FLOOR PLAN GENERA-TION

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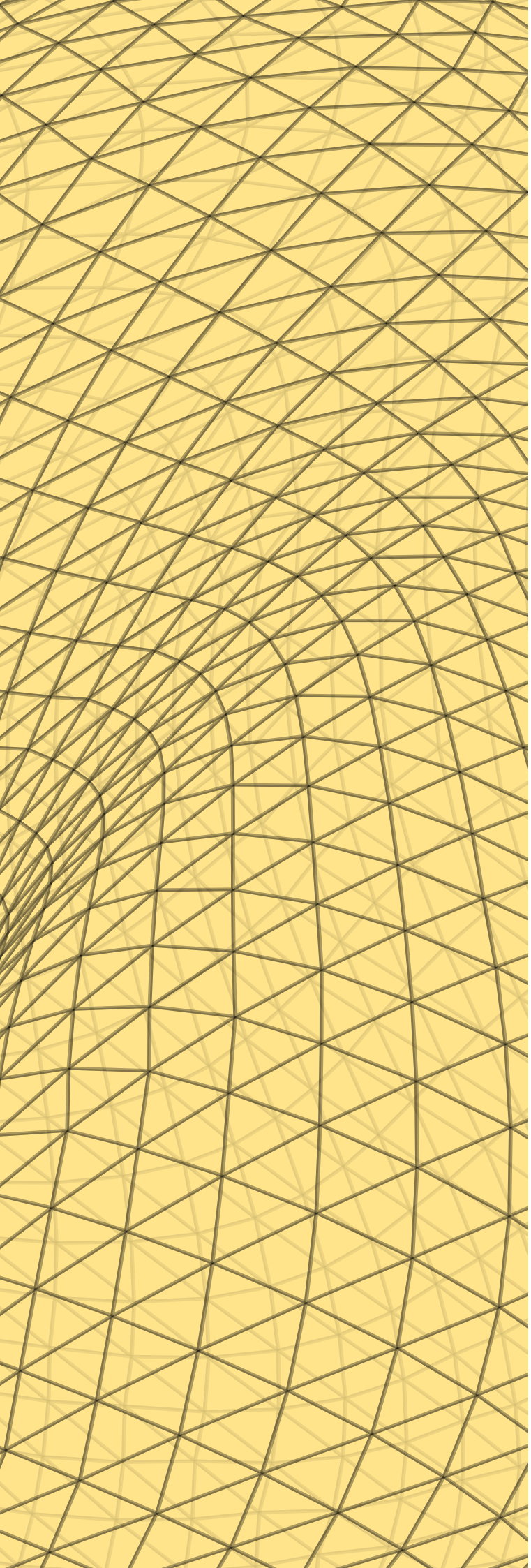


Introduction

The increasing application of computer science in a wide range of industries has become reality since the vulgarization of that technology and the facilitated access for a broader public. Applications are as diverse as the underlying mechanisms, ranging from simple code-based optimizations to simulations in all directions to fully digitized frameworks. That scientific fields such as natural, structural, economic, and engineering sciences benefit from increasing digitization is fairly natural and easily explained by the relevance of mathematical modeling, computational simulations, and the need for significant computational power, but this interaction is far less intuitive when considering the example of artistic or humanistic fields. This report examines the interaction between computer science and the field of architecture, which is situated between science and art. In particular, the topic of automatic floor plan generation is explored as a starting point for exploring applications such as simulation, analysis, data manipulation, and machine learning based on the generated data. Each of these topics has been extensively researched by academia in recent years and therefore provides extensive documentation of scientific reports. This explains why this work is partly based on third party work, but attempts to bring each topic together in a relevant way to create a workflow that can potentially provide new insights. Due to the significant amount of existing research and information, a comprehensive review and thorough reading of relevant research is essential. In addition, a significant emphasis is placed on the interplay between computer-based algorithms and the inherent creativity of the architectural profession, which is difficult to combine with digital tools. Thus, this is neither a purely scientific work nor an exclusively experimental investigation, but rather the structured documentation of a problematic investigation with sensitive consideration of interdisciplinary aspects.

Abstract

This project attempts to generate a synthetic dataset of architectural entities using parametric modeling to enable automation within a defined range of variability. To achieve this, several steps with different software libraries and algorithms are necessary, as the results of each step have to be analyzed and verified against different features. First, the focus is on the parametric generation of an apartment floor plan using Python, Blender's Sverchok, and various algorithms such as Voronoi diagrams, KD trees, and genetic algorithms. After generating a manifold spatial configuration, it can be analyzed from different geometric aspects using the Python library Topologic. It is important that these two steps are in constant exchange to combine the geometric data with the evaluation of the spatial analysis and to store the information in a file format suitable for the data. These formats can range from simple two-dimensional files to database formats or graphical data. With the help of topological analysis, apertures such as doors and windows can be integrated into the basic geometry in a variable pattern within the framework of defined spatial and architectural rules. The final step involves reconstructing the data in geometric form into a three-dimensional model that is finally enhanced, improved, stored and displayed in a common open source BIM format such as IFC using IFCOpenshell, BlenderBIM, Topologic and Opencascade.

In addition, a requirement is that the dataset can be easily supplemented with physical and environmental analyses, such as the use of light and radiation-based simulations with Radiance, Vi-Suite, Honeybee and OpenStudio, or a simulation of the energy behavior of the architectural object with Energy+, Vi-Suite-Energy and the core component of OpenStudio in order to add an evaluation layer. The evaluated geometric synthetic data can thus be used as training data for a machine learning model and should be able to counteract the traditional bias thanks to the synthetic data origin, in contrast to the common use of real life data by real estate companies or architecture firms.

Special attention is paid to the consistent use of python-based libraries to ensure the best possible compatibility of the individual software interactions. Furthermore, only open source projects are used for didactic, ideological and compatibility reasons. During the execution of the individual steps, possible problems, suggestions, solutions, proposals for improvement and last but not least ideas for further research of the topic are recorded, which are described in detail in the following report.

The apartment layouts generated show a high variance and allow a high degree of intervention and control in the generation process thanks to the parametric rule-based generation method. The advantages in the application in connection with machine learning are convincing, but will only be proven in the continuation of this work in a direct comparison with models trained on conventional data sets.

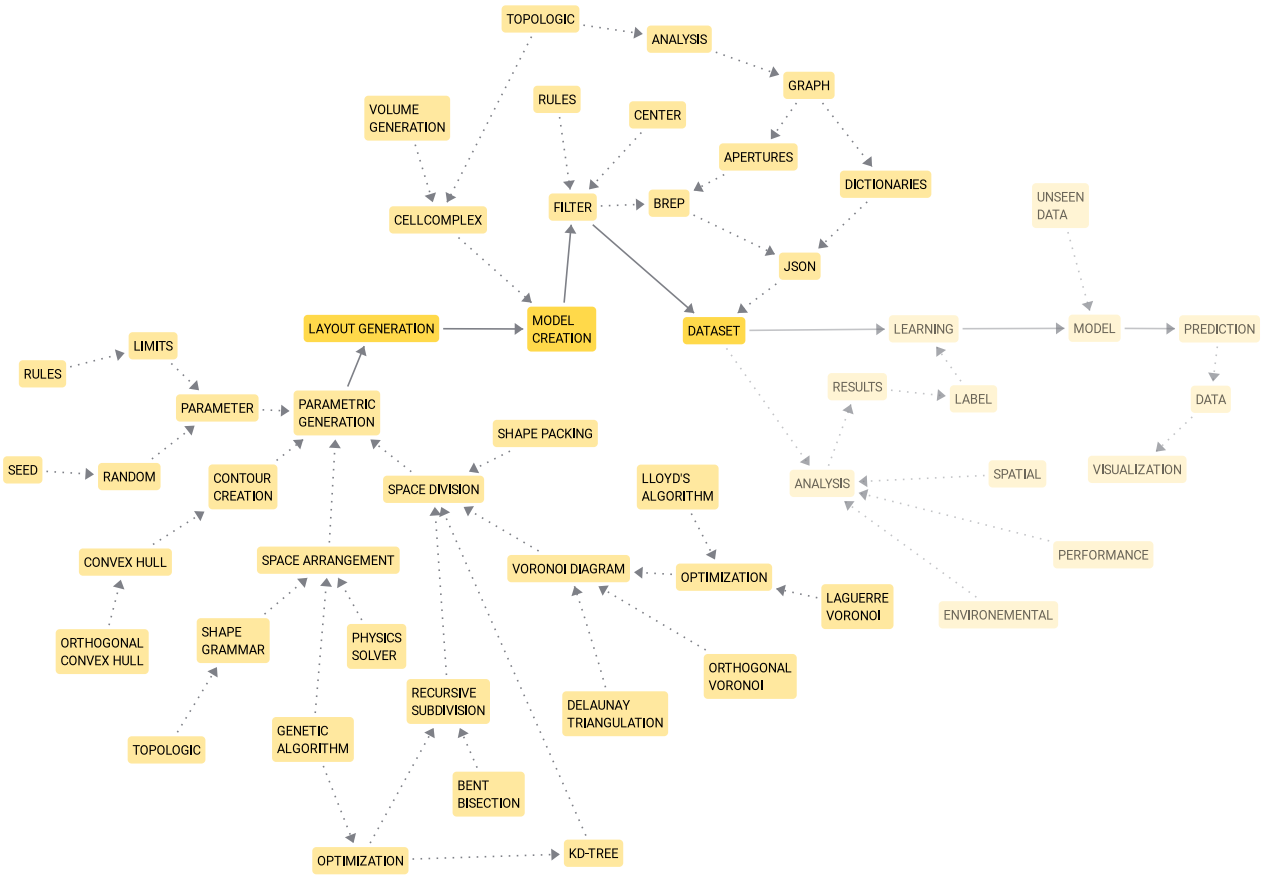


Figure 1: Process

Framework

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

The goal is to develop hypotheses about the future of architecture, taking into account all areas that may be of interest to the design process of the project. In every aspect of project development, it is important to consider the analysis of new scientific knowledge and explore the achievements of current science. However, it is equally important to base experiments on inventions that have emerged throughout history.

In this studio, the primary goal is not to invent new objects, but rather to deepen the investigation of a particular topic using all existing publications and research to formulate a relevant research hypothesis. The goal is then to begin a process of experimentation accompanied by meticulous documentation. The goal of this process is to find answers to the questions raised in the preliminary phase. In this way, the experimentation cycle advances the research and possibly leads to a concrete solution, but in any case raises new questions that can subsequently be pursued.

The operation of the studio is closely linked to the FabLab of the Faculty of Architecture, which provides access to numerous tools for design and experimentation. This space will also serve as a library for the skills acquired by each individual and thus for the emergence of collective knowledge. As a result of the restructuring related to the Covid 19 pandemic, the workshop has become a paperless studio, which means that the visual representations and research objects are predominantly digital.

Hypothesis

The use of intelligent neural networks and machine learning trained models to optimize traditionally manual processes is becoming the norm. Machine learning is no longer limited to computer science, but extends to any field as long as a database to be analyzed is involved or can be created. It is therefore not surprising that self-learning models have also found their way into architectural optimization.

However, the application of machine learning in architecture is far-reaching and can be useful in any project development process. For example, intelligent model parameterization can help find the appropriate shape even before a concrete project is modeled; mechanical analysis of existing conditions and constraints can be helpful in determining approximate volumetrics. In addition, it is possible to use intelligent algorithms to generate the layout of the interior space, proposing several adapted plans that can lead to a qualitatively improved experience for the occupants. This optimization is not limited to the two-dimensional space and can therefore provide suggestions for optimal circulation or daylight optimization throughout the building. In addition to the conceptual phase, it is also possible to optimize the BIM model through various machine learning algorithms. All these processes are no longer visions of the future, but have already become the standard, albeit often automated and therefore not directly visible. This report will focus mainly on the application of geometric, pseudo-intelligent and evolutionary algorithms in the conceptual design phase to try to automate the generation of floor plans in order to obtain an optimized plan through subsequent steps.

The premise of this work is the assumption that there is a direct relationship between external conditions such as spatial connections, solar radiation, shading, humidity, wind flow, heat generation, soil conditions, air quality, pedestrian traffic or traffic load and the quality of housing perceived by the occupants.

The main hypothesis addressed in this report concerns whether and to what extent synthetic architectural datasets generated by different algorithms can simplify, accelerate, and/or optimize the architectural design process and to what extent training machine-learning models on synthetic datasets leads to diversity in the results. Is it possible to automatically generate meaningful and architecturally sophisticated floor plan layouts? What are the advantages of synthetic datasets in architecture and what problems can be avoided? Furthermore, this paper investigates to what extent it is possible to perform a complete workflow from generation to simulation, analysis, prediction and back to generation without having to resort to proprietary software, thus describing a step towards the democratization of architecture and its digital tools.

State of the Art

Since this project deals with different topics, the collection of previous works is divided into hierarchical subgroups accordingly. First, the role and emergence of computational design will be considered with parametric, generative, and algorithmic design as subgroups. The origins date back to 1960, when Sutherland made a major step towards the automation of architectural drawings and the digital parameterization of the relationships between individual geometric entities with the SKETCHPAD software. In the years that followed, several individual approaches to modeling building information evolved, inspired by major computer conferences. The establishment of various computer-aided design software paved the way to visual programming interfaces, and with it, access to parametric and generative design tools for the masses. In this work, geometric parametric tools are focused on the visual interface of the Sverchok add-on for the blender three-dimensional machining software, which makes use of various Python libraries, in addition to back-end Python coding. The first goal of this thesis, the automatic generation of synthetic floor plans, has been widely researched as a topic and this with many vastly different tools that can be roughly divided into simple algorithms, intelligent algorithms, and machine learning algorithms. The group of simple algorithms is divided into geometric space partitioning by Voronoi diagrams and their derivatives such as Delaunay triangulation, Lloyd's algorithm, orthogonal Voronoi diagram, and weighted Voronoi diagrams. Also mentioned are approximation schemes for subdivision such as Cutmull-Clark and interpolating schemes such as Butterly subdivision surfaces. Kdimensional trees, originally from the family of such algorithms, differ from the previous ones, despite the essential similarities, by subdividing the input points as opposed to polygons, which allows sensitive control over control points. The slicing tree method forms the link between point-based and area-based subdivision. Another method of simple algorithms is the shape-grammar methodology, which allows rule-based geometry generation and thus room for variation within defined limits. This topic has gone through many variations, such as the CGA shape or parametric shape grammar, and is recognized as a programming language in its own right due to the successful simulation of Turing machines. Far enough away from these methods to define themselves as a distinct group are physical solution methods such as attraction models or the MagnetizingFPG algorithm, which are based on them to some extent. However, in this paper we will mainly focus on the latest and more interesting topology-based method developed by professor dr. Wassim Jabi. Topologic is not a layout generation method, but rather an Opencascade-based geometry processor that handles non-manifold topologies, reducing architectural spaces to simple cells and cell complexes. This method enables layout creation by combining the above methods and paves the way to a simple geometry-to-file workflow. In addition, topologic's boundary representation method facilitates environmental simulations for subsequent plan evaluation stages. However, by far the biggest advantage of topologic is its analytical approach to continuous space and relationship perception, which enables the arbitrary addition

of openings such as doors and windows, as well as the graphical generation of various topological parameters and, last but not least, an interface to common BIM file types such as IFC, BREP and JSON.
More relevant than the aforementioned approaches in the floor plan generation literature since the 1990s are intelligent methods such as evolutionary algorithms. These are input populations that undergo evolutionary fitness phases through biologically inspired mechanisms such as reproduction, mutation, recombination, and selection, leading to optimization of the fitness function. Evolutionary algorithms can be combined with simple geometric methods through goal definition and can also be used for optimization through evaluation analysis. Computational intelligence also includes machine learning and neural networks, which are by far the most widely used methods in the field of automated floor plan generation. However, the previously mentioned methods differ drastically from artificial neural network applications, as the latter are based on learning features in defined training datasets. In the context of plan generation, these datasets are real-world plans designed by humans. Thus, the computer-generated floor plans resemble the input drawings, but leave room for differentiation, which is limited by the learning process based on existing plans or the evaluation based on appropriately defined examples.

Process

This work is an experimental-explorative approach, i.e. the primary goal is not to achieve an optimized process, but rather to critically question the individual steps. Thus, by repeatedly questioning the method, insights can be gained that will be useful in subsequent phases. In addition, there is a significant focus on answering the questions formulated in the hypothesis, which means that the individual steps should be reflected on several levels 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 true, or whether this term is 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 is a thorough examination of the available libraries and their features to create a customized network diagram that covers the interactions. The open source community, through platforms such as Github, Gitlab, and OSArch community, provides a proper and direct exchange with developers and interested parties and a complete understanding of the functions and operations, as well as detailed documentation in most cases. 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 time and thus advance the ideas of the project.

Objectives

The experimental freedom explained above also leads to flexibility with respect to the defined goals. In general, there are objectives for each stage, but this does not mean that a step has failed if their outcomes are different from those expected or formulated in advance. For example, the parametric generation stage has as a desired outcome the generation of synthetically generated models that can be constrained by certain parameters. These can be the number of living rooms, the number of occupants, 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 minimal number of points. In the next phase, the simulations would generate new evaluation values that could be added to the geometry database. The next step would be to train a model that graphically describes the relationship between each value as accurately as possible. The final step is to create an accurate visualization of the predicted scenario.

