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Expanded Design: Creativity, Machine Learning and Urban Design

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Abstract

The introduction of automated algorithmic processes (e.g. machine learning) in creative disciplines such as architecture and urban design has expanded the design space available for creativity and speculation. Contrary to previous algorithmic processes, machine learning (ML) models must be trained before they are deployed. The two processes (training and deployment) are separate and, crucially for this paper, the outcome of the training process is not a spatial object directly implementable, but rather code. This marks a novelty in the history of spatial design techniques which has been characterised by design instruments with stable properties determining the bounds of their implementation. ML models, on the other hand, are design instruments resulting from the training they undertake. In short, training a ML model has become an act of design.

The application of ML models to creative domains such as urbanism reproposes fundamental computational issues such as the organisation and representation of knowledge. Their immediate impact on creativity regards the role of processes which are no longer involving the formalisation of knowledge through code, but rather with curatorial practices based on correlating diverse datasets representing elements of cities through statistics. These operations not only constitute an element of novelty in the field of computational creativity, but they also expand the purview of designers to include non-human actors, giving agency to concerns normally excluded from urban design, expand the range of scales from the body to the planet, and make different temporalities amenable to design manipulation, and offer an abstract representation of spatial features based on statistical correlations rather than physical proximity. The combined effect of these novelties that can elicit new types of organisation, both formally and programmatically. In order to foreground their potential, the paper will discuss the impact of ML models in conjunction with larger historical and theoretical questions underpinning spatial design. In so doing, the aim is not to abdicate a specificity of urban design and uncritically absorb computational technologies; rather, the creative process in design will provide a filter through which critically evaluate machine learning techniques.

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The paper conceptualises the creative potential of latent space by framing it through the figure of the paradigm. Paradigms are defined by Thomas Kuhn as special members of a set which they both give rise to and make intelligible. Their ability to relate parts to parts not only resonates with the technical operations of ML models, but they also provide a conceptual space for designers to speculate different spatial organisation aided by algorithmic processes. Paradigms are not only helpful to conceptualise the use of ML models in urban design, they also suggest an approach to design that privileges perception over structure and curation over process. When applied to urbanism, the creative process supported by ML models favours relations between diverse datasets over objects, that is, a lighter more agile kind of urbanism.

The application of such algorithmic models to design will be supported by the research developed by the students of Research Cluster 14, part of the Master in Urban Design at the Bartlett School of Architecture, University College London.

Keywords: Urban design, Architecture, Machine learning, Paradigms, Aesthetics, Creativity

Introduction

The work of urban designers, as many other creative disciplines, is increasingly consisting of a series of data manipulations to analyse and design cities. The recent penetration of effective machine learning (ML) models has marked a significant shift as the mechanics of generative computational procedures have been radically changed and, with it, their significance in the design process. If, on the one hand, the range and scale of operations performed by algorithms has massively increased, on the other, the theoretical discourse accompanying this technological transformation has been lagging behind. As a result, computational urban design now appears to be a rather theory-light field which struggles to conceptualise and instrumentalise the transformations afforded by ML models. This paper will address such theoretical gap by first foregrounding how the mechanics of ML algorithms can impact creativity.

The arguments proposed will concentrate on computation understood as both a more fundamental component of the digital and as a domain historically concerned with the organisation and representation of knowledge. In terms of the debate on the use of ML in design, this move will allow us to put less emphasis on the generation of images to focus on patterns, statistical distribution, and numbers. From the point of view of design discipline, to think of ML models as instruments for the re-organisation of knowledge implies that the urbanism of ML models will be more concerned with strategic rather than formal preoccupations.

The first part of the paper concentrates on the how ML models function, their 'materiality', so to speak, which will act as the basis to rethink design operations. The focus of the argumentation is not purely technical (how a particular problem is solved by ML algorithms), but rather conceptual, as it focuses on the relation between ML models and creative processes. The second part of the paper dwells on the figure of the paradigm as a conceptual instrument that helps us delineate some key relations and characteristics to rethink design in the age of machine learning. In fact, the main focus of this paper is neither to solely chart out the potential drawbacks of the introduction of ML models in design, nor to advocate for their use as purely functional, problem-solving technologies; rather, it is to explore how machine learning dislodges some received paradigms of digital design to provide a new conceptual space for creativity. The paper discusses a set of theoretical ideas to help frame the introduction of machine learning in design. As my research operates in the field of urban design, this will constitute the testing ground of the ideas and observations put forward in the paper.

