



数据智能实验室

Data Intelligence Lab



NEURAL INFORMATION
PROCESSING SYSTEMS

Get Rid of Task Isolation: A Continuous Multi-task Spatio-Temporal Learning Framework

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Motivations

➤ Exploring ST Intelligence across Tasks

**OOD Generalization
for ST Prediction**

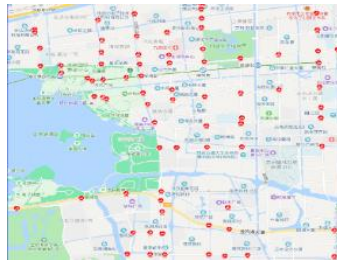
Temporal → Distribution shift over time series (distribution shift)
Spatial → Model transfer across cities (inter-city transfer, ...)



Remote sense



Trajectory



Road sensor



Traffic accident



Multi-task intelligence

A unified model for fast transfer, fine-tuning on different tasks of the same ST domain is highly required !

✓ Common ST associations for cold-start and challenging tasks

✓ Without re-training model for a different task

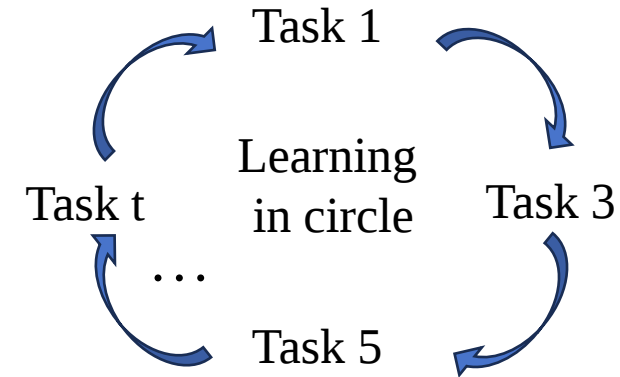
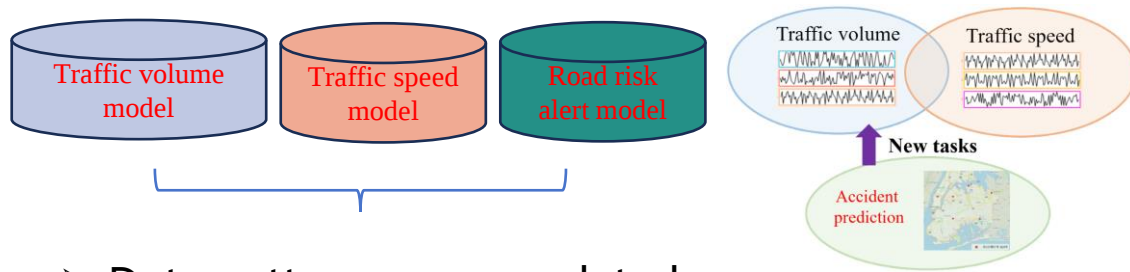
**Task-guided
Model Evolution
Green ST
computing**





Challenges & Solutions

➤ Challenges for ST Task Learning



- Data patterns are correlated
- Models are isolated, not shared and interactive
- Cold-start challenges for new tasks
- ❖ **How to capture commonalities among tasks ?**
- ❖ **How to utilize commonalities and personalities to enhance each individual tasks and new tasks ?**

