AoI-aware Incentive Mechanism for Mobile Crowdsensing using Stackelberg Game

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Outline

- Background & Motivation
- Related Work & Problem Formulation
- Basic Idea & Solution
- Evaluation & Conclusion

Background

Swarm intelligence

Air Pollution Monitoring

Weather Monitoring

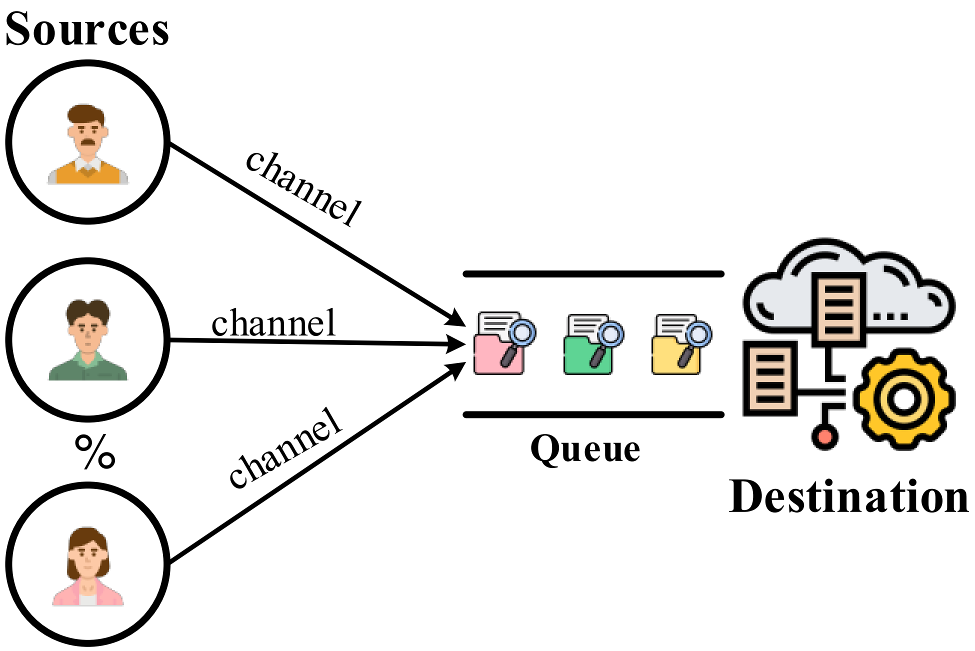
Intelligent Transportation

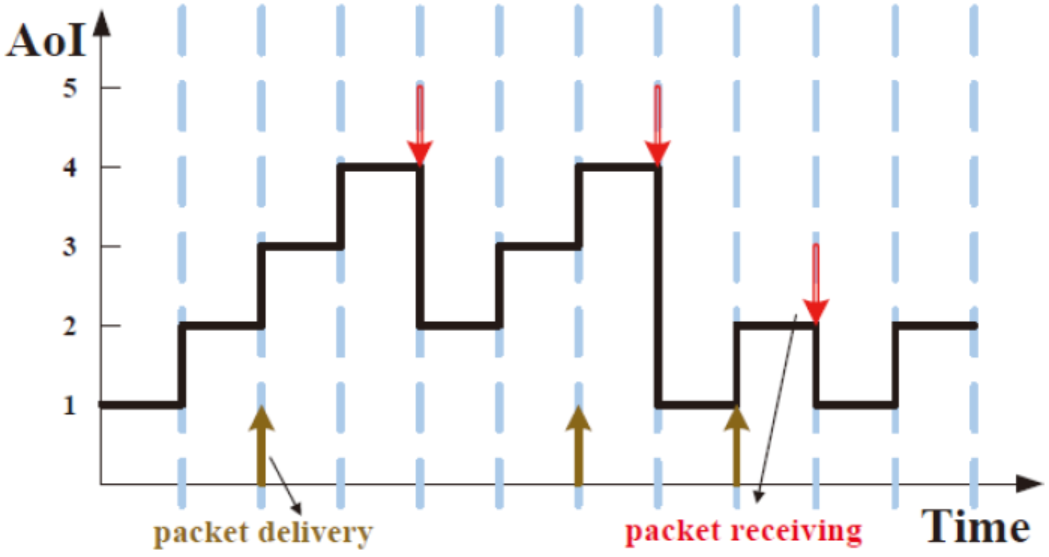
Indoor Management

Applications for Mobile CrowdSensing (MCS) systems

Background

Definition of Age of Information (AoI) : *how old the freshest received update is, the elapsed time of data from being collected by the worker to being received and processed by the platform currently.*





AoI evolution of an information source

Y. Sun, E. Uysal-Biyikoglu, R. D. Yates, C. E. Koksal, N. B. Shroff, "Update or Wait: How to Keep your Data Fresh," IEEE Transactions on Information Theory, vol. 63, no. 11, pp. 7492–7508, 2017.

Motivation

Example

- Data freshness → Service quality
- Social benefits： workers can share their collected data with their social neighbors

Key Challenges

■ **Strategy Determination :**

- Data Update Frequency
  - { Data valuation
  - Service quality
- Fresher data → Larger cost
- Trade-offs: the data update frequencies of all workers

■ **Incomplete Game :**

- Platform: the limited communication and processing capabilities
- Workers: compete for data update
- Social relationships → Unknown or incomplete

