UniST: A Prompt-Empowered Universal Model for Urban Spatio-Temporal Prediction

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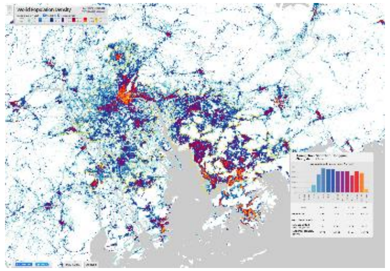
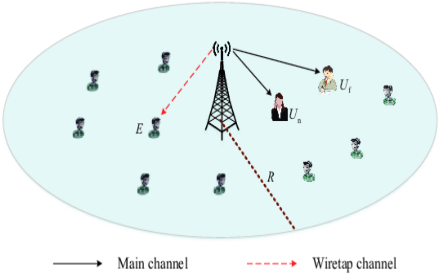
Urban Spatio-Temporal Intelligence

Planning and Building a Smart City

Urban Spatio-Temporal Intelligence

Diverse Spatio-Temporal Scenarios

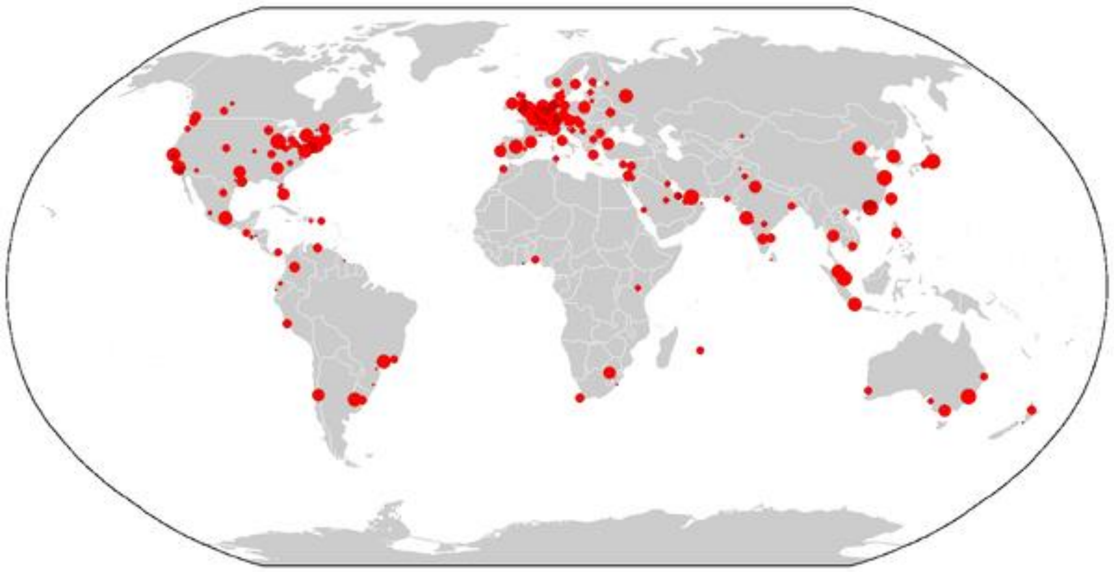


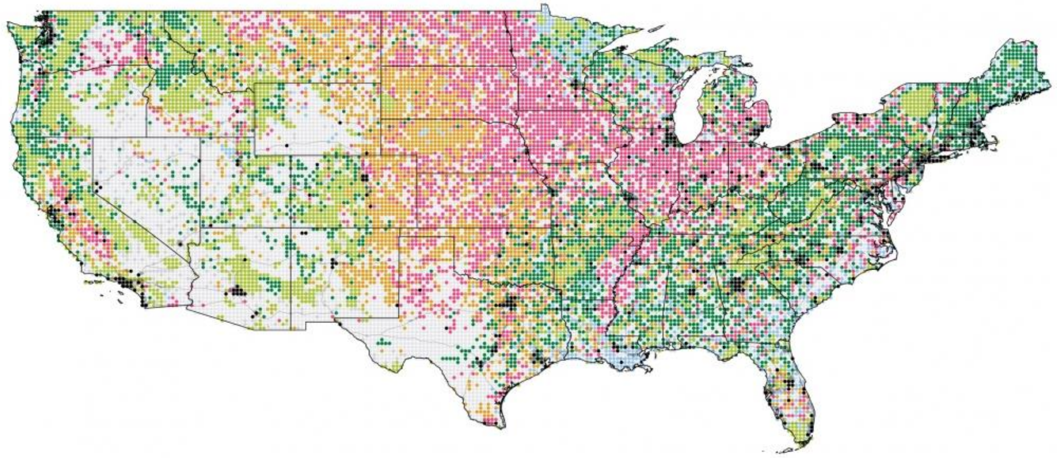


Various <u>domains</u>: human mobility, road traffic, network service, environmental pollution, power dispatch……

Urban Spatio-Temporal Intelligence

Diverse Spatio-Temporal Scenarios





Various cities around the world

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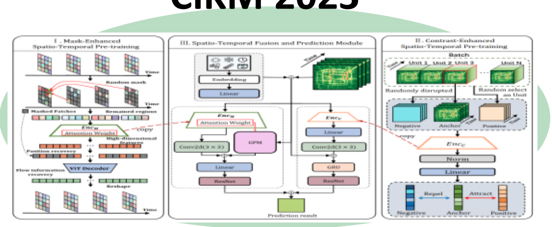
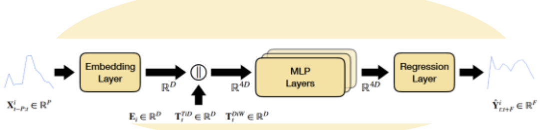
Existing AI models for ST data

