AoI-Guaranteed Incentive Mechanism for Mobile Crowdsensing With Freshness Concerns

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Published in: IEEE Transactions on Mobile Computing, 2024

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Agenda

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- MCS: Platform stimulates some workers (a.k.a., mobile users) via social networks to periodically collect the desired data from a group of points-of-interest (PoI) to provide data services (e.g., traffic monitoring, environmental sensing, etc.) for requesters.

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  - Age of Information (AoI) – the elapsed time of data from being collected by the worker to being received and processed by the platform.
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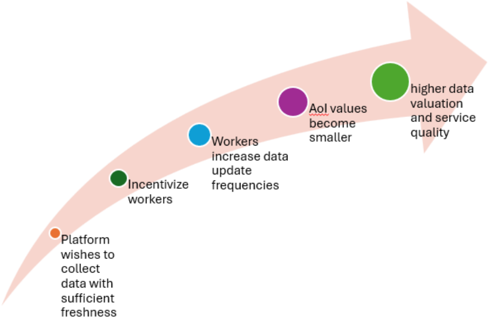
  - Workers share their collected data with their social neighbors to obtain extra social benefits (i.e., additional utility from data sharing among workers).

Incentive Mechanism Challenges



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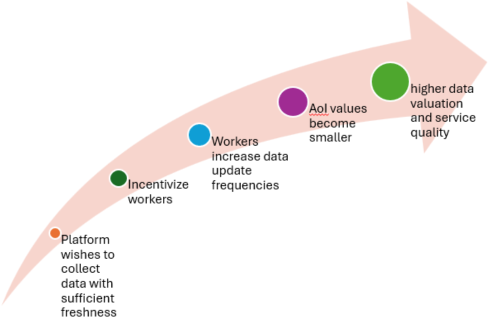

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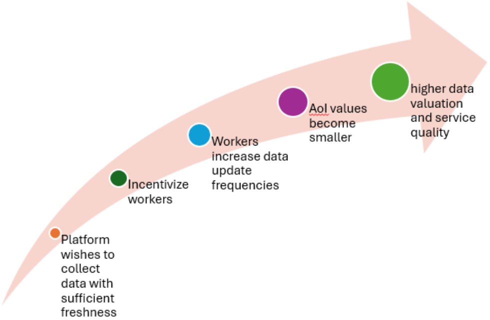

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- Incomplete information – workers social relationships unknown or incomplete.

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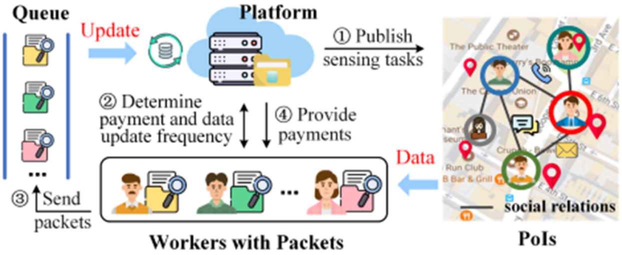
- Propose DIM, when each participant has no prior knowledge of the game. Based on the DRL technique, DIM enables learning the optimal strategy directly from game experiences.
- **Demonstrate effectiveness of the proposed AIM and DIM mechanisms' performance using real-world traces simulation.**

System Model



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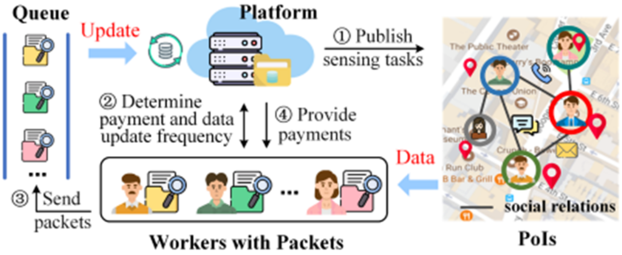

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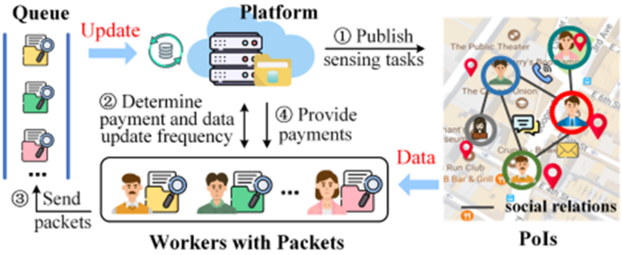

