Co-creation: Space Reconfiguration by Architect and Agent Simulation Based Machine Learning

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Abstract. This research is a manifestation of architectural co-creation between agent simulation based machine learning and an architect's tacit knowledge. Instead of applying machine learning brains to agents, the author reversed the idea and applied machine learning to buildings. The project used agent simulation as a database, and trained the space to reconfigure itself based on its distance to the nearest agents. To overcome the limitations of machine learning model's simplified solutions to complicated architectural environments, the author introduced a co-creation method, where an architect uses tacit knowledge to overwatch and have real-time control over the space reconfiguration process. This research combines both the strength of machine learning's data-processing ability and an architect's tacit knowledge. Through exploration of emerging technologies such as machine learning and agent simulation, the author highlights limitations in design automation. By combining an architect's tacit knowledge with a new generation design method of agent simulation based machine learning, the author hopes to explore a new way for architects to co-create with machines.

Keywords: Machine learning · Agent simulation · Co-creation · Artificial intelligence · Space reconfiguration

1 Background

Agent simulation based design methodology has been around for decades, studies such as space syntax, agent-based semiology have been investigating, simulating and predicting spatial occupation patterns. However, the results are restricted to analysis and evaluation, which are yet to allow the space to become responsive. The hypothesis of the research is, having a space able to reconfigure itself based on agent behaviors.

1.1 Agent Simulation in Architectural Design Methodology

What is the medium of architectural design? Here I'm referring to Archer [2], 'The essential language of Design is modeling. A model is a representation of something' ([2], p. 20). 'Thus design activity is not only a distinctive process, comparable with but

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different from scientific and scholarly processes, but also operates through a medium, called modeling' ([2], p. 18).

Simulation works as one of the mediums of architectural design. Banks et al. [6] explained a simulation is the imitation of the operation of a real-world process or system over time. Simulations require the use of models; the model represents the key characteristics or behaviors of the selected system or process, whereas the simulation represents the evolution of the model over time. Simulation, as an evolution of the models of ideas over time with execution from computers, works as a 'new' medium in the architectural design process.

The technological development enables simulation of agent, and the combination between design experience with agent simulation. Penn and Turner [8] studied space syntax based agent simulation, giving many agents simultaneous access to the same pre-processed information about the configuration of a space layout. Today, there is also agent based parametric semiology whose goal 'is to design a new, coherent system of signification, a new artificial architectural language, without relying on the familiar codes found in the existing built environments' [1].

1.2 Machine Learning in Design Scientific Research

What is design science? Bayazit [4] referred to Vladimir Hubka and Ernst Eder's definition, the term 'design science' is to be understood as a system of logically related knowledge, which should contain and organize the complete knowledge about and for designing.

Looking back at the origin and history of scientific development in design research, Norbert Wiener played an important role. His idea 'Cybernetics' 'became the model for rational behavior employed in economics, and obtaining information and making decisions using computer systems' ([4], p. 23). 'There was a close relationship between design research and the developments in the IT field, especially in cognitive sciences, and "artificial intelligence" (AI) and expert systems' ([4], p. 27).

Machine learning as a part of artificial intelligence, has recently been used in architectural design. Machine learning (ML) is the study of computer algorithms that can improve automatically through experience and by the use of data [7]. By employing machine learning in the architectural design process, design automation is implied and thus brings both opportunity and threat to architects and the architectural design creative process.

1.3 Agent Simulation Based Machine Learning as a New Generation Design Method

Human behavior study has played a significant and continuous role in design methodology. Baudrillard claims that our current society has replaced all reality and meaning with symbols and signs, and that human experience is a simulation of reality [3]. With technological development, simulation, which is a 'new' medium in architectural design, has been widely adopted and applied to human behavior, which is agent simulation. Agent simulation is an architectural design medium and a design method.

Machine learning as part of contemporary design sciences, has in its nature relation with design research. ‘Mutual influences of information technologies and design research were the requirements of the era’ ([4], p. 28). It makes sense to combine machine learning with agent simulation. It is worth noting that in this case, different from the conventional routine of design sciences that goes from design to analysis to redesign, such as shadow analysis or Karamba analysis, machine learning breaks the routine and adapts design according to analysis results automatically.

