

What You See Is What You Get

Data-Informed Workflow in Design for Architecture and Urbanism

by

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A thesis submitted in conformity with the requirements
for the degree of Master of Science in Computational Design

School of Architecture – College of Fine Arts
Carnegie Mellon University

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Abstract

This research leverages computer vision with statistical, computational, and urban design techniques to reveal insightful and helpful relations between spatial features and patterns of spatial use. Three case studies are developed in two locations, in Madrid and Pittsburgh, with distinct spatial and utilization characteristics for covering diverse conditions through two types of experiments. The first one develops a bivariate analysis between parameters from data that describe the layout and use of each location for identifying correlations between spatial features and utilization patterns. The second experiment uses machine learning techniques for spatial clustering supported by matching temporal signatures of the detected occupations by the developed computer vision algorithms.

The proposed design framework yields new types of data about people's interactions with their urban built environment for generating new knowledge to inform design and policy decisions more effectively and expanding the capabilities of practitioners for focusing on exploring new scenarios. This thesis advocates for expanding design through data.

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1 Introduction. Why?

This thesis aims to leverage technologies which have emerged in the last decades within computer science with architectural and urban design practice. The research is based on three main ideas. First, there are new technical means for gathering and analyzing data about our environment features and about our daily life, whose processing can generate new outputs (Batty 2013; Cisco 2017). Second, spatial design is not using the true potential of those new techniques neither tackling empirical and scientific approaches for expanding designers' capabilities¹. Third, despite the complexity of relations embedded into the designed built environment, it is possible to leverage new computational techniques with traditional design practice for providing new knowledge useful for design decision and policy making. Bridging computer science developments and design practices, this tries to offer an answer to the mutual disengagement between these fields. While design was one of the early adopters and enhancers of interactive computing, and there is a long tradition of exchanges between design and computer science in the history of computation, the impact of computational thinking and the possibilities enabled by new technologies have had a limited impact in the way that practitioners develop their projects. The irruption of computers is restricted to their use as tools.

The new technical possibilities have been fostered fundamentally by the availability of data and by the development of techniques and methods which can deal with and process that amount of information. Acknowledging these technical opportunities, this research focuses on bridging the data gap about the use of public spaces at the scale of pedestrian life for adding this knowledge to existing metrics and expertise of the physical environment. But this unstructured, complex, and noisy information needs to be processed using computational techniques able to make sense of it and to make them operative. Therefore, these techniques should not be considered anymore as alien to design practice, but enablers of new productive

¹ In terms of human-computer interaction, Licklider already set the foundational and aspirational metaphor of "symbiosis" between people and computers (Licklider 1960), which at that time wasn't fully accomplished. Still, in the turn of the new century, flow of information and thoughts is not that seamless, and machines are still seen as "second selves", which means, familiar but uncanny (Turkle 1984). Computers are not only tools, but its strangely unfamiliar behavior (Edwards 1997) is a barrier not overcome by design practitioners.

cooperation. More specifically, the research proposes leveraging computer vision, machine learning, and urban design techniques to identify operative correlations between spatial features and patterns of spatial use in real urban locations.

Among these promising new subfields developed in computer science, computer vision offers a plethora of new resources for analyzing and extracting information in a systematic way from our environment. Precisely, the title of this thesis "What You See Is What You Get", a paradigm in software design which explains how the program interface shows a visual output very similar to the final result (Myers & A. 1998). It refers, within the scope of this research, to the novel use of imagery as input for data collection by using computer vision techniques. Finally, data explicates the general data-driven approach followed by this research as a resource for guiding design decisions.

For the proposed framework three case studies are developed in two different locations which can provide different spatial and utilization conditions, plaza del Callao in Downtown Madrid, Spain, and the Cut at Carnegie Mellon University campus in Pittsburgh, Pennsylvania, US. The first two cases use Madrid as scenario, with two different conditions of occupation of the analyzed square: a base case and a temporary intervention. The third case is developed in the Carnegie Mellon University campus where the utilization patterns are completely different than the one found in a European city center. Two kinds of experiments are developed for each case study. The first one is a bivariate analysis between parameters that describe the spatial features, the detected utilization of space by the developed computer vision algorithms, the location of points of interests, and the environmental conditions. The second experiment uses machine learning techniques for spatial clustering from the analysis and matching of temporal signatures of the computationally detected occupations at each case study and location.

Exploring how these new data and their processing can be used for the benefit of spatial design in the built environment is central to this research. Additionally, this proposed framework is used for discussing relevant related topics to the use of new technologies in design practice, such as the influence of the built environment in peoples' behavior and how reverse engineering strategies can be used on behalf of design, the quality of the built environment, the hype of Smart Cities and its impact in urban form and design, the ethical

and legal issues of the use of data and its ownership, and how it can affect public policy and participatory design practices.

1.1 Disclaimer. Between Architecture, Urban Design, and Urban Planning

A quick initial note is pertinent for clarifying the disciplinary terminology used across this thesis, particularly for those practitioners educated in the North American tradition which sets a rigid boundary between Architecture, Urban Design, and Urban Planning practices. Many Times urban design is seen as an intermediate step in between Architecture and Urban Planning, and it is claimed by both disciplines (Frick 2009), leaving many times small room for a consideration of a field in its own. However, "clear differences can be identified between the intellectual territories claimed by architecture, urban design and urban planning" (Cuthbert 2008) from a systems point of view pointing out the divergences on the structure, environment, resources, objectives, and behavior for these three disciplines (Simon 1996). This taxonomy compromises on developing a reductionist understanding of the different professions and expertise, as limiting the scope of architecture to closed buildings design, while urban planning focuses on policy-making and strategical design, and urban design works with architectural elements and open space.

It can be stated that architecture is concerned only about social closure² and protection while urban design is centered on social interaction and planning on politics constrains rigidly the ability to understand the issues of contemporary cities (Cuthbert 2008). Additionally, it is opposed to heroic, modernist traditions of spatial design where the practitioner is responsible for the whole design, from the object scale to the territory and back to the object: the total design (Gropius 1962), "from the spoon to the city" (Ernesto Rogers 1952).

Between both approaches, it is possible to identify a common core of knowledge which crosses their boundaries and leverage the somehow arbitrary division of professions and the

² Social closure is a term used in Sociology that explains how groups build boundaries and identities in order to monopolize scarce resources (Murphy 1988). Apply to architecture, it refers to an interpretation of Marxist theories on social construction as integral part of social production, although the opposite is more frequent: architecture plundering social theory for gaining credibility (Dickens 1979).

cult to the all-powerful architect able to control every single aspect and scale of the design of the built environment. For the sake of simplicity in the language used in the research, common interests, topics, and coincident issues in the built environment are assumed for Architecture, Urban Design, and Urban Planning. Although the scales of intervention and the subjects of the interventions may be different, there are strategies, technology, and knowledge which can be applied to any single level of intervention, blurring the limits between disciplines. It is important to notice as well that although legal, professional, and disciplinary limits can be set, the physical organization of the built environment and the layers of information which are increasingly overlaying the physical context are continuous. While it can be argued that the logic of designing and functioning of a building as a closed and controlled place, is radically different than the bounding conditions defining an open space or the social constructs and economic flows which shape the territory; it is not less true that buildings, open spaces, and territory are linked without interruption. In fact, their limits are progressively vaguer, and their interrelations are better known.

Again, as it would be covered repetitively along this document, many of the ideas included in the text are not new -or at least, not completely new- but mostly forgotten by the corpus of mainstream design -architecture, urban design, or planning-. Particularly, this disciplinary separation was called into question by critics of pure Modernist architecture for more dynamic approaches towards spatial design as a whole from collective form, finding even counterproductive the distinction between architecture and urbanism (Ratti & Claudel 2015).

In general terms, for clarity, the terms Architecture and Design will be used indistinctly for referring to any discipline whose concern is the design of the built environment at any given scale. In this thesis, using the words Architecture or Design doesn't mean disregarding urbanism and planning, as they are included in an extended meaning with convergent interests. In the same sense, practitioners or designers would be used for referring generically to the professionals of any of these disciplines defined politically, legally, and culturally.

1.2 Structure of the thesis

The presented thesis is divided into three main parts covering respectively the theoretical introduction and contextualization for scaffolding the technological implementation

developed in the second part, and finally, the considerations and the research impact into design practice and public policy, as well as future work of the implemented framework:

The first part of the thesis contextualizes the scope of the research within the problematic of spatial design in connection with computational methods as a gap still to be bridged as part of the bigger picture of the systematic and computational approaches developed in the last decades. It introduces the main hypothesis of the research exemplified in the development of a new framework of design supported by the systematic study of the urban environment, yielded by the inquiry on the utilization of public spaces by novel computer science techniques. It includes the presentation of the expected contributions of this research from the technical, ideological, and disciplinary point of view; the previous lines of research and projects which support this research, and the framing of the data used.

These ideas enunciated in the first part support and contextualize the research question addressed technically in the second part of the thesis. The methodology proposed will yield new types of data about people's interactions with their urban context and produce new knowledge able to inform design and policy decisions. This second part expands both the technologies for data collection and analysis and a series of experiments for testing the implementations and the potential new generated knowledge, and it presents the results of the experiments in the studied sites and their interpretation.

The third part of the thesis expands the discussion about the implications and limitations of the results obtained from the applied links them to future action and strategies. As part of this extended discussion, the strategies, techniques, and methodologies used are linked to systematic, empirical, and even earlier-than-computers computational approaches towards Architecture, Urban Design, and Planning already introduced in the first part. It draws a line of thought, or mostly a network of relations, which links historical approaches and commonplaces of computation in design with some of the current cutting-edge, speculative, radical, and research-oriented practices in design. As consequence, it reveals also how those approaches have been evolving mainly within academia and as part of research initiatives, with a minimal impact in design practice thinking beyond the development of new tools supported by computers. Overall, it outlines a theoretical and a state-of-the-art discourse for the hypothesis to be tested by the technical experiments in the central part of the document. From the extensive number of topics, authors, schools of thought, and projects mapped, three

main themes are chosen for being considered particularly relevant for the project: The Shift in the Representation, Behavioral Architecture, and Datafication of a not so Smart City. As well, two more topics are included because of their current impact: participatory design and incremental urban interventions, and the ownership, privacy, and scopes of data and their novel implementations. Finally, in this part the future steps of this research, such as new implementations and testing sites.

2 Background

2.1 Research question. Spatial planning of a digital modernism

This project is framed by the rising digitation human activities and the addition of data as another layer of information in the urban environment. Although it can be argued that this intense informational perspective has not been yet truly engaged by the practitioners beyond its tools and for informing at some degree decision making, it raises questions of privacy, politics, and ethics. The irony of this situation is that the application of 'big data'³ is already a challenge (Kitchin 2016) without having been really implemented in the workflow of designers.

³ The use of 'big data' in design can be interpreted from two opposed but complementary perspectives: control and collaboration. The fascination for data as the most promising resource for giving value to a new productive and economic model (Lanier 2013), is supporting the argument that space makers should feed as much as data as possible into novel algorithms for being able to deliver better solutions for a more efficient, smarter city. However, its controversial derive into absolute surveillance is more than feasible. On the other end of the range of possible outcomes of the datafication of the city, the informational landscape can lead to an open-ended and enriching process of commoning the design of the city, allowing as many agents as possible to participate in the process of shaping the urban environment. Regardless of the possible interpretations proposed, or the possible implications which can be envisioned, the massive use of data rises as well ethical, social, legal, and political questions about privacy and the utilization of personal information. The role of the spatial designer can be understood as the proxy, or administrator, of these opposed positions, it means, simultaneously at the intersection of control, prediction, and simulation while enabling and fostering the participation of urban stakeholders. The architect understood as this mediator, can acknowledge and orient the power these databases, algorithms, and even newer computational techniques such as AI and Machine Learning, in order to affect the design of these stakeholders' environment. So, if the designer is a mediator between the built environment and the citizens, how should be the kind of skills, processes, loops, and logic embedded in an expanded -eventually, a new normal- workflow by computational techniques?

The engagement of new computational processes of thinking and making in spatial design practice faces many challenges. It is not only a question of political or ideological positioning, but it requires disciplinary development and the exploration of new knowledge territories. Despite the failure of the first wave of computational-oriented approaches to urban planning during the 1960s⁴, the alternative explorations over the following decades didn't fill the knowledge gap about the understanding of the process of urbanization and spatial design. The challenge faced by the recent new wave of computational-oriented studies is precisely being able to develop a "serious scientific theory of cities" (West 2011). It is about making sense of space and cities, its DNA, and what and how you can learn from it.

The orientation of this research towards the built environment is not completely alien to design practice. How can we develop new theories and tools for digging into the complexity and correlations between the built environment and how people inhabit that environment?

The effort for bridging this gap affects directly to the own role of spatial designers, although it can be explained as well in terms of means and material culture resulting from design practice. An integration of spatial design practice into intense computational workflows requires necessarily the consistent use of machine-readable documents, which is still far from being a standard -although promising advancements seem to be done in that direction (EUBIM Taskgroup 2017)-. Reformulation of the whole skills and knowledge valued into design practice needs to be as well leverage with the kind of background that computational thinking requires. So far, most of the initiatives -even if we consider them flawed, partial, or unsuccessful- towards the digitation of the built environment and the hype of smart cities

⁴ The new computational techniques and cybernetics theories framed a large part of the research activity after the Second World War including urban planning and design practice. Although the development of new tools and methods for designing defense artifacts -mostly aircrafts- played a key role for the deployment of Computer-Aided Design (Cardoso Llach & Forrest 2017) and they are at the origin of an important part of the design workflow used nowadays, other approaches focused on the systematic understanding of the complex dynamics shaping and regulating the functioning of human settlements has a completely different outcome. The determinism and optimism that drove these implementations for understanding, controlling and remediating urban, habitation, and social issues led to a narrow understanding of cities as closed systems. The outcomes of these simulations and systems were unable to predict real urban behavior, emergence of new states, and they were mostly used for self-legitimizing implemented urban transformation policies (Babcock 1972; Flood 2010).

have been alien to the activity of architects, urban planners, and designers. How can we leverage the practice with computational methods?

This research questions the messianic rhetoric commanding the current vision of the technocratic utilization of data in general, and in its version urban settlements represented by Smart Cities. The utilization of data within a positivist epistemology that interprets that there is an external reality which can be captured, measured, and recorded through collecting precise and objective data (Desrosières 1998). This 'God's eye' understanding of the data as neutral representations of the world are supported by this mechanistic and deterministic understanding of the world whose issues can be solved through technical means (Mattern 2013). However, this thinking is flawed because data is a mediated result of constructed agendas, ideas, interests, and means of collections (Onuoha 2017), "raw data" is always cooked (Jackson 2013). Neither data are neutral, nor the analysis and processing are independent of socio-technical contexts, and rather than showing the world as it is, these new technical means enabled by computation and data generates a new one (Kitchin et al. 2015). Additionally, to the misconception of fully objectivity of data and their methods, there is another set of important operational barriers for its implementation: the availability of large datasets, the tools and methods for processing that massive amount of data, and the knowledge of experts for dealing with such kind of approaches (Mantelero 2014).

The topics addressed in this document are complex and the references virtually endless. Just as guidance, an indicative and approximative map of ideas, individuals, and projects is presented for contextualizing this proposal. However, not all that content in this graph is included in this project. It is a support roadmap for scaffolding and providing the needed theoretical background of the three relevant topics developed in the first part of the thesis: The Shift in the Representation, Behavioral Architecture, and Datafication of a not so Smart City. Overall, this roadmap addressed the systematic, computational, and dynamic approaches toward design from the 19th century, with a key Gordian knot during the first age of computers and the first wage of cybernetics and control theory (around the period 1950-1970) following the Second World War. After the crisis of these approaches at the end of the 1970's, all the current trends aligned with smart cities, artificial intelligence, parametric design and the plethora of different approaches involving computation and design can be traced back to that knot.

The goal of the proposed experiments is unraveling the complexity embedded in the built environment where all those different components, changing at radically different paces, with different scales and agencies, shape the dynamic system which results as a city. However, the first aim of the experiments described below focuses on bridging the lack of information on the dynamic components of the system described. While there is a deep and exhaustive documentation of the physical environment, and there are precise environmental and climatic records from the last decades, there is a gap in the knowledge quick changes produced at the pedestrian scale.

2.2 Immediate precedents

The development of ubiquitous computing in the last years has fostered a plethora of new services for wayfinding and contextual information primarily, which has not only designed for the advantage of users but as well as a valuable resource for companies and providers for tailoring their products.



Figure 1. Visitor scanning her MagicBand at one of the Disney's park facilities. Photographer: Bob Croslin

Paradigmatic is the case of Disney, that started almost a decade ago to use data-driven solutions to improve its theme parks users' experience by speeding up waiting times and a more even distribution of visitors across its facilities. It showed that control rooms were not only for security or for expensive and mediatic spatial missions, but they could be beneficial for more trivial topics and the company created the Disney Operational Command Center for using high technology as a tool for a better user-center management of the park (Barnes

2010). Over the years, this utilization of data for improving the functioning of the park and the visitors' experience has been streamlined and expanded by the incorporation the MagicBand, a wristband which enabled users' tracking by RFID (Radio-frequency identification)⁵ through a network of beacons⁶ installed across their facilities. It does not stop there, as a team of mathematicians tries to analyze the data and find out patterns and clues for expanding the understanding of the functioning of the facilities. It provides real-time anonymous data on the utilization of rides and facilities of the park for serving the ultimate seamless magic experience (Qu 2018).

Similar approaches based as well on the location provided by beacons and RFID tags for tracking positions and registering behavior of people have been used in other locations with diverse goals. The use of this positioning technology expanded the advantages of real-time location-based services to indoor environments (Chawathe 2009) such as malls, museums (figure 2) and airports where traditional GPS was not applicable. It made possible a new catalog of implementations centered on improving the quality of services to users whether pretending to provide a relaxing holiday experience on a boat (Estes 2014) or developing proximity marketing strategies in malls (Lawlor 2016).

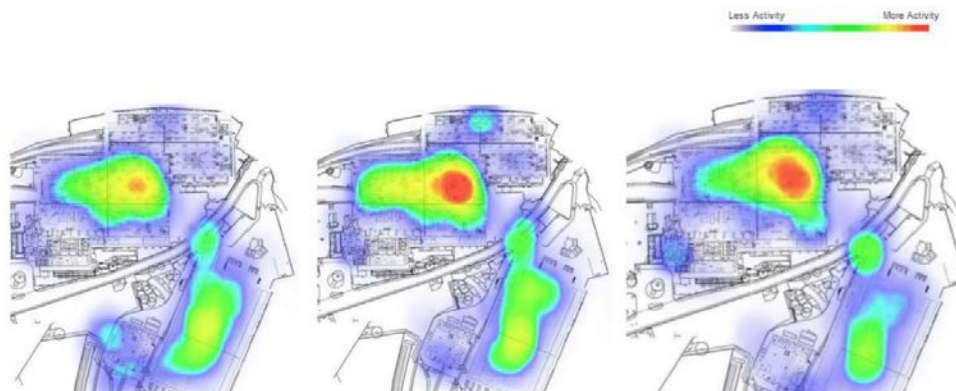


Figure 2. Heat-maps of the utilization of the space by visitors from cell phones positioning collected through beacons. Cisco and Polkaspots for the National Railway Museum, London. Source: <http://www.gizmodo.co.uk/2017/04/exclusive-heres-what-museums-learn-by-tracking-your-phone/>

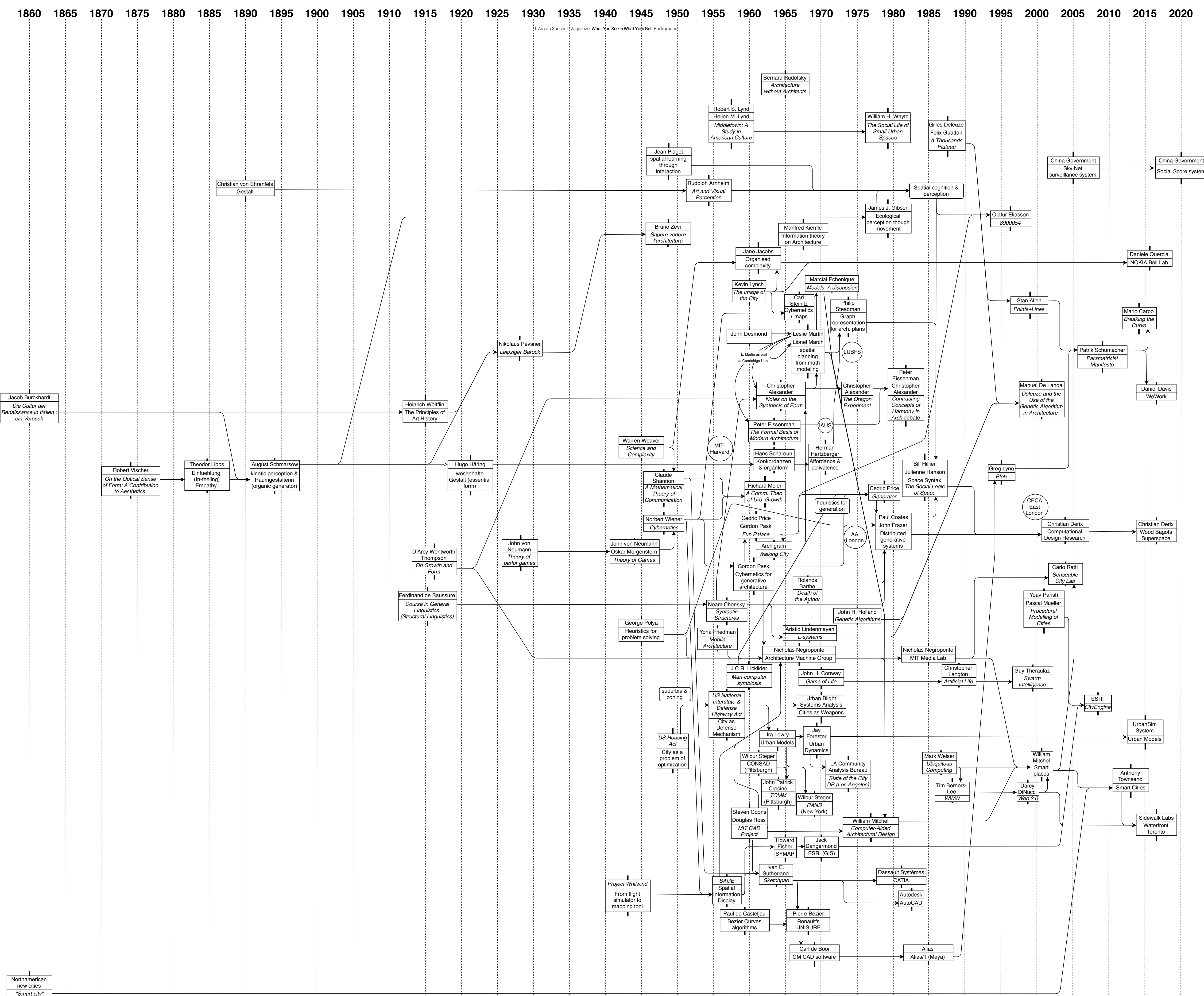
⁵ Radio-frequency identification (RFID) is one method for Automatic Identification and Data Capture (AIDC) that uses radio waves for identifying an object without needing to be in the line of sight of the reader (Ahson & Ilyas 2008)

⁶ Beacons are small low-consumption transmitters able to communicate with small devices. They use a Bluetooth Low Energy wireless connection (http://bfonics.com/what_is_beacon.php).

At the same time than these business-centered applications of high-precision location services beyond ubiquitous GPS, other research on relating the spatial tracking of people and their complex behavior from a combination of multiple empirical methods (Millonig & Gartner 2008) has been developed. These studies have focused their interests at different concrete topics related to the human process decision making and preferences in navigating the space. They have covered pedestrian movement modeling in the built environment from the crowd perspective (Helbing et al. 2001), and the simulation for the better performance of infrastructures (Daamen & Hoogendoorn 2003), to human-centered approaches for translating orientation visual clues affecting the decision making process in real environments to navigation services (Millonig & Schechtner 2007).

The collection of enough data in bounded spatial context even has allowed the development of accurate crowds simulation able to predict the behavior of people in bounded conditions (Zhou et al. 2012). The use of computational techniques for extracting precise data from the built environment and encoding spatial features is as well at the origin of the utilization and development of Space Syntax techniques. Within the context of this research defined by drawing connections between social relations and space configuration, the use of this type of metrics is as well related to the role of architecture as a behavioral and control device. Although it was developed for most of its history as a pure spatial analytical resource, Space Syntax has got back to its origins in the last years by engaging again generative tasks, not exactly as Paul Coates deployed generative simulations for grasping the correlations between social and spatial structures published in 1984 (Hillier & Hanson 1984), but at least for informing successfully and predicting the outcomes of real design projects (such as Fosters and Partners at Trafalgar Square in London -1996-, and Richard Rogers' masterplan of Pudong in Shanghai -1992-).

However, it is important to remind that the proposed research, as it could be said about the mentioned immediate precedents, is part of a larger territory of lines of interrelated research topics connected to new computational techniques, and the rise of complexity sciences during the 20th century (figure 3). All these topics are not covered in this document, but connections from the techniques implemented, background mentioned, and implications and discussion developed as consequence of the developed experiments can be drawn. This map is an unfinished thinking tool and it is still a work in progress.



2.3 Previous Work: Open Urban Television.

The proposed framework of experimentation is the result of previous research conducted on the topics of urban analytics, utilization of public space, from programmatic, political, and social perspectives. What started as a mostly almost artistic project with a strong critique component regarding the controversy on the appropriation of the use of public domain as political demonstration space, eventually evolved towards a more analytical and scientific resource for the empirical study of the utilization of cityscapes. The infrastructure provided by the use of cameras enabled a direct connection, methodological and theoretical, with previous perspectives of data collection, with the debate about control of information, and open a novel and unexplored field of study for urban informatics and spatial planning.

This project is not created from scratch for the purpose of this thesis proposal, but it is an expansion and a new iteration of previous research projects over the last 4 years focusing on the use of new technologies and data for urban planning, from a social, political, technical and disciplinary perspective.

Open Urban Television (OUT) was a project deployed in Madrid by Rodrigo Delso, Alberto Sáiz and myself in 2015 with the support of MediaLab Prado as part of the Connecting Cities Network funded by the European Commission. The project proposed the virtual augmentation of spaces of protest in the city of Madrid through the use of giant media facades as the one featured on the main entrance of Madrid MediaLab Prado. The control of this infrastructure would not be mediated by any privileged agent as in the traditional mass media, but the possibility of broadcasting (it means in this context, expanding) one of these protest spaces in the city through technology would depend on the direct action of citizens by their personal devices.

The project involved the installation of several streaming cameras in different locations of the city. Those chosen locations were the most frequent spots for public demonstrations, and in general, for city venues. Those spatial, social, mediatic and politically central. It raised two nested conflicts as well: the over-representation of the core of the city over the suburbs, and caused by this particular sampling, the biased selection of data when collecting information. It can be argued that the concrete goals, target, and scope of this project justified the selection of those spots because of their representational power. However, it conditions a particular view of the city, from the theoretical point of view, reducing it to its central spaces,

while it is maybe the suburb or the satellite city (Tarr 2010) are the most defining elements of the contemporary city (Fishman 1987). Regarding the data, the constraining scope of the monitoring will condition the possible outcomes which can be extracted, and without dismissing the value of the gathered data, “datasets are the result of their means of collection” (Onuoha 2017).



Figure 4. Network of cameras in Madrid city center for Open Urban Television project: (1) Puerta del Sol looking at Casa de Correos, (2) Puerta del Sol looking at Tío Pepe banner, (3) plaza del Callao, (4) calle de Alcalá and Cibeles, (5) calle de Alcalá and Gran Vía, (6) Gran Vía from plaza de España, and (7) Northern section of plaza de España.

The timing of the project was relevant due to the rising number of demonstrations on public spaces in Madrid related to the recent economic crisis (over 5,000 registered, according to the records of the Government Delegation in Madrid). This intense utilization of the public domain was at the origin of a controversial debate about the right of free use of the public space and the restrictions set by public authorities, whether they were motivated by political and ideological reasons or just by well-legitimated urban management arguments. The central event of all this extremely social and politically active impasse in Spain was precisely the so-called 15-M, Spanish Revolution or Indignados Movement (Gonick 2016), and it has been used extensively by a great number of scholars for developing research on digital humanities, sociology and new technologies, and the relationship between politics and architecture (and by extension, built environment in general) (Jaque 2017) which connected directly with the already mentioned implications of privacy and ethics, politics and sociology of new technologies based on networked digital infrastructure and the massive use of data (Kitchin 2016).



Figure 5. Open Urban Television project public presentation. Media Lab Prado, Madrid (Spain). September 11th, 2015

The use of cameras as a novel source of information for city planning -maybe not the case for control or smart cities approaches- is key in the development of Open Urban Television, and so it is for the present project. In fact, the presence of cameras, as one of the most obvious control devices found in cities around the world, is intimately related to the debate about the ownership of the data, and the access to information generated from the common ground by everybody. There are more than 4 million of CCTVs in the United Kingdom (BSIA 2013), and the Chinese government's tracking system for its new social credit system uses more than 20 million of cameras over the country (Smith 2017). However, the ownership and access to their publicly generated information remain shady, hidden, and inaccessible to citizens (Kitchin 2016). The equalization and democratization of the use of urban visualization were an objective and motivation for Open Urban Television, and this objective remains valid for the current research. Nevertheless, the goal is not expanded. Not only access to information coming from the collective action (aka daily life in the common ground) should be ensured, but it needs to be used and exploited for further applications. In this research, it is proposed that not only free access to information is enough, but that it can be used for decision-making and for transforming the structures of power based on collective action.

2.4 The Use of Data

Timing and positioning are crucial for tracking purposes, and the amount of information which is available in any context is endless. This method proposal is not willing to capture all the information available in the public space but focusing on useful information which has

been ignored until now. Not every single feature needs to be collected or mapped, as it would be counter-productive (Borges 1946), but identifying new fields made available by new technologies which can provide new understanding of how people inhabit the built environment. A handful classification based on two dimensions is outlined for framing the scope of the variables included: time scope and nature of the data.

Time scope refers to the rate of updating of a particular variable, to the needed temporal resolution for grasping it. It means, how quickly a targeted parameter is changing. The nature of the data explains the level of closeness to the real phenomena as a source of information, whether real data directly surveyed from reality or synthetic data generated algorithmically or through simulations.

At any given context, the factors which shape the built environment inhabited by people can be classified depending on their time scope. Dynamic elements, cyclic or slower changing environmental factors, and stable features. Dynamic elements refer to all moving components within the urban scene. Primarily, it means people, vehicles, and animals getting around. Those are elements whose conditions and positions are being updated in the scale of seconds, if not even in the scale of infinitesimal fractions of time. Cyclic or slower changing factors refer to environmental conditions which are shifting over time but at a much slower pace. They are mostly weather and lighting conditions, or even temporary urban interventions and occupations of the public space. Lastly, stable urban features refer mainly to what is understood commonly as the built environment, its tectonics. Buildings and spatial features which have belonged to the traditional practice of architects, urban designers, and urban planners.

The latter, the stable spatial features, are the physical components of the city and the main secular concern of the architectural and design practices. Buildings, walls, columns, fences, doors, holes, the topography itself -preexisting or designed-, roads, sidewalks, sculptures, fountains have been traditionally the fixed conditions for the human habitation of the space. They are, and have been, traditionally well documented and recorded. Most of the design practice expertise is based on experimenting with their conception, construction, modification, and eventually destruction. It matches the traditional tectonic-focused concern of architecture (Maulden 1986).

The cyclic and dynamic changing environmental factors are not that stable, and their documentation and recording in a systematic way are more recent. Their incorporation in a systematic and scientific way is even newer and needs to be traced back to the domestication of the climate (Michalski 2007). They are components of the built environment which affect the use of the space over time and can cause a completely different use of the physical layouts of the tectonic architecture.

Coming back to the nature of the data in relation to the real targeted phenomena, the data used for this research can be as well classified as synthetic or real data depending on how it is created. Synthetic data is artificially produced information that is not obtained directly from real-world events, it is, by direct measurement, but generated algorithmically (Parker 2003). The use of synthetic data has been increasingly important over the last times because of the improvement of their quality, it is providing the same results as real data, without compromising privacy (Patki et al. 2016). Additionally, they allow to simulate new scenarios or even overcoming the traditionally annoying fault of missing data (Richman et al. 2009).

This synthetic data does not diminish the value of real data. Both types should be complementary, and their hybridization is possible. In fact, one type real data is one of the novel contributions of this research as in the case of detections of activity from computer vision algorithms. This is precisely a really good example of real data and synthetic data integration, as data augmentation for training the neural networks required for these algorithms is based on the creation of more artificial training samples from real annotated data, as a valuable resource for producing new real data, it means, the detections.

The use of synthetic data in this research is as well circumscribed to the use of a number of metrics created mathematically for grasping special features, not naturally or directly observable through our senses. This set of extended measurements includes the metrics from Space Syntax (described below) and the measurement of the visual complexity from Google Street View Images.

Although other sources of data could be included too in this study, a combination of information spanning this classification is aforementioned focus the technical implementations: Computer Vision-based activity detection and its training data, points of interest in the urban context (POIs), sunlight simulation as weather conditions changing over

time, visual complexity computed from Google Street View and Google Images pictures in the area, and Space Syntax metrics generated from the physical features of a 3D digital model of the built environment to study.

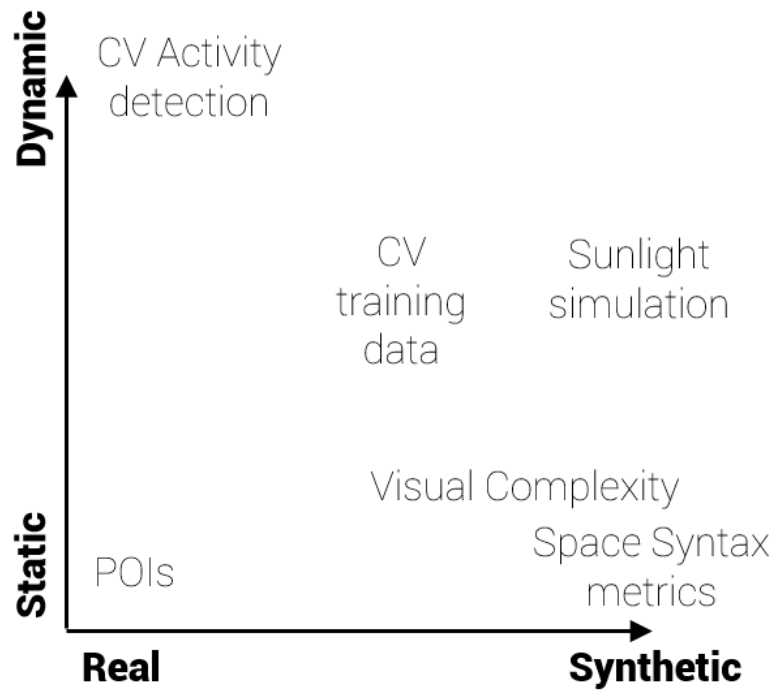


Figure 6. Types of data according to their nature and time range.

3 Hypothesis

The research proposal accounts for the complexity of the urban environment up to the point of being intractable problem questioning the positivist and deterministic of computational technologies, and in general the control of humans over nature idea embedded in science since the Renaissance. As an alternative to this framework, the thesis acknowledges the open character of the relations shaping a city, from spatial ones to social, cultural, political and economic ties and the diverse character of them.

Assuming that data is a technical and social construct determined by interests and means, the research identifies an informational gap and an underutilized resource for data collection which can yield a better understanding of the built environment. This supports the first hypothesis of this document: Computer vision techniques can capture new high-resolution data about the utilization of the built environment.

Leveraging this new type of data with machine learning and urban design techniques can yield new information about the interaction of people with the environment they inhabit and produce new knowledge that is able to inform design and policy making.

Additionally, two more topics are proposed to this research. Firstly, assuming the value of data for evidence-based decision making in design, it is possible to overcome the current issues about massive data collection regarding privacy and personal data. It can be argued that there is some bias embedded in all the developed system for data collection, some sort of fascination about surveillance and control. It can be argued that this is an implicit bias created from the academic-military research complex, but it should be put into question the technical possibilities of preserving the use of data in the less harmful way. Secondly, it is possible a computational data-oriented framework of design in the built environment with open-ended results, reactive to new inputs, and able to fit emerging new scenarios, in a completely different way than the mechanistic, positivist, and deterministic imposed by the historical development of simulations, predictive techniques, and other technologies.

3.1 Expected contributions

Although data-driven processes and computational techniques applied to design are not new in the case of Smart Cities and the new application supported by Information and Communication Technologies, formalization of strategies are missing (Bettencourt 2014).

The central goal of the experiments presented is double. Firstly, the exploration of a novel kind of data provided by the use of computer vision algorithms on real-time video imagery which can yield information about the patterns of utilization of the space. Secondly, the integration of this new kind of information with other existing databases or coming from other sources for building a better understanding of the relationships between the use of the built environment and its spatial features. The bigger picture of this knowledge involves being able to inform more effectively decision making in design and policy.

Therefore, the expected contribution from this research are:

1. Designing a Computer Vision algorithm specialized in the collection of data from the behavior and activity patterns in urban public spaces. It implies the collection of necessary annotated data from images for training a Convolutional Neural Network able to provide this kind of novel information
2. Identifying metrics for quantifying spatial features and people behavior in public spaces.
3. Finding correlations between spatial features and people behavior out of these data based on advanced statistics and state-of-the-art machine learning techniques.
4. Outlining a pipeline for including data-based decision making into design loops for urban space.
5. Leveraging data privacy issues and holistic approaches towards the use of data in design practice.
6. Informing current new trends in participatory design from an evidence-based and data-oriented perspective.

4 Methods

4.1 Proposed Data-informed Design Pipeline

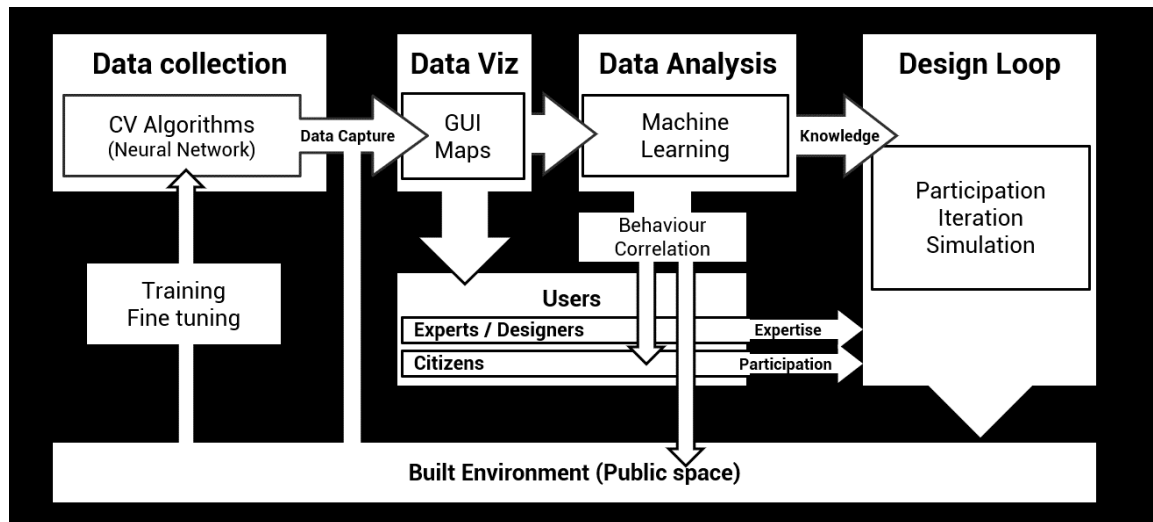


Figure 7. Proposed workflow pipeline.

On the whole, this research aims to outline a design methodology with an intense use of data for informing decision making in design. The approach is far from pretending to be deterministic in the way data can inform design results. By assuming a more holistic understanding of design process and built environment, it is expected to generate soft knowledge but based on precise, empirical, scientific able be included as part of design iterations.

The outlined pipeline is connected to the built environment, as the primary source of information and target of the research. For practical purposes, the whole process can be split into four main steps or phases which are dependent on the information flow, but whose implementation can be separated from the others.

In a data-driven process data collection is the first need to be covered. Data is used here broadly as it is referring to data of completely different nature, with different degrees of availability and that consequently require custom collection methods. For the proposed pipeline, already known types of data are combined with data captured using novel methods. One of the main contributions of the proposal is particularly these new ways of capturing aspects of the physical environment which were ignored or unknown before, and how to aggregate and leverage that new resulting data with existing information of the built

environment as a generator of original knowledge. Therefore, the use of the term data collection used in the pipeline needs to be understood broadly as it is referring at the same to different types of data, to different collection methods, and even to different tasks such as data selection, data collection, and data aggregation. For the sake of clarity, it is necessary to distinguish the different data sources, data types, data collection and data aggregation methods included in this step.

In general, all the data used for conducting the proposed experiments are created from scratch. The difference lies in the novelty of the methods used for data collection. The data used for the conducted experiments can be divided in metrics coming from well-established analytical frameworks - such as Space Syntax-, from more innovative approaches -such as computational perception-, from conventional urban planning practice, and finally, from a new source of information based on real-time data collection supported by computer vision techniques. The selected data focus on metrics for describing the perceptual and geometric features of the built environment, through properties already defined by analytical methods such as the aforementioned Space Syntax. There are additional known data related to environmental conditions and to activities and uses of the space which can be found in datasets or through surveying which is covered by these different methods of data gathering.

Nevertheless, a key contribution in this phase is not just the simple utilization of diverse types of data, but the identification of an informational gap not currently covered by common design practices, either data collection techniques. While the physical environment is well documented, and environmental climate conditions are well registered too, the use of the space at the scale of pedestrians is an unknown realm. Location technology operates accurately at the scale of meters, at the urban or metropolitan scale. It provides a pretty good picture of the upper-level dynamics and flows ruling the functioning of a whole city, but it is missing extremely valuable information at the scale of centimeters, at the scale that people experience the space. A number of different experimental deployments of tracking technologies have been tested for capturing this microscale spatial information, and some implementations of this valuable knowledge have been implemented in real settings such as the already mentioned beacons in airports, cruise ships, and malls, or for tracking visitors in amusement parks.

This new data is collected using state-of-the-art computer vision techniques based on deep learning from the information provided by video streaming. This use of real-time imagery as a source of information is a key contribution to the phase of the research. As an additional note, a requirement for using these detection techniques on images based on deep learning is the existence of manual annotation of the features to be detected, which means, an earlier collection of data.

