

IMAGINARY MAPS

A POSTHUMAN URBAN DESIGN METHOD BASED ON
NEURAL STYLE TRANSFER

Matias del Campo
Taubman College of Architecture and Urban Planning,
University of Michigan

Sandra Manninger
Taubman College of Architecture and Urban Planning,
University of Michigan

Alexandra Carlson
Michigan Robotics
University of Michigan

“Make no little plans; they have no magic to stir men’s blood.”

Daniel Burnham

ABSTRACT:

The main aim of this paper is to demonstrate and interrogate a design technique based on deep learning. The discussion includes aspects of machine learning, 2D to 2D style transfers and generative adversarial processes. The paper examines the meaning of agency in a world where decision making processes are defined by human/machine collaborations (fig.1), and their relationship to aspects of a Posthuman design ecology. Taking cues from the language used by experts in AI such as Hallucinations, Dreaming, Style Transfer and Vision, the paper strives to clarify the position and role of Artificial Intelligence in the discipline of urban design.



Fig.1: Results of 2D to 2D Style transfers based on Nolli plans and an image of the Moon: aspects of Estrangement and Defamiliarization profoundly speak in those results about a design ecology in a Posthuman era.

A POSTHUMAN TRAJECTORY

The Map. This icon of urban planning goes far beyond its mere meaning as an abstraction that allows to execute in a controlled manner the materialization of matter and space. It rather represents a vast collection of possible solutions for urban Problems. Considering the gigantic amount of data that a collection of maps spanning more than three millenia¹ represents It appears almost evident to use this enormous repository of urban imagination in the age of big data. A quick search on Google yields 8.920.000.000 images (Yes, that's almost nine billion results!) tagged *map*. The enormous vault that the discipline of urban planning has generated throughout the ages forms THE natural resource of our discipline, waiting to be mined and processed – not to copy or imitate existing urban design solutions, but to find bespoke solutions to specific problems. Urban planners and the respective students learn to differentiate urban textures through visual stimuli, i.e. seeing hundreds and thousands of images of specific maps of cities and projects in order to recognize planning styles² later. They learn to differentiate for example between Gothic, Renaissance, Baroque and Modern urban conditions through memorizing geometrical features and patterns. Neural networks (NNs), which are complex functions loosely based on the structure of the human brain, learn to perform visual tasks in a similar way, by both identifying and extracting meaningful texture and patterns within their input. This paper presents a possible application of a neural network-based image editing technique, called Neural Style Transfer¹⁸, to mesh not only low level pixel patterns, but also higher level geometric features, like roads, buildings, etc., between urban maps in an effort to create cities with novel styles. The research on this possibility started as a simple experiment for style transfer between maps in order to explore the opportunities as a design method³.

1 Introduction

It is almost impossible to judge maps on a purely pragmatic level. They always simultaneously talk about planning processes, economic environments, material preferences, political conditions and stylistic fashions of the time the urban design was created. Whether this be in the rigorous structure and geometrical purity of Renaissance Ideal cities, as exemplified in the concept of the *ideal town* as proposed by Leon Batista Alberti in *De Re Edificatore*⁴, or in the intricate voluptuous geometry of parametrically designed settlements such as Zaha Hadid's *Kartal Masterplan* for Istanbul⁵. In both cases it is not surprising that the intrinsic matter of

urban planning in a large scale involves aspects of ideology and utopia. Both examples mentioned above can be identified as representatives of ideologies that span areas beyond shape and geometry and involve political, social and economic conditions⁶. It might not surprise that in this extent they also represent a vessel and repository of the history of urban planning imaginations, and as such can be considered an enormous mine for new ideas on the nature of the city. Traditionally urban planners are trained during their studies to operate like data miners. Every new project is based on the hundreds and thousands of images ingested during the training received in architecture school. This image-based tradition is exploited in the 2D to 2D style transfer approach presented in this paper. However, it is not only about mining. What goes beyond the ability to simply ingest imagery, is the inherently human ability to perform pattern recognition. One of the aspects the human mind is particularly avid about, is to recognize events and objects, separate fore- and background. The ability to even recognize that an error or mistake inhabits the potential for a creative solution to a problem⁷. How can this, computationally rather difficult to grasp problem be harnessed to achieve image to image style transfer? This is where the aspects of the neural network's learned features, or what it has learned are salient pixel patterns within a given image, come into play. We can use trained neural networks to successfully quantify and define textures within images, and in the context of urban maps, we can create a 'city texture' and hallucinate⁸ its specific features in other images of city plans.

There are two main hurdles that need to be taken to successfully apply this technique to urban planning processes. On the one side is the database. What is the Neural Network working with? A couple of lines of code used to collect a dataset of images used in this paper can describe the process that the authors applied:

```
With
webdriver.Chrome(executable_path=driver_path)
as wd:

                                res =
                                fetch_image_urls(search_term,
                                number_images, wd=wd,
                                sleep_between_interactions=0.5)
```

The code scrapes the internet for images with particular labels as a first step to create a database as source for any form of style transfer, dreaming or hallucination. This is how we can tap into the existing resources of our own discipline in order to create novel outcomes. The second important aspect in this process is the training of the neural network. Let me

mention here a popular example to explain a method of training a neural network. Although handwritten checks are slowly fading out, there are still massive amounts of them written on a daily basis. In order to facilitate and speed up the process the reading and identifying the written numbers has been handed over to trained neural networks some time ago. NN's take in images of handwritten numbers as input and performs complex thresholding operations on the images' pixels to filter out relevant visual information (e.g., edges, curves), which it uses to ultimately form a prediction for what number is in the image. The accuracy of the network's prediction is evaluated using an error function and a ground truth label for the number captured by the image. The training of the networks starts with human intervention, in that a human tag the images, identifying the numbers (fig.2), as well as in how the error measurement is defined. How else should a machine learn what a six is, an eight, a nine, a zero etc.? How could an algorithm learn the large variety in hand writing styles that can drastically alter the appearance of a four? After being present thousands of hand-written examples, the Neural Network becomes better and better in understanding what the individual numbers are through an autonomous learning process (fig.3). Presto! Automated check reading.

