

RAVEN: Reverse Auction-Based Resource Allocation for UAV-Enabled Edge Computing

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Abstract

In this work, we explore the problem of optimal resource allocation in an Unmanned Aerial Vehicle (UAV)-enabled edge computing platform. In the existing literature, researchers have focused on developing edge platforms in the presence of UAVs and ground nodes. However, in real-world scenarios requiring temporary computing, such as augmented reality, industrial IoT, and situational events, deploying ground stations to enable edge computing is difficult. To address this issue, we propose a reverse-auction-based resource-allocation scheme, *RAVEN*, for UAV-enabled edge networks. The proposed architecture operates without a ground node, distributing all computations exclusively among the UAVs. In *RAVEN*, we aim to maximize overall system utility by employing a unique bidding strategy that ensures user satisfaction and solves the winner-determination problem for efficient resource allocation. We develop an algorithm that approximates the winner determination problem in polynomial time, facilitating practical implementation. We also evaluated the performance of *RAVEN* through simulations and theoretical analysis, demonstrating its feasibility and effectiveness.

CCS Concepts

• **Networks** → **Network resources allocation**; **Mobile ad hoc networks**; *Traffic engineering algorithms*; • **Theory of computation** → Algorithmic game theory.

ACM Reference Format:

Ayan Mondal, Mir Razee M., Vansh Kathnawal, and Karri Trivedi. 2026. *RAVEN: Reverse Auction-Based Resource Allocation for UAV-Enabled Edge Computing*. In *7th International Workshop on Drone-Assisted Wireless Communications for 5G and Beyond (DroneCom '26)*, October 26–30, 2026, Austin, TX, USA. ACM, New York, NY, USA, 6 pages. <https://doi.org/10.1145/3842435.3843956>

1 Introduction

Edge Computing is envisaged to bring data processing closer to the network edge. Unlike traditional centralized cloud computing, edge computing leverages computing resources in the access network, optimizing proximity to end users to improve latency. By extending edge computing platforms to mobile nodes, mobile edge computing (MEC) prioritizes proximity to users by situating computing resources near end users and reducing propagation delay. In this work, we consider using the Unmanned Aerial Vehicle (UAV) networks to enable the MEC platform. It provides temporary computation power at remote locations with ease. Integration of edge computing with next-generation networks is a pivotal aspect of MEC, as the high speed and capacity of 6G facilitate the deployment of highly scalable UAVs. UAV-enabled edge computing finds application across diverse use cases, including augmented reality, industrial IoT, and situational events. By processing data locally or near users, UAV-enabled edge computing reduces latency, making real-time applications more responsive. However, because a UAV has constrained computational and energy resources, the main challenge in a UAV-enabled edge computing platform is the decentralization of tasks and the efficient allocation of computational resources. Therefore, we need to design a scheme for the UAV-enabled edge platform to efficiently orchestrate computational resources while accounting for the energy capacity constraints of the UAVs.

Motivating Scenario: There are several applications of UAV-enabled edge computing platforms, as depicted in Figure 1. We specify a few examples in this paper. In agricultural



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DroneCom '26, Austin, TX, USA

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ACM ISBN 979-8-4007-2958-4/26/10

<https://doi.org/10.1145/3842435.3843956>

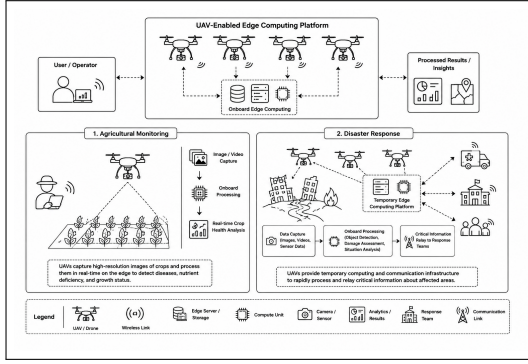


Figure 1: Motivating Scenario

applications, UAVs deployed over fields serve as edge computing platforms for real-time crop health analysis. On the other hand, as part of a disaster response team, we can use the UAV-enabled edge computing platform as a temporary computation platform and relay processed critical information about affected areas to the specific response teams.