Separate models for different spatio-temporal scenarios

MC-STL,
CIKM 2023



STID,
KDD 2022



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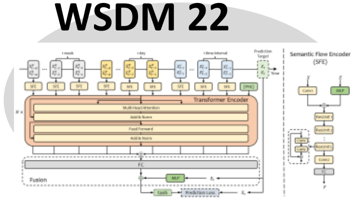
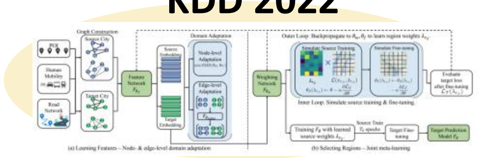
STGSP
WSDM 22



CrossTreS,
KDD 2022



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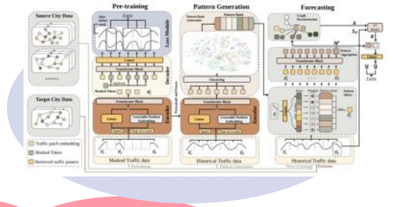
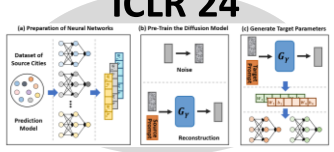
TPB
CIKM 23



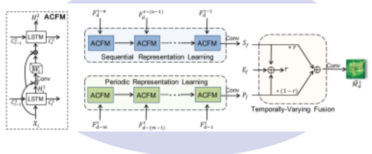
Urban spatio-temporal prediction
traffic prediction, flow prediction
......

Cross-city transfer learning

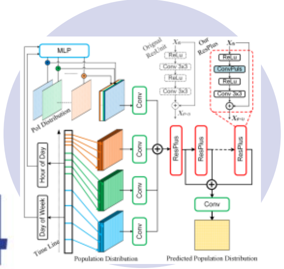
GPD
ICLR 24



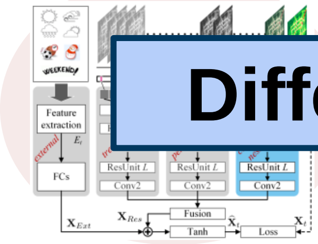
ATFM
MM 18



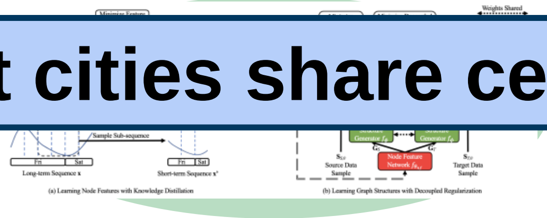
DeepSTN+
AAAI 19



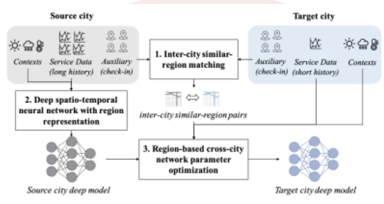
STResNet
AAAI 17



TransGTR,
KDD 23



Different cities share certain similarities



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Is it possible to build a universal model?

Urban spatio-temporal prediction

Cross-city transfer learning

Urban spatio-temporal universal model?

Cross-city
Cross-domain
One-for-all
Zero-shot prediction

Urban Spatio-Temporal Universal Model

LLMs

LVMs

?

Urban Spatio-Temporal Universal Model

LLMs

LVMs

ST data does not directly depend on language and images.

Urban Spatio-Temporal Universal Model

LLMs

LVMs

How far can we go from ST data alone?

