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SYNTHETIC SPACE SYNTAX:
A generative and supervised learning approach in urban design

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ABSTRACT

Until recently, the application of Space Syntax on design was predominantly limited to evaluation at a post-design or pre-design stage. For the model to engage in the conceptual development and synthesis of design there is a need to find a mechanism by which an analytical description of urban complexity could be translated into a synthetic description. For this purpose and in an attempt to find a plausible description for such mechanism, empirical models of space, form and function are devised in the course of design generation through the use of generative and nonparametric techniques. Generative growth algorithms were applied to evolve different street network structures. The structures were measured against existing urban networks to find the best performing growth iteration. The winning iteration was then used to derive form-function attributes for an urban area. A neural network model is trained on real data to predict target spaces given the configurations of street networks. Following this sequential modelling procedures, a description of the organised complexity of cities is retrieved from empirical models and reconstructed in a design experiment. This process serves as to support design decisions when tackling the complexity of large scale urban interventions.

Keywords: *Design Synthesis, generative urban design, Neural Networks, Complex systems, GeoComputation, Space Syntax*

Theme: *Architectural Design and Practice*

INTRODUCTION

In recent times, studies that explored urban design were witnessing a divide between research and practice. Research-based approaches build on analytical methodologies to construct explanatory models of urban phenomena. Practice-based approaches are explorative and assumption-based. Any attempts to bridge the research and practice were faced by non-trivial challenges. On the side of scientific research, rigour is much emphasised without regards to the uncertainty and ambiguity inherent in design as a human cognitive activity. On the side of design practice, creativity is at the essence of any design process and scientific reasoning comes only as to post-rationalize aesthetically-driven decisions. The problems that result from diverting towards one approach without considering the other have significant implications on the quality of future urban life. The dilemma that is present in both approaches triggers questions of the type; why do we need science in design? Can science provide more definitive answers to design and if so is knowledge-based design counter-creative? How does it play role in informing or restraining creativity? What type of mechanism is needed to convert an explanatory reading of architectural phenomena into a synthetic and yet creative design approach?

These questions deal with many terms that are in themselves subject to a broad spectrum of research in both sciences and arts. A term like creativity -for example- has been historically challenged in artificial intelligence (Boden, 1990), when creativity might simply be seen as the new, the aesthetically spectacular. The multiple definitions for such basic terms would clearly mystify the language of communication between sciences and arts. This makes the unpacking of our abovementioned questions a very challenging mission. The adaptation of complexity to serve in design reasoning for example requires a careful understanding of the complex composition that makes the built environment and how such composition can be rebuilt through a linear design process.

Due to the complexity intertwining urban systems, there is a need to frame the problem definition of cities before even tackling the problem of design (Alexiou *et. al.*, 2010). On the problem definition strand, research on the science of cities comprises a long history that spreads over the last century with the quantitative element becoming particularly more visible over the last three decades. One of the first calls for thinking systems in cities was that of Jane Jacobs (1964), where she made the assertion that cities similar to biological systems are matters of organised complexity. That call has paved the way for understanding cities as complex systems. Since then, engineering and scientific modelling approaches continued to shape the landscape of this discipline. Theoretical frameworks, such as that of Space Syntax, took an analytical stance with focus on the network structure of space and the social logic inherent in its representation (Hillier & Hanson, 1984). Others were more concerned by the patterns embedded in urban raster images (Ratti & Richens, 1999). With a focus on modelling, biologists and geographers have exchanged roles, looking for allometric scaling laws in urban systems (Bettencourt*et. al.*, 2007), (Batty *et. al.*, 2008).

Whether in urban design or simulation modelling, practice-based approaches were on a divergent path, aiming to explore the making of cities. In their practices, urban designers were clearly occupying the front of decision making. Due to the practicality of their work and limitations in time and resources, decisions were often made in direct response to problems on site relying mostly on professional expertise.

On the computational modelling strand, different scientific theories and models were adapted to support urban planning (Wu & Silva, 2009). Computational systems were mostly developed on the basis of building block as the elementary component of urban models. With few exceptions (Duarte *et. al.*, 2007), most of these systems were based on assumptions with not much account of actual urban patterns. Modelling approaches were mostly dedicated to simulate cities. Methodologies varied depending on the computational models used (Parish and Müller, 2001), (Stanilov, 2003), (Batty, 2005).

