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Augmented intuition

Encoding ideas, matter, and why it matters

Mathias Bernhard, Maria Smigielska, and Benjamin Dillenburger

Artificial intelligence (AI) promises to support the production of architecture along the entire process chain. A common challenge of both computational design and AI is the question of *encoding*. How can a design idea be formalized? How can design problems and ideas be modeled so computers can process them? What is the minimum number of parameters needed for maximum freedom in design? Can these parameters be dimensions of a feature vector? What concepts of AI can address the challenges of generating and evaluating solutions? This challenge is present in various phases within a digital design to fabrication routine: starting with the first design sketches and ending with the robotic fabrication. Each of the steps requires different approaches to encoding. When successful, AI can become an active partner in the creative part of the design and allow for a new kind of intuitive fabrication.

This chapter discusses the meaning of intuition, creativity, and intelligence in the context of architecture and how information technology can potentially support designers and augment their intuition. It starts with looking at how technology has been employed to support the design process throughout history, even before computers were invented. The general introduction sheds light on different creative processes, asking what creativity is and how it can be classified. It is followed by a description of two case studies conducted by the authors. Although these projects are very diverse in type, application, and scale, they showcase the potential and promising applications of AI in architecture once the design is digitally encoded. The chapter reflects on the current and categorical limitations of AI and concludes with an optimistic outlook on various possible creative applications of AI in the domain of architecture.

Computational design in architecture

As architects and designers, we are driven to converge knowledge at different stages during the creative process from the design to its physical realization. Architecture fuses the imaginary with the rational, experimental with functional, art with science. It has always been embracing the state-of-the-art knowledge and technologies of its time. Therefore, there is no surprise in discussing machine learning (ML) applications in an architectural context. It seems to be the natural sequel as architecture got familiar with concepts of encoding of architectural knowledge already before the rise of digital technologies.

Computation itself dates back long before the modern electronic computer was invented: Leibniz introduced the first mechanical calculator in 1685. Ada Lovelace came up with the first idea of a programming language for the Difference Machine of Charles Babbage around 1840. Furthermore, the gesture of encoding architectural knowledge has existed in an analog format in each historical epoch. Compendiums store architectural data, examples, models, and protocols relevant for their time, in varied modes of representation, including texts, images, or drawings. Treaties of Palladio in the Renaissance proposed a "compositional machinery needed to design new buildings that are instances of the style" (Stiny & Mitchell, 1978), while Durand suggested the modular assembly of basic architectural elements that could be recombined in countless permutations with a system of universal principles.

Already in the early days when computers filled entire rooms, architects were curious about how this technology could actively support the design process, beyond being a mere digital drafting board (Steadman, 1976). This inevitably brings up the question, how project ideas can be quantified and made machine-readable. How can the design space be encoded (see Figure 22.1), and what forms of AI could help explore it (Bernhard, 2019)? Recent advancements in digital technologies continue to explore those methods but in a faster and automated manner. Automation enables the creation of entire populations of configurations. Instead of crafting a single idea, one can generate large amounts of solutions and select the preferred option. As such, the design process has been shifted from a deterministic format toward a more selective one.

The design space can be built in multiple ways, for instance, with a parametric modeling technique that allows us to manipulate any geometry with a few variables. We can call the collection of all parameters a feature vector, whose dimensions are indeed often directly linked to metric dimensions of the physical object. The design space, the set of potential solutions, is constrained by a predefined topology. With every additional parameter (read: dimension) and its corresponding range, the possible combinations grow exponentially.

Many disciplines draw inspiration from nature when looking for problem-solving strategies. Computer scientists borrowed ideas from evolution to find suitable candidates in large populations. Genetic algorithms (GAs) help explore promising design directions

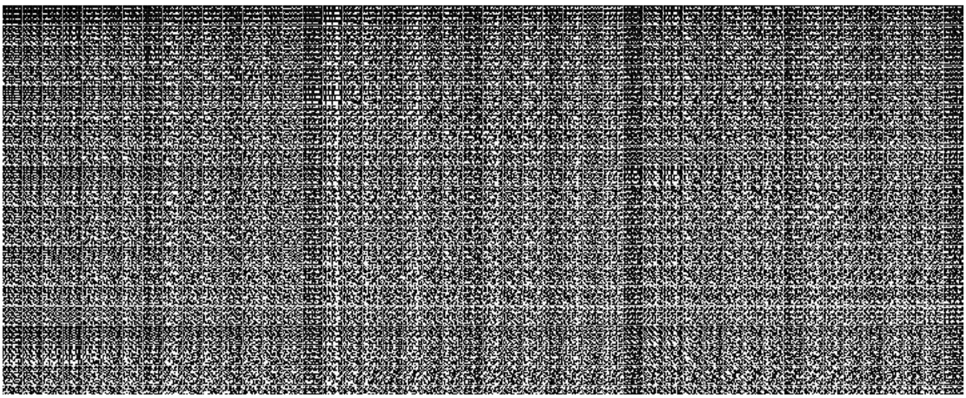

Figure 22.1 Part of the solution space of magnetic actuator combinations generating ferrofluid patterns in Proteus 2.0 project. Image: Maria Smigielska.

among numerous permutations using nature-inspired mechanisms of evolution, namely reproduction, mutation, and recombination. The jargon is borrowed from biology. The prototype model is called a genotype, and its instances with individual gene configurations are phenotypes. The difference lies in how the design space is traversed to find optimal solutions.

