Chapter
Using Call Data and Stigmergic Similarity to Assess the Integration of Syrian Refugees in Turkey

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Abstract

By absorbing more than 3.4 millions Syrians, Turkey has shown a remarkable resilience. But the host community hostility toward these newcomers is rising. Thus, the formulation of effective integration policies is needed. However, assessing the effectiveness of such policies demands tools able to measure the integration of refugees despite the complexity of such phenomena. In this work, we propose a set of metrics aimed at providing insights and assessing the integration of Syrians refugees, by analyzing the CDR dataset of the challenge. Specifically, we aim at assessing the integration of refugees, by exploiting the similarity between refugees and locals in terms of calling behavior and mobility, considering different spatial and temporal features. Together with the already known methods for data analysis, in this work we use a novel computational approach to analyze users' mobility: computational stigmergy, a bio-inspired scalar and temporal aggregation of samples. Computational stigmergy associates each sample to a virtual pheromone deposit (mark) defined in a multidimensional space and characterized by evaporation over time. Marks in spatiotemporal proximity are aggregated into functional structures called trail. The stigmergic trail summarizes the spatiotemporal dynamics in data and allows to compute the *stigmergic similarity* between them.

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1.1 Introduction

In the context of Syrian refugee crisis, Turkey is both an *effective* and *affected* country [25]. Indeed, it provides protection and facilities to more than three million refugees; but, on the other hand, an increasing hostility is emerging in the local Turkish communities, due to the magnitude and the duration of the humanitarian crisis [24]. In order to prevent the growing of societal tensions over Syrian refugees, there is the need to formulate effective long-term integration policies [7, 16]. However, the formulation of an effective policy demands tools aimed at evaluating and understanding the integration of refugees despite the complexity and the width of this phenomenon. In this context, great benefits can be provided by complementing the paper-and-pencil surveys, the interviews, and the focus groups with a data-driven approach [21].

An interesting approach is to use data mining techniques to analyze the aggregated behavior of users, finding a number of groups based on behavioral similarity [19]. This approach can reveal interesting social phenomena occurring among refugees and locals [23].

One source of data that offers great potential for this kind of analysis are information captured from mobile phones [14, 20], which have been used to analyze many effects of the migratory phenomena, i.e., the ones on political elections [13], job markets [32] or on the spread of epidemics [34].

In this work we analyze the Call Detail Records (CDR) datasets provided within the D4R challenge with the aim of unfolding which conditions can contribute to the integration of refugees. Moreover, we aim at providing some data-driven indicators of the integration of Syrian refugees in Turkey. By exploiting such indicators, policy makers could evaluate the effectiveness of the strategies aimed at fostering the integration of refugees. In the following, we provide the reader with few insights about how each one of the D4R datasets (presented in the first chapter of this book) can be used in our analysis, by taking into account the different features of each one of them, e.g. the number of individuals, spatial accuracy, and observation time windows. To list few examples: (i) the information contained in the Antenna Traffic Dataset (ATD) can be used to describe the spatial distribution of refugees calls, since it takes into account the whole population of refugees even if as a whole group; (ii) the information contained in the Fine Grain Mobility Dataset (FGMD) can be used to define trajectories of refugees and locals, or to assess refugee to refugee if this has more interactions (calls) with locals or other refugees, even if on a bi-weekly base; and (iii) the information contained in the Coarse Grain Mobility Dataset (GGMD) can be used for long-term analysis (several months or year-round), and district-wise trajectories, or analyzing the difference in calls' patterns.

In the following sections we present the analysis of these data. Specifically, in Section 1.2 we describe our approach and the metrics we aim to exploit. In Section 1.3 the experimental setup is depicted, and the results obtained are presented in section 1.4. Finally, we draw the conclusions of this study in section 1.5.

1.2 Method

In order to assess the integration of refugees, it is essential to establish metrics able to capture this phenomenon. These metrics should consider both on short (daily) and long (bi-weekly or monthly) term mobility and calling behavior of refugees and locals. Indeed, many works in the literature [33] highlight the improvement obtained by including individuals mobility and behavior in the model, with respect to pure statistical one. It follows the list of the metrics we propose for our analysis:

- *Residential Inclusion by District (RI)*: we can assume that most of the calls during the night and early morning hours come from people's homes. Indeed, based on this assumption many works in the field of the CDR analysis infer the location of an individual's home as the place from which he/she mostly call between 8 pm and 8 am [8]. Thus, by observing the percentage of calls made by refugees (via the ATD dataset) between 8 pm and 8 am per antenna $a \in d$ is possible to assess the coexistence of resident locals and refugees in a given the districts d and a given month m. This metric is defined between 0 (no resident refugees' in the district) and 1 (only resident refugees' in the district).

