

Prospects of AI in Architecture: Symbolicism, Connectionism, Actionism

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Abstract

The Architectural creation is always affected by technological development and available resources. The presence of computation and the advent of artificial intelligence opens new ways in architectural design and implementation, which is not only embodied in the technical application of the new medium, but present in the new design logic as well.

This paper provides an overview about the three main branches of artificial intelligence starting with a short introduction of the long-lasting relationship of computation and architecture. Starting from a theoretical base and reaching to the architectural application of symbolism, connectionism and actionism. The achievement of the research will point out how digital tools foster a novel design approach in architecture.

Keywords

Architecture, Connectionism, Actionism, Symbolicism

1. Introduction

Computation and architecture have had a close relationship since Antiquity. Although, the implementation of AI in the field has only recent instances. In order to see the current applications, this paper will examine cases in the triple division of AI in relation to architecture, with a feedback on the role of representation.

The key to illuminate the connection of AI and architecture is grounded in the Logician school. The development of computationalism assimilated with structuralist ideas in architecture leads toward the typological approach to design based on formal notions. The perception of natural language as a sign system is established in Semiotics, which refers to the study of sign process (semiosis). Any form of activity, conduct, or any process that involves signs, including the production of meaning. The model of Charles Sanders Peirce emphasises the relation between representation and the object and the interpretant using signs as transmitting systems.

Structuralism having its roots in three main areas: linguistics, anthropology and literary analysis, aimed to transmit architectural thought in universal sign system. The linguistic, semantic turn materialised in architecture in the '60s, '70s, and marked the way from structuralism, through rationalism towards computationalism. Rules and forms, such as models and methods appear in architecture in different scale. While structuralism was dealing with building scale, La Tendenza was interested in larger scale, examining the city. Which today can shift into even larger, planetary scale across computationalism.

Structuralism examines the relationship between the units in order to explain the whole. Influenced by Saussure, Claude Lévi-Strauss believed to simplify the masses of empirical data into generalized, comprehensible relations between units, which allow for predictive laws to be identified. In architecture Team X aimed to change the CIAM's doctrinaire approach to urbanism.

The Italian rationalist school, La Tendenza is in part a protest against functionalism and the

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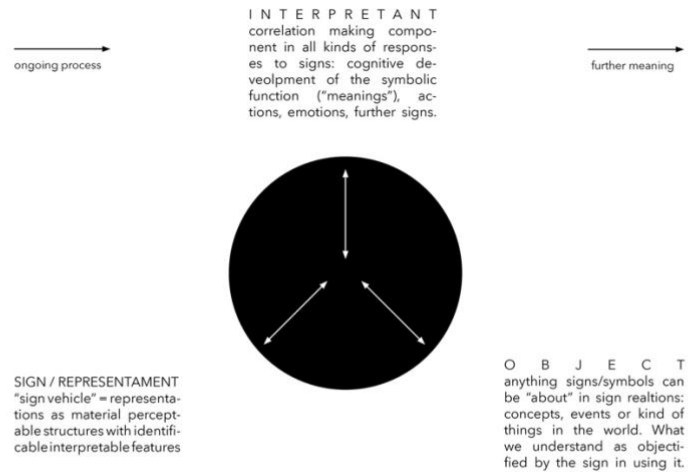
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Modern Movement, in part an attempt to restore the craft of architecture to its position as the only valid object of architectural study, and in part an analysis of the rules and forms of the city's construction. Type was not defined as an image or a thing to copy or imitate, but rather as an element, which can conceive of works that don't resemble one another. [1] This understanding of type is the closest approach to today's algorithmic methodological transmissions.



● SIGN, as a node of correlations that enables representational features to become a meaningful instance of symbol in its system / type.

Figure 1. Charles Sanders Peirce's triadic model of semiotics. C. S. Peirce, 1800s.

Computational semiotics understand Computer Systems as Sign Systems. (Fig. 1.) Although many fundamental computer science principles apply binary states, Peirce discovered that the human social-cognitive use of signs and symbols is a process that can never be binary, it's never either science and facts or arts and representations. Rather, the process of understanding symbols and signs is a process that covers everything from language and math to scientific instruments, images and cultural expressions. [3] In the architectural perspective image, vision, as the means of sign or representation in computational semiotics follow a significant role. The extensive use of AI in terms of the output dissolves the strictly typological segmentation of Architecture, while on the other hand for processing input it also uses types as classification.

In the 20th century the development of computer science took place parallel with architectural turns. Each computational approach has its reflection in architecture. (Fig. 2.) Inserting the waves of AI into the diagram of Charles Jencks from the 1940s until nowadays the impacts of the artificial zeitgeist become visible in the architectural styles as well. At the time the waves of AI did not have straight consequences in the design method, but mimicked similar approaches to the importance of nature or rules.

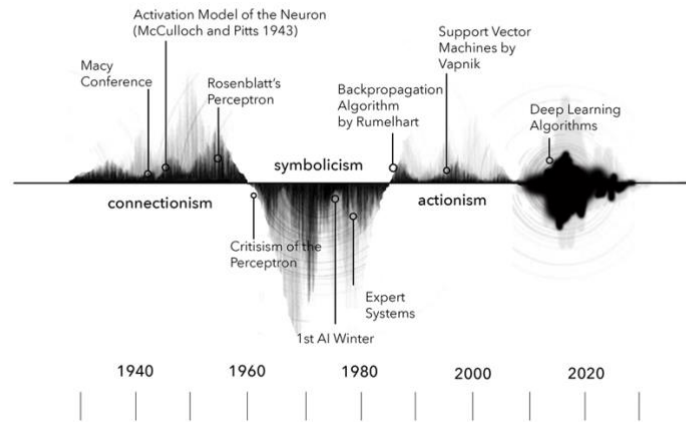


Figure 2. The three branches of AI in a consequent sequence. Melinda Bognar, 2020.

