École Polytechnique Fédérale de Lausanne
AR-598 Theoretical statement

CO-CREATION

Architect and creative AI

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2022

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Acknowledgements

There are many people to whom I would like to express my gratitude. First, I would like to thank my maître EPFL Christina Doumpioti for her insightful guidance. She knew where I wanted to go before I did. Without her expertise and recommendations, I would have been lost.

I wish to thank Professor Jeffrey Huang who sparked my interest in creative AI, more specifically GANs, during Deep City Zurich Studio two years ago. I would also like to thank Professor Bernard Cache who shared his passion for digital tools during geometry class for the first year EPFL students. As well, I wish to thank Professor Matthias Finger who led me to apprehend the potential AI has on changing Architectural Service Industry.

I want to thank Christine Bühlmann, a fellow architect, with whom we would often ponder about the impact digital tools and AI will have on the profession. As well, I would like to thank Jonathan Aeberli for the discussions we had about the ethics of AI, as well as its prospects.

Last but not the least, I would like to express my highest gratitude to my husband Einars and my mum. I thank my mum for her words "you can achieve anything if you put your mind to it" and I thank my husband for always making me food and listening to my crazy ideas.

Thanks to everyone who has led me to this work.

Abstract

Architecture embodies its time and technologies. Starting from 1990, the use of Computer-Aided design or CAD changed the way architects work as well as the architecture they can create. In 1992 Frank Gehry used CATIA® software to create a sculpture named Peix in Barcelona. Zaha Hadid Architects advocate the use of software[1] like MAYA®, Rhino® and Grasshopper®. In 2017, Mario Carpo defined *"the second digital turn"*, stating that *"the first digital turn in architecture changed our ways of making; the second changes our ways of thinking."*[2] This second revolution involves creative artificial intelligence allowing architects to conceive unprecedent projects.

The purpose of this research paper is to look at the state-of-art AI technology used in design phase and how it impacts the way architects are working and the designs they create.

To understand how artificial intelligence modifies the traditional workflow, we will look at the question in two parts. Firstly, we will look at AI techniques and models offered to architects by academia. Secondly, we will look how architects narrate the use of AI and how they employ those models in real life projects.

Urban projects tend to be completely modified by big data and creative AI. Smaller projects use AI for specific parts of the project. In artistic projects, AI becomes the core element, and the project is built around the technology.

Even though architects have started using AI in their projects only recently, we can already see the impact it has on their workflow and designs. Is this the future of architecture?

Introduction

The use of artificial intelligence in architectural practices is a recent phenomenon. Yet, the concept of Artificial Intelligence is older than one might initially think. It was first expressed by Lady Ada Lovelace in 1840s (Boden, 2016). The concept of AI is as old as the concept of computers themselves. The machine, which was the origin of Lady Ada Lovelace thinking, was the first general mechanical computer invented by Charles Babbage in 1834. Yet, fully functional devices only started appearing in 1940ies. The first programmable computer The Z1 was invented by Konrad Zuse in 1936. The same year Alan Turing invented The Turing machine that is considered the predecessor of the modern computer.

Inversely, as computer science developed itself in the last 80 years, it took inspiration from architecture as well. Molly Wright Steenson explains that *“the verb of digital structure for programmes and information architects’ designers is “architecting”: designing a system, working holistically from parts to wholes, operating from above, setting in place foundations from below.”* (Steenson, 2017) Sciences take inspiration from one another, as computer sciences look for definitions in architecture, architecture investigates digital science to understand itself and to look beyond traditional practices.

In the architectural sector, AI research and use have had an exponential growth starting from early 2000. In a collaborative review[3] published in 2019, researchers from Hong Kong, UK and Australia analysed 41’827 bibliographic records retrieved from Scopus. The first AI related article in the architectural domain was published in 1974. In 2018 there were 5’605 publications. The most researched subjects of AI in the AEC (Architecture, Engineering and Construction) industry were found to be optimization, genetic algorithm, neural networks, simulation, construction management, fuzzy logic and sets, machine learning and artificial intelligence in general. Some of the least studied subjects include optimum design, active control, life cycle assessment, mechanical properties, typology, and shape optimization. There are currently two powerhouses of AI research in the AEC industry: United States and China, each published more than 5’000 articles between 1974 and 2019 (Darko et al, 2020).

Another remarkable study was done by Lawrence Berkeley National Laboratory. Their research “State-of-the-Art on Research and Applications of Machine Learning in the Building Life Cycle”[4] was based on papers published on the Web of Knowledge platform. Analysing keywords in 9’579 papers, the researchers found that 44% of papers were directed on building design, 28% for control and lastly 16% for operations and maintenance. Regardless of the amount of the research in the domain, the researchers found that none of the studies were broadly implemented in AEC industry. The challenges of shifting knowledge from basic research to applied research employable in industry included the challenges of training data, model transferability, strong associated costs of technology and difficulty generalizing models (Hong et al. 2020).

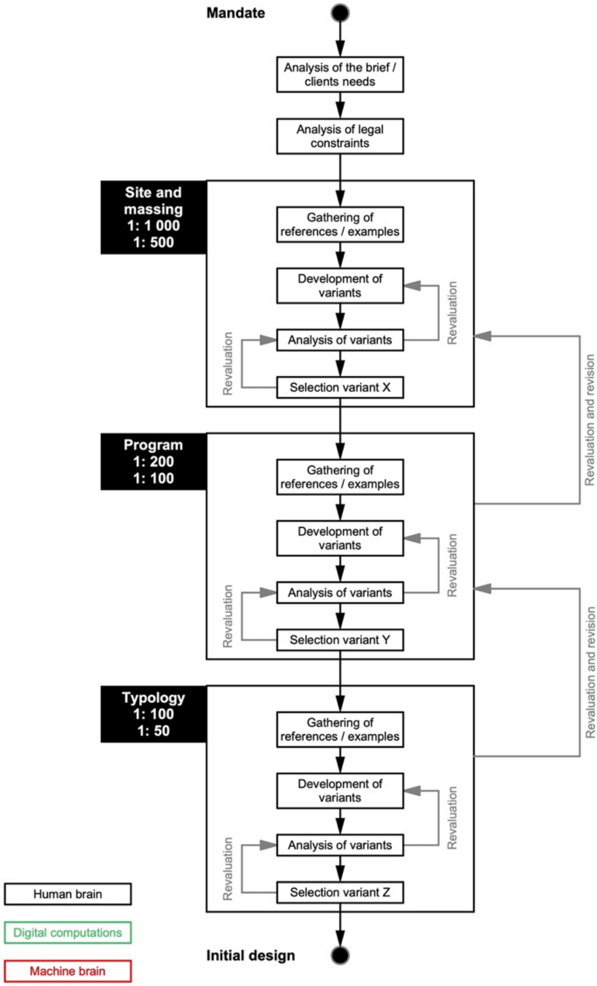
Knowing the extent of research for the design phase and its limited use in the industry, it makes one wonder who are the early adopters and how they are using and defining the technology. The term “early adopters” was coined by Everett M. Rogers in 1962. It defines the innovation adoption lifecycle going from innovators, early adopters, early majority, late majority and finally laggards.

This theoretical statement develops itself in two parts: firstly, we will observe the techniques and models of AI used mostly in academic sector, such as autoencoders AE, convolutional autoencoders CNN, generative adversarial networks GAN.

Secondly, we will analyse five case studies where architects have used AI techniques in design process. The analysis will cross different scales of projects. Urban scale will be represented by Deep Green project in Guatemala by ecoLogicStudio. Public competition will be represented by 24 Highschool project in Shenzhen by architectural office SPAN. Private mandate will be represented by NN_House 1 by Studio Kinch. Lastly, two architectural exhibitions will be represented by 3D GAN housing (Immanuel Koh) and Horizons (Certain Measures).

Only AI used for creative means will be part of selected case studies. Creative means here is defined as the capacity of AI to generate novel and unexpected ideas. Analysis will dwell on two pillars. Firstly, the narrative of the project itself and how AI intertwined into project descriptions given by architects. Secondly, what tools architects used and how they interlock with the project itself.

This research looks at how architects collaborate with a machine and responds to the fallowing research question: How does the use of AI change the traditional design workflow? Traditionally, the architect developed and owned his ideas and designs. How do architects co-create with creative AI today?



Traditional design process

Interpretation by the author

Techniques and models

There are numerous AI techniques studied and employed during the design phase. This list is not meant to be exhaustive as it only includes preselected ML techniques already used in architecture. Ongoing research adds new or improved techniques every month.

Now, in architectural and design domain, three groups of creative AI stand out: autoencoders AE, convolutional neural networks CNN and generative adversarial networks GAN. Yet, those are not the only techniques employed. In the fallowing section we will shortly look at different techniques with their applications, starting with AE, CNN, and GAN, followed by other models employed in architecture.

The preselected techniques can be categorized by the data input as follows:

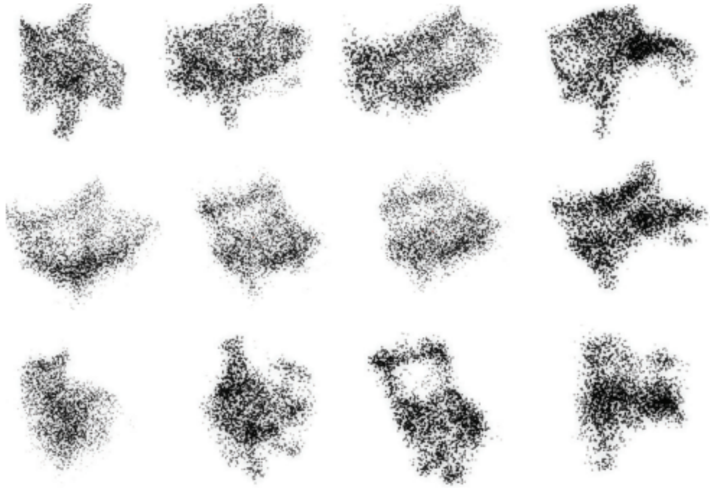
Text:	AttnGAN, cGAN (pix2pix)
Photo:	StyleGAN, CNN, NST
Sketch:	cGAN (pix2pix)
Graph:	House-GAN, BN
Voxels:	3D-GAN, NST
3D:	SOM,VAE, RvNN, StyleGAN, 3D-GAN
3D point clouds:	AE

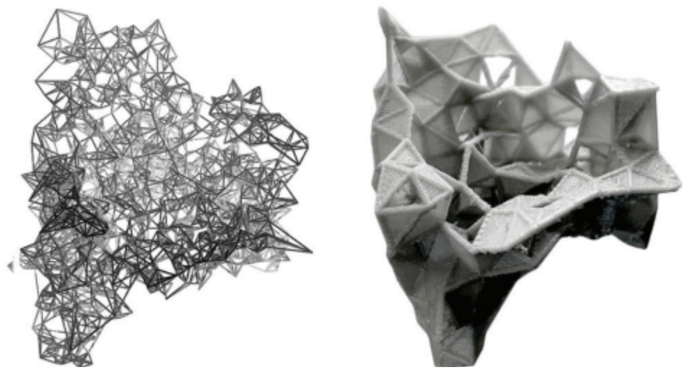
Autoencoder AE

Autoencoder AE is an unsupervised learning algorithm first introduced in 1980 by Hinton and the PDP group[5] and today there exist a wide variety of autoencoders. They are classified as linear (complex, real and finite fields) and non-linear (boolean, boolean/linear, neural network(sigmoidal) and Boltzmann Machines). This artificial neural network works with unlabelled data while omitting insignificant data. It has two parts: *"an encoder that maps the input into the code, and a decoder that maps the code to a reconstruction of the input"*[6].

Achlioptas et al (2018) worked with 3D point-clouds while combining an AE with a GAN. By training an AE they managed to recreate 3D shapes as complex as their initial input dataset, which they retrieved from ShapeNet repository. Altogether they worked with 57,000 models from 55 categories of objects. Their code is publicly available on github (https://github.com/optas/latent_3d_points).

Succeeding the previous research, Bidgoli and Veloso developed a data-driven generative system titled DeepCloud[7] in a form of web-based application. The same as Achlioptas, they obtained the data from the ShapeNet repository. The uniqueness of their application lies in the possibility to "play" in the latent space without need of coding. Their application comes as an alternative to parametric modelling as it explores a larger variety in design influenced by the data that was fed to it. The code of this project is made publicly available on their research paper (Bidgoli et al, 2018).





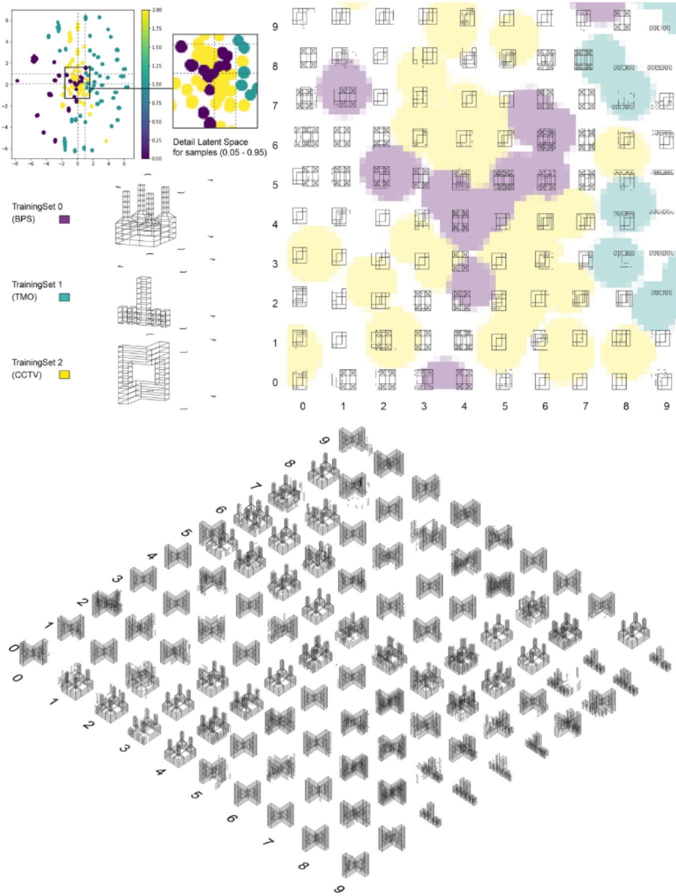
Top: chairs generated using DeepCloud; bottom left: structure; bottom right: 3D-printed chair with lower resolution

Source: Bidgoli, Ardavan, and Pedro Veloso. 2018. 'The Application of a Data-Driven, Generative Model in Design', 10. http://papers.cumincad.org/data/works/att/acadia18_176.pdf

Variational autoencoder VAE

A variational autoencoder VAE[8] is an artificial neural network first introduced by Diederik P Kingma and Max Welling in 2014. Initially intended for unsupervised learning, it is more widely used in semi-supervised and supervised learning. The same as previous autoencoder AE, it is composed of an encoder and decoder. The main difference lies in minimising the reconstruction error from encoded-decoded data. Instead of working with points, VAE encode inputs as distributions.

Miguel et al used VAE for deep form finding of structural typologies in their 2019 research paper[9]. VAE used was taken directly from original 2014 research paper mentioned above. The researchers aimed *[…] to present a methodology for generation, manipulation and form finding of structural typologies using variational autoencoders."* Initial geometries were done in Rhino®, then they were transformed into a connectivity map using Python and stored as plain text file. Another Python script was used to train the VAE. The researchers used three training samples and employed a technique called "data augmentation" to increase the number of samples to 3 000 by introducing variations. Altogether 9 000 samples were generated for the three models. In this experiment, the models handled around 150 million parameters. According the researchers, data should represent around 10% of the number of parameters. Thus, the optimal amount of training data should be around 15 million samples instead of 9 000 used in the experiment.



Top: VAE experiment no. 15: Battersea Power Station, Tate Modern and CCTV. Bottom: reconstructed wireframes from a grid of sample points taken from distribution.

Source: Miguel, Jaime de, Maria Eugenia Villafañe, Luka Piškorec, and Fernando Sancho-Caparrini. 2019. 'Deep Form Finding Using Variational Autoencoders for Deep Form Finding of Structural Typologies'. In Blucher Design Proceedings, 71–80. Porto, Portugal: Editora Blucher. https://doi.org/10.5151/proceedings-caadesigradi2019_514.

Generative recursive neural network RvNN

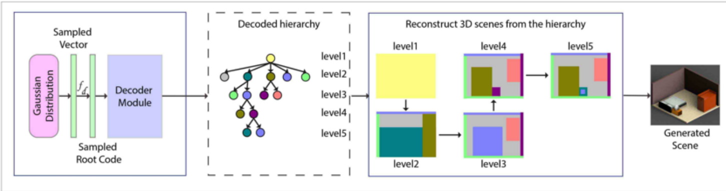
A recursive neural network is a deep neural network developed starting from 1990s. It applies the same weights over its data and produces predictions.

In architecture, RvNN was used in a combination with VAE by M. Li et al (2019) in a research titled “GRAINS: Generative Recursive Autoencoders for INdoor Scenes”[10]. Following their observation about indoor scene structures, they proposed to combine recursive neural network RvNN with a variational autoencoder VAE creating RvNN-VAE network. For them, indoor scenes are hierarchical, thus convolutional network (discussed in the next chapter) is not the best choice for indoor scene generation.

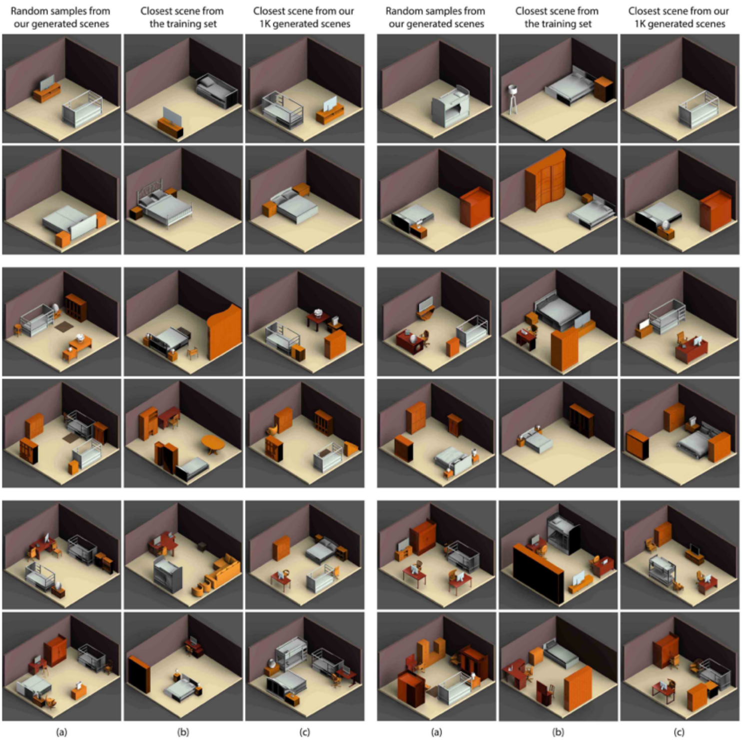
For the training they used a dataset of annotated indoor scenes. The data originated from SUNCG[11] dataset with 18 763 bedrooms, 4 440 living rooms, 5 974 kitchens and 3 774 offices. Every scene contained labelled objects, represented by bounding boxes or OBBs.

The combined variational recursive autoencoder RvNN-VAE contains an encoder and a decoder. The encoder looks at spatial properties of indoor scenes as well as the relations between different objects, thus creating object groups. The decoder generates new scenes retrieving objects from the initial labelled object groups.

In short, the encoder analyses and groups objects by labels and the decoder retrieves those objects to generate new 3D indoor scenes.



Overall pipeline of GRAINS scene generation



Bedrooms generated by GRAINS method (a), in comparison to (b) closest scene from the training set, to show novelty, and to (c) closest scene from among 1,000 generated results, to show diversity.

Source: Manyi Li, Akshay Gadi Patil, Kai Xu, Siddhartha Chaudhuri, Owais Khan, Ariel Shamir, Changhe Tu, Baoquan Chen, Daniel Cohen-Or, and Hao Zhang. 2019. GRAINS: Generative Recursive Autoencoders for INdoor Scenes. 1, 1 (May 2019), 21 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

Convolutional neural network CNN

The convolutional neural network CNN or ConvNet is an artificial neural network used for image analysis. It consists of three parts: an input layer, hidden layers, and output layer. It can have multiple hidden layers.

In architecture, CNN was used in 2018 by Wang et al in their research article “Deep Convolutional Priors for Indoor Scene Synthesis”[12]. Researchers used SUNCG dataset, and, after filtering, employed 8 398 bedrooms, 1 238 offices and 1 452 living rooms for training. 250 were used for validation and the remaining for CNN training.

The 3D scene was converted into 2D layout representation of five image channels. Overall room synthesis took 4 minutes for each room. Their final model is generated by continuously adding a new object into the scene. The adding of new objects depends on the objects already present in the scene. Every iteration can be decomposed into three steps: decision to add a new object, decision of the type of object and its placement and finally the insertion of object.

