DEEP WINNING FORM

Machine investigation of architectural quality

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Abstract. This paper showcases the development of Arch-Form, a platform that enables the investigation of underutilization of knowledge from architectural competitions, specifically within the Swiss architecture system. The aim is to leverage machine learning to analyse and understand architectural forms from school competition data spanning the past 20 years. The original contribution of this study lies in transforming competition results into a machine-learnable format, using 622 massing models to create 'architectural' point clouds. This methodology involves using 3D Adversarial Autoencoders (3dAAE) to encode and reconstruct these point clouds, experimenting with various structured formats such as uniform, horizontal and vertical g-codes. The main conclusion drawn is that machine learning can significantly aid in understanding and predicting architectural form preferences, documenting trends, and transformations in design. This approach enhances the computability of architectural forms. It offers a new perspective on how machines interpret and generate architectural data, contributing to a more comprehensive understanding of architectural evolution and societal preferences in design.

Keywords. Architectural Form, Architecture Competition, Machine Learning, Digital Representation, Point Clouds

1. Introduction

The architectural competition has long been a platform for experimentation and shaping appropriateness within various architectural cultures. As machine learning (ML) has been introduced to the field of architecture, remarkable results have demonstrated the ability of machines to learn and recognize patterns of data and generate new data. With this new capacity, the research will utilize the results of the well-organized Swiss architecture competition system as a dataset based on digital information from the past 20 years. As a means to investigate form, results from these

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competitions offer abundant data to analyse the evolution of forms and identify which forms are 'desired' by society. This paper investigates the research question: How can machines not only understand the intricacies of architectural forms but also transcend this understanding to judge the quality of the form?

In advancing previous research, this research further enhances the dataset format for improving the analytical reading and generative aspects (Kim & Huang, 2022). It also provides a visual interface to better understand machine reading of architectural form. The research utilizes 622 massing models from the results of the Swiss architecture competition, transforming them into 'architectural' point clouds for analysis with a 3D Adversarial Autoencoder (3dAAE) (Zamorski et al., 2019), which is a further developed version of autoencoder with a compact and efficient representation of point cloud models used in generation novel chair designs (Bidgoli & Veloso, 2018). The research aligns with a study on the collective analysis of forms in a particular city using deep learning, focusing on clustering based on morphological features. It investigates the relationship of building orientation on urban form identity, comparing datasets with orientation-embedded and orientation-normalized building forms to understand how direction reflects urban locality (Rhee & Krishnamurti, 2023).

The success of the training is evaluated through a comparative analysis between the input point clouds and the reconstructed point clouds. The multi-dimensional clustering strategies are developed to identify correlations across different formal groups. As part of speculative experiments, the interface visualizes the interpolation of 3D models to generate new architectural forms. The current research creates a machine-learned archive of architectural possibilities comprising a 3D dataset that indexes formal properties to the geometrical information of respective competitions and documents metadata such as architects, jury members, time factors, and rankings of the projects.

The research explores how architects can better comprehend and navigate the accumulated knowledge from architectural competitions that embody the methodological, representational, and communicative languages between humans and machines through machines' understanding of architectural forms.

2. Machine Judging

2.1. RETHINKING ARCHITECTURAL ARCHIVING

There have been many attempts to create digital archives of competition materials methodologically. These efforts involve deciduous data selection, classification methods, categorization, labelling, and presentation in a digital manner (Strebel & Silberberger, 2017). Some web-based digital archives have been developed into multiple readings of visualizing competition data, such as 3D photography of the models in the Canadian Competition Catalogue (CRC-ACME). The platform shows different readings of archives of the competition information and its winning entries, a map of competitions, and a compilation of model photos with the search system. Other platforms, such as the Seoul competition platform (Seoul Metropolitan Gov), German web platform competitions (Wettbewerbe Aktuell), and Konkurado (Web of Design Competitions) go beyond archiving and act as a platform for running the competition for tender processes. Another example is the interactive map as a platform to present the data of competitions (Association Le Concours Suisse) with search functions.

