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Artificial intelligence and machine learning in landscape architecture

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The questions of a rapidly changing climate and increased need for confronting social justice in environmental design pose an epistemological crisis in an age of upheaval. The role of new forms of intelligence becomes particularly important for the discipline of landscape architecture as it embraces the curation and choreography of living matter. The relationship between the designer and the living, the medium of landscape architecture, is fraught with a range of anachronisms that are coming to light in contemporary society.

The discipline of landscape architecture

In response to the environmental movement, the discipline of landscape architecture has adopted ecology as a model stemming from the teaching and practice of Ian McHarg. Through nearly 60 years of co-development with ecology, the early concept that the environment is a homeostatic system continually marching toward equilibrium through ecological succession has shifted toward nonlinearity and indeterminism. The contemporary view that has formed positions the environment in a constant process of unfolding with different landscape types emerging and disappearing. Projects such as the Downsview Park competition entry Emergent Ecologies (2000) as well as the Freshkills Park design (2003) have become exemplars for a design paradigm that focuses on emergence and open-endedness; landscape architects articulate process-based strategies that influence processes in different systems—ecological, socioeconomic, cultural, technological—imbuing those systems with agency resulting in landscapes that possess a range of open-ended outcomes.

In the 1990s, post-humanism made its way into the intellectual discourse, and the ecocentric and/or biocentric values in landscape architecture were further enriched by the theoretical frameworks of new materialism, actor-network theory, and object-oriented ontology. Jane Bennett’s scholarship has pushed landscape architects to develop a sensibility toward the biophysical world via relationality and through the promotion of agency across objects and beings. Bennett states that “bodies enhance their power in or as a heterogeneous assemblage…” and “…the efficacy of effectivity to which that term [agency] has traditionally referred becomes distributed across an ontologically heterogeneous field, rather than being a capacity localized in a human body or in a collective produced (only) by human efforts.”
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(Bennett, 2010). Vital materialism acknowledges the network status of things, and “there was never a time when human agency was anything other than an interfolding network of humanity and nonhumanity” (Bennett, 2010). Brett Milligan, founding member of the Dredge Research Collaborative, acknowledges Bennett’s thinking, expressing that “we need a language for reading the landscape and a corresponding design sensibility with similar capacities for inclusion and complexity” (Brett, 2011). Post-humanist vocabularies have been incorporated into landscape lexicons, and many designers rely on these concepts to describe the design of landscape as a joint effort of many intelligent agents and assemblages. Therefore, the discipline of landscape architecture is cultivating an understanding that the environment is a result of the co-production of a wide range of intelligent agents, and the role of a designer is moved away from the source of authorship to a choreographer or catalyst among different assemblages that all have certain capacity to influence the environmental processes in a meaningful way. In this manner, landscape design uses process-based strategies to bring forth the potential of different intelligences in the environment and co-produce a shared future.

Challenges

Based on this understanding of the discipline, there are challenges when considering artificial intelligence in the field of landscape architecture. The challenge can be articulated in three areas: anthropocentrism, individualism, and means-end reasoning. First, in AI research, machine intelligence is still conceived as modeling and replicating human intelligence using machines, thus reinforcing human-centric values through AI systems. However, different species, entities, systems or assemblages, including machines, relate to their environment very differently. Imposing a human standard to evaluate machine intelligence essentially limits the potential of AI systems beyond anthropomorphic automation, repeating the known at faster rates. In fact, in many areas, we have already seen examples of AI systems that exhibit unexpected outcomes shedding new light on how human perception can be conceived differently. For example, through deep reinforcement learning (DRL) and self-play technique, DeepMind’s AlphaGO series have not only beaten the best human GO player, but also come up with strategies that human GO players have never seen before and are unique to the machine. It should be recognized that the game of GO is a strategy board game originated in China more than 2500 years ago. It is assumed that we have exhausted best strategies to win games. However, AlphaGO has developed strategies based on its own understanding of the game. It challenges the GO players to question how little humans have explored the game. In 2019, using the similar self-play method, DeepMind developed another AI system called AlphaStar that has reached grandmaster level (the highest rank one can reach by competing with other players) in a real-time strategy game StarCraft II. The AI community regards this experiment as a breakthrough because real-time strategy games such as StarCraft are infamously known for their “combinatorial action space, a planning horizon that extends over thousands of real-time decisions, and imperfect information” (Vinyals et al., 2019). After watching or playing with AlphaStar, many professional players reported that AlphaStar has devised many new strategies that they can actually learn from, and they believe AlphaStar was an unorthodox player who has provided new ways to understand the game itself. One commentator even reports that watching the AI play the game is like watching a drunken kung fu master performing martial arts, awkward but somehow outrageously effective (Two Minute Papers, 2019). As we can see, if we start to take on a nonanthropocentric view toward understanding machine intelligence, and intelligence in general, we can see heuristic values in AI systems in helping us form multiple understandings of the environment. AI systems
could help to provide a wide range of possible environmental strategies that are beyond contemporary best practices, and such novel strategies are desperately needed when humanity is faced with unprecedented climate change that exists at scales beyond human comprehension.

