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Immigrant community integration in world cities

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As a consequence of the accelerated globalization process, today major cities all over the world are characterized by an increasing multiculturalism. The integration of immigrant communities may be affected by social polarization and spatial segregation. How are these dynamics evolving over time? To what extent the different policies launched to tackle these problems are working? These are critical questions traditionally addressed by studies based on surveys and census data. Such sources are safe to avoid spurious biases, but the data collection becomes an intensive and rather expensive work. Here, we conduct a comprehensive study on immigrant integration in 53 world cities by introducing an innovative approach: an analysis of the spatio-temporal communication patterns of immigrant and local communities based on language detection in Twitter and on novel metrics of spatial integration. We quantify the *Power of Integration* of cities –their capacity to spatially integrate diverse cultures– and characterize the relations between different cultures when acting as hosts or immigrants.

INTRODUCTION

Immigrant integration is a complex process involving a multitude of aspects such as religion, language, education, employment, accommodation, legal recognition and many others. Its study counts with a long tradition in sociology through concepts such as immigrant assimilation [1], structural assimilation [2] or immigrant acculturation and adaptation [3]. Over the last years, there have been advances in the definition of a common framework concerning immigration studies and policies [4], although the approach to this issue remains strongly country-based [5]. The outcome of the process actually depends on the culture of origin, the one of integration and the policies of the hosting country government [6]. Traditionally, spatial segregation in the residential patterns of a certain community has been taken as an indication of ghettoization or lack of integration [7]. While this applies to immigrant communities, it can also affect to minorities within a single country [8]. The spatial isolation reflects in the economic status of the segregated community and in social relationships of its members [9].

In global terms while international migration flows have remained almost stable over the last 20 years [10, 11], political and economic upheavals such as the Arab Spring and the Syrian civil war have brought the problem of migrants and their integration to the forefront of world news and even the academic press [12, 13]. A good part of newcomers concentrates in cities, and particularly in the large metropolises known as World Cities. These are centers that attract specialized immigration, driving important social and cultural transformations in cities worldwide [14]. The concept of Global or World Cities emerged in the 80s [15, 16] as strategic territories that articulate the international economic structure. According to Sassen [15], Global Cities are not only characterized by growing multiculturalism but also by a rising social polarization, which was finally materialized into an increasing social spatial segregation and gentrification processes. This assertion is still under debate in the area of social sciences, requiring its settlement further empirical evidence [17, 18]. Furthermore, immigrant integration has been the focus of many research studies, most of which conducted from national perspectives especially in European countries and the USA [5, 6, 8, 19, 20], and it is still in dare need of information sources beyond national census [12, 13, 21].

In parallel, the last few years have brought a paradigm shift in the context of socio-technical data. Human interactions are being digitally traced, recorded and analyzed in large scale. Sources as varied as mobile phone records [22–34], credit card transactions [35], or Twitter data [36–38] have been used to study mobility and land use in urban areas. Most of these works have been carried out in the zones where data was available, mostly inside cities or single countries. Twitter data has, however, the particularity of extending beyond national borders and, therefore, it allows researchers to analyze mobility and city hierarchies at an international level [36, 39]. Besides activity and mobility, the content of the tweets bears also a wealth of information starting by the language in which the text is written. The spatial distribution of languages has been investigated in Refs. [40–42], exploring as well the relations between languages trough multilingual individuals, and in Refs. [43, 44], where the spatial extension of Spanish and English dialects was examined. Of course, one of the weak points of Twitter as data source is its representativeness. This question has been boarded in Refs. [37, 45–47], find-

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ing acceptable coverage for the American, British and Spanish populations in terms of geographic allocation, race, religion and mobility, although the data shows a bias towards younger individuals. In this context, it is of special interest the mix of location and language detection. This issue opens the door to characterize foreign users in short visits, temporal or permanent stays. Arribas-Bel [48] published a first exploratory work on this direction using Twitter and census data in Amsterdam. Contemporarily, the use of phone call records to foreign countries has provided a picture of communities with external connections in the area of Milan [49]. When it comes to immigrant integration, there are less works but one that deserves mention is a study recently published by [50] who looked at the social ties (friendships and affinities) between immigrant communities by using data from Facebook. There have been diverse attempts to measure the degree of immigrant integration over the last years [51] by introducing a quantitative index, the Composite Assimilation Index (CAI), that quantifies the degree of similarity between native- and foreign-born adults in the United States, based on US census data. In [50], a similar measure of integration is considered based on the relative proportion of ties between immigrant people born in the US, compatriots living in the US, and inter-group friendships with immigrants from other countries.

In this work, we introduce a novel approach to quantify the spatial integration of immigrant communities in urban areas worldwide. By analyzing language in Twitter data, we are able to assign languages to each user paying special attention to those corresponding to migrant communities in the city considered. The individuals' digital spatio-temporal communication patterns allow us to define as well areas of residence. With this information, we perform a spatial distribution analysis through a modified entropy metric, as a quantitative way to measure the spatial integration of each community. The metric can be expressed in a bipartite network with the culture of origin in one side and the hosting cities, countries and languages in the other. These results lead us to categorize the cities according to how well they integrate immigrant communities and also to quantify how well hosting countries integrate people from other cultures.

MATERIALS AND METHODS

We selected 53 of the most populated cities in the world (see Figure 1a) and analyzed the geo-localized tweets originating in each city between October 2010 and December 2015 as captured from the Twitter API. The data was collected respecting Twitter's terms of service and privacy conditions. Several items are extracted from each tweet: user ID, geographical coordinates (latitude and longitude), date and time and the text of the tweet. In order to get a coherent picture in the different time zones, we convert the Twitter UTC time into the local timezone for each city. Be-

fore starting with the analysis, it is necessary to filter out non-human users from the dataset. This is fundamental in order to prevent result pollution by signals coming from automatic tweet generators (bots), which are not rare in social networks [52]. We found and disregarded tweets generated at the same time (with the precision of the second) by the same account. Moreover, we discard users who tweet more than three times per minute. Finally, we detect the speed of users moving through consecutive locations in order to filter out those traveling faster than a reasonable speed in urban areas (100 km/h or 62 mph). This procedure leaves us with a total of 350.9 millions of tweets posted by 14.5 millions of users in the 53 cities (see Table S1 in Appendix for detailed numbers per city).

We will propose below a metric to assess spatial segregation of immigrant communities that is not highly sensitive to the specific borders of the area studied. However, everything has its limits. The mix of local and immigrant population is different in urban and rural areas. It is important thus to attain a balance and ensure that the region considered contains the city, where the signal on immigrants is stronger, but it does not extend unnecessarily far from it. This means that we should agree on a city definition that can be applied around the world and it is large enough to include the whole metropolitan area. Unfortunately, generic definitions such as the Larger Urban Zone (LUZ) definition of Eurostat for Europe does not exist at the global scale. There are plenty of different ways of defining cities, with, for example, methods based on urban growth, percolation, attraction or fractal theory. All these methods require third party data such as population, built-up area or flows of commuters that is not easily available in a consistent form everywhere. To side step this difficulty, we use a very pragmatic definition based only on the Euclidean distance and consider all activity within a frame of $60 \times 60 \text{ km}^2$ centered on the barycenters listed in Table S2 in Appendix to belong to the city itself, dividing each city area using an equally spaced grid of 500×500 meters (Figure 1b).

Definition of the user's place of residence

As represented in Figure 1c, the place of residence of every user is defined as the most frequented grid cell between 8pm and 8am local time. To ensure that a user shows enough regularity and that he/she is really living in the city, and not just a visitor for a small period of time, we applied three filters: a minimum number of consecutive months of activity C, a minimum number of hours spent by the user in the most frequented cell N measured out of his/her consecutive tweets, and Δ as the ratio between N and the total number of hours of activity for each user (number of hours during which he/she has posted at least one tweet). The source code used to extract most visited locations from individual spatio-temporal trajectories



Figure 1. **Dataset and framework description**. The cities passed through the lens of our analysis are mostly distributed over four continents (a). Africa has been not considered due to the lack of data. We cover each city with a square grid in order to keep a homogeneous spatial division over the whole urban area where the users are going to be distributed (b), selecting resident users and their most frequent location thanks to their activity over space and time (c). In addition, we assign the users' most probable native language (d) and perform a spatial analysis over the cities (e) to get information about the population distribution in function of the language spoken by the users.

is available online¹.

Users who are active within a given city for at least three consecutive months are considered to be residents, so this establishes the first condition $C \geq 3$ months. The values of the other two parameters were determined empirically. In Figure S1 in Appendix, we plot the evolution of the number of users left in the dataset as a function of Δ for different values of N = [5, 10, 15, 20] in each of the 53 cities. As the shape of the curves is similar for different values of N, it does not seem to be a natural features that would allow us to define a clear cutoff. We fix $\Delta \geq 0.2$ and $N \geq 5$, as a trade-off between being relatively sure about the users' residence area and keeping enough number of users to have proper statistics. Table S3 in Appendix lists the final number of residents per city after this data cleaning procedure. Note that there are at least 1000 reliable users per city.