Archiving and its connected acts of description and organization express a point of view or narrative that can be an excellent lesson for designers and architects (Lam, 2021). The ML algorithms offered alternative views to organize and develop different narratives from the existing corpus of data. For example, the work (Klingemann & Doury, 2018) showcased how computer vision algorithms can be used to find the hidden relationships between thousands of artworks through visual connection. Digitalization offers archive new meaning through the decontextualization and removal of institutional authority (Birkin, 2020). ML also enables the distance reading of architectural information, as Witt (2022) demonstrated, offering new ways of comprehending what already exists and imagining the void in between.

The emergence of ML models has opened up new ways of interpreting architectural works, advancing research in areas like the analysis of architectural competitions in the context of school buildings. This involves acquiring formal knowledge of architecture to enable machine reading of form-correlated datasets, thus expanding our understanding of architectural competition winners. Unlike other building typologies, such as urban housing blocks, school competitions focus on understanding buildings as singular entities. To support this research, we have developed Arch-Form, an interactive interface designed to visualize competition data through a formal understanding of architectural form in multi-dimensional matter through ML.

2.2. ARCHITECTURAL POINT CLOUDS

Building on the previous work on the concept of 'architectural point cloud,' the current research provides several ways to invest in the relation and distribution of different models and the effect of point cloud type in the latent space. With a limited dataset, we wanted to experiment with the typical uniform point cloud, which is the most suitable one for learning architectural forms (Fig. 1). The different types of 'architectural' point clouds for include uniform point clouds, horizontal g-code-inspired point clouds, and vertical g-code point clouds. In this experimental process, two strategies are employed to scale the point clouds: constant vs. normalized scaled to 1×1×1 unit bounding box. Also, the orientation of models is considered: the aligned vs. original orientation.

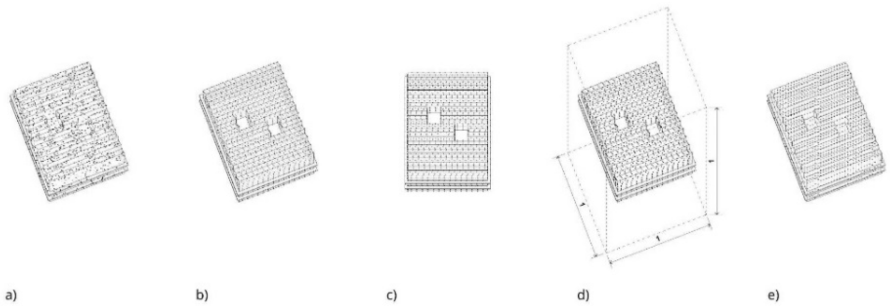

Figure 1. Different types of point clouds are a) uniform, b) horizontal, c) horizontally rotated, d) horizontally scaled, and e) vertically distributed point clouds.

To ensure that different types of architectural point clouds are comparable and meaningful for analysis, we trained the model in a way that encodes all types of point clouds into the same latent space. The training process is divided into two stages. In the first stage, the model takes only the uniform point cloud as input and tries to reconstruct the uniform point cloud as well. In the second stage, we fine-tune the model by randomly feeding different types of point clouds, but the output remains the corresponding uniform point cloud. With such a process, the model can encode different types of point clouds into the same latent space.

2.3. MAPPING THE LATENT SPACE

2.3.1. t-SNE vs UMAP

The interface provides options to view the latent representation in both 2D and 3D with t-SNE and UMAP. Both algorithms take the high dimensional latent code as input and reduce the dimension to either 2D or 3D, making it possible for humans to understand the distribution more easily. T-SNE is one of the most widely used dimension reduction methods. However, it is unable to preserve the feature in the global structure. UMAP, in contrast, can better keep the global structure, making the low-dimension visualization more intuitive and meaningful.

2.3.2. Metadata (rank, competition, jury, etc.)

Exploring the distribution of different models with the same metadata is one way to investigate the relation between form and its result in the competition (Fig. 2). The interface provides two ways for visualizing the cluster metadata — by colour and line. Although it might be easier to view the distribution of a continuous property, e.g., similarity, with a gradient colour distribution, colour is not easily distinguishable for discrete data, such as rank or competition (Fig. 3b&c).

