NEURAL INFORMATION PROCESSING SYSTEMS

NeurIPS 2023 Track on Datasets and Benchmarks

UUKG: Unified Urban Knowledge Graph Dataset for Urban Spatiotemporal Prediction

Yansong NING[1], Hao LIU[1,2], Hao WANG[3], Zhenyu ZENG[3], Hui XIONG[1,2]

[1]The Hong Kong University of Science and Technology (Guangzhou)
[2]The Hong Kong University of Science and Technology
[3]Alibaba Cloud Intelligence Group

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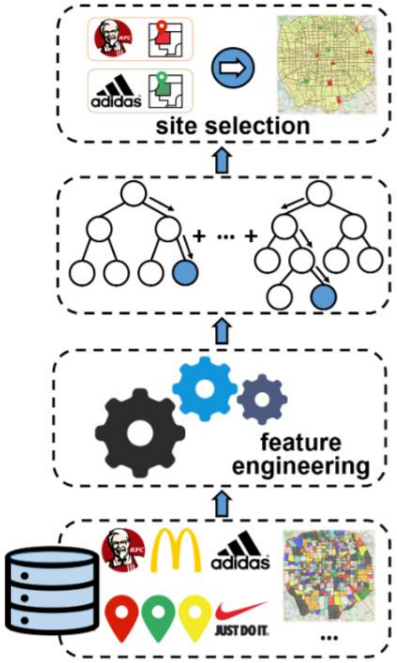
OUTLINE

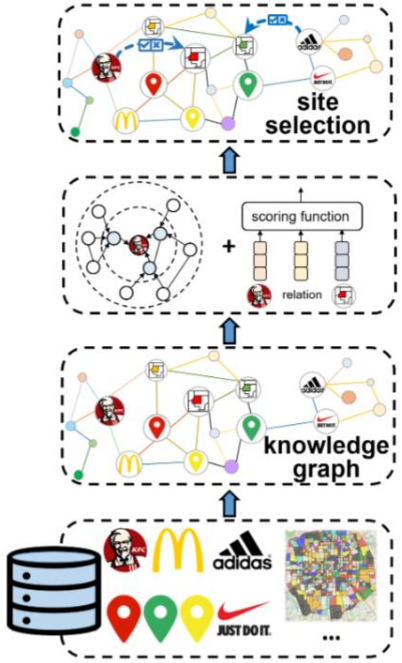
- **Motivation and Challenge**
- **Urban Knowledge Graph Construction**
- **Structure-aware Urban Knowledge Graph Embedding**
- **Knowledge-enhance Urban SpatioTemporal Prediction**
- **Conclusion and Future Work**

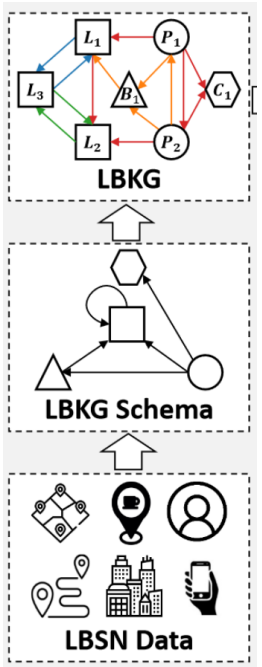
Motivation

Existing UrbanKGs

- Task-specific and publicly unavailable
- Limits the flourishing of knowledge-enhanced urban spatiotemporal prediction







[1] Liu, et al. Knowledge-driven site selection via urban knowledge graph. arXiv preprint arXiv:2111.00787 (2021). [2] https://www.iconexperience.com/
[3] Zhou, et al. Hierarchical knowledge graph learning enabled socioeconomic indicator prediction in location-based social network. Proceedings of the ACM Web Conference. 2023.

Challenge

How to Construct A Unified Urban Knowledge Graph

- The urban data describe the urban system from different aspects and granularities and they are usually disjoint
- It is appealing to extract and align heterogeneous urban knowledge in a unified graph organization

