An Experimental Study of Factor Analysis over Cellular Network Data

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Abstract-Mobile Network Operators (MNOs) are evolving towards becoming data-driven, while delivering capacity to collect and analyze data. This can help in enhancing user experiences while empowering the operation workforce and building new business models. Mobile traffic demands of users can give insights to MNOs to plan, decide and act depending on network conditions. In this paper, we investigate the behaviour of Istanbul residents using the cellular network traffic activity over spatial and temporal dimensions via exploratory factor analysis (EFA) using a major MNO's cellular network traffic data in Turkey. Our results reveal various time and spatial patterns for Istanbul residents such as morning and evening commuting factors, business and residential factors as well as nightlife and weekend afternoon factors as the most prominent cultural behaviour. The analysis results also demonstrate interesting findings such as tunnels and transportation paths selected by Istanbul residents may differ during morning rush work hour compared to evening rush after-work hour.

Index Terms—factor analysis, cellular data, spatio-temporal, mobile operators

I. INTRODUCTION

In the era of digital age, data can inform and empower transformations of all industry such as telecommunications, health, automotive and factories of future. Using the data as a commodity, organization institutions can detect important phenomena as early as possible, can forecast the outcomes that are vet to come (predictive) or can perform optimization for better modeling and outcomes (prescribe). Some of the enablers for this kind of process enhancement and gaining enterprise level intelligence from rich dataset are via machine learning and statistical methodologies [1]. The cellular data collected from various locations at different time provides rich and important context data to Mobile Network Operators (MNOs) for better decision making and operational process enhancements. For example, the collected data can provide insights into different mobility patterns for groups of subscribers over the observed duration periods after data analysis. This can enhance the capabilities of MNOs for providing personalized services for different customer segments based on their personalized experiences. The mobile data interaction can reflect the personal behaviour, preferences and objectives of users. For this reason, MNOs are working to improve operational efficiency, obtain predictive analytics and extract insights by analyzing massive dataset available in their premises.

For controlling and optimization of network operations, historical and contextual data analysis for modeling the traffic at cell level such as [2], [3], [4], [5] and profiling the user behaviour at different time scales such as [6], [7] based on mobile traffic demand exist in the literature. An analysis that relies on Exploratory Factor Analysis (EFA) using with realworld mobile traffic dataset for Milan and Paris cities are performed in [6]. The results reveal different network activity profiles in those two major European cities. In this paper, we further extend the EFA presented for Milan and Paris cities and study network activity profiles of Istanbul using real-world mobile traffic dataset of a major MNO in Turkey. Compared to previous works in mobile data analysis, our results reveal various mobile usage demands of Istanbul residents and also shed some light on cultural behaviour.

II. SYSTEM MODEL AND ARCHITECTURE

The proposed platform processes and analyzes network key performance indicator (KPI) data that is collected a priori from Operations Support System (OSS) of the MNO in Turkey. Fig. 1 demonstrates the general architecture of our utilized solution. The proposed architecture is composed of three main modules: (a) Data Collector Tier, (b) Analysis Tier, (e) Visualization Tier. The solution is based on utilization of the network KPI data together with open-source data analytics software and platforms. *Pandas* and *R* packages are used as data analysis tools utilizing data-centric packages. For map visualization, Folium visualization tool [8] and inside the Folium, Leaflet javascript [9] library are utilized.



Fig. 1: System Architecture for EFA and data visualization

In **Data Collector Tier** marked as step-(1) in Fig. 1, the data is collected from OSS similar to Fig. 2 and is transferred

into Pandas and R data analytics tools marked as step-(2). In Pandas, first the data in csv format is grouped by Site-ID and the latitude, longitude of the sites are appended into the existing csv data format. In step-(2), all the packet switched (PS) traffic corresponding to each Cell-ID for 4G are analyzed. An example of sum 4G traffic values for Besiktas and Umraniye District of Istanbul is given in Table I. Finally, a matrix with each Cell-ID as row and hourly median PS traffic values over a week in 4G as column matrix is constructed and fed into EFA for determining different factors from the cellular data traffic. After EFA, different factors and corresponding Base Station (BS) scores for each factor are obtained. Later, the anaysis results are visualized in Visualization Tier, marked as step-(3) in Fig. 1, where we utilize Folium & Leaflet maps in order to visualize the EFA scores of each cell sites for each obtained factor.

