Uncertainty-aware Probabilistic Travel Demand Prediction with GNN and VAE for Mobility-on-demand Services

Tao Peng

Content

- About me
- Problem
- Methodology
- Results

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About me

Tao Peng

PhD student (2nd year)

Smart Public Transport Lab

Department of Transport and Planning

Computer Science background

Software engineer work experience

Optimization, Deep learning, Reinforcement learning

Shared mobility

Smart Public Transport

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Mobility-on-Demand

- Mobility-on-demand services
- Challenges
  - Matching under constraints
  - Dynamic demand and supply
  - Resource allocation
  - Uncertainty
- Task
  - Travel demand forecasting
  - Uncertainty quantification

Related work

- Formulate as time series forecasting problem
  - Autoregression(AR, ARIMA)
  - Deep learning(DeepAR, RNN, LSTM)
- Time series with spatial information
- Spatiotemporal forecasting
- Uncertainty quantification
  - Parametric: distribution assumption, one single value -> parameters(e.g. mean and variance)
  - Nonparametric: percentile estimation, lower-upper bound estimation

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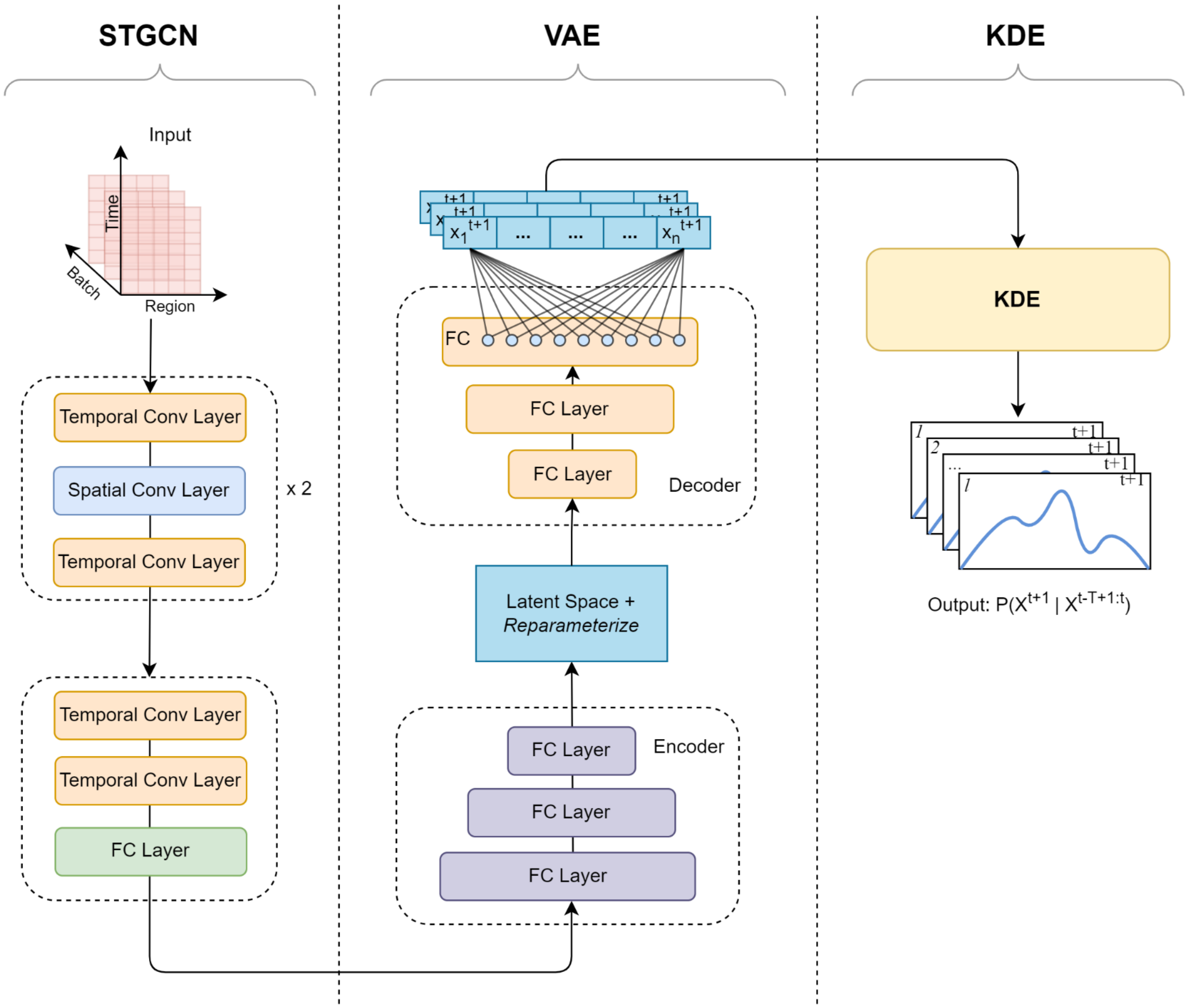
Framework



