AI AND ARCHITECTURE

Toward a Critical Methodology for Creativity Augmentation in Early Architectural Design Process

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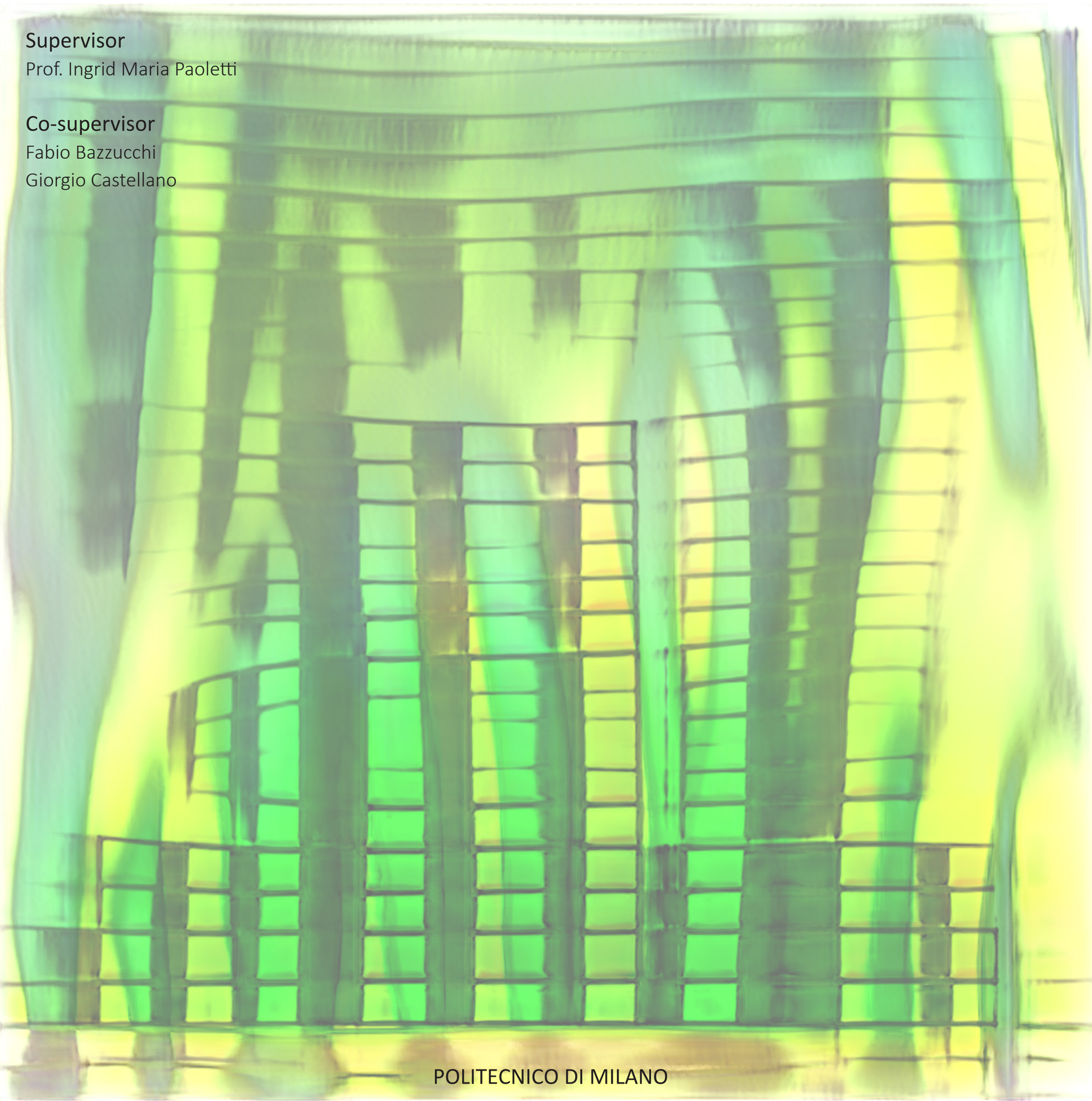

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Table of contents

Parole chiave:

intelligenza artificiale,

architettura;

metodologia;

creatività aumentata;

suggestioni architettoniche

La ricerca mira a definire una metodologia che stimoli la creatività nelle prime fasi del processo progettuale attraverso l'utilizzo dell'intelligenza artificiale; ne vengono affrontati sia gli aspetti teorici che operativi.
Lo sviluppo di nuove tecnologie ha sempre influenzato l'evoluzione delle varie discipline; un'analisi degli strumenti che hanno cambiato il modo di fare architettura durante il ventesimo secolo risulta quindi necessaria.

Un'intelligenza artificiale altro non è che uno strumento digitale la cui struttura interna è simile a quella del cervello umano. È uno strumento capace di elaborare grandi quantità di dati, da cui apprende e riesce a generare nuovi risultati.Il metodo attraverso cui un IA impara è però differente da quello umano: le reti neurali sono capaci di estrarre la struttura interna dei dati, cioè un pattern, un sistema di relazioni – non identificabile dal cervello umano – sulla base del quale le nuove soluzioni vengono generate.

L'abilità delle IA di apprendere dai dati ha stimolato l'insorgere di alcune domande sulla possibilità di questi strumenti di costruirsi una propria "memoria", se siano in grado di "sognare", o di essere creativi.
Nell'ultimo decennio, l'avvento dell'"AI Art" ha fortemente messo in discussione il concetto stesso di creatività, e molte applicazioni sviluppate di recente stanno già influenzando il modo in cui l'architettura viene pensata.

Il metodo sviluppato in questa tesi si orienta quindi verso l'integrazione della "creatività artificiale" all'interno del processo progettuale. Attraverso l'esplorazione dello spazio latente – la "scatola nera" di una rete neurale – il modello di intelligenza artificiale è in grado di generare delle suggestioni architettoniche tridimensionali, fornendo un punto di vista a volte "alieno" e "allucinato" al progettista.

Domande di ricerca:

- Quali risultati è possibile ottenere creando un'intelligenza artificiale personalizzata, considerando le competenze acquisite da un architetto durante il suo percorso accademico?

- Ai futuri architetti sarà richiesto un alto livello di competenza sul tema?

- Che livello di controllo da parte dell'utente risulta necessario su strumenti IA? E in quale fase del processo risulterebbe più efficace?

Abstract

Keywords:

artificial intelligence;
architecture;
methodology;
creativity augmentation;
architectural suggestions

The research aims to define a methodology to enhance creativity in the early architectural design process through the tool of artificial intelligence. Both theoretical and operative aspects are here discussed.
The development of new technologies has always affected the way disciplines evolve. An outlook across the twentieth century to understand the impact of new tools in architecture is here provided.

An artificial intelligence is a digital tool which internal structure is similar to the human brain's one. It is able to elaborate great amount of data, from which learns and generates new results. The way AI learns, however, is different from human one: it extracts internal data structure, patterns, relations, understanding the hidden rules that connect data, and from that generates new solutions.

The ability to learn from data questions whether AIs can construct their own memory, if they can "dream", or be creative. In the last decade, the advent of "AI Art" strongly questioned the concept of creativity itself, and very recently many researches and applications came out, which are already affecting the way architecture is conceived.

The methodology developed here is oriented toward the integration of AI creativity inside the design process. Through the exploration of the latent space – the black box of neural networks – the trained model is likely to generate three-dimensional architectural suggestions, providing an "alien" and hallucinated perspective.

Research questions:

- Which results can be obtained in programming a custom AI model, considering the competences developed during the academic career?

- Is a high level of expertise on this topic required for future architects?

- How much human control on AI tools is needed? And in which phase of the process human control is more effective?

Preface

Starting this research has been quite disorienting.

Artificial intelligence application in architecture is a cutting-edge practice, with many ongoing researches. Although the initial excitement, first readings and meetings made me recognise my lacks, I was missing many notions proper of the discipline. Finding a precise research direction, thus, has been quite challenging.

Many papers on the topic recently emerged, the great part of which describe more the technicality of the neural networks rather than the thoughts behind the research. The first book that gave me a quite general overview on the world of artificial intelligence is Artificial Intelligence and Architecture, From Research to Practice, by Stanislas Chaillou, a young French architect and AI researcher, which gives a quick but complete overview on AI first, and collects a series of current applications, software and researches on architecture.

Thanks to this book, I discovered the works of architects as Matias del Campo and Neil Leach. What caught my curiosity was their publication for the Architectural Design Journal, Machine Hallucinations, Architecture and Artificial Intelligence, a collection of researches which explore the way machines reason and create, questioning the concept of creativity and how to implement it in architectural field.

Inspired from that, I started to think about how to implement this hallucination inside the workflow of an architect.

Continuing the readings, I discovered that an actual limit of AI models is the possibility to work in three-dimensions. This is due to the high complexity from both structural and computational point of view.

Some application succeeded to generate 3D geometries from textual inputs, obtaining however very low quality masses with can just resemble the described object. Other applications recently developed tries to work with 2D data – images – to reach 3D.

Among them, the work of Mathias Bank Learning Spatiality, A GAN method for designing architectural models through labelled sections, shows how to embed information inside sections through colours and

to generate a series of images to compose a final three-dimensional representation of a building.
This process has been adopted for the methodology here developed.

The methodology consists of 4 main steps:

- Creation of the dataset
- Training the neural network
- Generation of images
- Assembly the images

Creating the dataset has been the easiest part of the process since 3D modelling skills have been developed during the academic career, but it was also the most time-consuming part. Indeed, it took one entire month to model all the chosen buildings.
Material have been collected mainly from the online architecture magazines Divisare and ArchDaily, and from the architecture firms' websites. From such material has been used as base for the modelling, done through Rhinoceros 3D, and the production of images through a Grasshopper algorithm.

For the training and generation part, a StyleGAN2 neural network have been used. Such model is largely employed for generative purposes; thus, many open-source models are available online.

Here the work of Derrick Schultz has been essential to procced. In his works, he investigate the creativity of AI in image generation and filmmaking production; on his Artificial Images YouTube channel, lectures about how to use his models are freely consultable.

Even so, the process has not been so streamlined: issues internal to the code about compatibilities often emerged and lines of code are difficult to understand from who never approached any programming language, even if explanations are given. This have been the initial operative barrier. Here, online resources as StackOverflow and ChatGPT have been useful tools to solve issues impossible to overcome without.

Then, two different platform have been considered for the training: Google Gsolab and Runway ML Lab, which propose different resources to complete the process. Such platforms have been useful also for the generative step, providing tools to explore the latent space – that is the mind – of the trained model.

Finally, the assembly process has been done through a second grasshopper algorithm, which dispose the images next to each other and convert them into points, resulting in a pointcloud representation of an hallucinated building.

The research does not pretend to be the best optimised methodology to implement AI inside architecture. It is proposed as application that firstly does not require a high level of expertise in machine learning, and allows designers to generate three-dimensional architectural suggestion which can be used as non-conventional inspiration for the early design process.

The thesis is divided in two sections:
THEORETICAL BACKGROUND and OPERATIVE PROCESS.

The first part is more discursive and introduce the development of AI through time. Although is generally agreed that Alan Turing – a British polymath who operated during the Second World War until the first years of 1950s and also known for inventing the “Turing Test” – is the first to address the potential of an artificial form of intelligence – it has been considered the first conceptualisation of an “artificial neuron” and an “artificial network”, happened in 1943, as starting point for the historical discussion.
Follow a selection of tools identified as paradigm shift in the architectural practice; the explenation of the different types of artificial intelligence and some selected in the architectural practice; the concept of creativity and the discussion around it, with chosen cases of AI creativity application in architecture.

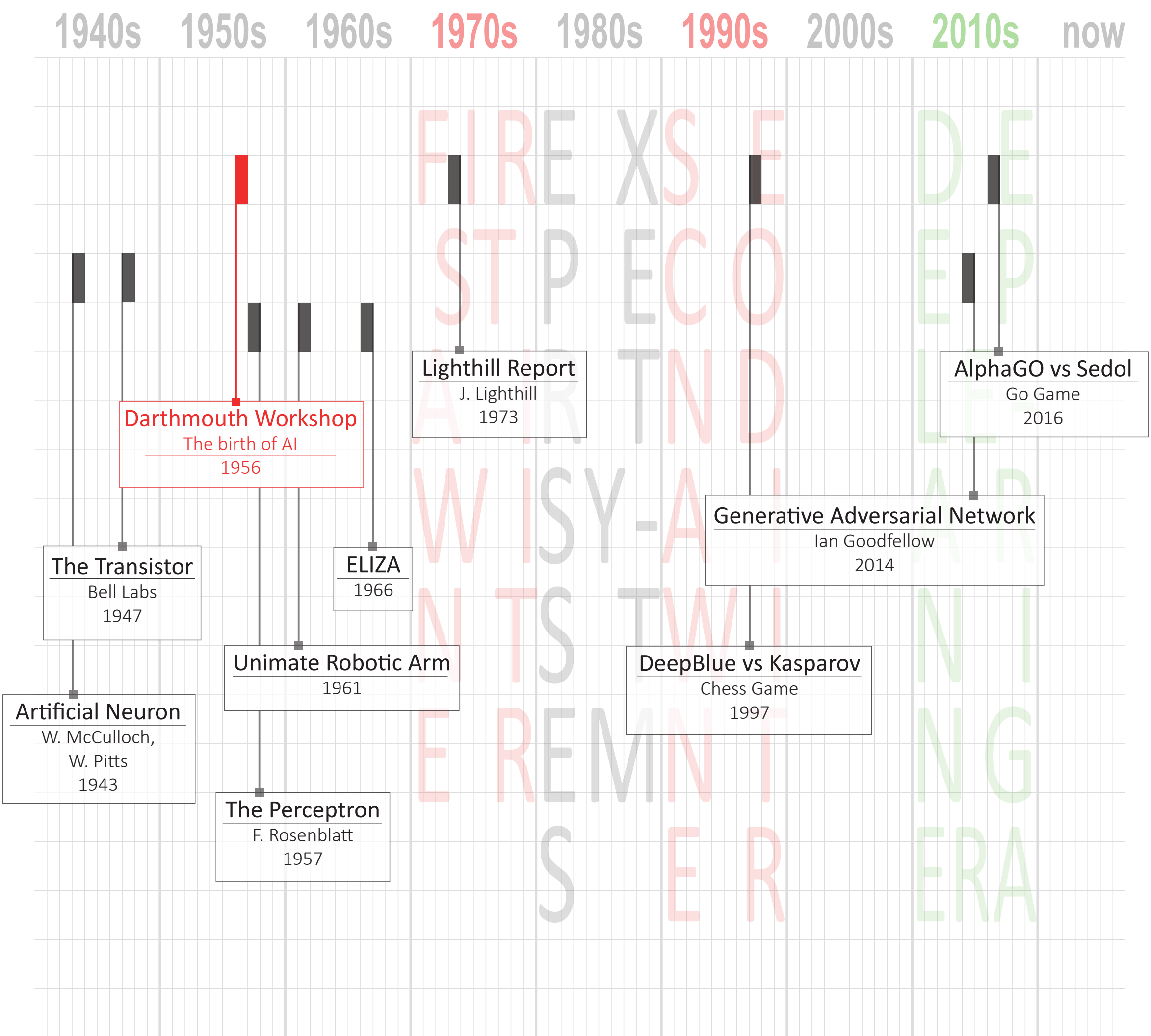
The second part is instead more descriptive. The overall process is explained step by step, discussing also the issues faced during the work done, and analysing the obtained results.

The thesis ends with some consideration about the possibility of controlling the interaction with the trained AI, comparing results obtained with a random process and a more guided one.
Some suggestions on future developments which could enhance the methodology itself are finally provided.

THEORETICAL BACKGROUND

Here introduced:

Artificial Intelligence (AI)
Machine Learning (ML)
Deep Learning (DL)
Tool as paradigm shift
Big data
Neural Network (NN)
Generative Adversarial Network (GAN)
Creativity
Machine Hallucination
Latent Space



AI's historical timeline, from early post war period up untill the contemporary Deep Learning era. (author)

1 HISTORY OF AI

1.1 First Approaches to AI

1 Bell Labs' Website, "The 1956 Nobel Prize in Physics"

From an historical point of view, it could be said that the second post-war period is a quite near past, but from the computer science development side it is quite far in time, mostly looking at the exponential development of technology from that period on.

The first scientific notion of "artificial network" is dated back to 1943, thanks to the work of the American scientists Walter Pitts and Warren McCulloch, which laid down a mathematical formulation of the biological neuron[1], describing the computation performed by a neuron to process a flow of data.

In 1947, then, at the Bell Lab – part of the American telecom company AT&T – some researchers came up with a new type of semiconductor device, the Transistor[1], a technology able to dimmer or amplify an electric signal. This new hardware allowed to materialise theoretical models in functioning prototypes, and few years later, in 1953, the American psychologist Frank Rosenblatt run a great experiment at the Cornell Aeronautical Laboratory using a custom-built hardware prototype: the Perceptron. Realised on a "learning" machine theoretical model, the Perceptron was designed to classify images, in the sense that it was able to tune its settings when exposed to arrays of images. What was important here is the prototype's ability to perform a self-corrective feedback loop, opening a new direction for the following researches.

The event which is historically identified as the birth of the Artificial Intelligence, however, is the Dartmouth Summer Workshop, held in the same years at the Dartmouth University. Such event aimed to codify the capacity of learning of the human brain, which functioning principles could have represented a new way of defining algorithmic logic:

> *"We propose that a 2-month, 10 men study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can*

Marvin Minsky, Claude Shannon, Ray Solomonoff and other scientists at the Dartmouth Summer Research Project on Artificial Intelligence. (©Margaret Minsky)

> *be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer"[2].*

Other technological inventions came in the following years.
Between others, the iconic Unimate (1961), the first robotic arm, developed for the General Motors' assembly line, which could perform tasks like transporting manufactured part and welding, and ELIZA (1966) [3], a model able to recognise patterns of casual conversations and to use them in a textual exchange with a user.

Gradually, experiments would spread beyond the research environment and be applied to real world problems. Herbert Simon, American cognitive psychologist, condensed the period zeitgeist in this statement:

> *"the simplest way I can summarise is to say that there are now in the world machines that think, that learn, and that create. Moreover, their ability to do these things is going to increase rapidly until […] the range of problems they can handle will be coextensive with the range to which the human mind has been applied"[4].*

1.2 AI Winters

In the 1960s-70s, and later in the 1990s, the AI discipline underwent two periods of self-doubt, known as AI winters.

Many factors were contributing to this reduction of confidence in AI technologies, which common origin is redirectable to overinflated expectations, but two particular events characterised the first period.

One setback came from United States, seeing that government's investments in developing instantaneous translation for the Cold War did not produce the expected results: the translation would have given a precise output only with words placed in the correct order[5]. In the meanwhile, British Professor James Lighthill published a controversial paper, the Lighthill Report (1973) – initially called "Artificial Intelligence: A General Survey"[6] – describing the general disappointment in the promises and expectations generated in the fields by the discoveries made so far and which did not produce the expected impact.
The influence of this publication got public fundings and researches in the AI discipline momentarily frozen or reassigned to other scientific domain.

In the 80s, a new generation of models and the availability of new hardware – and so computing power – took the confidence back to the discipline. These new models, called expert systems, allowed machine to

World chess champion Garry Kasparov playing against IBM's Deep Blue in 1997. (©Financial Times) reason (but not to learn) on a given knowledge base and a given set of rules, enabling them to infer the truth of new statements[2].

2 The MYCIN project (1972) at Stanford University, is one of the most iconic examples of expert system. It was meant to be used in medicine to identify infection-inducing bacteria, reasoning on a knowledge base of almost 600 rules[44].

After few years, however, expert system reached a plateau. Most of the models needed common sense, and they were "difficult to extend beyond the scope originally contemplated by the designers and to recognise their own limitations"[7]. Thus, for a second time fundings to the discipline were significantly reduced, and a second AI winter came.

During the 1990s and the first 2000s the learning models, left apart from expertise systems, became the centre of AI research. The possibility of overcoming the human being's intellect was one of the major objectives for AI, and two main events manifested this achievement – opening future discussions on human existence, human skills and on creativity.

One of the main human intellect manifestation have always been the Chess game, and the possibility that other forms of intelligence could beat humans have been amused for a long time.
In the 1997 this happened: the IBM's super computer Deep Blue beat for the first time the world chess champion Gerry Kasparov in a match; a total of six games, two won by Deep Blue, one by Kasparov, and three were drawn.

Deep Blue is a classic example of machine learning: with a given number of rules based on information distilled from games of chess experts, the model "learned" to play chess by playing thousands of games, determining many parameters not initially programmed; "for example, it was not programmed how to weight a safe king position, compared to a space advantage in the center. The optimal values for these parameters were determined by machine learning over thousands of master games"[8].

This event put AI again under the spotlight, it was a new beginning and a new wave of enthusiasm for the entire discipline, but this was not the only novelty. It was also the period of the development of new technologies, whose boosted this AI revival. The advent of Internet was crucial for data collection and analysis, allowing AI models to have a much broader quantity and variety of data to process and to grab information from. In parallel, new hardware able to process operations faster and faster have been developed and launched on the market. GPUs (Graphic Processing Units) became then more accessible, and their ability to parallelise operations – instead computing them sequentially – allowed to speed up the computation time.

South Korean professional Go player Lee Se-Dol during the fourth match against AlphaGo, during the Google DeeMind Challenge Match on March 13, 2016 in Seoul, South Korea. (©Getty Images)

1.3 The Deep Learning Era

On these foundations, the 2010s gave the birth to the term “deep learning”[3], as an acknowledgment that artificial networks would have been the core of the discipline from now on, opposed to the other architectures previously employed in AI research.

The second milestone event is about the GO Game, strategic game mainly diffused in the Asian continent. It happened in 2016, held in Seoul, South Korea.
A Go game between Korean 9-Dan professional Go player Lee Sedol, and AlphaGO, an AI model developed by DeepMind Technologies – a Google company. Although the Go game seems analogous to chess – they are both strategy games played on a black-white board – here the complexity is way more enormous, since the number of potential board positions is greater than the number of atoms in the universe .
Demis Hassabis, CEO of DeepMind, stated that, instead of embedded rules and heuristics, this model have been imbued with the ability to “learn”, and that its learning skills are more human-like, through practice and study[8].

The match consisted of five games and, against all the (human) prediction, AlphaGO won the first.But it is the second game that shacked the spectators’ mind: against a cautious Sedol, AlphaGo played an unexpected move – remembered as “The move 37” – which was so weird that people thought to be a mistake, but during the game was clear to the experts that such a move was a strategic one, which changed the rest of the game, making any move from Sedol ineffective.

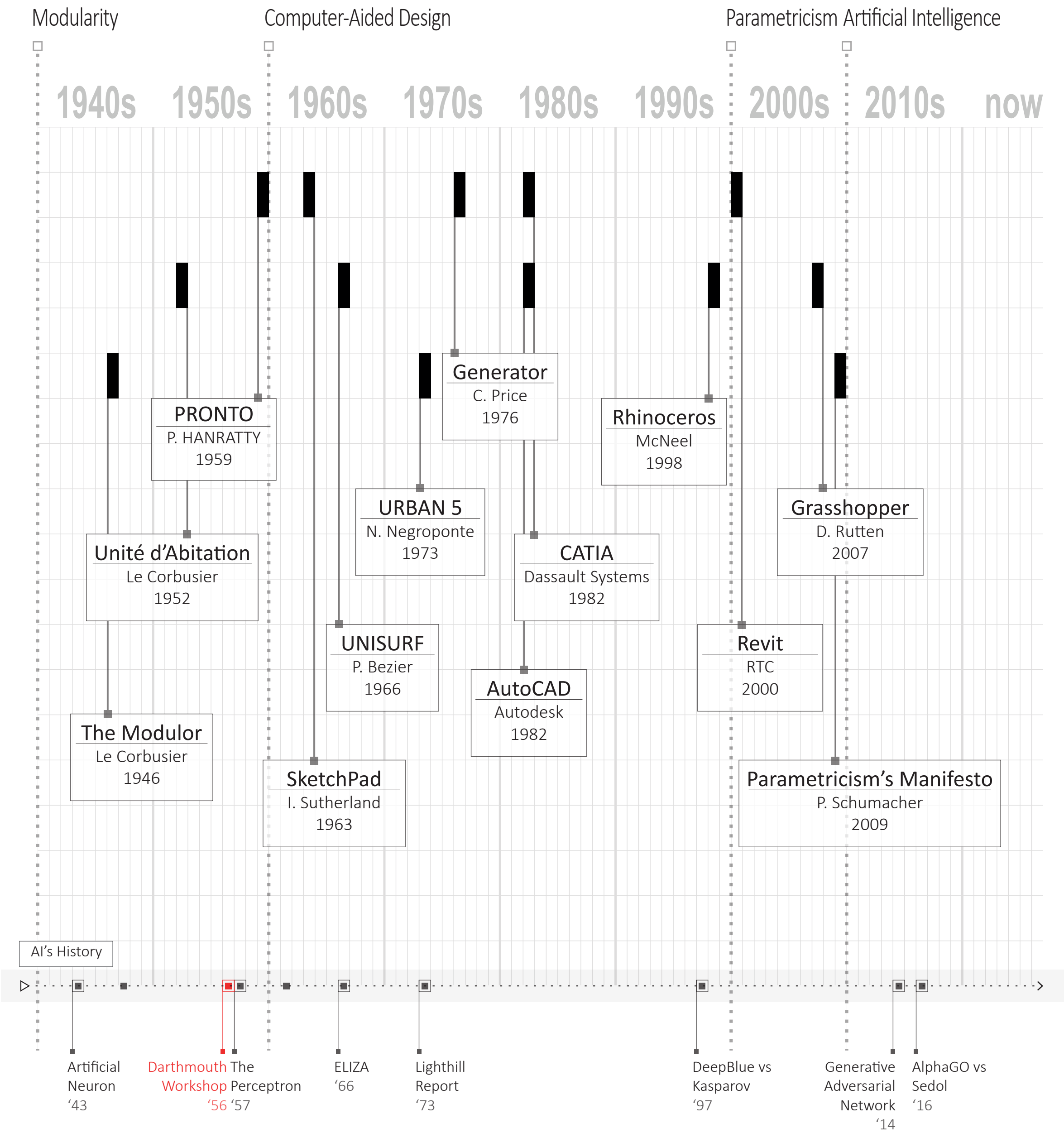
Many of those present questioned the creativity of that move. Hassabis went even further: “anyone can play an original move on a Go board by simply playing randomly. Yet a move can only be considered truly creative if it’s also effective. In that sense, Move 37’s decisive role in game two represents a move of exquisite computational ingenuity that not only changed the game of Go forever, but also came to symbolise the enormous creative potential of AI”[9].
Sedol himself was certain of that, starting also questioning creativity in humans’ moves: “AlphaGo showed us that moves humans may have thought are creative, are actually conventional” .

After facing the AI power, both Gerry Kasparov and Lee Sedol recognised creativity in the moves made by the AI. This brought to question the concept of creativity itself, and the limits in human creativity.
As Neil Leach points out, “the important question, then, is not whether AI could be considered creative, but rather if AI could be more creative than human beings”[8]. The topic is central in this research and will be discussed later with consideration on the architecture field.

3 The idea of “depth” refers to the possibility of adding more artificial neurons in the architecture of AI models, which increases their complexity. The structure of artificial neural networks (ANNs) is discussed in chapter 3.

4 Christopher Moyer, *How Google’s AlphaGO Beat a GO World Champion*, Atlantic, 2016

5 Greg Kohs (director), *AlphaGo*, 2017



Historical timeline of the main tools developed in Architecture since the second post war period. (author)

2 THE TOOL AS METHODOLOGY PARADIGM SHIFT

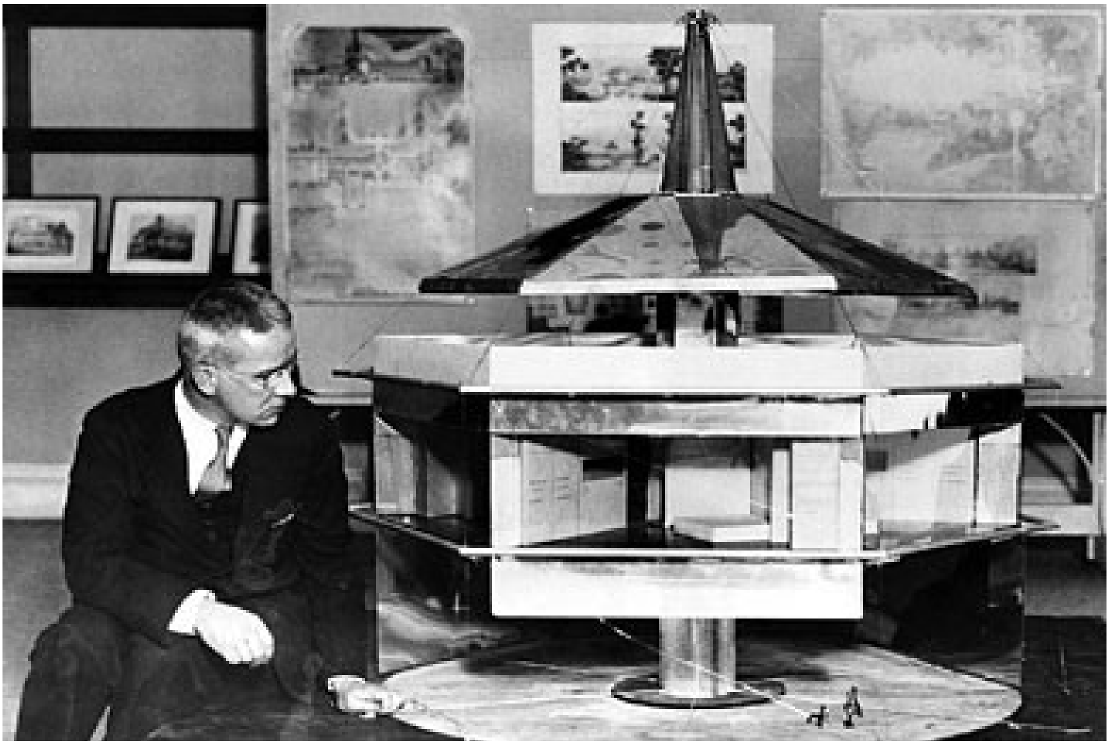
“All tools modify the gestures of their users, and in the design professions this feedback often leaves a visible trace: when these traces become consistent and pervasive across objects, technologies, cultures, people, and places, they coalesce into the style of an age and express the spirit of a time”[10]

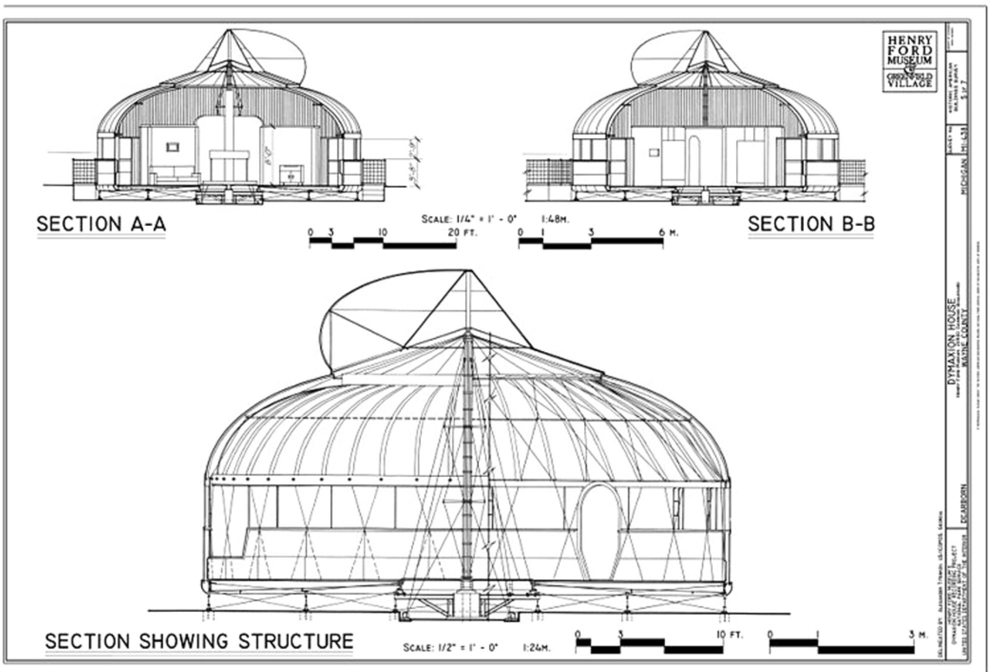
“Architects tend to be late in embracing technological change”[10].
As Mario Carpo writes, architects’ lateness in adopting innovative technologies is deeply rooted to their ancestor Vitruvius, who writes about structural systems and making processes used many years earlier: “Vitruvius refers for the most part to trabeated, post-and-lintel structures, and he doesn’t even mention arches or vaults”[10] in an epoch where those technology were already diffused within Roman architecture. And this is not the only reference to this tendency: for instance, Italian Renaissance did not consider the innovative construction processes developed during Gothic, which have been ignored in favour of a classical revival[11].

However, a turning point can be found in the Industrial Revolution period. The Industrial Revolution has introduced the new technology of assembly line, production industries learned how to apply it, developed a new production methodology, and how to deal with the concept of mass production.

This technology found huge issues when faces architecture. Yet, houses are almost impossible to be identically mass-produced and, for the greatest part of the late twentieth-century postmodernist architects, for which “every human dwelling should be a one-off, a unique work of art, made to measure and made to order”[10], this was never a good idea.
Maybe is this architects’ tendency that brought them to be one of the first category to adopt digital technologies, here supposed to be used for augmenting variability and customisation, rather than producing identical standardised copies.

> *“In the 1990s, the first generation of digitally intelligent designers had a simple and drastic idea. Digital design and fabrication, they claimed, should not be used to emulate mechanical mass production but to do something else, something that industrial assembly lines cannot do”[10].*





Top: Buckminster Fuller and the model of his Dymaxion house, 1930. (©Bettmann/Corbis)
Bottom: Cross-section drawing of the Dymaxion House, late 1920s. (online source: Double Stone Steel)

During the second half of twentieth century, thus, the relationship between architecture and technology started to emerge, and as technology improved and developed new tools, architecture changed his way, and as a limit showed up, technology provided a solution.
In this part of the thesis, I write about the way digital tools shifted the paradigm of the architectural design process: from CAD software, to the formulation of Parametricism, until the present days where tools became intelligent.

However, I wanted to insert as first an analog tool that influenced many aspects of the discipline, both practical and theoretical, and that is still present and guide different branches of design: the grid and the concept of modularity.

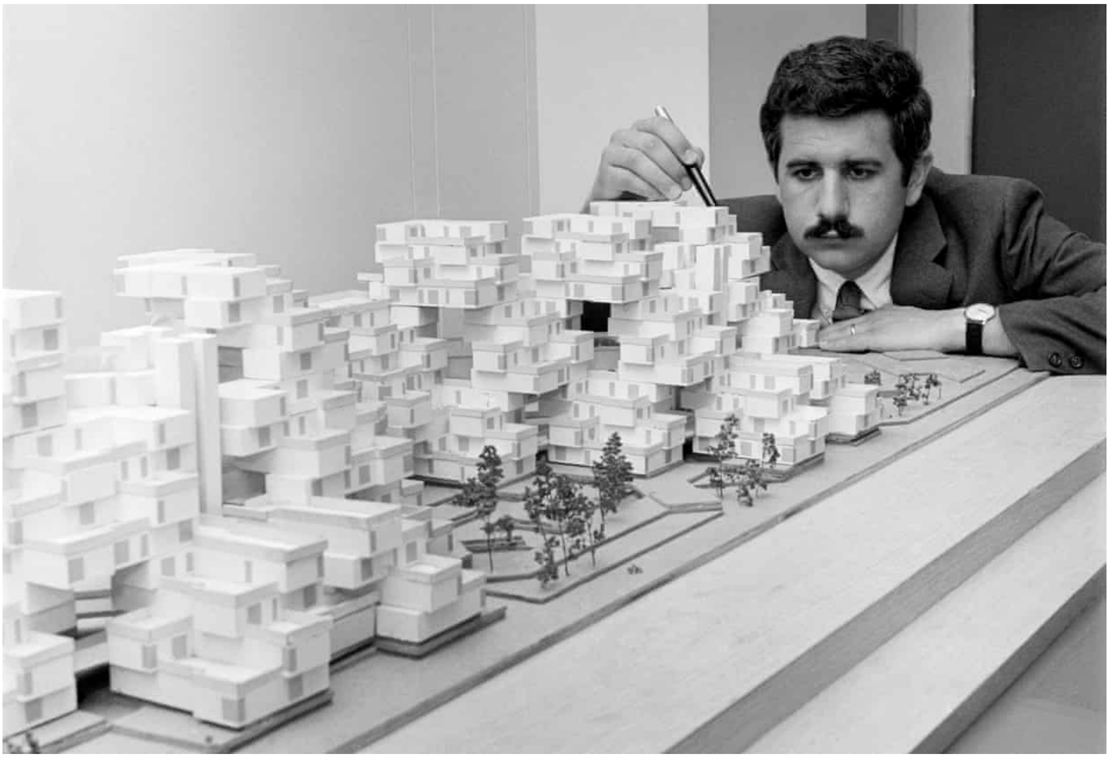
2.1 MODULARITY | The Grid

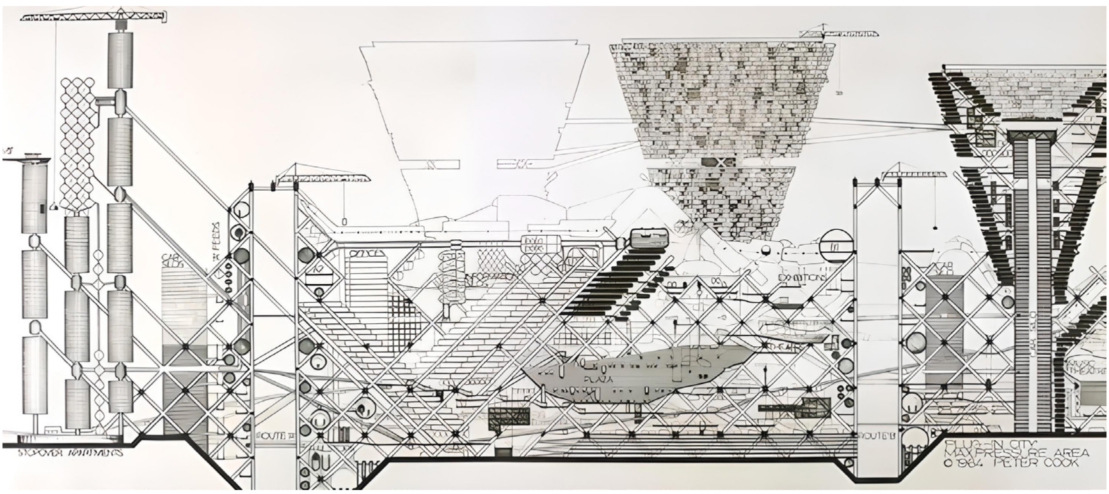
The concept of modularity emerges at the beginning of the 20th century. It has been theorised at the Bauhaus by the German architect Walter Gropius with the aim to technically simplifying the construction process while significantly reducing the relatives cost. Following its own theory, Gropius introduced in 1923 the concept of *Baukasten*, a new design methodology in which standard modules were meant to be assembled according to strict assembly rules to simplify the construction process. As such, modularity was meant to reduce the complexity and increase reliability in the construction process[12].

But was Richard Buckminster Fuller, in America, the one who pushed modular logic to the extreme. With his Dymaxion house, built in 1930, he integrated the networks systems – water pipes and heating, ventilation, and air conditioning (HVAC) – directly within the modules of the house. This allowed for a more efficient approach to building design, paving the way for the integration of technology and infrastructure in modern homes.

Modularity, then, expanded broadly within the discipline of architecture. On this respect, Le Corbusier was one of the main actors in the European architectural scene: with his Modulor concept, which metrics derive from the human body, Le Corbusier designed his buildings from the Unitè d'Abitation in Marseille 1952 to the convent La Tourette (1960).

Through this process of optimisation and modularisation, the tool of the grid always took a place in the task's definition. Architects started to adapt their work to the requirement of the modular principles: the tool of the grid, thus, have been the mean through which architects discovered a new methodology of designing, oriented to affordability and rapid assembling construction.





Top: Habitat 67, started as master's thesis project by Moshe Safdie. (©Bettmann/Corbis)
Bottom: The Plugin City diagram, by Archigram. (online source: ArchDaily)

However, toward the ends of the 1960s, some experimentation tried to bring complexity back to the discipline, exploiting the concept of modularity to conceive a different spatial configuration. Between others, a great example worth to mention is the Habitat 67 housing complex, designed by Moshe Safadie in 1967, which is still today a masterful demonstration of the modular approach: here, prefabricated housing units were assembled on site with cranes, and their irregular disposition was meant to generate equal closed and open spaces for all the families. The result, once again, is a combination of affordability of standardise modules and richness in variation across the overall design.

In the theoretical world, the Archigrams's Plugin City was the main – utopian – approach of modularity to urban studies. Formulated to represent a new envision of a modular metropolis, the project showed how cities, through the aggregation of modules on a 3D grid, could experiment the possibility of a modular vertical growth. The result is a megastructure thought to contain the access system through diagonal lifts and the servicing elements for food and wastes, with a substructure able to carry prefabricated dwellings. Also here, different sizes and compositions of the units would allow to enhance variety and overall complexity.

However, the modularity principles rapidly showed their limits.
This methodology was felt too much as reducing architecture to a simple assembly of modules aligned on a rigid grid, and architects found themselves as assembler of that predefined design systems, which production too often resulted to be quite monotonous. For these reasons, modularity gradually faded away throughout the 20th century[13].

Nevertheless, modularity established a new rational mindset among architects. The concept of grid, module and assembly still today deeply irrigate some of architecture's core principle, from structural systems to aesthetic purposes.

Ivan Sutherland sketching on his SketchPad. (online source: ResearchGate)

2.2 COMPUTER-AIDED DESIGN | The Spline

As previously discussed, 1980s was a strong revival for the computer science field, and it is in those years that CAD – Computer-Aided Design – software were launched on the market. Yet, the computer-aided philosophy started a couple of decades earlier.

At the turn of 60s, the American computer scientist and businessman Patrick Hanratty released PRONTO, thought for engineering design, quickly followed by SketchPad, the first true precursor to CAD. Programmed by Ivan Sutherland at the MIT, SketchPad was the first software which implemented a user-friendly interface and an interaction system, using a pencil as main input device.

The paradigm shift came with the introduction of a mathematical model aimed to define optimal curves construction, known as Bezier's curve, and its implementation into the digital environment. In the late 1950s and early 1960s the French scientists Pierre Bézier and Paul de Casteljau, both employers for the car industry, found two different parametric mathematical notations of general, free-form, continuous curve, then merged under the name of *Bézier Curves*[6]. "The spline, thus, is the smoothest line joining a number of fixed points"[10].

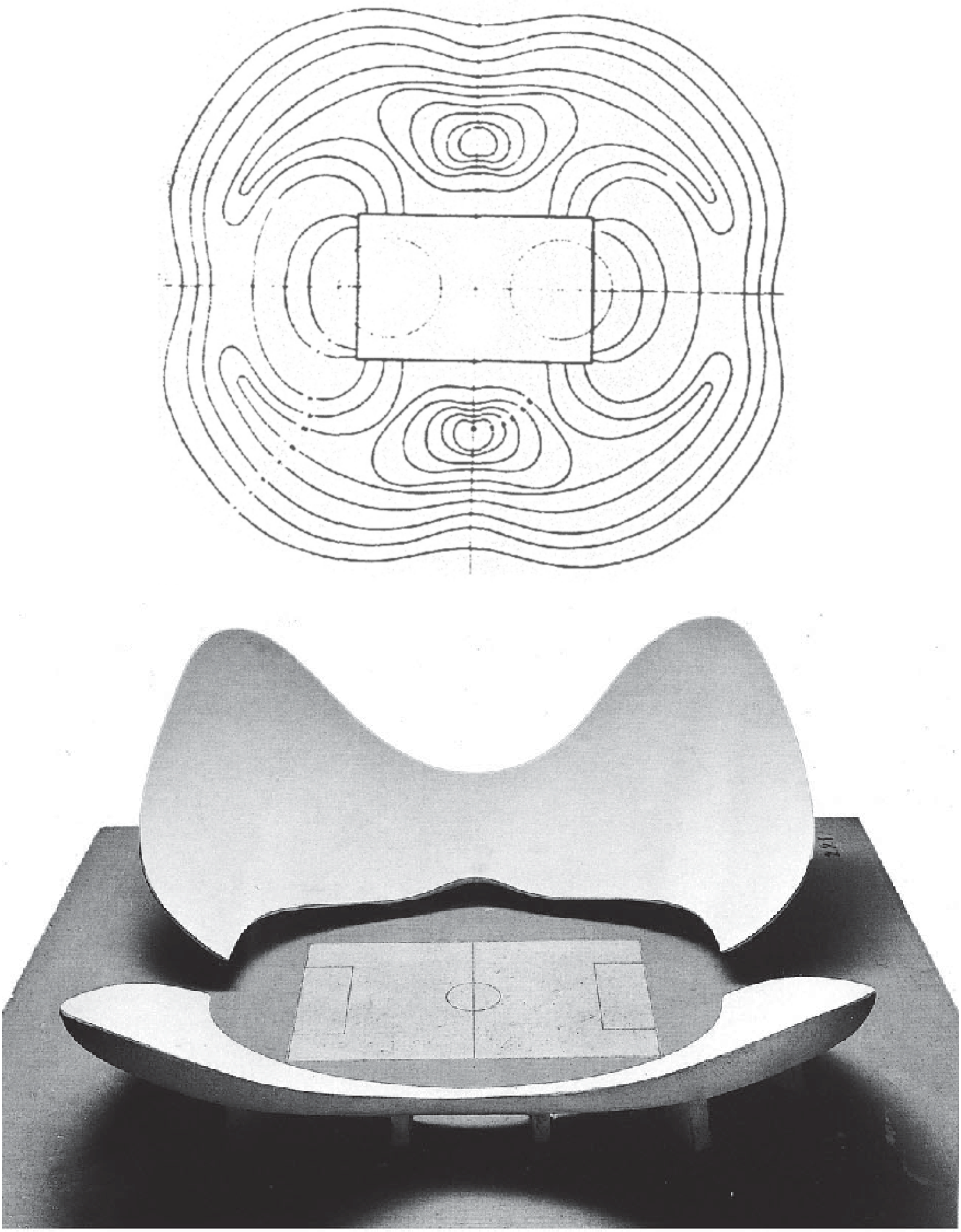
The diffusion of this technology in architecture came with the works of Frank Gehry. In 1990s he was looking for a CAD/CAM software to design the Barcelona Fish, symbol of the 1992 Olympic Games. Gehry has been referred to the Dassault's headquarter in Paris, where teamed up with the businessman Jim Glymph to initiate the use of their main software, CATIA, to solve the extreme geometries of Gehry's designs.

Today, Bezier's curves are generalized under the NURBS model (Non-Uniform Rational B-Splines), the most common contemporary notation for free-form curves in all design and manufacturing disciplines.
Starting from the 1990s, thus, the "spline epidemic" started to spread in architectural offices.

Architects widely adopted this new design method, enabling them to control complex geometrical shapes and create a clearer communication among designers. Its adoption brought sinuosity at the building scale, also becoming a stylistic feature for many architects[7] – between others, Zaha Hadid.

6 Actually the Bézier work is un upgrade of the mathematician Isaac Jacob Schoenberg points interpolation definition, the Basic Spline (B-Spline).

7 These tools, however, generate clean and streamlined objects and images from which every form of the human uncertain and imperfect gesture or analog sign have been removed – which was exactly the purpose Bézier and de Casteljau developed the model for.



Stadium M curvature plan and physical model, Luigi Moretti, 1937. (online sourse: ResearchGate)

2.3 PARAMETRICISM | The Algorithm

8 Schumacher P., *Parametricism as Style - Parametricist Manifesto*, London 2008

Also the way to reach the Parametricism, formulated in 2009 by Patrick Schumacher, began many decades earlier, founding some crossing point with the CAD development.

In 1960s, Luigi Moretti already encapsulated in his Stadium M project the potential of parametric modelling. In fact, for such project he defined nineteen design parameters, each of which was related to a set of mathematical equation that directly informed the final shape of the stadium. Changing one of that parameters would then bring to a different final shape[14].

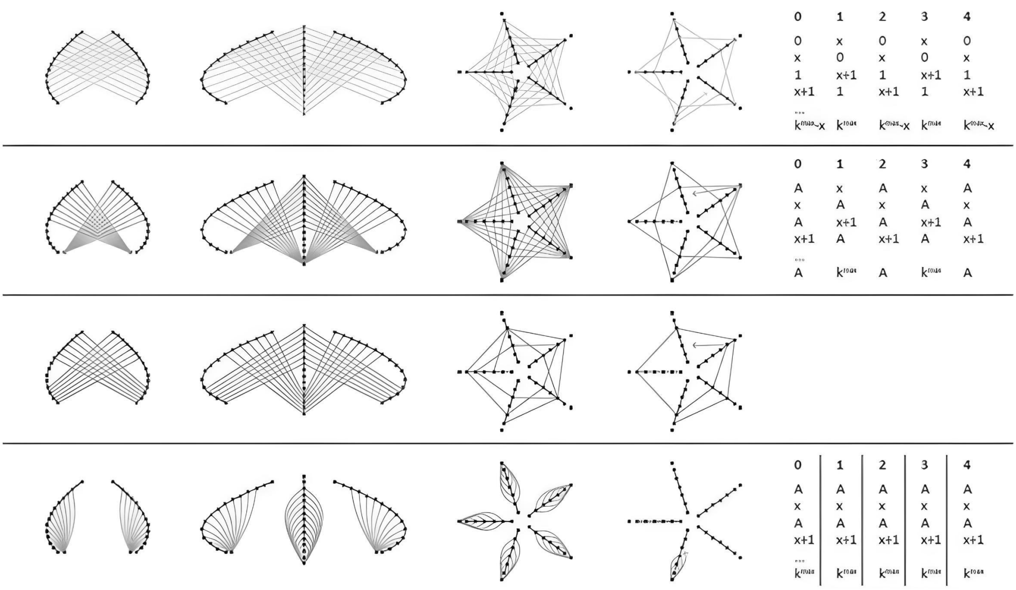
In the software environment, the possibility to manage the design through parameters was already implemented in the Sutherland's SketchPad, where every geometry traced by the designer was translated in a set of variables, which could be handled to change the geometry itself. But is with the introduction of Pro/ENGINEER in 1988, developed by Samuel Geisberg, that the parametric methodology has been consolidated. In the words of Geisberg, "the goal is to create a system that is flexible enough to encourage the engineer to easily consider a variety of designs and the cost of design changes should be as close to zero as possible", meaning the possibility of rationalising shapes into strict rules, to allow for reliable designs explorations[13].

Parametric modelling adoption accelerated the development of visual programming software, and in the 2000s, David Rutted developed Grasshopper, a graph-like interface software which could weave geometries, functions and parameters into sequential procedures, giving architects access to the programming logics without the actually need to learn any specific programming language.

The possibility to implement algorithms into the design process changed the design methodology and mindset of architects: this new level of systematisation partially shifted their attention on investing part of their design time in the definition of architecture's underlying rules, becoming both designers and programmers.

A new generation of architects/programmers, thus, flourished on this design spirit, and among others, Patrick Schumacher, in 2009, finally provided a unified theory of this movement with his manifesto "Parametricism, A New Global Style for Architecture and Urban Design"[8].

On a different but parallel line, and on the Big Data boom of the early 2000s, the concept of BIM – Building Information Modelling – started to emerge with the intent of documenting and managing all the metadata – such as quantities, materials, element properties – tied to



Top: ICD/ITKE Research Pavilion (2012), Stuttgart. (©ICD/ITKE University of Stuttgart)
Bottom: studies of carbon fiber’s and glass fiber’s wires organisation. (© ICD/ITKE University of Stuttgart)

building forms; here geometries are replaced by actual architectural objects, which carry their own set of properties and behaviour. While CAD drawings are representation of the building, BIM models propose themselves as a digital replica of buildings.

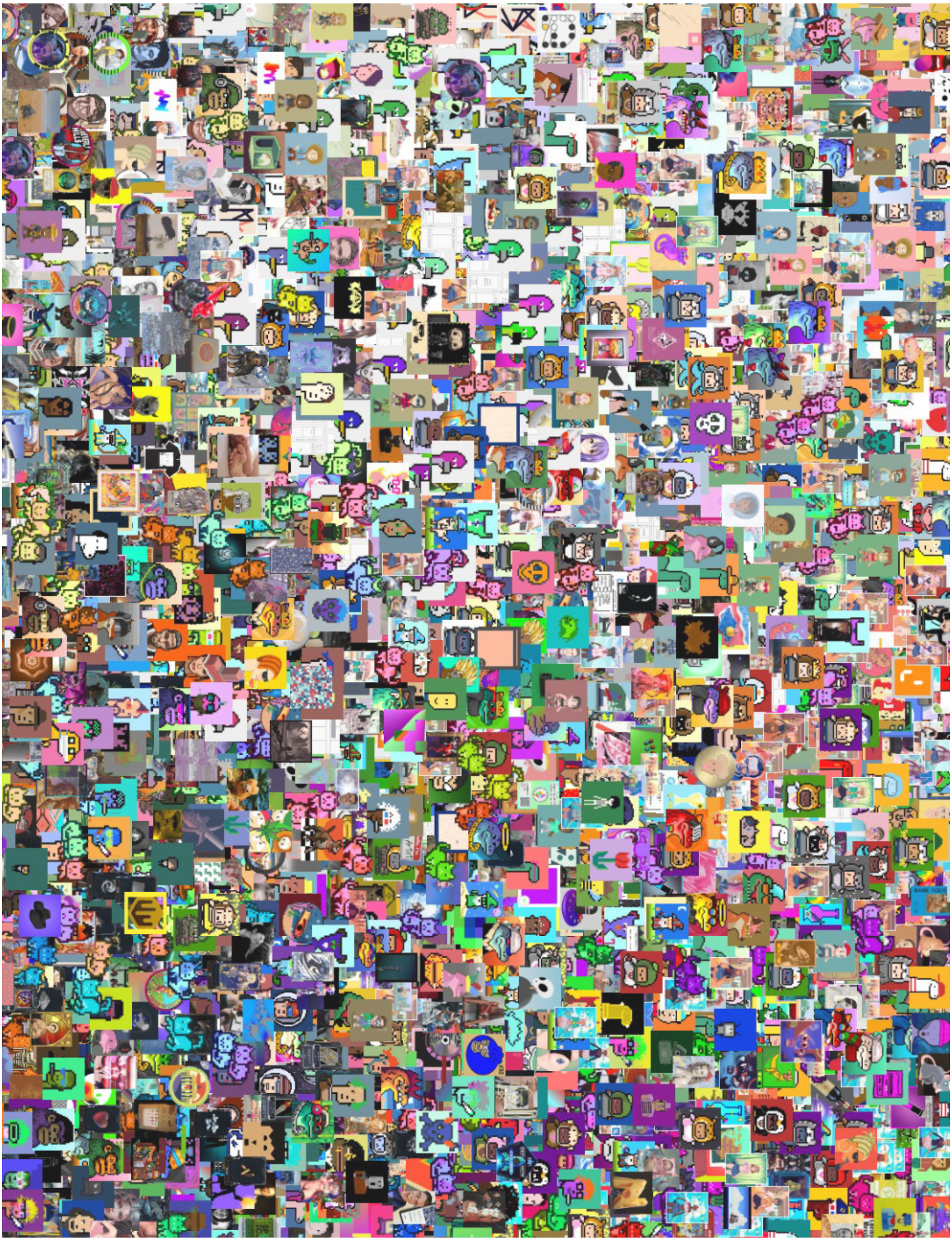
During the 2010s, however, parametric methodology started to be felt too strictly relate to efficiency, pushing aspects as space organisation, style and context consideration in the background. Many critiques also came about the impossibility of formulating explicit parameters and rules to embed essential architectural concerns such as sociological and cultural ones[13].

