Imaginary Plans
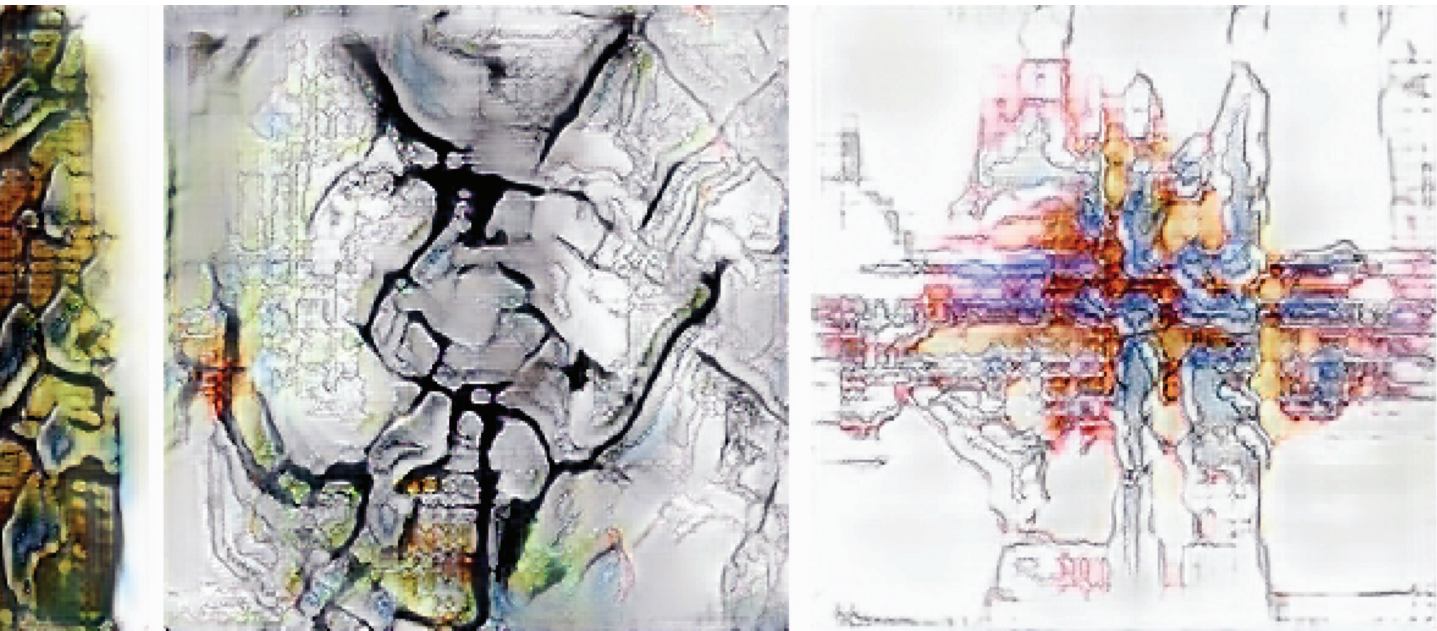
The potential of 2D to 2D Style transfer in planning processes

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ABSTRACT

Artificial Neural Networks (NN) have become ubiquitous across disciplines due to their high performance in modeling the real world to execute complex tasks in the wild. This paper presents a computational design approach that uses the internal representations of deep vision neural networks to generate and transfer stylistic form edits to both 2D floor plans and building sections.

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 (Figure 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 Architecture.

1   Results of 2D to 2D Style transfers based on plans: aspects of Estrangement and Defamiliarization profoundly speak in those results about a design ecology in a Posthuman era

