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Towards Capacity-Aware Broker Matching: From Recommendation to Assignment

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贝壳 找房大平台

Outline

- Background and Motivation
- Problem Statement
- Our Solutions
- Experiments
- Conclusion

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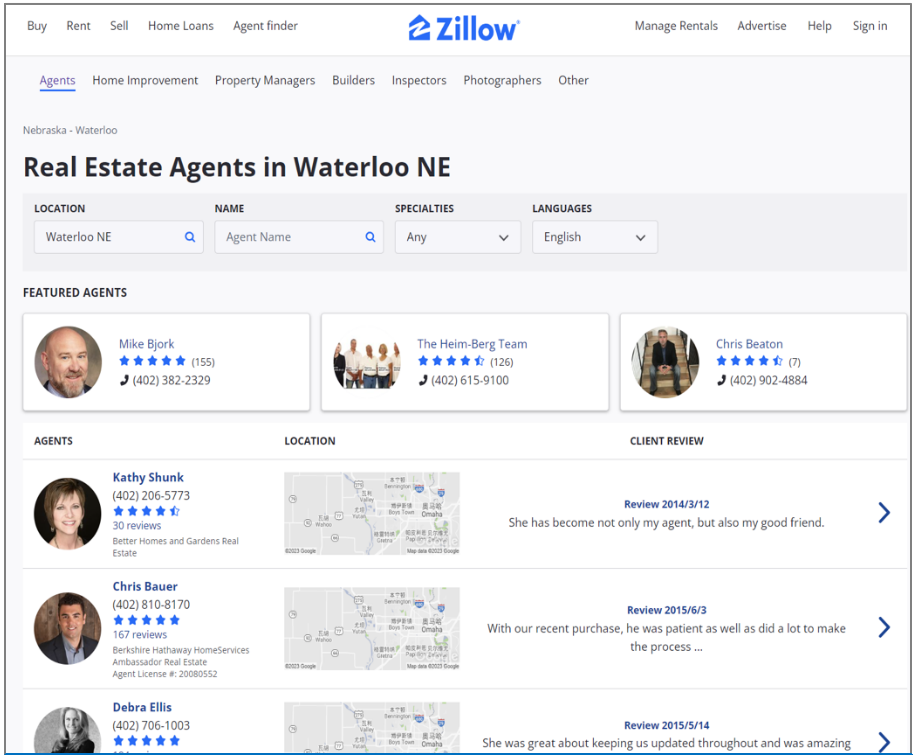
Background and Motivation

- **Online real estate platforms are using data-driven approaches to improve their service quality.**



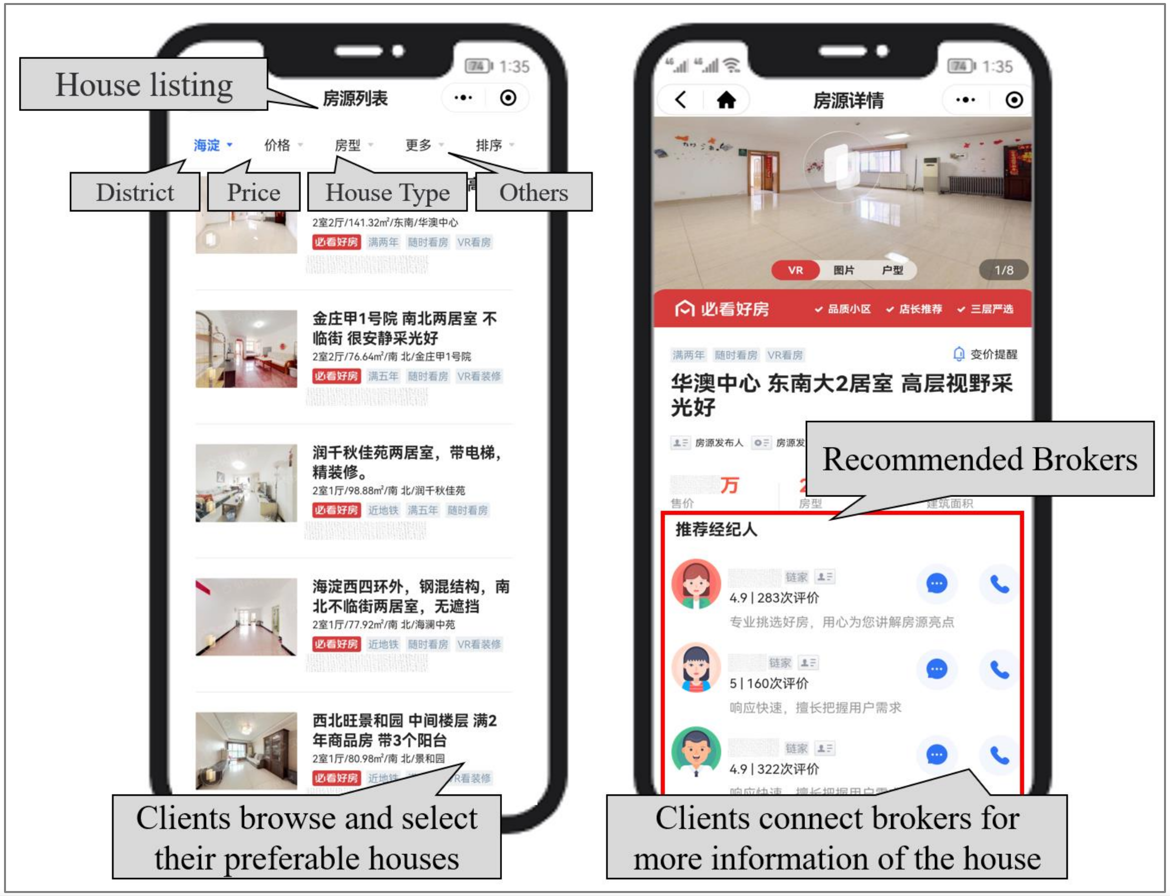
Broker finding service in Zillow

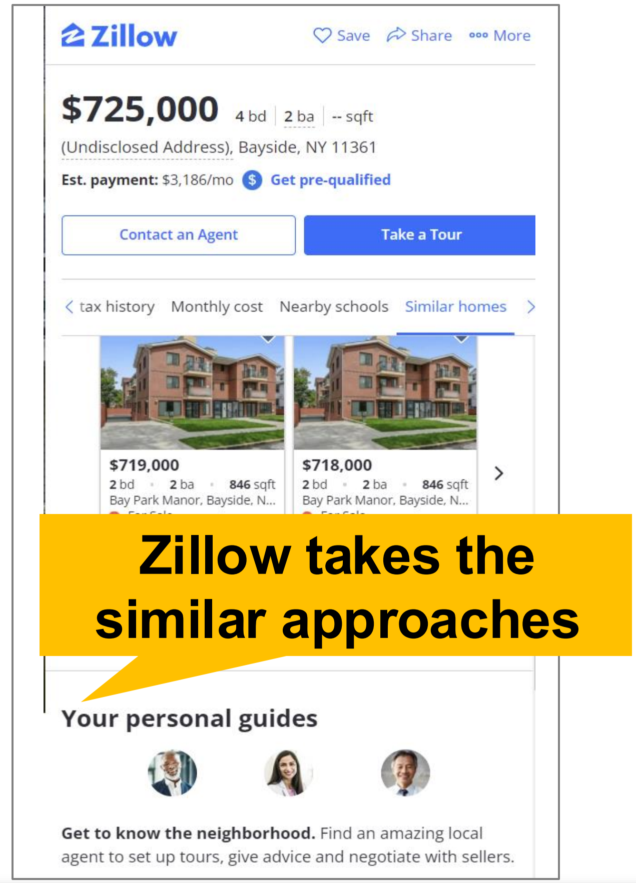
Broker recommendation in Ke holdings Inc.