On the other hand, such practice is strongly grounded in parallel researches, related to material behaviour and structural analysis.
The 2012 ICD/ITKE Research Pavilion was one of the first experiments to be entirely designed through computational tools. Here, considering the materials' properties, many similar structures resulted from a form-finding process were simulated to reach the final configuration – which also means that all the others failed under certain conditions.

This pavilion was the starting point for many other experiments in the field:

> *"through computational form-searching we can already design new structures of unimaginable complexity. But precisely because it is unimaginable, this posthuman complexity belies interpretation and transcends the small-data logic of causality and determinism we have invented over time to simplify nature and convert it into reassuring, transparent, human-friendly causal models"[10].*

The lack of projects with a similar structure was replaced here with thousands of analogue digital copies; such pavilio would have been impossible to realise without the computational power of the computer. Thanks to these tools, today it's possible to design and fabricate materials with variable properties, according to factors such as stress, compression forces, or global load distribution, somehow eliminating the constrains which came with the industrial standard.



Mapping the NFT revolution. (online source: Mauro Martino, mamartino.com)

2.4 ARTIFICIAL INTELLIGENCE | Big Data

9 In computer science the term refers to the internal structure of neural networks, discussed later in the thesis

10 3D geometries generation represent a current field of investigation since its complexity and computational power requirement. Topic discussed in the part of methodology

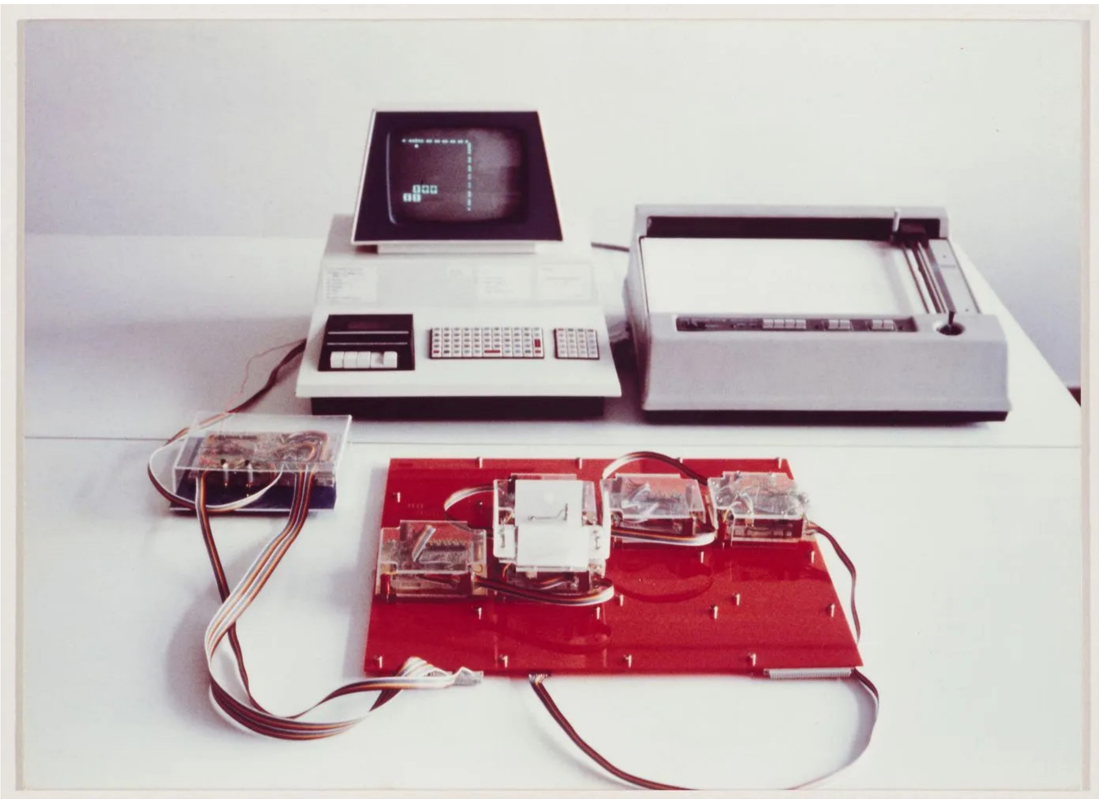
> *"Most Westerners of my generation were brought up in the terminal days of a centuries-old small-data environment. They laboriously learned to cope with its constraints and to manage the endless tools, tricks, and trades developed over time to make the best of the scant data they had. Then, all of a sudden, this data-poor environment just crumbled and fell apart—a fall as unexpected as that of the Berlin Wall, and almost coeval with it. "[10]*

Despite the crises of "AI winters" and the related common perception that have signed the end of AI, today it is evident that this is not the case. The research into AI technologies continued to progress, and silently nowadays are spread all around the human environment, cars, houses, smart devices, learning our behaviour, adapting themselves or suggesting better option for us. "This is one of the biggest problems with Al. Although developments in Al are continuing all the time, the general public is unaware of them. It therefore takes a high-profile public event to bring Al to their attention and show the general public what Al can do"[8].

This technological development have been boosted in the early 2000s by the advent of what is today known as the Big Data. As Carpo denote, "the term "Big Data" originally referred simply to our technical capacity to collect, store, and process increasing amounts of data at decreasing costs, [...] (as the) advantages of writing over orality, of print over scribal transmission, or to each incremental technical improvement of digital technologies for at least the last fifty years"[10].

Now, the term names the period we are living in, where data are into everything, constantly produced, processed – and sold. Data are now the resource around which most of the discipline gravitate, dividing the current period from the technologies developed until 1990s, the first digital turn[10].

Such overflow of data led, in the last decade, to the blossoming of countless deep learning applications. The variety and complexity of AI models have increased, and with it the variety of input able to be processed: convolutional neural networks (CNN), graph neural networks (GNN), generative adversarial networks (GAN), variational auto-encoders (VAE) – and many other architectures[9] – augmented the processing capacity of machines from just simple digits in the 50s, until today where such AI models are able to generate movies, sounds, text and 3D geometries[10].



The Generator Project, Cedric Price, 1976. (online source: Eliza Pertigkiozoglou, medium.com)

"Alphabetical writing records the infinite modulations of the human voice using a very limited number of standard graphic signs. Alphabetical files are data-light: a typed page contains approximately two kilobytes of data, which is more or less the amount of data that Cicero could have inscribed on a wax tablet when taking notes in the Roman senate. The same page, if recorded as a photographic picture in coarse black or white (binary) pixels, would weigh approximately 1,000 kilobytes, or five hundred times its alphabetic equivalent ... But the difference in cost between the storage of a slim alphabetical file and that of the same page recorded as a pictorial image is now practically irrelevant"[10].

Nevertheless, the democratisation of computational power allowed AI solutions to disseminate across all industries, including architecture.

An early attempt to introduce AI in the field of architecture have been made in the 1970s. Nicholas Negroponte[11] and Cedric Price[12] were working on two aspects of interaction between machine and human being: complementarity and autonomy, respectively.

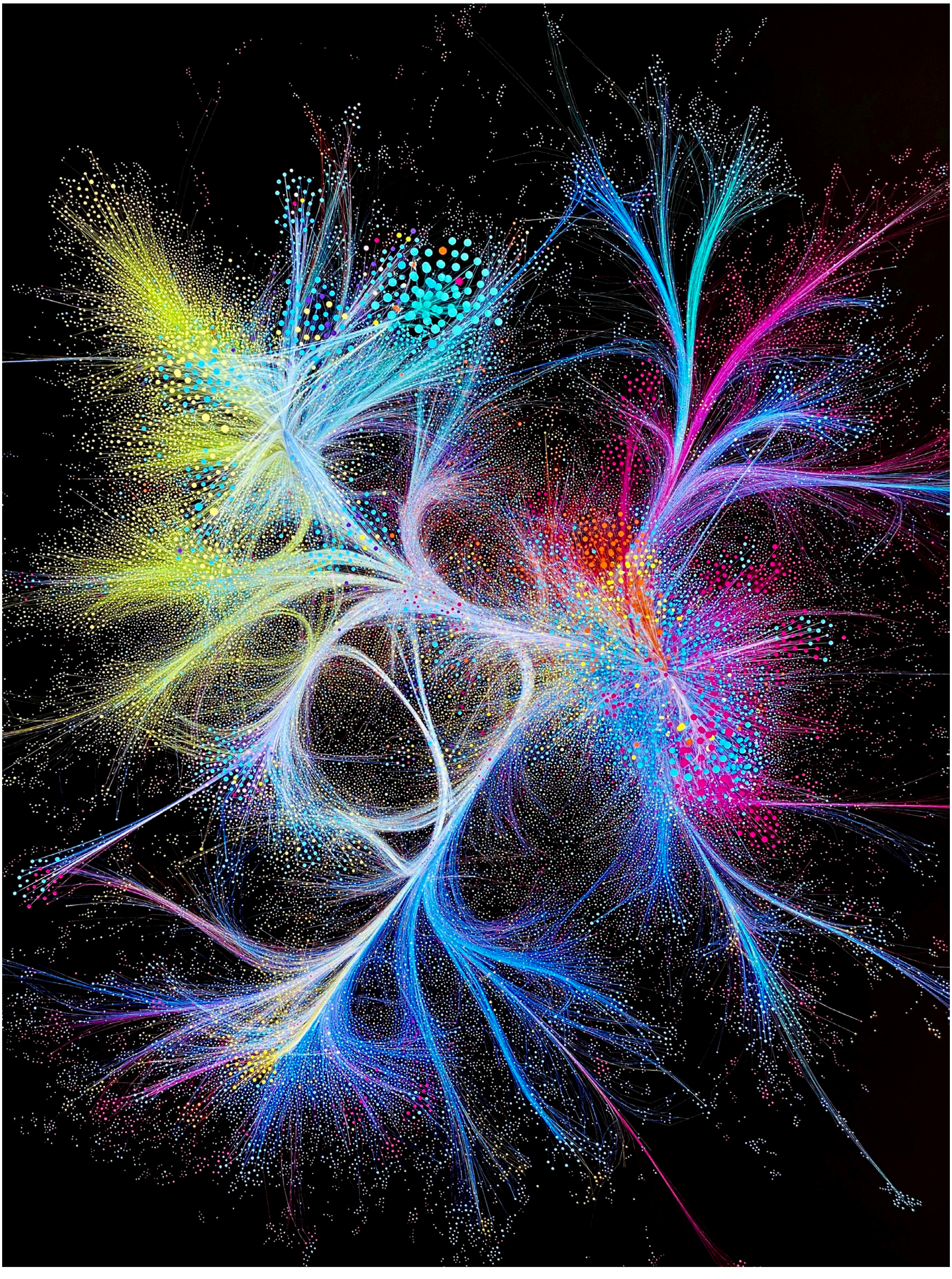
Negroponte explored the machine-designer complementarity through his Urban 5 software: designed to help architects with the room organization inside a floor plan, the software consisted of giving a set of rules to the machine – such as space adjacencies, optimal light conditioning – and the possibility to specify explicit parameters to the user. The software was also able to give feedbacks as object clash detection or to suggest an initial rough floor plan layout.

Price, instead, focused on the machine autonomy and self-adaptation developing The Generator, aiming for self-adapting buildings. The program was able to organize, following an orthogonal grid, a system of partitions inside a floor plan, also adapting them to the users' behaviour. Both Negroponte's and Price's research started the discussion on the AI-Architecture binomial.

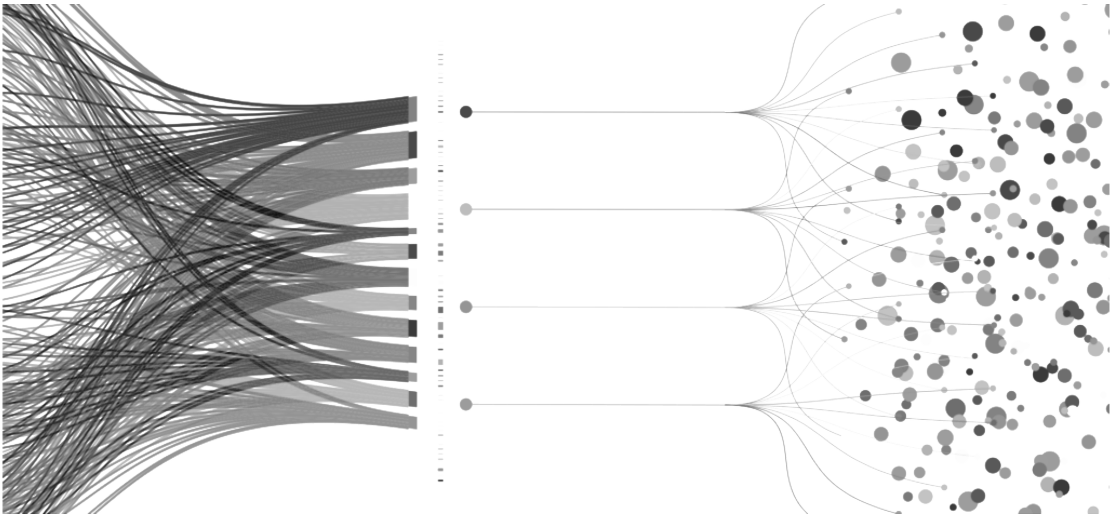
Very recently, a great number of experimentations on different aspects of architecture emerged. Despite the huge data availability, results to be hard to find suitable data for specific tasks, leading thus designers to realise their own personalised dataset.
Data could be whatever: application on energy efficiency and structural optimization, for instance, use values as structured data to feed the AI; for design and creativity purposes, instead, images found out to be a simpler way to embed information – that is, to structure – recognizable by a neural network.

11 Greek American architect and computer scientist, co-founder together with Jerome Wiesner of the MIT MediaLab; has formulated the relation bit-atom, starting the discussion on the digital-natural parallelism.

12 English architect and theorist of architecture, one of the firsts to introduce the concept of adaptability/flexibility in architecture with his Fun Palace.



150 years of Nature, 2019 (online source: Mauro Martino, mamartino.com)



Visualisation of the concept of structuring data (unstructured data on te left, structured data or the right). (online source: cdp.com)

13 IBM Cloud Education, *Structured vs Unstructured Data: What's the Difference?*, Ibm.com, 29 June 2021

In fact, data can be classified in structured data and unstructured data. Structured data are organised following a standard format and are easily decipherable by machine learning algorithms, but also easy to understand and interpret from the user. Examples of structured data include dates, names, addresses. The greater part of data produced are unstructured, means that are not organised in any predetermined manner – text, social media posts, sensor data are just some examples. These data require a high-level expertise to be analysed[13].

AI applications in architecture have been adopted structured data – often images – in order to address a specific result, such as façade design, floor plan design, environmental analysis. As will be explained, some AI models don't require structured data, meaning that data can be fed without a previous labelling process; the NN will understand the features by itself – such data, however, have to be produced/gathered, which is the most important part in the training of an AI, since good input data means good output generation.

The tool of AI will be discussed in deep in the following chapter, where an outlook on the main aspects of AI is given. Before reaching the core of the research, it is important to understand the structure of neural networks, since knowing the way they "reason" is crucial to understand how to implement them in the architectural workflow.

For the first time technology has given a tool to the practice that not only answers to the contemporary needs, but goes beyond, proposing alternative unseen solutions, and this probably is the greatest paradigm shift.

Narrow AI

- Focused on a specific, singular or limited task
- Fixed domain models provided by programmers
- Learns from thousands of labeled examples
- Reflexive tasks with no understanding
- Knowledge does not transfer to other domains or tasks
- No self-awareness, consciousness, ability to think
- Examples include image recognition, hyper-personalization, chatbots, predictive text
- *AIs here employed*

Broad AI

- Higher knowledge and more interaction possibilities
- Adaptability, Robustness and Efficiency
- Multi-tasking
- Multimodal, able to process different types of data
- Able of reasoning and abstraction
- Still without consciousness

General AI

- Full range of human cognitive abilities
- Perform general (human) intelligent action
- Self-learns and reasons with its operating environment
- Learns from few examples and or from unstructured data
- Leverages knowledge transfer to new domains and tasks
- At the moment represented only in fictions

Categorisation of AIs according to their intelligence skills. (author)

3 ARTIFICIAL INTELLIGENCE

14 Some new multimodal AI are already available, OpenAI have launched ChatGPT-4 on March 2023

The artificial intelligence has often been defined as a digital entity that mimics or simulate the intelligence of the human mind. Neil Leach quotes some recent definitions of AI: "AI seeks to make computers do the sort of things that minds can do" – Margaret Boden, 2016 – and "(It is) that field of research that is focused on developing computational systems that can perform tasks and activities normally considered to require human intelligence – John Keller, 2019.

Rather, as Leach itself denote, we should firstly considerate that "intelligence itself is not constrained by the limits of human intelligence"[8]. Actually, in the long term, AI is likely to exceed human intelligence: from a wider point of view, human intelligence merely constitutes the "human-level intelligence".

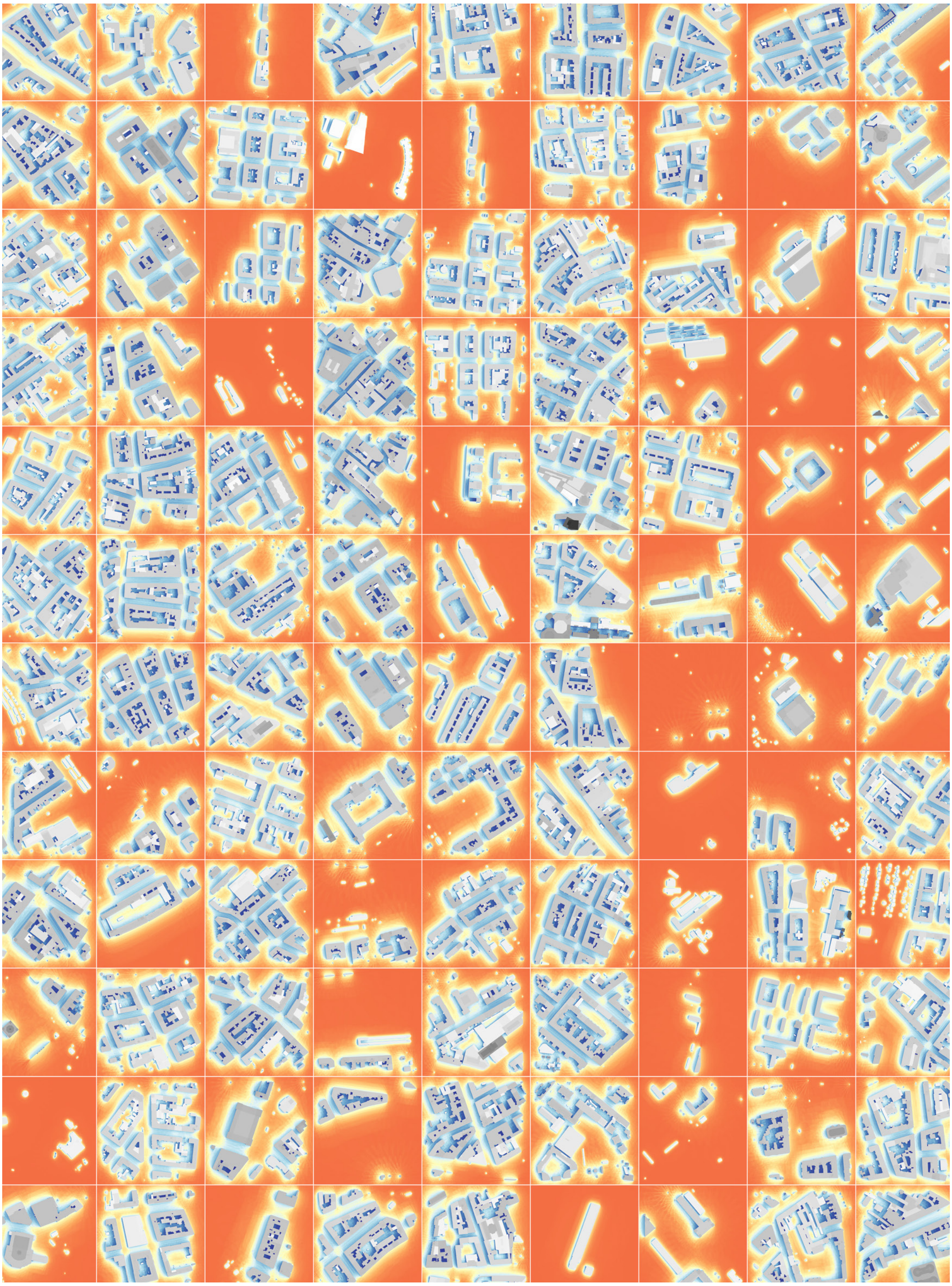
As discussed in the first chapter, already exist some fields in which humans are not the best anymore: if playing Chess and Go games are just examples, yet this is extendable to the whole domain of logic and statistic, where AI power largely outperforms human intelligence.
This denote that our intelligence is just a form of intelligence, which coexist alongside other forms, as biological intelligence and, now, artificial intelligence.

The realm of AI is divided in three levels of consciousness: the first category of AI is known as Narrow AI – or Weak AI or pattern-based AI – and comprehends models which potential is circumscribed to single and simple tasks, often human-driven. Its power is thus limited to solving problems by detecting patterns among data.

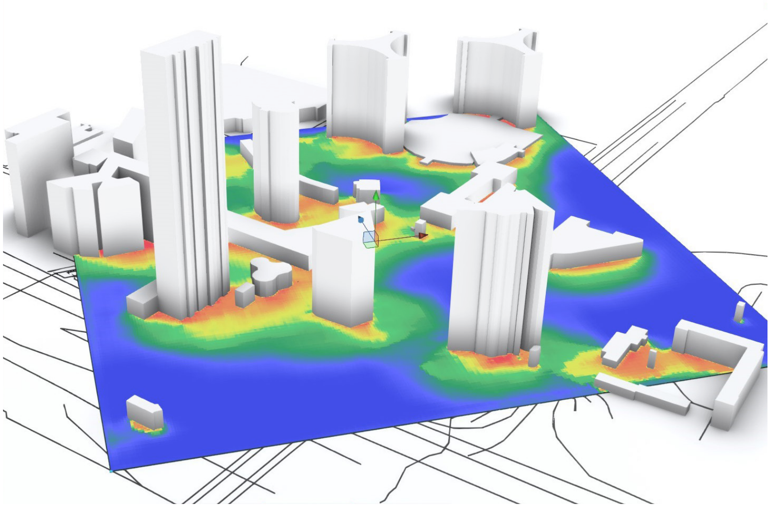
The next category is the Broad AI, which comprehend multimodal and multitasking models, means able to process and understand information from different sensory modalities like text, images, and audio, combining and integrating those data for a comprehensive understanding[14].

Final category is defined as General AI (AGI), which basically is AI with consciousness. Only represented as characters in movies and fictions (like the Terminator, Agent Smith in The Matrix or Sonny in I, Robot), AGI remains a long way off in reality.

The AI models discussed and the ones employed in this research are all part of the Narrow AI. Of them, many AI models are open-source, and users can try to develop their own customised neural network (NN).



Sampling of environmental analysis predictions generated by InFraReD. (source: Angelos Chronis, *An Intelligent Framework for Resilient Design*)

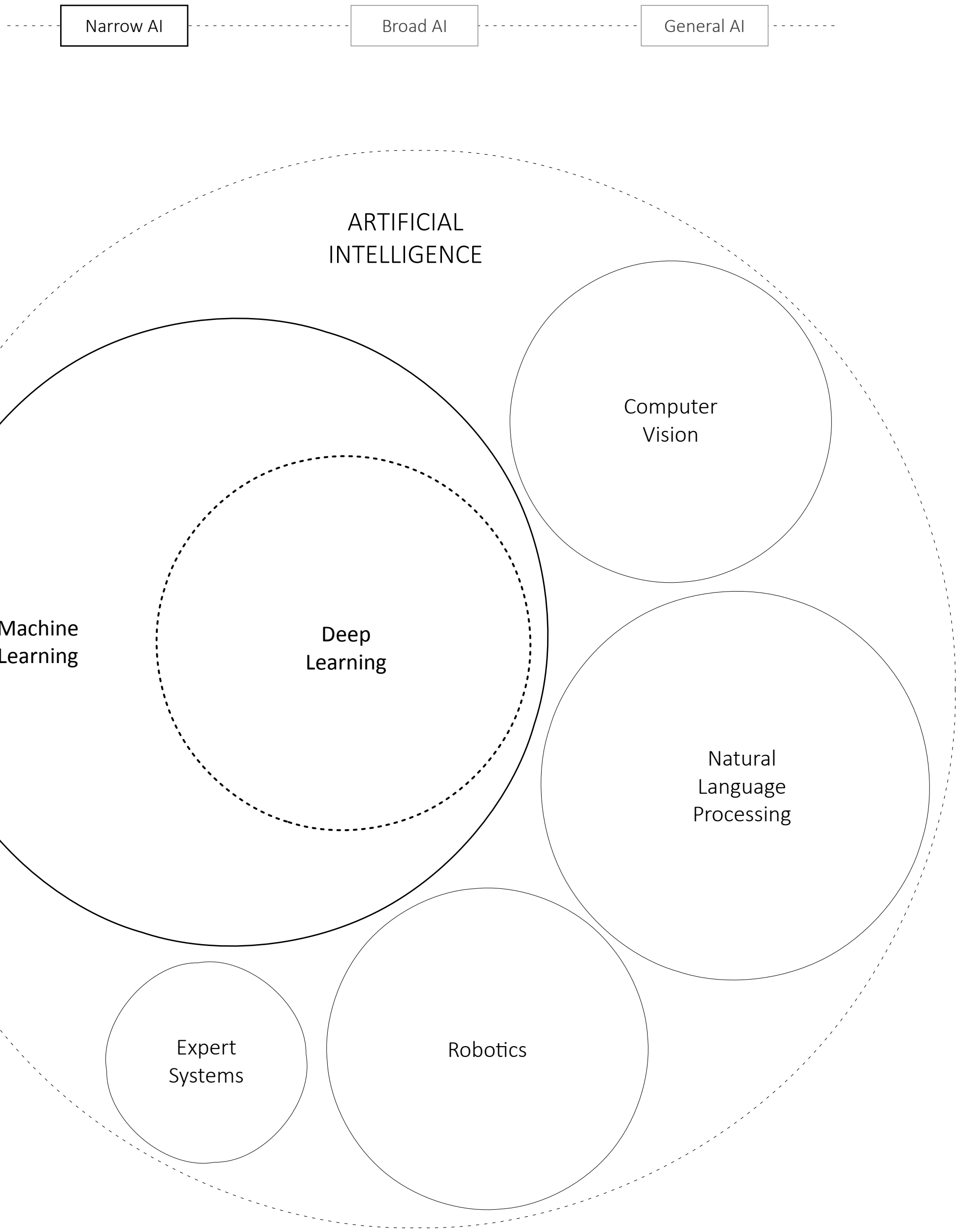


InFraReD interface.(online source: City Intelligence Lab, cities.ait.ac.at)

From such resources, many platforms are emerging, becoming proprietary tools that will change the design workflow forever.
Among others, important is the contribute of Theodoros Galanos and Angelos Chronis and their InFraRed, an AI-driven urban design platform developed in the Austrian Institute of Technology, in Vienna, which provides a novel workflow which embed environmental analysis into the early design process. The software provides real time solar radiation prediction for any urban geometry definition given as input, allowing designers to take such analysis into account already from the first steps of the project, looking for optimal performance solutions.

> *"Time and expertise together define what we can do, but in many ways they also define the limit of what we do, at least in practice. [...] (InFraRed provide) an easier access to these complex simulations, [...] allowing a fluid collaboration between designer and machine, grounded on, and driven by, performance. It solves the problem of time by simply bypassing the need for time and time-consuming simulations"[15].*

The neural network makes predictions, thus it is important to understand the accuracy of the outputs. Tests were made on two radically different urban tissues: in the United States (USA) have been conducted more than 20.000 simulations, almost 1300 sq.km of urban area; in Austria, the city of Vienna has been the target, with 52,42 sq. km of urban area covered by 5242 simulation. A comparison between real simulations and InFraRed's predictions showed a measured average error in the range of 5 to 20 percent and a time reduction of almost 99.95 percent – which is a fair trade off[16].



Schema of AI’s fields of investigation. (author)

3.1 Machine Learning

Within the realm of Narrow AI exist different forms of AI, which can be considered as nested within each other.

The first category comprehends the first versions of AI, known as “Classical AI” – or GOFAI (Good Old-Fashioned AI) – which were programmed to do specific tasks, without learning skills. Then, the advent of Machine Learning (ML) implemented the concept of “learning” in AI models, and the ability of train itself using vast quantities of data.

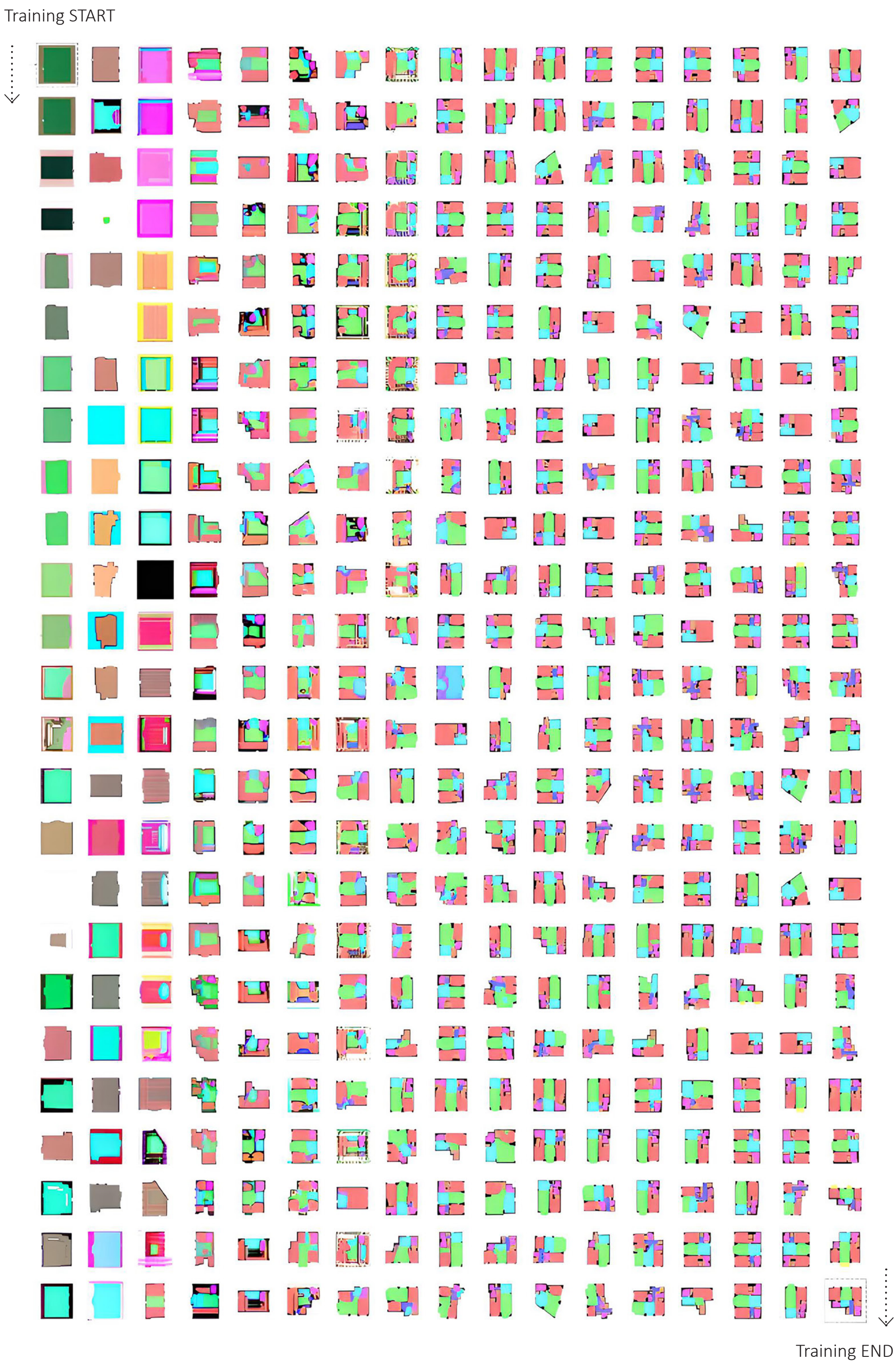
On the concept of machine learning there have been five different schools of thought, each of which questions the way machine learning model “behave”. However, only two philosophies are really significant to understand how the current models operate: the Symbolists and the Connectionists.
The school of “Symbolists believe in solving problems through inverse deduction, by using existing knowledge and identifying what further knowledge might be needed to make a deduction: ‘for symbolists, all intelligence can be reduced to manipulating symbols, in the same way that a mathematician solves equations by replacing expressions by other expressions’”[8][17].

The Connectionists instead attempt to reverse engineer the way brain works: “the brain learns by adjusting the strengths of connections between neurons, and the crucial problem is figuring out which connections are to blame for which errors and changing them accordingly”[17].
Differently from the models used in symbolic AI, then, connectionist AIs execute operations in parallel, are self-organising and works without the need of expert knowledge. “Sequential instructions are replaced by massive parallelism, top-down control by bottom-up processing, and logic by probability”[18].

It is evident that the Connectionists’ theory is the one that shaped the contemporary AI scenario.

Finally, Deep Learning (DL) is the last and more recent category, which already led to many significant advantages in the field of AI thanks to its capability to process huge amount of data – today considered by some “the new oil”. It is important to point out that the difference in capabilities between Classical AI and Deep Learning models is enormous, denoting how fast AI technology is growing.

The distinguish with normal ML relies in the NN’s structure. DL models are characterised by a way greater number of layers, able to compute millions of operations and thus weights. Thanks to their high



Training of the ArchiGAN neural network to generate internal spatial organisation from the building footprint. (online source: Stanislas Chaillou, *ArchiGAN, Artificial Intelligence x Architecture*) computational capacity, such networks are very much employed for computer vision tasks, as image generation, movie generation, data visualisation – GAN models, the ones used for this thesis and the most common for art and architecture applications, are indeed deep neural networks. Thanks to the acquired learning skills, NNs are now able to process data and generate outputs based on them, and the more the AI acquires agency, the more the needed human contribute is limited.

If it is true that ML shifts the control away from the user, is also true that the greatest contribute that AI can give us is to propose scenarios from its "point of view".

> *"Then Wolfram had another idea: he thought that, rather than making computers imitate us, we would be better off to let them work in their own way. He turned to cellular automata, a discrete mathematical model that had been known since the 1940s and had gained popularity in some postmodern circles in the 1970s. In 2002 Wolfram published a 1,280-page book, A New Kind of Science, claiming that, using cellular automata, machines can simulate events that modern mathematics cannot calculate, and modern science cannot predict"[10].*

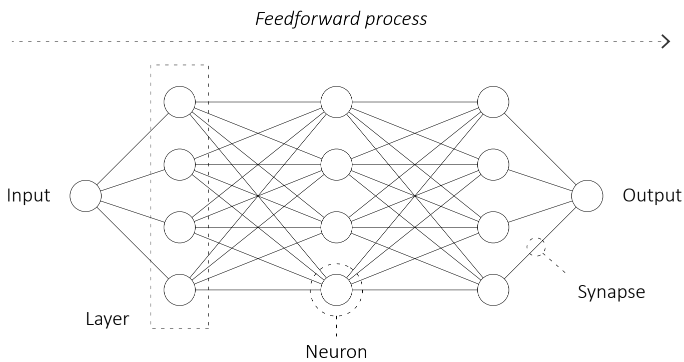
3.2 The Training Process

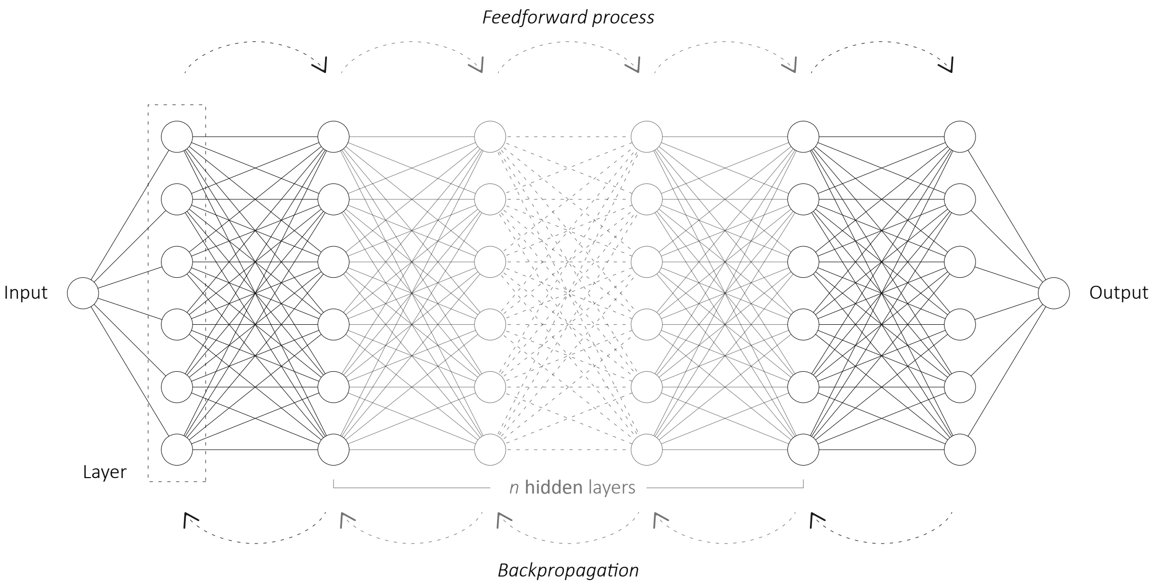
The initial prejudice was that AIs would have been able to generate everything on their own. Obviously, this is not the case; by itself, a neural network is just an empty box, it needs to be trained by a user on specific data in order to construct their own "world"[19], thus to acquire knowledge.

ML models are trained using examples – that is, data. The size and range of data determine the model's accuracy rate.
The answer to how and what a ML model learns depends on its training methodology, which can be classified as supervised, unsupervised or reinforcement learning.

Supervised learning is the most popular form of learning, where a model is trained to satisfy certain tasks to produce an already defined outcome.

This process is somehow similar to how humans learn to identify objects. With unsupervised learning there is no desired outcome, no target. The model is fed with unstructured data and by itself will find patterns inside them, revealing a previously hidden knowledge. As Kelleher defines unsupervised learning models, they are "a form of machine learning where the task is to identify irregularities – such as clusters of similar instance – in the data"[20].





Top: Structure of a Neural Network (author)
Bottom: Structure of a Deep Neural Network (author)

15 These terms are borrowed from neuroscience to describe mathematical elements of a model.

Reinforcement Learning, instead, is a learning technique which does not require labelled examples, but it's based on the logic of "punishment and reward", increasing the knowledge according to the nature of feedbacks ("correct" or "not correct"). Such training method is applied on already trained NNs.

To understand the way AI learns form training data an outlook on its structure is required.

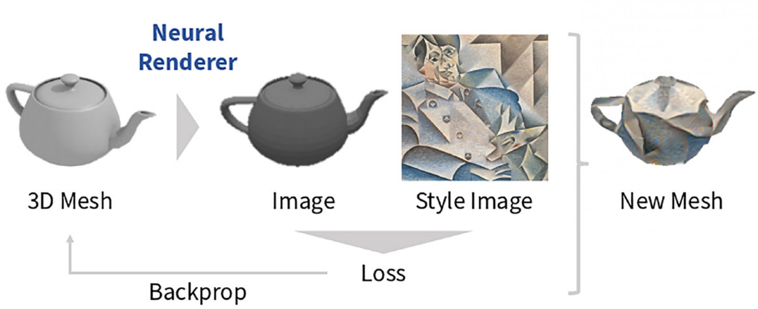
A neural network is a system which structure is based on the human brain's one, therefore it is composed by information processing units called *neurons*, and connections that control the flow of information between those units, called *synapses*[15].

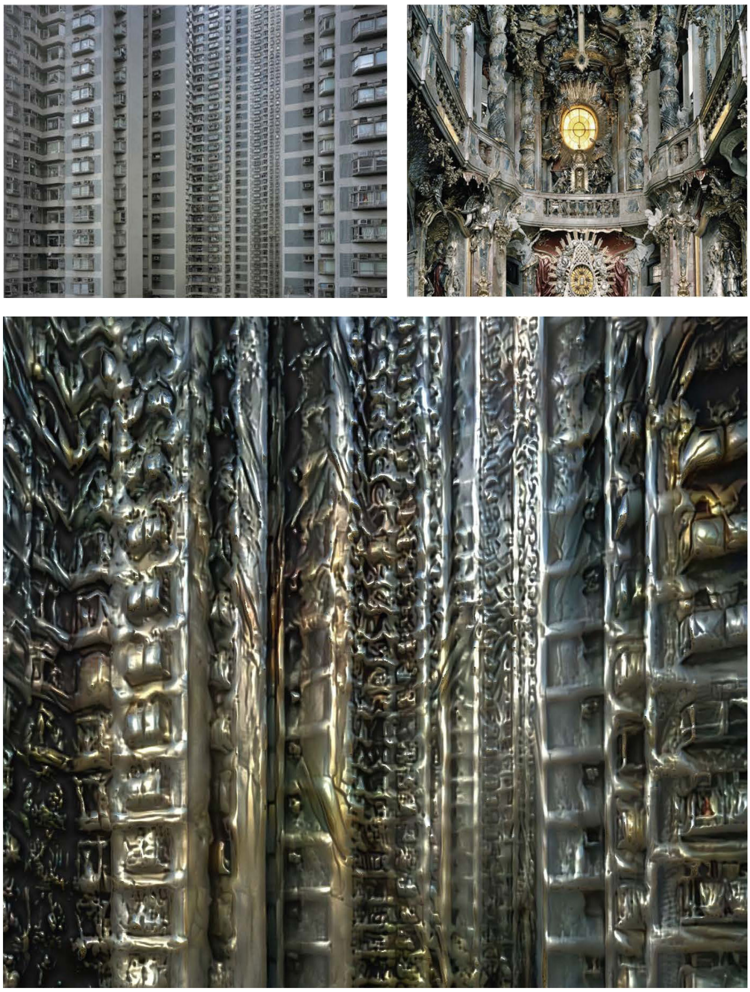
To be trained, a NN needs to be fed with a series of input-output pairs as examples – such as an image and its description. Then, the model will autonomously assign weights for each synapse according to what it has learned from such processed data, so that, testing the trained model, for any new input the output is likely to match an in the training examples.
To learn the different features of data, neurons are grouped into layers, which act as filters and operate in one direction – known as feed-forward process – from the input-layer to the output-layer, passing through a certain number of hidden layers.

Each neuron elaborates its input on the weight of the previous layer input connections, and their task is to filter out certain features of, for instance, an image before passing the new weight to neurons in the next layer. At the end of the process, the generated output is the most probable correct one. (diagramma dei pesi)

Deep learning introduced – and depends on – the concept of backpropagation. This process consists of a self-corrective loop, where information about prediction error propagates back through the layers of the network, recalibrating the weights of the original layers and orienting the system toward a more correct output. The generation of outputs is a probabilistic process, what backpropagation actually does is giving an error value as feedback of such prediction.

Backpropagation affects all the hidden layers every time that the model generates an output, independently form their quantity. Deep neural networks can thus be provided with a great number of layers, and so a more feature-filtering structure which can generate better outputs.





Top: diagram of a Neural Style Transfer process. (online source: Matias del Campo, *The Church of AI*)
Bottom: Style transfer research, Baroque stylistic features are transferred on an high rise building. (online source: *ibidem*)

3.3 Different ML models

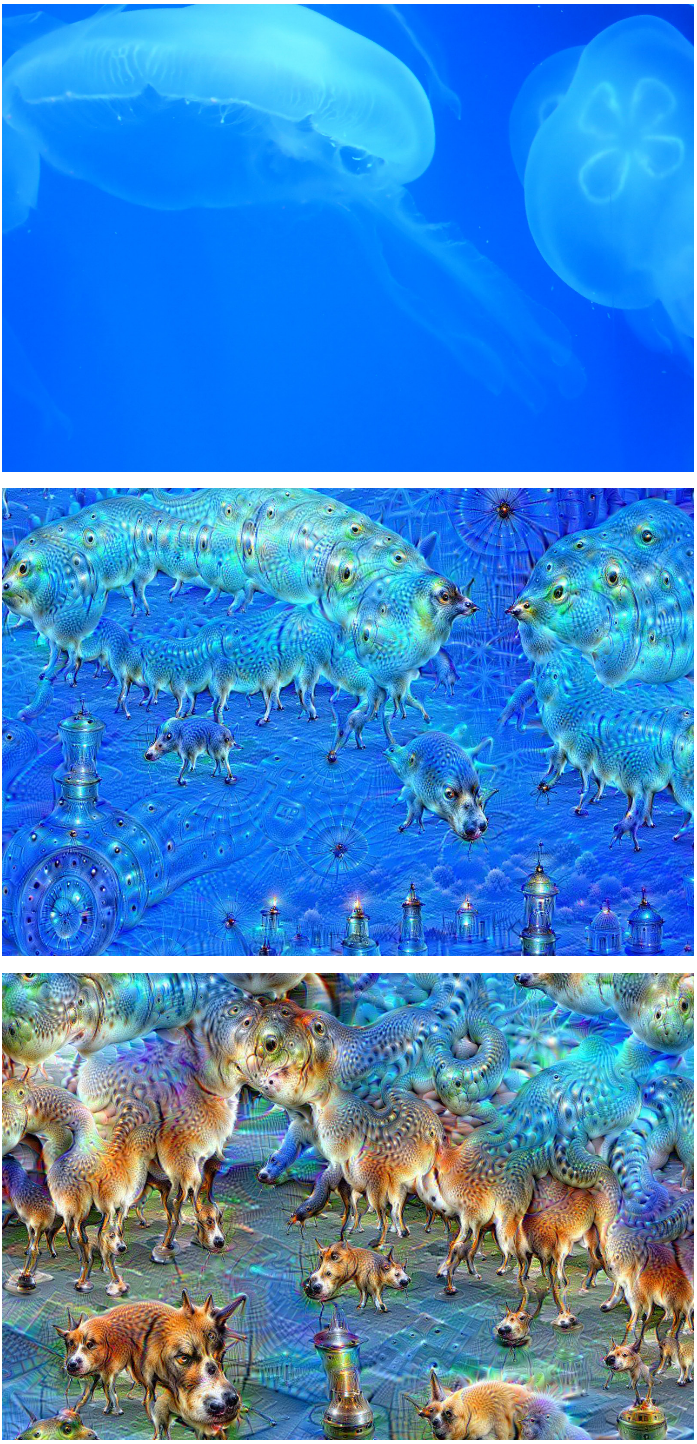
As previously mentioned, in the recent years ML application spread across disciplines, helped by the increasingly accessibility to performing hardware and open source models. CNNs, GNNs, VAEs, GANs, CANs, just to mention some of them. Within the realm of architecture, the most used neural networks are CNNs and GANs, for their ability to work with image data.

Convolutional neural networks (CNNs) are learning models which became popular for image classification. The structure of the network is based on the visual cortex of human brain, with various layers of neurons which detect increasingly complex features. Once these features reach the higher convolutional levels are used to feed a traditional neural network, which will return the highest confidence – the most probable – classification of the image.
Image classification is an important application of AI especially for the development of self-driving cars and facial recognition systems. In the field of architecture, the most diffused CNN application is the Neural Style Transfer[21].

The Style Transfer models have often been used for aesthetics purposes, since it is a process that allows to apply stylistic features on a target image. It requires two different datasets: a dataset A composed by a collection of target images; a dataset B which contain the styles to transfer on the target dataset.

The model learns to alter a given image so that it grabs the style from the second, without altering the original content. However, the process does not allow for any control – such as targeting only a component inside images – meaning that target images will be totally translated into a specific style. “We can iteratively change the pixel values of our input image such that the network’s representation of its style features, like texture and colour, resembles the network’s representation of the style features of the guide image, while making sure that the network’s representation of structural features in the input image, such as outlines of buildings or edges, remain unaltered” [19].

Matias del Campo developed some application which employed Neural Style Transfer methodologies. In his attempt of defining A Posthuman Design Method, for example, he applied such network to urban studies, questioning human creativity on urban planning process. “Style artifacts can be exaggerated to a point of hyperbole, transforming the natural balance/harmony of human style and design into a pareidolic and compositionally unstable, but novel form rooted in post-human (in the sense that they were not primarily authored by human ingenuity), but humanly accessible, architectural features”[19].



DeepDreem steps of translation form a gellyfish image into an hallucination of dogs (online source: Wikipedia)

In his work The Church of AI, then, he questioned whether an AI could create a novel sensibility, transferring the high detailed embedded in the Baroque style on simple normative architectural solutions[22].

GAN models are the most popular technique of image generation on which artists and architects are today experimenting. Idealised by Ian Goodfellow in 2014[23], Generative Adversarial Networks have undergone a rapid development in the last years.

A previous version of image synthesis network was DeepDream, a computer program developed at Google and released in 2015. This model reverses the flow of information of a CNN[16]: instead of having an image as input to recognise and classify, the process starts with a category and proceed to generate an image. For example, if a CNN can recognise an image of a dog and categorise it as "dog", DeepDream starts from the category "dog" and generate an image of it. "Although computational neural networks are trained to discriminate between images, they need to have some understanding of those images, and that is what allows them to also generate images, when operating in reverse"[8][17].

What the model often produces is a messy and surrealistic picture with many subjects in different poses; this is due to the fact that CNNs are invariant to poses, so when run backward they don't know in which pose to render the subjects. However, starting from an image instead of a noise image – that is "from zero" for ANNs – the network is able to analyse and optimise it:

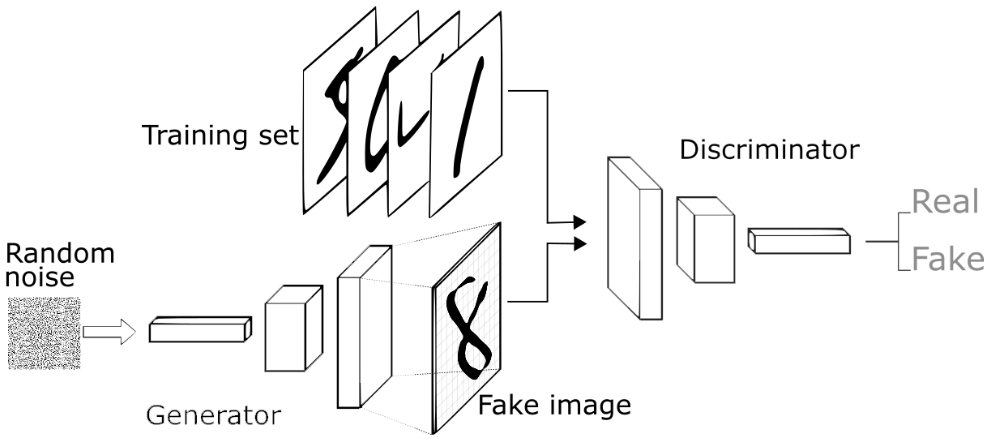
> *"We ask the network: "Whatever you see there, I want more of it!" This creates a feedback loop: if a cloud looks a little bit like a bird, the network will make it look more like a bird. This in turn will make the network recognize the bird even more strongly on the next pass and so forth, until a highly detailed bird appears, seemingly out of nowhere!"[24].*

Back to GANs, they pushed the standard of image generation to a next level in terms of precision – overcoming the poses issue that compromises DeepDream – and resolution.

These networks are not based on CNN but have their own *adversarial* structure. In fact, two different networks compete inside a GAN model, the Generator and the Discriminator. In such competition – keeping the example of image data – the Generator attempts to fool the Discriminator by producing images similar as much as possible to the ones provided as dataset, without actually "looking" at them. The Discriminator will judge the generated image, comparing it with the ones in the dataset, providing feedbacks – "real" or "fake" – to the Generator.

16 Pragmatically, the process is not exactly inverted since it computes non-linear operations.
More information about this can be found in the Blasie Aguerra y Arcas speech for TED Talk, *How Computers are Learning to be Creative*, 2016

17 As Neil Leach precise here, the neural network represents what it has learnt to associate to the category "dog" from the training dataset



Structure of a Generative Adversarial Network model. (online source: Thalles' blog, sthalles.github.io)

The revolutionary feature is that such networks train each other improve over time. The Generator finish its training when it succeeds in fooling the discriminator or when the user decide the generated outputs are good enough. Then, the Discriminator can be removed, and the trained model will generate images of the same reached quality.

From its invention, GANs has led to an explosion of research and development of different versions[18]. Thanks to its intuitive and simple to use nature, GANs is the most diffuse model for AI applications in art and architecture.

Examples of application into the artistic practice are CycleGANs and CANs. CycleGAN works with unpaired datasets and allows to transfer feature form the dataset A's domain to the dataset B's domain. Its workflow may be referred to a neural style transfer, but what actually does is to extract and transfer specific key features across the two domains. A famous example is the image-to-image mapping of the stripped pattern of a zebra onto a horse[25].

