MACHINE LEARNING IN HOUSING DESIGN

EXPLORATION OF GENERATIVE ADVERSARIAL NETWORK IN SITE PLAN/FLOORPLAN GENERATION

By

Chaoyun Wu

Bachelor of Architecture
Tsinghua University, 2015

Submitted to the Department of Architecture in Partial Fulfillment of the Requirements for the Degree of

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"Technology is therefore no mere means. Technology is a way of revealing. If we give heed to this, then another whole realm for the essence of technology will open itself up to us. It is the realm of revealing, i.e., of truth."

--Martin Heidegger

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ABSTRACT

Technology has always been an important factor that shapes the way we think about Architecture. In recent years, Machine Learning technology has been gaining more and more attention. Different from traditional types of programming that rely on explicit instructions, Machine Learning allows computers to learn to execute certain tasks "by themselves". This new technology has revolutionized many industries and showed much potential. Examples like AlphaGo and OpenAI Five had shown Machine Learning's capability in solving complex problems.

The Architectural design industry is not an exception. Early-stage explorations of this technology are emerging and have shown potential in solving certain design problems. However, basic problems regarding the nature of Machine Learning and its role in Architecture design remain to be answered. What does Machine Learning mean to Architecture? What will be its role in Architectural design? Will it replace human architects? Will it merely be a design tool? Or is it relevant to Architecture at all?

To answer these questions, this thesis explored with a specific type of Machine Learning algorithm called Pix2Pix to investigate what can and cannot be learned by a computer through Machine Learning, and to evaluate what Machine Learning means for architects. It concluded that Machine Learning cannot be a creative design agent, but can be a powerful tool in solving conventional design problems. On this basis, this thesis proposed a prototype pipeline of integrating the technology into the design process, which is a combination of Generative Adversarial Network (Pix2Pix), Bayesian Network and Evolutionary Algorithm.

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MACHINE LEARNING	PIX2PIX	DATA
DESIGN AGENT	HOUSING DESIGN	PERSONAL PREFERENCE
BAYESIAN NETWORK	EVOLUTIONARY ALGORITHM	SYSTEM

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My friends and family: for your unconditional love and support. Nothing is possible without you.

CONTENTS

FRAMEWORK

BACKGROUND

Machine Learning is a high-profile technology of our time. It came into public attention through its application in the gaming industry.

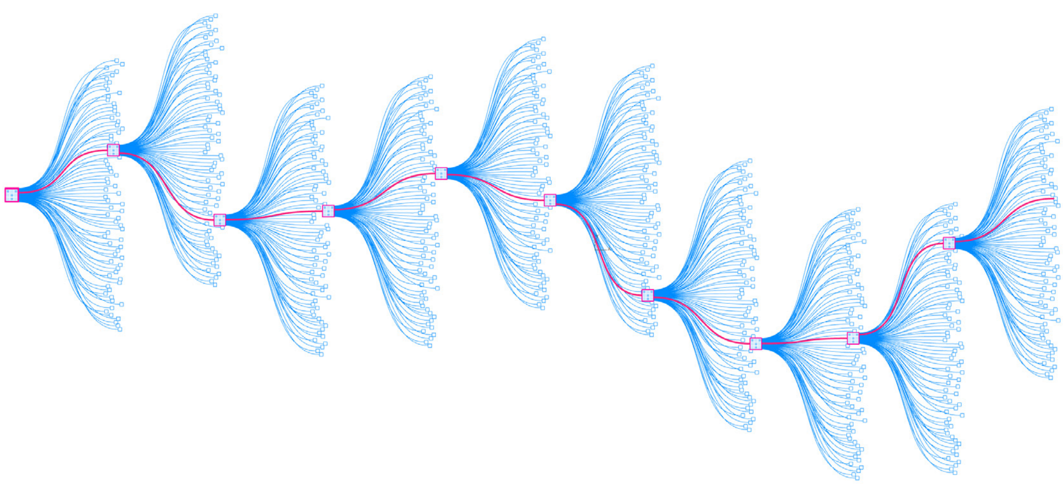
AlphaGo

In 2017, AlphaGo, a Machine Learning system developed by Google Deepmind, beat the best human player Ke Jie in the game Go. Go is a traditional chess game played in East Asia for thousands of years. It is a very complex game with 361 possibilities in the first move and 129599 in the second. It has been estimated that there are more possibilities (10^170 possible moves) in a game than the atoms in the observable universe[1]. The vast possibilities made it impossible for the computer to play the game using traditional programing: estimate every possibility and find the best move. The success of AlphaGo showed that Machine Learning technology can solve problems that are highly complex and intuitive.

OpenAI Five

OpenAI is developing a system called OpenAI Five that can play Dota 2, a multiplayer online battle game that requires a high level of collaboration, strategy, and improvising. The developing team observed that the system can formulate some strategies by itself to win the game. Although the system can only beat amateur teams with some restrictions to the rules, the goal of the system is to 'exceed human capabilities.' To achieve this goal, OpenAI Five plays an equivalent of 180 years of game daily[2] to train itself.

1: AlphaGo: The story so far. (n.d.). Retrieved August 12, 2019, from https://deepmind.com/research/case-studies/alphago-the-story-so-far#the_challenge.
2: Chan, B. (2019, December 6). OpenAI Five. Retrieved August 15, 2019, from https://openai.com/blog/openai-five/.



Above: Fig.1 Ke Jie playing against AlphaGo in 2016.
Below: Fig.2 Complexity of Go

Fig.3 OpenAI Five playing against a human team.

OpenAI Hide & Seek

Another game that OpenAI trained computers to play Hide and Seek, in which the game agents were divided into hiding and seeking teams. Through the learning process, the hiding team learned to use the walls and blocks to build a shelter to hide in. Soon after that, the seeking team learned to use ramps to climb up the walls and blocks to find the hiding team[3]. The strategies of both sides evolved throughout the learning.

However, the promise of Machine Learning is not just limited to gaming.

Medical

IBM is developing Watson Health that provides insights to health professionals based on data, analytics, and AI. Medical data was preprocessed to build the system which provides information about disease staging and financial cost[4]. At the same time, Google is developing Google Health, which diagnoses diseases based on Machine Learning technology[5].

Autonomous Driving

Autonomous driving is another application of Machine Learning that is under extensive tests and development. Automobile manufacturers like Tesla and BMW or car-sharing platforms like Uber or Didi or even search engines like Baidu are all investing heavily in this area. Autonomous driving would lead to changes in how we transport, reshaping the urban fabric as well as architectural typology such as parking lot.

3: Baker, B. (2019, October 29). Emergent Tool Use from Multi-Agent Interaction. Retrieved August 12, 2019, from https://openai.com/blog/emergent-tool-use/.
4: Watson Health: Get the facts: Solving Health Challenges thru AI. (n.d.). Retrieved August 12, 2019, from https://www.ibm.com/watson-health/about/get-the-facts.
5: Live yourhealthiest life. (n.d.). Retrieved August 12, 2019, from https://health.google/.

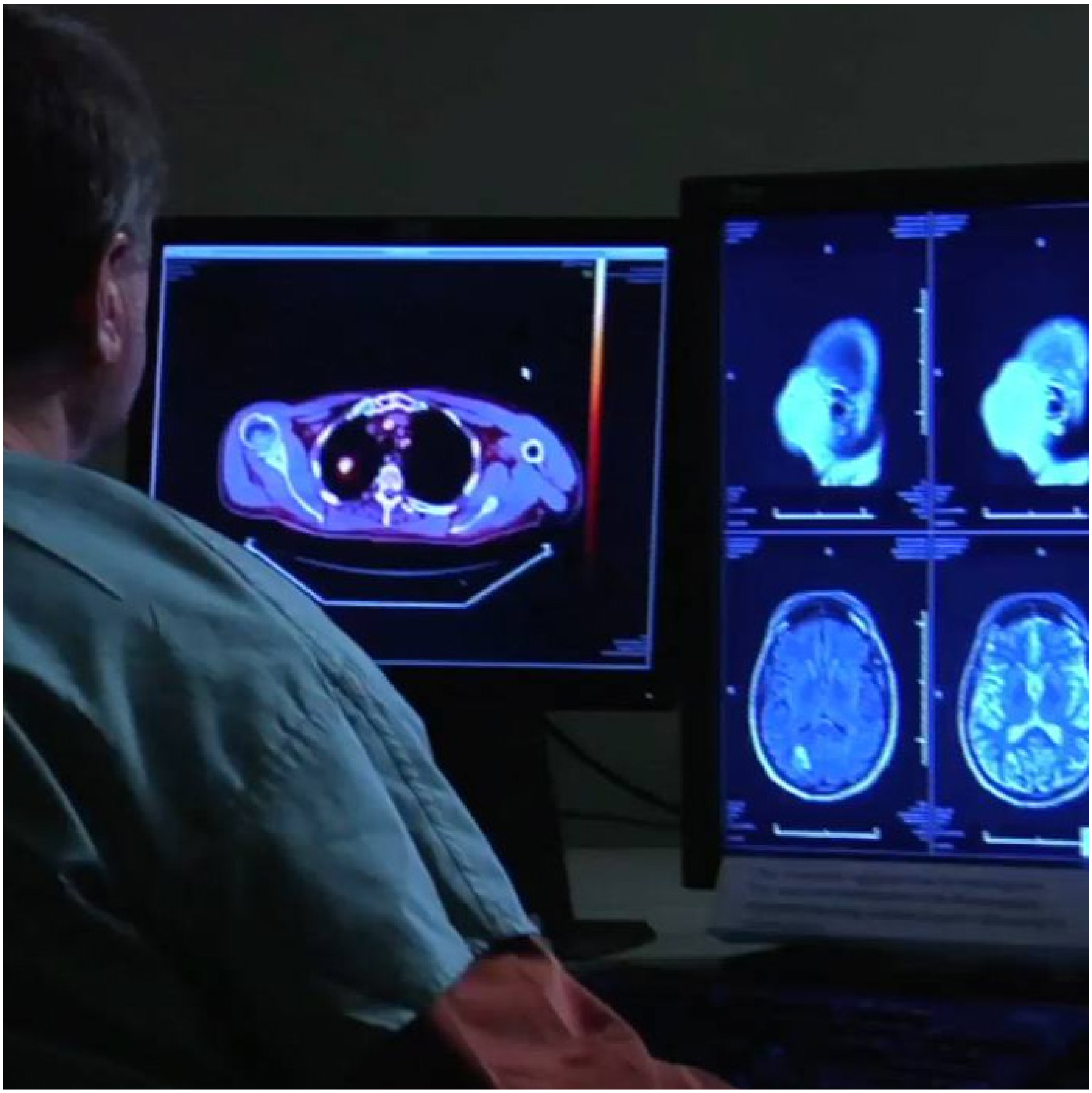


Fig.4 IBM Watson Health in application.

Fig.5 Autonomous Driving.

Product Recommendation

Over the past few years, online stores have accumulated a large amount of data about user preferences. Combined with Machine Learning technology, the data is used to make recommendations about products that users may like. This system works in real-time and helped online store sell more products.

Facial Recognition

More and more, facial recognition has become a standard function in electronic devices such as smartphones or laptops. It responds instantly and barely makes mistakes. Alibaba's payment company Alipay has applied the technology in online payment, allowing the user to make payment by a quick face scan[6]. Another company, Hikvision, although controversial, focused on applying this technology in video surveillance and security, grew into a unicorn company in just a few years.

6: France-Presse, A. (2019, September 4). Smile-to-pay: Chinese shoppers turn to facial payment technology. Retrieved August 15, 2019, from https://www.theguardian.com/world/2019/sep/04/smile-to-pay-chinese-shoppers-turn-to-facial-payment-technology.

Fig.6 Facial Recognition.

Fig.7 Alipay pacial recognition payment

DISCIPLINE EXPLORATIONS

The application of Machine Learning in design is still in its early explorations.

Gensler

Gensler used Natural Language Processing to analyze the feedback about buildings from surveys. The feedback was categorized into defined themes and visually clustered based on the commonalities. With the new tools of Machine Learning, the company can analyze thousands of pieces of feedback in a few seconds. According to the company, this helps to deepen the understanding of how users interact with buildings[7].

Autodesk

For form-finding, Autodesk has conducted a series of projects that optimizes the form of an object. The optimization utilized Generative Design algorithms and was based on structural and other design criteria. The method was utilized in many different kinds of projects, from the design of drones to lightweight components in automobiles, to bicycles, and industrial machinery. Autodesk even automated the design of its own Toronto Office using the Generative Design Method. Their algorithm considers design constraints such as windows, stairs and other elements that cannot be changed, as well as the personal preference of every individual that works in the space[8].

Spacemaker.ai

Spacemaker.ai is a startup that aims at using Artificial Intelligence to help designers "maximize the potential of the building site." The company has developed a system that generates building massing models that satis-

7: The Value Opportunities of Machine Learning Design Strategies: Gensler Research Institute: Research & Insight. (2019, April 1). Retrieved August 24, 2019, from https://www.gensler.com/research-insight/gensler-research-institute/the-value-opportunities-of-machine-learning-design.
8: Autodesk's New Toronto Office Displays Algorithm-Driven Generative Design. (2017, October 4). Retrieved August 23, 2019, from https://www.borndigital.com/2017/10/04/autodesks-new-toronto-office-displays-algorithm-driven-generative-design.

Fig.8 Gensler analyzed and clustered survey comments using Machine Learning.

Fig.9 A drone designed by Autodesk using Generative Design methods.

Fig.10 Design of Autodesk Toronto Office using Generative Design methods.

