Playing Dimensions: Images / Models / Maps

Conceptualizing Architecture with Big Data and Artificial Intelligence

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1 2D image data type example.

ABSTRACT

This article presents a novel architecture design workflow that explores the intersection of Big Data, Artificial Intelligence (AI), and storytelling by scraping, encoding, and mapping data, which can then be implemented through Virtual Reality (VR) and Augmented Reality (AR) technologies. In contrast to conventional approaches that consider AI solely as an optimization tool, this workflow embraces AI as an instrument for critical thinking and idea generation. Rather than creating new AI models, this workflow encourages architects to experiment with existing ones as part of their practice. The workflow revolves around the concept of "Canonical architecture," where data-driven techniques serve to traverse dimensions and representations, encompassing text, images, and 3D objects. The data utilized consists of information specific to the project, gathered from social media posts, including both images and text, which provide insights into user needs and site characteristics. Additionally, roughly 9,000 3D models of architectural details extracted from 38 different architectural projects were used. The primary objective is to assist architects in developing a workflow that does not suggest starting from scratch or a tabula rasa, but to work with already hyper-connected objects, be it text, images, 3D models, et cetera. These conceptualizations can then be enacted in game engines and/or experimented with in AR/VR platforms, while keeping their connections alive. Through this process, the framework aims to develop a sensibility of working with large amounts of data without losing focus, and letting the electric grounds of the internet help us in articulating projects.

INTRODUCTION: THE INDEXICAL AND THE GENERATIVE

The rapid advancement of AI algorithms and open-source datasets has revolutionized various industries, including architecture (Hovestadt, Hirscheberg, and Fritz 2020; Chaillou, 2021). Open-source datasets provide a vast amount of information that enhances architectural projects, while big data plays a vital role in training Generative Algorithms (GA) and optimizing Search Engine (SE) indexing. Generative Algorithms generate new information through interpolation (Newton 2019), whereas SE retrieves relevant results through efficient scanning and indexing based on specific keywords (Alvarez Marin 2020). Currently, there is a significant focus on GA using diffusion models, like mid-journey and DALL-e algorithms (Zhang et al. 2023b), trained on extensive internet-based big data. Moreover, powerful Large Language Model (LLM) algorithms, such as ChatGPT, have also surged in generating texts with user-friendly functionality (Zhang, et al. 2023a). With these algorithms, it is crucial to carefully construct questions to counteract the algorithms' tendency for unjustified responses, known as hallucination (Alkaissi and McFarlane 2023). Hence, the following question arises: how can these technologies be utilized to overcome the hallucination problem? This is where search engines introduce another methodology to address this problem. The output of a search engine is grounded in existing indices, always based on real data, thus circumventing the challenges of hallucination encountered with GA and LLM (Alkaissi and McFarlane 2023). The critical factor lies in the dataset to be parsed, emphasizing the importance of curation and personalization to address project-specific inquiries.

This article presents a framework that incorporates search engines into architectural design processes, advocating against starting from scratch and, instead, leveraging preexisting loaded data and information, including text, images, 3D models, and more. These conceptualizations can be further explored using traditional 3D software or experimented with in AR/VR platforms. Through this approach, the framework aims to cultivate a sensibility for working with vast amounts of data, while maintaining focus and effectively utilizing the available online resources to articulate architectural projects. As proof-of-concept, this methodology was applied in a 6-week-long workshop involving architecture students.

METHODOLOGY: ARTICULATING JOINTS IN MANY DIMENSIONS

This section is organized into three modules: Mapping Big Data, Collapsing Dimensions, and Staging Multi-dimensional Stories. These modules were applied to the initial conceptual stage in the design process.

