Paper Reading Sharing

NCF: A Neural Context Fusion Approach to Raw Mobility Annotation

李永康 2020/08/21

Motivation

most studies simply utilize POI check-ins to mine the concerned mobility patterns, the effectiveness of which is usually hindered due to data sparsity.

To obtain better POI-based human mobility for mining, in this paper, we strive to directly annotate the POIs associated with raw user-generated mobility records.

Introduction

- Human mobility

  location-based(focuses on the space and time aspects)

  activity-based(explains the purposes behind people's moves)

  point-of-interest (POI) based(people's movements between POIs)

- source of POI-based human mobility
  - Check-in records (they are sparse by nature / experimentally verifies that temporally sparse mobility may not exhibit any significant transitional relationships)
  - raw mobility annotation(proactive acquisition of POI-based human mobility from user-generated timestamped locations can provide both densely-sampled trajectories and reliable semantics to support numerous potential applications)

Raw mobility preprocessing

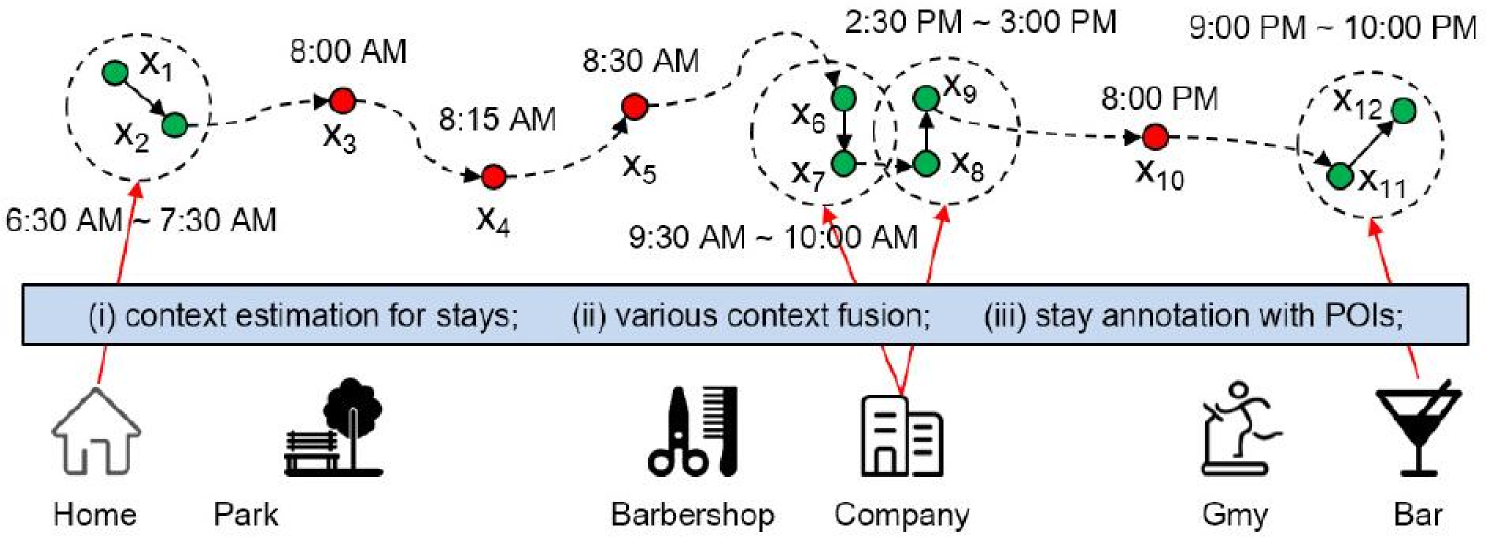


Figure 1. An example of raw mobility annotation, where points in green and red denote staying and moving mobility records, respectively, and each dashed circle represents a stay.

