Disentangling activity-aware human flows reveals the hidden functional organization of urban systems

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Increasing evidence supports the fact that cities are complex systems, with a broad spectrum of structural and dynamical features which lead to unexpected and emerging phenomena. Understanding urban dynamics at individual level – but also as the outcome of collective human behaviour – will open the doors to uncountable applications ranging from enhancing the sustainability and the resilience of the city to improving health and well-being of its inhabitants.

Here, we use a unique data set of longitudinal human flows provided by Foursquare, a leader platform for location intelligence, to characterize the functional organization of a city. First, we build multidimensional network models of human flows corresponding to different types of activities across time. We quantify the efficiency of flow exchange between areas of a city in terms of integration and segregation, respectively. Results reveal unexpected complex spatio-temporal patterns that allow us to gain new insight on the function of 10 megacities worldwide. We discover that large cities tend to be more segregated and less integrated, and that human flows at different hours of the day or between different types of activities enable the identification of different “cities within the city” which indeed show clear dissimilarities in terms of both functional integration and segregation.

Our analysis provides new insights on how human behaviour influences, and is influenced by, the urban environment and, as an interesting byproduct, to characterize functional (dis)similarities of different metropolitan areas, countries, and cultures.

I. INTRODUCTION

Cities are complex systems which process information, evolve and adapt to their environment [1]. To understand how complex systems – and cities more specifically – operate, it is thus important to quantify how information is processed in terms of integration and segregation. To this aim, on the one hand many relevant network descriptors have been introduced, based either on topological features or on dynamical ones, or both. On the other hand, integration has been reflected either in how information flow is accounted for by more complex topological models where multiple relationships co-exist simultaneously [2–5], namely multilayer systems [6, 7], or in causal effects observed in the time course of systems’ units [8–17].

Concerning the topological analysis of classical single-layer networks, to date a clear definition of integrated and segregated information flow is still debated and many proxies are used across a broad spectrum of disciplines, ranging from neuroscience to social and urban sciences [18–33], often indicating with the same name very different concepts.

The recent availability of a large amount of human-generated data enables the analysis of urban systems from different perspectives which could not be even considered until a few years ago [34]. In recent times, however, models and analytical tools inspired by complexity science are proliferating. More and more examples are providing convincing evidences of their fruitful application to real cities [35–40]. Applications range from human mobility [41–44] and traffic congestion [45–49], to energy consumption [50], air quality [51–52] and climate [53], health and wellbeing [54–57], and the associated topic of accessibility to important facilities like hospitals [58]. Indeed, the city can be seen as a growing complex system [59, 60] whose spatial organization [61, 62] dynamically experiences a transition from monocentric [63, 64] to polycentric [65, 66].

A particularly relevant perspective is provided by activity-aware information [67], such as the one provided by users of Foursquare – a leading location intelligence platform – which allows people to investigate human flows at different scales with unprecedented detail [68]. This type of data is of special interest because one can investigate the interplay between the structure of a city and the dynamics of its inhabitants to gain novel insights about the functional organization of the underlying urban ecosystem.

In this work, we stratify human activities in Foursquare to build network models describing the human movements across the urban space – from hours to months – within the different areas (see Methods) of 10 different metropolitan systems worldwide – namely Chicago, Istanbul, Jakarta, London, Los Angeles, New York, Paris, Seoul, Singapore and Tokyo – representing 3 continents.

By classifying existing activities into a few representative macro-categories (see Methods for details) we build a multilayer network [6, 7], where the flows encode how users move between venues of the same macro-category (e.g., from a pub to another one) and between venues of different macro-categories (e.g., from a pub to a cinema). In the following, we will refer to intra-layer flow to indicate movements of the first type, and to inter-layer flow to indicate movements of the second type.

