Spatiotemporal Multi-Graph Convolution for Ride-hailing Demand Forecasting

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Joint work with

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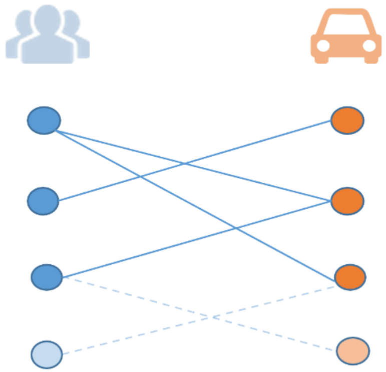
Introduction

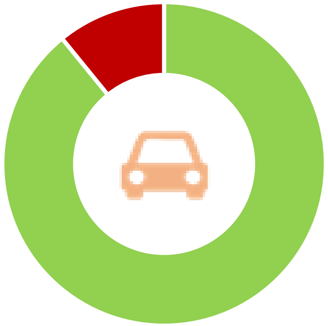
- More than 18 billion ride-hailing trips worldwide in 2018*
  - Twice as much as the world population.

- Benefit of better ride-hailing demand forecasting

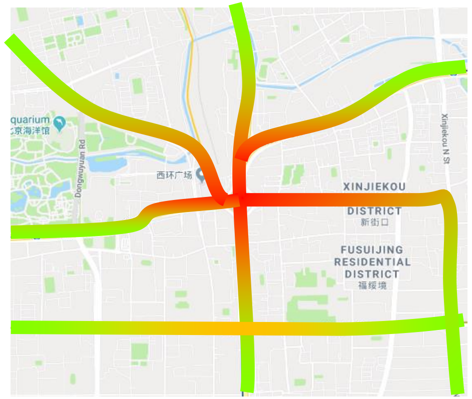
Better Vehicle Dispatching



Higher vehicle utilization



Early congestion warning

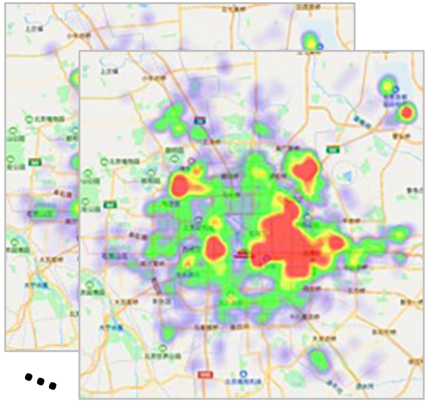


* http://www.businessofapps.com/data/uber-statistics/, Nov 2018.

Region-level Ride-hailing Demand Forecasting

- Input: past T observations of demands of all $|V|$ regions
- Output: demands of all $|V|$ regions in the next time stamp

Input



$\mathbb{R}^{T\times|V|}$

$f\colon \mathbb{R}^{T\times|V|} \rightarrow \mathbb{R}^{|V|}$

Output

$\mathbb{R}^{|V|}$

Complicated spatial and temporal correlations

Related Work

- Spatiotemporal forecasting on grid
  - Classical settings for demand forecasting problem
  - CNN-based approaches: region-wise relationship is Euclidean
    - DeepST/STResNet: Crowd flow forecasting (Zhang et al., 2017)
    - DMVST: Demand forecasting (Yao et al., 2018)

