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ADAPTIVE SPATIAL-TEMPORAL HYPERGRAPH FUSION LEARNING FOR NEXT POI RECOMMENDATION

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ABSTRACT

Next point-of-interest (POI) recommendation has been a trending task to provide next POI suggestions. Most existing sequential-based and graph-based methods have endeavored to model user visiting behaviors and achieved considerable performances. However, they have either modeled user interests at a coarse-grained interaction level or ignored complex high-order feature interactions through general heuristic message passing scheme, making it challenging to capture complementary effects. To tackle these challenges, we propose a novel framework Adaptive Spatial-Temporal Hypergraph Fusion Learning (ASTHL) for next POI recommendation. Specifically, we design disentangled POI-centric learning to decouple spatial-temporal factors and utilize cross-view contrastive learning to enhance the quality of POI representations. Furthermore, we propose multi-semantic enhanced hypergraph learning to adaptively fuse spatial-temporal factors through well-designed aggregation and propagation scheme. Extensive experiments on three real-world datasets validate the superiority of our proposal over various state-of-the-arts. To facilitate future research, our code is available at `https://github.com/icmpnorequest/ICASSP2024_ASTHL`.

Index Terms— Next POI recommendation, Hypergraph neural networks, Adaptive fusion learning

1. INTRODUCTION

Recent years have witnessed the blossom of point of interest (POI) recommender system, which helps users discover their potential interested places to alleviate information overload problem and facilitates locations related business, including travel planning, advertising and retail. In POI recommender systems, next POI recommendation is one of significant and fundamental tasks. Formally, it aims to provide suitable predictions for users in the next movement according to their historical behaviours [1, 2].

Generally, existing methods in next POI recommendation can be classified into two paradigms: sequential-based paradigm and graph-based paradigm. The key rationale behind the sequential-based paradigm is to treat next POI recommendation as a sequential prediction task and adopt sequential methods to model transitional patterns, ranging from Markov Chains [3] to recurrent neural networks (RNNs) [4, 5] and recent self-attention mechanism [6, 7]. However, sequential-based paradigm mainly focuses on sequential patterns mining but fail to explore collaborative signals [8, 9], which can overcome information cocoons problem and alleviate the data sparsity issue simultaneously. Inspired by the great success of graph neural networks (GNNs), graph-based paradigm mainly relies on GNN-based methods [9, 10, 11] or hypergraph neural network (HGNN) based methods [2]. It aims to capture collaborative signals and model complex relationships among high-order neighbors and has achieved considerable performances in next POI recommendation.

Despite effectiveness of the aforementioned approaches, two key issues still remain less explored. First, most previous studies have modeled user interests at a coarse-grained level (i.e., user-POI interaction level) and ignored fine-grained factors behind their interactions, resulting in suboptimal and coarse-grained user preferences. Second, existing GNN-based or HGNN-based methods mainly fused representations of fine-grained factors in a heuristic message passing way and neglected high-order feature interactions, making it hard to capture potential intricate relationships and complementary effects during the fusion process.

In this paper, we propose a novel model Adaptive Spatial-Temporal Hypergraph Fusion Learning (ASTHL) for next POI recommendation, to address above challenges. Firstly, we perform disentangled POI-centric learning, to model fine-grained spatial-temporal factors behind user-POI interactions. Specifically, we innovatively design a directed transitional hy-