Broker Matching is a central function for the platform

Background and Motivation

- **The real estate platforms usually takes the top-*k* recommendation for broker matching**

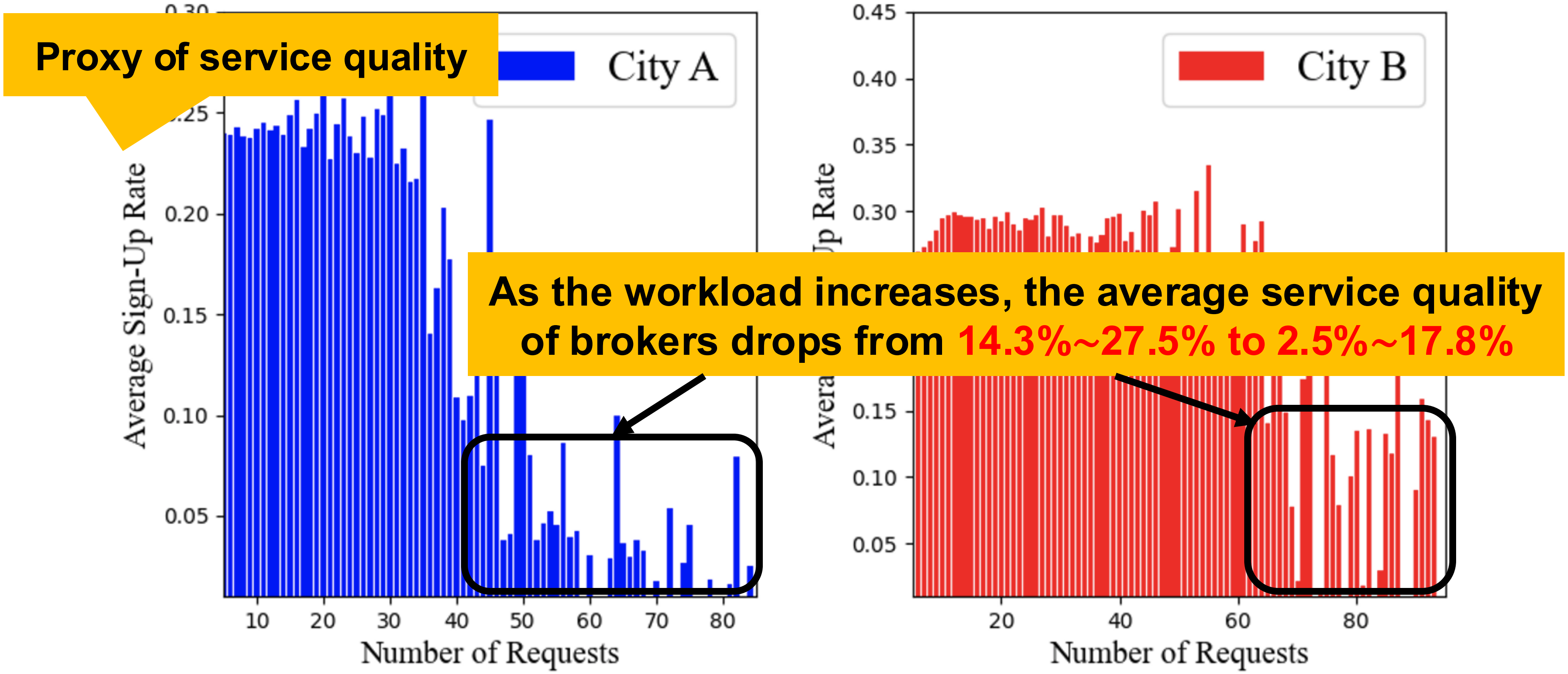




Top-*k* recommendation is common in broker matching

Background and Motivation

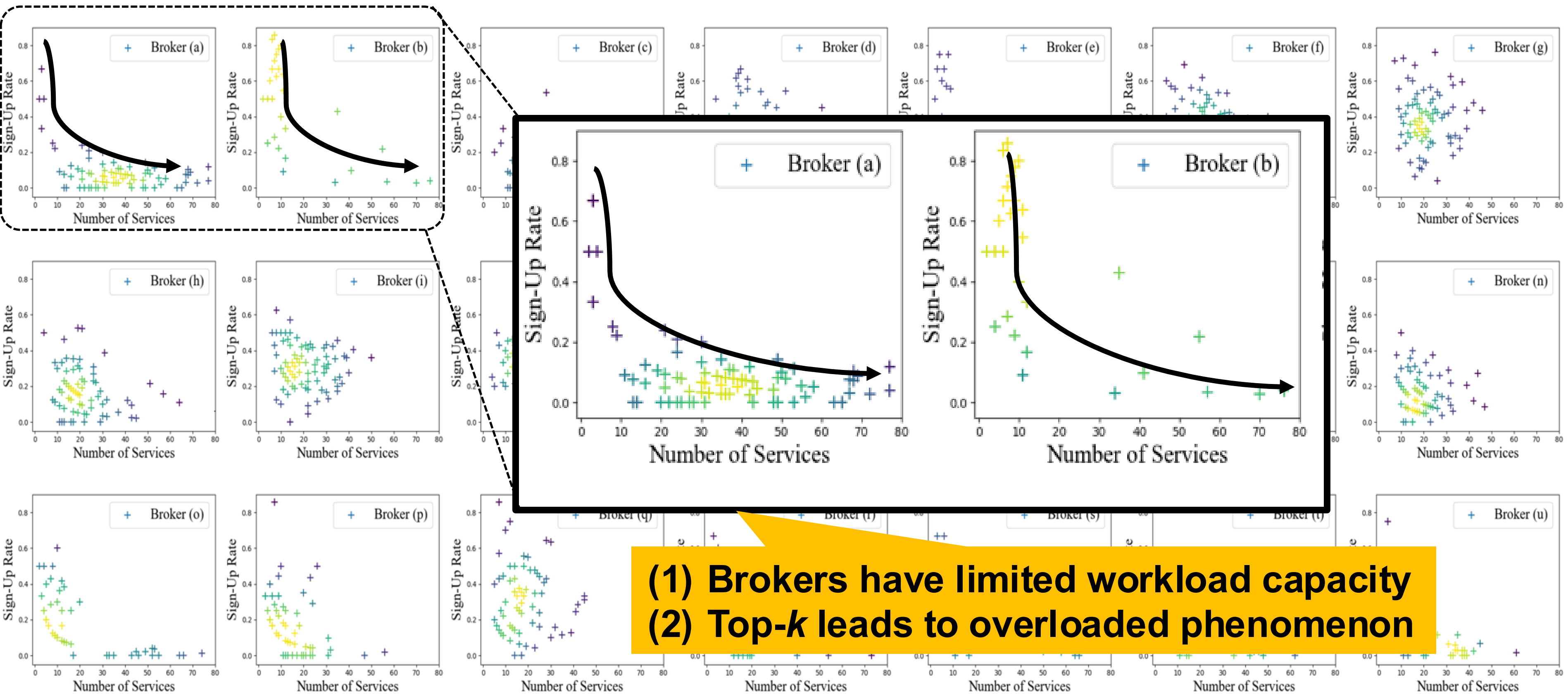
- **Top-*k* can lead to the *overloaded phenomenon*, i.e., most clients are matched to small brokers.**



Too much workloads can decrease the service quality

Background and Motivation

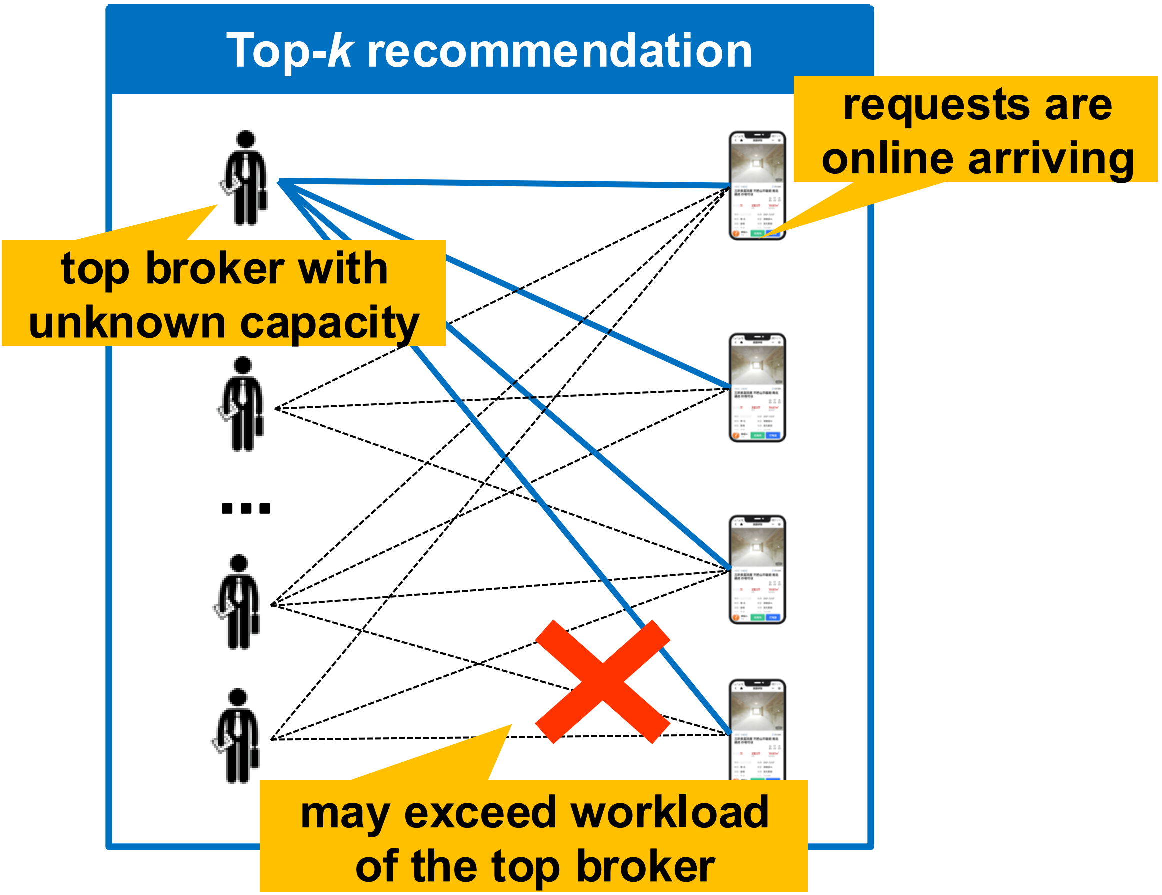
- **We further analyze the service quality of the top brokers with highest requests in City A.**



