



Intention-aware Sequential Recommendation with Structured Intent Transition

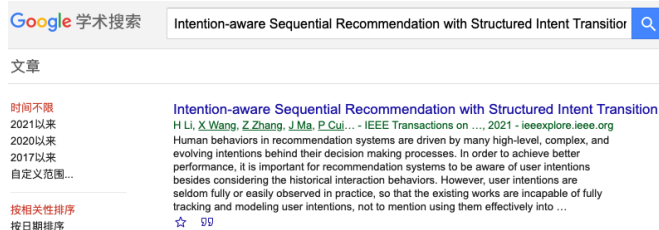
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Recommender Systems (RS) are Ubiquitous

□ A day in our life with Recommender Systems



07:00



10:00

Products related to this item

Sponsored @



14:00



17:00



07:40

09:00



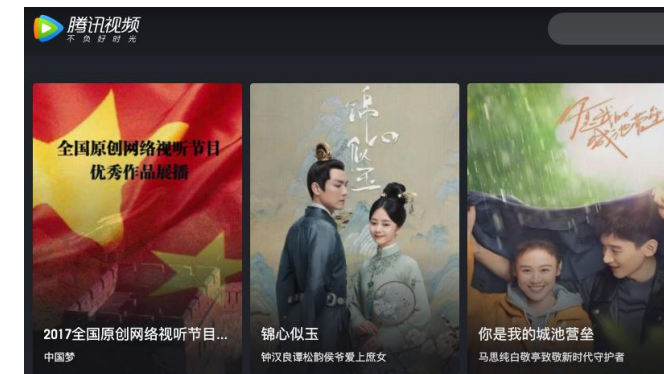
12:00



16:00



20:00



Problem of Today's RS: User Intentions

- ❑ Can RS understand the user intentions behind the behaviors?
- ❑ Behaviors are highly driven by user intentions in the real world.

amazon Deliver to Anchorage 99501 Sports & Outdoors ▾ baseball bat

Sports & Outdoors Sports & Fitness Outdoor Recreation Sports Fan Shop Sports Deals Outdoor Deals

Wish them a happy Easter

Back to results

KOTIONOK Baseball Bat 28 inch - Self-Defense Softball Black Bat - Home Defense Lightweight Aluminum Alloy Kids

Price: \$23.95 Get Fast, Free Shipping with Amazon Prime

- **Multipurpose** aluminum baseball bat is designed for people who need a multipurpose bat for both self defense and training. Unlike other baseball bats, which are used mainly for professional play or self-defense only, our bat is a great reasonable alternative
- Self defense bat - Our metal bat is an effective measure for a home defense and a safer alternative with kids in the house. The bat is multipurpose way of self defense for women and men
- Baseball daily practice - Proper fit and feel of our bat helps players to train effectively and build confidence. Our softball bat could be used with soft-core tee balls only, while it's not suitable for hard-core balls and machine balls. Great for baseball players of all levels
- Ultra lightweight baseball bat - Black baseball bat 28 inch made of a durable one-piece premium quality aluminum bat. The weight is 13 oz. The metal baseball bat is easy to swing. The rubber anti-skid grip tape absorbs shock and creates full control
- Modern design - Aluminum alloy bat has a smooth shape. It was designed with the perfect combination of power and control. Great gift for kids and adults