Projections, not Processes

To understand the impact of ML models on design and bridge the theoretical gap highlighted above, the initial notion this paper will challenge is that of process in digital design. Contrary to previous computational generative techniques, machine learning inverts the traditional relation between process and output. Rooted in the aesthetic of cybernetics, process has been the central tenet of computational design, the locus in which intuitions and rigour reinforce each other through implementation. The cybernetic motto "all process, no finality" perhaps best captures this attitude to design which has been characterised by the alignment of creativity and learning. If by creativity we refer to an exploration into fundamentally unknown domains, process becomes the methodological instrument through which one learns to navigate such open waters. To counterbalance the uncertainty of the exploration, process must be rigorous, reliable, and 'objective'; particularly, this last characteristics highlights the designers' search for an instrument of self-alienation able to negotiate between objective knowledge and subjective control. As a result, all the outputs generated under such premises must necessarily be 'perfect', as they are all deduced from a process that the designer has imbued with rigour and intentionality. Projects such as *Embryological House* by Greg Lynn[1] are architectural examples of such an approach. The project experimented with new tools for manipulating curves made available by three-dimensional software of the time to generate a vast range of designs for a house, each unique and yet all deduced from the same set of rules. The origin of the design process was a geometrical primitive (a sphere) that was subjected to a very large range of deformations abiding to a series of constraints. At the time, Lynn's project was often criticised because the design did not clearly converge towards a single, optimal solution (the best version of the house). Unable to single out the best exemplar, an additional question arose. A problem that could be understood as sort of architectural version of the 'halting problem' in computation; that is, the impossibility to determine when the design process ended, and how many variations were possible or necessary. In retrospect, however, both issues were irrelevant. Process acted as a guarantor that each output was qualitatively equal to the next, no matter how many permutations of the house were possible (all process, no finality). Lynn was clearly aware of the design paradigm underpinning his *Embryological House* as he invariably addressed these comments by pointing out that no version was better than any other.

The emphasis on process as tenet of digital design was also mirrored in language by describing process through a list of actions and, consequently, verbs. The question of 'how' a house (or an object in general) was designed took precedent over other considerations such as those represented by the questions 'what' and 'why', which were sidelined or

1 See Howard Shubert, "Embryological House," *CCA: Canadian Centre for Architecture*, https://www.cca.qc.ca/en/articles/issues/4/origins-of-the-digital/5/embryological-house.

implicitly addressed through the rigour of process itself.

Process, however, is precisely what ML models take charge of. Designers control the input datasets and observe what the ML model outputs, whilst having little or no understanding about what happens in between.[2] This marks a fundamental shift in the way we understand creativity as the computational architecture underpinning the design process no longer consists on performing actions (e.g. copy an object, deform it, etc.) based on a piece of code written by designers. Rather, ML models first and foremost output codes: that is, how to do something, or, in short, processes. The so-called training of an ML model, in which the model inductively adapts to input data to retain recurrent statistical features, is not the final product of the computational process; rather, it is an intermediate step that delivers a piece of code (e.g. trained neural network) that is then ready for its use. In fact, the training and the application of a ML model are two distinct activities that can be performed by different people at different times. In other words, the training of a ML model and its applications are co-determined: the effectiveness of the model depends on the quality of the input data and training cycles. It is worth noting that this condition constitutes an absolute novelty in the history of instruments for design. No matter how much flexibility design instruments provided, they always operated within the bounds set by predetermined rules, and therefore, were never co-determined with their applications. A pantograph, for instance, could be adapted through the manipulation of levers and springs, but the range of operations it could perform were determined once and for all at the moment of its fabrication. ML models, on the other hand, perform differently based on the input data they are trained on, and have a generic architecture that is independent from the context they are applied to. It follows that training a ML model is a design activity in its own right, a part of the creative process. On a theoretical level, we observe that deductive models no longer can account for such conditioning, and less totalising approaches better describe the co-determinist qualities of the training of ML models. To think about how creativity changes in the age of machine learning means to problematise this transformation and furnish it with a theoretical framework that foregrounds what is at stake. I will return to a more detailed discussion on the theoretical implications of this transformation by discussing how the figure of the paradigm can help us frame the technical novelties introduced by machine learning.

The training process required prior to deploying ML models also asks us to reflect on what notion of time is at work in such creative environment. Linear models such as those presupposed by induction and deduction may no longer be sufficient to describe the recursive qualities of the training ML models. As Yuk Hui, among others, discuss, the

2 This is clearly a major issue that has spun entire areas of research such the ones investigating the ethics of ML models or the developments of tools to investigate and interpret the operations of ML models (i.e. Explainable AI).

notion of time in the classical sciences moved from the linear-reversible time of cause and effect of mechanical devices to the linear-irreversible one of thermodynamics.[3] Cybernetics represents a paradigm shift as time transforms from linear to circular through the idea of recursion and the introduction of feedbacks. The training of a ML model belongs to this latter conception of time as the parameters of the model recursively adapt after each new instance is input to train the model. The linear time underpins both deduction and induction as both are characterised by linear sequences organising the relation between events and knowledge moving from the particular to the universal (induction) or in the opposite direction (deduction). Neither, however, are appropriate to describe the co-determining, recursive adaptability of ML models exhibited during the training process, nor can they account for the process of establishing correlations which rest upon the logic of stochastic and statistical distribution. The strict causality of classical inferential models is here abandoned in favour of multiple, stochastic, open modes of correlating diverse datasets which call for a different theoretical framework to be articulated. We will identify in the paradigm such a framework, especially for its particular-to-particular logic which escapes both linearity and universalisation.