Instead of individually setting the parameter values, they are generated and evaluated through a fitness function widely explored in design and architecture (Frazer, 1995). GAs make use of the stochastic patterns of the fitness landscape—not a simple function but not entirely random either—to search for suitable solutions more efficiently.

ML in architecture

However, data-driven approaches advanced by ML algorithms seem to open new models for the encoding of architectural knowledge that reach out beyond purely formal, analytic, or classification models and promote human creativity and intuition. Besides quantifying human ideas, research in AI also investigates whether even ideas could be generated by computers, by a form of artificial creativity. Given the increasing amount and ubiquity of available data, designers embrace AI possibilities and merge it with all artistic forms from visual to performing arts, including speech, vision, and language. Now, it is easier than ever to become a music composer (Newton-Rex et al., n.d.), generate "The Next Rembrandt" portrait (Thompson et al., 2016), paint like van Gogh with style transfer (Gatys et al., 2015), generate a personalized web design (Tocchini, 2014), write the longest novel ever (Ross, 2018), or create an unprecedented strategic move in the game of Go (Silver et al., 2016).

According to DeepMind cofounder and CEO Demis Hassabis (Hassabis, 2018), most of the abovementioned generative acts would be categorized as *interpolation* based on the principle of averaging or generalizing training examples. While it might sound like an achievement for a computer to obtain such a degree of generative capacity, from a designer's perspective, it means filling the design space with large quantities of different variants of the same idea, extracted from the given examples. Those conventional methods of supervised ML—classification, regression, and clustering—could be perfect candidates to use any architectural compendium as their training data. The last example of AlphaGo represents the next level

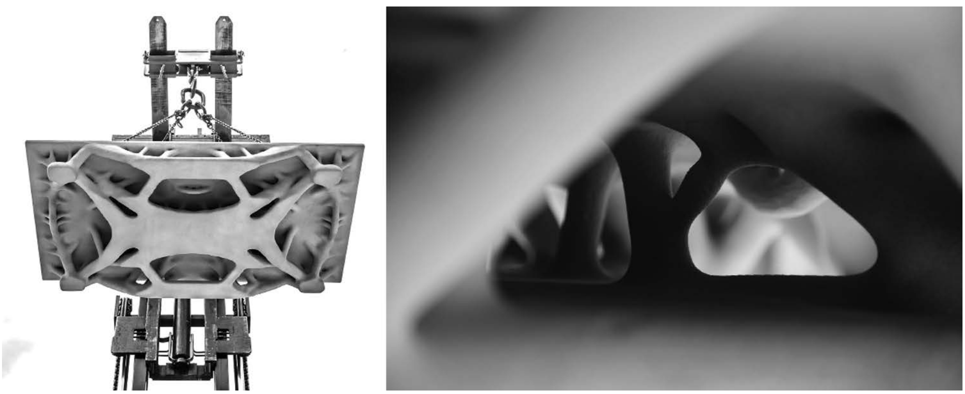

Figure 22.2 Concrete slab with optimized topology; left: view of the underside, right: close-up of the tubular structures. Photos: Andrei Jipa, DBT.

of the creative process described as *extrapolation*. It is characterized by extended boundaries within which AI finds new solutions, even though within the same context still.

What architecture and other creative industries strive for is to reach beyond replicating the existing ideas and create new original ones that allow rendering the impossible thought, think the unthinkable by "transforming the whole conceptual spaces and changing pre-existing assumptions," how cognitive scientist Margaret A. Boden formulates it (Boden, 2004). While this type of creativity, called *invention* by Hassabis, or *transformational creativity* by Boden, remains strictly a human domain, we firmly believe that the combination of human and machine intelligence can lead to unprecedented creative enhancement bringing alteration in overall architectural creation and production system.

How can we combine the two worlds, ML governed by statistics, combinatorics, and probabilities on the one hand and architecture driven by creativity, innovation, and surprise through the careful breaking of some rules on the other? How can architectural knowledge and ideas be quantified, formalized—encoded—for AI to be able to compute solutions and support the design process? And most importantly, how can this be achieved without losing the degrees of freedom for creative exploration needed by architecture? (Figure 22.2).

