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Mixing Individual and Collective Behaviours in Mobility Models

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Extended Abstract

Understanding human mobility and performing next-location prediction at the individual level is a challenging task [1, 3], which is critical for numerous research and practical applications, such as urban planning, public health and sociology. Knowledge of individual mobility patterns enables the development of effective policies that meet the needs of individuals and communities.

Recent studies suggest that the predictability of individual-level human mobility is limited by some intrinsic properties of mobility datasets. For example, the visitation frequency to places (e.g., points of interest) follows a long-tail distribution. Thus, if we aim to predict the next destination an individual will visit, a model will often see a limited number of frequently visited locations during the training phase while many other potential destinations may not be represented. This leads to a core problem in the prediction of locations not seen in training, defined as novel mobility prediction, a challenge where even state of the art deep recurrent models fail.

Inspired by the literature on the interplay between individual and collective decisions of intelligent systems, we design a model that leverages collective mobility decision dynamically to generalize mobility prediction for out-of-routine mobility traces. In our work we propose to support next-location predictors via collective origin-destination matrices [2]. We study minimal Markov models and exploit the physics-grounded definition of entropy as an effective definition of an individual's unpredictability seen in training.

Specifically, given a user u and its current trajectory point i, we retrieve its individual (IND) probability distribution T_{ij}^{IND-u} over all the possible target locations $\{L\}$. We then quantify the amount of uncertainty by measuring its Shannon's entropy:

$$\alpha_i^{IND-u} = \frac{1}{H_{max}} \sum_{j \in \{L\}} T_{ij}^{IND-u} \cdot log(T_{ij}^{IND-u}). \tag{1}$$

Where the normalizing factor H_{max}, defined as the maximum entropy over the set of possible destinations, allows α_i^{IND-u} to be understood as a compression rate. This allows us to bias the individual Markov model with the collective transition probability in an effectively parameter-free model that only requires the knowledge of inherent physical property of human trajectories (see Fig. 1). α_i^{IND-u} encodes how much collective (COL) behaviors should impact the prediction of the next location: this complex interplay is then encoded in the Markov-Chain (MC) transition matrix

$$MC_i^{IC-u} = MC_i^{IND-u} \cdot (1-\alpha_i^u) + MC_i^{COL} \cdot \alpha_i^u, \tag{2}$$

where IC stays for "Individual-Collective". We demonstrate the effectiveness of our approach by using a large-scale dataset that contains trajectories of more than 2 million users collected over nine months in 2020 in New York City, Seattle and Boston, provided by Cuebiq. We build collective and individual transition matrices from this dataset and use them to perform next-location prediction via our entropy-based model.

Our results show that our approach improves the accuracy of next-location prediction compared to existing state-of-the-art methods (see Fig. 2). The model biases the prediction probability when the unpredictability of movement is high or the model lacks information about individual mobility because it didn't see it during the training. Moreover, we also exploit this minimal entropy-based model to shed light on features of human individual mobility linked to the urban environment: specific urban areas are characterized by larger movement entropy and benefit more from the collective dynamics information. Furthermore, we investigate the changes in human mobility behavior and routines during the COVID-19 pandemic by analyzing the entropy and predictability of individual mobility trajectories.

Our approach not only improves the accuracy of next-location prediction, but also generalizes to the concepts of exploration of urban scenarios and sheds light inner properties of the mobility trajectories of the urban environments in areas characterized by high densities of POIs. Furthermore, the simplicity of our model allows it to be integrated into more complex mobility models by means of additional layers, to integrate collective mobility information.

The combination of collective origin-destination matrices and entropy-based models provides a powerful tool for predicting human mobility and exploring the dynamics of complex systems. We believe that this approach has the potential to open up new avenues of research in the field of computational social science and complex systems, and provide valuable insights into the behavior of individuals and communities in urban environments.