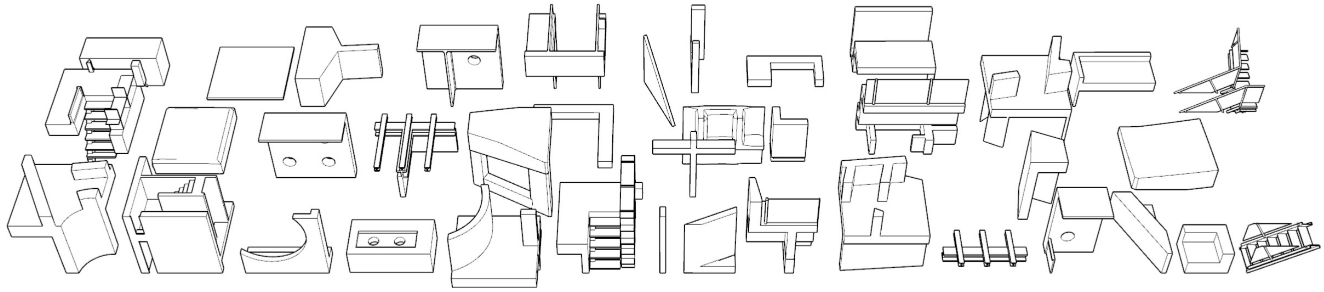
Mapping Big Data

Accessing the plenty

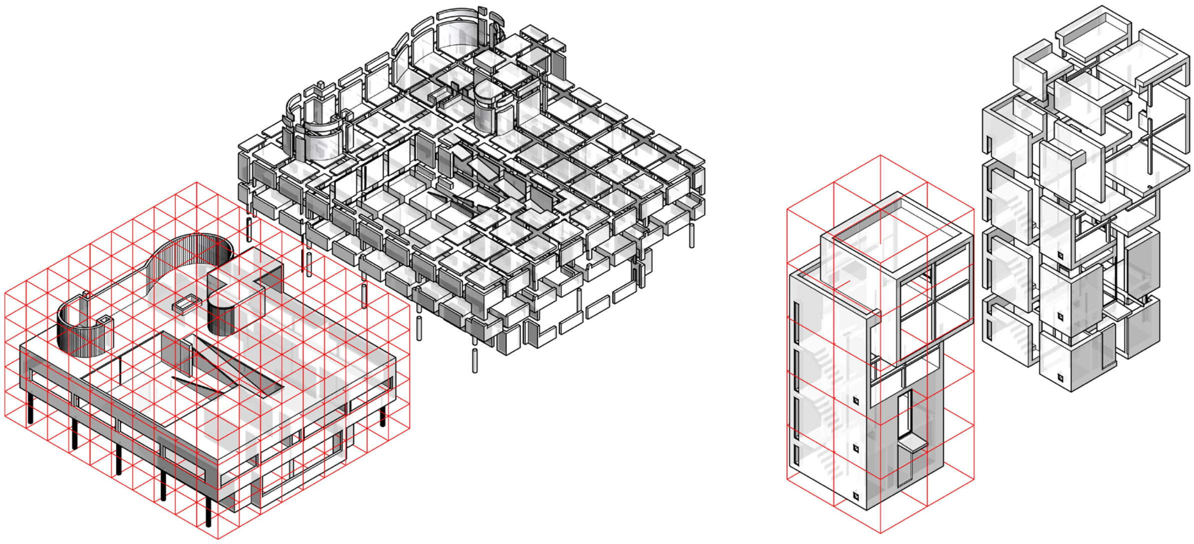
The workshop utilized AI algorithms to crawl the internet for information about site and users; and 3D models of 38 notable architectural projects (Appendix 1). Data were collected in two modalities - Images and 3D Models.

Images: To gather relevant data for our analysis, we employed an automated scraping tool specifically designed to extract social media posts (Figure 1). This tool allowed us to collect both images and text based on specified keywords, time ranges, and location criteria. The primary objective was to conduct a comprehensive site analysis and gain insights into user needs within a specific geographical context. This approach allows us to gather data encompassing various dimensions, such as sentiment (based on keywords), time (based on a specified time range), and geography (based on location criteria).

Models: We collected 3D models of canonical architecture, a total of 38 projects, mostly at the scale of small houses (See Appendix 1 for a list). These projects were drawn primarily from two publications curated by the authors as key projects of the 20th century (Davies 2006; Weston 2004). Moreover, the supplied CAD drawings gave a relatively precise foundation on which to reconstruct the 3D models of these projects (Figure 2).



2 3D data type example.



3 3D data segmentation process examples (Villa Savoye by Le Corbusier, 4x4 House by Tadao Ando).

Dimensional Transversality

The collected data was preprocessed by cleaning and optimizing the 3D data and image resizing for 2D data. We also used AI algorithms, such as autoencoders (Simonyan and Zisserman 2015) and Fourier transform (Bracewell 1965) to extract feature vectors and encode their modality into numerical representations.