Language assignment

At this point, we are interested in introducing a method to determine which languages each user speaks, or at least in which languages he/she tweets. If any of these languages is proper of an immigrant community, this most likely will identify the user as a member of that community. To do this, the language in each tweet is detected using the version 2.0 of the "Chromium Compact Language Detector" (CLD2), which returns the languages detected along with a confidence assessment. CLD2 implements a Bayesian classifier for detecting language from UTF-8 text. Twitter entities (urls, mentions, hashtags)

¹ https://github.com/maximelenormand/ Most-frequented-locations



Figure 2. Bipartite Spatial Integration Network. The network comprises of two sets: **L** of Languages and **C** of cities; the languages detected are connected to the cities set where the corresponding community of immigrants has been found. The weight of the edge corresponds to the values of $h_{l,c}$. The size of the nodes is proportional to its degree and the color to its mean strength.

that may difficult our language detection efforts are removed, and only the remaining text was given as input to CLD2. To obtain reliable results, we keep only tweets for which the detector returned a language with confidence level of at least 90%. Also, we aggregate close languages to take into account the uncertainty in the identification of "mutually intelligible" languages and dialectal varieties (see Table S4 in Appendix for more details).

As can be expected, there are users tweeting in more than one language. We create a dictionary of the occurrences of each language in each users' tweets pattern. English is one of the most frequent language per user, because of its diffusion as "lingua franca" for spreading information to the highest number of Twitter followers. Still since we are interested in finding the language representative of users' community of origin, we propose a language algebra in order to extract this information from the user's dictionary. Let us define as *Local* the official language of each city. There are cases where there can be more than one Local language coexisting in the same city, like Catalan and Spanish in Barcelona, French and Flemish in Brussels or French and English in Montreal. The same occurs for Dublin and Singapore (see Table S5 for a complete list of cities and languages). After defining the Local languages in each city, we assign to each user its most frequent language. In case of bilingual/multilingual users, we set as user's language the one which differs from English or the Local unless these are the only two languages in the dictionary. In this latter case, we define the user as speaker of the Local language. In case of three languages spoken by the same user, we adopted the same hypothesis, assigning to the user the "third" language spoken apart when only one or both between English and Local are in the dictionary. In general, we take the most popular language in the dictionary other than English and the Local ones. If there are only Local languages and English, we keep the Local. English can be only assigned if it is the only one in the dictionary. The final number of users left for the analysis with a reliable residence cell, per language identified and per city are displayed in Table S6 in Appendix. We consider languages in each city with 30 users or more.

RESULTS

Bipartite spatial integration network

To quantify the spatial segregation of each immigrant community in every city, we build a bipartite spatial integration network H (see Figure 2). Every language is connected to the cities where the corresponding immigrant communities has been detected. The weight of an edge between language l and city $c, h_{l,c}$, corresponds to the level of spatial integration measured with a new metric inspired by the Shannon entropy, but modified to take into account the finite character of the sampling of communities in our Twitter database. Shannon entropy-like descriptors have been used before in this context especially when considering the spatial segregation of ethnic minorities in the US cities [53]. Recalling that the cities have been divided in equal area grid cells and focusing first only on one generic city c, we can directly calculate from

$$s_{l,c} = -\sum_{i=1}^{N} p_{l,i} \log(p_{l,i}/\Delta x^2),$$
(1)

where N is the total number of cells and the index iruns over all the cells. Δx^2 is the area of the cells, it is added to make the entropy stable against changes of spatial scale as proposed in Ref. [54]. We take as unit the area our $500 \times 500 \ m^2$ cells and, thus, a change in cell size as those shown in the Appendix for 1×1 and 2×2 square kilometers requires a correction factor 4 and 16, respectively, as expressed in Equation (1). The distribution of the population is generally heterogeneous, so $s_{l,c}$ by itself is not telling us anything about characteristic features of the community *l*. To overcome this and also to take into account the finite sampling size, we introduce next a random null model. The $n_{l,c}$ users associated to language l in city c are drawn at random over the city cells according to the total distribution of users to obtain new fractions $p_{l,i}^r$ for language l in each cell i, and then we evaluate the following entropy:

$$s_{l,c}^{rand} = -\sum_{i=1}^{N} p_{l,i}^{r} \log(p_{l,i}^{r}/\Delta x^{2}).$$
(2)

This process is repeated R times to smooth out fluctuations and in this way we obtain an average $\langle s_{l,c}^{rand} \rangle$. Here, we are interested in the limit of large number of realizations, R, in which the users speaking language lwould be distributed at random within the local population (fully integrated). The reason to repeat the procedure instead of using in a single run the distribution of the full population is to maintain the effect of the finite number of users speaking l. The speakers of this community l can be more or less concentrated in certain areas than the general population. To assess this effect, we define for each city c and detected language l the ratio:

$$\hat{h}_{l,c} = \frac{s_{l,c}}{\langle s_{l,c}^{rand} \rangle}.$$
(3)

To make the metric further comparable across cities, we further normalized $\hat{h}_{l,c}$ by the value obtained for the local language(s) spoken in city c, $\hat{h}_{loc,c}$ (Table S5 in Appendix). If more than one local language is present in the city, the data for all these languages is aggregated to obtain a joint value of $\hat{h}_{loc,c}$. The final definition of the ratio of entropies is thus:

$$h_{l,c} = \hat{h}_{l,c} / \hat{h}_{loc,c}.$$
(4)

In this way, the information provided takes as baseline the local population and will inform us whether a specific group is spatially segregated or not. According to this definition, low values of $h_{l,c}$ are symptoms of segregation, whereas local languages and those distributed spatially in a similar manner are characterized by $h_{l,c}$ values close to unit. The values of this normalized ratio $h_{l,c}$ constitute the weights of the links in the bipartite network displayed in Figure 2.

The stability of the spatial entropy in function of different cells sizes (different scales Δx^2) is studied in the Appendix. We evaluate the relative error among the links of the bipartite network in function of Δx taking as reference the unit-like cell with 500 m side frame. Results are quite stable taking into account the spatial component of entropy related to the side size of the cells of 1000 and 2000 meters, respectively, as shown in Figure S6 in Appendix.

Evaluation of the migrant communities spatial distribution's accuracy

Twitter has the advantage of being a global source of data, but also the disadvantage of having several uncontrollable biases. Young people are usually overrepresented [45, 47], and most likely the people belonging to the diverse communities are adopting the technology in different ways. If the use of geolocated Twitter is widespread in the host country, this will depend on the maturity of the migrant community: second and third generations are more likely to behave as locals and to adopt generalized technologies in the host population than first generations. On the other hand, things may vary if the technology is already commonly accepted in the country of origin of the community. Certainly, there are communities that are not detected. According to the National Institute for Statistics of Spain (INE, http://www.ine.es), a total of 45,728 and 54,599 Chinese citizens are residing in Barcelona and Madrid provinces, respectively, in 2016. Provinces are territorial divisions that enclose the urban areas and that loosely correspond to the area of analysis taken for our Twitter data. However, the number of users detected tweeting in Chinese is below the threshold of 30 with a valid residence cell and, therefore, this community does not appear in either of these cities. In the case of this particular group, there may be various reasons for this situation including the relative novelty of Chinese migration to Spain with most of this people belonging to the first generation, as well as the existence of alternatives to Twitter in China such as Sina Weibo. The important question here is thus not whether we find all the communities, but whether we are able to say something meaningful about those detected.