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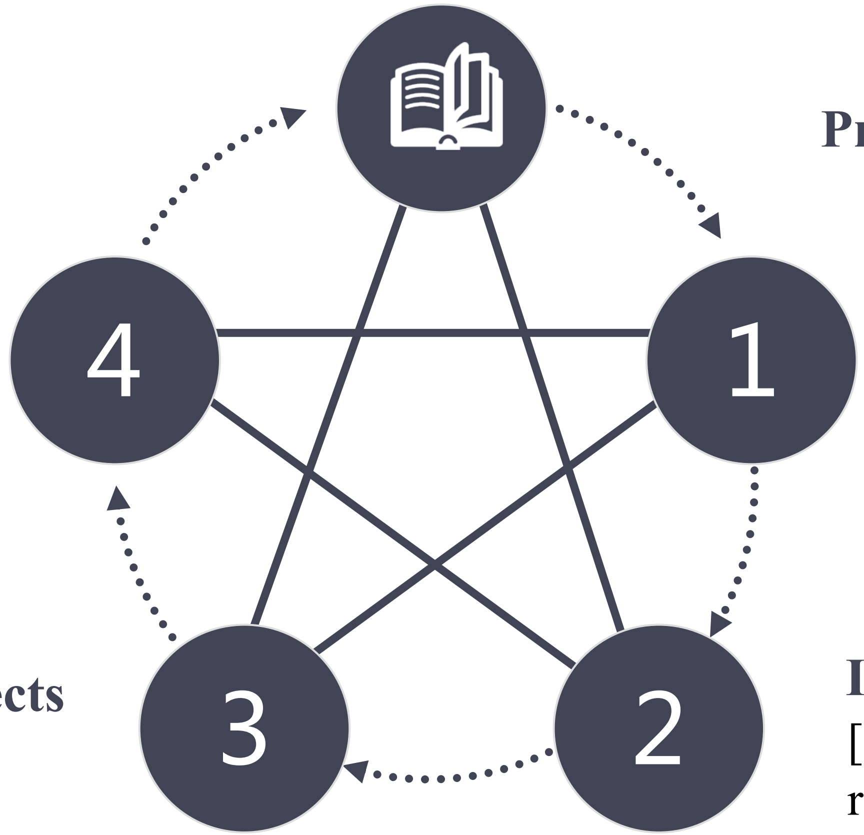
Related Work

Goal: Incentive mechanism design while considering data freshness and social networks



Pricing issue with AoI concerns

Auction, Game, Contract, DRL…

[1] X. Chen, et al., Timeliness-aware incentive mechanism for vehicular crowdsourcing in smart cities, TMC2022.

[2] B. Li , et al., Achieving information freshness with selfish and rational users in mobile crowd-learning, JASC2021.

Incomplete game

[3] Q. Xu, et al., Game theory and reinforcement learning based secure edge caching in mobile social networks, TIFS2020

Design with social network effects

[4] M. H. Cheung, et al., Make a difference: Diversity-driven social mobile crowdsensing, INFOCOM2017

AoI optimization

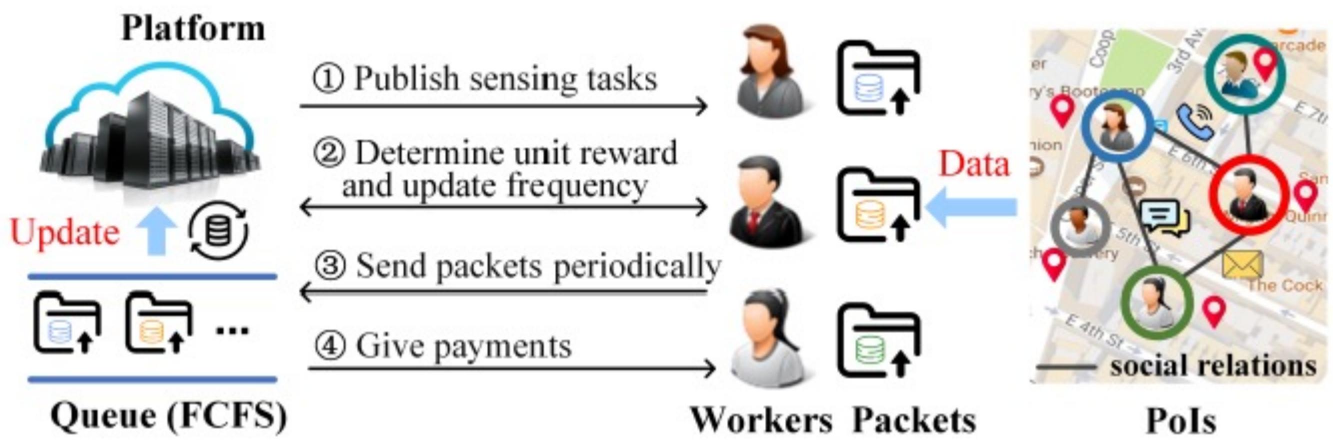
[5] Z. Dai, et al., Aoi-minimal UAV crowdsensing by model-based graph convolutional reinforcement learning, INFOCOM2022

[6] R. D. Yates, et al., The age of information: Real-time status updating by multiple sources, TIT2019

Problem Formulation

System Model

- **Workers {1,2,...,N}:** collect and uploads the data to the platform with data update frequency p_i
- **Unit-Reward** R_i**:** the reward per data update frequency paid to worker i → $\mathcal{R} = \{R_1, R_2, \dots, R_N\}$
- **Average AoI:** the time elapsed since the worker collects this data, $\delta_i(t) = t - U_i(t)$ → $\bar{\delta}_i$
- **Social networks:** an adjacency matrix $[v_{ij}]_{N*N}$; v_{ij} is the social influence of worker j on worker i.