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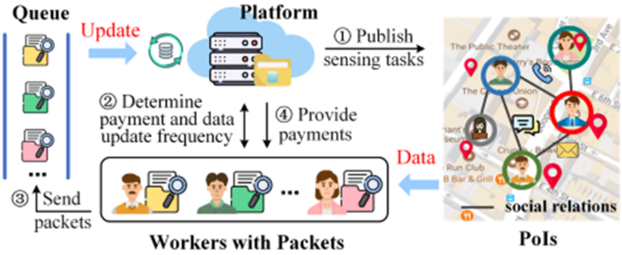

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- Unit-Remuneration (R_i): Payment per update frequency to worker i.

Utility Functions - Platform

Platform Utility Function:

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

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- $R_i p_i$: cost of remuneration paid to worker i

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Worker Utility Function:

$$\Omega_i(p_i, P_{-i}; s_i, a_i, b_i) = R(p_i) + \Psi_i(p_i, P_{-i}) - \Theta_i(p_i; s_i, a_i, b_i) = R_i p_i + \sum_{j \in N_i} \nu_{ij} p_i p_j - s_i(a_i p_i^2 + b_i p_i)$$

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Two-stage Stackelberg game

- **Two-stage Stackelberg game,** $SG\left(p_i, R_i; \varphi\right)$**, where** $\varphi = \{\, s_i, a_i, b_i \mid \forall i \in \mathcal{N}\} \cup \{\eta, c, d\}$ **is the set of all participants' parameters, with public (SPP) and unknown parameters (SUP).**

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  - **Subject to:**

$$\delta_i\left(p_i, P_{-i}\right) \ \leq \ \varepsilon, \quad \forall i \in N$$

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

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Average AoI $\overline{\delta}^T$ over the interval $[0, T]$:

$$\overline{\delta}^T = \frac{1}{T}\int_0^T \delta(t)\,dt = \frac{1}{T}\big(\text{area under the AoI curve}\big).$$

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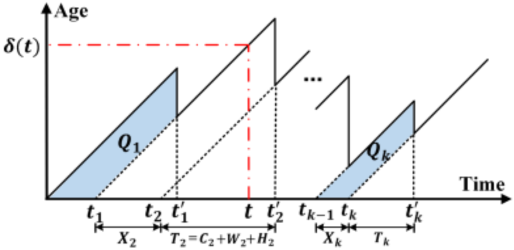

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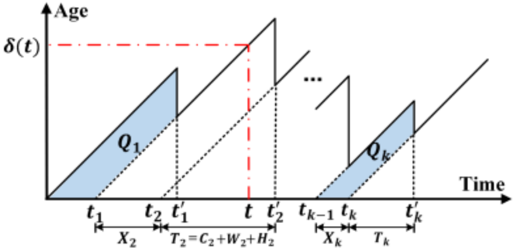

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AoI of Data for a Single Worker (continue)

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$p = \lim_{T\to\infty}\frac{I(T)}{T}$, indicate the data update frequency in the steady state.

$$\overline{\delta} = \lim_{T\to\infty}\overline{\delta}^T = p\big(\mathbb{E}[XT] + \mathbb{E}[X^2/2]\big). \tag{14}$$

AoI of Data for a Single Worker (Plugging M/M/1)

For an M/M/1, FCFS queue with arrival rate p and service rate μ, plus an added constant "collection time" β each time a service occurs:

- Effective service-time distribution has mean $\beta + 1/\mu$.
- Offered load: $\rho = p\big(\beta + 1/\mu\big)$.
- Mean system time (waiting + service): $\mathbb{E}[T] = \dfrac{\beta + 1/\mu}{1-\rho}$.
- Each update arrives after an exponentially distributed interarrival time X, $\mathbb{E}[X] = \dfrac{1}{p}, \quad \mathbb{E}[X^2] = \dfrac{2}{p^2}$

$$\bar{\delta} = \frac{(\rho - 1)\big(\rho^2 \; - \; \mu\,\rho\,\beta\big) + 1}{\rho\,\mu\,(1-\rho)}.$$

AoI of Data for Multiple Workers

Theorem 1: (AoI for Multiple Workers)

N workers compete for the data update through an M/M/1 FCFS queue, in which each worker i's data update frequency, collection time, serving rate, and offered loads are $p_i, \beta_i, \mu,$ and $\rho_i,$ respectively. Then, the average AoI $\bar{\delta}_i$ of worker i's data satisfies

where $\rho = \sum_{i=1}^{N} \rho_i, \quad \rho_i = \frac{p_i}{\mu}, \quad$ and $\rho_{-i} = \sum_{j \neq i} \rho_j.$

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- C_k: collection time.

