1 EFFICIENCY

[R1,R2,R3,R4] Thank you for the valuable feedback and suggestions. As suggested by the reviewer, we explicitly calculate the computation time (second) and GPU memory occupation (MB) at each epoch.

Model	Gowalla			Foursquare		
	Train	Inference	Memory	Train	Inference	Memory
Flashback	37s	302s	10237MB	54s	912s	14697MB
Graph-Flashback	85s	431s	9531MB	120s	1320s	13289MB
SNPM	306s	631s	10887MB	420s	1910s	16365MB
our	8s	100s	5061MB	13s	420s	7467MB

Table 1: Performance about efficiency.

2 COMPLETE ABLATION EXPERIMENTS

[R1, R2, R4, R6] We supplemented ablation experiments by removing the Potential Missing Nodes Completion Strategy (i.e., w/o PMNCS) and the Confidence-based Weight Approach (i.e., w/o confidence weight). Additionally, we added ablation experiments on the Foursquare dataset.

Model	Gowalla				Foursquare			
	Acc@1	Acc@5	Acc@10	MRR	Acc@1	Acc@5	Acc@10	MRR
MLP(student model)	0.1544	0.3484	0.4328	0.2467	0.2821	0.5912	0.6741	0.4221
ST model	0.1567	0.3618	0.4505	0.2523	0.2862	0.6054	0.6842	0.4311
KD	0.1556	0.3517	0.4376	0.2506	0.2866	0.5981	0.6792	0.4291
KD-singel	0.1602	0.3594	0.4487	0.2540	0.2912	0.6058	0.6883	0.4320
w/o mask	0.1662	0.3637	0.4542	0.2578	0.2951	0.6125	0.6957	0.4353
w/o ST distill	0.1656	0.3629	0.4536	0.2572	0.2932	0.6103	0.6923	0.4326
w/o PMNCS	0.1537	0.3480	0.4332	0.2446	0.2801	0.5901	0.6722	0.4207
w/o confidence weight	0.1588	0.3628	0.4516	0.2562	0.2893	0.6083	0.6892	0.4353

Table 2: Performance about ablation study.

3 COMPARED WITH OTHER BASELINE KNOWLEDGE DISTILLATION METHODS

[R2,R6]

Model	Gowalla				Foursquare			
	Acc@1	Acc@5	Acc@10	MRR	Acc@1	Acc@5	Acc@10	MRR
ExplanationIntervention	0.0672	0.1673	0.2238	0.1196	0.2126	0.4827	0.5560	0.3341
KRD	0.1591	0.3522	0.4336	0.2502	0.2902	0.5970	0.6769	0.4281
MMKD	0.1610	0.3554	0.4404	0.2551	0.2912	0.6047	0.6812	0.4334
MLP-POI	**0.1684**	**0.3689**	**0.4561**	**0.2602**	**0.2971**	**0.6167**	**0.6983**	**0.4379**

Table 3: Performance about KD.

Model	Gowalla				Foursquare			
	Acc@1	Acc@5	Acc@10	MRR	Acc@1	Acc@5	Acc@10	MRR
STAN	0.1502	0.3424	0.4261	0.2416	0.2801	0.5789	0.6574	0.4142
Flashback	0.1532	0.3473	0.4301	0.2442	0.2814	0.5813	0.6621	0.4176
GETNext	0.1562	0.3501	0.4342	0.2484	0.2877	0.5955	0.6745	0.4257
Graph-Flashback	0.1596	0.3550	0.4382	0.2533	0.2914	0.6009	0.6790	0.4291
SNPM	0.1634	0.3613	0.4472	0.2576	0.2931	0.6082	0.6873	0.4338

Table 4: Performance about the replacement of multi-teacher.

4 VARIOUS MODELS STRUCTURE OF THE MULTI-TEACHER SPATIAL-TEMPORAL MODEL

[R2, R5, R6] We employed the following four models to substitute for the multi-teacher model.

5 WHY SNPM WASN'T USED FOR INITIALIZATION?

[R2] We tried initializing both the student and teacher models using methods from SNPM, but obtained poor results. Specifically, the poor performance of initializing the student MLP model may be attributed to its initialization method, which focuses on capturing current sequence information, overlapping somewhat with the role of MLP in summarizing current sequence information.

Model	Gowalla				Foursquare			
	Acc@1	Acc@5	Acc@10	MRR	Acc@1	Acc@5	Acc@10	MRR
$\text{Student}_{\text{SNPM}}$	0.1522	0.3415	0.4211	0.2438	0.2787	0.5804	0.5594	0.4176
$\text{Student}_{\text{our}}$	0.1544	0.3484	0.4328	0.2467	0.2839	0.5896	0.6687	0.4213
$\text{Teacher}_{\text{SNPM}}$	0.1534	0.3429	0.4185	0.2478	0.2823	0.5864	0.6652	0.4251
$\text{Teacher}_{\text{our}}$	0.1567	0.3618	0.4505	0.2523	0.2873	0.6082	0.6914	0.4301

Table 5: Performance about using SNMP initialization.

6 COMPARISON BETWEEN THE SELF-ATTENTION MECHANISM (S.A.) AND MLP.

[R3] When the input sequence length is N, the input sequence size is D, and the hidden state is H, the computational complexity of self-attention is N^2, while the computational complexity of MLP is DH. Therefore, the computational complexity of self-attention is quadratic, whereas the computational complexity of MLP is linear.

7 SUPPLEMENTED BASELINE EXPERIMENTS.

[R4]

Model	Gowalla				Foursquare			
	Acc@1	Acc@5	Acc@10	MRR	Acc@1	Acc@5	Acc@10	MRR
HMT-GRN	0.1312	0.3112	0.3921	0.2201	0.2643	0.5578	0.6342	0.3941
STHGCN	0.1543	0.3462	0.4311	0.2461	0.2842	0.5917	0.6702	0.4232
MLP-POI	**0.1684**	**0.3689**	**0.4561**	**0.2602**	**0.2971**	**0.6167**	**0.6983**	**0.4379**

Table 6: Performance about additional baseline.

Lacks implementation details and hyperparameter tuning aspects. Additionally, regarding hyperparameter tuning, we will include experiments in the appendix based on the random walk length and the number of teacher models, along with the addition of the threshold for random sampling weighting and balancing weight in training strategy.