Predicting Human Mobility via Attentive Convolutional Network

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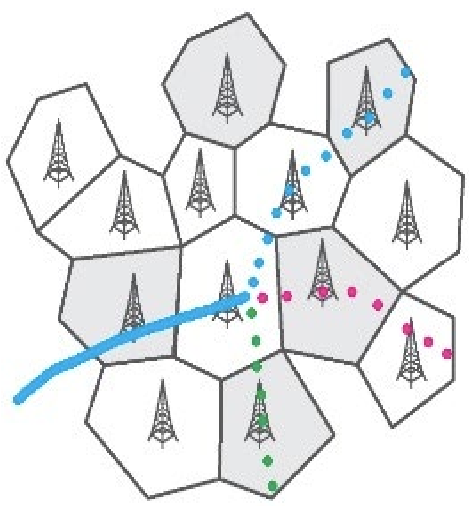
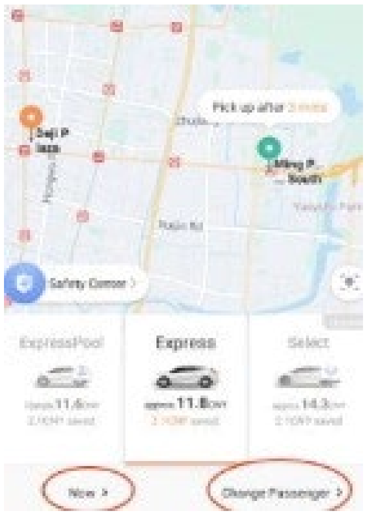
1. Introduction
2. Related Work
3. Solution
4. Experiment Result
5. Conclusion

1. Introduction

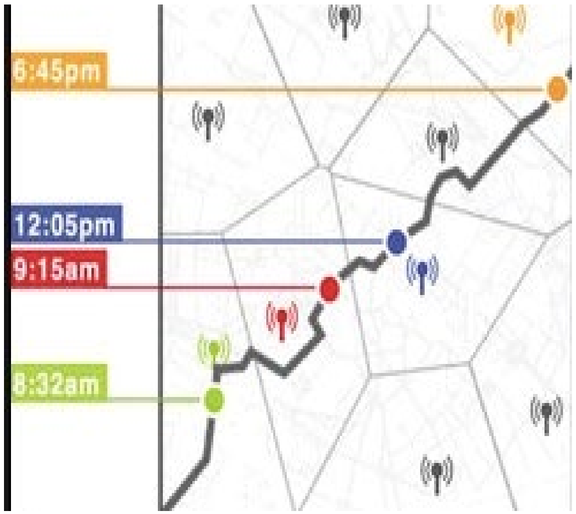
- Human mobility prediction is of great importance for various applications.
  - Intelligent traffic management
  - Smart city planning
  - Personalized recommendation



Mobility management



Estimating travel demand



Recommendation

1. Introduction

- Three unique characteristics on geo-tagged social media (GTSM) data
  - Extreme data sparsity: low-sampling and generated only when the users want to share their locations
  - High order sequential patterns: containing complex dependency relationships of human mobility and not all adjacent GTSM data has dependency relationships.
  - Evolving preference: human taste (i.e., long-term preference) for tagging is changing over time

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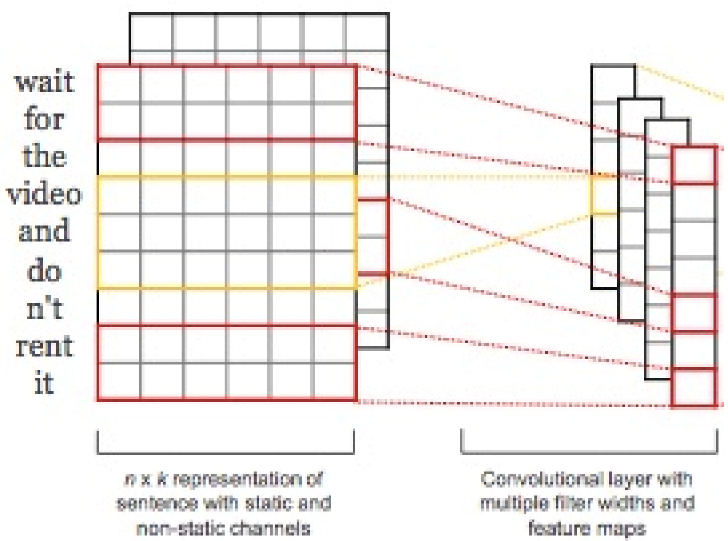
2. Related work

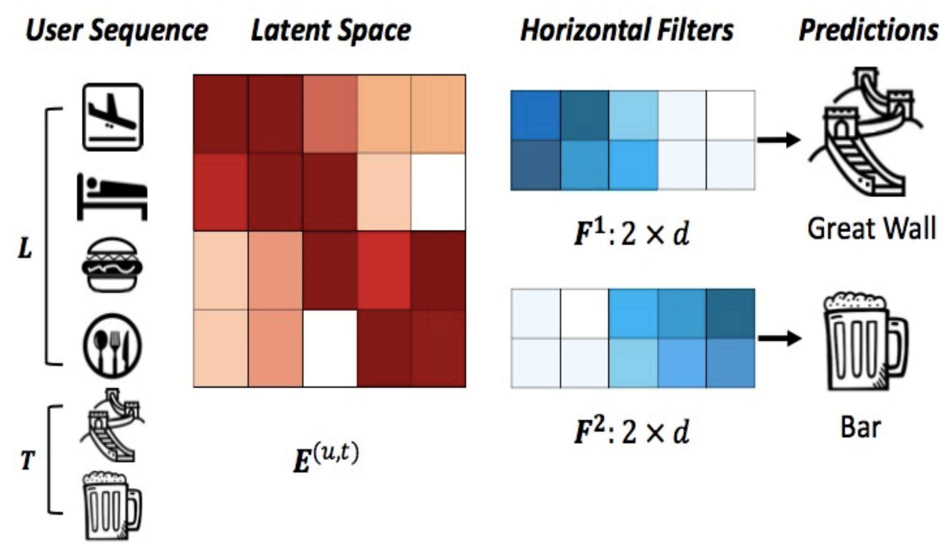
- Human mobility prediction
  - Pattern based approach:
    - Matrix factorization (non-negative MF, WMF)
    - Tensor factorization (TF)
  - Ignore sequential transition regularities and long-term preference
  - Model based approach:
    - Markov models (MC, HMM)
    - Recurrent neural network (ST-RNN, DeepMove)
  - Unable to model high-order sequential pattern

2. Related work

- Convolutional Neural Network (CNN)
  - Sequential modeling
    - Natural language processing (NLP)
    - Item recommendation



