Predicting Human Mobility via Graph Convolutional Dual-attentive Networks

Weizhen Dang
Tsinghua University
Beijing, China
dangweizhen@126.com

Haibo Wang*
Tsinghua University
Beijing, China
hbwang1994@gmail.com

Shirui Pan
Monash University
Australia
shirui.pan@monash.edu

Pei Zhang
Beijing University of Posts and Telecommunications
Beijing, China
zhangpei@bupt.edu.cn

Chuan Zhou
Chinese Academy of Sciences
Beijing, China
zhouchuan@amss.ac.cn

Xin Chen
Tsinghua University
Beijing, China
chenxinsteven@outlook.com

Jilong Wang
Tsinghua University
Beijing, China
wjl@cernet.edu.cn

WSDM 2022

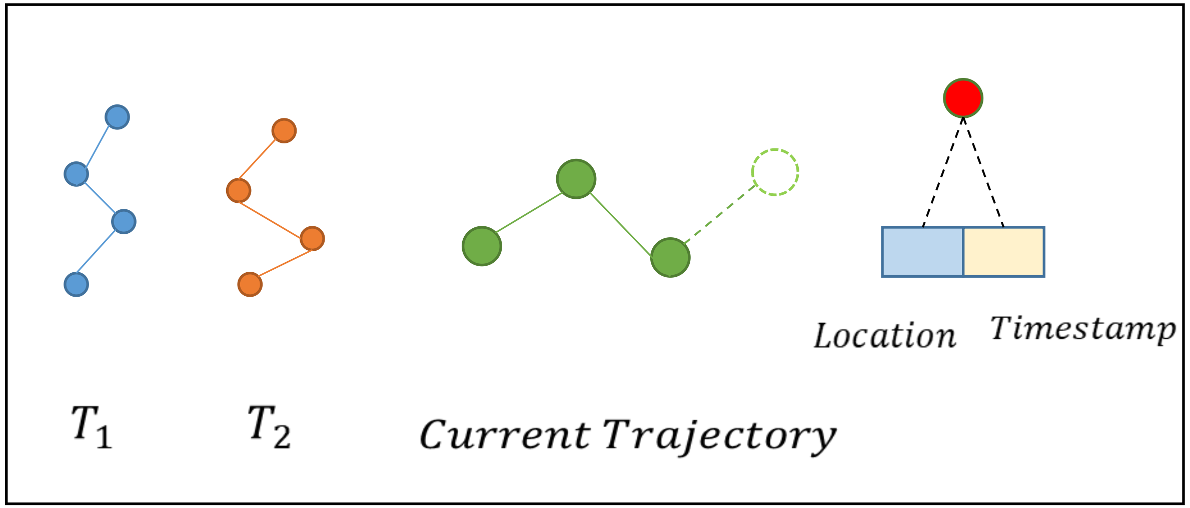
Code: https://github.com/GCDAN/GCDAN

Reported by Nengqiang Xiang

Introduction

Methods that already exist do not well cope with the sparsity and inaccuracy of trajectory data and the complicated high-order nature of the sequential dependency.

To solve the problems, this paper proposes a novel framework named Graph Convolutional Dual-attentive Networks (GCDAN).