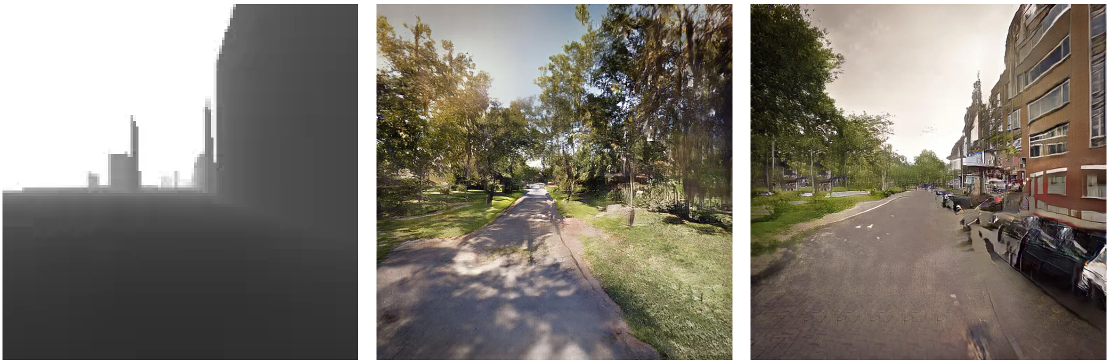
Creative adversarial networks (CANs) then are GAN models able to generate images outside the boundaries given by the training dataset, adding a creative extra-component. The Discriminator here gives two signals back to the Generator: the first is a simple "true/false" feedback, the second is a value which represent "style ambiguity", about how well the Discriminator can classify the generated art into established styles. "If the Generator generates images that the Discriminator thinks are art and also can easily classify into one of the established styles, then the Generator would have fooled the Discriminator into believing it generated actual art that fits within established styles. In contrast, the creative Generator will try to generate art that confuses the discriminator. On one hand it tries to fool the discriminator to think it is "art," and on the other hand it tries to confuse the discriminator about the style of the work generated"[26].

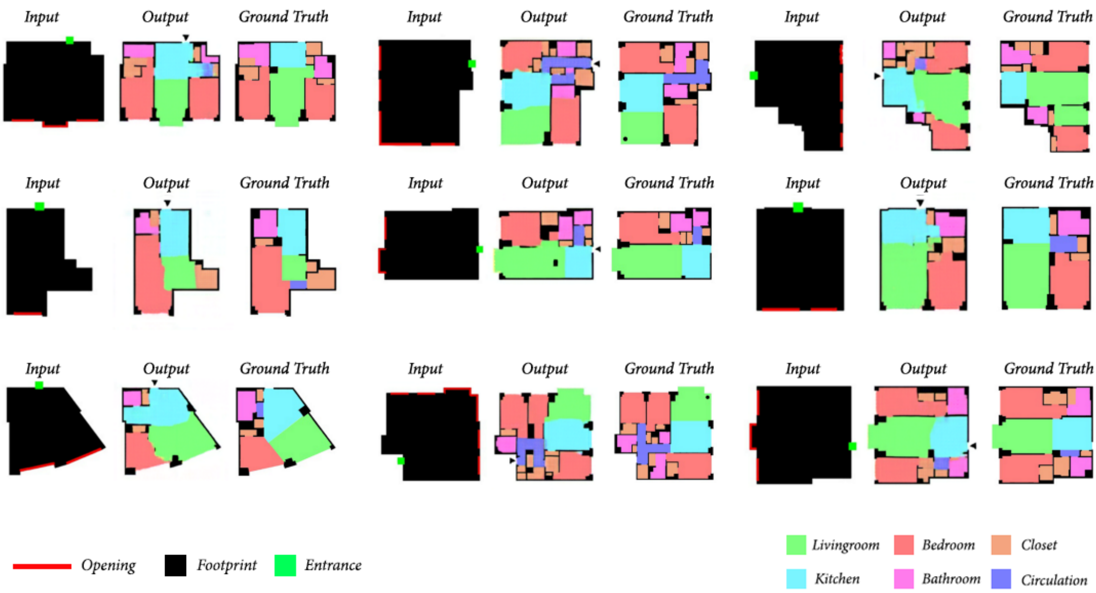
As already mentioned, the main contribution of AI in the architecture design process considers images as training data, which are the main visual tool to represent architecture, from diagrammatic to technical to rendered representations[19].

Considering the architectural scale, then, two main GAN models are employed in the research landscape: Pix2Pix and StyleGAN.

18 Avinash Hindupur published a list of named GANs on his website; Deep Hunt, *The GAN Zoo!*, 2017

19 It's good to specify, however, that representation is only one possible application. Indeed, "performance-based concerns are likely to be the area in which AI will have its greatest impact. [...] Concerns about improving the material performance of buildings and reducing carbon emissions have now become paramount"[8].





Top: GAN Loci translation from a depthmap to a real rendered image, respectively to Jacksonville, FL and Rotterdam, NL. (online source: Kyle Steinfeld, medium.com)
Bottom: ArchiGAN generative process. (online source: Stanislas Chaillou, *ArchiGAN, Artificial Intelligence x Architecture*)

3.3.1 Pix2Pix

The Pix2Pix is a version of GAN called conditional adversarial networks (cGANs). The “conditioning” consists of the training purpose, aimed to reach a specific outcome, rather than a random one.

Such model, developed in 2017, consist of pixel mapping across couples of images: “in analogy to automatic language translation, we define automatic image-to-image translation as the task of translating one possible representation of a scene into another, given sufficient training data”[27].

For its development, Pix2Pix has been tested on a dataset of annotated facades. The annotation was made through colours, discretising facades into a composition of elements, such as balconies, pillars, envelope material, windows and so on. Those labelled images have to be coupled with the realistic façade images, so that the network can elaborate the two pixel by pixel and, once the training is complete, it can textures a colour map image in an almost realistic rendered one. At this point, the user can create new colourful compositions and get a possible rendered representation in seconds, prefiguring a potential design appearance.

Pix2Pix ease of use allowed for a wide adoption. Moreover, the model develops its own loss function[20] – which is generally to be engineered – saving a lot of time in the process.

The Gan Loci project employed an approach to the façade one, implementing Pix2Pix to document the *Genius Loci*[21] of a city, “which is understood to include those forms, textures, colours, and qualities of light that exemplify a particular urban location and that set it apart from similar places” [28].

The model grabs his training data from Google StreetView API[22] for nine different cities, queried through coordinates for panoramic locations images; after cropping them in squared images[23], they constitute the RGB image of the scene. The second is a greyscale image that represent the depth-map of such scene, “with the value of each pixel representing the minimum distance from the camera to any occluding objects”[28]. Such depth-maps are computationally made through a function which decode information form the real image and convert them into a geometric representation, that is a collection of grey-scaled plans.

So, coloured images describe the urban scene and the greyscale images describes the depth of objects present in that scene. After training, it is possible to generate a synthetic real-looking urban scenes starting from greyscale depth-maps, which can come from a rough 3D model.

20 All the machine learning algorithms rely on maximising or minimising a function. The function to minimise is the loss function: it is the measure of how good a prediction model predicts the expected outcome. The higher the loss, the lower the accuracy.

21 “In his seminal work that defines a phenomenological approach, *Genius Loci: Towards a Phenomenology of Architecture*, Christian Norberg-Schulz argues that the design of cities and buildings must center on the construction of “place”, which he defines as a “space with a unique character””[28]

22 API (Application Programming Interface) is a software interface which allows thow different computer programs to communicate with each other. It behaves as a bridge between software.

23 It is not a proper cropping, rather is a conversion form equirectangular projection to cube-map projection

Human face images generated by a StyleGAN model trained on the FFHQ dataset.
(online source: Tero Karras, *A Style-Based Generator Architecture for Generative Adversarial Networks*)

24 *This-person-does-not-exist*, on this website is possible to generate face of people which do not actually exist

One of the main applications of Pix2Pix is the ArchiGAN, a tool developed by Stanislass Chaillou for his master thesis which allows for interaction and floor plan configuration[29].

The project consists of a chain of GAN models: the first is trained to generate building footprint based on the Geographic Information System (GIS); the second require an interaction with the user, which has to specify the entrance and openings position which the model can follow to generate the partitioning wall. Here the model is trained on a floorplan dataset labelled through colors, so its output is a layout with colored zones which represent the different rooms. The final model generates the furniture for each room based on its program – a bed in the bedroom, a sofa in the dining room and so on.

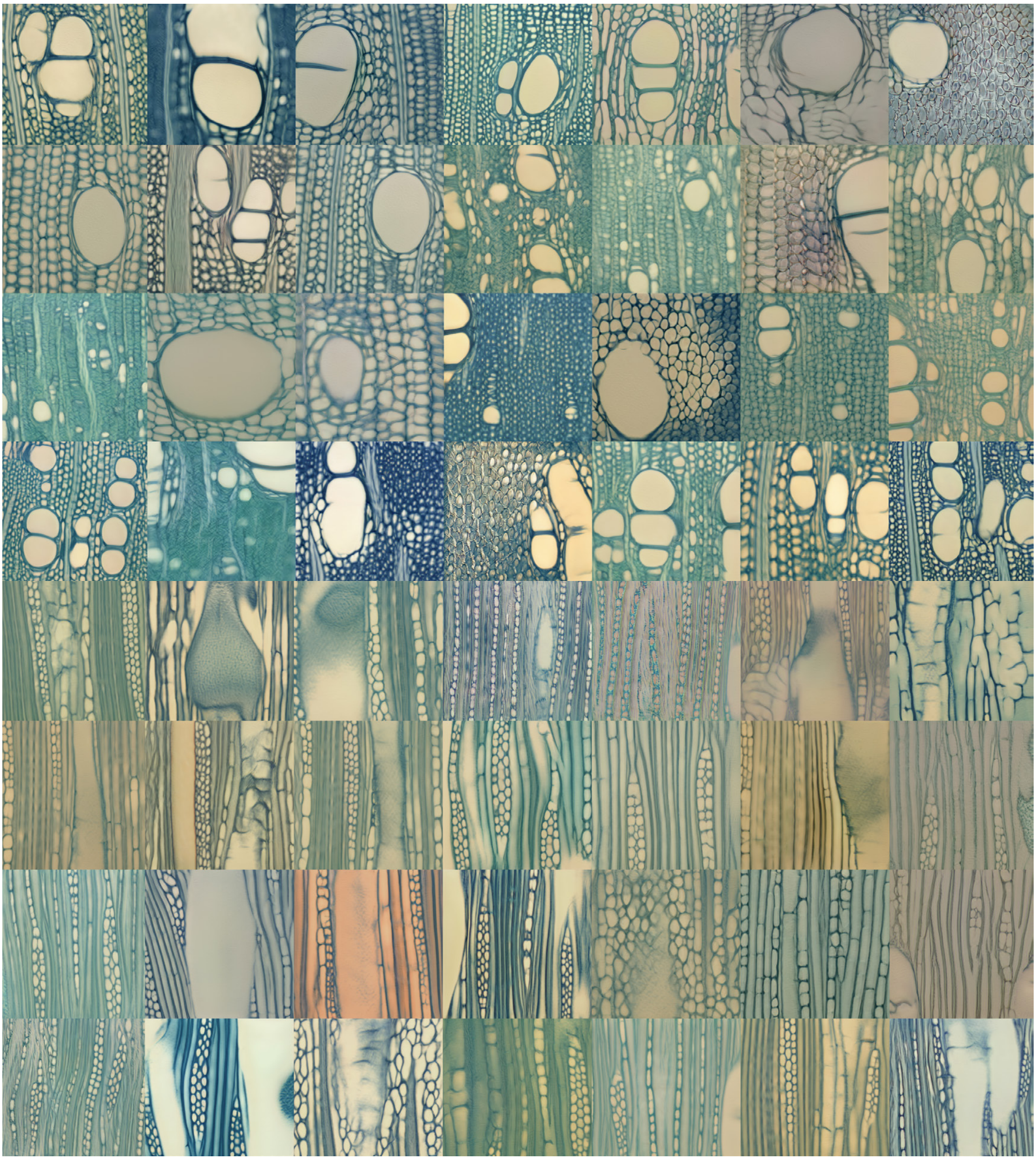
ArchiGAN allow the user for some post-process interactions, such as editing the initial footprint shape, or changing the position of openings; the model will automatically adapt the output.

The model presents however some limitation for architectural purposes: considering a multi-storey building, for instance, there is no guarantee for a coherent floor plans organization, or for structure alignments.
Moreover, the outputs are images, nowadays a non-conventional format to work on in architecture offices. It thus requires a one more step to vectorialise the results, and eventually to generate a 3D model.

3.3.2 StyleGANs

The StyleGAN is a model – based on the concept of Neural Style Transfer – which offer improvements in terms of resolution of generated images [30]. It is able to subdivide an image in categories: borrowing the example of human faces generation[24], the model can control from more general feature of a picture, such as pose, hair or face shape, to detail feature as the colours, which are respectively assigned from low-level layers to the high-level ones. The greatest advantage of this category of GANs is that does not require labelled images – actually the most time-draining part of the process – because it simply process the dataset and finds features autonomously.

The ability of StyleGANs is to generate images similar to the ones given as training dataset. As a standard GAN, when its training is finished - or when starts to produce good enough results - the model generates images of the same quality.



Sampling of the Archiwood Project dataset. (online source: Maria Kuptsova, mariakuptsova.com)

An application of the StyleGAN model is The Arbor, research developed by Maria Kuptsova and exposed ad the Biennale di Architettura of Venice, in 2021. The research aimed to understand the intelligence of natural beings, as plants, fungi, bacteria, insects and animals. “For example, the microscopic patterns of a plant contain information about the intelligent mechanism of photosynthesis, growth, eater and food distribution. Embedding the organisational principle of an organic material into a digital system would allow a form of hybrid materiality to be designed that might host biological intelligence within a digital structure”[31]

The project focused on timber, in particular on its material organisation, since, for building construction, its anisotropic properties are usually consider problematic, and thus the industry looks for uniform wooden elements. To understand the material, thus, Arbor have been trained on a collection of microscopic images developed by the ArchiWood[25] project about 995 different species, showing the distribution of vessels and fibres which compose the internal tissue of the material, characterised by variation in density and porosity, also giving structural information as stiffness and softness.

Thus, a StyleGAN2 model has been adopted as method of – hopefully – extracting the internal organisation from each image of the dataset, and generating new one to develop volumetric models[26].

Such volumetric models have been realised from a sequence of images, which represented hypothetical horizontal sections of the objects. The coherence between the images is due to the way their position inside the virtual space they inhabit, the latent space. In fact, the other – and most studied – feature of StyleGANs is that such models produce a latent space. This is one of the argument around which the thesis gravitates and – together with the topic itself – more architectural examples are discussed in the following chapter, in which the latent space – that is where the knowledge of the model homes – is explored to generate machines hallucinations.

25 *ArchiWood, Dataset of legacy documents about wood anatomical, morphological, and architectural traits for plant species in Madagascar*

26 How will be discussed in the project part of the thesis, it is not possible – at the state of the art – to get 3D geometries directly from the NN. StyleGANs – as GANs in general – produce a latent space, and only through a latent walk it’s possible to concatenate a series of images to translate in a 3D model – thus it is a 2D-to-3D process.
The process utilised in The Arbor is identical to the one employed in this thesis; will be deeply explained in the next chapter.

4 WANDERING INSIDE THE BLACK BOX

“Like industrial products embodied an artificial technical logic that went counter to that of natural hand-making (and many did not like that back then), computational products now embody an artificial logic that is counter to that of natural, organic intelligence—the mode of thinking of our mind, as expressed by the method of modern science (and many today do not like that). This may be one reason why the emergence of some inchoate form of artificial intelligence in technology and in the arts already warrants a more than robust amount of natural discomfort, and the feeling of “alienation”[10].

As Thom Mayne sustain, human intuition is limited, and it will soon run out of ideas[8]. This is due to the fact that human thinking is an a priori way of thinking, thus it is based on previous knowledge and already seen things. Neural networks, instead, allow us to generate outputs that could never be predicted, and they can make them instantaneously. This is also one of the big differences between computational tools and AI; computational tools like Grasshopper can produce many variation but still be produced manually, AI does it autonomously.

AIs employed in this thesis are GAN models which, as discussed earlier, are able to generate novel images from a given set of data. The generating process of such models came up to be unpredictable, indeed “there is no way to tell how or why they are performing certain operations. In this case they are little different to intuition. Both GANs and human intuition are black boxes”[8]. This is the reason why GAN models are considered more suitable for early experimental design; with their suggestive results can trigger imagination and open up new possibilities.

> *“Our techno-aesthetic inquiries into how the human mind makes sense of spaces focus on the symbiotic relationship between architecture, neuroscience, technology and machine learning”[32].*

In this chapter are discussed the three main topics on which the thesis pivots: the concept of creativity, machine hallucinations and latent space.

Creativity is an obvious topic to question at this point.
If a brain, human or artificial, is able to learn and elaborate the knowledge to generate something new, then the question whether this entity could be creative comes by itself.

Front:
Renaissance Dream installation in Palazzo Strozzi, Refik Anadol, 2022. (online source: Refik Anadol, refikanadolstudio.com)

Nevetheless, creativity has always been considered an exclusive human capacity. Crossing the 20th century, artists were considered different from ordinary people, their work doesn't follow any rational decision: it is all driven by intuition and expression of emotions. Art was the only domain of human creativity, and was assumed that artists needed years of training to acquire artistic skills such as drawing, composition and so on.

Today it is not the same. Since 1970s, contemporary art has become conceptual, focused on ideas, semantic.
Many say that "we are facing a crisis of imagination"[33]; AI models have maybe to be intended as an augmentation of the mind, a mental prosthetic, that can be used to expand our imagination. Thus, technology may help people to be creative and innovative, generating – or helping us to generate – unseen solutions.

The recent works of digital artists is indeed based on data to create outstanding data visualisation, which are both beautiful and imbued with knowledge. This brings to the generation of what are called machine hallucinations. Terms as Hallucination and Dreaming are actually borrowed from Neuroscience, where these terminologies are used to explain neurochemical mechanism and similarities between human dreams and drug-induced hallucinations.

Machine hallucination are expression of the machine creativity, which results in alien representations of something familiar to us – strange but familiar enough[34]

4.1 BNN vs ANN | Creativity

Biological neural networks (BNNs) and artificial neural networks (ANNs) have many terms in common. Intelligence, learning, neuron, synapse, are all words across the two domains.

However, "we should be careful not to conflate the way that machines 'learn' with human learning. Like other terms used for both AI and human intelligence, 'learning' does not necessarily have the same meaning in both contexts"[8]. In fact, even though the training techniques explained above refer to learning and teaching approaches similar to human ones, it is important to explicit what is learnt. While human beings learn by association – "this is a dog, that is a cat" – machine learning models learn patterns, relations within elements. Such elements have to be classified – labelled – to be recognized: from an image of a cow, labelled as "cow", the network understand that such pixel organisation represents a cow. Thus, the concept at the base can be similar, what is different is the learning methodology.

27 The alphabet, for example, is a strong classification method, which allow us to find data only remembering 26 letters

"Computers are not in the business of finding meanings and can use any huge, messy, untreated, and unprocessed random inventory just fine: they can search with- out sorting; hence they can predict without understanding"[10].

The meaning of "intelligence" used for machines is different from humans' one: AIs do not have consciousness[35] – as introduced in the previous chapter, in the current AI classification, a conscious AI would be an Artificial General Intelligence (AGI) which development seams very far in time – meaning that whether a machine can handle tasks impossible for human beings, it does not mean that it is aware of that.

On the other hand, human mind has a "storage limit". People do not have the ability to memorise huge quantity of information and to pick one when needed, that is the reason why human being has always the tendency of classifying[27]. We use classification when we study through mind maps, to find objects, to group files. Computer does not work like that, they search instead of sorting: "to search for the word "abacus" in a corpus of textual data, computers will scan the whole corpus looking for a given sequence of forty-eight 0s and 1s, and stop whenever that sequence shows up—regardless of how that corpus may or may not have been sorted"[10].

This is because, even if the structure of a neural network is inspired by the human brain's one, they don't work the same.
Compering BNN's and ANN's structures, the number of connections inside a neural network cannot match the complexity of the human brain. Moreover, there is a temporal component that affect the way information are encoded and processed, that is how human brain learns, a missing feature in ANNs. Nevertheless, ANNs, as already discussed, performs backpropagation to reduce the error in the output generation phase, which seams not present in human brain.

It is evident that both the human brain and the neural network have features that makes them different to one another, showing how there is not a better system, but are just similar structures that behave differently. The question whether AI can be creative is then a natural one.

Creativity has always been intended as a unique and special human ability, and the generative capacity of machines as an analytical skill embedded by the programmer. Some recent episodes in the field of art have shown, however, that AI can generate such a high quality artworks that people are not able to distinguish from human's anymore.

The Butcher's Son, Mario Klingemann, 2017. (online source: electricartefacts.art)

This have been the case of Edmond de Belamy (2018), a portrait generated by the Parisian art collective Obvious using CANs and which became the first AI-generated artwork to be sold at auction, or The Butcher's Son (2017), generated through GANs by Mario Klingemann and which is the first AI-generated artwork to be awarded with the Lumen Prize in 2018.

As previously introduced, GANs and CANs – as all the ANNs – are just machine learning models, empty boxes by default, waiting for data to process and to learn from. This means that by themselves they cannot produce anything. But isn't this similar to how human brain learns? For instance, what artists learns at school influences the way they make art, becoming part of their artistic background. At the same way, ANNs produce outputs base on the knowledge extracted from the dataset during training.

Such events brought to question what is intended as creativity.
Up until now creativity has been judged in terms of final outputs, based on the thinking of Margaret Boden, who also classified creativity in a series of genres: combinational, exploratory and transformational.
Combinatorial creativity is well represented by the collage technique, producing unfamiliar results from familiar images; exploratory creativity, then, is a set of results that may come up from a set of generative rules – practice as architecture, music and painting would be examples of explorative creativity; finally, transformational creativity is the process of selecting some characteristics which will affect the final result[36].

On the other hand, machines may have their own creativity categories, laid down by Demis Hassabis after the AlphaGO Game event: interpolation, extrapolation, and invention.

ANNs are designed for interpolation: from image datasets, they can extract features and generate new images with a combination of those features. GANs works exactly in this way, constructing their own world within different image features and interpolate them for output generation. Extrapolation is instead an ability familiar to human beings. For the reasons explained above, ANNs are not able to think outside the features horizon they create during the training; "they miss the requirement of being able to extrapolate and thus of being creative as to how we observe that process as it manifests in humans"[37].
Invention is the most challenging aspect to face, mainly because human mind works on resembling previous knowledge, generating things that only may appear novel. Thus, "it is challenging for the human mind to recognise genuine innovation because it lacks the means to understand or even perceive it"[34].

WDCH Dreams, by Refik Anadol, 2019. (online resource: Refik Anadol, refikanadolstudio.com)

28 Refik Anadol, *Art in the Age of Machine Intelligence*, TED Talk, 2020

However, as Neil Leach points out, “the three categories of creativity that Boden lists appear to be more like creative strategies than creativity itself. [...] She seems to categorise creativity in terms of the outcome, but should we not understand creativity in terms of the process of creation itself? Creativity might well be involved in generating a design, but creativity, surely, is what feeds that process”[8]. Moreover, the nature of the creative process is still hard to comprehend since much of it belongs to the realm of the unconscious[38]. Indeed, creatives are often unaware of what is influencing their creative process.

If creativity is not related to the final output but is embedded in the process, then it is possible to make a distinction between human creativity and machine creativity, and this is exactly what machine hallucination is about.

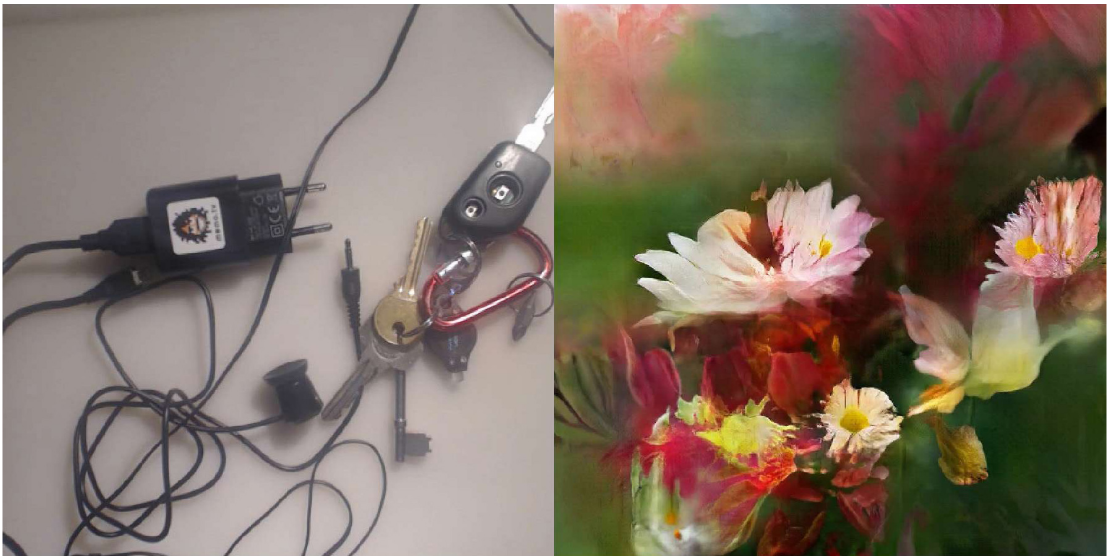
4.2 Machine Hallucinations

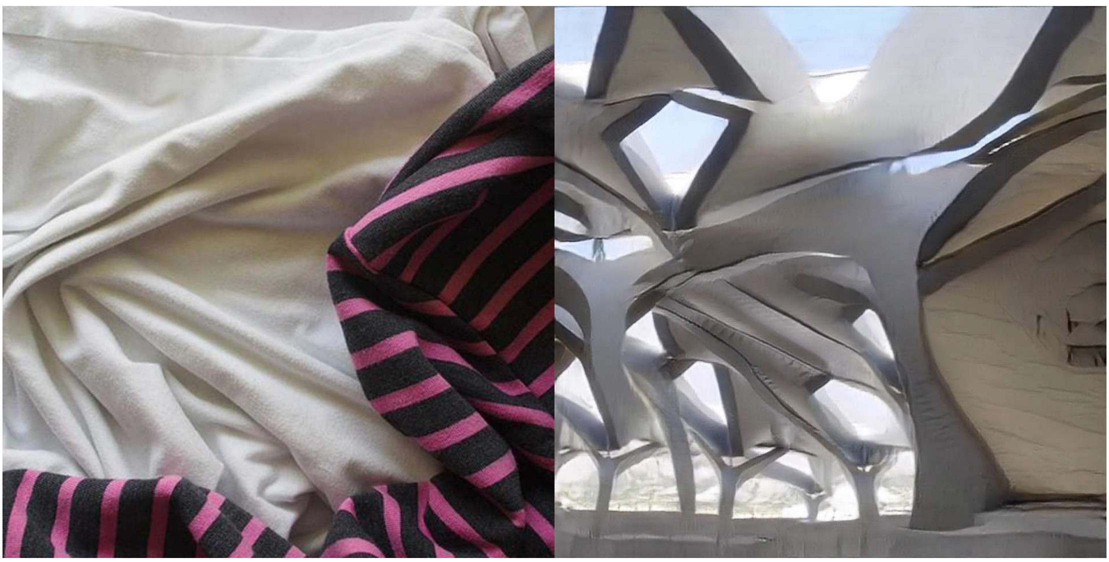
The concept of machine hallucination in the field of art comes from Refik Anadol, Turkish AI artist and today one of the main actors on the AI stage. In 2018, he was commissioned to produce a data sculpture to mark the 100th anniversary of the LA Philharmonic – today known as Walt Disney Concert Hall, a Frank Gehry’s masterpiece. The project was based on the historical archive of the building and the events it hosted during the years:

> *“we decided to collect everything recorded in the archives of the LA Philharmonic and WDCH. To be precise, 77 terabytes of digitally archived memories. By using machine intelligence, the entire archive, going back 100 years, became projections on the building’s skin, 42 projectors to achieve this futuristic public experience in the heart of LA, getting closer to the LA of Blade Runner. If ever a building could dream, it was this moment”*[28].

Giving a memorial heritage to an AI led Anadol to question whether that machine could also elaborate those memories: “what can a machine do with someone else’s memories? [...] If a machine can process memories, can (it) also dream? Hallucinate? Involuntary remember, or make connections between multiple person’s dreams?”[8].

Neuroscientist Anil Seth sustain that the human brain has little information about the outside world, thus it tries to “predict” what is happening on the base of sensorial information and previous experiences, performing what he defines as hallucination:





Top: *Gloomy Sunday*, Memo Akten, 2017. (online source: memo.tv)
Bottom: *Architectural Hallucination*, Fernando Salcedo, 2020. (online source: koozarch.com)

“if hallucination is a kind of controlled perception, then perception right here and right now is also a kind of hallucination, but a controlled hallucination in which the brain’s predictions are being reined in by sensory information from the world. In fact, we’re all hallucinating all the time, including right now. It’s just that when we agree about our hallucinations, we call that reality”[29].

Thus, hallucination depends on the way the thinking entity has been trained, the memories that inform its way of seeing the world. Computational Artist Memo Akten shows exactly this process in his Gloomy Sunday interactive experiment: if trained on a dataset of flower images, a neural network will see flowers into everything.

As Akten observes, “the picture we see in our conscious mind is not a mirror image of the outside world, but is a reconstruction based on our expectations and prior beliefs”[30]. This experiment is strictly related to the Seth’s statements on perception. For him perception is highly subjective, people don’t just perceive the world, they generate it according to our past experiences – that is our training.

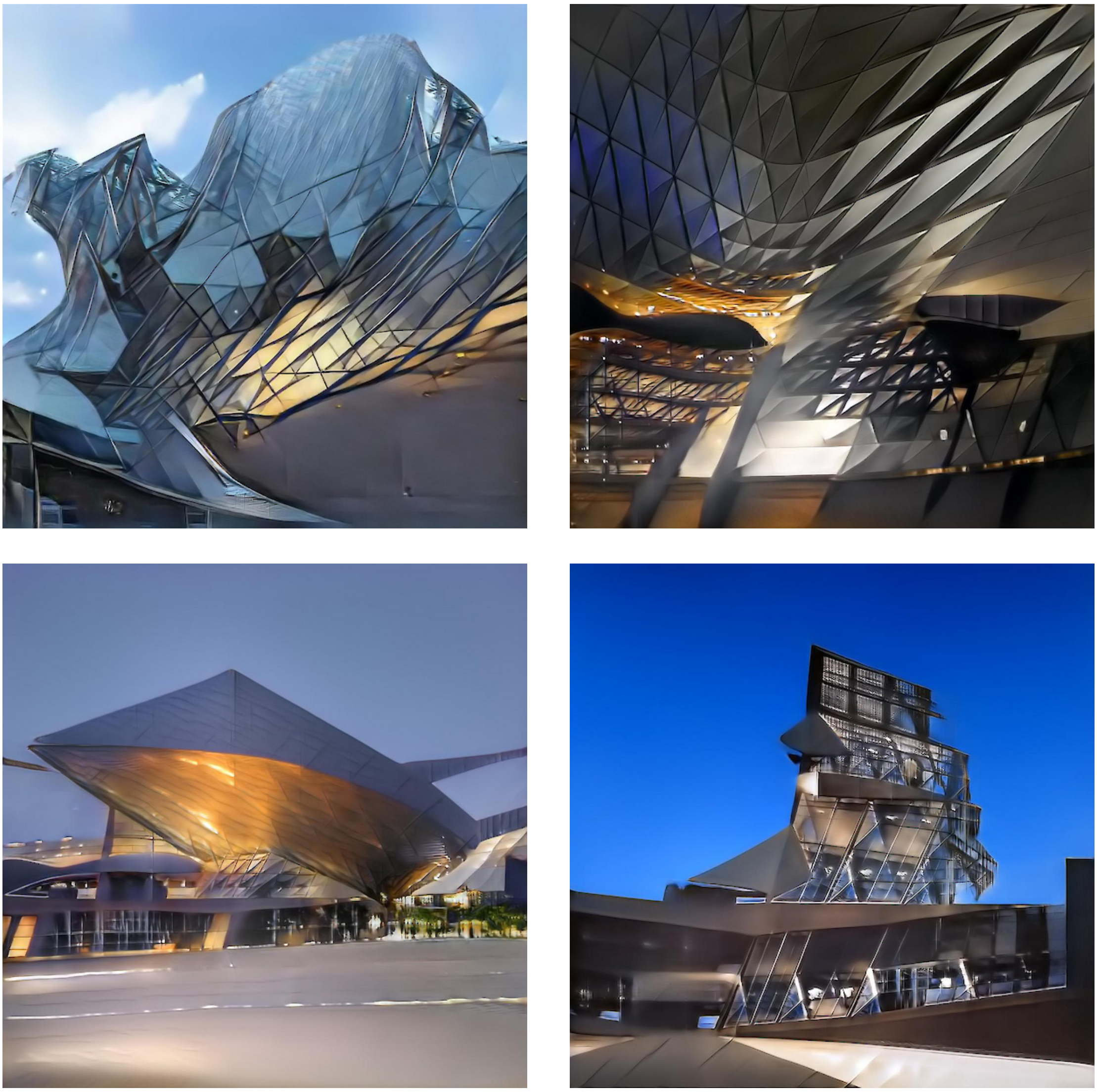
A similar project has been developed by Fernando Salcedo in 2020, named Architectural Hallucinations, with a NN trained on images of a research centre designed by Zaha Hadid Architects (ZHA), resulting in an AI model that reads images through an architecture filter. This experiment questioned the way architects see the world, reading potential building in everything:

“We could describe this process as a form of ‘architecturalisation’. In effect architects tend to ‘architecturalise’ the world and read it in architectural terms. [...] They see the world in terms of potential buildings. This allows architects to be inspired by various non-architectural items – such as biological entities and geological formations – and incorporate them into their architectural expressions. [...] As Derrida puts it, there is an ‘architecture of architecture’. Our understanding of construction is itself constructed”[39].

Recent applications in the field of architecture aim to overpass the creative limits of human being, constrained by past experiences and “training” as architect, which affect the way we perceive the world and evaluate design: “since we have no means of knowing whether we currently operate within a global maximum or local minima in design terms, what we perceive to be a good output is often a fairly conventional design”[40].

29 Anil Seth, *Your Brain Hallucinates Your Conscious Reality*, TED Talk, 2017

30 Memo Akten, *Learning to See: Gloomy Sunday*, 2017



Architectural suggestion images generated by DeepHimmelb(l)au. (online source: coop-himmelblau.at)

The Viennese architecture firm Coop Himme(l)blau (CHBL) has developed its own AI model – DeepHimmelb(l)au[31] – on the architectural material they have produced in many years of activity, to "explores the possibility – in connection with human beings – of teaching machines to be creative, to interpret, perceive, propose new designs, augment design processes and augment design creativity"[41]. The office works in an open process design methodology, where the dialogue is open to many actors, people, tools, intuition, and interpretation. This approach is inspired by – and starts from – the sketch, which is the medium for dialogue thanks to its undefined nature; then, is the process that turns such sketch into a building.

DeepHimmelb(l)au is for the Wolf Prix's office a tool which aims to amplify the intelligence of the practice, looking thus for design process augmentation. The network is a complex one, where a CycleGAN chained with other forms of GANs tries to "hallucinate" potential buildings. DeepHimmelb(l)au is fed with two unpaired datasets: dataset A contains sketches – geometrical morphs – while dataset B is based on CHBL projects. "The outcome is a video of a journey through an imaginary landscape of Coop Himmelb(I) au-like building forms. The important point to be stressed here is that these buildings do not actually exist. They are merely machine hallucinations"[8].

The possibility for DeepHimmelb(l)au to generate three-dimensional solution is still in progress, nevertheless it is able to generate high detailed images with hallucinated aesthetic.

> *"According to Michael Young, this unhandiness is a stylistic feature of today's digital avant-garde: the overwhelming richness of digitally created detail induces feelings of discomfort, or estrangement"[10].*

This estrangement sensation is what Matias del Campo names *Defamiliarisation*[32] and tries to investigate with his project The Robot Garden. The network here grabs information from the history of architecture imagery to generate strange visuals to inspire architecture design. He describes defamiliarization as the "visuals' ability to be strange yet familiar enough for us to recognise them as discernible objects"[34]

The project is based on a GAN model and a neural style transfer and uses what the neural networks have learned to invoke stylistic edits first on images – 2D – then on meshes – 3D. In an attempt to obtain a hallucinated output, the networks were trained on an extensive archive of images of stairs, columns and fountains. The resulting images represent a first attempt of hybridisation of such elements with the landscape: "do not show the features in total clarity but are rather the hallucinogenic dream of a machine trying to see these features in the landscape"[34].

31 More details on the Coop Himmelb(l)au website

32 The term itself was coined in 1917 by the Russian formalist Viktor Shklovsky, who "described an artistic technique that provoked the audience with imagery depicting everyday things in unfamiliar or strange ways", making the audience to observe the world through a different lens that introduce abstraction into the aesthetics of realism. The topic has been explored by Aaron Hertzmann in his GAN art, where he represents the concept of visual indeterminacy [34]

DeepHimmelb(l)au latent space visualisation. (online source: coop-himmelblau.at)

4.3 The Latent Space

33 Ekin Tiu, *Understanding Latent Space in Machine Learning*, 2020

The latent space is a hidden virtual multi-dimensional space at the hearth of AI models, which contains a compressed representation of data given to the model during the training.

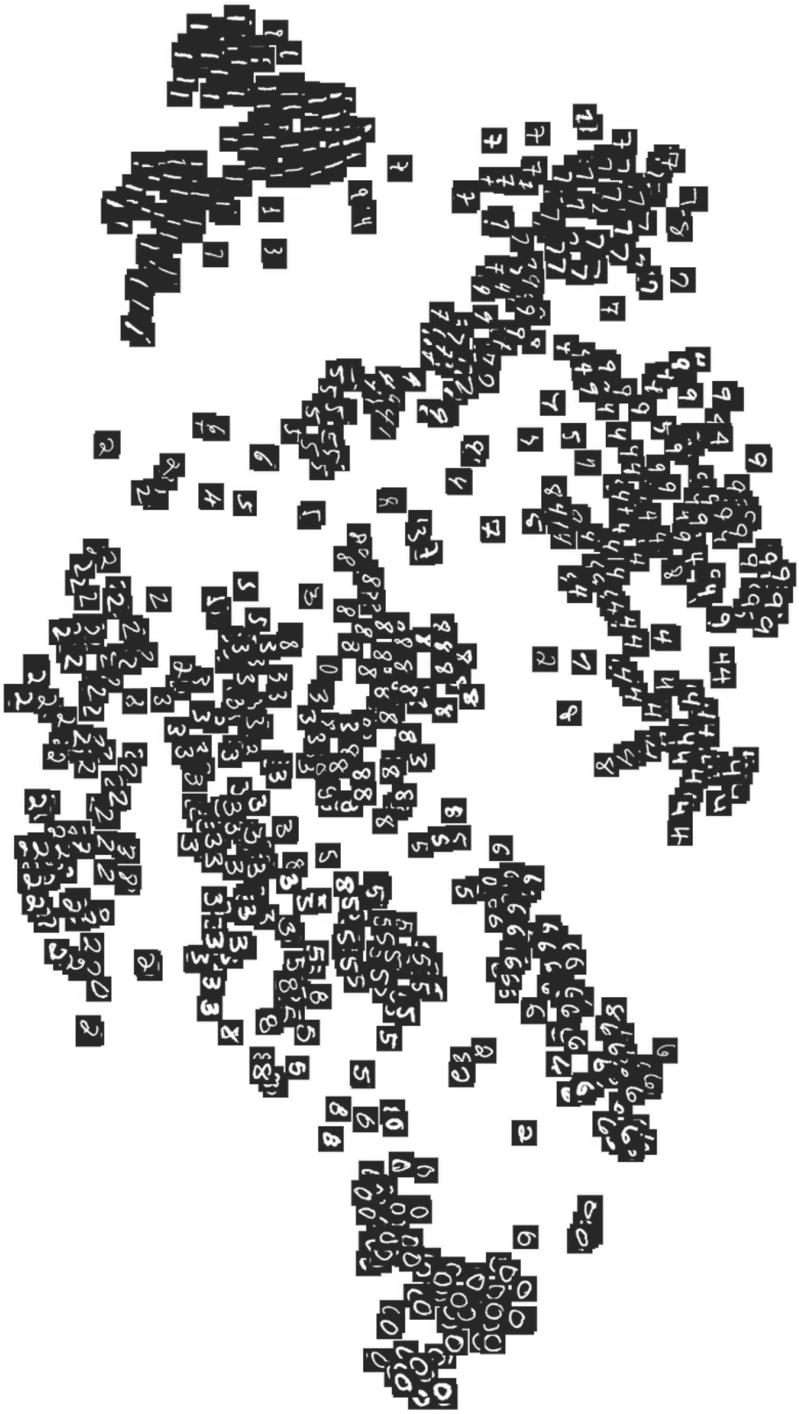
The dimensionality of the latent space is related to the number of features embedded into data, and “it is crucial to note that the feature each dimension respectively encodes is not directly at the user’s discretion, but rather gradually defined by the model during training”[13]. This means that the neural network might recognise feature in the data that were not foreseen by the user. This is the “latent” part of the process, hidden and unpredictable, and it is exactly the core of deep learning: “learning the features of data and simplifying data representations for the purpose of finding patterns” .

Data similarity inside latent space is translated into proximity, that means that things that looks alike are close to one another. Moreover, the space is consistent, meaning that taken two data points inside the space, there will always be a point in between which merge the features of the two. An example will be useful to clarify this process.

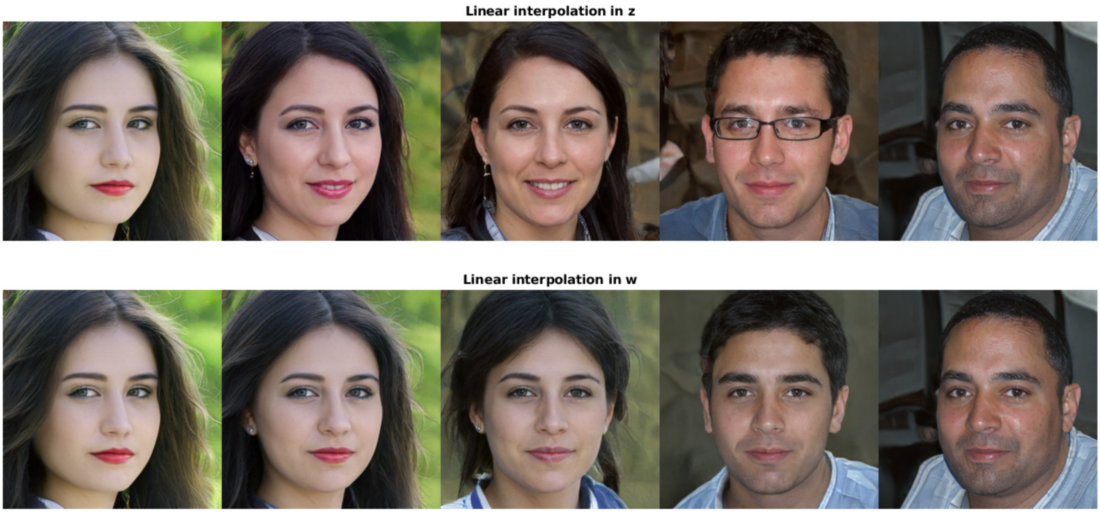
One of the most famous case is the human faces generation, borrowed from the original StyleGAN paper [30]. The model, trained on the FFHQ dataset – a set of 10.000 human face images – recognised different features into the images which have been embedded into the different dimension of the latent space. Once the training finished, the latent space was composed by 512 dimensions, populated by an infinite number of artificially generated images, that are all the possible outputs the model can return.

Each image corresponds to a point in the latent space, which has an array of coordinates – which correspond to the number of features embedded in such space – thus to its dimensionality. Therefore, asking for an output means to specify a vector that points toward a specific point.

In fact, vectors are the only tools which allow to wander inside the latent space, generating what are called latent walks. This will be better discussed later in the thesis, since this approach has been used to interrogate the model, but in brief, vectors represent paths which connect points, allowing to generate a series of images which makes us understand the composition of the latent space itself. It is also possible to generate videos – since they are nothing more than an array of images – from a point A to a point B; this better explain the consistency feature of such space, showing a progressive blending from the image-A to the image-B; this is called *interpolation*.



Latent space visualisation of a ML model trained on the MNIST dataset of handwritten digits.
(online source: @juliendespois, hackernoon.com



Results of two linear interpolations, respectively in Z space and in W space, inside a StyleGAN model trained on the FFHQ dataset. Since the Z space is "roughly" populated, some undesired features appear during the interpolation, such as teeth and glasses, which are not present neither in the first image nor in the last image. Interpolation inside W space, instead, is more coherent.

In the case of StyleGANs, two different kind of latent space are produced: Z space and W space[34].

The Z space can be considered as the "rough" space of the two. Investigating this space could make appear some undesired features: in fact it is considered a problem if during an interpolation from an image to another some features show up even if they are not present nether in the initial image, nor in the final one. The W space supply to this issue, called entanglement, resulting in a cleaner space – yet, Z space is more related to hallucinations in such sense.

The material that populates the latent space is generated on the patterns the neural network recognised inside the training images. Those images are thus the result of an AI creative process, where possible hallucinations may take place. As previously said, however, it is not possible to predict what a NN will learn during the training.

It is possible, in fact, that some features present in the fed data would miss in the outputs, which thus show only some of them. This phenomenon is called overfitting and in general is related to an important asymmetry inside the training dataset, such as the predominance of a specific type of data, or an excessive quantity of identical images. This could also bring the NN to exactly reproduce the training dataset, thus copying instead of learning. Tool as loop vectors here are perfect to understand if a model is affected by overfitting, allowing for a random exploration around the latent space.

34 Derrick Schultz, *StyleGAN2 In-Depth Week 3 (latent spaces, linear interpolations and noise loops)*, Artificial Images, 2020

At this point of the thesis all the topics related to AI and architecture have been touched upon, some in more depth, some less.
The research started with the intention to create an application which could connect artificial intelligence and architecture; to do that, a long way to understand the discipline was needed.

Among the applications faced during the readings, the possibility to use the machine creativity as additional point of view into the design process – that is machine hallucination – was the most interesting one, since it is intended not as an automatism of some part of the process, but as an augmentation of the creativity, which comes from a digital entity which reasons differently from humans, and can propose solutions under a novel light. Such solutions are intended to be considered in the early design phases, also because, at the time of writing, AIs are not able to design buildings by themselves. Architecture is a multidisciplinary practice which constantly requires choices, and performance ones are only a part of them. Choices related to the context – normative, urban, environmental, human – require consciousness and versatility, which current Ais are not able to handle.

That said, the second block of the thesis operatively shows the creation of a methodology which implements AI creativity inside the design process. Starting from the research goals will follow: the creation of a custom dataset, the training phase, and finally the opening of the black box, exploring a StyleGAN latent space, looking for architectural hallucinations.

OPERATIVE PROCESS

Here discussed:

Methodology
Dataset production
Training step
Latent space exploration
3D pointcloud visualisation

5 PROJECT | Creativity Augmentation

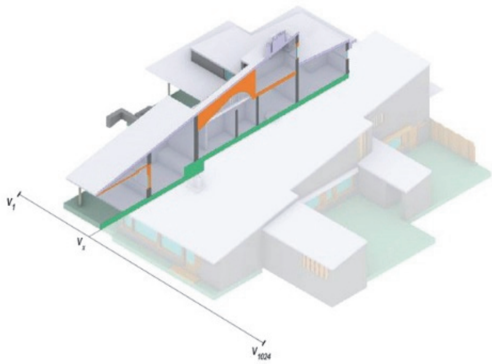
The research aims to define a design methodology to implement AI into the architectural creative process. This enhancement of creativity would be especially useful at the beginning of the design process, following the intention of other ongoing researches in proposing the introduction of data – as structural or environmental – in the early phases through simulation, allowing architects to consciously design following a streamlined process, instead of – as frequently happens – applying analysis on an already complete building, resulting in a doubled work fatigue or an naive design.

The dimension of creativity has recently been touched by text-to-image generative software: between others, Midjourney, Dall-E, and the very recent Adobe Firefly. Those applications are able to generate highly detailed images form textual prompts, allowing to render ideas in few seconds, augmenting both the creative process and the skill of designers in describing their thoughts.

This workflow, however, does not allow to reach three-dimensionality.
The conversion from images into solid geometries is not an easy task for machines. Exist the possibility to create pointclouds or meshes from a sequence of images taken all around a building, this technology is called photogrammetry. Applying such process to image-generation AIs, the images should be generated from any angle of the described building and, assuming that the software would be able to make it – it is not, every generated images is not related to the previous one, showing some differences in each generation – the final result would be just the envelop, no information about the spatiality of the building can be provided in this way.

The workflow developed here aims to reach the third dimension, developing an AI model able to generate three-dimensional hallucinations, providing references outside the ordinary, and alien to a proper architecture background.

The research has been addressed to the generation of building solutions that hybridise social residential buildings and expositive pavilions, with the intention to affect the building generation with spaces which are unusual for residences. The choice relied on the functional nature of these two categories of buildings: residences are built to stay, and humans find in dwellings their private and fixed space in the world.


V_1
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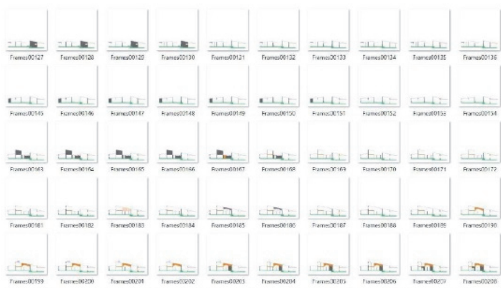
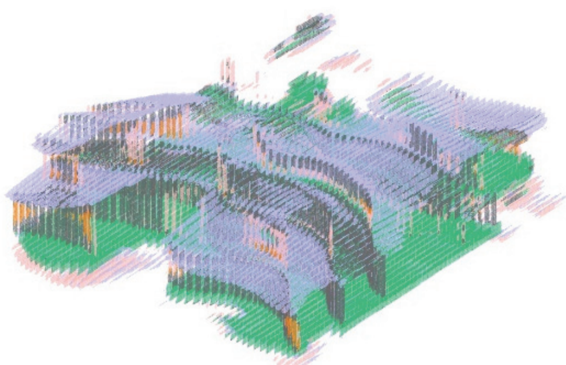




On the contrary, pavilions are often temporary structures, host functions for common activities and are often characterised by a strong relation with the environment, in terms of permeation in its most general meaning – from humans, nature, animals, to light, wind and rain.

The merge of this two antithetical architectures is likely to produce an hybridisation of the private and the public, providing suggestions for residential buildings with an opening attitude to the public space.

In practical terms, through a combination of computational tools and AI tools managed by the hands of the author, the methodology proposed here seeks for good quality 3D model hybrid-buildings generation with a sense-making space organisation, in order to provide a formal and spatial augmentation of creativity into the early design process.

5.1 Methodology

The process developed here has been inspired by the work of Mathias Bank in 2022 which aimed to apply 2D GANs to explore spatiality in architecture using 3D models of material-labelled buildings[42].
The ANN-based design methodology Bank used in his work is divided of four steps: collection, training, interaction and reconstruction.

The collection step consists of assembling a dataset of labelled images; labels here come from 3D properly-modelled buildings, in which colours correspond to specific building materials.

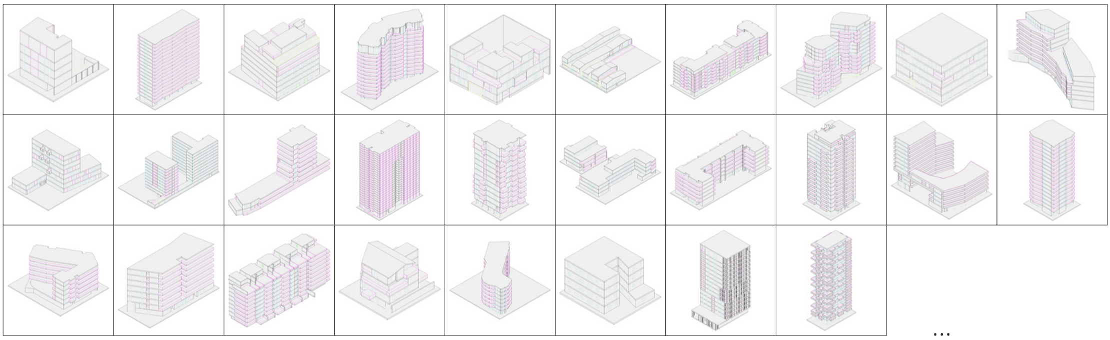
For the training step a StyleGAN2 model has been used since "its remarkable talent for producing synthetic results that appear eerily similar to the data on which they were trained"[42]. As discussed earlier, StyleGANs allow to create a latent space populated by images based on the fed training dataset; this defines a bias for the network and at the same time defines a domain of possible design solutions that the network can accommodate.

The interaction between humans and AI lay in the possibility of extract a series of images form the latent space's network through interpolation vectors. Once the images have been generated, a 3D model can be reconstructed translating such images into point clouds.
As well, the methodology developed here alternate computational tools and AI generative tools with a constant human interaction.