Second, we tend to apply an individualistic lens when thinking of intelligence, i.e., human intelligence, animal intelligence, and machine intelligence, and overlook the distributive quality of intelligence. The concept of hive intelligence or swarm intelligence speaks to the kind of capacity that only exists among an assemblage of entities, such as a colony of ants. This kind of intelligence can be understood as an emergent quality of the interactions between individuals based on simple rules. To some extent, understanding landscape as a co-produced effort recognizes the emergent intelligence among different agents. This type of hybrid intelligence is beyond the dichotomies of machine intelligence or human intelligence. However, current AI research lacks vocabularies and concepts for a nonindividualistic view for intelligence in both theory and practice. AI systems are considered as separated and distinctive models and algorithms that are designed and trained to perform a specialized task, such as image recognition algorithms with convolutional neural networks. This poses the second challenge for landscape architects to consider AI systems as an intrinsic part of a network of assemblages from which emergent behaviors are generated, thus limiting the designers to consider the open-endedness and the becoming and unfolding of the designed landscapes with embedded intelligent machines. In fact, some landscape experiments have already shown the possibility for hybrid intelligence. For example, designer Leif Estrada tested the sensing–processing–actuating framework in the project *Towards Sentience* using the geomorphology table at the Responsive Environments & Artifacts Lab (REAL) at the Harvard Graduate School of Design. The system is a sandbox consisting of a material feeder and a water outlet on the one end, and a series of sensors including ultrasonic distance detector and Microsoft Kinect sensor. The table can be used to simulate riverine hydro-morphology processes such as erosion and deposition. In one of the experiments, the designer proposed an actuating system called “attuner” that consists of a matrix of acrylic dowels connected to servomotors. Every dowel is separately driven by a servomotor, and the bottom portion of the dowel sticks into the sediments. When the servomotors turn, they drive the dowels moving up and down to influence the flow pattern, thus creating different landforms in the downstream of the sandbox. The topography is then live–tracked by the Kinect sensor above the table, forming a digital elevation model of the sandbox so that a series of high grounds and low grounds can be identified. This information then feeds back to the actuating system so that it could either build more land in a high ground by depositing more sand on it or erode the high ground away by directing more water toward it. The designer reported that the cyborg system exhibited a level of live updates and feedback that was beyond human capacity (Cantrell & Mekies, 2018). Even though there were no machine learning techniques involved in this experiment and the actuating was achieved through predefined rules, the results were inspiring. If we take a border definition of machine intelligence, the experiment represents a form of hybrid intelligence emerging from the interactions between machines and biophysical processes such as erosion and sedimentation.

Third, AI research cannot bypass the inherent means–end reasoning that is deeply rooted in Western thinking. In the Western philosophical tradition, one envisages an ideal form (*eidos*) as a model, and then, the model can serve as a goal (*telos*), which is at the same time an end that calls for actions. As French philosopher Francois Jullien puts:

> with our eyes fixed on the model that we have conceived, which we project on the world and on which we base a plan to be executed, we choose to intervene in the world and give a form to reality.

*(Jullien, 2004)*
Based on this line of reasoning, theory can be differentiated from practice, with the former being the basis for the model and the latter being a set of operations that make the model into reality. Most importantly, with the means-end relationship, the idea of effectiveness and measure can be tied into this habitual reasoning. Once a range of possible tools and actions are at hand, we can evaluate them and decide which one is the most effective. Efficacy becomes the concept that ties the means-end relation together. Finally, because we want to project an ideal model on the world and develop means to achieve this end, unexpected circumstances will always rise to undermine any plan of action and control regime, and thus, uncertainty denotes to those events that are outside the predictions allowed by the conceived model. Most AI systems are envisaged as means to an end; the industry of machine learning can be understood as a new wave of model-making for better prediction and control. Within a means-end reasoning, one is constantly challenged to deal with the tension between control and uncertainty. Nevertheless, contemporary landscape design theory and practice have bypassed the equilibrium and deterministic control paradigm and embraced the paradigm of emergence and an open-ended epistemology. This paradigmatic incommensurability poses another challenge to consider AI in the field of landscape architecture. Ideas such as prototyping are gaining their currency for they provide an alternative way for designers to approach ML and AI not as a means to construct simulations and predictive models, but as prototypes that inspire a wide range of possibilities (Figure 12.1).

