The Social Life of Small Urban Spaces 2.0

Three Experiments in Computational Urban Studies

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Abstract. This paper introduces a novel framework for urban analysis that leverages computational techniques, along with established urban research methods, to study how people use urban public space. Through three case studies in different urban locations in Europe and the US, it demonstrates how recent machine learning and computer vision techniques may assist us in producing unprecedently detailed portraits of the relative influence of urban and environmental variables on people's use of public space. The paper further discusses the potential of this framework to enable empirically-enriched forms of urban and social analysis with applications in urban planning, design, research, and policy.

Keywords: Data analytics · Urban design · Machine learning · Artificial intelligence · Big data · Space syntax

1 Introduction

William Whyte's well known study of "The Social Life of Small Urban Spaces" sought to understand what factors contributed to making a city's public space vibrant and engaging. He—and his team—used film, qualitative observation, and clever counting and mapping techniques to document people's use of public spaces in cities across the United States [9]. They observed how people moved around and used urban artifacts such as benches, waste baskets, building steps, sculptures, retail, and movable chairs. They were interested in determining what public space features made people comfortable, or made strangers engage with each other. While other strands of quantitative urban analysis exist [10–12], the visual and methodological repertoires employed by Whyte—and his ambition for an empirically-grounded practice of urban research—remain influential in urban studies, planning, and policy [13, 14].

This paper demonstrates how recent advances in computer vision and machine learning open the possibility for revisiting and extending Whyte's distinctive approach. It describes a novel framework for urban analysis that leverages computer vision, machine learning, and urban design techniques to study how people move around in and interact with environmental features in public urban spaces. Discussing three case

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studies, it demonstrates the framework's potential to enhance traditional spatial analysis tools, and to reveal the relative impact of urban features such as building form, vehicular traffic, and residential and retail functions on people's use of public space. The case studies span different urban conditions: a public square in a European old city at plaza del Callao in Madrid, Spain; a central lawn of a North American campus at Carnegie Mellon University in Pittsburgh, PA, and a public square in North America in Pittsburgh Downtown's Market Square.

The paper reports on the methods employed, and on the findings of each analysis. It concludes with a discussion of the potential of this framework to enable new, data enriched, forms of urban analysis with applications in urban planning, design, research, and policy. The aim of this framework is to leverage the data gathering, processing and analysis capacities of modern computation in order to create an enriched and nuanced portrait of the connection between urban spaces and the human experience. As the following sections show, the analysis of these data yields an unprecedently detailed portrait of the relative influence of urban and environmental variables on people's utilization of public space.

2 Methods

2.1 General Approach

Our portrait of each built environment is supported on three categories of data classified according to two parameters: time range –how frequently the data changes– and nature –how the data is generated– (Fig. 1): First, we account for spatial features including conventional urban design and planning parameters such as distances to Points of Interests (POIs) and sunlight, as well as "synthetic" parameters [7] derived from Space Syntax metrics such as compactness and occlusivity [4]. Second, we account for the visual complexity of the built environment using visual entropy [6], a measure of the perceptual and cognitive conditions of human experience in urban space [3, 6]. It's worth noting that this parameter evokes early 20th century Gestalt and constructivist postulates on spatial perception [1, 5, 8]. Finally, we account for geolocated levels of detection of activity in the space, which we classify by type (e.g. pedestrians, cars, trucks, buses, bikes, motorbikes, and police cars). These are derived computationally from anonymized video data captured on site using computer vision techniques.

These different data are aggregated into a spatial grid (Fig. 5), each cell indexing the corresponding parameters as an array of vectors with the same dimension. Thus codified, the collected data can be analyzed for correlations between the different variables in space. This data architecture, developed in Python data processing pipeline enriches conventional computational representations of the city, typically alien to this type of information and level of detail.

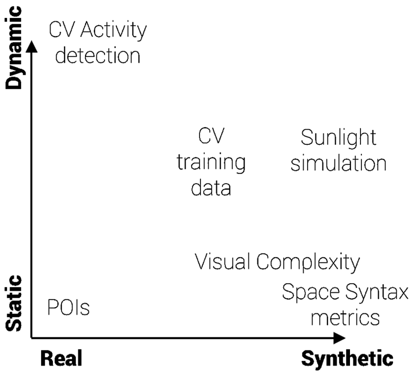

Fig. 1. Types of data according to their nature and time range.

