FLOOR PLAN GENERATION

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Contents

Introduction

Abstract

This project tries to intervene in the architectural design process by applying different prediction models in order to pre-select certain volumetrics based on user-defined properties. To achieve this, several steps with different software library and algorithm application are needed, since the domains to be obtained vary from geometric to environmental simulations. First, the focus is on the parametric generation of an apartment floor plan using Python, Blender's Sverchok and various algorithms such as lloyd, KD-Tree and Voronoi diagram. After generating a manifold spatial configuration, it can be analyzed from a variety of geometric aspects using the Python library TopologicPY. It is important that these two steps are in constant feedback exchange to combine geometric data with spatial analysis evaluation and to save it in a file format appropriate for the data. These formats can vary from simple CSV files to database formats to graph data.
Furthermore, the evaluation stage can be complemented by physical and environmental analyses such as the application of light and radiation based simulation using Radiance, Vi-Suite, Honeybee and OpenStudio. It is also possible to perform a simulation of the energy performance of the architectural object using Energy+, Vi-Suite-Energy and OpenStudio's core component.
The evaluated geometric synthetic data can then be used as training data for a machine learning model after adapting the data shape with Pandas using SciKit-learn, Tensorflow or Pytorch. Whether it will be a CNN, GAN or simpler algorythms like Random Forest will be determined based on the data properties.
The last step concerns the reconstruction of the data in geometric form into a three-dimensional model, which will eventually be extended, enhanced, stored and displayed in a common open source BIM format such as IFC using IFCOpenshell, BlenderBIM, Topologic, Opencascade and Homemaker.

Special attention will be paid to the consistent use of python-based libraries to ensure the best possible compatibility of the individual software interactions. Furthermore, for didactic, ideological and compatibility reasons, only open source projects will be employed. During the execution of the individual steps, possible problems, suggestions, solutions, proposals for improvement and, just as important, ideas for further research of the topic are noted, which are described in detail in the following report.
This project tries to explore an unconventional approach in the connection between architectural generative design, spatial and environmental simulation in combination with machine learning.

Framework

This report is part of a long line of research on the interaction between machine learning and architectural design. The following project was developed in the framework of the Architecture and Design Studio at the Université libre de Bruxelles, which is characterized by an openness to new technologies in connection with architecture. The studio's focus is to raise interdisciplinary questions between technology, research and architecture that can be freely developed without having to remain in their limited domains.

The aim is to develop hypotheses about the future of architecture, taking into account all areas that may be of interest in terms of the design process of the project. In every aspect of the project development, it is important to take into account the analysis of new scientific knowledge and to explore the achievements of current science. Yet, it is also important to base experiments on inventions that have emerged throughout history.
This workshop is not primarily about inventing novel objects, but rather to deepen the study of a given topic with all existing publications and research in order to formulate a relevant research hypothesis. The goal is then to begin a process of experimentation accompanied by meticulous documentations. The goal of this process is to find answers to the questions raised in the preliminary stage. In this way, the experimentation cycle will advance the research and may possibly lead to a concrete solution, but in any case will raise a new set of questions that can be pursued subsequently.
The operation of the studio is closely linked to the Fablab of the Faculty of Architecture, providing access to many tools for designing and experimenting. This space will also act as a library of skills acquired by each individual, and thus the emergence of collective knowledge. As a result of the restructuring around the Covid 19 epidemic, the workshop has become a paperless studio, which means that the visual representations are entirely digital.

Hypothesis

The use of intelligent neural networks and models trained through machine learning to optimize traditionally manual processes has become the norm nowadays. Machine learning is no longer limited to computer science, but extends to any domain as long as a database to be analyzed is involved or can be created. It is therefore not surprising that learning models have also found their way into architectural optimization.
However, the application of machine learning in architecture is wide-ranging and can be useful in any project development process. For example, intelligent parametrization can help find the adequate shape even before a concrete project is modeled, a mechanical analysis of the existing conditions and framework can be helpful to determine an approximate volumetry. Furthermore, it is possible to generate through intelligent algorithms the partitioning of the internal space and thus propose several adapted plans, which can lead to a qualitatively enhanced experience for the occupants. This optimization is not limited to the two-dimensional space and can therefore provide suggestions for optimal circulation or optimization of daylight incedence throughout the building. Besides the conceptual phase, it is equally possible to optimize the BIM model through various machine learning algorithms. All these processes are no longer visions of the future, but rather have become the norm, although often automated and therefore not directly visible. Furthermore, there are approaches that help construction workers realize a smart house or city project via the Internet of

Things. This report will mainly focus on the application of pretrained models, pseudo intelligent and evolutionary algorythms in the conceptual phase.
Premise of this work is the assumption that there is a direct relationship between external conditions such as space connections, solar radiation, shading, humidity, wind flow, heat formation, soil conditions, air quality, pedestrian circulation or traffic congestion and the occupant's perceived quality of living.
The main hypothesis treated in this report addresses whether and to what extent learning algorithms can simplify, accelerate, and/or optimize the architectural design process. Is the increasing application of intelligent architecture considered purposeful or will traditional values be lost? Is the application of artificial intelligence again just an idealized label or are there tangible benefits for both clients and architects? Furthermore, this thesis will investigate to what extent it is possible to perform a complete Workow from generation to simulation, analysis, prediction and back to generation without resorting to proprietary software and thus describe a step towards the democratization of architecture and its digital tools.

