Worker Selection Towards Data Completion for Online Sparse Crowdsensing

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Outline

I. Background and Motivation
II. Problem and Framework
III. Data Completion
IV. Importance Estimation
V. Worker Selection
VI. Performance Evaluation
VII. Conclusion

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I. **Background and Motivation**

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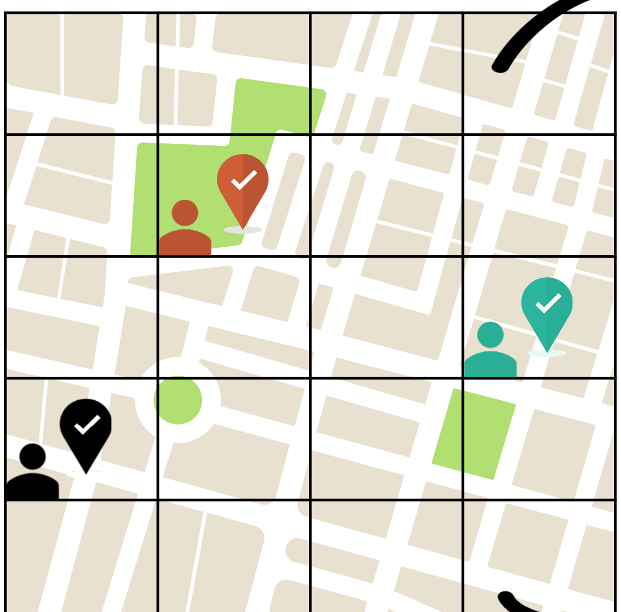
Mobile CrowdSensing (MCS)

- Recruit users with mobile devices to perform various sensing tasks



Traffic Monitoring

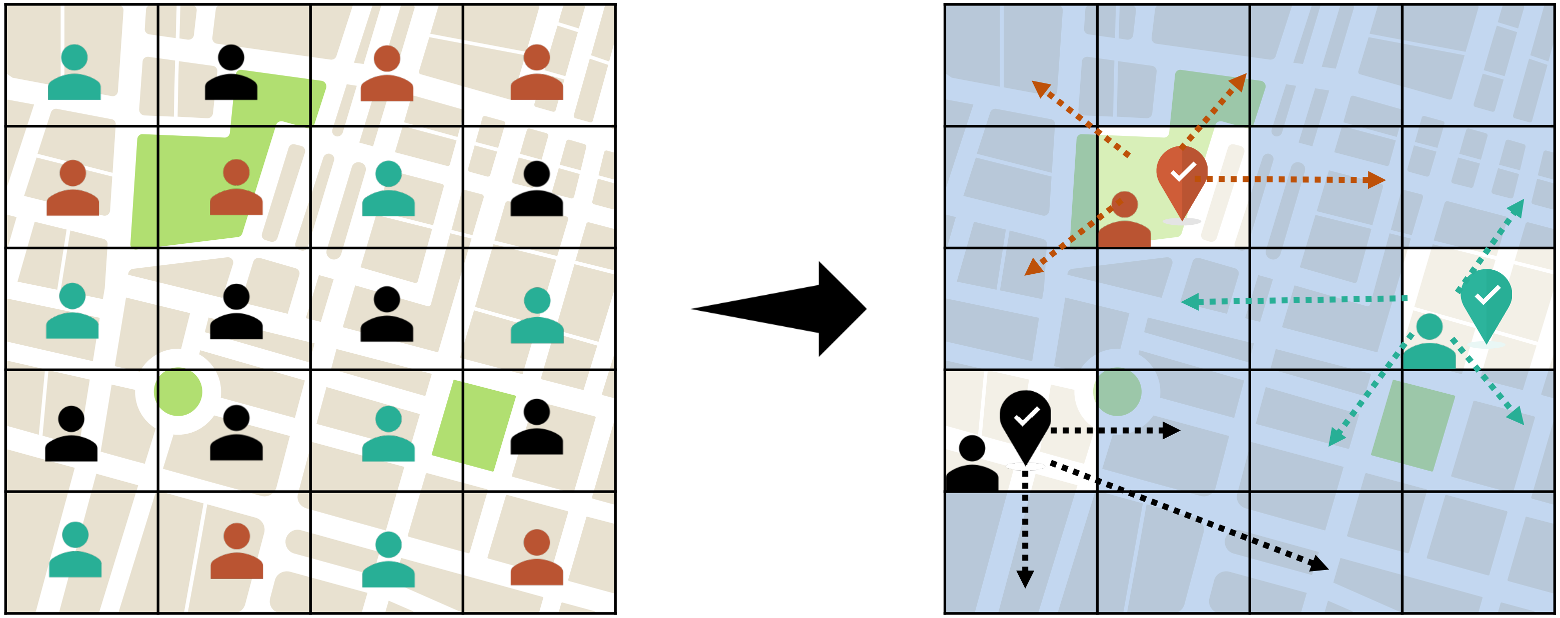
Air Quality Sensing

Crowdsourced Parking

... ...

