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

Yuxuan Liang[1,2], Songyu Ke[3,2], Junbo Zhang[2,4], Xiuwen Yi[4,2], Yu Zheng[2,1,3,4]

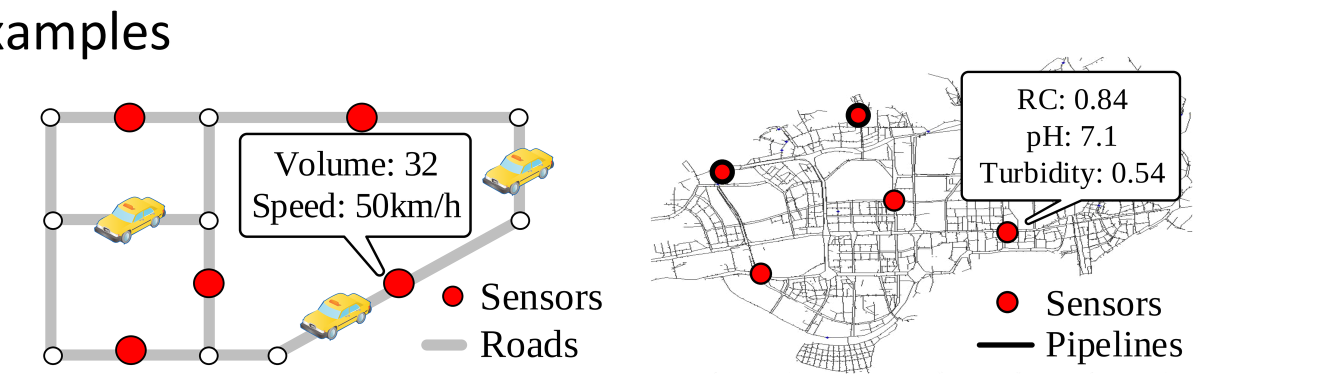
[1] Xidian University, Xi'an, China
[2] Urban Computing Business Unit, JD Finance, Beijing, China
[3] Shanghai Jiao Tong University, Shanghai, China
[4] Southwest Jiaotong University, Chengdu, China

Codes & Data

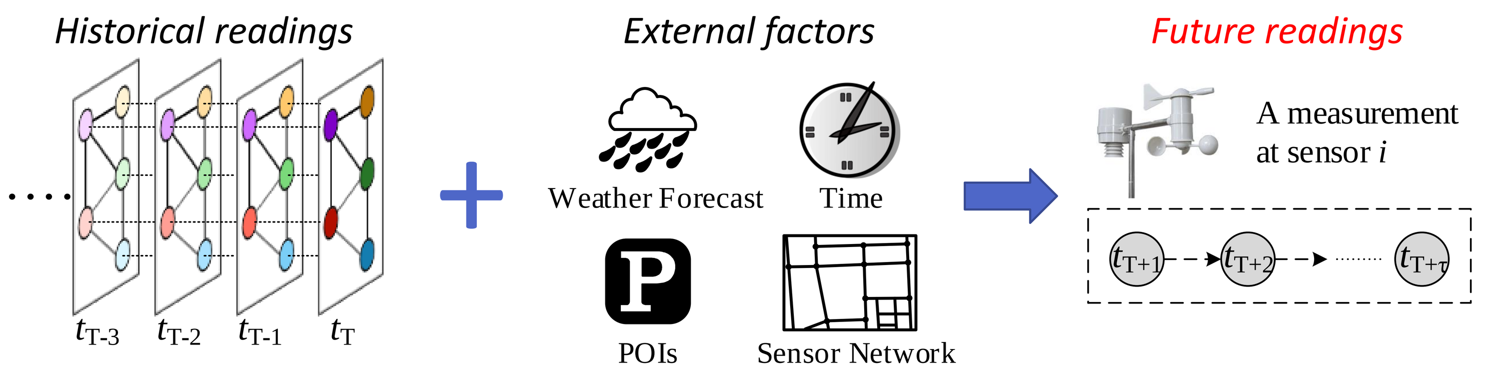
Introduction

Geo-sensory time series

- Sensors deployed in different geospatial locations
- Constantly reporting readings of different measurements
- Examples