Roll over image to zoom in

• Multipurpose - Our multipurpose bat



Play baseball



Gift



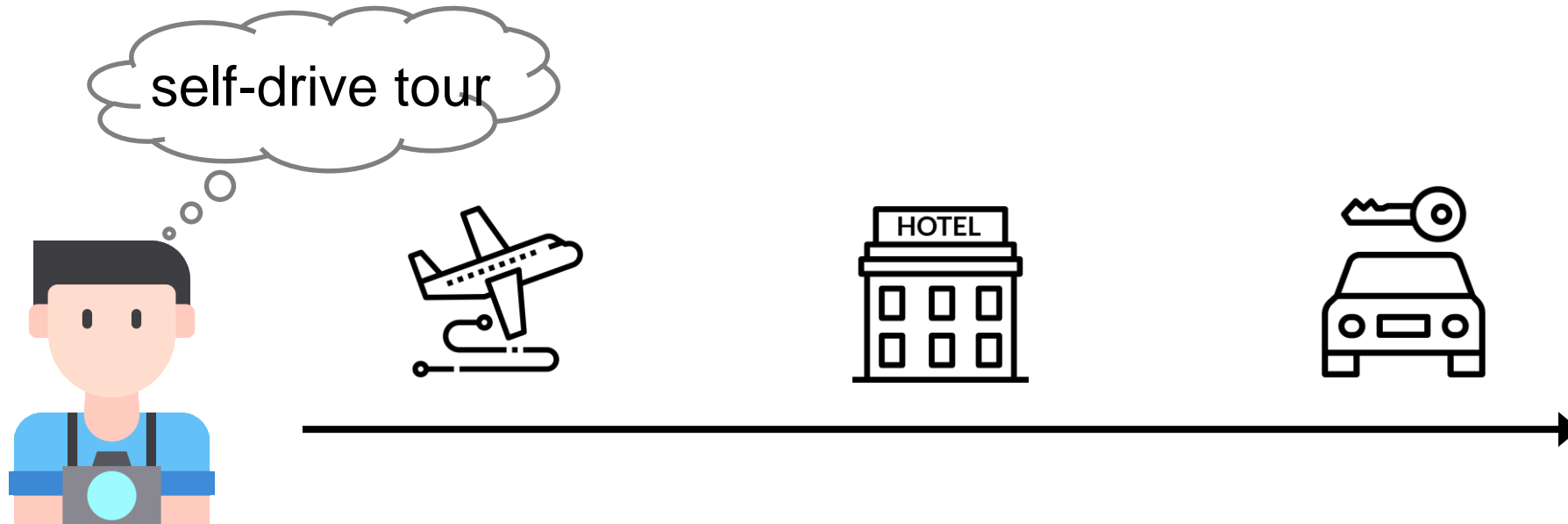
Self-defense



Attack

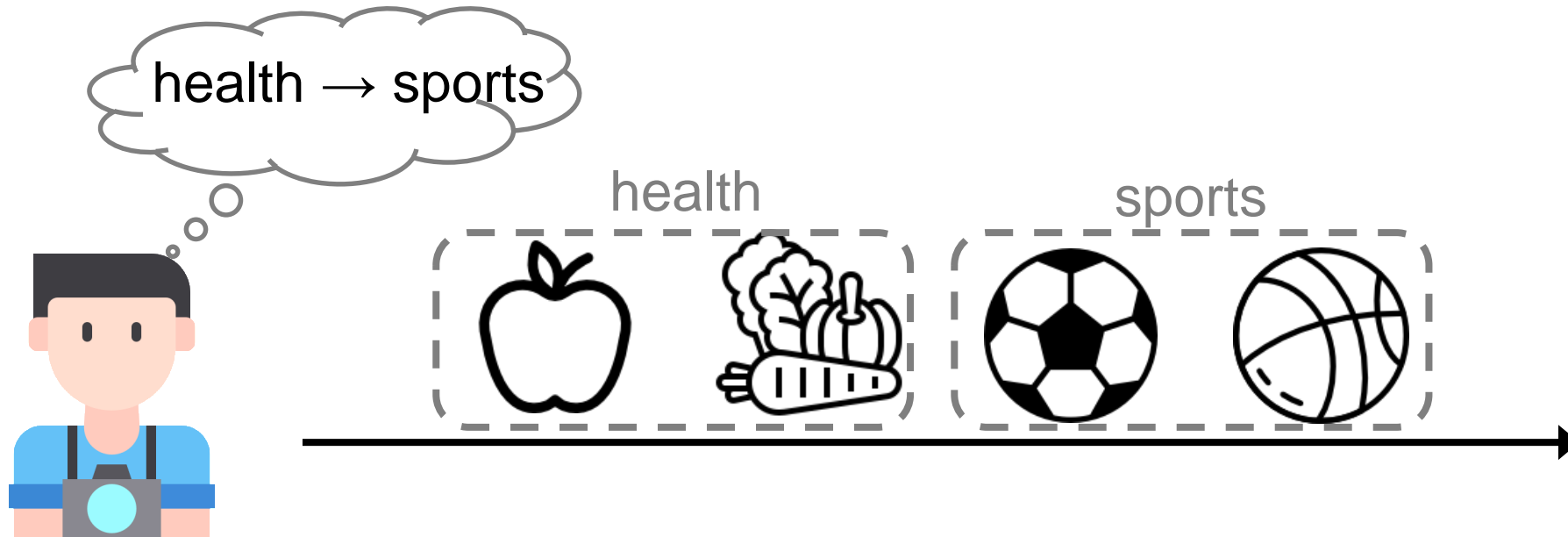
A Possible Solution: Learn from Sequence

- Identifying user intentions exactly from **one item** is difficult, but may be possible from **a sequence of items(behaviors)**.



Problem of Today's RS: User Intentions

- ❑ Can RS model the transition of user intentions explicitly?
 - ❑ In the real world, user intentions could be dynamic rather than static.
 - ❑ “dynamic” : “intent transition”



