CrowdCache: A Decentralized Game-Theoretic Framework for Mobile Edge Content Sharing

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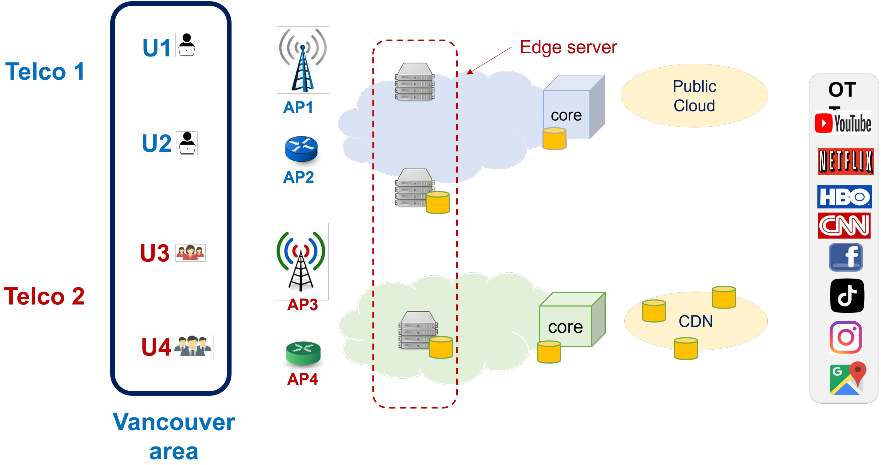
Outline

Edge cache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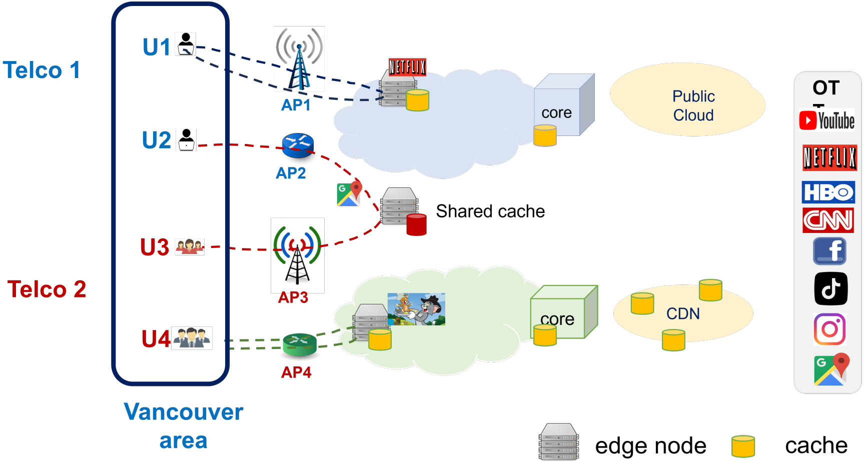
Edge cache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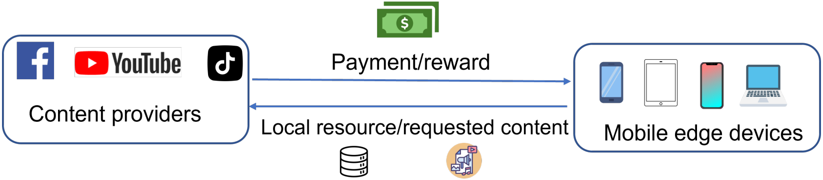
Crowdsourcing content sharing and caching

We consider a framework for mobile edge content sharing and caching via crowdsourcing, known as **CrowdCache**:

with crowdsourcing system:

- CP: recruit mobile edge devices to provide local storage for content cache.
- MEDs: request content services from the CP; earn incentives by providing local storage.



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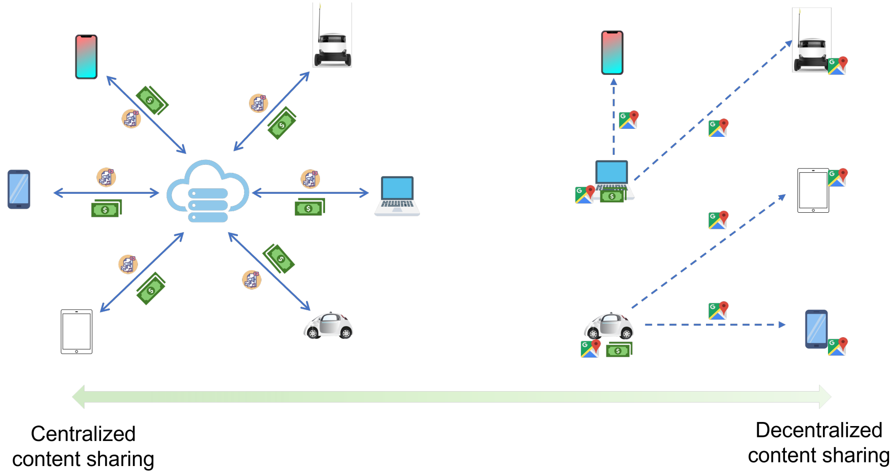
- CP: recruit mobile edge devices to provide local storage for content cache.
- MEDs: request content services from the CP; earn incentives by providing local storage.