An example for Human Mobility Predicting

Method

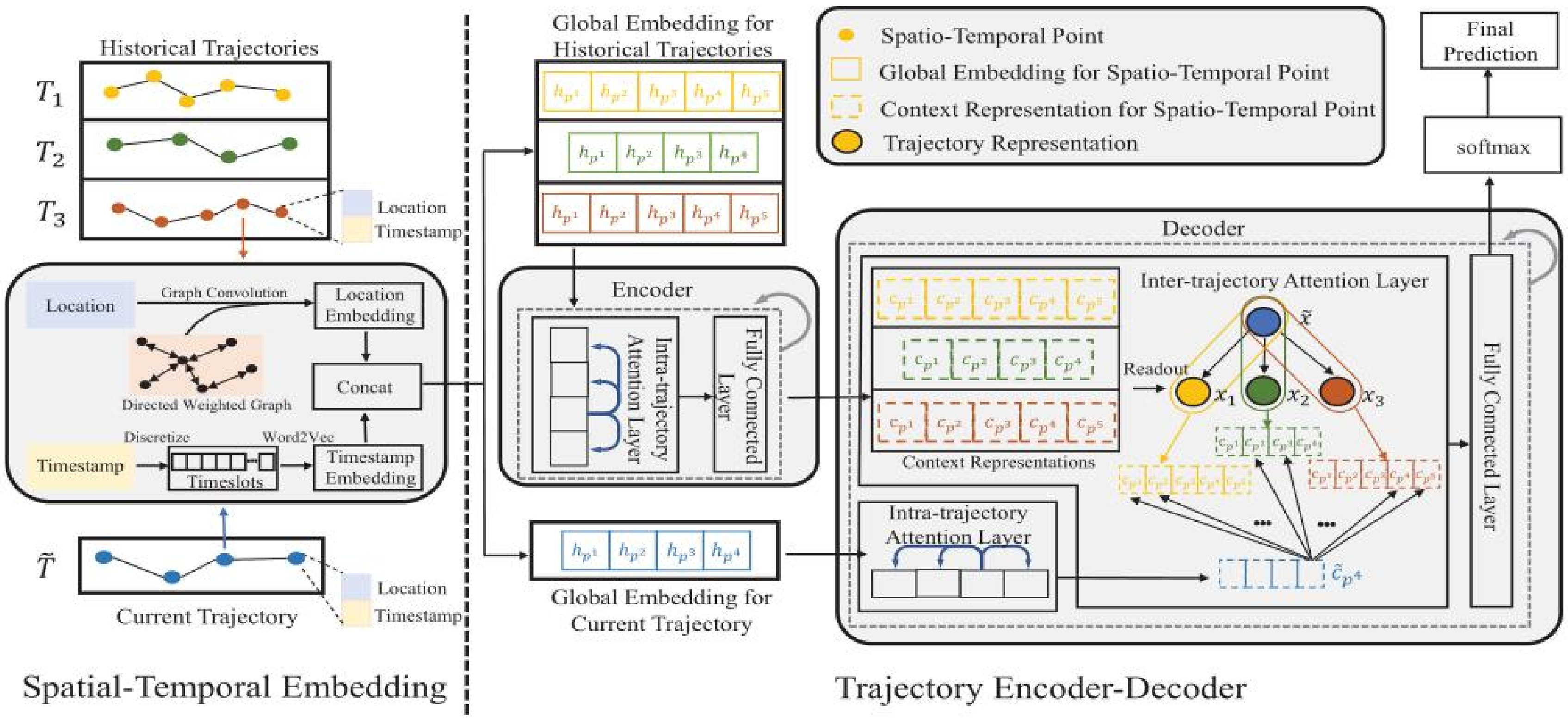


Figure 1: The overview of GCDAN. The spatial-temporal embedding module introduces the graph convolution and sparse embedding to learn representations of spatial-temporal points. The trajectory encoder-decoder module employs a dual-attentive mechanism. The intra-trajectory attention layer models the sequential dependence within a trajectory and generates the context representation for each spatial-temporal point. The inter-trajectory attention layer models the correlation between the historical trajectories and current trajectory and generates the final prediction.

Method

Problem Formulation

location identifiers: L=$\{l_1, l_2, \ldots, l_{|L|}\}$

spatio-temporal point: p=(l, t)

