DeepMove: Predicting Human Mobility with Attentional Recurrent Networks

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***Funing Sun*[3], *Fanchao Meng*[3], *Ang Guo*[3], *Depeng Jin*[1]**

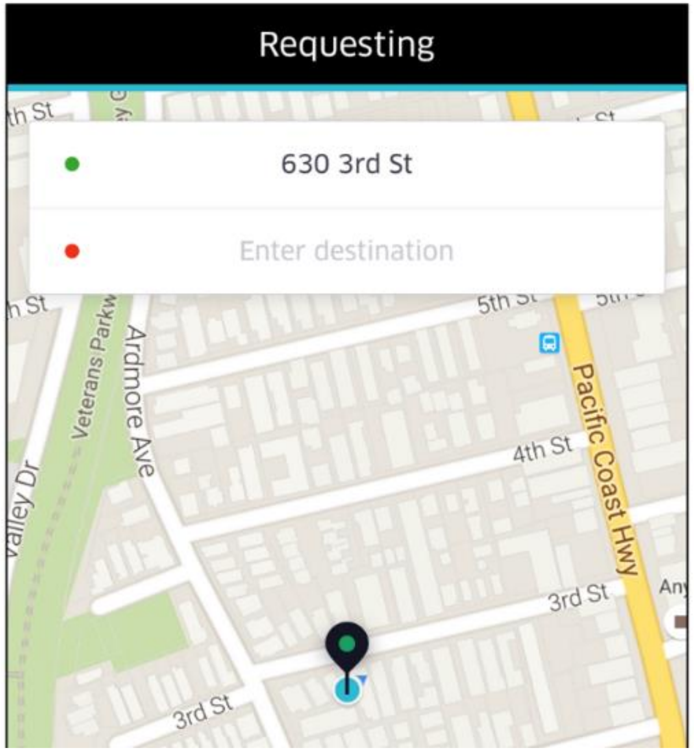
***Tsinghua University*[1]**
***University of Illinois at Urbana-Champaign*[2]**
***Tencent Inc.*[3]**

Background

Human mobility prediction is of great importance for a lot of location-based applications

Background

- ***Estimating travel demand for Uber and Didi***



https://blog.prototypr.io/uber-for-seniors-and-poor-visibility-dbaadca12a2a

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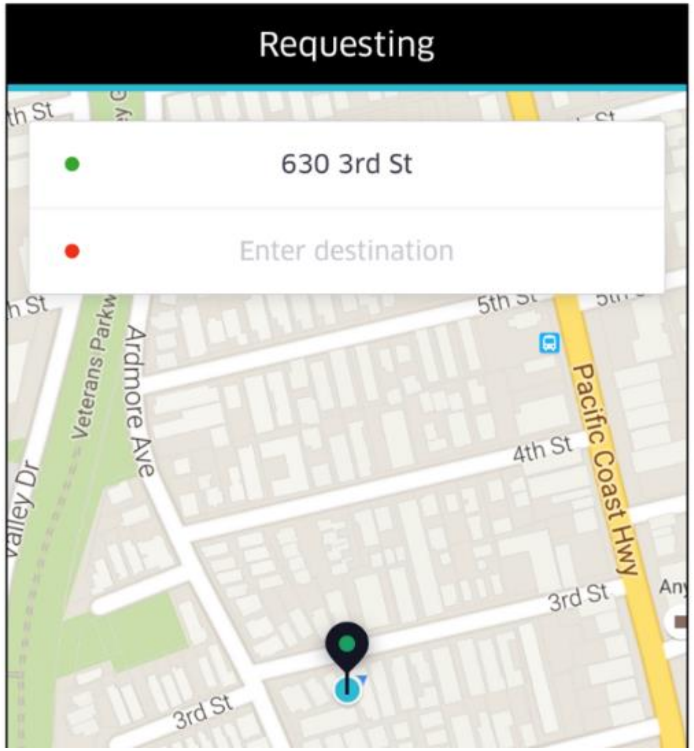
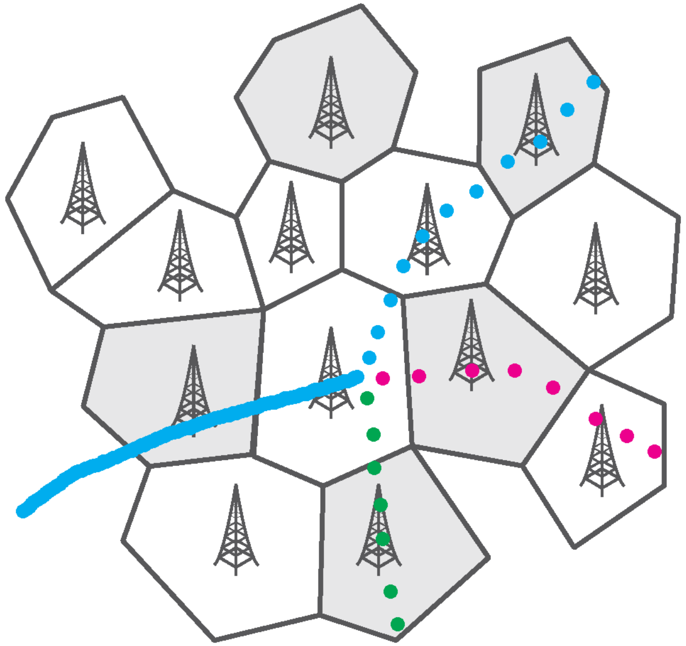


- ***Mobility management in mobile cellular network***



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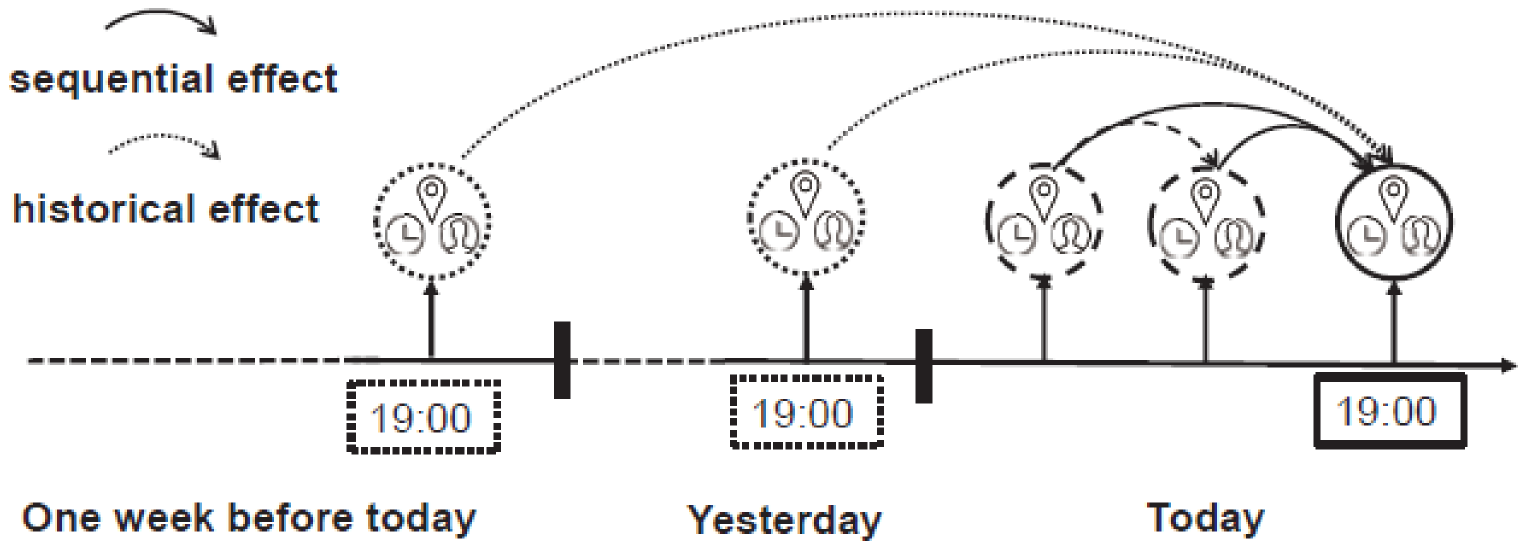
  - *With the fixed temporal resolution, we only care about predicting the* ***spatial context: location***

- ***We divide the whole trajectory of each person into two parts: current trajectory and trajectory history***
  - ***predict the next location*** *of the current trajectory with the help of current trajectory and trajectory history*

Our Intuition

Multi-level periodicity of human mobility:
daily routines**, **weekend leisure**, **yearly festivals,
*and even other **personal periodic activities***

Our Intuition



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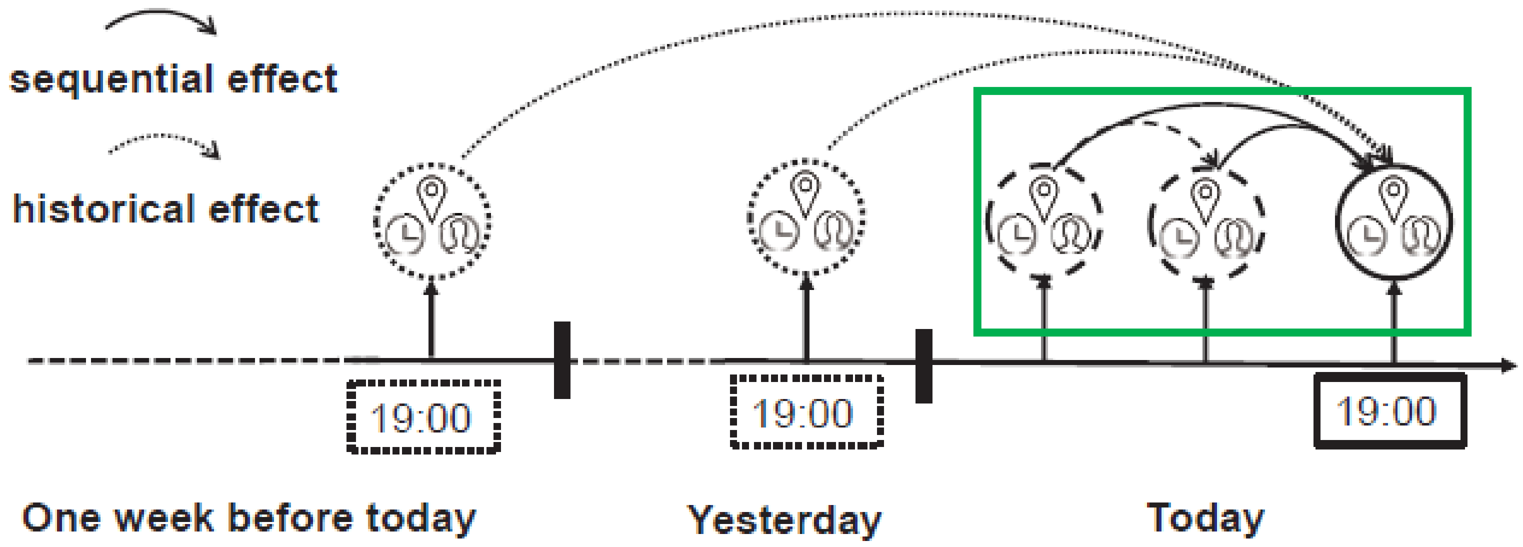

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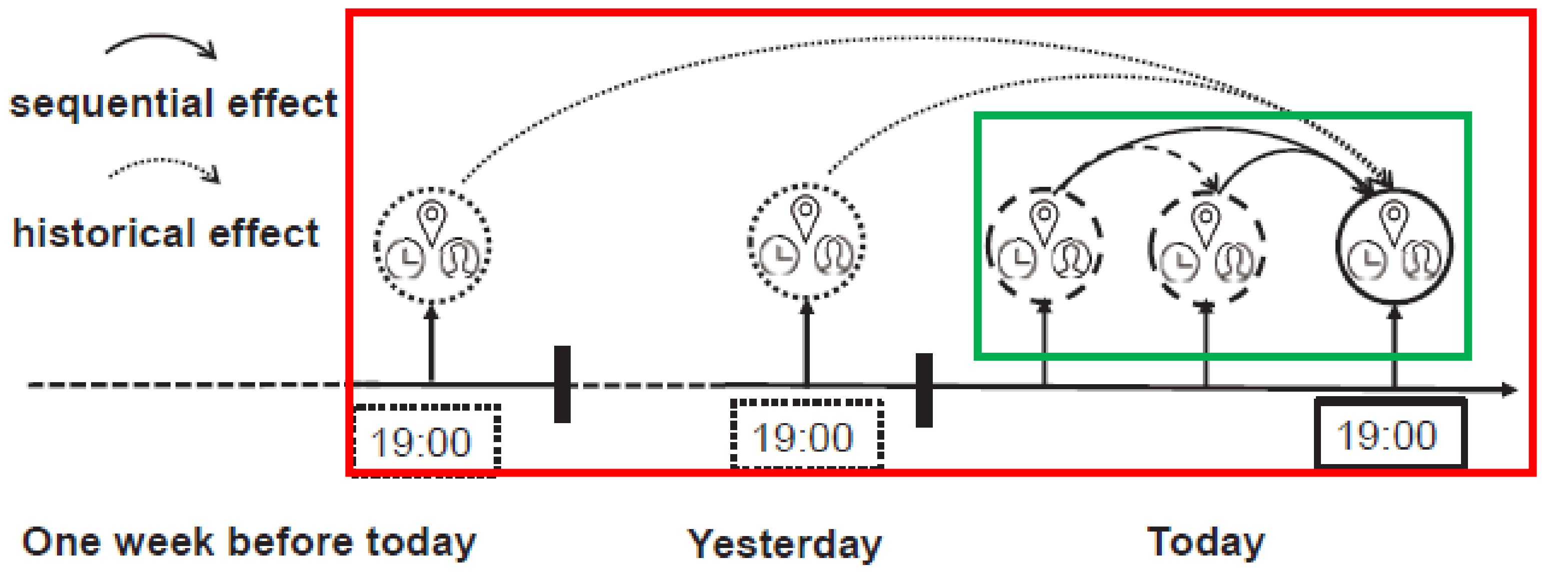

the sequential information influences the next mobility status

the periodical information takes effects

Challenges

- ***Multi-level periodicity of human mobility***
  - ***daily routines***, ***weekend leisure***, *yearly festivals and even other personal periodic activities*

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Challenges

- ***Multi-level periodicity of human mobility***
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- ***Complex sequential transition regularities***
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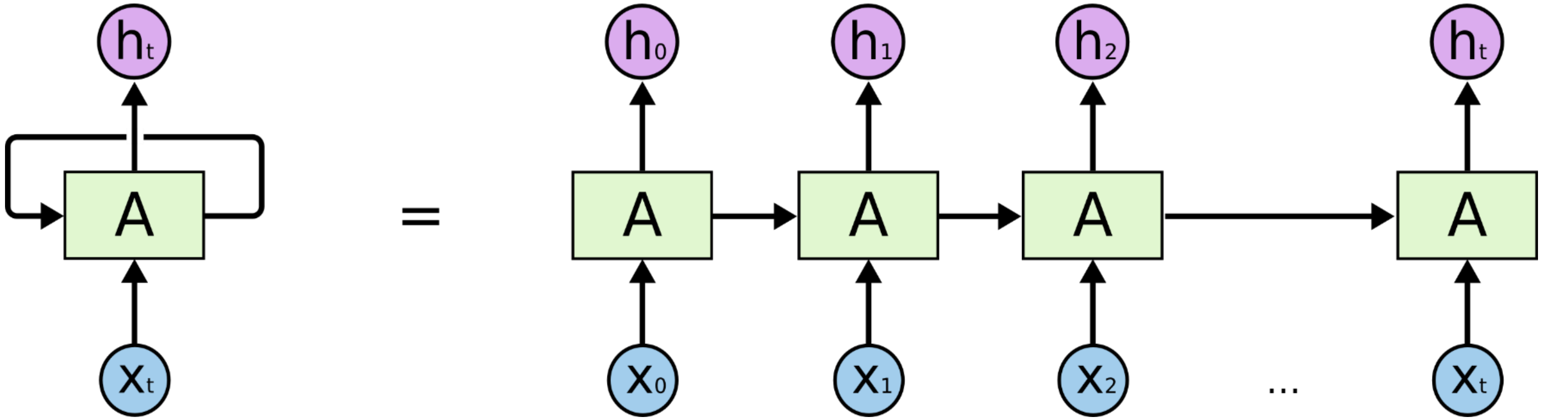
- ***Heterogeneity and sparsity of collected data***
    - ***low-sampling*** *and* ***random-sampling*** *nature in the data recording human mobility*

Recap: Recurrent Network & Attention



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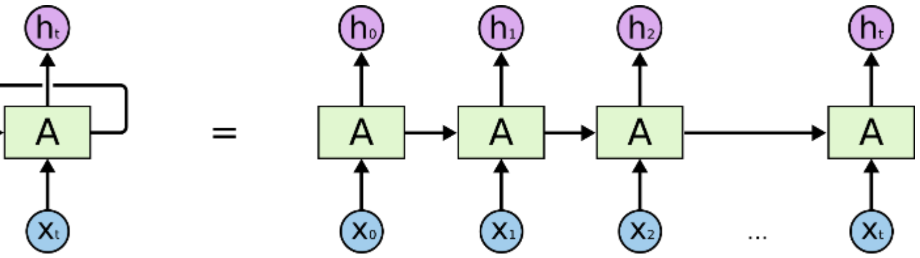

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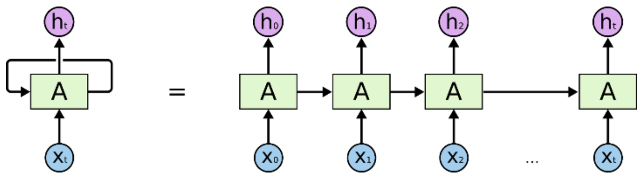

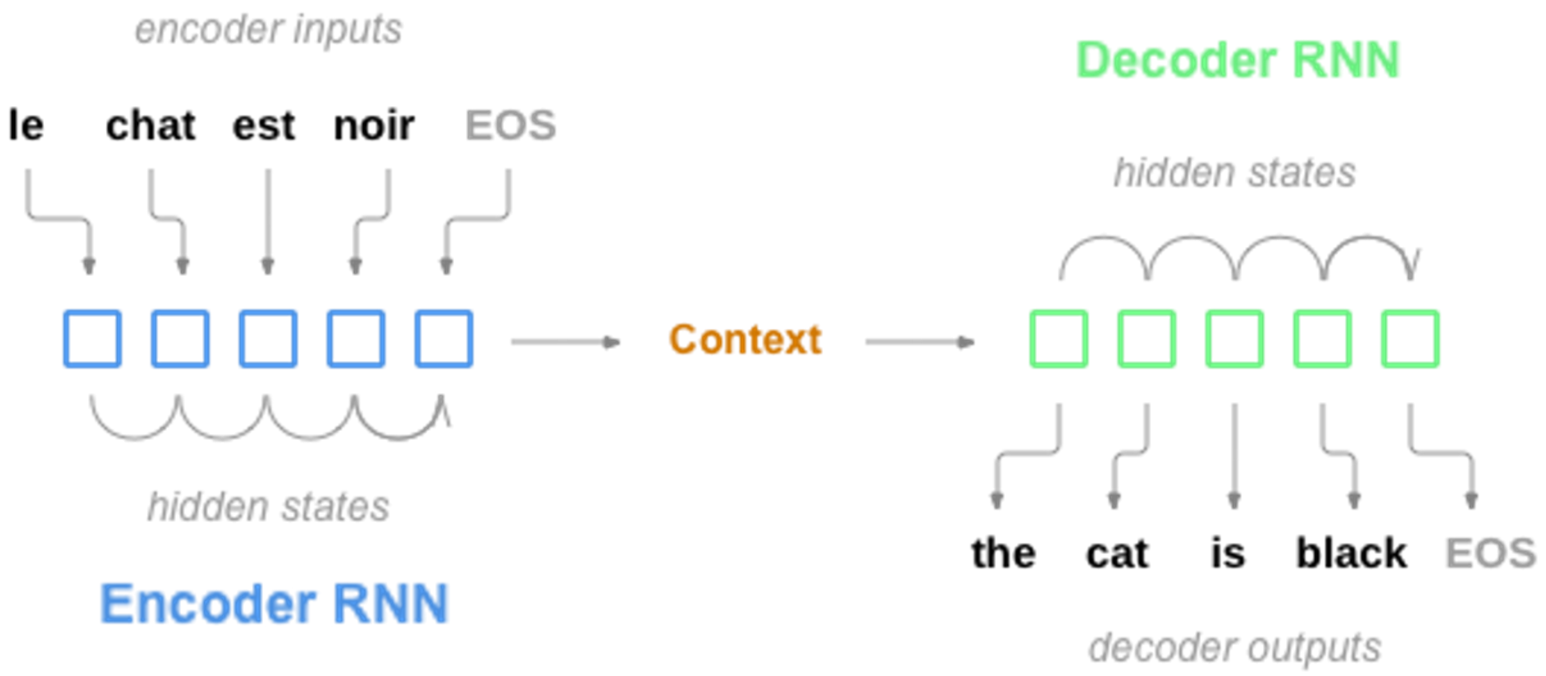

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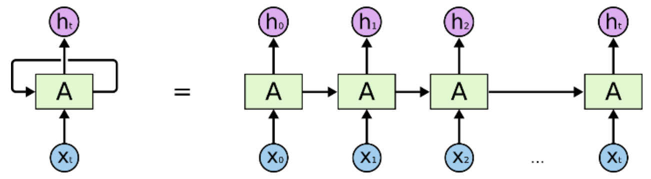

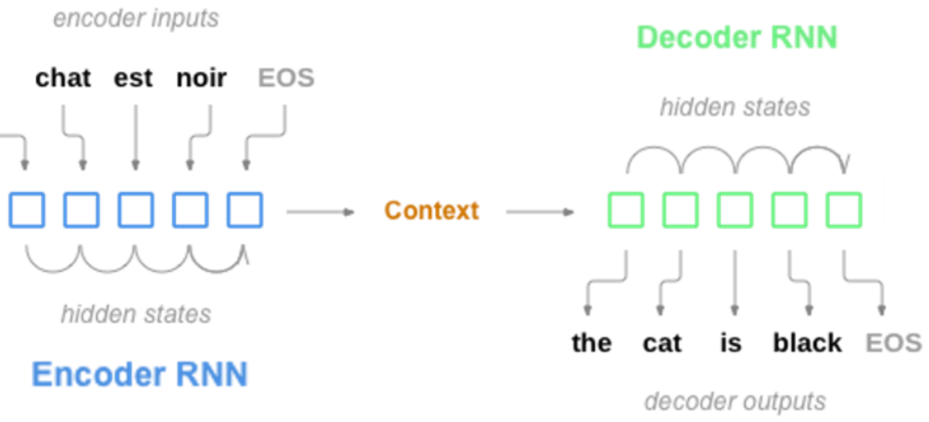

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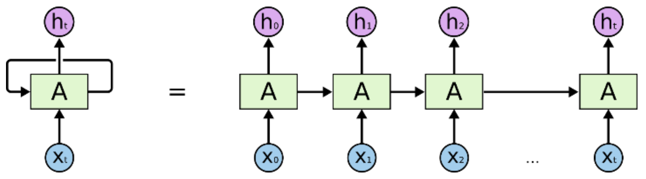

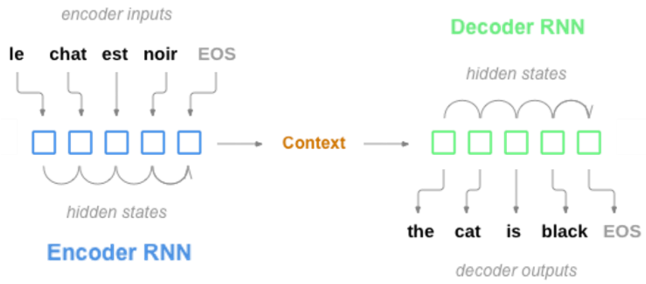

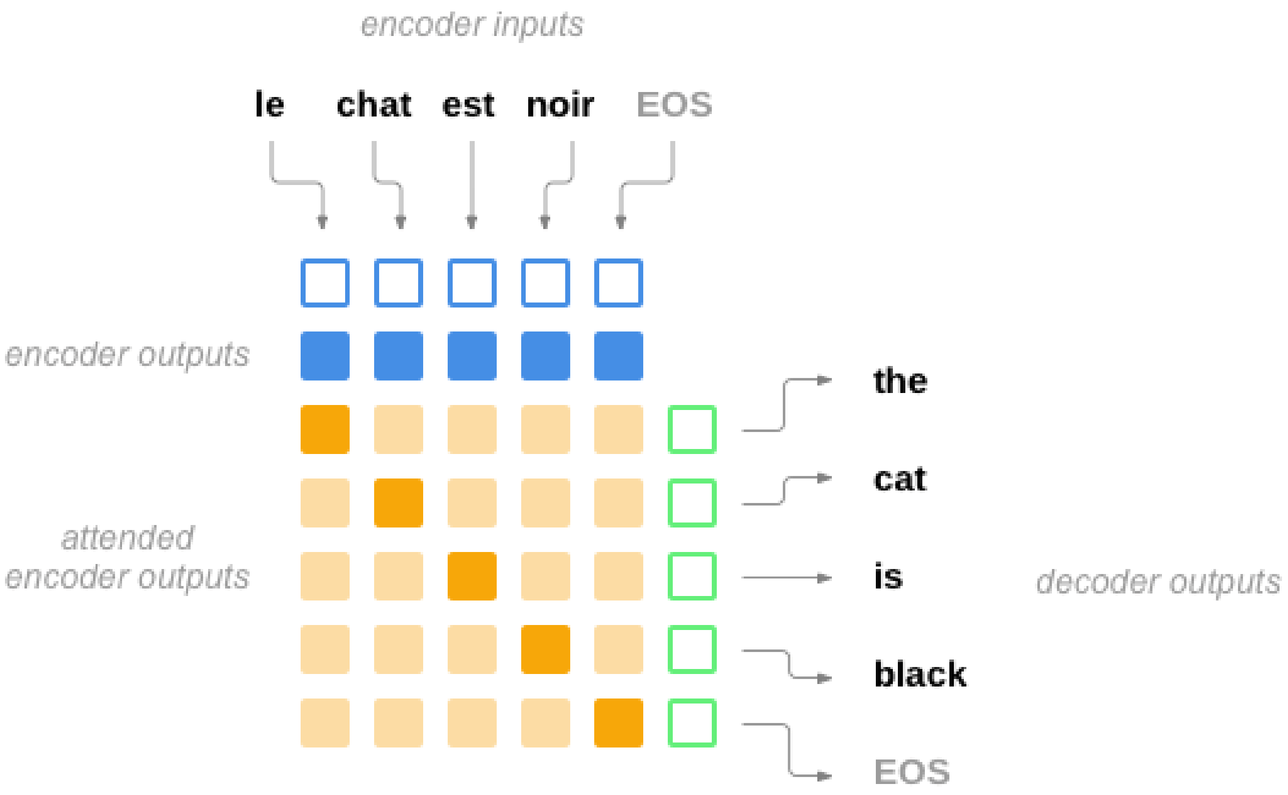

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An Overview of DeepMove

Recurrent Module

Simple Model

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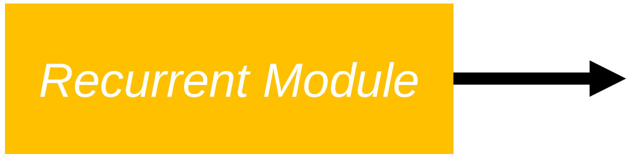