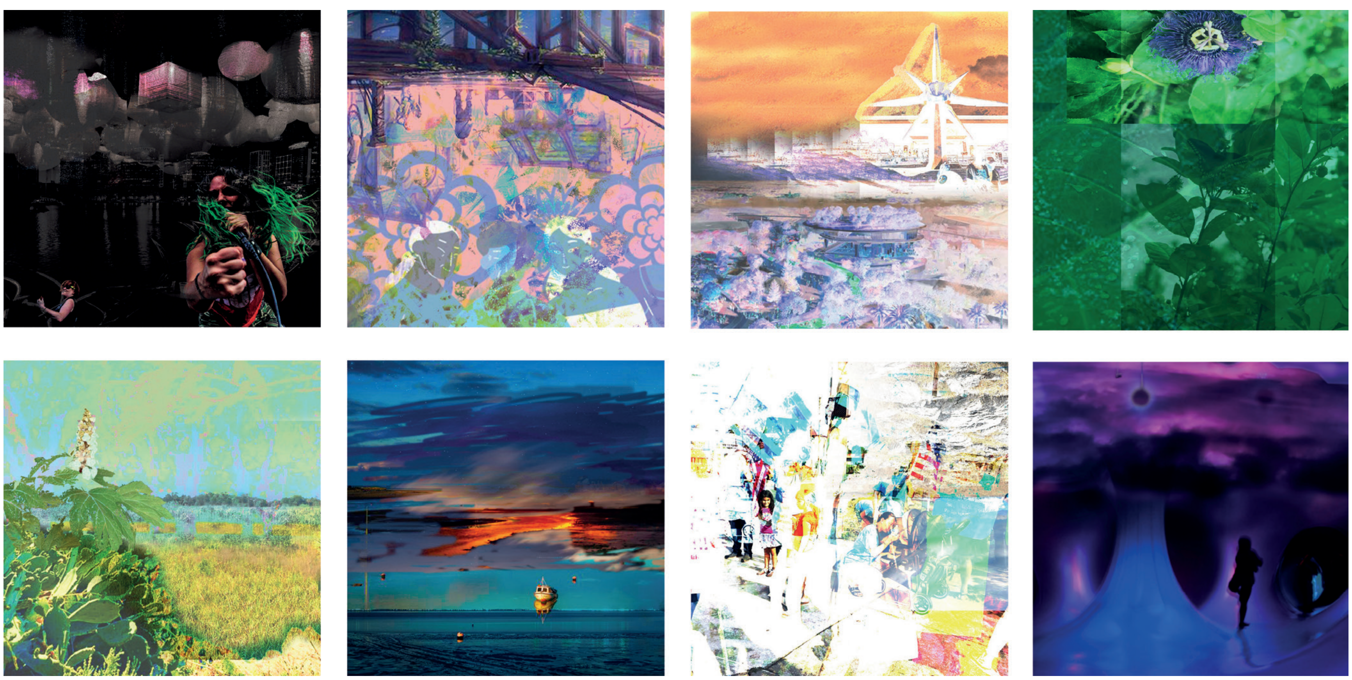
Images: We used a pre-trained Convolutional Neural Network (CNN) called VGG16 (Simonyan and Zisserman 2015) to extract feature vectors from the images. A convolutional neural network is a class of artificial neural networks specifically designed to process pixel data and detect complex imagery patterns that cannot be explicitly formulated using other methods. VGG16 was trained with a large image dataset of different objects to perform image classification tasks. A trained VGG16 iteratively conducts non-linear operations on the input image of 224 x 224 x 3 pixels to reduce the size of the input image by each operation, and eventually converts the input image to a 1,000-dimensional vector that represents the probability of the input image being each of the 1,000 predefined categories of objects. However, the final 1,000 categories are a rather limited way of looking and not fitting well with the concept of the workshop. The process of transforming pixel data non-linearly is useful and applicable to other kinds of images. Therefore, we modified the original VGG16 and discarded the final 1,000-dimensional output. The intermediate results, which are 2,048-dimensional vectors, were used as the feature vectors for the images. These vectors serve as the compressed numerical representation of the original images, and allow us to compare the similarity of two images, in terms of their styles and contents, rather than the pixel colors.

