Meta-Evolver: Evolutionary Strategy for Architectural Intelligence

Karolína Kotnour
FLOW studio, FACTU
kotnokar@fa.cvut.cz

Robert B. Lisek
IRSA
lisek@fundamental.art.pl

Abstract

Meta-Evolver is a tool that provides a visual representation of the various dynamic environment models that correlate in multi-layered systems. *Meta-Evolver* provides an environment for testing dynamic spatial adaptation, where the environment is composed of algorithms and parametric definitions.

This research uses advanced artificial intelligence (AI) methods (meta-learning) and cutting-edge technologies, including immersive environments and virtual reality (VR), to offer innovative methods of architectural creation. The ability to continuously learn and adapt from limited experience in a dynamic environment is an important milestone on the path towards building interactive spaces in modern architecture. We developed the tool *Meta-Evolver* to test spatial adaptation in dynamic environments and integrated the capability for interaction with a human user.

Introduction

This project proposes a new strategy for creating evolving architectural structures, based on the idea of adaptation to a dynamically changing environment through the use of advanced machine learning and AI methods. The evolving architecture uses physical and virtual processes that are transformed and assembled into structures based on environmental properties and capabilities. The computational models are used to process dynamic multidimensional forces, but are they suitable to be integrated into environmental intelligent models for architectural spatial adaptation? And to what extent are they capable of grasping composed spatial dynamical forces and defining the edge and trajectory of the self-evolved architectural environment? The project investigates a living dynamic system as a complex set of natural and cultural sub-processes, in which each of the interacting entities and systems creates complex aggregates. It deals with natural processes, communication flows, information networks, resource distribution, dense noise masses, and a large group of agents and their spatial interaction in the environment. By significantly expanding existing research, the project creates a meta-learning model useful for testing aspects of adaptation to a complex dynamic environment. This refers to the difficulty of designing artificial agents that can intelligently respond to evolving complex processes.

Architectural Intelligence

The future is under perpetual construction. It emerges from the interaction of billions of current activities, both natural and artificial (Rzevski 2014). Future architecture will be capable of perceptual interaction with its environment and will stimulate construction and growth with regard to the needs of natural and artificial aspects of a specific environment.

Architectural Intelligence is a set of evolutionary mechanisms that has the capability to adapt an architectural organism to a new environmental situation or behavioural patterns of its symbionts, in a short- or long-term interaction. Architectural Intelligence adapts, changes and accommodates the environmental dynamics and behavioral conventions. Architectural intelligence is taught by its architect.

The intelligence is encoded in the script of a neural networks model that is capable of rewriting existing code protocols, and therefore actively addressing acute issues of architecture for effective and dynamic adaptability. Our architectural approach proposes a theory of architectural adaptive systems. Intelligence can be seen as a form of adaptation, in which

knowledge is constructed by each individual through two complementary processes of assimilation and adaptation (Jean Piaget 1963). Adaptation is an evolutionary process as a result of which the body better adapts to a dynamically changing environment. If an organism cannot move or change enough to maintain its long-term viability, it will obviously go extinct. From this perspective, Architectural Intelligence is a set of methods that adapt architecture to environmental and social changes and instability. Architectural intelligence is a method of solving architectural problems. We propose the use of computer science techniques, in particular deep learning and meta-learning, to represent and analyse complex architectural and urban phenomena and to find and generate optimal spatial forms. Modelling complex natural processes requires computer science, and it is no coincidence that the development of computer science has been largely shaped by the construction of computer models that simulate natural processes. Using developed models, we generate intelligent architectural structures that provide sustainable environmental conditions for individuals and communities, based on their spatial experience and behaviour. Predictions generated from models with the use of neural networks actively solve difficult problems of architecture to allow it to effectively adapt to dynamic changes in the environment (Kotnour & Lisek 2020).

Evolving Architecture

Evolving Architecture is a large field with a few subfields such as Prescribed, Responsive, Interactive and Evolutionary or Living Systems. Each of these areas requires different expertise and often focuses on certain interaction strategies and techniques, as practiced by people like Michael Fox, Rachel Armstrong, Philip Beesley, and Heatherwick and UN Studio. Evolving Architecture uses the features of natural design processes and relies on dynamic adaptation to environmental changes. The analogies of evolving architecture can be

Fig. 1. *Evolving Architectures*, 2020, Karolína Kotnour.