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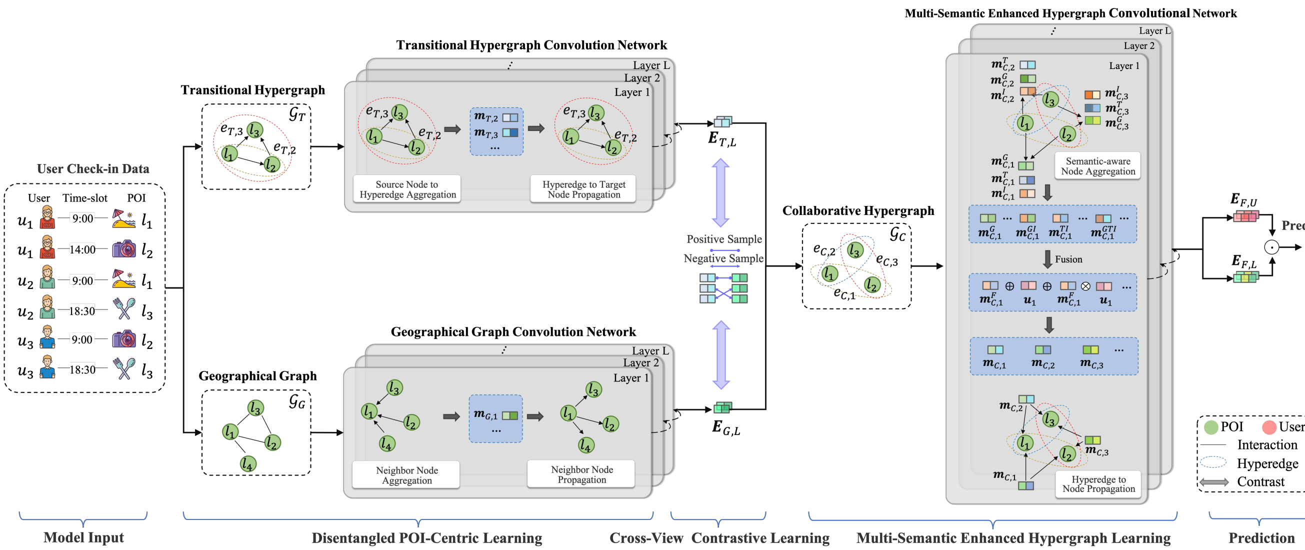

Fig. 1: The overall framework of our proposed ASTHL

pergraph and a geographical graph to depict transitional and geographical relationships among POIs in a global view. Different view-specific encoders are applied to learn decoupled spatial-temporal POI representations. Then, we optimize a cross-view contrastive objective after POI-centric disentanglement to capture complementary recommendation effects. Subsequently, we propose multi-semantic enhanced hypergraph learning to adaptively fuse disentangled POI representations for capturing complex high-order feature interactions. Finally, we predict user's next movement based on learned fine-grained representations.

In summary, the main contributions of our work are as follows: i) We propose a novel model ASTHL to learn fine-grained user preferences and facilitate high-order features fusion for next POI recommendation. ii) We design disentangled POI-centric learning and multi-semantic hypergraph fusion learning to decouple spatial-temporal factors and adaptively fuse them through well-designed aggregation and propagation scheme of hypergraph. iii) Experimental results on three public datasets have demonstrated the effectiveness of our ASTHL over various state-of-the-art methods for next POI recommendation.

2. METHODOLOGY

Let $\mathcal{U} = \{u_1, u_2, ..., u_{|\mathcal{U}|}\}$ and $\mathcal{L} = \{l_1, l_2, ..., l_{|\mathcal{L}|}\}$ be a set of users and POIs, respectively. Each POI $l \in \mathcal{L}$ has unique geographical coordinates (*longitude, latitude*) tuple. For each user $u \in \mathcal{U}$, we obtain her/his trajectory $s_u = \{l_{u,i} | i = 1, 2, ...\}$, where $l_{u,i}$ indicates user u visited POI $l_{u,i}$.

Given a target user u and her/his trajectory sequence s_u, the goal of next POI recommendation is to recommend top-K POIs that u may visit in the next timestamp.

As illustrated in Fig. 1, we first elaborate on the construction of transitional hypergraph and geographical graph and perform disentangled POI-centric learning to decouple spatial-temporal factors. Then, we introduce cross-view contrastive learning to maximize mutual information between the two views and apply multi-semantic enhanced hypergraph convolutional network for adaptive feature fusion.

2.1. Disentangled POI-Centric Learning

Disentangled Spatial-Temporal Hypergraph Construction. Geographical graph $\mathcal{G}_G = (\mathcal{V}_G, \mathcal{E}_G)$ aims to depict geographical relationships between two POIs. In geographical graph $\mathcal{G}_G$, nodes are POIs and edges $\mathcal{E}_G$ consist of POI pairs within a specific geographical threshold Δ_d. Geographical information is calculated according to longitude and latitude coordinates and Haversine distance [12] between two POIs. When geographical distance between two POIs is less than the predefined threshold, we set $a_G^{ij} = 1$, otherwise 0. Transitional information refers to directed transitional relationships between POIs. We construct transitional hypergraph $\mathcal{G}_T$ to describe transitional relationships among POIs in a global view. An hyperedge depicts the in-coming relationship and contains all source nodes given a target POI.