2   Günther Feuerstein, Visionary Architecture in Vienna 1958 to 1988 – Ernst u. Sohn Verlag 1985

INTRODUCTION

The Plan. This icon of architectural production 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 architectural problems. Considering the gigantic amount of data that a collection of plans and sections spanning several hundred years represents, it appears almost evident to use this enormous repository of the architectural imagination in the age of big data. A quick search on Google already yields 10,400,000,000 images (Yes, that's more than 10 Billion results!) tagged "plan" and 4,660,000,000 images tagged "section". These vast collections of images of course also contain noise, images that have nothing to do with plans and sections within an architectural tradition—this problem can be solved through tag checking and the combination of several tags with each other. The enormous vault that the discipline of architecture has generated throughout the ages forms THE natural resource of our discipline, waiting to be mined and processed—not to copy or imitate existing architectural solutions, but to find bespoke solutions to specific problems. This can be compared to the developments for example in Diagnostics where the large amount of existing diagnoses based on specific images (Radiographies, MRIs, Tomographic Scans, etc.) serve as the basis to train Neural Networks to deliver medical diagnostics with higher accuracy. Analogous to the medical field, Architects and Architecture students learn to differentiate for example styles through visual stimuli, i.e. seeing hundreds and thousands of images of specific projects (the discriminator in this case being the teaching faculty – more on the role of discriminators in Neural Networks in the technical section of this paper) in order to recognize styles later on. They learn to differentiate for example between Gothic, Renaissance, Baroque, and Modern architecture through memorizing geometrical features and material qualities.

We made use of that phenomenon in the development of the Neural Network presented in this paper. This paper presents a possible application of Artificial Intelligence (AI) to train a Neural Network (NN) to perform style transfers between plans. In particular we are speaking of a 2D to 2D style transfer based on pixels. The research on this possibility started as a simple experiment for style transfer between plans.

It is almost impossible to judge plans on a purely pragmatic level. They always simultaneously talk about planning processes, material preferences, and stylistic fashions of the time the plan was created. In this extent they also represent a vessel and repository of the history of architectural imaginations, and as such an enormous mine for architectural ideas. Traditionally architects 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

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perform pattern recognition. One of the key aspects that the human mind lies in the ability to to separate fore- and background, to recognize events and objects, to even recognize that an error or mistake inhabits the potential for a creative solution to a problem[1]. How can this, computationally rather difficult-to-grasp problem be harnessed in a 2D to 2D style transfer?

This is where the aspects of training a network come into play. The increased computational power allows to train networks successfully to look for specific features in plans, and dream those on to other images. 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 era[2] (Figure 2) and still evoke the spirit of particularly advanced architecture, albeit in a
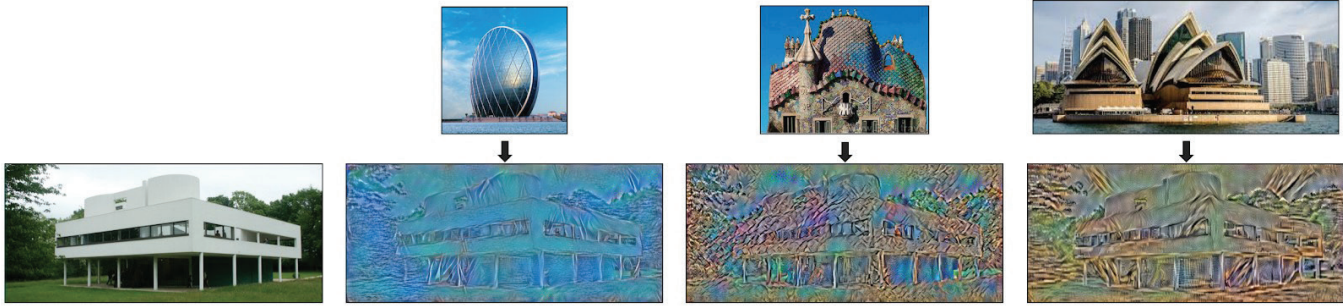
certain romantic and poetic fashion—which this paper is not about. It rather borrows the terminology from computer science and more specifically from machine vision research, which has its focus on developing Neural Network solutions for example for autonomously driving cars. Computer Science, as a discipline, borrowed the terms Hallucination and Dreaming from Neuroscience that developed this terminology in order to explain the behavior of common neurochemical mechanisms and the phenomenological similarities between human dreams and drug-induced hallucinations[3]. 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, leading to the conversation in this paper on Dreaming, Vision and Hallucination in regards of Imaginary Plans. Here we literally discuss machines hallucinating possible solutions.

In this paper we lay the ground for a fascinating possibility: a computational method to train Neural Networks to learn, recognize, and generate novel plan solutions for a variety of architectural features, styles, and aspects. Another possible application for this approach is the possibility to create an application that is able to analyze plans and check them for errors, for example their conformity to building code, their material 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.