Business goal

The CP may incentivize MEDs to share content with each other in a decentralized manner to enhance system efficiency

Decentralized content sharing



Decentralized content sharing

Benefits

(a) Reduce duplicate data transmission;
(b) Decrease backhaul capacity requirement;
(c) Alleviate congestion within backbone network;
(d) Due to the idle resources of numerous MEDs, reduce upfront investment costs for CP and network operators

System model

For MEDs,

- N MEDs indexed by $i = 1, \ldots, N$ (set $\mathcal{I}$)
- x_i denote the storage a MED is willing to provide
- $c_i(x_i)$ cost function of MED i:

$$c_i(x_i) = Q_i x_i^2 + h_i x_i, \quad \forall i$$

  where Q_i is the quadratic cost, and h_i is the linear cost of MED i.
- This quadratic form discourages excessive storage allocation.
- C_i: maximum storage capacity available for cached content on MED i.
- Capacity constraint: $0 \le x_i \le C_i, \ \forall i$.

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Objective

Each MED aims to maximize it own utility by determining its resource allocation decisions, taking into account costs and rewards

System model

For CP,

- The price for each unit of resource:

$$p(x) = \bar{P} - \gamma \sum_{j \in \mathcal{I}} x_j$$

  where $\bar{P}$ denotes the maximum unit reward offered by the CP
- γ: negative effect of other MEDs' benefits by sharing content, reflecting attitude towards the market demand for shared content:

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  where $\bar{P}$ denotes the maximum unit reward offered by the CP
- γ: negative effect of other MEDs' benefits by sharing content, reflecting attitude towards the market demand for shared content:
- Lower γ: encourage more MEDs to outsource their idle resources
- Higher γ: demand can be sufficiently fulfilled by existing participants

System model

- The price for each unit of resource:

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- The reward for MED i provided by the CP:

$$R_i(x_i, x_{-i}) = p(x)x_i, \ \forall i$$

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- function of x_i and other MEDs x_{-i} in the set $\mathcal{I}$.
- Marginal benefit: reward of MED i is diminishing as other intensify the engagement on content sharing.

System model

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- The reward for MED i provided by the CP:

$$R_i(x_i, x_{-i}) = p(x)x_i, \ \forall i$$

Thus, the utility function of each MED is defined as:

$$U_i(x_i, x_{-i}) = R_i(x_i, x_{-i}) - c_i(x_i), \ \forall i$$

Problem Formulation

We model this crowdsourcing mobile edge content caching and sharing problem as a non-cooperative game $(\Gamma = (\mathcal{I}, \{J_i\}, \{X_i\}))$.

- Local cost function for each MED:

$$J(x_i, x_{-i}) = -U_i(x_i, x_{-i}),\ \forall i = 1, \dots N$$

- Action set $x_i \in X_i = [0, C_i] \in \mathbb{R}$
- $x_{-i} \in X_{-i}$: joint action of all MEDs except MED i:
  $X_{-i} = X_1 \times \cdots \times X_{i-1} \times X_{i+1} \times X_N$
- Each MED seeks to minimize their local objective function without coordinating with other MEDs

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Nash Equilibrium

A solution to the game Γ is a Nash equilibrium (NE) $x^* \in X_1 \times \cdots \times X_N$ such that for every agent $i \in [N]$, we have:

$$J_i(x_i^*, x_{-i}^*) \leq J_i(x_i, x_{-i}^*), \quad \forall x_i \in X_i. \tag{1}$$

Existence and uniqueness of the NE

Recall the results connecting NE and solutions of variation inequality:

Definition 1: Variation Inequality [1]

For a set $K \subseteq \mathbb{R}^d$ and a mapping $g : K \longrightarrow \mathbb{R}^d$, the variational inequality (VI) problem VI(K,g) is to determine a vector $q^* \in K$ such that

$$\langle g(q^*), q - q^* \rangle \geq 0, \forall q \in K \quad (2)$$

The set of solutions to VI(K,g) is denoted by SOL(K,g)

Existence and uniqueness of the NE

Recall the results connecting NE and solutions of variation inequality:

Proposition 1.4.2 of [1]

Suppose a networked Nash Game Γ, where action sets of the MEDs $\{X_i\}$ are closed and convex, and the cost functions J_i are continuously differentiable and convex in x_i for every fixed x_{-i} from X_i. A vector $x^* \in X$ is a NE for the game Γ if and only if $x^* \in SOL(X, F)$ where F is the game mapping.

