

# GeoMAN: Multi-level Attention Networks for Geo-sensory Time Series Prediction

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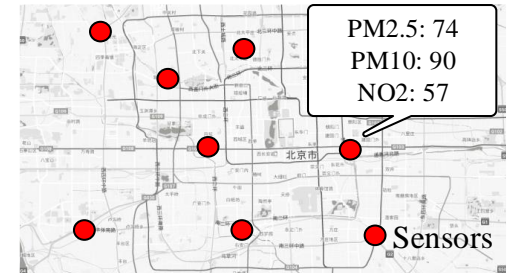
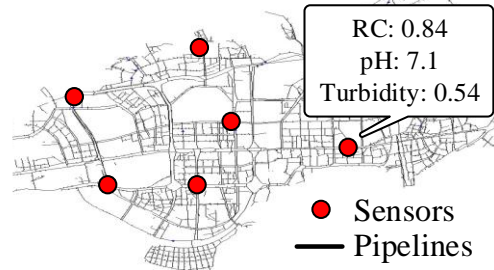
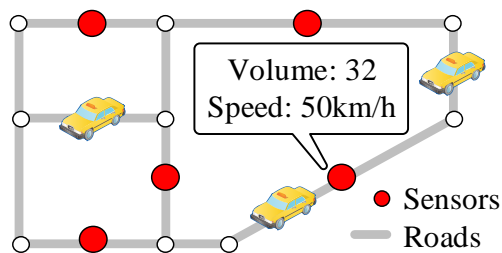


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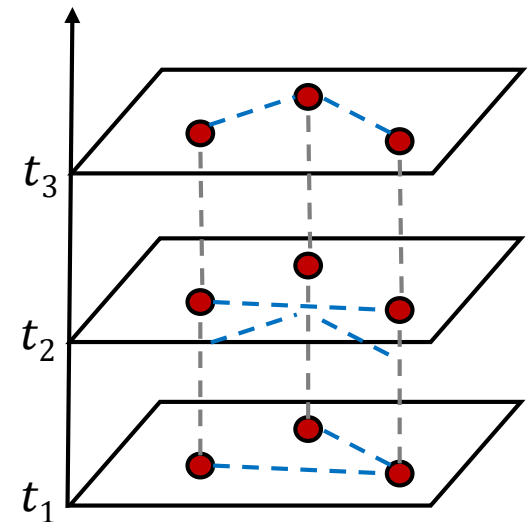
# Geo-sensory Time Series

- Massive sensors deployed in physical world



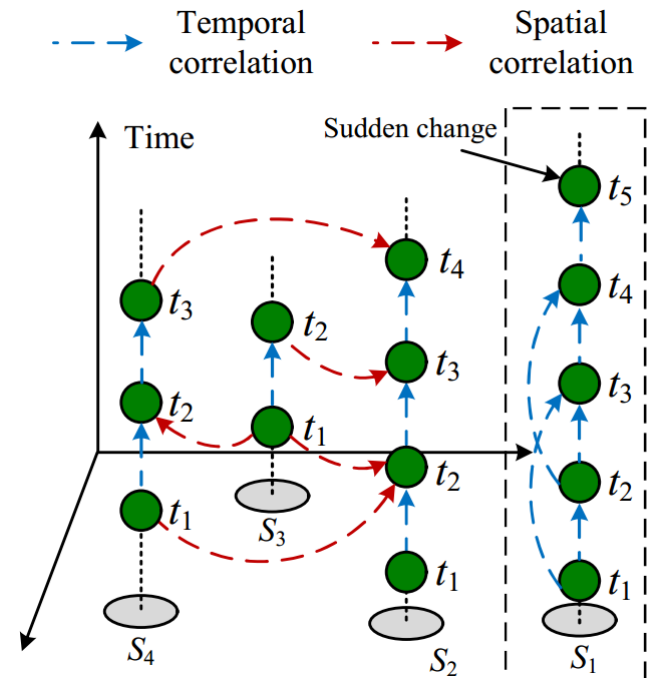
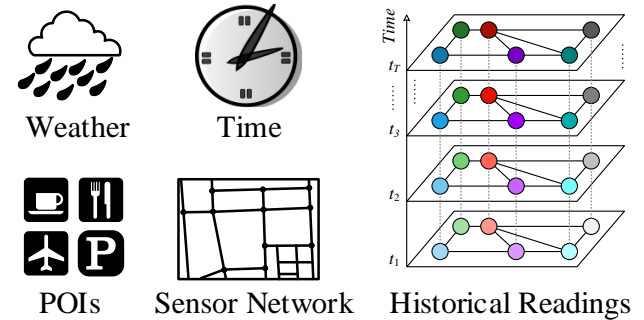
- Properties