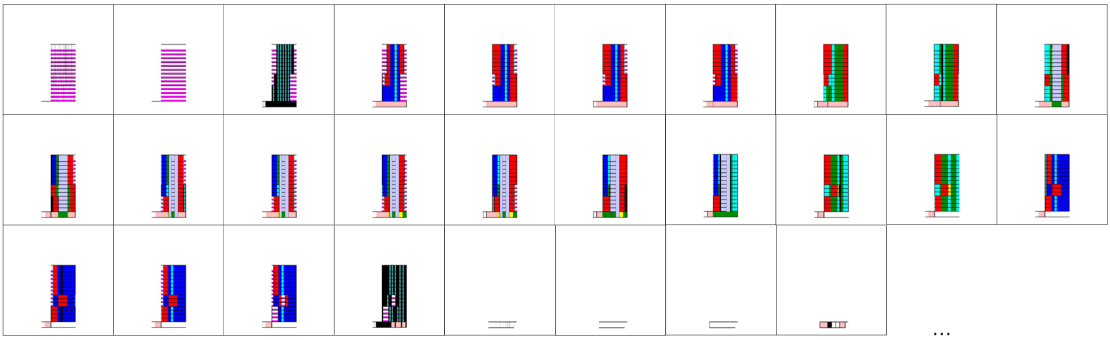
The selection of this approach among others relies in its compatibility with the research questions and in the current AI state of the art.
As discussed in previous chapter, AI applications in architecture are not going outside the two dimensions; there are however some attempts

Front:
Mathias Bank's methodology steps: 3D modeling of selected buildings; slicing process to produce the dataset; 3D reconstruction through generated images. (online source: Mathias Bank, *Learning Spatiality, A GAN method for designing architectural models through labelled sections*, 2022)

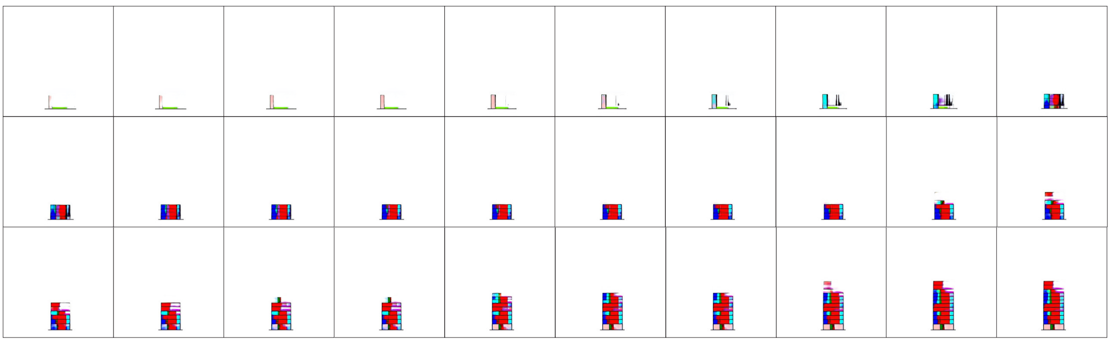
MODELLING



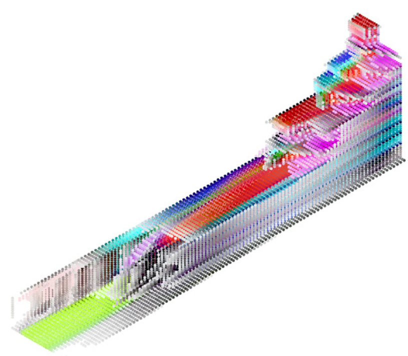
DATASET PRODUCTION



INTERPOLATION



RECONSTRUCTION



to generate 3D geometries from 2D images, but few of them tries to investigate the spatiality of a building. The ArchiGAN project previously explained succeeds in defining the internal organisation of a floor plan, where the NN learned from the dataset also a set of intrinsic rules embedded in those data, such as geometric proportions between spaces.

The methodology considered here is based on images of sections. Sections still show only two dimensions of a building – length-height (xz plane) or width-height (yz plane) – but here the third can be managed through the number of sections generated by the model. Information are embedded inside sections through colours, which represents the different kinds of functions – and thus spaces. The model should learn to reproduce such colours and to recognise a pattern within them, so that the generated images have a spatial coherence.

The generation process, then, is based on the latent space exploration where, as previously discussed, images as placed next to each other according to their similarities and features; thus, inside each dimension of the latent space, images are positioned differently. Once getting the images, a building can be reconstructed organizing them as an array of elements and converting them into coloured points, resulting into a point cloud visualisation of a building[35].

Latent space can be explored through "latent walks", which are nothing more than vectors which operate interpolation through specified points, and to which images are attached. It is not possible to understand where certain sections are positioned inside the space, but it is possible to randomly peek some points specifying a numerical value, called seed. It is used to represent the coordinates of a specific data inside the latent space, since it could have hundreds of dimensions and it would not be that practical to specify them all by hand. Thus, what a seed represent is an array of coordinates which brings to an image.

For the properties of proximity and consistency of the latent space it's known that around such seeds similar images are situated, so an interpolation between two seeds turns into a progressive transformation of one image into another.

As will be demonstrated, the quantity of selected sections is fundamental for the final configuration: more selected seeds to interpolate means a higher complexity and unpredictability; the selection of only two images, instead, would turn into an only one linear transformation. To find the balance is one of the first step and may vary according to specific needs, like the length of the generated building.

35 Neural networks able to process and understand voxelised 3D models are extremely large and produce very low resolution outputs. Point clouds, instead, are computationally more efficient for their sparse nature, thus can be used in AI informed 3D design. On the other hand, point clouds consist of – unordered – points, and so cannot offer any solid representation. Research on this topic are exploring the possibility of using meshes, more computationally efficient than voxels and with more geometrical information than point clouds.

Front:
Thesis methodology, applied on building spatial organisation. (author)

It is worth to remember that such sections are brand new images, generated by the trained model; it is also possible to find hallucinated sections with particular shapes, or that once the sequence of images has been reconstructed, to get unconventional buildings – hallucinated buildings. The hallucination is what the NN is likely to produce – since their way of reasoning is not scientifically defined yet – and what this research aims to embed inside the design process.

5.2 Dataset

The creation of the dataset has been one of the most important parts of the research, and definitely the more time consuming. To hopefully obtain desired outputs general data are highly unsuggested: as Sofia Crespo points out, networks trained on publicly available data or scraped from online sources would be very mundane, and will generate mundane latent spaces, which do not address to any specific mission[33].

> *"The network can be the most state-of-the-art, high-performing algorithm possible, but if you have a dataset that doesn't actually contain the information relevant to the task, then the networks are not going to learn to perform in the way that you want them to. As a result of this problem, we embarked on creating our own datasets where we can guarantee that this information exists within them, and then use them to start exploring what is really the design power"[37].*

The first step was, thus, to produce the StyleGAN dataset.
StyleGANs need a wide range of data to learn from and to enrich the latent space composition as much as possible. To make such dataset, a series of buildings have been selected: 28 residential building among towers, condos and courtyards, and 28 pavilions.

The chosen residential buildings are all part of the Italian contemporary residential architecture, thus built form late 2000s on. Such buildings have been selected according to the technical material available on physical and digital magazines or obtained as kind concession of architecture offices. The collected material resulted mainly from the province of Milan.

Pavilions instead are selected mainly from Expos, in particular the ones held in 2010 (Singapore), 2015 (Milan), 2020 (Dubai).

The selection of building only from Italian architecture is functional to not mix different solution which may embed different normative rules. The information the NN is likely to learn are thus related to an Italian architectural and normative scenario.

36 Considered building are not all the same size, some have just 3 floors, others more than 20. Since sections have to be proportional, the selected size image allow to get a clear representation also of the smaller building.

37 Actually is good practice to analyse the dataset before training to understand if there is unbalance between data – such as the preponderant presence of a colour over the others. It is generally done through an autoencoder, a NN which process the overall data and automatically classify them according to features

After collecting enough material, buildings have been modelled one by one using Rhinoceros 3D.
Have been modelled elements like the external walls and the internal partitions, the main entrances – to each apartment for residential buildings, just the public entrances for pavilions –, windows and the volume of each space inside the buildings.

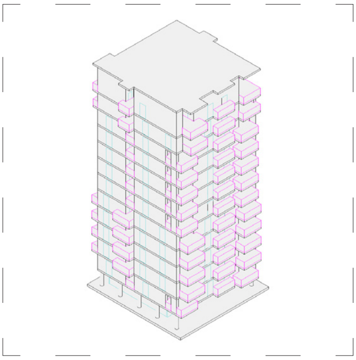
The modelling was necessary to produce the sections for the dataset, but it is also the step in which labels have been applied. In fact, as Bank suggest in his research, information can be embedded colouring different part of the building with different colours. Processing the images, then, the NN should understand the relation within colours and thus within the elements of a building.

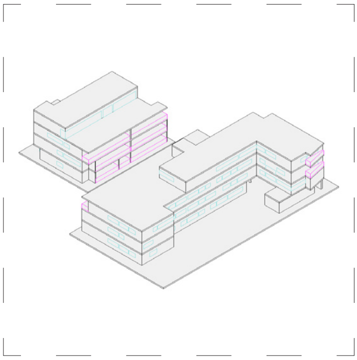
Here, 11 colours have been chosen to represent the different space and part of the building: black for walls and slabs, purple for balconies and loggias, red for dining rooms, violet for kitchens, blue for bedrooms, cyan for bathrooms and toilets, dark green for corridors, yellow for secondary spaces – such as storage space, studio room, meeting rooms –, light blue for vertical distribution spaces – stairs and lifts – light green for greenery and vegetation, pink for common spaces – for common activities. Colours which represent secondary spaces, vertical distributions, common spaces, and the greenery are the main ones that bridges the two typologies of buildings; this would hopefully allow to find different sections relatively next to each other inside the latent space.

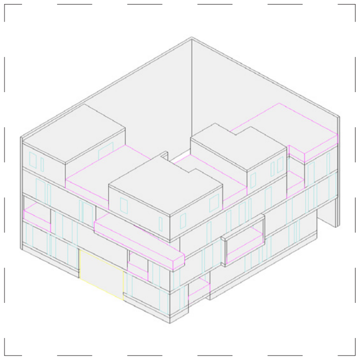
From the modelled buildings, sections have been extracted as jpeg images. This is done through a semi-automatic Grasshopper script, which allows to slice the models by an arbitrary step. The models have been initially sectioned every 0,50m, and a dataset of 9628 sections have been produced. A first check showed that many sections were presenting very little difference one to another, thus have been decided to cut in half the dataset – meaning a slicing step of 1 meter. After a second check to remove empty and meaningless sections, the final dataset is composed by 3952 images.

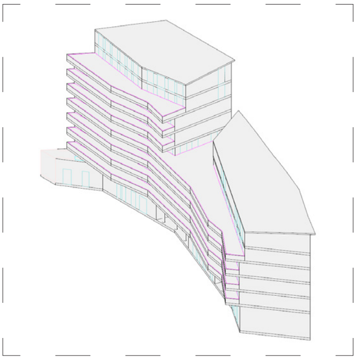
The image size is also an important factor, since critically affects the training time. As compromise between image definition[36] and time availability, 512px squared has been chosen for images size. As Bank did for his research, here the process borrows the technique developed by Hang Zhang in 2019, who investigates the latent space to construct 3D models [43]. To achieve such result, “his networks are trained on 2D slices of architectural 3D models which after training are capable of being reconstructed in the form of a series of black and white images”[42].

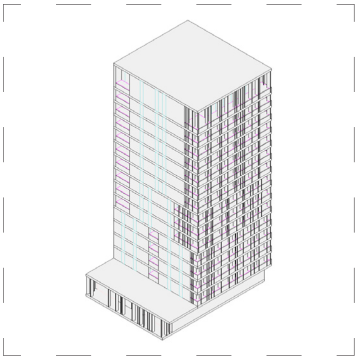
Now that the dataset is made, there is room to train the StyleGAN[37].

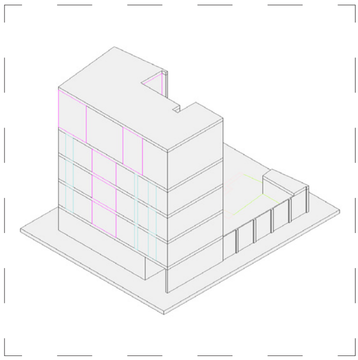

Residential Tower Nuovo Portello, CZA

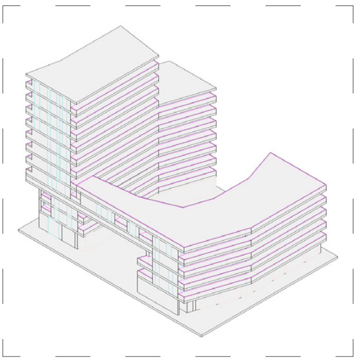

Residential Complex, Alvaro Siza

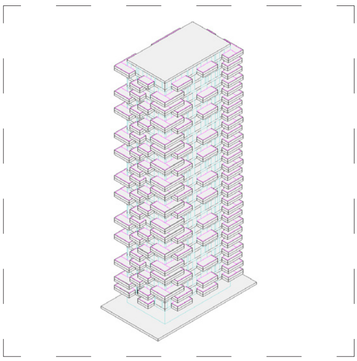

Condominio P, C+C04STUDIO

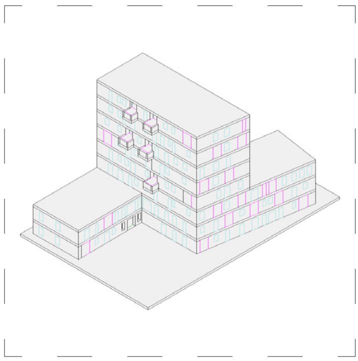

Corte Verde, CZA

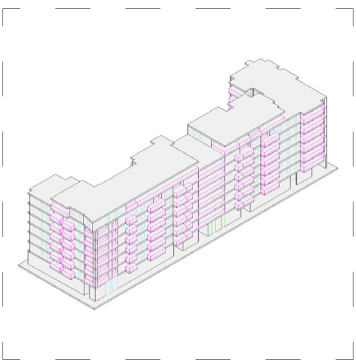

Cascina Merlata Housing, B22

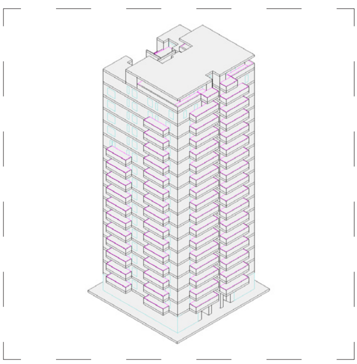

Urban Decor, Marcante-Testa

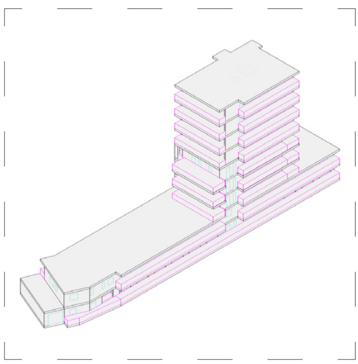

The Harbour, CZA

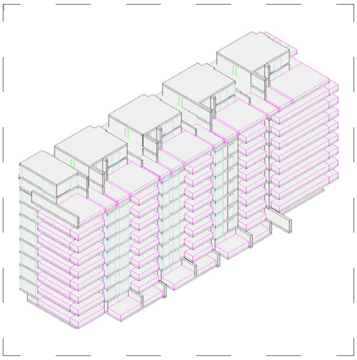

Bosco Verticale, SBA


Cefalù 24,

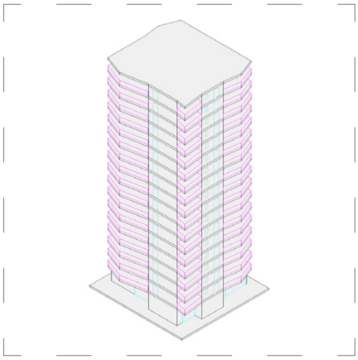

Palazzo Tazzoli, Picco Architetti


Torre Valdocco, Picco Architetti

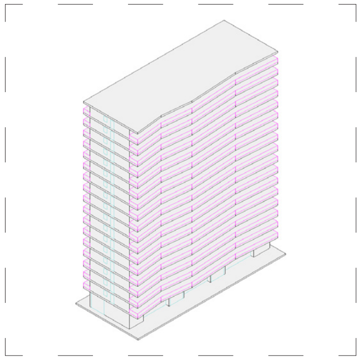

Social Housing via Cenni, RPA



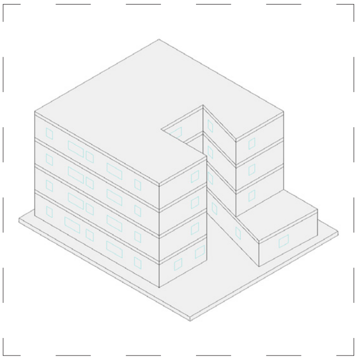
Jesolo Lido Condominium, Richard Meier



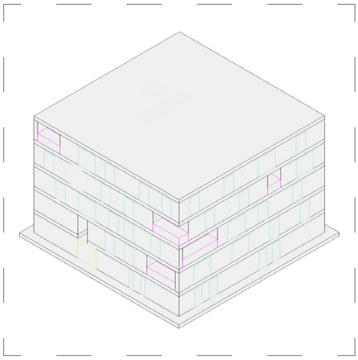
UPTOWN R2



UPTOWN R3

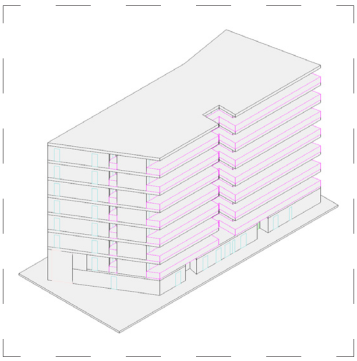


D residential building CZA

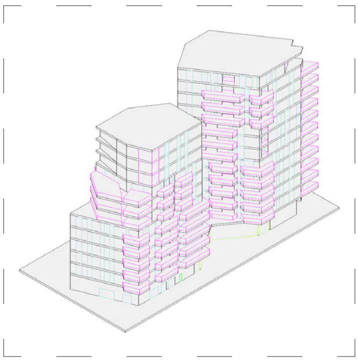


THE HUB, Calzoni Architetti

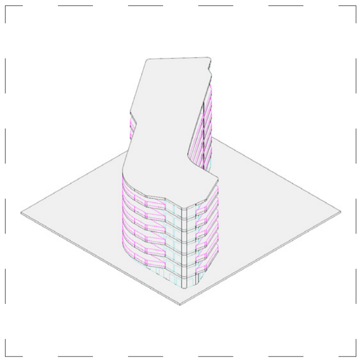
Residenze City Life, DLS



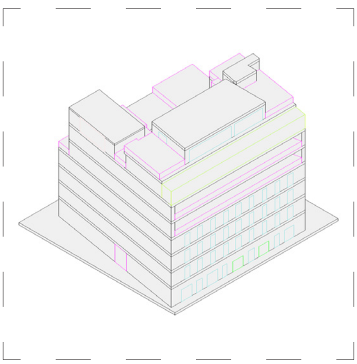
Residential slab buildings, CZA



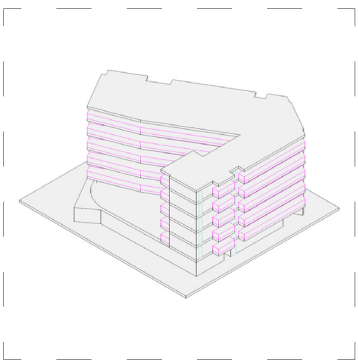
Complesso Novetredici, CZA



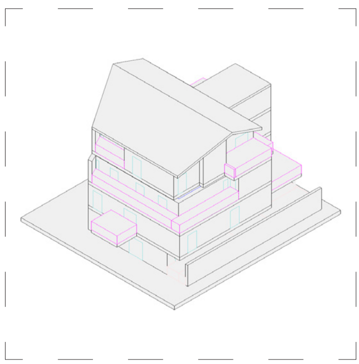
Residenze City Life, ZHA



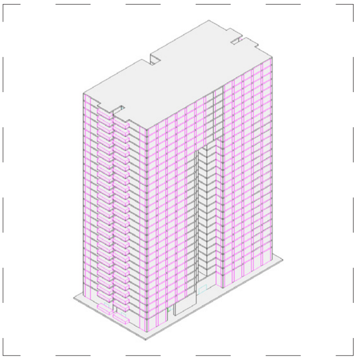
Monte Grappa Complex, Westway



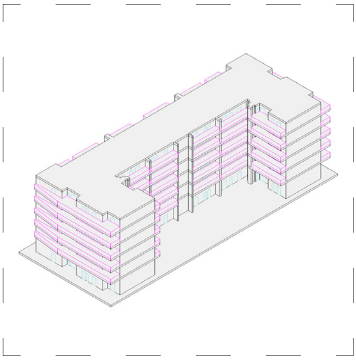
P17 Housing, Modourbano Architettura



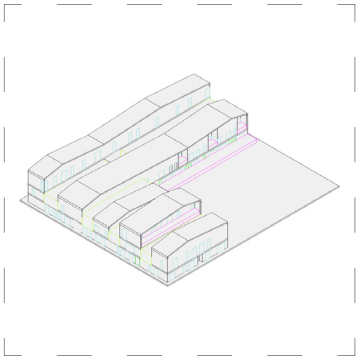
Residential Building, dap studio



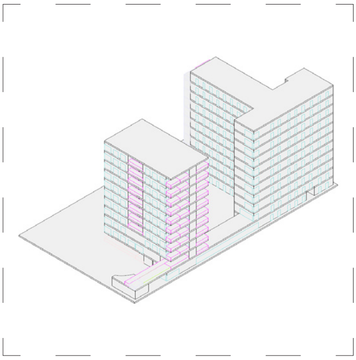
Torre Eurosky, Franco Purini



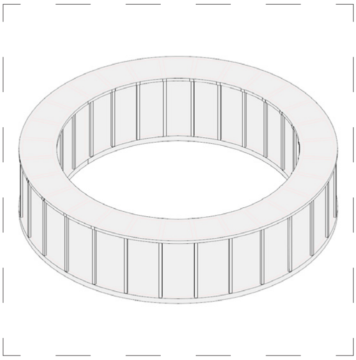
Affordable Housing, Kirimoto + partners



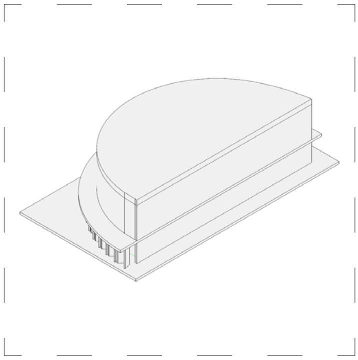
Residential complex, SBA



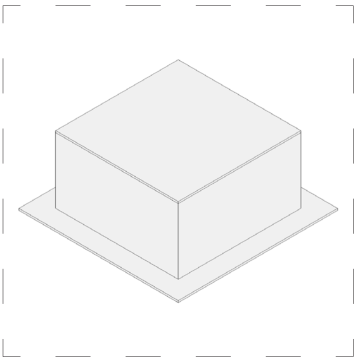
Residenza Universitaria, Costa Z. Associati



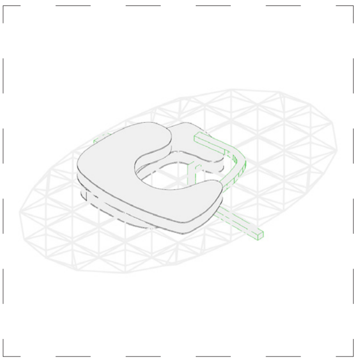
Antiroom II, Matteo Goldoni



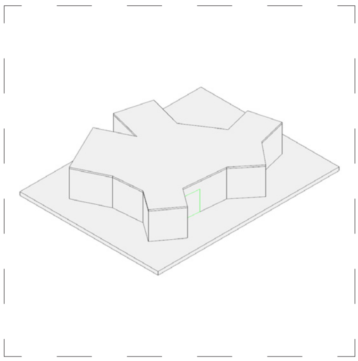
Austrian Pavilion, EXPO 2008



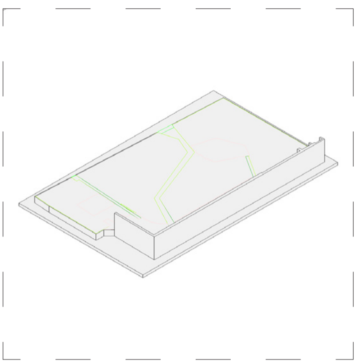
Kingdom of Bahrain Pavilion



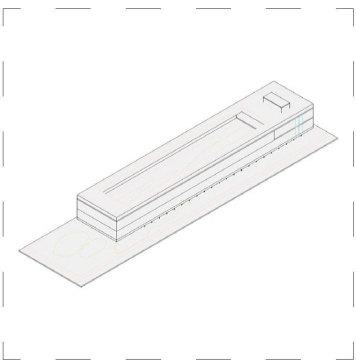
Blur Building, Diller Scofidio



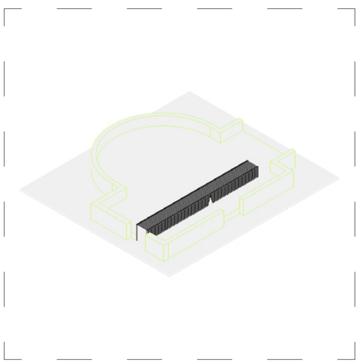
Caritas Pavilion, EXPO 2015



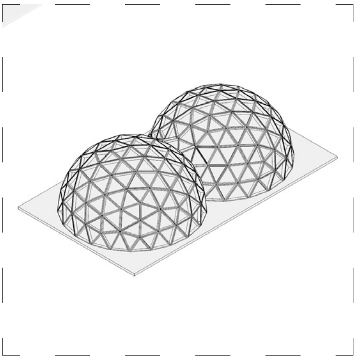
Giardino Comunitario, Atelier Verdure



Austrian Pavilion, EXPO 2015



Baratti Pavilion, Nicolò Spinelli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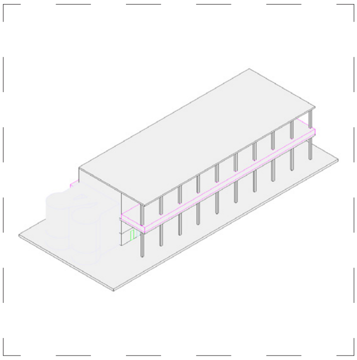
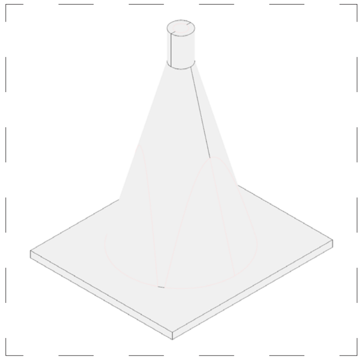
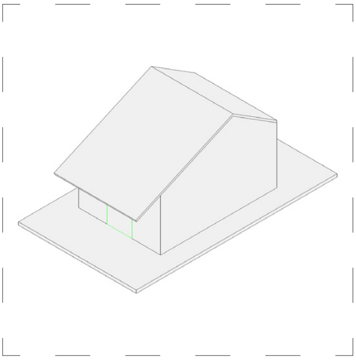

Cascina, Caruso Mainardi Architetti


XXI Triennale, Michele de Lucchi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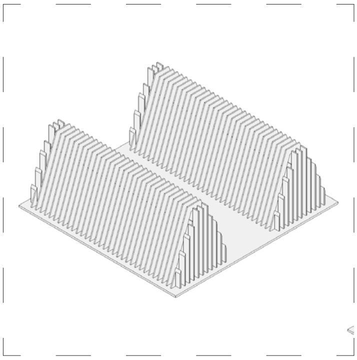
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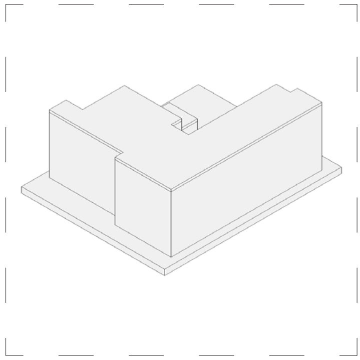
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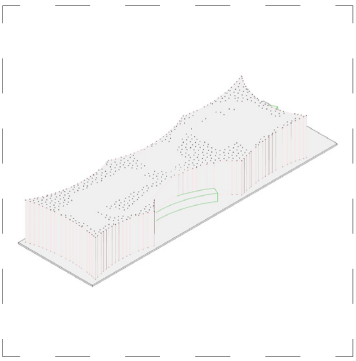
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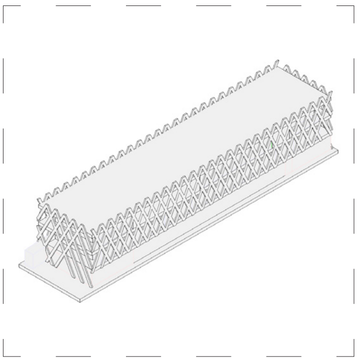
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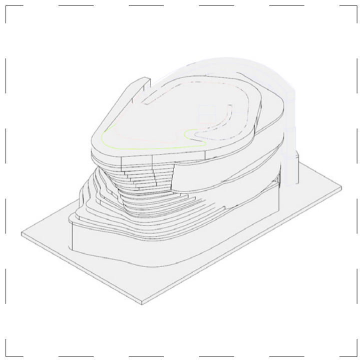
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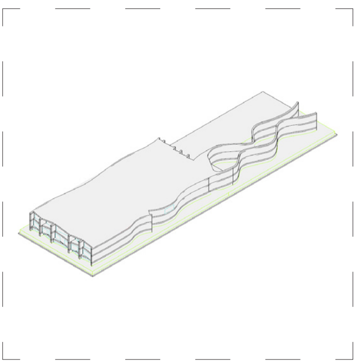
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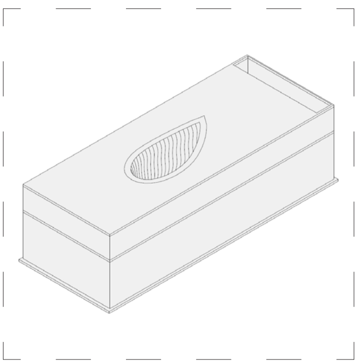
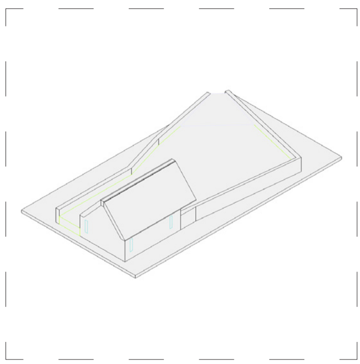
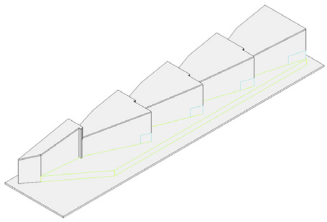
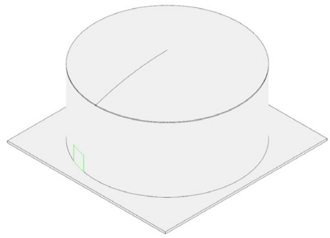

Finland Pavilion, EXPO 202

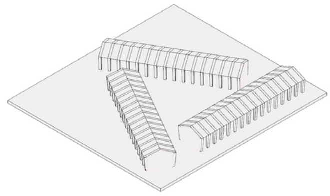

Museo Mecrì Pavilion, Inches Geleta



Slovenia Pavilion, EXPO 2015



Silo 468, Lighting Design Collective



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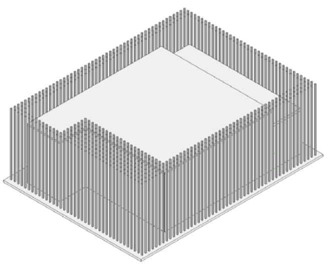
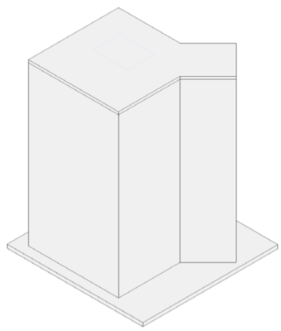
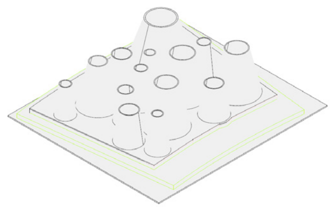