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—our approach is acutely aware of cultural and discursive dimensions. It is clear that a conference paper might not be sufficient in length to cover the entirety of the

implications in regards to architectural theory within a novel paradigm, thus the authors would like to apologize for the occasional brevity in the argument. 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. One, the technical expertise necessary to train Neural Networks successfully to obtain comprehensive results in pragmatic problems, such as plan optimization, structural optimization, and the consumption of material, all of which can be described as tamed problems dealing primarily with highly specified engineering issues. Two, lies in AI, that alternately allows the exploration of the wicked part of architectural design as well, pertaining to aspects of morphological studies, Style, and mood.

In the beginning of this research there was a preconception about the use of AI in architecture. This focus of this notion 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 hard[4]. 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), Cycle GANs, and more.

If we turn the focus back on its consequences for Architecture, we would claim that when these techniques are applied to design, they can blend a chronology of styles to create one dynamic style that captures and reflects a variety of design techniques over a period of time, including social and cultural evolution (Figure 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 posthuman (in the sense that they were not primarily authored by human ingenuity), but humanly accessible, architectural features.

Both of the presented 2D image editing methods have interesting implications for architectural applications, such as plans and sections. By employing this technique, it is possible to create style transfers between various plans, or to dream alien features into conventional plans. In the following the authors would like to explain the technical background of this approach, explaining the computational methods used in NN.

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 that input 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 to which it is connected 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—is learned directly from the image pixel intensi-ties. 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, 'Door' or 'Column'. The visual features that comprise this new image representation could be textural, like marble, concrete, glass or metal, or pertain to geometry and shape, like curves or corners. Thus, the 'Column' class may be

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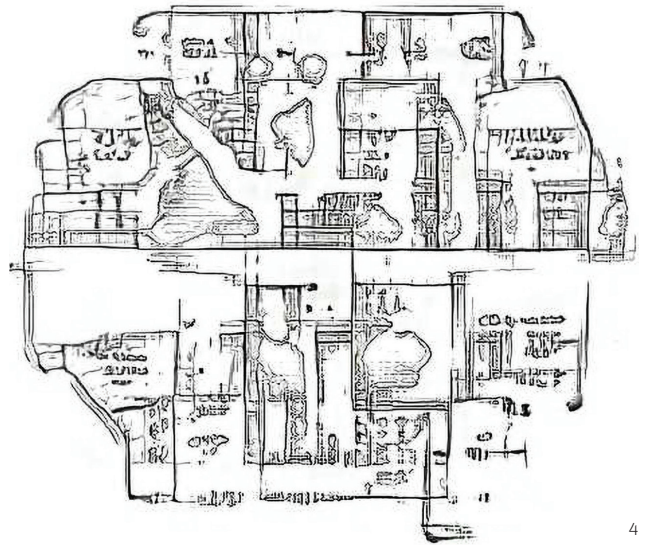
3   Iconic buildings in architecture can have their styles 'quantified' and transferred to other iconic buildings using the Neural Style Transfer method

4   Imaginary Plan; 2D to 2D Style Transfer result between a database of modern plans and a database of baroque plans

represented by a set of long vertical line features combined with stone textural features, whereas the 'Door' class could be represented by a set of corner and wood 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. 'Column', based upon the set of features extracted from the image by the preceding layers.

In this example, the CNN is trained for a discriminative task and functions as a prediction/classification machine.

Neural Networks also can be taught to perform generative tasks like image rendering. In the case of image generation, Neural Networks learn the distribution of visual information over all possible images in the input dataset. Conceptually, this means that the network learns to interpolate between the images in their training set to "imagine" previously unrealized images. The majority of the images in this paper were generated in this manner and form the core result of the presented process.

State-of-the-art generative networks are called Generative Adversarial Networks (GANs)[5]. In a GAN framework, the generative neural network, called the generator, is trained by a second neural network, called the discriminator. The generator network renders candidate images, and the discriminator evaluates them by comparing the rendered images to real images. Both networks are trained simultaneously, and they are adversaries to one another. The generative network's training objective is to "fool" the discriminator network by producing novel synthesized images that appear to have come from the set of real images. The discriminator, conversely, tries to detect patterns within the synthetic data that do not occur in real images. With this adversarial training strategy, the generator learns the distribution over real-world visual information, which results in the production of novel, photo-realistic images that trick the discriminator.

By learning to interpolate between images, we can build datasets that force the GAN to learn the space between images that capture different architectural semantic content, like topographic maps and city plans, to generate innovative plans and layouts.

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 two style transfer techniques, specifically Neural Style Transfer[6] and GANs[7].