the diameter of circles is 200meters,
ξD=200 meters
ξT=2 hours
ξS=10 minutes

mobility record $x = (l, t)$
U and P be the sets of users and POIs

Definition 1
(Trajectory) $T_u = [x_{1,}\ x_2, \dots\dots, x_L]$
A sub trajectory of T_u $T_u[i,j] = [x_{i,}, \dots\dots, x_j$

Definition 2
(Stay) given $\xi D, \xi T\ and\ \xi S$
sub-trajectory $T_u[i,j]$ is a stay
if (a) $dist(l_k, \bar{l}_{ij}) \leq \xi D$ holds for all $i \leq k \leq$
where $\bar{l}_{ij}$ is the mean of $\{l_i, \dots\dots, l_j\}$,
(b) $t_{k+1} - t_k \leq \xi T$ holds for all $i \leq k \leq j -$
(c)$t_j - t_i \geq \xi S$

Problem1(Raw mobility annotation)
Given a trajectory T_u, raw mobility annotation is to identify a set $S =$
$\{T_u[i,j]\}$
of stays from T_u and annotate a POI $p \in P$ to each $T_u[i,j]$ such that user u visits POI p when generating the mobility records included in $T_u[i,j]$

A neural context fusion approach

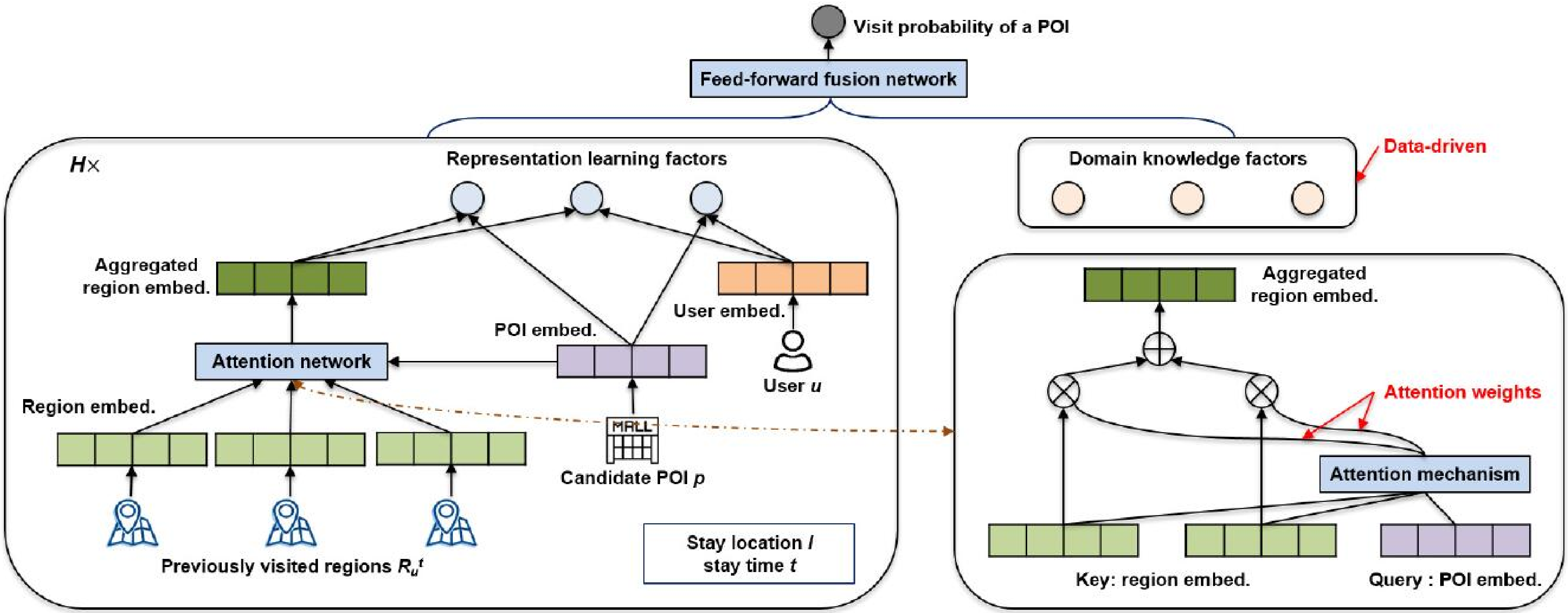


Figure 2. Framework overview of NCF

Input (a) a user $u \in U$ (b) location l and time stamp t of a stay $T_u[i, j]$
(c) a set R_u^t regions where user u stays before time stamp t (d) a candidate POI $p \in P$
Output the probability that u is visiting p when staying at location l and time stamp t

A neural context fusion approach

RL factors in the h-th (1 ≤ h ≤ H) head

- first RL factor

$$F_{pref}^{(h)}(\boldsymbol{u},\boldsymbol{p}) = \boldsymbol{MLP}^{(h)}\left(\boldsymbol{u}^{(h)}\right)^{T}\boldsymbol{MLP}^{(h)}(\boldsymbol{p}^{(h)})$$

$\boldsymbol{MLP}^{(h)}$ is a head-specific multilayer perceptron ($\boldsymbol{MLP}$) that performs a non-linear transformation