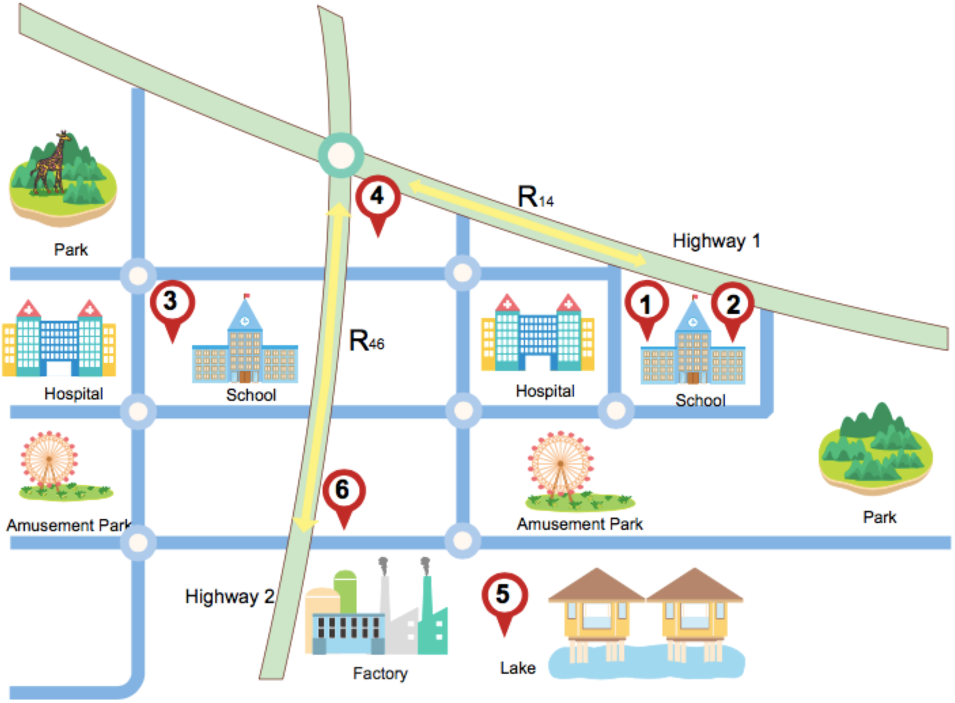
Hard to capture the **non-Euclidean** correlations

- Spatiotemporal forecasting on graph
  - LinUOTD: handcrafted feature + LR for demand forecasting (Tong et al., 2017)
