北京大學
PEKING UNIVERSITY

acm SIGSPATIAL

Multi-perspective Spatiotemporal Context-aware Neural Networks for Human Mobility Prediction

Chenglong Wang[1] & Zhicheng Deng[1]
School of Urban Planning and Design,
Peking University Shenzhen Graduate School, Shenzhen, China

Speaker: Chenglong Wang

HuMob Challenge 2023

November 13 @ ACM SIGSPATIAL

Contents

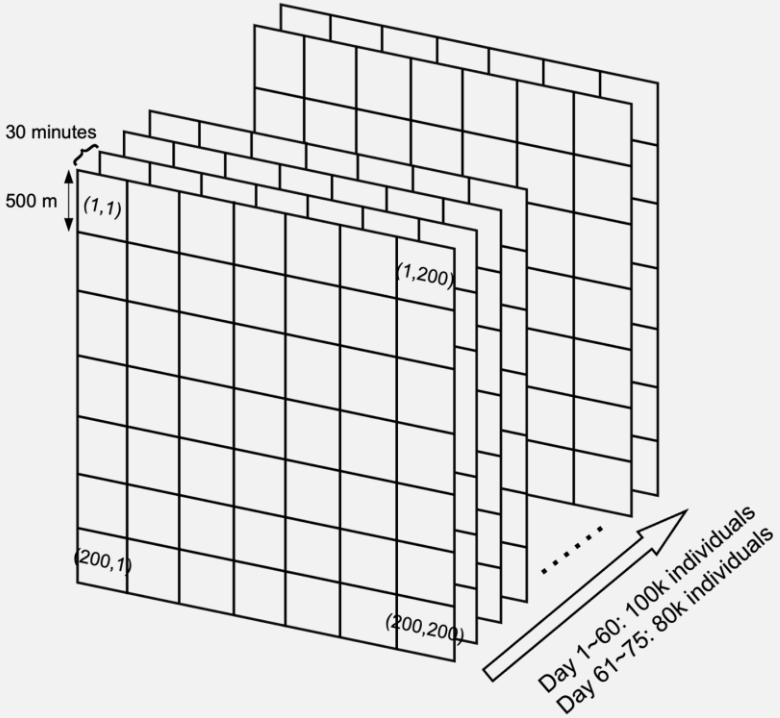
1

Problem Statements

2 Methodology

Data set

3 Experimental Results



HuMob data sets #1.

- Spatial resolution: 200×200 grids (500 ×500 meters).
- Temporal resolution: 30-minute intervals.
- Individuals: 80,000 – 75 days; 20,000 – 60 days.

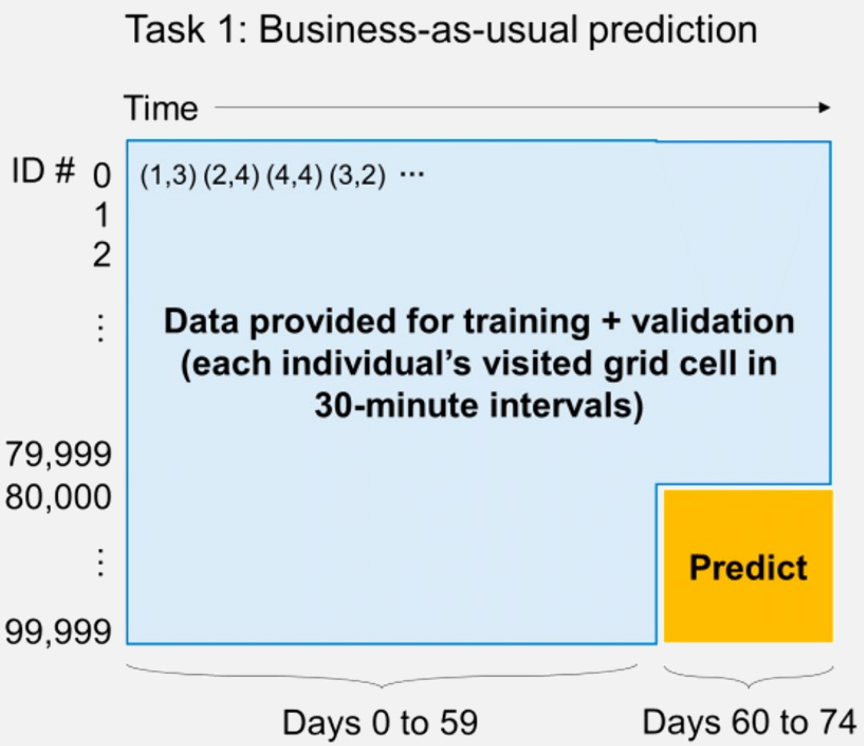
1

Problem Statements

2 Methodology

Challenges

3 Experimental Results



Task #1.