Sparse MCS

- MCS: a large number of workers
- Sparse MCS: sense a few and infer the rest



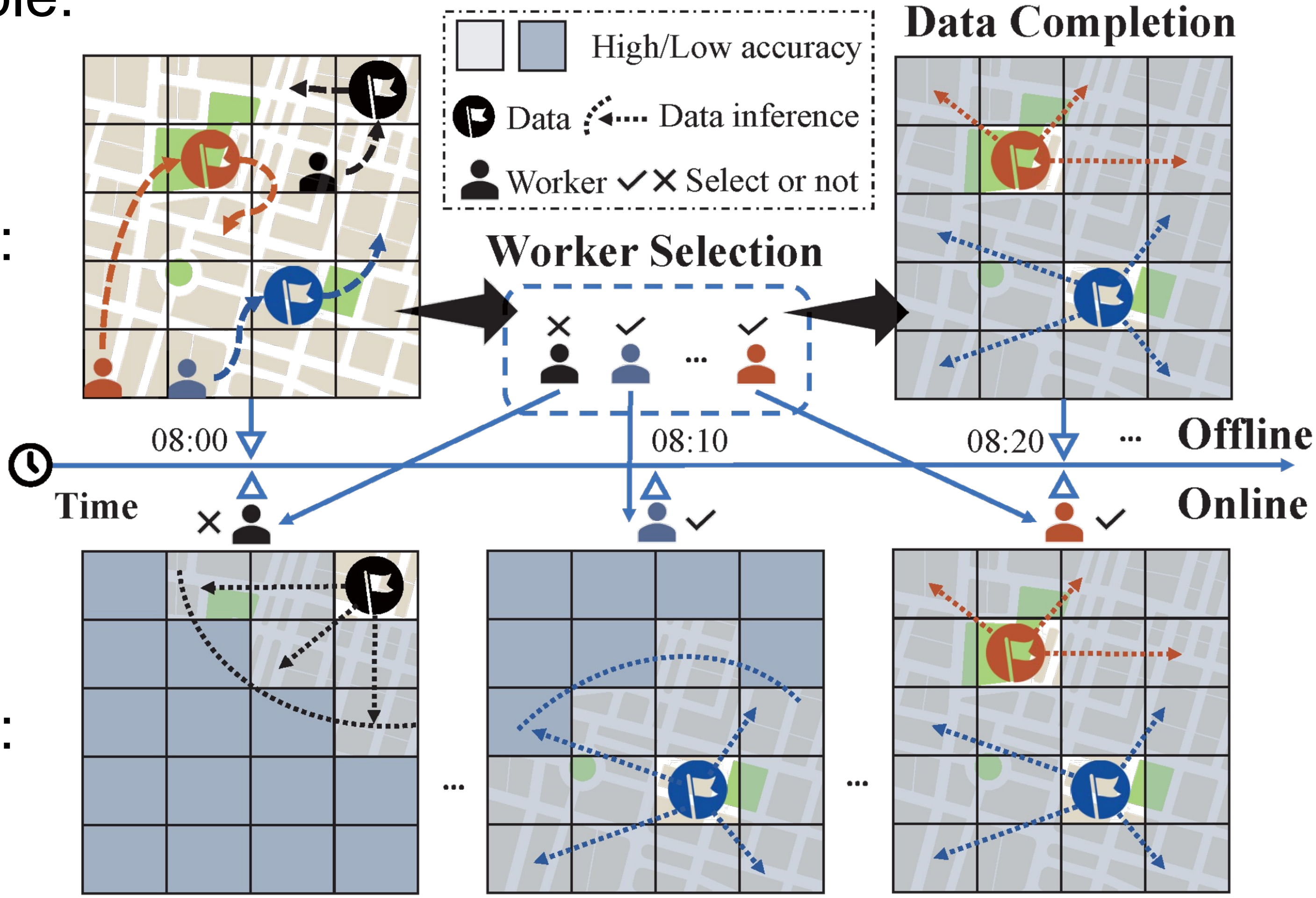
Offline vs. online

- Offline Sparse MCS
  - Pre-determined worker pool
  - Infer the rest after receiving all the data
- Online Sparse MCS
  - Workers participate in real time
  - Dynamically coming data
    - ✓ More realistic scenarios

Offline vs. online

- Example:

1. Offline:
2. Online:



Online Data Completion

- Intuitively: complete after receiving each new data
  - Cost a lot with high completion latency
- Alternatively: group data into batches
  - Still exist a lag between receiving and exploiting
- First challenge:
  - How to effectively exploit the dynamically coming data for **online data completion**?

Area Importance Estimation

- Some spatio-temporal areas are more important
  - Data from center areas ▶ the corner ones
- Area importance is time-varying
  - Newly obtained data ▶ the old ones
- Second challenge:
  - How to **estimate area importance** for improving data completion?

Online Worker Selection

- Instead of passively waiting for given data
  - Select workers to actively sense important areas for accurate data completion
- Online scenarios
  - Workers and data are invisible and hard to predict
- Third challenge:
  - How to select the **worker set** in an **online** manner to actively sense important area for accurate completion?