These specific issues urge landscape architects and scholars to think and theorize AI and ML differently. In this vein of research, responsive landscapes framework is foregrounded to emphasize responsive technologies not as a layer on top of, but as a network that is deeply interwoven with the environment. The diagram illustrates this shift in paradigm, highlighting the role of AI and ML in environmental practices. In a means-end relationship, mainstream AI research regards machine learning techniques as effective means in making predictive models for better control strategies (top). In this framework, uncertainty represents the gap between models and the environment, and we are challenged to close the gap by making more accurate models. In contrast, embedded within the paradigm of emergence, machine learning practices become prototyping practices and ML models become prototypes that offer a wide range of possibilities for the future (bottom). Uncertainty becomes the source for emergent behavior and possibilities.

Figure 12.1  Role of AI and ML in different paradigms of environmental practices. Trapped in a means-end relationship, mainstream AI research regards machine learning techniques as effective means in making predictive models for better control strategies (top). In this framework, uncertainty represents the gap between models and the environment, and we are challenged to close the gap by making more accurate models. In contrast, embedded within the paradigm of emergence, machine learning practices become prototyping practices and ML models become prototypes that offer a wide range of possibilities for the future (bottom). Uncertainty becomes the source for emergent behavior and possibilities.
embedded in, the environment (Cantrell & Holzman, 2015). In a thought experiment, scholars have imagined a DRL machine called “wildness creator” that can devise environmental management strategies that are beyond human comprehension and create “wild” places (Cantrell, Martin & Ellis, 2017). Real case studies and unpacking how engineers use machine learning to train models to manage stormwater systems have provided empirical evidence that intelligent machines could be deeply ingrained in the environmental processes. And, more importantly, a post-humanist ethics is needed to overcome anthropocentrism and recognize machine intelligence when theorizing and applying ML and AI in the landscape discipline (Zhang & Bowes, 2019). In light of post-humanism, the concept of “third intelligence” can help to theorize machine intelligence as one of many types of intelligence, such as human intelligence and material intelligence, that coevolve and co-produce the shared environment (Cantrell & Zhang, 2018).

Case studies across disciplines

In the past few years, the environmental management discourse has seen an emerging paradigm of research and practice that revolves around cybernetic models and uses technologies such as sensing networks, artificial intelligence, and machine learning to regulate, control, and manage environmental processes. Design professions have seen similar practices, such as sensing stations for site monitoring, portable sensing kits for participatory planning, and physical responsive models for environmental simulation. These explorations have a deep root in the cybernetics movement since the 1940s when an interdisciplinary team of scholars has converged onto a new theoretical model that is based on system and machine to understand biological, mechanical, and communicational processes. Over the past some 70 years, cybernetics movement has developed from early focuses on homeostatic system and negative feedback to contemporary concerns over emergence and open-ended behaviors of evolving systems. Most importantly, core concepts such as feedback, self-production, self-organization, and emergence have instilled into different disciplines including landscape architecture (Lystra, 2014). The field of cybernetics thus provides us with concepts and a common ground to discuss ML and AI with different disciplines, and cases from across disciplines can be understood, compared, and analyzed under a single framework. We can use concepts such as homeostasis, self-organization, feedback, feedback, and emergence to understand their concerns when different disciplines incorporate ML and AI in their research and practice (Figure 12.2).

Engineering

In the engineering professions, cyber-physical systems become the new frontier for environmental management. In these systems, data collected by sensors are often used to train models to predict scenarios for control strategies. A group of researchers from the University of Michigan is developing real-time watershed control infrastructure. By installing sensors and actuators in a stormwater system, their goal is to develop responsive infrastructures that can be implemented to allow large cities to control flooding and water quality in real time (see urbanlab.umich.edu/project/real-time-watershed-control). Similarly, at the University of Virginia, the School of Engineering has established a research incubator called LinkLab that brings together different engineering professions such as computer engineering, system engineering, and mechanical engineering, to explore cyber-physical systems, from autonomous cars to “smart cities.” Many of the models were built with TensorFlow and Keras.

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(keras.io) and were built on the Rivanna High-Performance Computer (HPC) (arcs.virginia.edu/rivanna), at the University of Virginia, using a graphical processing unit.

For example, a team at the LinkLab uses ML to build correlations between stormwater and transportation systems in a coastal city with the premise that the coupled system can better adapt to environmental disturbances such as sea-level rise and flooding induced by climate change. In order to better use crowdsourced weather data collected by hobbyists and concerned citizens using personal weather stations (PWSs) to facilitate the city’s decision-making process, some researchers have developed algorithms to evaluate the trustworthiness of the data collected by these PWSs distributed across the city (Chen, Behl & Goodall, 2018). It can be understood as a reputation system that can automatically score these stations based on their past performances relative to their neighboring stations. The goal is to ensure useful and trustworthy data for creating more reliable models for decision-making. Eventually, the algorithm itself should be able to evolve over time so that it can adapt to increasing numbers of PWSs and re-score stations if their performance was changed.