Regarding the data aggregation, it is interesting to notice that not only the kind of data affects the possible outcomes of the study, but as well the way that these data are integrated into a coherent dataset suitable for inquiry. Two main approaches are applied in those experiments: longitudinal time-based, and spatial aggregation.

The integration of well-known spatial and perceptual synthetic data (Parker 2003) with novel information about the utilization of the space from a phenomenological perspective is challenging because of the different nature of the information, although this hybrid approach can be used for reinforcing the validity and usefulness of both data sources. Comparatively to other approaches previously used for collecting this dynamic live data, some of them introduced as immediate precedents, the use of images from video cameras watching urban landscapes offers several advantages: avoiding privacy issues as the resolution and distance of the cameras make unfeasible capturing any kind of personal data (i.e. license plates or facial features), it is systematic, non-invasive, persistent, and the same system is versatile and robust enough for tracking any kind of element present in the space (i.e. not only people but vehicles, trends, obstacles, urban furniture, etc.).

4.2 Datasets

4.2.1 Space Syntax Metrics

Space Syntax is one of the few techniques resulting from the first computational wage applied to design that has obtained some level of success and a relatively long history -within the frame of the history of computers-. It is “a set of techniques for the representation, quantification, and interpretation of spatial configuration in buildings and settlements. Configuration is defined in general as, at least, the relation between two spaces taking into account a third, and, at most, as the relations among spaces in a complex taking into account all other spaces in the complex. Spatial configuration is thus a more complex idea than spatial

relation, which needs to invoke no more than a pair of related spaces. The theory of 'space syntax' is that it is primarily—though not only—through spatial configuration that social relations and processes express themselves in space." (Hillier et al. 1987)

Nevertheless, for this proposed technical implementation, the traditional approaches towards space syntax developed on graphs, and connectivity and axial maps which were the foundational core of Space Syntax is not addressed. On the contrary, for the analysis of a continuous, superficial, area such as an urban space -here we are making some sort of assumption for the 2D-, the technique developed by Benedikt for dealing with the relationships between a viewer and his or her immediate physical environment based on isovists was far more convenient. Isovists, defined as "the set of all points visible from a given vantage point" (Benedikt 1979), originally lacked the syntactic structure for aggregating them spatially in the way Space Syntax did, but this incompatibility has been explored thoughtfully (Turner & Penn 1999; Peponis et al. 1998; Batty 2001) solved and today isovists maps are completely integrated as part of the Space Syntax corpus.

Over the years more metrics were developed over the basic ones proposed by Benedikt. For the analysis of this research, a total of 17 different metrics are included, that are the ones available in the software used for the generation of the data: DeCodingSpaces Toolbox for Grasshopper (Abdulmawla et al. 2017) within the 3D modeling environment Rhinoceros.

Area	defines the surface covered visually from a vantage point based on its isovist.
Distance Weighted Area	it defines the surface covered visually from a vantage point based on its isovist with a user-defined function. (Kim & Jung 2014)
Perimeter	length of the boundary of the polygon defined by the sight lines of the isovist from a given vantage point.
Compactness	defines the ratio of the square of the perimeter to the area (Davis & Benedikt 1979).
Circularity	this is another compactness or roundness metric defined as $C = 4\pi A/P^2$, where C is circularity of the polygon defined by the visuals of the isovist from a given vantage point, while A and P denote Area and Perimeter of that polygon (Selkirk 1982).

Convex deficiency	this is a measurement for concavity, defined as the difference of the areas of the convex hull and the isovist polygon area divided by the hull area (Stamps 2005).
Occlusivity	measures the length of the surfaces of the obstacles blocking the rays (Benedikt 1979), which is equivalent to the depth to which the environmental surfaces are partially covering each other from the vantage point (Gibson 1983).
Min radial	the length of the shortest ray from the vantage point.
Max radial	the length of the longest ray from the vantage point.
Mean Radial	the mean of the rays from the vantage point.
Standard Deviation	the standard deviation of the rays from the vantage point.
Variance	second moment of about the mean of the length of the rays from the vantage point and it measures the dispersion of the perimeter relative to this vantage point (Benedikt 1979).
Skewness	third moment of about the mean of the length of the rays from the vantage point and it measures the asymmetry of the dispersion of the perimetry relative to this vantage point (Benedikt 1979).
Dispersion	Difference between the values of the mean and the standard deviation of the isovist's radial lengths (Conroy 2001).
Elongation	Average radial distance divided by the maximum radial distance (Stamps 2005)
Drift Magnitude	Distance between the viewer's position and the center of gravity of the polygon defined by the isovists (Peebles et al. 2007).
Drift Angle	Angular distance in degrees between the viewer's position and the center of gravity of the polygon defined by the isovists, relative to a horizontal line, it is, pointing to the East (Peebles et al. 2007).

Figure 8. Metrics used from Space Syntax techniques and available on DeCodingSpaces Toolbox for Grasshopper.

4.2.2 Visual Complexity. Computational Perception

The interest of measuring and grasping how people could perceive their physical environment was already pointed out by early spatial analysis pioneers. Cognitive conditions (Derix 2014) and psychological theories about the experience of the space was at the origin of early attempts for developing systematic and dynamic approaches to understand users'

environment during the beginning of the 20th century. The early Gestalt contributions on metrics for the perceived space were further developed by Rudolph Arnheim (Arnheim 1954) in the first systematic application of perception knowledge to visual arts (Simmel 1955), in combination with the already mentioned constructivist postulates of Jean Piaget as spatial learning from interaction in the environment (Piaget & Inhelder 1948) and Gibson's construction of perception through movement (Bornstein & Gibson 1980) set the basis for the spatial cognition construction implemented by Space Syntax and other creators playing with human perception.

The relevance of including this kind of data is explained by the cognitive approach in human-centric. It could be good to explain what's human-centric) spatial design. Among the approaches addressed in this research and its experiments, it can be distinguished two complementary schemas for untangling the complexity embedded in the relationship between space and users. A top-down outside-in approach which works with external spatial features for understanding how built environment configuration and features affect people. The other one is a bottom-up inside-out approach which studies and try to understand how human beings process the perception of their environment shaping their cognition. A hypothesis, or if preferred, a statement of this research is that although the implementation may seem biased towards the first approach, it acknowledges the importance of keeping both visions in mind. In the short history of the systematic, dynamic, and computational understanding of design there has been a larger development of these mentioned top-down approaches, although they are still emerging. However, although the theoretical scaffolding for supporting the cognition bottom-up approach was existing as well to the same degree, has been much lesser explored. On the one hand that can be justified arguing that the metrics and techniques for grasping spatial (external) features have been available earlier, and the knowledge of these upper-level external features was easier to obtain. On the other hand, our knowledge about the biological processes of cognition and the way of capturing internal neurological activity related to perception in human beings have been opaquer, and still, belongs to neurology related disciplines, one of the most challenging fields of current science. It has been relatively recently when it has been possible to start to understand in a precise and empirical way part of these perceptual and cognitive processes going on in our brains. As recognition of this branch of human-centric design, an attempt of using a dataset related to the perceived complexity of the user physical environment is included.

“Can some objective numerical measures on isovists be found to correlate with human judgements of the spatial complexity of a given environment? Would such judgements vary from vantage point to vantage point? Can overall judgements be determined from a chosen path?”

(Davis & Benedikt 1979)

The cognitive aspect of spatial perception was a concern even for researchers and scholars who were working on more top-down outside-in strategies, maybe precisely because of lacking the right tools for exploring the human mind and its structures for cognition. Anyhow, the challenging task of studying how the perception of the environment affect human experience has been tackled with different strategies. Because of the extremely high complexity of the built environment, it is hard to measure the diverse number of geometrical and visual aspects which define the space (Li et al. 2016). A metric for compressing and simplifying this complexity and combination of diverse parameters affecting the perception of space which has been used successfully in many psychological experiments (Stamps 2002; Berlyne & Madsen 2013) and in some urban perceptual studies (Li et al. 2016) is Visual Entropy. The concept of entropy comes from thermodynamics for measuring the level of chaos of a system, and it was later transferred to the information and communication theory to characterize the uncertainty of a signal source (Segal 1960). Therefore, Visual Entropy (VE) is a measurement of the visual complexity and diversity of features in images. The randomness of the image is computed by the formula:

$$VE = -\sum(p \cdot \log_2(p))$$

Where VE is the overall Visual Entropy value for the image and p denotes the probability that every normalized gray-scale pixel value appears.

The images used for the extraction of this metric are collected by scraping the spherical panoramas available at Google Street View and Google Photos database. An important assumption is made by using spherical images. Obviously, the image perceived by a person will depend on the direction toward which he or she is looking at. As the aim of this study is being able a general characterization of the space, spherical images are used as an aggregation of all the possible looks from different locations. The values of the sampled locations are at the end interpolate for finding a continuous field of VE values over the whole

area. For simplifying the calculations the luminance from the green channel is considered enough as it shows a better contrast (Sato et al. 1996).



Figure 9. Spherical picture #elnEulfqYJPKu96cAcm4RA at Callao Square, Madrid. Google Street View.

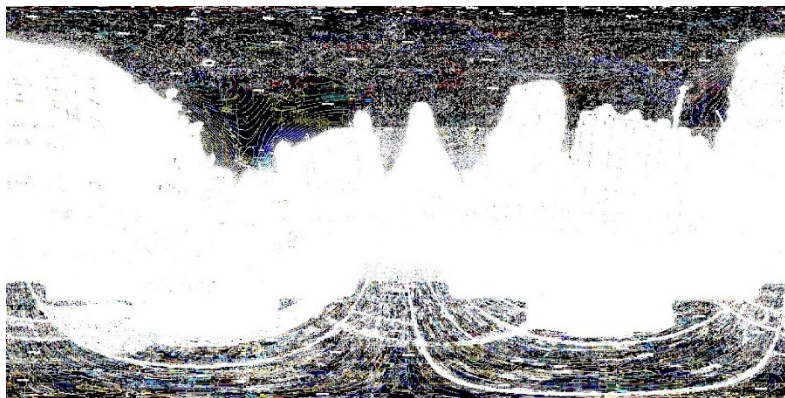


Figure 10. Spherical picture #elnEulfqYJPKu96cAcm4RA processed with Visual Entropy filter in Matlab.

4.2.3 Traditional Urban Planning: Points of Interest

Among the static features of the built environment, an additional important input for the exploration and understanding of the patterns of movement and utilization of the space are the uses found in the space. This information can be considered closer to the traditional and well-established analysis of urban design and planning practice. The main hypothesis supporting to include this kind of information is that the stores, transportation and main facilities in an urban environment will have a decisive impact on the behavior of users. The list of chosen facilities location doesn't pretend to be an exhaustive list of facilities, but just a test case for checking the weight of directly legible elements of the urban scenes by people. Differently than other features extracted from the urban environment, these Points of Interest

(POIs) are not an automatic consequence of the characteristics of spatial configuration and look of buildings and other elements, but the mediated result of economic, political and planning agents. These elements don't play their role in hidden levels of human cognition and decision making for orienting navigation and interaction in the space. On the contrary, they are few of the component in the urban environment which can be identified as drivers of action and decision for citizens. While it is hard to make people rationalize if a particular spatial pattern, a design of a building, or a series of visual and spatial parameters affect the way they move around the space; it is pretty straightforward to inquire people about their behavior in the space just based on clear destinations and facilities. This method of surveying and scanning the city is somehow related to the legibility introduced by Lynch as a way of freeing the perception of the city supported by sentimentalism and picturesque (Offenhuber & Ratti 2013).

4.2.4 Environmental Data

In the midpoint between the quickly changing information about the movement of people and vehicles in spaces and the patterns of utilization of the urban environment (the dynamic activity of a place), and the static features of the spatial configuration of the built environment (the buildings, the tectonics of the place), the changing weather and lighting conditions affect the pace of the city and how the space is used. These last-mentioned parameters change over time and at a slower pace and cause differences in the utilization of the same built context.

The discourse about the control of the climatic conditions in the built environment, indoors and outdoors, at the building level and at the city level, has been historically a core concern of design. Ensuring climatic comfort is central to design. This constraint instead of being seen as a driver for design, it could be considered as complementary: to use climatic conditions as a gateway for understanding the use of the space.

For simplifying the variability of this factor in the proposed model, only shadows and lighting conditions are considered. Temperature, wind, or rain are ignored at the level of the detailed analysis because there are not expected radical changes within the same day which could provoke distortions in the general observed trends from the big picture of levels of activity over the day. It means, only important weather changes within the same day can cause an

important distortion on the daily trends of activity. If a day is rainy, windy, cloudy, sunny, etc. in general, it may produce a difference comparatively with other days with different conditions, but the general trend can be equivalent (e.g. a rainy day can show a fewer number of pedestrians, but it expected that the peaks of activity will be around the same time than in a sunny day, although the particular figures can be different). Which is more interesting as a test for understanding how these environmental conditions can affect people is how small located changes may be connected to patterns of occupation of the space. Sunlight has a deep impact in the quality of space, and its study is fully incorporated to design practice. However, it is based mostly in general assumptions about how people may react and work when exposed to different levels of light, but there is a lack of empirical data about the actual effects.

Precisely, the fully integration of environmental design in professional practice offers many tools and resources for the study of these conditions in the built environment. Instead of surveying the real light conditions of the analyzed days, synthetic data is created by simulating occlusions, shadows, and sunlight in a virtual 3D model. This kind of environmental simulations are well-known and can offer data as accurate as real surveying as they follow well-study natural laws (Milošević et al. 2016). For this research, sunlight is simulated with the Ladybug plugin for Grasshopper within Rhinoceros environment (Roudsari et al. 2013).

4.2.5 Computer Vision Algorithms

"El ojo que tú ves no es ojo porque tú lo veas, es ojo porque él te ve"

(The eye you see is not an eye because you see it; it is an eye because it sees you.)

A. Machado, Proverbios y cantares (Proverbs and Songs).

Together with the general framework of embedding data in the open-ended design of the city in an effective way, the use of computer vision algorithms provides a novel kind of data bridging an informational gap about the utilization of the public space at a high resolution and on real time. The fast development since 2013 of deep learning techniques applied to image recognition had made possible a revolution in computer vision. Today, these techniques allow the identification of features in images with a greater accuracy than even human vision.

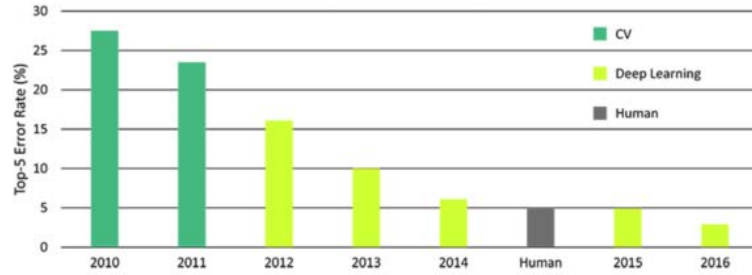


Figure 11. ImageNet Top-5 Classification Error over time. In 2015 CNNs overpassed human accuracy for object detection on images. (Recker & Gribble 2017)

The concurrence of readily available images of public spaces ('raw data', with all the mentioned reservations about their 'rawness') and techniques able to detect virtually anything on an image yields a new range of possibilities for the understanding of the use of space. Among these deep learning techniques which have expanded greatly the possibilities of computer vision, there are Convolutional Neural Networks (CNNs). This type of deep, feed-forward artificial neural networks (Karpathy 2016) base their performance on the training received from a dataset of labelled images that allows to fit the network parameters for being able to produce the targeted output as identification from any input. Therefore, CNNs are used in this research for analyzing real time imagery from the targeted urban spaces to study for identifying people, vehicles, and objects of interest.

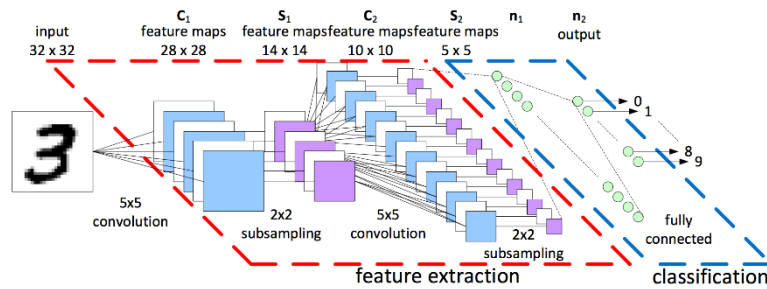


Figure 12. Generic CNN architecture for a handwritten digit recognition task (Peemen et al. 2011)

The existence of many already pretrained Convolutional Neural Networks for general purpose image recognition can be used for this research, but with some limitations. Most of the existing datasets of images are conceived and designed -again, it is a good example of the cultural and human construct that data are, even though it is assumed to be an accurate representation of reality- for human-height vision and autonomous vehicles. However, the proposed research requires the analysis of large urban spaces where bird's-eye imagery is most convenient. Although there are not datasets of this kind of images for deep learning, the own architecture and logic of CNNs make possible to use part of the training of general

purpose images, and then tuning the last layers of the network with the new features, for obtaining at the very end the desired output. This is fine-tuning, and it speeds up the implementation of these techniques to a great diversity of objectives.

Convolutional Neural Networks are made of layers of parallel interconnected neurons (units of processing) which identify features from the images from the simplest ones such as edges and gradients in the first layers, to complex shapes in the last layers, aggregating these increasingly complex characteristics of images that will lead to a level of certainty in the detection of a targeted class.

The architecture of Convolutional Neural Network used for the detection algorithm implemented is based on the YOLO ('You Only Look Once') (Redmon & Farhadi 2016) design because of its efficiency and high performance on detection on video images. Some important modifications for improving the detection of small features in the image, one of the main flaws of this architecture, as the targets of aerial imagery will be occupying small portions of the frame. Regarding the initial training of the CNN, COCO ('Common Objects in COntext') dataset is used because of its large diversity of its contextual recognition, large number of annotations (over 1.5 instances), and diversity of classes including some of the basic key detections expected from the activity in the streetscape such as people, cars, bikes, motorbikes, buses, and benches (Lin et al. 2014).

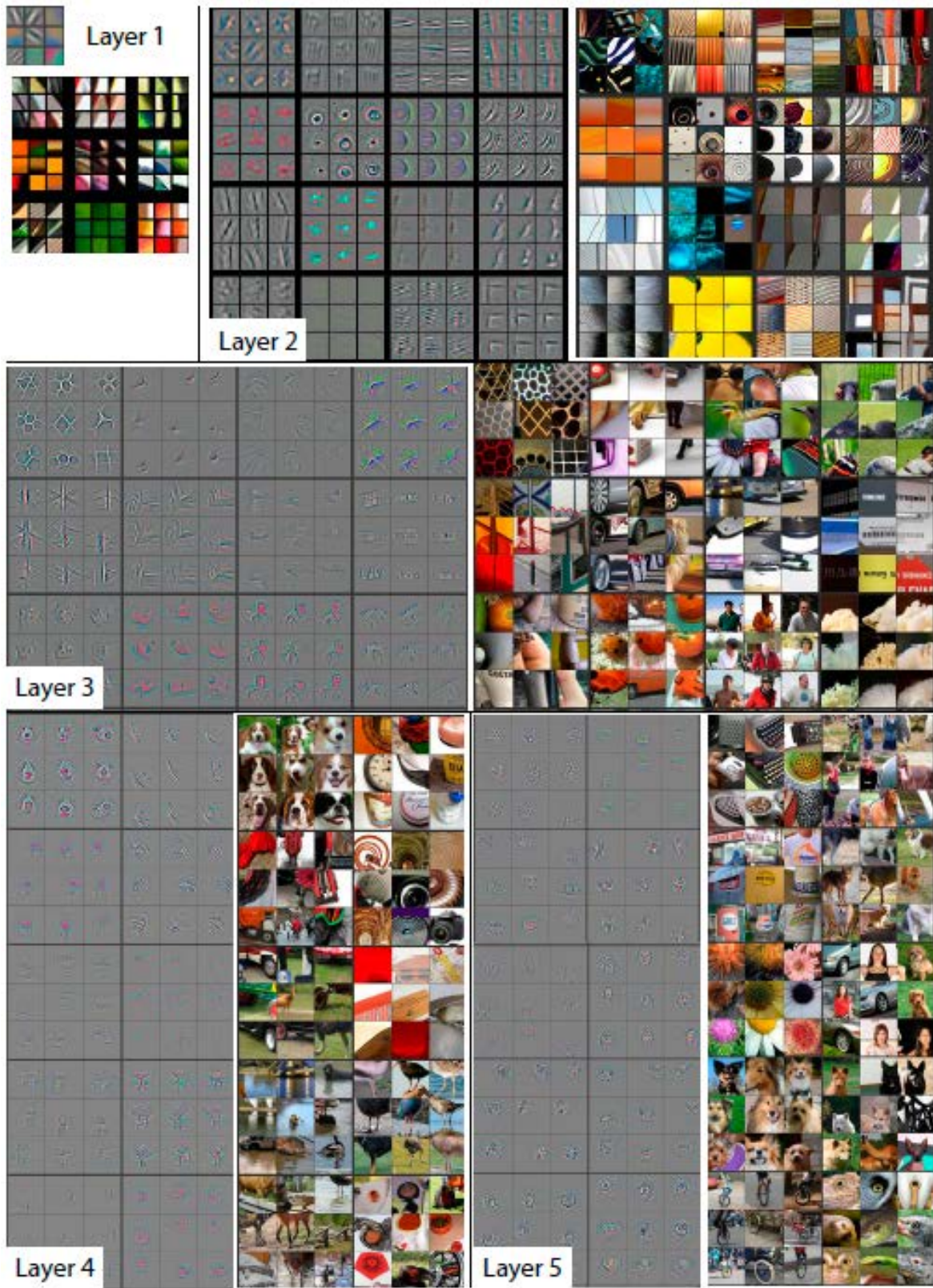


Figure 13. Feature maps of the different layers of a fully trained CNN (Zeiler & Fergus 2013).

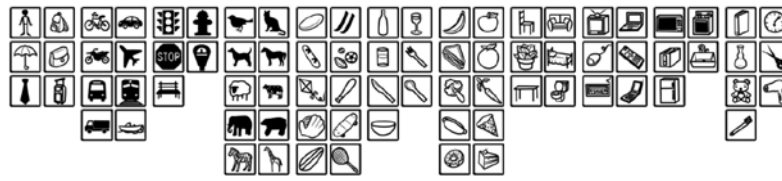


Figure 14. Classes recognized by COCO dataset. Source: <http://cocodataset.org/#explore>

However, these pretrained categories in the COCO dataset don't match the objectives of the research, as there are many classes which are not useful for urban scenarios. For this research, a new dataset of manually annotated aerial images is created identifying bounding boxes of basic categories which can offer a good indication of a level of occupation and activity in public spaces. These classes are: "pedestrians, cars, trucks, buses, bikes, motorbikes, and police cars". The images base for the annotation are 300 frames in different moments of the day, in different seasons, and with different lighting and occupation conditions of the cameras located at Puerta del Sol and plaza del Callao in Madrid. A group of 20 students of the School of Architecture of Madrid was hired during 7 hours for performing the necessary mechanical-turk after the necessary orientation for the accurate identification of features and outlining of bounding boxes on the provided labeling software LabelImg (<https://github.com/tzutalin/labelImg>). As a result, 63,000 annotations of any of the 7 targeted categories were collected. This dataset was used for the fine-tuning over the last layers of the pretrained CCN with COCO while preserving the first layers of the networks as they were completely functional.



Figure 15. Original frame (left), and frame with bounding boxes in green for manual annotation of features (right).

The detections generated by the Convolutional Neural Network are encoded as a list of bounding box coordinates, with the assigned most probable class. This direct information needs to be formatted in such a way that it could be useful for spatial analysis, which means that every single detection needs to have temporal and spatial coordinates to enabling its

utilization. Assigning a timestamp to every detection can be achieved with a resolution of seconds taking as reference the timing of the input video and their frames. Depending on the particular workflow it could be done on real-time from the computer clock, or on recorded images by aggregating timestamp information to the video. In the case of spatial coordinates, it refers to transform the 2D information of the location of the bounding box detection in frame coordinates to geographical coordinates (latitude, longitude) that can enable the integration of this information into the standards of spatial representation, including Building Information Modeling (BIM), City Information Modeling (CIM), and Geographical Information Systems (GIS). This transformation can be accomplished by applying an homography⁷ which is able to convert image coordinates into rectangular geographical coordinates, whose relation is expressed by the formula (in homogeneous coordinates):

$$\lambda \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \lambda \tilde{x}_i' = H \tilde{x}_i = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$$

Where $\tilde{x}_i$ denotes the homogeneous coordinates of the image frame, $\tilde{x}_i'$ denotes the homogeneous coordinates in the rectangular (Cartesian) projected geographical coordinates system, H is the homography matrix, and λ a scale factor defined by the distance between the focal point, the image plane, and the real object. The choice of a Cartesian projected coordinate system is preferred over spherical ones because of their more common utilization on maps, particularly at the scale of urban planning, and because of its easier integration into 2D and 3D modeling environments.

⁷ Homography is a projective transformation that defines the correspondence between two planar geometric shapes.

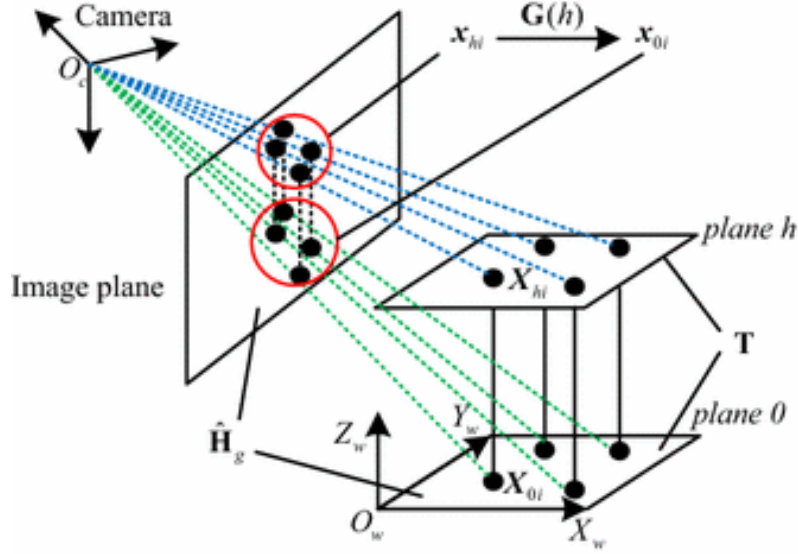


Figure 16. Geometric relationship between the image plane of the camera and the 3D environment to define a homography. (Zhang et al. 2017)

The estimation of the homography matrix (H) is obtained by solving the system formed by at least four corresponding pairs of points with their coordinates in image plane system and in the map projection system (Hartley & Zisserman 2004):

$$Ah = 0$$

$$\begin{bmatrix} 0 & 0 & 0 & -u_1 & -v_1 & -1 & y_1 u_1 & y_1 v_1 & y_1 \\ u_1 & v_1 & 1 & 0 & 0 & 0 & -x_1 u_1 & -x_1 v_1 & -x_1 \\ 0 & 0 & 0 & -u_2 & -v_2 & -1 & y_2 u_2 & y_2 v_2 & y_2 \\ u_2 & v_2 & 1 & 0 & 0 & 0 & -x_2 u_2 & -x_2 v_2 & -x_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & -u_N & -v_N & -1 & y_N u_N & y_N v_N & y_N \\ u_N & v_N & 1 & 0 & 0 & 0 & -x_N u_N & -x_N v_N & -x_N \end{bmatrix} * \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \\ h_{33} \end{bmatrix} = 0$$

For robustness of the estimation, a set of 14 matching pairs of points are used which minimizes the error by removing outliers with the implementation the algorithm M-estimator Sample Consensus (MSAC) algorithm (Torr & Zisserman 2000) on Matlab.



Figure 17. Warped example image before (left) and after homography transformation (right). Plaza del Callao, Madrid.

The resulting dataset from the detection algorithm with the embedded geometric transformations and timestamping generate an entry per detected feature in the following format:

file	frame_index	UNIX_time(s)	UNIX_time(ms)	left	right	top	bot	X_img	Y_img	X_3D	Y_3D	class	class_name
callao_20180406_041003	1	1522987803	1522987803333	435	453	567	599	444	599	440124.7627	4474589.255	0	pedestrian
callao_20180406_041003	1	1522987803	1522987803333	433	450	579	610	441	610	440124.8591	4474591.104	0	pedestrian
callao_20180406_041003	1	1522987803	1522987803333	338	401	652	701	369	701	440128.1624	4474603.425	4	truck

Figure 18. Example of the dataset of detections from Computer Vision Algorithm.

Where every row is a detected feature characterized by the following fields: *file*, *frame_index*, *UNIX_time(s)*, *UNIX_time(ms)*, *left*, *right*, *top*, *bot*, *X_img*, *Y_img*, *X_3D*, *Y_3D*, *class*, and *class_name*.

file	Origin recorded file used as source for detection
frame_index	Order of frame in the file video sequence where the detection is located.
UNIX_time(s)	Timestamp of the detection according to UNIX time in seconds in local time of the studied location.
UNIX_time(ms)	Timestamp of the detection according to UNIX time in milliseconds in local time of the studied location.
left	Location of the left edge of the bounding box of the detection in pixels in the coordinates system of the image frame.
right	Location of the right edge of the bounding box of the detection in pixels in the coordinates system of the image frame.
top	Location of the top edge of the bounding box of the detection in pixels in the coordinates system of the image frame.
bot	Location of the bottom edge of the bounding box of the detection in pixels in the coordinates system of the image frame.

<i>X_img</i>	Location of the midpoint in the bottom edge of the bounding box of the detection in pixels in the coordinates system of the image frame.
<i>Y_img</i>	Location of the midpoint in the bottom edge of the bounding box of the detection in pixels in the coordinates system of the image frame ⁸ .
<i>X_3D</i>	Longitude. Location of the detection in the Cartesian projected geographic system generated by the homographic transformation of <i>X_img</i> and <i>Y_img</i> .
<i>Y_3D</i>	Latitude. Location of the detection in the Cartesian projected geographic system generated by the homographic transformation of <i>X_img</i> and <i>Y_img</i> ⁹ .
<i>class</i>	Index of the trained class in the algorithm assigned to the detection.
<i>class_name</i>	Label of the trained class in the algorithm assigned to the detection.

Figure 19. Specifications of the dataset resulting from the Computer Vision algorithm

4.3 Data Aggregation

The different levels of aggregation of the collected and designed databased make their direct integration impossible. However, they can be linked using their information in common: space and time. This is the reason for ensuring an accurate labelling of computer vision-based data for allowing their integration. Among the strategies for linking data from different sources, it is possible to use a logic already used by Finite Element Analysis (FEA)¹⁰ and cellular automata (von Neumann 1966) techniques: splitting the analyzed space into discrete cells which are characterized by the aggregation of data coming from different sources at that location. The cells are an artifact which can integrate these diverse data, with different time scopes and spatial resolution. This dimensional uniformization of the analyzed space,

⁸ *X_img* and *Y_img* are the coordinates in pixels in the image frame coordinates system of the midpoint of the bottom edge of the bounding box. This coordinate is used as reference of the location of the detection on the ground, and it is taken as reference for the homographic transformation to figure out the geolocation of that detection.

⁹ Units may vary depending on the units used for the matching pairs of points utilized for the homography matrix estimation.

¹⁰ Finite Element Analysis (FEA) is the application of Finite Element Method used to mathematically model and numerically solve complex problems by simplifying the targeted design to a system of discrete points connected by the finite elements themselves. They mesh the original model and contain the properties, defining how the model will react (<https://www.plm.automation.siemens.com/global/en/our-story/glossary/finite-element-analysis-fea/13173>)

described by a finite number of cells with a fixed number of variables, enables the implementation of statistical and machine learning methods which requires a highly dimensional control as mathematical techniques.

Immediate outcomes of such analysis would be the identification of relative influence of variables from the environmental context regarding the registered utilization of the space, both spatially (quantitative-like) and programmatically (qualitative-like). This structure of the representational space is a constraint set by the functioning model of the Turing Machine paradigm¹¹. Alternative approaches to the representation model for the aggregation of the data, such as surveying the scanned space based on the gathered locations from the cameras as sample points, which could be populated as aggregation locations for the rest of data variable. It would lead to a slightly different kind of data structure, but always within the limitations of current design in computation.

¹¹ Turing machine refers to a mathematical model of computation that defines an abstract machine which operates on an infinite memory tape according to a table of rules (Turing 1948).

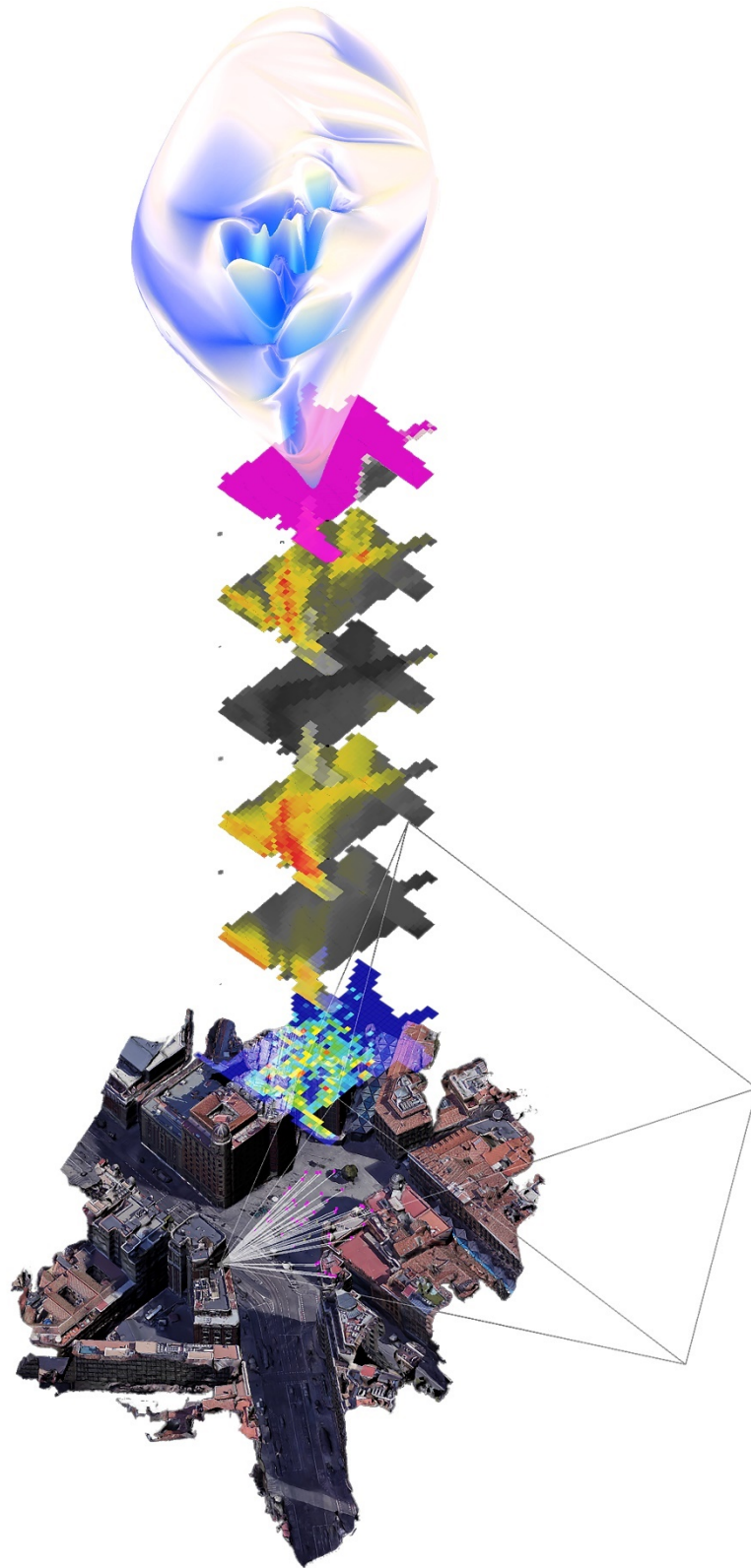


Figure 20. Aggregation of data on analysis discrete cells on plaza de Callao. Only some databases are shown, from top to bottom: Virtual Entropy, Space Syntax (SS) max radial, SS elongation, SS skewness, SS perimeter, SS area, aggregation of detection in discrete cells, and actual detection through Computer Vision algorithms in the 3D model.

4.4 Visualization

This homogeneous, robust and compact description of the urban environment spatial conditions doesn't provide only a consistent representation suitable for advanced computational techniques, but it allows a comprehensive system of visualization of the data. Visualization is fundamental for revealing data, communication, and immediate validation purposes. Two models of visualization are proposed: one for showing the information collected from the computer vision algorithms on the utilization of space as it is one of the novel components of the data collection, and another one for the aggregated data in the finite spatial cells, matching a computationally-friendly data structure and the new system of representation. Typologically, these visualization models belong to already well-known graphical techniques on scatter plot from for the position of detected features by computer vision algorithms running on cameras, and raster-like heat maps and visual polygons for the aggregated data on analysis cells.

Regarding the computer vision algorithm for detecting, it is able to provide a video output with the results of the detection, and it is almost a direct result of image segmentation techniques. Differently, the data visualization for the aggregated data is a consequence of the designed integration method and structure, it is, a jagged spatial matrix of discrete square cells which take different values for each dimension attribute according to the data at that location. Depending on the resolution (the size of the cell) it can offer results closer to a raster map (if the size of the cell is big) or to a heat map (with small cell sizes), although the latter. Finally, this spatial data structure can enable different representations through postprocessing: a more informative heatmap can be generated through cluster analysis, Z axis can be used for increasing the representation space of a 2D raster.

4.5 Analysis Strategy

The presented procedures of data aggregation are not only willing to ensure the compatibility of data for building a coherent database and for visualization purposes. More important is allowing the processing of the plethora of variables encoded in the data for analytical purposes. Statistical methods require a precise homogeneous structure of data and a consistent notation, which undoubtedly is opposed to the conventional mindset assumed in design practice. A systematic, almost algorithmic and mathematical description of the space

and the transformation and transformations planned for it -what we can consider as the core of the architecture practice- is rare, if not inexistent, in the common practice. The proposed transformation of the data precisely shows the intention of being able to perform a systematic analysis of empirical data with the goal of extracting new knowledge from the hidden patterns in the gathered information.

Before performing the analysis tasks, preprocessing of the data is necessary for avoiding bias in the analyses in any workflow, particularly in the newly generated data from detections by computer vision algorithms. The two most important issues detected in this sense are missing data in the temporal sequence due to missing frames, which can be fixed by imputing data from other days in the same time zone; and large differences in the magnitudes of the values of the features, that can be corrected by normalization (Raschka 2014). The detection of the algorithm happens at the scale of fractions of second, by frames, which generates a background noise in the data due to errors of detection in random frames (e.g. in a sequence of 10 frames, the same feature may disappear in some of them due to artifacts in the image because of video compression). This noise can be removed by smoothing the data by performing rolling averages, it means, averaging the number of detections per frame based on a window spanning several frames, seconds or minutes before and after the targeted frame.

Once the quality of data is checked, in general terms, the relations between the different variables presented can be inferred using regression analysis which is the most common technique for finding dependency between parameters. In a higher-level perspective, the possibilities of the analysis can be expanded if machine learning techniques are implemented. The use of more advanced statistical resources enables multi-variate analysis and prediction in more complex settings as it is the case.

The proposed strategy is developed in two directions: the incremental complexity of the statistical or mathematical techniques for figuring out dependencies and correlation between the studied variables and testing two modes of data aggregation supported by the discrete cells representation.

4.5.1 Bivariate Analysis. Temporal flattening of data.

The first mode of data aggregation stacks all the information within a given time range -in most of the experiments explained later, it is 24 hours-, with the information of collected databases summarized and combined at every one of the discrete cells. It allows testing the bivariate correlations between more than 30 variables considered: 17 variables from Space Syntax, 7 classes detected by Computer Vision algorithms, measurement of Visual Entropy, number of hours of sunlight, and the variable number of distances to urban features

Bivariate analysis, one of the simplest statistical methods for checking the empirical relationship between two variables (Babbie 2010) is computed with three different mathematical methods: Pearson's correlation coefficient, Spearman's rank correlation coefficient, and Kendall's tau coefficient.

Pearson correlation is a standard measurement of the strength of linear association between two variables (a and b) defined by the formula:

$$\rho(a,b) = \frac{E(ab)}{\sigma_a \sigma_b}$$

Where $E(a,b)$ denotes the cross-correlation between a and b, and $\sigma_a^2 = E(a^2)$ and $\sigma_b^2 = E(b^2)$. As any of the correlation coefficient used in this research, it has a value between -1 and +1, where -1 is an absolute negative correlation, +1 absolute positive correlation, and 0 means no linear correlation (Pearson 1895).

Spearman's rank correlation between two variables (a and b) is equivalent to the Pearson coefficient between the rank of those variables. It makes Spearman coefficient more appropriate for non-linear relationships and less sensitive to samples with outliers. It is computed, assuming that a and b are random variables, with the formula:

$$r_s = \rho_{rg_a rg_b} = \frac{cov(rg_a, rg_b)}{\sigma_{rg_a} \sigma_{rg_b}}$$

Where rg_a and rg_b are the ranked variables a and b, $\rho_{rg_a rg_b}$ is the Pearson coefficient of those ranks, $cov(rg_a, rg_b)$ denotes the covariance of the rank variables, and $\sigma_{rg_a} \sigma_{rg_b}$ are the standard deviations of these ranks (Spearman 1904).

Kendall's tau coefficient is, as Spearman's correlation, a measure of non-parametric rank correlation between two variables.

$$\tau = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}}$$

Where $n_0 = \frac{n(n-1)}{2}$, and n denotes data size; n_c is the number of concordant pairs of the variables a and b , n_d is the number of discordant pairs, and $n_1 = \sum_j \frac{t_j(t_j-1)}{2}$ (with t_j being the number of values of variable a tied at j th value) and $n_2 = \sum_k \frac{u_k(u_k-1)}{2}$ (with u_k as the number of values of variable b tied at k th value) (Kendall 1938).

In general, Spearman's and Kendall's correlation coefficients are particular cases of a more general correlation coefficient, and both are a correlation measure of monotonicity relationships. However, the latter is preferred because of its higher robustness and efficiency (Croux & Dehon 2010). Although the values computed by the three methods are used for comparison and evaluation of the results, Kendall's tau is preferred because it is more robust, it means less prone to error and less sensitive to small datasets.

All these metrics can be implemented easily in statistical and machine learning programming libraries such as Scikit-learn (Pedregosa et al. 2011) or Pandas (McKinney 2011) for Python.