To design with ML models is therefore not an issue of processes, but rather one of projections. The task is to move from the structural paradigm of processes without finalities of digital design under the auspices of cybernetics, to the environmental notion of projections in which the designer plays the role of both curator and receiver of the algorithmic operations of ML models. We can speak of projections first and foremost in technical terms: ML algorithms literally project data onto each other, be it through image-to-image, text-to-image, k-means or SOM algorithms. As we shall see, the operations of ML models involve a superimposition, an hybridisation of different data fields governed by statistics. The technical element that enables and guides the operations of data projection is the vector: a sort of mathematical Esperanto to which any phenomenon is reduced ensuring that the most disparate spatial data can be superimposed.[4] The combination of these technical features all point towards a relational approach to designing with machine learning: one characterised by the articulation of the relations and correlations between datasets made comparable by their vectorisation.

The vectorisation of different datasets also allows ML algorithms to cluster data by similarity according to new categories. For instance, the k-means algorithm will regroup input data to minimise variance within each cluster and, in so doing, will return a new representation of the input data that will differ from our perception because of the

3 Yuk Hui, "ChatGPT, or the Eschatology of Machines," *E-Flux* 137 (2023) https://www.e-flux.com/journal/137/544816/chatgpt-or-the-eschatology-of-machines/

4 For a critical framing of the importance of vectors in machine learning, see MacKenzie Wark, "Vector," in *A Hacker Manifesto* (Cambridge, MA; London: Harvard University Press, 2017).

algorithmic process employed. If the input data is highly varied, as in the case of urbanism in which social, morphological, ecological, etc. factors can be vectorised, the algorithmic process will provide a new clustering that can be interpreted as the projection of the different datasets onto each other. Moreover, as in the case of self-organising maps (SOM) algorithms, the new representation can also maintain the topological structure of the data; that is, a connection between input data and new representations. From the point of view of urbanism, these operation have profound significance. First, they expand the purview of designers both in terms of input data. For instance, datasets understood not to pertain to urbanism can actually be considered and speculated on: dietary habits, lifestyle choices, or environmental factors are some examples of such expansion which can be included elements, widening the scale or temporality of the factors considered by urbanists. Additionally, the algorithmic process returns novel representations that map out the strengths of the correlations between the diverse datasets; these can impact the scale, program, and distribution of intervention. Though we will return to this point in the final section of the paper, it is already noticeable that the implementation of ML models in urbanism can primarily address strategic rather than formal issues: the combination of diverse data will not return a new formal arrangement but rather a new portrait of the city from which to design. On the one hand, the use of ML models in design acquires qualities that are not solely visual and related to the endless proliferation of new images. On the other, it questions more fundamentally how and what kind of knowledge informs the creative process in urbanism and raises issues that concern the theory of urbanism, but just its practice.

In general terms, such operations of data projections allow designers to statistically extract the impact of certain data layers onto others; that is, the impact of a certain urban quality or behaviour (e.g. pollution, lifestyle choices, cognitive factors, morphological qualities, etc.) onto others. For instance, they can map the variation or the homogeneity with which a stack of data layers correlate: how a certain lifestyle correlates with a perceptual feature or socio-economic indicator. In some ways, we can say that for some of the algorithmic methods we listed, urban designers can have insights on the "-ness" of cities (in terms of connectedness, cognition, or perception). ML models in urbanism move the focus of the exploration away from 'how' something is conceived or implemented (this is the part that ML models take care of and provide some rationale for) to focus on 'what' and 'why'. Both lines of inquiry have much broader implications that cannot be exhausted by engineering or functional approaches as they touch on the theoretical, social, and political dimensions of design. To broaden the range of concerns also means to think more laterally to privilege data representing the experiential and perceptual, that is, qualitative aspects of urbanism. The centrality of actions and verbs is thus replaced by that of environmental qualities—the "-ness" of cities we mentioned above—which, in linguistic terms, are represented by adjectives and adverbs. The structural paradigm of cybernetics that focuses on process is substituted by the 'sensorial' one of ML models with ramifications, charging urbanism with possibilities that have been abundantly explored by artistic practices. What is at stake is to think of ML models as a series of techniques to 'listen' to the city through algorithmic operations, to move between its many registers, and broaden the field of urban design with inputs, concerns, and actors that go beyond the traditional anthropocentric focus of the discipline.