Due to the complexity of the field, studying cities as physical artefacts, as processes and as hubs for economic and social life was handled differently across these domains. In general, any focused methodologies faced non-trivial challenges (Webster, 2008). Some theorists took a sceptical position claiming that universal models ignore singularities, human experiences and often falling in the trap of scientific reduction (Vesely, 2004). Dispute on the validity of representation, the capacity of static descriptions to explain processes and the notion of spatial determinism were particularly posed against Space Syntax (Ratti, 2004). Difficulties in isolating variables and ruling out dependencies and interdependencies were at the core of criticism against any simplifying modelling approaches. Along with all that comes also the questionable usefulness of any assumption-based simulation approach. The adaptation of computational models to explain and simulate cities was mostly based on agglomerations of urban blocks. In that there is a clear disregard to street networks as arteries for commuting from all origins to all destinations. Attempts were made to grow streets rather than blocks (Parish & Müller, 2001). However, the mechanism used was predominantly based on repetition and subdivision in the street elements without accounting for the network properties of the generated grid. Moreover, the mechanism of such hierarchical models did not comply with the suggested lattice-like nature of cities (Alexander, 1965). Uncertainty continued to be a major issue in urban simulation models where estimates on population density play an important role in setting assumptions. The focus in all these modelling approaches was on producing city-like physical features without making it clear how actual historical growth patterns and form-function relationships inform modelling. This particular problem demands careful considerations for what makes the emergent social and economic behaviour that shapes cities complexity to avoid alienating computational models from real urban life. Of interest, is how to evolve urban form in such a way as to build on the analytical and explanatory descriptions of urban growth, an idea that follows Alexander’s early work on analysis-synthesis in design (1964) and is more recently raised by Penn (2006).

In an approach to embrace design in the study of urban complexity, the aim of this paper is to present a synthetic description of the organized complexity of cities. For this purpose, a knowledge-based model is devised to aid urban design decisions. The model proposed outlines a prioritized structure of design thinking. Prioritization is assigned following observations on the historical dynamics of urban form and function where space is seen to trigger economic activity and its associated formal manifestations. The empirical models outlined will enable the generation and evaluation of spatial structures. Additionally, the models will enable the prediction of form-function attributes. Creative variations on the outcome of this constrained process would test the application of science on design. In exploring the boundaries of rationalitybetween empirical knowledge and human creativity (Simon, 1957), there is the questioning of the validity of a structured approach in maximizing certainty about design decisions and in reducing constraints over creativity.

A PRIORITIZED STRUCTURE MODEL FOR URBAN DESIGN

Given the apparent complexity in urban systems, a structured approach is seen to be inevitable in response to the challenges posed in urban design. In essence, any structuring should be based on a prioritization model that gives preference for certain variables over others. For the model to be substantiated, it needs to be based on the fundamental functioning mechanisms of cities. A theoretical proposition on such prioritization needs to take into account the *generic function* of movement that is much valued in Space Syntax as the engine that energizes cities and drives their movement economies (Hillier and Penn, 1996a). Following Hillier's proposition for a design filtering model (Hillier, 1996), the *generic function* is a priority condition that makes spatial structures accessible. Hillier further identified a second and third design filters that are predominantly based on qualitative criteria. These criteria were determined by individual or communal cultural identity. According to Hillier, the first design filter can be approached by a set of 'discursive techniques' to minimize depth hence conserve on through-movement in an urban system. This model remained theoretical in essence, when design approaches utilized Space Syntax as an evaluative tool to reason about design decisions (Karimi *et. al.*, 2007).