AI applications in the early design and robotic fabrication

The following two case studies demonstrate the potential applications of ML in architectural design. They are examples of how AI can assist the designer in different phases of the process—virtually in the design and tangibly in the production phase. They operate at different scales—from entire wall elements to filigree metal rods. The projects collect and generate different types of training data—digitally synthesized through simulation and collected in the real world from physical experiments and apply different algorithms to produce different outputs. They show how AI can be integrated into the design process already now. Both projects have very specific, relatively narrow, and well-defined tasks to be addressed by the AI, thereby augmenting the designer's creativity as smart assistants. Eventually, in the nearby future, more and more narrow tasks may be widened and connected. But we believe that it will always be a creative dialog and exchange of the designer interacting with various forms of smart assistants (see Figure 22.9).

The pursuit of integrating AI applications in architecture should not be to provide a one-button hands-off solution from sketch to fabrication. However, a fascinating and promising world opens up to architecture if various smart assistants augment and support each other. What solutions would become possible if the AI-assisted creativity in the early design phase was not limited by the constraints of conventional manufacturing methods? What creations could be realized if the AI-assisted fabrication and materialization would not have to rely on human's limited imagination only?

The two case studies have in common that they both encode the design-relevant aspects of the samples to allow the computer to extract hidden patterns and complex mathematical functions. They make the design space computable—arriving at solutions given a specific input situation. In both cases, the extracted patterns are used in the decision-making process but not for the automation of design or delegation of the creative process to mere statistics. Instead, ML models are trained to assist the architect by doing what computers do better than humans and provide guidance based on "knowledge" extracted from vast amounts of data.

The first case study is a research project entitled *TopoGAN* and was developed by Dr. Mathias Bernhard, Reza Kakooee, Patrick Bedarf, and Prof. Benjamin Dillenburger at Digital Building Technologies DBT, ETH Zurich in 2020. Further technical details on the project, the method, and results are described in the paper *TopoGAN—Topology Optimization with Generative Adversarial Networks* in the proceedings of the 2021 Advances in Architectural Geometry AAG, Paris (Bernhard et al., 2021).

The second case study is a research project carried out by Maria Smigielska with further collaborations with ABB Cergy France, Pierre Cutellic (*The Front Desk* project for Art[n+1] gallery in Paris, 2016), Mateusz Zwierzycki (*The Means* project for Tallinn Architecture Biennale, 2017), and through educative workshops held internationally (Digital Knowledge at ENSA Paris Malaquais 2018, FHNW HGK Institute Industrial Design, Basel 2018) with a diversified robotic infrastructure at hand.

Case study 1: TopoGAN—topology optimization with generative adversarial networks

The strive for spanning large distances with slender beams has always also been an aesthetic one. The great master builders of gothic cathedrals demonstrated the elegance of artful force redirection through a highly performant use of materials. Increasing awareness of the devastating consequences of the construction industry's waste production calls for efficient deployment of natural resources. For structural design, topology optimization (TO) is a way to run finite element analysis (FEA) in a loop, converging the design to a target value. For example, this target can be the maximum stiffness of an element with a specified fraction of material (Bendsøe & Kikuchi, 1988; Bendsøe & Sigmund, 2003). The intricately branching lattices resulting from TO have typically been challenging to produce with conventional methods. Advances in digital fabrication—specifically additive manufacturing at large scales—have brought the use of TO as a design instrument for architectural components into the realms of possibility, as shown in Figure 22.2 (Aghaei Meibodi et al., 2017; Jipa et al., 2016).

However, setting up all the necessary boundary conditions for TO (such as loads, supports, voids, or fixed elements) and finally running multiple FEA solver epochs is very laborious, time-consuming, and requires advanced expert knowledge and specialized software. TO is, therefore, often performed once as an input for further refinement in the design process. It assumes a static set of constraints, and changing boundary conditions require a complete recalculation of the TO from scratch as if no solution had been computed before. The project *TopoGAN* addresses this dilemma (Bernhard et al., 2021). TopoGAN investigates the applicability of ML to the structural design of optimized topologies in an early design phase.

The trained model learns some kind of artificial intuition about the distribution of material. The model's suggestions are not numerically precise enough to replace an accurate simulation, but fast enough for an interactive working mode in an early design phase, where qualitative concepts are more important than quantitative precision. Because the ground truth—the real solution the ML model is supposed to predict or generate—can be simulated virtually, there is no need to collect training data in the wild and manually label it. Instead, an arbitrary number of synthetic training samples can be generated.

While the method is scale-independent, TopoGAN is applied to a building element, a three-by-three-meter wall. The walls are assumed to be loaded along the top edge and supported along the bottom edge. What varies among all the samples is the size, shape, position, and rotation of the openings. A total of approximately three thousand sample inputs in three different datasets are thus randomly generated (see Figure 22.3).