References

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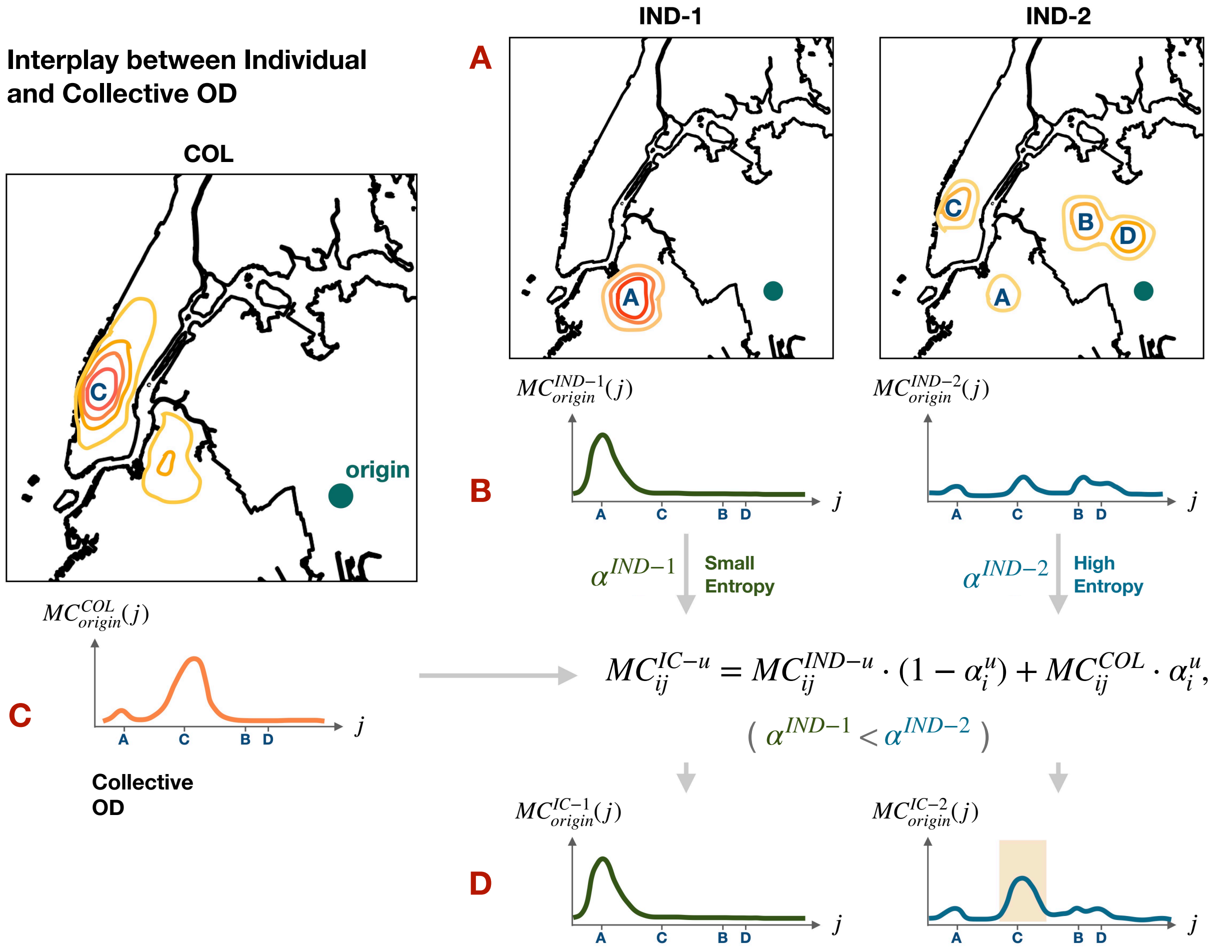

Figure 1: **Graphical depiction of the interplay between Individual and Collective Mobility:** **(A)** individual transition probabilities MC^{IND-u} are shown in the urban space: color intensity maps the probability of moving to one of four possible target locations form a given sample origin (green). Two exemplary individuals (1 and 2) are characterized by different distributions, **(B)** Individual 1's transition probability peaks in location A, this resulting in a small entropy. While user 2's transition probabilities are more uniform across possible targets (IND-2), thus having larger entropy and larger unpredictability. Collective flows MC^{COL} information **(C)** is integrated in the prediction via α^u_i, resulting in the MC^{IC} probabilities **(D)** where the collective biasing for IND-2 is larger due to its higher origin entropy, and a bias towards destination C appears in the distribution.