Most brokers performs better with proper workloads

Background and Motivation

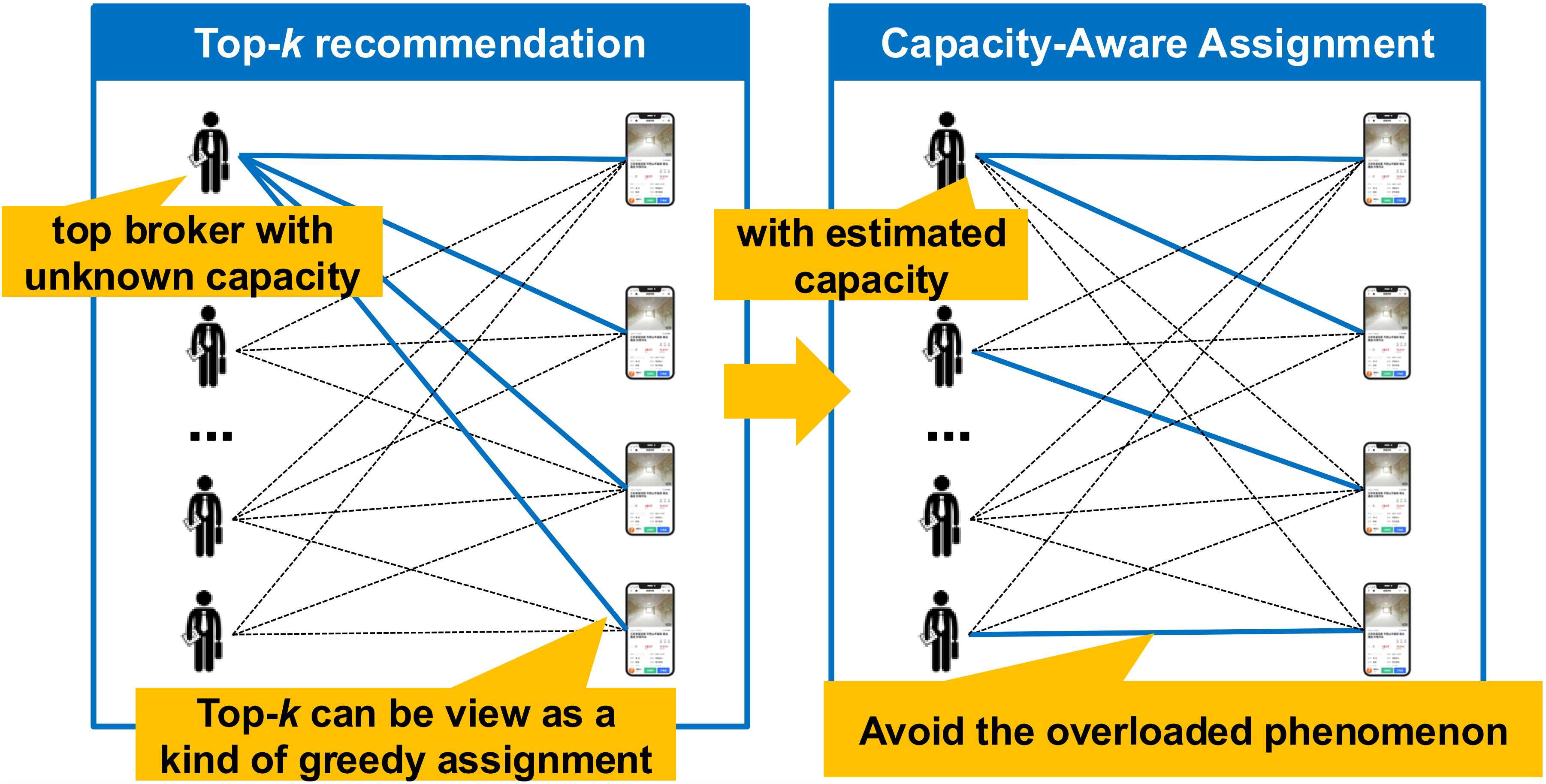
- **A few brokers are tasked to serve amounts of requests**



How to avoid the overloaded phenomenon and improve the utility of the real estate of the platforms?

Background and Motivation

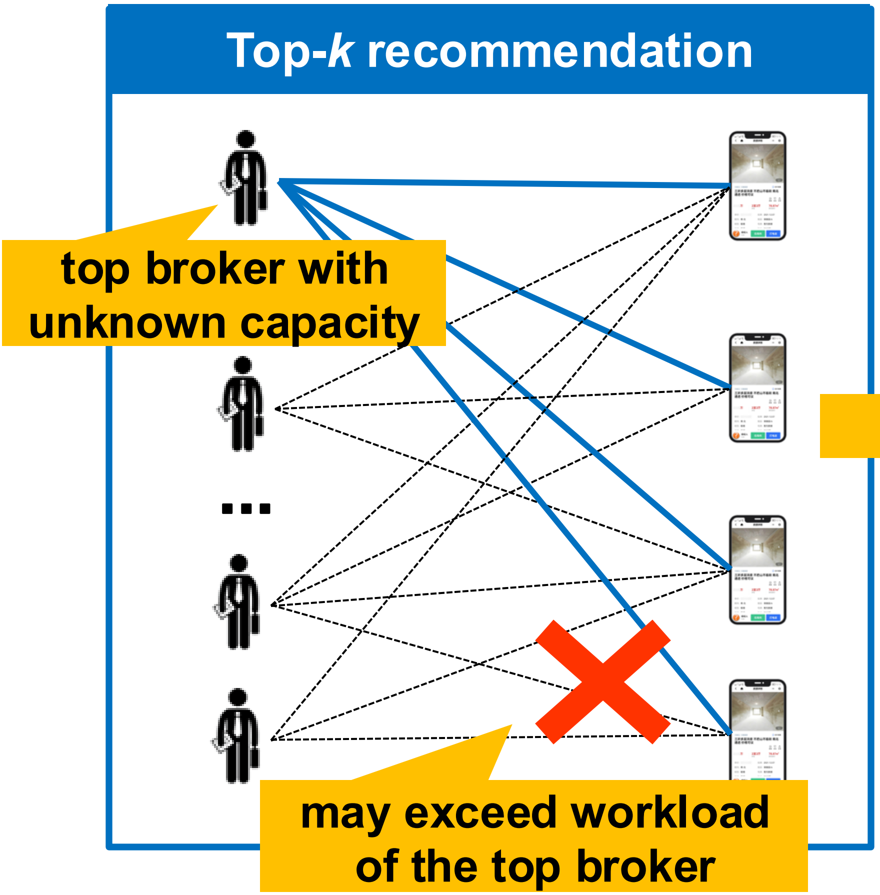
- **Towards capacity-aware broker matching**