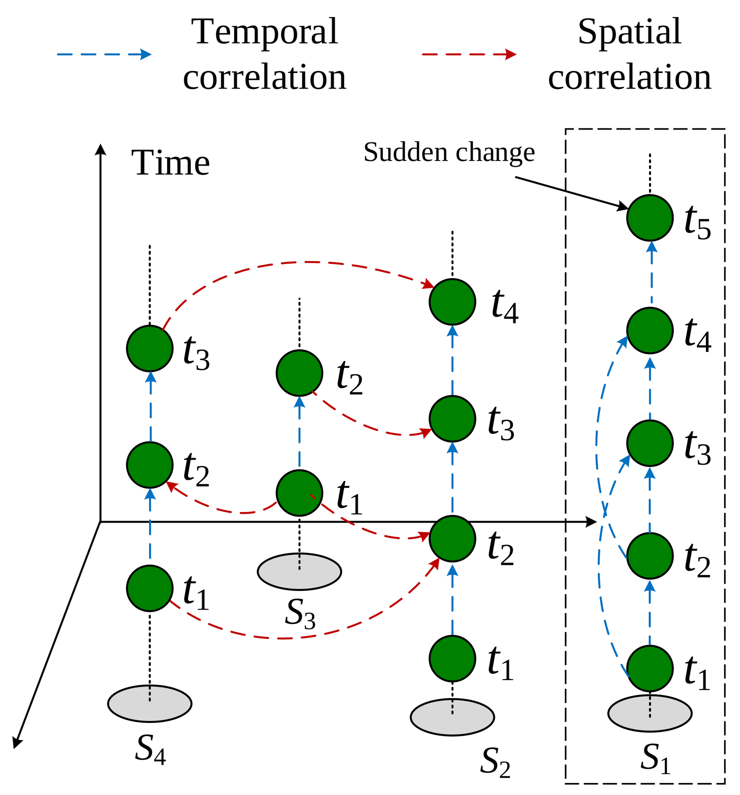


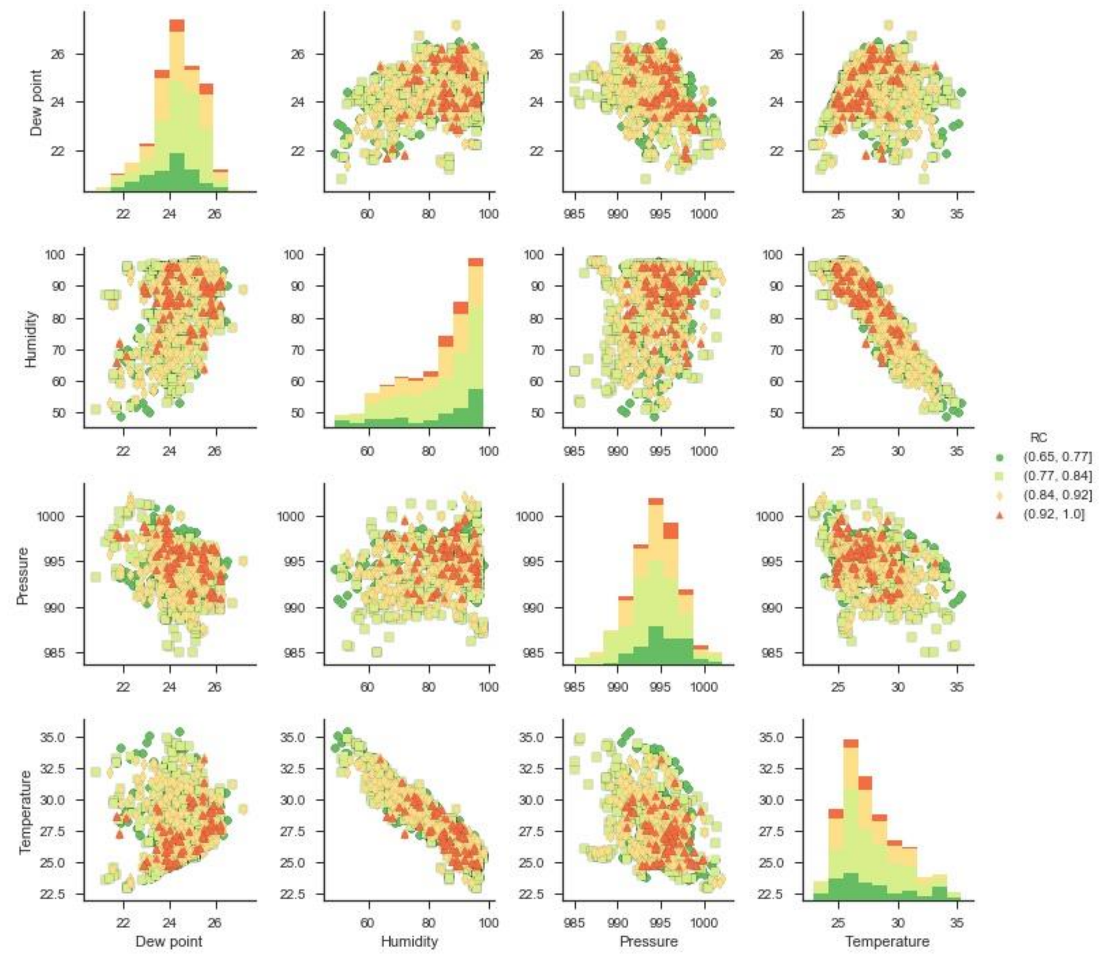
- Forecasting them is of great importance to our daily lives



