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TITLE:

# DECRYPTING THE BLACK BOX

a designer's journey into the infinite possibilities of ML in design

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# DECRYPTING THE BLACK BOX

A DESIGNER'S JOURNEY INTO THE INFINITE POSSIBILITIES OF ML IN DESIGN

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# //Abstract

# 1. Abstract

One of the most significant and revolutionary methods in modern computer science is machine learning (ML) [1]. It entails the unsupervised statistical inference of models from data. In design applications, these models hold great promise for creating and synthesizing new and sometimes innovative design alternatives. It enables creative practitioners—designers, artists, and architects—to produce novel results based on sample data. Machine learning is a powerful tool for solving complex problems, but it can also be difficult to understand and use effectively.

This thesis is my personal journey into the infinite possibilities of ML in design, more concretely into the possibilities of generative systems of volumetric forms. During this thesis, I have been exploring and documenting the challenges and opportunities of ML as a design tool, trying to make it more comprehensible and accessible for other designers. Through a series of three design-research experiments, I have investigated the potential of ML, more concretely, the use of the latent space — lower-dimensional vector space that captures the underlying structure or patterns in the data that the model is trying to generate— learned by ML models for design exploration, reflecting on not only my personal but also empirical takeaways from each experiment and providing guidance for readers who wish to repeat the experiments or try new ones inspired by my findings.

In experiment 1, I compare the parametric space with the feature space extracted from an ML model and show that the later can be used as tool for design exploration. Experiment 2 is a more exploratory project inspired by the mismatches between the way computers and humans understand everyday objects. With the training of an ML model in a chair dataset and the subsequent fabrication of one of the outputs, I explore the fundamental shift in design that the use of computational tools will have in the future, as well as the idea of authorship. Experiment 3 is an inquiry into alternative approaches to interacting with generative systems based on the interpretation and visualization of the latent space.

Overall, this thesis offers a personal perspective on the challenges and opportunities of using generative systems as a design tool and presents the latent space as an alternative way to interpret and analyze volumetric shapes. This thesis serves as a starting point for another creative practitioner that wants to embark on the journey of using machine learning in design. My experiments can serve as guidance for those interested in exploring the potential of latent space as a design exploration space, or for those who want to explore new ways of using machine learning to create richer forms. Through this thesis, I demonstrate that machine learning can be a powerful tool for improving creativity in design and offer insights into how designers can harness this technology to generate innovative and exciting outcomes.

# //Introduction

# 2. Introduction

The Guggenheim Museum in Bilbao, designed by renowned architect Frank Gehry in the early nineties, serves as a prime example of how computational tools revolutionized the field of design. To bring his visionary design to life, Gehry's hand-built models were meticulously translated into digital data using CATIA (Computer Aided Three-Dimensional Interactive Application)[1]. At the time, this cutting-edge software was predominantly utilized within the French aeronautical industry, and Guggenheim museum in Bilbao was the first building to be built using this technology.

Before the Guggienheim, the design field was already being transformed by the introduction of computational tools. Sketchpad, the pioneering CAD software developed by Ivan Sutherland at MIT [2] was introducing in early in the early 1960s. This groundbreaking software enabled designers to interact with the computer using a light pen and draw directly on the monitor, marking the beginning of a new era in design, computational design tools, allowing nowadays common actions in the design practice like undoing an action (control+Z).

For creative practitioners in fields like computational design, the fusion of design expertise and technical prowess unlocked a realm of previously unattainable possibilities. CAD software, as it was the case of CATIA, or Grasshopper and Rhino, empowers designers to envision increasingly intricate forms or even the study of design alternatives without needing to actually fabricate or prototype them.

Concurrently, the advent of advanced fabrication techniques, such as CNC machining, laser cutting and additive manufacturing (e.g., 3D printing) have facilitated the materialization of complex designs. Examples of this shift in design and fabrication could be like the case of Nectary [3], a modular system able to create an infinite number of morphological variations or the complex forms and structures out of planar linear stripes of the MARC FORNES / THEVERYMANY studio [4]. As a result, the marriage of design knowledge and computer science continues to redefine the boundaries of creativity and innovation that translate into volumetric forms that were previously inimaginable.

[1] a software suite for computer-aided design, computer-aided manufacturing, computer-aided engineering, 3D modeling and product lifecycle management, developed by the French company Dassault Systèmes.

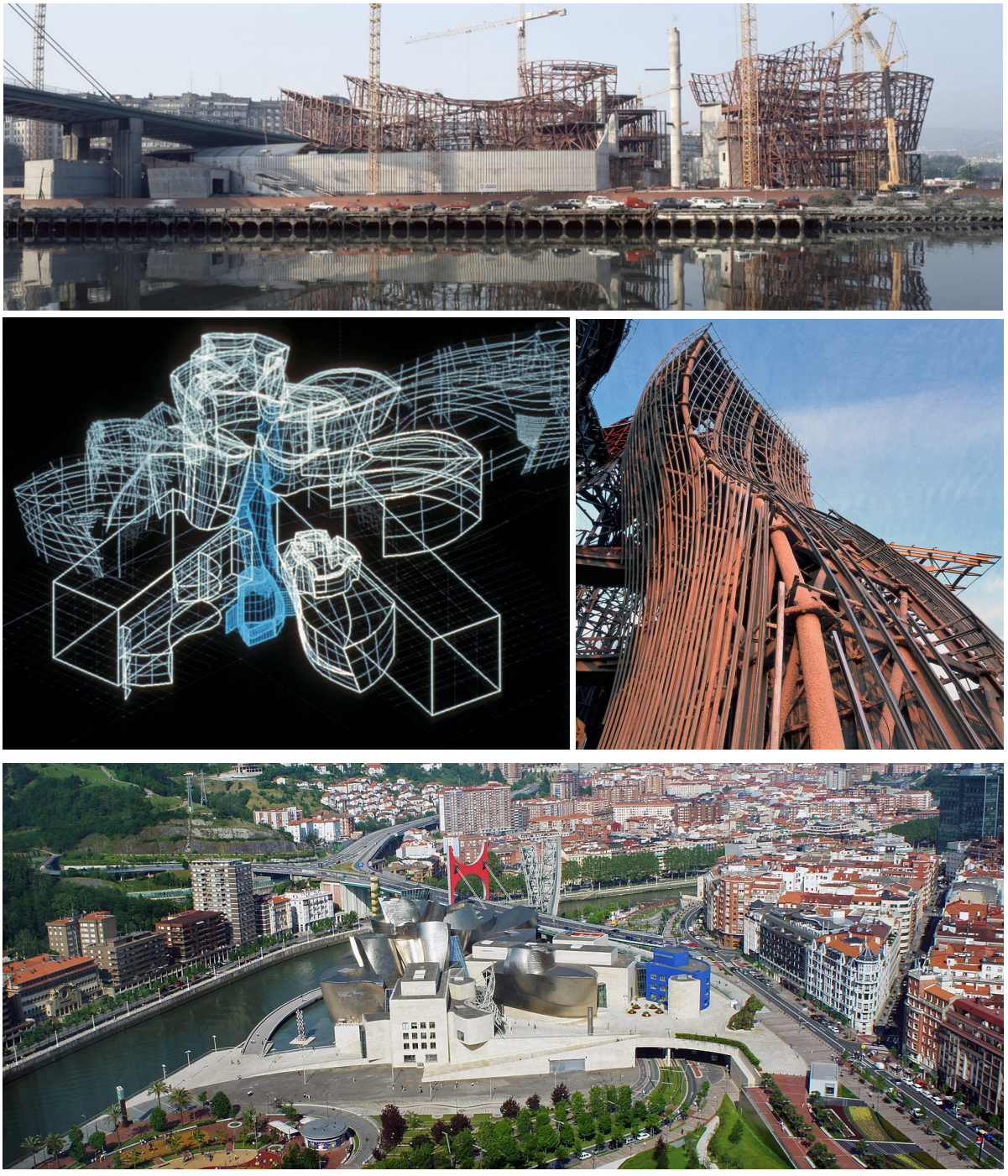


Figure 1. Photos from Guggenheim museum in Bilbao. Top: detail of the structure of the building during construction. Middle left: digital model of the volumetric shape of the building. Middle right: detail of the curvature of the building's structure. Bottom: panoramic view of the building and the surrounding buildings. Images retrieved from [7–9].

Initially, Gehry was hesitant to adopt this digital approach for the Guggenheim project, given the novelty of the technology. However, upon witnessing the ease of use and the impressive results that the software delivered, he quickly became a fervent advocate of the technology. CATIA enabled Gehry's team to navigate the complexities of the museum's design, which might have been insurmountable without the assistance of such advanced computational tools.

> *"CATIA provides a way for me to get closer to the craft ", says Frank Gehry,. " In the past, there were many layers between my rough sketch and the final building and the feeling of the design could get lost before it reached the craftsman. It feels like I've been speaking a foreign language, and now, all of a sudden, the craftsman understands me. Flat drawings of curved surfaces can be beautiful, but they are deceptive; with CATIA you can see how to build it." - Frank Gehry [5]*

The successful realization of the Guggenheim Museum in Bilbao stands as a testament to the transformative power of computational design and its capacity to facilitate the creation of architecturally groundbreaking structures.

Now, the emergence of machine learning (ML) as a groundbreaking addition to the design process represents the next frontiers in computational design, and is set to redefine the boundaries of creativity and innovation, much like CAD tools did in the past. As we have seen with the Guggenheim Museum in Bilbao, the successful adoption of novel technologies like CATIA facilitated the creation of architecturally groundbreaking structures. Similarly, the rise of accessible and user-friendly platforms like Nvidia, Google, and OpenAI, have paved the way for cutting-edge research and innovation in machine learning, empowering designers to explore the untapped potential of this technology. This thesis delves into the current state of machine learning, its potential applications, and the challenges and limitations that may hinder its understanding and utilization by creative professionals.

A notable example of the potential of ML in design is the first-ever AI-generated cover for Cosmopolitan magazine. While the cover reports that the image itself was generated in just 20 seconds, it is essential to recognize that the entire design process leading up to the creation of the final prompt, and consequently, the cover image, was significantly longer [6]. This highlights the importance of understanding the intricacies and iterative nature of the design process when integrating machine learning. However, trendy applications are mainly either text or image, three dimensional ML models, that are the

ones explored in this thesis, are not that popular yet even there is a lot of state of the art research on them.

As seen in the generation of the Cosmopolitan cover, generative systems in design offer seemingly infinite possibilities, raising the question of how designers can effectively narrow down and select the most suitable design solutions and alternatives for exploration. Machine learning models often utilize high-dimensional data, which can be challenging for humans to visualize, constrained by our understanding of the three-dimensional world. The task of clarifying and visualizing this complexity becomes crucial in bridging the gap between the virtual and physical realms.




Figure 2. First ever AI generated magazine cover retrieved from Cosmopolitan Magazine [10]

To effectively harness the potential of machine learning, designers must consider the limitations and possibilities of data representation in virtual environments, as well as the fabrication and materialization of these virtual concepts in the physical world.

The introduction of CAD and advanced fabrication methods has already significantly impacted the relationship between imagination and materialization in design. However, machine learning has the potential to revolutionize this process even further, redefining the boundaries between what can be conceived and what can be brought to life. As we

continue to explore and integrate machine learning into the design process, the creative landscape is poised to undergo an unprecedented transformation.

With the increasing ease and precision of machine learning, individuals with Internet access can now generate entire rooms, objects, buildings, cities, and ecosystems, further bridging the gap between imagination and materialization. This revolution surpasses the influence of CAD and advanced fabrication methods on design, ushering in a new era of creative potential.

In summary, the impact of machine learning on creative tasks is complex and multifaceted. This thesis, within the context of ML in design, aims to examine the current state of machine learning, exploring both its potential applications and the difficulties associated with using and understanding these models. Despite advancements in the field, significant challenges persist that can limit widespread adoption and use. Major challenges with machine learning models include the reliability of their outputs, which can sometimes be dysfunctional, such as an ML-generated chair missing half a leg. Additionally, interacting with these ML models is not very intuitive for novel users without a clear understanding of feature extraction or latent[2]space navigation. Moreover, training these ML models requires extensive and clean datasets.

[2] Latent space is a reduced-dimensionality vector space in which generative systems operate, learned during a machine learning training process by mapping the training data to a lower-dimensional vector space. It refers to a statistical representation of the underlying structure or patterns in the data that the generative system generates. This space is also known as the feature space as it is generated by the features extracted by the ML model during training.

The estimation of the statistical distribution of the training dataset is a fundamental phase in the ML model training process. It is at this stage that the latent space is produced. The hypothesis of this thesis is that latent spaces learned in both VAEs and GANs can be used as a space for design exploration. Therefore, the latent space is a core part of this thesis. Variational Autoencoder (VAE) and Generative Adversarial Network (GAN) are the two generative models used in this thesis, and even though their architecture and the way they learn the data are different, this thesis considers them equivalent for the purpose of visualization and analysis in design exploration.

## 2.1. Research questions

Machine learning (ML) is a new tool for design practice that is reconfiguring the whole design process. With generative systems capable of learning complex datasets and producing infinite outputs based on the data they have been trained on, there is enormous potential for exploring new possibilities in design.

In this thesis, I want to research the possibilities and limitations of the latent space learned by ML models as a tool to support creative practitioners for design exploration. Even the final question for this thesis is **How does the latent space within volumetric ML processes influence (or change) the way creative practitioners work on three-dimensional designs?** Therefore, I have divided it into more concrete questions and that are more related with each of the experiments in this thesis and that focus on how the latent space can be used as a new way to interpret design alternatives and construct design spaces with a big potential to as a design tool for the study of volumetric forms.

1. **How can the latent space help creative practitioners in design exploration?** *Can it help consider the infinite design variants while avoiding under-exploration of a subset of the design space?*

2. **Can creative practitioners construct a latent space from the different variants of an already existing object?** *What are the similarities and differences between the way machine learning and humans understand objects? What are the possibilities and limitations of representing the physical world virtually, and what are the implications of this for design practice?* **How can we effectively fabricate and materialize the virtual outputs of machine learning models, and what are the challenges and opportunities involved in this process?**

3. **How can the latent space be effectively visualized to be used as a design tool?** *Can latent space interpolation be used in order to communicate the complexity of ML for better design applications?*

## 2.2. Hypothesis

The use of computational design tools has significantly expanded the design space available to creative practitioners, resulting in a larger number of design alternatives that can be generated and compared[3]. However, this increased design space poses a challenge

[3] The fact that opening a 3D file in a computer that includes even the materials of the object, have allowed creative practitioners to compare design alternatives without the need to prototype. This has resulted in faster and more complex brainstormings were the only limitation is on the forms that the computer can generate.

in terms of comparing and making decisions. To address this challenge, the construction of the design space is crucial, requiring a solution that allows for both general decisions on a large scale and precise control over local comparison of design alternatives.

The latent space learned by machine learning generative models offers a new potential for design exploration. By incorporating the latent space as an additional design space, designers can produce or identify new design alternatives, variants, and unexplored terrains that challenge their existing design conventions and decisions. Through an investigation of the potential and limitations of using the latent space as a design space, this thesis seeks to provide insights into how creative practitioners can effectively use this space to enhance their design explorations and decision-making processes.

## 2.3. Structure of the thesis

The background section of this thesis explores the concept of randomness and infinite possibilities, drawing inspiration from literature and art. It begins by examining Jorge Luis Borges' "The Library of Babel," which serves as a metaphor for the overwhelming potential of the infinite. Next, the section further explores the concept of the infinite and randomness through the work of artist Jackson Pollock, whose seemingly chaotic yet captivating paintings raise intriguing questions about authorship and agency over randomness. The section then introduces the idea of using machine learning (ML) as a design tool to explore the infinite space of possibilities, focusing on the construction and technical details of the latent space.

In the subsequent sections, the thesis is organized around three smaller experiments, each presented as an article. Each experiment can be read independently, but when read in order, these three articles constitute the chronological development of the thesis and the author's personal journey into the possibilities and limitations of ML as a design tool.

In the conclusion and future work section, the key findings and results of the research are summarized, presenting a concise overview of what has been accomplished and discovered. The section also highlights potential future directions for research and suggests experiments that can serve as starting points for future investigations in this field.

# //Background

# 3. Background

This section is not a typical background chapter of a master thesis where previous scholarly work is briefly introduced. Later, in each of the experiments (see Chapter 4,5,6) previous research has tackled the research questions and area of study will be introduced and described.

The background chapter of this thesis is, instead, used to introduce two of my personal art references and inspirations for this thesis: *The Library of Babel* short story by writer Jose Luis Borges and the drip paintings by artist Jackson Pollock. These two authors' work is used to introduce the ideas of the infinite, randomness, and authorship; key concepts that frame this thesis.

After touring these ideas, an introduction to ML as a tool for design follows, along with a technical description of what the latent space is and how it is constructed[4].

## 3.1. The library of Babel - Jose Luis Borges

> *"The universe (which others call the Library) is composed of an indefinite and perhaps infinite number of hexagonal galleries, with vast air shafts between, surrounded by very low railings. From any of the hexagons one can see, interminably, the upper and lower floors. The distribution of the galleries is invariable. Twenty shelves, five long shelves per side, cover all the sides except two; their height, which is the distance from floor to ceiling, scarcely exceeds that of a normal bookcase. One of the free sides leads to a narrow hallway which opens onto another gallery, identical to the first and to all the rest. [...]*
>
> *Five hundred years ago, the chief of an upper hexagon came upon a book as confusing as the others, but which had nearly two pages of homogeneous lines. He showed his find to a wandering decoder who told him the lines were written in Portuguese; others said they were Yiddish. Within a century, the language was established: a Samoyedic Lithuanian dialect of Guarani, with classical Arabian inflections. The content was also deciphered: some notions of combinative analysis, illustrated with examples of variations with unlimited repetition. These examples made it possible for a librarian of genius to discover the fundamental law of the Library. This thinker observed that all the books, no matter how diverse they might be, are made up of the same elements: the space, the period, the*

[4] Note to the reader: reading this background chapter is not necessary to follow and understand the experiments of this thesis, that being said, these sections constitute a nice prelude for the work done on this thesis and give a wider overview of the intentions of this thesis.

