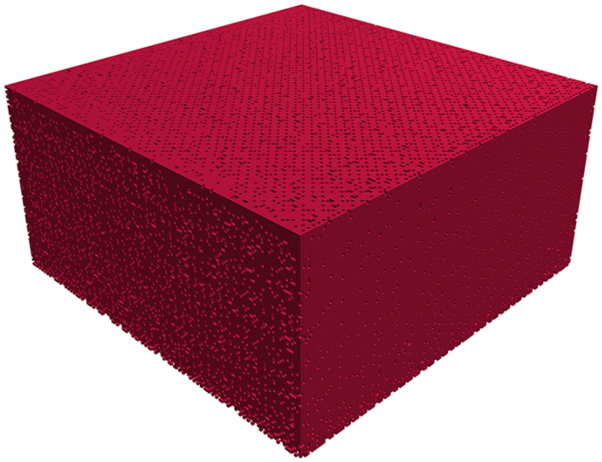

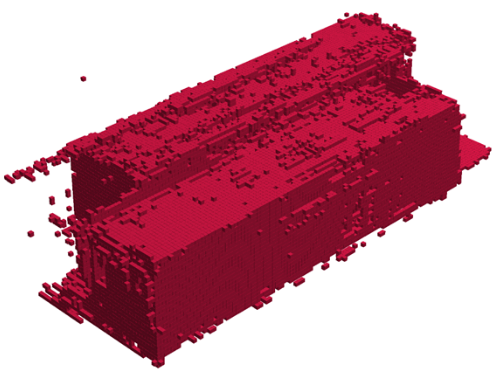

3D Generative Adversarial Networks to Autonomously Generate Building Geometry

Lisa-Marie Mueller
Main Mentor: Dr. Michela Turrin
Second Mentor: Dr. Charalampos Andriotis
Delegate of the Board of Examiners: Dr. Olindo Caso

June 27, 2023

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Problem Statement

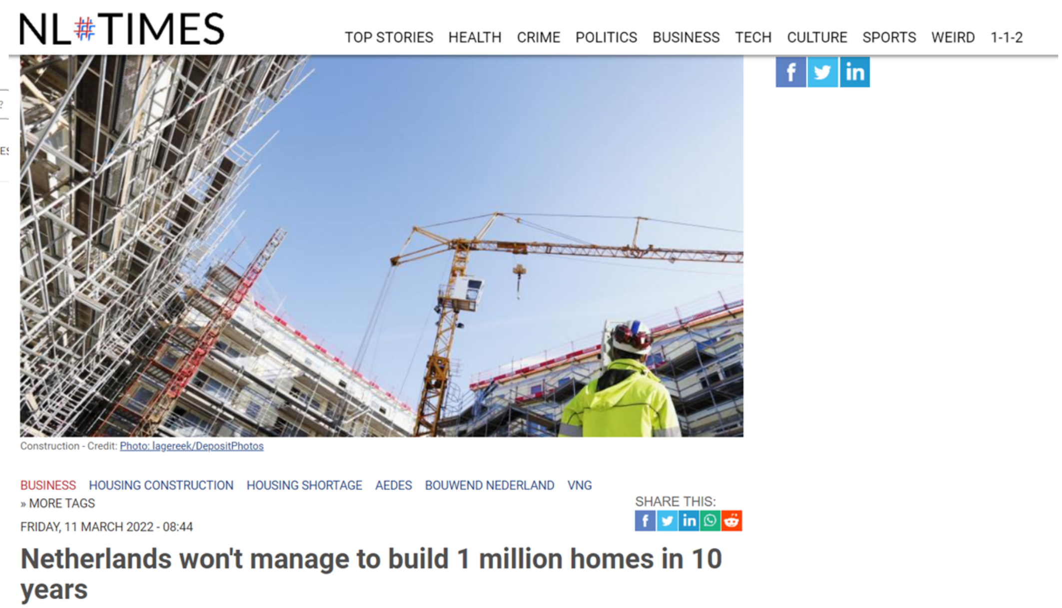

CAPITAL VALUE. Residential Real Estate Services

+31 30 72 71 700 How can we help you?

OUR SERVICES TO | EXPERTISES | PROPERTIES | NEWS | REFERENCES | RES

HOUSING SHORTAGE IN THE NETHERLANDS RISES TO 263,000 DWELLINGS

11 February 2019


NL TIMES

TOP STORIES HEALTH CRIME POLITICS BUSINESS TECH CULTURE SPORTS WEIRD 1-1-2

Construction - Credit: Photo: lagereek/DepositPhotos

BUSINESS HOUSING CONSTRUCTION HOUSING SHORTAGE AEDES BOUWEND NEDERLAND VNG

» MORE TAGS

SHARE THIS:

FRIDAY, 11 MARCH 2022 - 08:44

Netherlands won't manage to build 1 million homes in 10 years

Netherlands won't manage to build 1 million homes in 10 years. (n.d.)

Value, C. (n.d.).

Problem Statement

1.18%
increase

in demand per year

4.7% demand increase in 4 years

0.42%
growth

in AEC industry per year

2.1% industry growth in 5 years

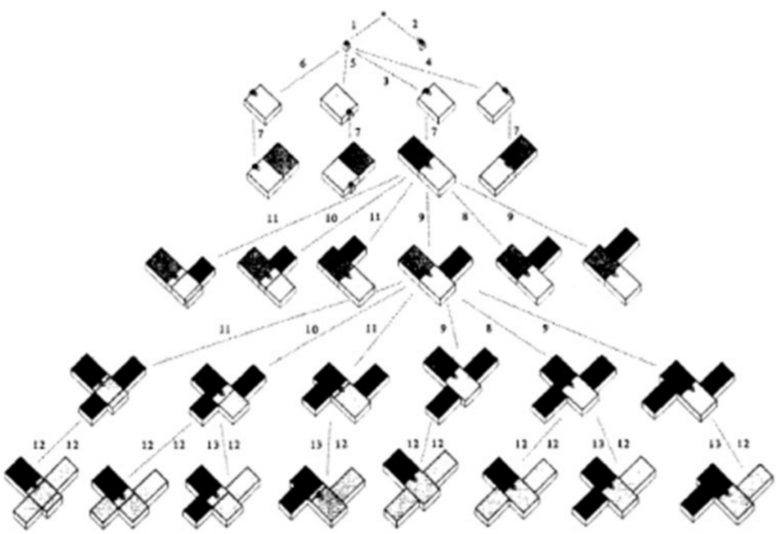
Value, C. (n.d.).

IBISWorld (2021).

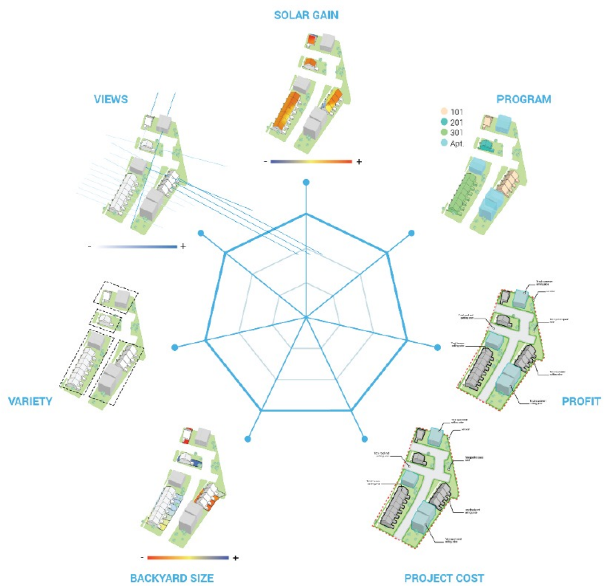
Problem Statement

To keep up with the rising demands for architecture, engineering, and construction services, the industry needs to radically rethink the design, planning, and construction process.

Design Automation



Shape Grammar

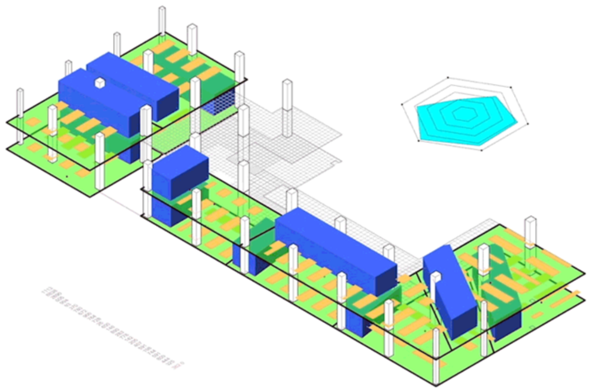


Generative Design

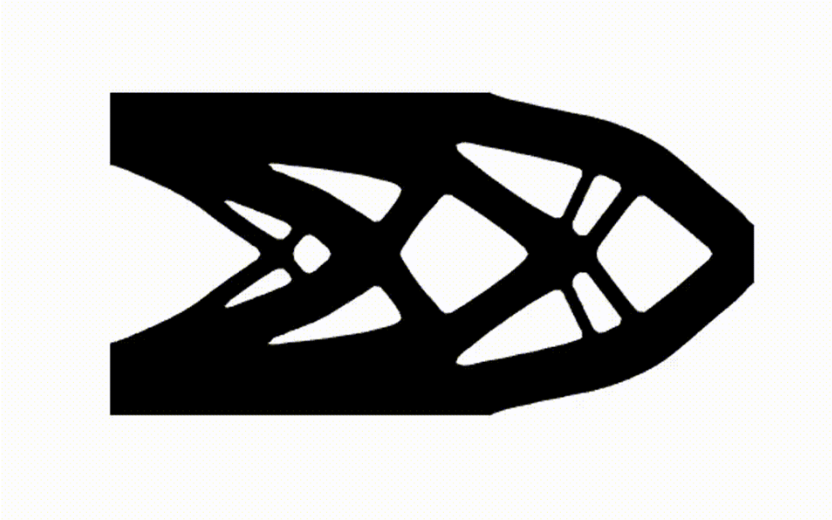
Koning and Eizenber (1981)

Souza (2020}

Design Automation



Generative Design

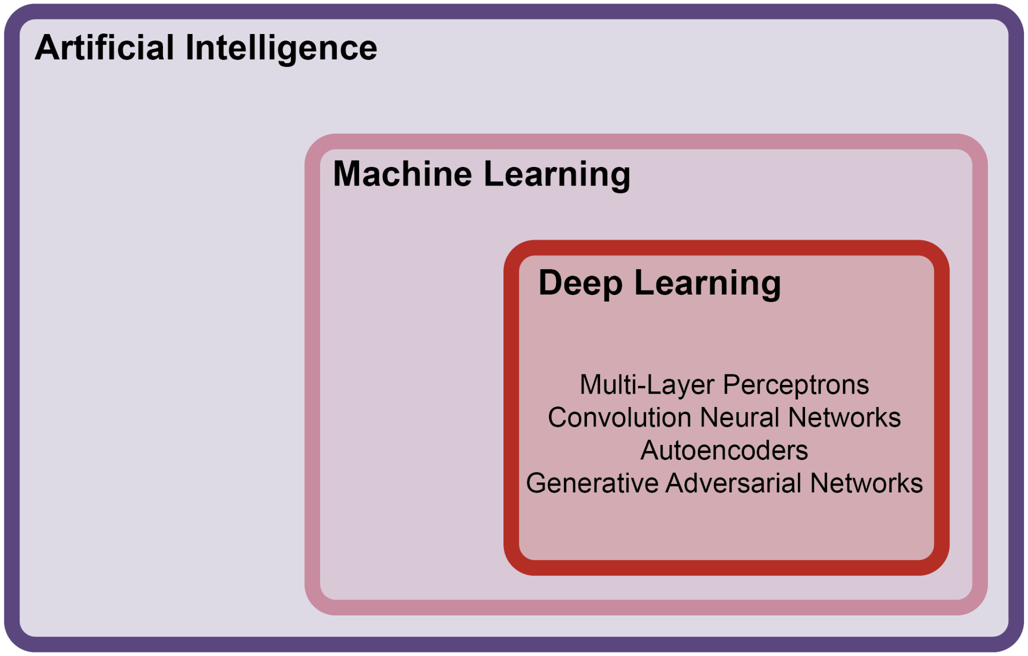


Machine Learning Integrated
Generative Design

Generative Design Primer (2021)

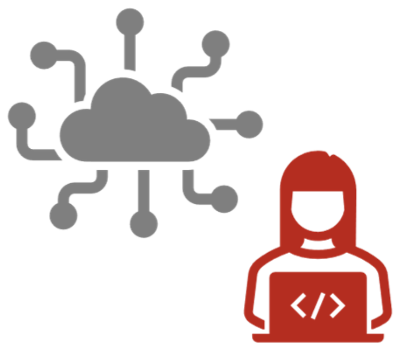
ITB (n.d.)

