Decoding Urban Interest: The Roles of Purpose, Transportation and Spatial Scale in City Mobility

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1. INTRODUCTION

Understanding urban mobility is essential for better city design, yet traditional models often overlook why trips occur and how people travel. Using the high-resolution NetMob25 dataset, we show that decomposing trips by purpose and transport mode may reveal distinct, more explainable patterns of urban interest. Our models achieve strong explanatory power in some cases, e.g., explained deviance (D^2) ≈ 0.7 for purchase and walking, but struggle to explain trips in certain instances, such as purchase visits made with a Car. We also explore Interest Networks (iNETs) based on co-visitation patterns to model urban dynamics beyond individual locations. The iNETs reveal that shared interest between areas is predictable for some purposes, like leisure, but not for others, such as work, highlighting how particular trip purposes shape collective mobility. This effect weakens at finer spatial scales (IRIS), where even our best-performing variables lose contrast, underscoring the need for more granular (e.g, communes) and context-aware descriptors.

2. DATA

We study data from the NetMob25 dataset. It captures a week of detailed mobility from over 3,300 Île-de-France residents using high-frequency GPS devices and validated travel diaries with the observation weeks drawn between Oct 2022 and May 2023. Each of 80,000+ trips is annotated with purpose and main transport modes. Structured across individual profiles, trip records, and raw trajectories, the dataset includes calibrated weights to support population-level analysis by correcting for sociodemographic and temporal sampling biases. We apply these weights in the visit counts and co-visitation analyses.

At the commune scale, we examine every municipality in Île-de-France, including the Paris *arrondissements*. From the official French data portal[1], we get key socioeconomic indicators: population, number of families, median disposable income, share of bachelor holders, social disadvantage index, and employment rate. For the IRIS scale (areas around 2000 residents), we get population data through the INSEE [2] platform. For both the commune and IRIS scale, Overture Maps[3] venues enrich the context; applying Scenes Theory[1], we average culturally weighted venue categories to derive 15 cultural dimensions for each commune and IRIS (see [2] for methodological details). Finally, OpenStreetMap road data, extracted via pyrosm, yield driving road intersection density (nodes with degree ≥ 3), completing our multidimensional dataset.

3. METHODOLOGY

We adopt a two-phase approach to model interest in urban areas: Phase i) to study the relationship between area features and the interest, and Phase ii) to study the co-visitation pattern between areas. We define the interest score for a region r (commune or IRIS) as $I_r = \text{round}\left(\sum_{u \in U_r} w_u\right)$, where U_r is the set of visitors to r, and $w_u \in \Re$ is the population weight of visitor u. We exclude visit frequency, aiming to capture the breadth of interest and to avoid skew from high-frequency visitors. Additionally, visits are labeled by trip purpose and main transport mode (for example, work trips made by car, or all leisure trips, regardless of mode). This allows us to identify whether a region functions primarily as a leisure destination, a work hub, or is preferentially accessed via specific modes of transport.

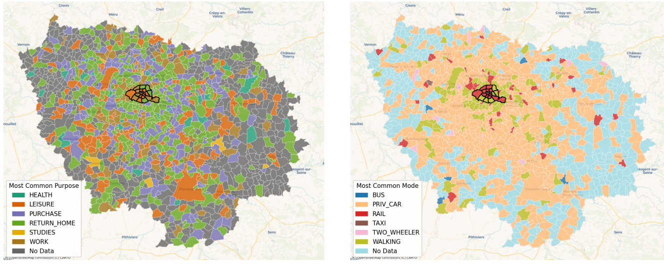
In phase i), interest scores are modeled using a Generalized Linear Model (GLM) with a Poisson distribution to obtain interpretable and comparable coefficients. Other distributions, including Negative Binomial, are explored, but the Poisson specification provides higher explained deviance (D^2) and shows no significant overdispersion. Model performance is assessed through random 5-fold cross-validation, while accounting for potential spatial autocorrelation. All available features described in Sec. 2 are initially considered; however, due to multicollinearity (high VIF), only four predictors with VIF $\lesssim 5$ are retained: population (available at both commune and IRIS levels), total venues, driving-intersection density, and the composite "Theatricality" cultural score. Theatricality represents the magnitude of a vector composed of the cultural dimensions Glamour, Neighborliness, Transgression, Formality, and Exhibitionism, and reflects how a place presents itself—higher values typically occur in areas rich in landmarks, galleries, and entertainment venues.