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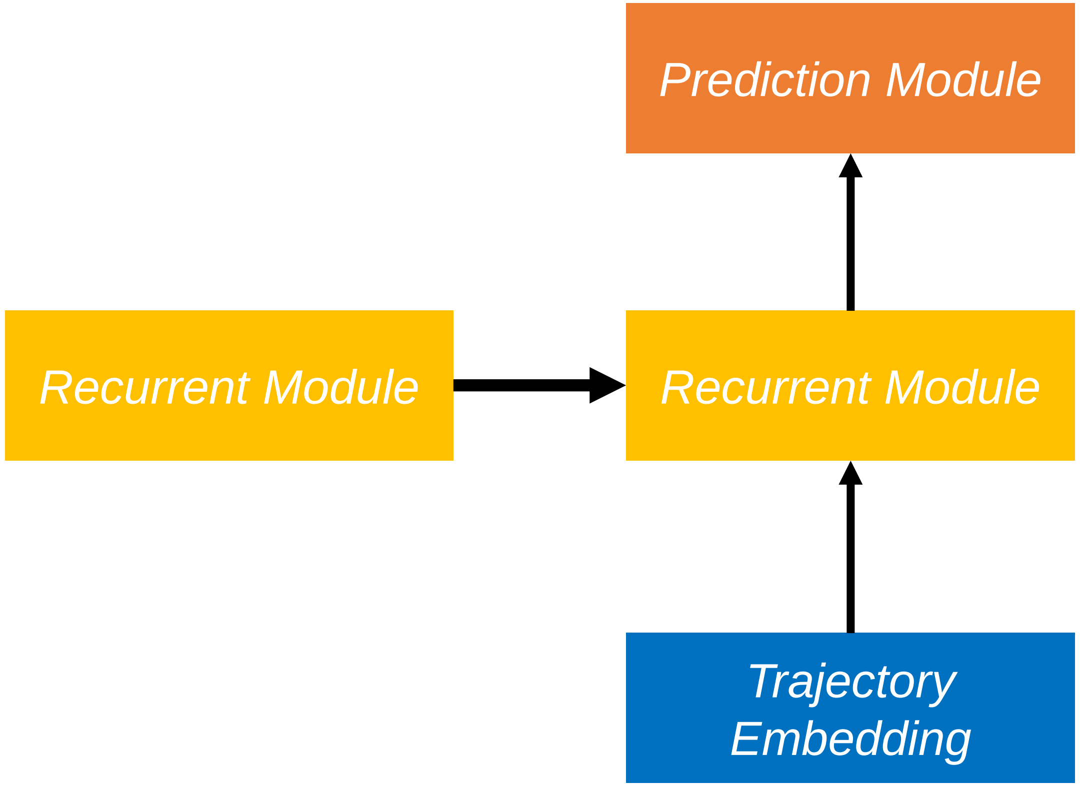

Simple Model **General Model**

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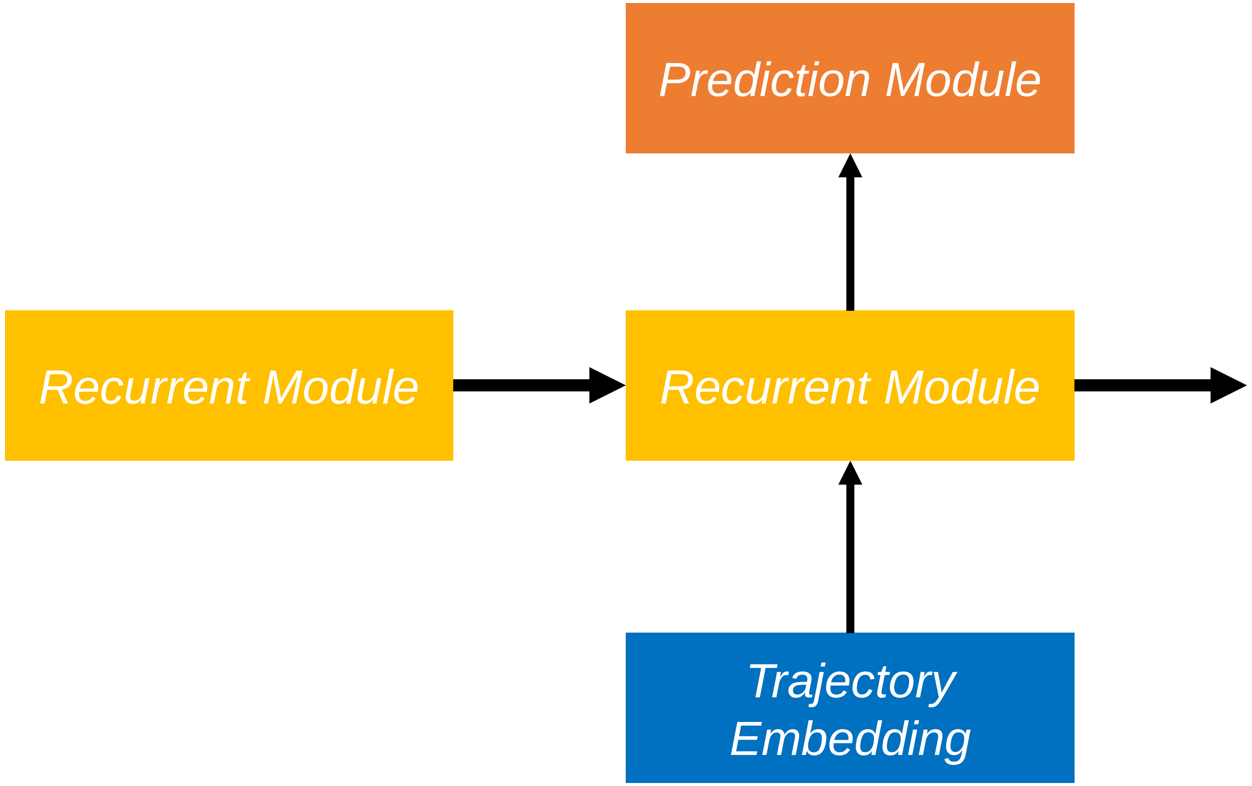

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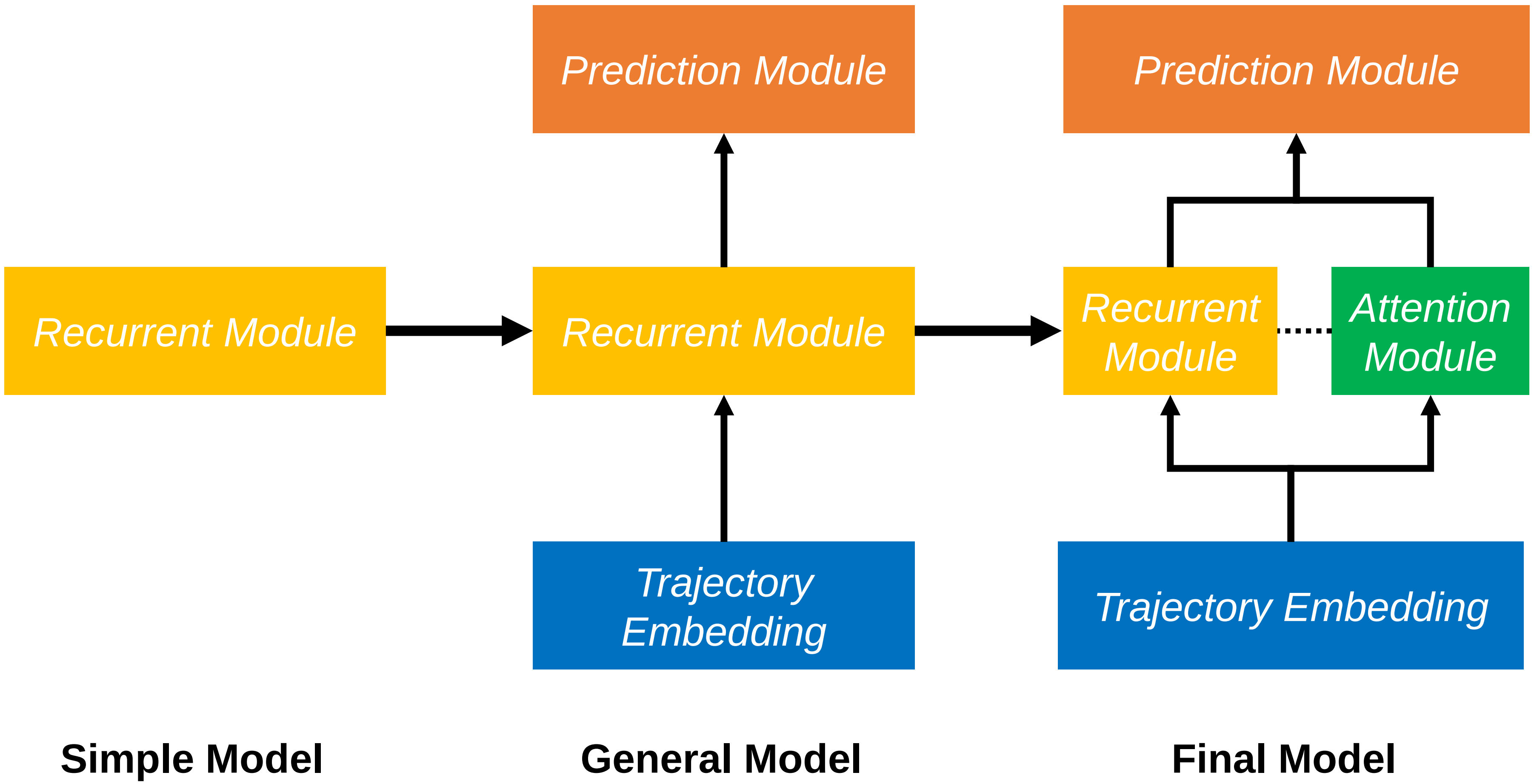
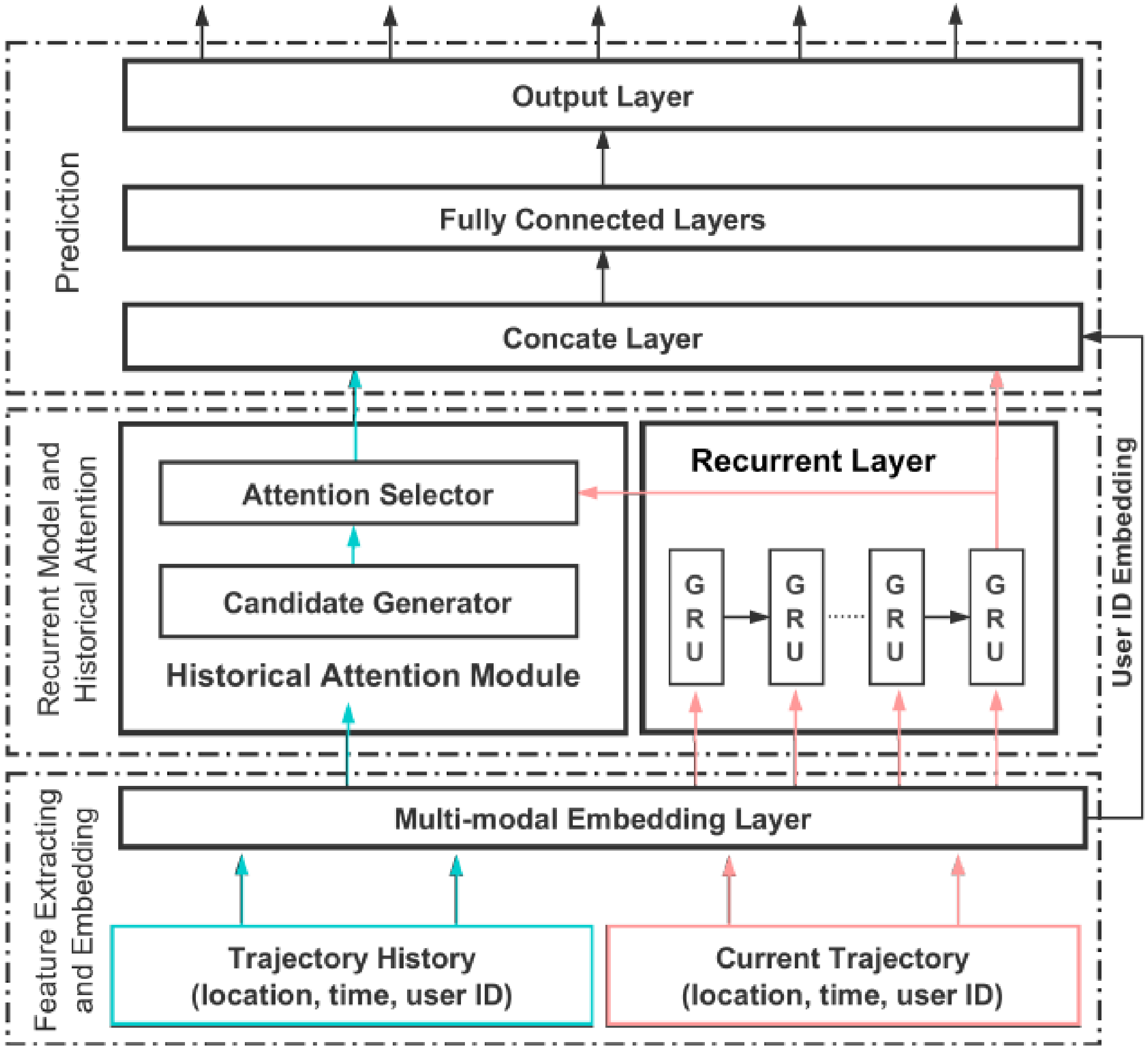
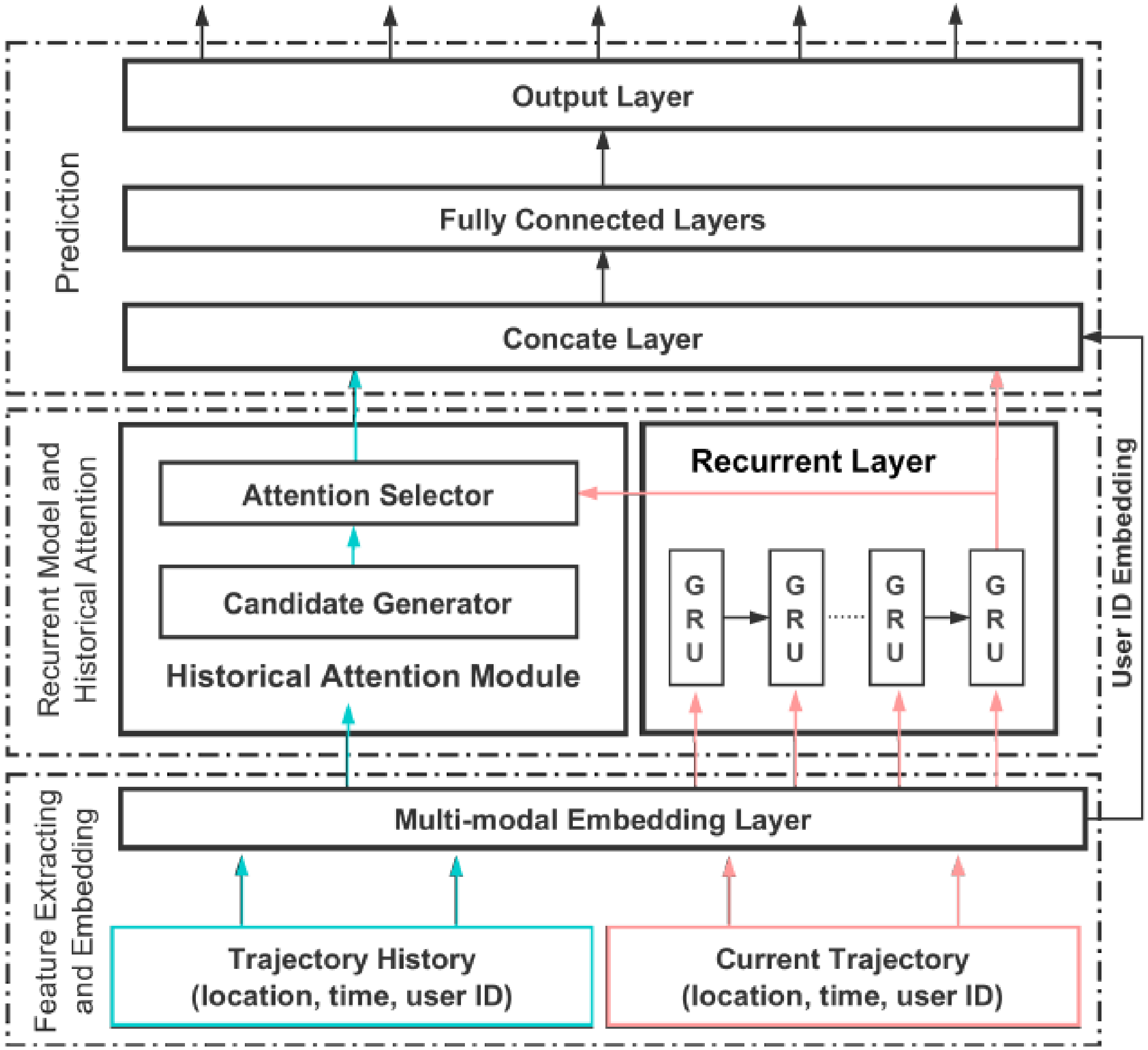


DeepMove



Output Layer
Fully Connected Layers
Concate Layer
Prediction
Recurrent Model and Historical Attention
Attention Selector
Candidate Generator
Historical Attention Module
Recurrent Layer
GRU
GRU
GRU
GRU
User ID Embedding
Feature Extracting and Embedding
Multi-modal Embedding Layer
Trajectory History (location, time, user ID)
Current Trajectory (location, time, user ID)

DeepMove



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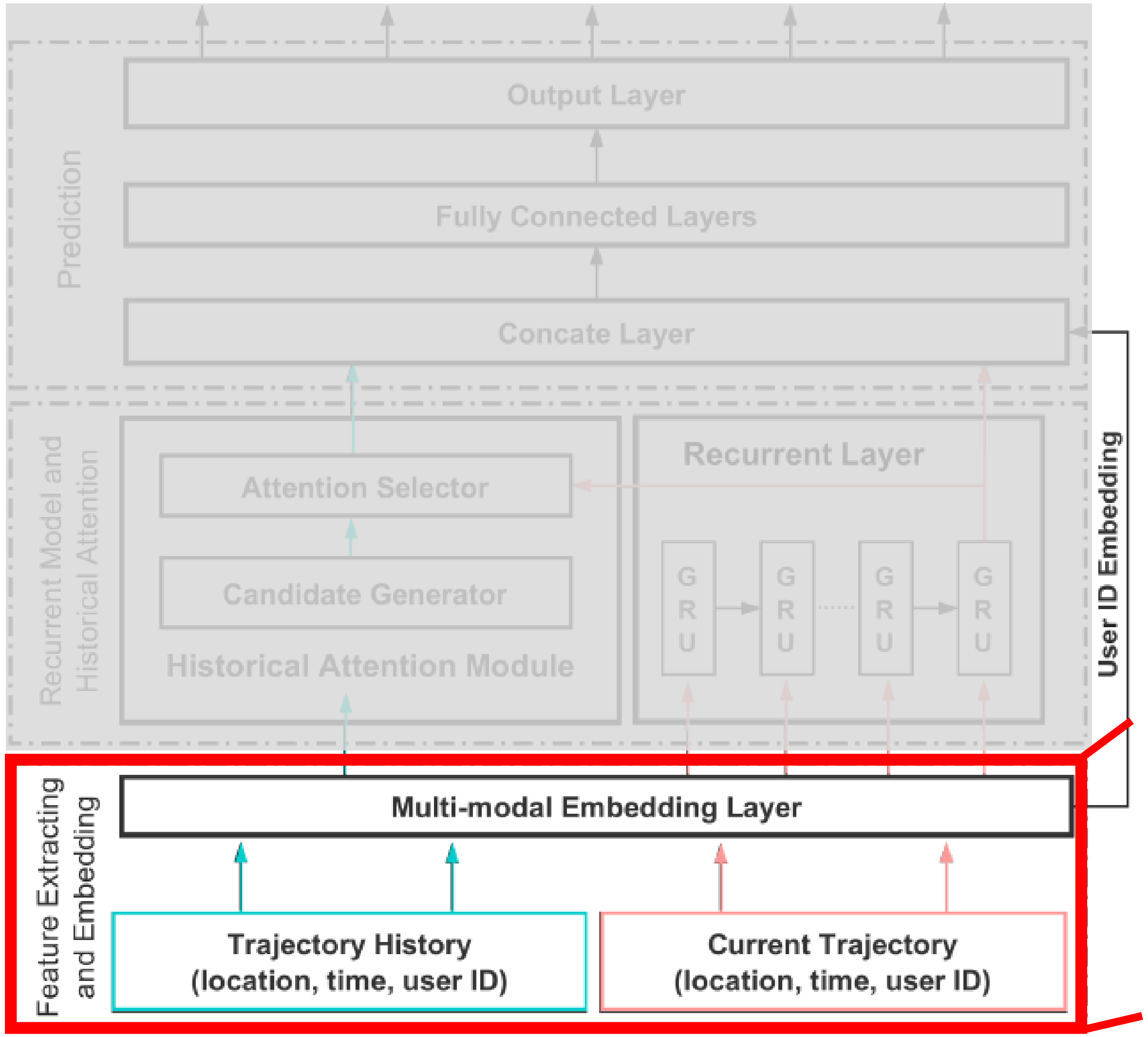
DeepMove-Multi-modal Embedding



- ***Multi-modal Embedding***
  - ***one-hot encoding***

    Location, Time, User-ID
  - ***sparse linear layers***
  - ***concatenate layer***

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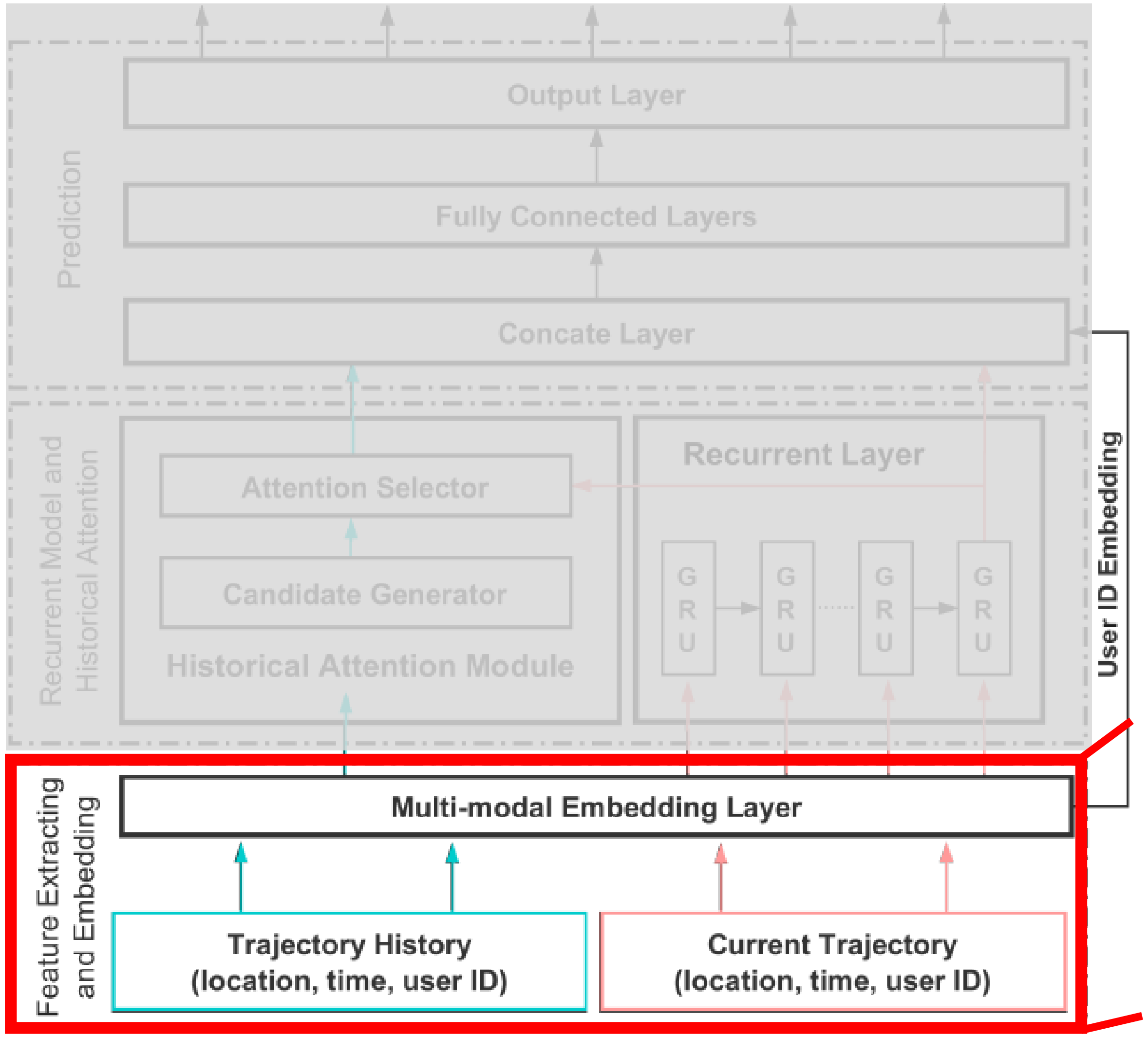

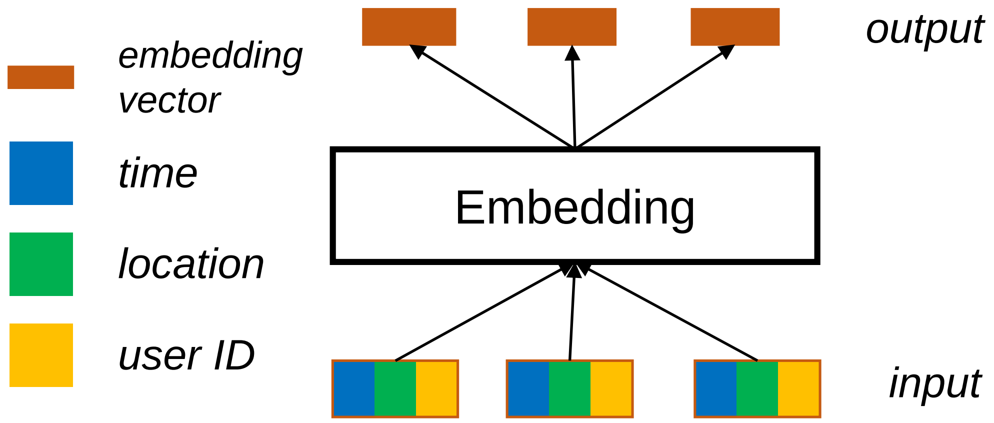

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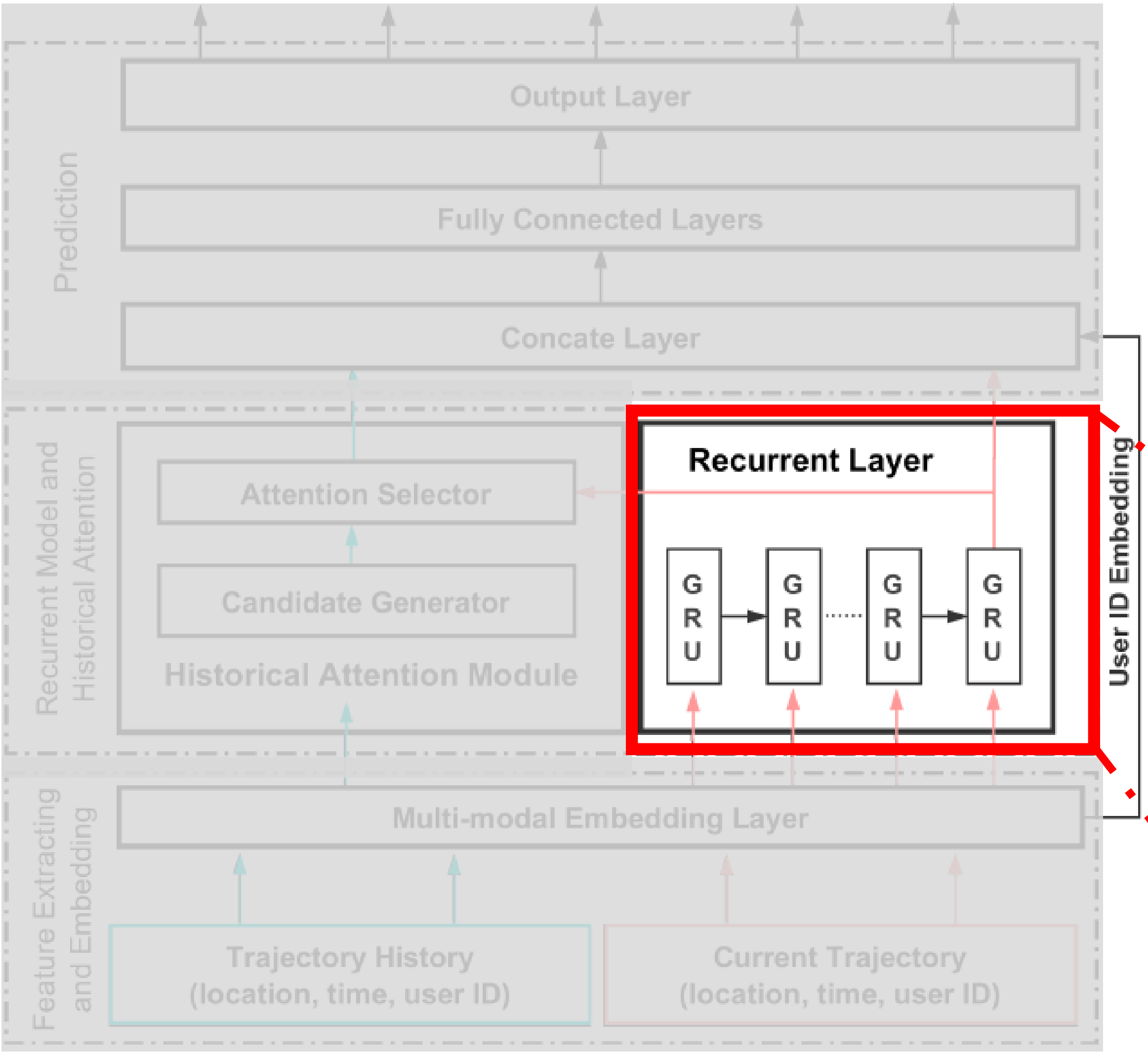