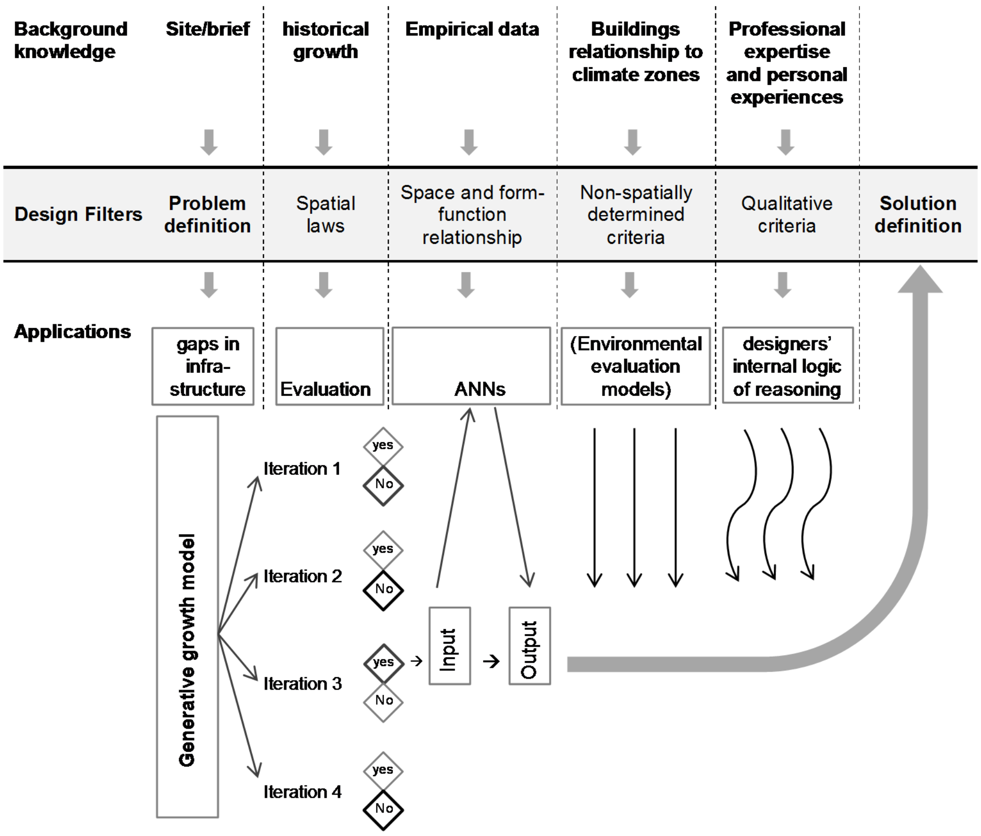

Figure 1: A prioritised structure model for urban design consisting of three main design filters. The first is determined by spatial laws of growth and generation. The second is a function of the relationship between space and form-function data. The third is refined by other non-spatially determined quantitative criteria (i.e. environmental measures). The fourth is purely subject to designers' internal logic of reasoning and qualitative choice.

For further engagement of Space Syntax in the making of design solutions, the model could be further adapted to serve in synthesizing designs. In that, space is hypothetically considered as a predictor of form-function. To adapt a synthetic description of Space Syntax, the prioritized structure proposed here–and discussed more extensively in (Al-Sayed, 2014a)-lists four sets of design filters (see figure 1). The first set defines the generative laws of urban space; here represented by segmental street networks. These laws were extracted from the historical evolution of urban form. The second set of filters depends on the first set to estimate form-function attributes from the temporal state of the spatial structure. The third set of design filters is not directly related to space but is determined by other types of quantitative criteria such as environmental and lighting measures. The fourth set of design filters are then qualitatively determined by designers or users to further shape design solutions. Given foreseen difficulties in fully automating a design process, it is inevitable for a designer to intervene in tuning data and selecting applicable evaluation measures. For that, it is suggested that while the first three design filters can be reasonably applied in separate stages, the designer's role will be gradually necessitated throughout the process as to further shape design features.

URBAN DESIGN EXPERIMENT

To explore the application of the prioritized structure model in urban design, an experimental approach will be followed. The process will involve generating a hypothetical urban grid and defining form-function attributes. This will be enabled by building a knowledge-base to evaluate generative spatial structures and to encode empirical data into non-linear predictive models. While the next two sections will be dedicated to outline this approach, the section that follows will explore creative variations on the predicted outcome of modelling. In exploring the boundaries of certainty and uncertainty, the experiment is set to unveil the role of designers in adapting knowledge to explore new forms of creativity.