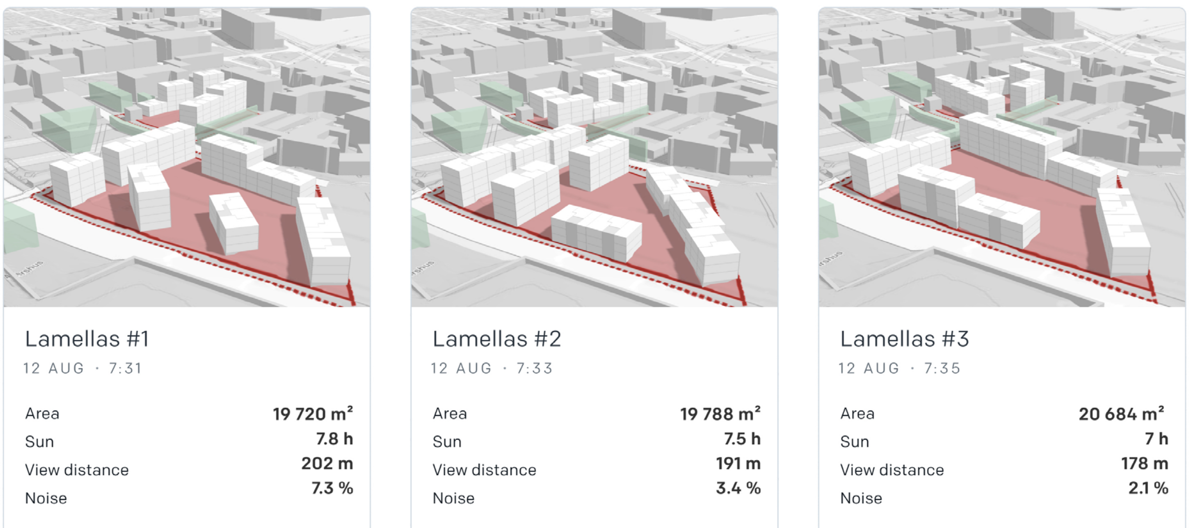


Fig.11 Building massing models generated by Spacemaker.ai.

Fig.12 Modernism-looking building image generated by XKool.

fy certain criteria using Machine Learning algorithms. The massing models were generated as well as detailed statistics and analysis. The system is designed to help designers with early-stage design explorations[9].

XKool

Xkool is a Chinese startup company similar to Spacemaker.ai. It provides a friendly user interface that allows users to edit the building massing models that the system generated[10]. Besides, it has also developed a tiny mobile app that can generate images of a Modernism style building within a second, proving that Machine Learning algorithms can be applied in styles and aesthetics of Architecture design.

9: Spacemaker. (n.d.). Retrieved September 4, 2019, from https://spacemaker.ai/.
10: 小库XKool-智能设计云平台. (n.d.). Retrieved August 25, 2019, from https://www.xkool.ai/?locale=en.

RESEARCH PURPOSE

Machine Learning technology is slowly changing the way we think about and operate Architecture design. However, since Machine Learning does not rely on explicit instructions, it is a little different from traditional types of programming tools. Machine Learning embodies independent capabilities to solve problems. Therefore, many questions remain to be answered: What does Machine Learning mean to Architecture? What kind of role will it play in Architecture? Will it change the way we practice architecture, just like Computer-Aided Design and Building Information Modelling? Will it be a tool that is only utilized by some designers? Will it replace human designers? Or at another extreme, will it affect Architecture at all?

This thesis seeks to explore with a specific type of Machine Learning algorithm called Pix2Pix, to investigate Machine Learning's strengths and weaknesses in solving design problems, and to evaluate what Machine Learning means for architects. On this basis, this thesis will propose a potential pipeline of integrating the technology into the design process, which is a combination of Generative Adversarial Network (Pix2Pix), Bayesian Network and Evolutionary Algorithm.

LIMITATIONS

Several conditions formulate the limitations of this research.

Data

It has been well accepted that a machine learning algorithm is only as good as its dataset. As much as the work of top designers was desired as the training dataset, the quantity of this type of data is not enough for a Machine Learning model training. Instead, this thesis uses commercial residential drawings[11] to train the Machine Learning models, which may not be as high quality as the work of top designers.

Therefore, this thesis is more about investigating Machine Learning's strengths and weaknesses in solving Architecture problems, rather than developing a system that generates high-quality design that is comparable to the work of design professionals.

Randomness

Although a programmer can control the training process of Machine Learning by adjusting key parameters, the training process is still a random one. For the same task, models may perform differently due to slight differences in the training dataset. Also, models trained at different times may perform differently. Sometimes a model that can generate reasonable results can be obtained with just a few thousands of epochs, but on other occasions, epochs needed to train a model that performs at the same level may vary.

Therefore, the experiments that were conducted in this study is more about a qualitative understanding of the

11: Drawings Retrieved from: https://www.floorplans.com/.

nature of Machine Learning in solving design problems. Although some quantitative metrics were utilized in the analysis of the outputs of Machine Learning algorithm, they are considered as ways of describing the analysis result. These metrics may not be a reference for other trainings in terms of quality.

Programming Skills

This study is also limited by the programming skills of the author, who comes from a design background rather than a computation one. The complexity and performance of the algorithm is not the primary goal of this study. This study is about a designer's curiosity into the nature of Machine Learning and how that affects design.

TECHNOLOGY

PIX2PIX

Pix2Pix is the Machine Learning algorithm that was used to conduct the experiments in this study. It belongs to a class of algorithms called Generative Adversarial Network (GAN), in which two Neural Networks compete with each other to generate a result that is similar to the training data. Pix2Pix was developed by a research team at the University of California, Berkeley. This algorithm is used to translate one image to another, without altering some basic features[12].

One example is shown in Fig. 13, Pix2Pix algorithm was used to turn colored rectangular shapes that represent different elements on a façade into a more detailed and photorealistic one[13].

Another example is a thesis project at Havard Graduate School of Design (Fig.14), the technology was used to generate apartment floorplans based on the footprint that was given[14].

12: Isola, P., Zhu, J.-Y., Zhou, T., & Efros, A. A. (2017). Image-to-image translation with conditional adversarial networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1125–1134.
13: Retrieved August 19, 2019, from https://affinelayer.com/pixsrv/.
14: Chaillou, S. (2019, July 9). AI & Architecture. Retrieved August 12, 2019, from https://towardsdatascience.com/ai-architecture-f9d78c6958e0.

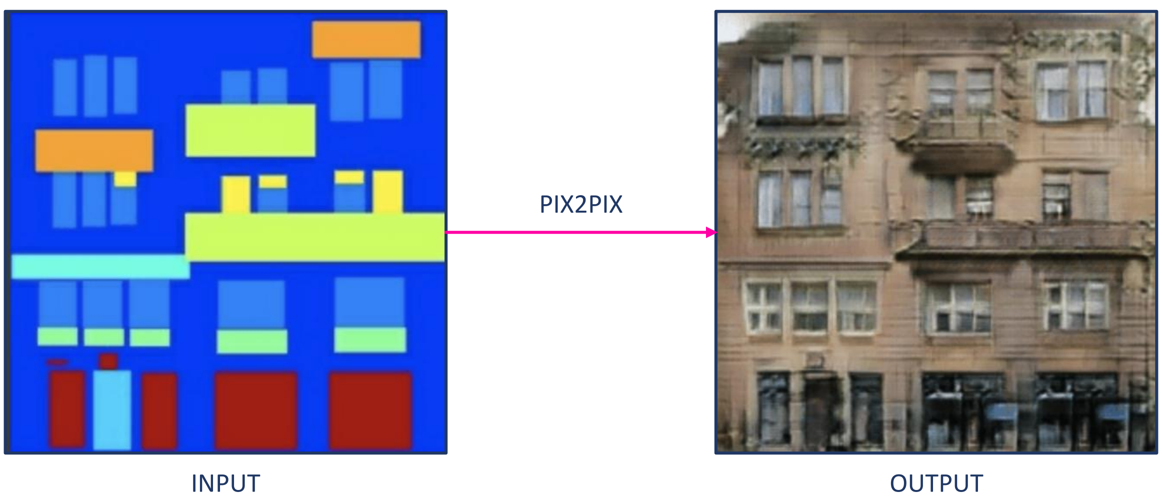


Fig.13 Building facade generated using Pix2Pix algorithm.

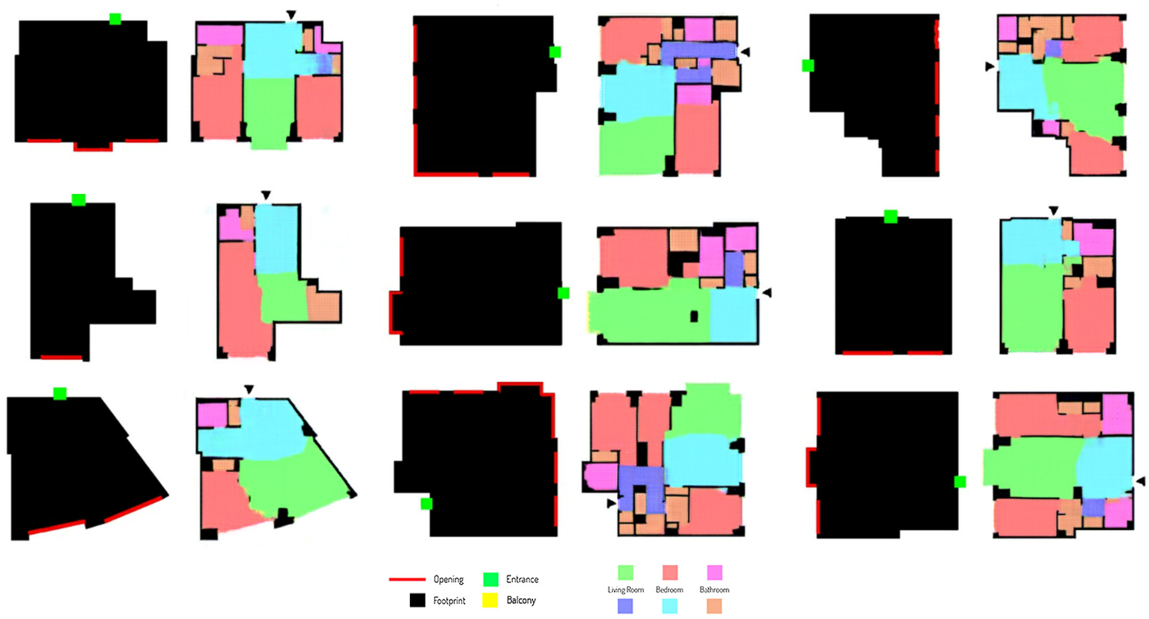


Fig.14 Floorplans generated based on apartment footprint in Stanislas Chaillou's thesis project.

BAYESIAN NETWORK

Bayesian Network is an algorithm that is used to find correlations between variables, and make predictions of unknown variables based on observed ones.

In this thesis, it was used to build relationship between user preference and architecture program. An earlier study from Stanford generated program requirements (which include room adjacency, room areas, and room proportions) using this method and turn the requirements into floorplans of houses with Evolutionary Algorithms[15].

15: Adão, T., Magalhães, L., & Peres, E. (2016). Ontology-based procedural modelling of traversable buildings composed by arbitrary shapes. Springer.

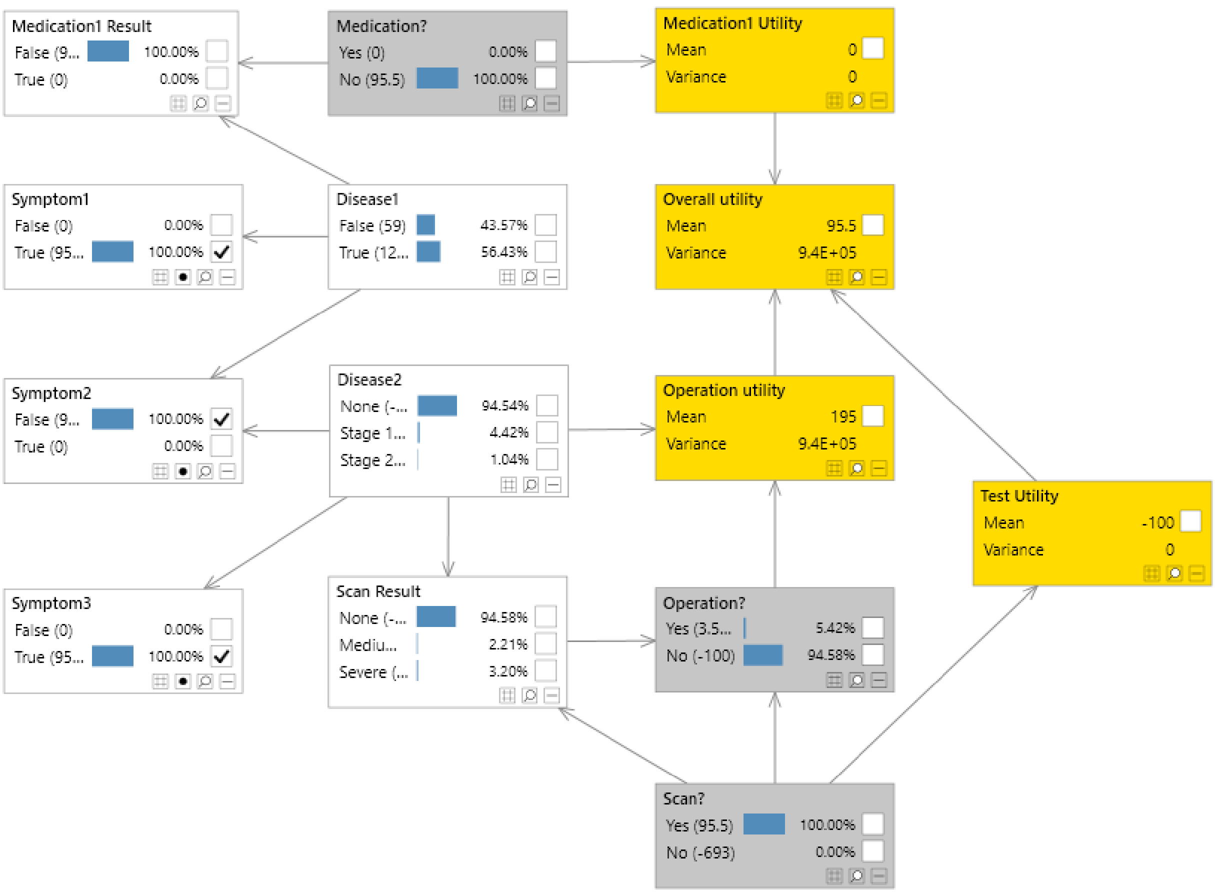


Fig.15 An example of Bayesian Network in finding correlations in medical data.