Roadmap

- ☒ Information Gathering
  - ☒ Resources
    - ☒ Code Repositories
    - ☒ Academic Papers
    - ☒ Books / Reports / Articles
    - ☒ Student Works
  - ☒ Bibliography
  - ☒ Adequate Software
    - ☒ Code Documentation
    - ☒ Explanatory Resources
- ☒ Geometric Generation
  - ☒ Methods
    - ☒ Algorithm
      - ☒ Evolutionary Generation
      - ☒ KD Tree
      - ☒ Physics Simulation
      - ☒ Shape Grammar
      - ☒ Shape Packing
      - ☒ Convex Hull
      - ☒ Voronoi Diagram
      - ☒ Orthogonal Voronoi
      - ☒ Lloyd Algorithm
      - ☒ Delaunay Triangulation
      - ☒ Power Diagram
      - ☒ Polygon Division
      - ☒ Recursive Subdivision
      - ☒ Recursive Bisection
    - ☒ Machine Learning

- ☒ Neural Network
- ☒ Classification

- ☒ Parametric Generation
  - ☒ Sverchok
  - ☒ Python
- ☐ Evaluation
  - ☐ Data Set Search
  - ☐ Comparison
  - ☐ Estethic Verification
  - ☒ Functional Verification
  - ☐ Ideological Verification
    - ☐ A Pattern Language

☐ Simulations / Analysis

- ☐ Environmental
  - ☐ Energy
    - ☐ Energy+
    - ☐ Openstudio-Energy
    - ☐ Ladybug
    - ☐ Vi-Energy
  - ☐ Lightning
    - ☐ Radiance
    - ☐ HoneyBee
    - ☐ Openstudio
    - ☐ Vi-Radiance
  - ☐ Air
  - ☐ Crowd
  - ☐ Urban
  - ☐ Life Cycle
- ☐ Spatial
  - ☐ Topologic
- ☐ Structural
- ☐ Usage
- ☐ Data Type Examination
- ☐ Verification

☒ Data

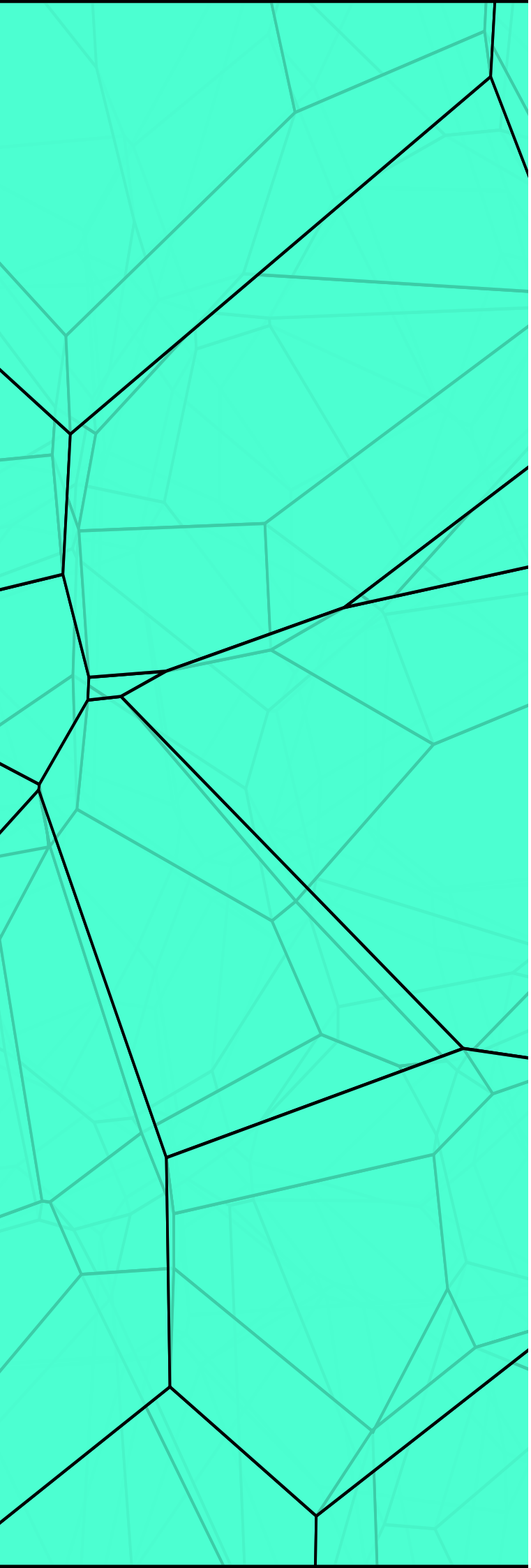
- ☒ Manipulation
- ☒ Data / Database Types
- ☒ Structure

☐ Training

- ☐ Methods

☐ Visualization

- ☐ Geometry Viewer



Layout Generation

The first stage of this work deals with the automated generation of different apartment layouts using various geometry processing software. An alternative to the generation approach is the acquisition of existing architectural datasets provided by real estate and research groups. Advantages of reality-based datasets are the certainty of architectural feasibility and construction of the individual plans, but disadvantages are a lack of learning process and a conservative approach in creative terms. Furthermore, there is a high risk of traditional bias due to the predominance of local and traditionally influenced architectural methods. Therefore, this experimental phase is primarily concerned with testing different Floor Plan generation methods and their derivatives as well as their possible combination. Simple algorithms like voronoi diagrams and intelligent methods like evolutionary algorithms are explained and evaluated in various experiments. Criteria for the evaluation are simplicity in the construction process, computing power, time and memory, integration and interaction with used software, purity of the generated geometry, readiness for the simulation stage, simplicity for data storage but above all spatial quality, creativity in form finding and feasibility. After experimentation, the most suitable method or combination of algorithms with respect to the following steps is selected and an appropriate set of different two-dimensional layouts is generated. In order to increase the variation in the synthetic dataset, results from different methods can be mixed, but they must not deviate from the generally defined quality level. Furthermore, it is a requirement to understand the functionality of the algorithms sufficiently to allow slight adaptations and combinations with other functions and to achieve variation in the individual applications. In general, simplicity is preferred to complexity, creativity to ordinariness and variation to repetition.

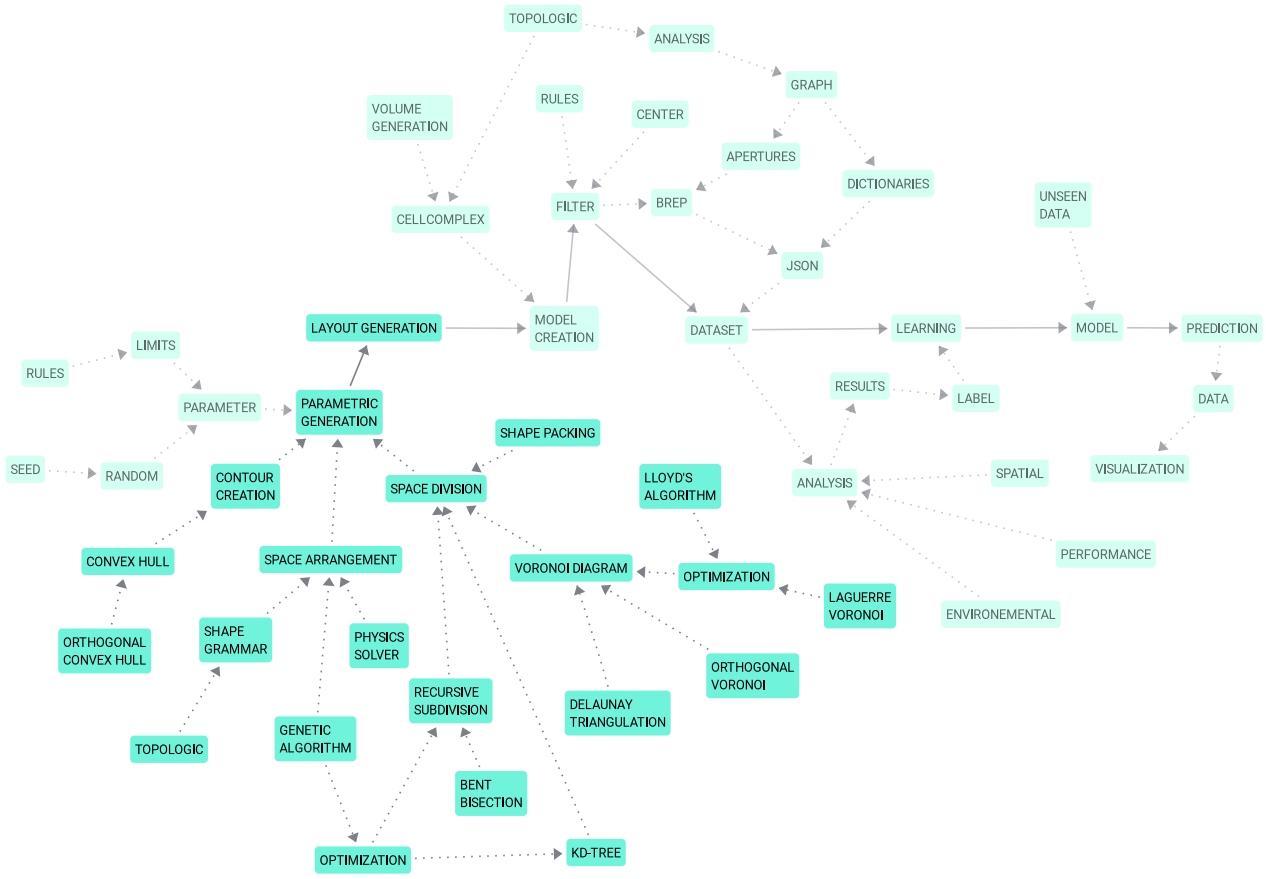
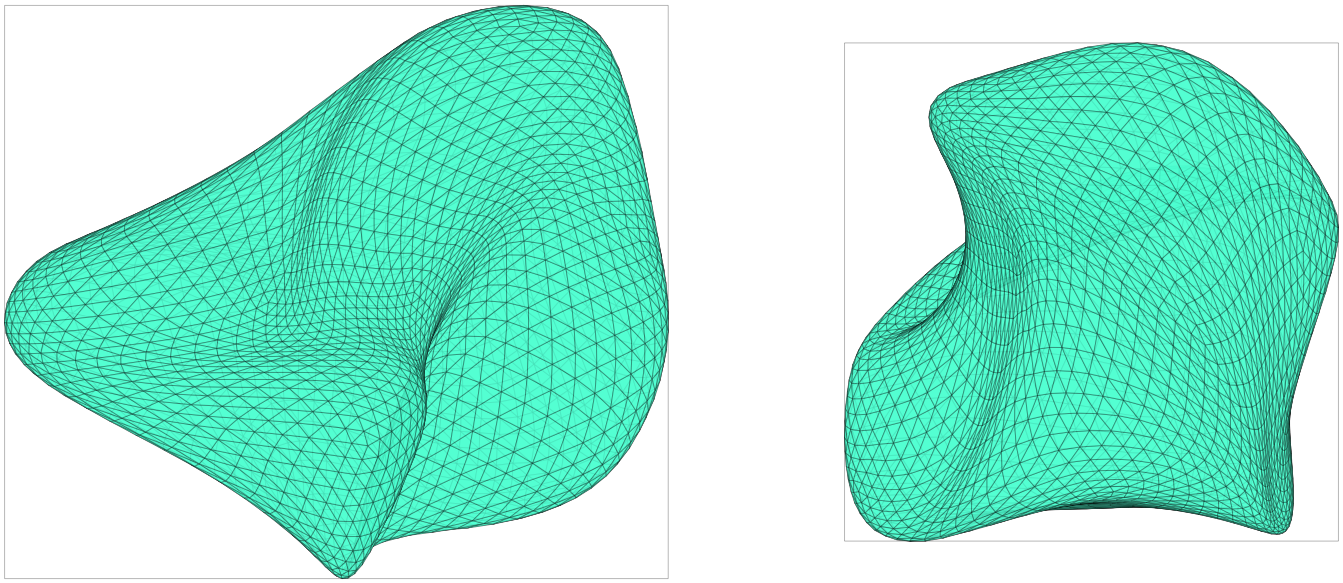


Figure 2: Layout Generation

Genetic Algorithm

The Genetic Algorithm developed by Holland and De Jong is an optimization model based on Darwin's natural selection-based theory of evolution in biology. Its operation is based on biological mechanisms such as crossover, recombination, mutation and selection by fitness evaluation acting on a population of defined size. Due to their mode of operation, genetic algorithms and their derivatives are particularly adaptable and offer a parallelization of the solution finding. However, for optimal application, the right parameters have to be set, such as crossover and mutation rate, population size, iterations and fitness boost. These parameters are problem-dependent and there is a risk of an undesired and non-optimized result if the starting conditions are set incorrectly. The construction of an evolutive algorithm begins with the determination of the variable function to be optimized, which consists of an unlimited number of components and has a tendency towards zero. After the framework conditions of the algorithm have been defined, the variables to be varied must also be determined, whereby it is important to ensure a proportional relationship between parameter variance and fitness evaluation function. In Figure 16, the surface area of the X- and Y-dimensional bounding box of an irregular three-dimensional body was defined as the fitness function. The population of the genetic algorithm acts on the three Eulerian rotation axes of the body and thus achieves a minimization of the Z-section of the irregular shape by iterative mutation and fitness evaluation.



(a) (b)

Figure 3: (a) Initial Rotation (b) Optimized Rotation

With increasing iterations and an increase of the population number, the optimum is progressively approached, but the question arises how such a method works theoretically and how it proves itself on more complex problems? In Python there are several established evolutionary algorithm libraries with different integration mechanisms ranging from native python implementation to Keras and Pytorch or even scikit-learn integration. Since this work is primarily focused on generation and manipulation of visual and three-dimensional entities, the python native Blender implementation of the Sverchok Genes solver was chosen as the experimentation tool. This provides a seamless integration into a visual scripting environment and thanks to Sverchok's Blender integration, Blender's features such as the variety of available export file formats can be easily used.
In order to test the floor-plan-layout-generation capabilities of the evolution algorithm in Blender, different rectangles with defined X and Y sizes are first generated parametrically, each of these space representations being anchored by its origin location and rotation in two-dimensional space. The shape of each unit remains constant and represents the space sizes of the different apartment components. However, the localization and orientation of these modules remains free and is defined as a population parameter.

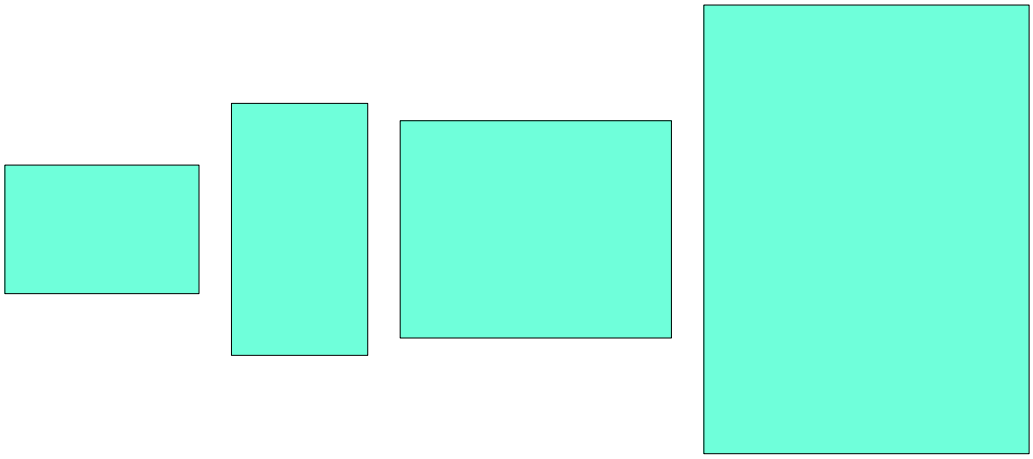
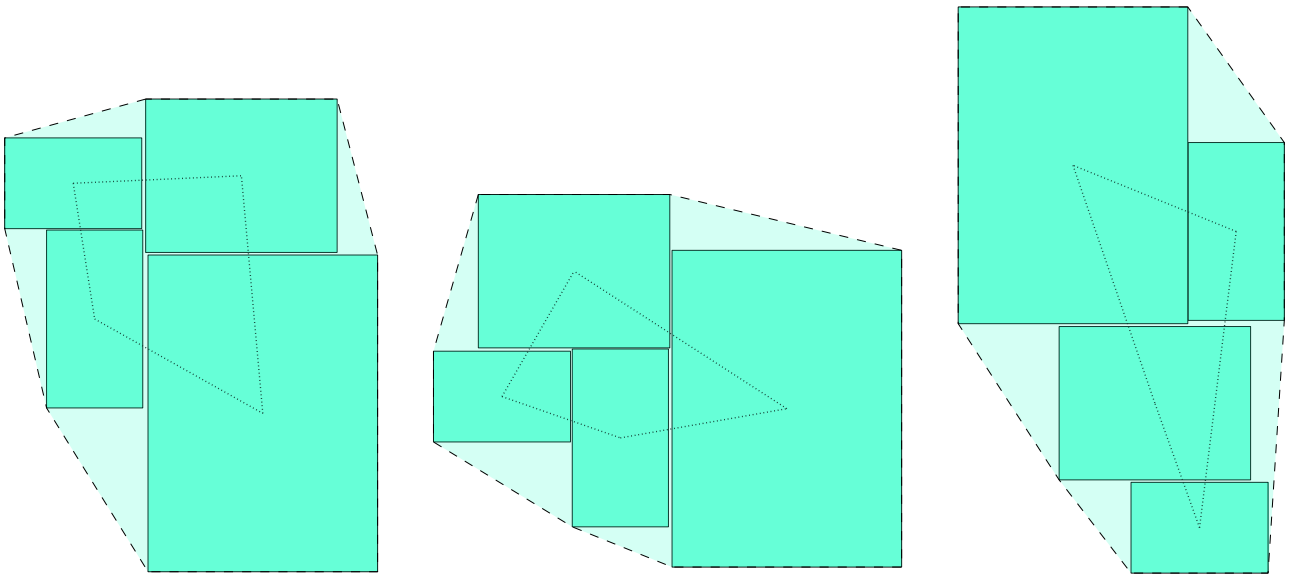


Figure 4: Inital Layout

The fitness function is composed of the total length of the path of the UV connection of the individual rectangle origins, added to the total area of the two-dimensional convex hull with respect to the Z-axis of the overall geometry. Thus, the smaller distance between the individual units is rewarded in parallel by the total area and the individual distance of the center points, while also avoiding the overlap of the individual rectangles. This is achieved by an irradiation function which evaluates the number of geometries formed by a constant check of the boolean intersection to see whether the total number increases. If this is the case, a defined irradiation variable is added to the fitness function. The population size is set to 500, the fitness boost to 5 and the mutation rate to 0.3 with an iteration of 5.



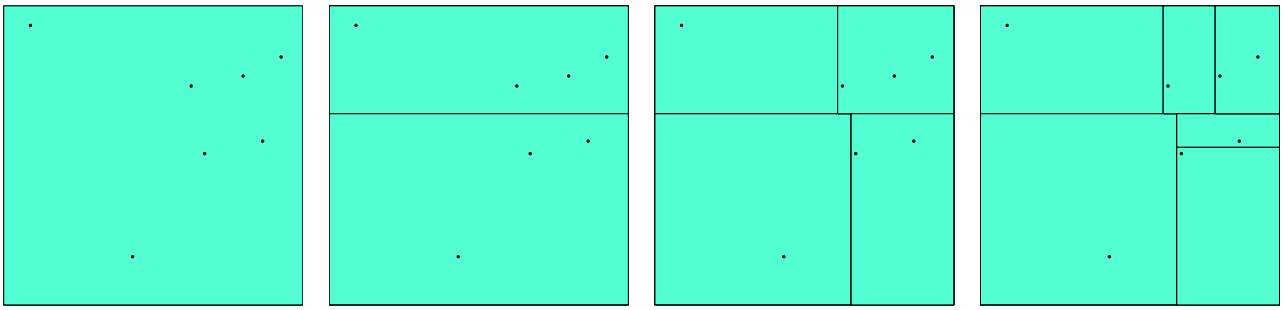
(a) (b) (c)

Figure 5: (a) (b) (c) Optimized Layouts

The different results generated parametrically by changing the random seed of the algorithm give random results with an interesting variance. Advantages of this method are the possibility of parameterization during the execution of the algorithm, a parallelization of the optimization, the possibility of defining different spatial relations by multipliers, the adaptability of the framework conditions and a variability of the obtained results. However, the main disadvantage is the constant distance between the spaces, which complicates the generation of boundary representation geometries and thus the complexity with respect to later environmental simulations or topological analyses. Furthermore, this increases the impurity of the geometry files to be stored. Possible solutions to this problem are a change of the framework and an extension of the irradiation function due to the overlap of the single units, which could integrate the size of the overlapping surface. Furthermore, it would be possible to implement a second method that could lead to the cleanup of the overall geometry, but there is a risk of altering the basic geometry by causing alternating non-orthographic angles.

K-D Tree

The k-dimensional tree data structure is a space partitioning primarily used in computer science for search algorithms and thus belongs to the family of binary space partitioning trees. It is the partitioning of point-clouds in a k-dimensional space. In this work I will limit myself to the two-dimensional space, since the floorplan layout can be described sufficiently in this dimension. In such a data structure, the dataset is divided into branches by nodes and branches, creating successive levels. Each of these branches leads to a leaf, which carries the coordinates of exactly one point.