Models: The models were built from scratch or refined into clean Non-Uniform Rational B-Splines (NURBS) geometry as a preparatory step. Each model was segmented into a matrix of eight-foot cubes using recursive boolean operations with a Rhino Grasshopper definition. Depending on project size, this would yield anywhere from 60 to 800 segmented cubes with embedded architectural elements (Figure 3). These outputs were automatically indexed based on relative spatial positioning, and exported as sorted OBJ files. The fragments were voxelized at roughly 1-1/4" voxel size using the Dendro mesh voxelization plugin (Oenning 2022) so that the geometric pattern could be processed and encoded using Fourier transform (Bracewell 1965). Fourier transform converts the original voxels into voxels of complex numbers that have the same size as the input. The output complex voxels describe the frequency compositions of the original voxels, where the lower-frequency part typically encodes the rough shape of the fragment, and the higher-frequency part encodes the information regarding geometric details. In our workshop, we kept the lower-frequency part (10 x 10 x 10 of the complex voxels). We discarded the remaining higher-frequency data, as the general shape plays a more influential role than the detailed patterns in the context of architectural forms and spaces. Also, the result voxels are converted from complex numbers to their absolute values.

Design Space Representation

After encoding the data modalities, we employed the Self Organizing Maps (SOM) algorithm (Kohonen 1982) to serve as our search engine for both types of data. The SOM performs the crucial task of visualizing the collected data in a condensed space, enhancing our ability to navigate and comprehend vast amounts of information. By utilizing SOM,

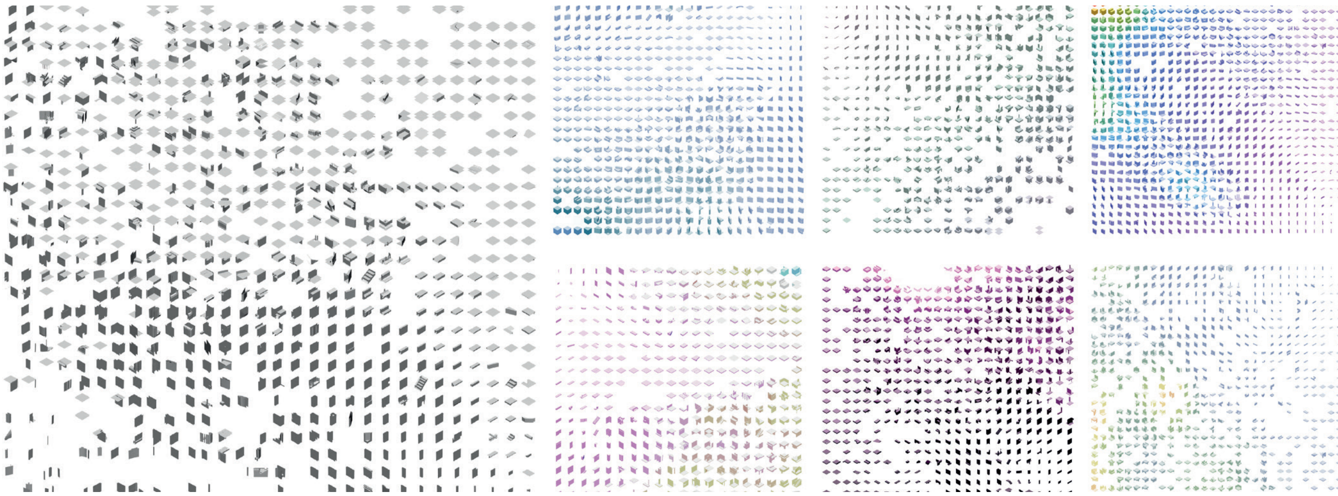
4 Self-Organizing Map (SOM) examples.



5 Atmospheric collage examples.

we can transform high-dimensional data into a lower-dimensional space or “maps”, while preserving the original topology. Typically, this transformed space is two- or three-dimensional, enabling us to easily visualize clusters of data that correspond to the underlying structure of the original space. This remarkable feature makes SOM an invaluable algorithm for capturing and representing intricate relationships within complex datasets. Furthermore, SOM exhibits versatility and performance, achieving an 85% success rate when compared to algorithms specifically designed for the same task (Kohonen 1982).

Maps Images: Using the SOM on the feature vectors of the collected images, the output map curates a selection of images organized/clustered based on their feature vector similarities (Figure 4). This map was used to create atmospheric collages indexing time and space (Figure 5). Since the data was collected using geo coordinates and posting time, we could create images representing these aspects from various personal viewpoints.



6 3D models voxelized SOM.