NLP



Recommendation

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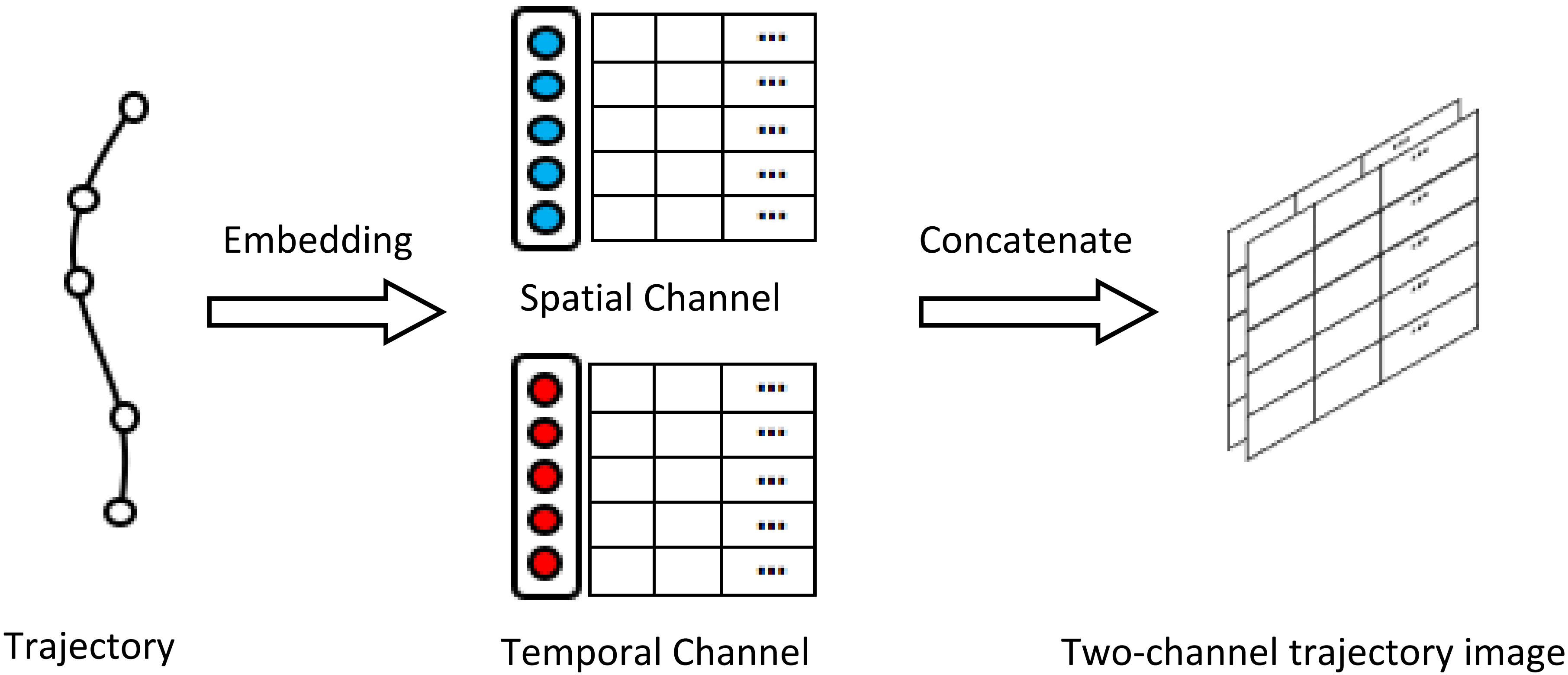
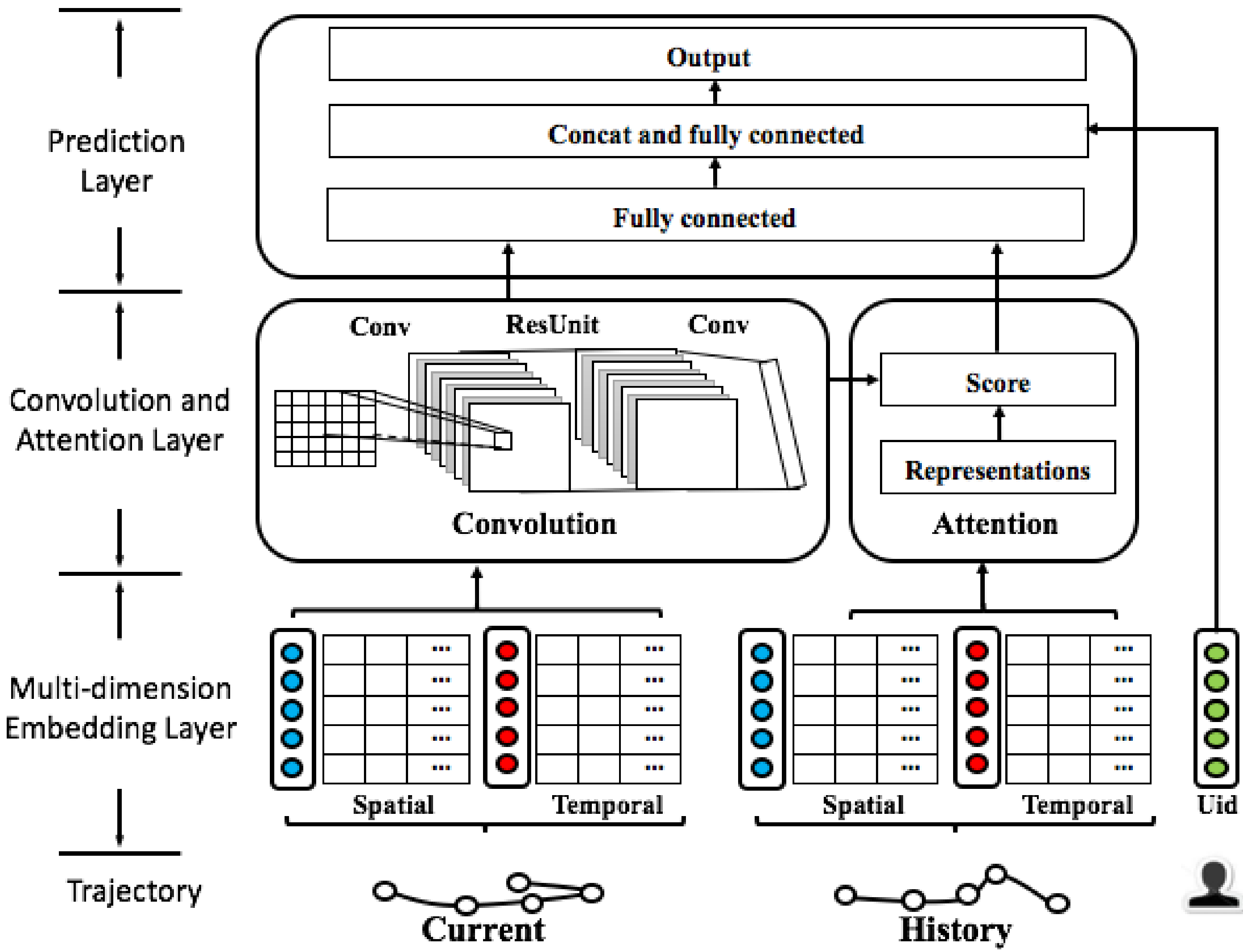
- DEFINITION 1 (Trajectory Sequence)
  - We define a spatio-temporal point **q** as a tuple of location **p** and time **t**, **e.g. q = (p,t)**. For a user ID **u**, trajectory sequence **T** is the aggregation of spatio- temporal points, i.e., $\mathbf{T_u = q_1 q_2 \cdots q_n}$.
- DEFINITION 2 (Trajectory)
  - Given a trajectory sequence $\mathbf{T_u}$ for a user **u**, trajectory is a subsequence of $\mathbf{T_u}$. The **k**-th trajectory with length **L** can be represented as $\mathbf{T_{u,k} = q_k q_{k+1} \cdots q_{k+L-1}}$.

- Problem description
  - Given the trajectory $\mathbf{T}_{u,k}$, predict the **next spatial context: Location.**
  - The trajectory sequence of each person is divided into two parts: current trajectory and up-to-date historical trajectory
    - **predict the next location** of the current trajectory with the help of current trajectory and historical trajectory.

- CNN based mobility prediction
  - Trajectory embedding → Trajectory map
  - Use convolution operation to search for sequential patterns as local features of the image.

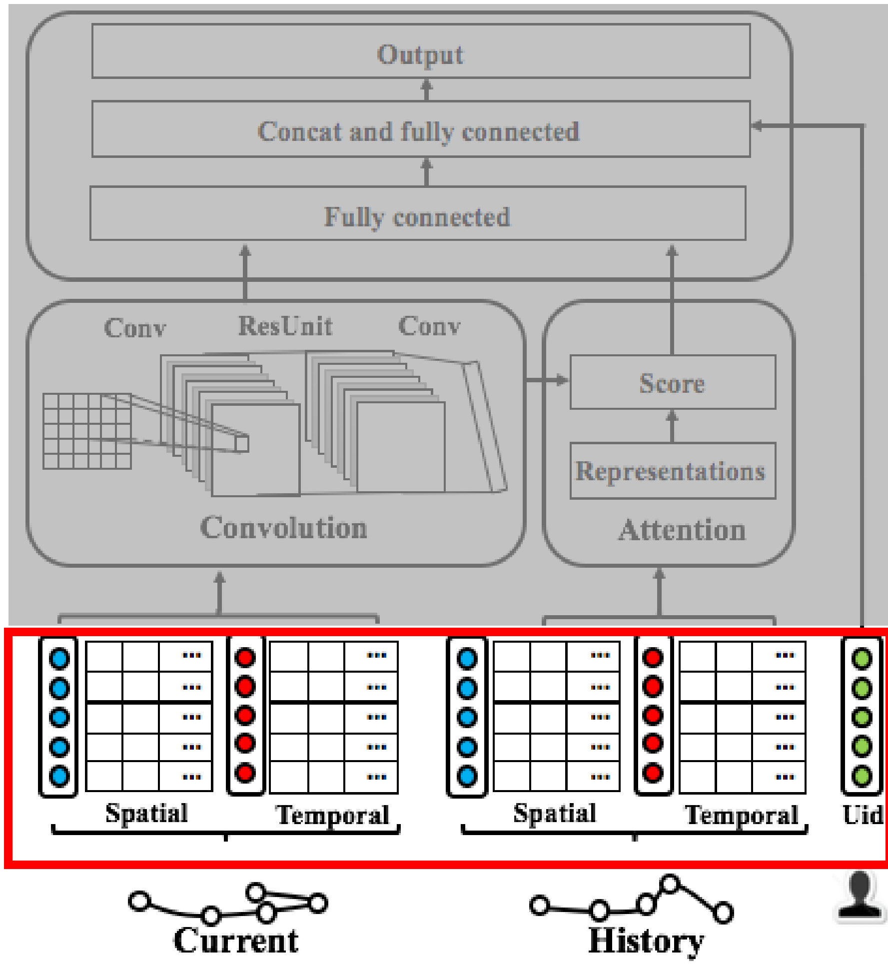


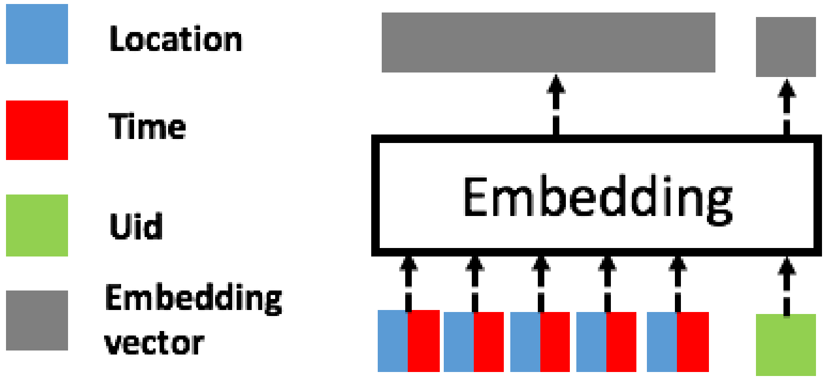
3. Solution



Architecture of attentive convolutional network (ACN)