Given the provided data, Task 1 of the challenge is to predict the movement patterns of the individuals in the 20,000 individuals during days 60-74.

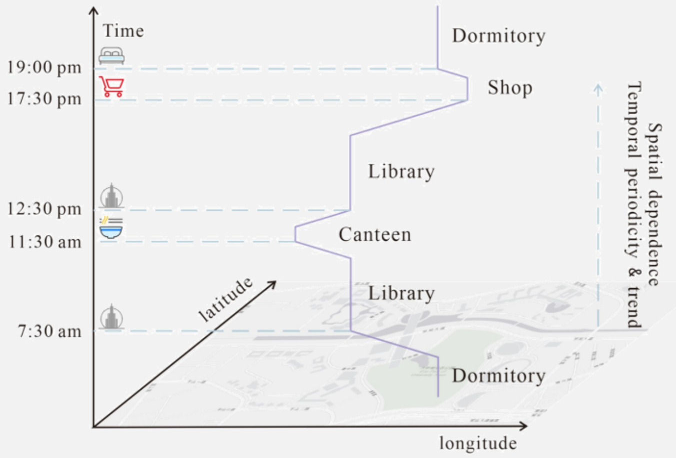
1

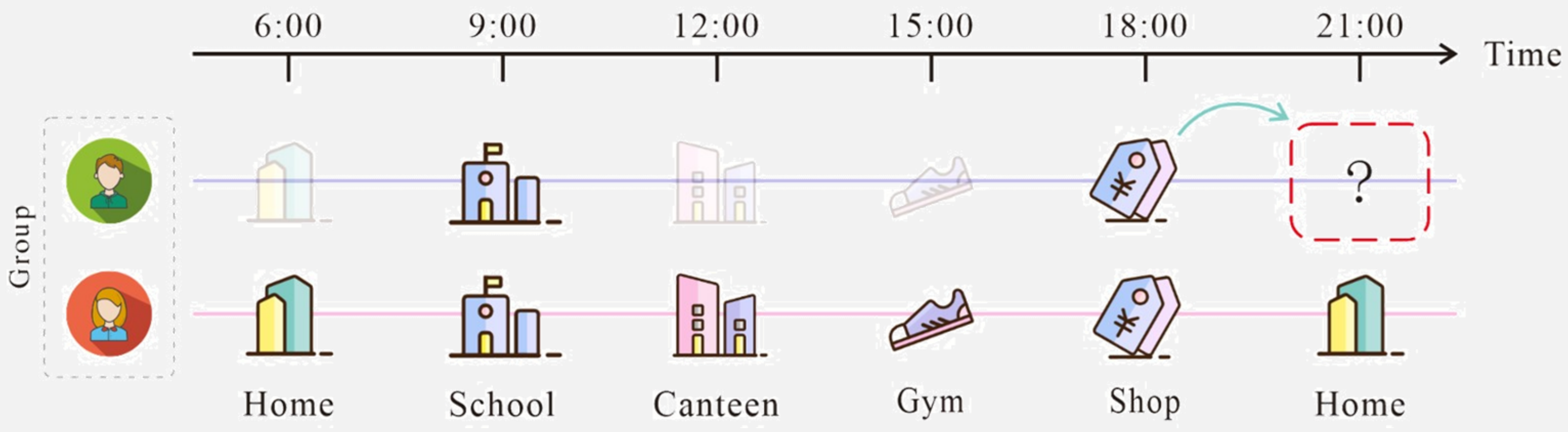
Problem Statements

2 Methodology

Key information

3 Experimental Results



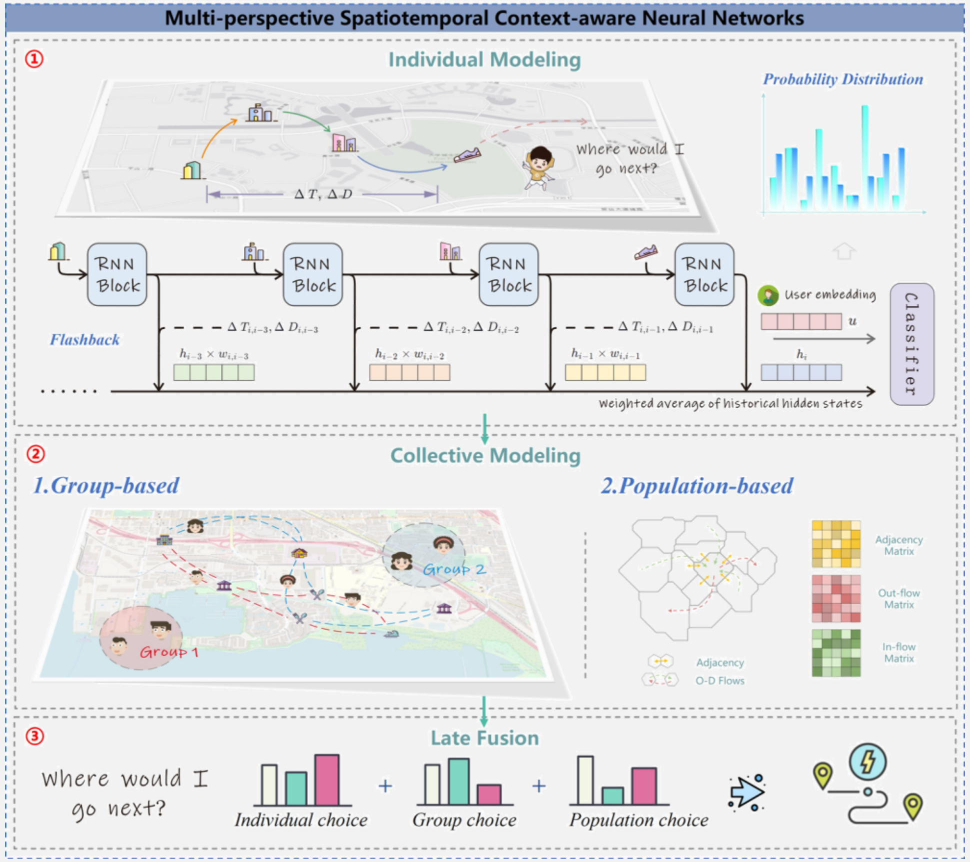


- **Temporal periodicity and trends:** human mobility posses a high degree of regularity and predictability.
- **Tendencies of similar groups:** people with similar characteristics make similar travel choices.

Our approach

- **Consideration of multiple perspectives:** The behaviors of individuals, groups, and the overall population are modeled and represented from macro, meso, and micro perspectives, respectively. Information fusion is achieved through late fusion, combining the representations.
- **Explicit spatiotemporal representation:** Spatiotemporal characteristics, such as temporal periodicity, trends, and spatial dependencies, are explicitly integrated when modeling individual trajectories.
- **Large-scale adaptability and competitive performance:** Competitive performance has been achieved on challenging large-scale human mobility data sets.

Pipeline



Multi-perspective Spatiotemporal Context-aware Neural Network (Our pipeline)