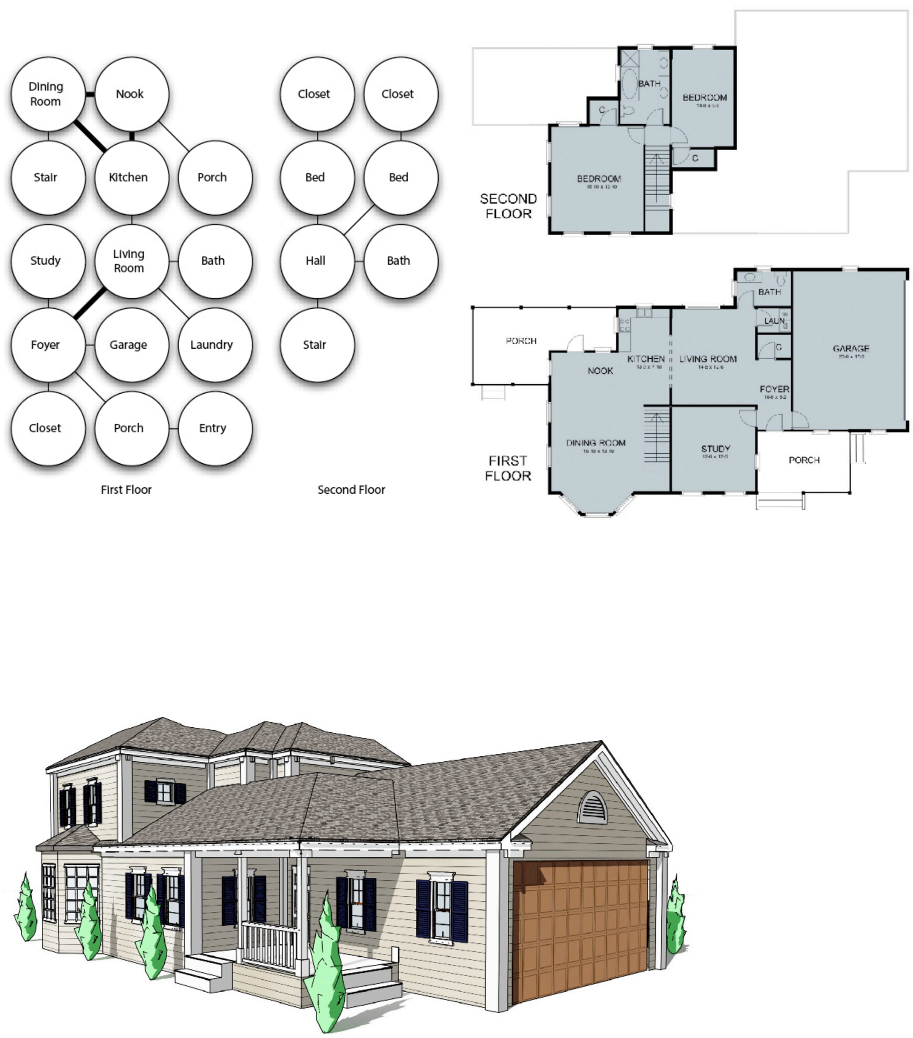


Fig.16 Floorplans generated using Bayesian Network and Evolutionary Algorithm.

EVOLUTIONARY ALGORITHM

Evolutionary Algorithm is inspired by biological evolution. In general, the algorithm makes mutations to a solution. If the mutation improves the solution against the evaluation criteria, it will be accepted; otherwise, it will be discarded. This process repeats over and over until an optimal solution is found.

Many researches have been done based on this method. One example was conducted by Caitlin Mueller and John Ochsendorf, optimizing the structural form in an interactive way[16].

16: Mueller, C., & Ochsendorf, J. (2013). An integrated computational approach for creative conceptual structural design. Proceedings of IASS Annual Symposia, 2013, 1-6. International Association for Shell and Spatial Structures (IASS).

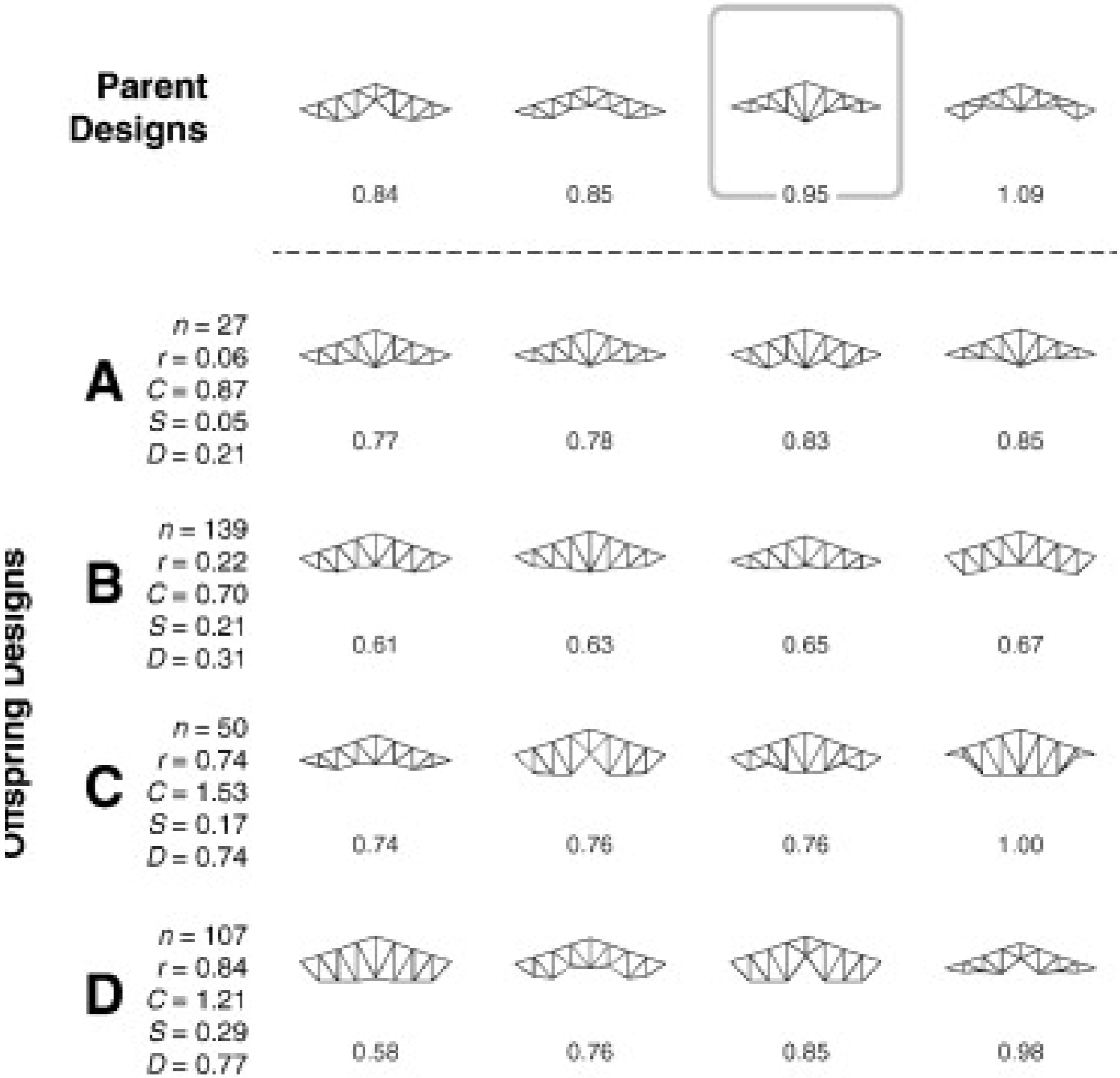


Fig.17 Struture form optimization using Evolutionary Algorithm.

EXPERIMENTS

EXPERIMENTS WITH PIX2PIX

To understand Machine Learning's strengths and weaknesses in solving design problems, the computer was trained to implement different design tasks using the Pix2Pix algorithm. The experiments were conducted in a sequence of an increasing complexity of the tasks, which include: 1) generating building footprint in an empty lot in Boston; 2) generating building footprint in cities with different urban fabrics, including Madrid, Melbourne, and New Delhi; 3) generating fully labeled 1st floorplan of a house in an empty lot in Boston and 4) generating partly labeled 1st floorplan in an empty lot in Boston. The machine learning model that was trained in the 3rd experiment did not produce satisfying results due to the complexity of the problem (this will be further analyzed later). Therefore, in the 4th experiment, only the rooms that were related to the site, such as living room and entrance were labeled to simplify the problem. The following of this paper will focus on the 4th experiment. The result of other experiments will be shown in the appendix.

MODEL TRAINING

Data Preparation

To train a Pix2Pix network, a pair of images should be provided as training data. On the left in Fig. 18 is an anticipated input, an image that describes the problem constraints. For example the location and the orientation of the lot, surrounding buildings and road. On the right is an anticipated output. In this case, it is partly labeled 1st floorplan of a house located in a lot.

In most trainings of this research, over 1,000 pairs of images like this were fed to the training process.

Training Epoch

Besides the quality of the data set, Training Epoch is another important factor that affects the result of the training. The larger the number of the epochs, the more reliable the output of the Machine Learning model becomes.

Dataset Volume

On the other hand, the volume of the dataset also affects the result. Larger data set will make it more difficult for the algorithm to train a model, taking more training epochs. However, models that were trained from a larger dataset apply to wider ranges of scenarios.

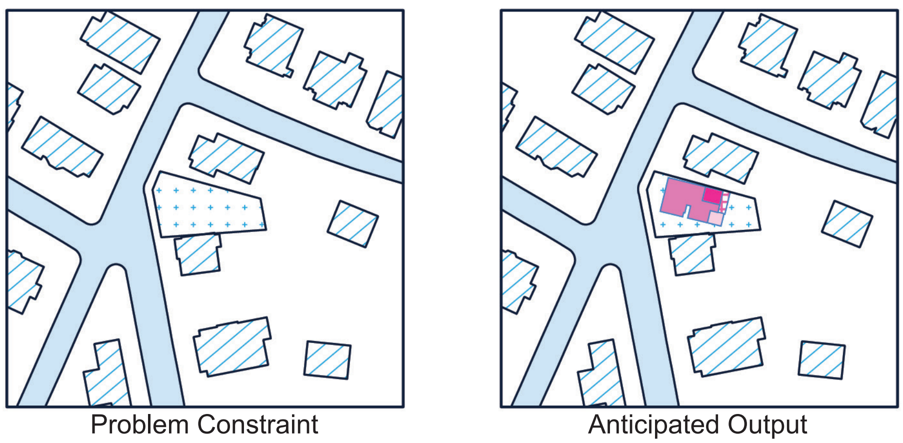
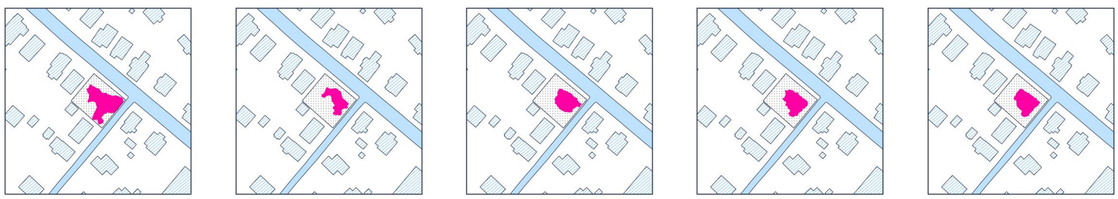


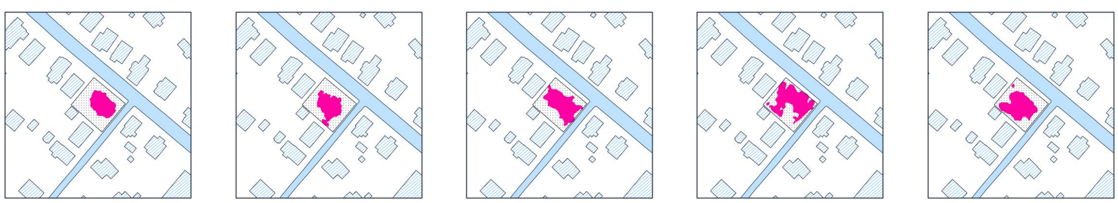
Fig.18 Some examples of training data.

Fig.19 Some examples of training data.

Fig.20 Some examples of training data.



7200 EPOCH | 28800 EPOCH | 43200 EPOCH | 50400 EPOCH | 72000 EPOCH



240 IMAGES 12000 EPOCH | 480 IMAGES 28800 EPOCH | 720 IMAGES 28800 EPOCH | 960 IMAGES 28800 EPOCH | 1200 IMAGES 28800 EPOCH

Above: Fig.21-1 Results generated by models trained with different training epochs.
Below: Fig.21-2 Results generated by models trained with different dataset volume.

OUTPUT

Once the training is completed, to generate an output, an input image is provided to the system, which is the image on the left in Fig. 22. The input image is exactly in the same format as the image that describes the problem constraints in the training dataset. It takes a matter of seconds for the system to generate an output based on the input image. An example of the output is shown on the right in Fig. 22. Although the floor plans generated in this experiment are in irregular forms, the following analysis will show that there are some architectural relationships/qualities that the Machine Learning learned in this process.