ACN—Multi-dimension Embedding

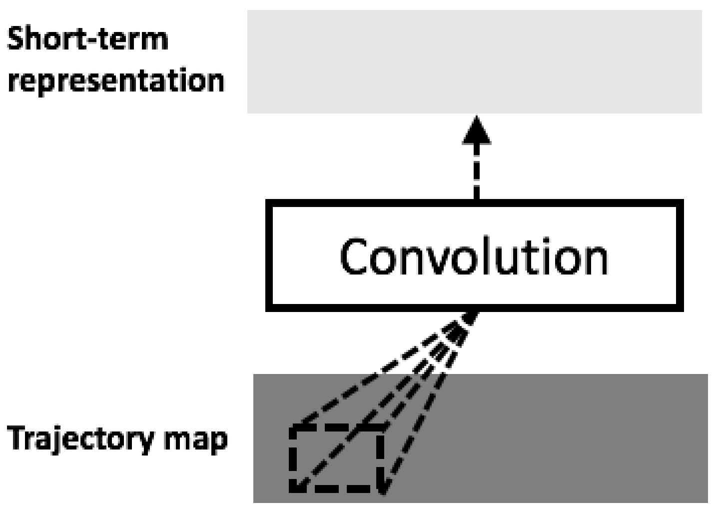




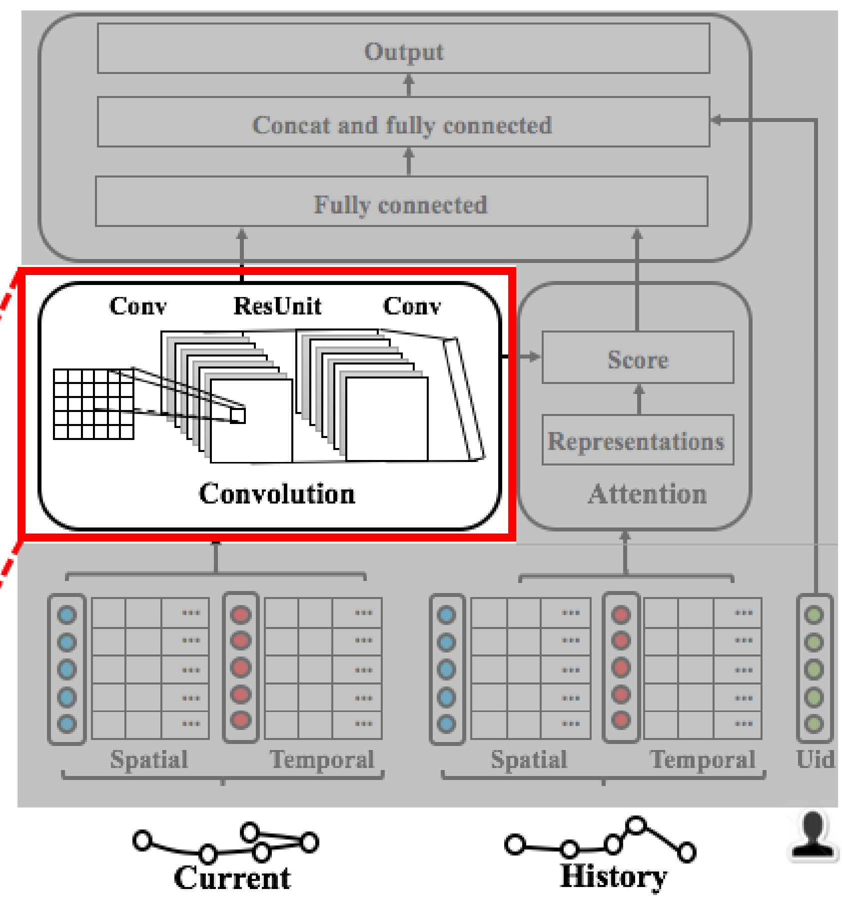
- **Multi-dimension embedding**
  - One-hot encoding
    Location, time, uid
  - Transformation matrix
  - Concatenate layer

3. Solution

ACN—Convolution module

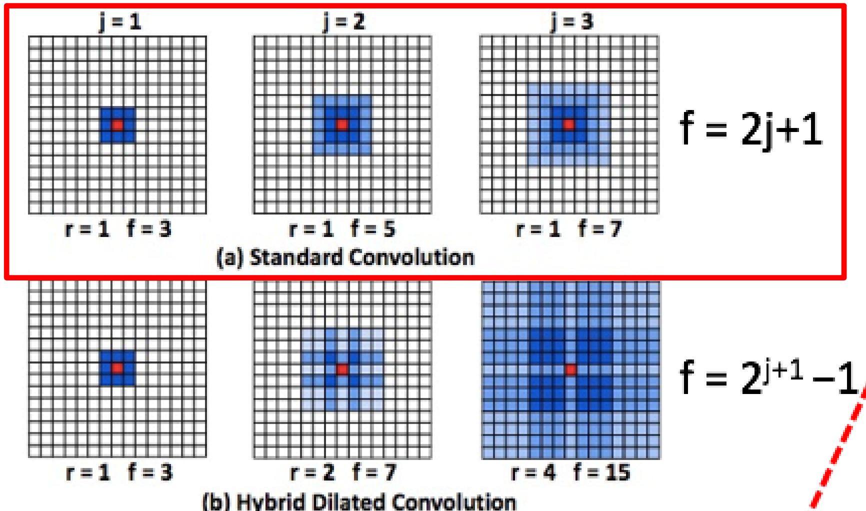


- **Convolution module**
  - Hybrid dilated convolution
  - Separable and shared convolution
  - Residual network



3. Solution

ACN—Convolution module



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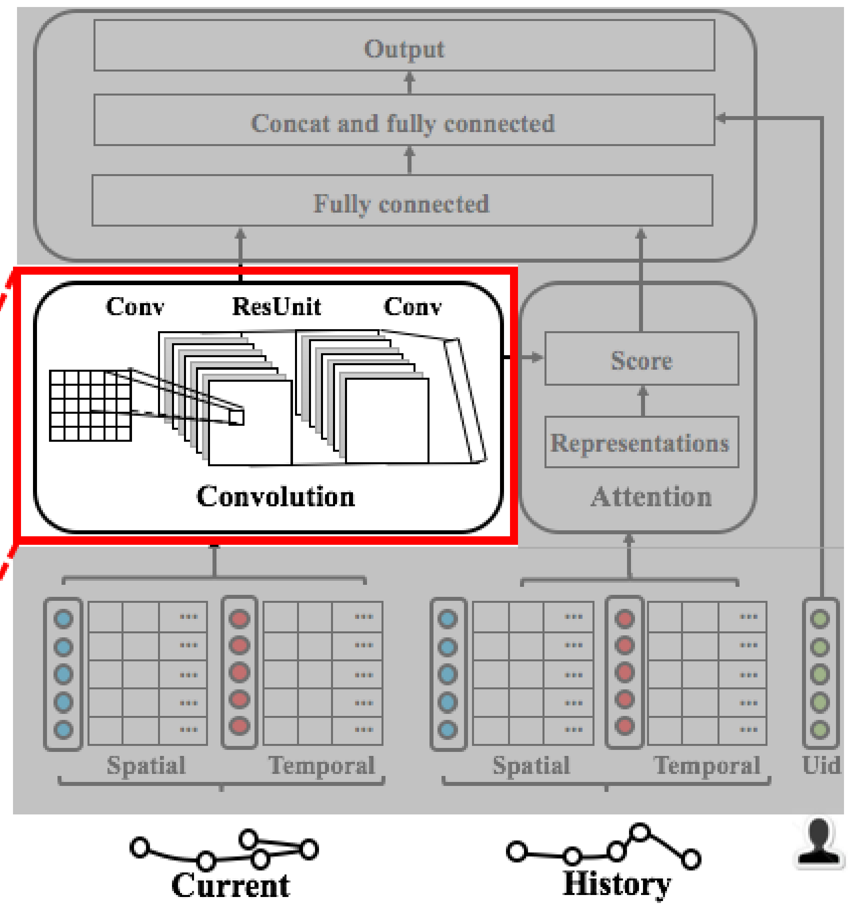
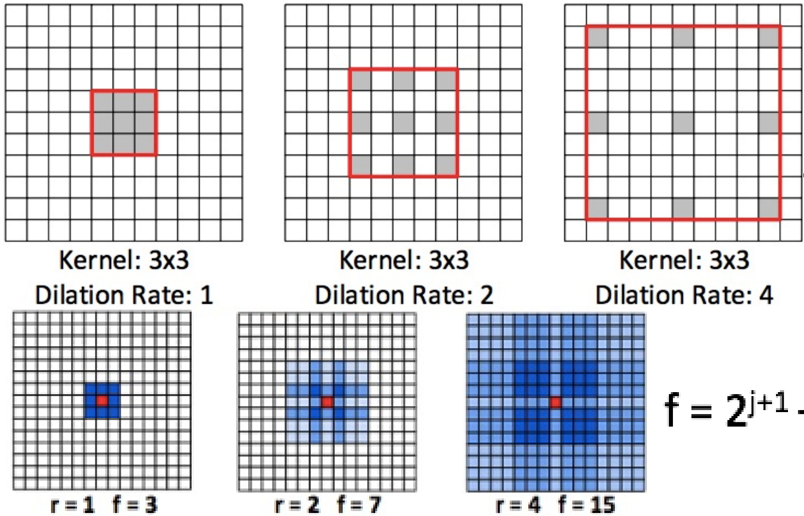