Urban Spatio-Temporal Universal Model

LLMs

DALL·E

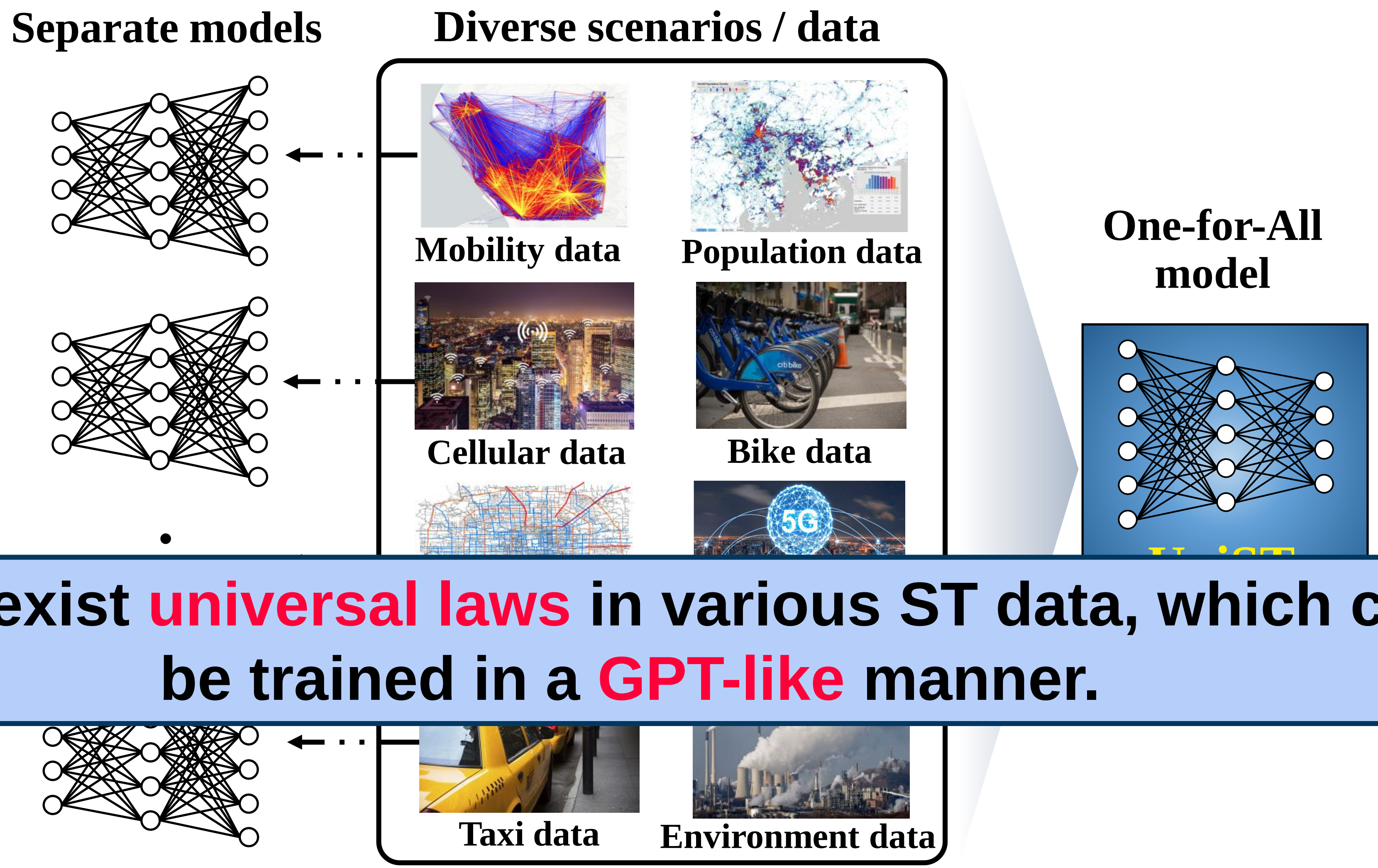
LVMs

Urban ST Universal Model

Universality

Generalization

Urban Spatio-Temporal Universal Model



There exist universal laws in various ST data, which can be trained in a GPT-like manner.

A universal model should be like

- ✓ *Scalability* with massive and diverse datasets
- ✓ *Self-supervised learning* to capture inherent relationships
- ✓ Powerful *generalization* capabilities