*comma, the twenty-two letters of the alphabet. He also alleged a fact which travelers have confirmed: In the vast Library there are no two identical books. From these two incontrovertible premises he deduced that* ***the Library is total and that its shelves register all the possible combinations of the twenty-odd orthographical symbols*** *(a number which, though extremely vast, is not infinite): Everything: the minutely detailed history of the future, the archangels' autobiographies, the faithful catalogues of the Library, thousands and thousands of false catalogues, the demonstration of the fallacy of those catalogues, the demonstration of the fallacy of the true catalogue, the Gnostic gospel of Basilides, the commentary on that gospel, the commentary on the commentary on that gospel, the true story of your death, the translation of every book in all languages, the interpolations of every book in all books.*

*When it was proclaimed that the Library contained all books, the first impression was one of extravagant happiness. All men felt themselves to be the masters of an intact and secret treasure. There was no personal or world problem whose eloquent solution did not exist in some hexagon. The universe was justified, the universe suddenly usurped the unlimited dimensions of hope. At that time a great deal was said about the Vindications: books of apology and prophecy which vindicated for all time the acts of every man in the universe and retained prodigious arcana for his future. Thousands of the greedy abandoned their sweet native hexagons and rushed up the stairways, urged on by the vain intention of finding their Vindication. These pilgrims disputed in the narrow corridors, proferred dark curses, strangled each other on the divine stairways, flung the deceptive books into the air shafts, met their death cast down in a similar fashion by the inhabitants of remote regions. Others went mad ... The Vindications exist (I have seen two which refer to persons of the future, to persons who are perhaps not imaginary) but the searchers did not remember that the possibility of a man's finding his Vindication, or some treacherous variation thereof, can be computed as zero."*

*The library of Babel - Jose Luis Borges*

"The Library of Babel" is a short story by Jorge Luis Borges, first published in 1941. It is considered one of his most famous works and it is characterized by its imaginative, philosophical, and highly paradoxical nature. The story is set in a vast library, which is said to contain every possible combination of 25 symbols, forming every book that has ever been written or will be written[5]. The library is described as a labyrinthine structure, with hexagonal rooms and spiraling staircases, and is inhabited by librarians who believe

[5] explore the library of Babel digitally in https://libraryofbabel.info/

that the library is the universe. The narrator of the story, who is a librarian himself, reflects on the nature of the library and the meaning of its contents.

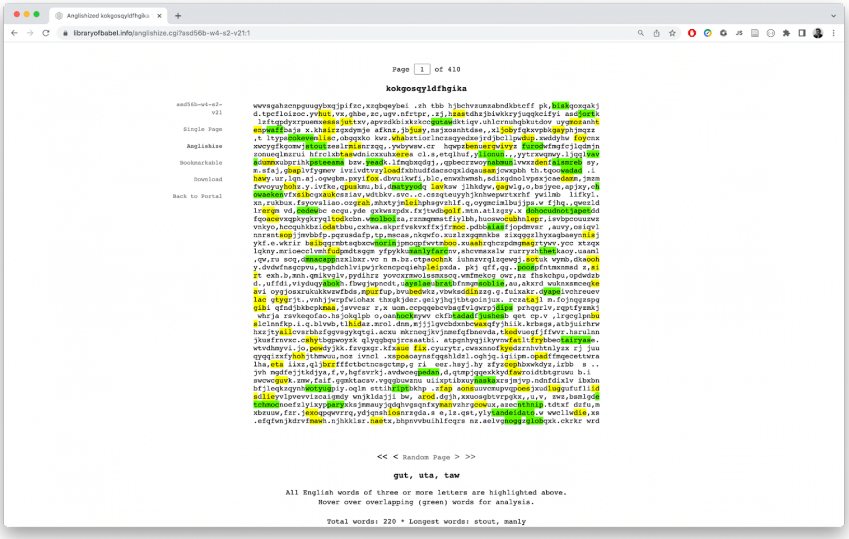



Figure 3. Screenshot of the https://libraryofbabel.info/ , a website that allows you to pick a random book from this library of Babel and analyse the random outputs and find english words.

This repository of knowledge in the library is both a blessing and a curse, as it contains the solutions to all questions and mysteries but is also plagued by the sheer enormity of its contents. The infinite nature of the library makes it nearly impossible for an individual to find a specific, meaningful piece of information amidst the overwhelming noise[6]. In this book, Borges explores the concepts of infinity and the limitations of human knowledge and understanding.

The library, representing an infinite and seemingly overwhelming amount of information, can be seen as a metaphor for the design exploration process. In this context, the designer is faced with an endless array of design variants to consider and compare. This vast expanse of possibilities can be both inspiring and daunting, as the designer must navigate the boundless sea of potential outcomes in search of the ideal solution.

The same way lucky visitors of the Library of Babel could discover never-before-seen theories, such as notions of combinative analysis illustrated with examples of variations with unlimited repetition, designers may find new innovative solutions for a design problem in the infinite possibilities of design exploration.

[6] The word noise is often use in this thesis. It is used to refer to something merely random, with no important information. Even noise is sound, however, we cannot hear/learn anything useful from noise.

Embracing randomness can lead to unexpected discoveries and solutions that might not have been reached through a more controlled, linear approach. Incorporating randomness in the design process, designers can break free from conventional thinking patterns and explore a more diverse range of possibilities, pushing to venture beyond the familiar and the conventional, and ultimately expanding the horizons of what is deemed possible in the realm of design. However, just as in the library, the challenge lies in filtering through the noise and identifying meaningful insights in the chaotic landscape of random ideas. Balancing the use of randomness with structured thinking and critical evaluation can help designers navigate the endless possibilities while still achieving purposeful and effective outcomes.

In the context of design exploration, embracing randomness can lead to unexpected discoveries and solutions that might not have been reached through a more controlled, linear approach. Designers can break free from conventional thinking patterns and explore a more diverse range of possibilities, ultimately expanding the horizons of what is deemed possible in the realm of design. However, navigating the endless possibilities of the design space can be challenging, and two concerns arise: How can designers separate valuable information from the noise? And, given that every design alternative is already part of the infinite design space, can a designer claim authorship over a concrete ideal variant? To address these concerns, designers can balance the use of randomness with structured thinking and critical evaluation, helping them filter through the noise and identify meaningful insights in the chaotic landscape of random ideas. With this approach, designers can navigate the boundless sea of potential outcomes in search of the ideal solution, ultimately achieving purposeful and effective design outcomes.

## 3.2. Pollock, Randomness and Authorship

Paul Jackson Pollock (1912-1956) was an influential American painter and a leading figure in Abstract Expressionism. His revolutionary "drip painting" technique, in which he threw paint onto a canvas laid on the floor, not only defined his artistic signature but also created a new language and area of exploration in the art world. This gestural painting style, characterized by spontaneity and action, propelled contemporary art forward and fostered the development of Abstract Expressionism. Pollock's work played a crucial role in establishing the United States as a leading country in contemporary art [1].

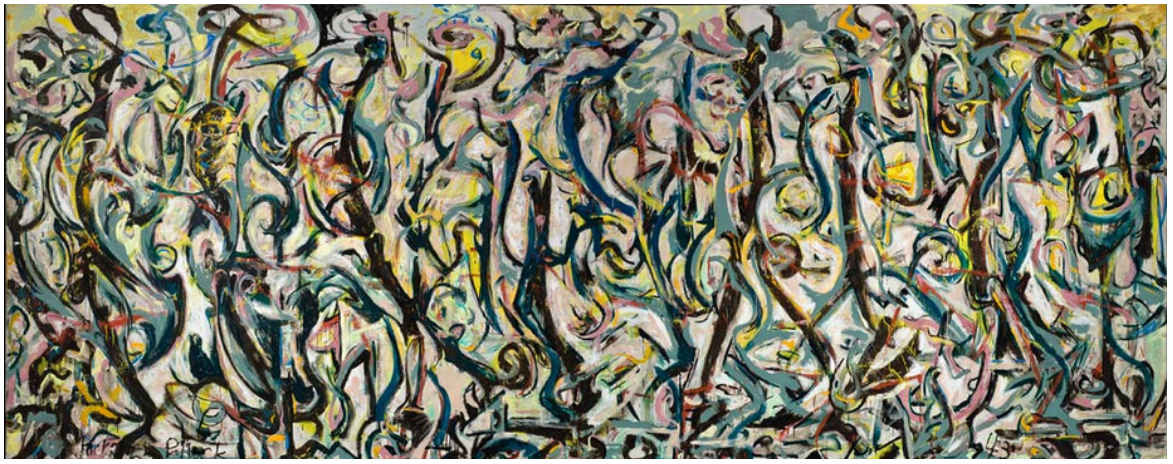


Figure 4. Pollock, J. (1943). Mura  Iowa City, University of Iowa Museum of Art .

Jackson Pollock was an artist who meticulously calculated each interaction with his work. Based on his artistic instinct, he would analyze the painting and then allow chance to determine the result when he threw paint onto the canvas. This groundbreaking approach transformed the history of art.

Pollock's method eliminated direct contact between the artist and the artwork. The brush transitioned from a traditional painting instrument to a tool for throwing paint onto the canvas. Concurrently, the canvas shifted from a vertical to a horizontal support, providing the artist with greater freedom of movement. This approach is evident in the photographs taken by German photographer Hans Namuth, which showcased Pollock at work in his studio. According to cultural critic and journalist Ferdinand Prost, these images helped transform Pollock from a reclusive, moody talent into America's first media-driven superstar of contemporary art – the chain-smoking, jeans-clad poster boy of Abstract Expressionism [2]. The photographs demonstrated that Pollock's work resulted from deliberate action rather than random paint splattering.



Figure 5. Jackson Pollock analyzing his work. Photograph by Hans Namuth c. 1950.

This aspect is particularly relevant to the present work, as it suggests that the artist's role shifted from a direct actor to an observer. Pollock did not paint predetermined images; instead, he released paint onto the canvas and later analyzed the results to decide how to proceed. This approach didn't diminish the artist's importance but rather reshaped the traditional concept of artistic creation. Pollock's paintings were not solely the products of his actions but also influenced by environmental and physical conditions. It would be intriguing to see how Pollock's actions would have manifested in different environments, such as those with stronger air currents or zero gravity [3]. Despite being considered easy to imitate, subsequent analyses of Pollock's work revealed unique relationships that are not easily replicable.



Figure 6. Jackson Pollock in his studio 1956-1957. Photograph by Hans Namuth.

However, it wasn't until 1999, when Richard Taylor's mathematical analysis showed that Pollock's paintings exhibited fractal patterns [4]. The term "fractals" was proposed in 1975 by mathematician Benoît Mandelbrot in his work "Fractals: Form, Chance, and Dimension" [5] to describe objects with recurring basic structures at different scales.

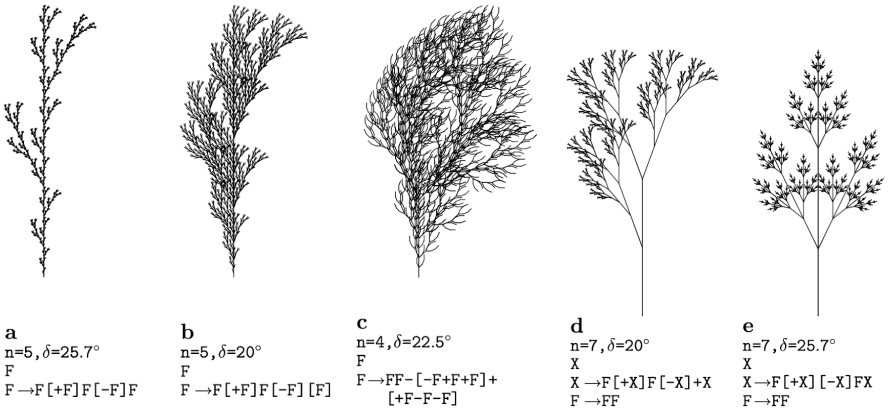



Figure 7. Examples of plant-like fractal structures generated by Lindenmayer systems. From the . ‘The algorithmic beauty of plants. ‘ Prusinkiewicz, P., & Lindenmayer, A. (1996) [12]

Many natural structures exhibit fractal patterns, which may explain the organic appearance of Pollock's work. It seems that Pollock managed to understand and capture the essence of nature in his art 25 years before the concept of fractals was introduced in mathematics.



Figure 8. Compication of a picture of the roots of a tree and the work of PollockNumber 32. From ‘Personla reflections Jackson Pollock's fractal paintings’ by R. Taylor. [7]

Perhaps now one can think that therefore, the value of Pollock's work is in the fractals and not the artist, however, the computer analysis of different paintings have allowed us to find a pattern in the artist's works. The artist's work has been compared to paintings made by others using the same technique and subsequent computer analysis has revealed that none of these paintings matched the fractal features found in Pollock's work. Confirming that Pollock's fractals were not just the result of throwing paint against a canvas but the consequence of a particular technique, a signature that today allows us to distinguish a real Pollock from an imitation with a 93% certainty [8].

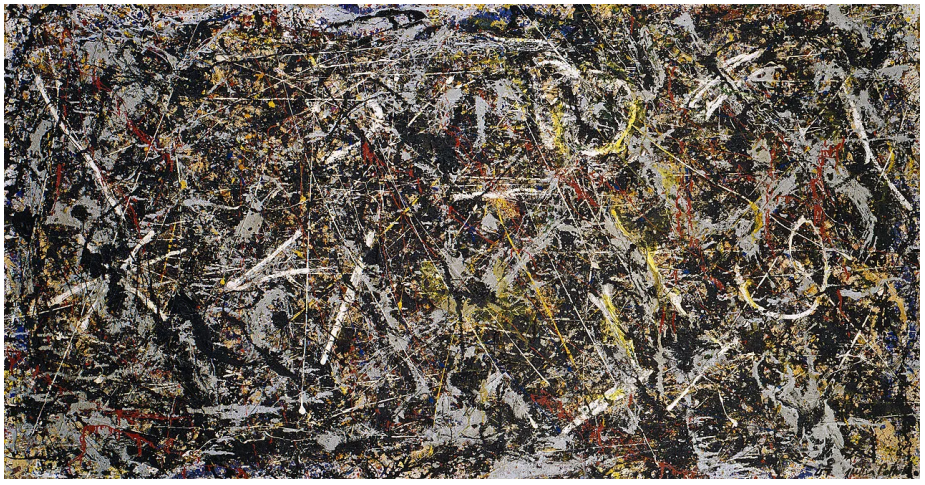


Figure 9. Jackson Pollock, P. (1947). Alchemy painting. The Solomon R. Guggenheim Foundation, Peggy Guggenheim Collection, Venice, 1976.

This shows that Pollock's value was in his meticulous observation and subsequent action. The style is preserved despite the distance from his work, despite not being a direct actor. Something interesting in this work, in which the designer distances himself from the object and becomes an observer once the algorithm starts working. Once the designer develops the algorithm, it stays in the background.



Figure 10. Jackson Pollock analizing his work. Photograph by Hans Namuth c. 1950.

When the designer begins the first phases of the design of a new product or service, he is conditioned by the result he wants to achieve. Despite using different design methodologies, the use of randomness allows us to get out of this comfort zone. Add uncertainty; or new possibilities, depending on how you look at it, in the design process as a tool for creativity. It is the search for these new forms, these new possibilities that motivate this work. The search for new addresses, which would not have been considered without the help of randomness.

The use of unexpected elements in both Jackson Pollock's paintings and randomness highlights the power of chance in the creative process. In Pollock's work, the dripped and

splattered application of paint creates unique and dynamic compositions that challenge traditional notions of composition and form. Similarly, designers can use algorithms and randomness to generate new and unanticipated outputs, but the ultimate result is heavily influenced by the agent making the decisions, whether it is Pollock's intuition and creativity, or the training loss function of the machine learning algorithm (as we will see in the next section). This comparison emphasizes the importance of balancing technology and human judgment in the creative process, as both Pollock and randomness demonstrate the potential for chance to generate exciting and innovative outcomes, but also the need for human intuition and decision-making to guide the direction of the final result. In the next section, we will explore how machine learning algorithms through their loss functions are able to infer the statistical distributions of the data they are trained on, serving as a tool to reduce noise and help the designers use randomness with a certain control.

## 3.3. Machine learning as a Design Tool to explore the Infinite Space of Possibilities

The advancement of machine learning research has opened up a vast field of possibilities for exploring and navigating the space of possibilities in the world of art and creativity. This section examines how ML tools can help designers and artists reduce noise and infinite options by focusing on the relevant and meaningful possibilities for humans. ML is a tool that will pick the books from the library of Babel that make sense, allowing the designers to only explore meaningful alternatives instead of getting lost in noise.

