

Uncovering Latent Patterns in Service-Level Spatiotemporal Mobile Traffic

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Abstract

As people increasingly rely on mobile applications for their daily activities and needs, the digital traces left by smartphones have become an essential instrument to provide information about human activities. In this work, we focus on identifying latent structures in mobile traffic by targeting the traffic generated by individual applications, whose correlation with the urban environment has yet to be explored. Therefore, our mobile traffic analysis considers a third application-related dimension in addition to traditional spatial and temporal ones. In this context, we show that tensor decomposition techniques can be applied to service-level mobile traffic and improve the identification and interpretation of patterns that may remain undiscovered if conventional approaches are adopted.

CCS Concepts

• **Networks** → **Network measurement**; • **Computing methodologies** → **Modeling and simulation**.

Keywords

Mobile Traffic Analysis, Pattern Recognition, Time-Series Analysis, Spatio-Temporal Analysis, Tensor Decomposition

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1 Introduction

The widespread adoption of mobile services has resulted in an exponential surge in mobile traffic as most people rely on mobile applications to carry out everyday activities. From communication

and entertainment to shopping and banking, mobile apps have become an integral part of modern life. The close interaction between the digital and physical worlds has motivated the use of mobile phone data to inquire into various urban phenomena such as human mobility [3, 10, 13], social interactions [15], socioeconomic inequality [17, 21], digital divides [16], and land usage [8, 12, 19]. In particular, the digital traces left by smartphones accessing the network have become a well-known basis for analyzing human activities at unprecedented scales. As such, a considerable amount of literature has been published on identifying human-related patterns in mobile phone activity data, including call detail records [5, 12, 18, 19], and mobile traffic demands [8, 9, 25, 26]. These studies have mainly focused on analyzing the spatiotemporal dynamics of mobile network activity to infer and characterize different urban functional areas, such as industrial, commercial, entertainment, and residential areas.

In this work, we leverage aggregated and privacy-preserving mobile traffic data at the level of individual mobile services in Paris, one of the largest metropolitan regions in Europe. Such a level of detail allows us to split the overall mobile traffic among a newer dimension related to applications, which has not been considered in previous spatiotemporal mobile traffic analysis. In particular, mobile phone traffic data can be organized in a tensor structure with three dimensions: space, time, and mobile services, which allows us to leverage tensor analysis methods to identify patterns in mobile traffic in an unprecedented way. In this work, we employ the most prevalent tensor decomposition techniques to discover hidden structured patterns in mobile traffic data. These tensor factorization approaches result in a set of pattern factors that can be simultaneously interpreted in the dimensions of space, time, and mobile applications.

This study presents the first endeavor to apply tensor decomposition techniques to study the relationship between mobile traffic dynamics and human activities in the urban environment. This innovative approach offers a compelling opportunity for future research and holds great promise for enhancing our understanding of mobile traffic consumption in urban areas.

2 Data Measurement and Processing

Our study builds upon the mobile traffic dataset available under the NetMob 2023 Data Challenge [14]. These measurements were collected in the production network of Orange, a major global

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operator with a leading market position in France. The network operator performed the traffic measurements using passive measurement probes to capture the 4G traffic traversing the mobile network across the country. The probes run dedicated proprietary classifiers that allow the association of individual TCP and UDP flows to the mobile applications that generate them. The dataset used for our study contains information about the traffic demands of 68 mobile services associated with spatial tiles ℓ of 100×100 m² at a 15-minute temporal granularity for 10 consecutive weeks. The traffic measurements employed in this paper concern Paris, the French capital city. Due to space limitations, we refer the reader to the original work [14] for further details.

