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

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Outline

- Motivation
- Our Method
- Experiments
  - Datasets
  - Comparative Results
  - Discussions
- Future Work

Motivation

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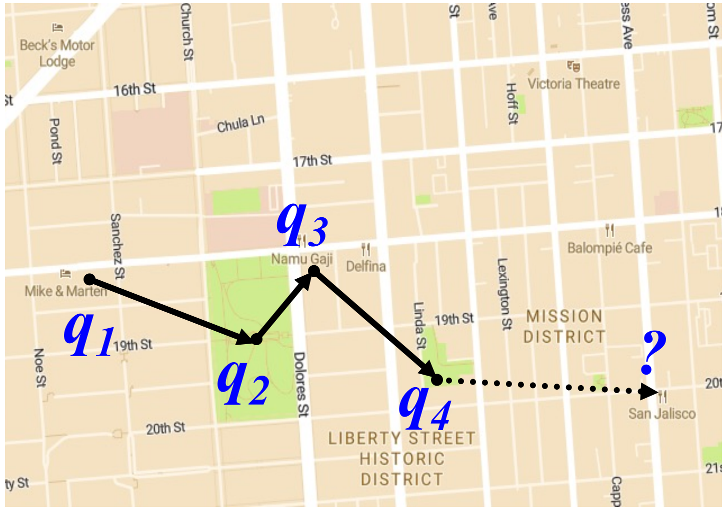
(1) Why next POI recommendation?



Where to go next?

Next POI RS

Users:

Recommend the interesting places

Business:

Attract more potential customers

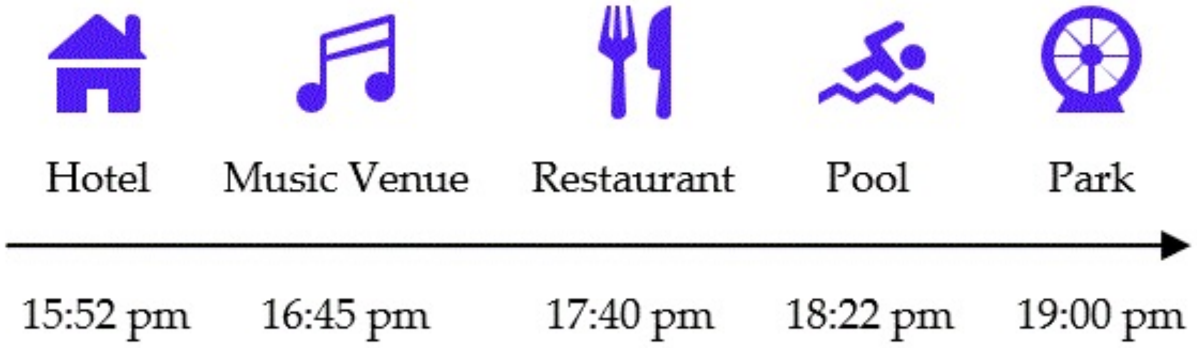
Motivation

(2) What affects the choice of where to go next time?

General taste — Long-term preference + Short-term preference — Sequential pattern

(3) How to learn users' preference?