Generative variations and the geometric filter

In search for local rules of growth in urban form, early Space Syntax experiments (Hillier & Hanson, 1984) presented a generative pattern of organization on the local scale of an urban area. The experiments have further led to the realization that longer lines tend to continue straight and shorter lines stop earlier to form near-right angles (Hillier, 2002). The process was identified as the *centrality and extension* rule. This simple rule can be implemented here as to govern the generative growth mechanism while allowing for a margin of randomness in the growth patterns (see table 1). The structures produced present varying syntactic properties. The syntactic properties can be either defined as the topological configurations of an axial map or the geometric configurations of a segment map. An axial map is a scale-free representation of the longest and fewest lines in a street network. The segment map is a broken description of the axial representation where each segment element between two street inter-junctions is considered as a separate element in the network. The segment network is based on geometric properties of angular turns between each segment and the other (Turner, 2000). To judge the urbanity of the generated structures, four invariants that were extracted from mapping historical growth in previous studies will be considered as criteria for urban pattern recognition;

1. The shortest angular path in the system renders out as a semi-continuous set of long lines.

2. Self-organisational behaviour leads to the formation of certain side-effects, where patches of dense structures distribute leaving similar distances in-between.

3. Local and global depth fits a log normal distribution. The distribution differs from that of random networks in that it shows a higher degree of skewness (asymmetry).

4. Urban axial systems exhibit high intelligibility and synergy[1] between the local and global.

[1] R2 coefficient between axial integration Radius 2 and global axial integration

The first three invariants were identified in (Al-Sayed *et. al.*, 2010), (Al-Sayed *et. al.*, 2012), (Al-Sayed&Turner, 2012), (Al-Sayed, 2013). The fourth invariant was observed by Conroy Dalton (2001). What is yet to be investigated is whether these invariants can be a natural product of a local generative rule.

	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Barcelona	random structure
Iterations						
Choice Rn						
∑TD/ NC	15726.2	11366.29	7747.37	8109.46	1756.161	3564.98
MMD R500metric						
Distribution KSL	0.09	0.15	0.088	0.1	0.035	0.04
Distribution Skewnes	-1.32	-1.15	-1.46	-1.5	0.28	-0.18
Syn Int	R^2=0.12	R^2=0.13	R^2=0.17	R^2=0.1	R^2=0.33	R^2=0.56
Syn	R^2=0.37	R^2=0.35	R^2=0.36	R^2=0.38	R^2=0.62	R^2=0.80

Table 1: Evaluating the four growth iterations against the spatial properties of Barcelona and a randomly generated structure. The generative code is written in Processing (Java). Spatial Structures are analysed using UCL Depthmap (Turner, 2011).

After generating four growth iterations, the structures were evaluated considering the above mentioned invariants and compared to an urban region in Barcelona and a randomly generated system. To evaluate against invariant 1, choice [SLW], a segment length weighted measure of the shortest angular paths across the whole street network, is calculated. A structure that has the highest 10% values is then extracted and evaluated. The structure's continuity is evaluated by measuring its normalized cumulative total depth values. Total depth is also an angular-based measure based on the sum of angular turns taken to reach any segment element in the system. A normalised reciprocal of this measure defined as segmental integration can help estimating the potentials for a street segment to be a destination in the urban system.

To evaluate against invariant 2, metric mean depth analysis (MMD) is calculated. The measure here simply represents average physical distance from each street segment to the neighbouring segments within a metric radius of 1000 metres (Hillier *et. al.*, 2007). Relating to invariant 3, the distribution of angular integration is evaluated through measuring the goodness of fit KSL test to check whether the values of angular integration follow a log normal distribution. In addition, the degree of skewness is compared to random and real systems. Skewness is a statistical moment that measures asymmetry in the distribution of values. Considering invariant 4, the R^2 coefficients of axial intelligibility are compared. Intelligibility is an axial graph measure that represents the relationship between streets that have high connections to other streets (connectivity) and streets that are more integrated in an axial system.

The evaluation measure of choice indicates that iteration 3 performs better than iterations 1, 2 and 4 (table 1). Calculating MMD for different radii does not identify clear patchwork patterns in the background network of any of the three variations. This measure needs to be calculated for larger systems to verify this result. Judging on KSL test, iteration 3 fits best with normal distribution, it also presents an indicator to a well differentiated structure (Skewness=-1.46). Considering the part-whole structural unity, the structure of iteration 3 is more intelligible than other iterations and reasonably similar in terms of synergy values. Yet, all three iterations present less competitive structures when compared to the deformed grid of Barcelona or even to a random system. Considering these findings, iteration 3 prevails as it presents an optimum foreground structure that conserves physical distance and angular turn costs. It also presents a structural differentiation that approximates actual urban structures. On aggregate, the angular depth in iteration 3 fits to a log normal distribution. The distribution exhibits a degree of asymmetry. Iteration 3 also presents a relatively more intelligible structure than other iterations. Despite the relative success of iteration 3, it still fails to be close to the configurational properties of a real urban structure. However, it does perform relatively better than other iterations. These results qualify iteration 3 for the second stage in the design experiment.