1.4 Co-creation with Architects

Adoption of machine learning in architecture design pushes forward the idea of design automation, which puts the role of the architect in question. It can relate back to Donald Schön’s study on designer behavior, which did not seem to relate to computer science back then, but here can be compared under the design automation discussion. Can machines replace architects by learning designer behaviors? And is machine learning, or design automation exempt from human/architect intervention?

The author would like to briefly answer the question from one aspect, without forming a comprehensive opinion. Tacit knowledge—as opposed to formal, codified or explicit knowledge—is knowledge that is difficult to express or extract, and thus more difficult to transfer to others by means of writing it down or verbalizing it. This can include personal wisdom, experience, insight, and intuition [9]. There is tacit knowledge in humans or architects that can hardly be conveyed, which is an important characteristic of architects. Architect design not only through accumulation of architectural knowledge, but all the other experiences form over the years and transforms to one’s unique tacit knowledge.

One can argue that machines can learn and therefore form a type of tacit knowledge as well, as machine learning learns through past experiences. Here it is important to note that the database that machine learning from, and is based on is created and structured by humans, which exempt machines from gaining unwanted information from humans. The unwanted information might become part of the contribution to the machine’s tacit knowledge. However, with unstructured or unwanted information in the database, the learning curve can be unnecessarily long, and might end in unsuccessful training. The database has human intervention, therefore the experience the machine gains is limited and structured, and differs itself from human knowledge.

The author wants to highlight the importance of co-creation between machine learning and an architect. By adopting the data processing strength of machine learning and the tacit knowledge of an architect, an architectural project can develop its most potential.

2 Application

The application part of this project mainly consists of four parts: Space, Agent, Machine Learning and Co-creation. Firstly, a space is needed to practice the design method within.; Secondly, an agent’s behavior in this space, which is the agent simulation that is used as a database for machine learning; Thirdly, the machine learning training principle and outcomes; Fourthly, An architect’s co-creation with the trained machine learning model.

2.1 Housing Precedents as Study Subjects (Space)

Even though modern buildings are generally different from ancient buildings, because of shared human behaviors in a living space, housing is a historically consistent, architecturally diverse typology, which allows a possible comparison between a modern building and an ancient building. Therefore, housing precedents are ideal for the study purpose of this agent simulation based project.

2.1.1 Precedents Principles

Twenty housing precedents were chosen as the study subject as they are historically consistent, architecturally diverse. Precedents chosen mostly have only one floor, which gives controllable parameters to study and compare among the precedents. Otherwise it will give unnecessary and uncontrollable parameters, such as how the stairs and lifts as a different agent behavior consideration for machine learning. However, It is difficult to find many representative one-floor housing precedents in classical architecture periods. In this case, the ground floor, where most active behaviors happen, is considered for the study (Fig. 1).

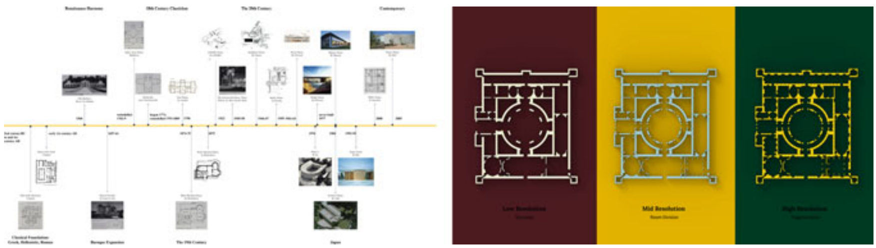

Fig. 1. Housing precedents timeline and three resolution illustrations. Images by Anni Dai

2.1.2 3D Model Preparation and Three Resolutions

In the process of transforming these precedents into 3d models for training, only the elements that are useful for machine learning and architectural representation are preserved. All the precedents are represented by their walls, the roofs and floors are hidden for the better observation and presentation of the project.

During the modeling process, the author observed that the building's room size, room density and room distance varies. The author decides to experiment the project on three different resolutions of these twenty housing precedents. Low resolution, where the walls are divided by structural integrity; Mid resolution, where the walls are divided by the size of the room; High resolution, where the walls are divided in 1.5 m blocks.