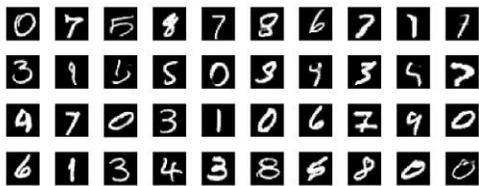


Fig 2: A set of random numbers, tagged by humans, serves as input to a Neural Network in order to learn to read the numbers autonomously. Image: James Le

Neural networks can be trained to perform much more complex classification tasks, such as differentiating between architectural styles. It is key to collect a large dataset that captures all possible variance of such styles so the NN can learn accurate and representative visual patterns for each class. The dataset used to train a neural network can be thought of as the 'world' the network exists in. We can then use these learned patterns as a way mathematically represent an image by decomposing it into its base spatial/geometric, style or texture features. For the author's the most exciting discovery in applying this technique is that by manipulating the weights/impact of style and spatial imagery the results produce unexpected, atmospheric and profoundly *other, defamiliarized and estranged* results. Estranged in a good way⁹.

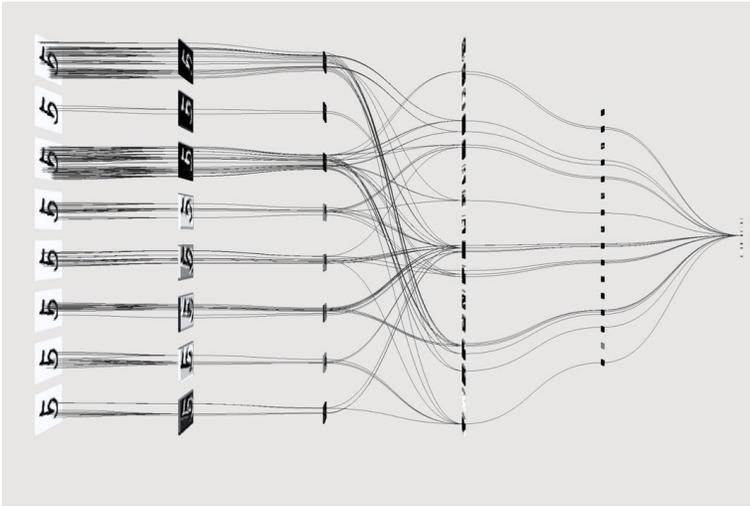


Fig.3 Sketch of a simple neural network to read numbers on a check. The network has 4 layers that allow it to increase the precision in reading the correct numbers. Please refer to the Methods section for more detail.

Image: James Le

TIPPING THE HAT TO NEUROSCIENCE

It is quite fascinating how computer science has adopted the vocabulary of neuroscience to explicate the processes invoked in NN, and the proximity of this language to the wording of architecture when it comes to the imagination of the discipline. Terminology like *Vision* and even *Dreaming* and *Hallucinating* made regular appearance in the manifest heavy postmodern era¹⁰ of the 1970ies, such as in the written works of Hans Hollein (Metaphor and Metamorphosis exhibition) and it was chronicled extensively in Gunther Feuerstein's oeuvre (fig.4) the terminology still provokes the spirit of particularly advanced architecture, albeit in a certain romantic and poetic fashion – which this paper is not about. The plot twist here being how this relationship to the terminology is currently being reinvented for the architecture and urban planning discipline by a series of young practitioners and their allies in computer science and robotics¹¹. Instead of adopting the term as a metaphor, it rather borrows the terminology from computer science and more specifically from machine vision research, which has its focus on developing Neural Network solutions for example for autonomously driving cars. The discipline of computer science themselves borrowed the terms *hallucination* and *dreaming* from Neuroscience who developed this terminology in order to explain the behavior of common neurochemical mechanisms and the phenomenological similarities between human dreams and drug-induced hallucinations¹². In this light it can be stated that a neurochemical mechanism and the synthetic ecology created with computational Neural

Networks share similar traits and are closely related, thus the conversation in this paper on *Dreaming, Vision and Hallucination* in regards of *Imaginary Maps*. Literally discussing machines hallucinating possible solutions.



Figure 4: Gunther Feuerstein, Visionary Architecture in Vienna 1958 to 1988 – Ernst u. Sohn Verlag 1988

In this paper we lay the ground for a fascinating possibility: a computational method to train neural networks to learn and recognize a variety of urban features, styles and aspects and possible ways to get neural networks to generate novel planning solutions. Another possible application for this approach is the possibility to create an app that is able to analyze urban plans and check them for errors – for example their accordance to code, their energy consumption, or their functionality. The approach however offers an entire set of possibilities that go beyond its application as a mere tool for optimization, thus provoking questions pertaining to the nature of creativity, agency and posthuman culture (Fig.5).