Overview


Artificial Intelligence
Machine Learning
Deep Learning
Multi-Layer Perceptrons
Convolution Neural Networks
Autoencoders
Generative Adversarial Networks

Imagine …

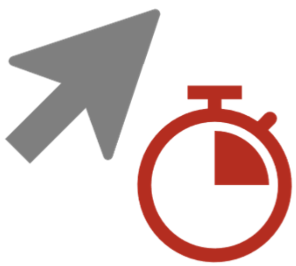
City Needs to Build new Affordable Housing Complex

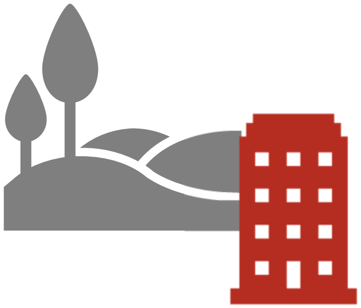


Inputs Site into Trained Model

Code-Compliant Design Results in Hours

Deep Learning





Housing Crisis Needs	Needs options quickly	Code-Compliant, healthy, and safe design	One typology: housing
Deep Learning Benefits	Trained model produces output on demand	Learns expertise based on training data	Generates site-specific models of learned typology

Typology: Multifamily Housing

Large-Scale, Sustainable Solution

Can Provide Affordable Housing Options

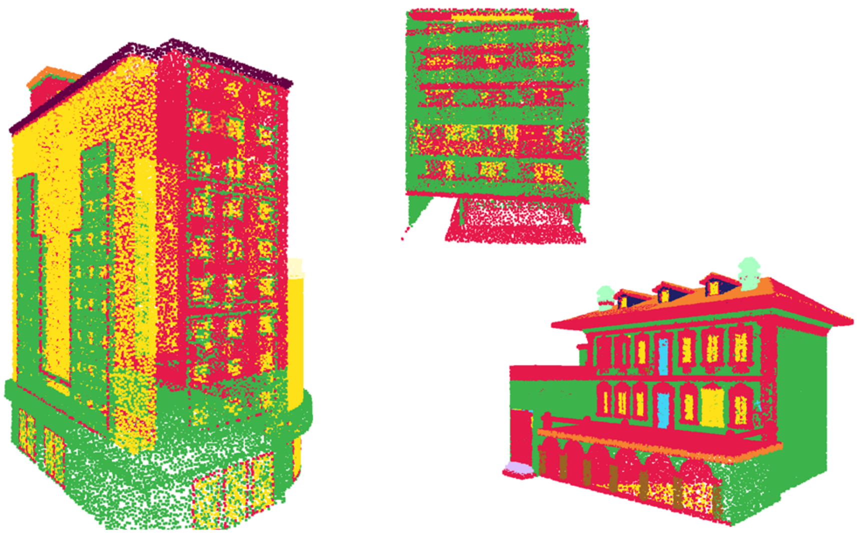
Has Repeating Patterns and Standardizations

Not Iconic Building Typology

Training Data

OPTIMAL : Multifamily Housing

10 models, not categorized

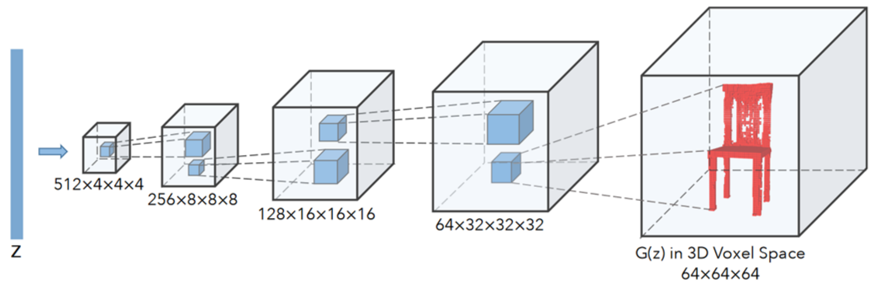


AVAILABLE : Single-Family Houses

Over 1,000 models

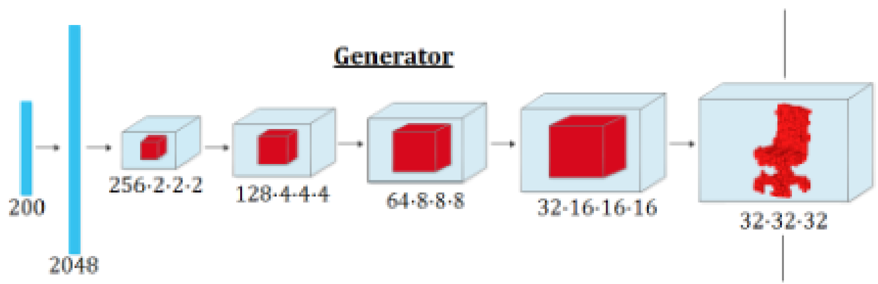
Existing Applications

3D GAN



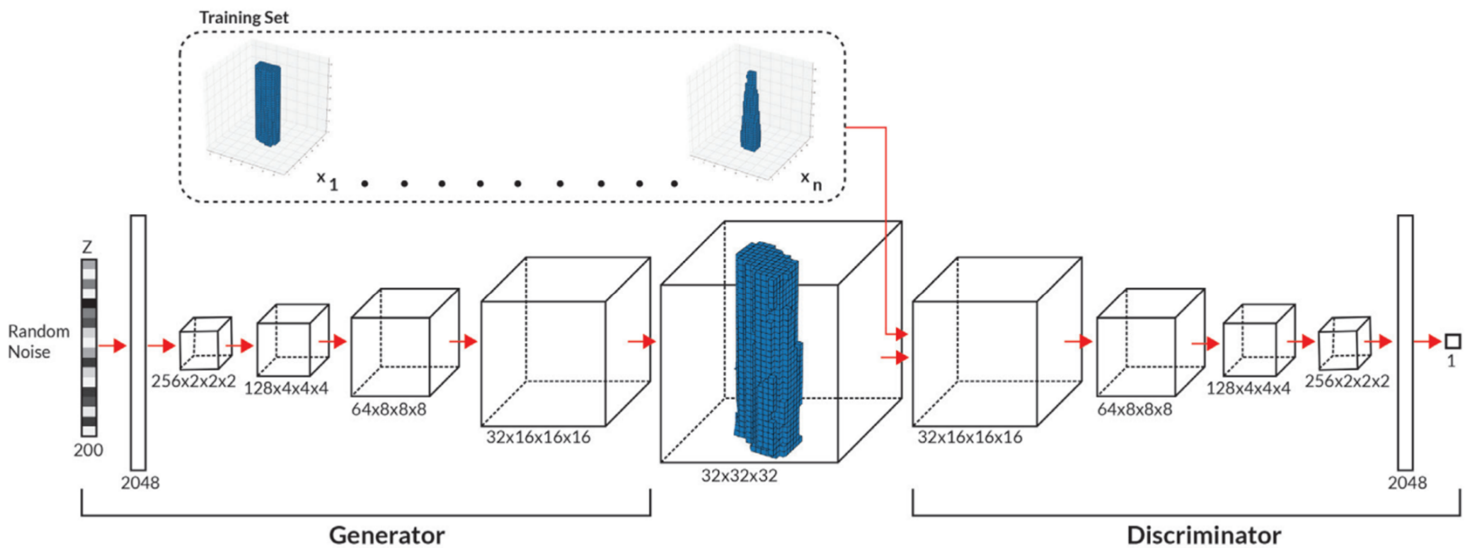
Wu, et al. (2016).

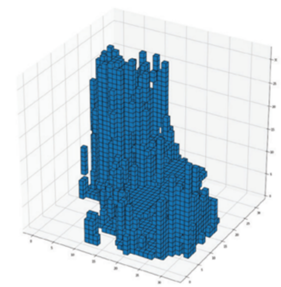
WGAN

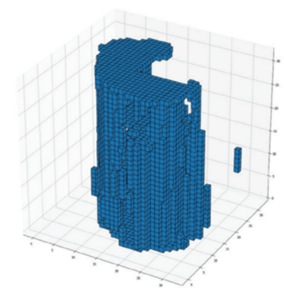


Smith and Meger (2017).

Gaps in Current Research

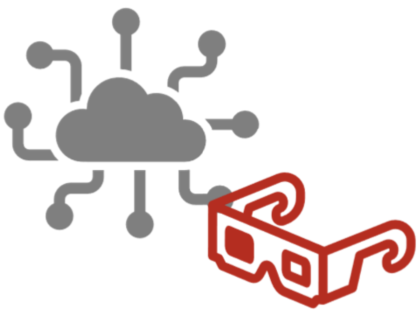




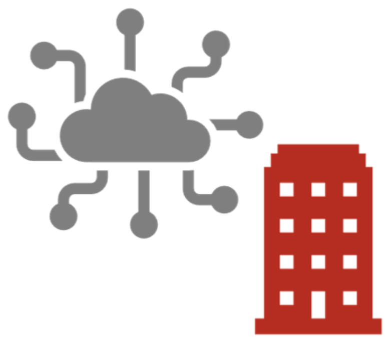


Newton (2019)

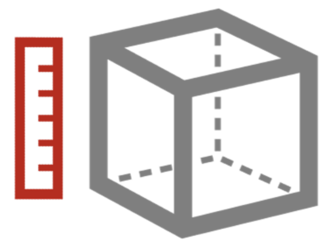
Gaps in Current Research



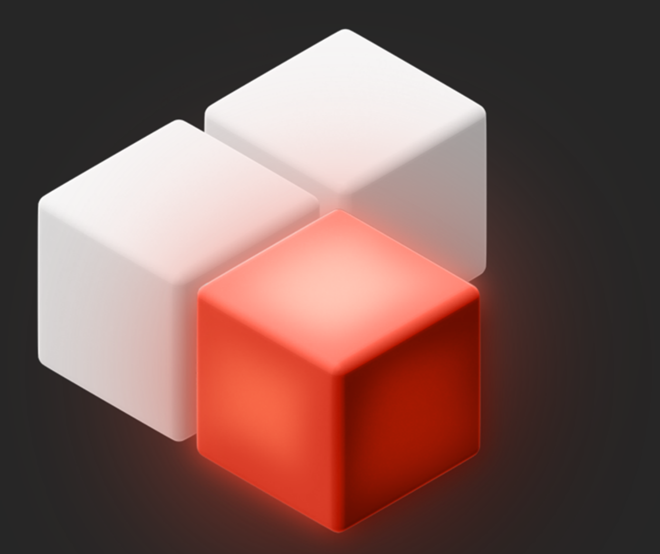
Limited research about GANs for creating 3D geometry



Limited applications of 3D GANs on architecture

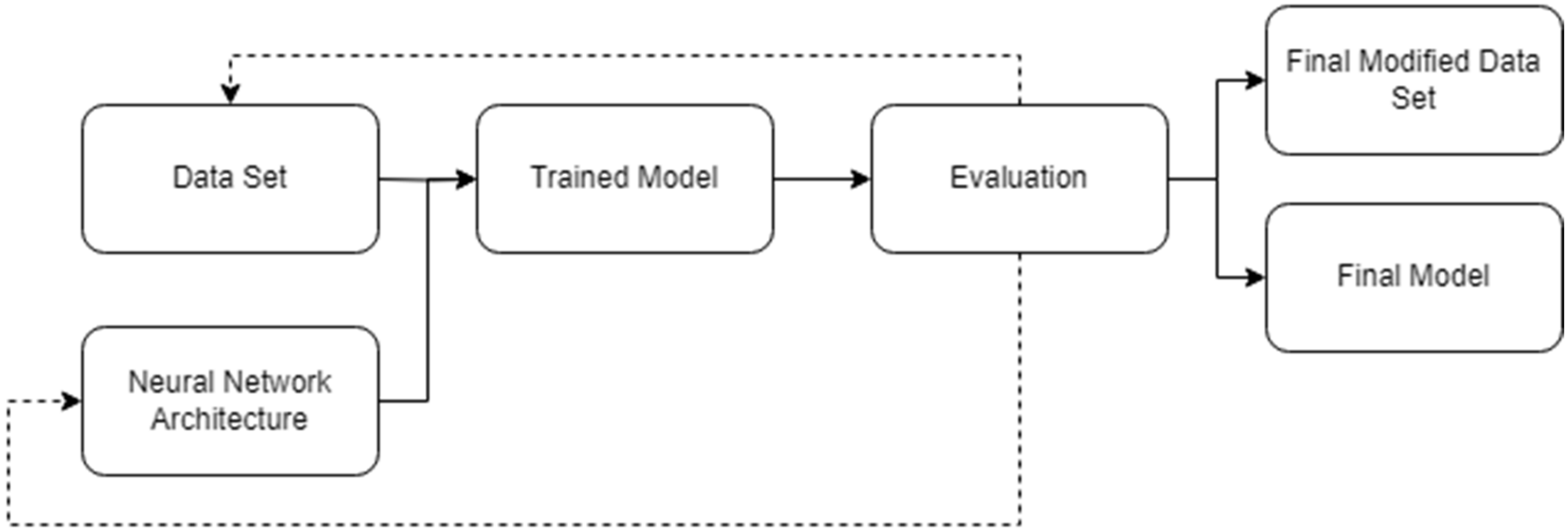


Too small geometry space



How can a GAN model be trained to produce 3D building geometry given 3D models of single-family houses as input?