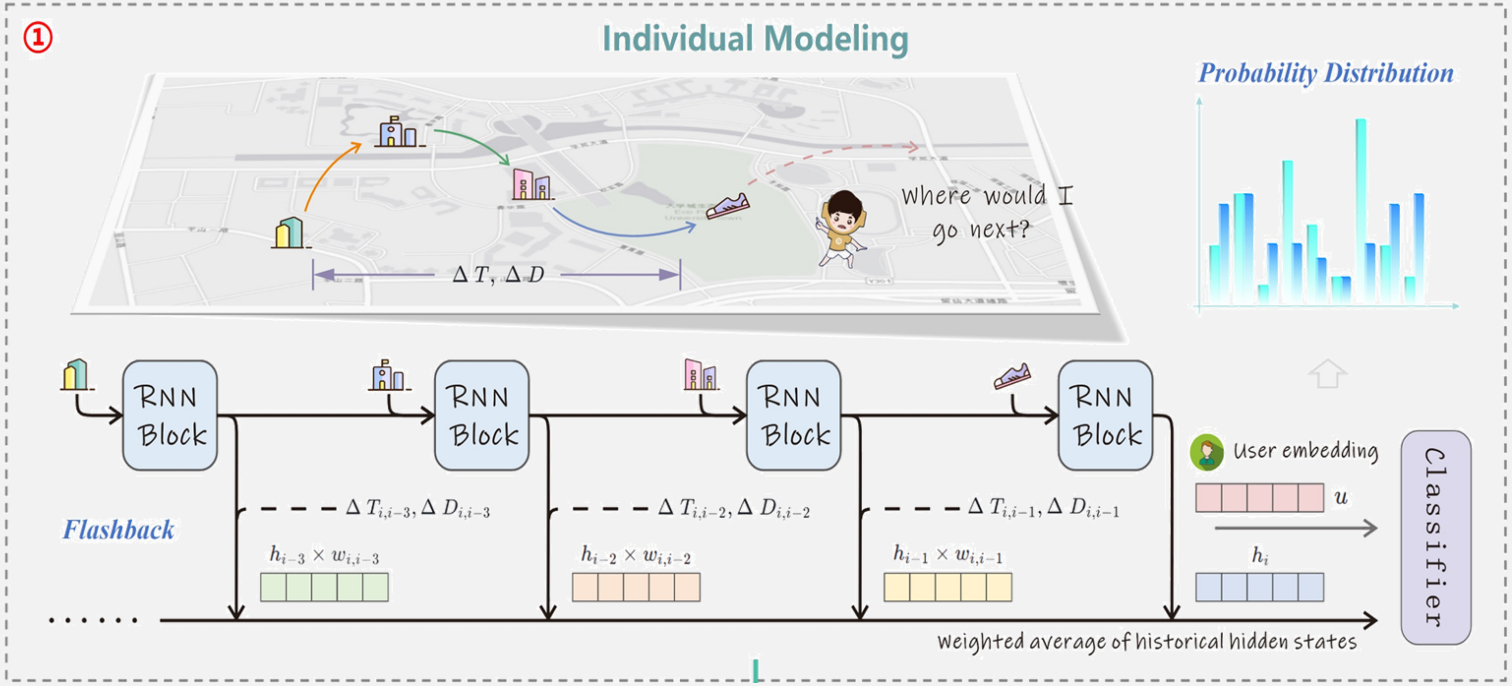
- Individual modeling: RNNs (Flashback) + spatiotemporal info.
- Collective modeling: group/population preference + auxiliary info.
- Late fusion: integrate individual and collective info.

2 Methodology

3 Experimental Results

1 Problem Statements

Individual modeling



[1] *Yang, D., Fankhauser, B., Rosso, P., & Cudre-Mauroux, P. (2020). Location prediction over sparse user mobility traces using rnns. In Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence (pp. 2184-2190).*

Spatialtemporally explicit modeling[1]

Assuming that the hidden states of user u_i before time α are $[h_{i,1},\ldots,h_{i,k},\ldots,h_{i,\alpha}]$, we weight and average them to obtain a comprehensive representationh_i:

$$h_i = \sum_{k=1}^{\alpha} w_{i,k} \cdot h_{i,k} / \sum_{k=1}^{\alpha} w_{i,k}$$

$$w_{i,k} = wt_{i,k} \cdot wd_{i,k}$$

$$wt_{i,k} = F_{daily}(\Delta T_{k,\alpha}) \cdot F_{weekly}(\Delta T_{k,\alpha}) \cdot e^{-\kappa \Delta T_{k,\alpha}}$$