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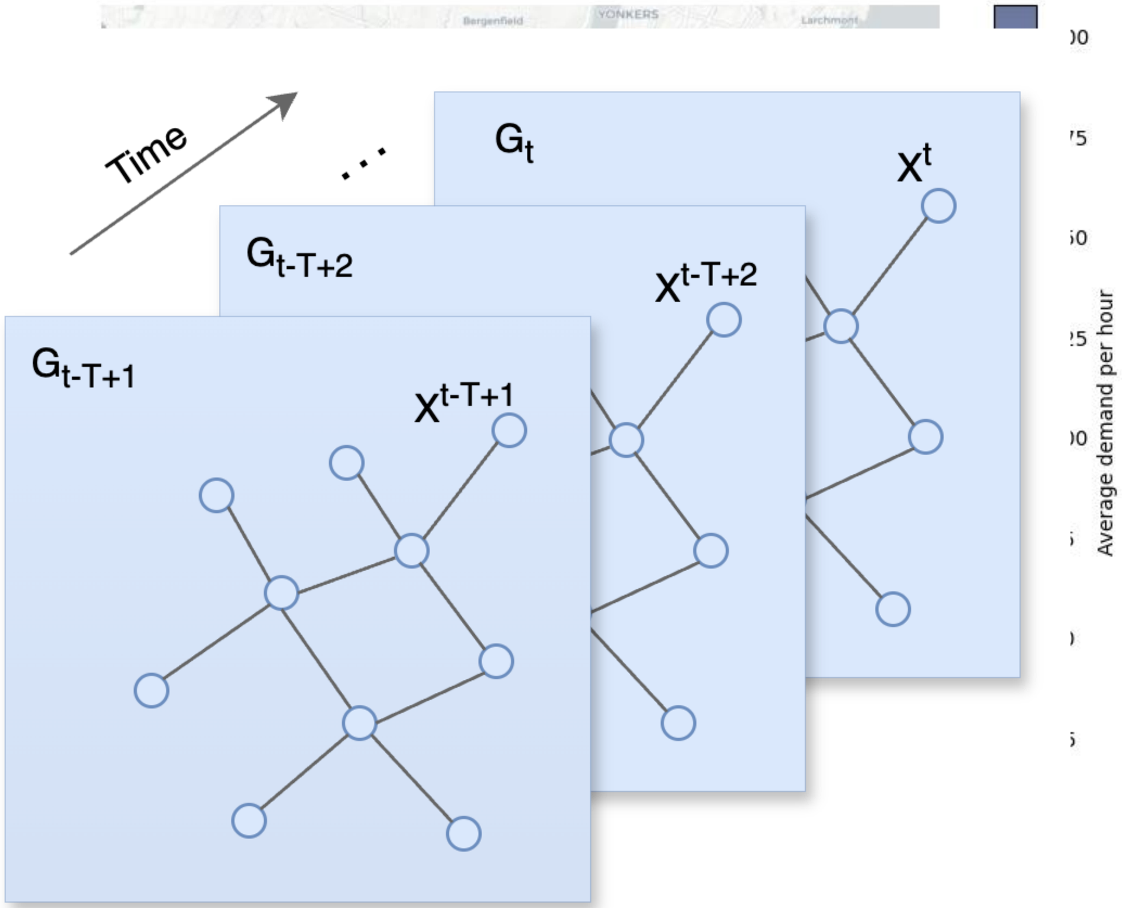