4.5.2 Spatial clustering based on temporal patterns of utilization

“Understanding our world requires conceptualizing the similarities and differences between the entities that compose it”

(Tryon & Bailey 1970)

The second proposed mode of aggregation for analysis does not stack all the data of a given period of time at each cell but looks at the temporal pattern and pace of occupation along a period of time of the analysis cells for clustering spatially the area of study and identifying the factors causing that behavior and grouping of similar locations. Clustering is an unsupervised machine learning technique whose main objective is descriptive, it is, discovering new groups from data instances based on their similarities. The used clustering method is agglomerative hierarchical, a bottom-up approach which starts with every observation in one cluster and. Then, clusters are successively paired as the process moves up the hierarchy until the desired

groups structure is obtained (Rokach & Maimon 2005). This method results in a dendrogram, a tree diagram which is a representation of the data structure of a nested grouping of instances layered in levels.

In this analysis mode, the focus is on data generated by computer vision algorithms because the main goal is classifying and typifying different areas of the studies are depending on the temporal patterns of utilization. This changing level of detections per cell over time provides a characteristic temporal signature for every location. For simplicity and for highlighting the similarities between cells, data can be binned in larger time spans than the original one referred to frames. As well, this binning can be seen as an additional smoothing, flattening outliers and preserving the high level important temporal features of each cell. Too much detail (and noise) using data with a resolution of fractions of second (it is, frames) can lead to the unfeasibility of grouping cells by their similarity of the temporal patterns of occupation, without underestimating that that noise may not be informationally relevant for classifying the data.

Matching the temporal signatures of the hundreds of analysis cells can be accomplished by applying bivariate statistical analysis in the same way that it is applied in the first analysis strategy. Given the capabilities of the three methods introduced for bivariate correlation (Pearson, Spearman, and Kendall's tau), it seems that Pearson is the only one which won't match the conditions of this analysis as it is constrained to identify linear associations, which is not the case. As a result, every single analysis discreet cell shows a correlation pattern with the rest of analysis cells, which can be used to cluster them by similarity. The method for the merging of clusters is based on a similarity measure created from a matrix of distances (denoted as $d[i, j]$, where i and j are two different clusters) between the observation vector, which are in this case the correlation signatures of each cell. This similarity measure can be computed according to different optimization criterion, which consider the distance between the newly formed cluster u and each v . In this case the implemented method takes the average method, whose distance matrix is obtained from the following formula:

$$d(u, v) = \sum_{ij} \frac{d(u[i], v[j])}{(|u| * |v|)}$$

For all points i and j where $|u|$ and $|v|$ are the cardinalities of clusters u and v , respectively (The Scipy Community 2016). This method is known as well as UPGMA (Unweighted Pair Group Method with Arithmetic Mean) algorithm (Sokal & Michener 1958), although the implementation is performed using the SciPy library for Python (Jones et al. 2014).

The result of the clustering is variable as it is obtained by cutting the dendrogram at a target similarity level. The lower the level in the hierarchy is, the higher the similarity level and a larger number of clusters is produced. The balance between the granularity of the obtained clusters (the number of the resulting groups) and the similarity between them is subject to the interpretation and description of the output.

4.6 Experiments

“It doesn't matter how beautiful your theory is, it doesn't matter how smart you are. If it doesn't agree with experiment, it's wrong.”

Richard P. Feynman

“The shift from an empirical, tradition-bound technics to an experimental model has opened up such new realms as those of nuclear energy, supersonic transportation, cybernetic intelligence, and instantaneous distant communication.”

Lewis Mumford, 1944 (Mumford, 1944, p. 304)

For testing the proposed framework and technology, a series of experiments are designed as proofs of concept with incremental complexity in their development. The complexity and, somehow, the open-ended character of this research, foster the incremental pace of each of those experiments. They share the same framework and understanding of the pipeline, with equivalent data, but, at every single iteration, they expand the exploration of the capabilities of the system and the kind of insights (and flaws) that it can provide.

As case studies, they offer direct feedback on the spatial, environmental, and functional conditions of each of the locations as their local conditions may affect the accuracy and precision levels of the system. These experiments acknowledge the local dependency of these techniques and they explore different approaches towards the same framework. This new method of extracting, analyzing and providing diagnosis and new knowledge for informing urban planning and design aims not to be deterministic, but an open platform able to adapt to different local conditions and to collect a different kind of features.

From a practical point of view, experimenting, at this point, is fundamental for knowing the generalization power of the training used for designing the extraction of data based on Computer Vision techniques. An important part of the predictive power of the whole framework is based on the training of the system. Neural Networks and deep learning techniques are based fundamentally on “learning” (LeCun et al. 2015), and it makes their results very dependent on the data used for training their inner parameters.

The common detection algorithms in their simplest version are pretrained for identifying common objects, animal, and people featured on pictures. However, the point of view used for this urban analysis method is novel for most of the available datasets of images frequently used for neural networks training. These datasets consist mostly of images from the point of view of a person, with an emphasis during the last years for autonomous driving purposes, conditioning the kind of perspectives and targeted features available.

Given the importance of the training for the precision of the data collection, a first experiment will be focused on the tuning of the algorithm capabilities for detecting a set of elements on the urban scenario.

Two locations are studied in different urban, geographical, legal, political, cultural, and social contexts. However, these locations share the pedestrian and walkable, whose implication will be discussed later. The first location is plaza del Callao in the historical center of Madrid, Spain. The second location is the Cut of the campus of Carnegie Mellon University in Pittsburgh, Pennsylvania, US. The differences and similarities between both locations are helpful for contrasting the capabilities and generalization power of the proposed technology and framework and assessing and confirming the consistency of results in different contexts. Additionally, for every location, different analysis scenarios with different occupation and utilization conditions are considered with the purpose.

4.6.1 Location 1: Plaza del Callao, Madrid



Figure 21. Location of plaza del Callao in the city of Madrid (left), old town of Madrid (center), and in Sol neighborhood (right).

Plaza del Callao is a public open space in the 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. Although being located in the old town of the city, its design is relatively recent, and it is connected to the opening of the new Gran Vía at the beginning of the 20th century. This new upscale street was designed for improving the habitational conditions and transit in the medieval and baroque old urban fabric of the city, linking the new urban extensions planned during the end the 19th century west and east of the old town. This situation explains how this urban space is the connector between the old 5-stories building in narrow streets from the 1800s and the newer American-inspired buildings with mixed uses on Gran Vía. After the urban renewal in the late 2010s which pedestrianized the whole area (except for the Northern edge with Gran Vía) which removed the roadways and urban buses stops, it extends the pedestrian commercial axis of Preciados-Carmen coming from Puerta del Sol, one of the most popular shopping areas of the city, and one of the most demanded streets for retail space in Europe. This configuration of the space makes much easier the connection of this shopping area with Gran Vía, which has experienced in the last years an important transformation from an activity centered on theatres, offices, and hotel, to upscale shopping area with new massive flagship stores. Together with this historical and commercial background, plaza del Callao has played an important role as space of protest, particularly after the overcrowding of Puerta del Sol after 11M movement which has forced to authorities and citizens collectives to look for alternatives: in 2015 there were 96 public demonstrations at this location according to the records of the Spanish Government Delegation in Madrid.

Under these circumstances, plaza del Callao matches two main factors which were prioritized for picking up the right location for the experiment: diversity of activities and ease of being covered. This urban location has a low proportion of visual occlusions and a very convex geometry. It is noticeable a rectangular urban square with a gentle slope southbound which does not affect the processing of the image. It allows having nearly the 100% of the surface of the square covered by a single camera. Additionally, it is a pretty convenient setting for being a pedestrianized space featuring a neutral surface finishing for identifying people, vehicles, and other elements over the background. To sum up, it is a relatively clean environment, with not a lot of visual noise, a good diversity of users and city functions where a high level of detection of a pretty large diversity of activities can be collected.

In this location, as the first testing site, two experiments are designed with different goals. The differences on these experiments are the occupation conditions of the square, for checking the basic hypothesis of being able to detect utilization patterns and the accuracy for grasp these changes.

4.6.2 Data from plaza del Callao

The data used for the experiments on plaza del Callao have different sources depending on their nature. Three big sources are utilized for the data depending on the data elaborated: 3D model of the built environment, spherical panoramas from Google Street View, and the video recorded from the camera located watching the square.

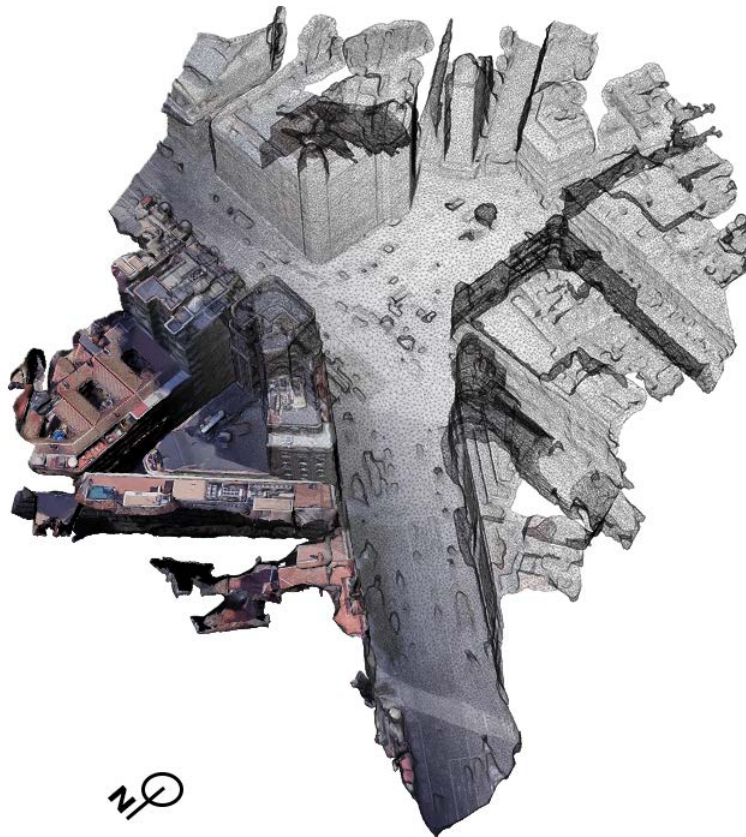


Figure 22. 3D mesh for plaza del Callao.

The 3D model is a mesh with texture of the square and surrounding buildings which is generated from information provided by city maps of the City Council of Madrid and the Community of Madrid (regional government), complemented with Google Maps imagery. For ensuring the interoperability of all the data generated in this model and the dump of external

data, for instance for visualization tasks, the mesh is scaled and georeferenced into the global projected ETRS89 using UTM coordinates for the zone 30N (the corresponding for Spain). This mesh is used for performing the Space Syntax analysis and extract its metrics. Moreover, this virtual environment is suitable for environmental simulations that can generate sunlight information.

Regarding the spherical panoramas used for computing the visual entropy of the environment, a total of 149 of spherical panoramas with a dimension of 6656 x 3328 pixels are scrapped from the databases of Google Street View and Google Photos which are detected within a radius of 500 m of the center of the plaza del Callao.

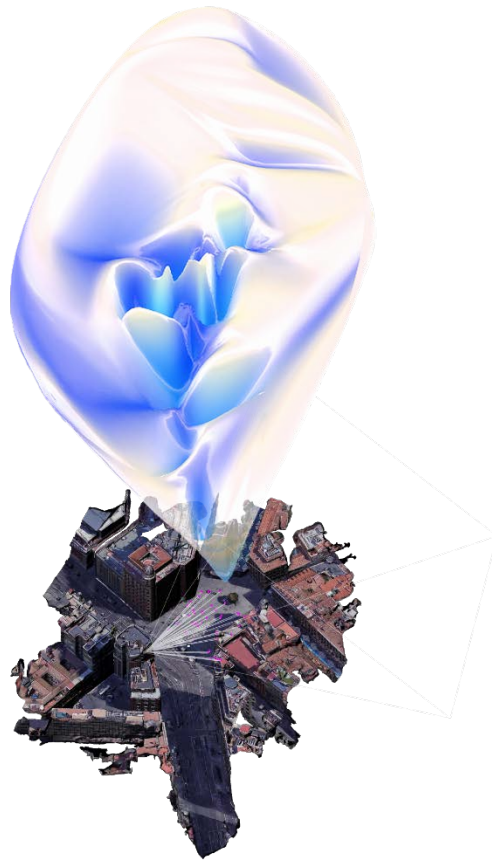


Figure 23. The height of the points of the surface denotes the value of the Visual Entropy.

The other kind of features linked to the static built environment are the points of interest in the area. The selection of these locations around the studied square respond mostly to the traditional urban design expertise and visual and topological references for citizens navigation, and it is inspired by the design of mental maps (Lynch 1960).

<i>Callao Metro Entrance</i>	Subway entrance located in the middle of the square.
<i>Eastern access from Gran Vía</i>	Access on the Northeastern corner of the pedestrian area connecting with the most commercial section of Gran Vía and crossing towards neighborhoods in the North.
<i>Starbucks</i>	The only two food places on the square are located on the Eastern side, Starbucks and Pans&Company.
<i>Access from calle del Carmen</i>	Access on the Southeastern corner of the square, leading to Sol and to the crowded pedestrian shopping area South of Callao. Access to two of the main departmental stores of the city: Fnac and el Corte Inglés
<i>Southern Access from calle Preciados</i>	Access on the Southern edge of the square, leading to Sol and to the crowded pedestrian shopping area South of Callao. Access to Fnac departmental store.
<i>Access from calle del Postigo de San Martín</i>	Access on the Southern edge of the square leading to a pedestrian historical and touristic area of the old town with many restaurants and coffee shops.
<i>Western access from calle Preciados</i>	Access on the Southwestern edge of the square leading to plaza de Santo Domingo. Pedestrian streets with a high concentration of restaurants.
<i>Callao Theatre</i>	The only theatre on the pedestrian area of the square.
<i>Western access from Gran Vía & calle Jacometrzo</i>	Access on the Northwestern corner of the square. It connects with the third section of Gran Vía leading to plaza de España with a high concentration of theatres, and with calle Jacometrzo where most of the urban bus terminals were relocated.
<i>Tree</i>	The only old tree remaining on the square from the preexisting urban design. It is located in the Southern part of the pedestrian area.

Figure 24. Points of Interest (POIs) chosen on plaza del Callao.



Figure 25. Selected Points of Interest (POIs) at Callao Square (Madrid).

Nevertheless, the most complex data collection is the necessary one for the computer vision algorithms. For this purpose, a capturing device located on the 8th floor of Palacio de la Prensa, on the North side of the square across Gran Vía, the only roadway of the square used by vehicles, which is not covered by the camera. Precisely, the camera covers mostly the pedestrianized space as the area where more information is missing.

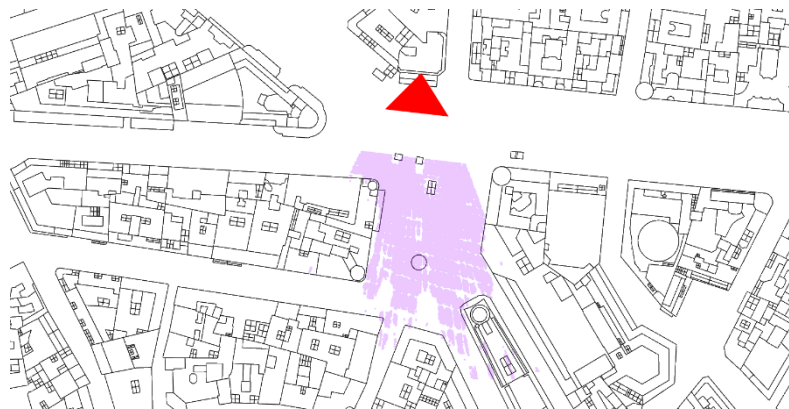


Figure 26. Coverage of detection of the camera on plaza del Callao.

Raw video in mp4 format at 3 fps, and at a resolution of 1280 x 1024 pixel in chunks of 5 minutes was recorded from a live streaming during a period of 12 days from 12:00 pm on April 1st, 2018 through 13:10 pm on April 12th, 2018. This database of videos was processed by the trained computer vision algorithm on 63,000 annotations of 7 classes aforementioned (*pedestrian, police-car, car, van, truck, bicycle, motorcycle*), which yield a valuable information about the quality of the collected data. Before to use the resulting data, it was checked their quality showing an obvious lack of detections in some parts of the observation period due to lack of video. That lack of base data it is likely to be caused by issues in the connection. Some patterns are very consistent as the lack of video captured between 4:00 am and 4:10 am or 4:20 am which seems to be caused by preprogrammed maintenance task in the server or in any of the routers involved in the connection. Anyhow, the lack of information at that time of the day does not seem to be critical as it coincides with the moments of lowest activity during the night. Other gaps in the sequence of data can be alternatively imputed with data from the same time range from days with equivalent conditions such as same weather and same day of the week. This is the preferred method for imputing missing data from the videos dataset. As average, about 1,200,000 detections were collected per day.

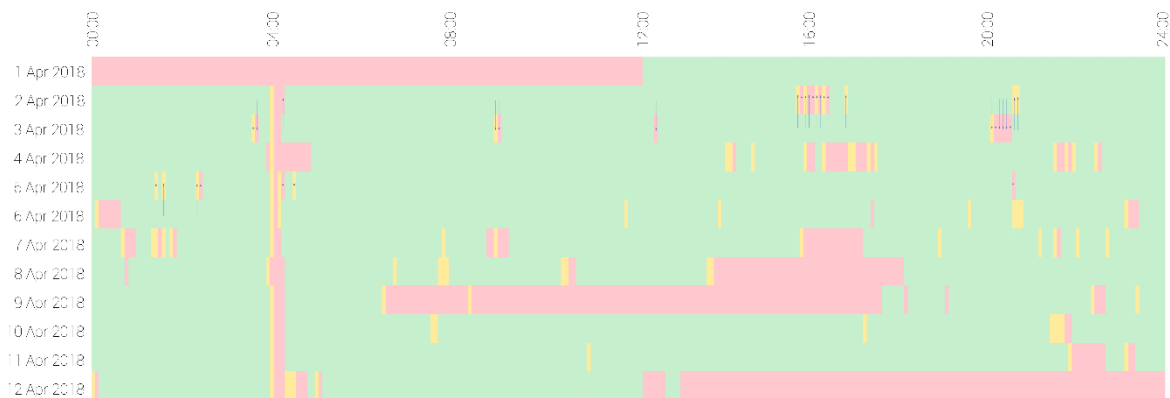


Figure 27. Chronogram with collected data from videos on plaza de Callao from April 1st to April 12th, 2018. Green denotes complete data, yellow denotes wrong data, and red means missing data.

The diversity of the situations of the data of these 12 days of observation, including different weather conditions, occupation patterns, and all the possible days of the week for accounting for the changing pace of activities within a week, provides a rich reference for performing the designed experiments.

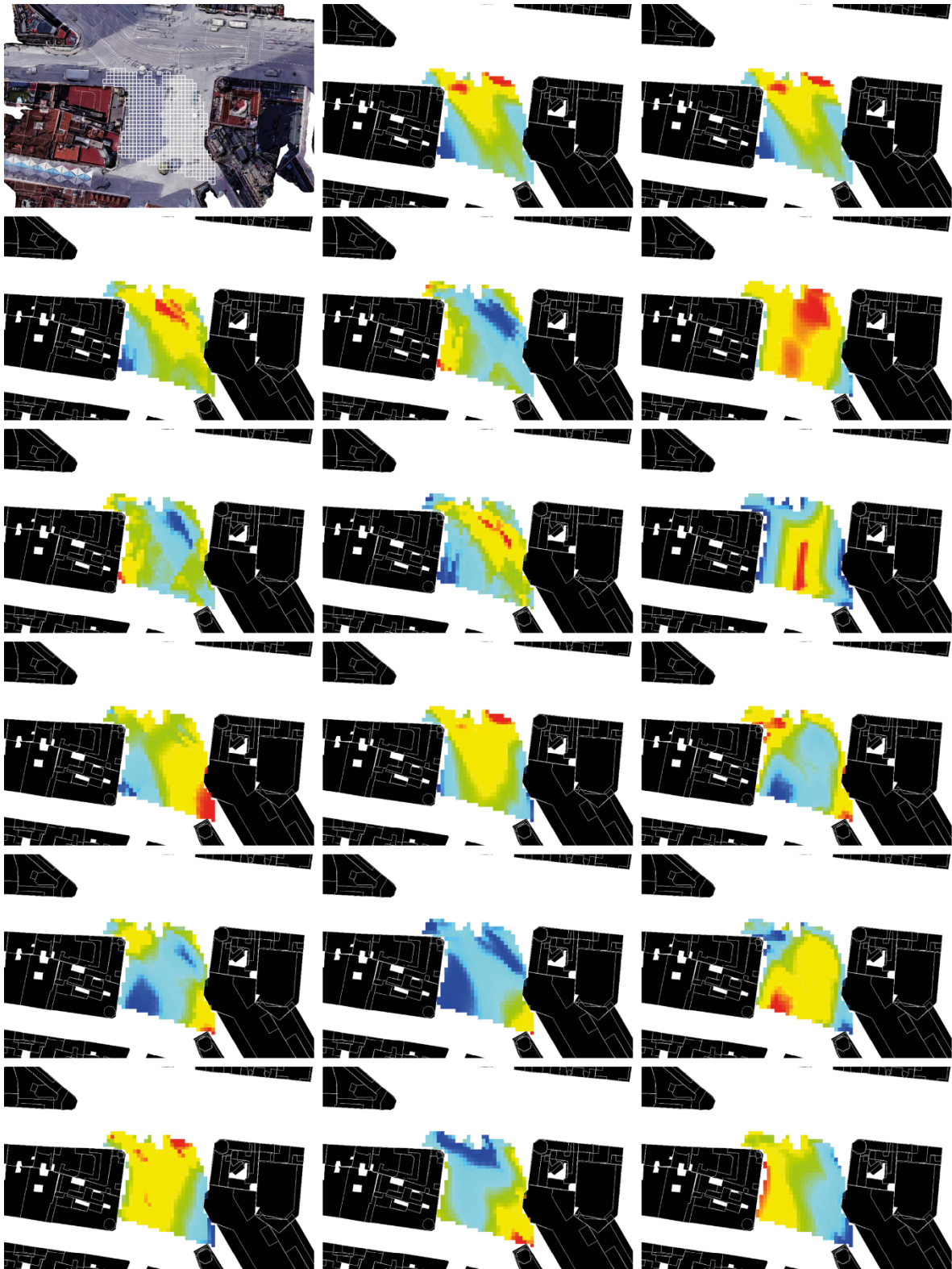


Figure 28. Analysis grid and Space Syntax metrics for plaza del Callao: 557 analysis cells, area, area weighted with distance, perimeter, compactness, circularity, convex deficiency, occlusivity, minimum radial distance, maximum radial distance, mean radial distance, skewness, dispersion, elongation, drift magnitude, and drift angle.

Again, it is important to remind that the spatial features associated to the static and tectonic built environment, such as Space Syntax metrics, Visual Entropy (VE) and Points of Interests (POIs), don't change over time and they are applicable to any given moment and experiment performed in the area. In the given framework, only the data coming from the computer vision detections and the changing environmental conditions such as weather and lighting are subject to change. All this data is aggregated using an analysis grid made of a jagged array of square discreet cells of 2 x 2 m matching the area with good quality detections from the camera (see Figure 26 on the previous page), totalizing 557 cells.

4.6.2.1 Experiment 1: baseline

4.6.2.1.1 Data

The goals of this first experiment with the data collected from plaza del Callao focus on assessing the successful and accurate tracking of selected features in the area supported by computer vision algorithms, consistent aggregation of the data from the different kind of sources and tuning their integration into the proposed framework. The context of this basic test and implementation is a scenario of regular occupation of the square with the simplest patterns of utilization of the space with a minimum level of obstacles and disruptions which can be used as reference situation for measuring changes and different states of activity.

Therefore, the activity and occupation scenario considered for defining a baseline for this experiment is that one without events or venues on the square during a weekday and with sunny weather. Furthermore, for data integrity it is chosen a day with the least information gaps, it means, that requires the minimum data imputation. Given these conditions, the data from the day April 2nd are taken as reference. This day is Monday, with sunny weather, and a maximum temperature of 17°C and a minimum of 5°C (the average for this period of the year is 16°C and 5°C). Regarding the missing or wrong data, only 8 out of 288 clips of video needed to be replaced. For this purpose, data from the following day, Tuesday, April 3rd is imputed as needed.

While data from the static built environment stays the same independently of changing occupation patterns, the accuracy of detections from computer vision algorithms needs to be assessed and evaluated.

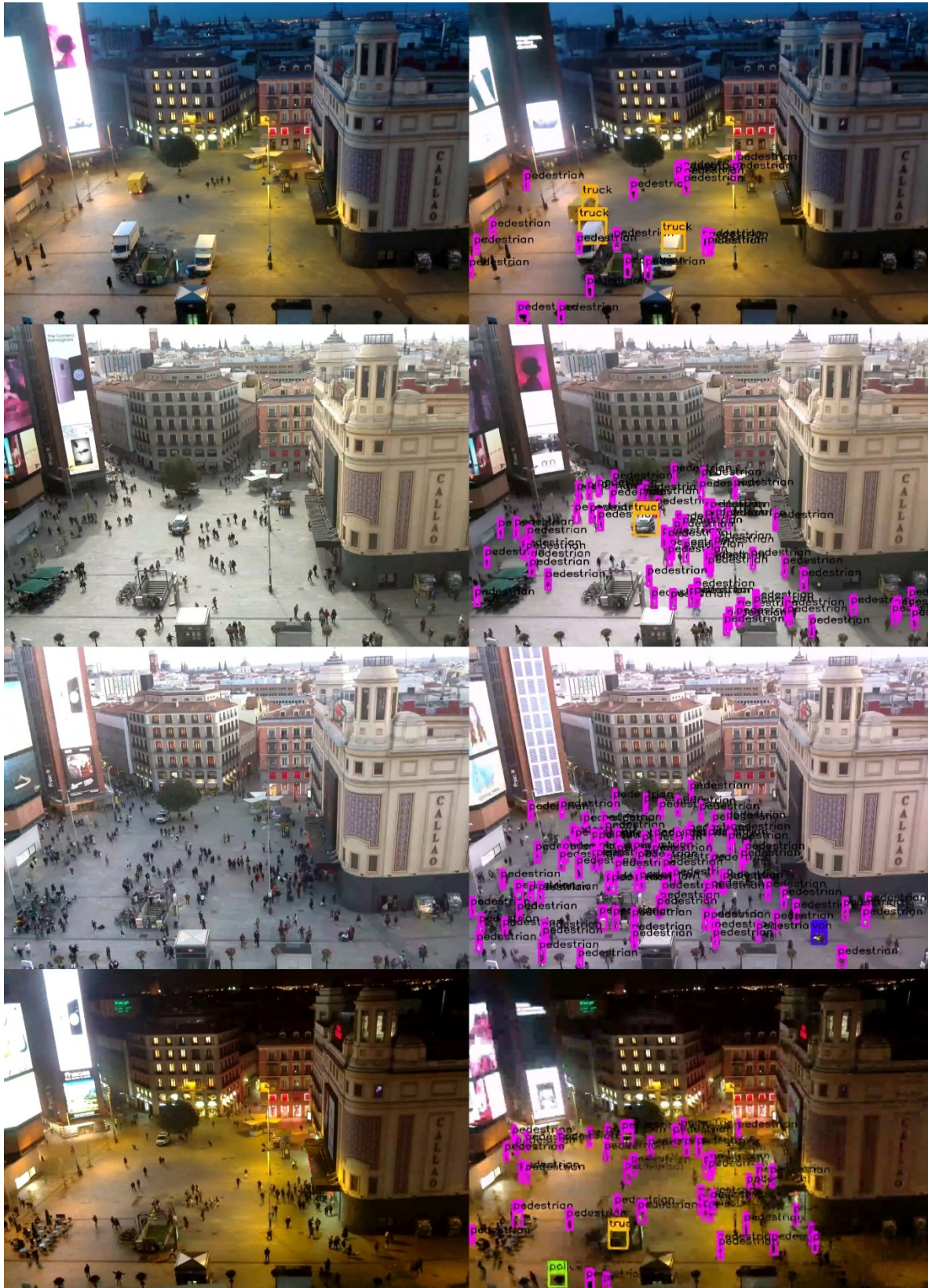


Figure 29. Samples frames from the video on April 2nd, at 7:40 am (with delivery vehicles), 2 pm, 8:25 pm, and 10:00 pm. Raw video (left), detections (right).

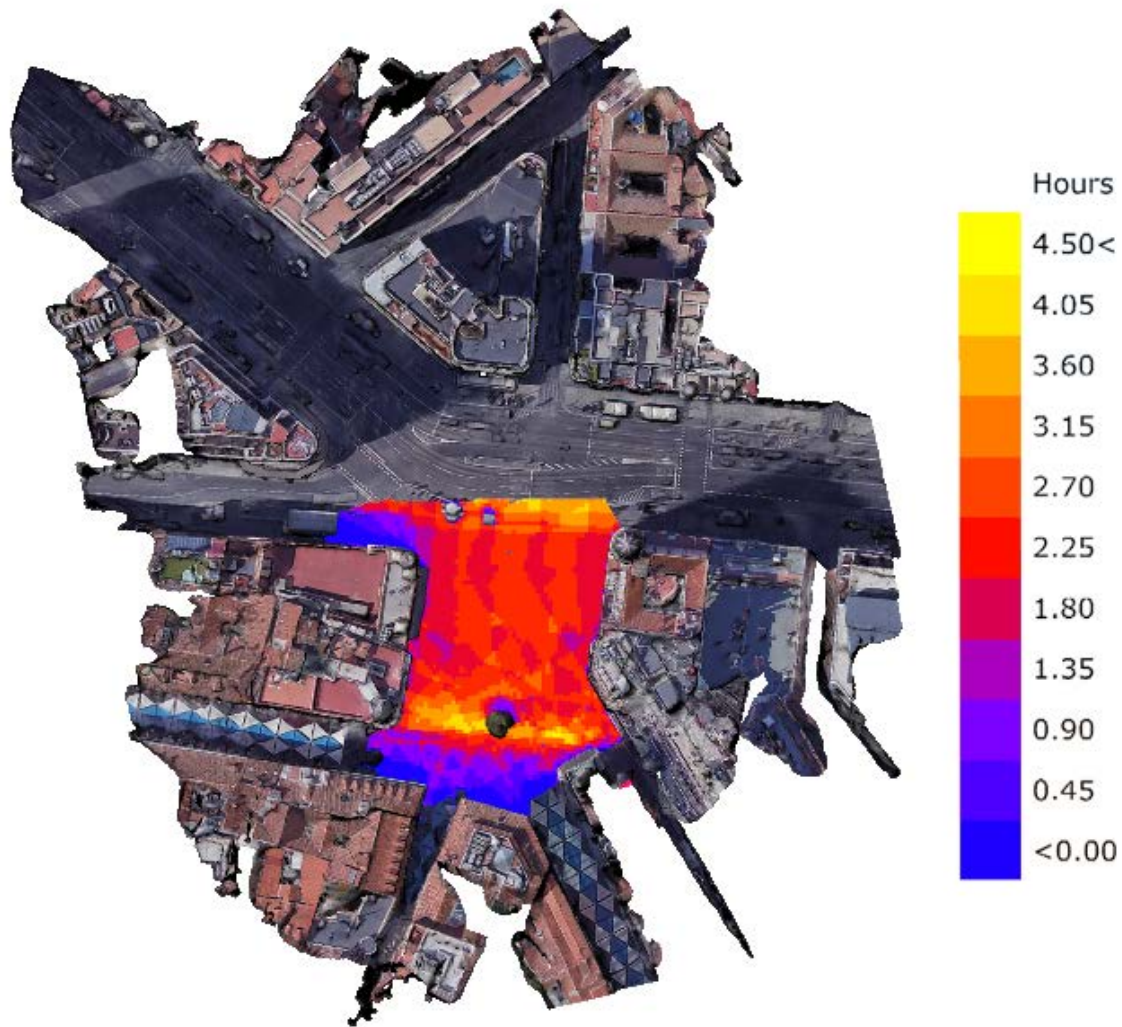


Figure 30. Simulation of sunlight hours on plaza del Callao on April 2nd, 2018.

Additionally, the environmental conditions related to hours of sunlight need to be simulated and computed for the given studied day.

4.6.2.1.2 Evaluation

The plotting of the number of detections on the videos from Monday, April 2nd allows to evaluate quickly their accuracy and assess some basic observations. The total number of detections without making a difference between the identified class (Figure 29) shows a complete picture of the general levels of activity in the studied space. The peaks and valleys of activity seem to match the observed and the expected pace of activity in the urban center of Madrid with two periods of highest activity during midday and during the evening, being the latter slightly higher and related to shopping, leisure, and commercial activities. Both

peaks are separated by a period of less activity, likely to be caused by the lunchtime (in Spain around 2:00 pm), and an extremely low level of detections during the night with a smooth gradient consistent with the expected transition from the late evening and towards the early morning.

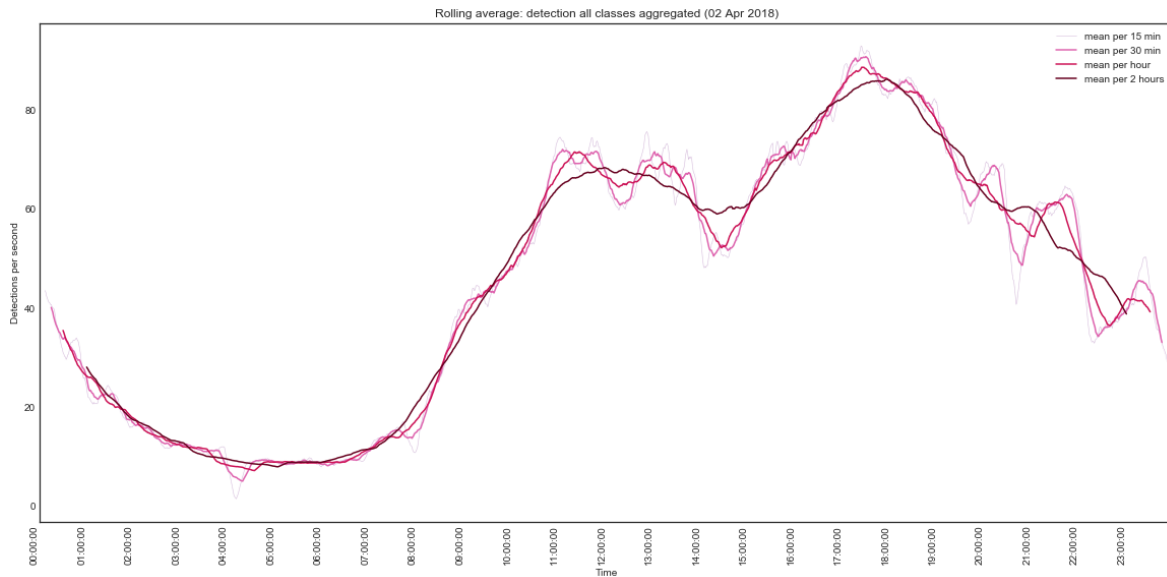


Figure 31. Total number of detections per second with all classes aggregated. April 2nd, 2018. Rolling average with different windows size is applied for data smoothing.

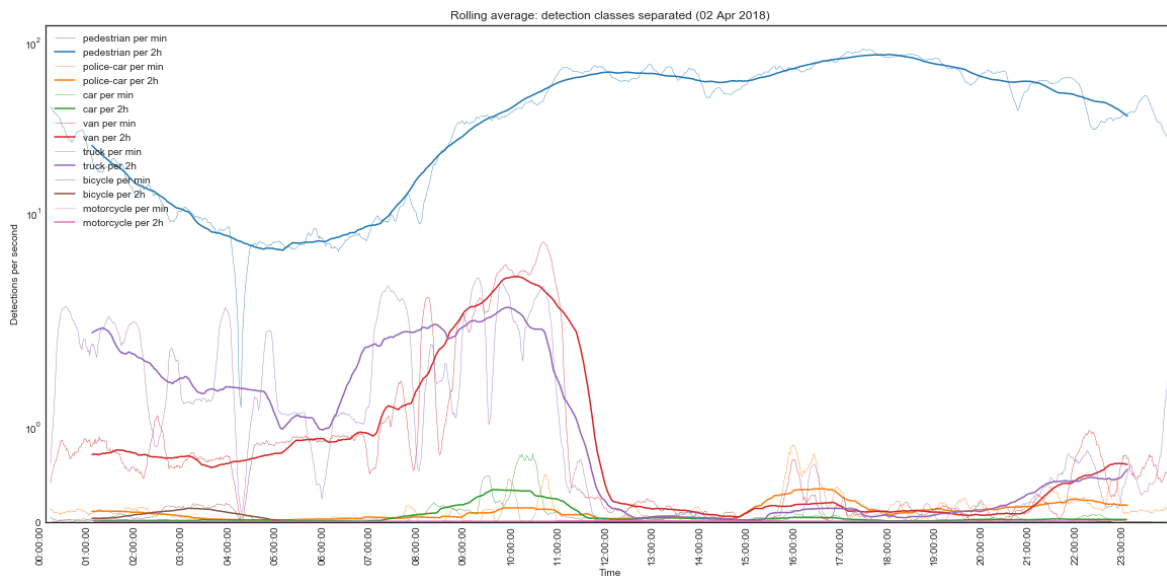


Figure 32. Total number of detections per second with classes separated. April 2nd, 2018. Rolling average with different windows size is applied for data smoothing. Notice the logarithmic vertical axis for comparisons.

When the same detections are separated by class (figure 30), different temporal profiles of these categories are observed during the day. Firstly, it is important to notice that the detection of pedestrians is between 1 or 2 levels of magnitude higher than for any other trained class. Among the targeted classes, two temporal trends can be distinguished. *Pedestrians* tend to concentrate their activity during the hours of daylight, while the other classes show a more intense activity during the night, particularly in the very early morning. It is consistent as well with the expected compatibilization of uses in a pedestrian and commercial area where service and delivery vehicles try to avoid opening hours and the most crowded periods of the day. Another interesting observation comes from focusing on the detection of *police cars*, whose most frequent detection seems to be in the evening, around the same time that the highest number of the pedestrian is detected in the images.

All these observations seem to match the sensitive and direct observation of images and the expertise around the use of the urban space in the central area of a Spanish city regarding the distribution of uses and their timing. Although basic, and other systems of validation of the detection can be implemented for counting precisely the number of right detections of the computer vision algorithms with testing and training sets, the general trends highlighted by the collected detections match the existing knowledge about the urban environment.

4.6.2.1.3 Analysis: bivariate analysis of features

After assessing the detection of the dynamic data from the utilization of the space, it is possible to aggregate all the different databases on the analysis grid made of discrete cells (see figure 25) as a method of dimensional homogenization already explained in the general methodology description. For the detections from the computer vision algorithms, for simplicity

The three presented methods for computing the bivariate correlation (Pearson, Spearman, and Kendall's tau) generates similar results, although Pearson's correlation coefficient is designed only for identifying only linear associations (Figure 31). The values of the correlations and their significances are analogous. The most obvious difference is the tendency of Kendall's tau coefficient to diminish all the coefficients, although there are no big changes.

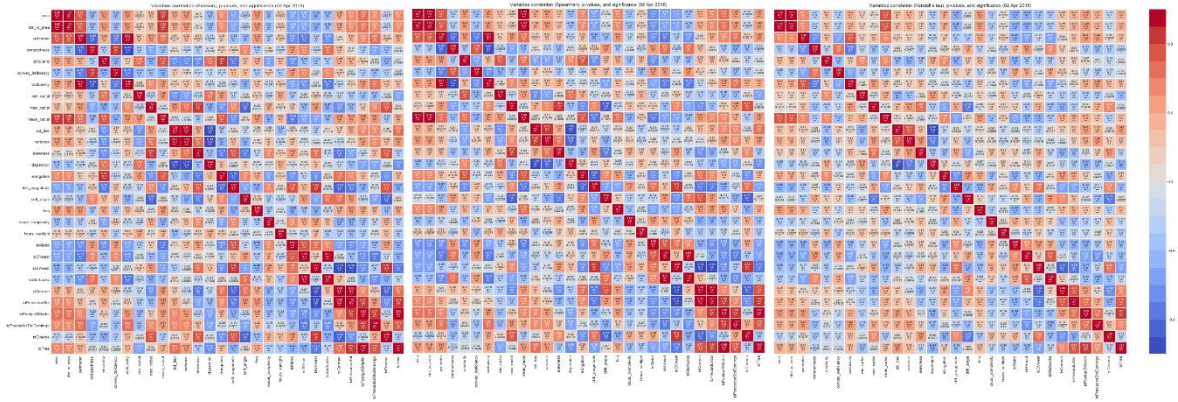


Figure 33. Comparison of the correlation matrix of all the variables with the three presented methods: Pearson's coefficient (left), Spearman's coefficient (center), and Kendall's tau (right). Data collected on plaza del Callao, April 2nd, 2018.

The main hypothesis of the research is finding the associations between the dynamic data from the detections of the computer vision algorithms and the spatial features represented by the plethora characterized the other datasets.

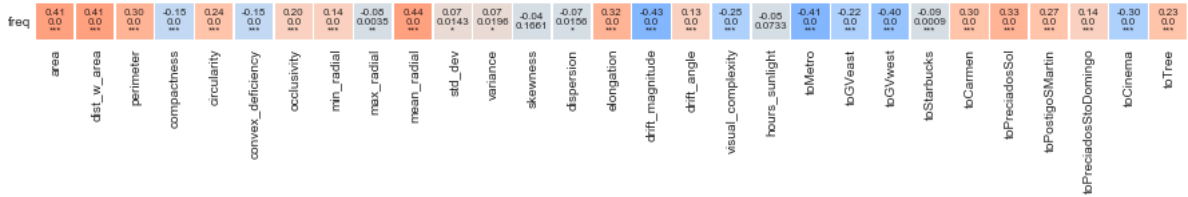


Figure 34. Kendall's tau correlation, p-values and significance between frequencies of activities detection on plaza del Callao and the other metrics considered.

Significance key: (***) : p-value ≤ 0.001 ; (**) : $0.001 < \text{p-value} \leq 0.01$; (*) : $0.01 < \text{p-value} \leq 0.05$; () : p-value > 0.05 , not-significant.

A preliminary verification of the bivariate statistical analysis between these metrics outlines the strongest correlations with the highest significance level between the intensity of the utilization of the space (*freq*) and the Space Syntax metrics of *area*, *mean radial*, and *drift-magnitude*. However, it shows a weak negative correlation with the measurement of Visual Complexity and nearly non-correlation with the hours of sunlight computed on the ground of the square. Regarding the distances to urban landmarks (Points of Interest) located around Callao, the interpretation is more straightforward. The clearer correlations with the utilization patterns in the space are obtained in connection with the subway entrance and the Western access from Gran Vía. In these last two cases, the negative correlation is explained by the way that the Points of Interest metrics is constructed: as a distance between every cell and the targeted location. Therefore, it makes sense that the shortest the distance, the largest the

number of people detected near that feature in the space, such in the case of the subway entrance.