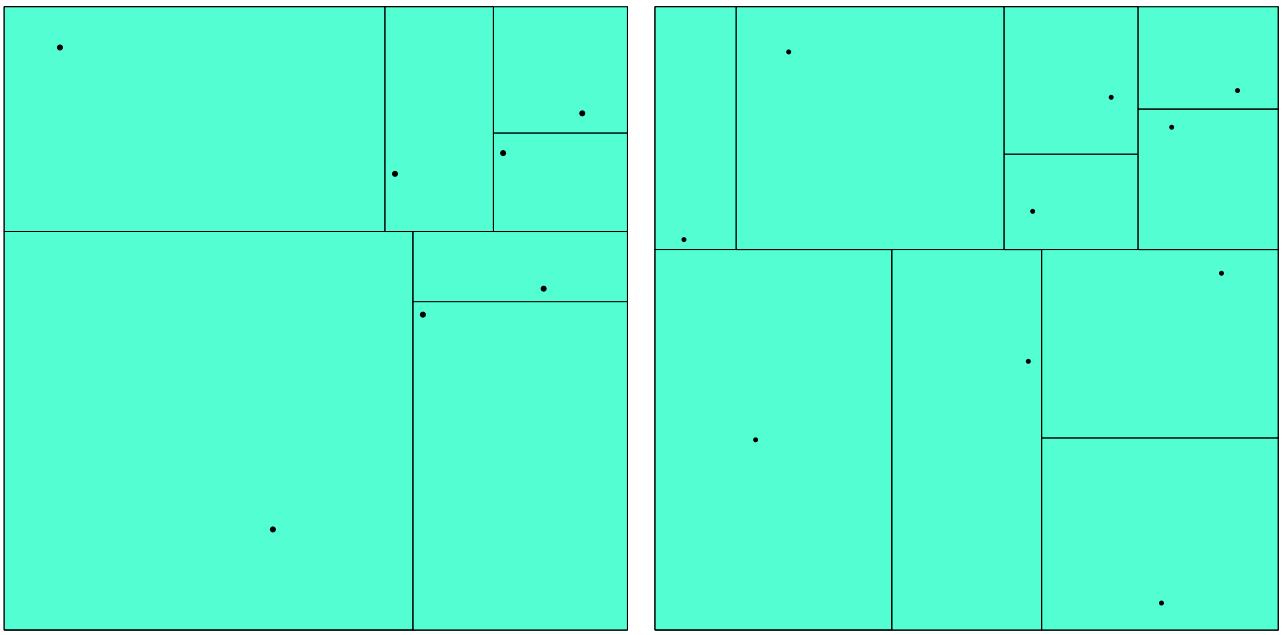


(a) (b) (c) (d)

Figure 6: (a) 0 Iterations (b) 1 Iteration (c) 2 Iterations (d) 3 Iterations

The functionality of such a data tree can vary, but the basic principles remain the same and can be implemented in a simple way in python without using external libraries, building the tree from the root upwards. First, the entire set of data points is considered and a sorting axis is determined based on the depth of the points. After these points have been sorted according to the axis, the node point is determined. This is located on the median of the point list and determines the coordinates of the subarea, which in the following step divides the point list into two child lists. The orientation axis of this intersection is also determined

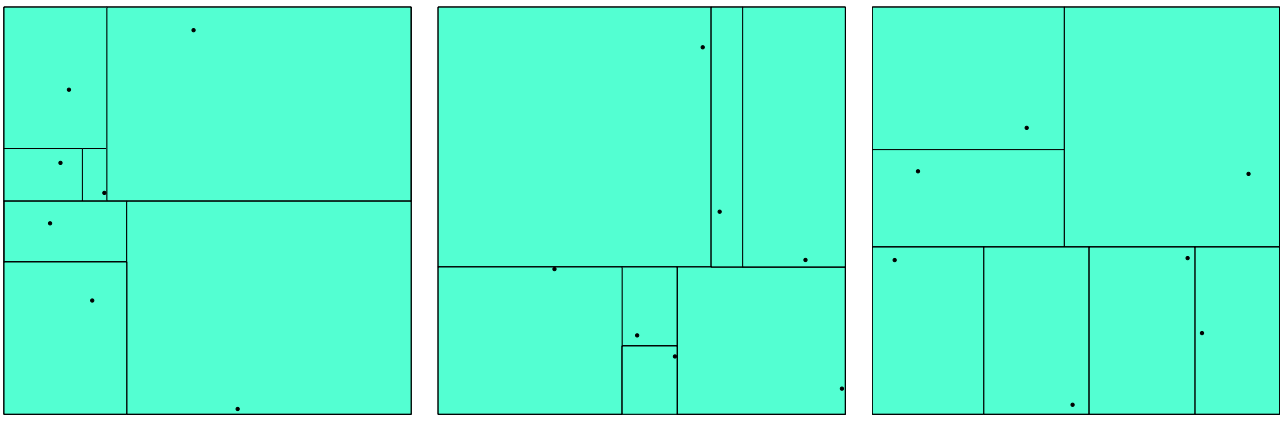
by the depth of the dataset to be split. If the data set to be divided consists of only one point, the leaf of the tree is reached and the iteration is terminated at this node. Thus, by repeating these steps, the complete tree is created using the logarithm.



(a) (b)

Figure 7: (a) 7 Room Layout (b) 10 Room Layout

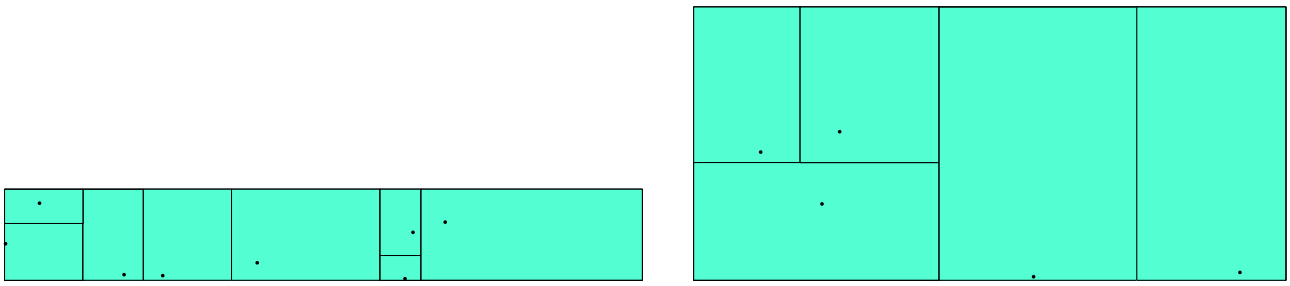
In Blender's Sverchok, creating a spatial K-d tree partition is relatively simple and requires only list manipulation, mathematical operators, slicing planes and loops. The points to be split and the corresponding planar area can be freely defined and are described in the examples shown by X and Y size defined rectangles and randomly selected points on this area. To avoid too small sheet spaces, a minimum distance between these points is defined. The number of these points is unlimited and can be defined accordingly, whereby their number determines the number of spaces of the floor-plan.



(a) (b) (c)

Figure 8: (a) (b) (c) K-D Tree Layouts

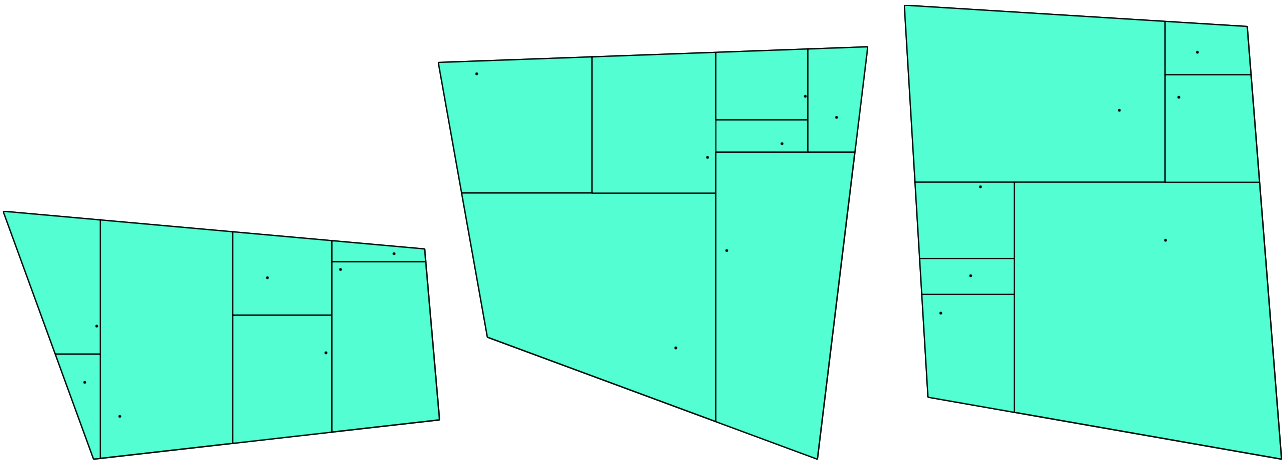
The main advantages of the described method are its speed and simplicity, the generation of natively connected units which simplify the export to boundary condition geometries, the possibility to parameterize the generation process, the determination of localizations of the individual spaces and the choice of the underlying volumetry of the contours of the plan.



(a) (b)

Figure 9: (a) (b) Rectangle Variations

The outlines of the individual shapes can assume any shape of the rectangles and are thus adaptable to the different frame conditions. Furthermore, it is possible without problems to determine more complex shapes as input geometries, from deformed rectangles to irregular polygons. However, this method also has its drawbacks, such as the difficulty of generating composite apartments in which individual units protrude beyond the floor-plan contour as isolated shapes. Thus, it becomes complicated to generate shapes such as terraced garages or irregular facades.



(a) (b) (c)

Figure 10: (a) (b) (c) Polygon Variations

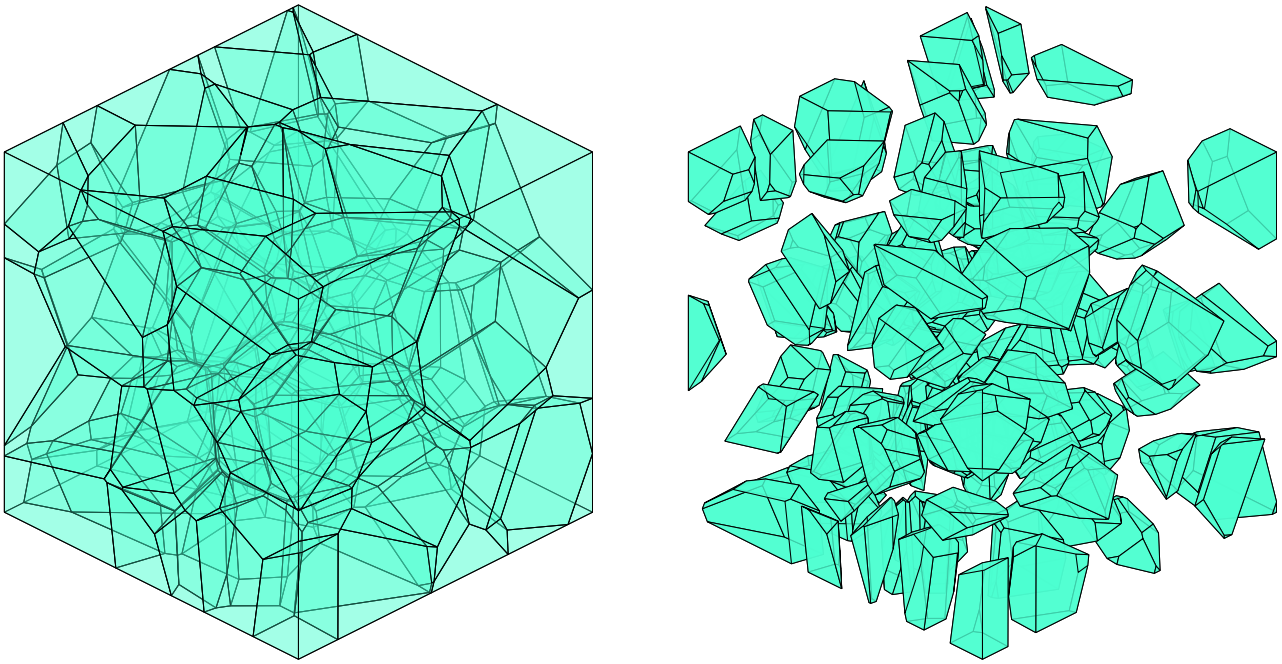
KD-Tree and Genetic Algorithm

A possible combination between the k-dimensional space partitioning method and the evolutionary algorithm could be to optimize the variables of space contour, space number, but especially the point coordinates with a user defined fitness function according to the desired results. Such a combination would optimize the floor-plan generation according to the objectives, but it would not solve

the above mentioned problems.

Voronoi Diagram

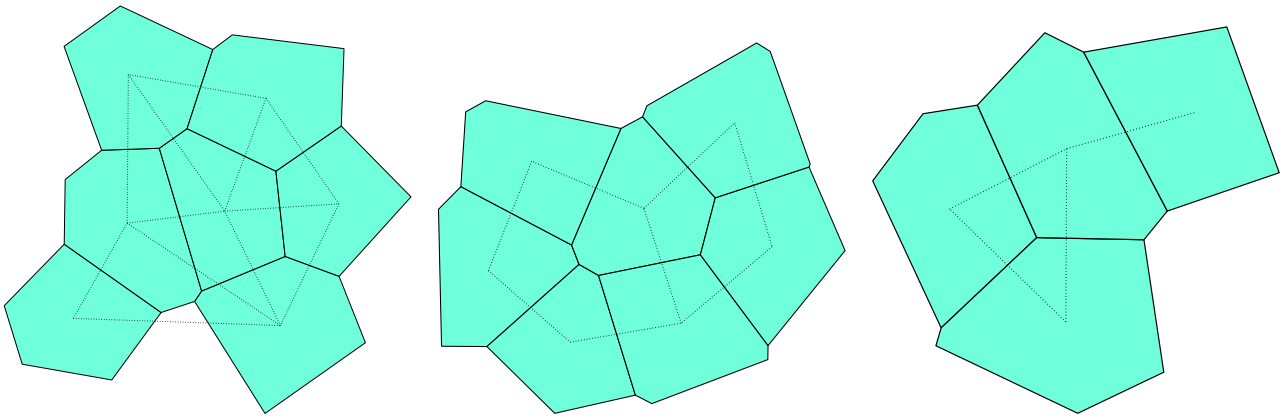
A Voronoi diagram is the decomposition of a defined body into so-called Voronoi regions. Here, points in the nth dimension are defined as the centers of the subdivision and the spans of these spaces are all points that are closer to its center than to any other point. Thus it is possible to subdivide any surface or volume into regions and avoid overlap or spacing between the subdivisions.



(a) (b)

Figure 11: (a) Spatial Voronoi (b) Separated Spatial Voronoi

For a successful Voronoi subdivision of a geometric body, only the initial geometry has to be defined, the dimension and the subdivision method have to be chosen, and finally the points of the Voronoi centers have to be determined. If possible, these points should be located on the basic body to be subdivided according to the dimension, but they can also be projected onto it by a defined thickness in the second dimension. With the Populate mesh node, these points can be placed on the body using different distribution methods.



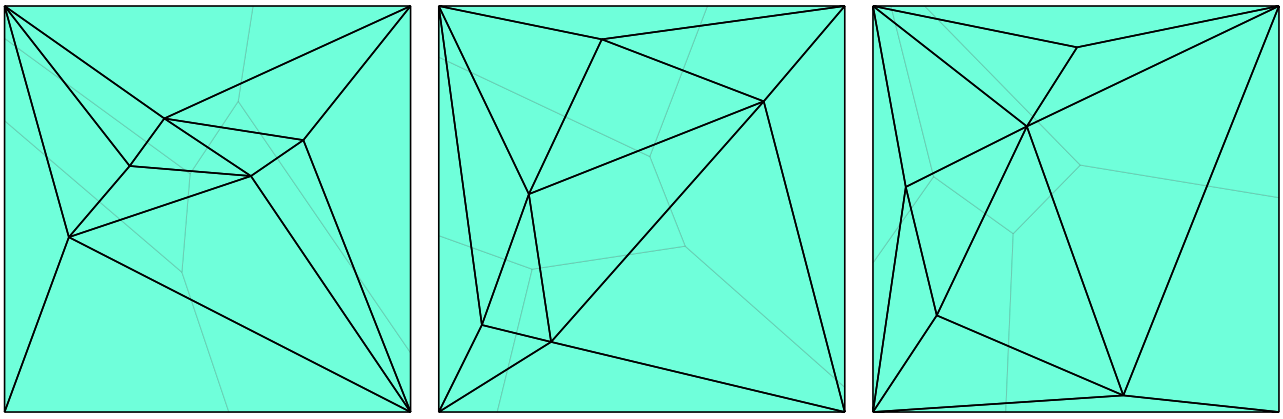
(a) (b) (c)

Figure 12: (a) (b) (c) 2D Voronoi Diagrams

The resulting room partitions can be varied with the advantage of being able to define the weight point of each room in advance. Basically, there are two different floor-plan typologies that can be generated. Those whose contour is predefined and therefore the process is directed from shape to interior partitioning and those whose geometric shape is determined by the interior partitioning and therefore the contour depends on the number of rooms and position of the seeds. The main difference is the organic irregular contour of the latter typology, which tends to vary but is difficult to reconcile with a predefined building framework.

Delaunay Triangulation

The seed point set that determines the Voronoi regions can also be represented in a mesh. The most common of these meshed representations is directly geometrically related to the Voronoi diagram and is called Delaunay triangulation. More precisely, the delaunay mesh describes the dual graph of the voronoi pattern. Every single triangle side intersects a Voronoi edge at a right angle and this exactly at its center.

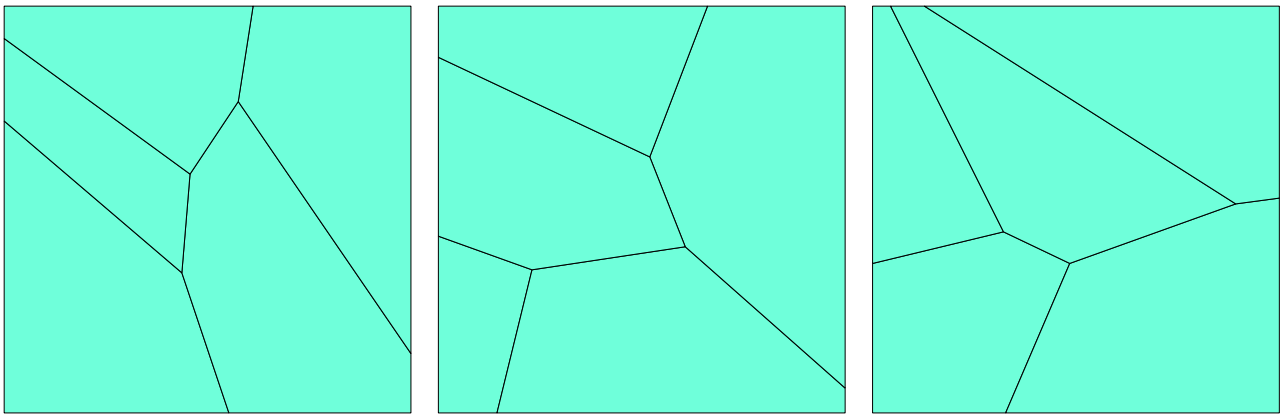


(a) (b) (c)

Figure 13: (a) (b) (c) Delaunay Triangulation Variants

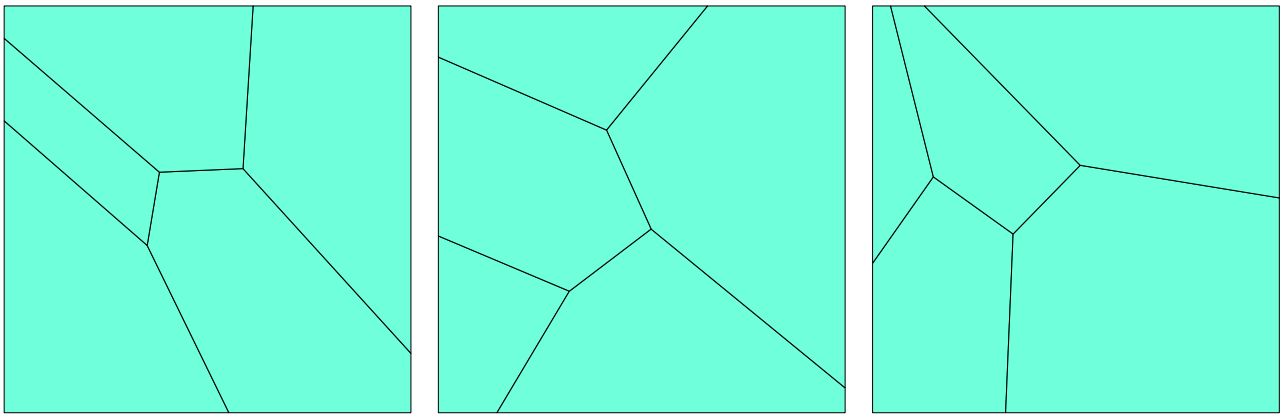
Lloyd's Algorithm

One of the most distinctive features of the voronoi subdivision based on randomly chosen points is the irregular shape of the individual regions. These shapes are all convex by definition, but their side length and number can vary greatly, and so can the interior angle of each side. In traditional architecture, the norm of designing orthogonal spaces has been established for simplicity and interior design aspects, and thus architects are accustomed to designing rectangular floor plans. To make a Voronoi subdivision approximate regular shapes, the seed points can be iteratively shifted using the Lloyd algorithm, thus increasing the compacity of the regions. This method consists of three distinct steps: first the voronoi pattern of points is calculated, in the following step the centroid of each of these voronoi regions is calculated and in the last step the seed point is shifted to the calculated voronoi centroid. After a few repetitions, a fair division of the total area into Voronoi regions and thus more regular shapes of the regions are obtained.
Apart from Lloyd's method, maximization, average and minimization of the individual region areas or edge lengths can also be used for relaxation of the generated mesh.