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  - ***Input:*** sequence of trajectory embedding vectors
  - ***Output***: sequence of trajectory hidden states

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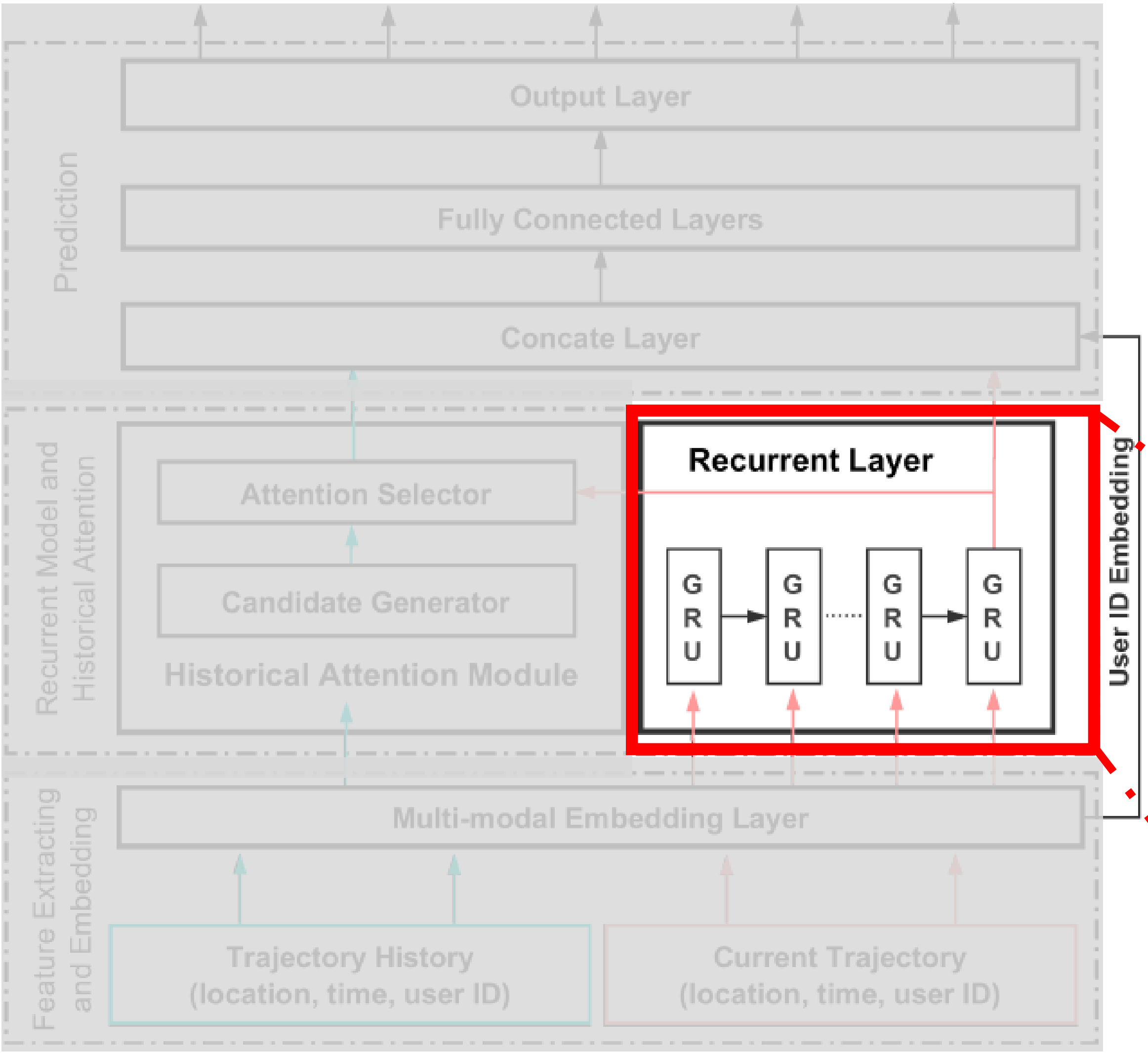

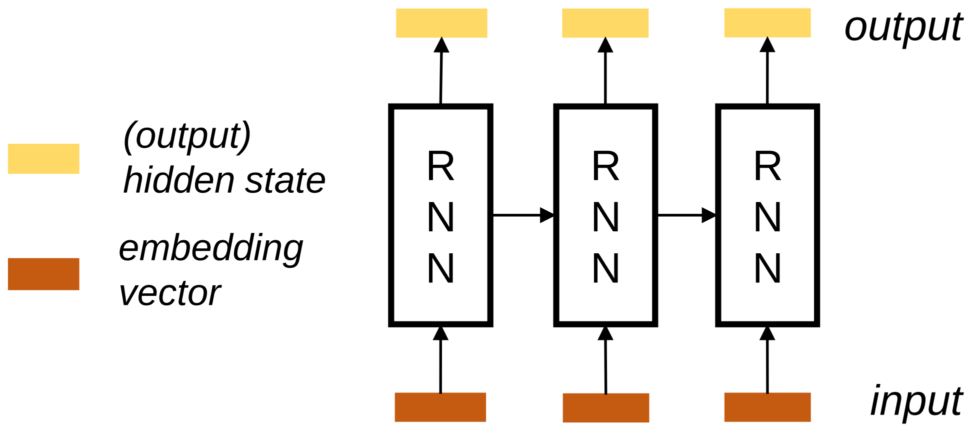

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DeepMove-Historical Attention

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  - ***MLP-based Generator***
  - ***RNN-based Generator***
- ***Attention Selector***
  - ***Score Layer for "correlation"***
  - ***Soft-max Layer***
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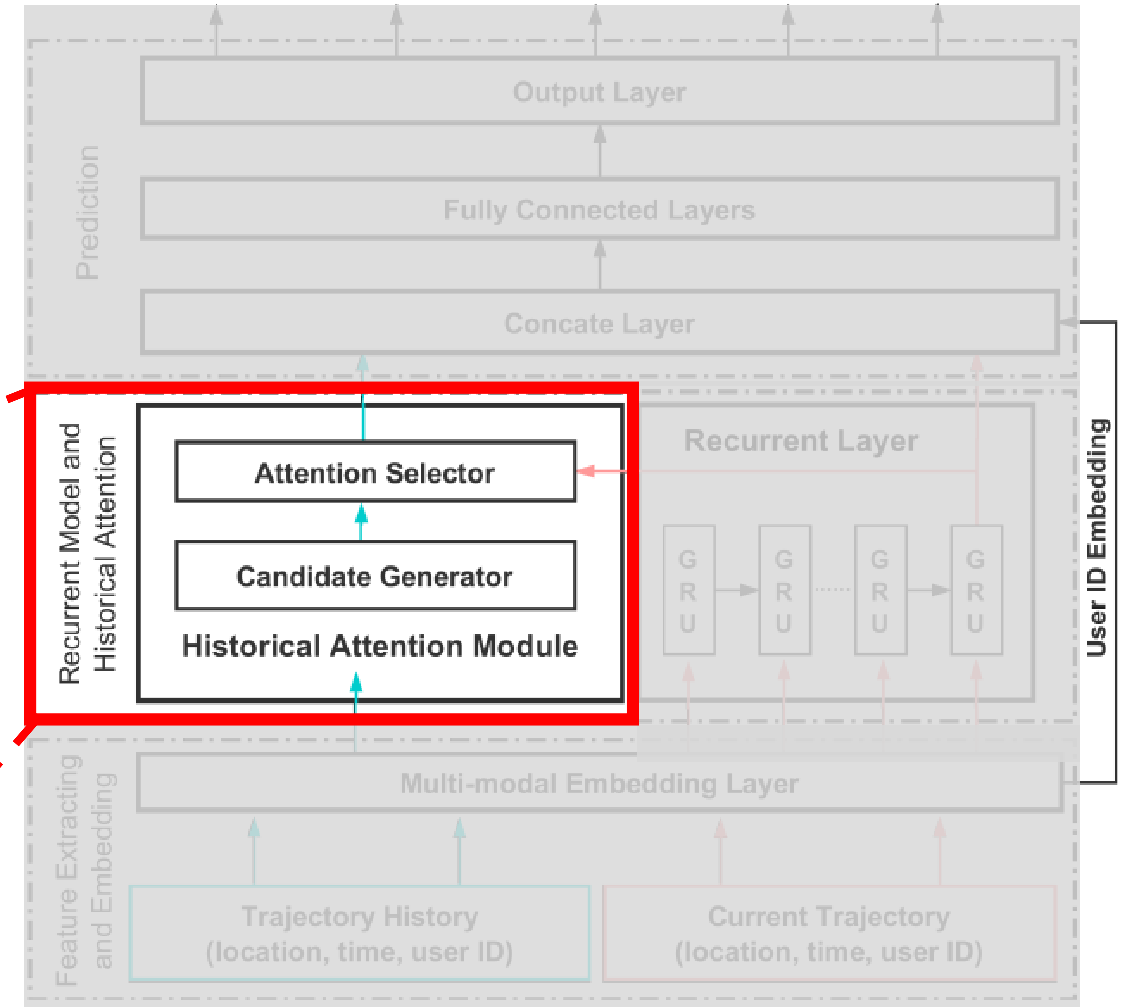

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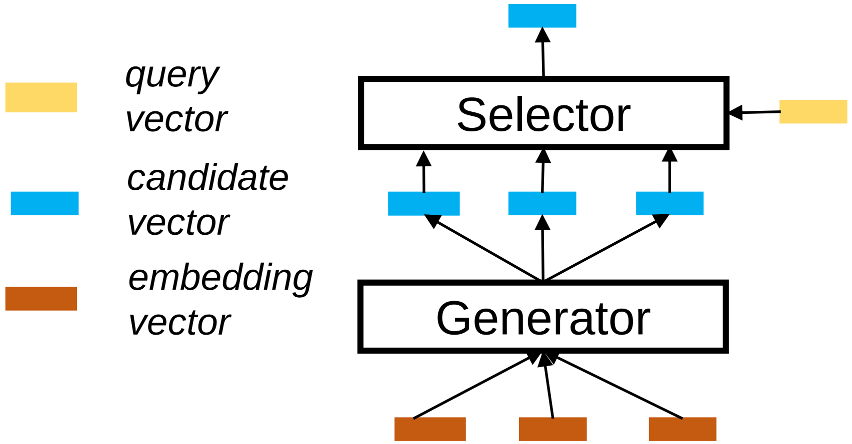

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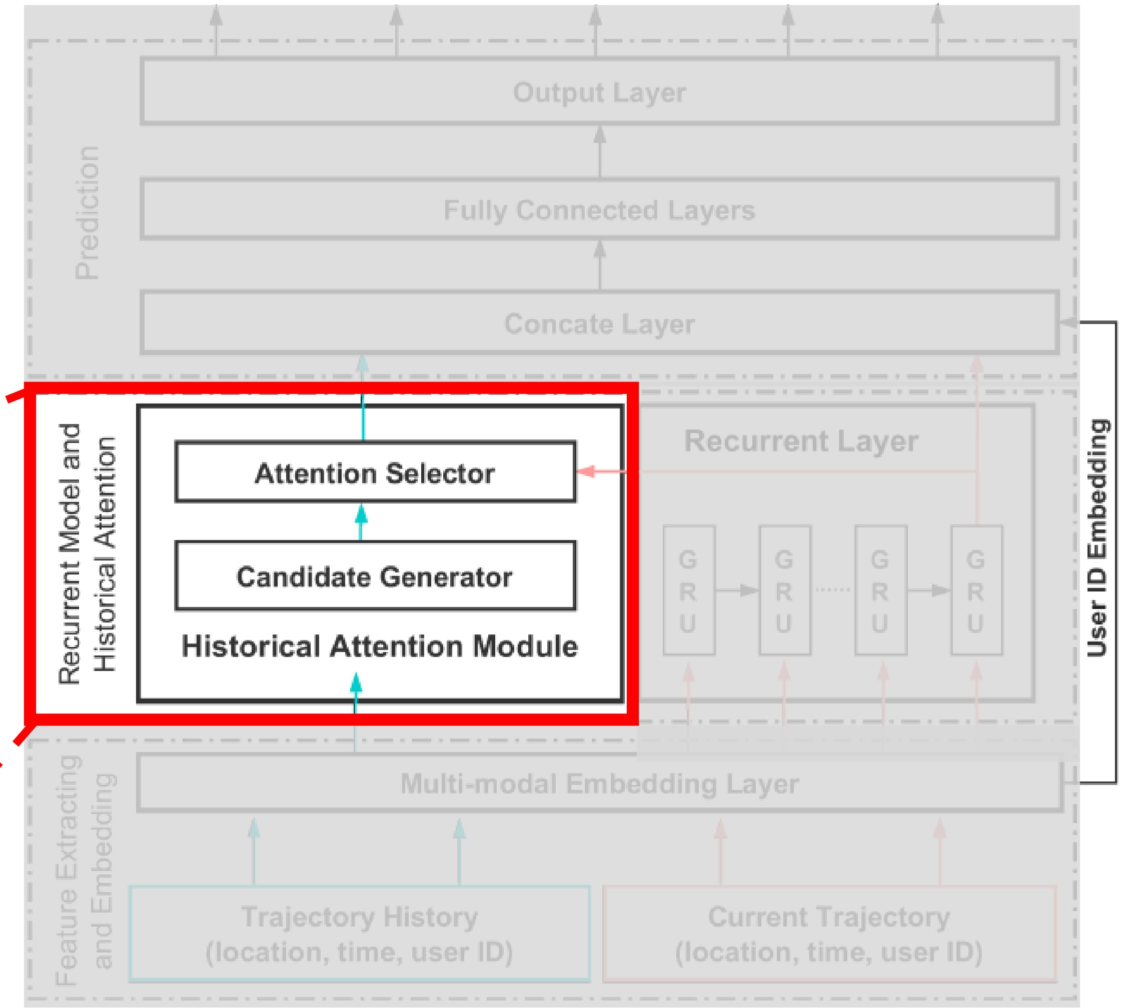

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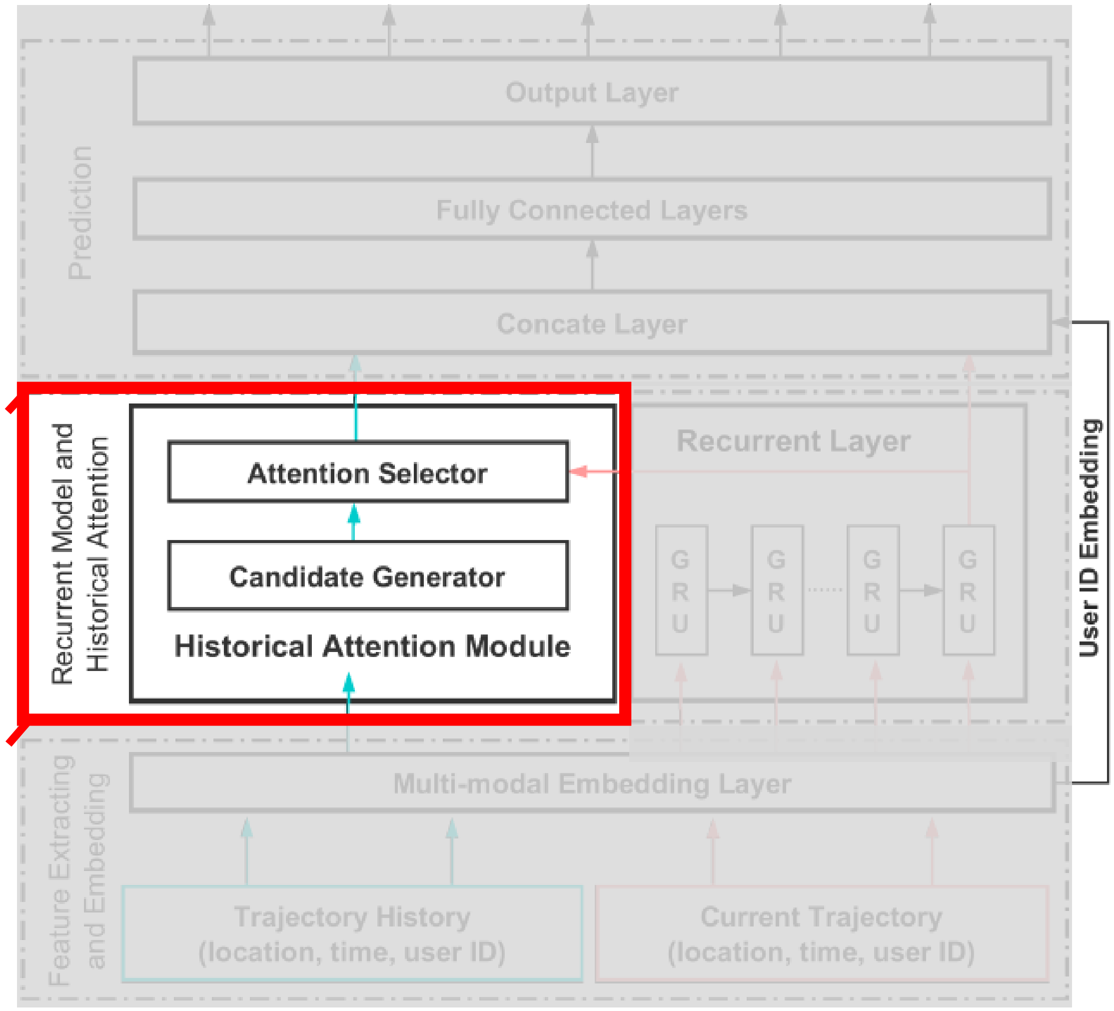

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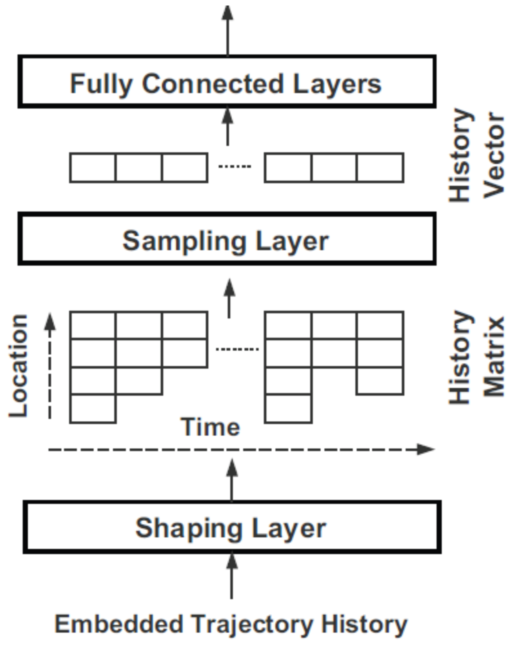

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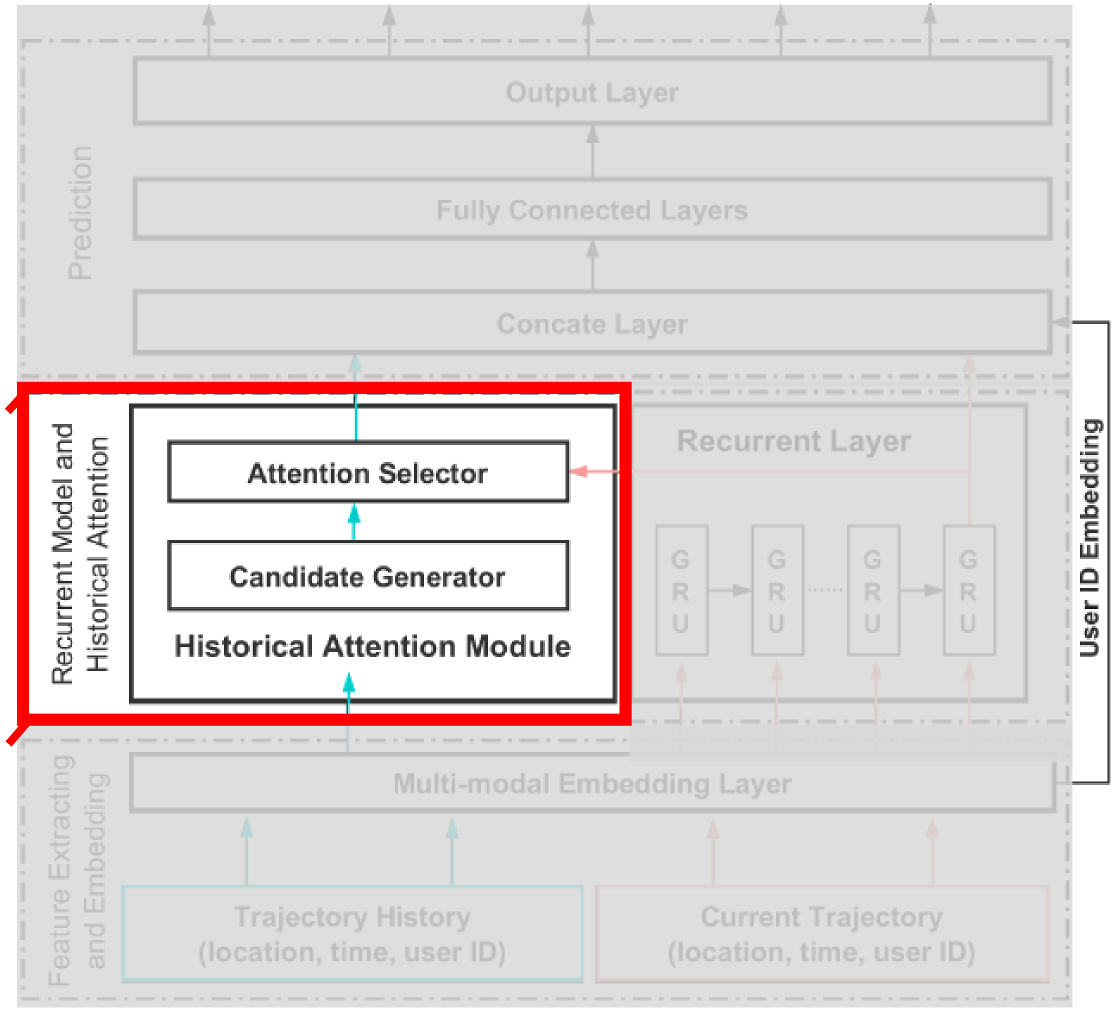

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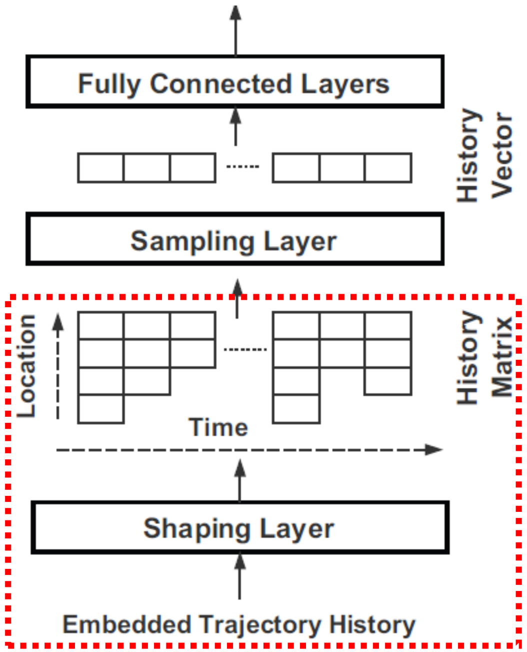

Shaping Layer

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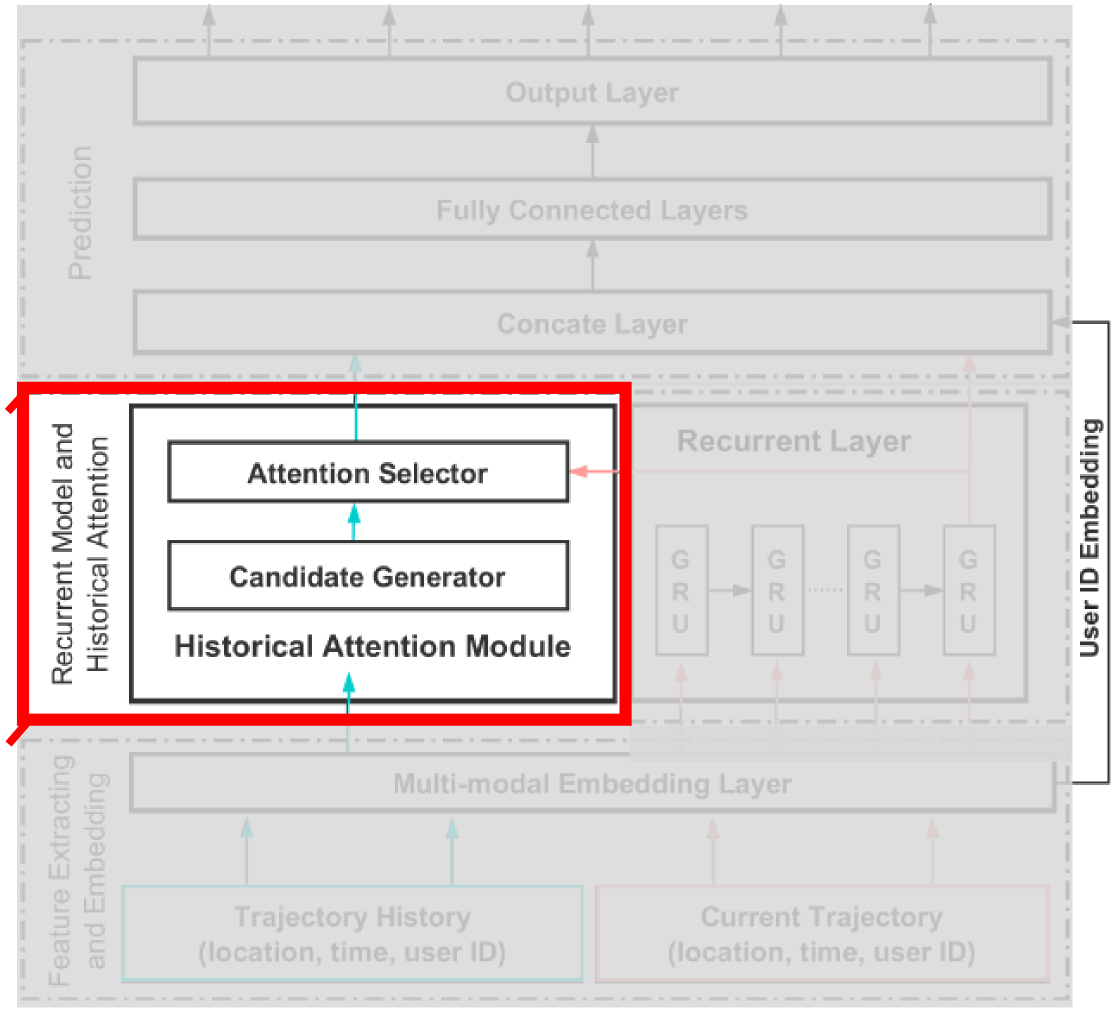
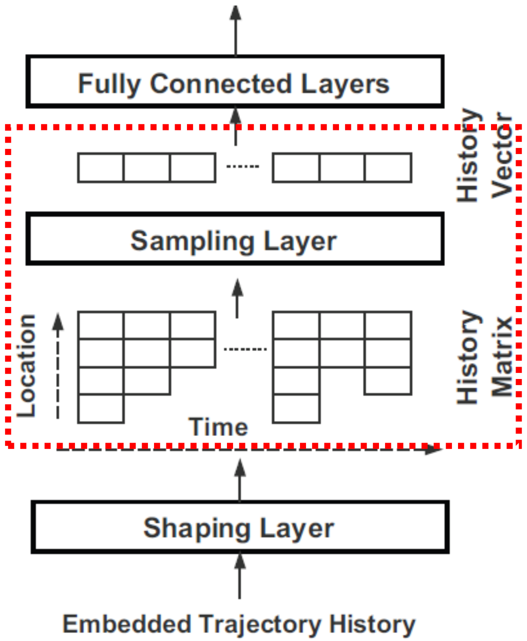