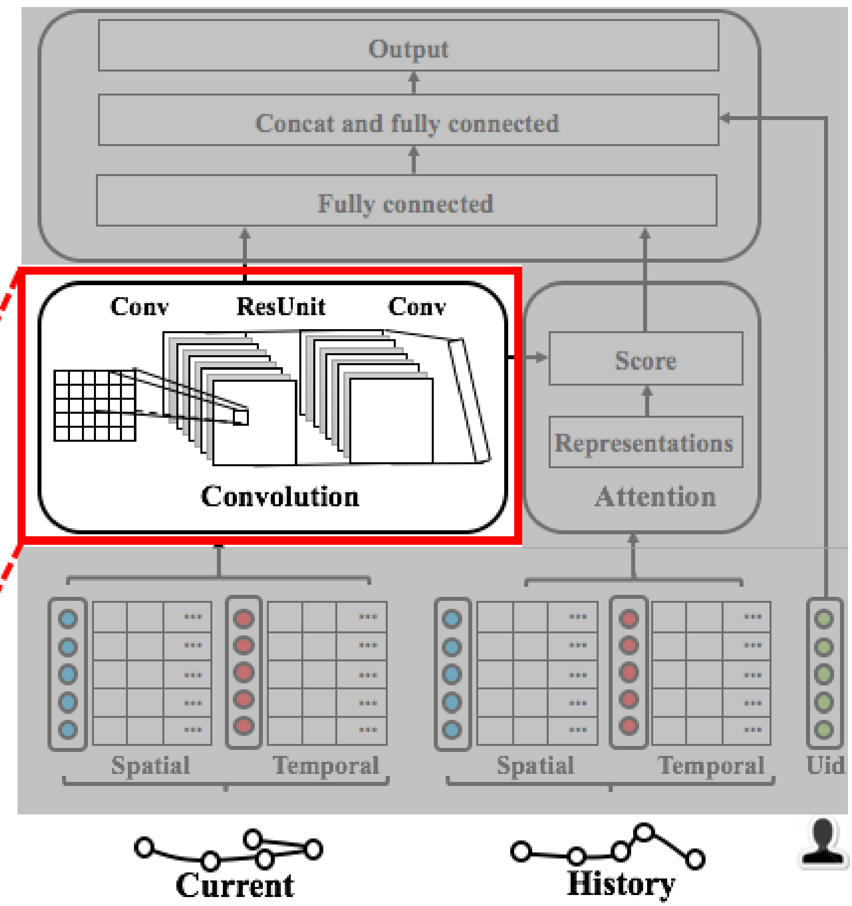
3. Solution

ACN—Convolution module



(b) Hybrid Dilated Convolution

$$f = 2^{j+1} - 1$$



- **Convolution module**
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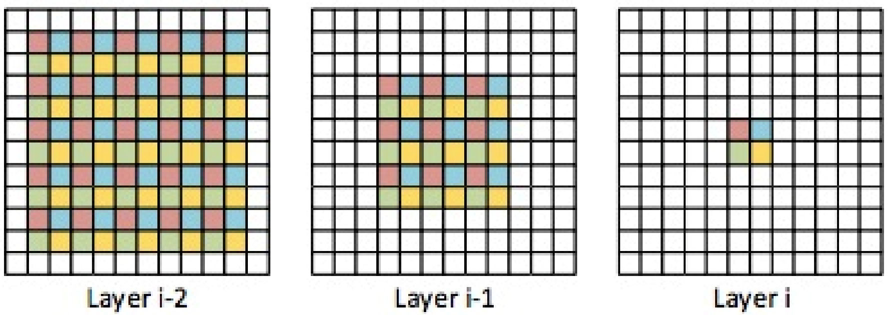
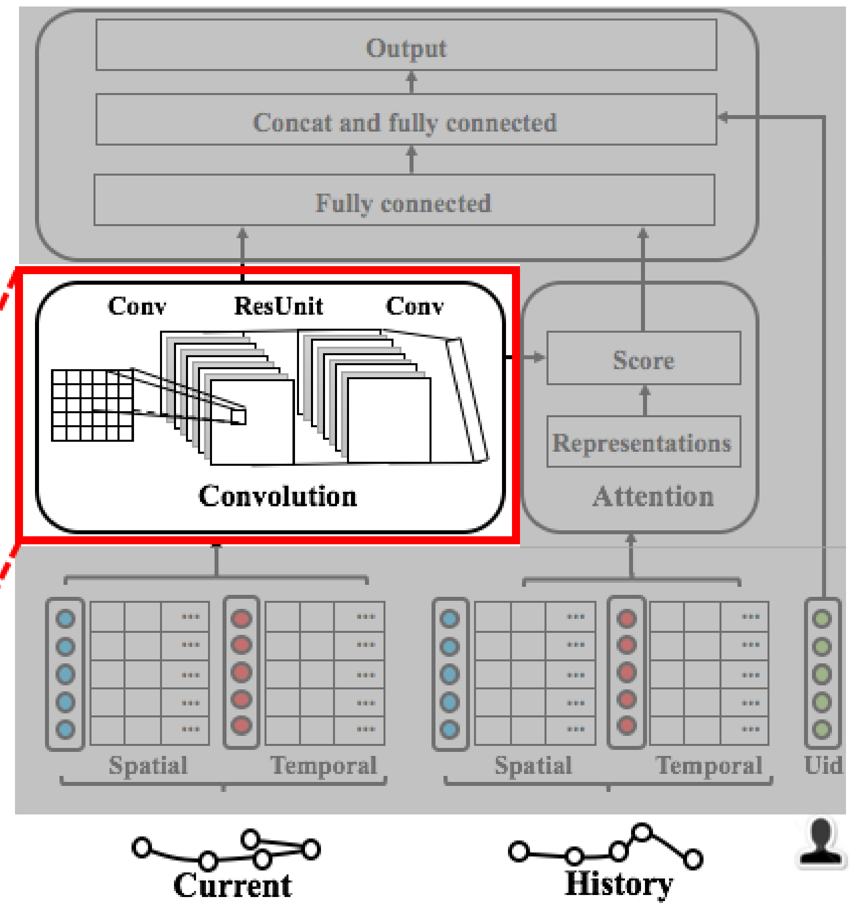
3. Solution

ACN—Convolution module

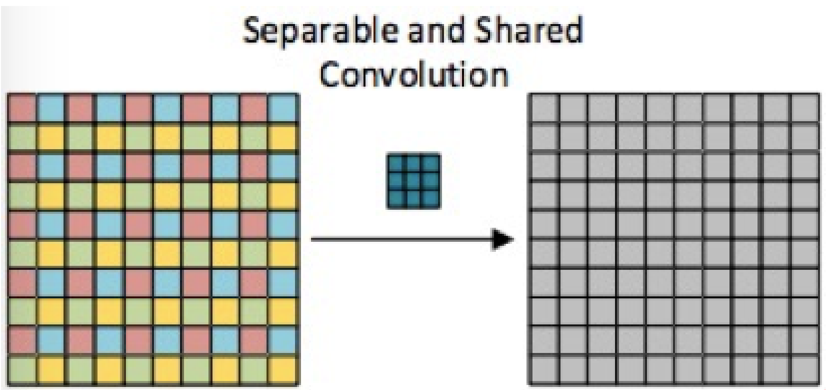


An illustration of gridding artifacts. Dilated convolutions with kernel size of 3 × 3 and a dilation rate of r = 2

- **Convolution module**
  - Hybrid dilated convolution
  - **Separable and shared convolution**
  - Residual network



ACN—Convolution module



Degridding method to improve the consistency of dilated convolution

- **Convolution module**
  - Hybrid dilated convolution
  - **Separable and shared convolution**
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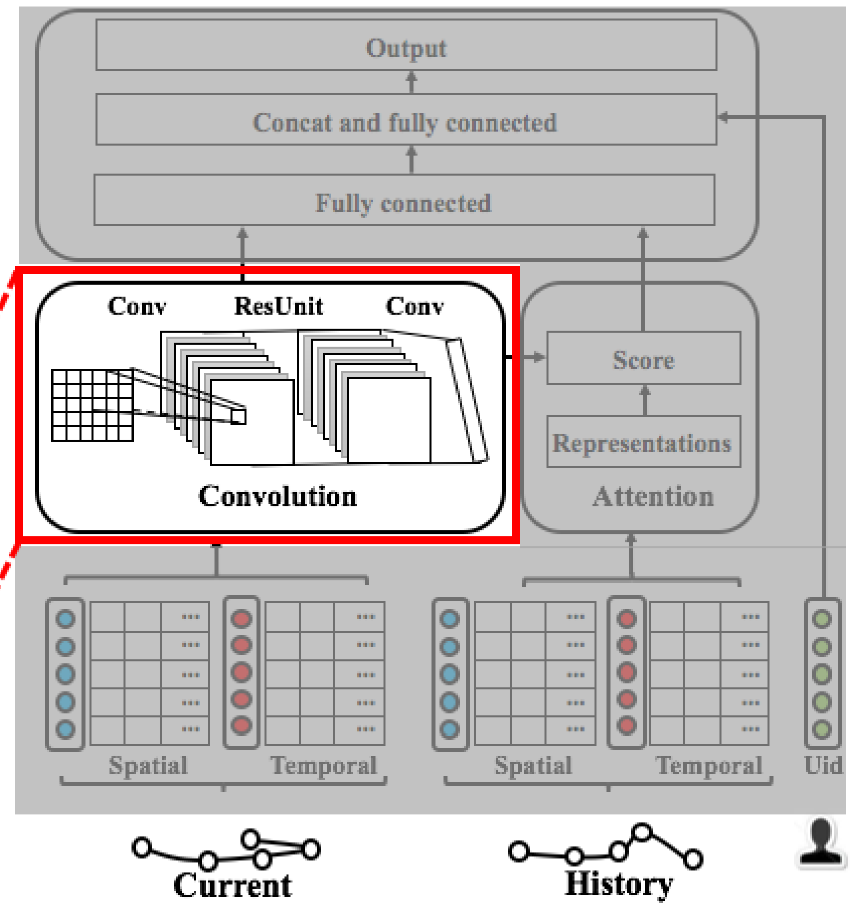
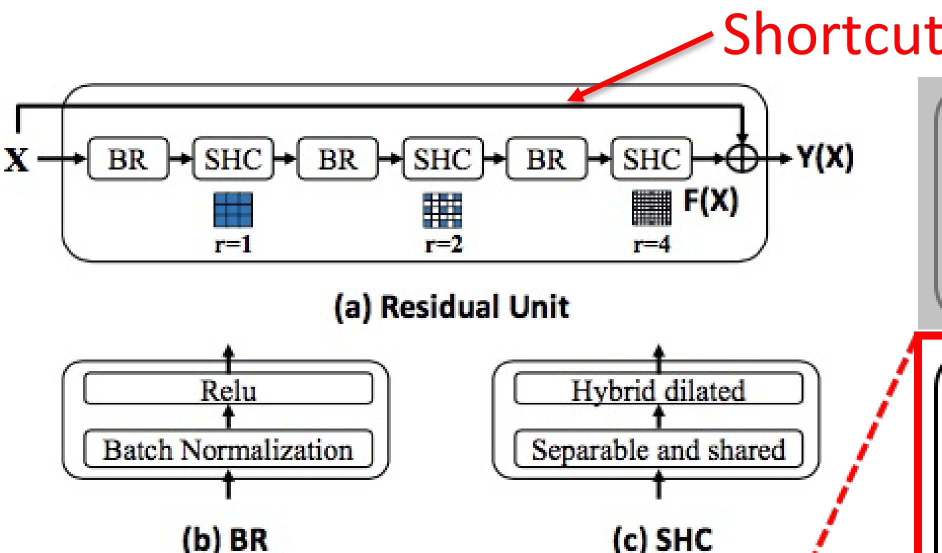
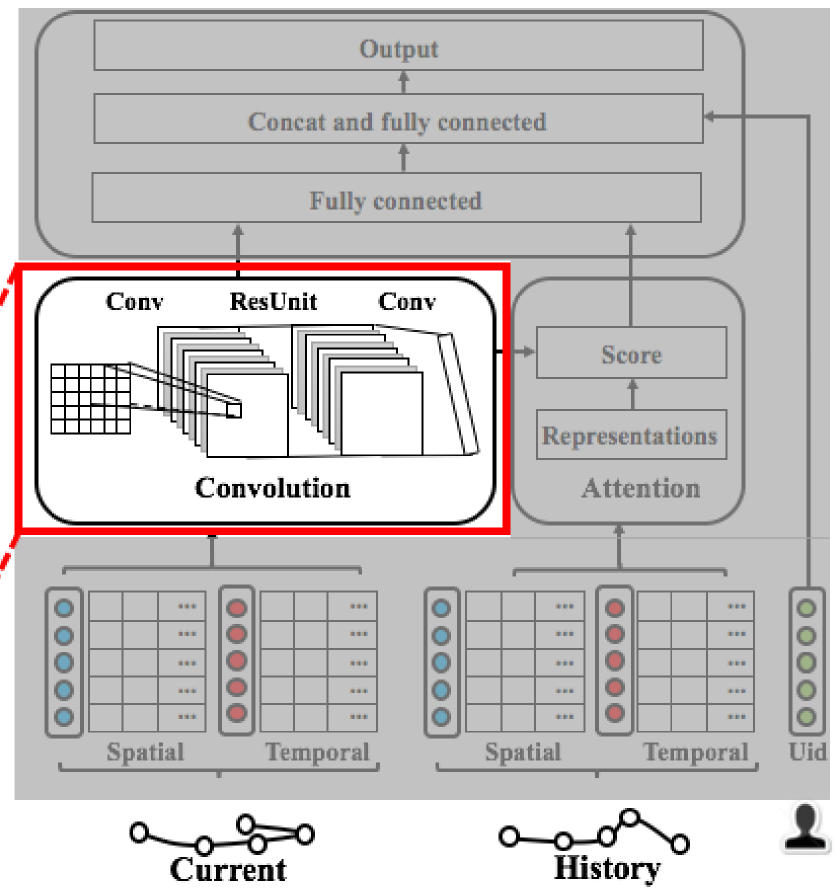