Sequence Modeling

□ Sequential Recommendation

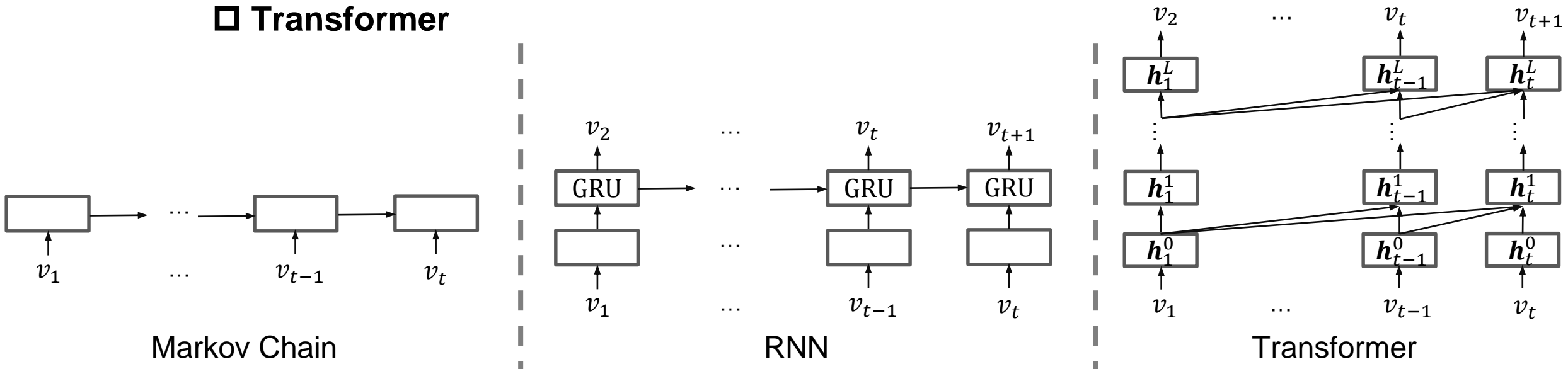
□ Order matters in real-world situations.

□ Sequence Modeling

□ **Markov Chain**: fails on long sequences, data sparsity problem

□ **Recurrent Neural Network**: fails on longer sequences, high cost

□ Transformer



Modeling User Intentions is Challenging

□ The existing methods capture behavior patterns. They fail to identify user intentions and model intent transition explicitly.

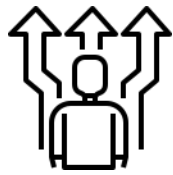
□ The properties of user intentions in Recommendation:



Unobserved



auxiliary information



Multiple



identify



Correlated



cognitive relations



Dynamic



intent transition

Problem

□ Intention-aware Sequential Recommendation

□ Goal: for each user, given the sequence of interacted items v_1, \dots, v_t with available description information, predict the v_{t+1} at time index $t + 1$.

□ Description information: title, categories, reviews...

□ We extract keywords from the description information and refer to these extracted keywords as *concepts*.

□ User intentions could be reflected in these concepts.