2.2 Agent Simulation (Agent)

2.2.1 Agent Simulation Rules

There are three typical agent types: Master, who is the owner of the building; Staff, who is serving the master and the guest, while responsible for cleaning the house; Guest, who visits the master and occasionally stays. Most ancient precedents have three agent types, while some contemporary ones which are highly private, therefore the guest agent is not considered as it is not the main intention of the buildings.

The author tries to make the agent's behavior comply with each building's specific situation. There is randomness in agent behavior that allows certain unpredictable developments that imitates the realistic scenarios (Fig. 2).

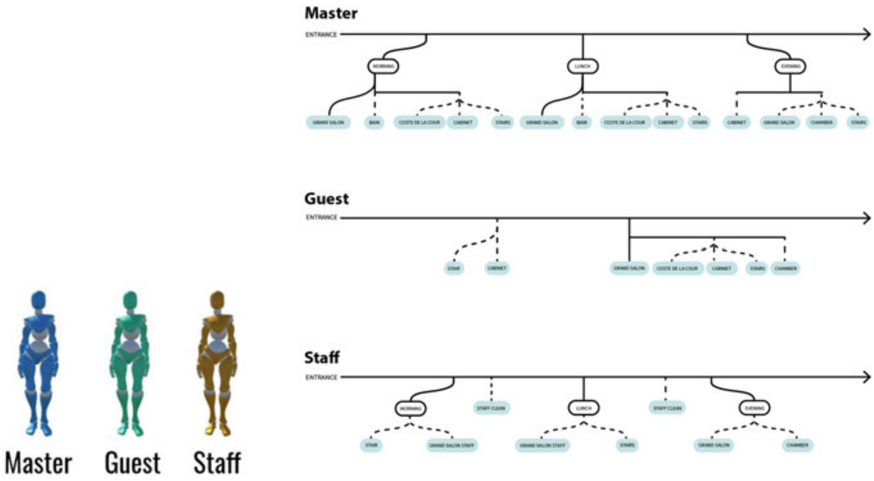

Fig. 2. Typical agent behavior. Image by Anni Dai

2.2.2 Agent Simulation Results

The complexity of the behavior is intentionally developed to use as many rooms as possible to gain the ideal training results. Each agent has different tendencies of space usage. For example, guest and master do not use the kitchen as much as the staff; guests have very limited access to rooms; Staff tend to access most of the rooms as they need to undertake a cleaning routine, while not spending as much time inside as the master, etc. The trail of agents movement is a direct representation of the room usage frequency (Fig. 3).

2.3 Machine Learning (ML)

2.3.1 Machine Learning Method

This project uses 'ML Agent', a Unity programme, as the Machine Learning Tool. Aas it was compatible with the 3d training environment, and Unity is compatible with agent simulation.

'ML Agent' uses reinforcement learning. In this project, each wall (gameobject) was given a ML brain. The author set the distance between agents and a wall as a goal. When an agent's distance to a wall is less than 1 m or exceeds 5 m, it is given a penalty

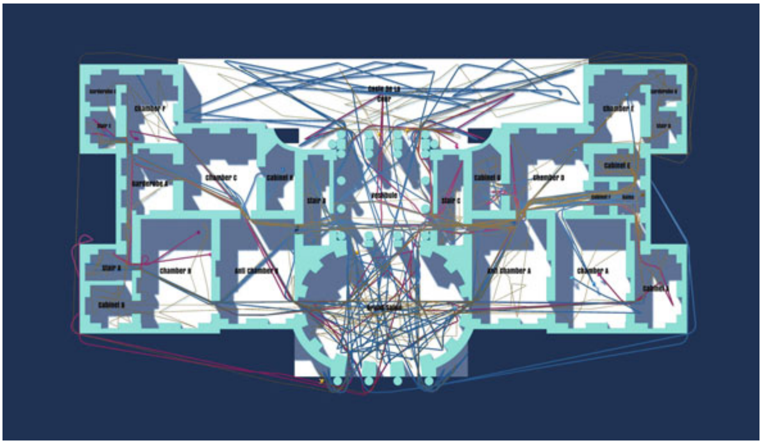

Fig. 3. Typical agent trail. Image by Anni Dai

(red); when an agent's distance to a wall is more than 1 m and less than 5 m, it is given a reward (green). Therefore, this project's training goal is to make the wall achieve a 'good' distance to the agents (Fig. 4).