The researchers made their code, data, and pre-trained models available on github (https://github.com/brownvc/deep-synth).

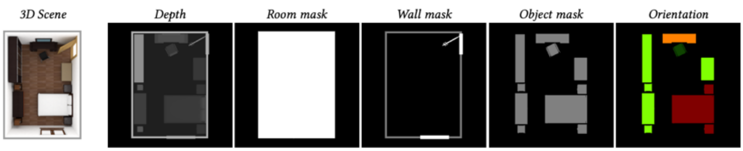
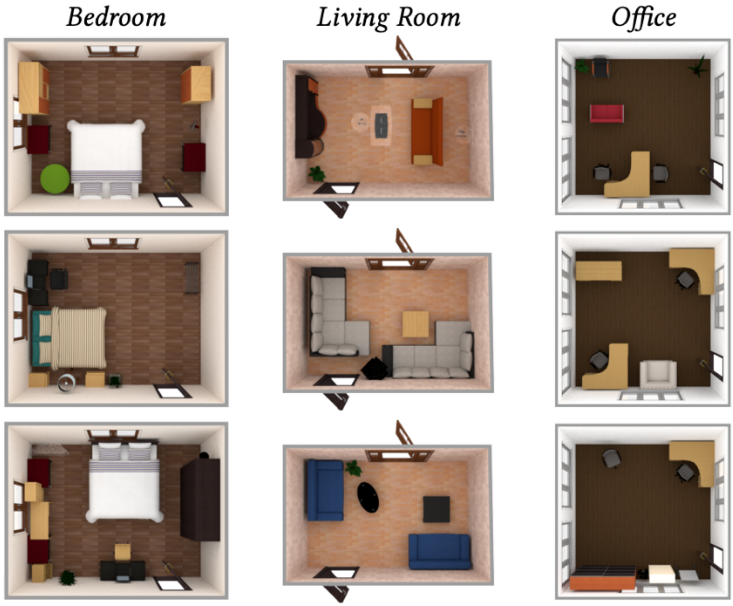
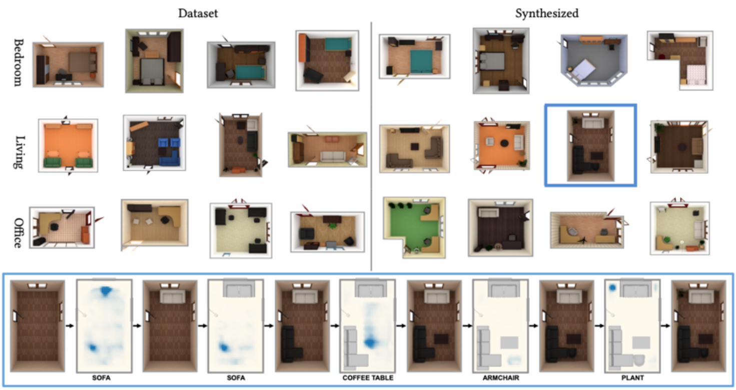


Image channels

Source: Kai Wang, Manolis Savva, Angel X. Chang, and Daniel Ritchie. 2018. Deep Convolutional Priors for Indoor Scene Synthesis. ACM Trans. Graph. 37, 4, Article 70 (August 2018), 14 pages. https://doi.org/10.1145/3197517.3201362



Synthesizing multiple scenes in the same room



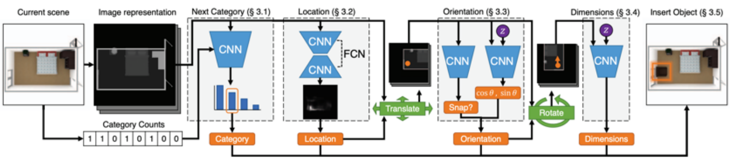
Synthesising method

Source: Kai Wang, Manolis Savva, Angel X. Chang, and Daniel Ritchie. 2018. Deep Convolutional Priors for Indoor Scene Synthesis. ACM Trans. Graph. 37, 4, Article 70 (August 2018), 14 pages. https://doi.org/10.1145/3197517.3201362

A year later Ritchie et al (2019) continued their experimentations with CNN in a research paper “Fast and Flexible Indoor Scene Synthesis via Deep Convolutional Generative Models”[13]. Their research presents an improved CNN for a faster indoor scene generation. The same as previous model, objects are inserted one by one, a new object with every iteration. The model predicts the category, location, orientation, and size of objects. Compared to previous model, this one not only synthesises new scenes but is able to complete partial scenes. The source code is again made available by researchers on github (https://github.com/brownvc/fast-synth).

After attacking the previous models’ limitations, they increased the calculation speed that now takes 2 seconds per scene synthesis (previously the double). The main model being CNN, inside of it the researchers use conditional variational autoencoder CVAE and conditional generative adversarial network CGAN. CVAE defines the orientation and a combination of CVAE and CGAN defines the dimensions of objects. The dataset was extracted from SUNCG, after data filtering, they obtained 6 300 bedrooms, 1 400 living rooms, 6 800 bathrooms and 1 200 offices.

Mixing of different techniques is something that can be found in multiple models, something that we already saw with variational recursive autoencoder RvNN-VAE.



Automatic object-insertion pipeline

Source: Ritchie, Daniel, Kai Wang, and Yu-An Lin. 2019. ‘Fast and Flexible Indoor Scene Synthesis via Deep Convolutional Generative Models’. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 6175–83. Long Beach, CA, USA: IEEE. https://doi.org/10.1109/CVPR.2019.00634.

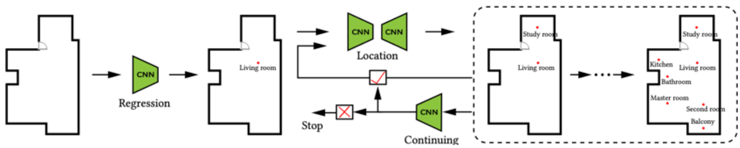
Synthetic virtual scenes generated CNN

Source: Ritchie, Daniel, Kai Wang, and Yu-An Lin. 2019. ‘Fast and Flexible Indoor Scene Synthesis via Deep Convolutional Generative Models’. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 6175–83. Long Beach, CA, USA: IEEE. https://doi.org/10.1109/CVPR.2019.00634.

In the layout generation, researchers collaborating from three Chinese universities published a paper titled “Data-driven Interior Plan Generation for Residential Buildings”[14]. Their method uses the outer walls as an input boundary, including entrance doors.

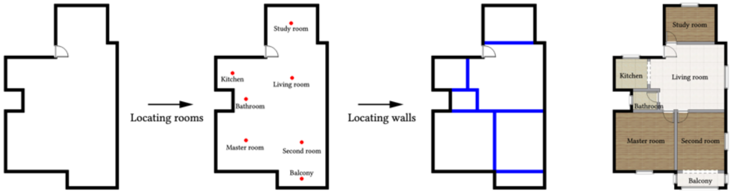
The researchers had created a large dataset of more than 80 000 floor plans from real residential buildings with labelled rooms and walls called RPLAN[15]. 94% of data was used for network training, 3% were used as a test set and remaining 3% as a verification set (Wu et al, 2019).

Similarly, as in previous models, every floor plan in a dataset is defined by channels. Here four channels were used, Wang et al 2018 used five channels. The first channel defines the area of the room, second defines the boundary, third defines semantics and walls of the room and the last channel is used to distinguish different rooms possessing identical labels. The different rooms in question were bathrooms, second rooms, balconies, living rooms, master rooms, kitchens, study rooms, storages, wall-ins, guestrooms, dining rooms, child rooms and entrances.

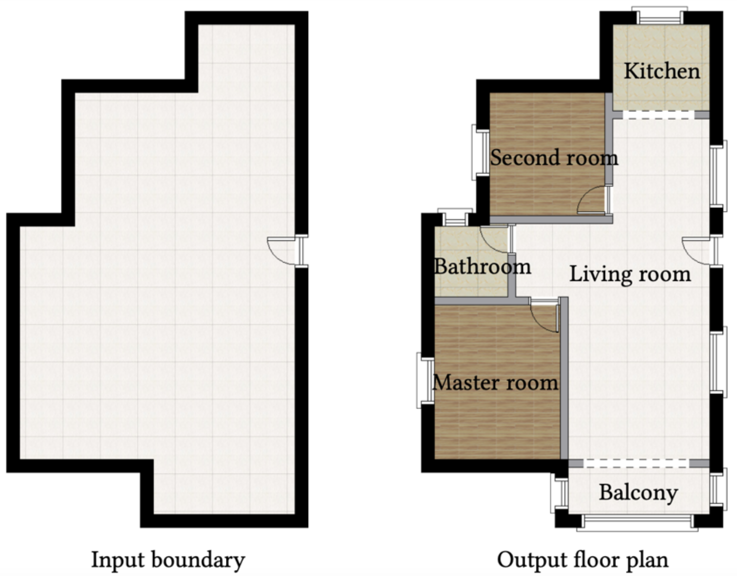


An iterative prediction model to predict room locations.

Soruce: Wenming Wu, Xiao-Ming Fu, Rui Tang, Yuhan Wang, Yu-Hao Qi, and Ligang Liu. 2019. Data-driven Interior Plan Generation for Residential Buildings. ACM Trans. Graph. 38, 6, Article 234 (November 2019), 12 pages. https: //doi.org/10.1145/3355089.3356556



Overview of the method



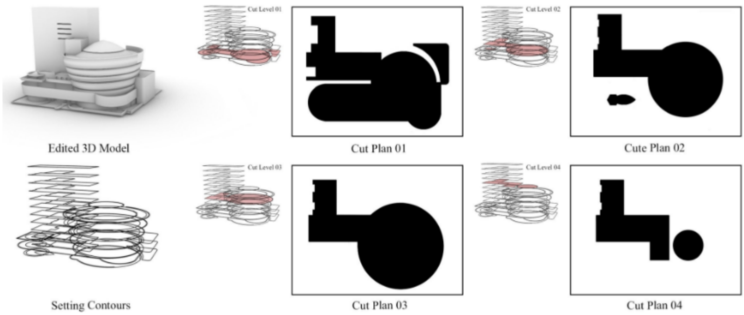
Automatically generated floor plan for one residential

Soruce: Wenming Wu, Xiao-Ming Fu, Rui Tang, Yuhan Wang, Yu-Hao Qi, and Ligang Liu. 2019. Data-driven Interior Plan Generation for Residential Buildings. ACM Trans. Graph. 38, 6, Article 234 (November 2019), 12 pages. https://doi.org/10.1145/3355089.3356556

Neural Style Transfer NST

Neural Style Transfer NST was first presented by Gatys et al in 2015 in their research paper “A Neural Algorithm of Artistic Style”[16]. It is an updated version of convolutional neural network CNN and specialises in texture recognition. Its objective is learning a style from original dataset and transferring it onto another image or video.

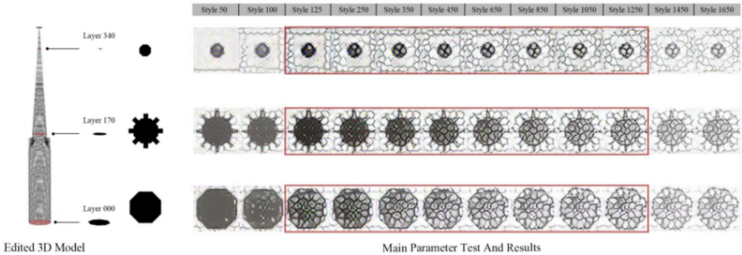
In architecture, Ren and Zheng presented their paper “the spire of AI, voxel-based 3D neural style transfer”[17] in 2020. As in other 3D-2D-3D models, the desired 3D model is first sliced into 2D pixel layers, then NST is applied onto those 2D layers and finally it is reconstructed back into 3D. The specificity here is that pixels of the image are replaced by voxel blocks and assembled in fully voxelised volume. The style comes from another image that is applied on the sliced 2D. Four style training parameters are available: content and style weight, the proportions of content weight and style weight.



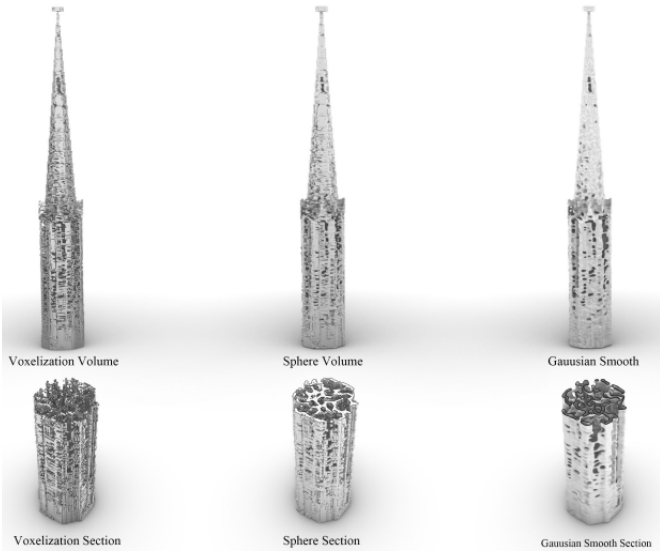
Abstraction Process of the Cut Content Plans in the 3D Model

Source: Ren, Yue and Zheng. 2020. ‘The Spire of AI - Voxel-Based 3D Neural Style Transfer’. In D. Holzer, W. Nakapan, A. Globa, I. Koh (Eds.), RE: Anthropocene, Design in the Age of Humans - Proceedings of the 25th CAADRIA Conference - Volume 2, Chulalongkorn University, Bangkok, Thailand, 5-6 August 2020, Pp. 619-628. CUMINCAD. http://papers.cumincad.org/cgi-bin/works/paper/caadria2020_091.

For they test experiment, the researchers employed the NST technique onto the spire of Notre Dame De Paris with the style from gothic window rose.



Generated Stylized Plans with Gradually Changed Style Weights



Final Conversion from Voxelization Volume to Gaussian Smooth

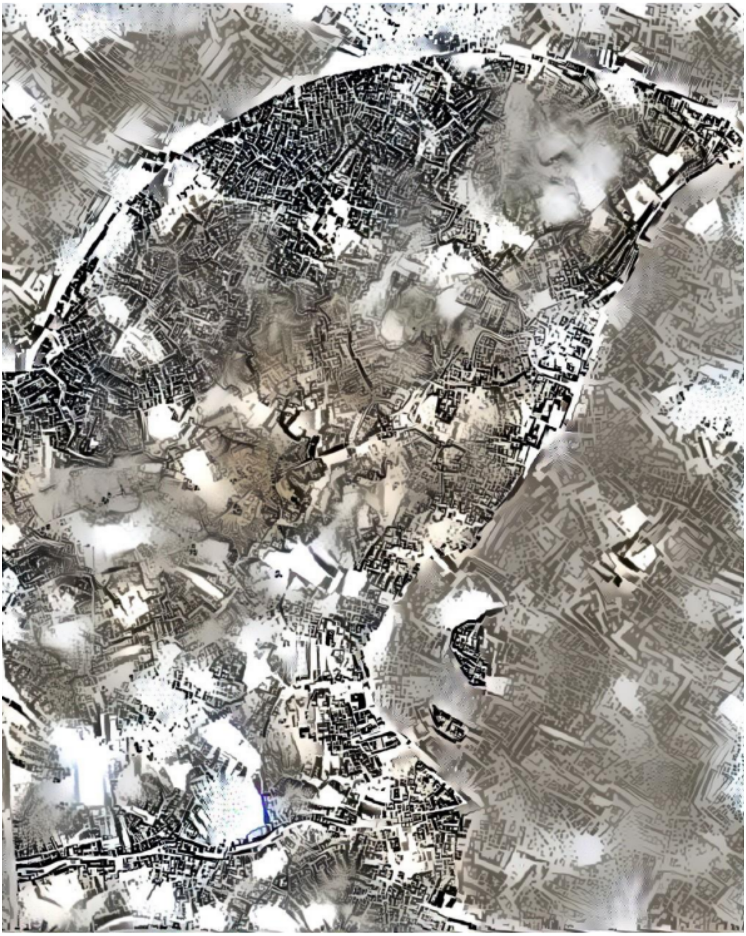
Source: Ren, Yue and Zheng. 2020. 'The Spire of AI - Voxel-Based 3D Neural Style Transfer'. In D. Holzer, W. Nakapan, A. Globa, I. Koh (Eds.), RE: Anthropocene, Design in the Age of Humans - Proceedings of the 25th CAADRIA Conference - Volume 2, Chulalongkorn University, Bangkok, Thailand, 5-6 August 2020, Pp. 619-628. CUMINCAD. http://papers.cumincad.org/cgi-bin/works/paper/caadria2020_091.

Another example of NST use was presented by Campo et al 2020 in a conference paper “Imaginary maps, A posthuman urban design method based on Neural Style Transfer”[18].

The study looked at the creativity of AI using historical maps. Nolli plans were projected onto cities, and then those generated maps were projected onto Moon.

Results of 2D to 2D Style transfers based on Nolli plans and an image of the Moon

Source: Campo, Matias del, and Sandra Manninger. 2020. ‘Imaginary Maps - a Posthuman Urban Design Method Based on Neural Style Transfer’. Utopia vs the City, January. https://www.academia.edu/41821231/Imaginary_Maps_a_Posthuman_Urban_Design_Method_based_on_Neural_Style_Transfer.



Result of Style transfer between a Dataset of Nolli maps of known cities (Rome, Barcelona, Manhattan, Washington DC) and a 19th century science plate depicting a detail of the moon's surface.

Source: Campo, Matias del, and Sandra Manninger. 2020. 'Imaginary Maps - a Posthuman Urban Design Method Based on Neural Style Transfer'. Utopia vs the City, January. https://www.academia.edu/41821231/Imaginary_Maps_a_Posthuman_Urban_Design_Method_based_on_Neural_Style_Transfer.

Generative adversarial network GAN

The generative adversarial network or GAN was first presented by Ian Goodfellow in 2014[19]. It is combined of two neural networks: generator and discriminator. The generator creates new images and discriminator tries to detect whether they come from dataset or are created by generator. With continuous learning, the generator improves into tricking the discriminator with his generated images. The code and hyperparameters are available on github (https://github.com/goodfeli/adversarial).

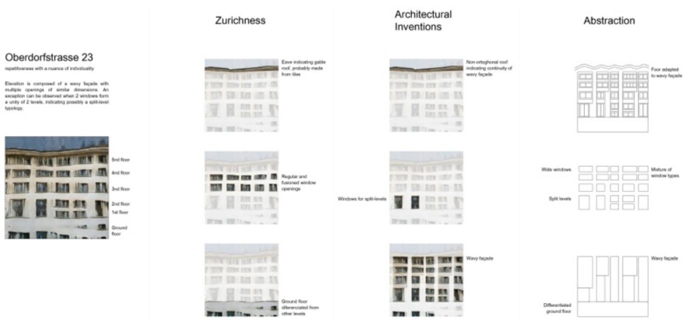
GANs were the author's first exposure to the use of artificial intelligence in architecture. During EPFL studio "Deep City Zurich" by EPFL MediaxDesign Lab, we had a chance to experiment with Self-Attention Generative Adversarial Network or SAGAN[20].

The process allowed to co-create with a machine and followed a predefined workflow[21]: data preparation, GAN training, selection of seed image, latent space interpolation and finally, selection and interpretation of final façade image. Our team increased the saturation of dataset images to accentuate the composing elements. The dataset contained 857 images of Zurich Altstadt. To translate the GAN image into architecture, critical analysis needed to take place. *"The critical analysis looked at 3 aspects of the image: non-orthogonal roof, windows and façade waviness. The façade possesses a bow window like extrusions with large proportions of solid walls. The roof follows the geometry of the building and is thus non-orthogonal as well. There are a multitude of opening options, indication differentiation of typology."*[22]

The architectural project then was constituted manually from the outside, as GANs façades designed the interior plans.

Seed and interpolation of the same building

Oberdorfstrasse façade – Rössligasse façade – South façade



GAN image critical drawing

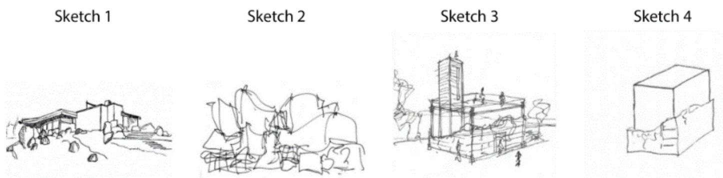
Source: Lorence, Iluta. 2020. '8 _ Iluta Lorence'. Deep City Zurich (blog). 13 December 2020. https://deepcityzurich.wordpress.com/2020/12/13/8-iluta-lorence/.

Conditional Generative Adversarial Network cGAN

Conditional Generative Adversarial Network cGAN was first introduced in 2014 by Mirza et al[23]. cGAN is an extension of traditional GAN containing the generator and discriminator which are then conditioned with extra information.