The associations identified with the Space Syntax measurements of *area*, *mean radial*, and *drift-magnitude* seem to point out that people, and other activities, tend to happen in areas with a larger field visibility. It is expressed by the area magnitude (the surface which is visible from the vantage point), and mean radial (the mean of the distance of the visual rays starting from the vantage point). Moreover, the negative correlation resulting from the association between the frequentation (*freq*) and *drift-magnitude* indicates that these locations with good visibility of the space tend as well to be relatively centered within the visible area, as *drift-magnitude* measures the distance from the vantage point to the geometrical center of the area seen from that point, so it is some sort of centrality measurement.

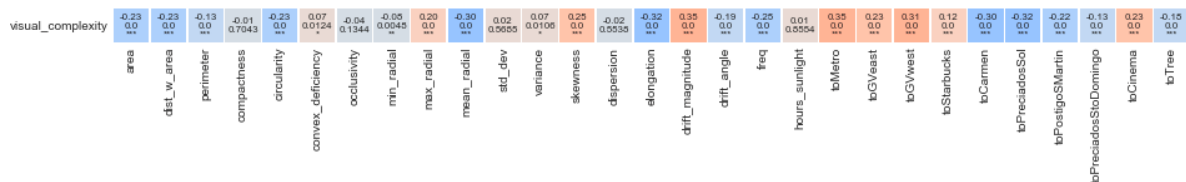


Figure 35. Kendall's tau correlation, p-values and significance between Visual Complexity on plaza del Callao and the other metrics considered.

Significance key: (**): p-value ≤ 0.001 ; (*): $0.001 < \text{p-value} \leq 0.01$; (*): $0.01 < \text{p-value} \leq 0.05$; (): p-value > 0.05 , not-significant.

Although low correlations levels are detected between visual complexity and Space Syntax metrics, some of the points of interest locations bring slightly higher values.

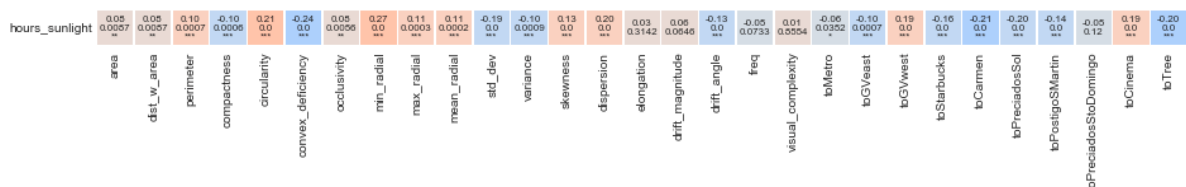


Figure 36. Kendall's tau correlation, p-values and significance between Hours of Sunlight on plaza del Callao and the other metrics considered.

Significance key: (**): p-value ≤ 0.001 ; (*): $0.001 < \text{p-value} \leq 0.01$; (*): $0.01 < \text{p-value} \leq 0.05$; (): p-value > 0.05 , not-significant.

The only relevant associations between the amount of sunlight during the day and the studied metrics are consistent with the geometry of the space. This is the case of the values of *circularity* and *min_radial*, that are two Space Syntax metrics which are referring to open spaces far from buildings and other occlusive obstacles.

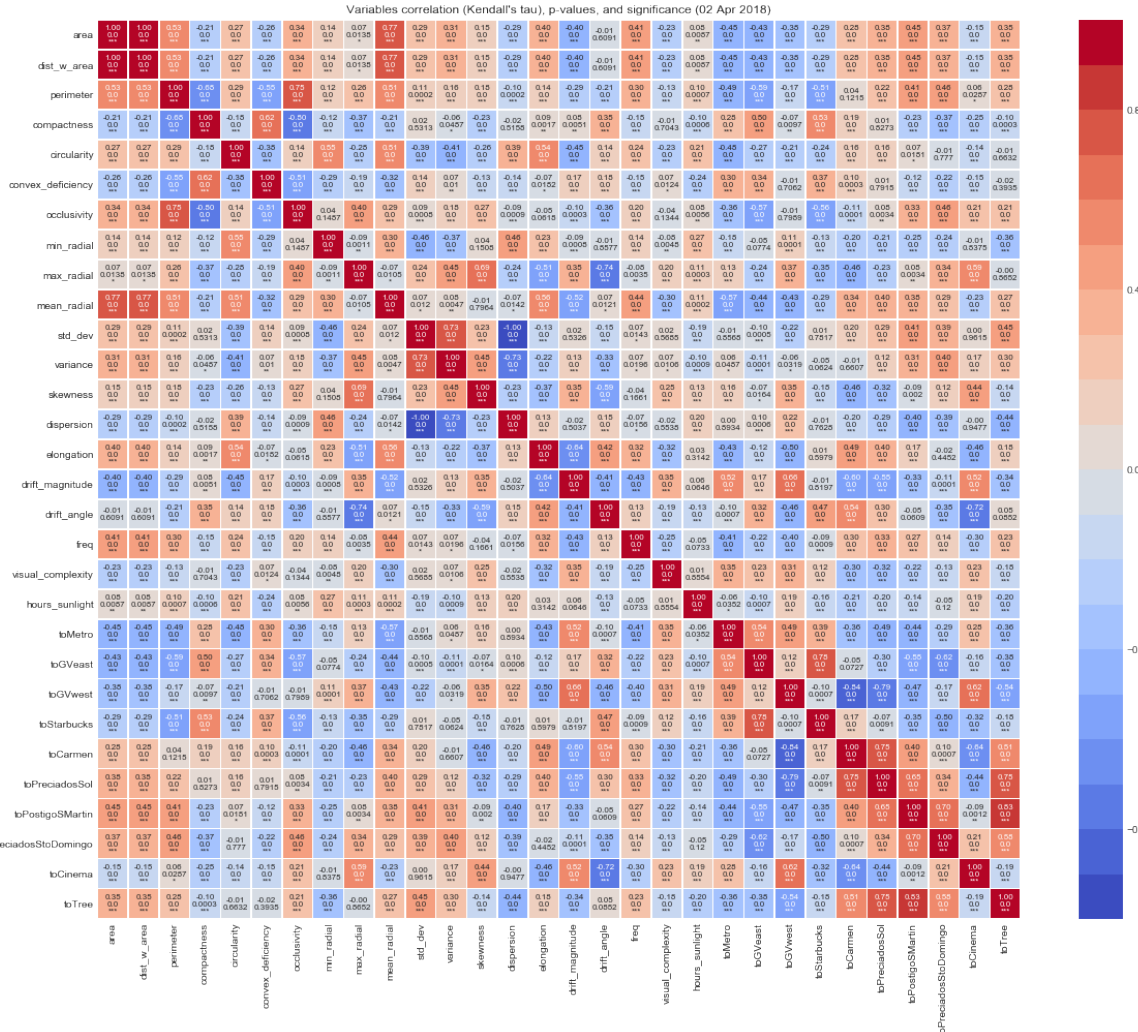


Figure 37. Full correlation matrix for Kendall's tau coefficient, p-values, and significance. Plaza del Callao, Madrid. April 2nd, 2018.

The interpretation of these results needs to be done looking carefully to the spatial and environmental conditions of this urban scenario. This square 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 channelled and compressed through these ways while spreading out across a square which has no remarkable landmarks by itself for making people stop by: it is a paved square mostly designed for venues and without any very welcoming spot. Given these spatial conditions, it would be expected to have a high level of detection precisely in the narrower areas closer to the streets. It should be noticed not only by detections density maps but more interestingly, by the Space Syntax metrics related to the directionality or skewness

of the perceived space from a vantage point enclosed on a street (*circularity, convex deficiency*), generating a strong correlation coefficient.

However, which is unexpected to the traditional treatment planned for this space is the assessment of the preference of people for positions of the square characterized by their centrality and relatively lack of asymmetry or directionality. The definition of these locations doesn't match positions close to the longitudinal and directional space of streets, but the mostly the center of the square.

4.6.2.1.4 Analysis: spatial clustering from matching temporal trends

As explained in the general methodology presentation, there are two modes of data aggregation which explore different aspects of the interactions between the dynamics of space occupation and the spatial features defining that built environment. The first analysis presented above draws associations between pairs of variables from the included datasets through bivariate analysis by stacking in the discrete analysis cells all the data from a day. The second mode of data aggregation focuses on the evolution over time of the detection in these analysis cells for grouping similar cells, it is clustering areas of the analyzed space, with an equivalent temporal pattern of utilization through the implementation of machine learning techniques. For attenuating the noise introduced by the detections of occupations on the square at the scale of fractions of second and smoothing the data, the counts are binned in periods of 15 min (figure 38).

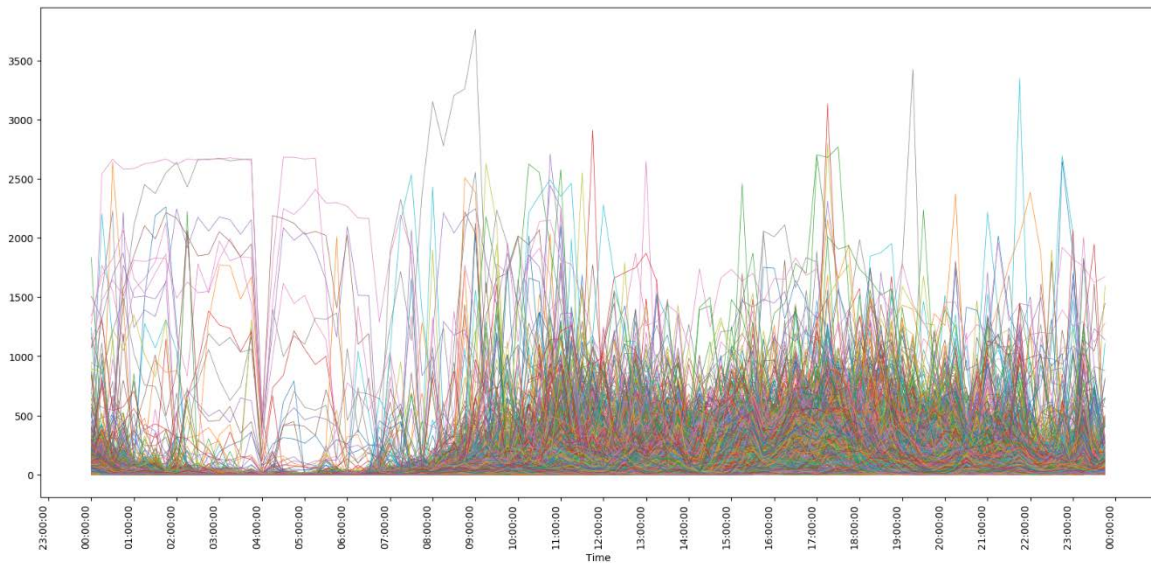


Figure 38. Number of detections of occupation per analysis cell binned in periods of 15 min. Plaza del Callao, April 2nd, 2018. Each line represents the evolution over one day of the detections of one of the 557 cells.

For matching the evolution over time of the set of 557 different occupation signatures, the bivariate analysis is applied to every pair of discrete cells. The time series correlation modeling can be performed statically applying any of the association methods already mentioned: Pearson, Spearman, and Kendall's tau coefficient. Each of these statistical techniques generates different correlation patterns outputs (left column of figure 37), highlighting parallel behavior between different groups of cells. However, from the diagnosis and evaluation point of view, all these results can be equally valid. The correlation results are not determinant, but the results of the grouping based on these associations.

Clustering data even when the rationale for the classification is unknown or when it is necessary to make sense of unstructured data is one of the advantages provided by unsupervised machine learning. The implementation of the bottom-up algorithm for grouping the cells is based on the construction of a hierarchical dendrogram which clusters iteratively the different cells defined by their temporal signature by similarity (see figure 39).

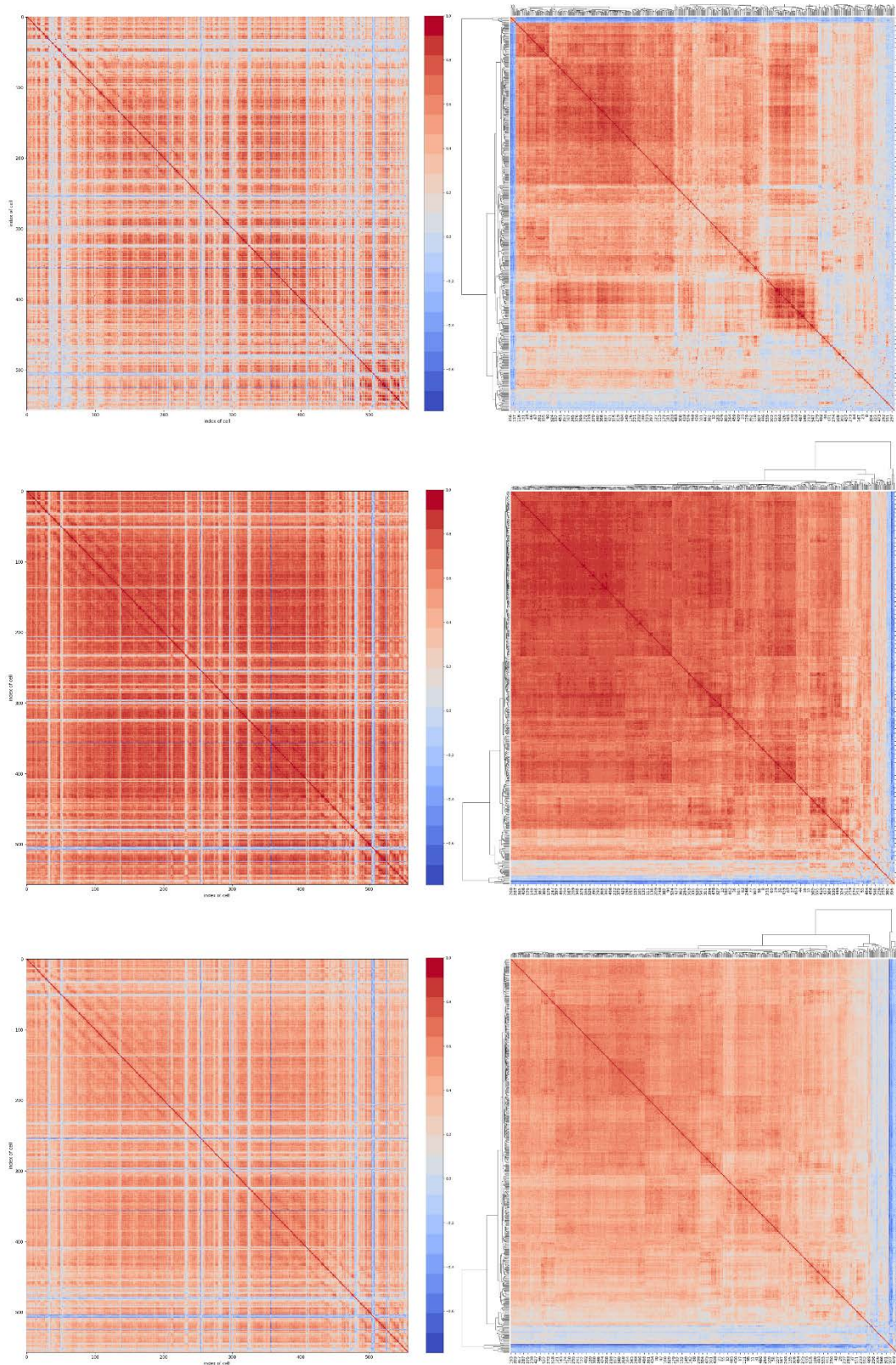


Figure 39. Clustering of the 557 discrete analysis cells based on similarity of their correlations of temporal patterns. Sorted by the index of the cells (non-grouped by similarity) (left). Clustered by similarity of temporal signatures (right). Methods: Pearson (top row), Spearman (Center row), Kendall's tau (bottom row).

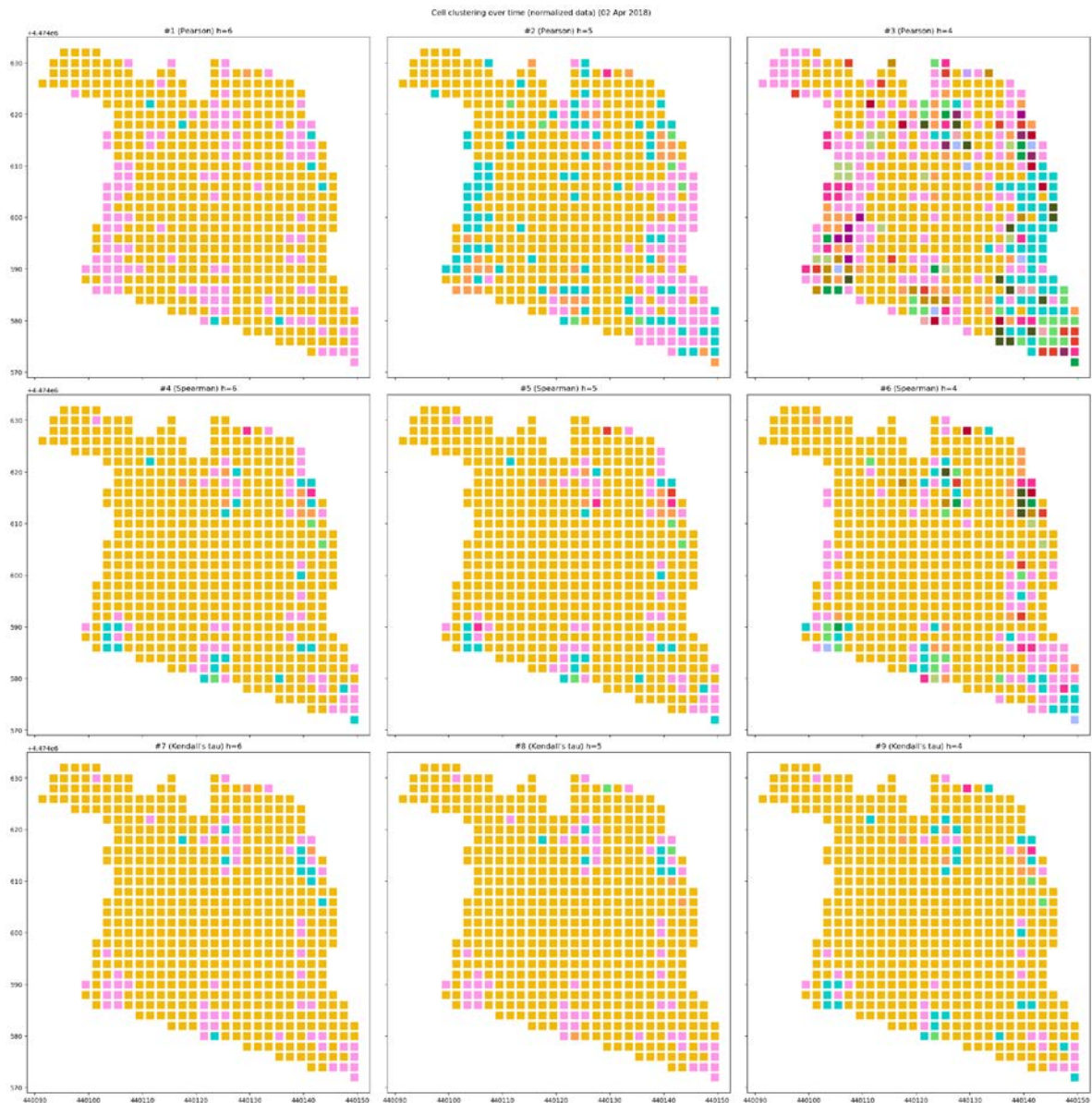


Figure 40. Resulting spatial clustering. Correlation methods are sorted in rows: Pearson (top row), Spearman (center row), and Kendall's tau (bottom row). Levels of hierarchy are grouped in columns: $h = 6$ (left column), $h = 5$ (center column), $h = 4$ (right column). Color code belongs to the identified clusters sorted from bigger to smaller. Plaza del Callao, Madrid. April 2nd, 2018.

The evaluation and interpretation of this clustering of time series are supported fundamentally by the results, the coincidences between the different correlation methods used, and their divergences. The different results obtained (figure 40) shows some consistency in the grouping of some areas independently of the method and level of clustering used. It seems that there is a high level of concordance in the identification of different dynamic behaviors in the areas surrounding the metro entrance, the tree, and the corners closer to calle Preciados and calle del Carmen in the Southeast of the square, to calle

Preciados and calle del Postigo de San Martín in the Southwest, and the Eastern access from Gran Vía at the Northeastern corner of the analyzed area. Moreover, the Eastern and Western edges of the square closer to the building seem to have a distinct pattern as well.

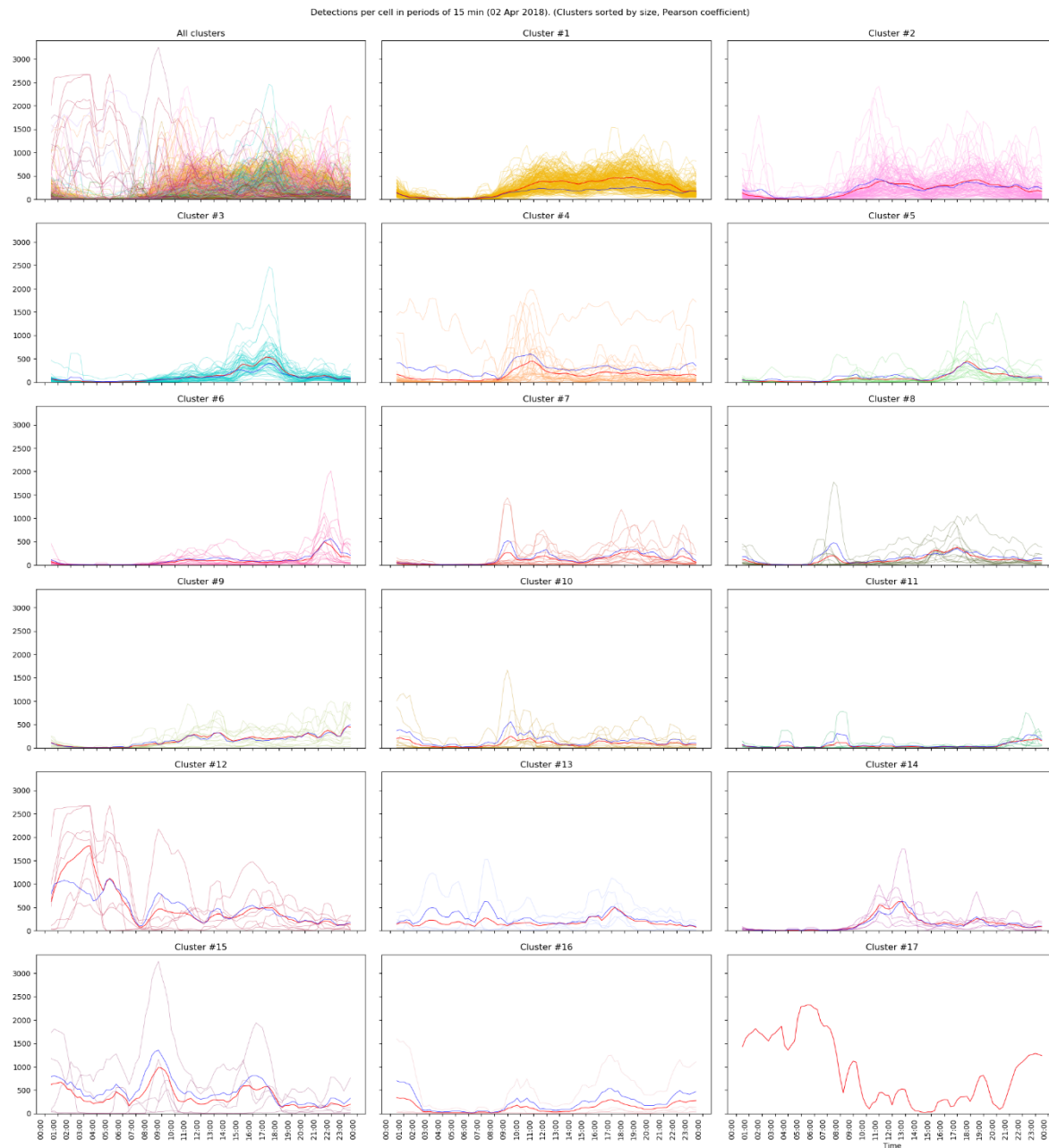


Figure 41. Temporal signatures of the 557 analysis cells grouped by similarity based on Pearson correlation and clustering cut at level 4 ($h = 4$) resulting in 17 different groups. The **red line** shows the **average values** for each cluster, and the **blue line** the **standard deviation**. These results correspond to the cluster #3 (top right in figure 40). Plaza del Callao, Madrid. April 2nd, 2018.



Figure 42. Temporal signatures of the 557 analysis cells grouped by similarity based on Spearman correlation and clustering cut at level 4 ($h = 4$) resulting in 12 different groups. The **red line** shows the **average values** for each cluster, and the **blue line** the **standard deviation**. These results correspond to the cluster #6 (center right in figure 40). Plaza del Callao, Madrid. April 2nd, 2018.

Nevertheless, this diagnosis at this level is far from being novel or insightful, as those highlighted areas could be identified from the traditional urban design expertise, this analysis doesn't seem to provide any special or additional information. But his actual value resides in two novel understanding of the space and its usage. Firstly, it is able to reveal the rationale behind the identification of these areas. It means, beyond just being able to point out that distinct areas of a space close to key points are different, the data generating this analysis can provide a precise temporal and functional definition of their singularity. Secondly, the introduction of precise metrics can unveil the behavior and nature of areas whose dynamics are blurrier or not as clear.

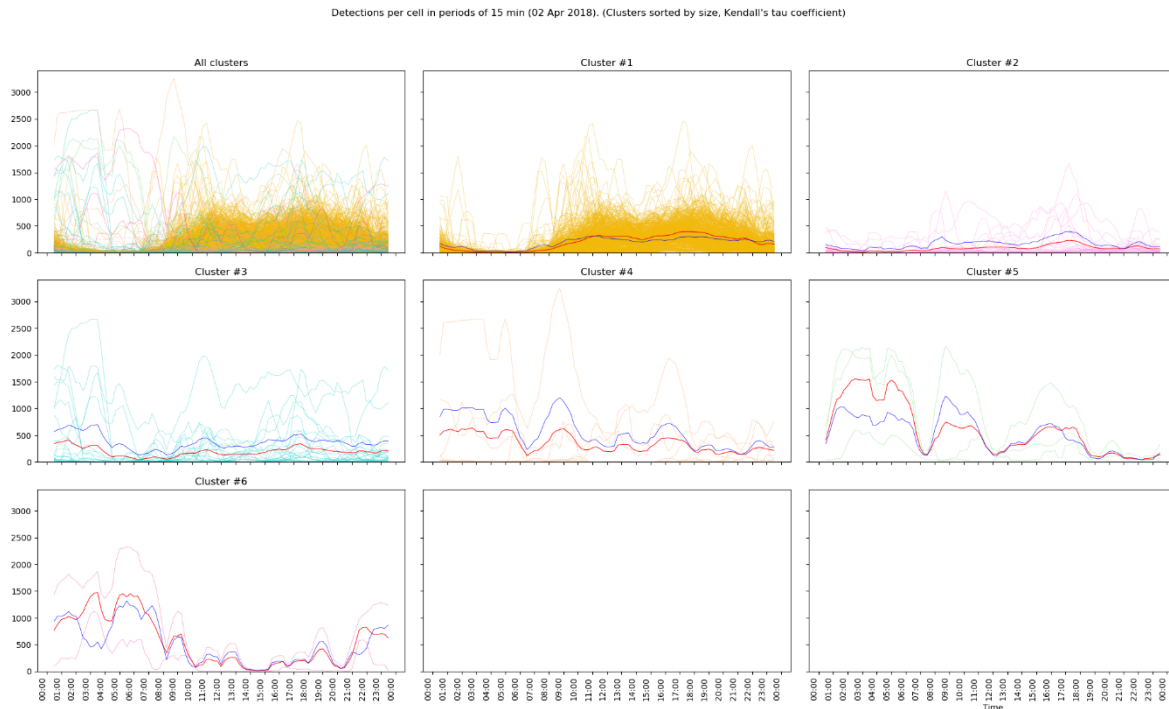


Figure 43. Temporal signatures of the 557 analysis cells grouped by similarity based on Kendall's tau correlation and clustering cut at level 4 ($h = 4$) resulting in 6 different groups. The **red line** shows the **average values** for each cluster, and the **blue line** the **standard deviation**. These results correspond to the cluster #9 (bottom right in figure 40).

Figures 41, 42, and 43 provide the disaggregated lecture of the time series and usage trends for each of the extracted clusters by the three presented correlation methods (Pearson, Spearman and Kendall's tau) and with a relatively low cut in the tree structures ($h = 4$). The utilization of a relatively low cut in the dendrogram is motivated for ensuring the untangling of the blurry or undefined areas of the larger cluster with a not as clear separation between different utilization patterns and scenarios over the day. While the apparent spatial clustering showed some consistency, the resulting clusters temporal descriptions show much lesser level of agreement. Firstly, while Pearson's coefficient generates up to 17 different clusters, Spearman and Kendall's tau correlations generates only 12 and 6 groups respectively. This is a quantitative difference, but as well qualitative as it is informing about the limiting power of Spearman and Kendall's tau coefficients for unravelling the blurry or gray areas of the square, as they are not able to scale the number of detected clusters in between too big and generic ones and just identifying too many when using even a lower cut. For the intended goal of separating different areas based on their temporal utilization patterns, it is as counterproductive to have too many clusters (too much granularity) as having too few of

them. The interpretation of this analysis that follow, will review at the same time the time series of the identified clusters (figures 41, 42, and 43) and their spatial distribution (fig. 40).

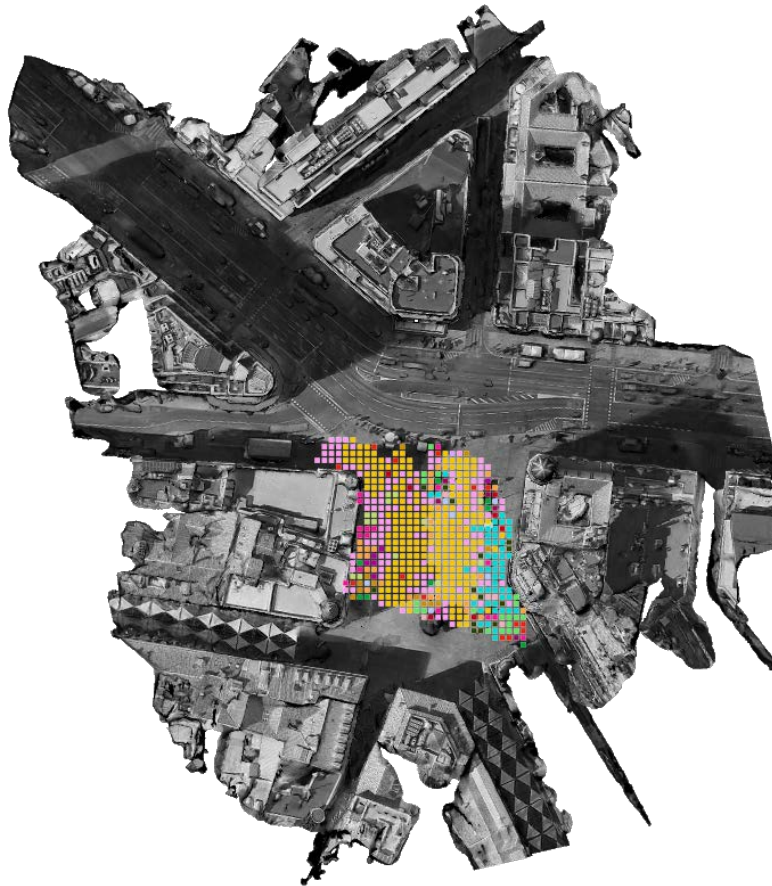


Figure 44. Spatial clustering of analysis cells on plaza del Callao generated by Pearson correlation similarity cut at level 4 ($h = 4$).

Even in the case of the largest group of cells (cluster #1, in warm yellow), there is not any strong agreement in the common temporal pattern. The spatial pattern of these cells tends to occupy the central part of the square, but the time series associated to them show a slightly different behavior. In general, the behavior of this largest group of cells matches the general trend of activities in the studies area, it means, lowest activity during the night, with two peaks of usage around midday and in the evening. Therefore, it can be said that these locations match the type. However, there are important differences as it can be seen by comparing the larger cluster on figures 41, 42 and 43. While the rank-based methods (Spearman and Kendall's tau, figures 42 and 43) include in this larger group a much diverse kind of temporal patterns, with obvious outliers and expressed on higher values of standard deviation, Pearson's correlation coefficient (figure 41) is able to keep a pretty narrow set of

cells in this group that matches the type expected behavior of plaza del Callao without including lots of outliers. Consequently, the following interpretation of results will focus more on Pearson's outcomes because its deeper level of detail and information that seems able to provide, although some connection to the other methods will be drawn sometimes.

Nevertheless, the spatial interpretation of this largest cluster in the case of Pearson's method locates this type behavior in the central areas of the square without obstacles, landmarks, buildings, or points of interest nearby. It is a similar outcome to the other methods, but with a more restrictive area, it is, a fewer number of cells matching that condition.

The following clusters start to include lesser and lesser number of cells. Therefore, they are showing really particular circumstances whose generalization power is limited. The number of cells included in these groups is much smaller, and except for those cases where a coherent spatial clustering is observed, isolated cells can be explained just by statistical reasons or as transitional locations, and they don't need to be assumed directly as locations with special features.

More importantly, the additional clusters that Pearson's coefficient is able to generate with specific trends ignored by the other methods are even more interesting. Cluster #2 (figure 41) isolates a group of cells that are included in the largest cluster of the rank-based methods. The trends of this Pearson's cluster #2 matches to some extent with the already general pace of the utilization of the space already identified in cluster #1. But more importantly, it highlights a group of locations that, while following the aforementioned pace, have a much more unstable level of activity. Differently than in the general trends of cluster #1, the cells in this group have prominent peaks of activity during the day and even in the late evening which is not detected in other groups. The spatial lecture of this group is more complex because of the large level of granularity of the clusters. However, it seems to be associated with the transition areas between the central locations of the square matching the typical behavior and the edges and zones closer to points of interest.



Figure 45. Spatial distributions of the 557 analysis cells grouped by similarity based on Pearson correlation and clustering cut at level 4 ($h = 4$) resulting in 17 different groups. These results correspond to the cluster #3 (top right in figure 40). Their correspondent temporal signatures are in figure 41. Plaza del Callao, April 2nd, 2018.

The review of other clusters generated by Pearson's method yields distinct temporal patterns different than the typical trend. Cluster #3 reveals locations with a higher level of detected

activity in the late afternoon, it is, only matches the second peak of activity of the typical trend identified in the studied area. Spatially this cluster is well defined, in the Eastern edge of the square. Considering that the shopping areas surrounding plaza del Callao are on the Eastern section of Gran Vía and along calle del Carmen and calle Preciados heading Puerta del Sol, it seems consistent that precisely the Eastern part of the square shows a higher level of activity.

Cluster #4 behaves almost as the complementary counterpart of cluster #3 regarding the two main activity peaks detected on Callao: it identifies these locations only displaying a more intense activity detected coincident with the typical later morning and noon peak, but not in the evening. The location of the cells belonging to this cluster mostly in the Southwest and slightly in the Northern corner seem to associate this pattern of utilization of the space centered in the morning with the areas with a highest concentration of food-and-drinks related businesses (restaurants and cafeterias in calle Preciados heading plaza de Santo Domingo and calle del Postigo de San Martín in the Southeastern corner of the square, and Starbucks and Pans&Company in the Northwestern side). However, cells within this group are as well located close to the Metro entrance and to the tree in the middle of the square.

Cluster #5 tends to focus on detecting the locations with peaks of activity in the late evening (from 6:00 pm to 9:00 pm), after the typical evening peak. This is the first real outlier trend extracted from the typical utilization pattern displayed by the general aggregated data. Their location looks pretty concentrated in the Southeastern corner of the analyzed area, it means, close to the streets heading to Puerta del Sol, and as well in the Southern edge of the analyzed area by the tree, and in some spots around the Metro entrance. This spatial distribution can be associated with the fading commercial activity of the shopping area between Callao and Puerta del Sol.

Cluster #6 isolates the cells whose activity is higher later in the evening (around 10:00 pm), it means, whose peak of detections is after the highest activity identified by cluster #5. This cluster is mainly located in the Western edge of the surveyed area, just in front of the theatre. Precisely, this temporal-spatial association is key for the interpretation of this cluster, as the schedule matches leisure times in the evening.

Clusters #7 and #8 are both a combination of early morning peaks and long tails of activity through the evening. The difference between both groups lies in the width of the distribution

during the evening, sparser in the cluster #7 with a stronger continuity between morning and afternoon activity. The distribution of the locations included in this last cluster is concentrated in the Southeastern third of the analyzed area. The association between both clusters is reinforced because of the largest concentration of cells belonging to cluster #8 on the Southeastern corner.

Cluster #9 reflects a uniform level of activity during daytime located to some spots around the tree in the South side of the analyzed area and the Southernmost edge close to calle del Postigo de San Martín and calle Preciados.

Meanwhile, cluster #10 highlights spots whose activity is concentrated before and after the night pause, which in Spain's social schedules can span in between 1:00 am and 8:00 am approximately. The locations of these cells are as well the Southern border of the surveyed area like in cluster #9, but as well some locations in the Northern edge by Gran Vía. The interpretation of these particular locations is more complex, as it can be associated to delivery and maintenance activities of the pedestrian areas which try to avoid the most crowded times, or they are just transition zones in between different areas. However, they are so sparse which is complicated to argue that it is due to special features and not just result of statistical artifacts.

Cluster #11 and #12 shows very sparse spatial distributions which hinder their interpretation as it is likely to be caused by transitional effect between different zones or just statistical artifacts. Cluster #11 isolates locations where activity is detected in very particular moments of the day and not at any other time. These moments are early in the morning (8:00 am), around midnight. The interpretation of cluster #12 is more interesting because of their temporal trends. It is the only group of cells whose more important activity is concentrated during the night, although it is a minority of the cells it reveals a particular temporal pattern. It could be associated to delivery vehicles and some of the outlined locations in this group match that usage pattern, although a consistent location over time should provide a bigger cluster than just a set of isolated cells. This is however expectable with the fix location that these delivery and service vehicles tend to occupy on the square.

Cells of clusters #13, #15, #16, and #17 are extremely sparse and their temporal patterns are not particularly distinct. However, cluster #14 shows a more concentrated spatial distribution

located on the western third of the square. Its temporal trend outlines most of the activity around noon. That area is close to the lottery and tourist information kiosks, so it can be linked to the activity of these facilities.

An interesting test of contrast for understanding the capabilities of clustering techniques is comparing the results with the same grouping but with a different cut point. Clustering outcome as mentioned is in fact generated by cutting the dendrogram at a given depth of the hierarchy. The extensive analysis developed above uses a cut at depth 4 in the dendrogram. The interpretation of the same grouping tree with a cut at the 5th level of depth is slightly different (time series of this clustering is in figure 46, and spatial clustering in figure 47).

Cluster #1 grouped most of the cells capturing the typical behavior captured all over the square. Its spatial distribution mostly corresponds to the central spaces of the square, far from the edges, buildings, obstacles and other key points (figure 47).

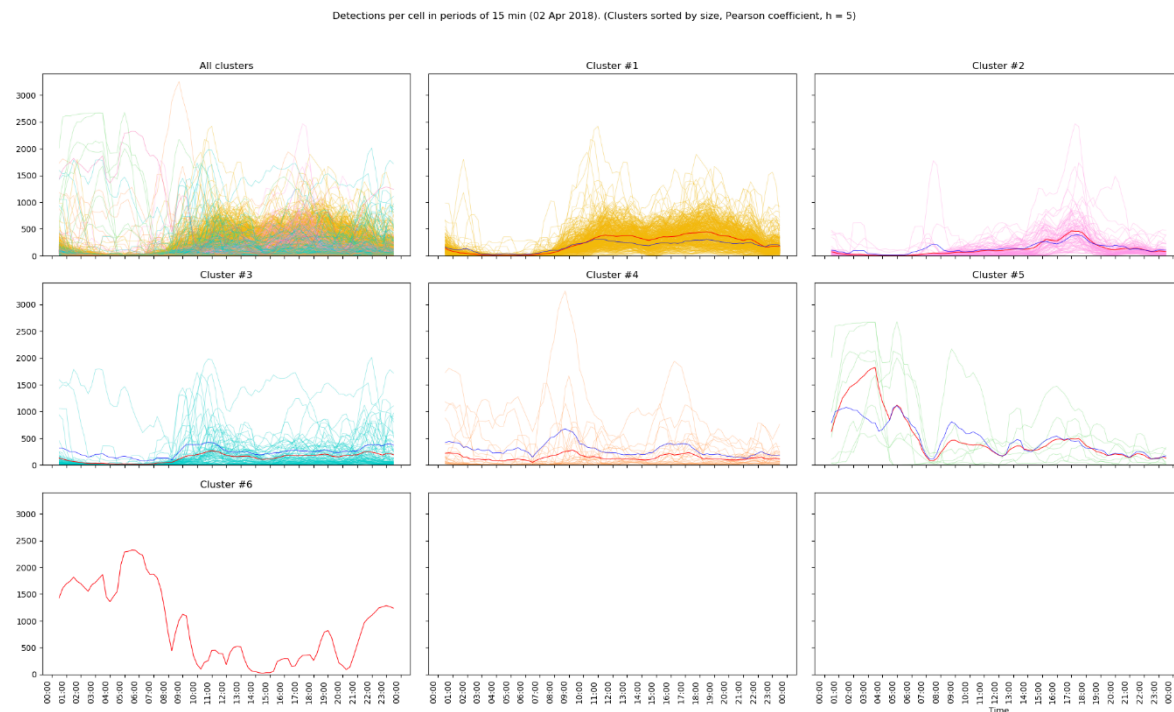


Figure 46. Temporal signatures of the 557 analysis cells grouped by similarity based on Pearson correlation and clustering cut at level 5 ($h = 5$) resulting in 6 different groups. The red line shows the average values for each cluster, and the blue line the standard deviation. These results correspond to the cluster #2 (top center in figure 40).



Figure 47. Spatial distributions of the 557 analysis cells grouped by similarity based on Pearson correlation and clustering cut at level 5 ($h = 5$) resulting in 6 different groups. These results correspond to the cluster #2 (top center in figure 40). Their corresponding temporal signatures are in figure 46.