$$\boldsymbol{MLP}^{(h)}(\boldsymbol{x}) = \boldsymbol{tanh}(\boldsymbol{W}_2^{(h)}\boldsymbol{tanh}\left(\boldsymbol{W}_1^{h}\boldsymbol{x} + \boldsymbol{b}_1^{(h)}\right) + \boldsymbol{b}_2^{(h)})$$

- Attention mechanism

input: candidate POI p as the query, regions in R_u^t as values

output: an aggregated region embedding $\hat{r}_u^{t(h)}$ as the attention output:

$$\hat{r}_u^{t(h)} = \sum_{r\in R_u^t} \frac{a^{(h)}(p^{(h)},r^{(h)})}{\Sigma_{r'\in R_u^t} a^{(h)}\left(p^{(h)},r'^{(h)}\right)}\boldsymbol{r}^{(h)}$$

$$a^{(h)}\left(p^{(h)},r^{(h)}\right) = \boldsymbol{MLP}_{\boldsymbol{attn}}^{(\boldsymbol{h})}\left(p^{(h)}\right)^{T}\boldsymbol{MLP}_{\boldsymbol{attn}}^{(\boldsymbol{h})}\left(\boldsymbol{r}^{(\boldsymbol{h})}\right)$$

$\boldsymbol{MLP}_{\boldsymbol{attn}}^{(\boldsymbol{h})}$使用$\boldsymbol{ReLU}$

A neural context fusion approach

RL factors in the h-th (1 ≤ h ≤ H) head

- Second RL factor (POI-based transition context factor)

$$F_{pbtr}^{(h)}(\mathcal{R}_u^t, p) = \mathsf{MLP}^{(h)}(\hat{\mathbf{r}}_u^{t(h)})^\mathsf{T}\mathsf{MLP}^{(h)}(\mathbf{p}^{(h)})$$

- Third RL factor （user-based transition context factor）

$$F_{ubtr}^{(h)}(\mathcal{R}_u^t, u) = \mathsf{MLP}^{(h)}(\hat{\mathbf{r}}_u^{t(h)})^\mathsf{T}\mathsf{MLP}^{(h)}(\mathbf{u}^{(h)})$$

A neural context fusion approach

- Domain knowledge factors （ three context factors ）

distance context factor $\mathrm{F}_{\mathrm{dist}}(\boldsymbol{p}, \boldsymbol{l})$

$$F_{dist}(p, l) = \exp(-\phi \cdot \mathrm{dist}(l, p))$$

$\emptyset$ within [0.001, 0.05]
$\mathrm{F}_{\mathrm{dist}}(\boldsymbol{p}, \boldsymbol{l})$ halves every (693, 14) meters