Nonparametric modelling of space-form-function

In this section, a nonparametric model will be applied using a soft computing technique based on Artificial Neural Networks (ANNs). Due to its robustness, nonparametric modelling was favoured over parametric modelling. The use of ANNs in modeling would enable a more plausible encoding of the data and the functioning mechanism that captures space, form and function relationships in cities. The ANNs allow for minimizing assumptions about the input and output data distribution and the type of data used, whether continuous, categorical, or binary. They are particularly useful in cases where complexity in the system relationships and imprecision in observations are issues that threaten the credibility of simpler models. This is particularly useful for urban data provided the foreseen difficulty in matching different categorizations of land uses -for example- for different cities and different planning systems. ANNs are also fault-tolerant towards redundant information coding, where there are hidden relationships between spatial measures or between socioeconomic variables. In addition, the application of nonparametric ANNs models was seen to simplify the course of design by resorting to one functioning description rather than many.

Artificial neural networks (ANNs) consist of layers and neurons that simulate human learning. The training of ANNs can help storing embedded functions that might be used to categorize information and provide projections given new situations. With such functionality, ANNs can be used to answer *what if* questions and generalize complex relationships on presumably similar situations to the situation used in the training. ANNs are used in many fields; including medical sciences, engineering, AI …etc. They are also known to be successful in the non-linear mapping and modeling in geography (Openshaw & Openshaw 1997; Openshaw, 1998; Wang, 1994; Zhou & Civco, 1996), (Li & Yeh, 2002). The downside in using ANNs is in the difficulty to describe the relationship between the input variables and the output variables. All the training takes place within a *black box* where it is not possible to identify the functional form of the response surface. Rather than the direct path from the X variables to the Y variables, which is the case of regular Regression, the neural networks incorporate intermediate layers.

Neural networks comprise a large class of different model architectures. Traditionally the ANNs are used to classify a set of observations. In most cases, the issue is in approximating a static nonlinear, mapping $f(x)$ with a neural network $f(x)_{NN}$, where $x \in R^K$. The ANNs model to be used in training space and form-function data in this section will consist of three layers, the input, output and a layer with hidden nodes in-between. The different layers are encoded in the *multilayer-perceptron* (MLP) model illustrated in (Figure 2). Three hidden nodes are considered in the middle layer, where activation functions that store weights and biases are embedded.The Artificial Neural Networks (ANNs) will be *fully connected* and will use a *feed-forward* mechanism. The network is *fully connected* since the output from each input and hidden neuron is distributed to all of the neurons in the following layer. The *Feed forward* mechanism of the model entails that the values would only move in the forward direction from input to hidden to output layers; so that no values are fed backwards to input or hidden layers. Due to the limited number of inputs (3) and outputs (4) and a fair amount of redundancy (correlation) between two spatial measures in the input layer, we chose simple network architecture using standard nonlinear least-squares regression methods.

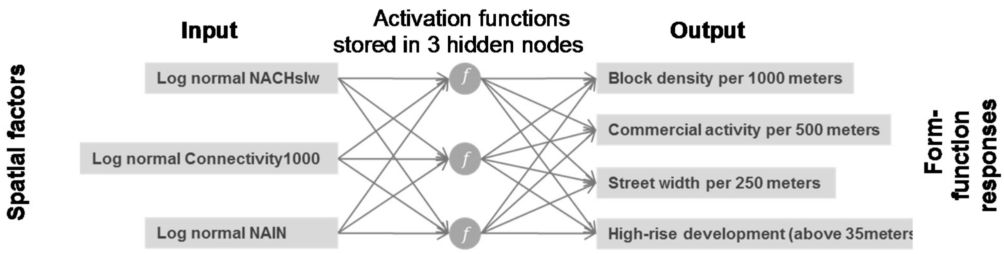

Figure 2: A neural network model applied to Barcelona, using normalized spatial measures of choice, integration and connectivity as factors and form-function attributes as response variables.