Fig. 2. *Evolving Architecture*, 2020, Karolína Kotnour.

understood not only in terms of the applied natural processes of development of forms through natural selection, but also in the restless tendencies towards optimization and self-organisation, which significantly improve the efficiency and power of diverse prototyping. Architecture involves designing for survival, designing for life, and emphasizes the need for a responsible approach to the transformation and formation of energy and materials. The solution to dynamic environmental problems is to link architecture with a contextual understanding of the structure of nature. Traditional documentation of architectural production and construction design is replaced by code as a set of instructions and calculation formulas that reflect and adapt to a specific dynamic environmental and spatial context. The proposed approach to understanding and designing architecture introduces a set of instructions and general principles of interaction with the environment, which John Frazer calls "the genetic code of architecture" (Frazer 1995). It is also necessary to create large groups of researchers, architects and urban planners that change and adapt the architecture of our cities and suburban areas to the new needs of their inhabitants.

At the same time, in computer science, methods inspired by the process of natural selection, such as genetic algorithms, have been widely developed: design, games, image processing and robotics, for example. Genetic algorithms are commonly used to generate high-quality solutions to optimization and search problems by relying on biologically inspired operators, such as mutation, crossover, and selection. A particular example is Hyper-NEAT, which we use to transform 3D objects. The principle of the algorithm is the simple weight evolution in a topologically static neural network (CNE) or the evolutionary adaptation of the covariance matrix (CMA-ES) strategy, to weight and topology evolution (NEAT) and intermediate weight coding (HyperNEAT). All algorithms encode artificial neural networks (ANNs), which are represented by weights and connectivity (also called topology). The first two algorithms search only the ANS weights, while the last two can also modify the topology.

The Genetic Code of Architecture

The Genetic Code of Architecture performs adaptation through changes in genetic configurations, which is primarily a search for co-adapted sets of various forms of genes, which together significantly augment the performance of the corresponding composite observable characteristics of an architectural style, or architectural organism. The technical word “phenotype” is used for the bodily manifestation of a gene, and the effect that a gene, in comparison with its alleles, has on the body, via development. The phenotypic effect of a particular gene might be, say, green eyes. In practice, most genes have more than one phenotypic effect, say green eyes and curly hair. Natural selection favours some genes rather than others not because of the nature of the genes themselves, but because of their consequences – their phenotypic effects. Genes, therefore, reach outside their “own” body to influence phenotypes in other bodies (Dawkins 1976, 2006). The phenotype is the product of the balanced and harmonious interaction of all genes. Natural selection tends to bring together those genes that constitute a balanced system.

The process by which genes are accumulated in the gene pool that collaborate harmoniously is called “integration” or “coadaptation.” The result of this selection has been referred to as "internal balance” (Mayr 1963). The genes act in many ways, affecting various physiological and morphological characteristics that are relevant to survival. All of these come together into the sufficient parameter “fitness” or

selective value. Similarly, environmental fluctuation, patchiness, and productivity can be combinations of environmental uncertainty (Levins 1968). The genetic adaptive plan develops in terms of an ever-changing population of chromosomes, which, interacting with the environment, provides a concurrent sequence of phenotype populations. For many purposes, it is convenient to represent a_l population as a probability distribution over the set of genotypes ai, where the probability assigned to genotype A E: a_l is a fraction of the total population consisting of that genotype (Holland 1992, Crow 1970).

Evolutionary Algorithms

Evolutionary algorithms is a term used to describe computer-based problem solving systems that use computational models of some of the known mechanisms of evolution as key elements in their design and implementation. They all start from a common conceptual base of simulating the evolution of individual structures by the processes of selection, mutation, and reproduction. The processes depend on the perceived performance of the individual structures as defined by an environment.

More precisely, EAs maintain a population of structures that evolve according to rules of selection and other operators, which are referred to as "search operators," (or genetic operators), such as recombination and mutation. Each individual in the population receives a measure of its fitness in the environment. Reproduction focuses on highly fit individuals, thus exploiting (exploitation) the available fitness information. Recombination and mutation perturb those individuals, providing general heuristics for exploration. EAs use stochastic processes, but the result is distinctly non-random.

Genetic algorithms (GAs) can be seen as a software tool used to find structure in data that might seem random, or to make a seemingly unsolvable problem more or less solvable. GAs can be applied to domains about which there is insufficient knowledge, or for which the size and complexity is too high for analytic solution. Examples are finding a best-fit solution, *not necessarily the perfect solution*, for crew and team planning, delivery itineraries, finding the most beneficial locations for stores or warehouses, building statistical models, and game-playing behavior (Beasley 1993). The genetic algorithm is a model of machine learning, a stochastic optimisation strategy that derives its behavior from a metaphor of some of the mechanisms of evolution in nature. Genetic algorithms are used for a number of different application areas; one example is multidimensional optimisation problems, in which the character string of the chromosome (machine of a population of individuals, arrays of bits or characters) can be used to encode the values for the different parameters being optimized.