ACN—Convolution module

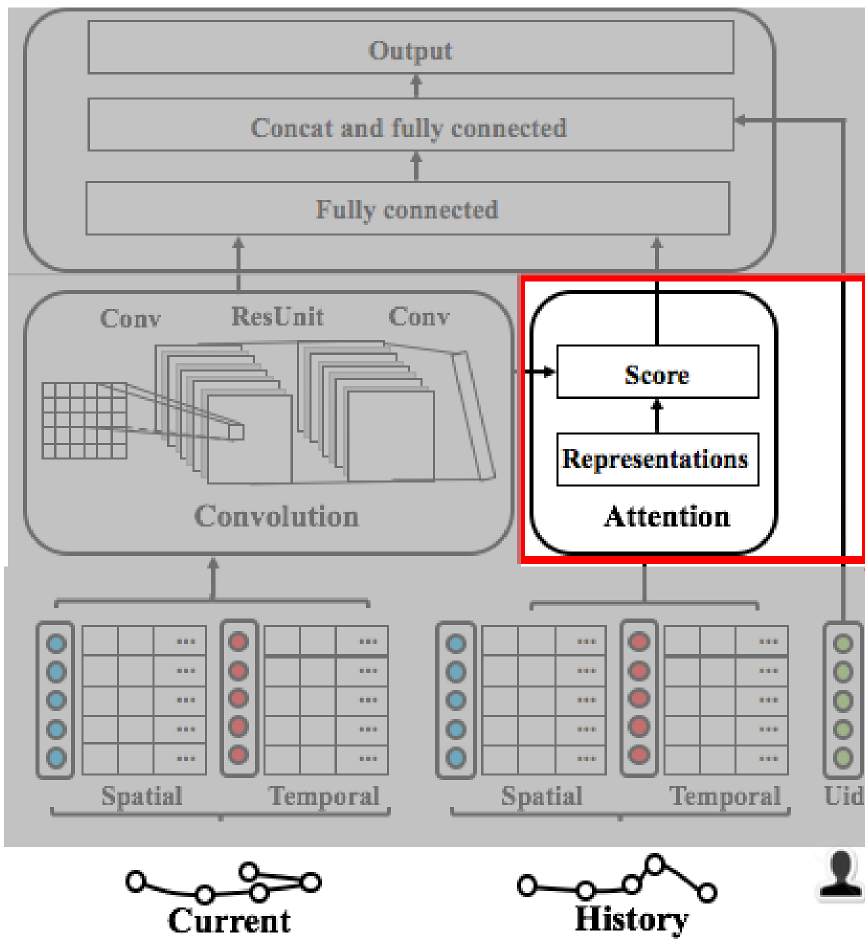


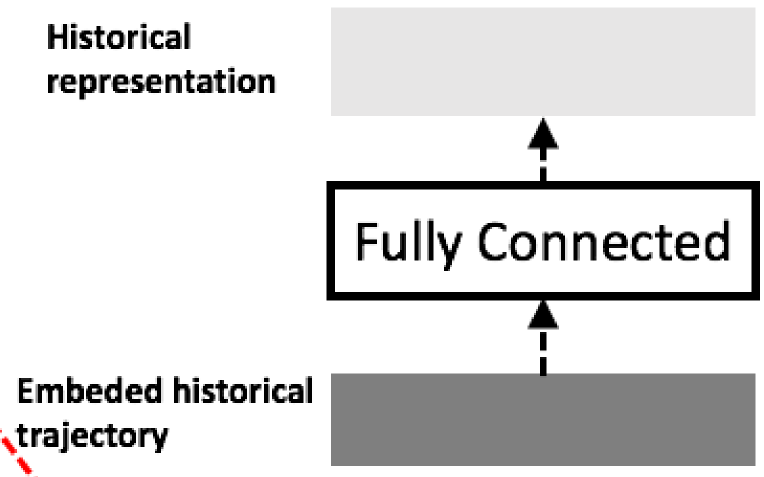


- **Convolution module**
  - Hybrid dilated convolution
  - Separable and shared convolution
  - **Residual network**

3. Solution

ACN—Attention module

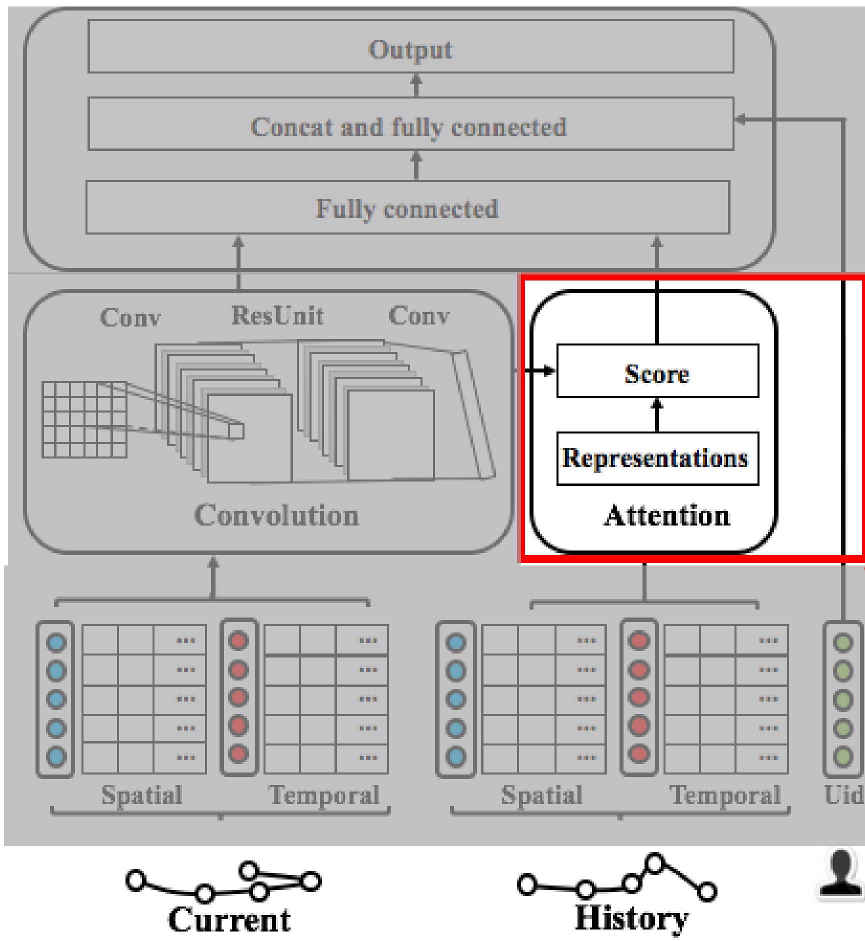


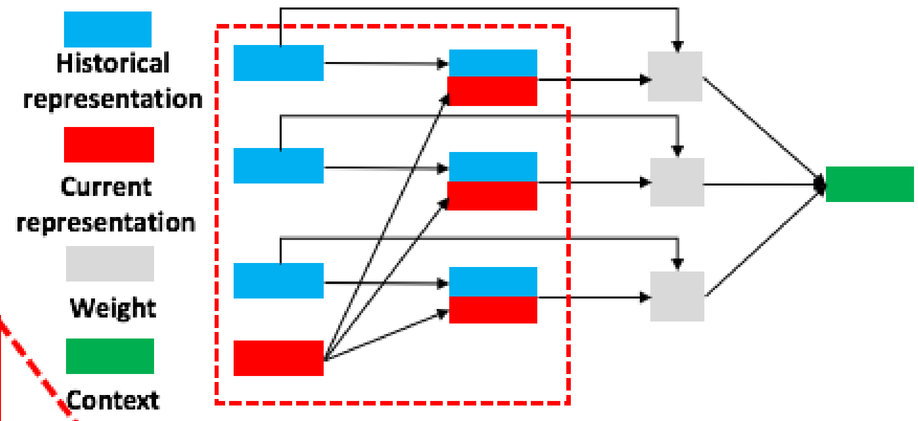


- **Attention module**
  - **Historical representation layer**
  - **Score function**
    - Calculating similarity
    - Soft-max
    - Weighted sum