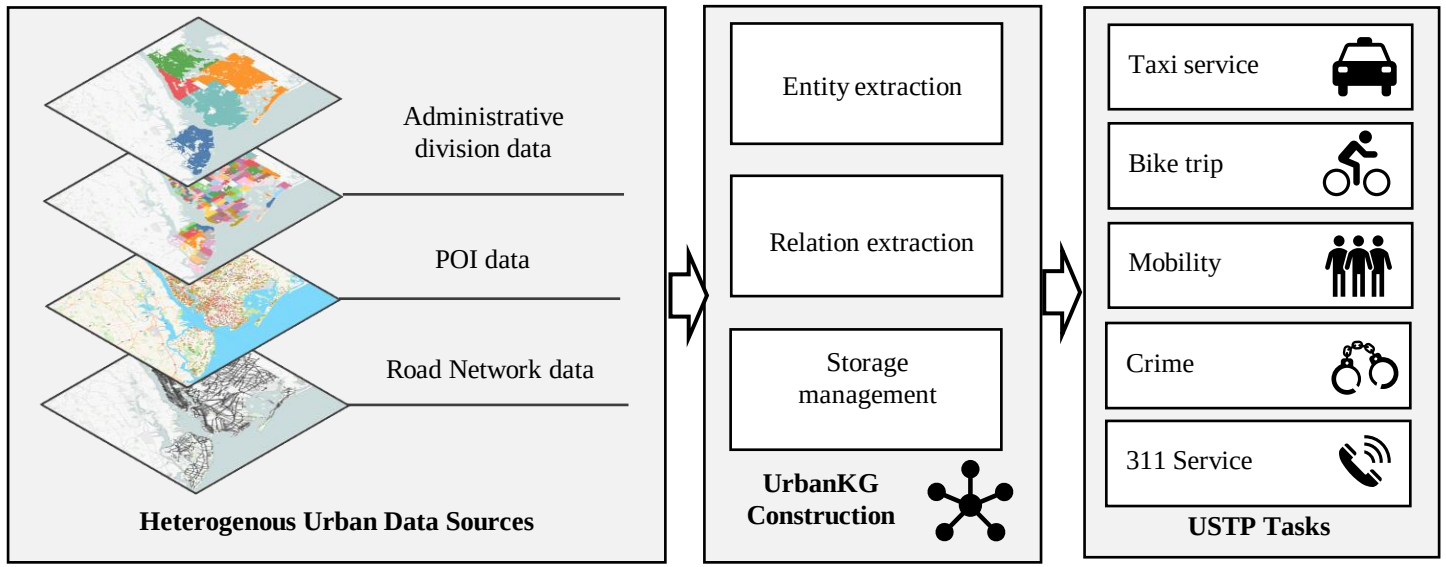
How to Preserve Complicated Structural Urban Knowledge

- Urban knowledge graph includes diverse structures such as hierarchy and cycle
- Capture such high-order semantic knowledge to empower downstream spatiotemporal prediction tasks

Unified Urban Knowledge Graph Dataset

Workflow

- Construct an urban knowledge graph from multi-sourced urban data
- Organize entities into a multi-relational heterogeneous graph
- Encode various high-order structural patterns in a unified configuration
- Facilitate joint processing for various downstream urban spatiotemporal prediction task



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Motivation and Challenge

Urban Knowledge Graph Construction

Structure-aware Urban Knowledge Graph Embedding

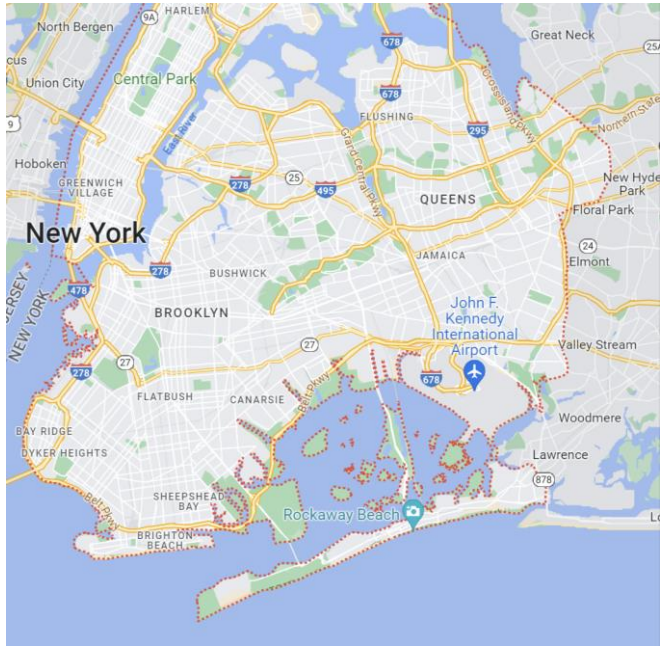
Knowledge-enhance Urban SpatioTemporal Prediction

Conclusion and Future Work

Urban Knowledge Graph (UrbanKG) Construction

UrbanKG Definition

- The UrbanKG is defined as a multi-relational graph $G = (E, R, F)$, where E, R, and F is the set of urban entities, relations and facts, respectively. In particular, facts are defined as set $\{\langle h, r, t\rangle | h, t \in E, r \in R\}$, where each triplet $\langle h, r, t\rangle$ describes that head entity h is connected with tail entity t via relation r



[1] https://www.google.com/maps [2] https://zola.planning.nyc.gov/

Urban Knowledge Graph (UrbanKG) Construction

Data Collection and Preprocessing

- Data sources: Open Street Map, NYC Gov and CHI Gov
- Data types:
  - ✓ Administrative division data: borough and area
  - ✓ Road Network data: segment and junction
  - ✓ Point-of-Interest (POI) data

