Active Sensing for Transformer Model in Sparse Mobile CrowdSensing

Deran Hao[1], En Wang[1], Wenbin Liu[1], Weiting Liu[1], Jie Wu[2], Yongjian Yang[1], and Jiang Yuan[1]

[1]Jilin Univ. and [2]Temple Univ.

Outline

I. **Background and Motivation**

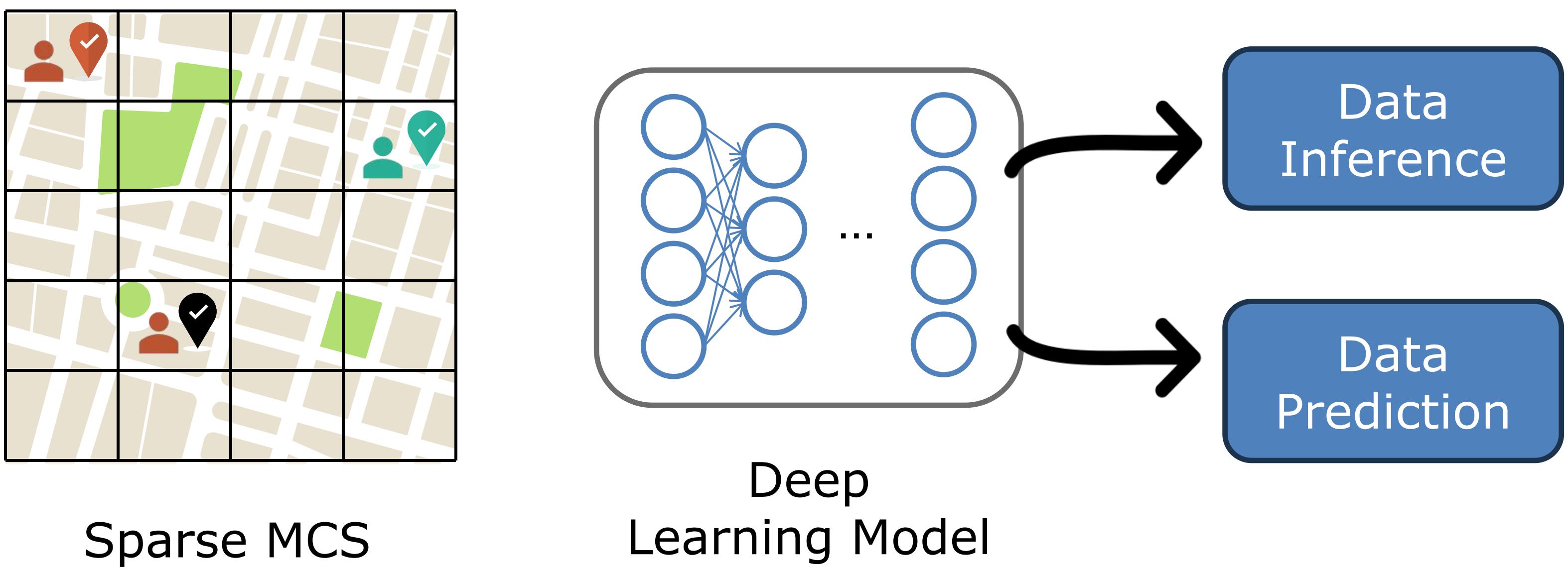
II. Method

III. Performance Evaluation

IV. Conclusion

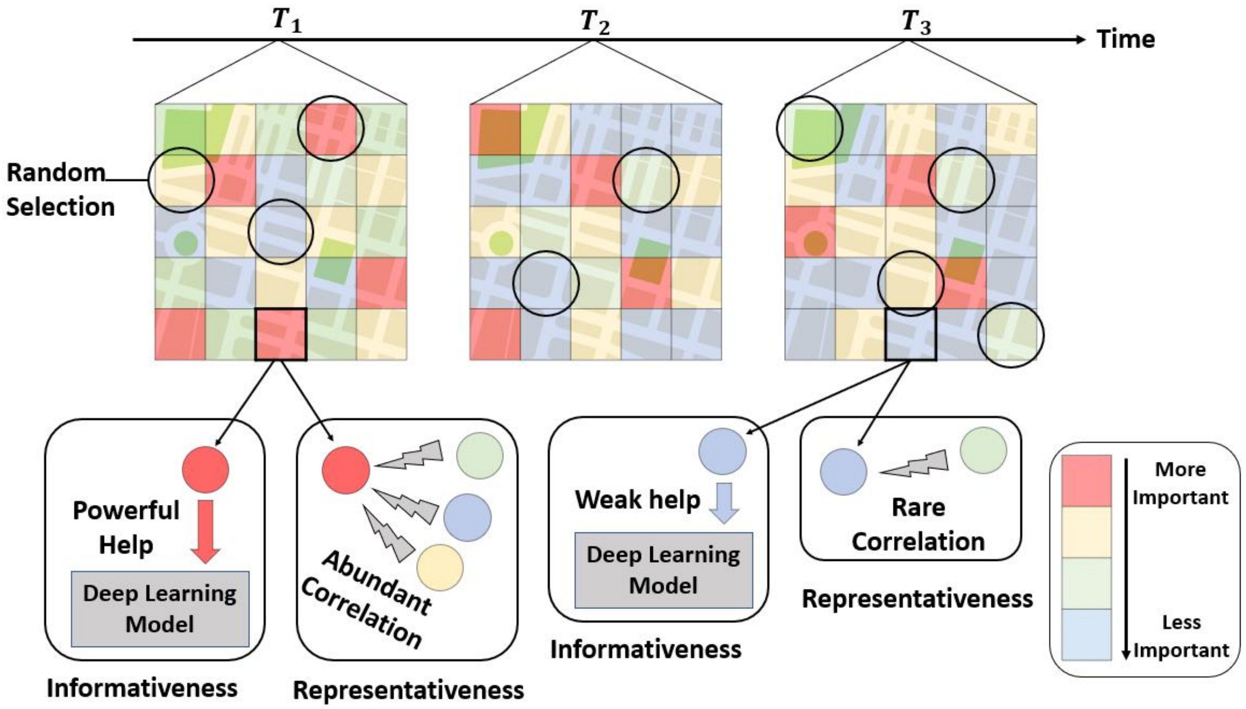
Moblie CrowdSensing & Deep-Learning Model

- Deep learning models are widely used in the downstream stage of Sparse MCS.



Data Importance

- The random method doesn't consider the importance of the data.



Data Importance

- ***How to evaluate the importance of spatiotemporal data?***

  - **Data Correlation**

→ One of the most typical characteristics of spatiotemporal data.

→*How to evaluate **the correlation of spatiotemporal data** between different spatiotemporal positions?*

- ***How to evaluate the importance of spatiotemporal data?***

  - **Data Importance for Model**

→ Data at different spatiotemporal positions have different importance for the model.

→ *How to evaluate **the importance of the spatiotemporal positions** for the Transformer-like model?*

