Trajectory-User Linking with Attentive Recurrent Network

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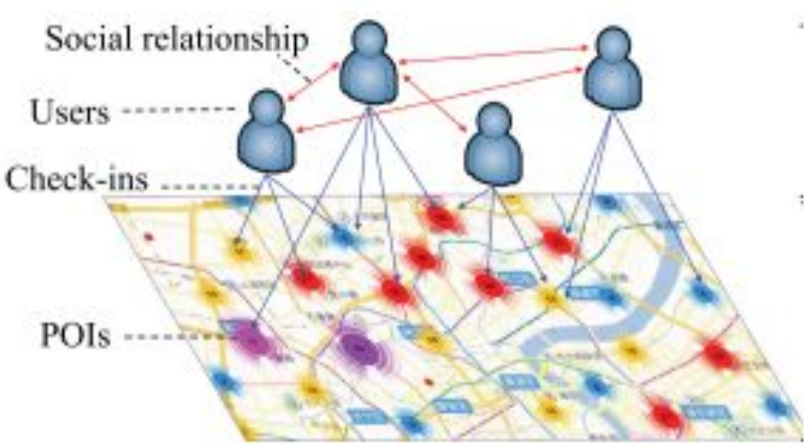
Introduction

- Application of Trajectory-User Linking
  - Personalized recommendation systems and location-based social networks.
  - Linking users cross-platform
  - Identifying the potential criminals



Related work

- **Trajectory-User Linking**
  - Traditional models :
    - Markov models (MC, HMM)
    - LDA, SVM
  - Have difficulty in constructing effective relationships among long term dependencies
  - Deep neural network models:
    - Vanilla RNN and its variant (LSTM, GRU, BiLSTM)
    - TUVAE
  - Failed to capture multi-periodic mobility regularities

Challenges

- Challenges
  - Data sparsity: conducted by user on voluntary basis and low-sampling.
  - High-order and multi-periodic patterns: vary among the changes of contextual scenarios and multi-periodic
  - Integrating more diverse features: previous models fail to utilize existing abundant features

Solution

DEFINITION 1. (Spatio-temporal Point)
The spatio-temporal point q is a tuple of timestamp t and POI $p \in P$, i.e., $q = (t,p)$.

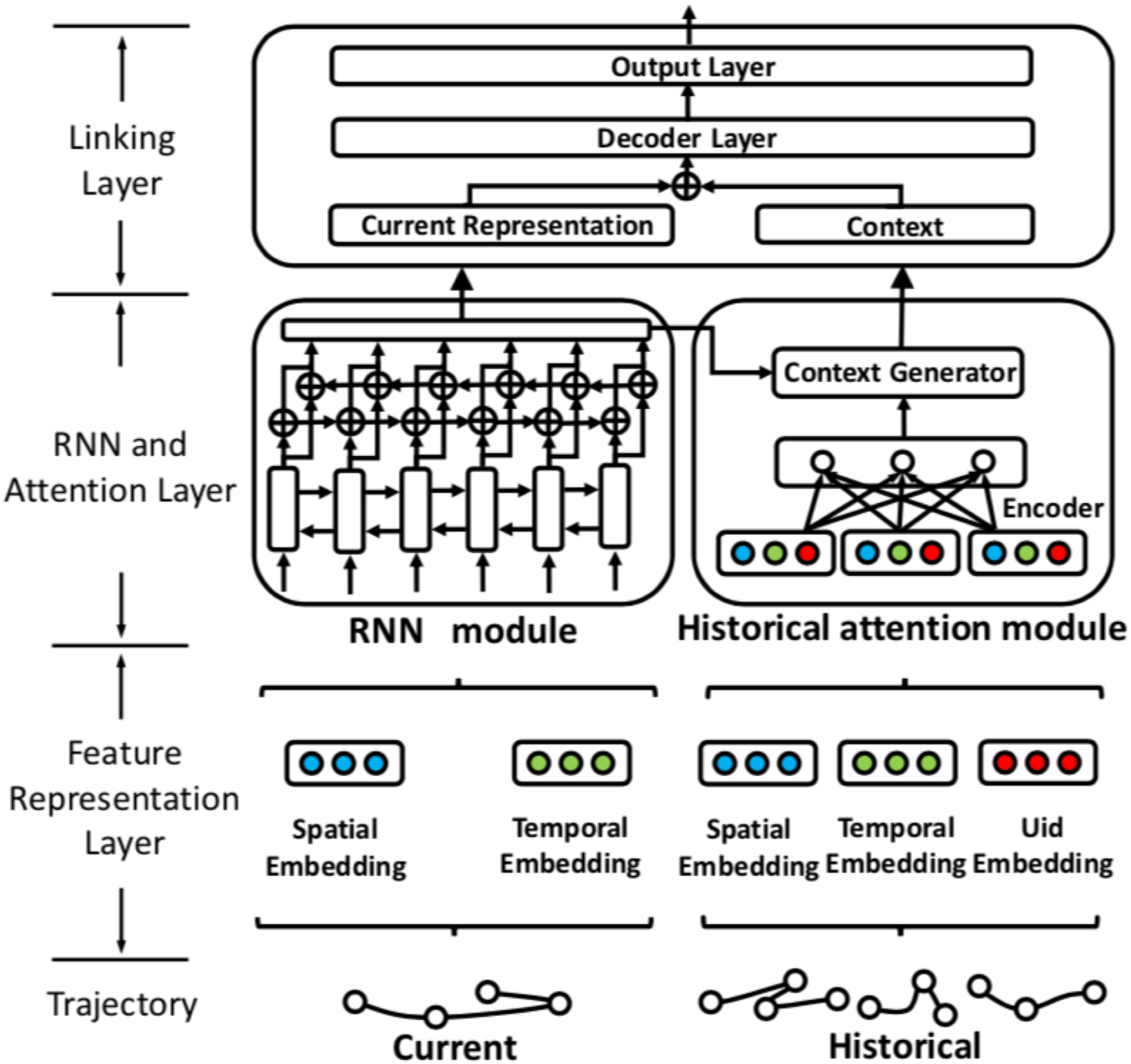
DEFINITION 2. (Trajectory)
Given a set of spatio-temporal points q_i generated by user $u_i \in U$ in a w-th time interval, the Trajectory is represented as $S_{u1}^{w} = q_{i1} q_{i2} \cdots q_{in}$ where q is listed by timestamp.