$$RI_{d,m} = \frac{|calls_{a,m}(R)|_{a \in d}}{|calls_{BS,m}(R) + calls_{a,m}(L)|_{a \in d}} \tag{1.1}$$

- *District Attractiveness (DA)*: A district is considered attractive if the flow of people who move to it is on average higher than the flow of people who move from there in a given month (i.e. the people netflux). As for the assumptions used in the RI metrics, a person resides in a given district and month if that district is the most recurrent location from which he/she makes calls between 8 pm and 8 am. Specifically, given $residentRefugee_{d,m} = \{R|r : home_r(m) = d\}$ i.e. the set of the refugees who live in the district d during the month m, the District Attractiveness (computed via the CGMD dataset) is defined as:

$$DA_{d,m} = |residentRefugee_{d,m+1}| - |residentRefugee_{d,m}| \tag{1.2}$$

- *Refugee's Interaction Level (IL)*: it is defined as the percentage of phone calls toward locals made by a given refugee in a given period, (computed via the FGMD dataset). It represents how much the refugee is socially connected to the locals [15], i.e. 0 means no calls toward locals and 1 means only calls toward locals. Each level is defined as a range of 20%

within this scale. In this, as in many studies in this field [27], we consider the IL a solid metric for measuring individual integration.

$$IL_r = \frac{|calls_{r \to L}|}{|calls_{r \to L}| + |calls_{r \to R}|} \tag{1.3}$$

- *Refugee's Mobility Similarity (MS)*: by collecting the locations of each call (via FGMD dataset) occurred during the day we can build the daily trajectories of an users' mobility. The similarity of the trajectories of refugees T_r and locals T_l implies the sharing of some urban space at the same time and may affect (or be affected by) the integration of the refugees [26] [22]. The computation of this similarity is based on the principle of *stigmergy*. Stigmergy is a self-organization mechanism used in social insect colonies [30]. Basically, individuals in the colony affect each other behavior by marking a shared environment with pheromones when a specific condition occurs (e.g. the presence of food). The pheromone marks aggregate with each other in the trail if they are subsequently deposited in proximity to each other, otherwise they evaporate and eventually disappear. Thus, the resulting pheromone trail steers the whole colony toward the region in which the condition above (e.g. the discovery of food) occurs consistently.
  This pheromone-like aggregation mechanism can be employed in the context of data processing [9], providing self-organization of data [35] while unfolding their consistent spatio-temporal dynamics [18]. The design of a stigmergic similarity can also include a parametric adaptation based on evolutionary computation and spatio-temporal context history. This approach based on computational intelligence represents a valid alternative to spatio-temporal similarities based on semantic rules, which are characterized by domain-dependence and limited adaptability even when applying evolutionary parametric adaptation [17].
  More specificaly, by exploiting *computational stigmergy*, each sample of the trajectory is transformed in a digital pheromone deposits (i.e. mark) and released in a three-dimensional virtual environment [10] in correspondence of each sample coordinate and time of appearance [12]. Marks are defined by a truncated cone with a given width. Marks aggregate in the *stigmergic trail*, which is characterized by evaporation (i.e. temporal decay δ). The evaporation may be counteracted if marks are frequently released in proximity to each other, due to their aggregation, whereas isolated mark progressively evaporates and disappear. Eq. 1.4 describes the trail T at time instant i.

  $$T_i = (T_{i-1} - \delta) + Marks_i \tag{1.4}$$

  Since only consistent spatio-temporal dynamics in data generate a stable pheromone trail, the trail itself can be considered as a summarization of these dynamics [11]. By matching trails, we provide a general similarity

measure for spatiotemporal patterns, called stigmergic similarity. The similarity between trails is obtained by using the Jaccard similarity [31, 10], i.e. the ratio between the volume of the intersection and the union of the stigmergic trails (Fig.1.1).
The stigmergic similarity of the spatiotemporal trajectories of refugees T_R and locals T_L (Eq. 1.5) is defined between 0 (completely different trajectories) and 1 (identical trajectories).