user: U=$\{u_1, u_2, \ldots, u_{|U|}\}$

trajectory: $T_u = p_u^1 p_u^2 \ldots\ p_u^m$

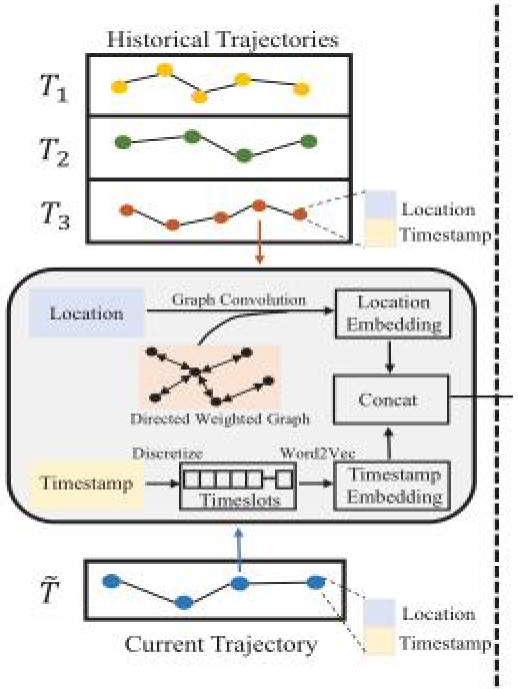
historical trajectories: $S_u = \{T_u^1, T_u^2, \ldots, T_u^{|S_u|}\}$

current trajectory: $\tilde{T}_u = p_u^1 p_u^2 \ldots\ p_u^n$

Spatio-temporal Embedding Module

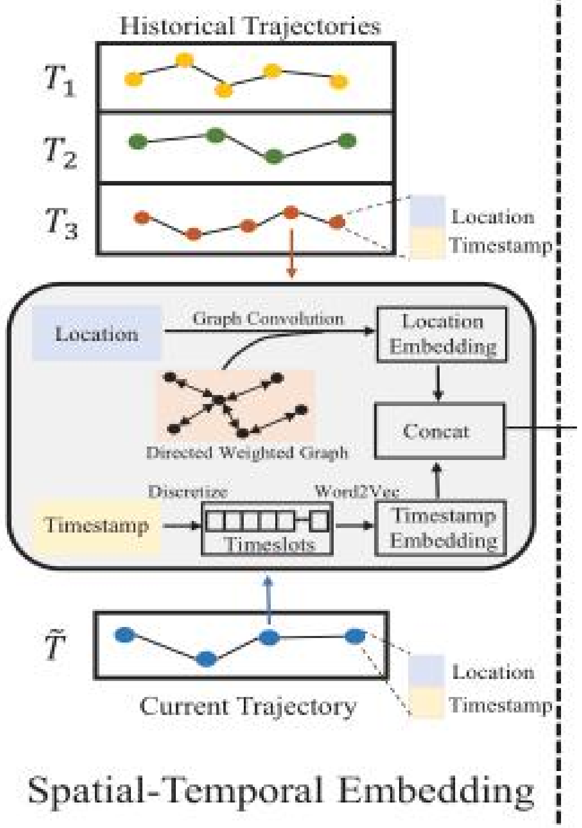
Timestamp Embedding:

$$\boldsymbol{h}_t = \Theta_T\ \mathbf{v}_t$$



Spatial-Temporal Embedding

Method



Location Embedding:

$$\begin{cases} w_{ij} = \frac{c_{ij}}{\sum\limits_{l_r \in L} c_{ir}} & \frac{c_{ij}}{\sum\limits_{l_r \in L} c_{ir}} > \frac{1}{|L|}, \\ w_{ij} = 0 & otherwise, \end{cases} \quad c_{ij}=(l_i, l_j) \quad (1)$$