While in the first phase, the proposed approach examines interest within areas, in Phase ii), it captures relationships between areas via shared visitors. This is helpful, for example, in guiding urban planners to promote more connections between regions of a city. To model this shared interest, we construct the iNETs: weighted undirected graphs where nodes represent regions (commune or IRIS), and edge weights are given by $w_{ij} = \text{round}\left(\sum_{u \in U_{ij}} w_u\right)$, with U_{ij} as the set of users who visited both i and j. Again, we use a Generalized Linear Model (GLM) with a Poisson distribution and a random 5-fold cross-validation. From the full set of candidate predictors, those with acceptable multicollinearity (VIF $\lesssim 5$) are retained: geographic distance between centroids, Euclidean distance of cultural vectors, cosine similarity of venue frequency distributions, and absolute differences in population and income (only population at IRIS-level, due to data availability). We also include average values of population, income, venues, and road density across the region pair as predictors. All predictors are z-scaled after aggregation or distance computation.

4. RESULTS AND DISCUSSION

To better contextualize the studied area (Ilê-de-France), we map dominant visit purposes (Fig. 1a). Paris (black borders) splits into leisure-focused arrondissements with tourist landmarks, work-oriented zones, and some residential areas. In terms of

[1] https://www.data.gouv.fr/
[2] https://www.insee.fr/
[3] https://overturemaps.org/



(a) Dominant visit purposes **(b)** Dominant visit transportation

Fig. 1. Analysis of visit patterns

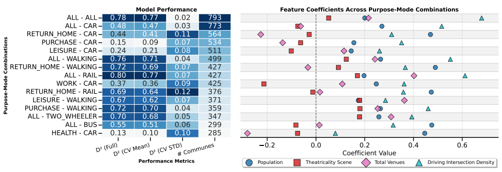


Fig. 2. Visitation GLM model performance and coefficients

transport (Fig.1b), Car dominates most of Île-de-France, while Paris relies mainly on rail and walking.

In Phase i), we apply the GLM to the commune-visitation data and obtain the results shown in Fig. 2. It reports the model's deviance-explained score (D^2 in the left) and the estimated coefficients (right) for each Purpose + Transportation combination, considering the 15 cases with the largest data volume, ordered by the number of communes exhibiting that type of visit.

Interest is well explained when considering all visits (ALL-ALL, i.e., purpose and transport mode are unspecified, with $D^2 = 0.77 \pm 0.02$), with road density as the main predictor. Among transport modes, Rail stands out ($D^2 = 0.77 \pm 0.07$ without purpose filter), where total venue count plays a stronger role compared to unfiltered visits. Return Home visits are well-explained across modes, especially walking and Rail ($D^2 = 0.69 \pm 0.04$ and $D^2 = 0.64 \pm 0.12$, respectively), driven by population and road density. Leisure and Purchase trips show similar explainability, in walking, with total venues and Theatricality emerging as stronger predictors. However, model explainability drops sharply for trips made by Car, the region's dominant mode (Fig. 1b), and varies by purpose: while Return Home by car achieves moderate explainability ($D^2 = 0.41 \pm 0.11$), Purchase trips are poorly explained ($D^2 = 0.09 \pm 0.11$). This highlights how trip purposes influence the way less constrained travel models, such as cars, interact with the urban form.