Challenges

- Dynamic spatio-temporal correlation
- External factors (*e.g.*, meteorology)





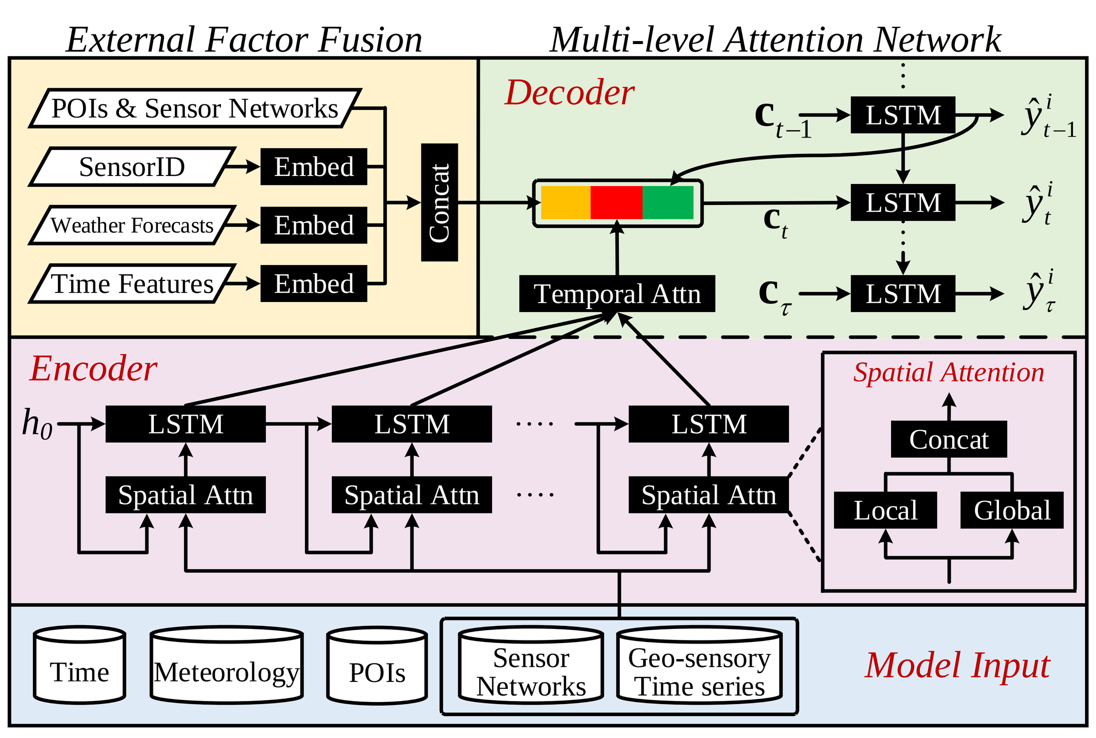
Methodology

Preliminary

- Suppose there are N_g sensors
- Each sensor generates N_l kinds of readings about different measurements
- Predict the target series of a given sensor over the next τ hours