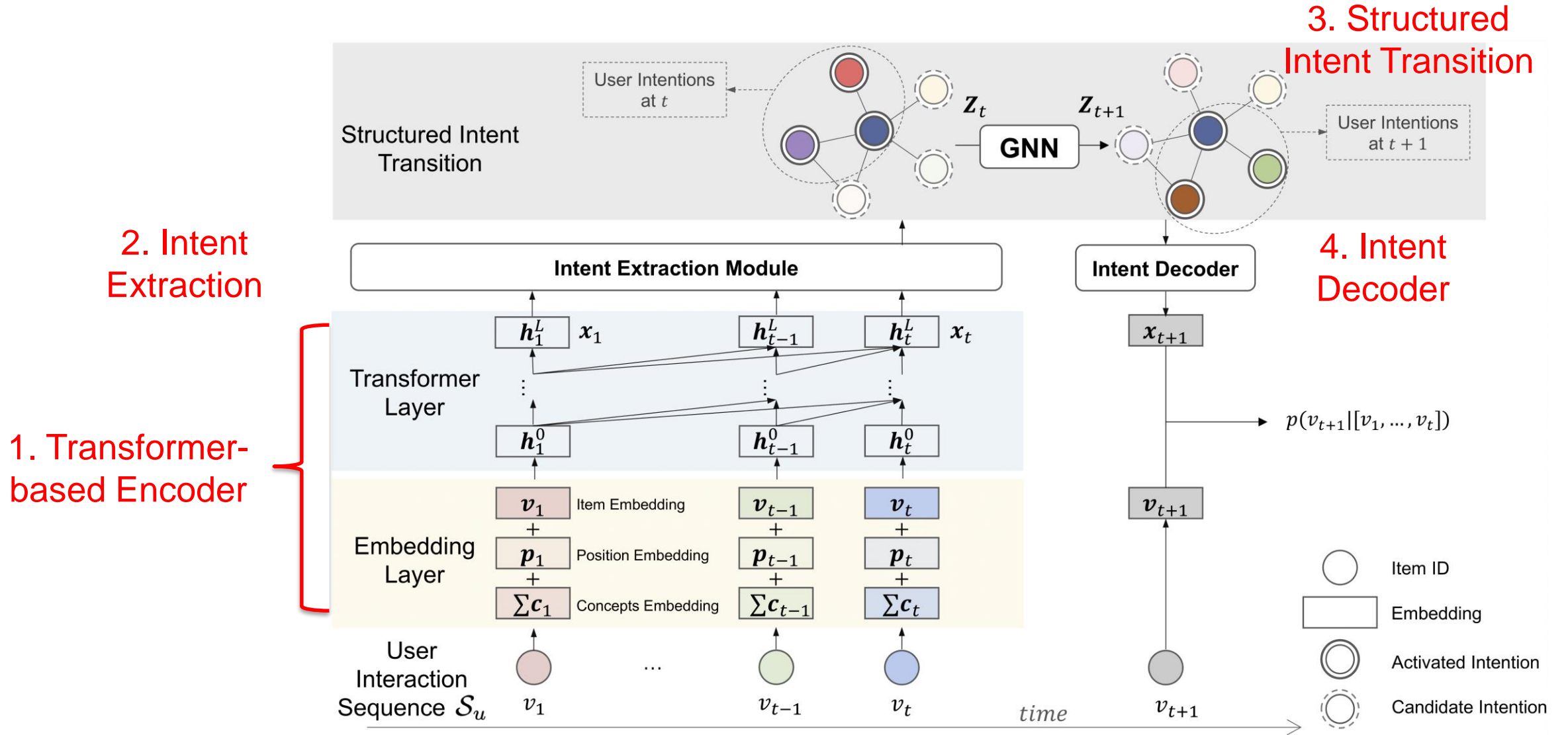
□ E.g.,

□ “Yes, it’s perfect for self-defense.” → “perfect” “self-defense”

□ “This might be great for my son playing baseball.” → “great” “son” “baseball”

Making it possible to identify intentions

Model Framework



Transformer-based Encoder

□ Embedding Submodule

□ Embedding (\mathbf{h}_i) = item (\mathbf{v}_i) + position (\mathbf{p}_i) + concepts (\mathbf{c}_j)
Item Property Order Potential Intents

□ Input hidden representation: $\mathbf{H}^0 = [\mathbf{h}_1^0, \mathbf{h}_2^0, \dots, \mathbf{h}_T^0]$ $\mathbf{h}_i = \mathbf{v}_i + \mathbf{p}_i + \sum_{e_{i,j}=1} \mathbf{c}_j$

□ Self-attention Submodule

□ Capture the dependencies among items within a behavior sequence

$$\mathbf{S}^l = \text{SA}(\mathbf{H}^l) = \text{Attention}(\mathbf{H}^l \mathbf{W}_Q^l, \mathbf{H}^l \mathbf{W}_K^l, \mathbf{H}^l \mathbf{W}_V^l)$$

$$\mathbf{H}^{l+1} = \text{FFN}(\mathbf{S}^l) = \text{ReLU}(\mathbf{S}^l \mathbf{W}_1^l + \mathbf{b}_1^l) \mathbf{W}_2^l + \mathbf{b}_2^l$$

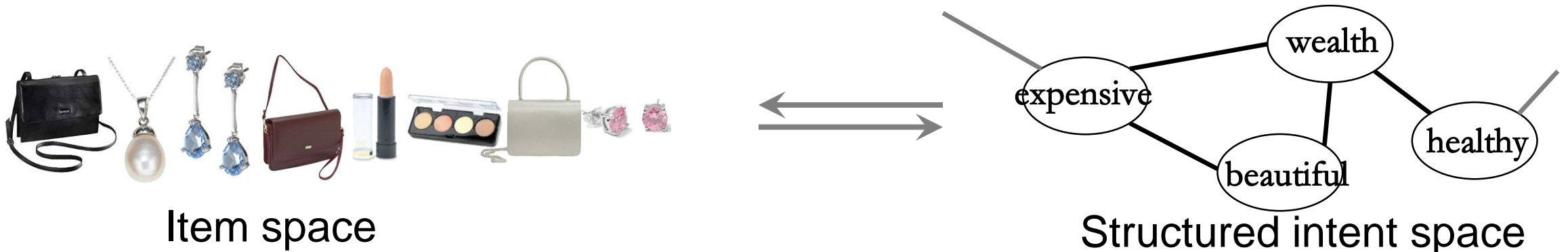
□ Goals: Learn users' behavior patterns and filter some noises

Intent Extraction

- In this step, we explicitly **extract explainable user intents** from the encoded sequence hidden representations $X = H^L$.
- Goal: Infer a multi-hot intention vector $\mathbf{m}_t = [m_{t,1}, \dots, m_{t,K}]$
 - $m_{t,k} = 1 \Leftrightarrow k^{\text{th}}$ concept belongs to the user intentions at time t
- A straightforward method: treating \mathbf{m}_t as a parameter to be optimized? (×)
 - over-parameterization; cause efficiency burdens
- We adopt a prototype-based method:
 - define K intention prototypes, calculate similarity $s_{t,k} = \frac{\mathbf{x}_t \cdot \mathbf{c}_k}{\|\mathbf{x}_t\|_2 \|\mathbf{c}_k\|_2}$
 - draw \mathbf{m}_t from $\mathbf{m}_t \sim \text{Categorical}(\text{Softmax}(s_{t,1}, s_{t,2}, \dots, s_{t,K}))$