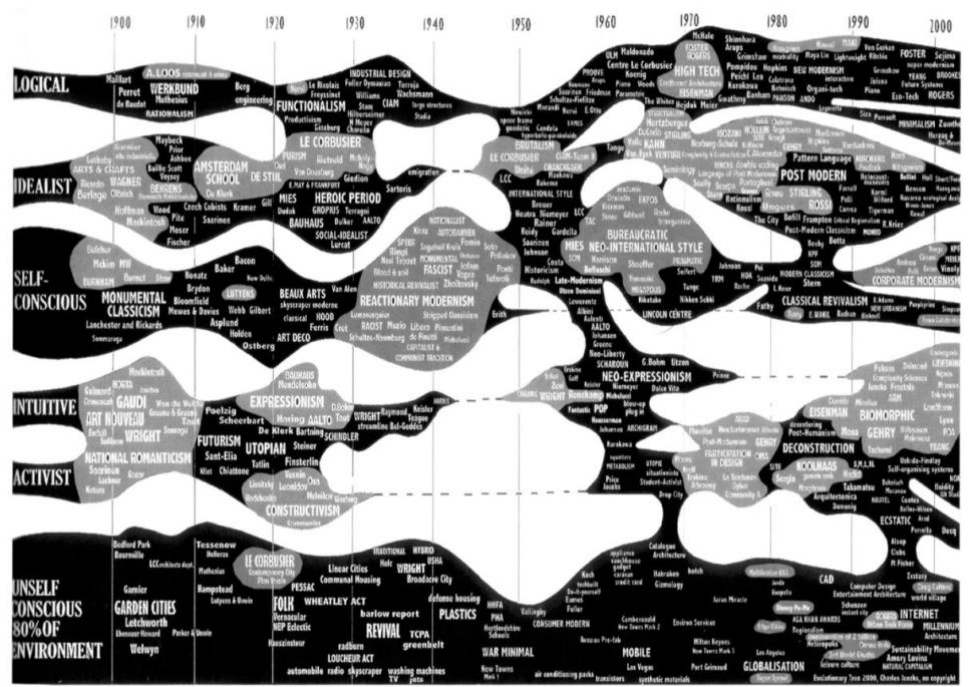


Figure 3. Timeline. Charles Jencks.

In order to position the actual roles of artificial intelligence in architecture the next chapter will follow the triple division of AI and its utilization in the different areas of architecture. Each AI sector works with different algorithms, which develop different results. AI can be used in various levels, such as design, construction, sustainability.

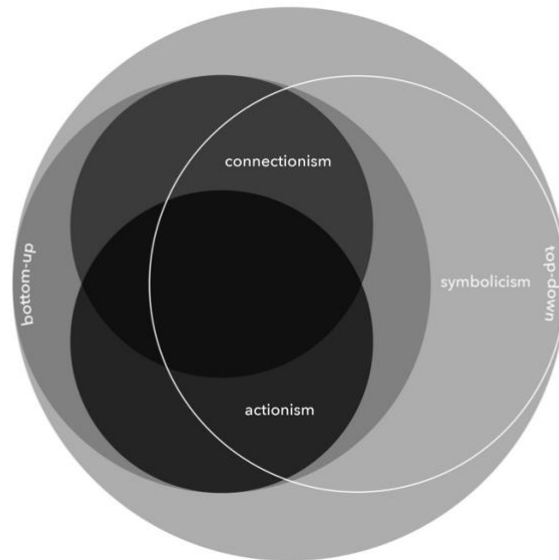


Figure 4. Venn diagram of the relation between the three branches of AI and the Architectural Design Methods. Melinda Bognár, 2020.

2. Connectionism in Architecture

2.1. Foreword

According to the theory of Deleuze humans judge things based on their environment and already known categories. We think about what things are based on quantification and qualification. While stem from the essential qualities, we should adapt to continuous change. How certain thoughts develop through the evolution of things. Usually, parallel developments merge into something new. In Deleuze's theory there are no two identical manmade things in the universe because of the difference of the hands, the materials and techniques.

Thinking about things we are generalising and constantly looking for resemblances. Generalising is the most basic action of thought. Whereas in order to generalise we must repeat. Newness occurs when we reorganise things and repeat them differently, replicating the original idea. The human mind rationalizes, judges, identifies things based on analogies. It sees things opposed to each other. When we do something new we also repeat something old. In every repetition there are different combinations.

The virtual is determined by the differential relations between what Deleuze terms ideas which are made up on multiplicities. Lots of configurations. The result is random, contingent. Ideas are combinations of representations and differences, assemblages. The multiplicity precedes the actual idea, it defines and creates its possibilities.

Virtual is the surplus of the present moment of any fixed identity which is grounded in the spaces between things. Virtual presents itself through a finite number of possibilities at any given time. [6]

Augmented possibilities provided by the digital era let each phenomenon to become expressed by systematic thought in a computable way. What AI does is to perform the statistical explanation of the ideas. What logician thinkers anticipated in the 16th century, AI now does by default. Usually things that are measurable are predictable. This is what clusters did before. A thing belonging to a group becomes more or less predictable. Based on past examples, which are somehow similar, we can forecast certain behaviours. Mathematically expressed ideas and their consequences are also predictable based on statistics. In order to make these statistics work machines examine past data and create logical patterns from them.

Architecture itself is a case study to see this phenomenon shifting from the physical to the virtual. All the built environment is a manifestation of some idea, the innate archetype, which earlier had been grouped with analogue methods through typologies, now it is being expressed by algorithms providing digital patterns.

Connectionism in AI has defined intelligence originated from bionic. With the brain model co-



founded by physiologist McCulloch and logician Pitts in 1943, a new way for studying the human brain structure and function model from neurons had been created. Therefore, in Connectionism, human intelligence behavior is achieved by imitating the connection mechanism and learning algorithm between neurons and the neural network. Artificial neural network technology as the core technology of connectionism, has the functions of learning and adaptation, self-organization, function approaching and massively parallel processing that can solve nonlinear, multi-variable, real-time dynamic system problems. Its model and improved models have broad prospects for application in intelligent systems. Meanwhile, the new method of deep learning is a deep neural network derived from the neural network model. Based on the current mature technology of cloud computing and big data, its models can be applied to feature learning and classification of large-scale data. [17]

The most populated area of deep learning is based on image processing, computer graphics and computer vision. An understanding of natural vision is crucial in order to position computational image processing. Besides learning from big data, deep learning classifies the examined data set. Which classification is not unknown for natural systems either. Humans classify information in order to understand it better and compress the amount of knowledge as well.

In Machine Learning (ML) an engine during its learning process based on the input dataset ascertains its own archetype of the given aggregation. This archetype is a set of rules, which has to be true in order to match the idea. Based on the stated archetype in image recognition the learning phase is followed by a labelling process. Therefore, the archetype in ML is the pattern generated from the learning dataset, by which identification becomes possible in further recognition processes. This is how the algorithm used in order to define the idea becomes the archetype in ML.

Deep Learning is the branch of AI that computes visual information in order to recognise and learn patterns from datasets. Deep Learning is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised.

These qualities makes connectionist AI related to architecture based on vision and classification. Neural Networks connected to the evolutionary timeline of architecture enrich the field with novel possibilities in the design process.

In the following steps my aim is to highlight the link between traditional architectural typologies and machine generated patterns through the field of architectural visualization. Amend the visualization pipeline with Neural-Network-based rendering leads to a practice where the rendered image is based on a given computational 3D model and the implemented dataset of images showing the preferred atmosphere.