The implications of these algorithmic operations cannot, however, be accounted by technical literature. ML models are not 'passive' tools, conduits to implement humans' thoughts, but are instruments of thought that have active agency on the outcomes they generate. As previous conceptual models for design and creativity no longer fit technologies such as ML models, the quest for different figures to conceptualise this condition emerges. The figure of the paradigm provides a useful framework to think about the introduction of ML models in creative processes in urbanism. Similar to data projections, paradigms provide a more agile way of thinking that no longer relies on linear operations of deduction or induction but establishes relational connections between different elements.

On Paradigms

The figure of paradigm is a key conceptual instrument to conceptualise the technical operations of data projection by ML models and explore them through design.

Though the contemporary debate on paradigms is fundamentally linked to Thomas Kuhn's seminal book,[5] a more fruitful and fitting elaboration is provided by Giorgio Agamben's essay "What is a Paradigm?"[6] Agamben develops the notion of paradigms beyond their role in guiding scientific revolutions to think of them as methodological instruments. His foray starts from the two main definitions of paradigm provided by Kuhn himself.[7] The first aims at identifying a scientific community which adheres to a shared (paradigmatic) set of models, techniques, and practices. The second one, more fitting for this discussion, conceives the paradigm as a single element within a set. What elevates such a singular element to the status of a paradigm is its ability to act as a common example for all the elements in the set. The paradigm both gives rises to and makes intelligible—at least in some of their qualities—all the members of the set generated. Kuhn calls such a set

5 Thomas Kuhn, *The Structure of Scientific Revolutions* (Chicago, IL: University of Chicago Press, 1970).

6 Giorgio Agamben, "What is a Paradigm?," in *The Signature of All Things: On Method*, trans Luca D'Isanto and Kevin Attell (New York: Zone Books, 2009).

7 Kuhn, 182.

"normal science."[8] Paradigms differ from inductive or deductive generalisations as they are figures which articulate a particular field without fixing explicit rules or identities. Kuhn in fact famously defined them as able to "guide research even in the absence of rules."[9] The agility of paradigms can extend forward in time as it can also play "an essential role in preparing the way for perception of novelty."[10] Agamben cites Foucault's discussion on the panopticon as an example of how paradigms work. Bentham's model for a prison referred to an actual example (not an abstraction) that Foucault singled out in order to both foreground a whole series of practices embedded in institutions (forming a set) and relate them to one another (making them intelligible and, more broadly, to foreground different disciplinary regimes).[11] We can draw an a analogy between the example of the panopticon and the operations of data projection performed by ML models. In the latter, a specific dataset is projected (correlated) onto one or more other datasets. The projecting dataset acts as a paradigm in regards to the projected ones: the different distribution of correlations emerging determines both what relations between data there might be (formation of sets) and the nature of their relation (intelligibility). However, because all such algorithmic operations are performed by translating all datasets into vectors, the range and scale of operations possible is vast and extends to include both physical and immaterial elements. In this sense the example of the panopticon might be limiting as it solely focus on physical, existing elements. As we shall see in Agamben's discussion, to think ML models through paradigms allow designers to significantly broaden the range of operations possible and, consequently, the remits of creativity.

Such expansion includes the ability to perform projections between massive datasets, but also, and perhaps more interestingly for this discussion, between different media. The recent emergence of multi-modal models,[12] which can extract features from a variety of sources, are particularly important for urbanism as they allow designers to link different aspects of space and experience: from the behavioural, to the morphological, but also the acoustic, visual, etc. These operations allow designers to question both processes and objects to give rise to new categories and new correlations between objects, events, or behaviours.

The Logic of Paradigms

In epistemological terms, we can draw a parallel between how paradigms move beyond

8 Kuhn, 10.

9 Kuhn, 42.

10 Kuhn, 57.

11 Agamben, 16–18.

12 Scott Reed et al., "A Generalist Agent," *Google DeepMind,* May 12, 2022. https://deepmind.google/discover/blog/a-generalist-agent/.

the linear generalisations of traditional logical operations of induction and deduction and how ML models operate on and impact design. Deduction moves from the universal to the particular in a linear fashion, providing an overarching structure that is simply too rigid to account for the statistical operations of data projections. The deductive model computationally aligns with a rule-based approach in which (pre)determined operations oversee the generation and ensure the consistency of all the outputs. This is the approach utilised, for instance, in Chomsky's linguistics, or in shape grammar in design.[13] Induction moves in the opposite direction, from the particular to the universal, and is a far more relevant category to describe how ML models are trained.[14] However, here we are focusing on the application of ML models to design operations; that is, what happens after the a model has been inductively trained. Both deductive and inductive logics aspire to generalised knowledge and, consequently, must provide a single method stringing together the particular and the universal.