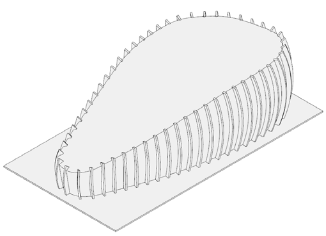
Hungarian Pavilion, EXPO 2020



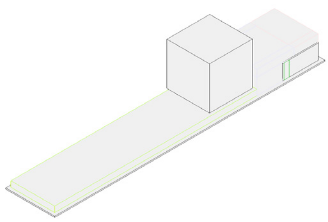
XXI Triennale, Souto de Moura



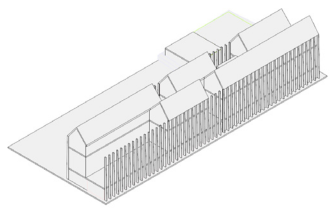
Spanish Paviliion, EXPO 2020



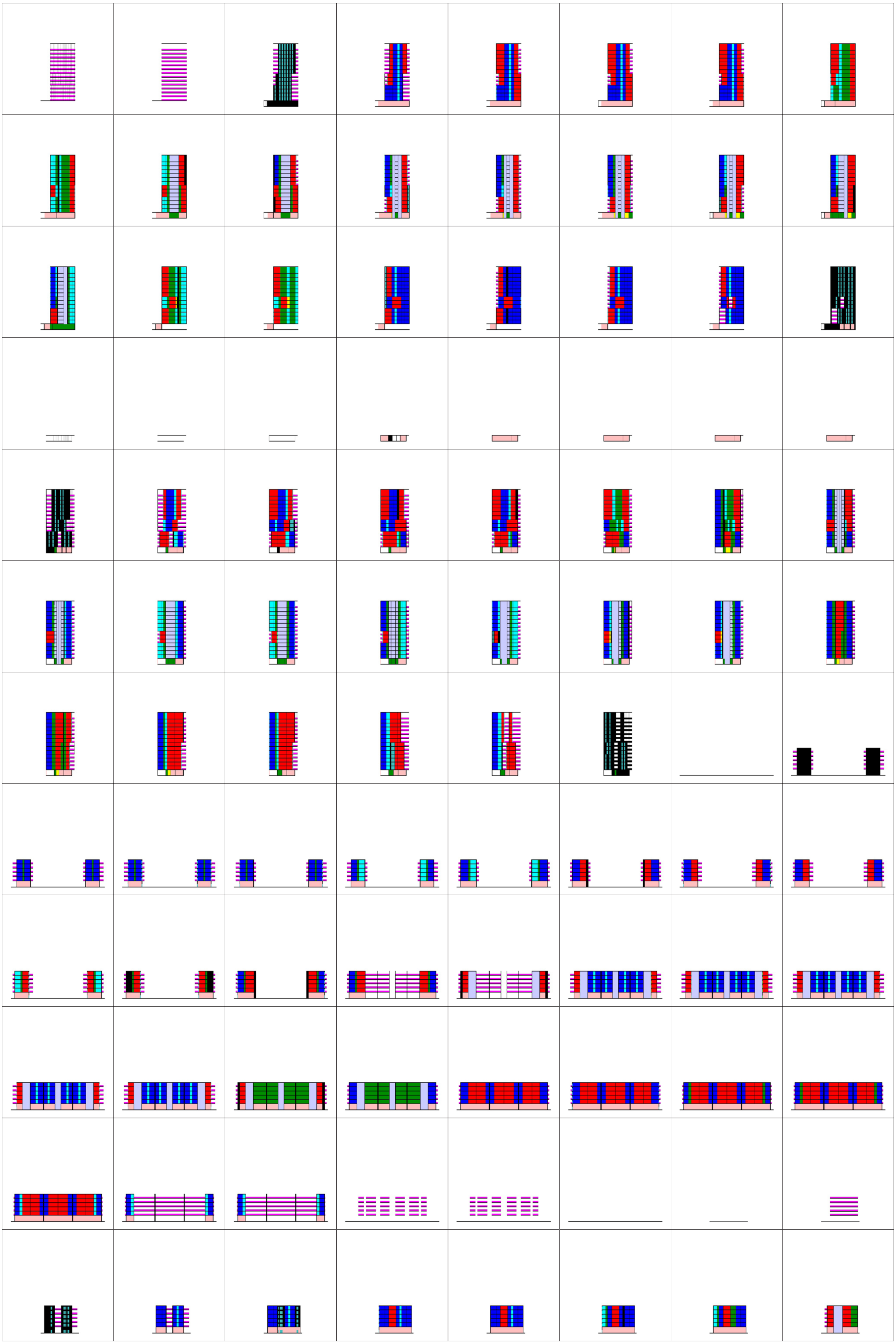
Unicredit Pavilion, Michele de Lucchi

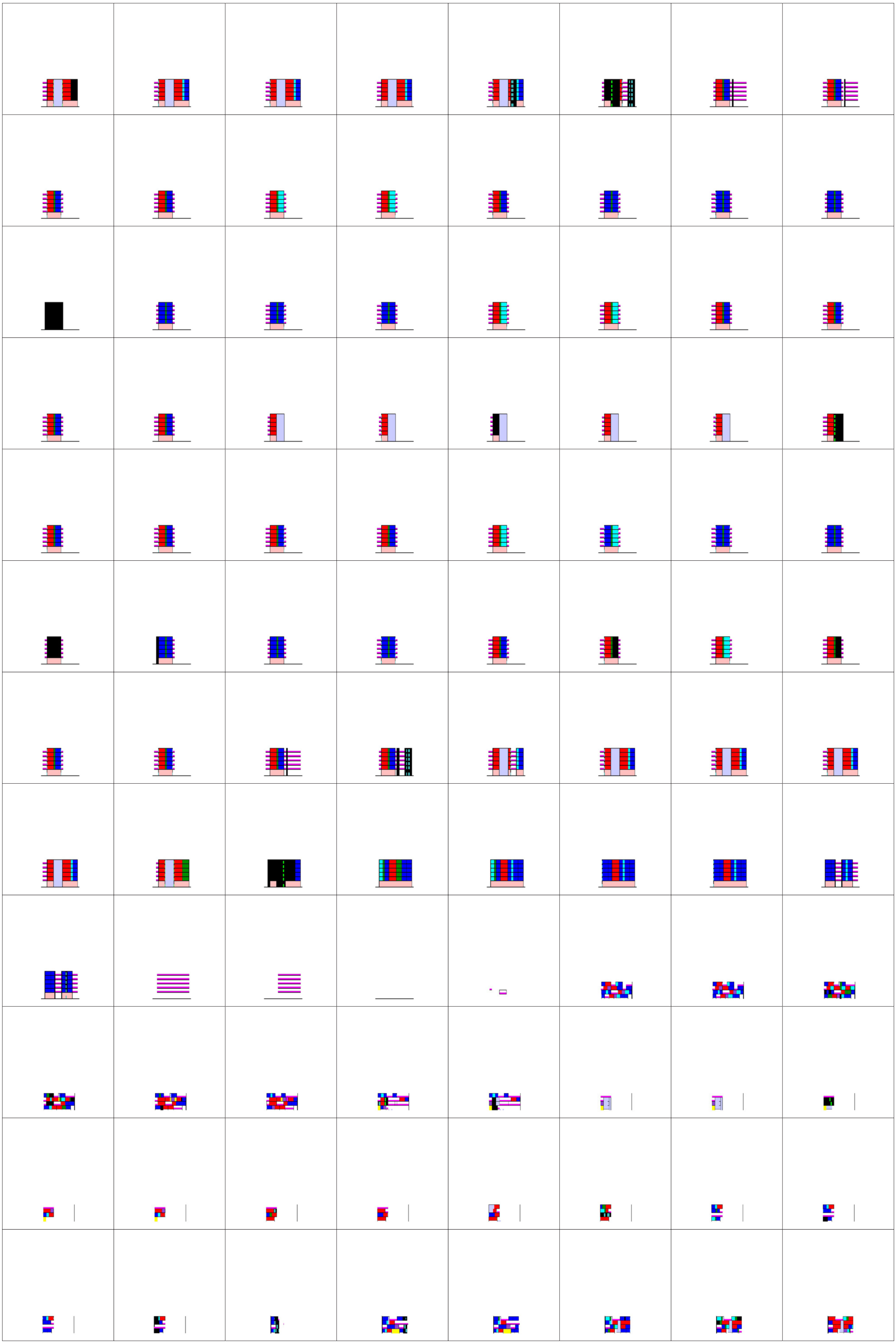


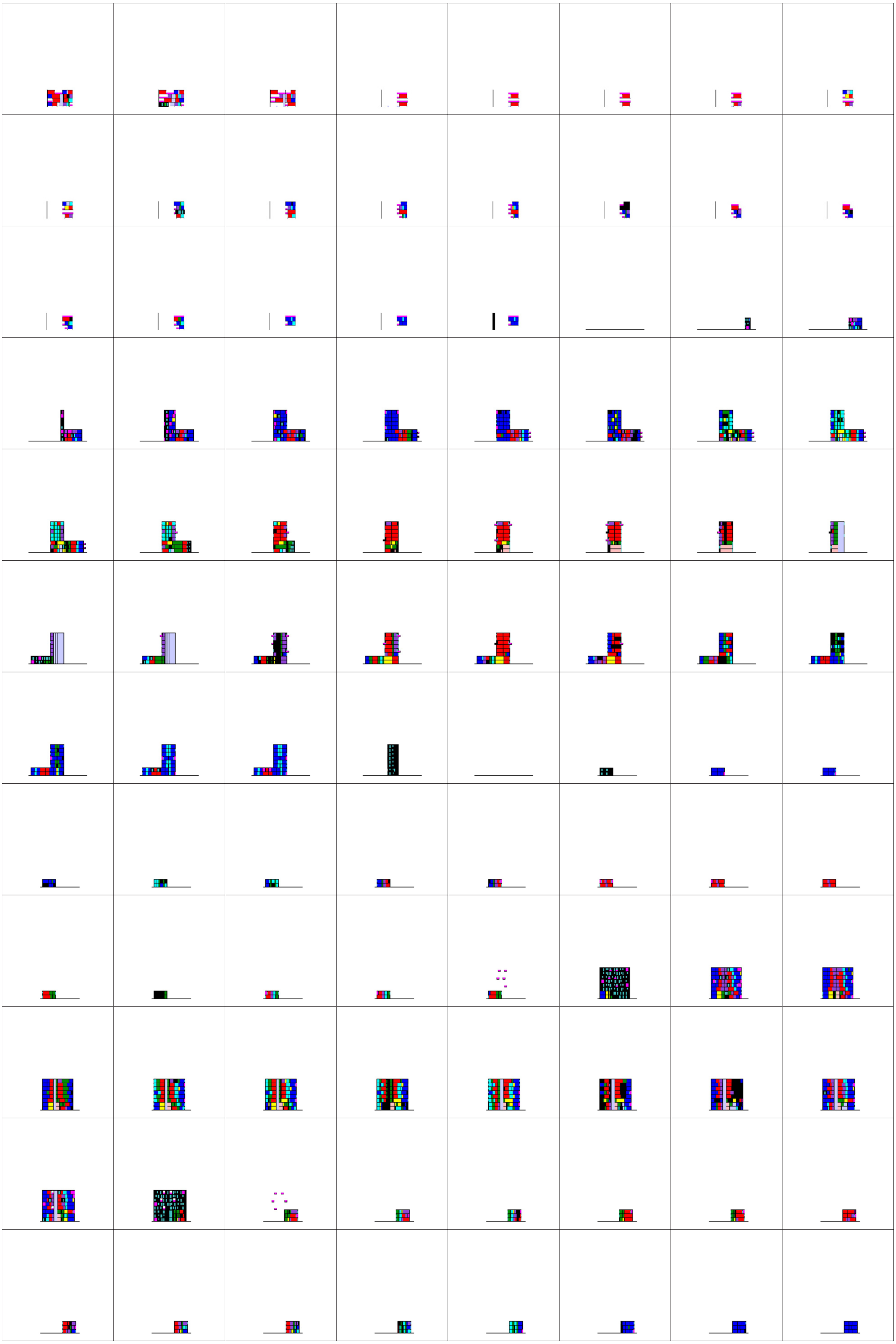
UK Pavilion, EXPO 2015

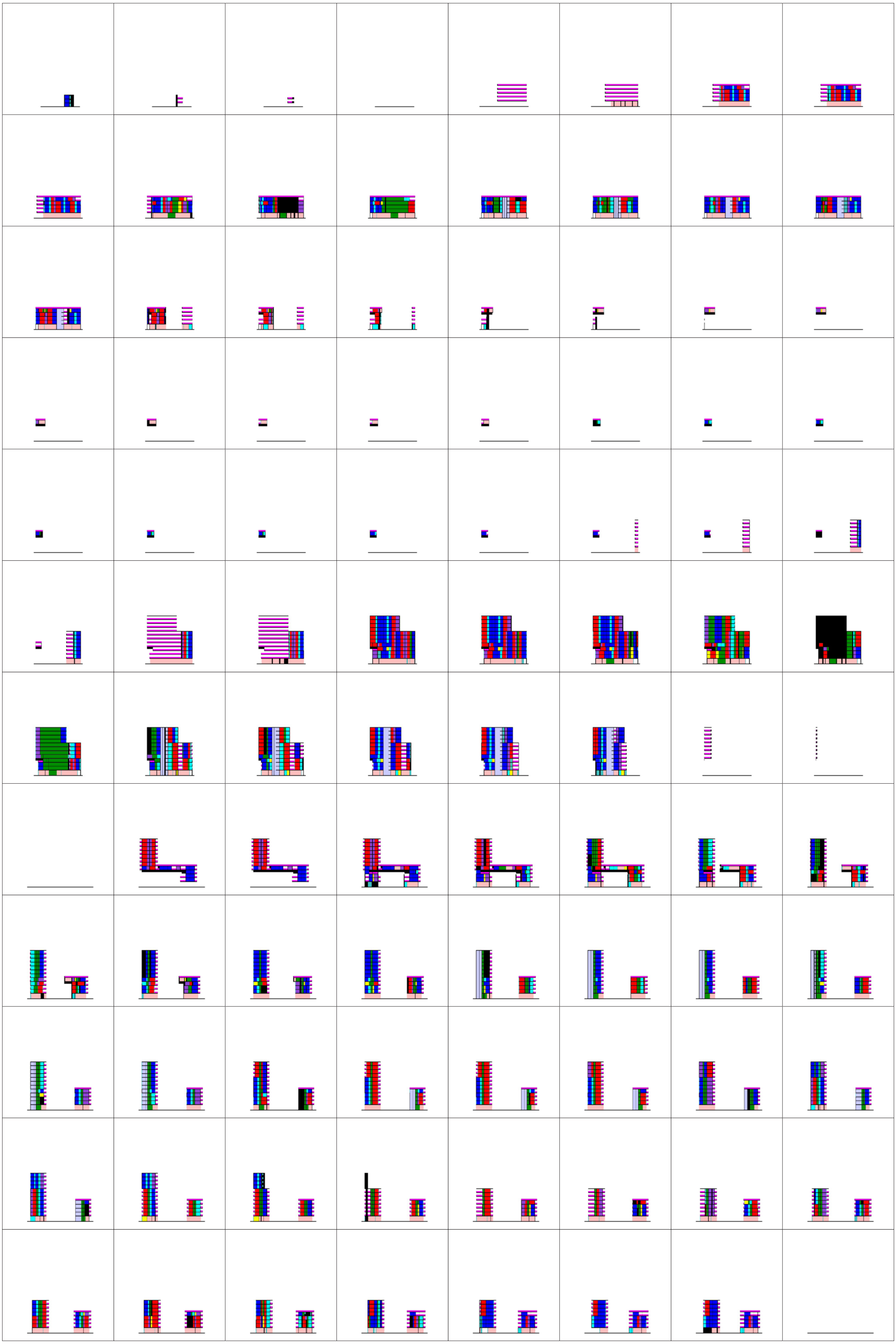


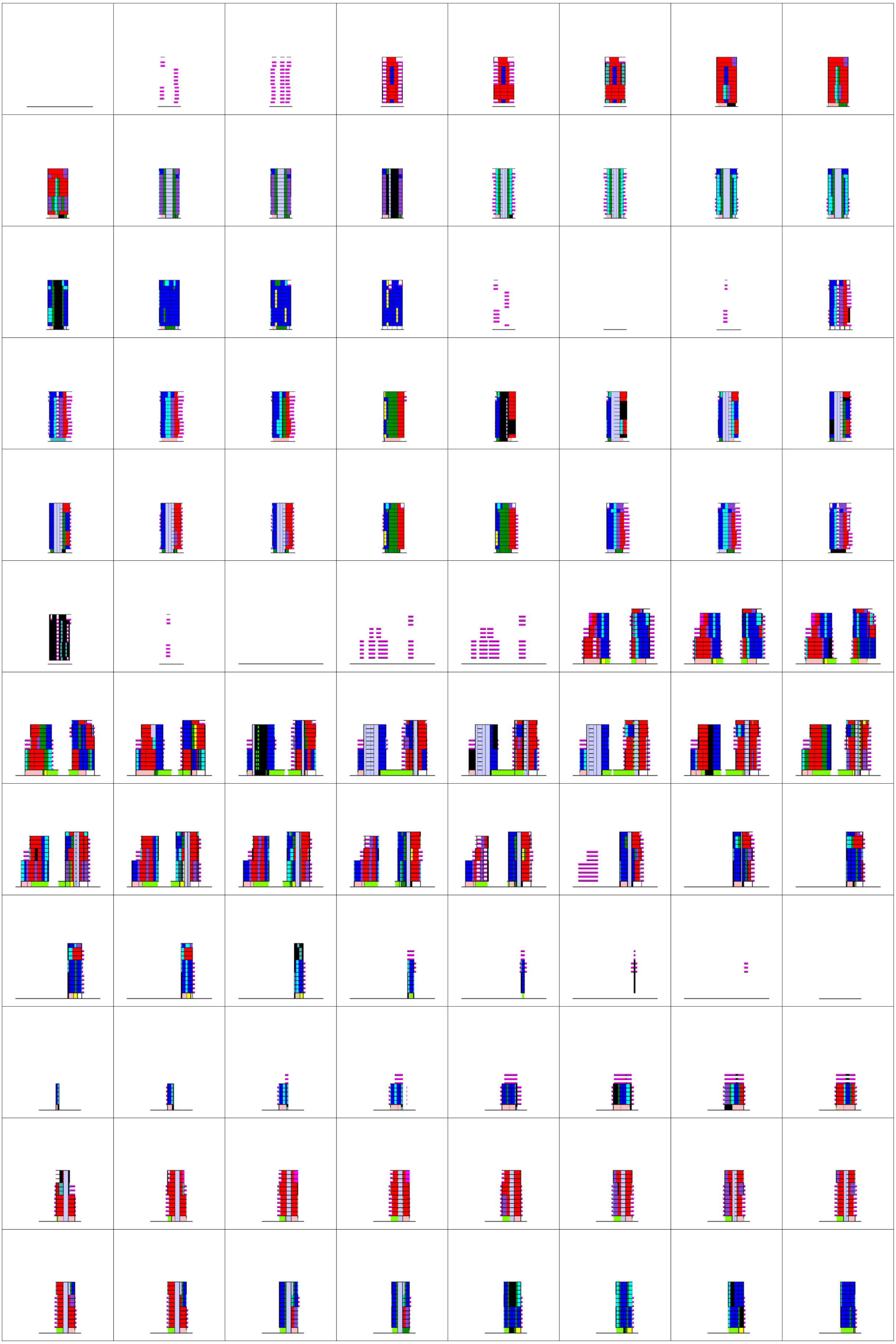
Spanish Pavilion, EXPO 2015

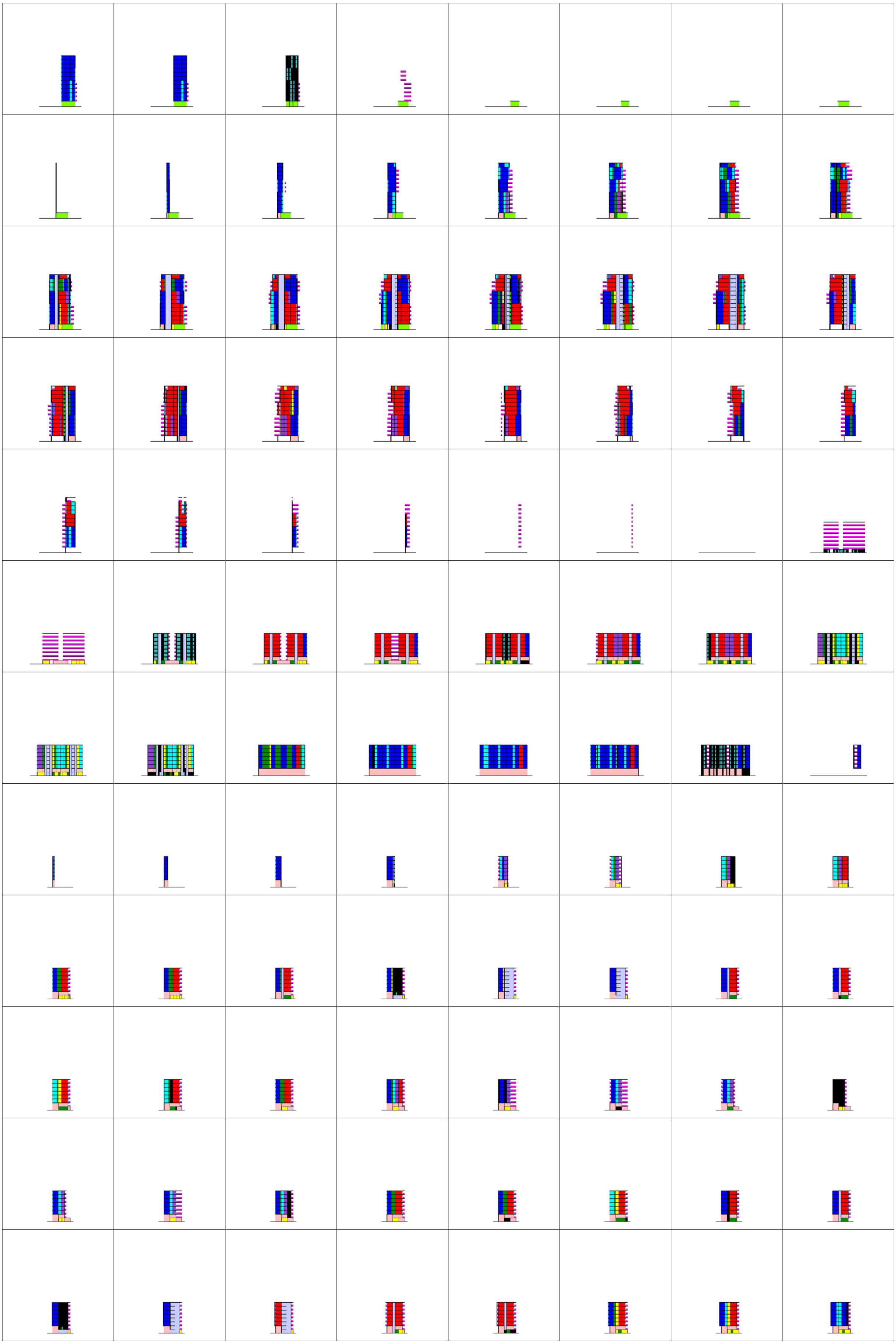


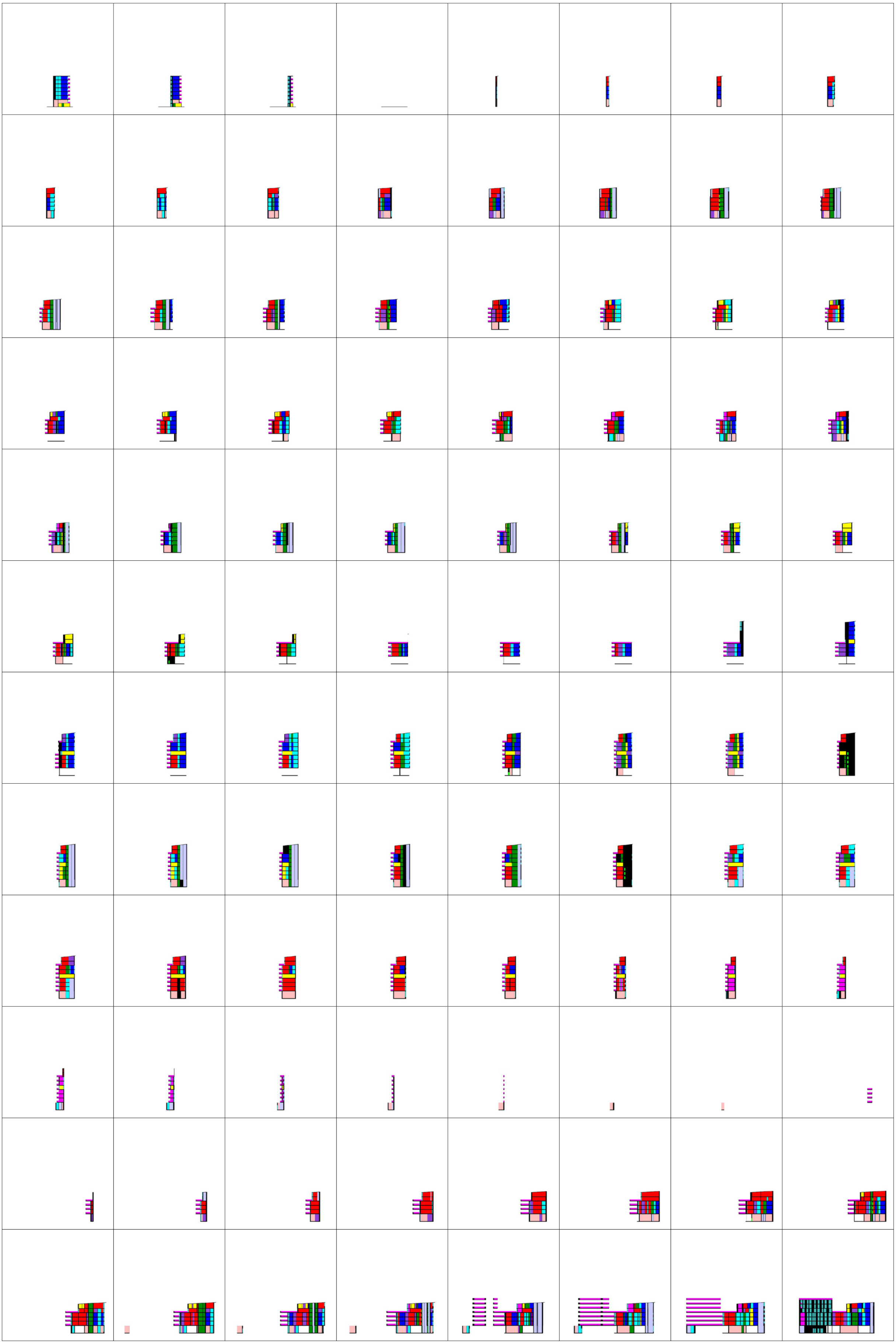


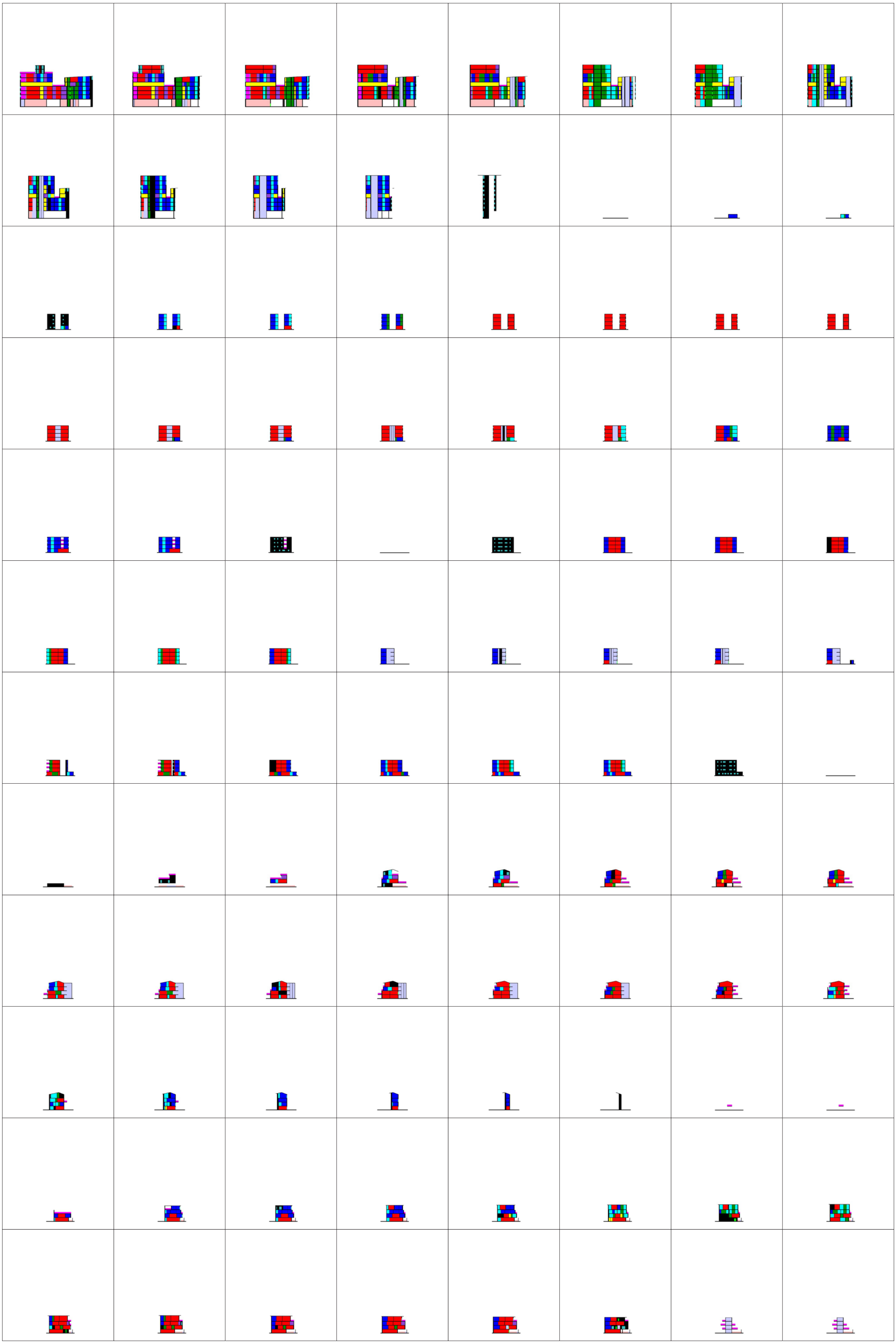


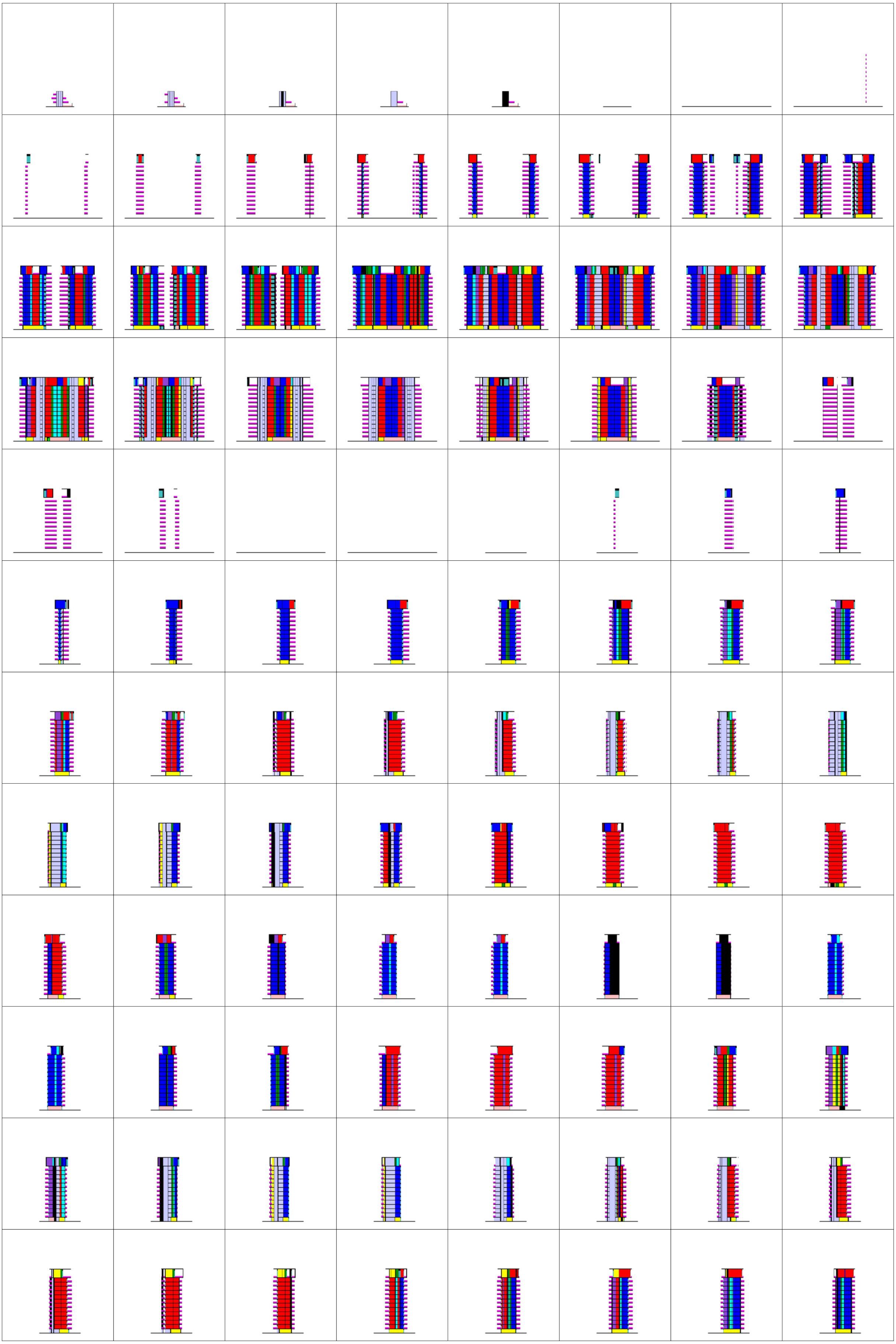


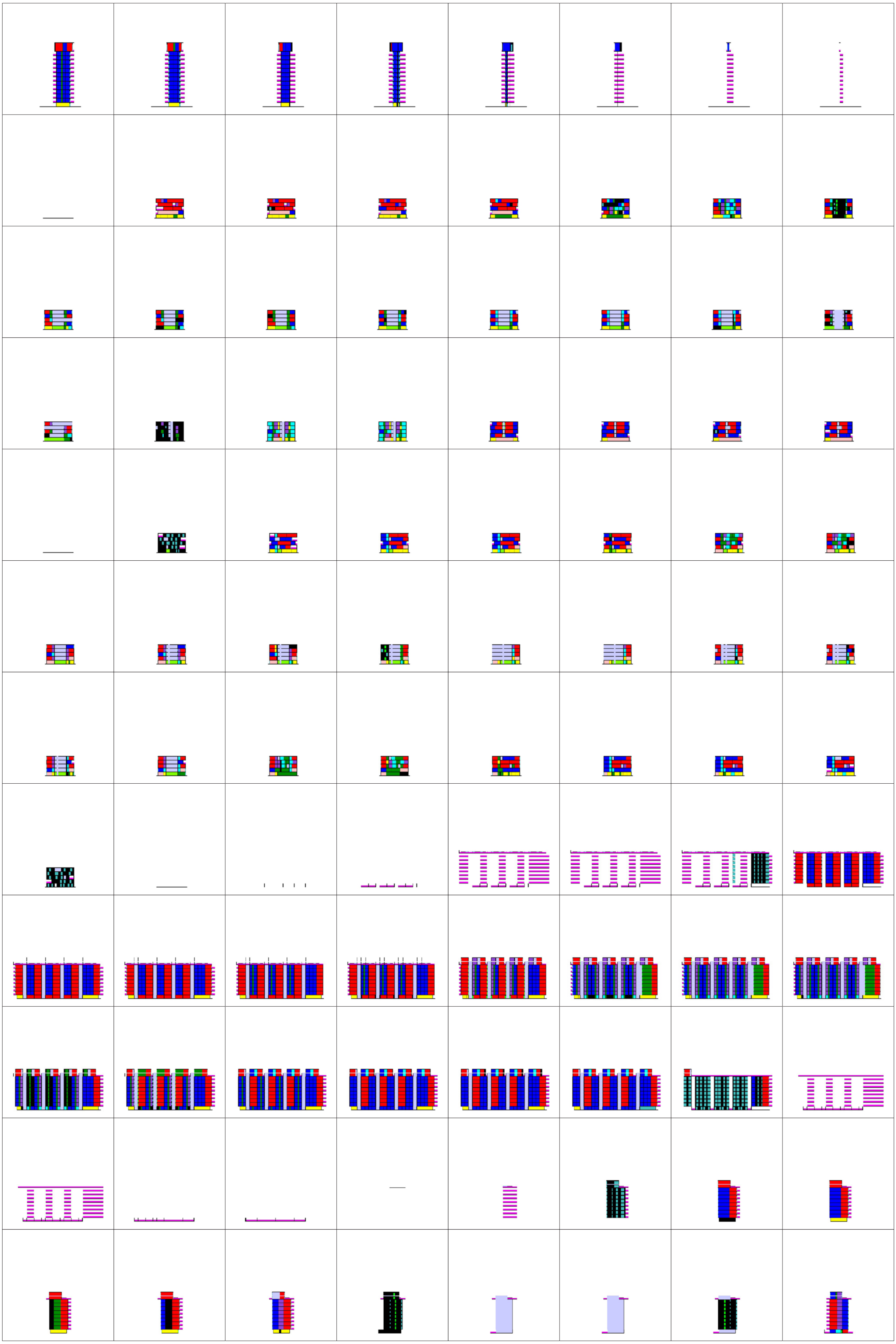


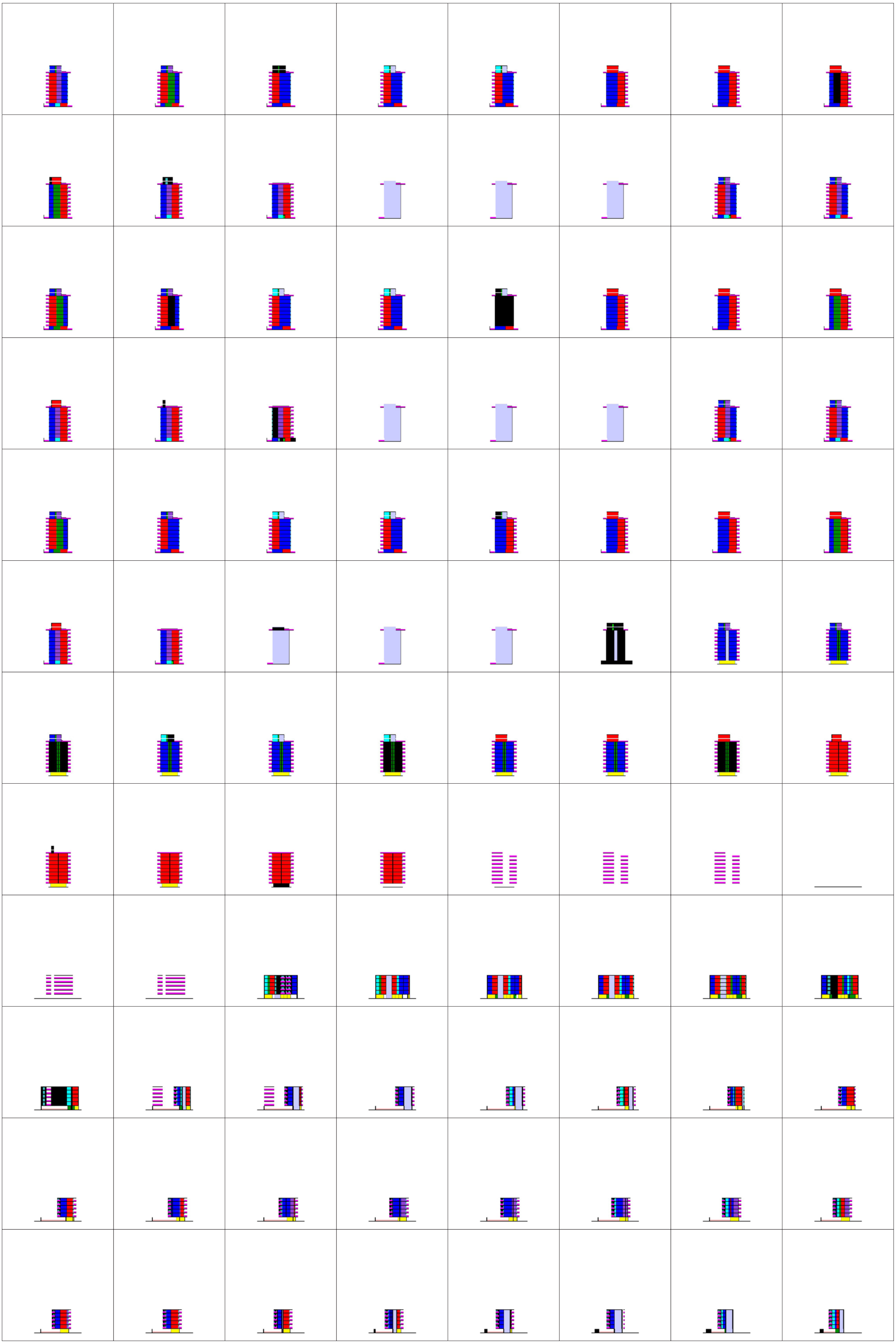


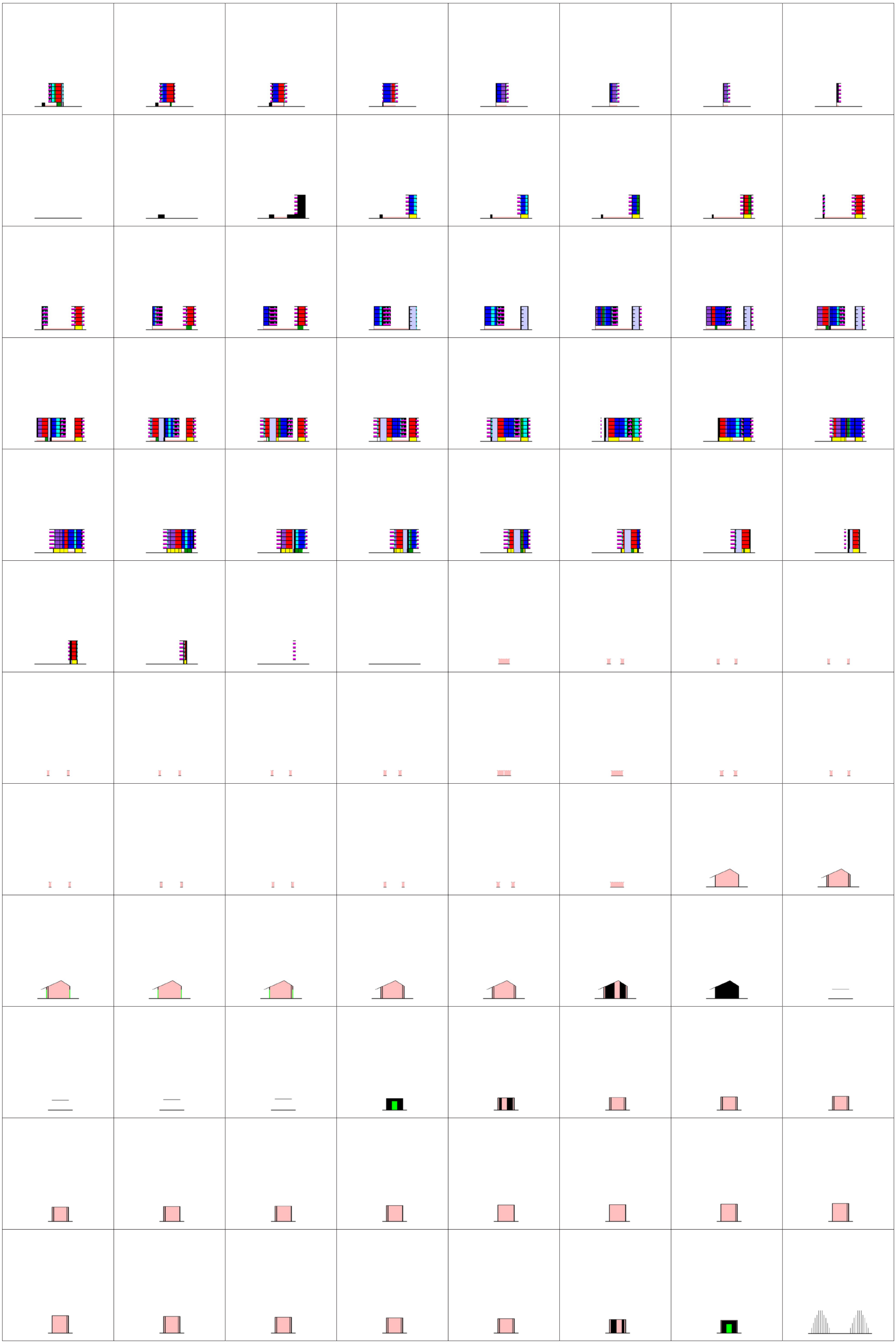


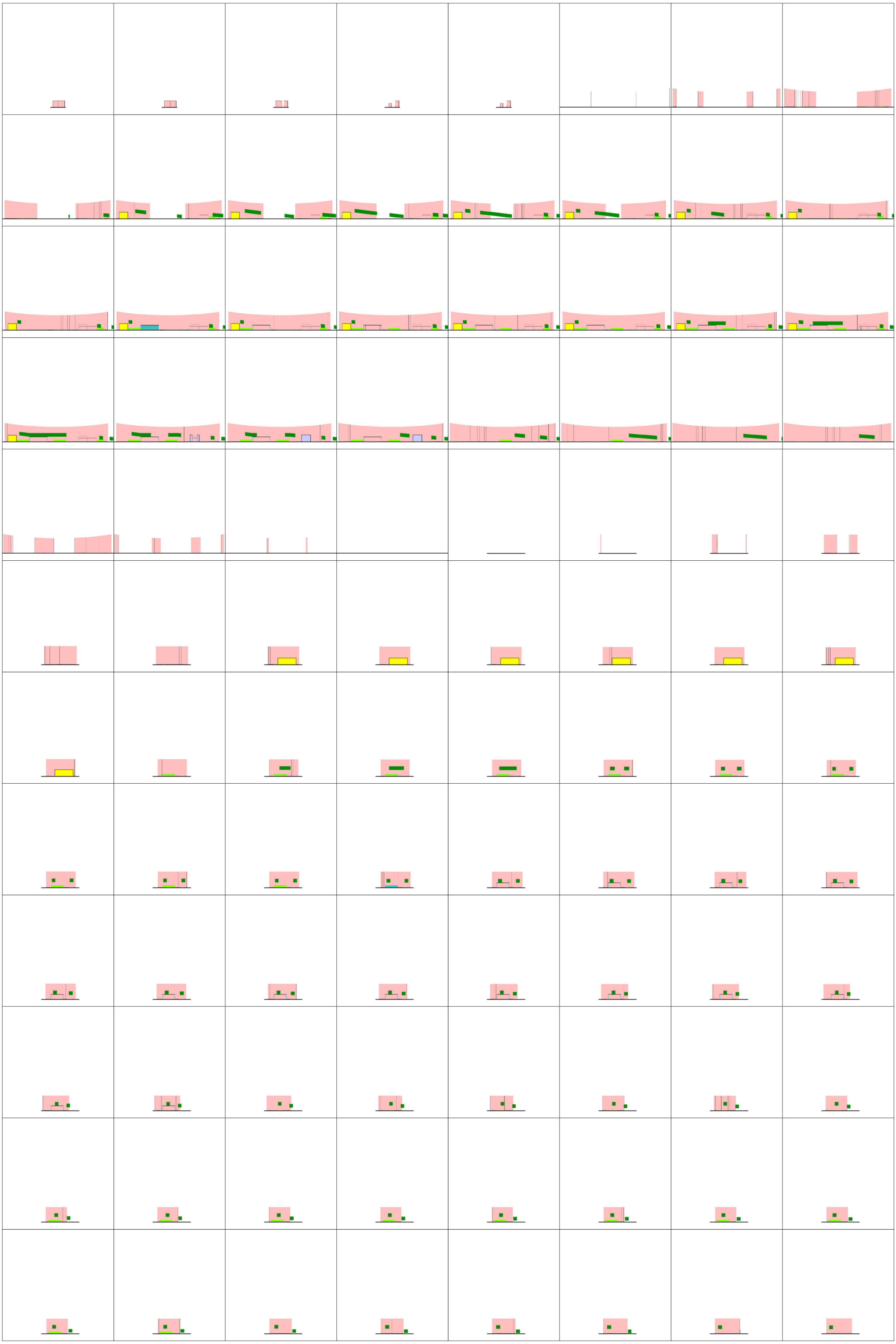


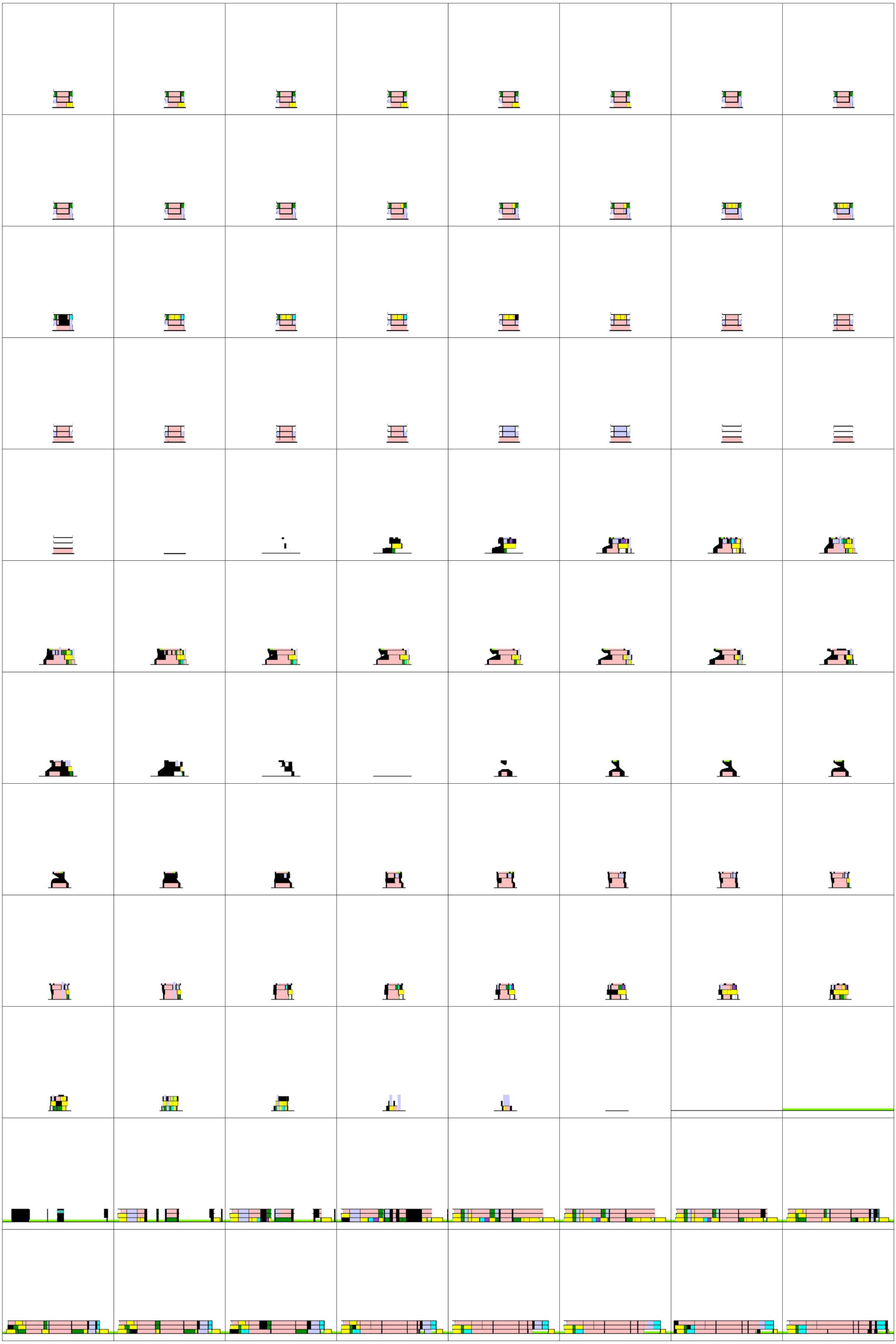


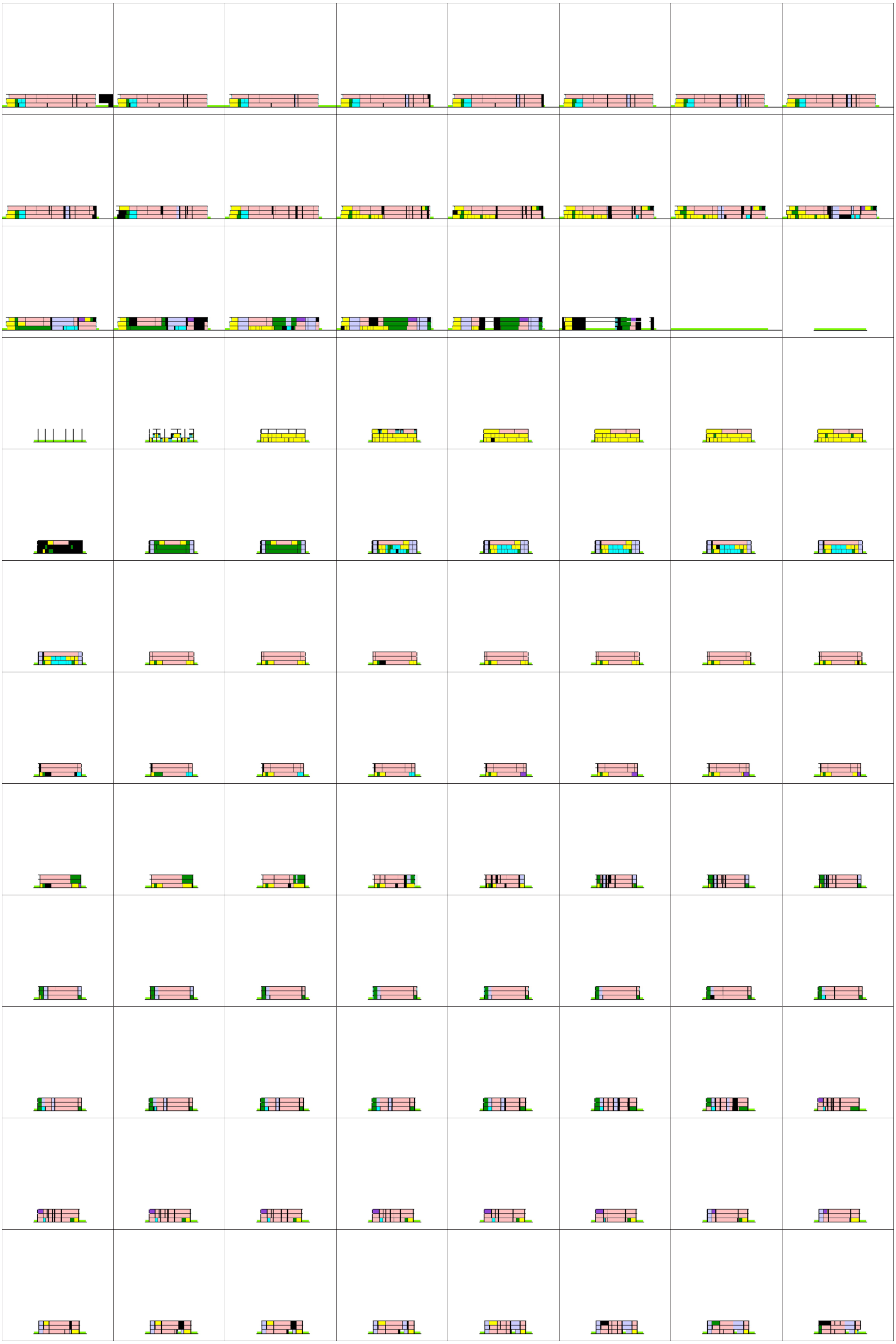


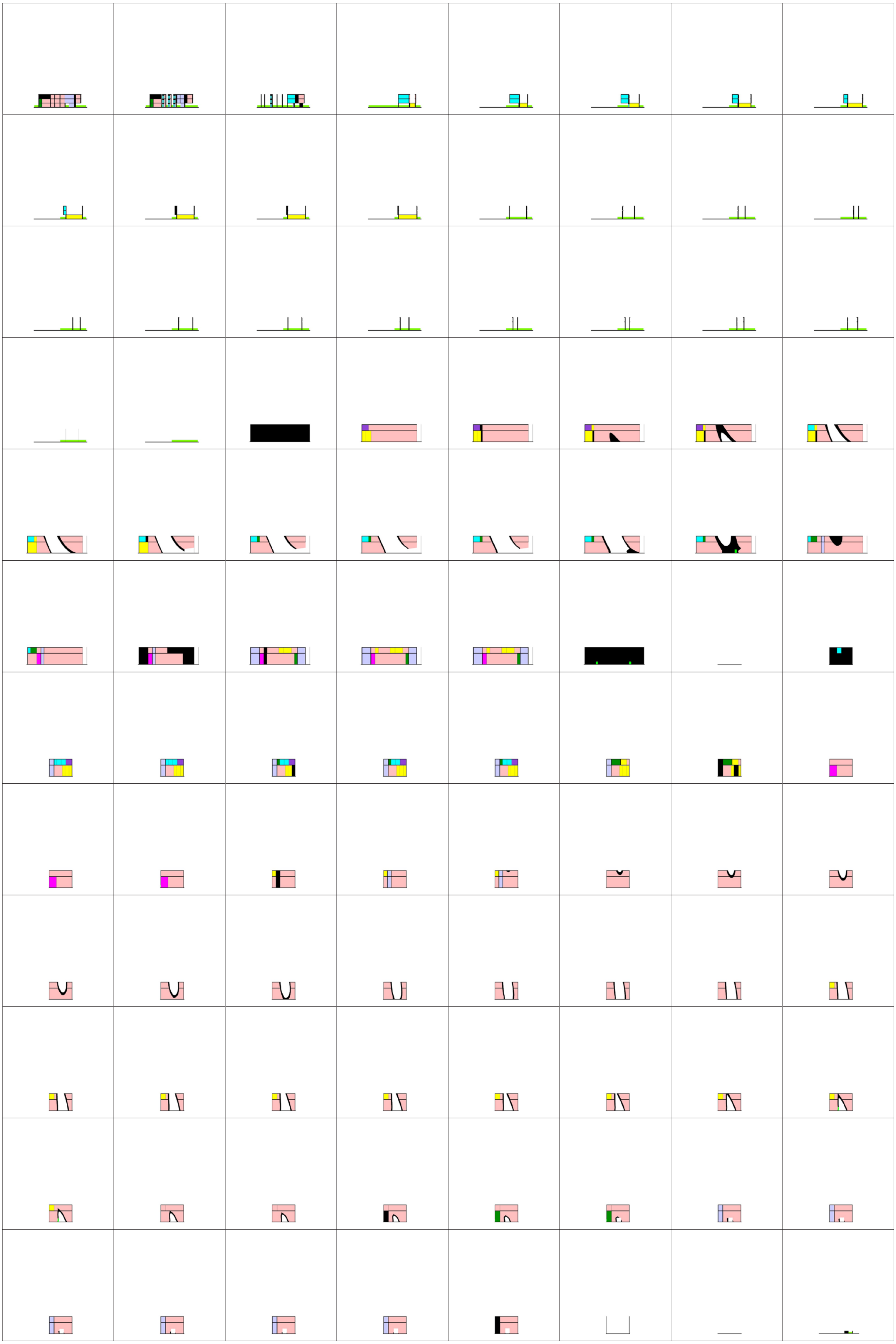


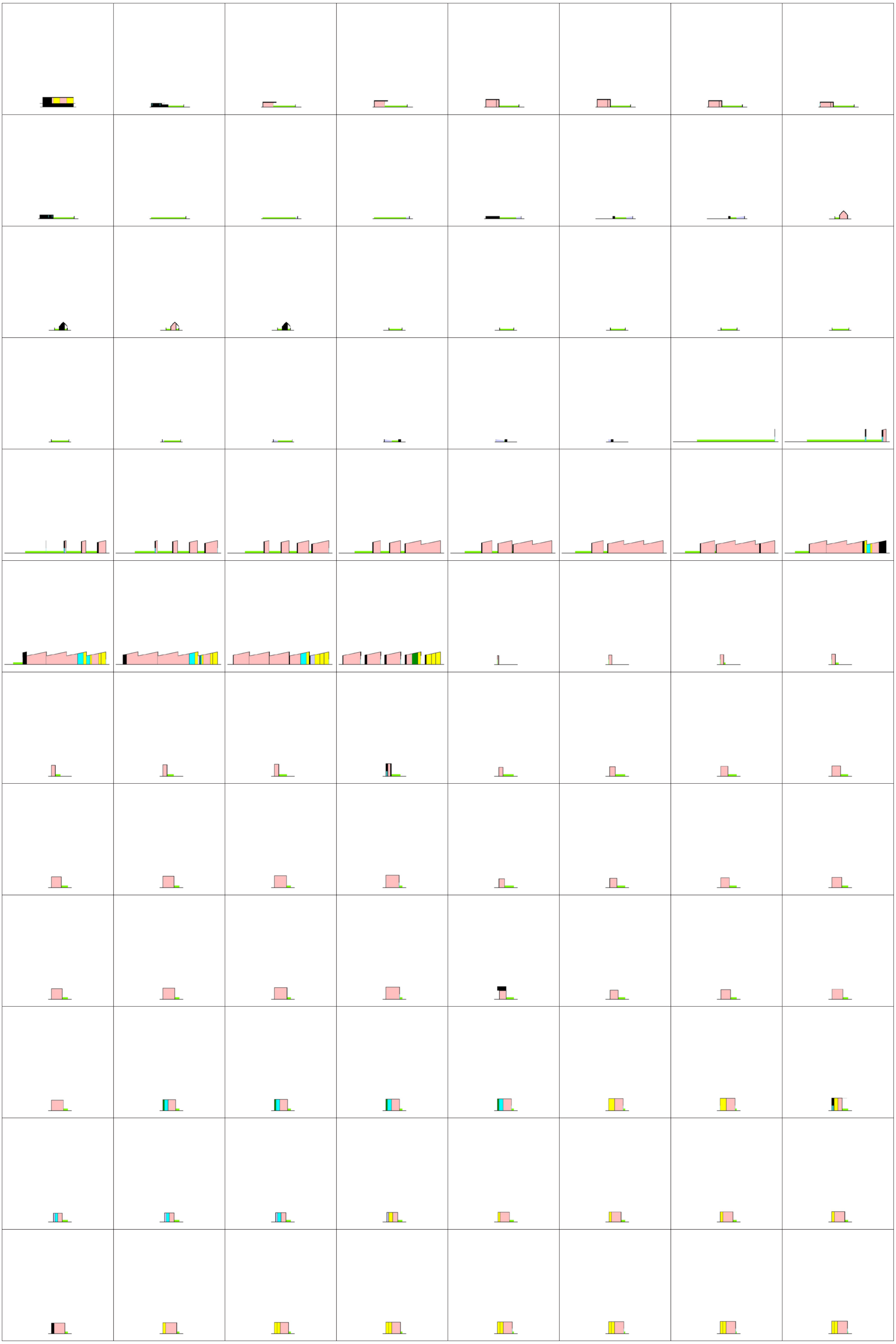


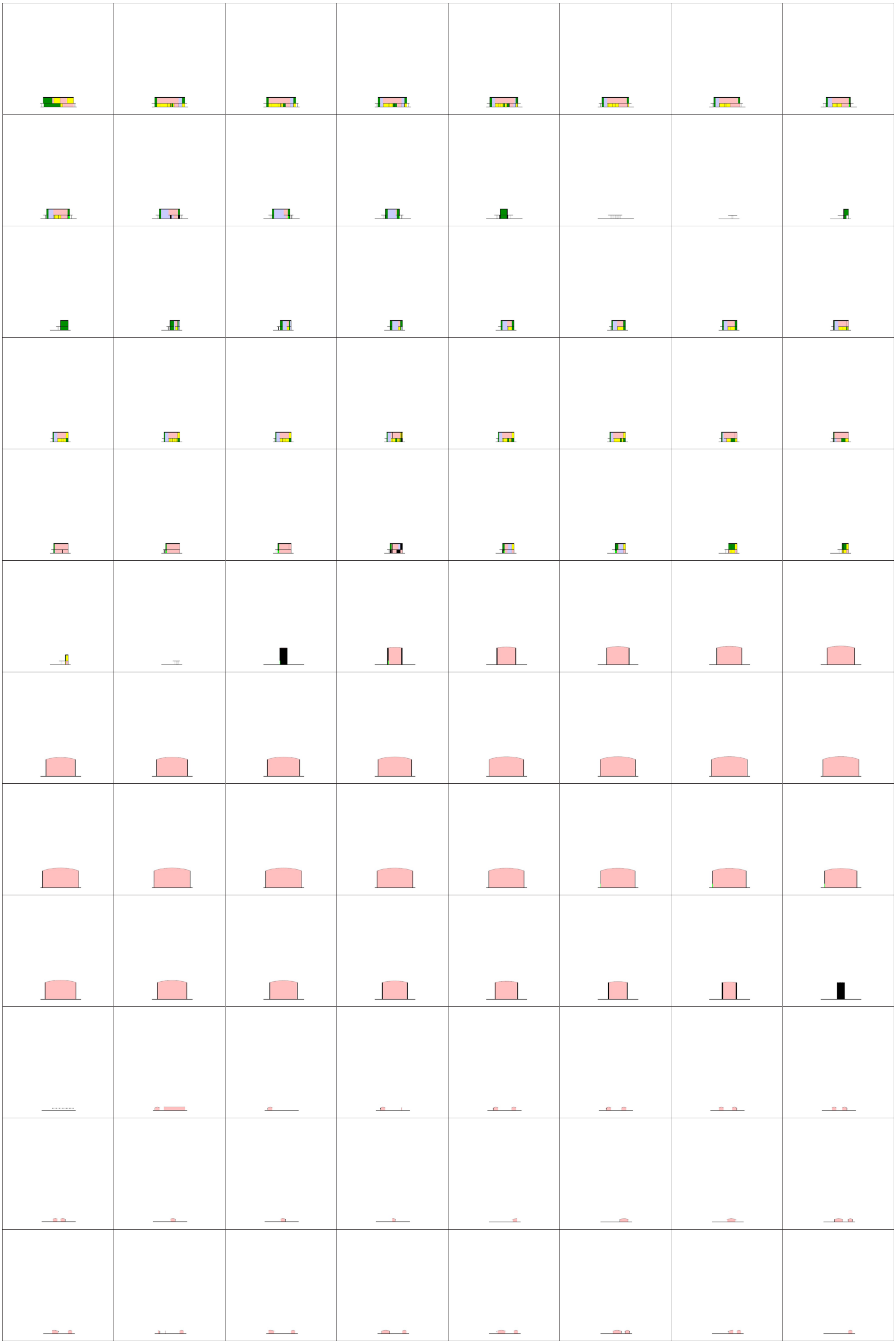


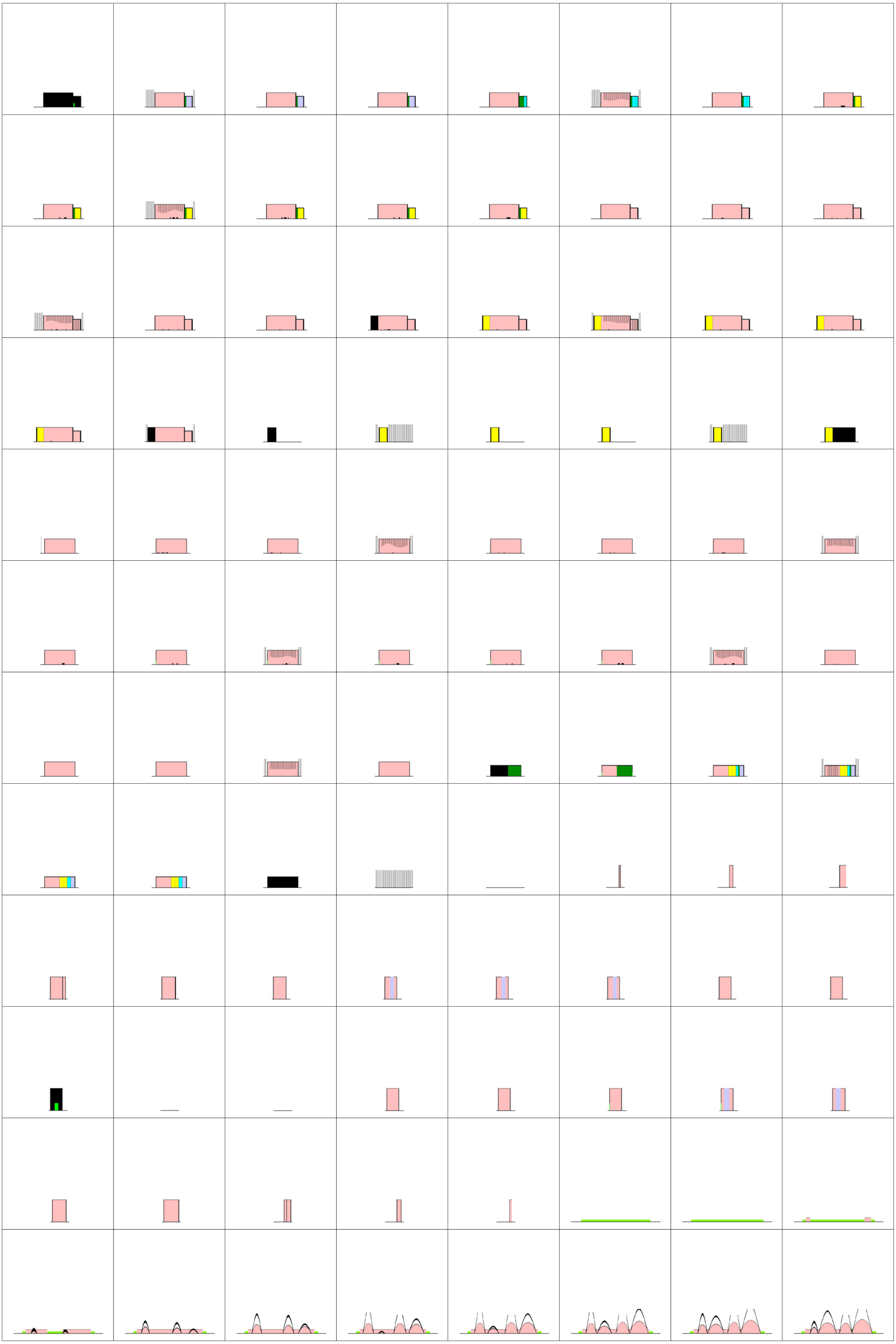


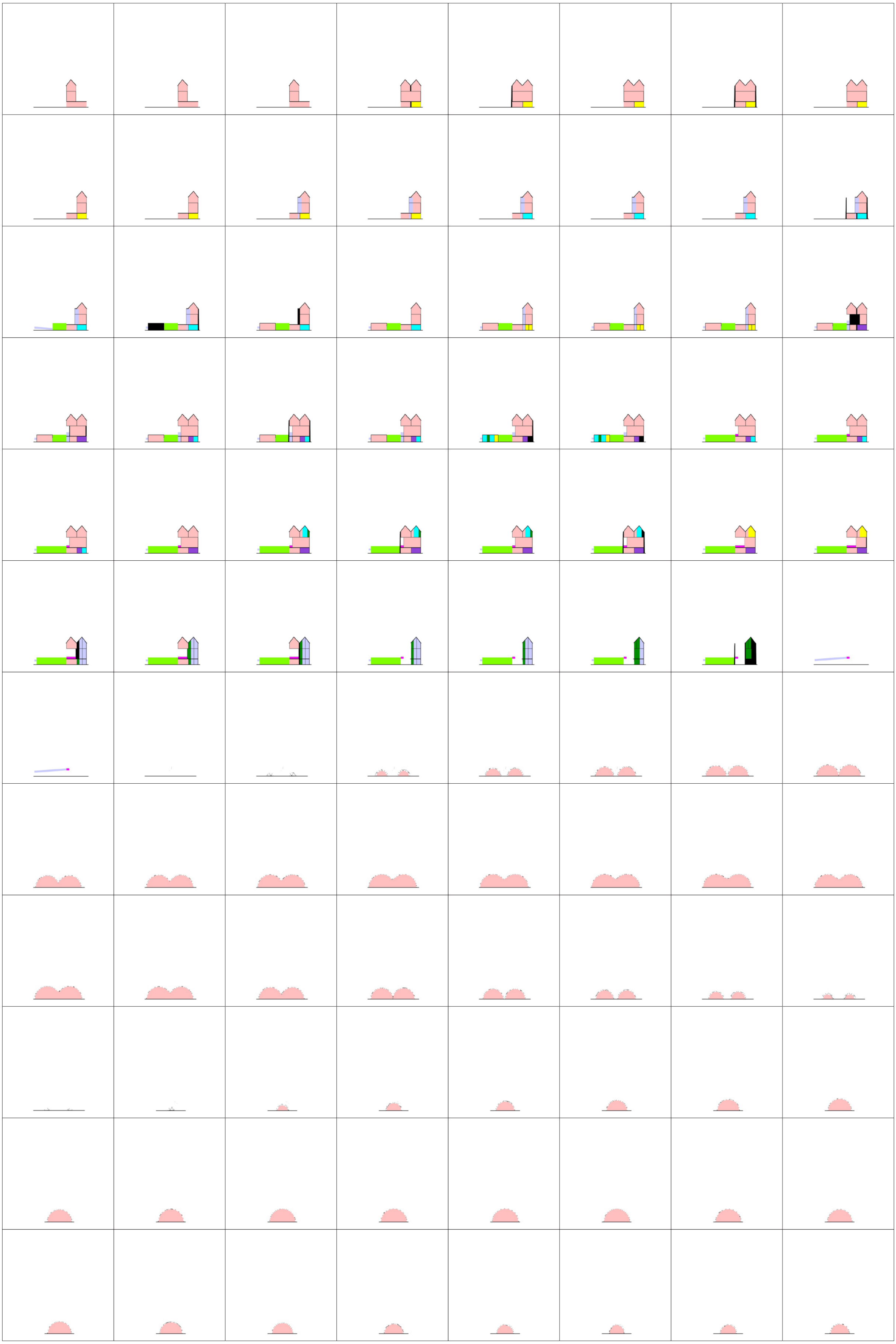


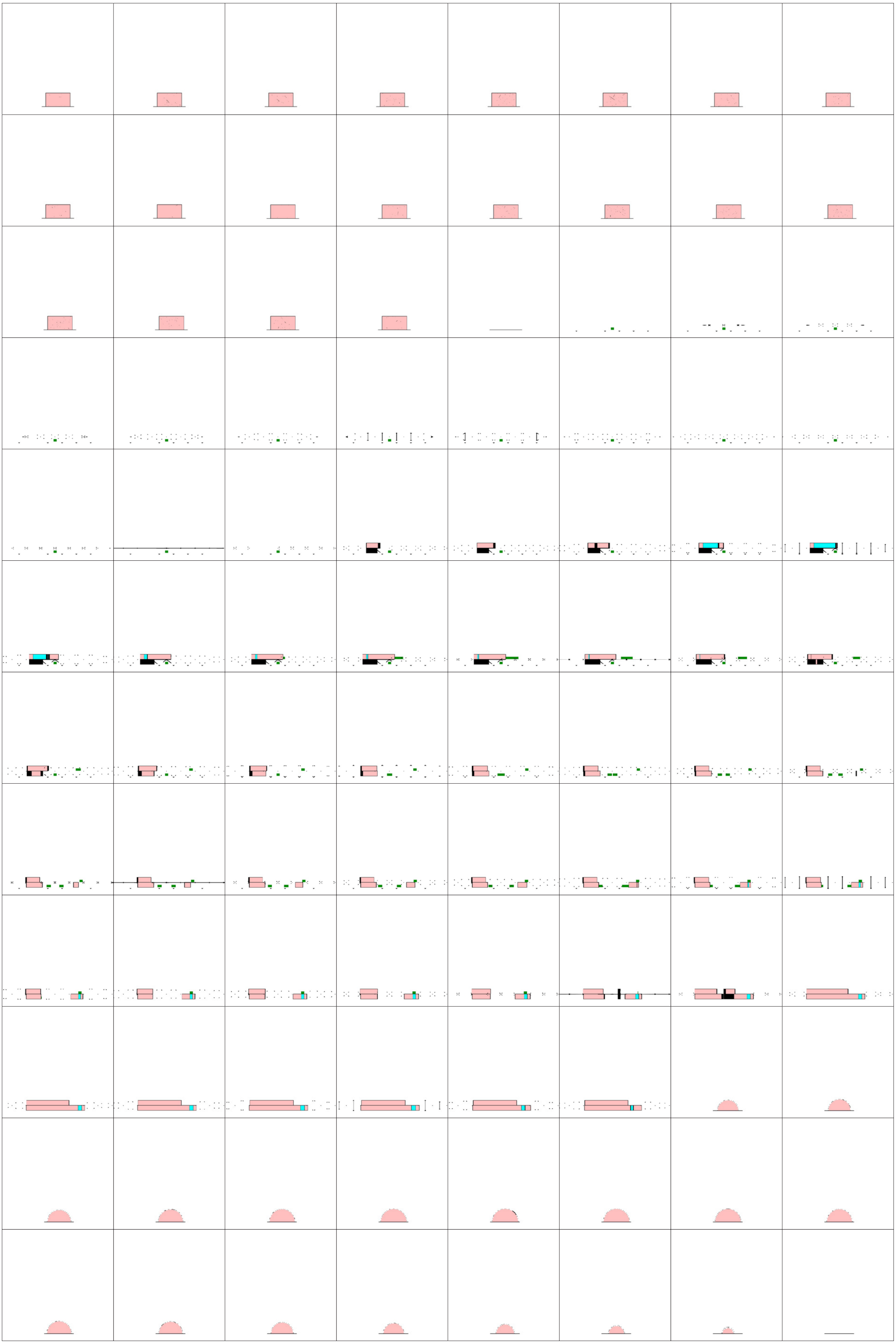


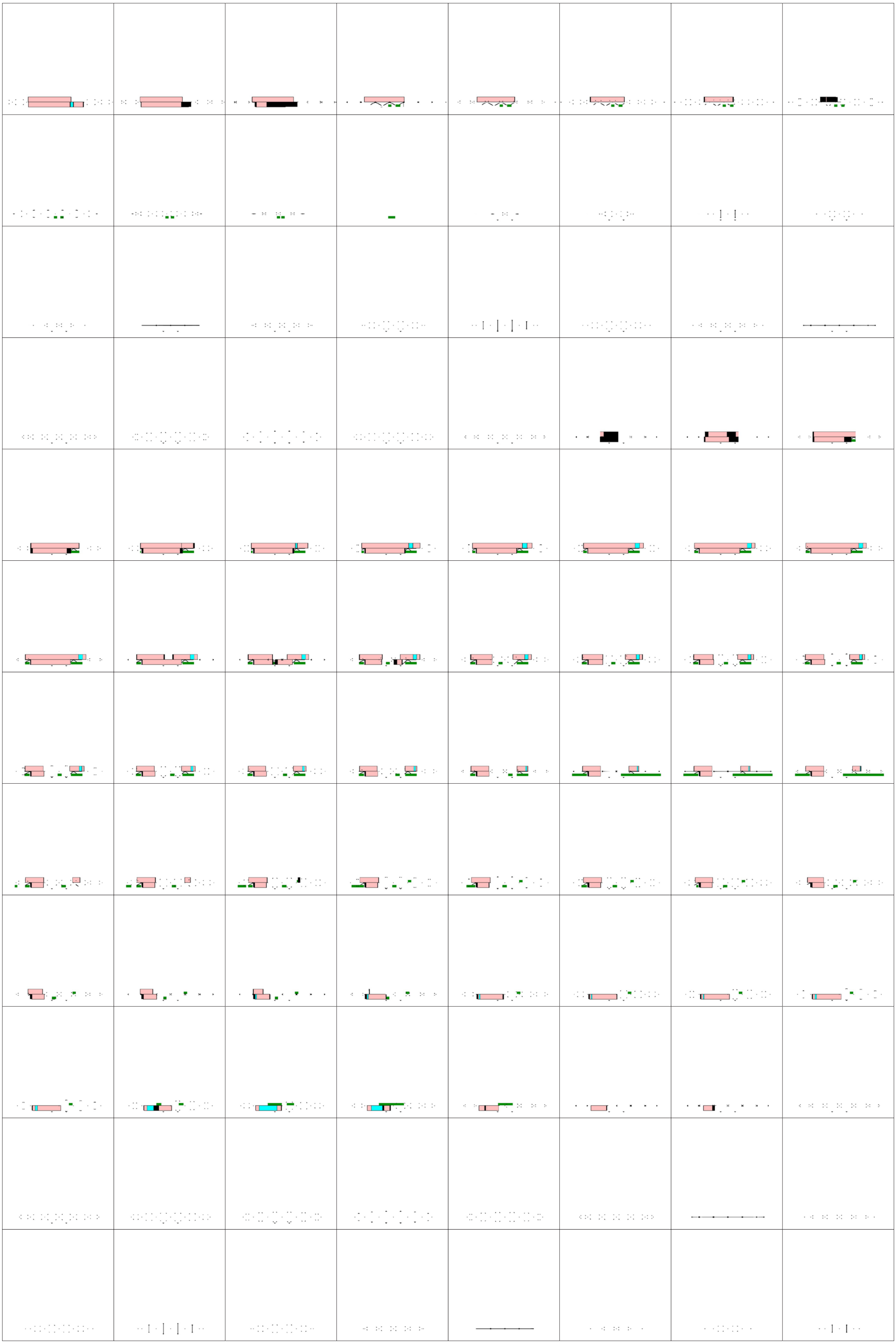


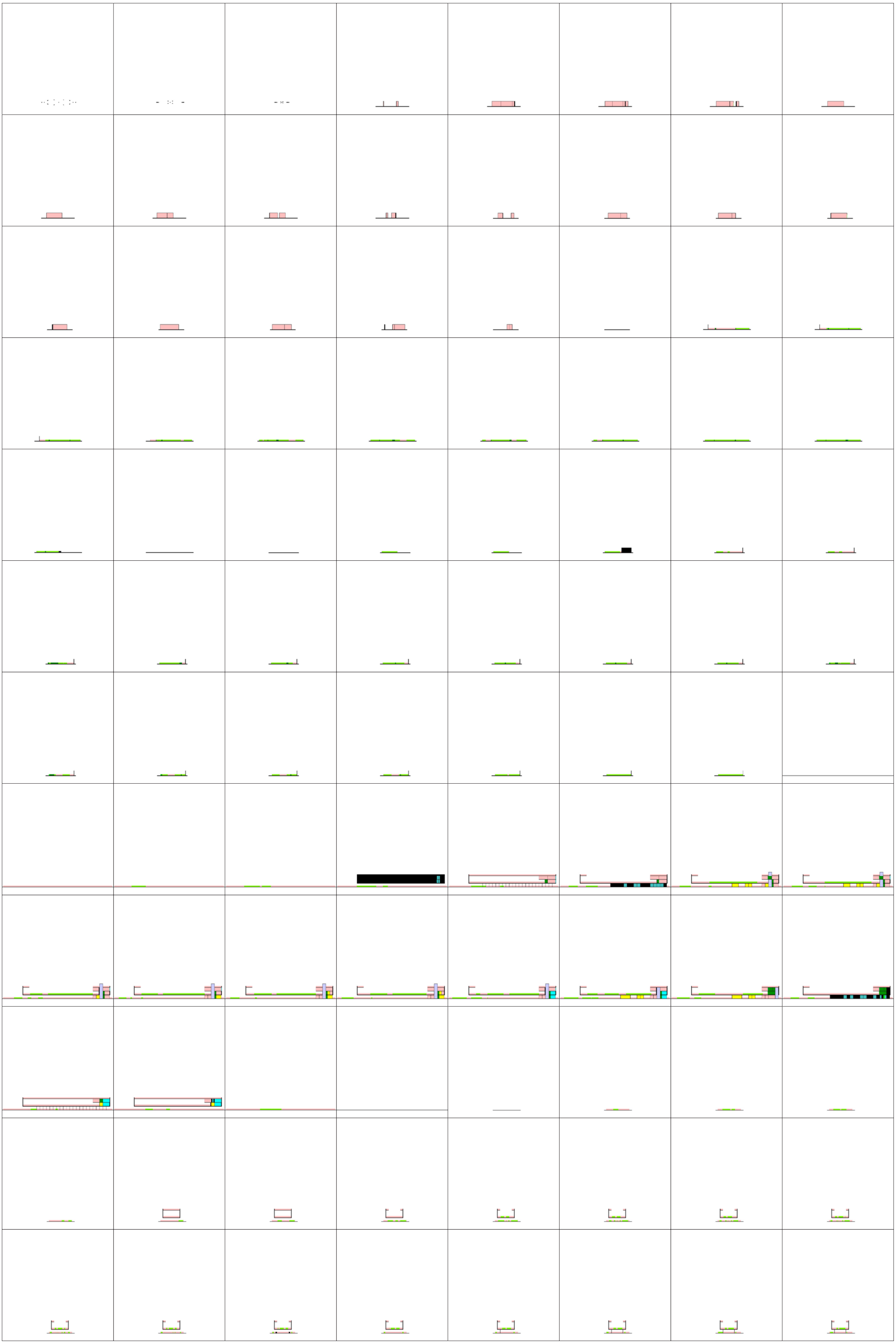


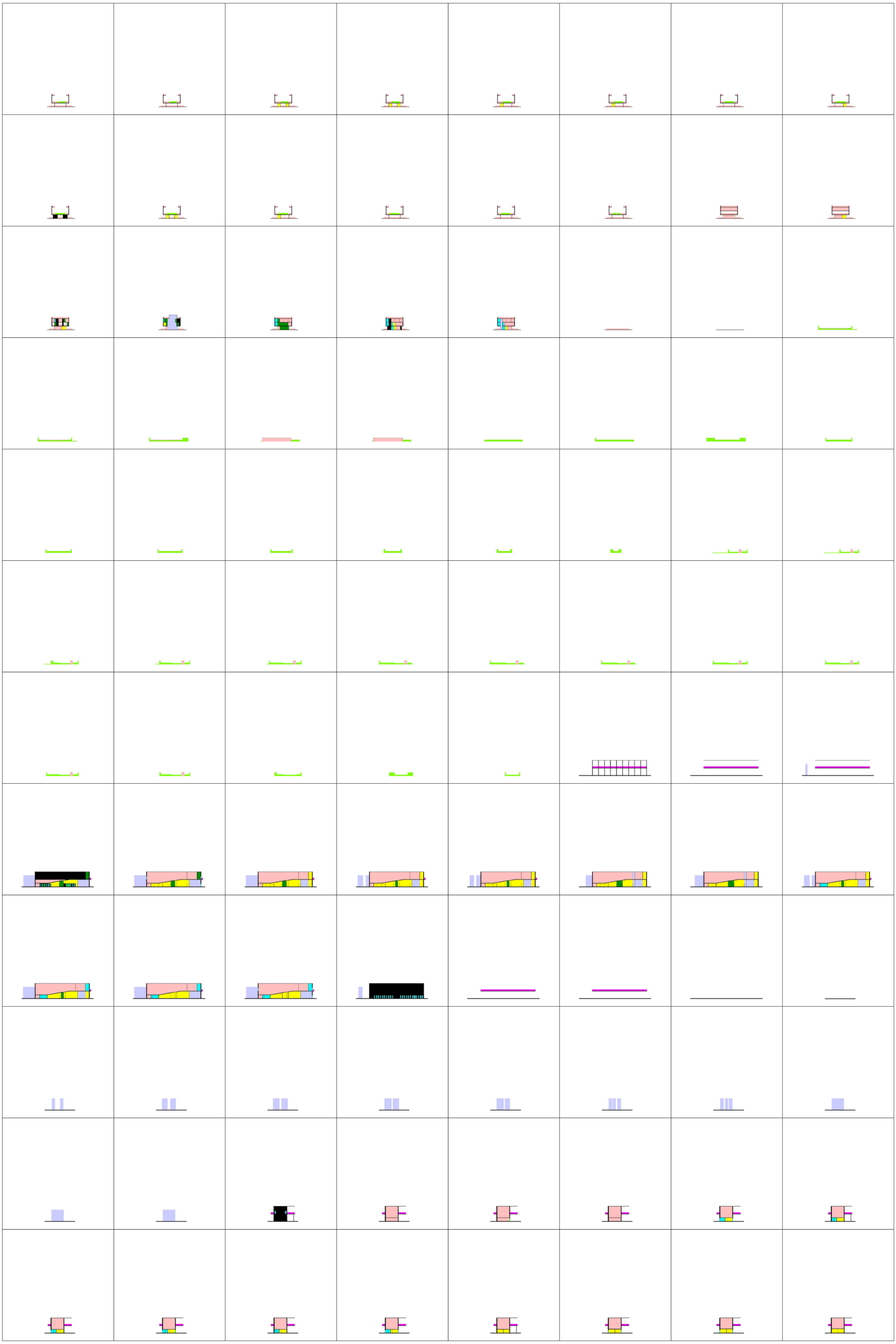


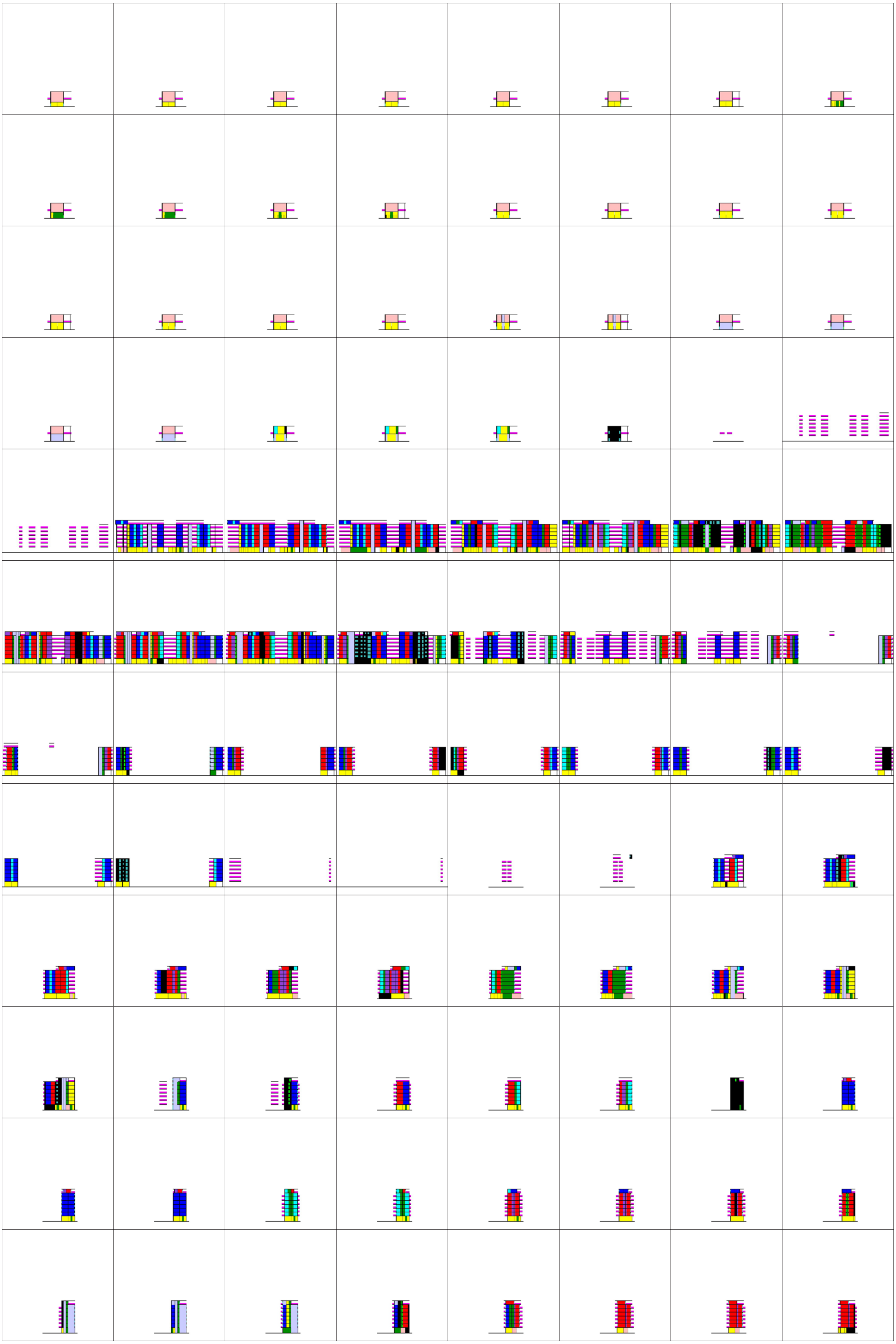


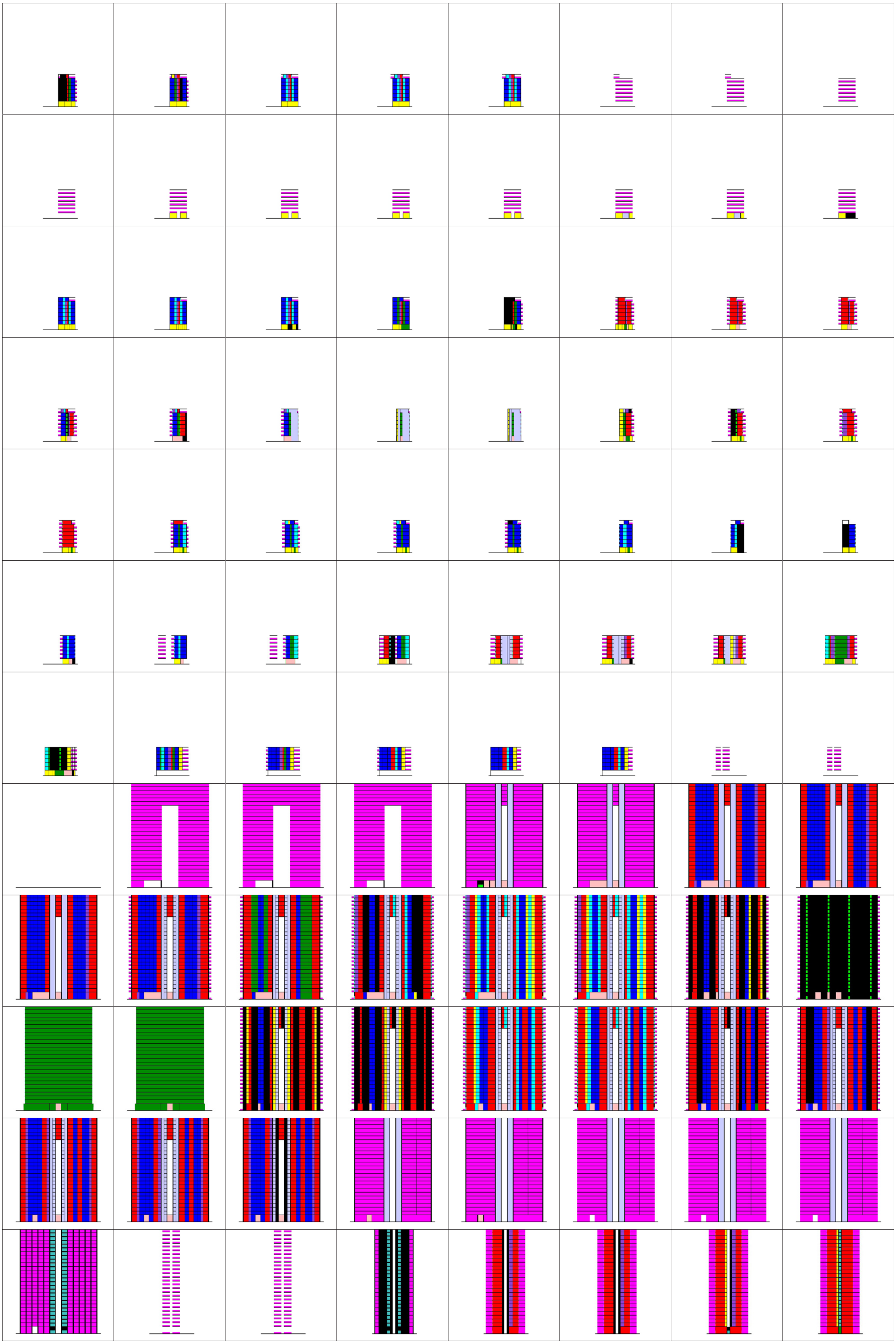


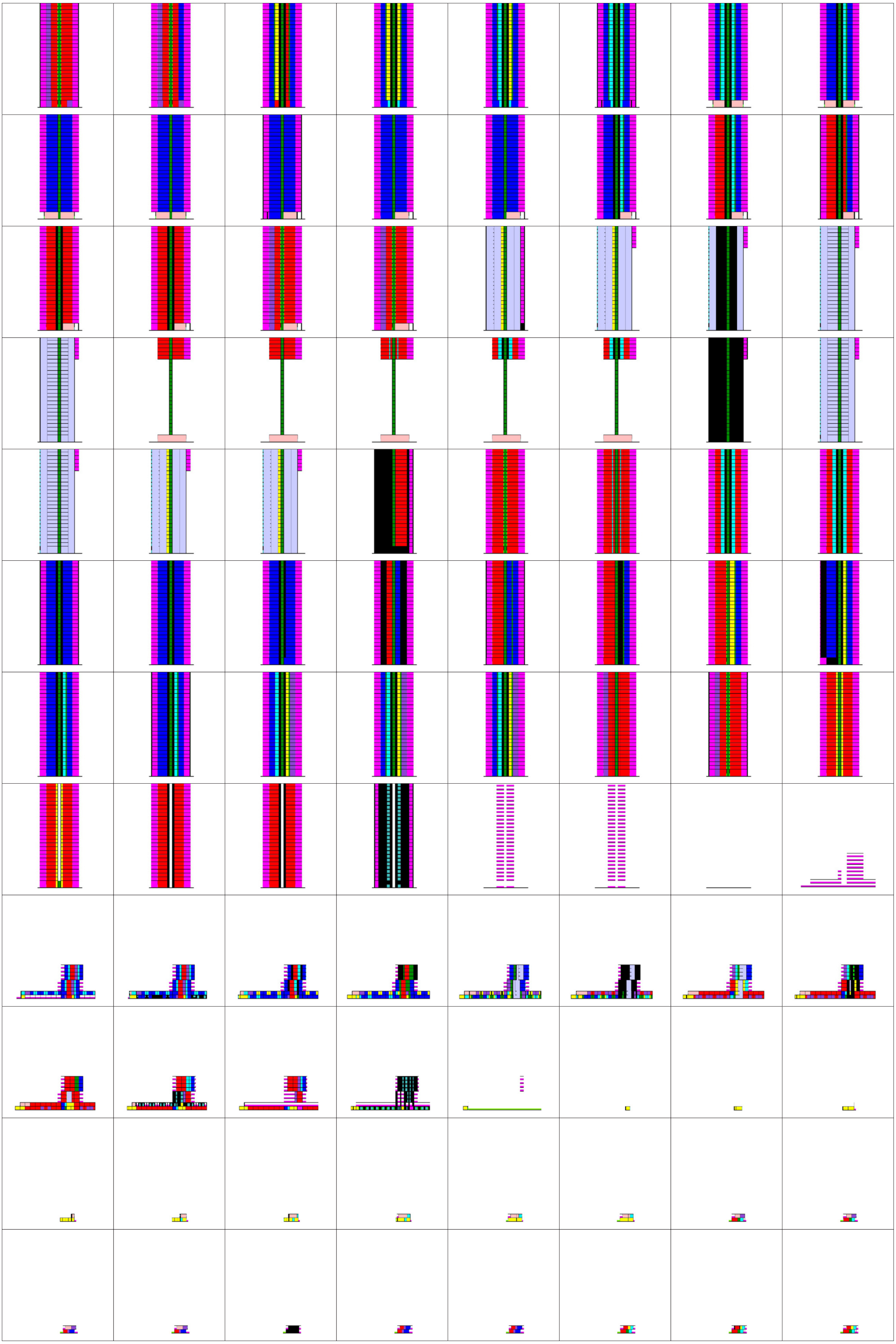


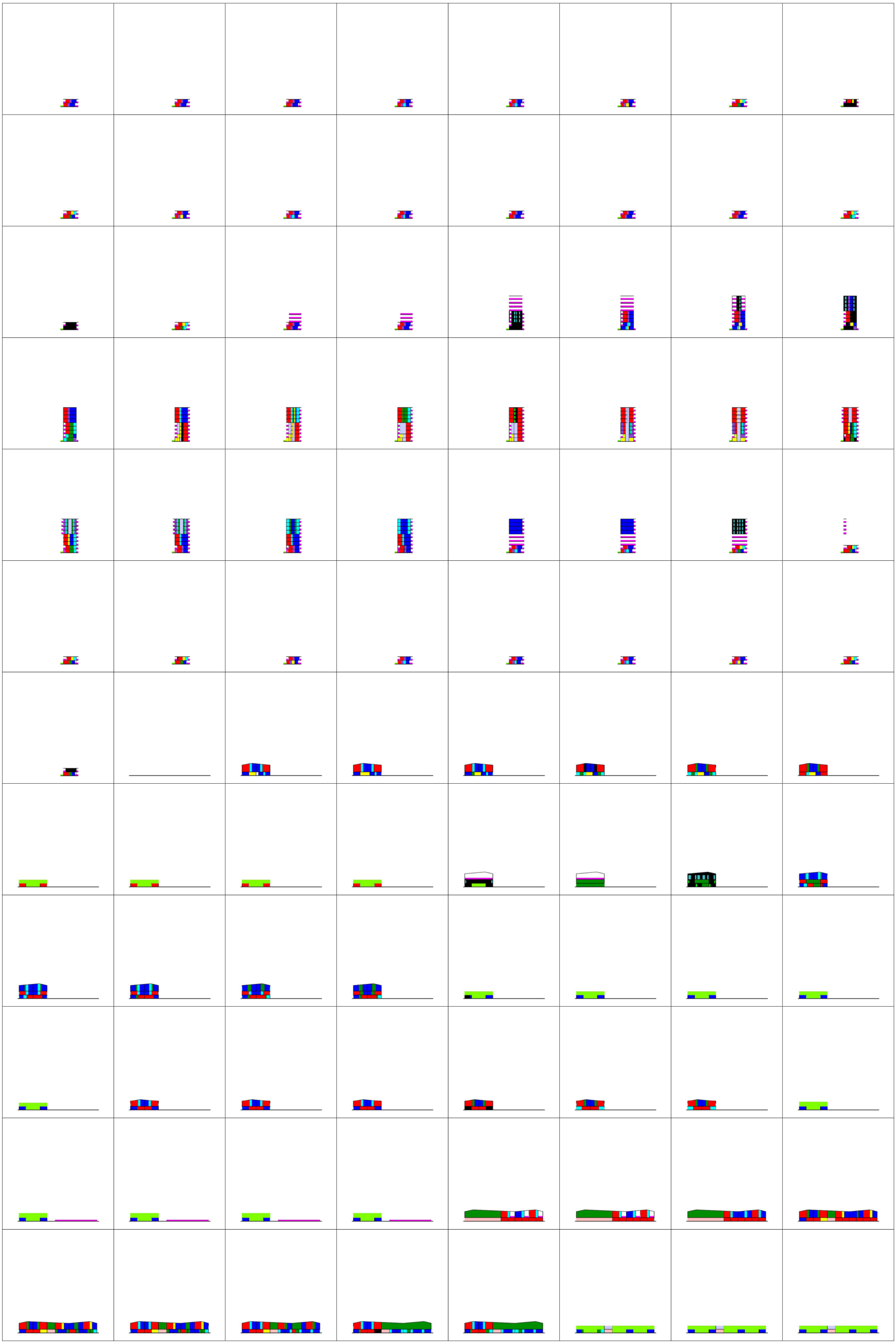


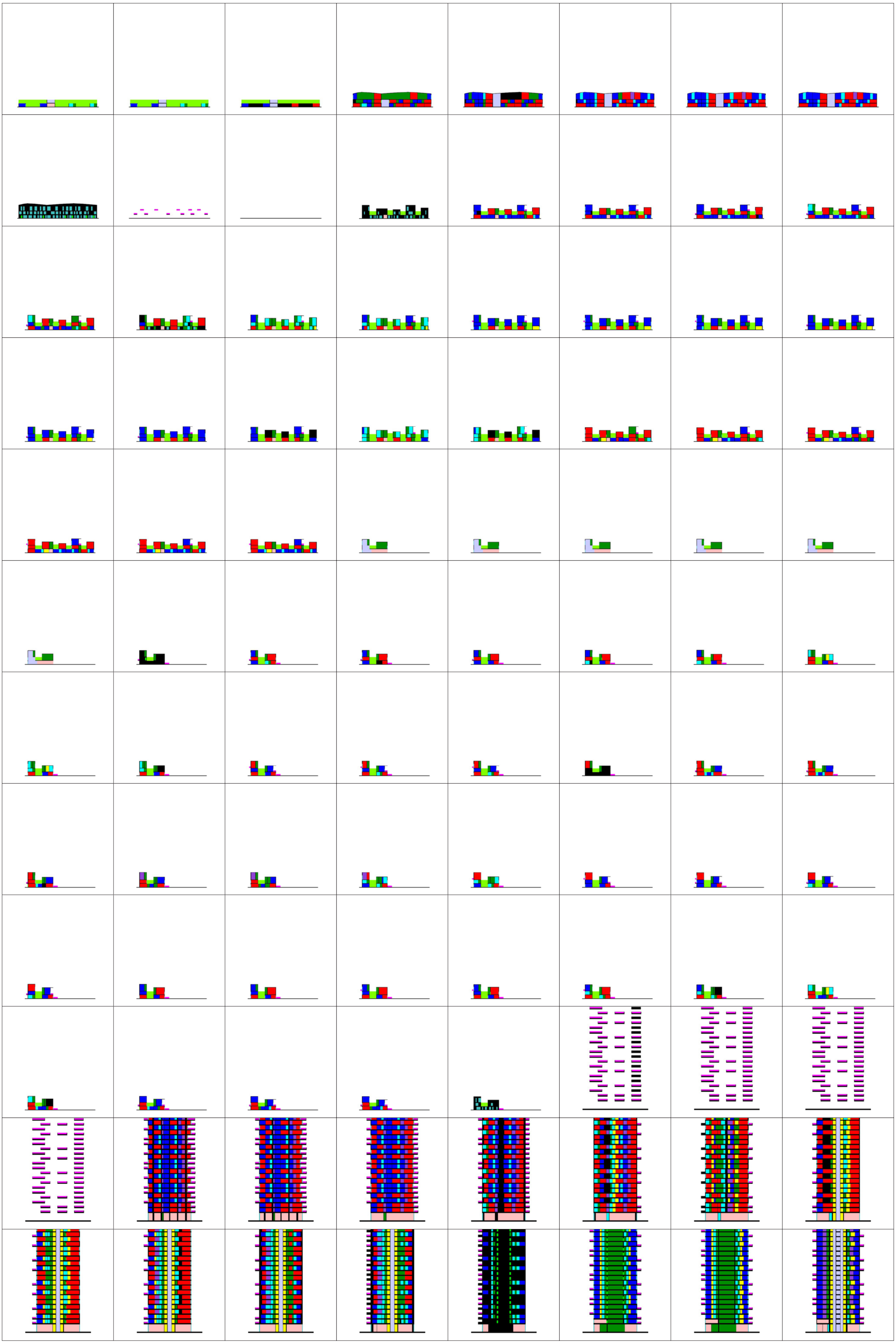


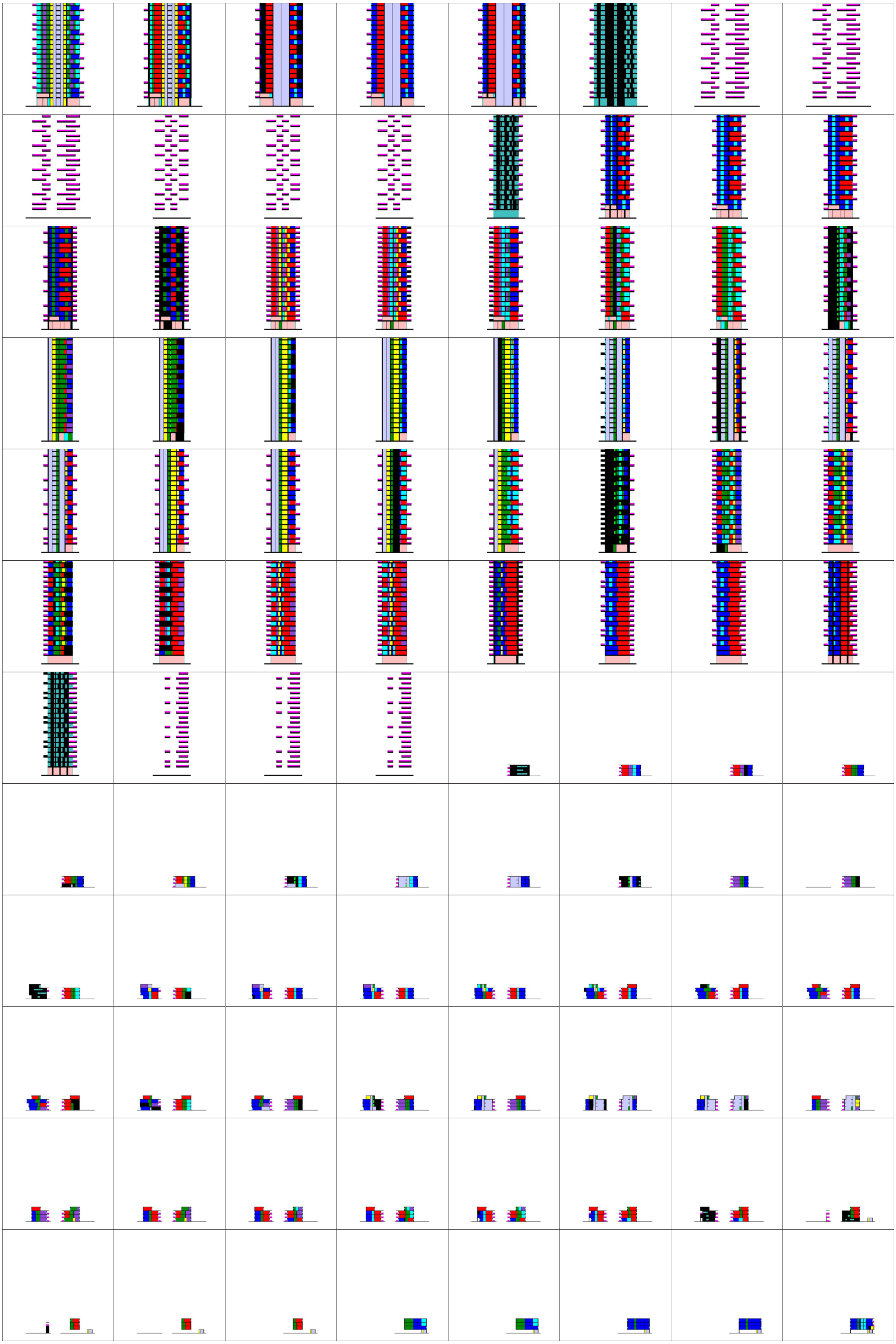