2.2. Neural Networks

2.2.1. General features

A Convolutional Neural Network or CNN is a foundational supervised deep learning model architecture, a class of DNN, deep neural networks, which are often used in image classification, achieving state-of-the-art performance. The input are image data, which are transformed into class predictions. The objective of supervised image classification is to map an input image, X , to an output class, Y . Within a CNN, there are many types of network layers, each with a different structure and underlying mathematical operations. Through a process called backpropagation, a CNN learns kernel weights and biases from a collection of input images. These values are also known as parameters, and summarize important features within the images, regardless of their location. These kernel weights slide across an input image performing an element-wise dot-product, yielding intermediate results that are later summed together with the learned bias value. CNNs create spatially aware representations through multiple stacked layers of computation. (Wang et al. 2020)

The CNN is most commonly applied to analysing visual imagery, but it is not only used in Computer Vision but also for text classification in Natural Language Processing (NLP). In terms of Computer Vision, in Image Processing CNNs help the machine recognize what it is seeing. Computer Vision is an interdisciplinary field of science that aims to make computers process, analyse images and videos and extract details in the same way a human mind does. In modern days, Computer Vision has found many areas where it can be utilized. It automates processes in a way that not only reduces human effort but also provides us with solutions to the task that could never have been solved by the limitations of human vision. [18]

In Deep Learning a Convolutional Neural Network is most commonly applied to analyzing visual imagery. It is a type of classifier that excels at assigning a class labels to data points. A



CNN is a neural network: an algorithm used to recognize patterns in data. CNNs utilize a special type of layer, aptly named a convolutional layer, that makes its other building blocks (tensor, neuron, layer, Kernel weights and biases) well-positioned to learn from image and image-like data. Regarding image data, CNNs can be used for many different computer vision tasks, such as image processing, classification, segmentation, and object detection. (Wang et al, 2020)

CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "fully-connectedness" of these networks makes them prone to overfitting data. Typical ways of regularization include adding some form of magnitude measurement of weights to the loss function. CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns.

$$\frac{3 \cdot 1 + 2 \cdot 2 + 8 \cdot 1 + 2 \cdot 2 + 2 \cdot 4 + 7 \cdot 2 + 2 \cdot 1 + 3 \cdot 2 + 9 \cdot 1}{16} = \frac{58}{16} \approx 4.$$

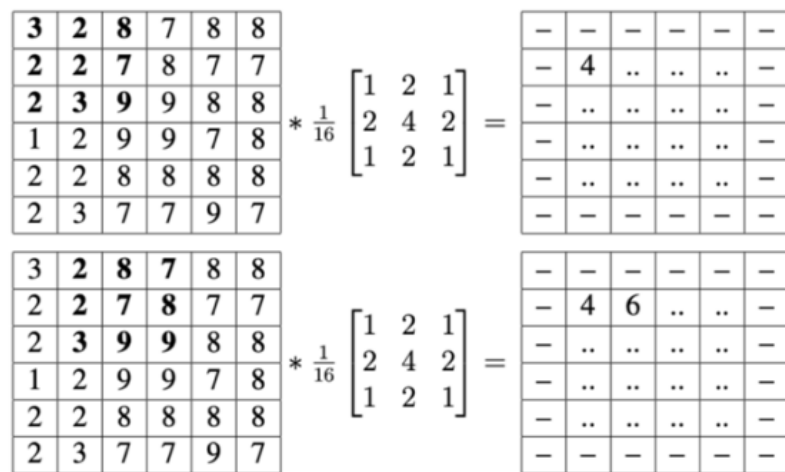


Figure 5. Convolutional filter: numerical explanation of the matrix of pixel encoding to smaller size

Regardless of their complexity, from the numerical perspective of machine learning, notions such as image, movement, form, style and decision can all be all described as statistical distributions of a pattern. From the point of view of the statistical model, three modalities of operation of machine learning are given: 1) training, 2) classification, and 3) prediction. In more intuitive terms, these can be defined as: pattern abstraction, pattern recognition, and pattern generation. [15]

Neural Networks in a Machine Learning process based on a data set learn certain similarities, which are repeated in every instance. This is the archetype, the main idea – named by Plato, Jung and Deleuze. These similarities provide a pattern based on algorithms. This way in machine learning the algorithm becomes the archetype. For a machine every pattern is explainable by certain codes, laws and orders.

2.2.2. Architectural application of NNs in Computer Vision

Image Classification

To achieve your computer or machine vision goals, you first need to train the machine learning models that make your vision system “intelligent.” And for your machine learning models to be accurate, you need high volumes of annotated data, specific to the solution you’re building. (Appen, 2019)

Since Computer Vision is traditionally used to automate image processing, its first task is image labelling. (Fig.6.) In urban environments it can distinguish the elements of the street not only in 2D images, but in 3D videos as well.



Figure 6. Image labelling. Appen, 2019

Neural Style transfer

Neural Style Transfer (Fig. 7.) is a complex algorithm that allows any image to be re-created in an infinite number of new ways and styles. By taking two images, a content image and a style reference image the neural style transfer algorithm “blends” them together and produces a resultant output image that appears to be both the content image and the style reference image at the same time. Though the baseline content and underlying geometric organization of this new image matches the original content image, the re-styled output image appears to be created in its own unique style, allowing us to reinterpret images in ways that we may have never considered or imagined before through traditional means. [9]



Figure 7. Image style transfer: input + style = output

2.2.3. Limitations

The challenges for computer vision may be mostly found in the amount of input data and quality of images. Another factor that causes hindrance to Computer Vision is the Knowledge of the model. If an object or image which was not present in the training set, the model will only show incorrect results. [18]

2.3. Generative Adversarial Networks, Conditional Adversarial Networks

2.3.1. General features

Third GANs used for unsupervised ML, which contains two competing models, run in competition with one and another. GANs are able to capture and copy variations within a dataset, are used for image manipulation and generation and work with competing Generator and Investigator networks. Given a training set, this technique learns to generate new data with the same statistics as the training set. For example, a GAN trained on photographs can generate new photographs that look at least superficially authentic to human observers, having many realistic characteristics. Though originally proposed as a form of generative model for unsupervised learning, GANs have also proven useful for semi-supervised learning, fully supervised learning, and reinforcement learning.

GANs learn a loss that tries to classify if the output image is real or fake, while simultaneously

training a generative model to minimize this loss. As GANs learn a generative model of data, conditional GANs (cGANs) learn a conditional generative model. This makes cGANs suitable for image-to-image translation tasks, where we condition on an input image and generate a corresponding output image. Where each output pixel is considered conditionally independent from all others given the input image. [10]

In Image-to-Image Translation Conditional Adversarial Networks, CANs not only learn the mapping from input image to output image, but also learn a loss function to train this mapping. This makes it possible to apply the same generic approach to problems that traditionally would require very different loss formulations. This approach is effective at synthesizing photos from label maps, reconstructing objects from edge maps, and colorizing images, among other tasks. [10]

GANs and CANs are methods of supervised learning, which is a function that maps an input to an output based on example input-output pairs. It infers a function from labelled training data consisting of a set of training examples. [12] A supervised learning algorithm analyzes the training data and produces an inferred function, which can be used for mapping new examples.