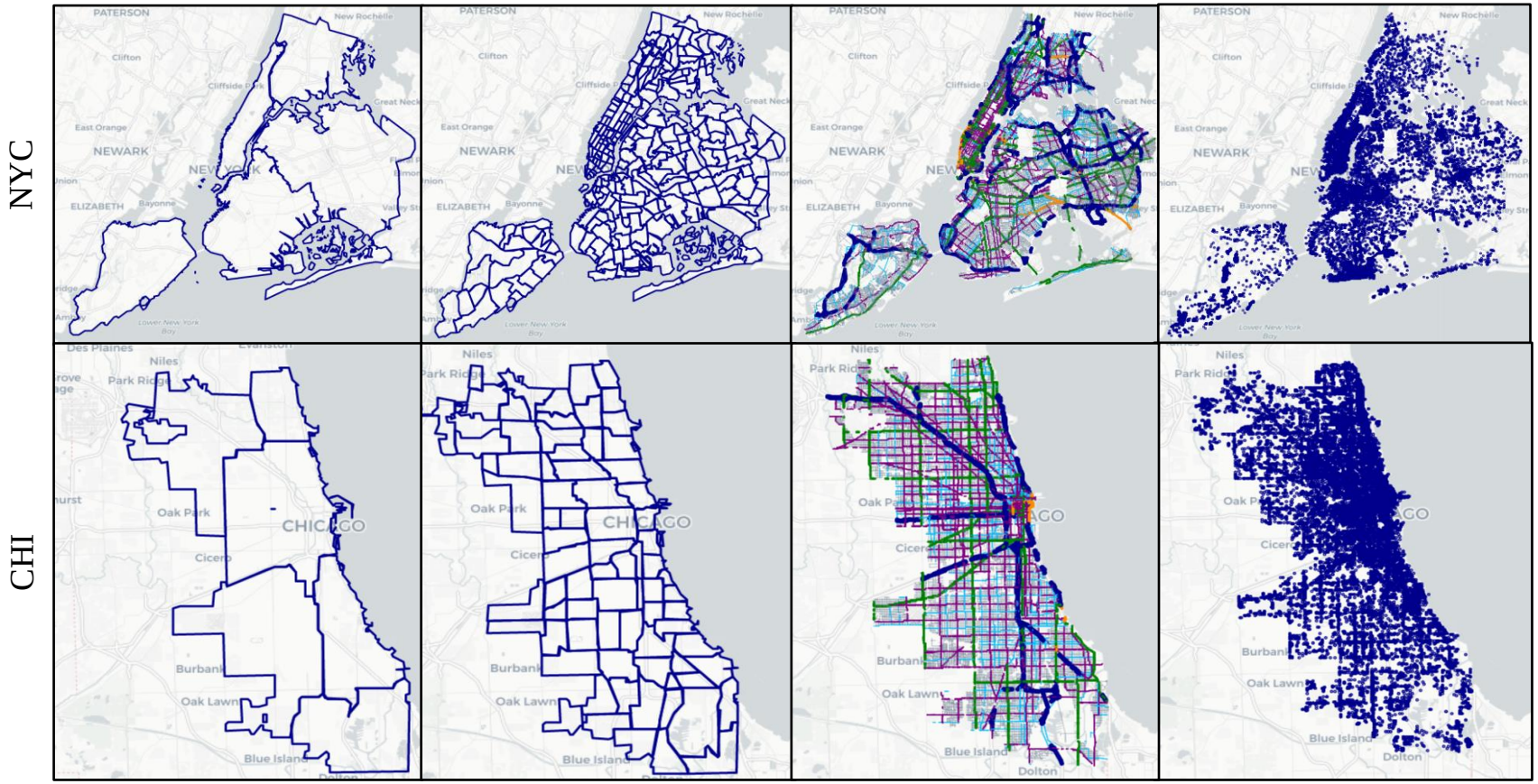
Dataset	Description	Sample format	Records New York	Records Chicago
Administrative division	Boundary	*["New Yorck", range(40.50, 40.91, -74.25, -73.70)]*	1	1
	# of Borough	*["Queens", polygon(40.54 -73.96, ...)]*	5	6
	# of Area	*["Jamaica", "Queens", polygon(40.69 -73.82, ...)]*	260	77
Road network	# of Segment	*[road id, road name, start junction, end junction, type, line range]*	110,919	71,578
	# of Category	*[191751, "Queens Boulevard", 59378, 4798, tertiary, line(40.73 -73.82, ...)]*	5	5
	# of Junction	*[junction id, junction type, coordinate]*	62,627	37,342
	# of Category	*[59378, crossing, coordinate(40.78 -73.98)]*	5	6
POI	# of POI	*[poi id, poi name, poi type, coordinate]*	62,450	31,573
	# of Category	*[34633854, "Empire State Building", corporation, coordinate(40.75, -73.99)]*	15	15

[1] https://www.openstreetmap.org/ [2] https://www.chicago.gov/ [3] https://www.nyc.gov/