- Each sensor has a **unique geospatial location**
- Constantly reporting **time series readings**
- With **geospatial correlation** between readings
- Prediction on geo-sensory time series**
  - Motivation: traffic control, air quality forecast...
  - Goal: predict **target series** at a sensor

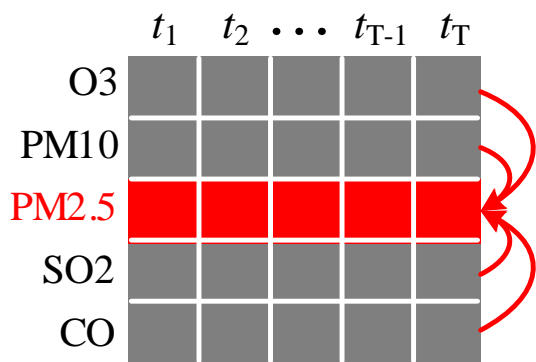
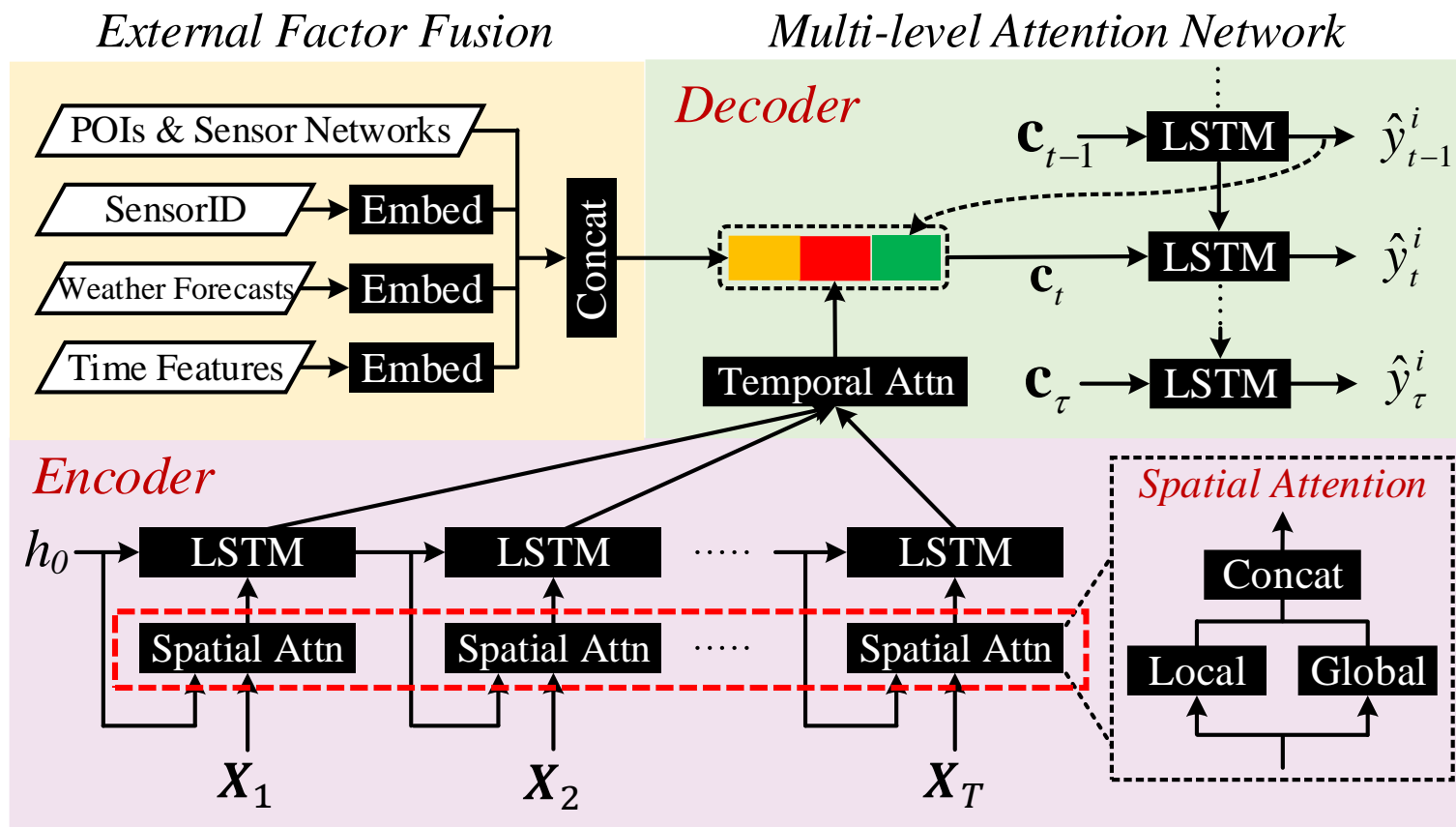


