The Routledge Companion to Artificial Intelligence in Architecture

Providing the most comprehensive source available, this book surveys the state of the art in artificial intelligence (AI) as it relates to architecture. This book is organized in four parts: theoretical foundations, tools and techniques, AI in research, and AI in architectural practice. It provides a framework for the issues surrounding AI and offers a variety of perspectives. It contains 24 consistently illustrated contributions examining seminal work on AI from around the world, including the United States, Europe, and Asia. It articulates current theoretical and practical methods, offers critical views on tools and techniques, and suggests future directions for meaningful uses of AI technology. Architects and educators who are concerned with the advent of AI and its ramifications for the design industry will find this book an essential reference.

Imdat As is the recipient of the prestigious International Fellowship for Outstanding Researchers and a grant from the Scientific and Technological Research Council of Turkey (TUBITAK). He researches and teaches at the Istanbul Technical University (ITU). Imdat received his BArch from the Middle East Technical University (METU), his MSc in architecture from the Massachusetts Institute of Technology (MIT), and his doctorate from the Harvard University Graduate School of Design. He has coauthored *Dynamic Digital Representations in Architecture: Visions in Motion* (Taylor & Francis, 2008). In 2011, he founded Arcbazar.com, a first-of-its-kind crowdsourcing platform for architectural design, which has been featured as one of the "Top 100 Most Brilliant Companies" by the *Entrepreneur* magazine. In 2017, he used Arcbazar's design data through a DARPA-funded research project to generate conceptual designs via artificial intelligence (AI). Imdat is currently heading the City Development through Design Intelligence (CIDDI) lab at ITU and investigates the impact of emerging technologies on urban morphology and the future of the city.

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Contents

List of contributors *viii*
Preface *xvii*
Acknowledgments *xxi*

PART 1
Background, history, and theory of AI **1**

1 Significant others: machine learning as actor, material, and provocateur in art and design 3
Kyle Steinfeld

2 Sculpting spaces of possibility: brief history and prospects of artificial intelligence in design 13
Daniel Cardoso Llach

3 Mapping generative models for architectural design 29
Pedro Veloso and Ramesh Krishnamurti

4 The network of interactions for an artificial architectural intelligence 59
Can Uzun

PART 2
AI tools, methods, and techniques **91**

5 Machine learning in architecture: an overview of existing tools 93
Ilija Vukorep and Anatolii Kotov

6 Fundamental aspects of pattern recognition in architectural drawing 110
Tyler Kvochick

7 AI as a collaborator in the early stage of the design 130
Sam Conrad Joyce

8 AI in space planning 160
Danil Nagy

9 Generating new architectural designs using topological AI 182
Prithwish Basu, Imdat As, and Elizabeth Munch

PART 3
AI in architectural research 205

10 Artificial intelligence in architectural heritage research: simulating networks of caravanserais through machine learning 207
Guzden Varinlioglu and Özgün Balaban

11 A deep-learning approach to real-time solar radiation prediction 224
Theodoros Galanos and Angelos Chronis

12 Artificial intelligence and machine learning in landscape architecture 232
Bradley Cantrell, Zihao Zhang, and Xun Liu

PART 4
Case studies of AI in architecture 249

13 Combining AI and BIM in the design and construction of a Mars habitat 251
Naveen K. Muthumanickam, José P. Duarte, Shadi Nazarian, Ali Memari, and Sven G. Bilén

14 Toward dynamic and explorative optimization for architectural design 280
David W. Newton

15 Synergizing smart building technologies with data analytics 301
Andrzej Zarzycki

16 Explainable ML: augmenting the interpretability of numerical simulation using Bayesian networks 315
Zack Xuereb Conti and Sawako Kaijima

17 Image analytics for strategic planning 336
Aldo Sollazzo

18 Urban development predictor: using development pipeline data to predict San Francisco's growth 350
Skidmore, Owings & Merrill (SOM)

19 AI in crowdsourced design: sourcing collective design intelligence 364
Imdat As, Prithwish Basu, and Sergey Burukin

20 Interfacing architecture and artificial intelligence: machine learning for architectural design and fabrication 380
Bastian Wibranek and Oliver Tessmann

21 Machining and machine learning: extending architectural digital fabrication through AI 394
Paul Nicholas

22 Augmented intuition: encoding ideas, matter, and why it matters 405
Mathias Bernhard, Maria Smigielska, and Benjamin Dillenburger

23 AI and architecture: an experimental perspective 420
Stanislas Chaillou

24 An anonymous composition: a case study of form-finding optimization through a machine learning algorithm 442
Akshay Srivastava, Longtai Liao, and Henan Liu

Index *453*

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(DNN) training by automatically parallelizing DNN workloads on fast network hardware. Prithwish recently served as an associate editor for the *IEEE Transactions of Mobile Computing* and was the lead guest editor for the *IEEE Journal of Selected Areas in Communications* (*JSAC*) special issue on network science. He has coauthored over 110 peer-reviewed articles (in conferences, journals, and book chapters) and has won the best paper award at the IEEE NetSciCom 2014 and PAKDD 2014. He was also a recipient of the *MIT Technology Review*'s TR35 (Top 35 Innovators Under 35) award in 2006.