Procedure

① The requester → the platform
A long-term sensing task

② Platform: optimal payment
Worker: optimal update frequency

③ Worker i: collect data from PoIs
→ Upload data packets with p_i

④ Pay rewards $\mathcal{R}$ to workers

Problem Formulation

➢ **Worker's Utility:** the reward + social benefits − cost

$$\Omega_i(p_i, P_{-i}) = R_i p_i + \Psi_i(p_i, P_{-i}) - s\left(a p_i^2 + b p_i\right).$$

The quadratic the cost function to collect data

The reward that the platform pays to worker i

Social benefits caused by the social network effects $\Psi_i(p_i, P_{-i}) = \sum_{j \in N_i} v_{ij}\, p_i p_j$

➢ **Platform's Utility** : the income that it can gain from all collected data − the total payments

$$\Phi = \eta \sum_{i=1}^{N} \left(c p_i - d p_i^2\right) - \sum_{i=1}^{N} R_i p_i.$$

Income: a linear-quadratic function of the data update frequencies of all workers

The sum of rewards paid to all workers

Problem Formulation

➢ **Two-stage Stackelberg game :** the platform is the leader and the workers are the followers

Game

Stage I [Leader Game]: $\Phi(p_i^*, R_i^*) \geq \Phi(p_i, R_i)$

Stage II [Follower Game i]: $\Omega_i(p_i^*, R_i^*) \geq \Omega_i(p_i, R_i)$

Subject to : $\delta_i(p_i, P_{-i}) \leq \varepsilon,\ \forall i \in \mathcal{N}$

$\sum_{i=1}^{N} p_i \leq \hat{p}$

1’AoI constraint

2’ Total data update frequency constraint

Incomplete Information Bayesian Sub-Game:

- ☐ The set of players *i*→ a set of N workers;
- ☐ The action of player *i* → the data update frequency p_i;
- ☐ The type of player *i* → the social network effects;
- ☐ The payoff of player *i* with its type and its action → the utility Ω_i;

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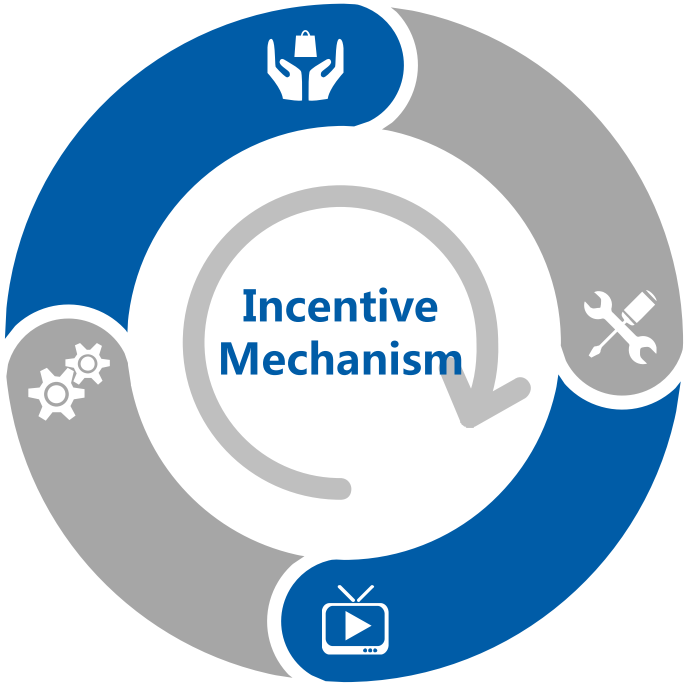
Basic Idea

1 Characterizing AoI of Data

- Derive AoI for a single worker
- Derive AoI for Multiple Workers:
  -- neighbors influence
  -- competitive N sources system
  -- the closed-form expression of
  average AoI of data

Solving the Follower Game 2

- Graph theory → Degree of a node f
  → the type of the worker
- Rewrite the utility function:
  -- the degree distribution
  -- average strategy of neighbors
- Optimal data update frequency $p^*(f)$