$$MS_{R,L} = \frac{|T_R \cap T_L|}{|T_R \cup T_L|} \tag{1.5}$$

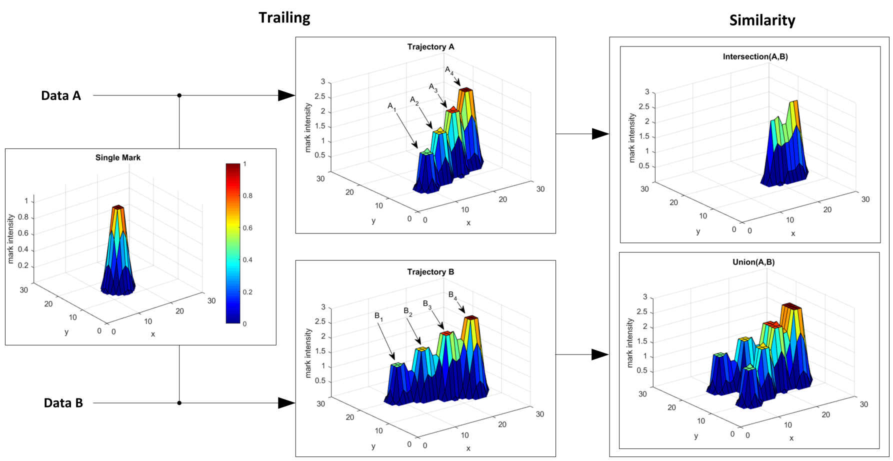

Fig. 1.1 Phases of the mobility similarity computation. We represent the trails obtained from the deposit of 4 consecutive samples (A_1, A_2, A_3, A_4 and B_1, B_2, B_3, B_4) of the trajectories (A and B), their intersection and their union, which are used to compute their similarity

1.3 Experimental Setup

Since our investigation includes an analysis of mobility, call behavior, and district characterization it is necessary to focus our research in areas that ensure (i) an high calling activity made by refugees. Indeed, in order to have representative behavioral models we have to avoid areas characterized by sparse data; and (ii) a good spatial resolution, which means an high density of antennas, since the granularity of the trajectories will be determined by this; in fact, with few antennas in the area under investigation, all trajectories will be roughly similar; and (iii) high number and diversification of districts per area; indeed, the district-based metrics can explain the settlement choice of each refugee. This effect is especially noticeable in the presence of many different districts close to each other since this allows refugees to move from one district to another according to their socio-economic integration level and its change in time. Therefore, our first survey aim at finding the areas with these characteristics. Thus, we analyze the density of antennas (Fig. 1.2) and the total amount of calls (in seconds) made by refugees (Fig. 1.3) with a spatial discretization of 10 km per squared areas over the whole Turkey by exploiting the ATD dataset.

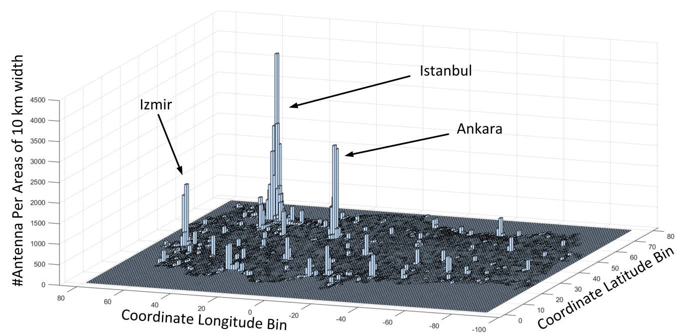

Fig. 1.2 Number of Antennas per squared area of 10x10 km.

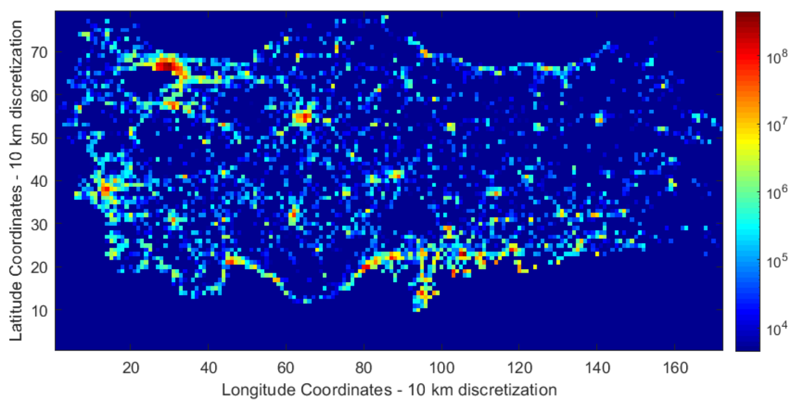

Fig. 1.3 Total amount of calls (duration) per squared area of 10x10 km. The metropolitan areas of Istanbul, Izmir and Ankara are the areas with the largest amount of calls.