$$wd_{t,k} = e^{-\eta \Delta D_{k,\alpha}}$$

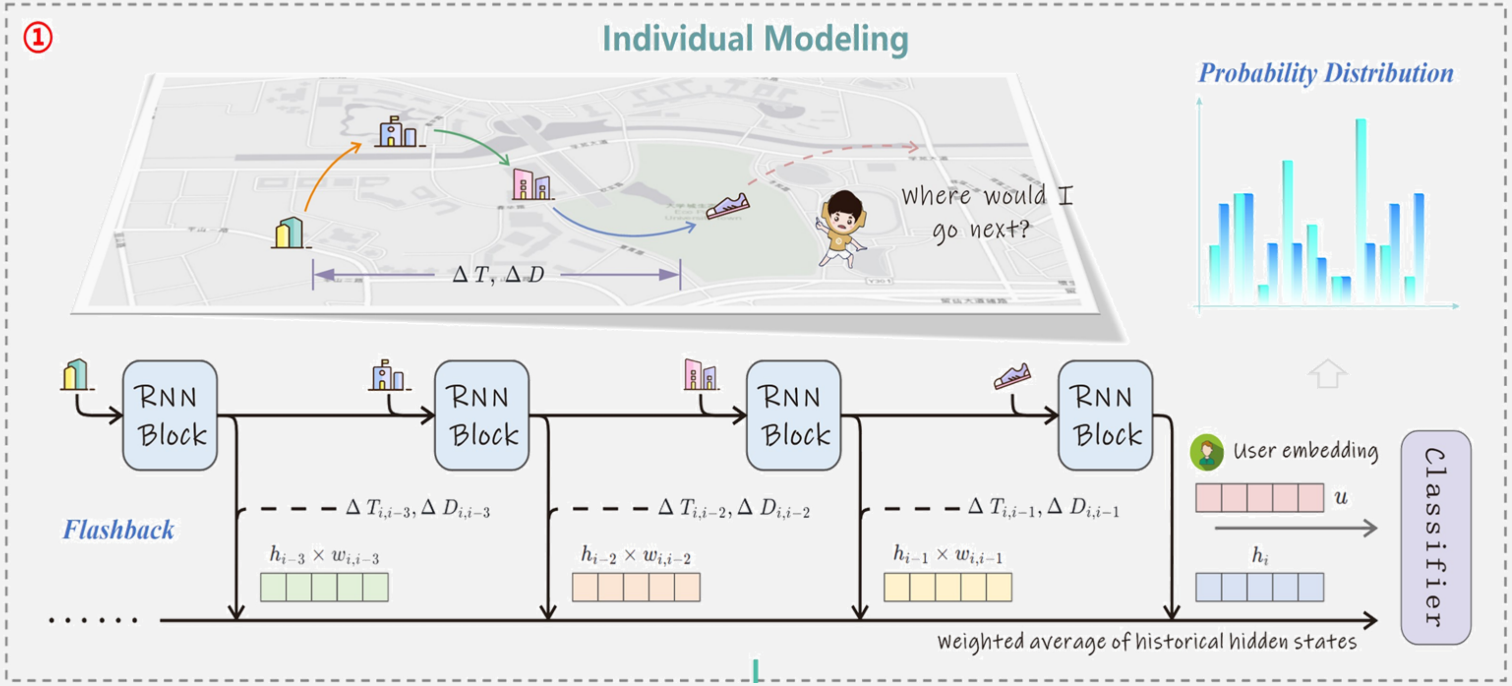
where ΔT, ΔD are calculated based on the temporal interval and Euclidean distance between trajectory points, and $Fdaily(\cdot)$, $Fweekly(\cdot)$ are hand-crafted functions that explicitly consider the temporal periodicity. κ, η are two hyperparameters that control the spatiotemporal decay rate.