Differently, cluster #2 isolates these locations with a more intense activity detected during the early evening. Except for some cells within this trend detected around the Metro entrance and around the lonely tree in the middle of the square, these cells are located in the Southwest of the square, for sure associated with the shopping and commercial activities of calle Preciados, calle del Carmen, and Gran Vía.

Comparing these different clustering yields some connection between the different resolutions offered by cutting at different depths. The cluster #2 of this last grouping is a more general version and it is connected hierarchically to the cluster #3 of the grouping generated at depth 4 ($h = 4$).

Cluster #3 temporal pattern displays a uniform level of activity during daytime with smooth peaks in the morning and in the late evening. The cells of this group are sparser, although with a tendency to cluster around the Westernmost edge of the square and at the Northeastern corner. These locations are precisely the ones associated with food-and-drink businesses and leisure locations, which matches the outlined schedule.

However, understanding the cluster #4 is much more complicated, as it refers to cells with a quite uniform level of detection through the whole day and discreet peaks in the morning and in the late afternoon as in the typical behavior extracted from the whole square. Sparseness

of cells and low number of them hinder and bias the interpretation, although the weak spatial clustering around the Metro entrance, the tree, and the Southwest and Northeast corners seems solid. It can be identified with just locations with a not exclusively daytime activity.

Cluster #5 with a depth of 5 in the dendrogram is in fact the already mentioned cluster #12 of the grouping generated at depth 4. This is a confirmation of the independent behavior of these locations, with a high level of activity during the night. This cluster is so different that it doesn't merge with other ones even if moving up in the dendrogram.

Finally, cluster #6 is the as well preexisting cluster #17 in the dendrogram cut at level 4. Due to the uniqueness and isolation of that particular location by the Metro entrance, and its resistance to be merged in the dendrogram can be used for at least highlight this location with a distinct overnight activity which can't be either explained by the regular Metro operation.

In general, the overview of the zoning motivated by temporal trends generated by computer vision detections on Callao seems consistent with the usage and features of the space. It provides however, a much more precise diagnosis about how the space is used. Extreme generalizations are not doable with the limited amount of data used, from the temporal point of view (it is only one day), and spatial (only information from one location is extracted). But, from the evaluation point of view it supports the application of these techniques for orient and support decision making in the public realm.

The different levels of resolution offered by the cuts of the hierarchical clustering dendrogram, as the comparison performed between the grouping generated by cutting the tree at level 4 and at level 5, are at the same time informative and an evaluation and assessment process. The hierarchical meaning of the clustering method used, groups by similarity the different clusters, which can be used as generalization process for avoiding excess of granularity on the groups separation. As well, it is not assumed that the same level of dendrogram can be as clear for explaining different processes. Actually, the grouping generated with a depth of 5 looks more straightforward for explaining the zoning of the space, although there is a loss of information and detail in the description of the space.

4.6.2.2 Experiment 2: occupation of the center of the square



Figure 48. Samples frames from video on April 5th with occupation of the center of the square, at 10 am, 2 pm, 6 pm, and 10 pm. Raw video (left), detections (right).

The presented experiments lack at some point the possibility of performing supervised and designed changes, it means controlled experiments, for assessing accurately the interaction between a small set of precise and intended changes and their effects in modifying the included metrics.

Although these precisely controlled experiments are not possible, the utilization of a public square which is frequently holding venues and events enables the opportunity of measuring the changes on the utilization patterns of that built environment given the different spatial occupations and interventions associated to these events. It can be viewed as an opportunistic use of others' designs for the purpose of this research.

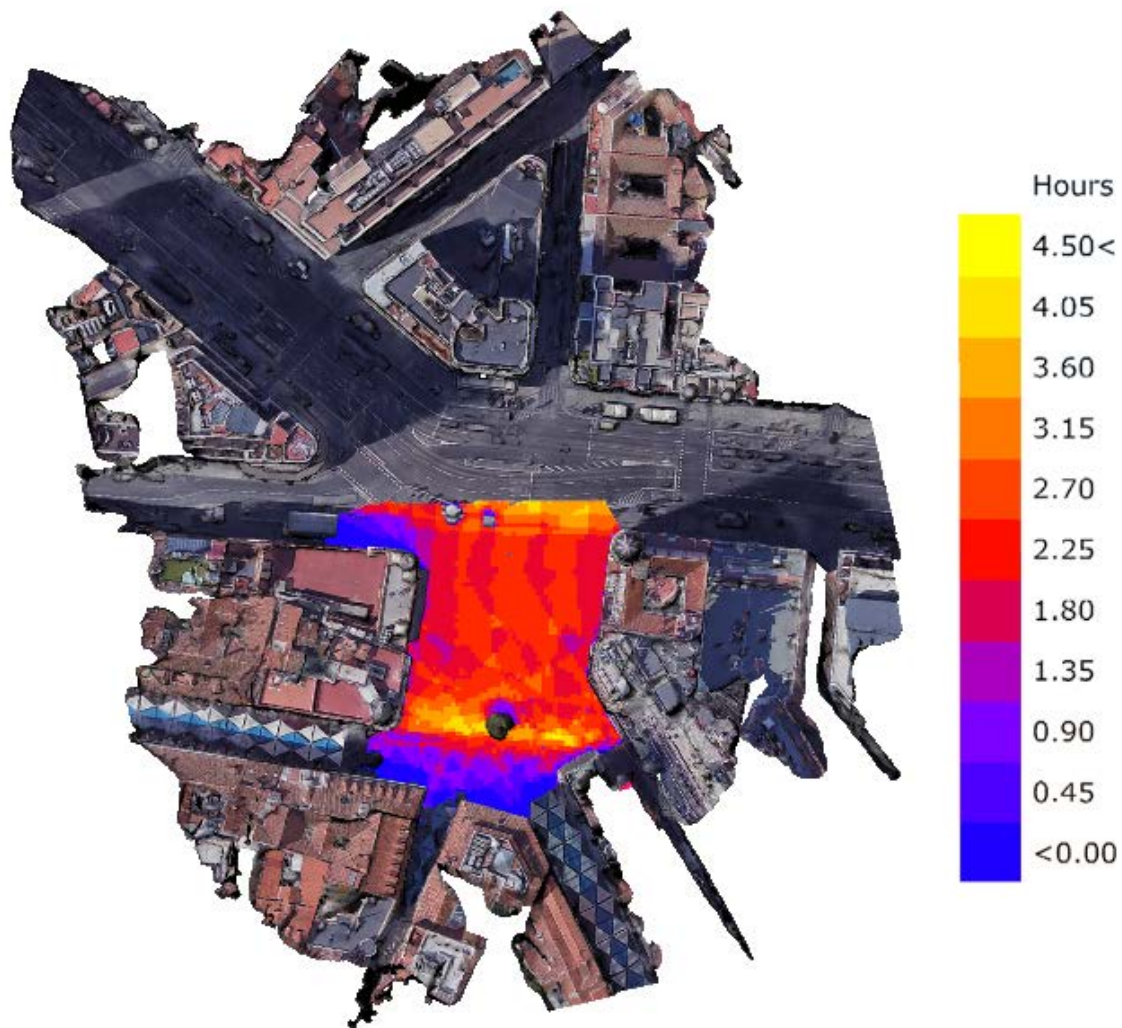


Figure 49. Simulation of sunlight hours on plaza del Callao on April 5th, 2018.

On April 5th, 2018 the central part of plaza del Callao was occupied by one of the many events happening in this square over the year. A green square of artificial grass was installed for, presumably, developing a promotional action related to soccer or sport activities (figure 46). This is not the most invasive and permanent installation that has been installed on this square, comparatively to temporal buildings and kiosks with one of two floors standing for several weeks. However, for the purpose of measuring the sensibility of the system for detecting changes in the patterns of utilization of the space, it can provide some good indication about the distortion caused by this kind of temporary obstacles, which can be extrapolated not only to commercial usages of the public space, but as well to city events, or to occupations due to works.

4.6.2.2.1 Data

The information collected and aggregated for this experiment is equivalent, and in many aspects, the same than the used for the base case. The differences are the computer vision detections and the simulation of sunlight hours and shadows (even if there is not a big difference in this last factor, it is worthy to preserve the precision facilitated by the synthetic data generated through simulation). Climatic conditions were as well similar during this day to the conditions found in the reference on April 2nd, with sunny weather and a temperature between 6°C and 19°C.

It is important to notice that they are precisely the dynamic factors which are changing, under relatively well-measured conditions: a well-delimited occupation in the center of the square, new detections from that day, and the lighting condition which are noticeable similar to the reference conditions.

In general terms, the total amount of detections during this day preserves the profile and trends of the data captured on April 2nd (figure 50). Two peaks of activity, one in the morning before noon, and a bigger one in the evening around 6:00 pm. However, two small differences are detected here when compared with the reference base day: the maximum value of detections in the evening is slightly higher, reaching up to 100 features captured per second (while on April 2nd that value was around 90), and a secondary peak of activity, or a sustained level of activity after the evening peak until midnight which wasn't clear (or present) before.

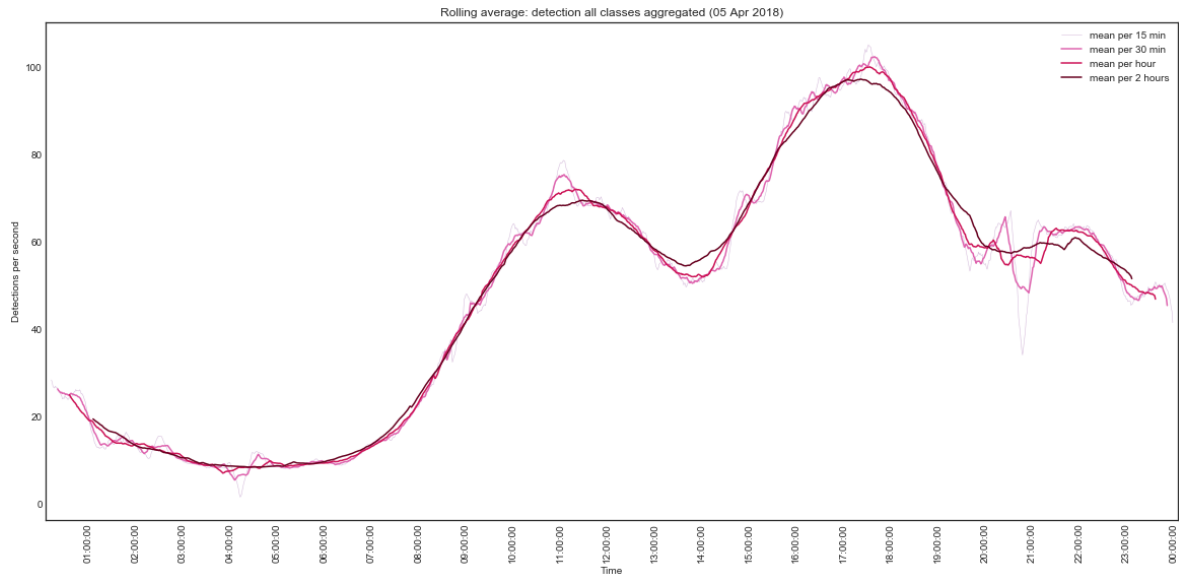


Figure 50. Total number of detections per second with all classes aggregated, plaza del Callao, Madrid. April 5th, 2018. Rolling average with different windows size is applied for data smoothing.

These detected changes are likely to be explained by the other major and more obvious difference of this day: it is Thursday while the base case is Monday. People enjoying leisure time outdoors in the evening is more common on Thursday than on Monday, which is consistent with the sustained activity during the last hours of the day, and even the higher peak at 6:00 pm.

The analysis of the detections discriminated by class (figure 51) yields a similar scenario to the already revealed in the base case without occupation of the space. Although the recognition of pedestrians is in between 1 and 2 orders of magnitude larger and commands the results of the algorithm, the most noticeable differences by class in this scenario are caused by the more frequent detection of trucks during the morning and the clear peak of police cars in the evening. The first feature can be caused by the targeted occupation of the square, which is not only the temporary facility itself but the vehicles and equipment that are required for its installation. The second difference, the peak of detections of police vehicles, matches the sustained pedestrian activity through the evening until midnight, so it can be argued that it is connected to security measure for nightlife.

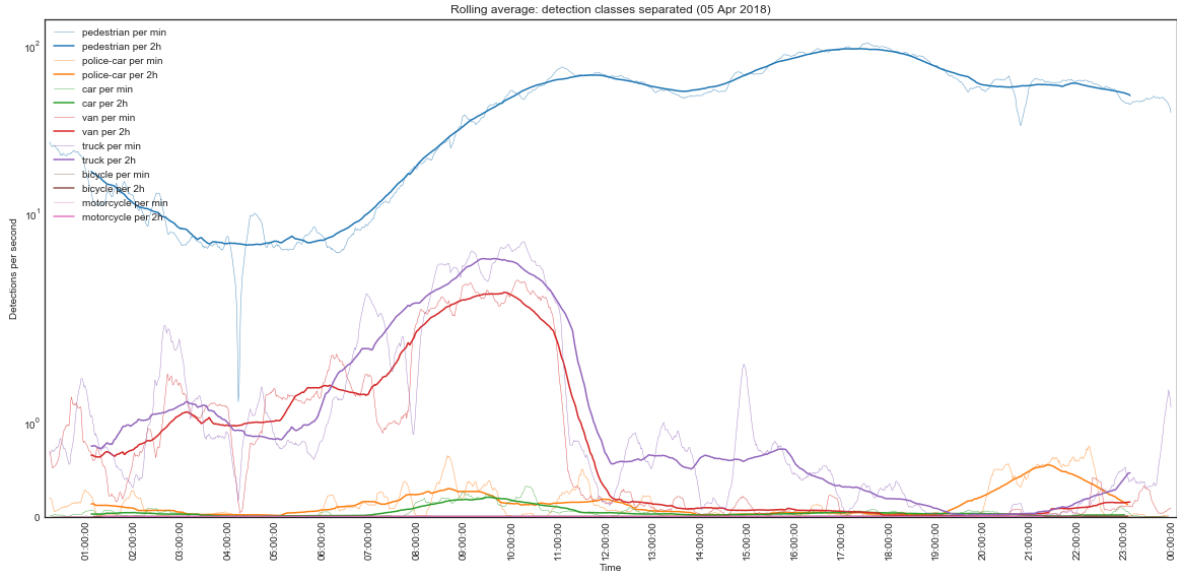


Figure 51. Total number of detections per second with classes separated, plaza del Callao, Madrid. April 5th, 2018. Rolling average with different windows size is applied for data smoothing. Notice the logarithmic vertical axis for comparisons.

4.6.2.2.2 Analysis: bivariate analysis of features

As observed in the base case, the three explored methods for finding correlations between variables show similar trends in their outcomes to the base case. Kendall's tau, the stricter methods for pointing out associations, displays the weaker correlation coefficient, but in the same direction than Pearson and Spearman's coefficients.

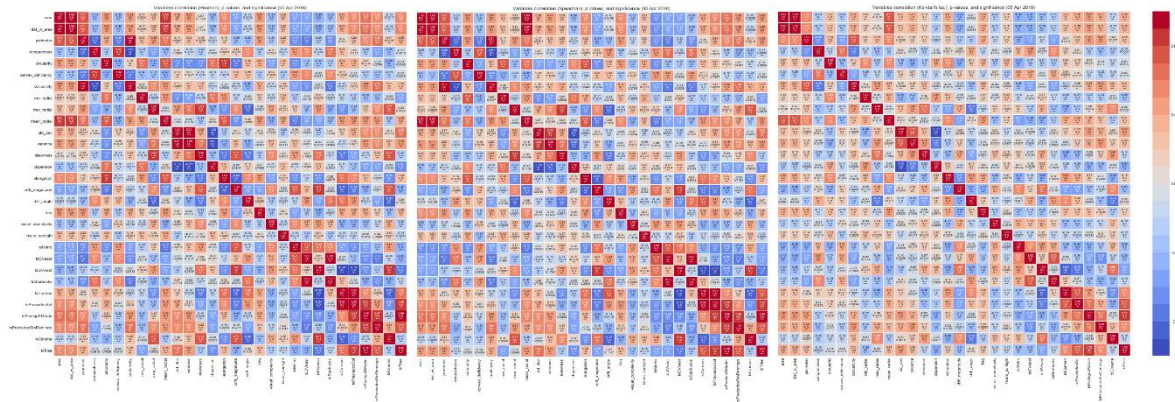


Figure 52. Comparison of the correlation matrix of all the variables with the three presented methods: Pearson's coefficient (left), Spearman's coefficient (center), and Kendall's tau (right). Data collected on plaza del Callao with the spatial occupation. April 5th, 2018.

The values of the correlations computed for the static features extracted from the built environment don't change, as they are the same. Therefore, the comparison should focus on

those parameters which are variable, changing and dependent of the data collected on April 5th, 2018: the frequencies of the computer vision detections on the utilization of the square, and the lighting conditions simulated for this day (figure 53).

For keeping the new condition as close as possible with the base case, Kendall's tau coefficient results are used because of the same reason argued in the base case: its intrinsic reduction of all the values, which is a safety measure for avoiding false positives.

Overall, there aren't important shifts in the values of these variables, but some interesting changes are observed. The Space Syntax metrics that in the base case seemed to be highly associated with a more intense utilization of the space (*area*, *mean radial*, and *drift-magnitude*) preserve very similar values: slightly lower for area and mean radial, and slightly larger for drift-magnitude. However, it is interesting the slight drop of the correlation coefficient with *area*, which can be associated with the occupation of a central position of the square which overlaps the locations which provide a vision of a larger area of the square. Interestingly, the correlation coefficient between the number of detections (*freq*) and *circularity* increases, which can be related to the rise of the value of the *drift-magnitude* correlation. It means that central positions with a balanced field vision in all the directions are even more frequently used than in the base case. It can be summarized as central but not as privileged positions are the preferred ones under the new circumstances generated by the occupation of the center of the space.

	freq	area	dst_w_area	perimeter	compactness	circularity	convex_deficiency	occlusivity	min_radial	max_radial	mean_radial	std_dev	variance	skewness	dispersion	elongation	drift_magnitude	drift_angle	freq	visual_complexity	hours_sunlight	toMetro	toGveast	toGVwest	toStarbucks	toCarmen	toPrecadosSol	toPosipioMartin	toPrecadosStoDomingo	toCinema	toTree
hours_sunlight	0.35 0.0 **	0.35 0.0 **	0.30 0.0 **	-0.17 0.0 **	0.39 0.0 **	-0.15 0.0 **	0.20 0.0 **	0.17 0.0 **	-0.11 0.0001 **	0.41 0.0 **	-0.50 0.0026 **	-0.01 0.7329 **	-0.05 0.0041 **	0.00 0.9874 **	0.34 0.0 **	-0.44 0.0 **	0.15 0.0 **	1.05 0.0 **	-0.23 0.0 **	0.01 0.0099 **	-0.40 0.0 **	-0.21 0.0 **	-0.36 0.0 **	-0.09 0.0009 **	0.25 0.0 **	0.39 0.0 **	0.23 0.0 **	0.10 0.0002 **	-0.25 0.0 **	-0.19 0.0 **	
area	0.15 0.0 **	0.15 0.0 **	0.14 0.0 **	-0.09 0.0016 **	0.23 0.0 **	-0.22 0.0 **	0.09 0.0025 **	0.24 0.0 **	0.11 0.0003 **	0.15 0.0 **	-0.15 0.0 **	-0.05 0.0407 **	0.12 0.0001 **	0.15 0.0 **	0.07 0.0079 **	-0.00 0.9129 **	-0.11 0.0002 **	0.01 0.6899 **	-0.04 0.1519 **	1.00 0.0 **	-0.10 0.0007 **	-0.14 0.0 **	0.12 0.0001 **	-0.17 0.0 **	-0.14 0.0 **	-0.11 0.0002 **	-0.06 0.0312 **	0.01 0.6674 **	0.17 0.0 **	-0.12 0.0 **	

Figure 53. Kendall's tau correlation, p-values and significance between frequencies of detections (*freq*) and hours of sunlight on plaza del Callao and the other metrics considered. April 5th, 2018.

Significance key: (**): p-value ≤ 0.001 ; (*): $0.001 < \text{p-value} \leq 0.01$; (*): $0.01 < \text{p-value} \leq 0.05$; (): p-value > 0.05 , not-significant.

Regarding the values related to the hours of sunlight, a general drop is observed although the magnitude of the difference is not huge. In general, a general loss of association between the patterns of utilization of the space and the distribution of sunlight through the day on the square is observed in this scenario. The interpretation of this effect is unclear because of lack

of additional observations and due to the weak correlation values, which diminish its actual impact. Nevertheless, a possible explanation is the distortion introduced by the occupation of the center of the square that hinders the utilization of the areas with fewer shadows. It is reasonable to consider if in fact the preference for sunny spots on the square is on purpose, or just a consequence of the constraining conditions of this built environment which shape the utilization of the space in such a way that the sunnier areas are more frequented.

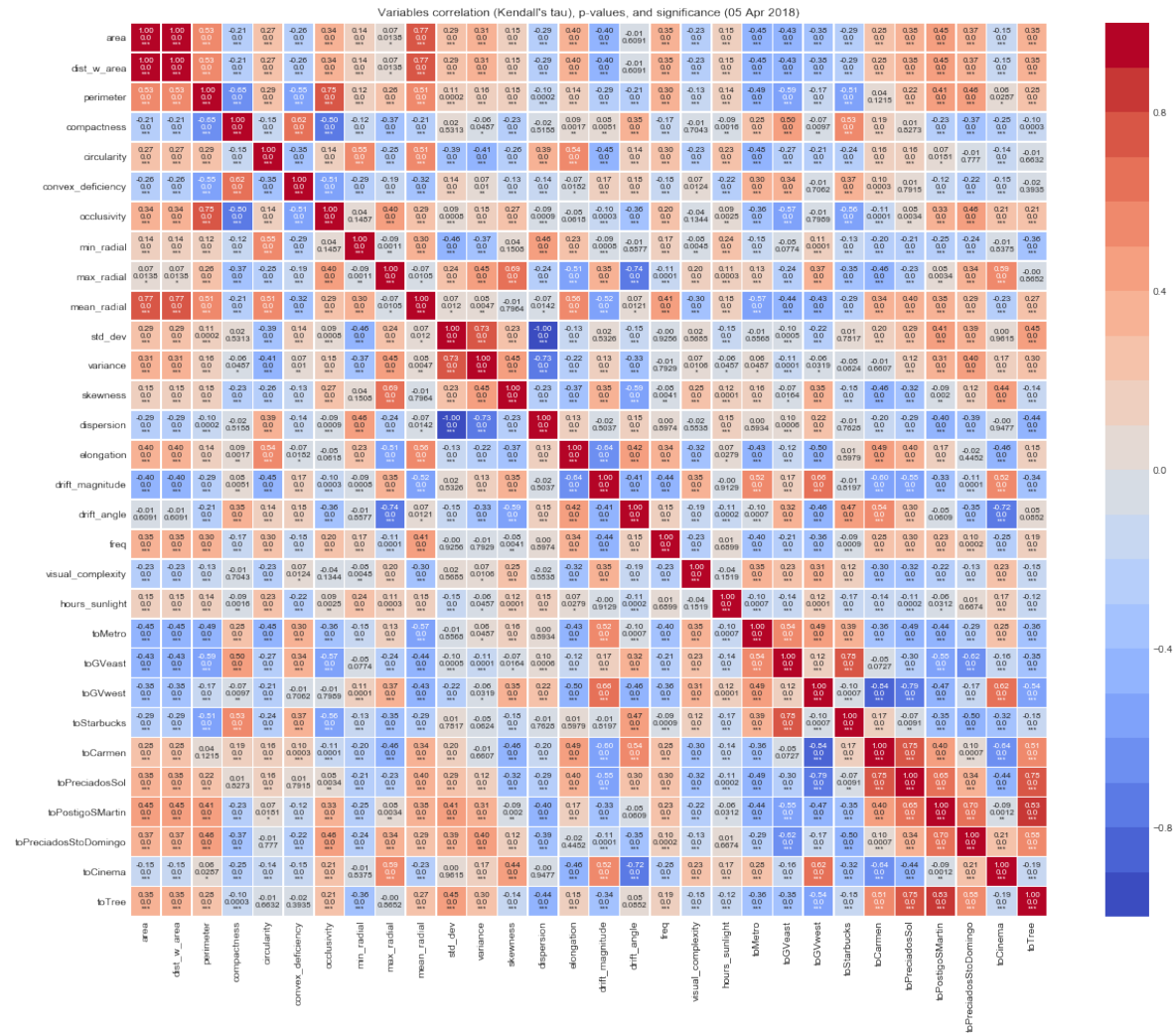


Figure 54. Full correlation matrix for Kendall's tau coefficient, p-values, and significance. Plaza del Callao, Madrid. April 5th, 2018.

Another interesting consideration regarding the interactions between sunlight conditions and the utilization of the space is that mainly seasonal changes are expected instead of day-to-day shifts, but the testing of different days can assess the validity of the measurements.

Anyhow, as the different sunlight pattern is extremely close to the reference day (there is only a difference of 3 days, check figures 49 and 30), it can be only due to a difference caused by a different utilization of the space, and somehow the venue going on during this day is affecting the pattern.

4.6.2.2.3 Analysis: spatial clustering from matching temporal trends

The spatial segmentation of the square based on the temporal profiles of utilization of each square on April 5th, 2018 resulting from the second mode of data aggregation explained in the general methodology description offers a different picture of plaza del Callao. Among the different methods, Pearson's correlation coefficient is used for matching the temporal profiles of the different cells, and the grouping generated by cutting the dendrogram at the 4th level ($h = 4$) for allowing an effective comparison with the explained base case.

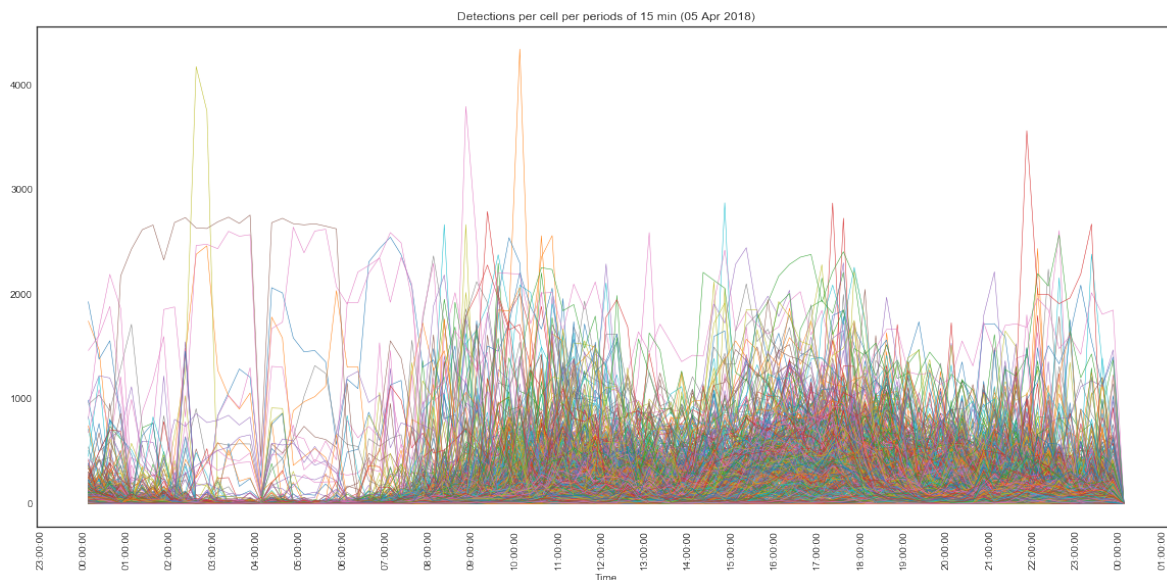


Figure 55. Number of detections of occupation per analysis cell binned in periods of 15 min. Plaza del Callao, April 5th, 2018. Each line represents the evolution over one day of the detections of one of the 557 cells.

The used classification method sorts the cells depending on the size of the group. This needs to be taken into account for comparing clusters between the base case on April 2nd and the current scenario on April 5th, as the equivalent clusters, if existing between both cases, don't need to follow the same order. However, correspondences between equivalences can be drawn based on their temporal signatures (figure 57) and spatial distributions (figure 58). The following analysis precisely tries to outline the similarities and divergences between the resulting clusters and grasping the effects of the differences of the new given scenario: the

occupation of the central part of the square and expected different pattern of usage of the space because of the day of the week. Although a larger number of clusters are generated out of the data on April 5th, due to the heuristics of the used methods it does not mean necessarily a different behavior. The smallest groups composed of few cells can be due to statistical artifacts without representing necessarily a distinctive behavior in a given location.

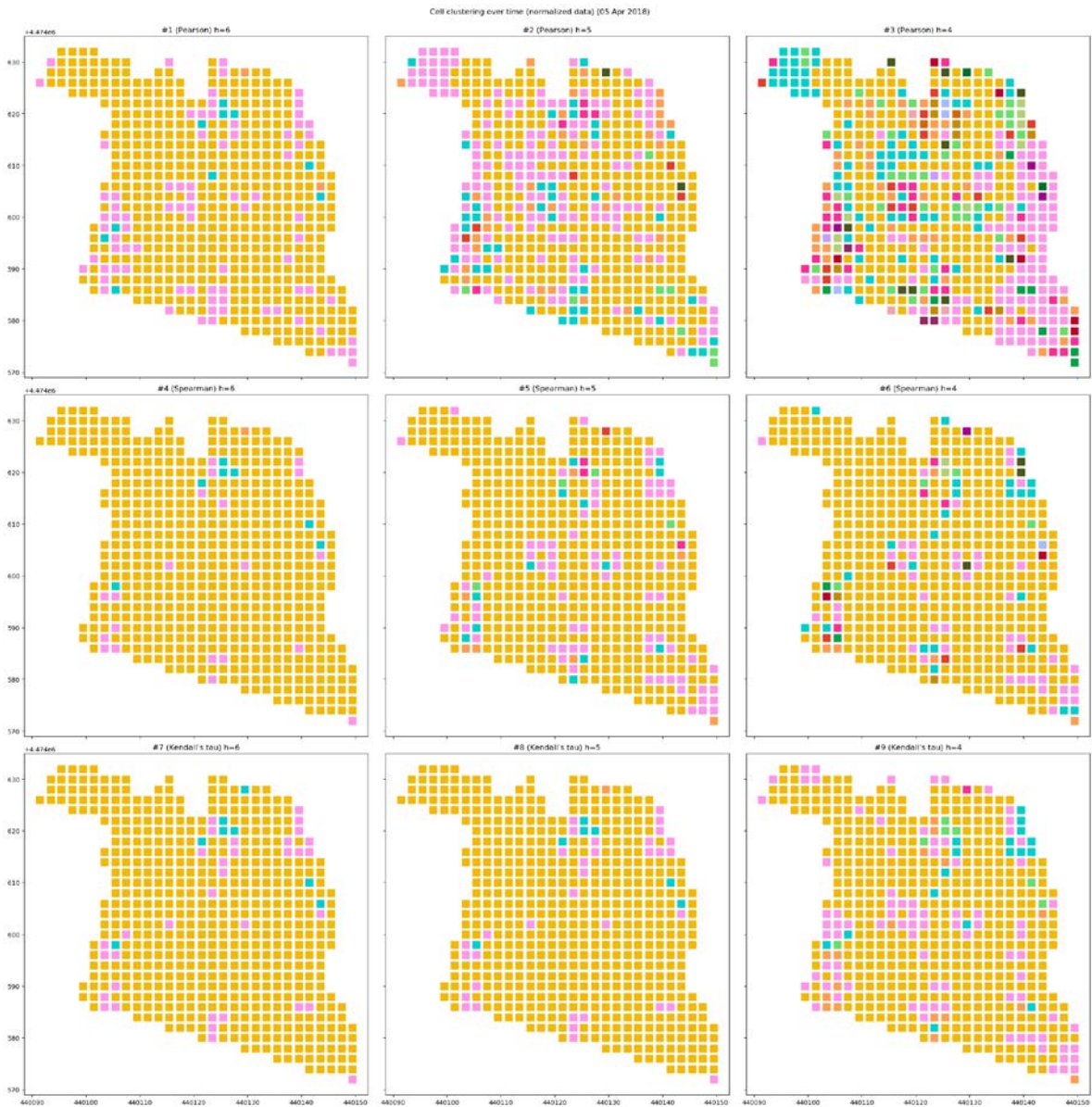


Figure 56. Resulting spatial clustering. Correlation methods are sorted in rows: Pearson (top row), Spearman (center row), and Kendall's tau (bottom row). Levels of hierarchy are grouped in columns: $h = 6$ (left column), $h = 5$ (center column), $h = 4$ (right column). Color code belongs to the identified clusters sorted from bigger to smaller. Plaza del Callao, Madrid. April 5th, 2018.

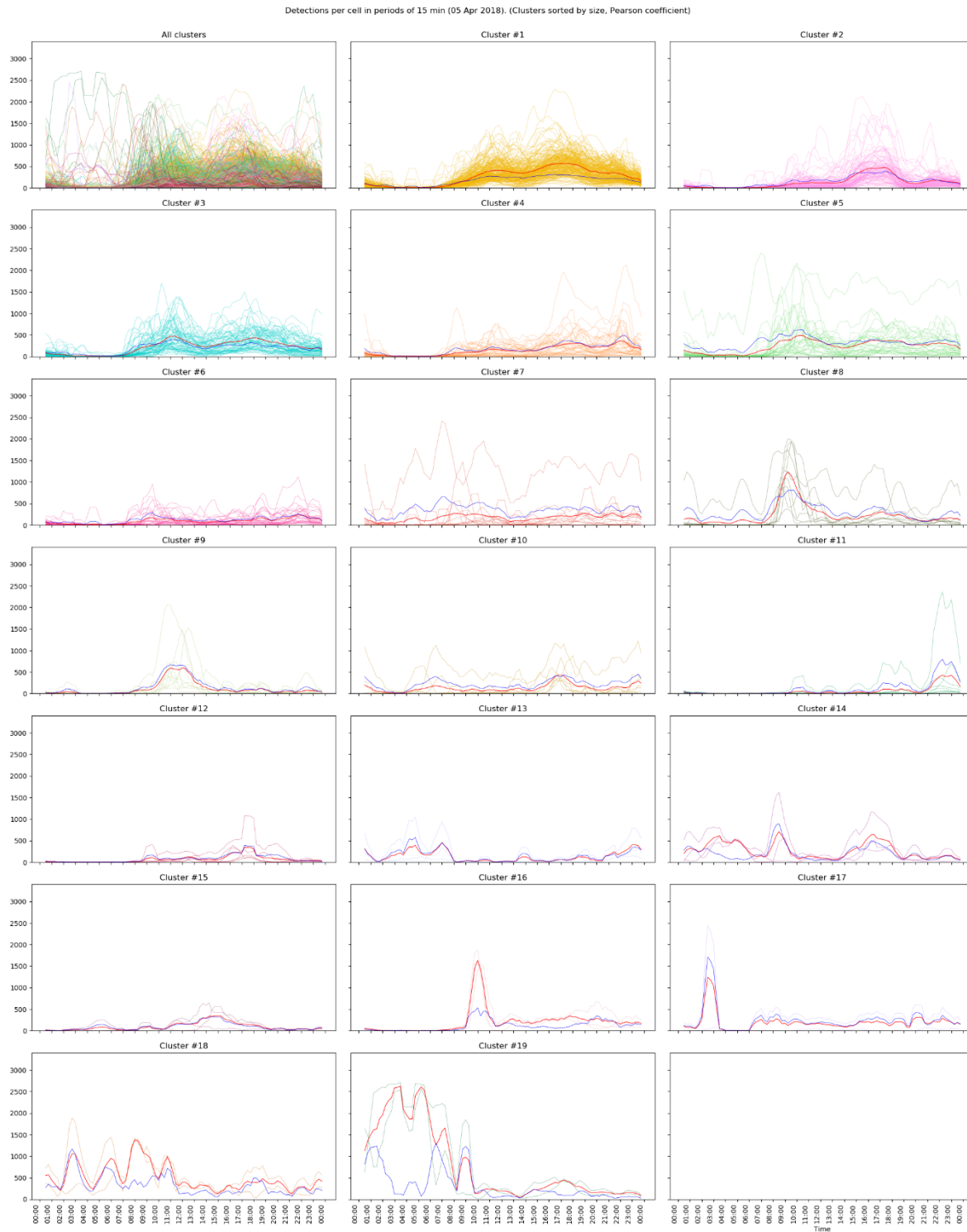
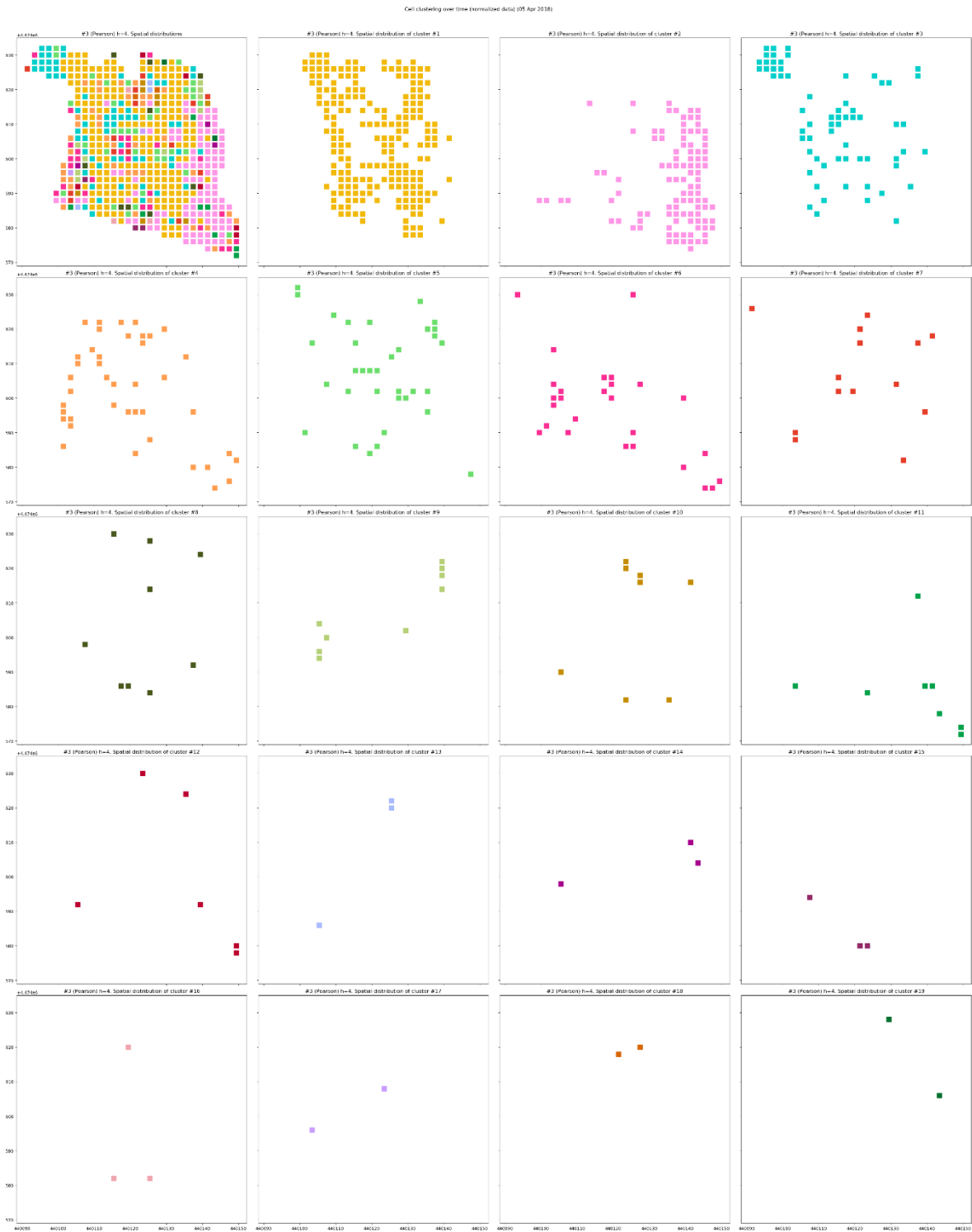


Figure 57. Temporal signatures of the 557 analysis cells grouped by similarity based on Pearson correlation and clustering cut at level 4 ($h = 4$) resulting in 17 different groups. The **red line** shows the **average values** for each cluster, and the **blue line** the **standard deviation**. These results correspond to the cluster #3 (top right in figure 56). Plaza del Callao, Madrid. April 5th, 2018.



The cluster #1 on April 5th matches the character of the cluster #1 of April 2nd. This group captures the general trend of the space as it covers most of the cells. Spatially, as in the base case, it includes the interstice of the square, the in-between space, far from any point of interest, building or key feature of the square. The temporal signature matches the general detection level described for this day (figure 50), and the main difference in the spatial distribution precisely subtracts the area surrounding the metro entrance, the edges of the square, and the area occupied by the temporary grass field. On the side, this confirms the detection of a distinguishing usage of that spot of the square.

Comparing the features defining cluster #2, with a temporal profiling extracting the cells with a higher level of activity in the evening, and a spatial distribution concentrated on the Eastern edge of the square matches the features of the cluster #3 of the base case.

Cluster #3 is somehow more interesting. Generally speaking, it is equivalent to the cluster #2 of the base case, with a time profile outlining the out-of-the-norm cells although matching at some degree the general pace but with more noise, more unstable and a larger variance and standard deviation. However, the spatial distribution is not quite similar. On April 5th, these more volatile cells are clustered around two main areas: the Northwestern corner of the sampled area, and precisely the cells located North of the occupied area on the center of the square. The first spot overlaps the cluster #2 of the base case, but the second spot by the temporary intervention can be assumed that is produced by this venue. One consequence can be extracted from this result: differently that it could be assumed because of a scheduled event in the middle of the square, it introduces quite a lot of irregularity into the utilization of -at least- part of the surrounding area.

A bigger divergence starts to be detected in the following clusters which are grasping behaviors located in very small areas with concrete profiles. Cluster #4 gathers together these locations with an increasing level of activity during the day, but with a slightly higher activity in the evening and in the late evening before midnight. Spatially, it combines the distribution of the reference clusters #2 and #4. However, it is very sparse around the square and it is difficult to identify the concentration of cells with this profile, but it seems to be located towards the Northwestern part of the square.

Cluster #5 is even spatially sparser, with some degree of attachment to the Eastern part of the square and temporarily its signature highlights locations with a more intense activity during the morning peak. This temporal profile matches the cluster #4 of the base case, but spatially there are mostly opposed, as the morning activity in the reference day was located mainly in some cells grouped in the West of the square.