In contrast to the approach of other practices and individual researchers working within this paradigm, such as XKool (Wanyu He), Shao Zhang (PennDesign) and MetroDataTech (Tang Ge) -which primarily rely on finding engineering and pragmatic solutions to architectural

problems- the approach of the authors is acutely aware of the cultural and discursive dimension of the proposed approach. It is clear, that a conference paper might not be sufficient in length to cover the entirety of the implications in regards of architecture theory within a novel paradigm, thus the authors would like to apologize for the occasional brevity in the argument.

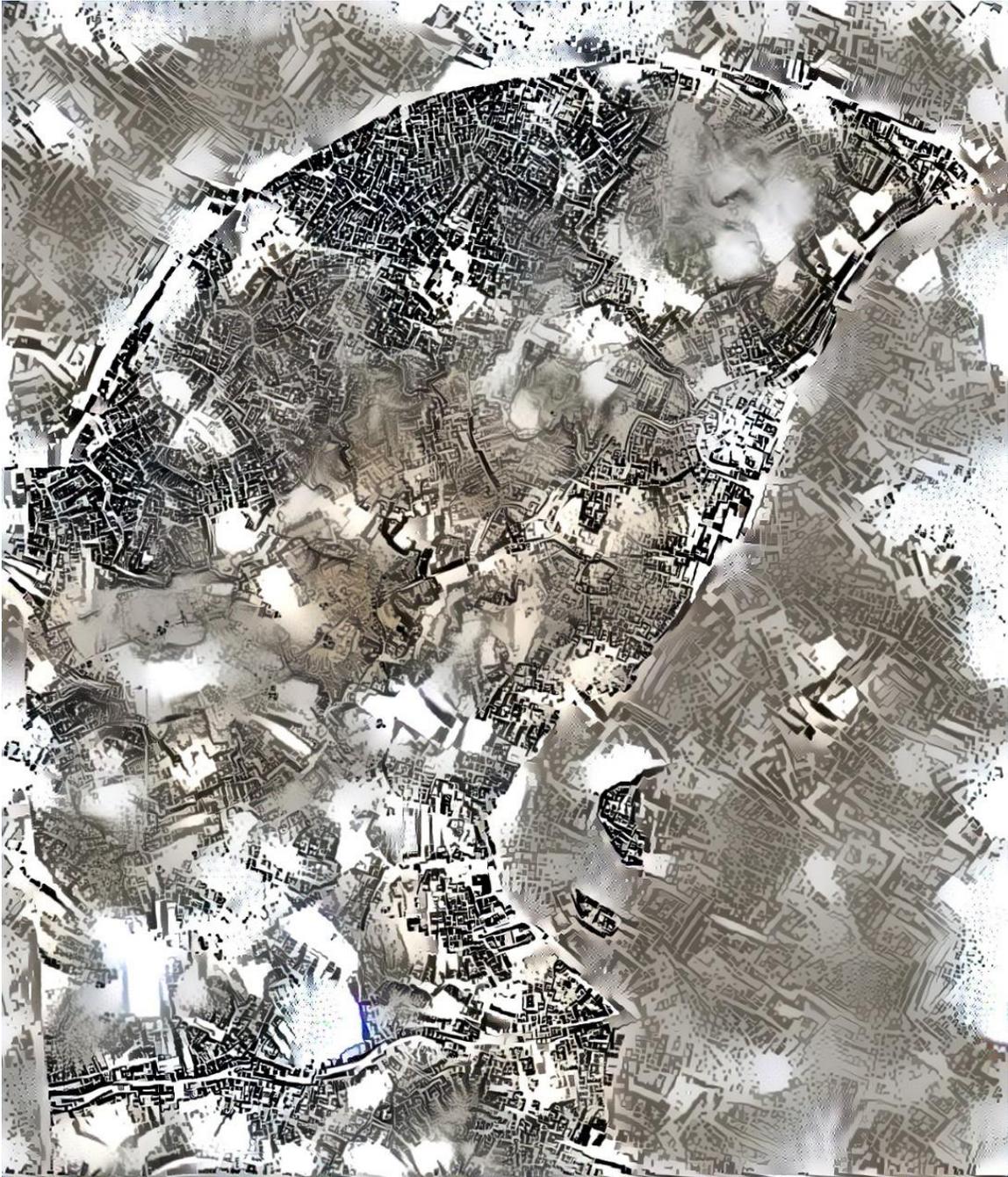


Fig.5 Result of Style transfer between a Dataset of Nocchi maps of known cities (Rome,

Barcelona, Manhattan, Washington DC) and a 19th century science plate depicting a detail of the moon's surface. These attempts can be considered experiments in Posthuman sensibilities. Can AI's be creative?

To further lay out the difference of the approach of the authors, and the beforementioned companies and researchers, we would like to propose the following:

There are two main paths of inquiry and critical interrogation: the technical expertise necessary to apply neural networks successfully to obtain comprehensive results in pragmatic problems, such as plan optimization, landscape optimization and the ecological footprint of the design. All of which can be described as tamed problems, dealing primarily with highly specified engineering problems. On the other end of the spectrum AI allows to explore the wicked part of architectural design as well, pertaining to aspects of morphological studies, creativity, style and mood.