In this work, we propose a reverse auction-based scheme, named RAVEN, for auctioning resources that combines a position auction and a generalized second-price auction (GSP) to achieve equilibrium. We design a bidding strategy for UAVs that calculates bids based on task popularity and their available resources. Considering that UAVs are rational entities, we argue that they aim to maximize their payoff by choosing an optimal strategy while ensuring user satisfaction. Finally, we formulate a *winner determination* scheme to select the optimal UAV-enabled edge node and provide an approximate greedy solution to the problem. In summary, the specific contributions of this work are as follows:

- (1) We propose a reverse auction game-based resource allocation scheme, RAVEN, for UAV-enabled edge platforms. We use a position auction and a generalized second price auction (GSP) to achieve an equilibrium point in RAVEN.
- (2) We design the utility functions for the UAVs and define their bid efficiency. Thereafter, we formulate the problem as a generalized mixed-integer program and prove its NP-completeness.
- (3) We propose a greedy approximation algorithm to solve the problem in polynomial time and evaluated the performance of the proposed scheme theoretically and through simulation over Google Colab¹.

2 Related Works

We studied existing literature on mobile edge computing and game-theoretic problems. Most current research focuses on

¹<https://colab.research.google.com/>

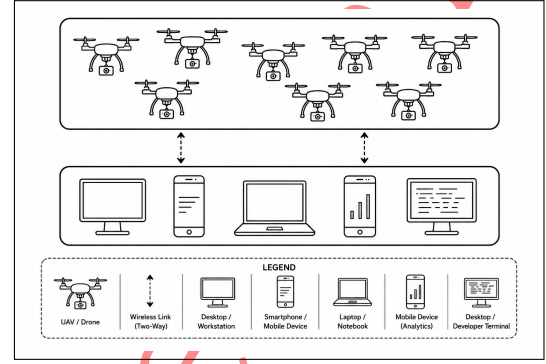


Figure 2: Schematic Diagram

computing data locally and offloading it to a ground node. Ma *et al.* [7] proposed a potential game to formulate the optimal allocation of tasks to UAVs. They proposed using a ground station alongside the UAVs to design the edge computing platform. Chen *et al.* [3] studied different game-theoretic models in the context of UAV platforms. However, it did not focus on using UAVs as an edge computing platform. Habiba *et al.* [4] proposed a software-defined mobile edge platform and designed an auction-based scheme for task offloading. However, for the UAV-enabled edge platforms, we cannot use the proposed scheme directly.

Additionally, Mkiramweni *et al.* [8] studied the application of game-theoretic approaches in the context of wireless communication in a UAV platform. Luo and Huang [6] proposed a heuristic-based task offloading scheme for UAV networks that accounts for non-cooperative UAVs. Agrawal *et al.* [1] proposed a game-theoretic resource allocation scheme for the software-defined edge platform while ensuring optimal throughput. In another work, Sun *et al.* [9] proposed two Double Auction-based resource mapping schemes for IoT and edge devices, incorporating dynamic pricing. Hosseini and Ghazizadeh [5] explored NOMA and developed an optimal resource-allocation scheme for UAVs. Cary *et al.* [2] proposed greedy bidding strategies for a repeated auction in the context of advertisements on a single keyword.

However, there is a need to revisit the problem of resource allocation for UAV-enabled edge computing. We observed that the aforementioned problem can be mapped to the ‘job scheduling’ problem, which is NP-hard; we turn to game theory to approximate the ideal scenario.

3 System Model

We consider the presence of multiple UAVs at predetermined locations. These UAVs are further divided into a set of closer regions, as shown in Figure 2. We assume that the UAVs select a central UAV in a round-robin manner, which acts

as a mediator among multiple UAV regions and is responsible for decision-making during resource allocation. The set of UAVs and the IoT user request with computation requirements are represented by N and K , respectively. The central UAV collects the requirements of the requested tasks and runs the allocation algorithm at regular intervals. The resource allocation decision depends on factors such as delays in computation and transmission to the UAV, and the availability of computing and energy resources on the UAV. IoT users initially send control messages to the nearest available UAVs; thereafter, these messages are forwarded to the central UAV. The central UAV is responsible for allocating the computational resources to the respective IoT user.