In order to ease analyses throughout the study, we interpolate the traffic reported in each tile ℓ onto a zoning defined by the French National Institute of Statistics and Economic Studies (INSEE). We retrieve the *IRIS zoning* produced by INSEE, which tessellates the French urban territory into statistical zones based on geographical and demographic criteria; IRIS zones have homogeneous surfaces and encompass populations of at most 2,000 local inhabitants. We then assign to each IRIS zone the demands associated with all tiles ℓ it covers. The traffic of tiles overlaying multiple IRIS zones is distributed proportionally to the fraction of the tile covered by each overlapping IRIS zone. The result of this processing are service-level time series $\mathcal{D}_a^z(t)$ of the traffic demand for each application a at each of 2,834 IRIS zones z covering the city of Paris.

2.1 Data Sampling

Each IRIS zone (hereinafter simply referred to as *zone*) in the dataset is associated to the traffic demands of 68 individual mobile services over 10 weeks at a temporal resolution of 15 minutes. However, given the high diversity of popularity and penetration of mobile applications, not all of them are statistically relevant to an analysis at an IRIS zoning resolution; indeed, many services have too few users or generate negligible and essentially random demands within each zone over 15 minutes. To tell apart the services that generate meaningful patterns from those that are too noisy to yield usable information, we change the granularity of time series $\mathcal{D}_a^z(t)$ to 1 hour by aggregating consecutive 15-minute time slots. Then, we define the *median week* time series of application a in zone z as

$$\tilde{\mathcal{D}}_a^z(\tau) = \text{med}(\mathcal{D}_a^z(t) : t \bmod T = \tau), \quad (1)$$

where the *med* and *mod* operators denote the median of a set and the modulo operation, respectively, whereas $T=168$ is the number of hours in one week. The expression in (1) returns the median traffic volume for service a in zone z at each hour τ of a complete week. In addition, since we are interested in analyzing consumption patterns instead of actual traffic volumes that can vary dramatically across zones, we min-max normalize all $\tilde{\mathcal{D}}_a^z(\tau)$ time series.

We further refine the original set of 68 applications based on their popularity and the quality of their median week time series across all the zones of the city. Thus, we obtain a subset of 30 mobile services that fulfill our requirement of reliability, including Instagram, Snapchat, Facebook, Twitter/X, YouTube, Netflix, Spotify, Gmail, LinkedIn, Uber, and Pokémon GO, among others.

Finally, we compile the resulting data into a tensor structure $\mathcal{X}^D$ organized in three dimensions: space, time, and mobile applications.

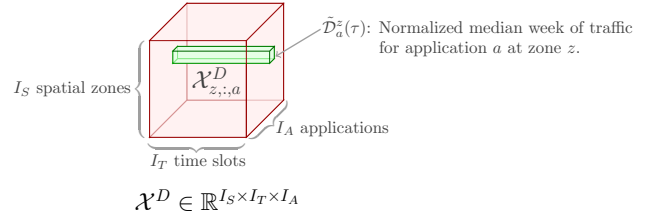


Figure 1: Tensor representation of the application-level spatiotemporal mobile traffic dataset.

The dimensions of the tensor $\mathcal{X}^D$ are $(I_S, I_T, I_A) = (2834, 168, 30)$. Figure 1 illustrates the tensor representation of the data.

2.2 Ethics Considerations

The measurements run to collect the data used for our study were performed by the operator for network management and research purposes, and temporarily stored within a secure platform at their own premises. The raw data processing was carried out in the same platform by personnel of the network operator, in full compliance with Article 89 of the General Data Protection Regulation (GDPR) [22] of the European Commission. The data collection and processing were approved by the Data Protection Officer (DPO) of the operator, and authorized by the relevant national privacy-protection agency. The researchers involved in our study only had access to the aggregate data, whose spatiotemporal resolution ensures that no data subject can be re-identified from the data, which in fact does not qualify as personal data in the GDPR acceptance.

3 Tensor Decomposition

In order to analyze our mobile traffic data tensor structure $\mathcal{X}^D$, we rely on different tensor decomposition models, which allow decomposing complex data into meaningful components and extracting unrevealed patterns. As detailed next, we consider the two most prominent tensor decomposition approaches, the CANDECOMP/PARAFAC or Canonical Polyadic (CP) decomposition, and the Tucker decomposition.