# Challenges

- Affected by many factors
  - Readings of previous time interval
  - Readings of other sensors in nearby regions
  - External factors: weather, time and land use
- Dynamic Inter-sensor correlations
- Dynamic temporal correlation



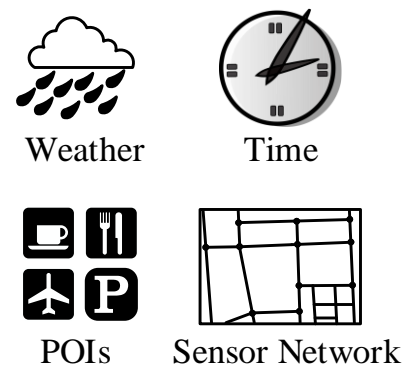
# Framework



Local spatial attention



Global spatial attention

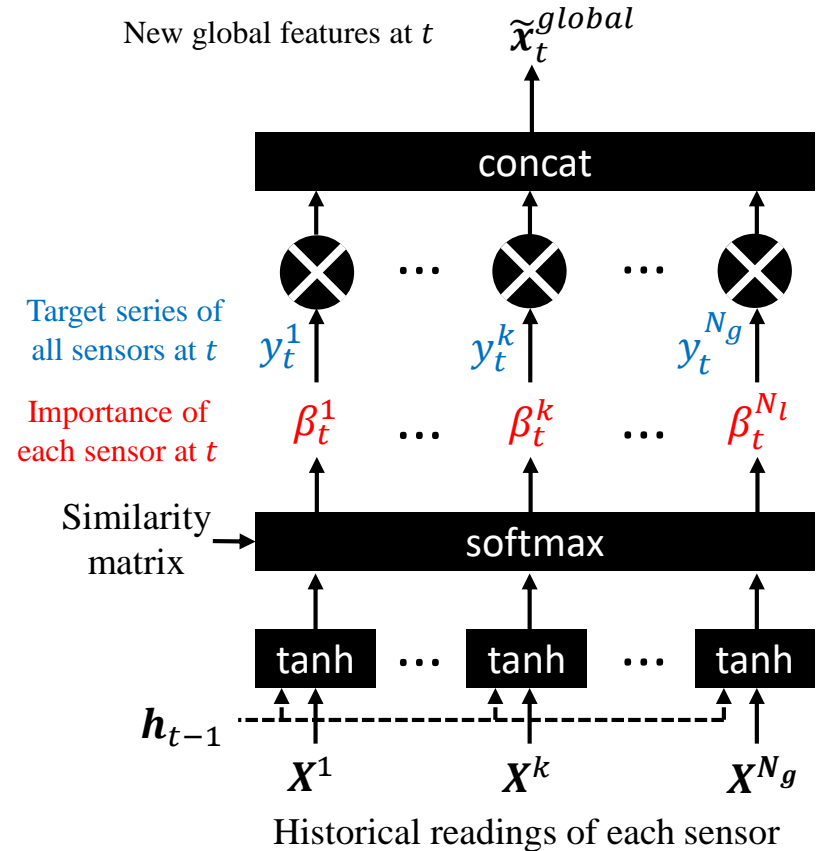
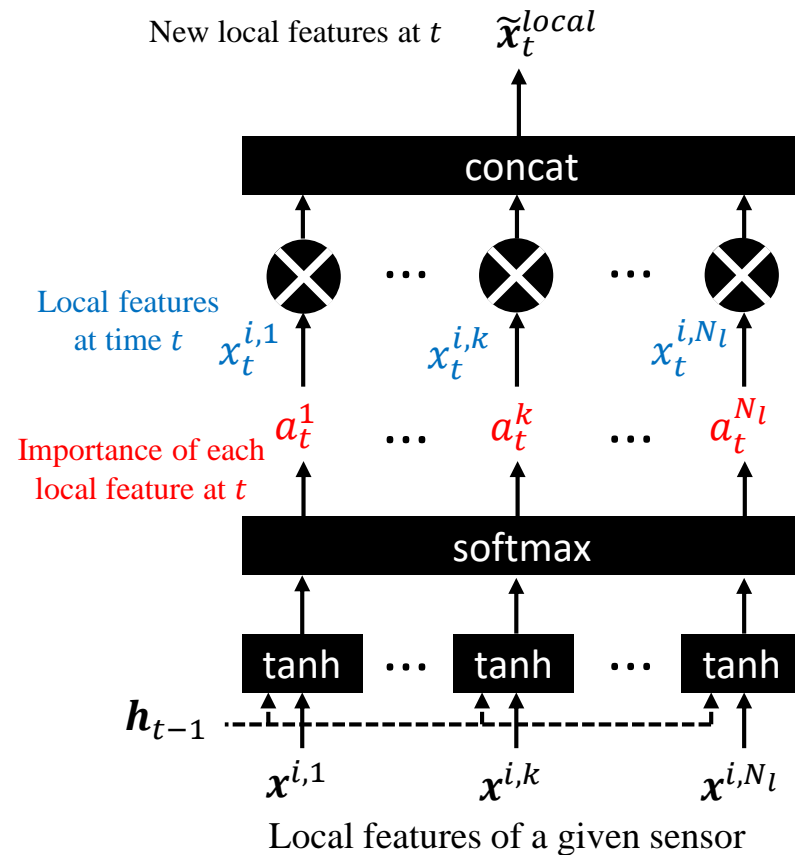