Framework


Data Set
Trained Model
Evaluation
Final Modified Data Set
Final Model
Neural Network Architecture

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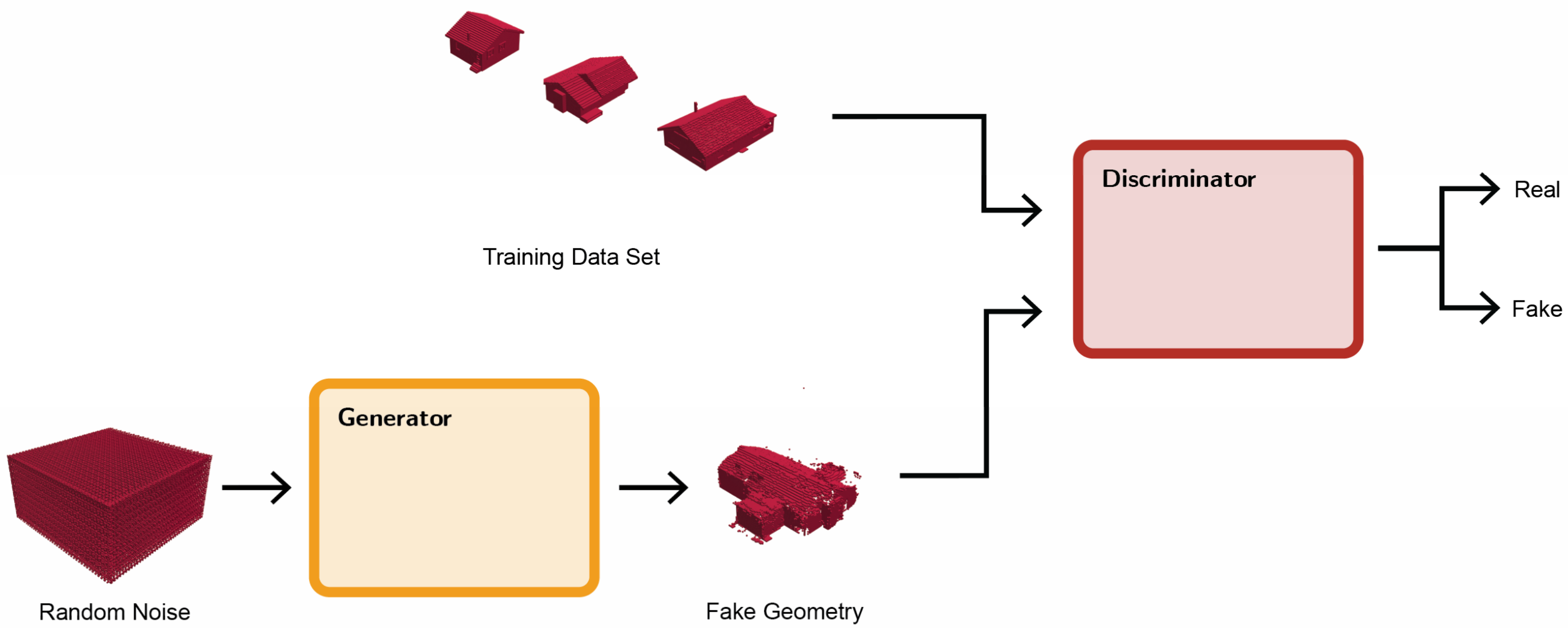
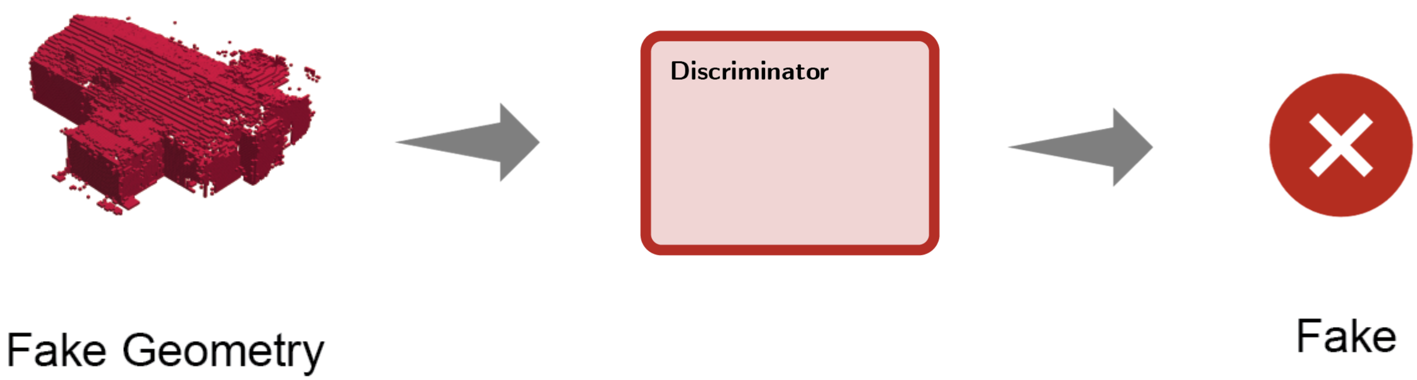
Generative Adversarial Networks

