

AI : Architects' Inferiority?

An exploration of the creative potential of machine learning algorithms

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Glossary

For this thesis I taught myself how to code, and outside of my field of expertise and into the world of computer science and more precisely machine learning. Here is a non-exhaustive list of some of the terms I encountered on this journey which could be helpful to someone not familiar with this field.

AI - Artificial Intelligence : In this thesis we will accept Max Tegmark's definition of narrow AI, which is the ability of non-biological agents to accomplish a narrow set of complex goals⁰⁰⁰¹

ML - Machine Learning : Al algorithms which can improve their own performance through experience.0001

ANN - Artificial Neural Network : A computer architecture in which a number of processors are interconnected in a manner suggestive of synapses in a human brain and which is able to learn by a process of trial and error.0002

GAN - Generative Adversarial Network

: ANN capable of automatically discovering and learning the regularities or patterns in input data in such a way that the model can be used to generate new examples that plausibly could have been drawn from the original dataset.0003

HIT - Human Intelligence Task : Task that requires human intelligence to complete. CAPTCHA are HITs.

Parametric Design : Design method where features are shaped according to algorithmic processes, in contrast to being designed directly. The term parametric refers to input parameters fed into the algorithms.0004

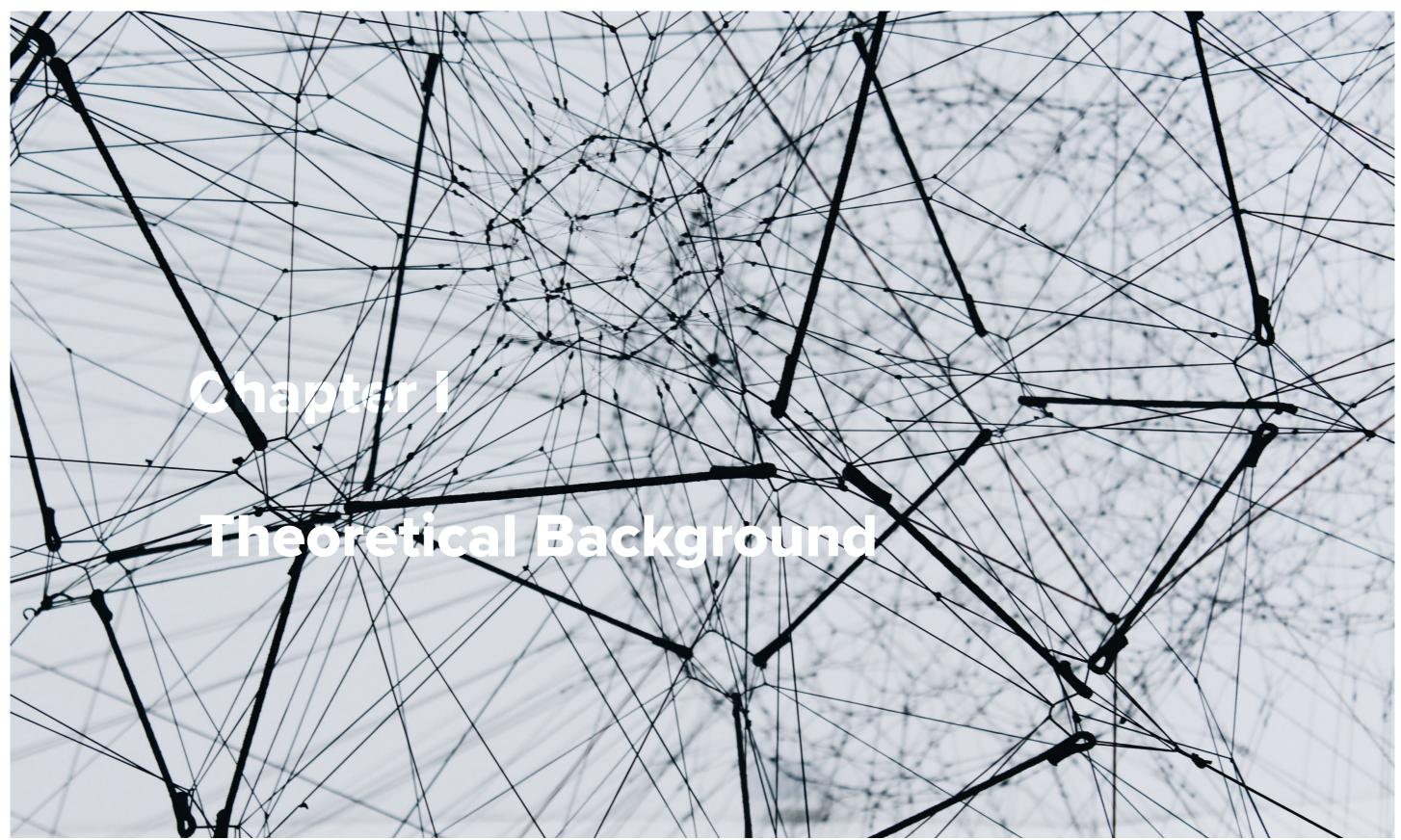
Genetic Optimisation : Parametric design subfield, where the input parameters are optimised by the computer rather than being decided by the user.

Overfitting and Underfitting : Overfitting: Overfitting

happens when a ML model models the input data too well, so it merely replicates it. Underfitting on the other hand happens if a ML model fails to model the training data, resulting in random noise.

Seed : Used to label one specific iteration of an ANN.

AI : Architects Inferiority?



'On Air' by Studio Tomás Saraceno. Source : Alina Grubnyak¹⁰⁰¹



Project premises

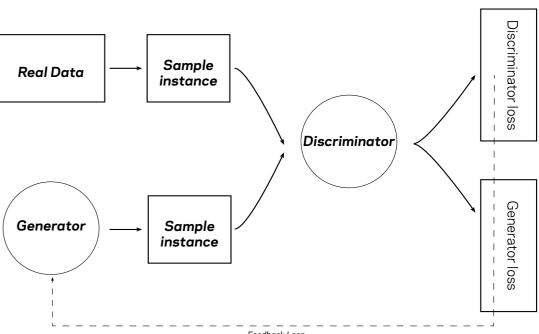
In the Spring of 2020, the world was put to a hold because of the COVID pandemic and many events were happening online rather than physically. This allowed me to digitally attend several conferences and symposiums on AI and architecture. As I was starting to think about my thesis, I got inspired by this new discourse for the architecture world and decided to focus my thesis work on learning more about it. I am not a computer scientist, and had back then no experience in coding. To simplify my learning processes, I decided to feed existing data into existing algorithms. This seemed like an easier way to enter the world of artificial intelligence.

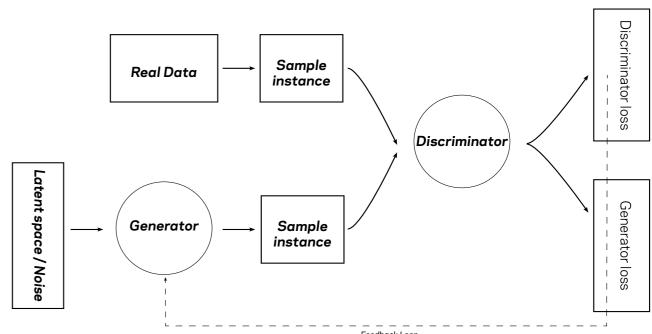
While reading on how AI can be applied to the disciplines of art and architecture, I found that Generative Adversarial Networks (GANs) were amongst the most named technologies. GANs are efficient ML algorithms able to generate new data based on training sets. They were invented in 2014 by Ian Goodfellow. They are a combination of two artificial neural networks, a generator and a discriminator, which compete against one another. The generator's goal is to fool the discriminator by trying

to imitate the training data, and the discriminator's goal is to distinguish between real and fakes. There is a feedback loop (independent backpropagation) so that over time the generator produces better samples, while the discriminator becomes more skilled at flagging synthetic samples.0005

Based on the very reduced amount of literature that was available at the time (or at least the literature I could understand), I decided to go with the most documented GAN architecture for image generation; StyleGAN, developed by NVIDIA.0006

This algorithm is openly available on the development platform GitHub⁰⁰⁰⁷, as well as some pre-trained networks it generated. These networks are Als able to generate images of people, bedrooms, cats... These images fascinated me because they are *almost* perfect. The longer one looks at them, the more unsettling they become.





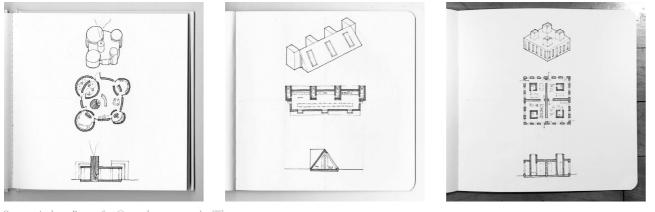
Architecture of a Generative Adversarial Network (GAN). Source:author



Portraits generated with StyleGAN. Source:NVIDIA

Feedback Loop (Training)

In order to use the algorithm to train my own network, I needed to first come up with a dataset. I read that to maximise chances of success, the training dataset should be as big as possible (the ones that NVIDIA used for their original paper were close to a hundred thousands images), or as consistent as possible. of architecture by Stanislas Chaillou⁰⁰⁰⁹. Chaillou is an architecture graduate who used GANs to generate floorplans for his master thesis. (Figure 1) I wanted to try to do a similar exercise as a training, so I resized the One House Per Day (OHPD) dataset to only keep the floor plan parts. I obviously ran into many



Source: Andrew Bruno for @one_house_per_day¹⁰⁰²

I thought about an instagram account called @one_house_per_day⁰⁰⁰⁸); In January 2020, Andrew Bruno started drawing one house per day in plan, section and axe and posting these images on this Instagram page.

The style was very consistent and the topic obviously interesting for me as an architect, so I decided to scrape the entirety of his account (it was around 300 at the time) and made a dataset out of it. Around that same time I attended a lecture on AI and the future complications, because I am again not a computer scientist. But this process was a chance for me to start learning new skills. I did not fully understand the math behind it (and in all honesty I still don't), but after countless days and nights of trial and error, googling countless cryptic error messages, I managed to make these novel, Al-generated images (Figure 2).

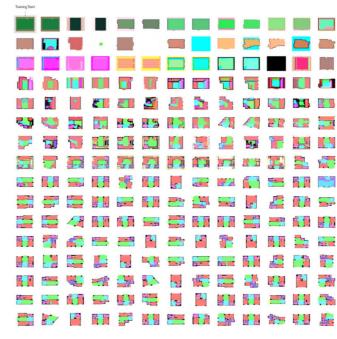


Fig. 1 Training Sequence. Source:Stanislas Chaillou¹⁰⁰³

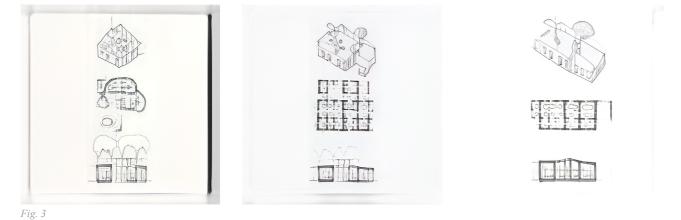


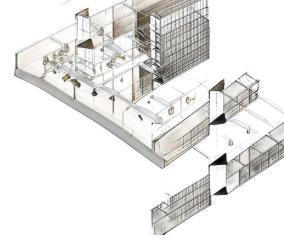
First attempt at generating images using GANs. Source: author

I recall being overwhelmed with excitement looking at
what most people saw as a pixelated Rorschach test,
because I could feel the start of some architectural
sense. There were walls which were getting thinner
in some parts, suggesting windows and doors, there
were rooms and corridors...generate a different kind of output was more efficient
than training a new one from scratch. For example
using an algorithm that generates humans faces and
teaching it to generate buildings works faster and
better than just telling it to generate buildings from the
start⁰⁰¹⁰. Which is exactly what I did, and these were
the images I generated (Figure 3).

The following year I started my thesis semester, the global interest for GANs grew, and therefore more material on the matter became available online. My coding skills increased accordingly, and I learned for example that repurposing a pre-trained network to

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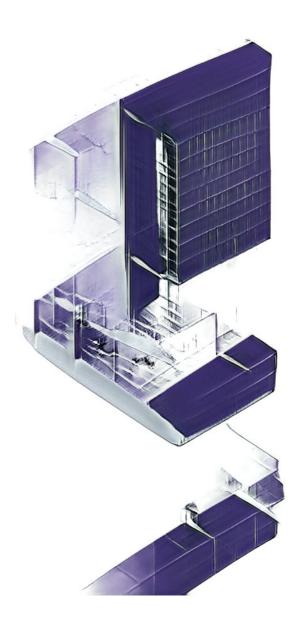
Second attempt at generating images using GANs. Source: author

This time I did not limit the training to just plans but extended it to the combo plan/section/axos. I wanted to see if the computer could understand the relationship between a plan and a section. Studying the results I believe it recognised the patterns to some (Figure 4) so much that I decided to start my thesis extent. Because these results look very promising,

I wanted to try something on a bigger dataset. That's when I scraped the instagram account @axo_madness of its 800 axonometric views and fed them to my algorithm. I liked the aesthetics of the resulting images work on these premises.



