UNVEILING SOCIAL VIBRANCY IN URBAN SPACES WITH APP USAGE

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1 Introduction

Recent advances in digital data availability [1] and computational methods [3] offer unprecedented opportunities to analyse cities at higher frequencies [2]. This ability, coupled with a focus on granular data sets, has unveiled nuanced inequalities across space, time, and socio-demographics [4].

Our study delves into the realm of Urban Vibrancy, the liveliness and energy defining urban spaces [5, 6, 7]. Measuring urban vibrancy has become synonymous with analysing mobile phone data due to its integration into daily life [8]. Urban features, such as buildings, highways, and 'Points of Interest,' play a pivotal role in shaping urban activity [9, 6, 10]. Their density and diversity attract a varied populace, influencing social interactions [11].

Building upon the works of [6] and [10], which emphasized the significance of third places in urban vibrancy, we employ the NetMob23 dataset—a comprehensive source of spatiotemporal mobile service usage data [12]. Focusing on France's three largest cities—Paris, Marseille, and Lyon—we explore the intricate relationship between app usage across diverse categories, urban environments, and the demographic composition of city dwellers.

2 Methodology

We draw upon three primary data sources to conduct our analysis: **NetMob23 Data Set, IRIS2000, and *OpenStreetMap* Data**

1. Digital Signatures

To explore mobile application usage across urban areas and socio-demographic groups, we create digital signatures from NetMob23 mobile network traffic data. Key steps include:

•Aggregating data into 'Weekdays' and 'Weekends' to capture behavioural differences.

•Spatially aggregating data using areal interpolation to match the resolution n of IRIS2000 cells.

•Grouping 68 mobile services into categories based on the Apple Store classification.

•Investigating correlations between up-link and down-link for each app category.

2. Urban Features

•Utilizing OpenStreetMap data to construct urban features.

•Classifying 'Points of Interest' (POIs) based on their impact on segregation and a socially-focused system for 'third places.'

•Calculating urban feature density and diversity for both 'Points of Interest' and 'Third Places.'

3. Socioeconomic Indicators:

•Calculating total enrolment and total out-of-school indicators.

•Calculating the dependency ratio using IRIS2000 population-level data.

Statistical Approach

1. Clustering Approach

•Employing HDBSCAN clustering algorithm on NetMob23 data to recognize distinct clusters of app usage.

•Using the silhouette method for optimal cluster number determination.

2. Spatial Modelling Approach

•Employing spatial regression models (spatial lag and spatial error models) to understand the relationship between urban vibrancy, urban features, and socioeconomics.

•Conducting standardization of variables for comparability.

•Using Moran's I analysis to evaluate spatial dependence.

•Deriving *total effects* to interpret changes in predictor units considering spatial spillover effects.

•**Temporal and Spatial Comparisons:**

•Separating modelling by time periods (weekdays and weekends) and cities for a comprehensive understanding.

•These methodologies provide a robust foundation for exploring the nuanced dynamics of urban vibrancy, integrating digital signatures, socio-demographic indicators, and spatial features.