Urban Knowledge Graph (UrbanKG) Construction

Entity Extraction

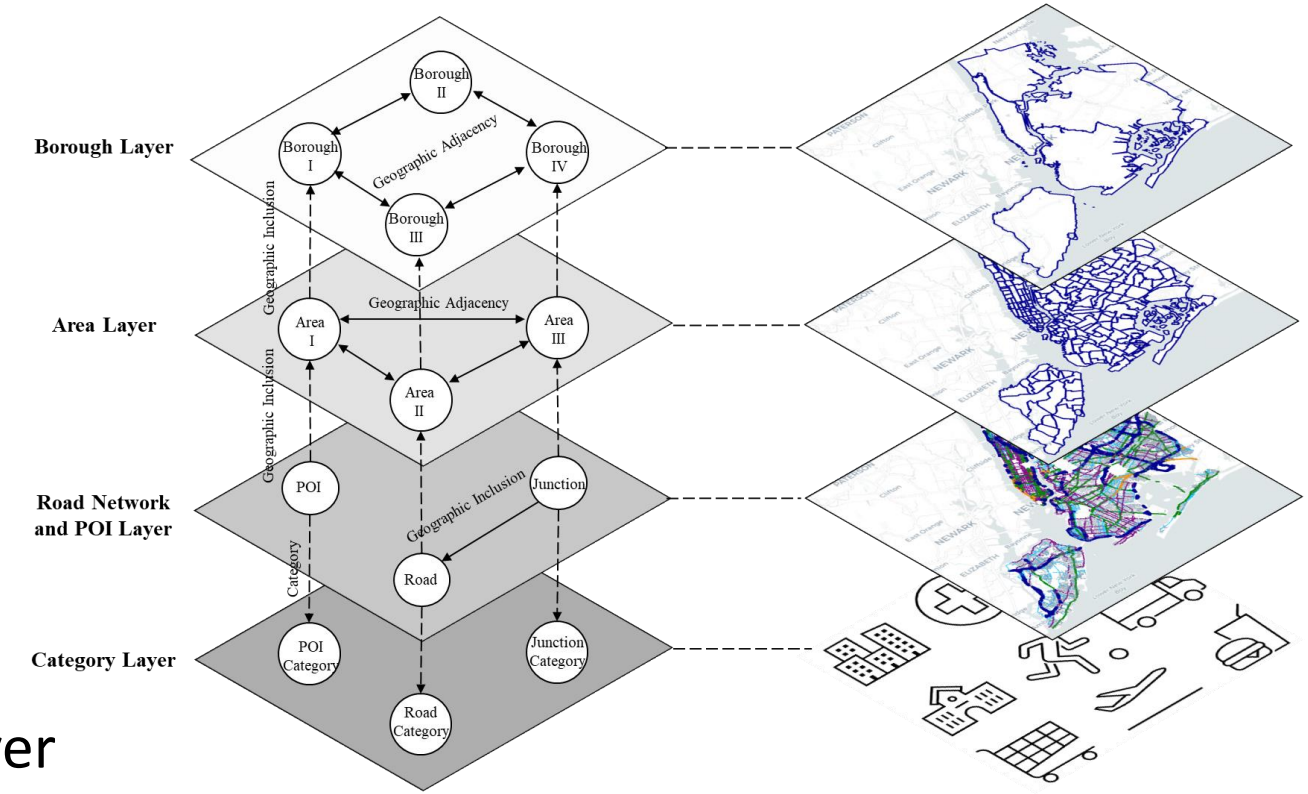
- Eight types of entities: borough, area, POI, road, junction, POI category, road category, junction category



Urban Knowledge Graph (UrbanKG) Construction

Relation Construction

- Three types of relations:
  - ✓ Geographic inclusion
  - ✓ Geographic adjacency
  - ✓ Category
- Four layers of UrbanKG:
  - ✓ Borough layer
  - ✓ Area layer
  - ✓ Road network and POI layer
  - ✓ Category layer



Relation	Symmetric	Head & Tail Entity	Abbrev.	Relation	Symmetric	Head & Tail Entity	Abbrev.
POI Locates at Area	×	(POI, Area)	PLA	Junction Belongs to Road	×	(Junction, Borough)	JBR
Road Locates at Area	×	(Road, Area)	RLA	Borough Nearby Borough	✓	(Borough, Borough)	BNB
Junction Locates at Area	×	(Junction, Area)	JLA	Area Nearby Area	✓	(Area, Area)	ANA
POI Belongs to Borough	×	(POI, Borough)	PBB	POI Has POI Category	×	(POI, PC)	PHPC
Road Belongs to Borough	×	(Road, Borough)	RBB	Road Has Road Category	×	(Road, RC)	RHRC
Junction Belongs to Borough	×	(Junction, Borough)	JBB	Junction Has Junction Category	×	(Junction, JC)	JHJC
Area Locates at Borough	×	(Area, Borough)	ALB	-	–	–	–

Urban Knowledge Graph (UrbanKG) Construction

Statistics of NYC and CHI UrbanKGs

- Two multi-level large-scale UrbanKGs
- Millions of triplets are preserved

Dataset	# Entity	# Relation	# Triplet	# Train	# Valid	# Test
NYC	236,287	13	930,240	837,216	46,512	46,512
CHI	140,602	13	564,400	507,960	28,220	28,220