In architectural domain, Chan et al (2020)[24] published a research paper titled “What machines read in architectural sketches”. Two cGANs were combined in a Cyclic-cGAN. More specifically, they used pix2pix[25], who was derived from cGAN in 2018.

The first cGAN transformed sketches to images and the second transformed images to sketches. The training contained 84 image-sketch pairs, where sketches were traced manually. 80 sets were used for training and remaining 4 were used for testing the network. They followed 7 step workflow starting from data preparation until generation of new images. Once the network was trained, the 4 sketches were put to test. What is remarkable in this experiment is the fact that cGAN assigned materiality and colours to the black and white sketches, as well as sky and ground level, none of whom were present in the sketch.



Black & white input sketches for the experiment

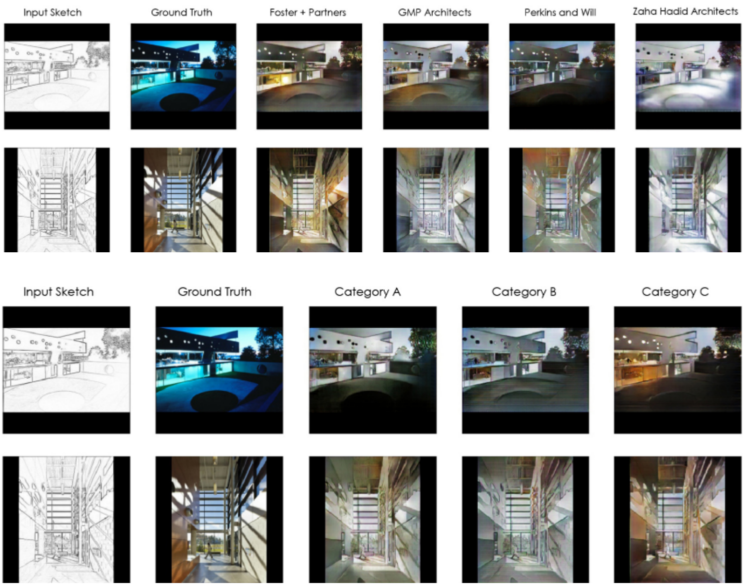
Source: Chan, Yick Hin Edwin, and A Benjamin Spaeth. 2020. ‘Architectural Visualisation with Conditional Generative Adversarial Networks (CGAN).’, 10. http://papers.cumincad.org/data/works/att/ecaade2020_017.pdf

Results generated by Cyclic-cGAN with 80 training data

Source: Chan, Yick Hin Edwin, and A Benjamin Spaeth. 2020. 'Architectural Visualisation with Conditional Generative Adversarial Networks (CGAN).', 10. http://papers.cumincad.org/data/works/att/ecaade2020_017.pdf

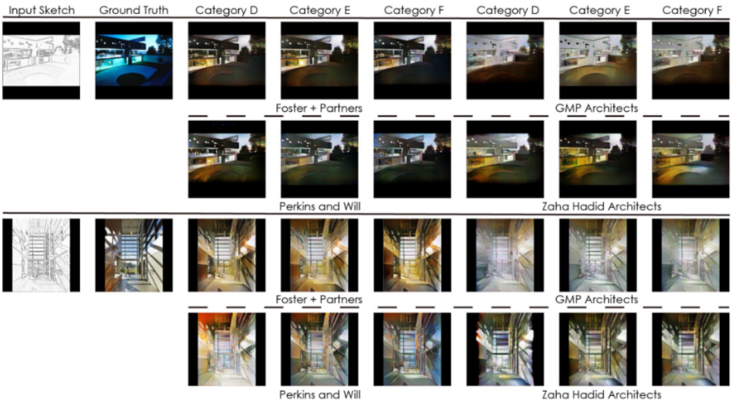
Another architectural use of Conditional Generative Adversarial Network cGAN was made by Zhou and Park in 2021[26]. The same as previous example, the used pix2pix. Their dataset contained 70 000 architectural images scrapped from Internet and 10 000 of them were labelled by architect, building category, project size, year, and location. Here the transformation of images to sketches were done automatically using XDog. The dataset was divided into 99% of images for training and 1% for testing.

This experiment allowed to train a cGAN (pix2pix) according to labels and then to apply specific label to a sketch.

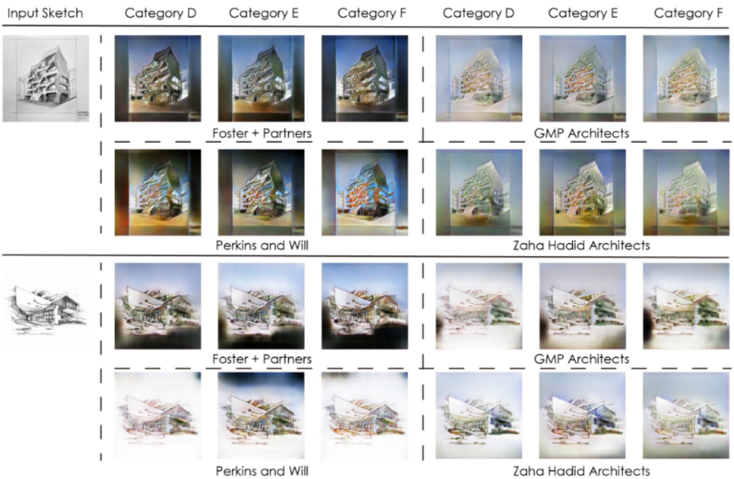


Above: Single attribute architect; below: single attribute building type

Source: Zhou, Yifan, and Hyoung-June Park. 2021. 'SKETCH WITH ARTIFICIAL INTELLIGENCE (AI)', 10. http://papers.cumincad.org/data/works/att/caadria2021_446.pdf



Multiple attributes: architect + building type.



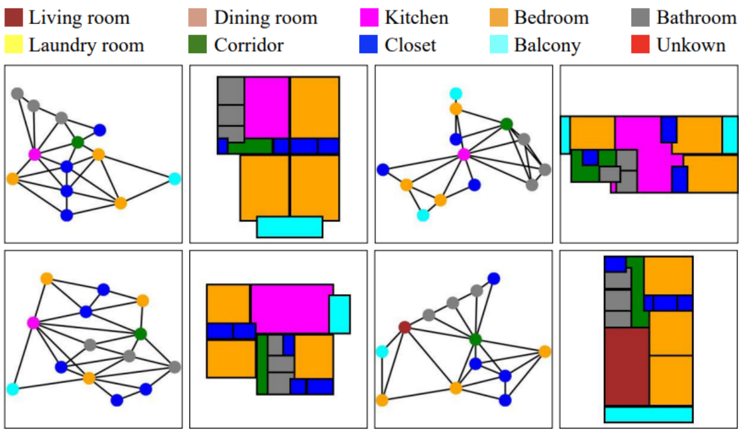
Predicted image based on sketch.

Source: Zhou, Yifan, and Hyoung-June Park. 2021. 'SKETCH WITH ARTIFICIAL INTELLIGENCE (AI)', 10. http://papers.cumincad.org/data/works/att/caadria2021_446.pdf

Relational Generative Adversarial Networks House-GAN

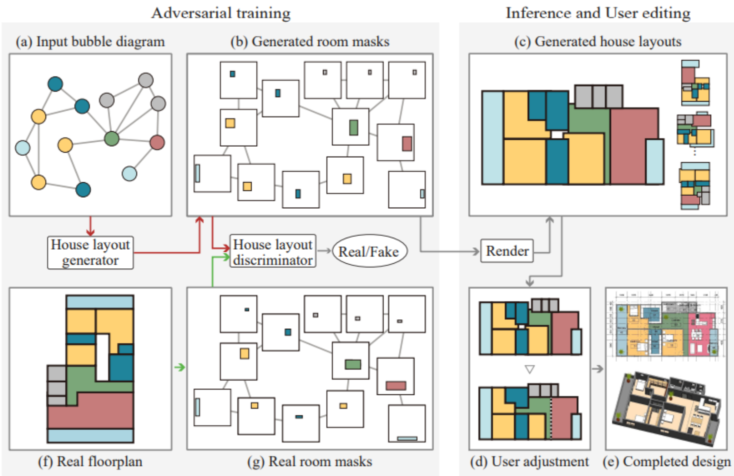
In 2020 a collaborative research[27] of Simon Fraser University and Autodesk Research proposed a variant of GAN who takes graphs as its input. The objective of House-GAN is to generate automated floorplans purely on the needs of clients presented as bubble-diagrams. All the code, data and pretrained models were made publicly available by the researchers[28].

The dataset used for training contained 117 587 floorplans, obtained from LIFULL HOME's database[29]. Researchers used floorplan vectorisation algorithm to generate the vector-graphics format, which was converted into bubble diagrams. Rooms, thus bubbles, were divided in 10 categories: living room, kitchen, bedroom, bathroom, closet, balcony, corridor, dining room, laundry room and unknown. The solutions were then analysed and compared to other techniques by three metrics: realism, diversity, and compatibility.

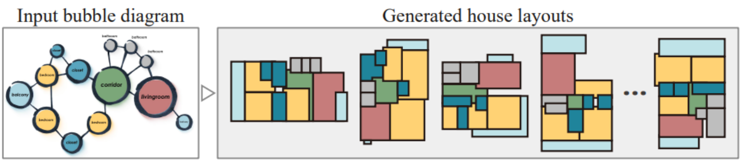


Sample bubble diagrams and house layouts

Source: Nauata, Nelson, Kai-Hung Chang, Chin-Yi Cheng, Greg Mori, and Yasutaka Furukawa. 2020. 'House-GAN: Relational Generative Adversarial Networks for Graph-Constrained House Layout Generation'. ArXiv:2003.06988 [Cs], March. http://arxiv.org/abs/2003.06988.



Floorplan designing workflow with House-GAN.



House-GAN is a novel graph-constrained house layout generator, built upon a relational generative adversarial network. The bubble diagram (graph) is given as an input for automatically generating multiple house layout options.

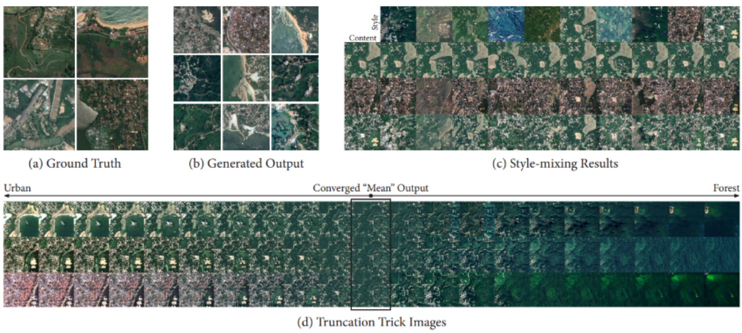
Source: Nauata, Nelson, Kai-Hung Chang, Chin-Yi Cheng, Greg Mori, and Yasutaka Furukawa. 2020. 'House-GAN: Relational Generative Adversarial Networks for Graph-Constrained House Layout Generation'. ArXiv:2003.06988 [Cs], March. http://arxiv.org/abs/2003.06988.

StyleGAN

StyleGAN is a generative adversarial network developed by Nvidia[30] in 2018. All code is made available by Nvidia on github (https://github.com/NVlabs/stylegan).

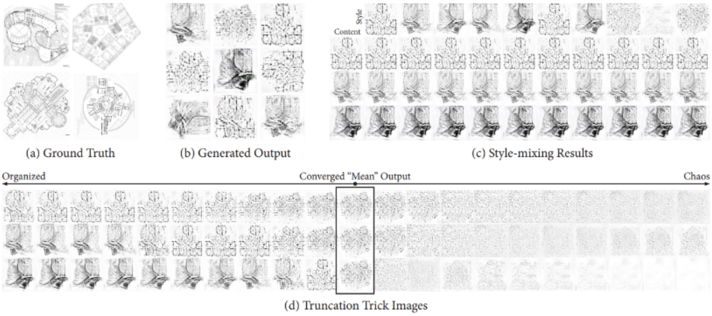
The following year, Zhang published a paper on the use of StyleGAN to generate 3D models[31]. Per Zhang, StyleGAN is best used for three types of results: "*similar fake images, style-mixing images, and truncation trick images.*"

The researcher used the method employed in medical CT images where *"each single image [functions as a] single-layer model information".* Eight trainings were involved in the process. 30 000 satellite images from Google Maps were used for "satellite image training". 2 000 plan drawings were used for "plan drawing training". 5 000 images of plans and sections were used for" plan and section drawing training". To improve the training quality, 5 more trainings were made from designed datasets (52 000 images) created by the researcher. He concluded that regardless of impossibility of using directly the generated, stretched 3D models, they still can serve as an inspiration as they produce unexpected results that goes beyond human imagination.

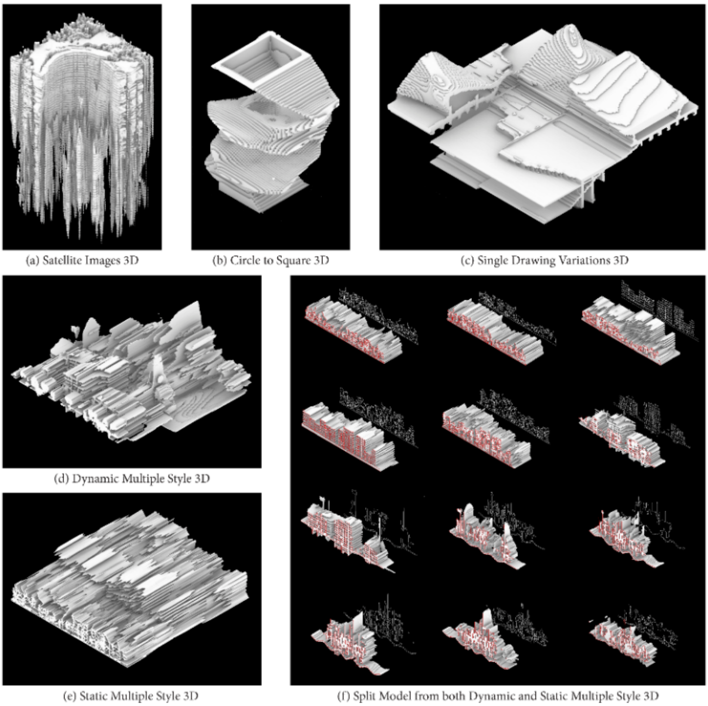


Training processes and results of collected satellite images

Source: Zhang, Hang. 2019. '3D Model Generation on Architectural Plan and Section Training through Machine Learning'. Technologies 7 (4): 82. https://doi.org/10.3390/technologies7040082.



Training processes and results of collected plan drawings



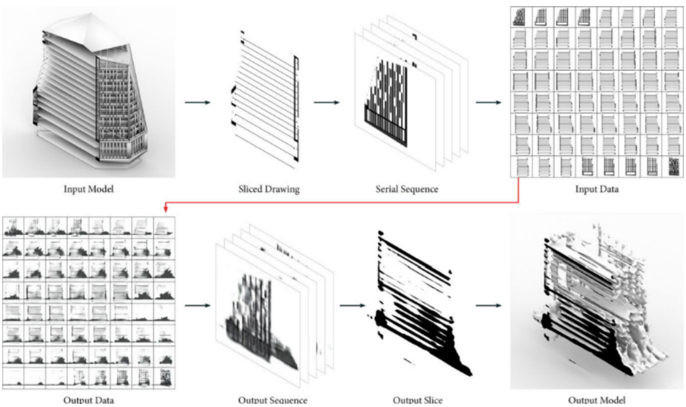
3D models generated from truncation trick images

Source: Zhang, Hang. 2019. '3D Model Generation on Architectural Plan and Section Training through Machine Learning'. Technologies 7 (4): 82. https://doi.org/10.3390/technologies7040082.

Hang Zhang and Ye Huang continued their work while mixing different types of GAN[32]. In 2020 they trained the model with six 3D buildings (Fallingwater, Sydney Opera, High Rise, NYC Guggenheim, Foundation, Gothic Church), again sliced similarly as in the previous research. In this experiment they combined StyleGAN with Waifu2X and pix2pix to increase training quality.

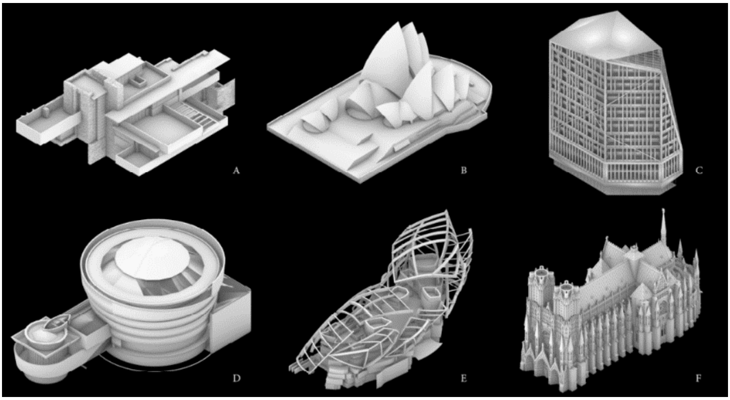
Initially the target models were sliced (medical CT images technique) for 64 times. Each sections resolution was 128x128. Then crossections were arranged into 8x8 grid, leading to an image of 128x128x64. This technique basically allows to transform a 3D building into 2D crossections then again to be reassembled into 3D building. StyleGAN was used as a main network. The researchers found that using multiple network trainings decreased the training quality as the generated results produced more noise.

First, they were able to reconstruct 3D building into 2D slices, then again into 3D. Secondly, they were able to transpose and blend different building models thus creating new, unseen ones in a quest of innovative form finding.

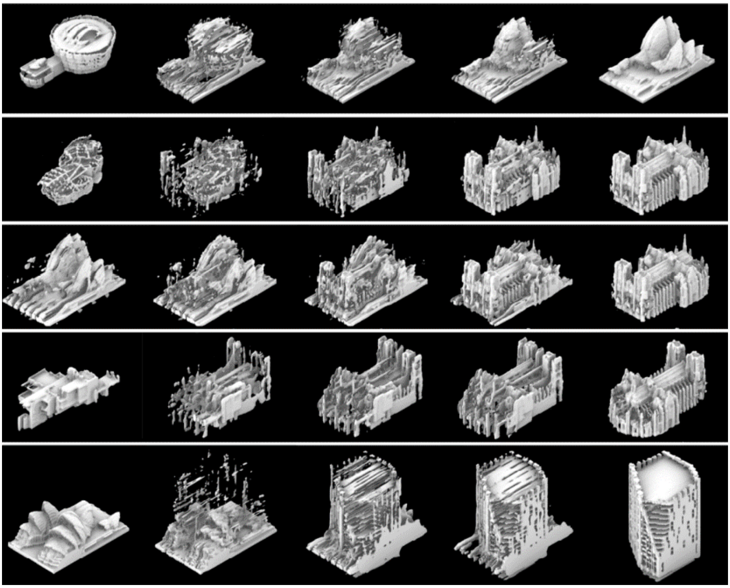


2D-3D Form Encoding and Decoding Workflow

Source: Zhang, Hang, and Ye Huang. 2020. Machine Learning Aided 2D-3D Architectural Form Finding. https://doi.org/10.13140/RG.2.2.18669.00484.



Resources of 3D models with different styles and forms.



Final 3D model based on the reverse compilation of the training results

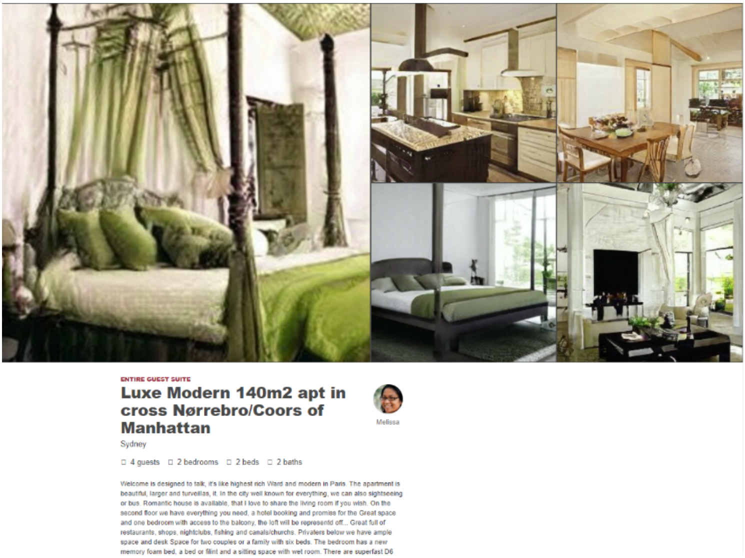
Source: Zhang, Hang, and Ye Huang. 2020. Machine Learning Aided 2D-3D Architectural Form Finding. https://doi.org/10.13140/RG.2.2.18669.00484.