Definition 2: Game mapping

The game mapping $F(x) : X \longrightarrow \mathbb{R}^N$ is defined as

$$F(x) \triangleq \left[\nabla_i J_1(x_1, x_{-1}), \ldots, \nabla_N J_N(x_N, x_{-N})\right], \quad \forall x_i \in X_i. \tag{2}$$

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Lemma 2

This game mapping is strongly monotone in X with constant $\mu = 2\min_{i \in \mathcal{I}} Q_i + 2\gamma > 0$. $J_i(x_i, x_{-i}), \forall i$ is strongly convex on $\mathbb{R}$ for every $x_i \in \mathbb{R}^{N-1}$ with constant μ

Existence and uniqueness of the NE

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Proposition 2.3.3 of [1]

Given VI(K,g), suppose K is closed and convex, and the mapping g is continuous and strongly monotone. Then, the solution set $SOL(X, F)$ is nonempty and is a singleton.

[1] F. Facchinei and J. Pang. Finite-Dimensional Variational Inequalities and Complementarity Problems.

Property

Theorem 3

Consider the game $\Gamma = (\mathcal{I}, \{J_i\}, \{X_i\})$. There exists a unique NE in Γ. Moreover, the NE is the solution of VI(X,F), where F is the game mapping.

Remark: Theorem 3 guarantees the existence and uniqueness of NE in this game Γ. However, the formulation of the NE based on VI(X,F) **does not consider the distributed nature of the proposed problem.**

Property

Next, we present the Lipschitz continuity of the gradient of local objective function J_i for all i. The following Lemma is crucial to ensure the convergence of the distributed algorithm to the NE [2].

Theorem 4

Consider the game $\Gamma = (\mathcal{I}, \{J_i\}, \{X_i\})$.

(a) The mapping $\nabla_i J_i(\cdot, x_{-i})$ is Lipschitz continuous on $\mathbb{R}^{n-N}$ for every $x_{-i} \in \mathbb{R}^{N-1}$ with a uniform constant $L_1 = 2(\max_{i\in\mathcal{I}} Q_I + \gamma) \geq 0$, *for all* $i \in \mathcal{I}$.

(b) The mapping $\nabla_i J_i(x_i, \cdot)$ is Lipschitz continuous on $\mathbb{R}^{N-1}$ for every $x_{-i} \in \mathbb{R}^{N-1}$ with a uniform constant $L_2 = \gamma\sqrt{N-1}$,*for all* $i \in \mathcal{I}$.

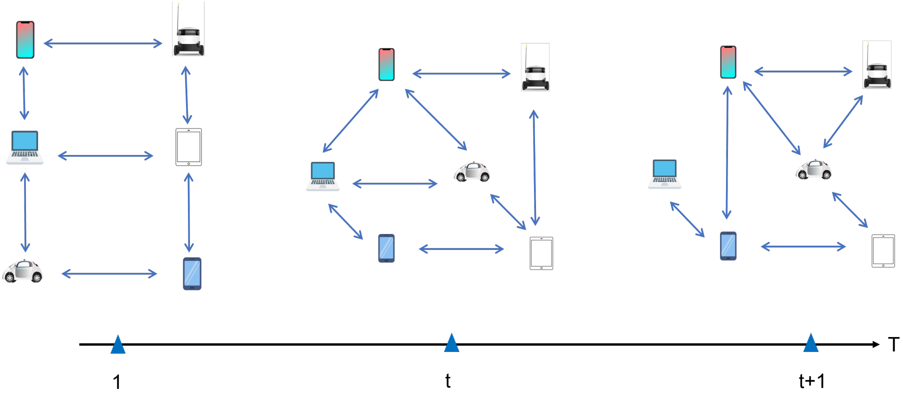
[2] D.T.A. Nguyen, D.T. Nguyen, and A. Nedić. "Distributed Nash equilibrium seeking over time-varying directed communication networks".

Contribution

Based on this crowdsourcing mobile edge content caching and sharing problem, we propose privacy-preserving algorithms to compute the NE:

- **Time-varying communication**: each MED may communicate with different neighbors at each round k.
- **Partial information exchange**: each MED only possesses partial information about their competitors actions through local communications (e.g., WiFi-Direct, LTE-Direct).
- **Decentralized local communication**: information exchange occurs solely between neighboring devices.