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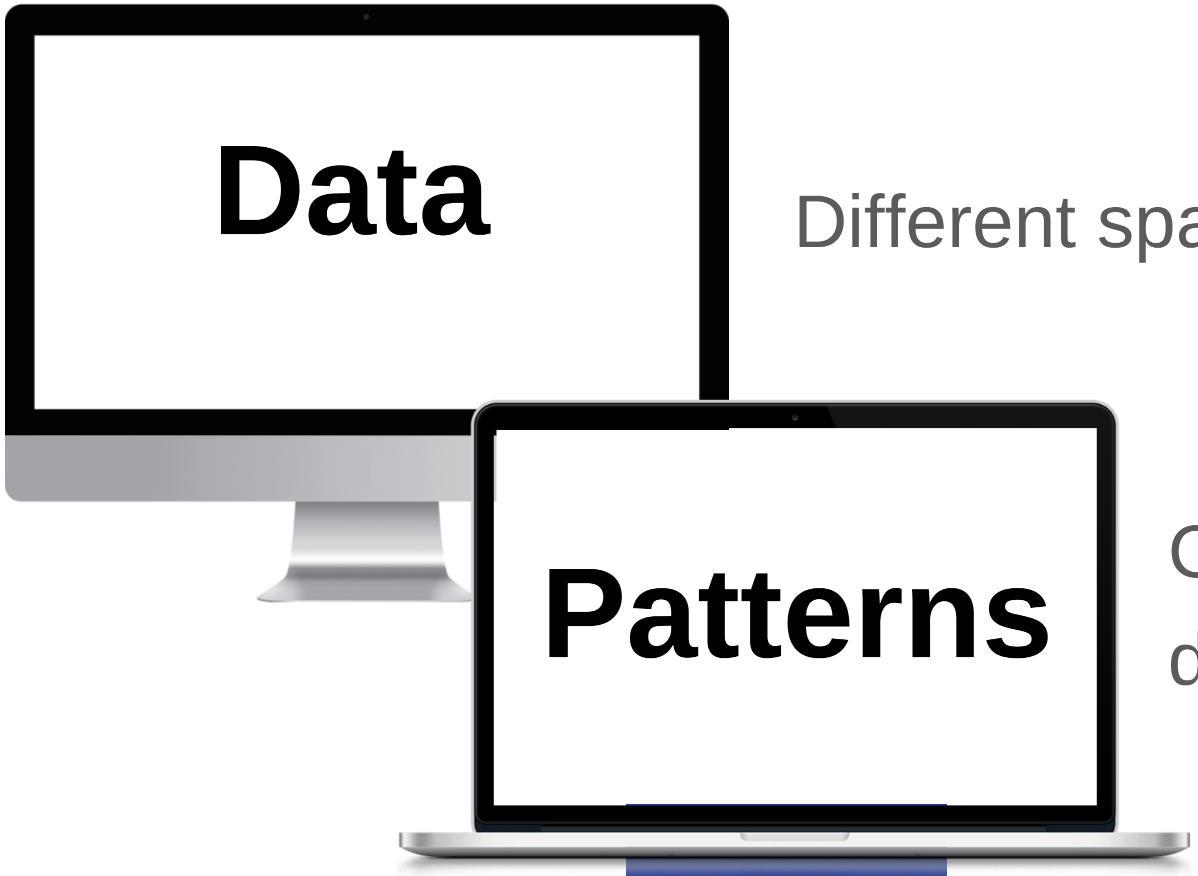
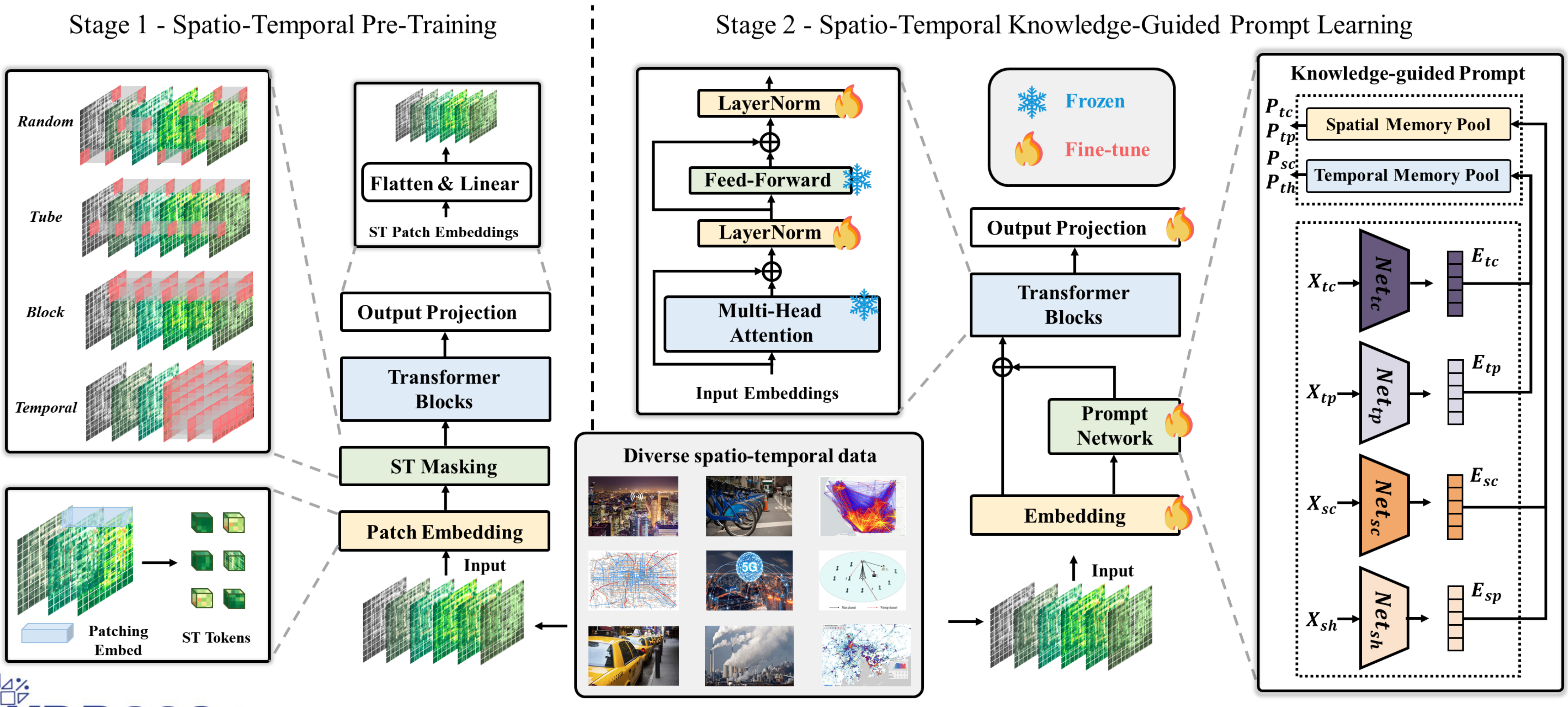
Two Challenges



