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Creation of Design-Thinking based Computational Design Tools through Combining Machine Learning Algorithms with Parametric Design Workflows

Abstract:

Current digital design tools rather focus on aspects of technical/engineering problem solving than creative ones. Therefore, these tools are more suitable for later design stage engineering task than the early stage design-finding and -thinking process. This is because CAD tools are mostly limited to predefined commands and thus their use is aimed for narrow/specific engineering tasks. Therefore architects/designers often create their own custom tools through methods of scripting or visual programming languages (Cudzik and Radziszewski, 2018). Architectural researcher Steinfeld argues that CAD tools are limited when it comes to creative architectural design activities because classical tools compel us to reason like a user rather than a designer: "Because a computer cannot see the way we see, they cannot help us to reason the way we wish to reason." (Steinfeld, 2017, p591) He concludes that these tools operate on the principle of inductive and deductive reasoning (logical and scientific reasoning) rather than the method of abductive reasoning, which is based off experiences. Cross argues it is because of the process of abductive reasoning that "designing (is) one of the highest form of human intelligence" (Cross, 2011, p 12) pointing out "...designers' reliance on what they regarded as 'intuition', and on the importance of an 'intuitive' approach." (p13). "The concept of 'intuition' is a convenient, shorthand word for what really happens in design thinking. The more useful concept that has been used by design researchers in explaining the reasoning processes of designers is that design thinking is abductive." (p14)

Steinfeld points out that "Machine Learning (ML) is abductive in nature" due to pattern recognition by learning from previously seen data ("past experiences"). "As a model of computation that facilitates abductive reasoning" ML is more align with process of human design thinking (Steinfeld, 2017, p592). Since design thinking has many non-quantifiable aspects, it would be difficult if not impossible for a designer to code his/her (or somebody else's) past design-based experiences and intuitions into a computer using the conventional programming/scripting tools. However, a designer could curate and select previous design data and feed it to an ML algorithm in order to extract those past design experiences.

For ML algorithms to perform at a satisfactory level, large training datasets are required (Geron, 2019). To acquire these datasets classical Parametric Design (PD) tools could be implemented (Sebestyen and Tyc, 2020). A designer could create or reuse multiple PD scripts in order to create a vast and diverse pool of geometrical objects, which function as training data/experiences for ML algorithms.

The aim is a design tool that enables a designer to explore design ideas based in the possible solution-space of the previous encoded memories to create novel design solutions due to the combination of different experiences. In the field of ML the concept of image *Style transfer* (Gatys et al. 2015) has been widely published. The idea consists of combining two curated images into one, where an ML algorithm can detect patterns of content and style in images. Afterwards the style of a chosen image can be applied to the content of a second image in order to receive an interpolation that is based on both style and content thus injection new meaning and experiences into this newly created image. Further generative ML algorithms such as GANs (Generative Adversarial Networks) can create novel unseen images based on previously observed image data. Unlike with style transfer, the user does not provide a style and content image but rather the entire set of training data images (the experiences) are encapsulated as 'the style' with the starting content being randomly produced by the machine. The output are new images in the style of the training set. Style transfer and generative ML techniques are mostly applied to 2D raster-images. Attempts have been made to transpose those into the third dimension mostly based of voxels (Wu et al. 2017). However, 3D style transfer projects in the field of architecture are still applying 2D style transfer to images and utilizes those 2D outputs to create 3D objects, such as Ren et al. did (2020). Truly 3D style transfer or ML based generative tools for the

purpose of geometrical exploration and creation are so far a novel idea, which is worth exploration due to the potential to create individual, experience-based tools for 3D design. Such a tool would lead to some profound question regarding style and content in the field of architecture and design: What is the style of a certain designer or architectural epoch and where runs the dividing line between content and style in an architectural assembly? Understanding where a tool strictly based on mathematics (ML) draws those boundaries could give a deep insight into these profound questions.

Implementing the above-mentioned concepts, I envision a tool where through each round of ML training a unique curated experience-based design instrument is created. The designer would attach labels (properties) to geometrical objects beforehand and show those geometries and their labels to the ML network for training. During training the ML algorithm would learn the relationships of geometrical objects to each other and their respective properties which are based on the original designer's experiences and intuitions.

Afterwards the designer could provide this novel tool with new geometry (or geometrical noise) and ask to morph it toward the direction of certain geometrical properties thus creating abductive based design hybrids between the supplied geometry and the learned past experiences. A reference project is Google's Deep Dream project which is 2D image based (Mordvintsev et al., 2015). Further the designer could ask the algorithm to transform a geometry he or she has already created into the style of a certain design (Style Transfer) or produce multiple novel geometries in the spirit an array of previously seen objects (generative ML algorithm). I invasion a 3D workflow where the designer can begin to 3D model using classical CAD tools; during any point of the process the designer can direct his/her individual ML tool to shape-morph the geometry towards the direction of a desired experience; the output could directly be modified by the designer using traditional tools, until he/she further instructs the ML tool to intervene. This human-ML design circle was inspired by Lui et al.'s interactive 3D modeling tool (2018).

Since the designer can train the ML model with geometry not designed by him/herself, this new tool encapsulates and ultimate creates objects based on multiple designers' experiences. The ability to inject other designers experiences into our own work at any stage of the modeling process is what makes ML based design truly novel: The result could be "the discovery of novel architectural opportunities dormant in its historical core matter and through the hallucination of machines." (del Campo, et al., 2020, p171).

Research Question, Aim, and Objectives:

Research question: What are the possibilities and necessary workflow steps in order to implement Natural Style Transfer (NST) and Generative Adversarial Networks (GAN) into the 3D digital form and design finding process? What is the usefulness of the output of such a generative 3D tool and what can we learn during this process regarding the concepts of architectural style and content?

Research aim: Explore and implement different ML algorithms techniques in order to inject designers' past experiences/intuitions/knowledge into prototypes of early stage design tools mainly aimed at geometrical object creation and/or modification. The aim is not to replace classical CAD and PD tools with ML but rather combine both in a meaning full way. Further, such a system is not aimed at replacing a human designer but fusing his/her knowledge and past experiences to create custom and powerful tools to explore undiscovered/hidden geometrical design solutions.

Research objectives:

1. Researching and developing geometrical design representation workflows, which are suitable for ML algorithms to act upon: Forster (2019) explains how Convolutional Neural Networks (CNNs) are implemented within different ML algorithms to perform generative tasks upon 2D images. 3D-CNN implementation also exists and could be used as an important building block for voxel-based applications. Another approach worth exploring would be the representation of 3D meshes via implementation of Graph Convolutional Networks (GCNs) or even more advanced tools such as Geometrically Exploited Object Metrics (Smith et al., 2019).

2. Research regarding the implementation of PD into the ML based design process: exploration shall be put on PD scripts of different complexity and an ML's algorithm ability to extract the underlying geometrical properties in order to do multi-classification, according to labels/experiences curated by the designer.

3. Implementation of different ML generative approaches with the findings outlined in research objectives 1 & 2. Exploration on aspects of 3D shape creation or morphing based on:
   - Analytical tools as described by Mordvintsev et al., (2015)
   - Generative Adversarial Networks (Foster, 2019)
   - Variational Auto Encoders (Foster, 2019)
   - Neural Style Transfer (Foster, 2019) (Gatys et al. 2015)

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