Fig. 4 Images generated on a GAN trained on 800+ axo views. Source:author



What is creativity?

If you are reading this, chances are you are human.

You experience the space around you through sight and hearing. You can feel walls by touching them. You can smell the distinctive scents of coffee, of spring flowers, of pizza which gives you clues on where you find yourself.

If you are reading this, chances are you are creative.

Maybe your work is even qualified of creative and involve designing spaces. Even if it doesn't, you are creative; everyday you use language to speak sentences that have never been spoken before. Creativity is to some extent what makes us human and has allowed our species to evolve into complex civilisations.



Why Are We Creative?. Source: Celluloid Dream

The documentary Why are we creative (Vaske, To help me approach the topic, I had a short discussion with Eva Hoff, an Associate Professor at the 2018)⁰⁰¹¹ condenses 30 years of interviews. The director Hermann Vaske asks artists, political leaders, Department of Psychology at Lund University and a scientists the same question : Why are you creative?. researcher inter alia on the measurement of creativity, The answers he got are as diverse as they are the development of creativity and imagination. interesting. It seems that creativity is a widely debated topic. In other words, everyone is creative, but differently.



Aloys Heitz (author) : It seems that the definition of creativity is a rather debated one. How would you define it?

Eva Hoff : There is not much of a debate regarding the definition of creativity, at least within the field of My hypothesis is that we can enhance human Psychology; most researchers agree than in its most creativity by using these algorithms, to help us think basic form, creativity is the ability to form unusual or outside of the box and getting inspired in ways we original ideas, given that these are also useful. This is have not thought about before. Maybe this brings the ground definition that Terese Amabile or Robert me to my next question, do you think creativity Sternberg give in their work, just to name two. inherently human, or could other agents (ie. a So it is important for an idea to be useful in order to machine) be creative too? be qualified of creative. You can do something very original but if it serves no purpose, it is not creative. I suppose people who work with artificial intelligence Usefulness can however be problematised in many seem to already say that it can be creative. different ways. In the field of the Arts for example, the I doubt it (laughs) but I know AI is getting better at it. concept can be extended to meaningfulness. This There are some animals that are creative (crows for

is where there might be a debate to define what is creative and what's not.

What about AI and architecture? Would you say AI is useful in this context?

example will fly very high up and drop some food they can't open up with their beak). There is experiments that determined that some birds and cats can find creative solutions to problem, with a bit of trial and error, but they can find new ways.

But to be creative, there is a need for a huge database, that's what humans have. If you have a lot of knowledge in an area, then you can possibly also invent new things, build upon the bases you have but without knowledge you can't be creative. If you haven't been taught an instrument, well you can't play it.

People often say that children are very creative, that is a little bit mistaken. Because children don't have a lot of knowledge and experience, what they do is more play or fantasy. What they do isn't necessarily novel nor useful. Of course it can happen, but it is more likely to be accidental. Adults are in a greater capacity to be creative than children. But on the other hand some adults listen too much to their inner knowledge and are afraid of stepping away from what they know. In that sense knowledge and experience can also be a hinder to creativity.

In AI, the equivalent would be overfitting (trying to replicate exactly the training data) on one end and generating random noise (chaotic result) on the other. Creativity would then be an equilibrium between copying what you know and have experienced, and doing something completely random and useless.

Exactly, and one of the major resources humans have in that sense is the ability to take inspiration from a completely different area. This is still within your experience and the realm of what you know, but this

ability to associate thoughts that seemingly have nothing in common to handle complex problems is a human characteristic. Humans also have the ability to make analogies in a way no other species can. I can think about and solve a complex problem I have even though I am doing something completely different or standing in a very different place, because I can connect these things.

There is a lot of famous inventions that have been using this analogy thought framework. In that sense, maybe machines lack this "out of the box" vision, and the ability to venture far off their area of expertise. Human creativity depends on coincidences, not all humans can invent the same things because the way they think about things and the way they solve problems depends on their knowledge and experience.

GANs are great at understanding patterns and becoming expert in a specific area (ie. Generating a specific kind of images) but they can't really get inspiration from other areas. Their creativity if they have any seems rather limited compared to humans'. But if we project ourselves in the future, do you see Al posing a threat to human creativity?

Creativity is a human characteristic. Everyone uses creativity in their everyday life, maybe in ways that are not novel or useful for the world, but at an individual scale they are.

This is a difference between what is called big 'C' Creativity, or when an idea changes an entire domain on a global scale, like the way Picasso would produce art, and small 'c' creativity. No one had done what Picasso did before, so he changed the way artistic representation worked.

If AI could create these shifts on a global sense, maybe it could threaten humans. But I don't see it threatening small 'c' creativity, which refers to the everyday life creativity, like experimenting a new recipe, trying a new outfit, etc. I don't think I would rather go to my phone and ask it for a way to solve my problem, I don't think that would ever happen because it would mean I stop thinking myself. It would be so much quicker for me to use my own brain. Al would not threaten creativity as a human characteristic.

To go back to the arts, would we program an AI to do new kinds of drawing? I wouldn't be surprised at all if some artists were already doing this. But then would the programmer be the artist? Or the program itself? And would these artworks even be sellable?

There is actually a young market for AI art. And I think your question on authorship is very relevant, it is a very complex problem.

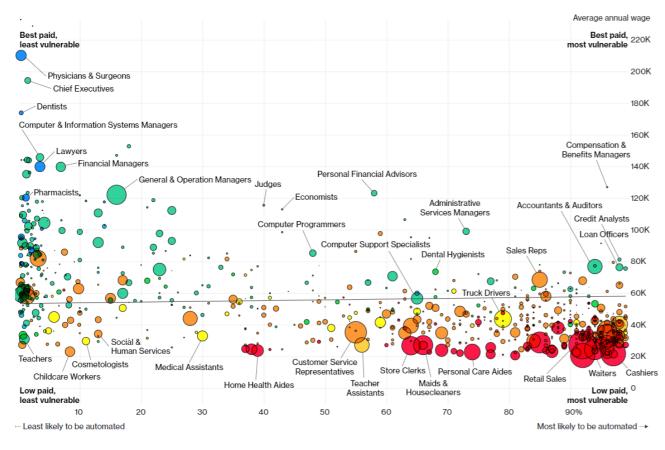
But certainly there is also pleasure in creating, when a painter paints, or a musician compose, there is a certain joy in that. Even though a machine could do it quicker, the artists would probably still want to do it themselves. Or what do you think, as a member of a creative domain?

There is definitely a thrive for creativity in architecture, but I can see how these algorithms could potentially be used to accelerate production and decrease costs. The issue is that these algorithms are managed by people who were not trained to design spaces and their influence on humans. There is a need for reflection on how we as architects can take ownership of this discourse.

I suppose you are right, it is better that you learn how to use it rather than letting it in the hands of people who don't have the kind of experience and knowledge a trained architect would. But then there is the question of how much it actually adds to a project. As I see it, I guess it could be another tool to get inspired, a way to invent precedents that don't exist, but I don't think it could take over the whole process, because construction projects are so incredibly complex.

Automatic architecture

In 2013, Frey and Osborne⁰⁰¹³ examined 702 jobs and ranked them based on the risk of them being automated. Jobs that require empathy, creativity or a high level of social intelligence were the least at risk. Thanks to these factors, architects were ranked 81 least likely to be automated, with a risk of 1,8%. At the bottom of the list (less than 1% risk) are occupations like nurse, psychologist or speech therapist, which all require human interaction, care for others and empathy. At the very top of this list (more that 95% risk) are bank, post office or library clerks. While these jobs also involve human interaction, they do not require a



Data:Frey & Osborne/Bureau of Labor Statistics. Source:Bloomberg¹⁰⁰⁵



high degree of social intelligence, which put them at risk.

This particular study has not been updated since then, Information Modelling (BIM) in architecture companies but it can be argued that these percentages might today.0014 increase unexpectedly thanks to advancements in However, architects have mostly just been transposing computational power and artificial intelligence. In The the manual work they used to do with pen and paper Second Digital Turn (2016), Mario Carpo argues that on to the computer. This is argued by Neil Leach in architects and designers embraced the digital turn of his essay There is No Such Thing as Digital Design the 1990s sooner than other fields because we could (2018)⁰⁰¹⁵. Therefore, despite most designers being digitally intelligent, these tools are mainly used as a see the enormous potentiality of mass-customisation. Bespoke and custom-made designs have always way to automate or accelerate manual processes. rhymed with high costs. The advent of Computer The democratisation of parametric design in Aided Design (CAD) softwares, along with digital architecture, both in academia and in practice, might fabrication, meant that we could use technology not to give the impression that architectural design has mass produce, but to mass customise. Going against gone truly digital. But I would argue that even though the trend of standardisation and mass-production, parametric design permit shapes that could not have digital design promised a future where everyone been done by hand, designers still follow a manual could enjoy bespoke products and environments, logic, detailing how scripts works, one command at a without investing significantly more money and time energy. After the burst of the internet bubble and I acknowledge that evolutionary algorithms (like the Grasshopper's component Galapagos, released in the in the rise of the participatory "Web 2.0", the 2000s saw major developments like Facebook or Wikipedia. late 2000s by McNeel) could challenge this theory, The design world shifted accordingly from mass but the fitness parameters required need human

Max Tegmark's illustration of Hans Moravec's "Landscape of human competences", where elevation represents difficulty for computers, and the rising sea level represents what computers are able to do.

Hans Moravec's Landscape of human competences. Source: Max Tegmark¹⁰⁰⁶

customisation to mass collaboration. The most notable example is the quasi systematic use of Building

decisions and this still leave too little room for true machine creativity.

There is here a need of precision of the difference between Parametric Design and ML.

While working on this thesis, several people asked me if I was using visual coding software Grasshopper. I understand the confusion as a generalisation of digital processes that use some sort of coding skills. But there is a major difference between parametric design and machine learning; In Grasshopper definitions and other coding languages, the rules are set. They follow

Parametric design

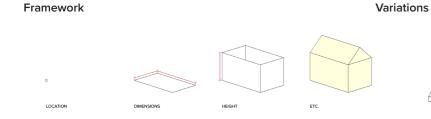


Diagram explaining the framework of parametric design. Source:author

Machine Learning

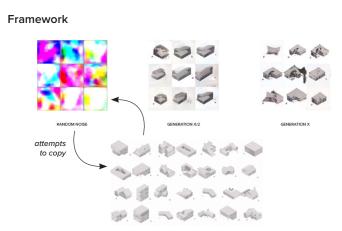


Diagram explaining the framework of machine learning. Source:author

a human logic because a human or a group of humans had to think about them. In machine learning, the rules are not explicit, they are found by the algorithm. ML algorithms learn to replicate characteristic, and humans don't have any kind of agency in the learning process. The program builds up its own intuition based on the data it is fed.

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See See

Computers are tremendously better at craft than we are. But what happens if they become better at formulating ideas?

There are some sounds we cannot hear, some light DeepBlue and AlphaGo are two programs that can we cannot see, some scents we cannot smell... What play chess and Go, respectively. Both programs have if there were also some thoughts we could not think entered history as the firsts to beat grand masters of ? Some ways of thinking our brains are effectively in tournament condition. In 1996, DeepBlue beat unable to produce? Garry Kasparov (back then world chess champion) This is where I see the true potential of GANs as by playing an "incredibly subtle move".⁰⁰¹⁶ In 2016, creative collaborators. Human bias means there AlphaGo beat Lee Se-dol (a Go master) with a " killer is a limitation to creativity, and these non-human move, a move no human player would have made"0017 collaborators could help us find new ways of In both these cases, the machine beat the humans by designing. "thinking" outside of the box and finding new ways of playing that were more efficient than the humans'. In the foreword of Robotic Building (2019), Mario Carpo These examples prove that anthropocentrism is explains that "in the 90s computers were seen as not relevant in machine creativity : computers have tools for making [...], today computers are again being

Variations

The idea and the craft

their own way of thinking and it is very different from humans'.

hailed as tools for thinking".⁰⁰¹⁸

Today we need computers for mathematical operations our brains can not deal with, but they remain tools; we give them some input and they give us a mathematically correct answer we were looking for.