Different spatio-temporal scales

Complex and varied spatio-temporal dynamics and patterns

20+ ST datasets, with over 130 million ST points → *UniST*



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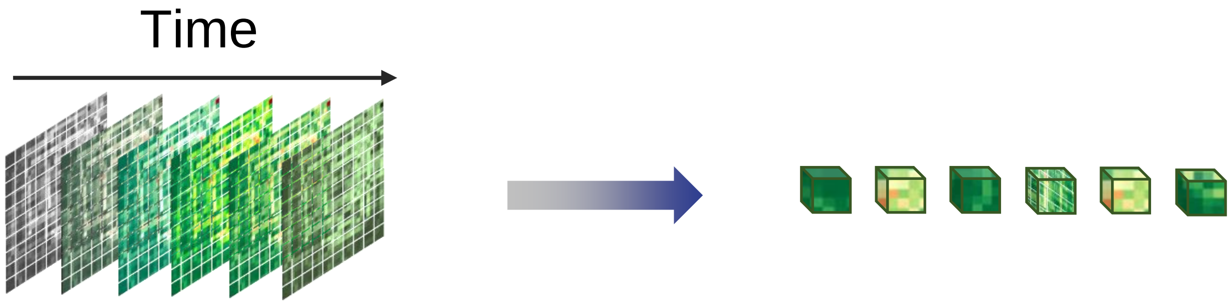
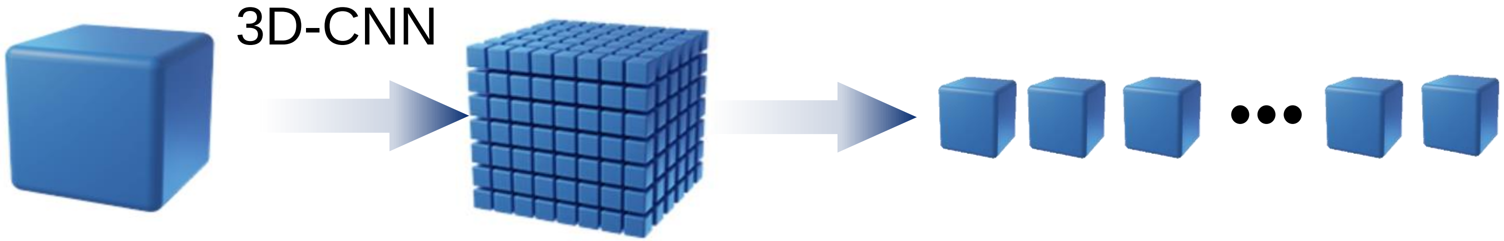
Spatio-Temporal Patching