Execution Delay. We consider that IoT users request tasks for offloading to UAVs with varying computational requirements. For each IoT user request k of type g_k , the required amount of data to be computed is denoted by d_k . Hence, considering that the required CPU cycles/byte is denoted by L_n for UAV n , the CPU resources needed for completing the request k can be calculated as:

$$\lambda_{k,n} = d_k L_n, \forall k \quad (1)$$

The IoT transmission rate during task offloading depends on the state of the wireless channel and the distribution of the available spectrum. At any given time, we assume the channel conditions remain constant. The notation for the channel power gain (h_k), transmission power (p_k), and allocated bandwidth ($B_{k,n}$) indicates the power transfer between IoT user k and the UAV n . We ignore the downlink transmission delay because it is negligible relative to the uploading delay. Therefore, the up-link transmission delay $\delta_{k,n}^{up}$ yield is as:

$$\delta_{k,n}^{up} = \frac{d_k}{r_{k,n}^{up}} \quad (2)$$

where $r_{k,n}^{up}$ denotes the maximum uplink data rate between IoT user k and the UAV n . The computation delay $\delta_{k,n}^{comp}$ at UAV n is calculated based on the clock frequency of the UAV's CPU and the required cycles for the task and evaluated as follows:

$$\delta_{k,n}^{comp} = \frac{\lambda_{k,n}}{c_n} \quad (3)$$

where c_n denotes the CPU cycles of UAV n per unit time. Hence, the uplink transmission latency and processing time make up the overall execution delay. Therefore, the execution delay at UAV and n is calculated as:

$$\delta_n = \sum_k (\delta_{k,n}^{up} + \delta_{k,n}^{comp}) y_{n,k} \quad (4)$$

where $y_{n,k}$ is a binary variable and defined as follows:

$$y_{n,k} = \begin{cases} 1 & \text{if the IoT request } k \text{ is allocated to UAV } n \\ 0 & \text{Otherwise} \end{cases} \quad (5)$$

Problem Scenario. In the context of edge computing with multiple UAVs, this work addresses the problem of optimal resource allocation, ensuring efficient allocation of computational resources from UAVs to multiple IoT users across multiple task types and minimizing energy consumption. While designing the solution for the aforementioned problem, we mainly focus on parameters such as energy-efficient resource allocation, maximum resource utilization, IoT user satisfaction, and scalability and robustness.

4 RAVEN: The Proposed Game-Theoretic Resource Allocation Scheme

In RAVEN, we consider that there is no ground station, and the computation is distributed among the UAVs themselves. Hence, we designed a game-theoretic model to capture the interactions between UAVs and users in a UAV-enabled edge computing platform, accounting for task types, UAV computational capacities, and user preferences. Motivated by the work of Habiba *et al.* [4], we use a reverse-auction mechanism to design the interactions among the central UAV² and the set of UAVs. The central UAV then conducts a reverse auction in which all other UAVs participate as Bidders and submit bids for all requests, trying to sell their Computational resources. The winning bidder is allocated the task.

Justification for Using a Reverse Auction Game. In contrast to traditional auctions, reverse auctions use game theory to swap the roles of buyers and sellers. In a reverse auction, several buyers bid to acquire a good or service, with the seller serving as the auctioneer. The lowest bidder wins the auction as the buyers compete by placing bids. This strategy is frequently employed in procurement processes, where buyers seek to negotiate the best price from sellers. Buyers may save money by participating in reverse auctions, which encourage competition among sellers. Reverse auctions offer an intriguing field of study in game theory, as buyers and sellers employ different tactics during the auction. In RAVEN, IoT users engage as buyers in a position auction conducted by the central UAV, the *auctioneer*. The UAVs are bidders offering their computing resources. Using a *Generalized Second-Price Auction*, we aim to solve the winner determination and bidding strategy problems in RAVEN.

²The UAV is chosen for the centralized coordination for that round of resource allocation.

Utility of UAVs. The utility function of the UAVs signifies the degree of satisfaction with respect to the parameters – amount of computation acquired and delay in service. Additionally, the predicted profit and associated allocation cost of a UAV determine its usefulness for different types of tasks. Allocating resources for computing task offloading affects each UAV's energy consumption profile. We define the energy consumed e_n by UAV n for each resource unit as $-e_n = \alpha_n \kappa_n c_n^3$, where κ_n is a constant parameter representing the capacity of each core being switched per clock cycle. We use α_n as a weighting parameter to calculate the financial cost of energy use.

