag{4}$$

where the first term denotes the probability that u_k delivers the received data packet with at least one one-hop neighbor of u_j, and the second term is the probability that none of the members of $\rho_t \setminus u_k$ can delivers the received data packet with at least one one-hop neighbor of u_j. Hence, the *exclusive influence* can be expressed as the multiplication of these two terms.

Therefore, the optimization problem in this paper can be formulated as

$$\max_{\rho_0} \frac{1}{t} \sum_{x=1}^{t} |\rho_x| \tag{5}$$

It is obviously that we should select the initial coalition leader set ρ_0 to optimize the expected number of UAVs receiving the data packet in task diffusion process. There are some conventional methods in graph theory to solve problem (5) such as betweenness centrality and closeness centrality. However, these methods cannot accurately measure the relative importance of each coalition member. Hence, we need to adopt a suitable approach to accurately quantify the cumulative contributions for any single member.

3 Cooperative Game-Based Task Assignment

Game-theoretic solutions have recently been applied into the analysis network centrality. Particularly, the Shapley value in cooperative game can effectively measure the relative importance of single player to a group of players [14]. In general, if the characteristic function is defined as the influence of a node on other nodes over a graph, the Shapley value can be adopted to measure the influence of each node on other nodes. Consequently, the Shapley value in the a given game can be used to measure the centrality of a node over a graph, which has a high degree of flexibility to capture the relative importance in both social and physical domains. Now, we will formulate the optimization problem as a coalition game, and then adopt the Shapley value to measure the importance of each coalition member.

Based on the graph model above, the social-aware coalition game can be defined as $\mathcal{G} = (U, C, v)$, where U denotes all the players (UAVs), C represents the coalition structure of U, and v is a characteristic function assigning each coalition in the structure a value. Since the coalition formation problem can be solved by the some existing methods [8], we assume that the coalition structure is given by $C = \{c_k\}_{k=1}^{K}$, and mainly focus on the coalition leader selection based on the value (characteristic function) design. The value of a given coalition c_k is denoted as $v(c_k)$. Based on the aforementioned diffusion model, it is obvious that the diffusion process Λ is determined by the directed influence, one-hop and multi-hop neighbor set. Therefore, the value function for the coalition game $\mathcal{G}$, reflecting the cumulative *undirected influence* can be defined as

$$v(c_k) = \begin{cases} \sum_{u_i \in U \setminus c_k} \sum_{u_j \in c_k} \theta \lambda_u(i,j), & \text{if} \quad c_k \neq \emptyset; \\ 0, & \text{Otherwise.} \end{cases} \tag{6}$$

where θ represents the price parameter to quantify influence. In this way, the value function in (6) will be a monetary value and of transferable utility (TU) [14]. The higher value function indicates a higher probability of delivering the data packet to other UAVs.

Now, we adopt the Shapley value of TU game $\mathcal{G}$ to measure the contribution of each coalition member to the value function of any subset s_k belonging to coalition c_k compared to UAVs in c_k, which is given by

$$\phi_i(c_k, \mathcal{G}) = \sum_{s_k \subseteq c_k \setminus u_i} \frac{(|c_k| - |s_k| - 1)!|s_k|!}{|c_k|!}(v(s_k \cup u_i) - v(s_k)) \tag{7}$$

The Shapley value can measure the degree of collaboration between two coalition members. Then, we illustrate the relationship between Shapley value of u_i and its exclusive influence on UAVs in other coalition, which corresponds to the case that some coalition member without the ability to communicate with its leader directly, so they need assistance from other coalitions to forward data packet.