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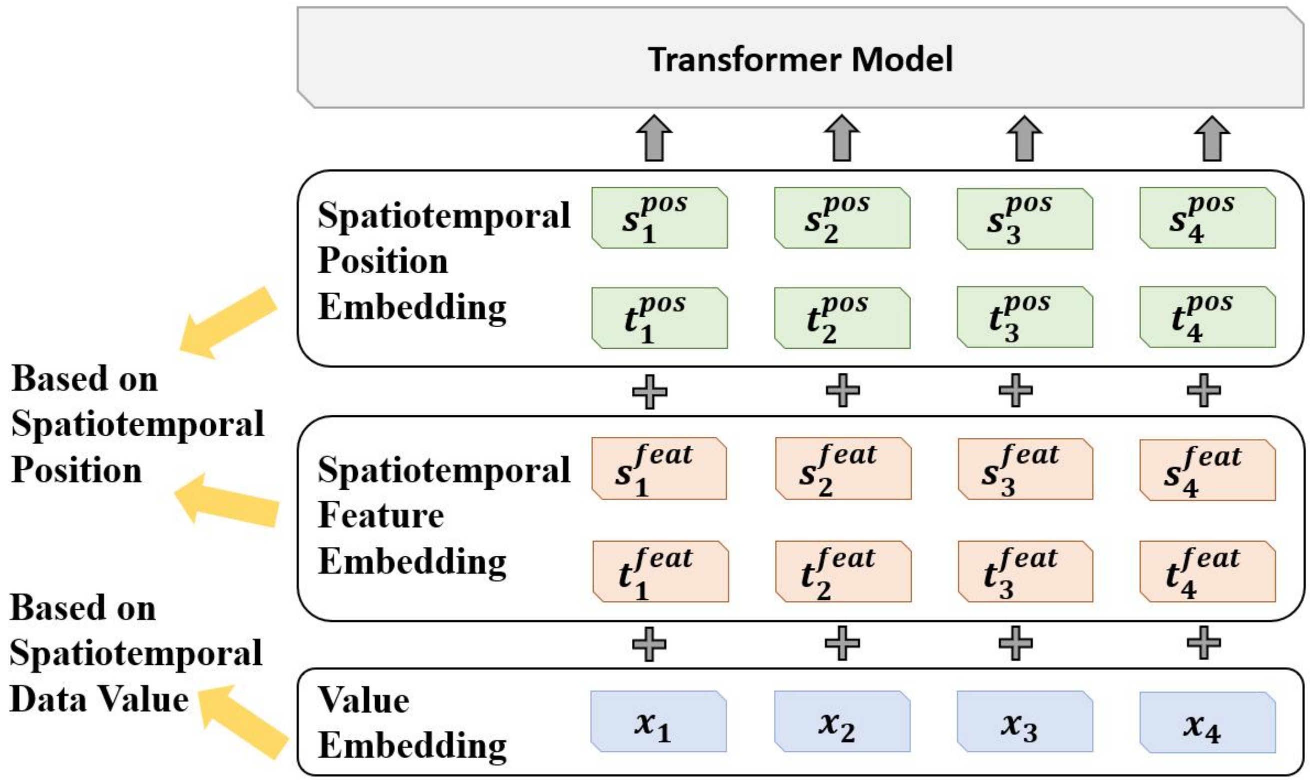
Representativeness

- Choose the most critical one among the complex spatiotemporal correlations – ***similarity.***
  - Similarity is always important in various sensing tasks.
- Q: How to evaluate the similarity?
- A: Using the high-dimensional feature vectors from the Encoder.

$$Rep_i = \sum_{i \neq j,\, j \in N} F_i \cdot F_j$$

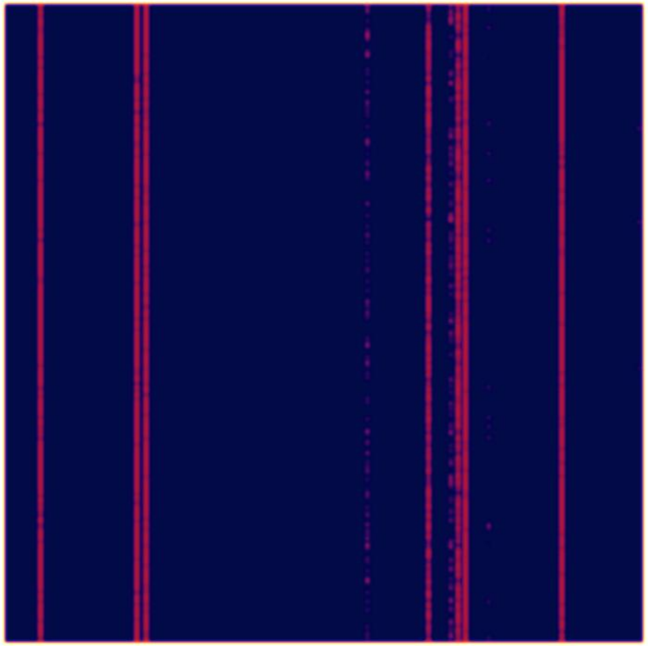
- The spatiotemporal embedding layer



Informativeness

- For the Transformer, the self-attention mechanism is the key component.