The conditions set up by paradigms differ from the ones described as they do not require a predetermined set of procedural rules to function. As for Foucault's panopticon, one particular data instance can be projected onto a whole set of other data objects in ways that no longer require hierarchical distinctions between particulars and universals. In fact, under the figure of the paradigm, the whole notion of the universal becomes untenable; what the paradigm relates are always particulars, albeit in varying distributions. Similarly, ML models allows designers to elevate a particular data object to the positions of a paradigm and project it onto other datasets. The data projections performed by the ML model return a map of the statistical distribution of correlations of how a particular dataset maps onto different ones. In other words, the model produces a map of statistical relationships that provide the basis for further interpretations and speculations.

In urbanism, a variety of computational techniques can support the use of data as paradigms. In regards to the notion of particulars, geo-referenced datasets provide a representation of a given area with unprecedented resolution and granularity: data points can be remapped from ten to one meters intervals. Such datasets can be compared to other ones without compression to seek for correlations. Such correlations can impact the strategic qualities of the interventions proposed in terms of location, scale, and program. For instance, the group *Sensory Balance*[15] compared about twenty datasets of spatial features of areas of London to discover a drastic divide between day and night life in different parts of the

13 See George Stiny and James Gips, "Shape Grammars and The Generative Specification of Painting and Sculpture," *Information Processing* 71 (1972).
14 See Anna Longo, *Jeu de l'induction: Automatisation de la connaissance et réflexion philosophique*, (S. San Giovanni: Edition Mimesis, 2022), 159–186.
15 Liu Jie, Ping Yang, Wu Hu, and Wang Huiye, *Sensory Balance*, B-Pro research Cluster 14, Bartlett School of Architecture, University College London (UCL), 2024.

capital, including affluent ones. To avoid spurious correlations, the group tested this initial observation to eventually use them to conceive an urban project around night life. It is important to point out that, contrary to previous mapping techniques, there is no trading between scale and resolution in data projections: the size of the area considered can be enlarged without a resolution loss. More sophisticated machine learning algorithms such as General Adversarial Networks (GANs) can also be hacked for similar purposes. Instead of the using conditional GAN models (pix2pix) for image imitation, the input layers of the model can be hacked to represent different and yet thematically connected aspects of an area. The model can then be trained to project data distributions of different aspects. *Equiticity*[16] uses this technique to re-design a part of central London around issues of mental health and spatial cognition. The conditional GAN model is trained on data on mental health either related personal experiences or physical spatial attributes. These input layers are then used to speculate different spatial and programmatic arrangements distributions. In other words, the input data act as paradigms that orchestrate different spatial qualities such as colour distribution, distribution of open spaces, etc., thus moving between formal, perceptual, and programmatic aspects of design. The effect is that of expanding the range of urban aspects to consider when designing. The expansion we refer to is however not one marked by the slightly authoritarian claim that urbanism is the sole discipline that can accurately and appropriately deal with any aspect of urban life. To the contrary, to expand the purview of urbanism beyond its traditional concerns should be seen as way to open up dialogue with aspects of cities which are important and yet neglected as well as to think of design as a platform for exchange.

Finally, the logic of paradigms resonates with that of the operations of data projection we detected in ML models. Analogous to paradigms, the operation of data projections escape the generalisations of deduction and induction, and, consequently, their claims of objectivity as what returned depends on many arbitrary factors such as the type of data compared, the type of projection, etc. However, far from being a limitation, the designed (arbitrary), open, and incomplete nature of data projections is conducive to a new type of urbanism that can move between the immaterial and physical, objects and events, and the personal and collective.

The Paradigm as Relations

Agamben's search for a different epistemological figure takes him to the paradigm, a move resonating with our quest for a conceptual framework to think creative operations with ML models. Particularly, the open, 'localised' (opposed to the universal generalisations of classical models of logical inference), character of paradigms better describes the

16 Tejaswini Deshmukh, Shriyansh Jain, and Aalok Joshi, *Equiticity*, B-Pro research Cluster 14, Bartlett School of Architecture, University College London (UCL), 2023.