The concept of the space of possibilities is abstract, representing all possible combinations of elements within a specific domain, similar to the library of Babel. For instance, in the realm of two-dimensional art and design, this space encompasses all conceivable images and styles that can be created from a given image. While theoretically infinite, in reality, only a small subset of these possibilities is meaningful and relevant to humans. An example of this is shown in the following image, which displays the difference in output before and after the training of a Generative Adversarial Network (GAN) [9]. Figure 11. on the left, exhibits random colors (noise), while the image on the right portrays grumpy cats. This is because the GAN was able to infer the statistical distribution the dataset of cat pictures used for training. . Among all the noise, among all the possible possibilities of combinations of colors, the GAN has been able to learn what an image of a grumpy cat is.

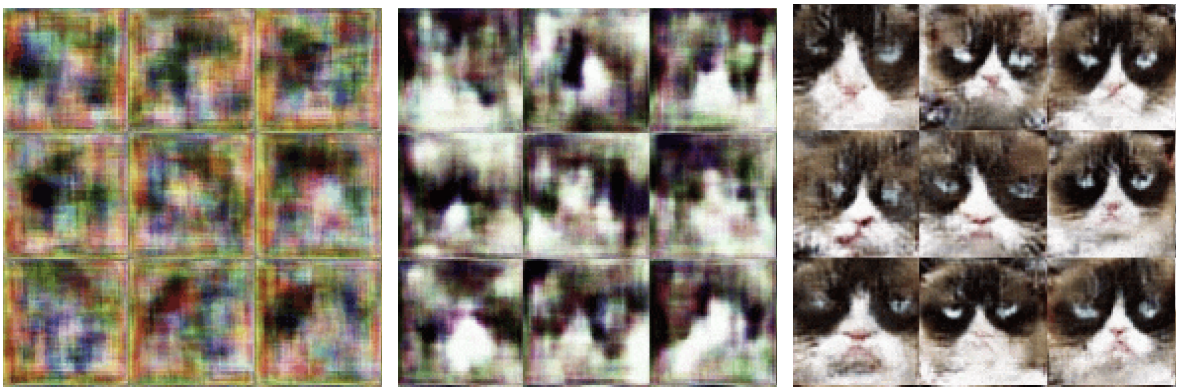


Figure 11. Outputs of the training of a simple GAN in a dataset of grumpy cats. On the left the initial outputs of the model, mainly noise. On the center, outputs of the middle of the training, where the GAN has learned the colors and some features like the eyes can be imagined. On the right, results of the end of the training where the cats faces can be differentiated. [7]

By inferring statistical distributions from the data they are trained in, the role of ML in design is to act as a guide that helps artists and designers navigate this infinite space of possibilities and help them focus on the ones that actually make sense. ML models can identify and explore subsets of possibilities that are relevant and meaningful to humans, eliminating noise and irrelevant options. For example, instead of generating random and noisy images, an ML tool can explore and generate images that are stylistically coherent and conceptually relevant to a specific theme or style, like the previous grumpy cats. Additionally, ML tools can learn from input data provided by artists and designers, allowing them to adapt and refine their results based on user preferences and needs.

By reducing noise and irrelevant options, ML models offer significant potential to revolutionize the field of design by enabling artists and designers to navigate and explore the infinite space of possibilities in a more efficient and effective manner, ultimately enhancing creative processes and enabling the development of innovative and unique designs. The integration of ML tools in the world of art and design not only facilitates exploration and experimentation but also has the potential to redefine the boundaries of human creativity and artistic expression. Among all the different new options that ML development has brought to design, this thesis focuses on the use of the latent space as a new tool for design exploration of volumetric forms. By using DL to extract design features from 3D models, a well-distributed design space can be constructed from the latent space that offers a new mechanism for exploring the diversity of options in large design spaces and visually comparing design alternatives. If introduced into the early stage of design, this approach has the potential to enhance the design exploration process.

[7]More information about this project in https://tomascbzn.com/IS.html

# //Experiments

# 4. Experiments

This thesis is an umbrella of three design-research experiments. Each of the experiments will be presented as an article, so each can be read as a single unit text, without needing to read the rest of this thesis, however, the three experiments are connected between them. Experiment 1[8] and 3[9] keeps the original style, language and formatting of the conferences where they were submitted to maintain a visual reference to the communities in which they were described.

**- Experiment 1** proposes the latent space as a new tool for design exploration. This experiment is a comparison between the parametric space and the feature space using VAE as the ML model

***Overview.*** *This experiment compares the parametric design space with a feature space generated by the extraction of design features using deep learning (DL) as an alternative way for design space exploration. In this comparison, the parametric design space is constructed by creating a synthetic dataset of 15.000 elements using a parametric algorithm and reducing its dimensions for visualization. The feature space — reduced-dimensionality vector space of embedded data features — is constructed by training a DL model on the same dataset. We analyze and compare the extracted design features by reducing their dimension and visualizing the results. We demonstrate that parametric design space is narrow in how it describes the design solutions because it is based on the combination of individual parameters. In comparison, we observed that the feature design space can intuitively represent design solutions according to complex parameter relationships. Based on our results, we discuss the potential of translating the features learned by DL models to provide a mechanism for intuitive design exploration space and visualization of possible design solutions.*

**-Experiment 2** continues over experiment 1, but this time training the VAE on a dataset of already existing objects.

***Overview****. This experiment explores the mismatches between the way computers and humans understand volumetric objects and their potential impact on the future of design and fabrication. It presents an experiment in which a machine learning model is trained with a database of already existing object, chairs, and one of the outputs is fabricated as a speculative experiment on the the shift in design and authorship of the development of*

[8] This paper was already published in CAADRIA 2023 conference as:
Pedroso, T. C., Rhee, J., & Byrne, D. (2023). Feature space exploration as an alternative for design space exploration beyond the parametric space.

[9] This paper will be presented as a technical demonstration in the Creativity and Cognition 2023 conference as:
Browsing the Latent space: A New Approach to Interactive Design Exploration for Volumetric Generative Systems

*ML. The article discusses the challenges in representing 3D data in digital form and the different methods used to generate ML models that are able to learn this data. The result is a chair designed by a computer and built by a designer. The material and technique decisions made in the fabrication process highlight the discrepancies between human and computer perceptions of essential components of an object. This leads to a thought-provoking artwork that raises questions about the future of design and the role of humans and machines in the creative process. Overall, the experiment demonstrates the potential but also the limitations of machine learning models to generate not just digital models, but also physical objects that are both functional and visually appealing.*

**-Experiment 3** continues with the analysis of the latent space as a space for design exploration that was done in experiments 1 and 2, however, instead of using a VAE, this experiment builds over the limitations of experiment 2 and uses a Generative Adversarial Network (GAN).

***Overview.*** *This experiment introduces an interactive tool called "Browsing the Latent Space" (BLS), which explores the potential of latent space visualization and interpolation in 3D generative systems for design space exploration. By visualizing and interpreting the abstract space in which the outputs produced by generative systems operate (the latent space), users gain a better understanding of how the model generates its outputs, and can explore underlying patterns and structures in the data. Using the GET3D generative model, this demonstration showcases how latent space manipulation can enhance the creative process and provides an intuitive and interactive way to explore, remix, and create new chair designs. Allowing interaction with and manipulation of the generative system's outputs in real-time, this tool supports increased awareness of the latent space as a resource for a designer's understanding of generative systems and creative exploration.*

# //Experiment_1

LATENT SPACE EXPLORATION AS AN ALTERNATIVE
WAY OF LOOKING AT DIGITAL OBJECTS BEYOND
THE PARAMETRIC SPACE

# FEATURE SPACE EXPLORATION AS AN ALTERNATIVE FOR DESIGN SPACE EXPLORATION BEYOND THE PARAMETRIC SPACE

## 1. Introduction to Experiment 1

Parametric modeling has acquired widespread acceptance among creative practitioners as it allows the synthesis of various design options and solutions. Changing the parameters in this modeling process, either manually or randomly, can rapidly create a vast set of design variations (Toulkeridou, 2019). Navigating the resulting *parametric design space* — where the design variants are topologically placed by their parameters — is part of the *design exploration* process — a crucial step in the development of new alternatives and design solutions. Exploration of the parametric design space allows creative practitioners many benefits: to reach satisfying solutions, better define design problems, and understand the opportunities and limitations of the possible solutions.

Despite these benefits, design exploration is laborious within the parametric space and challenged along two fronts: comparison and selection (Fuchkina et al., 2018). Parametric design exploration is an iterative process that focuses on the variation of these individual parameters, rather than on the relationship among them (Yamamoto and Nakakoji, 2005). Hence, comparing one design solution with others by their parameters alone does not always result in a superior solution; for example, the variants generated by the local combination of parameters might not match the design requirements. Moreover, infinite alternative design solutions can be generated by inputting new parameter values. Thus, the parametric design space consists of a huge amount of design variants that cannot be fully or sufficiently explored.

We propose an alternative way to construct and examine the design space, by extracting features from a DL model. By comparing and analyzing how the DL *feature design space* differs from the parametric design space, we illustrate the potential of feature design space for design practitioners during the design exploration process and provide a new way to compare, examine and select the design alternatives based on the exploration of a properly constrained design space.

No previous approach to compare the parametric design space and feature design space as design exploration tools has been found. To demonstrate how the feature space compares to the parametric space, we designed an experiment to construct both a parametric design space and a feature design space using the same dataset. The dataset consists of 15.000 synthetic 3D models produced by a parametric algorithm with five parameters. This parametric design space consists of five axes; each axis corresponds to each of the parameters that are used as inputs of the parametric algorithm. Subsequently, this same dataset is used to train a DL model to compress the data into a feature vector of 128 dimensions. Both the parametric space (five-axes) and the feature space (128 axes) are not directly visualizable due to their high dimensionality. Nevertheless, as visual feedback plays an important role in design exploration (Bradner, Iorio and Davis, 2014), we employ a dimensionality reduction algorithm (t-SNE) to the design space. We are able to illustrate the design exploration space, showing how the data is distributed across both the parametric and feature design spaces.

In the next section, we describe the generation of the dataset, as well as the construction of parametric design space and its visualization. In Section 3., we illustrate how training a DL model resulted in a feature space for design exploration and comparison with the parametric approach. Then, in Section 4., we will compare, contrast, and discuss the characteristics of the DL feature space and the parametric space. (Figure 1.)

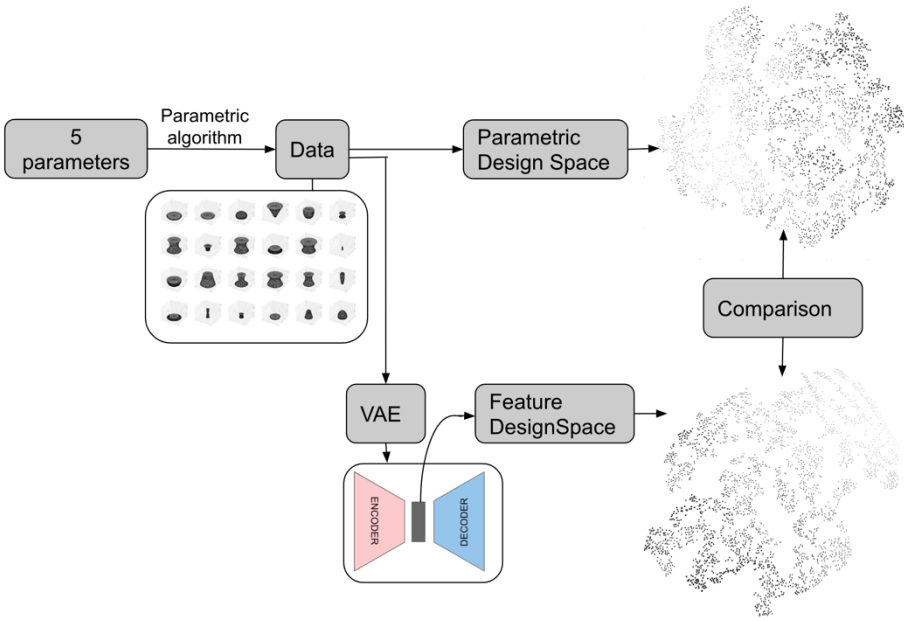



Figure 1. The overall process of comparing parametric design space and feature space from deep learning

## 2. Constructing Parametric Design Space

### 2.1. DATASET GENERATION

To conduct a design space comparison, a simple parametric modeling system was designed: a parametric algorithm for generating different styles of vessels. As with handcraft of pottery wheel throwing, a simple Bezier curve with three control points was turned around an axis to generate each 3D digital vessels; the form of each vessel is specified by the five parameters that were used as inputs. These parameters, as can be seen in Figure 2, are: the height of the vessel, the width of the base, the width of the top opening, and the horizontal and vertical coordinates of the central control point of the Bezier curve that are used to create the curve of the form. The five parameters are represented as a vector, and each vector corresponds to a specific 3D model of a vessel.

Using this system, we created a 3D vessel dataset by randomly generating a total of 15.000 different vessels. The total shape of the parametric representation of the vessel dataset is [15.000, 5], however, as it will be explained in the next section, only 3.000 vessels were used for the space exploration and visualization, so this will be a design space of size [3.000, 5].

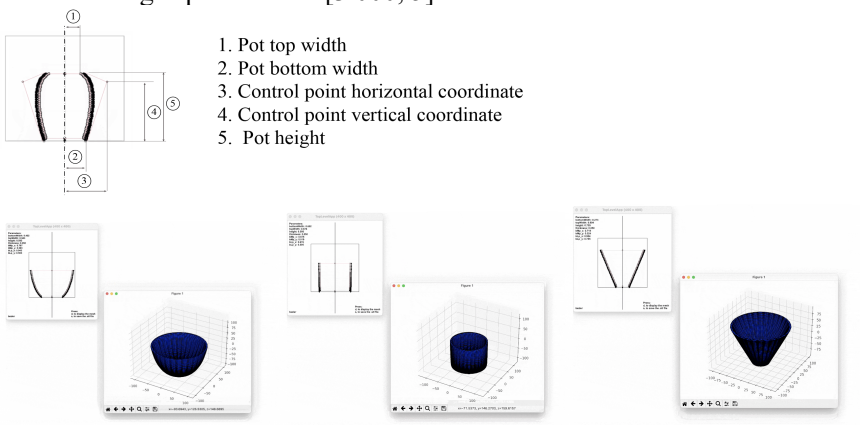



Figure 2. Upper: An illustration of the dataset parameters. Lower: Three illustrative examples from the dataset with the parameters and the resulting 3D form side-by-side.

### 2.2. DIMENSIONALITY REDUCTION

As a five-dimensional space makes it hard to compare models and to visualize and compare the characteristics, we employed a dimensionality reduction process to reduce the space to two-dimensions and enable the objects to be plotted and compared to one another. Figure 3. shows the overall process of visualizing the space using t-Distributed Stochastic Neighbour Embedding (t-SNE) algorithm

(van der Maaten and Hinton, 2008). t-SNE is a popular dimensionality-reduction algorithm for visualizing high-dimensional data. The hyper-parameters used for this reduction are: perplexity: 30; learning rate: 200; and iterations: 1.000.

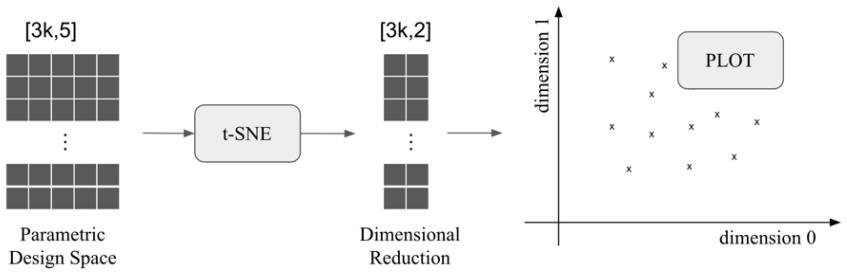



Figure 3. Illustration of the dimensional reduction process for the 3D vessel dataset, and the construction of a parametric design space.

After dimensional reduction, each point in the plot represents the corresponding embedding of a vessel in the parametric design space. Each point is expressed as a 2D image of the profile cut section of the corresponding vessel. Figure 4. represents the reduced parametric design space of the dataset.

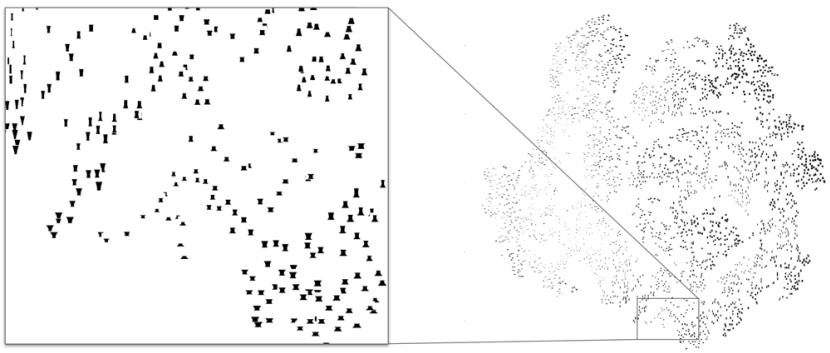


Figure 4. A 2D visualization of the parametric design space of the vessel dataset. Inset image: a detailed section for a subset of the models.

## 3. Constructing the Feature Space

To construct the design space based on the features and not the parameters, we used a Variational Autoencoder (VAE) as a tool for extracting the morphological features of the vessels. VAEs (Kingma and Welling, 2013) are a type of generative deep neural network used for statistical inference problems as they generalize a probabilistic distribution of the given dataset and synthesize new data samples from that distribution. VAEs are composed of two modules: *encoder* and *decoder*. The encoder abstracts the input data into smaller dimensional vectors, latent vectors, and the decoder reconstructs the latent vector back into a 3D shape. During the encoding process, the network captures and extracts the features of the

input data. These features can be topologically placed in the data space, namely, *latent space.* In the latent space, the distance between two data points represents the degree of resemblance of data: the closer points, the more resembled. We translate this latent space as the feature space for an alternative way to explore the design space.