External factors fusion

# Spatial Attention

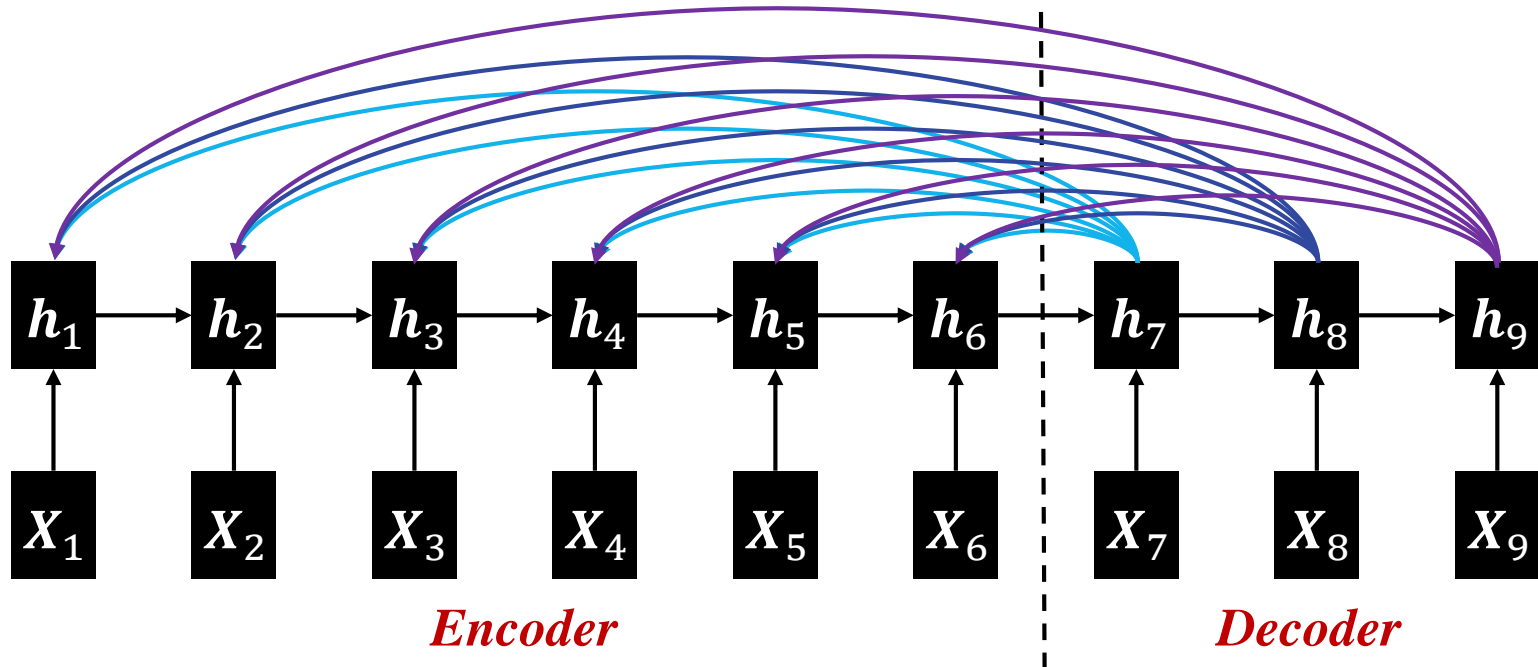
- Local spatial attention
  - Local features  $\Leftrightarrow$  target series

- Global spatial attention
  - Select relevant sensors



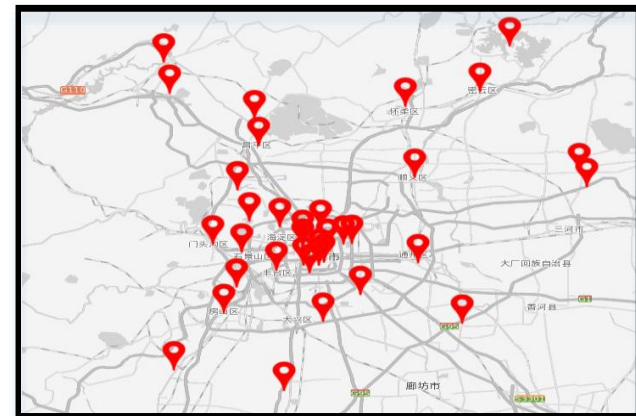
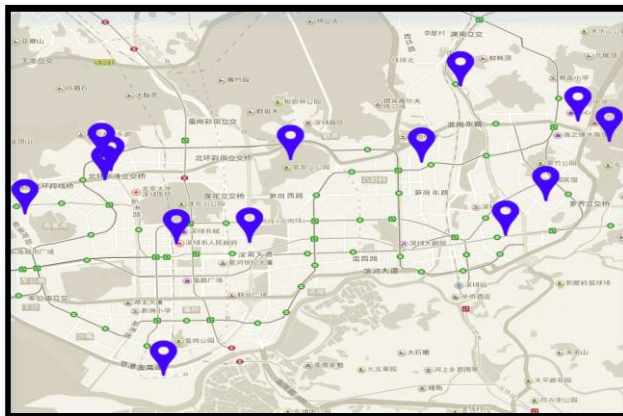
# Temporal Attention

- Sequence-to-sequence architecture
- Select relevant **previous time slots to make predictions**



# Evaluation

- Task 1 - water quality prediction
  - Water quality data
    - Residual chlorine
    - 10 kinds of time series
    - From 14 sensors in Shenzhen
    - Update each 5 minutes
  - Meteorology data
  - POIs data
- Task 2 - air quality prediction
  - Air quality data
    - PM2.5
    - 19 kinds of time series
    - From 35 sensors in Beijing
    - Hourly updates
  - Meteorology data
  - POIs data