We stacked data (Fig. 4) corresponding to 24 h periods and analyze their correlations longitudinally during the day (Figs. 3, 5 and 6). Broadly speaking, the relations between the different variables presented can be inferred using regression analysis. This allows for testing bivariate correlations between the more than 30 variables considered. Bivariate analysis—one of the simplest statistical methods for checking the empirical relationship between two variables [2]—is computed with three different mathematical methods with similar outcomes: Pearson's correlation coefficient [15], Spearman's rank correlation coefficient [16], and Kendall's tau coefficient [17] (Fig. 5). Additionally, in the campus case, we segmented the data corresponding to different zones based on patterns of pedestrian utilization. Video of each site was captured using cameras located at a distance to keep the data anonymous.

An important technical challenge was to accurately map the data collected from the video into a digital geometric model of the site. We achieved this by using different machine learning methods, including deep learning to detect and identify correlations in the features in the images from different sources, and other statistical techniques. The resulting model innovatively matches temporal signatures of the detected occupations with a digital representation of the site to offer a detailed portrait of people's behavior in that urban space over a period of time.

The first two case studies illustrate the framework's initial implementation in Madrid and Carnegie Mellon University. They both include a bivariate analysis of the parameter-space of each site which measures correlations between spatial features and patterns of spatial use. The third—and more advanced—case study illustrates a multi-camera activity detection strategy, which is introduced in order to account for a more complex urban space. In this case a bivariate analysis is developed using historical weather data. New detectable objects are added to the system (i.e. urban furniture). Finally, a controlled experiment changing the location of furniture is introduced for a sensitivity test and to interrogate the framework's capacity to yield actionable planning and design insights.

2.2 First Case Study: Plaza del Callao (Madrid, Spain)

Plaza del Callao is a public open space in central Madrid located at the intersection of Gran Vía, calle Preciados, calle del Carmen, calle del Postigo de San Martín, calle de Jacometrezo, and calle de Miguel Moya. Despite being located in the city's old town, its design is relatively recent—it aligns with the opening of the new Gran Via at the beginning of the 20th century. It's important to note that Plaza del Callao is located in one of the denser and more compact areas of the city. It is not a space for staying, but mostly a crossroad between very active areas of the city center. Narrow and lively streets connect to Callao, and the flow of people is channeled and compressed through these pathways while spreading out across a square which has no remarkable landmarks or resting areas: it is simply paved square (Fig. 2).

Fig. 2. View of plaza del Callao, Madrid (Spain)

Table 1. Data specifications for location 1.

Data description	Source	Features
Space Syntax metrics	3D model	Area, Distance Weighted Area, Perimeter, Compactness, Circularity, Convex deficiency, Occlusivity, Min radial, Max radial, Mean radial, Standard Deviation, Variance, Skewness, Dispersion, Elongation, Drift Magnitude, Drift Angle
Sunlight simulation	3D model	Continuous numeric value

(*continued*)

Table 1. (*continued*)

Data description	Source	Features
POIs	3D model	10 locations (metro entrance, Eastern access from Gran Vía, Starbucks, access from calle del Carmen, access from calle Preciados, access from calle del Postigo de San Martín, Western access from calle Preciados, Callao Theatre, Western Access from Gran Vía and calle Jacometrezo, tree)
Activities detections	CV system	Latitute, longitude, time, class (pedestrian, car, police car, bike, bus, truck, motorbike)
Visual complexity	Google Street View	Continuous numeric value

The data (Table 1) for this case study comes from three sources: (a) a 3D model of the built environment elaborated in Rhinoceros from information available at Google Maps and from NASA digital elevation models; (b) spherical panoramas from Google Street View; and the (c) anonymous video data recorded with a camera specially located in the square for this project. The 3D model is used for simulating the sunlight conditions and for the space syntax analyses of the physical environment. The period of observation lasted 12 days, from 12 pm on April 1st, 2018 through 1:10 pm on April 12th, 2018. An average of 1.2 million detections were collected per day. The data analyzed in this paper corresponds to a subset of this dataset including 24 h of data from April 2nd, 2018.

Aside from considering the patterns of pedestrian occupation detected using the cameras, we considered space syntax metrics characterizing users' perception of the directionality and centrality in the space provides insights into the underlying factors affecting pedestrian movements.