3. Solution

ACN—Attention module





Calculating similarity

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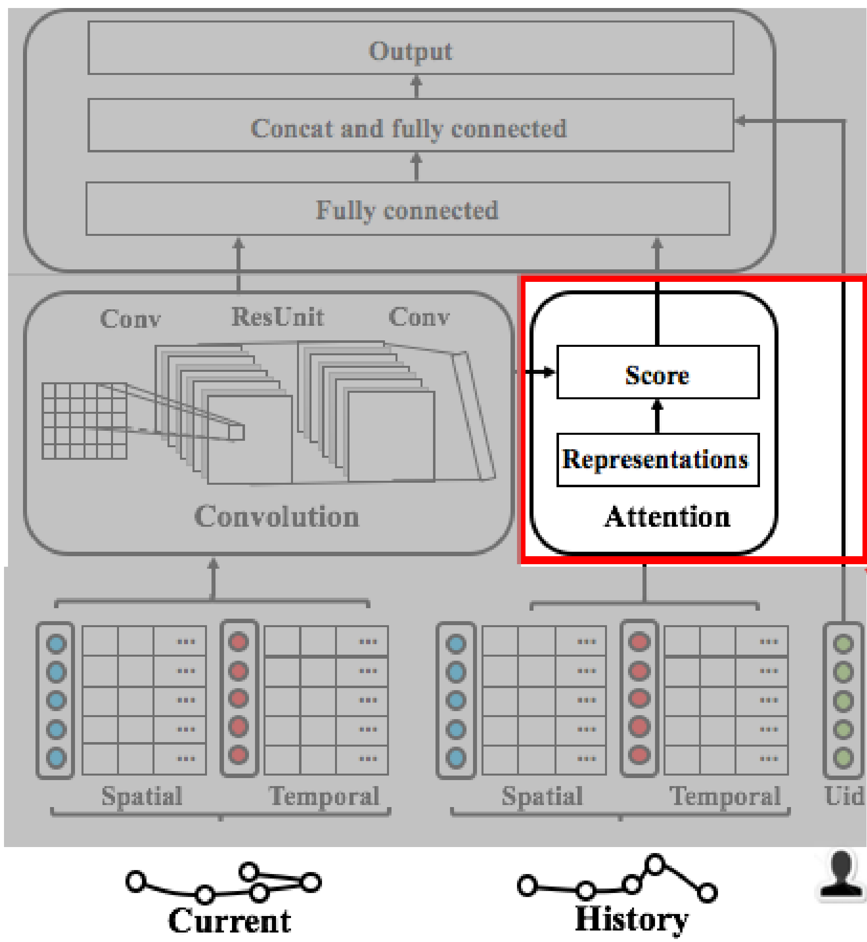
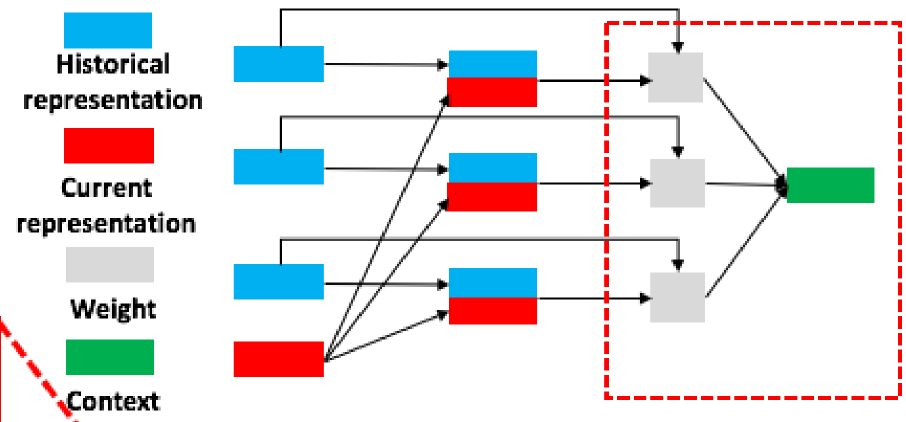
3. Solution

ACN—Attention module





Soft-max and weighted sum

- **Attention module**
  - Historical representation layer
  - **Score function**
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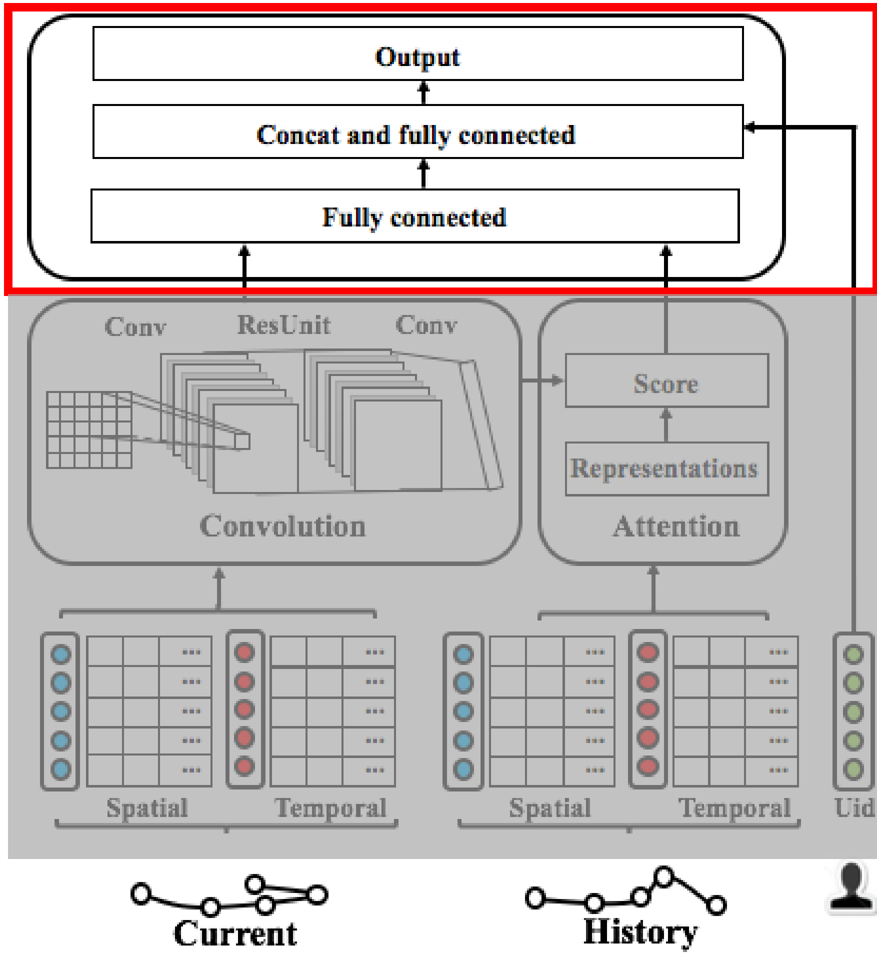
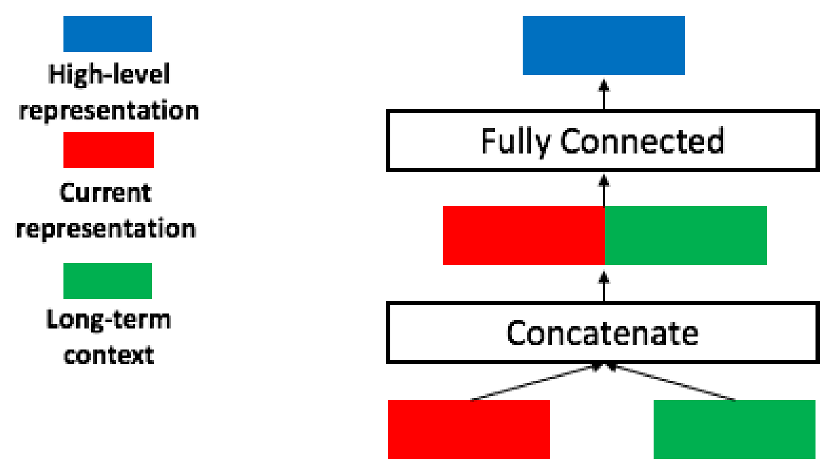
    - Weighted sum

3. Solution

ACN—Attention module

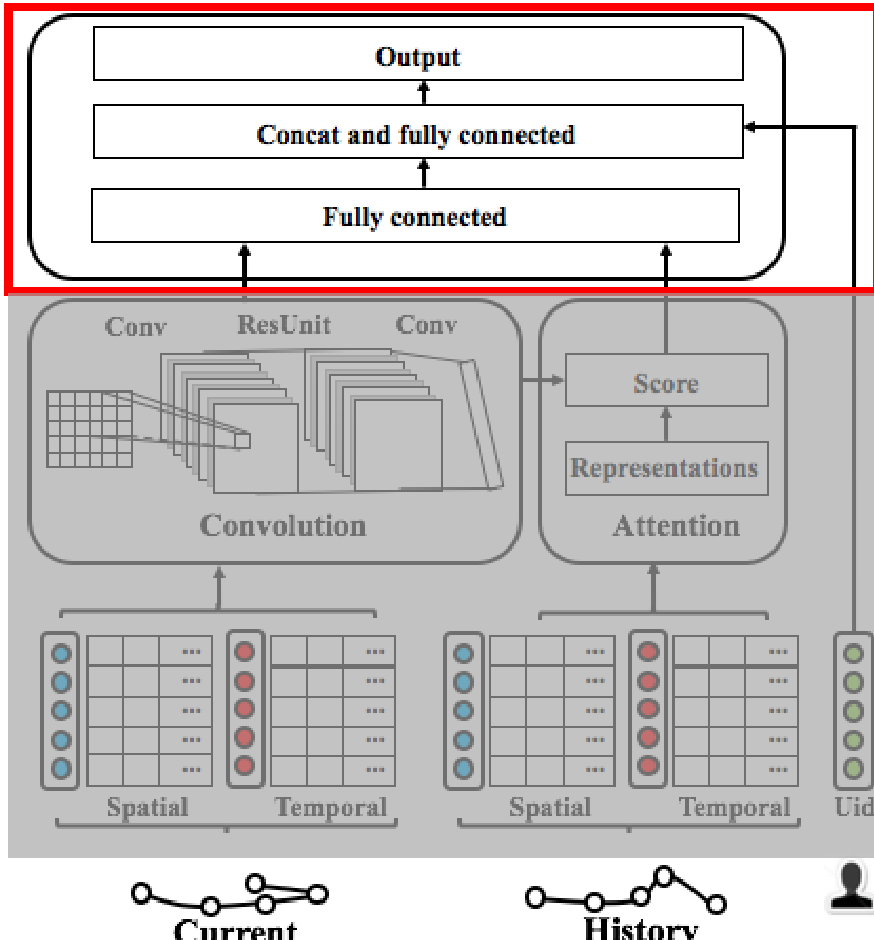


- **Prediction layer**
  - **Current representation and long-term context**
    concatenate + fc
  - **Human personal preference**
    concatenate + fc + soft-max