### 3.1. DATA PRE-PROCESSING

Different representations of 3D data have been used in DL research, like point clouds (Achlioptas et al., 2018), meshes (Ranjan et al., 2018), or *voxels* (Wu et al., 2017). As resolutions of the data is not key for our purpose rather than the extracted features of it; and because we will implement a VAE for this experiment that needs fixed space inputs for the Convolutional Neural Networks (CNNs), we will be representing our 3D data with voxels. Voxels are discretized three-dimensional grids containing a binary value of volumetric occupancy of an object; they distinguish between the elements on the grid that are filled with material and those that are empty. The size of the voxel will determine the number of divisions of the grid, consequently, the resolution at which we represent our 3D models; the larger size, the more detailed 3D models. In this experiment, we used 32-sized voxels so that a 3D vessel model is represented by 32x32x32 grid, the shape of the entire dataset is [15.000, 32, 32, 32]. Finally, the dataset was then divided into two groups: 80% of the dataset (12.000 vessels) was used for training the DL model, and the remaining 20% (3.000 vessels) was used for testing the model and the parametric and feature space analysis and comparison.

### 3.2. TRAINING

For training the model, we adopted the VAE architecture implemented in 'Adversarial Generation of Continuous Implicit Shape Representations' (Kleineberg, Fey and Weichert, 2020). The encoder consists of four residual blocks. Each residual block is composed of a 3D convolution layer, followed by a batch normalization and a Leaky ReLu activation layer. The decoder, on the contrary, comprises four residual blocks. Each block starts with a batch normalization, followed by a Leaky ReLu activation layer, and finally a 3D transposed convolution layer. The following hyper-parameters are used for training the VAE with the voxelized vessel dataset: batch size 32, Adam optimizer (Kingma and Ba, 2015), learning rate 5e-. The model was trained in Google Colab Pro using the Nvidia Tesla T4 GPU.

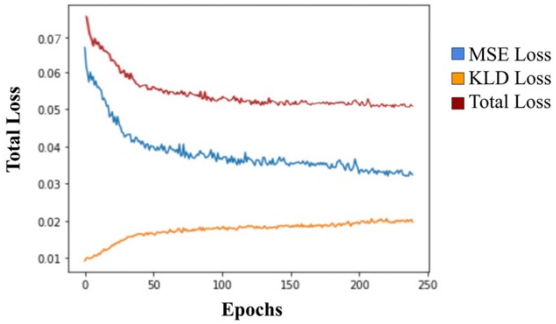



Figure 5. Training process losses.

The model was trained for a total of 240 epochs. We early stopped the model before the model started to overfit, Figure 5. The loss function used during training was a combination of two losses. The first one, is the Kullback–Leibler divergence (KLD) loss (Kullback and Leibler, 1951), with a weight in the total loss formula of 1. This function is a measurement of the difference between two statistical distributions. The second loss is the Minimum Square Distance (MSE) loss (Sammut and Webb, 2010). It is used as the reconstruction loss and measures the error between the input voxels and the reconstructed output. Figure 6. shows the reasonable quality of the reconstruction of the training result after 240 epochs. To ensure the performance of the model, it was evaluated using the test set and showed that the model maintained the accuracy with the new dataset, which shows that the model generalizes well to new data and is able to encode never seen before 3D vessels.

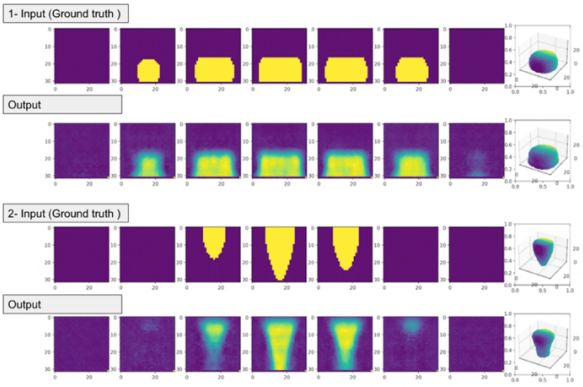



Figure 6. Two examples of reconstructions from the trained VAE: the section slides and 3D voxels of the ground truth (the top row of each example) and the reconstruction (bottom of each example).

## 3.3. DIMENSIONALITY REDUCTION

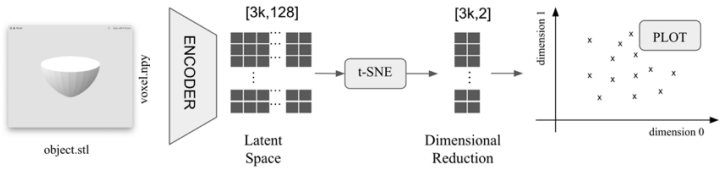



Figure 7. Feature space generation and visualization diagram.

Once the VAE is trained, the encoder is used to extract the features of each vessel in the test dataset from 32.768 dimensions, the size of each voxelized vessel, into 128-dimensional vectors, the latent vectors. Consequently, the entire test dataset of the vessels is represented into vectors whose total shape is [3.000, 128].

Like in the parametric case, 128 dimensions are non-visualizable so the same process as in Section 2 is followed. t-SNE algorithm is used to reduce the dimensionality of each vector and plot the resulting two dimensions in an image with the section of each of the vessels (Figure 7.). The hyper-parameters used for this reduction are: perplexity: 50; learning rate: 700; and iterations: 3. Figure 8. shows the results of distributed feature vectors in the reduced dimensional space, the feature space.

## 4. Comparison Between the Design Spaces

Figure 8. visualizes the feature design space and shows how vessels with similar characteristics have been clustered together. Thinner vessels are located at the top right of the image. In contrast, the bigger and thicker vessels are coordinated in the lower bottom corner. The figure illustrates how the VAE model is able to interpret the relationship between the parameters and their influence on the morphological shape of the outputs.

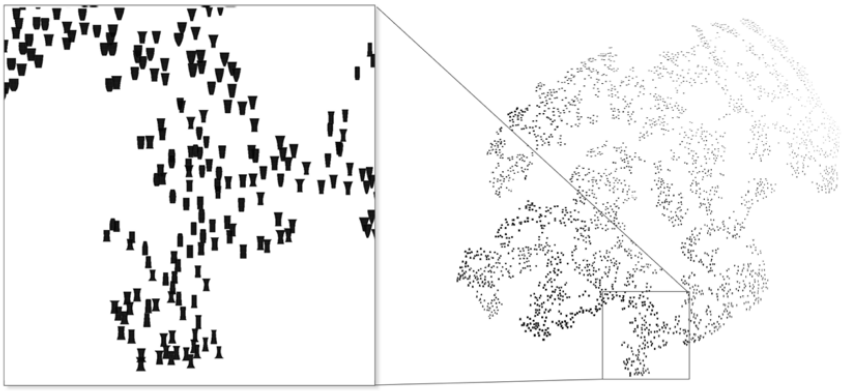


Figure 8. A 2D visualization of the feature design space of the vessel dataset. Inset image: a detailed section for a subset of the models.

Within the parametric space, organization of the design alternatives in the 2D space is contrary to expected relationships. Figure 4 illustrates how concave vessels were gathered at the bottom of the image. If the height of the vessels is considered, however, we can see that this parameter was not considered when clustering the vessels. Instead, the parametric space is based on each parameter independently, and not on the relationship among them. Therefore, we observe that parametric design space insufficiently expresses the relationships between the the combinations of the parameters and final form characteristics of the vessels. This is in contrast to the feature space; in Figure 8, a gradual change in the shape or concavity, as well as height or width is observed.

To further examine and compare the characteristics of both design spaces, we used a clustering, algorithm: a Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Ester M et al., 1996). It is one of the most common clustering algorithms that finds core samples of high density and expands clusters with them. Figure 9. shows the results of this clustering.

The parametric design space has a total of seven clusters: three of them large, and four of them small. It shows how the parametric design space doesn't provide enough information to intuitively compare the design variants locally, this space shows extreme changes in vessel forms even in the same cluster. The feature design space, on the contrary, has a total of nine clusters: six main big clusters, and three smaller ones. In the feature design space, we can trace smooth changes in the forms as we move through the different clusters (local changes) and along the whole image (global changes). Shorter vessels are located on the top, while taller ones are on the bottom. If we move on the horizontal axis, the curve that generates the vessels goes from a concave shape on the right to a convex shape on the left. This gives the designer the ability to locally compare similar design alternatives.

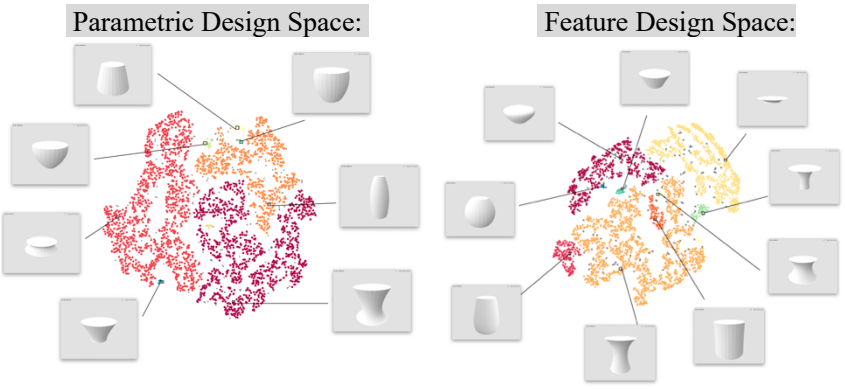



Figure 9. Final visualization and clusters of the parametric and feature design spaces with representative vessels of each group.

## 5. Conclusions and Future Work

Using a custom synthetic dataset and a VAE model, we construct the parametric and the DL feature spaces for a set of vessels. Comparing these two design spaces, we observed an improved distributions of design alternatives in the DL feature space. When the multi-dimensional parametric design space is projected into a 2D space (see Figures 4. and 9. left), the resulting clusters are not sufficiently relevant to the morphological characteristics. On the other hand, when the multi-dimensional DL feature space is projected into a 2D space (see Figures 8. and 9. right), the clusters have sufficient relevance to the features of the data that they represent.

Based on this comparison, we found that the combination of individual parameters in the parametric design space is limited in representing the morphological characteristics of the shapes. However, we showed that DL models can be used to extract design features from 3D models and that the extracted features are more complex than the combinations of individual parameters. Hence, we conclude that if the extracted features include information of the relationships between the parameters, those features can construct a well-distributed design space. We believe this has opportunity to enhance design exploration. For example, if introduced into the early stage of design, it could offer a new mechanism to intuitively explore the diversity of options in large design spaces and to visually compare design alternatives. For that reason, we propose the dimensionally-reduced DL feature space as a tool for design space exploration that creative practitioners can use as a new way for looking at objects beyond the parametric design space.

While our results are promising, it is important to note that our exploration is limited to a single dataset and DL model. Future work will address this by expanding this comparative study to larger datasets, datasets with increased diversity of design outputs, and datasets generated by more complex parametric algorithms. Additionally, our work has only focused on formal aspects of the design outputs. As illustrated by the work of Danhaive and Mueller (2021), when more complex objective functions are taken into consideration, the computing time will increase drastically. Therefore, potential limitation of this method could be the computing time required to process for more complex datasets and objective functions. Accordingly, we plan to investigate potential optimizations for this as well as the affordances of other types of DL models to perform the feature extraction. This would additionally help to better characterize the different potentials of DL in design exploration.

# //Experiment_2

DESIGNED BY A COMPUTER, BUILT BY A DESIGNER.
FABRICATING A CHAIR GENERATED BY AN ML MODEL

**DESIGNED BY A COMPUTER, BUILT BY A DESIGNER. FABRICATING A CHAIR GENERATED BY AN ML MODEL**



Figure 4.2.1 On the left physical chair fabricated by a designer. On the right, the mesh of the chair designed by the ML model.

## 4.2.1. Introduction to Experiment 2

This experiment aims to explore the potential shift in the way we design and fabricate everyday objects — namely chairs —, through the critical analysis of the mismatches between the way computers and humans understand them and using this difference as a source of creativity. By training an ML model with a database of chairs, the objective is to fabricate one of the outputs and analysis the possible shift in design and fabrication that the use of ML will have in the future, as well as raise questions about authorship in design. Who is the author of a chair that was designed by an ML model trained on 6k chair 3D models each generated by 3D designers, fabricated by a CNC router, and assembled by a designer?

In the previous experiment, a synthetic dataset generated by the designer was used, but for this project, a more complex dataset was chosen. Instead of defining an object with parameters, the approach is to use existing objects to define the object itself. The ML is

able to infer what the object is by learning from the dataset it has been trained on, eliminating the need for the designer to input parameters or think about the design algorithm needed to create the object. This approach will provide further insights into the potential of ML in design and fabrication, and how it can help bridge the gap between human and machine design understanding.

The chair was chosen as the everyday object to train the ML model due to its significance in the history of design. From a designer's point of view, the whole story of design can be explained using chairs as an example, starting with Thonet n.14 chair and the industrial revolution and mass production [1], passing throught the Bauhaus and Marcel Breuer's iconic Wassily chair [2] and continuing with the Memphis group and Italian Postmodernism with the Bel Air chair by Peter Shire [3]. The chair serves as a prime example to illustrate the story of design [4–6], making it the ideal object to represent our era in the book of the history of design, particularly in light of the current moment where ML is playing an increasingly important role in creative tasks. A chair designed by a computer is a particularly fitting example for this current period or time highlighting the potential of ML to revolutionize the design process.



Figure 4.2.2 From left to right, Thonet n.14 chair, Wassily chair, Bel Air chair and the chair generated in this experiment.

From a computer science/technical point of view, in order to train an ML model, the bigger the dataset, the better; this is because the model has more examples to learn from before overfitting. I decided to use the Shapenet dataset [7], a large-scale repository of 3D models designed to support computer science research in computer vision and computer graphics and that is one of the main datasets used in the ML industry. As the purpose of this project is to see if the ML model is able to understand the object it is trained in, this is a great dataset as contains enough 3D objects to train a 3D ML model. More concretely, I will train the ML model in the chairs dataset as it is the object with more models on Shapenet. A total of 6778 different chair models, the total number of 3D models in the shapenet chair dataset, are in  are used to train the ML model.

The first part of this experiment, the CS technical challenge, consists of the training of the ML model. On the second part, the fabrication challenge, one of the outputs of the model is made into a full scale object.

### 4.2.2. Background of Experiment 2

One of the main challenges in training an ML model to learn everyday objects is the representation of the physical data in digital form. To represent 3D data and let ML models learn it, researchers started using voxels when working with 3D data as they could use already existing techniques for two-dimensional data [8]. Recent studies have shown different approaches like point clouds [9], meshes [10], or even Signed Distance Fields (SDF) that offer a more accurate and detailed representation of the data [11]. SDF don't discretize space; instead, they utilize a completely continuous distance field, which is both efficient and expressive. The SDF approach has unlimited resolution, can model any shape topography, guarantees watertight surfaces, and can be effortlessly converted into meshes, voxels, or point clouds. For this experiment, the SDF values are rearranged into a voxel volume so the better quality of the SDF representation is combined with the voxel grid structure that is easier to use 3D CNN (convolutional neural networks), for this experiment, the SDF of the shapenet dataset from [12, 13] are used.

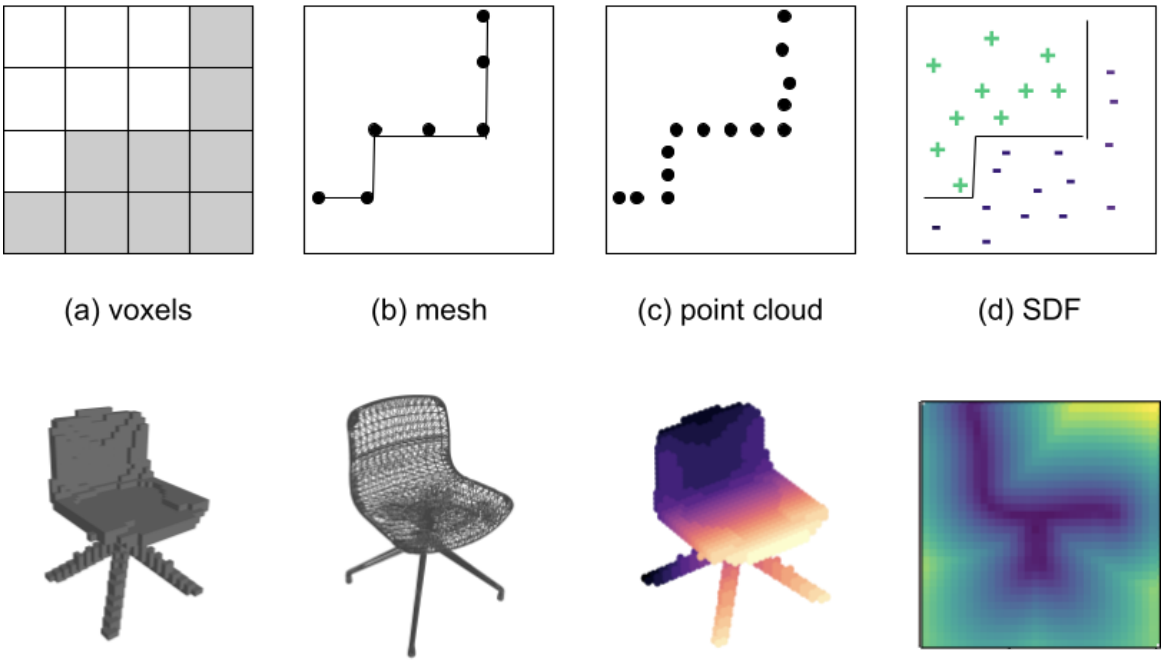



Figure 4.2.3. On the top, a diagram of the different 3D object digital representation forms, and on the bottom, a digital chair from the dataset represented by each of these methods.