Results: A Geography of Pedestrian Use

Our analysis shows low correlation between areas with greater amount of sunlight and the areas most used by pedestrians (see correlations on Fig. 5). Unsurprisingly, the Subway entrance is a key attractor of pedestrian traffic. Other points of interest around the square seemed to have comparatively little impact on pedestrian behavior. Interestingly, the central areas of the square are the most important for pedestrian use as indicated by the centrality measures (area, mean radial, and drift magnitude) generated by space syntax techniques. Finally, the Easternmost areas of the plaza are more frequently used during the evening, while morning activity tends to concentrate on different spots around the West part of the square (Fig. 3). This may correlate with the character of the commercial uses in that part of the square.

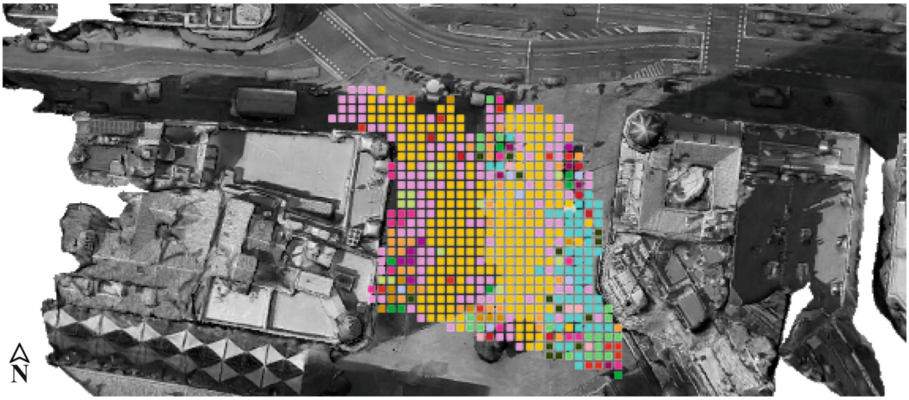

Fig. 3. Spatial segmentation based on temporal patterns of use. Each color is a different cluster of cells where the temporal patterns of pedestrians' detection is similar. (Color figure online)

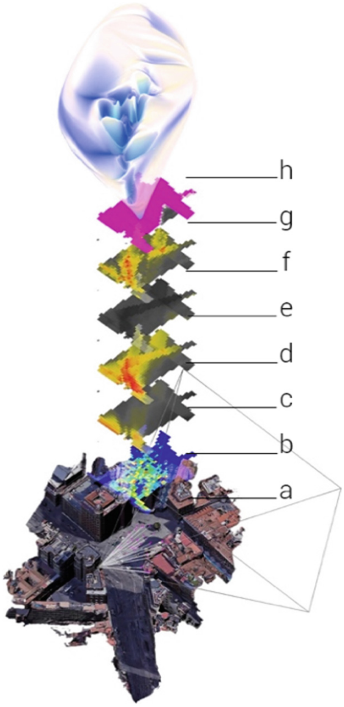

Fig. 4. Multidimensional aggregation of data on analysis discreet cells in one of the studied locations (plaza del Callao). Only some databases are shown, from top to bottom: (a) 3D environment Virtual Entropy, (b) aggregation of pedestrian detections (c) Space Syntax (SS) area, (d) SS perimeter, (e) SS skewness, (f) SS elongation, (g) SS max radial, (h) Space Syntax (SS) max radial, (h) Visual complexity Z graph.