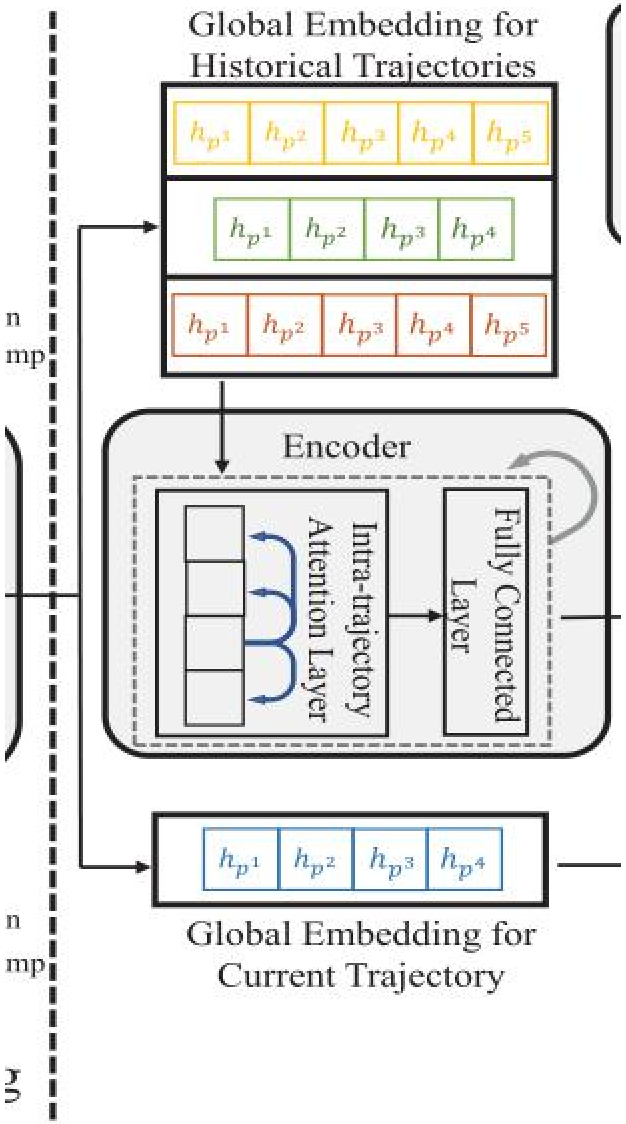
$$H_L = \sum_{k=0}^{K-1} \sigma\Big((D_O^{-1}W)^k V_L \Theta_k^0 + (D_I^{-1}W^{\mathrm{T}})^k V_L \Theta_k^1\Big), \quad (2)$$

$D_O = diag(\boldsymbol{W}\mathbf{1})$ and $D_I = diag(\boldsymbol{W}^{\mathrm{T}}\mathbf{1})$

$H_L = (\boldsymbol{h}_{l_1}, \ldots, \boldsymbol{h}_{l_{|L|}})^{\mathrm{T}}$ $\quad H_L \in \mathbb{R}^{|L| \times d2}$

$\Theta_k^0 \in \mathbb{R}^{|L| \times d2}$ and $\Theta_k^1 \in \mathbb{R}^{|L| \times d2}$

Method



Global Embedding:

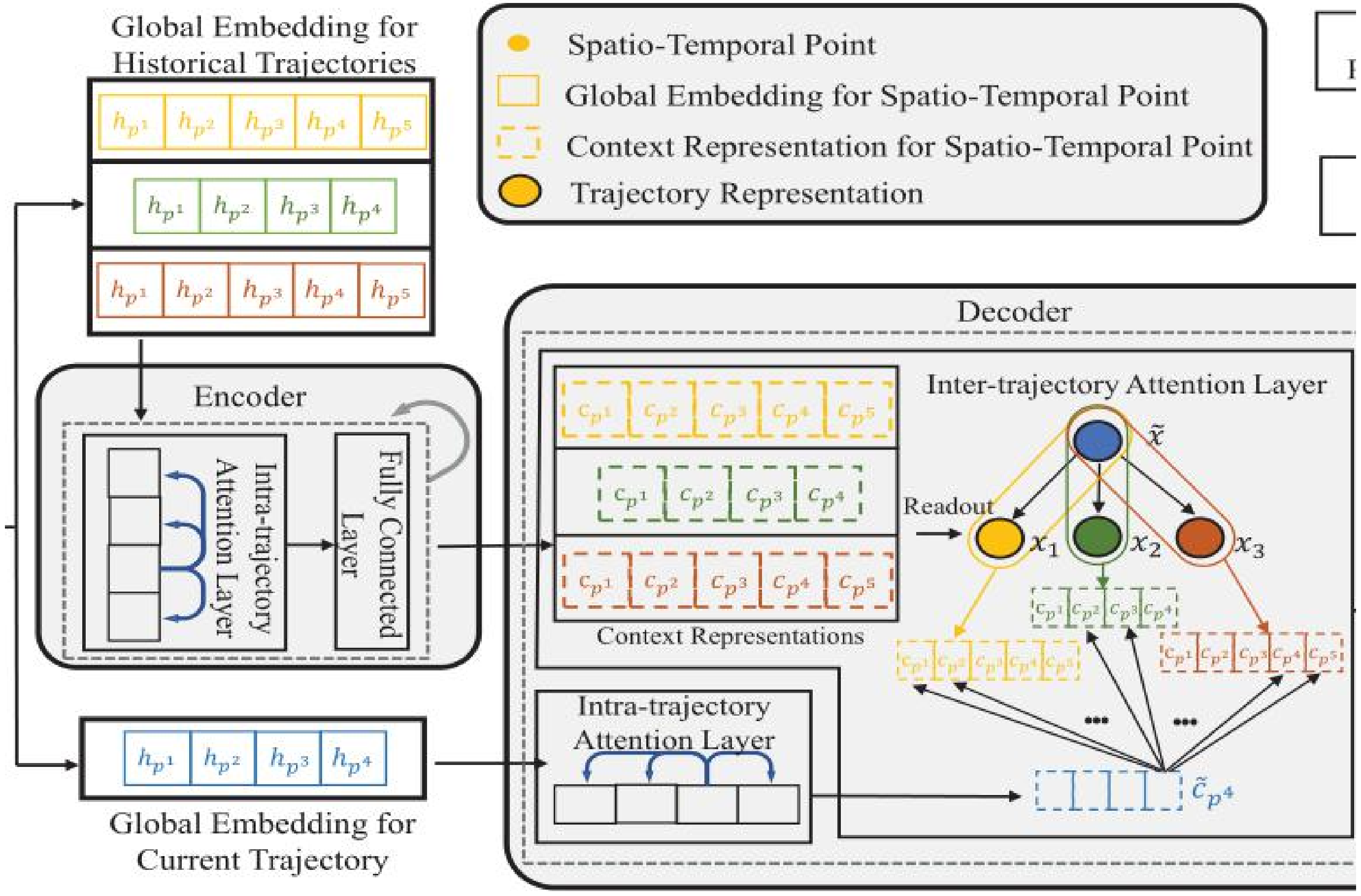
$$\boldsymbol{h}_p = \boldsymbol{h}_t \,||\, \boldsymbol{h}_l \qquad \boldsymbol{h}_p \in \mathbb{R}^{d1+d2}$$