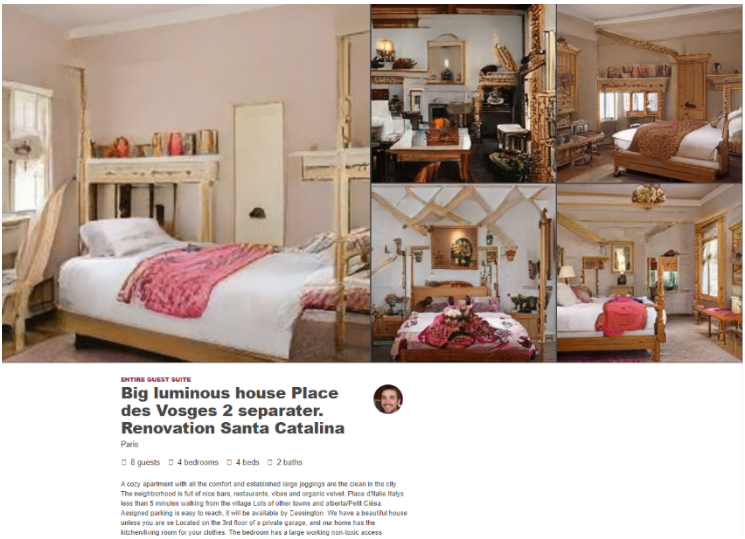
StyleGAN was used in the creation of the website https://thisrentaldoesnotexist.com/ where Christopher Schmidt, a software engineer by day, played with Airbnb Listings.

Schmidt wrote in the introduction of the website: *“This rental does not exist. It never did. It was imagined by a machine; having looked at millions of pictures of bedrooms, millions of pictures of people, and hundreds of thousands of Airbnb listings, it was able to create this result. None of the pictures, nor the text, came directly from the real world. The listing titles, the descriptions, the picture of the host, even the pictures of the rooms: They are all fevered dreams of computers.”*

StyleGAN code was used unchanged from Nvidia github[33]. Schmidt obtained images from pretrained models produced by Nvidia, using two datasets of profile images and bedrooms. Text data was obtained from OpenDataSoft’s Airbnb Listings[34]. New text was created using TensorFlow’s “Predict Shakespeare with Cloud TPUs”[35].

With every new refresh of the webpage, a new listing appears. Numerous similar experiments are accessible on “This Repository Does Not Exist”[36], an assembly of AI generated faces, cats, birds, art, anime, shoes, lyrics, quotes, resumes, words, and even start-ups.





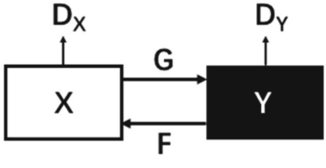
Source: https://thisrentaldoesnotexist.com/

CycleGAN

CycleGAN, first presented by Zhu et al[37] in 2017, allows the transposition of styles from two collections of images. Without paired examples, a common strategy for other networks, CycleGAN can translate source image onto target image. The code was made available by researchers on github (https://github.com/junyanz/CycleGAN and https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix).

In architecture, CycleGAN was presented by Li et al[38] 2021 in "Proceedings of the 2021 DigitalFUTURES". They used a selection of world-renowned buildings, altogether 100 sketches and 100 images. 80 of those were used for training and remaining 20 for testing. The CycleGAN has two generators and two discriminators combined in a ring structure. During the training process, the sketch is generated onto image domain and then reconstructed back into a sketch. Inversely the photo from image domain is generated as a sketch and then reconstructed back as image. On the right, Real_A is the original sketch and Real_B is the original image. The reconstructions are in columns Rec_A and Rec_B.

In their experiment, Li et al were successful in using CycleGAN for reconstruction of images form sketches and sketches from images.



The network architecture of CycleGAN

Source: Li, Yuqian, and Weiguo Xu. 2022. 'Using CycleGAN to Achieve the Sketch Recognition Process of Sketch-Based Modeling'. In Proceedings of the 2021 DigitalFUTURES, edited by Philip F. Yuan, Hua Chai, Chao Yan, and Neil Leach, 26–34. Singapore: Springer. https://doi.org/10.1007/978-981-16-5983-6_3.

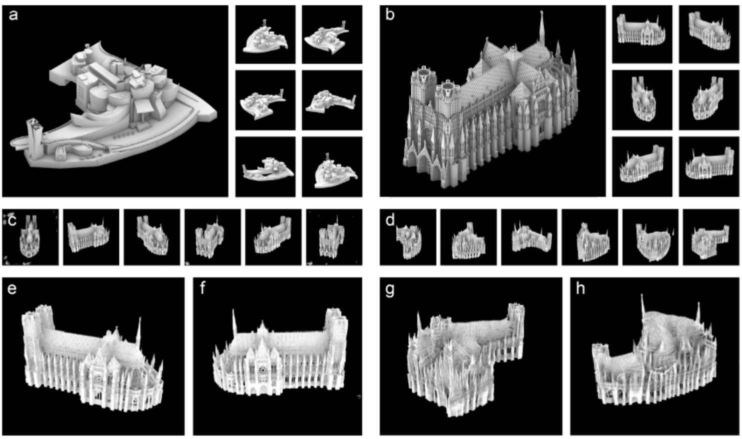
The results of the test training

Source: Li, Yuqian, and Weiguo Xu. 2022. 'Using CycleGAN to Achieve the Sketch Recognition Process of Sketch-Based Modeling'. In Proceedings of the 2021 DigitalFUTURES, edited by Philip F. Yuan, Hua Chai, Chao Yan, and Neil Leach, 26–34. Singapore: Springer. https://doi.org/10.1007/978-981-16-5983-6_3.

We already saw a research by Zhang using StyleGAN in 2019 for 3D generation. In 2020, Zhang and Blasetti continued their study using CycleGAN in a paper titled “3D Architectural Form Style Transfer through Machine Learning”. CycleGAN here was compared with pix2pix performance.

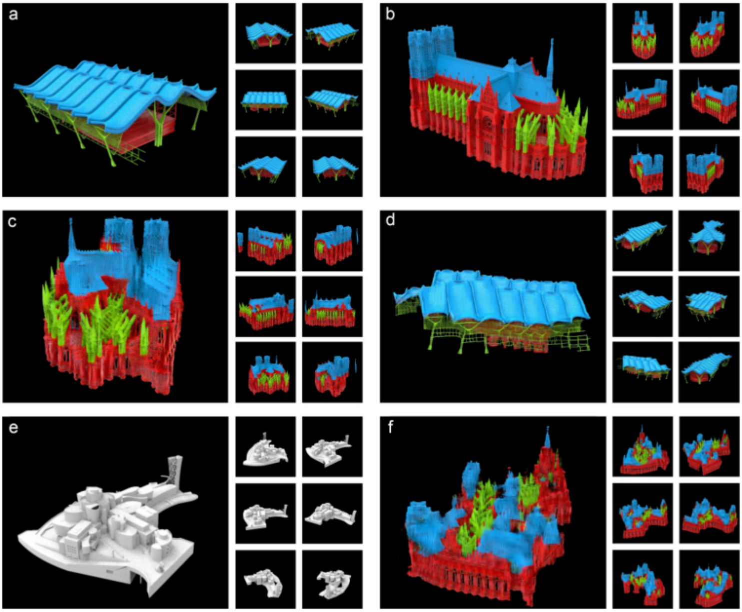
Similar as in previous study, they proceeded by slicing 3D into 2D layers and then reconstructing them back into 3D. Both, the content model, and the style model were sliced into 2D layers. After that they employed another method by viewing the 3D model from different sides.

The advantage of this technique lies in the architectural fidelity of content model, the style model only applies its pattern onto content model.



Style transfer results from CycleGAN (unpaired) and Pix2Pix (paired) at 10242 resolution for each single view: (a) Original input Model. (b) Target input Model. (c) Image Results from CycleGAN. (d) Image Results from Pix2Pix. (e) 3D Result from CycleGAN. (f) 3D Result from CycleGAN. (g) 3D Result from Pix2Pix. (h) 3D Result from Pix2Pix.

Source: Zhang, Hang, and Ezio Blasetti. 2020. 3D Architectural Form Style Transfer through Machine Learning (Full Version). https://doi.org/10.13140/RG.2.2.16791.52645.



Results through CycleGAN with color tagged, double direction and additional input of style transfer at 10242 resolution for each single view: (a) Original input Model. (b) Style B Model. (c) 3D Result from Style A to B. (d) 3D Result from Style B to A. (e) Additional Input Model. (f) 3D result of Additional Model from Style A to B.

Source: Zhang, Hang, and Ezio Blasetti. 2020. 3D Architectural Form Style Transfer through Machine Learning (Full Version). https://doi.org/10.13140/RG.2.2.16791.52645.

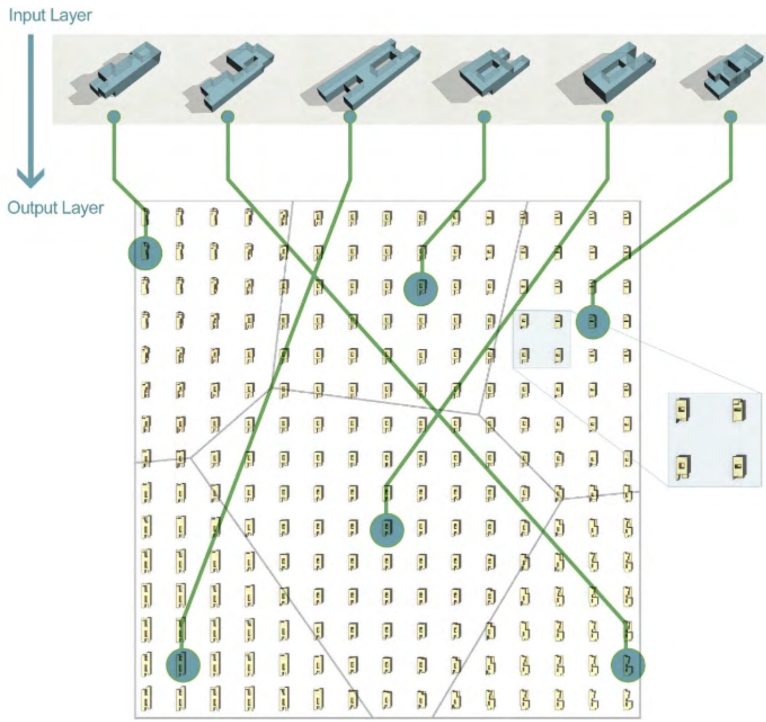
Self-Organizing Map SOM

Self-organising map SOM is a non-supervised learning algorithm developed by Finnish professor Teuvo Kohonen in 1982. It operates in two modes: training and mapping, and it employs competitive learning in the process.

In architecture, self-organising maps SOM were used in 2015 by Mohamed Zaghloul[39] to design alternatives of a villa by non-linear morphing between 6 initial variants. Zaghloul used Rhino®, Grasshopper® and Mathematica® to implement his SOM code. His research is not about data optimisation, rather data understanding. He transforms an architectural project as a matrix of vectors.

Zaghloul's objective is classifying and clustering design data to integrate it into design process. The input data contains 6 design alternatives encoded as matrices. After applying SOM algorithm on those matrices, the result is displayed as 2D topological map that morphs between the initial designs. The uniqueness lies in the fact that it is possible to change the weights of SOM neurons, thus creating non-linear morphing.

According to Zaghloul, SOM can help observe architectural data from another perspective. It discovers patterns, *"understands and manipulates the data entities in a holistic way".* No structure is given in advance, the algorithm finds it itself, especially possibly hidden patterns. In this case the computer is not simply instructed to execute a command, it gives unforeseen information to the architect employing SOM, thus augmenting the design process.



SOM input layer: 6 design alternatives of villas. Output layer: a non-linear morphing in between 6 design alternatives.

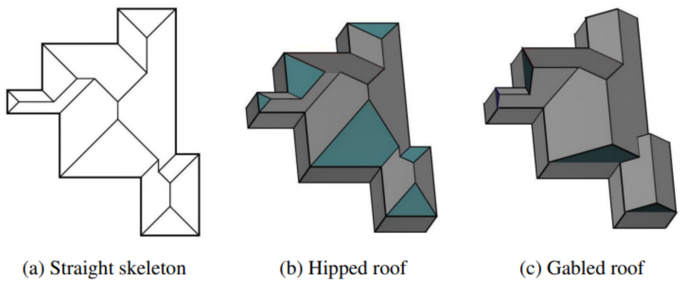
Source: Zaghloul, Mohamed. 2015. "Machine-Learning Aided Architectural Design: Self-Organizing Map Generates in between Design Alternatives." In Proceedings of the 18th Generative Art Conference, 283–93. Venice: GA, page 291

Bayesian network BN

"Bayesian networks (BNs), also known as belief networks, belong to the family of probabilistic graphical models (GMs). These graphical structures are used to represent knowledge about an uncertain domain" (Ben-Gal, 2008)[40].

In architecture, Bayesian network was used by researchers at Stanford university in 2010. Merrell et al explored the design of residential buildings with the help of machine learning. They trained Bayesian network on real-world design programs to represent the probability distribution of spaces. Then new samples can be generated using the distribution as well as modified versions with fixed attributes.

Their dataset contained 120 manually encoded architectural programs. The encoded attributes contained the area, footprint, type of rooms and their areas and connections between different rooms. Once the network is trained with attributes represented in a bubble diagram, it can generate a typological layout by optimisation. For this, Merrell et al used Metropolis algorithm. The optimisation process took 35 seconds for the iterations represented on the right. The roof volume was generated using straight skeleton algorithm.



Roof construction

Source: Merrell, Paul, Eric Schkufza, and Vladlen Koltun. 2010. 'Computer-Generated Residential Building Layouts'. In ACM SIGGRAPH Asia 2010 Papers on - SIGGRAPH ASIA '10, 1. Seoul, South Korea: ACM Press. https://doi.org/10.1145/1882262.1866203.

Floor plan optimization going from 200, 2 000, 20 000 and 100 000 iterations

Computer-generated residences

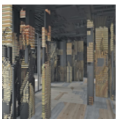
Source: Merrell, Paul, Eric Schkufza, and Vladlen Koltun. 2010. 'Computer-Generated Residential Building Layouts'. In ACM SIGGRAPH Asia 2010 Papers on - SIGGRAPH ASIA '10, 1. Seoul, South Korea: ACM Press. https://doi.org/10.1145/1882262.1866203.

Case studies

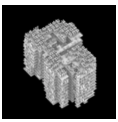
The selection of case studies will look on how AI is used in different scale real-life projects made by outstanding architects. For every project we will first look why it represents a shift from traditional workflow, then how it changes the way architects work and finally what this project offers. All case studies are considered as early adopters and thus guide us into the possible future of architectural practices. Projects in this selection were made in the last 5 years. It includes urban, architectural, and artistic representations.

Urban project Deep Green
ecoLogicStudio
Claudia Pasquero and Marco Poletto
Guatemala, 2021

Competition 24 Highschool by
SPAN
Matias Del Campo and Sandra Manninger
Shenzhen, China, 2020



Housing NN_House 1
Kinch
M Casey Rehm
Joshua Tree, California, 2018



Art installation 3D GAN housing
Immanuel Koh
17th Venice Architecture Biennale,
Italian Virtual Pavilion (CityX Venice), 2021

Art installation Horizons
Certain Measures
Andrew Witt and Tobias Nolte
2018

Deep Green, Guatemala

Our first case study combines creative artificial intelligence with big data. It is an urban scale project covering the city of Guatemala and is developed by ecoLogicStudio, led by architects Claudia Pasquero and Marco Poletto. Deep Green[41] was commissioned by United Nations Development Program (UNDP) and was finalised in 2021. Developed with the help of AI, it analysis re-greening scenarios of Guatemala.

ecoLogicStudio advocates that with the increasing complexity of our urban environments it is extremely difficult to leave urban planning to individual human minds. To tackle the complexity of urban planning, all available tools should be considered. They write about *"collective agency and intelligence"* as a possible solution. Collective agency can be obtained by mixing human mind, digital tools, and artificial intelligence.

The project tackles sustainable development of cities first-hand. ecoLogicStudio aspires creating resilient cities for both humans and wildlife. Deep Green invites nature back into the cities, that have become too sterile from our activities. They tackle two important aspects of cities: water and land. More precisely, the diminishing drinkable water and land degradation that leads to desertification, erosion, and pollution. They look for innovative solutions that would be able to re-green and re-wild our cities.

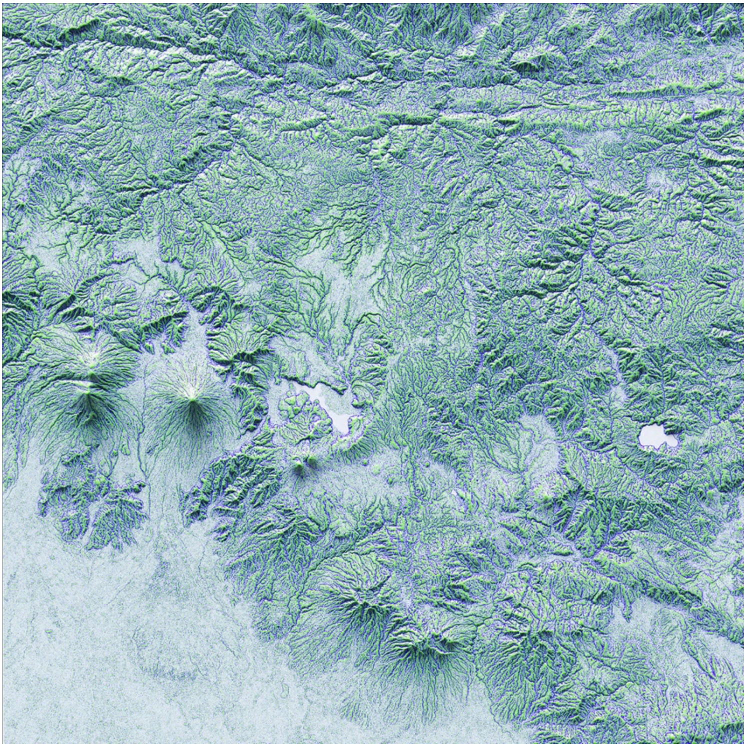
With current global awareness of our limited earth, one cannot ignore the complexity of our city planning. At the same time cities represent a part of the solution. They are mines of resources and data. With the right tools, cities have the capacity to improve livelihoods of its inhabitants as well as invite the nature back into them creating a new hybrid city. Instead of simply responding to problems and crisis, we can simulate how our decisions will age with time and we can anticipate future problems, thus increasing the resilience.

To tackle de problem, ecoLogicStudio proceeded by specific steps. First, they defined the research challenge. According to UN, in 2018, 55% of world population lived in cites. In 2050 it is expected to reach 68%. As cities will host majority of human population, they are the most at risk of catastrophic effects of climate change. At the same time, because of their scale, cities are a perfect location for reversing those effects.

ecoLogicStudio invites us to rethink the cities as a complete systems, *“redesign their infrastructure, rethink consumption patterns and circularity.”* They urge us to rethink what comes out and in the cities. ecoLogicStudio proposes us to revaluate city waste management, water use, energy production as well as air pollution.

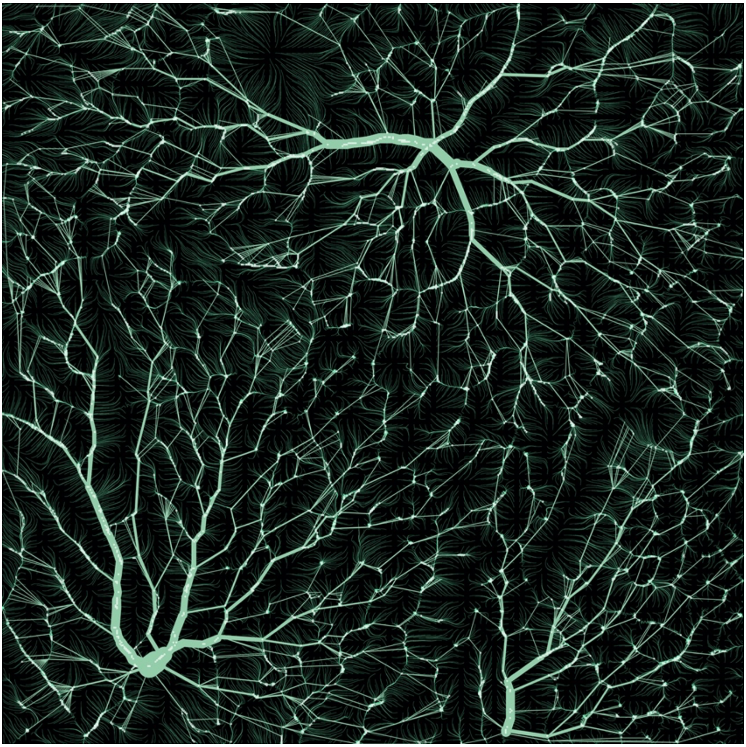
It reminds one of the beginnings of industrial cities. The time when the hygiene and pollution of cities made their inhabitants sick. The solution of that time was to bring air and light. Today we tackle new problems, the use of resources and our changing environment. Yet, the solutions cannot be limited anymore to the individual appartement block or the width of streets. Today’s complex problems needs to be tackled as systems, sophisticated combinations of varied factors all intertwining with each other. The same goes for solutions. Cities need a system of varied solutions and architect must be able to evaluate them. Plus, solutions need to be location based. People living in the specific environment can offer an ingenious solutions unexpected to outsiders. These solutions can be obtained as data, almost as statistics of city.