Besides the input, the training data also requires the ground truth, the actual result of the TO for a given wall layout. Each sample takes approximately one minute to run 50 epochs of TO on a 128 × 128-pixel input image. This number was identified to be sufficient in most cases to have the changes below a certain threshold per additional epoch. The TO on the inputs is batch processed using a Python implementation of the algorithm (Aage & Johansen, 2013), and its result is concatenated with the input to one training pair image. As the TO algorithm is deterministic, it is run once per randomly generated wall scheme only.

As its name suggests, TopoGAN uses a generative adversarial network (Goodfellow et al., 2014), where two neural networks compete and mutually improve each other's performance. The generator network tries and learns to produce output images that pass as real, while the discriminator network tries and learns to distinguish between real and fake. Instead of generating output from normally distributed random noise, the generator learns a conditional function to translate from an input to an output image, as shown in Figure 22.4 (Isola et al., 2016). The number of possible outputs for TopoGAN, grayscale images of 128 × 128 pixels, is gigantic. Even for a tiny thumbnail of 5 × 6 pixels with only black or white colors allowed, the number of possible images is 230=1'073'741'824, over 1 billion solutions.

For what is known as the curse of dimensionality (Bellman, 1957), an exhaustive enumeration to find the best solution is impractical or impossible. Hence, encoding on a higher, more abstract level has to be found. This is where the specific ML model architecture—multilayer convolutional neural networks (CNNs), the building blocks of all computer vision nowadays—unfold its real strength (Krizhevsky et al., 2012). In stacked levels, they extract simple gradients first, edges or textures next, and then ever more complex features such as patterns, parts, and finally objects further up the hierarchy to compress the essence of an image to a reduced number of dimensions. In TopoGAN, the number of dimensions in the last layer is 524'288. On the one hand, half a million values are still too much to control manually, like in a parametric design setup. On the other hand, these numbers are also meaningless

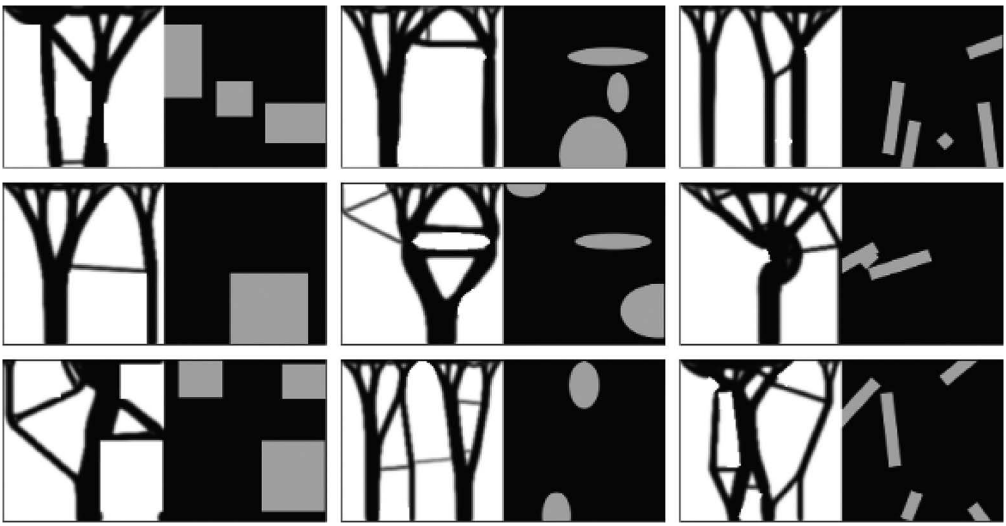

Figure 22.3 Three training samples from each of the data sets with rectangular, elliptic, and rotated linear openings. Image: Mathias Bernhard, DBT.

as they are abstractions. They do not represent the length of an edge or the diameter of a hole. They are coordinates in a project-specific metric space, where redundancies are out of the equation and only relative differences count. Similar topologies are close to each other, dissimilar ones are further apart.

Obviously, to only simulate one solution does not justify the effort of generating 1'000 samples (1 minute each is more than 16 hours of calculation time), and then training a model for another few hours. But once the model is trained, being able to generate an output in a tenth of a second is a game-changer. It is not only about eventually winning time in the long run, but the fast response makes ML-based TO a suitable candidate to be integrated into a computer-aided design (CAD) environment.

Whenever the design changes, whenever windows are moved around or scaled, TopoGAN can display these changes' structural implications in real-time by running interactively alongside the design software. Instead of being a separate process disconnected from the CAD environment, it can be integrated, immediate, and responsive. TopoGAN does not pursue the unique goal of performance by speeding up one instance of TO. Instead, with immediate feedback provided within the CAD environment, architectural and structural design can be evolved in parallel, without one of them being set first and the other suffering from the inherited consequences. Aesthetics and efficiency become the tandem they always deserved to be.