State of the Art

The company Finch3d has developed an algorithm that creates adaptive plans. Thus, it is enough to specify the number of people who will live in the apartment and the shape of the project. The algorithm then proposes plans for the interior. This is not an intelligent algorithm, which means that it is not a learning process, but rather rules linked to conditions. In addition, Stanislas Chaillou has done extensive work on generating 2D plans using Artificial intelligence at the Harvard University in 2019. It is based on a principle of visual plan recognition by Weixin Huang and Hao Zheng in 2018. What is interesting about Chaillou's work is that the algorithm generates several different proposals and also learns through a feedback loop. It has also been experimenting with different architectural styles. The idea of generative design has been explored by several protagonists. For example, Joel Simon optimized a school building based on two different criteria. The objective was to optimize the incidence of light and, in another experiment, to shorten the circulation. The results of the individual optimization researches were amazingly organic building forms and a compositional reshaping of the entire building.
For a project of a bridge in Amsterdam, Mx3d used a generative algorithm which, through static analysis and organic shapes, resulted in a number of optimally adapted bridge designs.
In the paper "Learning From Main Streets" Oh, Smith and Koile explain how machine learning can be used in urbanism. The model is trained to analyze a complex urban network and its infrastructure on a large scale, enabling the architect to integrate his work into the environment in a context-sensitive way. In this example we are dealing with GIS based training data.
In the article 'Towards Machine Learning for Architectural Manufacturing in the Age of Industrie 4.0' published in the International Journal of Architectural Computing, Thomsen et al. describe potential implications of machine learning algorithms in the AEC industry. It is argued that there are two moments in the design

process that can be optimized by intelligent mechanisms: the data creation and the fabrication process. Also interesting is the importance outlined in this article of evaluation functioning as a feedback loop to improve results.
To understand the term generative design in more detail, the paper 'Design Optimization in Early Project Stages. A Generative Design Approach to Project Development' by Rohrmann. In summary, generative design processes are based on generative algorithms which belong to the family of evolutionary algorithms. The basis of these is simple and in principle not very different from the biological evolution we know: A population is generated which has different random characteristics and a defined mutation rate. In the following stage, the survival and fitness of the individuals is observed and evaluated. Finally, the number of fit genes is increased and the number of less fit genes is decreased.
The most apropriate contemporary example of a generative design approach in urban planning was developed by Sidewalk labs, a subsidiary of google. The goal of this project is similar to the approach of this work. Through parametric generation of bigdata based on defined characteristics such as open space, daylight and density, the architect is able to optimize in advance the further formal research and thus base any further design process on appropriate fundamentals. The architect involved in the design process is offered a variety of urban scenes, which in turn can be parameterized to meet the desired characteristics both aesthetically and functionally.
Finally, it is important to consider the available simulation and analysis software that meets the requirements: flexibility, compatibility and functionality. Radiance is a light analysis suite originally developed by Greg Ward in 1985 which has increasingly become the standard in architectural light simulation and the basis of many analysis tools, for example the Grasshopper plugin Ladybug and Openstudio. Advantages of this software are the open access to the source code and the open source license. Furthermore, Radiance's open le format .rad allows unlimited compatibility.
EnergyPlus is an open-source software specialized in energy management developed by the US department of energy. It provides analysis for heating, cooling, ventilation and water use in buildings. This is primarily a building internal simulation. Furthermore, Openfoam can be used for simulation of complex fluid ows (wind, water and heat), CalculiX for finite element analysis of constructive elements, Code Aster for multiphysical analysis (seismic analysis, acoustics, fatigue, stochastic dynamics, etc.) and JuPedSim a framework to investigate pedestrian dynamics.
The projects mentioned in the state of the art all provide very interesting and diverse approaches to the unification of machine learning and architecture. Due to the limited nature of this work, the focus will be on the generative design approach demonstrated in Sidewalklabs. However, it is not possible to reproduce the underlying processes, so this work will attempt to achieve similar results while disclosing each individual process. A focus is put on the adaptability of the process, in other words, what kind of simulation is chosen as a characteristic has no influence on the ow

of the process, so no significant changes need to be made after adapting the objectives.
After a closer look at the existing examples of different applications of machine learning in the AEC industry, it becomes clear that fears of a loss of aesthetic qualities and a reduction of the architectural profession to a computer scientist are not confirmed. On the contrary, it even allows the participants to invest the additional energy available in the aesthetic research process and thus to produce work of higher quality. This means that the application of artificial intelligence has earned its place in architecture, engineering and construction and will definitely result in some interesting symbioses in the future.

