Graduation Plan

Master of Science Architecture, Urbanism & Building Sciences

Graduation Plan: All tracks

Submit your Graduation Plan to the Board of Examiners (Examencommissie-BK@tudelft.nl), Mentors and Delegate of the Board of Examiners one week before P2 at the latest.

The graduation plan consists of at least the following data/segments:

Personal information	
Name	Lisa-Marie Mueller
Student number	5619521

Studio		
Name / Theme	Design Informatics	
Main mentor	Dr. Michela Turrin	Design Informatics
Second mentor	Dr. Charalampos Andriotis	Architectural Engineering, Machine Learning/Artificial Intelligence
Argumentation of choice of the studio	The architecture, engineering, and construction (AEC) industry has been slow to adapt technological solutions. Currently, there are many challenges like the demand for new housing which require innovative solutions. I believe that the intersection of informatics, specifically artificial intelligence (AI), and architecture can provide solutions that allow for more people to access well-designed spaces.	

Graduation project	
Title of the graduation project	3D Generative Adversarial Network to Produce Context-Responsive Novel Building Geometry
Goal	
Location:	The project proposes to generate architectural designs based on a training data set. Due to the available data, there will not be a specific site but instead various created artificial sites.
The posed problem,	While the AEC industry is growing at slow rates, the demand for new construction continues to increase. The industry cannot keep up with these demands including the demand for new houses. The pressures are not only leading to a scarcity of buildings, but also a scarcity of design services. Affordable housing is most at risk of becoming a catalog of poorly designed buildings. Current solutions like shipping container homes and tiny home communities provide sub-par living conditions and look at small-scale, unsustainable approaches [Rippingale, 2014; McManus, 2022] . This is where the AEC industry can benefit from innovation. Machine learning models have already been trained to generate novel images and art. Philosophically, it is still possible to debate if machine learning models are creative, but it has been shown that they can complete creative tasks [Marr, 2020]. Within the AEC industry the applications of machine learning models have been more limited but there are a number of example. These include models that generate two-dimensional (2D) images like generative floor plans [Keshavarzi and

<table>
<tr><td></td><td>Rahmani-Asl, 2021; Carta, 2021], novel site layouts [Spa, 2023; Tes, 2023], and context-responsive building massing envelopes [Vesely, 2022]. In other industries, there are also some applications in three-dimensions (3D). For example, Wu et al. [2016] developed 3D Generative Adversarial Network (GAN) architecture for generating 3D objects. This provides the opportunity to expand upon this existing research and take these innovations from the computer science field into the architecture, engineering, and construction fields.</td></tr>
<tr><td>research questions and</td><td>Research Question
How can a 3D Generative Adversarial Network model be trained to produce novel building designs on a site considering adjacent buildings?
Sub-Questions
What are key aspects of a training data set that are required for generating 3D building designs?
What level of detail (LOD) and voxel resolution is required in the training data to identify design features in a generated building?
How can 3D Generative Adversarial Networks generate novel, feasible building facades which respond to context?
How can soft criteria be encoded to optimize generated buildings?
What are the challenges and benefits of using 3D GAN for architectural design?</td></tr>
<tr><td>design assignment in which these result.</td><td>This thesis aims to explore one step in the larger challenge of automating design by researching the opportunities of applying deep learning models to the design of buildings. I propose a method based on 3D GAN [Wu et al., 2016] neural network architecture to train a model that can generate novel building geometry considering the adjacent buildings as context. The model is trained on a data set BuildingNet v0.1 [Selvaraju et al., 2021] which will be modified for the purposes of this thesis. The modified dataset will then also be made available so that it can also be used for future application including other research related to generating novel 3D building geometry. The existing data set contains labeled 3D building models which will be pre-processed to remove site geometry and scaled to relate to real-world dimensions.

In addition to providing the modified dataset, another final deliverable will be a trained model that can generate novel, feasible building geometry with a consideration of adjacent buildings as the context and visualizations of the generated geometry. If the training of the model progresses without unforeseen challenges, there is also an opportunity to incorporate optimization of the generated model.</td></tr>
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Process

Method description

The research framework for this thesis focuses on developing the data set and the neural network architecture of the Generative Adversarial Network (GAN). Additionally, if training the model progresses without further challenges, there is an opportunity to research how optimization can be incorporated into the proposed workflow. A graphic overview of the methods that will be implemented in this thesis can be seen in Figure 1 at the end of this section (method description).