3. Solution

ACN—Attention module



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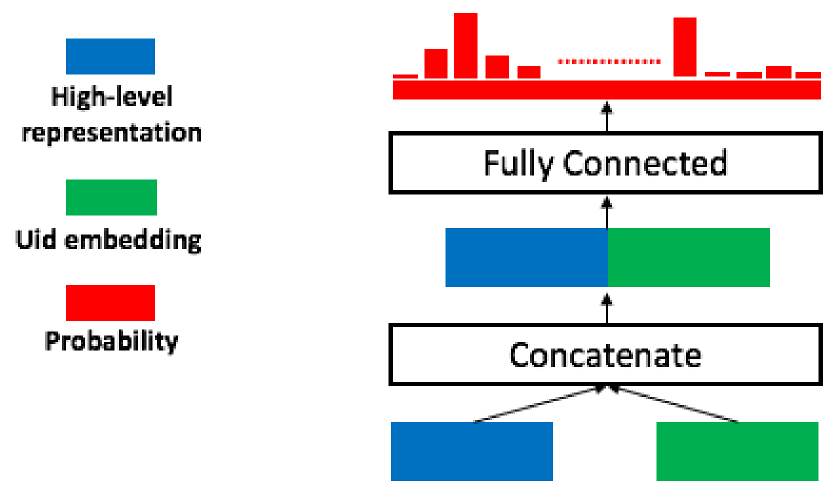
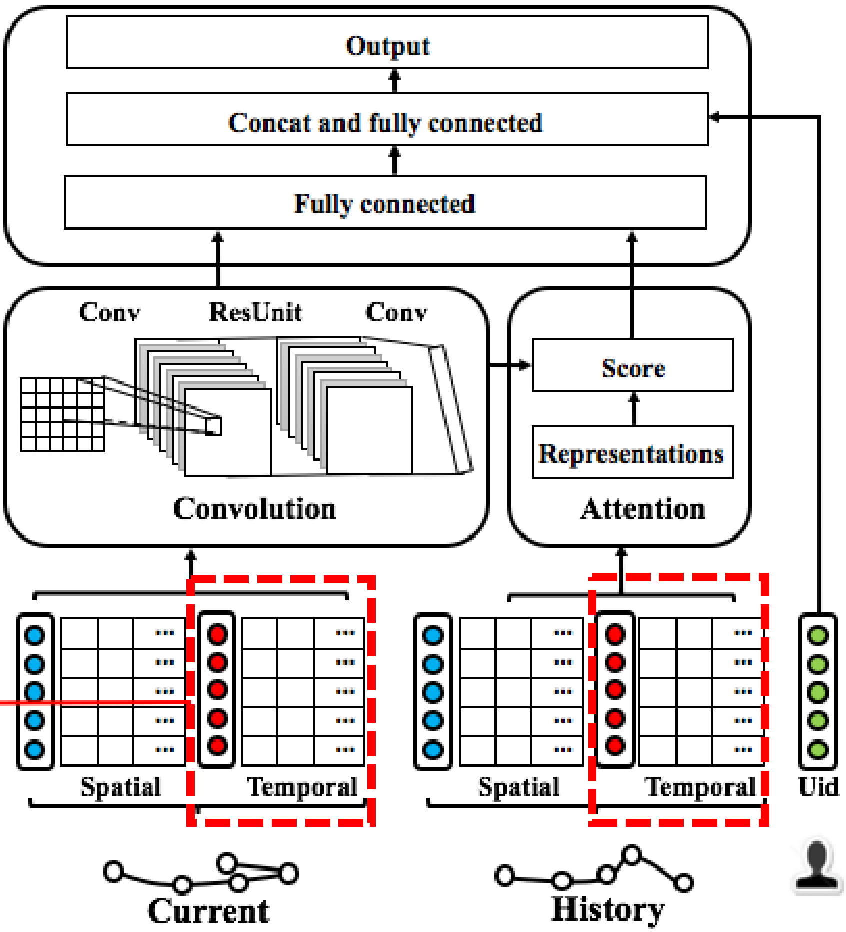


3. Solution

ACN



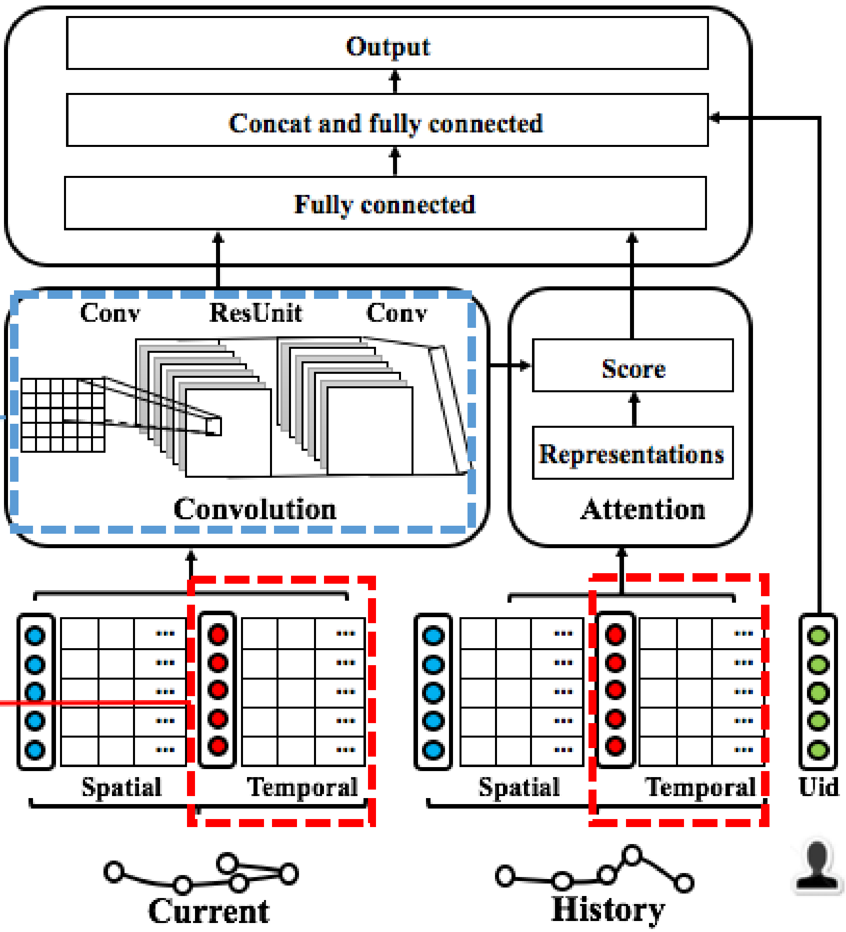
The time embedding captures time-dependent relations.

3. Solution

ACN

The convolution module captures high-order sequential pattern.

The time embedding captures time-dependent relations.

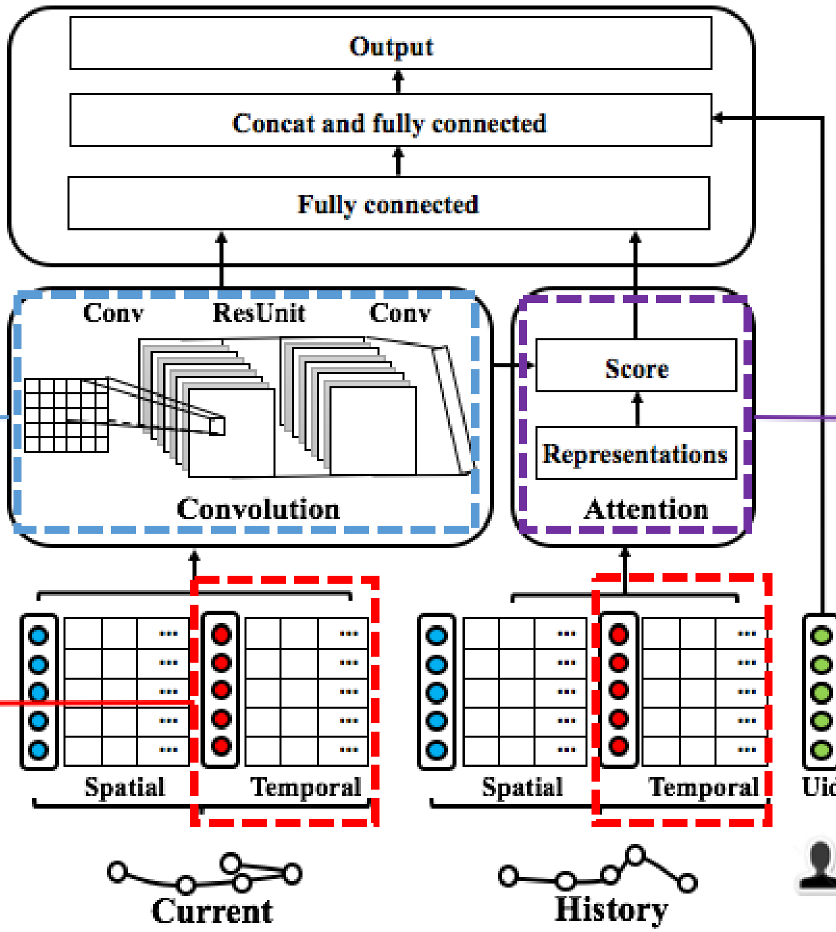


3. Solution

ACN

The convolution module captures high-order sequential pattern.

The time embedding captures time-dependent relations.