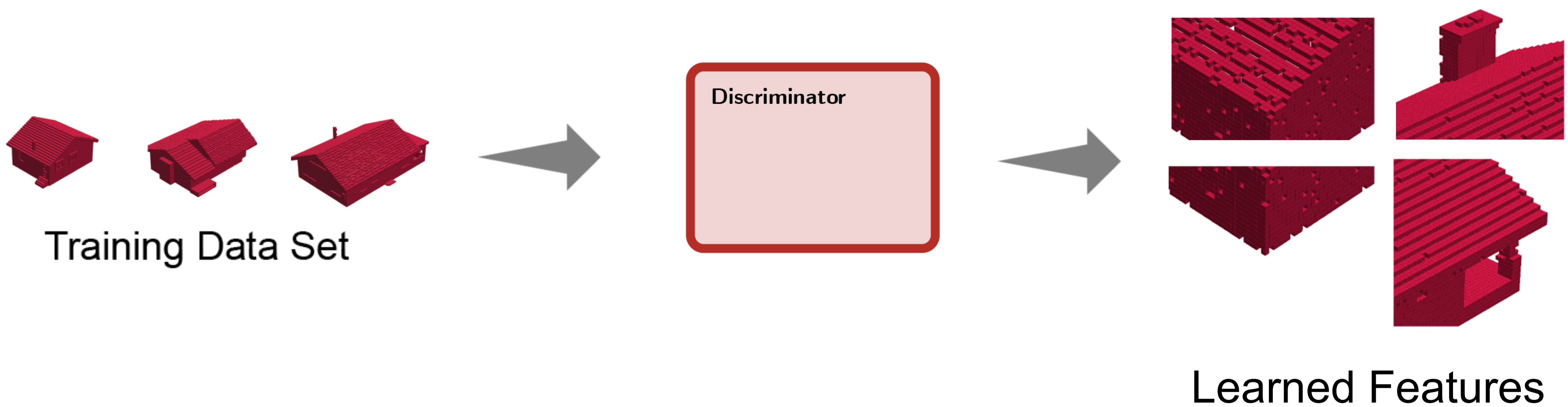


Concept: Goodfellow, I., et al. (2014). Image: Lisa-Marie Mueller

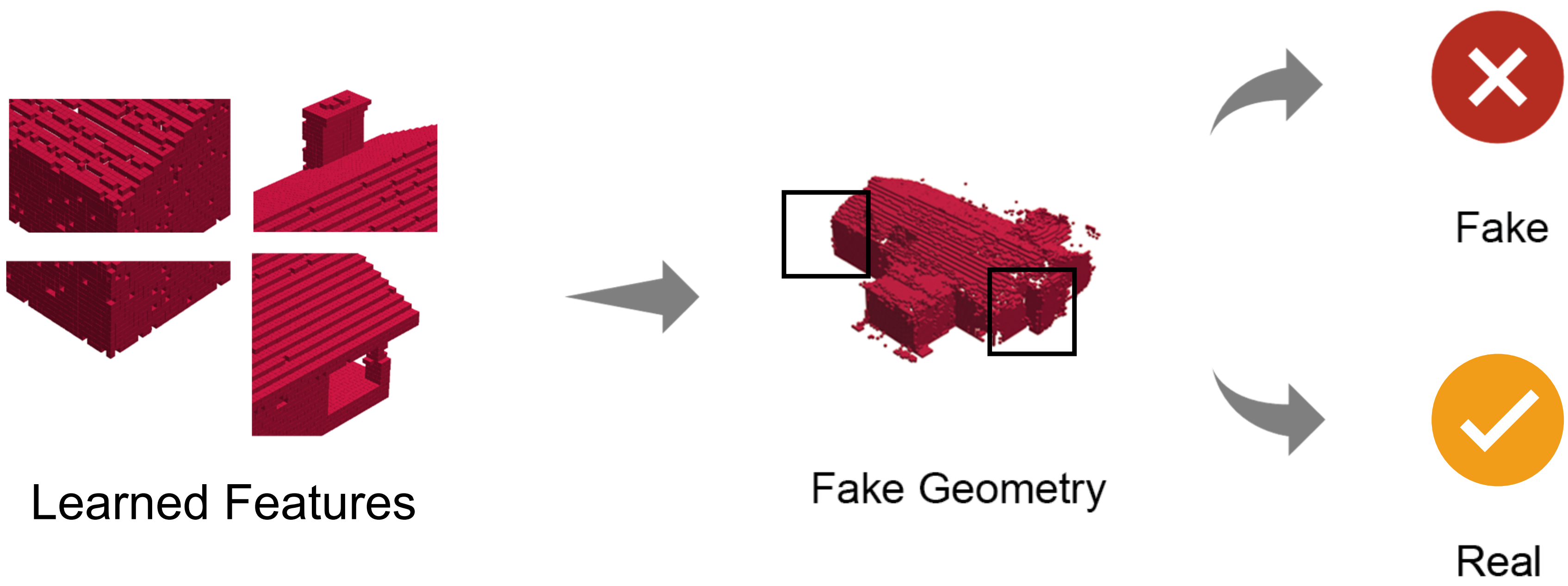
GAN Discriminator Goal



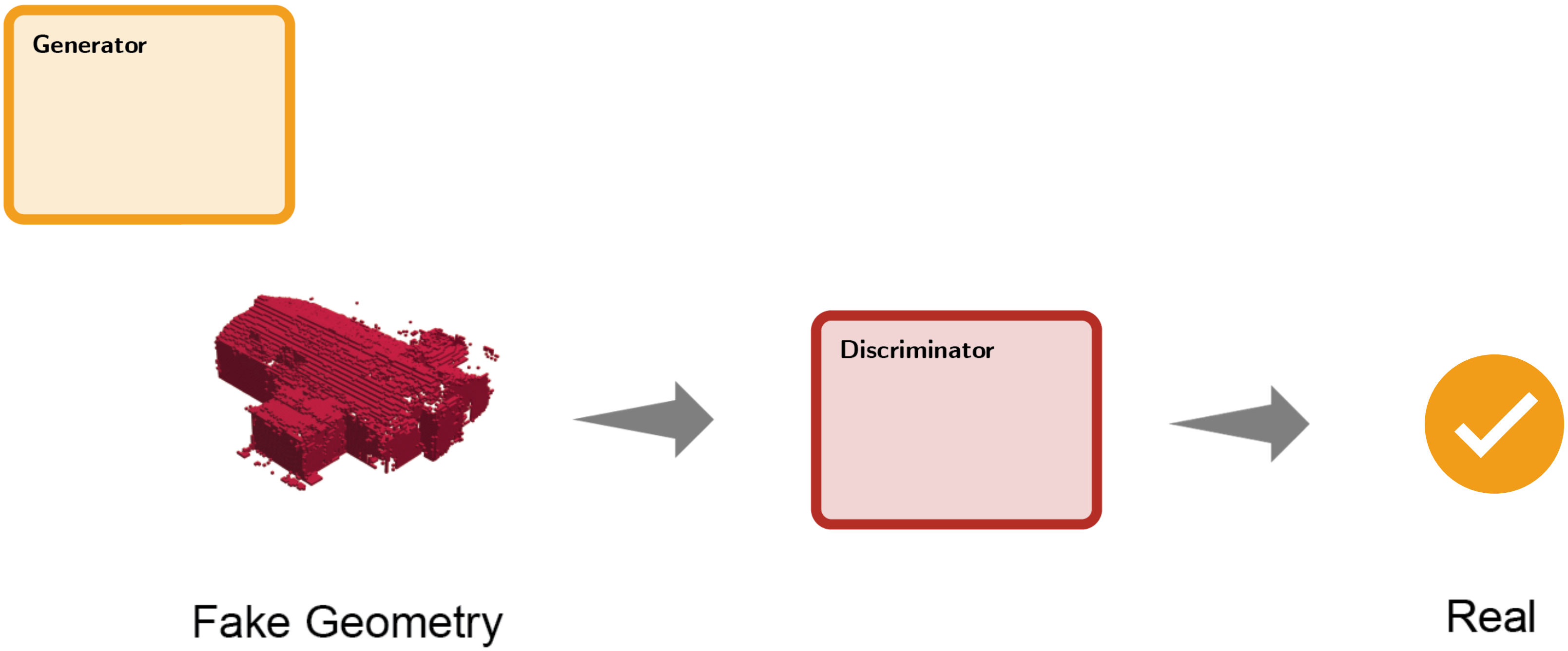
GAN Discriminator Goal



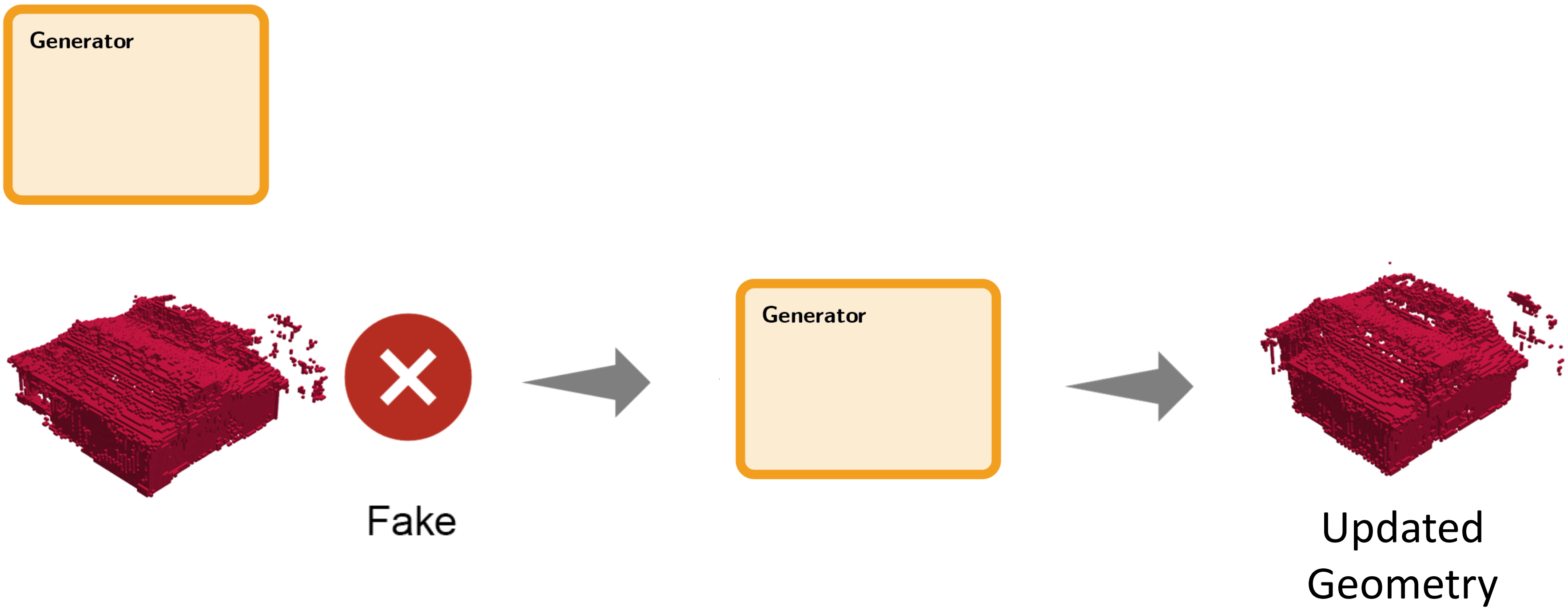
GAN Discriminator Goal



GAN Generator Goal

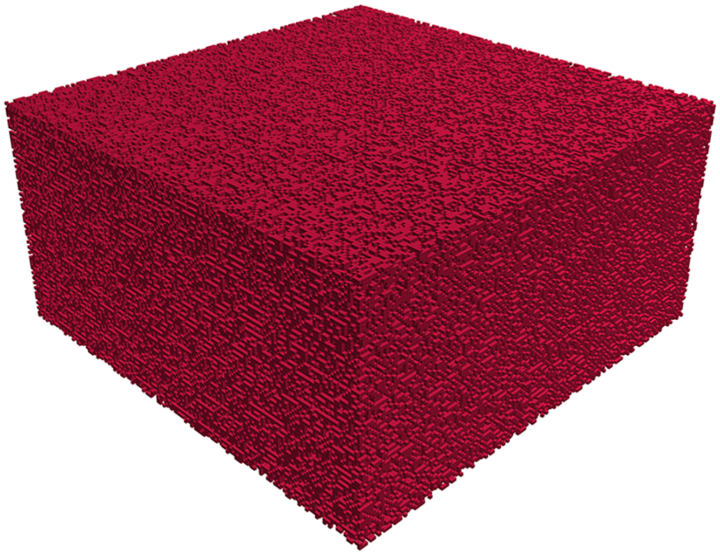


GAN Generator Goal

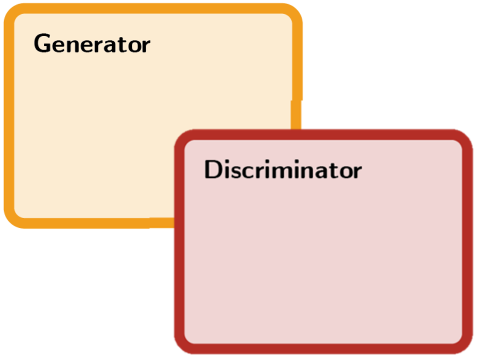


Generator Training

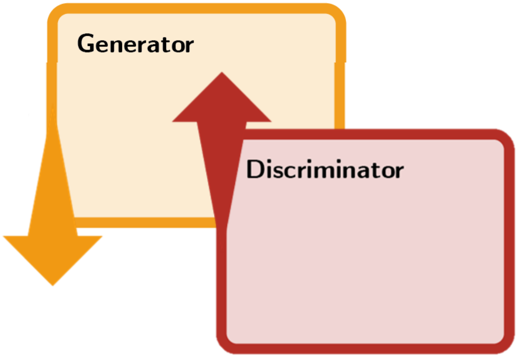
Generator



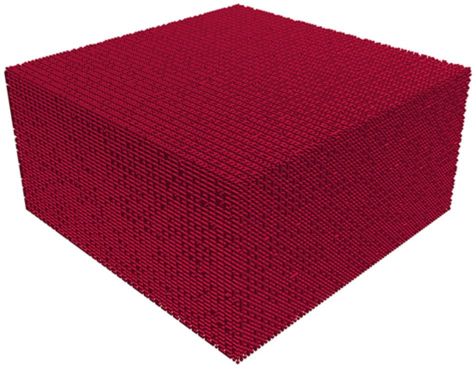
Notoriously Difficult to Train



Two Neural Networks Trained Simultaneously



Improvement to One Comes at Cost to the Other



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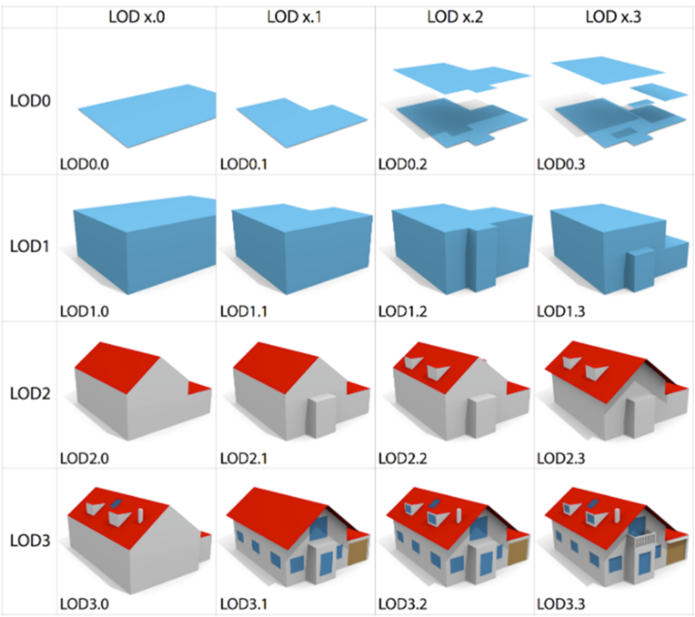
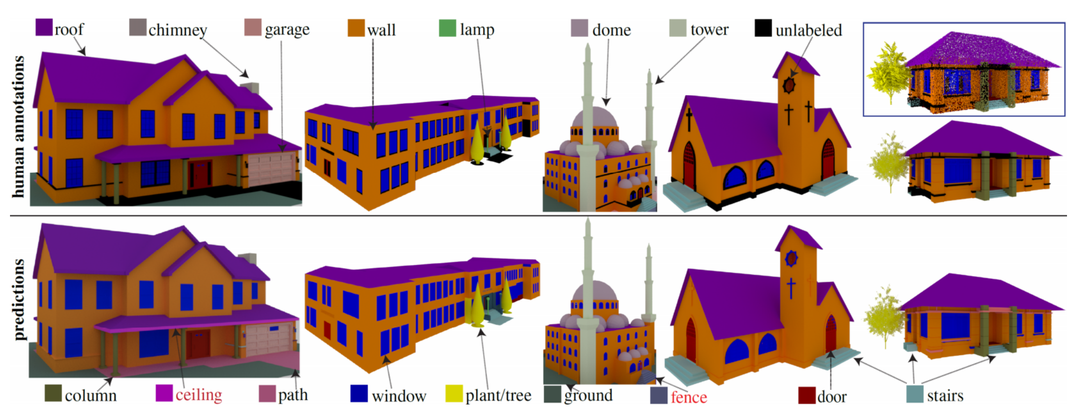
Data Set



BuildingNet v 0.1



Biljecki, F., et al. (2016)

Selvaraju, P., et al. (2021).

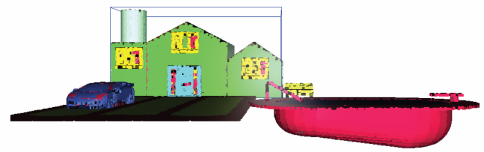
Processed Data Set for Release

Clean Data Set

Cleaned Dataset

Selecting Typology
(913 Models Left)

Clean Models – Data Set of 913



Original Model

Cleaned Model

For Thesis

100 Cleaned Models
Single-Story
Single-Family
House

Two-Label

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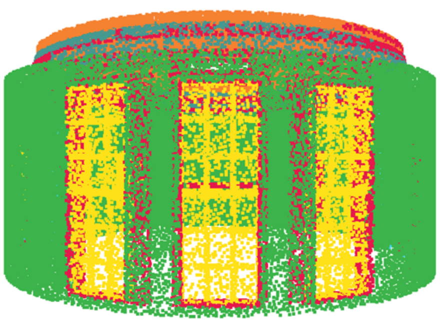
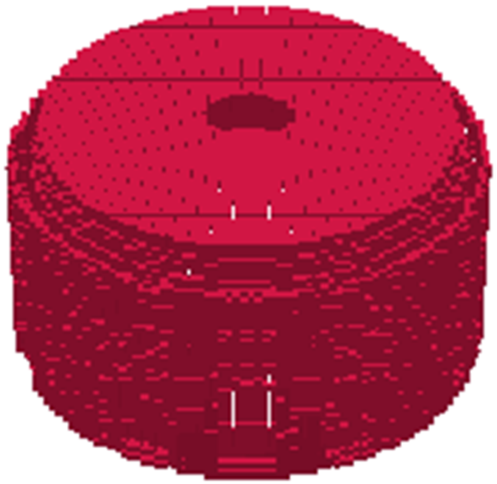
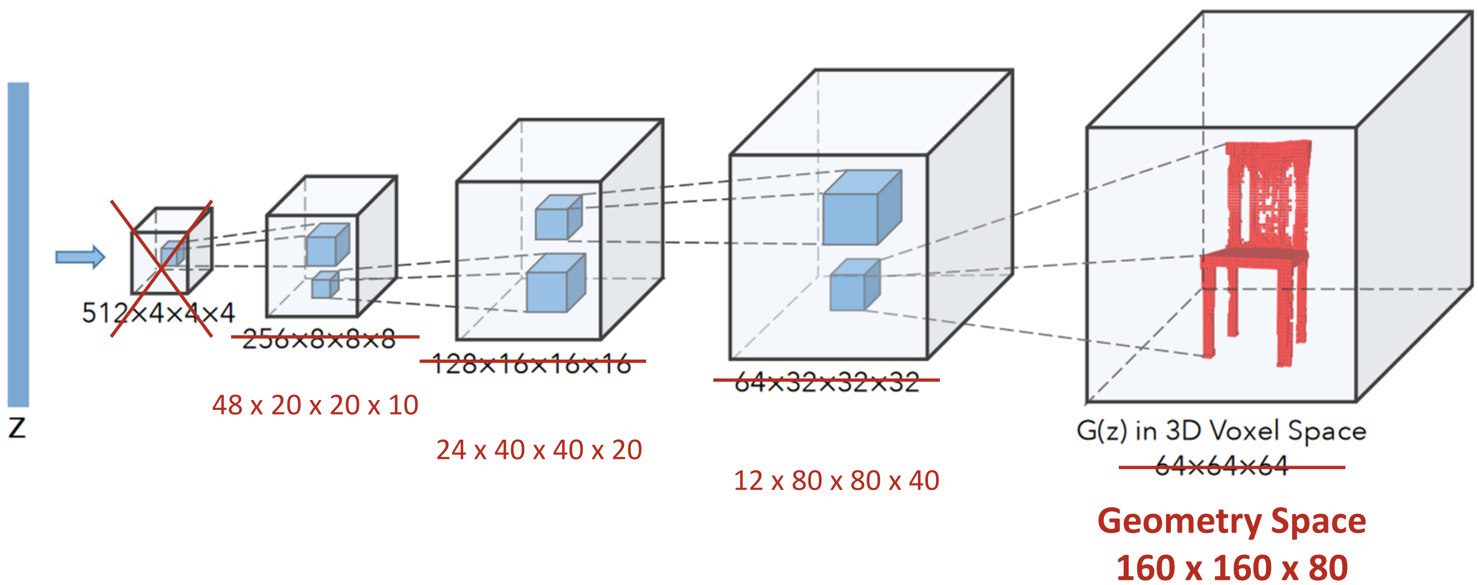
WGAN vs DCGAN | 1 model