Given the complexity of today’s city planning, we need to consider all the available data to make the best-informed decisions. The city planning cannot rely on strategies developed a century ago. We need today’s solutions for tomorrow’s problems.



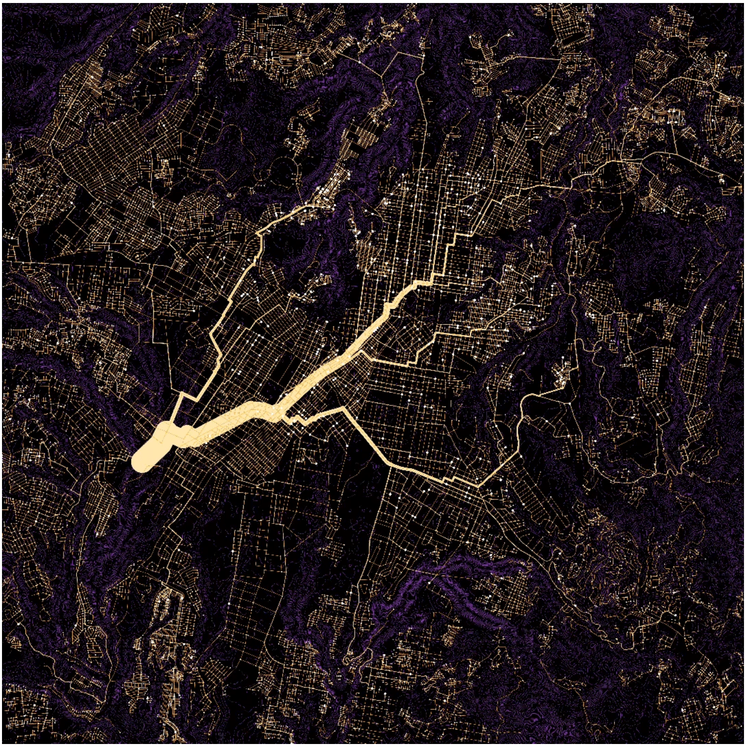
Water Flow Pattern analysis of the territory surrounding the city of Guatemala. The image is a false colour rendering of the mesh derived from NASA's global Digital Elevation Model

Source: 'Deep Green | EcoLogicStudio'. n.d. Accessed 8 November 2021. https://www.ecologicstudio.com/projects/deep-green.



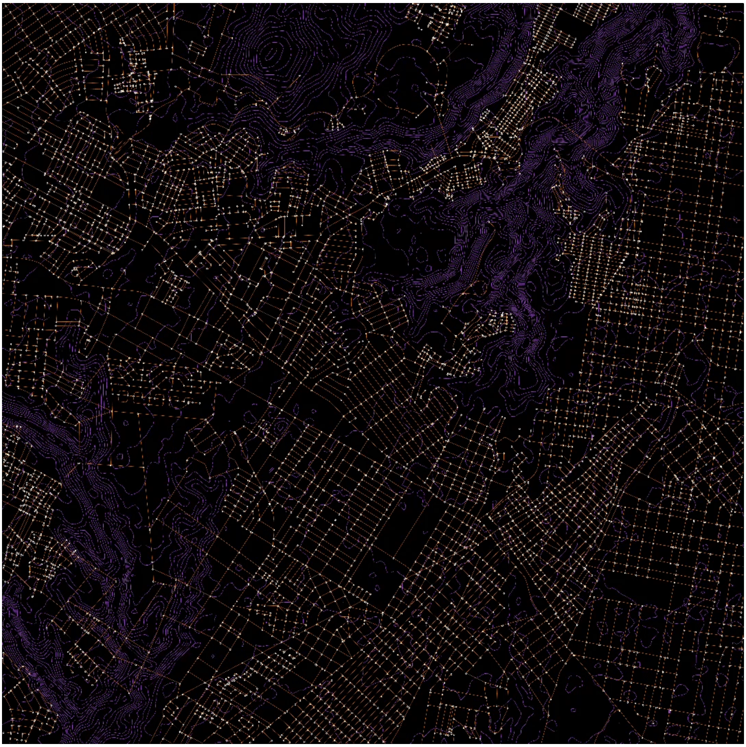
Rainwater collection analysis for the City of Guatemala. The image is computed through a combination water flow simulation patters and minimal networks on the DEM mesh of Guatemala City topography

Source: 'Deep Green | EcoLogicStudio'. n.d. Accessed 8 November 2021. https://www.ecologicstudio.com/projects/deep-green.



Local to municipal waste collection networks in the city of Guatemala. Image algorithmically computed from GIS map, satellite map and DEM model analysis by means of minimal path algorithm. The analysis also takes into account the result of the local waste collection analysis

Source: 'Deep Green | EcoLogicStudio'. n.d. Accessed 8 November 2021. https://www.ecologicstudio.com/projects/deep-green.



Emergent local waste collection networks in the city of Guatemala.

Source: ‘Deep Green | EcoLogicStudio’. n.d. Accessed 8 November 2021. https://www.ecologicstudio.com/projects/deep-green.

To respond to the complexity of city planning and to simulate possible futures, Deep Green uses data of urban areas and infrastructures. Then they use algorithms to analyse it and later to simulate scenarios of resilient urban development. The main idea is to observe and analyse cities with the help of machine mind that has stronger computational capacities than human mind. It allows to understand biological systems better as il looks for patterns with less bias than humans. Machine observes and communicates pure data, without misconceptions of human mind.

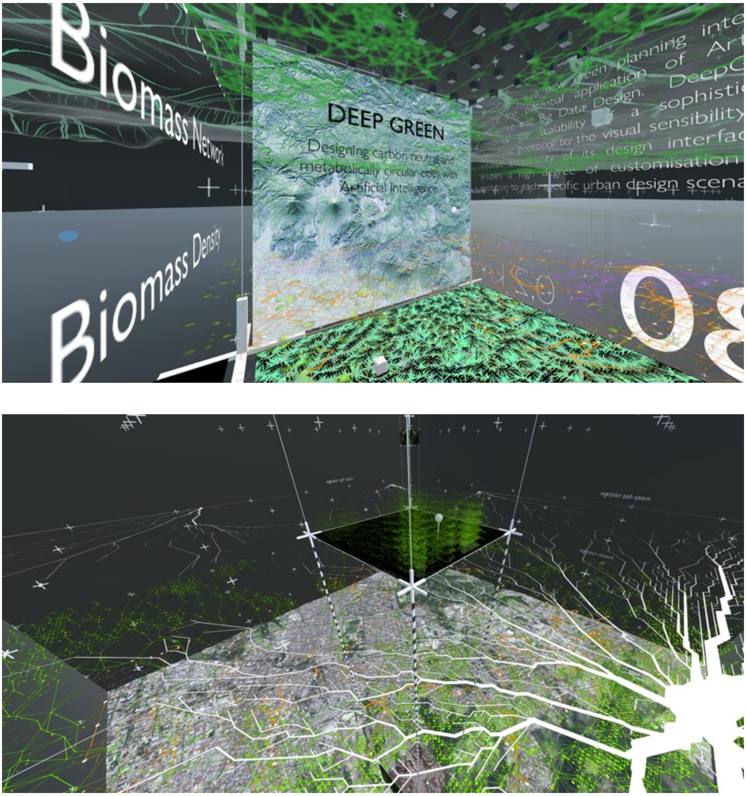
Deep Green was developed as a toolkit, to be applicable to any city in the world considering the specificities of site. The data used is mostly open source, thus easily accessible for architects. ecoLogicStudio's toolkit has been already used in Aarhus, Tallinn, Barcelona, Caracas, Vranje and Mogadishu to *"simulate the evolution of restorative urban networks"*.

For the city of Guatemala, the most urgent issue is waste management. *"99% of Guatemala's 2,240 garbage sites have no environmental systems and are classified as illegal."* Deep Green goes beyond traditional urban design tools such as "zone, *boundary, scale, typology and program."*

The specificity of Guatemala City is the terrain. Volcanoes and mountains render the terrain highly unstable. Originally this Central American city was rich in biodiversity. Yet, human activities combined with unorganised urbanisation had fragilized the ecosystem. The city has tropical savanna climate that is prone to early effects of climate change.

ecoLogicStudio objective is to merge bottom-up activities of citizens with top-down activities of municipality, the country (it is the capital of Guatemala country) and international level represented here by UNDP. The grassroots movement Deep Green looks at is the local waste recycling activities born from the necessity of citizens, as the large dumping sites were often too far away.

For the city of Guatemala, two strategies emerged: re-wilding of the city and the increase urban agriculture to tackle the risk of starvation. With the help of simulations, it was possible to evaluate the impact of chosen strategies on the level of whole city as a system.



Deep Green interface

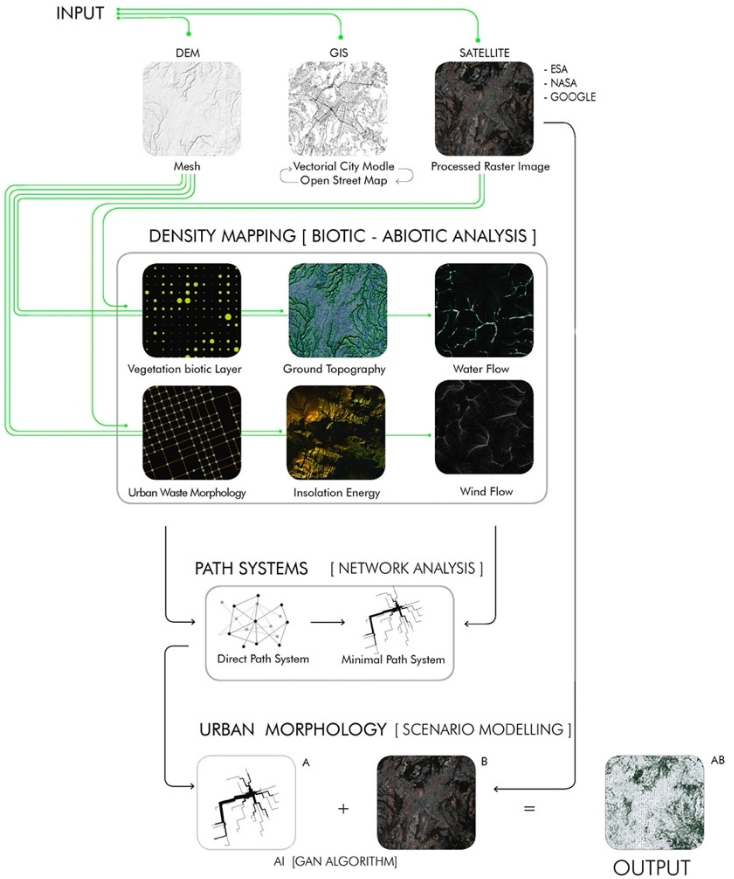
Source: Wright, Tim Powell. 2021. 'Deep Green'. Melbourne School of Design. 25 March 2021. https://msd.unimelb.edu.au/the-climate-imaginary/ecologicstudio/deep-green.

ecoLogicStudio chosen means of representation are quite traditional with drawings and rendered images with the extra of Virtual Reality room[42] experience. It allows one to be emerged into the data and possible futures. According to the architects, this toolkit has three important ingredients: urban data, machine learning and immersive visual output. With the help of Virtual Reality room, it is possible for all stakeholders (planners, city officials, press) to meet and discuss possible futures.

Deep Green's workflow was published by architects showing the interaction of all design ingredients. The input data comes from three sources: DEM (digital elevation model) mesh, GIS (geographic information system) vectorial city model and open street map and lastly satellite imagery from ESA (European Space Agency), NASA and Google. Then they made a biotic – abiotic analysis of 6 subjects: vegetation biotic layer, ground topography, water flow, urban waste morphology, insulation energy and wind flow. Then two path systems are analysed: direct path system and minimal path system. Lastly GAN algorithm is used to transpose satellite imagery on the network analysis. Architects named the algorithm employed GAN_Physarum[43] in their article titled "Deep Green, Coupling Biological and Artificial Intelligence in Urban Design".

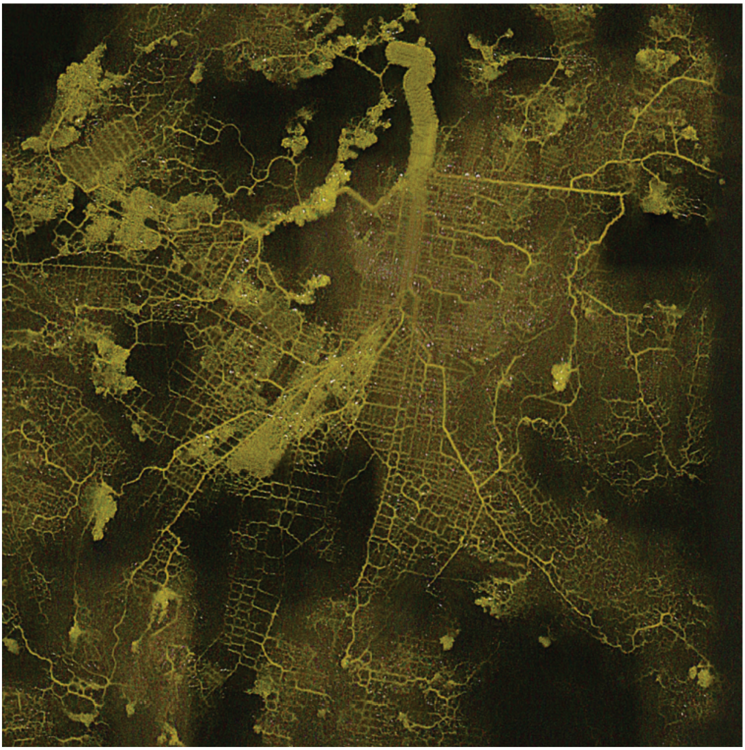
It is a CycleGAN that is fed two data sources: urban morphology (the 6 analysis maps) and biological growth patterns of slime mold. The objective of the GAN_Physarum is to train CycleGAN to behave as a biological organism that can be then employed as design tool. This is an excellent example of teaching a machine how to think and behave as a living organism.

The GAN_Physarum has four phases: first data gathering (urban and biological), secondly training the model for 200 epochs, then fallows the testing phase and lastly the merging of all previous images. The architects call this process "la dérive numerique".



Deep Green workflow diagram

Source: 'Deep Green | EcoLogicStudio'. n.d. Accessed 8 November 2021. https://www.ecologicstudio.com/projects/deep-green.

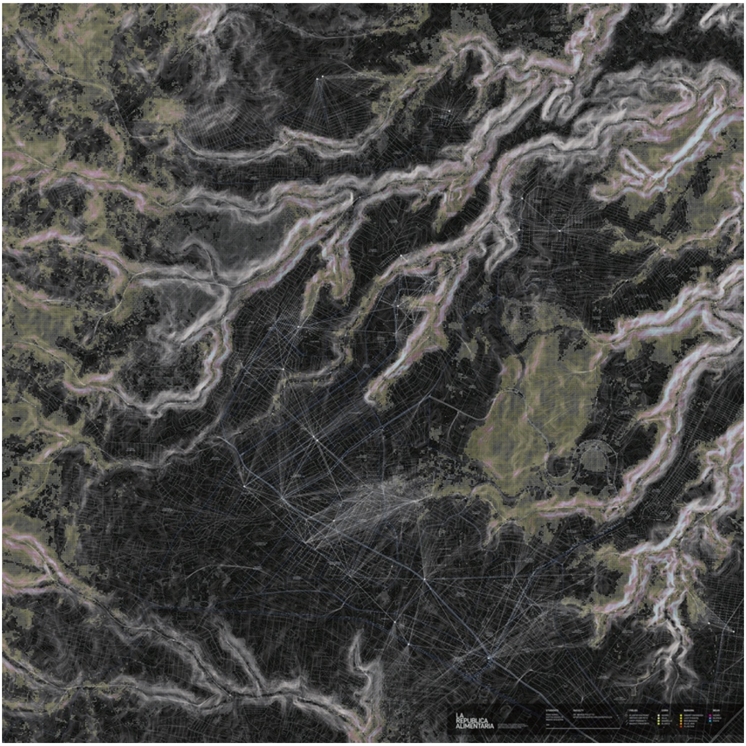


Reinterpretation of the municipal waste collection networks of Guatemala City using the GAN_Physarum algorithm; algorithm training based on Physarum polycephalum behaviour.

Source: Pasquero, Claudia, and Marco Poletto. n.d. ‘Coupling Biological and Artificial Intelligence in Urban Design’, 10.
http://papers.cumincad.org/data/works/att/acadia20_668.pdf

Redefined morphology and materiality of two overlapping systems: local to municipal waste collection networks and the vegetation network in Guatemala City; algorithm training based on Physarum polycephalum behaviour.

Source: Pasquero, Claudia, and Marco Poletto. n.d. 'Coupling Biological and Artificial Intelligence in Urban Design', 10.
http://papers.cumincad.org/data/works/att/acadia20_668.pdf



La Republica Alimentaria, simulated plan for extended urban agriculture in Guatemala City. Proposed application of the DeepGreen tool to tackle the issue of food security. The plan illustrates the territory of Guatemala City as a potential for growing the 3 main staple foods for the city. It also simulates the interaction between the plots and the existing urban infrastructure to support the emergence of a local market of produce distributed in key areas of the city where low-income population is at high risk of starvation. Plan developed in collaboration with the Master in Advanced Architecture at IAAC, Barcelona.

Source: 'Deep Green | EcoLogicStudio'. n.d. Accessed 8 November 2021. https://www.ecologicstudio.com/projects/deep-green.

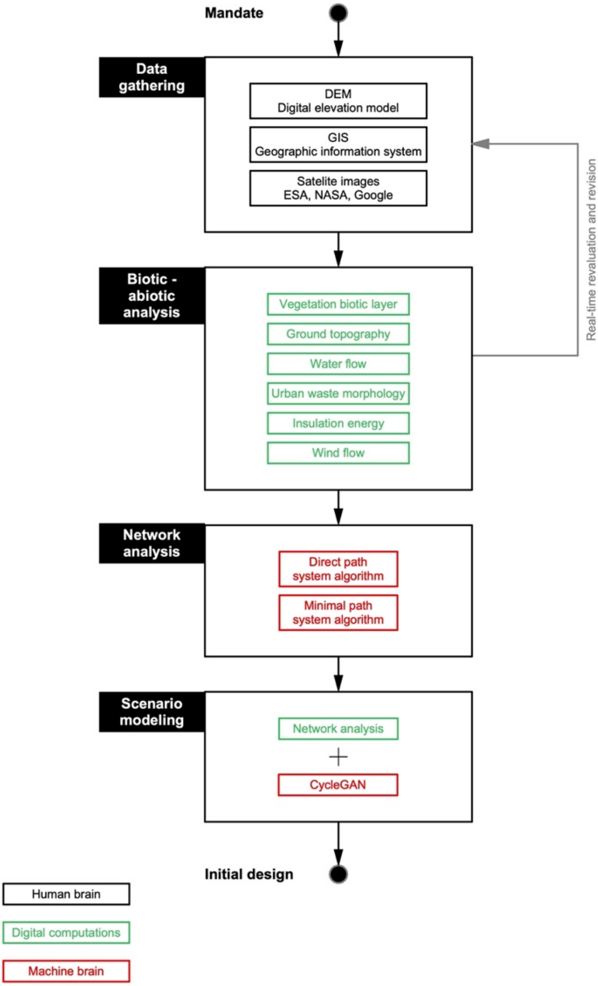
Extract of Guatemala City simulation

Source: ‘Deep Green | EcoLogicStudio’. n.d. Accessed 8 November 2021. https://www.ecologicstudio.com/projects/deep-green.

In conclusion, the first case study shows us, architects, that the use of creative algorithms can completely change the traditional workflow. Big data goes hand in hand with AI. At the same time, it completely changes our perception about urban design. The idea is still the most important aspect, yet the origin from it results from the statistics of the city.

ecoLogicStudio are extremely open about the techniques and methods of their work. They explain in great details their workflow, the techniques of obtaining their solutions. Claudia Pasquero talks about the *"gardening of the data"44,* a process that allows the spectator to immerse himself/herself in the wastes amounts of data to observe correlations. In Deep Green machine learning is represented as is simply another layer of information, having equal value as other data. According to Marco Poletto, ML allows us to go *"fast forward of re-greening of the city".* ML algorithm is fed with satellite images to compute selected scenarios. The biggest advantage of Deep Green, according to Marco Poletto, is that it allows updating the interface real time. As the satellite imagery is constantly updated, the same goes for Deep Green interface. It allows the city to observe the evolutions of implied solutions as well as modify the strategy if needed. Thus, Deep Green is not a final, singular solution but an evolving one. Marco Poletto quite directly calls it *"new kind of planning*", planning that is collective, open and evolutive.