In the course of the research conducted by the authors investigating the implementation of AI based algorithms into planning processes the authors made a crucial discovery. In the beginning the sentiment, and prejudice, was that AI can generate everything on its own. It became very quickly very obvious that this is not the case. As described above Neural Networks rely on initial human training to do anything. It is not said however that once sufficient Neural Networks have been trained by humans, they might be able to solve problems entirely autonomous. In the case described in this paper, the notion's focus was on the ability of NN to develop morphologies of architecture entirely independent and divorced from human agency. It did not take long to understand that AI faces a great amount of stereotypical ideas, and fears, based on a lack of factual information. The vast number of Blogs and Internet pages spreading misinformation on the prospects of AI makes finding a proper reference hard¹³. The fear is fueled in addition by comments such as *The development of full artificial intelligence could spell the end of the human race....It would take off on its own, and re-design itself at an ever-increasing rate. Humans, who are limited by slow biological evolution, couldn't compete and would be superseded.* By Stephen Hawking's¹⁴, and Elon Musk's comment on Artificial Intelligence: *"With artificial intelligence, we are summoning the demon."*¹⁵ During the work on the research presented in this paper, which primarily focused on 2D to 2D style transfer, it became very clear how much the behavior of a NN is dependent on the training and parameter tuning conducted by a human being (see argument above). In a sense this means if an AI turns *"demonic"* it does so only because of the training it received – channeling the malignant traits of the human mind¹⁶. The main stumbling block is the generalization of the problem. In

addition, there is a major problem with the assumption that “Jobs get Lost” This generalized assumption needs to be met with a healthy dose of skepticism and needs a critical interrogation. On the one side Jobs transform into something different, on the other hand it is possible to think about jobs in general in an alternative way. The economic concepts that are currently in operation will not be able to cope with the changes at hand pertaining to AI and Automation – as they are profoundly rooted in the 19th century economic thinking of the industrial revolution which are not applicable any more¹⁷. The way we think about jobs have to transform with the surge of AI and Automation. All of these points describe the ecology of the conversation, the intellectual atmosphere that the research started to touch upon in the initial phase of the project, in regards of grasping the scale of this paradigmatic shift. On another note it can be stated that the term AI is profoundly vague as it describes an entire array of computational techniques such as Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), and many more.

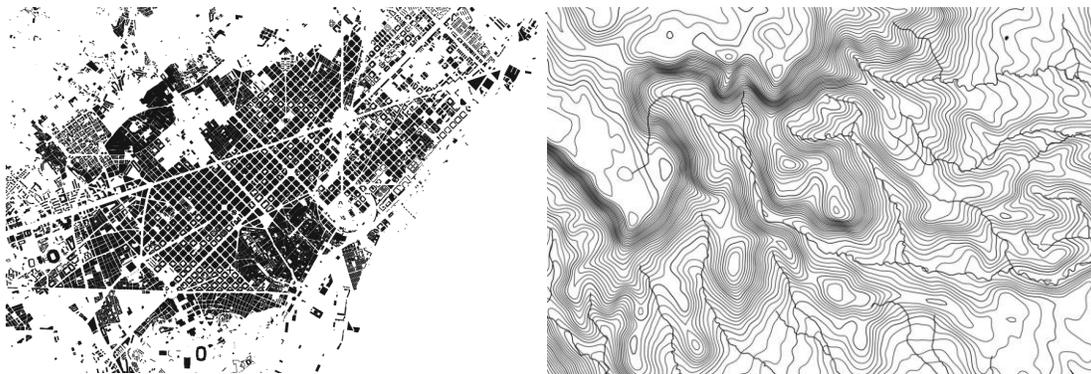


Fig.6: Style example: Nollli map of Barcelona, target example: Topo lines of a hills (source: Schwarzplan.de, Bundesforste)

If we turn the focus back on its consequences for urban design the authors would claim that when these techniques are applied to design, they can blend a chronology of styles to create a *dynamic style* that captures and reflects a variety of design techniques over a period of time including social and cultural evolution (fig.3). Style artifacts can be exaggerated to a point of hyperbole, transforming the natural balance/harmony of human style and design into a pareidolic and compositionally unstable, but novel form rooted in post-human (in the sense that they were not primarily authored by human ingenuity), but humanly accessible, architectural features. An example for this approach was tested by the authors by creating a database of Nollli maps of various cities scraped from the web and applying this *style* to various target images (fig.6). In a playful approach we chose images such as 19th century science plates

of the moon, topo lines of alpine areas and random Asian cities as target files. The resulting images serve as a first proof of concept of a possible Neural Network technique for the design of cities. Further work on this technique will be conducted in the upcoming semesters. The goal is to gain better control of the Neural Network by implementing rulesets in order to give more weight to specific solutions. For example, the rulesets defined by Christopher Alexander in *A Pattern Language*. It would be highly interested to see how these rulesets can be applied to an urban condition.

The presented 2D image editing method has interesting implications for 2D urban design applications. By employing this technique, it is possible to create style transfers between various city plans, or to hallucinate alien features into conventional maps. Exemplary demonstrated by creating style mash ups between rural areas and city plans, or mutants of various urban conditions. In the following the authors would like to explain the technical background of this approach, explaining the computational methods used in NN.