2 **Methodology**

3 Experimental Results

1 Problem Statements

Individual modeling



User modeling

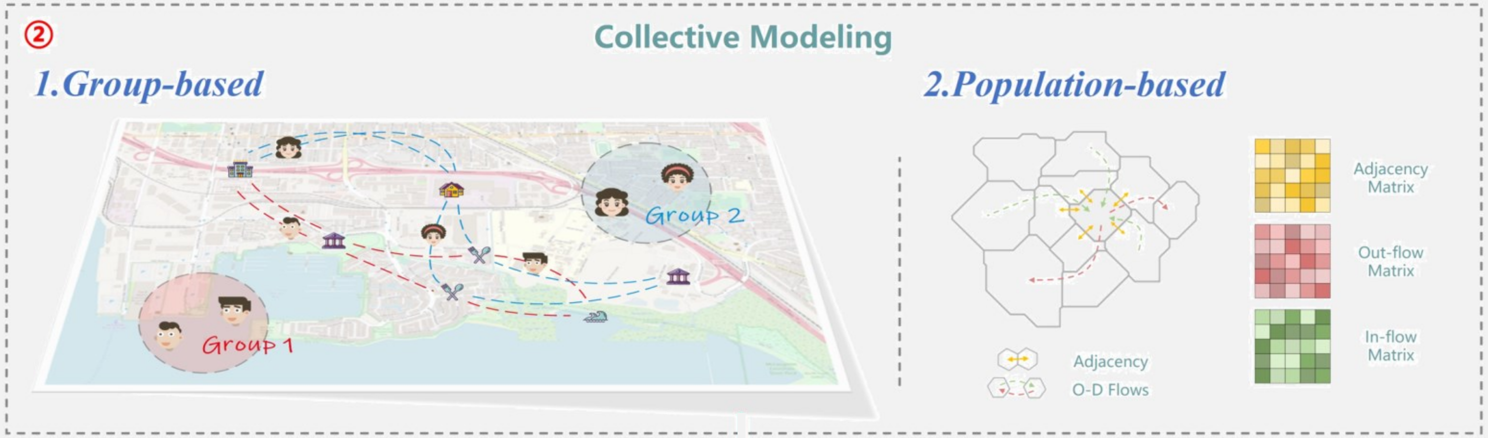
Users have their own travel preferences. To effectively model this property, we initialize a vector embedding s for each user, and the final representation of user u_i is:

$$v_i = h_i \oplus s_i$$

where $\oplus$ represents the vector concatenation.

[1] Yang, D., Fankhauser, B., Rosso, P., & Cudre-Mauroux, P. (2020). Location prediction over sparse user mobility traces using rnns. In Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence (pp. 2184-2190).

Collective modeling



Population modeling

At the collective level, human mobility forms a space of flow, which reflects the connections between spatial units. When user u_i is located in $p_{i,\alpha}$ at time $t_{i,\alpha}$ and its historical information is scarce, we can use the property of the flow space to assist in predicting the next location. That is, users tend to choose the next location closely connected to the current location:

$$p_{i,\alpha+1} = argmax(MT_{[t_{i,\alpha}, p_{i,\alpha}, :]})$$

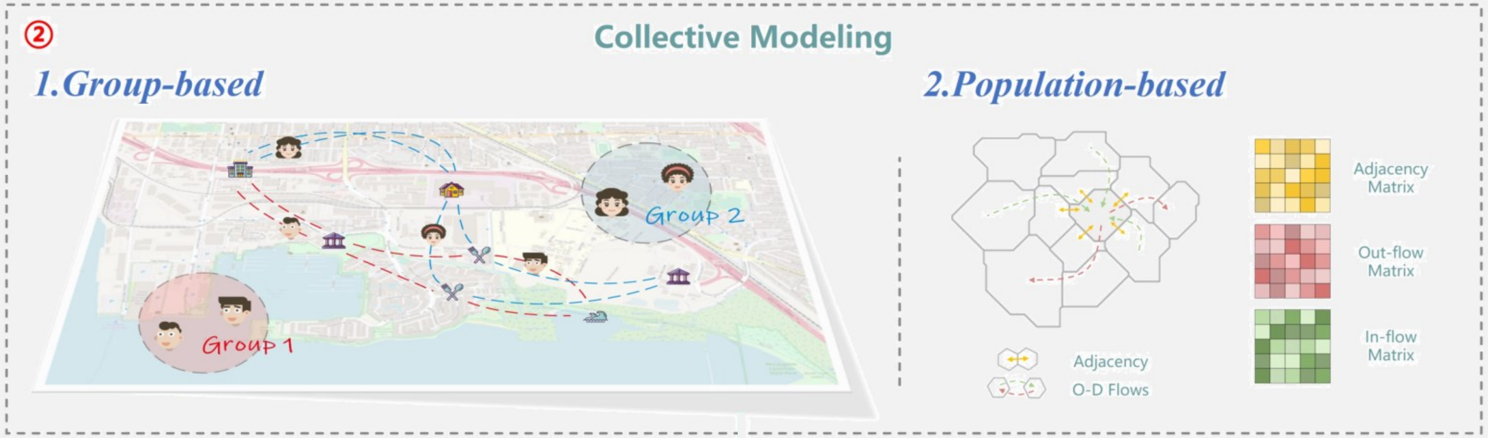
where MT is a three-dimensional tensor that records the flow between two spatial units at any time interval, and $argmax(\cdot)$ is a function that returns the index of the maximum element.