Solution

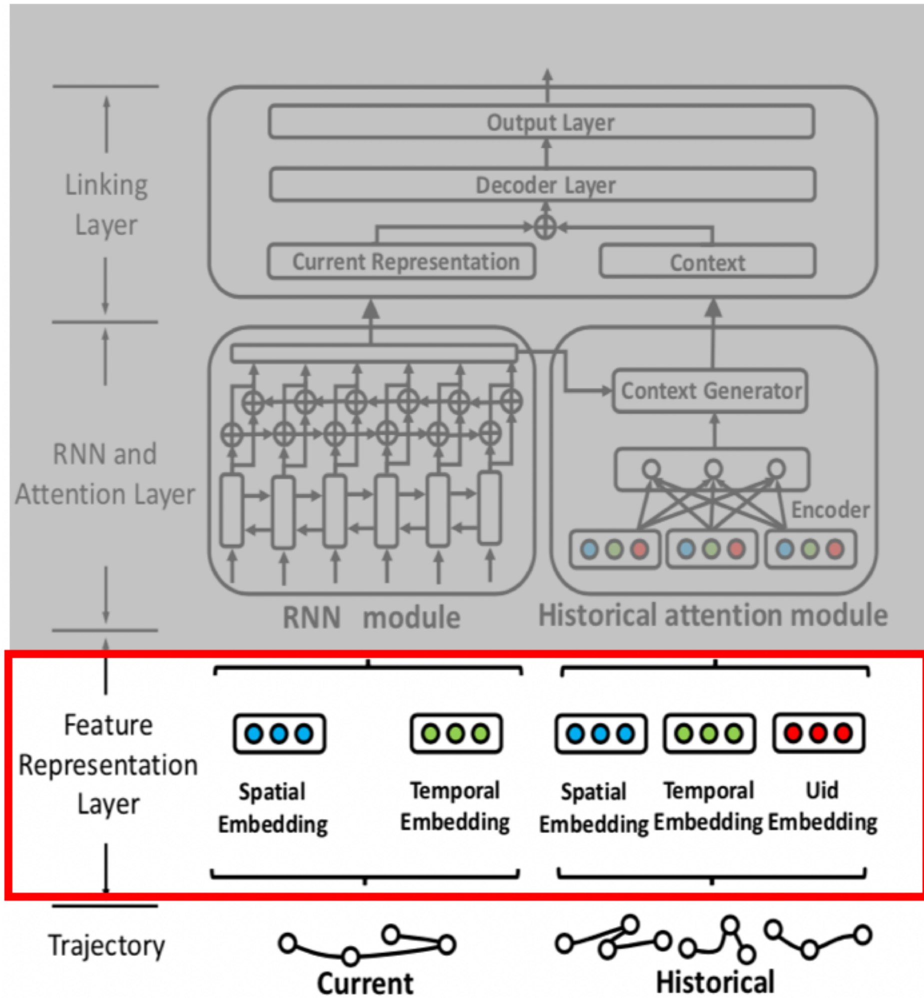
- Problem description
  - Given the current unlinked trajectory $\overline{s^w} = \{q_1, q_2, \cdots, q_m\}$ and corresponding historical trajectories $\mathcal{H}^{\mathrm{w}}$,
  - TUL task aims to provide a mapping function that links the unlinked trajectory to users:

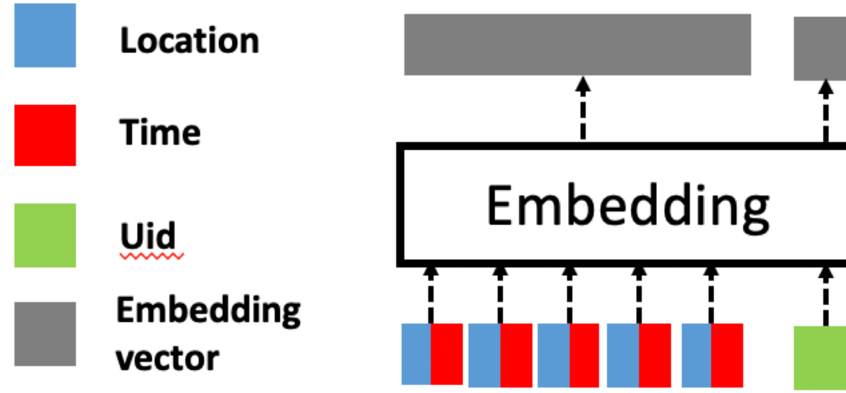
$$\overline{s^w} \rightarrow \mathcal{U}.$$

Solution


Linking Layer
RNN and Attention Layer
Feature Representation Layer
Trajectory
Output Layer
Decoder Layer
Current Representation
Context
Context Generator
Encoder
RNN module
Historical attention module
Spatial Embedding
Temporal Embedding
Spatial Embedding
Temporal Embedding
Uid Embedding
Current
Historical