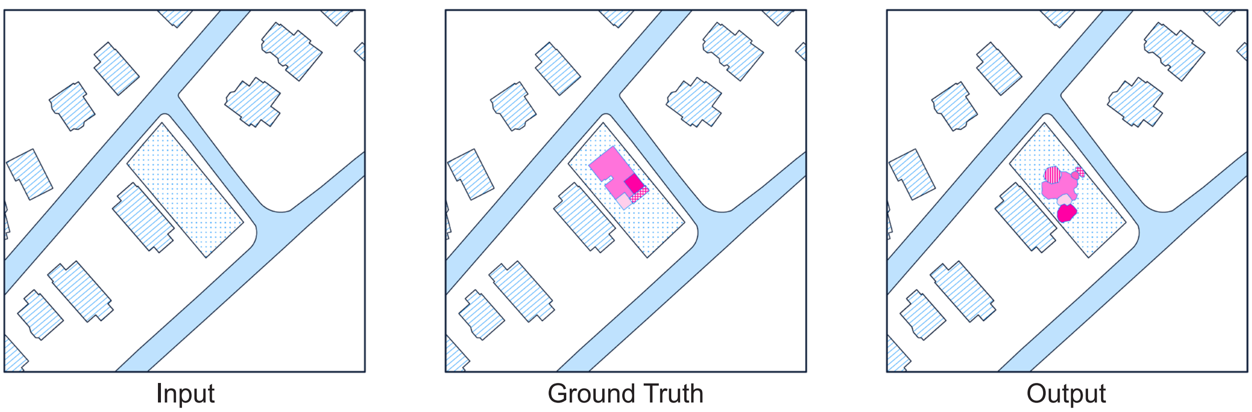


Fig.22 Some examples of Machine Learning output.

Fig.23 Some examples of Machine Learning output.

Fig.24 Some examples of Machine Learning output.

ASSESSMENT

The training output was further assessed to evaluate what had been learned by the computer. For different experiments, different criteria may apply. In the case of generating partly labeled 1st floorplan on an empty lot, 5 criteria were used to evaluate the outputs.

Relationship between the Result Floorplan and the Lot

The result floor plan was assessed to see if it is located within the land lot. Although it is a very simple problem for humans, it is still a basic architectural relationship that needs to be tested for computers, especially when no explicit instructions were involved.

The metric was defined as the ratio of the intersection area between the floor plan and the land lot, to the total area of the floor plan. The value is 1 when the floor plan fully locates within the site and is 0 when it is completely out of the site.

Room Areas

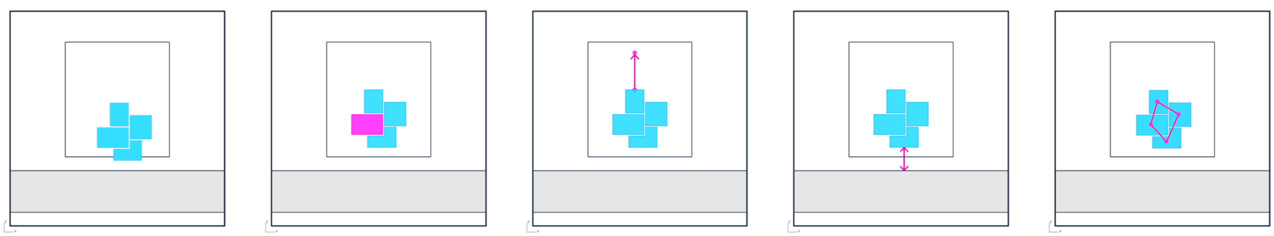
To determine if the areas of the rooms are within reasonable ranges, hundreds of commercial residential floor plans were analyzed to obtain the reasonable ranges of room areas. The result of this analysis is shown in the Appendix.

When the area of a given room locates within the range, it is rated as acceptable; otherwise, the further the area of a room is located from the area range, the less acceptable it becomes. The area of each room will be assessed in this way and the average evaluation value of all the rooms will be taken as the area score of the whole floor plan.

View
For most houses, a good view from some important rooms such as the living room or dining room is very important. Here, the view is rated as ‘good’ if some of these important rooms faced to a yard, which is a good spot to look at in most housing projects; ‘acceptable’ if they have an indirect view to the yard; and ‘bad’ if they face the walls of another building.

Accessibility
If the main entrance and the garage face to the road the result floor plan has good accessibility.

Room Adjacency
The adjacency relationship of each room is also evaluated. The output floorplans with more reasonable adjacency relationships are rated higher. For example, adjacency between a kitchen and a dining room will contribute to a higher evaluation, and adjacency between a dining room and a washroom will probably lead to a lower value.



Site Area View Accessibility Adjacency

Fig.25 Assessment criteria.

Fig.26 Some examples of output assessment.

Fig.27 Some examples of output assessment.

ANALYSIS

The outputs of the trained model are tested against these criteria to evaluate how well the Machine Learning algorithm learned about certain Architectural factors.

However, it is not enough to evaluate one outcome of the algorithm. By assessing over 100 results that were generated, it is shown that over 90% were correct in locating the building within the lot, 70% were correct about the areas of each room and their adjacency relationship, and over 50% were correct about the view and accessibility.

These results show that through the Machine Learning algorithm, the computer can learn about Architectural qualities/relationships such as areas and adjacency. Other experiments showed many more factors such as dimensions, orientation, alignment, and geometric features can be learned by computer through Machine Learning. It should also be pointed out that all these architectural qualities/relationships that can be learned are the ones shown in a format that can be processed by a computer, in this case, a drawing.

Machine Learning also makes mistakes, which shows its limitations. In most of the training images, a lot is a rectangular form. However, when an irregular lot is given to the algorithm to generate footprint, it may fail to generate anything (Fig. 29-1). Also, when the relationship between the road and the lot did not fit into the most common patterns, the system fails to generate a legitimate result (Fig. 29-2). Sometimes the building may exceed the land lot (Fig. 29-3). And sometimes

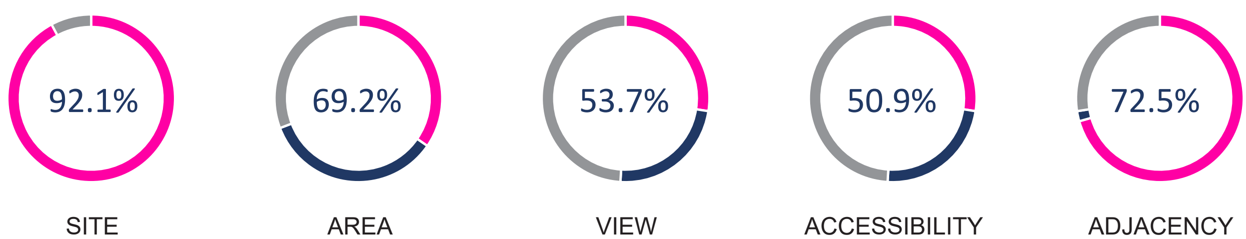


Fig.28 Assessment result.

when the problem is too complicated, the result becomes less reliable (Fig. 29-4).

These mistakes show that Machine Learning cannot apply what was learned to a new scenario that is a little different from the frequent patterns it learned. Therefore, Machine Learning can not be a creative tool. It is good at generating conventional solutions to conventional problems, but it may not be able to create new solutions by itself.

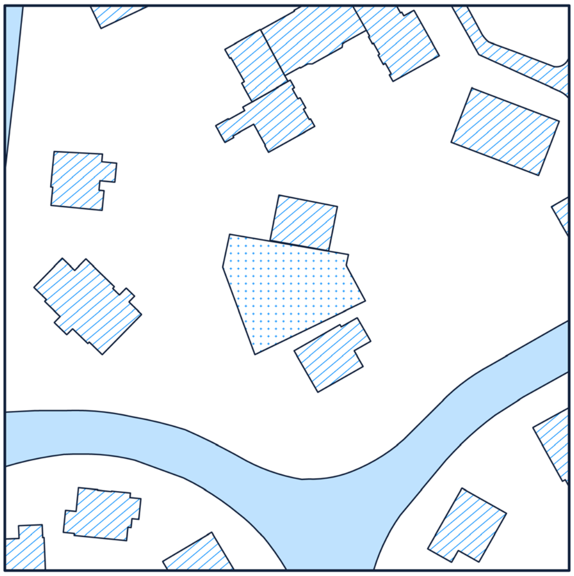


Fig.29-1

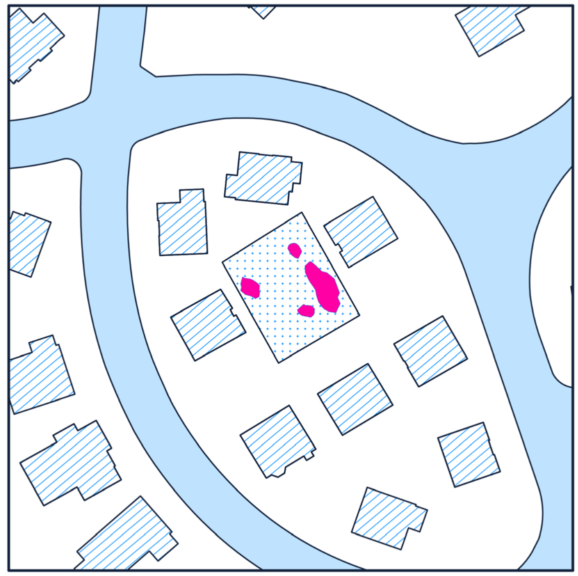


Fig.29-2

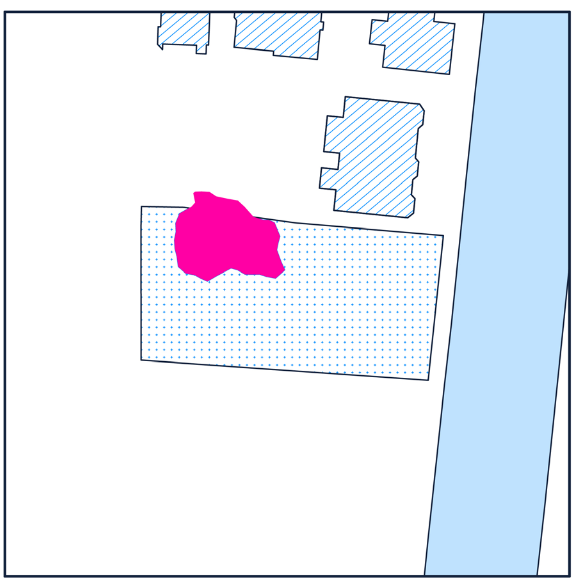


Fig.29-3

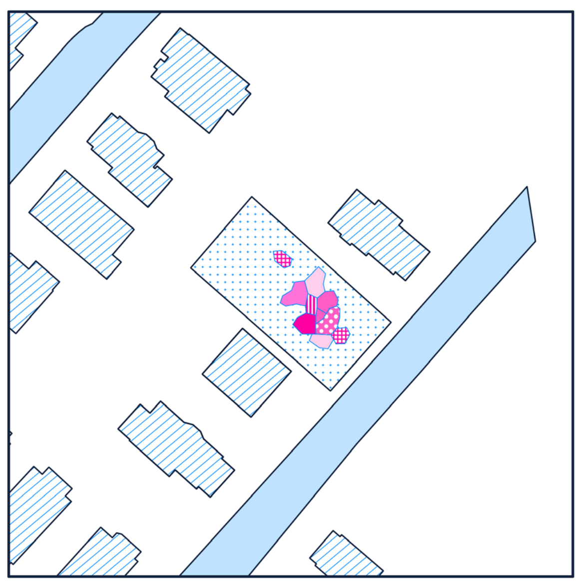


Fig.29-4

Fig.29 Typical mistakes in outputs.

SUMMARY

Machine Learning generates results based on the patterns that appear in a dataset. It cannot generate solutions outside the patterns it had seen. Therefore, it is not a creative tool. The solutions that are generated relies heavily on the training dataset. The dataset needs to be large enough, and fit into recognizable patterns for the computer to learn. This is another reason why top designers' work cannot be used for this study, since different designers may have different styles from each other.

However, based on the experiments, a Machine Learning system that can automatically solve basic design problems is possible. Machine Learning actually can learn about any patterns, no matter if it is about the physical relationship between architectural elements or conceptual ones, as long as the pattern can be represented in a way that the computer can process. Another strength of Machine Learning is that it can produce large quantities of outputs in a short amount of time.

APPLICATION

Based on previous analysis, Machine Learning technology can be engaged in the design process in many different ways. It can be a tool that helps designers to exploit possible solutions to a problem. It can also be a tool that processes a large number of tasks in a limited amount of time. Also, in cases when architects are not available or affordable, which is a very common scenario for low-income groups or in countries that have no culture of hiring architects for smaller personal projects, Machine Learning has a great role to play.

The second part of this thesis focuses on the third scenario, and propose a prototype pipeline that engages machine learning in the housing design process. It considers how to combine Machine Learning with other design factors that cannot be integrated into the training dataset of Machine Learning (for example personal preference) and propose a combination of various techniques to provide the final solution.

FRAMEWORK

In addition to the Machine Learning system that can process conventional architectural problems, personal preference is another important factor in housing design. Since personal preference cannot be shown in a site plan for our Pix2Pix algorithm. It will be combined with the output of Machine Learning through Evolutionary Algorithm to produce the final result. The evolutionary algorithm takes the user preference as evaluation criteria and optimizes the output produced by Machine Learning against these criteria. For this to work, personal preference needs to be translated into architectural criteria first, such as room adjacency, areas, proportions, etc.