Disentangled Spatial-Temporal Encoder. Before encoding, we initialize user embeddings $\mathbf{U} \in \mathbb{R}^{|\mathcal{U}| \times d}$ and POI embeddings $\mathbf{L} \in \mathbb{R}^{|\mathcal{L}| \times d}$ via look-up table, where d denotes embedding dimension. Geographical graph convolutional network encoder $\mathrm{Encoder_G}$ is applied to learn geographical POI representations as $\mathbf{E}_{G,L} = \mathrm{Encoder_G}(\mathbf{A}_G, \mathbf{L})$, where $\mathbf{E}_{G,L} \in \mathbb{R}^{|\mathcal{L}| \times d}$. Here, we choose LightGCN [8] as encoder. To capture global transitional relationships of POIs, we design a directed transitional hypergraph convolutional network as:

$$\mathbf{m}_{T,e} = \mathbf{AGG}_{n2e}(\{\mathbf{l}_i | l_i \in e\}) \tag{1}$$

$$\mathbf{l}_{T,j} = \mathbf{AGG}_{e2n}(\{\mathbf{m}_{T,e} | e \in \mathcal{E}_{l_j}\}) \tag{2}$$

where we aggregate source node embeddings $\mathbf{l}_i$ to generate medium message $\mathbf{m}_{T,e}$ and propagate related hyperedge embeddings to target node l_j to refine its representation. We implement $\mathbf{AGG}_{n2e}(\cdot)$ and $\mathbf{AGG}_{e2n}(\cdot)$ with mean pooling. After propagating L layers, we average the embeddings obtained at each layer and output transitional POI embeddings as $\mathbf{E}_{T,L} \in \mathbb{R}^{|\mathcal{L}| \times d}$ and geographical POI embeddings as $\mathbf{E}_{G,L} \in \mathbb{R}^{|\mathcal{L}| \times d}$.

2.2. Cross-View Contrastive Learning

Aiming to capture cooperative associations between geographical and transitional views, we design cross-view contrastive learning to augment view-specific POI representations. In particular, we take the same POI of different views as positive pairs (e.g., $(\mathbf{e}_{G,l}, \mathbf{e}_{T,l})$) and treat views of different POIs as negative pairs. Inspired by InfoNCE [13], we define our contrastive loss as:

$$\mathcal{J}_{CL} = \frac{1}{|\mathcal{L}|} \sum_{l \in \mathcal{L}} -\log \frac{\exp(s(\mathbf{e}_{G,l}, \mathbf{e}_{T,l})/\tau)}{\Sigma_{l' \in \mathcal{L}} \exp(s(\mathbf{e}_{G,l}, \mathbf{e}_{T,l'})/\tau)} \tag{3}$$

where $s(\cdot, \cdot)$ is cosine similarity function and τ is a temperature hyerparameter.

2.3. Multi-Semantic Enhanced Hypergraph Learning

Collaborative Hypergraph Construction. To depict user-POI interaction relationship, we construct a collaborative hypergraph $\mathcal{G}_C = (\mathcal{V}_C, \mathcal{E}_C)$. We represent each user's trajectory s_u as an hyperedge and POIs within it as nodes.

Multi-Semantic Enhanced Hypergraph Convolutional Network. Since POIs in an hyperedge carry geographical, transitional and collaborative semantics, we propose a multi-semantic enhanced hypergraph convolutional network to encourage adaptive high-order feature interactions. To maintain their distinction, for hyperedge $e_{C,1}$, we separately aggregate POI embeddings under different semantics (e.g., geographical semantic aware message $\mathbf{m}^G_{C,1} = \mathbf{AGG}_{n2e}(\{\mathbf{l} | l \in e_{C,1}\})$, transitional message $\mathbf{m}^T_{C,1}$ and interactive message $\mathbf{m}^I_{C,1}$). Aiming to capture fine-grained representations, we generate fine-grained message embeddings by multiplication. For example, geographical and transitional aware message embeddings $\mathbf{m}^{GT}_{C,1}$ is defined as Eq.4. Then, we concatenate message embeddings and apply a multi-layer perceptron network to fuse them as $\mathbf{m}_{F,1}$. Since an hyperedge reflects user's visiting pattern, we introduce user embeddings to combine the connection between user and POIs as

$$\mathbf{m}^{GT}_{C,1} = \mathbf{m}^G_{C,1} \otimes \mathbf{m}^T_{C,1} \tag{4}$$

$$\mathbf{m}_{C,1} = (\mathbf{m}^F_{C,1} \oplus \mathbf{u}_1 \oplus \mathbf{m}^F_{C,1} \otimes \mathbf{u}_1)\mathbf{W}^F \tag{5}$$

	#Users	#POIs	#Check-ins	#Sessions	Sparsity
NYC	834	3,835	44,686	8,841	98.61%
TKY	2,173	7,038	308,566	41,307	97.82%
Gowalla	5,802	40,868	301,080	75,733	99.87%