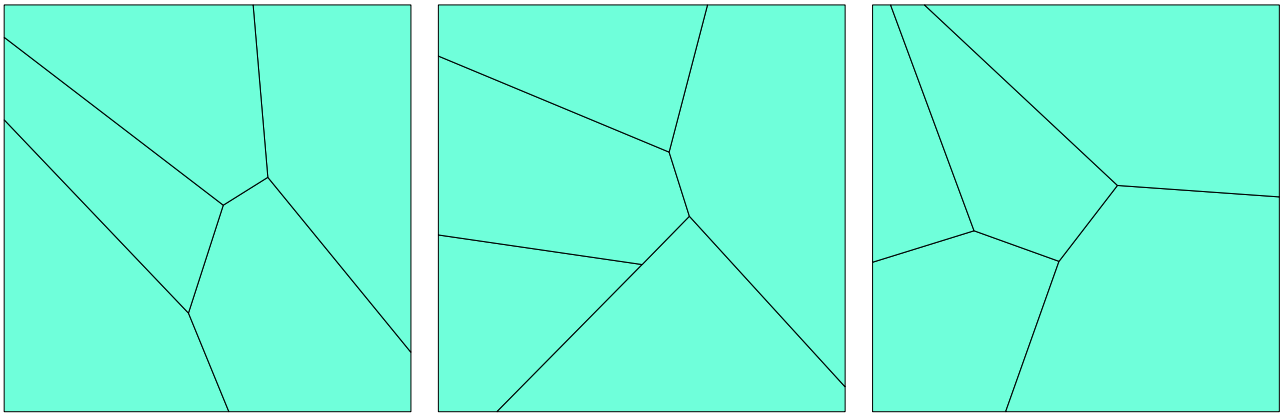
(a) (b) (c)

Figure 14: (a) Voronoi I (b) Voronoi II (c) Voronoi III



(a) (b) (c)

Figure 15: (a) Lloyd Variant I (b) Lloyd Variant II (c) Lloyd Variant III

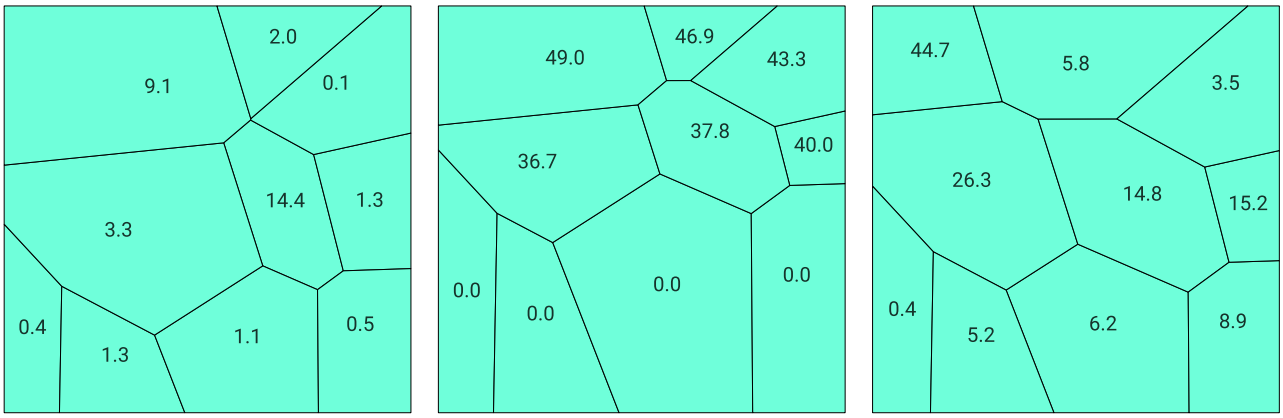


(a) (b) (c)

Figure 16: (a) Relaxed Diagram I (b) Relaxed Diagram II (c) Relaxed Diagram III

Laguerre-Voronoi

The most interesting variation of the voronoi daigram is called Power diagram or Laguerre-Voronoi diagram. In contrast to conventional Voronoi's, the distance function is not described by half of the length but can be defined individually as a radius function of the respective regions. This allows a parametric control over the individual space sizes.



(a) (b) (c)

Figure 17: (a) (b) (c) Weighted Voronoi Diagrams

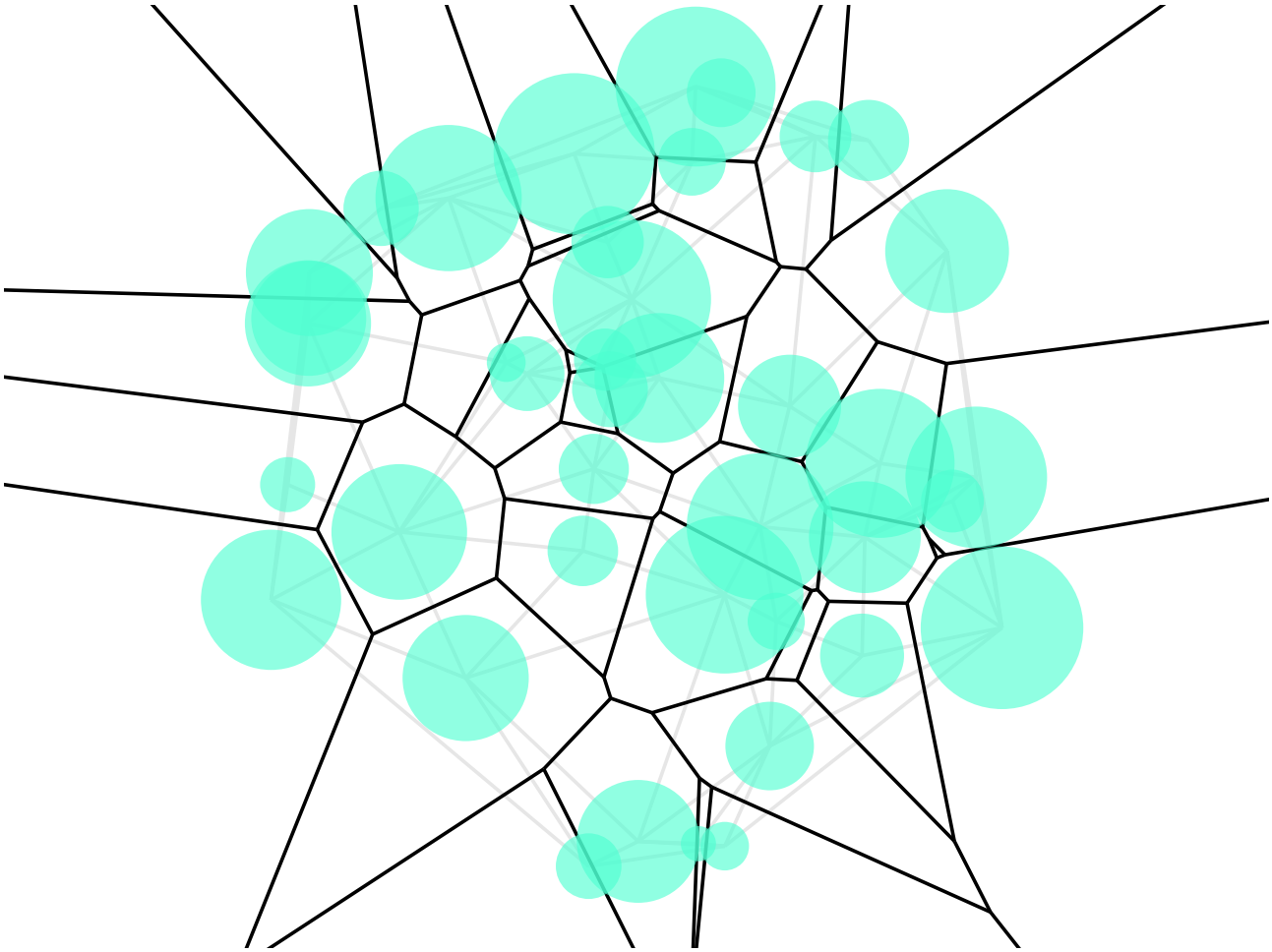
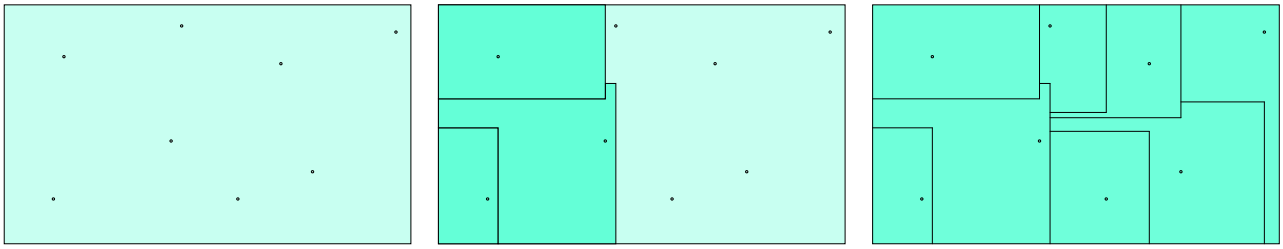


Figure 18: Power Diagram

To implement the radius distance function in sverchok blender the rule: every voronoi diagram in the nth dimension is the weighted diagram in the n-1th dimension was applied. In effect, this means that a third value w can be added to the x and y dimensions of the individual seeds of the two-dimensional diagram, which describes the weight and thus the weighted distance function.

Orthogonal Voronoi Diagram

Another less common variant is the rectangular voronoi which has the particularity that each voronoi region describes an orthogonal polygon and is therefore of special interest as an interface between traditional floorplan generation and irregular spatial planning.



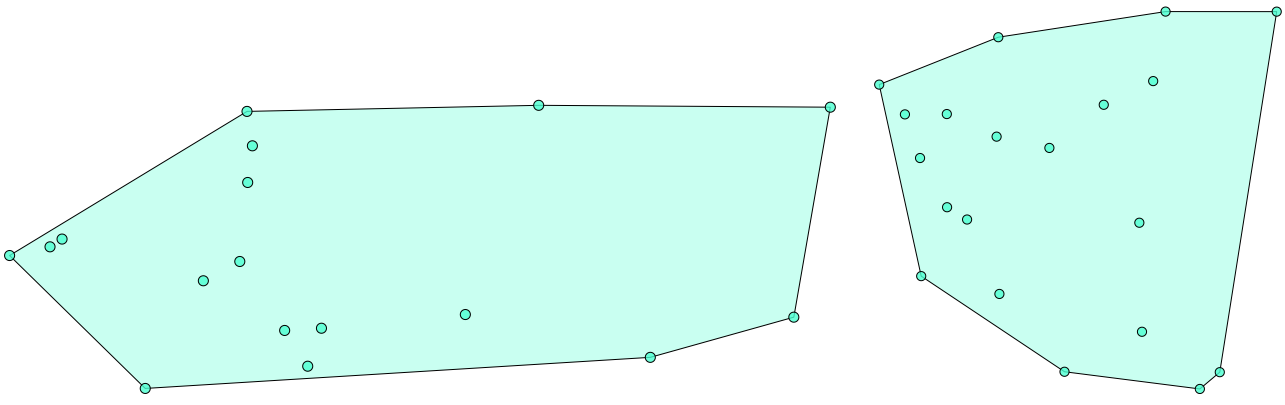
(a) (b) (c)

Figure 19: (a) Initial Seeds (b) 3 Iterations (c) Complete Orthogonal Voronoi Diagram

The generation of this diagram is based on a sweep algorithm with a predefined direction and skyline. First, the distance between the first two points in the dataset is considered, then a boundary is drawn orthogonal to the sweep line and at half the distance of the two points. The skyline is then moved to this limit and delimits the area orthogonal to the first point. These steps are repeated until each region is delineated.

Convex Hull

To determine the convex hull of a point cloud, different algorithms can be used whereby the final result remains the convex body containing all points. In the context of the present work, this method is different from the previous ones, since it is rather a method that defines the outline of the floor plan to be created, rather than a method for dividing the space.



(a) (b)

Figure 20: (a) (b) Convex Hull Variants

Orthogonal Convex Hull

Since the generated tension surface is an irregular convex polygon, its non-orthogonality makes it difficult to adopt as a conventional floor plan. However, the orthogonal convex hull, in which the con-

nected outer points are connected by orthogonal lines, can provide a suitable alternative.

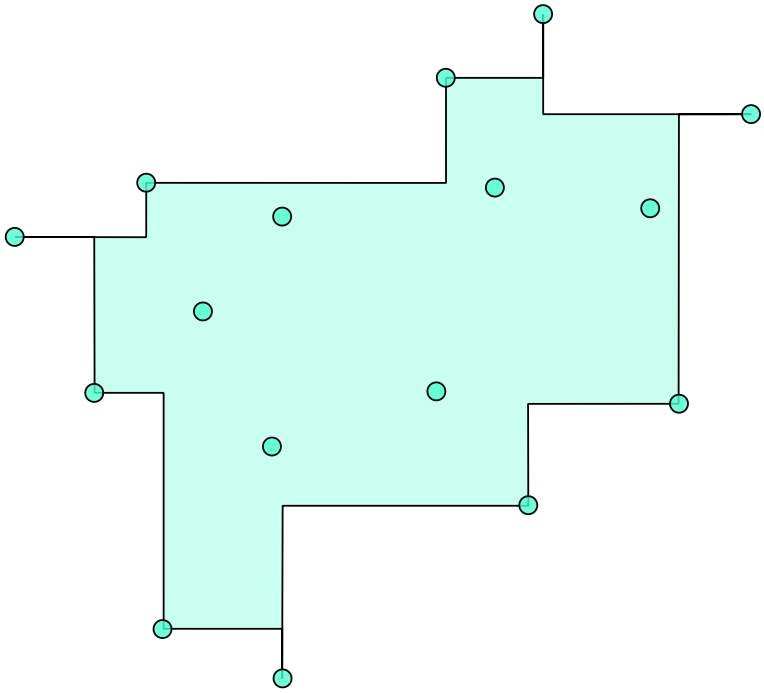
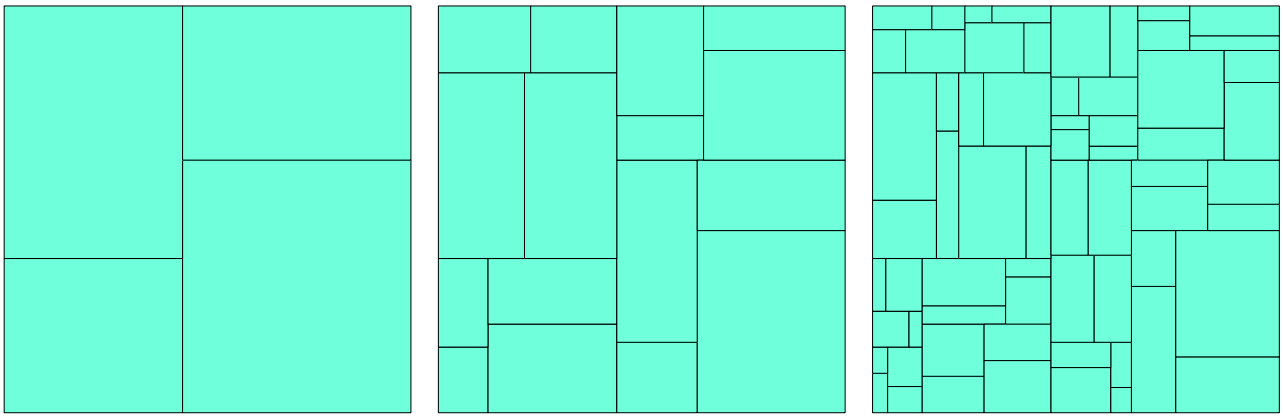


Figure 21: Orthogonal Convex Hull

The resulting outlines are similar to those of a conventional floor-plan and can be reconstructed into spatial units by applying previously seen algorithms to the points located in the inner body. The disadvantage of this method of convex outline generation is, however, the separation caused by the convex orthogonality of some points which are only bound to the generated plan by a line.

Recursive Subdivision

This method is similar to the K-dimensional tree algorithm in that it is also an iterative subdivision of a total area into subunits. An important difference in the recursive subdivision approach lies in the fact that there are no predefined points that define the space. Only a coordinate for the intersection axis point and its intersection axis is defined. The ratio of the intersections can be defined or randomly parameterized.



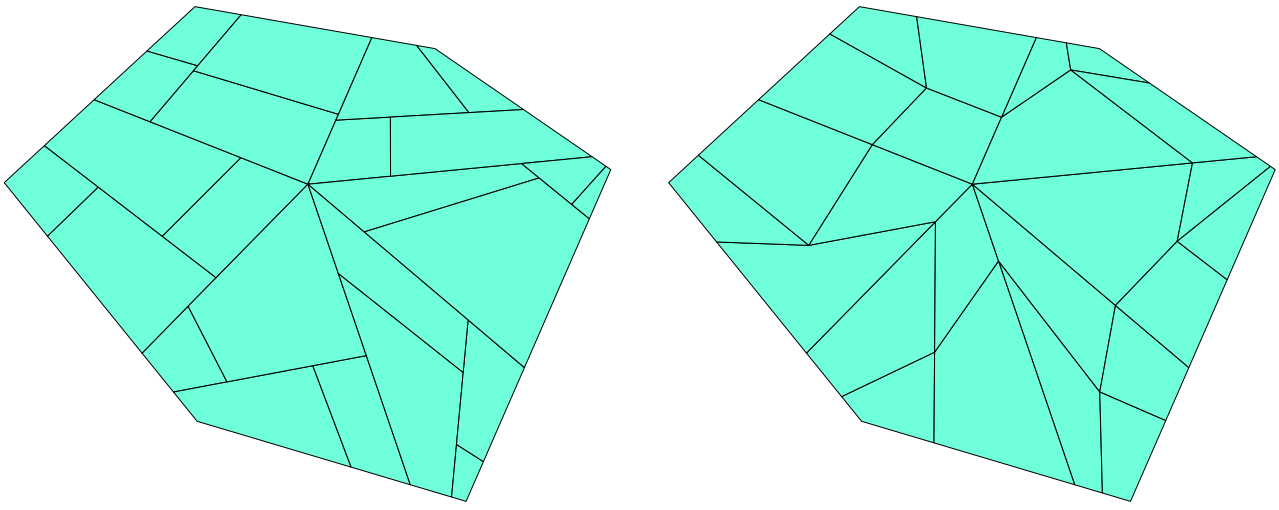
(a) (b) (c)

Figure 22: (a) 2 Iterations (b) 4 Iterations (c) 6 Iterations

A clear advantage of this algorithm is its simplicity, however, the ground bodies to be divided are limited to quads and the subdivided compartments are quadrilaterals as well. Furthermore, in the normal iteration, each of the subdivided shapes is subdivided into the exact same number which provides regularity in the subdivision but at the same time complicates variation.