Regarding the location of the temporary occupation, cluster #6 is more pertinent as it is the other resulting group that has a collection of cells which is overlapping the intervention in the middle of the square. Its temporal pattern is quite sustained through the day, with discreet peaks early in the morning and late in the evening. Spatially it is closer to the reference cluster #6, and temporally to cluster #7.

The rest of the resulting clusters don't show any recognizable spatial pattern, which makes unfeasible in principle to assess if their signatures are caused by a consistent particular and located behavior or just it is a product of statistical artifacts or transitional areas.

4.6.2.3 Local Diagnosis on plaza del Callao

Although the results obtained from both experiments performed on plaza del Callao should be considered provisional or limited, some trends are already outlined. Given the relatively small size of this urban square and the uniform treatment used for its current design, it is counterintuitive the noticeable spatial segmentation based on uses at different times of the day. This space conceived and design as an isotropic and uniform urban environment has not uniform patterns of utilization as it is extracted from the second mode of analysis the collected data.

In more general terms, the correlations resulting from the first mode of aggregating the data in the discreet cells through the whole day, reject the influence of some environmental conditions in the quality of the space -if we assume that it is linked to the way that people use it-. The first experiment results outline a small effect of sunlight conditions into the way that people use the space, and the second experiment reinforces that picture. This is an interesting finding which should be subject to additional tests as it comes into conflict with one of the most fundamental and most widely used factors for good design such as lighting conditions.

The associations between patterns of utilization and spatial features of the space point out as well another interesting implication considering the traditional character assumed for this location. Except for the presence of the subway entrance in the middle of the square, the rest of it is mostly seen as a crossroads linking important and popular streets of the city. By itself, plaza del Callao has not points of interest. Because of this, it could be assumed that the gateways of the square leading to the streets are the most used spots of this place, but, the central positions of Callao seem to have a much more important role. This is supported by the centrality measures (*area*, *mean radial*, and *drift magnitude*) which appear connected to the location where a higher number of detections are detected.

Anyhow, more important here than the particular findings, it is to acknowledge that there is a much richer and more complex number of situations going on the square which the, until now, proposed and implemented designs have ignored. There is a granularity of situations, timing, uses and characters around this location which are not taken into account, while other factors which historically are integrated more frequently into the process of design may have a minor impact.

4.6.3 Location 2: the Cut on Carnegie Mellon University Campus

4.6.3.1 Experiment 3



Figure 59. Location of the Cut of Carnegie Mellon University campus in the city of Pittsburgh, PA (left), in the area of Oakland-Shadyside-Squirrel Hill (center), and within the campus (right).

The third experiment is developed in a completely different built environment: the Cut (one of the meadows located in the historical core of the campus of Carnegie Mellon University in Pittsburgh, Pennsylvania, US. 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 selection of this location is double. On one side, it can provide a type of utilization of the space very different from the one found in an urban square in the historical center of a European city. This utilization of the space is affected by the rigid schedule of an educational center which dominating the activity of the area. This setting is opposed to the diversity found in a city, and this pace can be captured as well by the proposed techniques. On the other side, the spatial configuration is as well very different from the compact setting found in the historical core of Madrid analyzed in experiments 1 and 2, with a more open landscaping and broader perspectives typical not only on American university campus but as well suburbia areas and parks.



Figure 60. The camera installed for the data collection at CMU campus.

This change of setting is as well used for testing some additional differences from the first location. A new type of camera is used, a GoPro Silver Hero4 with local storage instead of the video streaming used in the two previous experiments on Callao. The use of a different piece of hardware made as well possible to test wide angle lenses which can facilitate in the future

larger fields covered with only one camera, it means, more potential data. The only prerequisite for ensuring the correct transformation of the 2D coordinates of the detected features on video frames to geographical coordinates is removing the lens distortion by knowing the camera parameters. Except for this innovation, the specifications of the imagery are preserved, with a resolution of 1280x1024 pixels at 3 frames per second for keeping as close as possible to the experiments on Callao.



Figure 61. Distortion correction. Original image (left), undistorted image (right).

However, all this set of differences faced for this location are even more useful for testing the performance and generalization capabilities of the training applied for tuning the detection algorithm for extracting the features. The training set used is entirely made of annotated features from images selected from the different cameras located in Madrid. The CMU location presents different perspective and distortions, as well as cultural and local differences such as different kind of vehicles, different color patterns of the objects in the scene, and different built environment texture which may affect the accuracy of the algorithm.

Therefore, this experiment is justified for checking the generalization possibilities of the framework deployed on plaza del Callao from the technical point of view, but as well for finding how the metrics used in a completely different location can point out results and correlations between the distinct pattern of utilization of this space and its design features. If general trends can be found in a different location, or even if they are not the same, at least if the same framework can be applied.

4.6.3.1.1 Data

The data collected with a camera located on the stand of the spotlight of the leftmost window of the room DH3012 from 8:00 am to 9:00 pm on April 30th, 2018. Weather conditions are within the average range expected for this season, with a maximum temperature of 19°C and

a minimum of 2°C. Although it was pretended to have the most standard with the minimum number of disturbing elements which could alter the use of the space, it is important to take into account the presence of an inflatable structure left of the fence and some tents and other temporary facilities in the area.

The same kind of datasets are considered for this location, it means: running simulations for finding the sunlight conditions on April 30th, computing Space Syntax metrics from the geometric features for this location, Visual Entropy from the Street View images dataset available on Google servers, the points of interest, and of course the detections through computer vision techniques of the seven trained features.

Although the use of wide angles increases the field of vision of the camera, still, the level of detections in the background and farthest distances is lower. For avoiding this implicit bias in the collected data, the area covered by the analysis grid is not all over the Cut, but only in that area with a good quality of collected data by the computer vision algorithms (figure 60).



Figure 62. Distribution of detections by the computer vision algorithm on the CMU campus, from 8:00 am to 9:00 pm, on April 30th, 2018.

One of the already mentioned visual features of this space is the openness of the general setting. The possibility of reaching visually far from almost any vantage point on the Cut, generate some that some results of Space Syntax metrics are useless, such in the case of Maximum Radial. In this case, these metrics are removed for avoiding inconsistent or confusing outcomes in the analysis.

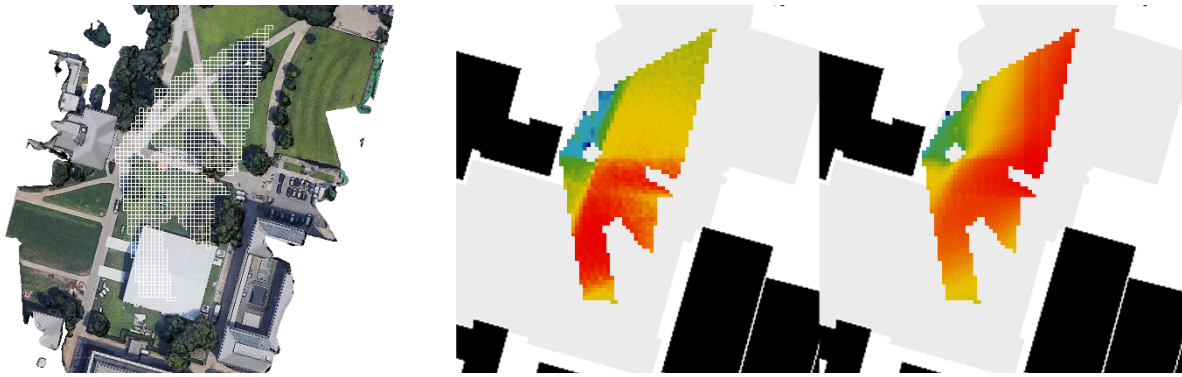


Figure 63. Analysis grid and some of the Space Syntax metrics for CMU Cut: 1286 analysis cells, area, and circularity.

The points of interest which are considered of relevance for the navigation of users on campus and for the utilization of this space are the Fence, the intersection of the path by the flagpole, the inflatable sled -as it is already there-, the area in front of the main entrance of Doherty Hall, and the path heading towards the Hunt Library.

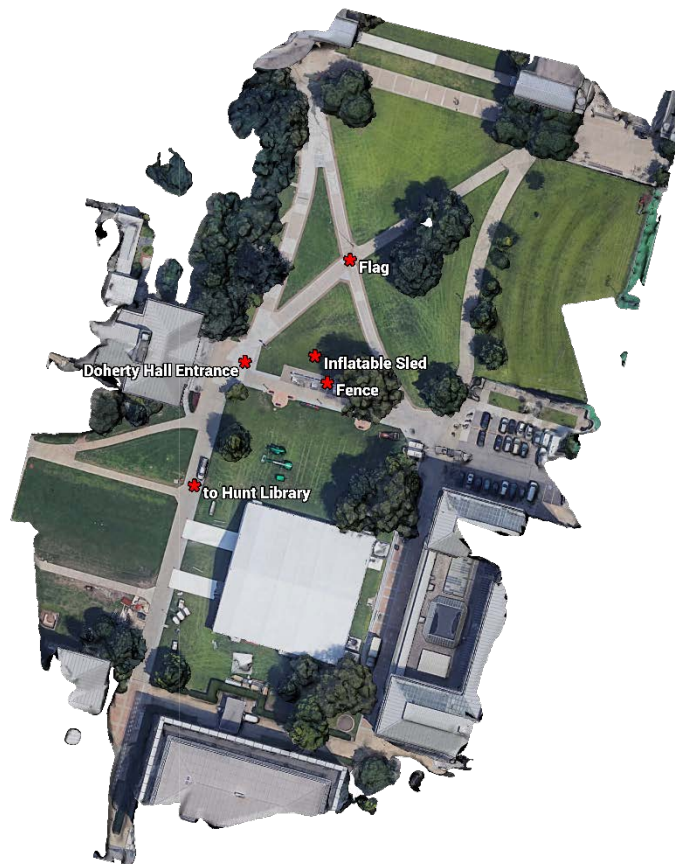


Figure 64. Selected Points of Interest (POIs) considered on the Cut of Carnegie Mellon University campus, Pittsburgh, PA.

The preliminary analysis of the data detected through the computer vision algorithm brings slightly different results, as expected when compared with the data from plaza del Callao in Madrid (figure 65). The general trend observed during the day is defined by a pretty uniform period of high activity sustained in between noon and 16:00 pm, with two really discreet peaks of activity on the edges of that “plateau” of activity. Out of that period of time in the central hours of the day, the activity decreases noticeably, except for a light rise late in the evening around 20:00 pm.

More interesting than this big picture is the distinctive trait of the pace of the detections which was not observed in the setting of plaza del Callao in experiments 1 and 2. Checking the rolling average of figure 63 with a window size of 30 minutes, a recurrent wave is detected with an approximate amplitude of 1 hour.

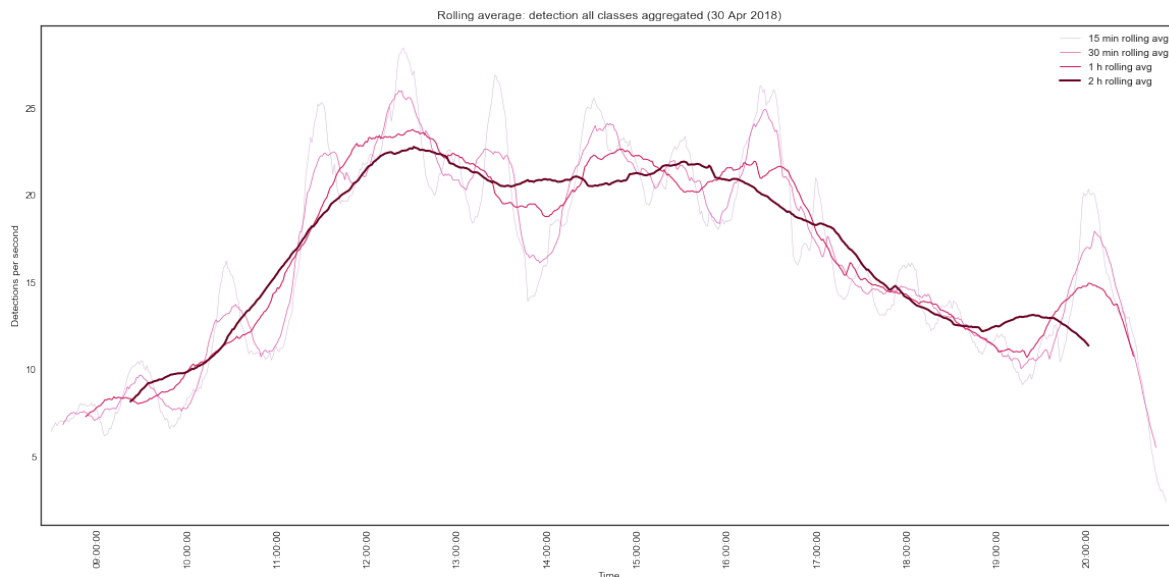


Figure 65. Total number of detections per second with all classes aggregated on the Cut of Carnegie Mellon University campus, Pittsburgh, PA. April 30th, 2018. Rolling average with different windows size is applied for data smoothing.

Given the constraining schedule of classes ruling the functioning of the pace of a university campus, this behavior seems to match precisely that timing: classes period of around 50 minutes to 1 hour. Additionally, most of the undergrad courses are ending around 16:00 pm, which is supported by the dramatic drop in activity after that hour.

When observed the detections separated by class (figure 66), still the number of pedestrians is far larger than any other trained class, which is consistent in this location without

roadways. However, the detection of the other features provides additional assessment and evaluation of the developed technique of collecting data. The identification of trucks and vans, although it is not expected on the pedestrian areas of campus, was biased because of the presence of trucks for the installation of the inflatable sled and some of the temporary facilities North of the Fence. Differently, the detection of police cars at CMU is more questionable. The completely different color livery of police cars on campus than the ones used in Madrid -and which have been used as a training set for that class- is a reasonable doubt for trusting directly the outcome of the computer vision algorithm. The verification of the frames around 16:00 pm and 17:00 pm confirms that this is a false positive mostly caused by some particular lighting conditions affecting the white tends present during the analyzed day.

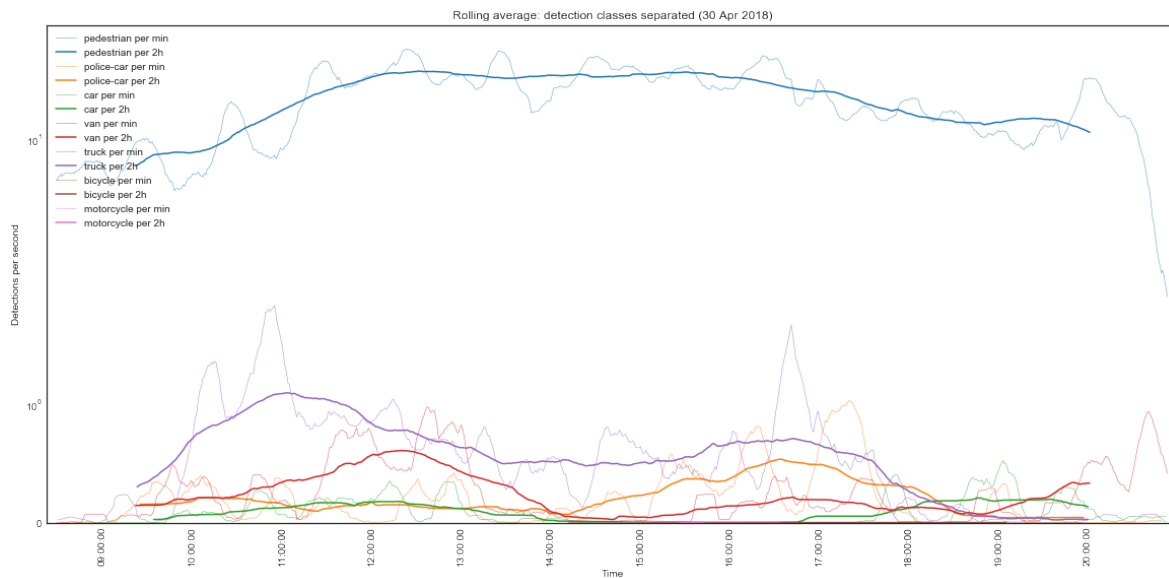


Figure 66. Total number of detections per second with classes separated, the Cut at Carnegie Mellon University campus, Pittsburgh, PA. April 30th, 2018. Rolling average with different windows size is applied for data smoothing. Notice the logarithmic vertical axis for comparisons.

In general terms, the false positives are very informative about the flaws of the generalization of a training supported by locally collected data when applied to other cultural or geographical contexts. However, the big picture is still able to bring meaningful precise patterns of utilization of the space.

4.6.3.1.2 Analysis: bivariate analysis of features

The methods applied for analyzing the data extracted from the CMU Cut are the same than the used in the experiments performed on plaza del Callao, it means, two different modes of aggregating the data: a bivariate analysis of features between each pair of variables with all the data aggregated on the discrete analysis cells, and another different representation of the collected information based on defining each analysis cell by its temporal signature of detections from the computer vision algorithm.

The computation of the correlations generated from the first mode of aggregation of the data brings a similar outcome to the one found in Callao's data: the three different mathematical methods give a similar picture, with associations between the variables in the same sense. Kendall's tau coefficient provides the least exaggerated values, while Pearson's outcome outlines stronger correlations (figure 67). Although this general behavior matches the previous experiments on Callao, the level of divergence between the three mathematical methods is higher in this case, they are not small differences as in the experiments 1 and 2. In general, Kendall's tau correlation coefficient is almost half of the values provided by Pearson's coefficient, while Spearman's coefficient is somehow halfway between both, although the latter sometimes provides values much closer to Pearson's method than to Kendall's values, even if both are rank based metrics. Therefore, Kendall's tau questions the robustness of the conclusions drawn from the analysis. At least, what can be extracted from the comparison is that detections have a clearer relationship with Space Syntax metrics.

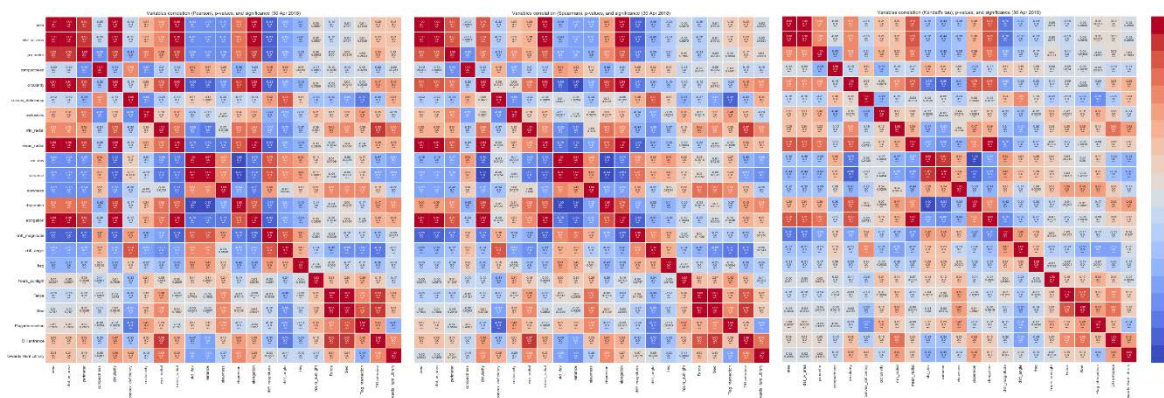


Figure 67. Comparison of the correlation matrix of all the variables with the three presented methods: Pearson's coefficient (left), Spearman's coefficient (center), and Kendall's tau (right). Data collected on the Cut at Carnegie Mellon University campus. April 30th, 2018.

The magnitude of these relations is much lower in Kendall's tau (figure 68), but the pattern is clear. In general, detections of activity (*freq*) show a negative correlation with the variables linked to central or privileged locations (*area*, *perimeter*, *circularity*, *mean_radial*) while they show a positive association with metrics linked to visual and statistical skewness of the vantage point in relation to the overall setting (*standard deviation*, *variance*, *drift_magnitude*).

This behavior can be explained precisely by the particularities of this setting, with the flows and activities strongly conditioned by the paved paths running close to buildings. Although the planning of the campus offers large views and perspective, the use of the space is conditioned by the implicit functional utilization of the space.

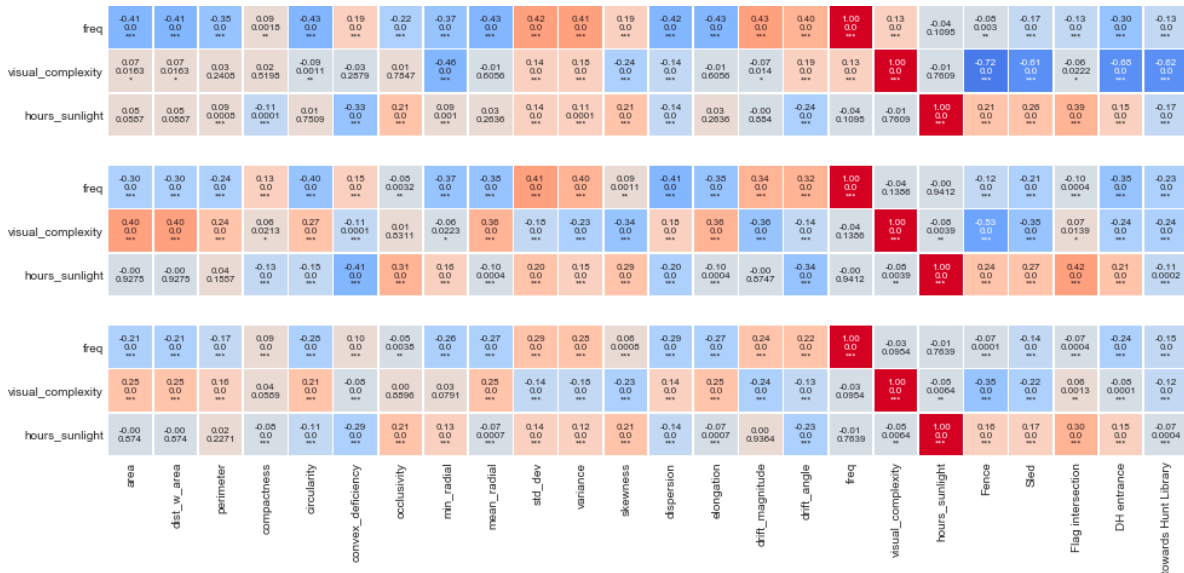


Figure 68. Pearson's coefficient (top), Spearman's coefficient (middle), and Kendall's tau correlation coefficient (bottom), p-values and significance between frequencies of activities detection on the Cut of Carnegie Mellon University campus and the other metrics considered in the analysis, April 30th, 2018.

Significance key: (**): p-value ≤ 0.001 ; (*): $0.001 < \text{p-value} \leq 0.01$; (*): $0.01 < \text{p-value} \leq 0.05$; (:): p-value > 0.05 , not-significant.

Another interesting trend much more clearly outlines here than in the previous experiments is a negative correlation between the computed visual complexity and the distance to some of the considered Points of Interest (POIs). Although the same drop of the strength of this correlation is observed depending on the mathematical method used, being weaker for Kendall's tau, the negative trend with the distances to the Fence, the inflatable shed, the entrance of Doherty Hall, and on the path towards the Hunt Library can be interpreted as being perceptually much noisier environment the areas surrounding these locations. It is

consistent with the design of these spaces, as they are precisely the places with a higher number of elements (lights, benches, trash cans, etc.). However, only the presence of Doherty Hall seems to be related, very slightly, to a higher level of detections from the computer vision algorithms which makes sense as the activity on campus is driven by the function of the different educational buildings.

A good assessment of the collected data on the CMU Cut is evaluating the influence of the presence of Doherty Hall in the patterns of utilization. It is expected that most of the traffic will be connected to the entrance of this building as it is the main point of interest in the area covered by the camera. The negative r -value outlined by the correlation between the detections (*freq*) and the distance to Doherty Hall is a discreet but solid indicator of that association: the smaller the distance to the entrance, the highest the number of featured detected by the computer vision algorithm.

As a whole, the trends brought by the aggregation of data collected at the Carnegie Mellon University campus show a completely different behavior. It is expected that, due to the much more regulated functioning of the monoculture logic controlling the utilization of an educational campus, that the use of the space will be much more restricted by the scheduling of activities in the different buildings. Moreover, the different approach towards the design of the space, with well-defined segregated areas of different types of pavement, is opposed to the homogeneous treatment decided for plaza del Callao in Madrid. This design decision introduces an implicit bias or conditioning into the expected use of the space by people. However, it can be as well instrumentalized as an assessment and evaluation method for checking the capacity of the proposed technique for grasping these expected patterns.

4.6.3.1.3 Analysis: spatial clustering from matching temporal trends

The second mode of aggregation focuses again on the classification of location and spatial segmentation yielded by the temporal signatures of the detections binned at each of the 1286 discreet analysis cells (figure 69).

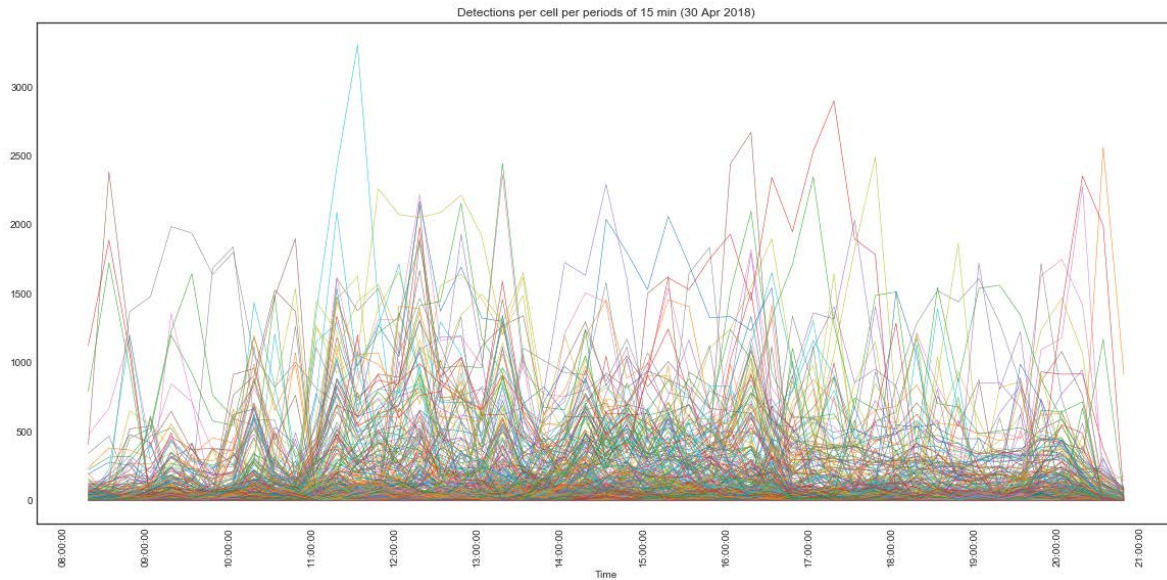


Figure 69. Number of detections of occupation per analysis cell binned in periods of 15 min. The Cut at Carnegie Mellon campus, Pittsburgh PA, April 30th, 2018. Each line represents the evolution over one day of the detections of one of the 1286 cells.

One important difference observed in this dataset collected on the Cut of CMU campus is the lack of detections in a large number of locations. Although locations with a fewer number of detections are cleared out from the area to be divided into discreet analysis cells, this vast space surveyed by the camera show large underused areas. This is consistent with the own planning of this built environment, with defined paths and large grass prairies which are barely used by some people for shortcutting or for playing some sports and hanging out during leisure times. These “empty” cells are clearly identified in the correlation matrix drawn for matching similar temporal signatures (figure 70).

The level of sparseness of the temporal matching is as well more pronounced, with fewer apparent clustering, or weaker associations between cells. This is detected by the deeper cut necessary for grasping big groups of cells. Comparing to the range of depth between 4 and 6 used in the data from plaza del Callao, for getting the same level of detail on the clustering it is necessary to use depths between 9 and 7 (figure 71). It is already an important difference on the character of this place.

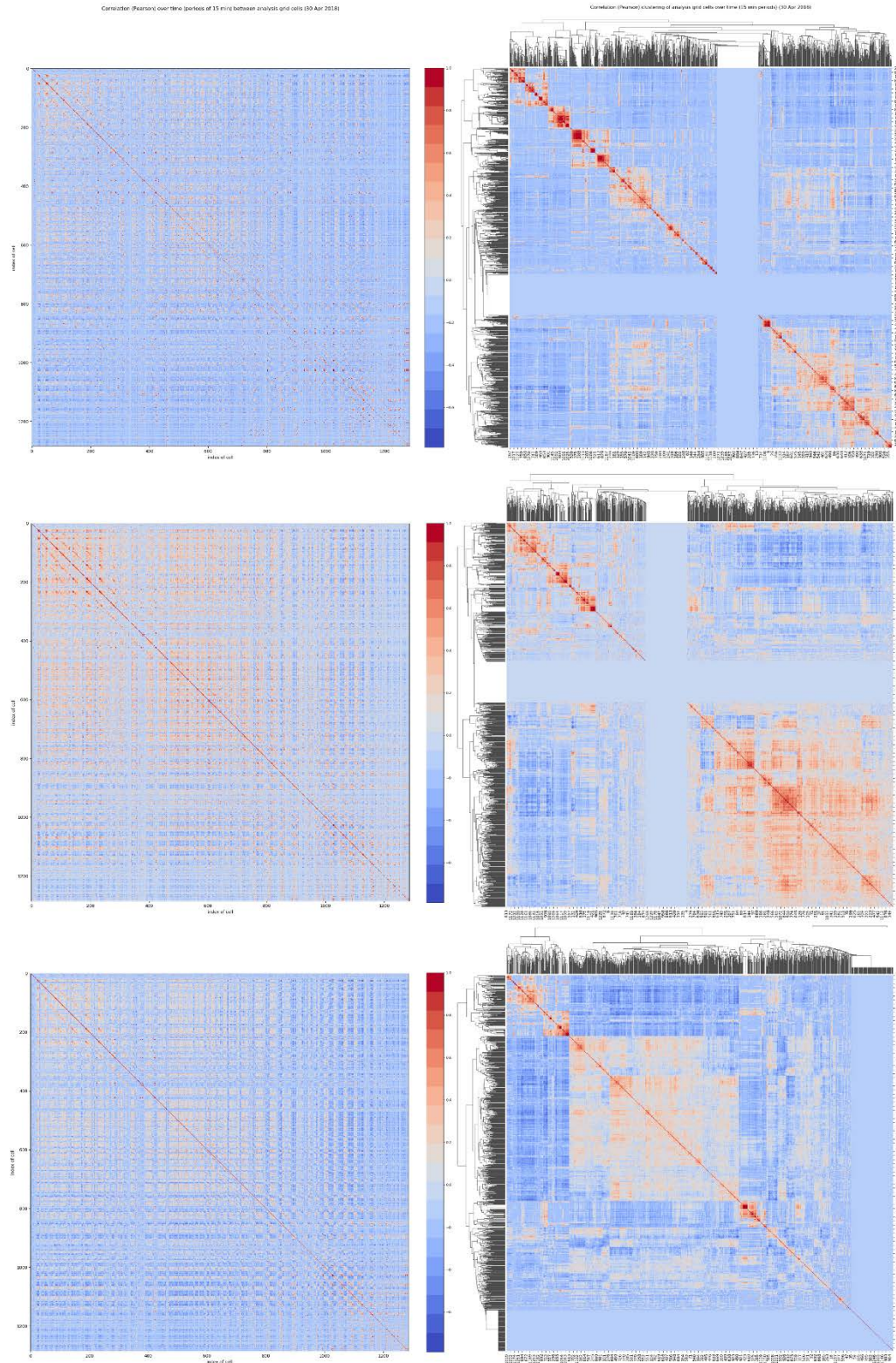


Figure 70. Clustering of the 1286 discrete analysis cells based on similarity of their correlations of temporal patterns. Sorted by the index of the cells (non-grouped by similarity) (left). Clustered by similarity of temporal signatures (right). Methods: Pearson (top row), Spearman (Center row), Kendall's tau (bottom row). Data collected at the Cut of CMU campus, Pittsburgh PA, on April 30th, 2018.



Figure 71. Resulting spatial clustering. Correlation methods are sorted in rows: Pearson (top row), Spearman (center row), and Kendall's tau (bottom row). Levels of hierarchy are grouped in columns: $h = 9$ (left column), $h = 8$ (center column), $h = 7$ (right column). Color code belongs to the identified clusters sorted from bigger to smaller. The Cut at CMU campus, Pittsburgh PA. April 30th, 2018.



Figure 72. Temporal signatures of the 1286 analysis cells grouped by similarity based on Pearson correlation and clustering cut at level 7 ($h = 7$) resulting in 16 different groups. The **red line** shows the **average values** for each cluster, and the **blue line** the **standard deviation**. These results correspond to the cluster #3 (top right in figure 71).
The Cut at Carnegie Mellon University campus, Pittsburgh PA. April 30th, 2018.

Again, for facilitating a comparison task the chosen clustering scenario is chosen for being as close as possible to the experiments 1 and 2. The grouping solution generated by Pearson's correlation coefficient is chosen at a degree of group detail on the same level that the targeted outcomes on the previous experiment. However, the sparseness of the temporal profiles of this dataset required a deeper cut at level 7 as mentioned earlier.

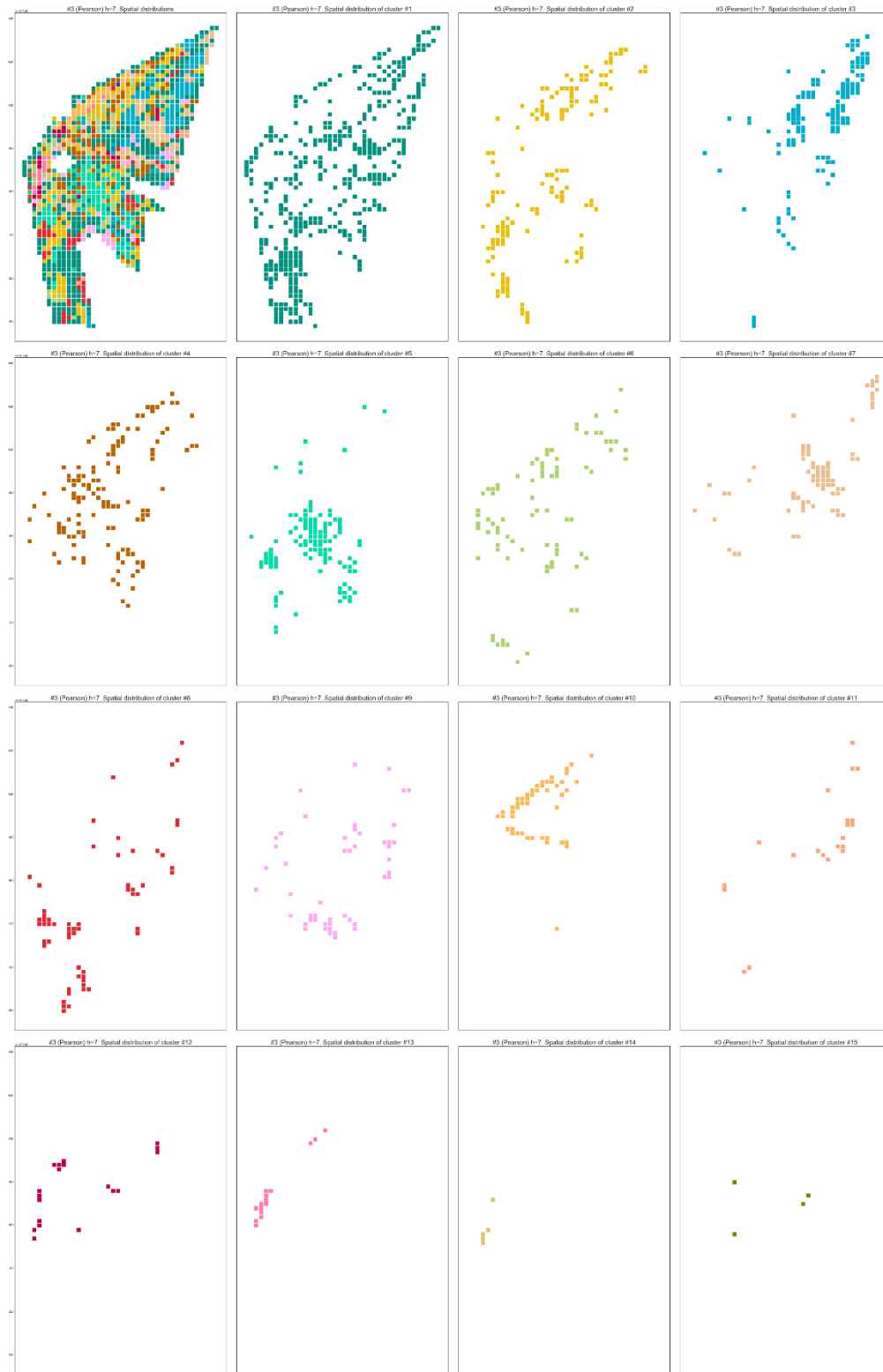


Figure 73. Spatial distributions of the 1286 analysis cells grouped by similarity based on Pearson correlation and clustering cut at level 7 ($h = 7$) resulting in 16 different groups. These results correspond to the cluster #3 (top right in figure 71). Their correspondent temporal signatures are in figure 72. The Cut at Carnegie Mellon University campus, Pittsburgh PA, April 30th, 2018.

Among the identified clusters, the outcome shows a different structure from the compact mixed setting of plaza del Callao in Madrid. A quick check of the average values of each of these clusters (red thick line on charts of figure 72) indicates that many of these clusters have a very low level of detection through the observation period from 8:00 am to 9:00 pm. For instance, cluster #1 which is the largest of the identified groups of cells, has an average level of utilization detected close to 0. Spatially (figure 72) it is very sparse around the whole surveyed area, with a higher density on the grass far away from the camera, which can be consistent with the lack of use of many of these areas. The same pattern is observed in clusters #5, #7, #14, and #15: average near to zero, it is, lack of activity, in areas covered by grass away from the paved paths.

The locations belonging to the cluster #2 show a more informative picture. Its temporal signature has a peak of detections around 15:00 pm. Spatially these cells are located in adjacent areas to paved paths but already on the surfaces covered by grass. Given the utilization distortions induced by the trends and extraordinary activities developed during this day on the grass, this group can be linked to them. Clusters #3 and #4 spatially are complementary to the locations of cluster #2 while matching temporal patterns with peaks of activity early in the morning and around noon respectively.

Interestingly, the spatial distribution (figure 73) of clusters #6, #7, #10, #11, and #13 matches the location of the paved pathways. It assesses the ability of the designed framework for capturing distinctive patterns and expanding the understanding of how even obvious built environments work. In this case, a different behavior is expected on footways than on grassed areas, and it can be predicted from the traditional design expertise. However, the applied techniques are able to specify and differentiate nuances and details within this basic classification. Therefore, while cluster #6 highlights sections of the pathways with more activity in the evening, cluster #7 locations have their peaks of activity early in the morning and late in the evening. Spatially, cluster #10 is the group that draws more clearly the pathways North of the Fence and grasps the general pace of the detections in the whole surveyed area with a larger peak in the morning. Meanwhile, cluster #11 and #13 identify parts of these paved pathways farther to the East and towards the Hunt library whose most crowd moments are at the end of the day and in the evening respectively. Cluster #13 is, in this sense, the complementary group of cluster #10: both capture the most common

detection patterns during the day, the first one highlights the evening active areas, and the second one these spots with more activity in the morning. Finally, cluster #12 covers locations on the pathways whose peaks of detections are both in the morning and in the evening.

4.6.3.2 Local diagnosis at the Cut of CMU

In spite of the limited amount of data collected at this location, the general trends captured and found through the analysis and processing of the data seem to match the expected behavior of this setting. 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 it is detected by the data capturing techniques used for the experiment.

This preprogramming of space is grasped by the way that people navigate throughout the space in between building, avoiding shortcuts and following the predefined paths. It invalidates at some extreme the correlations between Space Syntax metrics and use of the space as the latter cannot be explained by the spatial features but by the design constraints of paths and pavement differentiation. Additionally, all the metrics considered in the first mode of analysis, the perceptual ones to the environmental ones represented by sunlight, are somehow conditioned by the strongest effect of people behavior of paths. In this sense, this experiment has almost and evaluation purpose as it is easy to test the accuracy of the results and if they match the existing design of the campus.

Regarding the second mode of aggregating data, with a focus on the activity detections and their temporal signatures, there are two main outcomes to be pointed out. On a first level, the system is able to detect and distinguish with a pretty high degree of accuracy the two spatial domains in which the outdoors space of the CMU campus is broadly divided: the aforementioned paths and grassed prairies. On a second level of differentiation, the clustering method can identify different temporal patterns within each of those main domains of the space. Morning activity is clearly driven by circulations coming in and out to Doherty Hall (at least for its important influence in the analyzed area). As the day goes on, the activity is sparser and highest level of activities are detected in other areas. Another interesting trend is

detected during the later afternoon and evening, which is the increasing importance South of the Fence and at the Intersection of the College of Fine Art Lawn and the Mall.