Framework

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



Temporal Attention

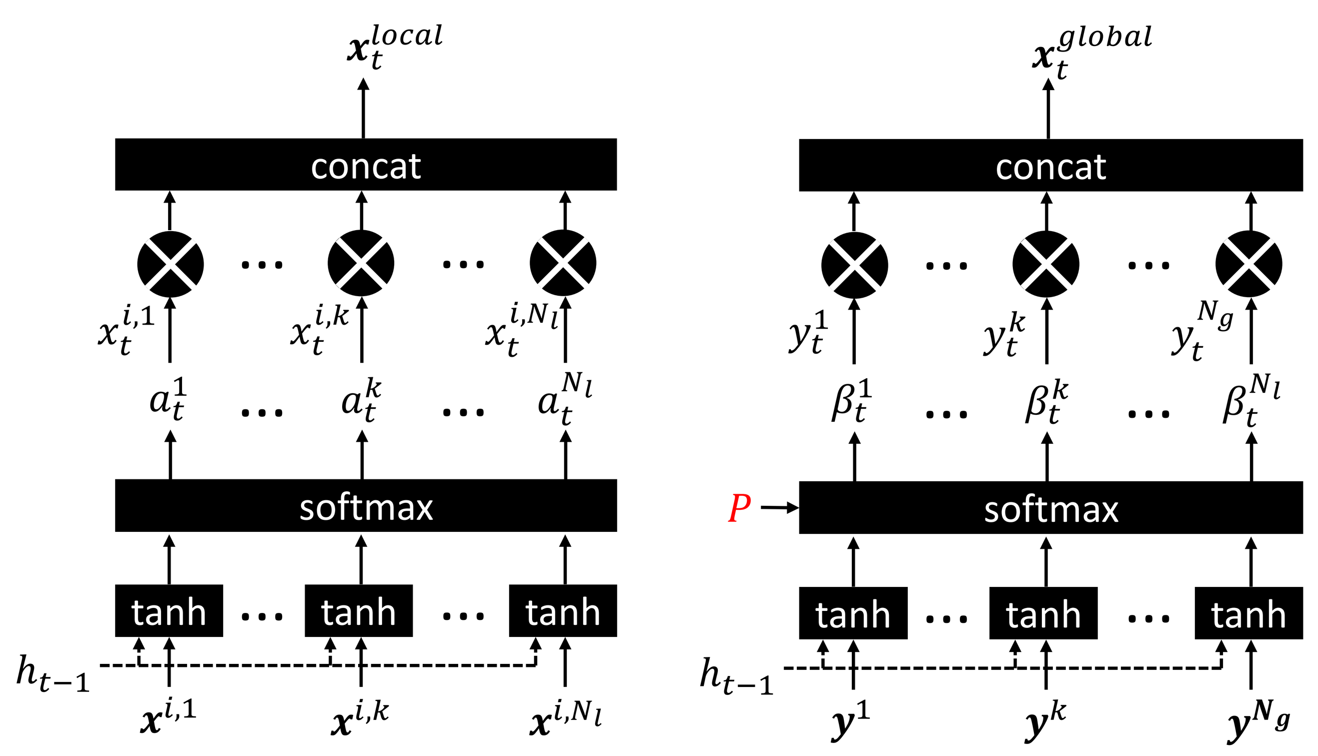
- Select relevant historical time slots to make predictions

$$u_{t'}^{o} = \mathbf{v}_d^\top \tanh\left(\mathbf{W}_d'\left[\mathbf{d}_{t'-1};\mathbf{s}_{t'-1}'\right] + \mathbf{W}_d\mathbf{h}_o + \mathbf{b}_d\right),$$