2.3.2. Architectural application

The analogy of pix-to-pix is used in the project of Stanislas Chaillou [5] in his ArchiGAN project. This was based on studied floorplan examples and certain features of related architectural styles. The statistical approach could serve as standard optimization techniques.

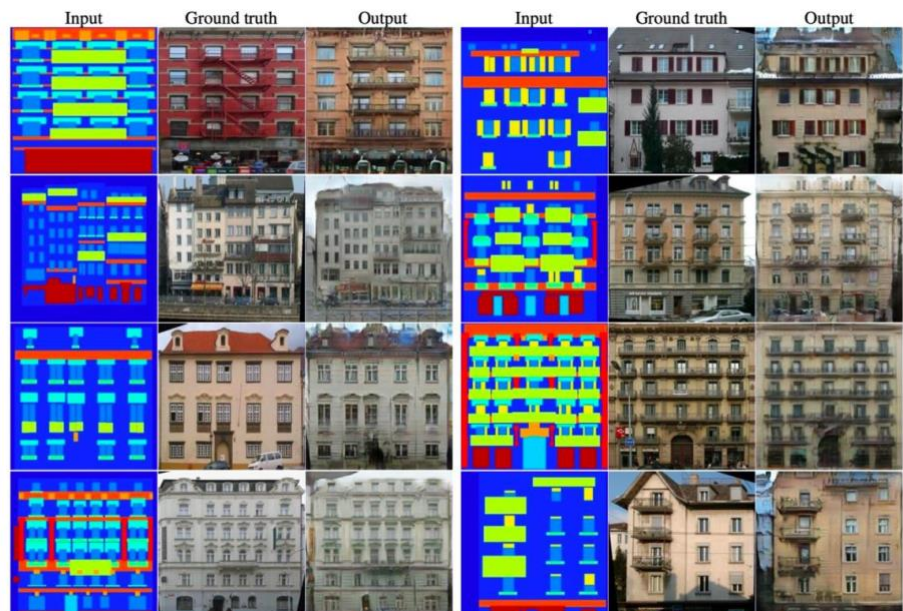


Figure 8. Example results of facade labels, photo compared to ground truth. Isola et al. 2018.

2.3.3. Limitations

A striking effect of conditional GANs is that they produce sharp images, a hallucinating spatial structure even where it does not exist in the input label map. Where the possibility of error is the greatest is the learning dataset. Creators should be very careful of the language of the learning data types. For instance if an NN is learning only CAD models, this will determine its output language. Thus the result strongly mimics the input despite of the ability to hallucinate certain information.

2.4. Auto Encoder

2.4.1. General features

The Boltzmann machine and Auto Encoder use the Markov decision chain. A Boltzmann machine (also called stochastic Hopfield network with hidden units) is a type of stochastic

recurrent neural network. It is a Markov random field. It was translated from statistical physics for use in cognitive science. The Boltzmann machine is based on a stochastic spin-glass model with an external field, i.e. a Sherrington–Kirkpatrick model that is a stochastic Ising Model applied to machine learning.

An autoencoder is a type of artificial neural network used to learn efficient data codings in an unsupervised manner. The aim of an autoencoder is to learn a representation (encoding) for a set of data, typically for dimensionality reduction, by training the network to ignore signal “noise”. Along with the reduction side, a reconstructing side is learnt, where the autoencoder tries to generate from the reduced encoding a representation as close as possible to its original input, hence its name. Several variants of the basic model exist, with the aim of forcing the learned representations of the input to assume useful properties. Examples are regularized autoencoders (Sparse, Denoising and Contractive autoencoders), proven effective in learning representations for subsequent classification tasks, and Variational autoencoders, with their recent applications as generative models. Autoencoders are effectively used for solving many applied problems, from face recognition to acquiring the semantic meaning of words.

A Hopfield network is a form of recurrent artificial neural network popularized by John Hopfield in 1982, but described earlier by Little in 1974. Hopfield networks serve as content-addressable (“associative”) memory systems with binary threshold nodes. They are guaranteed to converge to a local minimum and, therefore, may converge to a false pattern (wrong local minimum) rather than the stored pattern (expected local minimum).

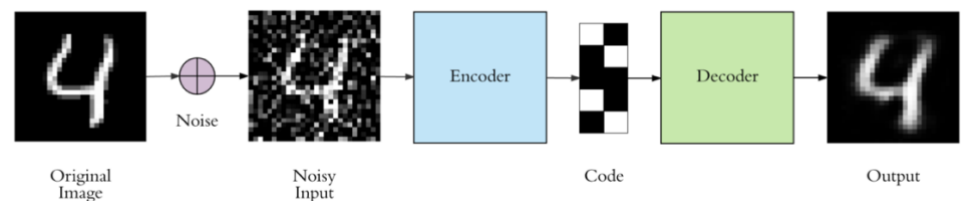


Figure 9. Auto Encoder

2.4.2. AutoEncoder in Architecture

AE as a technical feature can support other AI implementations. Collaborating with different neural networks or other branches it can be applied well to study noisy images in the research of aged or poorly protected data. Such as its use for black-and-white image colouring.

2.4.3. Limitations

An autoencoder is not a standalone feature of AI, it is always coupled with other expedients, usually supporting a visual output. This application is appropriate for indirectly investigating the notion of archetype in a pixel generated world. Assimilating the idea of ECS (Entity–Component–System) with the autoencoder’s hidden layer, it is visible that both are appropriate for data compression and storing enough information to create the outcome. The difference is that while ECS always looks for unique, different outputs, the autoencoder decodes an output similar to the input.

3. Symbolicism in Architecture

3.1. Foreword

Each Wittgenstein in his works investigates the idea of understanding and misunderstanding. A certain expression means different images to different receivers. Thus by the same linguistic code the possible amount of meaning variations are endless. He studied how communication between people goes wrong. Wittgenstein in *Tractatus Logico-Philosophicus* argued that language works by triggering within us pictures of how things are in the world. In his view words enable us to make pictures of facts, and constantly swap pictures between us. Communication typically goes wrong because other people have the wrong picture of what we mean. Problems in communication start because we do not have an accurate picture of what we understand in our own heads.

In his second book, *Philosophical Investigations*, Wittgenstein argues that thinking is not just about pictures, but it is rather like a kind of tool that we use to play different games, or patterns of intentions. His point is that all kinds of misunderstanding arise when we do not see the kind of game someone is involved in.



With the parallel development of system theory and information theory, the computer system as a sign system creates the connection between computation and linguistics as a rule-based circuit as well. This approach already introduces one significant branch of AI, which is rooted in the logician understanding of thinking.

No training, no massive amounts of data and no guess work. It represents problems by using symbols and uses logic to search for solutions. Symbols can be anything, numbers, letters, pictures, etc. This is how Siri works based on Boolean logic. Being able to search and reason. The AI defined by symbolism originated from mathematical logic in the 1930s and the application of the computer as a logic deduction system promoted the development of AI. The basic element of cognition for symbolism in AI is the symbol. By abstracting information and behaviours into a physical symbol system based on symbolic rules and using the computer logical deduction rules to imitate human abstract thought, simulation of intelligent behaviour is realized.

