Article

Cities, from information to interaction

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Abstract: From physics to the social sciences, information is now seen as a fundamental component of reality. However, a form of information seems still underestimated, perhaps precisely because it is so pervasive that we take it for granted: the information encoded in the very environment we live in. We still do not fully understand how information takes the form of cities, and how our minds deal with it in order to learn about the world, make daily decisions, and take part in the complex system of interactions we create as we live together. This paper addresses three related problems that need to be solved if we are to understand the role of environmental information: (1) the *physical* problem: how can we create and preserve information in the built environment? (2) The *semantic* problem: how do we make environmental information meaningful? And (3) the *pragmatic* problem: how do we enact environmental information in our lives? Attempting to devise a solution to these problems, it proposes a framework to approach how information bridges minds, environment and society, and helps us create large-scale systems of interaction.

Keywords: information; cities; interaction; environmental information; entropy; scale; enaction

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1. Complex systems in relation: minds, cities and societies

Look outside your window. You will see differences in shapes and sizes between buildings, perhaps some taller and more concentrated in certain parts of the city. You will see that these buildings are connected to streets, and that some of these streets are also likely to be different from one another. Even if you have never been in this city or area before, you can walk around and find someone or something you need in a busy street a couple of corners away. You can find your way around it. When you choose a place, you join a situation that culminates networks of previous interactions that you never thought about, but were a condition for you to be there at that moment. All these situations are of course part of a larger structure. In fact, you are living within a pattern – the interplay of recognizable relations and surprising variations, of hierarchy and contingency. As these patterns involve tangible spaces, social activities and possibilities of action, this is a *material*, *cognitive*, and *social* interplay – all at once. You are living in the interplay of minds, cities, and societies. Although these three things are complex systems in their own right, the interesting thing

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is that they end up relating to each other. By working together, minds, cities and societies somehow 'merge' into one immensely interactive system.

This article focuses on how humans create information in their environments in physical and non-physical forms, and use this information to live and put their actions together in order to form complex systems of interaction. It does so drawing from different traditions: from information theory and cognitive studies to complexity theories of cities and social systems theory. It also intends to overcome certain limitations of theories that deal with these as isolated systems. For instance, we learn from cognitive science about how humans relate to information in their environment. In spite of challenges of empirical demonstration, a number of approaches assert that our minds not only decode information from the environment, but also extend themselves into it. Our cognitive activity is embodied, situated, and shaped by its continuous interaction with the environment [1–4]. Theories of the extended mind assert a causal flow as the mind uses resources in the environment and vice versa, a two-way interaction [5]. The cognitive system is seen as a network of internal representations (not only of a single person, but several persons) extending into the external environment, as information structures bring changes to 'the face of the city' [6–8]. We wish to explore other possibilities related to how information is created and preserved in the built environment, and how it expresses and supports our interactions.

That means exploring how we deal with environmental information in order to perform, and how we make the *transition from information to interaction*. This transition seems to lie at the heart of a truly systemic problem: how do we put our actions together in a way to create a society? How can individual actions develop into a coherent system of interactions? Or put another way, how can we coordinate individual decisions performed by large numbers of people? We will argue that the way we organize ourselves as societies depends crucially on how we deal with information, particularly the information encoded in our environment. One thing that minds, cities and societies have in common is information. They depend on it. Minds process information; societies exchange information in order to exist; the built environment contains structures that might be cognized as information. In short, these systems process, share and preserve information. A step further, they seem to relate to each other through information. Following previous approaches, we will argue that this relationship begins with our ability to encode information in the built environment – for instance, producing regularities and differences in urban space. Minds and agency will cognize and enact this environmental information, putting it to use. In short, our hypotheses are that *cities are crucial sources of information*, and that this *environmental information affects how people perform and coordinate their actions*. Of course approaching these possibilities requires certain methodological steps.

2. Introducing the information-interaction system

Shannon and Weaver's [9] seminal book was the starter of most discussions on information and probably is the most important text written on it so far. Interestingly, the way Weaver approached the problem of communication offers a remarkable potential to understand how information bridges physical, cognitive, and interaction systems. Essentially, he posed three questions: "A. How accurately can the symbols of communication be transmitted? (The technical problem.) B. How precisely do the transmitted symbols convey the desired meaning? (The semantic problem). C. How effectively does the received meaning affect conduct in the desired way? (The effectiveness problem)" [10] (page 4; cf. [11,12]). We suggest that the relationship between our minds, environment and actions involves similar issues:

1. The *physical* problem: how do we encode and decode information from the environment?
2. The *semantic* problem: how do we make environmental information meaningful?
3. The *pragmatic* problem: how does environmental information affect our actions?

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We will see that information is somehow embedded in tangible spatialities that humans create as their environment. In turn, semantic information is created in the form of meaningful contents, as positions and places associated with certain activities. We seem to cognize places as settings related to our actions and to a shared idea of what they socially entail. Finally, the pragmatic problem involves how we use information decoded from the environment to actually guide our actions and create interactions. We propose to handle these forms of information in three overlapping, interacting dimensions (figure 1).

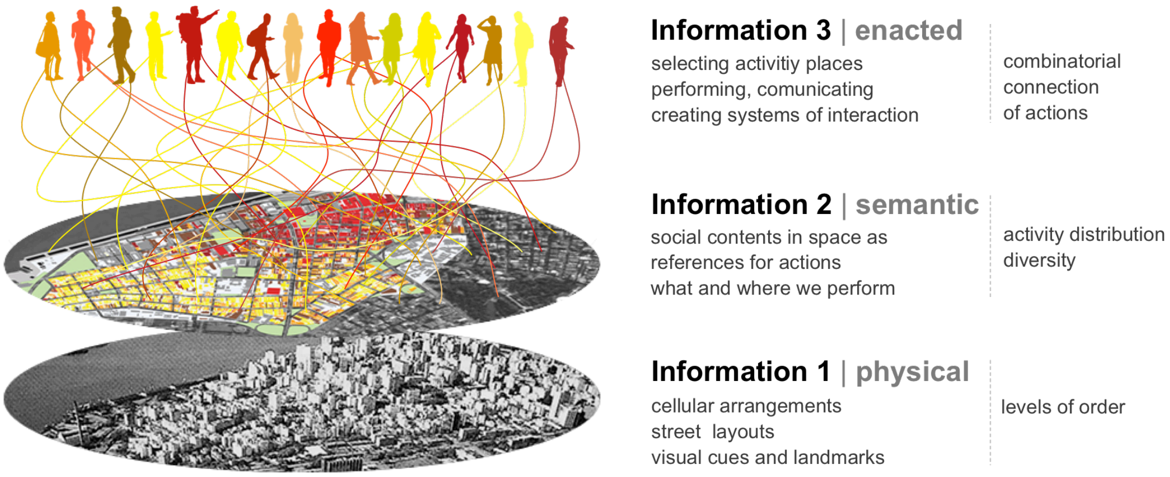

Figure 1. Environmental information (**1**) physical space and (**2**) semantic space, and enacted information (**3**): substantive components and measurable properties.

Classic spatial theories deal with these forms of information to different extents. For instance, Lynch's [13] 'image of the city' operates mostly at the level of information 1, as it deals with paths and physical cues related to cognition and navigation. Hillier's [14] space syntax grasps patterns of accessibility in street networks relating to cognition, movement and encounter. Haken and Portugali's [7,8] synergetic inter-representation networks bridge Shannon and semantic information as basis for actions in the city, but without the systemic dimension of social interaction.

