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

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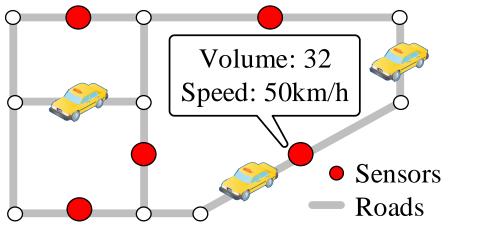


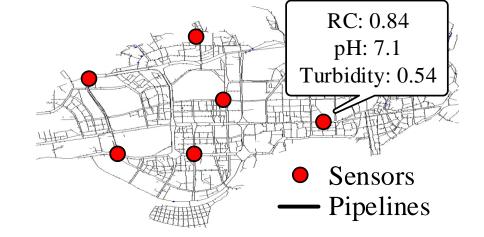


# Introduction

## **Geo-sensory time series**

- Properties
  - Each sensor has a unique geospatial location
  - Reporting time series readings about different measurements
  - With geospatial correlation between their readings
- > Examples

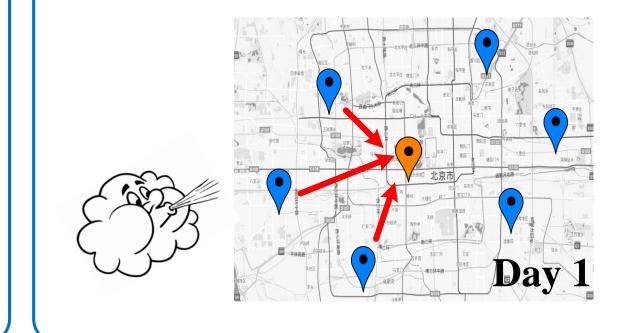


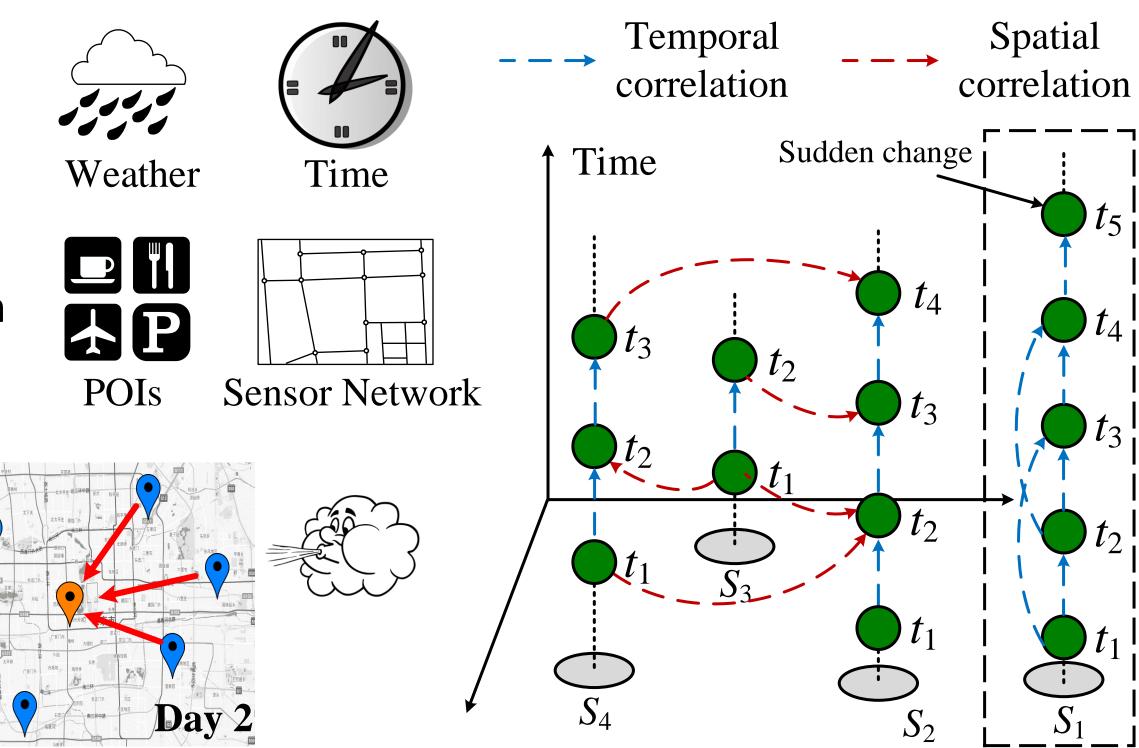


- > Goal
  - Predict target series of a sensor over several future hours

## Challenges

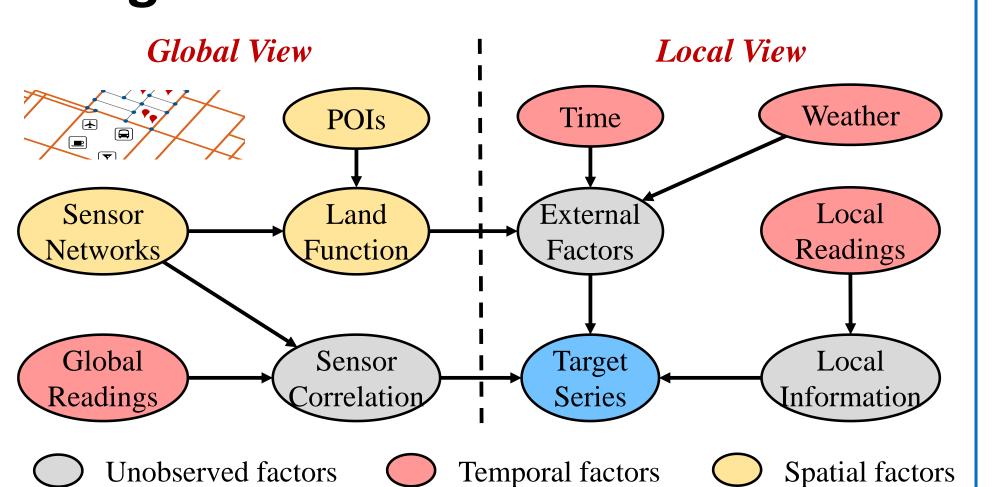
- Affected by many factors
  - Readings of previous time interval
  - Readings of nearby sensors
  - External factors
- Dynamic inter-sensor correlation
- Dynamic temporal correlation