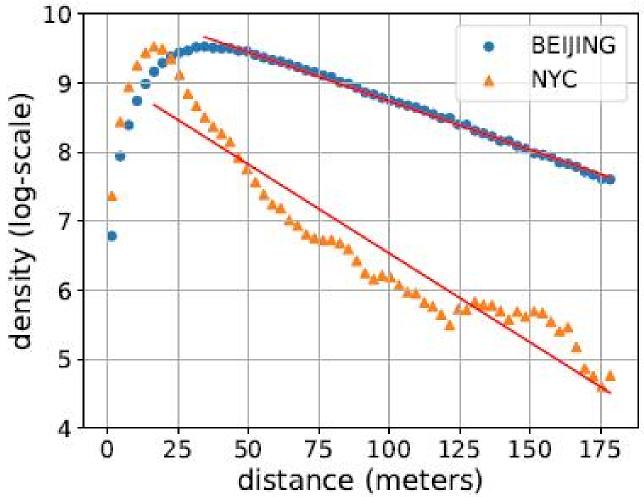


Figure 3. Distribution of distance between stay locations and POIs

A neural context fusion approach

The time factor $F_{time}(p,t)$

$Q_{p,k}$ denote the number of map queries of POI p in time slot $k \in \{1,...,T\}$ of a day

$$A_{p,k} = \begin{cases} 0, & \text{if } \max_{k'} Q_{p,k'} = 0; \\ \frac{\log(Q_{p,k}+1)}{\log(\max_{k'} Q_{p,k'}+1)}, & \text{otherwise.} \end{cases}$$

In this study, we consider two-hour time slots, T = 12. Note that two hours is a reasonable length of time for most POI visit purposes.

The popularity context factor $F_{popu}(p)$

$$F_{popu}(p) = log(\sum_k Q_{p,k} + 1)$$

their candidate POIs (the top-100 nearest POIs around the stay location)

