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❖ Background & Motivations

- Predicting human mobility is an important trajectory mining task for various applications, ranging from smart city planning to personalized recommendation system.
- While most of previous works adopt GPS tracking data to model human mobility, the recent fast-growing geo-tagged social media (GTSM) data brings new opportunities to this task.
- Three challenges predicting geo-tagged social media (GTSM) data: 1) **extreme data sparsity**; 2) **high order sequential patterns of human mobility** and 3) **evolving preference of users for tagging**.
- The main motivation of our research is that the state-of-the-art models to predict human mobility are RNN based, which has many constraints.
 - Inspired by many methods in NLP and sequence modeling, we want to have a try with CNN.

❖ Methods

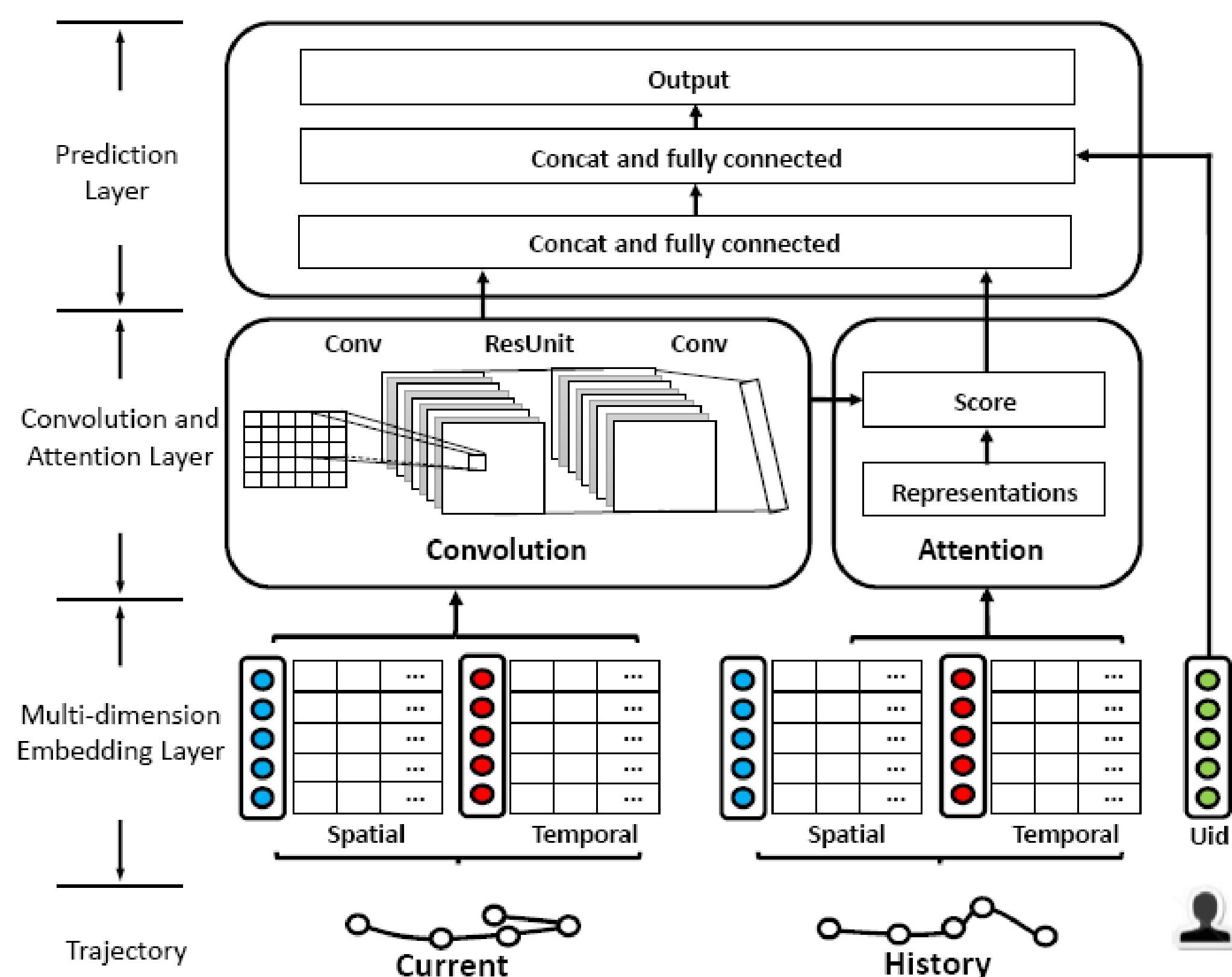


Fig 2: The Architecture of ACN.

- We propose an attentive convolutional network (ACN) model to predict human mobility from sparse and complex GTSM data.
 - Specifically, we regard the embedded trajectory as an image and use convolution filters to search for sequential patterns as local features of the image.
- We design HSC which is combined of Hybrid dilated convolutions and Shared and Separable Convolutions in convolution module.