Process

This work is an experimentally exploratory approach, meaning the primary goal is not to achieve an optimized process, but rather to critically analyze the individual steps. Thus, by repeatedly questioning the method, insights can be gained that will be beneficial in the following phases. Moreover, an essential focus lies on answering the formulated questions presented in the hypothesis, which means that the individual steps should be reected on several layers in order to gain not only technical, but also moral, ethical, and social insights.
First, the topic of parametric automated plan generation must be addressed in depth. In today's world, artificial intelligence is used as a kind of selling point, a solution to all complex problems, which raises the question of whether this assessment is truthful, or is this term simply associated with idealized solutions? Once these questions are answered and a concrete concept has emerged from the abstract term, it becomes possible to think about connections between architecture and machine learning that simplify existing design processes, blueprints, simulations or constructive procedures.
Just as important as a clear understanding of the subject matter an in-depth review of the available libraries and their functions, in order to create a customized network diagram covering the interactions. The open source community, through platforms such as Github, Gitlab, and OSArch-community, provides an appropriate and direct exchange with developers and interested individuals and a complete understanding of the functions and procedures, as well as, in most cases, detailed documentation. With the help of various forums and exchanges with developers, it is possible to gain a comprehensive understanding of the software in question in a relatively short period of time, thus advancing the ideas of the project.

Objectives

The experimental freedom explained above also leads to flexibility in terms of the defined aims. In general, there are objectives for each stage, but this does not mean that a step has failed if they turn out differently than expected or formulated in advance. Thus, the stage of parametric generation has as a desired result the generation of synthetically generated models that can be constrained by certain parameters. These can be the number of living rooms, the number of residents, the area, the volume or the shape of the floor plan. The end result of this phase should be a database of the different geometries that describes each situation as accurately as possible while still requiring a minimum amount of points. In the next stage, the simulations would generate new evaluation values that could be added to the geometric database. Further, the next stage is to train a model that describes the relationship between the individual values as accurately as possible by means of a graph. Finally, the last stage is to provide an accurate visualization of the predicted scenario.

Roadmap

- ☐ Information Gathering
  - ☐ Search Resources
    - ☐ Code Repositories
    - ☐ Academic Papers
    - ☐ Books / Reports / Articles
    - ☐ Student Works
  - ☐ Create Bibliography
  - ☐ Adequate Software
    - ☐ Code Documentation
    - ☐ Explanatory Resources
- ☐ Geometric Generation
  - ☐ Available Methods
    - ☐ Algorithms
      - ☐ Evolutionary Generation
      - ☐ KD-Tree
      - ☐ Pulga Physics
      - ☐ Shape Grammar
      - ☐ Shape Packing
      - ☐ Orthogonal Convex Hull
      - ☐ Voronoi
      - ☐ Orthogonal Voronoi
      - ☐ Lloyd
      - ☐ Delaunay
      - ☐ Power Diagram
      - ☐ Polygon Division
      - ☐ Recursive Subdivision
      - ☐ Recursive Bisection
      - ☐ Recursive Angled Bisection
      - ☐ Surface Population
      - ☐ Point Cloud
    - ☐ Machine Learning
      - ☐ CNN
      - ☐ GAN
      - ☐ Random Forest
  - ☐ Parametric Generation
    - ☐ Sverchok

            - ☐ Grasshopper
        - ☐ Evaluation
            - ☐ Data Set Search
            - ☐ Comparison
            - ☐ Esthetic Verification
            - ☐ Functional Verification
            - ☐ Ideological Verification
                - ☐ A Pattern Language

- ☐ Simulations / Analysis
    - ☐ Familiarization
        - ☐ Environmental
            - ☐ Energy
                - ☐ Energy+
                - ☐ Openstudio-Energy
                - ☐ Ladybug
                - ☐ Vi-Energy
            - ☐ Lightning
                - ☐ Radiance
                - ☐ HoneyBee
                - ☐ Openstudio
                - ☐ Vi-Radiance
            - ☐ Air
        - ☐ Spatial
            - ☐ TopologicPY
            - ☐ IFC
            - ☐ Blender BIM
        - ☐ Structural
    - ☐ Usage
    - ☐ Data Type Examination
    - ☐ Verification

- ☐ Data Manipulation
    - ☐ Database Types
    - ☐ Data Preparation

- ☐ Machine Learning
    - ☐ Methods

- ☐ Visualization
    - ☐ Back Feeding
    - ☐ Geometry Viewer

- ☐ Pertinence Study
    - ☐ Usage Application

Epilog

Conclusion

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Discussion

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Further Readings

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Future Works

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