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- C_k: collection time.
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- W_k: wait time.
- H_k: handling time.

where $\rho = \sum_{i=1}^{N} \rho_i, \quad \rho_i = \frac{p_i}{\mu}, \quad$ and $\rho_{-i} = \sum_{j\neq i} \rho_j$.

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- **A Bayesian Nash equilibrium is a strategy profile where each player's strategy maximizes their expected utility, given their beliefs about the other players' types and strategies.**

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2. **Solve the platform, leader (stage-1) game, to derive the optimal unit-remuneration R_i^* paid by the platform.**

Solving the Bayesian Sub-Game

$$\Omega_i(p_i, P_{-i}; s_i, a_i, b_i) = R(p_i) + \Psi_i(p_i, P_{-i}) - \Theta_i(p_i; s_i, a_i, b_i) = R_i p_i + \sum_{j \in N_i} \nu_{ij} p_i p_j - s_i \left(a_i p_i^2 + b_i p_i \right) \tag{3}$$

- **Set social network influence $\nu_{ij} = \nu$ for all i, j ($i \neq j$).**

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- **Using the "Configuration Model", randomly chosen social network neighbor of worker i has the degree distribution $\overline{F}(f) = \dfrac{F(f)f}{(\sum_{f' \in G} F(f')f')} = \dfrac{F(f)f}{\underline{f}}$, where $\overline{P_{-f}} = \sum_{f \in G} \overline{F}(f) p(f)$.**

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- **Thus utility of the worker with degree f can be represented as follows:**

$$\overline{\Omega}_f(p(f), P_{-f}) = R(f)p(f) + \upsilon p(f) f \overline{P_{-f}} - \left(ap^2(f) + bp(f) \right) s.$$

Worker's (Follower) Optimal Strategy

Definition (Bayesian Nash Equilibrium (BNE))

A BNE is defined as a strategy profile that maximizes the expected payoff of each player for the given types and strategies performed by other players.
A strategy vector $\Gamma = (\Gamma_1(\psi_1), \Gamma_2(\psi_2), \ldots, \Gamma_N(\psi_N))$ is a Bayesian Nash Equilibrium if and only if the following condition is satisfied for each player i:

$$\Gamma_i(\psi_i) \in \arg\max_{p_i \in P_i} \Omega_i(p_i, \Gamma_{-i}, \psi_i, \psi_{-i}).$$

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Theorem (Follower's Optimal Strategy)

Given any unit remuneration $R(f)$, the closed-form expression of the action (i.e., data update frequency) of the follower game is:

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

where $\overline{R} = \sum_{f \in G} \overline{F}(f) R(f)$ *and* $\overline{f} = \sum_{f \in G} \overline{F}(f) f$.

Platform (Leader) Game With Constraints

- **Platform utility function when applying the configuration model:**

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

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- **where optimizing $\overline{\Phi}(R(f))$ with the AoI and the total update frequency constraints:** $g(R(f)) = \delta_f(R(f)) - \epsilon \leq 0, \qquad g'(R(f)) = N \sum_{f} F(f)p(f) - \hat{p} \leq 0.$

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- **Finding optimal solution, using Lagrangian function:**
  $\mathcal{L}(R(f), \zeta) = \overline{\Phi}(R(f)) + \zeta_1 g(R(f)) + \zeta_2 \tilde{g}'(R(f))$, **where ζ_1 and ζ_2 the Lagrangian multipliers.**