Model: Let **X** be a $N \times 1$ vector of observed variables, i.e. phenomena of interest such as Download (DL), Upload (UL) traffic or number of users on a given BS in this paper. The fundamental equation for factor analysis is defined as [6]

$$\mathbf{X} = \mathbf{AF} + \mathbf{U} \tag{1}$$

where **A** represents $N \times K$ matrix of common factor pattern coefficients that describe importance of each factor to every variable, **F** represents $K \times 1$ vector of unknown normalized common factors, i.e., a small number (K<<N) of complex relationships among variables and **U** represents $N \times 1$ vector of unknown unique factors that are specific to a single variable. Hence, (1) is a weighted combinations of the common factors in **F** and the unique factors in **U**. Together with EFA solution, by analyzing variable observations from a set of samples, EFA can identify common/unique factors, and numerical relationships that describe how much each common factor explains each variable [10].

In our analysis, in order to determine the number of factors to extract, we have utilized *parallel analysis* where the largest eigenvalues of the data correlation matrix is selected. For factor rotation, we have selected *promax* for maximizing the high loadings using R project [11].

TABLE I: An example of sum 4G traffic values for Besiktas and Umraniye District of Istanbul.

District	DL Traffic (GB)	UL Traffic (GB)	No. of Users (avg.)
Besiktas	4,239,906.386	488,613.8446	67,460.33
Umraniye	9,460,358.224	870,681.5689	142,626.2021

TABLE II: Statistics of Analyzed Cellular Data in Istanbul.

# of rows	6,264,286
# of districts	40
PS DL traffic (average per day, Gb)	18,318.87544
PS UL traffic (average per day, Gb)	1,793.451409
Obser. Duration	1 month
Average # of active users	284.5
N, K	$7 \times 24, 10-13$



Fig. 2: An illustrative architecture for cellular data collection in OSS.

III. NETWORK FACTORING BASED ON TRAFFIC USAGE

Using the spatio-temporal characteristics of cellular data, we investigate the performance of utilizing EFA over different considered variables, i.e. DL, UL and number of users at each BSs. Our focus is on summarized data on a period of one-week and 24 hours that can represent cellular traffic data collected over a one month period. For this reason, similar to [6], one month data is condensed into one single median week, i.e. the median of all measurements are obtained for each hour and day of the week for each site in Istanbul.

Dataset: Our dataset consists of cellular network traffic in Istanbul of a major MNO in Turkey. The statistical parameters of the utilized data is given in Table II. In our *Dataset* there exists PS traffic (both data and Voice over LTE (VoLTE)) from geographically distributed region in the country dated from 29 November 2017 to 26 December 2017. The data fields we have utilized consist of hourly average of DL and UL traffic data and number of active user equipments (UEs) for PS data in 4G network infrastructures as well as date, region, city, district, Site-ID and Cell-ID information of each BS. Total number of rows in the data is 6,264,286. Hence, the mobile traffic is large enough to perform statistical significant studies.

Interpretation of EFA: Using EFA, we can obtain different factors which show both temporal and spatial data traffic demands over various day time and week days. When we observe the EFA scores of each BS, we can induce which specific cells belong to each EFA factor. After performing EFA over our dataset, *optimal* number of different factors, denoted by K, in our analysis is obtained to be 13 for UL, 10 for DL and 12 for number of users. For the selected six factors of Fig. 3 and Fig. 4, we have identified different patterns in various regions and time. Other factors have also emerged which indicates some anomalies or special day events which we have excluded due to space limitations.