[1] https://www.cntraveler.com/ [2] https://www.telegraph.co.uk/

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Motivation and Challenge

Urban Knowledge Graph Construction

Structure-aware Urban Knowledge Graph Embedding

Knowledge-enhance Urban SpatioTemporal Prediction

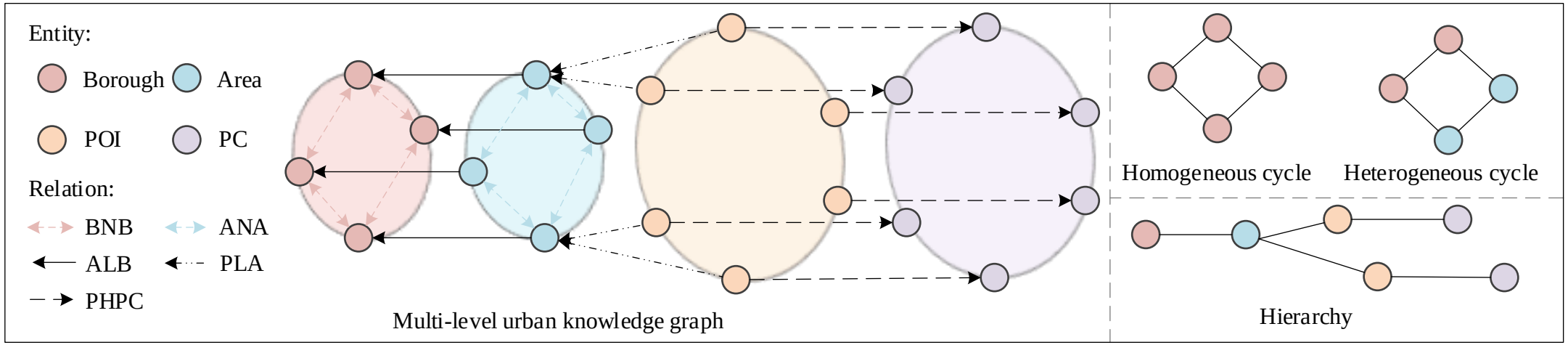
Conclusion and Future Work

Structure-aware Urban Knowledge Graph Embedding

Qualitative and Quantitative Structural Analysis

- High-order hierarchy: modeling such hierarchy empowers to uncover deeper semantics
- High-order cycle: geographic semantics could be induced by the topological cycles

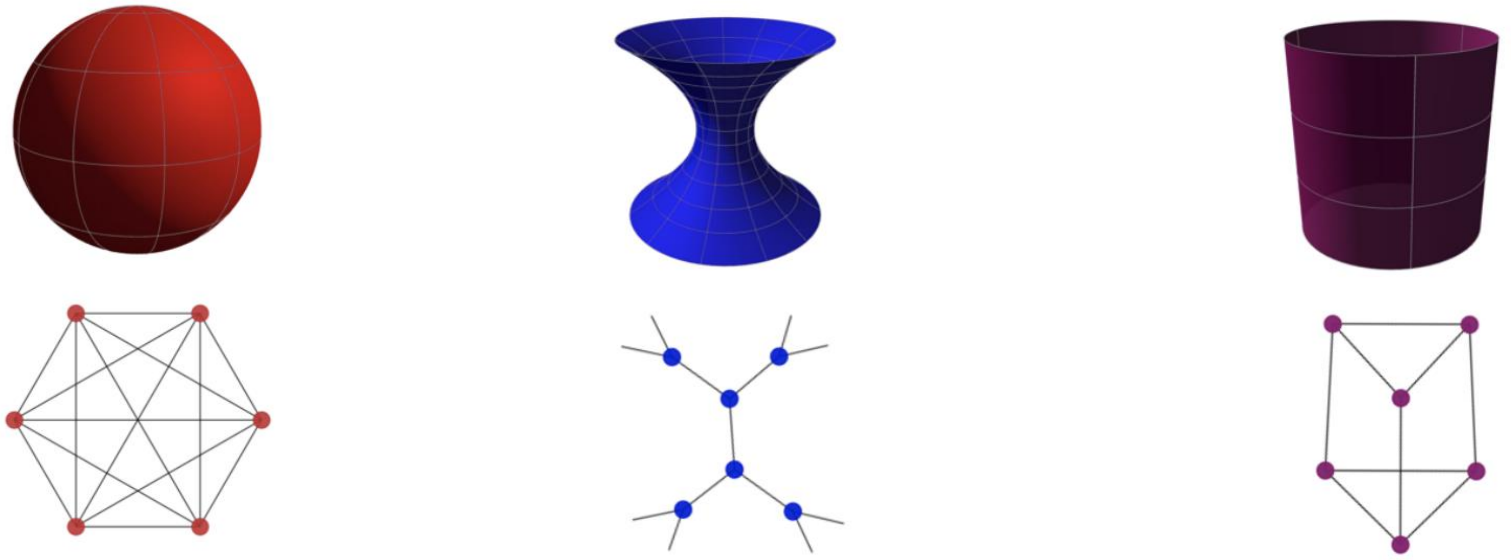
Dataset	# Entity	# Relation	# Triplet	# Train	# Valid	# Test	# Cycle	# Hyperbolicty
NYC	236,287	13	930,240	837,216	46,512	46,512	1,090,884	$\delta = 0$
CHI	140,602	13	564,400	507,960	28,220	28,220	532,108	$\delta = 0$



Structure-aware Urban Knowledge Graph Embedding

Derive Non-Euclidean Methods on UrbanKG Embedding

- Hierarchical structures are suitable to be represented in hyperbolic space
- Cyclic structures are suitable to be modeled in spherical space
- Model cycles and hierarchies in product space (i.e., the combination of hyperbolic and spherical space) simultaneously



spherical space　　hyperbolic space　　product space

[1] Giovanni, et al. Heterogeneous manifolds for curvature-aware graph embedding. ICLR 2022 Workshop on Geometric and Topological Representation Learning. 2022.