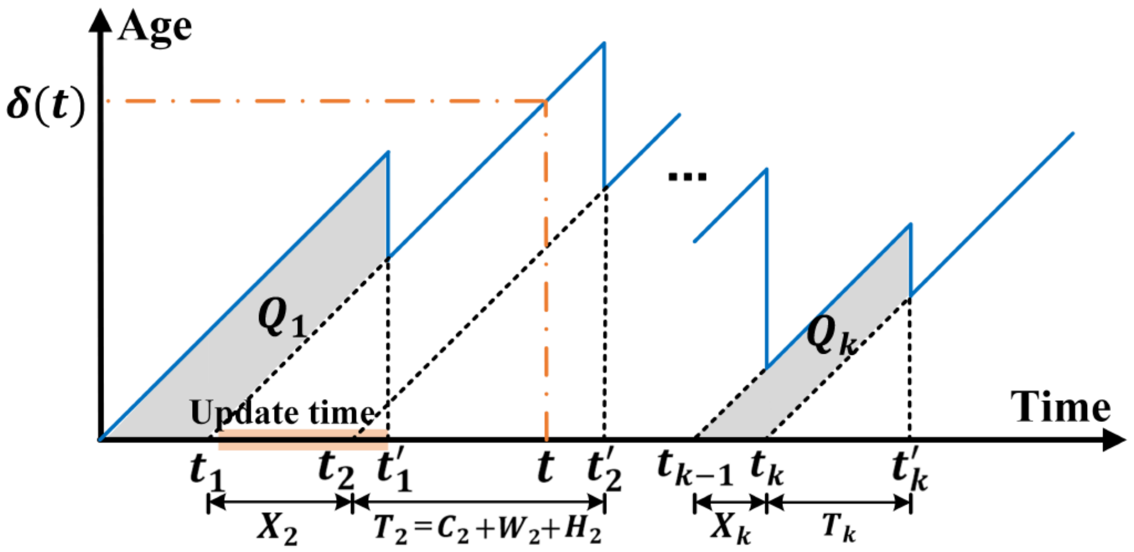
3 Solving the Leader Game

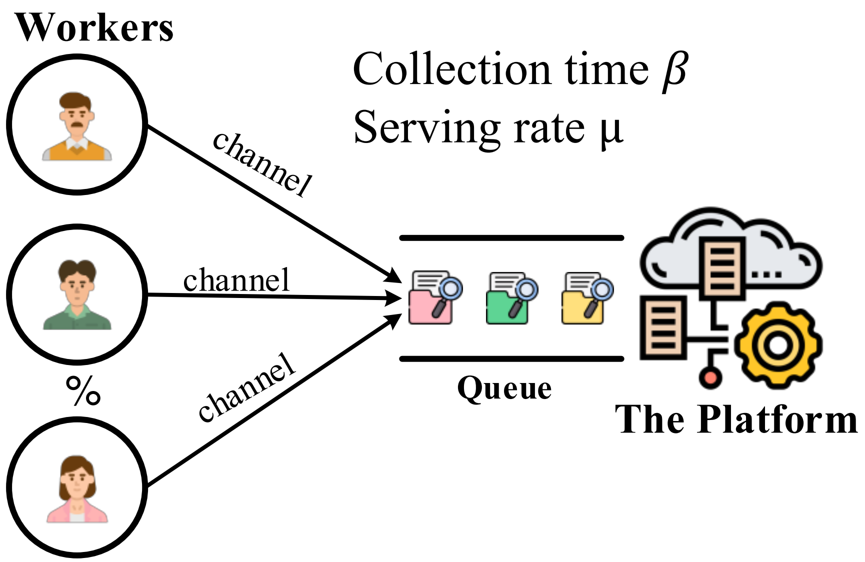
- Rewrite the utility function:
  -- substitute $p^*(f)$ to Φ
  -- AoI and total frequency constraint
  -- Karush-Kuhn-Tucker (KKT) conditions
- Optimal unit-reward $R^*(f)$

Algorithm & Analysis 4

- Propose the AoI-Aware Incentive (AIAI) mechanism
- Follower game
  -- Bayesian Nash Equilibrium
- Unique Stackelberg equilibrium

Characterizing AoI of Data





AoI for a single worker

$$\bar{\delta}^T = \frac{1}{T}\left(Q_1 + \sum_{k=2}^{I(T)} Q_k + T_{I(T)}^2/2\right)$$
$$= \frac{Q_1 + T_{I(T)}^2/2}{T} + \frac{I(T)-1}{T}\frac{1}{I(T)-1}\sum_{k=2}^{I(T)} Q_k.$$

→ $\bar{\delta} = lim_{T\to\infty}\bar{\delta}^T = p(\mathbb{E}[XT] + \mathbb{E}[X^2/2])$

→ $\bar{\delta} = [(\rho-1)(\rho^2-\mu\rho\beta)+1]/((1-\rho)\rho\mu)$

AoI for Multiple Workers

$$\mathbb{E}(X_kT_k) = \mathbb{E}(X_kC_k) + \mathbb{E}(X_kW_k) + \mathbb{E}(X_kH_k)$$
$$= \mathbb{E}(X_k)\mathbb{E}(C_k) + \mathbb{E}(X_kW_k) + \mathbb{E}(X_k)\mathbb{E}(H_k)$$

↓

$$\bar{\delta}_i = \frac{\alpha\beta_i}{\sum_{j\in\mathcal{N}_i} \upsilon_{i,j}} + \frac{p_i/\mu^2}{1-\rho_{-i}}\left[\frac{\rho_i\rho_{-i}}{(1-\rho_{-i})^2} + \frac{\rho_i/(1-\rho)}{1-\rho_{-i}} + \frac{\rho_{-i}}{\rho_i}\right] + \frac{1}{\mu} + \frac{1}{p_i}$$

Solving the Follower Game

Step 1

- Derive the expected utility of each worker

$$\omega_i(p_i, P_{-i}, \mathcal{R}) = \mathbb{E}[\Omega_i(p_i, P_{-i}), \mathcal{R}]$$
$$= R_i p_i + \upsilon p_i \mathbb{E}[\sum_{j \in \mathcal{N}_i} p_j] - (a p_i^2 + b p_i) s.$$

- Worker's type → the degree:

$$\omega_i(p_i, P_{-i}, \mathcal{R}) = R_i p_i + \upsilon p_i f \overline{P_{-i}} - (a p_i^2 + b p_i) s.$$

Step 2

- Degree distribution: $F(f)$
- Derive the utility of the worker with degree f

$$\omega_f(p(f), P_{-f}) = R(f) p(f) + \upsilon p(f) f \overline{P_{-f}} - (a p^2(f) + b p(f)) s.$$

- Bayesian Nash Equilibrium, BNE:

$$\Gamma_i(\psi_i) \in argmax_{p_i \in \mathcal{P}_i} \Omega_i(p_i, \Gamma_{-i}, \psi_i, \psi_{-i}).$$

Step 3

- Apply the partial derivative:

$$\frac{\partial \omega_f(p(f), P_{-f}, \mathcal{R})}{\partial p(f)} = R(f) + \upsilon f \overline{P_{-f}} - (2ap(f) + b)s.$$

- Derive the average data update frequency of neighbors $\overline{P_{-f}}$

$$\overline{P_{-f}} \approx E[p(l) || l \in G] = (\overline{R} - bs)/(2as - \upsilon \overline{f})$$

Step 4

- Given any unit-reward R(f), the closed-form expression of the action:

$$p(f) = \frac{1}{2as} R(f) - \frac{b}{2a} + \frac{\upsilon f(\overline{R} - bs)}{2as(2as - \upsilon \overline{f})}$$

Solving the Leader Game

Follower Game

Optimal data update frequency:

$$p(f) = \frac{1}{2as}R(f) - \frac{b}{2a} + \frac{vf(\overline{R} - bs)}{2as(2as - v\overline{f})}$$

