

Linking Network Topology and Mobility Function: Toward Transferable Mobility Agents Across Cities

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1 Introduction

Urban mobility arises from the interplay between the structure of transport networks and the behavioral dynamics of their users [1,3]. Understanding this relationship is key to developing realistic and transferable models of movement. This work proposes a network-based framework that links the topology of a city’s road network with the functional patterns of real taxi flows. Using New York City as a case study [4], we examine how network geometry, travel times, and clusters structure shape observed mobility, and how these insights can inform the design of topology-aware agent-based models. Such agents are essential for studying alternative mobility scenarios [6], such as car-sharing [2] or demand-responsive transport, in cities where empirical trip data are limited or unavailable.

2 Approach

The New York City road network is modeled as a weighted directed graph, where edge weights represent travel times. A random walk on this graph provides a structural baseline of accessibility through its stationary distribution π , which represents the long-term probability of reaching each node when movement depends solely on network connectivity and travel-time weights. Figure 1a shows the road network colored by node visitation probabilities for both the stationary distribution and real taxi data, together with their probability distributions. This comparison captures how taxis use the network in practice, highlighting the influence of external functional factors such as public transport coverage.

To quantify differences between theoretical and empirical usage, we compute the Jensen–Shannon divergence between their node probability distributions [5]. We then compare the real taxi data to several source–target $s - t$ simulation models (activity, gravity, hub, random, and zone). Figure 1b illustrates the mismatch between the empirical and simulated visitation probabilities, showing that standard models reproduce the overall structure of flows but fail to align with the true spatial distribution of demand.

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To analyze these discrepancies at a coarser scale, we cluster trip origins and destinations separately using the K-Means ($k = 30$) algorithm on the weighted network. The resulting origin and destination clusters for both real and simulated trips are shown in Figure 2. Finally, we construct a cluster-to-cluster flow matrix representing the probability of trips connecting each origin cluster to each destination cluster (Fig. 3).

3 Discussion

Figure 1a reveals that while the stationary distribution concentrates visits on central nodes, reflecting structural accessibility, real taxi flows are more evenly distributed across the city. This divergence highlights how taxi usage depends on additional functional factors, such as the presence or absence of public transport alternatives, rather than topology alone. More importantly, making these deviations explicit allows us to characterize how functional demand relates to network properties such as node centrality, degree, or cluster membership. Formalizing these relationships enables their transfer to other networks, providing a foundation for topology-aware mobility models in data-limited settings.

In Figure 1b, the comparison between taxi data and a representative $s - t$ model shows that, although the simulated visitation distribution is relatively flat and spread across the network, it emphasizes different areas than those observed in reality. The model does not reproduce the spatial organization of demand—central and peripheral zones are visited in proportions that differ from empirical patterns. These discrepancies indicate that current agent rules capture general movement dispersion but fail to encode how demand relates to specific structural features of the network, such as centrality, or local connectivity.

Cluster analysis (Fig. 2) highlights these differences at the mesoscale. In real taxi data, a few central clusters attract most destinations from various origins, forming clear demand hubs and structured inter-cluster corridors (Fig. 3a). In contrast, the simulated cluster-to-cluster heatmap (Fig. 3b) shows a more diffuse pattern with demand spread across many clusters and lacking dominant centers. This absence of concentration reveals that simulated agents miss the hierarchical organization of real mobility, reinforcing the need for topology-aware behavioral rules that condition agent choices on structural descriptors.

Overall, understanding how real taxi flows diverge from the structural baseline provides a concrete way to link network topology and functional demand. Quantifying these deviations defines how process and structure interact, offering direct guidance to bias and improve source–target models. Embedding such topology-informed rules into agents’ decision mechanisms could yield more realistic and transferable simulations. These simulations can support the design of data-efficient mobility systems and enable applications such as car-sharing, demand-responsive transport, and urban mobility policy planning.