- Self-attention scores → ***A long-tailed distribution***.



$$Inf(i) = \sum_{l} \sum_{i \neq j,\, j \in N} \frac{q_j k_i^T}{\sqrt{d_k} \times l}$$

Actively Select

- The importance scores of spatiotemporal positions i:

$$S(i) = Rep(i) + Inf(i)$$

- Actively select the top K spatiotemporal positions.

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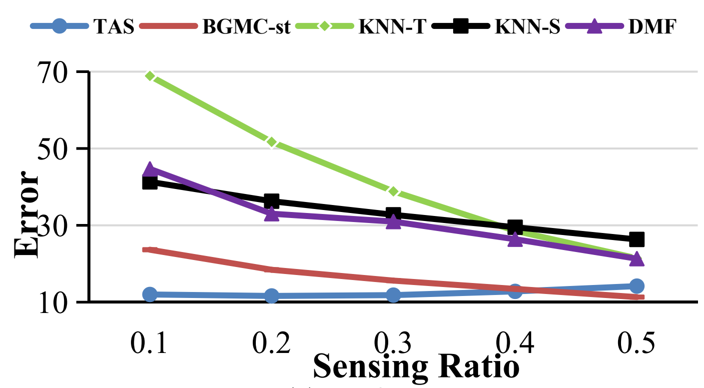
Data Set

- Urban Environment: Humidity & PM2.5
- Urban Traffic: Traffic Volume Viewer

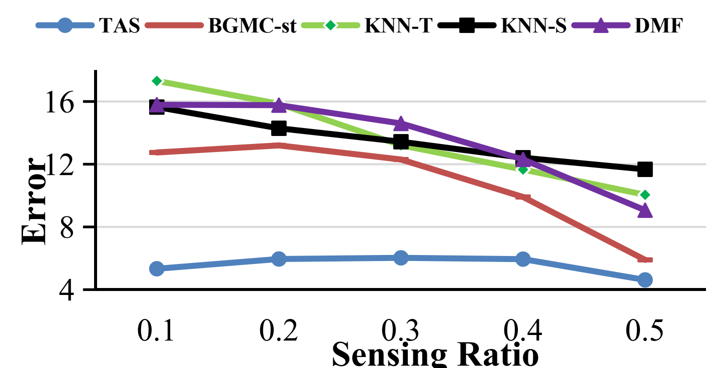
Task Type	*Urban Environment*		*Urban traffic*
Data Sets	Sensor-Scope	U-air	Traffic Volume Viewer
City	Lausanne(CHE)	BJ(CHN)	NSW(AUS)
Data	Humidity	PM2.5	Traffic flow
Subareas	57 subareas	36 subareas	30 checkpoints
Cycle	$0.5h$	$1h$	$1d$
Duration	$7d$	$11d$	$1y$
Mean	84.52	79.11	19095.73
Std. Dev.	6.32	81.21	26750.79
Unit	%	$\mu g/m3$	n

Main Result

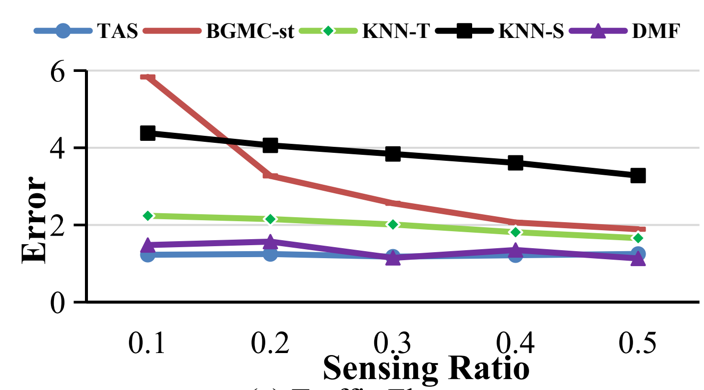
- Inference accuracy under different sensing ratios with different inference methods.