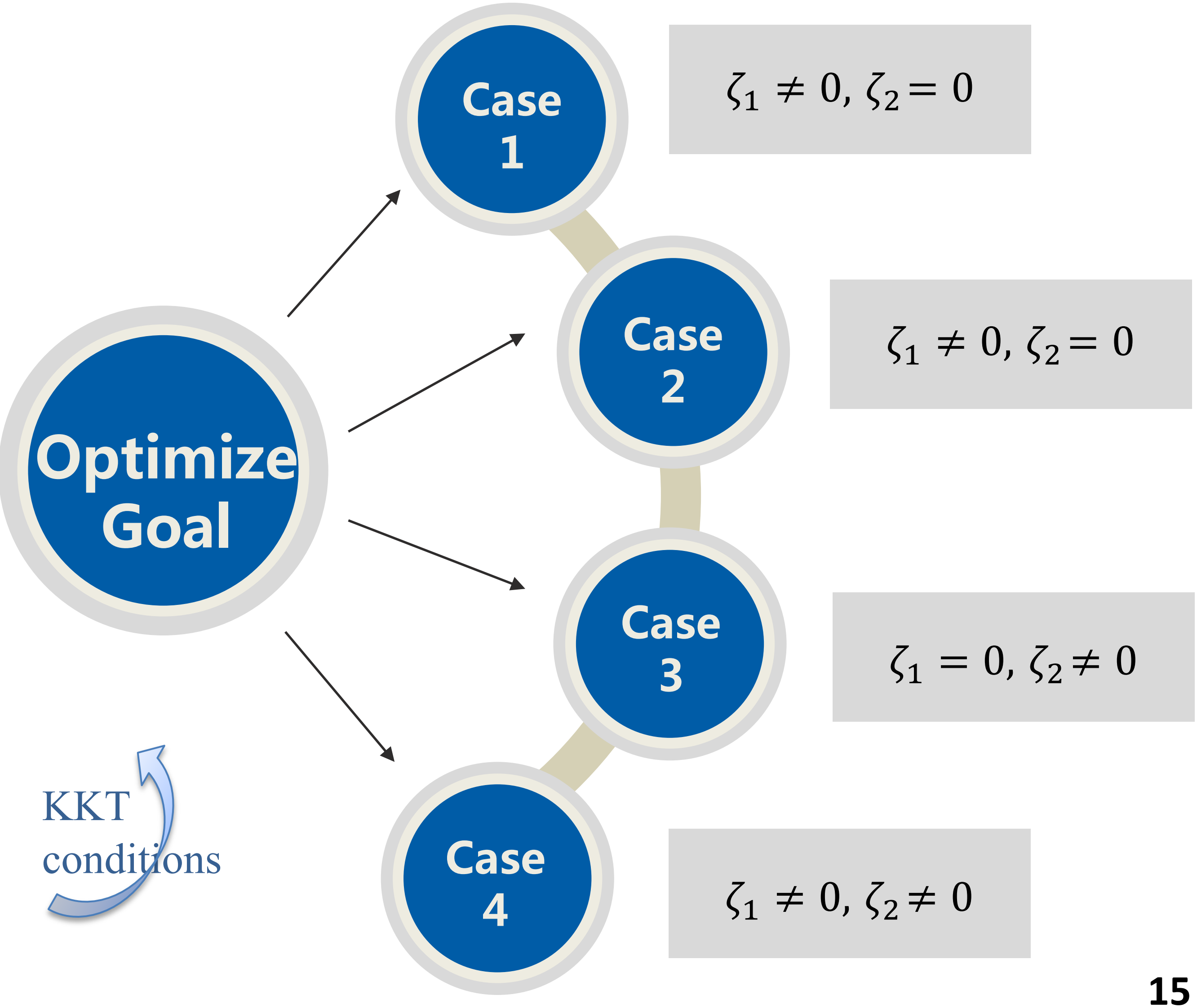
Substituting to Φ

$$\phi = \mathbb{E}[\Phi] = \mathbb{E}[\eta \sum_{i=1}^{N} (cp_i - dp_i^2) - \sum_{i=1}^{N} R_i p_i]$$
$$= N \sum_{f \in G} F(f)[(\eta c - R(f))p(f) - \eta d p^2(f)]$$

$$\max \phi(R(f))$$
$$\text{s.t. } g(R(f)) = \delta_f(R(f)) - \varepsilon \le 0,$$
$$g'(R(f)) = N\textstyle\sum_f F(f)p(f) - \hat{p} \le 0$$

Lagrangian function

$$\mathcal{L}(R(f), \zeta) = \phi(R(f)) + \zeta_1 g(R(f)) + \zeta_2 g'(R(f))$$



Algorithm

Algorithm 1: The AIAI mechanism

input : degree distribution $F(f)$, worker i's degree f, and some public parameters a, b, c, d, η, s;

output: $R^*(f)$, $p^*(f)$, Φ^*, and Ω_i^*;

Platform: Determine its tentative optimal strategy (i.e., the unit-reward $R^*(f)$) according to Eq. (31);

for *each worker* $i = 1 \in \mathcal{N}$ **do**

  Determine its tentative strategy (i.e., the data update frequency $p_i^*(f)$) based on $R^*(f)$ and Eq. (32);

if $\delta_i(p_i, P_{-i}) \leq \varepsilon$ *for* $\forall i$ **then**

  if $\sum_{i=1}^{N} p_i \leq \hat{p}$ **then**

    Platform: Obtain Φ^* according to Eq. (33);

    Worker i: Obtain Ω_i^* according to Eq. (34);

  else Solving Eq. (36) and $g'(R(f))=0 \Rightarrow R^*(f)$;

    Platform: Update its strategy as $R^*(f)$;

    Worker i: Update $p_i^*(f)$ based on $R^*(f)$;

    Calculate Φ^* and Ω_i^* based on Eqs. (33) and (34);

else

  if $\sum_{i=1}^{N} p_i \leq \hat{p}$ **then**

    Solving Eq. (35) and $\partial\mathcal{L}/\partial R(f)=0 \Rightarrow R^*(f)$;

  else Solving Eq. (37) $\Rightarrow R^*(f)$;

  Platform and Workers: Update $p_i^*(f), R^*(f), \Phi^*, \Omega_i^*$;

The leader (i.e., the platform) gives its strategy

each follower (i.e., worker) determines its strategy based on the strategy of the platform

Case 1: $\zeta_1 \neq 0, \zeta_2 = 0$

Case 3: $\zeta_1 = 0, \zeta_2 \neq 0$

Case 2: $\zeta_1 \neq 0, \zeta_2 = 0$

Case 4: $\zeta_1 \neq 0, \zeta_2 \neq 0$

Equilibrium Analysis

Lemma

- ✓ The follower game exists at least one pure Bayesian Nash Equilibrium.