Trajectory Position Coding:

$$\boldsymbol{pos}_i(j) = \cos\left(\frac{i}{C^{\frac{j-(j\%2)}{d_1+d_2}}} - \frac{(j\%2)\pi}{2}\right); \qquad (3)$$

$$\boldsymbol{h}_{p^i} = \boldsymbol{h}_{p^i} + \boldsymbol{pos}_i$$

Method



Trajectory Encoder-Decoder

Trajectory Encoder-decoder Module

Encoder:

$$sim_p(\boldsymbol{h}_{p^i}, \boldsymbol{h}_{p^j}) = \frac{\exp\left(f(\boldsymbol{h}_{p^i}, \boldsymbol{h}_{p^j})\right)}{\sum_{r=1}^{m} \exp\left(f(\boldsymbol{h}_{p^i}, \boldsymbol{h}_{p^r})\right)}, \tag{4}$$

$$\boldsymbol{c}_{p^i} = \sum_{j=1}^{m} sim_p(\boldsymbol{h}_{p^i}, \boldsymbol{h}_{p^j}) \boldsymbol{h}_{p^j}, \tag{5}$$

Decoder:

$$\boldsymbol{x} = \frac{1}{m} \sum_{j=1}^{m} \boldsymbol{c}_{p^j}, \tag{6}$$

$$sim_t(\widetilde{\boldsymbol{x}}, \boldsymbol{x}_i) = \frac{\exp\left(f(\widetilde{\boldsymbol{x}}, \boldsymbol{x}_i)\right)}{\sum_{r=1}^{|S|} \exp\left(f(\widetilde{\boldsymbol{x}}, \boldsymbol{x}_r)\right)}, \tag{7}$$

$$\boldsymbol{v}_{p^n} = \sum_{i=1}^{|S|} sim_t(\widetilde{\boldsymbol{x}}, \boldsymbol{x}_i) \sum_{j=1}^{m} sim_p(\widetilde{\boldsymbol{c}}_{p^n}, \boldsymbol{c}_{p^j}) \boldsymbol{c}_{p^j}, \tag{8}$$