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- **Since it is a convex optimization problem, the optimal solution must satisfy the Karush-Kuhn-Tucker (KKT) optimality conditions:**

$$\left.\frac{\partial \mathcal{L}}{\partial R(f)}\right|_{R(f)=R^*(f)} = 0, \quad \zeta_1 g(R(f)) = 0, \quad \zeta_2 \tilde{g}'(R(f)) = 0,$$

$$g(R(f)) \leq 0, \quad g'(R(f)) \leq 0, \quad \zeta_1 \geq 0, \quad \zeta_2 \geq 0.$$

Platform (Leader) Game With Constraints (continue)

Case 1: $\zeta_1 = 0, \zeta_2 = 0$, both constraints are inactive. Plus the sum over all $l \neq f$: the first-order derivative of $\overline{\Phi}(R(f))$ be equal to zero:

$$\frac{\partial \overline{R}}{\partial R(f)} = \overline{F}(f), \quad \frac{\partial p(l)}{\partial R(f)} = \frac{\nu_l \overline{F}(f)}{2as(2as - \nu f)} = \Delta \overline{F}(f) l \quad (l \neq f),$$

$$\frac{\partial p(f)}{\partial R(f)} = \frac{1}{2as} + \frac{\nu f F(f)}{2as(2as - \nu f)} = \frac{1}{2as} + \Delta F(f) f \quad (l = f),$$

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$$\frac{\partial \bar{\Phi}}{\partial R(f)} = NF(f)\left[-p(f) + (\eta c - R(f) - 2\eta dp(f))\left(\frac{1}{2as} + \Delta\overline{F}(f)f\right)\right]$$
$$+N\sum_{l \neq f} F(l)\left[(\eta c - R(l) - 2\eta dp(l))\Delta\overline{F}(f)f\right] = 0.$$

Maximum Platform and Worker Utilities

Considering social network is seen as a configuration model with large numbers of workers, optimal unit remuneration:

$$R^*(f) = \frac{2a^2\tilde{s}^2}{(2as\Delta\overline{F}(f)f+1)(as+\eta d)+as}\left[\frac{b}{2a} - \Delta f(\overline{R}^* - bs)\right] + \left(\Delta\overline{F}(f)f + \frac{1}{2as}\right)$$

$$\left(\eta c + \frac{b\eta d}{a} - 2\Delta f\eta d(\overline{R}^* - bs)\right) + \Delta f\left[-\left(1+\frac{\eta d}{as}\right)\frac{\Lambda^*}{f} + \frac{\eta(ac+bd)}{a} - 2\Delta\eta d(\overline{R}^* - bs)\overline{f}\right].$$

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The optimal data update frequency of worker i:

$$p_i^*(f) = \frac{1}{2as}R^*(f)-\frac{b}{2a}+\frac{\nu f(\overline{R}^*-bs)}{2as(2as-\nu\overline{f})}$$

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$$\Phi^* = N\sum_{f\in G} F(f)\left[(\eta c - R^*(f))p^*(f) - \eta d(p^*(f))^2\right].$$

$$\Omega_i^* = R^*(f)p^*(f) + \nu p^*(f)fP_{-f} - \left(a(p^*(f))^2 + bp^*(f)\right)s.$$

AoL Constraint Active

Case 2: $\zeta_1 \neq 0, \zeta_2 = 0$, AoI constraint $g(R(f)) = \delta_f(R(f)) - \epsilon \leq 0$ is active.

$$g(R(f)) = \frac{\alpha\beta}{f\nu} + \frac{p^2(f)}{\mu^2\breve{\rho}}\left(\frac{\rho_{-i}(f)}{\mu(\breve{\rho})^2} + \frac{1}{\breve{\rho}\mu(1-\rho(f))} + \frac{\rho_{-i}(f)\mu}{p^2(f)}\right) + \frac{1}{\mu} + \frac{1}{p(f)} - \epsilon = 0,$$

where:

- $\breve{\rho} = 1 - \rho_{-i}(f)$ represents the remaining service capacity.
- $\rho(f) = \dfrac{\sum_f p(f)}{\mu}$ is the total offered load.
- $\rho_{-i}(f) = \dfrac{\sum_f p(f) - p(f)}{\mu}$ represents the load from other workers.