Another team has adopted model predictive control (MPC) strategy in a simulated stormwater management system. This simulated system has two watersheds converging into one stream. Without any control, downstream will be flooded during rainfall events. Two retention ponds with floodgates were added, one for each watershed before the confluence. Degree of openness and closeness of the floodgates decides how much water the retention ponds can hold. The goal is to close the floodgates before heavy rains so that the ponds can hold more water to prevent flooding in the downstream, or to open the gates to let the water out before the ponds get too full and induce flood in the upstream. The researchers have trained an MPC model that can use weather forecast data to predict the behavior of the stormwater system and device strategies accordingly. In later iterations, the control strategies found by the MPC model can practically eliminate flooding downstream and, at the same time, maintain the water level at the retention pond close to a target level—to maximize the capacity of these ponds (Sadler, Goodall, Behl & Morsy, 2018).
In this experiment, humans decide the ultimate goals of the MPC model—to prevent flooding and maximize the capacity of the retention infrastructures. This goal implicitly limits other strategies the model can come up with. In other words, an unstated premise or value is that flood is ultimately bad, and we need to eradicate and control in one way or another. We sympathize with the goal to reduce flood, which is commonly held by many because of the perceived urgency. And we try to be reflexive and not to romanticize flooding without seeing its damage to people and their lives. As landscape architects, we know the importance of flood events to floodplains and riverine ecosystems. In many design projects, landscape architects tend to design more complex strategies to utilize flood rather than control and eliminate it. If we take the “wildness creator” idea more seriously, can a DRL-based agent understand the stormwater system in its own way thus to come up with its unique goals? Instead of controlling and eliminating flood, can some of the DRL strategies drive the stormwater system in such a way to use the flood event so that we can benefit from the process?

In fact, the next goal for the researchers in the LinkLab is to explore DRL and its potential in environmental management. Here, we have observed a paradigm shift in environmental modeling from physics-based simulation to a state–space modeling approach. In the MPC strategy, the Storm Water Management Model (SWMM) was used to train the agent. SWMM is essentially a physics-based simulation developed by the Environmental Protection Agency (EPA) for stormwater management; it is essentially based on a set of mathematical equations that scientists come up with to describe hydrological systems. Physics-based simulation takes a long time to run, and training the MPC agent requires days of computation on a HPC, whereas, in the DRL approach, what is constructed is essentially a state–space model, which represents a system with a set of input and output as well as state variables. For example, a coastal-city water system can be described through water level on different testing nodes, groundwater level, precipitation, tide level, and other environmental variables. In this representation, no physics is involved. The DRL agent is trying to construct its own representation of the system with these state variables through trial and error. In a way, the DRL method bypasses the physics and mathematical equations that humans come up with to describe a hydrological system. To some extent, the DRL agent “invents” its own rule for the environment. However, in this scenario, the DRL agent is highly mediated by sensing networks. In other words, if there is a flood event in the blind spot of the sensing network, then the DRL will confidently believe that there is no flood in the system at all.

The experiment and research in environmental engineering presents challenges but, more importantly, merits further investigation in the area of DRL-based machine learning techniques and state–space modeling approaches. A paradigm shift can be articulated. The ML techniques are moving away from automation and optimization of existing workflows in environmental management and toward a reconceptualization of different workflows based on human–machine intelligence. Machines play a role that is more than a layer of infrastructure through which humans expand control regimes. Instead, they become an intrinsic part of the socio-technical network for decision-making by providing another pair of eyes, which examines the environment through state–space representation.

Ecology

Rapid advances in technology now offer a number of cost-effective tools to collect ecological and biological data at large spatial landscapes over long survey windows. For example, advances in battery technology have revolutionized wildlife telemetry and mapped out
animal movements at continental scales. Visual sensor networks and images collected by satellites, drones, and camera traps have made it easier to track changes at the landscape scale. However, the rise of cheap and powerful sensors has created an increasing amount and type of data, which far exceeds traditional ecological data analysis methods. These new technologies require to couple with faster computing algorithms and automated approaches to process and analyze these data. Machine learning attempts to extract knowledge from messy data, and it is relatively open-minded about the meaning of the data and the relationships between different kinds of data, which are recognized as holding great promise for the advancement of understanding and prediction about ecological phenomena. These modeling techniques are flexible enough to handle complex problems with multiple interacting elements and typically outcompete traditional approaches, making them ideal for modeling ecological systems.