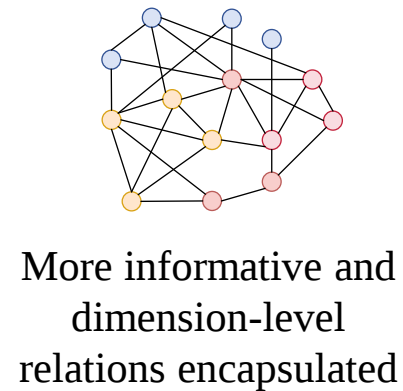
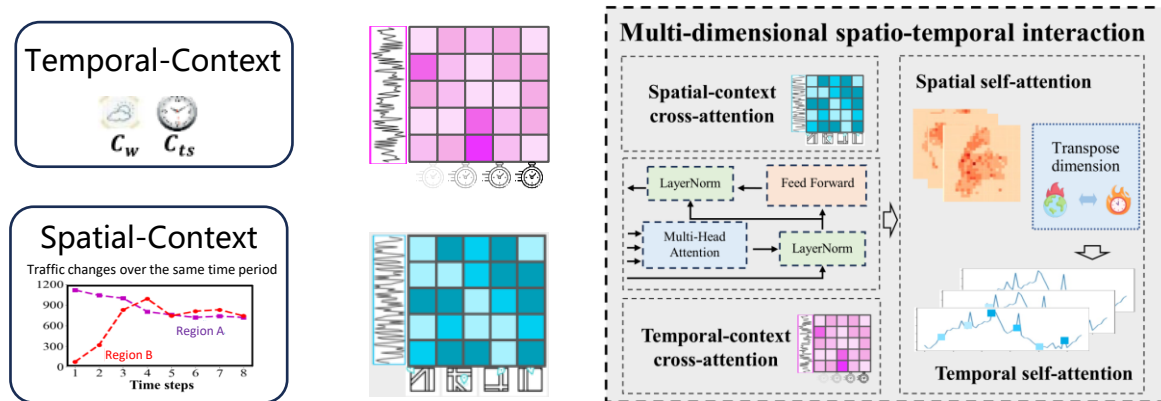
- ✓ **Cross-interaction of different dimensions of data**
- ✓ **Capture the model behavior through rolling training, and decouple the common/individual patterns**



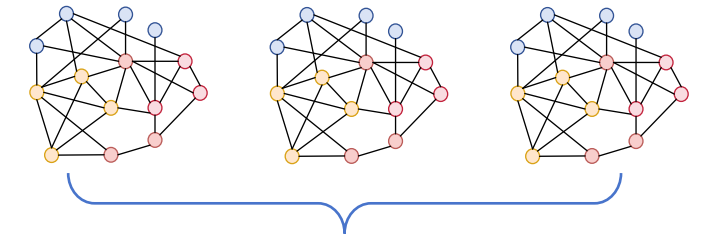
Continuous Multi-task SpatioTemporal (CMuST)

➤ ST Intelligence for Task Continuous Learning

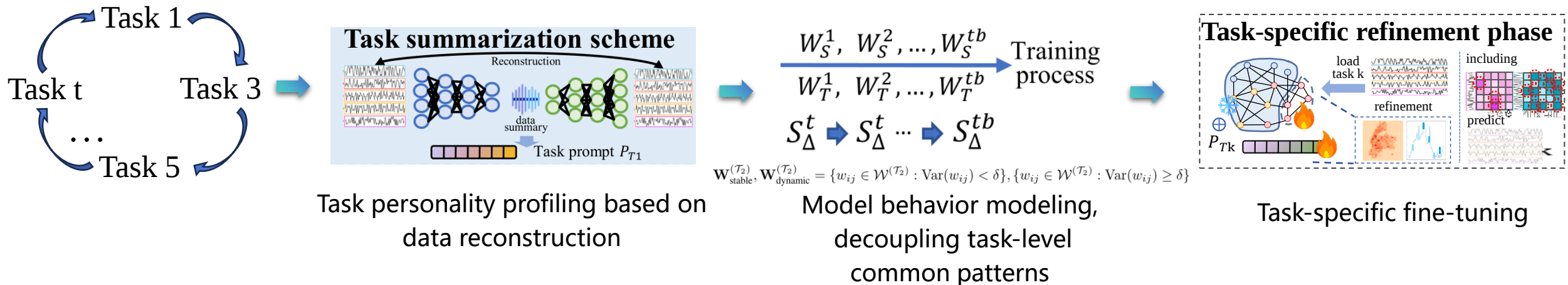
➤ Multi-dimensional Spatio-Temporal Interaction (MSTI)



Multi-dimensional, multi-perspective spatial and temporal interaction



➤ Rolling Adaptation (RoAda)