Is TopoGAN creative? Maybe not, as it learns a mapping function for a clearly defined and very constrained engineering problem. As long as the windows in the input do not span the entire width of the wall—preventing the loads from being redirected to the supports—there *is* one and only solution the TO algorithm will output. This cannot be said for the plethora of architectural challenges where genuine creativity is needed—not for *finding* a solution in proximity to other solutions for similar problems, but for *inventing* a suitable response to an unseen question. Is TopoGAN artificially intelligent? Maybe, as its accomplishments are still surprising and astonishing. It was able to learn and apply hard numerical constraints without being explicitly programmed. For example, it learned to avoid the openings by distributing

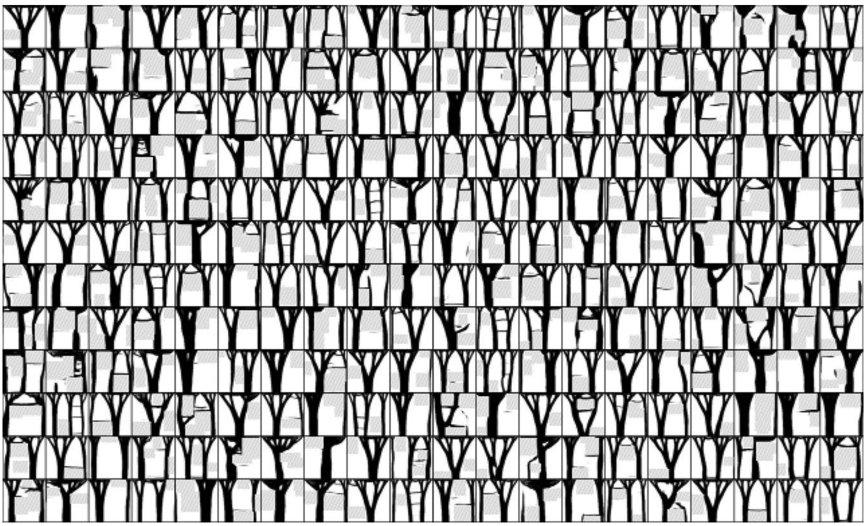

Figure 22.4 The 240 outputs of the TopoGAN generator network for previously unseen inputs (dotted surfaces). Image: Mathias Bernhard, DBT.

material and hence deviating forces around them, but also a more complex constraint like the desired volume fraction within a few percent of error from the target value. TopoGAN may not invent original solutions itself, but it can stimulate the architects' creativity. Playing with the constraints and discovering the consequences in real-time, the resulting material distribution becomes a design choice rather than an irrevocable law to obey.

This behavior awakens the interest and provides confidence that ML models such as TopoGAN can help beyond the very constrained setting of the described case study. Given the right amount and diversity of training data, it may learn to generalize, extract patterns, and applicable rules for more complex or dynamically changing boundary conditions. The concept can be transferred from structural design to other engineering problems, such as fluid dynamics or thermal insulation.

Case study 2: Robotic rod bending technology

While there is more and more attention given to ML applications in architectural design, the topic of fabrication remains a bottleneck on the way to physically evaluate or materialize new ideas. The industrial revolution has divided the field of manufacturing into the standardized industrial production in large quantities that is generally slow in embracing new technologies (Hossain & Nadeem, 2019) or artisanal hand-making with unique solutions beyond financial reach for most of the architectural projects. The first promise of individualized production appeared with the introduction of digitization to manufacturing and early concepts of mass customization (Toffler, 1970). However, it did not allow for much of a formal design differentiation as the system was dedicated to one specific fabrication process. It did not help in the areas where human knowledge cannot be replaced with a versatile machine, including dealing with complex materials (Figure 22.5).

Figure 22.5 The Front Desk project at Art[n+1] gallery, Paris 2016. Photo: Leslie Ware.

The *Bendilicious* research project (Smigielska, 2018) tries to bridge this gap by proposing a simple, yet versatile, open, but automated fabrication solution with the example of metalwork. Metals as architectural material have celebrated the progress of both technology and civilization for centuries. It has traditionally occupied an ambivalent place of wonder and fear due to its mysterious, both solid and liquid properties requiring high skills and knowledge of specialized craftsmen. A cold-forming bending process with manual table benders has not changed until the mid-90s, when the first conceptual schemes of computer integration shifted this technology from a labor-intensive and hazardous process to a safer, faster, and almost fully automated one (Dunston & Bernold, 2000).