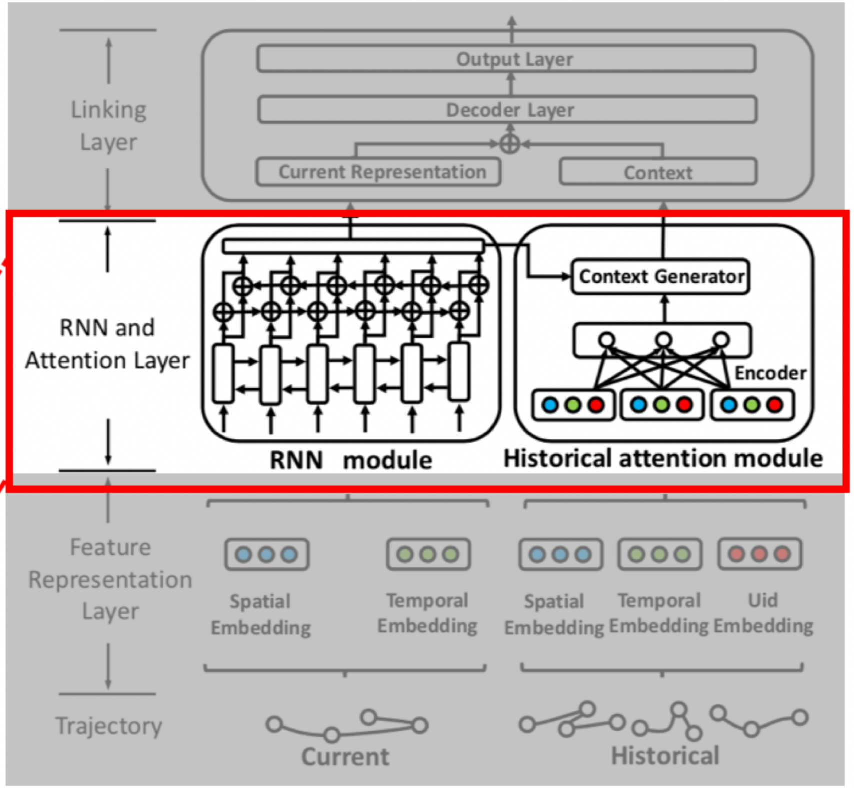
Solution





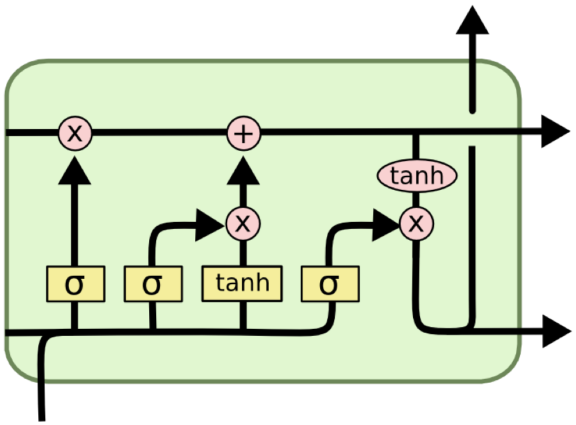
- **Multi-dimension embedding**
  - One-hot encoding
    Location, time, uid
  - Transformation matrix
  - Concatenate layer

Solution



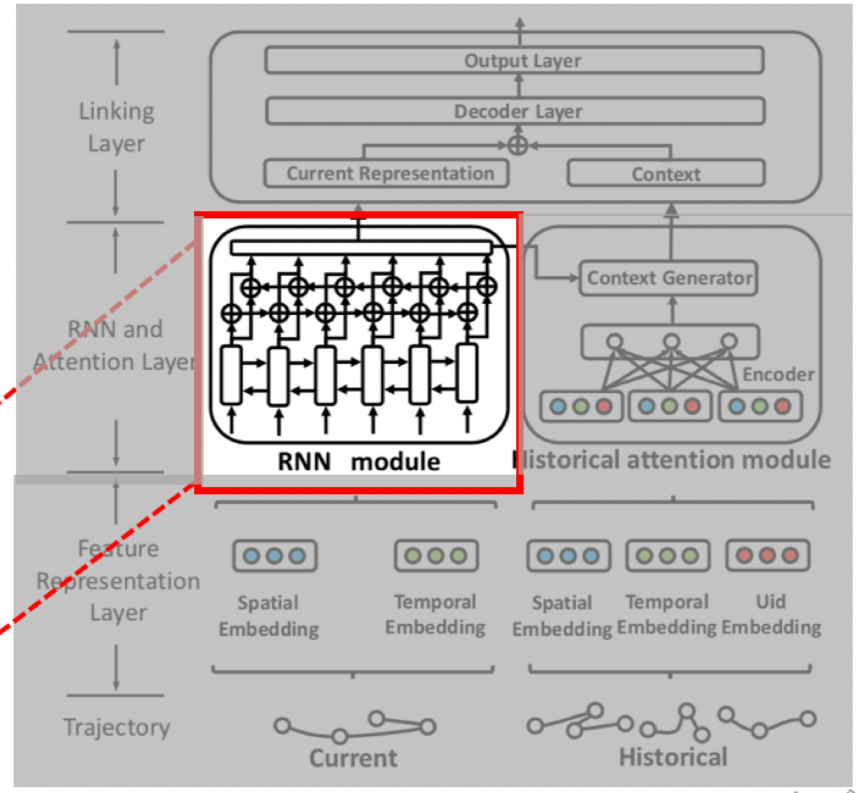
- **RNN and Attention Layer**
  - RNN module
  - historical attention module