Once the digital data is available, researchers have used various methods to generate ML models that are able to learn this data (shape synthesis), such as Variational Autoencoders (VAE) [13], Generative Adversarial Networks (GAN) [10, 15], or even 2D text-to-image diffusion models that are trained to perform text-to-3D synthesis [13]. For this project, and serving as a continuation of the previous experiment, a VAE is used. A range of research working with continuous shape representation have used a likelihood-driven autoencoder or autoencoder approach to learn the latent embeddings [12,13,17].

While these methods have been successful in the shape synthesis of new 3D models of everyday objects, they have not focused on the fabrication of physical objects. Parallel to computer science research, there have been some recent design projects that have used ML models as tools for the concept and creation of the final shape of the products. For example, the Oio Store sells a ML-generated spoon, where the ML model generated 2D images were used as references for the final design of the spoon [18]. Similarly, the Aire GAN project used a GAN model to generate different sneaker designs. In this work, one 2D image output generated by the GAN was selected as a reference for the final product, was modeled, and ultimately designed by a human into a workable volumetric design [19]. Both of these projects are therefore limited because they rely on using the generation of two-dimensional of images that to model the final physical object. Consequently, these projects still do not address the full range of physical considerations that would exist when attempting to fabricating an object as similar as possible as the output of the ML model. As designers move from images to the final object, fabrication-based decisions must be taken into account.



Figure 4.2.4. From left to right, IOI soon, airgan sneakers and Psychedelic Forms.

The Psychedelic Forms project is a notable exception as it uses a text-to-3D model to generate various sculptures [20]. Unlike other projects, the final 3D-printed sculptures in this project are the actual output of the ML model, addressing the challenges of transitioning from the digital realm to materialization. In this project, the final 3D-printed sculptures are the actual output of the ML model. Therefore, deals with the physical

problems that going from the digital realm to materialization. However, as they are sculptures, the final function of the object is primarily aesthetic and conceptual. There is no functional need as is found in products. However, in this experiment, the functional needs of a chair must be considered; the outputs not only need to look like a chair but also work like a chair. If a person is not able to sit on the final object, it cannot be considered a chair. This functional aspect will be, as it will be written afterward, a technical fabrication challenge.

## 4.2.3. DIGITAL PART. Synthesizing the 3D model

### 4.2.3.1. Dataset preparation

The Shapenet dataset [7] was utilized to train the ML model for this project, which is one of the primary datasets frequently used in the ML industry. This dataset is ideal for this project's objectives, as it includes a wide range of 3D models from popular public repositories, enabling the ML model to understand the object it is trained in. A total of 6,778 chair models were used to train the ML model. This dataset contains the 3D models as meshes, however, for our model we need to first convert the chairs from a mesh into SDF value voxels. The mesh to voxel function proposed in [13] is used to create a voxel volume of size of 32x32x32 from the mesh, where each element contains the SDF value. In 3D space, an implicit field [12] assigns a value to every point, enabling the posterior extraction of the shape as an iso-surface. The field takes a point's coordinates and a feature vector that encodes its shape, and generates a value indicating whether the point is inside or outside of the shape. An implicit field assigns a value to each point in the voxel.

The following image shows the 3 cuts of this voxel of a random chair in the dataset. It can be seen how the values are in a range -1 to 1, negative if they are inside the mesh, and positive if they are outside.

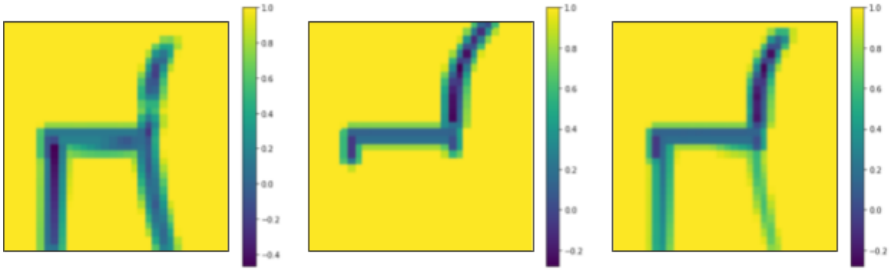


Figure 4.2.5. Three different sections of one of the voxelized chairs in the dataset.

### 4.2.3.2. Model training

To train the model, the VAE architecture implemented in 'Adversarial Generation of Continuous Implicit Shape Representations' [13] was adopted for training the model. The

encoder was composed of four residual blocks, each comprising a 3D convolution layer, batch normalization, and a Leaky ReLu activation layer. Compressing each of the inputs into a latent space of size 64.The decoder, on the other hand, consisted of four residual blocks, with each block starting with batch normalization, followed by a Leaky ReLu activation layer, and finally, a 3D transposed convolution layer, that decodes the latent vector of size 64 back into the input voxel size of 32x32x32. The voxelized vessel dataset was used for training the VAE with the following hyper-parameters: batch size 32, Adam optimizer [21], and a learning rate of 0.00005.. The model was trained using the Nvidia Tesla T4 GPU on Google Colab Pro.

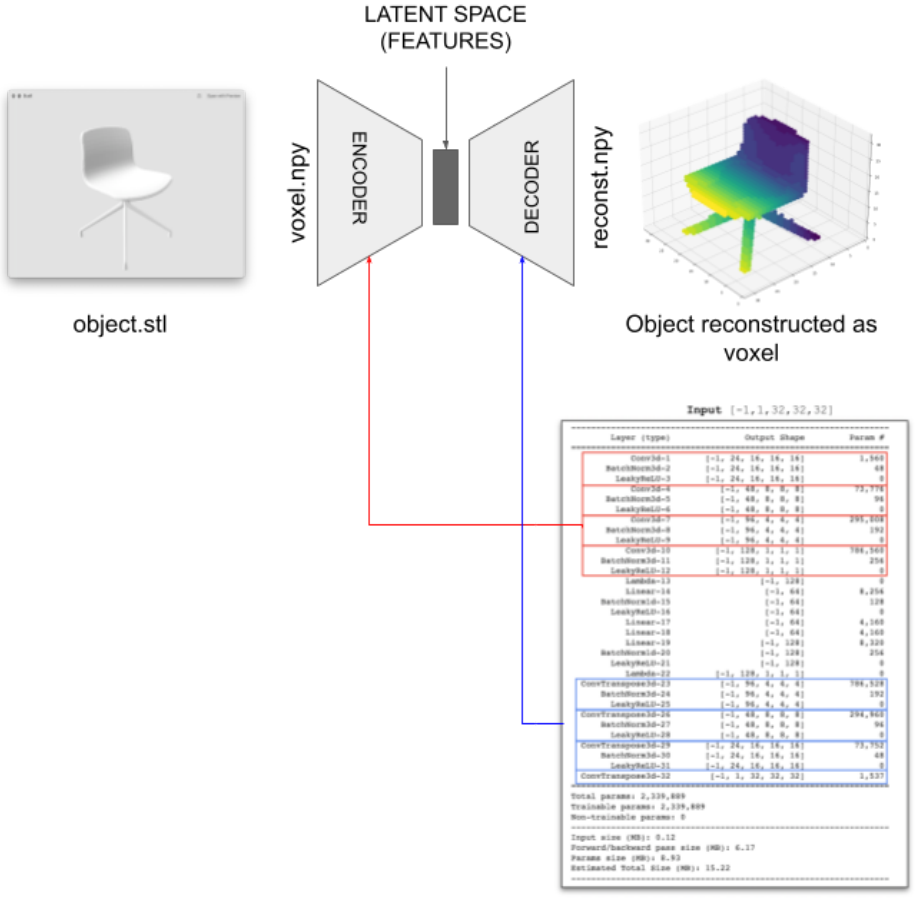



Figure 4.2.6. Diagram of the VAE training for this experiment and a summary of the architecture of the Encoder and Decoder.

The model was trained for a total of 300 epochs, and an early stopping method was employed before overfitting occurred. During training, a combination of two losses was used for the loss function. The Kullback–Leibler divergence (KLD) loss [22] was the first loss, with a weight of 1 in the total loss formula, which is a measurement of the difference between two statistical distributions. The second loss, the voxel difference, evaluates the difference between the reconstructed output and the input voxels in the VAE training process. It determines the elements in the input and target tensors that have different signs and then computes the average sum of these elements.

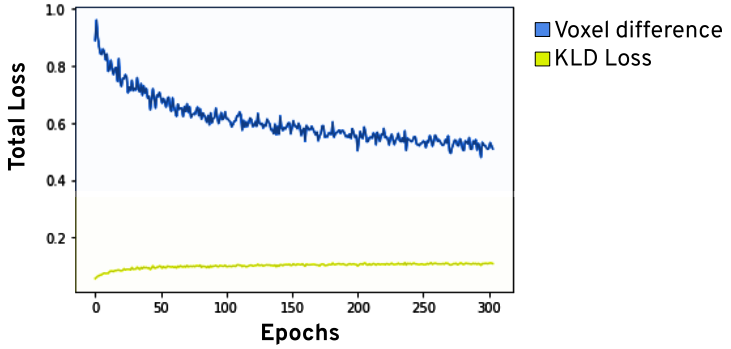



Figure 4.2.7. Graphic of the loss functions during the training of the VAE.

The reasonable quality of the reconstruction of the training result after 300 epochs is evaluated using the test set and found to maintain accuracy with the new dataset, indicating that the model could generalize well to new data and encode previously unseen chairs.

Once the model is trained, the marching cubes algorithm [23] is used to reconstruct the final meshes of the chairs given the voxel grid output of the VAE. The following image shows on the top the reconstructed mesh, and on the bottom, 7 different cuts of the voxel grid.

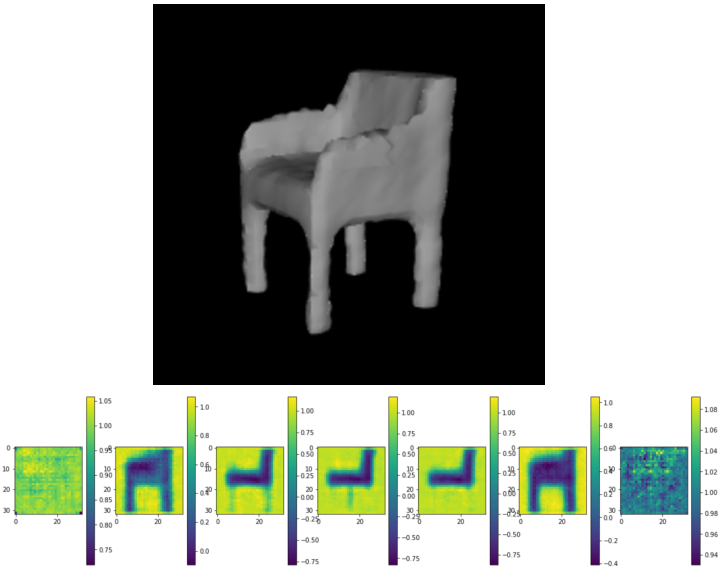


Figure 4.2.8. A random output of the VAE after 300 epochs of training.

#### 4.2.3.3. Results and discussion

Following the same dimensional reduction and visualization techniques as the ones used in the previous experiment, the following images show the latent space visualizations of the trained VAE. The first image shows the ground truth and the second one the reconstructed 3D models.

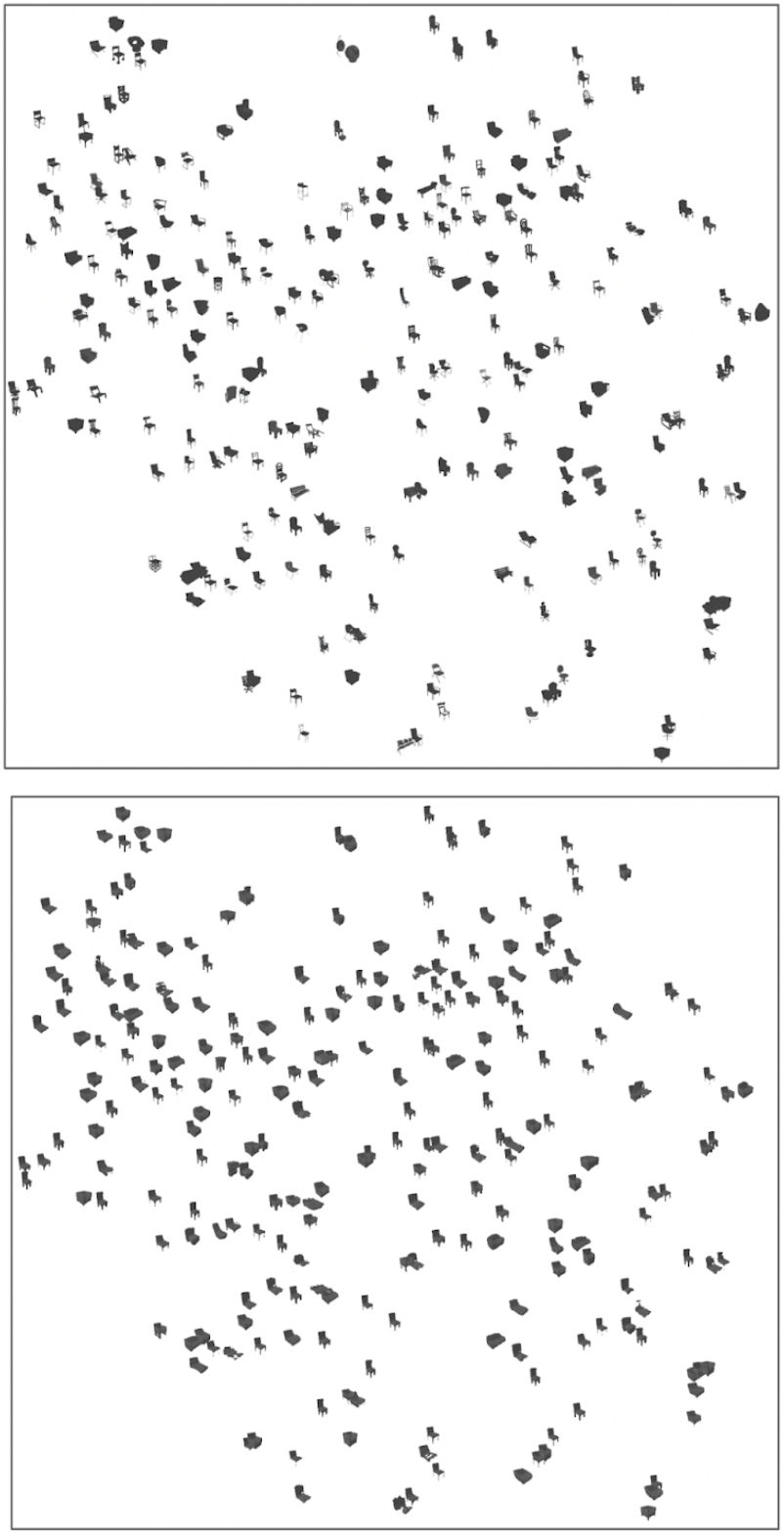


Figure 4.2.9. On top a visualization of the latent space using screenshots of the ground truth chairs, on the bottom, same visualization but using screenshots of the reconstructed chairs by the VAE.

In these images, it can be seen that although the trained model is able to generate 3D chairs, it is not able to reconstruct each of the 3D models. It is not able to generalize to the diversity of the dataset. Some of the reasons for this can be that the VAE is not complex enough to learn all the complexity of the models or that the orientation of the dataset, especially in the cases of chairs with wheels, makes it complicated for the model to reconstruct the models. Another option could be that the chairs in the training data are not properly aligned. Even though the chairs are scaled using their bounding box and all have the same general orientation, they may not be properly centered with respect to the voxel grid, or in the case of chairs with wheels, this may not be aligned at all. A proper and rigorous alignment of the training data is fundamental in the training of ML models. An example of this is the case of face alignment used on the Flickr-Faces-HQ Dataset (FFHQ) used by Nvidia for their styleGAN and that showed improved results [24, 25].

In the following image, we can see two famous chair designs on the left and on the right the general reconstruction that the VAE does. The Figure demonstrates how VAEs are a type of deep learning model that has strong capabilities in compression tasks. However, it is important to note that VAEs struggle with generalizing and learning the intricacies of complex designs. Despite their effectiveness in compressing data, VAEs may not be the optimal choice for tasks that require a higher level of understanding and processing of complex information like the case of the generation of design spaces from the learned latent space during training.