In the last 30 years, it has been widely applied in different subfields in ecology. In 1999, Fielding introduced the machine learning methods to the field through his pioneering book (Fielding, 1999). By integrating computer science, mathematics and statistics, he predicted a future methodological shift in ecological statistics. Currently, machine learning in ecology is mostly used in species distribution modeling and species recognition applications, including audio recognition exercises, species recognition from images, and animal behavior and population dynamics modeling. Some common algorithms include maximum entropy, classification and regression trees, boosted regression trees, random forest, genetic algorithms, Bayesian machine learning, support vector machines, and artificial neural networks (ANNs).

Taking conservation measures as an example, effective wildlife monitoring techniques are a key component of a conservation measure program. However, the standard approach to biodiversity monitoring by human observer is constrained by its costs, survey scale, bias from human observations and disturbance for those sensitive survey sites. Though the cheaper and more powerful hardware may replace human observers, the inherent stochasticity of natural systems—storms, droughts, diseases—adds noise to biological surveys. A greater challenge for large-scale wildlife monitoring projects is the ability to analyze data to quantify events of interest (vocalizations, images of individuals, area covered by vegetation type, etc.) in a cost-effective manner. Better and more cost-effective conservation monitoring methods are needed to improve inference and drive adaptive management of conservation projects. Conservation Metrics, a company that focuses on applying machine learning methods on measurement of conservation outcomes, presents several working case studies, which employ deep learning to empower biologists to analyze petabytes of sensor data from a network of remote microphones and cameras (Klein, McKown & Tershy, 2015). Their software can be used to perform specific tasks such as exploring audio and image data to search for expected species and flag unknown or unexpected events, creating labeled datasets to train and refine models, and manually reviewing and auditing the output of existing models trained to classify events of interest. This system, which is being used to monitor endangered species and ecosystems around the globe, has enabled an order of magnitude improvement in the cost-effectiveness of such projects. The approach can also be expanded to encompass a greater variety of sensor sources, such as drones, to monitor animal populations, and habitat quality, and to actively deter wildlife from hazardous structures. It presents a strategic vision for how data-driven approaches to conservation can drive iterative improvements through better information and outcomes-based funding mechanisms, ultimately enabling increasing returns on biodiversity investments.
Agriculture

Agriculture plays a critical role in the global environment and economy. Due to rampant industrialization and urbanization, the continuous reduction of arable land area and expansion of the population, there are pressures that place urgent demands on smart agriculture to yield rational resource distribution, reduction of production cost, improvements to the environment and an increase in crop quality and yield. With the development of the Internet of things, artificial intelligence and robotics, precision agriculture has arisen as a new field that can use data-driven approaches to increase agricultural productivity while minimizing its environmental impact.

The data are provided by a variety of different sensors from monitoring real-time agricultural environment and status of crop growth. And by using machine learning, more accurate analysis can provide a better understanding of the operational environment (an interaction of dynamic crop, soil, and weather conditions) and the operation itself (machinery data), leading to more accurate and faster decision-making (Liakos, Busato, Moshou, Pearson & Bochtis, 2018). The data-driven strategies in agriculture are quite similar as the applications in ecology. In agriculture, machine learning is widely used in applications such weather data predictions, water and soil management, and crop and livestock management. Most frequently implemented machine learning models include ANNs, SVM, regression, Bayesian models, ensemble learning, and clustering. Yield prediction and disease detection are the most significant topics in precision agriculture and also where machine learning methods are most used.

Yield prediction in precision farming is considered of high importance for the improvement of crop management and fruit marketing planning. Once the yield is site-specifically predicted, the farm inputs such as fertilizers could be applied variably according to the expected crop and soil needs. A variety of approaches, models and algorithms have been presented and used to enable yield prediction in agriculture. Simple linear correlations of yield with soil properties have been proposed based on a limited number of soil samples.