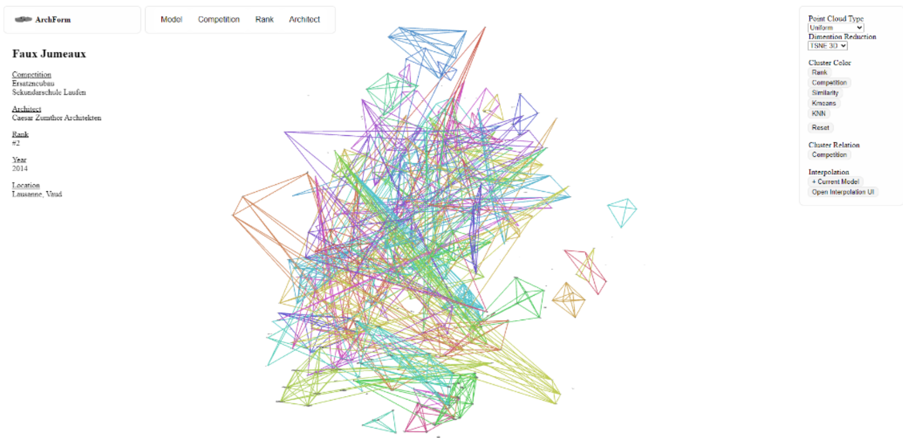

Figure 2. Image of the interface showing the metadata (left), search function (top), and machine learning analysis visualization (right), with cluster relations between different competitions with machine reading of forms in 3D (middle).

Therefore, the interface provides line-based clustering visualization, which links all the models that share the same property or lie in the same analysis group. For example, we can connect all models within the same competition. With such links, we can quickly tell if there are outliers, in terms of form, in one competition. We can further analyse its performance and build constructive design strategies in future competitions.

2.4. MULTI-DIMENSIONAL CLUSTERIZATION

2.4.1. K-means

The initial idea is to show the clustering of the architectural form (Fig. 3d). However, there needs to be a meaningful way to elaborate the clustering as we still need labelled semantic information. This feature will provide an easily integrated socket for visualizing future training results.