As shown by our results, the cities of Istanbul, Ankara and Izmir are the most promising areas to conduct our analysis since they have the larger density of antennas and the larger calling activity made by refugees. This result is also comforted by other external data sources [6] and by the results provided in the first chapter of this book. Due to these reasons, those 3 cities are ideal areas to analyze both mobility and interaction with the locals. In addition, Istanbul's metropolitan area alone consists of 69 districts with a variety of different characteristics (e.g., different housing costs or job opportunities). For this reason, our analyses on districts will be focused on Istanbul.

1.4 Results and Discussion

In this section, we describe the process and discuss the findings of our analysis.

1.4.1 Districts Attractiveness and Residential Inclusion

We analyze the relationship between the District Attractiveness and the Residential Inclusion of the refugees in each district of Istanbul. In order to do so, we compute the correlation between each district's yearly (i.e. averaged over 2017) Residential Inclusion (RI) and the District Attractiveness (DA). Figure 1.4 shows the correlation matrix obtained with the yearly RI and DA per district.

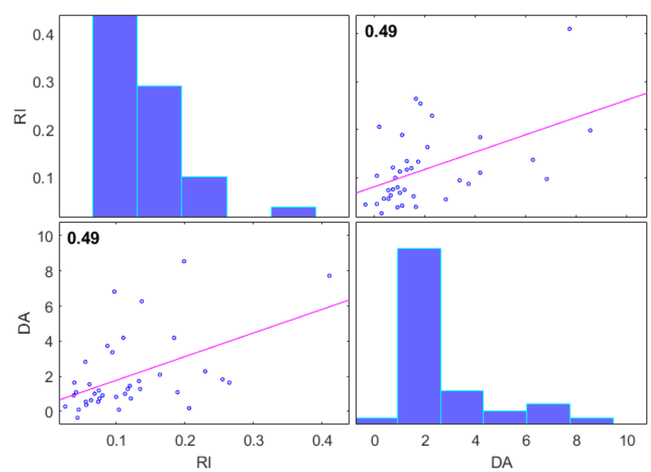

Fig. 1.4 Correlation matrix obtained with the yearly RI and DA per district. On the diagonal the distribution of the average RI and DA respectively, whereas the others are the bivariate scatter plots with a fitted line.

With a correlation coefficient equal to 0.494 and a p-value of 0.0016 we can consider RI and DA significantly and positively correlated. This means that refugees are more likely to move and stay in districts with a greater the refugees' number.

To understand the order of magnitude of the amounts we are talking about we show the distribution of RI by month and district (Figure 1.5).

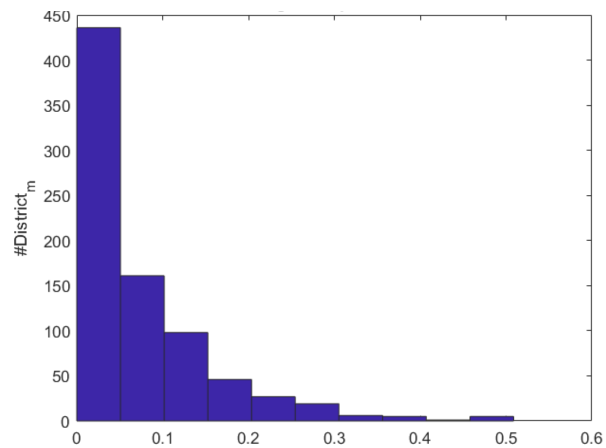

Fig. 1.5 Histogram of the distribution of RI per each district in Istanbul and each month.

In Figure 1.5 it is evident that many districts have a low RI, thus depicting a scenario of minor coexistence of refugees and locals in most of the districts. Moreover, in the few districts (and months) with higher RI, the RI value never exceeds 50% (which would depict a ghetto-like scenario). Thus, the more evenly distributed the residents (locals and refugees in an area) are, the greater the attractiveness of the district.

1.4.2 Mobility and Interaction with locals

Another fundamental driver of integration can be the sharing of urban spaces with the locals [29]. However, its positive contribution in the integration dynamics it is not obvious. Indeed, it can allow the progressive integration in the social structure of the hosting city. However, on the other hand the shared urban areas may not be easily defined and perceived as a safe space [28] thus leading to the occurrence of social tension in those areas.