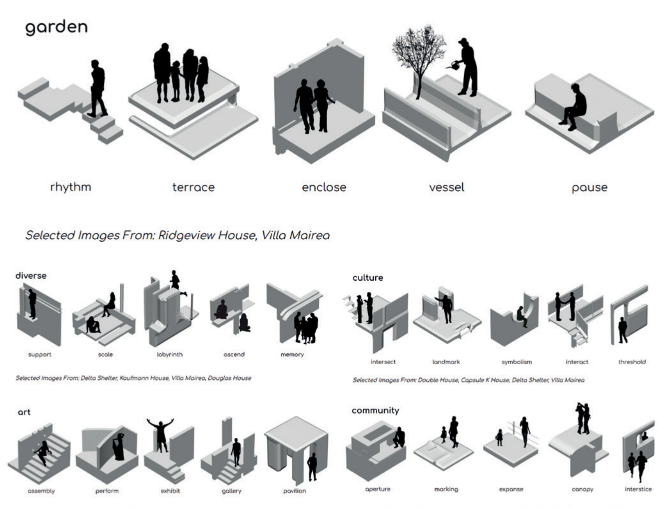
Maps Models: Using the SOM in the feature vectors of the 3D models, we were able to create a subsample of selected details, as similar details were clustered together (Figure 6). Since the eight-foot cube dimension always captures a substantial building element (floor/ceiling/facade/circulation), distinct features with unique elements stand out, while generic ones are filtered out. These are assessed for desirable properties, and utilized as seeds for the design proposals (Figure 7).

Collapsing Dimensions

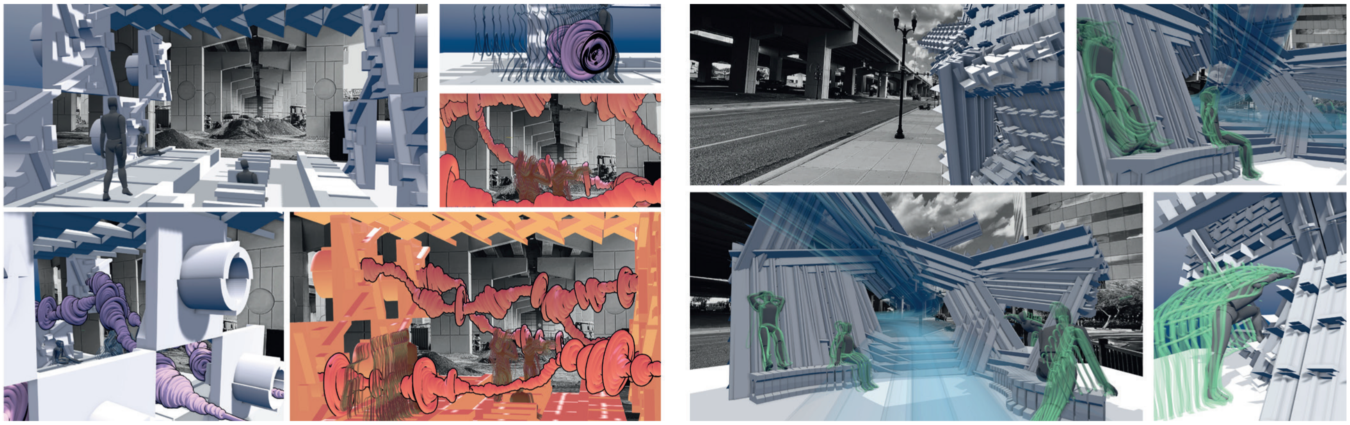
Participants used the Oculus Quest 2 and Gravity Sketch, a VR modeling program, to explore the potential of body-scale modeling to generate derivatives of selected canonical building details, including the created atmospheric images (Gravity Sketch Ltd. 2022). Referencing the SOM of 3D details created previously, participants chose details that embodied specific spatial properties, and arranged them loosely in an exquisite-corpse *cadavre exquis* (Brotchie and Gooding 1991) style arrangement, taking into account site, scale, and relative spacing between these fragments to correspond with expected programmatic ideas and requirements. These were imported into Gravity Sketch to be simultaneously experienced and manipulated at 1:1 scale in VR. This sets up a situation where the 3D details helped bracket very specific spatial conditions, while the interstitial space remained for participants to bridge, interpret, and morph. Simultaneous collective work between participants occupying the shared VR workspace across scales led to an exquisite corpse-style assemblage of proposals that occupied the site with sensitivity to both the detail scale internally, as well as the urban scale externally (Figure 8). The sketchy nature of the VR modeling tool juxtaposes with the precision of the surface modeling, and simultaneously offers the suggestive speculation of a sketch with the precise grounding of scale and site.