Going step by step, let us consider first the influence of the geographical area chosen on the structure of the bipartite network between language communities and cities paying special attention to the weights of its links. For this, recall that we have selected areas of $60 \times 60 \text{ km}^2$ around the barycenter of the 53 cities considered. These areas have been further divided in cells of $500 \times 500 \text{ m}^2$, which are the basic units of the analysis. The 53 cities are large megalopolis, still one



Figure 3. Evaluation of the migrant communities spatial distribution. (a) Box plots of the relative change $\epsilon_{l,c}$ of the link weights in the bipartite spatial integration network taking as reference the 60 km side frame. (b) The entropy ratio $h_{l,c}$ for three examples of communities with more than 1000 detected users (Spanish in Chicago and Miami and Portuguese in Madrid). A random sub-sampling is extracted and the calculated ratio of entropies is displayed as a function of the sample size. (c) The ratio of entropies $h_{l,c}$ as a function of the community size in number of users with a valid residence for all the communities. Every points represent a linguistic community in a city. The red vertical line marks the level of 30 users taken as a threshold. In the inset, it is shown a zoom-in with the details of the main plot. (d) We present the results concerning the ratio of entropies of a null model in which users belonging to a immigrant community is allowed to reside only in a subset N_0 of cells. In the numerical examples, the system contains $100 \times 100 = 10000$ cells. The figure shows how the ratio of entropies changes with the number of users in the immigrant community and how the curves depend in first order on the ratio between the number of users and N_0 .

can wonder if a square frame of 60 km side is enough to cover all of them, or whether we are including rural areas that could pollute the results. To check the stability of the network in function of the size of the city boundaries, we evaluate the relative error among the edge weights for different side sizes (20, 40, 80 and 100 km) using as reference the original 60×60 km² frame. In particular, the relative change $\epsilon_{l,c}$ of the link weights in the bipartite spatial integration network taking as reference the 60 km side frame is computed as follows,

$$\epsilon_{l,c} = \frac{h_{l,c} - h_{l,c}^{ref}}{h_{l,c}^{ref}} \tag{5}$$

where $h_{l,c}^{ref}$ represents the edge weight for $60 \times 60 \ km^2$ frame. Box plots displaying the distribution $\epsilon_{l,c}$ values for different frame side sizes can be found in Figure 3a. The network weights are stable for frame side sizes ranging from 40 to 80 km. Beyond these values, the differences are increasing, the influence zone is too limited or extended far away from the center into rural areas or other neighboring cities. The value of 60 km for the side size is thus a safe choice. It is also worth nothing than the number of detected languages increases with the size of the frame. This number is however quite stable for box sizes ranging from 40 to 80 km ($\pm 6\%$ of the reference value). We perform the same analysis over the cell side size, taking as reference the 500 m side frame. Results are still quite stable increasing the size to 1000 and 2000 meters, respectively, as shown in Appendix Figure S7.

A next question to consider concerns the minimum number of users needed to obtain a stable measure of $h_{l,c}$. The number of users for whom we can detect a residence area per community are not very high (Table S6 in Appendix), and in addition we have set a threshold of at least 30 users to accept the data of a community. Where this value is coming from? To get a first impression of the effect that the user number has on $h_{l,c}$, we select some of the most populous migrant communities, delete a fraction of their users at random and plot in Figure 3b the value of $h_{l,c}$ as a function of the remaining users. Every random extraction produces a different value of $h_{l,c}$, so in the plot we depict the average and the error bars obtained from the standard deviation. Besides, we mark with a shadowed areas the values between which $h_{l,c}$ lies for the extractions with the largest number of users. The results depend on the particular community, but in general the values of $h_{l,c}$ enter in the shadowed areas between 10 and 100 users, 30 corresponds to the middle ground in logarithmic scale. A more systematic check can be seen in Figure 3c. There, a scatter plot with every value of $h_{l,c}$ for couples language-city is depicted as a function of the number of users associated to the particular community. After 30 users, there is no more clear dependency between $h_{l,c}$ and the number of users so it must reflect the spatial distribution of the communities. It is also possible to perform a more detailed check in a controlled environment by introducing a null model in which the local population is randomly but uniformly distributed across the grid forming the city, while the immigrant population can only appear in a subset N_0 of cells. In those cells the immigrants are also distributed uniformly and randomly. By tuning the number of immigrant users and N_0 , one can explore how the metric $h_{l,c}$ reacts to finite numbers (see Figure 3d). When the number of immigrants detected is smaller than N_0 , they are indistinguishable from the local population and thus the ratio $h_{l,c}$ starts in one. As the number of immigrant users gets over N_0 , the fact that their residence is restricted to a certain area of the city becomes evident and $h_{l,c}$ decays towards a fixed value. As can be seen in the inset of Figure 3d, the main control parameter of the null model is the ratio between the number of immigrant users and N_0 . The curves showing $h_{l,c}$ as a function of the number of immigrants collapse by considering them as a function of such ratio. In general terms, the metric $h_{l,c}$ reaches a stable value once the number of immigrants is between 10 and 20 times larger than the cells where the community concentrates N_0 . This model is a worst-case scenario for testing $h_{l,c}$, since the immigrants distribute uniformly while in more realistic applications if a ghetto exists the concentration density will not be uniform. In this latter case, lower number of users are required to measure the stable value of $h_{l,c}$.

Finally, we have been also able to run a comparison between the spatial distribution of the communities

City	Language	Ι	Z-value	Autocorrelation
	Total	0.63	236.5	Positive
	Spanish	0.62	217.0	Positive
	English	0.50	230.5	Positive
Dancolona	French	0.37	151.5	Positive
Darcelona	Italian	0.28	125.8	Positive
	Portuguese	0.32	151.2	Positive
	Arabic	0.08	89.9	Random
	East-Slavic	0.21	112.8	Positive
	Total	0.71	66.5	Positive
	English	0.34	35.9	Positive
	Spanish	0.27	28.1	Positive
London	French	0.25	32.1	Positive
London	Italian	0.26	31.9	Positive
	Portuguese	0.15	18.5	Positive
	Arabic	0.34	48.5	Positive
	Total	0.62	268.6	Positive
	Spanish	0.62	267.3	Positive
	English	0.32	159.2	Positive
Modrid	French	0.37	151.5	Positive
Mauriu	Italian	0.26	146.3	Positive
	Portuguese	0.44	204.9	Positive
	Arabic	0.07	41.5	Random
	East-Slavic	0.06	37.7	Random

Table 1. Comparison of linguistic communities detection between census and Twitter. Global Moran's I for a set of common languages detected in Barcelona, London and Madrid. The z-values are calculated after 99 permutations. The last column refers to the quality and significance of the spatial autocorrelations detected.

detected in three cities for which the data from census offices was available. These cities are Barcelona, London and Madrid, and for the comparison we use data from the so-called Continuous Register Statistics in Spain and the Census Office in the UK. In the Spanish case, the information is collected when people residing in a certain area must inform the municipal authorities for tax purposes and to obtain social services such as health care. The smallest spatial units for this dataset are census tracts, so Twitter data must be translated into the same geographical units (see the Appendix for further details). We employ the Anselin Local Moran's I [55] to analyze the level of spatial correspondence of the main migrant communities. This metric provides information on the location, size and spatial coincidence of four types of clusters: a) highhigh clusters of significant high values of a variable that are surrounded by high variables of the same variable; b) high-low clusters of significant high values of a variable surrounded by low values of the same variable; c) low-high clusters of significant low values of a variable surrounded by high values of the same variable; and d) low-low clusters of significant low values of a variable surrounded by low values of the same variable. The details are included in Appendix, but a summary with the most important results for a set of linguistic communities common to the three cities are shown in Table 1. The comparison between the location of the residence areas detected with Twitter and those registered in the census is in general good



Figure 4. Clusters of cities and Power of Integration. In (a), three groups of cities show similar behavior in the number of communities detected and in their levels of integration. The length of the vectors represents the number of languages (communities) detected in each city; the color scale is representative of the decay of the entropy metric; the *Power of Integration* metric lead us to evaluate the potential of each city in uniformly integrating immigrant communities within its own urban area according to entropy values. In (b), decay of $h_{l,c}$ for the cities in each cluster. The points correspond to the values of the elements of $\vec{E_c}$ for each city placed in the x axis according to their index normalized to the total number of languages in *c*. The colors are for cities in the different clusters (C1 blue, C2 red and C3 green), and the lines are minimum square fits to the values of entropy ratios of each cluster.

and significant, except for some of the immigrant communities such as Arabic in Barcelona and Madrid or East-Slavic in Madrid where the results lose significance and are compatible with a random distribution.

Power of Integration

Once the limits of the data and the method to assess the spatial segregation levels of foreign communities have been checked, it is the moment to advance and study what can be said about the way that the cities integrate the foreign groups detected in Twitter. To this end and starting from the bipartite spatial integration network, we perform a clustering analysis based on the distribution of edge weights $h_{l,c}$. For each city c, the weights of the edges are sorted in descending order and stored into a vector $\vec{E_c}$. This vector $\vec{E_c}$ contains thus the information on how many foreign linguistic communities have been found in the city c and it quantifies how they are integrated. We can compare next the vectors $\vec{E_c}$ of pairs of cities to assess whether they behave in a similar way respect to the integration of external communities. Similarity metrics usually require the two vectors compared to have the same length. This difficulty can be overcome easily by adding zeros at the end of $\vec{E_c}$ until reaching the maximum length observed in the network L_{max} , namely, for London. We then perform a clustering analysis to find cities exhibiting similar distribution of edge weights by using a k-means algorithm based on Euclidean distances. The results of the analysis are confirmed by repeating the clustering detection with a Hierarchical Clustering Algorithm yielding the same results (see Figure S2 in Appendix).