Theorem 1. *The Shapley value of $u_i \in c_k$, can be calculated as the exclusive influence of u_i on other UAVs that are not in c_k, which is given by*

$$\phi_i(\mathcal{G}) = \sum_{\mathcal{N}_j^m \cap \mathcal{N}_i \neq \emptyset} \frac{\theta}{1 + |\mathcal{N}_j^m|} \tag{8}$$

Proof. Based on the expression of *exclusive influence*, the Eq. (7) can be rewritten as

$$\phi_i(c_k, \mathcal{G}) = \sum_{s_k \subseteq c_k \setminus u_i} \frac{(|c_k| - |s_k| - 1)!|s_k|!}{|c_k|!} \sum_{u_j \in U \setminus s_k} \lambda_u(i, j) \tag{9}$$

Given a coalition s_k and $u_i \notin s_k$, the u_i is viewed to have a exclusive influence another u_j. if and only if there is no intersection between the multi-hop neighbor set of u_j and the one-hop neighbor sets of all coalition members in s_k, satisfying that $\{\cup_{u'_i \in s_k} N_{i'}\} \cap N_j^m = \emptyset$. According to [9], the probability of satisfying this condition equals to $\frac{1}{1+|\mathcal{N}_j^m|}$. Moreover, if u_i wants to deliver task to the multi-hop neighbor set of u_j, at least one multi-hop neighbor of u_j must belong to one-hop neighbor set of u_i, which implies $\mathcal{N}_j^m \cap \mathcal{N}_i \neq \emptyset$. Hence the Theorem 1.

Given the expression of Shapley value for each coalition member, the strategy of selecting coalition leader can be summarized as follows:

- All UAVs are divided into different coalition by mission types and they exchange context information in both social domain and physical domain. The ground controller constructs virtual graph models based on the physical link condition and social tie.
- In each coalition, the coalition member with highest Shapley value among the members of its coalition will be elected as the coalition leader. Then, the ground controller sends the data packets about different task to the coalition leaders. The coalition leaders first broadcast the data packet to its one-hop neighbor, and all coalition member will help other members within or without its coalition, by acting as the multi-hop relay node.

The main computational complexity consumption of proposed scheme comes form the computation of Shapley value. Firstly, the original Shapley value formula needs to consider $\mathcal{O}(2^{|N|})$ coalitions [9], which causes too large computational complexity consumption in the dense network. According to Theorem 1, the complexity can be simplified to only calculate the node degree and the number of shortest path in graph model. Herein, the complexity of calculating the node degree and calculating the shortest path can be represented as $\mathcal{O}(|N|)$ and $\mathcal{O}(|E_d| + |N| \log |N|)$, respectively.

4 Simulation Results and Performance Analysis

In this section, we compare our proposed social coalition-aware task assignment scheme, termed as "SCTA" with other benchmarks including betweenness centrality, closeness centrality, random selection, and our proposed scheme without considering the social tie. We conduct the simulation in a three-dimensional $(2 \times 2 \times 2\,\text{km}^3)$ space, where all UAVs are randomly distributed and in the relatively stationary state. The main simulation parameters are given as follows: bandwidth $B = 10\,\text{MHz}$ for each channel, the noise power density equals to $-174\,\text{dBm/Hz}$, the transmit powers of UAV are set to $30\,\text{dBm}$, the duration for each time-slot is $1\,\text{ms}$, the distance threshold to determine the close neighbor is