Structured Intent Transition

- In this step, we model intent transitions with GNN.
 - Learn a personalized intent feature matrix $\mathbf{Z}_t = [z_{t,1}, \dots, z_{t,K}] \in \mathbb{R}^{K \times d'}$
 - From item space to intention space $z_{t,k} = m_{t,k} \text{MLP}_k(\mathbf{x}_t)$
 - Model the intent transition on the concept graph \mathbf{A} (ConceptNet)
 - Pre-defined concepts and their relations can be treated as knowledge; underlying cognitive activity is stored in the connections among concepts.
 - We adopt the message-passing framework $\mathbf{Z}_{t+1} = \mathcal{F}(\mathbf{Z}_t, \mathbf{A})$



Intent Decoder

□ After obtaining the future intent features Z_{t+1} and intent vector \mathbf{m}_{t+1} , the intent decoder is defined as:

$$\mathbf{x}_{t+1} = \sum_{k=1}^K m_{t+1,k} \text{MLP}'_k(\mathbf{z}_{t+1,k})$$

□ Recommendation probability of item v_{t+1} :

$$p(v_{t+1} | [v_1, v_2, \dots, v_t]) = \text{Softmax}(\mathbf{x}_{t+1} \mathbf{V}^T)$$

□ Objective Function $\mathcal{L}_u = \frac{1}{|\mathcal{S}^{(u)}|} \sum_{v_{t+1} \in \mathcal{S}^{(u)}} -\log p(v_{t+1} | [v_1, v_2, \dots, v_t])$

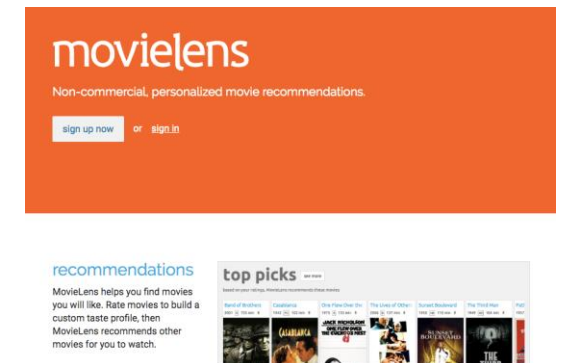
Experiments

- **We aim to answer the following three questions:**
 - **Q1:** How does our method perform compared with other state-of-the-art sequential recommendation methods?
 - **Q2:** Can our method identify explainable user intents and model the structured intent transition accurately?
 - **Q3:** Is the intent extraction and structured intent transition module helpful in our method?

Experimental Settings

□ Datasets

- **Amazon:** contains a large number of product reviews from *Amazon.com*
 - We choose the “Beauty” category dataset.
- **Steam:** a popular online video game platform
- **Epinions:** a popular online consumer review website *Epinions.com*
- **MovieLens:** a dataset about movie rating, including ML-1m an ML-20m



Experimental Settings

□ Datasets preprocessing procedures

- convert all reviews/ratings to implicit feedback of 1
- remove users and items if they have fewer than 5 records
- build the interaction sequence sorted by the timestamps for each user
- obtain concepts of items from the available meta-data
 - e.g., items' descriptions, reviews, etc.

TABLE 3: Statistics of the datasets.

Dataset	#Users	#Items	#Interactions	Avg.length	Density
Beauty	40,226	54,542	0.35m	8.8	0.02%
Steam	281,428	13,044	3.5m	12.4	0.10%
Epinions	5,015	8,335	26.9k	5.37	0.06%
ML-1m	6,040	3,416	1.0m	163.5	4.79%
ML-20m	138,493	26,744	20m	144.4	0.54%

TABLE 4: Statistics of preprocessed concepts of the datasets.

Dataset	#Concepts	#Edges	Avg.concepts/item
Beauty	592	2,791	4.45
Steam	229	472	4.49
Epinions	114	467	5.50
ML-1m	96	327	1.94
ML-20m	316	842	4.21

Experimental Settings

□ Evaluation metrics

□ Hit Rate (HR)
$$\text{HR}@k = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \delta(|\mathcal{T}_u \cap \mathcal{R}_{u,k}| > 0)$$

□ Normalized Discounted Cumulative Gain (NDCG)

$$\begin{aligned} \text{NDCG}@k &= \frac{1}{Z} \text{DCG}@k \\ &= \frac{1}{Z} \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \sum_{i=1}^k \frac{\delta(r_{u,i} \in \mathcal{T}_u)}{\log_2(i+1)} \end{aligned}$$

□ Mean Reciprocal Rank (MRR)

$$\text{MRR} = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \frac{1}{\text{rank}_u}$$