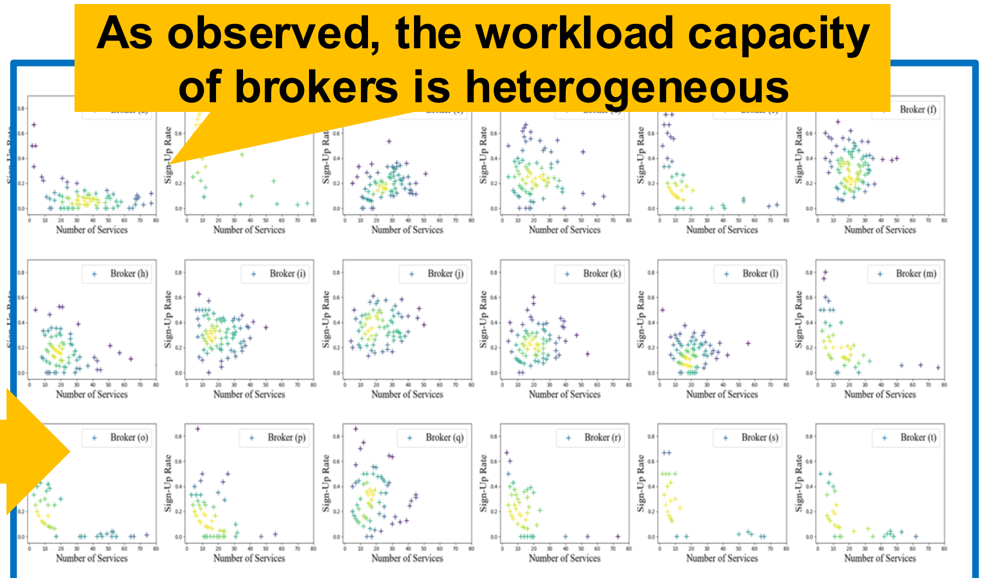


Solution: from recommendation to assignment

Background and Motivation

- **Towards capacity-aware broker matching**



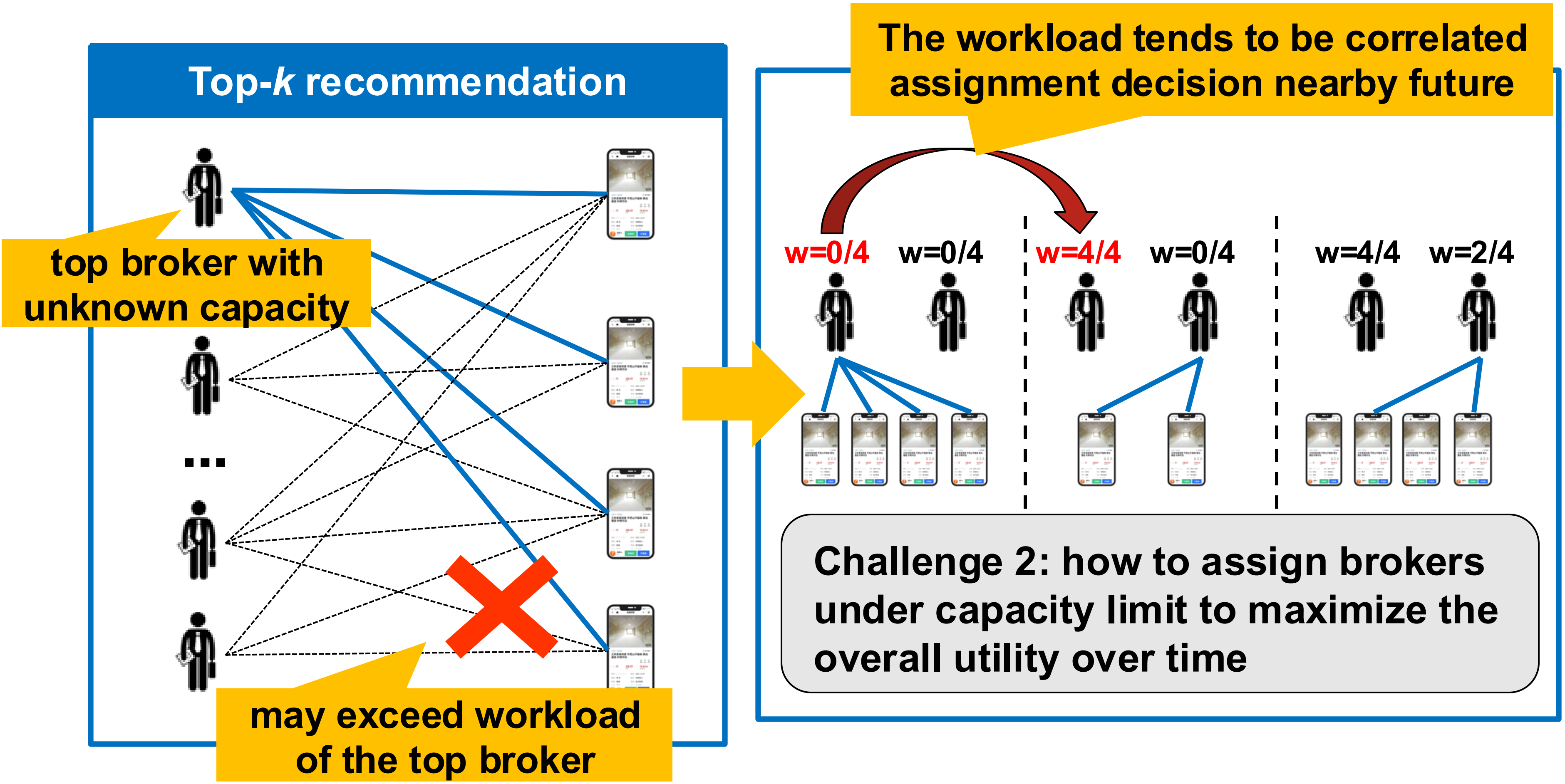


Challenge 1: how to estimate the broker-specific workload capacity

How to avoid the overloaded phenomenon and improve the utility of the real estate of the platforms?

Background and Motivation

- **Towards capacity-aware broker matching**



How to avoid the overloaded phenomenon and improve the utility of the real estate of the platforms?

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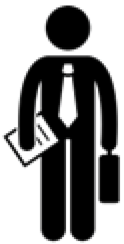
Problem Statement