(a) PM2.5



(b) Humidity



(c) Traffic Flow

Main Result

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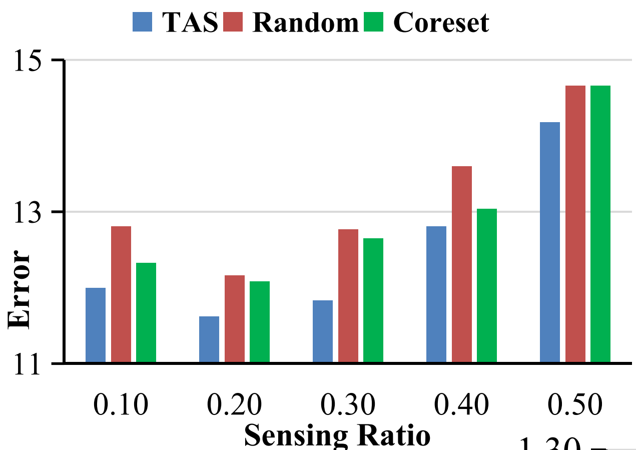
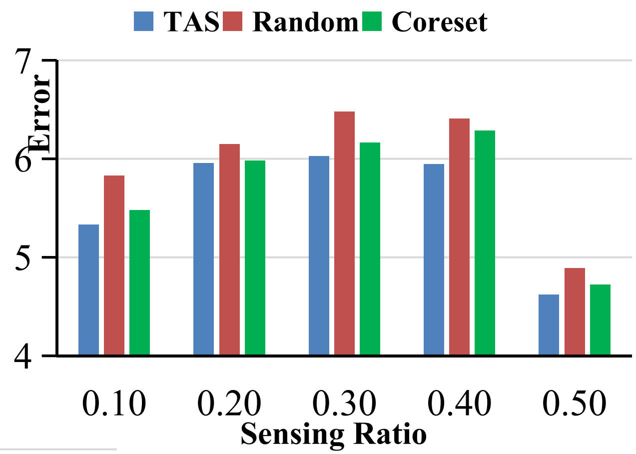
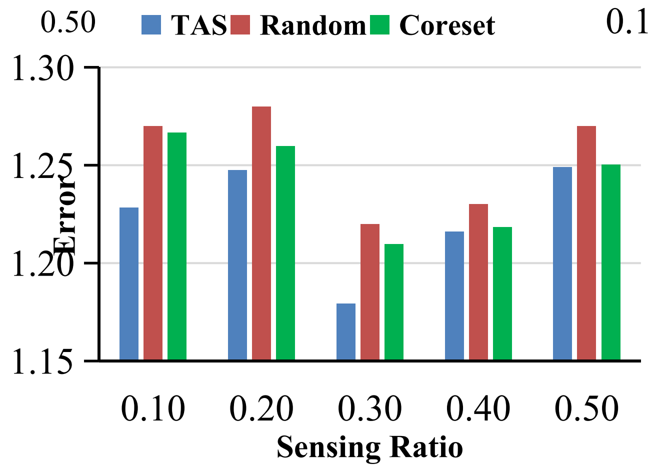


(a) PM2.5



(b) Humidity



(c) Traffic Flow

Main Result

- Error increase compared to TAS on three data set.

Sensing Ratio	0.10	0.20	0.30	0.40	0.50
TAS-Inf	5.12%	1.34%	4.04%	4.28%	3.68%
TAS-Rep	3.44%	1.36%	2.68%	2.91%	2.74%
Random	9.33%	3.29%	7.49%	7.82%	5.84%
TAS-Inf	5.41%	3.64%	7.24%	6.50%	2.21%
TAS-Rep	1.38%	1.47%	2.12%	2.41%	1.94%
Random	6.72%	4.70%	7.90%	6.21%	3.42%
TAS-Inf	4.93%	1.03%	5.29%	1.51%	2.12%
TAS-Rep	2.25%	1.03%	2.98%	0.91%	1.50%
Random	6.89%	5.30%	7.03%	2.32%	3.39%

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Conclusion

- What is an active sensing method?
  - Actively selecting important spatiotemporal positions to sense the training data.
- How to evaluate the importance?
  - Representativeness → Similarity.
  - Informativeness → Self-attention Scores.
- How about the performance?
  - Three experiments have demonstrated the performance of the method.

Thank you!

Q&A