Since $g(R(f))$ depends on $p(f)$, and $p(f)$ is determined by $R(f)$, combine the derivative of the utility function with the derivative of the AoI constraint to ensure both are met:

$$\frac{\partial\bar{\Phi}}{\partial R(f)} + \frac{\partial g}{\partial R(f)} = 0.$$

Total Data Update Frequency Constraint Active

Case 3: $\zeta_1 = 0, \zeta_2 \neq 0$, total data update frequency constraint $g'(R(f)) = \sum_f F(f)p(f) - \hat{p} \leq 0$ is active, and the system needs to adjust $R(f)$ and $p(f)$ to bring it back within bounds.
$L(R(f), \zeta_2) = \bar{\Phi}(R(f)) + \zeta_2 g'(R(f))$, where $g'(R(f)) = \sum_f F(f)p(f) - \hat{p}$.

For optimal $R^*(f)$ derivative the Lagrangian with respect to $R(f)$ and set it to zero:

$$\frac{\partial \bar{\Phi}}{\partial R(f)} + \zeta_2 \frac{\partial g'}{\partial R(f)} = 0.$$

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$$R^*(f) = \frac{as(\eta c - bs + \zeta_2)}{2as + \eta d}\left(1 - \frac{f}{\underline{f}}\right) + \frac{2asf\hat{p}}{N\underline{f}} + bs - 2as\Delta f(\overline{R} - bs),$$

where:

- $\bar{f} = \sum_f F(f)f$ is the average degree,
- $\hat{p}$ is the threshold for total update frequency,
- ζ_2 is determined by solving $g'(R(f)) = 0$.

Activating Both Constraints

Case 4: $\zeta_1 \neq 0, \zeta_2 \neq 0$, AoL and total data update frequency constraints are active.

$$\frac{\partial \bar{\Phi}}{\partial R(f)} + \zeta_1 \frac{\partial g}{\partial R(f)} + \zeta_2 \frac{\partial g'}{\partial R(f)} = 0,$$

along with: $g(R(f)) = 0, \quad g'(R(f)) = 0.$

- Solving this system is complex because of nonlinearity of functions and the interdependencies betrween constraints and the utility function.
- Numerical methods (e.g., Bisection, Newton's, etc.) are employed to approximate.
- Iterative Process.

The AoI-Guaranteed Incentive Mechanism (AIM)

Algorithm 1: The AoI-Guaranteed Incentive 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-remuneration $R^*(f)$) according to Eq. (37);

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

  Determine its tentative optimal strategy (i.e., the data update frequency $p_i^*(f)$) based on $R^*(f)$ and Eq. (38);

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. (39);

    Worker i: Obtain Ω_i^* according to Eq. (40);

  else Solving Eq. (42) 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. (39) and (40);

else

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

    Solving Eq. (41) and $\partial\mathcal{L}/\partial R(f)=0 \Rightarrow R^*(f)$;

  else Solving Eq. (43)$\Rightarrow R^*(f)$;

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

The BNE Analysis

Lemma 1: The follower game has at least one pure Bayesian Nash Equilibrium (BNE).

Proof: if the Bayesian sub-game satisfies the (Milgrom-Shannon) Single Crossing Property of Incremental Returns (SCP-IR), the Bayesian subgame has at least one pure BNE.

- The partial derivative of the follower's payoff function with respect to their strategy p_i and others' strategies P_{-i} is:

$$\frac{\partial^2 \bar{\Omega}_i(p_i, P_{-i}, R)}{\partial p_i \partial P_{-i}} = \nu f > 0.$$

  This indicates that the payoff increases with others' strategies.

- The second-order partial derivative with respect to p_i^2 is:

$$\frac{\partial^2 \bar{\Omega}_i(p_i, P_{-i}, R)}{\partial p_i^2} = -2as < 0,$$

  confirming concavity of the payoff with respect to p_i, which satisfies the SCP-IR.

The BNE Analysis (continue)

Lemma 2: Uniqueness of the Bayesian Nash Equilibrium

The Bayesian sub-game has at most one BNE if the following condition is satisfied:

$$\left| \left(\frac{\partial^2 \overline{\Omega}_i (p_i, P_{-i}, \mathcal{R})}{\partial p_i \, \partial P_{-i}} \right) \Big/ \left(\frac{\partial^2 \overline{\Omega}_i (p_i, P_{-i}, \mathcal{R})}{\partial p_i^2} \right) \right| < 1, \quad \forall\, i \in \mathcal{N}.$$

The left-hand side represents the interaction between the strategies of player i and others.