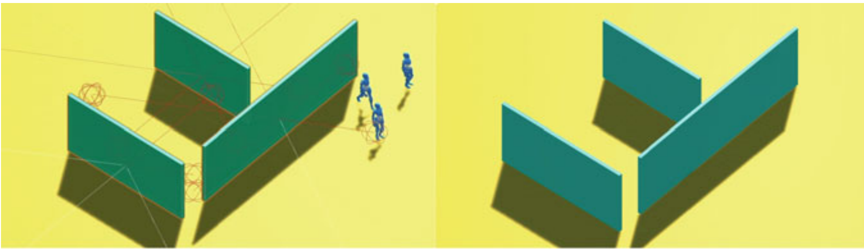

Fig. 4. Machine learning training diagram. Animated GIF by Anni Dai

The detection of the distance between agents and a wall used the Raycast 3D component. The wall is detecting agents within 10 m radius, it is tested as a good distance that will use less time to train. 10 m for a typical housing architecture is a big enough radius for a room. Using the Raycast 3D component has proven to be efficient to train a large amount of walls.

This project used the high resolution of twenty housing precedents as a training dataset, as it has the most walls for training. The result was the most comprehensive compared to other resolutions while not overbearing the computer. After 50,000,000 (50 million) steps, the trained result turned out satisfying. This trained model was then applied to each building again as an inference behavior, for further development (Fig. 5).

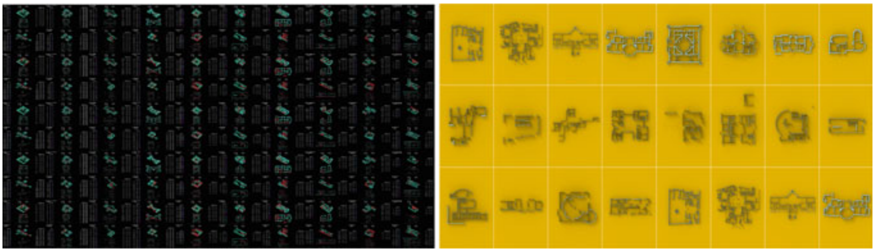

Fig. 5. Machine learning training overview and trained outcome. Image by Anni Dai

2.3.2 Machine Learning Training Outcomes

The training results typical developments are: entry creation, area increase, area reduction, room creation and new connection.

In general, the conclusion from this training outcome is, the room size increases as more agents use it, and reduces in size the less it is used. Machine learning only recognizes the frequency access of the room, and ignores the actual parameters, such as agent's time spent and functional differences between rooms.

2.4 Co-creation and AI Compliments (Co-creation)

As we have noticed from the machine learning training results above, there are limitations in this training. The other aspects of a housing architecture, for example, the amount of time an agent spent in a room, the activeness of different functional rooms, etc. should have been considered as part of the space reconfiguration parameter, however cannot be comprehended in this machine learning training outcome.

2.4.1 AI Compliments

Room Size and Room Height

To make each room size not only respond to agents' visiting frequency, but the realistic functional needs as well, the author assigned each room with a different **time weight** and **agent quantity weight**, which allows specific control over the room size and height. Room size is decided by measuring the distance between the wall and the center of the room constantly. Room height is associated with the agent quantity and amount of time spent in the room. The programme accumulates and averages the results (Fig. 6).

$$\begin{aligned} \mathit{Ideal\ Room\ Size/Height} = {} & \mathit{Current\ Room\ Area/Height} \\ & \left(\frac{\mathit{Agent\ Quantity}+1}{\mathit{Current\ Room\ Area}} \times \mathit{Agent\ Quantity\ Weight}\right) \\ & \frac{\mathit{Agent\ Room\ Time}}{\mathit{Time\ Weight}} \end{aligned}$$

Fig. 6. Room size and height adjusting diagram. Animated GIF by Anni Dai

2.4.2 Co-creation

The human interaction parts come in where the weights are adjusted. This project created a UI where the **agent quantity weight** and **time weight** (mentioned above) of each room are presented and to be used by the architect. This is where the co-creation happens. While the programme still runs a machine learning model, the user or the architect can have real-time observation of the building. By tweaking the slider on the UI, Architects use their tacit knowledge to decide on how big the rooms should be, while the machine learning model is still processing and suggesting potential connections and entries. Machine Learning reads agent behaviors and makes suggestions on space layout, while architects use their tacit knowledge controlling and correcting mistakes the machine cannot recognize. Co-creation uses both sides advantages and makes the most of architectural design (Fig. 7).