generative operations of ML models and helps conceptualise them. To further qualify the 'localised' nature of paradigms, Agamben quotes Aristotle's passage in which the paradigm is described as a "part with respect to the part, if both are under the same but one is better known than the other."[17] Against the strict structure of formal logic, the paradigm proposes the figure of the analogy. Rather than establishing prior knowledge as rules and first principles, such as in the case of deductive logic, the analogy implies that paradigms utilise prior knowledge as a stepping stone that will eventually furnish conclusions based on either empirical or hypothetical knowledge that can be reasoned about. In other words, the paradigm, as for many aspects of the design process, is an instrument for speculation, for probing possibilities (what ML models allow through the projection of different data layers represented as vectors) even if such connections only have an intelligible rather than sensible quality. One consequence of this condition is the closer alignment between conceptual and practical approaches to design, which will be the object of the next paragraph. Here, it is worth highlighting the possibility that moving between empirical and hypothetical aspects of cities widens the remits of design by giving voice to a greater variety of actors. By exploiting the combined technical possibilities (data projections) and thinking of them as speculative paradigms to speculate new scenarios, the design process can both start from and include conditions and phenomena that traditionally have not been deemed to pertain to urban design. To a certain extent, this is what we can already experience in multi-modal ML models such as text-to-image ones, in which a prompt in a certain medium (text) is projected onto a different one (image). For urbanism, the area of research which concerns us, the examples are multiple and rapidly evolving: the possibility to rethink notions of identity, the role of non-human actors, and the relation between the individual and the collective are all amenable to design manipulations.

Element-Form (Theory and Practice)

In his essay, Agamben focuses on Victor Goldschmidt's reading of Plato's definition of paradigm. In the *Statesman*, Plato writes that "A paradigm is generated when an entity, which is found in something other and separated in another entity, is judged correctly and recognised as the same, having been reconnected together generates a true and unique opinion concerning each and both."[18] The ability to detect communalities and relations between diverse datasets is what ML models allow designers to perform and what paradigms offer to their conceptualisation in the creative process. However, Goldschmidt adds to this discussion the notion of the "element-form"[19] which incorporates both

17 Aristotle, *Prior Analytics*, 69a13-15, quoted in Agamben, 19.
18 Plato, *Statesman*, 278c, quoted in Agamben, 23.
19 Victor Goldschmidt, *Le paradigme dans la dialectique platonicienne*, (Paris: Vrin, 1985), 53, quoted in Agamben, 25.

a sensible (the objects identified) and a mental component (relationship). In fact, "the paradigmatic element is the relationship,"[20] that is, the mental ability to detect and connect the presence of the entity in separate objects. This observation resonates with the possibilities enabled by vectorisation to use ML models to straddle between empirical, immaterial, and speculative domains to question previous hierarchies informing the design of urban spaces.

It follows that the relation implied by the paradigm cannot be already given; rather, it is the result of an intentional, arbitrary decision, it is produced and generated "by 'placing aside', conjoining together', and above all, by 'showing' and 'exposing'."[21] In short, the paradigm results from an act of design. The fact that establishing a relation between datasets is an action performed by an algorithm does not suspend intentionality; rather, it makes possible to complete correlations at a scale, complexity, precision, and range previously impossible. Nevertheless, the designer constantly partakes in the process: by selecting the paradigmatic data layer(s), studying the outcomes and iterating the process to alter it. In other words, the introduction of algorithmic processes linking data changes the way in which such intentionality is expressed and implemented, but does not suppress it. Establishing relations between datasets therefore takes a variety of registers contemplating playfulness and speculation as different options can be played out and tested. Such approach overturns the common critique that accuses ML models to lack objectivity and attempts to correct it in order to make them more efficient and neutral with respect to their aims. Granted that objectivity is an historical category subjected to varying factors,[22] through the paradigm, we can reverse this perspective and accept a basic and fundamentally unavoidable condition of ML models: that is, they have biases resulting from the data used in training, etc. Through the paradigm we have a conceptual instrument to both expose the artificiality and arbitrariness of the training of ML models and to declare the intentions animating the design process. Within this account of ML models, to design is more akin to guiding such models tasking them with precise and explicit aims or agendas.

An Expanded Urbanism

What kind of implications do the technical and conceptual shift prompted by the introduction of machine learning models have on design, and urbanism in particular? The first aspect to address is the position of the designer vis-à-vis the creative process as the introduction of ML models re-patterns our understanding of the city through a series of computational operations that vastly exceed that of humans in terms of scale, speed, and

20 Goldschmidt, 77.
21 Agamben, 23.
22 See Lorraine Daston and Peter Galison, *Objectivity* (New York: Zone Books, 2007).

logic. ML models elevate the algorithmic apparatus to an instrument of thought whose mode of reasoning differs from that of humans due to the use of stochastic and statistical methods. No longer relying on human knowledge to be formalised into computer scripts, ML models inductively extract statistical patterns from input data to predict outputs. The cybernetic aesthetic in which the "machine demands that functions are supplied with cognitive and creative solutions in order to acquire a *knowing-how*, a practical mode of thinking driven by learning"[23] no longer holds. As the role of the designer shifts from supplying "cognitive and creative solutions" to curating input datasets and evaluating outputs, the centrality of processes is eroded in favour of automated reasoning governed through neural networks which alters the traditional definition of creativity. As a result, the figure of the designer aligns itself more with that of the curator able to orchestrate, correlate, and organise work that s/he is not the author of. To think of these operations through the figure of the paradigm provides a conceptual framework that matches the technical logic of machine learning without mimicking it. The kind of urbanism that results abandons the procedural tour-de-force of cybernetics to reinvent itself as a 'lighter' practice, able to operate strategically rather than solely through form and that is able to engage different, more diverse aspects of urban life through data (beyond the ones urbanists are traditionally concerned with).