At the IRIS scale, the GLM explains almost none of the variation in interest ($D^2 \leq 0.03$), regardless of purpose–mode combination. Only a few cases, such as ALL–ALL, ALL–CAR, and ALL–RAIL, reach modest values ($D^2 \sim 0.12$). This sharp drop in explainability suggests that visits to micro-zones (with about four IRIS per commune) are less influenced by the general area characteristics we analyzed. Predictors that help differentiate broader areas lose contrast at this finer resolution—for example, intersection density can separate urban cores from suburbs, but is nearly uniform across adjacent IRIS within the same neighborhood. Under this uniformity, current predictors likely fail to capture the localized and purpose-specific factors that shape interest. Incorporating finer-grained features, segmenting by demographic group, or focusing on specific regions (e.g., central Paris) may offer better explanatory power, due to localized patterns (e.g., high tourism).

In Phase ii) of our study, these insights help understand the results of shared interests modeling across the city. Using iNETs,

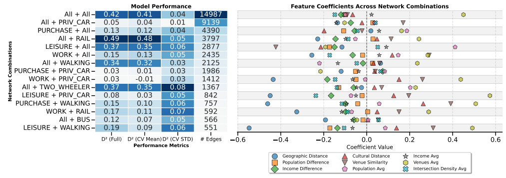


Fig. 3. iNETs GLM model performance and coefficients

we model networks of co-visitation where visits share the same purpose and transport mode. We then fit a separate GLM to each of these network combinations. The general iNET (ALL-ALL) has one of the strongest explainability ($D^2 = 0.41 \pm 0.04$, in Fig. 3, left), with shared interest between communes driven by proximity, venue density, and similarity in venue types (Fig. 3, right). A similar explainability holds for the Rail iNET, without considering purpose, and the Leisure iNET, without considering transport mode, where lower intersection density also plays a role. This is consistent with Fig. 1a, which highlights leisure visits to landmark-rich communes, such as those with castles or historical sites. In contrast, models for other purposes, such as Work, Purchase, and Health, explain little variation in shared interest. This divergence occurs because shared interest in leisure is likely driven by visitors seeking areas with comparable amenities and cultural scenes, whereas work co-visitation is tied to specific destinations, like two different office buildings, whose locations are uncorrelated by the analyzed area-level features.

In the IRIS iNETs, the GLM with area-level characteristics again fails to explain the interest ($D^2 \lesssim 0.03$). This occurs across all purpose–mode combinations, reinforcing earlier findings that the analyzed area-level features are insufficient at this finer scale.

5. CONCLUSION

Decomposing urban mobility by trip purpose and transport mode reveals behavioral nuances often missed in aggregated analysis. For communes, purchase/leisure - walking visits align well with area-level descriptors like venue density and cultural vibrancy; Return home and, separately, Rail trips align with population, while car-based and fine-scale patterns (e.g., IRIS level) are less predictable. Interest Networks (iNETs) further expose how trip purpose and transportation mode shape shared interest across regions, with leisure purpose and Rail transportation showing higher explainability than work or purchase-related visits with our current features. The understanding of how leisure areas are connected, for example, may guide urban planners in actions to promote more connections between different areas of the cities. Finally, these findings suggest that, because some cases show strong explanatory power while others do not, improving the spatial descriptors, by incorporating finer-grained data, spatial lag, demographic segmentation, land usage and studying temporal dynamics can deepen our understanding of urban interest across multiple scales and better capture the diversity of mobility behaviors.

6. ACKNOWLEDGEMENTS

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REFERENCES

1. D. A. Silver and T. N. Clark, *Scenescapes: How qualities of place shape social life* (The University of Chicago, 2016).
2. F. R. Gubert, G. H. Santos, M. Delgado, *et al.*, "Culture fingerprint: Identification of culturally similar urban areas using google places data," in *Proc. of ASONAM*, (Rende, Italy, 2025), pp. 286–297.