Bent Bisection

Since this method is based on the repetition of subdivision algorithms, the variation by combining different subdivision methods is virtually indefinite. Even slight modifications such as a randomly determined crease in the division plane can provide amazing variation. If one or more iterations are replaced by a division into quads by the centeroid of the form, the regular character of this recursive subdivision can be varied further.



(a) (b)

Figure 23: (a) Quad And Recursive Subdivision (b) Recursive Quad Division

Shape Grammar

By means of established shape rules and a shape engine which acts as a selector and interpreter, different shapes can be generated based on the formulated geometric rules such as orientation, boolean operations, multiplication and deplacement. Together with a start rule, an indefinite number of transformation rules and a termination rule, several shapes respecting different constraints can be generated by serial or parallel iteration. In this work the parametric shape grammers are of interest, because here the rules are based on variables and thus a repeated execution of the generation with randomly generated, but certain limits located variables by variation of the random seed unpredictable shapes arise, which however always respect the implied geometric conditions. Furthermore, it is possible to view the process after the execution of each stage and thus have a finer choice of the output geometry. The floor plans generated in this way have the advantage that the spaces touch each other exactly on one or more lines, thus allowing further processing in boundary representation.

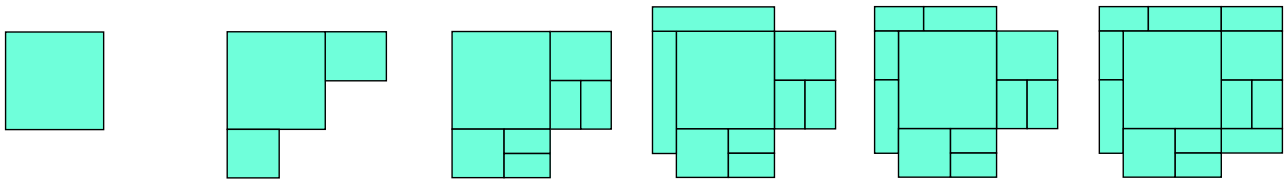
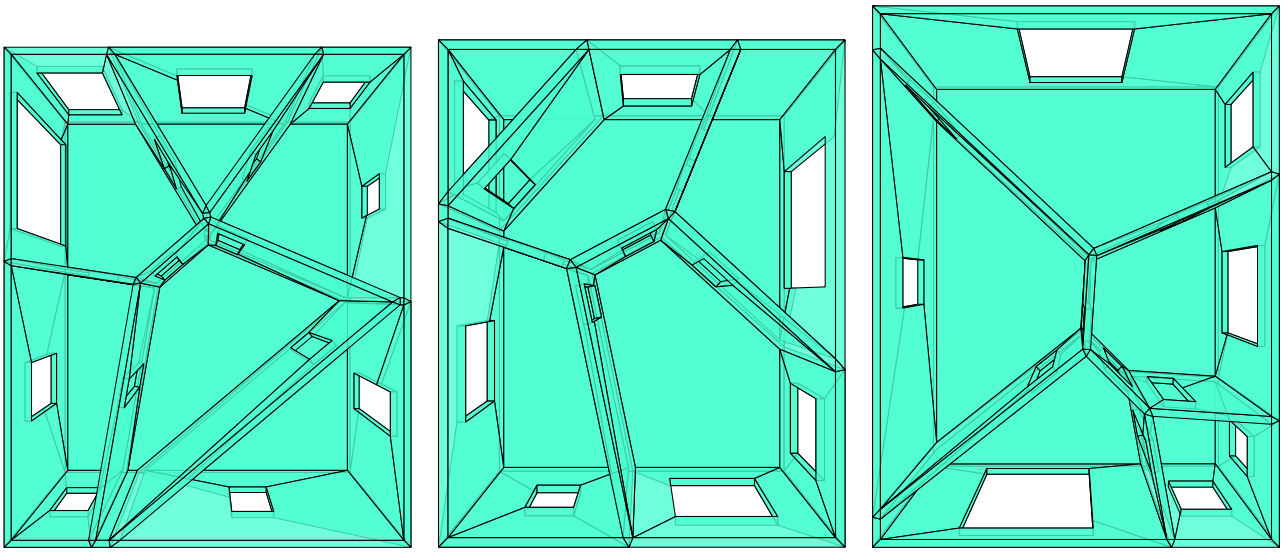


Figure 24: Shape Grammar Generation

Topologic

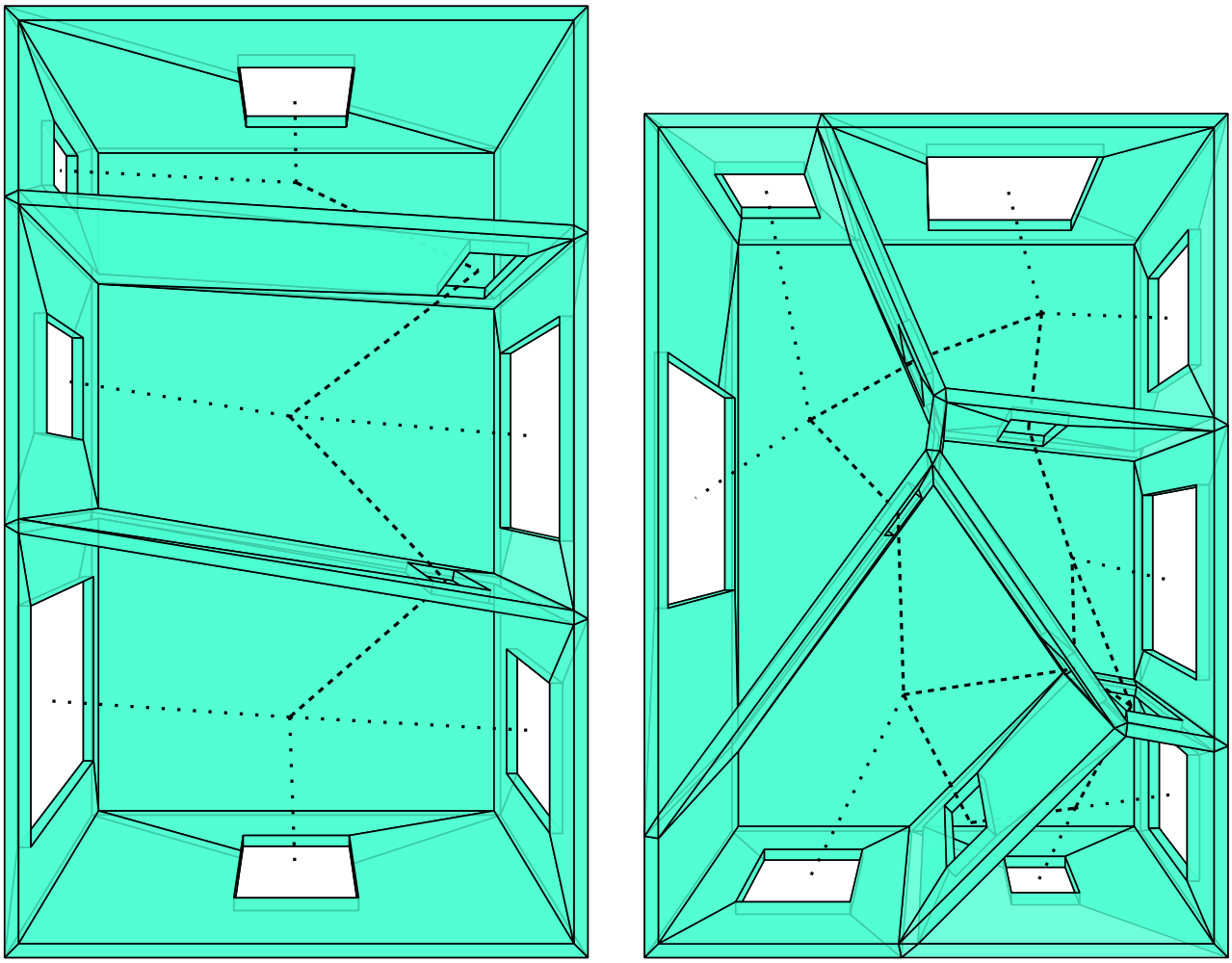
Topologic python library is not primarily a shape grammar engine, but by processing the topological relationships in the geometry, it is possible to establish shape rules and thus enhance the generated partitions. The functionality of the TopologicPy library is based on non manifold topologies similar to boundary representations and opencascade shapes. The architectural geometry is extremely simplified and consists only of single layer surfaces. Thanks to the hierarchical structure of the library, it can easily switch from larger units like CellComplex, Cell and Cluster to smaller units like faces, edges and vertex by querying the entire topology. Furthermore, a major advantage of using topologic is a seamless interface between geometry processing and environmental simulation such as energy performance or light simulations thanks to Openstudio, honeybee and ladybug bindings. However, in terms of floor-plan generation, the topological analysis capabilities are of primary importance.



(a) (b) (c)

Figure 25: (a) (b) (c) Aperture Enhanced Models

If the two-dimensional floor-plan layouts generated by the aforementioned methods are converted into Topologic geometries as a surface list, a proper data exchange between blender's sverchok geometry and the geometry processed by Topologic can be ensured. Thus, mentioned surfaces are first extruded along the z-axis and desired space height and registered as cells in a cellcomplex. At this point it is essential that the space contours touch each other on at least one side but without overlapping. After the cellcomplex generation, which is analogous to the apartment generation, the interior and exterior walls of the whole complex can be separated by parameterizable queries and retrieved with their respective geometry. In the following step it is then possible to retrieve a point on each wall surface and, in combination with the geometry normal, to read its corresponding matrix, which in turn allows to generate parametric window and door surfaces on the walls. Thanks to topologic's aperture integration, these openings can then be stored as surface apertures for each individual wall and integrated into the cellcomplex.



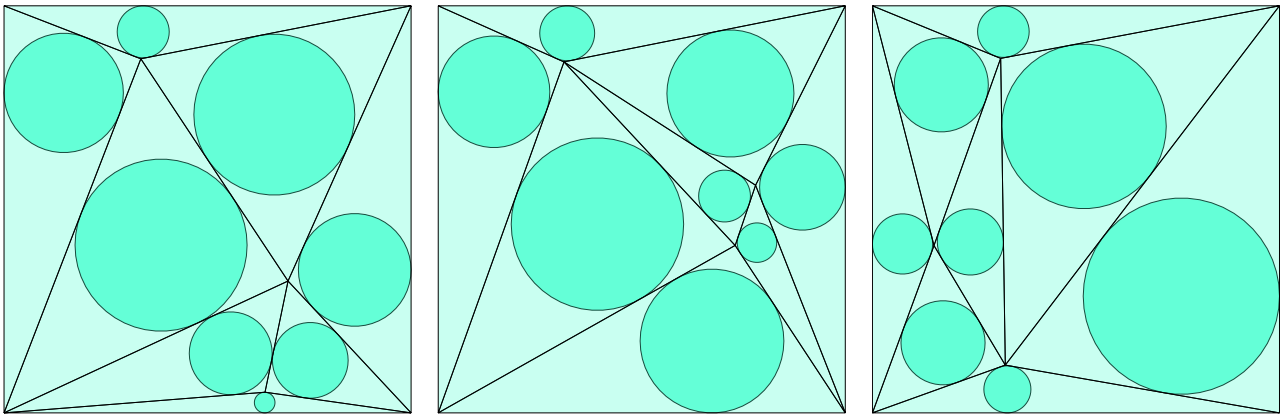
(a) (b)

Figure 26: (a) (b) Topological Graph To Exterior / Internal Apertures

Through these sequential processes, plausible three-dimensional apartment models can be generated with integrated circulation and window openings. Now that the apertures have been integrated into the cellcomplex, any relational connection of the spaces and apertures can be queried and used for analysis purposes using the Topologic's graph function.

Shape Packing

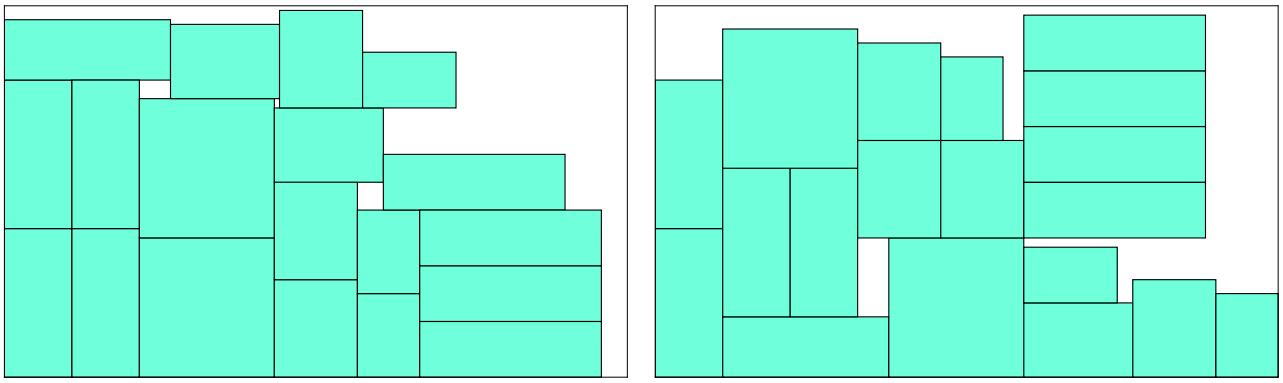
The family of shape packing algorithms deals with the topic of inscribing defined shapes with fixed dimensions into an equally fixed container. These methods are relevant in connection with the problem of automated floor-plan generation, since almost all parameters can be defined in advance. These parameters include the number of rooms and their exact shape, but also the exact dimensions of the plan outline.



(a) (b) (c)

Figure 27: (a) (b) (c) Delaunay Triangulation With Inscribed Circles

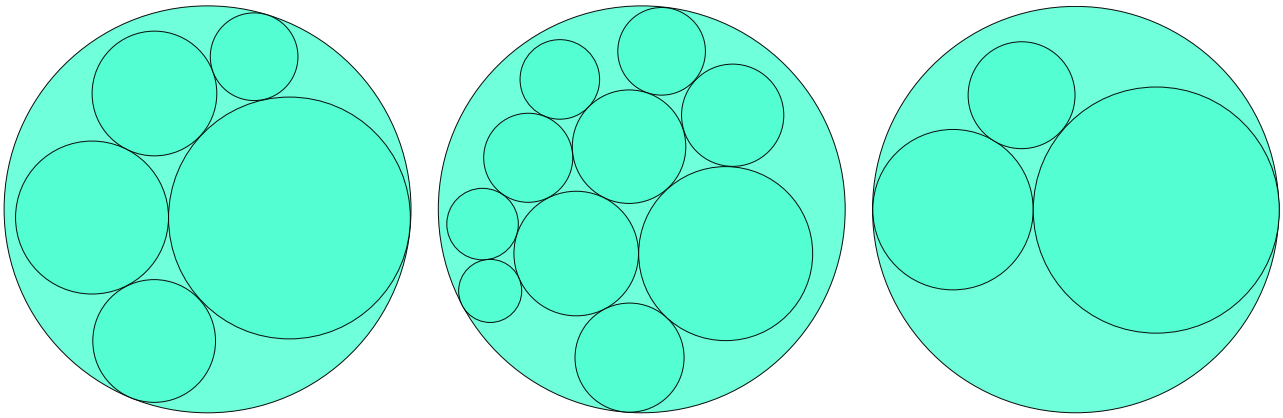
Three families of shape packing problems are distinguished, those where the container is unlimited and those where the container is limited in three or two dimensions. In this work, the methods of shape packing in two dimensions with limited container size are of particular importance. In a two-dimensional body triangulated by point projection delaunay, the largest possible circles can be inscribed in the respective triangles, thus creating a space division defined by the radius.



(a) (b)

Figure 28: (a) (b) Bin Packing Problem

The bin-packing problem describes the problem of the most space-efficient packing of an exact number of well-defined rectangles in a certain number of containers. Furthermore, the exact position of the best possible packing of a set of circles with defined radii can be calculated by a circles in circle packing algorithm.

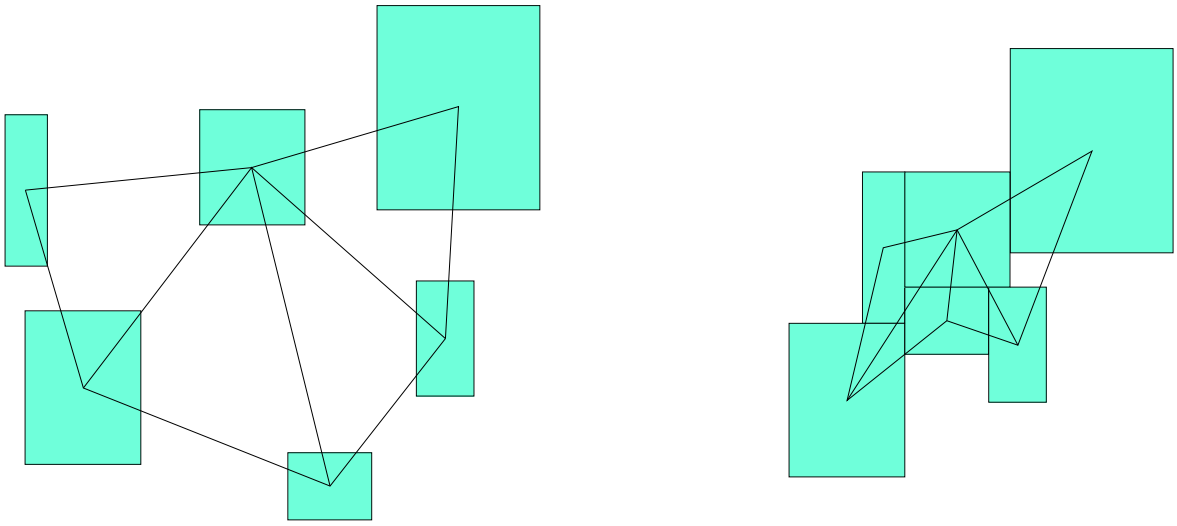


(a) (b) (c)

Figure 29: (a) (b) (c) Circles In Circle Algorithm

Physics Solver

Similar to the genetic algorithm variant of floor-plan generation, physic engines can be used to create different plan layouts. In this work, Bullet physics was used thanks to its blender integration and ease of interaction. Required for the successful execution of this generation method are only the pre-defined single room sizes as two dimensional geometries in euclidean space. In the next step, the relation network which is simulated by the attraction network has to be defined. This mesh should connect the centroids of the space compartments with each other to avoid undesired results.