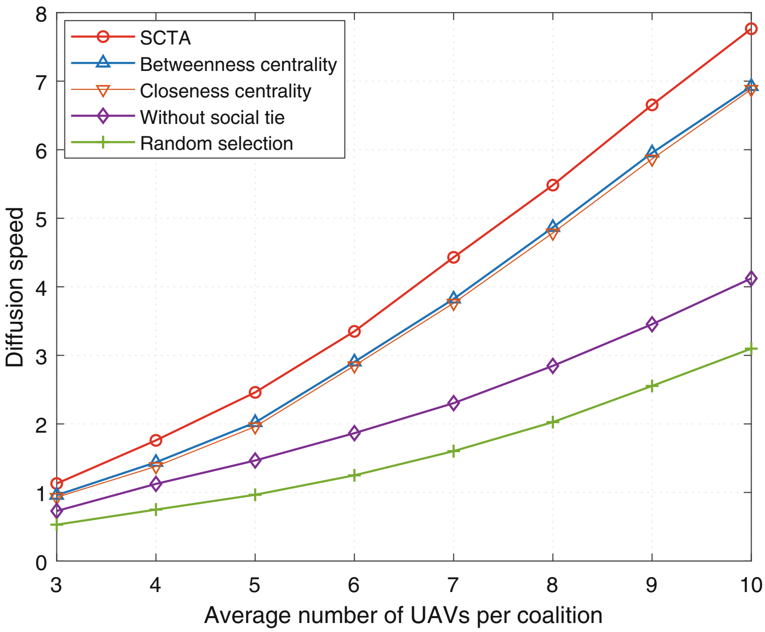

Fig. 2. The diffusion speed with varying number of UAVs per coalition.

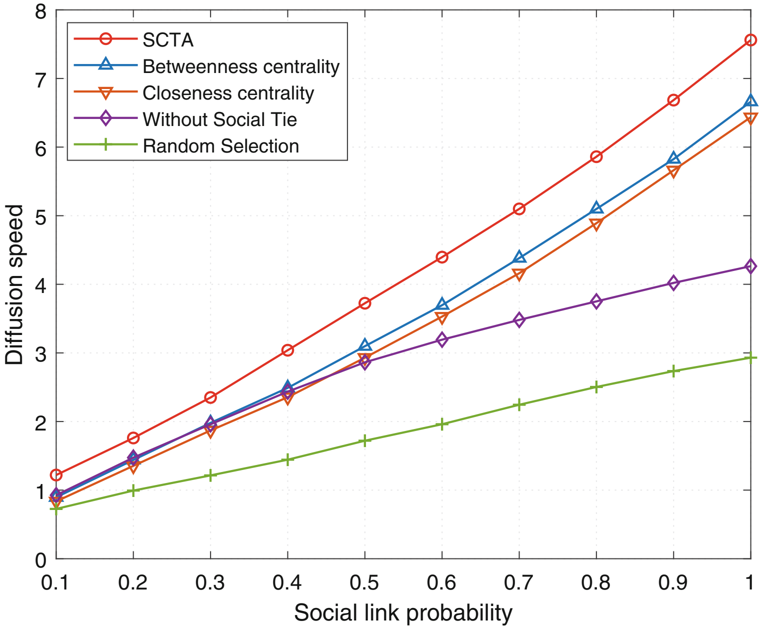

Fig. 3. The diffusion speed versus the social link probability.

400 m, and the size of each data packet is 1000 bits. To simplify, the internal of social tie is uniformly selected within [0, 1].

Figure 2 compares the diffusion speed attained by our proposed SCTA with other benchmarks. The diffusion speed of task represents the average difference between the number of UAVs that received the data packet during two consecutive time slots. The number coalition is set to 10. In this figure, it is obvious that the diffusion speed increases with the number of UAVs per coalition, and our proposed scheme can always achieve the optimal performance. This is because the betweenness centrality and closeness centrality do not comprehensively consider the relative importance in coalition leader selection. In general, the closeness centrality always select the coalition leader which is close with other coalition members, and betweenness centrality always select the coalition leader which are in the most of the shortest path sets.

In Fig. 3, the diffusion speed is shown with varying probability that the social tie exists, where the number of coalition is 10, and the number of UAVs is set to 10 per coalition. We aim to investigate the impact of social relationship on the task diffusion. It can be seen that the diffusion speed increase with the social link probability. It is worth mentioning that, as the social link probability increases, the advantage of our proposed algorithm is more obvious. Therefore, the rational utilization of social attributes can effectively enhance the performance of task assignment.

5 Conclusion

In this paper, we proposed a novel social coalition-based scheme for task assignment in Flying IoT, where the UAVs, as coalition members, can self-organize their task delivery process. Based on the SIoT paradigm, the UAVs can build the social networks of objects without human intervention. To model the collaborative effect, we construct three different graph models, and a cooperative coalition game is formulated. For this game, we adopt the Shapley value to measure the contribution of single coalition member to each other, and then dynamically select a leader for each coalition. Simulation results proved the superiority of our proposed scheme in terms of diffusion efficiency.

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