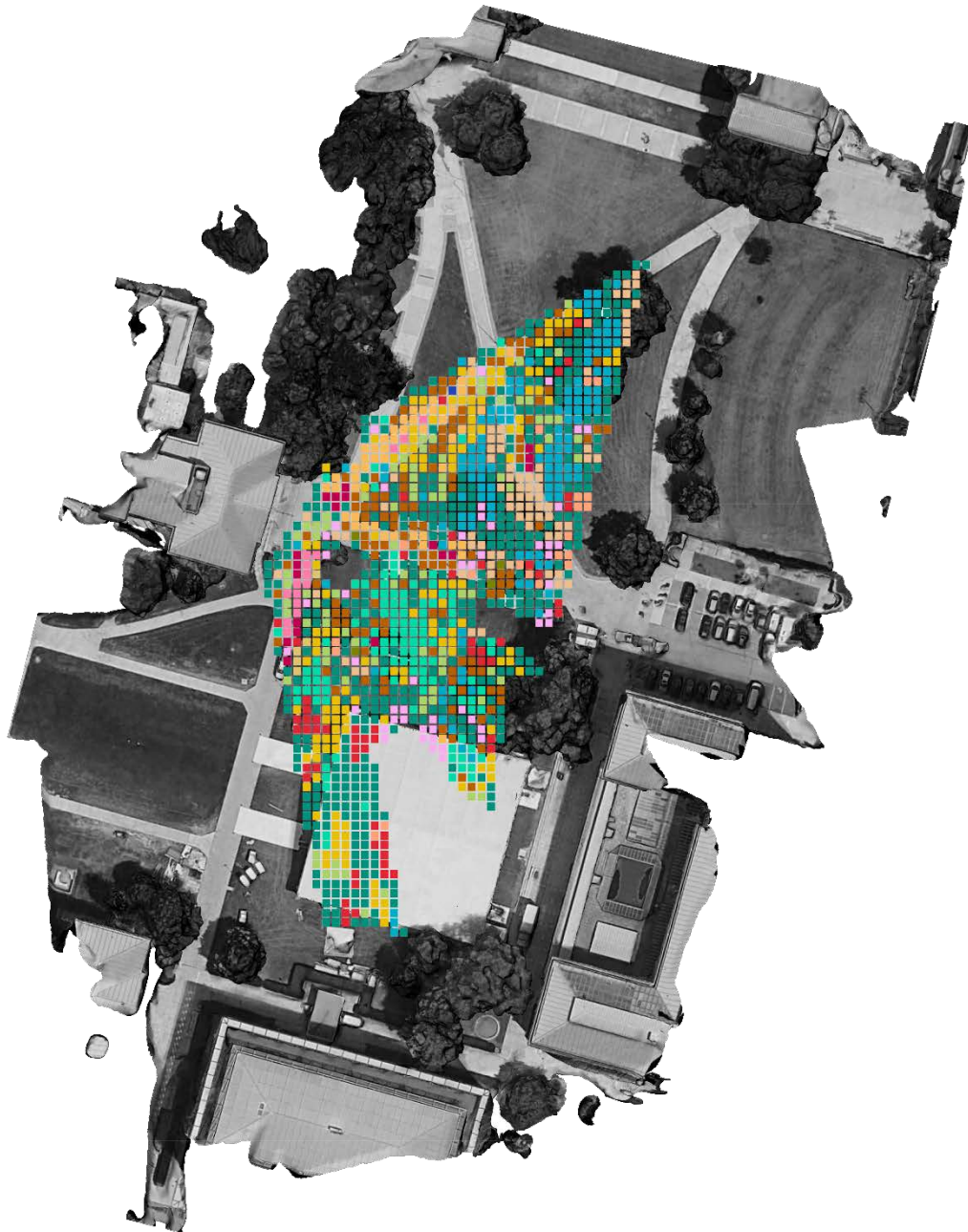


Figure 74. Spatial clustering of analysis cells on the Cut of Carnegie Mellon University campus, Pittsburgh PA, generated by Pearson correlation similarity cut at level 7 ($h = 7$).

5 Limitations and Discussion

5.1 Limitations of current work

The proposed framework is a first attempt to build a systematic approach to holistic urban and spatial analysis able to provide clues and insights for designers about how the existing spatial context affect the behavior of people in space. At the same time, by expanding the results and relations extracted from the gathered data it is possible to predict with some degree of certainty some of the effects of envisioned interventions in the analyzed space. However, some considerations need to be made about the scope of the presented work. Firstly, regarding one of the most important contributions of this work, which is the collection of real-time high-precision data from video imagery, the current algorithm is not able to the continuous tracking of entities. Not only the spatial location of isolated features over time is a valuable piece of information, but the actual tracking of movement, speed and trajectories would provide a much deeper understanding of the navigation conditions of the space. Regarding environmental data, the model is considering lighting conditions. It would be as well important to include temperature and weather conditions in a more longitudinal study. About the spatial features aggregated in the model, there is an implicit bias by using fundamentally 2D analytical tools. The development of 3D spatial analysis techniques is not as well-documented and standardized, but it would provide in urban environments a richer and deeper picture of the perception of the space. Finally, the computational perception analysis done is the most uncertain as it is clearly the less developed and most innovative of the proposed analysis frameworks. No doubt, the improvement in any of these aspects of the data collection would improve the analytical power of the research. Additionally, a more diverse study of different urban environments could conduct to more general guidelines for designers. Somehow, the question about the local specificity of the conditions of a particular urban setting, and the chance of generalizing them to other places around the city is a question which requires further exploration. From a more prospective and speculative point of view, the possibilities of real-time data collection can yield new

This framework presented on this document provides a new set of techniques for gathering novel data from the built environment and for integrating a different kind of information able to provide insightful knowledge for design. Focusing on the new information provided, it is generated fundamentally by the use of computer vision techniques. It can be seen as a new iteration in the topic of learning from the urban environment by just watching, but this time enabled and expanded by computational techniques. This new source of information is very

sensitive to errors and biases, as there are many small factors which can alter the detected features and distort the outcomes and their consequent relations with other features.

The current implementation of the computer vision detection algorithm, although it reaches up to a 70-80% of accuracy, can be very sensitive to changing lighting conditions and to the depth of field. It causes for instance that its precision can vary through the day, as during the moments with sharp contrasting shadows, missing part of the information. The latter is a more pressing issue because it brings very noisy data in the background of the image, it is, in the farthest areas from the camera. It is the main reason for limiting the surveyed area in both locations even though theoretically the camera is covering a much larger area. This is crucial as it reduces the amount of surveyed space and restrains the collected data to part of the space, missing part of the picture in other close spots which needs to be taken into account for understanding the overall working of the studied built environment.

An important side consequence of this lack of higher accuracy of the system is the impossibility of performing precise tracking of detected features on the scene, which would be able to provide useful and novel information on trajectories, followed paths, and speed vectors of moving objects and people getting around.

At a higher level, and as well affecting the capacities of the convolutional neural network for features detection in urban spaces, the scope and diversity of the used training data limits the accuracy and generalization of the technique to slightly different scenarios and perspectives. The current training data is extracted from frames collected from cameras located in Madrid, which bounds the kind of perspectives and features which can be detected. That's the main interest of the third experiment in a different location. Although that the used training can handle a diverse number of situations and some degree of change on the capturing circumstances, and in fact, it is working at a high degree at CMU campus, some of the categories because of their local specificities such as police cars should be reinforced. As well, it is problematic some of the initial categories considered, as introducing a differentiation between trucks and vans that the algorithm tends to mix up because of their similarities.

Not only the data generated by the novel detection system supported by computer vision techniques is responsible for some of the limitations of the results, but the scope and quality of the other datasets and metrics included.

Space Syntax is one of the most successful computational techniques applied to urban planning and architecture, widely used in building industry and integrated into many design workflows. However, its application is subject to limitations in the way of conceptualizing and encoding the space (Ratti 2004), and the implementation here used assumed a 2D vision of the built environment. It simplifies the complexity of the analyzed space and dismisses information which may affect the experience of people. Expansions and generalizations of Space Syntax and isovists techniques for 3D environments have been proposed, as well as the use of more precise scan and survey techniques yielded by a greater power of computation not available when these techniques were initially developed (Ratti & Richens 2004; Ratti 2005).

In general, it can be said that more data should be useful. The current research proposes a framework for integrating different kind of datasets at different levels of definition. However, it would be necessary a precise previous exploratory work for identifying these metrics which are really affecting the use and the experience of spaces. New metrics on environmental factor, on physical properties of the built environment, materials used for pavement, noise, gradients of temperature, advertisement, signs, etc. A plethora of potential sources of information affecting these behavior-space associations which are not currently considered could be integrated into the framework. Particularly metrics for encoding the characteristics of the space and how people perceive it are important but not extremely explored with some simplistic implementations, such as Visual Entropy.

One of the goals of the research is being able to understand how spatial features can affect the utilization of a given built environment. Although an important amount of information is collected particularly in the case of plaza del Callao, the findings are particularly conditioned by the possibility of generalizing the results and overcoming bias. This distortion is doubly introduced, at a local scale by missed conditions which are changing over time (daily, weekly, seasonally), and in general spatial terms by not accounting for more locations than only two which would make possible to findings on how spatial feature affect people's behavior across different urban settings providing some sort of generic rules. Precisely, the findings of how

people move for example on plaza del Callao are bounded to the experiment conditions, without the possibility to extrapolate to other seasons or other similar urban settings due to the lack of data. As well, it hinders the analysis of the uniqueness character of each city or location (Lehrer 2010).

Beyond the novel detection system proposed, and the used datasets, the analysis techniques, and their results are even more important for the generation of new findings. Two modes of data aggregation are proposed: the first one on a static treatment of the information aggregating all the collected data in discrete cells, the second one with a dynamic time-dependent approach in mind as an alternative way of grasping the complexity of the utilization of urban and architectural spaces. But other approaches which can reveal more meaningful results are possible, starting by combining the time-dependent approach, but integrating all the multi-dimensional data of the first approach. Currently, the proposed analysis is only basic approaches.

5.2 Future work

The immediate next steps for this research are the improvement of the computer vision algorithm for extracting features from video frames. A third implementation of this algorithm is currently under development and it is expected to have a much higher accuracy and robustness, without unstable detections over time and without the already commented issues for identifying on the background and noisiest areas of the images. As well, and related to this new implementation of the algorithm, a reduction of the depth of the network architecture for improving the performance, and the development of a more precise evaluation method for testing the accuracy would be needed as the differences between implementations start to be small and hard to be detected by the naked eye.

The computer vision algorithm development is a research on itself almost independent of the holistic and broader scope covered by this thesis. Therefore, it seems that in the future it will have more business-oriented applications too. The prizes obtained in the competitions for startups ActúaUPM 2017, organized by the Polytechnic University of Madrid, and by the Arquia Foundation made possible to introduce this technology for capturing data to a number of companies and technologists. This opened the implementation of the technology in

different scopes quantification of urban spaces and crowd studies for big events, advertising, and for real estate development.

The tuning and improvement of this method of detection rely as well on the kind of hardware used and in streamlining the flow of data collection and processing. The possibility of applying this methodology to pre-recorded and to live streaming video requires as well different data treatment and storage which need to be addressed and explored. Additionally, different types of camera should be tested for taking into account quality of image and frame resolution which can affect the detection precision or the angle of the lenses which can facilitate the survey of a larger area.

With a more practical approach in mind and looking for new urban contexts to learn from them, the deployment of a new pilot research project using the whole analysis framework is proposed on Market Square in Pittsburgh (figure 73). The interdisciplinary perspective of this research with a focus on affecting design and policy decision making called the attention of Metro 21 at Carnegie Mellon University as an interesting technology and approach for address some concerns in the city. In March 2017, after the successful urban refurbishment of Market Square, Pittsburgh Downtown Partnership and the City of Pittsburgh decided to remove one of the most popular features which helped to regain this space to citizens: its chairs and tables. Although no causal link was drawn, it was justified as a temporary solution for dealing with the persisting misdemeanors in the area. However, no alternatives have been proposed yet, the issue still exists, and it is unknown how design decisions may affect precisely the utilization of the space. This informational gap can be covered by this technology and it can yield patterns of utilization of the space and inform how public authorities and space managers can make their decisions more effectively.



Figure 75. Market Square, Pittsburgh PA. Source: Google Maps

For this and future implementation of the analysis framework, new metrics should be implemented together with new settings of capturing devices. Among additional data which could be included, there are 3D Space Syntax techniques, active tracking of objects and people on the scene, multi-camera capture, and more precise weather and environmental parameters.

One important factor to be considered with the application of this computer vision algorithm to different locations is the training set. Depending on the particular targeted classes of interest for a given research project, and on the local specifications it may be necessary to fine-tune the convolutional neural network for grasping details off the general detection patterns. It would involve additional manual annotation and training routines, or even different algorithm settings depending on the location.

Further developments in technology rely fundamentally on the amount of processed and collected data. It is not unfeasible to think that once enough data is collected, classification and mass profiling of people or behaviors on the images would be a possible outcome. Much of the advances in machine learning and predictive techniques require enough tagged or classified data for computers to learn how to understand unseen information, but once behaviors on a location start to be classified, it would be possible for an appropriately trained and programmed algorithm to predict and classify attitude, conducts, goals, and behaviors of people in the space. These possibilities seemed to be behind the foreseen scenarios where this technology can help on defense and public safety tasks, although ethical, legal, and political issues are more obvious under the circumstances drawn by these applications.

A less controversial scenario where this novel information on the utilization of public spaces and how people behave in them is the valuable source of data for teaching autonomous devices to navigate crowded spaces and how to interact with complex environments where people move freely. Current technology barely can make autonomous vehicles to navigate on their own through the much more controlled conditions of a roadway. However, data on how people move across space is scarce.

5.3 Discussion

The proposed framework for informing policy and design decision making on this document is closely connected to two rising phenomena frequently present in current architecture and urbanism practices. This connection is not only conceptual or theoretical, but novel ways of approaching design workflows, from a technological, empirical and precise perspective can have a positive impact in how the different stakeholders involved in the process of city making understand these tasks.

5.3.1 Trends in Participatory Design

“The strong feeling is that participation, or rather pseudoparticipation, is being used as a socially acceptable shield behind which the authors can develop their technically-determined ideologies.”

(Blundell-Jones et al. 2005)

There are a number of different -actually, countless- factors to be considered in city making. It can be seen -and it has- as an intractable problem. But it does not deny the value of information which can be extracted from the urban realm. The unbalanced situation that people is facing with the concentration of data in few stakeholders and the lack of political and social counterbalances put at risk the possibility of real participation and control of prosumers of information. The need of information about the city, the well-being of its inhabitants and the performance of its infrastructure seem to be a trend which has come to stay. But the access to this information is still mostly opaque. Making more transparent data can break the informational dominance of the current datascape. This bivalent situation on the use of data between participatory work and concentration of information in few agents has been favoring mostly the latter. This is connected to the paternalistic understanding of the common ground by public authorities, using techniques close to manipulations for affecting the criteria of citizens for judge projects and persuade voters of new

policies. In this unbalance relation, the chance of giving to people tools for discovering by themselves the impact of their decision-making is greatly more pedagogical.

Simultaneously with the dissolution of unidirectional media and information broadcasting enabled by new technologies, fundamentally ubiquitous computing in personal devices and Internet, citizens have wanted to engage decision making in the public sphere. Governmental transparency and accountability and participatory trends have their translation in city-making processes in participatory open processes for design competitions, just as another stakeholder in the city, and collaborative negotiation processes for managing public spaces in bottom-up organizational structures represented in the new civic commons (Baldauf 2016).



Figure 76. Puerta del Sol occupation during the 15M movement, spring 2011. Madrid. Source: <https://crimethinc.com/2016/04/05/feature-from-15m-to-podemos-the-regeneration-of-spanish-democracy-and-the-maligned-promise-of-chaos>

Checking again the previous work which supported the current research, it is clear the political and social involvement of their motivations, at the intersection of the right of use of the public space in Madrid for any purpose, from political demonstration to economic utilization. However, embedded in this open-ended conflict of different agendas concerning the use of the city, it was symptomatic the first reaction of public authorities in the city after the end of the massive occupation of Puerta del Sol (figure 74) trying to remediate the tensions and safety risks in the use the most popular urban scenarios for political demonstration by redesigning them.



Figure 77. Winning proposal by Linzasoro&Sánchez Arquitectura for the redesign of Puerta del Sol, Madrid. 2014

Although the trigger for fostering this redesign was a well-defined set of issues related to public safety and compatibility of uses, the selected projects weren't addressing any of these parameters into the design (figure 75). Or even with more obvious political agendas in mind, some of the ideas drawn by the city council included the occupation of the space for constraining the possible uses.

These first movements were forecasting a change in the way of tackling urban transformation in Madrid, engaging the most frequent interest of citizens in involving themselves in the configuration of their built environment. Since then, the city as many others around the world has incorporated more democratic participatory practices in daily management, in the design of urban spaces, and even in the allocation of part of the resources for city budgeting.

In the same way that the digital revolution of the last decades popularized these collaborative mindsets by making available the required infrastructure for making them a feasible alternative at a big scale, the first theories of collaboration in design practice that emerged during the mid-20th century were a side effect of technologies and systematic methods for problem solving from computational techniques (Archer 1965). This systematic understanding of problem-solving applied to design domains was an important innovation but at the same the origin of the limitations of its implementation for urban planning. Although dynamic systems and simulations became a popular resource in this first wave of computational approaches in design, their failure is connected to the difficulty or impossibility to frame social design purely from a systematic and procedural point of view as in a machine. Even with today's computational power, the so-called "wicked problem" (Rittel & Webber

1973), is an unbeatable barrier which questions the deterministic approaches given to the use of technology as an enabler of new design methods. The outcomes of these approaches were far from being challenging as they offered very basic solutions reduced to the lowest common denominator, or on the other side answer very curated by experts' agendas.

This biased understanding of collaborative and participatory design, although not that obviously connected to technologically systematized processes yielded by computation, is still present. It raises the question of how these commoning processes are designed, managed and constructed. The position of this research, while recognizing this background and historical approaches to city making, is not trying to provide single solutions or definitive scenarios. It is neither intended for scaffolding the collaboration process between different stakeholders in the city from an organizational point of view nor for extending or updating urban cybernetics methods abandoned mostly in the 1970s. The underlying thought is mostly connected with providing precise and empirical knowledge about the outcomes of design and policy-making decision. While recognizing the open-ended character of the design and construction of the built environment, it explores ways of generating a critical vision of the functioning of cities.

When considering these new hypermediated participative processes in cities, it is not clear the kind of information provided for evaluating and assessing the quality, convenience, functioning, or effects of design proposals. Accepting a decision-making process more open to different stakeholders, including design experts, city officers, politicians, funders, and citizens (among others), how is it this processed informed? How are the projects assessed and evaluated? There are several examples of this poorly process without leaving the city of Madrid. In the case of the international competition for the refurbishment of plaza de España (figure 76), the 70 accepted projects were voted publicly by citizens in the first phase, although the most voted ones were finally rejected for the second phase due to technical reasons after the expert filtering (Costantini 2017).



Figure 78. Four of the 70 accepted proposals for the redesign of Plaza de España in Madrid. This is the kind of documentation provided to citizens for evaluating the different projects. Source: <https://www.somosmalasana.com>

Here, two questions are suggested. First, what kind of real power is given to people for taking into account their choices for decision making if just immediately after their preferences are completely ignored. It may be justified because of technical reason, as in this case, but then the second question comes up: non-experts have the right tools for evaluating these design proposals in an effective and informed way? A third one, related to the initial argument of this discussion can be added: is this dysfunctional process made on purpose for actually selling top-down processes, as much managed by experts and designers as before, with a nice participatory-simulated branding?

It is precisely within this context were developing a common ground for discussion, criticizing and assessing of urban environment from empirical information understandable for everybody, experts and non-experts are extremely valuable. It would reject informational or decision-making abuse for any stakeholder and it would leverage the different agendas embedded in the complex city-making process. Representation, visualization, and information are key resources.

5.3.2 Incremental Urban Interventions

Connected somehow to a more sensitive governance style, the top-down design approaches are as well engaging more persuasive and welcoming -maybe just clever for their own purposes- ways of intervening in the built environment. They are developing techniques for generating a broader agreement in constant negotiation with the critical mass of people inhabiting the city for being able to perform changes in a more concerned, reactive, and interconnected urban environment. These interventions in the space changing dynamically on-the-fly are dependent on reacting appropriately

to changes as part of that collective agreement. It is in this framework where control and management of information, including its collection, can play an important role.

Another effect to the rising concern of citizens and non-experts stakeholders across cities in the way that public authorities and city governments face urban transformation processes is the shift towards incremental urban interventions (van Karnenbeek & Janssen-Jansen 2018). The power of minimal low-intensity interventions in public space was already explored as transforming strategy for urban setting in well-studied examples such as the more than 700 Aldo van Eyck's playgrounds in Amsterdam (Lefaivre et al. 2002). However, the convergence of economical constraints -sometimes maybe more apparent than real ones- and public concern about government accountability together with the hypersensitivity of the latter to the reaction of 21st century hyperconnected public opinion have enhanced this kind of urban interventions. The timing has been as well the right one, encompassing economic, political, and social crisis to the replacement of a star-architects system to a more socially engaged kind of design.

Anyhow, current policymaking in cities is unfeasible to be successful without the participation, agreement, and implication of social-urban agents. The empowerment of not-decision-makers in cities through social networks and other technological augmentations have made traditional decision-makers to account for a broader range of sensibilities and needs in urban settings.

One of the issues in this context is how to make progress and accomplish a particular agenda in such a demanding setting, where more than ever the constant negotiation between stakeholders in the city is present. Even though many of these agendas have a conventional top-down approach which should clash with the participatory mood of current politics, incremental intervention looking for a progressive consent of users are increasingly more common.

There are two possible interpretations of this trend, which can be understood as an optimistic and a pessimistic vision. The optimistic version assumes that secular decision makers in cities find real value in the feedback that they can receive from listening citizens, for designing interventions in the urban space able to adapt over time and to be tuned to people's needs. Urban transformation is understood under these circumstances not as static and

prescriptive, but dynamic and reactive, open to change. Meanwhile, the pessimistic interpretation of this trend is somehow connected to the already mentioned pseudo-participation in design. In this scenario, top-down approaches to design from predefined agendas are not any more socially accepted so they have needed to find tactics to get people's approval. Incremental urban interventions become a tool of persuasion and ideological soft confrontation for getting public opinion's acquiescence. It is likely that both readings are happening at the same time, and even within the same project, there are components from both sides.

The pessimistic reading of these incremental process doesn't need to be understood only as a mean manipulating resource -if a nearly moral judgment can be used here-. While acknowledging the different sensitivities inhabiting the urban space, it enhances the expert view by facing real conditions and tries to engage and to adapt dynamically the project to these bounding constraints and more importantly it tries to persuade, convince and operate as a social transforming device.

This position is probably clearer if explained with the concrete examples related to the banning of traffic in many urban centers around the world. Two projects aiming a less car-centric design of congested urban centers looking for additional pedestrian spaces are the ones developed in Times Square in New York City (figure 77) and Paris-Plages. Even in both cases, with societies sensitive and concerned about environmental issues, any plan for reducing the amount of space for vehicles usually faces a lot of social opposition and generates hot controversies. However, in both cases, the new gained pedestrian spaces have been very successful despite the initial opposition. How's it possible? The use of temporary, quick, and inexpensive interventions almost as testing projects during holiday periods made possible to check its functioning with people. As well, the lack of big works, only with superficial treatment helped by making evident their reversibility. After collecting information and feedback from users, and implementing them into several iterations during a few years in successive design loops, and small changes over time, they accomplished successfully a change that at the beginning nobody seemed to like.

In this iterative, open-ended process of urban intervention, whether it is for questionable manipulating purposes or because of really caring about others, an effective, fast, precise, and non-invasive method for collecting data that matter for a project can make a difference.



Figure 79. Times Square "Pavement to Plazas" transformation, New York City. Source: NYCDOT/Earthpowernews

The interest of collecting systematic and empirical data for understanding the way that people use urban spaces as a resource for design is linked to the early steps of Quantifying Urbanism initiated by Whyte with his observations of the life of small urban spaces across Manhattan (Whyte 1979). Which is more incredible is that still urban planners collect data manually, in tedious, consuming, and unprecise survey campaigns. However, a catalog of new technologies able to generate data from the direct observation of real world is ready to use: the already mentioned RFID, infrared sensors, GPS and cell phone coverage, or the fundamental for this research, computer vision.

These techniques for extracting data from physical settings have been used in retail environments, but what is now possible is to go deeper and extract data from the utilization of the space and cross-reference them with what people may be thinking. While Whyte developed his quantitative analysis of urban spaces, Robert Propst conducted workspace research which would generate eventually the modern cubicle (Propst 1966). This parallelism is relevant to overcoming the purely intuition-driven practice traditional in design is what some architecture industry related companies like WeWork (Sisson 2018), Woods Bagot's Superspace (Derix & Dalton 2016), Zaha Hadid or even furniture manufacturer as Steelcase (Denny 2018) are currently exploring, and they are focusing mostly on workplaces. And differently than parametricism and generative approaches, they develop an agenda interested in a human-centric vision of design enabled by new technologies instead of a space directly curated by algorithms:

"The space is performing in a way that suits your needs, without overtly being a space of the digital"

Daniel David, WeWork (Sisson 2018)

Still, there is a gap in linking these approaches to an urban scale setting, although some important progress is being made for deploying a real implementation such in the Sidewalks neighborhood in Toronto (Sidewalk Labs 2017). These inherited technologies which have been used at some extreme in current Smart Cities are aimed to generate deeper transformations in policy making and in the physical landscape enabled by an unintrusive use of data and algorithms.

What these changes in the building industry are forecasting is the value of informational feedback loops as an inestimable resource of knowledge for evaluating and testing design, for learning from people behavior, and tuning experts' decisions accordingly to users' needs in a seamlessly way.

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Annex: A Historical Perspective. Expanding the Discussion

In connection with the broader network of projects and lines of thought which new technologies and computational techniques yielded for design practice during the 20th century, three additional relevant topics are discussed from a more historical perspective in mind. Therefore, this last part is presented as an annex to the thesis, as part of a research in progress and lines of thought to be developed in future steps of this work. Their provisionality and gaps are closely related to the previously mentioned work in progress of the map introduced at the beginning of the document (figure 3).

At the same time, these three topics are related to questions already discussed previously in this document. They rise matters which can be used for expanding the considerations of this project and for drawing relations to other technological-driven design approaches. These topics are not plotted here as definite overviews, but open discussions to be developed in next steps of this research. They will need to be expanded and connected to many other ideas while expanding the map which introduces this document.

More concretely, the shift in the representation faces the importance of visualization and graphical encoding of information as an operational tool for planning, for designing, and for making understandable and transparent the information for human beings. The latter is particularly important given the extreme complexity of the systems that are being created by the addition of more datasets and parameters. In the case of Behavioral and control architecture, it accounts for the role of the design of spaces as a political device and how it can be used for affecting the behavior of people. It almost represents a perversion of the framework proposed in this document, it means, the instrumentalization of spatial knowledge. Finally, the third topic covers a critical vision of Smart Cities as a simplistic implementation of technological devices which could be positively used for the design practice, but which are providing a very limited effect in spatial transformations. Worse than these unaccomplished expectations, there are the risk and controversies about a poor management of privacy related to massive used of data.

The Shift in Representation

The product of spatial design is conditioned deeply by the means, processes, and tools available for its production (e.g. Gehry's Bilbao Guggenheim wouldn't have been possible without the development of appropriate CAD software). Each architecture has been the result of its own time. The new means and opportunities facilitated by using computers during the 20th century have enabled a more precise and complex definition of space. The number of variables encoded into the built environment is virtually endless, with a level of precision never reached before. But its implications are beyond the pure representational purposes, as it involves a shift in the scientific understanding of nature, and it yields new strategies for communicating with technology for expanding our range of action. It is, machines shaped us and our understanding of the world, for being able to work with them instead of simply using them.

“To grasp space, to know how to see it, is the key to the understanding of the building”

Bruno Zevi (Zevi 1948)

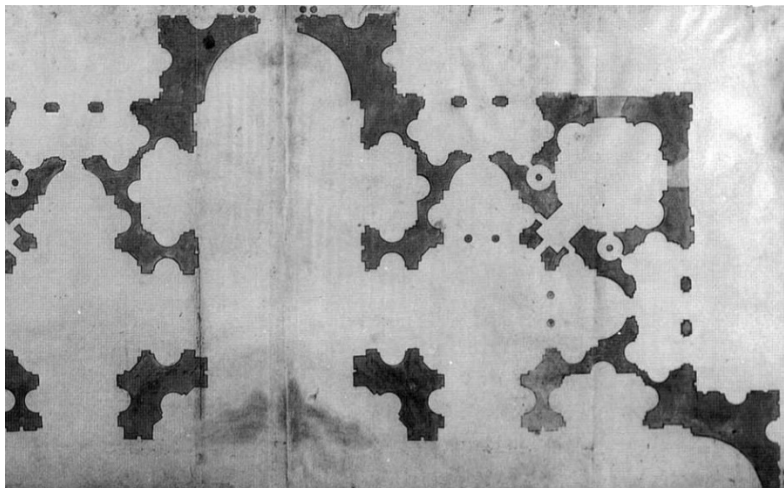


Figure 80. St. Peter's plan. D. Bramante (1506).

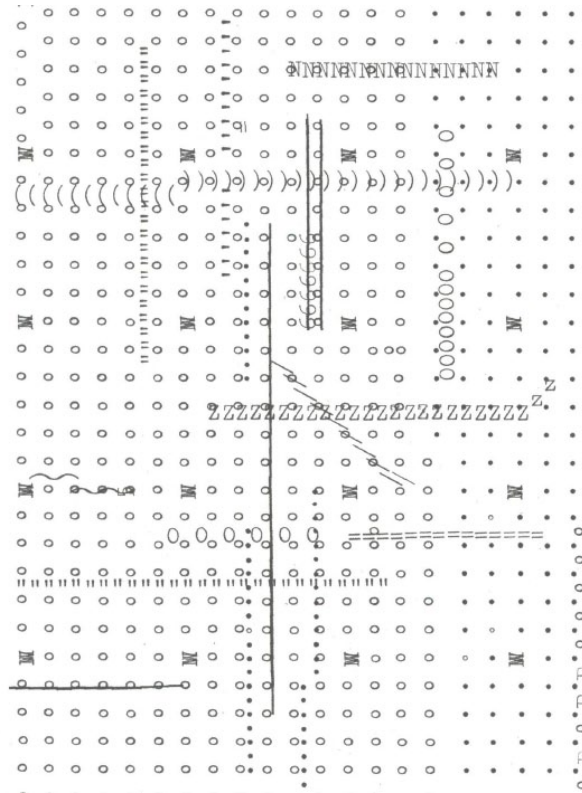


Figure 81. Non-Stop City, Archizoom (1970).

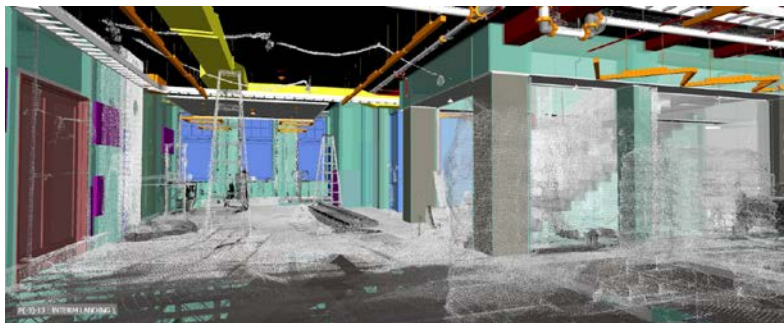


Figure 82. BIM + VR integration, Paracosm (2016).

If we compare the classic architectural plan drawings from the Italian Renaissance with some of the first computer-mediated design documents from the mid-20th century, and with a state-of-the-art architecture 3D visualization, we can recognize how different they look. In the classicism tradition document, the representation code is basically reduced to a binary landscape: Black and white; Filled and empty. The understanding of the built environment is limited to an articulation defined by those spaces occupied by constructive components drawn in black, and the space available for users in between those black spaces represented in white (more precisely, the lack of ink).

Differently, if we observe a current state-of-the-art architecture plan the degree of information coded into the drawing is much higher. This is not only because of the larger number of layers of information or an increasing level of sophistication in construction from monolithic single-layered structures to multi-layered highly-technical designs. Although, proof of the latter can be seen just by looking at how many lines and symbols may have appeared where before only a black filling -or a lack of it- was drawn. More interestingly, a continuous surveying of every single point of the represented space is taking place.

This change can be understood as a dimensional gain, going from a monochrome bitmap image (displaying exclusively black -0- and white -1- pixels) to a multichannel 32-bits color image with a rich virtually continuous gradient of colors and hues with different levels (Lévy 1987).

The standards for a graphic architectural representation developed during the Renaissance meant at that time an innovation in the definition of the role of the designer. It set a difference comparatively to the previous models of spatial planning and architectural design represented by the authority expressed in the written word following the paradigm set by Vitruvius' *De architectura* (Vitruvius Pollio. et al. 1914) and the regression of the discipline from that rationalisation embodied in the medieval practice based on the living materiality of construction driven by groups of artisans, builders, and master masons. The birth of this Renaissance novelty can be located on Alberti's *De Re Aedificatoria* (Alberti 1988) distinction between the drawing of the building (*lineamenta*) and the construction of the building (*structura*). It is precisely on this drawing artifact where the geometrization of architecture is described and the mathematization of the representation is more obvious (Cardoso Llach 2012). This scientific measurement of a present and future (projected) reality is not completely new in the Renaissance, as there are precedents in classic ancient architecture -which after all is the source of the humanistic revolution of the 1400's in Italy- and even in the mastery collective design action of Middle Ages. Anyhow, what is common to this system is the mathematical technology associated, whose more advanced construct is the fraction.

However, the shift in the representation of architecture by the digital revolution requires a previous change, from fractions to decimal numbers (Stevin & Norton 1608; Lynn 2005). It means moving from a framework of thinking dominated by proportions between the part and

the whole, and between parts themselves, to a system where every single point could be described individually but within a continuous interconnected system.

The change of the representation is a consequence of these past changes, based on the combination of notational systems, with Albertian representation, and data processing using the computer as the universal representational machine (Cardoso Llach 2012). But it goes beyond and at the same time, it is performative and generative towards architecture and design (Sheil et al. 2016). In the most analytical strict form, it can be referred to infinitesimal calculus as a different paradigm of describing reality.

The binary, black and white representation reflects a top-down approach towards design which traditionally dominated the design practice. It was defined based on objects, on classical compositional rules, and on relationships between objects through hierarchy and control of the environment to shape a whole. However, the continuous registering of the space manifests a bottom-up understanding of how the environment is configured, through a complex set of local relations between individual agents or entities.

“Form matters, but not so much the forms of things as the forms between things.”
(Allen 2015).

The digital framework seems to be introduced here as a must for the continuous and high-fidelity representation of the space, but it is necessarily true. The computational processing of information has helped to outline this practice, but computational thinking predates the birth of computers (Häring & Joedicke 1982).

Interestingly there is a major contradiction. From a continuous analog information processing landscape which is giving binary representations of the space, to a digital discrete informational landscape which is providing a continuous, infinitesimal, description of the space.

There is an important and deeper representational difference in this shift which affects the understanding of the informational space. While in the traditional analogical image blank space can be informationally empty, in the digital image, because of the technical coding, it requires the same density of information. The contrast figure-background is not anymore operational, but the interaction between different fields of information (Allen 2015).

The shift in the representation is a vector of transformation operating at many different levels, with instrumental and methodological repercussions. It is not only a purely formal-aesthetic change but a knowledge shift (Carpo 2014). Considering the mechanistic understanding of the scientific method, and how particularly Westerner thinkers and scientists have traditionally modeled the world, there is a novelty in this approach. The classical scientific approach assumes that nature can be controlled, idealized. No matter the complexity of the phenomena, it can be described as a sum and composition of more or less sophisticated, most of the times, mathematical models. Those models following laws are validated as far as they are able to replicate noticeable the targeted portion of reality. They are refuted as soon as it is discovered that their outcome is not matching the behavior observed. An important note here it is to recognize that the technological improvement of instruments of measurement and observation has been pulled the understanding of the reality forward, making previous understandings of reality turn obsolete. And at the same time, the need to model more complex phenomena required more sophisticated mathematical knowledge, it is new representations. Representation, technology, and knowledge through modeling have been the drivers of the scientific development.

The knowledge shift didn't happen suddenly in the last few years with the popularisation of the use of computers and a much higher power of information processing, but this trend belongs to a longer historical transformation. The Second War World modified the American scientific structures and it is at the origin of the Cold War Military-Industrial-Academic Complex (Leslie 1993). The collaborative and interdisciplinary networks of scholars and researchers with different backgrounds generated new ways of working. The term "Trading zone" (Galison 1996) refers precisely to a new paradigm of research based on simulations enabled by new computational tools in the mid-20th century whose birth is at the development of new methods for simulating the effect of nuclear bombs. It is not still a complete breakdown with the stochastic understanding of reality but it announces some distancing from the ideal Platonic mathematical model. However, it made possible the cooperation from different practitioners, in defense-oriented research, and later on in other fields.

Within this context of interdisciplinary trends in research, specifically in the domain of design, during the first wage of computational approaches for spatial planning in between the 1950's

and the 1970's new attempts of merging representation of space with more scientific mindsets were developed. The use of computers required a translation of the existing representational techniques from spatial planning to the language of these new machines. It was a basic requirement, a prerequisite for making possible the computational treatment of space and its conditions. It meant almost redeveloping from scratch the already existing knowledge and expertise since the Renaissance for representing on 2D the 3D spatial condition, but this time, in a computer. This encoding task was started at MIT by Larry Roberts, but it opened new possibilities on the use of the representations of space in computer for a more complex set of operations and associations (Coons 1963) not even imagined previously in the historical architectural drawing.

This fundamental encoding of the Westerner tradition of spatial representation in drawing for the computer was only the first example of a series of expansions in the ways of representing the space of the human experience and the kind of interaction which could be modeled in a computer. Two independent schools in the United Kingdom were the origin of the new representational paradigms needed for exploring new generative systems for spatial design (Derix 2014): the Architectural Association (AA) and the Centre for Land-Use and Built Environment (LUBFS) at Cambridge University. Both schools followed extremely different approaches caused by the goals and background of their promoters, and their different exploration led to different representations that made possible different ways of processing information and generating new systems of spatial organization. On the one hand, at the AA in London, Paul Coates and John Frazer were two architects who were interested in the use of computation for designing and started to explore the use of self-organizing systems. On the other hand, LUBFS was mainly formed by researchers looking for new mathematical representations of topological space (Derix 2014).

New ways of representation were not only exclusive of the results from the LUBFS scientists' activity, but Coates and Frazer's work on autonomous systems as well provided new models of representations derived from their distributed systems. It expanded the possibilities of the cybernetic machine-like closed system to a distributed system formed by multiples agents, programmed individually, but whose interaction led to emergent non-predictable behavior defining the global state of the system. It established a different paradigm of systems control. Parameters and linear algorithms are not here hard-coded in a deterministic way, but it is an

emergent intelligence from the local action happening in the system which defines the behavior.

Part of the science framework established during the second half of the 20th century is facing a turning point enabled the massive capacity of data collection, storage, and processing. Some scholars announce the end of the classical scientific paradigm, turning into outdated the need of generalizing, simplify and idealize reality within laws, models, and mathematical algebra through a virtually endless collection of data points for describing the reality (Carpo 2014). This new paradigm questions the prerequisite of a generalizable a priori model for understanding the reality. Even, within the most aesthetic manifestations, representations of complex geometric through well known digital artifacts as meshes and NURBS surfaces start to show alternatives based on point clouds (Nurulize 2017) in a very graphical parallelism of data points.

“Nothing exists except atoms and empty space, everything else is opinion.”

Democritus



Figure 83. Atom view 3D representation based only on point clouds.

This shift has even deeper implication from the point of view of human-machine interaction. Generalization and flexibility are human skills. We are able to “program ourselves contingently” (Licklider 1960) while being extremely incompetent for dealing with that massive amount of repetitive well-formatted data machines are very fast and accurate at. It can be argued that technological evolution during the last 50 years has been driven for the desire of overcoming the machine as a “partner in thought” (Turkle 1984) for reaching the Licklider’s dream of the cognitive simulation (Edwards 1997).

These new ways of encoding information populating the space and defining its features are not denying the value of older methods. But they need to be enhanced for embracing new approaches to design. Computational thinking applied to design conditions and restrains these representations because of the implicit models of data structures and processing methods (Carranza 2014). There is a discussion left open at this point about the limits set by computational methods for enabling design workflows. One of the constraints acknowledged by this research is the tension or lack of agreement between the mathematical precision of computer-based approaches and the loose intuition-based knowledge that has driven design practice. There are trade-offs in both perspectives, but different representation yields different levels of information which can be implemented in design, even from the intuition-based practice.

Even the human intuitive perception of time is overcome by the computers, displaying a picture of reality which eludes human understanding. The increase of resolution affects time perspective too as shown in such a harsh context as financing, where most of the operations are controlled automatically by cryptic algorithms for High-Frequency Trading (HFT) (Aldridge 2013)

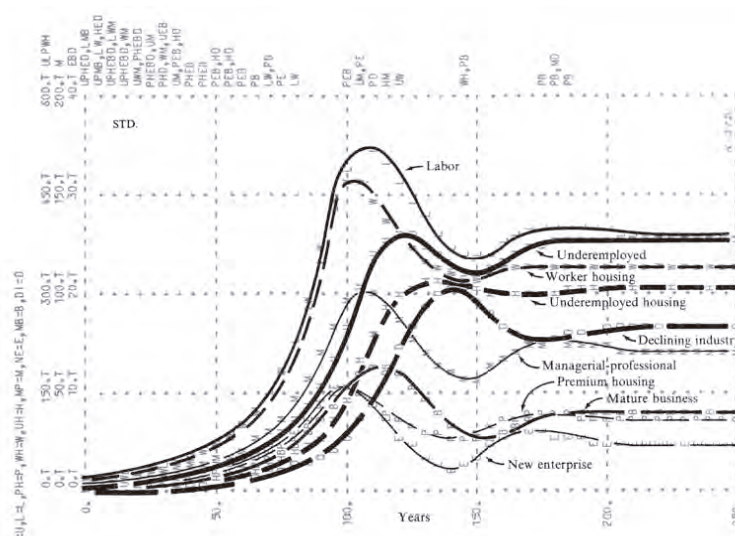


Figure 1-1 Life cycle of an urban area—250 years of internal development, maturity, and stagnation.

Figure 84. Life Cycle of an Urban Area, J. Forrester. 1969

What You See Is What Your Get explores different sources of information whose incompatible representation and aggregation modes clash with conventional design practice based on intuition and knowledge curated by experience. The open-ended character of the research

discusses the integration of novel modes of visualization and representation as the necessary translation for integrating this novel knowledge into design workflows. But at the same time, it advocates for the transformation of design expertise for accepting, using, and embracing the use of empirical knowledge.

Behavioral and Control Architecture

Whether historical architecture was criticized as an instrument of power or due to its lack of scientific analysis beyond the oversimplified narrative offered by the evolution of formal styles, spatial design engaged a frenetic evolution over the last 100 years. The theories developed around the beginning of the 20th century proposing the influence of perception, including the experience of the space, in the construction of human cognition. Early computational techniques tried to collect data for assessing these theories, but it has been much more recently when the merging of a more precise understanding of cognitive processes operating in human beings, and how the perception of physical world affects people through more accurate sensing techniques. This knowledge can effectively enable the instrumentalization of spatial design for determining people behavior as already exploited in retail spaces. However, the same knowledge can be used differently for predicting and enhancing affordances of the space, as part of the open-ended evaluation and testing process of design.

“We shape our buildings, and afterward our buildings shape us”
Winston Churchill, 1924

The influence of the built environment on people's behavior and perception is intrinsic to the history of architecture. We find examples of more or less on purpose planned use of this kind of resources in ancient classical architecture (Darling 2004), in the dynamic perception of baroque spatiality (Deleuze 1993), for defensive purposes in bent-gateways (Siano 2013) or complex bastion forts (Duffy 2006) or as political device for social control in early urban planning (Shapiro 1982). However, an empirical and scientific use of it, and its utilization as a source of knowledge for spatial design beyond purely perceptual aspects haven't been introduced in the corpus of architectural discourse until much more recent times.