Figure 4a shows the three clusters (C1 in blue, C2 in red and C3 in green) obtained after applying the clustering algorithms. These three clusters are characterized by the different rhythm of decay of the entropy values in $\vec{E_c}$ as can be seen in Figure 4b. The first cluster C1 including cities like London, San Francisco, Tokyo or Los Angeles shows the slowest decay. These cities contain in general a number of communities, which are spatially distributed closely mimicking

the local population. In the other extreme, the cluster C3 comprises cities with few or none migrant communities and displaying a high level of spatial segregation for the groups detected. In some cities of this club such as Guadalajara or Lima, we could only detect after applying filters the local languages. However, there are others like Toronto, Miami, Dallas, Rome or Istanbul for which the number of communities is comparable to the cities in the other clusters but the decay of the entropy is way much faster. The communities in their respective \vec{E}_c are highly isolated in comparison with the local population or with similar communities in cities of C1. Finally, there is a middle ground in the cluster C2 containing cities as New York, Paris, Philadelphia, Chicago and Sydney. We introduce a new metric in order to summarize the distribution of entropy and to assess the city's *Power of* Integration (Table S7 in Appendix). This metric is defined, for each city, as:

$$P_c = \frac{L_c}{L_{max}} Q_2 \left(1 - IQR\right),\tag{6}$$

where L_c is the number of languages spoken in city cand L_{max} is the maximum number of languages across the whole set of cities, Q2 is the median value of entropy and IQR the interquartile range used as a measure of dispersion. P_c is maximum when the median of the entropy ratio distribution is one or over, IQR = 0and the number of languages hosted by city c is the maximum. On the other extreme, it tends to zero when there are no hosted language, the languages are spatially isolated with $Q_2 = 0$, or when the IQR = 1covering the full range of values. The top three ranking cities in each cluster according to the Power of Integration are displayed in Figure 4a. According to the full ranking of cities by their *Power of Integration* (Table S7 in Appendix), the metric is able to capture the contribution in the spatial integration process within each urban area: cities belonging to cluster C1 comprises values of P_c ranging from Tokyo's 0.41 to London's 0.79; the former city shows good integration of massive communities coming from South Korea, Philippines and China. On the other side, the British capital shows almost full spatial mixing of a very large number of foreign communities. Cities belonging to cluster C2 are characterized by values of P_c ranging from Jakarta's 0.10 (characterized by mixing segregation behaviors in a scenario of spatial uniformity of most of the communities) to the 0.37 reached on the urban area of Philadelphia; here we found several communities that are uniformly spread within the city, whereas segregation appears focusing on the Arabic speaking community. The cluster as a whole mixes first segregation behaviors in a scenario of several communities involved in the process. Finally, cluster C3 is when both low number of immigrant communities are not well uniformly distributed within the urban areas, proved by the fact that P_c are very low. Brussels's 0.01 is due to the low values of entropy of the Turkish community within a scenario of few immigrant communities. Toronto, on the other side, is characterized by

a very high number of immigrant communities (comparable to cities found in the cluster C2), not being well spatial integrated within the urban environment. This leads to a P_c value of 0.12. Note that the clusters are obtained directly from the similarity between vectors $\vec{E_c}$ for each city, and later their character is explained by using the decay of the ratios $h_{l,c}$ in the vectors and P_c .

Language Integration Network

The bipartite spatial integration network can be also be projected into the language side to gain insights on the level of integration of languages into the different countries (see Table S8 in Appendix). We do the analysis at the country level because we assume that the integration of the immigrant communities is similar across the cities of the same country. When there are more than one city in the country, we take the average value of the entropy $h_{l,c}$ to build the network. The best and the worst cases of integration are displayed in Figure 5 left and right. Before proceeding to the analysis, it is important to mention that English has been excluded from the network because of its role as "lingua franca" [56]. Moreover, the role of English is dominant mainly in the worst links in terms of integration (see Figure S3 in Appendix for more details). We select two thresholds of levels of integration of language in countries: in the top set (Figure 5 left) the strong *Power of Integration* of UK cities (London and Manchester) sets its dominant role in uniformly spatial integrating several communities. Several patterns of uniform spatial integration appear, such as the Italian community in Venezuela, and the Spanishspeaking in Germany, Singapore and Turkey; the latter country shows uniformly distributed communities of Spanish people (due to historical migrations of Spanish Jews dating as far back as the 15th century), and Kurdish (largest ethnic minority in Istanbul). South-Slavic and East-Slavic communities keep their traditional presence in Russia and Germany. Increasing the threshold of the link weights, UK leads in the role of hosting diverse communities and some other patterns emerge, such as the German presence in Japan and UK. By contrast (Figure 5 right), Arabic rises as the most common spatially segregated community followed by French-speaking communities that appear to be spatially concentrated in other European countries such as Germany and Turkey. Increasing the threshold further, results in more forms of segregation appearing in Canada (East-Slavic, French and Tagalog), Australia (Malay and Japanese), Brazil (French) and Philippines (Italian and Spanish). Note that the segregation can occur on the two extremes of the economic spectrum: poor people may need to live in ghetto-like areas but also wealthier communities may concentrate with respect to the general local population as it seems to be the case for Italian and Spanish speaking minorities in the Philippines or the English speaking community in Rome.



Figure 5. Language Integration Network. We select the sub-network representative of the best levels of spatial integration of languages in countries and display it on the left of the figure. The network is formed by the top 10% links according to the entropy distribution (the spread of the values can be seen in the boxplot (a) in comparison with all the values of $h_{l,c}$). In addition, we include an extra 10% of links (dash-lines) to the network, those between 10% and 20% best links (their spread is in the boxplot (b)). In the network only nodes that belong to the top set are highlighted. Similarly, on the right, the worst levels of spatial integration of languages in countries are shown. We filter out the bottom 10% links according to the entropy distribution (their spread of values is in the boxplot (c)), and add an extra 10% of links to the network (dash-lines), those links between the 10% and 20% worst in the ranking. Their spread is in the boxplot (d). As before, only the nodes that belong to the worst set are highlighted.

DISCUSSION

People are constantly moving within cities and countries, looking for jobs, experiences or just for better life conditions, facing the fact of the integration in habits and laws of new local cultures. Migration flows have been studied so far by means of surveys and census data that cover from the number of people living outside their country of birth to place of residency to features of the labor market. However, census and surveys have the disadvantage of a very high cost, geographical limitations and, typically, they have slow update frequencies. Recent works by experts in the area highlight the dare need of more agile data sources about mobility and settlement patterns of immigrant and refugee communities.

Rather than using these classical sources, in this work we explore the capability of the online social networks to provide information about the integration of immigrant communities. In particular, we use Twitter to connect users to their residence place and via a language "algebra" to determine their cultural background. This allows us to study how spatial and linguistic characteristics of people vary within the cities they are living in, and how the cities spatially integrate the diversity of languages and cultures characteristic of the global metropolises today. It is necessary to admit the potential biases of the data: the social network penetration through socio-economic hierarchies, age, generations and countries is different. This is precisely the reason why we do not detect all the possible communities in the cites under consideration. Still we have introduced a method compressing a metric that is not so sensitive to the small numbers in the users detected. As can be seen, in the validation exercise the results in the cities where we can compare with the census are significant for communities with more than 30 users. This method in general measures how well different communities are spatially integrated/segregated within urban areas. Our findings provide a new way to observe the patterns of historically immigration of people to urban areas, and any potential changes that might arise in the areas of residence. We are able to move beyond the estimation of past, current and foreshadowed global flows toward a better comprehension of the integration phenomena on a city scale. Residents' online communications can thus let us assess in an indirect way if

- E. W. Burgess and R. E. Park. Introduction to the Science of Sociology. University of Chicago Press, 1921.
- [2] M. M. Gordon. Assimilation in American Life : The Role of Race, Religion and National Origins, volume 4. 1964.
- [3] J. W. Berry. Immigration, acculturation, and adaptation. Applied Psychology, 46(1):5–34, 1997.
- [4] A. Ager and A. Strang. Understanding integration: a conceptual framework. *Journal of Refugee Studies*, 21(2):166–191, 2008.
- [5] H. Entzinger and R. Biezeveld. Benchmarking in Immigrant Integration. Managing Integration. The European Union's Responsibilities Towards Immigrants, 1(August):123–136, 2005.
- [6] T. Gonul. A Comparative Study of the Integration of the Turks in Germany and the Netherlands. *Migration Letters*, 9:25–32, 2012.
- [7] D. S. Massey and N. A Denton. American apartheid: segregation and the making of the underclass. Harvard University Press, Cambridge, MA, USA, 1993.
- [8] D. S. Massey and N. A Denton. Trends in the Residential Segregation of Blacks, Hispanics, and Asians: 1970-1980. American Sociological Review, 52(6):802, 1987.
- [9] M. Oka and D. W. S. Wong. Spatializing Segregation Measures: An Approach to Better Depict Social

the cultural background has been kept inside communities, although impacted on different levels by local welcoming and hosting policies. This method provides an extra alternative to the toolkit of researchers in sociology and urbanism as well as direct view in close to real time on the potential problems of integration that may appear in different areas of the cities, a knowledge that can be of great value to public managers.