This kind of AI has developed a variety of technologies, such as heuristic algorithms, expert system as well as the theory and technology of knowledge engineering, which laid down the foundation for early AI applications. Expert system is a typical algorithm of symbolism in AI, which designs an artificial computer program based on expertise to solve complex problems. Due to the characteristics of heuristic, transparency, and flexibility, the expert system has high adaptability and accurate calculation ability for practical problems. [17]

A similar approach can be found in the Physical Symbol System Hypothesis research of Newell and Simon. A physical symbol system consists of a set of entities, called symbols, which are physical patterns that can occur as components of another type of entity called an expression (or symbol structure). Thus, a symbol structure is composed of a number of instances (or tokens) of symbols related in some physical way (such as one token being next to another). At any instant of time the system will contain a collection of these symbol structures. Besides these structures, the system also contains a collection of processes that operate on expressions to produce other expressions: processes of creation, modification, reproduction and destruction. A physical symbol system is a machine that produces over time an evolving collection of symbol structures. Such a system exists in a world of objects wider than just these symbolic expressions themselves. [13]

Systematic classification weaves our lives from daily routine to organise biological patterns. Classification makes individual pieces belong to certain clusters, with the aim of more effective information processing. Taxonomy can be considered as a way of deductive logic, and also investigates set theory. Typological organisation assumes a certain hierarchy in the system.

In architecture typological thinking started to emerge in the 1800s, when respect for the past started to increase and the need for optimal solutions became a goal. Typologies served as a basics of industrial production and economic design thinking. Today typologies are still determining traditional architectural design while speculative architecture requires new notions.

Table 1. Relation of mediums and ideas. Melinda Bognár, 2020

	archetype/idea	type
position in creation	anterior	posterior
notation	indefinite	definite
symbol	mental image	general image
form	ideal	concrete



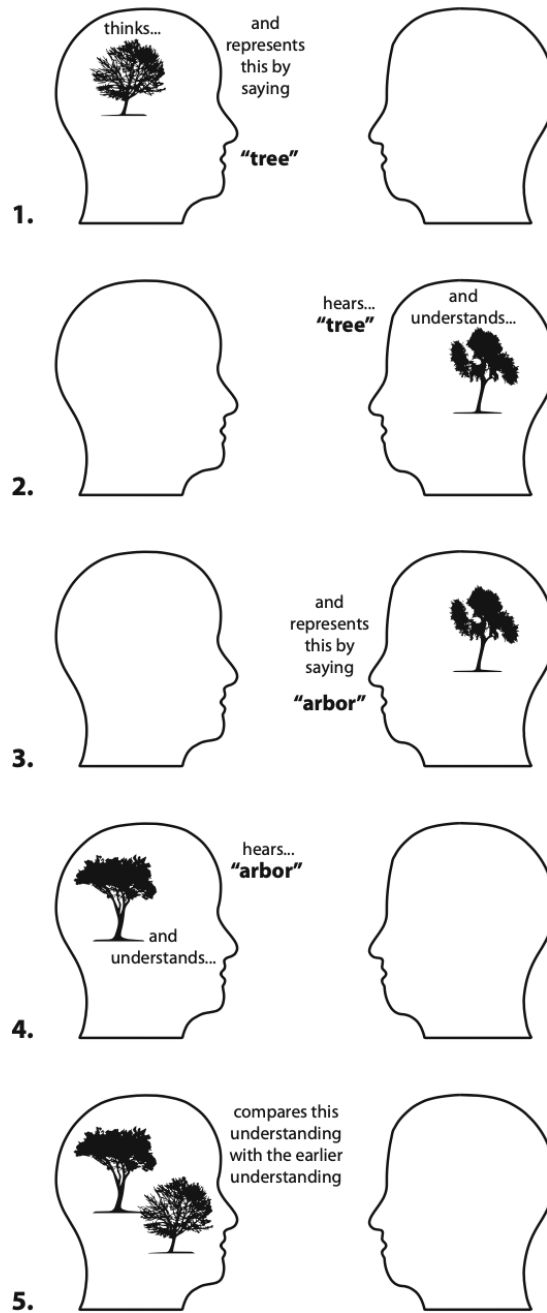


Figure 10. Achieving close-enough understandings through conversation, as described by Gordon Pask and Glanville. Herr and Fisher, 2020

3.2. Analogue Computing based on Symbols

3.2.1. General features

Expressing buildings as computational notions emerged in the 1800s. Typologies and the idea of combining different typologies in a certain amount of variations (Christopher Alexander) was the first significant attempt to calculate architecture. This pursuit was defined by the available means of communication, though at the time computation was performed in an analogue way. Later, even after computers were invented, for a long time experiments were still performed manually.

3.2.2. Architectural application

“Sebastiano Serlio wrote his Books on Architecture as a manual for architects, in which he extracted and systematized proportional relations from classical buildings into a grammar and syntax, a ‘system’, which could be applied via ‘transmutation,’ Serlio reduced the available examples into a reliable ‘code’ to serve as a shared language, applicable to any building typology. A reduced and precise language of spatial primitives, Serlio’s code can be understood to a proto-BIM system, one whose core values are not market availability or construction efficiency, but harmonic proportions.” (Bava, 2019)

Architecture research groups emerged after the Second World War. In 1967 Leslie Martin established a research group in Cambridge, where Philip Steadman¹³ in the 1960s was occupied with land use and built use studies. Besides significant inventions, like the first cathode ray tube touch screen or the first university computer – EDSAC, Richard Stibbs and Philip Steadman were working on a room layout system in 1967. They were establishing the schematic types of built forms with constant parameters, by working on density simulation of environmental performance. They created a model of activities monitoring students, then performed a simulation of student activity patterns, examined the geometry of the environment, and also questioned representation.

In the 1980s they were researching access graphs, and created the same access graphs for different buildings. They catalogued and counted possibilities, and finally represented plans and forms by binary codes. (Fig. 11.) (Fig. 12.)

