MARS: Matching Attribute-aware Representation for Sequential Recommendation

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Paper   Code

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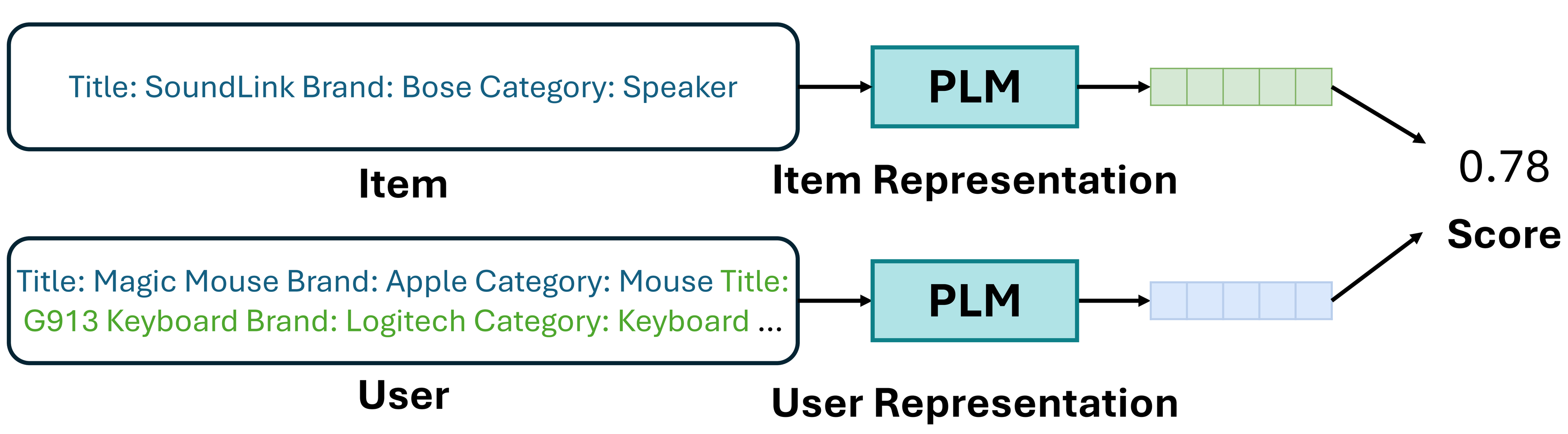
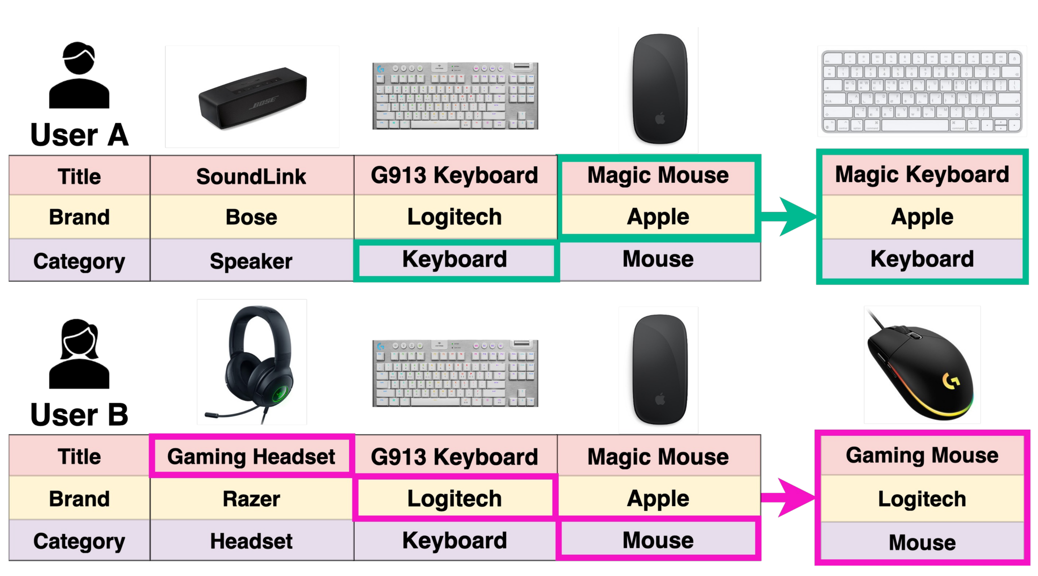
Problem Definition