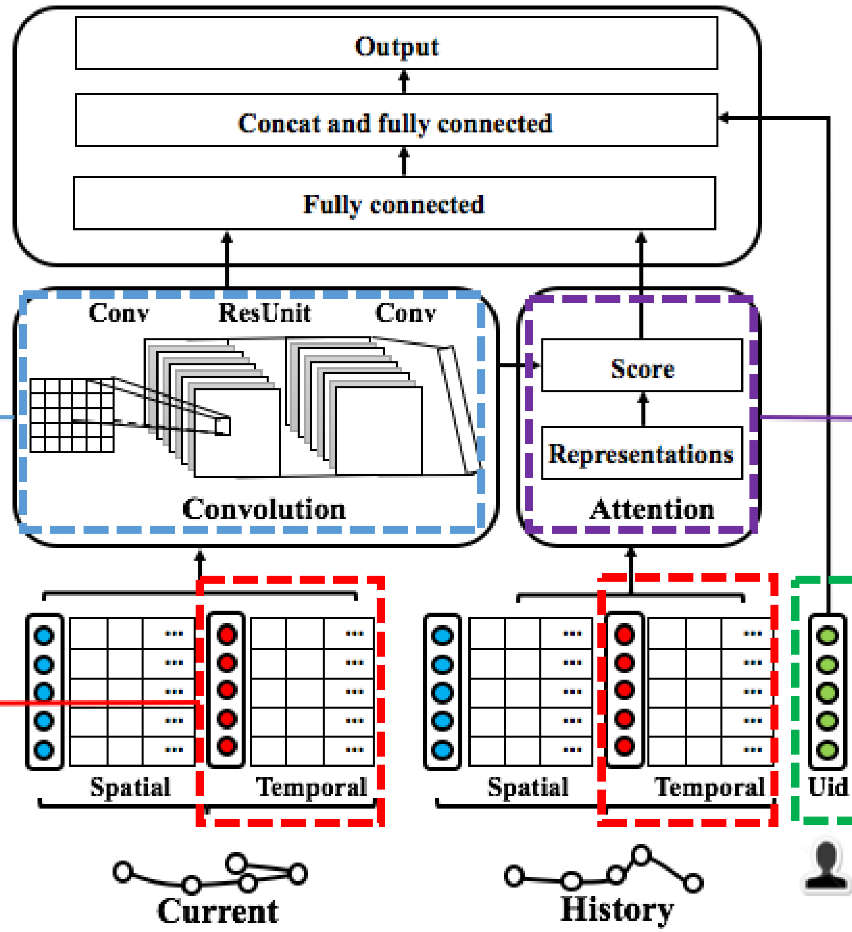
The historical attention module learns from historical data to 1) alleviate data sparsity; 2) evolving long-term preference

3. Solution

ACN

The convolution module captures high-order sequential pattern.

The time embedding captures time-dependent relations.



The historical attention module learns from historical data to 1) alleviate data sparsity; 2) evolving long-term preference

Uid embedding captures user personal preference

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4. Experiment Results

- Dataset:

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; $|S|$: sparsity.

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

- Evaluation metric:

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

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

4. Experiment Results

- Baselines:
  - Traditional:
    - MC: widely used mobility model working with state transition matrix
    - MF: factorizes users-locations matrix to generate user general preferences
    - FPMC: subsumes both MC and MF for mobility prediction.
  - RNN-based:
    - RNN: a basic deep neural network for sequential modeling
    - ST-RNN: extends RNN to model continuous spatio-temporal contexts
    - Deepmove: an enhanced version of RNN with history attention mechanism

4. Experiment Results

- Experiment design:
  - Question1: what is the performance of our model as compared to other state-of-art methods?
  - Question2: what is the effect of the key hyper-parameters, such as length of trajectory and embedding size?
  - Question3: what is the influence of each of ACN’s components?

4. Experiment Results

- Question1:

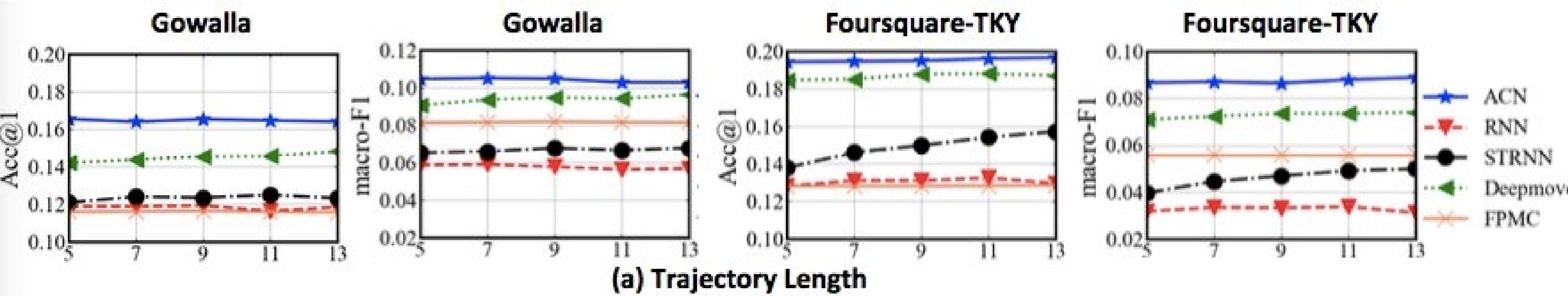
Table 2: Performance comparison on three public GTSM datasets.

Dataset	Metric	Traditional			RNN-based			Ours	Improv.
		MC	MF	FPMC	RNN	ST-RNN	Deepmove	ACN	
Gowalla	Acc@1	0.1151	0.0555	0.1163	0.1191	0.1249	<u>0.1480</u>	**0.1668**	12.70%
	Acc@5	0.2381	0.1227	0.2377	0.2596	0.2848	<u>0.3097</u>	**0.3247**	4.84%
	Acc@10	0.2701	0.1446	0.2707	0.3112	0.3464	<u>0.3759</u>	**0.3854**	2.53%
	macro-F1	0.0806	0.0223	0.0819	0.0601	0.0666	<u>0.0964</u>	**0.1047**	8.61%
Foursquare-TKY	Acc@1	0.1281	0.1299	0.1281	0.1325	0.1572	<u>0.1881</u>	**0.1966**	4.52%
	Acc@5	0.2758	0.2460	0.2761	0.3059	0.3435	<u>0.3906</u>	**0.4002**	2.46%
	Acc@10	0.3345	0.2793	0.3369	0.3724	0.4102	<u>0.4624</u>	**0.4698**	2.03%
	macro-F1	0.0555	0.0360	0.0560	0.0337	0.0499	<u>0.0735</u>	**0.0888**	14.40%
Foursquare-NYK	Acc@1	0.1242	0.1225	0.1265	0.1570	0.1634	<u>0.1907</u>	**0.2173**	13.95%
	Acc@5	0.2594	0.2292	0.2604	0.3489	0.3551	<u>0.3926</u>	**0.4131**	5.22%
	Acc@10	0.3024	0.2624	0.3027	0.4192	0.4251	<u>0.4731</u>	**0.4855**	3.49%
	macro-F1	0.0646	0.0677	0.0648	0.0814	0.0841	<u>0.1140</u>	**0.1302**	14.21%

- Traditional < RNN-based < CNN

4. Experiment Results

- Question2:



  - Our model outperforms all other baselines on all lengths of trajectory.
  - The metrics Acc@1 and macro-F1 increase when the length of trajectory increases, however decrease when the trajectory becomes longer. This can be explained by the reason that for extremely sparse dataset, a longer trajectory tends to introduce extra information and more noises.

4. Experiment Results

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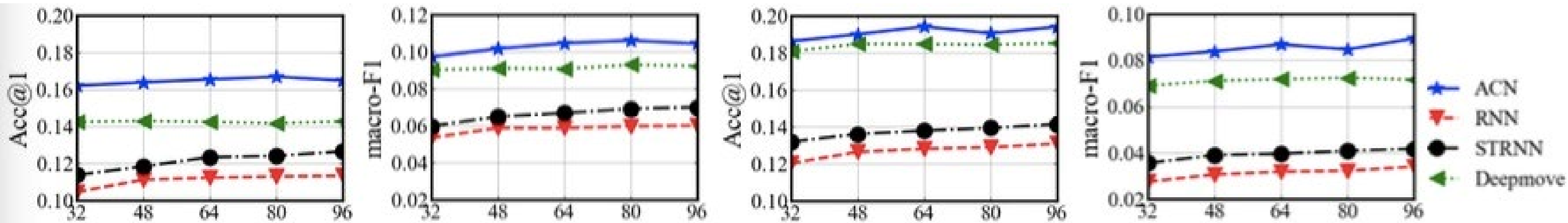
- Question2:



(b) Embedding Size

  - Our proposed model consistently outperforms all other baselines on all embedding sizes.
  - A larger embedding size does not necessarily lead to better performance because of overfitting issue. A model achieves its best performance when dimension size is properly chosen.

- Question3:
  - For x ∈ {**no, a, r , ar** }, ACN-x denotes ACN with component x enabled where **a** denotes attention mechanism and **r** denotes residual network.

Table 3: Acc@1 and macro-F1 vs. ACN components

Component	Gowalla		Foursquare-TKY	
	Acc@1	macro-F1	Acc@1	macro-F1
ACN-no	0.1603	0.0970	0.1903	0.0840
ACN-r	0.1641	0.1003	0.1924	0.0864
ACN-a	0.1650	0.1037	0.1928	0.0883
ACN-ar	0.1668	0.1047	0.1966	0.0888

  - ACN-ar achieves the best performance by jointly using all parts of ACN.

- Question3:
  - For x ∈ {**no, d, s, ds** }, ACN-x denotes ACN with component x enabled where **d** denotes hybrid dilated convolution and **s** denotes separable and shared convolution.

Table 3: Acc@1 and macro-F1 vs. ACN components

Component	Gowalla		Foursquare-TKY	
	Acc@1	macro-F1	Acc@1	macro-F1
ACN-no	0.1563	0.0944	0.1914	0.0866
ACN-d	0.1563	0.0946	0.1931	0.0876
ACN-s	0.1568	0.0947	0.1936	0.0875
ACN-ds	0.1668	0.1047	0.1966	0.0888

  - ACN-ds achieves the best performance by jointly using all parts of ACN.

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5. Conclusion

- We are firstly to propose a novel attentive convolutional network on sparse GTSM data
  - Regard the embedded trajectory as an image, using convolution filters to search for sequential patterns as local features of the image.
  - Design HSC which is combined of Hybrid dilated convolutions and Separable Convolutions to model high-order sequential patterns.
  - Use an attention mechanism to learn long-term preferences of users from history trajectory.
- Interesting future directions
  - Consider external feature like Point of interest and tweets to conduct semantic mobility prediction.

Thanks！