Hierarchical Long and Short-term User Preference Modeling for Sequential Recommendation

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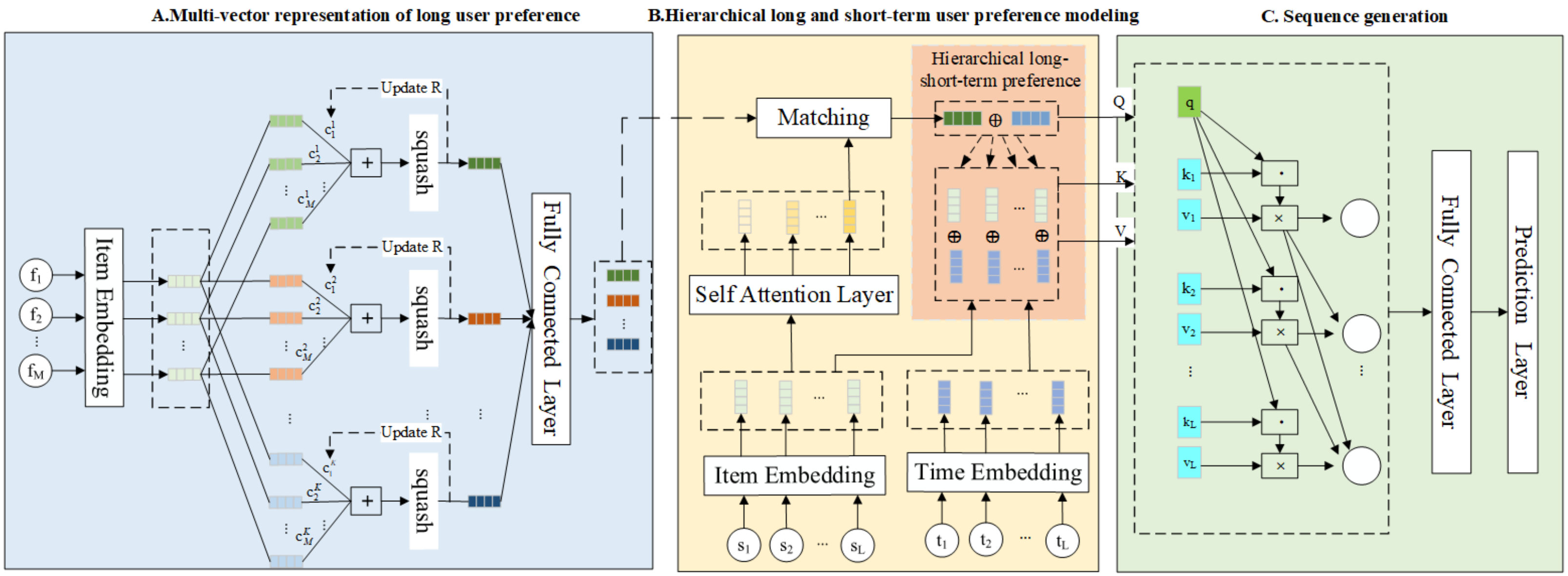
Problems & Ideas

- Existing sequence recommendation methods fail to:
  - simultaneously capture the multi-faceted nature of long-term preferences and temporal variations in short-term user interests.
  - establish inherent connections between users' long-term preferences and the dynamics of short-term interests.
- Ideas: an end-to-end hierarchical long and short-term sequential recommendation model designed to effectively capture the hierarchical relationship between long-term user preferences and short-term interests.



Main Contributions

- Contributions:
  - We propose a hierarchical long and short-term sequential recommendation model that utilizes a dynamic routing mechanism to adaptively aggregate users' long-term interests, along with a self-attention layer to aggregate short-term interests, effectively capturing dynamic changes in user interests across different temporal scales.
  - We design a hierarchical matching mechanism for long and short-term interests, introducing dynamic matching of current short term interests with long-term preferences and incorporating a time-encoding mechanism to generate the final user interest representation, thereby improving recommendation accuracy in complex behavioral scenarios.

Table 1 Performance Comparison (in%) of Different Models on HR@10 under Random Negative Sampling Evaluation

Type	Model	Amazon Toys	Amazon Book	MovieLens-1M	Yelp	Beauty
Non Time-Aware	SASRec	46.26	78.29	80.20	46.21	44.18
	BERT4Rec	38.87	79.90	75.59	39.95	46.29
	Caser	37.52	76.74	76.92	33.50	26.39
	STAMP	38.86	70.78	74.44	87.56	42.25
Time-Aware	TiSASRec	<u>47.66</u>	78.53	<u>80.66</u>	47.97	28.18
	MEANTIME	47.62	<u>82.02</u>	79.66	66.31	46.65
	TiCoSeRec	44.31	80.23	79.04	87.22	48.62
	FEARrec	46.55	79.94	75.94	<u>88.33</u>	<u>48.63</u>
	HLSUP	**50.47**	**83.92**	**81.41**	**89.41**	**61.49**

For each positive user-item interaction, 100 negative samples were randomly drawn from items that the user had no interaction with during the corresponding time period, and were combined with a positive sample to form training instances. The top-10 recommendation results were evaluated using hit rate (HR@10). Experimental results are presented in Table 1.