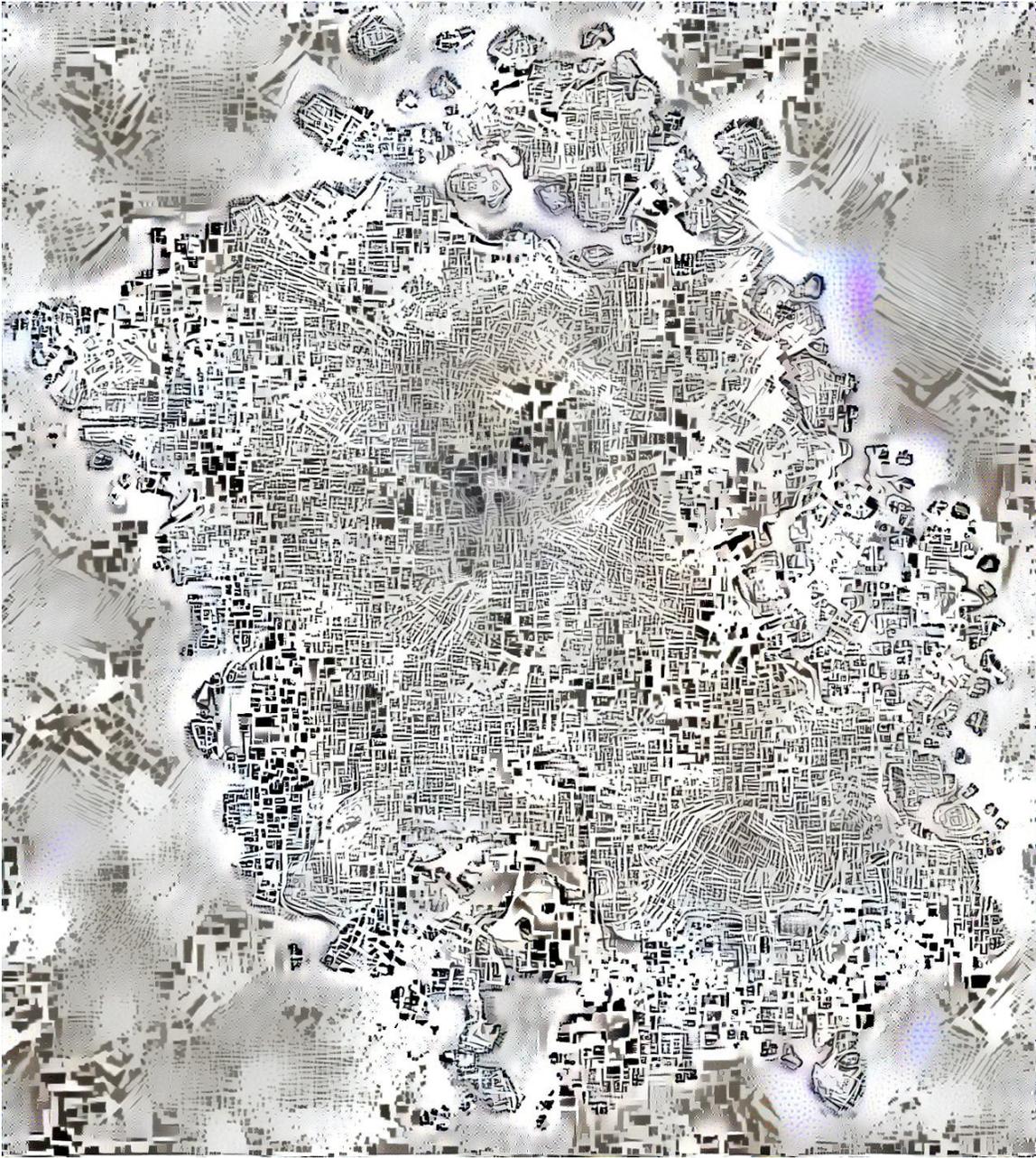


Fig.7 Imaginary City Map. 2D to 2D Style transfer result between a database of Nolli plans of various cities as a style and a 19th century science plate of a moon crater as a target image.
Cities on the Moon

2 Background – Generative Adversarial Neural Networks and the 2D visual world

Artificial neural networks are computing systems that are designed to loosely emulate the hierarchical structure of the human visual cortex. A neural network is comprised of processing nodes, called *neurons*, that are organized into groups, called *layers*, based upon how they connect to other nodes in the network. Input information flows through a neural network in a feed-forward, hierarchical manner: Each neuron in the network receives input from neurons in the preceding layer and transforms it into a new representation via a nonlinear function, which acts as a threshold that filters out relevant information captured by its input. This new representation becomes the input to the neurons it is connected to in the proceeding layer.

The way in which neurons are connected and transmit information are specific to particular tasks and need to be learned from input data. In this paper, we are interested in purely visual tasks and modeling visual information, so the following sections only consider convolutional neural networks (CNN), which are designed to operate on images.

The set of filtering transformations the network performs on images, and consequently the novel ways the network represents salient visual information captured by the images, are learned directly from the image pixel intensities. For example, in image classification, a neural network transforms an input image into a new representation by decomposing it into a set of visual features that makes the semantic image content easy to classify as, for example, ‘Street’ or ‘Plaza’. The visual features that comprise this new image representation could be textural, like tar, concrete, greenery or shadow, or pertain to geometry and shape, like curves or corners. Thus, the ‘Street’ class may be represented by a set of long, continuous line features combined with stone textural features such as pedestrian crossings or green striped in the middle of the road, whereas the ‘Plaza’ class could be represented by a set of corners and polygonal features. These visual features are extracted sequentially by the network, where the first layers filter out simple lines, edges and textures, and the later network layers filter out the sets and combinations of these features, such as corners. The final network layer predicts the semantic class label, e.g. ‘Street’, based upon the set of features extracted from the image by the preceding layers. (fig.7)

In this example, the CNN is trained for a discriminative task, and functions as a prediction/classification machine. For this kind of task, the network learns only to model the visual information that maximally differentiates the semantic classes present in the dataset.

3 Methods - or: Modeling the Style of the Real World

Independent of the task, neural networks learn how to represent images in terms of color, texture, and geometric structure. These representations can be used to perform image manipulations that result in unique design. In the following subsections we discuss the specifics of the style transfer technique called Neural style transfer¹⁸, which was used to generate the the images in this paper and forms the core result of the presented process.