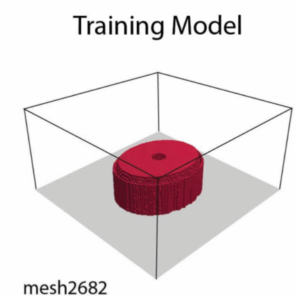




State of the Art Architecture: 3D GAN

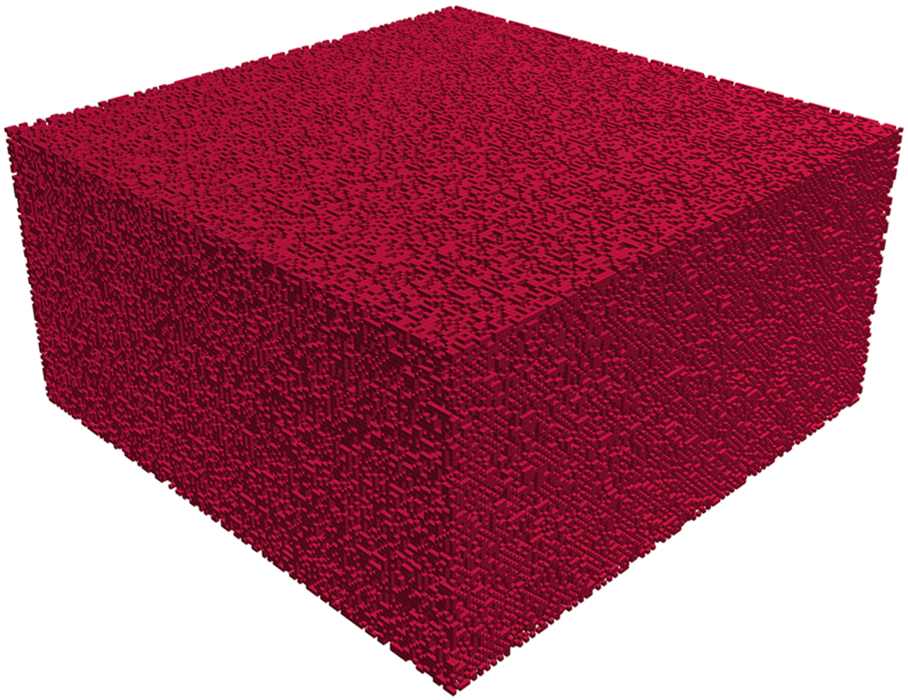
Starting Architecture



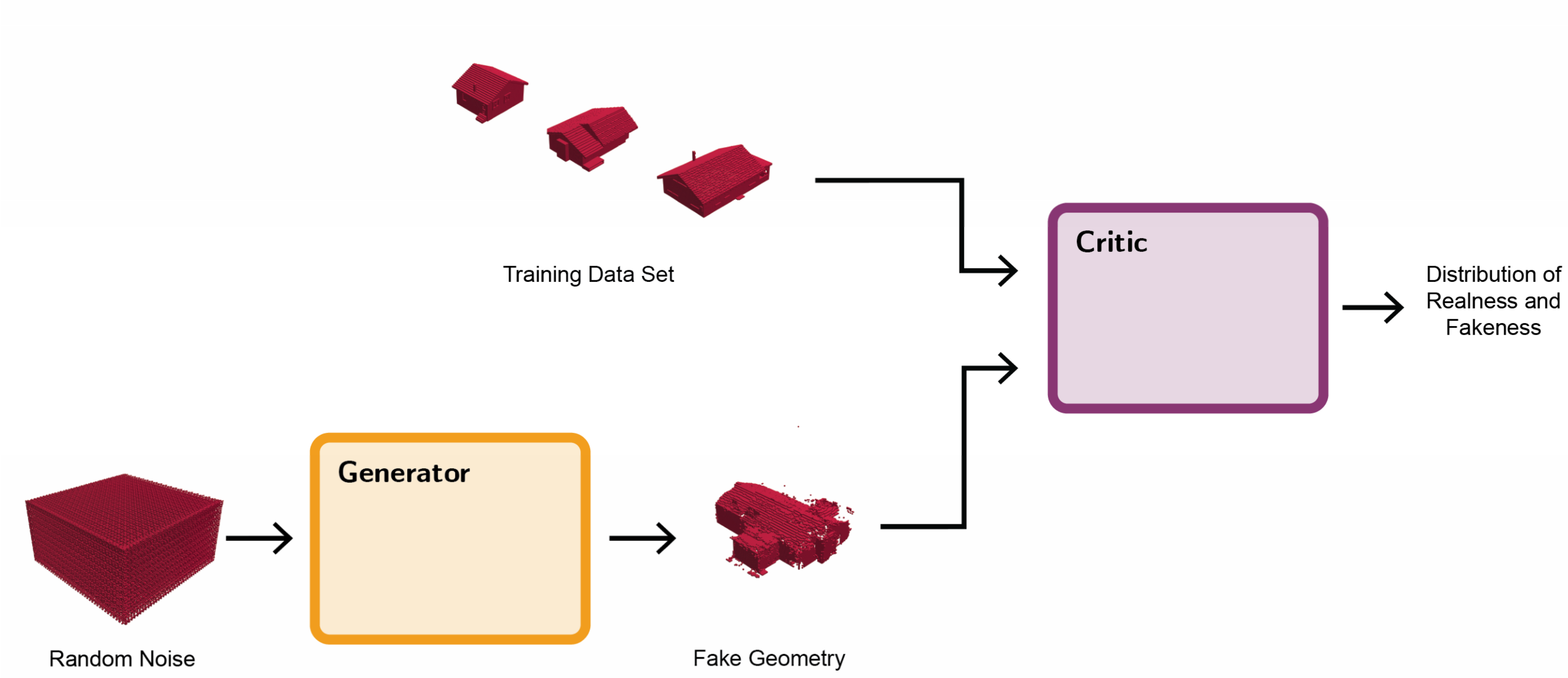


Wu, et al. (2016).

Vanishing Gradients Problem

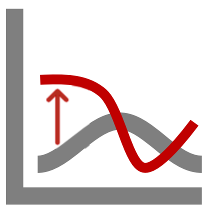


Generative Adversarial Networks



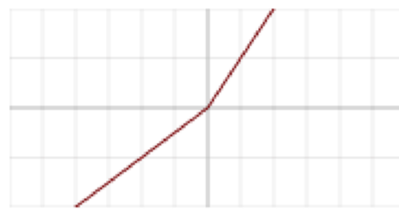
WGAN vs DCGAN Hyperparameter Results

WGAN AND DCGAN



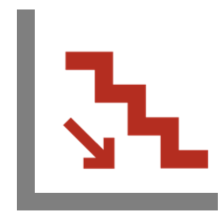
Wasserstein Loss

Necessary for Stable Training



Leaky ReLU

Necessary for Stable Training

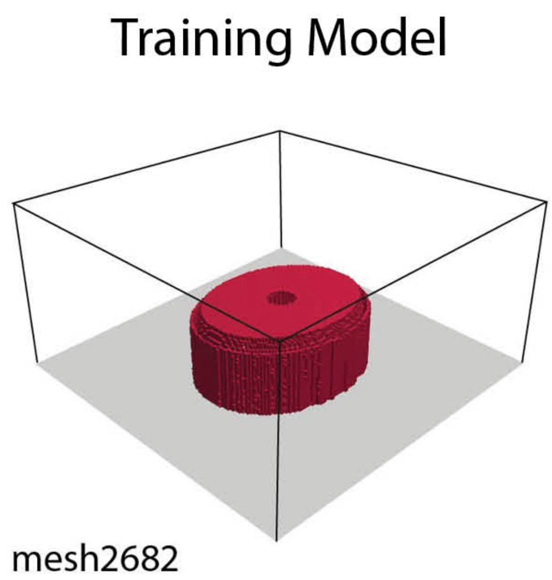


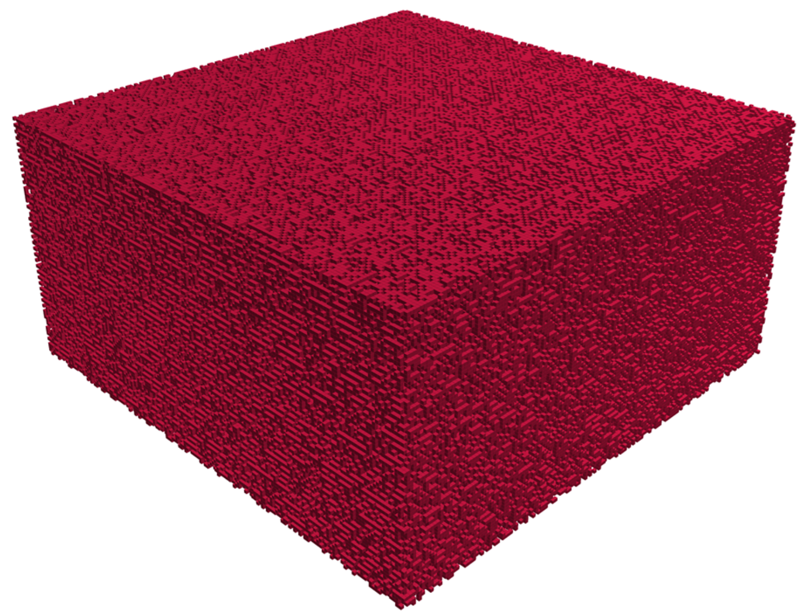
Learning Rate Decay

Positive Impact on Training

WGAN 11G | 1 Model

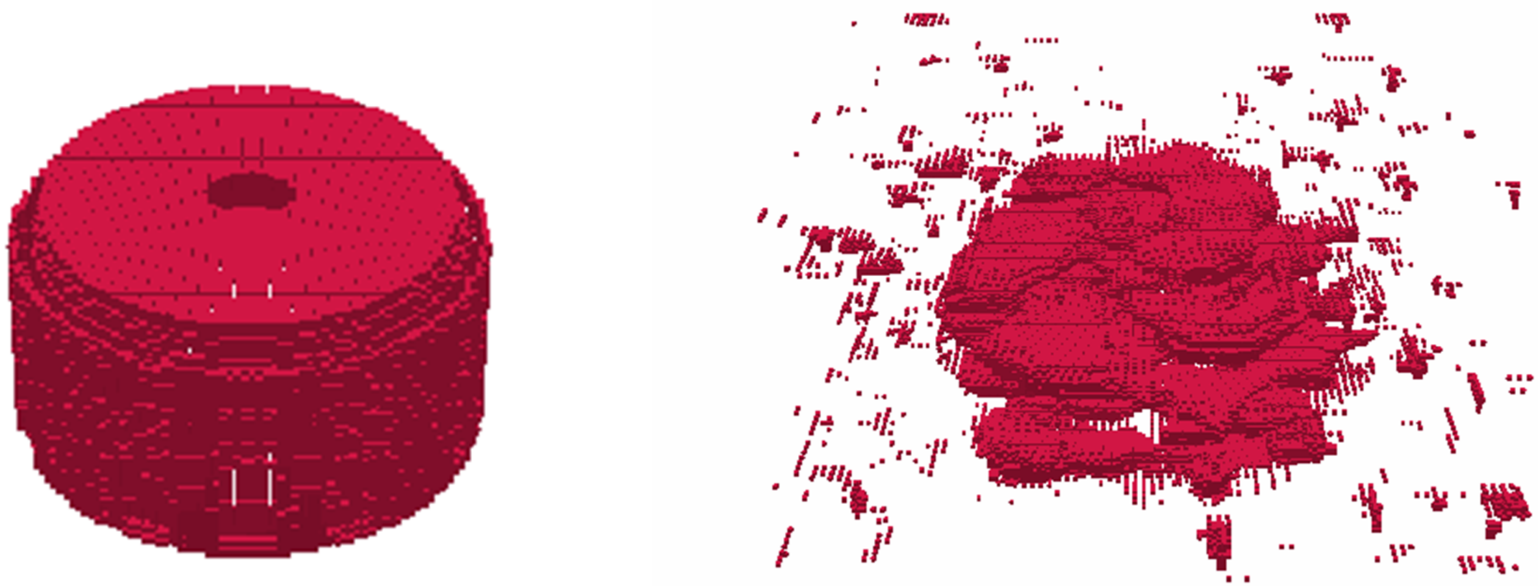
11	4 Layers	48-24-12-2
G	Leaky ReLU + Learning Rate Decay	





WGAN 11G | 1 Model

11	4 Layers	48-24-12-2
G	Leaky ReLU + Learning Rate Decay	



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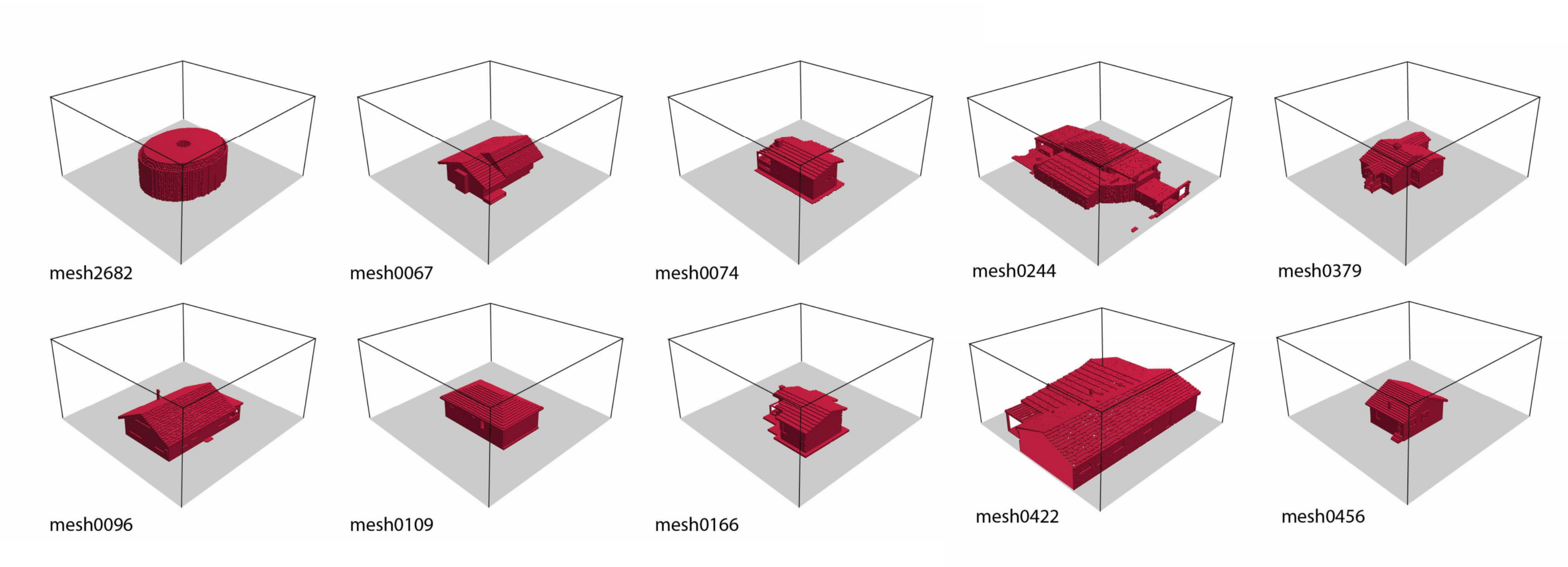
Data Set Examples | 100 Models

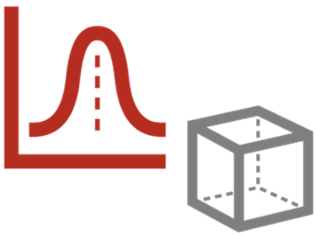


WGAN 11G | 100 Models

11	4 Layers	48-24-12-2
G	Leaky ReLU + Learning Rate Decay	

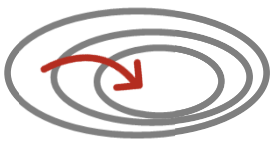
11G
Result at 7999 epochs

Hyperparameters factors and results



Batch
Normalization

Negative Impact



RMS Prop

Helped Improve Training

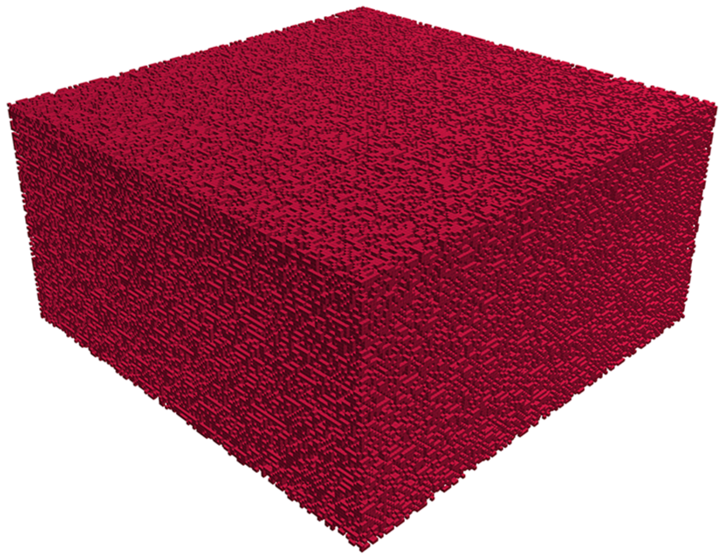
~~Weight Clipping~~ |
Gradient Penalty

Helped Improve Training

Architecture 11R

11	4 Layers	48-24-12-2
R	RMSProp + Gradient Penalty	

11R
5599 epochs of training



11R
training

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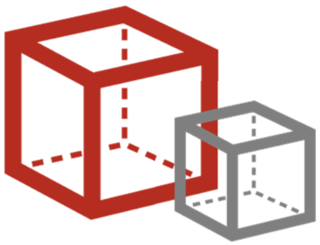
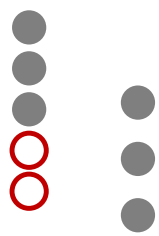
Depth and Width factors and results