To address all parts of the primary research question, a selection of methodologies are required for each part. The focus of the research is on modifying the existing data set and training a model to generate novel building designs. This will primarily involve applying the design science methodology [Simon, 1970].

The 3D GAN model will also need to be evaluated based on its performance. Because GAN models are not trained with a loss function like other deep learning models are, the loss cannot be used as a metric to objectively asses the training progress or the quality of the model. After a review of the various metrics, two qualitative metrics were selected:

- nearest neighbors: generated samples are reviewed next to their nearest neighbors in the training set
- network internals: the internal representation of models like the space continuity will be illustrated and the learned features will be visualized [Mehralian and Karasfi, 2018; Zeiler and Fergus, 2013; Bau et al., 2017]

Additionally, two quantitative metrics were selected:

- Frechet Inception Distance (FID) [Heusel et al., 2017] is used to evaluate the quality of the generated geometry. A lower FID score means that the generated object is more realistic and that the object matches the statistical properties of a real model. [Kurach et al., 2018]
- Generative Adversarial Metric (GAM) Compares two GANs by starting a competition between the two and having them swap discriminators and generators. During the training phase, the discriminator and generator of the Model 1 are paired together and the discriminator and generator of Model 2 are paired together. During the test phase, the discriminator of Model 1 is paired with the generator of Model 2 and vis versa. [Im et al., 2016]

There will be additional methodologies implemented to address the sub-questions:
What are key aspects of a training data set that are required for generating 3D building designs? A key step for training a GAN model to generate novel building designs is the data set. The proposed data set, BuildingNet v0.1 [Selvaraju et al., 2021], was originally developed to label building features in 3D building models. Because the data set will now be used to train a deep learning model that generates buildings, the data set needs to meet requirements that are different than the purpose it was originally created for. This sub-question will be addressed through a literature review and by experimenting and testing.

What LOD and voxel resolution is required in the training data to identify design features in a generated building? The building models in the data set used to train the model will be voxelized because the GAN model will be generating buildings from voxels. The size of the voxels are impacted by the available memory and the size of the buildings so the trade-off between memory usage and resolution will be an important consideration. This sub-question will be addressed through exploratory research by experimenting and testing.

How can 3D GAN generate novel, feasible building facades which respond to context? The deep learning model architecture will be based on an existing architecture for neural networks called 3D GAN [Wu et al., 2016]. The existing architecture needs to be tested with the new objective and training data and the architecture may need to be adjusted. This sub-question will be addressed through a literature review and through exploratory research by experimenting and testing.

How can soft criteria be encoded to optimize generated buildings? If the training process does not reveal additional challenges, it may be possible to explore methods of optimizing the generated building designs. This sub-question will be addressed through a literature review and through exploratory research by experimenting and testing.

What are the challenges and benefits of using 3D GAN for architectural design? Based on the research, the results will be observed and evaluated to determine what additional progress can be made and if the goals of the research were accomplished.