Cartography

As an essential part of landscape design process, the act of mapping is a subjective extraction of landscape structures, features and process into an abstraction expression. This part examines cartography as a discipline, how artificial intelligence is reshaping the traditional methods, with the aim to correlate to the landscape design. The methods of map-making have been closely related to the evolution of technology. Each major evolution in technology, from the first bird perspective observation of the land from balloon to the emergence of technology of photography, satellites images, and private drones, has significantly shifted the way how maps are made. Before machine learning and computer vision technique were used into map-making, computation methods have already been applied through different aspects to enhance the map-making workflow. Taking the example of mapping of vegetation, NDVI (normalized difference vegetation index) is a classical programming approach for mapping greens, by computationally calculation of infrared colored data to enhance the mapping of greens. The later computer vision method is an advanced algorithm with more efficiency and accuracy, while the advent of machine learning algorithm combined with computer vision significantly expands the capacity of automation of mapping. Machine learning algorithms are able to automatically identify, classify and segment the patterns of the satellites images; thus, in the example of mapping vegetations, not only the greens can be mapped out from reds, but the tree canopies can be mapped out of grasslands, by automatically segmenting their different patterns.
Microsoft have used machine learning techniques to map 125,192,184 building footprints in all 50 US states and have published as open-source data to compare with local-sourced data. The automated processes not only significantly release the human labor, but also are much less error-prone, which allow massive data transmission from raster to vector information in such a large-scale project. Besides the mapping of vegetations and buildings, we can imagine that machine learning can be used to identify and automate mapping of any pattern that can be perceived by human eyes. These semantic segmentation methods in the field of computer vision have been extensively employed to map out all the kinds of things from satellite imageries: buildings, roads, swimming pools, wind turbines, oil and gas wells, land use and land cover types, etc. (descarteslabs.com). The sources of data are not limited to satellite images, private drone photography and open-source street images are also widely used as a data resource for mapping elements in the real world. For example, Mapillary, a commercial organization, provides street-level imagery data. They applied semantic segmentation methods to identify the street objects, such as utility poles, streetlights, and mailboxes, and map these elements to serve as data source for cities and private companies. These machine-generated map features are great supplements for traditional survey-based map features.

The machine learning method is also used to analyze the human’s perception of the environment, which in traditional ways may not be able to be quantified (Naik, Philipoom, Raskar & Hidalgo, 2014). The social science literature has shown a strong connection between the visual appearance of a city’s neighborhoods and the behavior and health of its citizens. However, this research is limited by the lack of methods that can be used to quantify the appearance of streetscapes at high enough spatial resolutions. In the project developed by MIT media lab, “Street Score” is used to describe a scene to understand algorithm that predicts the perceived safety of a streetscape, through training data from an online survey with contributions from more than 7,000 participants. The group first studies the predictive power of commonly used image features using support vector regression. Using Street Score, high-resolution maps of perceived safety for 21 cities were produced for the Northeast and Midwest of the United States at a resolution of 200 images/square mile, through scoring 1 million images from Google Street View images. These datasets are useful for urban planners, economists and social scientists who look to explain the social and economic consequences of urban perception.

In another project, the group used the same strategy but taking time-series street-level imagery, rather than static imagery, to serve as critical data source for mapping the change (Naik, Kominers, Raskar, Glaeser & Hidalgo, 2017). The group used time-series Google Street View to measure changes in the physical appearance of neighborhoods of five US cities. Through critically connecting the output map with economic and demographic data, they correlate the measured changes with neighborhood characteristics to determine which characteristics predict neighborhood improvement, thus providing support for classical urban design theories. By connecting with other geographical data, the value of using computer vision and machine learning algorithms in the field of cartography is not only the replacement of human labor, but the establishment of a critical analysis and an innovative perspective to understand the physical world.

Current uses in landscape architecture

The broad range of scale in landscape discipline separates the application of machine learning across territorial-scale and site-scale formal design. At the territorial scale, the work is most akin to regional planning, a multidisciplinary field overlaying natural sciences such as
ecology, geology, and hydrology, and social sciences such as planning and sociology. This correlation enabled a range of applications of artificial intelligence and machine learning explored in these interdisciplinary areas, such as applications of automating land use classification, study of patterns and processes in ecology and river systems, and comprehensive GIS analysis. However, when it comes to the field of design, especially small-scale landscape design projects, there are few public projects. The works include post-occupancy analysis and evaluation, quantification of perception in cultural landscape, and the generative design of topography (Zhang et al., 2018).

Post-occupancy evaluation is a comprehensive examination of the performance of a project after it has been built, to evaluate whether the design goals were met. For landscape design projects, the process of post-occupancy evaluation usually includes rigorous observations and survey of users through a relatively long time range, as well as photographic analysis and behavioral or preference mapping of the place. The use of machine learning would free designers from handling repetitive observation and data-heavy analytical work. Intrigued by the potential of AI for the field of landscape architecture, the XL Research and Innovation Lab at SWA Group, an internationally recognized landscape architecture practice, has experimented with and tested machine learning to better document the spatial distribution of people in small public spaces to identify new patterns of social life (Schlickman, Ying & Zhang, 2019). The measurement methodology is based on the seminal work of William Whyte’s book The Social Life of Small Urban Spaces, but with key updates on the survey methods by computer vision and machine learning algorithms. Using ten recently constructed small public sites in New York City as a laboratory, the team collected video footage of each site, and ran the footage through machine learning algorithms to identify people in each space and recorded their movements. What ultimately resulted from the machine learning exercise was a series of pedestrian heat maps, indicating areas of low traffic to areas of high traffic within each site. The new method not only saved time of manually tabulating user behavior data, but also provided much higher resolution of collected data. As a prototype, the methodology shows promise as similar data collection and data processing techniques can be used across a wide array of projects, developing new representation of use patterns, and possibly providing generative potentials for new projects.