Appendix

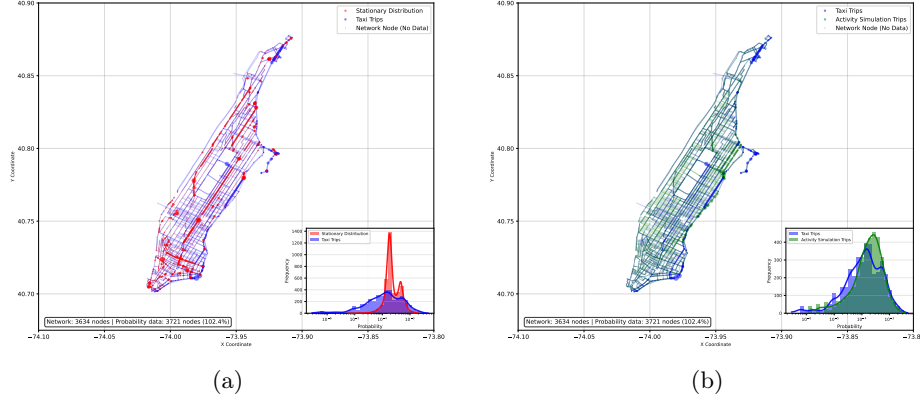


Fig. 1: Comparison of node visitation probabilities on the road network. (a) Stationary distribution (structural baseline) versus real taxi data, showing how functional use diverges from network accessibility. (b) Real taxi data versus the activity source–target model, highlighting how simulated demand differs in spatial emphasis and intensity.

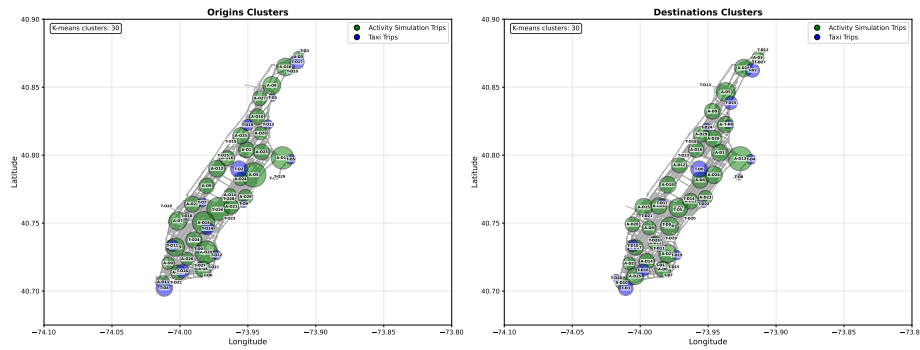


Fig. 2: Origin and destination clusters for real taxi trips and simulated trips using the activity source–target model, obtained through K-Means method.

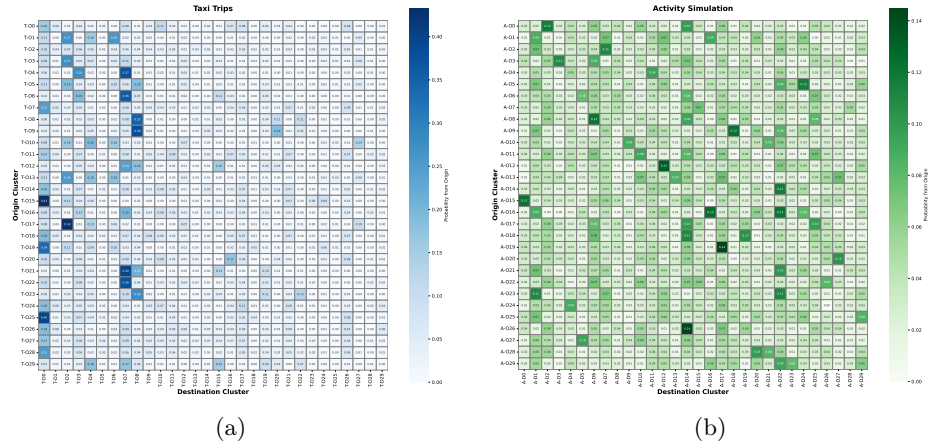


Fig. 3: Cluster-to-cluster flow matrices: (a) real taxi data and (b) activity source–target model, showing differences in inter- and intra-cluster flow intensity.

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