However, the problem of the dependency on human expertise was only addressed in early 2000 when ML was integrated to help adaptively compensate for the variable springback effect. Unequally distributed internal compression and tension forces make the material want to return to its initial shape (Dunston & Bernold, 2000). This technology was incorporated and black-boxed by heavy industry, leaving little space for custom or one-off projects.

Bendilicious also utilizes ML algorithms to encode and predict the material's deformation behavior but in a simplified and open format. We developed a simplified fabrication model consisting of a single robotic arm with a custom end effector (see Figure 22.6) and a portable rod–holding station. The robotic system serves a function of both a gripper and a bender (as opposed to standard computer numerically controlled bending machines). Along with the hardware development, the digital workflow was entirely embedded in Grasshopper—the visual programming environment of the CAD software Rhinoceros—to provide continuity of the information flow between different phases of project development: from concept design iteration, FEA, geometry rationalization, and generation of production data informed by material behavior. The software containing design-to-fabrication processes is based on both existing plugins and custom-made tools that do not require any intermediate conversion to external software or machine code.

The data representing the nonlinear material behavior were collected from physical experiments and then encoded in a regression model. The third polynomial function stems from data points of desired angle and their respective resulting springback value, which was harvested with the photo average-angle readout. While this method could be easily automated with available computer vision, adaptive threshold, and line recognition algorithms, our simple photo readouts of only 120 data points guaranteed the prediction precise enough

Figure 22.6 A simplified robotic bending hardware setup. Photo: Maria Smigielska.

for fabrication and assembly of two large space-frame projects. *The Front Desk* of the size 550 × 140 × 75 cm consisted of linearly assembled 800 unique elements, each between 12 and 100 cm long, with the number of bends ranging between 2 and 7 and with a total amount of 2'400 unique bending values (see Figure 22.5). The other project *The Means* was of the size 50 × 50 × 220 cm consisted of more complicated 3D elements with an increased length of 60–120 cm, and twice the number of bends, ranging between 6 and 14 each (see Figure 22.7).

Is the ML methods directly creative? No, but the project brings a change on many other levels. First, it aims to finally develop a simplified, versatile, and decentralized mode for the future building industry. It promotes diversified over standardized solutions, as the robotic arm, once trained, performs the same marginal cost of production for identical or unique items. Such a model is applicable off-site as a flexible alternative to overconstrained, centralized industrial systems, and routine and hazardous manual work. An additional benefit lies in its potential for on-site fabrication. The springback value is dependent on many of the chart factors, such as changing room temperature, metal thickness, type, quality, etc. By coupling robotic systems with visual and environment probing sensors, the trained model of, e.g., the neural network could predict according to those changing conditions. Additionally, with an online ML strategy, the data can be progressively gathered during production, grow bigger, and more varied over time with each new project, which significantly improves the precision of prediction, as well as the flexibility of the system that can be used in various site and daily conditions.

Such a fabrication method occurs to be far from a hardcoded industrial system and reminds more of a craftsmen's work, who develop their skill and build necessary tacit knowledge over time through experience and practice. With those amplified cognitive abilities, the robotic system gains a material intuition that allows for a more intricate and meaningful communication with the physical world. Shifting the long process of material knowledge acquisition to the machine is the key to successful automation for both encapsulation of complex material behavior and sophisticated artisanal and autographic fabrication requiring higher cognitive processes. Such an approach pushes the concept of digital fabrication beyond mass customization or "nonstandard seriality" introduced by Mario Carpo (Carpo, 2011)

Figure 22.7 View of The Means project during Tallinn Architecture Biennale 2017. Photo: Maria Smigielska.

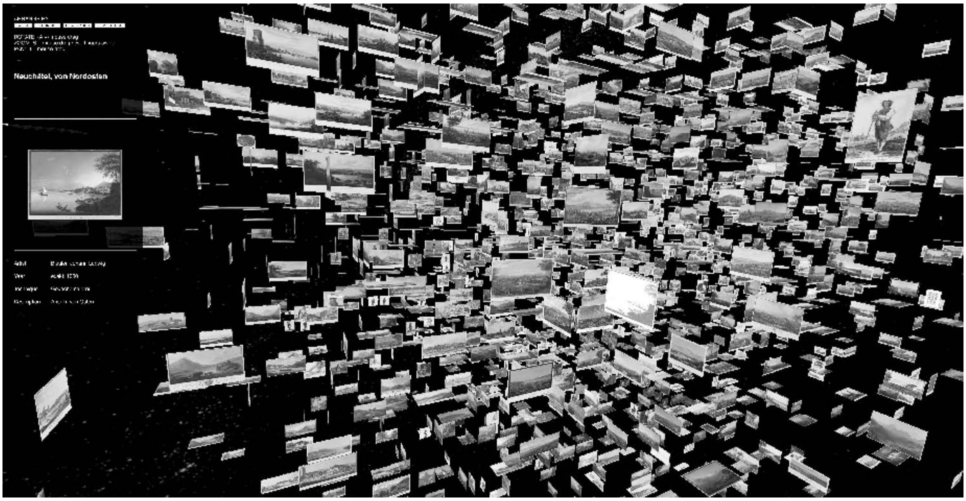

Figure 22.8 Gugelmann Galaxy: A browser application for exploring a large image collection in 3D, with a detailed view of the selected item. Images can be arranged by four different custom criteria. Image: Mathias Bernhard.

toward automated digital crafts for both existing and future materials such as complex, synthetic, and graded composites.