Our main goal is to better characterize the functional organization of a city through the lens of network science. To this aim we measure to which extent different areas of the city facilitate human flows – i.e., functional inte-
FIG. 1. **Modeling Structure and Function of Urban Systems.** *Left:* Urban structural backbone of the 10 megacities considered here, as described from their street networks (data obtained from Open Street Map [67]). *Middle:* Urban functional networks described by the Foursquare data. The nodes are obtained by dividing the area analysed into cells of 500m × 500m. The edges are subsequent check-ins that might be between activities of the same type (intra-links: e.g., Food-Food, Tourism-Tourism) or different types (inter-links: e.g., Food-Tourism, Food-Sport). The collection of layers and inter-layer flows defines a multilayer network [4, 6, 7], i.e., a multidimensional functional representation of the urban areas. *Right:* The mobility flows between areas are captured as the edges’ weights. In the example, describing New York City, we can observe the different spatial distribution of flows between and across different activity layers (see also Fig. 2).

II. RESULTS

**Overview of the data set.**— The Foursquare data rendered available for the Future Cities Challenge [70] describe 24 months of check-ins between April 2017 and March 2019 (included). The 10 world mega-cities included in the challenge are Chicago, Istanbul, Jakarta, London, Los Angeles, Tokyo, Paris, Seoul, Singapore and New York City (see Fig. 2 left). The extensive characteristics of the datasets are shown in Tab. I. The flows between different areas are derived by subsequent check-ins to the Foursquare’s location-based services and coarse grained with a 500m × 500m granularity (see Fig. 2 middle, and Methods). In the data provided, check-ins are already aggregated by couple of venues (origin and destination), month and hour of the day (morning, midday, afternoon, night, and overnight). The metadata of the venues include a *category* field which describes the type of venue in great detail (e.g.: Knitting Stores, Mini Golf Courses, Rock Clubs, ...). We defined a set of macro-categories we used to define a limited number of layers (see Methods and Fig. 2 middle). By disentangling the mobility flows into a multilayer network structure, we are able to quantify the differences in the functional organization of the different “cities within a city” that are outlined by movement between different types of activities in a limited number of layers (see Methods and Fig. 2 right).

In Figure 2 we can visually inspect some examples of activity-aware layers. Remarkably, for all the cities considered in this study, the intra-layer connectivity characterizing the transport layer provides a natural link between our functional analysis and the underlying structure of the city. In the data, however, it can be clearly seen in cities where public transport is well developed and largely used, such as Tokyo or Seoul, way more than cities where private transportation is dominant, such as Los Angeles and Istanbul.

**Quantifying Functional Integration and Segregation.**— and to which extent there are separate clusters of areas characterized by within-cluster flows larger than between-cluster flows – i.e., functional segregation – (see Methods for details) [68]. By considering those measures simultaneously, it is possible to characterize how well human flows mix through the city according to the existing distribution of venues and the way residents use them. In fact, the dichotomy between integration and segregation – often improperly used as antonyms – is relevant for improving our understanding of the interplay between the urban structure, social relationships and human behavior. To avoid confusion in the reader, it is worth remarking that our measure of integration and segregation is not related to population or cultural mixing [69], but only to how cities are lived by their users.
Disentangling human flows. We illustrate here, for four of the ten cities studied in this paper, the strikingly distinct views on the functional organization of a city extracted by isolating intra- or inter-layer flows. These maps outline the different “cities within the city” which we disentangle by decoupling the urban flows into activity-aware multilayer networks.

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TABLE I. Foursquare data set extensive characteristics. The figures here are aggregated for all layers, hours, and comprise all 24 months. The linear size \( L \) is here estimated as the square root of the total area covered by the data after the aggregation into squares of 500m \( \times \) 500m.

| City       | #Venues | #check-ins | L (km) |
|------------|---------|------------|--------|
| Chicago    | 13904   | 10629110   | 18.9   |
| Istanbul   | 113752  | 13083383   | 39.3   |
| Jakarta    | 21813   | 9281181    | 27.6   |
| London     | 22689   | 10146880   | 24.0   |
| Los Angeles| 15868   | 10362146   | 23.6   |
| New York City | 32971 | 11048584   | 19.3   |
| Paris      | 13588   | 9521723    | 16.6   |
| Seoul      | 15545   | 9347489    | 18.1   |
| Singapore  | 23324   | 9691517    | 23.5   |
| Tokyo      | 57810   | 11545155   | 30.4   |

Synthetic Models. — As previously mentioned, we focus on urban integration and segregation. Integration quantifies, in terms of information exchange efficiency, the ability of a city to favor the flow of people across its areas. Segregation, on the other hand, evaluates the strength of segregated communities, areas of the city with strong flows inside the area and weak inter-areas flows (see Methods for further details).