In order to understand the contribution of sharing the same urban space with the locals, we analyze the relationship between the Mobility Similarity and the Interaction Level on a daily bases. Specifically, we create the cumulative trajectories of the group of refugees with a given Interaction Level, i.e. the stigmergic trails obtained with all the samples of the people in that group. Then, we compute the Mobility Similarity with the cumulative trajectories obtained with an equally sized group of locals. Regarding the size of these groups, it is worth highlight that the Mobility Similarity measure is sensitive to the number of users employed in the creation of the cumulative trajectories, i.e. the more the users the higher the likely to have more similar cumulative trajectories. In addition to this, the size of the groups with a given Interaction Level varies significantly according to it (Fig. 1.6).

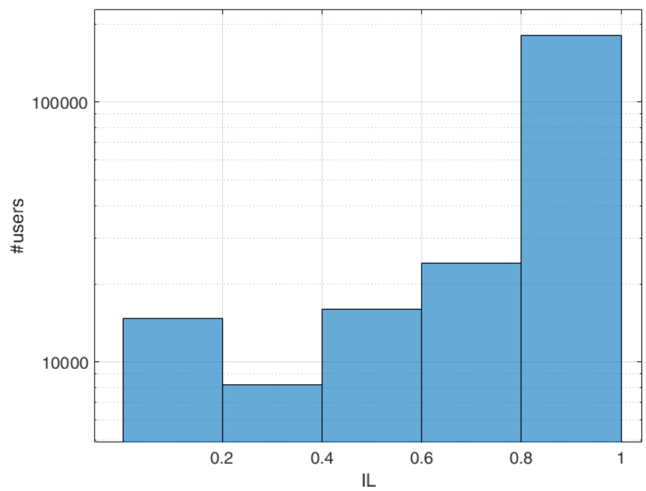

Fig. 1.6 Number of refugees in Istanbul according to their Interaction Level (FGMD). The smallest group is made up of 8184 people. The figure is in Log scale.

Thus, in order to have a fair comparison between the similarities computed with different groups, we set the size of each group as the minimum size among all the groups. Finally, we collect the Pearson correlation coefficients between the Interaction Level of each group and the resulting Mobility Similarity. We repeat this procedure multiple times by randomly subsampling the people for each group larger than the smallest one. The 95% confidence interval of the correlation coefficients results as 0.91 ± 0.01 in Istambul, 0.83 ± 0.06 in Ankara, and 0.92 ± 0.04 in Izmir. On the basis of the obtained results, it is possible to claim that the more the refugees have interactions with locals, the more they share urban spaces with the locals. This allows us to say that sharing of urban spaces is a positive factor in the dynamics of integration of refugees. Thus, the policies designed to improve refugees' integration should take into account Mobility Similarity to assess their impact.

1.4.3 Integration and Social Tension

Since the Mobility Similarity and Interaction Level are able to capture the integration of refugees, we now attempt to use them to study the effects of the events that are certainly caused or can cause the disruption of refugees' integration: the occurrence of social tension. In order to look for the features that characterize a social tension, it is necessary to start with few examples of publicly known social tensions. Specifically, we collect a set of such events and we compare the Mobility Similarity and Interaction Level in 2 weeks before and after each event. We have found a number of occurrence of such events by searching for them over the internet [5] [3] and exploiting a publicly available news collector, i.e. the GDELT Project [2]. The GDELT Project monitors the world's broadcast, print, and web news from all over the world and makes it possible to query them according to locations, subjects involved, and emotions. By querying for events involving refugees in Turkey, we were able to obtain a pool of potential events that we checked manually to select only the ones related to actual social tensions and police interventions. The final pool of events taken into consideration is displayed in Table 1.1.

Date	**Location**	**Source**
March 6	Izmir	[1]
April 12	Istanbul	[4]
May 15	Istanbul	[5]
May 16	Istanbul	[3]

Table 1.1 Dates and locations of the social tension events taken into account.

Once these events have been identified, we study the impact of these social tension by calculating the Mobility Similarity (with repeated trials according to the methodology described in the last section) and the percentage of calls made toward the locals, according to the Interaction Level of the refugees. These measures will be derived with data from different periods (FGMD dataset). In order to make them comparable and highlight the fluctuations with respect their average across different periods, a normalization with (i.e. divided by) their average per period is performed. Finally, we present the ratio between MS and the percentage of calls in the two weeks before and after each event. If this ratio is greater than 1, it indicates that after the event, the integration measure taken into consideration has decreased. As an example, in the Figure 1.7 we show the results obtained with the event of May 16 in Istanbul.