Time varying communication graphs



Time varying communication graphs

We define this time-varying communication graph as follows:

- **Time varying undirected graph**: $\mathbb{G}_k = (\mathcal{I}, E_k)$ where $\mathcal{I}$ is the set of MEDs, E_k is undirected link;
- **Unordered link** (i, j): MED i can receive information from MED j, and vice versa.
- **Neighbor set**: neighbour set for every MED i:

$$\mathcal{N}_{i,k} = \{j \in \mathcal{I} \mid (i, j) \in E_k\} \bigcup \{i\}$$

Remark: The sets of neighbors $\mathcal{N}_{i,k}$ always include MED i. Every MED (node) i has a self loop in each graph $\mathbb{G}_k, \forall k$

Time varying communication graphs

Assumption 1

The time-varying undirected graph sequence $\{\mathbb{G}_k\}$ is B-connected. There existis an integer $B \geq 1$ such that the graph with edge set $E_k^B = \bigcup_{i=kB}^{(k+1)B-1} E_i$ is connected for every $k \geq 0$

Remark: This assumption ensures:

(a) After B-rounds of communication, there exits a path between any pair of MEDs in the system.

(b) No MED is isolated from the rest of the system.

Time varying communication graphs

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Intuition:

(a) This assumption is easily satisfied as long as MEDs are within the coverage area of cellular or Wi-Fi networks.

(b) MEDs must be connected to the network for communication with CP and other MEDs if deciding to share content and local storage.

Nash Equilibrium

Lemma 1

For all MED $i \in [m]$, action set X_i is closed and convex and cost function $J_i(x_i, x_{-i})$ is convex and continuously differentiable in x_i for each $x_{-i} \in X_{-i}$

Definition 1: First-order Optimality Condition

$x^* \in X$ is a NE of the game if and only if for all $i \in [N]$, we have:

$$\langle \nabla_i J_i(x_i^*, x_{-i}^*), x_i - x_i^* \rangle \geq 0, \quad \forall x_i \in X_i. \tag{2}$$

or equivalently,

$$x_i^* = \Pi_{X_i}[x_i^* - \alpha_i \nabla_i J_i(x_i^*, x_{-i}^*)], \quad \forall i \in [N], \tag{3}$$

where $\alpha_i > 0$ is an arbitrary scalar.

Traditional algorithm

Basic algorithm

- Initial point $x_i^0 \in X_i$
- Each agent i updates its decision at time k as follows:

$$x_i^{k+1} = \Pi_{X_i}[x_i^k - \alpha_i \nabla_i J_i(x_i^k, x_{-i}^k)] \quad (4)$$

where $\alpha_i > 0$ is the step-size.

- x_k^i: MED i's actual decision at time k.
- x_k^{-i}: actual decisions of MEDs other than i at time k.

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- x_k^i: MED i's actual decision at time k.
- x_k^{-i}: actual decisions of MEDs other than i at time k.

Remark:

(a) Require that every agent i has access to all other agents' decisions x_{-i}^k at every time k

(b) Require full information about competitors' cost functions (privacy concerns)

Algorithm

Each agent i updates its decision at time k as follows:

Basic algorithm

$$x_{k+1}^{i} = \Pi_{X_i}[x_k^i - \alpha_i \nabla_i J_i(x_k^i, x_k^{-i})].$$

Distributed Algorithm

$$x_{k+1}^{i} = \Pi_{X_i}[z_{k+1}^{ii} - \alpha_i \nabla_i J_i(z_{k+1}^{ii}, z_{k+1}^{i,-i})]. \quad (5)$$

where $\alpha_i > 0$ is the step-size.

- z_k^{ij}: MED i's estimate of the decision x_k^j for MED $j \neq i$.
- $z_k^i = (z_k^{i1}, \dots, z_k^{ii}, z_k^{iN})^\intercal \in \mathbb{R}^N \quad (\mathbf{z_k^{ii}} = \mathbf{x_k^i} \in \mathbb{R})$
- $z_k^{i,-i} \in \mathbb{R}^{N-1}$: the estimate of MED i for the decisions of the other MEDs

Algorithm

Algorithm 1: DCrowdCache

Initialization: arbitrary initial vectors $z_0^{i,-i} \in \mathbb{R}^{N-1}$ and $x_0^i \in \mathbb{R}$
For each time $k = 0, 1, \dots,$ every MED does the following:

(1) Receives z_k^j and $|\mathcal{N}_{jk}|$ from neighbors $j \in \mathcal{N}_{ik}$;

(2) Sends z_k^i and $|\mathcal{N}_{ik}|$ to neighbors $j \in \mathcal{N}_{ik}$;

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(3) Calculates the weights using Metropolis weights:

$$[W_k]_{ij} = \begin{cases} 1/(1+\max\{|\mathcal{N}_{ik}|, |\mathcal{N}_{jk}|\}, & \text{if} \quad j \in \mathcal{N}_{ik} \setminus \{i\}, \\ 0, & \text{if} \quad j \notin \mathcal{N}_{ik}, \\ 1 - \sum_{\ell \in \mathcal{N}_{ik}} [W_k]_{il}, & \text{if} \quad j = i; \end{cases}$$

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(3) Calculates the weights using Metropolis weights:

(4) Updates the action x_{k+1}^i and estimates $z_{k+1}^{i,-i}$ by

$$x_{k+1}^i = \Pi_{X_i}\left[\sum_{j=1}^N [W_k]_{ij}[z_k^j]_i - \alpha \nabla_i J_i\left(\sum_{j=1}^N [W_k]_{ij} z_k^j\right)\right],$$

$$z_{k+1}^{i,-i} = \sum_{j=1}^N [W_k]_{ij} z_k^{j,-i}, \qquad z_{k+1}^{i,i} = x_{k+1}^i;$$

Algorithm

Algorithm 2: DCrowdCache-m

Initialization: arbitrary initial vectors $z_0^{i,-i}, z_{-1}^{i,-i} \in \mathbb{R}^{N-1}$ and $x_0^i, x_{-1}^i \in \mathbb{R}$
For each time $k = 0, 1, \dots,$ every MED does the following:

(1) Receives z_k^j and $|\mathcal{N}_{jk}|$ from neighbors $j \in \mathcal{N}_{ik}$;

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Algorithm

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$$[W_k]_{ij} = \begin{cases} 1/(1+\max\{|\mathcal{N}_{ik}|, |\mathcal{N}_{jk}|\}, & \text{if} \quad j \in \mathcal{N}_{ik} \setminus \{i\}, \\ 0, & \text{if} \quad j \notin \mathcal{N}_{ik}, \\ 1 - \sum_{\ell \in \mathcal{N}_{ik}} [W_k]_{il}, & \text{if} \quad j = i; \end{cases}$$

(3.1) Weight on each edge is inversely proportional to the large degree at its two incident nodes;

(3.2) Self-weights are chosen such that the sum of weights at each node is 1.

Algorithm

Algorithm 2: DCrowdCache-m

Initialization: arbitrary initial vectors $z_0^{i,-i}, z_{-1}^{i,-i} \in \mathbb{R}^{N-1}$ and $x_0^i, x_{-1}^i \in \mathbb{R}$
For each time $k = 0, 1, \ldots,$ every MED does the following:

(1) Receives z_k^j and $|\mathcal{N}_{jk}|$ from neighbors $j \in \mathcal{N}_{ik}$;

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$$x_{k+1}^i = \Pi_{X_i}\left[\sum_{j=1}^N [W_k]_{ij}[z_k^j]_i - \alpha \nabla_i J_i\left(\sum_{j=1}^N [W_k]_{ij} z_k^j\right)\right] + \beta_i(x_k^i - x_{k-1}^i)$$

$$z_{k+1}^{i,-i} = \sum_{j=1}^N [W_k]_{ij} z_k^{j,-i} + \beta(z_k^{i,-i} - z_{k-1}^{i,-i}); \quad z_{k+1}^{i,i} = x_{k+1}^i$$

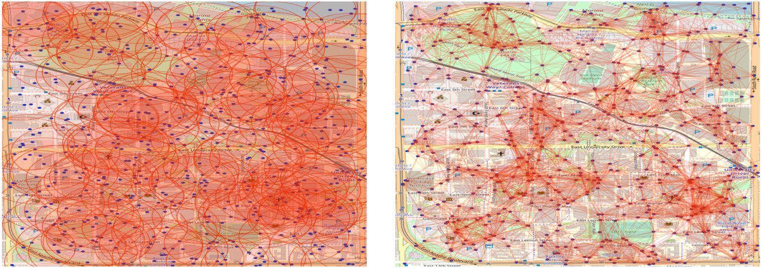
Key takeaways

- **DCrowdCache** and **DCrowdCache-m** share the same structures to compute NE.
- **DCrowdCache-m** integrates the heavy-ball momentum [3,4,5] and consensus-based gradient method, resulting in different updating rules of estimates.

[3] B. Polyak. "Some methods of speeding up the convergence of iteration methods" Comput. Math. & Math. Phys., vol. 4, no. 5, pp. 1–17, 1964

Numerical settings

- Coverage range for each device is within the range of $[150, 200]$ meters [5].
- Generate initial locations of $N = 2^9$ MEDs from the ASU Tempe campus [6].



(a) MEDs coverage areas

(b) MEDs connections

Figure: Mobile edge devices (MEDs) locations at ASU campus

Numerical settings

- Coverage range for each device is within the range of $[150, 200]$ meters [5].
- Generate initial locations of $N = 2^9$ MEDs from the ASU Tempe campus [6].
- In each iteration, the MEDs randomly move within the designated range, and their new locations and coverage ranges are used to create a communication graph among them.
- $Q_i, \forall i$ is randomly generated from $U[0.01, 0.1]\$$ per hour.
- $h_i, \forall i$ is randomly generated from $U[0.05, 0.15]\$$ per hour.
- $c_i, \forall i$ is randomly from the values 16, 32, 48, and 64 GB.
- $\bar{P}$ for each unit of storage is set to 1 (normalization).