- **Capacity-Aware Assignment (CAA) problem**



Broker

workload capacity of broker

sign-up rates of broker, i.e. the proxy of utility

a broker $b \in \boldsymbol{B}$, $b = (\boldsymbol{x}_b, w_b, c_b, s_b)$

attributes of broker

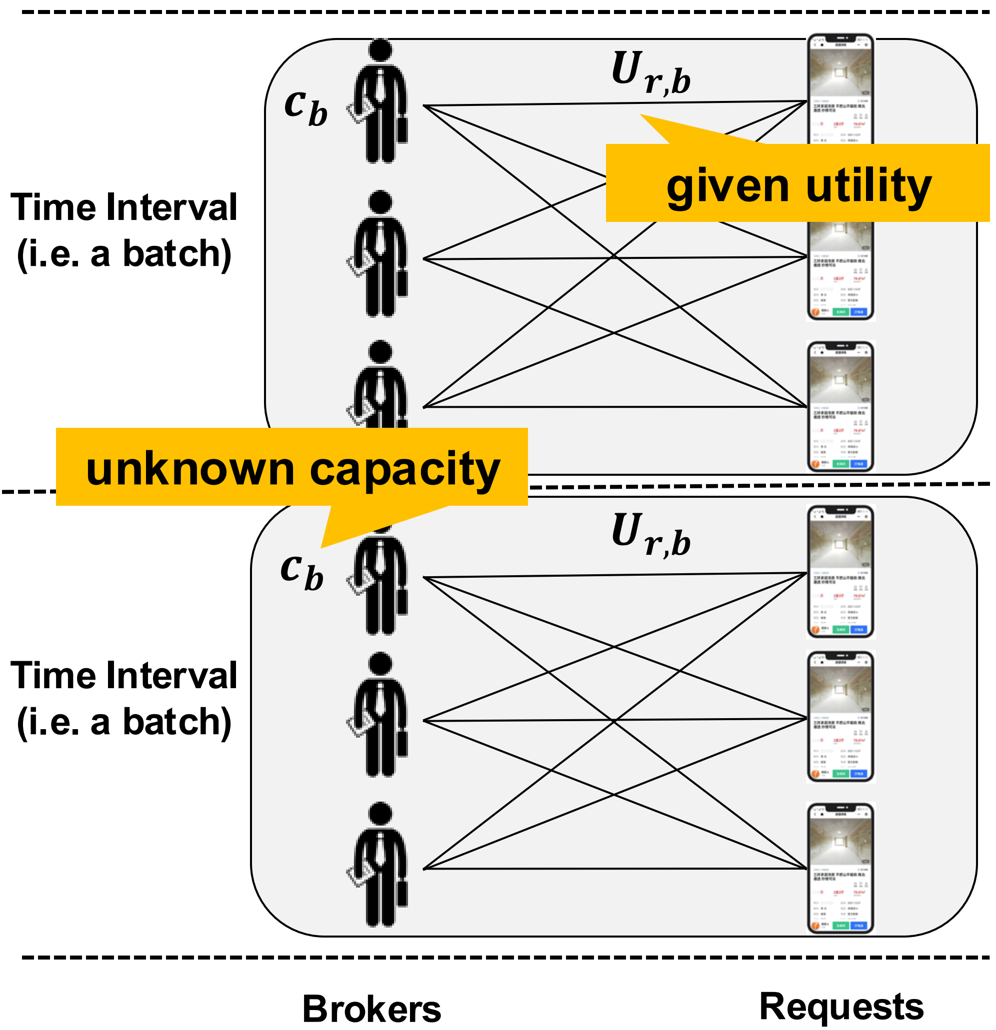
workload of broker

Attribute Type	Attribute	Description
Basic Info.	Age	Broker's age.
	Working Year	The working years as a broker.
	Education	Education background (*e.g.*,undergraduate, master).
	Title	Job title (*e.g.*,assistant, clerk, manager).
Work Profile	Response Rate	The rate of the broker's response to a request in one minute.
	Dialogue rounds	The average dialogue rounds via the App in recent 7/14/30/90 days.
	Number of Housing Presentation	The number of broker's presenting houses offline in recent 7/14/30/90 days.
	Number of Presentation via VR	The number of broker's presenting houses via VR in recent 7/14/30/90 days.
	Time of Presentation via VR	The time of broker's presenting houses via VR in recent 7/14/30/90 days.
	Number of Consultation via Phone	The number of broker answering clients via phone in recent 7/14/30/90 days.
	Time of Consultation via Phone	The time of broker answering clients via phone in recent 7/14/30/90 days.
	Number of Consultation via App	The number of broker answering clients via App in recent 7/14/30/90 days.
	Time of Consultation via App	The time of broker answering clients via App in recent 7/14/30/90 days.
	Number of Maintained Houses	The number of houses currently maintained by the broker.
	Number of Served Clients	The number of clients who are served by the broker in recent 7/14/40/90 days.
	Number of Housing Transactions	The number of housing transactions through the broker in recent 7/14/40/90 days.
Preference	Districts Information	Broker's preferable communities and area around POIs.
	Housing Information	Broker's preferable price, area and type of houses.

Key step：to estimate the unknown workload capacity

Problem Statement

- Capacity-Aware Assignment (CAA) problem



Maximizing Total utility:

$$\max \sum_{i \in I} \sum_{r,b} u_{r,b} \mathcal{M}_{r,b}^{(i)}$$

is 1 if broker b is assigne d to request r, and is 0 otherwise

Capacity Constraint:

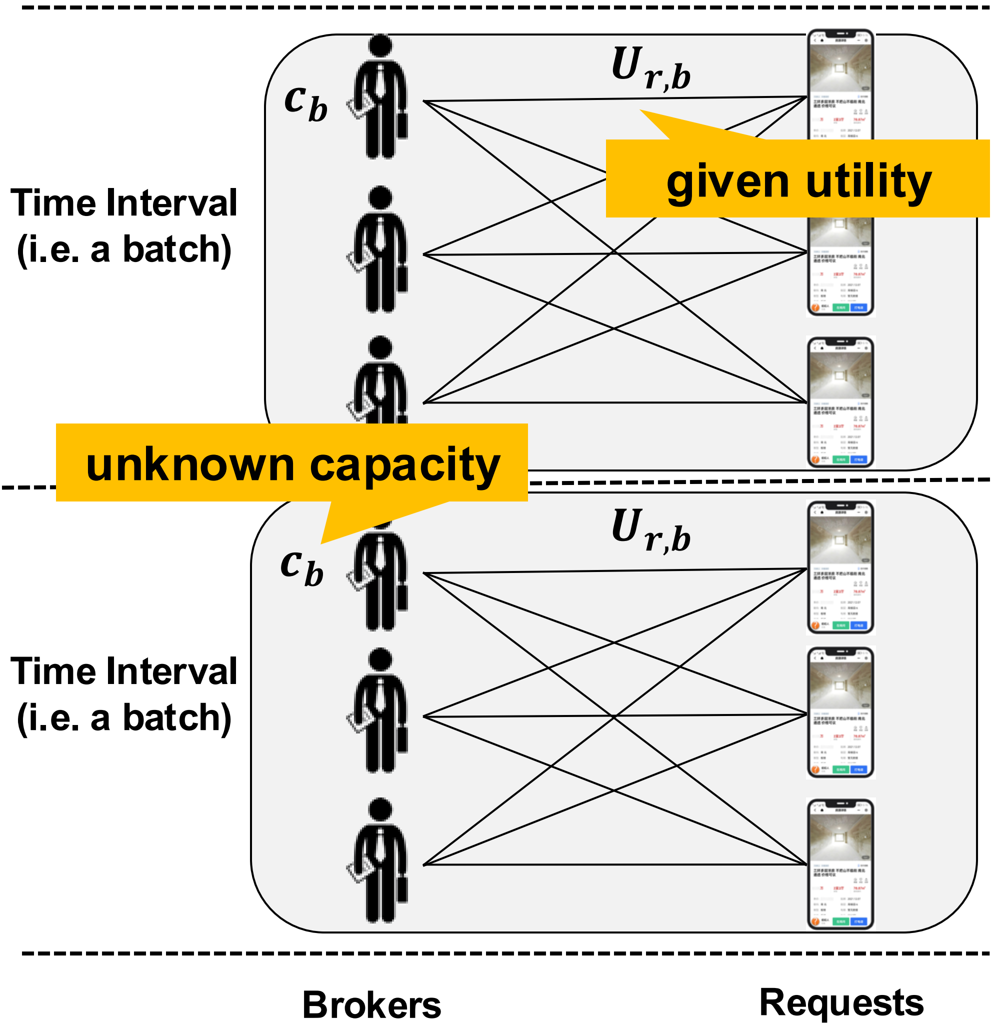
$$\forall b, \sum_{i \in I} \sum_{r} \mathcal{M}_{r,b}^{(i)} \le c_b$$

c_b is unknown capacity of brobker b to be estimated

Formulate broker matching as the batched assignment

Problem Statement

- **Capacity-Aware Assignment (CAA) problem**



Remarks:

- The **batched assignment modeling** is the first time to be catered for broker matching for online real estate platforms.
- A unique challenge of the CAA problem against the general batched assignment lies broker's **capacity is not given in advance.**

Objective: Maximum the total utility over time

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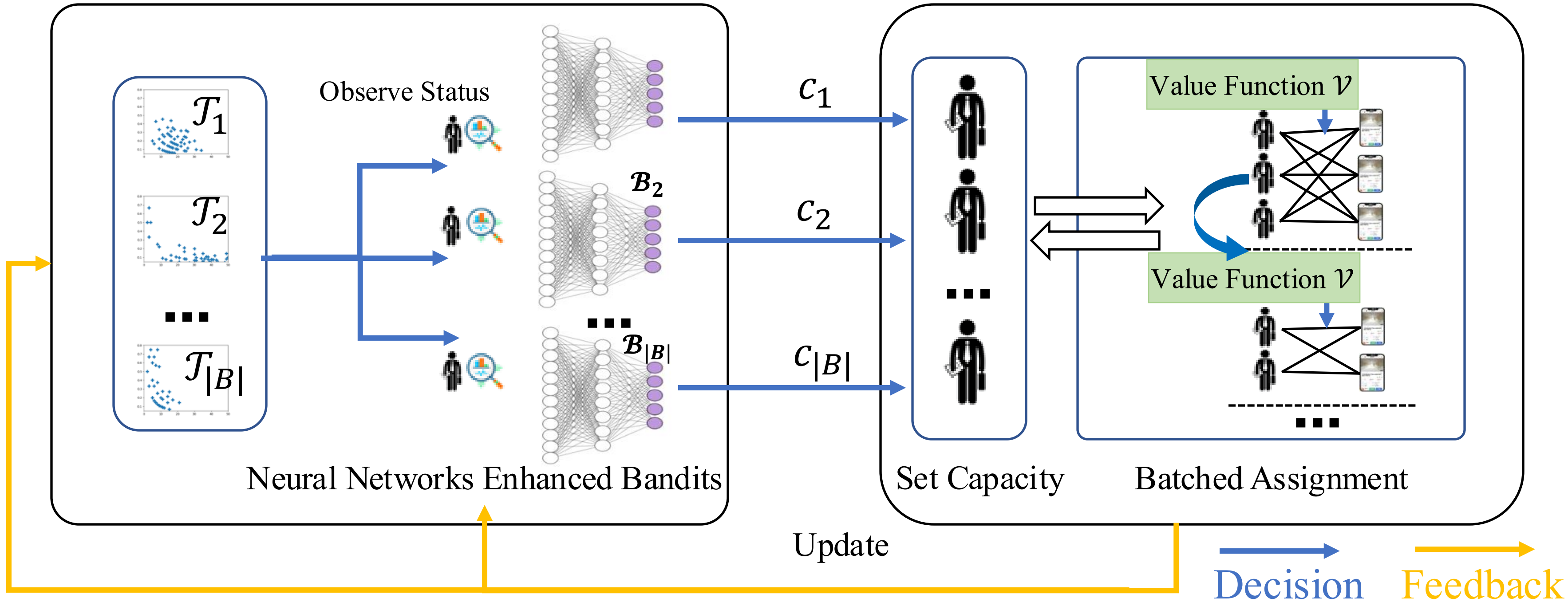
Our solution