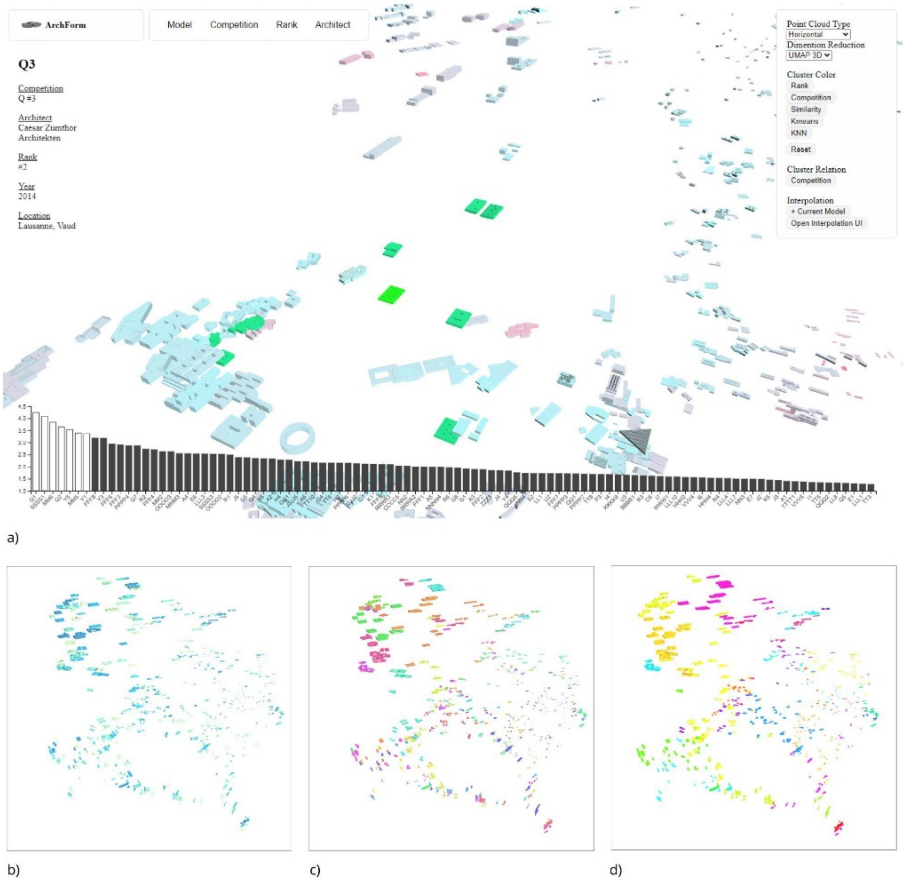

Figure 3. Image of the interface showing: a) 3D UMAP of forms coloured by similarity with selected competition model and similar models in form, b) coloured by ranking, c) coloured by competitions, and d) coloured by formal cluster.

2.4.2. Similarity

To answer the question, "Which form is similar to another?" from the ML model's view, the most intuitive way is to visualize the similarity across different models' latent codes. Although the result of t-SNE or UMAP provides some clue of similarity, the information is distorted with the loss of high-dimensional data. Thus, there should be another way to showcase the similarity directly with the high-dimensional latent code. The interface visualizes the similarity in two ways: bar chart and colour (Fig. 3a). First, the user should choose the "target model" to explore, and the system will draw all the other models based on their similarity -- the most similar model would be blue, the most unlikely one would be red, and the rest would be the linear interpolation of blue and red based on the similarity. The bar chart quantifies the similarity, which makes it easier to tell how different these models are. To explore the variation of the latent representation across different point cloud types, when switching the point cloud type on the interface, which translates the model to the corresponding position assigned by the new dimensional reduction method, the color representing the similarity preserved as well as the order of the models in the bar chart. In this way, humans can visually see the ML model's perspective transformations toward different types of point clouds.

2.4.3. K-Nearest Neighbor (KNN)

Besides the global view of similarity, another way to explore locally is through the k-nearest neighbour, where the system finds k models with the most similar forms from the target and uniformly paints them with a randomly assigned color (Fig. 3a green highlight). Likewise, when the point cloud type changes, the colour does not change. Furthermore, if KNN is queried again, the system finds its k-nearest neighbours with the new point cloud type. Instead of erasing the previous colour and replacing it with the new one, the colour is painted additively. We can tell if the nearest neighbours change across different point cloud types and if one model is the target's neighbour regardless of the change of point cloud types.

2.5. FORMAL INTERPOLATION-GENERATION

2.5.1. Interpolation

The equation governs the linear interpolation $\sum \quad (L_i \times W_i) \,/\, \sum \quad W_i$, where L_i is the latent code of model i, and W_i is the weight of model i, which is a user-defined parameter. The system linearly interpolates the form with the user-defined weight to generate forms of, for example, 10% of Model A, 20% of Model B, and 70% of Model C by assigning the weight respectively (Fig. 4). The user can select two or more entries and set the weight of each model. The corresponding interpolation would be generated based on the linear interpolation on the latent space. Latent space interpolation can create new architectural forms embodying different winning entries' qualities.

We adopted multiple methods to reconstruct the mesh from the point cloud to visualize the interpolated result better (Fig. 5). PolyFit (Nan & Wonka, 2017) can generate a watertight mesh with sharp edges and flat walls, which might be a suitable algorithm for reconstructing an architectural 3D model. However, since it's based on point cloud segmentation and plane estimation, it requires a clean and dense point cloud.

The interpolated point cloud generated by 3d-AAE contains many noisy outliers. Also, it does not have enough points in the smaller segment to support the plane estimation, making PolyFit fail to produce satisfactory results.