 - The former increases the receptive fields exponentially to capture high order sequential patterns from lengthy trajectory, while the latter is a powerful degriding method to preserve local information consistency.
 - We propose using an attention mechanism to learn long-term preferences of users from history trajectory.

➤ Statistics of the dataset

Datasets	$ \mathcal{U} $	$ \mathcal{P} $	$ \mathcal{R} $	$ \mathcal{S} $
Gowalla	1989	40121	134	0.9966
Foursquare-TKY	2293	24321	229	0.9906
Foursquare-NYK	1083	15624	183	0.9883

Table 1: The description and statistics of three datasets. $|\mathcal{U}|$: number of users; $|\mathcal{P}|$: number of locations; $|\mathcal{R}|$: average length of trajectory sequence; $|\mathcal{S}|$: sparsity.

❖ Experiments & Results

➤ Experiment 1: Our model vs. Baselines

- Results shows that ACN consistently outperforms the existing state-of-art methods on a variety of common evaluation metrics.

Gowalla	MC	MF	FPMC	RNN
Acc@1	0.1151	0.0555	0.1163	0.1191
	ST-RNN	Deepmove	Ours	Improve
Acc@1	0.1249	0.148	0.1668	12.70%

Foursquare TKY	MC	MF	FPMC	RNN
Acc@1	0.1281	0.1299	0.1281	0.1325
	ST-RNN	Deepmove	Ours	Improve
Acc@1	0.1572	0.1881	0.1966	4.52%

Table 2: Performance comparison on public GTSM datasets.

➤ Experiment 2: Impact of key hyperparameters

- We exam the impact of the key hyperparameters one at a time by holding the remaining hyperparameters at the optimal settings.