Method

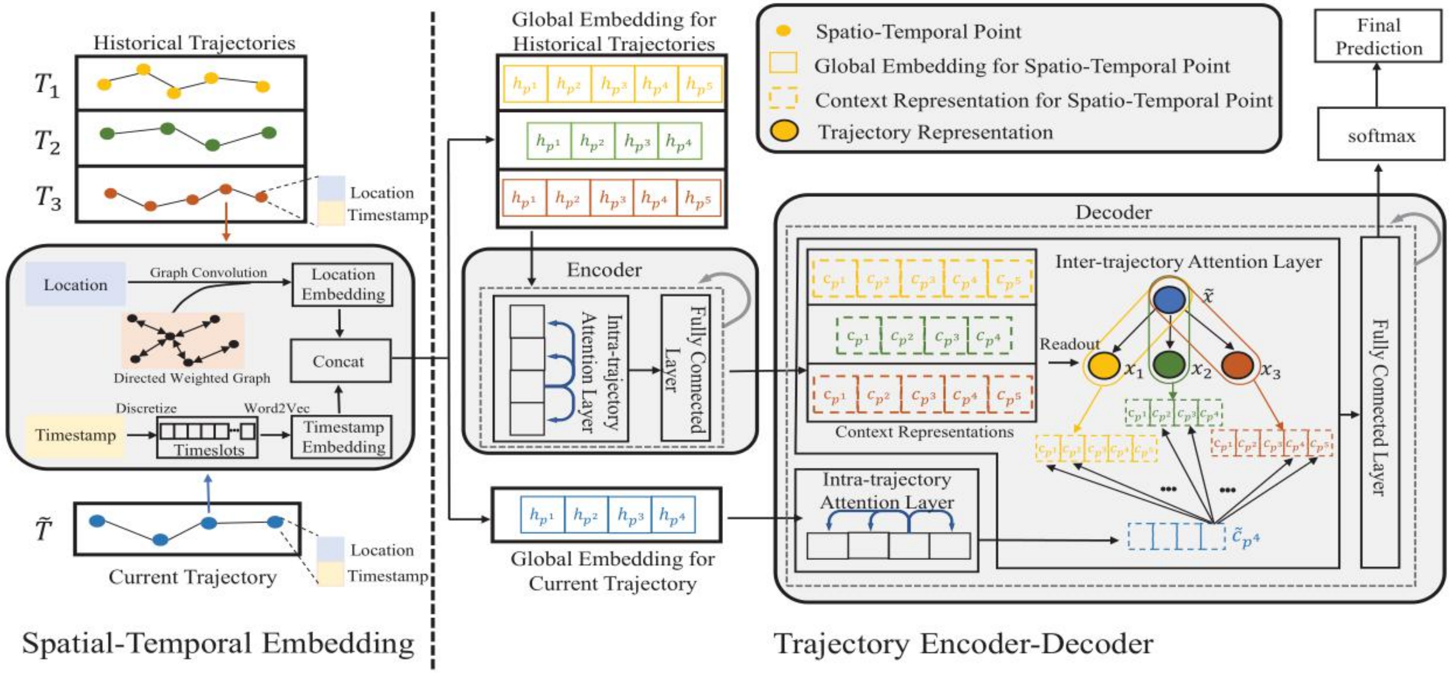


Figure 1: The overview of GCDAN. The spatial-temporal embedding module introduces the graph convolution and sparse embedding to learn representations of spatial-temporal points. The trajectory encoder-decoder module employs a dual-attentive mechanism. The intra-trajectory attention layer models the sequential dependence within a trajectory and generates the context representation for each spatial-temporal point. The inter-trajectory attention layer models the correlation between the historical trajectories and current trajectory and generates the final prediction.

Objective Function

$$\hat{\boldsymbol{y}} = softmax(\hat{\Theta}\boldsymbol{v}_{p^n}), \tag{9}$$

$$\mathcal{L}_c = -\sum_{u \in U} \sum_{i=1}^{|L|} \boldsymbol{y}_u^i \log \hat{\boldsymbol{y}}_u^i, \tag{10}$$

$$\mathcal{L} = \mathcal{L}_c + \alpha \mathcal{L}_{reg}, \tag{11}$$

Experiments

Table 1: Dataset statistics.