[5] https://github.com/swinedge/eua-dataset

[6] https://github.com/duongnguyen1601/CrowdCache-dataset

Performance analysis

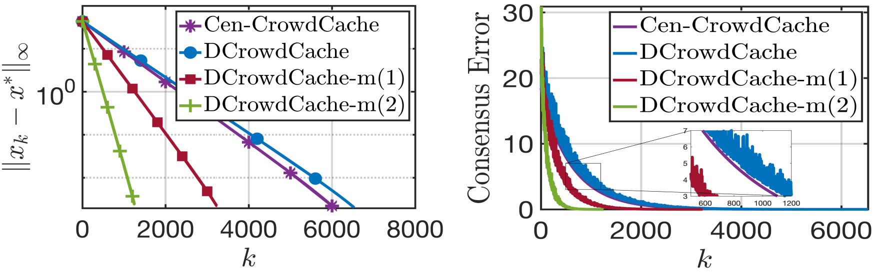


Figure: Convergence properties: The numerical results are computed with $\alpha = 20$. **Cen-CrowdCache**: Centralized communication that braod casts information from all MEDs; **DCrowdCache-m(1)**: $\beta = 0.5$; **DCrowdCache-m(2)**: $\beta = 0.8$

- **DCrowdCache-m** converges faster than the **DCrowdCache**
- Larger momentum (β) leads to faster convergence.

Sensitivity analysis

- **Proposed**: proposed decentralized NE seeking algorithm.
- **Heuristic**: use 20% of the maximum idle resources from MEDs, as long as the utility is positive.
- **Average**: use 50% of the maximum idle resources from MEDs, as long as the utility is positive.

Sensitivity analysis

Γ: scaling factor to scale down/up γ regarding base value generated in the default setting.

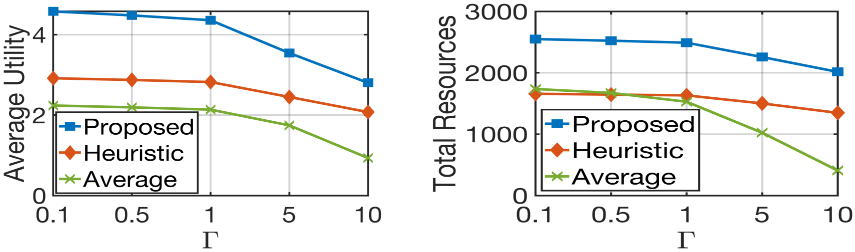


Figure: Impacts of γ

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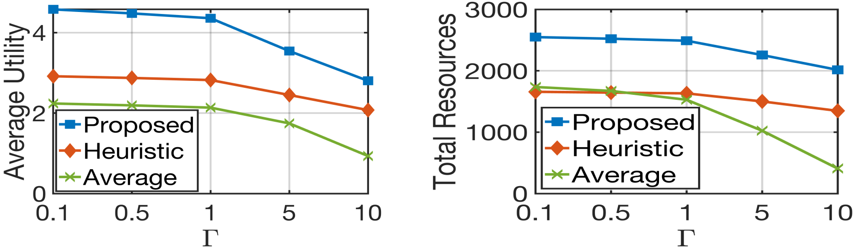

Figure: Impacts of γ

- Decreasing γ leads to a higher utility: the unit reward increases, motivating more MEDs to contribute their resources to the system.

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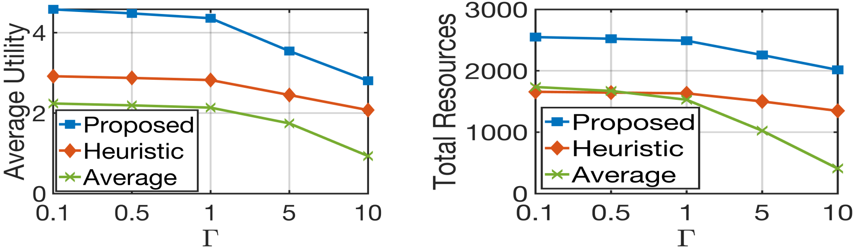

Figure: Impacts of γ

- Decreasing γ leads to a higher utility: the unit reward increases, motivating more MEDs to contribute their resources to the system.
- Increasing γ leads to a lower utility: discourages MEDs to reduce their contributions, avoiding over-provisioning cost

Sensitivity analysis

Λ: scaling factor to scale down/up the maximum unit price ($\bar{P}$) regarding base value generated in the default setting.