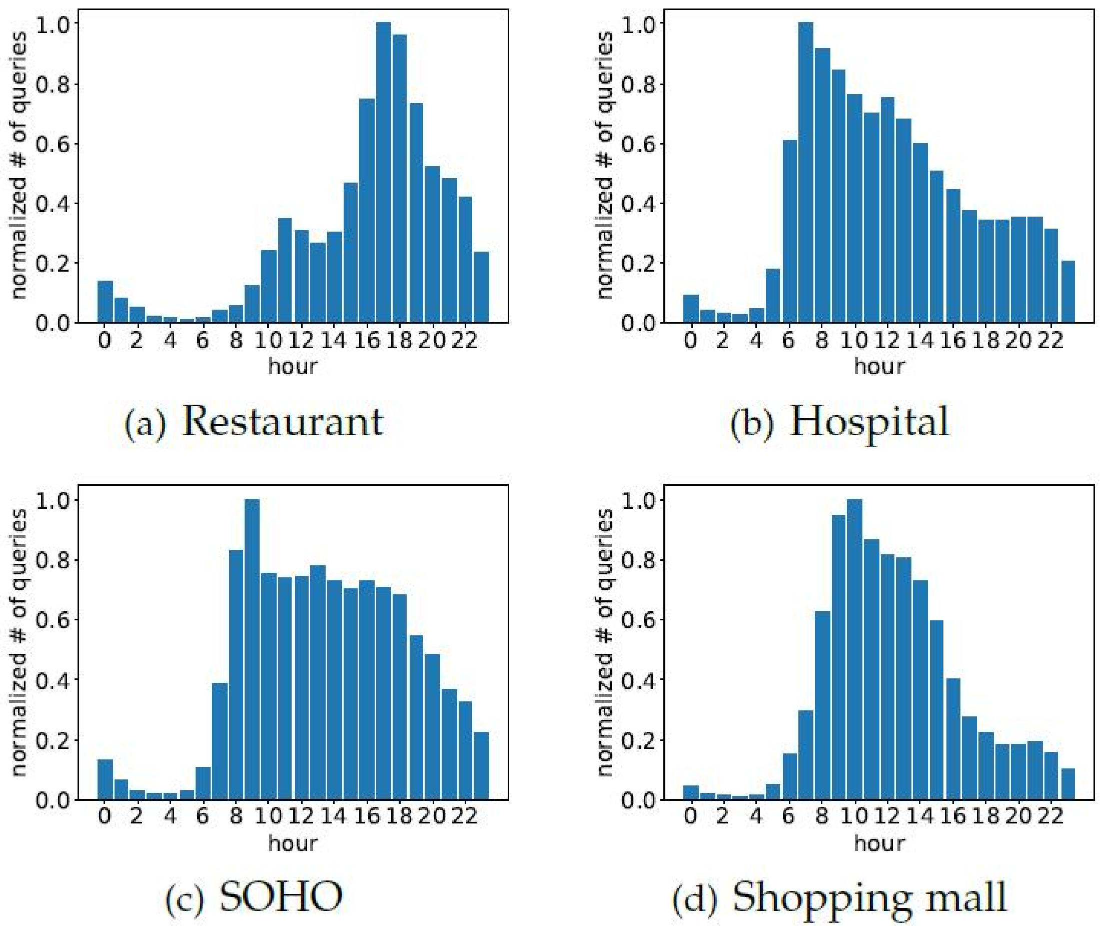


Figure 4. The number of hourly map queries for POI activeness

A neural context fusion approach

Training and Inference with Context Fusion

$$\mathbf{f} = [F^{(1)}_{pref}(u,p), F^{(1)}_{pbtr}(\mathcal{R}^t_u,p), F^{(1)}_{ubtr}(\mathcal{R}^t_u,u),$$
$$\ldots,$$
$$F^{(H)}_{pref}(u,p), F^{(H)}_{pbtr}(\mathcal{R}^t_u,p), F^{(H)}_{ubtr}(\mathcal{R}^t_u,u),$$
$$F_{dist}(p,l), F_{time}(p,t), F_{popu}(p)].$$

For each candidate POI p of a stay of user u at location l and time stamp t

$$Pr(u,l,t,p) = \mathbf{W}_3\mathrm{ReLU}(\mathbf{W}_2\mathrm{ReLU}(\mathbf{W}_1\mathbf{f} + \mathbf{b}_1) + \mathbf{b}_2),$$

$\hat{y}$是所有候选POI的访问概率组成的向量，y是真实POI对应的索引的one-hot 向量
损失函数为 y和$softmax(\hat{y})$的交叉熵损失

Experimental Setups

Table 2
Data set statistics

Description	# of stays	# of users	# of POIs	# of regions
BEIJING	436,728	26,917	1,341,663	62,534
NYC	146,325	1,083	318,162	45,935

Table 3
Accuracy (Acc) comparison with different fraction f of training data

Data set	Method	10%	20%	30%	40%	50%	60%	70%	80%	90%	Avg.
BEIJING	Dist	0.0678	0.0678	0.0678	0.0678	0.0681	0.0675	0.0675	0.0676	0.0673	0.0677
	HMM	0.1287	0.1603	0.1820	0.1967	0.2094	0.2187	0.2270	0.2354	0.2434	0.2002
	LTR	0.2760	0.3294	0.3554	0.3675	0.3790	0.3899	0.3934	0.3961	0.4065	0.3659
	MRF	0.2142	0.2819	0.3245	0.3571	0.3804	0.3985	0.4149	0.4286	0.4414	0.3602
	GE	0.2212	0.3072	0.3411	0.3583	0.3662	0.3720	0.3770	0.3797	0.3817	0.3450
	NCF(3)	**0.3853**	**0.4229**	**0.4491**	**0.4829**	**0.4984**	**0.5053**	**0.5284**	**0.5343**	**0.5452**	**0.4835**
NYC	Dist	0.2683	0.2681	0.2678	0.2687	0.2683	0.2680	0.2671	0.2709	0.2666	0.2682
	HMM	0.2811	0.2966	0.3132	0.3307	0.3465	0.3589	0.3708	0.3823	0.3914	0.3413
	LTR	0.3939	0.4194	0.4252	0.4484	0.4580	0.4522	0.4712	0.4764	0.4896	0.4483
	MRF	0.2984	0.3681	0.4188	0.4620	0.4927	0.5230	0.5429	0.5652	0.5810	0.4725
	GE	0.3677	0.3387	0.3394	0.3377	0.3421	0.3414	0.3368	0.3414	0.3398	0.3428
	NCF(3)	**0.6120**	**0.6728**	**0.7192**	**0.7520**	**0.7664**	**0.7797**	**0.7981**	**0.8061**	**0.8133**	**0.7466**