Sequential recommendation aims to recommend the following items to users based on their interaction history.
Text-based sequential recommendation leverages **pre-trained language models(PLMs)** to encode user/item representation using textual features.



Motivation



- User interests can be **spread across multiple items and attributes.**
- Users can focus on **different attributes for the same item.**

It is essential to identify user interests in an **attribute-wise manner.**

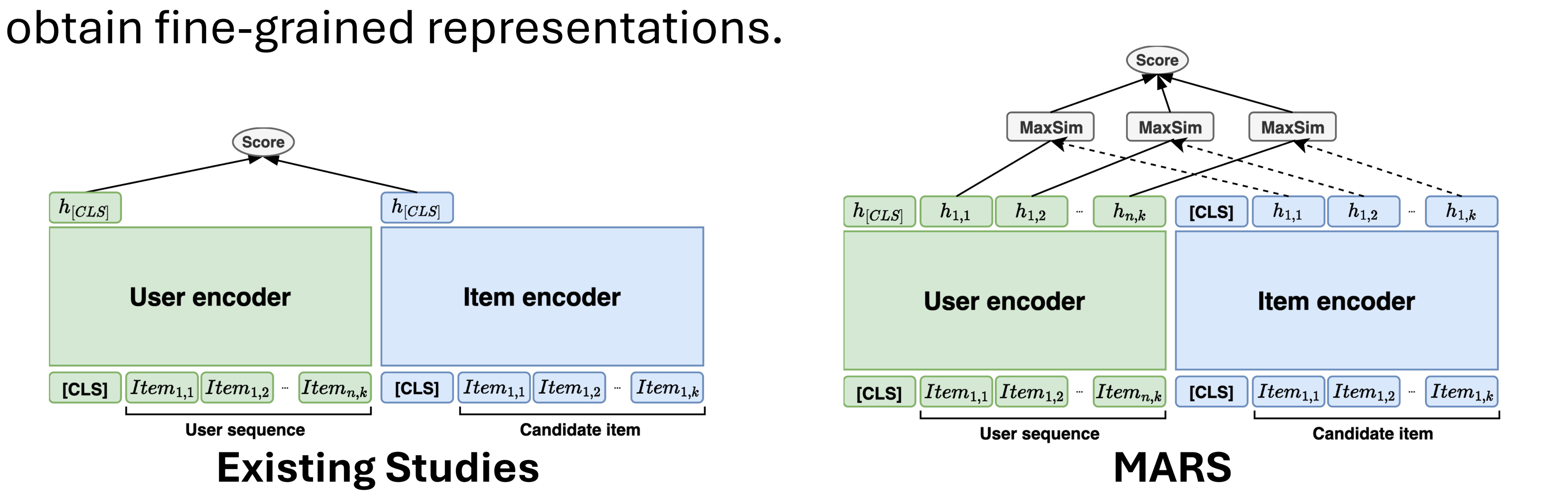
Takeaways

- ✓ **MARS** is a text-based sequential recommendation framework that effectively captures **attribute-aware user/item interactions**.
- ✓ **Attribute-aware text encoding** captures the fine-grained user preferences based on textual attributes of items.
- ✓ **Attribute-wise interaction matching** identifies the attribute-level preference of users.

Overview

Existing studies represent the user/item as a **single vector**.
However, single vector fails to capture **preferences for specific attributes** (*e.g.*, Logitech, Keyboard).