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Preface

Over the last few years, research in AI has exploded thanks to fast developments in deep learning systems—a branch of AI, which uses neural networks that loosely mimic the inner workings of the human brain. Deep learning has been utilized on a wide range of every-day applications, from voice recognition systems, such as Siri and Alexa, to self-driving cars, to online recommendation systems, language translation, and pricing algorithms. Deep learning algorithms discover latent patterns and relationships in large amounts of data, which may not be apparent to humans looking at it independently. For example, one can train a neural network to recognize dogs by training it with millions of dog images. Once the system knows what an image of a dog entails—by means of a discovered internal representation—it correctly predicts and classifies a dog in new images, even if the training data did not contain any samples of dogs looking like the one in the test sample. In 2015, the accuracy of neural networks identifying objects in images has surpassed that of human vision (He, Zhang, Ren & Sun, 2016). This is important, for example, for autonomous cars, where the instant discrimination of objects in real-time video feeds is essential to the success of steering cars safely on the road.

More broadly, the field of *AI and ML* consists of *unsupervised learning*, where algorithms work toward detecting patterns in unlabeled data; *supervised learning*, where algorithms *train* on labeled data and perform classification or prediction tasks on new *test* data; *generative algorithms*, which attempt to generate new samples given some input parameters; and *reinforcement learning*, where algorithms interact with a stochastic environment and interact with it to make utility-optimizing decisions. Not surprisingly, besides deep learning, AI—and ML in general—has a rich ensemble of other branches that researchers have extensively explored and are still actively exploring. Some of these branches are classified under symbolic or rule-based AI, e.g., expert systems, genetic algorithms, swarm intelligence, and so on; others make heavy use of statistical reasoning, e.g., support vector machines, Bayesian reasoning, and of course artificial neural networks; and, yet others are a hybrid of these two approaches, e.g., robotics.

However, using AI in architecture is complicated. Architecture is not a two-dimensional labeling problem but presents us with a three-dimensional spatial problem that is shaped by a broad set of interdependent issues. In his treatise *De Architectura*, written in 80 BC, Vitruvius wrote that any successful architecture should provide for function, beauty, and structure. And, Walter Gropius in *Scope of Total Architecture* claimed that "good architecture should be a projection of life itself that implies an intimate knowledge of biological, social, technical and artistic problems" (Gropius, 1970). Architecture thus needs to respond to (im)material and contextual conditions as well. As Gropius (1970) says, architecture has to "satisfy the human soul" and has to inevitably respond to aesthetic questions and structural efficiency and deal with contextual, ideological, sociocultural, and economic constraints and opportunities.

Therefore, AI has to be able to deal with three-dimensional space and at the same time respond to questions dealing with the wider scope of architecture.

Throughout history, architects developed various tools and techniques to describe the three-dimensional space and communicate their design intentions, e.g., drawing conventions, design templates, pattern books, and so on. In 1979, Lothar Haselberger, an architectural historian at the University of Pennsylvania, discovered one of the earliest templates used in architecture—at the Temple of Apollo, 334 BC, in Didyma, Turkey. Various geometric diagrams were incised onto the temple's inner cell depicting scaled-down blueprints that masons were using while building the columns. Similarly, researchers at Stanford University, at the Digital Forma Urbis Romae Project (formaurbis.stanford.edu), discovered pieces of an entire plan drawing of the city of ancient Rome, chiseled on an 18-m to 13-m marble wall at the Templum Pacis, dating back to 203 BC. Other graphic conventions emerged piecemeal over centuries, e.g., section cuts in the 13th century, perspective views in the 15th century, and axonometric drawings in the 17th century (Ackerman, 2000). These graphic conventions make up the drafting toolkit architects are still using today to communicate and execute their design work. Early computer-aided design (CAD) applications have translated them into digital media, mainly replacing paper and pencils with a monitor and mouse.

However, the use of computers in a more substantive manner has been a popular topic of research since the early 1960s, e.g., shape grammars, expert systems, and fractals, and later in the 1990s, agent-based modeling, L-systems, simulations, and animations. From the early 2000s onward, CAD software moved gradually to smarter parametric and building information modeling (BIM), which captures additional data beyond geometry, such as materials, scheduling, cost, and so on. BIM and software plug-ins such as Grasshopper and Dynamo offer visual programming interfaces for architects to formulate and generate rule-based parametric designs.

Recent developments in AI are furthermore shaping the next generation of computer-aided design tools. AI offers immense opportunities, and it may not only produce another novel toolkit for architects but also has the potential to cause a deeper disruption in the profession. If effective, AI will have an impact on architecture that can be compared to the invention of perspective drawing in the Renaissance. Ackerman (2000) argues that the latter was as important as the introduction of the paper to the world. It will fundamentally challenge how we conceive and produce architecture. What if, for example, AI could automatically generate multiple design solutions to a given architectural problem? For an architect, it could be similar to sourcing solutions from a team of colleagues working simultaneously on a given problem set. The architect could review the results, pick a particular solution, and tweak it further. Or, more interestingly, what if another AI system could tailor solutions directly to the client? In this scenario, a client could input various constraints and receive a fit solution that a local contractor could implement, perhaps even 3D print on the site. Although these scenarios are still elusive—at least end-to-end—current work in the field suggests a big leap forward toward automated design, deviating radically from traditional design approaches—a development that unavoidably poses important questions for architectural theory and raises puzzling issues for those who are concerned with the future of architectural practice and education.