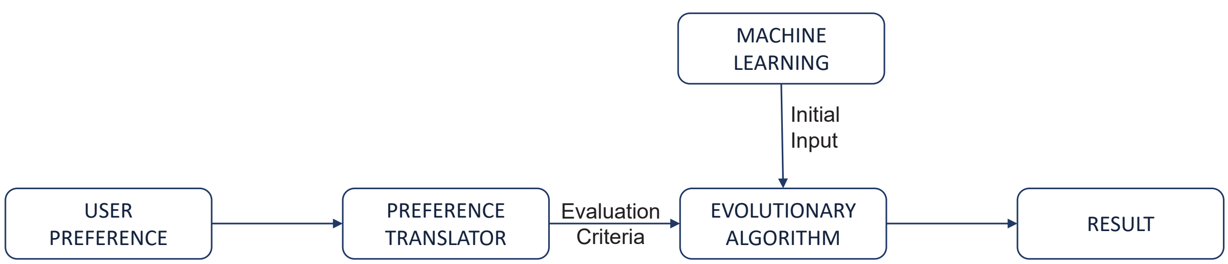


Fig.30 Framework of protype pipeline to engage Machine Learning in housing design.

PREFERENCE TRANSLATOR

To build the preference-to-program translator, a dataset of personal information and the preferred architectural scheme should be fed to the machine. The computer takes in this information and finds correlated factors using the Bayesian Network (Fig. 31). Fig. 32 shows all the information that is derived from the dataset described. This information accumulates as the system iterates over a dataset of user preferences, which results in a preference translator.

PRECEDENT RESIDENTIAL FLOORPLAN

GENDER	MALE	LOCATION	BEIJING
AGE	UNDER 35	EDUCATION	HIGH SCHOOL
INCOME	MIDDLE INCOME	MARITAL STATUS	SINGLE
BRIGHT/DARK	DARK	SPACIOUS/EFFICIENT	CLASSIC
CLASSIC/MODERN	CLASSIC		

Fig.31 Iteration over user information and preferred housing scheme.

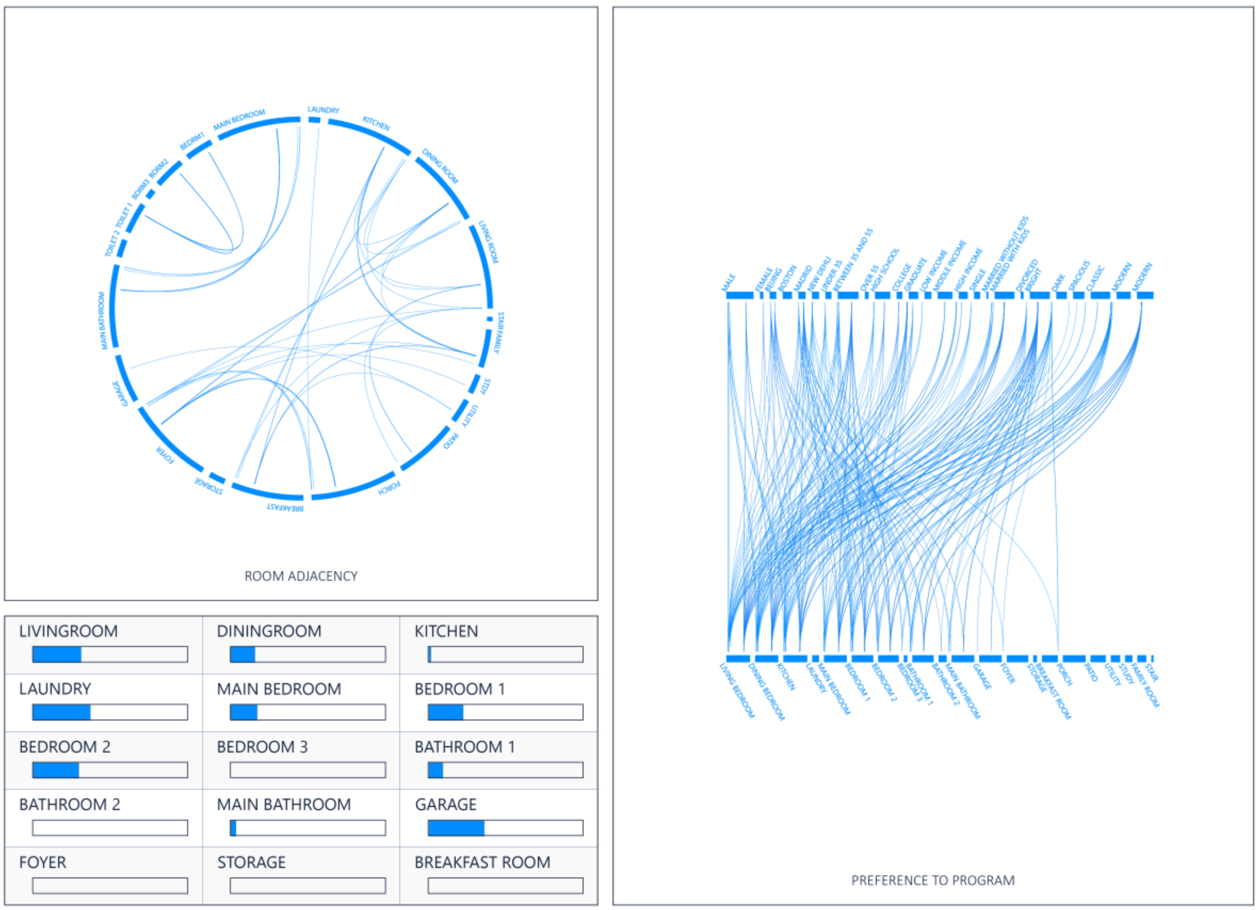


Fig. 31 Information derived from user information and preferred housing scheme.

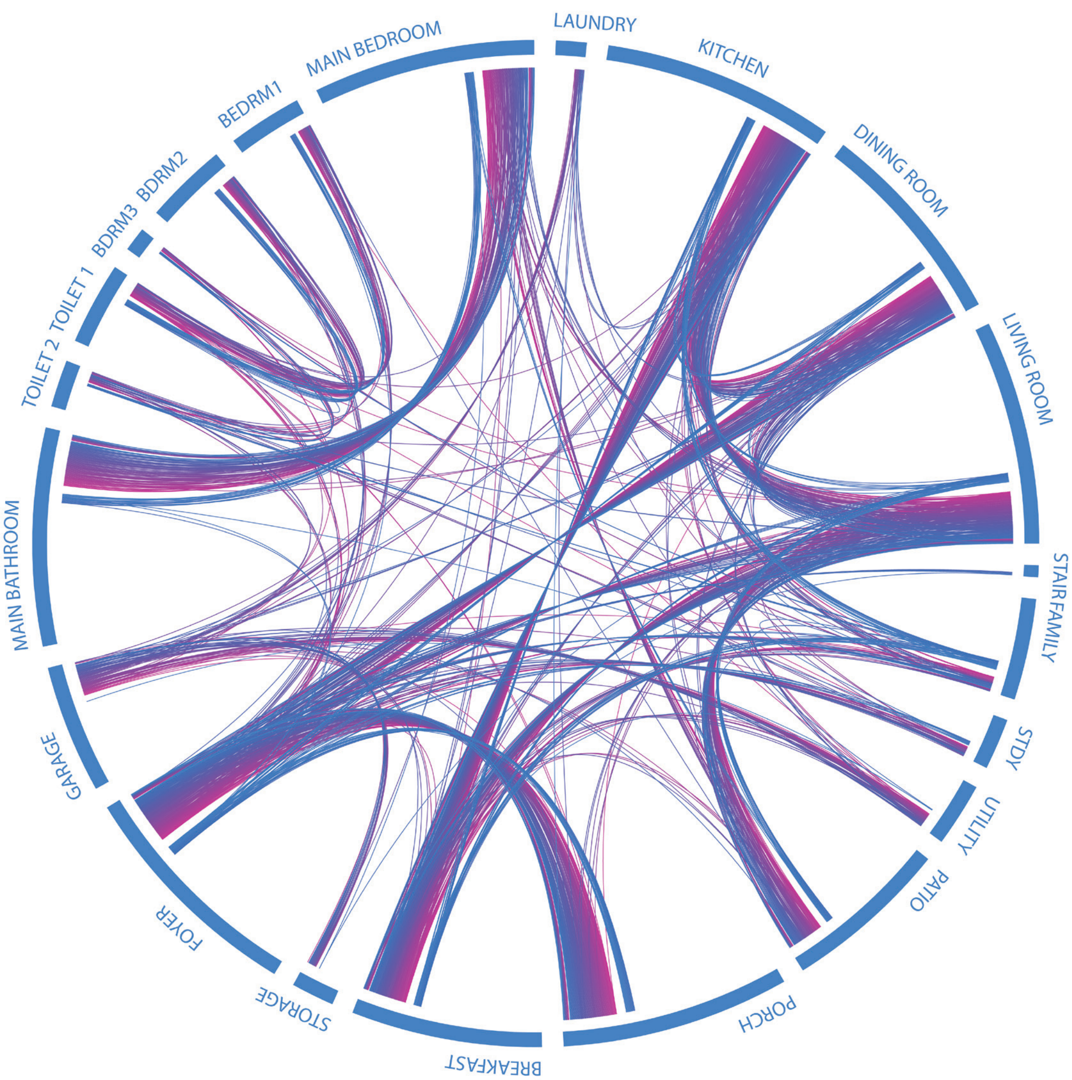


Fig.32 Room adjacency relationship derived from precedents.

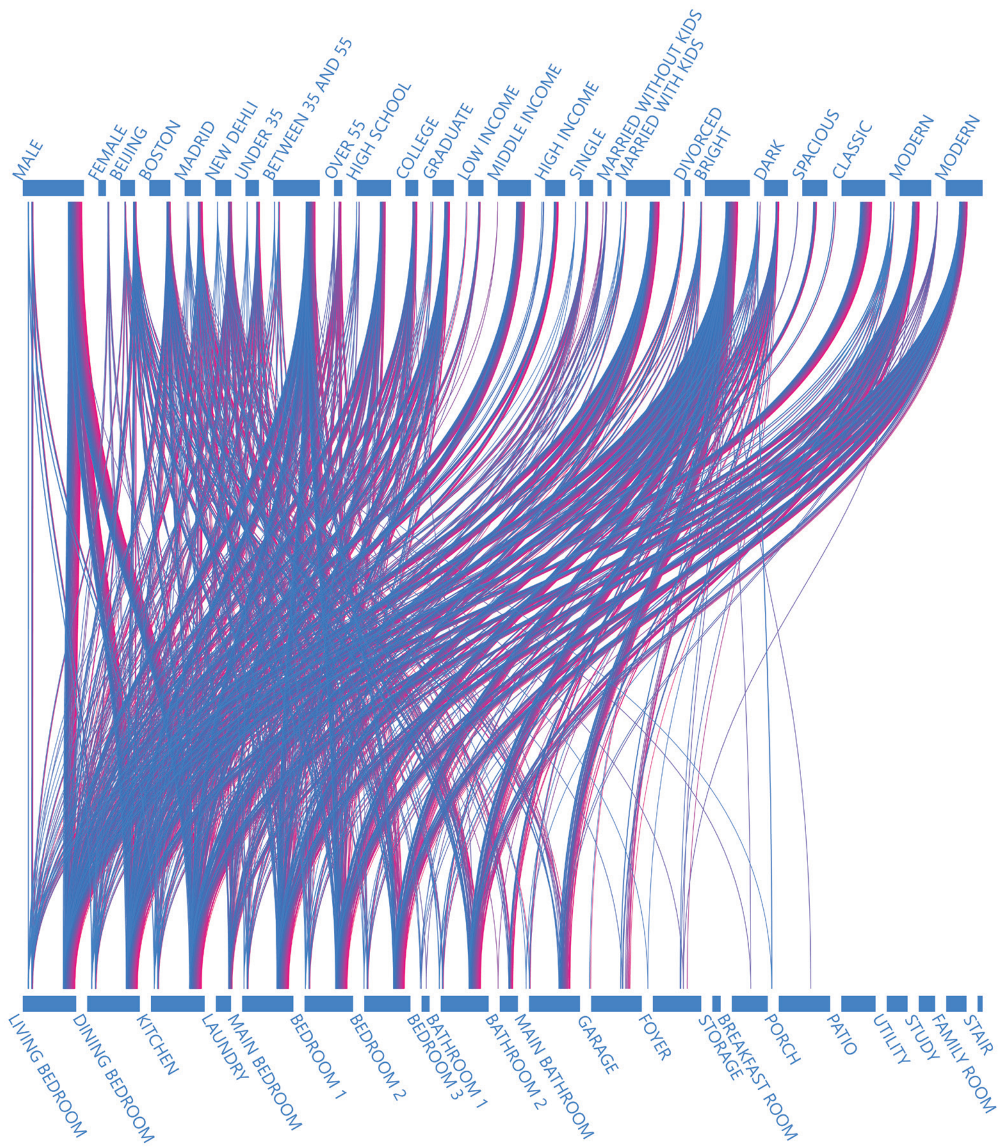


Fig.33 Bayesian Network to translate user information into architectural scheme.

PREDICTING PROGRAM

Once the preference translator is built, it can predict a preferred scheme when information about the user is provided. Fig. 34 shows an interface that collects information about the user. When more information is specified, the program criteria narrow down. Eventually, the program criteria with the greatest likelihood are taken as the evaluation criteria for the Evolutionary Algorithm.