Solution

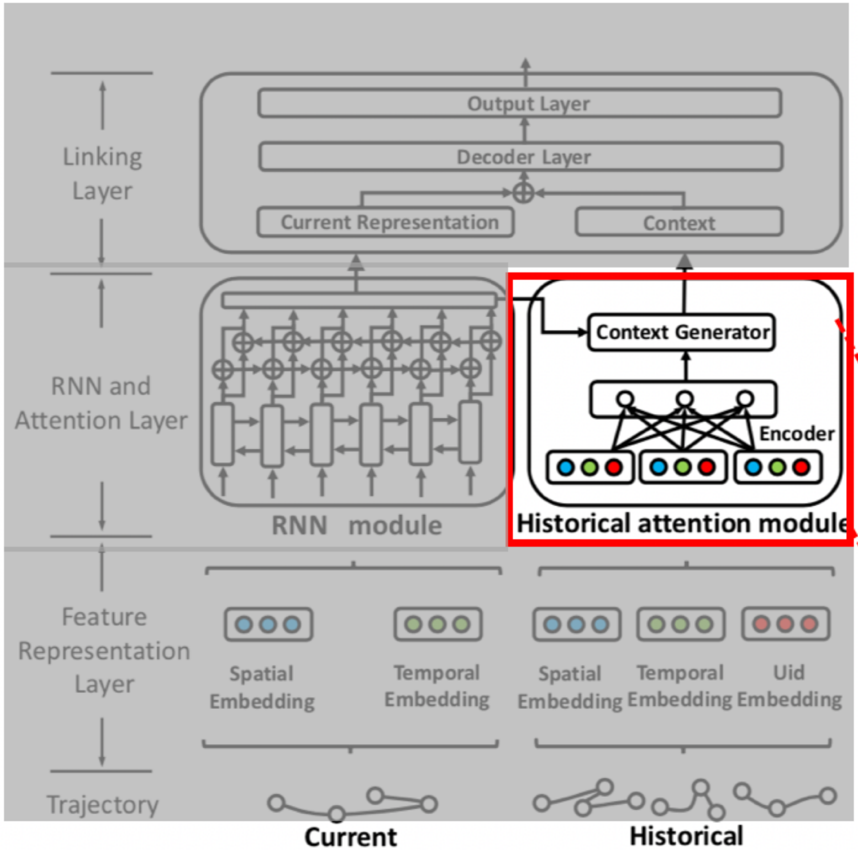


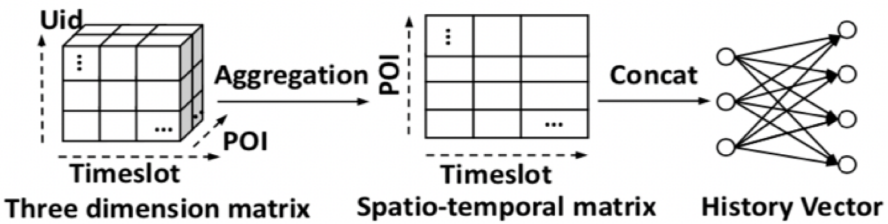
$$h_t = [h_t \oplus h_t]$$

- **RNN and Attention Layer**
  - RNN module
  - historical attention module



Solution

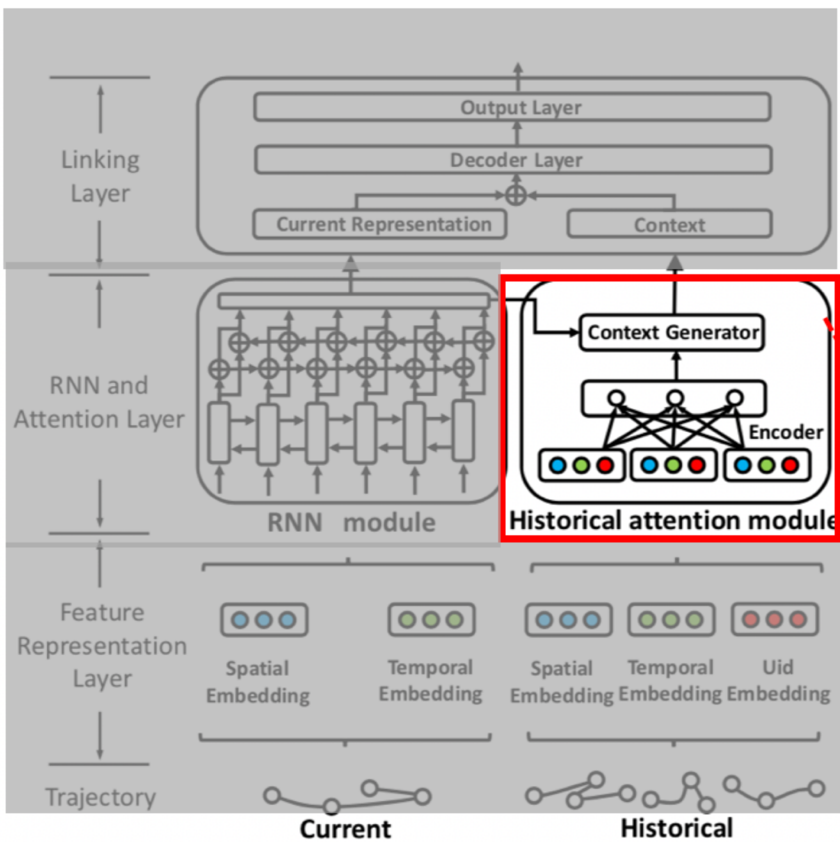


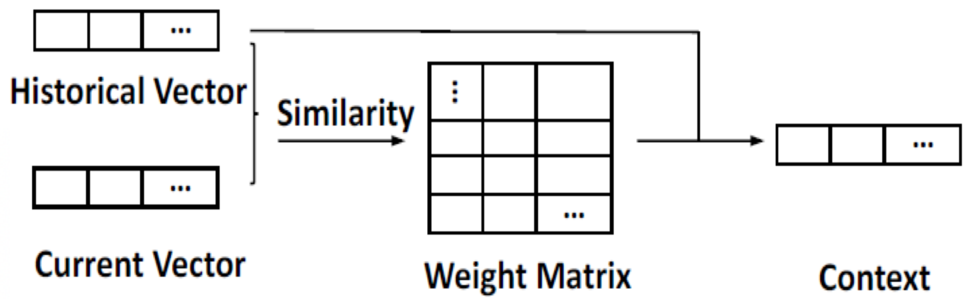


(a) History feature encoder

- **Attention module**