In this book, we explore how AI is currently used by architectural researchers and practitioners. In four parts: (1) theoretical and historical background; (2) AI-based tools, methods, and technologies; (3) AI in architectural research; and (4) case studies of AI used in real-world projects—this book gives a broad overview of AI in architecture and offers a variety of perspectives. It contains 24 illustrated contributions examining illustrative work on AI from around the world, including the United States, Europe, and the Far East.

Content

In Part 1 of the book, we give an overview of the history of computation and situate AI within the overall context of computer-aided design in architecture. We discuss how AI differs and relates to traditional means of architectural design and production. Kyle Steinfeld discusses how AI/ML can be used in the architectural field to generate controlled new designs (as an *actor*), to help human designers to tap into prior architecture/design knowledge (as the *material*), or to even act as a *provocateur* to stimulate creative action directly at the start of the design process. Daniel Cordoso gives an overview of the history of ML as it relates to architecture. In particular, he shows how the experimental tradition of computational aesthetics and design underpins present-day approaches to architecture and AI. Pedro Veloso and Ramesh Krishnamurti map the scope of generative design tools. Can Uzun analyzes the "social" network of outstanding contributors to the AI field and how different fields of study "interacted" with each other to shape the emerging field of "artificial architectural intelligence."

In Part 2, we survey state-of-the-art AI-based tools, methods, and technologies. We highlight the ones that have been particularly explored in architecture—with examples of where and how they have been used. We introduce various branches of AI, e.g., ML, evolutionary algorithms, fuzzy logic, and so on—and examine their applicability in architectural design. Ilija Vukurep and Anatolii Kotov give an overview and evaluation of the existing ML tools, e.g., ones that perform multi-objective optimization, via concrete design examples. Tyler Kvochick provides a general overview of AI and how its components can be useful for classifying common structures found in architectural design. Sam Joyce shows us how AI has been used as a collaborative tool in the early stages of the design process, i.e., the conceptual design phase, which he breaks down into the site analysis, creative design ideation, and iteration with user feedback. Danil Nagy investigates the use of AI and optimization algorithms in space planning, e.g., assigning programs to available spaces. And the editors discuss how succinct graph-based and topology-based representations of building information enable one to run cutting-edge graph-AI algorithms to discover patterns and generate novel designs.

In Part 3, we explore the application of AI in architectural research. Gulden Varinlioglu and Özgün Balaban present a case study where they use AI to predict and identify long-lost caravanserais along the historic silk road in Anatolia. Theodore Galanos and Chronis Angelos present their work on using AI in real-time solar radiation prediction, and Bradley Cantrell et al. discuss how AI has been used in landscape architecture and debate how it differs from AI applications in other fields of research.

In Part 4, we present the best practice models showcasing the use of AI at various phases of a building's life cycle, from conceptual design to fabrication. We structured this part into three categories of AI use-cases, loosely adjusted from Kyle Steinfeld's introduction, i.e., the discussion of AI/ML as an *actor*, *material*, and *provocateur*. The first set of articles examine AI as an *aid* in the design and/or production processes, for example, in optimizing various aspects of design, fabrication, structure, and so on; the second set of articles present AI as controlled *coauthors*, where it works hand in hand with architects in probing architectural solution spaces. And, the last set of articles explore AI as a *disruptor*, for example, in generating unprecedented designs in a freer manner.

Naveen K. Muthumanickam et al. demonstrate the use of AI to 3D print a series of enclosed spaces developed for NASA's Mars Habitat Centennial Challenge. David Newton elaborates on multiobjective optimization and presents us with two stimulating case studies where AI has been used in housing projects and in the development of intelligent façade systems. Andrzej Zarzycki discusses how continuous data analytics can enable smart building technologies. Zach Xuereb Conti and Sawako Kaijima offer an overview of explainable AI, whose goal is to explain the relationship between the human-understandable structural features and functions of designs. Aldo Salazzo presents AI in urban image analytics and strategic planning processes for Barcelona. SOM (Skidmore, Owings & Merrill) describe their work on an AI-based future urban development predictor they used for San Francisco—from a plethora of currently measurable features. And, the editors discuss online crowdsourcing, and how AI has been utilized in its modus operandi. The next three articles focus on AI-enabled robotics applied to architectural production. Bastian Wibranek and Oliver Tessman explore modular design processes, concepts for autonomous robots, and man–machine collaboration that challenges the classical separation between design and construction, and demonstrate these through inspiring case studies. Paul Nichols investigates the application of AI algorithms in robotic fabrication of structures such as metallic "stressed skins." Mathias Berhard et al. show how AI has been used in encoding ideas and matter in robotic fabrication as well as for generating compliant designs—by using topology optimization and GANs hand in hand. Stanislas Chaillou showcases thought-provoking AI-generated architectural layouts obtained by training GANs on images of architectural floor plans, and Akshay Srivastava et al. illustrate how "form-finding" optimization algorithms from AI have been integrated in design generation and evaluations.

In this book, we give an overview of AI, situate it within the broader architectural technologies discourse, and showcase its current use-cases in architectural research and practice. We offer critical views on the prevailing tools and techniques and suggest future directions for meaningful uses of this nascent technology. Architects and educators who are concerned with the advent of AI and its ramifications for the architectural design space can take this book as an essential reference. It is the most comprehensive source available that surveys the state of the art of AI as it relates to architecture and discusses major questions around this fascinating topic. AI is a fast-moving field of research and many more articles will undoubtedly be written on topics related to this book by the time it is published. We hope the reader will find this particular collection of articles as a useful starting point to their journey in research on AI in architecture.