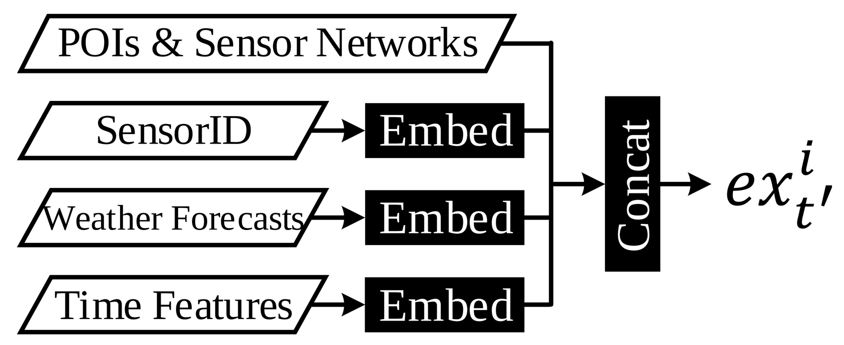
$$\gamma_{t'}^{o} = \frac{\exp\left(u_{t'}^{o}\right)}{\sum_{j=1}^{T}\exp\left(u_{t'}^{j}\right)}, \qquad \mathbf{c}_{t'} = \sum_{o=1}^{T}\gamma_{t'}^{o}\mathbf{h}_o,$$

Spatial Attention

- Local spatial attention: select relevant local features
- Global spatial attention: select relevant sensors



External Factors Fusion



Encoder-decoder Achitecture

- New encoder input

$$\tilde{\mathbf{x}}_t = \left[\tilde{\mathbf{x}}_t^{local};\tilde{\mathbf{x}}_t^{global}\right]$$

- Update decoder hidden state

$$\mathbf{d}_{t'} = f_d\left(\mathbf{d}_{t'-1},\left[\hat{y}_{t'-1}^{i};\mathbf{ex}_{t'};\mathbf{c}_{t'}\right]\right)$$

- Output generation

$$\hat{y}_{t'}^{i} = \mathbf{v}_y^\top\left(\mathbf{W}_m\left[\mathbf{c}_{t'};\mathbf{d}_{t'}\right] + \mathbf{b}_m\right) + b_y$$

Model Training

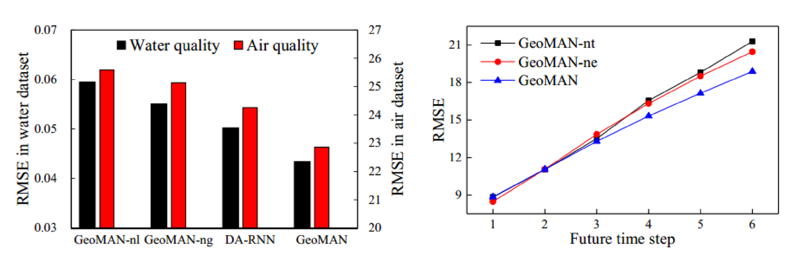
- GeoMAN is smooth and differentiable
- Loss function

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

- Optimizer: Adam

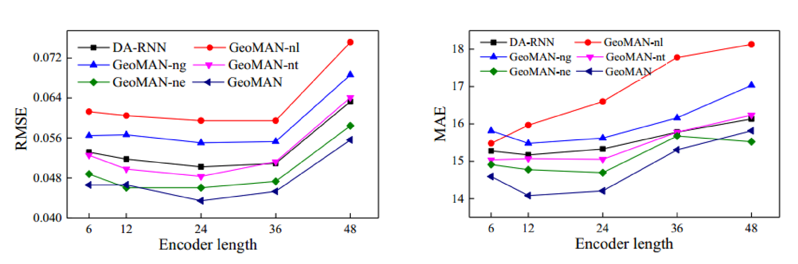
Results

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
GeoMAN	**4.34E-02**	**3.02E-02**	**22.86**	**14.08**