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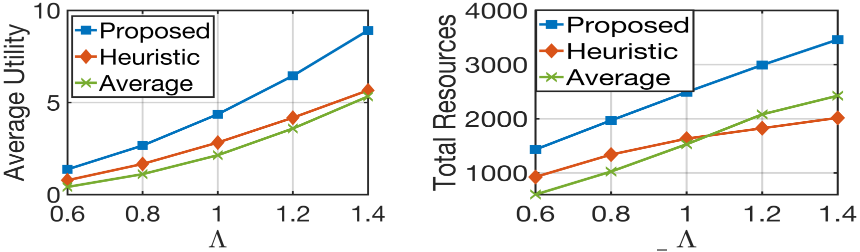

Figure: Impacts of maximum unit price $\bar{P}$

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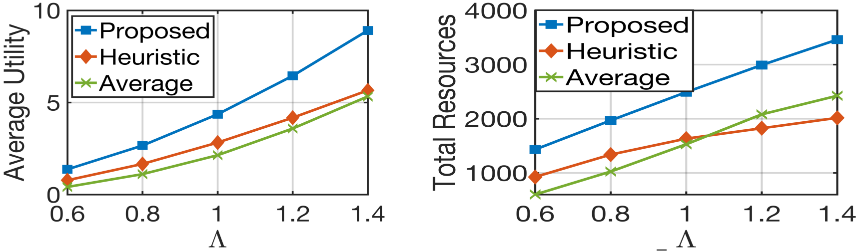

Figure: Impacts of maximum unit price $\bar{P}$

- Increasing $\bar{P}$: incentivize the MED to supply more resources to the platform, resulting in a higher average utility for the MEDs.

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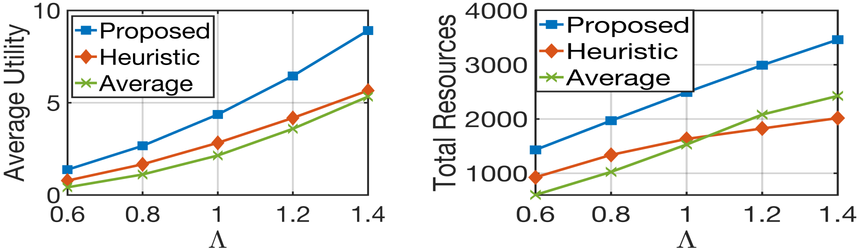

Figure: Impacts of maximum unit price $\bar{P}$

- Increasing $\bar{P}$: incentivize the MED to supply more resources to the platform, resulting in a higher average utility for the MEDs.
- Increasing $\bar{P}$: access a larger resource pool, leading to operational scalability, improved user experience.

Sensitivity analysis

Ψ: scaling factor to scale down/up the quadratic cost parameter (Q_i) regarding base value generated in the default setting.

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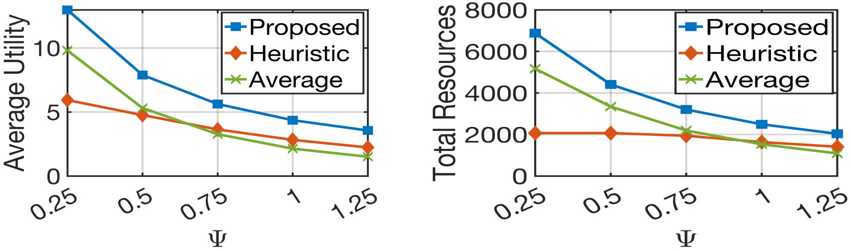

Figure: Impacts of quadratic cost Q_i, for all $i \in \mathcal{I}$

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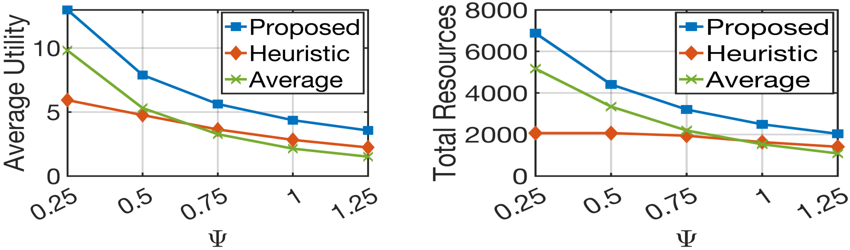

Figure: Impacts of quadratic cost Q_i, for all $i \in \mathcal{I}$

- Increasing Q_i: MED may reduce the amount of outsourcing resources, leading to a decrease in the amount of idle resources available for outsourcing,

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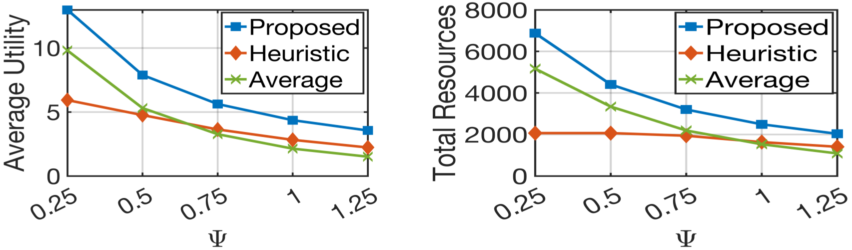

Figure: Impacts of quadratic cost Q_i, for all $i \in \mathcal{I}$

- Increasing Q_i: MED may reduce the amount of outsourcing resources, leading to a decrease in the amount of idle resources available for outsourcing,
- Quadratic cost coefficient leads to more rapid decrease in the marginal utility of outsourcing additional resources

Sensitivity analysis

δ: scaling factor to scale down/up the linear cost parameter (h_i) regarding base value generated in the default setting.