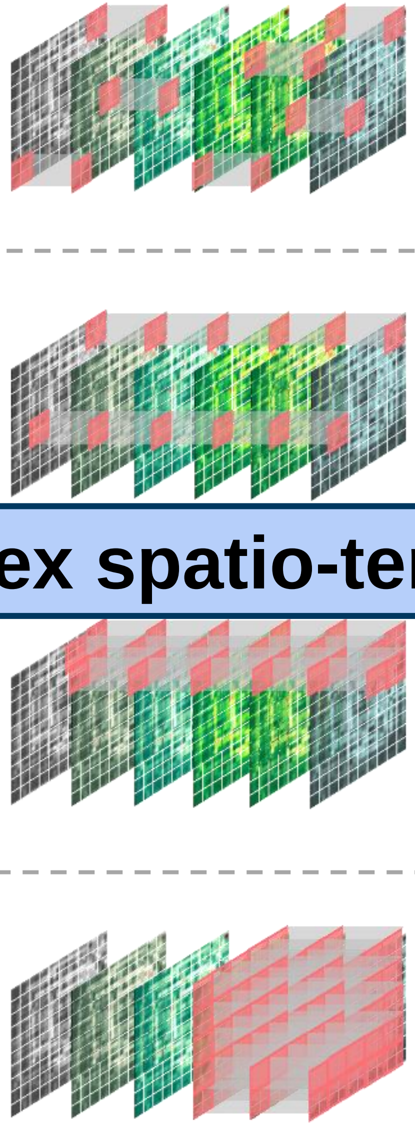
Patching: ST data → Sequential units





Spatio-Temporal Pre-training

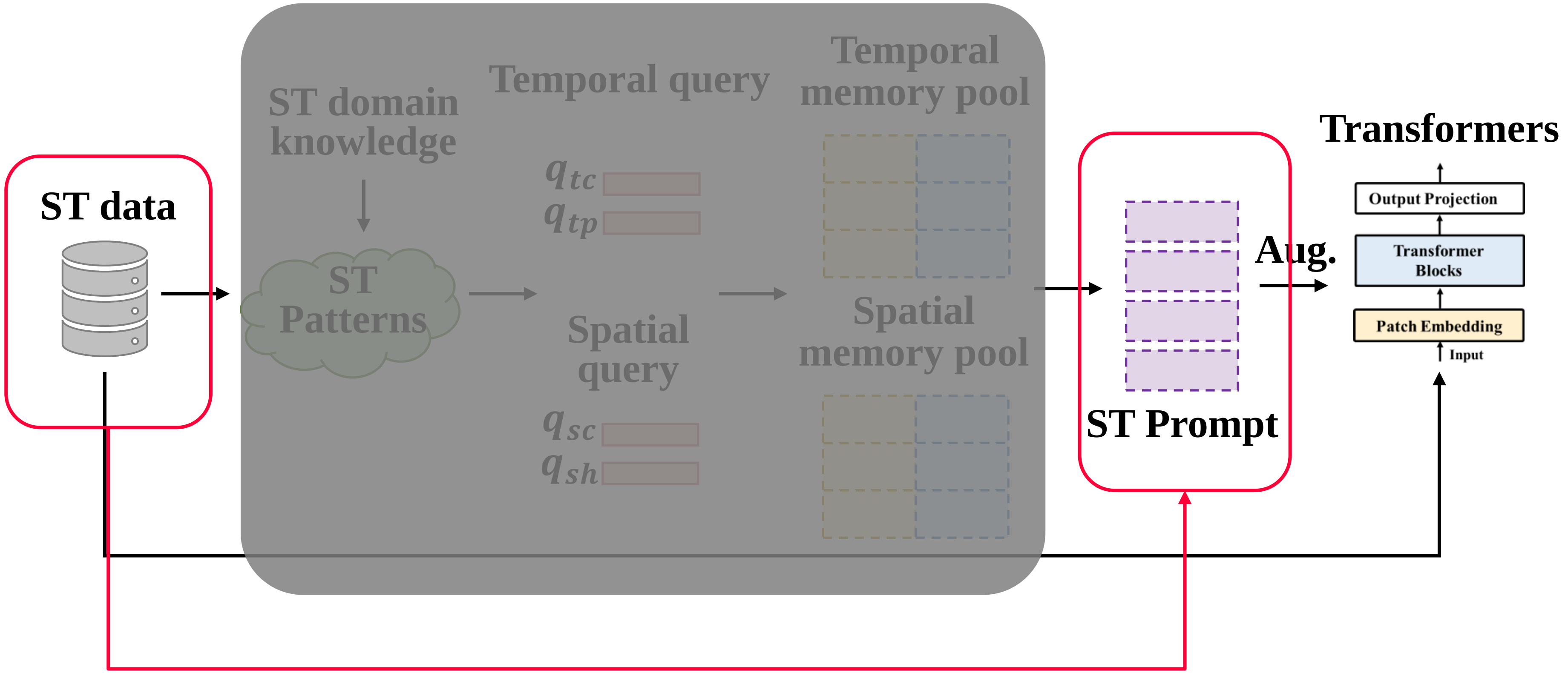
ST SSL



Random	Fine-grained ST relationships
Tube	Spatial extrapolation
Block	Spatial transfer
Temporal	Causal relationships

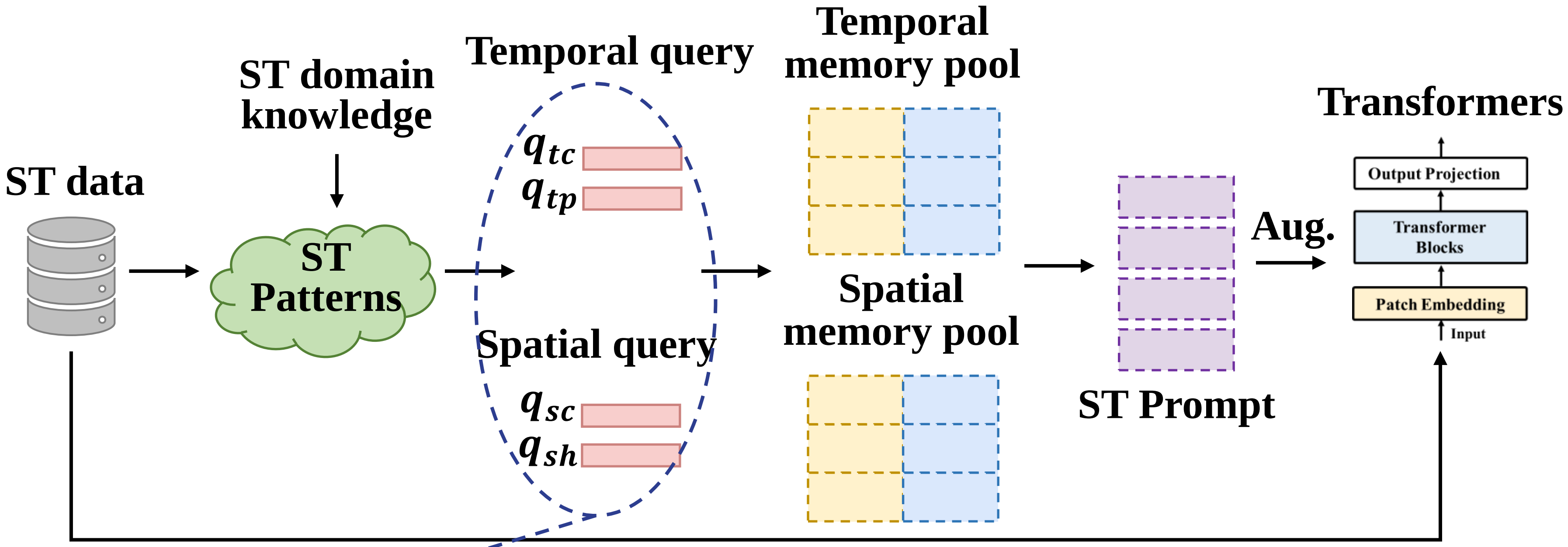
Capture complex spatio-temporal dynamics