Context Information
- Category of POI
- Check-in time

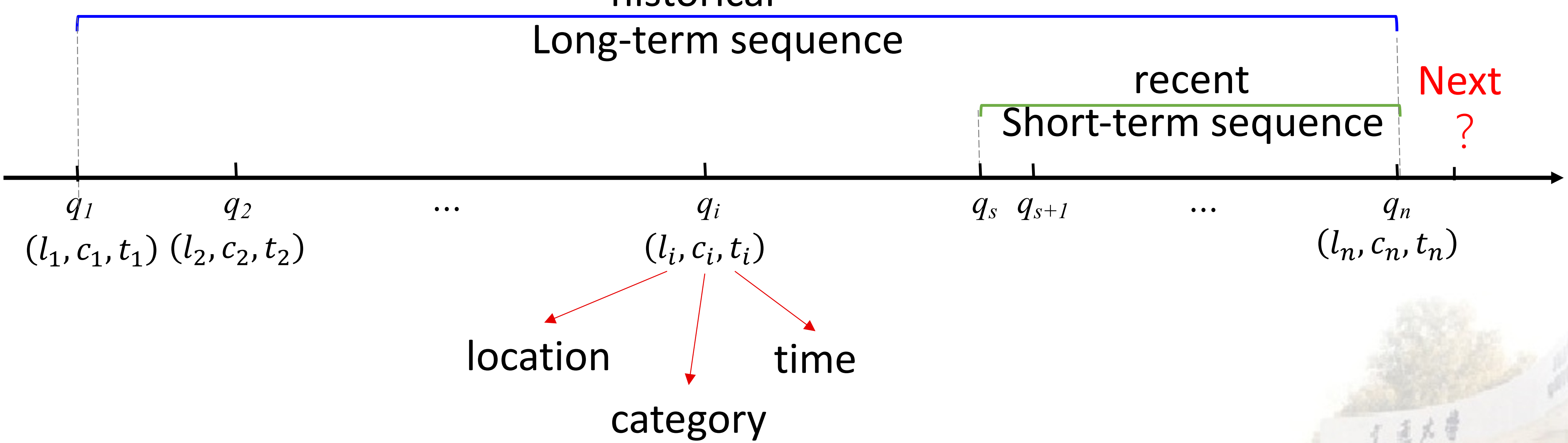


Our Method

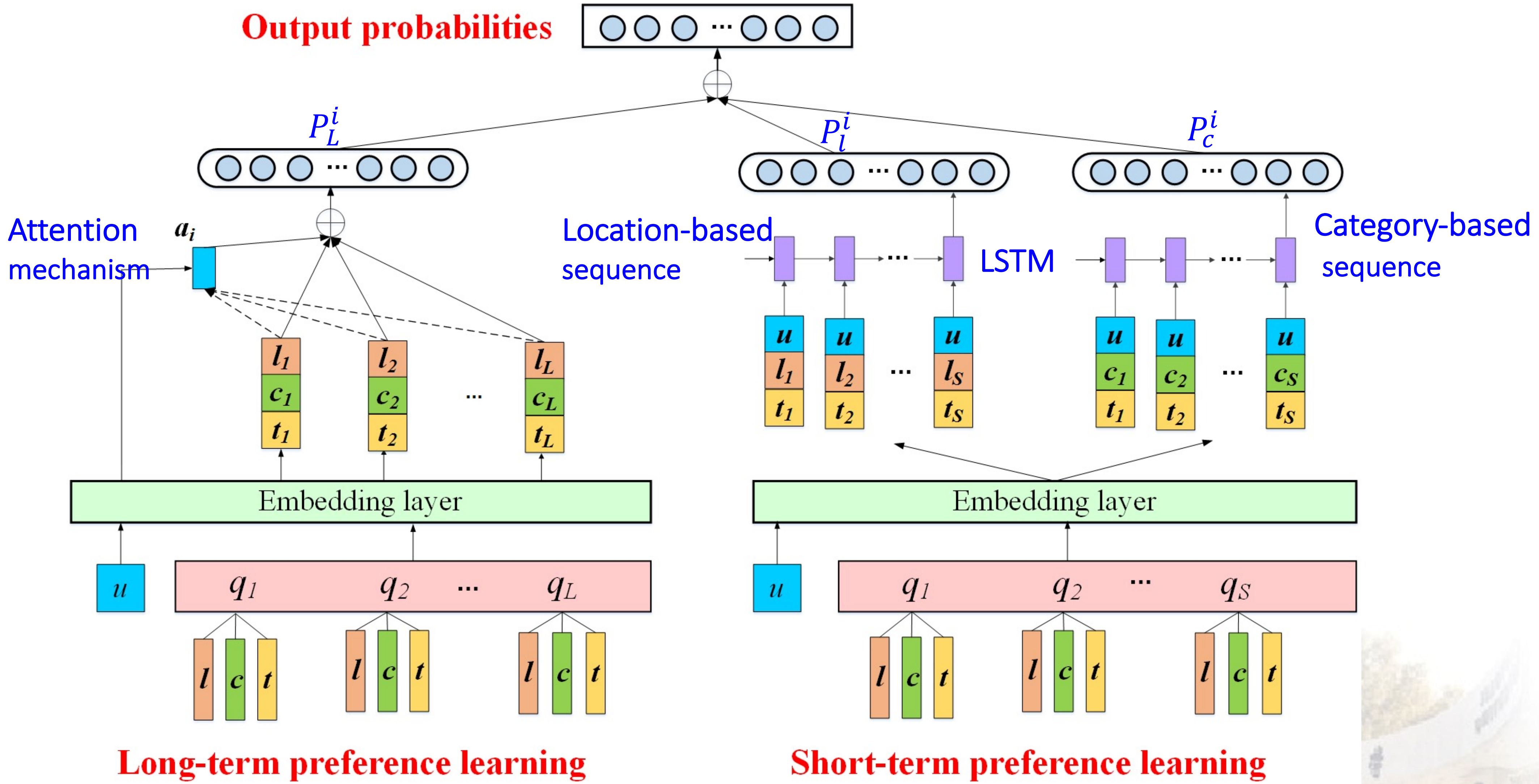
Long- and Short-term Preference Learning model (LSPL)

Long-term preference + Short-term preference

Data definition:



Our Method


Output probabilities
P_L^i
P_l^i
P_c^i
Attention mechanism
a_i
Location-based sequence
LSTM
Category-based sequence
l_1 c_1 t_1
l_2 c_2 t_2
l_L c_L t_L
u l_1 t_1
u l_2 t_2
u l_S t_S
u c_1 t_1
u c_2 t_2
u c_S t_S
Embedding layer
Embedding layer
u
q_1 q_2 ... q_L
u
q_1 q_2 ... q_S
l c t
Long-term preference learning
Short-term preference learning