Dataset	Gowalla	Foursquare	WiFi-Trace
Time duration	1 year	1 year	2 week
Users	857	886	3642
#(Record)	129679	82575	1011049
#(Trajectory)	8568	7974	41937
#(Location)	20006	10497	251

for each dataset. In our experiments, we select the first 75% of trajectories for each user as the training data and the rest 25% as the testing data. In addition, 10% of the training data is used as the validation data.

Experiments

Table 2: Gowalla

Metrics	MC	FPMC	LSTM	ST-RNN	DeepMove	GCDAN
Acc@1	0.1188	0.1204	0.1252	0.1279	0.1338	**0.1377**
Acc@5	0.2056	0.2066	0.2453	0.2568	0.2731	**0.3086**
Acc@10	0.2306	0.2307	0.2907	0.3112	0.3299	**0.3780**

Table 3: Foursquare

Metrics	MC	FPMC	LSTM	ST-RNN	DeepMove	GCDAN
Acc@1	0.0818	0.0835	0.0912	0.1057	0.1245	**0.1613**
Acc@5	0.1753	0.1762	0.1824	0.2368	0.2790	**0.3417**
Acc@10	0.2252	0.2257	0.2120	0.2787	0.3360	**0.4093**

Table 4: WiFi-Trace

Metrics	MC	FPMC	LSTM	ST-RNN	DeepMove	GCDAN
Acc@1	0.1612	0.3231	0.5685	0.5702	0.5729	**0.5912**
Acc@5	0.3173	0.5169	0.7821	0.7918	0.8030	**0.8064**
Acc@10	0.3882	0.6843	0.8473	0.8523	0.8707	**0.8726**

Experiments

Table 5: Ablation Study.

	Gowalla	Foursquare	WiFi-Trace
GCDAN-base	0.1311	0.1580	0.5768
GCDAN-tc	0.1340	0.1607	0.5815
GCDAN-gc	0.1336	0.1597	0.5895
GCDAN-full	0.1377	0.1613	0.5912

The above experimental results demonstrate the effectiveness and superiority of GCDAN.

Experiments

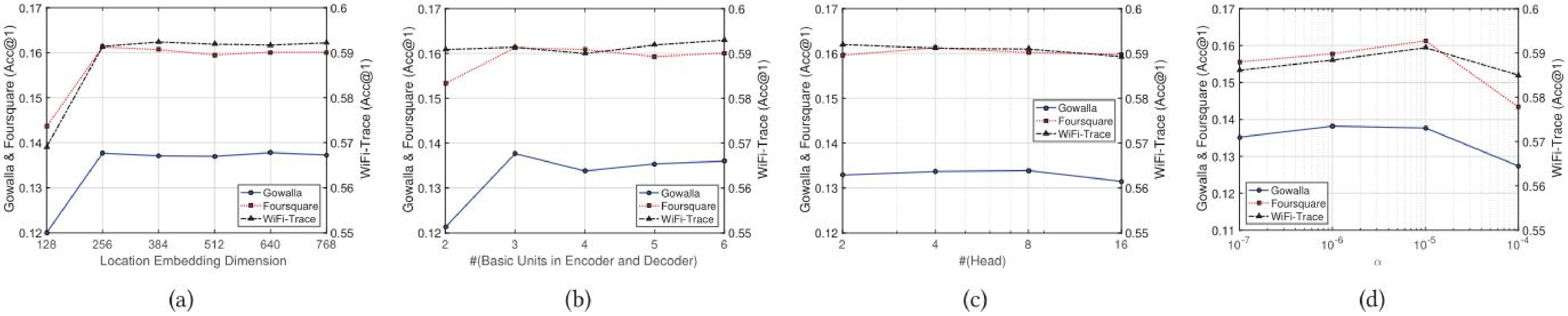


Figure 2: Results of parameter sensitivity *w.r.t.* **(a) the location embedding dimension, (b) the number of basic units in encoder and decoder, (c) the number of heads of the multi-head attention mechanism and (d) the balance hyper-parameter** α **in Eq. (11)**

Thanks