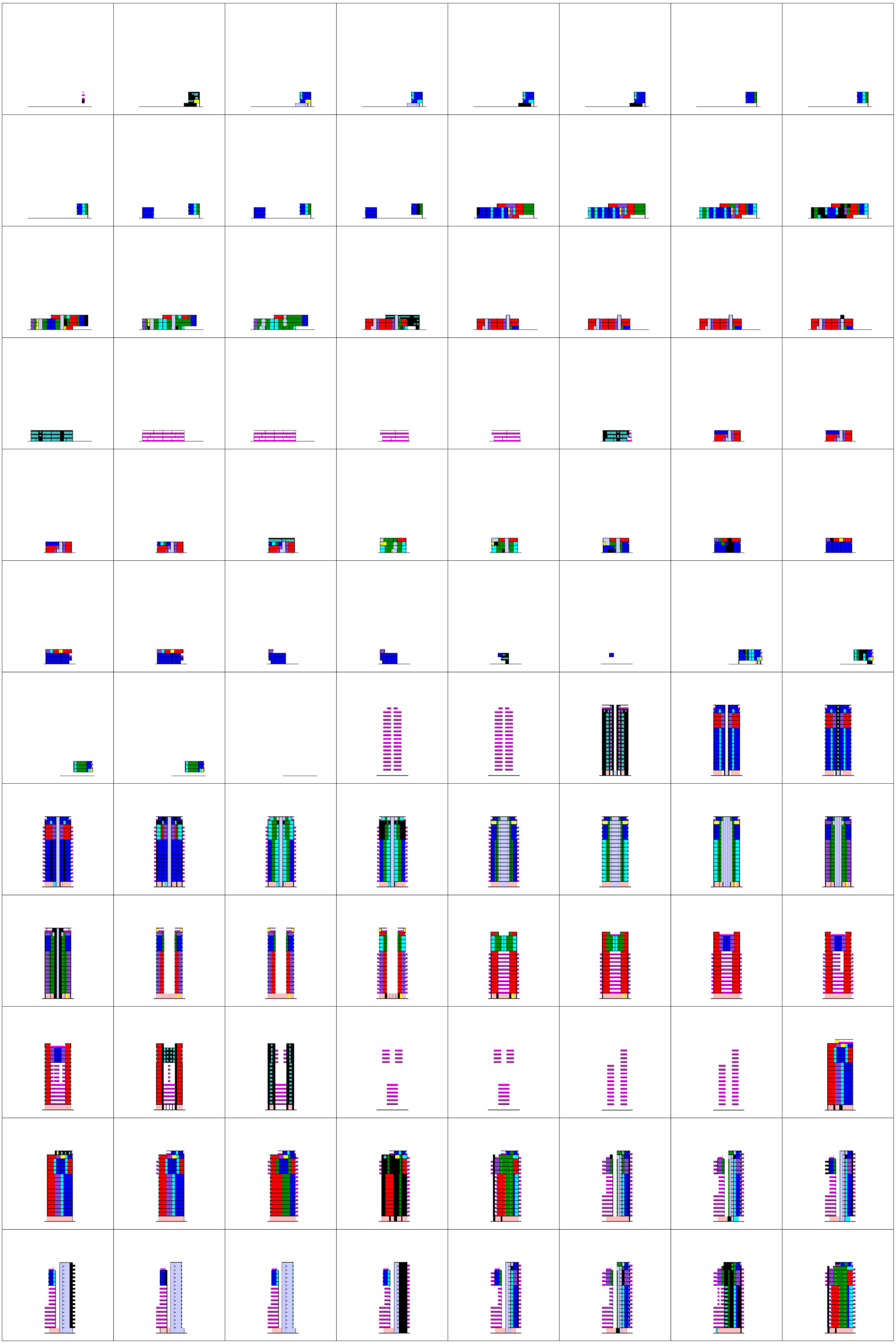


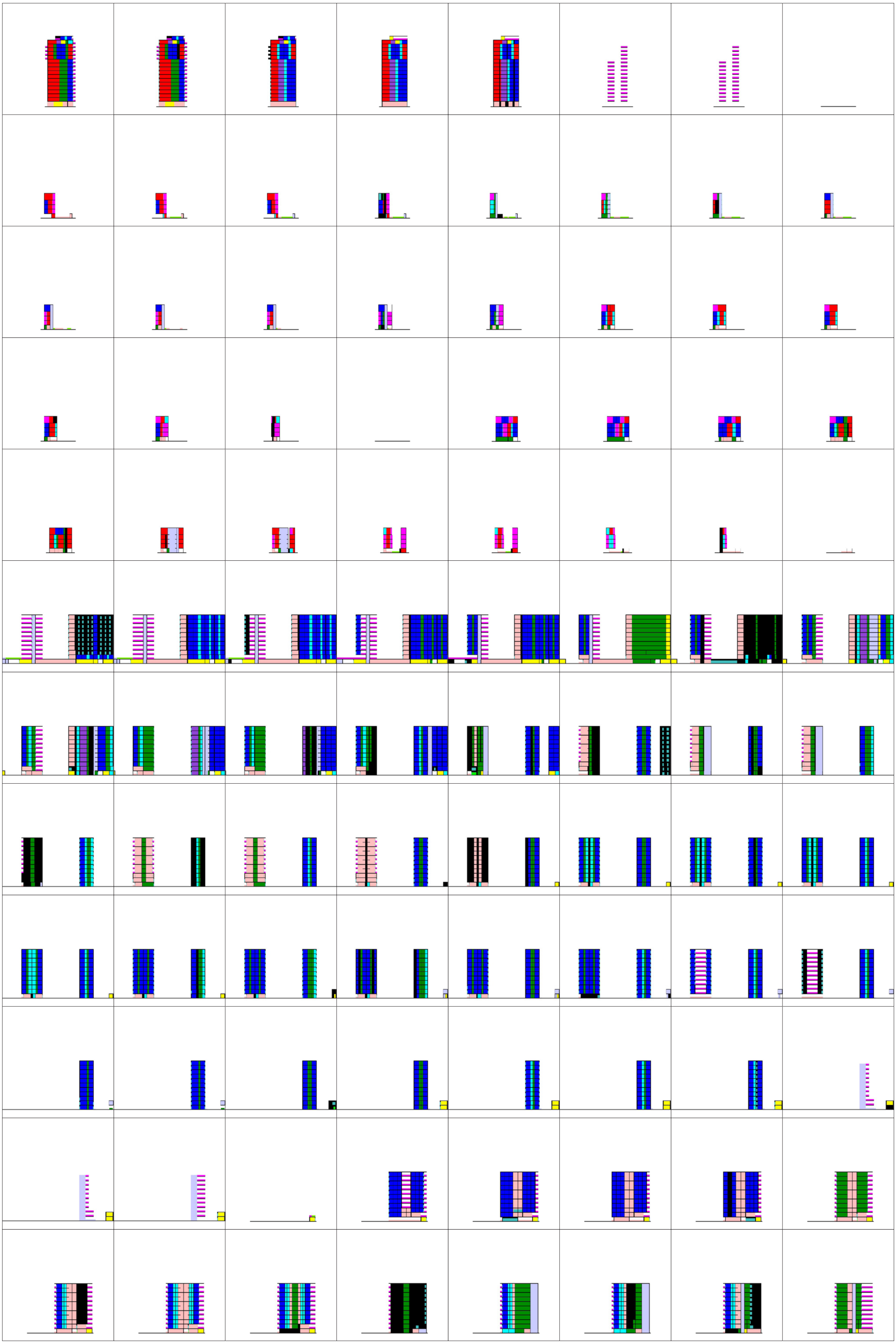


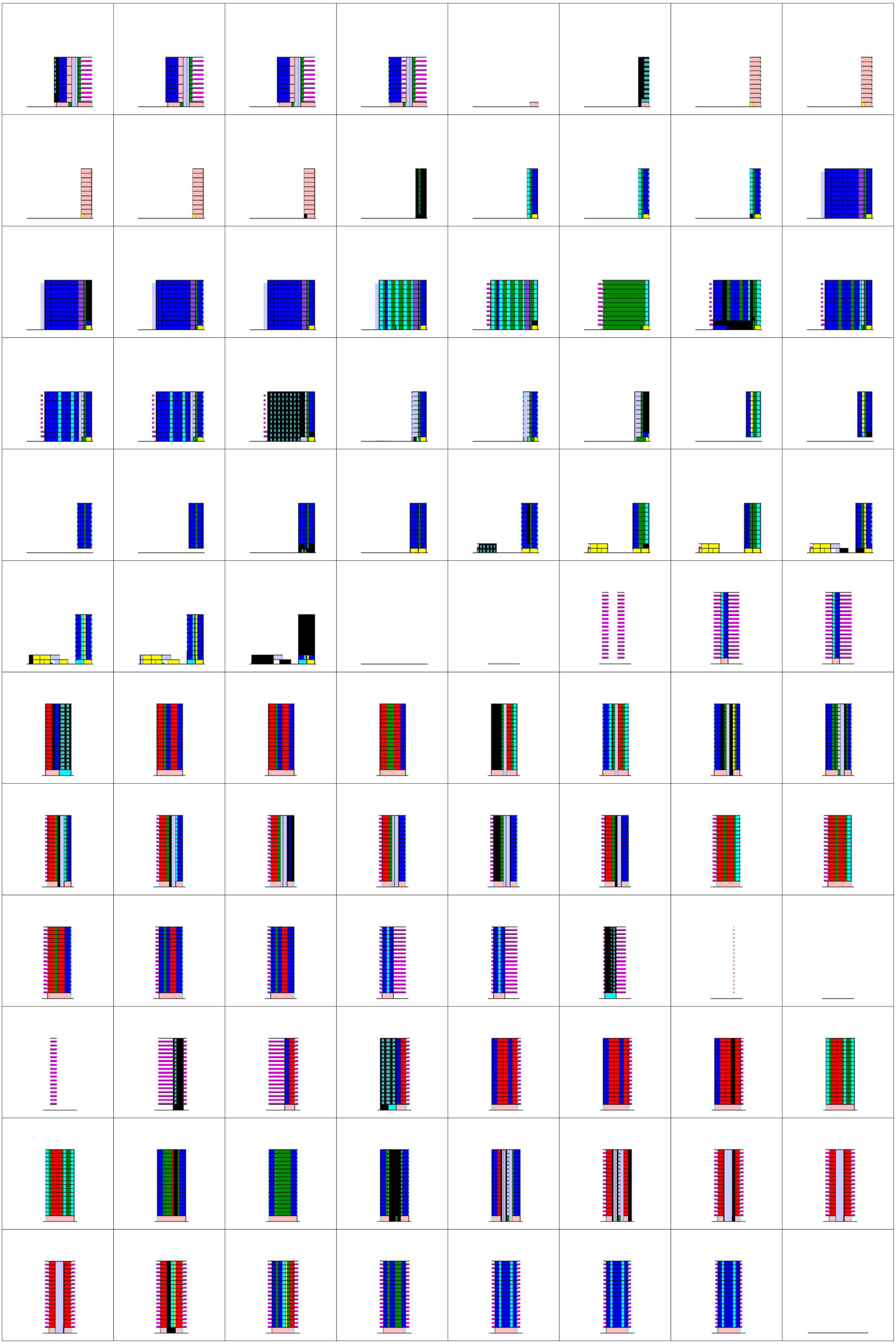


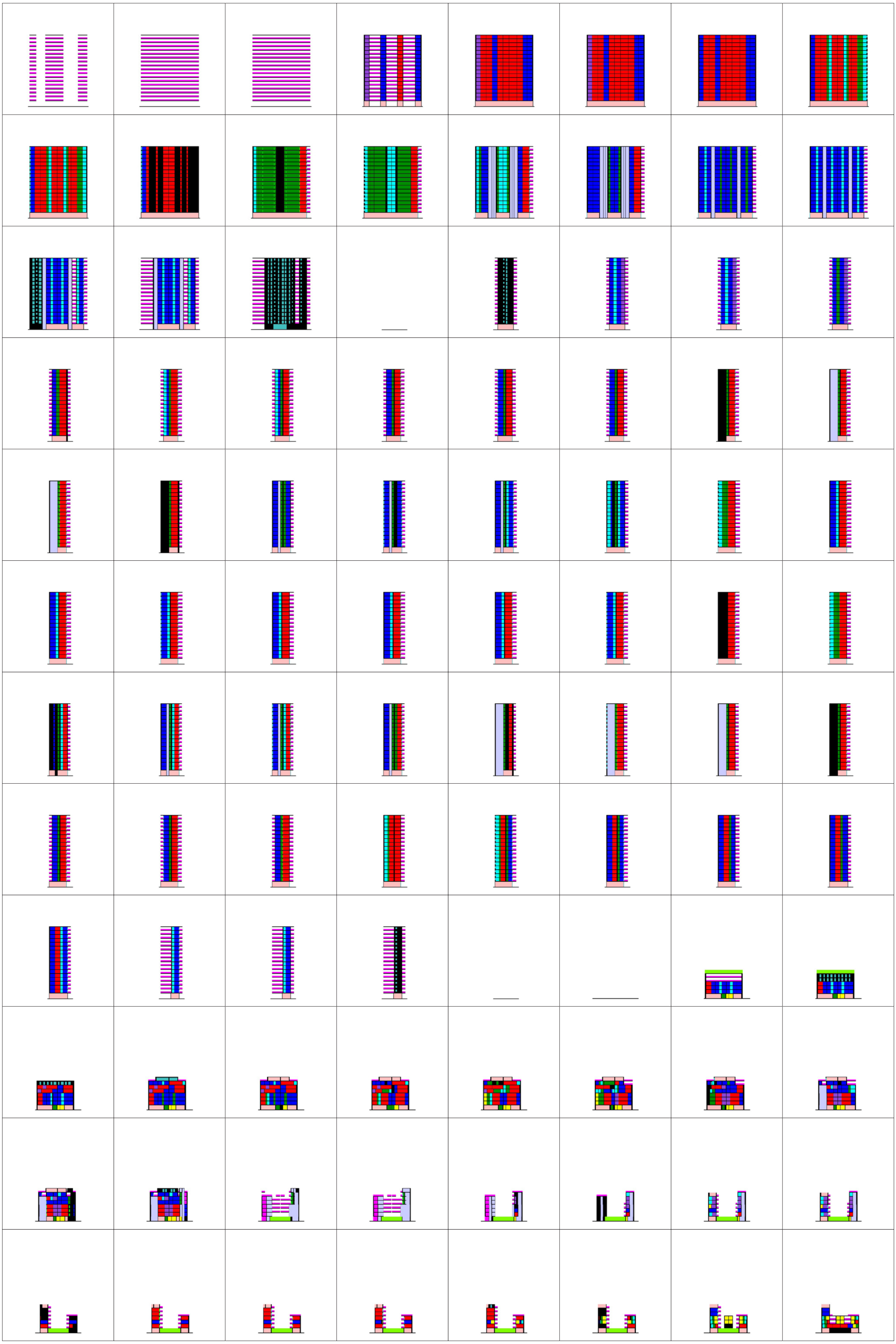


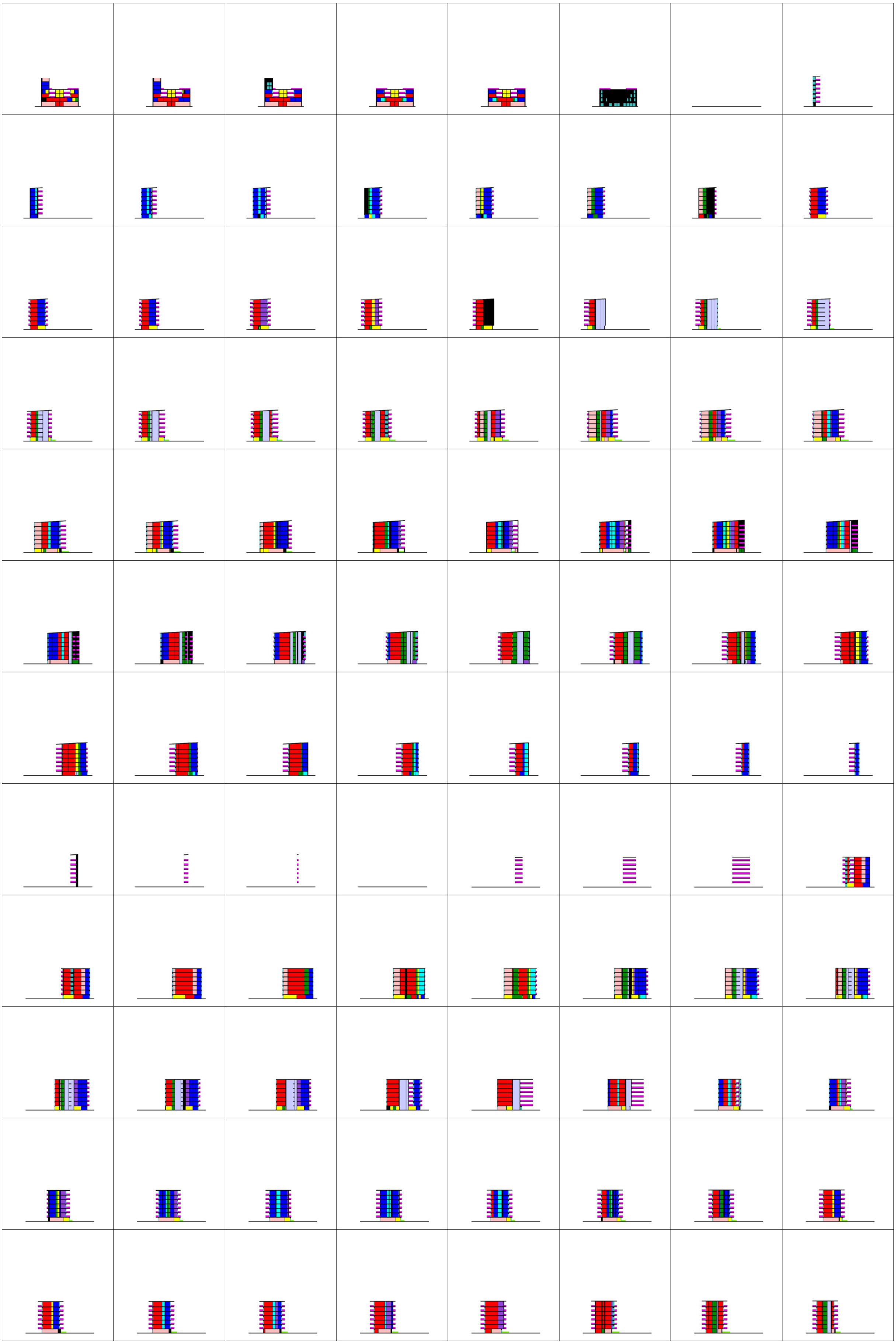


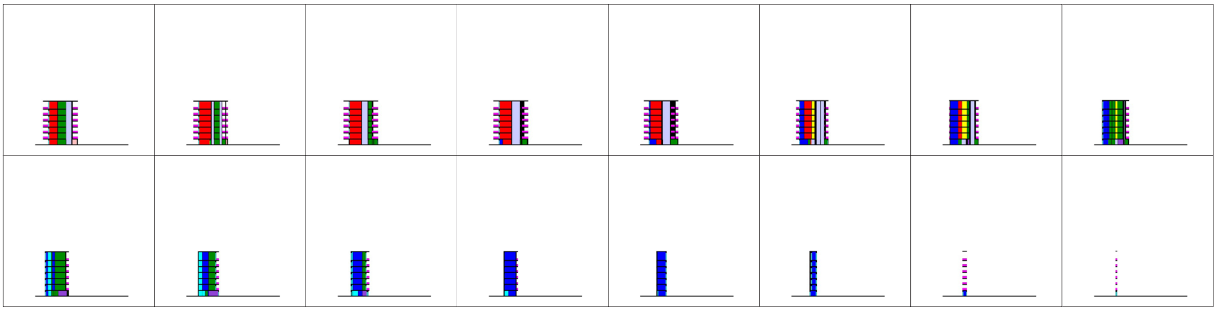


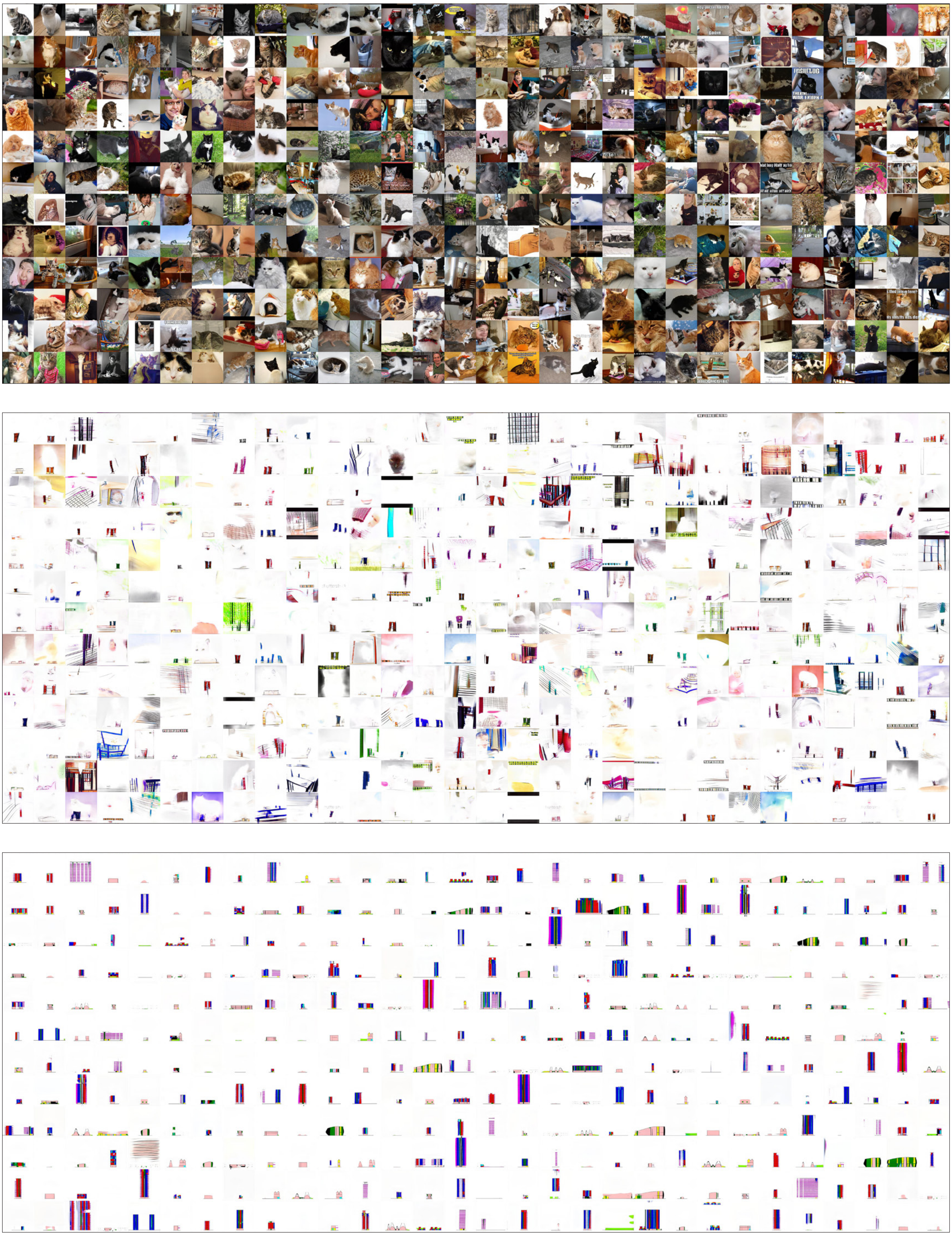












Training process. Image transformation from cat generation to section generation. (author)

5.3 Training

> *"A neural network is comprised of processing nodes, called neurons, that are organized into groups, called layers, based upon how they connect to other nodes in the network. Input information flows through a neural network in a feed-forward, hierarchical manner: Each neuron in the network receives input from neurons in The preceding layer and transforms it into a new representation via a nonlinear function, which acts as a threshold that filters out relevant information captured by its input. This new representation becomes the input to the neurons it is connected to in the proceeding layer"[19].*

Among other ANNs, GANs have been chosen because of their ease of use and the wide community of developers, which provide open-source codes[38]. During the training, the model process the overall dataset many times. Each computing cycle through the full training dataset is referred to as an epoch of training. After each epoch, backpropagation is performed and weights are recalibrated. Typically, optimal outputs require a lot of training epochs[39], and the time for each epoch may vary according to the nature of input data. In the case of images, the amount of pixel is a crucial factor.