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AUTHOR CONTRIBUTIONS

F.L., M.L., G.R. and J.J.R. designed and performed research; F.L., M.L., M.H.S.O. and B.G. retrieved data; F.L., M.L., M.H.S.O. and B.G. analyzed data; and F.L., M.L., M.H.S.O., G.R., B.G. and J.J.R. wrote the paper.

Relationships. Cityscape: A Journal of Policy Development and Research, 17(1):97–113, 2015.

- [10] G. J. Abel and N. Sander. Quantifying global international migration flows. *Science*, 343(6178):1520–1522, 2014.
- [11] D. Butler. What the numbers say about refugees. *Nature*, 543:22–23, 2017.
- [12] Editorial article. Data on movements of refugees and migrants are flawed. *Nature*, 543:5–6, 2017.
- [13] H. Dijstelbloem. Migration tracking is a mess. *Nature*, 543:32–34, 2017.
- [14] J. Beaverstock. Lending Jobs to Global Cities: Skilled International Labour Migration, Investment Banking and the City of London. Urban Studies, 33(8):1377– 1394, 1996.
- [15] S. Sassen. The global city: introducing a concept. The Brown Journal of World Affairs, XI(2):27–40, 2005.
- [16] J. Friedmann. The World City Hypothesis. Development and Change, 17(1):69–83, 1986.
- [17] M. Samers. Immigration and the global city hypothesis: Towards an alternative research agenda. International Journal of Urban and Regional Research, 26(2):389, 2002.
- [18] C. Hamnett. Social Polarisation in Global Cities: Theory and Evidence. Urban Studies, 31(3):401–424, 1994.

- [19] S. Musterd. Social and ethnic segregation in Europe: Levels, causes, and effects. *Journal of Urban Affairs*, 27(3):331–348, 2005.
- [20] F. D. Bean and G. Stevens. America's Newcomers and the Dyamics of Diversity. Russell Sage Foundation, 2003.
- [21] K. Phalet and M. Swyngedouw. Measuring immigrant integration: The case of Belgium. *Studi Emigrazione*, 1(152):773–804, 2003.
- [22] J. Reades, F. Calabrese, A. Sevtsuk, and C. Ratti. Cellular census: Explorations in urban data collection. *Pervasive Computing, IEEE*, 6(3):30–38, 2007.
- [23] M. C. González, C. A. Hidalgo, and A.-L. Barabási. Understanding individual human mobility patterns. *Nature*, 453:779–782, 2008.
- [24] J. Reades, F. Calabrese, and C. Ratti. Eigenplaces: analysing cities using the space and time structure of the mobile phone network. *Environment and Planning* B: Planning and Design, 36(5):824–836, 2009.
- [25] V. Soto and E. Frías-Martínez. Automated land use identification using cell-phone records. In *Proceedings* of the 3rd ACM international workshop on MobiArch, HotPlanet '11, pages 17–22, New York, NY, USA, 2011. ACM.
- [26] J. L. Toole, M. Ulm, M. C. González, and D. Bauer. Inferring land use from mobile phone activity. In *Proceedings of the ACM SIGKDD International Work-shop on Urban Computing*, UrbComp '12, pages 1–8, 2012.
- [27] T. Pei, S. Sobolevsky, C. Ratti, S. L. Shaw, and C. Zhou. A new insight into land use classification based on aggregated mobile phone data. *International Journal of Geographical Information Science*, 28:1988–2007, 2014.
- [28] T. Louail, M. Lenormand, O. Garcia Cantú, M. Picornell, R. Herranz, E. Frías-Martínez, J. J. Ramasco, and M. Barthelemy. From mobile phone data to the spatial structure of cities. *Scientific Reports*, 4:5276, 2014.
- [29] A. Amini, K. Kung, C. Kang, S. Sobolevsky, and C. Ratti. The impact of social segregation on human mobility in developing and industrialized regions. *EPJ Data Science*, 3(1):1–20, 2014.
- [30] M. Tizzoni, P. Bajardi, A. Decuyper, G. Kon Kam King, C.M. Schneider, V. Blondel, Z. Smoreda, M.C. Gonzalez, and V. Colizza. On the use of human mobility proxies for modeling epidemics. *PLoS Computational Biology*, 10:e1003716, 2014.
- [31] P. Deville, C. Linard, S. Martin, M. Gilbert, F. R. Stevens, A. E. Gaughan, V. D. Blondel, and A. J. Tatem. Dynamic population mapping using mobile phone data. *Proceedings of the National Academy of Sciences (USA)*, 111:15888–15893, 2014.
- [32] S. Grauwin, S. Sobolevsky, S. Moritz, I. Gódor, and C. Ratti. Towards a comparative science of cities: Using mobile traffic records in New York, London, and Hong Kong. In Marco Helbich, Jamal Jokar Arsanjani, and Michael Leitner, editors, *Computational Approaches for Urban Environments*, pages 363–387, Cham, Switzerland, 2015. Springer International Publishing.
- [33] V. Blondel, A. Decuyper, and G. Krings. A survey of results on mobile phone datasets analysis. *EPJ Data Science*, 4:10, 2015.
- [34] T. Louail, M. Lenormand, M. Picornell, O. Garcia Cantú, R. Herranz, E. Frías-Martínez, J. J. Ra-

masco, and M. Barthelemy. Uncovering the spatial structure of mobility networks. *Nature Communications*, 6:6007, 2015.

- [35] M. Lenormand, T. Louail, O. G. Cantú-Ros, M. Picornell, R. Herranz, J. M. Arias, M. Barthelemy, M. S. Miguel, and J. J. Ramasco. Influence of sociodemographics on human mobility. *Scientific Reports*, 5:10075, 2015.
- [36] B. Hawelka, I. Sitko, E. Beinat, S. Sobolevsky, P. Kazakopoulos, and C. Ratti. Geo-located twitter as a proxy for global mobility patterns. *Cartography and Geographic Information Science*, 41:260–271, 2014.
- [37] M. Lenormand, M. Picornell, O. Garcia Cantú, A. Tugores, T. Louail, R. Herranz, M. Barthélemy, E. Frías-Martínez, and J. J. Ramasco. Cross-checking different source of mobility information. *PLoS ONE*, 9(8):e105184, 2014.
- [38] M. Lenormand, A. Tugores, P. Colet, and J. J. Ramasco. Tweets on the road. *PLoS ONE*, 9(8):e105407, 2014.
- [39] M. Lenormand, B. Gonçalves, A. Tugores, and J. J. Ramasco. Human diffusion and city influence. *Journal* of The Royal Society Interface, 12:20150473, 2015.
- [40] A. Magdy, T. M. Ghanem, M. Musleh, and M. F. Mokbel. Exploiting geo-tagged tweets to understand localized language diversity. In *Proceedings of Work*shop on Managing and Mining Enriched Geo-Spatial Data - GeoRich'14, pages 1–6, 2014.
- [41] D. Mocanu, A. Baronchelli, N. Perra, B. Gonçalves, Q. Zhang, and A. Vespignani. The Twitter of Babel: Mapping World Languages through Microblogging Platforms. *PLoS ONE*, 8(4):e61981, jan 2013.
- [42] R. Jurdak, K. Zhao, J. Liu, M. AbouJaoude, M. Cameron, and D. Newth. Understanding human mobility from Twitter. *PLoS ONE*, 10(7):35, 2015.
- [43] B. Gonçalves and D. Sanchez. Crowdsourcing dialect characterization through twitter. *PLoS ONE*, 9(11):1–10, 2014.
- [44] G. Doyle. Mapping dialectal variation by querying social media. In Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, pages 98–106, 2014.
- [45] A. Mislove, S. Lehmann, Y.-Y. Ahn, J.-P. Onnela, and J. N. Rosenquist. Understanding the Demographics of Twitter Users. In *Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media*, pages 554–557, 2011.
- [46] E. Bokányi, D. Kondor, L. Dobos, T. Sebk, J. Stéger, I. Csabai, and G. Vattay. Race, religion and the city: twitter word frequency patterns reveal dominant demographic dimensions in the United States. *Palgrave Communications*, 2:16010, 2016.
- [47] L. Sloan. Who tweets in the united kingdom? profiling the twitter population using the british social attitudes survey 2015. Social Media + Society, 3(1):2056305117698981, 2017.
- [48] D. Arribas-Bel. The spoken postcodes. Regional Studies, Regional Science, 2(1):458–461, 2015.
- [49] P. Bajardi, M. Delfino, A. Panisson, G. Petri, and M. Tizzoni. Unveiling patterns of international communities in a global city using mobile phone data. *EPJ Data Science*, 4(1):3, 2015.
- [50] A. Herdağdelen, B. State, L. Adamic, and W. Mason. The social ties of immigrant communities in the united states. In *Proceedings of the 8th ACM Conference on Web Science*, WebSci '16, pages 78–84, New

York, NY, USA, 2016. ACM.