If the interaction is sufficiently weak, the uniqueness of the equilibrium is guaranteed.

Result: When the condition $\nu f_{\max} - 2as < 0$ is met, the uniqueness of the BNE is ensured.

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Result: When the condition $\nu f_{\max} - 2as < 0$ is met, the uniqueness of the BNE is ensured.

Stackelberg Game Equilibrium: The leader in the Stackelberg game can optimize their strategy with the certainty that the followers' response is unique and predictable (as derived from Lemmas 1 and 2).

Unique Stackelberg Equilibrium

Theorem (Unique Stackelberg Equilibrium)

The optimal incentive strategy $\langle p^*(f), R^*(f)\rangle$ determined by AIM constitutes the unique Stackelberg equilibrium while satisfying AoI constraints.

- **Uniqueness of Equilibrium**
  - In Stage I, $R^*(f)$ is derived as the unique optimal solution for the platform's utility maximization.
  - In Stage II, $p^*(f)$ forms a unique Bayesian Nash Equilibrium (BNE), as shown in the equilibrium analysis.

  Together, these ensure that the entire Stackelberg game has a unique equilibrium.
- **AoI Constraints**
  The AoI constraint, $g(R(f)) = \delta_f(R(f)) - \epsilon \leq 0$, ensures that the age of information for workers' data is below a specified threshold. This constraint is satisfied as part of the incentive mechanism design, ensuring that all workers' data meet the freshness requirement.

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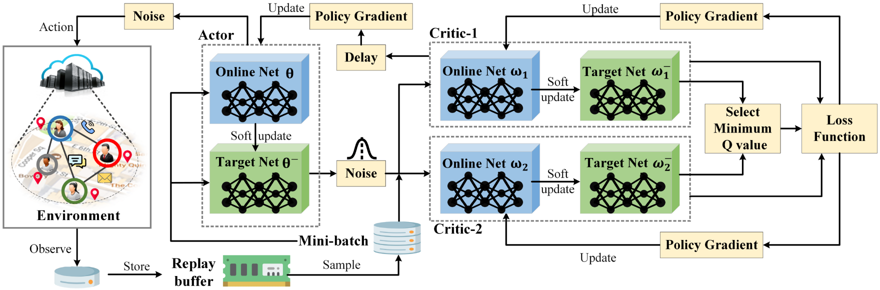
  - **The target networks used to compute the target actions and the target Q-values of the next state.**

DIM Learning Framework (continue 1)



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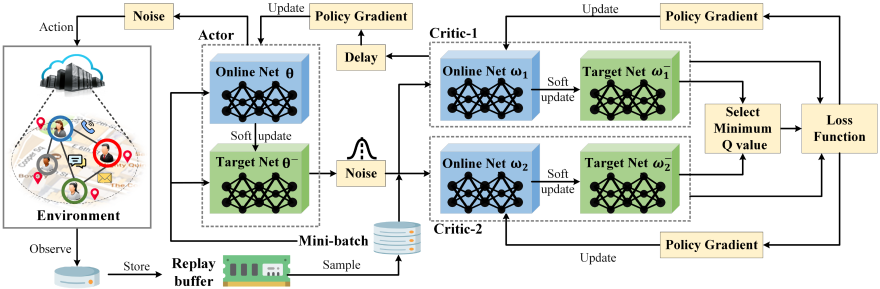

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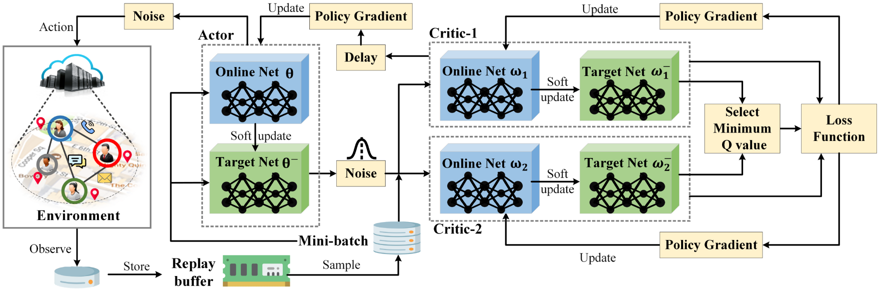