Figure 8: Iconic buildings in architecture can have their styles ‘quantified’ and transferred to other iconic buildings using the Neural Style Transfer method. (Image: Alexa Carlson)

The objective of this image editing method is to alter a given input image so that it captures the style of a second, ‘style guide’ image without altering the original content, i.e., the geometric/spatial structure of the input image.

As previously described, an input image can be decomposed into specific visual features by projecting it into a given network layer, i.e., transforming it into the set of visual features learned by that layer. The network layer representation of the image not only provides information as to what type visual features are present in the image, but also where they occur within the image. Thus, through an optimization process, we can iteratively change the pixel values of our input image such that the network’s representation of its style features, like texture and color, resembles the network’s representation of the style features of the guide image, while making sure that the network’s representation of structural features in the input image, such as outlines of buildings or edges, remain unaltered. This technique allows us to have a quantifiable metric of style that can be used to probe how the 3D nature of buildings, and other architectural components, like streets and buildings, are decomposed and represented in this 2D space. As shown in Figure 8 and Figure 9, this new style representation of a building can be fused with other buildings to generate novel architectural types.

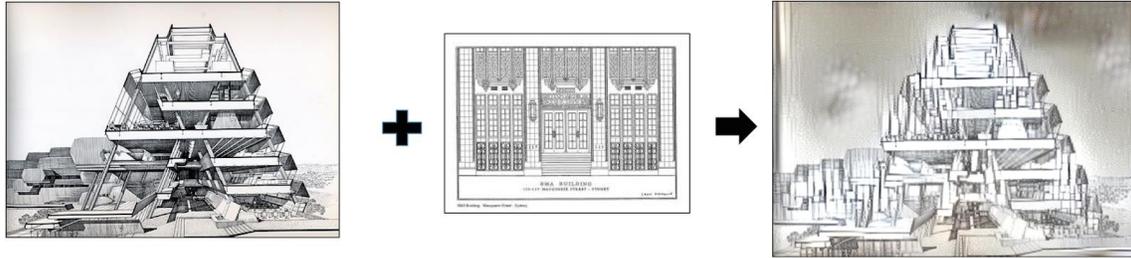


Figure 9: Using the same Neural style transfer method, we can apply the architectural style of one building section onto another to produce a novel, different architectural style.

Style transfer in addition to its technical abilities evokes memories to the discussion on style in architecture. It is indeed amusing that the term *Style* returns into conversations about architecture and urban planning via neuroscience and computer sciences, as if it comes back to haunt the discipline and remind them of the importance of its own tradition in this crucial conversation, with proponents such as Gottfried Semper²⁰ and Alois Riegl²¹.

4 Conclusion – The Defamiliarization of the City, or: An Alternative Utopia

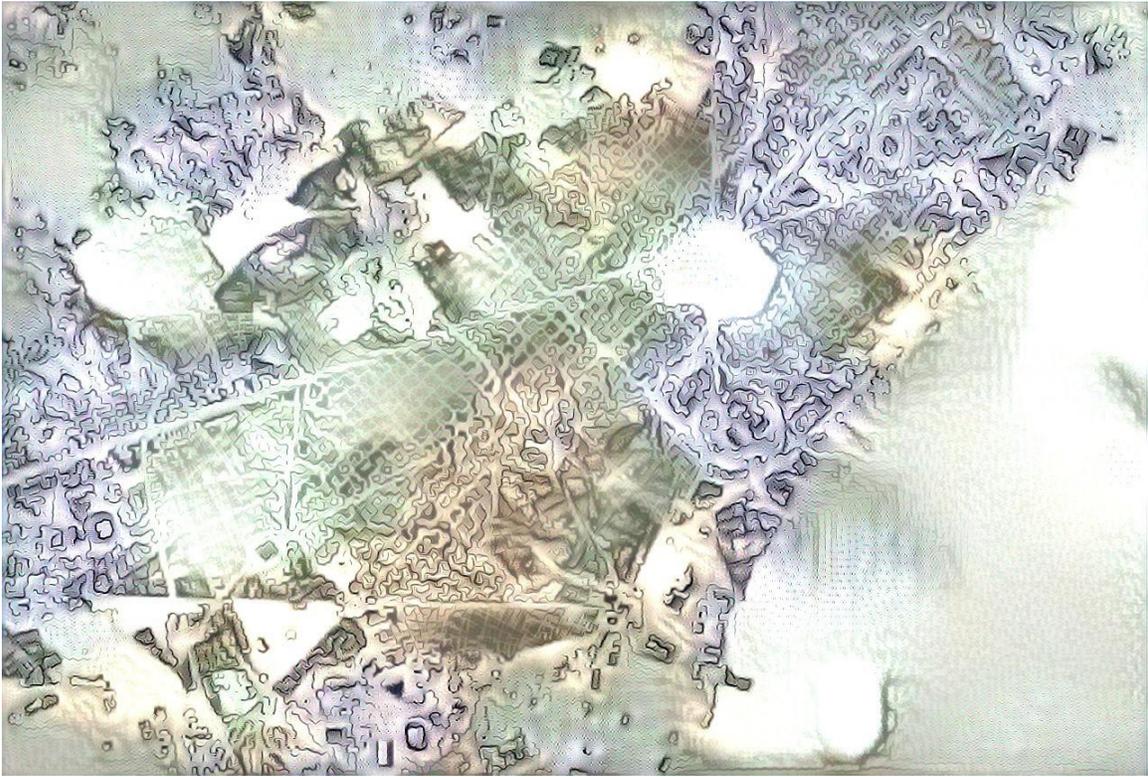


Figure 10: A Posthuman design of a City. This image was created using a NN to hallucinate features of one known map (Barcelona) into a random landscape. See also Fig.6