Figure 1

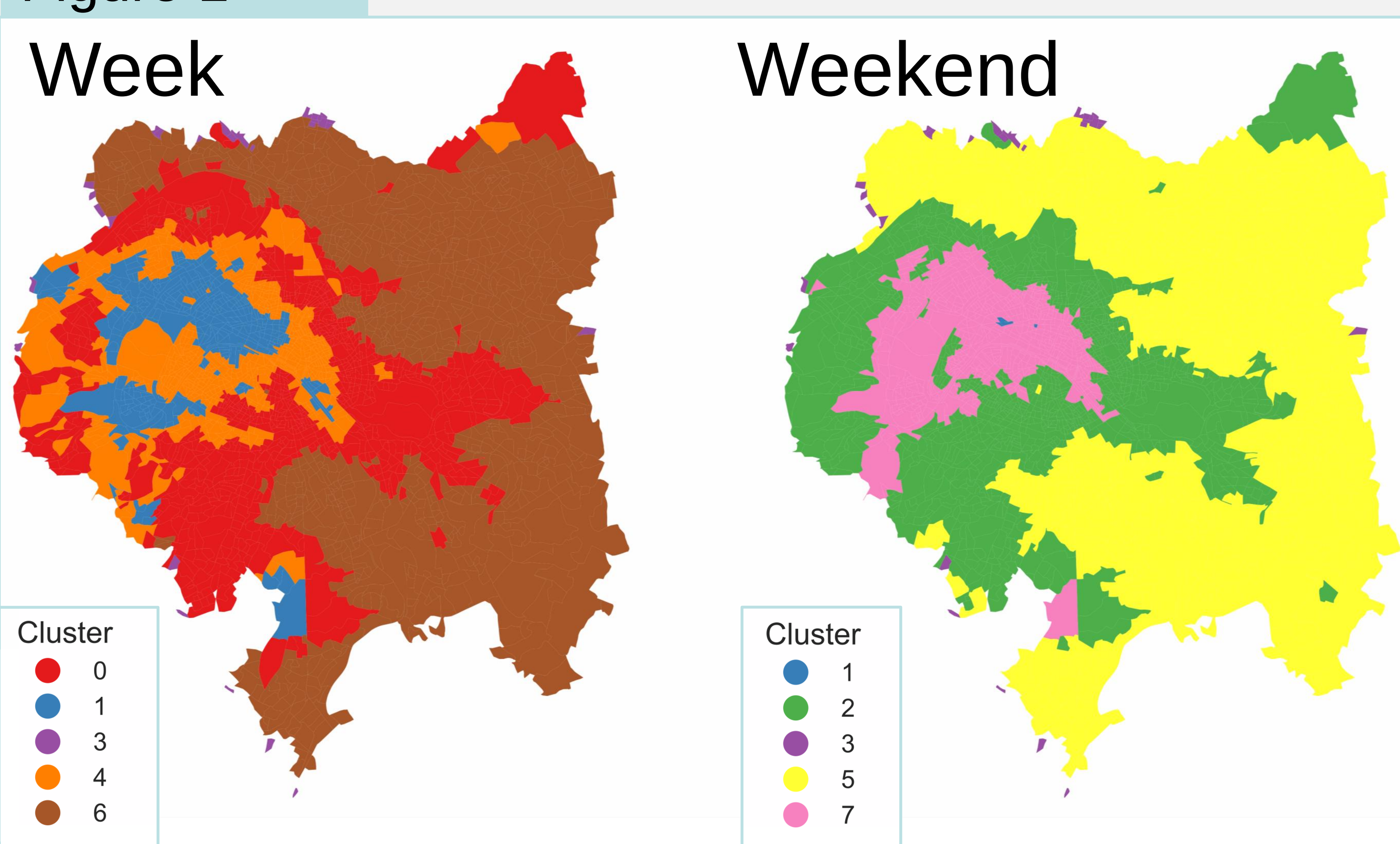

Figure 1 Cluster maps. Paris' clusters using the IRIS2000 geometry [18]. Here, the maps of Paris are coloured by cluster for the (left) 'week' (Monday–Thursday) and (right) 'weekend' (Friday–Sunday).

3 Results

Table 1

City	Temporal aggregation	labels	No. Tracts	Area
Paris	Week	0	909	244.15
	Week	1	375	66.04
	Week	3	28	4.55
	Week	4	641	113.99
	Week	6	965	415.53
	Weekend	1	4	0.29
	Weekend	2	1136	271.31
	Weekend	3	28	4.55
	Weekend	5	1107	473.32
	Weekend	7	643	94.8

Table 1 Descriptive statistics for each city, in each period, and under each label. The table shows the number of IRIS2000 cells (sum) and the total area (km2.) in each cluster [18].

1. App Clustering in Cities

Observations: Cities exhibited distinct clusters during the week and weekend, with Paris displaying the most diverse patterns.

2. Spatial Regression Analysis

Week vs. Weekend Differences:

- Work-related app usage, such as video conferencing and professional development, showed significant results.
- **Paris vs. Aggregate Model Group:** Similarities observed, suggesting Paris influenced the overall trends.
- **Professional Networking Model:** The strongest effect was found for education enrolment density in the week, indicating a negative association.
- **Dependency Ratio:** Showed contrasting effects, indicating varied app usage in family-oriented areas.

3. City-Specific Insights

•**Paris Model Group:**

- Negative association between education enrolment and professional networking during the weekend, possibly indicating leisure engagement.
- Positive relationship between population dependency ratio and professional networking, consistent across both week and weekend.

•**Pseudo-R-squared Values:** Despite limited significant results, the spatial regression models demonstrated high explanatory power, capturing spatial dependencies not explained by independent variables.