Table 1: Dataset statistics

where $\mathbf{W}^F \in \mathbb{R}^{d \times d}$. After that, we collect message from related hyperedges to refine the representation of node l as $\bar{\mathbf{l}}_C = \mathbf{AGG}_{e2n}(\{\mathbf{m}_{C,e} | e \in \mathcal{E}_l\})$. Through propagating L layers, we average embeddings of each layer and output representations of collaborative view. After that, we obtain final user and POI representations $\mathbf{E}_{F,U} \in \mathbb{R}^{|\mathcal{U}| \times d}$ and $\mathbf{E}_{F,L} \in \mathbb{R}^{|\mathcal{L}| \times d}$ by element-wise addition from above three views.

2.4. Prediction and Optimization

For user u and target POI l, we compute the score via dot product as $\hat{\mathbf{y}}_{u,l} = \text{softmax}(\mathbf{e}^T_{F,u}\mathbf{e}_{F,l})$ and formulate the learning objective as a cross-entropy loss function:

$$\mathcal{J}_{Rec} = -\sum_{u \in \mathcal{U}} \sum_{l \in \mathcal{L}} \left(\mathbf{y}_{u,l} \log(\hat{\mathbf{y}}_{u,l}) + (1 - \mathbf{y}_{u,l}) \log(1 - \hat{\mathbf{y}}_{u,l})\right) \tag{6}$$

where $\mathbf{y}_{u,l}$ equals to 1 if user u visits the POI l and 0 otherwise. Finally, we integrate the self-supervised loss with our recommendation loss into a multi-task learning objective as $\mathcal{J} = \mathcal{J}_{Rec} + \lambda_1 \mathcal{J}_{CL} + \lambda_2 \|\Theta\|_2$, where $\|\Theta\|_2$ represents the $L2$ regularization of all parameters for preventing over-fitting issue under the control of λ_2. λ_1 denotes the weight of self-supervised signals.

3. EXPERIMENTS

3.1. Experimental Setup

Datasets. We conduct experiments on three public LBSN datasets: Foursquare-NYC (NYC for abbreviation), Foursquare-TKY (TKY) [14] and Gowalla [15]. Following the same setting as [2, 4], we eliminate unpopular POIs, split each user's trajectory into sessions within one day and remove too short sessions. The first 80% sessions of each user are used for training and the rest for testing. The statistics of pre-processed datasets are shown in Table 1.

Metrics. We adopt Recall@K and Normalized Discounted Cumulative Gain (NDCG@K) with the K $\in \{5, 10\}$ to reflect the rate of the label within top-K recommendations and the quality of ranking lists.

Baselines. We compare our framework with following representative methods for next POI recommendation, including i) statistical-based method UserPop; ii) RNN-based methods STGN [5] and LSTPM [4]; iii) self-attention-based method STAN [7]; iv) GNN-based methods LightGCN [8], SGRec [9] and GETNext [16]; v) graph or hypergraph contrastive learning based method DisenPOI [17] and HCCF [18].

Method	NYC				TKY				Gowalla			
	R@5	R@10	N@5	N@10	R@5	R@10	N@5	N@10	R@5	R@10	N@5	N@10
UserPop	0.2866	0.3297	0.2283	0.2423	0.2229	0.2668	0.1718	0.1861	0.0982	0.1489	0.0907	0.1336
STGN	0.2371	0.2594	0.2261	0.2307	0.2112	0.2587	0.1482	0.1589	0.1600	0.2041	0.1191	0.1333
LSTPM	0.2495	0.2668	0.2425	0.2483	0.2203	0.2703	0.1556	0.1734	0.2021	0.2510	0.1523	0.1681
STAN	0.3523	0.3827	0.3025	0.3137	0.2621	0.3317	0.2074	0.2189	0.2449	0.2878	0.1837	0.1942
LightGCN	0.3221	0.3488	0.2958	0.3042	0.2213	0.2594	0.1977	0.2098	0.2356	0.2590	0.1801	0.1915
SGRec	0.3451	0.3723	0.3052	0.3178	0.2537	0.3213	0.2221	0.2447	0.2395	0.2813	0.1862	0.2002
GETNext	0.3572	0.3866	0.3079	0.3094	0.2686	0.3282	0.2212	0.2242	0.2425	0.2882	0.1986	0.2003
DisenPOI	0.3577	0.3831	0.2979	0.3071	0.2692	0.3314	0.2263	0.2332	0.2485	0.2979	0.1838	0.1927
HCCF	0.3534	0.3745	0.3025	0.3134	0.2689	0.3253	0.2325	0.2429	0.2451	0.2933	0.1936	0.2005
ASTHL	**0.4119**	**0.4477**	**0.3597**	**0.3707**	**0.2967**	**0.3509**	**0.2358**	**0.2506**	**0.2827**	**0.3271**	**0.2285**	**0.2402**
%Improv	+15.15	+15.80	+16.82	+16.65	+10.22	+5.79	+1.42	+2.41	+13.76	+9.80	+18.03	+19.80