Imdat As and Prithwish Basu

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Imdat As and Prithwish Basu

Part 1

Background, history, and theory of AI

1

Significant others

Machine learning as actor, material, and provocateur in art and design

Kyle Steinfeld

Artificial intelligence is a famously slippery concept, not because it is difficult to grasp, but rather because we hold a dynamic understanding of intelligence. It has been long observed (McCorduck, 1979) that once a capacity previously thought of as uniquely human is replicated by a machine, this capacity is redefined as an act of computation rather than one of true intelligence. In what has become known as the "AI effect," chasing the constantly moving target of mimicking human "intelligence" is a problem acutely felt in research, as major successes in AI are "soon assimilated into whatever application domain they [are] found to be useful in" (McCorduck, 1979). This shifting of goalposts may present frustration for AI researchers, but it also offers those of us in domains that benefit from advances in AI, such as architectural design, a different sort of opportunity.

The "AI effect" observes that, with each advancement in AI, the learned capacity – playing chess, identifying objects in images, composing a sonnet – is devalued as a mechanistic act: an act of calculation rather than a unique product of a creative mind. While this re-framing may blunt the significance of the achievement for those researchers who seek the advancement of AI, it simultaneously requires that intelligence itself be reconsidered by the rest of us. It is through this process that, in the service of maintaining the gilded position of human consciousness, the inability to precisely define intelligence is laid bare, reduced to "whatever machines haven't done yet" (Tesler, 1970). While such a challenge to the preeminence of human intelligence suggests that we might adopt a defensive posture, a posture that may explain some portion of the anxiety surrounding architectural applications of AI that may be observed today, we might instead focus on the benefits of the self-reflection latent in the AI effect. A clear-eyed examination of the nature of the newly learned abilities of machines may offer us new insight into, and renewed appreciation of, related human capacities. The AI effect cuts two ways: devaluing the significance of advancement in the science of the artificial, while simultaneously mobilizing a reconsideration of the human.

It is for this reason that, despite legitimate concerns regarding the broad and potentially negative social impacts of automation in design, I remain optimistic that the "assimilation" of recent advances in AI holds promise for the advancement of architectural design. It is this optimism that leads me to expect that we may look back at this time, not as the moment when the creative intelligence of a human designer had been effectively supplanted by some artifice, but rather as a moment of opportunity to reconsider what it means to act as a creative author in the first place. And so, rather than marking this time with a defense of those many aspects of design that have not yet (and may never) be threatened by automation, let us instead consider the ways in which this moment might, as similar proceeding moments have done, catalyze a reconsideration of the relationship between the tools of design and the culture of architectural production.

In this spirit, we may observe that the introduction of tools based upon machine learning (ML) represents one moment in an established history of adjustments of our engagement with descriptions of form and space. To the graphical and mathematical descriptions that characterized CAD in the early 2000s, we added procedural and logical descriptions with the advent of scripting and parametric modeling, and now have begun to take seriously descriptions based on data and generative statistics. For clarity, while I refer to previous models as "computer-aided design" to disambiguate emerging models as "machine-augmented design," I leave it to the reader to determine for themselves the gravity of this difference. As each of these previous shifts has reconfigured our position as authors, as well as our relationship with our work and the way we work with others, we may apply a set of lenses here similar to those that have been applied in the past. Following these previous efforts, to fully account for any pivot from one model of computer assistance to another, we are obligated to take stock of at least three broad categories of change:

- How a new model might facilitate different forms of subjectivity in design; to position us differently as individual authors in relation to our work.
- How a new model might upend existing networks of power; to support a new division of labor or engender a redistribution of design authorship.
- How a new model might necessitate different forms of knowledge; to require new competencies of designers or encourage new alliances between architects and other disciplines.

Such a project, however urgent, demands more than the constraints of this chapter allow. For now, while there are good reasons to look at how machine-augmented design tools will organize design activity differently at social and societal levels, let's adopt a more modest focus. Seeking a position within the long-studied history of the relationship between technologies of design and an architect's subjectivity, here I'll consider the narrow question of how ML tools might impact design activity at the individual level – the level of a sole human author in collaboration with a machine "partner."

In the sections that follow, I offer a sketch of a number of models that may be observed based on emerging trends in machine-augmented design practice. Each may be defined in terms of how it situates the use of ML in design differently. Speaking in such terms, and in summary, these models are ML as actor, ML as material, and ML as provocateur.

I'll begin with an account of those who see ML as an "actor" in design that is usefully regraded as on a par with human actors. Here, I'll mention a number of designers and fine artists who seek to uncover and instrumentalize the way a neural network "sees," and who set their work in relation to the essential qualities of neural networks in a manner that recalls certain aspects of the Modernist project. Next, we acknowledge those who take the position that ML is more like a new form of design "material." This work may be seen as holding to a well-established model for the integration of digital techniques into design culture, one that draws from a long craft tradition that predates the profession itself. Finally, we present a model for the use of ML in design as a "provocateur" and, in the spirit of the surrealist concept of automatism, draw from the capacity for ML as an instrument of the associative and imaginary rather than the rational.