Outline

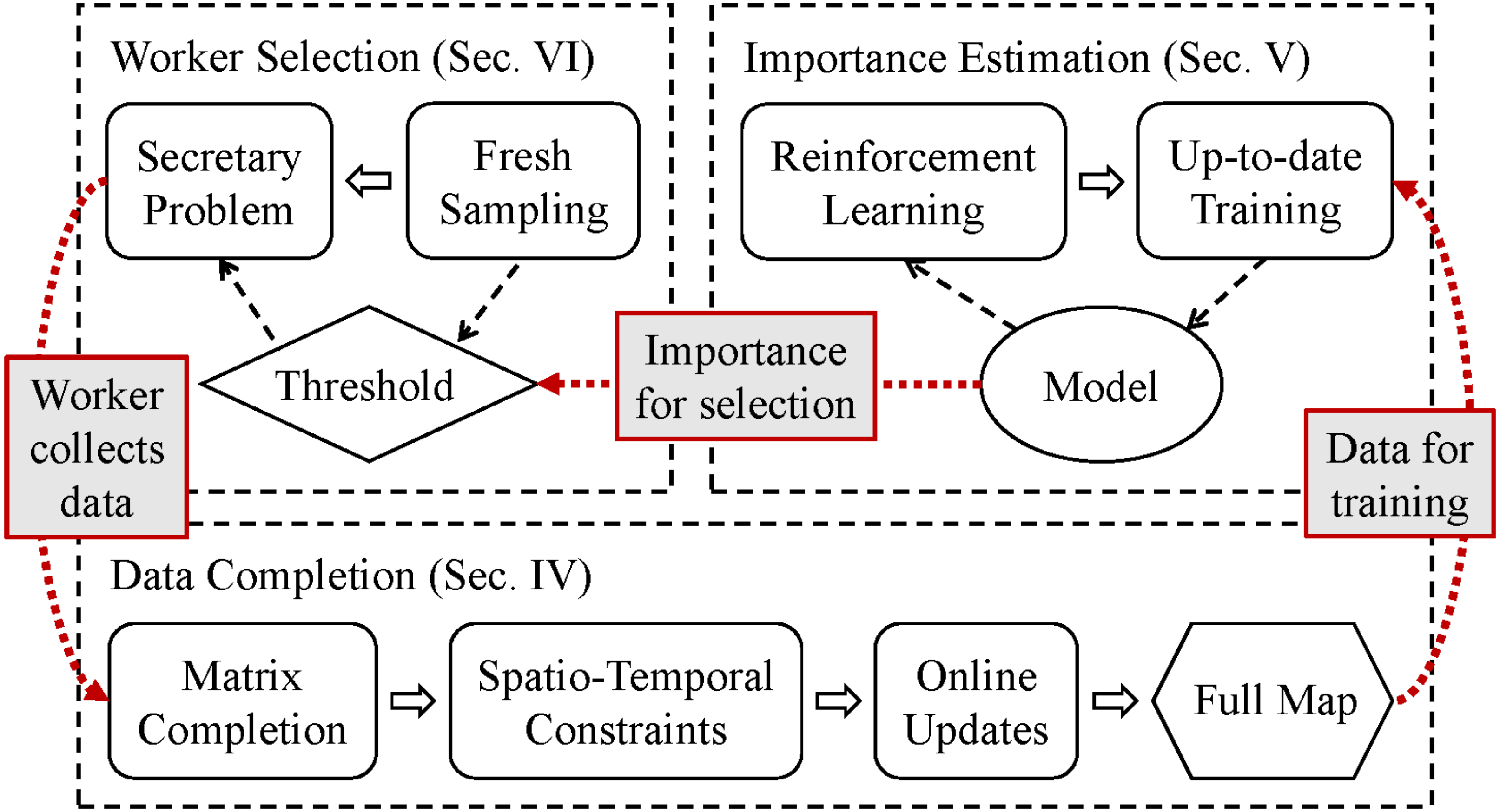
Problem Formulation

- **Problem** [Worker Selection Towards Data Completion for Online Sparse MCS]:
- Given a set of tasks with m sensing areas and n cycles, under a budget B and the duration T, our problem is to select a set of sequential participating workers μ
- Goal: minimizing the total completion error

$$\begin{aligned} \text{minimize} \quad & \sum_{t=1}^{T} \varepsilon(Y, \hat{Y}_t) \\ \text{subject to} \quad & \hat{Y}_t = f(Y_t'),\ \mu \subseteq W,\ \sum_{u_i \in \mu} c_i \leq B \end{aligned}$$

Framework Overview

- Online Sparse MCS (OS-MCS)



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Online Data Completion

- A. Matrix Completion

1. In the physical world, the sensing data naturally exist with some correlations (*low-rank matrix*)

$$\min \ \operatorname{rank}(\hat{Y}), \qquad \text{s.t.}, \hat{Y} \otimes M = Y'.$$

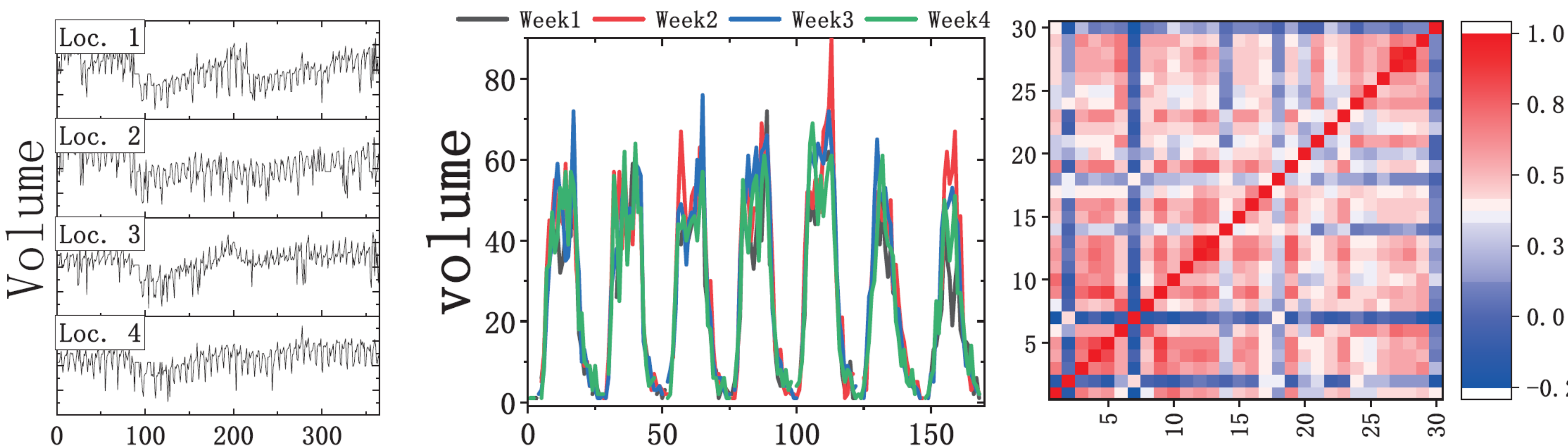
2. Factor the low-rank matrix into the latent spatio-temporal feature matrices

$$\hat{Y}_{m\times n} = U_{m\times r} V_{n\times r}^T$$

$$\min \ \|(Y' - UV^T) \otimes M\|_F^2 + \lambda(\|U\|_F^2 + \|V\|_F^2)$$

Online Data Completion

- B. Spatio-Temporal Constraints
  - ✓ Usually, there exist spatial and temporal correlations (*continuity, periodicity, and similarity*)