Experiments

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Datasets

Two public Foursquare check-in datasets [4]:
New York City (NYC) and Tokyo (TKY)

Information: user ID, POI ID, category name, GPS and timestamp

Table 1. Datasets Statistics

	#user	#location	#category	#session
NYC	1,083	38,333	398	11,415
TKY	2,293	61,858	385	28,727

[4] Dingqi Yang, Daqing Zhang, Vincent W. Zheng, et al. Modeling user activity preference by leveraging user spatial temporal characteristics in LBSNs. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2014, 45(1): 129-142.
https://sites.google.com/site/yangdingqi/home/foursquare-dataset

Comparative Results

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Table 2. Performance Comparison With Baselines

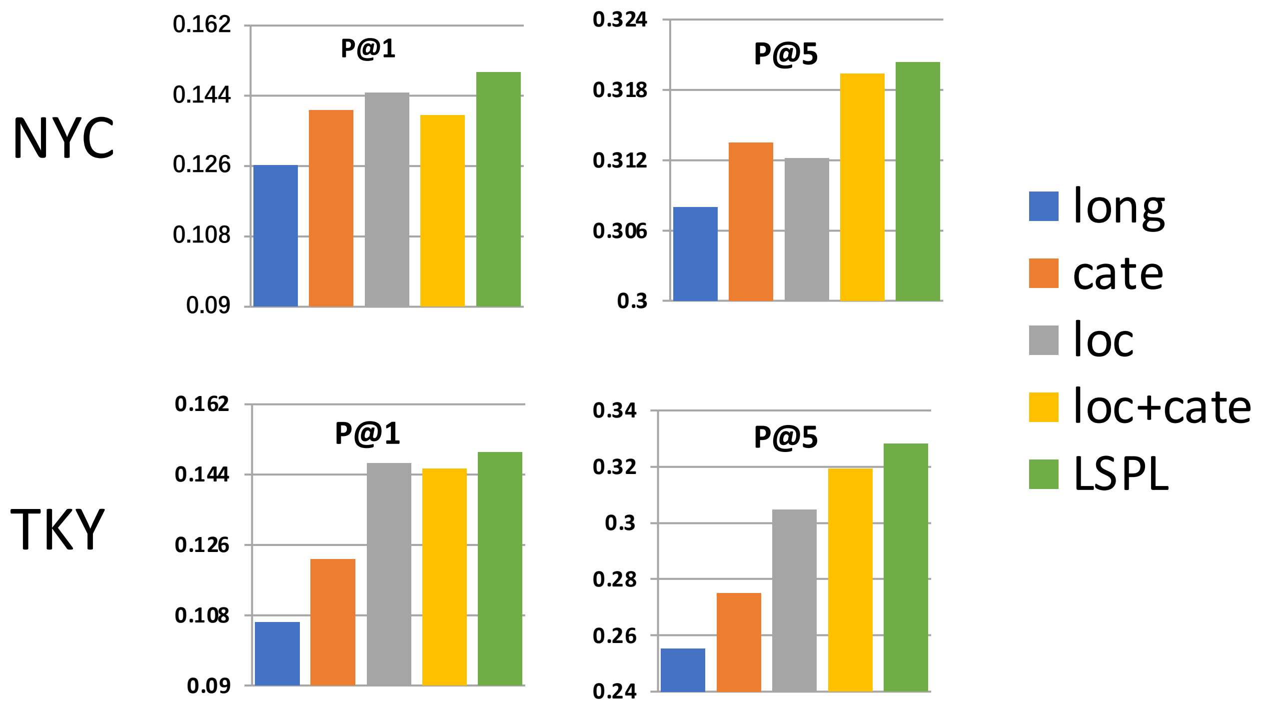
Datasets	Methods	p@1	p@5	p@10	p@20	MAP@20
NYC	FPMC [1]	0.0892	0.2262	0.2943	0.3895	0.1483
	SHAN [2]	0.1353	0.1779	0.1896	0.2019	0.1545
	DeepMove[3]	0.1408	0.2946	0.3630	0.4052	0.2101
	LSPL	**0.1501**	**0.3204**	**0.3901**	**0.4461**	**0.2257**
TKY	FPMC [1]	0.0655	0.1725	0.2385	0.2944	0.1128
	SHAN [2]	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**

Observations

- Our model outperforms the baselines.
- DeepMove shows better performance than FPMC and SHAN.

[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.

Discussion



Discussions

- 'long' is the worst one under P@1 and P@5.
- Models with only one module show poor performance.
- Our LSPL model is the best.

long: Variant model with only the long-term module
loc: Variant model with only the location-level module
cate: Variant model with only the category-level module
+: take another factor into consideration
LSPL: Our model with long- and short-term preference learning module.

Future Work

- Incorporate more context information
- Consider sequential information for long-term preference learning
- Dynamic preference learning

Thank You & QA

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