Experimental Setups

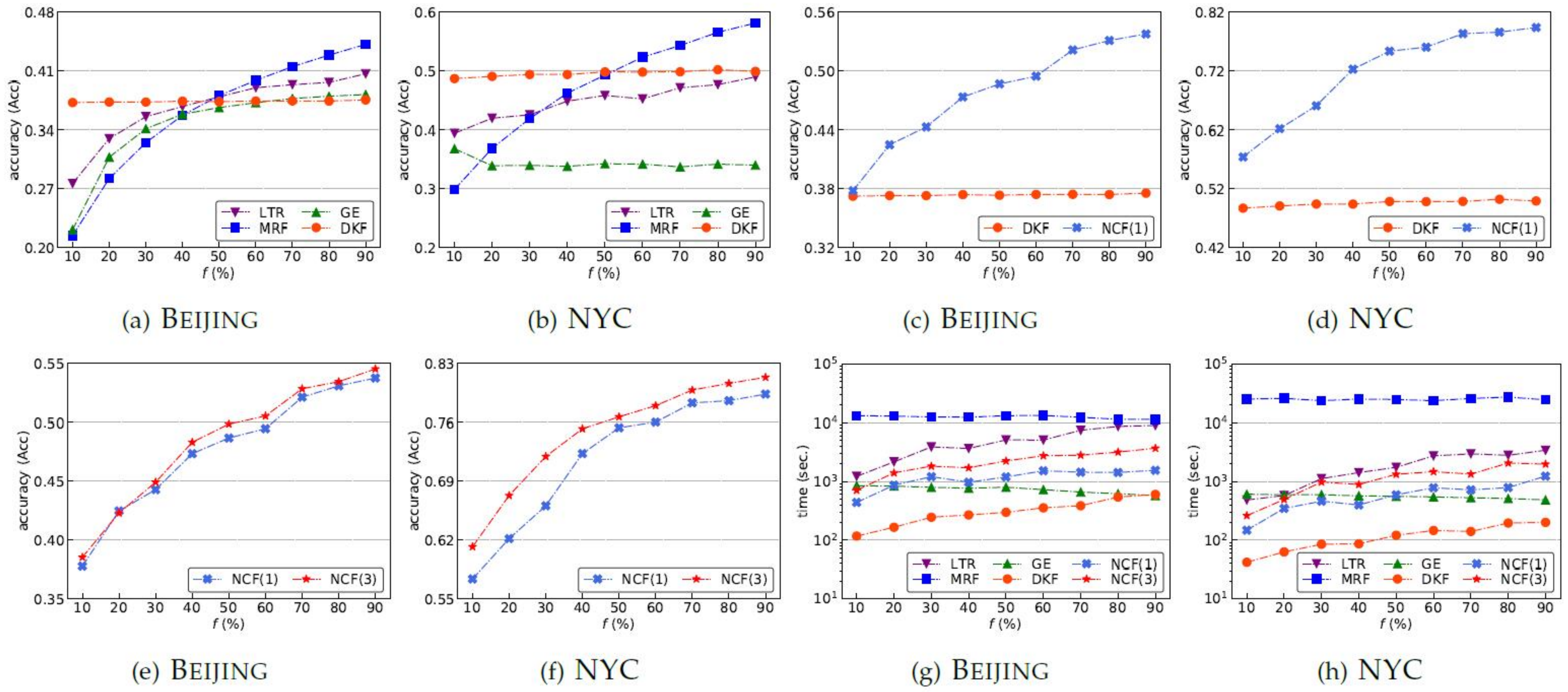


Figure 5. Ablation study (a)–(f) and efficiency evaluation (g)–(h)