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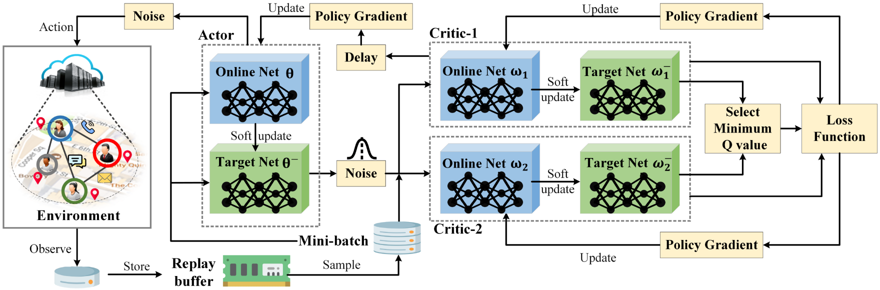

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- Actor network update frequency is less than the critic networks to mitigate policy oscillations, reduce overfitting risks, and stabilize the training process.
- Random noise promotes more diverse exploration and reduces the tendency to exploit a single action.

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- **The experience (i.e., current state, action, reward, and next state) is saved in the finite-size replay buffer, which used for the network update.**

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  - Reward Function:

$$\Upsilon(\mathbf{s}^t, \mathcal{R}^t) = \varrho_1 \Phi(P^t, \mathcal{R}^t) - \varrho_2 \left[\frac{\sum_{i=1}^{N} p_i^t - \hat{p}}{\hat{p}} \right]^+ - \varrho_3 \sum_{i=1}^{N} \left[\frac{\delta_i^t - \epsilon}{\epsilon} \right]^+,$$

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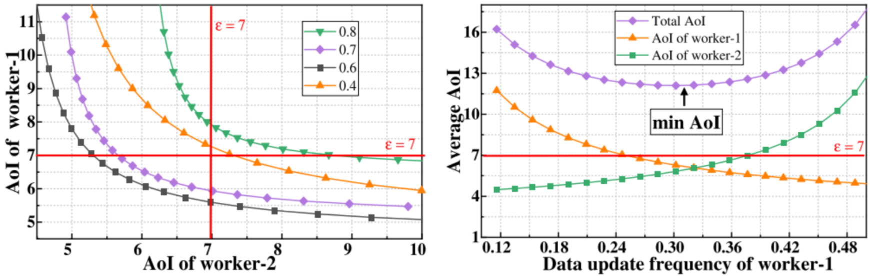
4. **Platform: (possibly) samples mini-batches from replay buffer $\rightarrow$ updates neural networks.**

Evaluation of AoI



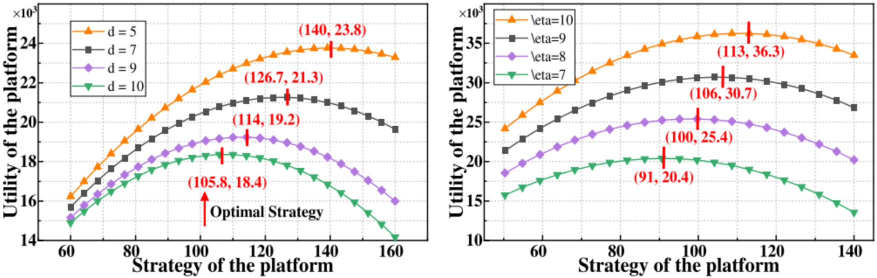
(a) worker-1's AoI vs. worker-2's AoI (b) total AoI and each worker's AoI

Evaluating AoI: two workers, fixed total load $\rho_1 + \rho_2 = \hat{\rho}$.

(a) AoI value of worker-1 decreases with the increase of worker-2's AoI value.

(b) AoI optimization problem depends on both the total load $\hat{\rho}$ and the allocation of data update frequency among workers.