It is apparent that the social tension affects the behavior of the refugees by reducing the amount of shared urban space with the locals (i.e. lowering the Mobility Similarity after the event). Moreover, in terms of calls made toward locals, the social tension event affects the group of refugees with lower level of interaction with locals way more than the more integrated groups.

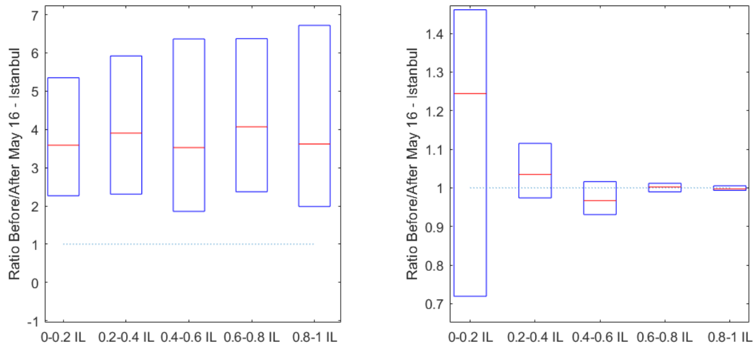

Fig. 1.7 Mobility Similarity (left) and the percentage of calls made toward refugees (right): ratio between the values two weeks before and two weeks after the 16th of May in Istanbul. A ratio greater than 1 indicates that, after the event, the integration measure taken into consideration has decreased. The ratios are separated for different ILs of the group of refugees.

Indeed, on average, they exhibit a lower percentage of calls made toward locals and a greater variability. Moreover, this trend is confirmed on every event we are taking into account, as shown in the the aggregate results in Figure 1.8. Indeed, the quartiles of the percentage of calls made toward locals are arranged as [0.55, 1.05, 1.41] with the refugees with the lower Interaction Level, whereas are [0.98, 0.99, 1] with the refugees with the greater Interaction Level. Here, even the MS results more affected in the group of refugees with lower Interaction Level, who tend to be more segregated after the social tension event. Indeed, the median of the distribution of the ratios obtained with the Mobility Similarity with the lower and greater Interaction Level are respectively 5.31 and 3, which means that the Mobility Similarity of the refugees with lower Interaction Level decreased 77% more with respect to the refugees with greater Interaction Level. Based on the obtained results, the proposed metrics result able to capture the effect of a social tension and should be taken into account when addressing application such as attempting to identify or measure the impact of social tension events.

1.5 Conclusion

In this work, we have proposed a set of metrics to assess the integration of Syrian refugees in Turkey. Each refugee-related measure takes into account their behavioral and spatio-temporal patterns with different approaches. Specifically, (i) the Interaction Level assesses the social integration of a refugee by employing the amount of calls made toward locals; (ii) the Mobility Similarity exploits the daily mobility of refugees is analyzed by means of the stigmergic similarity, a biologically-inspired computational method that al-

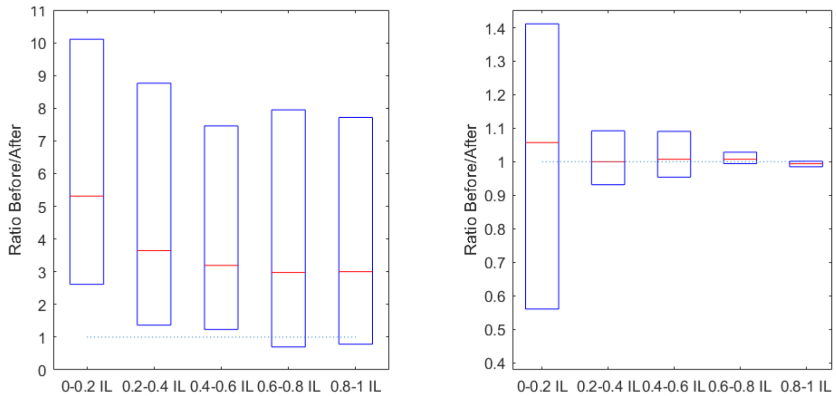

Fig. 1.8 Mobility Similarity (left) and the percentage of calls made toward refugees (right): ratio between the values two weeks before and two weeks after each social tension. A ratio greater than 1 indicates that, after the event, the integration measure taken into consideration has decreased. The ratios are separated for different ILs of the group of refugees.