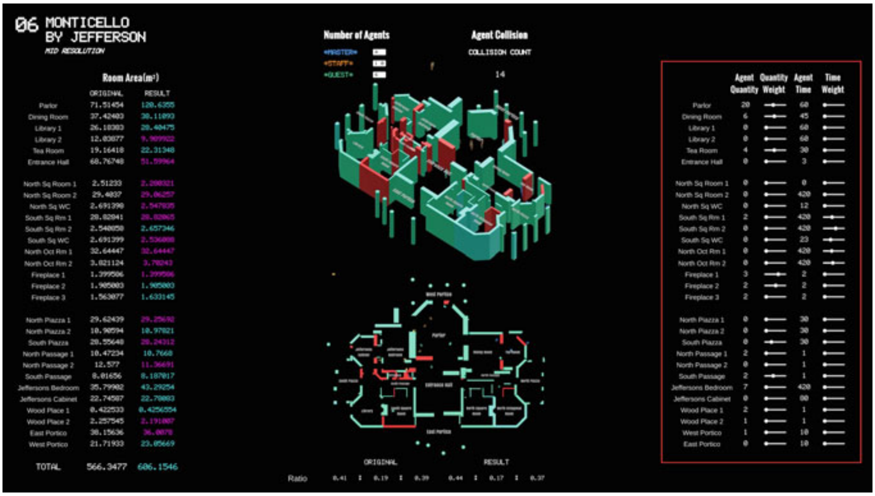

Fig. 7. Co-creation indication diagram. Image by Anni Dai

3 Summary

3.1 Results Comparison

Three Resolutions

The high resolution, in overall, varies the most from the original building. The example below shows representative similarities and differences among the 3 resolutions. All three resolutions create connections between rooms. However, the low resolution often eliminates and simplifies rooms; mid resolution creates more room size variations; high resolution tends to create spaces and creates openings at unprecedented places (Fig. 8).

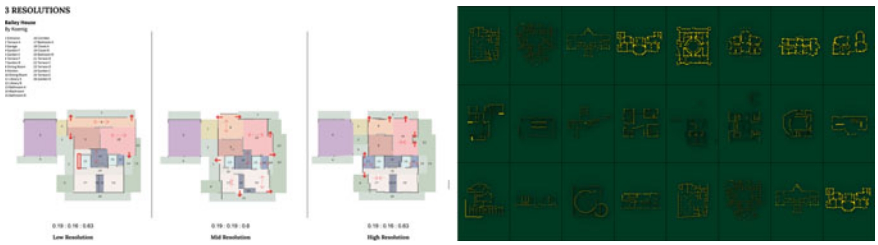

Fig. 8. Three resolutions and twenty precedents comparison diagrams. Image by Anni Dai

Twenty Precedents

Among the twenty housing precedents, the author finds modern buildings tend to have less variation compared to the ancient and classical buildings. Influenced by minimalism, most modern houses simplify room functions to only what was necessary. While in ancient houses such as 'Villa of the Mysteries', rooms such as pharmacy, furnace, are not used as often as any functions in modern architecture. While in classical architecture, rooms such as 'anti chamber', 'rotunda' were included because of their ritual value or aesthetics. Circulation was an important part of the modern house design, which is another reason why this research has less influence on modern buildings than on the ancient and classical buildings.

4 Conclusions

This paper first looked at the theory background on simulation and agent simulation's role in architectural design methodology, and machine learning's role in design scientific research. Then the author argued the concept of design automation, and proposed agent simulation based machine learning as a new generation design method, along with the importance of co-creation between machine's data processing ability and an architect's tacit knowledge.

This research was an attempt on creating a co-creation between machine learning and an architect. The result achieved the research purpose. However there is room for improvement. The co-creation is restricted within room size and height, which can be developed into specifying wall positions. The flexibility of agent simulation can be further explored to where agent positions can be adjusted in real time, and further explore how it will reflect on space reconfiguration.

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