Our theoretical model places the physical form at the bottom as it provides an elementary but fundamental dimension of information related to our cognition and navigation in the environment. The *physical dimension* includes the arrangement of spatial elements like buildings and streets, and the relations between them. Also, it is a very stable form of information, changing slowly, which is a powerful condition (cf. [12,15]). In turn, the *semantic dimension* has to do with what we do in places and how such places support our actions. It is associated with the diversity of activities, which offers more possibilities of information. Its stability depends on how long actions are performed in those places, and how long their meanings are retained in people's memories, so it changes more easily. Environmental information 1 and 2 are inseparable, but they are not isomorphic or necessarily intrinsic to each other. Although a building is created to support certain activity, it can be used for different activities in time, sometimes with not need for physical adaptation (e.g. a house becomes a shop or an office). So physical information tends to remain, while semantic information depends on ongoing actions and memories afforded by the building. Finally, the *enacted dimension* of information includes the effects that relations of spatial elements and their meanings have over individual action, triggering possibilities of interaction between agents [11]. Enacted information is created in the transitions between cognition, action and interaction. It produces and works with environmental information, when we use the latter to make individual decisions and communicate.

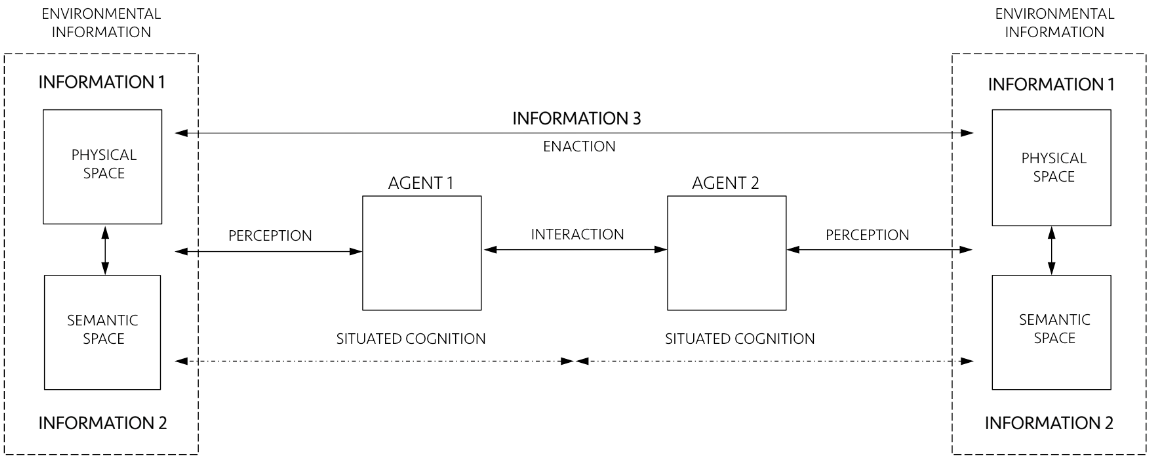

Figure 2. Schematic diagram of a general information-interaction system.

Now let us see more closely what each layer individually is and how they interact as a single system putting minds, cities and societies together (figure 2). We will approach this set of relations in the following general form. The environment that humans create as their own is composed of tangible and non-tangible structures, an interplay of physical spatialities (*information 1*) and meaningful settings of social activity (*information 2*). *Agents 1 and 2* encode and decode information from the environment, as they relate to it through *perception* and *situated cognition*. In turn, cognition emerges from distributed processes, a collective operation produced by interactions between agents in active relation to their environment. Agents create their cognitive powers by creating the environment in which they exercise those powers [16], while actively regulating the conditions of that exchange [17]. It also extends into action and interaction. Possibilities for individual action depend on *environmental information* and on the orientations and interactions of agents themselves. This extension of perception into the environment and into the coordination of actions is the very definition of 'enaction' [1], or what we call *information 3*. Of course all these items and relationships involve a vast literature and need a more detailed definition. Let us address them following the three-layered conceptual architecture proposed above.

3. Environmental information 1 | physical space

Since Shannon's [18] pioneering work on the mathematical theory of communication and Wiener's [19] cybernetics, the notion of information took other disciplines by storm in the 1950s and 1960s [20]. Shannon arrived at a clear description of information through a probabilistic definition of entropy, also explored by physicist Boltzmann [21] before him. For both, entropy is a measure of the uncertainty of a system. The greater the number of potentially transmitted messages (Shannon) or the number of distinct microscopic states of a thermodynamic system (Boltzmann), the higher the corresponding entropy [22]. Shannon's definition of information was proposed in the context of the problem of transmission of data, noise and channel capacity, from the point of view of engineering ([9], pages 27, 31). He realized that the level of probability of different arrangements of signs could account for the level of information embedded in them. Despite the enormous impact of Shannon's idea in different areas, it has certain implications. Weaver [10] (page 19) himself pointed out that the idea that "greater uncertainty, greater information go hand in hand" seems deeply counterintuitive. Since Boltzmann, entropy is associated with disorder [22,23]. Physical arrangements with higher

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entropy are characterized by higher levels of randomness, unpredictability or uncertainty. In turn, levels of predictability may be associated with order. Ordered structures contain correlations such as similarities, consistencies and associations that are the 'substance' of information [24], like pieces of "coherence above and beyond the bunching and scattering" entities [25] (page 1034). In this sense, information is the pattern of organization of matter and energy [26] (page 10) – like regularities in the arrangement of molecules in a piece of glass, organized parts composing a machine, or the pattern of activity location taking the form of a central business district in a city. A step further, information is a property of recognizable differences and internal correlations in systems that can be decoded by the system itself or by other systems. Information does not require a conscious receiver, but it carries transmissible codes that can guide change in physical processes, behaviour in living systems, and understanding in conscious entities (cf. [27]). It involves intelligibility, but not necessarily 'meaning', as Shannon and Weaver [9] correctly asserted.

The idea that physical things can encode information is not new in theories of cities either. It is at the heart of Lynch's [13] spatial elements recognized by people, guiding their navigation in the environment, along with memory and representation, even though he did not quite use the term 'information'. Rapoport [28] (page 19) explicitly asserted that "physical elements of the environment do encode information that people decode". Hillier and Hanson [29] thought of non-representational meaning embedded in physical configurations, as patterns guiding way-finding correlated with patterns of co-presence. Haken and Portugali [7,8] have seen information latent in street layouts and built form. Supposing that these theories are right, the fact that information can be encoded in physical structures is very interesting. Information lasts longer when preserved in tangible entities [24]. If physical spaces materialize information, we would have a form of expressing information continuously – as long as these spatialities are out there. We could encode information in the built environment and decode it while living in it. All these forms of information materialized in physical space could be contextual resources useful to guide our actions. Such a property would open extraordinary cognitive and practical possibilities.

But how could humans encode information in the built environment in the first place? At this point, there seems to be no definite answer to this question. Research in spatial information seems to mostly focus on how we *decode* information from the environment, for instance the role of visual perception, visual variables in navigation, and spatial decision making (e.g. [30,31]). In turn, empirical work in neuroscience has confirmed that the memory of an environment may be stored as a specific combination of place-cell activities [32]. Neural algorithms integrate information about place, distance and direction, forming a directionally oriented, topographically organized neural map of the spatial environment. 'Grid cells' in the brain are activated whenever the animal's position coincides with any vertex of a hexagonal regular grid spanning the surface of the environment. Grid cells are critical for vector-based navigation, which can be combined with path-based strategies to support navigation in challenging environments. In addition, the mental map is anchored to external landmarks, but it persists in their absence, suggesting that this grid-like position system may be part of a generalized, path-integration-based map of the spatial environment [33–35].