- **<u>L</u>earned <u>A</u>ssignment with <u>C</u>ontextual <u>B</u>andits**

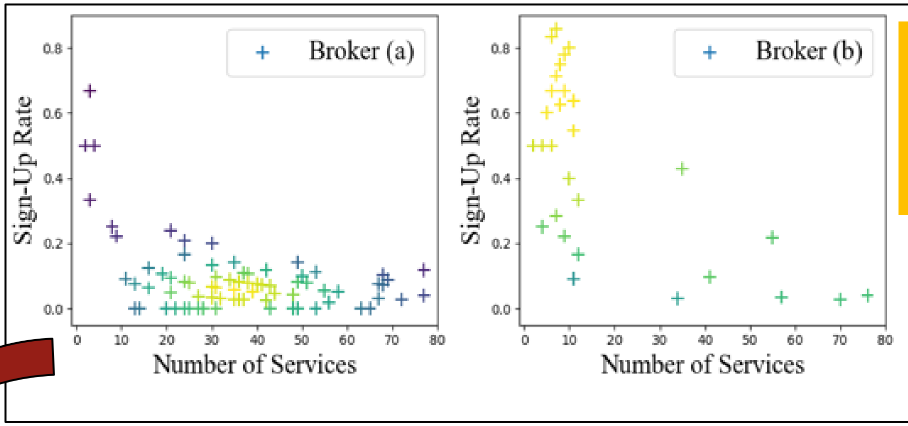
Workload Capacity Estimation → **Capacity Aware Assignment**



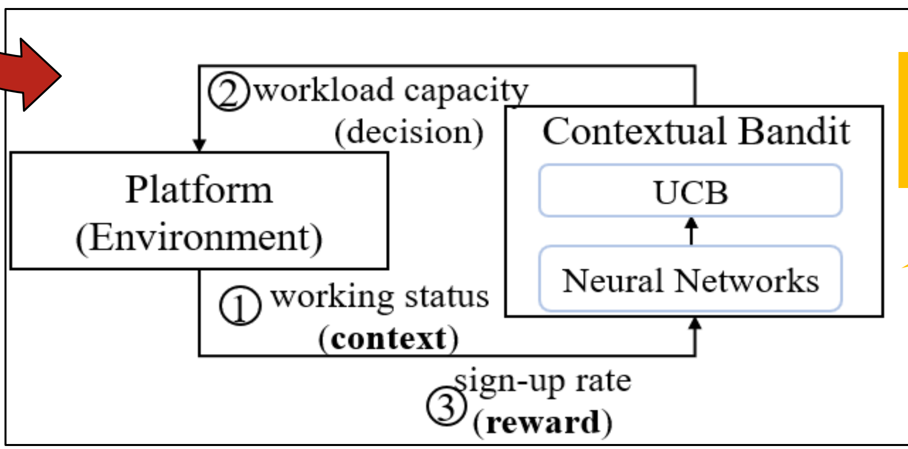
LACB estimates the unknown broker-specific capacity and assigns brokers to clients from a global view

Our solution

- **Step 1: Learn the broker-specific workload capacity via NN-enhanced contextual bandits**



As observed, the relationship between a broker's performance and her/his workload is complex

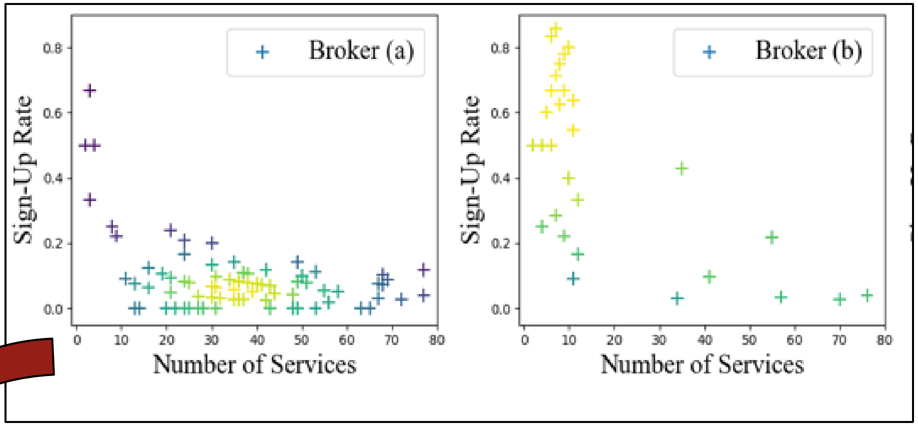


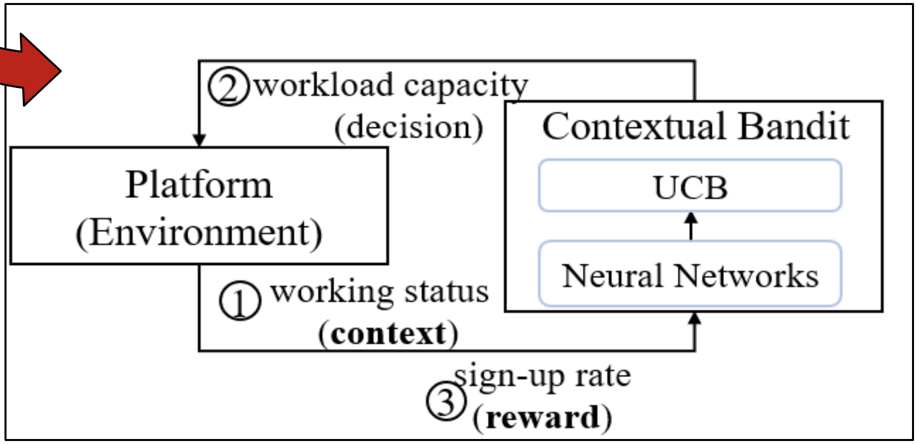
we model such non-linear complexity via neural networks

model the capacity estimation as a contextual bandit

Our solution

- **Step 1: Learn the broker-specific workload capacity via NN-enhanced contextual bandits**





Using neural networks to calculate the rewards of a capacity decision
$$S_\theta(\mathrm{x}, c) = W_L \cdot \sigma_{L-1}(\cdots \sigma_1(W_1[\mathrm{x}; c]))$$

Using the UCB to make a decision
$$UCB_{\mathrm{x},c} = S_\theta(\mathrm{x}, c) + \alpha\sqrt{g_\theta \mathrm{D}^{-1} g_\theta}$$