In our account of each of these models, we draw from creative practices in the fine arts and architecture alike and seek to identify those past thinkers that appear to hold sway over approaches taken by current adherents. Further, we seek to address a number of practical questions:

- Is it possible to discern any new authorial roles or new domains of action for a creative author? Where are the new loci of authorship?
- What decisions would be left to the machine (indirect, differed authorship) and which would be claimed by a human author closer to the execution of a design?
- By what qualities would we recognize a practice that follows this model? What are the related tools, methods and procedures?
- What are the currencies of this new practice? Which performances of a design would an author value?

ML as actor

Among the designers and artists working with ML, there are those who seek to establish an authorial position in relationship to a nominal "machine intelligence" that operates as a co-creator on a par with, or acting as a surrogate for, a human counterpart. Here, authors operate in a necessarily indirect way, as orchestrators of formal systems of training, generation and selection that effectively serve as "a machine that makes the art."[1] Often in this context, efforts are made to uncover some essential quality or predilection associated with the underlying technology, an effort which we may observe in claims of revealing the way a machine "sees" or "understands space" differently than humans do.

Recalling recently developed approaches in architecture, such as generative design and emergent design [see Nervous System (Rosenkrantz, 2011) and Casey Reas (Reas, 2006)], and less proximate practices that originate in the art world [see Sol LeWitt and Joan Truckenbrod (Paul, 2018)], the role of a creative author working in this way is decidedly hands-off and is often limited to the establishment of a system that facilitates the emergence of forms and patterns. Authors typically refrain from guiding this process of generation and, at times, even forgo selecting from among the iterations that are produced. This position of "deferred authorship" (Steinfeld, Fox, and Spatzier, 2014) is not a new form of subjectivity in the arts and design, but may be seen as a radical extension of a form that extends at least as far back as the 1960s.

We may recognize a practitioner of this model by the degree to which an ML process is personified as an independent actor in the creative process. Particularly devoted adherents to this approach may at times invoke the "posthuman," a term that acknowledges that "the boundaries between human and computational cognition are increasingly blurred" (del Campo, Manninger, and Carlson, 2019). For those adopting such a position, the limited nature of today's decidedly narrow (Jajal, 2020) AI tools does not appear to diminish the utility of regrading them as a form cognition on a par with human thinking. No matter the degree of devotion of an author, we may observe that the performances and properties valued in the artifacts produced by such a model are often left unspoken or are related to the revelation of some essential quality of ML itself. Because authors necessarily operate at a meta-level, as composers of a system rather than participants in it, they often avoid claims or justifications that center themselves, and tend to step aside as an objective presenter of what their machine counterpart has produced. Since, at times, the system for producing artifacts (rather than the artifacts themselves) is seen as the authored work, in place of value claims related to artifacts, we find more elaborate observations on what "it," the system, did.

As an extension of previous trends – such as generative design, procedural design, and a passing interest in theories of complexity and emergence in design[2] – the rhetoric surrounding this model of creative practice in architectural circles tends toward the grandiloquent. In contrast to these relatively breathless accounts, it is notable that those who work more closely with the underlying technologies tend to be more direct in articulating that the personification of an ML "partner" in creative production is a contrivance, but a useful one.

A clear exemplar of this directness is the artist Tom White, whose works "The Treachery of ImageNet" and "Perception Engines" employ image classification models to produce abstract ink prints that reveal the visual concepts latent in a number of widely used computer vision processes. Speaking of this work in 2018, White outlines his position as a refreshingly nuanced expression of "machine intelligence" without negating his own subjectivity. Speaking in 2018, White states:

> I think of the computer as a tool or – if I'm being gracious – as a collaborator… I'm setting up a system where the computer can express itself, but the intent is my own. I want people to understand how the machine sees the world.
>
> *(Kazmin, 2018)*

Mario Klingemann, another AI art practitioner exhibiting work in the same 2018 exhibition, adopts a starker position, more forcefully asserting: "I am the artist, there is no question at all. Would you consider a piano the artist?" (Kazmin, 2018).

The forthrightness of Klingemann and White stands in stark contrast to the way that similarly positioned architectural designers describe their work. In the project "Imaginary Plans," architects Matias del Campo and Sandra Manninger collaborate with computer vision specialist Alexandra Carlson to propose ML systems that "learn, recognize, and generate novel plan solutions for a variety of architectural features, styles, and aspects" (del Campo, Manninger, and Carlson, 2019). While, at the time of writing, the work remains at a nascent stage, the stated ambition is a clear illustration of the desire for an autonomous "machine intelligence" in design. We can see this reflected in the range of claims surrounding new forms of architectural authorship that operate systemically rather than compositionally, for example, the notion that we might design through a process of style transfer, such that "iconic buildings in architecture can have their styles 'quantified' and transferred to other iconic buildings" (p. 415); or that we might design through a curation and mixing of imagistic influences, such that "floor plans [may] emulate aesthetic elements from the other nonfloor-plan images" or "be fused with other buildings to generate novel architectural types" (p. 416). While the underlying technologies are still in development, the "Imaginary Plans" project demonstrates how some designers are interested in uncovering radical new subjectivities "that question the sole authorship of human ingenuity" (p. 417).