Training is the most resource-draining part, in terms of time and computation. Starting from zero, the training process would take several months to be complete. To reduce the timing, pretrained model are frequently used as base for training, using the transfer learning property. Pretrained models are already-trained networks which generate good quality outputs; it is possible to train on such models with a custom dataset, and after few epochs the generated subjects change to the custom one[40].

The chosen pretrained model have to match the version of the employed network – a pretrained model of StyleGAN1, for instance, is not compatible with StyleGAN2 networks – and the images it generates have to be the same size of the new dataset to be compatible. Many researches that adopt a StyleGAN model are based on the FFHQ pretrained model.

The chosen model is a StyleGAN2-ADA-Pytorch[41], and Google Colab[42] and ML Lab by Runway[43] were chosen as training platforms. After some trials, ML Lab was the best alternative since the possibility of fully training a model in a couple of days, while Google Colab, since provides only one GPU, would have taken almost one month for a complete training – and related expenses – without leaving space for eventual upcoming issues[44]. However, Colab have been useful for the testing part since it embeds some interpolations scripts.

38 Unfortunately, no graphical user interface (GUI) is provided for these tools; users face an array of lines of code to execute. Lack of knowledge in programming may affect the workflow, since versions' compatibility issues comes frequently and can be difficult to fix

39 Although there is no guarantee that the result will continue to improve

40 It is also true that a model trained form zero is likely to better learn the dataset features

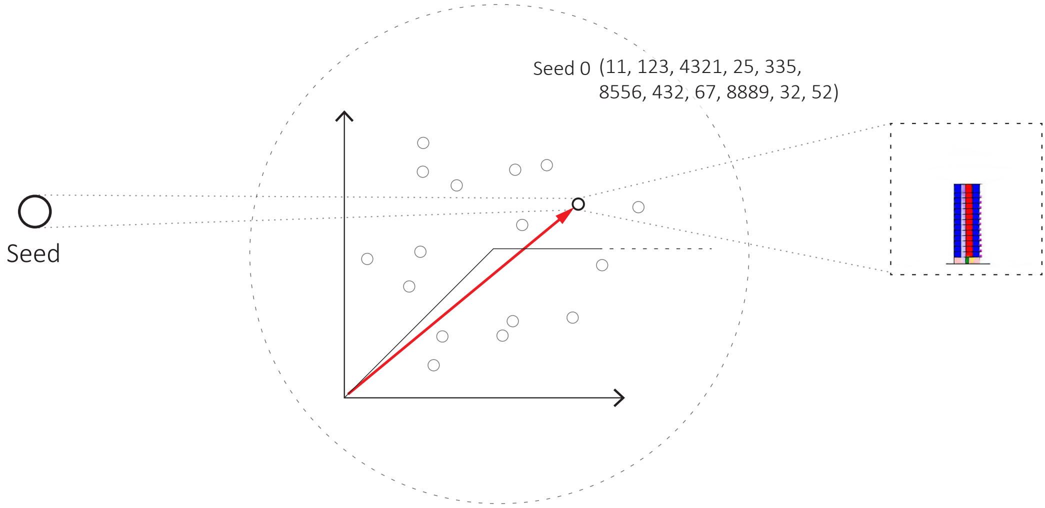
41 The model is open-source, developed by Derrick Schultz

42 Goole Colab is an hosting platform which allows to run code using hardware provided by Google itself

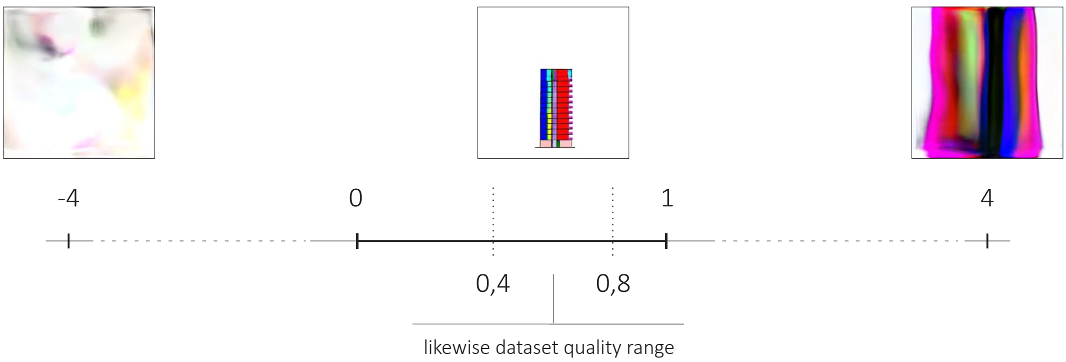
43 Runway is a web platform which provvides AI tool for image and video generation. Today the software is more oriented in AI video-editing tools, keeping the training features in a separate application called ML Lab. So far, the testing features which allowed to explore latent space seams are not working anymore

44 It is possible to train AI model in local on available machines. The employment of those platform was necessary since the unavailability of a proper infrastructure.

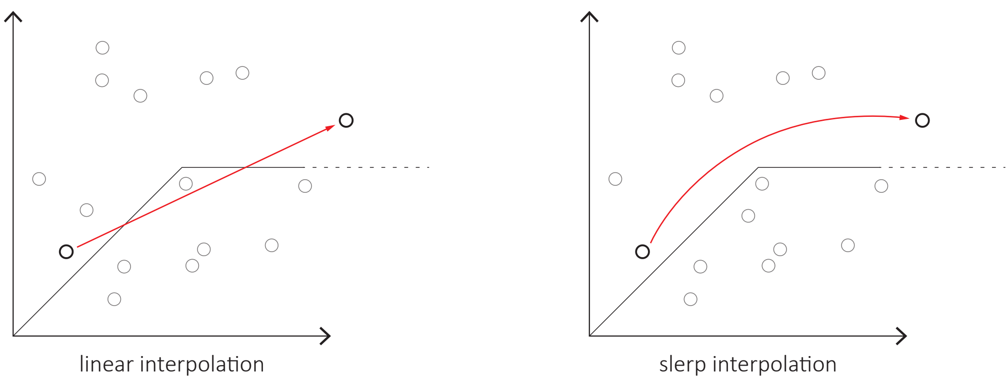
Multi-dimentional space



Truncation Diagram



Interpolation



5.4 Interaction and Reconstruction

As explained in the previous chapter, the generative process involves the exploration of the StyleGAN's latent space.

Firstly, some tools which allow this interaction need to be explained: *seed*, *truncation* and the different kinds of interpolation.

As already seen, a seed is a numerical value which refers to an array of coordinates that localise a data across the dimensions of the latent space. In other words, each seed generates a random vector, and to that vector correspond a point. Since in computer science the real random does not exist, if we recall the same seed keeping the other factors all the same, we will obtain the same output – that is same vector, same point, thus same image. The process to pick an image from the latent space is called inference and can be performed infinite times since the number of seeds tends to infinity because of the consistency of the space.

Another necessary value for interpolation is the truncation value. It is a floating number which determine the fidelity of output images to the training dataset in terms of subjects. It can be imagined as cropping the latent space, defining a subdomain within vectors can move. A lower value means a lower truncation of the space.

The standard range for the truncation value is from 0 to 1: within this range generations are still familiar to the dataset, even if moving toward 0 is already possible to get hallucinated images. Outside of this range, outputs progressively turn into a resemble of stains. Thus, a less truncated space brings to less realistic images; here, a truncation value of 0.5 has been adopted.

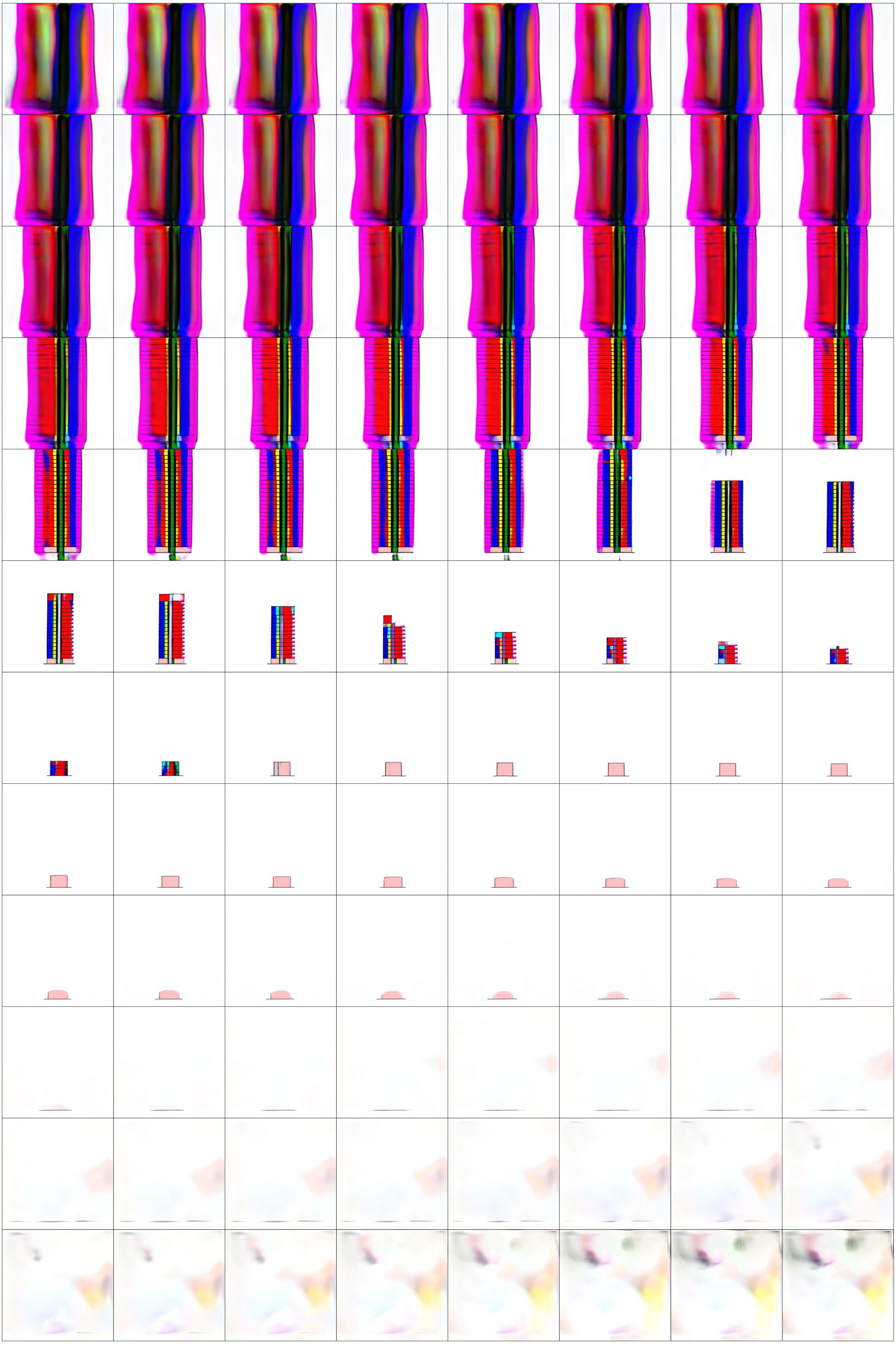
Last setting is to define which kind of interpolation to employ for the latent space exploration. Exist many kinds of interpolation based on mathematical definitions. The model used here provides the two main interpolation techniques: linear interpolation and slerp interpolation.

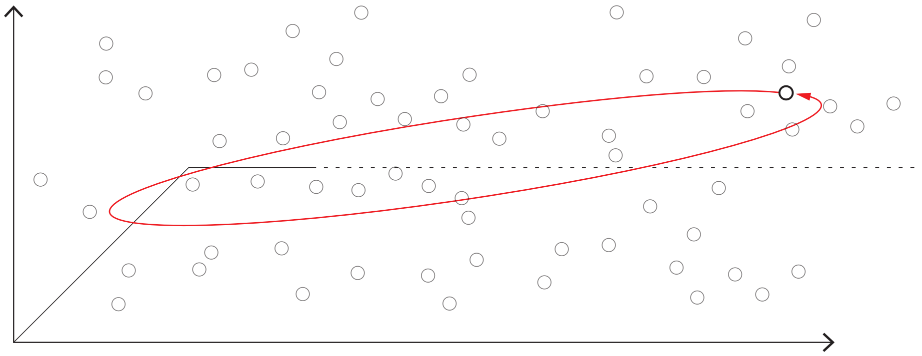
The result of the both turned out to be quite similar: linear interpolation can be imagineds as a broken line which connect the targeted seeds; the slerp interpolation follows an arched path, interpolating different points. However, at low dimensions the difference in results is very low, indeed slerp interpolation in more recommended for high dimensionality latent spaces. Linear interpolation, then, is more coherent with generations oriented to 3D object.

Front:
Top: diagram on the concept of *seed*. It is a number which embed an array of coordinates, and thus the vector that point is such direction. (author)

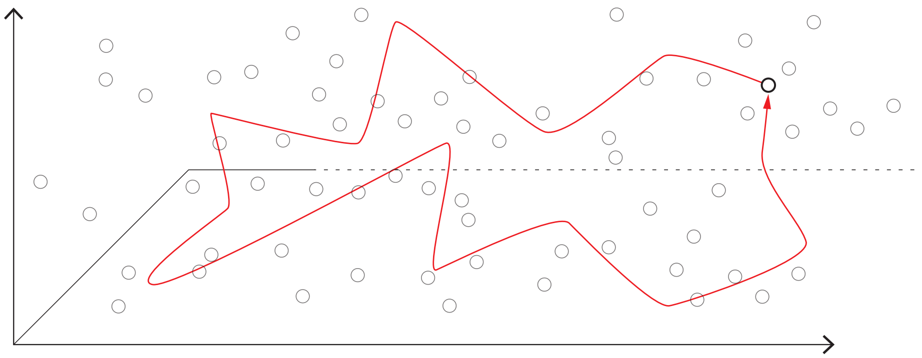
Middle: diagram on the concept of *truncation*. The value indicates the output generation fidelity to the training dataset quality; within the 0-1 range optimal results can be achieved. (author)

Bottom: diagram to represent the different kind of interpolation tested, *linear interpolation* and *slerp interpolation.* (author)





circular loop interpolation



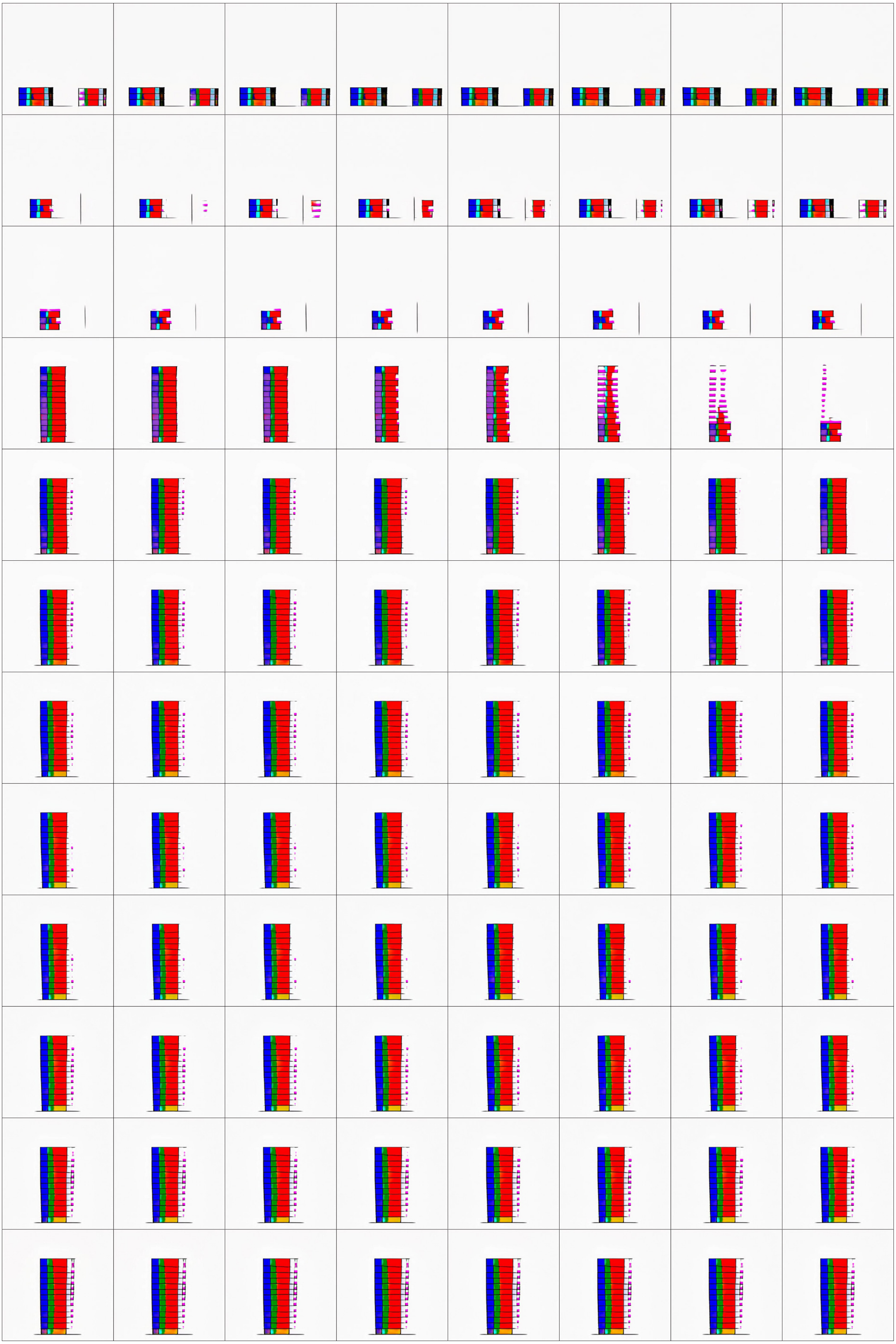
noise loop interpolation

Front:
sampling of a truncation video across one seed, sliding the truncation value from -4 to 4. As visible, initial and ending images are less faithful since too far from the optimal truncation range. Inner images, instead, are more similar to the one of the training dataset. (author)

Top:
visual representation of the *circular loop* interpolation and *noise loop* interpolation. (author)

Other two interpolation methods are available in the model, useful to have a glance on the variety of the latent space composition. Such vectors are loops and ask for a seed, a truncation value and the diameter of the range in which these vectors can wander, expressed as pure number. Loop vectors are also used to check if there is overfitting inside the model.

The output of the interpolations is a series of section, seen as a sequence of video frames. By default, the model generates 24 frames for each interpolation between two seeds; such value can be easily changed.
For the project purpose, the number of frames have been changed according to the number of seeds selected for the interpolation, in order to always get 100 frames in total. Such sections, placed at 0,50m one to another, compose an almost 50 meters long 3D representation – 49,50m since one frame is the “zero” position.

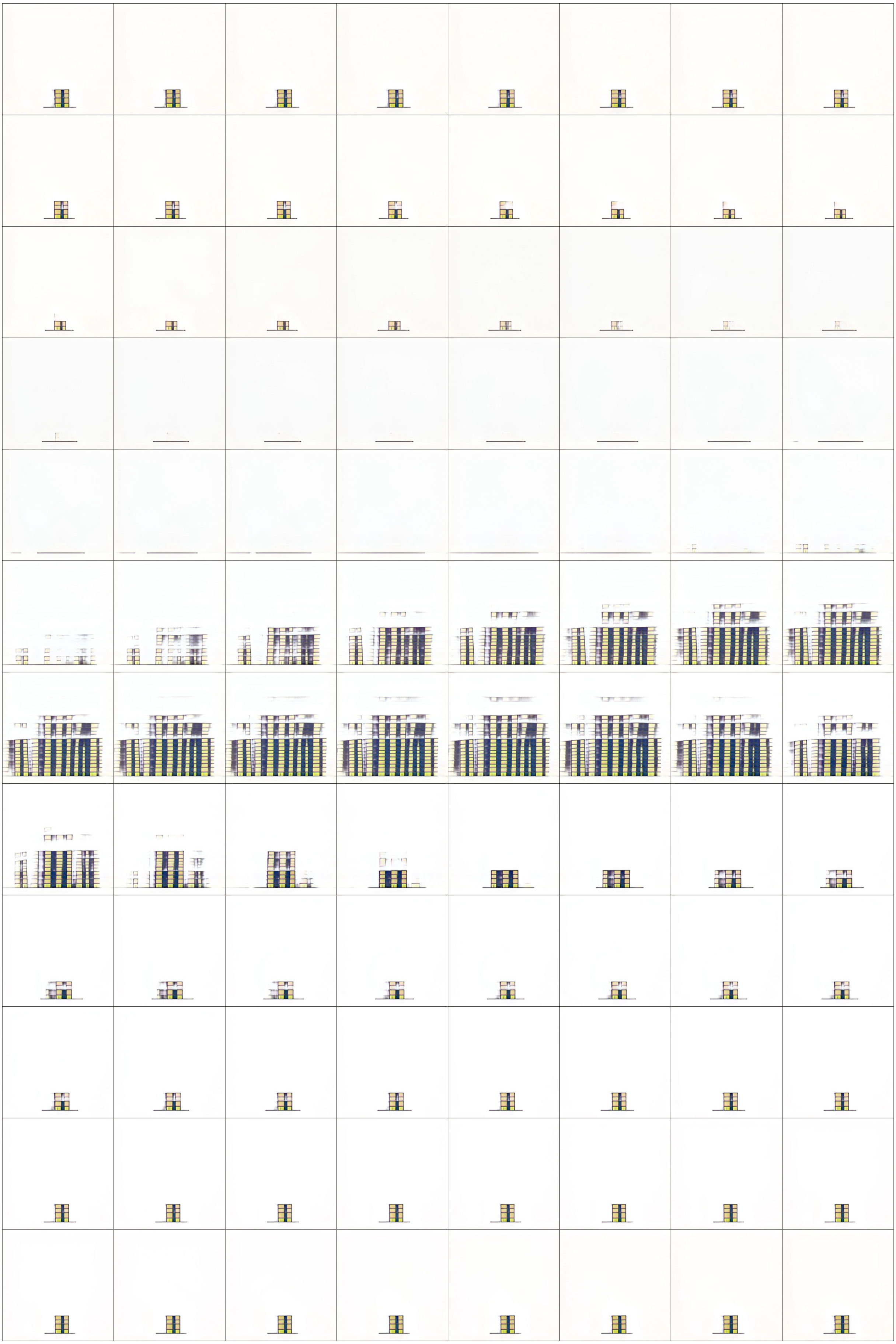


6 Results

In this section are analysed the results obtained from the latent space explorations.
An initial result has been generated at the beginning of the process, using a small dataset of just three buildings, all residential, in order to check which feature the model was learning, and if generation tools actually worked. Here the slicing was done without taking into account the dimensions of the different buildings; the methodology from the Bank research has been literally applied, generating 400 images slicing the three buildings in both x and y direction.

For StyleGANs, a complete training consists of 25.000 steps – that are cycles.
This first test has been made on a model trained for 5.000 steps, and the FFHQ pretrained model was used as starting point. Outputs resulted well defined with precise colours, without blending them too much. The generation comes from a linear interpolation between a three-storey residence and a tower building. It is possible to see that the first part of the building shows the transformation from the low section to the tower, while the second part looks like a settling toward the targeted image. As the interpolation shows, all the features were learned.

Front:
frame sampling of the first interpolation done for the research. An extremely reduced dataset have been used, but still features were learned.



After this first trial, the final model have been trained on the complete dataset, initially made out of 9628 images. The employed platform was ML Lab, by Runway, and again, the FFHQ pretrained model as starting point.

The training was completed in a couple of days and tests were made at two different training moments, half way – 10.000 steps – and at the end of the process. Unfortunately, loop interpolations showed that the latent space composition of such model was really poor in terms of features and sections' shapes. In fact, only two colours present in the dataset were learned: green – vegetation – and pink – common spaces – together with shades of green and blue, missing in the training data. Moreover, such colours changed during the training; in fact at half training other shades of colours, mainly around blue and yellow.
For some reasons, thus, the model overfitted.

To understand the issue, another model has been trained on the same dataset, this time a StyleGAN1 model on a different pretrained model, trained on nebulas images.
StyleGAN1 learned all the features embedded in the dataset; this can be assessed to the presence of a multitude of colours already in the pretrained model.
However, StyleGAN1 have been totally replaced from StyleGAN2 and StyleGAN3 for obvious better performances, thus no availability of tools to explore a StyleGAN1 latent space have been found. Due to the different internal structure of StyleGANs, the tools developed for StyleGAN2 are not compatible with its previous version.

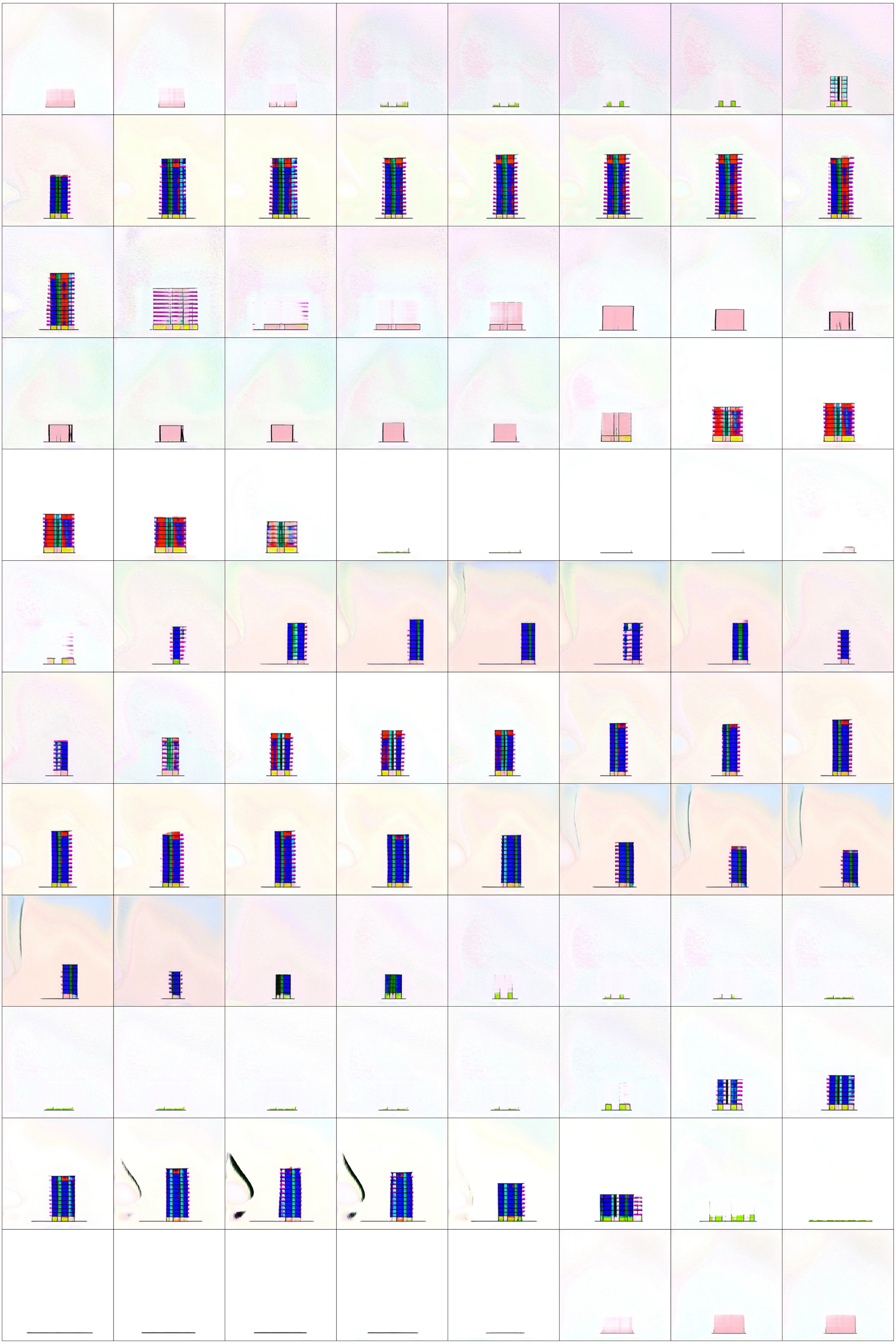
As last tentative, another model has been trained, this time using Google Colab. ML LAB does not allow to upload custom pretrained model; users have to use the ones provided from the website.

For this new tentative, thus, a different pretrained model – which generates images of cats – has been uploaded and selected as starting point for the training[45]. Due to low temporal resources, the training has been run for just 1000 steps. To this point,, the network already changed the subject of generations and started to produce good results – even if at this step the model generates images very much similar to the ones inside the dataset, almost coping them.
To go on with the process, such model has been assumed as completely trained.

45 Here it is possible to find many different pretrained models:

Front:
frame sampling of a noise loop interpolation inside the overfitted StyleGAN2 latent space. As visible, few colours and a low variety of shapes have been learned.

The generation process, as already explained, is based on an interpolation vector which pick points – and thus sections – inside the latent space. At the end of the process, it generates a short video of such interpolation. Isolated frames are also provided.



Videos of interpolations are the first material to analyse before moving to the 3D visualization. Through the video it is possible to understand if desired features are present, according to what the designer is looking for. It also provides a glance of how the pointcloud would looks, giving a prefiguration of the final shape from the array of sections and allowing to evaluate whether can be interesting or not.

This is actually a quite fast check: for example, a video composed by 100 frames is almost 4 seconds long, since the model considers 24 frames per second (fps) and to create a dense enough pointcloud, sections need to be disposed quite next to each other – 0,50m is here adopted. Thus, from interpolation of 100 images it is possible to get buildings almost 50 meters long, and through videos such buildings can be quickly checked. This allows to examine many possible buildings in few minutes; then, the selected one can be processed for 3D visualisation.

Conversion and assembling of images have been done through a Grasshopper algorithm. The time required for this process depend on the computational power available on the machine in use; each pointcloud made for the thesis purpose took an average of 10 minutes to get processed and visualised on the screen[46].
According to the density of points, pointcloud can be very much detailed. For images conversion it is a good practice to define the pointcloud resolution using numbers that are multiples of the original image resolution. A full conversion would turn each pixel into a point. However, keep the full resolution for 100 images of 512x512px is a very huge computational load for the machine employed in this thesis – the time increase or decrease exponentially for this operation – thus the resolution has been reduced to a quarter, generating 1 point each 4 pixels[47].

The pointclouds here generated, thus, are not highly defined but good enough to address the requirements.

As said, the final outputs depends on the section shapes and on the number of seeds picked for the interpolation. For the seeds selection, two criteria have been explored: choosing the seeds according to the related section and picking then randomly.

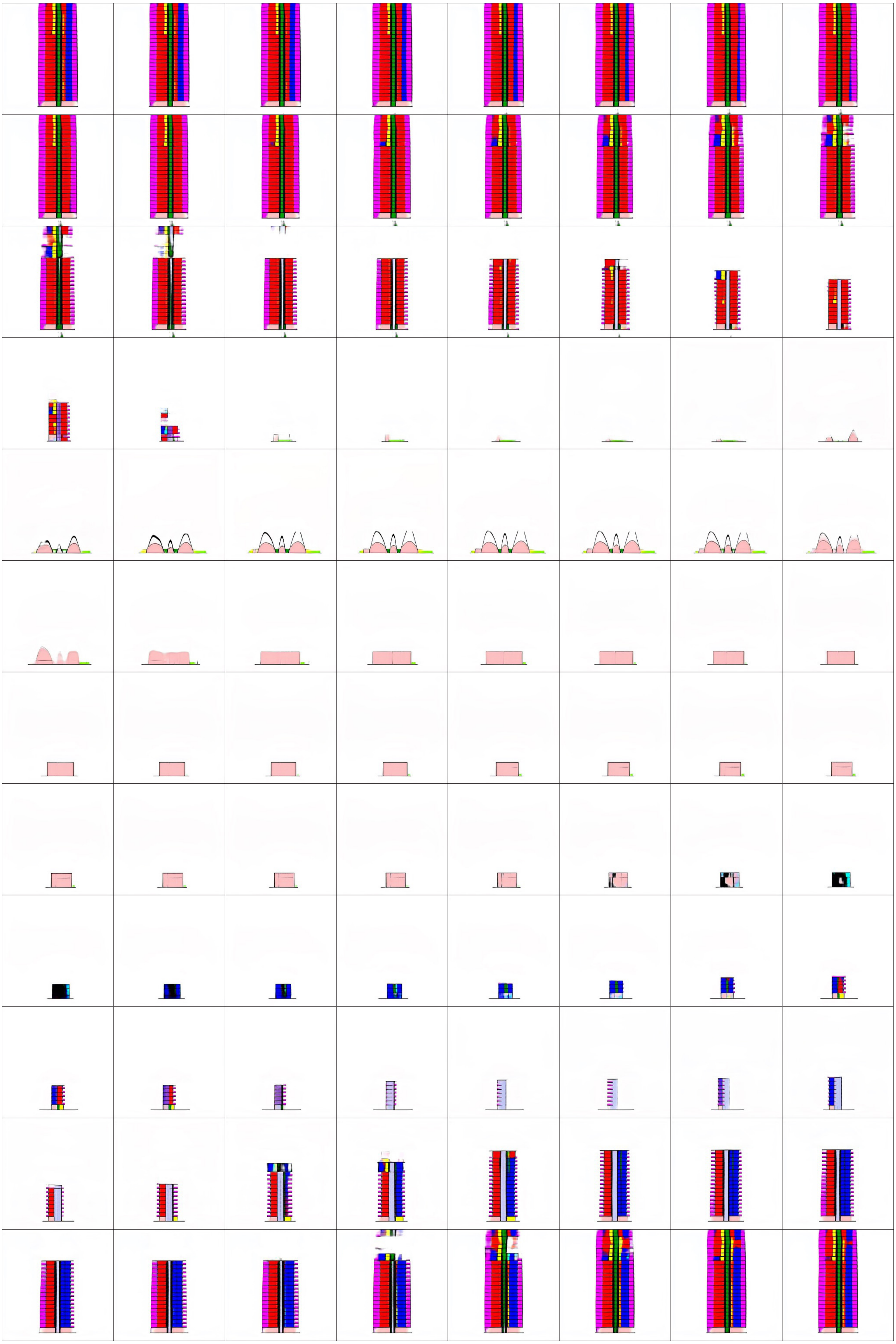
Knowing the position of all the sections inside the latent space is impossible due to its high dimensionality[48]. The only way to choose seeds consciously is, thus, to generate an arbitrary number of seeds, analyse them one by one and select the desired one to guide the interpolation. To test it, 500 images have been generated, analysed and categorised.

46 The machine employed is a MacBook Pro 15", 2018, 2,2 GHz Intel Core i7 6 core CPU, Radeon Pro 555X 4 GB GPU, 16 GB 2400 MHz DDR4 of RAM

47 Considering that a squared image of 512px is made out of 262.144 pixels, the computer should have generated and managed 26.214.400 points. The reduction applied allowed to get satisfying quality results with 1.638.400 points

48 Some algorithms like *t-sne* allows to project the latent space on a plane (2D) or on a three-dimensional space. This provides a visualisation of data composition of the latent space at the cost of a high simplification of it. Still, the data's seeds are not provided

Front:
frame sampling of a noise loop interpolation inside the StyleGAN1 latent space. As visible, almost all the features have been learned.



Have been picked seeds from 0 to 500: since to a seed correspond a random vector, sequential seeds do not correspond to sequential sections. It took almost 20 seconds to generate the images.

Categorising them required instead more efforts.
Categories were defined not for building typologies but according to their shape – for instance, a tall section may correspond to a tower building or a high condo; as well, small sections may correspond to small residences or pavilions.

The 500 sections have been divided in "high", "small", "double", "large", "elements". From such categories, sections have been selected to generated variation of condos, towers, and courtyard buildings.

The "random approach" was more streamlined: seeds number have been randomly generated and used for interpolation, without any information on the picked sections. Evaluation have been made on the interpolation video. Thus, neither categorisation process nor image selection was needed. The time saved allowed to iterate the process many times more and to analyse more possible configurations; the selection thus shifted on videos, analysing the features embedded and the section's flow of transformation. Once selected, the videos' frames are used to generate the pointcloud.

The research proposed itself not only as a tool for hallucinated formal reference, but mostly as a method to generate suggestions from an internal organisation point of view.

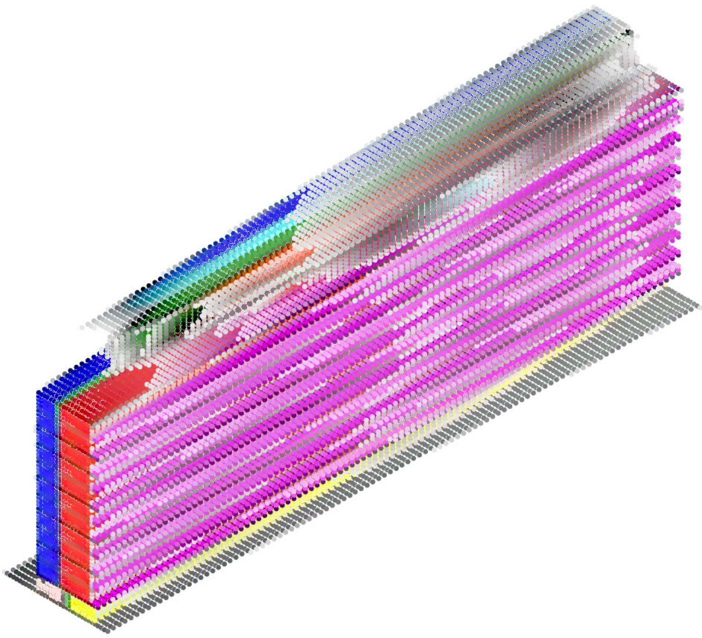
To verify such functional disposition coherence, floor plans of such buildings have been extracted. The representation through colours is intended to be a diagrammatic one and, again, the resolution of such plans is related to the pointcloud's density.

As visible in the next pages, spaces have organic shapes, similar to muscle bundles or fluid streams. Spaces' organisations looks chaotic in the most of the generated plans; still, some feautures are already visible at a first glace. The greatest part of ground floors are composed by feature tipical of a proper residential ground floor organisation, with common spaces, secondary spaces, corridors, toilets, vertical distribution and vegetation. In others, then, also private functions punctually show up, such as dining rooms, bedrooms, which are part of the hallucination the neural network provides.

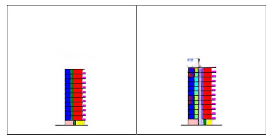
Upper floors, instead, are longitudinally developed in solutions generated by just two images. As is visible, then, the most the considered seeds are, the most chomlex the generation become.

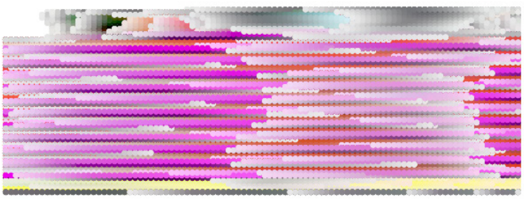
Front:
frame sampling of a noise loop interpolation inside the definitive StyleGAN2 latent space. As visible, almost all the features have been learned.

Generation No.1 _ selected seeds: 93 - 126 _ residential condo

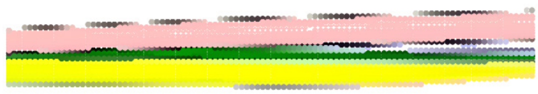


Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure

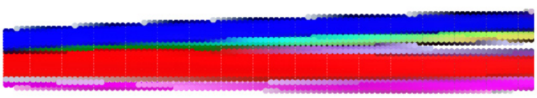




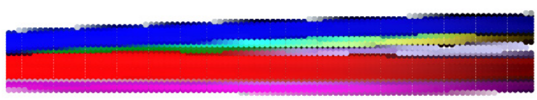
South elevation



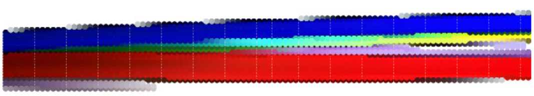
Ground Floor



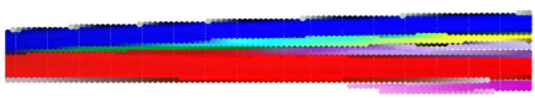
First floor



Second floor

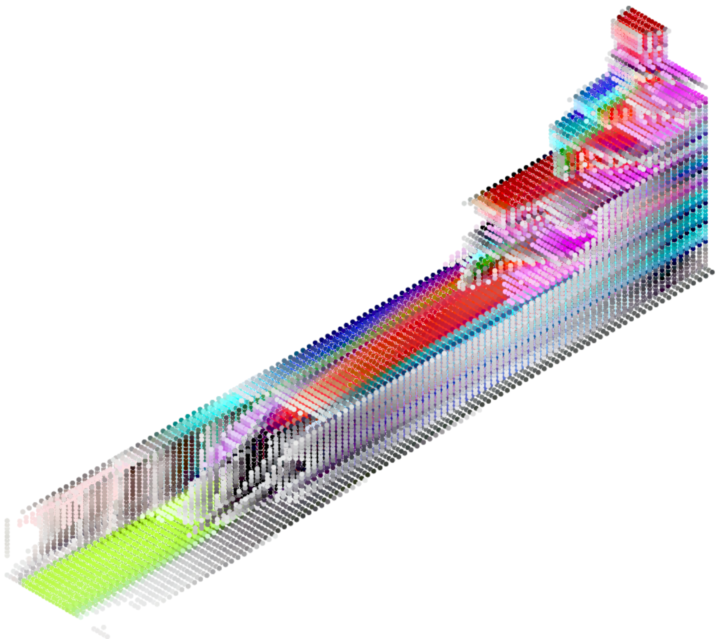


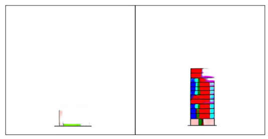
Third floor

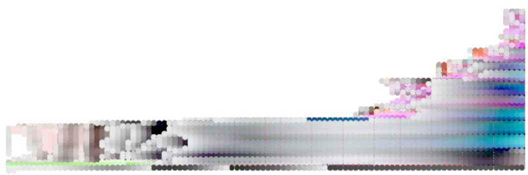


Forth floor

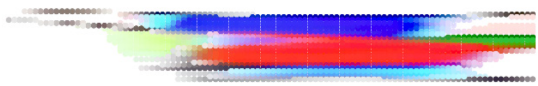
Generation No.2 _ selected seeds: 464 - 195 _ residential condo



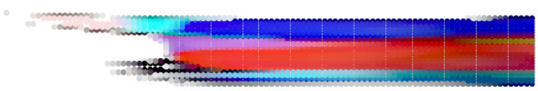




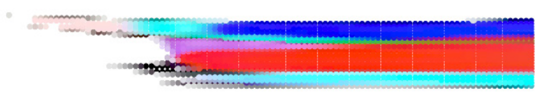
South elevation



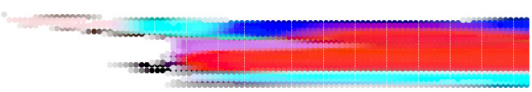
Ground Floor



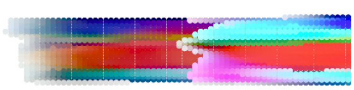
First floor



Second floor

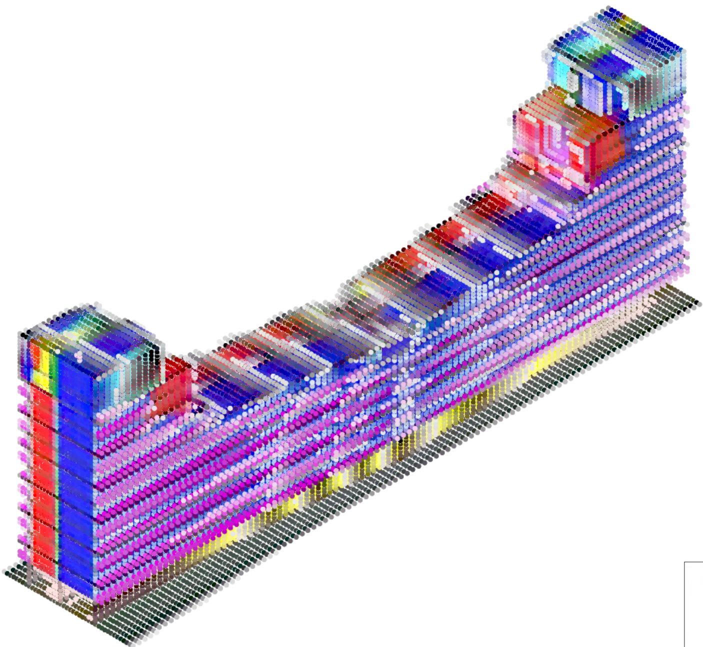


Third floor

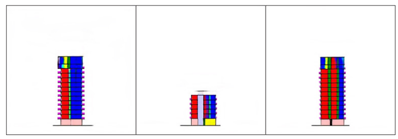


Forth floor

Generation No.3 _ selected seeds: 233 - 417- 19 _ residential condo

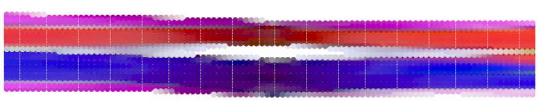


Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure

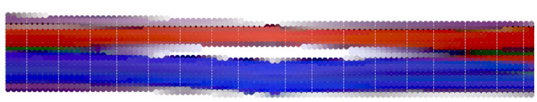


South elevation

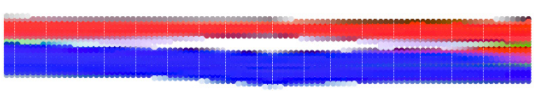
Ground Floor



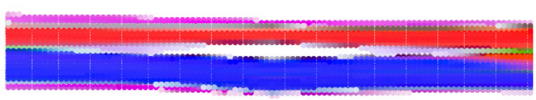
First floor



Second floor

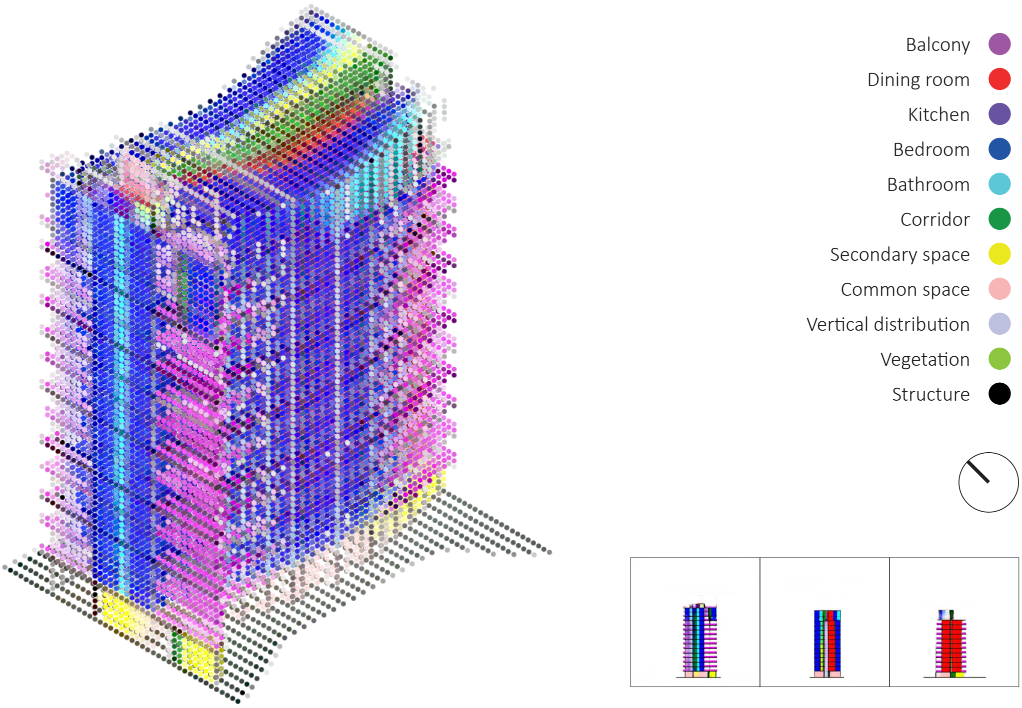


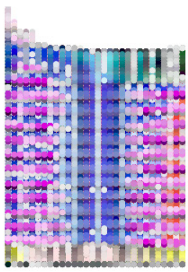
Third floor



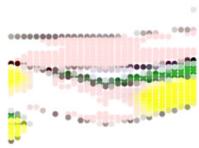
Forth floor

Generation No.4 _ selected seeds: 434 - 72- 135 _ residential tower

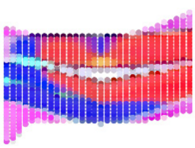




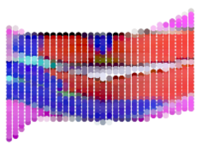
South elevation



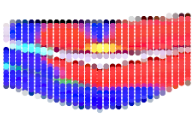
Ground Floor



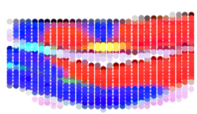
First floor



Second floor

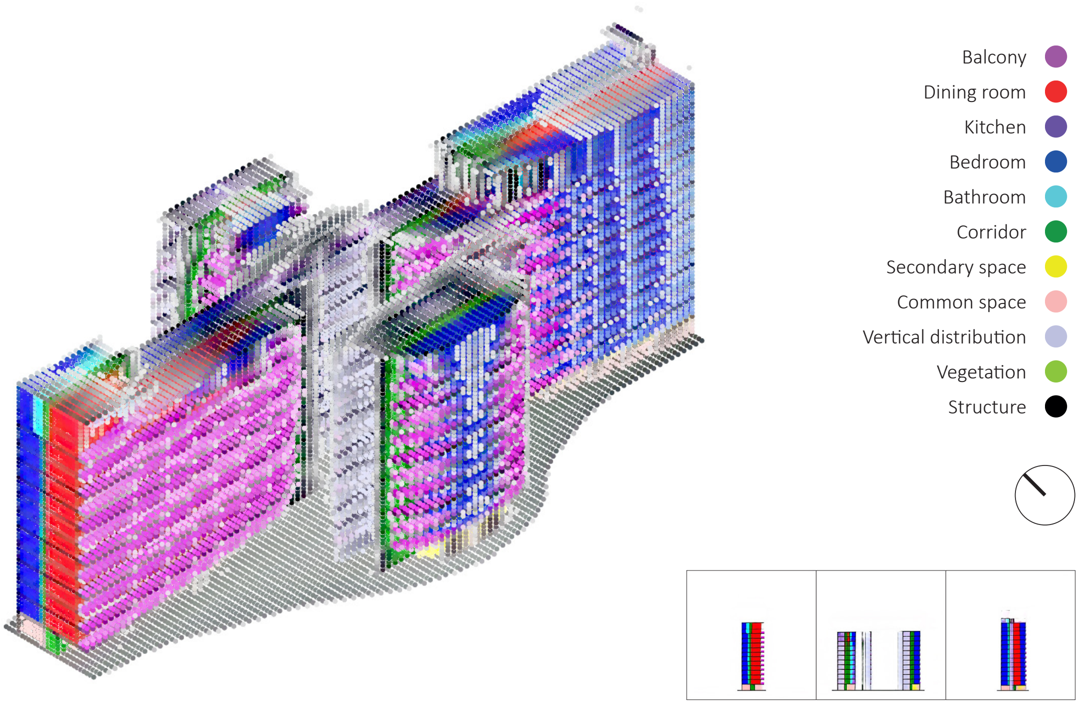


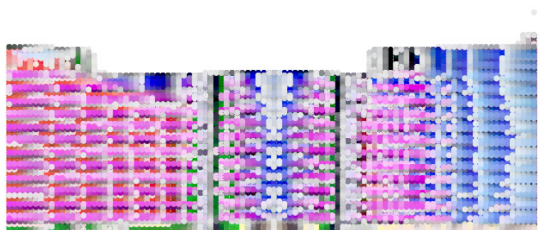
Third floor



Forth floor

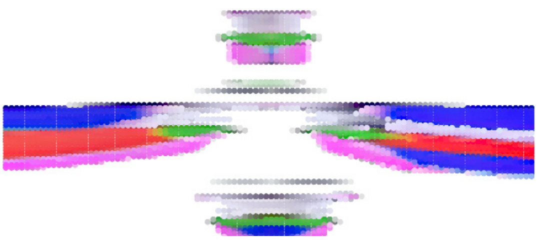
Generation No.5 _ selected seeds: 226- 402- 391 _ residential courtyard