3.1 CP Decomposition

The CP decomposition [2, 11] is a popular method for decomposing a tensor into a sum of rank-one components, *i.e.*, vectors. For an N -order tensor $\mathcal{X} \in \mathbb{R}^{I_1 \times \dots \times I_N}$, its CP decomposition is defined as

$$\mathcal{X} \approx \sum_{r=1}^R f_r^{(1)} \otimes f_r^{(2)} \otimes \dots \otimes f_r^{(N)}, \quad (2)$$

where R is the rank of the decomposition and $f_r^{(n)} \in \mathbb{R}^{I_n}$ is a rank-one tensor. For a given rank R , the goal of the CP decomposition is to solve the following optimization problem,

$$\min_{\mathcal{Y}} \|\mathcal{X} - \mathcal{Y}\|_F, \quad (3)$$

where $\mathcal{Y} = \sum_{r=1}^R f_r^{(1)} \otimes f_r^{(2)} \otimes \dots \otimes f_r^{(N)}$ and $\|\cdot\|_F$ is the Frobenius norm of tensors. In our analysis, we employ the alternating least squares (ALS) algorithm to find an approximate solution for (3), which is the standard approach to compute the CP decomposition.

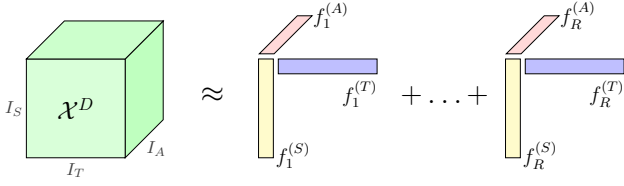


Figure 2: CP decomposition of $\mathcal{X}^D \in \mathbb{R}^{I_S \times I_T \times I_A}$ into a sum of rank-one components.

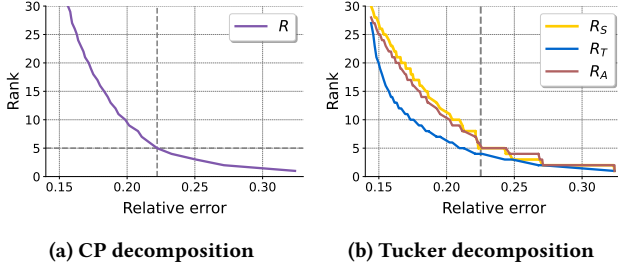


Figure 3: Rank selection in function of the decomposition relative error.

As described in Section 2, our dataset is represented by a three-mode tensor $\mathcal{X}^D$ with dimensions $(I_S, I_T, I_A) = (2834, 168, 30)$ representing space, time, and mobile applications respectively. Therefore, we are interested in the three-way CP decomposition with rank R that uncovers the most prominent patterns in the data. Figure 2 shows the desired decomposition of $\mathcal{X}^D$ into R factors, where each n th factor is represented by a spatial component $f_n^{(S)}$, a temporal component $f_n^{(T)}$, and an application component $f_n^{(A)}$.

Given that the CP decomposition takes a tensor $\mathcal{X}$ and the desired rank R as input, selecting an adequate rank is a critical step. A satisfactory rank R balances the interpretability of the resulting CP decomposition, *i.e.*, obtaining a low-rank approximation, and the goodness of fit of the model measured via the relative error δ , defined as

$$\delta(\mathcal{X}, \mathcal{Y}) = \frac{\|\mathcal{X} - \mathcal{Y}\|_F}{\|\mathcal{X}\|_F}. \quad (4)$$

Therefore, a common approach is to begin with a lower guess for the rank R and increase it to find a suitable CP decomposition. Figure 3a shows the relative error associated with different rank- R decompositions of our data tensor $\mathcal{X}^D$. Based on these results, we select a rank $R = 5$ for the CP decomposition, as it assesses the trade-off between increasing the rank R (model complexity) and reducing the relative error.