Whereas "Imaginary Plans" seeks an autonomous generative tool to architectural design, we might also consider the possibility of an autonomous analytical tool. The generative adversarial network (GAN) Loci project (Steinfeld, 2019) proposes just this. Here, a GAN is trained to produce synthetic images intended to capture the predominant visual properties of urban places. Imaging cities in this manner represents the first computational approach to documenting the forms, textures, colors, and qualities of light that exemplify a particular urban location and that set it apart from similar places. The conceit of the project is that something like the genius loci of a city may be captured not as seen through the eyes of a human inhabitant, but rather from the viewpoint of a "machine intelligence." We might observe that the resulting images evoke GAN-ness just as much as they suggest the cities from which they are drawn.

This criticism, that a work speaks more of the process by which it was produced than it does to any external subject, may be fairly applied to much of the work produced under the ML-as-"author" model. Indeed, reflecting on the examples discussed in this section, we could reasonably argue that what has been captured is speaks more to the essential qualities of the underlying ML model than it does any inherent features of the world, which is both the strength of the "actor" approach and its failing.

ML as material

There are those who regard ML as a new form of design material, and, evoking the long tradition of developing tacit knowledge through the accumulation of direct experience, seek to cultivate a mastery of this new form in combination with well-established practices. As discussed above, when regarded as an "actor," we might seek out the tendencies and predilections of a constructed machine intelligence, just as we might with a human co-creator. In contrast, when regarded as a "material," we would be more interested in the properties and capacities of this medium in their active application, just as we might with any other expressive mode. This is to say that there are designers who seek to master the affordances of ML by engaging in a material practice similar to those employed by a craftsperson. This position is well summarized by the adage "we shape our tools, and thereafter our tools shape us."[3]

Adopting such a position relative to digital media is in no sense new. Writing in the mid-1990s, Malcolm McCullough argued that the actions and mind-sets supported by digital design media are not so different than those supported by traditional media. Where traditional media enables us to act in a visual and tactile way, computers "let us operate on abstractions as if they were things" (McCullough, 1996). McCullough draws out the continuities between traditional and digital crafts by describing the evolving notion of "type" across paradigms: In a craft context, a "type" refers to a particular material tradition; in an industrial production context, a "type" refers to a particular process of formation; and in software, a "type" refers to a particular conceptual abstraction. We might speculate that ML would occupy an interesting place in McCullough's account. In one sense, a "type" in ML operates as a conceptual abstraction, and may be seen as an extension of the general software type. In another sense, and in contrast to the explicit Object-Oriented-Programming construction of types in software (Ko and Steinfeld, 2018), because ML allows for implicit definition – either "by example" in a supervised learning context or discovered in an unsupervised learning context – an ML "type" may be better understood to recall certain aspects of traditional craft practices.

Following McCullough, we would recognize a practitioner of the "material" model of creative ML by the balance of attention paid to the situational curation of a training set in the service of creating a unique generative tool, and the brandishing of this tool in the crafting of a creative product. Whereas others find subjective positions at the meta-level – through the authoring of systems – those adopting a craft's mind-set operate at the meso-level – through direct engagement. While, as in the previous model, the development of a system is a central part of the creative process, the "system" in a material context is regarded more as a custom-built tool to be wielded by a master craftsperson.

Such an approach is widespread among early adopters of AI in the visual arts. In a spirit that recalls a number of craft traditions, Sougwen Chung, an artist who works with ML systems trained on images of her own drawings, claims to seek to uncover the "inherent, shared fallibility" of human and machine systems alike (Chung, 2019). Similarly, Helena Sarin, a visual artist and software engineer, notes that "neural art can still be personal and original, especially when generative models are trained on your own datasets" (Sarin, 2019). Finally, I would highlight the striking work of Scott Eaton, a mechanical engineer and anatomical artist who uses custom-trained image-to-image translation models as a "creative collaborator" in his figurative drawings (Eaton, 2020). Like Chung and Sarin, Eaton invests time in both shaping his tool, through the meticulous construction of a dataset of his own figure drawings, and allowing his tool to shape him, mastering the craft of augmented drawing through hours of daily sketching.

The Sketch2Pix drawing tool was largely inspired by Eaton's work, both in its technical approach and in its position as a tool of machine-augmented creativity. Sketch2Pix is an augmented architectural drawing tool developed to support sketching with automated image-to-image translation processes (Isola et al., 2016). The tool encompasses a "full stack" of processes required for novice users to conceptualize, train, and apply their own custom-trained AI "brushes." This holistic approach is critical to supporting the ML-as-"material" approach: First, a designer defines an indexical relationship between a hand-drawn mark and the qualities of an image it is mapped to, and only then identifies the "reason" for these images through the active composition of a drawing.

ML as provocateur

Disruption has long been shown to be a powerful tactic in stimulating creative action (de Bono, 2015). As such, it is perhaps no surprise that the notable capacity of AI for "weirdness" (Shane, 2019) should find application among artists and designers as an upender of stale practices, an instigator of new ideas and an agent of chaos. We may recognize a practitioner of ML as "provocateur" by their acceptance of a machine-generated artifact as a point of departure that mobilizes, or a catalyst that propels, a larger creative process.