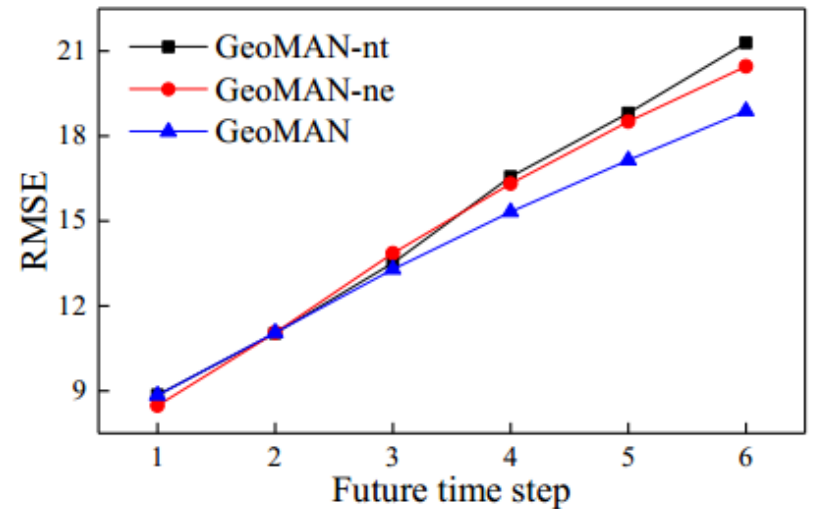
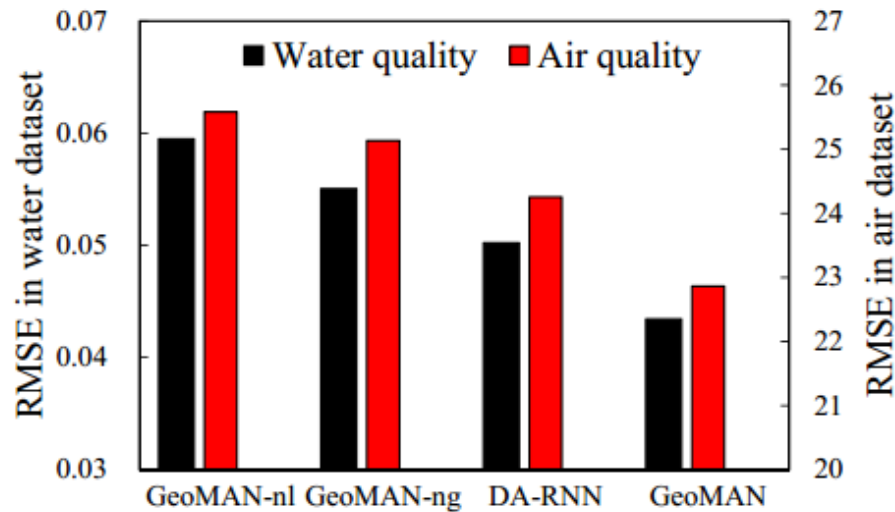


# Results

Method	Water Quality		Air Quality	
	RMSE	MAE	RMSE	MAE
ARIMA	8.61E-02	7.97E-02	31.07	20.58
VAR	5.02E-02	4.42E-02	24.60	16.17
GBRT	5.17E-02	3.30E-02	24.00	15.03
FFA	6.04E-02	4.10E-02	23.83	15.75
stMTMVL	6.07E-02	4.16E-02	29.72	19.26
stDNN	5.77E-02	3.99E-02	25.64	16.49
LSTM	6.89E-02	5.04E-02	24.62	16.70
Seq2seq	5.80E-02	4.03E-02	24.55	15.09
DA-RNN	5.02E-02	3.52E-02	24.25	15.17
<b>GeoMAN</b>	<b>4.34E-02</b>	<b>3.02E-02</b>	<b>22.86</b>	<b>14.08</b>