Structure-aware Urban Knowledge Graph Embedding

Experimental Setup

- Problem formulation: Learn low-dimensional embeddings of entities and relations. Evaluate UrbanKG embedding using the link prediction task, which aims to predict the missing head or tail entity for a triplet $\langle h, r, t \rangle$
- Baselines:
  - ✓ Euclidean models: TransE, DisMult, ComplEx, MuRE, TuckER, QuatE
  - ✓ Non-Euclidean models:
    - Hyperbolic space: MuRP, RotH, RefH, AttH, ConE
    - Spherical space: MuRS
    - Product space: M2GNN, GIE
- Evaluation metric:
  - ✓ MRR, the mean of the inverse of correct entity ranking
  - ✓ Hits@K, the percentage of correct entities in top-K ranked entities

Structure-aware Urban Knowledge Graph Embedding

Results

- Almost all non-Euclidean (i.e., hyperbolic and spherical space) embedding methods outperform Euclidean embedding method
- Product space obtains the dominant performance as it can capture hierarchies and cycles simultaneously

Type	Space	Model	NYC				CHI			
			MRR	Hits@10	Hits@3	Hits@1	MRR	Hits@10	Hits@3	Hits@1
Euclidean models	E	TransE	.507	.563	.528	.470	.485	.556	.501	.436
	E	DisMult	.401	.478	.433	.355	.395	.479	.469	.394
	E	MuRE	.516	.613	.545	.468	.493	.601	.536	.437
	E	TuckER	.513	.609	.541	.466	.488	.584	.525	.423
	C	RotatE	.274	.363	.309	.220	.306	.385	.336	.258
	C	ComplEx	.259	.357	.305	.195	.304	.385	.337	.253
	C	QuatE	.321	.388	.347	.282	.396	.490	.427	.345
Non-Euclidean models	S	MuRS	.528	.622	.552	.478	.501	.619	.536	.437
	H	MuRP	.545	.635	.570	.497	.519	.634	.555	.456
	H	RotH	.526	.601	.550	.472	.511	.626	.548	.447
	H	RefH	.524	.610	.549	.473	.509	.629	.542	.451
	H	ATTH	.539	.603	.556	.503	.514	.610	.542	.463
	H	ConE	.542	.629	.563	.485	.513	.617	.535	.465
	P	M2GNN	.561	.638	.578	.521	.540	.651	.571	.481
	P	GIE	.573	.665	.600	.523	.552	.660	.580	.498

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Knowledge-enhance Urban SpatioTemporal Prediction

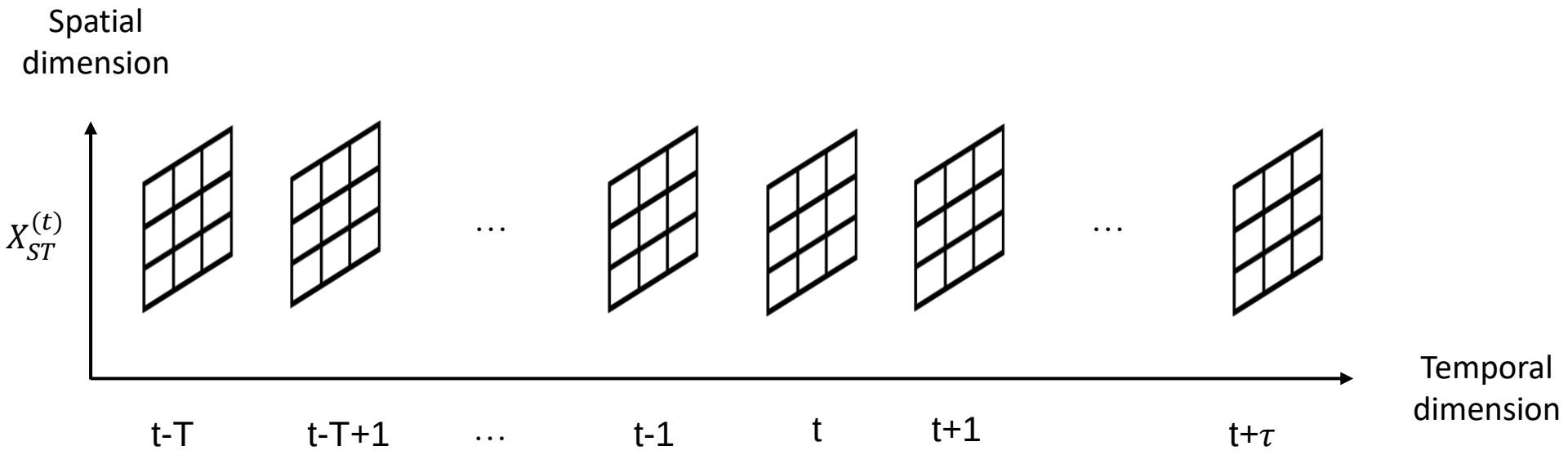
Conclusion and Future Work

Knowledge-enhance Urban SpatioTemporal Prediction

Problem Formulation

- Knowledge-enhanced urban spatiotemporal prediction (USTP) task aims to learn a multi-step prediction function f based on past observations $X_{ST}^{(t)} \in R^{N \times C}$ and the UrbanKG G:

$$\left(X_{ST}^{(t)}, X_{ST}^{(t+1)}, \ldots, X_{ST}^{(t+\tau)}\right) = f\left(\left(X_{ST}^{(t-T)}, X_{ST}^{(t-T+1)}, \ldots, X_{ST}^{(t-1)}\right), G\right)$$