3.2 Tucker Decomposition

Over the last decades, the Tucker decomposition [20] has been widely used for pattern discovery, as it can efficiently summarize complex multidimensional data by a set of global factor matrices that represent underlying patterns in the data, and a core tensor that captures the relationship between these patterns.

Formally, the Tucker decomposition of an N -order tensor $\mathcal{X}$ of dimensions $I_1 \times \dots \times I_N$ is defined as

$$\mathcal{X} \approx \mathcal{G} \times_1 F^{(1)} \times_2 F^{(2)} \dots \times_N F^{(N)}, \quad (5)$$

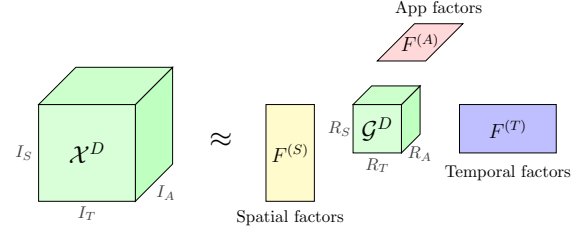


Figure 4: Tucker decomposition of $\mathcal{X}^D \in \mathbb{R}^{I_S \times I_T \times I_A}$ into a core tensor $\mathcal{G}^D$ and factor matrices $F^{(S)}$, $F^{(T)}$, and $F^{(A)}$.

where $\mathcal{X}$ is decomposed into a core tensor $\mathcal{G} \in \mathbb{R}^{R_1 \times \dots \times R_N}$ multiplied (using the n -mode tensor product $\times_n$) by N factor matrices $F^{(n)} \in \mathbb{R}^{I_n \times R_n}$. We refer to the core shape $r = (R_1, \dots, R_N)$ as the multilinear rank of the decomposition.

The optimal problem of the Tucker decomposition can be stated as in (3) with $\mathcal{Y} = \mathcal{G} \times_1 F^{(1)} \times_2 F^{(2)} \dots \times_N F^{(N)}$. It is worth noting that an approximated solution for (3) could result in a core tensor $\mathcal{G}$ much smaller than the original tensor $\mathcal{X}$, *i.e.*, a low multilinear rank approximation.

Several algorithms have been proposed to compute the Tucker decomposition, most of which are based on the higher-order singular value decomposition (HOSVD) of a tensor, a generalization of the matrix singular value decomposition [1, 4, 23]. In the HOSVD, the N factor matrices in (5) are constrained to be orthogonal, and they are iteratively computed from the mode- m flattening of the tensor $\mathcal{X}$ through each of its N modes. In this work, we select the Sequentially Truncated HOSVD (ST-HOSVD) [23], which shrinks the tensor $\mathcal{X}$ after computing each factor matrix, thus reducing the number of operations while obtaining a good approximation of (3).

Considering our data tensor $\mathcal{X}^D$, we are interested in the three-way Tucker decomposition with multilinear rank $r^D = (R_S, R_T, R_A)$ that uncovers the most prominent patterns in space, time, and mobile applications. Figure 4 illustrates the desired decomposition of $\mathcal{X}^D$ into a core tensor $\mathcal{G}^D$ and a set of factor matrices.

For the traditional Tucker factorization, the multilinear rank r is an input parameter that determines the core tensor shape. In practical terms, r represents the number of factors or prevalent patterns we aim to extract along each dimension, which is not reasonable to know beforehand in many real applications. To overcome this drawback, different algorithms have been proposed to solve the fixed-accuracy low multilinear rank approximation problem [6, 7, 24], *i.e.*, to find the minimal multilinear rank r for which $\delta(\mathcal{X}, \mathcal{Y}) \leq \varepsilon$, where $\delta(\mathcal{X}, \mathcal{Y})$ is the relative error defined in (4), and $\varepsilon \in (0, 1)$ is the allowed accuracy tolerance for the Tucker decomposition $\mathcal{Y} = \mathcal{G} \times_1 F^{(1)} \times_2 F^{(2)} \dots \times_N F^{(N)}$.