Baselines

□ Non-sequential methods

- PopRec, BPR-MF, NCF

□ Sequential methods

- Markov chain based methods: **FPMC**, **Caser**

- RNN based methods: **GRU4Rec**, **GRU4Rec+**

- Transformer based methods: **SASRec**, **BERT4Rec**

Experimental Results

□ Recommendation Accuracy

Datasets	Metric	PopRec	BPR-MF	NCF	FPMC	GRU4Rec	GRU4Rec ⁺	DGCF	Caser	SASRec	BERT4Rec	ISRec	Improv.
Beauty	HR@1	0.0077	0.0415	0.0407	0.0435	0.0402	0.0551	0.0626	0.0475	0.0906	0.0953	0.1233	29.38%
	HR@5	0.0392	0.1209	0.1305	0.1387	0.1315	0.1781	0.1835	0.1625	0.1934	0.2207	0.2734	23.88%
	HR@10	0.0762	0.1992	0.2142	0.2401	0.2343	0.2654	0.2778	0.2590	0.2653	0.3025	0.3594	18.81%
	NDCG@5	0.0230	0.0814	0.0855	0.0902	0.0812	0.1172	0.1241	0.1050	0.1436	0.1599	0.2020	26.33%
	NDCG@10	0.0349	0.1064	0.1124	0.1211	0.1074	0.1453	0.1543	0.1360	0.1633	0.1862	0.2296	23.31%
	MRR	0.0437	0.1006	0.1043	0.1056	0.1023	0.1299	0.1381	0.1205	0.1536	0.1701	0.2081	22.34%
Steam	HR@1	0.0159	0.0314	0.0246	0.0358	0.0574	0.0812	0.0564	0.0495	0.0885	0.0957	0.1450	51.52%
	HR@5	0.0805	0.1177	0.1203	0.1517	0.2171	0.2391	0.1825	0.1766	0.2559	0.2710	0.3622	33.65%
	HR@10	0.1389	0.1993	0.2169	0.2551	0.3313	0.3594	0.2934	0.2870	0.3783	0.4013	0.5072	26.39%
	NDCG@5	0.0477	0.0744	0.0717	0.0945	0.1370	0.1613	0.1392	0.1131	0.1727	0.1842	0.2570	39.52%
	NDCG@10	0.0665	0.1005	0.1026	0.1283	0.1802	0.2053	0.1717	0.1484	0.2147	0.2261	0.3036	34.28%
	MRR	0.0669	0.0942	0.0932	0.1139	0.1420	0.1757	0.1400	0.1305	0.1874	0.1949	0.2612	34.02%
Epinions	HR@1	0.0075	0.0151	0.0155	0.0162	0.0169	0.0176	0.0188	0.0164	0.0217	0.0220	0.0282	28.18%
	HR@5	0.0339	0.0472	0.0538	0.0578	0.0629	0.0737	0.0736	0.0733	0.0822	0.0866	0.1129	30.37%
	HR@10	0.0831	0.1005	0.0975	0.1083	0.1280	0.1380	0.1353	0.1351	0.1358	0.1462	0.1949	33.31%
	NDCG@5	0.0206	0.0316	0.0338	0.0373	0.0431	0.0456	0.0491	0.0444	0.0530	0.0534	0.0699	30.90%
	NDCG@10	0.0358	0.0464	0.0474	0.0512	0.0565	0.0657	0.0656	0.0642	0.0701	0.0724	0.0962	32.87%
	MRR	0.0430	0.0540	0.0543	0.0546	0.0681	0.0700	0.0693	0.0668	0.0699	0.0705	0.0885	25.53%
ML-1m	HR@1	0.0141	0.0914	0.0397	0.1386	0.1583	0.2092	0.1770	0.2194	0.2351	0.2863	0.3184	11.21%
	HR@5	0.0715	0.2866	0.1932	0.4297	0.4673	0.5103	0.4485	0.5353	0.5434	0.5876	0.6262	6.57%
	HR@10	0.1358	0.4301	0.3477	0.5946	0.6207	0.6351	0.6032	0.6692	0.6629	0.6970	0.7363	5.64%
	NDCG@5	0.0416	0.1903	0.1146	0.2885	0.3196	0.3705	0.3162	0.3832	0.3980	0.4454	0.4831	8.46%
	NDCG@10	0.0621	0.2365	0.1640	0.3439	0.3627	0.4064	0.3660	0.4268	0.4368	0.4818	0.5189	7.70%
	MRR	0.0627	0.2009	0.1358	0.2891	0.3041	0.3462	0.3105	0.3648	0.3790	0.4254	0.4589	7.87%
ML-20m	HR@1	0.0221	0.0553	0.0231	0.1079	0.1459	0.2021	0.1760	0.1232	0.2544	0.3440	0.3505	1.89%
	HR@5	0.0805	0.2128	0.1358	0.3601	0.4657	0.5118	0.4361	0.3804	0.5727	0.6323	0.6484	2.55%
	HR@10	0.1378	0.3538	0.2922	0.5201	0.5844	0.6524	0.6252	0.5427	0.7136	0.7473	0.7689	2.89%
	NDCG@5	0.0511	0.1332	0.0771	0.2239	0.3090	0.3630	0.3267	0.2538	0.4208	0.4967	0.5024	1.15%
	NDCG@10	0.0695	0.1786	0.1271	0.2895	0.3637	0.4087	0.3809	0.3062	0.4665	0.5340	0.5401	1.14%
	MRR	0.0709	0.1503	0.1072	0.2273	0.2967	0.3476	0.3278	0.2529	0.4026	0.4785	0.4841	1.17%