2 Methodology

3 Experimental Results

1 Problem Statements

Collective modeling



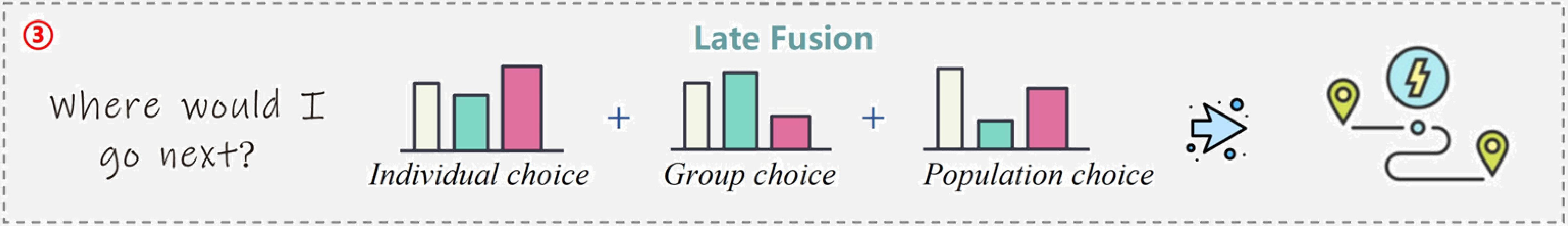
Group modeling

Furthermore, There are distinct groups within population, and as we know, male and female or the young and the old have complete different travel behaviors. Therefore, we take into account the group of users in the model. Specifically, we first use a similarity based trajectory clustering method to classify trajectories, then identify different groups of users, and calculate the connections between spatial units for different groups of users. The next location for user u_i belonging to a specific group $g_l \in G$ will be selected according to this formula:

$$p_{i,\alpha+1} = argmax(MG_{[g_l, t_{i,\alpha}, p_{i,\alpha}, :]})$$

where MG is a four-dimensional tensor that records the flow between two spatial units of any group at any time.

Late fusion



Late fusion

Finally, we integrate the information from individual and collective modeling to achieve prediction of human mobility:

$$p_{i,\alpha+1} = argmax(\theta_1 MT_{[t_{i,\alpha}, p_{i,\alpha}, :]} + \theta_2 MG_{[g_l, t_{i,\alpha}, p_{i,\alpha}, :]} + \theta_3 \sigma(v_i))$$

where θ_1, θ_2, θ_3 are hyperparameters that control the relative contributions of 'individual-group-population', and σ represents a multilayer perceptron with a softmax function. We use cross-entropy as the loss function. Due to the complete differentiability of the entire process, we can achieve end-to-end training. For predicting multi-step spatial positions, we loop through the model in the form of autoregression.

3 Experimental Results

$$GEO-BLEU = BP * \exp(\sum_{n=1}^{N} w_n \log q_n)$$

$$DTW(X,Y) = min\{c_p(X,Y)\}$$

GEOBLEU	DTW
0.2987	41.88

Metrics & Results.

DTW focuses on the similarity of sequences globally, while GEO-BLEU focuses more on local features.

Our model achieves competitive performance in predicting human mobility. We evaluate our methodology on the Task 1 validation data and obtain GEOBLEU at 0.2987 and DTW at 41.88.

北京大學
PEKING UNIVERSITY

acm SIGSPATIAL

Thank you for your Listening!

HuMob Challenge 2023

Presented by Chenglong Wang
SUPD-GeoAI Lab