The use of AI, Big Data and Virtual Reality is in the core of Deep Green. CycleGAN interlock effortlessly in the workflow of the project. On the other hand, the workflow of this urban project is completely different from traditional one and completely changes the way architect works. Architect here is a curator of data, a searcher of correlations and teacher of machines not a divine genius able to predict future.



Deep Green workflow

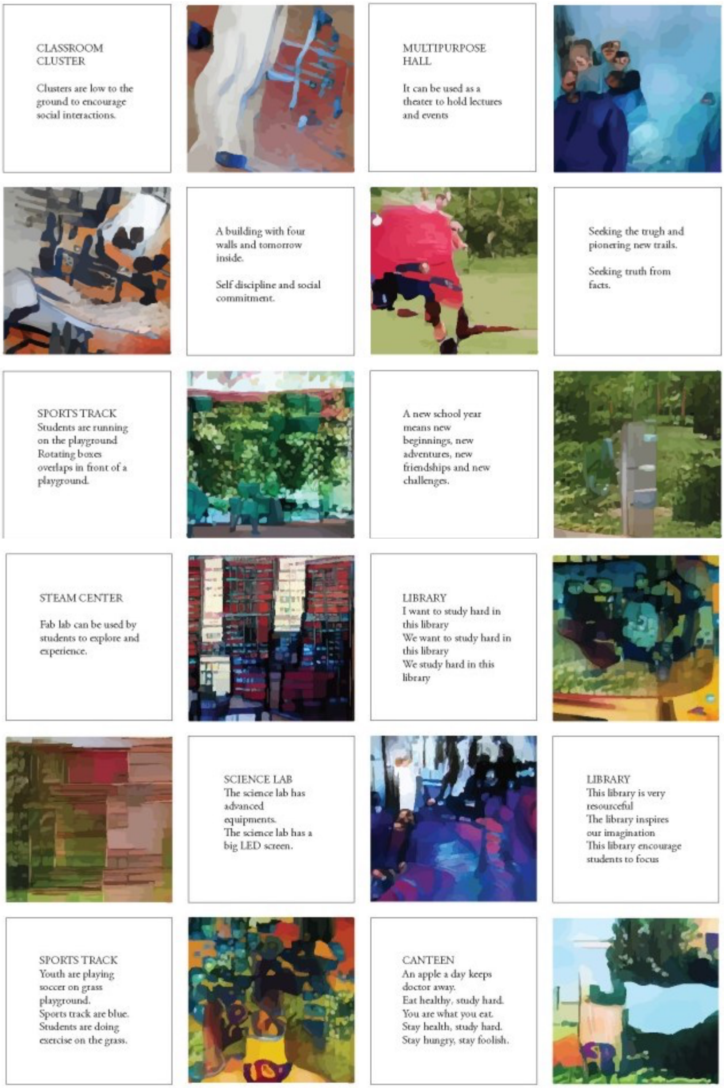
Interpretation by the author

24 Highschool - Peaches & Plums Shenzhen, China

The second project we will discuss was developed by Matias Del Campo and Sandra Manninger (architectural office SPAN) and it represents a shift from a traditional workflow as well. Traditionally, the “creative spark” would come from an enlightened architect, especially when talking about architectural competitions. The winners of the competition of 24 Highschool in Shenzhen disrupts the traditional perception that ideas comes either from references (history, nature and so on) or within the architect’s mind. Here, artificial intelligence comes as a third source of inspiration. Two main resources will be used to describe the 24 Highschool: the official architect’s website[45] and a research paper[46] explaining the technique itself. It should be noted that the competition was won in Shenzhen, one of the most technologically advanced cities in the world.

The competition titled “Peaches & Plums” dates to 2020. It will accommodate around 3 000 students and will span across 110 000 m^2. Firstly, the concept tackles the core idea of learning with concepts such as self-organised learning and adaptive learning. It comes as an opposite to traditional 20th century idea that a learning facility should be a megastructure. The architects wanted the 24 Highschool function as a “learning village” where students become a part of a community. The project takes inspiration from hill settlements and their poetic appearance. This poetry is then transposed into architectural design with the help of creative AI.

The competition brief became a poem that served as design bases. Both, human mind, and machine mind, became a design tools. The brief in this case had two uses, firstly it responded to the needs of clients and secondly it became a creative ingredient. “*This architecture was literally spoken into existence,”* writes SPAN architects.



AttnGAN Results

Source: SPAN. 2020. 'Peaches & Plums'. SPAN. 12 December 2020. https://span-arch.org/peaches-plums/.

SPAN architects define *“artificial intelligence as a design driver*”. AI plays a key role in the communication of the project. “*This project is a pioneering example of the use of artificial intelligence as a driving force of design,”* writes the architects.

The design tasks are subdivided in human and machine tasks. First, design team tackled the massing taking into consideration the topography, the environment, and programmatic needs. Then machine learning algorithm projected what it had learned from the brief onto the massing made by humans.

ML gave the « creative spark » to the architect, yet it was always the architect who were responsible for proportions, selection and overall decisions. Creative algorithm’s solutions were used selectively according to architects liking. The colouring pattern came from a machine too. As the machine tried to interpret the language it gave both the proportions and colours of project. Combining all results from ML, one can observe a strong visual identity. This identity is one of community creation tools employed by architects. The colours given by machine unifies future users: students, teachers, and other employees. The coloration transcends building volumes and projects itself on the terrain made from different materials and varied vegetation.

SPAN used artificial intelligence cleverly, responding to specific design needs and AI current capabilities. Yet this project demanded more work than traditional project with the supplement of data preparation and interpretation. The fusion of AttnGAN poetry and architects defined massing demands fine tuning. The network gives proportions, yet scale is up to humans.

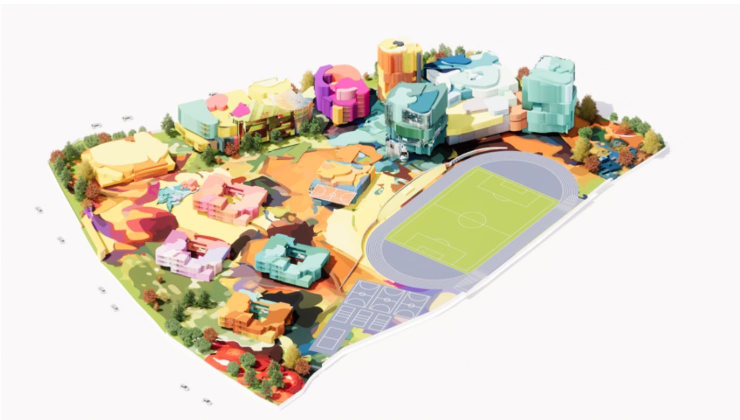
There is a certain unity of human-machine workflow in the project. Each participant, both human or machine, complements and feeds his design partner with information.

Applications of AttnGAN Generated Images
[above: GAN generated image; below: its application on volumes]

Extract of site axonometry

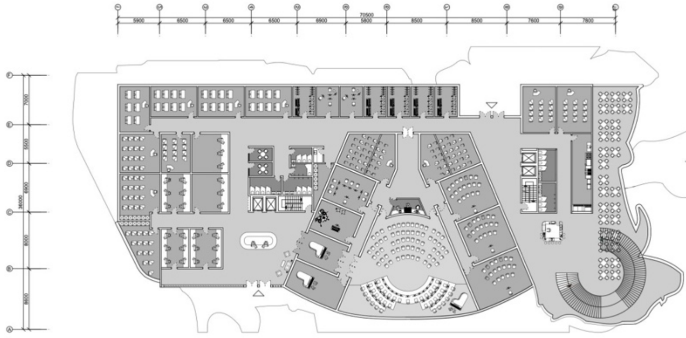
Source: SPAN. 2020. ‘Peaches & Plums’. SPAN. 12 December 2020. https://span-arch.org/peaches-plums/.

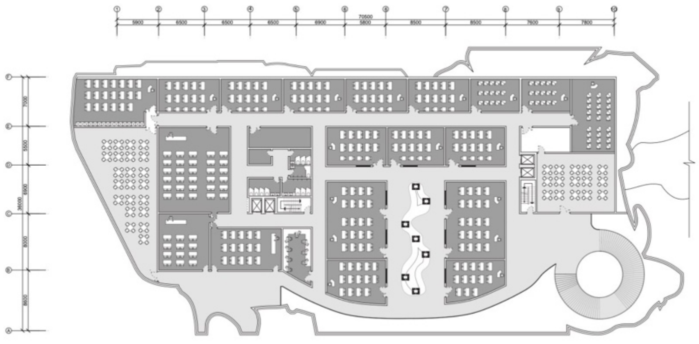
Site plan



Site axonometric massing

Source: SPAN. 2020. 'Peaches & Plums'. SPAN. 12 December 2020. https://span-arch.org/peaches-plums/.





Final plans

Source: SPAN. 2020. ‘Peaches & Plums’. SPAN. 12 December 2020. https://span-arch.org/peaches-plums/.

When we observe final black and white plans, they appear conventional. Yet all render images possess a vibrant, artistic vibe. The colours are dispersed in non-rational manner, almost as a surreal painting. It comes as a complete opposite to a longstanding idea that AI lacks creativity and is able simply execute commands from its human masters. Here, AI comes as an inspiration, a noble quest to transform words into architecture.

As we observed in preceding paragraphs, SPAN underlines an ongoing change. A change in education system, that comes as bases for planning new campuses, and a change in architectural practices where AI becomes a design partner. Yet the use of AI in this project represents only a small part of the whole process from idea to constructed building. In the fallowing paragraphs, we will look how exactly the AI was used in the 24 Highschool project. A detailed explanation was given by Mathias del Campo during the 26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2021, with a fallowing publication titled “Architecture, language and AI”.

Architects used Attentional Generative Adversarial Network or AttnGAN for short as creative drive for this competition. The uniqueness of this project lies in the use of text as creative input, translated in colourful images later used in design process. Traditionally, the idea would come from a creative spark in architects mind, then translated into design. Use of text as creative spark is quite revolutionary, especially knowing the numerous AI techniques available to architects today. Using language as design tool expands architects design possibilities.

The same as in previous case study, SPAN architects are extremely transparent about the techniques and methods employed in the project. They openly share where they obtained the data, what algorithms they used and what difficulties they encountered. The 24 Highschool undoubtedly serves as a reference for future architects interested in AI creativity.

SPAN used Microsoft COCO (Common Objects in Context)[47] database for generation of images, available on github[48]. The dataset contains 91 object types with a total of 2,5 million labelled instances in 328 000 images. The objective of COCO is object recognition, yet SPAN used this database in a different manner. Normally used for object detection, SPAN architects used it for image generation. With the help of AttnGAN, architects were able to extract the essence of the design brief in images.

Attentional Generative Adversarial Network - Sample of Result

Source: Matias del Campo. 2021. 'ARCHITECTURE, LANGUAGE AND AI'. https://caadria2021.org/wp-content/uploads/2021/03/caadria2021_389.pdf.

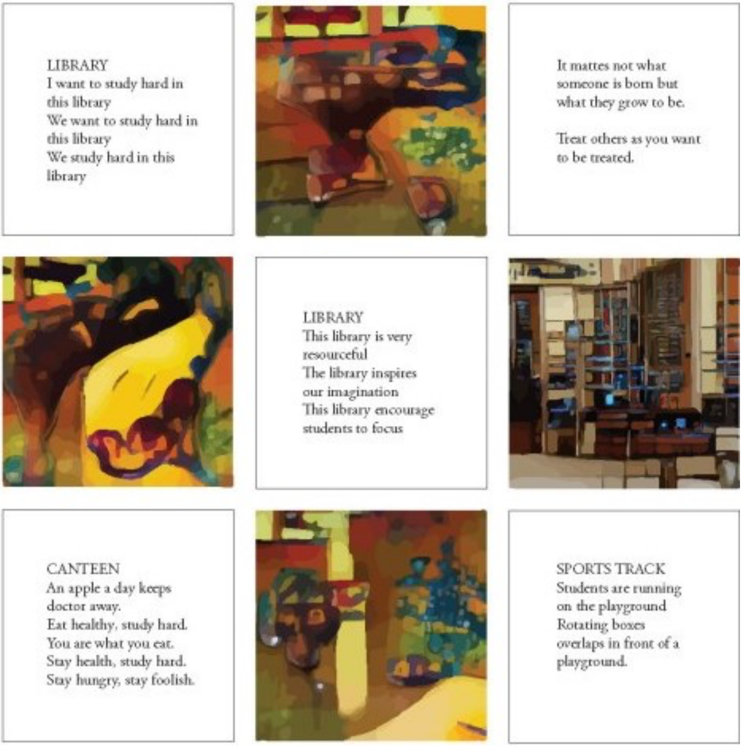
The initial phase of project did not differ from traditional workflow. Site massing was done by humans using digital tools while considering multiple variants. The design team decided to scatter the volumes on North-South axes with classrooms on the south corner. They used natural topography of the site and emphasised it by placing tallest volumes on the highest point. This allowed to place the parking lot above water table, reducing the construction costs.

As in a traditional workflow, the analysis of competition brief and legal restrictions and boundaries was done by design team. Yet architects aspire to automate this process too with the help of parametric design to be able to guarantee an optimal solution.

At the same time, another SPAN team was working with AttnGAN[49]. The attentional generative adversarial network is used for text-to-image generation and directs its “attention” to specific words.

GANs indeed seem to be the most widely used in architectural practices now. As we saw in the “techniques and models” section, there is a wide range of different GANs, AttnGAN being one of them. The standard GAN consists of two parts: generator and discriminator. Images are fed into the algorithm and the generator tries to fool the discriminator with fake images until the discriminator agrees that all images are real. AttnGAN is slightly different. The same as traditional GAN it has two parts. But the first part is an attentional generative network that looks at singular words as well as whole sentences in a shape of vectors. The second part is a Deep Attentional Multimodal Similarity Model.

The main objective of these two components is to extract imagery from sentences and individual words. The sentences selected for the training were a combination of the brief and intended activities.



AttnGAN Results

Source: SPAN. 2020. 'Peaches & Plums'. SPAN. 12 December 2020. https://span-arch.org/peaches-plums/.

Once the graphical sense was extracted from words and sentences, SPAN used Grasshopper 3D to analyse the images and divide them according to colour regions. Then those colour regions were projected onto the initial massing. The colours gave the massing a unique heterogenous façade. SPAN specified that multiple back and forth were needed to obtain right proportions for the project. Even though AttnGAN provided imagery, it was scaleless and needed human eye for its application.

Mathias del Campo concluded in his conference paper that *“the major finding of this paper is […] the proof of concept that this approach can produce viable architectural designs.”*

At the same time, he openly discussed the limitations of this technique, such as the use of traditional workflow with human design team for the most part of design process. Another disadvantage of their design method was mentioned the generation of solely exteriors or interiors and not both at the same time. The technique allows patching onto surfaces, yet those patches are not interconnected. Again, design team was responsible for interconnecting them manually.

Mathias del Campo defined language as a “design weapon”. Words serve not only for communication means but can become a design tool with the right technology. The use of creative AI, here AttnGAN creates unique images and designs that are “*somewhere between abstraction and the surreal full of instances of estrangement and defamiliarization in an architecture that can be described as something different, alien, strange and wonderfully beautiful - maybe the first genuine 21st century architecture.”* (del Campo, 2021)

The PE center and dorms of the 24 Highschool. This image shows the distinct hand of the GraphCNN in full color. The coloration created by the process was embraced and forms a distinct feature of the project.

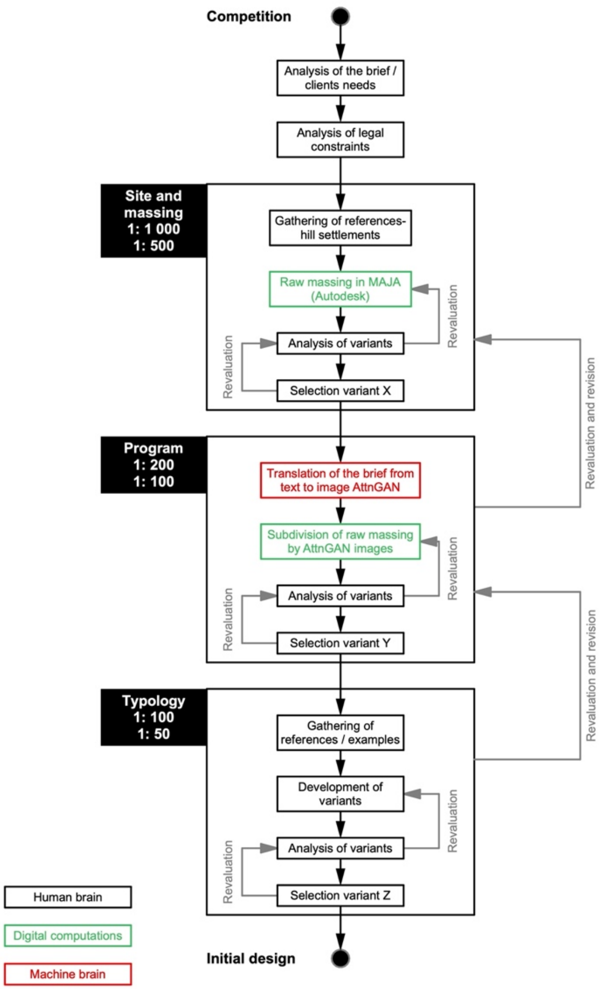
Source: Matias del Campo. 2021. ‘ARCHITECTURE, LANGUAGE AND AI’. https://caadria2021.org/wp-content/uploads/2021/03/caadria2021_389.pdf.

In conclusion, the 24 Highschool project by Matias Del Campo and Sandra Manninger shows perfectly how AI can be employed in an architectural project. At the same time, architects are transparent when explaining the techniques employed, encouraging future use of this method. Data sources are cited, as well as the steps leading to final project. Interestingly, they describe the shortcomings of the method as well. It should be noted that both architects Matias Del Campo and Sandra Manninger span across professional and academic domains. Both have published excessively on the subject. The Curriculum Vitae[50] of Matias Del Campo accounts 44 architectural projects in China alone.

For the competition of 24 Highschool AI plays a key role in the communication of the project. The AI is not used to increase the speed nor automate the creative process. Neither it robs the architect from creativity. AttnGAN serves almost as calculator of the essence of words and sentences. Yet it is the architect who selects the dataset used in the training. As well it is the architect who defines the words and sentences for AI to calculate. The final images were the representation of machine understanding of the language used. Different datasets would produce different results.

At the same time, it is the architect who interprets the AttnGAN results and transposes them on volumes. 24 Highschool project perfectly shows the possible co-creation artificial intelligence offers to architects. It indeed changes the traditional workflow, yet it is the architect who defines this change.

It would be important to note the fact that the competition was won using AI. This could possibly indicate the readiness of clients to accept novel solutions in design process. As the use of AI was previously limited to academic or research projects, it transcends today into professional domain.



24 Highschool workflow

Interpretation by the author

NN_House 1, Joshua Tree, California

The third case study looks at how architects can co-create with AI on a private mandate. The housing project was developed in 2018 by Studio Kinch, led by M. Casey Rehm. Three main sources are used for the analysis: a publication in Architectural Design[51], a lecture at Texas Architecture[52] and a lecture at AA Visiting School ShenZhen[53].

The project went through different phases. It started as a small vacation home of around 110 m^2 or 1 200 ft^2. Then it tripled to become a 325 m^2 or 3 500ft^2 *"giant party pad on a desert site"* or three Airbnb units. The project was stopped because of financial reasons.

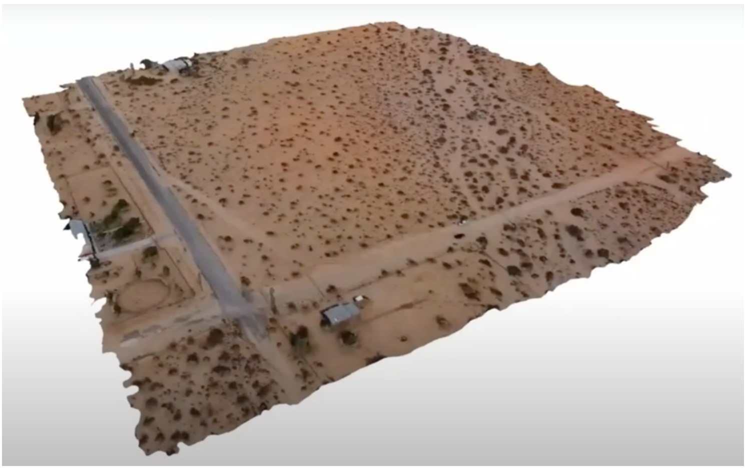
For the design process Kinch first proceeded with a complete LIDAR site scan to assess the ground conditions. This scan was used for series of explorations of the site. M. Casey Rehm looked on how AI could generate a plan differently than he, as an architect, would. Two architectural precedents were used: Mies van der Rohe's Brick Country House, drawn in 1923, and Alvar Aalto's Villa Mairea built in 1939.