While the material encoding is not strictly an architectural question, it does change how the knowledge circulates in the design-to-production workflow. During a standard architectural workflow, design intention is being crafted with the knowledge of engineering, structure, material, and fabrication in a unidirectional and sequential manner. Digital data helps to bridge design with fabrication in a seamless way, but it is the material encoding that tightens this relationship, understood not only as a continuous but more importantly, bidirectional, fully informed, and negotiable workflow.

Johan Östling, Professor for the history of knowledge, describes such a model of knowledge exchange as circular (Östling et al., 2018). It assumes the movement of information in both directions. Such reciprocity not only allows to transmit the information from A to B but also assumes the transformation of the information during those passages. This assumption allows for a more vibrant and reciprocal relationship between architecture, construction, and material engineering by offering a powerful holistic system over a compartmentalized and discontinuous disciplinary approach.

It also actively changes the role of the architect who retrieves the control over the fabrication process, which was ubiquitous before the historical Albertian cutoff that separated conception and construction through the introduction of notational architecture. Whether the motivation was to maintain the intellectual and artisanal authorship as for Brunelleschi, who built his dome in Florence, or mainly because there is no means to notate and translate the design intention to fabrication language as with the example of Antoni Gaudí, who himself built parts of the Sagrada Familia (Carpo, 2011). This gesture opens up a vast field of experimentation for architectural design research, which might reshape the roles and capacities of architects and other practitioners.

As Roberto Bottazzi puts it, "the means of expression available at any given time determine the bounds of architectural imagination" (Bottazzi, 2018). Through expression, we understand what is possible to be constructed both virtually and physically. Therefore, we

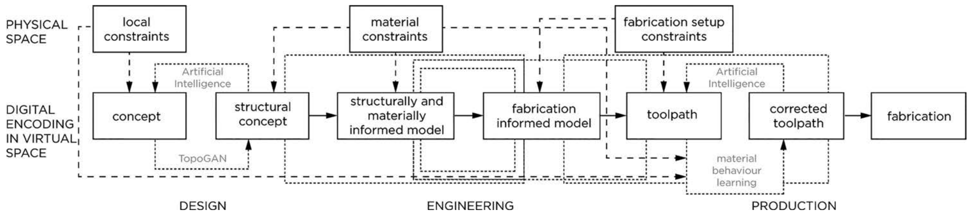

Figure 22.9 Human intelligence augmented by AI in different phases of an architectural project. Image: Authors.

try to highlight the importance of AI explorations in both design and fabrication to amplify and augment architectural creation with those two case studies.

AI in design opens up what can be imagined, while AI applied in the robotic fabrication and material domains not only facilitates the materialization of innovative ideas but also has a chance to drive them. We tend toward design innovation, understood broader than geometrical diversity within standard solutions, but more importantly, as a creation of new, particular architectural systems that incorporate new materials, requiring custom production chains (Figure 22.9).

Conclusion

The encoding scheme is of utmost importance, as its number and type of dimensions directly translate into the design space—the number and diversity of possible solutions. Any design can be reduced and compressed to the chosen number of features. Conversely, the reduction in encoding also means that any design can be recovered by decoding the latent vector into a full solution. This assumes that all designs are instances of the same building plan, or to express it in evolutionary design jargon, phenotypes with a common genotype.

However, correlation does not imply causation. The ability to encode two designs in a custom metric space does not permit the reverse conclusion that these metrics were the driving parameters generating the design. A model where the control points of building outlines are encoded in polar coordinates—distance from centroid and angle from X-axis—excludes a courtyard house by design. Given a large enough corpus of raw material, ML can extract common denominators and measure similarities among the individual samples. This allows the training of a classification system to detect architectural styles in photographs (Shalunts et al., 2011; Zhao et al., 2018). It works in hindsight, for buildings that already exist. But even the most elaborate model trained on the most extensive collection of Baroque architecture will only be able to generate more Baroque architecture. The results may well be impressive, and maybe even fool historians, as richly orchestrated compositions arranged in the style of Johann Sebastian Bach do with experts of classical music.