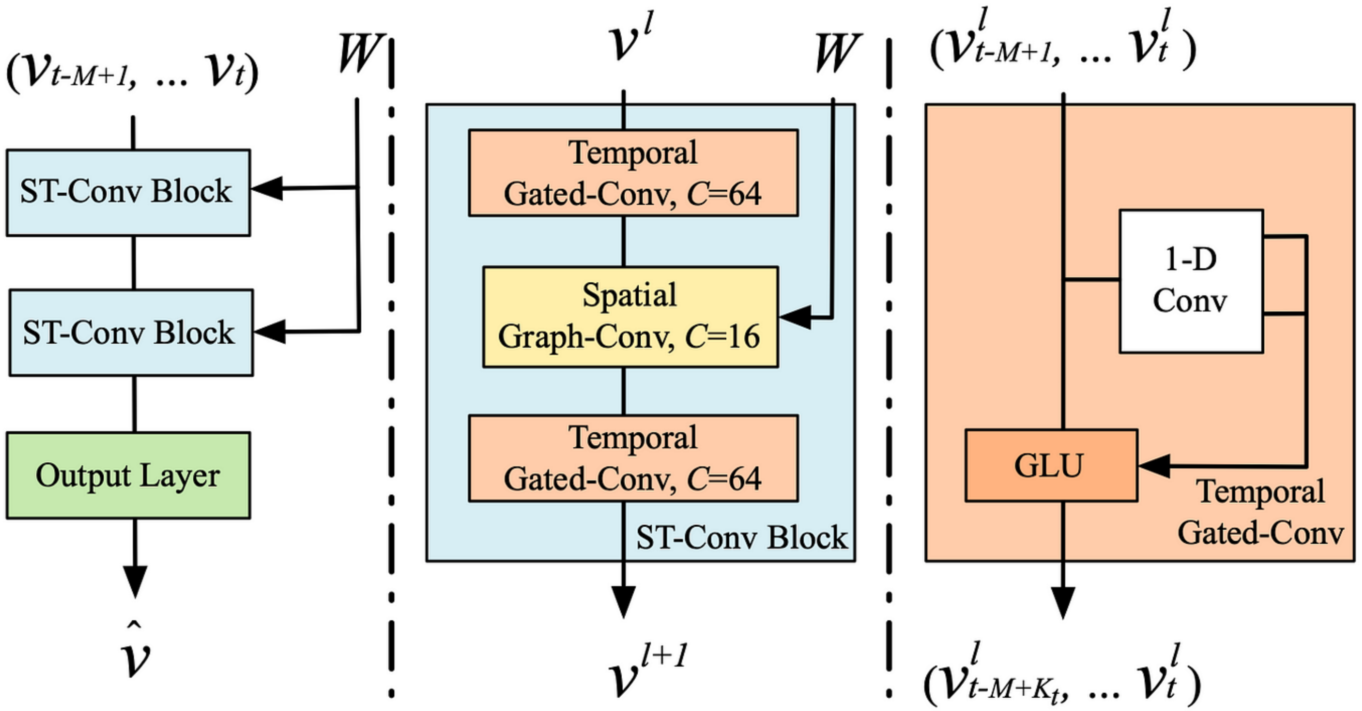
Data process