In this sense, levels of regularity and predictability in spatial arrangements could be cognitively useful to anchor agents' internal system of navigation. Agents might capture levels of physical information by recognizing regularity in frequencies of spatial events in the built environment. Such spatial consistencies would guide navigation, allowing inferences about areas of a city beyond one's field of visibility. If that is the case, the greater the variation of elements in the environment, the fewer the regularities that allow inferences about the broader structure. If that is the case, which spatial arrangements contain more physical information? Chess experts show greater memory for chess-typical arrangements of pieces than random arrangements [36]. We suggest that agents create

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information 1 by engendering levels of order in the deepest constituents of built form, namely cellular aggregations. Imagine a two-dimensional space in the shape of an orthogonal cell grid. Cells occupy positions in this grid, composing different arrangement, like the archetypal cases in figure 3. These arrangements display different levels of order, apparent in the frequency of distances between cells. An extreme case is the orthogonal arrangement (figure 3, case 1). Perfectly regular arrangements like this are rare events in the set of possible arrangements, so they seem like drops of order in a sea of disordered states. In most states, cell distribution tends to contain low internal correlations, like cases 2 and 4. In case 3, positions follow a patterned distribution. Some order is also visible in case 5, a spiraled pattern. The sixth case brings deformed rings, like those found in 'organic' urban grids. Capable of generalizing contiguity between cells while keeping permeability, the very formation of such rings is a highly unlikely event.

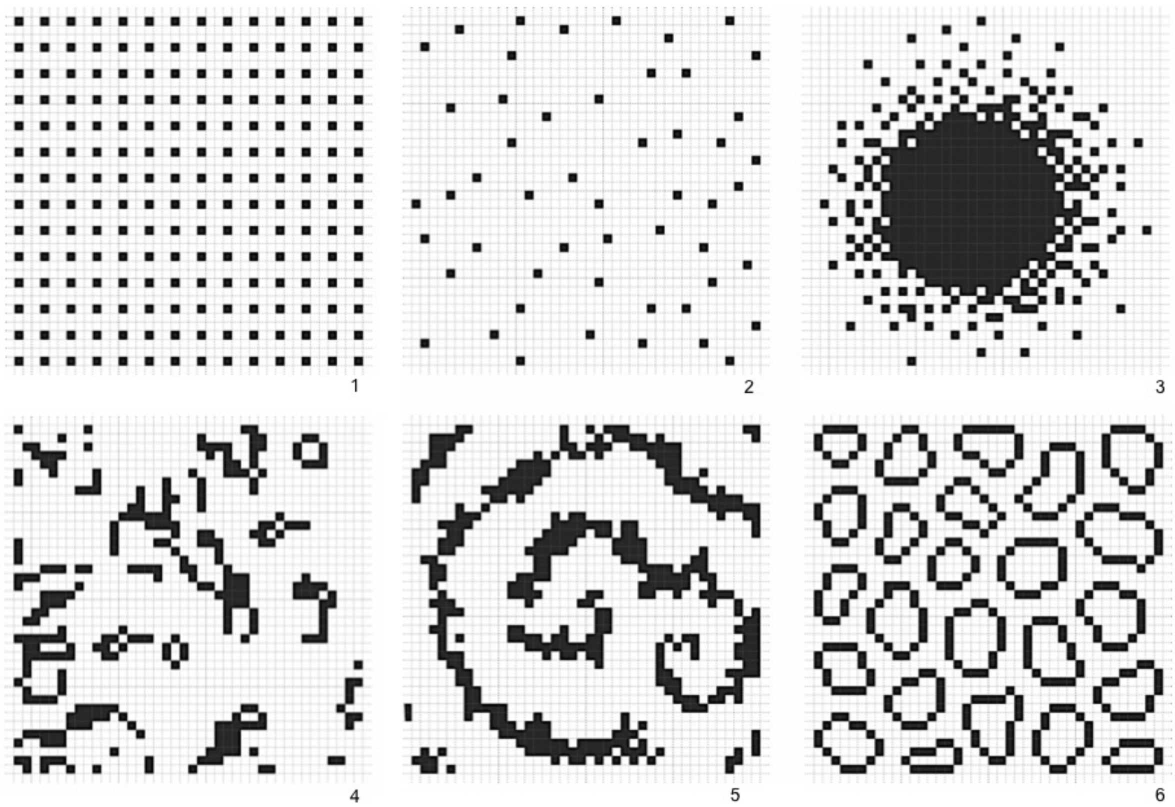

Figure 3. Information 1 in physical space: archetypal arrangements with different levels of order.

We can measure environmental information 1. Approaches to visual information have adopted measures of information density and entropy to assess the amount of redundancy and grouping related to cognitive efforts to extract task relevant information [37,38]. We may pursue such possibility measuring levels of predictability in physical arrangements using statistical concepts. A measure of information 1 should be able to grasp regularities and variations in real configurations and different urban situations (figure 4). For this purpose, we suggest to measure Shannon entropy. As we have seen, high entropy corresponds to high levels of randomness or unpredictability in a system. In contrast, the presence of regularities, structures and patterns corresponds to lower entropy. Such measure can be explored to characterize and classify cities or urban areas from different regions and spatial traditions.

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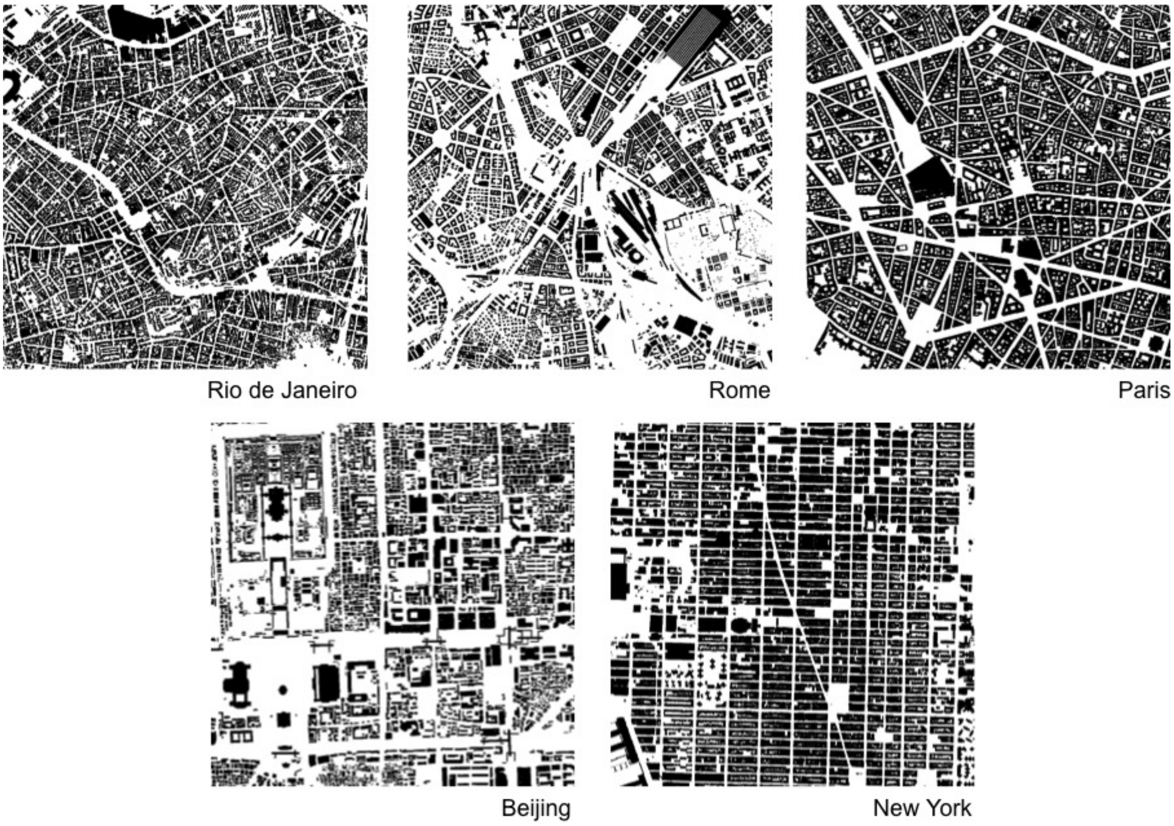