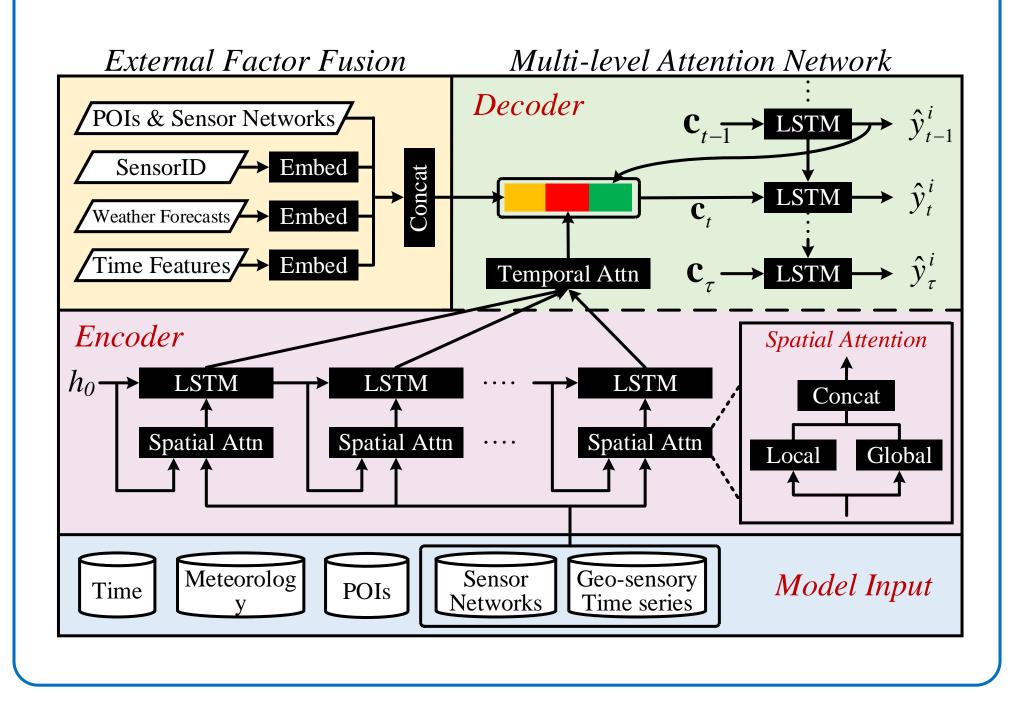
# Methodology

## Insight



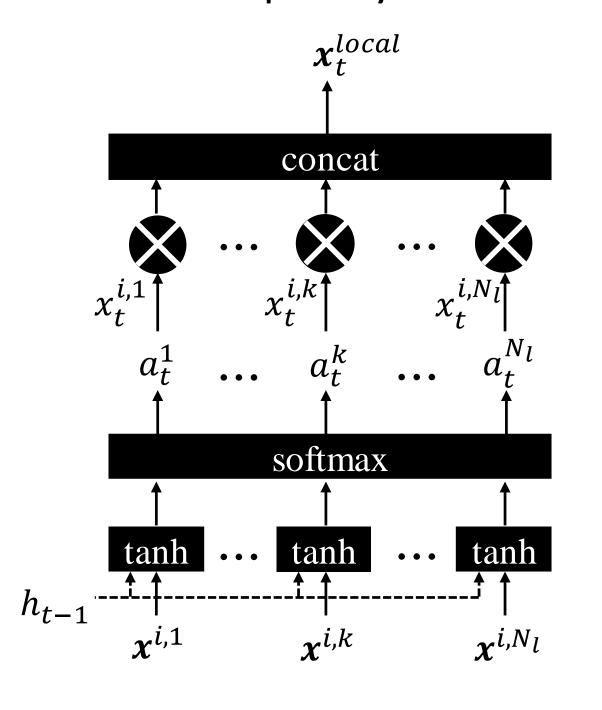
## Framework

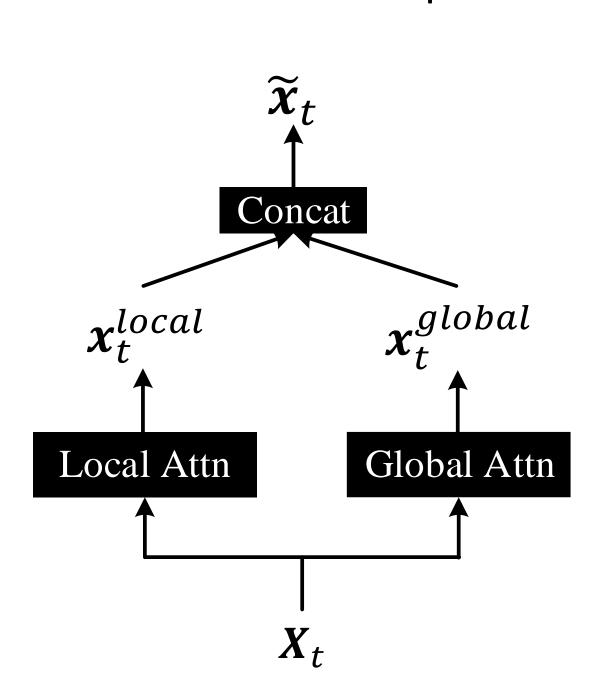
- ➤ Multi-level attention network
- Spatial attention
- Temporal attention
- > External factors fusion module