  - DCRNN/ST-GCN: Graph convolution based traffic forecasting (Li et al., 2018a, Yu et al., 2018, Li et al., 2018b, Yan et al., 2018)

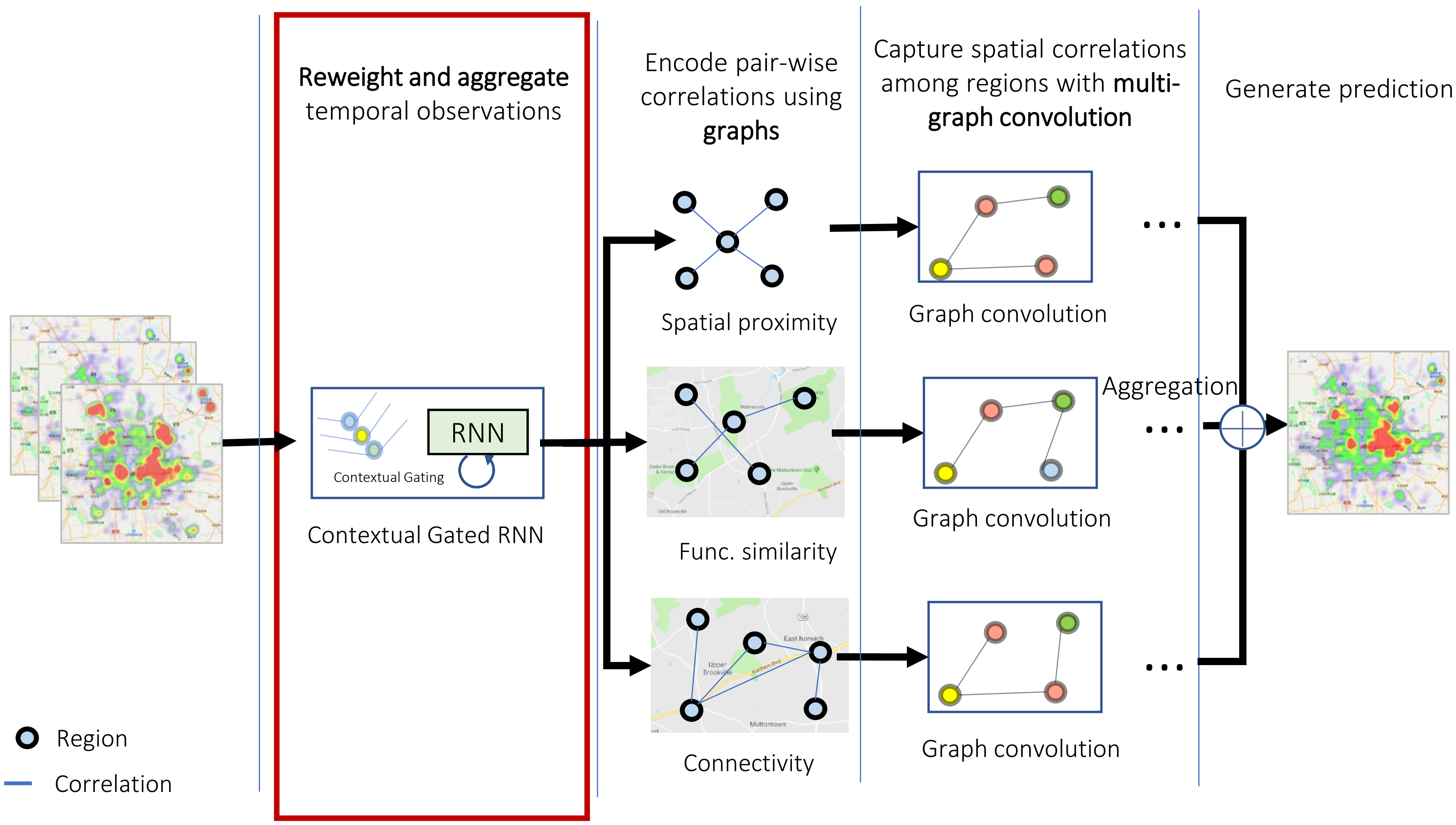
Hard to capture the **multimodal** correlations