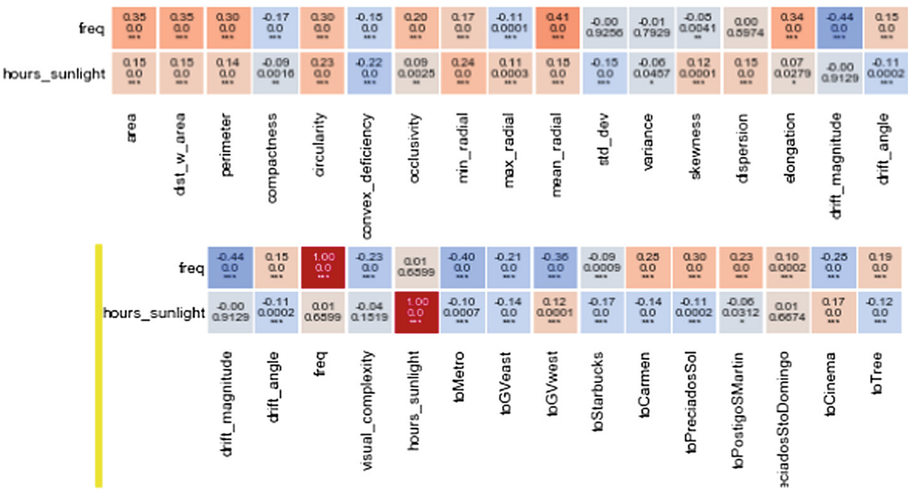

Fig. 5. Detail of correlation matrix for plaza del Callao, Madrid. Values and significance for *freq* (detections of pedestrians in the space) and *hours_sunlight* (number of sunlight hours).

2.3 Second Case Study: Carnegie Mellon Campus Lawn (Pittsburgh, PA)

The second case study focuses on a completely different urban environment: the "Cut," one of the meadows located in the historical core of the campus of Carnegie Mellon University in Pittsburgh, Pennsylvania, US (Fig. 6). This is the biggest open public space of the campus, located between the College of Fine Arts, and the tennis courts by the Margaret Morrison Carnegie Hall in the East and the School of Drama, Doherty Hall, and Baker Hall in the West. It is a key area for the functioning and communication of the campus as it is the main crossroads connecting some of the main facilities of the campus with a clear pedestrian character. It highlights the walkable character of the environment, as well as a place for gathering and leisure whose best-known landmark is the Fence.

The three sources for data are detailed in Table 2. The timeframe for this location is shorter and covers 13 h of data, from 8 am to 9 pm on April 30th, 2018. The shorter period explored in this location allows us to focus on the quicker patterns of use in a university campus—where night activity is almost nonexistent comparatively with the center of a large European city.

Fig. 6. Perspective of location analyzed on central lawn of Carnegie Mellon University campus in Pittsburgh, PA (USA)

Table 2. Data specifications for location 2.

Data description	Source	Features
Space Syntax metrics	3D model	Area, Distance Weighted Area, Perimeter, Compactness, Circularity, Convex deficiency, Occlusivity, Min radial, Max radial, Mean radial, Stadard Deviation, Variance, Skewnes, Dispersion, Elongation, Drift Magnitude, Drift Angle
Sunlight simulation	3D model	Continuous numeric value
POIs	3D model	5 locations (flag, Doherty Hall entrance, inflatable Sled, fence, path to Hunt Library)
Activities detections	CV system (wide angle lenses)	Latitute, longitude, time, class (pedestrian, car, police car, bike, bus, truck, motorbike)
Visual complexity	Google Street View	Continuous numeric value

Results: A Map of the Campus' Everyday—With Few Surprises

Our analysis shows that pedestrian behavior is strongly conditioned by the design of paved paths. We found that space syntax metrics relating to the perception of urban space have little effect on the behavior of people (Fig. 7). Finally, we found higher levels of activity during the morning closer to education buildings entrances. Afternoon activity moves towards the central part of the lawn (Fig. 8).

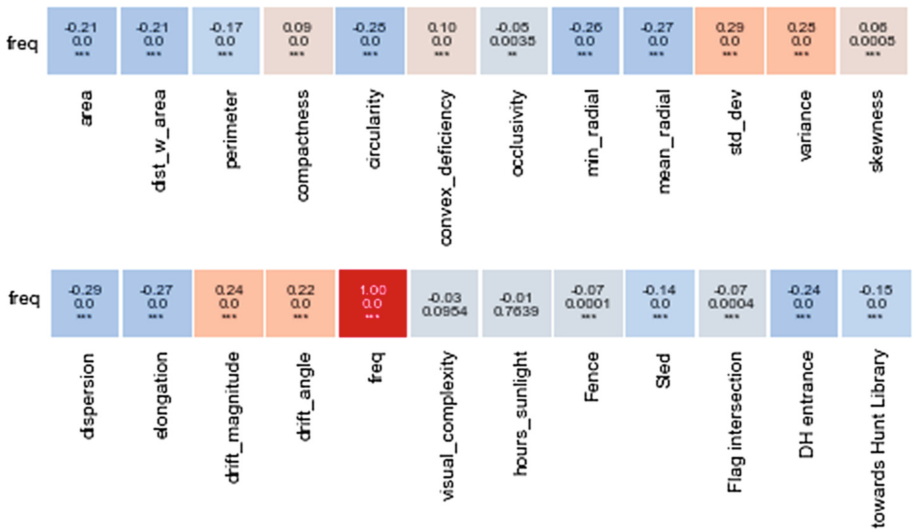

Fig. 7. Detail of correlation Matrix for Carnegie Mellon University campus (the whole matrix is equivalent to the one shown on Fig. 3). Only freq-related values (detection of pedestrian) are shown: correlation coefficients and significances with other parameters are shown.