Evolutionary Strategies in Architecture Meta-learning

Deep artificial neural networks (DNNs) are multilayer networks of nodes and connections between nodes (weights), typically trained via gradient-based learning algorithms, namely backpropagation. The next step is to research and implement Evolutionary Strategies, which means transformation of architectural objects in time. This can be done by modifying selected layers in the neural network or by using the population-based genetic algorithm (GA). We evolve the weights of a Deep Neural Network by applying additive Gaussian noise in such a way that the general features of the training class of 3D objects are kept, but their evolution is possible. We created a mechanism for controlling the hyper-parameters of the neural network and ipso facto for controlling generated output numbers that represent new 3D objects. In this way it is possible to create a fully universal object generator and propose a new method of designing complex original architectures. The evolution strategy described above is a step toward research focused on the self-organization of complex structures from random elements. This method is general enough to become the starting point for meta-learning research and creating a universal toolkit that supports architects and designers.

Working with large data sets obtained from a changing environment requires advanced machine-learning methods. We tested different AI methods and approaches for modelling and generating new architectural forms. In particular, we used Transformers, which work by using convolutional neural networks, together with attention models, making them much more efficient than previous models. We previously tested recurrent neural networks (RNNs), long short-term memory networks (LSTMs) and variational autoencoders (VAEs). The transformer model is a seq2seq model, which uses attention in the encoder as well as the decoder. Transformers have been used for many (conditional) sequence-generation tasks, such as machine translation, constituency parsing, and protein sequence generation, and can be used for architecture design. Transformer models consist of an Encoder and a Decoder. The Encoder takes the input sequence and maps it into a higher dimensional space (n-dimensional vector). This abstract vector is fed into the Decoder, which turns it into an output sequence, which can be in any sequence of numbers, symbols, etc. The attention mechanism looks at an input sequence and decides at each step which other parts of the sequence are important. Self-attention is an attention mechanism relating different positions of a single sequence to compute a representation of the sequence. Self-attention can be intuitively explained using a text example. When reading this text, you temporarily focus on the words, but at the same time your mind retains the important keywords in the text to provide context.

In our research, we worked with sequences of numbers that represent 3D objects as positions of its particles or elements and velocity. Our approach for analyzing and creating evolving architecture is based on meta-learning, which is the next generation of AI systems. Meta-learning goes by many different names: learning to learn, multi-task learning, transfer learning, zero shot learning, etc. People easily transfer knowledge acquired from solving one task to another more general task. This means that we naturally recognize and apply previously acquired knowledge to new tasks. The closer the new task is related to our previous experience, the easier it is to master. In contrast, popular machine-learning algorithms deal with individual tasks and problems. Transfer learning attempts to change this by developing methods to transfer knowledge acquired in one or more source tasks and using it to improve learning in a related target task. The goal of transfer learning is to improve learning in the target task using knowledge from the source task.

Techniques enabling knowledge transfer will constitute significant progress in AI and architecture. We have developed a learning strategy for a set of neural network modules that can be combined as needed regarding environmental qualities. We train different modular structures on a set of related tasks and generalize it to new tasks, composing the learned architectural modules in a new way. For composing, we use concatenation, addition, and product operators. We quickly learn something about a new task based on previous tasks without training our model from scratch. Our system finds two or more suitable modules that can be combined as an optimal solution for a new task.

Meta-Evolver

We defined the framework for the adaptive agent-based model for dynamic environments, based on data from generated random numbers and soundscapes. We outlined and established the architectural strategy of the multi-platform system for generative modelling based on input datasets. The framework for a visual representation of the dynamic models was generated, resulting in correlated layers.

The main task was adapting an agent to new environments and creating a new multi-agent environment and architecture for testing aspects of continuous adaptation. The whole model was parameterized, and the communication protocols were integrated into the digital environment. The aim of the method was to present dynamics as a sequence of tasks and train agents to use the dependencies between successive tasks. We created a meta-learning model for the problem of the continuous adaptation of an artificial agent in a complex

dynamic environment. We conducted observation-based research on these generated correlations and defined the possible dispositions of forming patterns and structures.

The model can be applied to various dynamic environments and after pre-training of agents can effectively adapt and generate architectural dispositions, structures, and environments.

The three different and complementary 3D environments and experiments are 1) adaptation in a dynamic environment created by changes in the structure of the parametrized environment; 2) adaptation in a multi-agent environment created by the presence of multiple learning actors (interdepended datasets and transformation matrices), and 3) adaptation in a dynamic environment created by the interaction of a human user with an adaptive artificial agent. The immersive dynamic environment is created using virtual reality (VR) and sound synthesis. The model keeps the transformation of 3D objects and sound synthesis as synchronous processes.