The introduction of ML models in urbanism expands the purview of designers by offering an instrument that allows for curatorial, qualitative use of data in creative processes. The analogy here is with the consumption of music through digital platforms. The use of internet services to access music has only ostensibly made listeners more passive in their reception. However, as Ben Ratliff shows, listening to music through a digital platform can be charged with critical and even creative qualities that have the potential of emboldening the listener.[24] Ratliff lists twenty different strategies that can be overlaid onto the vast dataset in order for new readings and experiences to emerge. Besides once again emphasising strategic thinking over formal resolution, we can speculate an analogy between the creative listening engendered by digital music platforms and the feedback algorithm governing backpropagation in ML models. As we have seen, ML models such as GAN or k-means allow designers to project datasets onto each other and, in so doing, chart out the "-ness" of cities through data. In other words, ML models open up a conceptual space that can be occupied by other preoccupations, similar to the ones identified by Ben Ratliff. More precisely, Ratliff's twenty different strategies, once superimposed onto the vast archive of recordings available online, reveal a new representation of the database and emancipate the position of the listener. Speed, density, discrepancy, etc. are some of the paradigmatic qualities—the "-ness" we spoke of—Ratliff projects into the

23 Luciana Parisi, "The Alien Subject of AI," *Subjectivity* 12, no. 1 (2019): 29.

24 See Ben Ratliff, *Every Song Ever: Twenty Ways to Listen to Music Now* (London: Particular Books, 2016).

large database of songs to elicit new readings of it. In both Ratliff's work and the data projections performed by ML models, the trajectory of the creative process is inverted: users 'backpropagate' their agency (through listening or data projections) and, in so doing, turn what is traditionally understood as the end point of process (the consumption of music through listening or the evaluation of the outcome of a computational process) into the starting point for different connections and readings to foreground. Such operations engender an expansion of the set of concerns underpinning urban design.

The re-categorisation of datasets occurs in the so-called latent space. In general terms, the latent space provides a compressed representation of the input datasets in which similar input data (according to the architecture of the neural network employed) are positioned in close proximity. Such technical operations open up the possibility to think of urbanism as an art of connections. This conceptual shift allows urbanism to rethink its process, aims, and roles through the possibilities endowed by machine learning. Urban design can engage the city in a way that is closer to the actual experience of the space; that is, not structured by hierarchical, pre-determined and fixed categories, but rather emerging from elements and experiences that are heterogeneous in terms of their conception (arbitrary or aleatory), duration (instantaneous or permanent), and kind (objectual, behavioural, atmospheric). In this sense, the design instruments are "…not a means to an end, but an experimental method or a *knowing-how* tending towards the determination of this or that result."[25]

How can designers leverage these conceptual spaces? What spaces for design speculations do machine learning methods introduce? These questions redefine the posture designers can assume in approaching urban issues. Manoeuvring between different aspects of the city, responding to automated correlations, be able to re-describe phenomena through the lenses of paradigms all presuppose a positions of humbleness in regards to the urban condition based on the acknowledgement that cities are complex constructs that escape both singular narratives and all-encompassing design methods. The position of the designer must be more inquisitive and speculative, informed by a clear agenda, and be able to detect and exploit the outputs generated by ML models. Such agency can also include non-human actors, expand the voices participating in the design, as well as engage the experiential and environmental qualities of urbanism without immediately or solely relying on physical objects such as buildings.

The introduction of machine learning methods in urban design is therefore less about the automation of thought or the symbolic representation of empirical urban facts, and more about rethinking the agenda for urbanism. Though increases in computational power are

25 Parisi, 43.

a necessary condition for this transformation, what offers the most interesting and radical perspectives for design is the possibility to articulate a different creative process. Rather than a search for rules guiding the design process through deduction, data projections operate as "…the result of experimental reasoning, starting from hypothetical account of unknowns and proceeding with the search for low-level patterning."[26]