Functional organization of empirical Urban Systems.— We use the results above as a reference in our analysis of real cities, shown in Fig. 4. More specifically, we stratify human flows by month of the year and by activities, to analyze the corresponding mobility networks. Results are intriguing: the functional organization of some urban systems can dramatically change in different periods of the year (left panel), ranging between small-world and random geometric organization. Comparing with the bottom panel, we notice that the values of segregation for the single months are approximately the same as the aggregated 2 years, and is the value of integration that shows a clear drop. This shows the danger of having under-sampling which could yield to incorrect view on a city functioning by under-estimating its integration. Even if the underlying urban structure changes slowly, or not at all, the functional use of the city, as observed through Foursquare data, may instead display significant variations. When flows are instead aggregated over a long period of time (bottom panel) our view on cities tends to be more compatible with random geometric models, suggesting that the functional organization of large mega-cities is strongly influenced by intermediate-distance movements, captured by random geometric Fig. 1 that the largest the area \( A = L^2 \) covered by a square RGG the more the network is segregated and the less it is, at the same time, integrated. Indeed, here again integration and segregation seem to be very strongly correlated and increasing the radius have a similar effect as reducing the spatial extension.
FIG. 3. **Functional organization of synthetic urban models.** *Left:* small-world networks according to the Watts-Strogatz model (see Methods) with different rewiring probabilities (multiple points) and dimensions (from 1D to 3D, encoded by color). The dashed line represents the linear regression relating integration and segregation for this class of models, whereas the solid line is $y = 1 - x$ and it is shown as a reference. *Right:* random geometric networks (see Methods) with different characteristic spatial scale (encoded by color) and different rewiring probabilities (encoded by size). Qualitatively, this class of models clusters along the $y = 1 - x$ line.

geometric models but not by the lattice underlying the small-world model. More in detail, these intermediate distances would here fall beyond the 500m–1000m scale characteristic of lattice first neighbors in the square tiling that we used for describing the urban space (see Methods), but do not represent the long range – across-city – movements, that in our model would be captured by rewiring the existing connectivity.

The fact that some of the cities seem to be even more “integrated and segregated at the same time” than a rewired RGG suggests that the network might be characterized by sparsely connected spatial patches. This result suggests, indeed, that also other complex network models characterized by a mesoscale organization – such as the broad family of stochastic block models – might be suitable candidates for modeling the complexity of megacities.

It is worth checking if this pattern is an intrinsic feature of urban systems or if it is proper of some specific activity layers. To this aim, we perform targeted attacks on each layer of the corresponding multilayer network and measure the response of the systems in terms of changes in segregation and integration. In the bottom panel of Fig. 4 we observe how removing those flows coming from a specific activity type significantly changes urban functional segregation. This is especially true if the activity is Transport, whose removal yields the rightmost outliers in the figure. An even stronger variation would be observed in the integration and segregation restricted to movements between similar layers.

Finally, in Supplementary Figs. 2 and 3 we can observe different “cities within a city” by comparing snapshots of the urban flows at different times of the day or between different types of activities. Indeed, the variability observed for these disaggregated functional networks can be compared with the variability among different cities. Comparing different hours, we find that urban functional integration is systematically higher at daytime and lower in the night, while it is difficult to identify common patterns across cities in its evolution along the day.