DeepMove-Historical Attention



Sampling Layer
Shaping Layer

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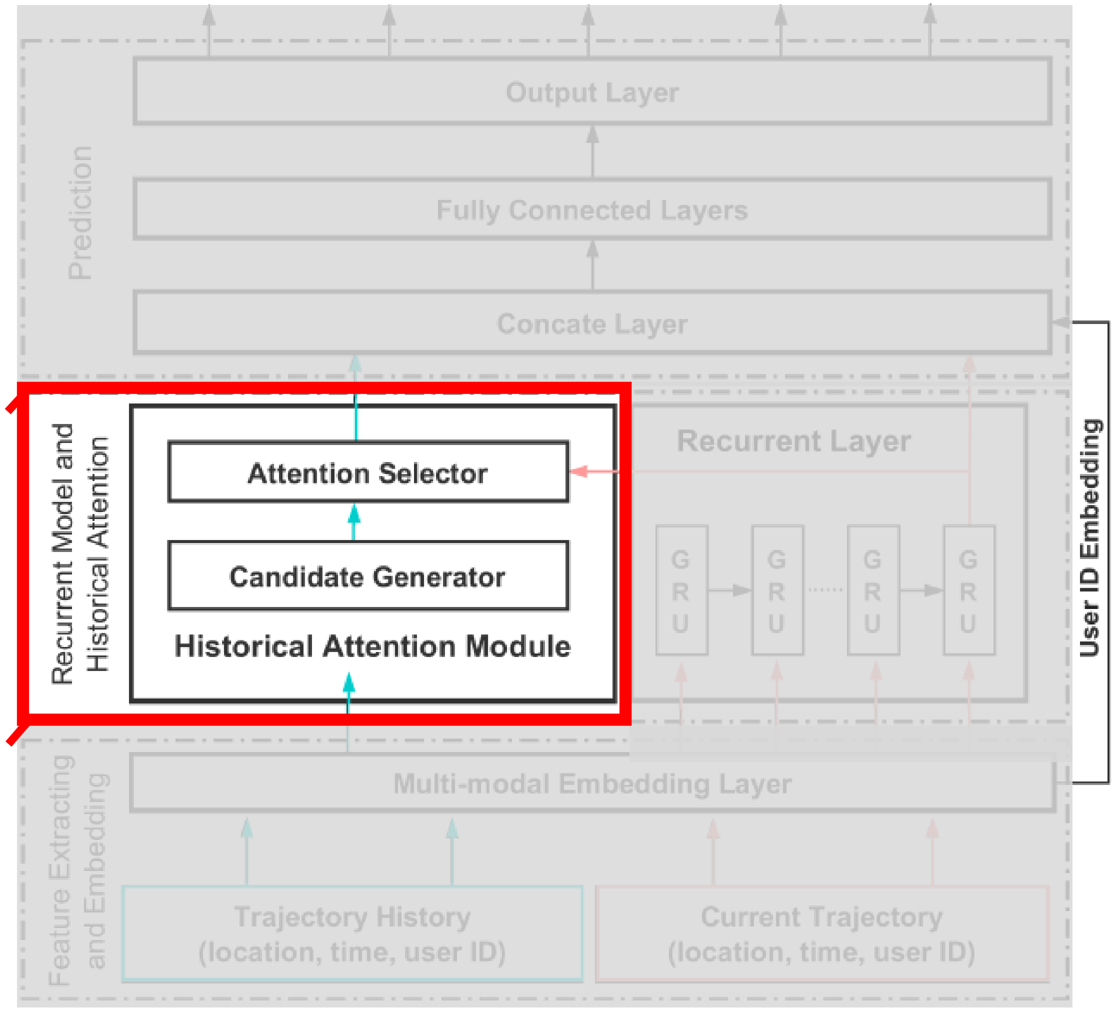

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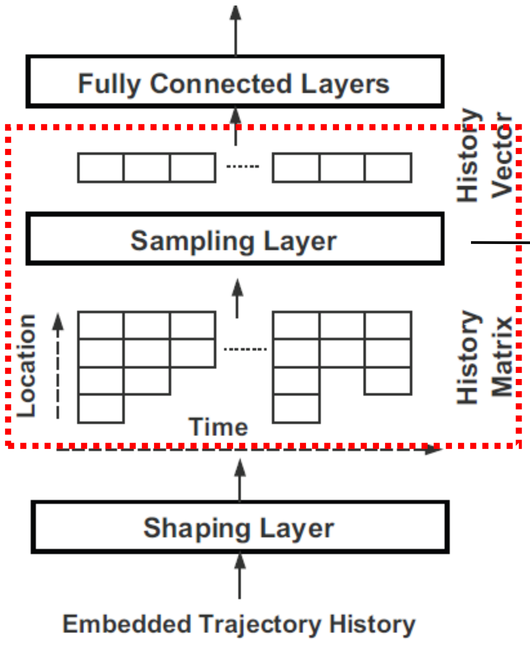
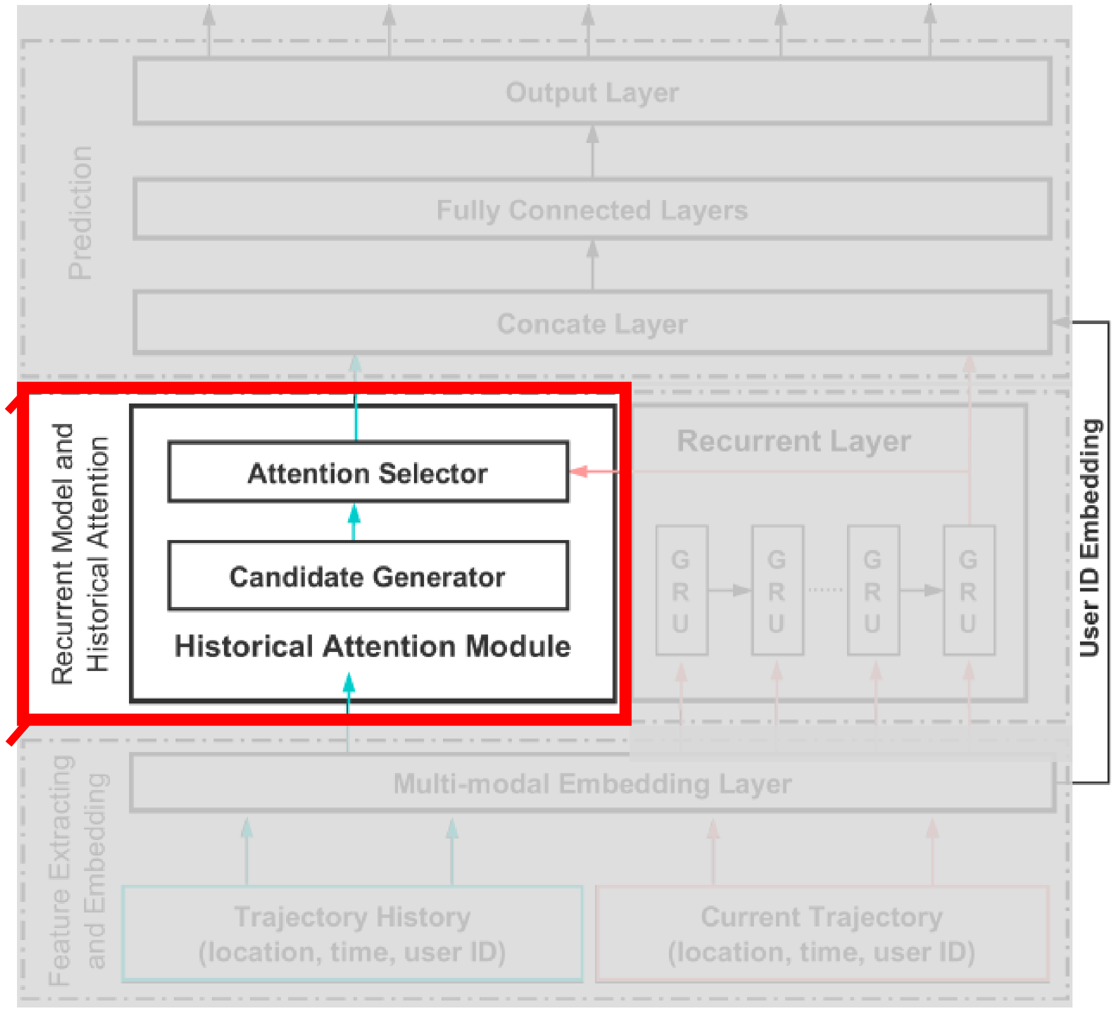


Average sampling
Maximum sampling
None sampling

Sampling Layer
Shaping Layer



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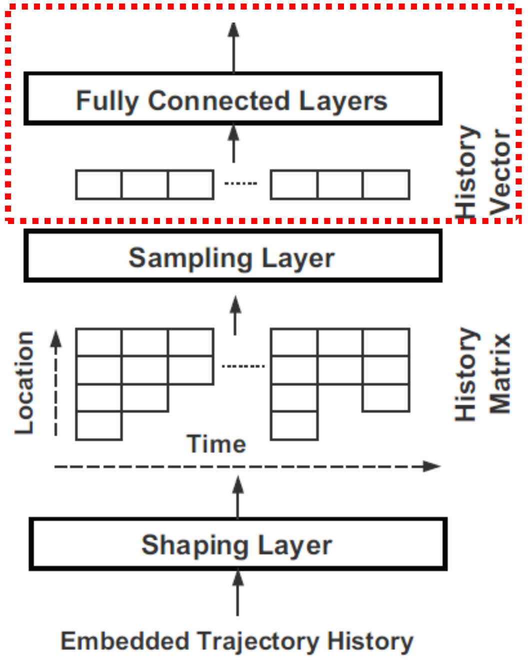
DeepMove-Historical Attention



FCN Layer
Sampling Layer
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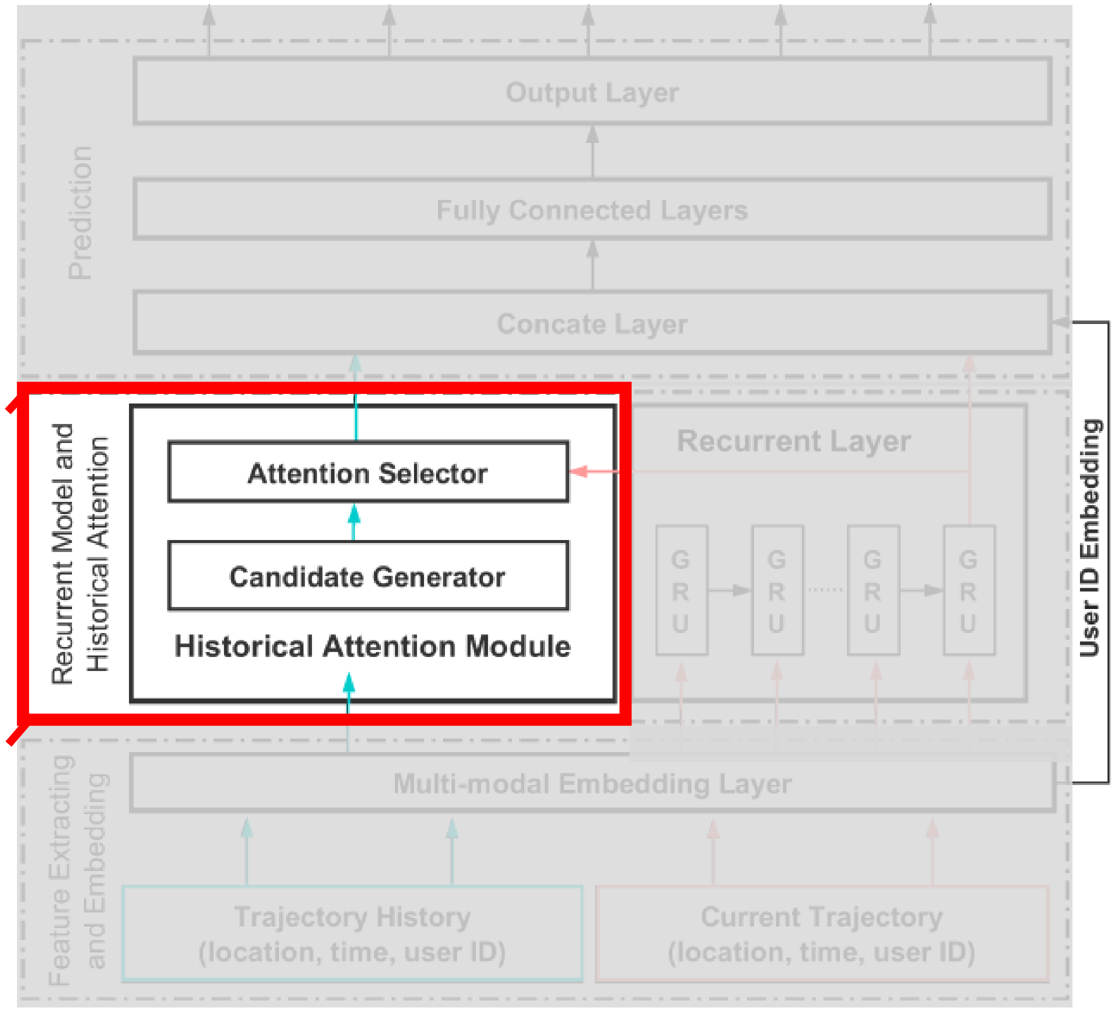

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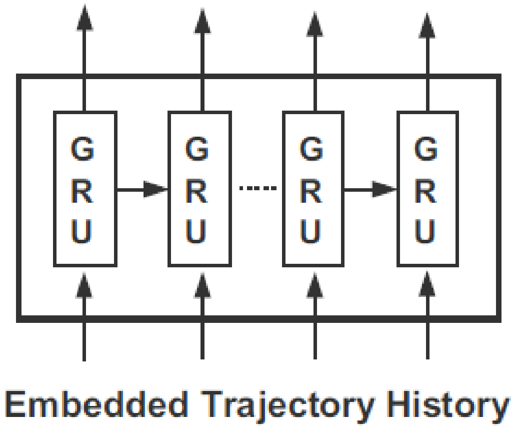

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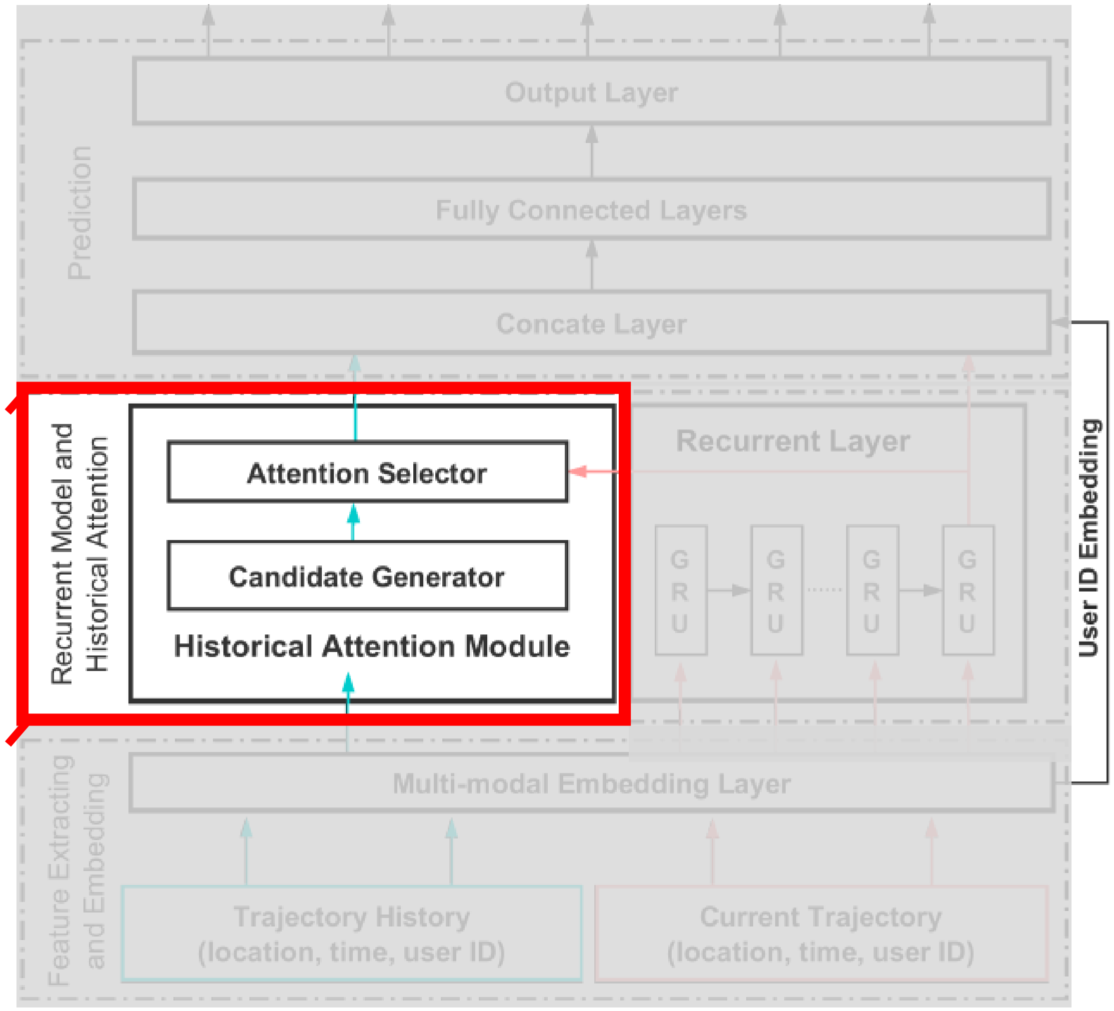

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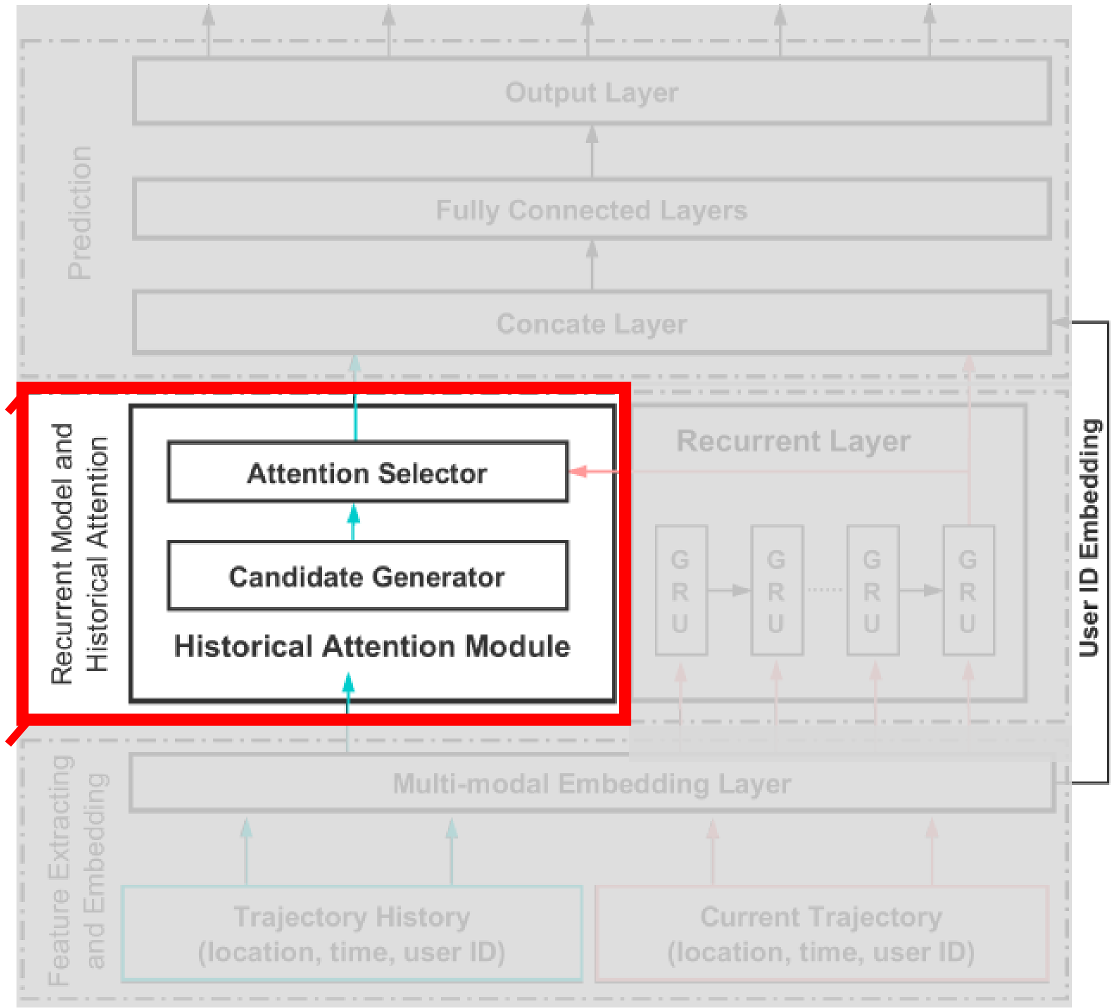

- Candidate Generator
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  - *Score Layer for "correlation"*
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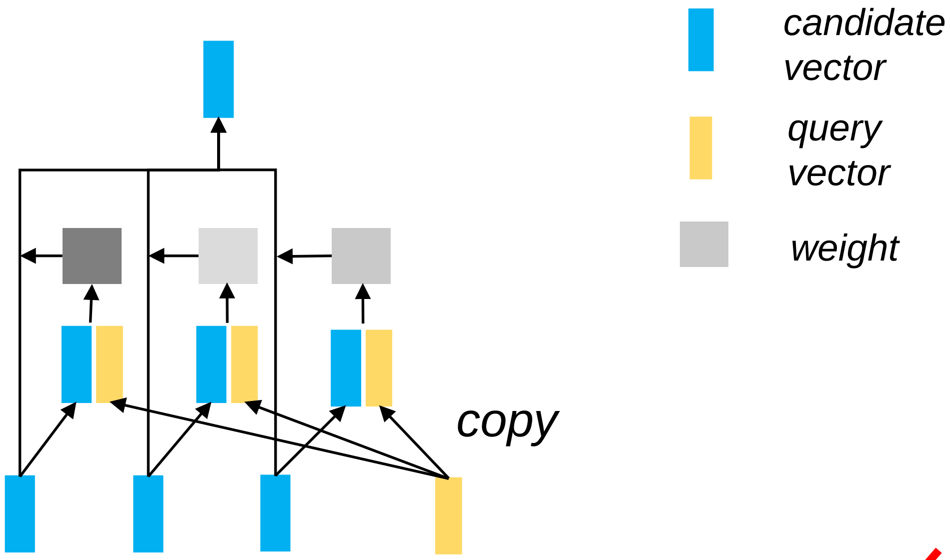

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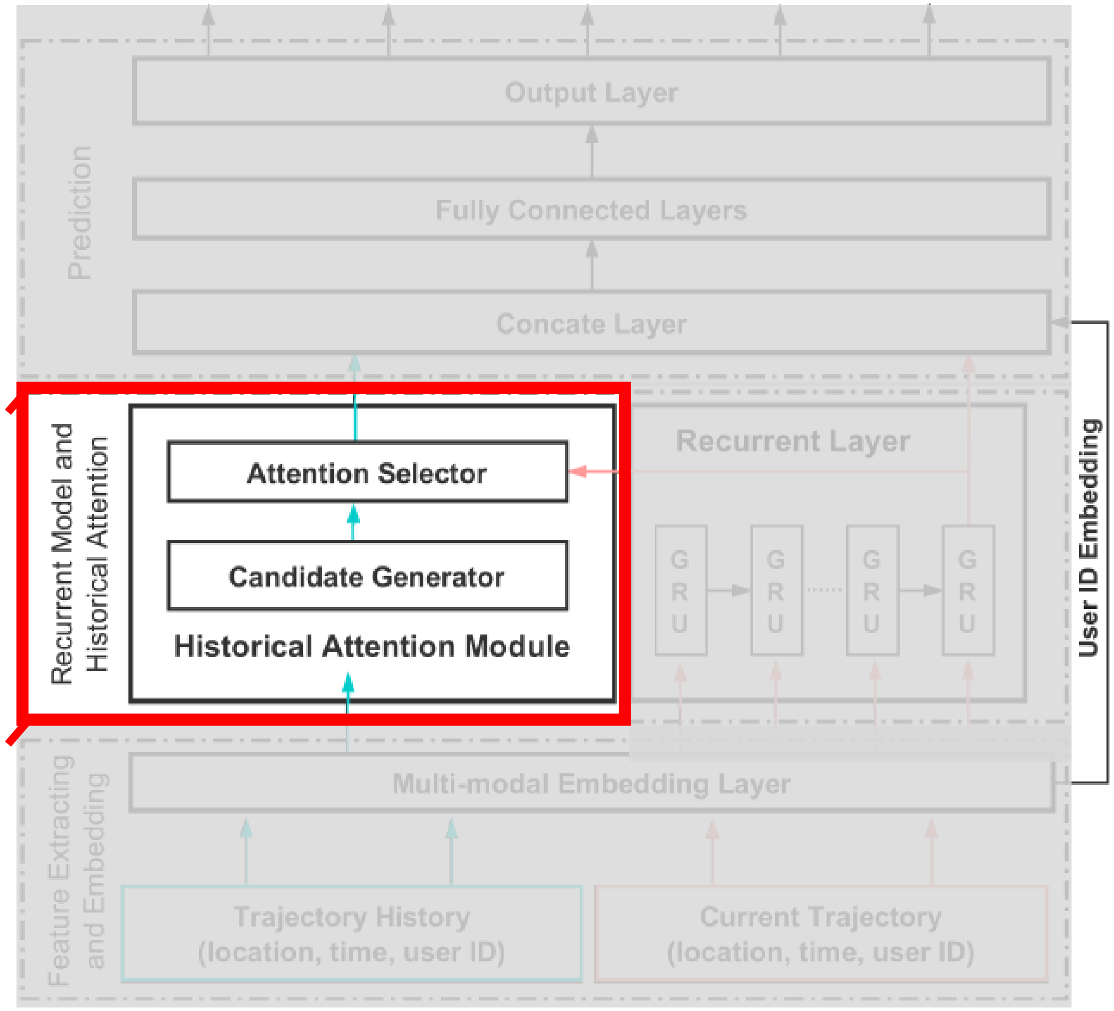

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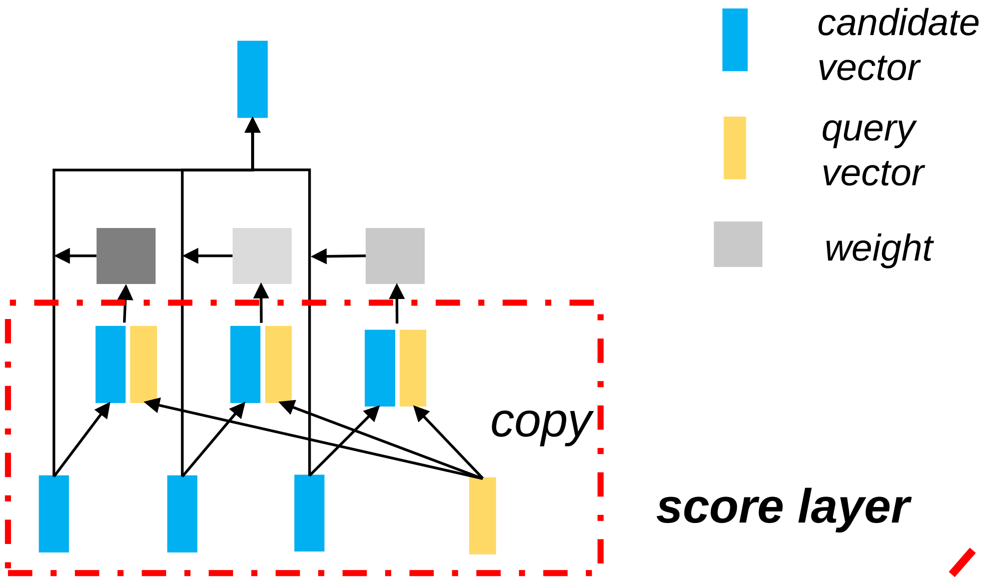