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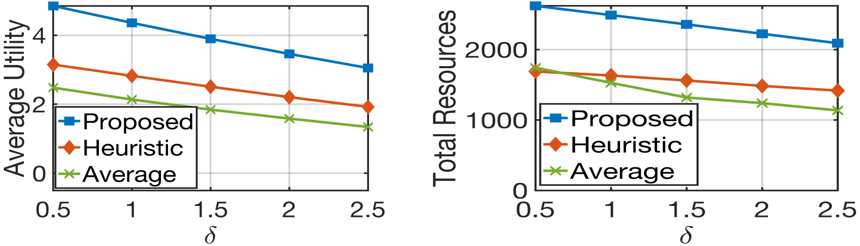

Figure: Impacts of linear cost h_i, for all $i \in \mathcal{I}$

Sensitivity analysis

δ: scaling factor to scale down/up the linear cost parameter (h_i) regarding base value generated in the default setting.

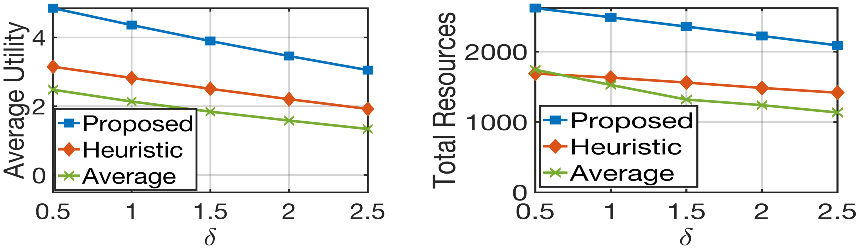

Figure: Impacts of linear cost h_i, for all $i \in \mathcal{I}$

- Quadratic cost coefficient leads to more rapid decrease in the marginal utility of outsourcing additional resources

Numerical results

N	**DCrowdCache**		**DCrowdCache-m** ($\beta = 0.5$)	
	# Iterations	Run time (s)	# Iterations	Run time (s)
2^8	2973	0.035	1474	0.018
2^9	5791	0.099	2876	0.053
2^{10}	10812	0.437	5407	0.239
2^{11}	19951	1.519	9978	0.858
2^{12}	37541	8.482	18734	4.464

Table: Average performance over 1000 simulations.

Conclusions and future work

Conclusions:

- Introduced a novel privacy-preserving framework to tackle the decentralized mobile edge content caching and sharing problem, where MEDs can share their cached content with neighbors.
- Operated over a time-varying communication graph, ensuring that users' privacy is preserved throughout the process.
- Examined the convergence of the algorithm over a time-varying undirected communication network.

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- Introduced a novel privacy-preserving framework to tackle the decentralized mobile edge content caching and sharing problem, where MEDs can share their cached content with neighbors.
- Operated over a time-varying communication graph, ensuring that users' privacy is preserved throughout the process.
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Future work:

- Consider more complicated local objective function and its impact in context of this problem
- Explore more complex generalized game models containing local constraints and coupling constraints among agents' decisions.

THANK YOU!

Notations

- $z_i^k = (z_{i1}^k, \ldots, z_{im}^k)' \in \mathbb{R}^n$: agent i's estimate of the joint action x
- $\{\pi_k\}$: sequence of stochastic vectors satisfying $\pi_{k+1}' W_k = \pi_k'$ (see Lemma 2 in [2])
- $\hat{z}_{\pi_k}^k = \sum_{i=1}^m [\pi_k]_i z_i^k$: weighted-average of the estimates
- x^*: an NE point of the game
- We define the matrices:

$$\mathbf{z}^k = \begin{bmatrix} (z_1^k)' \\ (z_2^k)' \\ \vdots \\ (z_m^k)' \end{bmatrix} = \begin{bmatrix} x_1^k & z_{12}^k & \ldots & z_{1m}^k \\ z_{21}^k & x_2^k & \ldots & z_{2m}^k \\ \vdots & \vdots & \ddots & \vdots \\ z_{m1}^k & z_{m2}^k & \ldots & x_m^k \end{bmatrix},$$

$$\hat{\mathbf{z}}^k = \mathbf{1}_m (\hat{z}_{\pi_k}^k)', \quad \mathbf{x}^* = \mathbf{1}_m (x^*)'$$

[2] Angelia Nedić and Alex Olshevsky. Distributed optimization over time-varying directed graphs.