Al Art already exists today, and there are numerous artists who use ML to create, but wether it is Mario Klingemann referring to the ANNs he works with as his paintbrushes⁰⁰¹⁹ or Refik Anadol using data as pigment⁰⁰²⁰, computers are still mostly used as tools and therefore encaged by human limitations. I want to challenge this notion by exploring the potentiality of seeing computers as collaborators instead of tools.

As Slavoj Žižek agues in the documentary Why are we creative (Vaske, 2018), "True creativity is order. Any idiot can have an outburst of creativity, but it is putting ideas into form that truly define creativity."0011. Computers deal well with order, with their memory depending on location and precision. On the opposite, human memory is autoassociative; it works with association rather than location or precision. We saw earlier that this is one of the characteristics that enables us humans to be so creative, formulating abstract thoughts and drawing inspiration from seemingly unrelated areas. In that sense, I wonder if using ML algorithms as collaborators in creative industries could enhance our creativity, bridging the gap Žižek mentions : we deal with the creativity outbursts because they come naturally, whereas the computer puts it into form because they are inherently order.

I said earlier that computers are better at craft than we are. On this matter, we have to reflect on what

craft means for us as humans, and how we celebrate imperfections. Mass-produced objects are cheaper, because of the economy of scale, than hand-crafted ones. We also attribute more value to handcrafted objects because we know someone spent time fabricating them.

Portrait d'Edmond de Belamy (2018), is a print on canvas realised by the French art collective Obvious.⁰⁰²¹ The artwork was generated by a GAN, trained on a set of 15 000 portraits taken from online art encyclopaedia WikiArt, and spanning from the 14th to the 19th century.⁰⁰²² It went down in history as the first piece of art created using artificial intelligence to be featured in a Christie's auction, selling for \$432 500.

This introduces the question of tool and authorship.



Edmond de Belamy (Obvious (collective), 2018). Source: Obvious¹⁰⁰⁷

In the case of a 14th century portrait, the author is the painter, the tool is the paint brush and the support

is the canvas. Edmond de Belamy was allegedly created by Obvious. But should credit be also given to the thousands of painters who painted the different portraits in the training dataset? To Robbie Barrat, who wrote the specific code Obvious used to generate the portrait publicly available on his GitHub page?⁰⁰²³ To lan Goodfellow, who invented the principle of GANs altogether? Or even to the Artificial Neural Network (ANN) in itself? Despite being non human, it did craft the image.

Whereas these notions were very clear and

This sentence from Mario Carpo in The Second Digital anticipating the evolution of aesthetics on the long Turn (2016) brings us to extrapolate that the use of term is an extremely hard endeavour. What we deem technologically advanced and the aesthetics we computational collaborative agents in architectural design will lead to new styles. Styles that would associate to it varies greatly over ever shorter period originate in human design but would be inherently of times (Figures 5 & 6). alien, because not created by human beings per se. The widely recognised 3D-printed architectural project Digital Grotesque imagined by Michael Hansmeyer and Benjamin Dillenburger, and exhibited in two exhibitions in France in 2013 and 2017, sets a first milestone in what post-human aesthetics would look like.0025

Of course, looking back at history, it seems like

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straightforward with a traditional painter, they become blurry and interconnected in the world of AI Art.





Fig. 5 The evolution of what we see as technologically advanced is very fast paced. Sources : see references 1008, 1009, 1010, 1011 & 1012. (p.100)



Fig. 6 Digital Grotesque II (Dillenburger & Hansmeyer, 2018). Source: Fabrice Dall'Anese¹⁰¹³



Seed 4197. Exterior view. Source: author

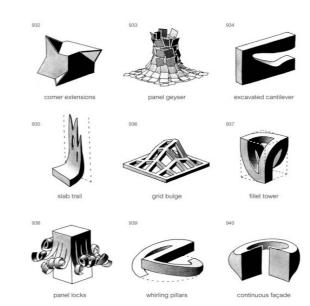
Siteless architecture

The ultimate goal of this potential design framework was never intended to solve all form finding and to put architects out of job. I rather intend to explore the potential of machine learning as an extension of the tools that are used today in concept design phases.

To illustrate and test this feature the best, I decided to design a building.

This building is meant to be a summer house for a family of four, as this is the most rudimentary architecture program I could come up with. This fictional family would have a substantial budget which would allow me to gain a certain freedom in terms of material choices.

Since this thesis investigates a concept design generation framework based mainly on form finding, the building site is not so relevant. In this regard, throughout the project I always considered a rectangular flat site, in Southern Sweden, without any specific condition.



Siteless building forms. Source: François Blanciak¹⁰¹⁴













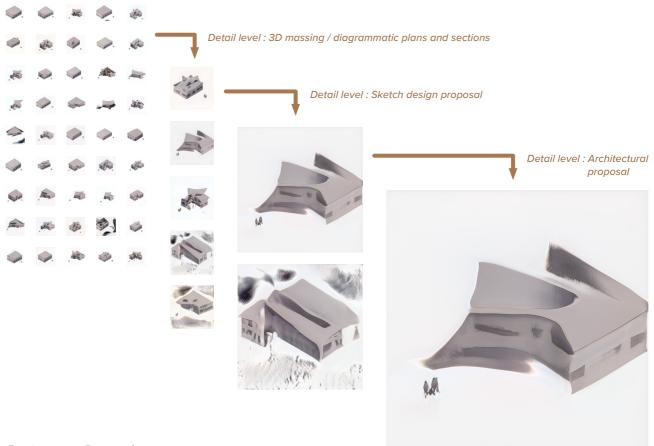


A new architectural design framework

Presentation of the design process

Along with coming up with an architectural proposal for a summer house, I explored several roles that architects might take in the future. In this regard, I distributed the design process into four different roles. The different roles informed each other greatly and by consequent, the structure of the thesis adopted a

temporal linearity rather than following the four parts one after the other. In the following pages, and as I explain the design process, the different roles I took will be highlighted by the colour scheme specified below.



Curation process. Source: author

CONCEPTUAL ARTIST

In this role I will produce a dataset of precedents to train the algorithm on. This conceptual process means that I will have control over what the algorithm will understand as a summer house. In other words, the algorithm will be an extension of my architectural style.

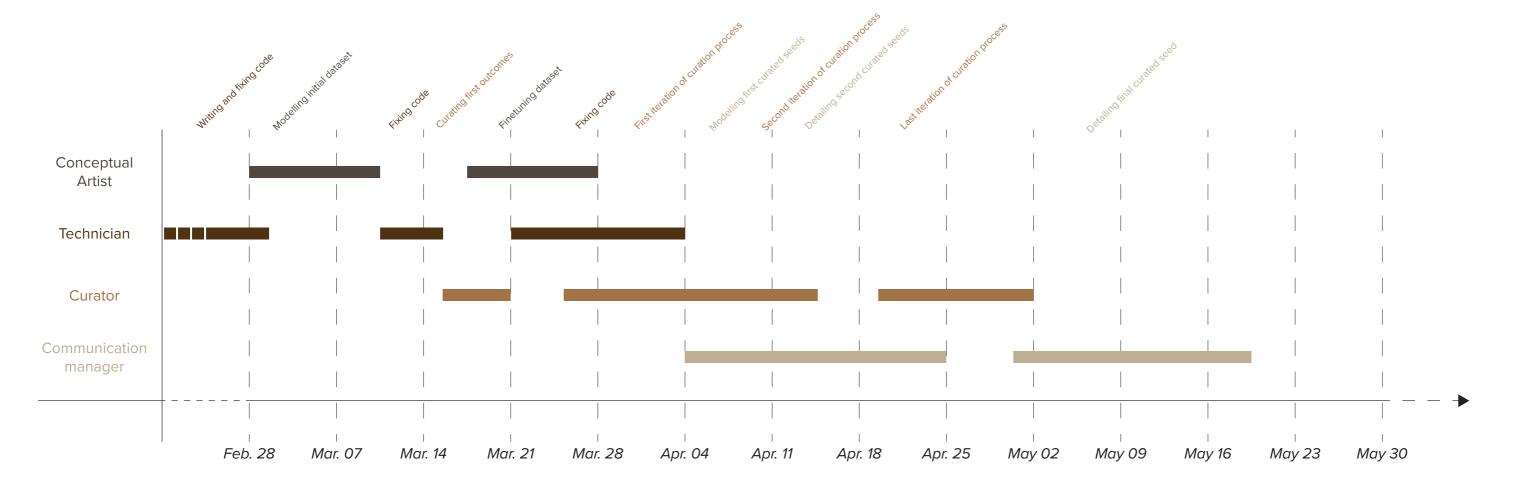
TECHNICIAN

If you were to go on any job search portal right now and type "architect" in the search bar to look for open positions, most results would advertise roles in IT services, IT consulting or IT engineering. The world of data science already chose the nomenclature of our field to name theirs. In this role I will design digital structures, rather than physical ones, by writing and fixing a Generative Adversarial Network (GAN).

CURATOR

Once the GAN has been trained and starts amount of machine-generated typologies and curate them to a decreasingly

COMMUNICATION MANAGER



Timeline of the design process. Source: author

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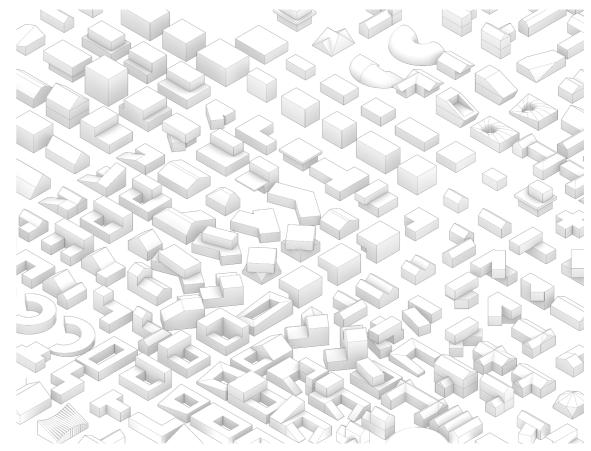
Step 01: creating the initial dataset

To start this project, I needed data.

In order to start training my GAN, and based on my previous experience with existing datasets, I evaluated that in order to have acceptable results, the minimum size of the training dataset is 200.

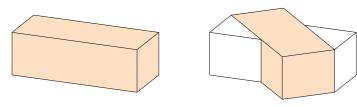
I thus imagined 200 family homes typologies inspired by houses found in the Scanian countryside.

Creating that amount of houses required an effective framework in order to cut down modelling times. I started by creating just massings.



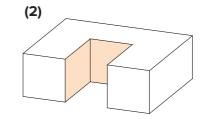
Massing dataset. Source: author

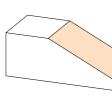
(1)

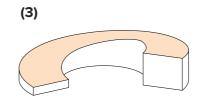


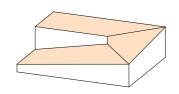
These massing were at first responding to basic geometric rules : basic blocks being rotated, superposed, mirrored, etc. (1) As these basic configurations were being exhausted, I moved to adding pitched roofs, slopes, inner courtyards, etc. (2)

Towards the end of the series, and as inspiration was drying out, I added some rather experimental or unusual structures. (3) I deemed this form diversification crucial to get a greater range of results, to teach the algorithm that a house can come in many shapes.

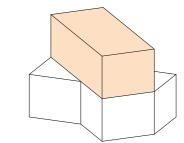


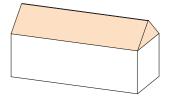


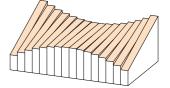




Massing buildup methods. Source: author







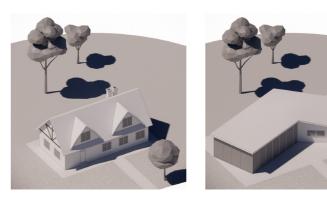


Having this database of solid objects, evoking to some extend the work of François Blanciak¹⁰¹⁴, I created a small library of processes to add details (grasshopper definitions to generate stairs, balustrades and glass curtain walls/families of blocks for windows and doors/groups of poly surfaces for dormers and chimneys...).

These images show the first attempt at making the detailed houses. The level of details is still rather rough because I wanted to first test the algorithm's ability to understand the general shapes before adding more complex notions. In order to give these houses a sense of scale, I placed them on a little context disk with very basic landscaping.

All 200 of these houses are laid out on the next double-page.