Moreover, since auctions are based on monetary profit, we introduce a popularity factor for auctioned tasks, represented by the hit ratio θ_k for each task k . It portrays the types of tasks the bidder prefers over others. We consider the *valuation* v_n of each UAV as $f(e_n)$, i.e., $v_n = f(e_n)$. Motivated by the work of Habiba et al. [4], we define the utility function $\mathcal{U}_{k,n}$ of each UAV n for executing the task k , as follows:

$$\mathcal{U}_{k,n} = (\Pi_k - \theta_k v_n) x_{k,n} \quad (6)$$

where the cost of performing a requested task k is denoted by Π_k ; and $x_{k,n}$ represents the amount of unit resources requested from the UAV n for the task k by a central UAV.

Auction Game for UAVs. As offloading requests reach the central UAV, A auction slots are created for each task type. The requests arrive at the central UAV as $\{d_k, g_k\}$ for each task k . Thereafter, the central UAV broadcasts a proposal message containing different information, such as the task type, task hit ratio, and the price allocated to the task in the previous auction round. We assume that UAV n has ω_n^{rem} units of computational resources available and aims to sell them by bidding in the auction. The UAV follows a *Greedy Bidding Strategy* [4], and chooses a bid strategically to maximize its payoff value of the utility function. The bid submitted by UAV n for task k is denoted $b_{n,k}$. After the bids are determined, the central UAV determines the auction winner and allocates the resource to its respective IoT user, as depicted in Figure 3.

Bidding Strategy for the UAV. We consider a recurring auction with ϕ rounds, where ϕ is constant, and a fixed set of N players. In every new round of the repeated auction, the UAVs can adjust their bids. The primary goal of each UAV across multiple auction rounds is to maximize its utility. We assume that the recent past can be a precise predictor of the future, leading to a greedy bidding strategy in which a player bids on the assumption that no other player changes their bid, thereby maximizing their payoff. In other words, given the chosen strategies in the recent auction round, each UAV calculates a bid so that its current bid does not reduce

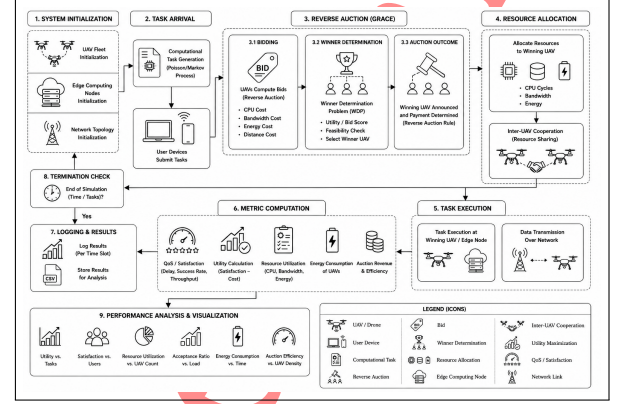


Figure 3: Flowchart of RAVEN

its payoff [2]. Mathematically,

$$\Pi_{k-1}^{(t-1)} x_{n,k-1}^{(t-1)} - b_{n,k}^{(t)} x_{n,k}^{(t-1)} \geq \theta_{k-1} x_{n,k-1}^{(t-1)} v_n - \theta_k x_{n,k}^{(t-1)} v_n \quad (7)$$

where $[\cdot]^{(t)}$ denotes the value of the parameter at auction iteration t and $t \leq \phi$.

Hence, motivated by the work of Cary et al. [2], we consider that the previously assigned values for the specified task types are $x_{n,k}^{(t-1)}$ and $\Pi_k^{(t-1)}$ and update the bids of tasks as follows:

$$b_{n,k}^{(t)} = \begin{cases} \theta_k v_n, & \text{if } k = 1 \\ \theta_k v_n + \frac{x_{n,k-1}^{(t-1)} + x_{n,k}^{(t-1)}}{2} \left(\Pi_{k-1}^{(t-1)} - \theta_{k-1} v_n \right), & \text{if } 1 < k \leq K \end{cases} \quad (8)$$

