indicators such as *displacement distribution* and *gyration radius distribution* measuring how far individuals typically move based on geo-located tweets. Similarly, the authors in [18] proposed a network of places built upon Foursquare's venues and model human mobility by considering temporal and network dynamics inferred from user's check-ins. Gabrielli et al. [6] proposed a technique to analyze human trajectories of residents and tourists by semantically labeling source and destination spots. Based on time-evolving networks, the work in [7] identifies and ranks collective features for epidemic spread, by tracking human movements with wearable sensors.

Activity-based human behavior. Some previous works have identified and explained periodical movement-based patterns by activity-based human behavior. In [29], the authors proposed a model representing transition probabilities of travel demands during a time interval and suggested that travel demands can be associated with fixed locations under some circumstances. Jiang et al. [11] explained when, where and how individuals interact with places in metropolitan areas based on activity survey data in Chicago. The work shows daily patterns as eigenvectors and employs K-means clustering to identify groups of individuals based on their daily activities on weekdays and weekends. From taxi trips in Shanghai, the work in [20] shows how to detect basis patterns for collective traffic flow and correlates them with trip categories and temporal activities such as commuting to/from work in the mornings and evenings. Linear combinations are used to describe macro patterns and non-negative matrix factorization for detecting how many different patterns exist in a day.

Differentiation of our work. The novelty of our approach relies on: (1) a multidimensional pattern recognition process using NTF [4] to identify different mobility behaviors in taxi data, (2) the expansion of activity-based human mobility behavior into a hypothesis-based schema built upon human beliefs and (3) quantifying the plausibility of beliefs for mobility behavior using HypTrails [23].

8. CONCLUSIONS

In this paper, we have presented an innovative approach for discovering and characterizing patterns in human mobility behavior. It (i) clusters transition data using non-negative tensor factorization (NTF) and (ii) characterizes these clusters using the Bayesian HypTrails method. Our experiments on taxi data from Manhattan identified several patterns of human mobility and characterized them using Foursquare and census data. As one example, we discovered a group of taxi rides that end at locations with a high density of party venues on weekend nights. The strength of this approach relies on the fact that the interpretation of the clustering results can be easily characterized with high level hypotheses using HypTrails.

Our work extends recent research concerned with a better understanding of human mobility. We have demonstrated that human mobility is not one-dimensional but rather contains different facets including (but not limited to) time and space. Future research can benefit from our methodological and experimental concepts presented in this work. A more fine-grained view on human mobility can also facilitate e.g., city planners, traffic control and location-based recommender systems. In the future, we aim to generalize our findings by studying similar data (e.g., bike trips or geo-tagged tweets) available for New York and other cities. In doing so, we could not only unveil novel general patterns of mobility, but also discover similarities and differences between cities.

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