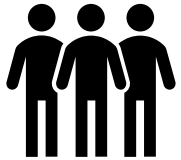


Knowledge-enhance Urban SpatioTemporal Prediction

Incorporating UrbanKG Embedding

- Five USTP tasks:
  - ✓ Taxi service: predict future area-level taxi inflow and outflow
  - ✓ Bike trip: forecast future road-level bike inflow and outflow
  - ✓ Human mobility: forecast future human inflow and outflow
  - ✓ Crime: binary classification
  - ✓ 311 service: binary classification
- Incorporate the UrbanKG by concatenating the entities' embeddings with the taxi flow features, e.g., $X_{ST}^{(t)} \in R^{N \times C_{taxi'}}$ where $C_{taxi'} = C_{taxi} \| e_{area}$, e_{area} is the embedding of area entity and $\|$ denotes the concatenation operation





Knowledge-enhance Urban SpatioTemporal Prediction

Statistics of Five USTP Datasets and Baselines

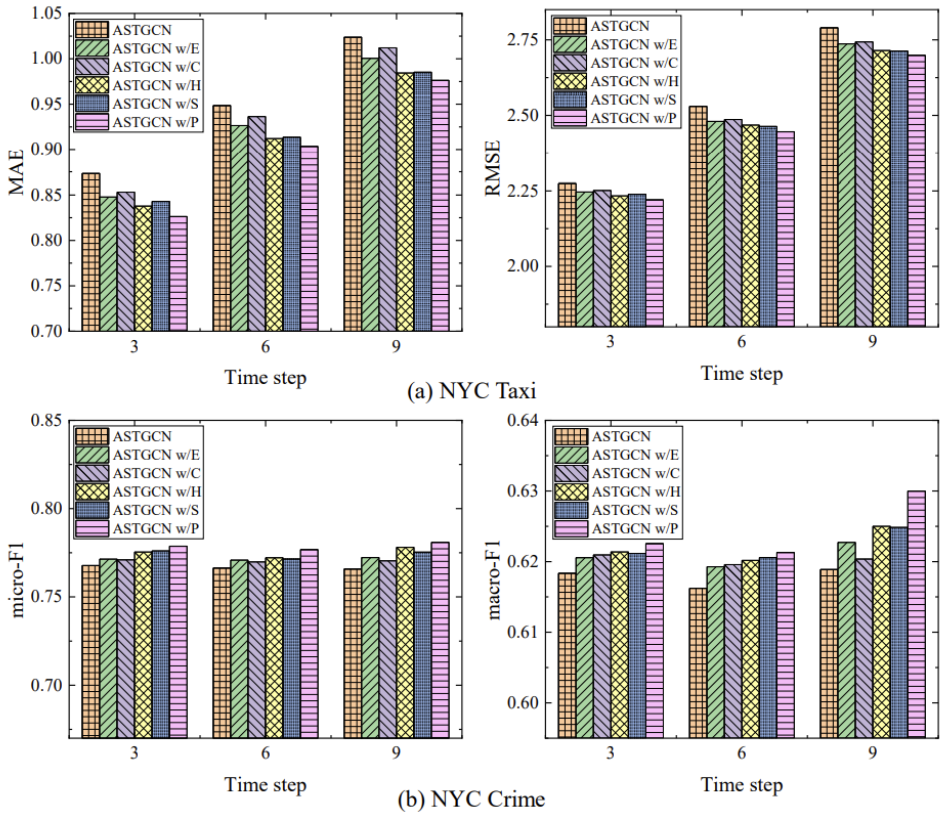
- Same dataset construction way for NYC and CHI
- Baselines:
  - ✓ Auto-Encoder, LSTM
  - ✓ STGCN, ASTGCN
  - ✓ MTGNN
  - ✓ AGCRN
  - ✓ TGCN, HGCN

Dataset	NYC					CHI				
	Taxi	Bike	Mobility	Crime	311 service	Taxi	Bike	Mobility	Crime	311 service
# of records	1,118,584	383,919	1,052,232	389,551	3,141,153	3,826,868	1,085,690	939,543	202,291	1,821,949
# of vertices	260	2,500	1,600	260	260	77	1,500	1,000	77	77
Time span	04/01/2020-06/31/2020			01/01/2021-31/12/2021		04/01/2019-06/31/2019			01/01/2021-31/12/2021	
Time interval	30 minutes			120 minutes		30 minutes			120 minutes	

Knowledge-enhance Urban SpatioTemporal Prediction

Comparison of UrbanKG Embedding Space Variants

- UrbanKG embedding could enhance USTP tasks regardless of which space they come from
- Hyperbolic space and spherical space embedding demonstrate greater performance improvement
- Embedding derived from the product space yields the most substantial benefit for both urban flow forecasting and urban event prediction



Knowledge-enhance Urban SpatioTemporal Prediction

Results

- UrbanKG embedding consistently improves the accuracy of five USTP task
- UrbanKG embedding consistently improves the accuracy of six existing USTP models