The objective of these image editing methods 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 of visual features are present in the image, but also where they occur within the image. Thus, we can 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, are decomposed and represented in this 2D space. As shown in Figure 3, this new style representation of a building can be fused with other buildings to generate novel architectural types.

Style Transfer using Generative
Adversarial Neural Networks

To generate a hybrid of architectural styles, we take advantage of how GANs learn to model the distribution of visual information in the real world, i.e., by learning to interpolate between the images within the training dataset. We collected a dataset of images whose content spanned the range of standard floor plans, topographical maps, city plans, satellite maps, and abstract architecture/art. When a GAN is trained on this specially curated dataset, it learns the textural, color, and geometric properties that connect and define the visual space between the images in the dataset. The trained GAN can be used to produce novel images that incorporate elements/visual features across all the styles in the training dataset (floor plans, topographies, maps). In effect, the GAN can be used to generate unseen and unique floor plans that emulate aesthetic elements from the other non-floor-plan images. We use Nvidia's Progressive Growing GAN (PG-GAN) to train a model of our dataset. 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 via neuroscience and computer science, 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 Semper[8] and Alois Riegl[9].

CONCLUSION—
THE DEFAMILIARIZATION OF THE PLAN

As described in the introduction to this paper, the plan is a cultural staple of the architecture discipline. It is the medium that best captures the intentionality of architectural project in an abstract medium as a two-dimensional surface. In architecture discourse the line, the plan, and the abstract representation of materiality have played major roles; these always have 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 *De re aedificatoria*, pertaining to the distinction between "lineament," the line in
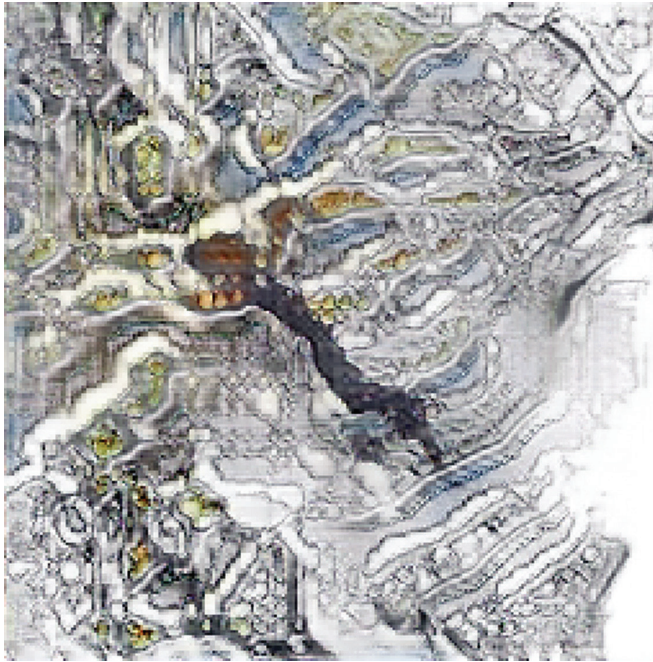
5   The defamiliarization of the plan
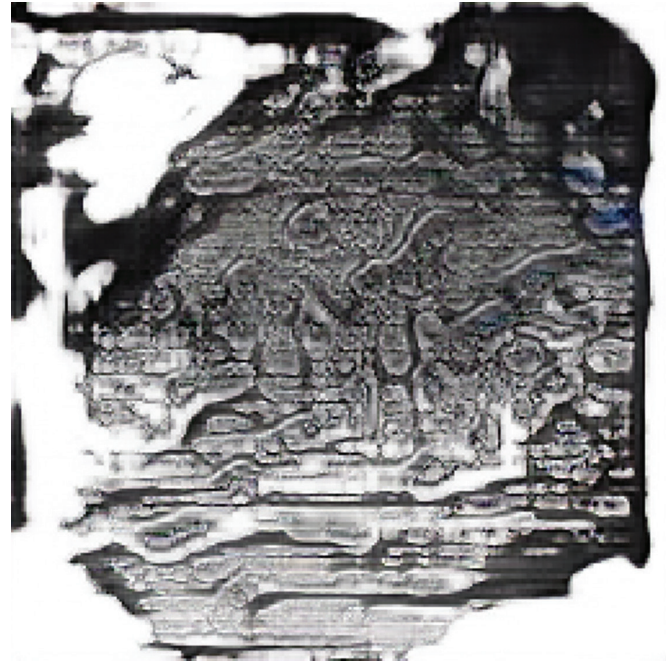
the mind of the architect, and "matter," the material presence of the building. This particular distinction plays a key role in architectural design, and the conceptualization of the architectural project, throughout the history of western architecture. Le Corbusier described this at the heyday of modernism 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 examples[10] 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 GANs that are able to produce results that question the sole authorship of human ingenuity? Well, there is always the chicken & egg problem: the origin of GANs, NNs, etc. in the human mind, and these tools' ability 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 the creation of an even field between these two thinking processes. In a materialist tradition, thought 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 Dreaming and Hallucinating. If this position