Table 2: Performances comparison on three datasets in terms of Recall and NDCG. The best and the second best performances are bolded and underlined, respectively. The relative improvements are calculated between the best and the second best scores

Implementation Details. For baselines, we firstly preserve the settings provided in original papers and fine-tune hyperparameters on three datasets. For our ASTHL, we adopt Adam as optimizer with a learning rate of $1e^{-3}$, λ_1 of $1e^{-1}$ and λ_2 of $1e^{-5}$. We set embedding dimension d as 128 and batch size as 100. Distance threshold Δ_d is chosen as 2.5km for NYC and TKY, and 100km for Gowalla. The layer number L and temperature τ are searched from $\{1, 2, 3, 4, 5\}$ and $\{0.1, 0.5, 1, 5, 10\}$, respectively.

3.2. Results

Comparison with Baseline Methods. The results of all the methods are reported in Table 2. For the results, we have the following observations. First, our ASTHL consistently outperforms all baselines on three datasets in terms of all evaluation metrics. We contribute the improvements to the following aspects: i) Modeling fine-grained spatial-temporal factors behind user-POI interactions through disentangled POI-centric learning. ii) Adaptively capturing high-order feature interactions for fine-grained representations via multi-semantic enhanced hypergraph learning. Second, graph- or hypergraph-based methods that leverage non-consecutive POIs information perform better than those sequential-based methods. Third, our ASTHL performs better on sparser NYC and Gowalla datasets but a little weak on TKY, for it would introduce noise and affect ranking quality when modeling fine-grained factors behind more frequent interactions.

Ablation Study. We conduct an ablation study to examine each component (e.g., w/o G that removes geographical view and others are similar to it) of our ASTHL and have following observations from Table 3. First, the removal of collaborative view indicates the importance of modeling fine-grained spatial-temporal factors behind interactions via multi-semantic hypergraph learning. Second, the removal of geographical view proves spatial factor is more important than temporal factor in next POI recommendation.

Method	NYC		TKY		Gowalla	
	R@10	N@10	R@10	N@10	R@10	N@10
w/o G	0.4345	0.3552	0.3368	0.2464	0.3189	0.2315
w/o T	0.4456	0.3637	0.3389	0.2476	0.3196	0.2327
w/o C	0.4324	0.3547	0.3341	0.2451	0.3171	0.2303
w/o CL	0.4401	0.3643	0.3402	0.2459	0.3219	0.2336
ASTHL	**0.4477**	**0.3707**	**0.3509**	**0.2506**	**0.3271**	**0.2402**

Table 3: Ablation study on key components of ASTHL

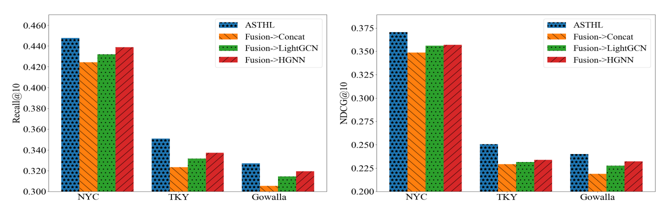

Fig. 2: Further study of fusion methods

Further Study of Fusion Methods. We maintain other parts of ASTHL and replace fusion part with concatenation, LightGCN and HGNN [19]. As shown in Fig. 2, ASTHL consistently outperforms all variants and HGNN variant performs better than concatenation and LightGCN variants. It proves the importance of modeling high-order feature interactions via multi-semantic enhanced hypergraph learning.

4. CONCLUSION

This paper proposes an Adaptive Spatial-Temporal Hypergraph Fusion Learning (ASTHL) framework for next POI recommendation. Our ASTHL firstly performs disentangled POI-centric learning to decouple spatial-temporal factors. Additionally, it facilitates high-order feature interactions for fine-grained representations via adaptive multi-semantic enhanced hypergraph learning. Experimental results on three datasets demonstrate the effectiveness of our ASTHL.

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