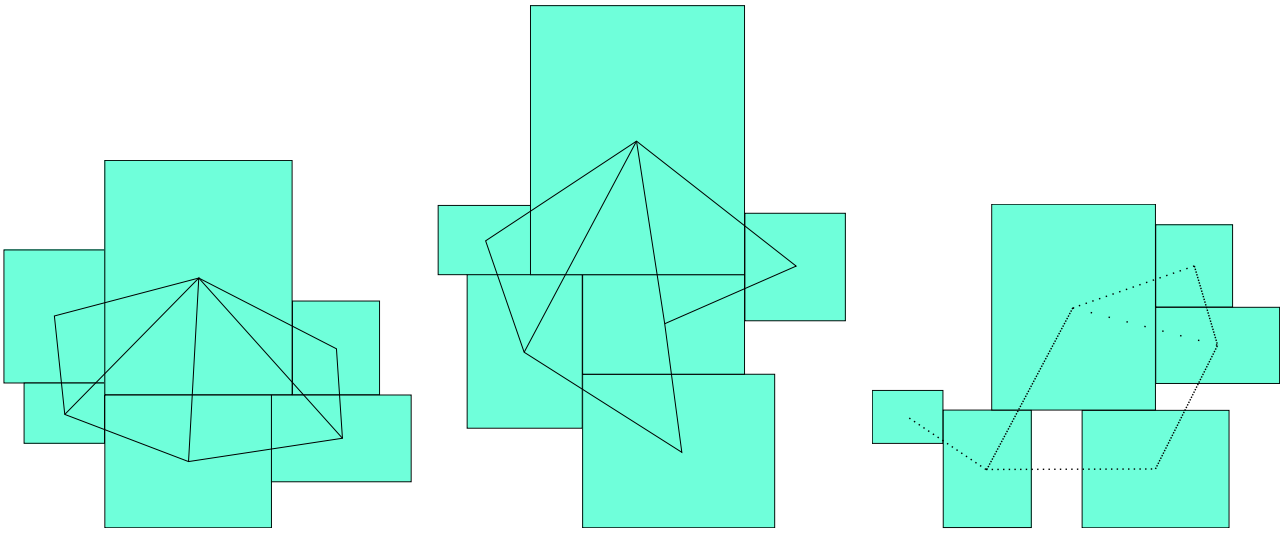


(a) (b)

Figure 30: (a) Initial Position (b) Final Position

Thanks to the physic solver, the units can be defined as solid bodies with active collision, which prevents interpenetration. This is counteracted by the spring attractions forces that act on the net lines between the body centers of gravity to different degrees. During the execution of the simulation, the number of solver steps acts as a time variable and thus the animation can be played. The final results generated in this way can vary greatly in their layout

depending on the start position seed and the random noise seed which is added to the attraction forces. By varying the spring forces, the topological relationship between the spaces can be regulated, thus allowing for diversity in generation.
Advantages of this method are the conclusive results in the traditional architectural sense and the possibility to define in advance the individual space dimensions, orientations and their topological relationships. However, similar to the results of the evolutionary algorithm, the main disadvantages are an impure end geometry with minimal distances between the single units and a time and memory consumption in the simulation process.



(a) (b) (c)

Figure 31: (a) (b) Physics Simulation Result Variants (c) Simulation With Different Attraction Forces

Data Driven Approaches

In the field of computer science, machine learning processes for architecture generation have been strongly established for several years. The different approaches vary strongly and therefore also their output and their application. However, there is an analogy in all data driven approaches which makes an application to layout generation inappropriate: The learning algorithms of amazing accuracy are invariably based on a data set from the real world and thus show a constant variance bias which is caused by the functionality of such approaches. Either the model to be trained is directly taught on the basis of selected floor plans that are considered to be suitable, or a generator designs objects with the help of random noise, which increasingly develop into apartment floor plans. However, also here the elementary part of the mechanism is formed by the discriminator which communicates to the random noise generation as feedback how far the generated object resembles a conventional plan.

Method of Choice

In order to generate a comprehensive data set, as many different floor-plan layout design methods as possible are integrated, as well as their different variants. At the moment only the KD-Tree and Voronoi and its derivatives provide satisfying results. Possibly, a genetic algorithm could increase the variance of these methods by

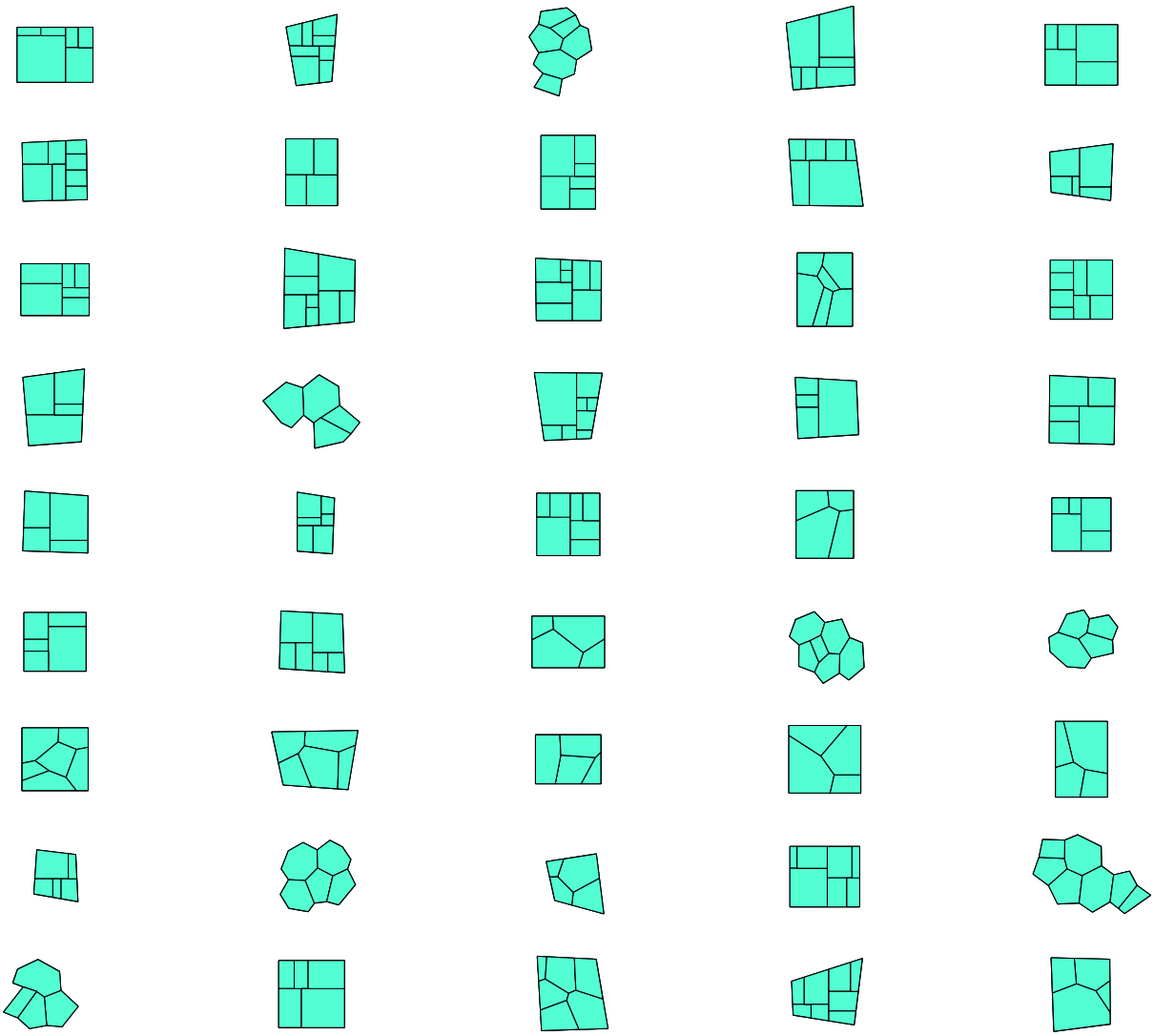
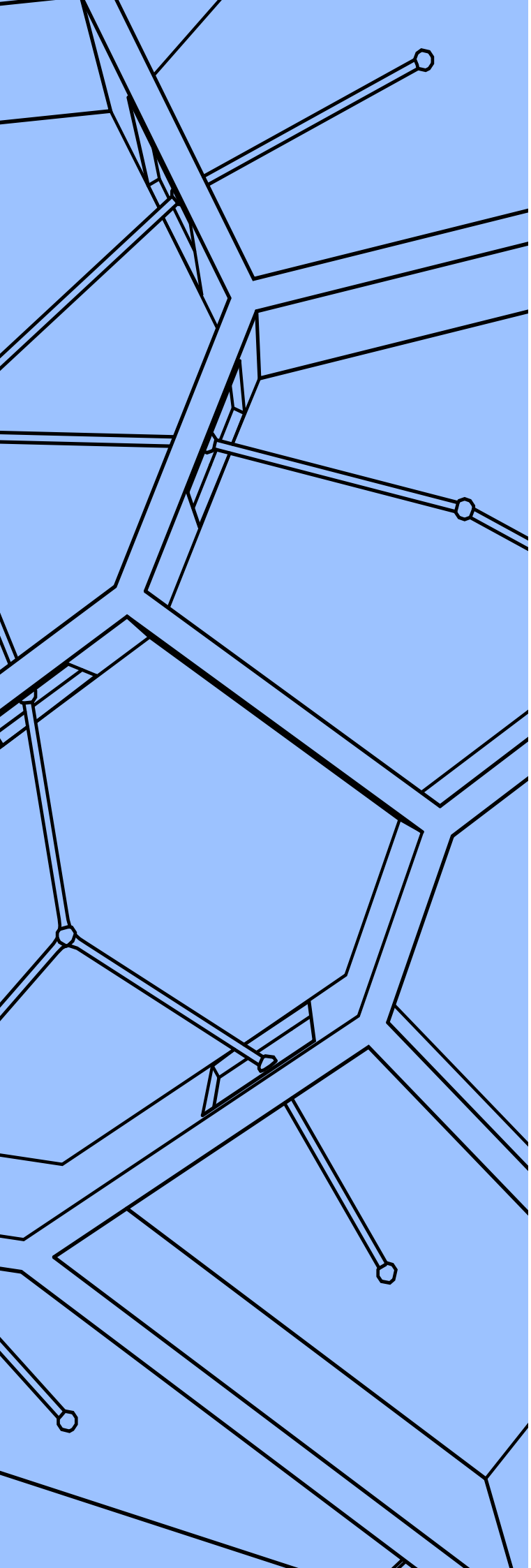


Figure 32: Results

optimizing individual selection characteristics. Furthermore, an integration of the recursive subdivision method would be conceivable, but its results are similar to those of the KD-Tree, but surpassed by the latter because of the adjustability through the seed points. The remaining methods described have significant drawbacks that prevent their integration into the dataset generation process, such as the need for an additional gap removal algorithm between the individual areas. This is theoretically possible, but is not necessary at the moment, as it turns out that the dataset is sufficiently versatile due to a well-considered parameterization of the variables of the KD-Tree and Voronoi method. As explained in the next section, the generated geometric data are filtered after their generation. In order to avoid that a large part is sorted out, the parameterization must avoid the filter characteristics and, if necessary, cause a seed change through a feedback.



Data

This stage deals with the manipulation of the geometric data obtained as a result of the generative phase. Through geometric operations, the two-dimensional layout plans are first converted into volumetrics and stored as a topological cell complex. For this purpose, the data formats JavaScript Object Notation and boundary representation will be examined in closer depth and their structure will be understood in order to understand and exploit the respective advantages and disadvantages as well as potential possibilities for data modification through python interaction. For the consideration of which formats are useful for geometry storage, properties such as: size, compatibility, readability, structure and efficiency will be considered. In all these considerations, the most important criteria is the possibility to process the data in the analysis and simulation phase and especially in the learning phase. Once the individual structures of the formats have been understood, the filtering process of the collected data set can begin, whereby the floor plans are automatically checked and sorted according to defined architecturally based rules in order to minimize the error rate in the learning process and to evaluate the data set. It is important to distinguish generation errors caused by inappropriately defined parametric boundaries from technical errors, as the former can be corrected by adjusting the basic parameters. The next step is of high importance, as it involves the addition of apertures such as doors and windows, which are an elementary part of the simulation stage. In order to allow the greatest possible variability of the dataset, the dimensions, placement and orientation of these elements are also generated in a parametric way, paying great attention to the architectural rules of such placements, but also generating the greatest possible variety of different results. Finally, the generated results are evaluated, possible improvements are identified and stored as a data set in the appropriate data format.

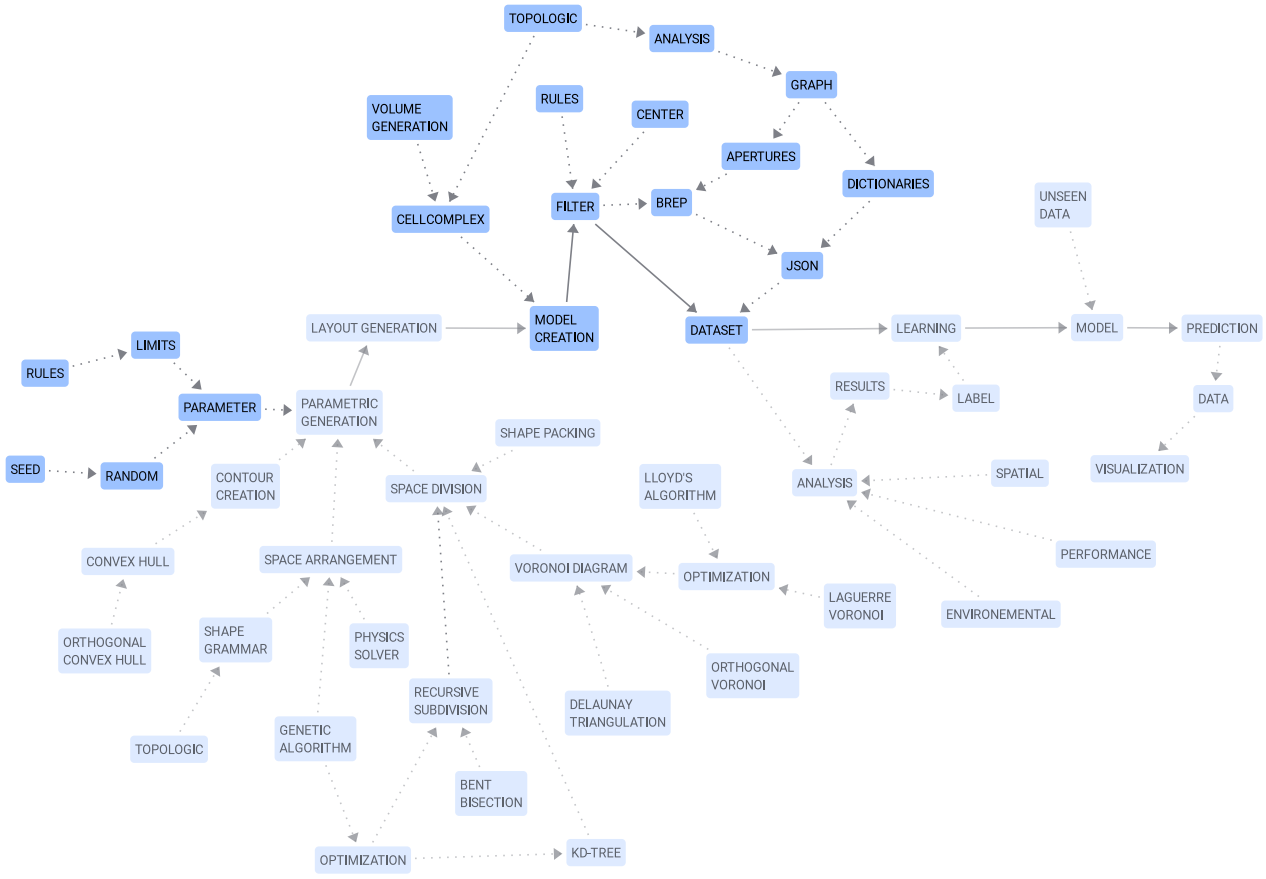


Figure 33: Data Augmentation

Volume Creation

In order to move from two-dimensional space partition layouts to apartment volumetries, the surfaces must be extruded along the z-axis. This step is integrated in the layout generation for simplicity reasons and is based on the Sverchok node 'extrude region' which extrudes the input vertex with its corresponding faces following a defined matrix. In order to make the visualization of the generated geometries more truthful, the two-dimensional partition walls generated in this way are converted to three-dimensional bodies with a defined thickness using Blender's integrated solidify modifier in complex mode. However, this operation is not applied to the volumetries to be stored as this would unnecessarily complicate the simulation steps in the next stage and increase the data size.

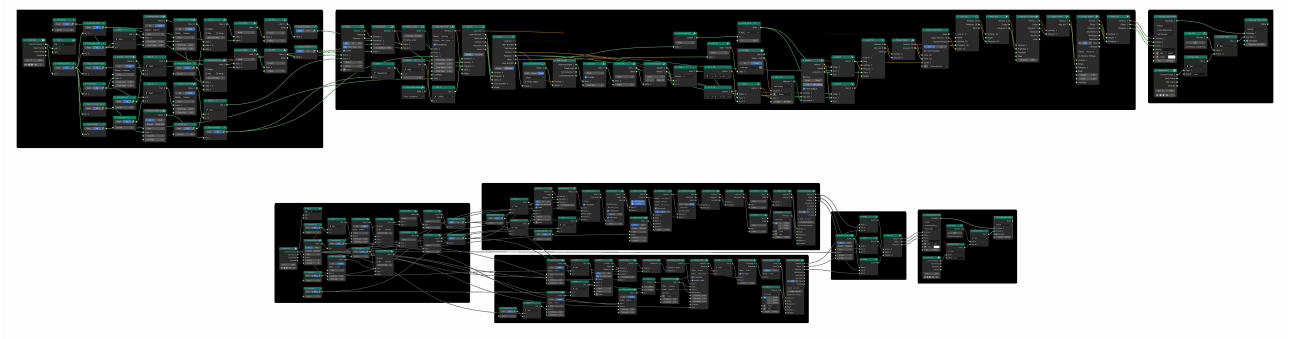


Figure 34: Geometry Generation with Extrusion

Filtering

After the desired number of apartment geometries has been generated and saved, it is essential to sort the data by quality attributes to remove any errors from the dataset, otherwise the simulation and learning process could produce erroneous results. To achieve this, the three-dimensional objects are imported parametrically into Blender using sverchok and topologic. Since topologic's understanding of the geometry was used to divide the volumes into relational elements and each of the appartments should form a cell complex, each individual file can now be classified as defective or satisfactory on the basis of simple predefined rules by querying the desired properties or the defective characteristics. Finally, the faulty files are removed from the dataset.