is taken, then the conclusion is that AIs can think, and form original language[11] or shape[12] as much 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 (Figure 5). This approach, on the one side, critically interrogates the unique position of the human mind when it comes to creative processes, and on the other side, 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 multiplicious solutions found by architects throughout the ages and employs mining big data to create possible novel solutions to planning problems.

ACKNOWLEDGEMENTS

NOTES

1. See also Greg Lynn's entire conversation on "Happy Accidents."

2. Think of Coop Himmelblau's manifests of the 1970s, or Hans Hollein's flirt with the terms Visionary, also Neil Spiller's Peter Cook book Visionary Architecture: Blueprints of the Modern Imagination, or Gunther Feuersteins book Visionary Architecture in Vienna 1958 to 1988.

3. Barry L. Jacobs, "Dreams and hallucinations: A common neurochemical mechanism mediating their phenomenological similarities." Neuroscience & Biobehavioral Reviews, vol. 2, no. 1 (1978): 59-69.

4. See articles "Find Out If a Robot Will Take Your Job" at https://time.com/4742543/robots-jobs-machines-work/; and "Conspiracy Theories and Legends: Artificial Intelligence" https://steemit.com/science/@vitruvianman/conspiracy-theories-and-legends-artificial-intelligence. Accessed July 13, 2019.

5. See also N. Srnicek and A. Williams, Inventing the Future (London/New York: Verso, 2015).

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

7. Hiroharu Kato, Yoshitaka Ushiku, and Tatsuya Harada, "Neural 3d mesh renderer," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2018): 3907-3916.

8. Gottfried Semper, Der Stil in den Technischen und Tektonischnen 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): 13.

9. Alois Riegl, Stilfragen: Grundlegungen zu einer Geschichte der Ornamentik (Berlin, 1893)

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

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

12. 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 Christie's for the sum of $432,000, and was promoted by the auction house as the first painting solely created by Artificial Intelligence.

Matias del Campo is a registered architect, designer, and educator. His obsessive interrogation of mood and atmospheric effects is fueled by the opulent repertoire of computational design and fabrication methods as well as philosophical inquiry, which together form a comprehensive design ecology. He is the co-founder of the architectural practice SPAN, which he established together with Sandra Manninger. He currently serves as Associate Professor of Architecture at the A. Alfred Taubman College of Architecture and Urban Planning at the University of Michigan. The practice's work was featured at the 2012 Venice Architecture Biennale, at ArchiLab 2013 at the FRAC Centre, Orléans, France, the 2008 and 2010 Architecture Biennale in Beijing, and in the 2011 solo show 'Formations' at the Museum of Applied Arts (MAK) in Vienna.

Sandra Manninger is a registered architect, teacher, and researcher. She is co-Principal of SPAN. The focus of the practice lies the integration of advanced design and building techniques that fold nature, culture, and technology into one design ecology. Her work is part of the permanent collection of the FRAC Collection, the Luciano Benetton Collection, the MAK & the Albertina in Vienna. She has written and presented papers at numerous conferences and her work has been published extensively in numerous magazines and books. She currently serves as Assistant Professor at Taubman College School of Architecture and Urban Planning, University of Michigan.

Alexandra Carlson attended the University of Chicago for her undergraduate degree, where she studied psychology and physics. She is currently a Robotics PhD candidate with the Ford Center for Autonomous Vehicles at the University of Michigan. Her graduate studies focus on robust computer vision for autonomous vehicles. Her research develops an experimental framework that identifies visual features within images that contribute to the failure of deep neural networks (e.g., noise from the camera, as well as noise from the surrounding environment), and then uses these insights to develop neural network architectures that can more effectively distinguish between objects.

IMAGE CREDITS

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