lows to compare spatio-temporal patterns (i.e. the spatio-temporal trajectories of refugees and locals), whereas (iii) the District Attractiveness and the Residential Inclusion are two districts-wise descriptive metrics aimed at evaluating the attractiveness of a district and the amount of refugees living in it. According to our results, (i) the Mobility Similarity is positively and significantly correlated with the Interaction Level of refugees, which means that sharing urban space with locals actually improves the integration chances; (ii) the integration can be fostered by the simultaneous presence of refugees and locals who reside in the same area in a fair amounts; and (iv) both Mobility Similarity and the amount of calls made toward the locals are affected by events such as social friction involving refugees, which means that such event can be even identified by using MS and IL; moreover, the behavior of the less integrated refugees is significantly more affected by this kind of events. Given the promising results obtained with these metrics, their application should be further explored on different scenarios in the future works. For example, by retrieving more data about other cities we can gain more insights and employ a different spatial resolution for the geospatial analysis.

References

[1] (2018) 130 migrants intercepted in Aegean heading for Chios. Also available as `http://www.ansamed.info/ansamed/en/news/nations/greece/2017/03/06/130-migrants-intercepted-in-aegean-heading-for-chios_b60eec09-29a6-42a6-b846-3e747f71f000.html`

[2] (2018) Gdeltproject. Available at https://www.gdeltproject.org/
[3] (2018) Istanbul police evacuate refugees after clashes with locals. Also available as https://www.trtworld.com/turkey/istanbul-police-evacuate-300-refugees-after-clashes-with-locals-358027
[4] (2018) Kurdish militants claim responsibility for Turkey tunnel attack. Also available as https://www.reuters.com/article/us-turkey-blast/kurdish-militants-claim-responsibility-for-turkey-tunnel-attack-idUSKBN17E0MW
[5] (2018) One killed in brawl between locals and Afghan, Syrian migrants in Istanbul. http://www.hurriyetdailynews.com/one-killed-in-brawl-between-locals-and-afghan-syrian-migrants-in-istanbul-113111
[6] (2018) UNICEF Turkey Humanitarian Situation Report 7 MARCH 2017. Available at:. Available at https://www.unicef.org/appeals/files/UNICEF_Turkey_Humanitarian_Situation_Report_March_2017.pdf
[7] Ager A, Strang A (2004) The Experience of Integration: A qualitative study of refugee integration in the local communities of Pollockshaws and Islington. Research Development and Statistics Directorate, Home Office
[8] Alexander L, Jiang S, Murga M, González MC (2015) Origin–destination trips by purpose and time of day inferred from mobile phone data. Transportation research part c: emerging technologies 58:240–250
[9] Alfeo AL, Appio FP, Cimino MGCA, Lazzeri A, Martini A, Vaglini G (2016) An adaptive stigmergy-based system for evaluating technological indicator dynamics in the context of smart specialization. In: Proceedings of the 5th International Conference on Pattern Recognition Applications and Methods, SCITEPRESS-Science and Technology Publications, Lda, pp 497–502, DOI 10.5220/0005645204970502
[10] Alfeo AL, Cimino MGCA, Lepri B, Pentland S, Vaglini G (2017) Stigmergy-based modeling to discover urban activity patterns from positioning data. In: SBP-BRiMS The International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction and Behavior Representation in Modeling and Simulation (SBP-BRiMS 2017), LNCS 10354, pp 292–301, DOI 10.1007/978-3-319-60240-0_35
[11] Alfeo AL, Barsocchi P, Cimino MGCA, La Rosa D, Palumbo F, Vaglini G (2018) Sleep behavior assessment via smartwatch and stigmergic receptive fields. Personal and Ubiquitous Computing 22(2):227–243, DOI 10.1007/s00779-017-1038-9
[12] Alfeo AL, Cimino MGCA, Egidi S, Lepri B, Vaglini G (2018) A stigmergy-based analysis of city hotspots to discover trends and anomalies in urban transportation usage. IEEE Transactions on Intelligent Transportation Systems 19(7):2258–2267, DOI 10.1109/TITS.2018.2817558
[13] Altindag O, Kaushal N (2017) Do refugees impact voting behavior in the host country? Evidence from Syrian Refugee inflows in Turkey

[14] Avvenuti M, Cimino MGCA, Cresci S, Marchetti A, Tesconi M (2016) A framework for detecting unfolding emergencies using humans as sensors. SpringerPlus 5(1):43, DOI 10.1186/s40064-016-1674-y