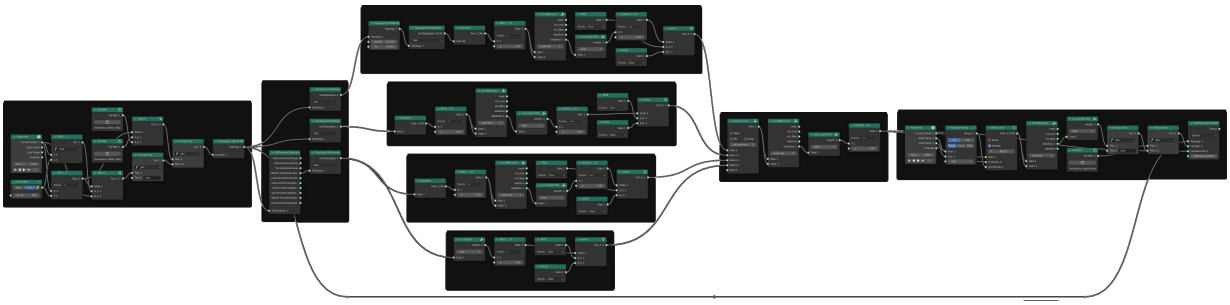


Figure 35: Geometry Filtering

Boundary Representation

The Brep file format is a geometric description of three-dimensional bodies and their relation to each other. An essential feature of the format is the description of the objects by their bounding surfaces alone, which in the simple example of a rock consist of six surfaces and in a sphere model of only one surface. The individual elements are divided into sub-shapes by their topology and can thus be adequately described by seven individual elements such as vertex, edge, wire, face, shell, solid and compound solid. Thus it is possible to describe and store complex bodies by assemblies of simpler bodies using boolean operations.

```
1  CASCADE Topology V1, (c) Matra-Datavision
2
3  Locations 0
4
5  Curve2ds 4
6  1 0.4099 0.8804 -1 0
7  1 0.4099 -0.8804 0 1
8  1 -0.4099 0.8804 0 -1
9  1 -0.4099 -0.8804 1 0
10
11 Curves 4
12 1 4.70816 1.071499 1.65997 1.11022e-16 0 -1
13 1 4.70816 2.832301 1.65997 0 -1 0
14 1 4.70816 1.071499 0.84002 0 1 0
15 1 4.70816 2.832301 0.84002 -1.11022e-16 0 1
16
17 Polygon3D 0
18
19 PolygonOnTriangulations 0
20
```

```
Surfaces 1
1 4.70816 1.9519 1.249999 1 0 0 -0 0 1 0 -1 0

Triangulations 0

TShapes 10
Ve
1e-07
4.708168 1.071499 1.65997
0 0

0101101
*
Ve
1e-07
4.70816887037135 1.07149969339381 0.840028778320181
0 0

0101101
*
Ed
1e-07 1 1 0
1  1 0 0 0.819942443359638
2  1 1 0 0 0.819942443359638
0

0101000
+10 0 -9 0 *
Ve
1e-07
4.70816887037135 2.83230126787587 1.65997122167982
0 0

0101101
*
Ed
1e-07 1 1 0
1  2 0 0 1.76080157448207
2  2 1 0 0 1.76080157448207
0

0101000
+7 0 -10 0 *
Ve
1e-07
4.70816887037135 2.83230126787587 0.840028778320181
0 0

0101101
*
Ed
1e-07 1 1 0
1  3 0 0 1.76080157448207
2  3 1 0 0 1.76080157448207
0101000
+9 0 -5 0 *
Ed
1e-07 1 1 0
1  4 0 0 0.819942443359638
2  4 1 0 0 0.819942443359638
0

0101000
+5 0 -7 0 *
Wi

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```
0101100
+8 0 +6 0 +4 0 +3 0 *
Fa
0  1e-07 1 0

0101000
+2 0 *

+1 0
```

Listing 1: BREP Example

The Python library Topologic bases its basic functions on a similar abstraction as the Boundaryrepresentation partitioning method, making data storage in Brep format the most obvious and effective method of geometry description. To be more precise, Topologic's geometry manipulation is based on the 3D modeling kernel open-CASCADE Technology and is therefore bound to solidmodeling in its functionality. The element subdivision is basically only distinguished by the naming of the different elements. Thus, a solid represents a cell unit in topologic, a solid assembly becomes a cell complex under the condition that any volume is contiguous or has an edge or vertex in common and a collection of cell complexes without intersection is described as a cluster.

JSON

The open standard file format JavaScript Object Notation is a data structure that allows to store several different dictionaries and arrays in human readable form. Due to its intuitive structure, JSON files have found wide use in web and API exchanges, as individual keys and values can be retrieved through simple queries. Furthermore, contrary to the assumption, it is a language-native file format and thus enables a flawless cross-language and cross-program exchange of information.

```
{
  "firstName": "John",
  "lastName": "Smith",
  "isAlive": true,
  "age": 27,
  "address": {
    "streetAddress": "21 2nd Street",
    "city": "New York",
    "state": "NY",
    "postalCode": "10021-3100"
  },
  "phoneNumbers": [
    {
      "type": "home",
      "number": 212 555 1234
    },
    {
      "type": "office",
      "number": "646 555-4567"
    }
  ],
  "children": [],
  "spouse": null
}
```

Listing 2: JSON Example

The file example demonstrates the storage of personal information where each individual value is assigned to a key and can

be retrieved just as easily with the help of this key. Furthermore, in this example, individual dictionaries are combined into arrays which thus form the values for higher-level keys and thereby facilitate the structure of the file.

Topologic

As already described in the Brep section, the Topologic library is based on OpenCASCADE technology, which in turn is based on the Boundary representation model. Thus, in Topologic it is possible to decompose architectural volumes into their individual elements and to query these elements on request using defined criteria. It is interesting that it is also possible to trace the relations of the individual elements and their connections and thus it is possible to query without problems, for example, the fastest way from room A to room B without having to go through room C or which rooms with south windows are adjacent to room C and room D. Of course, such topological analyses are just as easy to perform manually for less extensive architectural objects, but topologic's strength lies in larger projects and parametric analyses such as in the case of this work.

Apertures

Essential for meaningful energy and light simulations are apertures like windows and doors, which are currently missing in the generated layouts. With the help of Sverchok it is relatively easy to cut rectangular holes in the two-dimensional partition and exterior walls, but this would only complicate the geometry unnecessarily by converting previously rectangular walls into polygons. The solution to this problem and the architecturally sensible placement of apertures, since not every room has to be connected to every adjacent room, can again be found in the topologic python library. It is possible to calculate the minimum spanning tree of the connection graph of all rooms and thus obtain a list of those walls where a door leads to an optimal circulation through the apartment. Furthermore, topologic can store apertures in its geometry as additional brep data without affecting the basic geometry.

Structure

```
[
    {
        "brep": "topology_00001",
        "cellApertures": [],
        "cellDictionaries": [
            {
                "dictionary": {
                    "area": 33.44,
                    "id": 0,
                    "type": "room"
                },
                "selector": [
                    1.491212715639101,
                    0.18688301956760373,
                    1.25
                ]
            },
            {
                "dictionary": {
```

```
                    "area": 14.2,
                    "id": 1,
                    "type": "room"
                },
                "selector": [
                    2.5635190468646725,
                    -3.0991602704456733,
                    1.25
                ]
            },
            {
                "dictionary": {
                    "area": 34.79,
                    "id": 2,
                    "type": "room"
                },
                "selector": [
                    -2.4800350291326527,
                    1.085227288601124,
                    1.2500000000000002
                ]
            }
        ],
        "dictionary": {
            "id": 1,
            "rooms": 3,
            "surface": 82.43,
            "type": "flat"
        },
        "edgeApertures": [],
        "edgeDictionaries": [],
        "faceApertures": [
            {
                "brep": "topology_00002",
                "dictionary": {
                    "id": 0,
                    "type": "door"
                }
            },
            {
                "brep": "topology_00003",
                "dictionary": {
                    "id": 1,
                    "type": "door"
                }
            },
            {
                "brep": "topology_00004",
                "dictionary": {
                    "id": 0,
                    "type": "window"
                }
            },
            {
                "brep": "topology_00005",
                "dictionary": {
                    "id": 1,
                    "type": "window"
                }
            },
            {
                "brep": "topology_00006",
                "dictionary": {
                    "id": 2,
                    "type": "window"
                }
```

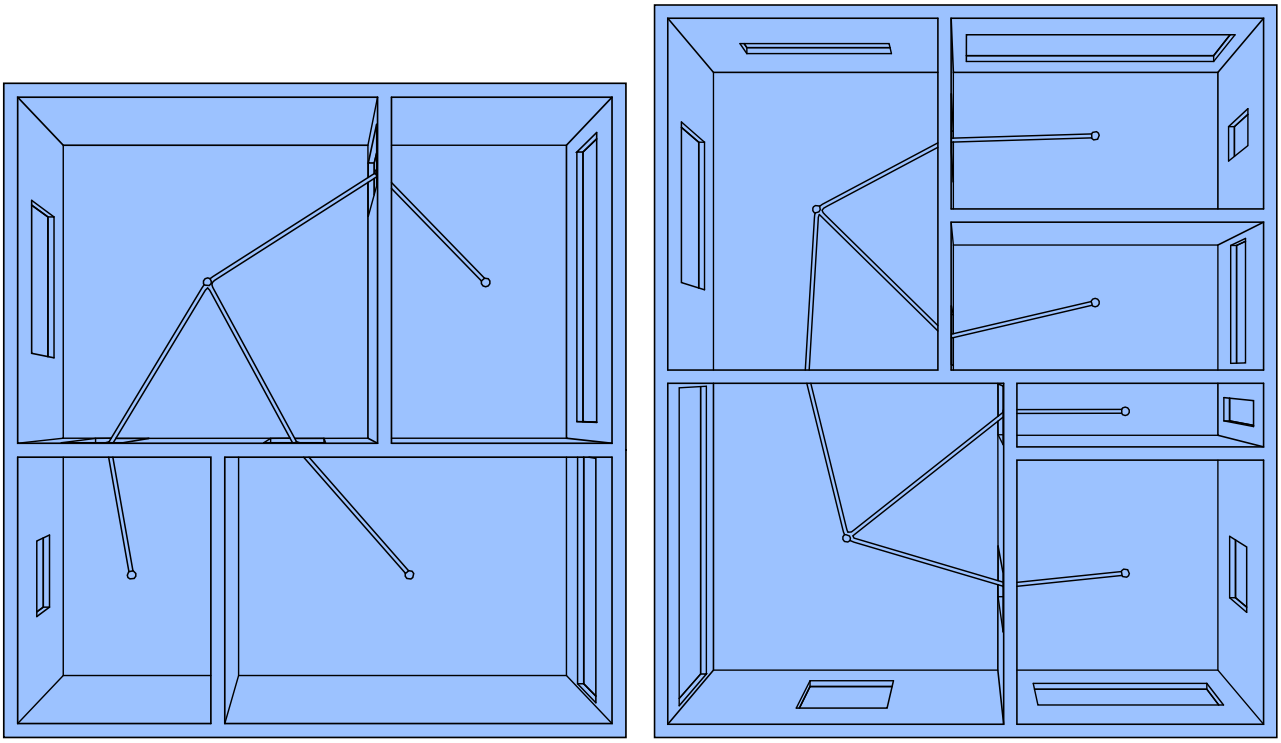
```
            }
        ],
        "faceDictionaries": [],
        "vertexApertures": [],
        "vertexDictionaries": []
    }
]
```

Listing 3: Topologic JSON Example

This example shows that for each wall with a window and a door a separate Brep file is referenced which contains the geometry of the respective aperture. Furthermore, added dictonarries are visible, such as individual identification numbers of the elements as well as type information or room sizes in square meters.

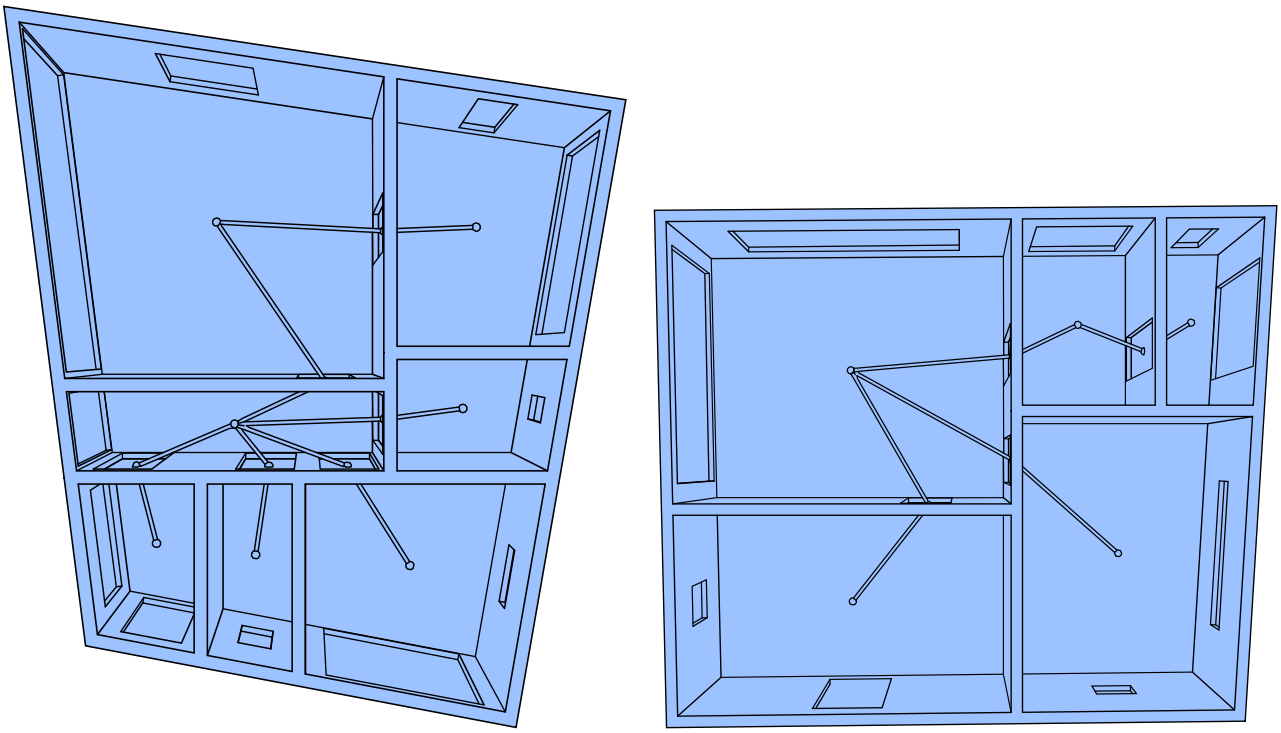
Results

The generated end results show a great variance in shape, number of rooms, space allocation and layouts. Furthermore, the generated doors describe in most cases an architecturally logical circulation path and form interesting results in all cases. The windows are also generated with great variance, but are currently still relatively arbitrary and not in correlation with the room sizes, but limited only by the available facade area. This should be remedied by integrating the room size and topological position of the adjacent room into the generation formula.



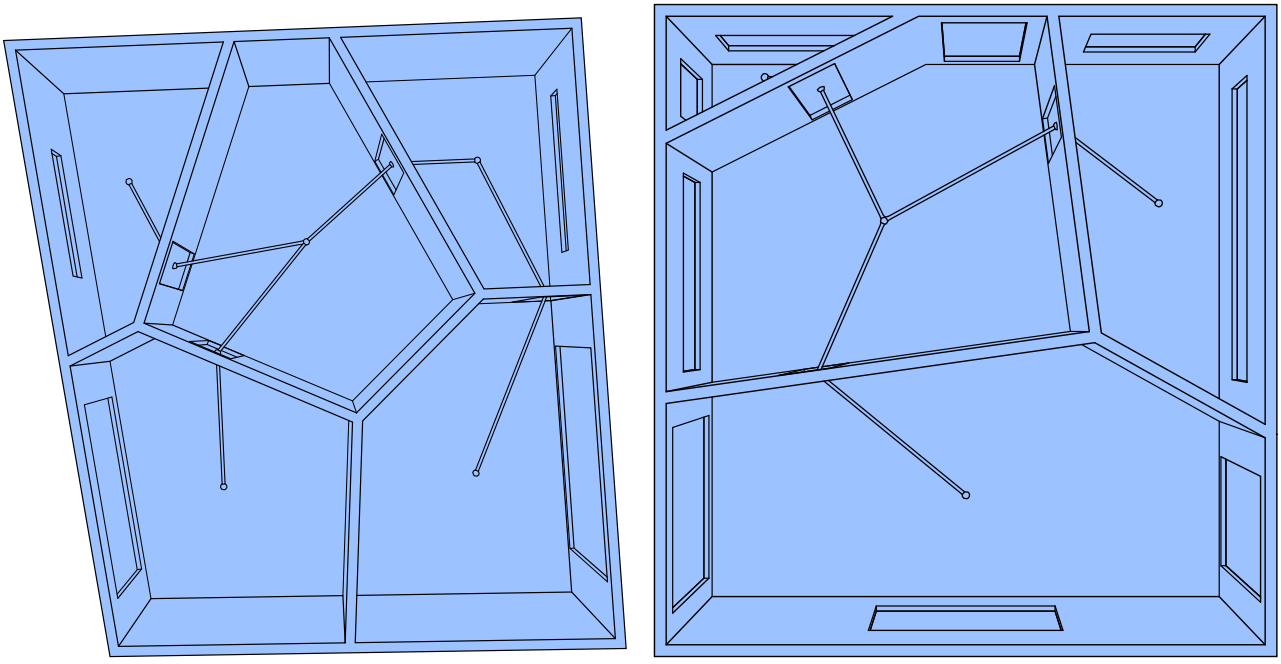
(a) (b)

Figure 36: (a) (b) KD-Tree Variants



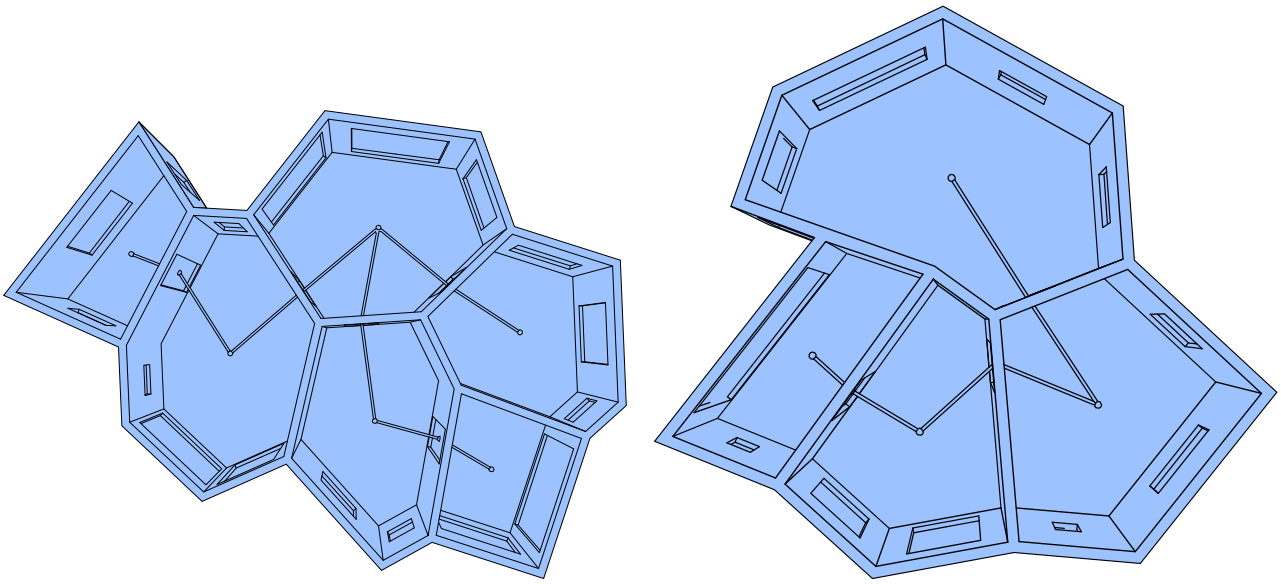
(a) (b)

Figure 37: (a) (b) Deformed KD-Tree Variants



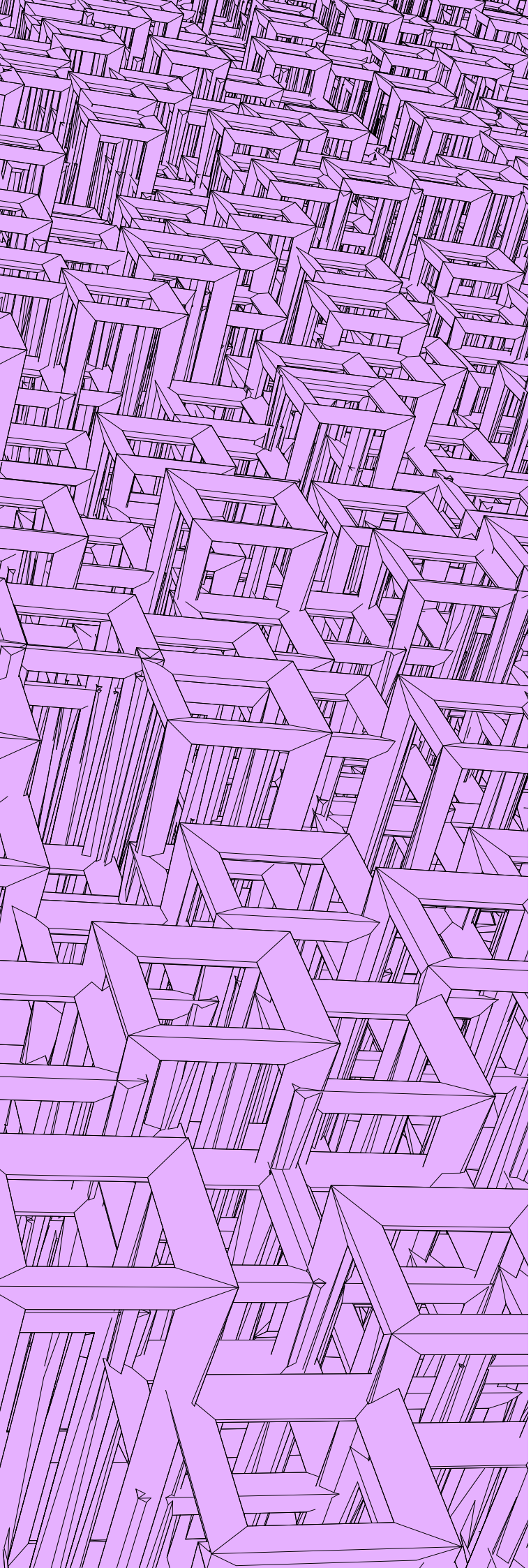
(a) (b)

Figure 38: (a) Rectangular Voronoi Variant (b) Deformed Voronoi Variant



(a) (b)

Figure 39: (a) (b) Voronoi Variants



Analysis

Due to time constraints, the data evaluation stage will not be an integrated part of this work, but will constitute the main focus of the following work. Furthermore, in all preceding steps the possibility of data set evaluation by means of simulations and analyses was included as a relevant method of evaluation. Thus, the stored geometries consist of non-manifold geometry boundary representations which are well suited for environemental and topological analysis and furthermore, care was taken to keep the data size of the individual architectural objects and their geometries as small as possible. By storing typologies, individual identification numbers, geometric characteristics and geometric coordinates in the geometry JSON file as key value dictionary pairs, these properties can be queried in the analysis stage in an effective way. Possible analysis approaches include energetic analysis using EnergyPlus, light analysis using Radiance, fluid dynamics using Openfoam, finite element analysis using Elmer, acoustics using I-Simpa, crowd simulation using vadere. Furthermore, topological analyses can be performed with Topologic and eventually additional simulations like firedynamics with FDS. A special focus will be put on graph-based analysis of geometric units, as this has proven to be a promising topological analysis option and allows several different graph machine learning methods as well as data storage in multidimensional graph datasets. Each of the different approaches also requires knowledge from related fields such as physics and chemistry, which must be acquired for successful evaluation and execution of the simulation.