MARS represents the user/item with **multiple vectors** using **item attributes** to obtain fine-grained representations.



MARS (Matching Attribute-aware Representations for Sequential Recommendation)

Challenge 1. How do we represent a user/item to represent multiple attributes? → **Attribute-aware Text Encoding**

MARS obtains attribute-wise user/item representations, allowing **fine-grained attribute-level preference** to be represented.

Challenge 2. How do we calculate the matching score considering complex user interests? → **Attribute-wise Interaction Matching**

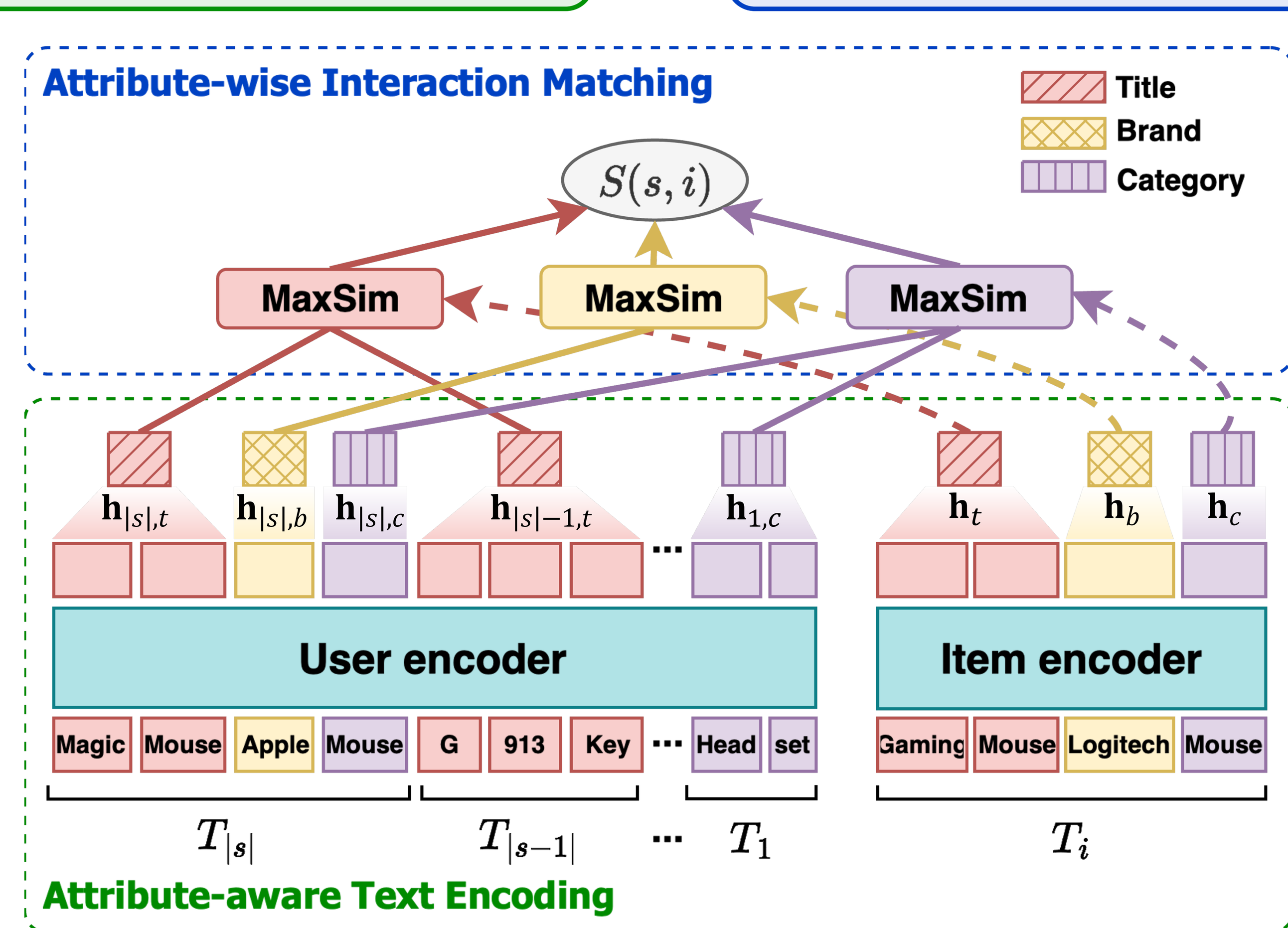
MARS captures intricate user-item relationship by calculating **attribute-wise matching scores.**