Model	NYC					CHI				
	Taxi MAE/RMSE	Bike MAE/RMSE	Mobility MAE/RMSE	Crime Micro/Macro-F1	311 service Micro/Macro-F1	Taxi MAE/RMSE	Bike MAE/RMSE	Mobility MAE/RMSE	Crime Micro/Macro-F1	311 service Micro/Macro-F1
GRU	1.802/3.587	0.920/1.115	1.003/1.318	-/-	-/-	3.372/8.895	1.431/2.619	1.157/1.800	-/-	-/-
LSTM	1.425/2.769	0.832/0.994	0.984/1.227	-/-	-/-	3.075/9.076	1.359/2.259	1.107/1.682	-/-	-/-
AE	1.399/2.484	0.701/0.898	0.956/1.233	56.42/52.12	65.68/59.64	3.313/11.64	1.416/2.706	1.148/1.721	57.49/57.27	54.67/55.34
STGCN	0.835/2.069	0.221/0.558	0.553/0.976	76.80/63.10	81.15/78.50	1.967/6.014	0.632/1.537	0.458/1.138	71.86/68.71	79.67/79.47
STGCN w/P	0.781/1.942	0.201/0.543	0.542/0.947	77.56/64.26	81.98/79.15	1.844/5.826	0.625/1.501	0.414/1.064	72.18/68.93	79.92/79.83
Improv %	6.47%/6.14%	9.05%/2.69%	1.99%/2.97%	0.99%/1.84%	1.02%/0.83%	6.25%/3.13%	1.11%/2.34%	9.61%/6.50%	0.45%/0.32%	0.31%/0.45%
MTGNN	1.289/2.275	0.967/1.041	0.963/1.163	72.88/58.61	79.32/75.75	2.167/5.965	1.153/1.723	1.081/1.504	68.48/66.46	76.72/76.32
MTGNN w/P	1.183/2.118	0.920/1.021	0.891/1.083	73.47/60.02	80.28/77.85	1.975/5.882	1.083/1.641	0.983/1.399	71.73/68.65	78.29/77.99
Improv %	8.22%/6.90%	4.86%/1.92%	7.48%/6.8%	0.81%/2.41%	1.21%/2.77%	8.86%/1.39%	6.07%/4.76%	9.07%/6.98%	4.75%/3.30%	2.05%/2.19%
AGCRN	1.315/2.391	0.958/1.038	0.945/1.148	65.98/60.62	75.68/69.64	2.403/7.277	1.187/1.768	0.213/1.281	64.14/63.35	71.18/67.07
AGCRN w/P	1.208/2.221	0.875/0.983	0.901/1.067	67.75/61.88	76.35/72.57	2.255/6.945	1.093/1.621	0.205/1.258	66.51/65.27	72.87/70.54
Improv %	8.14%/7.11%	8.66%/5.30%	4.66%/7.06%	2.68%/2.08%	0.89%/4.21%	6.16%/4.56%	7.92%/8.31%	3.76%/1.80%	3.71%/3.03%	2.37%/5.17%
ASTGCN	0.832/2.141	0.231/0.579	0.566/0.973	76.69/61.62	80.82/77.45	1.849/5.323	0.745/1.822	0.505/1.259	71.77/68.45	79.18/78.93
ASTGCN w/P	0.805/2.012	0.220/0.564	0.558/0.944	76.94/62.34	81.28/78.85	1.822/5.198	0.690/1.754	0.463/1.191	72.22/68.90	80.09/79.98
Improv %	3.25%/6.03%	4.76%/2.59%	1.41%/2.98%	0.33%/1.17%	0.57%/1.81%	1.46%/2.35%	7.38%/3.73%	8.32%/5.40%	0.63%/0.66%	1.15%/1.33%
TGCN	1.701/3.198	0.337/0.685	0.654/1.118	75.22/63.19	77.56/72.96	2.112/6.645	1.127/2.583	0.702/1.665	70.62/66.41	77.89/77.57
TGCN w/P	1.578/2.887	0.319/0.664	0.635/1.054	76.01/63.65	79.29/73.47	1.997/6.502	1.052/2.341	0.677/1.586	71.26/68.38	78.49/78.25
Improv %	7.23%/9.72%	5.34%/3.07%	2.91%/5.72%	1.05%/0.73%	2.23%/0.70%	5.45%/2.15%	6.65%/9.37%	3.56%/4.74%	0.91%/2.97%	0.77%/0.88%
HGCN	1.337/2.285	0.951/1.138	0.971/1.200	76.04/62.26	75.68/69.64	2.765/7.849	1.159/1.794	0.661/1.277	67.57/62.31	74.67/73.53
HGCN w/P	1.282/2.124	0.879/1.036	0.921/1.104	76.70/63.25	77.41/72.76	2.609/7.781	1.092/1.682	0.637/1.146	69.17/65.7	75.87/75.32
Improv %	4.11%/7.05%	7.57%/8.96%	5.15%/8.00%	0.87%/1.59%	2.29%/4.48%	5.64%/0.87%	5.78%/6.24%	3.63%/10.2%	2.37%/5.44%	1.61%/2.43%

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Conclusion and Future Work

Conclusion

- To the best of our knowledge, UUKG is the first open-source urban knowledge graph dataset compatible with various aligned USTP tasks
- Urban high-order structure modeling is important for urban knowledge representation and structure-aware KG embedding methods could capture them effectively

Limitation

- All experiments were conducted in two US metropolises and we only consider concatenation operation for embedding fusion

Future Work

- Derive extra multi-modal data (e.g., images, reviews) to enrich the UrbanKG and introduce more USTP tasks (e.g., trajectory prediction and site selection)

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Our Github repository will be continuously updated!
https://github.com/usail-hkust/UUKG

Thank You!
Q & A

Contact us if you have further questions.

✉ yning092@connect.hkust-gz.edu.cn, liuh@ust.hk