Figure 4. Spatial distributions in real cities ($9,000,000\ m^2$ windows, 1000×1000 cells).

We propose to assess Shannon entropy as a proxy to disorder in cellular arrangements extracted from public map repositories of cities such as Google My Maps. Background picture bases were prepared and exported in high resolution, filtering layers and converting entities into solid raster cells. We proceeded to test and analyze trade-offs between resolution, computation and precision in results for distinct scales. We finally chose geographic areas of $9,000,000\ m^2$. Images underwent a resizing process for 1000^2 cells, were converted to a monochrome system through GIS, and then into a matrix of size 1000×1000 cells with binary numerical values. Then we employed an approach usually applied for estimating the entropy of sequences of symbols encoded in one-dimensional strings [39]. This approach has been widely used for different type of datasets, from natural languages, speech analysis and behavioural sequences to DNA and spike emissions in neurons. However, estimating entropy is far from trivial. For datasets corresponding to one-dimensional strings, the most straightforward method consists in defining the block entropy of order n, where blocks are string segments of size n:

$$H_n = -\sum_k p_n(k) \log_2[p_n(k)]. \tag{1}$$

The sum runs over all the k possible n-blocks and corresponds to the Shannon entropy of the probability distribution $p_n(k)$. The Shannon entropy of the considered system [39] is:

$$h = \lim_{n\to\infty} H_{n+1} - H_n = \lim_{n\to\infty} H_n/n \tag{2}$$

which measures the average amount of randomness per symbol that persists after all correlations and constraints are taken into account. This approach can be applied to our problem once we have defined the blocks for a two-dimensional matrix [40]. The most intuitive idea is to consider a block of size n as a square which contains n cells. To obtain the sequence of H_n also for n values that do not correspond to squares, we will consider blocks that interpolate perfect squares, as described in Figure 5.

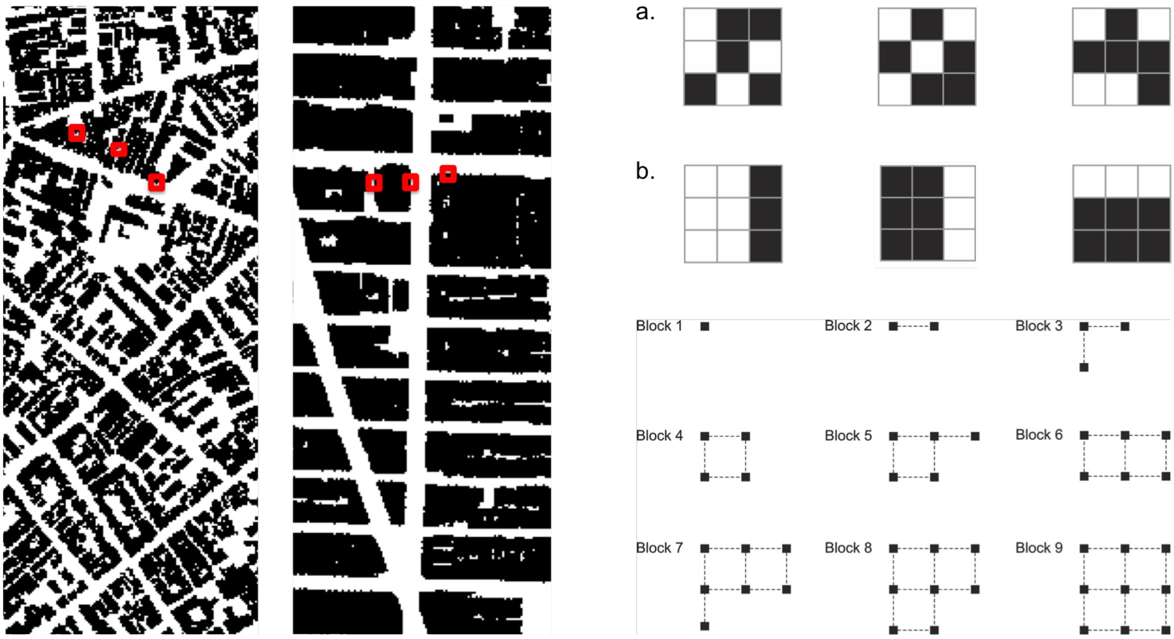

Figure 5. Entropy in different areas: Rio (left) shows a great deal of variation of configurations like (**a**). In turn, configurations like (**b**) are frequently found in Manhattan (right). Essentially, $p_n(k)$ in equation 1 accounts for the number of times every possible configuration k appears in the map for a block of size n. A high frequency of certain configurations, like in Manhattan, brings the entropy measure closer to 0, i.e. to higher levels of physical order. This procedure for estimating entropy was applied for cell blocks with different sizes. Here we show the first nine blocks; other block sizes were generated through this approach. Note that there is no unique natural way to scan a 2D matrix [40]. Different forms of interpolating cells do not seem to influence the estimation of H_n.

Relation 2 gives precisely the entropy for a theoretical infinite set of data. In real situations where the dataset is finite, our method estimates the probabilities of distinct arrangements of cells within blocks up to a certain length n, counting their frequencies, and then estimates the limit. For example, for H_1, it is sufficient to have knowledge of the symbol distribution $p_1(2)$, which is approximated by the frequency of 0 and 1 present in the dataset. Note that if our data were a purely random set, h would coincide with H_1, and $p_1(2)$ would give a full account of the spatial configuration. This is obviously not true for urban situations, where strong long range correlations are present. In this case, estimating entropy is a difficult task, as taking them into account means computing H_n for a large n. In fact, the estimation of h is good when the spatial range of correlations and memory is smaller than the maximum size of the block entropy we are able to compute. This estimation can be rendered difficult because of the exponential increase of the number of distinct cells arrangements in blocks with n ($k = 2^n$). For instance, there are 512 different configurations for blocks with only 9 cells. Difficulties in capturing longer correlations lead to the overestimation of h. This is the case if sufficient care is used in estimating each H_n. Otherwise, as strong fluctuations are already present for moderate block lengths n, the estimates H_n are usually underestimated. These two concurrent effects may jeopardize the estimation of entropy.