- Map are divided into regions by post code and adjacency matrix are generated based on this division.
- For each region, trip records are aggerated into one-hour intervals, so the time step is one hour
- The data set is converted into a series of graphs



Spatio-Temporal Graph Convolutional Networks



Yu, B., Yin, H., and Zhu, Z. (2017). Spatio-temporal graph convolutional networks: A deeplearning framework for traffic forecasting

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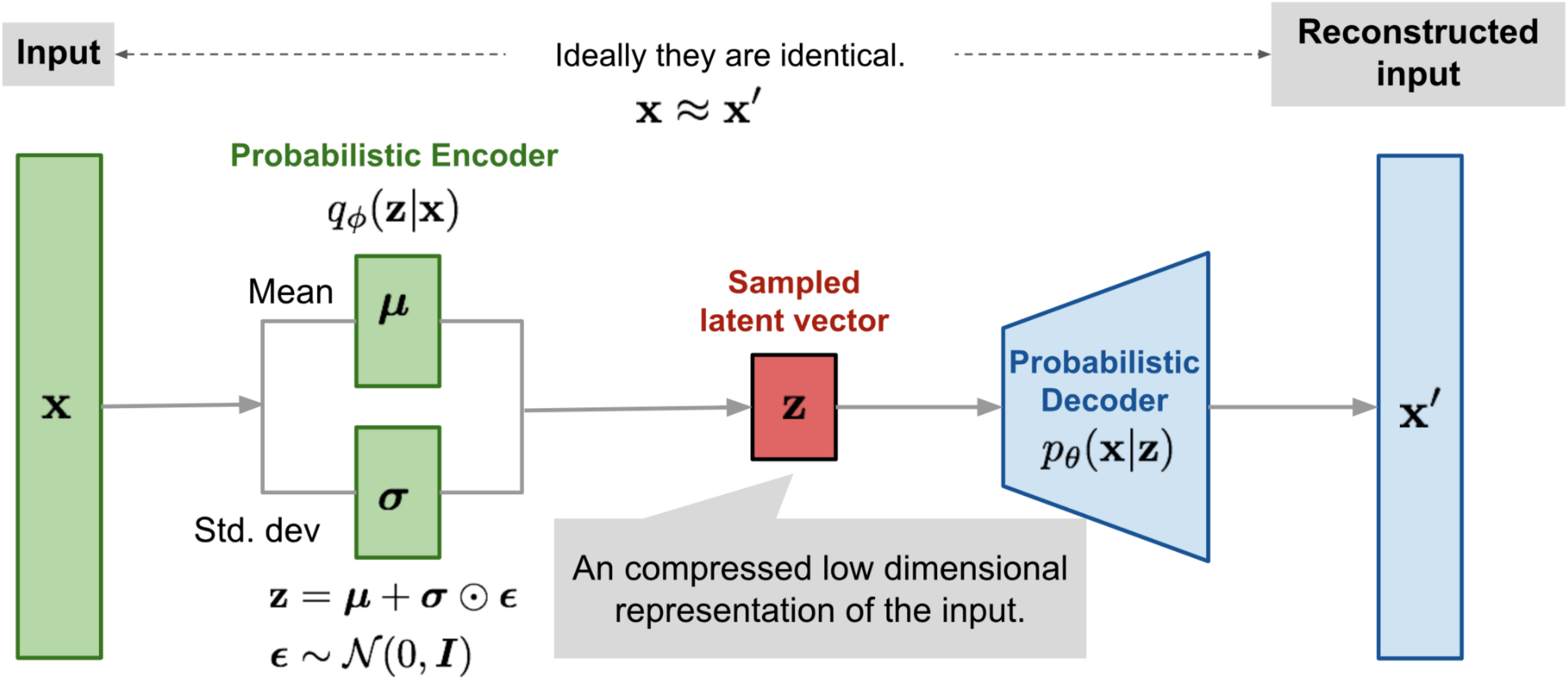
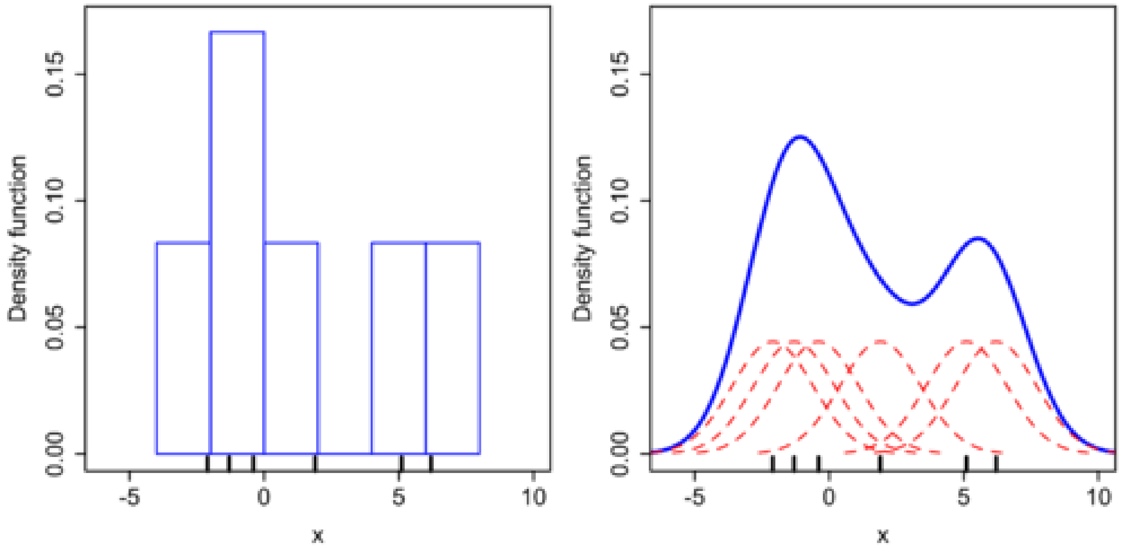
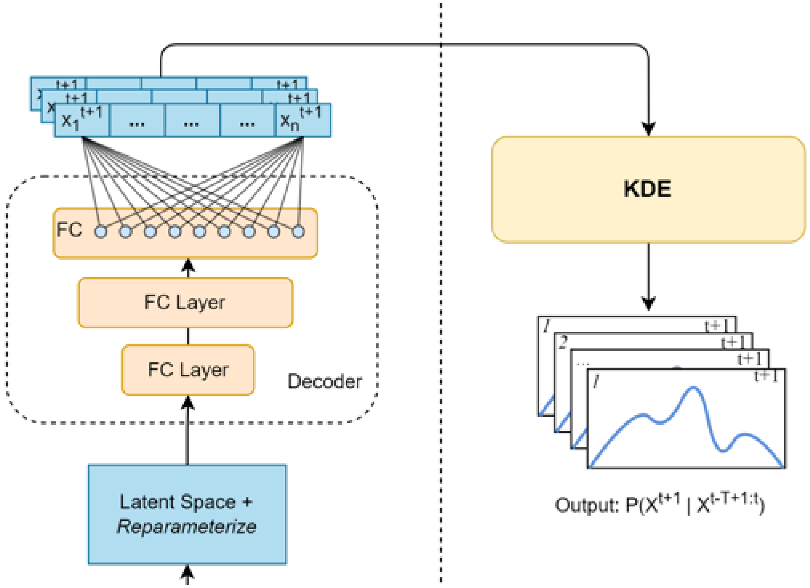
Variational autoencoder