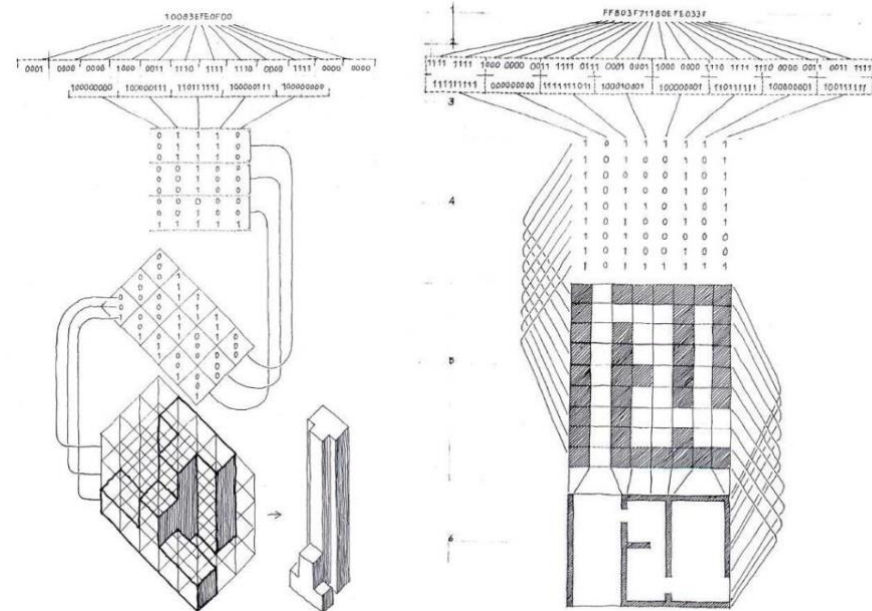


Figure 11. Lionel March: architectural relationship in binary diagrams, redrawn from his *Architecture of Form*, 1976.

Figure 12. March and Steadman’s mathematical formulae of plans, redrawn from their *Geometry of Environment*, 1974.

In the 1960s Eisenman was searching for a linguistic model in architecture. “Cardboard architecture” which neglects the architectural material, scale, function, site, and all semantics associations in favor of architecture as “syntax”: conception of form as an index, a signal or a notation. So to me, it seems like between the object and the idea of the object, your approach favors the latter. The physical house is merely a medium through which the conception of the virtual or conceptual house becomes possible. So while the work was interested in syntax and grammar, it was interested to see what the analogical relationships were between language and architecture. And of course that’s when I get into working with Jacques Derrida. Architecture is about the relationship of the sign to the signified. [2]

3.2.3. Limitations

These approaches were extremely time consuming and complicated to implement into daily routine. Although they anticipated BIM and paved the way towards Symbolicist AI applications and created the intellectual framework of computation of geometries.

3.3. Expert Systems

3.3.1. General features

J-N-L Durand¹⁵ invented his typologies to create a cheap and economically effective building solution. This kind of optimisation and prediction appears in Symbolicist AI. Such as the approach of French structuralism by Claude Levi Strauss to simplify the masses of empirical data into generalized, comprehensible relations between units, which allow for predictive laws to be identified.

Expert systems were on the increase in the 80s and they were based on reliable predictions. An expert system is a computer system that emulates the decision-making ability of a human expert. Expert systems are designed to solve complex problems by reasoning through bodies of knowledge, represented mainly as if-then rules, the first truly successful forms of artificial intelligence (AI) software.

3.3.2. Architectural application

BIM and now BIM Chain provides a typical CAD language to process thoughts. However, the parametrization of design has been proven over the past 10 years. Parametric modelling failed to account for (1) the compounded effect of multiple variable at once, (2) the imperative of space organization and style over strict efficiency, (3) the variability of scenarios, and finally (4) the computational cost of simulations.

Independently of its technical shortcomings, parametric design is flawed by its theoretical premise: Architecture may be the result of a fixed number of parameters, that the architect could simply encode, as an abstraction, away from its context, its environment and its history. The main role of Symbolicist AI is to help decision making. SpacemakerAI, a Norwegian company has developed a game-changing AI technology that helps users discover smarter ways to maximize the potential of a building site. The product lets the user generate and explore a multitude of site proposals, sort out the best ones, and provides detailed analyses for each of them. It enables a fantastic level of insight and a collaborative workflow among architects, engineers, real estate developers, and municipalities. In the interest of better real-estate development, solutions are based on input data and preferences.

Spacemaker combines expertise from a wide range of fields including architecture, mathematics, physics, machine learning, and optimization. The system provides the user with a creative set of high-quality site proposals. By applying machine learning with reinforcing mechanisms across the system, it improves its optimization algorithms after every run. [16]

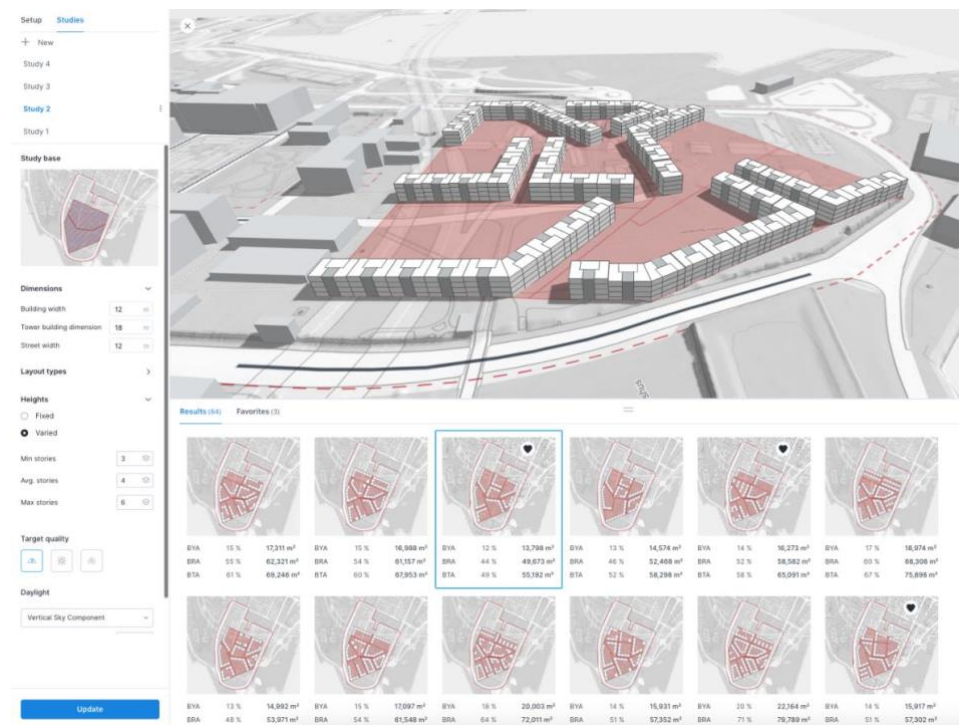


Figure 13. Optimal distribution of real estate developments. SpacemakerAI, 2020



Described as “the world’s first” AI-assisted design and construction simulation software for the property development sector, Spacemaker claims to enable property development professionals, such as real estate developers, architects and urban planners, to quickly generate and evaluate an optimal environmental design for any multi-building residential development. To achieve this, the Spacemaker software crunches various data, including physical data, regulations, environmental factors and other preferences. [14] Similar to Spacemaker’s intentions, XKool is the Chinese version of the company, in terms of generating optimal solutions based on local regulations.