□ Sequential > Non-sequential

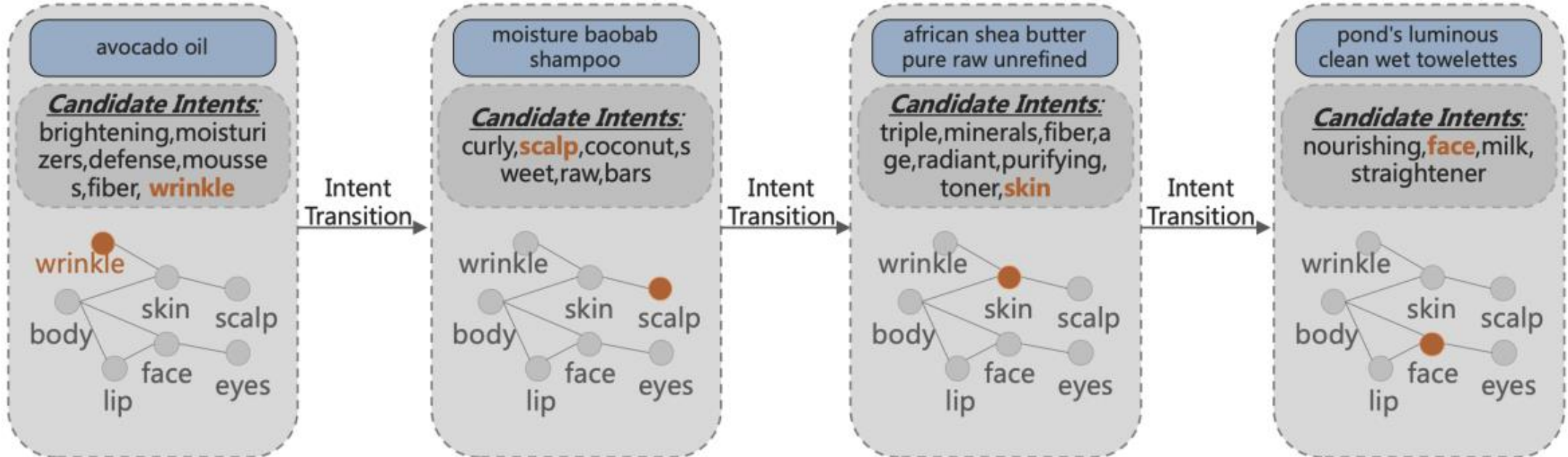
□ Self-attention can provide large performance gains.

□ Our method outperforms all the baselines.

□ The sparser the dataset, the larger the improvement of our method.

Experimental Results

□ Showcases of Intent Extraction and Structured Intent Transition

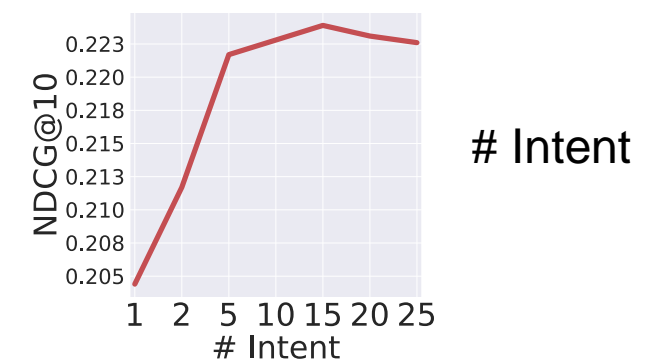
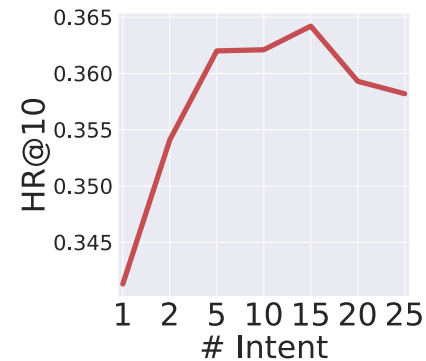
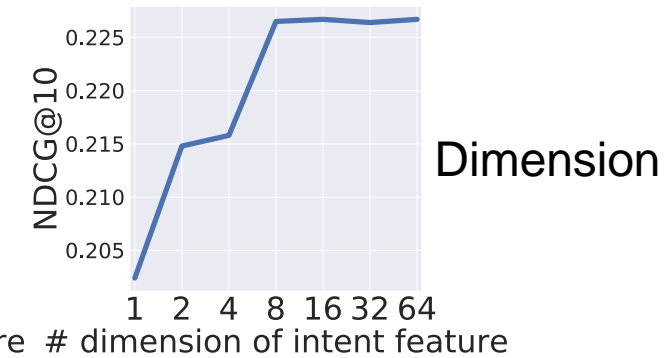
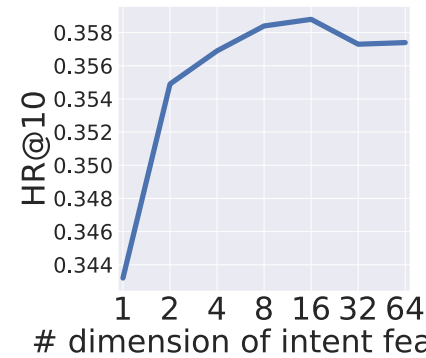