Kernel density estimation

- Approximates the probability density function of a random variable by smoothing the distribution over the observed samples





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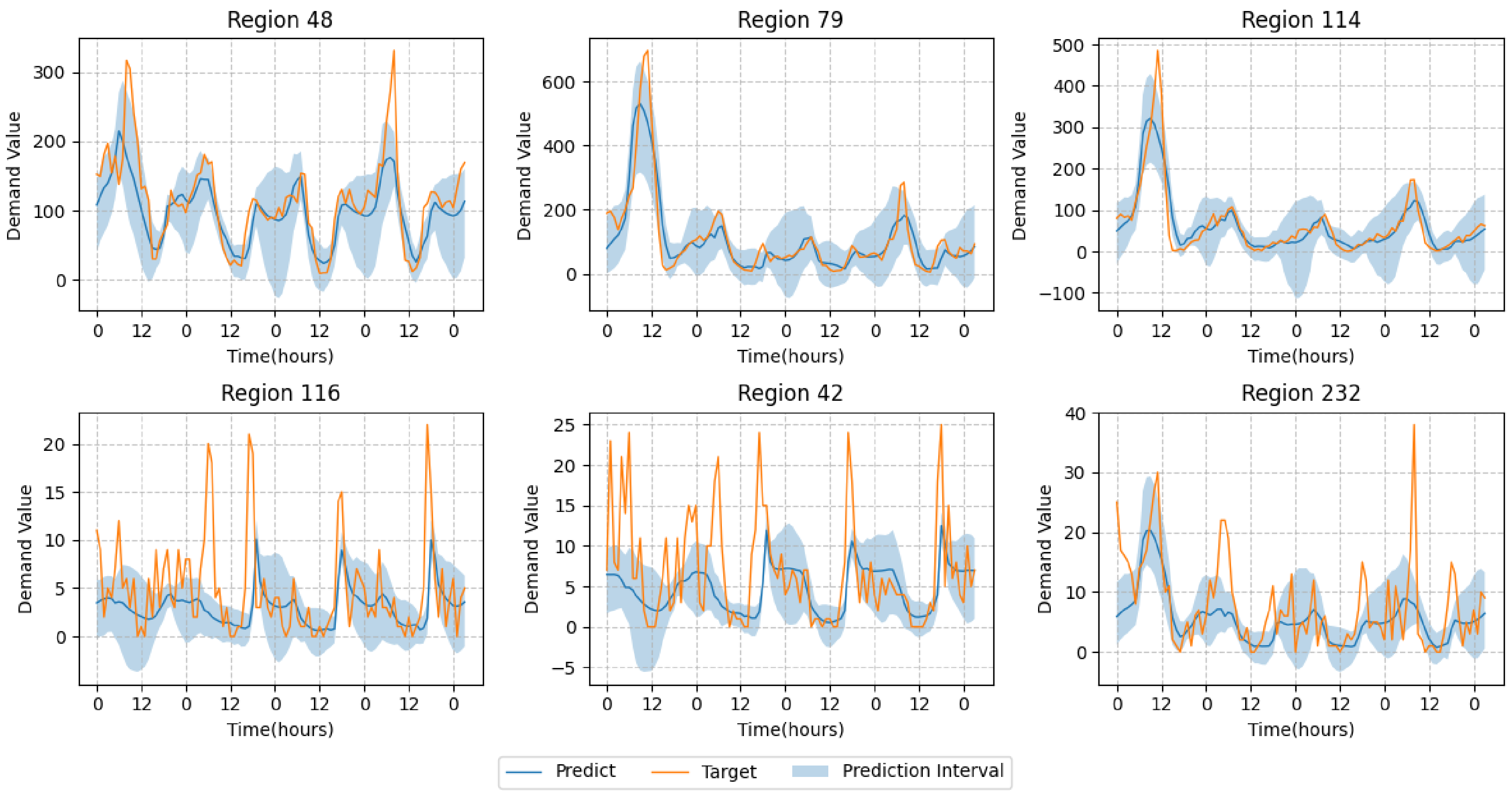
Performance

- MAE
- RMSE
- MPIW
- CRPS
- IS
- Time

Table 3: Comparison of redictive results across models (S+N: STGCN+Normal, S+L: STGCN+Lognormal, S+V: STGCN+VAE, our proposed model; model names abbreviated due to space constraints).