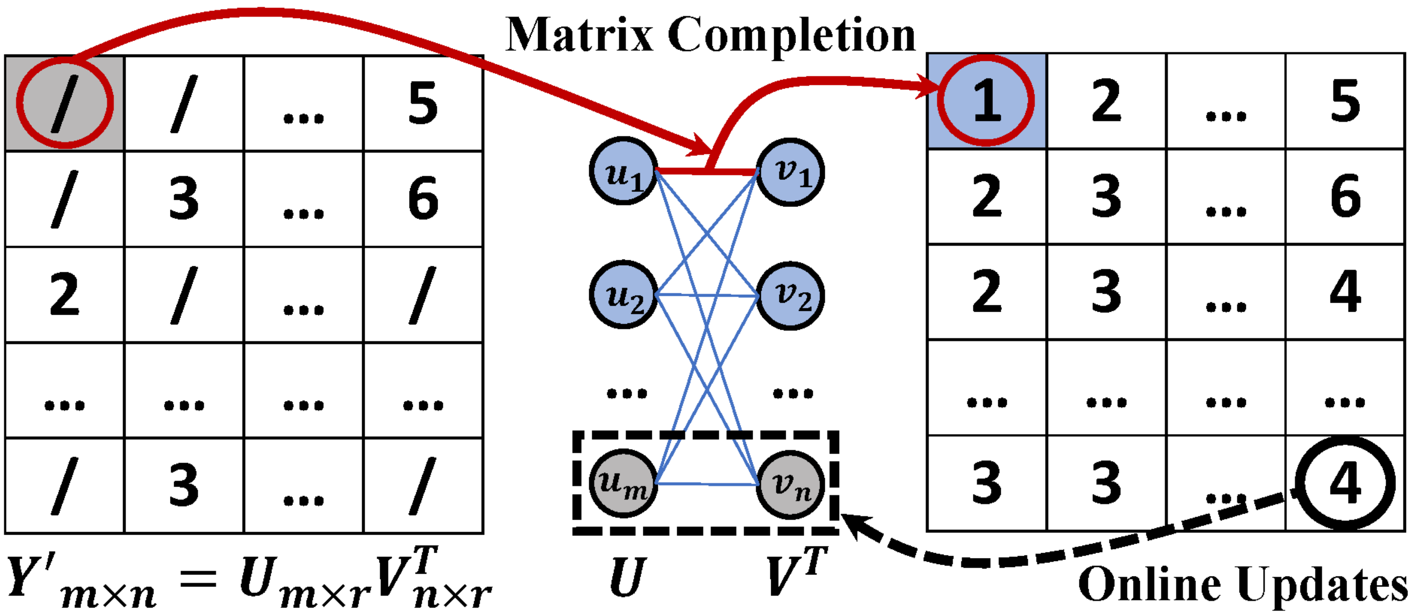


(a) Continuity (b) Periodicity (c) Similarity

$$\min \| (Y' - UV^T) \otimes M \|_F^2 + \lambda (\| U \|_F^2 + \| V \|_F^2) + g(\mathbb{T}) + h(\mathbb{S})$$

Online Data Completion

- C. Online Updates
  - ✓ With a new coming data, the new spatio-temporal matrices *U/V* are close to old ones (*update tall matrices*)



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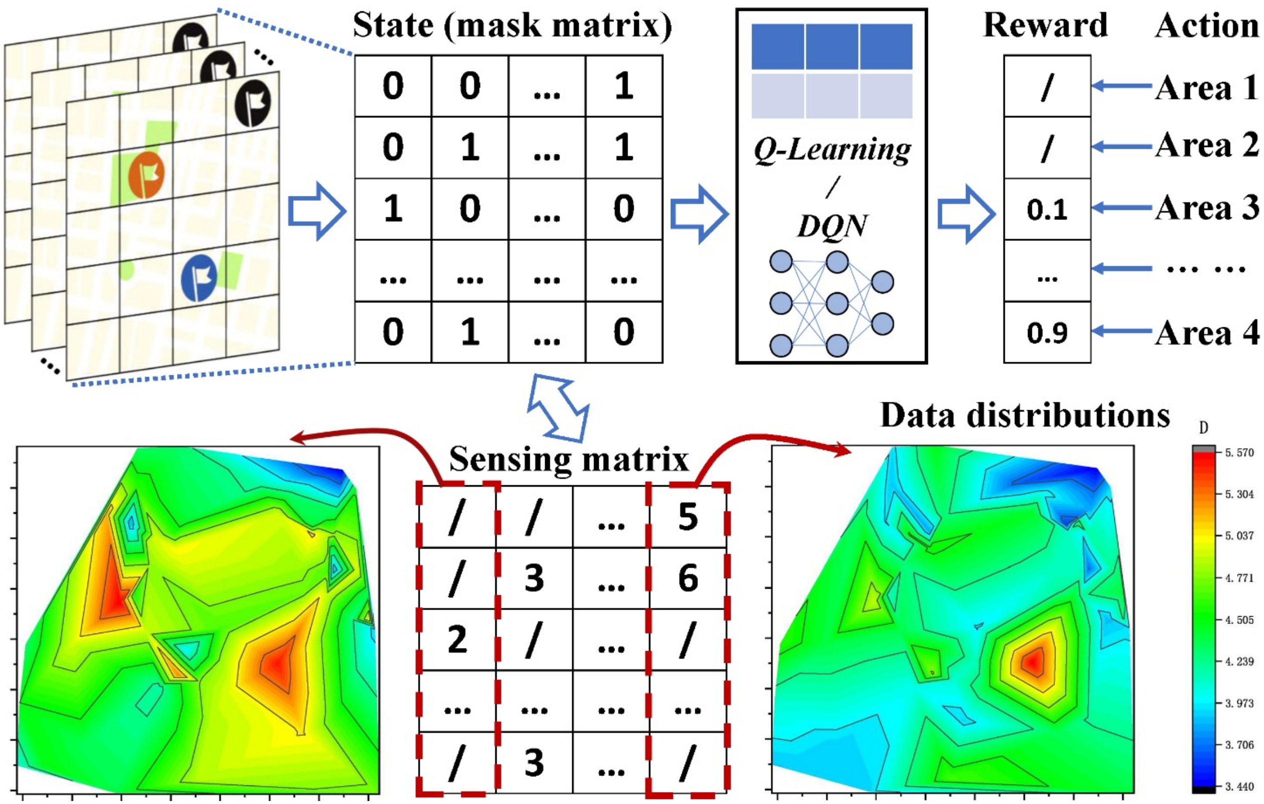
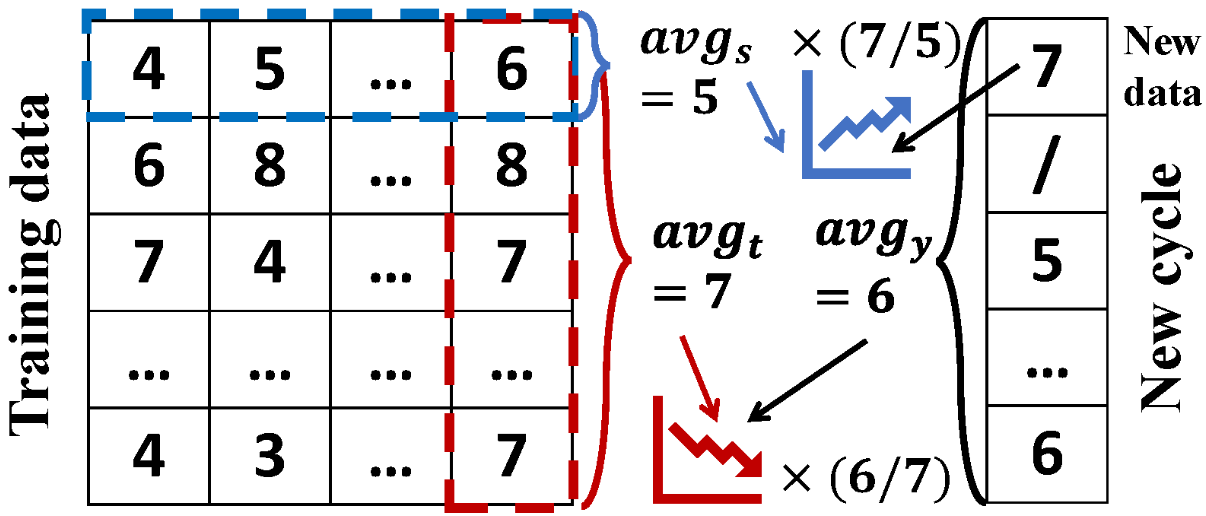
Area Importance Estimation

