Table 1: Performance Comparation With Baselines

Data	Method	P@1	P@5	P@10	P@20	MAP@20
NYC	FPMC	0.0892	0.2262	0.2943	0.3895	0.1483
	SHAN	0.1353	0.1779	0.1896	0.2019	0.1545
	DeepMove	0.1408	0.2946	0.363	0.4052	0.2101
	LSPL	**0.1501**	**0.3204**	**0.3901**	**0.4461**	**0.2257**
TKY	FPMC	0.0655	0.1725	0.2385	0.2944	0.1128
	SHAN	0.1084	0.1527	0.1684	0.1813	0.1296
	DeepMove	0.1282	0.2488	0.2923	0.3289	0.1820
	LSPL	**0.1497**	**0.3281**	**0.3986**	**0.4596**	**0.2162**

and time D^t, the dimension of the hidden state and the batch size. Considering the vocabulary size of them, we set the dimensions of users, POIs, categories and time to be $D^u = 50$, $D^l = 300$, $D^c = 100$ and $D^t = 20$ respectively. The batch size is set to be 32, and the learning rate is 0.001.

5.4 Comparative Results

In this paper, 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.

We can observe that SHAN and DeepMove show an increase of 4.61% and 5.16% compared with FPMC under P@1 on the NYC dataset. However, SHAN shows poor performance under P@k with k = 5, 10, and 20. Compared with SHAN, DeepMove shows an increase of 0.5%-20% under all k of P@k, and 5.56% under MAP@20. Moreover, our model outperforms the compared methods on both datasets measured by all the metrics. Concretely, for P@k on the NYC dataset, our method is almost 5%-9% higher than FPMC, 1%-24% higher than SHAN, and 1%-4% higher than DeepMove. For MAP@20, our method outperforms FPMC, SHAN and DeepMove by 7.74%, 7.12% and 1.56% respectively. For P@k on the TKY dataset, our method is almost 8%-16% higher than FPMC, 4%-28% higher than SHAN, and 2%-13% higher than DeepMove. For MAP@20, our method outperforms FPMC, SHAN and DeepMove by 10.34%,8.66% and 3.42% respectively.

5.5 Discussions

Besides the performance comparison of the proposed model with the existing FPMC, SHAN and DeepMove, we also discuss some variants of our method to demonstrate the importance of each part of our model.

1) **LSPL_long**: variant model with only the long-term module.
2) **LSPL_loc**: variant model with only location-level module.
3) **LSPL_cate**: variant model with only category-level module.
4) **LSPL_loc+cate**:variant model with only the location- and category-level preference learning module.

Due to space limitation, we just investigate the performance on NYC dataset. The performance is illustrated in Fig.2. 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 in both datasets. That's because there's no sequential information for long-term preference learning. Meanwhile, the models with merged modules such as LSPL_loc+cate show better performance, and our LSPL model shows the best performance. It indicates that it is effective to integrate users' long-term and short-term preference.

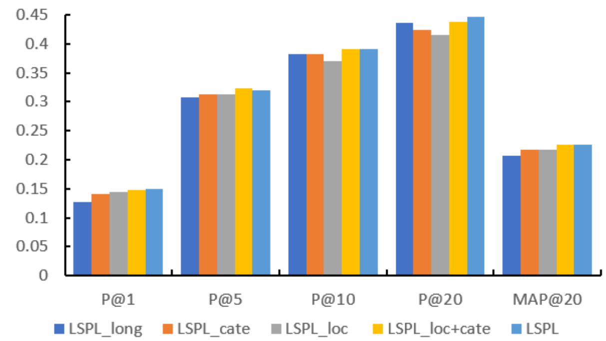

Figure 2: Comparison results of variant models.

6 CONCLUSION AND FUTURE WORK

In this paper, we proposed a unified model jointly learning users' long- and short-term preference for next POI recommendation. In long-term module, we characterize contextual features of POIs and capture the long-term preference via attention mechanism. In short-term module, we learn the location- and category-level preference by two parallel LSTM models. At last, we integrate the outputs of long- and short-term module to obtain the ranked list of candidate POIs. The experiments demonstrate that our model outperformed the state-of-the-art methods on real-world datasets. In future work, we would incorporate more context information into the model to further improve the performance.

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