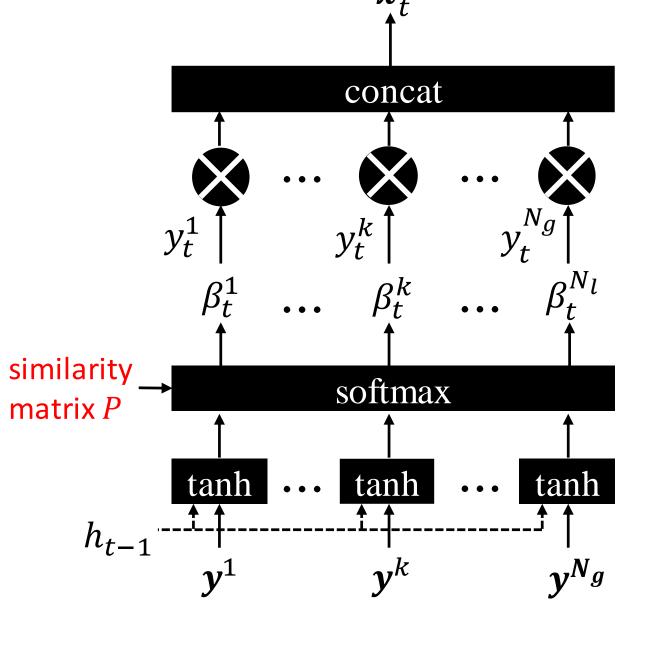


## **Spatial Attention**

- > Capture dynamic inter-sensor correlation
- > Local: adaptively captures the correlation between target series and local features (other series)
- > Global: adaptively select the relevant sensors to make predictions