In our analysis, we employ a greedy search based on the ST-HOSVD where the multilinear rank is sequentially increased until the condition $\delta(\mathcal{X}, \mathcal{Y}) \leq \varepsilon$ is satisfied. Figure 3b shows the obtained multilinear rank $r^D = (R_S, R_T, R_A)$ for different tolerance values ε . Accordingly, for $\varepsilon < 0.225$, the ranks R_S , R_T , and R_A rapidly grow in order to meet the allowed tolerance. As we are interested in the most prominent factors that produce a sufficiently good approximation of the original tensor $\mathcal{X}^D$, we select a tolerance $\varepsilon = 0.225$ and, consequently, a multilinear rank $r^D = (5, 4, 5)$ for the Tucker decomposition in the dimensions of space, time, and

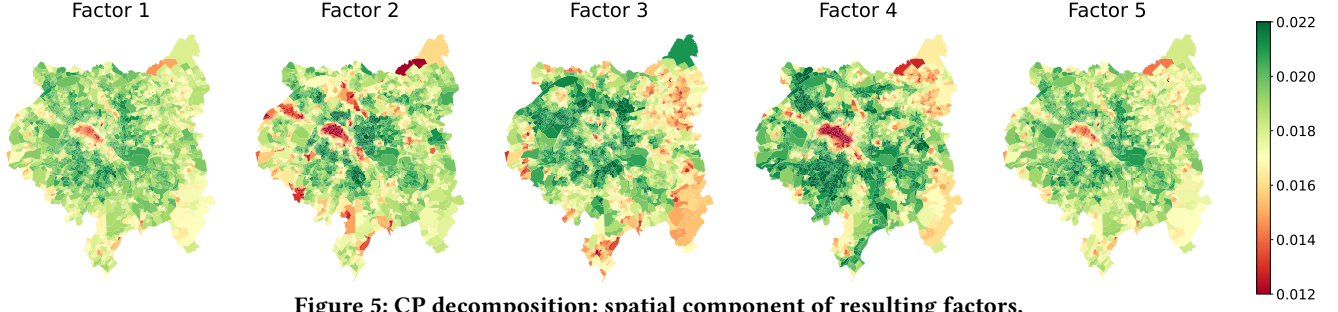


Figure 5: CP decomposition: spatial component of resulting factors.

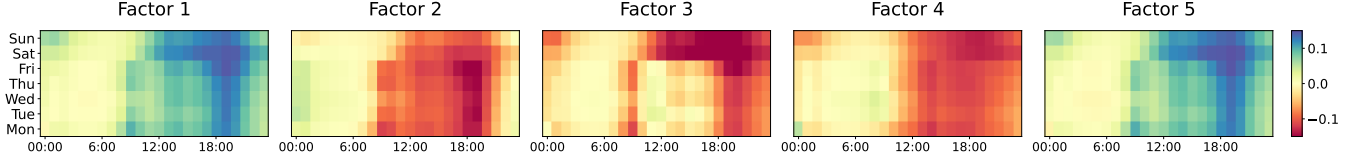


Figure 6: CP decomposition: temporal component of resulting factors.