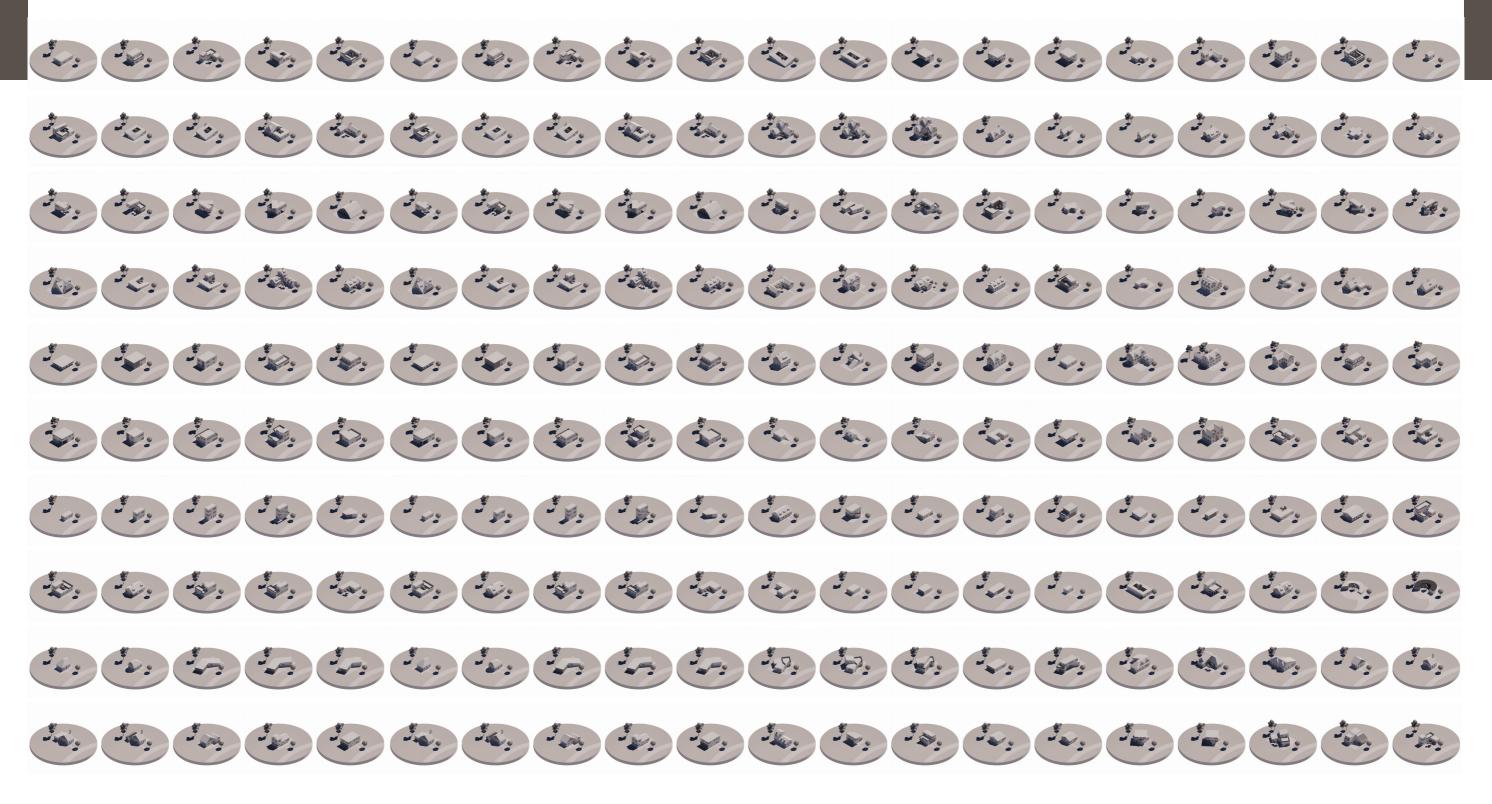
Detailing process. Source: author











Initial dataset. Source:author

Step 02 : training the networks on the initial dataset

By the time I started the design phase of my thesis project, I had already had some experience using the algorithm and successfully generated at least two sets of novel images. The code was working well and when I started training my first dataset, I was not expecting to run into any problem. However, I noticed the time frames of one training cycle were much longer than when I was training networks on the axomadness dataset or the OHPD one : In March 2021, the speed of one epoch training was 482 s/kimg (second per 1000 images). In March 2022 it is 1879.27 s/kimg.

I could not really explained such a huge disparity in training time, because the images were the same size and I was using the same algorithm... Since the start of my interest in ML, I have been using the platform Google Colab, which allows to run code using Google's GPUs in the cloud. This service is free and accessible from any computer because it is online. When I first used it, I was allocated Tesla V100 GPUs. This is amongst the world's most advanced

GPUs, it is used in the most cutting-edge Al centres worldwide and is worth several thousands of dollars. This is one of the reason Colab became extremely popular; anyone with an internet connection could get access to state of the art processors, for free. Since then, Google has downgraded the GPUs available and according to several reddit posts, no one, not even the paying subscribers, get the coveted V100s anymore⁰⁰²⁶. So I have to train my dataset on K80s and T4s GPUs, which have respectively 3 and 1,5 times less transistors (hence 3 to 1,5 times slower) than V100s, on which I trained the axomadness and OHPD datasets.



First acceptable output from the GAN. Source:author





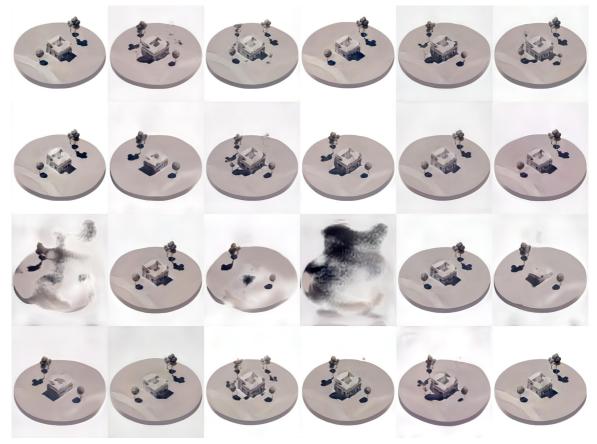




First outputs from GANs trained on the initial dataset. Details. Source:author

Using the first database, I quickly started to realise that the little landscape disk, here to add a sense of context and scale was in fact adding to much disturbance for the GAN. It was not really focusing on the building but rather on the trees around. In these examples one can see the buildings look very similar while the changes are focused on the surroundings.

I thus had to go back to my conceptual artist role and to edit out this context disk.



First outputs from GANs trained on the initial dataset. Source:author

Step 03 : fine tuning the training dataset



Example taken from the second edited dataset. Source: author

I went back to the dataset to edit the landscape disks out. In order to keep a general sense of scale in the images, I added some scale figures to the models. The level of detail is still quite rough but it worked fairly well. As seen on these examples, an architectural sense started to develop and most of these images would be

understood as buildings by anyone looking at them. Since the overall massing remained a bit blurry and it was hard to understand the inner room layout, I decided to add the same houses seen in wireframe mode, to see if the algorithm could perceive the depth of the houses and develop a more three dimensional understanding.

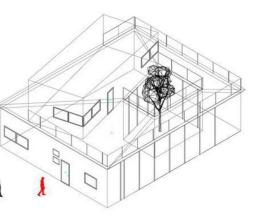
The third database was a failure as all attempts were leading into this kind of overall blur. I expect that to be caused by an enormous amount of lines, causing a graphical confusion.



Outputs from GANs trained on the first edited dataset. Source: author



Outputs from GANs trained on the second edited dataset. Source:author



Example taken from the third edited dataset. Source:author

If all these wireframe line drawings were to be superposed, the resulting image would be a very confusing blur.

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Step 04 : curating the raw outputs

I thus went back to the neural networks trained on the second database and used them to generate over 1600 images that I sifted by eliminating the seeds (1) that looked too similar. This curation pass, allowed me to reduce their number to 150.

I then started to evaluate these remaining seeds based on two criteria: their pragmatism and their boringness.

I evaluated them one by one and placed them on this two axis diagram, which is an actual depiction of how I proceeded. I did not have a clear method, but rather pinned them on a wall based on my own taste and in comparison to one another.

BORING

Outputs from GANs sorted according to their pragmatic and chaotic characteristics. Source:author

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PRAGMATIC

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Step 05 : diagrammatic proposals



The next curation pass was to assess which of these seeds could be developed into interesting architectural concepts.

Here, my role shifted towards a communication manager's one, because I had to start translating what the algorithm has given me into an understandable architectural concept.

I selected five that I could model into diagrammatic proposals. The detailing level here is minimal and rather abstract, to keep this step as an early conceptual design stage.

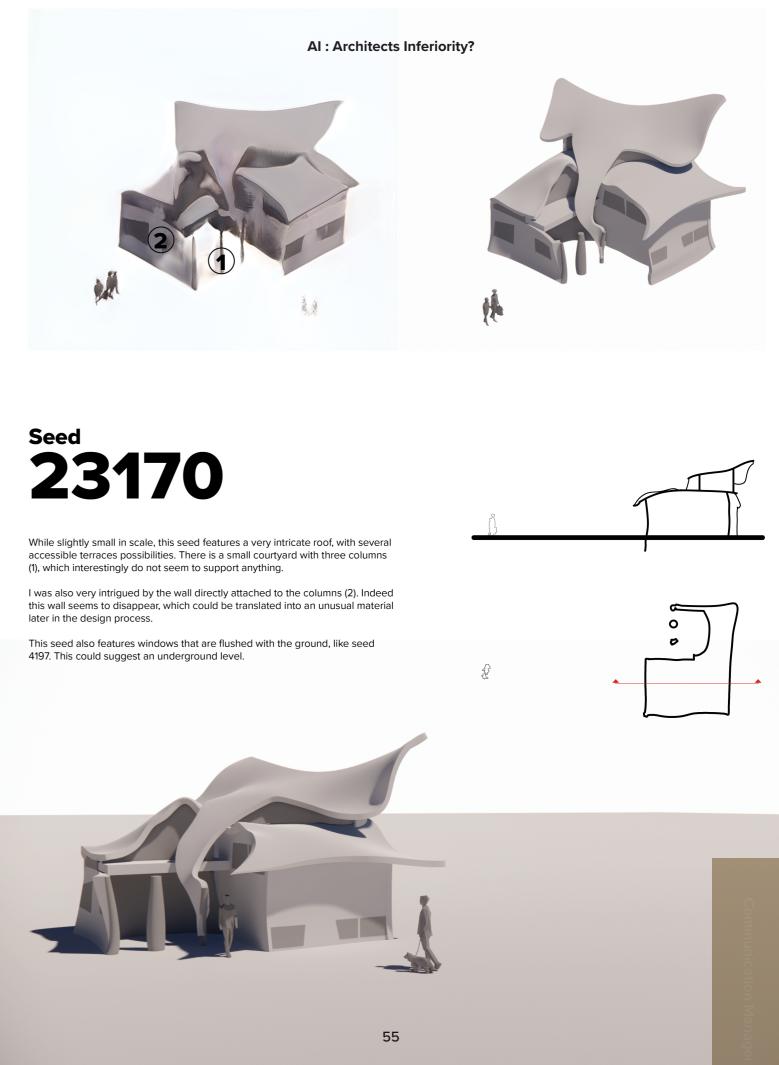
Since the dataset was made from axonometric views of only one angle of the building, I had

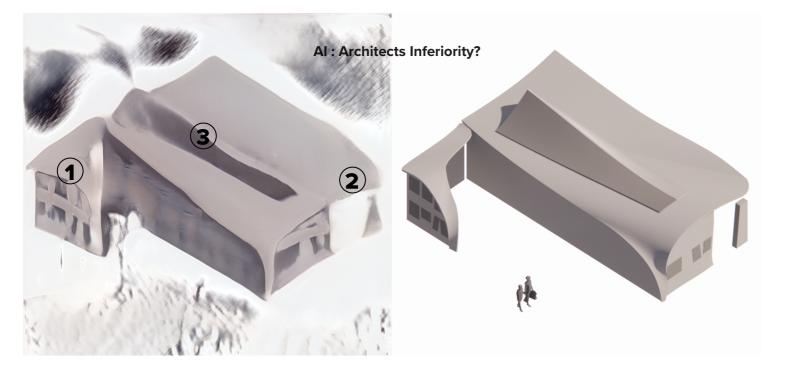
to use some imagination to model the other two facades. Sometimes, like with seed 17054 with its extended roof suggesting a glazed facade, some visible elements were implying the existence and nature of hidden ones. In most cases, the other two facades were for this phase just plane and blank.

In terms of scale, I did keep in mind the scale figures from the GAN outputs. However, in some cases I adjusted the dimensions slightly into an overall that was more fitting. For example, seed 0168 got slightly bigger during the translation to 3D, while seed 4197 decreased slightly in size.