Larger Kernel Size



More Channels

More Layers

No Positive Impact

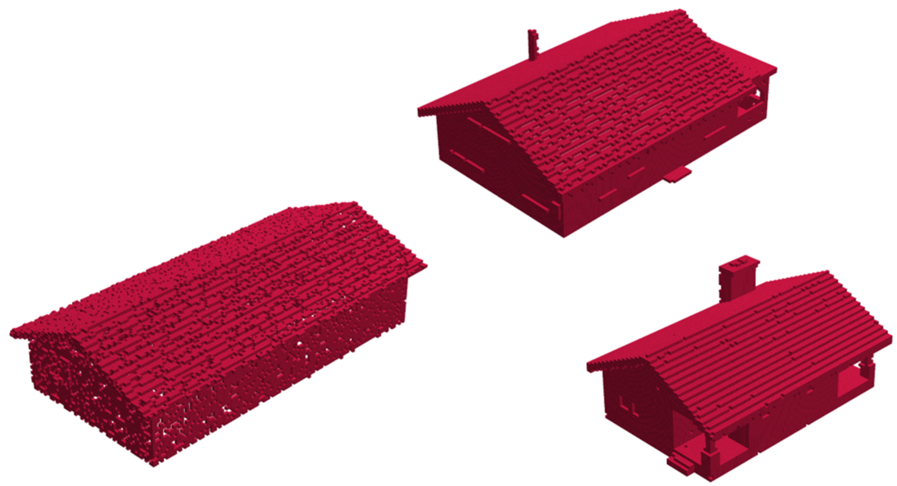
Helped Improve Training

Helped Improve Training

16 R

16	**10 Layers** | **96-96-48-48-24-24-12-12-2-2**
R	RMSProp + Gradient Penalty

16R
after 5600 epochs training

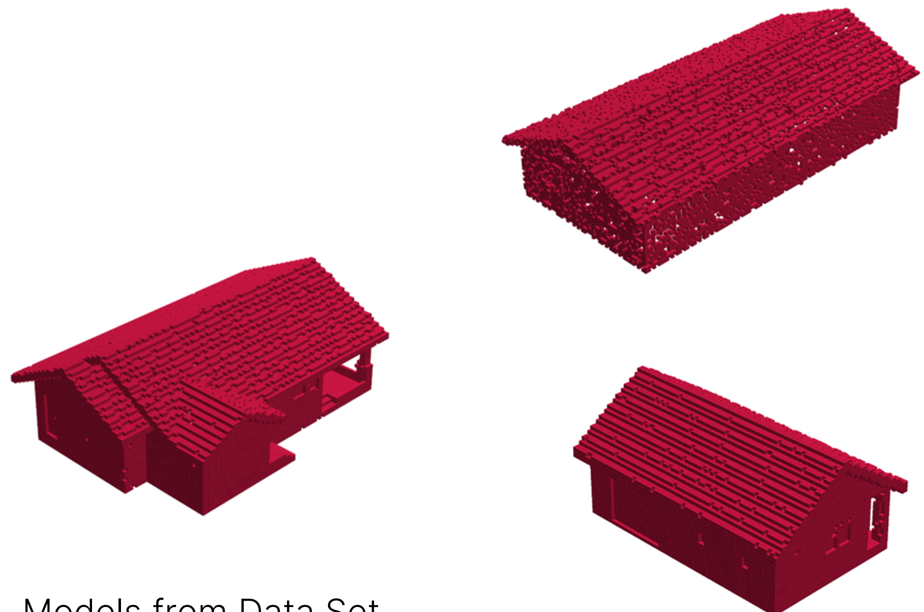


Models from Data Set

17 R V1

17	**10 Layers | 192-192-96-96-48-48-24-24-2-2**
R	RMSProp + Gradient Penalty

17R V1
after 2600 epochs training

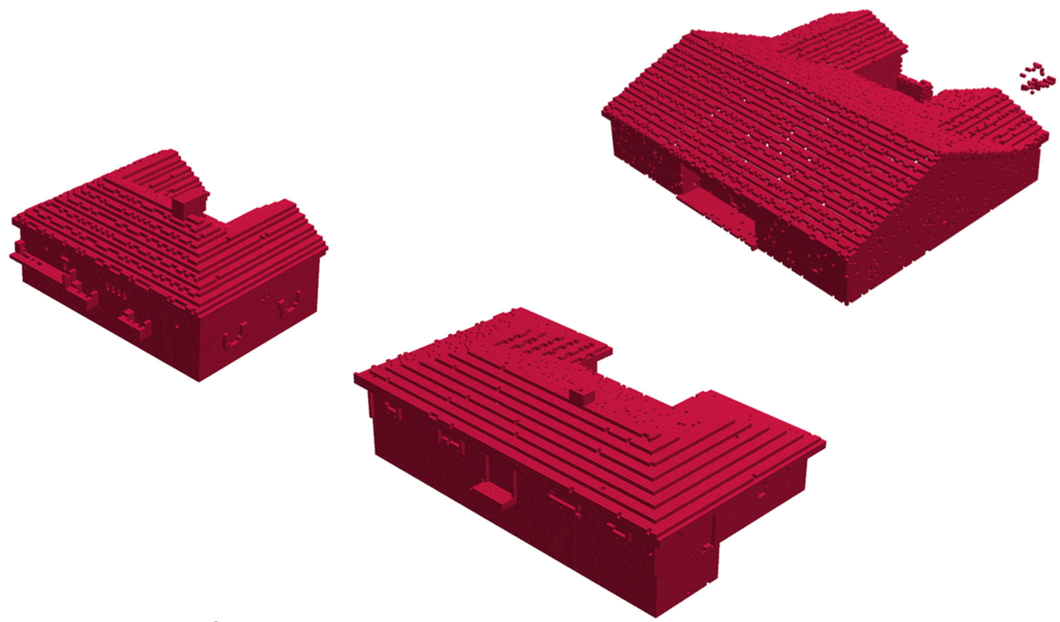


Models from Data Set

17 R V2

17	**10 Layers**	**192-192-96-96-48-48-24-24-2-2**
R	RMSProp + Gradient Penalty	

17R V2
after 2600 epochs training



Models from Data Set

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Evaluating Trained Models

17R V2
Epoch 7400

Model from Data Set

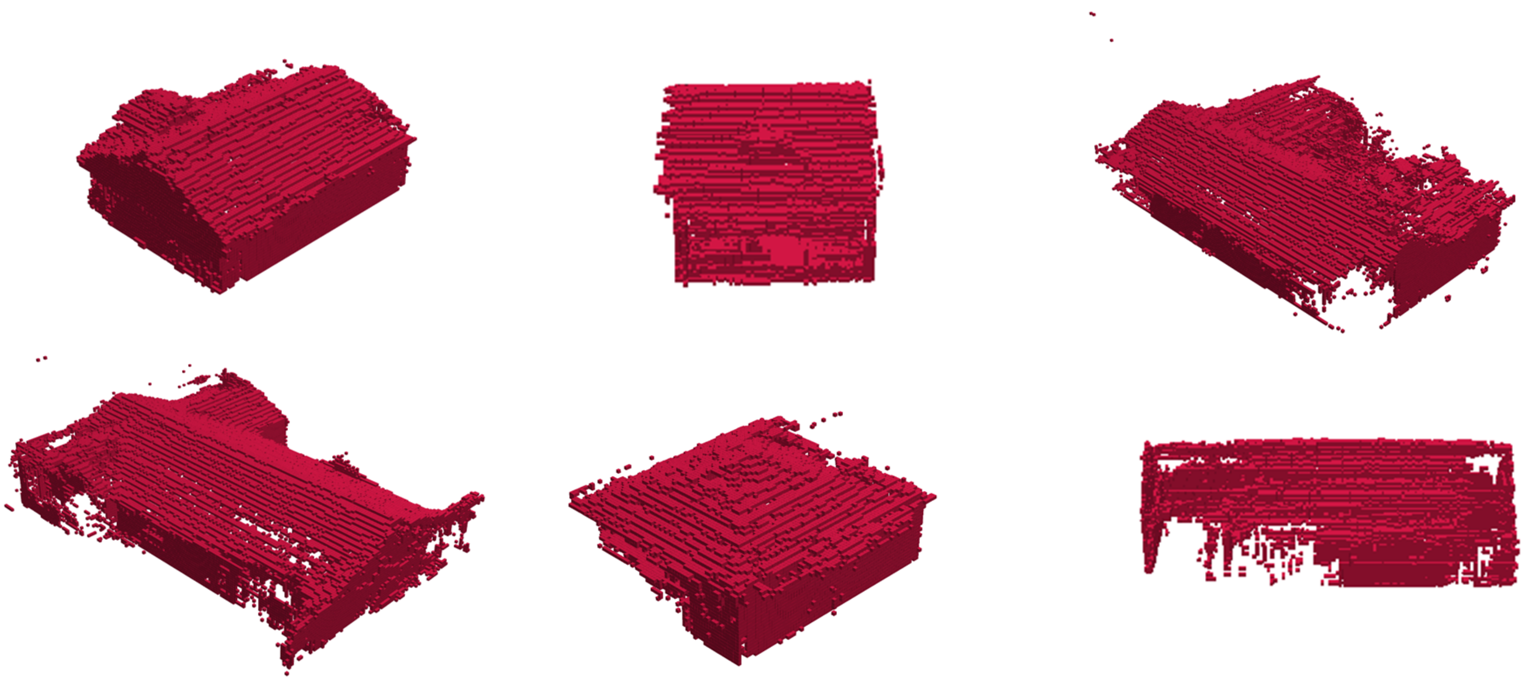
Best Performing Architectures

16R
after 3400 epochs training

17R
after 4000 epochs training

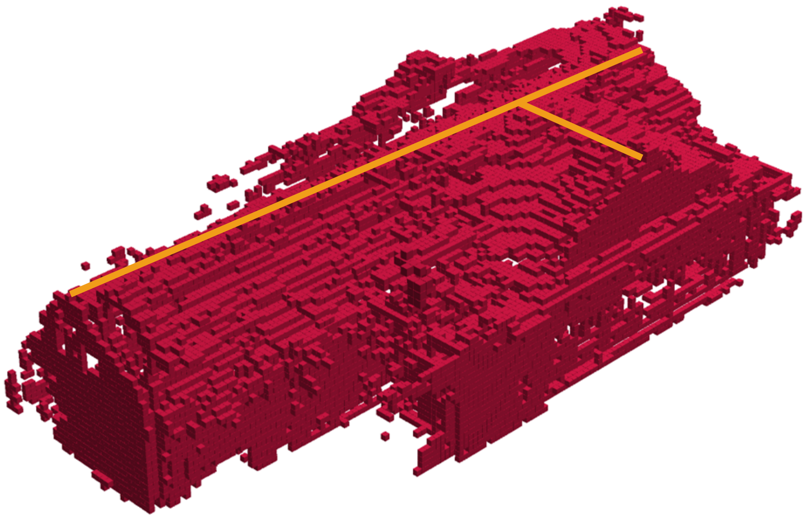
17R V2
after 3400 epochs training

Generated 100 models

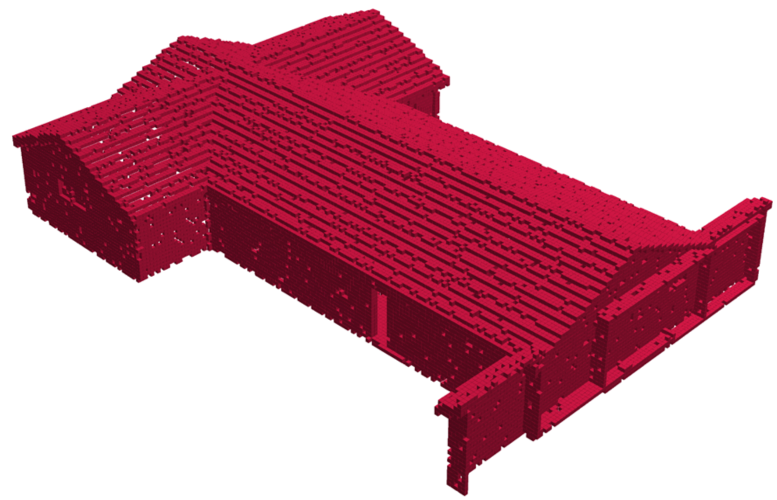


Analyzing Results | 17R V1

17	**10 Layers | 192-192-96-96-48-48-24-24-2-2**
R	RMSProp + Gradient Penalty



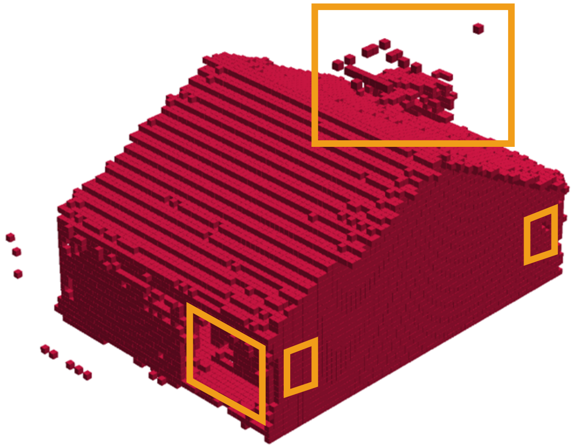
Generated Model 43



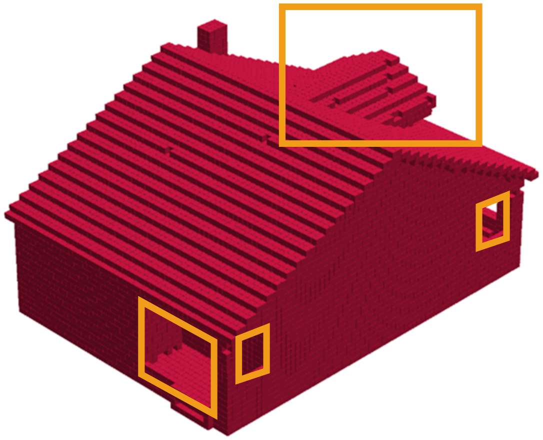
From the data set

Analyzing Results | 17R V2

17	**10 Layers |**	**192-192-96-96-48-48-24-24-2-2**
R	RMSProp + Gradient Penalty	