In our specific case with just two symbols, the estimation of H_n is surely not reasonable when $2^n \approx N$, where N is the number of elements in our dataset [41]. So in our situation where we work

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with a matrix with 10^6 cells, this condition is verified for $n \approx 20$, which means blocks of squares with a linear length smaller than 5 cells, which corresponds to 15 m. It follows that if a city has internal correlations larger than 15 m, the entropy estimation using block entropy will be over-estimated.

Results corresponding to the estimation of the H_n/n and the corresponding entropy h for five cities are shown in Figure 6.

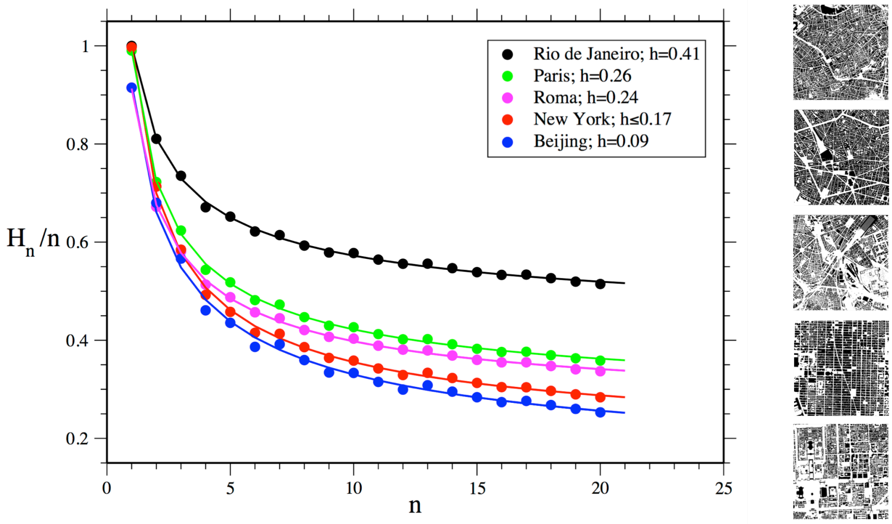

Figure 6. Measuring Shannon entropy: estimated values of H_n/n for five distinct cities. Continuous lines represent the best fitting of our data using the function: $a + b/n^c$. The fitted values of a give a reasonable extrapolation of the Shannon Entropy h of the dataset. Values are reported in the legend. Note that the obtained value for New York is surely overestimated.

The north area selected in Rio de Janeiro shows the highest level of disorder among selected areas of cities. This implies a lower level of physical information. To a large extent, these results make empirical sense. However, it is less clear why Manhattan would have higher disorder than the area selected in Beijing, given the highly regular grid structure of the former. The reason for this finding can be ascribed to the maximum size of the cell block used for estimating entropy in our method, which has a linear size much smaller than the actual urban blocks in Manhattan, and elsewhere. Limited to the considered cell blocks, our measure is only able to grasp parts of Manhattan's large urban blocks, regular on their borders but irregular on the inside. In turn, Beijing's actual urban blocks are less regular in relation to one another, but very regular in themselves.

Finally, this approach allowed us to use different block sizes for measuring physical information present already at small local scales. Probabilities of empty cells and built cells are similar for blocks with one cell for all analyzed urban areas, suggesting that cities in different regions and spatial traditions share a similar proportion of empty and built cells, which was a surprising finding. In turn, block sizes larger than one cell were able to show stronger differences in block entropy levels between cities, as expected. Differences in values were more pronounced as block sizes increased. These results are consistent with the general expected behaviour for block entropies in dependence of the block size for any system. It is interesting to note how physical information can be grasped even at small scales and that disorder is shown to decrease as the size of cell blocks analyzed increases, as larger scales of order and correlation begin to matter.

If we wish to improve the statistical robustness of our analysis, increasing the number of cells in our dataset, we can follow two paths. The first is increasing map size. However, this is limited by the size of cities and by the fact that we need relatively continuous urban areas in order to compare them.

Large geographical interruptions like mountains or lakes may interfere with the frequency of blocks configurations, and should be avoided. The second is increasing map resolution. In this case, we must increase the maximum value of n. However, the presence of large homogeneous features and the noise produced by finer resolutions increase fluctuations in the estimation of the block entropy, leading to a strong underestimation of entropy.

At this stage, our approach takes account of the physical information latent in the arrangements of cells capturing relations of proximity, but eventually missing some correlations at large distances. However, cellular growth shapes larger structures and paths as fundamental morphological features of cities – a subject explored in other works [7,42–44]. In addition, there are other forms of physical information, such as three-dimensional differences between buildings, physical cues and landmarks [45,46]. Forms of estimating the effects of such aspects of physical information will be subject for further work. Levels of regularity in physical space seem useful informational features in cognition and navigation (cf. [7,8,14]). But are they all that the environment can offer? There might be a limit to the extent of information that physical space can encode, even if ordered to preserve information. Environmental information needs to be more differentiated out if it is to get closer to levels of differentiation found in actions. So how could urban space support more information?

4. Environmental information 2 | semantic space

A number of theories have attempted to expand Shannon's pioneering ideas on information as messages comprising symbols encoded in well-formed strings of signals into different types of information theory, in a way to deal with the second communication problem pointed out by Weaver [10] (pages 4, 26). That would be the existence of another dimension to information related to the *interpretation* of transmitted signs, or "how precisely do the transmitted symbols convey the desired meaning", involving a receiver able to subject the message to a second decoding. Indeed the specificity of semantic information requires clarification about its place among different types of information theory. In this sense, Floridi [47] identifies three fundamental concepts: (i) information as *well-structured data*; (ii) information as *meaningful* well-structured data; and (iii) information as meaningful and *truthful* well-structured data. Shannon's theory falls into the first category, since it deals messages comprising uninterpreted symbols. The second category consists of *theories of weakly semantic information* (TWSI). Finally, theories that make reference to alethic values and place truth as a condition for information fall into the third category, 'strongly semantic information' (TSSI). Examples here are Dretske [48,49] and Floridi [50]. In turn, our approach to (environmental) semantic information falls into the second category: one can encode and decode semantic information from the environment with no resource to statements of truth or untruth. Alethic values do no apply since environmental information does not depend on such statements in order to be cognized.

Let us look into these theories a little more closely. The first attempt to deal with the semantic problem of "what symbols symbolise" involving contents or designata of symbols can be found in Carnap and Bar-Hilliel's [51] (page 147) formal theory of semantic information. They connected a probabilistic notion of information with the contents of statements in language systems. Later on, Mackay [52] proposed a quantitative theory of qualitative information. Interestingly, Barwise and Perry [53,54] and Dretske [48] have developed such possibilities into what they call *situation semantics*. 'Situations' are limited parts of the world: events and episodes are situations in time, and scenes are visually perceived situations (Barwise and Perry, 1980). Situation theory is geared to address the way *context* facilitates and influences the rise and flow of information [55].