Identified EFA factors are shown in Fig. 3 and Fig. 4. The locations of each cell-IDs over the selected six EFA factors of DL, UL and number of active users are plotted as heatmap using Folium map visualization format. From these figure, we

Factor	Labeled Areas	Description	
DL 1	Residential Areas	Large population residential areas in western part of	
		European side and eastern part of Anatolian side	
No. of Users 1	Office, Campus and Industrial Areas	University campuses and business zones in Maslak, industrial areas around Basaksehir and commercial zones around Besiktas, Fatih in European side and Uskudar and Kadikoy (commercial regions) and Dudullu (industrial regions) in Anatolian side	
No. of Users 2	Malls, Touristic Areas and Leisure Activity	Historical Regions (Sultanahmet, Kapalicarsi, Galata tower), Shopping centers in Maslak and Bakirkoy, Leisure time activity on coastal side and Boshoporus view sites	
DL 2	Morning Commuting	Commuting traffic from Anatolian side into European side over bridges Metrobus line in European side and Avrasya tunnel entrance and exit points	
DL 3	Evening Commuting	Evening CommutingMetrobus express bus line in European side and Highway hub in Anatolian side	
DL 4	Farmer's market, Major Bus Terminal and Airport, nightlife area	Wholesale food market and Esenler Bus Major Terminal in Bayrampasa Ataturk airport and nightlife (Taksim, Besiktas area)	

TABLE III: Factors Analysis Descriptions in Istanbul

can observe that e.g. for Number of User Factor 1 of Fig.3c, there exists high traffic between 9 am to 6 pm from Monday to Friday, whereas for DL Factor 3 of Fig.4c, high network utilization exists between 6 am to 9 am. Table III explains the observed factor analysis labels and corresponding location descriptions in Istanbul. From Fig. 3, we can observe how the cells belonging to DL Factor-1 of Fig. 3a and Fig. 3b are highlighting the areas that are mostly populated with local residents, where most of the residential areas are located. Most of the network activity is around residential centers such as Bagcilar, Gungoren, Alibeykoy in European side and Umraniye, Sultanbeyli in Anatolian side. Geographical areas where Number of Users Factor 1 as shown in Fig. 3c and Fig. 3d are mostly related to university campuses, office and industrial areas of Istanbul. This is in line with the properties of Number of Users Factor 1 of Fig. 3c which characterize the working hour traffic between 8 am to 5 pm belonging to BSs whose mobile data traffic activity surges during working hours. Number of Users Factor 2 of Fig. 3e and Fig.3f, on the other hand, characterize the touristic, shopping and leisure activity areas in Istanbul. The historic city center Sultanahmet, Kapalicarsi, Galata Tower that are major touristic attractions for foreigners and local tourists, big shopping malls for local residents such as Istinye Park in Maslak (northern European side). Cevahir and Zorlu Center in Levent (middle European side), Mall of Istanbul, Ataturk airport shopping center (AVM), Marmara Forum, Galeria, Forum Istanbul, Ikea, Atakoy Plus (in southern European side) are highlighted in Number of Users Factor 2 of Fig. 3e and Fig. 3f. Another dimension in Number of Users Factor 2 that overlaps with the shopping mall activities is indication of the leisure occupations of Istanbul residents around both Anatolian and European coastal sides as well as Boshoporus view regions.

We can also observe different patterns from the other factor profiles. DL Factor 2 and DL Factor 3 of Fig. 4 show the commuting behaviour of Istanbul residents. In Istanbul, most of the residents live in Anatolian side and commute to European side of Istanbul for work. Therefore, after work between 5-8 pm

of Fig. 4a and Fig. 4b, there exists coherent usage of public transport services, e.g. Metrobus express bus line used by local commuters is running in major locations of Istanbul can be clearly observed from Fig. 4b). During morning commuting hours between 7 am to 9 am of Fig. 4c and Fig. 4d, the scores are somehow distributed around entrance from Anatolia side into European side due to existence of non-uniform starting hours of businesses (ranging from 6 am to 9 am) and Metrobus line is less visible compared to evening commuting. In DL Factor 3 of Fig. 4c and Fig. 4d, other active areas that morning commuters frequently use are entrance and exit points of Avrasya tunnel (which runs under Marmara sea between Anatolian side and European side) where morning commuters enter from Anatolian side and exist into European side. We can also notice the interesting fact that commuter behaviour around usage of Avrasya tunnel is only visible in morning commuter behaviour, not in evening commuter behaviour.