Items are represented by **attribute-wise vectors.**

- We obtain separate vectors for each attribute by mean-pooling the hidden states of the tokens representing each attribute.

Users are represented by **attribute-wise vectors for each item** in the sequence.

Method	# of item reps.	# of sequence reps.
UniSRec (KDD'22) Recformer (KDD'23)	1	1
MARS	# of attributes	# of attributes × # of items in seq.



The score is **calculated for each attribute** and then **aggregated** to obtain the final score.

- We employ **MaxSim** to dynamically match target item with various interests within the user sequence.

ex) Score for attribute 'Title' S_t between sequence s and item i

$$S_t(s,i) = \max_{t \in \{1,2,\dots,|s|\}} \cos(\mathbf{h}_{k,t}, \mathbf{h}_t)$$

The final score is calculated by **summing the scores of all attributes.**

Experimental Results

MARS shows **performance improvements** when compared to **ID-based**, **ID + text**, and **text-based** methods.

Dataset	Metric	SASRec	BERT4Rec	FDSA	S³Rec	UniSRec	MIRACLE	Recformer	MARS
Scientific	R@10	0.1350	0.0616	0.1160	0.0745	0.1040	0.1006	0.1435	**0.1533**
	N@10	0.0840	0.0365	0.0827	0.0462	0.0720	0.0829	0.1002	**0.1086**
Pantry	R@10	0.0781	0.0441	0.0664	0.0540	0.0548	0.0512	0.0840	**0.0928**
	N@10	0.0487	0.0289	0.0441	0.0293	0.0386	0.0379	0.0535	**0.0591**
Instruments	R@10	0.0934	0.0699	0.0766	0.0723	0.0828	0.0871	0.0941	**0.1082**
	N@10	0.0632	0.0459	0.0537	0.0447	0.0642	0.0720	0.0691	**0.0846**
Arts	R@10	0.1342	0.1048	0.1275	0.0823	0.1095	0.1140	0.1501	**0.1684**
	N@10	0.0908	0.0646	0.0918	0.0581	0.0830	0.1005	0.1094	**0.1306**
Office	R@10	0.1187	0.0985	0.0999	0.0723	0.0990	0.1098	0.1263	**0.1571**
	N@10	0.0841	0.0701	0.0715	0.0450	0.0810	0.0982	0.0920	**0.1270**

Ablation study shows that both attribute-aware item representation and matching is effective.

Dataset	Metric	Representation [BOS]	Representation Item	Matching Mean	Ours MARS
Scientific	R@10	0.1373	0.1441	0.1420	**0.1533**
	N@10	0.0991	0.1039	0.1016	**0.1086**
Pantry	R@10	0.0790	0.0897	0.0832	**0.0928**
	N@10	0.0527	0.0568	0.0553	**0.0591**
Inst.	R@10	0.0935	0.1046	0.0993	**0.1082**
	N@10	0.0742	0.0823	0.0775	**0.0846**
Arts	R@10	0.1531	0.1652	0.1534	**0.1668**
	N@10	0.1201	0.1296	0.1216	**0.1326**
Office	R@10	0.1342	0.1527	0.1384	**0.1588**
	N@10	0.1095	0.1215	0.1091	**0.1270**