Spatio-Temporal Prompt-tuning



Customized prompt

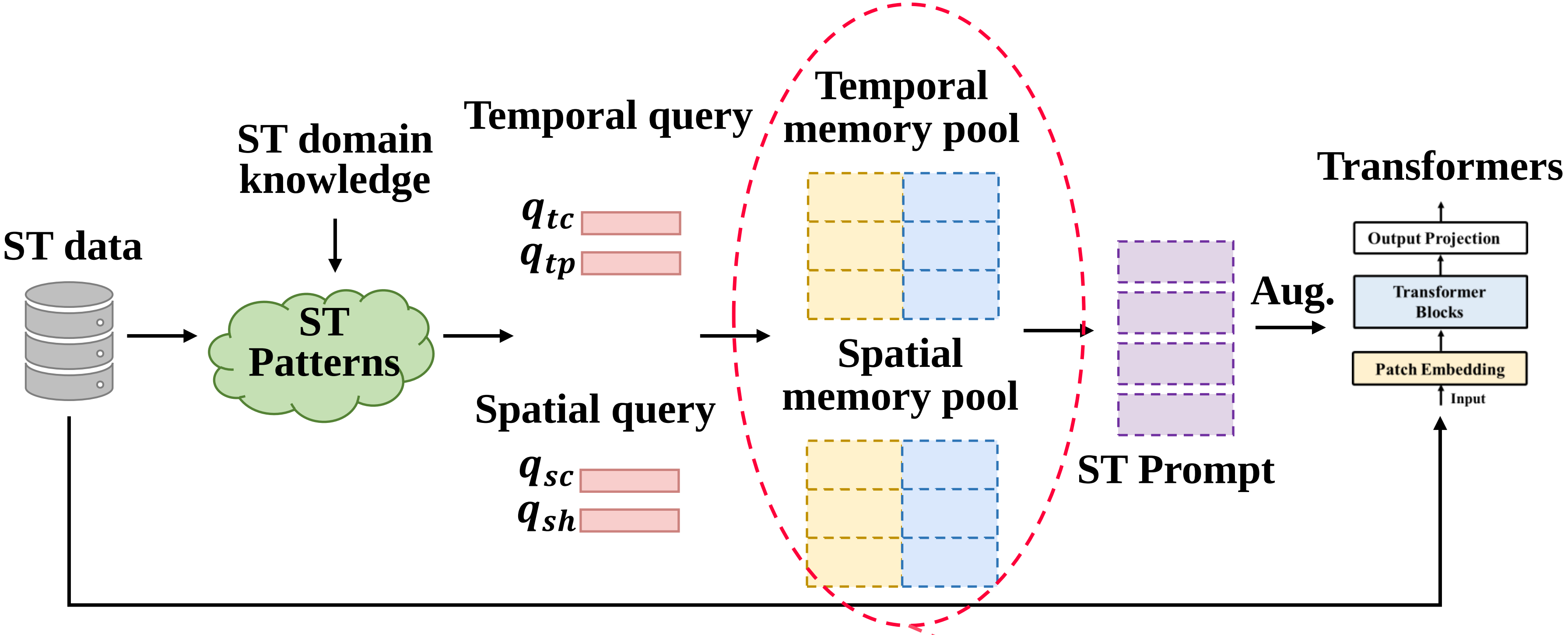
Spatio-Temporal Prompt-tuning



- ➢ **Temporal closeness**
- ➢ **Temporal period**
- ➢ **Spatial closeness**
- ➢ **Spatial hierarchy**