Multimodal Correlations among Regions

- Spatial proximity
  - Region 1 and 2
- Functional similarity
  - Regions with similar context show similar demand patterns
  - Region 1 and 3
- Road connectivity
  - High-speed transportation facilitate correlation
  - Region 1 and 4

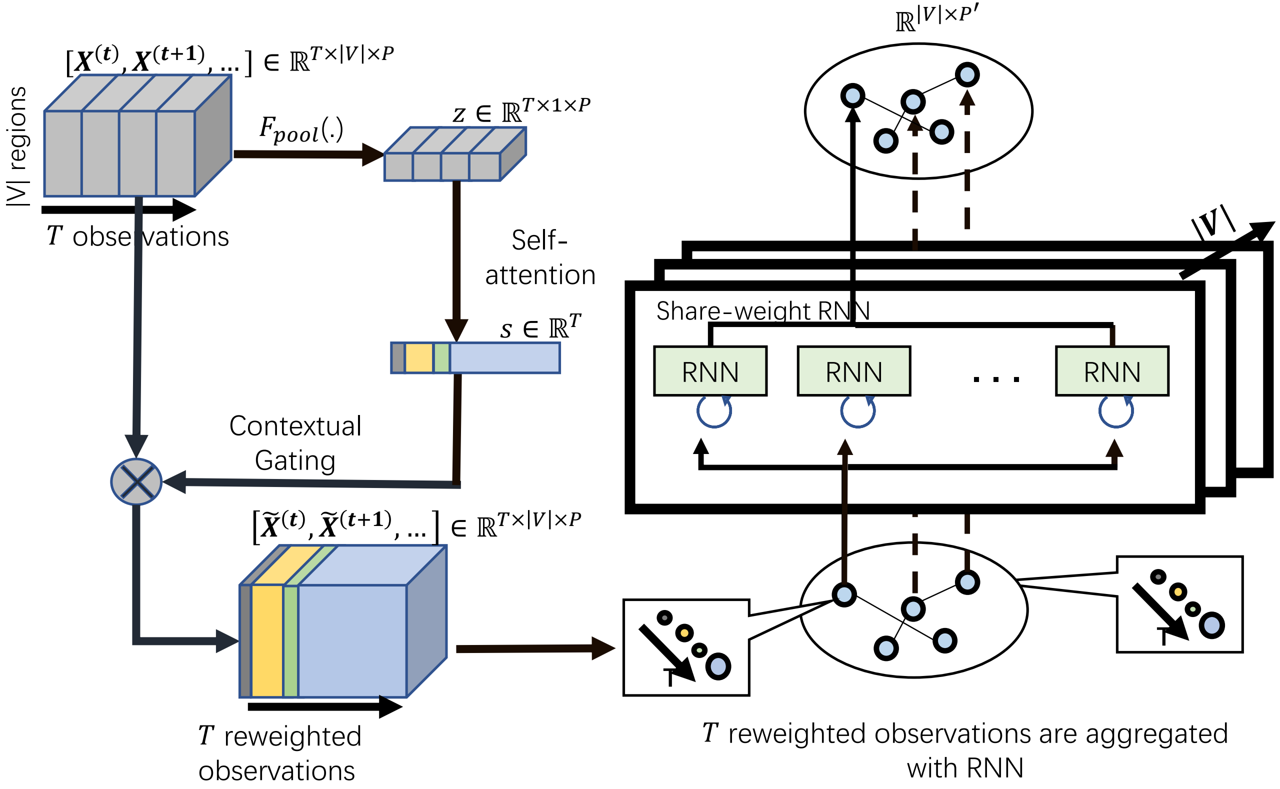