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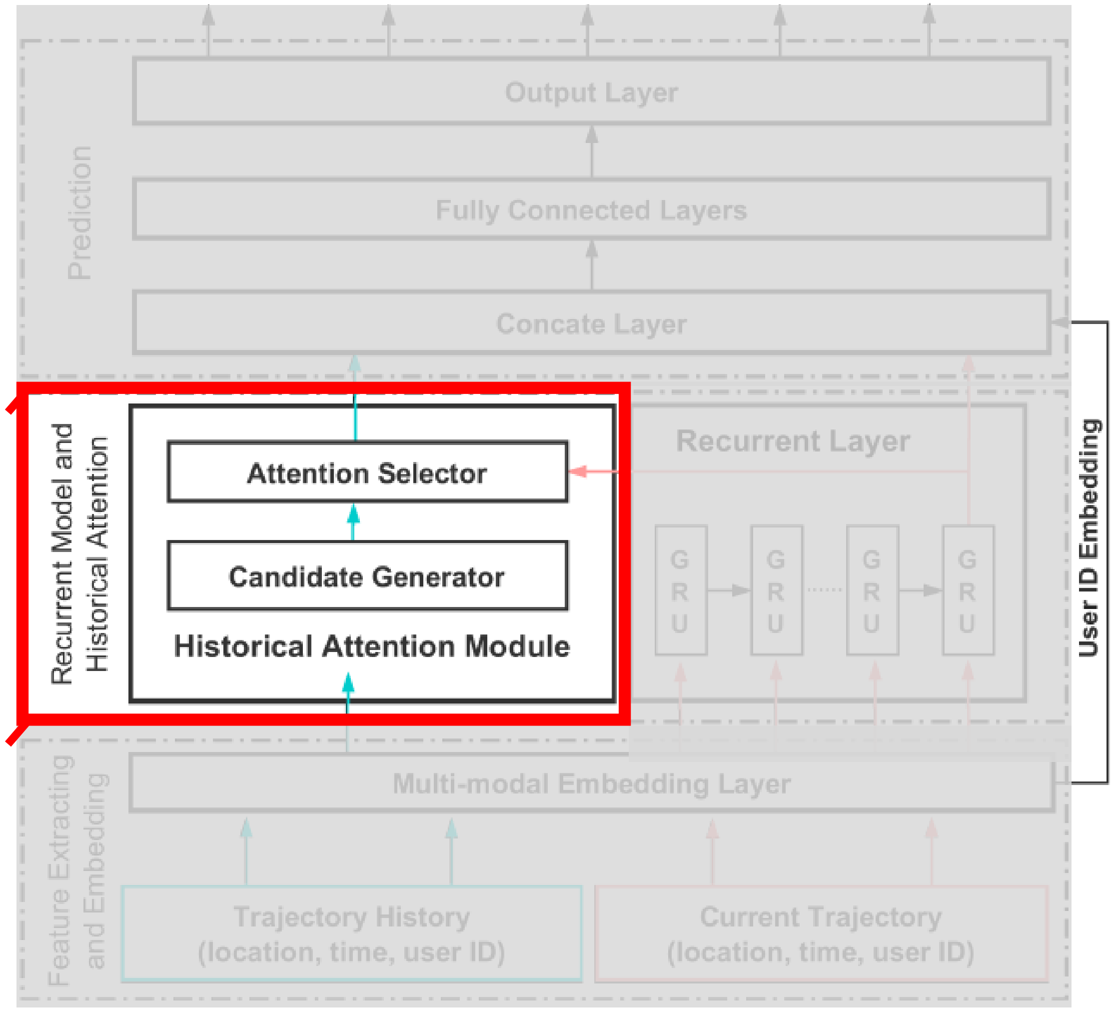

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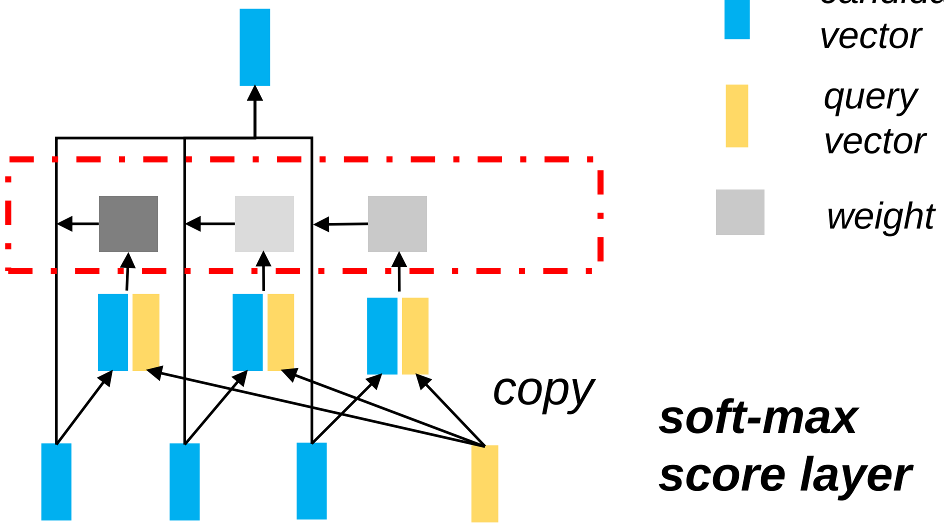

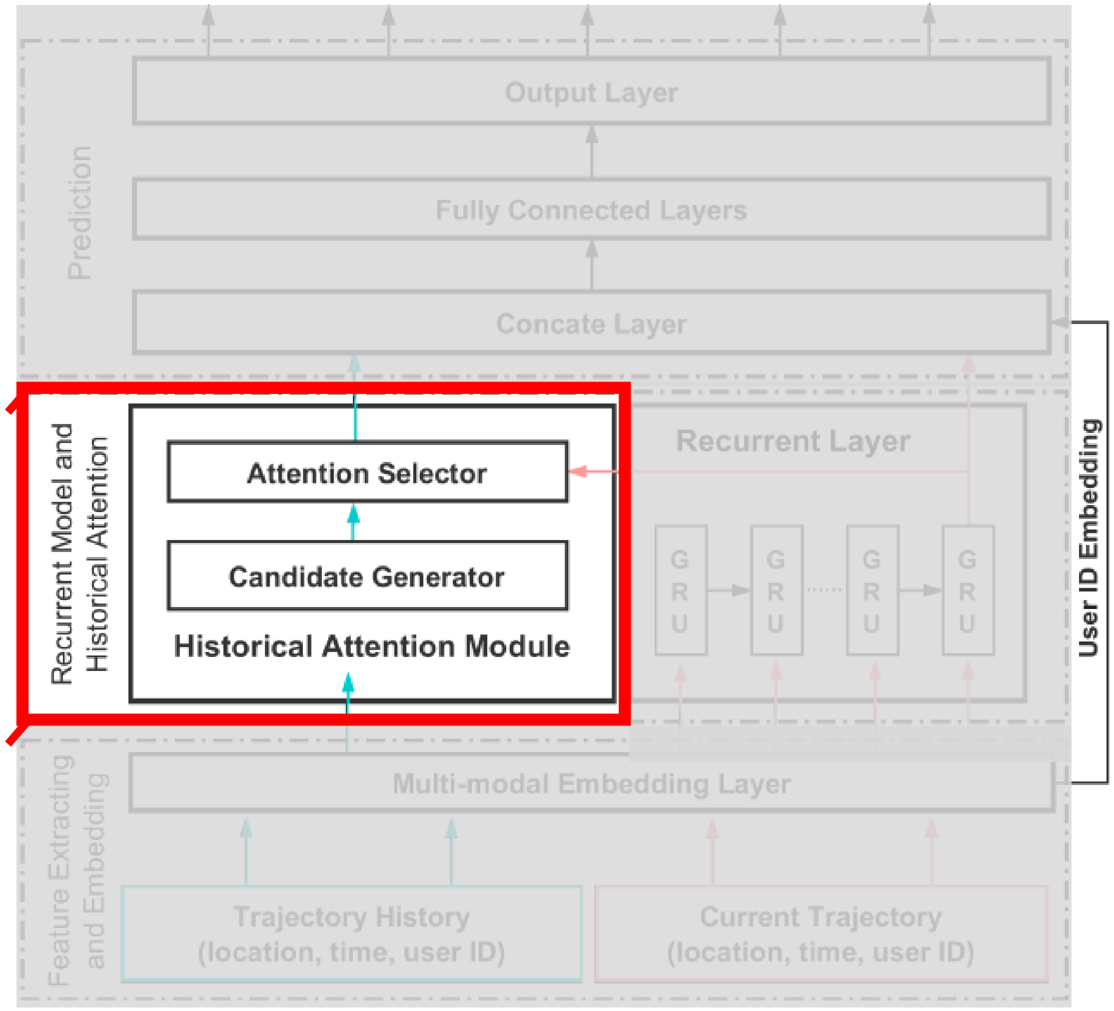

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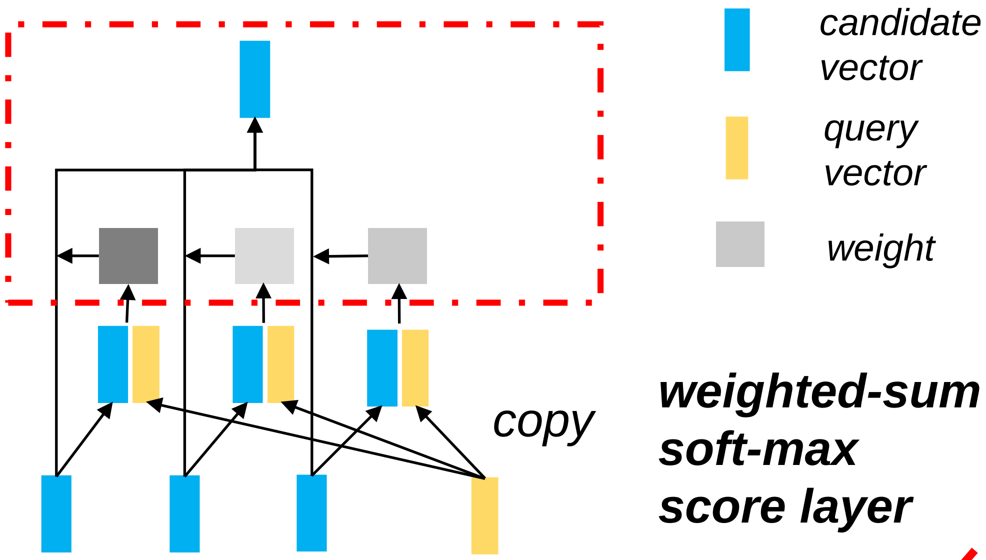

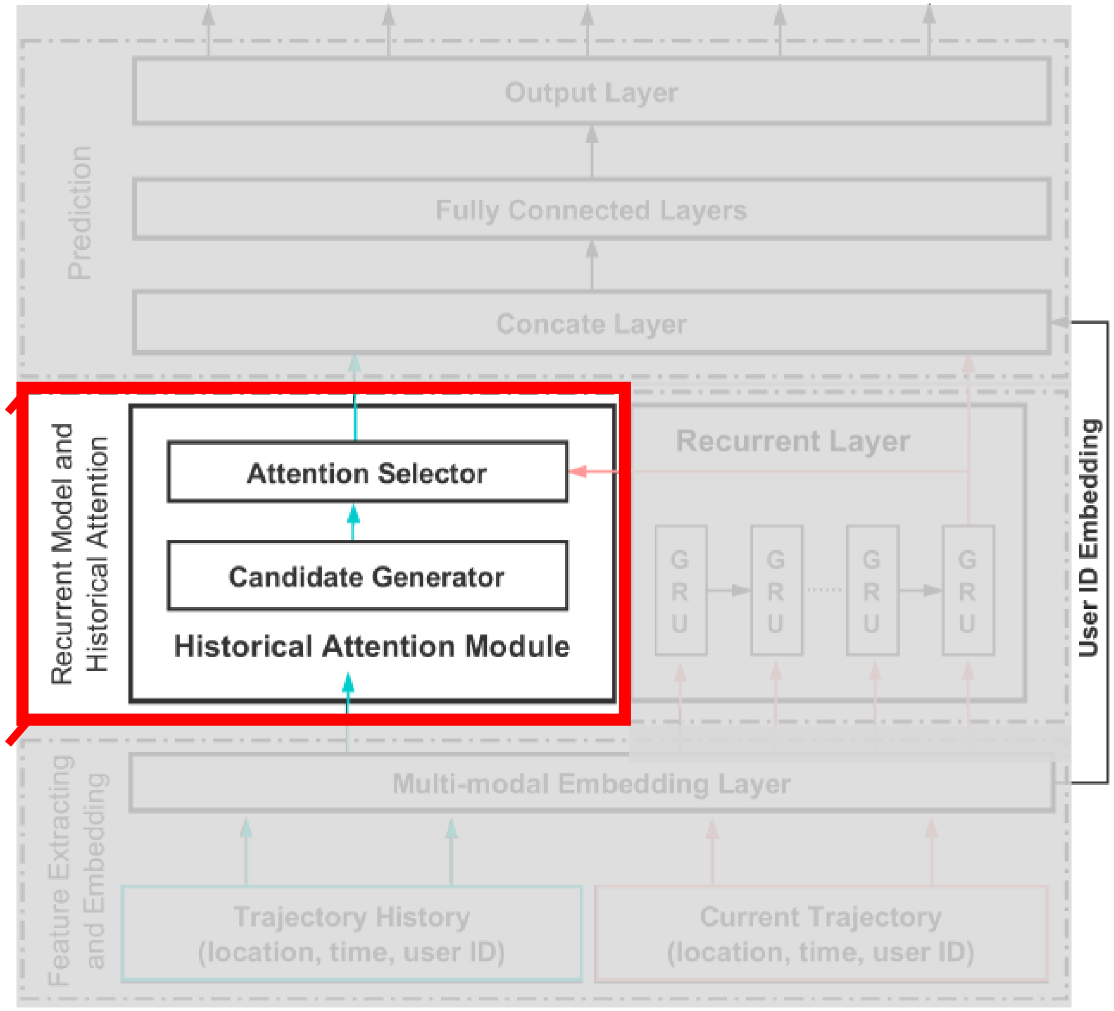

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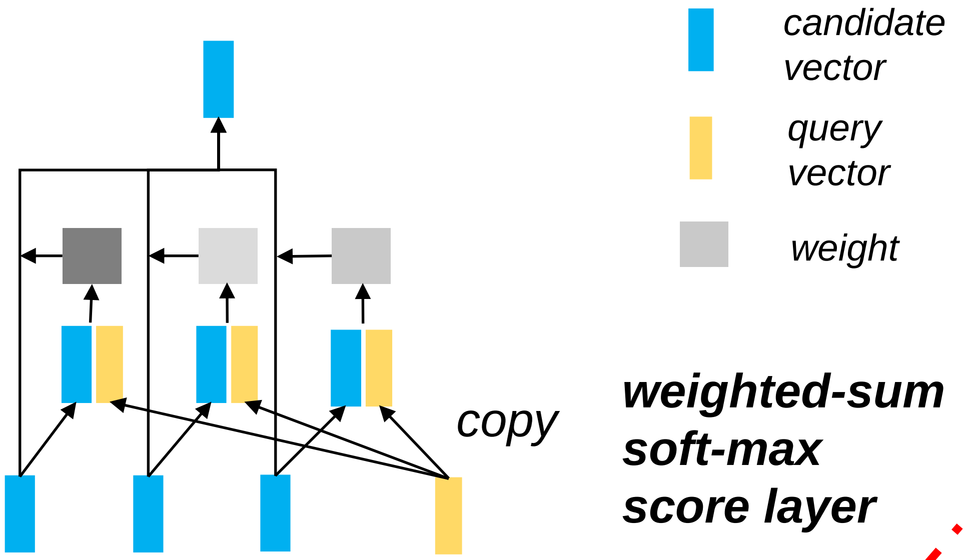
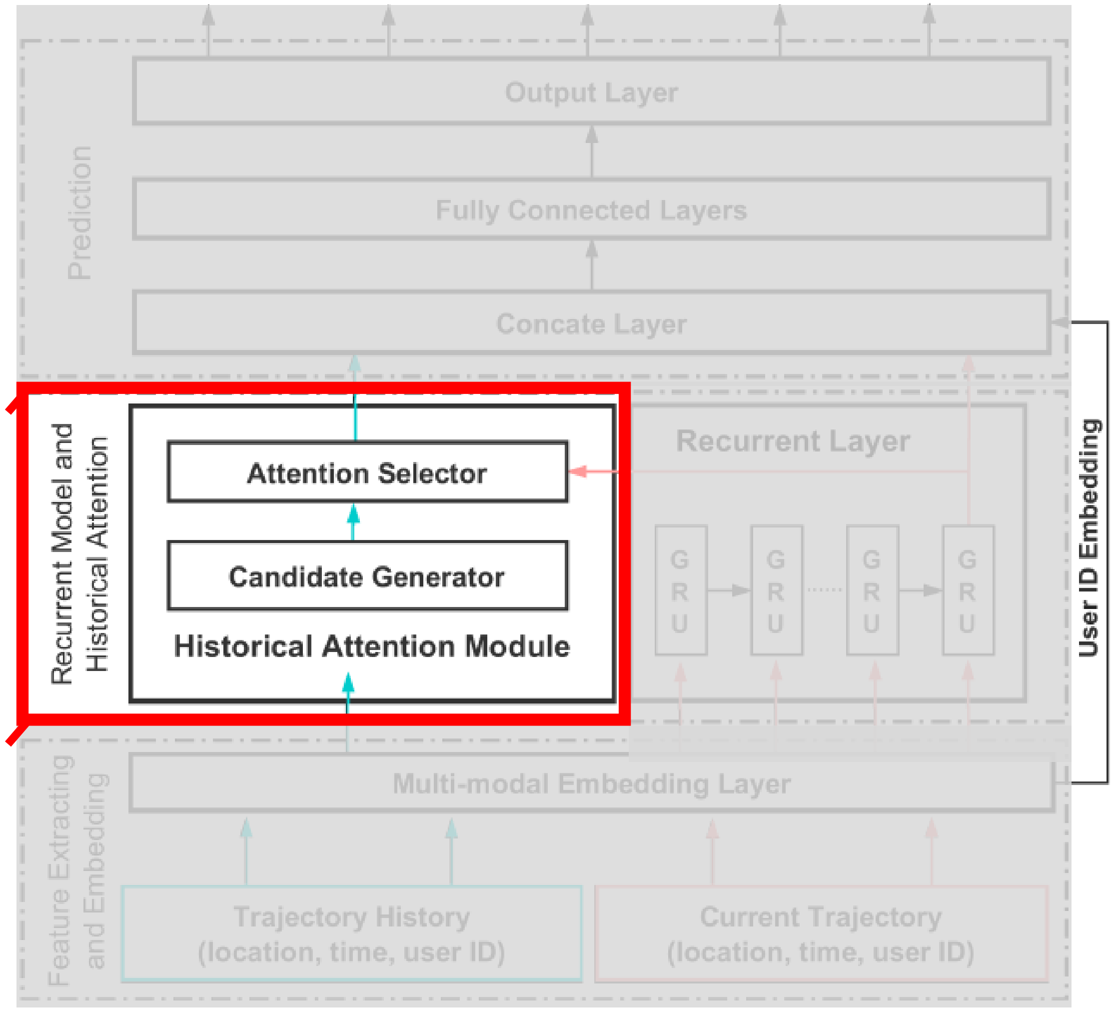
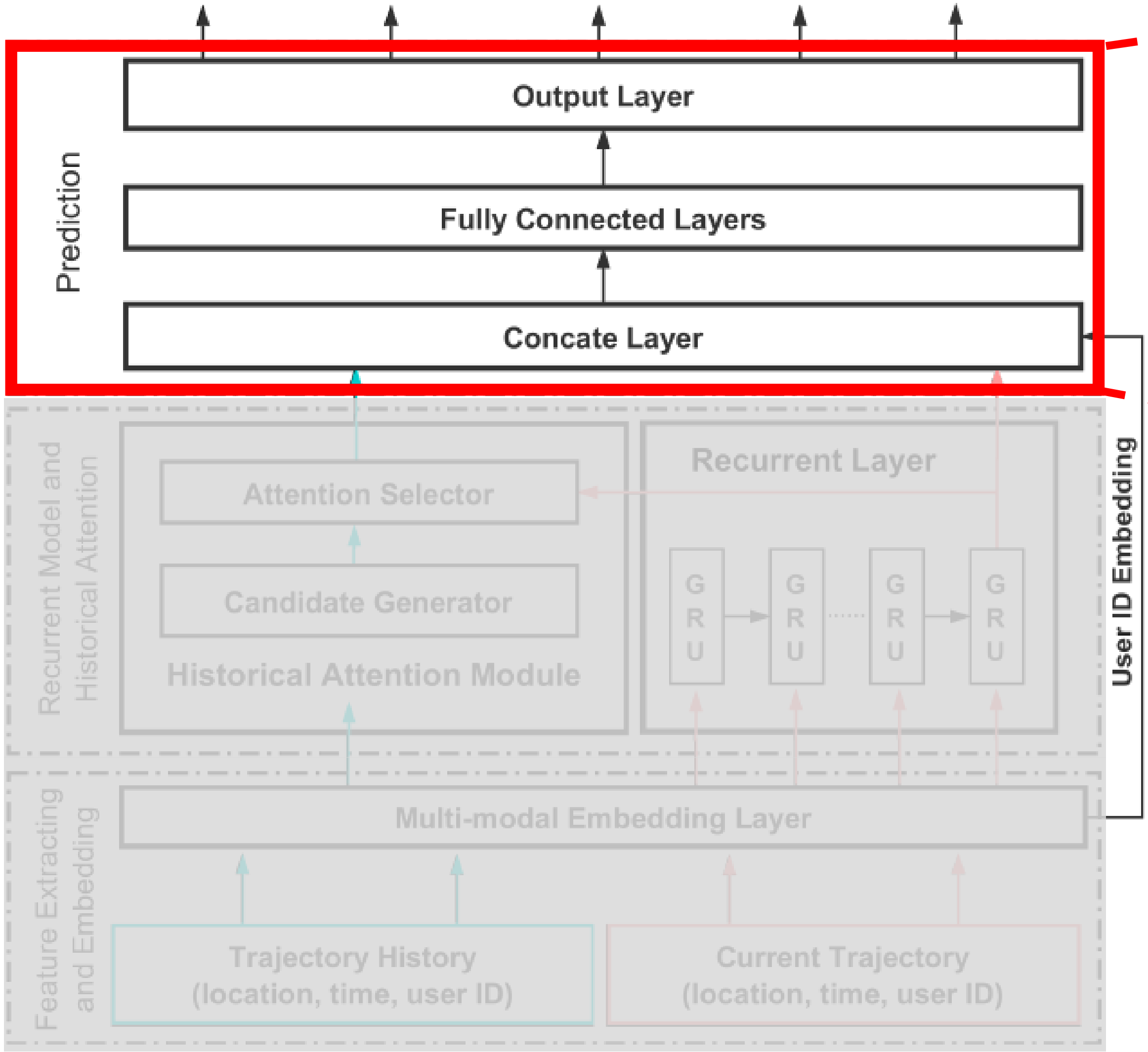
DeepMove-Historical Attention





- Candidate Generator
- ***Attention Selector***
    - *Score Layer for "correlation"*
    - *Soft-max + Weighted Sum*

DeepMove-Prediction Module



- ***Prediction Module***
  - ***concatenate + FCN + soft-max***
  - ***Input:*** vector representations of next location
  - ***Output:*** probability distribution of next location

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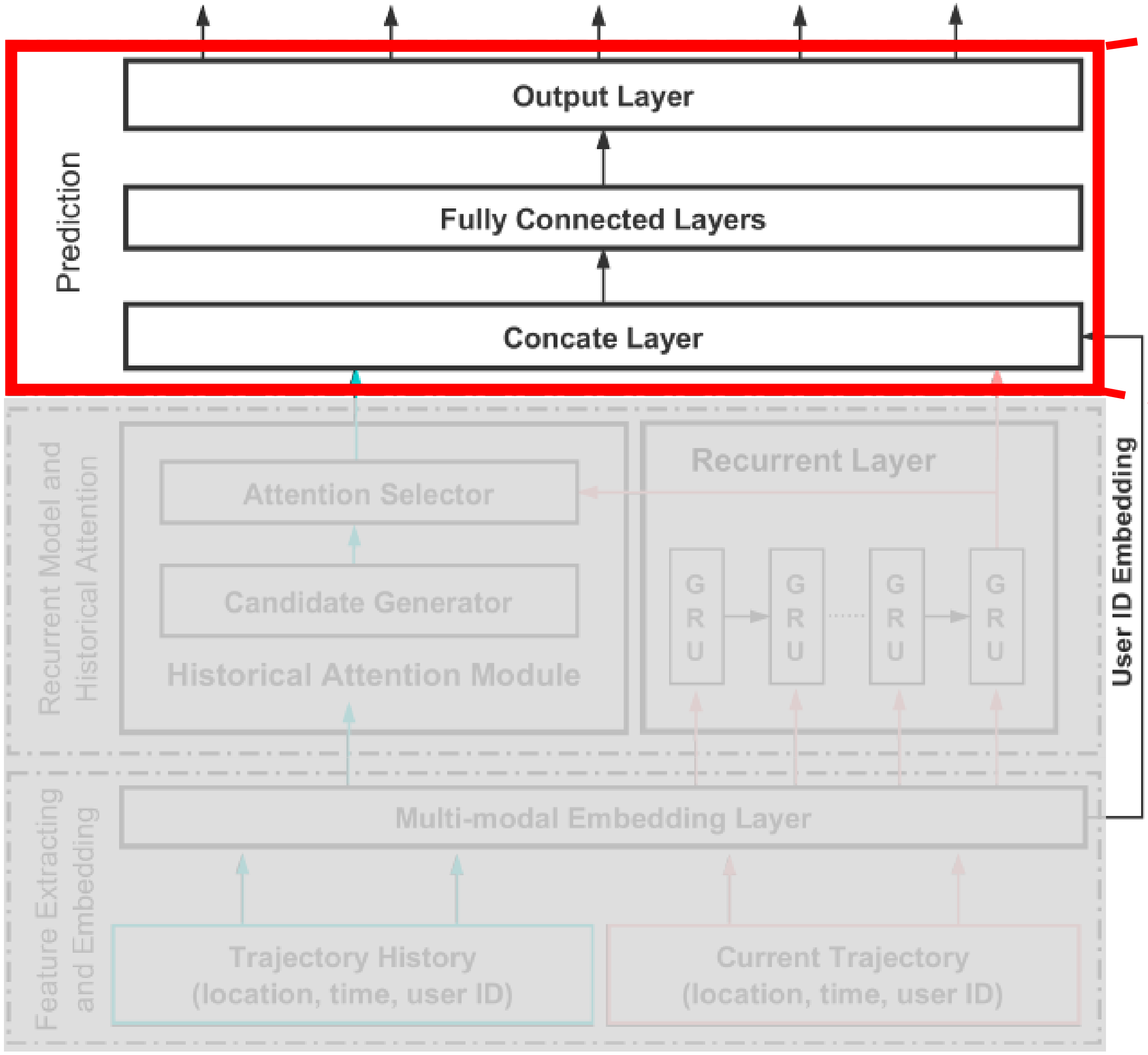