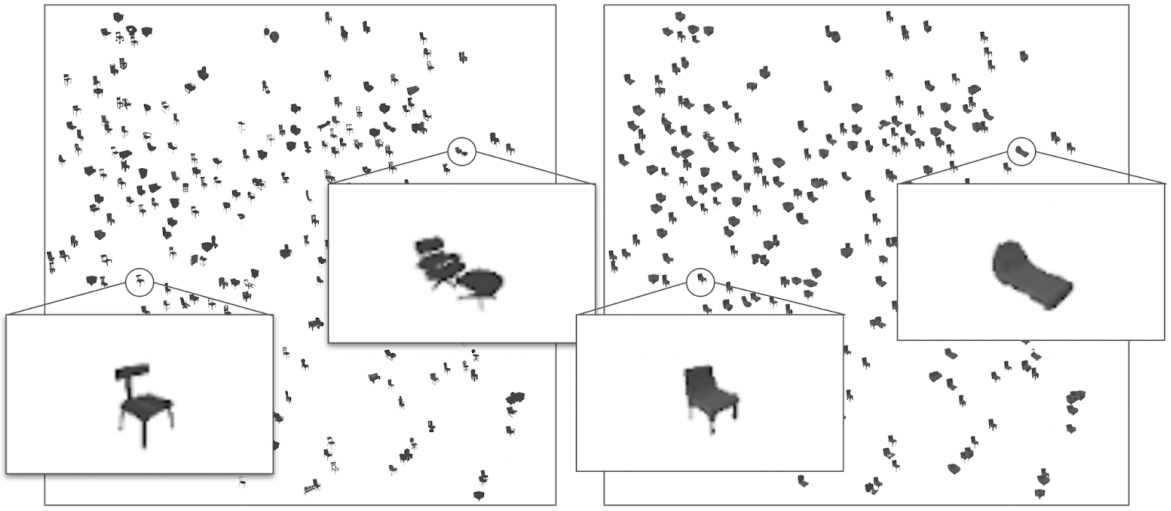


Figure 4.2.10. Comparison of the inputs (ground truth, on the left) and outputs (reconstructions, right) of the VAE.

The image below illustrates a series of outputs obtained through the use of the VAE model. Despite the fact that the VAE model may not provide an optimal latent space for design exploration purposes, the results of the model's training exhibit intriguing shapes

that have the potential for use in the next phase of the experiment. These shapes will be leveraged for the development of speculative design and case studies aimed at exploring the limitations and possibilities associated with the generation of tangible outputs through the fabrication of the 3D use of machine learning models.



Figure 4.2.11. Random outputs of the VAE.

## 4.2.4. PHYSICAL PART. Constructing the output:

Figure 4.2.9. shows the chair that was randomly selected among the outputs of the VAE for fabrication. This chair model is a typical result of the compression process that the VAE has in the chairs. Both Figure 4.2.10. and 4.2.11. show similar chair models to the one fabricated. It should be noted that the two missing legs have a small floating mesh remainder that is too minute to be fabricated.

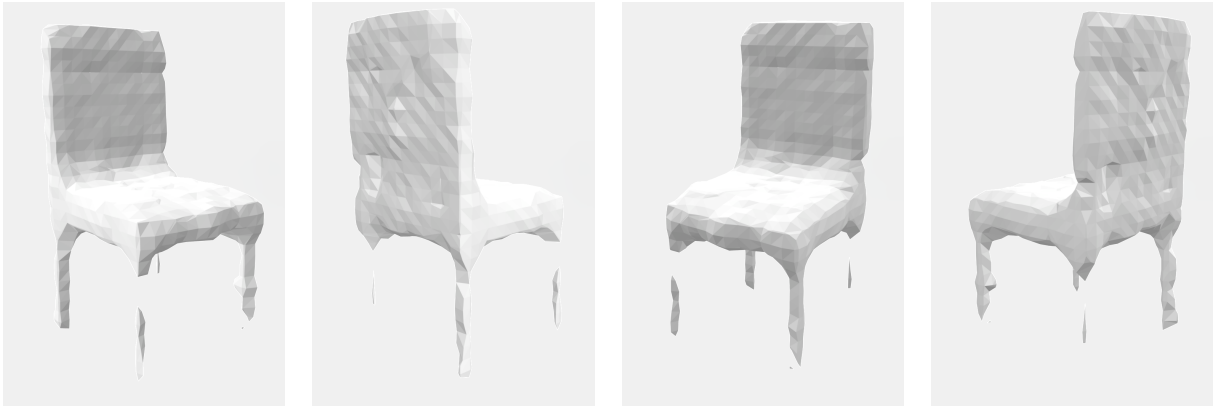


Figure 4.2.12. Output of the VAE that will be fabricated.

#### 4.2.4.1. Material and fabrication method selection

In this section, we will discuss the material and technique decisions made to prototype one of the outputs of the ML model generated in our project. In order to properly show the mismatches between the way humans and computers understand everyday objects, we decided to fabricate the chair in a way that would highlight this duality. We were inspired by the duality of the existing and missing parts of furniture designs in the 'My Old New' series by artist Tatiane Freitas [26], as depicted in Fig 4.2.10, and the Torn Lamps by Artifex [27].

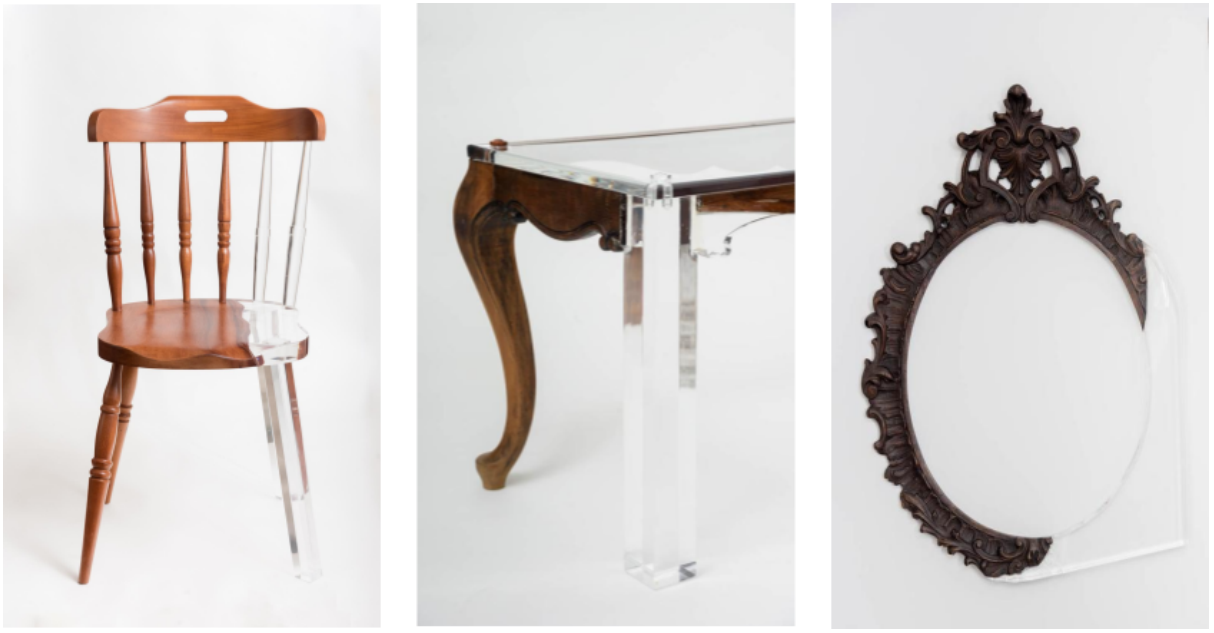


Figure 4.2.13. Images from different objects of the 'My Old New' series by artist Tatiane Freitas.

For the output of the ML model, we chose to use a CNC router to shape the 3D mesh in wood. CNC routing is a computer-controlled cutting machine that can use the generated 3D mesh to cut the final shape, this allowed us to create intricate designs and details that would have been difficult or impossible to achieve using traditional woodworking methods.We were able to accurately reproduce the complex shapes and curves of the ML-generated 3D mesh. For the type of wood, we chose plywood as the material for the chair's main body because it is strong, lightweight, and easy to work with.

To fabricate the missing leg parts of the ML-generated chair and give the appearance that they are 'floating' in their corresponding location, we used poured epoxy resin, more concretely, Majestic Deep Pour 2 Casting Epoxy. The decision to use poured epoxy resin for the missing leg parts of the ML-generated chair was not only practical but also metaphorical. Resin was selected because of its transparency, which symbolizes the

fundamental elements that were not generated by the ML model but are essential for the chair's functionality. The use of resin highlights the discrepancy between what a computer perceives and what humans understand as essential components of an object. The result is a chair that not only functions as a comfortable and sturdy seating solution but also hope to serve as a thought-provoking artifact that challenges our understanding of a ML-enabled design process.

#### 4.2.4.2. 3D model pre-processing

To fabricate the chair using the CNC router, the 3D model had to be cut into smaller pieces in order to be machined. The CNC router used was a ShopBot's Buddy CNC router with a .500-inch down-cut end mill of a maximum depth of 2 inches. Therefore, the 3D model was cut into max 2-inch thickness pieces as seen in the diagram of Figure 4.2.14. To decide where exactly to divide the model, we tried to make the cuts in order to maximize the detail on the side of the piece that would be machined. Figure 4.2.14. shows the resulting cuts and the 15 pieces that compose the chair.

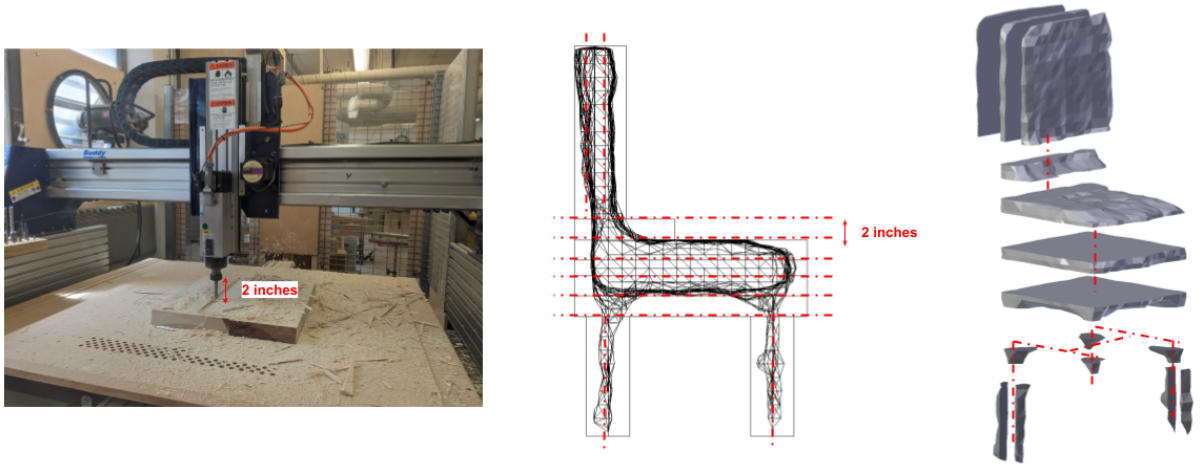



Figure 4.2.14. On the left, image of the CNC router. In the middle detail of the cuts done in the 3D mesh of the chair for fabrication. On the right, the 15 pieces in which the chair was sliced.

#### 4.2.4.3. Chair fabrication

Once the 3D model was divided into separate piece for fabrication, each piece's mesh was introduced into Aspire CNC software to program the machining and generate the toolpath for the CNC router.

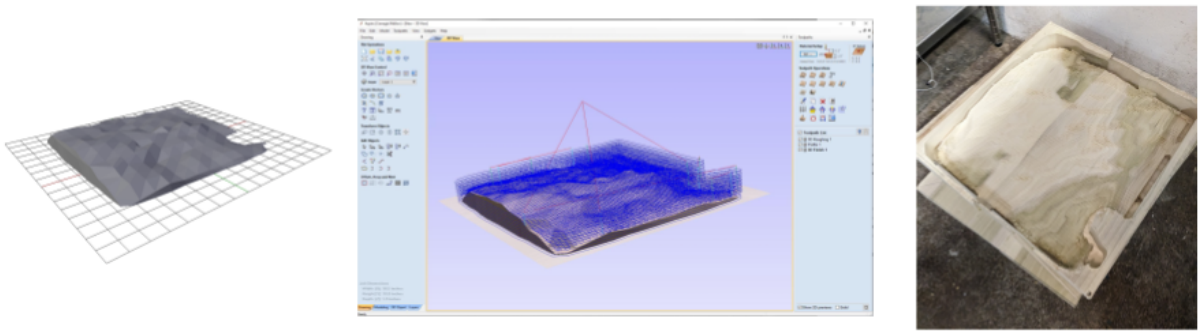


Figure 4.2.15. On the left, 3D mesh of one of the pieces of the chair. In the middle, screenshot of Aspire software with the generated toolpath for the CNC router. on the right, piece after machining.

Once the machine was done, the parts were manually cut out to remove extra material. The surface was also sanded to remove any rough edges and imperfections, resulting in a smooth and polished surface. The pieces of the legs were glued together and a mold for each of the legs were created. The poured resin was applied in two layers, with a final thickness of 2.5 inches, to ensure that the legs would be strong and stable enough to withstand the weight of a person sitting.



Figure 4.2.16. From left to right, process of cutting out the remaining material after the CNC machining, detail of the clamps keeping the different pieces of the chair together while the glue dries. Detail of the mold for the resin. Resin pouring process of the four legs of the chair.



Figure 4.2.14. Two different perspective views of the physical and digital chair.

### 4.2.5. Findings

Through the process of producing the ML-generated chair, we uncovered several mismatches between the way humans and computers understand everyday objects. Despite our aim to fabricate the output of the ML model as similar as possible to the 3D mesh generated by the VAE, we found that there were still limitations regarding the material properties and dimensions as well as the limitations of the CNC router itself. We also discovered that time was a limiting factor, and that better results could have been achieved with a smaller miller head which would have exponentially increased the fabrication time. Nevertheless, as seen in Figure 4.2.14. both the digital and physical outputs of this experiments show high formal similarity.

As designers, we learned that more consideration needs to be given to the selection of the model to fabricate. We now understand the importance of taking into account the limitations of the fabrication process, such as the 2 inch maximum thickness limitation. In future experiments, we would hand-pick the model to be fabricated, simplifying the fabrication process.

We are pleased with the outcome of the project, as the chair not only serves its function as a comfortable and robust seating solution but also presents a thought-provoking piece that challenges our comprehension of an ML-driven design process. However, the limitations we encountered during the fabrication process highlight the need for further discussions about the relationship between technology and design. Both fields are in constant communication, and advancements in either area influence the other. Moreover, this experiment has highlighted the impact that advanced manufacturing methods can have on this type of project. For example, if we had access to a CNC router with more degrees of freedom, we could have potentially machined the entire chair from a single block of wood[10], eliminating the need for gluing the 15 separate pieces together. As such, there is a need to explore how new and improved manufacturing techniques can support the production of complex designs and shapes. Further research is necessary to address the challenges that arise during fabrication and to discover how new technologies can be applied to facilitate the production of complex designs.

### 4.2.6. Conclusions of Experiment 2

In this project, we explored the potential of using machine learning models to learn a latent space of an already existing object and studying the potential for creative practitioners of using this latent space as an space for design exploration. However, our results show that while the VAE model was able to generate unique and intriguing chair

[10] This would have increased considerably the cost of this project, however, the economical factor has not been discussed in this experiment. Nevertheless, this kind of results cannot be mass produced and are one of a king design pieces.

designs, it struggled with generalizing to the diversity of the dataset which didn't result in a properly composed latent space. VAEs are good compression ML models, but cannot be used to generate a latent space from complex design variants. For future work, more complex ML models like Generative Adversarial Networks (GANs) could be used, as it is the case of the recently published GET3D GAN model by Nvidia [10] that shows a better result in training and in generation of new outcomes.

Nevertheless, the results of the model's training exhibit intriguing shapes that have potential for use in speculative design and case studies for tangible fabrication of ML model outputs. This experiment is a critique to the current state of ML research that often tends to remain in the digital realm and neglects the limitations that physical materials and the fabrication process would have in the ML model outputs. A good example of a consideration of the fabrication methods in the training of ML models is the case of [8] that experimentally test the impact of altering properties of the dataset for better additive manufacturing results.

The final result of our project, the ML-generated chair fabricated with wood and resin, serves not only as a functional object but also as a thought-provoking artwork that challenges our understanding of the design process. By highlighting the mismatches between the way humans and computers understand everyday objects, our chair serves as an example of how the limitations in ML can also serve as a tool for fostering creativity. The chair's unique design features missing leg parts that were reconstructed using poured epoxy resin, symbolizing the fundamental elements that were not generated by the ML model but are essential for the chair's functionality. The limitations of ML models as a method for generating complex designs provide a fertile ground for experimentation and exploration, leading to new and unexpected outcomes that push the boundaries of traditional design processes and forms. The chair serves as a tangible representation of this idea, inviting viewers to reflect on the relationship between technology, design, creativity, and authorship.