Spatiotemporal Multi-Graph Convolution Network

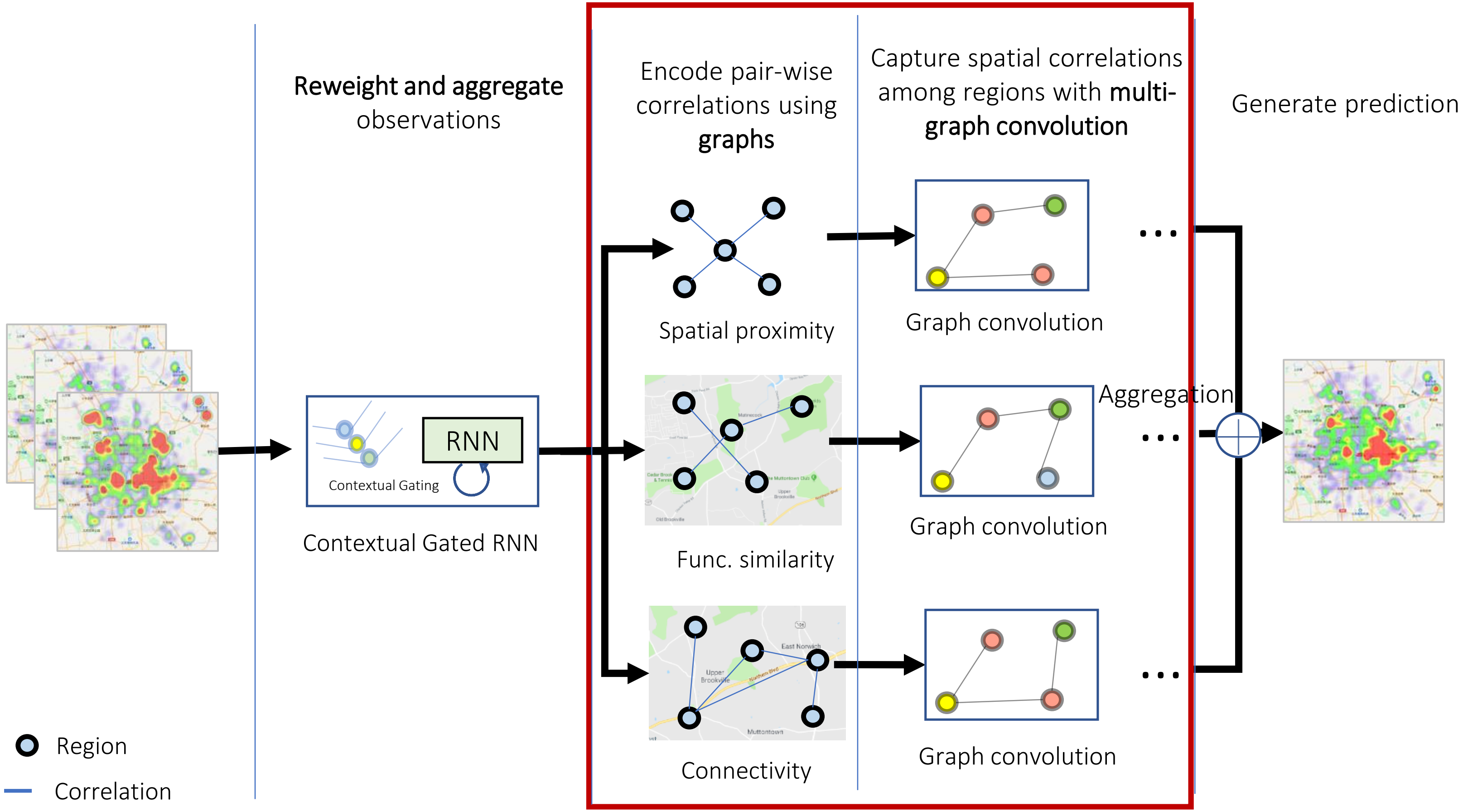


CGRNN: Context-aware Temporal Aggregation

- Summarize contextual information
- Calculate gates based on interdependencies between observations with self-attention
- Reweight observations with gates
- Aggregate reweighted observations with share-weight RNN