The five seeds selected to move to the next detailing phase. Source:author





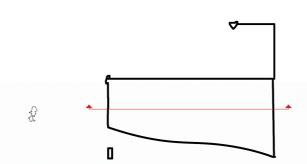


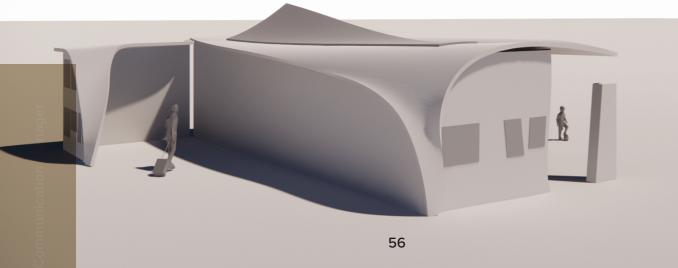
Seed 17054

This seed is rather conservative in shape but features two elements that I deemed interesting; A sort of semi-covered outdoor element (1) and a roof that extends past the facade line (2) indicating a shaded facade and maybe suggesting a glazed one.

There is also a dark elongated spot on the roof (3). Since darker colour meant glass in the training dataset, I read this as skylights, which would increase the light qualities of the interior.



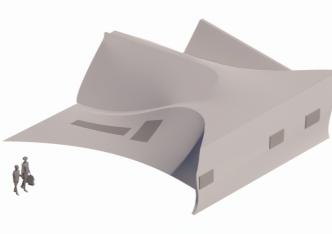


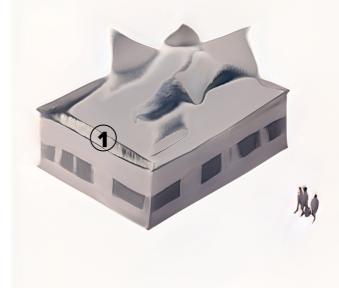










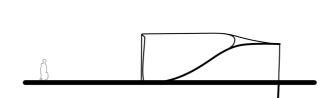


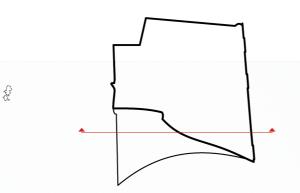
Seed 4197

This seed presents a roof that seems to be parted in three, with one part lowering to the ground. This could be understood as an accessible roof (1) just like in seed 79722.

It also showcases a wall that seems to go lower than ground level (2), just like seed 23170, with three windows flushed with the ground. My understanding of this is an underground level, with these windows as skylights.

What is more the human figures gave an acceptable scale to the overall house, that fits the program.



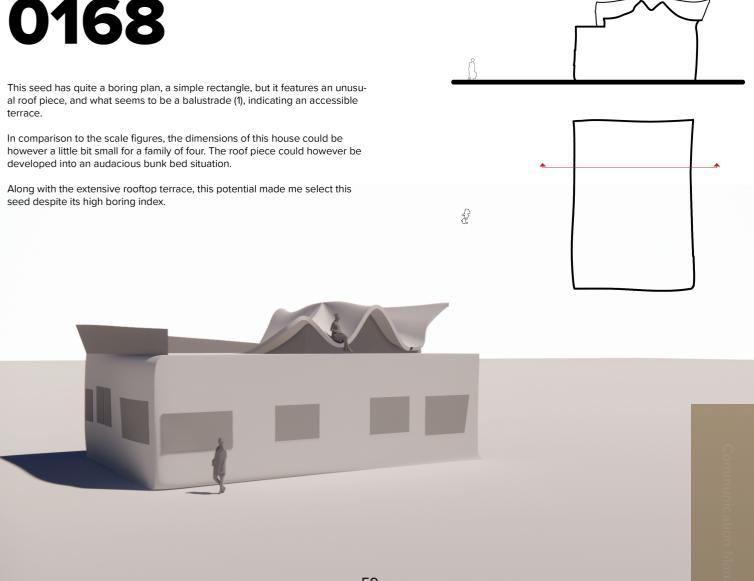


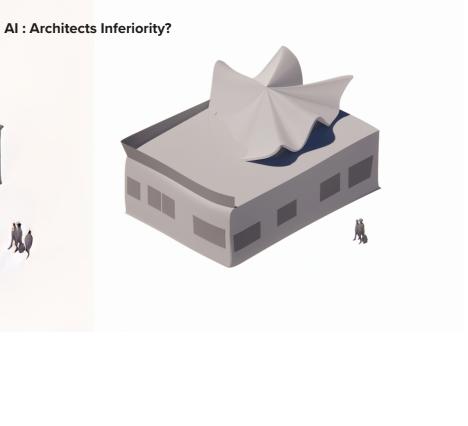
Seed 0168

terrace.

In comparison to the scale figures, the dimensions of this house could be however a little bit small for a family of four. The roof piece could however be developed into an audacious bunk bed situation.

seed despite its high boring index.



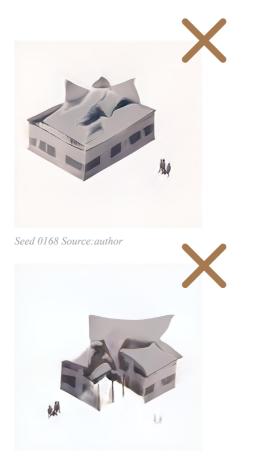


Step 06 : selecting two seeds for further detailing

With these five seeds selected and modelled, I did some additional analysis to determine two I could develop further, and imagine their interior spaces and atmospheres. Since I selected all five of them for specific properties I deemed interesting, I decided to proceed by elimination.

First, I decided to cull seed 0168 because while the rooftop could be developed into something novel, the overall shape of the building was quite boring and not really showing the full potential of AI aided design, or at least in a rather timid way.

On the other hand, I chose to remove seed 23170 because the overall shape was quite chaotic, and while it suggested interesting spaces, its interior would have almost certainly been very crooked in some places. Lastly the scale was very small for a family of four and would have needed a lot of extra thinking when it comes to interior planning.



Seed 23170 Source: author

Since seeds 4197 and 29722 both showcased similitudes in their accessible roofs and double level floorplan, I decided to select only one between the two. This was not an easy decision to make but I had a slight preference for 4197, since a traditional typology of the pitch roofed farmhouse was still visible, only with a twist : a part of the roof lowered to blend with the ground. I thus eliminated seed 79722 and was left with seeds 4197 and 17054 to move on to the next curation phase.



Seed 4197 Source: author



Seed 79722 Source: author



Seed 17054 Source:author

Step 07 : detailling two seeds

Seed 17054

In this phase I took an outside-in approach, which is the opposite of what architects usually do.

I started oriented the seeds the same way I imagined the training dataset, which means looking at them from South West. I started by placing the windows on the plan diagrams to understand where the openings would be and to give me clue regarding the internal layout. For seed 17054, this meant placing a glazed wall on the north facade, as well as modelling this pitch roof with skylights (1).

- 1.1 Entrance hall
- 1.2 Bathroom
- 1.3 Master Bedroom
- 1.4 Kitchen
- 1.5 Living/Dining room



Seed 17054. GAN-generated axo view. Source:author



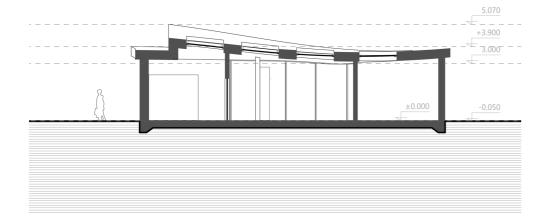
Seed 17054. Axo view. Source:author



(A

Seed 17054. Ground Floor Plan. 1:200 Source:author

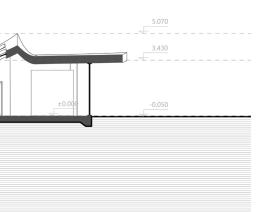
1.6 Bedroom 1 1.7 Bedroom 2



Seed 17054. A Section. 1:200 Source: author

Seed 17054. B Section. 1:200 Source: author

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Seed 17054. Exterior view. Source: author



Seed 17054. Interior view. Source: author

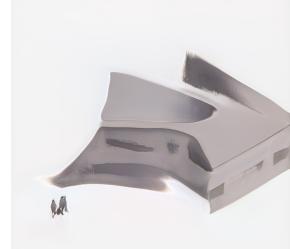
Seed 4197

For seed 4197, I modelled an underground level and decided to dress the part of the roof that blends with the ground with some windows, which become skylights.

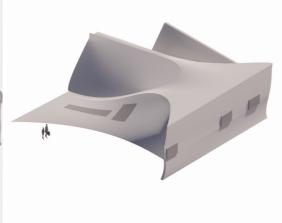
close as possible to the machine's vision. With this seed I had more square meters and thus

From then on, the process was quite organic and I imagined the interior space to the best of my architectural abilities, while trying to keep as

was able to add a guest room (2.8), a pantry (2.5) and a laundry room (2.7), but the program remains a house for a family of four, like with seed 17054.

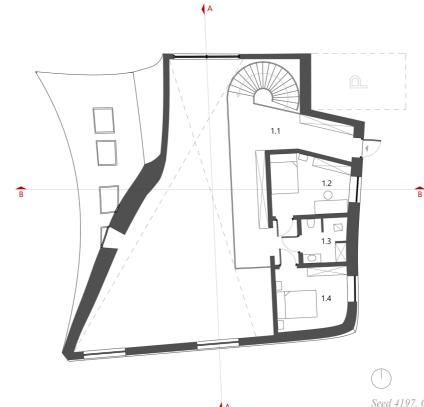


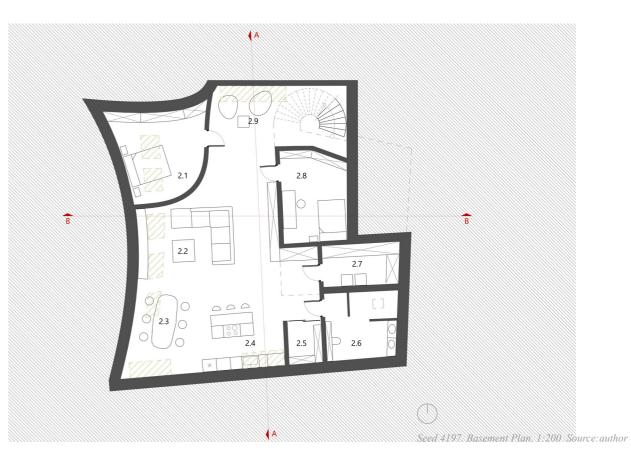
Seed 4197. GAN-generated axo view. Source:author



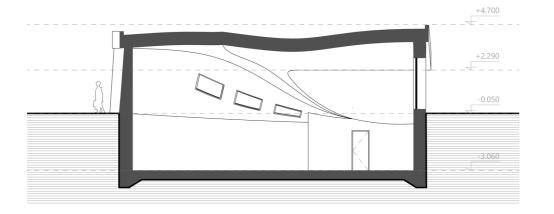
Seed 4197. Axo view. Source:author

1.1 Entrance hall	2.3 Dining room
1.2 Bedroom 1	2.4 Kitchen
1.3 Bathroom 1	2.5 Pantry
1.4 Bedroom 2	2.6 Bathroom 2
1.5 Terrace	2.7 Laundry room
2.1 Master Bedroom	2.8 Office/Guest room
2.2 Living room	2.9 Lounge