Proof:

$$\partial^2 \omega_i(p_i, P_{-i}, \mathcal{R})/\partial p_i \partial \overline{P_{-i}} = vf > 0,$$
$$\partial^2 \omega_i(p_i, P_{-i}, \mathcal{R})/\partial p_i^2 = -2as < 0.$$

⇒ The follower game meets the Single Crossing Property of Incremental Returns.

Theorem

- ✓ The optimal incentive strategy $(R^*(f), p^*(f))$ determined by the AIAI mechanism constitutes the unique Stackelberg equilibrium while satisfying AoI constraints.

Proof:

The platform in Stage I uniquely determines $R^*(f)$: only associated with the constant input ⇒ Given $R^*(f)$, workers can pick their optimal data update strategies ⇒ No one can improve its own utility by deviating from the optimal strategy during the process.

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Evaluation

Experimental Settings

01

Real Dataset

- Chicago Taxi Trips
  taxi driver → worker
- SNAP (Gowalla)
  mobile users → social friendship

02

Parameter settings

- N ranges from [50, 300]
- The conversion parameters s and η change from [6, 20] and [7, 10]
- a=5, b=1, c=40, d=5, s=6

03

Compared Algorithms

- Auction-based algorithm
- Contract-based algorithm
- AIAI-NS mechanism

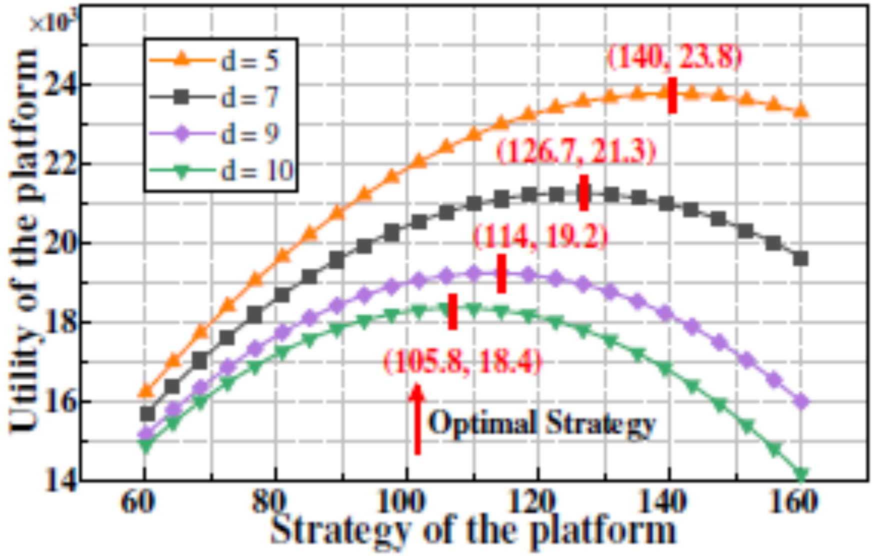
04

Evaluation Metrics

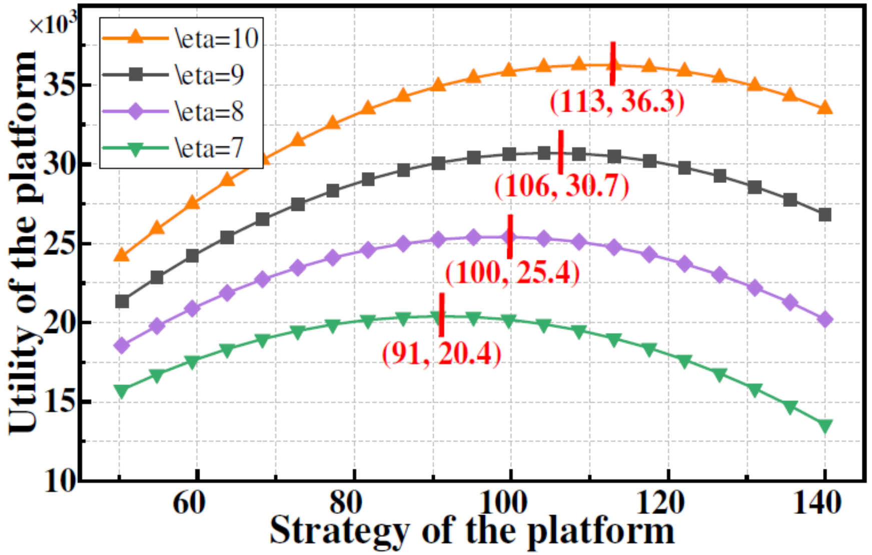
- AoI
- Worker/Platform's Strategy
- Worker/Platform's Utility

Evaluation

- The existence of the Stackelberg equilibrium for the platform:



(a) quadratic parameter d



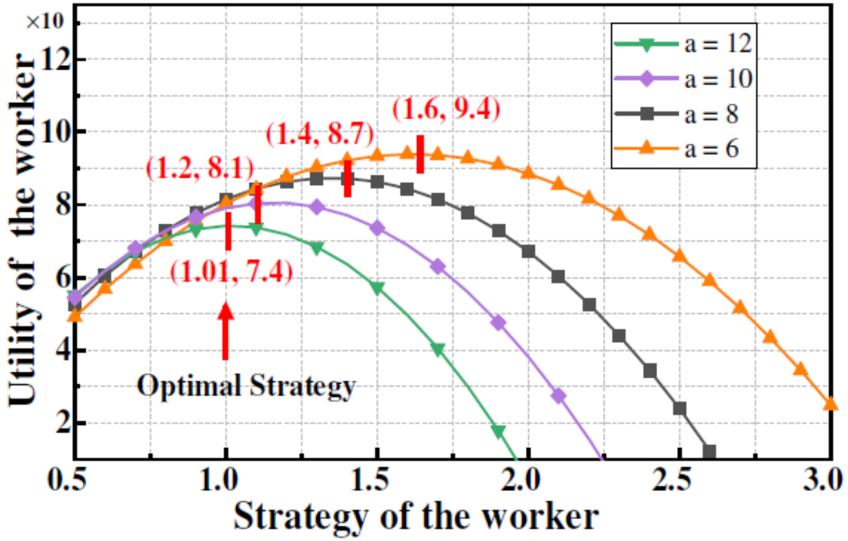
(b) conversion parameter η

Influence of the strategy of the platform under different d

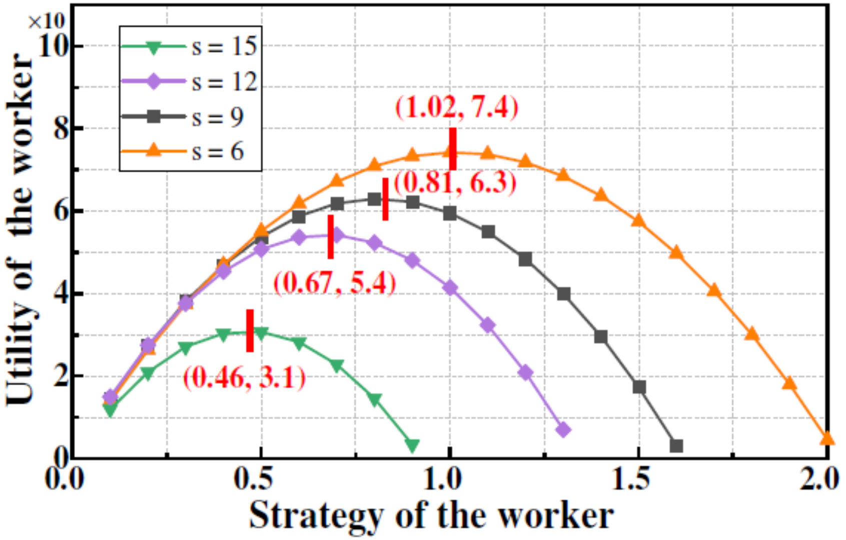
Influence of the strategy of the platform under η

Evaluation

- The existence of the Stackelberg equilibrium for workers:



(a) quadratic parameter a



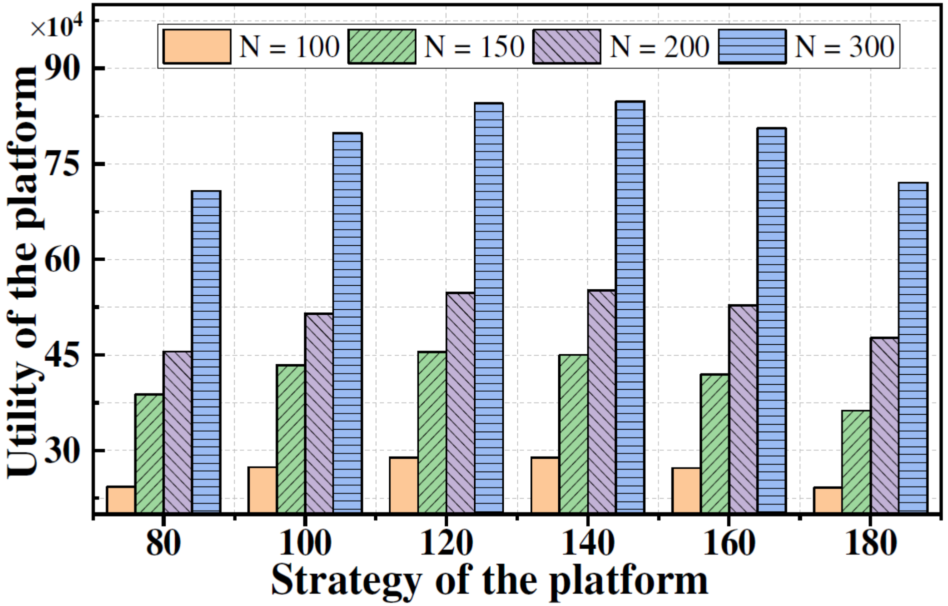
(b) conversion parameter s

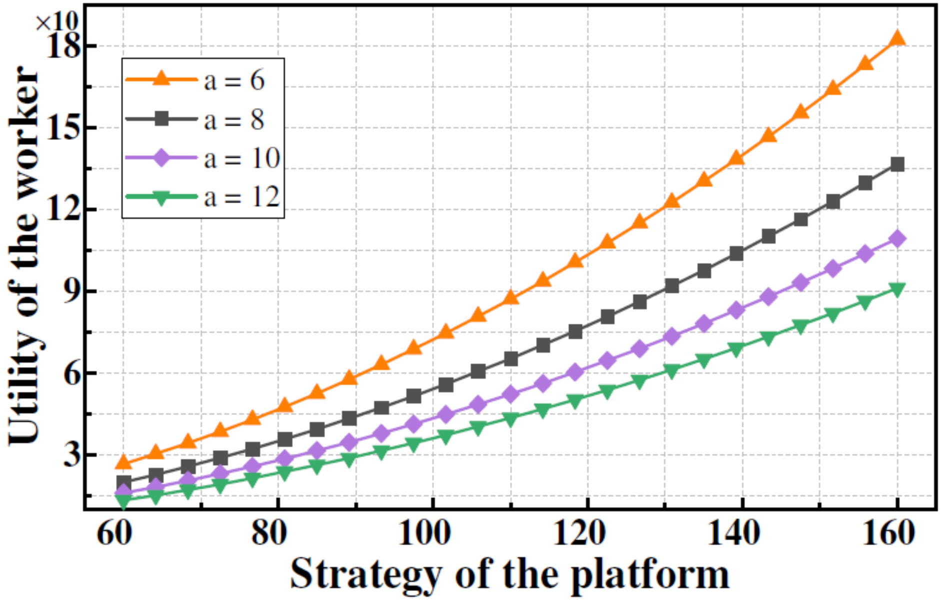
Influence of the strategy of the worker under different a