When looking at different activities, is even harder to observe common patterns between cities. Segregation and integration of human flows between venues belonging to the same activity layer exhibit high variance with the “food” and “lodging” layers which to be systematically among the more integrated and least segregated. To better understand these differences, in Fig. 5 we link the average values of segregation measured for flows between the same categories across all cities with the corresponding weighted average of geographical distances between nodes. We observe a bulk of correlated points and four clear outliers: two of them represent the typical “second place” of a commute (work or education), one the natural long-range linking layer of transportation, and lastly the locations not associated to a macro category and left as “unknown” (see Methods). Excluding the four outliers,
FIG. 4. **Functional (re-)organization of empirical urban systems.** We consider the multilayer networks of human flows for each city (encoded by color). Solid and dashed curves are as in Fig. 3. **Top:** Flows are stratified according to different months (multiple points). Remarkably, some cities exhibit a large variability across time, ranging from a functional organization resembling random geometric networks to one resembling small-world functional organization. Paris, London, Tokyo and Istanbul seem to vary similarly to small worlds, whereas Chicago, Jakarta, Seoul, Singapore, New York and Los Angeles exhibit a high variability in monthly segregation, associated to higher average values of integration. **Bottom:** Flows are stratified according to different macro-categories used in this work (see Method) and targeted attacks are performed on the layers of each multilayer urban system. Each point corresponds to integration and segregation measured after removing a specific layer of activity. Flows are stratified according to human flows, is of paramount importance for designing more efficient and smart urban systems and targeting drops in cities having larger extension $L$. We argue that this trend might be a direct effect of geometric constraints, as observed in random geometric networks, leading to an increased amount of segregation when, *ceteris paribus*, we consider networks of larger extension (see Supplementary Fig. 1).

**A bridge with the urban spatial organization: hotspots’ analysis.**—Our network analysis of the urban functional organization of megacities leads to a result that, remarkably, create a bridge between network science and quantitative geography. In fact, the organization of cities can be also understood in terms of mobility hotspots [38], i.e., areas characterized by exceptional human flows. The top panel of Fig. 7 shows that the larger the city the lower is the fraction of nodes which are identified as hotspots using the method introduced in [38]. At the same time, a larger fraction of hotspots is associated to high integration and low segregation (see the bottom panel of the same figure and Supplementary Fig. 5). From a network science perspective, hotspots encode high-degree hubs in the urban functional organization and our results suggest that high-integration and low-segregation features are favored by the abundance of this class of hubs rather than by the presence of a few central nodes.

**CONCLUSIONS**

Understanding how cities process information, here encoded by human flows, is of paramount importance for designing more efficient and smart urban systems and...
communities. By considering together multiple activity-aware mobility networks, a functional proxy for the underlying backbone of a city, we have characterized 10 large-scale urban systems in terms of their integrated and segregated flows, revealing interesting spatio-temporal patterns that would otherwise remain hidden without multilayer modeling and analysis.

More specifically, we have shown how network-based analysis can support, and further expand, ongoing discussions about and novel understanding provided by the ICT-data driven quantitative urbanism [38]. For growing cities, it is expected a transition from a monocentric to a polycentric organization, characterized by a sub-linear growth of the number of hotspots with population [63]. Similarly, in the urban functional networks we have extracted from the Foursquare data we observe that in the larger cities hotspots cover, in proportion, a smaller fraction of the total area. However, our analysis of urban segregation and integration suggests a rather different description than that one suggested in [38]: we provide evidence that large polycentric cities are characterized by a smaller fraction of hotspots (or hubs) and consequently they appear to be more segregated and less integrated than smaller, and monocentric, cities.

From a more methodological perspective, our analysis highlights the importance of data sources for the analysis of the interplay between the city and its main users, i.e., the citizens. Thanks to the unique data set provided by Foursquare we have been able, on the one hand, to quantify the effects of incomplete information: missing human flows related to one activity type dramatically alters the estimated urban segregation. On the other hand, the analysis of longitudinal data at different temporal resolutions, from hours to months, reveals that some cities dynamically change their functional organization even if...
their backbone does not, whereas other cities do not show the same variability. This allows us to gain novel insights on urban and human behavior in terms of dynamical reorganization of the system. Our analysis of attacks targeted towards specific layers unraveled the importance of different types of human flows for integrating (or segregating) a urban system, revealing the emergence of the phenomenon of cities within a city.

Lastly, from a modeling perspective, we discover that many features of complex megacities can be understood from simple mechanisms related to geometric constraints and city’s characteristic size, with larger cities tending to be more segregated and less integrated. Random geometric models with long-range connections seems to be a good candidate to reproduce the most salient features measured from empirical data and further research is required in this direction to confirm this finding for a wider spectrum of urban systems. Interestingly, the interplay between heterogeneities in the underlying network connectivity and spatial constraints might be responsible for the emergence of integrated/segregated structures that might be reflected in the functional organization of the city, and future research should point in this direction to gain new insights.