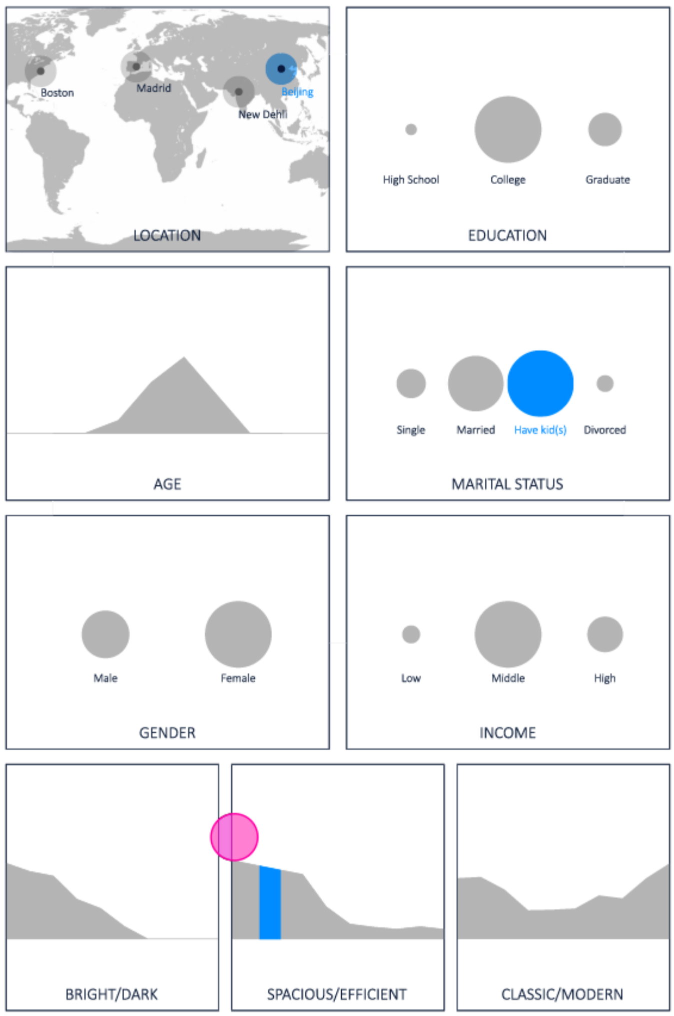


Fig.34 Interface to specify user information.

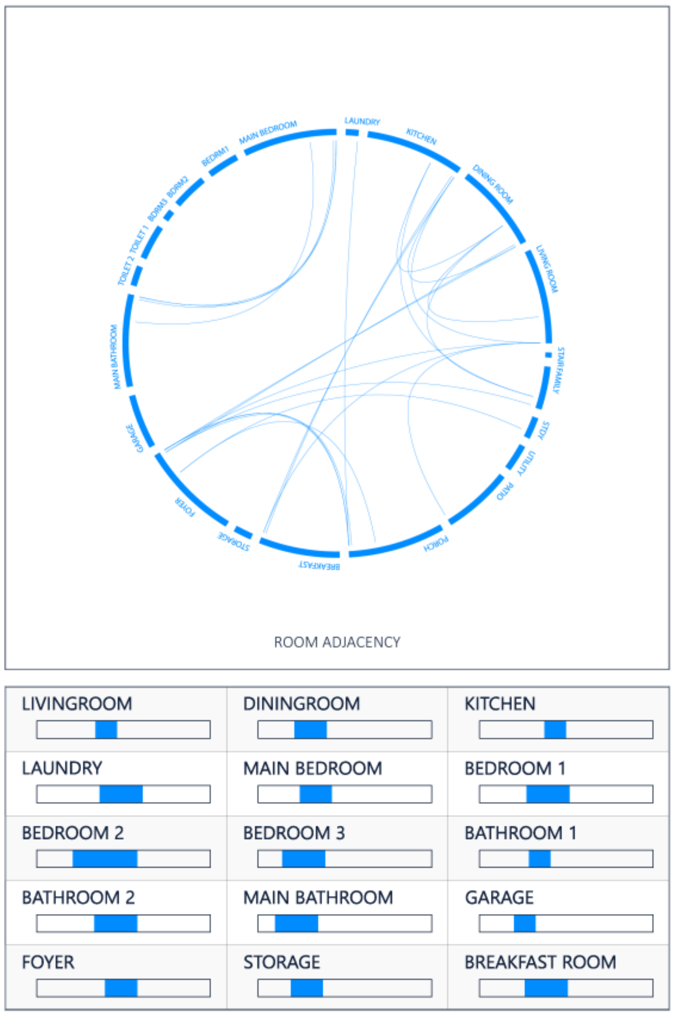


Fig. 35 Program requirement as more user information specified.

GENERATING BUILDINGS

The Evolutionary Algorithm takes the floorplan generated by Machine Learning as an initial input. The irregular form floorplan is approximated to a grid. Mutations like shifting the walls will be applied to the floorplan, and the ones that result in a higher evaluation score will be accepted. The optimization process can happen simultaneously in different floors and can be turned to 3-dimensional. This process repeats until an optimal result is reached.

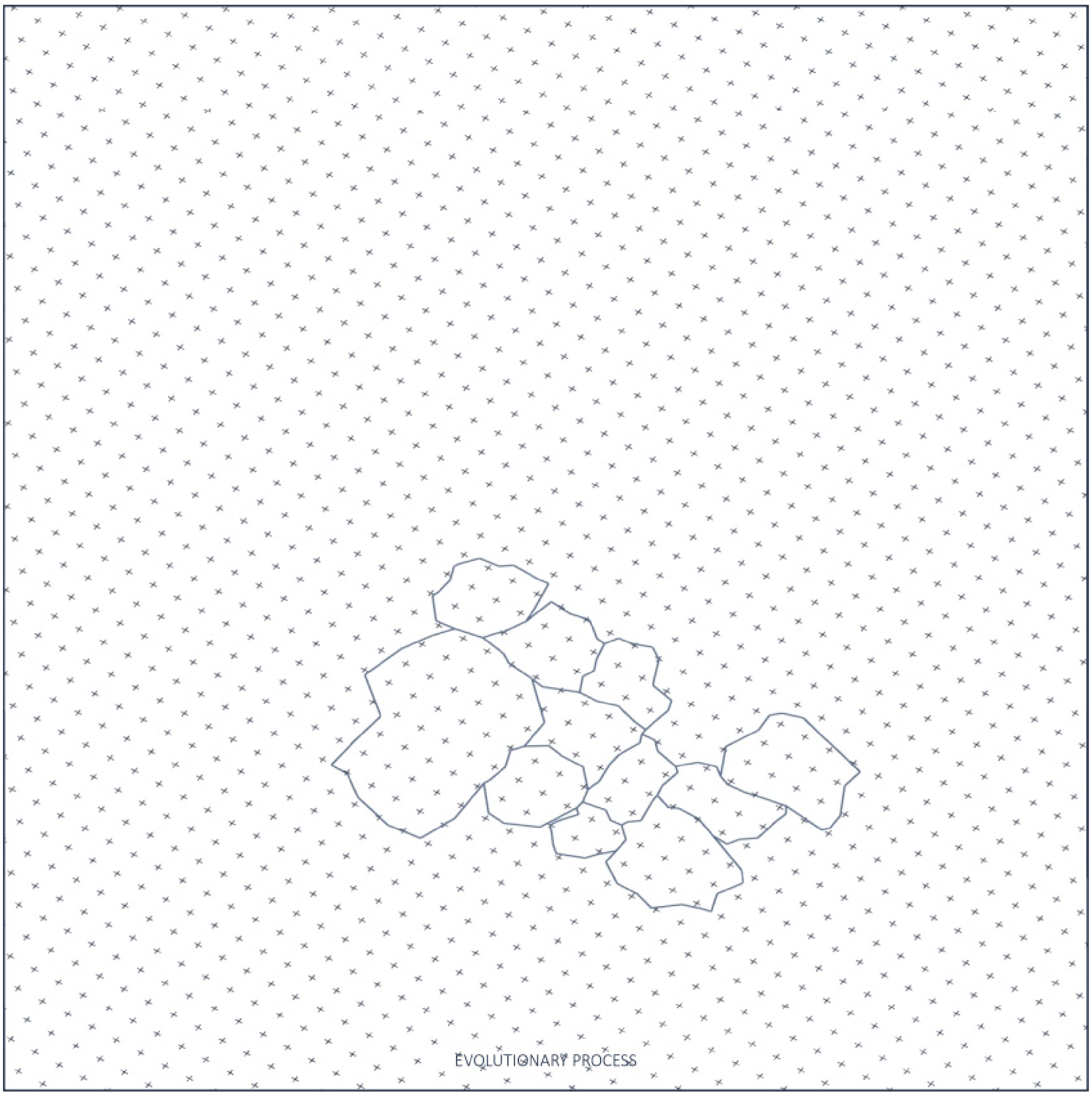


Fig.36 Evolutionary Algorithm taking output of Machine Learning as initial input.

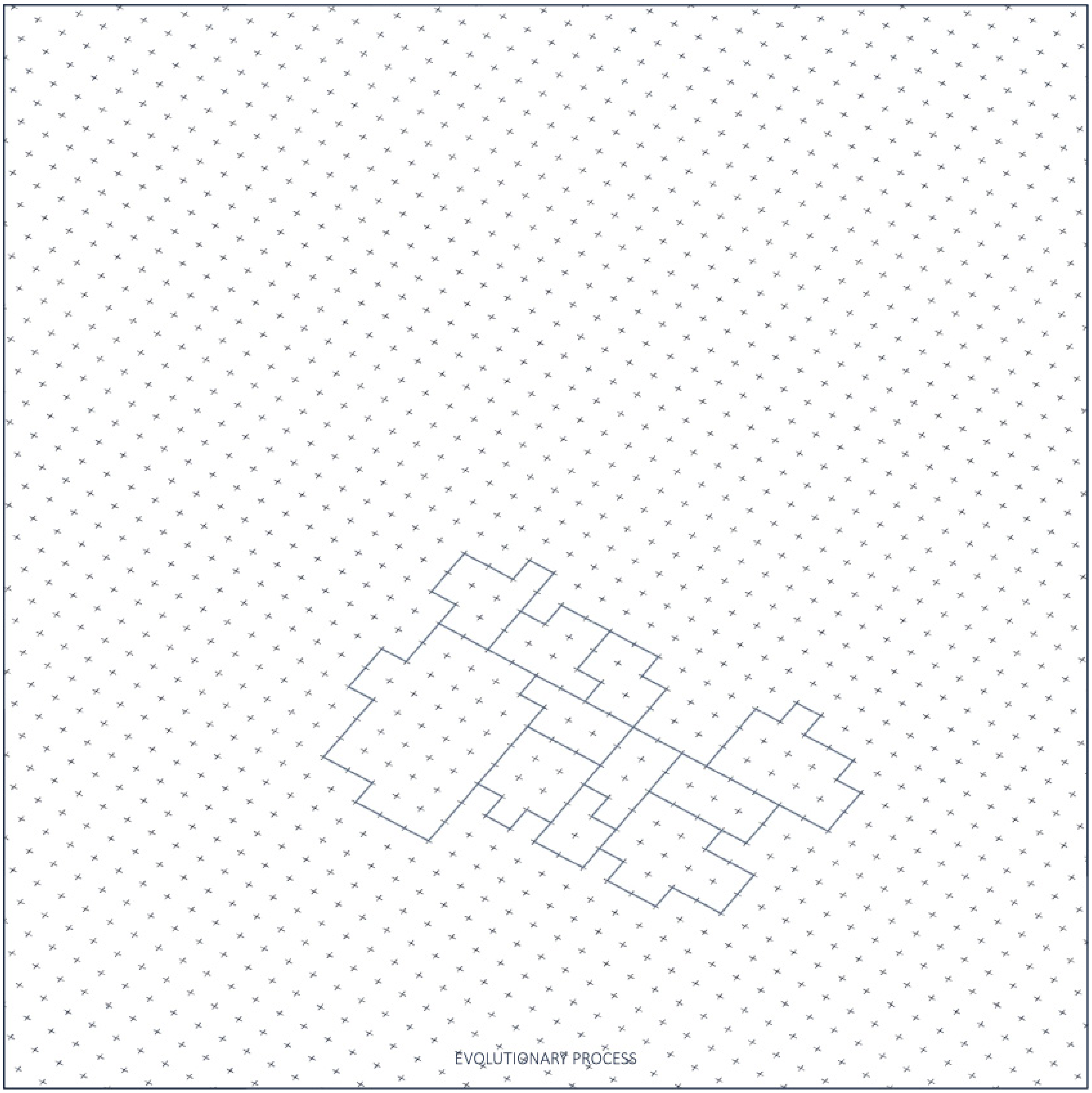


Fig.37 Machine Learning output approximated to a grid.