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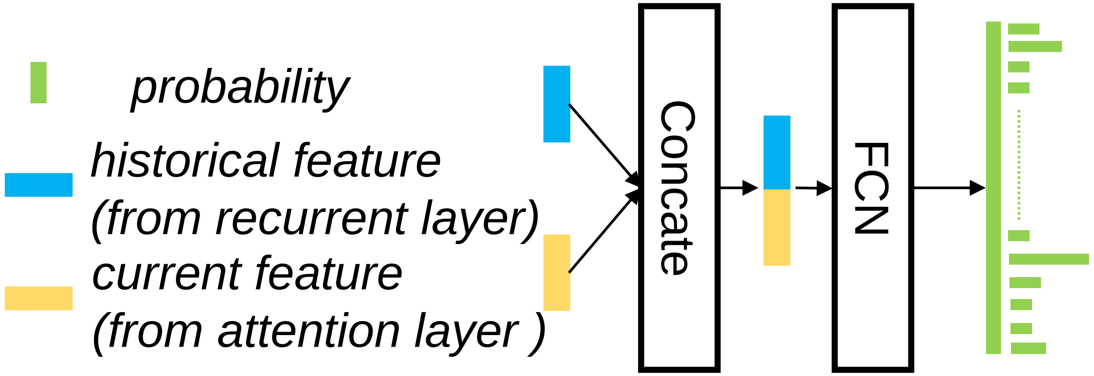
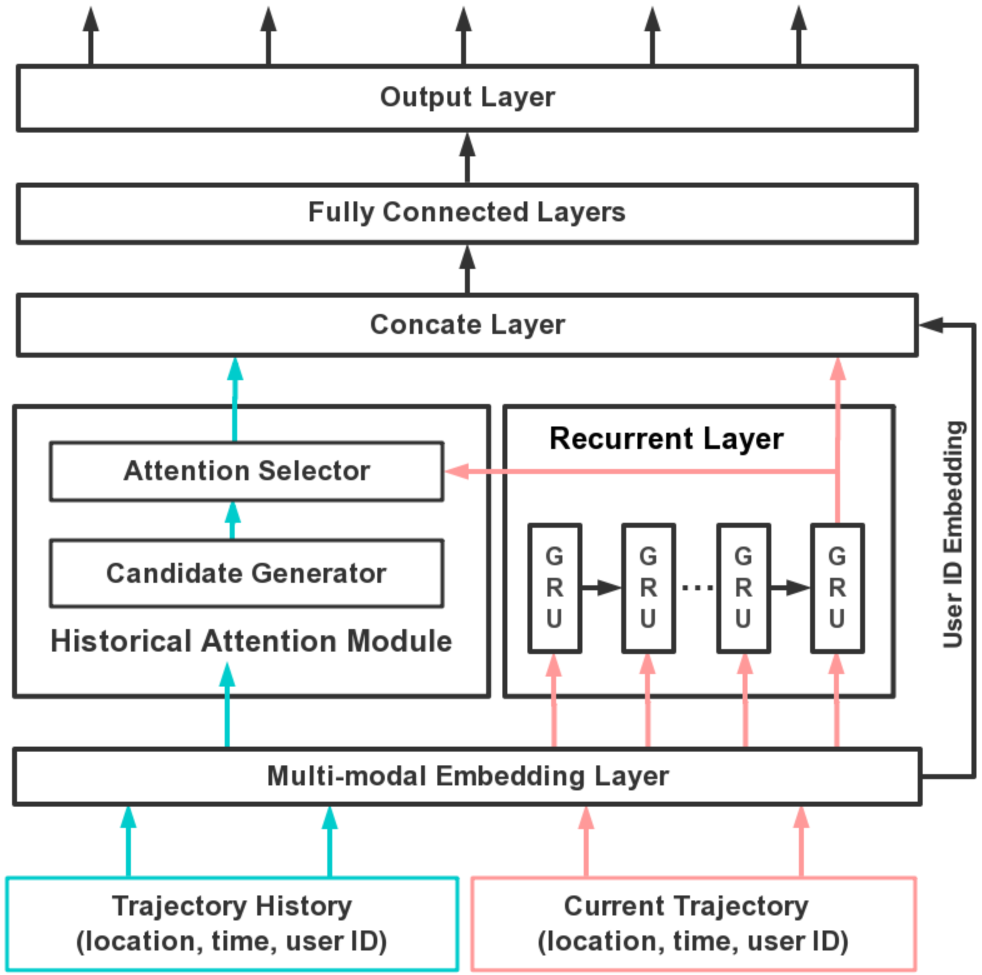


DeepMove-Recap



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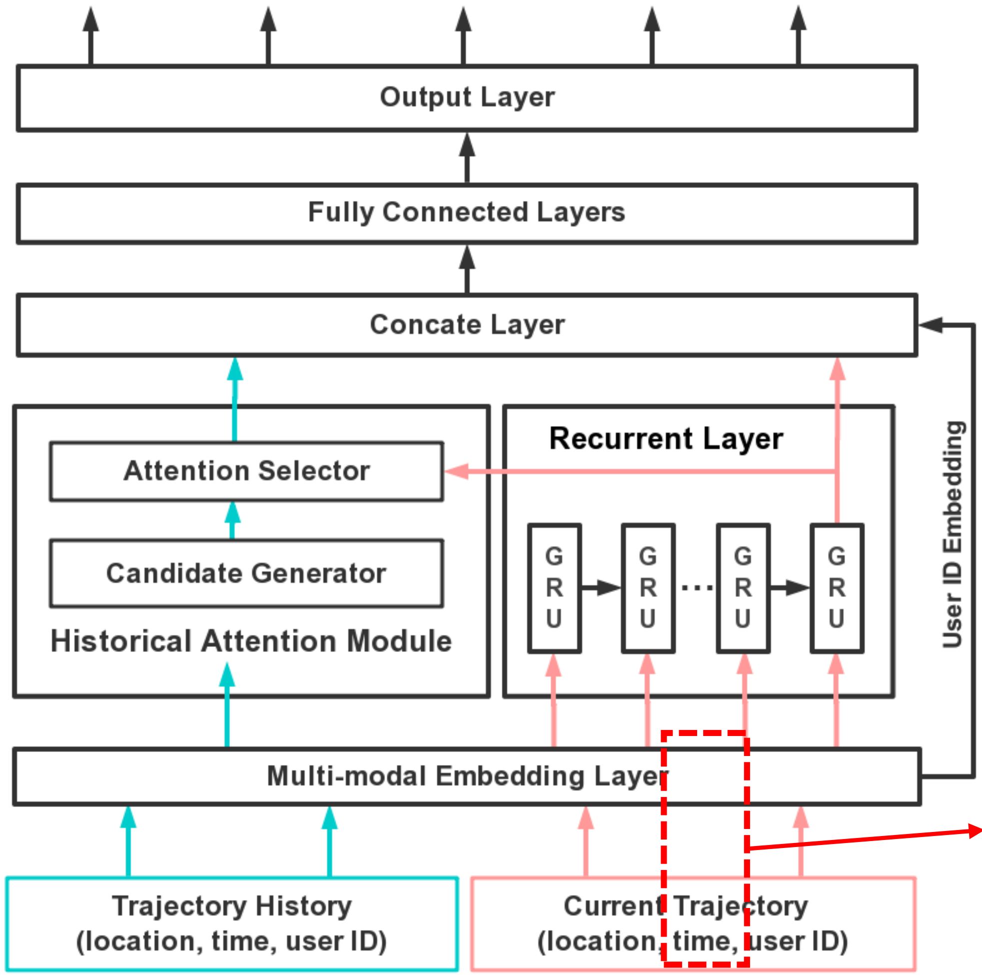

The time embedding enables ***time-dependent relation*** *capturing*

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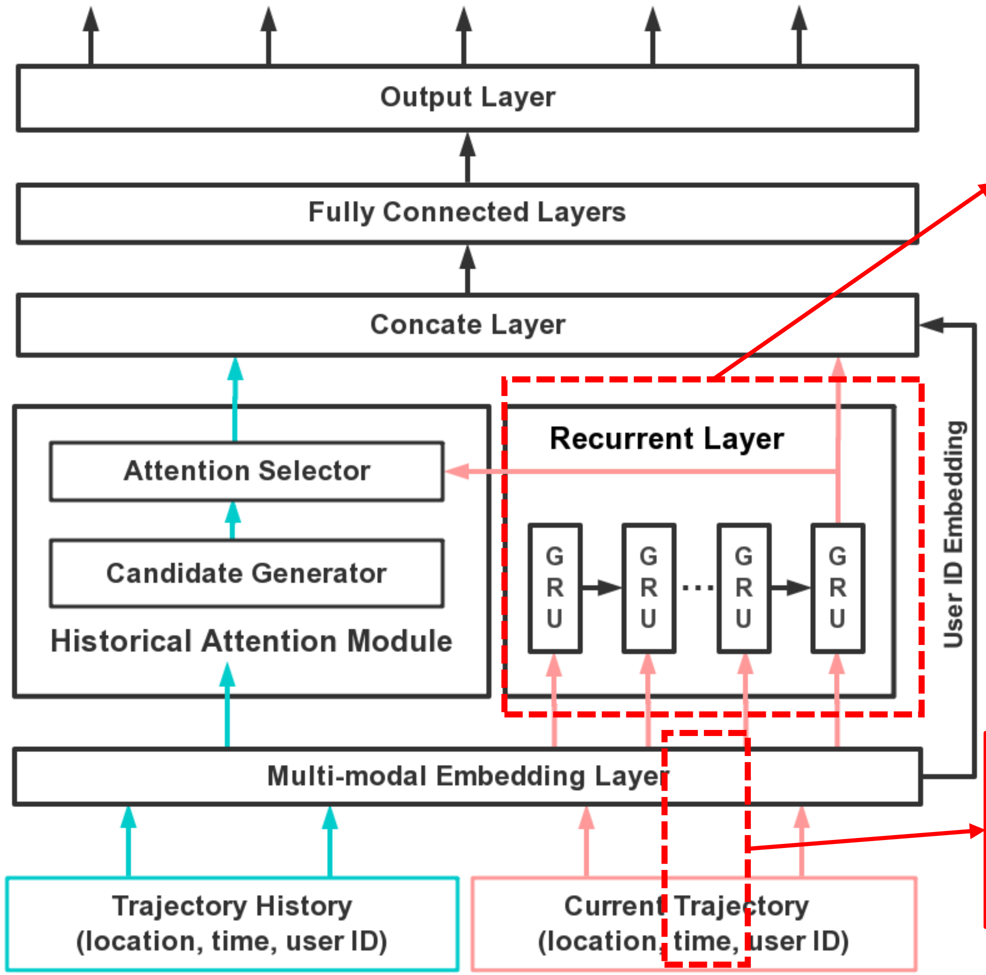
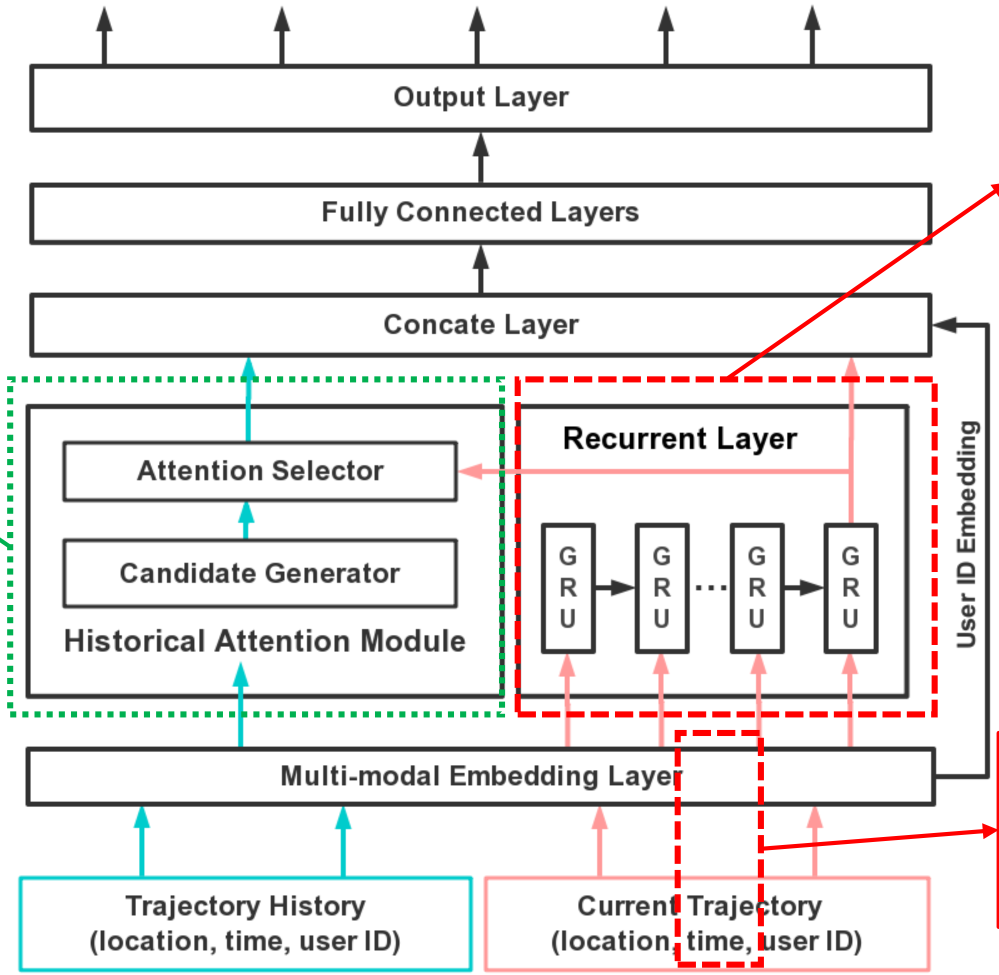


The recurrent unit enables the ***high-order relation*** *capturing*

The time embedding enables ***time-dependent relation*** *capturing*

DeepMove-Recap

The historical attention enables **multi-level periodicity** capturing



The recurrent unit enables the **high-order relation** capturing

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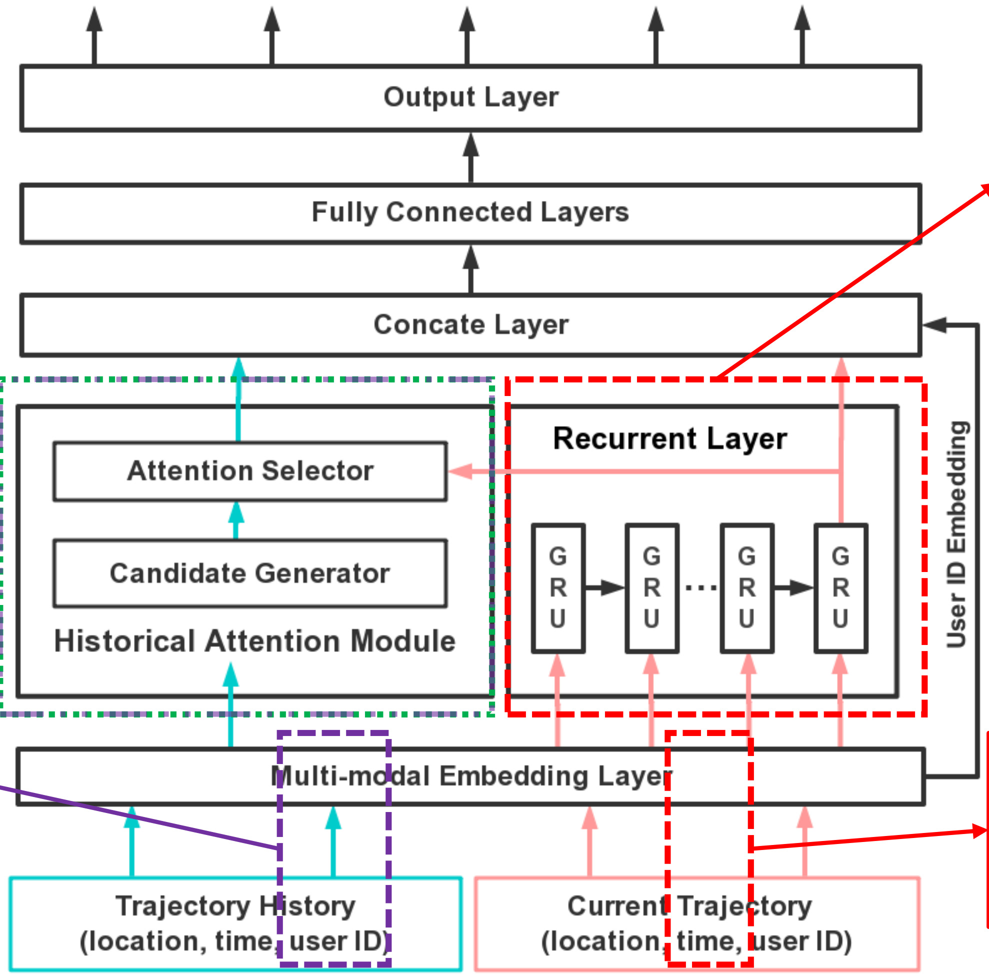
DeepMove-Recap

The historical attention enables ***multi-level periodicity*** *capturing*

The historical attention and user embedding enable *personalization modelling*



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Datasets

Dataset	Foursquare	Mobile Application	Cellular Network
City	New York	Beijing	Shanghai
Duration	1 year	1 month	1 month
Users	15639	5000	1075
Records	293559	15007511	491077
Locaitons	43379	31522	17785
Loc./User	40	48	40

Table 1: Basic statistics of mobility datasets.

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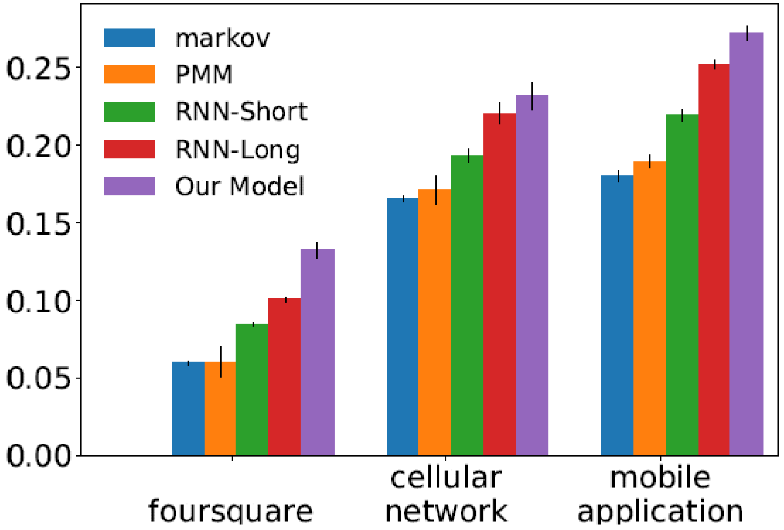
Table 1: Basic statistics of mobility datasets.

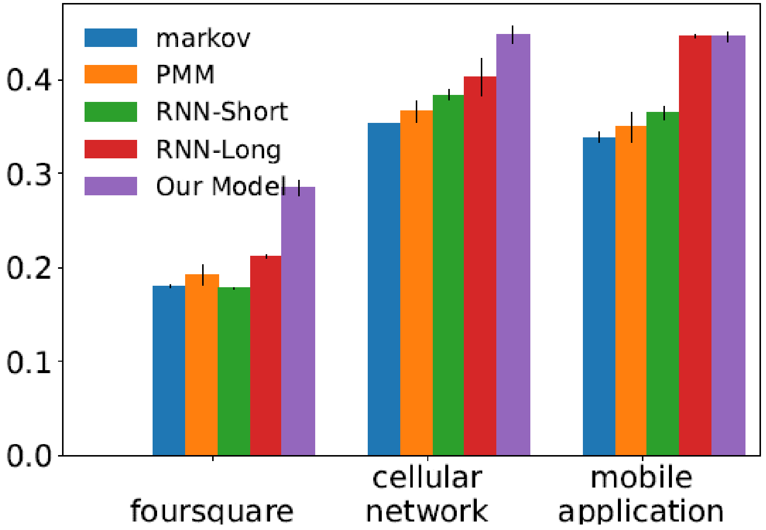
Baselines

- ***Markov:*** *widely used mobility model working with state transition matrix*
- ***PMM:*** *spatiotemporal mixture model with considering periodicity*
- ***RNN-based:*** *simple version of our propose model without attention*

Quantitative Evaluation



(a) top-1 prediction accuracy



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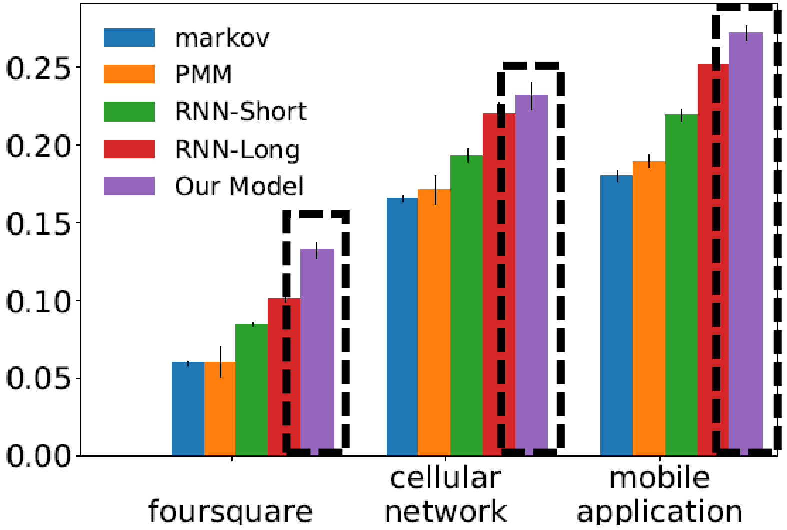

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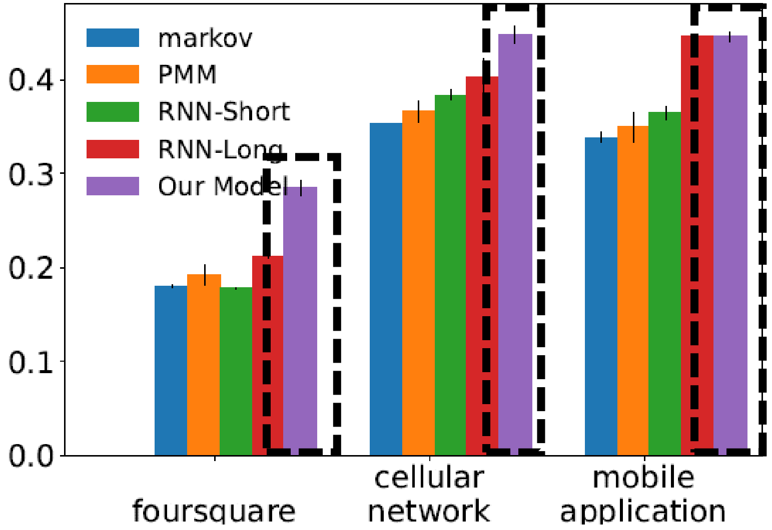

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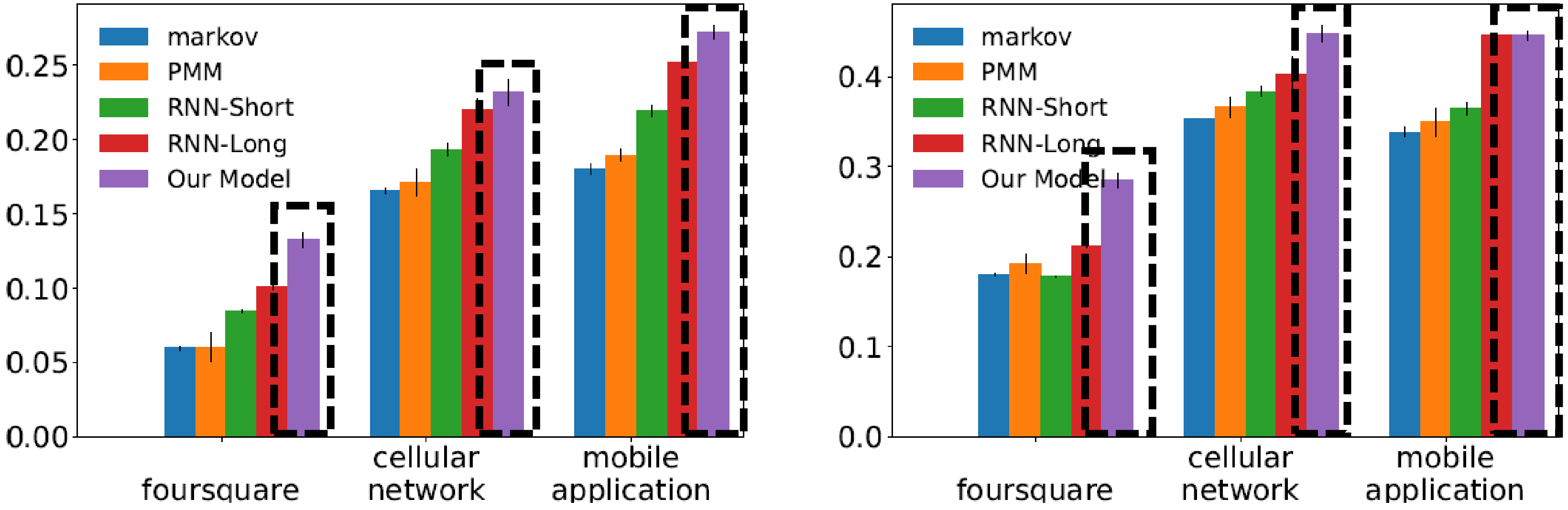

(a) top-1 prediction accuracy

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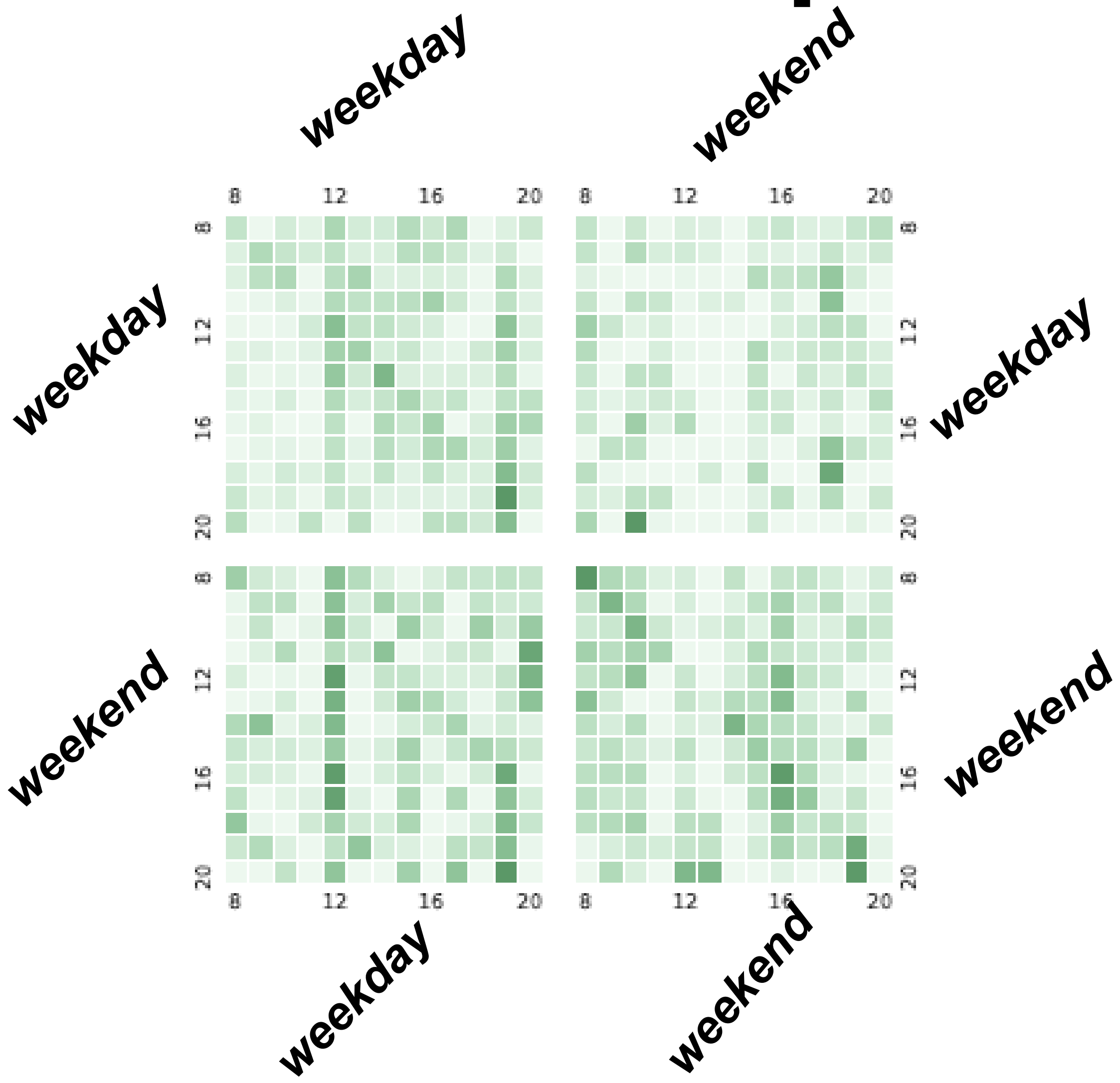
Our model outperforms than all three baselines by 10%

Reason Interpretation



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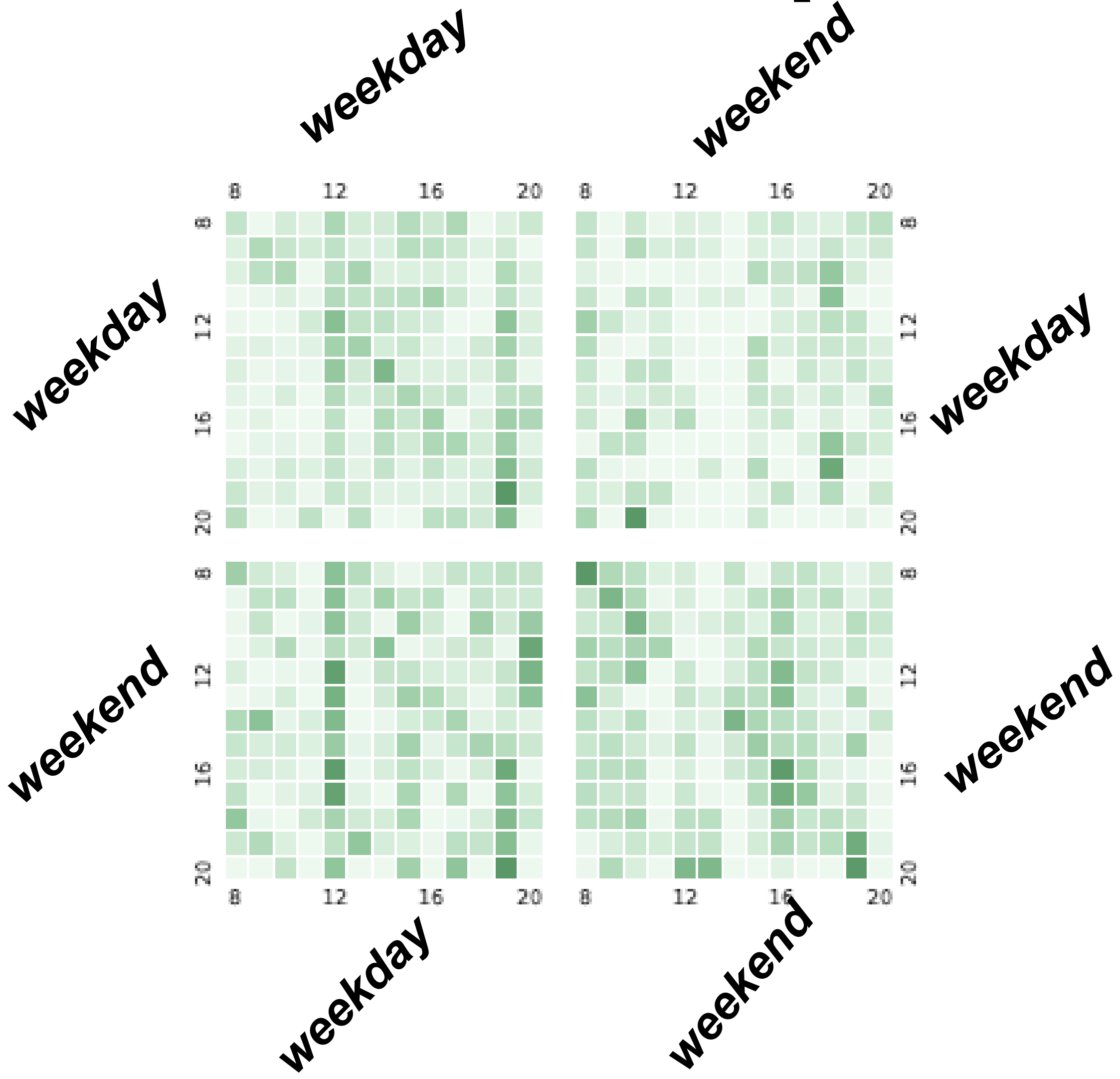

Visualize the attention weights from historical attention module.