III. METHODS

Geographic coarse-graining.— We reconstruct the flows network by aggregating data over areal units of 500m × 500m, in all 10 cities considered. Flows are reconstructed from subsequent check-ins into Foursquare venues, ignoring the order (undirected network). Flows inside the same area have been integrated into a self-loop link only if the check-ins were between two different locations. Subsequent check-ins in the same location have been excluded from the analysis.

Temporal stratification.— We decouple the functional use of a city i) at different hours of the day (morning, midday, afternoon, night, overnight), and ii) in different months of the year.

Activity stratification.— We use Foursquare’s rich system of categories and manually associate them to a reduced number of macro-categories (food, lodging, tourism, work, religion, services, education, health, sport, transport, entertainment, leisure, public, housing and commercial). We do not use these categories that did not fit any macro-category have been labelled as ‘unknown’. These categories allow us to build “activity-aware multilayer networks”, where activities of different types are associated to different layers of our model. Flows between activities of the same macro-category are encoded by intra-layer links, while flows between different categories are encoded by inter-layer links.

Measuring functional integration.— We measure to what discussed above for measuring functional segregation, or how strongly the units are organized in into M non-overlapping blocks, is the modularity

\[
Q = \sum_{u \in M} \left[ e_{uu} - \left( \sum_{v \in M} e_{uv} \right)^2 \right]
\]

where \( e_{uu} \) is the proportion of links inside module \( u \), while \( e_{uv} \) accounts for the connectivity between two distinct modules \( u \) and \( v \). More in detail, our measure of segregation is the maximum value of the modularity that we find using the Louvain algorithm. We also verify that the observed modularity is significant, by comparison with the values of \( Q \) computed over an ensemble of configuration models obtained reshuffling the network. Finally, note that here, instead, we used the weights defined by flows. Values of \( Q \) for weighted and unweighted networks are indeed comparable, as opposite to what discussed above for \( E \), and using weights here allowed us to better discern the characteristics of different layers.

Synthetic network models.— We use two standard synthetic network models for our analysis. We first consider a class of networks characterized by small average geodesic distance: the Watts-Strogatz (WS) model. Starting from a regular graph, e.g. a two-dimensional lattice, each link has a probability \( p \) of being rewired, that is removed and re-placed randomly in the network. If \( p \) is large the resulting WS network will look more like an ER random graph than the original lattice. WS networks are also highly clustered, where nodes tend to form closed triangles. WS model are usually referred to as small-world networks. Alternatively to WS, we study also the simplest network model actively involving the spatial dimension model is the random geometric graph (RGG), where nodes randomly distributed in space are connected if they are closer than a fixed threshold distance. The RGGs share many important properties with regular lattices, in particular they are not “small world”. For this reason, similarly to the WS case, here also for the RGG we perform a rewiring with probability \( \alpha \).

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SUPPL. FIG. 1. Segregation and Integration of Random Geometric Graphs of different sizes. In this paper, we generate RGGs by i) throwing $N$ nodes in random locations in a square of edge $L$; ii) connecting all nodes $i,j$ with distance $d(i,j) < r$; iii) rewiring a fraction $\alpha$ of edges. Here, to study the effect of size, we generate networks with identical node density $N/L^2$ and with no rewiring $\alpha = 0$. For each value of $L$ and $r$ we averaged the values of segregation (modularity $Q$ and integration (Global efficiency $E$). The result show that, in this scenario, segregation and integration are strongly anti-correlated. High integration is attained for small networks ($L = 10$) with large $r$, while the opposite yields high segregation.
SUPPL. FIG. 2. Segregation and Integration at different hours of the day.
SUPPL. FIG. 3. Single Layer Segregation and Integration.

SUPPL. FIG. 4. Average Single Layer Integration versus edges characteristic distance. Similarly to what observed in Fig. [4] if we exclude four outlying layers, the characteristic length of edges on a layer and the layer’s Functional integration are correlated (here, more precisely, anti-correlated).
SUPPL. FIG. 5. **Functional integration versus fraction of hotspots.** Conversely to what observed in Fig. 7, the Functional integration of a city is larger for cities with a larger number of hotspots per unit area.