Experiments have formed in the application of machine learning research in new forms of pedagogy that test the relationship between the designer and new ways of mapping or seeing the environment. In the summer of 2020, in the workshop “Imaging Landscape: Computer Vision and Landscape Perception” at the DigitalFUTURES 2020 Conference, the group explored the use of computer vision and machine learning in the field of landscape architecture, to develop an effective approach to quantify the subjective perception of landscapes. Previous research on the visual impact of landscape is limited by the lack of methods that can be used to quantify perceptions or analyze large amounts of image data samples. In the workshop, the instructors challenged the conventional perceptual study in the landscape design process. Through data mining and visualization of urban image data, spatial formation, landscape element composition, and landscape perceptions were analyzed from the perspective of machine intelligence rather than the existing empirical measurement methods.

In this one-week workshop, students downloaded 150,000 Google Street View images of the entire Berlin metropolitan area, with a density of 50 meters. Students used semantic segmentation and instance segmentation to quantify the objective environment elements appearing in these street view images and obtained the quantitative measurements of these images such as green vision rate, sky ratio, sidewalk ration, and the number of pedestrians, bicycles, cars, motorcycles, etc. On the basis of these data, 300 pieces of different images were
randomly selected as the training set for pairwise comparison, and an online questionnaire system was created to collect students’ opinions on style, ecology, sense of security, enclosure, aesthetics, accessibility, etc. The group collected about 2,000 questionnaires and used the Microsoft TrueSkill algorithm to translate the preference model of street view images to a classification model with a score of 0–10. By using machine learning on the classification model, students performed the score prediction of eight personal perception dimensions of the entire Berlin street environment, with a prediction error around only 1.2 score. Through computer vision and machine learning, the participants were able to translate the street view image dataset into high-resolution maps of perception scores of the entire city. Each group of students then developed their own project based on this dataset, to explore social, ecological and economic consequences of urban perception (Figure 12.3).

One of the students’ projects was to identify and analyze East Berlin moments in the reunited city through mapping and to systemize their findings through the perception data and ratings. As Berlin was physically divided due to the wall, the government has been working on reunification through integrated developments for decades. The maps of urban functions through points of interest indicate that a reunified, lively central urban area has been formed. Yet traffic network analysis tells that minor divides in the physicality of the urban fabric still exist between the east and west sides behind the veil of a unified Berlin. The students selected Friedrichstrasse Street and Carl-Max-Allee as research objects due to their important roles in the west and east parts. Empirically, sky exposure of Carl-Max-Allee is significantly higher, while ratings for security and accessibility are lower. Through trial and error, they applied different combinations of the data matrix to Berlin’s central area, in order to study if specific patterns could help to find leftover fragments of East Berlin. Then, they overlaid the areas with top 10% ratings of tree and sidewalk exposure, and selected where data are clustered as study areas and identify if their characteristics unify the ones in West Berlin. They used the same method to analyze more urban typologies with ratings of

Figure 12.3  Computer vision of streetscape: Semantic segmentation and instance segmentation are used to analyze the landscape elements appearing in street view images. Quantitative measurements are obtained, such as green vision rate, sky ratio, sidewalk ration, and the number of pedestrians, bicycles, cars, motorcycles, etc.
bicycle, building, street, sky and wall to understand if and how such areas keep traces of their past while being physically reunified to a city. Such research method and result will provide valuable reference and guideline to future development of the areas in East Berlin still lacking unified characteristics (Figure 12.4).

Another group of students explored how Berlin’s public spaces could adapt to the COVID-19 pandemic with social-distancing measures. To mitigate the demand for outdoor activities in the summer and the need for maintaining safe social distances, they proposed tactical recommendations for Berlin’s streets and squares. The proposals were derived from comparative studies with citywide GIS analysis of sidewalk width and points of interests, as well as computer visioning of pre-COVID Google Street Views and post-COVID webcam footages from some of Berlin’s popular public spaces. This set of analyses aimed at utilizing technologies to shed light on how urban lifestyle in dense city centers may be sustained under the challenges of a public health crisis.