To enable the decoding and encoding of urban form-function relationships, the *pixelmapper* method was used (Al-Sayed, 2012). The *pixelmapper* was devised in mapping form-function variables against spatial configurations. Data was binned in two overlapping polygon layers and was further projected against a third polygon layer with higher resolution to preserve the accuracy of representation (see figure 3). The *pixelmapper* was first used in binning space-form-function data for the two urban regions under study. It was then adapted to serve in the context of design.

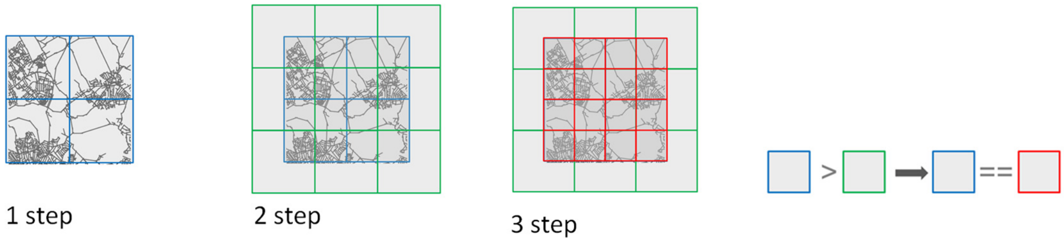

Figure 3: Binning data for correlations; storing data and spatial configurations in two overlapping grid reference layers and selecting the highest values in a third higher-resolution reference layer.

To explore the application of a nonparametric ANNs model in urban design, we reused activation functions that were previously trained and validated on the case of Barcelona and tested on Manhattan's urban structure (Al-Sayed, 2014b). We then used the learning functions to forecast a 2D target space for form-function attributes given the winning growth iteration obtained in the previous section. Geometric measures of street network configurations were given a priority role in defining form-function attributes. Form attributes included building height and density as well as street width. Functional attributes defined the relationship between spatial structure and the overall commercial zoning of the associated areas.

For the input layer, three spatial measures were used as factors, namely; normalised choice [Segment length weighted] (NACHslw), normalised integration (NAIN) and aggregate connectivity per 1000 square unit (Connectivity1000). All measures were computed using UCL Depthmap software (Turner, 2011). NACHslw is an angular measure of graph betweenness that is both normalised and weighted by street segment length. Choice in segment analysis calculates the shortest putative paths across the street network (Turner, 2000). NAIN is a normalised and angular-weighted measure of a graph's closeness. The normalisation follows a recently invented method that weights the effort made by shortening journeys by the cost in total angular depth in the spatial network (Hillier *et. al.*, 2012). Connectivity is equivalent to degree in graph theory. It is here summed up for every 1000metre square unit of a *pixelmapper* layer. Both NACHslw and NAIN can be limited to a certain metric radius that can define their graph neighbourhood. Here we use the full radius of the two measures that is radius *n* covering all nodes in the graph. Before using the continuous variables as input in the ANNs model, their values were to be normalized to avoid the effect of different network sizes. For the normalisation, a lognormal probability function was used to map the values to the range [0, 1]. The dependent responses are a mix of continuous variables running in *regression* mode (Block density per 1000 metric square) and ordinal variables running in *machine* mode (commercial activity, street width above 30 meters, high rise above 35 meters). The positive presence of the ordinal response variables was marked as 1 and the negative presence is 0.

Forecasting form-function attributes for the winning growth iteration

The ANNs model extensively discussed in (Al-Sayed, 2014b), was found to be effective at predicting form-function variables for a given spatial structure. The *pixelmapper* method used in mapping empirical data was reused here to define the approximate features of the urban space. The attributes of the solution space were then defined within that resolution level (figure 4). The street width response was estimated directly from the NACHslw values and further informed by the ANNs predictions. The rest of the estimated attributes were fully automated assuming a full correspondence between the spatial measures and the response variables. The automation was subject to the accuracy of the ANNs model and the scale of representation. To produce a smooth representation of the target spaces, positive values (1) for ordinal responses were replaced by their correspondent probabilities.