The trends seem to match the expected behavior of this setting, which is highly conditioned by students' highly-regimented class schedule. As it has been already pointed out, the spatial design of the common areas at Carnegie Mellon University campus is defined by a clear separation between the communication pathways with a concrete pavement, and the greenery of grassed areas in between. It conditions the patterns of utilization of the space, and this trait is picked up by our analysis. An important benefit of this case study was to test the framework for capturing special structure information from the behavior (it means, pedestrians' detections) without implicitly introducing this information in the system. Accordingly, we are able to automatically detect the underlying segregation of the space in paved paths and grass just by inferring it from the data (Fig. 9)—a feature that plays an important role in our third and last case study.

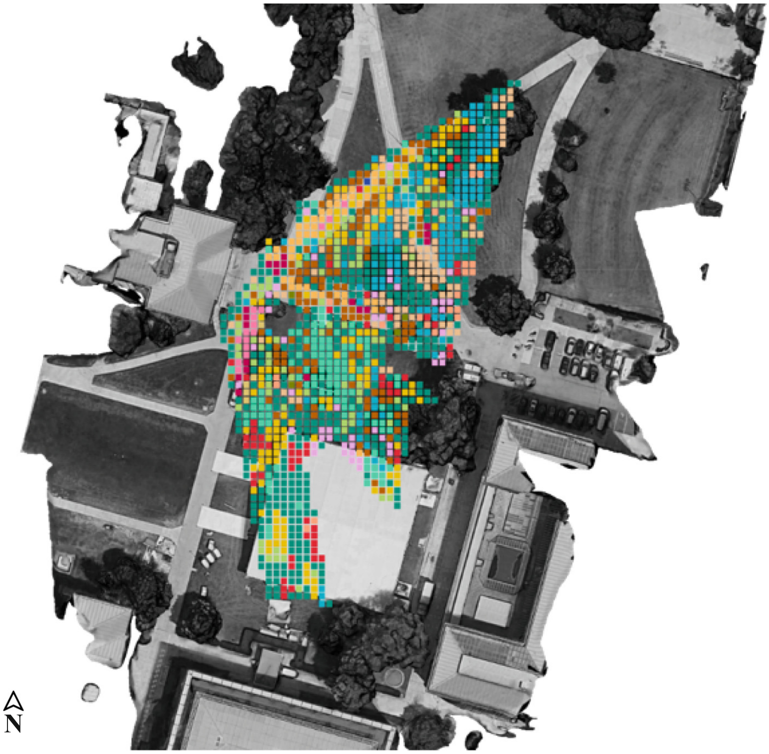

Fig. 8. Spatial segmentation of the central lawn at Carnegie Mellon University campus based on common temporal pattern of utilization. Paths and paved areas are identified.

2.4 Third Case Study: Market Square (Pittsburgh, PA)

Our third and last case study is located in the main urban public space of downtown Pittsburgh: Market Square. This is one of the few spots of the city with a pure built-up

Fig. 9. Cameras use for Market Square data collection. Pittsburgh, PA (USA).

and very urban setting, surrounded by dense commercial activity. The closest example to a traditional "European" urban square embedded in a dense city fabric. As many downtown areas in North America's rust-belt cities, it has a complicated history of economic and environmental degradation. However, during the last several years, it has been central to important urban renovation efforts. In this context, the city of Pittsburgh has been collaborating with the Pittsburgh Downtown Partnership (PDP) for more than 20 years with the goal of improving this area. Currently, this organization is the main stakeholder in activating and taking care of downtown. As part of this collaboration Market Square was renovated in 2006, and since then PDP has sought to establish this iconic space as a vibrant activity hub.