[15] Blumenstock J, Fratamico L (2013) Social and spatial ethnic segregation: a framework for analyzing segregation with large-scale spatial network data. In: Proceedings of the 4th Annual Symposium on Computing for Development, ACM, p 11

[16] Carpi E, Pinar Senouguz H (2018) Refugee Hospitality in Lebanon and Turkey. On Making The Other'. International Migration

[17] Ciaramella A, Cimino MGCA, Lazzerini B, Marcelloni F (2010) Using context history to personalize a resource recommender via a genetic algorithm. In: Intelligent Systems Design and Applications (ISDA), 2010 10th International Conference on, IEEE, pp 965–970

[18] Cimino MGCA, Lazzeri A, Vaglini G (2015) Improving the analysis of context-aware information via marker-based stigmergy and differential evolution. In: International Conference on Artificial Intelligence and Soft Computing, Springer, pp 341–352, DOI 10.1007/978-3-319-19369-4_31

[19] Figueiredo MAT, Jain AK (2002) Unsupervised learning of finite mixture models. IEEE Transactions on pattern analysis and machine intelligence 24(3):381–396

[20] Gundogdu D, Incel OD, Salah AA, Lepri B (2016) Countrywide arrhythmia: emergency event detection using mobile phone data. EPJ Data Science 5(1):25, DOI 10.1140/epjds/s13688-016-0086-0

[21] Hardy K, Maurushat A (2017) Opening up government data for Big Data analysis and public benefit. Computer Law & Security Review 33(1):30–37

[22] Hebbani A, Colic-Peisker V, Mackinnon M (2017) Know thy neighbour: Residential integration and social bridging among refugee settlers in Greater Brisbane. Journal of Refugee Studies 31(1):82–103

[23] Hübl F, Cvetojevic S, Hochmair H, Paulus G (2017) Analyzing refugee migration patterns using geo-tagged tweets. ISPRS International Journal of Geo-Information 6(10):302

[24] içduygu A (2015) Syrian refugees in turkey. The Long Road Ahead Washington: Migration Policy Institute

[25] Keyman EF (2016) Turkey at the heart of the refugee and ISIL crises: Can the buffer state be a solution. Rev Int'l L & Pol 12:5

[26] Licoppe C, Diminescu D, Smoreda Z, Ziemlicki C (2008) Using mobile phone geolocalisation for socio-geographical'analysis of co-ordination, urban mobilities, and social integration patterns. Tijdschrift voor economische en sociale geografie 99(5):584–601

[27] Lifanova A, Ngan HY, Okunewitsch A, Rahman S, Guzmán S, Desai N, Özsari M, Rosemeyer J, Pleshkanovska R, Fehler A, Others (2016) New Locals: Overcoming Integration Barriers with Mobile Informal and Gamified Learning. In: Proceedings of the International Conference on Information Communication Technologies in Education, pp 132–141

[28] Lyytinen E (2015) Refugees' Conceptualizations of Protection Space: Geographical Scales of Urban Protection and Host–Refugee Relations. Refugee Survey Quarterly 34(2):45–77

[29] Madanipour A, Cars G, Allen J (2000) Social exclusion in European cities: processes, experiences, and responses, vol 23. Psychology Press

[30] Marsh L, Onof C (2008) Stigmergic epistemology, stigmergic cognition. Cognitive Systems Research 9(1-2):136–149

[31] Niwattanakul S, Singthongchai J, Naenudorn E, Wanapu S (2013) Using of Jaccard coefficient for keywords similarity. In: Proceedings of the International MultiConference of Engineers and Computer Scientists, vol 1

[32] Silm S, Ahas R (2014) Ethnic differences in activity spaces: A study of out-of-home nonemployment activities with mobile phone data. Annals of the Association of American Geographers 104(3):542–559

[33] Singh VK, Bozkaya B, Pentland A (2015) Money walks: implicit mobility behavior and financial well-being. PloS one 10(8):e0136628

[34] Tompkins AM, McCreesh N (2016) Migration statistics relevant for malaria transmission in Senegal derived from mobile phone data and used in an agent-based migration model. Geospatial health 11(1 Suppl):408

[35] Vernon D, Metta G, Sandini G (2007) A survey of artificial cognitive systems: Implications for the autonomous development of mental capabilities in computational agents. IEEE transactions on evolutionary computation 11(2):151–180