Influence of the strategy of the worker under s

Evaluation

- Influence of the number of workers and the strategy of the platform:



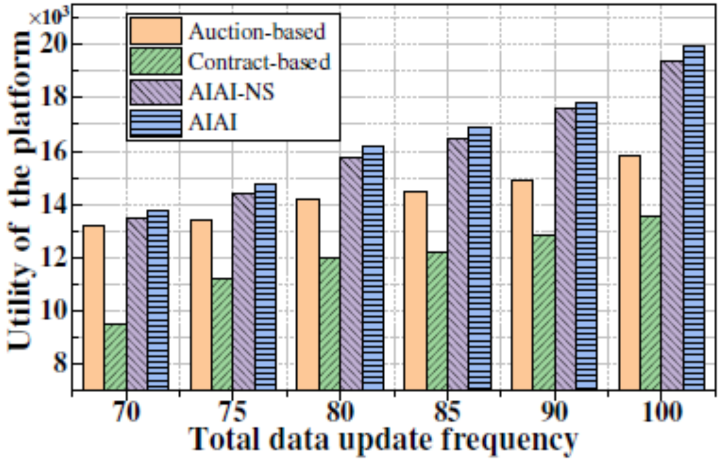


Utility of the platform under different *N*
→ *Increasing N can improve the profit of the platform*

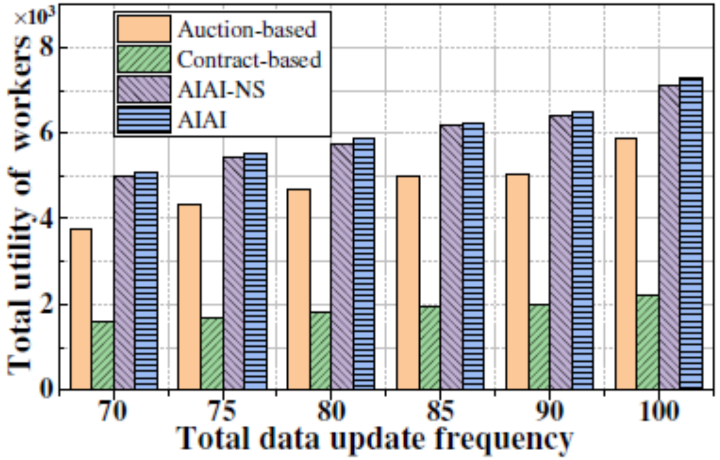
Utility of the worker under different *PS*
→ *Investing more money can incentivize each worker to update data*

Evaluation

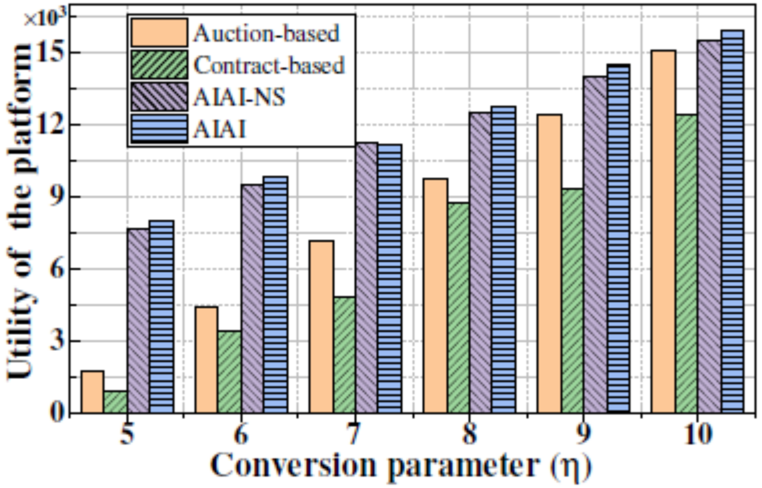
- Different incentive mechanisms and varied parameters



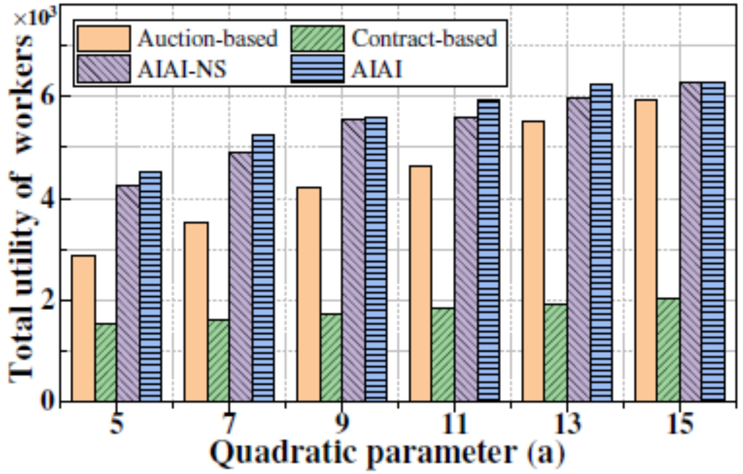
(a) PU vs. $\hat{p}$



(b) total SU vs. $\hat{p}$



(c) PU vs. η



(d) total SU vs. a

Conclusion

- ✓ We investigate the MCS incentive mechanism design issue with AoI guarantee and social benefits.

01

- ✓ We model the problem as a two-stage Stackelberg game, embedded with an incomplete information Bayesian sub-game.

02

- ✓ We derive the optimal strategies of this game and prove that these optimal strategies form a unique Stackelberg equilibrium.

03

- ✓ We propose the AIAI mechanism
  -- the platform and workers can obtain their optimal utilities;
  -- meet the AoI constraint.

04

- ✓ Extensive simulations on real-world traces validate its great performance.

05

Thank you for your attention!

Question?

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