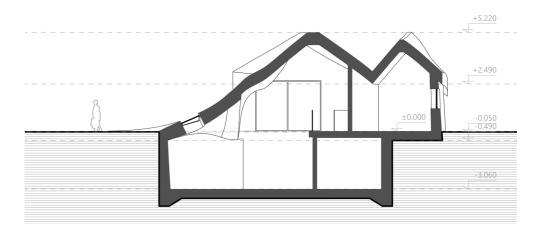




Seed 4197. Ground Floor Plan. 1:200 Source:author

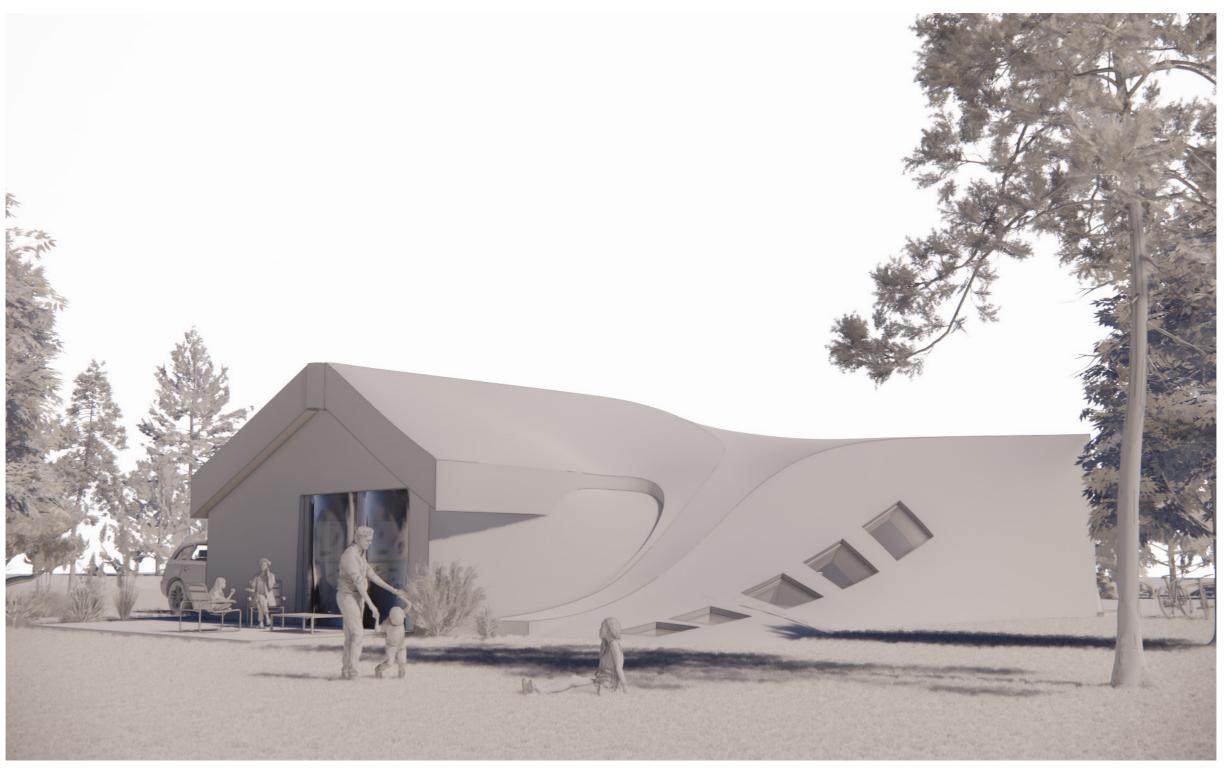


Seed 4197. A Section. 1:200 Source: author



Seed 4197. B Section. 1:200 Source: author

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Seed 4197. Exterior view. Source: author

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Seed 4197. Interior view. Source: author

Step 08 : selecting the final seed

inviting.

The last curation step is to chose one of the seeds and develop it into a full architectural proposal. I did this by analysing plans, sections and views I had, and decided which one would be the most interesting. I followed my architectural sense to chose seed 4197, because I deemed the overall shape more intriguing and the interior atmosphere more

Furthermore, I felt like seed 4197 better transposed the fact that I used an artificial intelligence in the design process, whereas as much as I liked seed 17054, it remains more conventional.





Seed 4197. Exterior view. Source: author

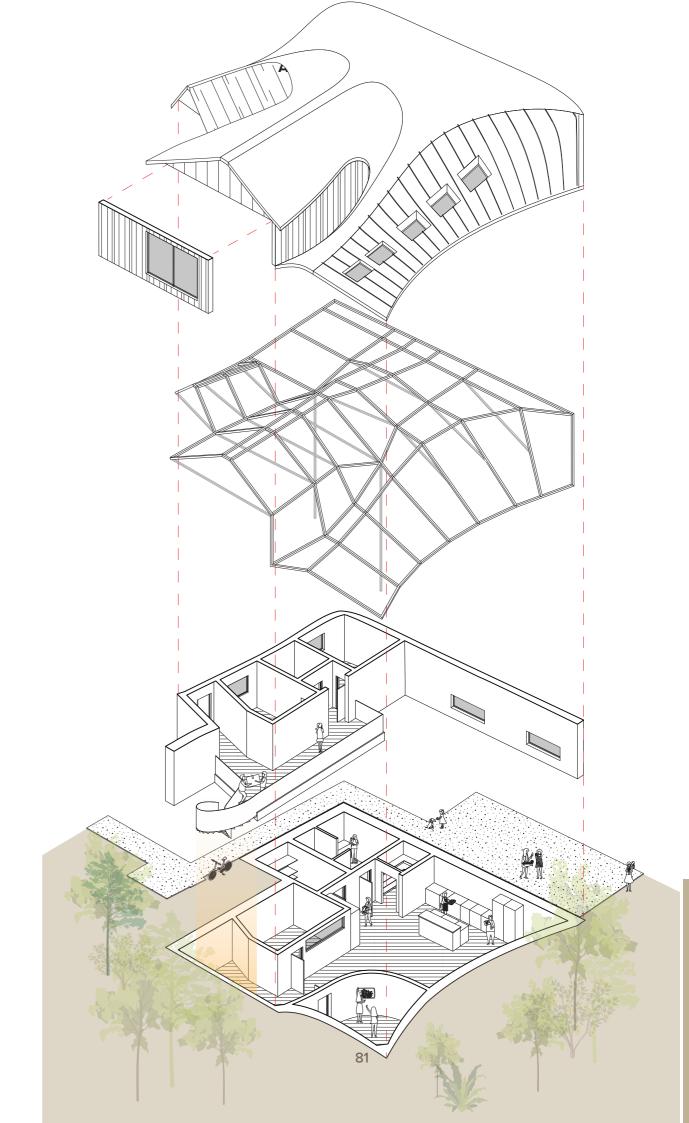
Step 09 : final architectural proposal

This phase marks the end of my role as a design coordinator and of the design part of my thesis. In order for this phase to succeed, I had to make a believable constructible architectural proposal, that could be a competition entry or be chosen by a client willing to build their summer house.

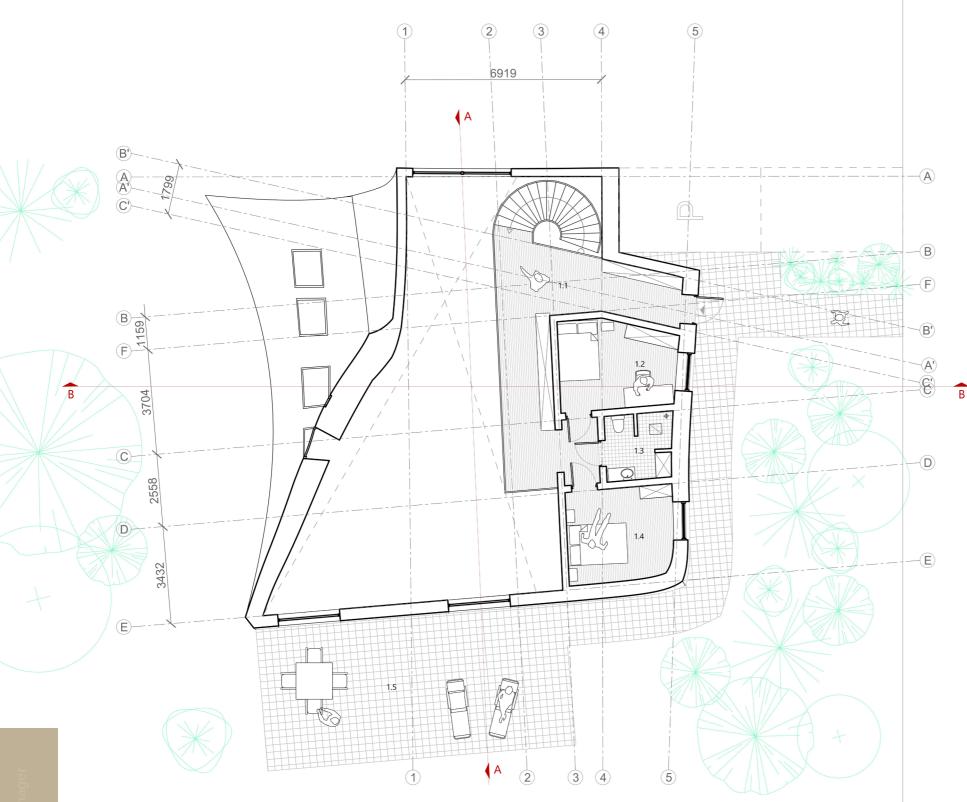
I developed my plans and sections into more detailed drawings, and extracted an axonometric view of the proposal. I edited the views to more realistic renders to convey the atmosphere.

In this part of the thesis, I let myself be guided by my architectural sense. There is here an interesting reflection to consider; wether this so-called architectural sense exists and if so what is it made of. I would argue that it comes with training. I knew what would make the most sense because I have been designing buillings for a few years now. Of course in my studies as in practice, design is always motivated and legitimated by different factors like orientation, flows, structural impact, etc. But maybe I assimilated all these factors so inherently that they effectively form an architectural sense.

For example, it was my understanding that the roof was suggesting an underground level (see page 58). Perhaps another designer would have instead seen a ceiling that meets the ground and shelters storage. This individual understanding of the design process demonstrates that this framework leaves after all little space for the machine to truly be creative and would vary greatly depending on the collaborating architect.



ommunication Manage



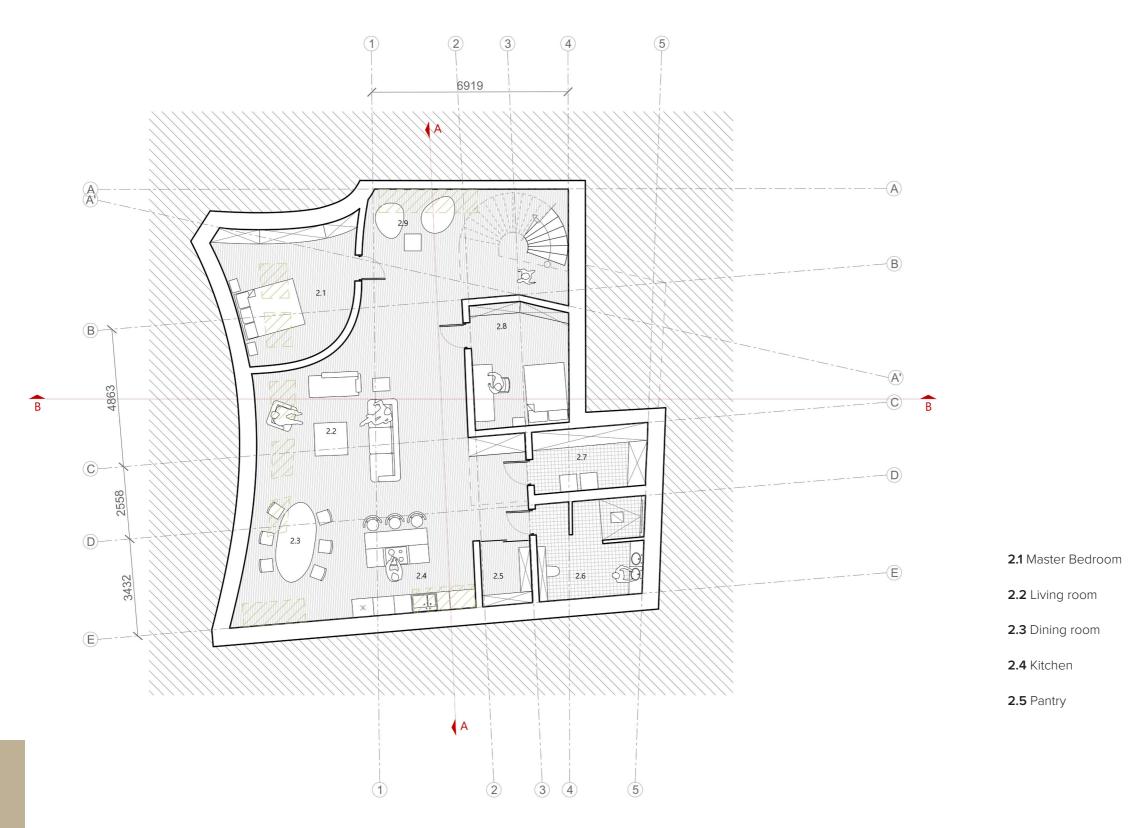
When it comes to designing the interior layout, I had to mostly use my own creativity as I only had vague clues regarding the indoor layout of the building. I knew more or less where the windows were, at least for two facades, as well as the assumption that there was an underground level. This gave me a starting point to layout the rooms. I used standard measurements to place bedrooms, bathrooms, kitchen, etc. Because of the obvious wealth of the family who would have this house, I made sure to be consistent and include some premium features they would likely request, such as a large walk-in shower, or a kitchen island.