Isolating a single signal rather than the average of signals and messages, Dretske adapted elements of Shannon's theory to produce a theory of semantic information in which semantic content reduces to the *intentional content* of information, i.e. physical signs used to transmit encoded

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symbols produced by a source have intentional content. In addition, the informational content of p is determined in terms of the content that p carries with respect to a given situation. The semantic content of natural signs is the material states of affairs that caused them to be configured the way they are, i.e. destination and source are correlated in terms of structure [56] Natural signs are *indicators* and "what they mean is what they indicate to be so" [49] (page 18). Reminding Husserl's [57] earlier view, indication is the relation that realizes the intentional information content of a signal [48]. This implies a *relational* view of meaning, i.e. where the meaning of an expression is a relation. Echoing Wittgenstein [58], this relation is constituted by *meaning-in-use* linking actions to situations. Accordingly, semantic meaning is created through indications between actions and situations, as a relational construct, a reference to things, actions, other meanings [59] – and perhaps *places*.

Furthermore, and also of great interest to our approach, semantic information in Dretske's sense can also exist as an objective and *mind-independent* feature of the natural world and can be quantified. This is known as *environmental information*. Situation theorists require some presence of information immanent in the environment, as nomic regularities [47]. Environmental information can arise by virtue of regularities in the world, and it depends on information sources where situations are spatiotemporal structures. The overall context can contribute features to the meaning of signs and utterances in that context. The situation supports information [55,60–62]. The idea of an inherently informational environment semanticized by cognitive references and meanings-in-use brings environmental information to a direct relationship with action. Spatializing Wittgenstein's and Dretske's views, people would recognize the meaning of a place in the traces and artefacts left by previous or ongoing actions, and associate these traces with their spatial milieu. Spaces 'mean' as much as our acts, precisely because they are semanticized by our acts. Semantic information renders space endogenous to action. Space not only *represents* the activity, it is also *enacted* and, as such, laden with meanings. Semantic space finds a level of differentiation similar to categories of actions or activities, as they share at least part of the same informational nature (see [7,63] on semantic categorization).

The physical dimension of environmental information takes on meaning when relations of spatial elements stand for some social content, and trigger associations with our actions. It is equivalent to the interpretative aspect of information [11]. But what is the informational potential added by semantic meanings encoded in the built environment? We could think of the difference between environmental information 1 and 2 like the difference between a black and white image and a colour image. In comparison with tones of grey, colours are more diverse and contrasting. New possibilities emerge, as each colour finds its own palette of tones, leading to an enormous increase in combinatorial possibilities (figure 7).

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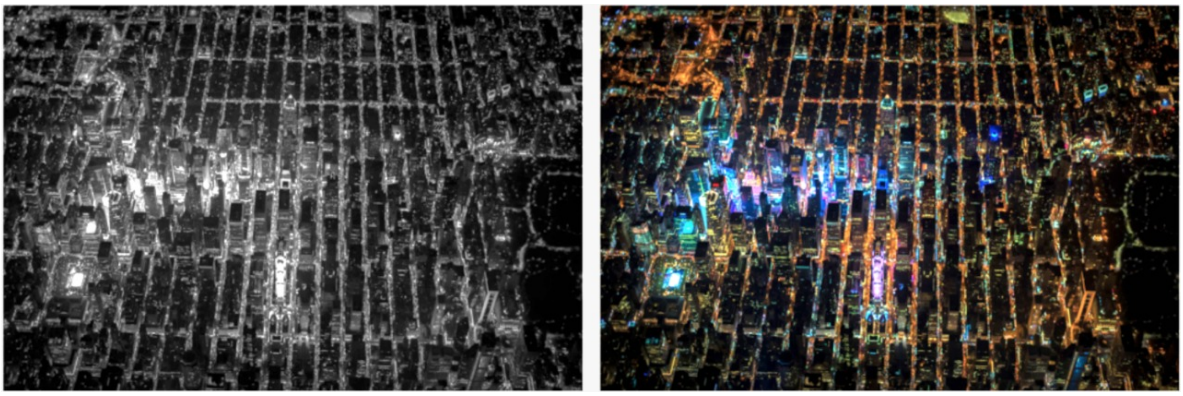

Figure 7. Differences and combinatorial possibilities increase dramatically in the passage from grey to colour scales. Photo: Vincent Laforet.

Many studies in cognitive science and spatial information theory have asserted associations between physical features and semantic contents in cities. Certain cognitive processes trigger associations with elements of the environment through the incorporation of socially acquired information [64,65]. Information is classified into potentially shared categories [7,55,66]. Non-spatial information can be integrated or associated with spatial information [67], as semantic categorical grouping processes relate to spatial features such as roads to organize point-based locations [63,68–70]. Such form of 'semantic clustering' can have effects on the memory of spatial locations [71]. The probability of a building or place to evoke a collectively shared mental representation is enhanced by its physical appearance and visual identity, along with its visibility and location in the environment and the social information associated with activities performed there [6,72,73]. In other words, we load the built environment with information. Our knowledge of spatial properties and patterns can integrate semantic, visual, and configurational aspects projected into an urban environment as 'symbolic off-loading' (cf. [3]). A non-physical thing like meaning may control and change the physical world [74].

The semantic dimension mediates the physical and the enacted, and is essential to connect space to actions, and guide interactions as combinations [11]. The references of meaning to matter increase the power of the environment to inform agents. Encoding the physical world using semantically structured mental models brings advantages. People can build instructions about events in the environment in an indexical form [75]. This enables us to build *inferences* – say, when we try to identify a street where we could find certain activity. In perceiving something, we perceive not only its observed form, but also the potential information enfolded in it [7]. This property seems crucial for our actions in the environment. Activity places generate cognitive and practical differences and complementarities in the environment. Accordingly, diverse activities in urban areas mean more opportunities for action [45]. Activities may reveal a form of synergy spatially manifested in the form of proximity, categorical grouping and clustering [76]. In other words, among features of the built environment that encode information 2, we find the relational distribution of activities. Local adjacencies between different semantic contents in buildings might create interesting complementarities from the point of view of agents in their efforts to perform and coordinate actions.

We can also measure environmental information 2. Semantic similarity has been proposed as a measure to determine the difference between feature type definitions [76,77]. We argue that a key point is to measure the *diversity* of social contents in buildings and places. However, such social contents may hold different meanings for different people. Like the understanding of words in a sentence [17], two people probably will not share a same semantic understanding of a built environment. The reason for this is that meanings do not lie only in space: they also lie in people's

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minds, which is the very definition of situated cognition. That means that external representations hardly could capture the plurality of meanings individually recognized in space. However, we can methodologically deal with meanings collectively encoded in urban space. We propose to do so through semantic maps [78]. Semantic maps can represent any form of social content in urban space, including interactions in activity places. They do not necessarily capture individual interpretations and private memories of places, but they capture socially shared meanings of places. These socially shared meanings are part of the knowledge of a social world and its environment, and should be enough to support our understanding of the social role of places, i.e. their role in supporting our actions and interactions. Like any kind of social and environmental knowledge, it must be built heuristically in situation-based behaviour in our daily interactions and context [6,16,79,80]. For simplicity, we choose classic categories in urban studies, namely land uses varying from public squares to residential buildings, and apply them in the empirical analysis of two archetypal urban areas (figure 8, left).

Figure 8. Semantic maps: real (top) and fictitious (bottom) distributions of land uses in Porto Alegre's CBD, Brazil on the left, with corresponding H_j^m values on the right. These values are calculated for $m = 10$, with the cell j corresponding to a pixel of the image on the left. The calculation is run over a gray-scale copy of the maps on the left. Source: Authors based on Maraschin's (2014) land use map.