- A. Reinforcement Learning
  - ✓ Connect areas with completion accuracy directly



Area Importance Estimation

- B. Up-to-date Training
  - The sensing data may change a lot over time
    - ✓ Keep the model up-to-date
  - ➤ Utilize gradual changes in adjacent cycles and areas



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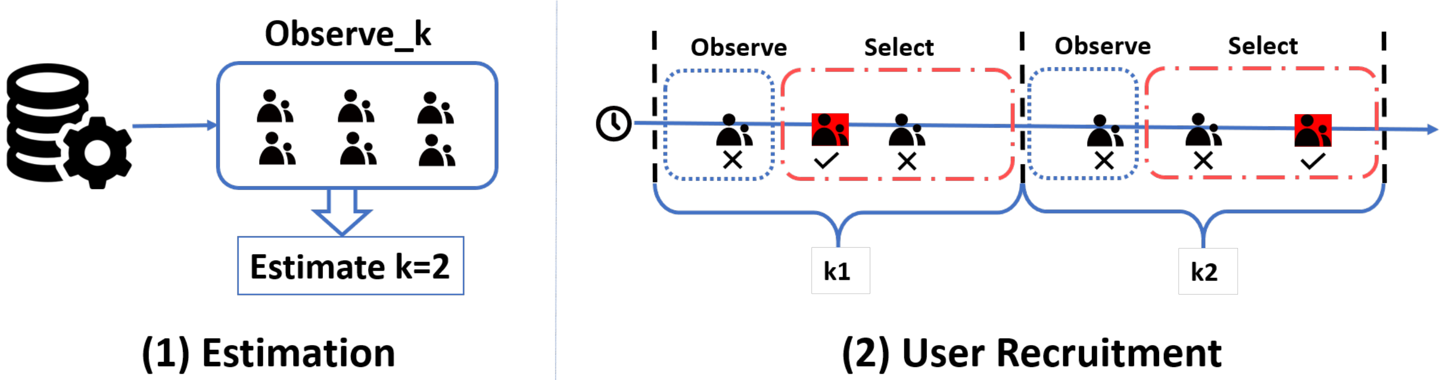
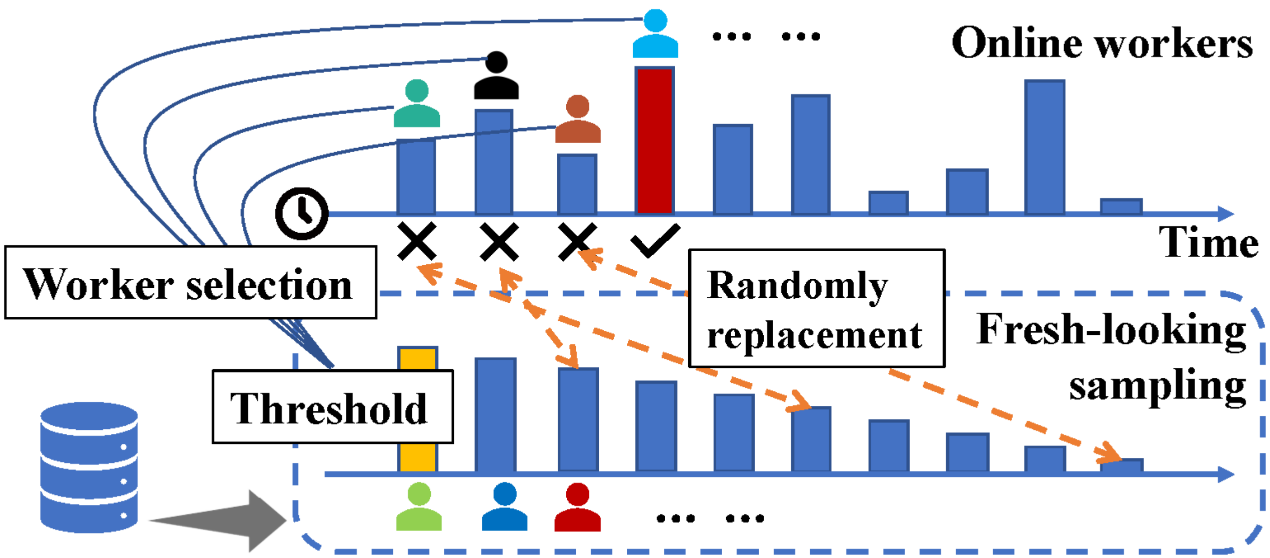
Online Worker Selection