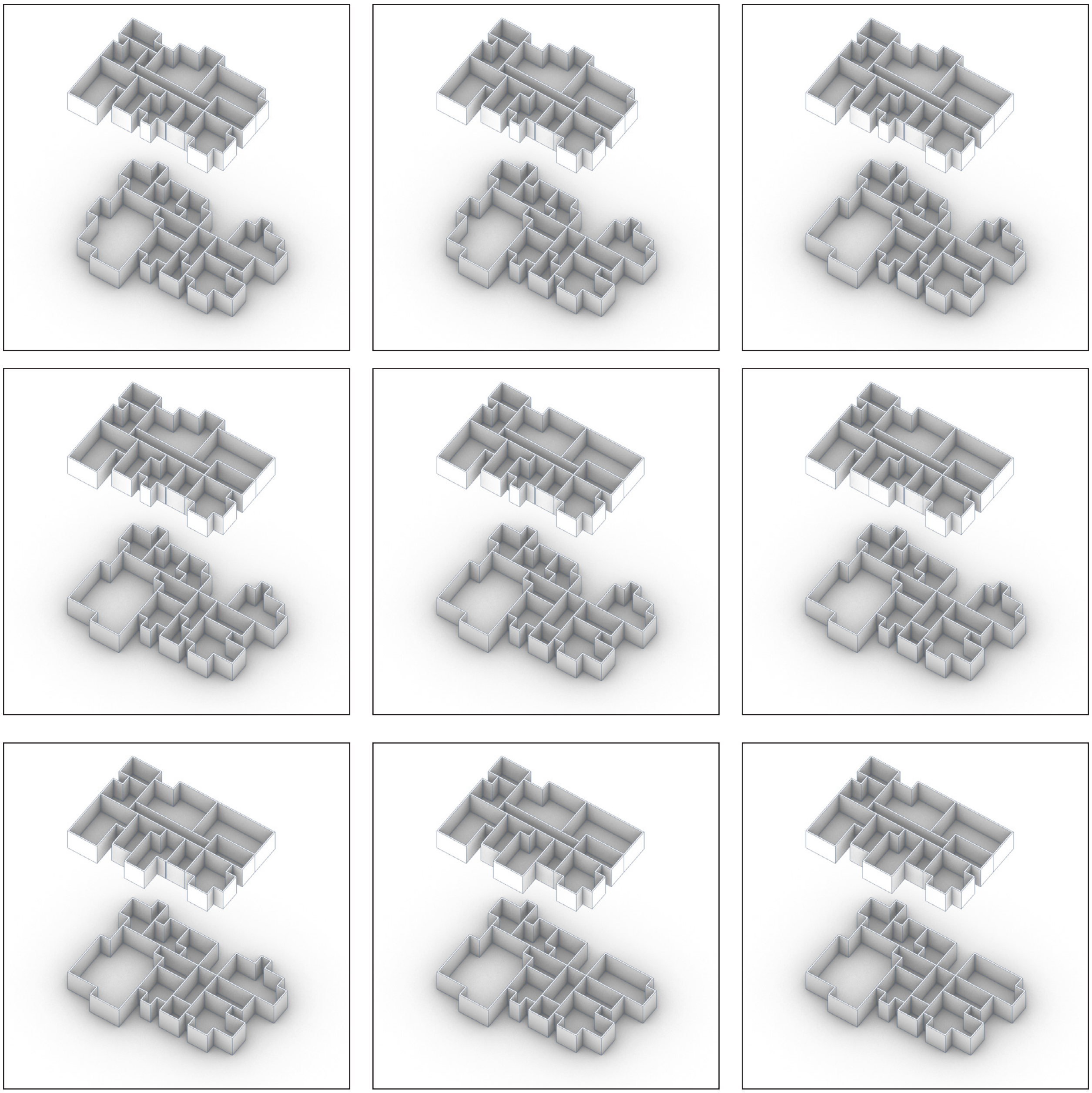


Fig.38 Evolution process.

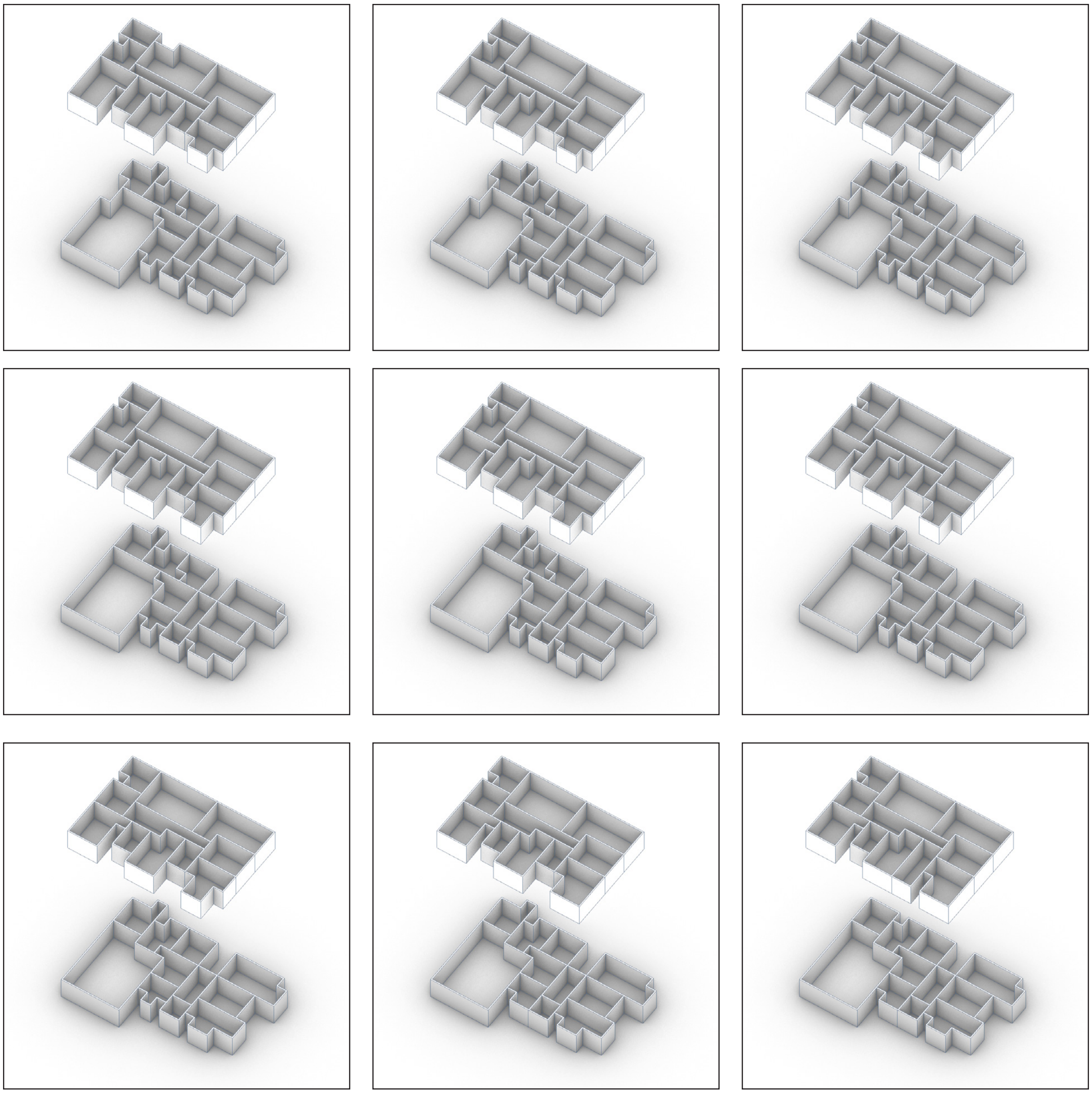


Fig.39 Evolution process.

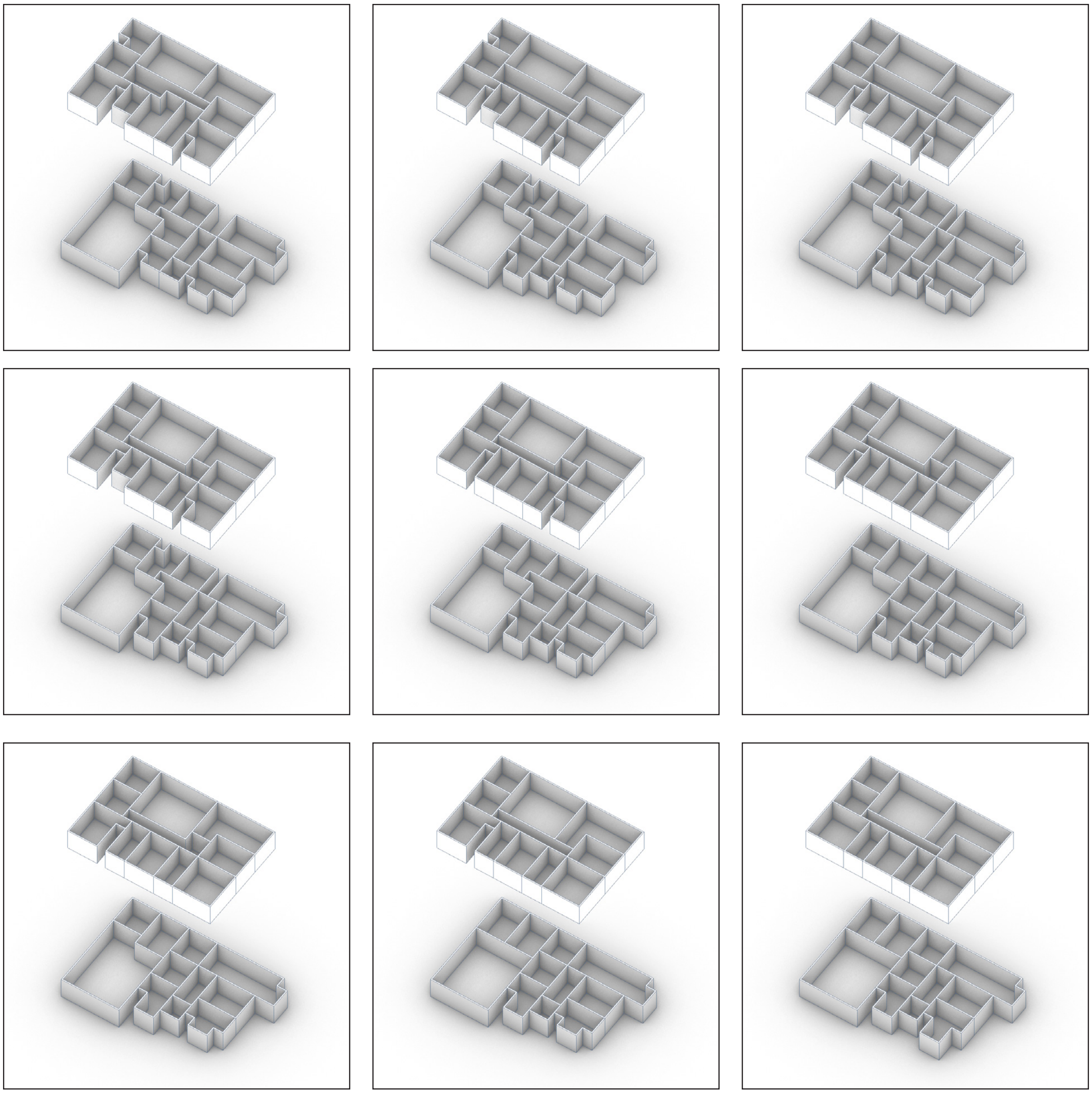


Fig.40 Evolution process.

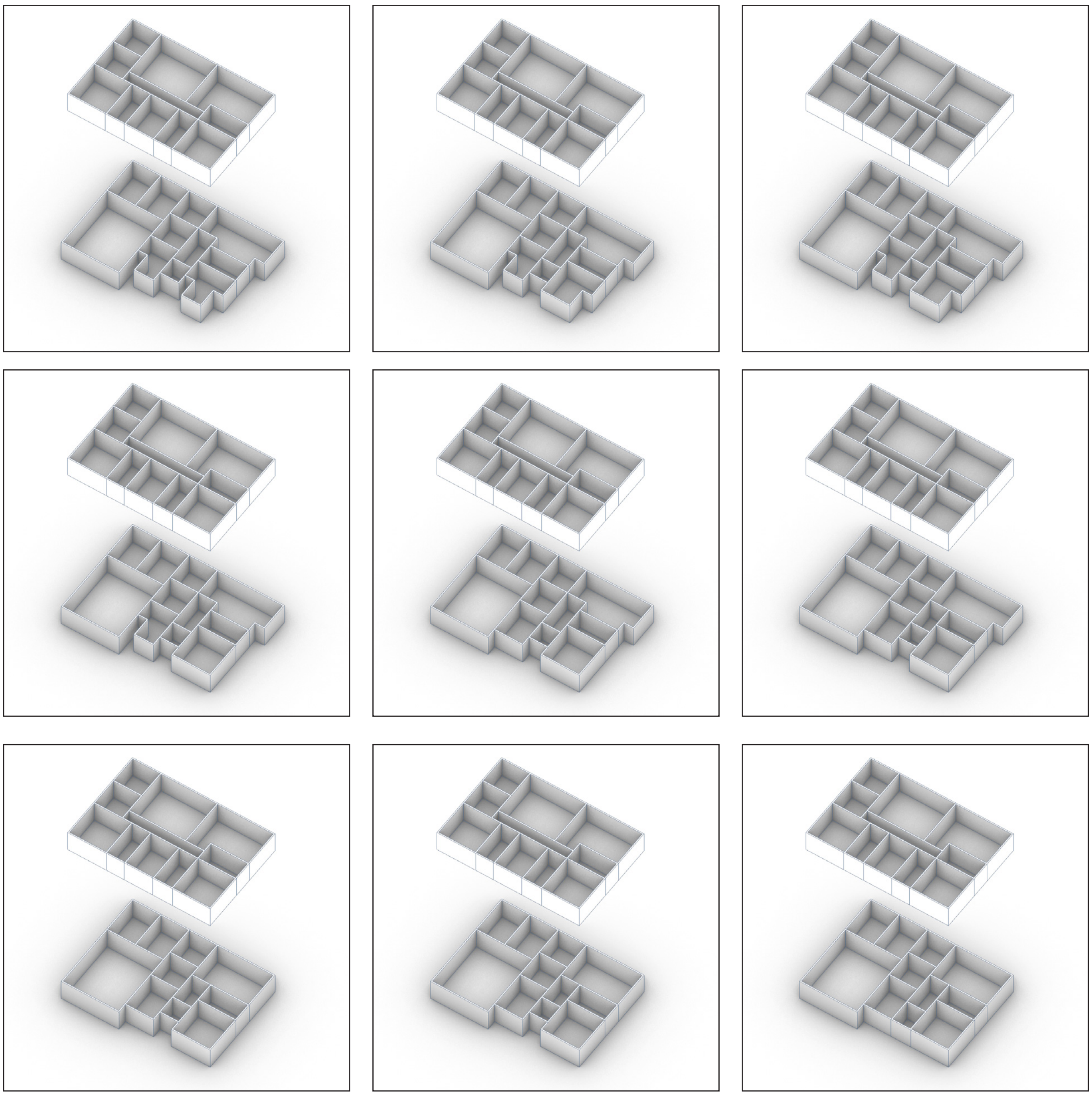


Fig.41 Evolution process.