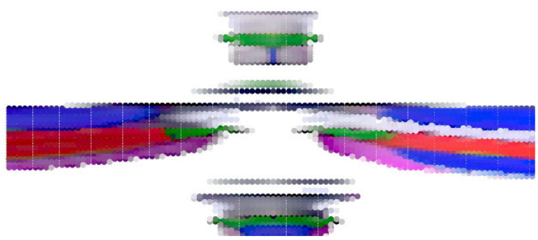


South elevation

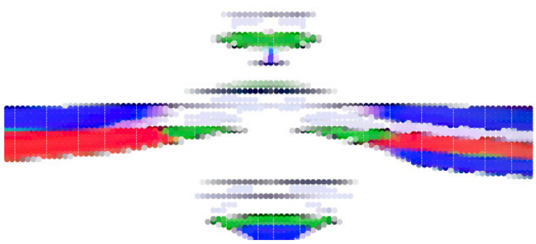
Ground Floor



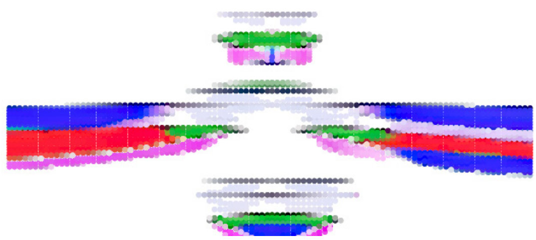
First floor



Second floor

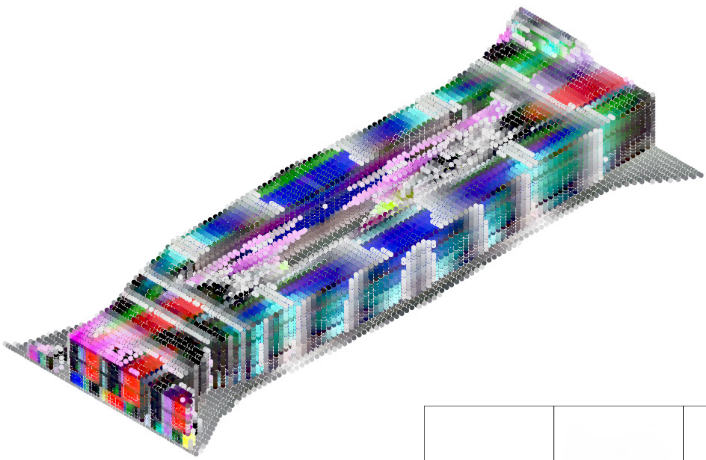


Third floor

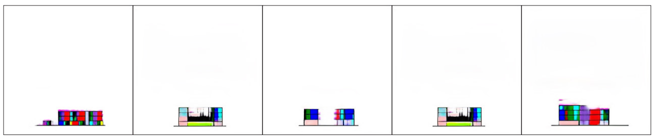


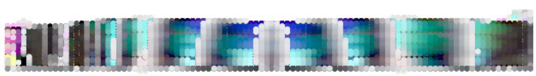
Forth floor

Generation No.6 _ selected seeds: 306- 389- 258- 389- 171_ residential courtyard

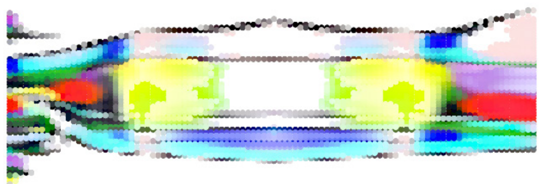


Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure

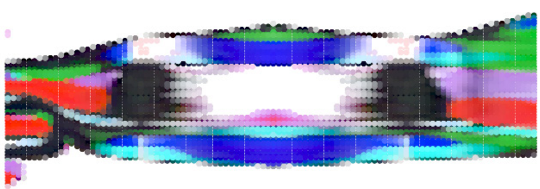




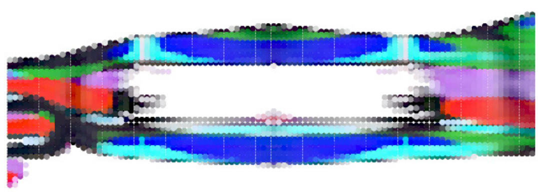
South elevation



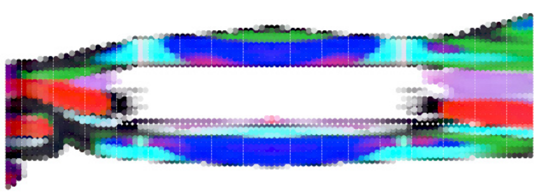
Ground Floor



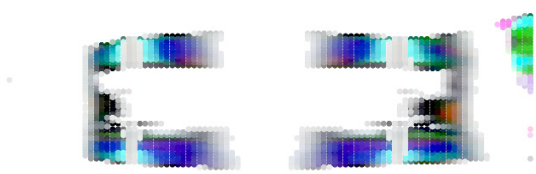
First floor



Second floor

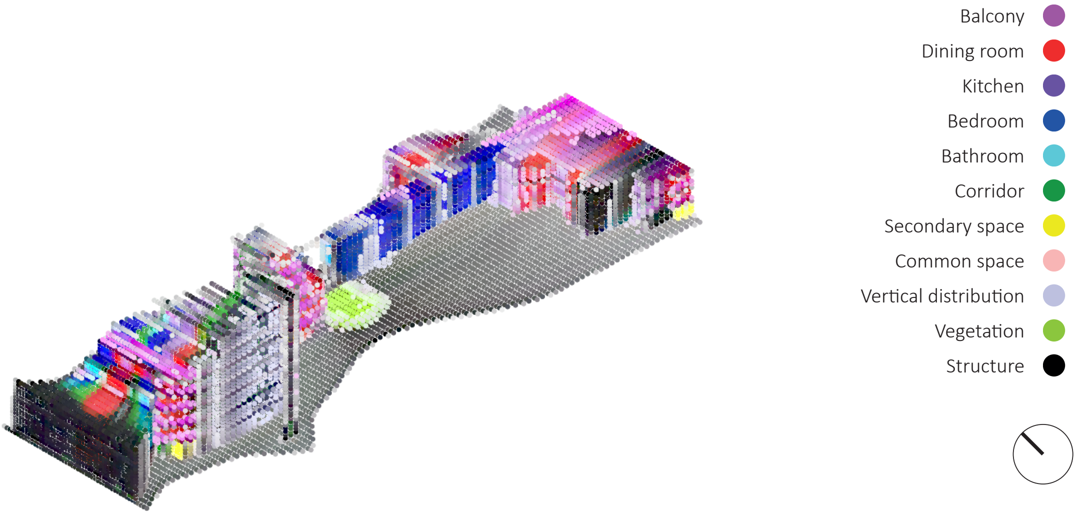


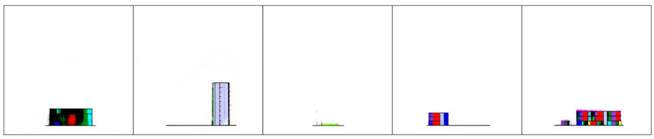
Third floor

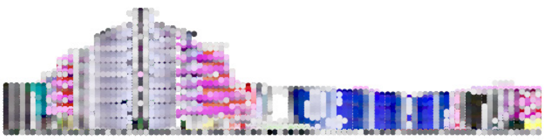


Forth floor

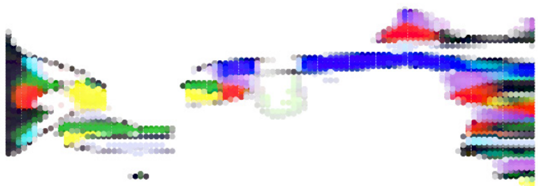
Generation No.7 _ selected seeds: 308-211-75-138-305 _ residential courtyard



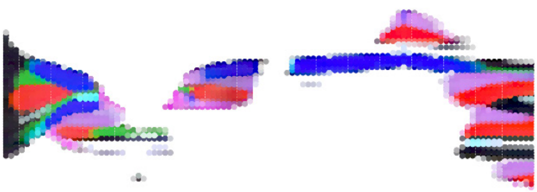




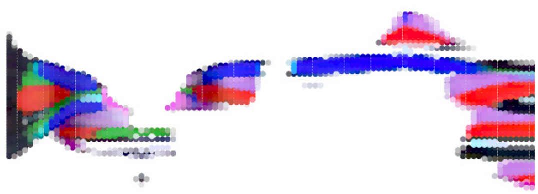
South elevation



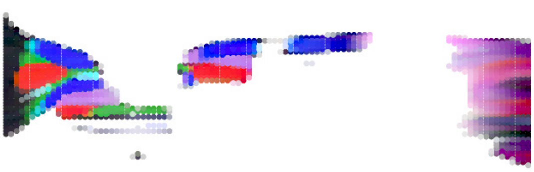
Ground Floor



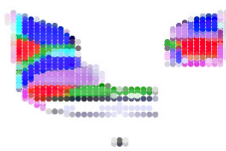
First floor



Second floor

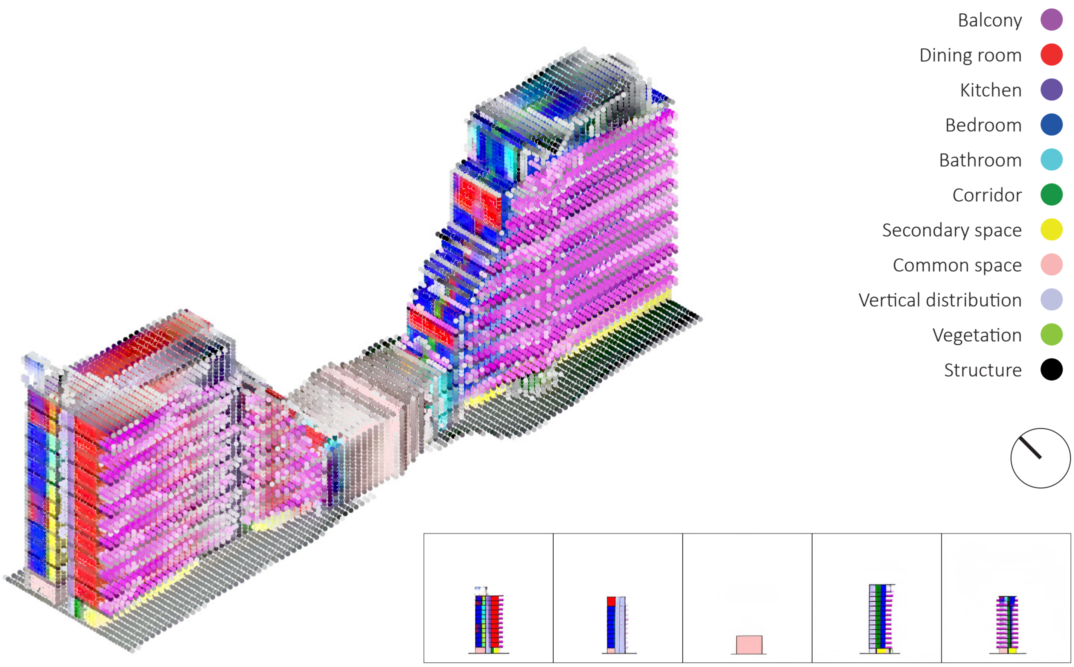


Third floor



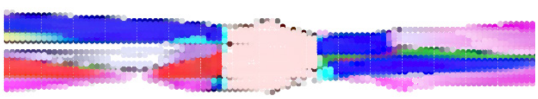
Forth floor

Generation No.8 _ selected seeds: 126-156-179-424-362 _ residential condo

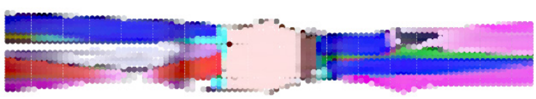


South elevation

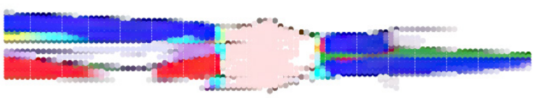
Ground Floor



First floor

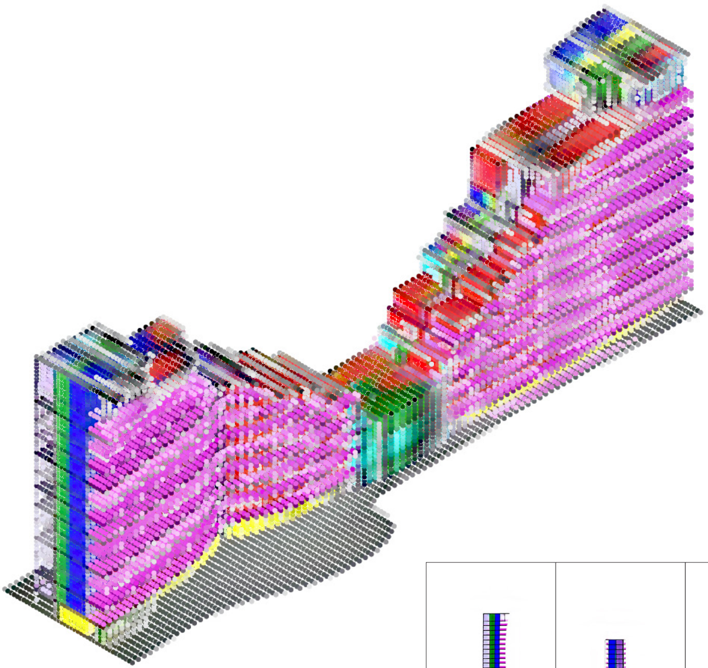


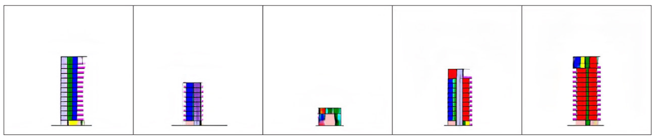
Second floor



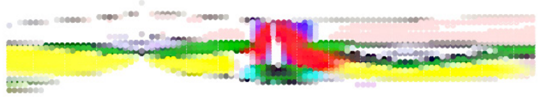
Third floor

Generation No.9 _ selected seeds: 424-390-489-436-288 _ residential condo

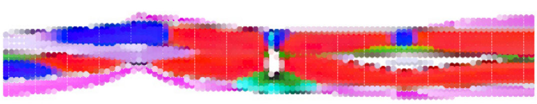




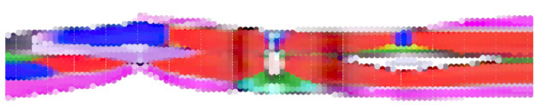
South elevation



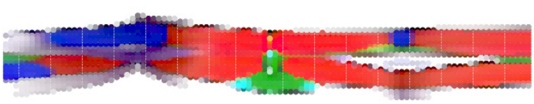
Ground Floor



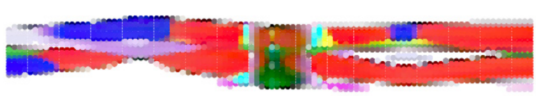
First floor



Second floor

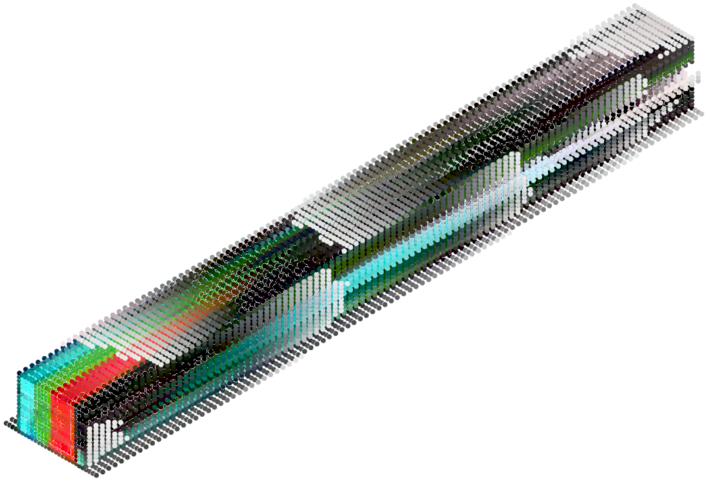


Third floor

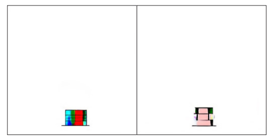


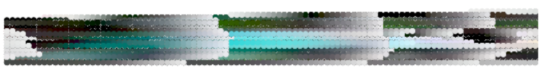
Forth floor

Generation No.10 _ randomised seeds: 4873694-3127875

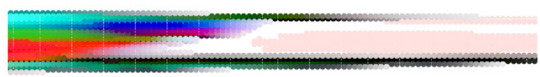


Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure

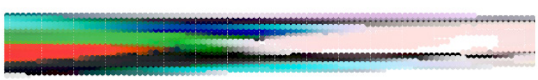




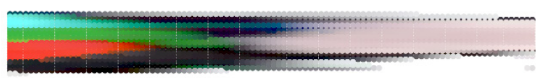
South elevation



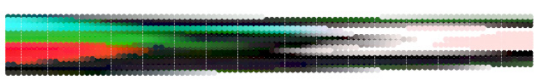
Ground Floor



First floor



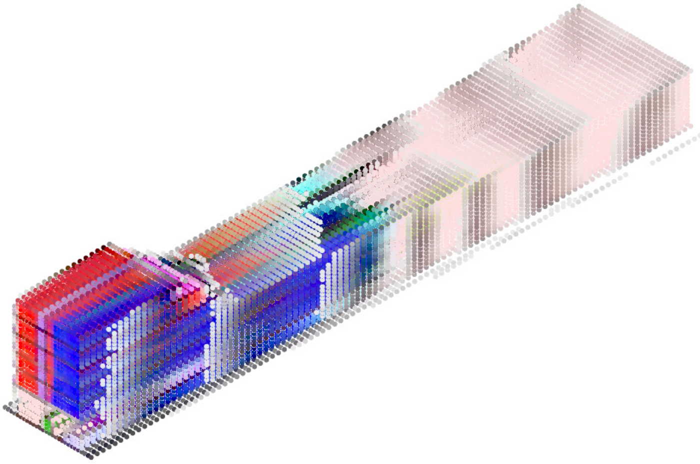
Second floor

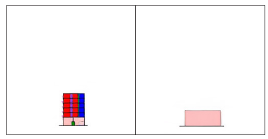


Third floor

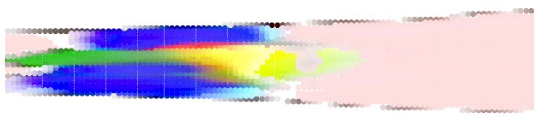
Forth floor

Generation No.11 _ randomised seeds: 568320-1876567

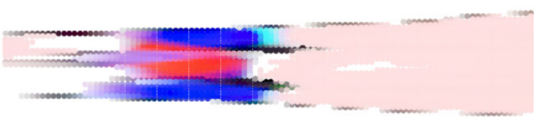




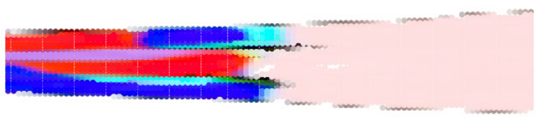
South elevation



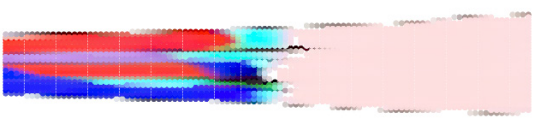
Ground Floor



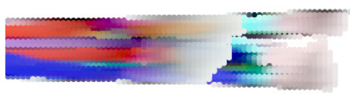
First floor



Second floor

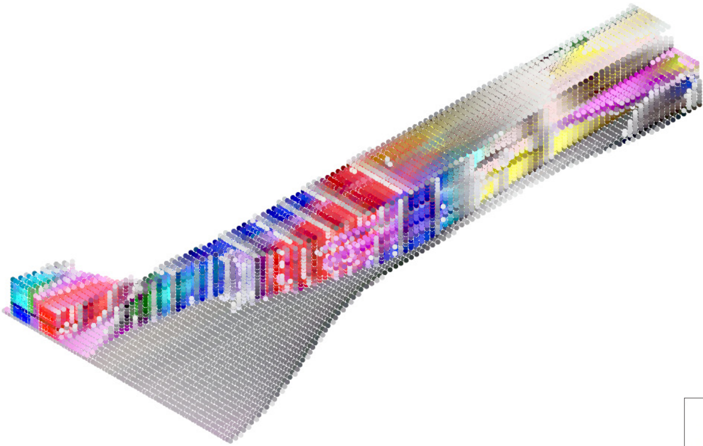


Third floor

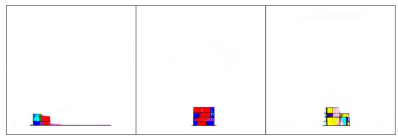


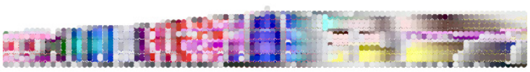
Forth floor

Generation No.12 _ randomised seeds: 2539503-2680011-1345770

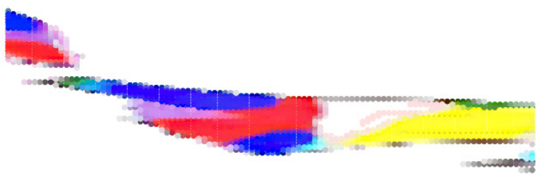


Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure

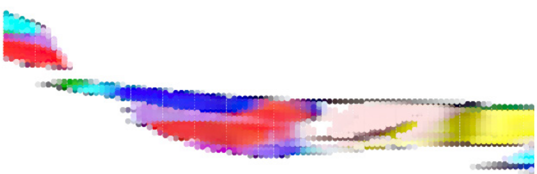




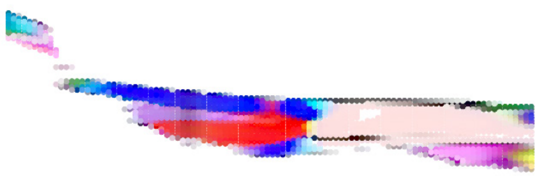
South elevation



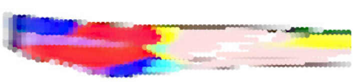
Ground Floor



First floor



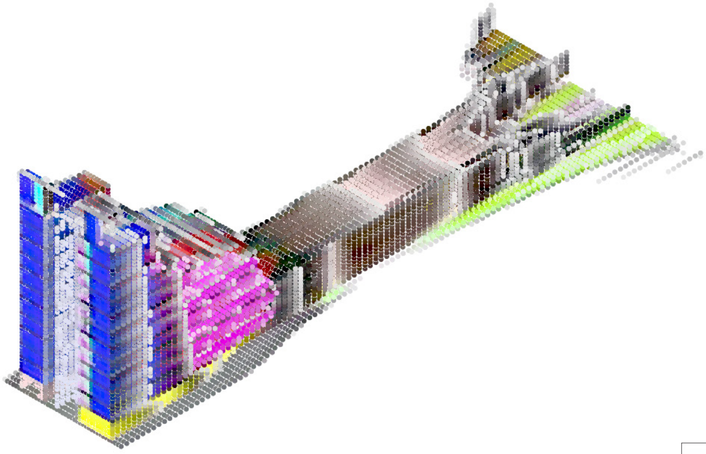
Second floor



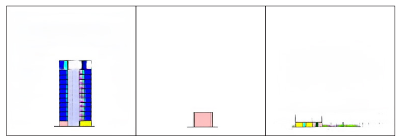
Third floor

Forth floor

Generation No.13 _ randomised seeds: 1780102-3168008-3643398

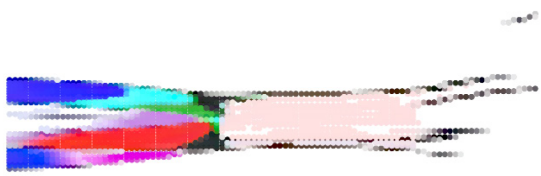


Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure

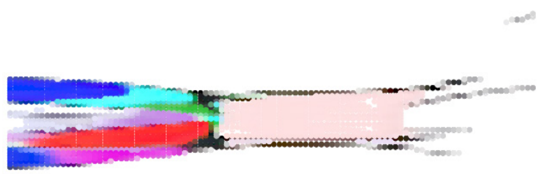


South elevation

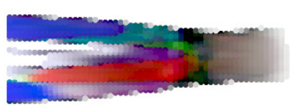
Ground Floor



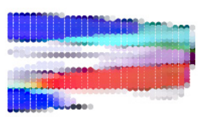
First floor



Second floor

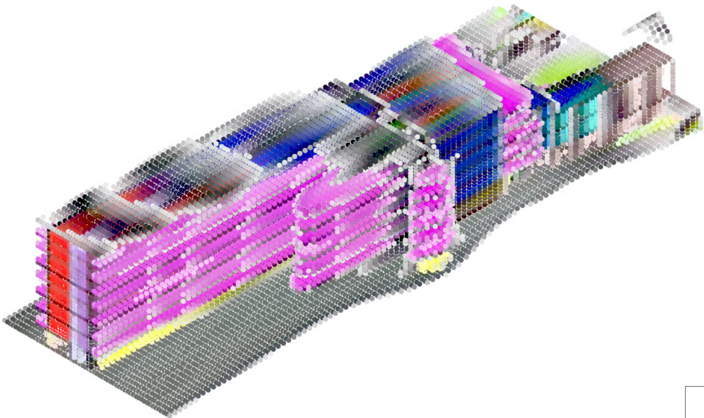


Third floor

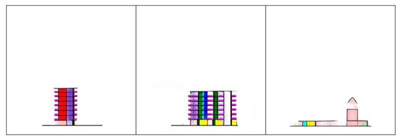


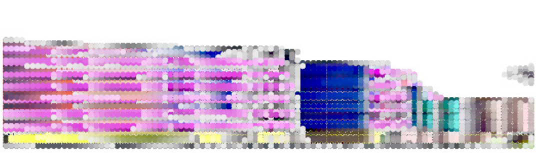
Forth floor

Generation No.14 _ randomised seeds: 2154928-4467299-306272

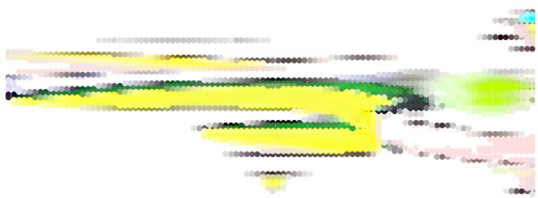


Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure

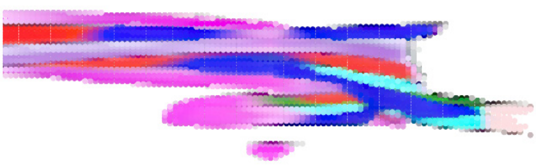




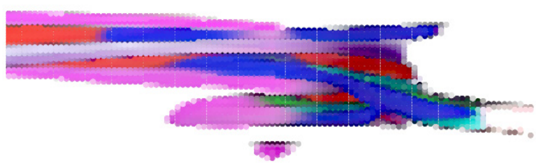
South elevation



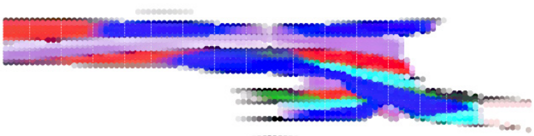
Ground Floor



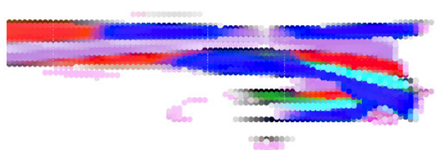
First floor



Second floor

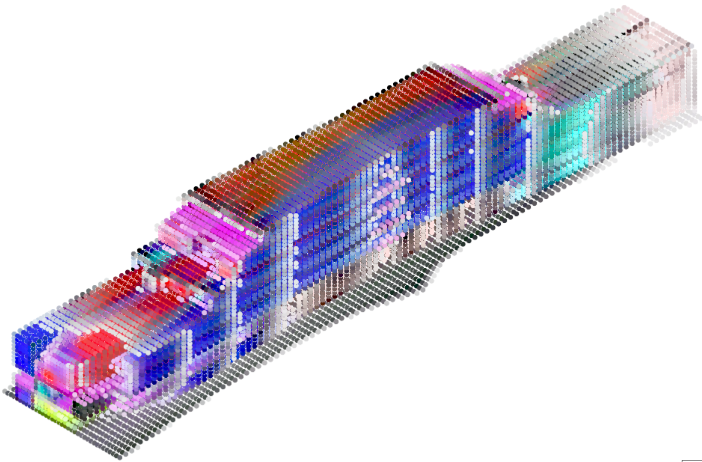


Third floor

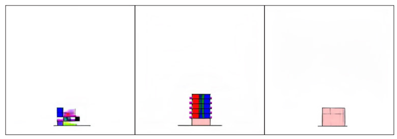


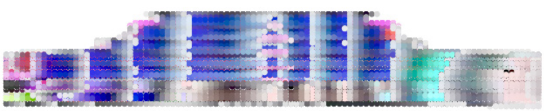
Forth floor

Generation No.15 _ randomised seeds: 1892383-4288840-1847168



Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure

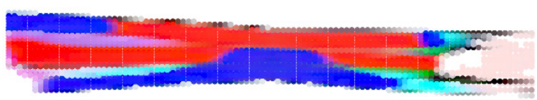




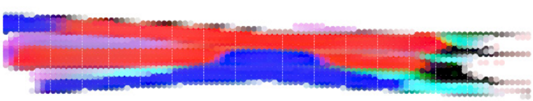
South elevation

Ground Floor

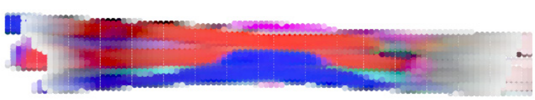
First floor



Second floor

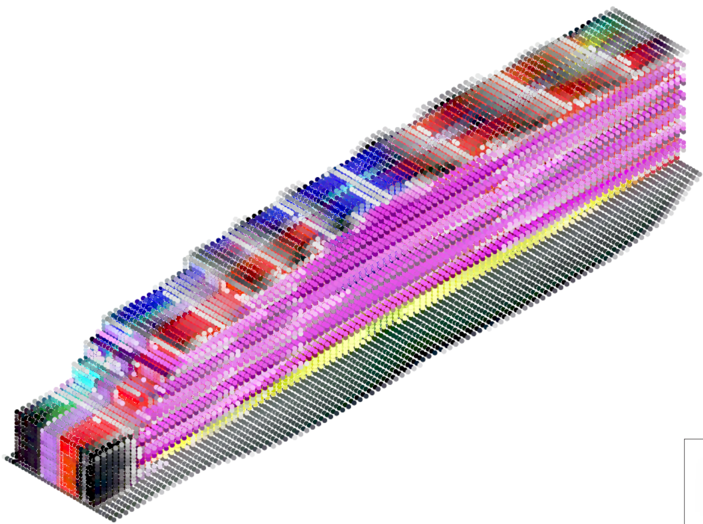


Third floor

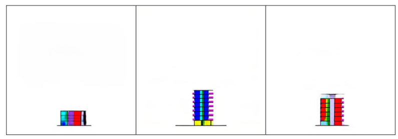


Forth floor

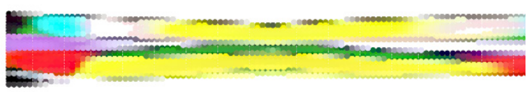
Generation No.16 _ randomised seeds: 3319873-4585409-2464528



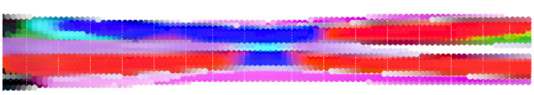
Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure



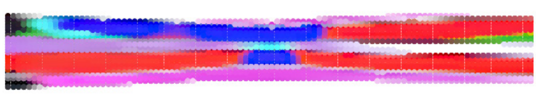
South elevation



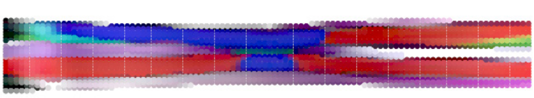
Ground Floor



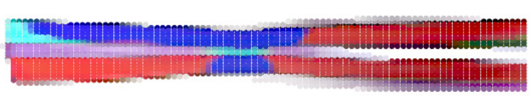
First floor



Second floor

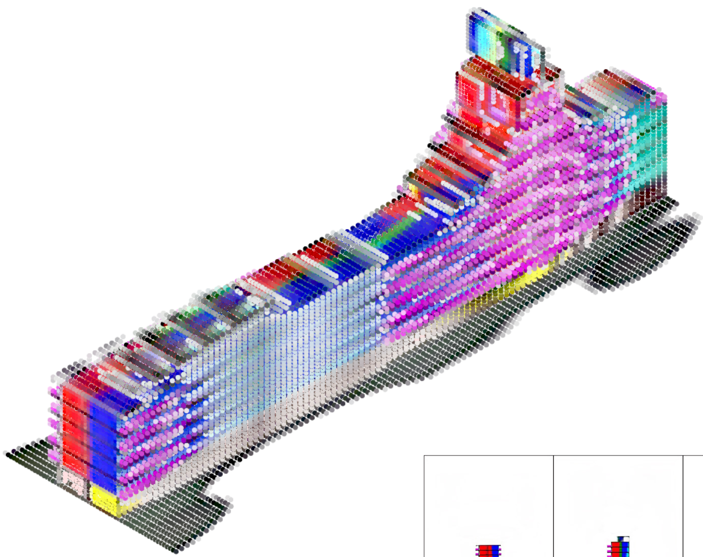


Third floor

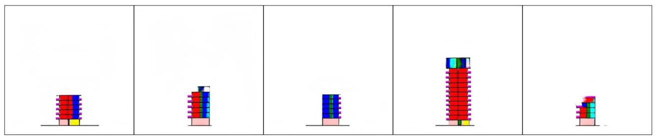


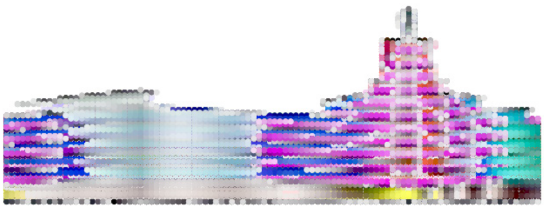
Forth floor

Generation No.17 _ randomised seeds: 3313243-3669654-127435-2823555-255936



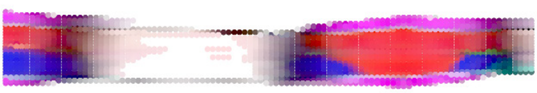
Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure

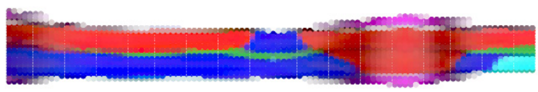




South elevation

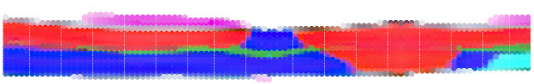
Ground Floor

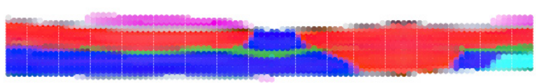




First floor

Second floor

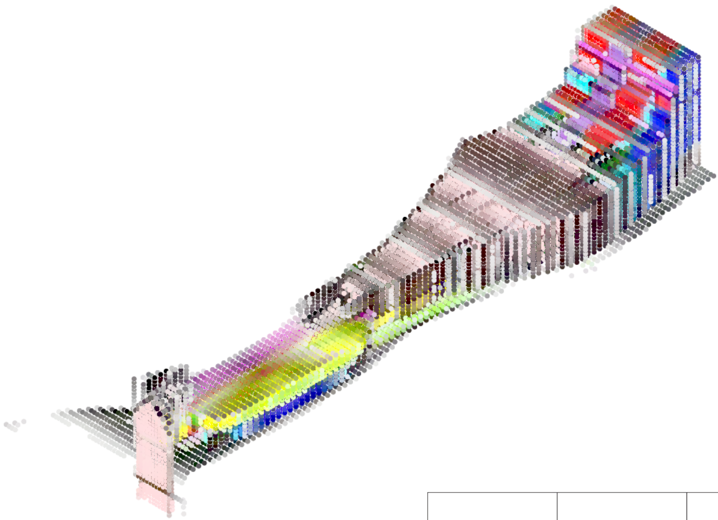




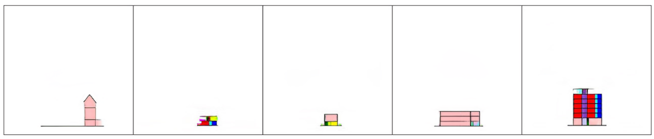
Third floor

Forth floor

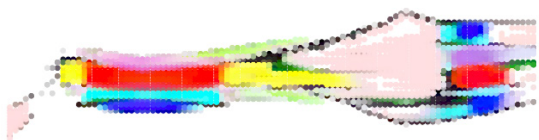
Generation No.18 _ randomised seeds: 706778-4415674-2837662-155671-986975



- Balcony
- Dining room
- Kitchen
- Bedroom
- Bathroom
- Corridor
- Secondary space
- Common space
- Vertical distribution
- Vegetation
- Structure



South elevation



Ground Floor

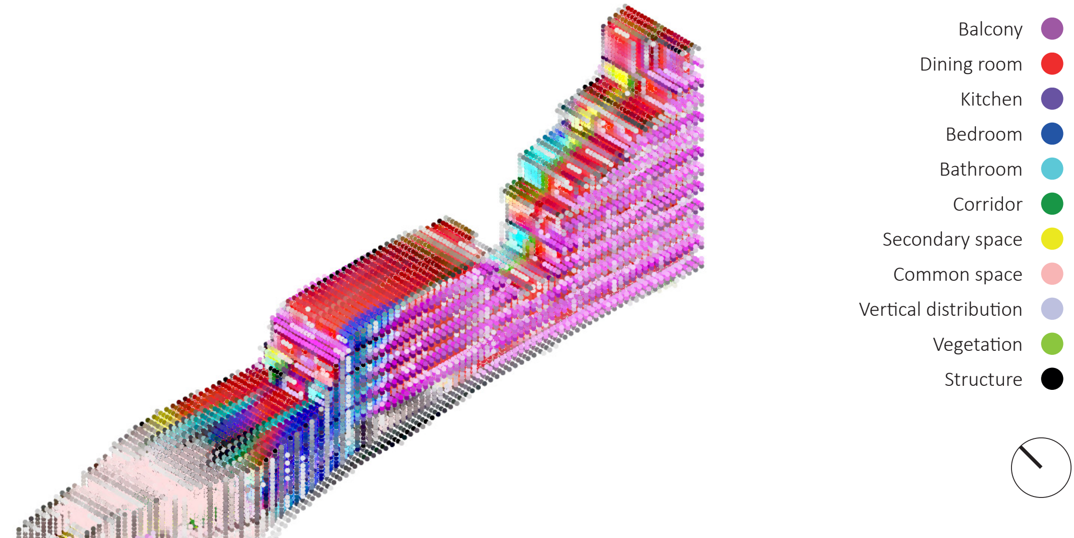
First floor

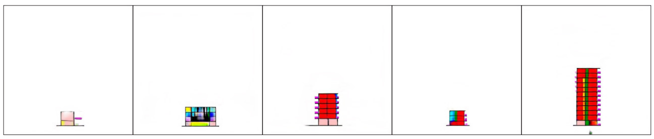
Second floor

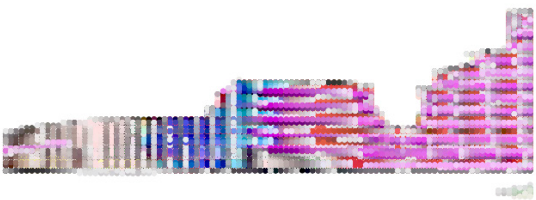
Third floor

Forth floor

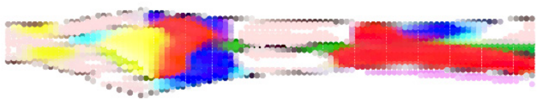
Generation No.19 _ randomised seeds: 2286831-1564027-434573-21013-4386899



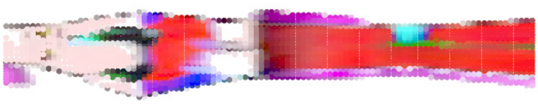




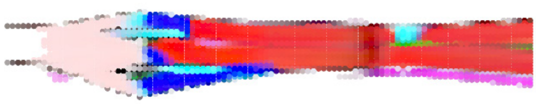
South elevation



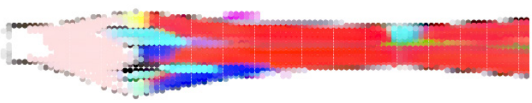
Ground Floor



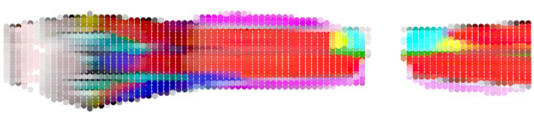
First floor



Second floor

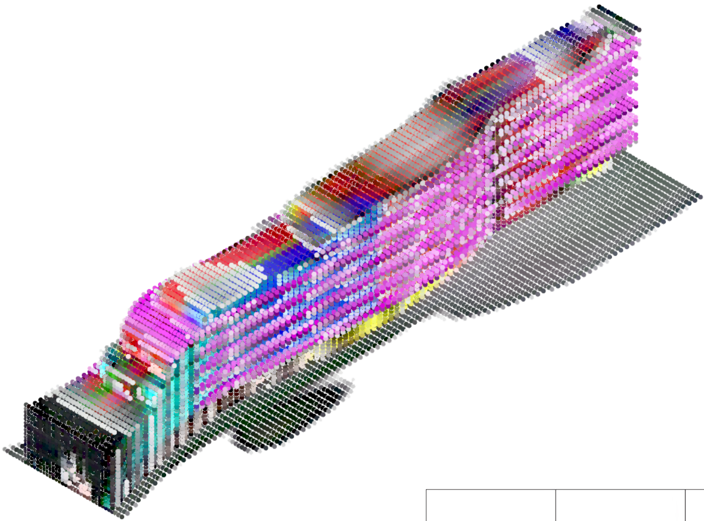


Third floor

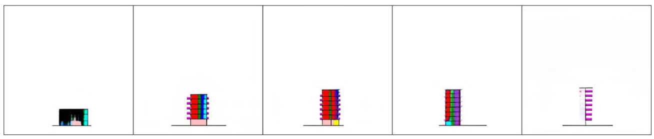


Forth floor

Generation No.20 _ randomised seeds: 4503624-93529-1648582-3195305-2603421

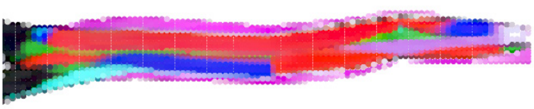


Balcony
Dining room
Kitchen
Bedroom
Bathroom
Corridor
Secondary space
Common space
Vertical distribution
Vegetation
Structure

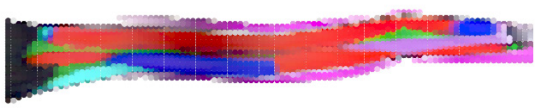


South elevation

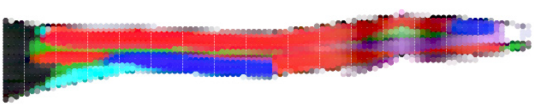
Ground Floor



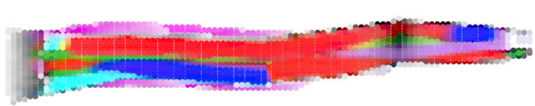
First floor



Second floor

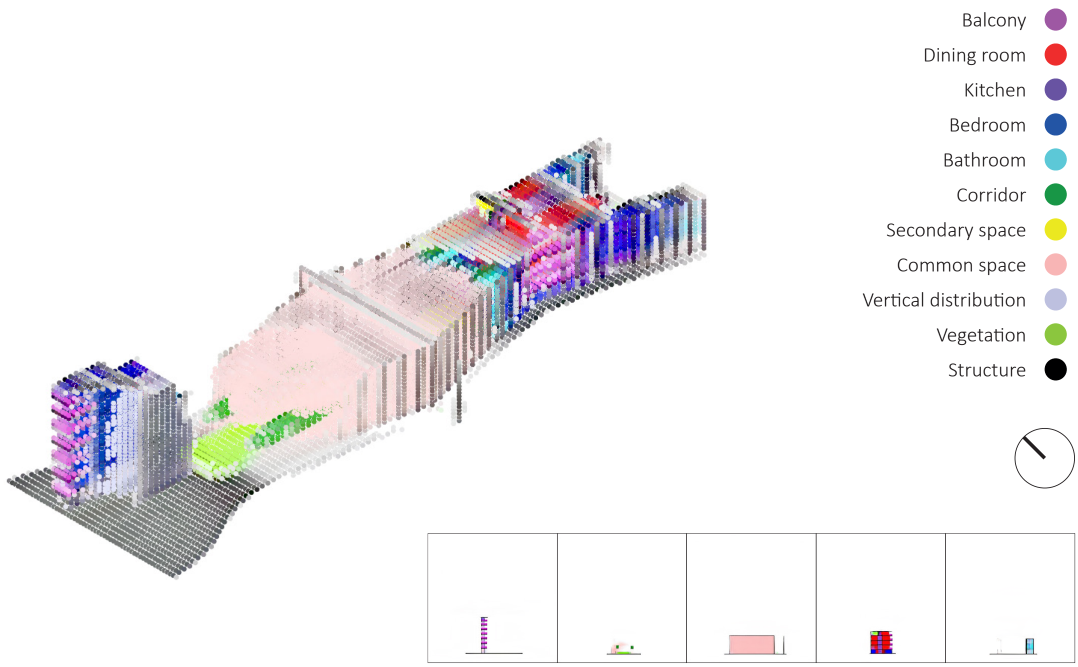


Third floor

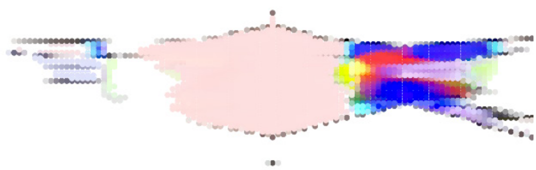


Forth floor

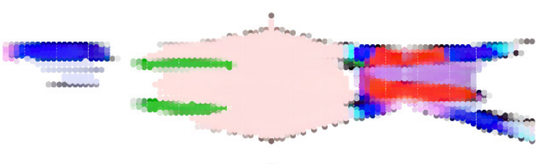
Generation No.21 _ randomised seeds: 4343656-2758687-2439311-995045-3363625



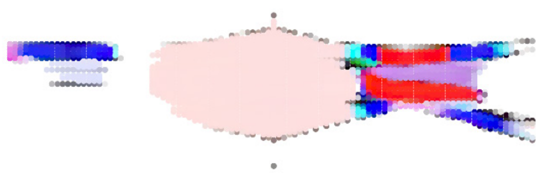
South elevation



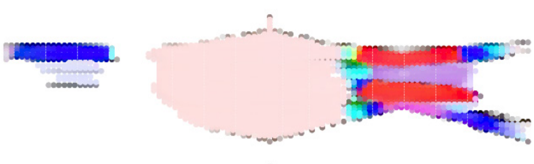
Ground Floor



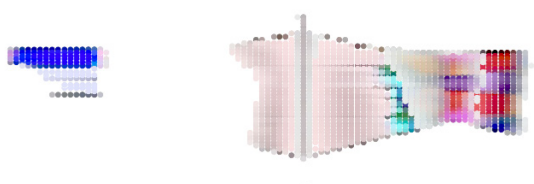
First floor



Second floor



Third floor



Forth floor

Discussion and Future Developments

The methodology developed here is supposed to implement the AI way of thinking inside the early design process, generating non-conventional suggestions, looking for a creativity augmentation in the architectural project from both spatial organization and formal point of views.

A GAN model has been employed and trained on labelled images of buildings' sections in order to "teach" the NN about how spaces – functions – are organized within a shape. The chosen building typologies have been Italian social residential building and expositive pavilions, chosen to infer the NN with notions about spatiality of the both, looking for hybridisation of the private and the public spheres. This data localisation – the model bias – constitutes a boundary for the model application.

After many trials, a NN succeeded in learning all the features embedded inside the training data, and even if the training was still in its initial part, it has been assumed as completed to proceed with the generative part of the methodology. At the end of the process, thus, it was possible to generate, exploring the StyleGAN's latent space, a sequence of novel sections to convert into a three-dimensional representation of a building.

The results have been generated following two different criteria: selecting, and thus guiding, the generative process or randomly picking sections, going for a wild exploration, blind about results.

The selecting process implies a previous image generation, analysis, categorisation, and finally the choice by the user. However, also after categorisation choosing the sections can be quite tedious: many sections might look similar, presenting just some internal differences. For what have been experienced, those similarities brought to take other choices without a meaningful reason, widening the time spent in this step. Moreover, the number of sections considered – 500 – was just an infinitesimal part of all images which populate the latent space of the model.

The randomised process, instead, is more linear. Sections are randomly picked, and videos of interpolation are generated. Videos are the only element to analyse: once the most interesting ones have been selected, they can be converted into pointclouds. The absence of limits and time-consuming operations promotes the usage of the generative tool, which is the main feature of the process that provide the creativity augmentation.

Thus, the second criteria is the one which better represent the nature of the process. This is also more adapt for the early design phase, where ideas come and go, making this continuous generative flow ideal for the process.

It is worth to notice, however, that even though a personal evaluation favoured the randomness and repetitiveness, the selection process triggers another way of design. In fact, choosing between a predefined number of sections is already part of a design process augmented by the AI. The suggestion here stops before reaching the three dimensions, since the choice made would reconduct the human conceivable range of possibilities, based on the self-knowledge.

The obtained results are the testimony of the actual possibility of creating a custom AI model without being necessarily experts of the field. Obviously, competences in programming and on such discipline in general are more than welcomed and may avoid many headaches.

The development was initially naively approached; during the experimentations and facing errors, then, the process became increasingly conscious. This supports the idea that new technologies have to be understood when they emerge, and for users there is no better approach than learning by doing.

Knowledge about data and what making a custom dataset implies have been acquired, together with an understanding of the neural network learning process. Producing a custom dataset means also constructing a custom language that connects with the AI. Additional procedures to apply in this phase of the process are related to the analysis of the produced data: neural networks as auto-encoders can process the data to give an outlook on composition, understanding if there is redundancy or unbalance between data's features.

The training step was where issues started to come up. Used to complete software with clean interfaces, architects never face coding, matter of software developers. Dealing with such problems without programming experience can be quite annoying; however, the designers' attitude to problem solving may help finding the right solutions.

The NN did not complete the training process because of missing resources, both temporal and economical. A good point would be to construct a proper infrastructure to use for training, with multiple GPUs to split the computational load and thus reducing the required time. A complete training then can be performed, achieving the final version of the model, which have to be tested to verify the level of learning, the latent space variety, and the generations' coherence in terms of spatial organisation.

The creativity augmentation, thus, has been addressed. The model is able to generate hallucinated 3D building's visualisation as suggestion for design. This address also the aim of combining two different kind of intelligences, artificial and human, which union is likely to produce a genuine novelty. As in the Korean Go competition in 2016, which showed the power of deep learning to the world. Whether the most talk about the creativity of the already cited Move 37, less people give importance to another great achievement. In the fourth game, almost up against the wall, Sedol performed the Move 78, making too complex for AlphaGO to evaluate the next optimal move; the AI model started to perform no-sense moves until resign. It was actually an unusual move – with 1/10.000 of probability of being played – but in the words of Sedol: "at that point of the game, it was the only move I could see". This can be intended as the interaction of two different kind of intelligences that push each other to the limit, performing something unseen before.

The generation approach here adopted is likely to be overcome in the next future. GAN models, as all the NNs early introduced, are part of the Narrow AI category, thus can perform one specific task. Currently, AI development has moved to the next category, the Broad AI. Here NNs are multimodal, able to manage multiple kinds of data at time, and to produce as well. Nevertheless, it is not possible to know if and when AIs would be able to process 3D data in a meaningful way.

Until those days, the 2D-to-3D process here adopted, which uses an array of newly generated slicing – here sections – to generate a three-dimensional geometry, results to be the most effective one, providing both an envelope and an internal structural coherence of the generated object.

In addition to the implementation barely suggested, some structural ones may bring this process to the next level.

Already from the database creation, adding labels related to technical aspects – for example the number of floors – may allow to better structure the latent space, providing new features for exploration.

A greater improvement may come, then, from the NN chaining. In fact, since such model can be trained to address one specific task, to chain different neural network would be the option to address different sequential ones. An example would be related to the output's format: raster files are not ideal for architectural workflow, which needs vector file to compatibly work with CAD software. Creating a chain with a NN able to convert such images in good quality vector files would be already a great step forward.

Finally, a little note on whether is good or not to embrace such technology is needed.

Here have been showed different AI models, from InFraReD and ArchiGAN to the creative experiments of Anadol, del Campo, to DeepHimmelb(l)au. Whether such neural networks generate novel solutions or just suggestions, outputs are nothing more than predications, elaborated upon patterns extracted from the data fed during the training process.

> *"Identifying a behaviour pattern only provide true insight if the recipient understands and trusts the information an ML system places before them"[44]*

Thus, obviously it is up on designers to decide whether to integrate these technologies inside their design process. Still, the opportunity that such tools provide can be game changing for many aspects of the practice.

As Neil Leach reports from a conversation with Maria Dantz from Spacemaker, "we do not think that AI is going to replace anything. But we do firmly believe that in the workplace of the future architects who use AI will replace the ones who don't"[8].

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