Experimental Results

□ Ablation studies and hyperparameters sensitivities

TABLE 5: Performance comparison of ISRec and variants.

	Beauty		ML-1m	
	HR@10	NDCG@10	HR@10	NDCG@10
ISRec	0.3594	0.2296	0.7363	0.5189
w/o GNN	0.3311	0.2095	0.7222	0.4978
w/o GNN&Intent	0.3092	0.1965	0.7058	0.4731
BERT4Rec + concept	0.3037	0.1886	0.6987	0.4824
SASRec + concept	0.3061	0.1845	0.6972	0.4643



Conclusions

- We study the intent-aware sequential recommendation with structured intent transition.
- Why can't the current Sequential Recommender Systems make us satisfied enough?

知其 **然**，而不知其 **所以然**

User Behaviors

User Intentions

**Modeling user intentions with GNN:
Try to promote human-like Recommender Systems.**

References

- ❑ W.-C. Kang, *et al.* “Self-attentive sequential recommendation.” ICDM, 2018.
- ❑ F. Sun, *et al.* “Bert4rec: Sequential recommendation with bidirectional encoder representations from transformer.” CIKM, 2019.
- ❑ J. Tang, *et al.* “Personalized top-n sequential recommendation via convolutional sequence embedding.” WSDM, 2018.
- ❑ R. Speer, *et al.* “Conceptnet 5: A large semantic network for relational knowledge.” in The People’s Web Meets NLP. Springer, 2013.
- ❑ X. He, *et al.* “Neural collaborative filtering.” WWW, 2017.
- ❑ S. Wang, *et al.* “Intention2basket: A neural intention-driven approach for dynamic next-basket planning.” IJCAI, 2020.
- ❑ N. Zhu, *et al.* “Sequential modeling of hierarchical user intention and preference for next-item recommendation.” WSDM, 2020.
- ❑ Y. Cen “Controllable Multi-Interest Framework for Recommendation.” KDD 2020.

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PDF

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29
Full
Text Views



Abstract

Authors

Keywords

Metrics

Media

Abstract:

Human behaviors in recommendation systems are driven by many high-level, complex, and evolving intentions behind their decision making processes. In order to achieve better performance, it is important for recommendation systems to be aware of user intentions besides considering the historical interaction behaviors. However, user intentions are seldom fully or easily observed in practice, so that the existing works are incapable of fully tracking and modeling user intentions, not to mention using them effectively into recommendation. In this paper, we present the Intention-Aware Sequential Recommendation (ISRec) method, for capturing the underlying intentions of each user that may lead to her next consumption behavior and improving recommendation performance. Specifically, we first extract the intentions of the target user from sequential contexts, then take complex intent transition into account through the message-passing mechanism on an intention graph, and finally obtain the future intentions of this target user from inference on the intention graph. The sequential recommendation for a user will be made based on the predicted user intentions, offering more transparent and explainable intermediate results for each recommendation. Extensive experiments on various real-world datasets demonstrate the superiority of our method against several state-of-the-art baselines in sequential recommendation in terms of different metrics.

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Haoyang Li; Xin Wang; Ziwei Zhang; Jianxin Ma; Peng Cui; Wenwu Zhu.

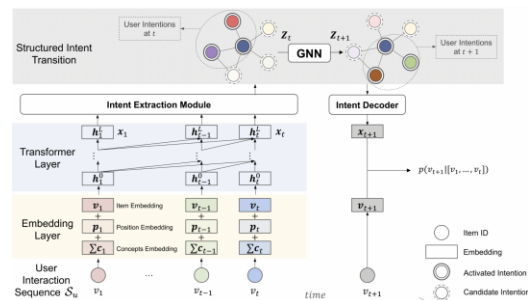
Intention-aware Sequential Recommendation with Structured Intent Transition. *IEEE TKDE*, 2021.

Thanks!



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Model Framework



Experimental Settings

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 - We choose the "Beauty" category dataset.
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