  - **History feature encoder**
  - context generator

Solution





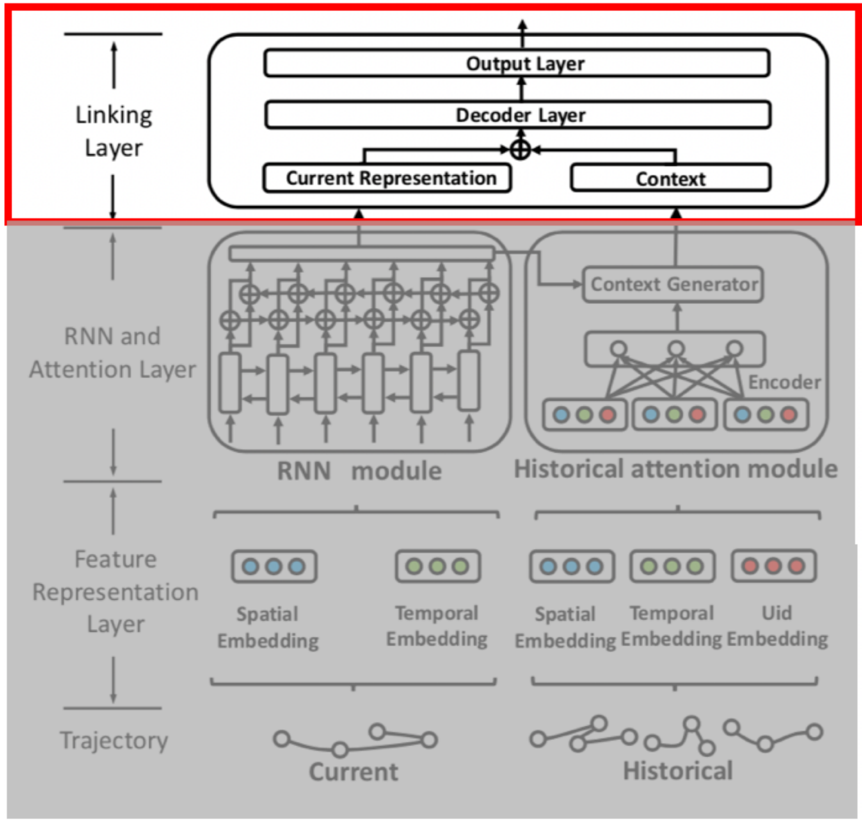
$$a_{i,j} = \frac{exp(f(h_t, h_{i,j}))}{\sum_{i1}\sum_{j1} exp(f(h_t, h_{i1,j1}))}$$

$$c = \sum_i \sum_j a_{i,j} h_{i,j}$$

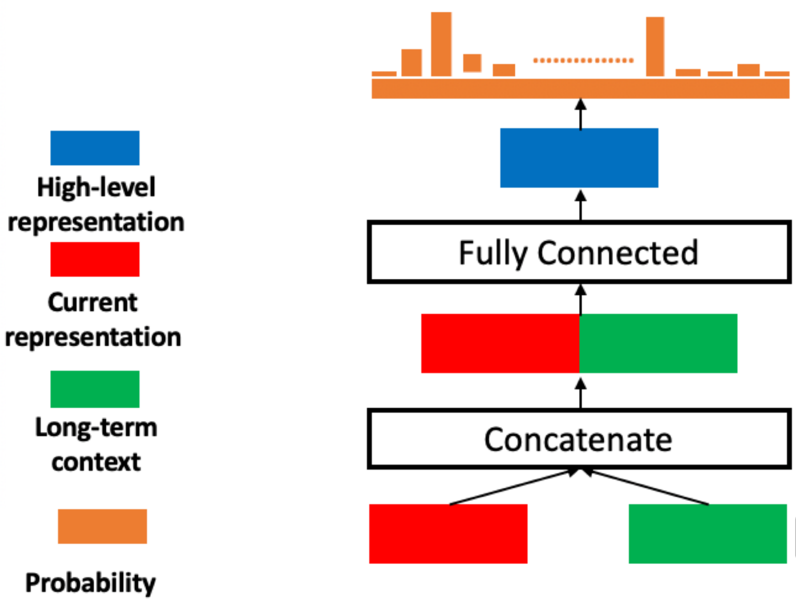
- **Attention module**
  - History feature encoder
  - **context generator**