Another area of interest for the discipline of landscape architecture has been in the generative potential of artificial intelligence and machine learning to produce new methods of topographic analysis and formation. One experimental project uses generative adversarial networks to study topographical features of a set of given sites and trains the machine learning model to automatically design new topography (Bao, 2019). To prepare the large amount of terrain data for the training algorithms, more than 135k samples in a given area were prepared by using 30-m Global Digital Elevation Model (GDEM) data. After enough training sessions, the model can generate new terrain models with similar features as the input terrains, which can be used for further design and research of such terrain patterns. This experiment produces a design heuristic between the designer and the machine, creating comparisons between sites via similar topographic models. As the elevation data of the GDEM 30-m high-altitude resolution are not high enough, the details of the terrain cannot be displayed. But if the model is fed by high-precision data, either natural or designed terrain

Figure 12.4  Map of perception score of greater Berlin: Through running image segmentation and machine learning on 150,000 Google Street View images, the visual impact of landscape is quantified as eight perception scores on enclosure, aesthetic, accessibility, ecology, etc.
data, it shows potential to produce design iterations and new ways of exploring various terrain forms. On the other hand, if a similar method is applied for much broader region with different topographical features, the model can also be used for extracting and analyzing features in an unprecedented way.

While not utilizing machine learning, specifically the work of the Harvard Graduate School of Design, REAL is using physical sediment models that are tied to sensing arrays, producing a relationship between real-time sensing and feedback. REAL has conducted research that examines the potential of responsive technologies across a variety of scales focusing on systems at the territorial scale and the manipulation of indeterminate land building using real-time sensing, robotics, and adaptive management techniques. The research and lab have recently found a new home at the University of Virginia School of Architecture where a team of academics, including myself, Brian Davis, Matthew Seibert, Andrea Hansen, Xun Liu, and Zihao Zhang, are developing the platforms and interfaces for a nascent suite of design tools to confront adaptive design protocols. As a prototyping platform, the system has facilitated many research and design projects over the years. The geomorphology table and the ongoing series of experiments shed light on the construction of autonomous systems, devising strategies that are outside of human comprehension (Figure 12.5).

If we take on a more general definition of machine intelligence, then the experiments here present an uncharted territory for exploring artificial intelligence—to explore intelligence as a hybridized and emergent property between technological and biophysical agents. As we have seen, one of the problems in today’s machine learning research is that machine intelligence is understood as a localized property within the machine itself, overlooking the
fact that machines have always been deeply embedded in a network of distributed systems. As post-humanist scholars have pointed out, what we understood as agency—be it human or machine—has always been distributed across a field of heterogeneous assemblages. In the process of individuation, “some entities are detached from their background and called ‘actors.’ They are made to conceal and stand for the web of relations that they cover. They become the place where explanation, moral, causal, and practical stops” (Knappett & Malafouris, 2008).

**Adaptation and epistemology**

What we understand as machine intelligence is always hybridized by other forms of intelligence within and around a machine, and the “machine” only functions as a carrier of the perceived effectiveness, which is co-produced by many other actors. Within the many cases presented, artificial intelligence and machine learning produce expanded potential but lack ways to address the three concerns of anthropocentrism, individualism, and means-ends reasoning. The research at REAL using the geomorphology table reflects an understanding of intelligence as distributed qualities across the “more than machine whole.” In the experiment, the perceived “machine intelligence” is achieved by the processes in not only mechanical systems, but also hydrological and geological systems. Most importantly, the designers off-load their intelligence onto the cyborg, diversifying the “machine intelligence.”

What does this then say for the future of machine intelligence within the complex milieu of the environment and the discipline’s intent to engage the complexities of ecological and sociocultural systems? Understandably, many methods point to ideological solutions, and without careful implementation, the use of machine learning will produce a strengthening of ideological concerns. These solutions to complex ecological and social problems may be optimized via machine learning but limit the solution space that is needed and further exacerbate the outcomes of means-ends reasoning. The discipline’s never-ending search for epistemological frames that validate our knowledge of interactions with society and ecology needs to be reconsidered. Is it worthwhile to say that epistemology as we know it is insufficient? Due to the fact that the complexity of the environment and related problems are beyond human knowledge, requiring a heuristic or adaptive approach to environmental design?

Going forward, it is important to imagine a nascent epistemology of realism, an erasure of ideals that most importantly points to a clear connection between technics, the material, and the predictive. A mode of working in design that asks for biological, geological, climatic, and machine collaborations that produce new knowledge through their interactions. Like many experiments in representation that have developed collaborations between machines and humans, we can imagine an adaptive approach that is aided in real time by machine intelligence. This posits the introduction of an adaptive epistemology that sets goals based on a priori investigations stemming from the construction and maintenance of landscape and territory. This would be scalable, traversing across site, territory, and planet with attempts to connect intervention with prediction. The future of these systems relies on age-old concepts of interaction (cybernetics) but through the extension of human cognition in real time within the machine.

**References**


AI and ML in landscape architecture