Using the layer-transfer to train a personalized capacity estimator

Learn the broker-specific workload capacity

Our solution

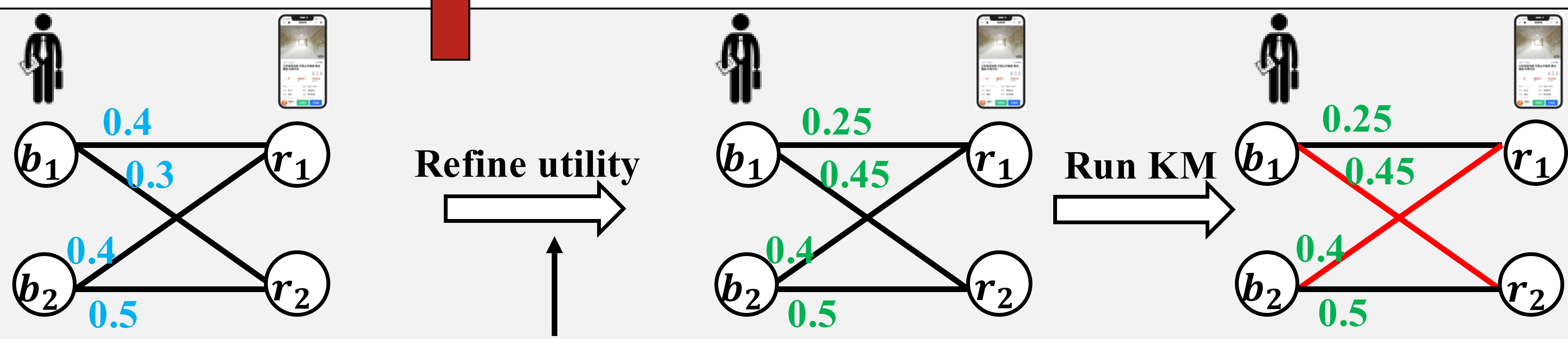
- **Step 2: makes assignments by accounting for the dependency of assignments across batches**

Can calculate the future rewards under broker's different workload

$\mathcal{V}(cr)$: **the expected utility when a broker's residual capacity is** cr

We can update the $\mathcal{V}(\cdot)$ **by Q-learning**

$$\mathcal{V}(cr) \leftarrow \mathcal{V}(cr) + \beta[u + \gamma\mathcal{V}(cr') - \mathcal{V}(cr)]$$



$$cr_1 = 4, cr_2 = 2$$

$$u'_{1j} = u_{1j} + \gamma\mathcal{V}(cr_1 - 1) - \mathcal{V}(cr_1)$$
$$u'_{2j} = u_{2j}, \quad j = 1, 2$$

$$M = \{(b_1, r_2), (b_2, r_1)\}$$
$$cr_1 = 3, cr_2 = 1$$

■ The original utility ■ The refined utility

Making capacity aware assignment via value function

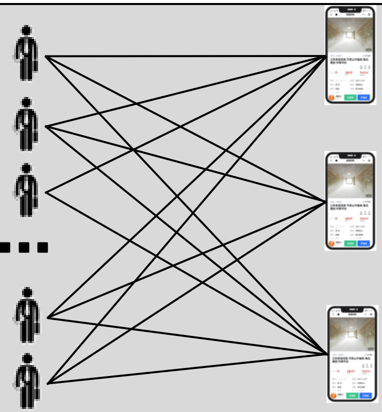
Our solution

- **Accelerating Assignment via Broker Selection**

In a batch (time interval)

Thousands of brokers

Only tens of requests

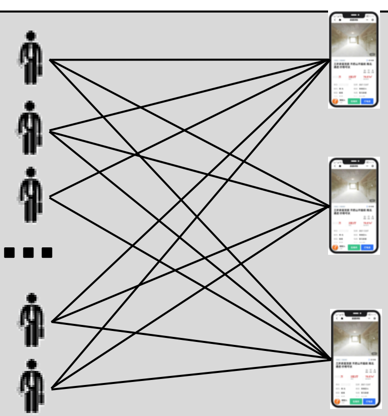


The unbalanced bipartite graph

Theorem 2. *Given a bipartite graph $G = < U, V, E >$ ($|U| \leq |V|$), and let $opt_{\mathcal{M}}(u)$ be the matched vertex of u in the optimal assignment $\mathcal{M}$. There exists an optimal assignment $\mathcal{M}$, such that for any vertex $u \in U$, we have $opt_{\mathcal{M}}(u) \in Top^{u}_{|U|}$, where $Top^{u}_{|U|}$ is a set of vertices with $|U|$ largest edge weight among all vertices connected u.*

Corollary 1. *Given an imbalanced bipartite graph $G =< U, V, E >$, we need at most $|U|$ candidate vertices for each vertex $u \in U$ to find an optimal assignment,* i.e., *taking the $Top^{u}_{|U|}$ as the candidate set for any $u \in U$.*

Hundreds of brokers



A much smaller bipartite graph

Not all brokers are needed in assignment, and |R| brokers for a request is enough

Optimize the efficiency for unbalanced assignments

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Experiments

- **Dataset**
  - **Real-world Datasets: 3 Cities from Ke Holdings Inc.**

TABLE IV: Real-world datasets.

City	Dates	Brokers	Requests
City A	Aug. 1 $\sim$ Aug. 21, 2021	5515	103106
City B	Jul. 1 $\sim$ Jul. 21, 2021	8155	387339
City C	Jun. 8 $\sim$ Jun. 28, 2021	3689	74831

  - **Synthetic Datasets:**
    - **Vary the number of brokers**
    - **Vary the number of requests**
    - **Vary the number of covering days**
    - **Vary the degree of imbalance, i.e. |R|/|B|**

Factor	**Setting**
The number of brokers $\|B\|$	500, 1000, **2000**, 5000, 10000
The number of requests $\|R\|$	10K, 20K, **50K**, 100K, 200K
The number of covering days Day	7, 10, **14**, 17, 21
The degree of imbalance σ	0.005, 0.01, **0.015**, 0.02, 0.05

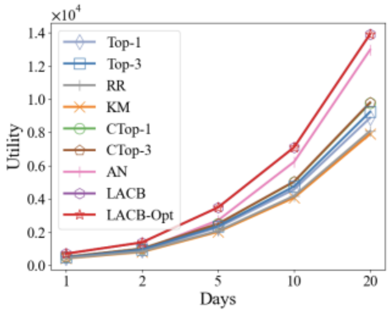
- **Experiments are conducted on a simulator of Ke Holdings Inc., takeing the same utility function deployed**

Experiments

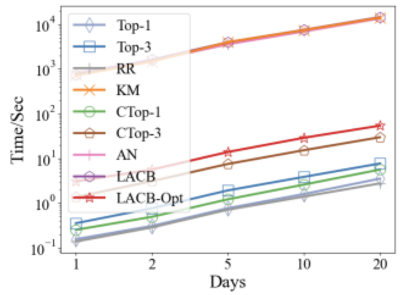
- **Comparing methods**
  - **Top-K Recommendation (Top-K)**
  - **Randomized Recommendation (RR)**
  - **Kuhn–Munkre algorithm (KM)**
  - **Constrained Top-K (CTop-K)**
  - **Assignment with NeuralUCB (AN)**
  - **LACB/LACB-Opt (ours)**
- **Evaluation metrics**
  - **Total Utility**
  - **Time Cost**

Experiments

- **Results on real world datasets**

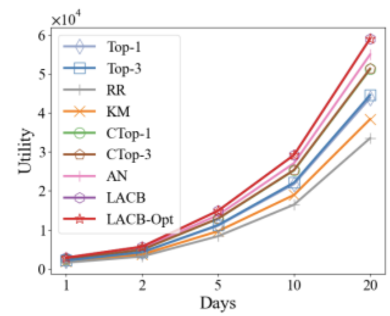


(a) Utility of City A

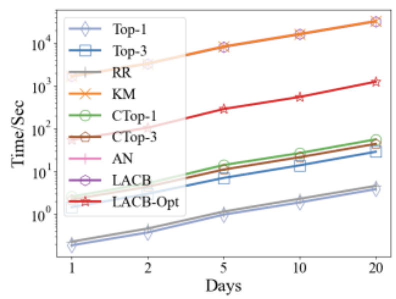


(b) Time of City A

LACB achieves the highest total utility

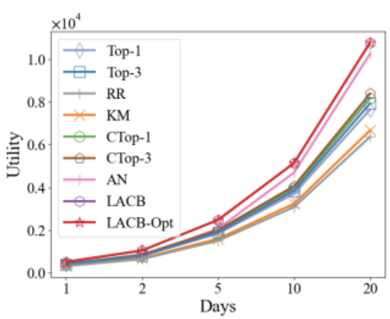


(c) Utility of City B

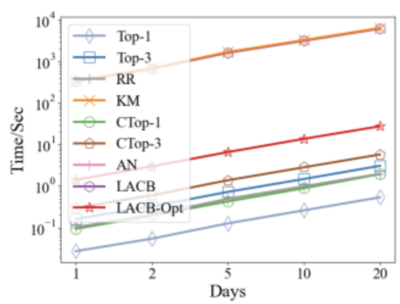


(d) Time of City B

LACB-Opt and LACB perform the same in total utility



(e) Utility of City C

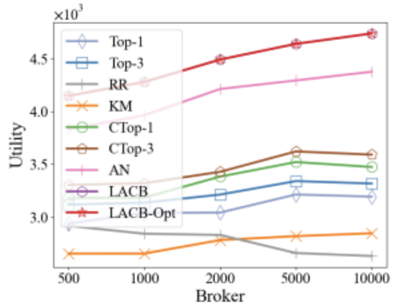


(f) Time of City C

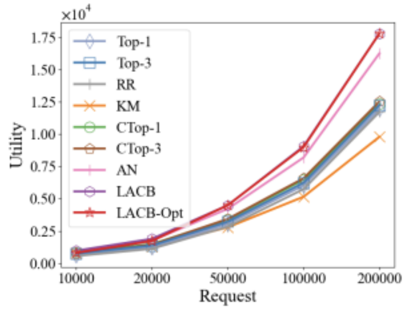
LACB-Opt is competitive compared to Top-*k*, CTop-*k* and RR in the running time