The use of creative prompts in such a way is not a new tactic in the arts and design. Writing in the 1960s and extending the work of the surrealists, Pierre Boulez used the term "aleatorism" (Riley, 1966) to describe compositions resulting from actions made by chance. Later, in the mid-1970s, Brian Eno and Peter Schmidt published their well-known "Oblique Strategies" project (Eno and Schmidt, 1975), a series of prompts, printed on cards and randomly selected, in order to overcome creative blocks. Edward de Bono wrote exhaustively on the subject of the role provocation plays in creative process, coining the term "po" to describe an intentionally disruptive stimulus that is used to facilitate creative thinking (de Bono, 2015).

In contrast to the embrace of randomness found in some of these examples, ML offers a variation on creative provocation that has not been previously instrumentalized in quite the same way. To refine the well-described phenomenon of "AI weirdness" (Shane, 2019), I would suggest that, when employed as a creative prompt, a more productive quality might be termed the "AI uncanny." This distinction, separating the unrecognizably foreign from the disquietingly familiar, draws attention once more to the central locus of authorship critical to any application of ML in design: the dataset. To be specific, we can see that creative authors might willfully curate a dataset to produce ML systems that are "primed" to generate creative prompts with a particular character. This suggests the application of "directed" chance as a creative prompt, in contrast to the surrealist use of random chance. In this way, while the inner workings of an ML system are largely beside the point, certain affordances may be introduced to influence the properties of the artifacts they produce. For example, a neural net might be trained on a dataset that describes a particular genre of music, or a particular style of painting, not in order to faithfully reproduce these forms, but rather to provide an auspicious point of departure for an author who wishes to be so influenced. In this way, the ML system is not assigned any meaningful agency, nor is it regarded as a material to be mastered, but rather functions as an externalized or collectivized "association engine" to kick-start the creative process.

A clear example of the use of ML as a creative prompt may be found in the work of the dance punk band YACHT, most visibly in their album "Chain Tripping," which was nominated for Best Immersive Audio Album in 2020. Described as an AI "concept album," ML played a role at nearly every step of the production of this work, from the music itself, to the machine generation of lyrics and song titles from the band's previous albums, to a collaboration with AI artists (such as Tom White and Mario Klingemann, mentioned above) in the design of the album cover and promotional materials. Most relevant here is YACHT's approach to the composition of melodies and beats. In order to train a model called MusicVAE (Roberts et al., 2018a, 2018b) developed by the Magenta team at Google, YACHT compiled a dataset of the band's previous recordings. Once trained, MusicVAE allows for the blending of melodies, like the blending of colors on a painter's palette, in the resulting latent space of the band's own musical history. This process "allowed the band to find melodies 'hidden in between songs' in their back catalog" (Mattise, 2019). For our purposes, "Chain Tripping" is notable not only for this uniquely positioned generative tool, but for how YACHT deployed this tool in a larger creative process that clearly demonstrates the use of ML as a catalyst that propels creative action. Initially faced with a "massive body of melodic information" generated by machine (and expressed as MIDI data), the band treated this information only as point of departure. From there, "it became the humans' turn" (Mattise, 2019) to interpret, adapt, and compose the final work.

A similar example of the use of ML as a provocative starting point is the short film Sunspring (Sharp, 2016). Like "Chain Tripping," the originating document for this creative work, the film's screenplay, was generated by an AI based on a corpus of relevant historical material. Here, director Oscar Sharp and AI researcher Ross Goodwin collaborated to create a recurrent neural network dubbed "Benjamin," trained on a corpus of sci-fi screenplays from the 1980s and 1990s (Newitz, 2016). Just as MIDI data is not music, a textual screenplay is not a film. As such, the artifacts produced by Benjamin became fodder for the creative action of all the downstream parties responsible for interpreting and translating this screenplay into a film, including the actors, directors, set designers, and costume designers. In describing the value of Benjamin, a literal automaton, in their creative process Goodwin and Sharp echo sentiments found in mid-20th-century manifestoes on surrealism (Breton, 1969): "machines can help us be more classical, more personal, and more original" (Goodwin and Sharp, 2017).

In a final example that both hews closer to architectural design and precisely demonstrates the use of ML as an automatism to stimulate human imagination, we would present the work of Philipp Schmitt and Steffen Weiß. Here, as with the above examples, ML is positioned as a provocateur or "mind-bender" to catalyze a design process, in this case for the design of chairs. In 2018, Schmitt and Weiß trained an ML model, the widely used GAN DCGAN, on a corpus of images of iconic 20th-century chairs, and then allowed this model to generate hundreds of new images. These synthetic images were intentionally imperfect representations of chairs – some were blurry, some were nonsensical, and many were barely recognizable as objects at all. Perfect depictions of new chair designs were not the aim; rather, the authors sought to generate compelling "visual prompts for a human designer who used them as a starting point for actual chair design concepts" (Schmitt and Weiß, 2018). For this purpose, clear images are less desirable than those images that flicker between the suggestion of an object and the presentation of impediments to direct interpretation. For Schmitt and Weiß, "'seeing the chair' in an image is an imaginative and associative process. It pushes designers away from usual threads of thinking toward unusual ideas that they might not have had otherwise" (Schmitt and Weiß, 2018).

It was precisely this activation of an associative faculty that was sought by an undergraduate design studio at UC Berkeley in the Spring of 2020. The studio sought to understand how ML tools might function as tools of creative provocation in particular, and tools of early-stage design more broadly. In one exercise, students employed two separate ML models – one for the generation of text, and a second that generates images from textual captions – to create scenographic storyboards that were read as depictions of site and program, and that animated the beginning of a larger design project. By introducing novice students to experimental ML tools and processes, this studio illustrates the broad utility of these tools as design provocations.