Semantic information can be measured as levels of diversity found in land use distributions, analyzing local adjacencies between neighbour cells. In principle, we could do so by measuring entropy using the same procedure used for information 1. Unfortunately, the fact that now we should analyze a system characterized by more than two numerical values is an obstacle for a reasonable estimation of frequencies, which limits the effective possibility of estimating the h values. For this

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reason, we suggest a different measure. For each cell j we define a block of cells correspondent to a square of linear size m, centered in j. Inside this square, we measure the land use distribution, which is approximated by the frequency of the different z values present in the block: $f^m(z)$. Then we estimate the value of:

$$H_j^m = -\sum_z f^m(z) log_2[f^m(z)]. \tag{3}$$

Here the sum runs over all possible z values. Note that even though this measure has some analogy with the previous entropy estimation, it is indeed different. We are simply measuring an entropy-based scalar index for characterizing the local distribution of different land uses in a given neighbourhood of j. This process can be run for all cells present in the matrix, and it is analogous to some algorithms used in image processing. A graphic analysis representing all the estimated H_j^m values can be produced. Applying this approach to our two cases, we obtain the results presented in figure 8 (right). The graphic analysis shows points of high diversity in both maps, corresponding to local interfaces between land uses, a form of information potentially attractive to agents. Interestingly, the real distribution seems to contain more points of local semantic information than the fictitious, arbitrary distribution. This is incidental, of course. These cases are intended to illustrate the potential usefulness of the method. Nevertheless, let us see how these two forms of environmental information can be part of interaction.

5. Information 3 | enacted

Reminding Weaver's [10] third problem of communication ("How effectively does the received meaning affect conduct"), we finally reach the problem of how agents use environmental information 1 and 2 practically, in order to coordinate their actions. We called this form of exchange 'enacted information' or information 3. The term 'enaction' can be found in a number of approaches, from Bruner's (1966) description of knowledge as acquired and manifested through action to Varela's [1] 'paradigm of enaction'. Our use of the term shares aspects especially with the latter. The approach relates to emerging paradigms based on 'embodiment', 'situatedness', and the relevance of cognition for action [3,81]. Enaction is 'embodied' in the sense that cognition depends upon the experience of a body with sensorimotor capacities 'situated' in a more encompassing biological, psychological and cultural context [1]. A step further, agents enact their cognitive domain by actively and asymmetrically regulating the conditions of their exchange with their environment. Enactive approaches evolved in opposition to computational cognitivism, and reject the traditional pole of seeing the mind as only responding to environmental stimuli [17]. Instead, enactive approaches focus on how sensory inputs from the environment guide actions, and actions modify sensory returns and the environment itself, in perception-action loops. Interaction with the physical and social environment makes a measurable difference in cognition and vice versa [1].

Social interaction is also emblematic in enaction research. Embodied social interaction is seen as 'mutual participatory sense-making' involving the emergence of roles, values, dispositions to act, and meanings [1]. Meaning belongs to the relational domain established between the internal dynamics of the agent and elements in the environment. It is inseparable from the context-dependent, embodied activity, without being beyond the reach of scientific understanding. Agents "cast a web of significance on their world": exchanges with the world are inherently significant for the agent. In turn, meaning is derived from information processing. Through meaning and interaction, agents extend beyond the strict confines of the body into the socio-linguistic register [1].

At this point we reach a key aspect of enaction: *how coordination between social interactors emerges*. The emission and reception of signals in language gives rise to the modulation and coordination of actions. There is 'communication' only if the signal mediated interactions between agents result in a coordination of actions [82]. The semantic dimension of information endows the enacted dimension with a fine structure, and vice versa [11]. This inherent connection is consistent with previous approaches seen to support the idea that agents rely on environmental information in order to perform. For instance, Floridi [47] (page 23) asserts that entities like animals and biological mechanisms (e.g. a photocell) "are capable of making practical use of environmental information even in the absence of any (semantic processing of) meaningful data", which relates closely to our view of information 1. In turn, as in information 2, alethic values and truth statements do not matter in enacted information, since agents are able to coordinate actions even based on wrong or untrue information. Although untrue information does interfere, it also triggers courses of actions that change social systems.

Now, given the enormous number of possibilities of interactions in a city [43], how can environmental informational help us select actions and solve the combinatorial problem of actualizing interactions? For instance, do different spatial patterns and activity distributions affect this combinatorial process? Would different levels of diversity in activities (information 2) have different effects on levels of entropy in people's actions? We propose to assess probabilities of combinations of actions in different spatial scenarios, such as those in figure 9.

Figure 9. Diagram of agents converging in a fictitious, nearly random distribution (left), and in a real, patterned one (right).

One way to do this is quantifying the amount of environmental information available for agents in their decisions. We tested that idea through an 'enaction' model able to assess Information 3. Like situation semantics, our model considers agents, types of action, spatial and temporal locations, situations (represented by activity places) and parameters able to capture aspects of the agent's cognitive behaviour, namely the ability to track and recognize social situations, make decisions based on their individual orientations, and change their own actions and the semantic environment. Our agent-based model (ABM) based on a city as a linear structure is able to represent the minimal sufficient aspects of environmental information 1 (physical distance between positions representing places) and information 2 (semantic differences in the information contents of cells). The linear form of this city allows continuous movement across a sequence of locations, eliminating centrality factors while taking into account periodic boundary conditions in order to reduce border effects, eliminating the role of topology while isolating the problem of physical distance [83].

Our *hypothesis* is that, as (a) physical proximity latent in environmental information 1 tends to increase interactions between agents [84–86], its association with (b) information 2 created by diversity in locational patterns increases the potential for interactions and the coordination of actions, leading to reductions in the entropy of action in enacted information 3.

In each time-step, agents select and visit a specific cell within the city. The decision on which action to perform next may be influenced by three different conditions: namely, (i) latent orientation, representing the tendency of a single agent to act around a particular type of action, initially randomly distributed; this condition remains over time; (ii) current action performed by an agent as she selects an activity place in order to perform a new action; this means an influence of the current action, while allowing gradual changes of orientation in time influenced by other agents and activities; and (iii) activity places where agents perform specific types of action. Agents select activity places closer to their latent orientations and current actions, while being influenced by those activities. Visiting agents also influence places, but places change at a slower rate. Agents co-evolve with their semantic environment. To illustrate how orientations are constantly updated, consider that agent i selects an activity place located at x′. We considered as the current action of the i-th agent and the activity performed in a place located at the position of the city, both in time. We quantify action orientations weighting the three variables (latent orientation σ_i, current action σ_i, and activity place $\sigma_{x'}$). Orientations will be updated according the rule:

$$\sigma_i(t+1) = \frac{1}{\alpha+\beta+\gamma}\left(\alpha\sigma_i^{in}(t) + \beta\sigma_i(t) + \gamma\sigma_{x'}(t)\right). \tag{4}$$

The type of activity will be updated according the rule:

$$\sigma_{x'}(t+1) = \sigma_{x'}(t) + \theta\sum_{i\in x'}\sigma_i(t), \tag{5}$$

where θ is a parameter sufficiently small. That is, places are less influenced by agents than the other way round. This means that at every time-step, a place would have its type of activity closer to the average of orientations of its visitors.