3.3.3. Limitations

Symbolic systems, like expert systems are based on logic modelling human symbolic behaviour, in order to solve a problem. They are a good choice when rules are obvious and can be explicitly entered as symbols into a knowledge base. Boolean logic is a good example to decide if something is true or false. During the process the participants are named as they become symbols. In terms of architecture this approach is may be put to efficient use when we have to consider regulations. For example, if a building should satisfy energy regulations or site-specific demands.

4. Actionism in Architecture: Circularly-causal Feedback Systems

4.1. Foreword

Each Actionism usually referred interchangeably with Cybernetics, especially with second-order Cybernetics based on the research of Gordon Pask from the 1970s.

Cybernetics offers an abstract philosophical approach to design as a creative epistemic practice. In the Cybernetic understanding design is an open-ended process. (Fischer and Herr, 2019)

In the late 1950s, there was a profound and serious attempt to turn design into a scientific activity, to rationalise it. This approach originated at the Hochschule für Gestaltung in Ulm, and found the “new” science of cybernetics as one of its sources of strength, which was at the time, in the way in which we humans look for a universal answer, ambitiously promoted as a new science that would allow us to solve all our problems. It was, therefore, obviously significant for design.

At the turn of the 1960s into the 1970s the movement towards explicit scientific rationality as the sole generator of objective design “solutions” (the term is redolent of science) began to wane, and, at about the same time, thinkers in cybernetics began to investigate the paradox that the way cybernetic systems were discussed failed to reflect the nature of cybernetic systems: Cybernetic systems were presented using the traditional scientific device of the detached observer, even though they spoke of systems in which the observer (the sensor) is anything but detached: that is the point of feedback! (Fischer and Herr, 2019)

In 1969, Gordon Pask¹⁶ published a paper that explicitly proposed a vital connection between cybernetics and architecture. “The Architectural Relevance of Cybernetics” (Pask, 1969) was one outcome of an extraordinary series of debates and presentations centred around the theme of limits to science. Pask’s central argument concerned conversation. Three years before he officially published on conversation theory, he explained how conversational exchange could help the client and the architect develop a proposal that becomes better than it would have been if the architect had simply been briefed by initial instruction. [7]

4.2. Shape Grammars

4.2.1. General features

In the 1950s parallel with the development of computer science Chomsky¹⁷ examined generative grammars, in the 1960s Fu¹⁸ pattern grammars, and in the 70s Stiny and Gips¹⁹ researched shape grammars. Shape Grammars combine shapes and transformation rules to create patterns or in the subdivision of space, and have consequently been used in design and architecture. The relationships and operations are all spatial (e.g. similarity, rotation) rather than symbolic. It also shows the formal equivalence of traditional symbolic computations. [8] In the sense of visual sign system Isotype (International System Of Typographic Picture



Education) created in the 1920s by Otto Neurath can be considered as the ancestor of Shape Grammars. The aim of the Isotype was to show economic concepts in pictures - for those who do not understand writing - so his aim was to be available to knowledge to everyone. Neurath's picture language deviates radically from the fundamental tenet of Saussurian linguistic theory: the arbitrariness of the sign within the necessarily closed semantic system of verbal language. Neurath's ISOTYPE language, by contrast, is founded on the idea that the sign is not arbitrary but is instead rooted in the world. [4] Differently from Isotype when designing a shape grammar, one is designing a system for design, that can output many variations.

TURING MACHINE	EQUIVALENT SHAPE GRAMMAR
FINITE SET OF TAPE SYMBOLS $\{s_0, s_1, \dots, s_m\}$ where s_0 is "blank"	$V_T =$ $\{ \square, \square, s_0, s_1, \dots, s_m \}$
FINITE SET OF STATES $\{q_1, q_2, \dots, q_n, \text{halt}\}$	$V_M =$ $\{ \cup, q_1, q_2, \dots, q_n \}$
FINITE STATE CONTROL there are three types of 5-tuples: $(q_g, s_h, q_j, s_k, \text{left})$ $(q_g, s_h, q_j, s_k, \text{right})$ $(q_g, s_h, \text{halt}, s_k, -)$	SHAPE RULES corresponding shape rules:

Figure 14. Turing Machine and Shape Grammars. Stiny and Mitchell, 1978.

4.2.2. Architectural application

A shape grammar consists of shape rules and a generation engine that selects and processes rules. In computation theory shape grammars define a formalism to represent visual (and spatial) thinking, that handles ambiguities that symbols do away with. It is a specific part of production systems that generate geometric shapes. In philosophy shape grammars are not created through learnt or imposed definitions but through those that have a practical meaning at a given point in time, that values the continuity of matter (instead of discrete parts) and flexibility in how to cut it up into its parts. (Özkar and Kotsopoulos, 2018)

The theory was first introduced at the second half of the 20th century by George Stiny and James Gips, providing generative solutions. At the time they used manual techniques like painting to describe the method of computational process. Shape grammars introduced design as calculation, with the idea of expanding the meaning of calculation to visual thinking. Design is calculating was the starting point in 1971 and the reasoning behind the visual product was described using a grammar-like formalism with a vocabulary of a set of rules and a series of computations that produce design as they were sentences.

Stiny usually equates the terms design, visual reasoning and calculation. Also calculation and computation are often interchangeably used in his papers. Counting can be described as the root of both calculating and computing, based on discrete elements. Also counting is one aspect of reasoning.

How do we calculate with shapes? Does visual thinking exclude calculation or does calculation reduced accounting excluded visual and spatial kinds of thinking. Shape grammars state that one really has to be able to see to be able to count. First we need to identify discrete parts in a visual image to be able to calculate it. So we can divide the images to the smallest possible discrete bits, each assigned a different value. But these small sections remain irrelevant in the perception of the whole painting.

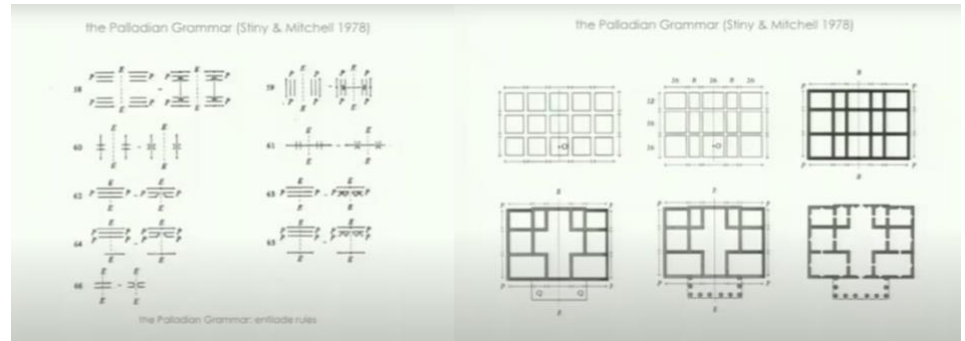


Figure 15. The Palladian Grammar. Stiny and Mitchell, 1978
 Figure 16. The Palladian Grammar Enfilade Rules. Stiny and Mitchell, 1978