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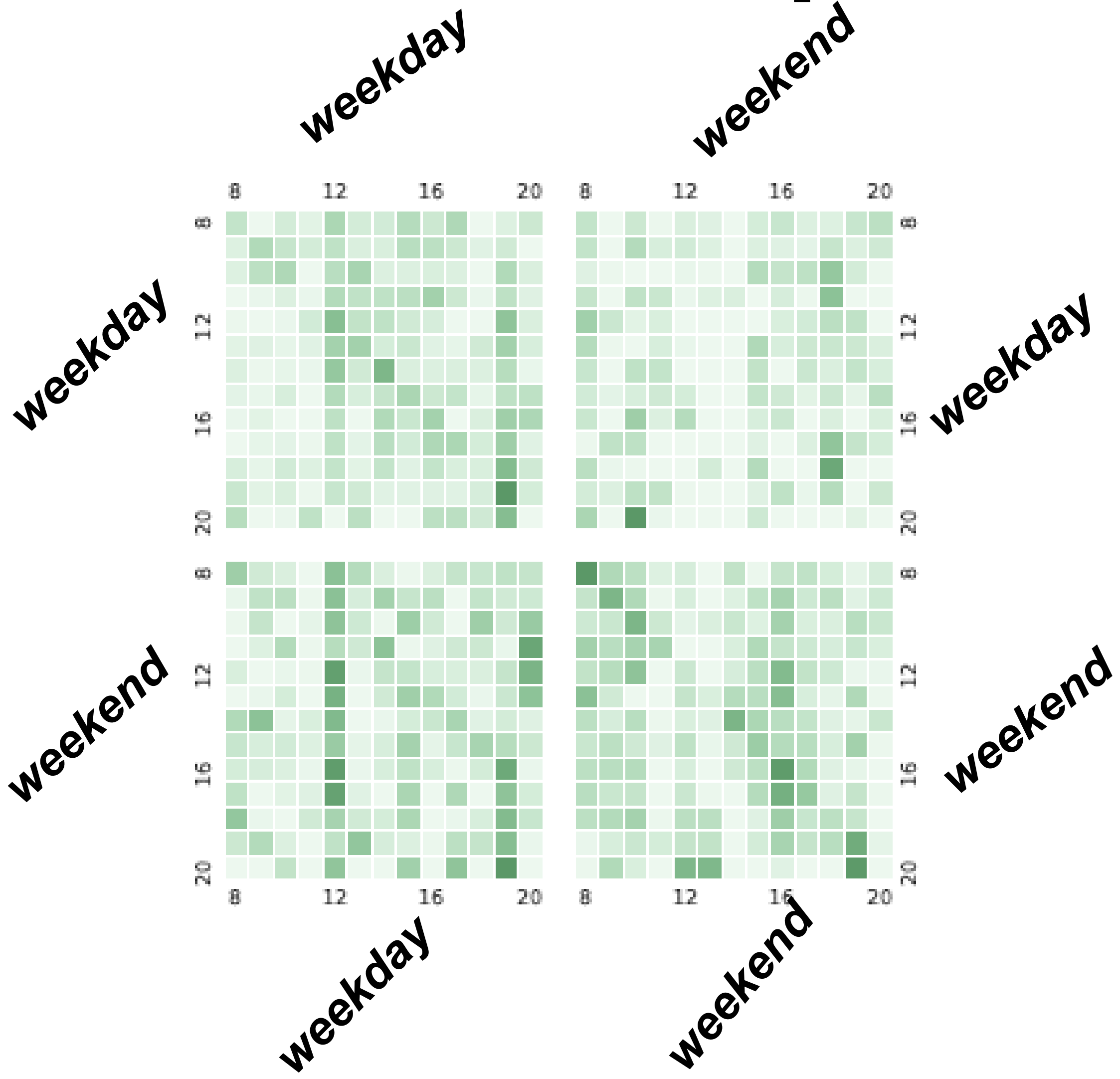

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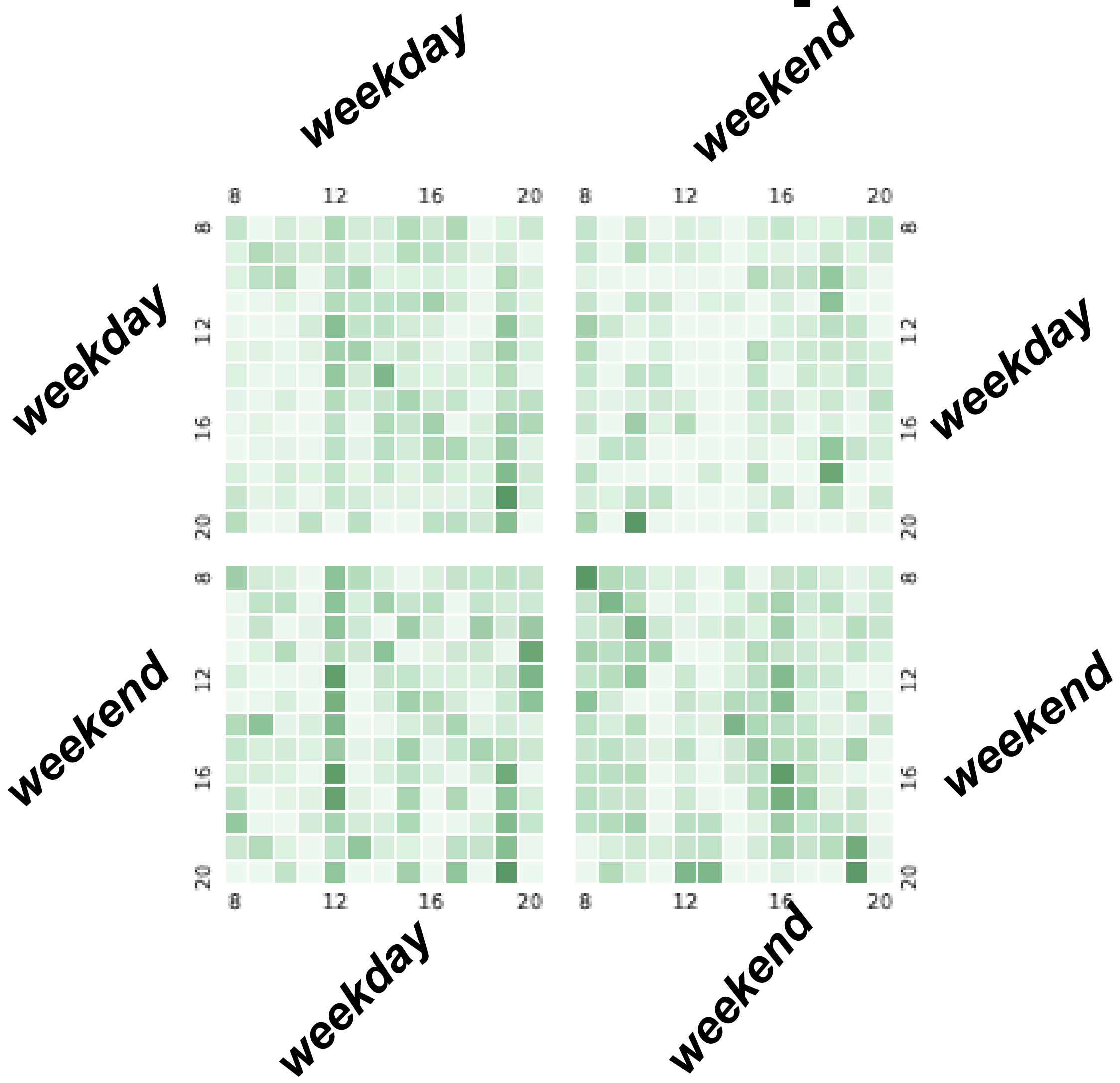

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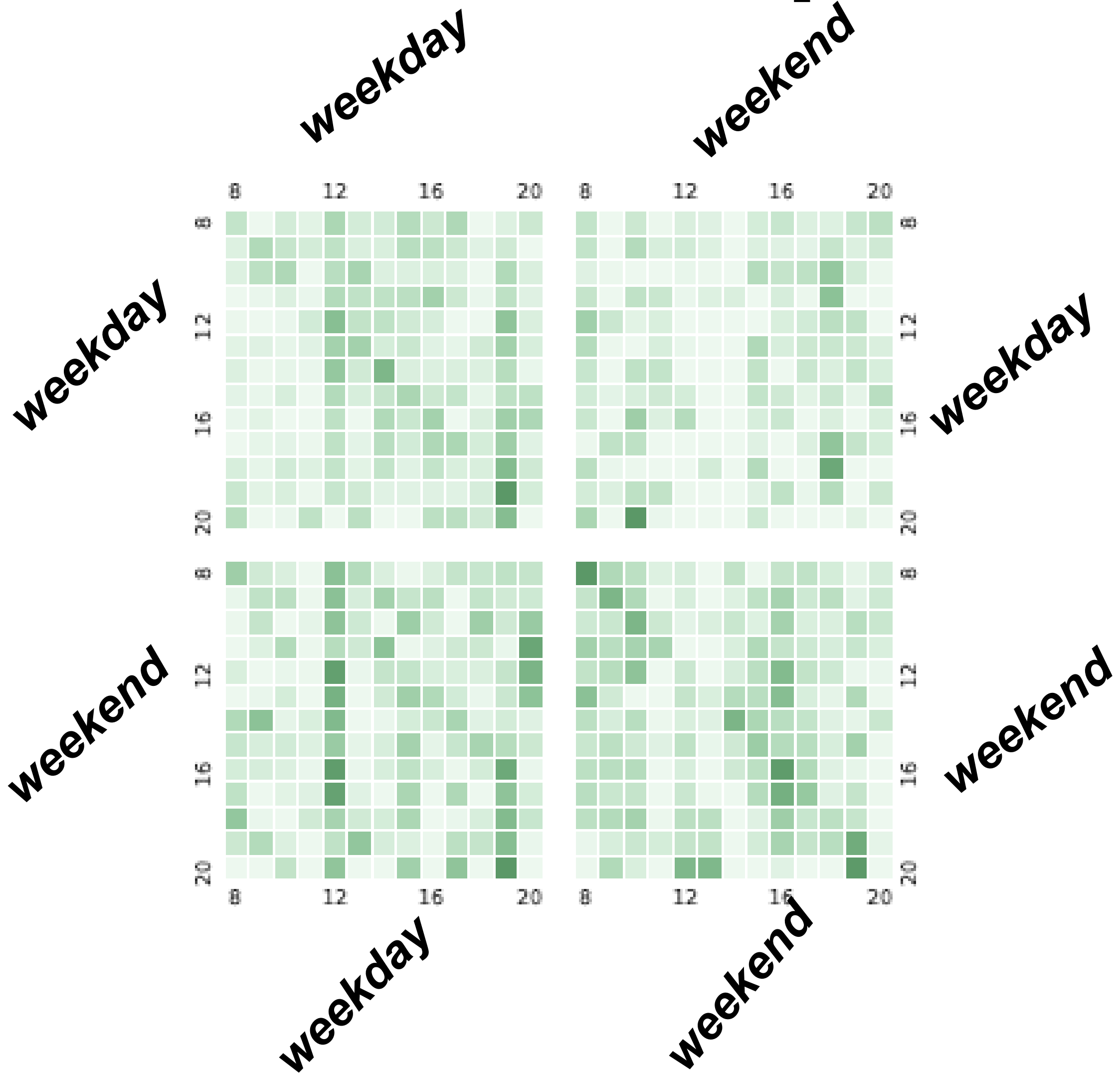

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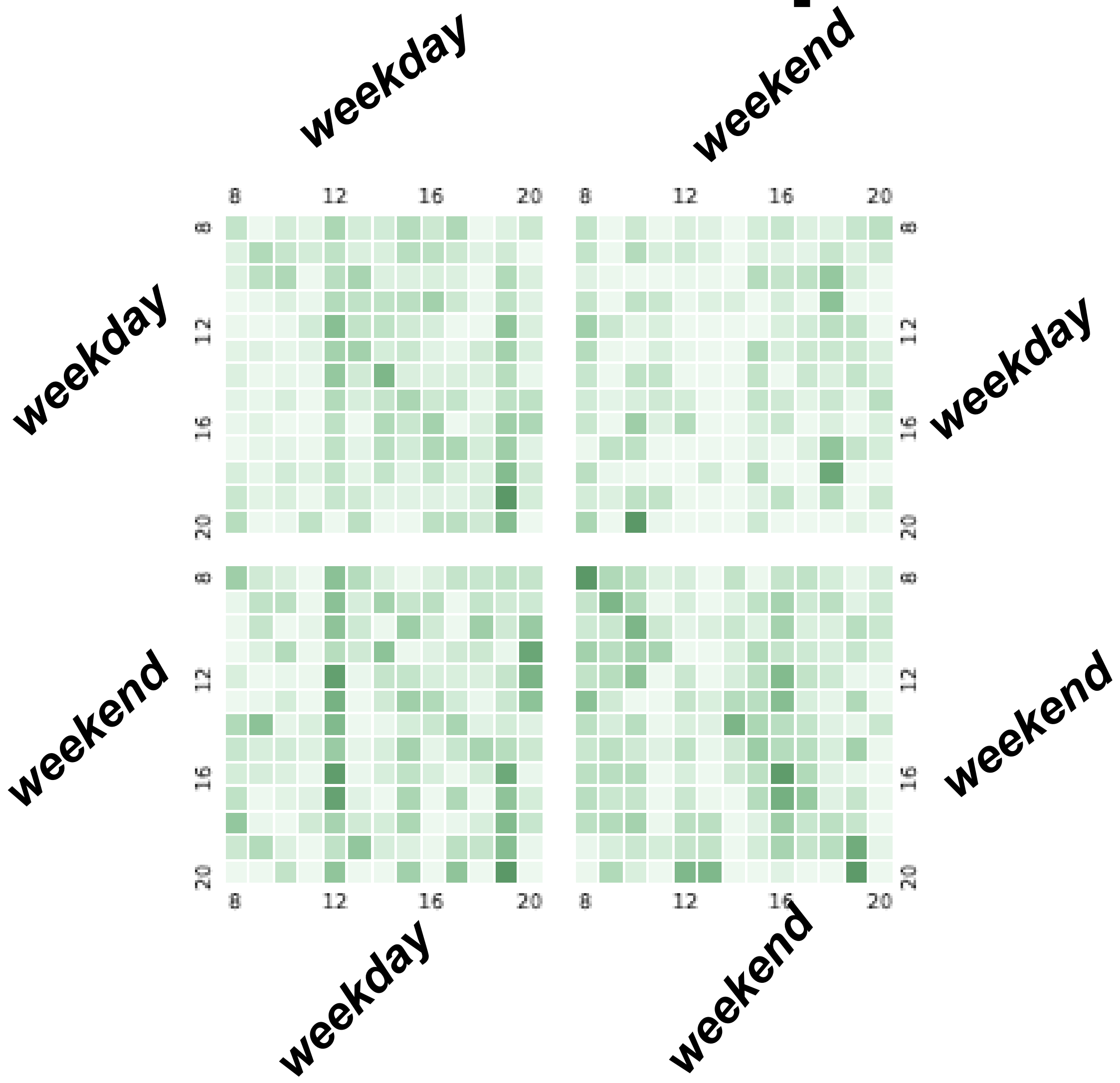

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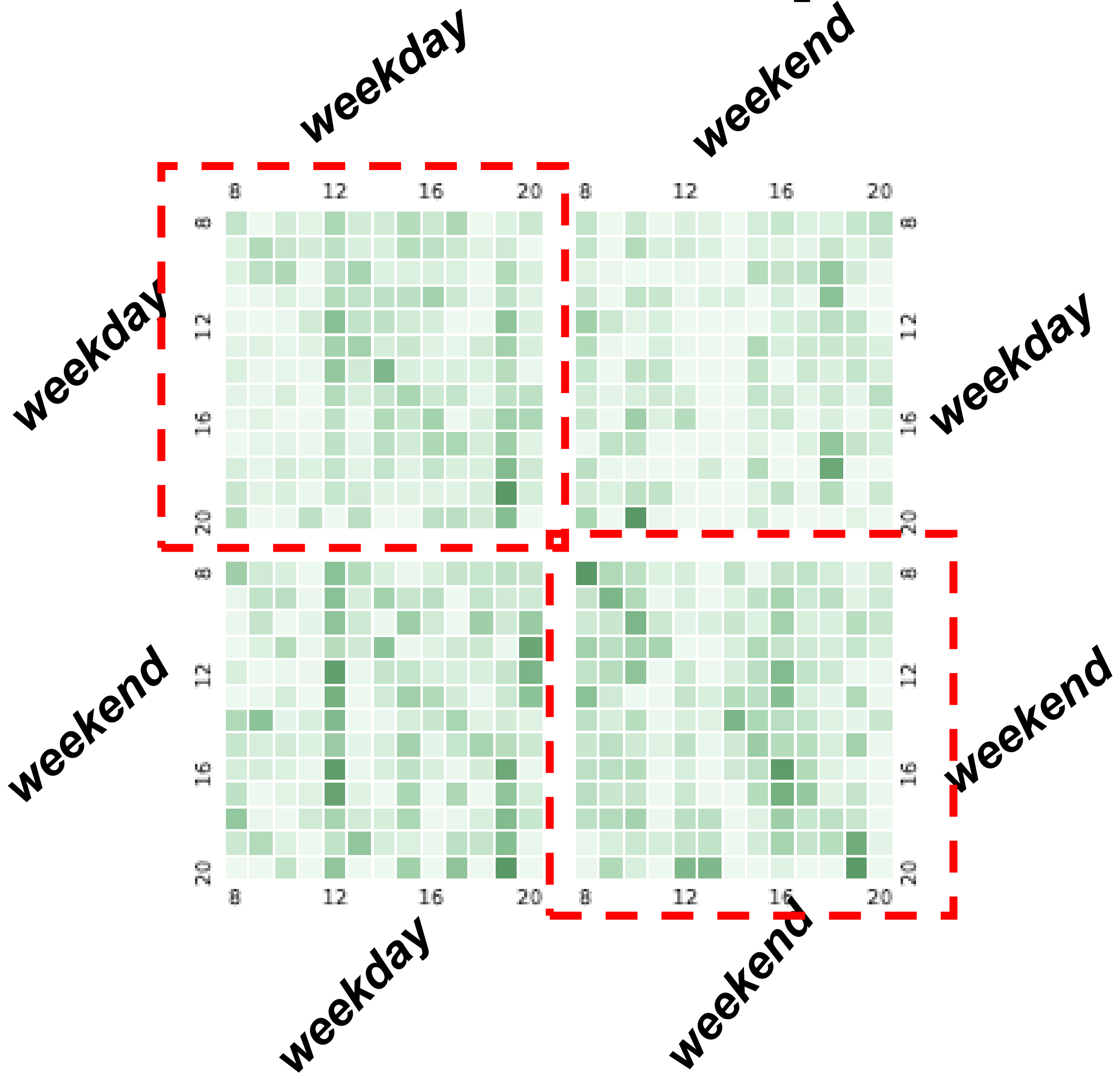

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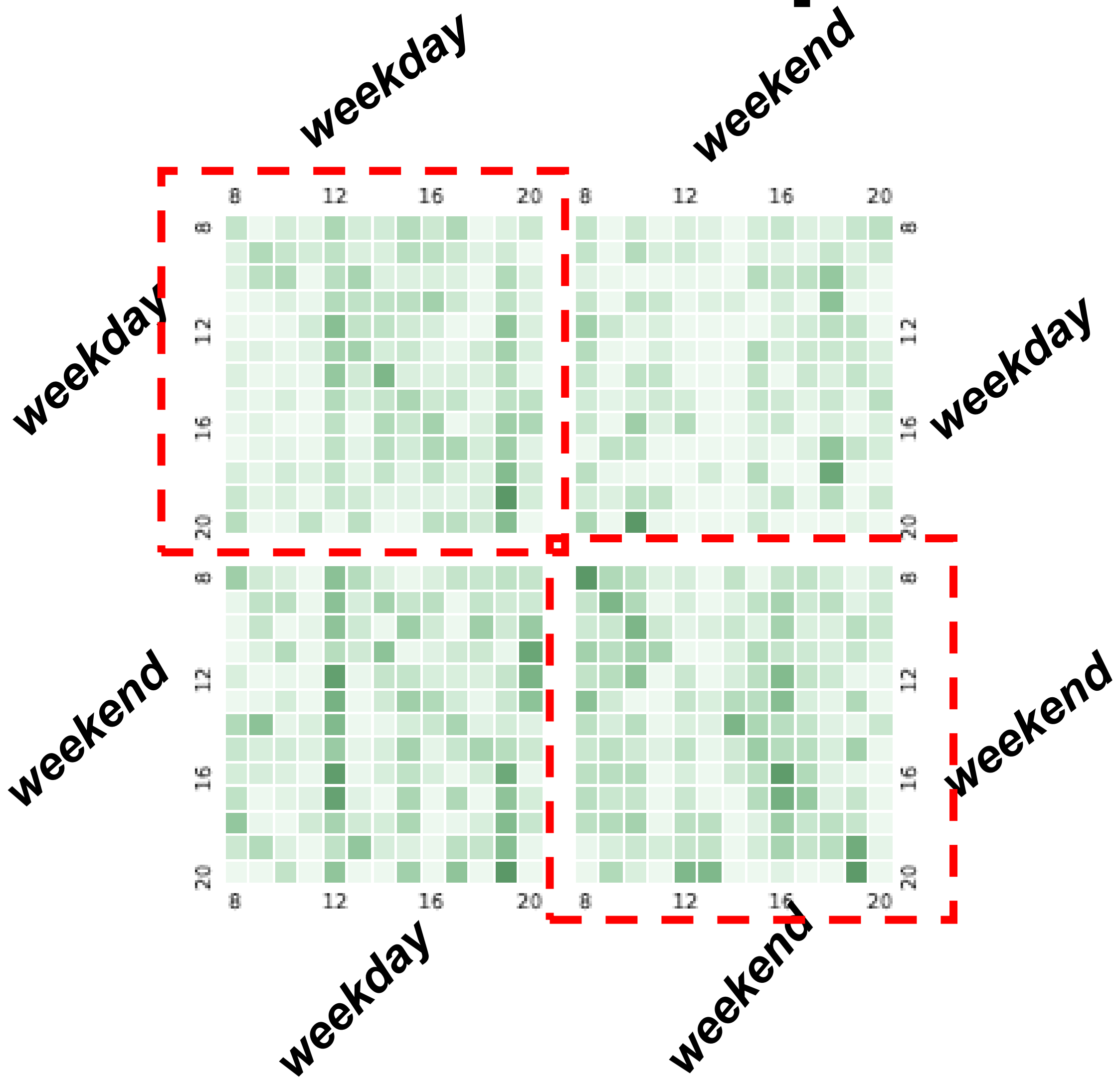

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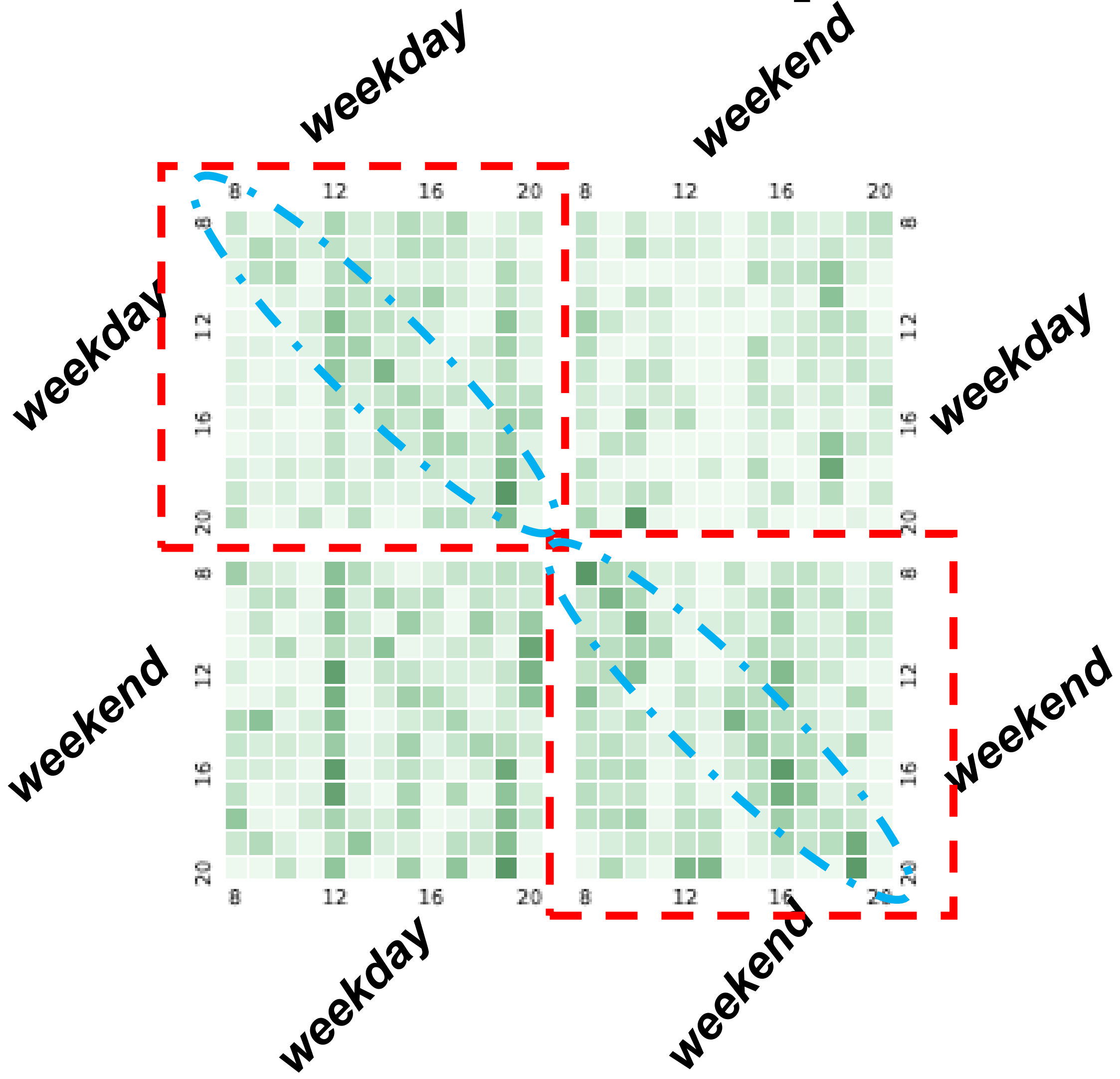