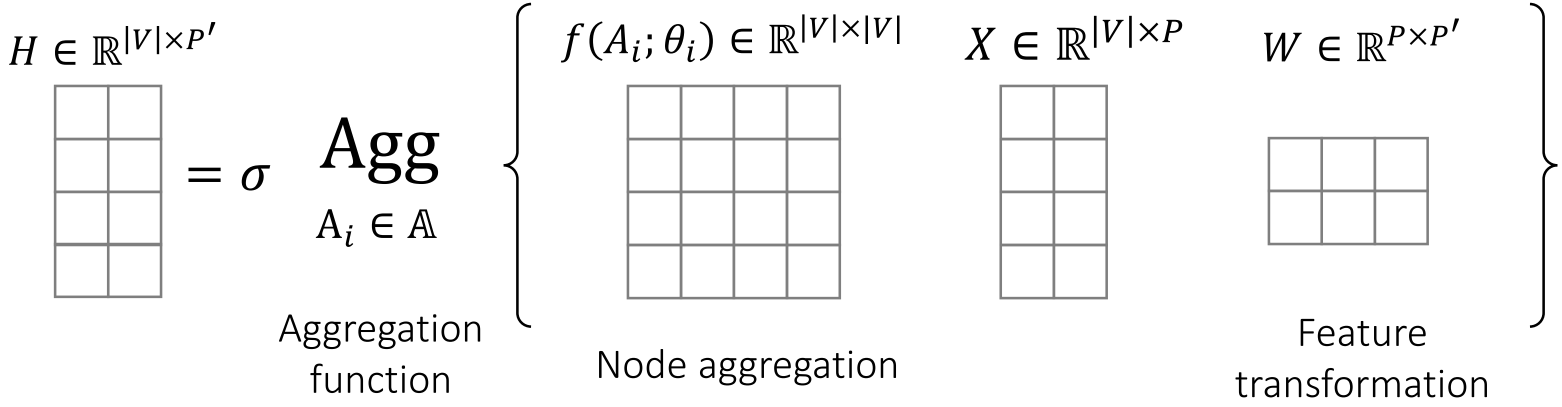


Spatiotemporal Multi-Graph Convolution Network



Multi-graph Convolution

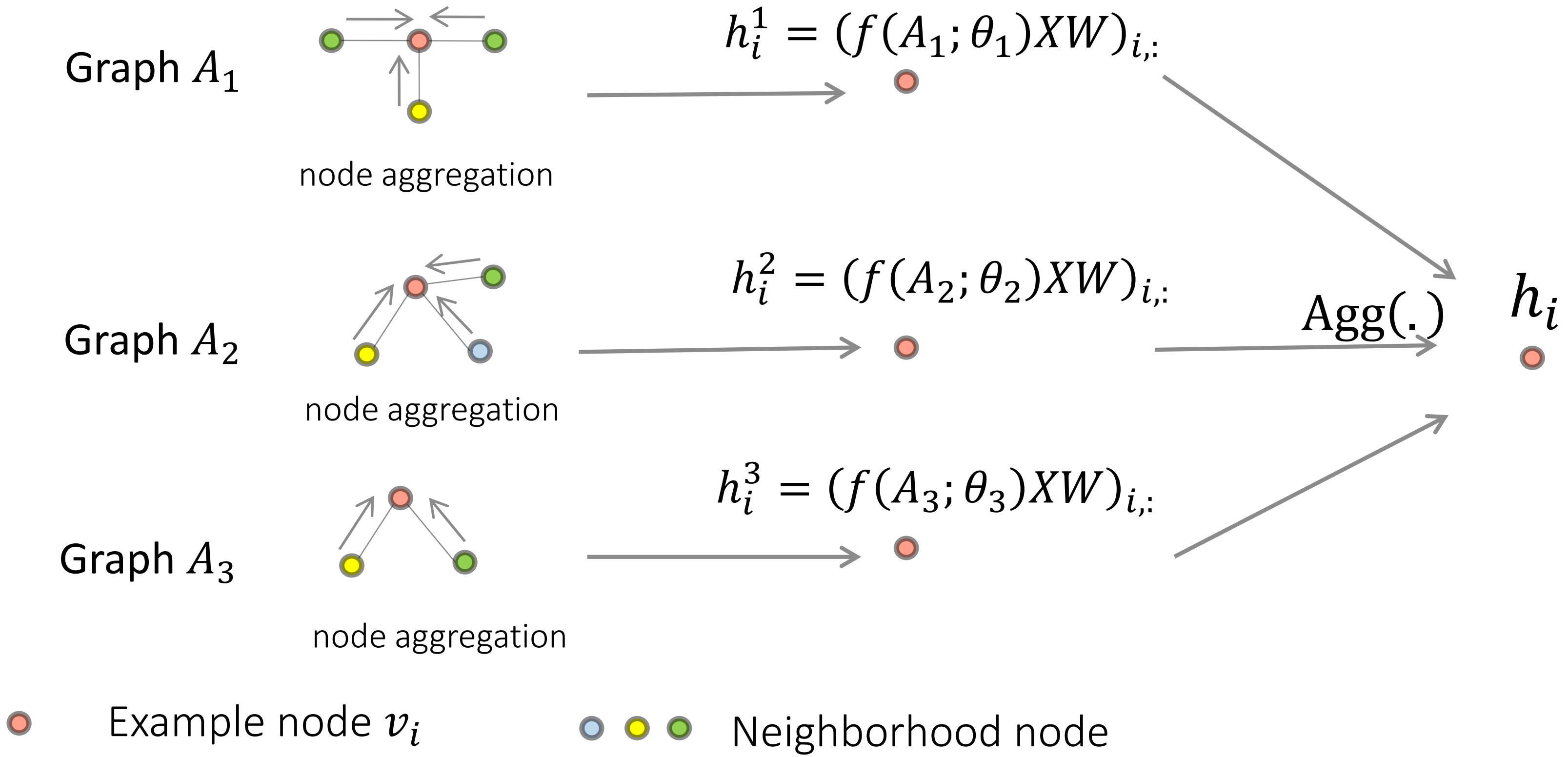
$$H = \mathrm{MGC}(X) = \sigma\Big(\underset{\mathrm{A}_i \in \mathbb{A}}{\mathrm{Agg}}\; f(A_i;\theta_i)XW\Big)$$