4.2.3. Limitations

The Actionist AI in architecture is the most design-oriented approach in terms of taking into account the user, such as the environment, and the interaction of the participants. Design cybernetics aims to foster rigour that is independent of adopted procedures, and therefore offers no methodology. In essence, it seeks to avoid exercising restrictive control over the other, while pursuing increased numbers of choices and delight in the interactions between our individual and collective selves. (Fischer and Herr, 2019)

4.3. Cellular Automaton

4.2.1. General features

As its name suggests, ‘agent’ is an interactive as well as distinctive individual. Agent in architectural design could include any aspects such as designer-agent, pedestrian-agent, city-agent, material-agent and robot-agent. In different fields, agent varies as research need changes. In 2010, according to the concept of life-death correlation of near cellular automata in ‘Conway’s Game of Life’, Kuo J. and others in ETHZ, individuals, architecture and community served as agents, thus they simulated the natural expansion of cities from the perspective of multi-scale agent network. If the multi-agent method mentioned above is restricted to design itself, then the following ‘soft robot’ based on behavioral and environmental perception completely serves as an agent of the overall fabrication process. In 2016, Brugnaro G. gave an example of weaving rattan. Without pre-setting its action route, the robot equipped with Kinect360 could sense its surroundings in real time. (Wei 2018)



Figure 17. Cellular Automaton, Langton's ant. Chris Langton, 1986.

4.2.2. Architectural application

Digital technology allowed an evolution of morphological thinking in the 20th century, giving it new life in the concepts of emergence, non-linear and self-organising systems, stimergy and agent-based modelling. CA is used to generate free correlations based on neighbouring relations. The idea of having a building scale automated structure was first mentioned by Cedric Price.



In the '60s Archigram presented Plug in city. This provocative project suggests a hypothetical fantasy city, containing modular residential units that “plug in” to a central infrastructural mega machine. The Plug-in City is in fact not a city, but a constantly evolving megastructure that incorporates residences, transportation and other essential services, all movable by giant cranes. Persistent precedents and concerns of modernism lie at the heart of Plug-In City’s theoretical impulse, not being limited to the concept of collective living, the integration of transportation and accommodation to rapid change in the urban environment. Evolutionary building elements, the possibility of space morphing and continuous building extension by the building itself are all experiments. John and Jukia Frazer’s evolutionary Architecture investigates the physical application of CAs.

4.2.3. Limitations

Cellular Automaton has a comprehensive multi-agent approach with behaviouralism, which is shaping the holistic idea of unbiased design. CA has great promise, and there are huge challenges in its effective application.

5. Reflections

AI has the potential to input, process and transmit information in a recurrent way. Instead of creating a delimiting model, AI lets the computer to create intermediary parameters, from information either collected from the data or transmitted by the user. Based on learnt data, the machine can generate solutions emulating the statistical distribution of the information shown to him during the learning phase. The paradigm shift brought by AI is to free the computer from predetermined commands. Since not all rules and parameters are declared upfront explicitly by the user, the machine can unexpectedly unveil underlying phenomena and even try to emulate them.

Each branch of Artificial Intelligence reflects different interpretation of the archetype. Although in general all understand it as the intangible mental essence independent from formal restrictions. The Jungian Theory of Archetype [11] is mimicked the most in Actionism. Platonian is connected to Connectionism and Aristotole’s theory reflects in Symbolicism. (Table 3.).

Table 2. Reflections of the three branches of AI in Architecture. Melinda Bogнар, 2020.

	input	medium	output	relation to archetype	role of representation
connectionism	Image/video	Neural networks, deep learning	Image/video	Original pattern from which copies are made - Plato	significant
symbolicism	rules	Algebraic computation	optimisation	Human thinking as the mechanical manipulation of symbols - Aristotole	negligible
actionism	Unstructured data	Reinforcement learning	Recursive Design	“Archetypes are not static but in a continuous dramatic flux.” – Carl Jung : Letters Vol.2.	necessary

Several implications of Artificial Intelligence are already in practice in architecture. Together with the initial aspirations of Nicholas Negroponte to calculate optimal design as an assistant there are wide range of variations. While Neural Networks are utilized in computer vision, visualization, Expert Systems are appropriate to apply rules for certain tasks, and Cellular Approach is a feedback system to participatory design intentions. Looking at Actionism as part of systems theory²⁰, its application in architecture as a sign system²¹ is associated to linguistics and the works of Post-Modern Architects²². While structuralism proposes to understand through the medium, the structure modelled on language, Post-structuralism denies that the signs are constantly valid and fixed. Rather suggests to examine the object itself and

the surroundings. Based on these approaches Symbolicism is the successor of Structuralist approach, while Actionism is rather Post-Structuralist.

Since Structuralism type has a different meaning as a possibly unique element, which attitude percolates through the development of AI to architecture, providing each time a unique instance of the same mental cluster rooted in the Jungian archetype. Reflecting to the Symbolicist approach, architectural typology popularised by Christopher Alexander might be the ancestor of the idea. Based on certain rules, and definite elements, which could have been combined to fulfil a certain need. (Fig.18.)

On the other hand the Typology of Architecture in terms of the understanding of Quatremere the Quincy is related to Connectionism. Based on similar qualities each built element is connected to a broader, general cluster. This one is strongly relational with the understanding of set theory²³ in mathematics. Quatremere regarded type as a theoretical idea and the model, which he saw as form to be emulated, similar to Jean Nicolas Louis Durand, who defined type through function, he isolated forms from their archetypal meanings.

The role of representation (Table 3.) was different in distinct understandings. Type defined by Quatremere and Durand understood type as theoretical idea, independent from form. Same as Aldo Rossi, who considered type as a principle prior to form. While Christopher Alexander's typology based on patterns explicitly investigated to formal notations and their combination. Originated in the approach of Sebastiano Serlio and Gottfried Semper, who argued the language of typology, as architectural grammar is the combination and manifestation of archetypal conditions. Following the logician and rationalist principles, with possible manifestations in Symbolicist AI.

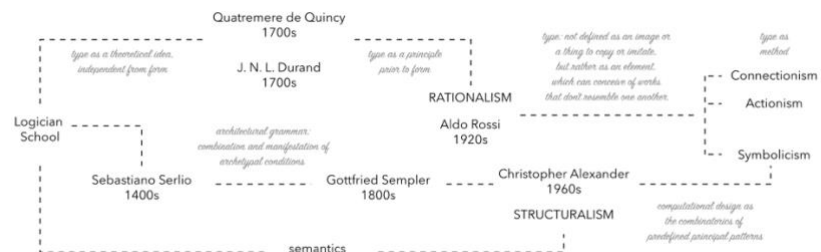


Figure 18. Understanding of type in different periods. Melinda Bognar, 2020.

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