- A. Secretary Problem-based Worker Selection
  1. Estimation k (*budget and time constraints*)
  2. Online Segmented Recruitment: non-submodular k-Secretaries Problem (*online recruiting process*)



Online Worker Selection

- B. Fresh-looking Sampling
  - Construct a sample worker set to approximate the first *1/e* workers[1]



[1] S. Ehsani, et al, "Prophet secretary for combinatorial auctions and matroids," in *Proceedings of the Twenty-Ninth Annual ACM-SIAM Symposium on Discrete Algorithms*. SIAM, 2018, pp. 700–714.

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Five typical sensing tasks

- Environmental monitoring
  - PM2.5[2], Temperature, Humidity[3]
- Urban sensing
  - Traffic[4], Parking[5]

	Environmental Monitoring			**Urban Sensing**	
	PM2.5	**Temperature**	**Humidity**	**Traffic**	**Parking**
City	Beijing (China)	Lausanne (Switzerland)		New South Wales (Australia)	Birmingham (UK)
Sensing areas	36 areas each with 1k*1km^2	57 areas each with 50*30m^2		30 subway stations	73 car parks
Cycle & Duration	1 hour & 11 days	0.5 hour & 7 days		1 day & 1 year	0.5 hour & 77 days
Mean Std.	79.11 ± 81.21	$6.04 \pm 1.87°C$	$84.52 \pm 6.32\%$	19095.73 ± 26750.79	647.97 ± 657.23

[2] Y. Zheng, et al, "U-air:when urban air quality inference meets big data," in *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2013, pp. 1436–1444.

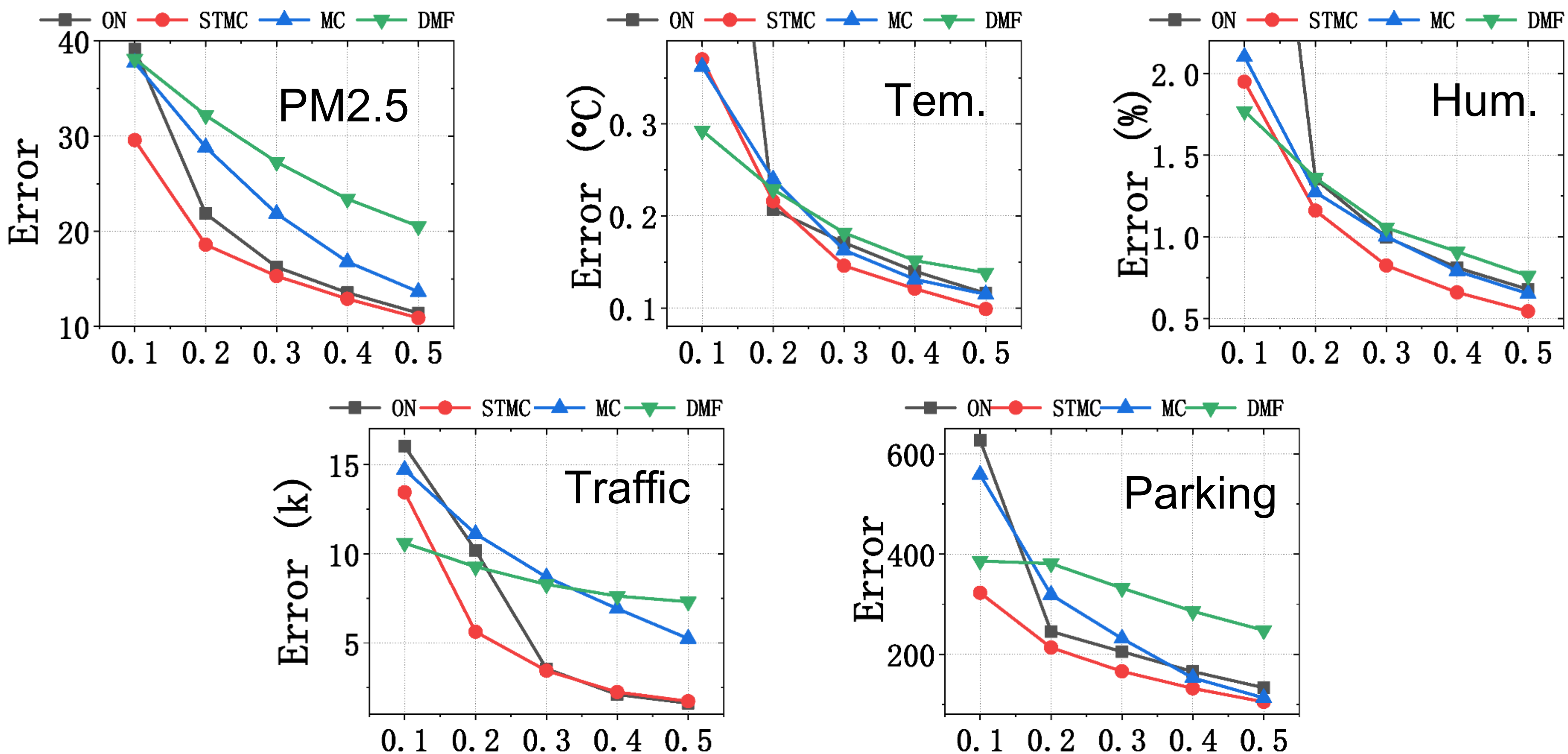
[3] F. Ingelrest, et al, "Sensorscope: Application-specific sensor network for environmental monitoring," *ACM Transactions on Sensor Networks*, vol. 6, no. 2, pp. 1–32, 2010.