Data was collected over a period of 5 weeks, from August 24th to September 28th, 2018, using four cameras placed in different locations around the square (Fig. 9). The multiple cameras were an innovation of this case study and were key for providing a good coverage of the space—over 97% of the square's surface. Another improvement relative to the other two case studies is that the system is able to detect a larger repertoire of classes. Public urban elements such as umbrellas, tents, seats, and tables, for example, are added as objects of interest that might enrich our portrait of the activities taking place on the square. During the 5-week period 3,200 h of video were captured, and over 250 million of detections were processed. A final feature of this analysis is the observation of specific changes to the urban furniture, which enabled us to study the impact of these changes on the activity on the square and its spatial distribution.

In addition to the bivariate analysis, a quantitative and qualitative comparative analysis of the data is performed checking the alignment between weather conditions and levels of utilization of the square (Table 3).

Table 3. Data specifications for location 3.

Data description	Source	Features
Weather information	Historical data	Hourly historical record on temperature and rain
Activities detections	CV system (4 cameras)	Latitude, longitude, time, class (pedestrians, trolleys, seats, tables, sun umbrellas, tents, cars, pickups, vans, trucks, bikes, motorcycles)

Results: A Detailed Picture of Pedestrian Activity

Our analysis of Market Square, which was longer and more technically complex, yielded interesting insights concerning three different aspects of this urban space. First, it allowed us to study the impact of weather over relatively long periods of time (Fig. 10). Second, it allowed us to study the spatial distribution of activities in relation to specific changes on the square's urban furniture layout. Finally, it allowed us to examine how special events impact the amount of people visiting the square, and their behavior.

Concerning weather, while our analysis shows how short and episodic periods of rain have little effect on the medium- and long-term activities on the square, it also shows how rain has an immediate effect on pedestrian activity (Fig. 10). On the other hand, persistent and longer periods of rainy conditions have a very different effect on activity levels detected on the square. In average, they cause a drop of 60% of the activity on the square. Interestingly, however, there is a "compensation effect" the following day, which can show an activity increase ranging between 20% and 30%. This trend can have important implications on activities planning and design changes on the square. It allows to predict important shifts on activity level on the square depending on weather conditions.

Regarding the spatial distribution of activity, the levels of correlation between pedestrians' presence and furniture is moderately high. In general terms, the central part of the square is used around 8 times more than the edges and trees quadrants. Additionally, these patterns seem to be closely connected to the distribution of elements around the square: urban furniture and tents for markets (Fig. 11).

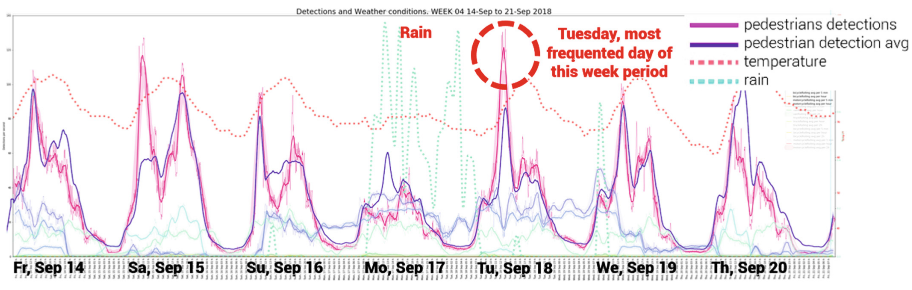

Fig. 10. Pedestrian detections and weather information for Market Square, Pittsburgh PA.

In order to study the effect of urban furniture distribution on pedestrian activity, we changed the location of the chairs and tables. Instead of concentrating all these elements in the central part of the square, we placed them under the trees, closer to the edges of the square. This produced a significant shift in pedestrian activity by redistributing the occupancy between the edges of the square and the center. It means that the difference between central and peripheral use of the square was 4 times higher with this new setting for the urban furniture, rather than 8 times higher as recorded in the previous setting (Fig. 12), while the absolute activity level of the square was similar.

We were also able to observe how the events and venues programmed in the space (i.e. markets, concerts, games and shows for kids, yoga sessions, etc.) have an important effect on pedestrian use. The measurable increase of activity in the space during the last week of August—when daily events are programmed for the summer season—is around 20%. Later on, from a more qualitative point of view, the succession of events generates some degree of synergy which causes a rise in the number of people in the square. This suggests that event frequency (i.e. events programmed over several days) has an important "snow-ball" impact on the square's activity trends (Fig. 13).