As described in the introduction to this paper the urban map is a cultural staple of the architecture discipline. It is the medium that best captures the intentionality of the urban project in an abstract medium as a two-dimensional surface. In architecture discourse the line, the plan, the abstract representation of materiality has played a major role, and it always has been interpreted as the result of human cognition and mind. This can be illustrated as a core idea in the architectural theory of for example Leon Battista Alberti, as expressed in the *De re aedificatoria*, pertaining to the distinction between “lineament,” the line in the mind of the architect, and “matter,” the material presence of the building. This particular distinction plays a key role in architectural design, and the conceptualization of the architectural project, throughout the history of western architecture. Le Corbusier described this at the heyday of modernism in the twentieth century like this: “Architecture is a product of the mind.” The distinction between mind and matter can be found in Vitruvius, in the distinction between “that which signifies and that which is signified”; at the Accademia di San Luca in Rome, between *disegno interno* and *disegno esterno*; or in Peter Eisenman’s distinction between *deep aspect* and *surface aspect* in architecture, to name just three examples²² that profoundly describe the planning process as a particular ability of the human mind. What position does the discipline have when it comes to understanding the potentialities of applications such as NN’s that are able to produce results that question the sole authorship of human ingenuity? Well, there is always the chicken & egg problem: NN’s origin in the human mind. That they are able to autonomously generate plan solutions is in itself not yet proof for thinking or even intelligence. However, if we take the philosophical standpoint of materialism it would allow to create an even field between these two thinking processes. In a materialist tradition though itself is just the result of material processes in our brain, neurochemical reactions able to form thought. This was briefly described above in the section explaining the origin of the terminology used in this paper such as *Hallucinating*. If this position is taken, then the conclusion is that AI’s can think as much, and form original language²³ or shape²⁴ as humans can, the only difference being that their neural processes are not based on neurochemical processes but computational processes within another material paradigm. In this paper, we present the possibility to utilize AI applications for the generation of planning processes. In particular the application of style transfers with NNs. This approach on the one side critically interrogates the unique position of the human mind when it comes to creative processes and in addition questions aspects of creativity in planning processes. In a design ecology where the boundaries between human and computational cognition are increasingly blurred, the presented process harvests the multiplicitous solutions found by architects throughout the ages and employs mining big data to create possible novel solutions to planning problems.

In an outlook it can be stated that this is only a first attempt in the area of the critical interrogation of planning in architecture in the age of AI. In fact, there is still a lot to be done. The first, alien, results achieved in this paper can only be seen as a first tapping into the potentialities of this approach. From tapping into novel design direction that rather talks about how machines see our world - with all its wonderfully strange results in terms of morphologies, chromatics and possible theories, to profoundly pragmatic approaches. It is feasible to speculate about the pragmatic applications of the findings in this paper. The possibility to create an application as a corrective tool in the planning process. Through datamining (Fig.5) it would be possible to create a NN that can analyze plans to see for example if they comply with local building codes. Or the plans can be analyzed to see if they are functional at all. All of these abilities need to be trained, heavily relying on human judgement at the beginning, but increasing its abilities after a period of training.

Further research needs to be done to dive deeper into the opportunities presented in this paper. In this extent the work on this problem can be considered a work in progress. The refinement of the algorithm allows to continue the conversation laid out in the conclusion of this paper. The authors of this paper have already started refining the approach and are looking forward to the in-depth interrogation of this posthuman design ecology.

References:

- 1: The authors refer here to the map of the Babylonian city of Nippur – ca. 1400BC
- 2: *Style* in this context of conversation is borrowed from computer science to describe a specific computational problem.
- 3: The full paper contains a glossary explaining the mathematical background of the work done by the authors. By request the authors can provide the code for others to replicate the results.
- 4: Leon Batista Alberti, *De Rei Edificatore*
- 5: *Zaha Hadid Masterplan Istanbul*
- 6: *Just think about Patrik Schuhmacher's Theoretical oeuvre and the schism it has created in the discipline by provoking with neoliberal statements. In the process creating a counter culture in Digital Design opposing the neoliberal position and adopting instead a leftist, Accelerationist Ideology.*
- 7: See also Greg Lynn's entire conversation on "Happy Accidents"
- 8: See Glossary
- 9: Graham Harman, *Weird Realism: Lovecraft and Philosophy*, Zero Books, Hants, UK, 2012, p.93
- 10: Think of Coop Himmelblau's manifests of the 1970ies, or Hans Hollein's flirt with the terms Visionary, also Peter Cook Visionary Architecture, or Gunther Feuerstein's Book: "Visionary Architecture in Vienna 1958 to 1988"
- 11: See for example the work of Stanislas Chaillou, Daniel Bolojan, Guvenc Ozel, Daghan Cam, Alisa Andrasek and many more.

12: Jacobs, Barry L., Dreams and hallucinations: A common neurochemical mechanism mediating their phenomenological similarities, *Neuroscience & Biobehavioral Reviews*, Volume 2, Issue 1, Elsevier, London 1978, p. 59-69

13: <https://time.com/4742543/robots-jobs-machines-work/>

<https://steemit.com/science/@vitruvianman/conspiracy-theories-and-legends-artificial-intelligence>
(visited July 13th 2019)

14: Hawkings, Stephen., excerpt from an Interview with the BBC given December 2nd, 2014

15: Musk, Elon., Q&A during the MIT Aeronautics and Astronautics department's Centennial Symposium in October 2014.