The intended construction material was CLT, assembled by a robot. Thus, the traditional regularity dictated by human calculation abilities and labour was replaced by non-standard forms, something that Kinch continued to study in their later projects, like the proposition of Tallinn Experimental architecture Biennale.

In this project AI plays an important role, as the massing and typological variants were created by convolutional neural network CNN. The network was interacting to point cloud information of the site yet remaining loyal to training data of iconic modernist houses.

Project rendering

Source: Rehm, M Casey. 2019. 'Complicit: The Creation Of and Collaboration With Intelligent Machines'. Architectural Design 89 (2): 94–101. https://doi.org/10.1002/ad.2417.



LIDAR site scan

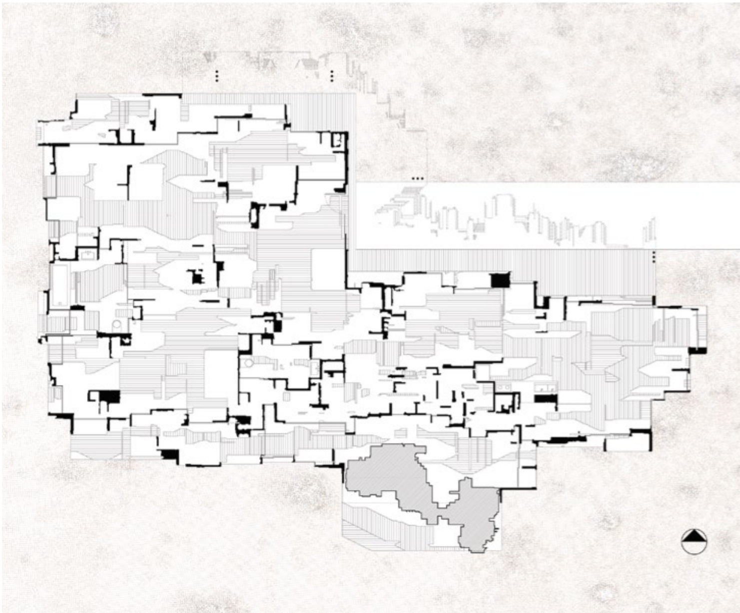
Source: SoomeenHahm Design. 2020. AAShenZhen_Keynote02_Casey Rehm. https://www.youtube.com/watch?v=EK76am9QAjg.

As it often happens, creative AI is used to create many variations. The image on the right is the favourite iteration of M. Casey Rehm, presented in Goldsmith Lecture. This is not the last, neither the most realistic. He explained that they passed through many typological variants with more or less enclosed areas. Many alternatives were created after discussions with the clients.

The house plan is not “clean”, there is *“a lot of debris*”. Yet it allows us to perceive a plan and typology from the perspective of a machine. There is “*a lack of certain hierarchy*” that could be expected from traditional architectural plan. The plan, designed by machine, expresses its understanding of a “*void and mass*” as a way of delimiting and creating spaces. The constraints that normally binds architects mind, are absent. There is no immediately apparent hierarchy between rooms, nor minimum width of circulation, neither minimalization of loadbearing materials. Yet, once observing the plan any architect can define which areas are intended for living, sleeping or storage and where are windows and balconies. This technique liberates architect from ever-increasing norms and regulations. The project is not a result of constrains, it is pure machine creativity.

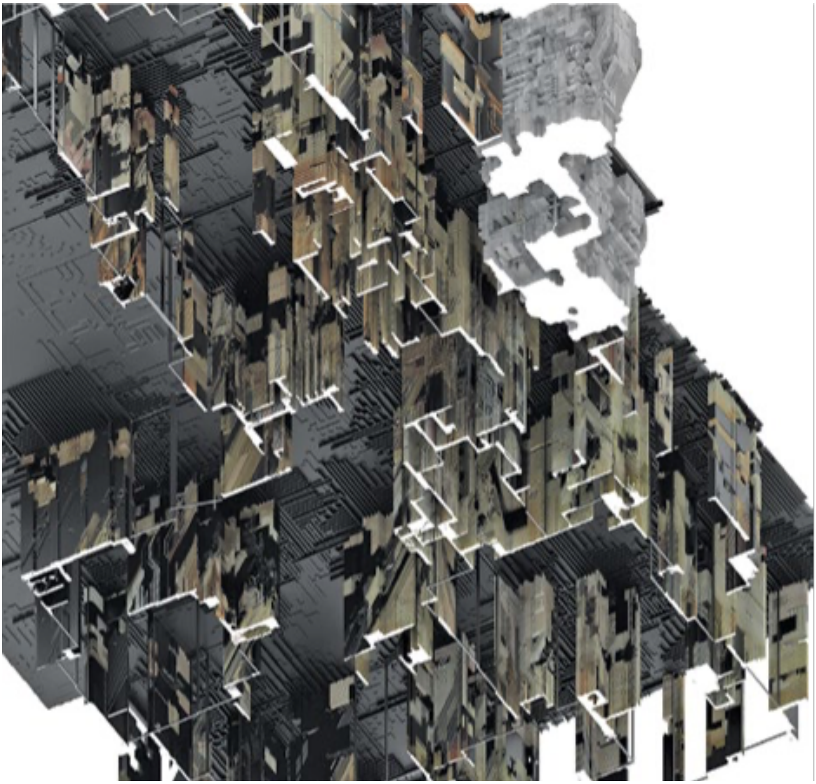
The plan certainly embodies the reference projects, yet the typology possesses a certain degree of randomness. The machine is not bound by domestic spaces nor norms. Its priority is the topography expressed in point-cloud. Spaces are more implied than physically defined leaving it to the architect to attribute their use. Here again, the creative AI is used to inspire the architect. Two minds collaborate: human and machine. But it is up to the architect to interpret what the machine thinks.

As per M. Casey Rehm, Kinch work *“privileges non-human agents”* perception. He is interested on how machine can translate complex data onto design and requestions *“what is significant in architecture”.*



One of many typological iterations

Source: Rehm, M Casey. 2019. ‘Complicit: The Creation of and Collaboration with Intelligent Machines’. Architectural Design 89 (2): 94–101. https://doi.org/10.1002/ad.2417.



Worm's-eye view

Source: Rehm, M Casey. 2019. 'Complicit: The Creation Of and Collaboration With Intelligent Machines'. Architectural Design 89 (2): 94–101. https://doi.org/10.1002/ad.2417.

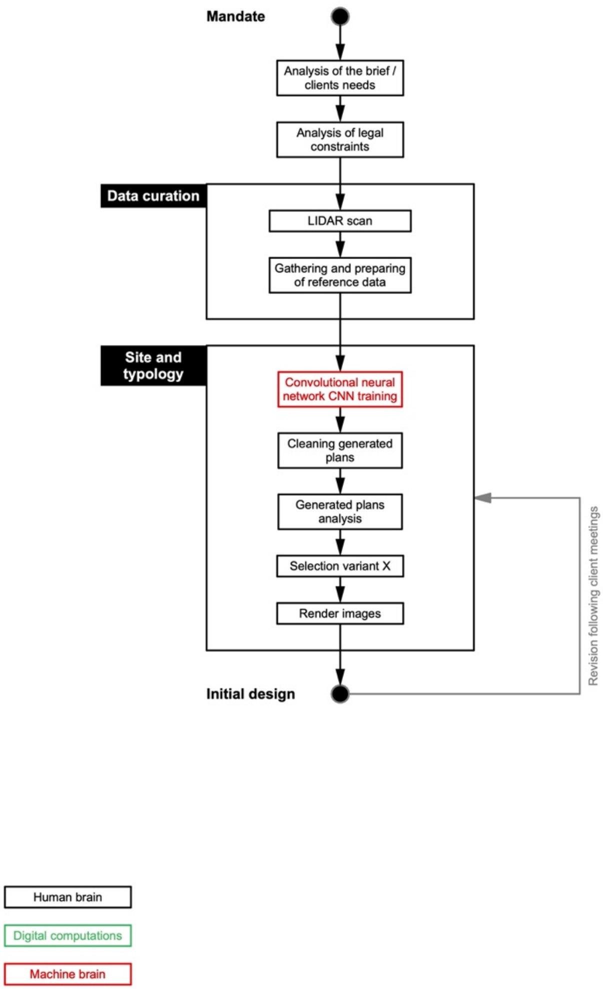
Interior perspective

Source: Rehm, M Casey. 2019. ‘Complicit: The Creation Of and Collaboration With Intelligent Machines’. Architectural Design 89 (2): 94–101. https://doi.org/10.1002/ad.2417.

In conclusion, NN_House 1 perfectly shows that AI is not reserved to urban scale nor public buildings but can be applied to private mandates as well. Of course, the use of AI depends on the willingness of clients to explore innovative design solutions.

As for Kinch, the effect AI has on architecture is much more important than the specific techniques or models employed. Even though M. Casey Rehm mentions the use of convolutional neural networks CNN, he does not detail how they were used specifically. Yet he describes excessively on the impact it has on the architecture compared to more traditional design process and how the machine perceives architecture compared to humans.

The project of NN_House 1 and its description highlights us how architects might describe their pieces in the future. Kinch is open about the data used as references, that were fed into the algorithm to control the desired outcome. Yet they don’t share their dataset. This is something that we could expect from other private practices in the future.



NN_House 1 workflow

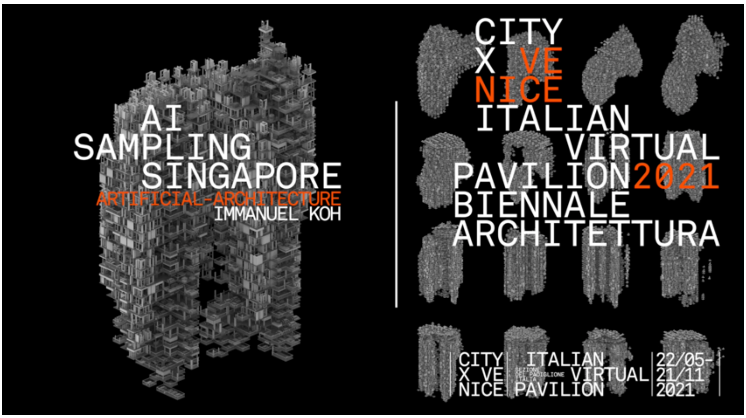
Interpretation by the author

3D GAN housing

Our fourth case study will look at a project presented during the latest, 17th, Venice Architecture Biennale at Italian Virtual Pavilion (CityX Venice) by Immanuel Koh.

Multiple resources will be used for the analysis of the work: aiarchitects website[54], CityX Venice[55] and DigitalFUTURES[56] YouTube channel, Immanuel Koh's vimeo channel[57] and Melbourne School of Design presentation[58].

The project focuses on semantics of buildings and is trained using a large 3D dataset in a combination with 3D generative adversarial network or 3D-GAN. The dataset contains all high-rise public housing buildings of the city-state. The objective of this work is to create new samples of 3D residential high-rise appartements that embody the essence of Singapore.



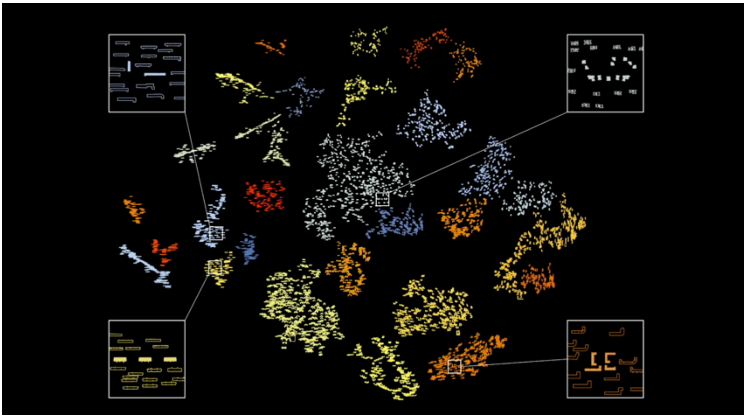
CityX Venice poster

Source: CITYX Venice Italian Virtual Pavilion. 2021. CITYX VENICE - Immanuel Koh: AI Sampling Singapore. https://www.youtube.com/watch?v=ZeMDFFeCA0E.

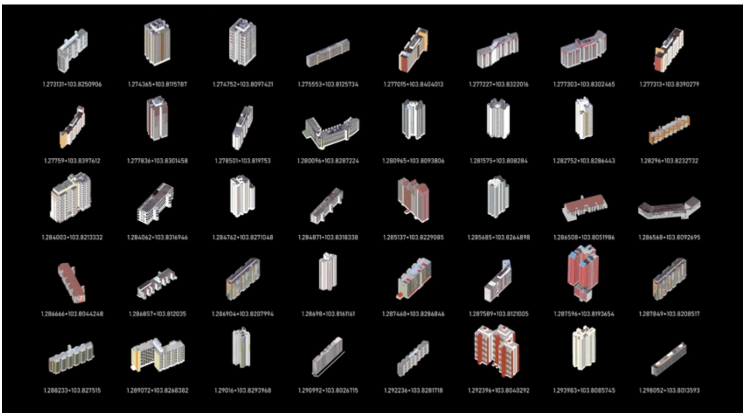
Singapore

Source: CITYX Venice Italian Virtual Pavilion. 2021. CITYX VENICE - Immanuel Koh: AI Sampling Singapore. https://www.youtube.com/watch?v=ZeMDFFeCA0E.

The objective of the project was to learn Singaporean public housing geometries and to generate new volumes. Three ingredients were studied: the massing, the texture, and semantics.



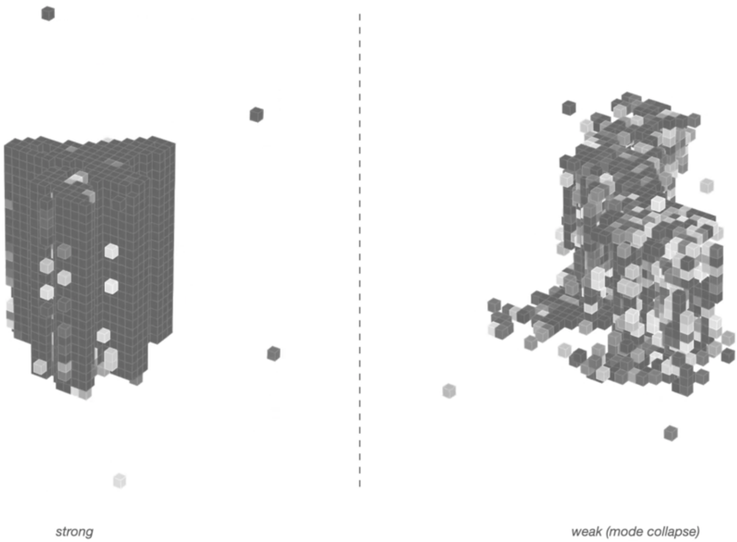
Selected data points of public housing buildings in Singapore



Extract of the dataset

Source: CITYX Venice Italian Virtual Pavilion. 2021. CITYX VENICE - Immanuel Koh: AI Sampling Singapore. https://www.youtube.com/watch?v=ZeMDFFeCA0E.

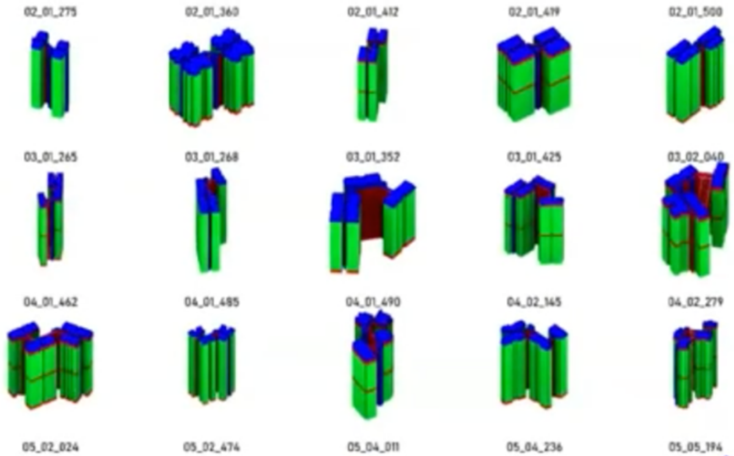
The data was studied by two aspects. First, they studied general shape represented by voxels. The voxels were 3x3 meters. The colour of boxes indicated their “probability”, weather it could possibly exist in space or not. The darker the colour, the higher probability. The lightest boxes represent unrealistic configuration. In the training there was the problem of “mode collapse”, where *“the model refuses to diversify […] and is converging into sameness of form”* explains Immanuel Koh. On the right side, the machine is not sure whether the voxels should be black, or white or should they disappear altogether. On the left side the model is sure about the general shape of the building, thus majority of voxels are dark.



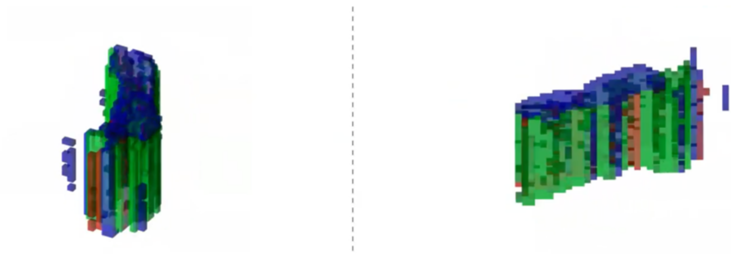
Voxels - constructive and deconstructive plasticity

Source: CITYX Venice Italian Virtual Pavilion. 2021. CITYX VENICE - Immanuel Koh: AI Sampling Singapore. https://www.youtube.com/watch?v=ZeMDFFeCA0E.

The buildings per se are not the most important factor in the dataset according to Immanuel Koh. The most important element is semantics. Semantics here mean the organization of volumes by its components: public spaces, circulation, roof, appartements, both interior and exterior.



Semantic colouring of dataset



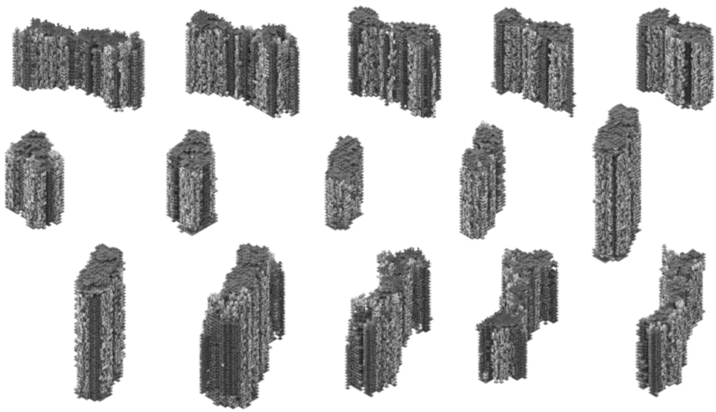
Semantic latent walk

Source: Melbourne School of Design. 2021. MSD at HOME_ and AA Visiting Schools Melbourne Presents: Immanuel KOH. https://www.youtube.com/watch?v=PfNVoXSGSIk.

The second phase of training by semantics training took about 2 weeks. It was done on the Cloud because Google Collab proved impossible. In the final model, different elements appear. We can observe staircases, walls, floors, communal space, all morphing trough the latent space.

Semantic versus 3D GAN latent walk

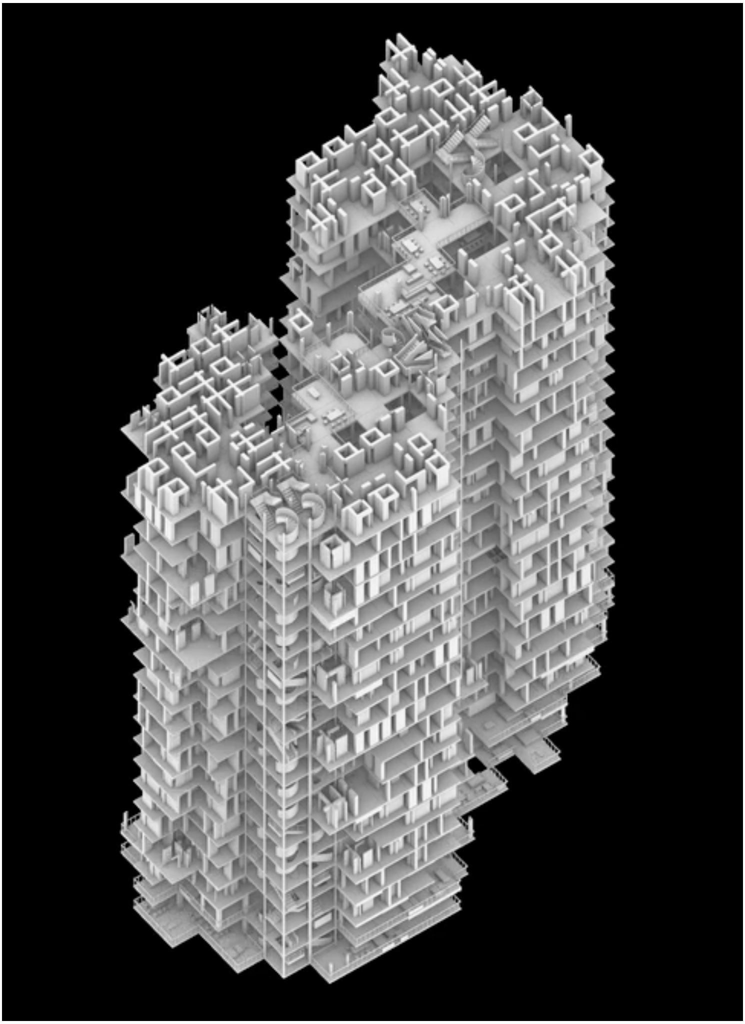
Source: Melbourne School of Design. 2021. MSD at HOME_ and AA Visiting Schools Melbourne Presents: Immanuel KOH. https://www.youtube.com/watch?v=PfNVoXSGSIk.