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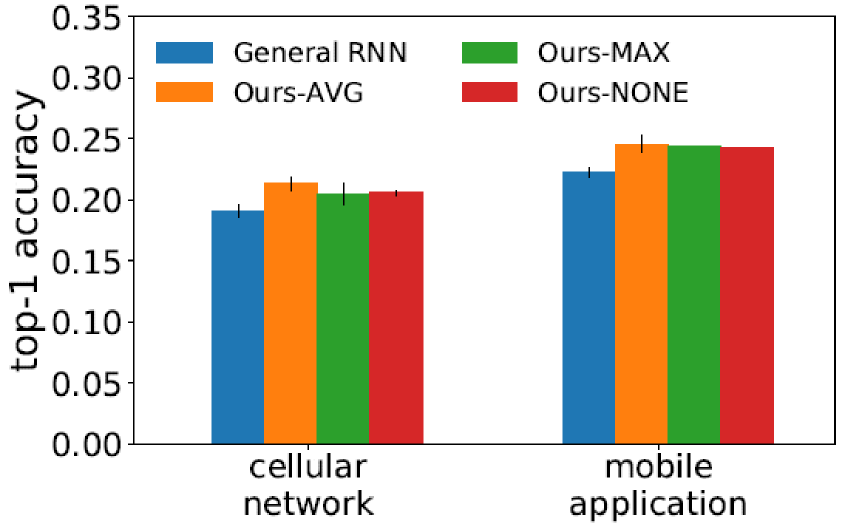
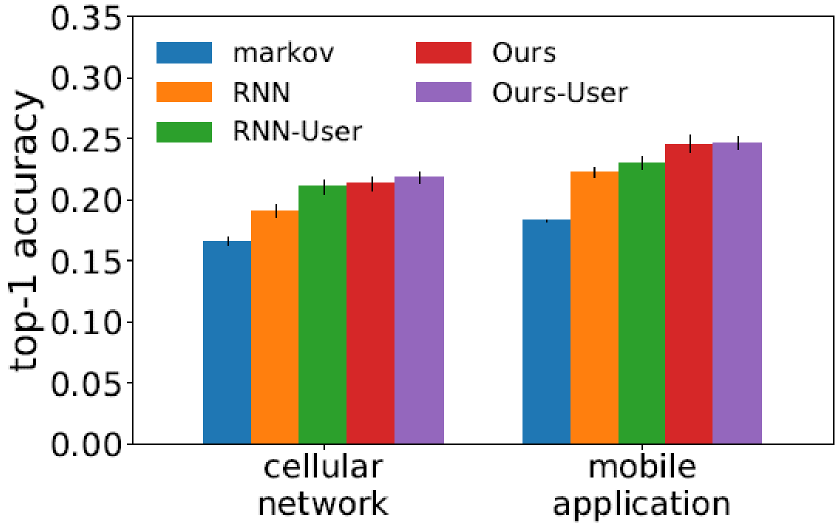
Model Variations



(a) sampling strategy



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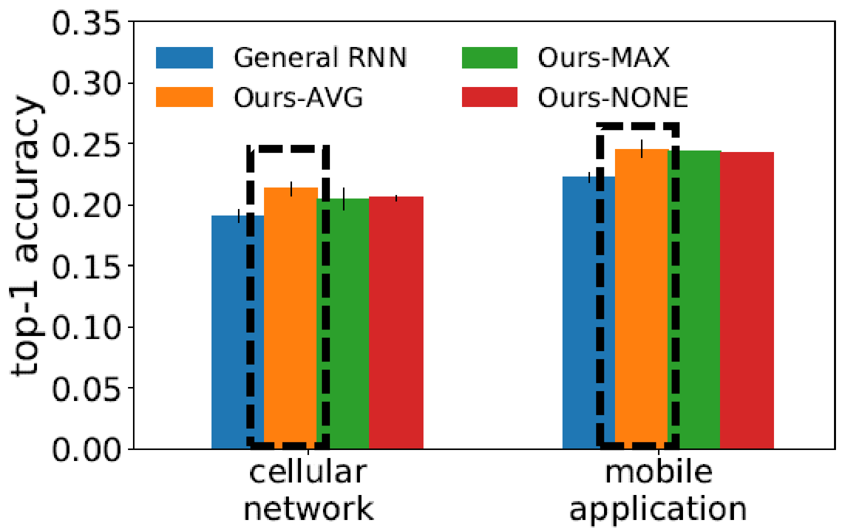

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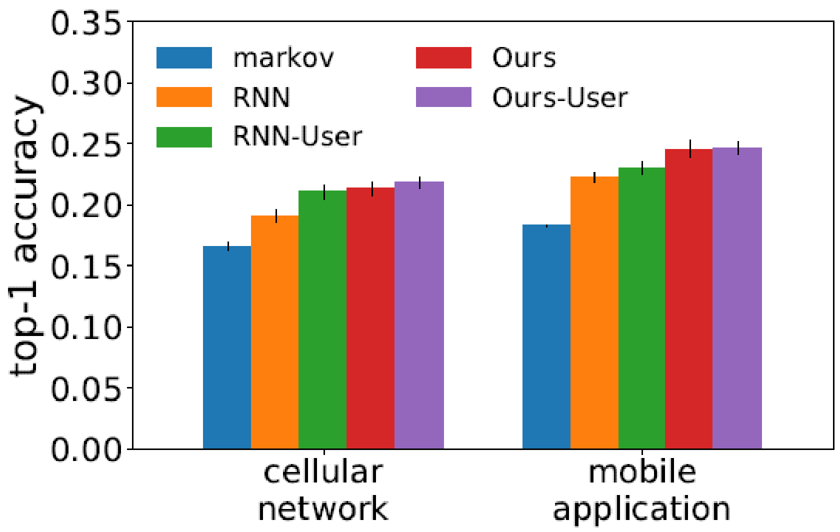

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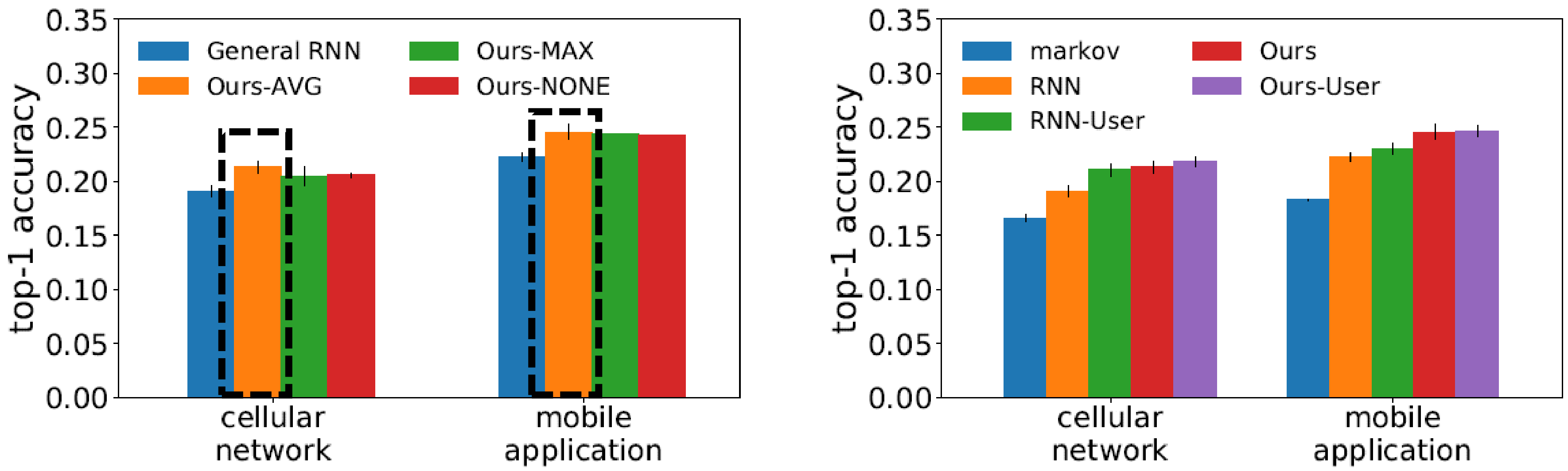

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The average sampling mechanism performs best.

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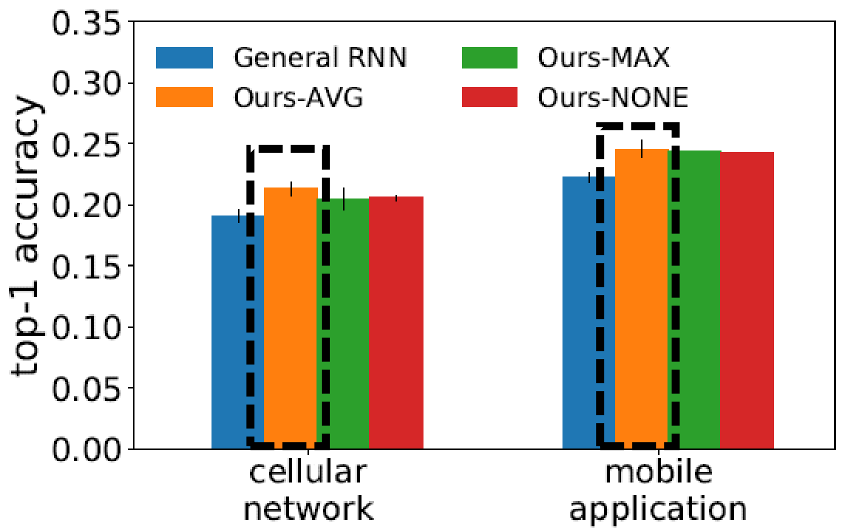

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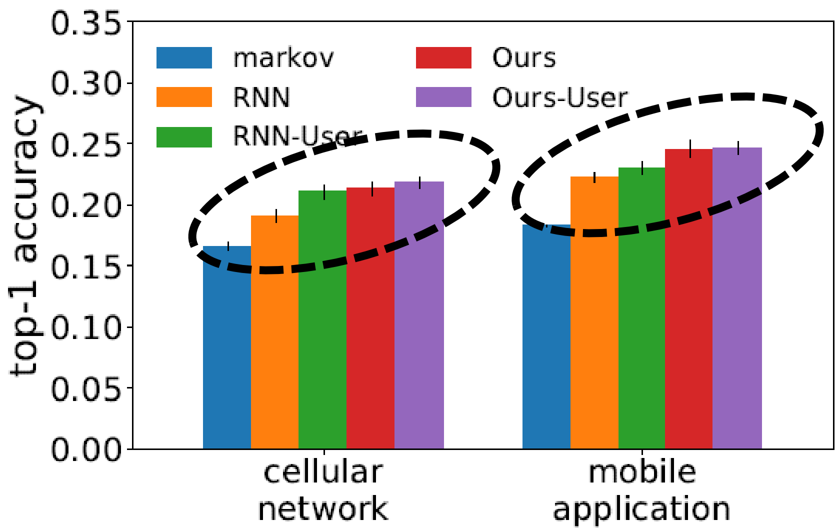

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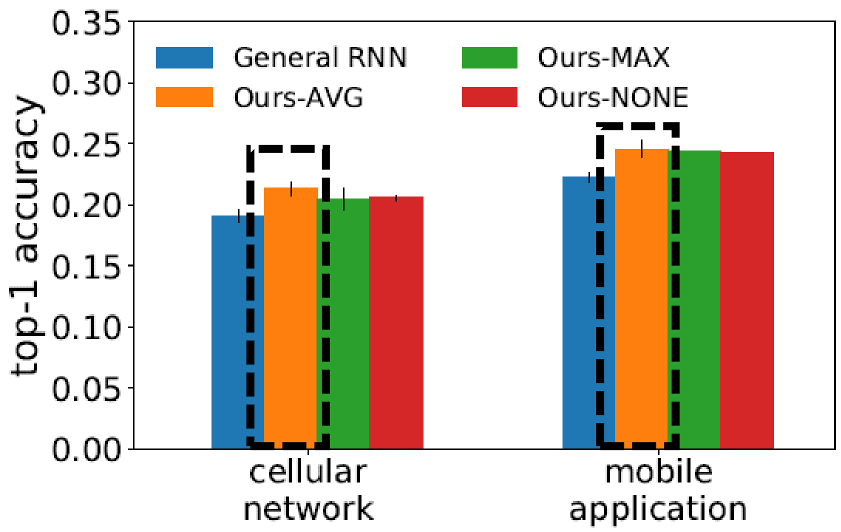

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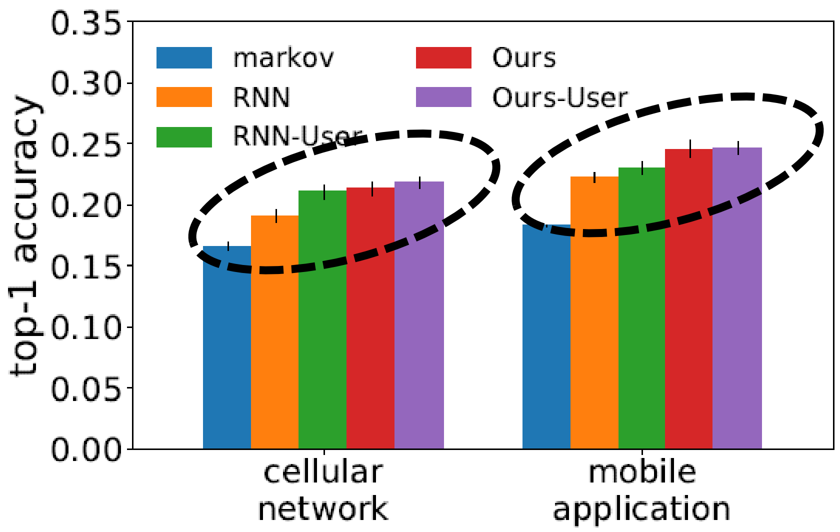

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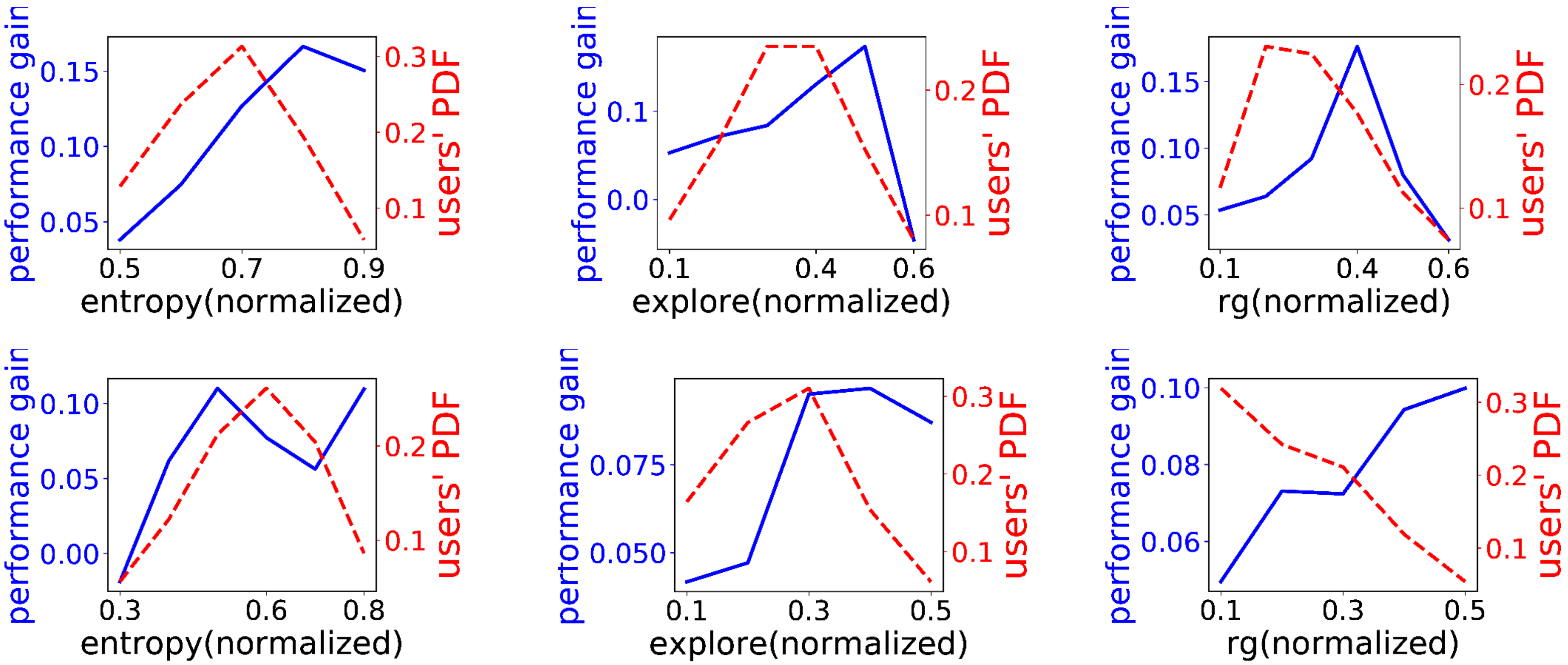
The historical trajectory can be useful to identify person.

Evaluation on User Groups



Cellular Network

Mobile Application

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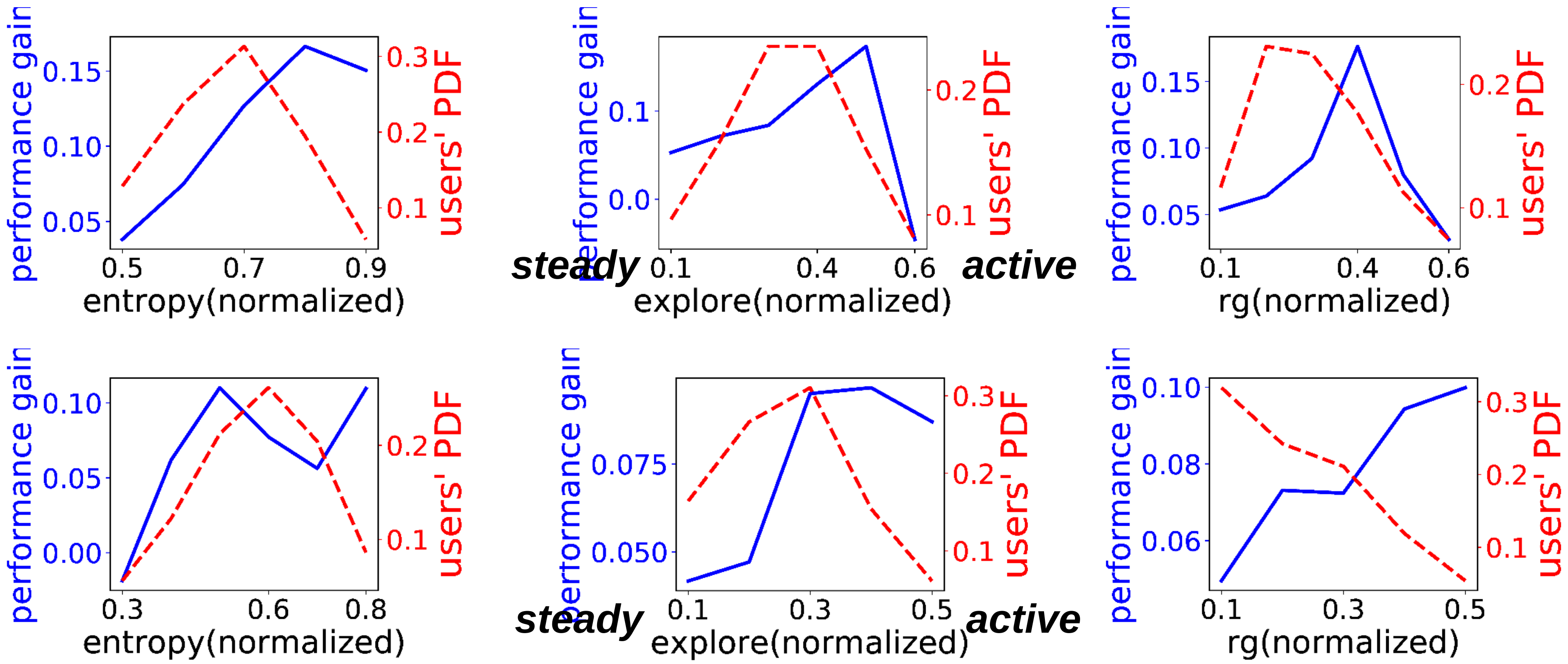

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horizontal-axis: bigger entropy/explore/rg means more active.

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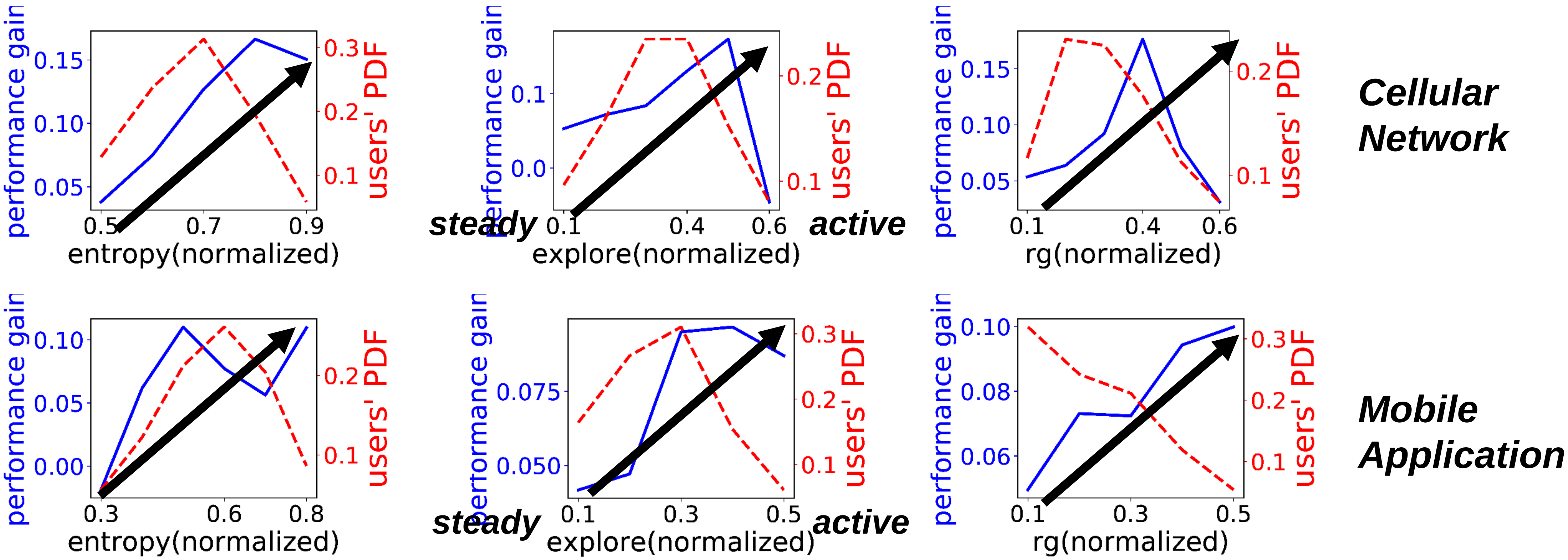

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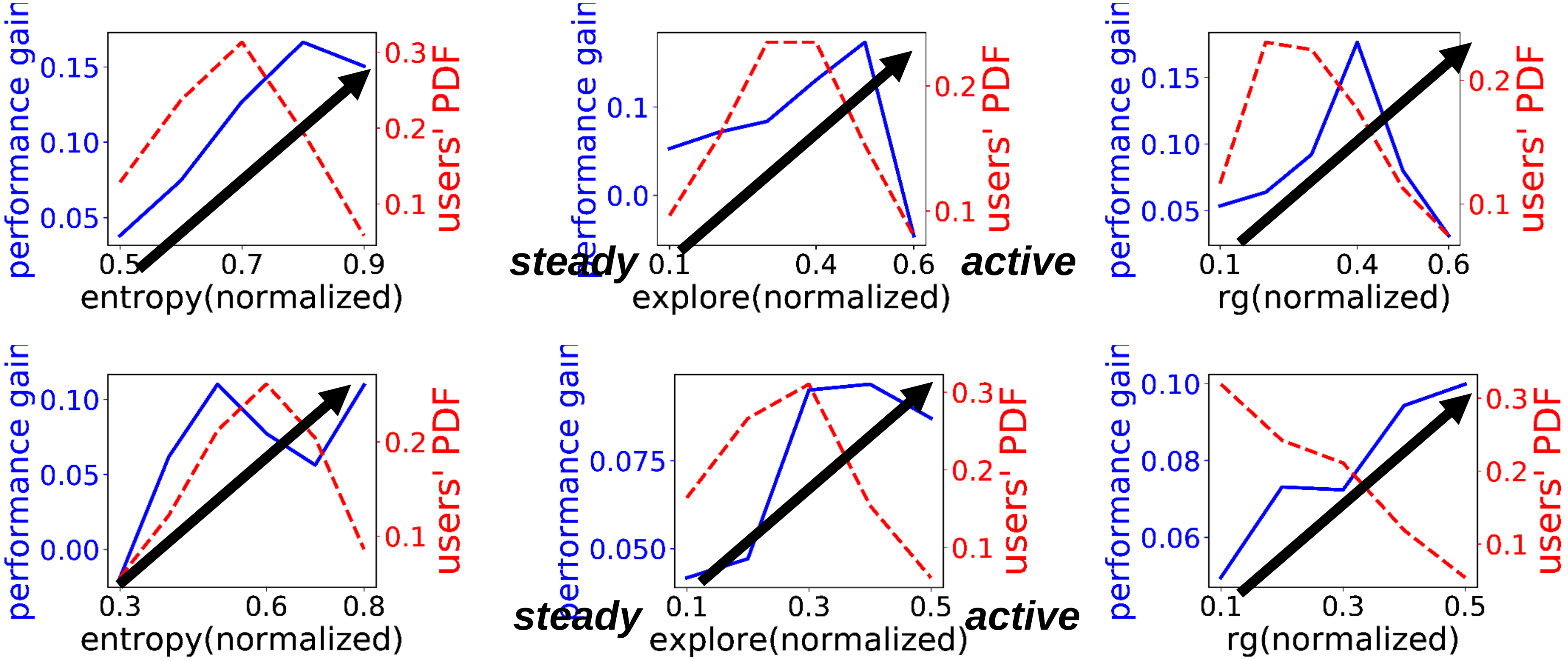

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Our model performs better for these active <u>moving</u> users.

Summary

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- ***Interesting future directions***

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- ***Interesting future directions***
  - *Considering **external information** like Point of Interest to enable semantic mobility prediction.*
  - *Accelerating the model training and improve the performance on **dense duplicate trajectory**.*

Thanks!

Jie Feng

[***feng-j16@mails.tsinghua.edu.cn***](mailto:feng-j16@mails.tsinghua.edu.cn)

In the near future, codes will be released in : https://github.com/vonfeng/DeepMove