16: See also Jeff Larson, Surya Mattu, Lauren Kirchner and Julia Angwin, *Machine Bias* -

17: See also: N. Srnicek, A. Williams, *Inventing the Future*, Verso, London, New York, 2015

18: Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. "A neural algorithm of artistic style." arXiv preprint arXiv:1508.06576 (2015).

19: Kato, Hiroharu, Yoshitaka Ushiku, and Tatsuya Harada. "Neural 3d mesh renderer." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

20: Semper, Gottfried, *Der Stil in den Technischen und Tektonischen Künsten oder praktische Ästhetik: Ein Handbuch für techniker, Künstler und Kunstfreunde (Band 1): die textile Kunst für sich betrachtet und in Beziehung zur Baukunst.* Verlag für Kunst und Wissenschaft Frankfurt am Main, 1860, P.13

21: Riegl, Alois, *Stilfragen: Grundlegungen zu einer Geschichte der Ornamentik*, Berlin 1893

22: Hendrix, John S., "Leon Battista Alberti and the Concept of Lineament" (2011). *School of Architecture, Art, and Historic Preservation Faculty Publications*. 30.

23: See for example the *Bob & Alice* experiment by the Facebook AI Research group. Two chatbots were programmed to discuss economic problems with each other. Once the test ran overnight the two bots started to develop their own language.

24: See for example the artwork Portrait of Edmond de Belamy created by Paris based art collective *Obvious* using a Generative Adversarial Network. It was sold at Christies for the sum of \$432.000, and was promoted by the auction house as *the first painting solely created by Artificial Intelligence*

25: Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. "A neural algorithm of artistic style." arXiv preprint arXiv:1508.06576 (2015).

5 Glossary – Mathematical Supplementary

We provide the mathematical formulation for the different 2D to 3D image editing methods in this section. Each of the following descriptions treats a neural network as a function whose parameters/weights map the input space of images to the output space of labels, or into the activation/feature space of a given network substructure, e.g. a layer or neuron. Additionally, when the term *error* is used, we are referring to calculating the Euclidean distance between two quantities. This is denoted by $|\dots|$ in the following equations and definitions.

Style Transfer

Using the learned representations of a pretrained image classification neural network, VGG-16, we can define a training objective that is based upon the spatial features, or ‘content features’ of the input 3D mesh, which we assign the name m and the 2D ‘style features’ of the second, user-provided guide image, which we assign x .

To make the shape of the generated mesh, m , similar to that of m , the 3D content loss can be defined as:

$$\ell(m|m^c) = \sum_{v_i, v_i^c \in m, m^c} |v_i - v_i^c|^2$$

Where v is the set of vertices for the manipulated mesh m and v is the set of vertices for the original content mesh m .

The style loss is defined to be the same in the 2D image case using the rendered/rasterized image that is output from the 3D Neural mesh renderer:

$$\ell(m|x_s, \phi) = |M(f_s(R(m, \phi))) - M(f_s(x_s))|_F^2$$

Where R is the 3D neural renderer function that projects the 3D mesh m to a rasterized 2D image, ϕ is the viewing angle at which to rasterize m , f_s is the pretrained VGG-16 network (used as a function) that projects the rasterized image into the feature space/representation of a specific network layer, and M is the Gram matrix function, which acts as a metric of style. The feature layers of the VGG-16 network used were *conv1_2*, *conv2_3*, *conv3_3*, and *conv4_3*. These two losses are summed to make the final objective, which is minimized via backpropagation to make the output mesh object.

2D to 3D vertex optimization

This method is similar to style transfer, but instead of using the learned feature representations to manipulate the mesh, the training method minimizes the error between the input mesh rasterized into a silhouette image and a user-provided guide silhouette image, $x_{\text{silhouette}}$. To rasterize a silhouette image from a mesh, the 3D neural mesh renderer is paired with a neural network that generates a silhouette image from the output of the mesh renderer. The training objective is to minimize the difference between the rendered silhouette image and the reference/guide silhouette image via backpropagation:

$$\ell(m|x_{\text{silhouette}}) = |R(m|\phi) - x_{\text{silhouette}}|^2$$

3D Deep Dreaming

Deep dreaming, whether it is applied in 2D or 3D, is a visualization technique that allows us to qualitatively determine what visual features a given substructure of the network has learned. Conceptually, it makes assumptions similar to the grandmother cell hypothesis in Neuroscience: there is one neuron that is trained to be the detector for the face of a grandmother. Thus, this process of deep dreaming is more like hallucinating or pareidolia; the network is emphasizing vague pixel patterns in the image if those patterns resemble something that the neuron has learned to detect. In essence, we are seeing what the network is ‘seeing’ in the image.

To achieve deep dreaming, the training objective is to maximize the activation of a specific neuron, layer, or class by changing the values of the input image pixel intensities over many iterations. In 3D, the same objective is used to manipulate the vertices of a mesh object. Let $f(x)$ be the GoogleLeNet pretrained neural network as a function that outputs an activation/feature map for the input image x at the specified neuron. The 3D neural mesh renderer is used to transform the mesh m into an image, which is then fed into GoogleLeNet to produce an activation map for the chosen neuron. A neuron in layer *inception_4* from GoogleLeNet was used for all of the mesh manipulation.

The training objective for 3D deep dreaming to be optimized is

$$\ell(m) = -|f(R(m, \phi))|_F^2$$

where $R(m, \phi)$ is the rasterized image given the input mesh and viewing angle and f is the GoogleLeNet pretrained network that projects an image into the representation of the specified neuron.