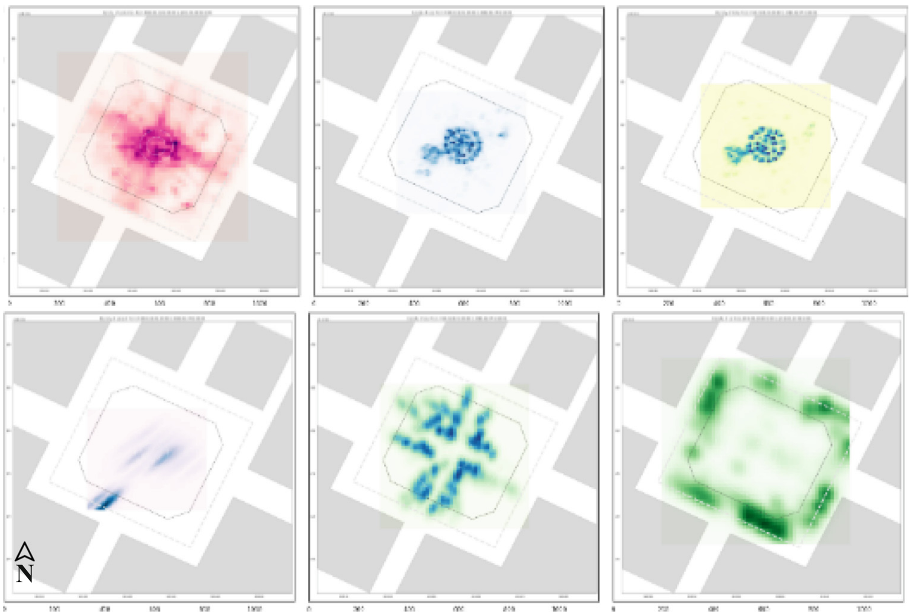

Fig. 11. Spatial distribution of pedestrians, seats, tables, sun umbrellas, market tents, and vehicles on Market Square. Initial setting. Thursday September 6th.

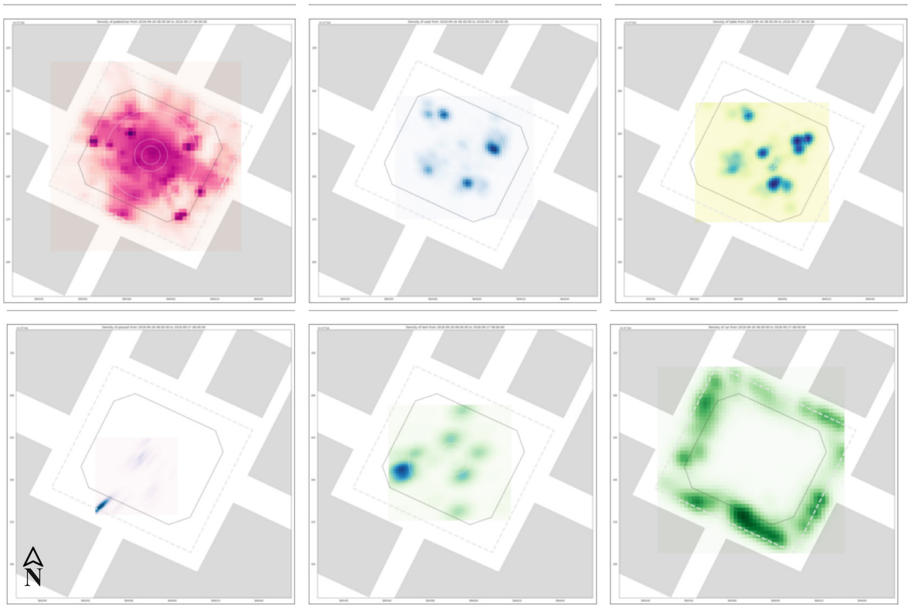

Fig. 12. Spatial distribution of pedestrians, seats, tables, sun umbrellas, market tents, and vehicles on Market Square. After modification of urban furniture. Wednesday September 28th.