Conclusion

The sections above outline three emerging models for machine-augmented design, detail how these are beginning to be applied in practice, and take stock of the emerging subjectivities. Understood as an "actor," at times imagined as a surrogate for or a coequal participant alongside a human actor, we find authors exploring new ways of "viewing the world" through the eyes of a machine intelligence, as well as the emergence of an important new locus of design authorship: the training dataset. Understood as a "material," we find efforts to leverage the unique capacity for ML to capture tacit knowledge through the accumulation of direct experience, efforts that further the project of bringing digital practices into closer harmony with craft practices. Finally, understood as a "provocateur," we find ML practices that seek to stimulate creative action at the start of a design process by supporting the associative over the deductive (Steinfeld, 2017), the "imaginary rather than the rational" (Schmitt and Weiß, 2018).

We might speculate that the examples presented here, however anecdotal, not only indicate a coming shift in the way design tools operate, but also suggest that this shift might accompany a broader reconsideration of the relationship between the tools of design and the culture of architectural production.

Notes

1 Adapted from "The idea becomes a machine that makes the art," attributed to Sol LeWitt in 1965 (Kosuth, 1966).

2 See Andrasek (2015), Snooks and Jahn (2016) and others of the time that offer unqualified and eager personifications of computational processes.

3 Attributed to Churchill or McLuhan or Maeda.

* An earlier version of this article was published in German in: *Machine Learning: Medien, Infrastrukturen und Technologien der Künstlichen Intelligenz*, edited by Christoph Engemann and Andreas Sudmann. Bielefeld: Transcript, 2017.

1 There are many terms used in the literature, such as generative system, generative model(ing), and generative design. In fields such as systems engineering and cybernetics (Ashby, 1956), system is used to comprehend the studied phenomenon as a cohesive organization composed of interacting parts that together produce results not obtainable by the parts in isolation. The term model refers to the representation of a system. We opted for the term generative model for three reasons: (1) it describes representations of concrete generative systems; (2) it can be considered an instance of

models used for design conception; (3) it also unifies the nomenclature of the diverse areas ad dressed in the chapter, such as mathematical models, geometric modeling, parametric modeling, agent-based models, rule-based models, and adaptive models in machine learning. We use the term generative design when we refer to an architectural practice or method that uses generative models.

2 While our representation is unique and represents our approach to the topic, it certainly has prece dents in the literature, such as Fischer and Herr (2001), Cagan et al. (2005, p. 172), Gänshirt (2007, pp. 78–79), Bohnacker et al., (2012, p. 461), Veloso and Krishnamurti (2019).

3 In the case of form-finding models, the formulation requires constraining existing natural phe nomena to make their behavior work as an algorithm for form exploration. In the case of a written procedure to generate a building element, the execution stage depends on the designer.

4 While the taxonomy shown here is not exhaustive, it is broad enough to subsume earlier classifica tions that were based, perhaps, on finer considerations, for example, AI techniques such as knowl edge representation, case-based reasoning, and expert systems. Some of the techniques might be a special case of the existing blocks or might fit in between the blocks.

5 These building blocks are related to a specific aspect of generative modeling, so it is important to distinguish them from the algorithms that they comprehend. For example, the Category "Opti mization" is mostly based on optimization algorithms for design synthesis. However, optimization algorithms are very general and can be applied for other ends, such as training neural networks (see Section "Learning").

6 For example, it is possible to rank sets of solutions based on their hypervolume in the objective space, to combine the different objectives in a singular fitness dimension, or to look for the non dominated elements in the set of solutions. Dominance is characterized between two solutions. A solution "a" dominates a solution "b" if it is no worse than "b" in all objectives and it is better than "b" in at least one objective. A solution is nondominated if no other solution in the set dominates it.

7 For example, calculus requires access to a continuous and differentiable function, and classic optimization techniques usually restrict the problem formulation to a specific analytical form, such as a convex space (Radford & Gero, 1988, pp. 48, 90; Boyd & Vandenberghe, 2004, pp. 1–2).

8 These examples are metaheuristics that use higher-level strategies inspired by nature to explore good solutions to an optimization problem (Brownlee, 2012). Genetic algorithm is inspired by evolutionary biology and uses natural selection operators (crossover and mutation). Simulated annealing is inspired by the process of annealing in metallurgy and uses a decreasing temperature to reduce the exploration of random solutions over time. Particle swarm optimization is inspired by the swarm behavior, such as flocking, and uses multiple particles to move, based on shared information of the positions of the best-known solutions.

9 The term composition is related both to function composition and architectural composition. In mathematics, this is an operation that sequentially applies two or more functions (e.g., g(f(x))). In architecture, it is related to the process of creating an architectural configuration.

10 While there is an overlapping, it is important to distinguish the idea of generative models for design (the topic of this chapter) from generative models in machine learning.

11 Usually it is assumed that there is no correlation between the dimensions, so the encoder can output the vectors with the mean and the variance (or the logarithm of the variance).

12 This workflow relies on the Markov property, so the probability of moving to a state s and receiving a reward r is only dependent on the information stored in s and the action a selected.

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