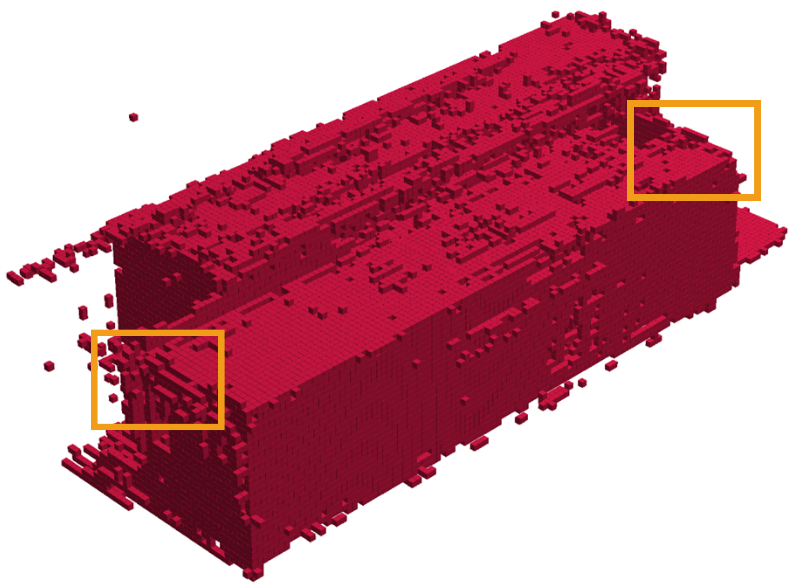
Generated Model 8



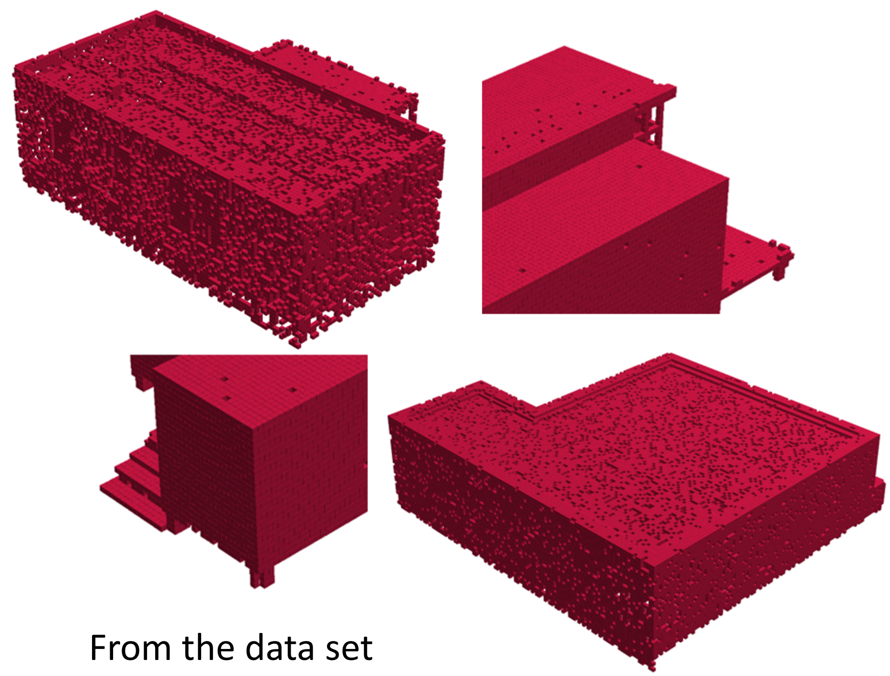
From the data set

Analyzing Results | 17R V2

17	**10 Layers |**	**192-192-96-96-48-48-24-24-2-2**
R	RMSProp + Gradient Penalty	



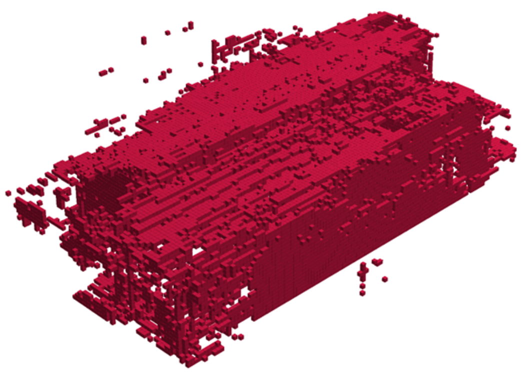
Generated Model 60



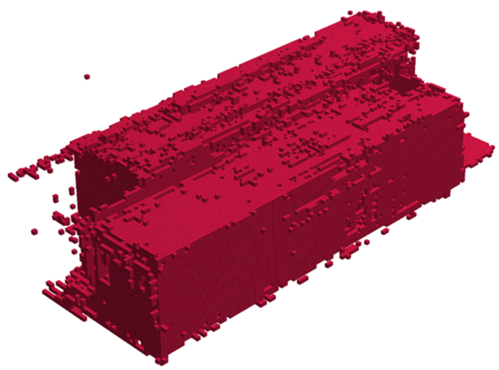
From the data set

Analyzing Results

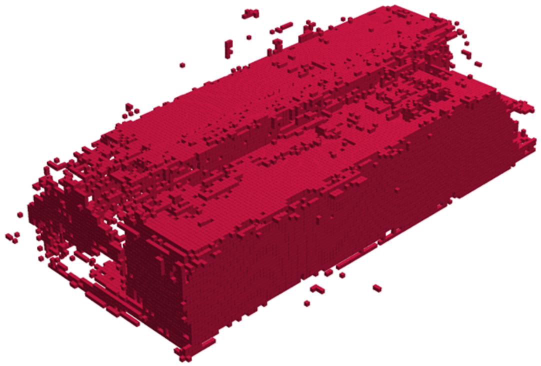
17	**10 Layers | 192-192-96-96-48-48-24-24-2-2**
R	RMSProp + Gradient Penalty



Model 58

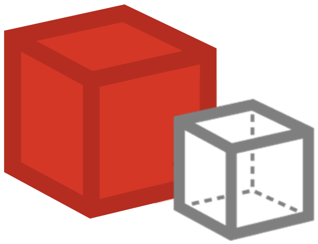


Model 60

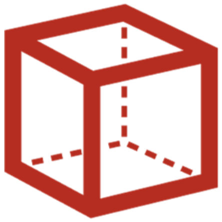


Model 95

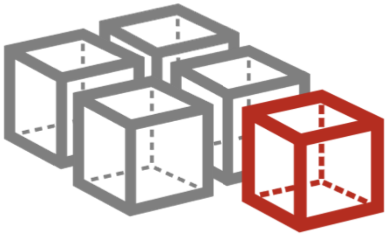
Inputs



Solid Filled Models



Rectangular Prism
Input



More Training
Models

No Positive Impact

No Positive Impact

Requires deeper and
wider architecture

Important to train
on large data sets

Improved 3D WGAN | 17 R

17	**10 Layers | 192-192-96-96-48-48-24-24-2-2**
R	RMSProp + Gradient Penalty

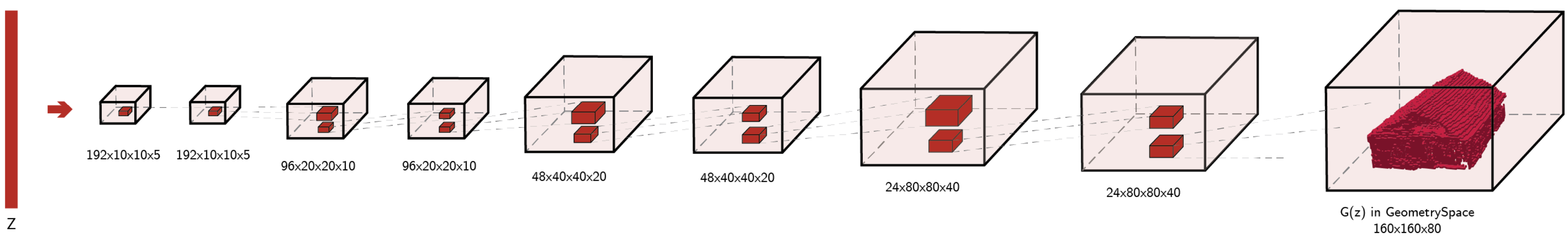


Table of Contents

Data Set and Source Code

https://doi.org/10.4121/4d82052e-650c-4775-8bd9-623df68991b6.v1

https://github.com/lm2-me/3DWGANHouses

Jupyter Notebook to Generate Geometry

jupyter generate_17R Last Checkpoint: a day ago (autosaved)

Logout

File Edit View Insert Cell Kernel Widgets Help | Trusted | Python 3 (ipykernel)

Run | Markdown

Generated Geometry with Architecture 17R

Through her thesis "3D Generative Adversarial Networks to Autonomously Generate Building Geometry", Lisa-Marie Mueller researched how Generative Adversarial Networks can be used to produce building geometry. Through the exploration completed in the thesis, two architectures performed the best. Architecture 17R uses Leaky ReLU in the generator and the critic, uses RMSProp as the optimizer with a fixed learning rate, and implements gradient penalty. The architectures has 10 layers with the following number of channels 192-192-96-96-48-48-24-24-2-2.

This notebook loads the weights of the trained network and allows users to generate new geometry using the trained network models. The generated geometry is then visualized in the notebook.

Before running this notebook, please make sure tensorflow is installed in your conda environment and that you activated this environment. An env file is included on GitHub.

In [ ]:
```
#imports and initialize variabless
import tensorflow as tf
import os
import PIL
from PIL import Image
import math

import wganv17R as gan
import utilities.ganutilities as util

save_location = 'generated/images'
generated_matrices = 'generated/generated_matrices'
```

In [ ]:
```
#load network weights
generator = gan.make_generator_model()
discriminator = gan.make_discriminator_model()
```

What are the **challenges** and benefits of using GAN for architectural design?

Parameter Tuning

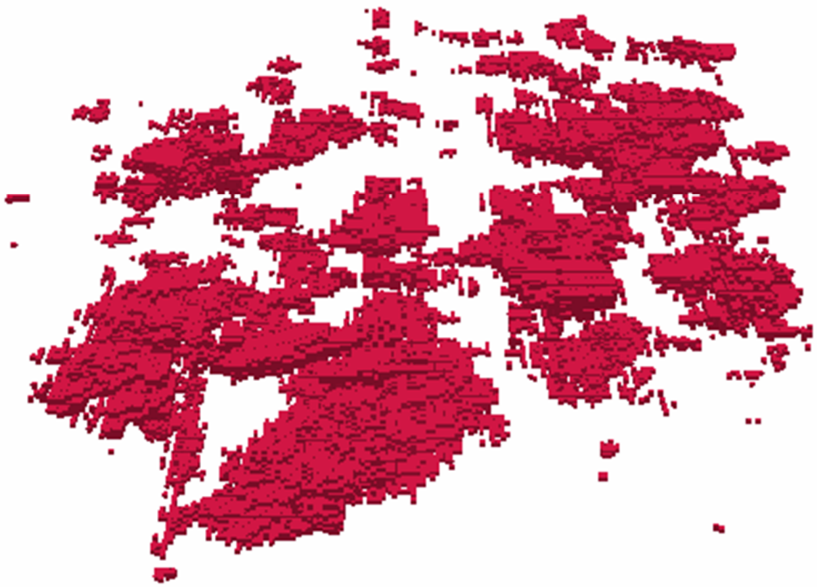
- Takes time
- Trial and error

Unstable Training

- Can have many causes
- Same cause doesn't always have consistent solution

Large Training Data Set

- Need to have a lot of training data
- Minimum 100 models, in the thousands is more ideal



What are the challenges and **benefits** of using GAN for architectural design?