Experiments

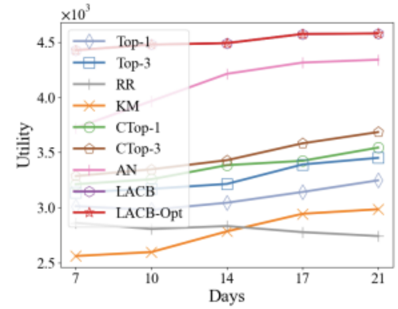
- **Results on synthetic datasets**



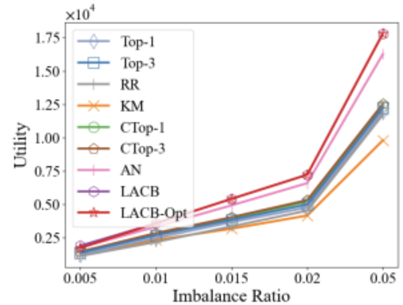
(a) Utility of varying $|B|$



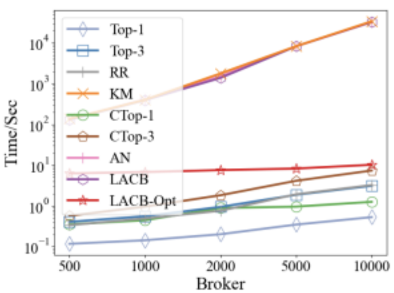
(b) Utility of varying $|R|$



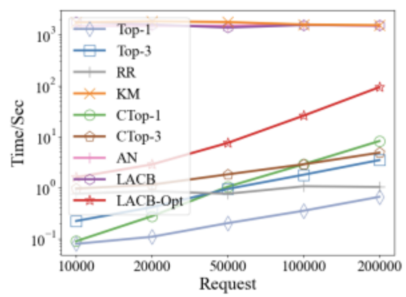
(c) Utility of varying Day



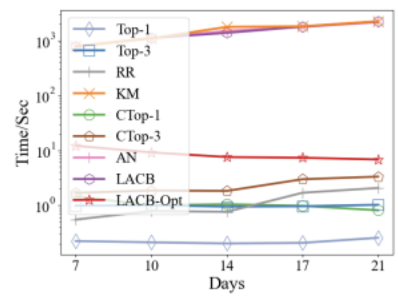
(d) Utility of varying σ



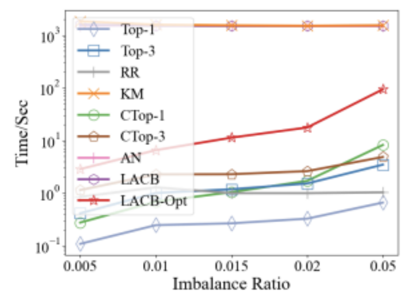
(e) Time of varying $|B|$



(f) Time of varying $|R|$



(g) Time of varying Day



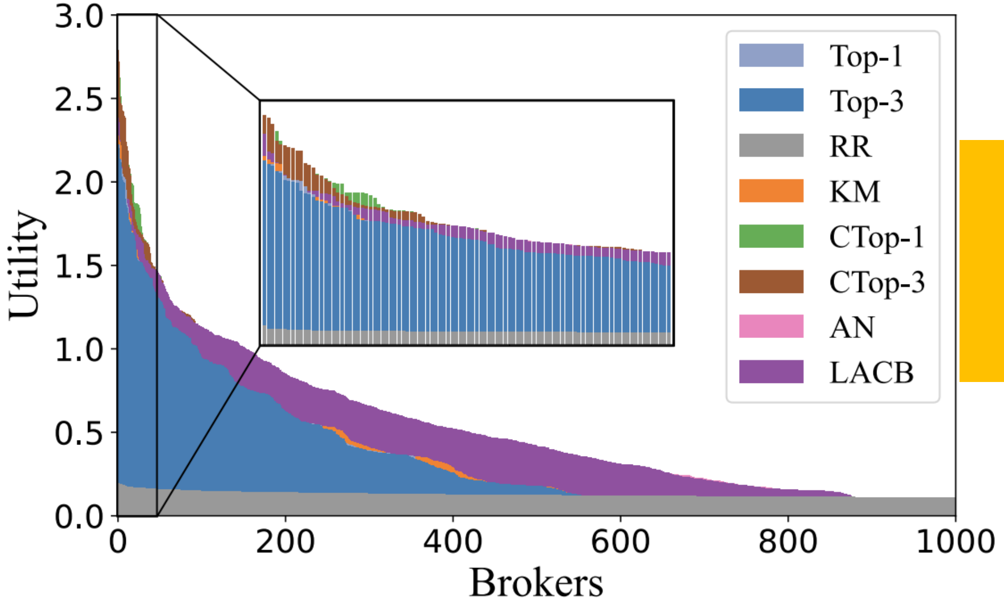
(h) Time of varying σ

LACB achieves the highest total utility

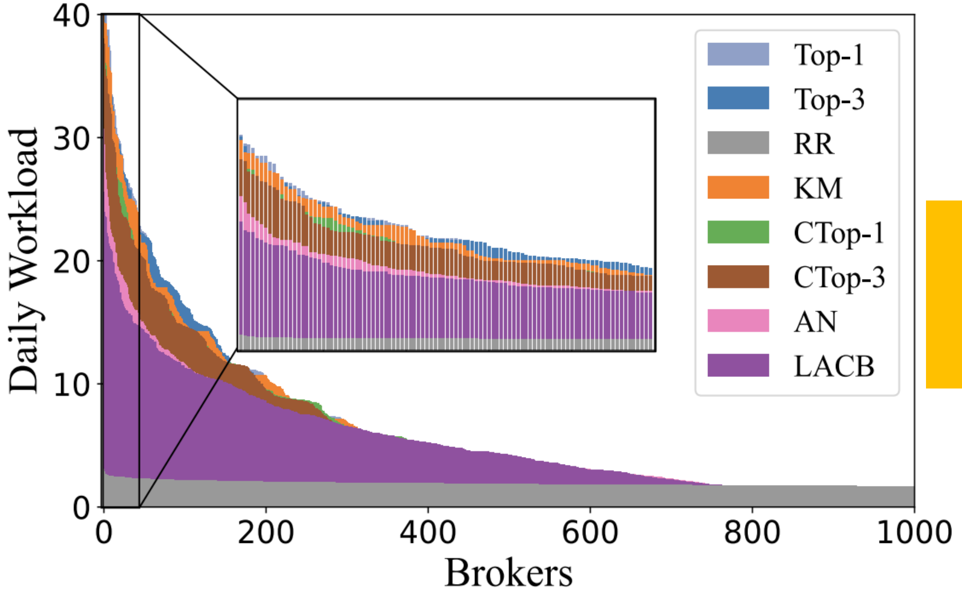
LACB-Opt is 16.4~1091.9 times faster than other KM-based algorithm

Experiments

- **In-depth Analysis of Brokers**



Compared with Top-K, 72.0%~82.2% brokers in LACB have an improvement in utility



The workloads of top brokers in LACB are the second lowest

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Conclusion

- **Identify the overload of top brokers problem for online real estate platforms.**

- **Design LACB, a data-driven capacity-aware assignment scheme for broker matching and accelerate the assignment via broker selection.**

- **Conduct extensive experiments on real world datasets from Ke holdings Inc., and results validate the efficiency and effectiveness of our solutions.**

Q & A

Thank You