Enacted information is measured as a function of entropy: consider $N(\sigma,t)$ the number of agents with an action orientation σ at the time t. The total population is $N = \sum_\sigma N(\sigma,t))$. We can compute the frequency (or density) $\rho(\sigma,t)$ of this orientation within a population with:

$$\rho(\sigma,t) = \frac{1}{N}N(\sigma,t). \tag{6}$$

The entropy level for any distribution of orientations is:

$$S(t) = -\sum_\sigma \rho(\sigma,t)\ln\Big(\rho(\sigma,t)\Big). \tag{7}$$

This describes how uneven is the probability of finding different action orientations. Higher values mean that different actions have almost the same probability to happen, while lower values indicate a system with clear action trends. The reduction of entropy implies that the probability of certain actions increases, that is, actions grow in similarity. In the limit, as entropy falls to zero, all agents in the system would reach the same action. Differences in the weight of factors over the

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next action may lead to quite different levels of social entropy, in interfaces of simplified systems of action, information, and space. We tested two scenarios: one where proximity between cells latent in physical information does not matter to agents in their decisions (blue line) and one where it matters (red line). Figure 10 shows the probability distribution of actors performing different action types at the start (left) and at the end (right) of simulations, The scenario where proximity between activity cells matters increases dramatically the coordination of action. Results are averaged for 30 runs for each of 125 combinations of parameters.

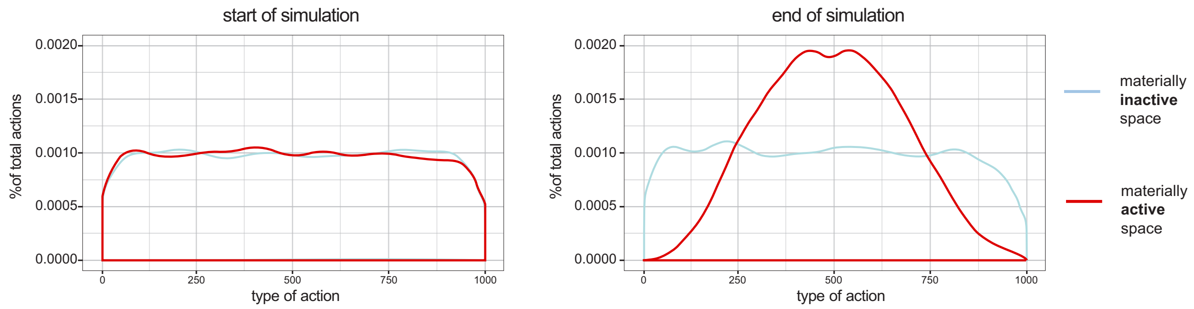

Figure 10. Histograms of probability distribution of action types at the start (left) and at the end (right) of simulations, in scenarios where distance between activity places is not considered (blue line) and distance is considered (red line).

We found structure in the relation between selection factors and the reduction of action entropy. Informational contents in urban space play a key role in the reduction of action entropy (red lines in figure 9). Urban space materializes gradients of difference in potential interactions, from less to more recognizable, costly or likely. Placing simple criteria like proximity as an aspect of physical information in selecting activities, the model shows that space becomes a means for producing differences in the probabilities of interaction, increasing chances of certain selections. Environmental information 'contaminates': they align their actions through the informational content of places. This general reduction of action entropy implies that the probability of certain interactions increases. In practical terms, this means more alignments between agents and more connections between actions. As an information environment, cities become a referential frame creating differences in the probabilities of interaction, helping to solve the combinatorial problem of connecting actions in a system.

6. From information to interaction: concluding remarks

This paper aimed to understand connections between minds, cities and societies, and more specifically, how environmental information becomes part of interaction and the problem of coordination of actions in social reproduction. It proposed a three-layered conceptual approach to the relations between environmental information and interaction. It also proposed measures to assess *environmental information 1* as levels of regularity in configurations of physical space; *environmental information 2* as diversity in the social contents of adjacent activities in semantic space; and *enacted information 3* as levels of coordination of action mediated by physical proximity and semantic contents.

Inspired by Weaver's [10] levels of communication problems, we addressed the relation of minds, cities and societies through three questions: (i) how do we encode and decode information from the physical environment? (ii) How do we make environmental information meaningful? (iii) How do we use environmental information to coordinate actions? Methodologically, this implied three problems: measuring information 1 in physical space; measuring information 2 in the

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distribution of semantic contents in urban space; and modelling how agents deal with environmental information 1 and 2 in order to coordinate actions in information 3. Developing a framework to begin to answer those three questions, we explored different types of information theory, from Shannon's theory of well-structured data to Dretske's situation semantics and Varela's concept of enaction, and did so in the following senses:

1. We analyzed *environmental information 1* looking at spatial structures as cellular arrangements through Shannon entropy, and assessed order and regularity in the built environment, assumed to guide orientation and navigation.
2. We measured *environmental information 2* as a function of diversity in local relations between social activities. Information 2 is powerful because it is created by action itself, so it is highly differentiated. This allows environmental information to go beyond the limits of physical space into virtually endless relations of meanings, and serve as a resource of great combinatorial power in the process of selection of actions to be performed and agents to interact with.
3. We modeled the influence of the environment in *enacted information 3*, simulated as action types in an ABM. Proximity inherent to physical configurations in information 1 and semantic contents in information 2 were seen to increase the convergence of action types. Contrary to isolated systems where order inexorably dissipates in time, the entropy of action decreases as the system of agents is open to and co-evolve with its physical and semantic environment. Aspects of information 1 and 2 find key roles in solving the combinatorial problem of action coordination.

A number of procedures are underway for further developing this approach. Fist, we intend to expand the approach to information 1 beyond regularity and entropy, looking into broader spatial structures in cities, introducing more sophisticated measures of statistical complexity. Second, we hope to expand the approach to information 2 beyond diversity, now looking into the effects of *specialization* and *concentration* of social activities, especially those with power to attract agents looking for associations based on functional complementarity. Another issue is the integration of physical and semantic environmental information. Recent approaches have been paying attention to this relationship in different ways (e.g. [8,76]). Information 1 seems associated with orientation and navigation, while information 2 seems closer to the perception and selection of performance opportunities. They also change according to different temporalities. These forms of environmental information cannot be reduced to one another. However, they are still deeply associated. Relations between configuration, physical cues and semantic references remain a key area for further study.

We also expect to develop a database of environmental information for a large number of cities from different regions of the world, which will allow us to systematically assess them as informational resources, a dimension of urban, social and economic performance. We hope to see *whether different cities carrying different levels of environmental information could affect how inhabitants perform and coordinate their actions*. Our hypothesis is that certain environments would ease cognition, navigation and efforts of interaction. Finally, these three forms of information, particularly information 3, are hard to assess empirically. In order to validate this model, we hope to explore the heuristics of how people actually perceive and enact information in the built environment through cognitive experiments performed in Virtual Geographic Environments (VGE) [79,87].

Interaction systems require a high capacity to access and recombine information into on-going and future connections. They are 'information-hungry'. This dependence requires different types of information. Environmental information seems to play a part in the continuous creation of interactions. The fact that cities preserve social information in durable space and in soft semantic structures would help order grow. Only by means of a structure that restricts the quasi-endless combinatorial possibilities of interaction, this system can acquire sufficient internal guidance to make

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its own reproduction possible. By distributing sufficiently recognizable differences in the probability of interactions, cities ease the local reproduction of a society. The city helps us convert information into interaction. The interfaces of cognition, environment and action reveal a deep connection. Self-organizing in themselves, they also seem co-dependent – and more. They seem to shape each other and emerge as an integrated system in its own right. This integration of minds, cities and societies happens through information. *Information is the bridge*.

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