[4] T. for NSW. (2019) System of traffic volume viewer. @ONLINE. [Online]. Available: https://www.rms.nsw.gov.au/about/corporatepublications/statistics/traffic-volumes/aadt-map/index.html

[5] D. H. Stolfi, et al, "Predicting car park occupancy rates in smart cities," in *International Conference on Smart Cities*. Springer, 2017, pp. 107–117.

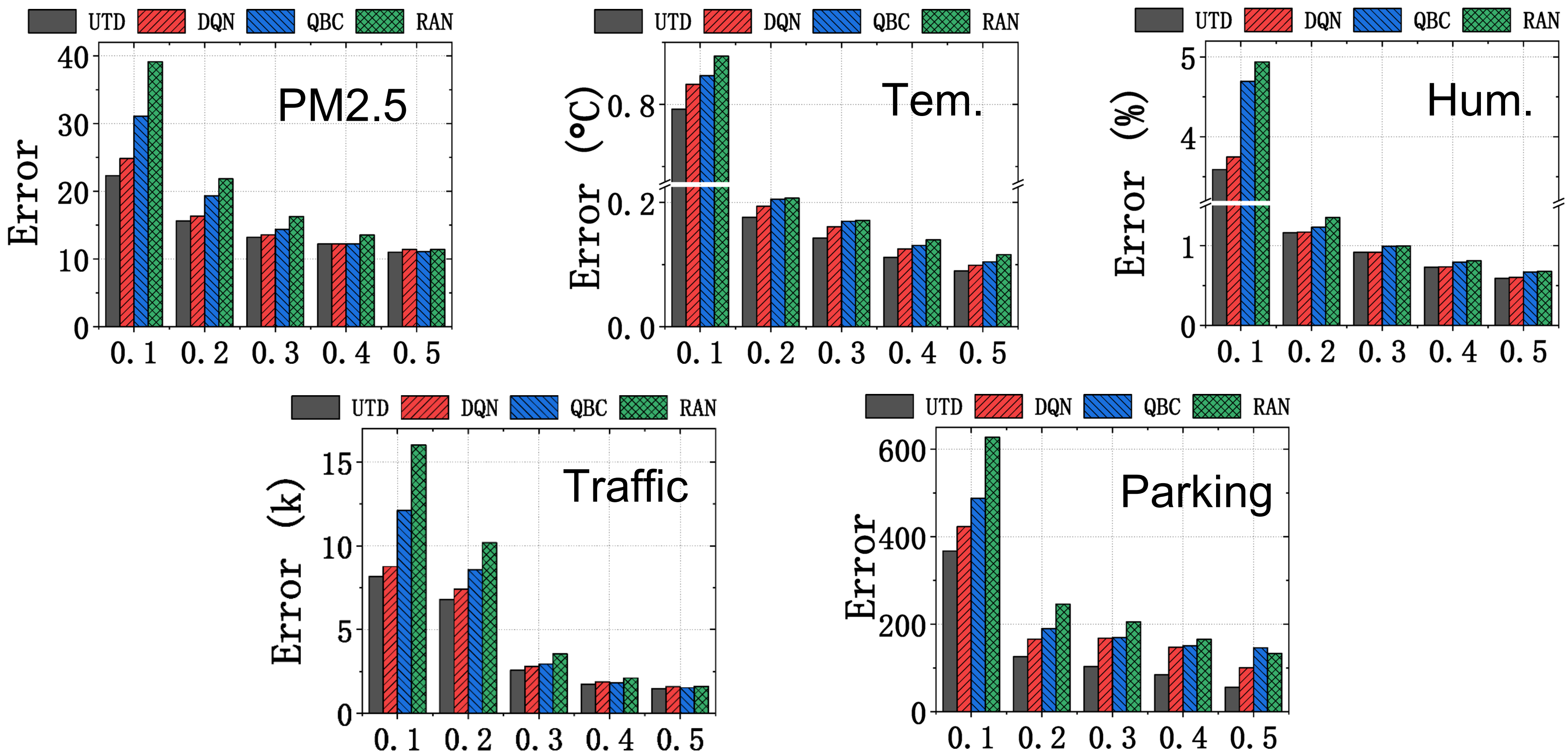
Main results

- Data completion under randomly selection



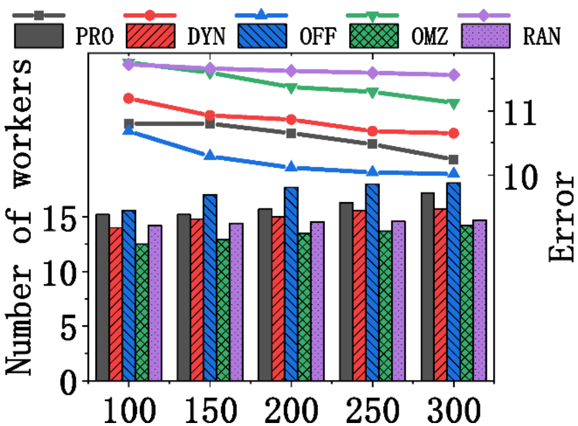
Main results

- Importance estimation-guided data completion

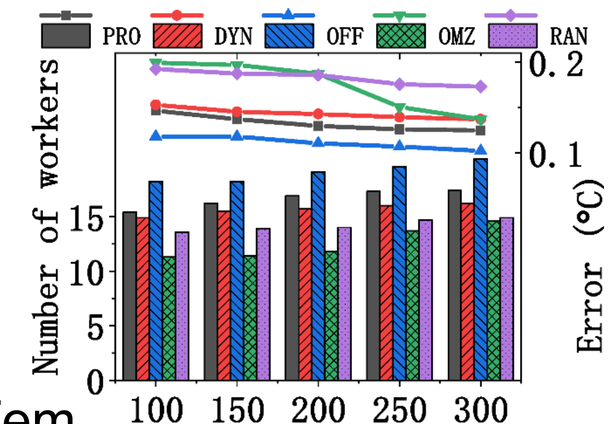


Main results

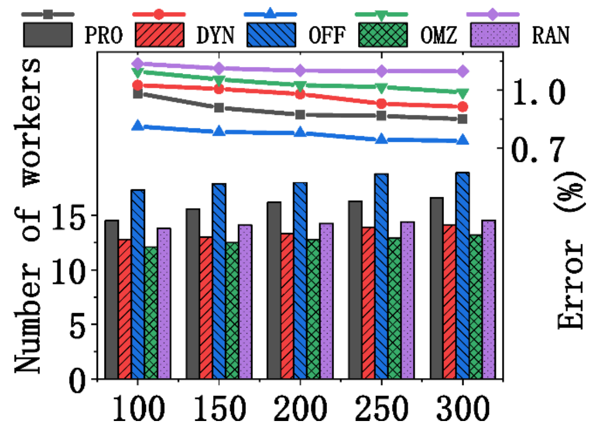
- Worker selection towards data completion