# //Experiment_3

BROWSING THE LATENT SPACE A NEW APPROACH
TO INTERACTIVE DESIGN EXPLORATION FOR
VOLUMETRIC GENERATIVE SYSTEMS

# Browsing the Latent space: A New Approach to Interactive Design Exploration for Volumetric Generative Systems

**Link to prototype website:** https://tcabezon.github.io/ls-exploration-tool/

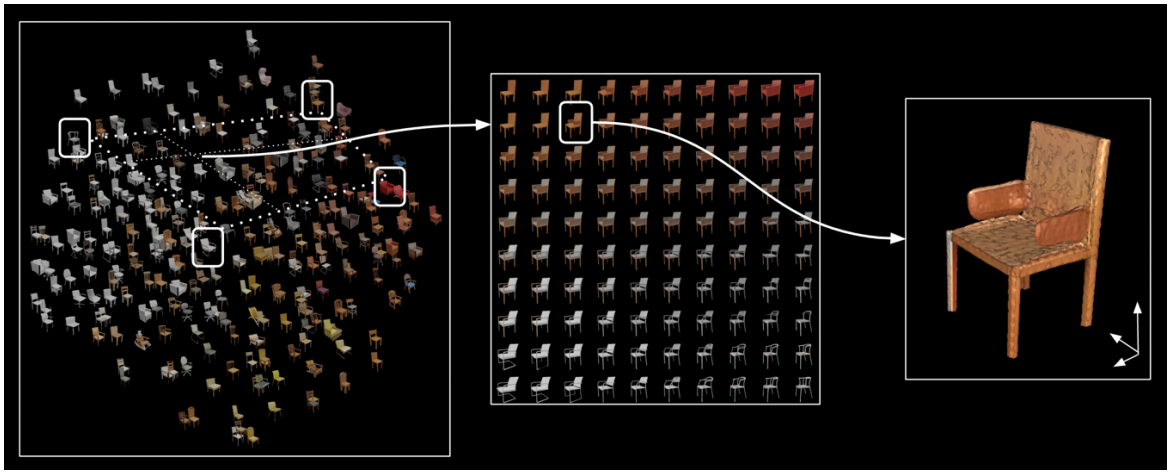


Figure 1: Left: Latent space Visualization. Center: Interpolation of four chair models. Right: View of the resulting 3D chair.

## 1 INTRODUCTION

Generative systems have become increasingly popular in recent years, with applications spanning various domains, from art and design to music and literature [1–3]. However, interactions with these systems are often limited to running the model and obtaining a random and unpredictable result, this is, an output produced by the generative system using a random latent vector without any intentional input from the user. In this demonstration, we inquire about a different approach to interact with generative systems through the interpretation and visualization of the latent space and the use of latent space interpolation as a tool for design exploration with generative systems giving the user more understanding and control over the outputs.

In this experiment, we focus on the design of chairs as an example of a creative process that has historically relied on remixing previous works [4, 5]. Drawing inspiration from this remix culture within a specific design practice, we introduce a method to enhance the creative process by providing a more intuitive and interactive way to explore, remix, and create new designs using generative volumetric systems. Our approach interprets and visualizes the latent space, revealing the underlying patterns and structures within the data to a designer, while interpolation of this design space enables the generation of meaningful outputs situated between elements within it. Previous work has soon how feature editing is possible within the latent space [6, 7] or how latent space visualization helps reveal significant connections between data points [8] both useful strategies for design exploration.

A latent space refers to a statistical representation of the underlying structure or patterns in the data that the generative system generates. Also known as the feature space, this space is learned during a machine learning training process by mapping the training data to a lower-dimensional vector space. Latent space interpolation, therefore, allows

to manipulate the different features of the chairs extracted by the model during training. This not only gives control over the final outputs of the generative system, like color, shape, legs… but also gives the designer an understanding of the way the system interprets what a chair is based on the features that were extracted.

In addition to showcasing the value of latent space visualization and interpolation in generative design, this experiment aims to demonstrate the interaction between users and generative systems through the creation of a working prototype. This is intended to showcase the potential for design exploration of generative systems. For the prototype, we use the recently released GET3D [9] Generative Adversarial Network (GAN) model that Nvidia presented at the last NeurIPS 2022 conference. Generative systems have been gaining popularity in the design community due to their ability to generate high-quality designs in different domains from 2D images to 3D objects like the ones in this demonstration.

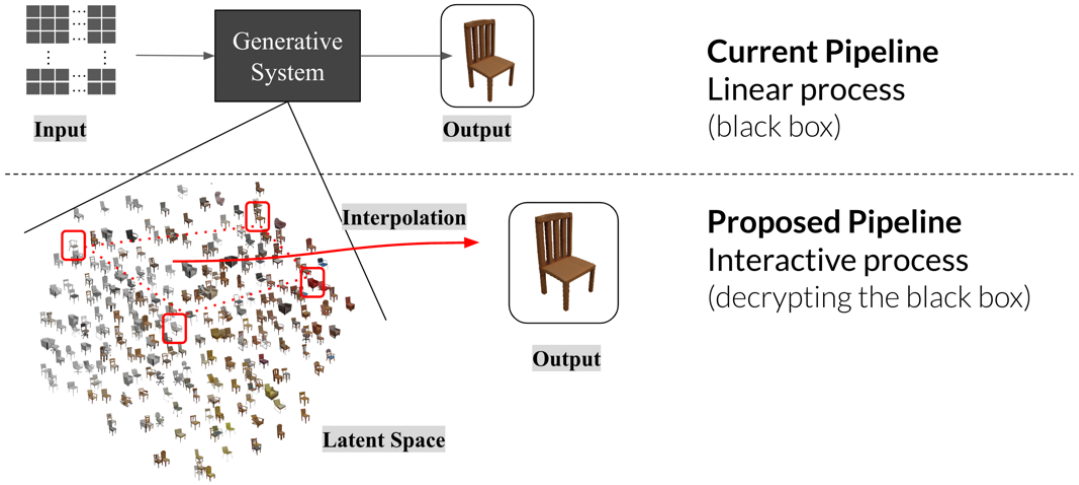



Figure 2: Comparision of the traditional Generative Systems' pipeline compared with the pipeline proposed in this demonstration.

## 2 BACKGROUND OF EXPERIMENT 3

In recent years, the exploration of latent space tweaking has gained attention in the field of generative systems. This approach involves manipulating the latent space of deep neural networks to generate new outputs that meet specific criteria. Several studies have explored the potential of latent space tweaking for improving the creative process. For instance, Interfacegan.[6] presents a method for interpreting the disentangled face representation learned by GANs (Generative Adversarial Networks), while Ganspace [10] focuses on discovering interpretable GAN controls. These studies demonstrate the potential for latent space tweaking to enable more intuitive and interactive exploration of generative systems. Another example of latent space tweaking with creative applications was presented in [11], where different high rise building form is modifying by editing the latent vector.

In addition to latent space tweaking, there has been significant interest in visualizing the "black box" of neural networks, in order to gain a deeper understanding of how they operate. Visualization techniques allow researchers to understand the patterns and structures within the data ,and provide insights into the functioning of generative systems. For example, an interactive node-link visualization of convolutional neural networks was presented in [12], while [13] focused on crafting the weights of a convolutional neural network to make a drawing. These studies demonstrate the potential of visualization techniques to enable more effective understanding of generative systems.

The importance of visualizing latent spaces and their relationship with training data encoding and spacial relationships was demonstrated in [8]. In the field of architecture and design, the ability to understand and manipulate latent spaces can have significant implications for the design process. By gaining a better understanding of the relationships between features and design outcomes, designers can use generative systems to generate new designs that meet specific criteria. Overall, the exploration of latent space tweaking and visualization techniques holds significant potential for improving the creative process in various fields, including architecture and design.

## 3 INTERACTION

There are three main elements of the interactive BLS web tool: the latent space visualization, the interpolation tool, and the resulting 3D chair preview. The three parts of the interaction, as depicted in Figure 1., move from a larger more general visualization of the generative system — that depicts the underlying structure of the data (the latent space, which is a vector space)— to a more specific and focused depiction of an individual model of a chair (corresponding to a latent vector). Technical details of how each part of the tool was developed are offered in the next section.

The interaction starts with a latent space visualization, where the user can interact by zooming and panning through all of the chairs generated with GET3D. A dimensionality reduction algorithm is used to generate a visualizable two-dimensional latent space. This dimensionally reduced space shows how chairs are located and grouped in the latent space based on their texture latent vector. This means that similar texture chairs are located closer to each other.

The user is able to click on the 'Interpolation Tool' button. This opens the interpolation tool. The user can pick 4 chairs from the 6 chair models already pre-prepared for this function[1]. Once the models are chosen, a 10x10 grid of chairs is shown with the interpolated elements. The user can hover over this grid to see a larger image of each of the chairs and explore how the features of the chair gradually change from one element of the grid to another. When clicking on any element of the grid, an interactive 3D view of the picked chair is shown, allowing the user to inspect it from any angle.

## 4 TECHNICAL IMPLEMENTATION

The implementation of the approach involves generating and visualizing the latent space of the GET3D generative system. GET3D is a Generative Adversarial Network (GAN) that consists of two different networks, a generator, that creates fake data samples that aim to be indistinguishable from training samples by inferring the statistical distribution behind the training data, and a discriminator, that evaluates the authenticity of the generated samples. For this work, we only use the generator, as we did not train a model and instead used an already pre-trained model published by Nvidia. We used the generator to map a normal distribution of random vectors — the latent vectors — to their corresponding 3D chairs.

### 4.1 Generating the Latent Space

To generate the latent space, we need to run the generative system to generate the different chair models. For each chair output by the generative system, we need to provide two random latent vectors that are used by the generator as the input to generate a 3D chair. One input vector for the texture, and another one for the geometry or shape of the chair. Therefore, for each pair of input vectors, we have one output chair (see Figure 3.).

[1] Due to memory restrictions of the web application, only six different chair objects are selected for this initial version of the interpolation tool.

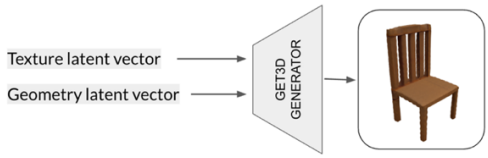



Figure 3: Diagram of the generation of a chair in the GET3D ML model.

*4.1.1 Generating the 3D Models, Data Gathering*

To generate the latent space, a total of 256 random pair vectors were used to generate the 3D models of chairs that are used in this demonstration. In order to make sure that the whole latent space is represented, we used random vectors from a normal distribution to generate the chairs. For the texture of each chair, a random vector of size 9x512 is used, as this is the size of the texture latent space. For the shape, a random vector of size 22x512 is used.

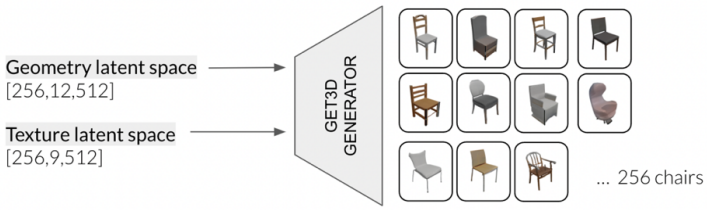



Figure 4:Diagram of the generation of the elements in the latent space for this demonstration.

*4.1.2 Generating the latent space, Data visualization*

As high-dimensional data is difficult to visualize, and each point in the texture latent space has a size of 9x512, we used the t-SNE dimensionality reduction algorithm [14] to generate a two-dimensional representation of the latent space. To do this, we flattened each latent vector by reshaping it into a one-dimensional array of size 4.608 and then we use t-SNE to reduce it into two dimensions. For this visualization, we decided to use the texture latent space. Each point in the visualization corresponds to a chair model generated by the generative model, with the texture latent vector used to position the point in the latent space. To provide additional context and meaning to the visualization, we then associated each point with an image of the corresponding chair as shown in the diagram of Figure 5.

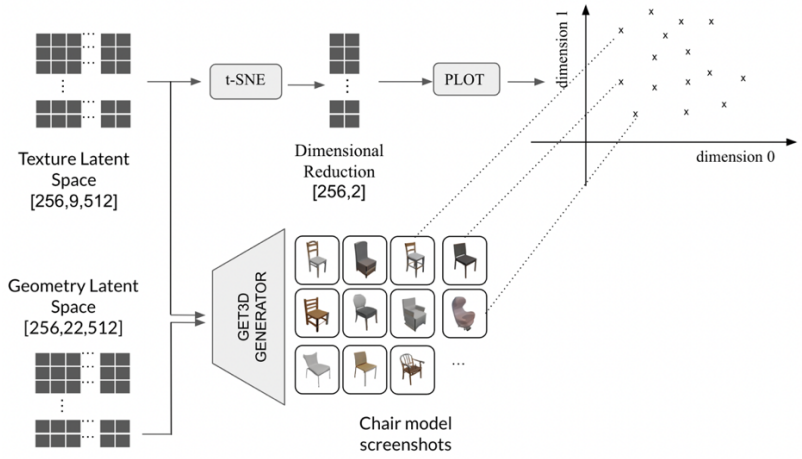



Figure 5: Diagram of the generation and visualization of the latent space into a two-dimensional map.

Figure 6. is the resulting visualization of the latent space. This visualization shows how, on the left side, the chairs with more metallic or white textures are located. While on the top left, more red textures can be found, and if we move down, more green or yellow ones. This clustering illustrates that the GET3D model is able to discern the relationships between different textures and generate proper outputs accordingly. In fact, in the next part, the interpolation between different texture features can be explored, as well as between different geometry features, showing the understanding of chair features that the generative system learned during training.

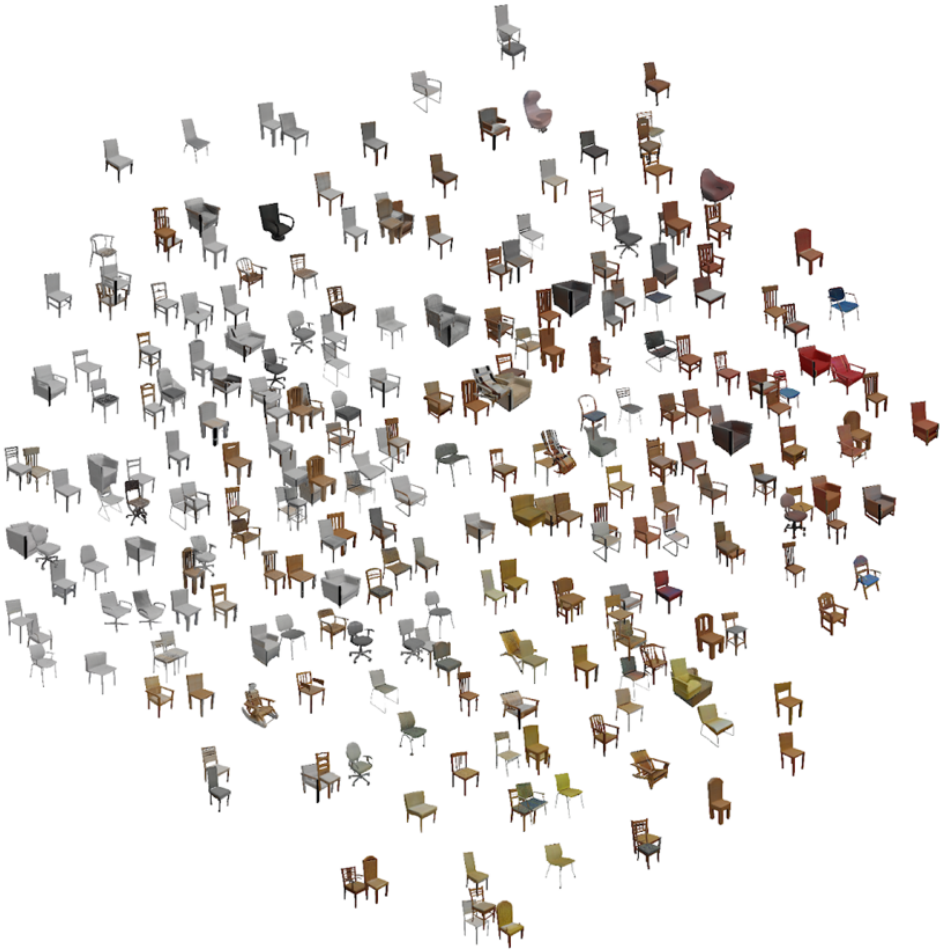


Figure 6: Resulting two-dimensional representation of the texture latent space.

### 4.2 Interpolation

Interpolation is a common mathematical technique that involves finding a point that lies between two given points. In the context of generative design, interpolation can be used to manipulate the latent space of a generative system in order to create new designs by combining the features of the points being interpolated [15]. This interpolation generates chair designs that didn't exist in the dataset but instead represent an amalgam of those interpolated.

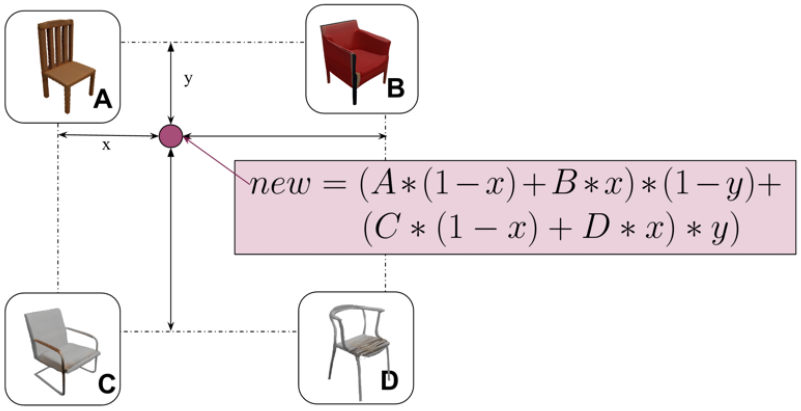



Figure 7: Diagram of the interpolation process in the latent space between 4 different chair models.

This interpolation tool allows the exploration of the features learned by the generative system. The intermediate chairs will show the progressive change of the features. Because GET3D has two input latent vectors, one that corresponds to the shape features and the other one that corresponds to the texture features, the resulting interpolated chairs will be interpolating both of these latent vectors and show gradual changes between the shape and texture features of the chairs. Figure 8 shows two different linear interpolations between two chair models.



Figure 8: Resulting chairs of the linear interpolation between chair designs in the latent space.

### 4.3 Model Visualization

When the user clicks on one of the intermediate interpolation outputs, a 3D view of the chair is loaded that lets the user explore the generated output of the generative system, instead of just an image of the chair. To create this visualization, the three.js [16] javascript library is used to load the shape output of the GET3D model (a .obj file) and the texture output of the model (a .png file).