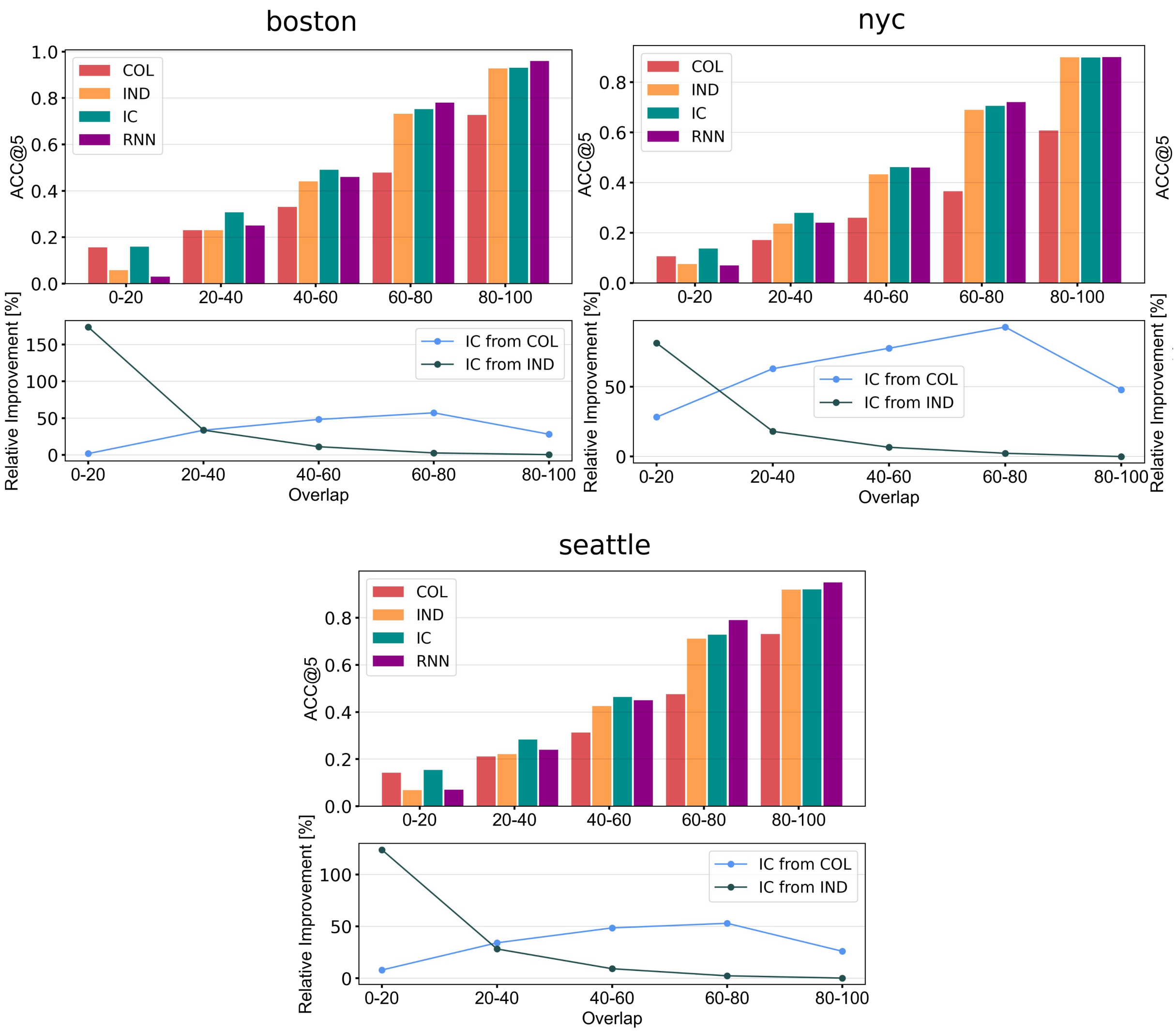

Figure 2: **Accuracies in having the correct destination in the top 5 predicted locations with highest confidence (ACC@5):** Individual, Collective and IC Markov-based models are compared to predictions from R-NN deep models for NYC, Boston and Seattle in the pre-covid period. Models are tested in different scenarios for novel mobility seen during the prediction phase (quantified via the longest common subsequence (LCSS) overlaps between training and test sets). The Individual-Collective model shows a relative improvement in accuracy, with respect to the individual Markov model, up to 150 % in the case of small overlaps (test trajectories characterized by mostly novel transitions not seen in training), where the collective behavior's information aids the predictive capabilities.