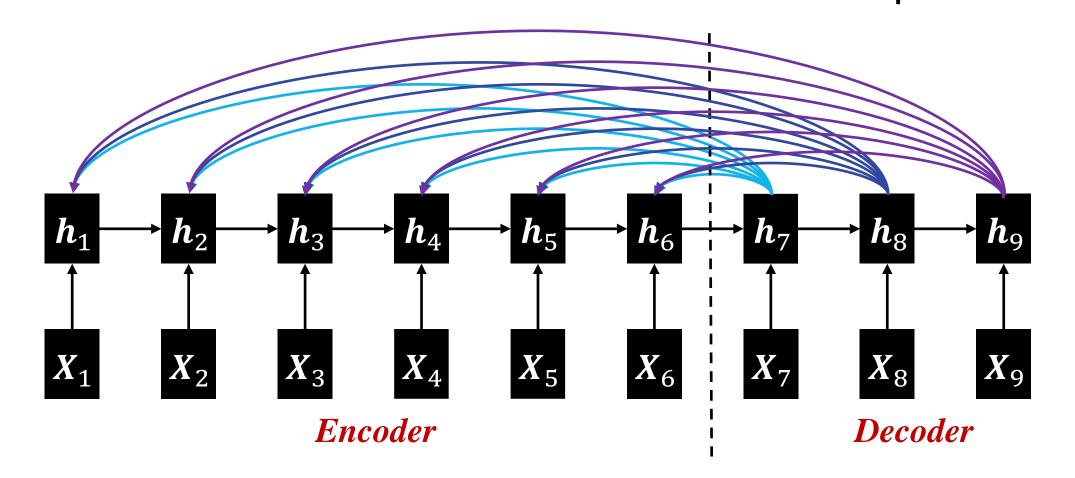






#### **Temporal Attention**

> Select relevant historical time slots to make predictions



#### **Model Training**

- > Encoder-decoder + Multi-level attention
- ➤ GeoMAN is smooth and differentiable
- Loss function: MSE

$$\mathcal{L}( heta) = \left\| \hat{\mathbf{y}}^i - \mathbf{y}^i 
ight\|_2^2$$

➤Optimizer: Adam

## Results

#### > Datasets: water quality dataset & air quality dataset

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
GeoMAN	4.34E-02	3.02E-02	22.86	14.08

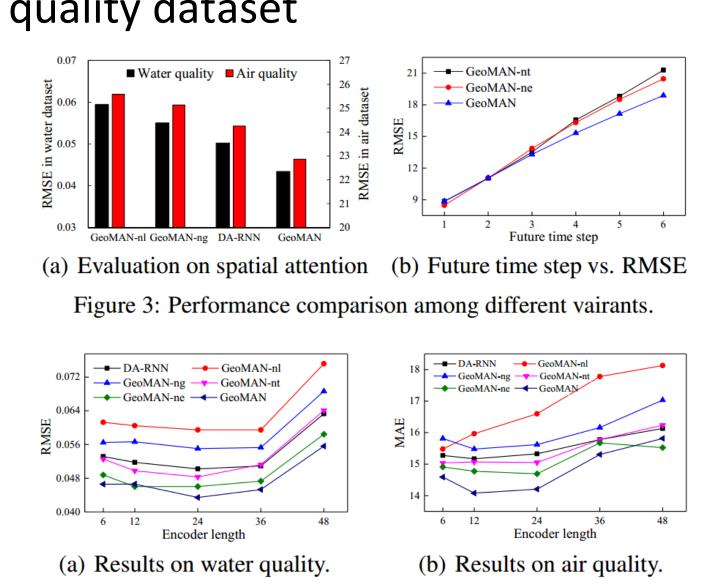


Figure 4: Encoder length vs. metrics over the two datasets.

# Visualization

