Long- and Short-term Preference Learning for Next POI Recommendation

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Abstract

Next POI recommendation has been studied extensively in recent years. The goal is to recommend next POI for users at specific time given users' historical check-in data. Therefore, it is crucial to model users' general taste and recent sequential behavior. Moreover, the context information such as the category and check-in time is also important to capture user preference. To this end, we propose a long- and short-term preference learning model (LSPL) considering the sequential and context information.

Fig.1 The sample of the check-in sequence of one user

Methods

The illustration of the overall framework is shown in Fig.2. We learn the long-term preference with the attention mechanism. For short-term preference, we feed the location-based and category-based sequences into two LSTM models respectively to learn the location-level and the category-level preference. Finally, in the output layer, we combined the output of the long- and short-term together.

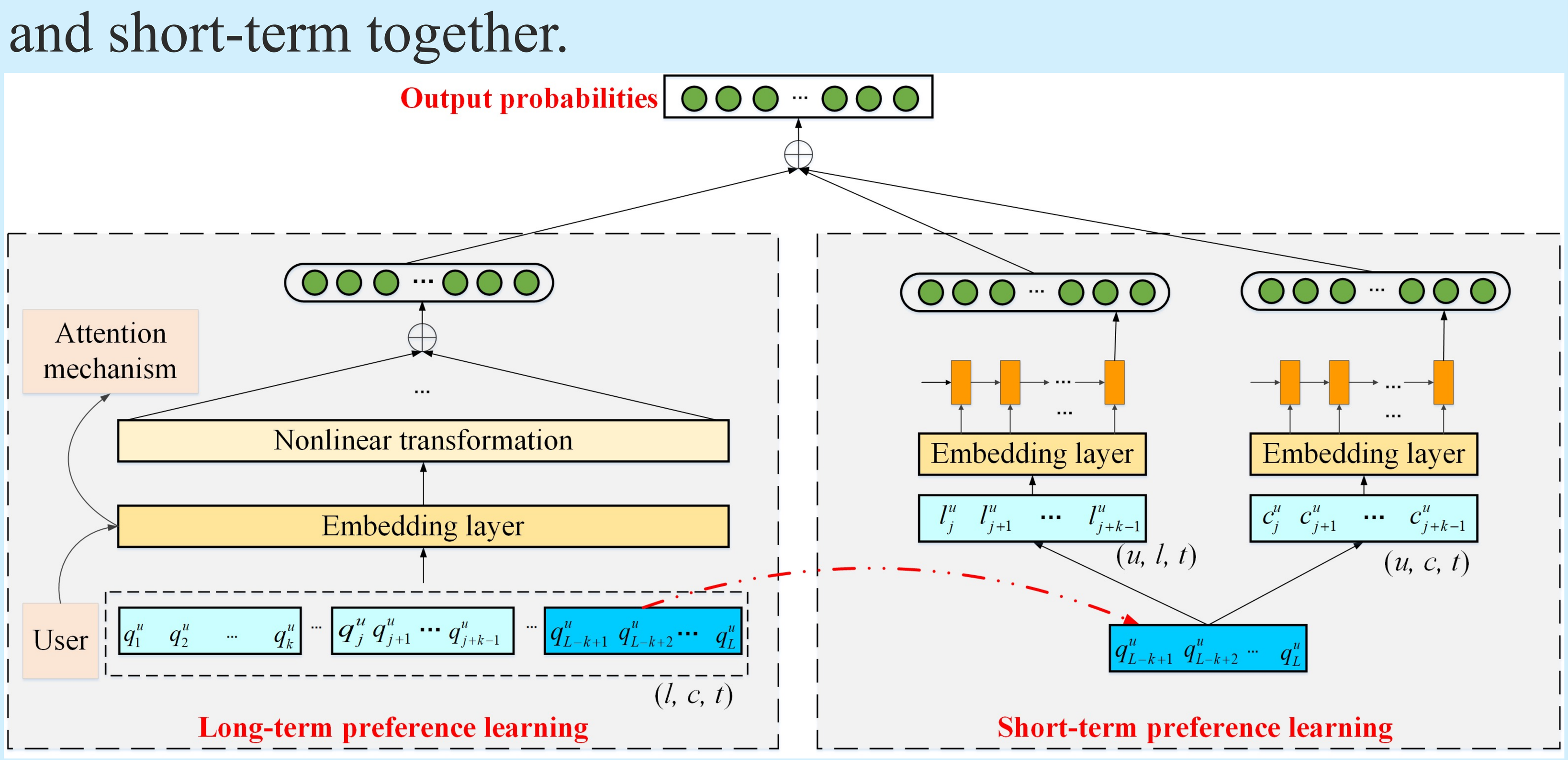

Fig.2 The overall architecture of LSPL model

Results

We use precision@k (P@k) and MAP@k to evaluate the performance of different methods. P@k indicates that whether the ground truth POI appears in the top-k recommended POIs and MAP@k measures the order of our recommendation list. The performance is illustrated in Table 1.

Table 1. Performance Comparation With Baselines

Datasets	Methods	p@1	p@5	p@10	p@20	MAP@20
NYC	FPMC [1]	0.0892	0.2262	0.2943	0.3895	0.1483
	SHAN [2]	0.1353	0.1779	0.1896	0.2019	0.1545
	DeepMove [3]	0.1408	0.2946	0.3630	0.4052	0.2101
	LSPL	0.1501	0.3204	0.3901	0.4461	0.2257
TKY	FPMC [1]	0.0655	0.1725	0.2385	0.2944	0.1128
	SHAN [2]	0.1084	0.1527	0.1684	0.1813	0.1296
	DeepMove [3]	0.1282	0.2488	0.2923	0.3289	0.182
	LSPL	0.1497	0.3281	0.3986	0.4596	0.2162

We can observe that SHAN and DeepMove show an increase of compared with FPMC on the NYC dataset. Compared with SHAN, DeepMove shows an increase under all metrics. Moreover, our model outperforms the compared methods on both datasets measured by all the metrics.