Use after Training

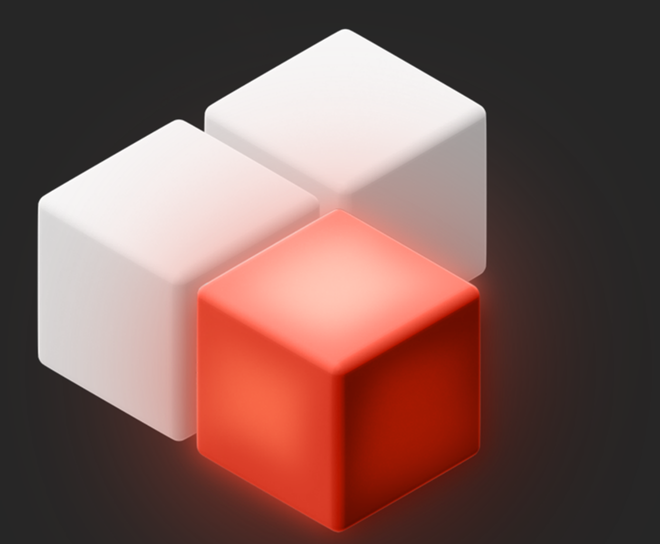
- Once model is trained, can be used repeatedly with little cost
- Training can be updated as more data is available

Use for Complex Problems

- Detects patterns in the data
- No need to define rules

Multi-Disciplinary

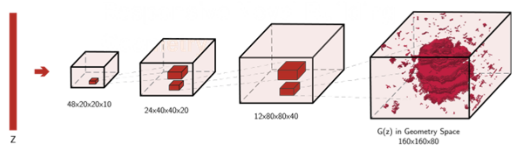
- Research method can be applied to other deep learning research
- Developed architecture can be applied to other disciplines



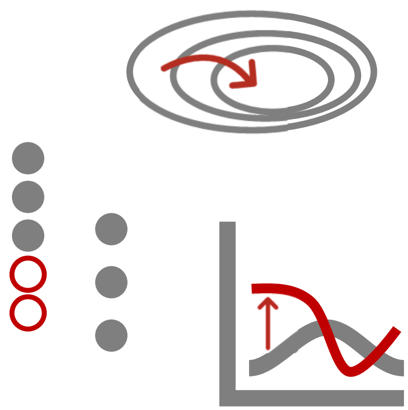
How can a GAN model be trained to produce 3D building geometry given 3D models of single family homes as input?

Research Questions

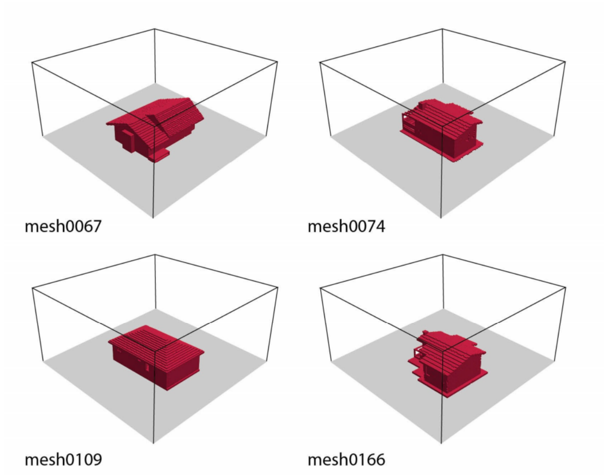
Conclusion



New WGAN architecture

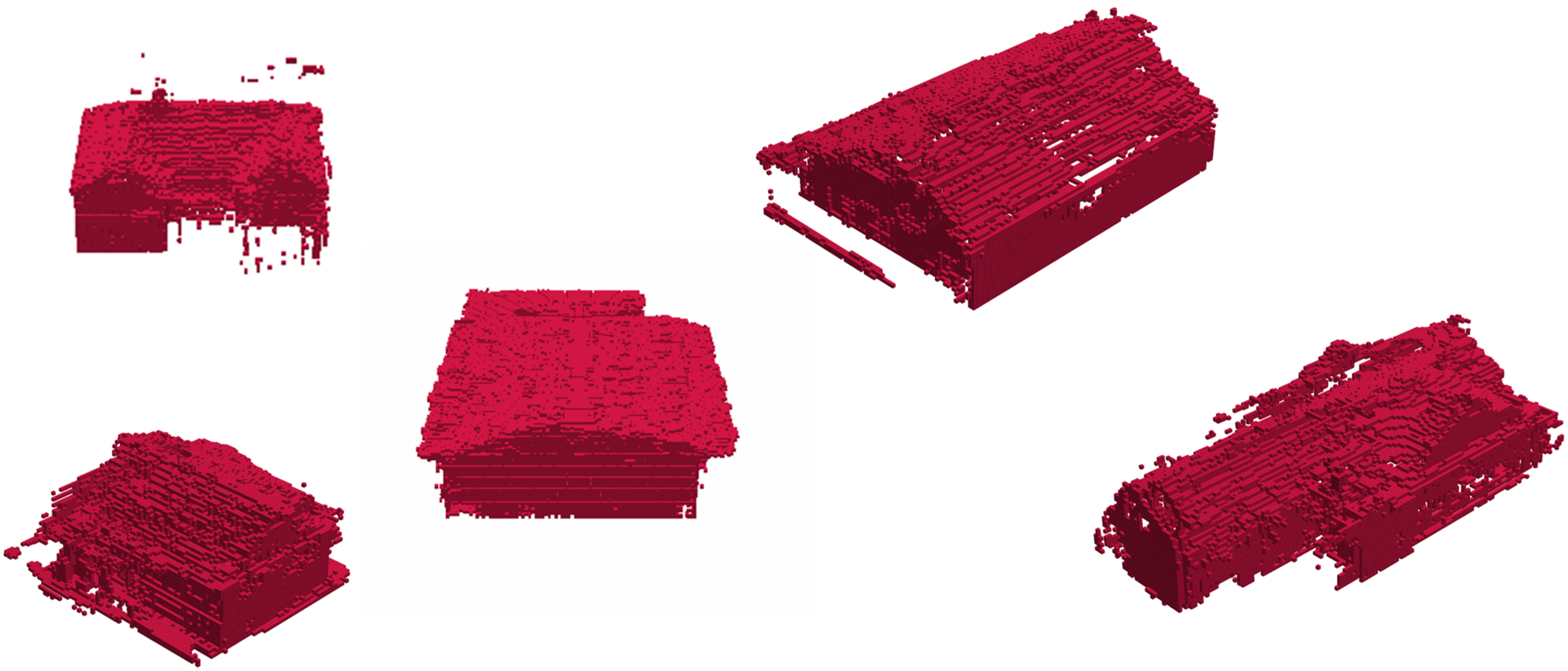


Incorporated Key Hyperparameters that were Identified Through Experimentation



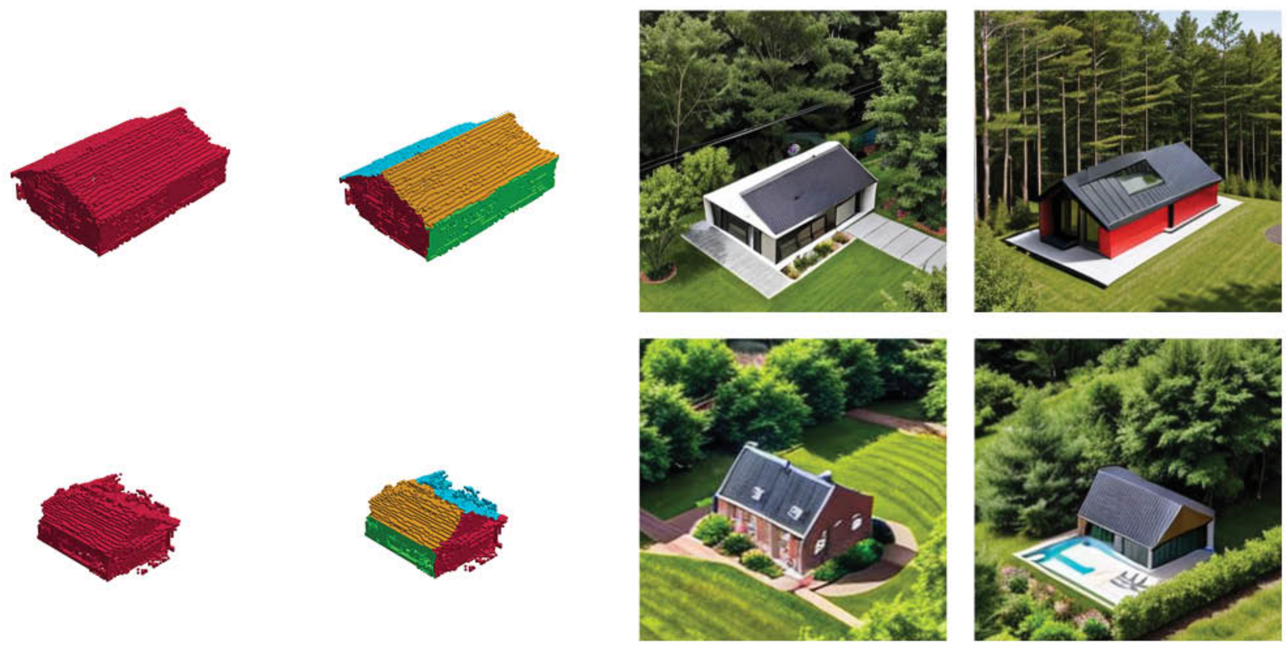
Trained on revised building data set

Reflection

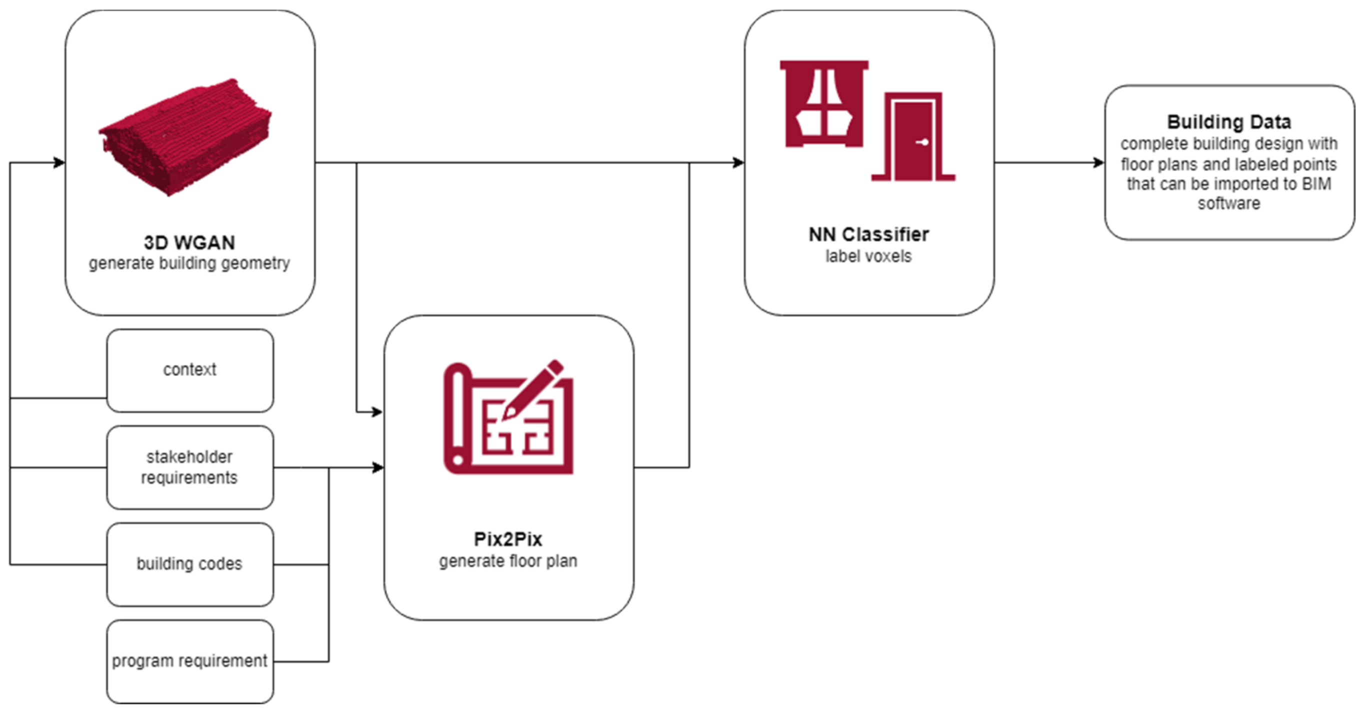


Bigger Picture

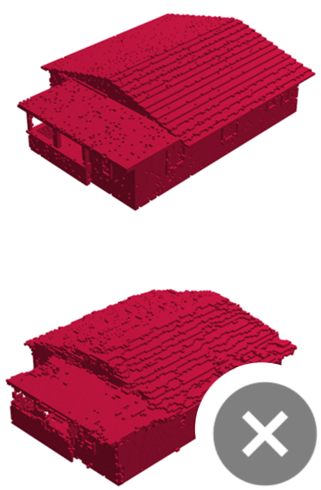
generated model colored input AI image generator output



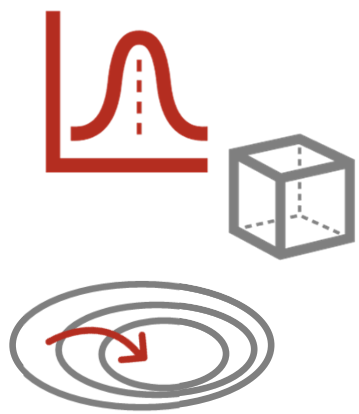
Bigger Picture



Future Research



Memorization Rejection

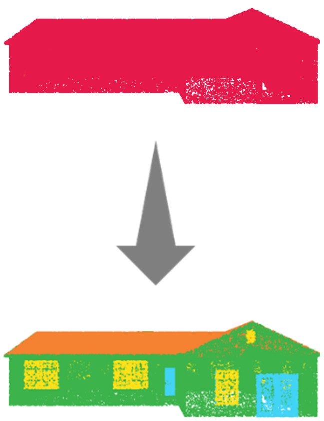


Additional
Hyperparameters

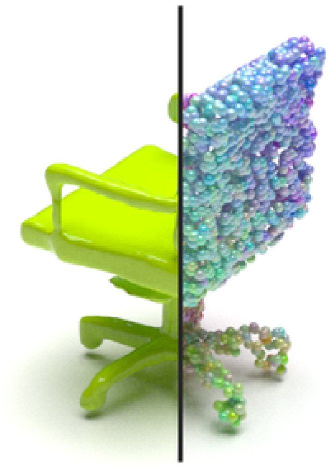
Data Augmentation

Context-Responsive and
code-responsive design

Future Research



Label Generated Geometry



Xiaohui, Z., et al. (2022)

Other Generative Methods

Integrate Analysis

User Input to Modify Output

Thank You!

Lisa-Marie Mueller

27.06.2023

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