- [51] J. L. Vigdor. Measuring Immigrant Assimilation in the United States. Civic Report No.53. Manhattan Institute for Policy Research, 2008.
- [52] Z. Chu, S. Gianvecchio, H. Wang, and S. Jajodia. Who is Tweeting on Twitter: Human, Bot, or Cyborg? In Acsac 2010, page 21, 2010.
- [53] M. J. White. Segregation and Diversity Measures in Population Distribution. *Population Index*, 52(2):198–221, 1986.
- [54] M. Batty. Spatial Entropy. Geographical Analysis, 6:1–31, 1974.
- [55] L. Anselin. Local indicators of spatial association-LISA. Geographical analysis, 27(2):93–115, 1995.
- [56] S. Ronen, B. Gonçalves, K. Z. Hu, A. Vespignani, S. Pinker, and C. Hidalgo. Links that speak: The global language network and its association with global fame. *Proceedings of the National Academy of Sciences (USA)*, 111(111):E5616, 2014.
- [57] L. Anselin, I. Syabri, and Y. Kho. GeoDa: An introduction to spatial data analysis. *Geographical Analy*sis, 38(1):5–22, 2006.

APPENDIX



Figure S1. Number of reliable users as a function of N and Δ . Each line represents the trend of each city in the number of users according to the ratio between N and the total number of hours of activity for each user (Δ). Set as C=3 the number of months for consecutive activities, (a) refers to N=5, (b) to N=10, (c) to N=15 and (d) to N=20.



Figure S2. Comparison of a k-means and hierarchical clustering algorithms over the vectors of the Bipartite Spatial Integration Network. C1, C2 and C3 are the clusters obtained through both algorithms, choosing as 3 the initial number of clusters to assign to the k-means analysis.



Figure S3. **Distribution of degree and weights in H with and without English**. Distribution of weights for the full network (a) and in the network obtained removing English from the nodes of the Bipartite Spatial Integration Network (b). As shown, English is dominant in the worst links in terms of spatial integration.

SUPPORTING TABLES

City	tweets	users
Amsterdam	2082040	175107
Atlanta	4896616	250803
Bandung	7980207	487209
Bangkok	9389888	265672
Barcelona	2249807	168189
Berlin	703551	64360
Bogota	3370596	195830
Boston	3500542	206385
Brussels	1434065	84140
Buenos Aires	18421250	459534
Caracas	1376503	108769
Chicago	5008746	304844
Dallas	6650105	253760
Detroit	3885662	144775
Jakarta	28304891	1260903
Dublin	1516170	89259
Guadalajara	704530	62403
Houston	5337061	193876
Istanbul	19438021	838347
Kuala Lumpur	16730001	412560
Lima	1356562	94234
Lisbon	3341088	57201
London	11167058	698424
Los Angeles	12458292	600476
Madrid	5605452	275857
Manchester	6940211	337083
Manila	19453573	449308

City	tweets	users
Mexico City	4458228	322462
Miami	3716735	241676
Milan	1493614	103383
Montreal	631844	52851
Moscow	2805144	141589
Nagoya	3941030	162606
New York	12960258	734100
Osaka	10607046	351628
Paris	10929091	335553
Philadelphia	5841765	247875
Phoenix	2970897	136501
Rio de Janeiro	20907590	295565
Rome	1240080	96213
Saint Petersburg	1124887	63828
San Diego	2267882	164061
San Francisco	4615005	284215
Santiago	3022229	148786
Sao Paulo	18744302	371032
Seoul	1338750	118509
Singapore	7530611	292571
Stockholm	784807	51729
Sydney	1226072	80349
Tokyo	15029229	644683
Toronto	2281968	150786
Vancouver	660837	58984
Washington	6515118	330808

Table S1. Number of tweets and users detected in each city after filtering out bots and multi-user accounts.

City	Latitude	Longitude	City
Amsterdam	52.370216	4.895168	Mexico
Atlanta	33.748995	-84.387982	Miami
Bandung	-6.914744	107.609811	Milan
Bangkok	13.727896	100.524123	Montre
Barcelona	41.385064	2.173403	Moscov
Berlin	52.519171	13.406091	Nagoya
Bogota	4.598056	-74.075833	New Y
Boston	42.358431	-71.059773	Osaka
Brussels	50.85034	4.35171	Paris
Buenos Aires	-34.603723	-58.381593	Philade
Caracas	10.491016	-66.902061	Phoeni
Chicago	41.878114	-87.629798	Rio de
Dallas	32.78014	-96.800451	Rome
Detroit	42.331427	-83.045754	Saint I
Jakarta	-6.211544	106.845172	San Di
Dublin	53.349805	-6.26031	San Fr
Guadalajara	20.67359	-103.343803	Santiag
Houston	29.760193	-95.36939	Sao Pa
Istanbul	41.00527	28.97696	Seoul
Kuala Lumpur	3.139003	101.686855	Singap
Lima	-12.047816	-77.062203	Stockh
Lisbon	38.725299	-9.150036	Sydney
London	51.511214	-0.119824	Tokyo
Los Angeles	33.95	-118.14	Toront
Madrid	40.416775	-3.70379	Vancou
Manchester	53.479324	-2.248485	Washir
Manila	14.599512	120.984219	

City	Latitude	Longitude
Mexico City	19.42705	-99.127571
Miami	25.788969	-80.226439
Ailan	45.465454	9.186516
Montreal	45.50867	-73.553992
Moscow	55.755826	37.6173
Vagoya	35.181446	136.906398
New York	40.714353	-74.005973
Dsaka	34.693738	135.502165
Paris	48.856614	2.352222
Philadelphia	39.952335	-75.163789
Phoenix	33.448377	-112.074037
Rio de Janeiro	-22.903539	-43.209587
Rome	41.892916	12.48252
Saint Petersburg	59.93428	30.335099
San Diego	32.715329	-117.157255
San Francisco	37.774929	-122.419416
Santiago	-33.46912	-70.641997
Sao Paulo	-23.548943	-46.638818
Seoul	37.566535	126.977969
Singapore	1.352083	103.819836
Stockholm	59.32893	18.06491
Sydney	-33.867487	151.20699
Tokyo	35.689487	139.691706
Foronto	43.653226	-79.383184
/ancouver	49.261226	-123.113927
Vashington	38.907231	-77.036464

Table S2. Coordinates of the centers of the frame for each city.

City	Resident Users	City	Resident Users
Amsterdam	4986	Mexico City	18079
Atlanta	8474	Miami	7754
Bandung	27818	Milan	4243
Bangkok	25659	Montreal	2613
Barcelona	9957	Moscow	9673
Berlin	1301	Nagoya	7589
Bogota	19353	NewYork	34325
Boston	8989	Osaka	16348
Brussels	2325	Paris	19757
Buenos Aires	48934	Philadelphia	13679
Caracas	4613	Phoenix	9259
Chicago	15397	Rio de Janeiro	37177
Dallas	15549	Rome	1994
Detroit	10652	Saint Petersburg	3819
Jakarta	98997	San Diego	5014
Dublin	5480	San Francisco	25504
Guadalajara	3459	Santiago	10066
Houston	11413	Sao Paulo	21862
Istanbul	101556	Seoul	3099
Kuala Lumpur	41084	Singapore	20997
Lima	2003	Stockholm	2668
Lisbon	4321	Sydney	4751
London	37402	Tokyo	75929
Los Angeles	70592	Toronto	8737
Madrid	15447	Vancouver	2298
Manchester	23836	Washington	10147
Manila	20093	_	

Table S3. Total number of residents users detected in the cities.

Detected language	Aggregated group	Detected Language	Aggregated Group
Albanian	Albanian	Kurdish	Kurdish
Arabic	Arabic	Lettonian	Baltic
Belarusian	East Slavic	Lituanian	Baltic
Bosnian	South Slavic	Macedonian	South Slavic
Bulgarian	South Slavic	Malay	Malay
Catalan	Catalan	Norwegian	Northern European
Chinese	Chinese	Polish	West Slavic
Croatian	South Slavic	Portuguese	Portuguese
Czech	West Slavic	Romanian	Romanian
Danish	Northern European	Russian	East Slavic
Dutch	Dutch (including Flemish)	Serbian	South Slavic
English	English	Serbo-Croatian	South Slavic
Faroese	Northern European	Slovak	West Slavic
Finnish	Finnish	Slovenian	South Slavic
French	French	Southern Sotho	Southern Sotho
German	German	Spanish	Spanish
Greek	Greek	Swahili	Swahili
Haitian	Haitian	Swedish	Northern European
Hungarian	Hungarian	Sundanese	Sundanese
Icelandic	Northern European	Tagalog	Tagalog
Indonesian	Indonesian	Thai	Thai
Irish	Irish	Turkish	Turkish
Italian	Italian	Ukrainian	East Slavic
Japanese	Japanese	Vietnamese	Vietnamese
Javanese	Javanese		
Korean	Korean		

Table S4. Language aggregation process. A main Aggregated group has been associated to each language detected in the framework, to overlap "mutually intelligible" issues in the detection.