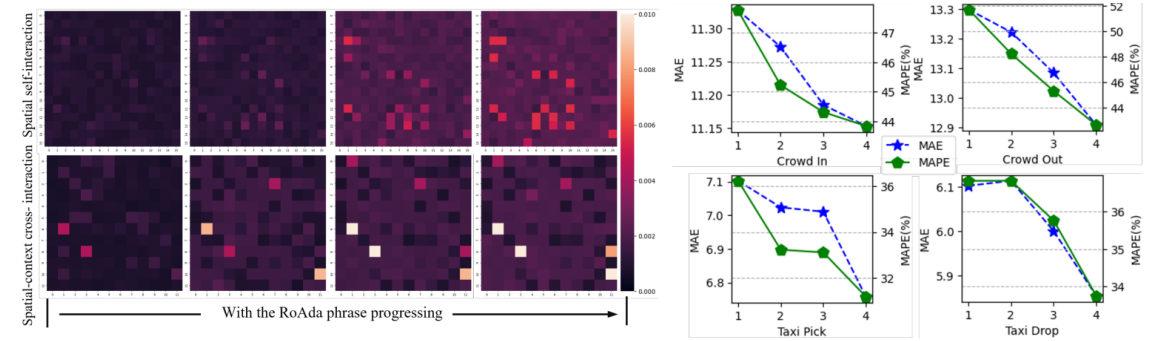
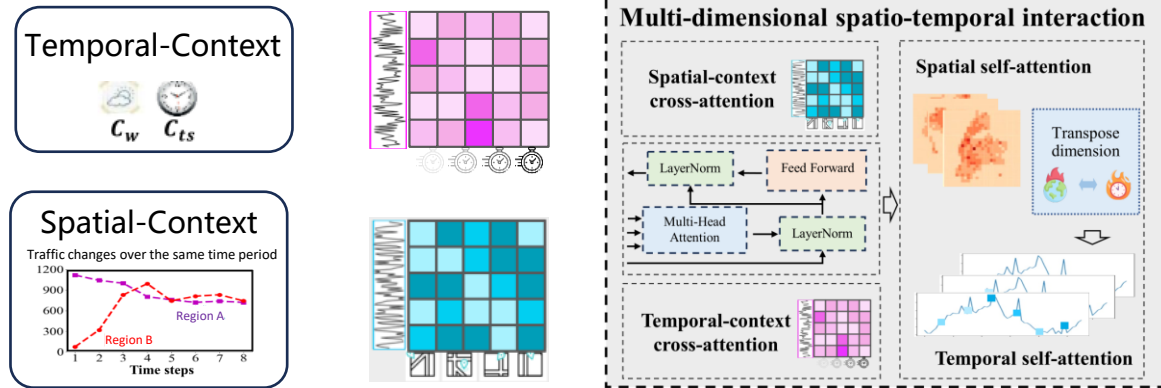




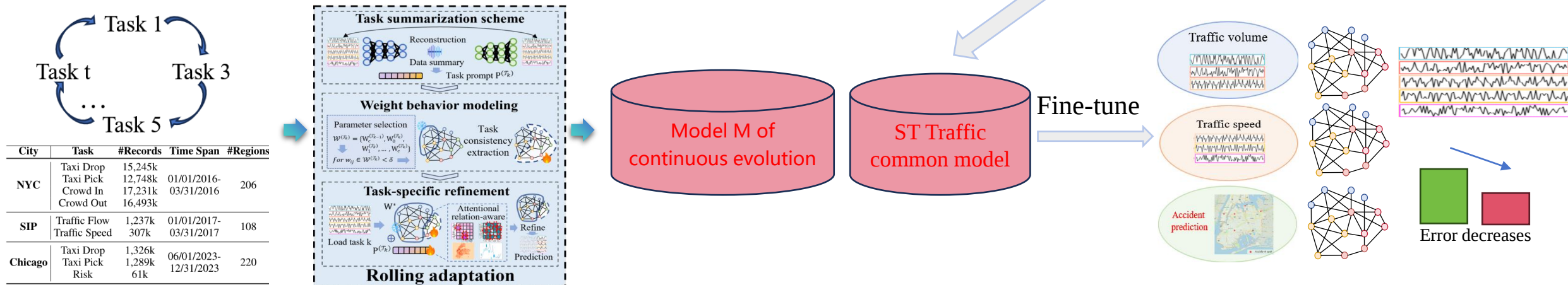
Continuous Multi-task SpatioTemporal (CMuST)

➤ ST Intelligence for Task Continuous Learning

➤ Multi-dimensional Spatio-Temporal Interaction (MSTI)



➤ Rolling Adaptation (RoAda)





Experiments

➤ Datasets

- **NYC**: Includes three months of crowd flow and taxi hailing from Manhattan and its surrounding areas in New York City. Tasks: *Crowd In*, *Crowd Out*, *Taxi Pick*, and *Taxi Drop*.
- **SIP**: Contains records of *Traffic Flow* and *Traffic Speed* within Suzhou Industrial Park over a period of three months.
- **Chicago**: Comprises of traffic data collected in the second half of 2023 from Chicago, including three tasks: *Taxi Pick*, *Taxi Drop*, and *Risk*.