Auction Winner. To identify the winner in the auction game, we determine which bidders should be allocated which items to maximize the auctioneer's revenue. The challenge is to find an allocation that satisfies the constraints while optimizing a specified objective function. In RAVEN, we consider the *Combinatorial Reverse Auctions* process, in which a buyer seeks to purchase a set of items from a set of suppliers; the problem is to determine which suppliers should be awarded contracts to provide specific items. We define bid efficiency as a constant parameter encompassing the required resource quantity, actual resource availability, bidding prices, satisfaction indices, and hit ratios. Mathematically, the bid efficiency η_n of UAV n [4] is evaluated as:

$$\eta_n = \log \left(\frac{a_n}{b_n} \right) \quad (9)$$

where $a_n = \sum_{k=1}^K a_{n,k}$ and $b_n = \sum_{k=1}^K \gamma_{n,k} \theta_k b_{n,k} \omega_n^{rem}$; $a_{n,k}$ denotes the amount of the computation resource units requested from UAV n for task k ; and $\gamma_{n,k}$ represents satisfaction level of IoT user for request k against the bidding of UAV n . We argue that each IoT user aims to get a high satisfaction factor; hence,

we get:

$$n' < n, \text{ if } \gamma_{n',k} < \gamma_{n,k} \text{ and } n \neq n' \quad (10)$$

In RAVEN, the bid of each UAV includes the bidding price $b_{n,k}$ for request k and the amount of resources available to perform the tasks ω_n^{rem} . Hence, after receiving the bids from the UAVs, the centralized UAV aims to maximize the system performance by considering the following:

$$\max \sum_{n=1}^N \eta_n x_{n,k} \quad (11)$$

$$\text{s.t.} \quad C1: \sum_{n=1}^N x_{n,k} \geq \sum_{n=1}^N \sum_{k=1}^K a_{n,k} y_{n,k} \quad (12)$$

$$C2: \sum_{k=1}^K x_{n,k} \leq \omega_n^{rem} \quad (13)$$

$$C3: \sum_{k=1}^K y_{n,k} \leq 1 \quad (14)$$

We argue that the optimization problem is a variant of the generalized mixed-integer problem with minimum quantities, which is NP-complete. Hence, to achieve a polynomial-time solution, we use a greedy approximation algorithm in RAVEN. In RAVEN, we sort the UAVs by their bidding efficiency in decreasing order and allocate resources greedily. The greedy resource allocation assigns each task to the UAV with the highest bidding efficiency that also has sufficient resources and energy to perform it. We argue that the first part of RAVEN has a complexity of $O(\max\{N \log N, K \log K\})$. On the other hand, the greedy resource allocation process has a complexity of $O(N)$.

Complexity Analysis. Computational time complexity of the algorithm Sorting the UAVs takes $O(N \log N)$ time per task type, and sorting the tasks by required resource amount takes $O(K \log K)$ time. Assigning the tasks using the greedy approximation algorithm takes $O(KN)$ time in the worst case. Combining everything, the proposed scheme, RAVEN, runs in $O(KN \log N + NK + NK \log K)$ time in the worst case.

5 Performance Evaluation

We consider a UAV offloading space with a varying number of users requesting offloading tasks ranging from 200 to 1000. The results presented are from simulations run for 100 rounds per user set, where in each round, users randomly request any task type and receive a random offloading data size.

Simulation Setup. The simulation was run on Google Colaboratory³, which used a 2-core CPU at 2.2 GHz and 12

³<https://colab.research.google.com/>

GB of RAM. The simulation for 100 rounds took around 7 seconds to complete, averaging 0.07 seconds per round when allocating resources to 1000 users. The detailed simulation parameters are presented in Table 1.

Table 1: Simulation Parameters

Parameter	Value
Number of Candidate UAVs (N)	5
IoT User Range (K)	200:25:1000
Task Profiles Deployed (M)	3
Auction Settlement Base Price ($\Pi_{\min}$)	10

Satisfaction of offloading users. Figure 4 shows the average satisfaction per user. It is determined by the amount of resources allocated to the user and the service delay. We observe that at a low number of IoT devices, the satisfaction is higher. However, it degrades steadily as the number of IoT devices increases. With high user density, data rates decrease due to channel sharing and a long processing queue.