City	Local Culture	City	Local Culture
Amsterdam	Dutch	Mexico City	Spanish
Atlanta	English	Miami	English
Bandung	Indonesian	Milan	Italian
Bangkok	Thai	Montreal	French/English
Barcelona	Spanish/Catalan	Moscow	East-Slavic
Berlin	German	Nagoya	Japanese
Bogota	Spanish	New York	English
Boston	English	Osaka	Japanese
Brussels	French/Flemish	Paris	French
Buenos Aires	Spanish	Philadelphia	English
Caracas	Spanish	Phoenix	English
Chicago	English	Rio de Janeiro	Portuguese
Dallas	English	Rome	Italian
Detroit	English	Saint Petersburg	East-Slavic
Jakarta	Indonesian	San Diego	English
Dublin	English/Irish	San Francisco	English
Guadalajara	Spanish	Santiago	Spanish
Houston	English	Sao Paulo	Portuguese
Istanbul	Turkish	Seoul	Korean
Kuala Lumpur	Malay	Singapore	Malay/Chinese/English/Tamil
Lima	Spanish	Stockholm	Northern-European
Lisbon	Portuguese	Sydney	English
London	English	Tokyo	Japanese
Los Angeles	English	Toronto	English
Madrid	Spanish	Vancouver	English
Manchester	English	Washington	English
Manila	Tagalog		

Table S5. **Cities and local languages**. Each city has been associated to its main local language; Barcelona, Brussels, Dublin, Montreal and Singapore have been related to more than one language due to the coexistence of multiple languages in the same urban area.

Amsterdam					4383		247		34	51																	55					138			
Atlanta					38		7747		148								_		_	-			144		_		305				_				
Bandung							182							21847			-	116	_	-	3132				_			2484			_		_		
Bangkok				55			493		40					47			154		368											47	24339		_		
Barcolona			1516				103		72								101						57				7055				- 1000		_		
Barcelona		42	1010			40	140		20	770													57				60					71			
Deilin		43				42	149		30	119																	09				_	71			
водота							45																				19304								
Boston		109			30		7570		156					112		173	31						218				439			39					
Brussels					1449		81		632																							99			
Buenos Aires							46									601							3001				15267								
Caracas																60							278				4231								
Chicago		55					13277		250	197						206						49	160				1006			84		36			31
Dallas		32					13694		222														218				1186		74	69					
Detroit		36					9964									107							108				347			47					
Dublin		57					4232		142	58					327	57					34		190				180			35					31
Guadalajara																											3427								
Houston		44					9808																183				1269			57	_				
stanbu		207				33	99		152								_			432					_		119				_	00443	;		
Jakarta							1932							95798			33	236	52		752							113			-		_		
Kuala Lumpur		55		1209			1124							10751				200	46		27570							62		71			_		
		55		1230			1134							10/01		\vdash			40		21310	\vdash					1050	υz							
Lima																											1956								
Lisbon							65																4052				139								
London	92	584			138	99	30742	122	918	357	46		62	414		552	84				216	206	545	118	48		956		131	176	32	419			213
Los Angeles		556		44		100	59637		1159								269		96			323	880				6451			690	39	129		78	86
Madrid							152		148							144							1065	35			13792			36					
Manchester		136			86		21105		322	235				243		291					94	476	284			44	292			74		43			41
Mani l a							1264		50							37											62			18620					
Mexico City							90		95							144											17674								
Miami							4968		119	81		57				74						249	155				1961			37					
Milan							92		56							3766											147			75					
Montreal		34					896		1410							52							31		_		122				-				
Moscow						5816	138										-		_						3511						_	39	33		
Nagova				48			44										7303		37				75							41					
New York		101		10	110	62	27072		723	453				424		505	79					144	590				3/01			225	_	1/10		_	60
Oselve		101		110	115	02	00		720	400				727		000	15050		120			144	000				0401			220	44	145			00
Usaka		4.40		112		07	99		40050							407	10002		120		04		040		44		000				44	07			
Paris		148				37	292		18250	39						127	30				31		213		41		383					67			
Philadelphia		74					11910		217	212		72				201					112		217				475			73					33
Phoenix							8264		92	117						66							99				532			47					
Rio de Janeiro									70							216							36050				802								
Rome							124		32							1585											105			54					
Saint Petersburg						2180	46																		1540										
San Diego		142					3869		59	56				46									67				660			44					
San Francisco		75		49	84	45	20980		614					336		287	149		30		89	110	347				1611			357		66		59	161
Santiago							41		35														396				9578								
Sao Paulo									64							154							20970		_		605				_				
Seou							188							47			140		2426						_						123				
Singapore				1040			3574		75	62				5222			57	48	84		10349		40				46	58		238					
Stockholm							157															2325					46					34			
Sydney		55			_		3820		100	46				81		87	69			-	33		66		_		103			00	-	30			
Tokyo		40		540		47	020		140	40				157		50	72965		420		50		55				120			106	160				
Токуо		40		049	25	+/	330		149	+/				137		140	, 2000 04		429		28	$\left - \right $	470	50			120	_		130	100	64		_	54
I oronto		83			35	32	6951		264	94						140	94						178	90			353			238		64			51
Vancouver							1808		150								54						51				78						$ \rightarrow $		
Washington		128					8520		200	154											59		168				676			88					
	nian	abic	alan	ese	utch	avic	lish	nish	nch	nan	leek	itian	rian	sian	rish	lian	ese	ese	ean	dish	alay	ean	ese	nian	avic	otho	nish	ese	ahili	alog	Thai	kish	bek	ese	avic
	Mbar	Ari	Cati	Chin	õ	st-SI	Eng	Fin	Fre	Gerr	Ģ	Hai	unga.	ones	-	ta	apan	avan	Kor	Kur	Ň	urop	tugu	omar	h-Si	л-Sc	Spai	ndan	Sw.	Tagi	2	Turt	ΠZ	nam	st-SI.
	4			2		Eas							Τ	pu			зŗ	ŝĻ				Ш. Д	Por	Я	Sout	uther		Sur						Viet	We
																						rthei				SoL									
																						No													

Table S6. Number of resident users per language and per city.

Cluster	City	Q1	Q2	Q3	IQR	P_c	Cluster	City	Q1	Q2	Q3	IQR	P_c
C1	London	0.81	0.91	0.95	0.13	0.789	C3	Buenos Aires	0.23	0.51	0.80	0.57	0.029
C1	Manchester	0.91	0.95	0.96	0.06	0.543	C3	Caracas	0.25	0.50	0.75	0.50	0.022
C1	Los Angeles	0.87	0.93	0.96	0.09	0.518	C3	Dallas	0.19	0.34	0.40	0.20	0.071
C1	San Francisco	0.77	0.83	0.92	0.15	0.522	C3	Detroit	0.19	0.39	0.45	0.26	0.064
C1	Tokyo	0.71	0.80	0.87	0.16	0.413	C3	Guadalajara	1.00	1.00	1.00	0.00	0.000
C2	Philadelphia	0.88	0.90	0.92	0.04	0.375	C3	Houston	0.51	0.57	0.63	0.12	0.087
C2	Paris	0.76	0.81	0.90	0.14	0.336	C3	Istanbul	0.16	0.57	0.69	0.52	0.071
C2	Singapore	0.81	0.86	0.95	0.15	0.319	C3	Lima	1.00	1.00	1.00	0.00	0.000
C2	New York	0.31	0.64	0.85	0.54	0.180	C3	Lisbon	0.16	0.32	0.66	0.50	0.014
C2	Kuala Lumpur	0.83	0.87	0.90	0.07	0.246	C3	Manila	0.11	0.22	0.53	0.41	0.023
C2	San Diego	0.82	0.88	0.93	0.12	0.236	C3	Mexico City	0.54	0.74	0.82	0.28	0.070
C2	Boston	0.65	0.80	0.88	0.23	0.241	C3	Miami	0.27	0.41	0.43	0.16	0.121
C2	Chicago	0.53	0.82	0.84	0.31	0.247	C3	Milan	0.57	0.76	0.78	0.21	0.103
C2	Dublin	0.57	0.79	0.87	0.29	0.220	C3	Montreal	0.61	0.69	0.72	0.11	0.107
C2	Sydney	0.27	0.65	0.75	0.48	0.161	C3	Moscow	0.66	0.72	0.76	0.10	0.113
C2	Washington	0.72	0.82	0.84	0.13	0.217	C3	Osaka	0.25	0.83	0.99	0.75	0.037
C2	Madrid	0.61	0.91	0.94	0.33	0.159	C3	Phoenix	0.41	0.47	0.56	0.15	0.105
C2	Nagoya	0.76	0.86	0.97	0.22	0.146	C3	Rio de Janeiro	0.33	0.47	0.63	0.29	0.044
C2	Bangkok	0.40	0.77	0.84	0.43	0.133	C3	Rome	0.78	0.79	0.88	0.10	0.124
C2	Berlin	0.44	0.77	0.90	0.46	0.108	C3	Saint Petersburg	0.40	0.80	0.90	0.50	0.035
C2	Jakarta	0.42	0.63	0.82	0.40	0.099	C3	Santiago	0.21	0.38	0.61	0.40	0.030
C3	Amsterdam	0.30	0.52	0.74	0.44	0.063	C3	Sao Paulo	0.30	0.48	0.67	0.37	0.040
C3	Atlanta	0.10	0.21	0.41	0.31	0.026	C3	Seoul	0.28	0.29	0.60	0.32	0.034
C3	Bandung	0.36	0.66	0.77	0.41	0.068	C3	Stockholm	0.25	0.37	0.56	0.32	0.033
C3	Barcelona	0.36	0.60	0.80	0.44	0.044	C3	Toronto	0.10	0.33	0.47	0.37	0.117
C3	Bogota	0.25	0.50	0.75	0.50	0.011	C3	Vancouver	0.19	0.38	0.46	0.28	0.047
C3	Brussels	0.12	0.24	0.62	0.50	0.011							