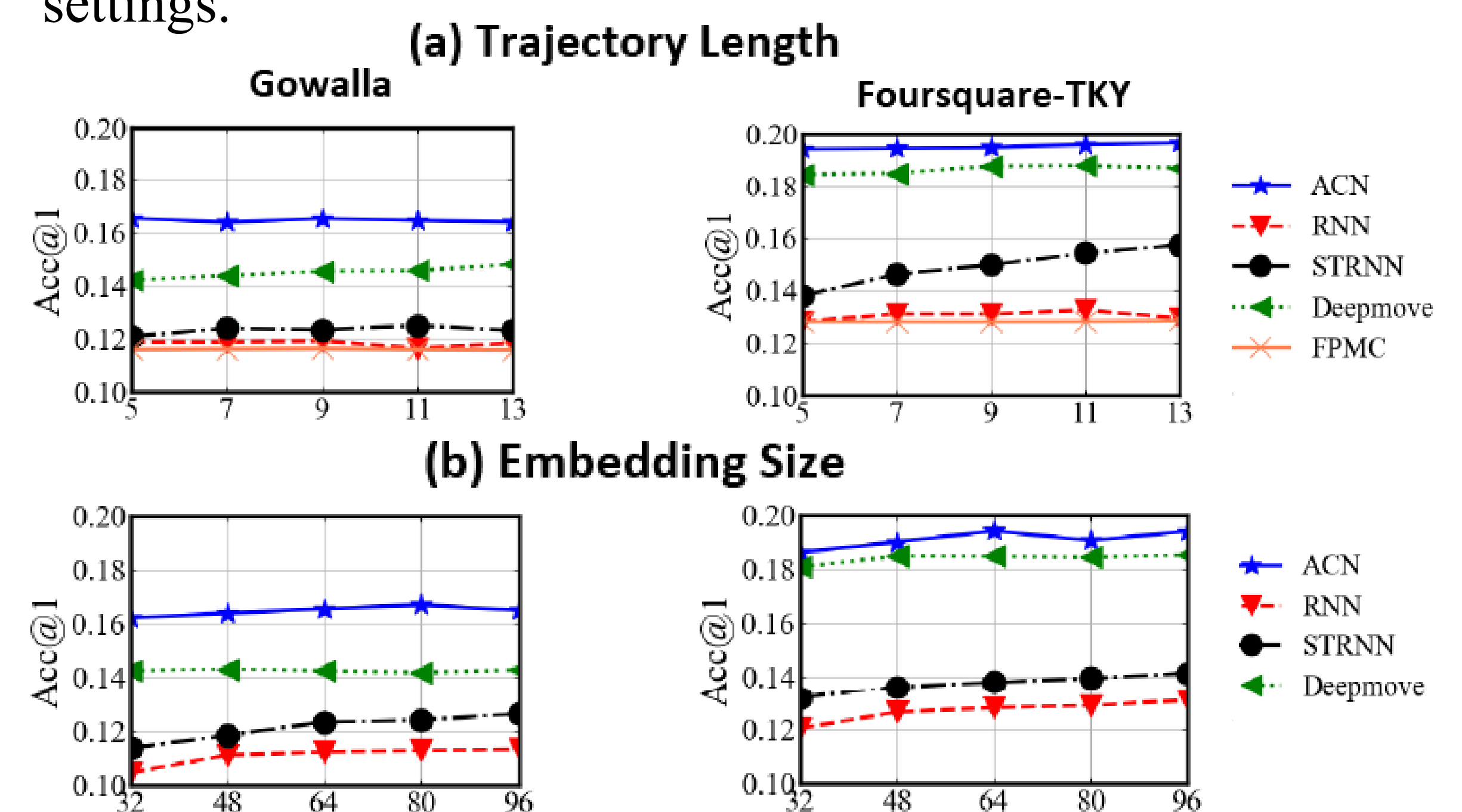


Fig 3: Impact of key hyperparameters. (a) ACC@1 vs. the length of trajectory. (b) ACC@1 vs. the embedding size.

➤ Experiment 3: Ablation study

- We conduct experiments to analyze each component while keeping all hyperparameters at the optimal settings. ACN-s denotes ACN with ss-conv, ACN-d denotes ACN with dilated conv, ACN-no denotes ACN without ss-conv or dilated conv, ACN-sd denotes ACN with both dilated conv and ss-conv.

Gowalla	ACN-s	ACN-d	ACN-no	ACN-sd
Acc@1	0.1568	0.1563	0.1563	0.1668
macro-F1	0.0947	0.0944	0.0946	0.1047

Foursquare TKY	ACN-s	ACN-d	ACN-no	ACN-sd
Acc@1	0.1936	0.1931	0.1914	0.1966
macro-F1	0.0865	0.0876	0.0866	0.0888

Table 3: The contribution of ACN's components.

❖ Conclusion & Future work

- We propose a novel solution to predict human mobility on sparse and complex GTSM data.
- Our experiments on three GTSM datasets suggest ACN consistently outperforms the existing state-of-art methods on a variety of common evaluation metrics.
- We want to conduct more experiments and focus more on the explainability of our model in the future.