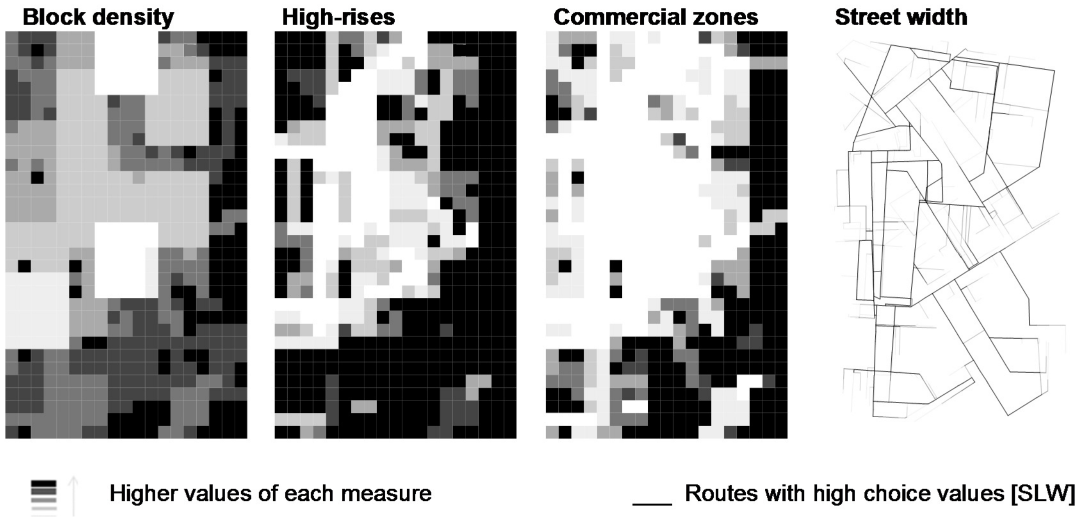

Figure 4: Responses for form-function estimated by applying the trained and validated ANN model. The spatial network measures of iteration 3 were used as factors in the ANNs.

CONCLUSIONS

The design approach presented here builds on a theoretical model and a design experiment established in (Al-Sayed, 2012) and more extensively discussed in (Al-Sayed, 2014a). The theoretical model was based on the preferential role of space in defining urban form and function. Other quantitative and qualitative criteria were assumed to come at later design stages to further shape the features of design solutions. In our design approach, three filtering processes were followed to explore the application of the theoretical prioritization model on design. The first set of design filters were applied to recognise the urbanity of a generative network structure. Four growth iterations were evaluated and compared to a random system and a section of Barcelona's grid structure. The evaluation helped selecting a growth iteration that successfully reproduced the spatial properties witnessed in real cities. The generative process was fully automated. Yet, the evaluation revealed few shortcomings that were either related to faulty evaluation or to the directional growth mechanisms implemented. Some shortcomings stemmed out of the difficulty to automate a recognition system for certain spatial measures, particularly those related to the definition of clusters. In what concerns generative growth, it was seen that any improvement on the model performance would necessarily require plausible negative and positive feedback mechanisms to be considered.

The second set of design filters used in the prioritization model entailed the utilisation of another knowledge-based model. An estimated description of urban form-function was defined using a feed-forward neural network mechanism. Considering space as a predictor of urban form and function, the model was trained, validated and tested on empirical data from Barcelona and Manhattan. The data was mapped using a spatial aggregation technique called the *pixelmapper*. Accordingly, a system-based design model was devised using the ANNs model that defined a relationship between street network measures and data on form-function (Al-Sayed, 2014b). The ANNs model was fully automated to estimate the formal and functional attributes of the generated iteration. The approach was intended to establish a city-to-city supervised learning approach where a model is trained on a data set, validated on a different data set and devised to forecast formal and functional attributes for a hypothetical urban grid. The third design filter was not utilised here as it required an interdisciplinary account on other quantitative measures.

This work presents a structured procedural approach to urban design considering a set of prioritisations, where, a functioning space is given the preference to ensure a sustainable design outcome. In evaluating, decoding and encoding urban systems the intention was to adapt designs to reflect on the natural organised complexity that cities evolve and enforce despite planning interventions. The adaptation of the resultant descriptions to design is not thought to restrain creative explorations.

It is concluded that despite attempts to present knowledge as a solid product of pure rationality, in practice; scientific knowledge is often subject to the constructs of representations and measurements. This should not avert designers from acquiring scientific knowledge or deter scientists from exploring creative synthesis of analytical descriptions. By exchanging roles, both scientists and designers could explore new creative dimensionalities of science. Empirical knowledge acts as to ascertain the first steps towards modelling urban problems, yet it presents no determinism over the subsequent course of design actions. It is at the essence of this investigation that whilst knowledge comes as to support design reasoning – particularly in what concerns unravelling urban complexity-, it does not frame designers' creativity.

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