The areas highlighted by DL Factor 4 of Fig. 4e and Fig. 4f show the activities between 2-4 am where major bus station, major airport, wholesale market hall as well as nightlife areas in Istanbul are highlighted around those times. The geographical cells that have high scores belonging to DL Factor 4 demonstrate wholesale market hall where all the goods (fruits and vegetables) are stocked for servicing the next day. DL Factor 4 is also indicating nightlife occupations of Istanbul residents that overlap with terminal (bus and airport) activities.

IV. CONCLUSIONS

In this paper, we have investigated hourly cellular traffic data and performed factor analysis over the collected dataset of one month of a major cellular mobile network operator in Turkey. The results reveal that there exists different patterns of traffic over different factors depending on the day of the week as well as time of the day. Our results have revealed major residential, business, touristic and market areas as well as morning and evening commuter paths of residents in Istanbul depending on the behaviour of cellular network usage over





(b)









Fig. 3: (a) DL Factor 1 (b) DL Factor 1 Map (c) Number of Users Factor 1 (d) Number of Users Factor 1 Map (e) Number of Users Factor 2 (f) Number of Users Factor 2 Map

different time zones. As a future work, we are working on extending the analysis over one year period that can also cover the special events and holidays.

REFERENCES

- D. Naboulsi, M. Fiore, S. Ribot, and R. Stanica, "Large-scale mobile traffic analysis: a survey," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 124–161, 2016.
- [2] U. Paul, A. P. Subramanian, M. M. Buddhikot, and S. R. Das, "Understanding traffic dynamics in cellular data networks," in *INFOCOM*, 2011 Proceedings IEEE, pp. 882–890, IEEE, 2011.
- [3] X. Lu, E. Wetter, N. Bharti, A. J. Tatem, and L. Bengtsson, "Approaching the limit of predictability in human mobility," *Scientific reports*, vol. 3, 2013.
- [4] C. Song, Z. Qu, N. Blumm, and A.-L. Barabasi, "Limits of predictability in human mobility," *Science*, vol. 327, no. 5968, pp. 1018–1021, 2010.
- [5] O. Narmanlioglu, E. Zeydan, M. Kandemir, and T. Kranda, "Prediction





(b)







(d)

(c)



Fig. 4: (a) DL Factor 2 (b) DL Factor 2 Map (c) DL Factor 3 (d) DL Factor 3 Map (f) DL Factor 4 (g) DL Factor 4 Map

of active ue number with bayesian neural networks for self-organizing lte networks," in *Network of Future (NoF), 2018 Proceedings*, London, UK, 2017.

- [6] A. Furno, M. Fiore, and R. Stanica, "Joint spatial and temporal classification of mobile traffic demands," in *INFOCOM-36th Annual IEEE International Conference on Computer Communications*, 2017.
- [7] D. Naboulsi, R. Stanica, and M. Fiore, "Classifying call profiles in largescale mobile traffic datasets," in *INFOCOM*, 2014 Proceedings IEEE, pp. 1806–1814, IEEE, 2014.
- [8] "Folium: Python Data Visualization." https://folium.readthedocs.io/en/

latest/, 2017. [Online; accessed 06-Dec.-2017].

- [9] "Leaflet: an open-source JavaScript library." http://leafletjs.com/, 2017. [Online; accessed 06-Dec.-2017].
- [10] S. A. Mulaik, Foundations of factor analysis. CRC press, 2009.
- [11] "Principal Components and Factor Analysis." https://www.statmethods. net/advstats/factor.html, 2018. [Online; accessed 19-Jan.-2018].