After the completion of the simulation and analysis stage, the individual data with their evaluation results should be combined in an optimal way and thus complement the data set with labels. This requires an understanding of data set manipulation as well as a general understanding of data structure.

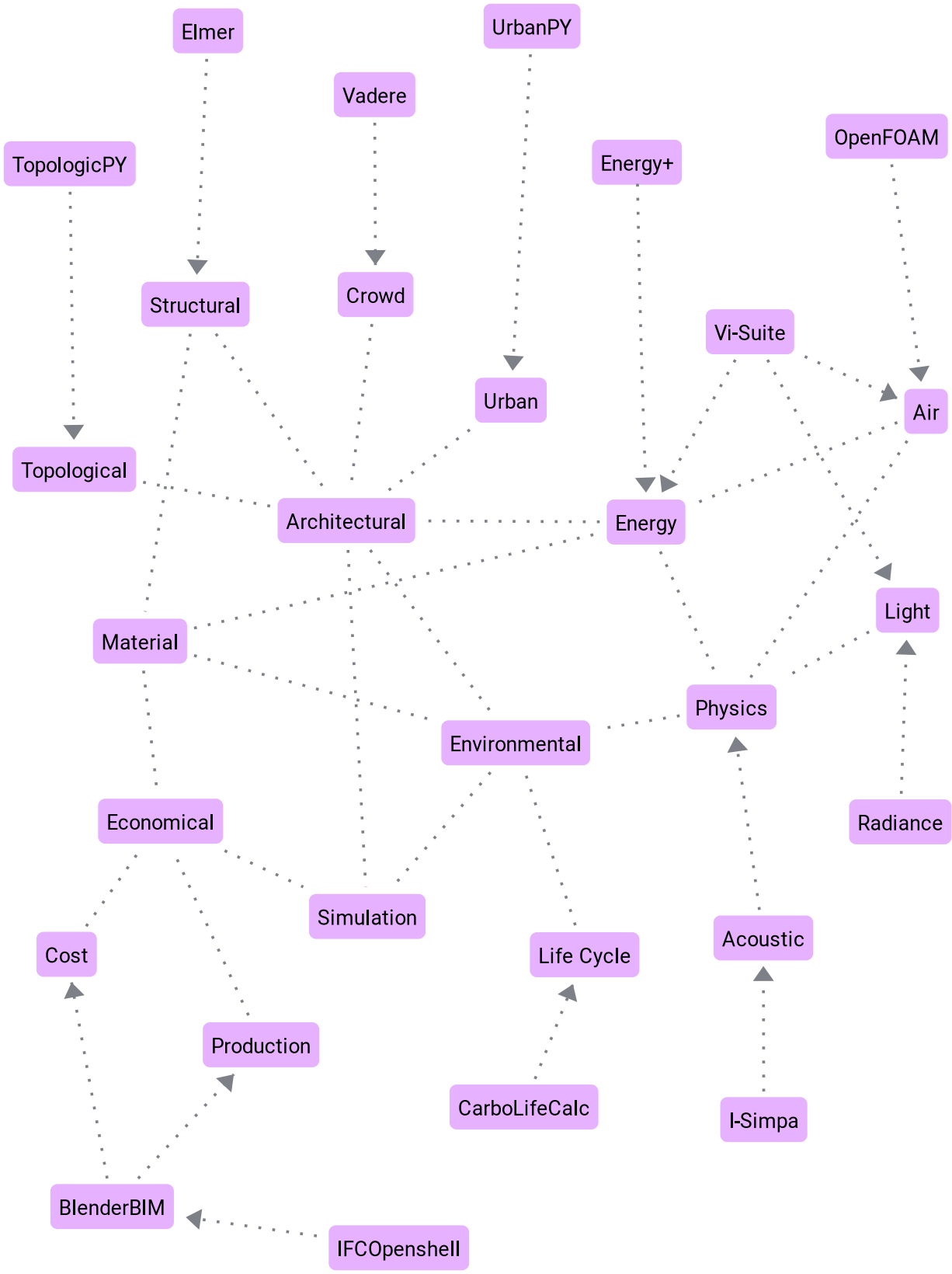


Figure 40: Simulation Libraries

ENERGY PERFORMANCE: 0.8
DAYLIGHT FACTOR: 0.6
LAYOUT RATING: 0.3
THERMAL COMFORT: 0.6
LIGHTNING COMFORT: 0.4
ACOUSTIC COMFORT: 0.9

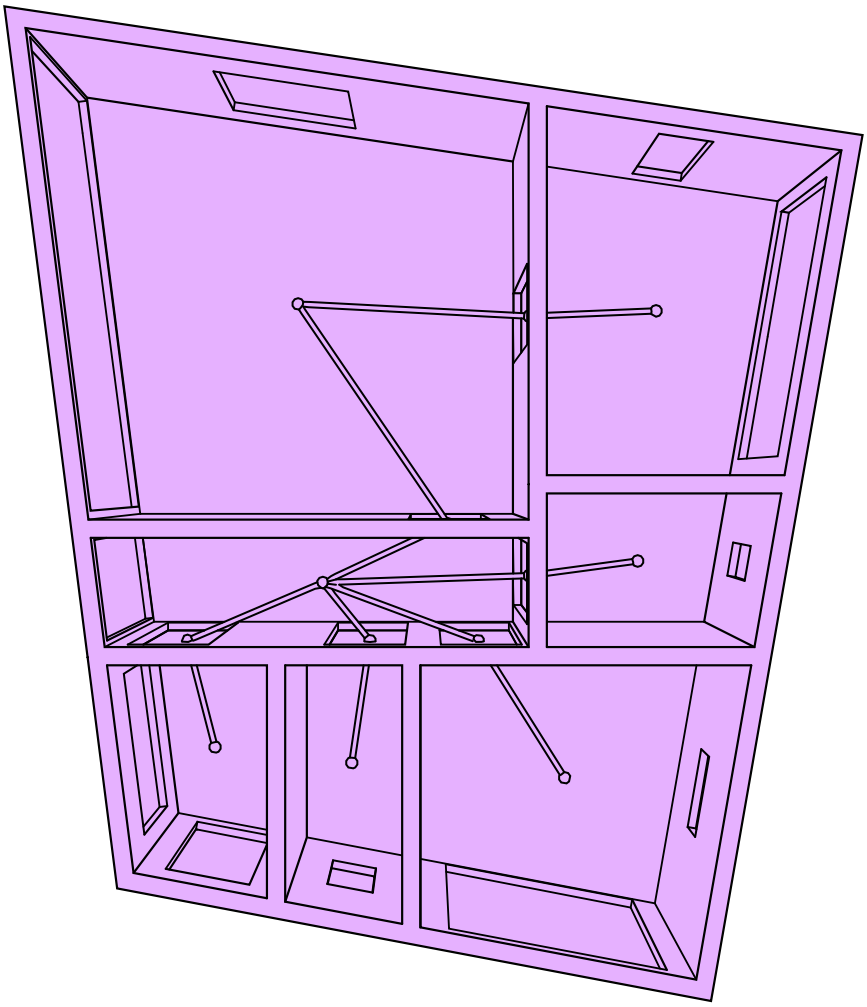
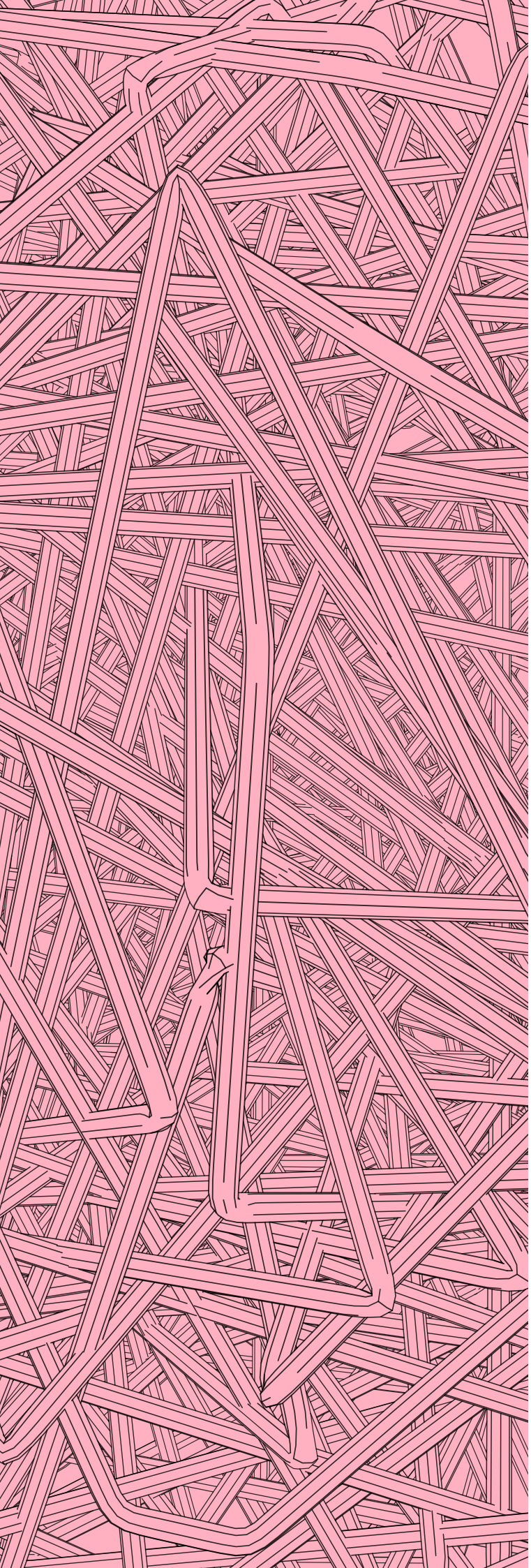


Figure 41: Expected Result

In theory, each of the individual apartment geometries should be evaluated using a variety of simulation methods and provide an indication of its performance in the respective areas. Thus, geometric data is given meaning and can be used in the learning phase as training data for the machine learning and training. In the most favorable case, this is represented by a factor ranging from zero to one, which provides information about the subject matter under investigation and the performance quotient achieved.

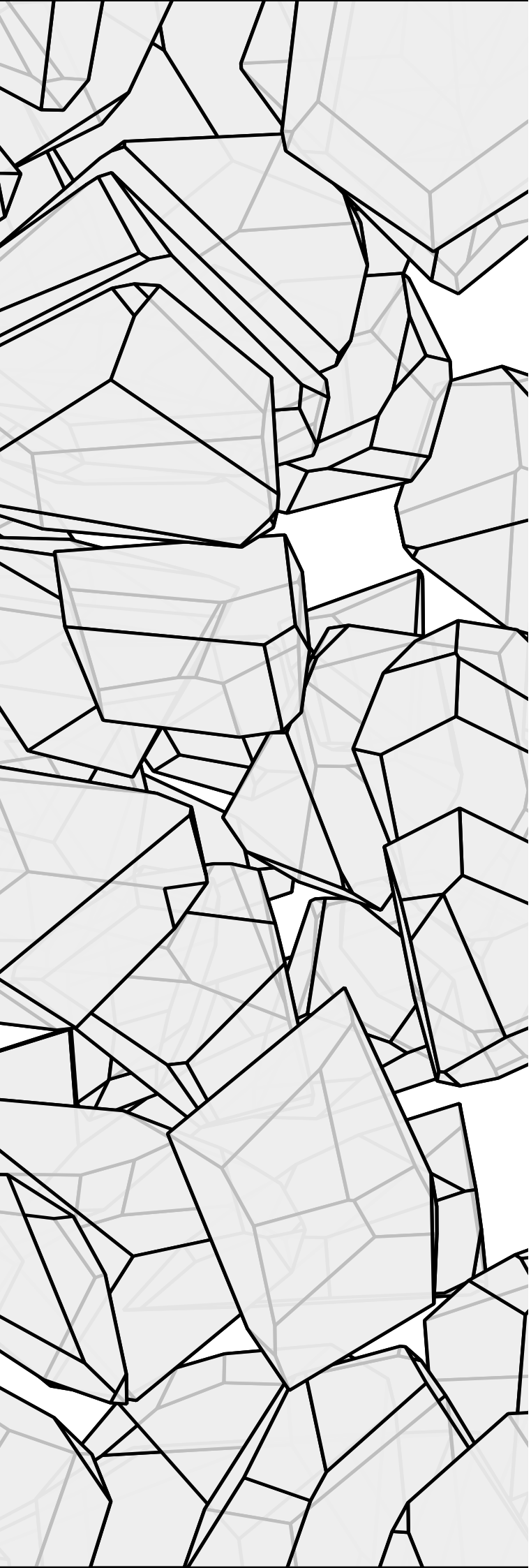


Learning

After the data set has been supplemented with the corresponding evaluation labels, it will be possible to analyze the relationship between the basic data and the achieved score using machine learning. Like the analysis step, the model training will not be part of this work but will be explored in detail as a separate topic in the following work. Nevertheless, the generation of the synthetic data set and its geometric data manipulation is the fundamental building block for a successful application of machine learning processes.

The exact methodology of the training stage cannot be defined at this stage, as the evaluation has not yet started and the training method and different ML approaches are highly dependent on the nature of the datasets. Basically, it is planned to experiment with a variety of different methods and approaches with diverse data to compare their performance, accuracy and results as well as potential applications.

This stage requires an extensive study of various computer science fundamentals to evaluate which method can lead to relevant results and in subsequent steps how the selected methods can be applied in a practical case. For this purpose a familiarization with file types like: CSV, GraphDB, Neo4j, SQL, JSON and DGCNN, data manipulation and visualization tools like Pandas, Numpy, matplotlib, pickle and mathutils, machine learning libraries like Tensorflow, pytorch and scikit-learn. An essential part of this stage will be the exchange with professionals from the computer science field and feedback in various communities, since a fundamental basic understanding must be learned to effectively and properly arrive at the desired end result, an optimization in the architectural design process through instant feedback on the quality of different characteristics of the object to be designed.



Conclusion

The goal of generating an architecturally sophisticated as well as diverse synthetic apartment dataset has been achieved and is clearly reflected in the visualization of the results. Furthermore, knowledge about the use of essential geometry processing programs as well as mathematical and topological python libraries was gained, which led to an optimization of the overall process through continuous evaluation of the generated results. An important requirement for the methodoligy of this work was to use only open-source information such as code and libraries or projects. This did not present any obstacles in the overall work, but in some cases even enabled a direct exchange with the respective development teams, whereby possible problems could be solved and suggestions for improvement of the used tools could be implemented. The essential steps of the simulation and the machine learning model training have not yet been started in this work, however, the essential foundations to start these steps without difficulties in the following work have been set.

As already described in the end of the data chapter, the final apartment floor plans show architectural plausibility as well as great variance with respect to important characteristics. Furthermore, an important requirement of the methodology was to reduce the time and computational demands by reducing the data to the most essential, which was achieved by using the topologic library and data storage in boundary representation format as well as JSON format for reference structure. Concerning the form generation process it is to be said that attention was paid to a collection as different as possible methods and approaches of importance. It is regrettable that in the end only the Voronoi and K-D Tree algorithms and their derivatives were used for the final space partitioning generation.

Discussion

It remains debatable whether the unusual forms of the individual apartment floor plans are evidence of architectural diversity or whether they are rather unconventional forms contrary to the western building tradition. In fact, some of the generated forms have spaces or facades that meet in non-orthogonal angles. In my opinion, this is welcome as long as these angles do not go beyond a certain extreme that would make the living space uninhabitable. Furthermore, the interior spaces created by the voronoi diagram subdivision are often pentagonal or even beyond. This is also considered an unusual design, but in my opinion it does not present any disadvantages in use as long as the polygonality does not result in excessively sharp angles. Some of the unbounded Voronoi floor plans show very irregular facade outlines which makes sense only in free and non-oriented project environments, this should be noted as information and distinguishing characteristic in the database in order to consider possible neighborhood influences in the energy simulation in the simulation step.
In some generated cases, the main circulation graph crosses small spaces that could essentially be used only as toilets, bathrooms or storage rooms, thus creating an architecturally unsound trajectory. This should be taken into account in the upcoming work within the filtering process and should be considered as an exclusion criterion for just such apartment layouts. In general, the geometric generation process should include a rough idea of the number of rooms and especially the use of rooms, such as the generation of commodities and sanitary units, which can be seen as essentially constant with insignificantly varying apartment sizes. This would also allow the use of adapted apertures such as a variation in the window position for the toilets or even the size of the windows in a possible storage room. Each of these changes seems to be feasible and unproblematic, but requires a rule-based intervention in the generation process that could induce traditional biases and thus jeopardize the variability of the dataset. Therefore, it is important to consider neutral information and examples when applying these rules.

Further Readings

Since this work is based to a large extent on the Python library topologic developed by Prof. dr. Wassim Jabi, which is currently evolving at an astonishing pace and acquiring new features on a daily basis, it is recommended to follow Jabi's publications and code repositories. Furthermore, the OpenSource architecture community community.osarch.com provided an essential platform for information exchange between like-minded people and hosts information of significant value.

Future Works

As already mentioned several times in the course of the research, this work is considered as a preliminary study for the following master thesis, which will deal with the following steps of the simulation and the learning process and finally with their function and application. In the following thesis the findings of this work will be revisited and possible improvements will be made in order to have an optimal data set as a starting condition and basis. Furthermore, we will deal with the copmuterscience related topics as well as with the ecology related simulations.

Used Software

Geometry

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SciPy (Version 1.8.0) [Computer Software]. (2001). Retrieved from https://scipy.org/

Sverchok (Version 1.1.0) [Computer Software]. (2012). Retrieved from https://github.com/nortikin/sverchok

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Simulation

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Tools

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