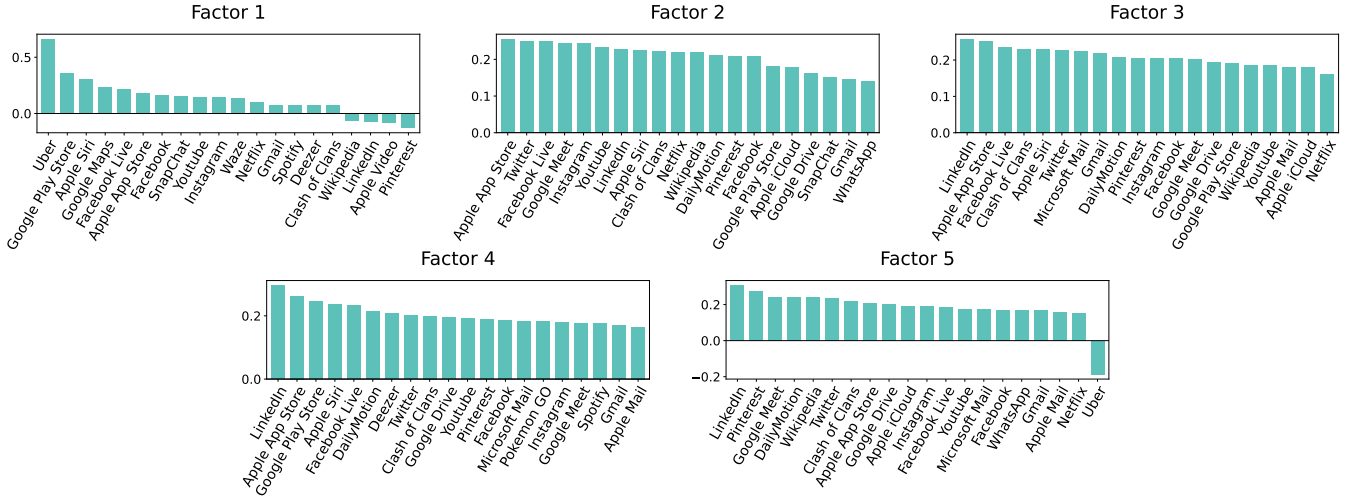


Figure 7: CP decomposition: application-related component of resulting factors. For visualization purposes, only the 20 applications with higher absolute values are shown in each case.

applications. Also, it is important to note that, as shown in Figure 3, both selected decompositions are associated with a concordant level of accuracy, allowing a fair comparison of the results obtained.

4 Results

Following the procedures described in Section 3 to decompose the data tensor $\mathcal{X}^D$, we obtain a CP decomposition with 5 latent factors, as well as a Tucker decomposition characterized by 5 spatial factors, 4 temporal factors, 5 application-related factors, and a core tensor. Next, we present some of the insights gained from these approaches.

4.1 CP Factors

Figures 5, 6, and 7 show the five CP factors across the dimensions of space, time and applications, respectively. Unfortunately, these factors are rather impractical for our main purpose as they are highly

correlated among each other, and therefore, only a low number of patterns can be easily distinguished in each dimension. Looking into the spatial component of factors, most of them exhibit a recognizable purple region in the center of the city (factors 1, 2, 4, and 5). Further inspection reveals that this area corresponds to the most prominent commercial/office region of the city, which discourages the use of these factors to characterize different functional urban areas. Similarly, the temporal components are mainly limited to describing day/night patterns and typical commuting hours. Also, the application-related components of factors 2, 3, and 4 describe patterns that simultaneously affect all applications, making the consideration of service-level traffic futile. Therefore, we found this approach to be impractical for the identification of latent structures in service-level mobile traffic.