Solution

DeepTUL- Linking Layer

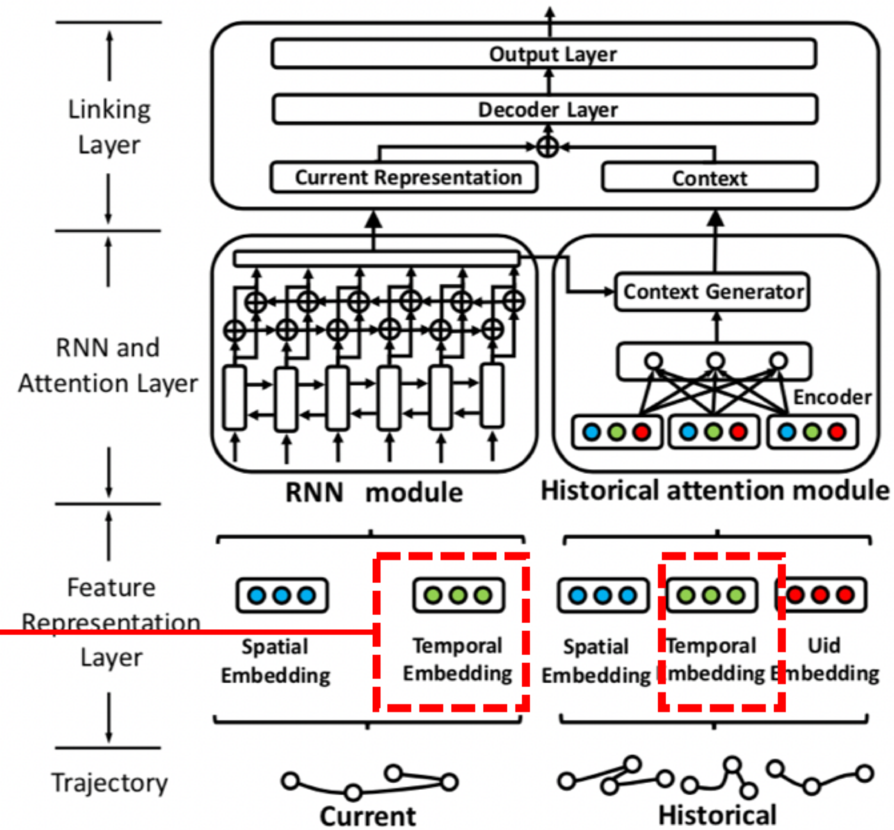


- **Linking layer**
  - **Current representation and long-term context**
    concatenate + fc + soft-max



Solution

The time embedding captures time-dependent relations.

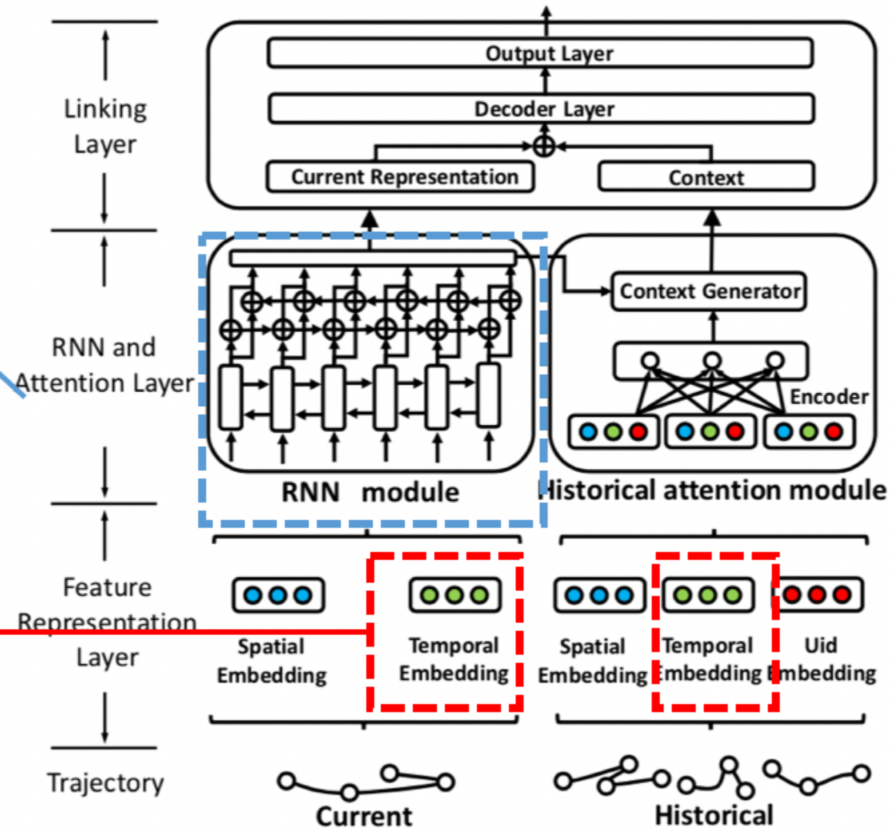


DeepTUL

Solution

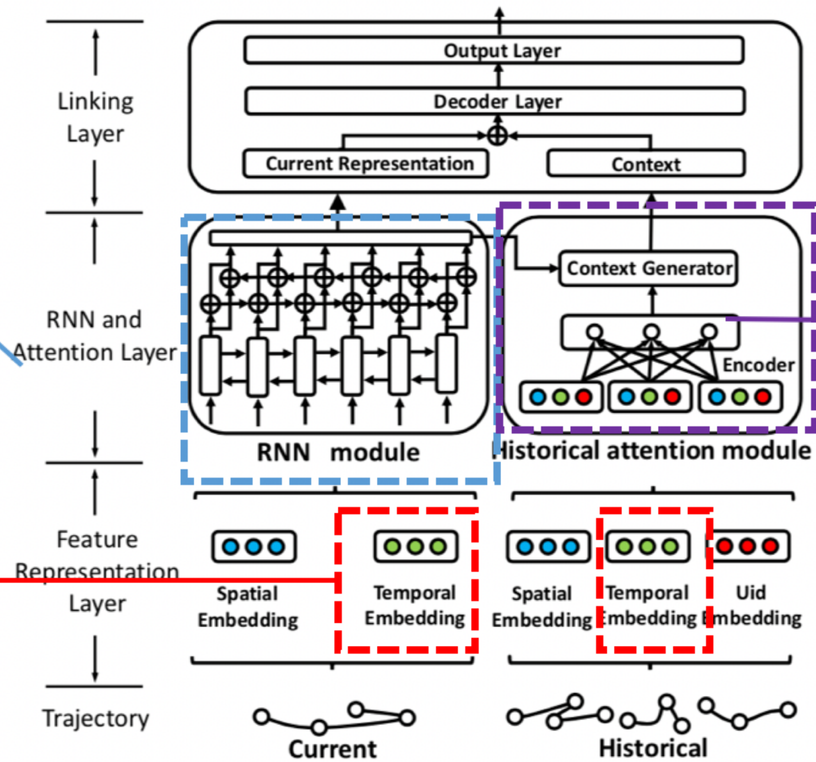
Bidirectional Long Short Term Memory (BiLSTM) to capture high-order and complex sequential information in current trajectory

The time embedding captures time-dependent relations.



DeepTUL

Solution



Bidirectional Long Short Term Memory (BiLSTM) to capture high-order and complex sequential information in current trajectory

The time embedding captures time-dependent relations.