Table S7.	Power	of	Integration	of	Cities.

City	Local Culture	City	Local Culture
Amsterdam	Netherlands	Mexico City	Mexico
Atlanta	USA	Miami	USA
Bandung	Indonesia	Milan	Italy
Bangkok	Thailand	Montreal	Canada
Barcelona	Spain	Moscow	Russia
Berlin	Germany	Nagoya	Japan
Bogota	Colombia	New York	ŪSA
Boston	USA	Osaka	Japan
Brussels	Belgium	Paris	France
Buenos Aires	Argentina	Philadelphia	USA
Caracas	Venezuela	Phoenix	USA
Chicago	USA	Rio de Janeiro	Brazil
Dallas	USA	Rome	Italy
Detroit	USA	Saint Petersburg	Russia
Jakarta	Indonesia	San Diego	USA
Dublin	Ireland	San Francisco	USA
Guadalajara	Mexico	Santiago	Chile
Houston	USA	Sao Paulo	Brazil
Istanbul	Turkey	Seoul	Korea
Kuala Lumpur	Malaysia	Singapore	Singapore
Lima	Per	Stockholm	Sweden
Lisbon	Portugal	Sydney	Australia
London	ŪK	Tokyo	Japan
Los Angeles	USA	Toronto	Canada
Madrid	Spain	Vancouver	Canada
Manchester	ŪK	Washington	USA
Manila	Philippines	_	

Table S8. City/Country Correspondence.

EVALUATION OF THE MIGRANT COMMUNITIES SPATIAL DISTRIBUTION ACCURACY

Validation data was extracted from the Continuous Register Statistics of the Municipal Register, regarding the cities of Madrid and Barcelona. The smallest spatial units for this dataset are census tracks, of which the latest available geometrical boundaries for both study areas are the corresponding to 2013. It is well known that census tracks cover all the territory (not only populated areas) and that their size depends on the population density of an area, i.e. the more population density, the smallest the size and vice versa, in order to ensure that all census tracks have a similar number of inhabitants. This means that low density census tracks are larger than those corresponding to the city center, thus integrating non populated territory. For this reason, complementary data about the exact location of the residential areas is needed in order to properly geo-reference population data from census track statistics. In this research, information was extracted from the "Downloads of data and cartography by town" service of the SEC, the point of access to electronic services provided by the Directorate General of Land Registry of Spain. This data was transformed in order to obtain the surface devoted to each land use in each urban parcel. Some data treatment was required in order to obtain the number of people residing in each 500 x 500 m² grid cell according to the main language spoken in the country of origin. S9 Table shows the correspondence between country of origin and the languages detected in the main part of this paper. It is important to notice that not all the countries in the world are present in the original table.

Country of Origin
Germany
Bulgaria
France
Italy
Poland
Portugal, Brazil
United Kingdom
Romania
Russia, Ukraine
Morocco, Algeria
Spain, Argentina, Bolivia
Colombia, Cuba, Chile, Ecuador
Paraguay, Peru, Dominican Republic
Uruguay, Venezuela
China
Pakistan

Table S9. Correspondence between languages detected in Twitter users and country of origin.

The second step in data treatment was to locate where people in each census track actually live according with the location of residential land. We selected the blocks containing some surface devoted to residential use from the cadastral dataset. With the use of a Geographic Information System (GIS) we were able to intersect these polygons with the census track boundaries, and to assign the population of each census track to its residential land, proportional to the size of each residential polygon within each census track. Finally, the resulting dataset was intersected with the grid used in the previous parts of this research in order to obtain the estimated number of residents of each language in each grid cell.

Anselin Local Morans I is a well-known statistic that provides information on the location and size of four types of clusters: a) high-high clusters of significant high values of a variable that are surrounded by high variables of the same variable; b) high-low clusters of significant high values of a variable surrounded by low values of the same variable; c) low-high clusters of significant low values of a variable surrounded by high values of the same variable; and d) low-low clusters of significant low values of a variable surrounded by low values of the same variable. While the typical tools available in most GIS software solutions allow for univariate analysis, GeoDa is an open source product that also allows the computation of bivariate analysis [57], thus enabling the identification of spatial clusters in which high values of one variable are surrounded by high values of the second (i.e. lagged) variable (high-high clusters) and so on.

Bivariate global Moran's I (S10 Table) indicates the existence of positive spatial autocorrelation between the location of tweets and residential areas. In general terms, there is a high positive spatial correlation in both study areas (Morans I = 0.6). The z and p values have been evaluated through 99 permutations. This value remains high for local language (Spanish in Madrid and Spanish and Catalan in Barcelona). The spatial autocorrelation of foreign languages is a bit lower, which might be in part due to the inconsistencies between Twitter language and available countries of origin in the official statistics (i.e. United Kingdom is the only country of origin for English speakers and so are Morocco and Algeria for Arabic languages). Anyway, Arabic is the only language whose tweets show a random spatial pattern in relation with the location of resident population from Morocco

Language	City	Ι	Z-value	pseudo p-value	Spatial Autocorrelation
Total	Barcelona	$0,\!63$	$236{,}51$	0,01	Positive
	Madrid	$0,\!62$	$268,\!62$	0,01	Positive
Spanish	Barcelona	$0,\!62$	$216,\!99$	0,01	Positive
	Madrid	$0,\!62$	267, 29	0,01	Positive
English	Barcelona	$0,\!50$	$230,\!53$	0,01	Positive
	Madrid	$0,\!38$	$190,\!62$	0,01	Positive
French	Barcelona	$0,\!37$	$151,\!51$	0,01	Positive
	Madrid	0,32	$159,\!25$	0,01	Positive
Italian	Barcelona	$0,\!28$	$125,\!84$	0,01	Positive
	Madrid	0,26	$146,\!32$	0,01	Positive
Portuguese	Barcelona	$0,\!32$	$151,\!20$	0,01	Positive
	Madrid	$0,\!44$	204,95	0,01	Positive
Arabic	Barcelona	$0,\!08$	89,88	0,01	Random
	Madrid	$0,\!07$	41,50	0,01	Random
East-Slavic	Barcelona	$0,\!21$	$112,\!83$	0,01	Positive
	Madrid	$0,\!06$	$37,\!66$	0,01	Random

Table S10. Data Validation. Global Moran's I.

or Algeria in both cities, whereas tweets in English in Barcelona and tweets in Portuguese in Madrid are highly positively spatially correlated with resident population from the UK and Portugal or Brazil, respectively.



Figure S4. Data Validation (1/2). Distribution of Spanish native users in Madrid, according to official statistics and to our framework of language detection process.



Figure S5. Data Validation (2/2). Distribution of Portuguese native users in Madrid, according to official statistics and to our framework of language detection process.



Figure S6. Relative error of the spatial entropy in function of Δx . Box plots of the relative change $\epsilon_{l,c}$ of the link weights in the bipartite spatial integration network taking as reference the unit-like Δx as the cell side frame of 500 meters, with respect of 4 and 16 times the Δx for cell side sizes of 1000 and 2000 meters, respectively.



Figure S7. Relative error of link weights in function of the cell side size. Box plots of the relative change $\epsilon_{l,c}$ of the link weights in the bipartite spatial integration network taking as reference the 500 meters cell side frame.