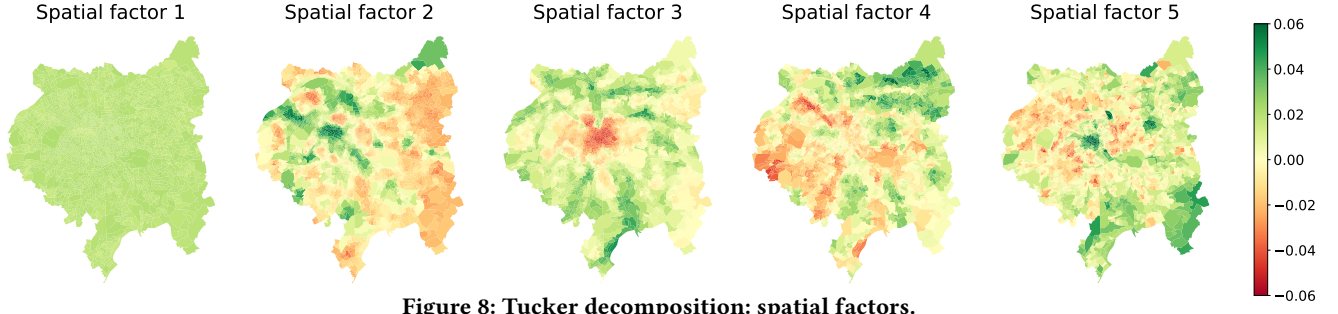


Figure 8: Tucker decomposition: spatial factors.

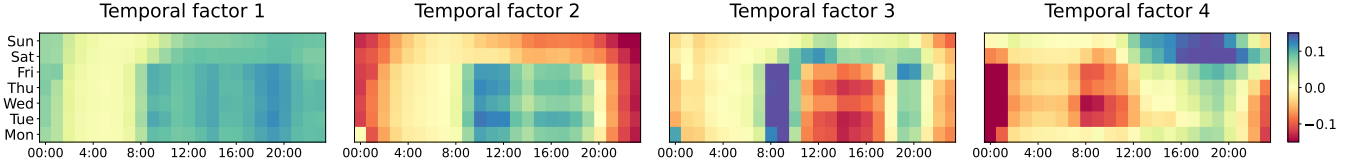


Figure 9: Tucker decomposition: temporal factors.

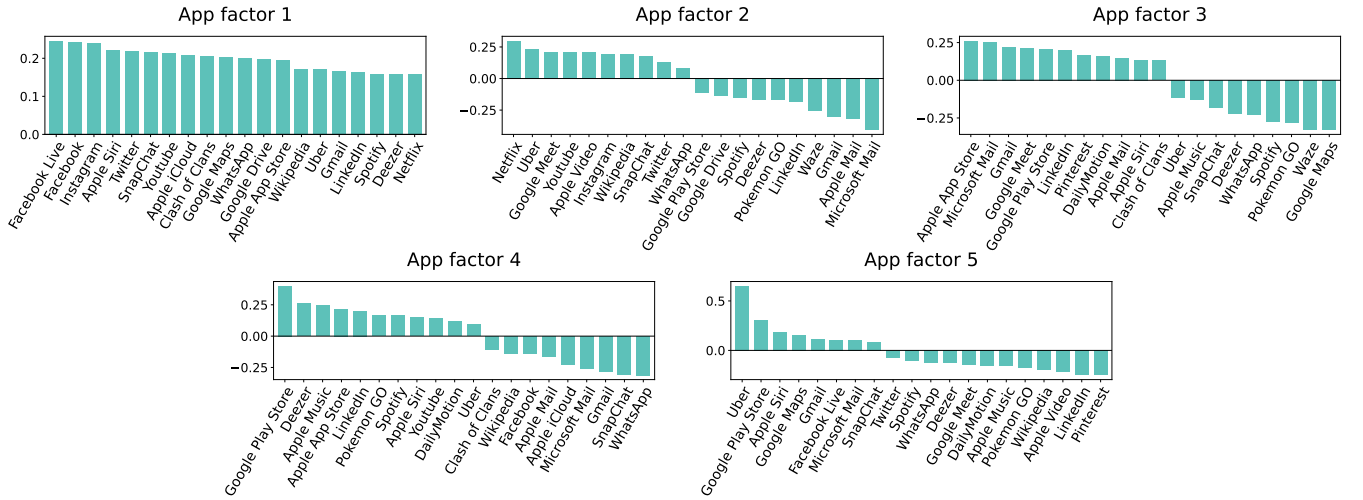


Figure 10: Tucker decomposition: application-related factors. For visualization purposes, only the 20 applications with higher absolute values are shown in each case.