1.2 Bedroom 1 1.3 Bathroom 1 1.4 Bedroom 2 1.5 Terrace

1.1 Entrance hall

Seed 4197. Ground Floor Plan. 1:150 Source:author





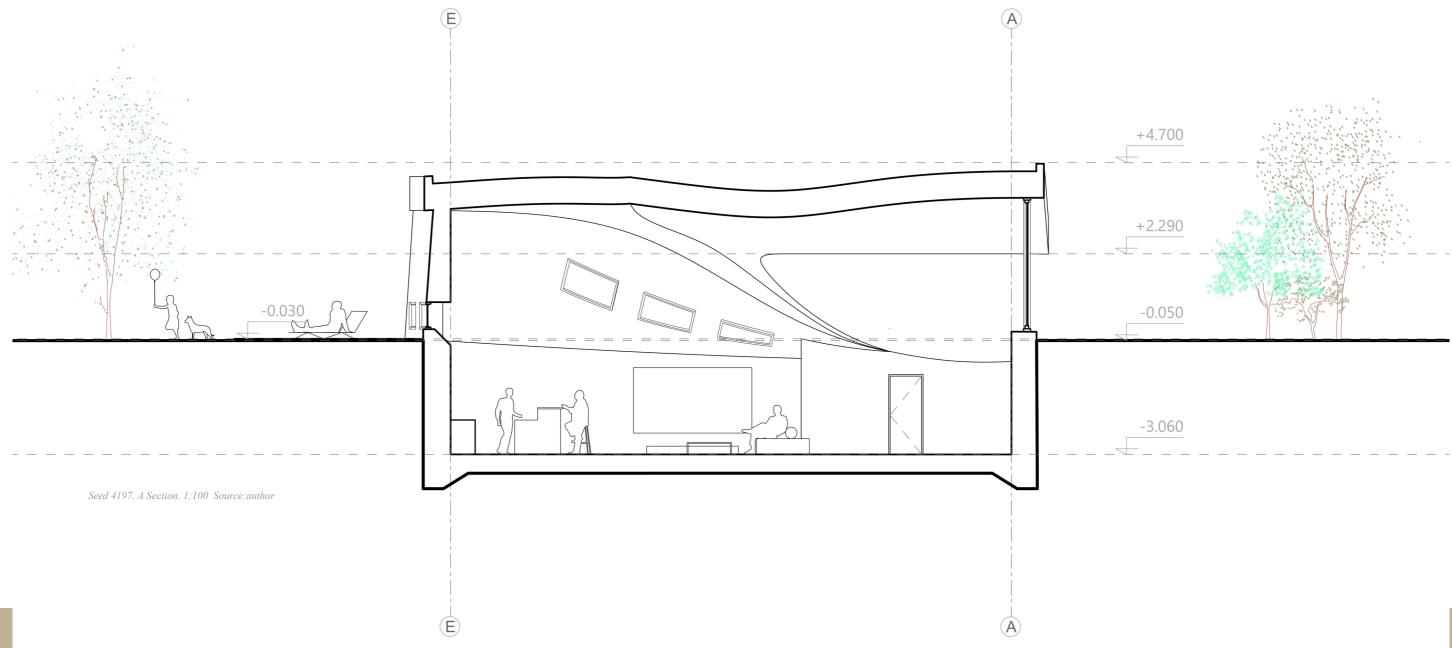
Seed 4197. Basement Plan. 1:150 Source:author

2.6 Bathroom 2

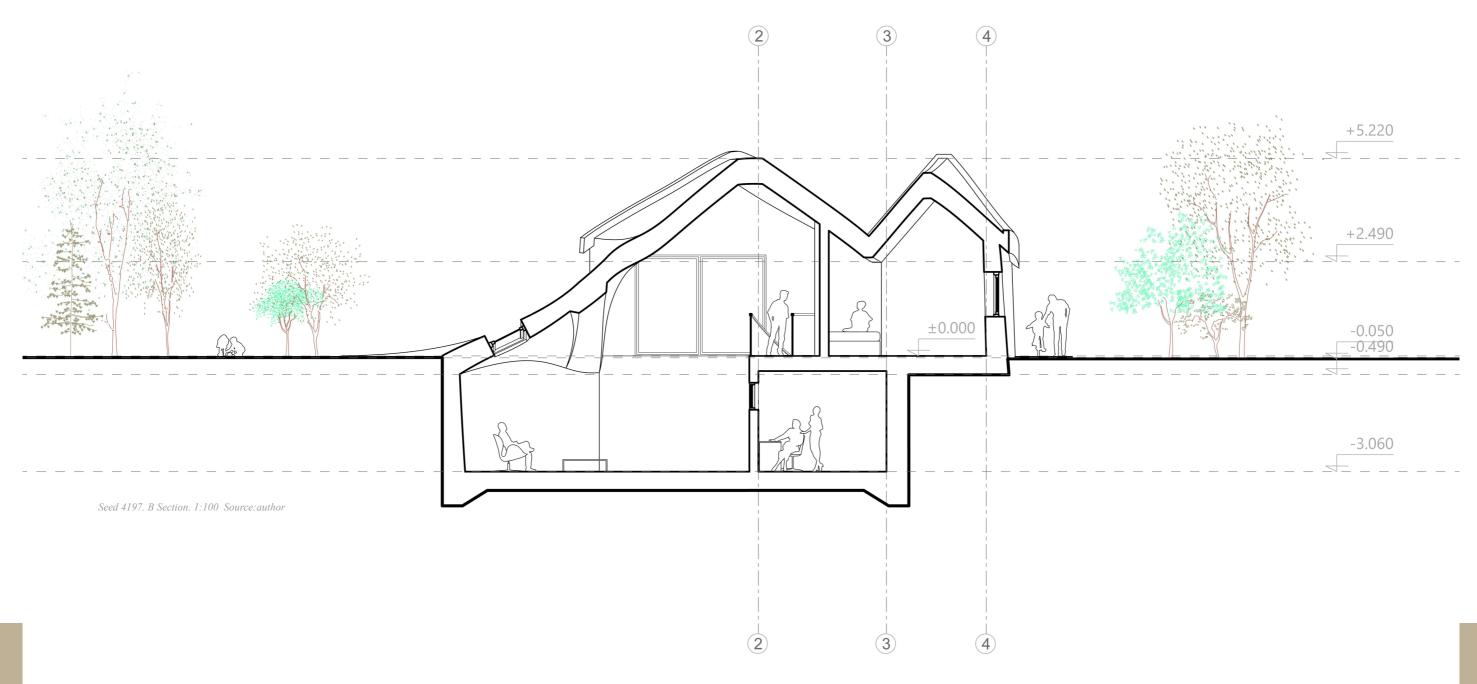
2.7 Laundry room

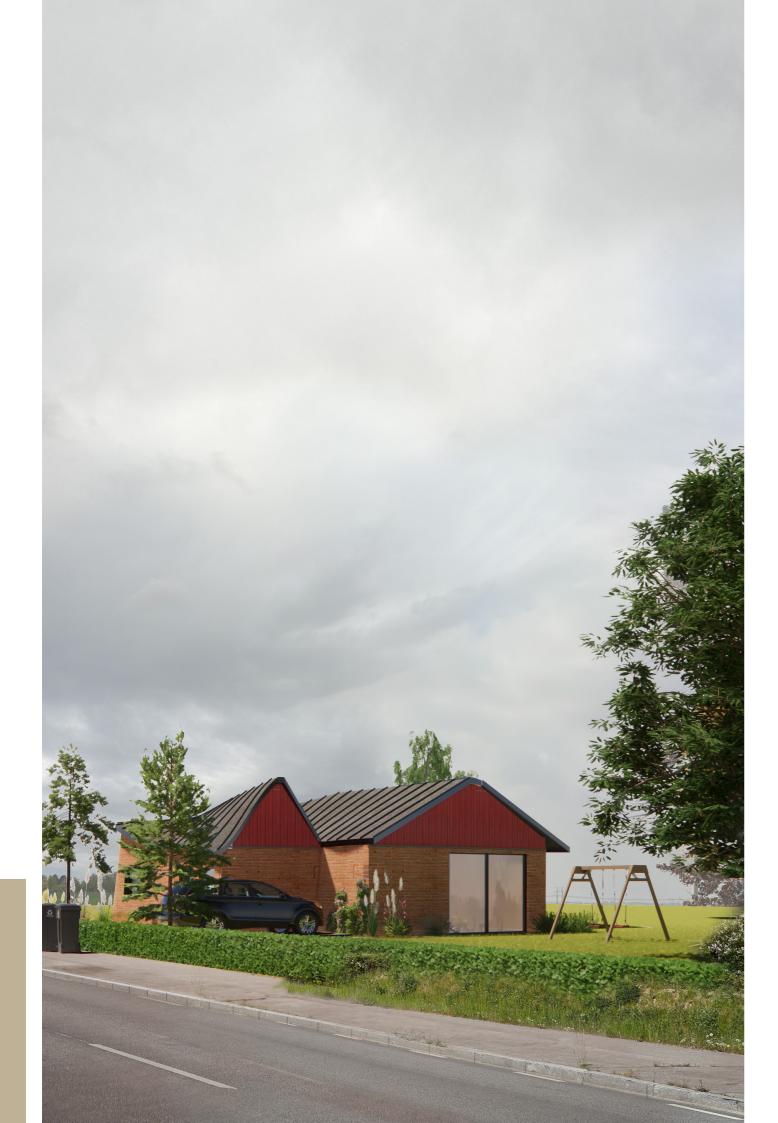
2.8 Office/Guest room

2.9 Lounge

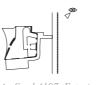


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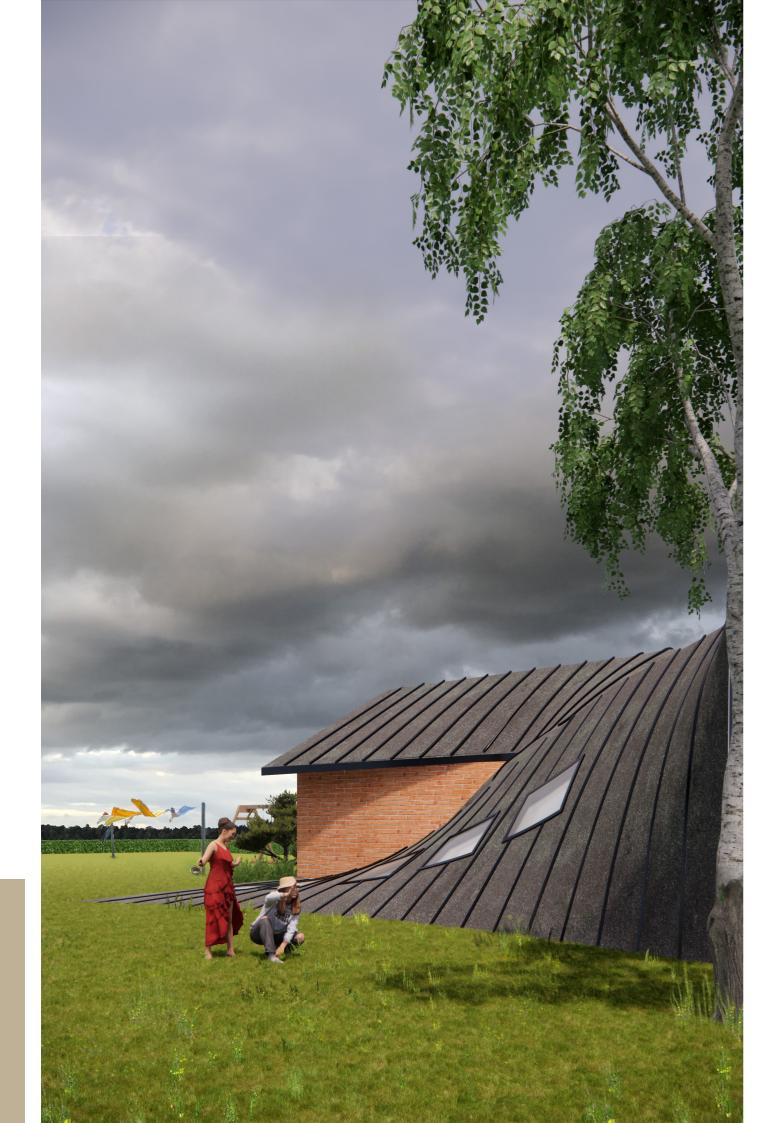


• Seed 4197. Exterior view. Source:author

Seed 4197. Exterior view. Source: author



Communication Manager





Seed 4197. Exterior view. Source: author



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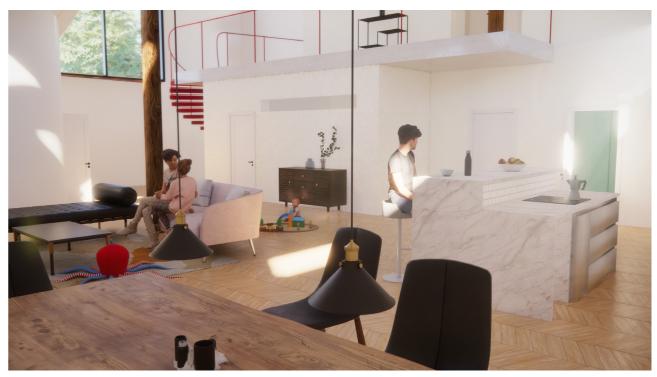
Seed 4197. Interior view. Source: author





Seed 4197. Interior view. Source: author





To reflect on this last part of the design process, I would say that it is as interesting as it is hard to approach a building without contraints, at least in terms of program and layout. In plan I did try to follow the outputs of the algorithm as close as possible, which meant that some walls do curve. I extended this approach further, as the interior walls are more curvy along curvy external walls, and more orthogonal where the algorithm showcased a more conservative massing.