Examples of such a shift from process to projection can be seen in two projects among the many that have been developed within the MArch in Urban Design at The Bartlett School of Architecture at UCL. *Accent Diffusion*[27] (Fig.1) utilises ML models to address issues of identity in urban design. ML models are used to project sound onto data about building morphologies. More precisely, the model detects the subtle differences between sound recordings of a given set of sentences pronounced in the many accents present in London and projects them onto a vast database of formal configurations. The sound-to-form projection not only generates a vast repertoire of elements to compose with, but also each element is a hybrid of different parts of the dataset that, as an analogy, echoes the richness, complexity and entanglements of different cultures in London. Identities do not emerge from hardening differences, but rather by re-assembling them into novel combinations. Not only does the ML model provide a method to engage domains that are customarily outside the purview of urban design (e.g. verbal expressions and accents, which in this project represent the "-ness" of data investigated), but it also allows designers to operate across different media all contributing to the urban experience (in this case, from sound to geometry). *Mood-ulated Subtopia*[28] (Fig.2), on the other hand, utilises ML models to design the urban experience from the point of view of the individual, and their cognitive spatial perception. The project imagined an urbanism of ray casting, the computer graphic techniques which generates rendering of digital scene by projecting a light beam in space. The resulting design proposes a soft urbanism built around ephemeral, qualitative aspects of space that capitalised on the possibilities of machine learning.

26 Parisi, 44.
27 Yiwen Qian, Xuming Cai, Yiheng Xu, and Muskaan Mardia, *Accent Diffusion*, B-Pro Research Cluster 14, Bartlett School of Architecture, University College London (UCL), 2023.
28 Jiwen Bian, Rajita Jain, Trishla Chadha, and Zhaoyi Wang, *Mood-ulated Suptopia*. B-Pro Research Cluster 14, Bartlett School of Architecture, University College London (UCL), 2022.

Fig. 1 – Catalogue of design elements output by the sound-to-form ML model. Yiwen Qian, Xuming Cai, Yiheng Xu, and Muskaan Mardia, *Accent Diffusion,* B-Pro Research Cluster 14, Bartlett School of Architecture, University College London (UCL), 2023.

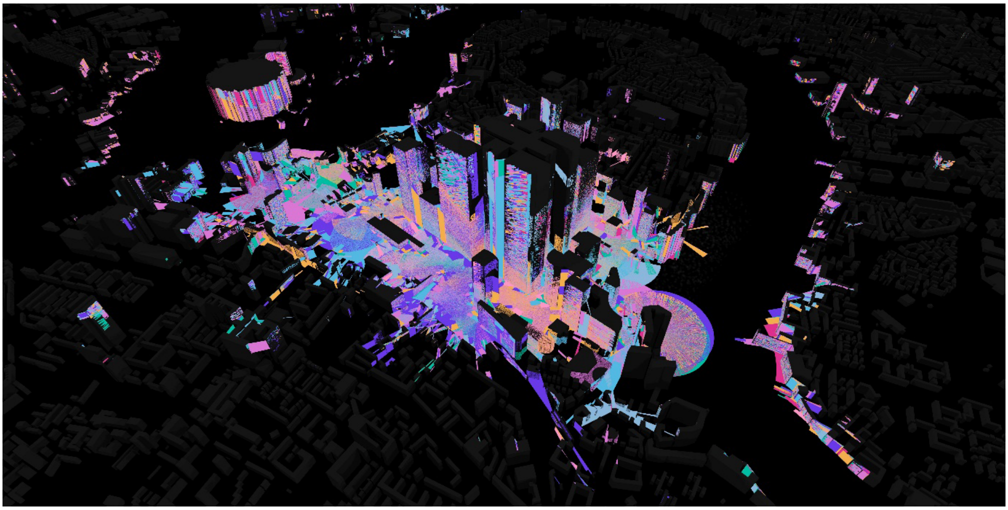

Fig.2 – Computer rendering showing the projection of data onto the city's surfaces by following the Ray Casting method. Jiwen Bian, Rajita Jain, Trishla Chadha, and Zhaoyi Wang, *Mood-ulated Suptopia*, B-Pro Research Cluster 14, Bartlett School of Architecture, University College London (UCL), 2022.

The introduction of ML models in creative disciplines such as urban design represents more than a mere technological or functional improvement of the current status quo. A closer inspection of the mechanics of ML models not only reveals the centrality of the training process, but it also inverts the relation between process and output that has characterised creativity in digital design. This new condition cannot be exhausted through technical analysis alone, as it gives rise to profound questions regarding the methods and aims of design. The possibility to project diverse datasets onto each other both moves the position of the designer towards that of a data curator and expands the range of qualitative aspects for urban environments to engage. To think this condition through paradigms not only means to furnish it with theoretical instruments, but also offers an opening towards a type of creative process less preoccupied with structural or procedural issues and more receptive to environmental, qualitative, and sensorial aspects of design. This is a territory for imagination that urban designers should inhabit and develop a sensibility for. Such transformations necessarily imply strengthening the ability to listen to different actors in the city: the many voices that can populate the design process and that will include algorithmic processes such as machine learning.

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