# Results

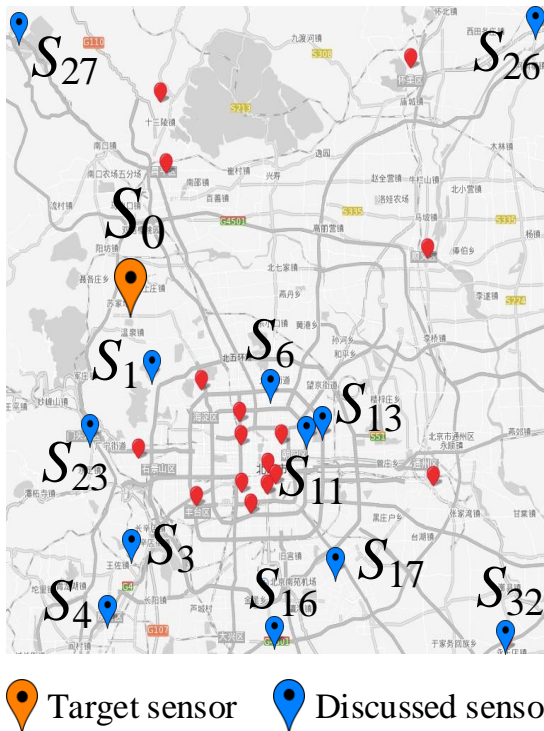


(a) Evaluation on spatial attention      (b) Future time step vs. RMSE

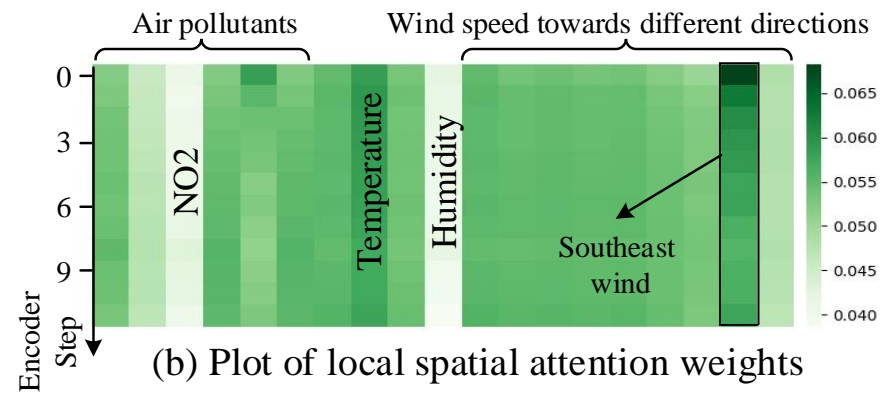
Figure 3: Performance comparison among different variants.

# Visualization: Dynamic Correlation

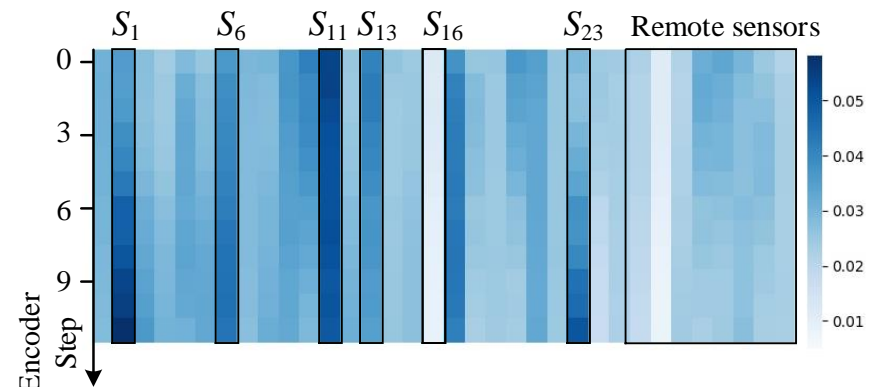
- Case study over air quality dataset
  - Discuss on sensor  $S_0$
  - 4:00 to 16:00 on Feb. 28, 2017



(a) Air quality stations in Beijing



(b) Plot of local spatial attention weights



(c) Plot of global spatial attention weights

# Conclusion

- A very fundamental but challenging task
  - Dynamic inter-sensor correlation
  - Dynamic temporal correlation
  - External factors
- Our method
  - Multi-level attention network
    - Spatial attention: captures the dynamic inter-sensor correlation
    - Temporal attention: captures the dynamic temporal correlation
  - External factor fusion
- Results
  - More accurate
  - Easily interpreted

# Thanks!



## We are Hiring!



**Data & Code**

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