Source: CITYX Venice Italian Virtual Pavilion. 2021. CITYX VENICE - Immanuel Koh: AI Sampling Singapore. https://www.youtube.com/watch?v=ZeMDFFeCA0E.

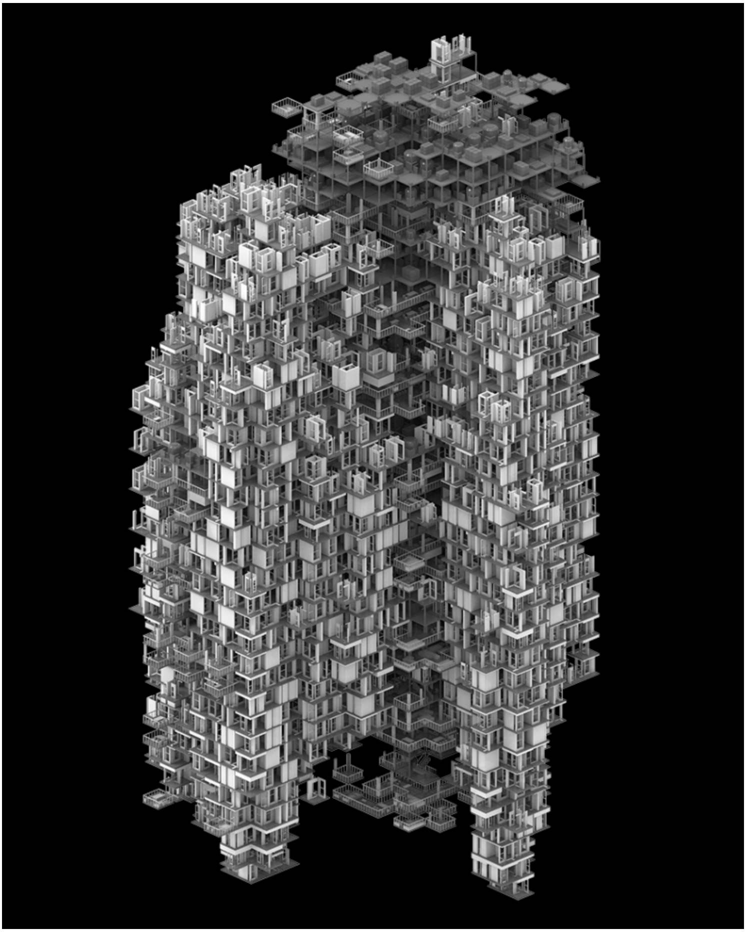
Extract from 3D-GAN-Housing (Exteriority)

Source: 'Immanuel Koh'. n.d. Vimeo. Accessed 6 January 2022. https://vimeo.com/immanuelkoh.



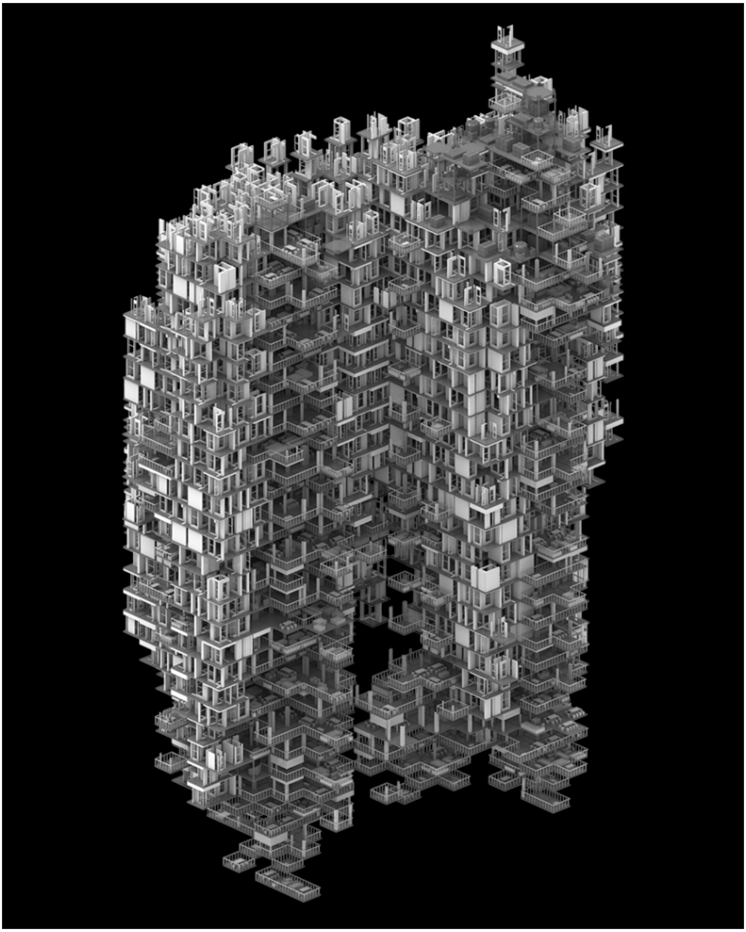
Extract from 3D-GAN-Housing (Interiority)

Source: 'Immanuel Koh'. n.d. Vimeo. Accessed 6 January 2022. https://vimeo.com/immanuelkoh.



3D-GAN images published on aiarchitects

Source: ‘IMMANUEL KOH’. 2020. Aiarchitects.Org (blog). 29 December 2020. https://aiarchitects.org/portfolio/immanuel-koh/.



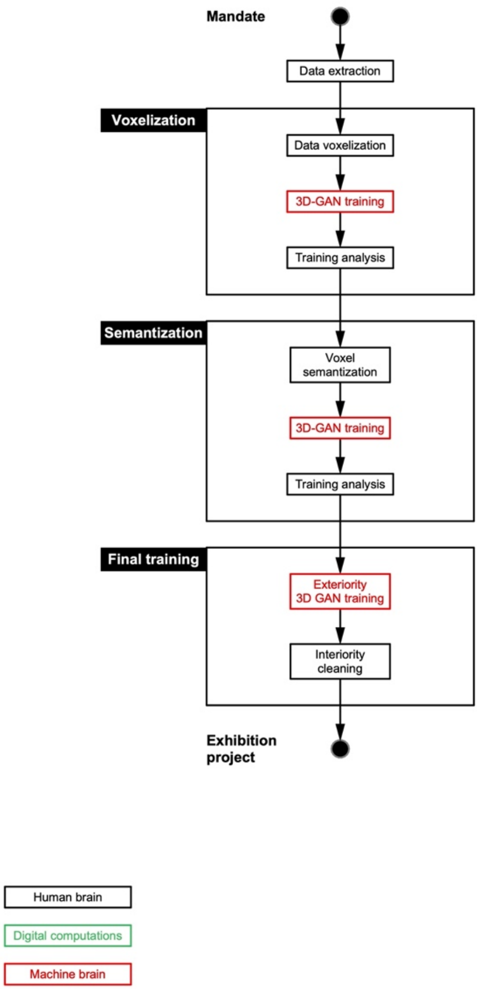
3D-GAN images published on aiarchitects

Source: 'IMMANUEL KOH'. 2020. Aiarchitects.Org (blog). 29 December 2020. https://aiarchitects.org/portfolio/immanuel-koh/.

The project presented by Immanuel Koh at CityX Venice 2021 shows the evolutive 3D-GAN training process. The architect explains in detail the dataset used and different 3D-GAN trainings. Starting from initial trainings, we can observe the increasing complexity of the project. The process goes through two preliminary trainings before final interior-exterior training. Voxelization process determines realistic versus unrealistic combinations. Semantization process details the voxels into program elements: stairs, roof, appartements and terraces. In the exteriority training we can still observe a lot of “noise”, especially in handrailing (but there IS handrailing and furniture). Interiority training appears to be cleaned in Rhino® (not specified by the architect), as it does not possess any training debris, the same as projects final images.

This project shows in detail the importance of data, the complexity of model training and risk of mode collapse. 3D GANs results appear “realistic”, as it results from complex data. In 2016 Singapore National Research Foundation (NRF) published the intention on creation of Singapore virtual twin called “Virtual Singapore”[59]. Not yet made available to general public, it includes previously mentioned semantic 3D modelling.

With continuous digitalization of our physical world, we can expect more elaborate open-source datasets, as in Virtual Singapore. For example, in Switzerland[60] we can already use general 3D shapes of existing buildings including outer walls and roofs, though it does not possess details such as windows nor doors.



3D GAN housing workflow

Interpretation by the author

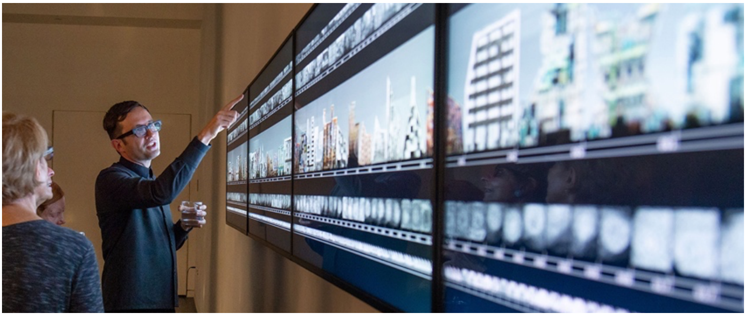
Horizons

The final case study unites art and architecture in a form of an installation. Conceived by design office Certain Measures, led by Andrew Witt and Tobias Nolte, it was presented in three exhibitions in 2018: Le Laboratoire-Cambridge MA, The Factory Contemporary Art Center-Ho Chi Minh City, Storrs Gallery-UNC Charlotte.

Certain Measures specializes in projects using machine vision and classification of data. One of the first projects of Certain Measure was titled "Mine the scrap"[61], where they used machine vision to scan "garbage" and used AI to optimize possible final constructions. This technique of scanning & generating were explored in other projects like "Cloudfill"[62] and "Kintsugi++"[63]. Certain Measures explored the technique of scanning & classifying in a project titled "A machine view of cities"[64], where they scanned entire cities like Shanghai, Berlin, Groningen and Liverpool, as well as "The Neo Classifier"[65], where they looked at the elements constituting neoclassical buildings. Assemblance of data and its categorisation play an important role in their research. Without the help of digital tools, it would have been impossible.

The project "Horizons"[66] works like an endless elevation of a fantasy city. It was inspired by the book of Ed Ruscha titled "Every Building on the Sunset Strip". Certain Measures asked themselves "*what if we could extend that book forever using AI?"*

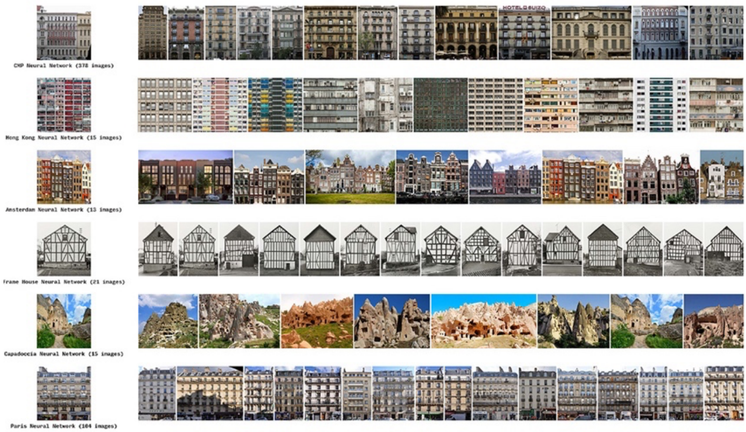
The exhibition is composed of five layers. The top one displays the training set used in GAN training. The second layer shows raw machine generated images. The highest layer displays the "imagined city", where the generated images had gone through a cleaning process. The fourth layer shows "building fingerprints" containing analytic information used for classification. In the last line, there is the archive of buildings created by AI.



Exhibition of Horizons with Andrew Witt on the left

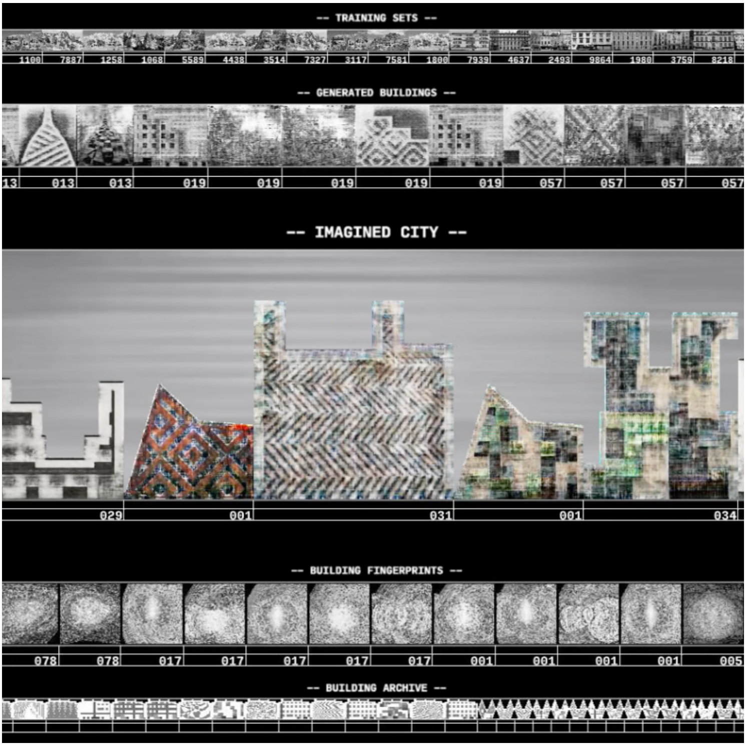
Source: 'HORIZONS — Certain Measures'. n.d. Accessed 17 November 2021. https://certainmeasures.com/HORIZONS.

For the training of Neural Network Certain Measure used varied images: 104 represented Paris, 15 Cappadocia, 21 frame houses, 13 Amsterdam, 15 Hong Kong and 378 CMP images.



Dataset

Source: 'HORIZONS — Certain Measures'. n.d. Accessed 17 November 2021. https://certainmeasures.com/HORIZONS.



Extract from Horizons

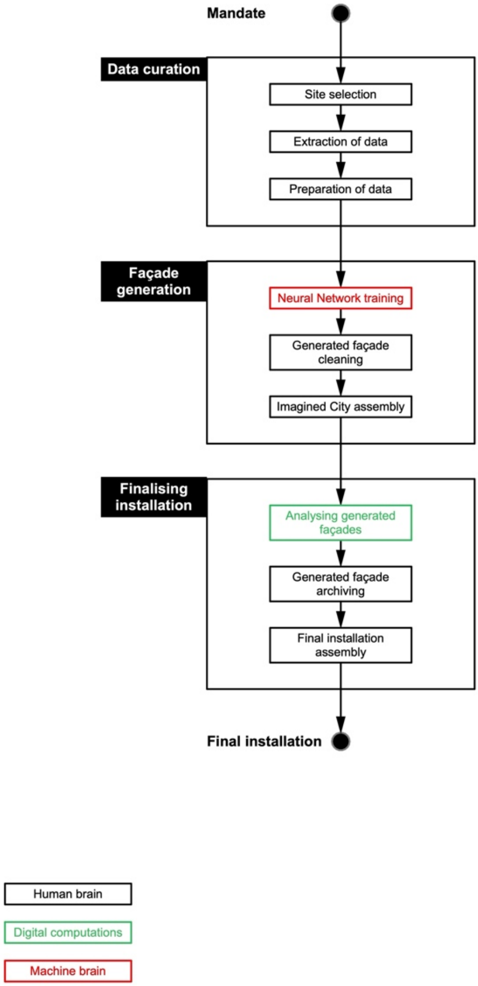
Source: ‘HORIZONS — Certain Measures’. n.d. Accessed 17 November 2021. https://certainmeasures.com/HORIZONS.

Extract from Horizons

Source: 'HORIZONS — Certain Measures'. n.d. Accessed 17 November 2021. https://certainmeasures.com/HORIZONS.

The project “Horizons” serves as a manifestation of AI capability to create “endlessly”. Data curation represents an important part in the whole process. The selection of data undeniably impacts the generated output. Yet one should not neglect the process of extracting and preparing the training data sets. Even though architects have traditionally looked at precedents, with the use of AI, we need to prepare our data for machine to understand it. Once machine can understand our data, we can feed it limitless amounts of it. Here lies the biggest difference of human generated and machine generated output. Humans can multitask limited number of precedents or inspirational aspects. AI does not possess these limitations.

Co-creating with AI opens new, unprecedented creative possibilities. At the same time, new tasks appear on architect’s agenda. Architects become curators of data and guide AI to their desired direction.



Horizons workflow

Interpretation by the author

Conclusion

The experiments and projects presented in this study represent early adopters and have yet to become mainstream practices. For this reason, it is imperative to observe these developments, both to see how they impact design workflow and projects themselves. It is possible that some of these techniques will take over, while others will die out for varied reasons.

This work looked at research question: How the use of AI changes the traditional design workflow? To have a global overview, we looked at it in two parts: techniques and models coming from academia and case studies coming from the industry.

The techniques and models present in first section show the vast variety of tools freshly available to architects. Without the general grasp, architects can lose themselves in the waste land of possibilities. The techniques discussed here are by no means exhaustive, many more are available for other phases of projects starting from initial phases until the maintenance of buildings. We looked at autoencoders, convolutional neural networks, generative adversarial networks, self-organising maps, neural style transfers and Bayesian network.

In the case study section, we observed how architects co-create with artificial intelligence. Different real-life projects were highlighted: an urban project, a winning competition, a private mandate, an architectural exhibition, and art exhibition. Both projects and architects here stand out from standard practices with their collaboration with artificial intelligence. When architects co-create with intelligent, creative AI, the product manifests the intelligence of a machine.

The use of creative AI clearly changes the way architects design. New tasks and new possibilities appear. In some cases, it increases architect’s workload, as on becomes the curator of data. Other times, it allows architects to create unimaginable or incalculable things for the human mind. For architects, this is certainly an exciting time, as they have always questioned the limits of possible. Explaining a machine “what is architecture and how to design” before certainly seemed impossible, today it is more on the range of “complex” and maybe tomorrow it will become as natural as CAD.

Combining the techniques and case studies, we can observe two trends emerging: complete modification of urban planning workflow and automatization of repetitive typological design. Both trends come from data availability. Urban data today is mostly open source and municipalities invest heavily in digitalisation of urban environments, like in Guatemala and Singapore projects. Simultaneously, mass scale appartement bloc datasets allow extremely fast design generation process. “*The future is already here – it’s just not very evenly distributed*,” as William Gibson said.

At the same time, one needs to address that human, thus architect, stays in the center of architecture. It is impossible for AI to replace the architect, as concludes Belém et al 2019 in their research paper “On the Impact of Machine Learning, Architecture without Architects?”[67]. Similarly, Joyce et al 2021 describes in their paper “Limits to Applied ML in Planning and Architecture”[68] that *“architecture is primarily for humans and driven by human needs.”* Architect is an interpreter of those needs. Big data and artificial intelligence allow architects to understand human needs better to offer best possible solutions, especially for complex design problems.

This theoretical statement was done in a preparation of final Master Project, where two simultaneous housing projects will be designed from scratch and will be constructed in the fallowing years. These two projects on two plots will become an opportunity to co-create with AI using the techniques present in this study. The Master Project will conclude the design phase and examine how design workflow might change for architects in the near future.

Abbreviations

AEC	Architecture, Engineering and Construction
AI	Artificial intelligence
ANN	Artificial neural networks
AttnGAN	Attentional Generative Adversarial Network
AE	Autoencoder
BN	Bayesian network
CNN	Convolutional neural networks
COCO	Common Objects in Context
DEM	Digital elevation model
GAN	Generative Adversarial Network
GIS	Geographic information system
Lidar	Light detection and ranging
ML	Machine learning
NN	Neural network
NST	Neural Style Transfer
RvNN	Generative recursive neural network
SOM	Self-Organizing Map
UNDP	United Nations Development Program
VAE	Variational autoencoder

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