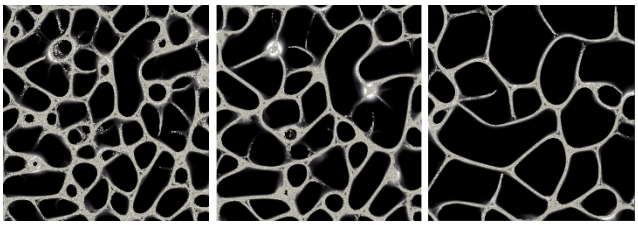

Fig. 4. *Evolutionary Self-Organization*, 2020, Karolína Kotnour.

Dynamic environments

In our view, urban and architectural structures are complex multi-dimensional structures in which natural processes and interactions of large groups of agents, communication flows, information networks, and others are intertwined and undergo continuous transformation. A dynamic environment is any space that surrounds us whose structure changes over time or is modified by groups of agents. There are closed spaces with relatively well-defined boundaries and others that do not have well-defined boundaries, which we can call open spaces. These environments are usually rich, complex, and unpredictable, and can generate significant "noisy" data, and unstructured and sometimes very dynamic changes.

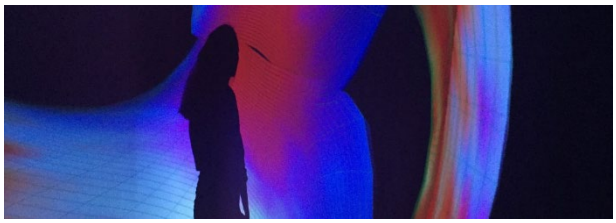

Fig. 3. *Meta-Evolver*, Immersive Installation, 2020, Karolína Kotnour and Robert B. Lisek, VR.

Tests in immersive spaces

An interesting direction of research on modern architecture is related to the problem of immersion, and creating virtual environments and sound spatialisation. Virtual environments also provide an excellent space for testing machine-learning methods. Restrictions introduced during the pandemic motivated us to study the potential of AI and virtual architecture for the evolution of society. Our research focused on the role of presence, flow, immersion, and interactivity. We were particularly interested in the problem of presence and flow in VE. Presence is defined as the subjective experience of being in one place or environment, when physically situated in another. Presence is a normal awareness phenomenon that requires directed attention and is based in the interaction between sensory stimulation and environmental factors that encourage and enable immersion. Flow is a state of experience in which a person is completely absorbed and immersed in an activity. We researched relations between presence, adaptation and interactivity, such as how interactivity and adaptation improve the experience of presence. We tested our meta-learning approach in a virtual environment. The project proposed a new method of operation in virtual architecture and a strong concept that will influence future social structures.

Conclusion and Future Research

The proposed AI model of Transformers provides variability and flexibility in dynamic environments. The meta-learning approach provides the sustainable possibility of implementing already tested and trained models

from other domains and areas of machine learning to the field of architecture.

In terms of evolutionary strategy for architecture, the new support tools in the form of software for researching and developing evolutionary architectures should be developed. The above research is fundamental to an architecture of the future that will be well adapted, in particular, to a flexible safe architecture that accommodates mass migration and crisis situations such as pandemics.

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Biographies

Robert Lisek, PhD, is an artist, mathematician and composer, who focuses on exploring complex dynamic environments (biological, computational and social) and creating agents that learn to learn through "feedback" with an evolving environment and transform the methods and algorithms they use. He is involved in the number of projects focusing on media art, immersive art and storytelling. Drawing on post-conceptual art, software art and meta-media, his work intentionally defies categorization. Lisek is a pioneer of art based on machine learning and artificial intelligence (AI). Lisek is also a composer of contemporary music, and author of many projects on the intersection of spectral, stochastic, AI music and noise. His scientific research interests are category theory and high-order algebra. He has exhibited at 300 exhibitions and concerts, including Ircam Center Pompidou, ZKM Center for Art and Media Karlsruhe, MAXXI Rome, STEIM Amsterdam, PRADO Museum, WORM Rotterdam, ARCO Madrid, Venice Biennale, LMCC NYC, Ars Electronic, and Siggraph. More at: http://fundamental.art.pl.

Karolína Kotnour is an architect and artist dedicated to architectural spatial and audio-visual production. She focuses on creating future-evolving architecture by transforming methods from neuroscience, machine learning, and immersive and sound spatialization research. In her projects and installations, she connects and synchronizes architectural and sound structures. She claims "the reciprocal confrontation of sound waves is a liberated contour of space." She is interested in "space as evolving over time, in parallel, and with mutual confrontations and reflections." with a significant role played by human acoustic presence and performance. She observes extreme space phenomena, such as "acoustic black holes" and the transformation of sound vibrations in their surroundings. She is PhD research fellow at the FLOW Studio in the Faculty of Architecture CTU, Prague.