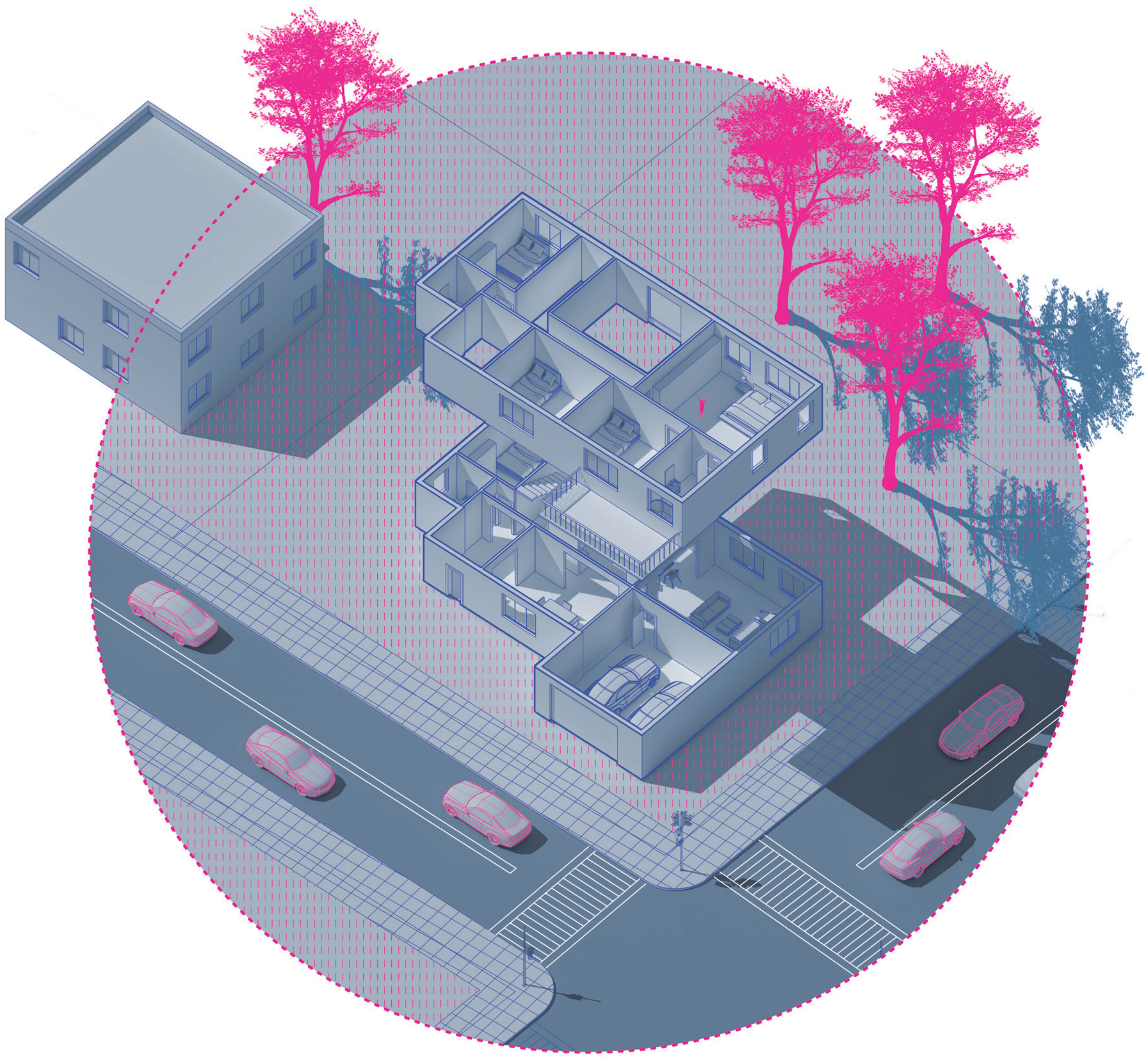


Fig.42 A example of generated house scheme.

CONCLUSION

The performance of Machine Learning algorithms relies heavily on the training dataset. The dataset should be large enough to include most scenarios for the computer to learn. Through Machine Learning algorithms, the computer learns about how to execute certain tasks by recognizing frequent patterns in the training dataset. Machine Learning algorithms are not able to generate new solutions beyond the training dataset. Therefore, Machine Learning is not a creative tool. Machine Learning, as it is now, can never replace human designers as creative thinkers.

However, Machine Learning also shows strengths in processing large quantities of tasks in a limited amount of time. Thus, it can be a powerful tool in processing conventional problems. The strengths of Machine Learning make it a complementary tool to enhance human designers' capabilities.

There are many possible ways of engaging Machine Learning technology in the design process. This thesis focused on how Machine Learning can be a relatively independent design agent to bring design expertise to the masses. This goal cannot be realized by one single type of Machine Learning algorithm alone. To integrate Machine Learning in the design process, multiple techniques need to be combined into a pipeline to deliver the final result.

Just as is happening in many other industries, Machine Learning is slowly changing Architecture. I believe, in the future, utilizing Machine Learning in design will be a new norm in the Architecture industry, just as 3D modeling or Building Information Modelling. Architects, equipped with Machine Learning, can continue to make the world a better place. This new relationship is best described by Ke Jie, the Go player that was defeated by AlphaGo 2 years ago, in a recent TV show: "Now I practice with Artificial Intelligence…Two years ago I saw it as my opponent… Now it is my partner or a necessary part of my life…"

Fig.42 Houses generated.

APPENDIX

RESULTS OF OTHER EXPERIMENTS

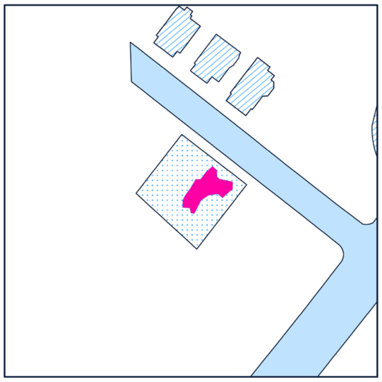


Fig.43-1
Generating foot-
print on an empty
lot

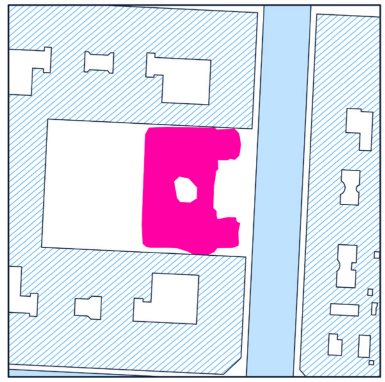


Fig.43-4
Generating
footprint in
Madrid

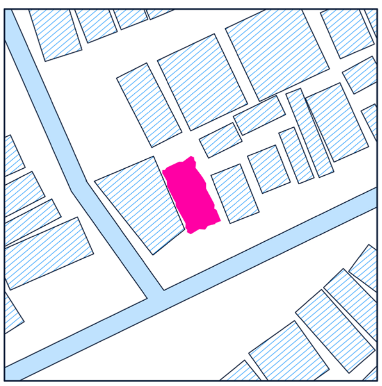


Fig.43-2
Generating foot-
print in New Dehli

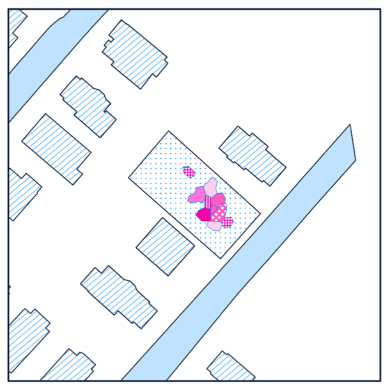


Fig.43-5
Generating 1st
floorplan on an
empty lot

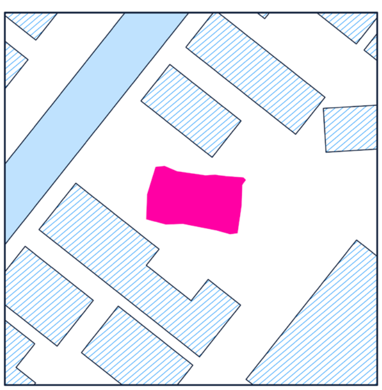


Fig.43-3
Generating
footprint in Mel-
bourne

PRECEDENT ANALYSIS

ROOM	MAXIMUM AREA (SQM)	MINIMUM AREA (SQM)
Livingroom	53.62	9.43
Dining Room	29.05	4.54
Kitchen	40.53	6.06
Laundry	10.35	1.38
Main Bedroom	56.61	8.09
Bedroom 1	34.90	7.58
Bedroom 2	32.86	6.06
Bedroom 3	21.59	10.30
Bathroom 1	12.62	2.42
Bathroom 2	17.26	1.47
Main Bathroom	56.06	6.81
Garage	77.39	14.98
Foyer	30.53	2.15
Storage	45.15	2.26
Breakfast Room	35.54	2.74
Porch	93.13	1.06
Patio	80.47	4.57
Utility	12.14	1.79
Study	36.29	6.34
Family Room	48.93	4.41
Stair	8.77	1.07

Fig.44 Ranges of room areas derived from precedents.

FINAL PRESENTATION

Fig.45 Final presentation.

Fig.46 Final presentation.

AFTERTHOUGHTS

In my discussions with other designers about this study, some disagree that Machine Learning is not a creative tool. According to them, the irregular floorplans that were generated in my experiments could provide a great opportunity to develop new ways to think about floorplans or even architectural forms. I agree that the forms that were generated by Machine Learning could be a way to stimulate imagination, but there is a fundamental difference in considering Machine Learning's role in Architecture design. One of the questions that this study sought to answer was whether or not Machine Learning can replace human designers. Machine learning is considered as an entity that has the potential to be an independent design agent and the potential to be compared to human designers. However, the idea of considering Machine Learning as a tool to stimulate imagination is also an interesting way of considering Machine Learning's application in design, especially when we have identified that Machine Learning cannot generate new solutions by itself.

Another interesting point is that Machine Learning can be a great tool to show the unconscious bias of designers. In this case, Machine Learning can be used to learn and analyze our work as designers, and by analyzing the results that were generated by the trained Machine Learning models, the patterns in the way we design can be shown, and the strengths and weaknesses of certain design methods or conventions become obvious. Machine learning can be a third eye that shows our limitations and helps with the development of our design abilities.

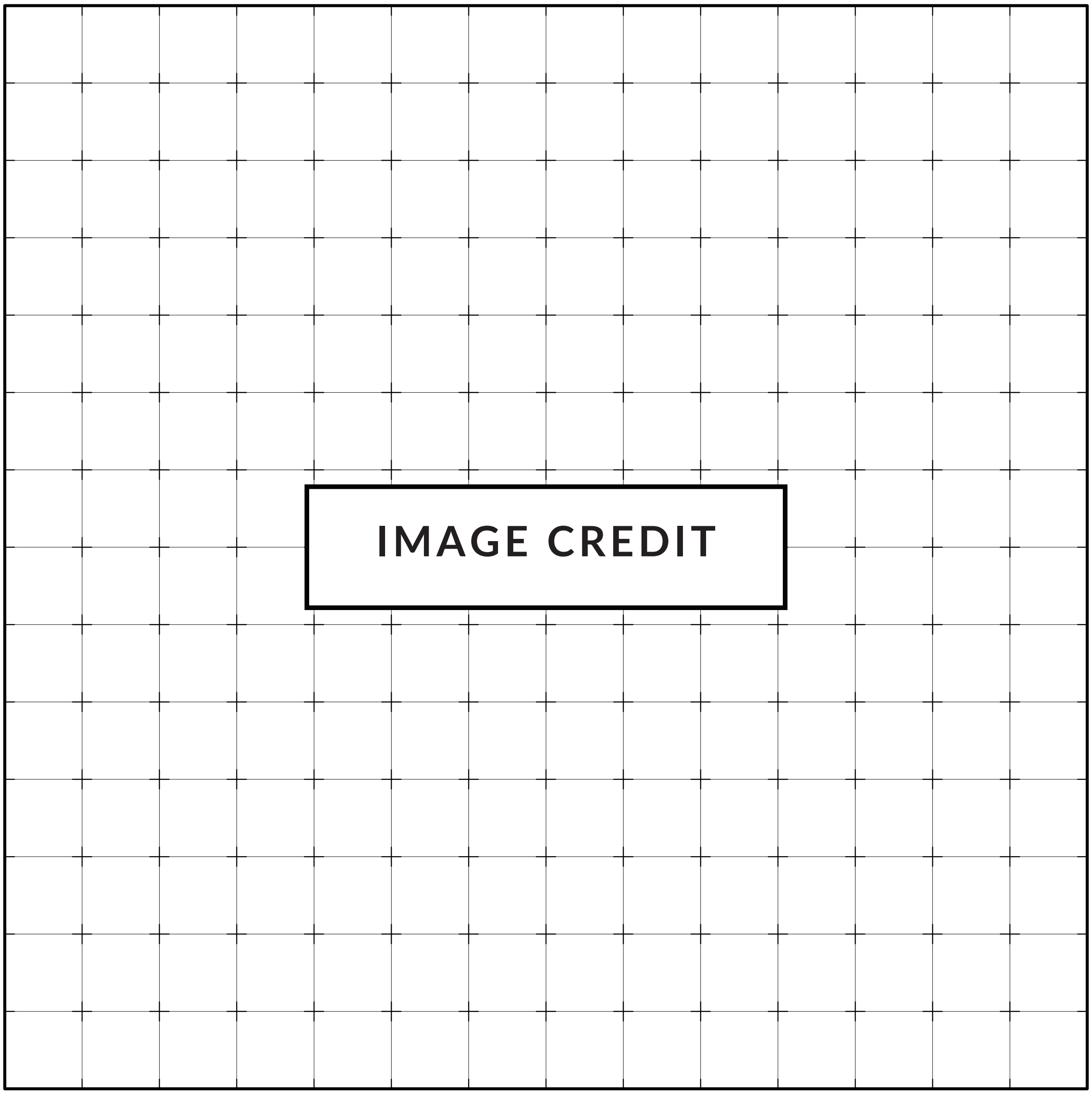


IMAGE CREDIT

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