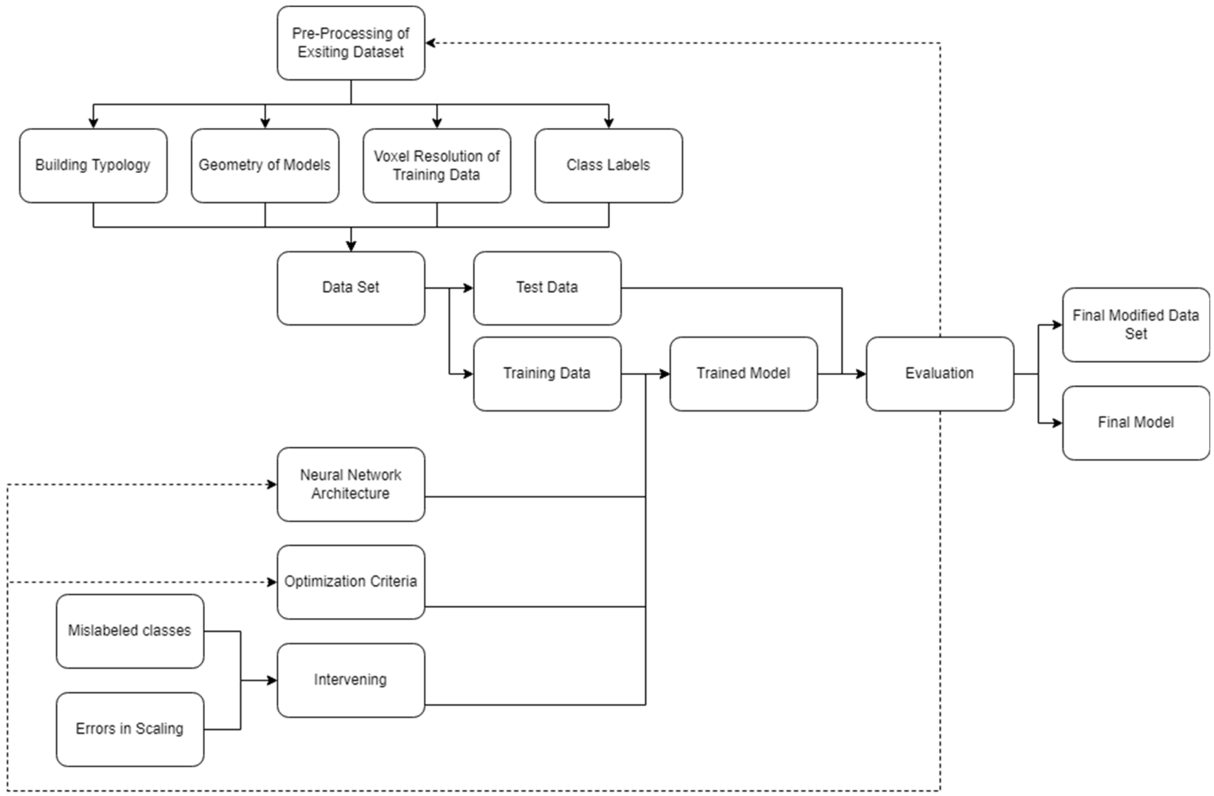

Figure 1: The research framework of the thesis for modifying a data set and training a model to generate novel building geometry.

Literature and general practical preference

The thesis builds upon existing research in the fields of computer science, environmental psychology, design, and engineering. The main areas of research include reviews focused on deep learning models, specifically Generative Adversarial Networks (GANs), design and optimization applications of deep learning, and the analysis of soft criteria for design through the lens of environmental psychology.

GANs networks build upon a number of principles that range from the early developments published in the 1900s to contemporary discoveries and applications. It is important to understand the foundational principles of neural networks [McCulloch and Pitts, 1943] like the perceptron [Rosenblatt, 1958] and how these principles then evolved to the application of multi-layer perceptrons [LeCun et al., 1998; Rumelhart and McClelland, 1987; Werbos and John, 1974]. These concepts provide the foundation that contemporary deep learning research builds upon.

With a specific focus on GANs, there are a number of contemporary sources that provide additional background. The neural network architecture will include 3D applications of convolutional neural networks [Bengio and Lecun, 1997]. GANs [Goodfellow et al., 2014] and the architecture for 3D GANs [Wu et al., 2016] form the most recent developments that this thesis will more directly expand upon.

Until now, the detailed list of references to be consulted is formed as follows:

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Reflection

1. *What is the relation between your graduation (project) topic, the studio topic (if applicable), your master track (A,U,BT,LA,MBE), and your master programme (MSc AUBS)?*

   The MSc AUBS programme focuses on innovation within the fields of architecture and engineering. This relates directly to my thesis topic as my thesis is looking at innovative approaches to the design process by applying deep learning to an architectural problem. The building technology track focuses on integrating design and the technical disciplines. This means the program has a multi-disciplinary focus that encourages students to explore topics that connect different fields. I am following this multi-disciplinary process by connecting expertise from the design, engineering, and design informatics fields through my thesis. My topic requires knowledge that is very specific to the built environment and also requires utilizing research from the field of informatics. Combining these two unique specialties, allows me to explore a topic rooted in design and engineering with a new lens.

2. *What is the relevance of your graduation work in the larger social, professional and scientific framework.*

   The existing research on deep learning applications within the architecture, engineering, and construction industry has been completed by various private companies so there is a lack of published information in the area of automating design for buildings. These gaps present opportunities to expand the industry knowledge about how to automate the design process which would provide access to thoughtful design to a wider audience. This thesis will help to address this missing knowledge.

   The research that will be conducted in this thesis develops strategies to automate the design process which also expands upon generative design tools that are used today. In the future, the generative design tools could propose more than massing, site layouts, and floors plans. This research lays the foundation for these tools to propose designs for 3D building systems. There is an opportunity for future researchers to expand upon the topic and also to explore how GAN networks and other deep learning models could design not just building geometry but also building systems.