The historical attention module learns multi-periodic nature of user mobility from labeled historical trajectories to augment the RNN module for trajectory-user linking.

DeepTUL

Experiment Results

- Dataset:

Dataset	$\lvert\mathcal{U}\rvert$	$\lvert\mathcal{T}_t\rvert/\lvert\mathcal{T}_e\rvert$	$\lvert\mathcal{P}\rvert$	$\lvert\mathcal{R}\rvert$	$\lvert\mathcal{T}_r\rvert$
Check-in	209	16151/4144	2877	191	[1,27]
	108	8681/2226	2166	204	[1,17]
WLAN	209	9632/2503	33	387	[1,42]
	108	4976/1294	33	411	[1,38]

- Evaluation metric:

$$Acc@K = \frac{|\{s \in S : l^*(s) \in L_K(s)))\}|}{|S|}$$

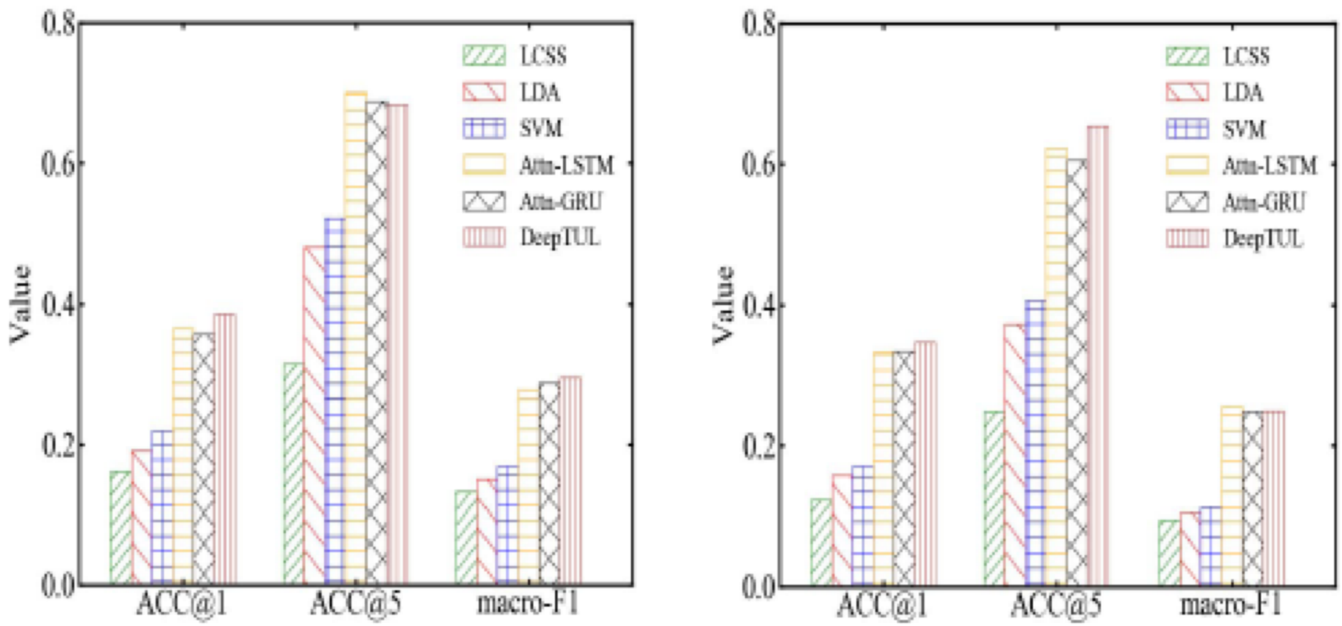
$$\text{macro-F1} = \frac{2 \times \text{macro-P} \times \text{macro-R}}{\text{macro-P} + \text{macro-R}}$$

Experiment Results

- Baselines:
  - Traditional models:
    - LCSS: Longest Common Sub-Sequence
    - LDA: The Linear Discriminant Analysis
    - SVM: The Support Vector Machine
  - RNN models:
    - Variants: GRU, LSTM, BiLSTM
    - TUVAE: RNN with Variational AutoEncoder (VAE)

Experiment Results

- Compared with traditional models:



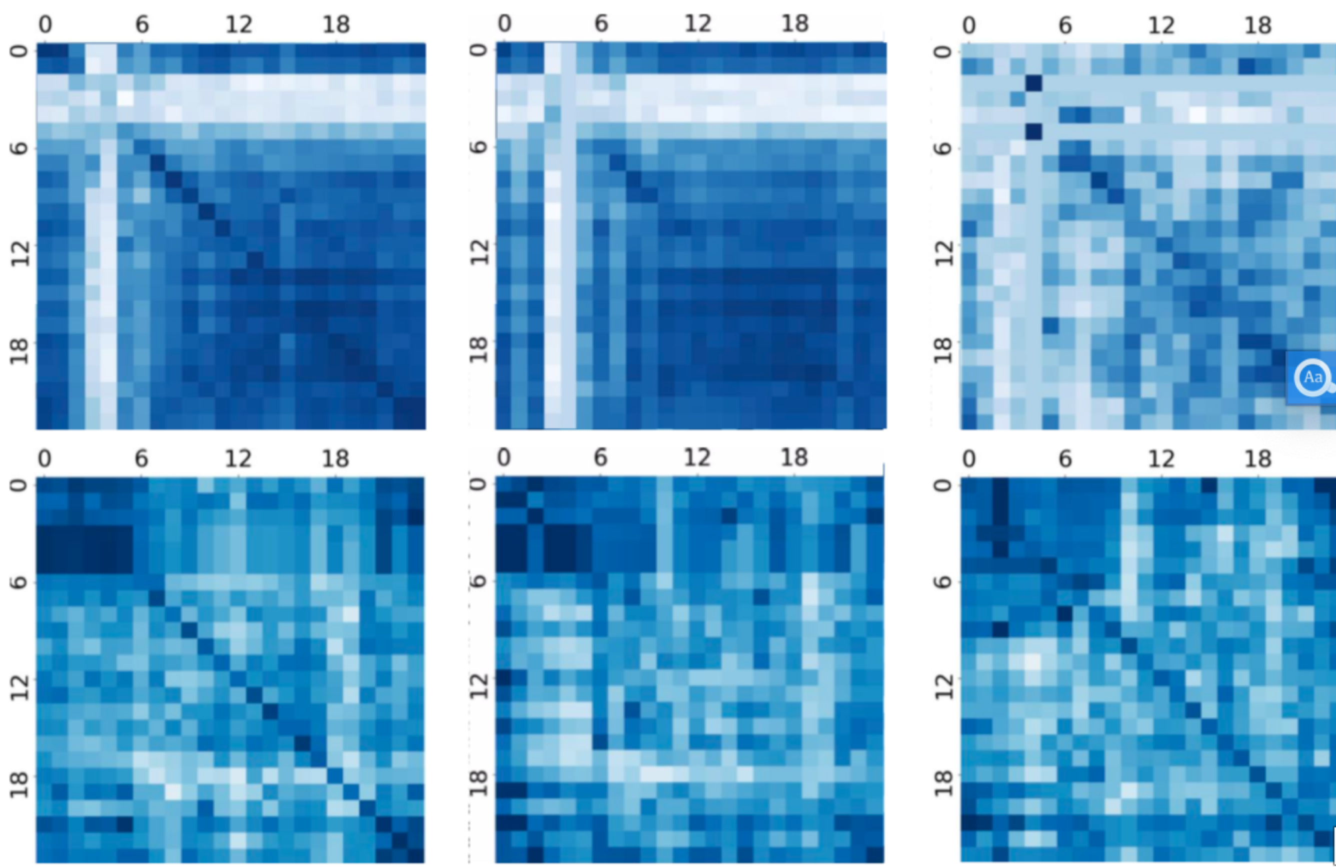
(a) $|\mathcal{U}|$=108   (b) $|\mathcal{U}|$=209

Experiment Results

- Compared with RNN models:

Dataset	Method	ACC@1	ACC@5	macro-P	macro-R	macro-F1
		$\lvert\mathcal{U}\rvert$=108				
WLAN	TULER-LSTM	23.20%	52.75%	12.70%	16.58%	14.38%
	TULER-GRU	24.21%	52.82%	15.45%	17.10%	16.23%
	BiTULER	26.14%	56.46%	16.29%	18.89%	17.49%
	TULVAE	26.68%	56.15%	16.50%	19.26%	17.77%
	Attn-LSTM	<u>36.53%</u>	**70.12%**	27.91%	27.60%	27.75%
	Attn-GRU	35.76%	<u>68.89%</u>	<u>28.77%</u>	<u>28.71%</u>	<u>28.74%</u>
	DeepTUL	**38.54%**	68.27%	**29.46%**	**30.18%**	**29.82%**
Check-in	TULER-LSTM	63.10%	74.11%	<u>58.62%</u>	51.77%	54.98%
	TULER-GRU	63.33%	74.88%	**60.64%**	52.32%	<u>56.17%</u>
	BiTULER	63.37%	74.92%	58.11%	52.44%	55.13%
	TULVAE	63.64%	74.79%	58.49%	<u>52.68%</u>	55.43%
	Attn-LSTM	<u>68.12%</u>	80.30%	56.85%	52.64%	54.66%
	Attn-GRU	66.70%	**81.02%**	55.49%	51.45%	53.39%
	DeepTUL	**69.24%**	<u>80.61%</u>	58.56%	**54.50%**	**56.46%**

- Interpretation of attention mechanism:



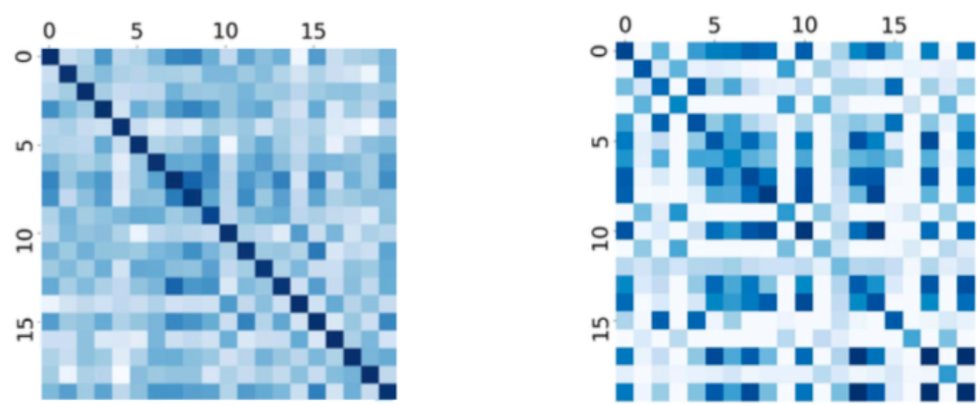
Check-in

WLAN

Weekday vs Weekday | Weekday vs Weekend | Weekend vs Weekend

- Interpretation of different value:

WLAN($|\mathcal{U}|$=209)		Check-in($|\mathcal{U}|$=108)	
Acc@1	macro-F1	Acc@1	macro-F1
0.2750	0.1824	0.6690	0.5398
0.3213	0.2361	0.6792	0.5530
0.2758	0.1837	0.6701	0.5489
0.3469	0.2500	0.6924	0.5646



(a) Check-in (b) WLAN

- Conclution
  - Feature representation layer to capture multiple features and converts them into dense representations
  - An attention mechanism to augment the RNN model to capture multiperiodic nature of user mobility

Thanks！

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