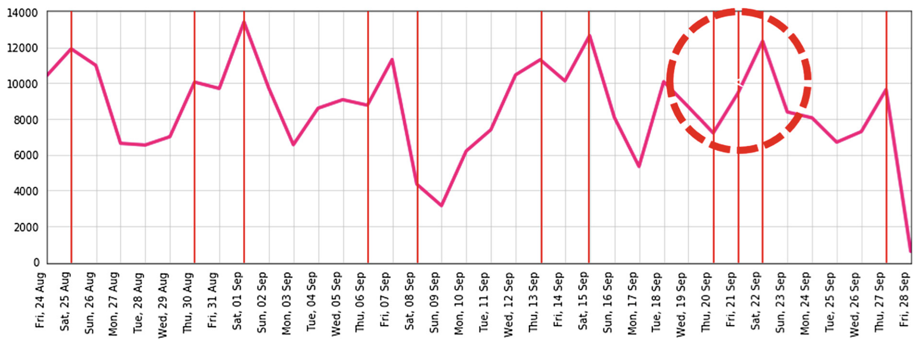

Fig. 13. Total count of people per day during the whole data collection period. Red lines indicate events programmed in the space. (Color figure online)

3 Conclusion

3.1 Contributions

We have introduced a novel framework for urban analysis that leverages computational techniques, along with established urban research methods, to study how people use urban public space. Through three case studies in different urban locations, we have shown how machine learning and computer vision techniques may assist us in producing unprecedently detailed portraits of the relative influence of urban and environmental variables on people's use of public space. As shown above, this framework has the potential to enrich our empirical accounts of urban activity, and has multiple applications in urban planning, design, research, and policy. We thus build on a tradition of quantitative urbanism, updating it to reflect recent developments in computer vision and machine learning. More specifically, we show specific applications of machine learning—from the simplest linear regressions to the use of deep learning techniques—to urban data. We think there is great potential in these methods to make visible trends and patterns hidden in historical data, thus helping ground architectural and urban hypothesis.

An additional contribution of this research is the data themselves. The datasets including the anonymous data for the three case studies can be downloaded from [19]. We invite other urban researchers to study these urban conditions, ask different questions, and perhaps enrich—or challenge—our own interpretations.

3.2 Limitations

Our approach has important limitations. First, it is key to acknowledge that urban life comprises a much richer repertoire of situations and experiences that inevitably escape any computational framework [20]. There is an indescribably finer granularity to urban life, situations, timing, uses, and experiences which exceed the technical formalizations of our framework. For this reason, we think of our framework not as a replacement but rather as a complement to other types of analysis and reflection, including ethnographic engagements across media, and other forms of qualitative research. In the future, we expect to work on these "thicker" urban descriptions combining computational as well as qualitative, ethnographic, and visual data and interpretations.

Second, despite the academic nature of this project, a latent risk in any framework leveraging algorithmic techniques of observation and analysis is that it is misused as a tool of surveillance and/or policing. To minimize this risk, we took measures to prevent the system from capturing data that would enable the identification of individuals. The cameras, for example, were placed at a certain distance from the activity, making identification difficult if not impossible. In addition, the computational techniques employed deliberately focus on patterns of movement and activity, and not on individual behavior. Finally, the data collected is abstract and the source data is disposed immediately after the analyses.

Finally, aside from the non-digital factors considered above, the data currently considered in the framework has important gaps and limitations. There is missing data, as well as limitations on the collected data. There is, for example, an implicit bias in using 2-D analytical tools [18] to the study of a complex 3-D environment. There is room in our field for developing better spatial analysis techniques offering insight into the perception of the space. Our approach to measuring these factors, while somewhat innovative, is the most uncertain.

3.3 Future Work

The methods and evidence described above open questions as well as avenues for future work. On a technical level, improving the computer vision algorithm for extracting features from video frames would yield immediate analytical benefits. Further, adding new detectable features, and active tracking of objects, would enrich the analysis as well as overcome visual occlusions. Similarly, reducing the depth of the network architecture for improving performance, and developing a more precise evaluation method for testing accuracy, would increase the reliability of the results.

Expanding the project to other urban conditions, while refining our repertoire of questions, will offer additional insight, and start to configure a comparative approach to computational urban studies. To achieve this, the technical instruments, frameworks, and processes employed need to be streamlined.

Finally, as indicated above, we are interested in further developing this framework and in combining it with other forms of analysis and media. Our larger goal is to be able to produce "thicker" accounts of urban life, which can serve as reference for urban designers, scholars, and researchers, and which reflect glimpses of the incommensurable spatial and sensorial complexity of urban experience.

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