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

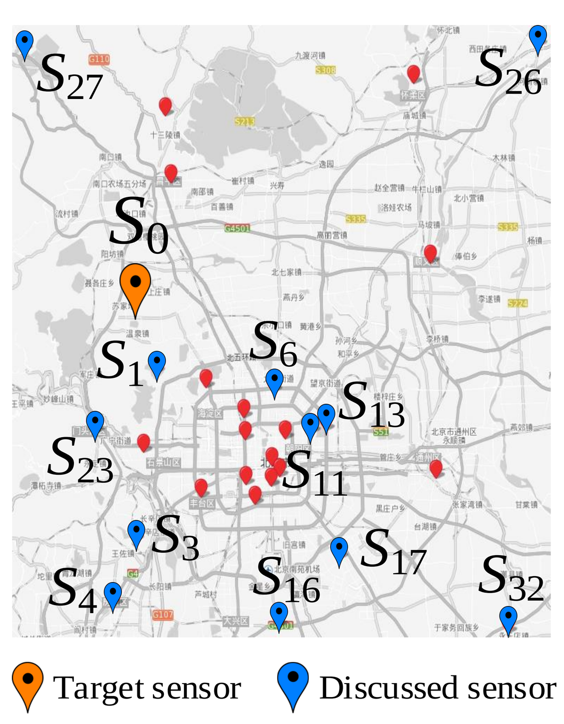
Figure 3: Performance comparison among different vairants.



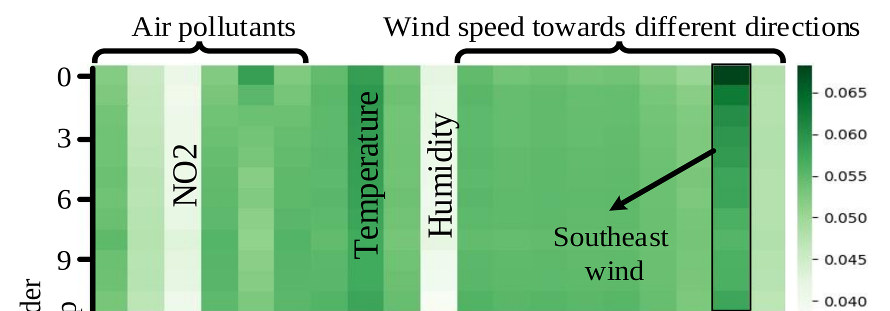
(a) Results on water quality. (b) Results on air quality.

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

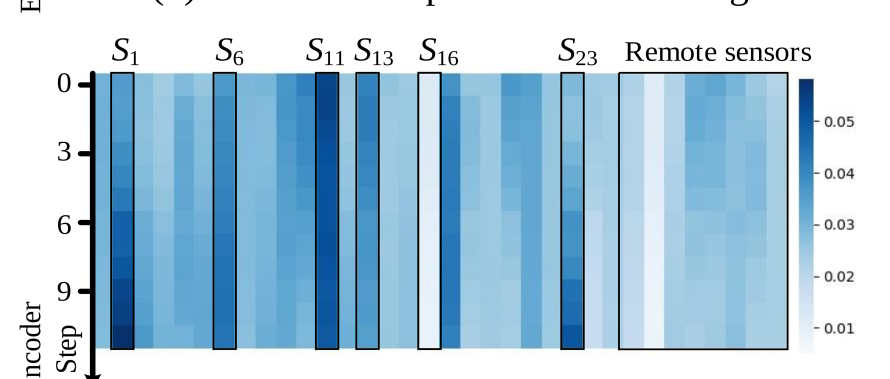
Attention Visualization



(a) Air quality stations in Beijing



(b) Plot of local spatial attention weights



(c) Plot of global spatial attention weights