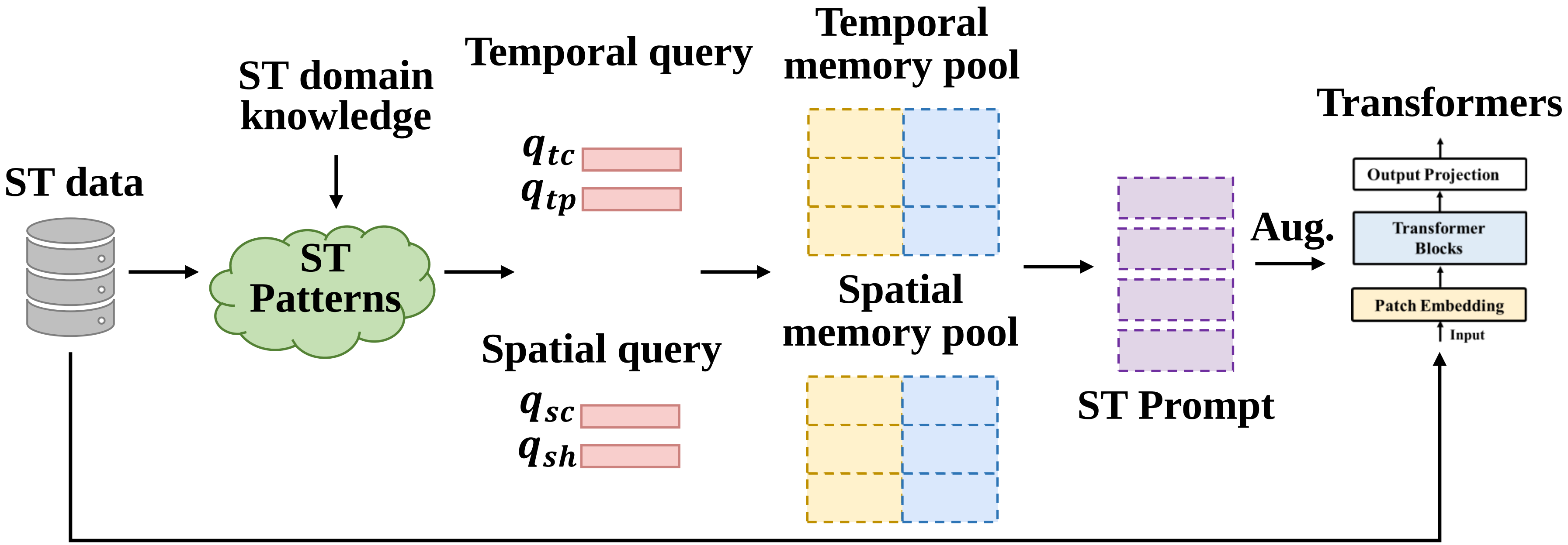
Data reformulation

Spatio-Temporal Prompt-tuning



External memory pools
shared spatio-temporal patterns

Spatio-Temporal Prompt-tuning



Address varied spatio-temporal patterns

Performance Evaluations

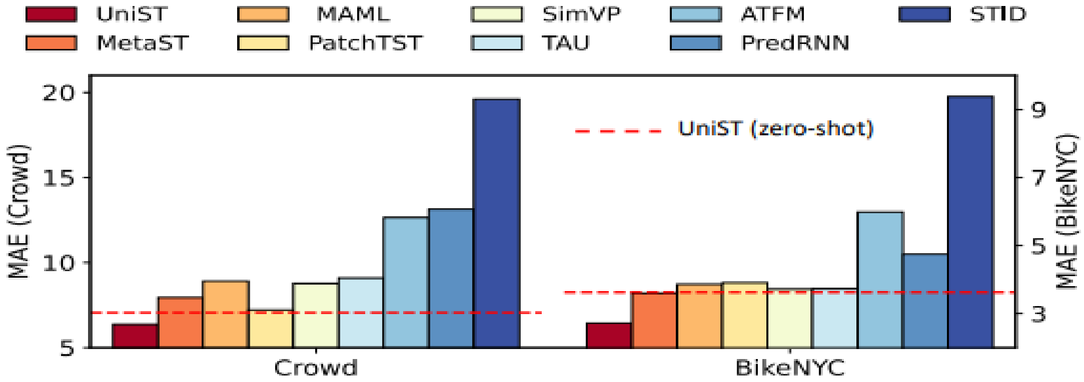
Long-term and short-term prediction

One model for one dataset

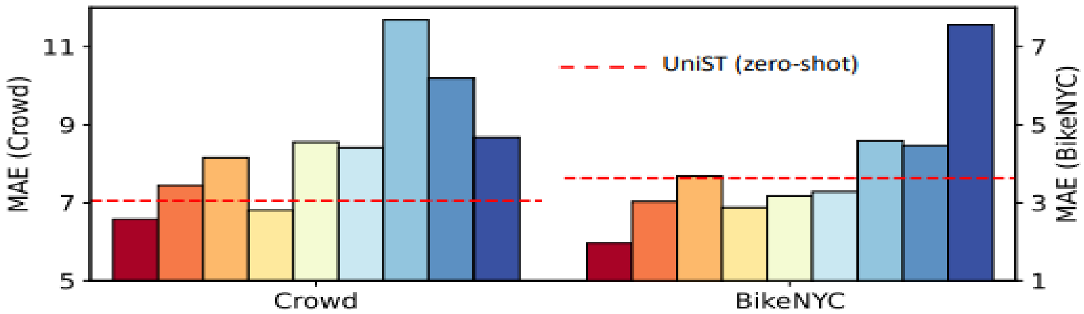
Model	TaxiBJ		Crowd		Cellular		BikeNYC		TrafficJN		TDrive		TrafficSH	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
HA	53.77	29.82	17.80	6.79	72.94	27.57	11.41	3.43	1.38	0.690	150.2	74.5	1.24	0.771
ARIMA	56.70	39.53	21.87	10.23	81.31	40.22	12.37	3.86	1.20	0.651	211.3	108.5	1.17	0.769
STResNet	45.17	30.87	5.355	3.382	24.30	14.32	8.20	4.98	0.964	0.556	220.1	117.4	1.00	0.723
ACFM	37.77	21.59	4.17	2.34	22.79	12.00	3.93	1.67	0.920	0.559	98.1	51.9	0.833	0.566
STID	27.36	14.01	3.85	1.63	18.77	8.24	4.06	1.54	0.880	0.495	47.4	23.3	0.742	0.469
STNorm	29.37	15.71	4.44	2.09	19.77	8.19	4.45	1.66	0.961	0.532	54.3	47.9	0.871	0.579
STGSP	45.04	28.28	7.93	4.56	39.99	21.40	5.00	1.69	0.882	0.490	94.6	47.8	1.02	0.749
MC-STL	29.14	15.83	4.75	2.39	21.22	10.26	4.08	2.05	1.19	0.833	54.2	28.1	1.00	0.720
PromptST	27.44	14.54	3.52	1.54	15.74	7.20	4.36	1.57	0.953	0.490	47.5	22.8	0.811	0.523
MAU	38.14	20.13	4.94	2.35	39.09	18.73	5.22	2.06	1.28	0.697	48.8	22.1	1.37	0.991
PredRNN	27.50	14.29	5.13	2.36	24.15	10.44	5.00	1.74	0.852	0.463	54.9	25.2	0.748	0.469
MIM	28.62	14.77	5.66	2.27	21.38	9.37	4.40	1.62	1.17	0.650	51.4	22.7	0.760	0.505
SimVP	32.66	17.67	3.91	1.96	16.48	8.23	4.11	1.67	0.969	0.556	46.8	22.9	0.814	0.569
TAU	33.90	19.37	4.09	2.11	17.94	8.91	4.30	1.83	0.993	0.566	51.6	28.1	0.820	0.557
PatchTST	42.74	22.23	10.25	3.62	43.40	15.74	5.27	1.65	1.25	0.616	106.4	51.3	1.10	0.663
iTransformer	36.97	19.14	9.40	3.40	37.01	13.93	7.74	2.53	1.11	0.570	86.3	42.6	1.04	0.655
PatchTST(one-for-all)	43.66	23.16	13.51	5.00	56.80	20.56	9.97	3.05	1.30	0.645	127.0	59.26	1.13	0.679
UniST(one-for-all)	**26.84**	**13.95**	**3.00**	**1.38**	**14.29**	**6.50**	**3.50**	**1.27**	**0.843**	**0.430**	**44.97**	**19.67**	**0.665**	**0.405**

Reduce prediction error significantly with a unifiedly-trained model

Zero-shot capabilities



(a) Performance on Few-shot (1%) and Zero-shot Scenarios



(b) Performance on Few-shot (5%) and Zero-shot Scenarios

Zero-shot setting outperforms few-shot (1%, 5% samples) baselines

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Future Work

More universal

- more formats, graph-based ST data, trajectory
- more domains, natural / earth system

THANK YOU

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tonight, 6:30 PM-9:30 PM

poster number: 78

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