Figure 2

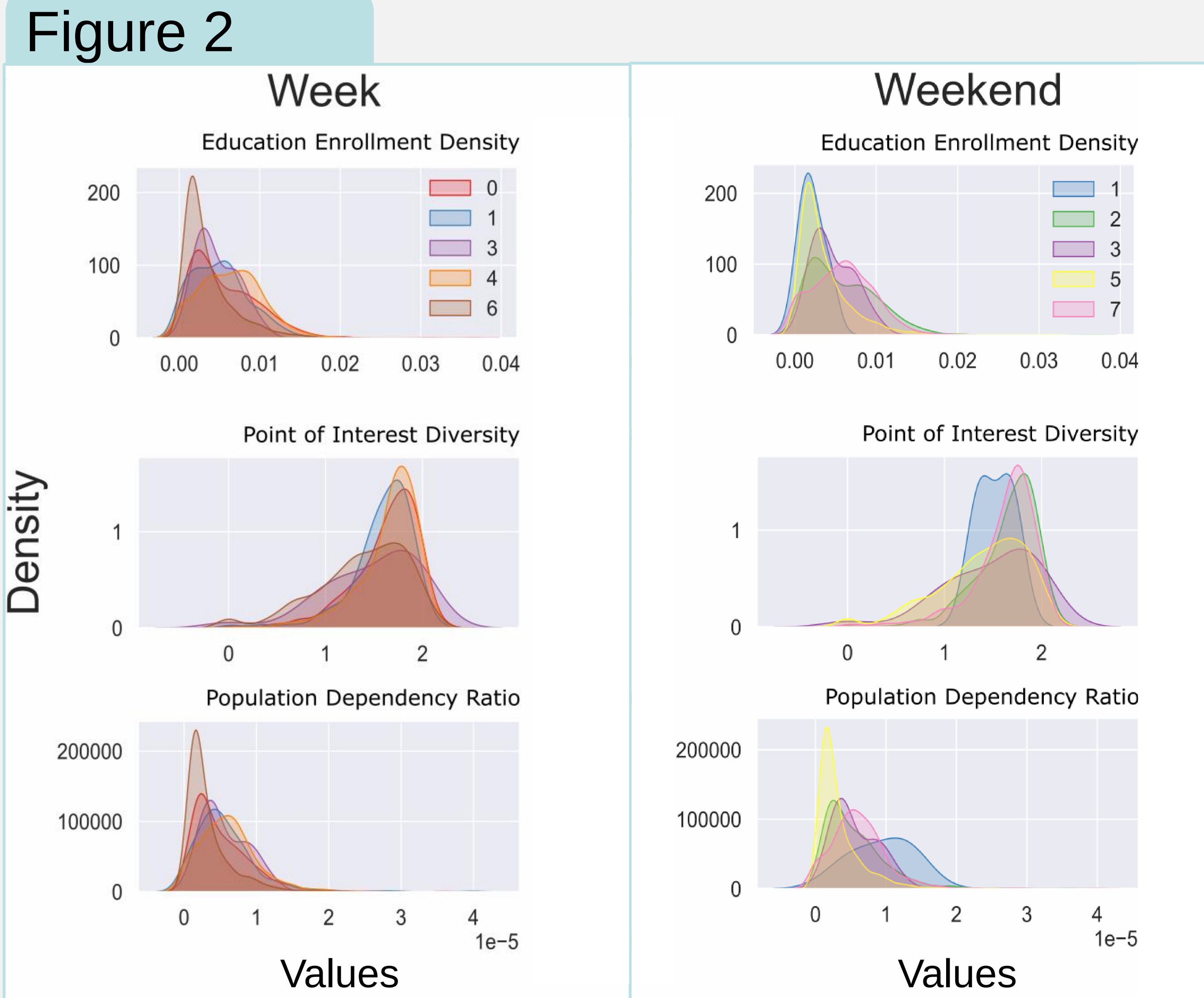

Figure 2 Cluster attribute histograms. Paris' clusters using the *IRIS2000* geometry [18]. Here, histograms show each independent variable that was included in a series of univariate analyses. For each variable, we partition the data giving each cluster.

4 Conclusion

This study reinforces the significance of computational methods in understanding urban environments, merging sociological concepts with computational social science. While contributing evidence to the discourse on urban vibrancy, we recognize the need for additional research to draw definitive conclusions. Our findings underscore the nuanced interplay between urban dynamics, sociodemographic factors, and the evolving digital landscape, offering valuable insights for future urban studies.

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