Valuation. The valuation, depicted in Figure 5, is calculated as the sum of valuations for each user. As mentioned in the winner determination problem section, we aim to maximize valuation, ensuring that UAVs that provide services with a higher satisfaction index and lower prices are preferred over others. As shown in Figure 5, it gradually increases with the number of users and becomes steeper as the number of offloading requests increases, due to resource constraints. We observe that as the number of IoT applications increases, the auctioneer can exploit diversity gains by selecting only the highly profitable tasks that yield a high efficiency index η_n . The plateau represents the absolute hardware saturation point. Due to physical limitations such as utilizing maximum computation capacity or a low remaining energy, the UAVs opt out of provisioning services.

Resource Utilization Rate. The resource utilization rate is the average ratio of used resources to available resources across all the rounds, as shown in Figure 6. Here, we observe a high utilization rate as the number of users increases, driven by increased demand. It behaves inversely to the served rate. We observe that low-capacity networks reach peak utilization sooner than higher-capacity networks. We argue that the greedy reverse auction successfully minimizes idle hardware overhead under high demand.

Request Served Rate. The served rate, presented in Figure 7, is the average ratio of the number of users served to the number of users. We observe a decrease in as the number of users increases, because with more offloading users, resources become insufficient to perform tasks due to limited

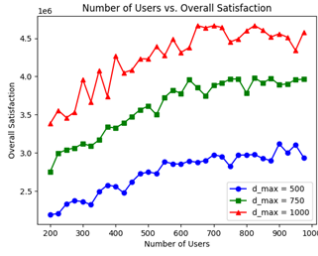


Figure 4: Satisfaction

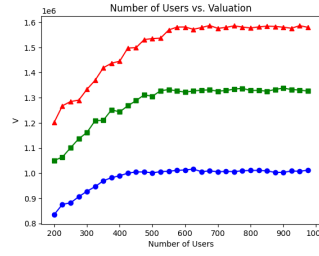


Figure 5: Valuation

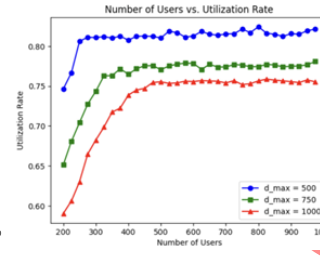


Figure 6: Utilization Rate

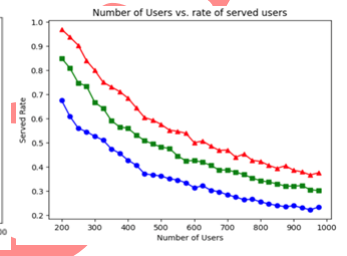


Figure 7: Served Users

energy and computational resources. With a low user density, there is a high amount of remaining aggregated computation and energy resources. However, with a high number of IoT user, the UAV network hits a scarcity bottleneck, and the request served rate drops.

6 Conclusion

We presented RAVEN, a novel reverse-auction-based resource allocation scheme for UAV-enabled edge computing platforms. By formulating the strategic interplay between resource-constrained UAV edge nodes and heterogeneous IoT users using a combination of position auctions and generalized second-price (GSP) mechanisms, the framework maximizes system utility while balancing user satisfaction, energy expenditures, and task popularity. To address the inherent NP-completeness of the generalized mixed-integer winner determination problem, we introduced a greedy approximation algorithm that computes near-optimal resource allocations in polynomial time. We conducted extensive simulations on Google Colaboratory. The empirical results demonstrated robust performance, showing that the system maintains exceptional resource utilization metrics and steady valuation scaling under increasing demand, though ultimate request-serve rates and per-user satisfaction are bounded by the physical and energy-capacity limitations of the UAV edge network.

While the current model manages independent sub-regional auctions, our future research will focus on expanding RAVEN to support seamless cross-region task offloading. This extension aims to further minimize end-to-end latency, reduce localized load spikes on individual sub-regions, and prevent resource exhaustion. Additionally, we intend to investigate alternative dynamic pricing mechanisms and perform granular parametric optimizations to simulate real-time edge auction environments with higher fidelity.

Acknowledgments

This work is partially supported under the PRAYAS Scheme by the IIT Bhilai Innovation and Technology Foundation (Ref. No. IBITF/Note/EIR-PRAYAS/SanctionLetter/2024-25/0897).

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