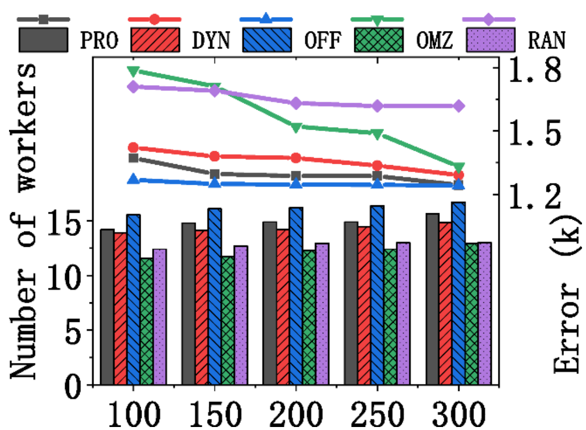
PM2.5



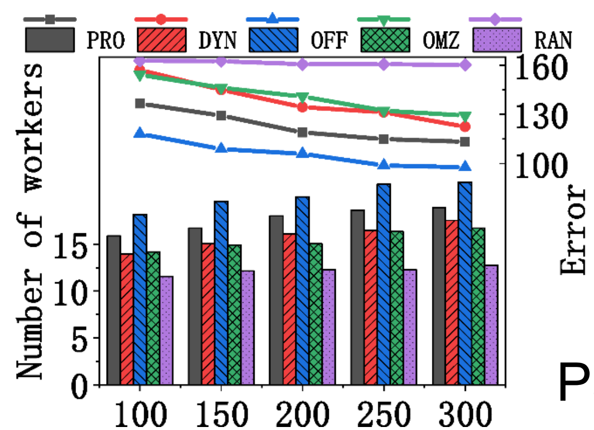
Tem.



Hum.



Traffic



Parking

Main results

- Spatio-temporal weights and running time:

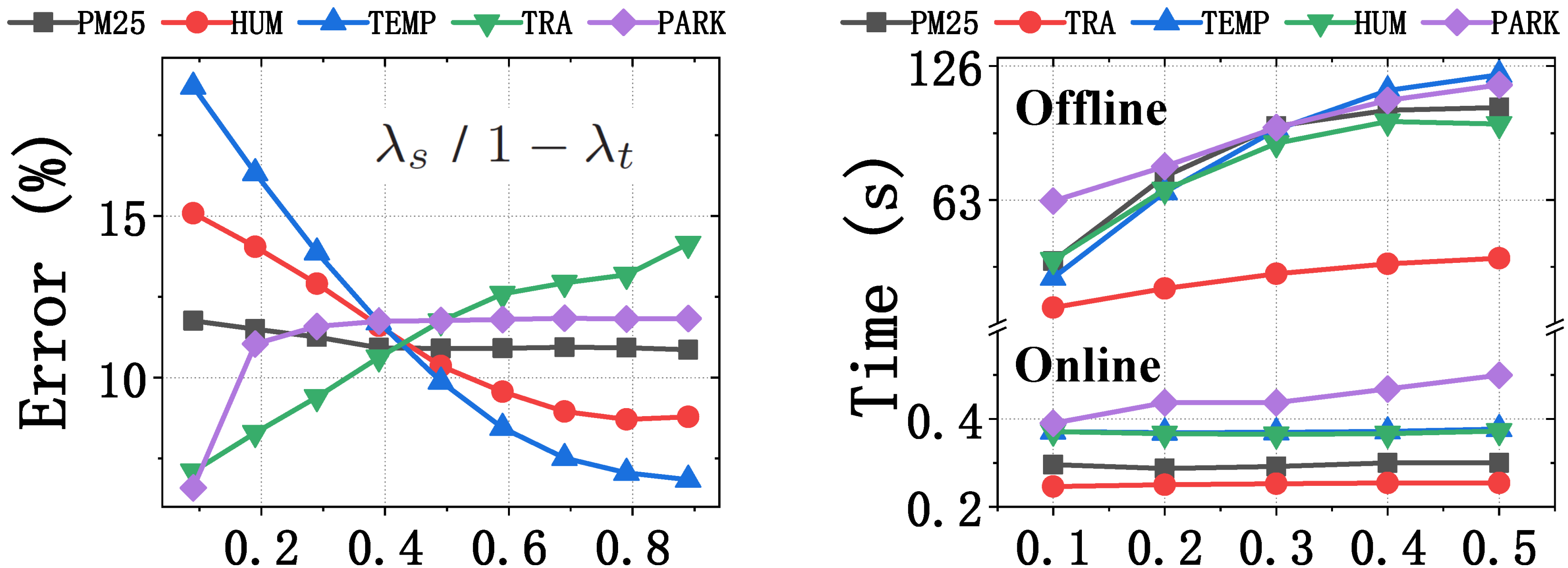


TABLE III: Running time

ON	STMC	MC	DMF	KNN-S	KNN-T	GP
0.32	73.87	55.19	24.81	0.05	0.05	0.03

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Conclusion

- *Online Sparse Crowdsensing*:
  - Select suitable workers to actively sense important areas for online data completion
- *Framework OS-MCS*:
  - Matrix Completion with Online Updates
  - RL-based Estimation with Up-to-date Training
  - Online Selection with Fresh-looking Sampling
- *Extensive Evaluation*
  - Five typical sensing tasks (in two types)

Q&A

Thank you!

Q&A