ML models have become stunningly good at discovering patterns to not only classify but also synthesize new instances based on probability distributions—talented forgers able to create credible shams. Are AI-assisted CAD tools a modern version of Sebastiano Serlio's Regole Generali (Serlio, 1537)—crutches enabling the mediocre architect to produce more of the same? Is a masterpiece one that artfully breaks with conventions? Philosopher Sean Dorrance Kelly calls artificial Bach compositions "mimicry," excluding "by design" a new Schönberg who fundamentally changed what music is, creating pieces different in kind and not just variations on existing ones (Kelly, 2019). The outliers, the nonconformists, often brought a culture forward by shifting the gravity center in the encoded space.

This anthropomorphic understanding of technologies in which we perceive AI as the one to directly mimic the human brain and machine that directly replaces human muscle might trigger the competitive dichotomy of a man versus machine. However, technologies are indeed unlike us, even if they can automate and replicate almost anything, we create that can be measured or quantitatively described. AI can process more information and faster than us, machines construct larger or significantly smaller elements with much higher precision than us, but they lack human intuition and radical creativity.

AI calculates solutions to quantifiable problems in no time, but it does not make sense of the problem itself. Therefore, AI for architectural design should neither be about replacing the designer by a competing automated building synthesizer nor about lights-out factories. Instead, the computer can become a powerful assistant in a cocreative process, like in the idea of Centaur—a mythological hybrid of two species that complete and empower traits of their individuals in such a symbiotic scenario.

AI can act as a smart librarian, providing previous answers to similar questions drawn in fractions of seconds from extensive collections, eventually proposing required adjustments (Yoo et al., 2020). It can act as a curator, helping to sort and cluster collections along custom dimensions defined by the user (Bernhard, 2016; Bernhard et al., 2015). These can be dimensions not previously available in the data but extracted, encoded, and eventually unveiling unexpected neighborhoods and providing new insights. The project *Gugelmann Galaxy* demonstrates this use of ML in a browser application (see Figure 22.8). It allows building new models for more meaningful interaction (Smigielska, 2020), where the computer can even disappear entirely and learn the designer's preferences by correlating brain activity with changing patterns the designer is exposed to during the training phase, as shown in Figure 22.10 (Smigielska & Cutellic, 2018). Elaborate ML models using multiple layers of convolutions (CNNs) can learn very intricate qualitative patterns in high-dimensional spaces, beyond quantitative parameters. What may appear as mere collections of meaningless numbers becomes very informative and unveiling when being visualized (Olah et al., 2017).

AI has the potential to enhance architects' creativity by speeding up tedious processes and providing immediate responses by providing a trigger for a new idea to be developed or by tightening the design-to-production process. It tries to bridge the gap between human and machine intelligence by developing models that encode higher cognitive capacities, like intuition, required in architecture and other creative industries. It also allows the architect

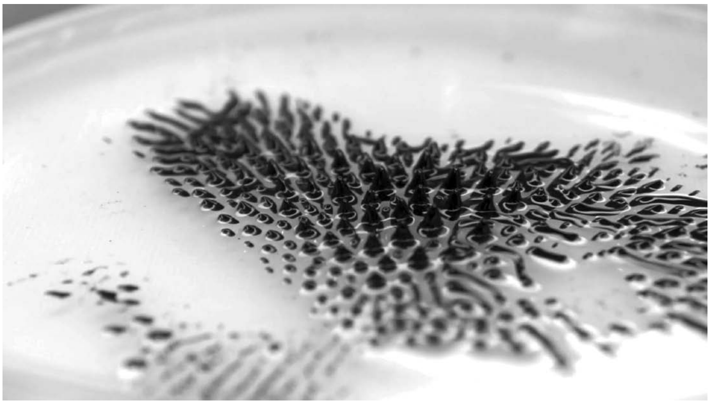

Figure 22.10 Ferrofluid patterns in Proteus 2.0 project. Photo: Maria Smigielska.

for more intricate communication with the physical world by opening and diversifying possible modes of production. While former developments in digital technologies addressed mainly geometrical complexity and design freedom, AI has the chance to affect architecture at multiple scales and dimensions. Thus, it requires a massive leap of experimentation and imagination, which might remain the biggest challenge for designers on the way to build architectural scenarios through AI models and methods.

As theorist Stephan Trüby has stated, architecture is "perhaps the most complex cultural technology that humanity has produced" (Trüby, 2017), and therefore its quality is difficult to measure. It is not about maximizing a target value of a function such as stress or compliance. Instead, it is arguable and uncertain if a function to measure quality even exists. If so, its parameters are unknown, more complex, impossible to be evaluated from the perspective of a single discipline, and far less intuitive to describe than most conventional features extracted for image classification. While it is impossible to encode all the architectural interests at once, we can progressively harness the AI models' powerful ability to find hidden and often inexplicable connections in vast amounts of data, to guide our decision-making among myriads of options.

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