- $f(A_i;\theta_i)$: function of adjacency matrix A_i with parameter θ_i
  - Polynomial of graph Laplacian, graph attention etc.
- Agg: Aggregation function
  - Sum, average, attention-based aggregation

Multi-graph Convolution

$$H = \sigma(\mathrm{Agg}\ f(A_i; \theta_i)XW)$$

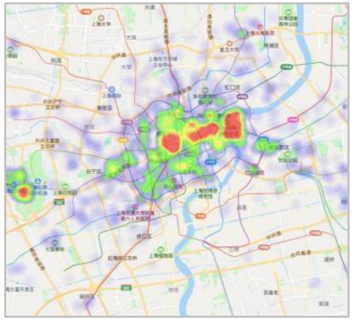


Datasets

- Beijing:
  - 1296 regions, 19M samples
  - 10 months in 2017
- Shanghai
  - 896 regions, 13M samples
  - 10 months in 2017
- POI/Road network
  - OpenStreetMap

Beijing

Shanghai



Experiments

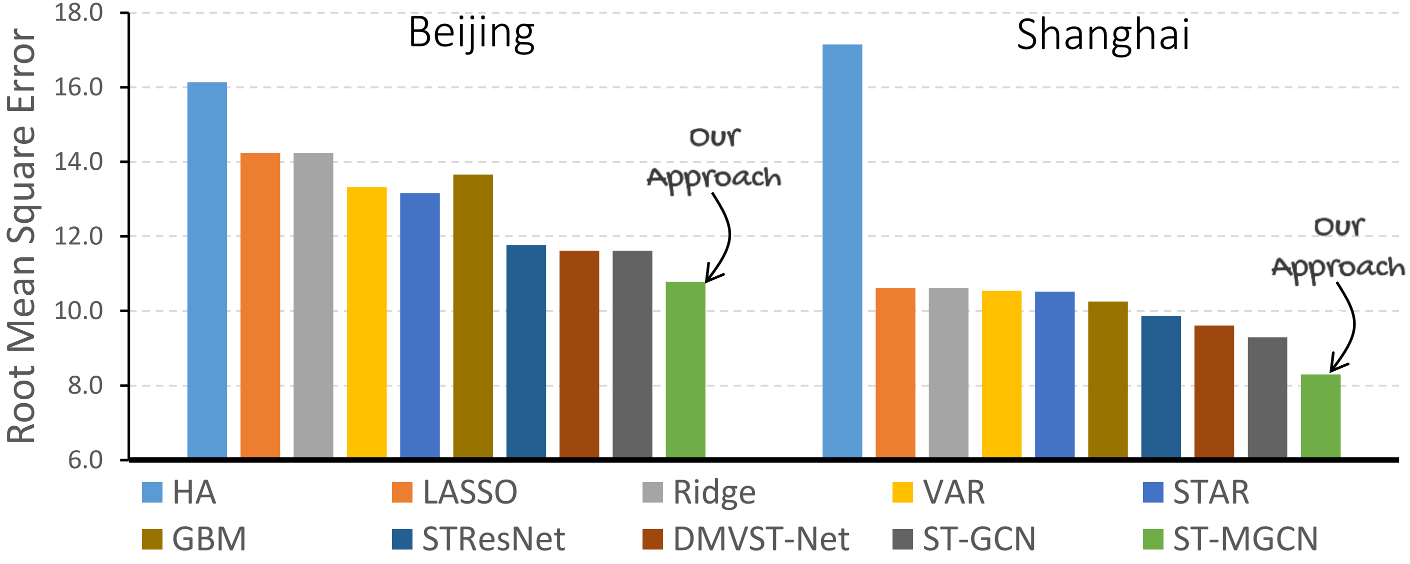
- Baselines
  - Historical Average (HA)
  - Linear Regression (LASSO, Ridge)
  - Vector Auto-Regression (VAR)
  - Spatiotemporal Auto-Regressive Model (STAR)
  - Gradient Boosted Machine (GBM)