Staging Multi-Dimensional Stories

The previous work (atmospheric images and exquisite corpse-style assemblage) produced with this workflow was placed within the environment of the game engine Unity (Unity Technologies 2023) to crystallize architectural proposals. Game engines excel at employing objects constructed through many modeling techniques through any software. Not only that, but game engines are media agnostic and can deploy any media; text, images, movies, animations, drawings, renders; spaces, thereby finding their coherence, not in the specificity of the media or geometries, but in the grounding of the narratives. A scenographic setting was composed by combining many media that actively discuss and construct architectural proposals through scale, context, elements, and details, living in multiple worlds at the same time. The games of architectural design, such as mass versus void, inside



7 3D models selection process.



8 Collaborative VR modeling proposals from exquisite corpse arrangements.

versus outside, and geometry versus texture, were used as tools for the composition and presentation of each project.

Another innovation brought on by game engines is real-time rendering, which suggests that the space of design is never without textures, materials, and renderers. Participants could test out compositions with the lighting and context in place, collapsing the traditional workflow of drawing-modeling-rendering. Within this workflow, rendering is not as a "representational device" but as an operative space, where multiple media could be played in parallel, going beyond a simulation of photo-realism to a projective stylization within the mechanics of storytelling. The previously mapped images and models, and VR sketches, are placed within a rendering environment where the post-processing takes precedence over geometric modeling (Figure 9). Always focused on the narrative layer of the project, game engines deal with objects that are always active, communicating asynchronously with each other within a space that is also always alive.