Discussions

We also discuss some variants of our method to demonstrate the importance of each part of our model.

LSPL_long, LSPL_loc, LSPL_cate denote variant model with only the long-term, location-level, category-level module, respectively. LSPL_loc+cate denotes variant model with only the location- and category-level preference learning module.

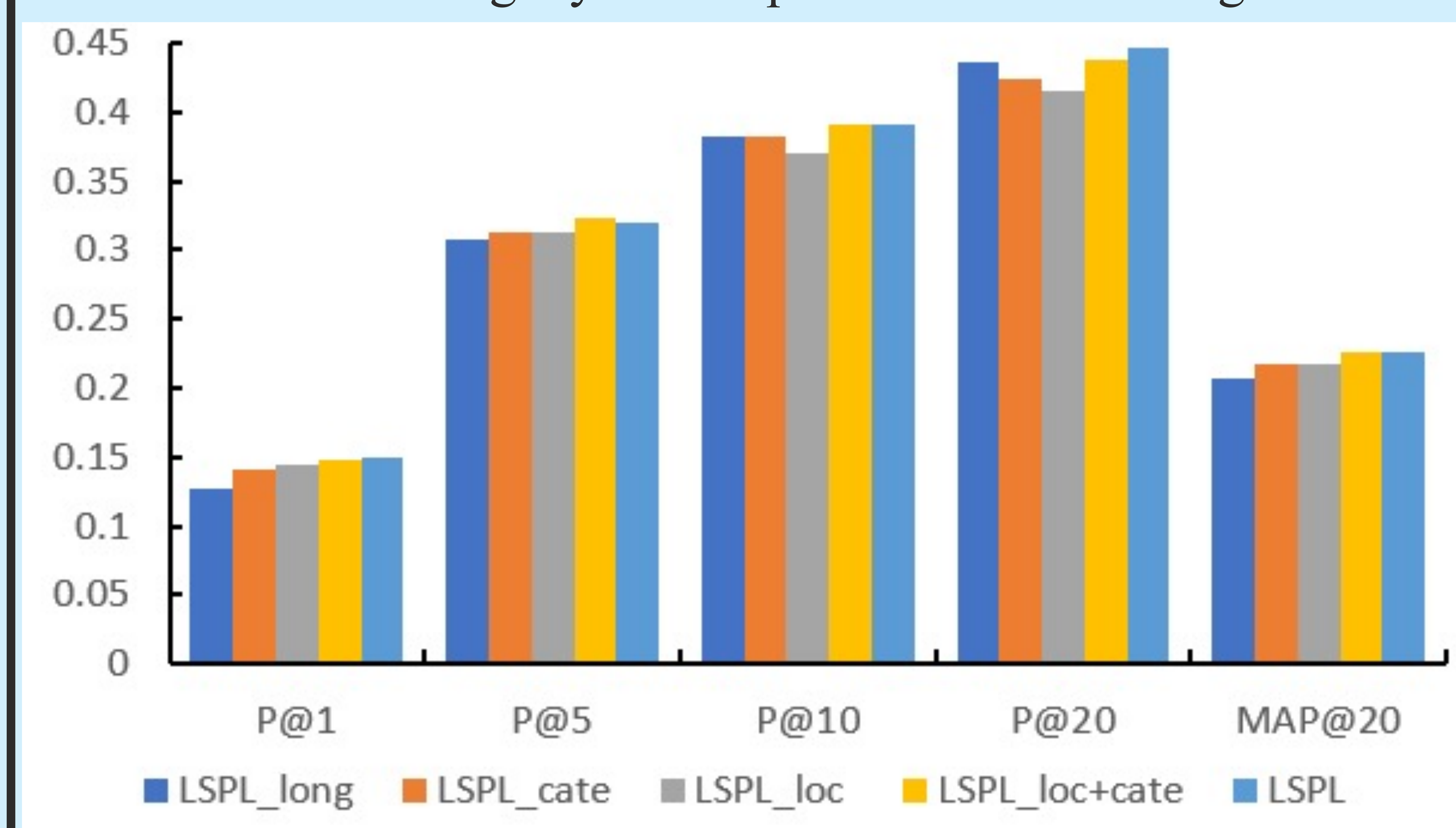

Fig.3 Comparison results of variant models.

We can conclude that the models with only one module show poor performance. LSPL_long is the worst one under P@1 and P@5. That's because there's no sequential information for long-term preference learning. Meanwhile, the models with merged modules show better performance, and our LSPL model shows the best performance. It indicates that it is effective to integrate users' long- and short-term preference.

Conclusions

In this paper, we proposed a unified model jointly learning users' long- and short-term preference for next POI recommendation. We integrate the contextual information to learn the preferences of users. The experiments demonstrate that our model outperformed the state-of-the-art methods on real-world datasets. And it is necessary to consider the long- and short-term preference. In future work, we would incorporate more context information into the model to further improve the performance.

Acknowledgements

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References

[1] Steffen Rendle, Christoph Freudenthaler, Lars Schmidt-Thieme. Factorizing personalized markov chains for next-basket recommendation. In Proc. WWW, 2010.
[2] Haochao Ying, Fuzheng Zhang, Yanchi Liu, et al. Sequential recommender system based on hierarchical attention networks. In Proc. IJCAI. 2018.
[3] Jie Feng, Yong Li, Chao Zhang, et al. Deepmove: Predicting human mobility with attentional recurrent networks. In Proc. WWW, 2018: 1459-1468

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