5(a) & 5(b) Domain knowledge factors

5(c) & 5(d). Representation learning factors.

5(e) & 5(f) Multi-head architecture

5(g) & 5(h) Efficiency comparison

Experimental Setups

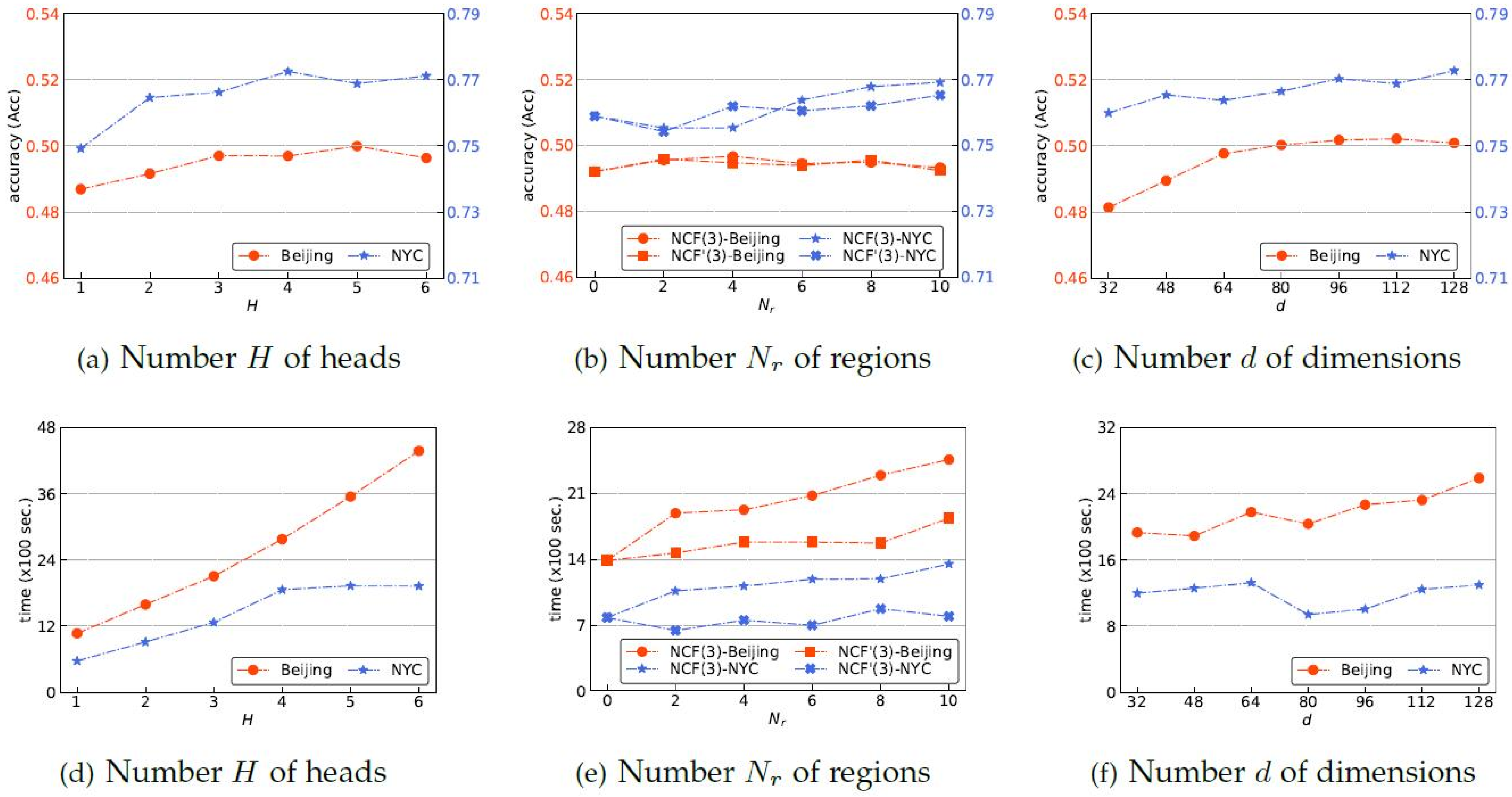
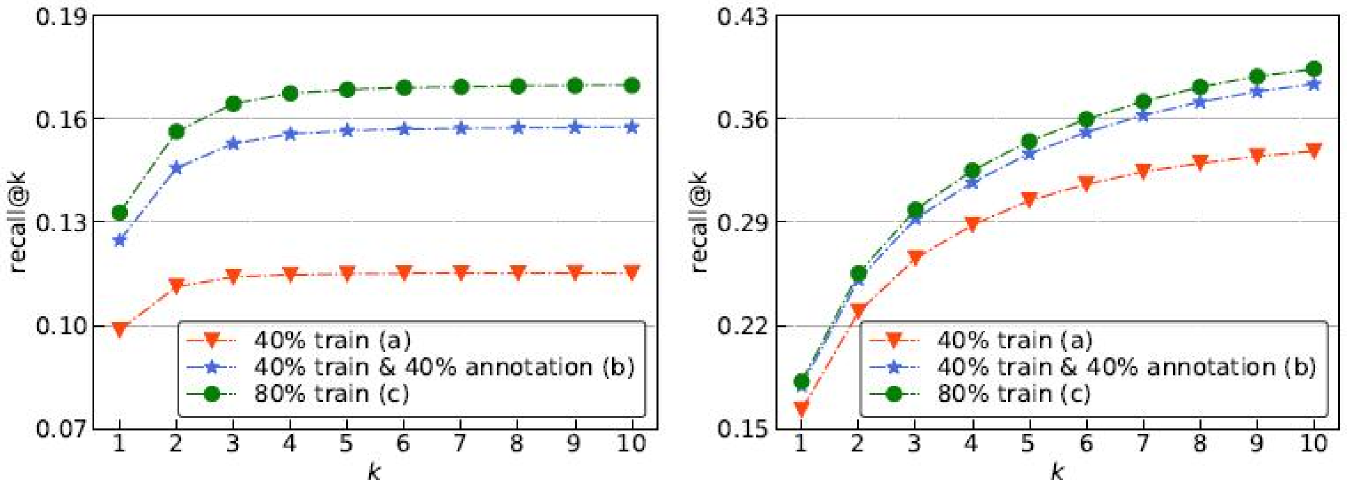


Figure 6. Parameter sensitivity (the left and right y-axes of Figs. 6(a)–6(c) correspond to the Acc on BEIJING and NYC, respectively)

Experimental Setups



(a) BEIJING (b) NYC

Figure 7. Utility of raw mobility annotation

Table 4
Accuracy (Acc) comparison with Stay- and User-level splits ($f = 50\%$)

Data set	Dist	HMM	LTR	MRF	GE	NCF(3)
BEIJING(S)	0.0681	0.2094	0.3790	0.3804	0.3662	**0.4984**
BEIJING(U)	0.0679	0.1486	0.2774	0.0685	0.1046	**0.3495**
NYC(S)	0.2683	0.3465	0.4580	0.4927	0.3421	**0.7664**
NYC(U)	0.2669	0.2787	0.2361	0.0988	0.0686	**0.5440**

NCF(3) significantly outperforms other baselines at the 0.01 level, paired t-test, with both stay- and user-level splits.