  - Spatiotemporal Residual Network (ST-ResNet), with Euclidean grid
  - Spatiotemporal graph convolutional network (ST-GCN), with road network graph
  - Deep Multi-view Spatiotemporal Network (DMVST-Net), with Euclidean grid, SOTA for ride-hailing demand forecasting

- Task
  - One step ahead ride-hailing demand forecasting

Experimental Results

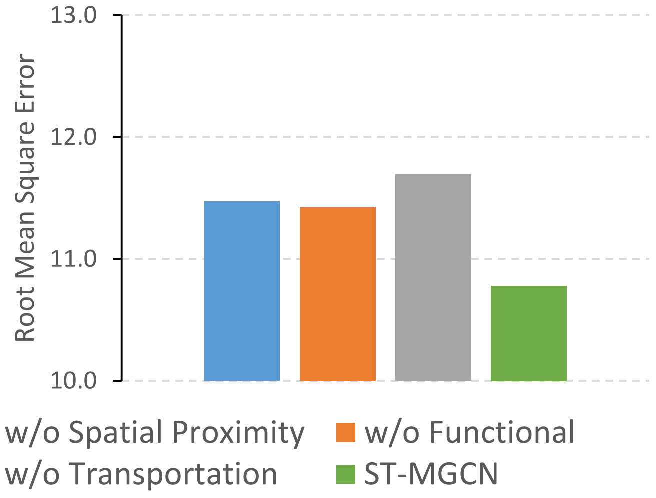
- ST-MGCN achieves the **best performance** on both datasets
  – 10+% improvement*.



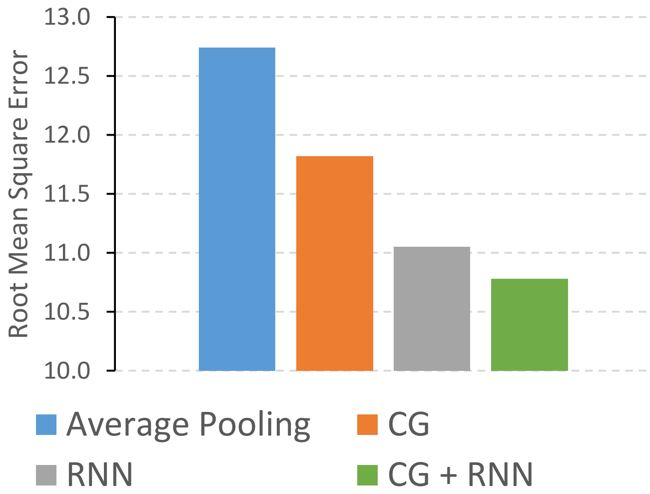
* In terms of relative error reduction of RMSE.

Experimental Results

- Both spatial and temporal correlations modeling are necessary
  - Removing either graph component leads to **significantly worse** performance.
  - With **CGRNN**, ST-MGCN achieves the best performance.



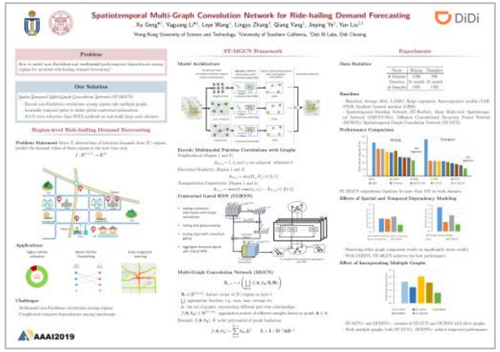
Effect of spatial correlation modeling



Effect of temporal correlation modeling

Summary

- Spatial: encode **pairwise correlations** into multiple **graphs**
- Temporal: **reweight** (self-attention) and **aggregate** (RNN)
- Result: **10+%** improvement on **real-world large-scale datasets**



Scan to download the poster

Reference

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Thank You!

Q & A