Metric	Region	Point forecasting	Probabilistic forecasting					
		STGCN	S+N	S+L	DeepAR	BNN-LSTM	DGGP	S+V
MAE	All	5.7487	5.8504	24.3598	11.0107	10.0087	8.4483	**5.4094**
	Low demand	0.9431	0.9548	1.7435	**0.7750**	1.6095	1.4297	0.8815
	High demand	27.2737	27.7788	125.6621	56.8581	41.8215	37.5961	**25.6908**
RMSE	All	29.3497	26.0853	64.9564	35.6128	32.5472	35.2685	**19.9317**
	Low demand	2.4184	2.3556	4.0361	2.7630	3.4655	3.2143	**2.1532**
	High demand	68.5096	60.8557	151.8075	83.1558	56.0011	62.3789	**46.2324**
MPIW	All	-	29.4285	13761.1612	29.1572	31.2340	34.8921	**23.8823**
	Low demand	-	3.3382	16234.3577	**1.2152**	4.6783	5.1234	6.0574
	High demand	-	146.2911	2683.3019	154.3143	154.9125	167.4532	**103.7229**
CRPS	All	-	22.8911	24.4993	20.9385	19.8754	21.3467	**17.1134**
	Low demand	-	3.5585	2.2019	**0.9861**	1.5432	1.6789	1.0643
	High demand	-	109.4855	124.3728	110.3097	98.7654	105.4321	**88.9996**
IS	All	-	76.7607	13761.1699	41.9638	38.5476	45.1234	**19.4128**
	Low demand	-	35.5485	16234.3681	**3.5794**	4.8765	5.2345	3.8665
	High demand	-	261.3572	2683.3020	213.8939	198.7654	220.9876	**89.0475**
Time	Train(min)	15	15	15	45	35	210	17
	Test(min)	1	1	1	5	5	20	2

Visualization of example locations



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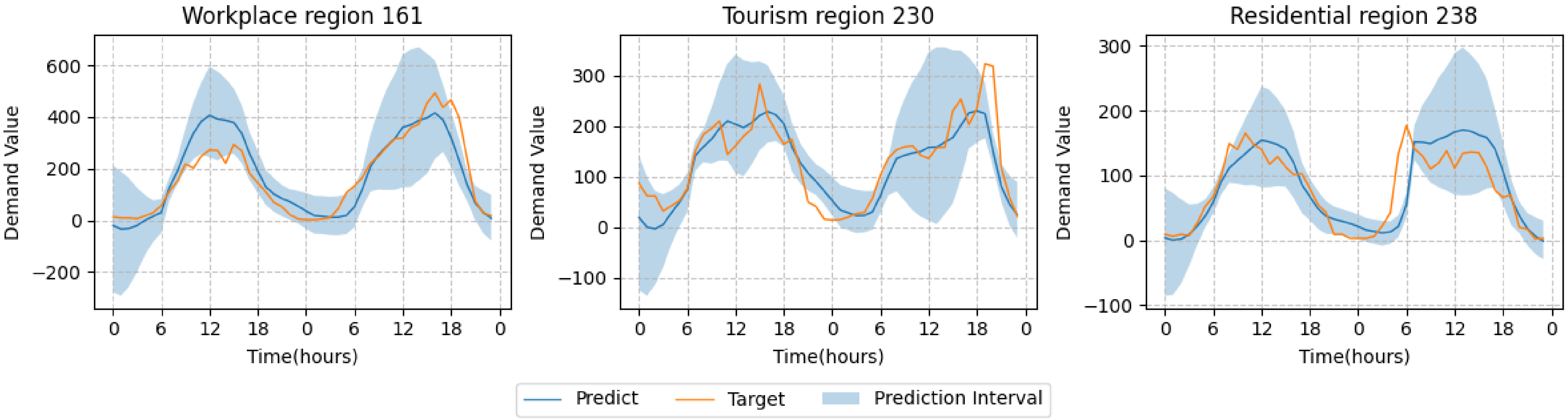
Uncertainty quantification



- Showing the different travel pattern at different regions
- Align with the real world

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Thank you for your attention

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