City	Task	#Records	Time Span	#Regions	#Time Steps	Time Interval
NYC	Taxi Drop	30,245k	01/01/2016-03/31/2016	206	4368	30mins
	Taxi Pick					
	Crowd In					
	Crowd Out					
SIP	Traffic Flow	1,237k	01/01/2017-03/31/2017	108	25920	5mins
	Traffic Speed	307k				
Chicago	Taxi Drop	3,291k	06/01/2023-12/31/2023	220	10272	30mins
	Taxi Pick	61k				
	Risk					

➤ Comparison with existing ST models

Datesets		NYC				SIP		Chicago		
Methods	Metrics	Crowd In	Crowd Out	Taxi Pick	Taxi Drop	Traffic Flow	Traffic Speed	Taxi Pick	Taxi Drop	Risk
DCRNN	MAE	17.5289	19.5667	10.8188	9.6142	12.5326	0.7044	3.0624	2.5793	1.1174
	MAPE	0.5939	0.5695	0.4330	0.4818	0.2455	0.2686	0.4237	0.4816	0.2504
AGCRN	MAE	11.5135	13.1569	7.0675	6.0066	15.8319	0.6924	2.3542	2.0884	1.1183
	MAPE	0.5094	0.4773	0.3753	0.3665	0.2926	0.2744	0.4092	0.4046	0.2505
GWNEN	MAE	11.4420	13.2992	7.0701	6.1171	13.0529	0.6900	2.3671	2.0434	1.1197
	MAPE	0.4778	0.6171	0.3713	0.3514	0.2483	0.2655	0.3912	0.4044	0.2514
STGCN	MAE	11.3766	13.3522	7.1259	5.9268	15.3501	0.7111	2.3781	2.1427	1.1184
	MAPE	0.5018	0.4318	0.3234	0.3339	0.3041	0.2660	0.4074	0.4331	0.2507
GMAN	MAE	11.3414	13.1923	7.0662	6.0912	13.0368	0.6952	2.3663	2.0316	1.1182
	MAPE	0.4782	0.6065	0.3652	0.3468	0.2464	0.2678	0.3953	0.4036	0.2516
ASTGCN	MAE	14.2847	17.1582	9.1430	7.7063	16.4896	0.6980	2.5091	2.1520	1.1175
	MAPE	0.6396	0.5922	0.4607	0.4524	0.3104	0.2682	0.4593	0.4413	0.2502
STTN	MAE	12.1994	14.1966	7.6716	6.3816	15.1751	0.6939	2.2996	2.0355	1.1214
	MAPE	0.4757	0.4744	0.3600	0.3763	0.2881	0.2625	<u>0.3893</u>	0.4133	0.2518
MTGNN	MAE	11.4350	13.3072	7.0736	6.1162	13.0486	0.6989	2.3692	2.0361	1.1201
	MAPE	0.4785	0.6185	0.3782	0.3502	0.2475	0.2687	0.3979	0.4073	0.2578
STEP	MAE	11.2328	13.1043	6.9619	5.9101	12.0032	0.6970	2.3592	2.0168	1.1190
	MAPE	0.4537	0.4361	0.3248	0.3379	0.2391	0.2638	0.3914	0.4019	0.2507
PromptST	MAE	11.0036	13.0237	6.8711	5.8797	11.8620	0.6921	2.3576	2.0065	1.1186
	MAPE	<u>0.4465</u>	<u>0.4358</u>	<u>0.3265</u>	<u>0.3382</u>	<u>0.2375</u>	0.2632	0.3913	<u>0.4012</u>	0.2511
CMuST	MAE	<u>11.1533</u>	12.9088	6.7581	5.8546	11.5811	0.6843	2.3264	2.0034	1.1172
	MAPE	0.4384	0.4265	0.3118	<u>0.3375</u>	0.2279	0.2585	0.3872	0.4009	<u>0.2503</u>

➤ Experiment Design

- **Single-task learning**: Treat different task sets as separate datasets to train and test the models respectively, train 5 times and take the average results.
- **Multi-task learning**: Align the features of different types of data in the same city into the same graph, and concatenates the data features for training the model.