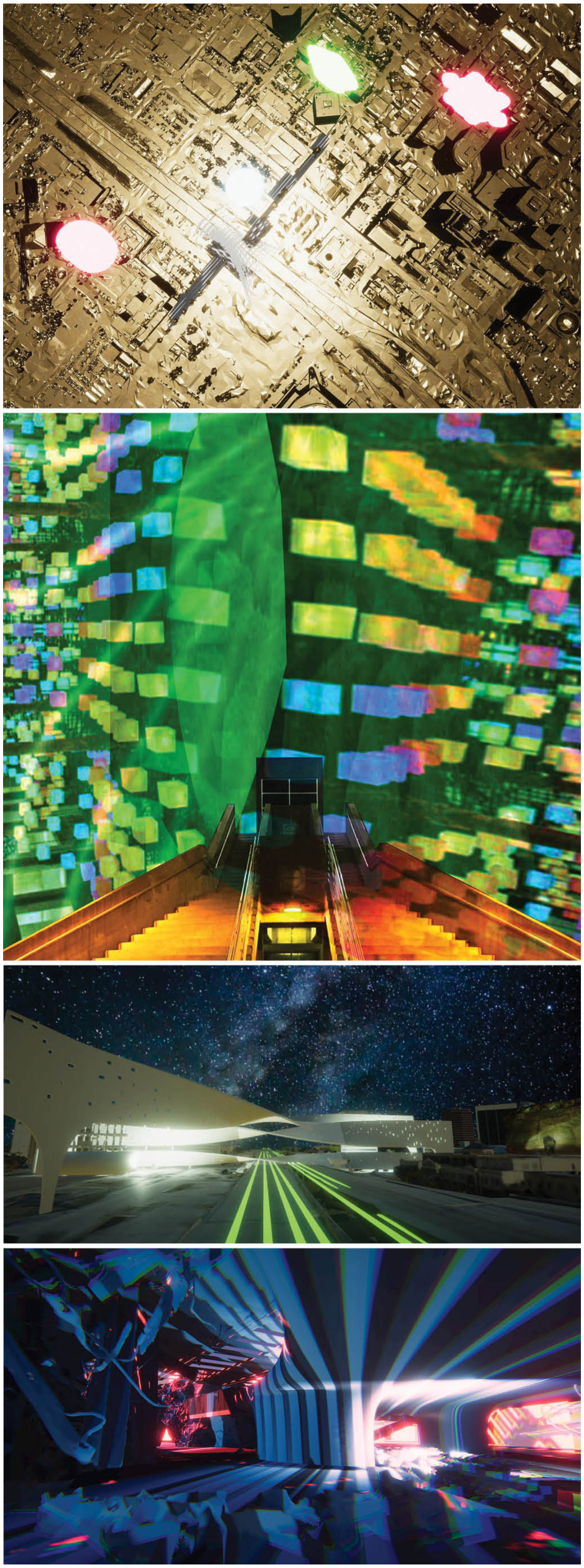
DISCUSSION AND CONCLUSION

The proposed workflow introduced an approach to integrating AI and storytelling technologies into architectural design, revolutionizing a traditional process. Leveraging AI algorithms for data collection, processing, and visualization enables architects to gather and analyze vast amounts of data, providing deeper insights into user needs, and urban and spatial issues. By utilizing VR-based modeling and collaborative virtual workspaces, participants engage in an interactive and creative design process that fosters innovation and produces unique proposals. The application of AI search engine techniques, instead of generative algorithms serves as analytical, conceptual, and geometric tools that complement human interpretation, emphasizing the designer's intent, rather than subsuming human creativity under the machine. The incorporation of post-processing techniques and pre-modeled 3D objects prioritizes the storytelling aspects of architectural design. This data-driven approach, combined with real-time storytelling techniques and VR technologies, offers a multi-scalar platform for ideating and developing architectural proposals, bridging the gap between n-dimensional connections and tangible representations. By tapping into online and curated datasets, projects developed through this workflow achieved a high level of specificity, while remaining grounded in big data. The role of the architect plays in many dimensions, articulating projects in the new scale of big data without succumbing to the shortcomings in the large, generalized databases, but instead creating personal libraries, keeping the human scale firmly embedded within the design process.

REFLECTIONS AND OUTLOOK

Incorporating multiple datasets into a unified mapping procedure poses challenges due to inconsistencies in formats and limited accessibility to proprietary data. Converting and formatting these datasets for the mapping process can be time-consuming. Furthermore, the size of 3D models used in segmentation raises questions. While an initial fixed dimension of eight feet was chosen as a compromise, a more adaptable approach would involve dynamically scaling the size based on project complexity, dimensions, and unique features. This ensures that voxelization captures meaningful configurations and avoids generic segments. Additionally, incorporating additional layers of information, such as materials and textures, could expand beyond geometric mapping.

By utilizing real-time rendering and game engines, architectural representations can span various dimensions and multimedia spaces, encompassing plans, sections, perspectives, pixels, voxels, and maps. This approach enables the development of workflows tailored to



9 Staged scenographic storytelling settings.

individuals and projects. As generative image models advance, it is crucial to define the architect's role in visualizing the proposal and understanding the impact of these imaging techniques.

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APPENDIX 1: LIST OF PROJECTS

01.Therme Vals, Peter Zumthor
02. Douglas House, Richard Meier
03. Villa Shodan, Le Corbusier
04. Kaufmann Desert House, Richard Neutra
05. Villa Maire, Alvar Aalto
06. Mobius House, UN Studio
07. LLC Vienna, Zaha Hadid
08. Maison Bordeaux, OMA
09. Ridgeview House, Zack de Vito
10. Farnsworth House, Mies van der Rohe
11. Koshino House, Tadao Ando
12. Hanse lmann House, Michael Graves
13. Peconic House, Mapos
14. Villa Savoye, Le Corbusier
15. Jewish Museum, Daniel Libeskind
16. Haus Schminke, Hans Scharoun
17. Double House Utrecht, MVRDV
18. Smith House, Richard Meier
19. Horiuchi House, Tadao Ando
20. Falling Water, Frank Lloyd Wright
21. La Tourette, Le Corbusier
22. Fire Island House, Richard Meier
23. Schroder House, Gerrit Rietveld
24. Sayamaike Museum, Tadao Ando
25. Lovell Beach House, Rudolf Schindler
26. Case Study House No.22, Pierre Koenig
27. Capsule K House, Kisho Kurokawa
28. Slit House, Architects H2L
29. 4X4 House, Tadao Ando
30. Delta Shelter, Olson Kundig
31. Fisher House, Louis Kahn
32. Casa DeCanoas, Oscar Niemeyer
33. Tallon House, Ronald Tallon
34. Kalmann House, Luigi Snozzi
35. Casa Gaspar, Alberto Campo Baeza
36. Magney House, Glenn Murcutt
37. Barcelona Pavilion, Mies van der Rohe
38. Shell House, Kotaro Ide

IMAGE CREDITS

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