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Seed 4197. Interior view. Source: author



The design of this house was in the end mostly imagined by me, rather than by the algorithm. It is in effect a rendition of what I was able to read in the images the GAN generated. This might be a collaborative process indeed, and we will adress this question in the following chapter.

Conclusion

In this thesis I investigated the potential of GANs as a creative architectural collaborator, through the design of a summer house.

Whereas AI algorithms are mainly used today in the building industry to optimise structural beams, sunlight exposure or other numerically measurable components, I wanted to test their ability to tackle more abstract notions.

Therefore instead of using an algorithm to optimise my design, I translated the algorithm's design into an architectural proposal.

I supposed such a novel framework would prove or dismiss the potential of AI as creative architectural collaborator.

While the output images from my networks were compelling by their non-human qualities, many of them looked similar, which might have been a result of overfitting because of too small of a dataset. Even though the outputs came in immense number, some of them were very boring or completely random. We have seen before that an outburst of ideas is not very useful if they are not properly ordered and put

into form⁰⁰¹¹ so we can argue that the creative part of the process resided with me rather than the algorithm.

I dispute the argument that GANs are creative, as they have no agency. My networks seem to fit into the base definition of creative (the images they generated were novel and useful). However I was the agent curating the outputs and evaluating their originality and usefulness, I was the entity in control of the creative process. There is here a notion that is essential to mention; human interpretation. As humans, we tend to give anthropic qualities to inanimate objects. For example, the first instance of what is dubbed 'computer art' dates back to the 1960s when a plotter malfunctioned at Bell Labs in the United States and produced random lines that A. Michael Noll (a scientist working there with one of the world's first computers) saw as a deliberate artistic gesture.⁰⁰²⁷ Of course there is to this day no proof that any computer ever got its own agency.

In my thesis, my role as a communication coordinator became so prevalent it proves the relevance of architects, even in a Al-driven project. The GAN

on itself could not have produce an acceptable premises and curate the machine-generated results, architectural proposal. Therefore even if ML algorithms the build environment could turn into a hellscape. are today a new discourse for the architecture While ML algorithms might produce an immense field, there is according to this thesis no proof that amount of architectural sketch concepts, someone a professional shift will happen, from architect as who is spatially and designedly educated is still designer to architect as curator. needed to curate or create a training dataset and However, I believe it is still important that we as assess the outputs.

architects keep getting educated on this discourse, so that we can take part in the discussion and prove why our job is relevant in an age where HITs (Human Intelligence Tasks) can be automated.

While I was working on this thesis, Mark Zuckerberg advertised his "Builder Bot", an "Al concept [that] enables you to describe a world, and then it will generate aspects of that world for you [in the metaverse]".0028

As impressive at this sounds, the creativity of the billionaire as much as the graphic aspect of his metaverse makes the whole scene feel tragic rather than groundbreaking. Granted, this technology is disruptive and could actually have game-changing applications in the architectural world. But if the metaverse is the internet revolution it claims of being, these digital spaces should be shaped by people with architectural design background.

This video illustrates precisely why architects would still be needed, even in a world where buildings were to be machine-generated; You can have the most complex generator program with the easiest input method (voice-control in this case), if the human in control is unable to properly articulate the



A sad example of what lack of creativity looks like. Source: Mark Zuckerberg¹⁰¹⁵

The human factor here is more important than the machine's and for this reason this particular thesis does not prove that the framework I use is an effective way for GANs to be creative collaborators.

However there could be other type of framework where the machine has more control over the process, and less importance is given to buildability or different ways to use these algorithms in the architecture profession. One of them could be generating precedents, instead of sketch proposals. In that scenario, I would have looked at the results the networks would have given me as a source of inspiration, taking some aspects from one, some aspects from another and imagining a new building based on these.

Textual references list

0001 _ Tegmark, M., Life 3.0 : Being Human in the age of Artificial Intelligence. (pp. 39 & 50). Penguin Books.

0002 _ Merriam-Webster. (n.d.). Neural network. In Merriam-Webster.com dictionary. Retrieved May 9, 2022, from https://www.merriam-webster.com/dictionary/neural%20network

0003 Brownlee, J. (2019, June 17). A Gentle Introduction to Generative Adversarial Networks (GANs). Machine Learning Mastery. https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/

0004 Parametric Design. In Wikipedia. Retrieved April 27, 2022 from https://en.wikipedia.org/w/index. php?title=Parametric design&oldid=1085013325

0005 _ Karpathy, A., Abbeel, P., Brockman, G., Chen, P., Cheung, V., Duan, R., Goodfellow, I., Kingma, D., Ho, J., Houthooft, R., Salimans, T., Schulman, J., Sutskever, I., Zaremba, W. (2016, June 16). Generative Models. OpenAl. https://openai.com/blog/generative-models/

0006 Karras, T., Laine, S., Aila, T., (2018, December 12) A Style-Based Generator Architecture for Generative Adversarial Networks, NVIDIA.

0007 _ Karras, T., Hellsten, J., stylegan2. NVIDIA Research Projects. [GitHub Depository]. GitHub. https://github. com/NVlabs/stylegan2

0008 _ Bruno, A. [@one_house_per_day]. Posts [Instagram profile]. Instagram. Retrieved June 2020, from https://www.instagram.com/one_house_per_day

0009 _ Chaillou, S., (2020, May 14). Al + Architecture, Symmetry. [Online Conference]

0010 Karras, T., Aittala, M., Hellsten, J., Laine, S., Lehtinen, J., Aila, T., (2020, June 11). Training Generative Adversarial Networks with Limited Data. NVIDIA, Aalto University.

0011 _ Vaske, H. (Director). (2018). Why Are We Creative : The Centipede's Dilemma [Film]. Emotional Network.

0012 _ Hoff, E., Personal Communication, April 13, 2022

0013 _ Frey, C. B., & Osborne, M.A. (2013). The Future of Employment: How Susceptible are Jobs to Computerisation. Oxford University Press.

0014 _ Carpo, M., (2017). The second digital turn : design beyond intelligence. (p. 23). The MIT Press.

0015 Leach, N. (2014). There is No Such Thing as Digital Design. In D. Gerber & M. Ibanez (Eds.), Paradiams in Computing: Making, Machines, and Models for Design Agency in Architecture (pp. 148-158). eVolo Press.

0016 _ Latson, J. (2015, February 15). Did Deep Blue Beat Kasparov Because of a System Glitch?. TIME. https:// time.com/3705316/deep-blue-kasparov/

0017 _ Miller, A. I., (2019). The Artist In The Machine : The World Of Al-Powered Creativity. (pp. 50-51). The MIT Press.

0018 _ Carpo, M. (2019, March). Foreword; The Age of Computational Brutalism in M. Claypool, M. Jimenez Garcia, G. Retsin, V. Soler & J. Werfel (Eds.), Robotic Building : Architecture in the Age of Automation (p. 8). Edition DETAIL.

0019 _ Sotheby's. (2019, February 8). The Hypnotic Allure of the Al Art Generator [Video]. YouTube. https://www. voutube.com/watch?v=Jjv3m5oWICA

0020 _ Refik Anadol [@refikanadol]. (2020, May 18). Can data become a pigment? A question that we asked to start our nature inspired data paintings [Video]. Instagram. https://www.instagram.com/p/CAW8uLSjpns/?hl=en

0021 _ Obvious [Art Collective]. (2018). Edmond de Belamy [GANs Algorithm, Inkjet on Canvas]. Christie's New York, New York, NY, United States. https://www.obvious-art.com/portfolio/edmond-de-belamy/

0022 _ Nugent, C. (2018, August 20). The Painter Behind These Artworks Is an AI Program. Do They Still Count as Art? TIME. https://time.com/5357221/obvious-artificial-intelligence-art/

0023 Barrat, R. (2017, August 9). Portrait GAN. art-DCGAN. [GitHub Depository]. GitHub. https://github.com/ robbiebarrat/art-DCGAN

0024 Carpo, M., (2017). The second digital turn : design beyond intelligence. (p. 55). The MIT Press.

0025 _ Anonymous User, [N00MKRAD]. (2021, August 29). Colab Pro no longer gives you a V100, not even a P100, you now pay for the (previously free) Tesla 4. [Online forum post]. Reddit. https://www.reddit.com/r/ MachineLearning/comments/pdwxxz/d colab pro no longer gives you a v100 not even a/

0026 _ Chaillou, S., (2020, May 14). AI + Architecture, Symmetry. [Online Conference]

0027 Miller, A. I., (2019). The Artist In The Machine : The World Of Al-Powered Creativity. (p. 40). The MIT Press.

0028 Mark Zuckerberg, (2022, February 23), Inside The Lab: Building for the Metaverse with AI [Live]. Facebook. https://www.facebook.com/zuck/videos/677947796579229

Images references list

1001 _ Grubnyak, A., Photo [Photograph]. Unsplash. Retrieved April 20, 2022 from https://unsplash.com/photos/ ZiQkhl7417A.

1002 _ Bruno, A. [@one_house_per_day]. Posts [Instagram profile]. Instagram. Retrieved June 2020, from https://www.instagram.com/one_house_per_day.

1003 _ Chaillou, S., (2019, June 8), Al + Architecture, Towards A New Approach. (p.28). Harvard University. https://www.academia.edu/39599650/AI_Architecture_Towards_a_New_Approach.

1004 _ Vaske, H. (Director). (2018). Why Are We Creative : The Centipede's Dilemma [Film]. Emotional Network.

1005 _ Dwyer, P., Sam, C., Diamond, J. (2017, July 7). A College Degree Lowers Job Automation Risk. [QuickTake]. Data from "The Future of Employment: How Susceptible Are Jobs to Computerization?" by Carl Frey and Michael Osborne. Bloomberg. https://www.bloomberg.com/graphics/2017-job-risk/.

1006 Tegmark, M., Life 3.0 : Being Human in the age of Artificial Intelligence. (p. 53). Penguin Books.

1007 _ Obvious [Art Collective]. (2018). Edmond de Belamy [GANs Algorithm, Inkjet on Canvas]. Christie's New York, New York, NY, United States. https://www.obvious-art.com/portfolio/edmond-de-belamy/.

1008 _Cerino, A., Photo [Photograph]. Unsplash. Retrieved March 27, 2022 from https://unsplash.com/photos/ idwpKeO-ZWk.

1009 _ Mestry, A., Photo [Photograph]. Unsplash. Retrieved March 27, 2022 from https://unsplash.com/photos/ UBhpOlHnazM.

1010 _ Saiko. Own work, CC BY 3.0 [Photograph]. Retrieved March 27, 2022 from https://commons.wikimedia. org/w/index.php?curid=55033088

1011 _ Apple Inc. [Company]. Retrieved March 27, 2022 from https://web.archive.org/web/20070629150410/ http://www.apple.com/iphone/guestionsandanswers.html.

1012 _ Deweerdt, A., Photo [Photograph]. Unsplash. Retrieved March 27, 2022 from https://unsplash.com/ photos/kJ2xdKJZZ9k.

1013 _ Dall'Anese, F. (2016). Installation at Centre Pompidou [Photograph]. https://www.michael-hansmeyer.com/ digital-grotesque-II.

1014 _ Blanciak, F., (2008, February 29). SITELESS: 1001 Building Forms. The MIT Press.

0015 _ Mark Zuckerberg. (2022, February 23). Inside The Lab: Building for the Metaverse with AI [Live]. Facebook. https://www.facebook.com/zuck/videos/677947796579229



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