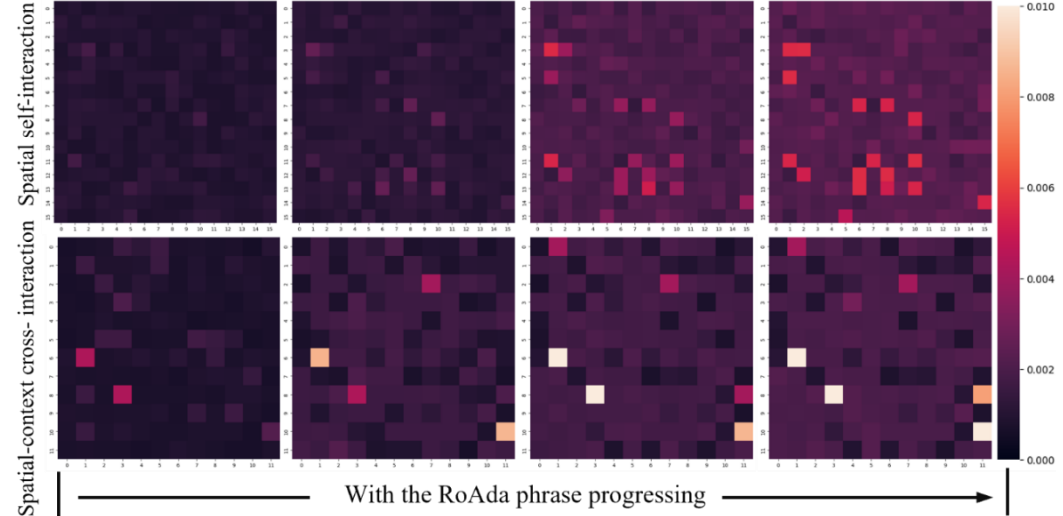
Experiments & Conclusion

➤ Robustness in data-scarce scenarios

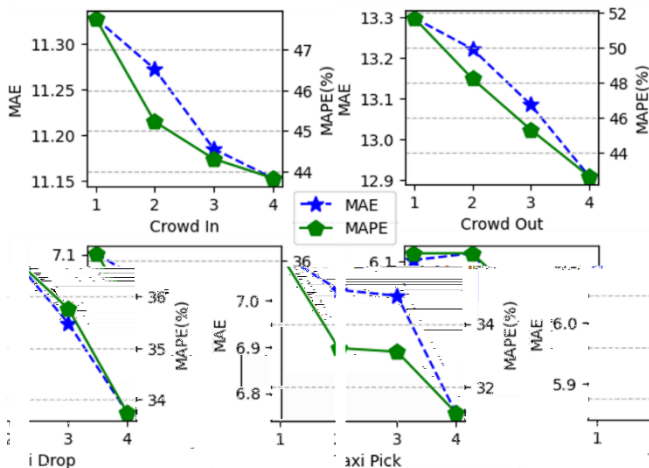
Reducing part of the spatial nodes, as well as extending the time interval to reduce the number of samples, to investigate the robustness in challenging with limited data.

model	NYC for Crowd In							
	25% nodes		50% nodes		2 times interval		4 times interval	
	MAE	MAPE	MAE	MAPE	MAE	MAPE	MAE	MAPE
GWNET	13.7648	0.4825	12.4637	0.4731	20.2547	0.4465	20.6487	0.4958
STEP	13.1827	0.4772	12.2393	0.4612	20.1936	0.4436	20.1465	0.4915
PromptST	12.8362	0.4719	12.0361	0.4607	19.8465	0.4384	19.5238	0.4872
CMuST	12.1611	0.4506	11.2864	0.4470	18.2925	0.4279	18.4084	0.4797

➤ Visualizing attention weights



➤ Performance with task increasing



➤ Contributions

- ✓ The first continuous multi-task spatiotemporal learning framework, reinforcing individual correlated learning task in collective perspective.
- ✓ Propose two innovative learning modules, MSTI and RoAda, enabling common and individual pattern extraction.
- ✓ Construct multi-task ST learning benchmarks for three cities.



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Thank You for Listening

References

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