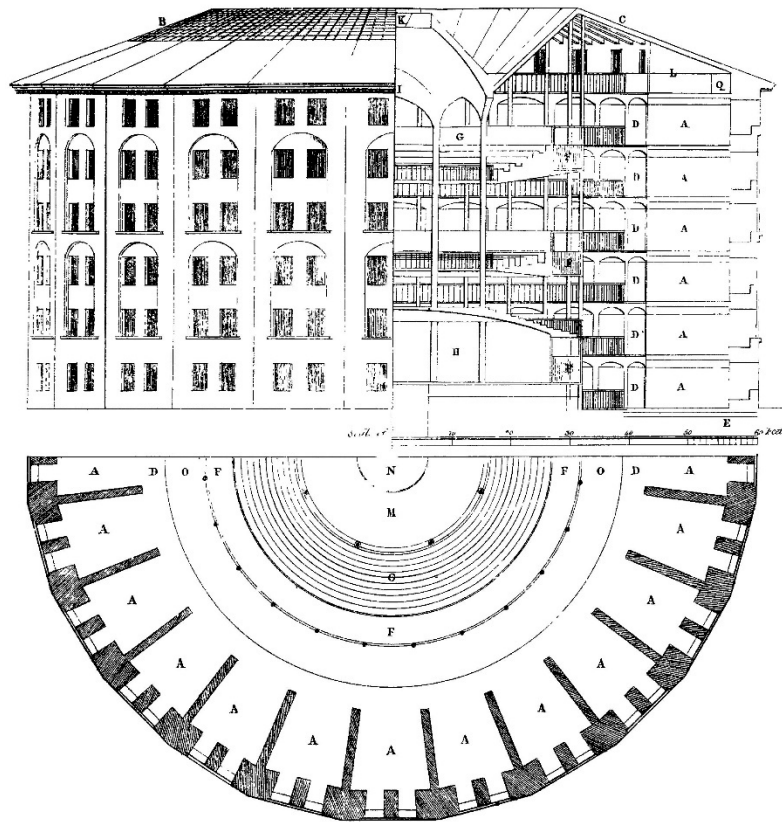


Figure 85. Jeremy Bentham's Panopticon plan, elevation, and section cut.

In more contemporary terms, and with a larger impact on space configuration, the study of the influence of architectural and urban settings on people was already explored for control purposes during the 18th century. In 1780 the English philosopher and jurist Jeremy Bentham envisioned the perfect prison design that he called the Panopticon (Bentham 1843)¹². It was a circular building, with the cells for inmates in the periphery of the building monitored from

¹² Mentioning the Panopticum as an architectural device for power connect directly with Foucault's thoughts on the pairing of power and knowledge. He uses precisely this architectural example for showing and internalized coercion formalized as a spatial design. Two associations are explored in this layout by Foucault: a system for social control and the idea of power-knowledge. Therefore a power and knowledge generated a self-reinforcing circular process enabled by the accurate use of spatial planning (Foucault 1978). This chapter when discussing the relationship between the knowledge embedded in the design of spatial layouts and their influence in people behavior are referring to this possible instrumentalization of architecture, purposely or not, for orienting human action.

a single central "Inspection Lodge". It was conceived as an architecture of control and power, which was affected to affect psychologically to their users. It can be considered as one of the first examples of using design-based strategies for an on-purpose modification of human behavior. This idea of the Panopticon is going to be recurrent during this document, with a contemporary reformulation through the use of cameras and images as one of the most valuable sources of information.

The relationship between control tactics and change in the state of the mood of the city has been explored and formulated under different structures. The modification of the behavior of space users (it means citizens in the case of cities) modifies the dynamics of the city, and at the same time, it can be promoted directly through spontaneous self-surveillance. This horizontal -maybe bottom-up, if preferred- can be contrasted through a top-down architecture of control, from the aforementioned Panopticon to the ultra-technological version of cameras control rooms. Different reinterpretations of the same topic: watch and being watched as changing factor though self-control: *We are the lucky possessors of a city order that makes it relatively simple to keep the peace because there are plenty of eyes on the street.* (Jacobs 1961).



Figure 86. IBM Operations Center for the Prefeitura of Rio de Janeiro (Brazil).

A commonplace in the history of architecture and city making is the assumption of how buildings, and in general, the urban form, could influence society and modify its behavior. Independently of the goal of operating under that mindset, either for control (Bentham 1843), economic performance (Garnier 1910; Muñoz Sanz 2015) societal change (Rosenthal

1994)¹³ or just with the open-ended aim of improving society, this understanding is highly connected to a scientific and mechanistic understanding of the world. However, traditionally there have been extremely few attempts at outlining an empirical and scientific knowledge useful for designers on those links between the built environment and people behavior.

From understanding architecture in the terms of the historical evolution of formal styles and construction techniques to be seen as a dynamic and performative device with the power to affect people and its social construct through space, there is a long evolution. Even omitting the precedents of artifacts from classical and baroque tricks, it is from the end of the 19th century when the shift in the way scholars understand architecture speeded up. August Schmarsow was one of the precursors of advocating for a scientific approach to art (*Kunstwissenschaft*), focusing on a purely spatial approach to architecture when he redefined it as the "creatress of space" (*Raumgestalterin*) in his inaugural lecture at the University of Leipzig in 1893. His proposal is new because of explaining architecture from a dynamic model. This generative approach is based on the sensorial experiences collected from the movement of people through space, and this experience is what makes possible to engage and forming architecture. This concept is what Schmarsow named 'kinetic perception' (Schmarsow 1893).

This revolutionary and ground-breaking coined term applied directly to the conception of architecture was in fact not developed isolatedly, but it was possible due to the particular structure of research in arts and culture developed in Germany during the end of the 19th century. This research ecosystem of blurred disciplinary boundaries had a very human-centric connecting thread on a common interest for understanding the interaction between individuals and between them and their environment, whose foundations were already led by Jacob Burckhardt (Burckhardt 1860) situating to the human being as an active transformative agent. It is within this ecosystem where the foundational psychology theories for Schmarsow's approach: the complementary aesthetic concepts of empathy (*Einfühlung*) by Robert Vischer and Theodor Lipps. While the first one focuses on the sensorial experience

¹³ The role of the architecture of the Russia avant-garde was social transformation, materialized the new house-commune type as a social condenser whose best-known example is the Ginzburg and Milini's Narkomfin in Moscow (1928-30).

derived from the embodiment of individuals within their environment (although visibility is seen as key to a fully embodied experience) (Vischer 1994) as generative process in aesthetics, Lipps explains his aesthetics from the correlations between internal cognitive structures in the individual and the external objects (Lipps 1923).

Schmarsow is not the only scholar who expanded the study of the process of creation of architecture from those new ideas of aesthetics, and somehow his 'kinetic perception' contribution can be seen as an alternative to Wölfflin's to architecture form (Gullberg 2016). Differently than in the theory proposed by Schmarsow where the movement through space activates individual's sense of space (*Raumgefühl*) and spatial imagination (*Raumphantasie*), the latter saw the external object as a simple milieu (*Umwelt*) (Wallenstein 2004) without that dynamic and organic component (*Raumgestalterin*). Ultimately, it can be seen that Schmarsow's theory is somehow closer to the more sensorial approach of Vischer while the more static assumptions by Wölfflin are more related to psychological isomorphisms pointed out by Lipps, and which remind to some of the Gestalt ideas about cognitive isomorphisms (Köhler 1920) which were booming around the same time.

The exploration of a systematic and organic way of facing the architectural design was a common topic among practitioners in Europe during the 1920s and 1930s. Hugo Häring proposed the concept of 'intrinsic form' (*wesenhafte Gestalt*) as a way of defining the relations between user and space (Häring & Joedicke 1982). It establishes a clear parallelism with the previous developed ideas of aesthetics by Vischer and Lipps, but in this case, it will be implemented by an architect: the construction should receive the form of the function which needs to perform as a human organ. Therefore, formal requirements within an organic framework of design should not be determined by external factors, but as a result of the research from the 'intrinsic form' (Häring 1951).

Häring used precisely one project of an elementary school by Hans Scharoun as the perfect example of his ideas about organic design. Their harmony towards the relations between users of space and the space itself as the foundation of an organic approach to design was already stated by Adolf Behne in 1923 (Behne 1926) when he matched Häring and Scharoun approaches with the Developmental Mechanics of Organisms (Roux 1895). The presence of Häring at the CIAM and in the after Second World War architecture and planning circles was progressively dismissing due to personal and ideological confrontations in the avant-gardist

group of practitioners leading the profession (García Roig 2004), and his reduced literary production has left us with few examples of his ideas. However, in the case of Scharoun, it can be observed the deployment of an architectural design methodology based on the empirical knowledge based on these correlations between space and user, that originally are named '*Konkordanzen*'. Nevertheless, due to the lack of determinism in these structures, Scharoun was just able to simulate these relations of concordant structures, which explains the coined term by him for explaining his methodology: 'Improvisations' (Janofske 1984; Derix 2014).

A half-century after the development of the first theories which accounted for the relations between space and users as a basic construct of architecture, small guidance existed, and even fewer systematic treatment had been developed. Bruno Zevi recovered some of the Wölfflin ideas to update them even though not few scholars have pointed out his more radical political and ideological bias. Zevi engaged the rupture with classicist architecture based on formal style evolution, not by scientific conviction, but as an opposition to an architecture that he considered as an expression of ruling power. Even so, he expanded the scope of the active configuration of architecture through movement in two aspects: exceeding the limits of the individual and envisioning the process of creating architecture as a society builder (Tournikiotis 1999), and by enriching the physical dimensionality of experiencing space with time. Although the work of Zevi is ascribed to a genealogy of thought coming from Burckhardt, Wölfflin, Giedion, and Pevsner, it agrees with Schmarsow in situating the movement through space as the key action for generating architecture. However, opposed to the latter, Zevi provides more guidance such as starting every single project from scratch, as the very first one, from a list of needs and functions (Zevi 1974). It reminds strongly of the criticism argued by Häring when describing the limitations of the formal suggestions of historic styles (Häring 1951). In this more ideologically-driven perspective by Zevi, it is important to notice how what he uses as an argument for supporting his critique to classicism, the use of architecture as a top-down instrument of power, is today a valid discourse. And the computational methods deployed over the last decades establish a controversial relationship with the control of users. Even further, an enforcing role of spatial design can be detected when using it for conditioning users' behavior in the built environment.

Anyhow, it is necessary to frame historically (and technically) the development of these systematic approaches towards design for understanding the limitations which were already recognized by Scharoun. Schmarsow and Wölfflin kept a fundamentally theoretical approach which doubtless was extremely useful for the development of more applied systematic approaches to architecture by practitioners such as Häring and Scharoun. However, the latter accounted for the lack of determinism, which at some point can be completely true as it will be discussed later in this document. Scharoun needed to restrict himself to an almost making-up of the whole real empirical experience of the building for informing the design, what means acknowledging the lack of necessary tools for accomplishing and testing these plotted theories. He was missing tools, technology, experience and protocols for providing real and empirical content for those newly created approaches to design. This is the framework which can be paired with some kind of computational thinking before the use of computers, but it was already paving the way for the adoption of computationally-enabled technology.

The new interdisciplinary research environment fostered by defense purposes and highly centered around the use of new computational tools created after the Second World War was key for the birth of the first computational metaphor and philosophy of technology: Cybernetics (Turner 2006). Wiener materializes this new field of thought working on defense systems, for tracking and shooting down aircrafts and the crucial contribution of his work was conceptualizing the behavior of a natural system into a self-regulating mechanism whose behavior can be described by mathematical formulas. He actually gave rise to cybernetics as "the scientific study of control and communication in the animal and the machine" (Wiener 1965). Here control wasn't centralized, but it responded to the internal dynamics and probabilistic interaction between its components. As a result, this framework expanded the until then known human capabilities, didn't transfer either all the control to machines as autonomous entities, but mostly the newly expanded capacities came from shared control. As it can be seen, this context was aligned with the already mentioned Licklider's man-computer collaboration (Licklider 1960).

This systematic vision of human organizations would find a direct connection with the urban environment when Jane Jacobs states on her *The Death and Life of Great American Cities* that cities were systems of "organized complexity, where the numerous spatial constituents

are highly interconnected and dependent on each other" (Jacobs 1961). For explaining the kind of problem a city is and how to deal with it, she used the classification of created by Warrant Weaver in 1958 for contextualizing the kind of issues science faced: "problems of simplicity; problems of disorganized complexity; and problems of organized complexity" (Weaver 1958). Problems of simplicity are ones where two variables are related to each other. This is the only kind of problems, so far, where human knowledge has accomplished a major progress. The second type, problems of disorganized complexity, are those ones made up of large systems with many variables which are subject to analysis through statistical analysis. It was the third type, problems of organized complexity, where also those large systems with many variables, but this time they are connected, affecting each other in intricate feedback relations that causes change over time.

Weaver and Jacobs considered urban systems as problems of organized complexity, although they faced this diagnosis with opposite moods. While Weaver trusted in the development of a larger computing power during the next years for being able to tackle these complex intractable problems following the optimistic technological logic of his previous works in cybernetics and, again, closely related to defense systems; Jacobs complained about the short-sightedness of urban theorists assuming urban issues as problems of simplicity and of disorganized complexity, and accounted for the intractability of the complexity of relationships, interests, needs, and activities embedded in the city.

Weaver worked with Norbert Wiener in the development of new Fire Control mechanisms during the Second World War. But both were conscious about the value of these new systems, and the thought and logic behind them beyond warfare. In these terms, Weaver expressed the importance of Wiener's ideas: "When this war is over, the theory and mechanization of smoothing will be one of the outstanding contributions of the NDRC fire control group" (Mindell 2002). In effect, Wiener, the father of Cybernetics as a discipline, quickly exceeded the purely engineering and defense-focused approaches of the new field and extended this system mindset to human organizations in *The Human use of Human Being: Cybernetics and Society* (Wiener 1954), and expanded the approach of the possibility of information processing including the last theories on information and communication theory, precisely developed by Weaver and Claude Shannon in their *Mathematical Theory of Communication* (Shannon & Weaver 1949). Consequently, the understanding of cities as

complex systems which should be analyzed and controlled efficiently was the ground for the application of new cybernetic theories. The processing of the information coming from the plethora of sources and parameters present in the urban environment could be controlled through a complex network of interconnected feedback loops. Although the initial approach towards cybernetics was closer to an adaptive system responsive to the interactions between humans, machines, and events as it was envisioned by Wiener for providing a bottom-up counterbalance to the typical top-down command -again, it was developed within a military context-; this first strategies were more focused on the top-down control of the system.

In the same way than cybernetics theory was generated in a warfare context, and their approaches were applied to urban planning, cities became in the years after the Second World War defense devices which were subject to be controlled as radar systems or artillery. Several phenomena happened around the same time after the war. On the one hand, the huge amount of resources invested in military-oriented research needed to be readdressed for other issues, among them, urban planning. On the other way, the trend in research and the irruption of computers into science gave birth to some sort of fascination on computer-based analysis, turning into paramount exploring and processing larger amounts of data (Dutta et al. 2013).

Christian Derix highlights three main waves in the development of computational methodologies for encompassing the human-centric trend in architectural design already announced by these pioneers: space as Heuristic Generation, Interactions in the Field, and Cognitive Conditions (Derix 2014).

As already mentioned when discussing about the new modes of representations that the use of computers caused during the first wage of digitation, there are two British research centers key in the development of new systems of computationally mediated spatial planning: the Architectural Association (AA) and the Centre for Land-Use and Built Environment (LUBFS) at Cambridge University. Coates and Frazer are at the origin of many of the current algorithms used for spatial design such as evolutionary algorithms, agent-based modeling, Lindenmayer Systems, and cellular automata. LUBFS scientists created a series of new metrics, graphs, and networks for space representation. As the whole, they set the basis for much of the generative design practice today although its impact on daily practice is small.

A different kind of computational development over the last years has been computational cognition. This new field of research tries to expand and to provide empirical information and support to many of the theories developed initially by Gestalt scholars, and later developed by Rudolf Arnheim's perception theories (Arnheim 1954), paired by Jean Piaget with his spatial learning fed by incremental knowledge from experience and interaction, and James J. Gibson's ecological perception through movement in a convergent way with Schmarsow's 'kinetic perception'. At the origin of these cognitive and psychological theories, it can be found again the blurry disciplinary boundaries fostered in Germany during the end of the 19th century, which as result caused the birth of novel scientific theories, methods, and approaches. The complexity of the processes that regulate human cognition in general, and in particular, spatial human perception, has been available -and only partially- recently due to the higher power of computation for developing more accurate models and collecting enough data.

The evidence of the relevance of this new field, but as well of its novelty is well shown by recent experiments which are able to validate some of the perceptual and phenomenological theories about the experience of space already pointed out by key theorists in the 20th century such as Jane Jacobs and the intractable experience of the city (Jacobs 1961) and the work about mental map developed by Kevin Lynch (Lynch 1960). In the case of Jacobs, the new availability of data and powerful analytical tools, even unimaginable back in the 1960s is validating empirically some of these powerful ideas about how to promote life in the city (De Nadai, Fondazione, et al. 2016; De Nadai, Vieri, et al. 2016)

Particularly, these two recent contributions from the computational side of spatial planning open new inside-out and bottom-up perspectives for the understanding of people's behavior in the built environment. Distributed systems expand the possibility of modeling complex social and multi-agent settings and allow to simulate and predict outcomes from individual actions. In the same way, the cognitive approach to perception is able to contribute with arguments about the inner functioning of individuals and, more importantly, empirical information -if not even explanation- about the relations between users and stimuli -spatial features if it is preferred-. This opens the opportunities of designers to impact more effectively into inhabitants of space, although the risk of manipulating authoritarianism is real,

even without the conscience of the subjects of that cognitive transformation [informative dominance ref].

From a more pragmatic and operative point of view, these different computational developments required a design framework able to articulate, scientifically and empirically, the experiments for testing the design framework proposal. Space Syntax has been precisely one of the few computational techniques used for outlining correlations between people behaviors and spatial features. It has yielded a more scientific, it is, quantifiable, vision of the built environment.

“Should we feed all the data for a given problem to a computer? Why not? Because the machine not only uses data based on questions that can be answered with a yes or a no. And the computer itself only responds with a yes or a no. Moreover, can anyone claim that all the data have been assembled? Who is going to legitimate this use of totality? [...] Doesn’t the machine risk becoming an instrument in the hands of pressure groups and politicians? Isn’t it already a weapon for those in power and those who serve them?”

(Lefebvre 2003)

Herman Hertzberger, as a structuralist, advocates for an Architecture that shouldn't provide any closed final solution for a problem, but rather a framework to solve a plethora of issues. It means being flexible and adaptable over time and depending on the needs of users. It is the application of the perceptual psychology concept of affordance as a mediation between the intentions of design and how space is used. It is translated in how forms can orient actions and behavior.

What You See Is What You Get operates in this understanding of architectural practice that can learn from the possibilities of affecting the experience of people. It is not deterministic or utilitarian in its proposal, it does not advocate for a particular orientation of this knowledge. The approach is even more basic because it explored methodologies for generating that novel knowledge, a framework. Over 30 parameters are considered, 100 more could be included, different analysis methods implemented. What is worthy in this research is the exploratory work inquiring about a more flexible empirical and open-ended vision of environmental planning in connection with how its occupants behave because of it.

A not so Smart City

“[...] the city is a computer, the streetscape is the interface, you are the cursor, and your smartphone is the input device. This is the user-based, bottom-up version of the city-as-computer idea, but there’s also a top-down version, which is systems-based. It looks at urban systems such as transit, garbage, and water and wonders whether the city could be more efficient and better organized if these systems were “smart.”

(McFedries 2014)

Neither ‘Smart City’ is a completely new term (it appeared in the 19th century), nor the city is a lab (Meisterlin 2014). The mechanistic reductionist understanding of linear computational processes (following the example of the Turing Machine) is not allowing to tackle a transformation in the processes of city design. The paradigm of an absolutely monitored city from the engineering point of view, which is translated into a simplistic approach by filling the conventional urban realm with thousands of sensors adding a new -somehow alien- technological layer flooding the physical realm. While the current hype of the engineered Smart City has focused mostly on increasing infrastructural performance, there is a higher lever need for improving exchanging processes as a way for a better quality of life of its inhabitants. However, it is unclear which is the role of those users who are at the same time producers of information, and beneficiaries of this new technology that is out of their control in between centralized centers of information that remind top-down cybernetic approaches from the 1970’s and bottom-up collaborative approaches. The role of the information citizen-prosumers is as unclear as for the physical dimension of this technological-mediated city which is not able to articulate a different physical and spatial narrative than the one provided by the augmented reality and access to geolocated information.

A map is not the territory it represents, but, if correct, it has a similar structure to the territory, which accounts for its usefulness.

(Korzybski 1933)

Cities are “the most complex of human inventions, ... at the confluence of nature and artifact” (“Mais la vie urbaine ...représente la forme la plus complexe et la plus raffinée de la civilisation, ... se situe au confluent de la nature et de l’artifice.”) (Levi-Strauss 1955). However, until relatively recent times they haven’t been subject to scientific study (March 2002). The encoded complexity embedded in cities have been historically processed through local knowledge and leveraged over time. The constraining dominance of town planning

approaches in urban research limits the capacity to understand the complexity of the problems and policies in contemporary cities. The expertise of designing cities have been mostly concerned by the elaboration of its bureaucratic plans, it is, the means themselves, and not by the actual matters and social processes which shape the city. This framework needs to be reformulated, and a different socio-scientific approach needs to be developed (Cuthbert 2008).

Since the end of the World War II, humanity has been experiencing a huge development of new technologies which eventually have caused a digital convergence as illustrated by Nicholas Negroponte in the 1980's (figure 85). In this first industrial convergence telecoms, media, and computing tended to overlay and to generate a unique digital ecosystem. This mediamorphosis (Fidler 1997) from the Convergence 1.0 is already consolidated, although this process is still undergoing¹⁴ and the second convergence tries to be outlined: how and which fields will be integrated into a single digital ecosystem. It is expected that fabrication (Kostakis et al. 2016) and medicine (Majumdar & Bansal 2010) will be integrated and eventually it is imagined that every single service single industry will be operating in a common, converged digital environment.

The city can be in the center of the discussion about spatial planning, not only because the dissolution of the limits in between scales of what are considered different disciplines, such as architecture, urban design, and planning; but because its design is much more decisive in people's life, it is structural to complex urban settlement, and its design and modification requires a much higher amount of coordination, investment, resources, and ultimately time. But beyond practical reason, it is structural to social life: "More important than buildings are the spaces between them" (Foster 2012), as they belong to the common sphere. Differently than buildings, they are inserted in longer shaping process and their constraints for restarting from scratch are stronger. They can be subject to constant modification, but their overall conditions are much more complicated to change, due to its character -but not only reduced to it- of infrastructure.

¹⁴ In 2010 the New York Times director, Arthur Sulzberger, stated that the journal eventually will stop printing

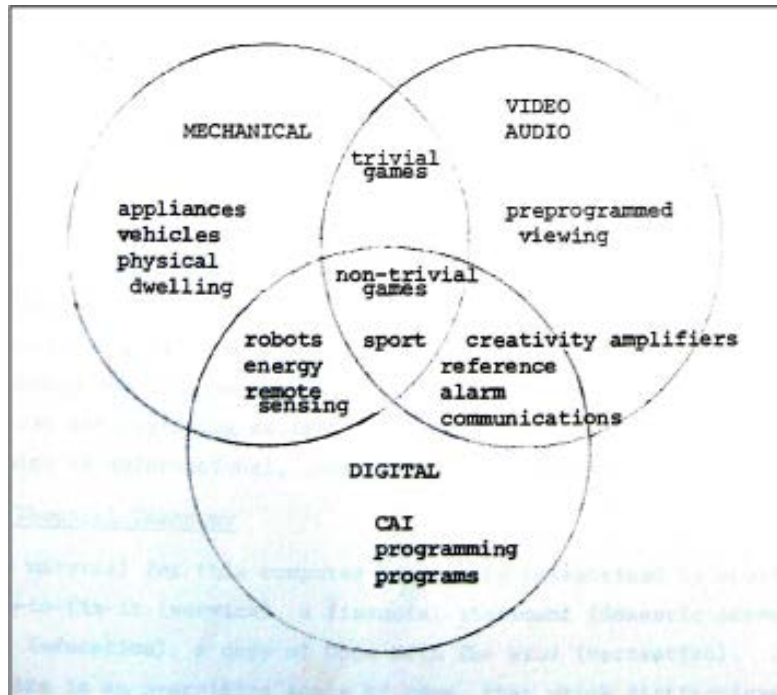


Figure 87. Nicolas Negroponte's Venn Diagram for media convergence. (Negroponte 1977).
Source: (Steenenson 2014)

Despite the technical and methodological change fostered by digitalization which has affected every single discipline of human activity, architecture and city making is supported by traditional expertise without being affected by new means of production. It doesn't mean that practice hasn't been affected by new technologies (such as CAD, BIM, CIM, etc.) but that digitalization has expanded the manual methods within human capabilities. Opposed to other disciplines, new technologies haven't been used for expanding the capabilities of the discipline, but just as reflect and representation of an already existing mindset.

Let's picture how does the process of city making look like in a regular Western city, although it could be extended to any city around the world with an organized planning department as it is the common practice across the world. The current main concerns of city planning focus on economic sustainability and safety¹⁵, implemented mostly from the economic and political power. The timeframe of those city making processes usually spans over a decade, and it requires a laborious manual process of negotiations between the different stakeholders in the city for balancing their diverse requirements and agendas. This intricate net of

¹⁵ Conversation with Steve Quick on February 9th, 2018

interests is coded in complex plans of actions which oversee at a high level the future development of the city and which determine the formal shape of the city. Consequently, the future buildings and urban spaces design will need to accommodate into that scheme. Two interesting immediate outcomes can be extracted from this workflow: the result is completely insensitive to quick changes or unexpected needs that a dynamic entity as a city may need (no time, no way of readjusting the pieces of the complex equation with the new components), and manual and labor-intensive work for adjusting all the components in a resulting urban code (legal and formal) extremely dependent on the considered conditions. It means: if something changes in the stakeholders' agendas, it is likely to be necessary to redo the whole plan from scratch.



Figure 88. D.C. Simpson's Office, Vancouver BC (1950).

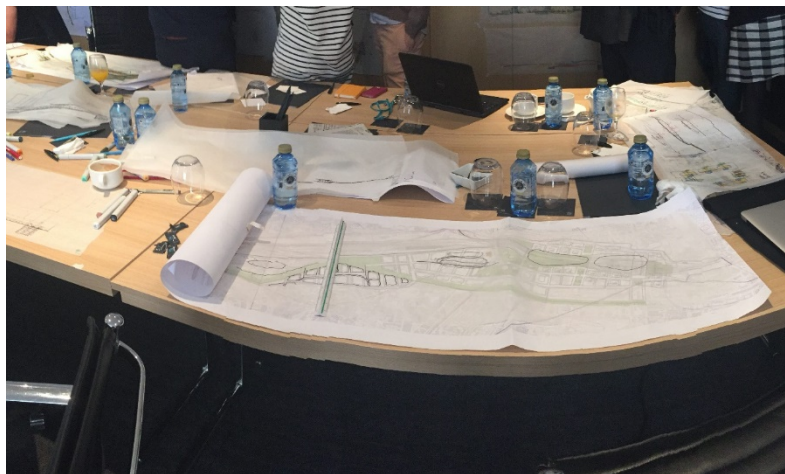


Figure 89. Castellana North design process, Madrid, Spain (2017).

It is expected that over those long periods of time while city-making design is conceived, stakeholders' agendas may change, which will affect to the whole result of the process

codified in urban codes and the shape of the city itself. This process has been preserved unchanged during the last decades, and even though digital tools have altered some tasks of the process, it hasn't modified the actual dynamics of the process.

It is not just constraining the efficiency of the process from the economic and politics point of view but disregarding the use of the new technologies as operative tools in the process skips a fundamental part of the knowledge which is embedded into the cultural, social, political and functional complex enweaving the shape of the city.

Regarding this research, what is important is the central role of data as a resource for architects, urban designers, and planners. Data-driven design practice can be approached from different perspectives, such as modeling and iterating through hypothetical scenarios, matching users' needs, increasing the transparency and understanding of processes, or improve policy making (RIBA & ARUP 2013). While data-driven approaches have been transforming intensively other industries like healthcare, marketing, banking, and transport (Manyika et al. 2011) many of the practitioners in spatial disciplines are alien to the discussions developed in the last years around Big Data applications and the hype of Smart Cities.

“We increasingly experience cities mediated by digital technology... we need a discipline that doesn't really exist yet, a merger of urban design and urban planning with urban informatics, with networked public space”.

John Tolva, 2013 (Stott 2013)

Traditional urban planning in the best scenario has been fed with static data for analytical purposes. Here, two different dimensions can be considered: time and scope. New technologies yield the real-time generation of contact data, and in urban environments, it created a whole trend around the topic of “sensing cities”. Scope-wise, the use of the data needs to go beyond the simple analytical vision and being integrated into actual solutions for the complex machine that a city is.

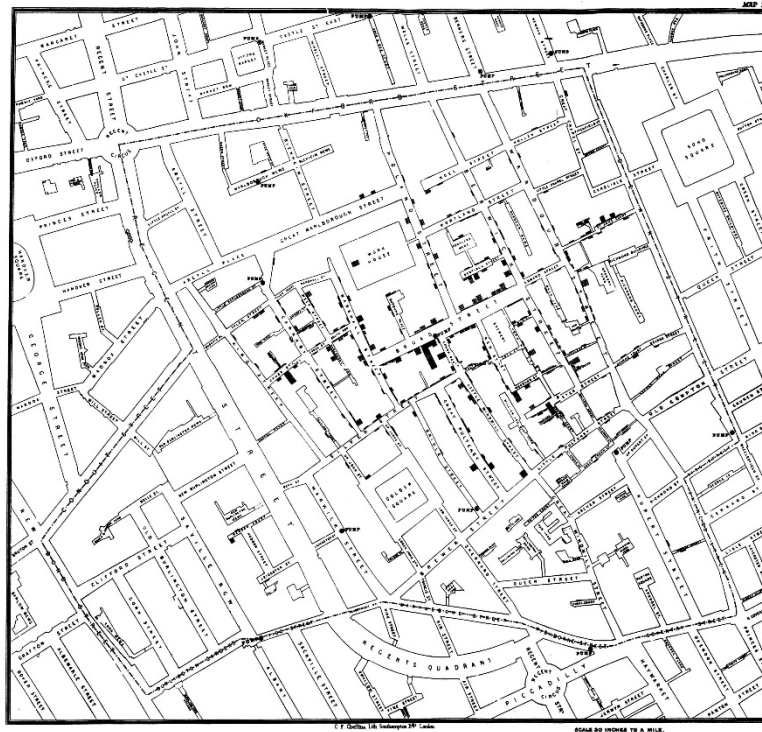


Figure 90. Cholera outbreak map (Snow 1855).

The collection of massive and diverse data may reveal hidden relationships and correlations between different parameters. The technical challenge is not anymore, the actual collection of information, but the practical ability to process and understand that new knowledge. The processing challenge can be considered overcome by machine learning and deep learning techniques able to make sense of complex datasets, including unstructured ones. However, this discovery needs to be paired with the development of urban theory (Bar-Yam 2015) for providing interpretation and contextualizing the novel evidence.

Examined under current trends, the use of the data in cities is directly related to the digital landscape and the mediatic impact of the blurry term of smart cities. This mindset, in spite of its lack of concretion, has recovered, reframed, and even fostered the treatment of city planning from the perspective of data.

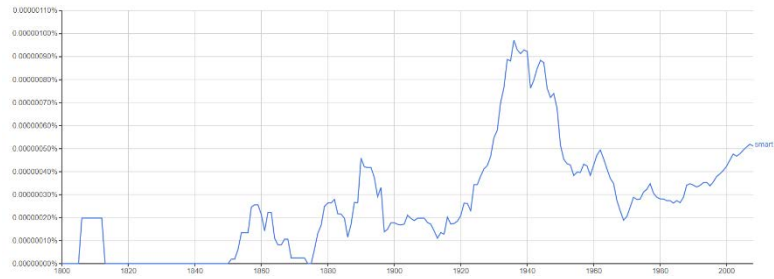


Figure 91. Occurrences of the term "smart city" in publications indexed on Google Books. Period: 1800-2018.
Source: Google N-gram Viewer

“Oh of course” said Peabody, “they deserve great credit for all this, don t they? They had great tracts of good land emigrants came and settled there the country grew, and the population increased hey couldn’t help it no how they could fix it but naterally (sic) they are a slow conceiving slow believing slow increasing people when left to themselves. There ain’t a smart city in Canada.”

“What do you call a smart city?” I asked, “for I never heard the term before.”
“Well, I’ll tell you,” he said; “I was goin’ down the Mississippi oncet in a steamer and the captain who was a most gentlemanlike man was a Mr. Oliver (that I used to call Oliver Cramwell, he was such an everlastin’ eater), and we passed a considerable of a sizeable town.” Sais the captain to me, ‘Peabody,’ sais he, ‘that’s a smart town and always was. Ten years ago when I was steward of a river boat, we wooded at this place, and there didn’t seem to be any folk there, it looked so still; so as I walked down the street, I seed a yaller cotton oil coat a-hangin’ out of the shop door; I tried it on and it fitted me exactly, and as there was nobody there to receive the pay, I walked off intending, of course, to pay for it next time I came that way. I hadn’t gone a few yards afore I was seized, had up afore the justice, tried, convicted, received thirty nine lashes on my bare back, and upon my soul, it was all done, and I was on board the steamer agin’ in twenty minutes.’ Now that’s what I call a smart place. [...]

The Season Ticket.-No. VIII. Our Neighbours and Distant Relations. Published on Dublin University Magazine: A Literary and Philosophic Review (Anon 1859)

The current overwhelming presence of Smart City as a crossword for almost any research proposal or project involving cutting-edge technologies and urban realm makes to lose the perspective of the use of such a term. Neither it is used properly for what it could mean, nor it has a unique connotation. The term was coined in the mid-1800's for referring mostly to the rapidly developing cities in the Midwest of the United States and all over North America where economic and social opportunities were emerging at a fast pace (Wright 1870). This connotation, mostly from the political, social and cultural point of view applied to efficient well-managed cities was the most frequent during the 20th century, and greatly popular in the 1920's, 1930's and 1940's. It is important to notice a distinctive feature that distinguishes the term 'Smart City' in this historical period from its current meaning: it does not involve the use of technology. It is evident that the use of the term dropped after the World War II (as shown in the Google N-gram chart in figure 89)¹⁶, around the same time the first wave of computation emerged, and it wasn't applied to the control and cybernetics approaches which dominated most of the computational-driven strategies applied to urban and spatial planning in the 1970's.

In spite of the fuzzy use of the current definition of "Smart Cities", it is possible to outline some convergence after the recovery of the utilization of the term since its recovery in the 1990's mostly centered around the idea of the use of Information and Communication Technologies (ICT) with regard to modern urban infrastructures (Albino et al. 2015). From this early idea, extremely focused on an engineering perspective, it would be somehow simplistic just to consider a narrow understanding of current smart cities initiatives as mere implementations of digital tools in urban environments. On the contrary, independent of the particular definition of the core constituents of smart cities approaches, either technology, management and organization, and politics (Alawadhi et al. 2012) or ICT, sustainable development, and the human factor of their citizens (Picon 2015); they are closely related to questions of sociology, anthropology, and politics (Picon 2015).

¹⁶ N-gram is a contiguous sequence of n number of items in a text or chain of characters. It is a probabilistic and computational model widely used for text-mining for finding sequences of character in big corpus. Its origin is at the early experiments performed by Claude Shannon on Information Theory (Lin et al. 2012).

In the succession of phases of evolution of the contemporary city encompassed by the technological progress defined by the sequence the walking city, the networked city, the metropolitan or suburbia city, and the outer city (Tarr 2010), the urban realm defined by smart cities (sensitized city) evolves from mere control and management of flows to master the events going on within it.

Facing the deep irruption of technology in the urban environment two opposed interpretations are arisen as unbridgeable: top-down design that reminds suspiciously to the cybernetics from the first wave of computing back in the 1960's, and a bottom-up approach enabling and fostering collaboration between individuals for designing cities from the collective action. Both approaches imply to reduce the driving force for the initiative to different active agents or stakeholder in urban policy making: large IT corporations in the first exposed extreme, civic platforms and individual hackers in the second. Although the presence of these agents is real, the ecosystem is not reducible to a sum of radical extremes (Townsend 2013), but it includes anybody in the city, from the big corporation to the independent hacker, to policymakers and users of technology. It seems optimization is the only important goal of smart cities.

“The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.”

(Weiser 1991)

This desired whole new urban ecosystem would be enabled by a new network of ubiquitous and powerful devices that can monitor and process the information gathered out of the urban phenomena, in real-time at any location. This new Panopticum results in a massive amount of new data. Inside this urban paradigm is where the generation of insights directly from the algorithmic processing of different kinds of data is envisioned (see figure 90) as a way of revealing unattended patterns almost automatically and hopefully obtaining a more realistic modeling of cities functioning (Picon 2015). The automation of these processes controlled by automatic algorithm seems to be forecasting the shift from a model of human-machine cooperation to a dystopian technological determinism.

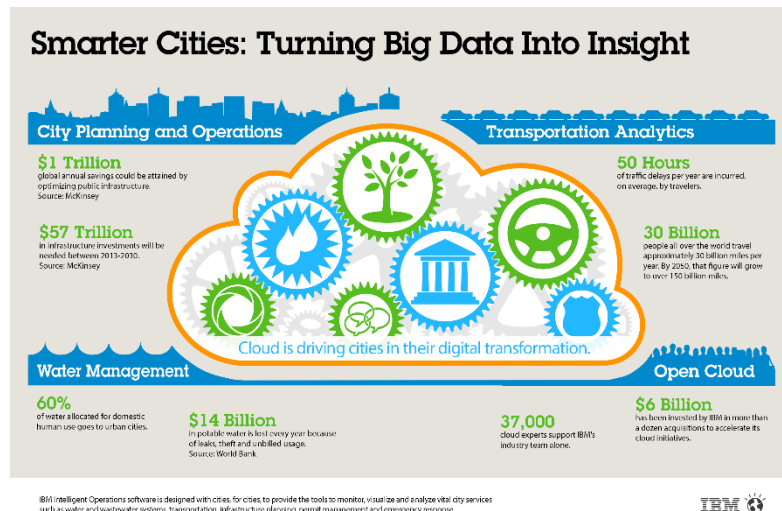


Figure 92. IBM Watson vision of insight from the processing of Big Data through Machine Learning for Smart Cities. Source: <https://www-03.ibm.com/press/us/en/photo/42063.wss>

This announced technological determinism enabled by algorithms connects directly with the cybernetics and system controls principles dominating the computational scene for planning between 1950 and 1970 that generated the urban dynamics trend (Forrester 1969): the city described as a series of nested feedback loops defined from a finite number of parameters, although the wicked problem of the city (Bettencourt 2013), or the intractability of its complex nature from purely mechanistic computational approaches. From the networked city described by the interconnection of different infrastructures and flows to the event-city (Virilio 2002) which is explained by the scenes and narratives told/built within it. This kind of urban landscape built based on narratives and stories may explain the lack of physical impact from a traditional urban planning perspective: the city of venues, of slogans, of images and marketing campaigns, of temporary urban interventions. Which is particularly interesting in this city defined by events is how they are finally included in the urban planning discourse more than 50 years after the first Wiener's theories of cybernetics based on feedbacks generated from the interaction between human operators, machines, and more importantly, events around them.

Two innovations that didn't exist 50 years ago can be pointed out: computational techniques, aka algorithms used for processing information and generating new knowledge, are not the same, and the massive power of computation is fed and feeds simultaneously an insatiable amount in information never collected before.

Machine Learning can be still defined using its original explanation as the discipline in computer science which would make able computers to learn without being explicitly programmed (Samuel 1959). Machine learning allows computers to change, tune and make more accurate their algorithms and behavior from advanced statistical analysis methods. The problems that Machine Learning can address are traditionally classified into three types:

Supervised learning is used when tagged data is provided. It offers to machines “correct” answers to tune its behavior for being able to make successful classifications and predictions.

Unsupervised learning is applied when no labeled data is provided, and it depends on the computer to figure out the inputs by making sense of the data on its own by clustering or pattern finding.

Reinforcement learning trains computers to determine the best behavior in a dynamic environment to reach a defined goal. In this paradigm, there are no wrong or right answers, but mostly different approaches and strategies which shape the decision making in the algorithm in such a way that getting closer to the objective is rewarded for fostering that preferred behavior.

Machine learning and its deep impact on artificial intelligence are the most promising and fastest growing field of computer science. It has been pointed that Artificial Intelligence can be have a similar transformative impact as electricity reached at the beginning of the 20th century (Andrew Ng 2017), which has been shown in fields such as medicine (Kononenko 2001), finance (Lee et al. 1996), genetics (Libbrecht & Noble 2015), or linguistics (Sebastiani 2002).

Although some attempts have been proposed for using advanced statistical techniques in design, the lack of methods for parametrizing consistently the factors involved in the design of architectural and urban spaces make undoable their application.

Last but not least, the other novelty to wrap up this extended discussion is privacy issues caused by massive data collection and its controversial utilization. The presented project on this document precisely avoids the collection of private data and offers alternatives without generating conflicts on the use of large amounts of information. The current undergoing

events of the misutilization of personal data collected on social media (check Cambridge Analytica issue (Rosenberg et al. 2018) has intensified the already existing suspicions about what popular big service IT companies were doing with the information provided by individual users in return for free products such as email, maps, cloud storage or messaging.

If it is accepted that the use of data is worthy because it may help for solving issues, for understanding the functioning of our social, economic and political systems, or just for discovering hidden patterns for the good of science, it should be questioned which the motivation is for the fascination for collective in the meanwhile private and individual information. Well-defined political and ideological agendas can be guessed behind these approaches as the heritage of previous policies on mass-surveillance.

Every single time that even part of this framework has been presented to a third party, the recurrent question has been its implication for privacy. The authorization by the Institutional Review Board at Carnegie Mellon University and the approval for the collection of data on campus had a common point the question, concern, and caution on the protection of potentially private data which may be collected. Once this issue was cleared, the possibility of collecting interesting, potentially useful, and novel data without challenging the increasingly restrictive rules on private data protection became almost an advantage.

It does not mean that the framework presented in *What You See Is What You Get* is risk-free, as other ways of reverse-engineering data for figure out more than apparently "raw" data can tell, but this project enhances alternative ways of scraping reality for data from politically and socially responsible.