## 5 CONCLUSION AND FUTURE WORK

This demonstration showcases a web-based tool, "Browsing the Latent Space" (BLS), that enables users to explore the underlying structures and design relationships within generative systems, specifically Generative Adversarial Networks (GANs). We use the example of the GET3D chair generation model to showcase these possibilities. Our experiment shows the potential of latent space visualization and interpolation in generative systems to provide an intuitive and interactive way to explore, remix, and create new chair designs while getting a better understanding of the way generative systems operate and how latent spaces are generated. We believe this approach could be applied as a creativity support tool for designers or as a tool to support design education. Future work will examine these possibilities.

The authors are aware that this demonstration uses pre-trained data. This could be improved in future iterations by using cloud model inference. This change would increase processing time challenging real-time interactions.

While our results are promising, our experiment is limited to a single generative system and the a-priori specification of the number of elements of the latent space. Future work could explore how this approach can be applied to other generative systems, as well as developing more sophisticated algorithms for dimensionality reduction that allow bi-directional projections like UMAP or three-dimensional data visualizations.

# //Conclusion

# 5. Conclusions

## 5.1. Results and Limitations

The analysis and visualization of the latent space throughout the three experiments have provided valuable insights into the capabilities and limitations of deep learning models in design exploration. It shows that ML models are capable of extracting enough features from the data they are trained on and creating a well-arranged latent space with big potential for design explorations as it displays design variants with similar features closer to each other. More concretely, each of the three experiments of this thesis demonstrates the following:

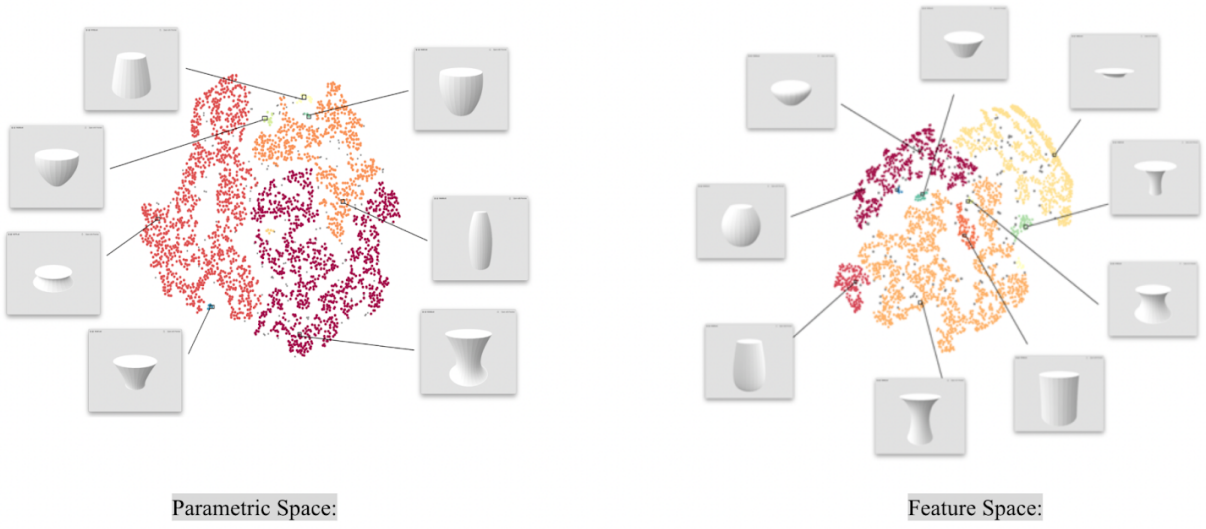



Figure 5.1. Parametric and Feature design comparison.

Firstly, In Experiment 1, as shown in Figure 5.1, I found that deep learning models can extract complex design features from 3D models, resulting in an improved distribution of design alternatives in the feature space. However, this experiment was limited to a simple dataset resulting from a parametric algorithm.

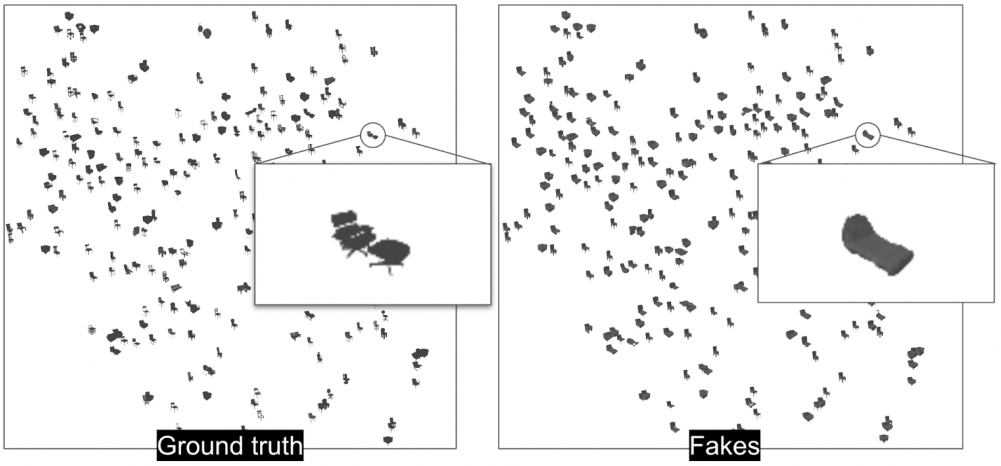



Figure 5.2. Latent space visualization of experiment 2. On the left, ground truth of the VAE, on the right, reconstructed models or fakes.

Secondly, Experiment 2 continued the exploration of VAE as a tool to learn latent spaces that could be used for design exploration, but this time on a more complex dataset of already existing objects, in this case, 6k different design variants of chairs. This experiment showed the use of VAEs as compression models. However, I found that VAEs are effective in compressing designs, but they struggle to generalize and learn the particularities of complex designs. This limitation highlights the need for more advanced models that can capture the complexity of design features and use the learned latent spaces as design spaces for design alternatives.

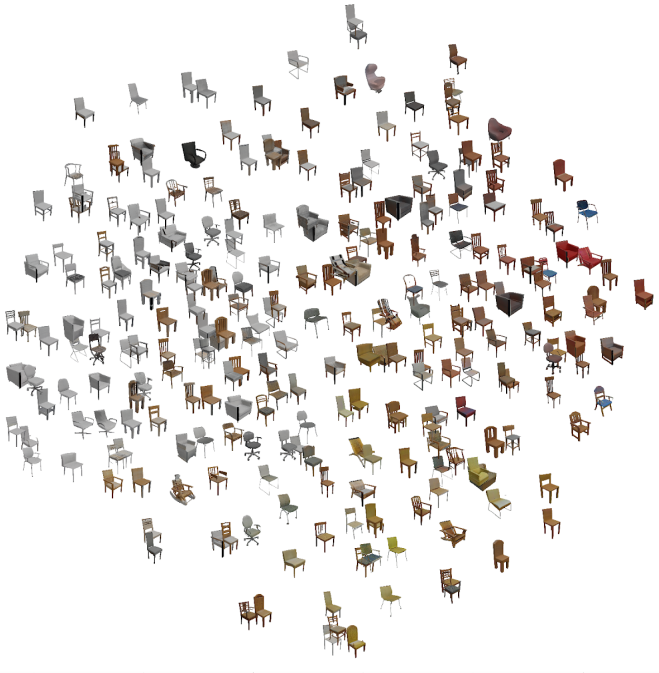


Figure 5.3. Visualization of the latent space of Experiment 3.

Thirdly, Experiment 3 focused on GANs as a more complex ML generative model. This experiment used the pertained chair generation model from NVidia's GET3D project. These experiments showed, as seen in Figure 5.3. , that GAN models can generalize and learn the particularities of complex designs. Even more, the interpolation tool in this experiment shows, Figure 5.4., that GANs apart from extracting features such as texture, color, material, legs, arm supports, etc., they can also interpolate among features, showing gradual changes of these. This experiment serves as a proof that the semantic information encoded in the latent space is able to realistically and functionally modify the attributes of the chairs.



Figure 5.4. Resulting chairs of the linear interpolation between chair designs in the latent space.

In the case of Experiment 2, even though the latent space learned during training of the VAE was limited for design exploration, the outputs of the generative system showed interesting formal results of chairs which lead to a more experimental project of fabricating one of these outputs. Through this practice-based research project, the limitations of DL technology in fabricating physical objects have been identified, highlighting the tendency for AI technology to remain within the digital realm. However, these limitations have also served as a source of inspiration and creativity. In particular, the resulting chair made with wood and resin demonstrated the mismatches between form and function, underscoring the need for careful consideration of the fabrication process of ML models are going to be used as part of the design process, or even more if an ML model is going to be the only agent in the process.

## 5.2. Contributions

This thesis has made significant contributions to the intersection of design and ML. By exploring the potential of using latent spaces learned by ML models as alternative design spaces for exploration this thesis proposes a different pipeline in the design process that designers may include in their practice. Through the experiments, three different ML models were analyzed and their latent spaces were visualized. A thorough analysis was

conducted to identify the affordances and limitations of using these spaces as design spaces.

Overall, the exploration of latent spaces has demonstrated that deep learning models can extract complex design features and understand formal aspects, proving that these latent spaces can be used as a space for design exploration. By utilizing the GET3D pre-trained model, a whole design space of chair variants was created, allowing for the gradual tweaking of features like leg shape, material, and armrests between two different design alternatives. This serves as a powerful tool for design analysis and variant consideration.

Experiment 2 revealed limitations in distributing design alternatives on the latent space based on formal features, highlighting the importance of selecting a proper DL model that can generalize to the complexity of the dataset. Additionally, the second part of this experiment, the fabrication of the chair, revealed the limitations of volumetric generative systems and the importance of considering the designerly labor of taking a generative system output into a tangible form. This experiment highlights the need for further exploration and development of generative systems that are more easily translated into physical objects. The experiment serves as an example for posterior scholars of the importance of the selection of materials and the advanced manufacturing processes available in the final result. Nevertheless, this research project has demonstrated the potential for combining AI technology with traditional methods to create alternative design processes and use the technical and physical limitations as a source of creativity.

After reflecting on the contributions, I would like to outline some resources that future design scholars and practitioners may find relevant or helpful for their own research. Firstly, the dataset that was created for experiment 1 is made available for further research in the field[12]. Secondly, the visual interface that was developed in experiment 3 is also made public[13]. This interface offers a tool for designers and researchers to better understand and explore the latent space of generative systems easily through the web, making it more accessible to other users.

## 5.3. Future work

As part of the end of my Masters program, this thesis had to have an end. However, as with every research process, the end is just a stop in the journey. If someone was to continue this journey, I would like to point out some possible directions in which to

[12] link to the dataset of the 15k 32x32x32 voxelized vessels used in experiment 1: https://drive.google.com/drive/folders/1r_a6AxZ6go-c0DT2CyQS5dgOcu1mOs-5?usp=sharing

[13] Anyone that wants to access the code used to visualize the latent space on the web can be available online in the following github repository: https://github.com/tcabezon/ls-exploration-tool

continue, nevertheless, this should serve as a guide in case it is needed, but not as an obligation. It would be a pleasure to see how someone follows this journey in new directions, especially the not expected directions.

Two main directions are explored in this thesis, using latent spaces as a design space for design exploration and the physical fabrication of ML model outputs. In the case of continuing with the first direction, future work could consider embedding 3D objects into the latent space, as explored in "Image2StyleGAN: How to Embed Images Into the StyleGAN Latent Space?" [1]. Or even further, embedding objects into the latent space using 2-dimensional images as a reference as shown in [2] or [3]. Furthermore, feature tweaking directions could be explored in the latent space using bidirectional techniques such as UMAP [4].

On the other hand, in the case of continuing with the second direction, ML models trained in other objects could be explored, such as the lamp dataset from ShapeNet, or even more, a personal curation of a dataset of a meaningful object could be considered. Apart from different objects, other materials or other fabrication methods such as 3D printing could be considered.

## 5.4. Author's notes

My journey into ML, and trying to decrypt the black box was possible because ML research and models were public and accessible. Architectures, although difficult to understand, were accessible. So decrypting the black box even though it has been a tedious task, was possible.

However, since ML as a service is being monetized by private companies, ML models are not transparent anymore. Even the use of ML is easier to use than ever, and even more popular than ever, ML models are actual black boxes. The users use these models doing requests to servers where these ML models are run, but access to the architecture of the models themselves remain secret. ML models are black boxes where you get an output from an input, with no option to see what happened inside, the parameters of the models stay secret.

While ML use is becoming more accessible than ever for the masses, I am afraid that ML models will remain in-decryptable as access to the parameters or architectures will not be public. Unfortunately, future researchers that want to continue this thesis of 'decrypting the black box' will not have access to SOTA models to study and analyze.

## 5.5. Conclusions

The exploration of latent spaces in deep learning models has demonstrated the potential of well-trained ML models to be utilized for design exploration. The visualization of latent spaces has been identified as a useful tool for aiding in design exploration.

Additionally, experimentation with volumetric generative systems and the fabrication of these digital objects have also shed light on the limitations and potential of generative systems. However, this limitation has served as a source of inspiration and creativity creating a space for unexpected outcomes of forms and possibilities. It also emphasizes the value of combining ML technology with traditional methods to create innovative design processes.

Although this thesis is limited to three experiments involving different models within a rapidly evolving field, it serves to offer a series of case studies that demonstrate the potential of ML models as a tool for creative practitioners in design exploration. By providing designers with a feature space for design exploration, the integration of ML into the design pipeline offers a new strategy for creative decision-making.

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## Abstract and Introduction


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## Background


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## Experiment 1

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## Experiment 3

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## Conclusions

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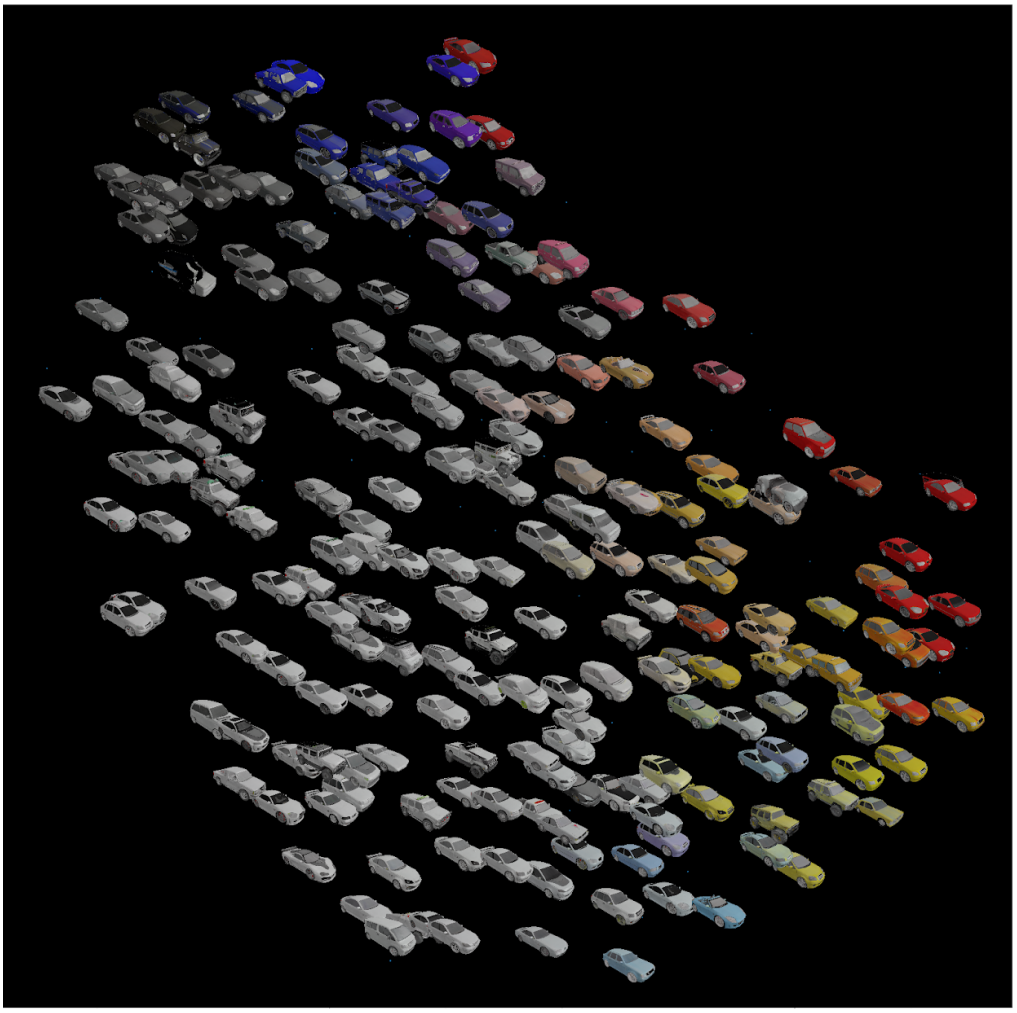
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# Appendix A

For  experiment 3, the chair generative system of get3d was chosen. However, other models could have been used in order to generate other objects.  Nvidia has published the models to generate chairs, tables, cars and motorcycles (models trained with the Shapenet dataset). On the project website of GET3D other objects like houses, animals or human bodies can be seen.[14]

The following image shows the results of visualizing the latent space of the GET3D car pertain model:



[14] https://nv-tlabs.github.io/GET3D/