Evaluation of AIM - Platform

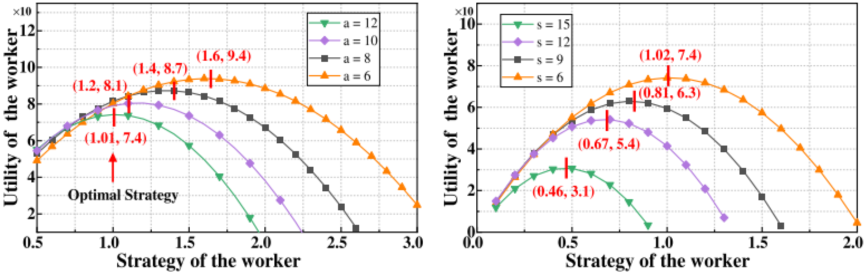


(a) quadratic parameter d (b) conversion parameter η

Evaluating AIM: Platform Strategy Vs. Utility with different parameters.

- PU will always find a maximum point.
- A small d or a larger η will result in the growth of the optimal *PS* and the optimal *PU*.

Evaluation of AIM - Worker

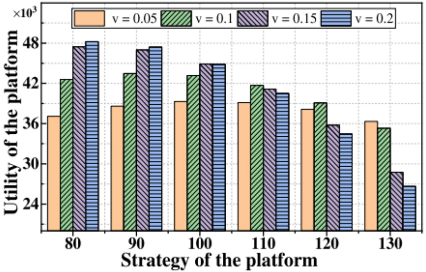


(a) quadratic parameter a (b) conversion parameter s

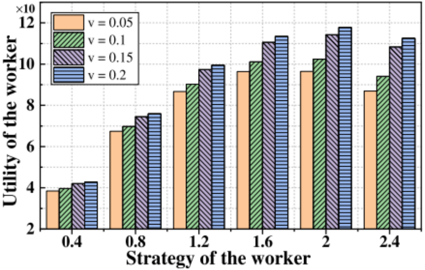
Evaluating AIM: Worker Strategy Vs. Utility with different parameters.

- WU find a maximum point.
- worker's utility increase when applying a smaller a or s since the cost of the worker becomes smaller.

Evaluation of Social Network Effect



(a) utility of the platform



(b) utility of the worker

Evaluating Influence of social network effects:

- Enlarging social network effect coefficient υ from 0.05 to 0.2, enables both the worker and platform to achieve higher utility.

Evaluation of Different Incentive Mechanisms

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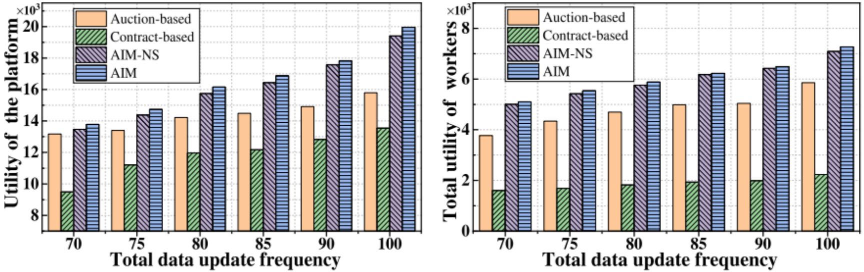
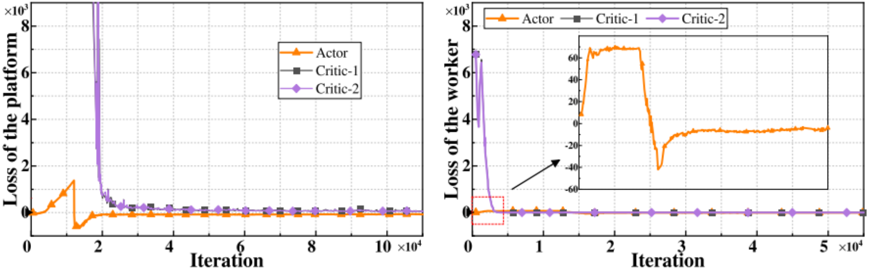


(a) PU vs. $\hat{p}$ (b) total WU vs. $\hat{p}$

- When $\hat{p} = 100$, the achieved PU of AIM is about 47.3% and 26.4% higher than those of the contract-based and auction-based algorithms on average, respectively.

Evaluation of DIM Conversion

Evaluation of DIM Conversion via training loss:



(a) loss of the platform (b) loss of the worker

- Both the actor network and two critic networks of the platform tend to a stable state as the training time increases.

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Performance Evaluation:

- Experiments with real-world data validate the efficacy of AIM and DIM.
- Both mechanisms outperform baseline methods in utility optimization and AoI guarantee.

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