4.2 Tucker Factors

Contrarily to the CP decomposition, each of the obtained Tucker factors exhibits a unique and well-defined pattern. With respect to the five spatial factors shown in Figure 8, we can note some important spatial patterns, such as the contrast between residential and commercial/office areas (green and red areas in the spatial factor 2, respectively) as well as the major commuting lines in the city (spatial factor 3). Also, Figure 9 displays clear temporal dynamics, e.g., the day/night cycle (temporal factor 1), typical office hours (temporal factor 2), and peaks in commuting activity (temporal factor 3). Besides, application-related factors in Figure 10, highlight different sets of mobile services, such as business-related apps (app factor 3) and video streaming (app factor 2).

The simultaneous analysis of these factors yields a total of $5 \times 4 \times 5 = 100$ different pattern combinations. Nevertheless, not all

of these factor relationships are equally relevant. Figure 11 depicts the importance of all the combinations of factors, as characterized by the absolute values of the core tensor. Thus, the core tensor indicates the most relevant factor relationships, some of which are summarized in Table 1 along with a potential explanation of the observed patterns.

5 Conclusions

In this work, we explore the application of the most prominent tensor decomposition approaches to unveil patterns in service-level mobile traffic data. Our results show the feasibility and usefulness of these high-dimensional data analysis techniques to identify pattern structures along the dimensions of space, time, and mobile services. The identification of those latent structures propitiates the infer of urban land use and functional areas from service-level

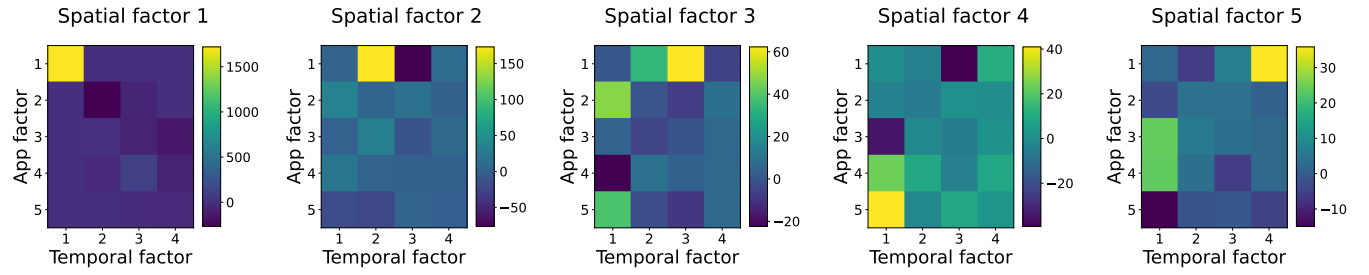


Figure 11: Tucker decomposition: core tensor.

Space	Time	App	Potential description of patterns
1	1	1	Traces of the circadian rhythm in mobile traffic consumption across all regions and services.
2	2	1	Generalized consumption of mobile services in commercial and office areas during working hours.
2	2	3	Prominent consumption of business-related services (i.e., LinkedIn, Google Meet, and email services) in commercial and office areas during working hours.
3	3	1	Generalized consumption of mobile services attributable to travelers to the city center during typical commuting hours.
3	1	2	Specific traffic consumption along major commuting lines. Increased usage of video streaming and social media, and reduced consumption of business-related apps.
5	4	1	Generalized consumption of mobile services in leisure areas (i.e., restaurants, shopping malls, and parks) during weekdays' afternoon and weekend afternoon and evening hours.
5	1	4	Reduced consumption of email and messaging services in leisure areas during all days.

Table 1: Summary of some of the most prominent combinations of factors in the Tucker decomposition of $\mathcal{X}^D$.

traffic demands, which may enhance urban spatial planning and management. The outcomes of this study motivate the application of similar decomposition approaches that may improve the interpretation of latent patterns, such as the use of non-negative tensor decompositions and the incorporation of newer dimensions to the high-dimensional analysis of mobile traffic.

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