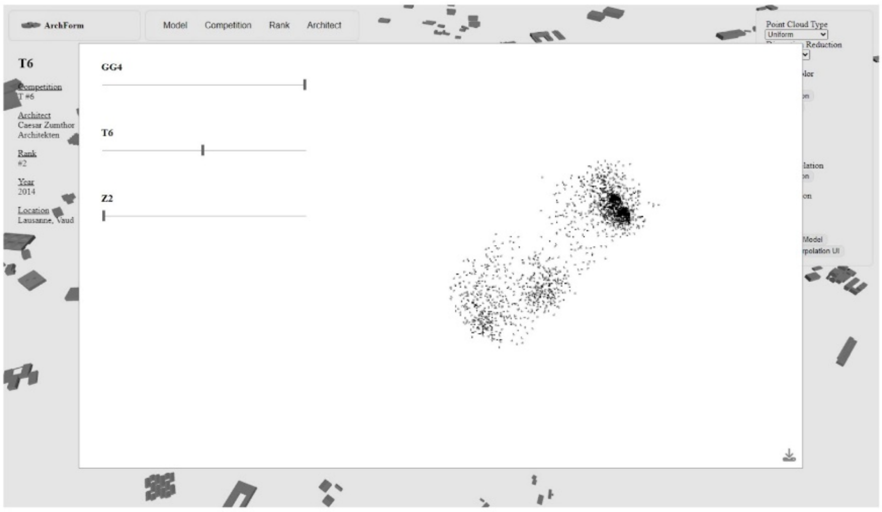

Figure 5: UI for form interpolations.

On the other hand, with Rhino's function Proximity3D or ShrinkWarp, models with more meaningful forms can be reproduced. Proximity3D aggregates points and connects them with lines, which can then be turned into meshes. However, it does not guarantee the result to be a solid volume and often produces degraded results when the input contains noise. ShrinkWrap creates a 3D alpha shape over the point cloud (Portaneri et al., 2022), which guarantees that the result is a watertight solid volume. The result can be further processed with QuadRemesh to eliminate the defects.

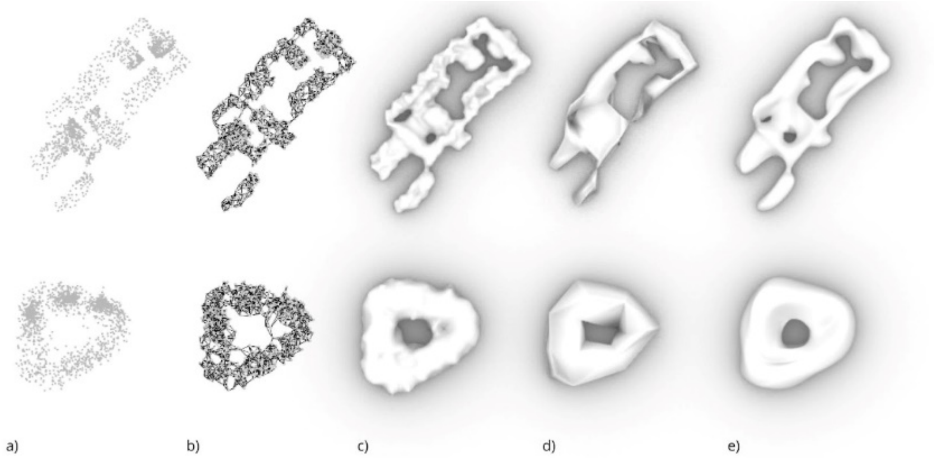

Figure 5: (a) interpolated point cloud, result formed by (b) Proximity3D, (c) result formed by ShrinkWrap, (d) ShrinkWrap + QuadRemesh, and (e) ShrinkWrap + QuadRemesh, turn into SubD.

3. Results and Discussions

3.1. FROM HIERARCHICAL TO RELATIONAL ARCHIVE

Arch-Form employed dimensionality reduction strategies such as t-SNE and UMAP to extract meaningful low-dimensional structures from the high-dimensional latent space combined with visualization techniques showing clustering and similarities, facilitating an understanding of the relational characteristics between different forms. The ability to map the latent representation of the architectural form in conjunction with traditional architectural metadata can provide insightful interpretations. For example, Figure 6 shows how the shortlisted entries from the same competition are relatively close to each other, presumably because the formal results of the building mechanically respond to the context, brief, and programs. However, on some occasions, one or two entries are away from the rest of the entries from the same competition, denoting the distinct formal proposition, which can indicate innovation or the 'out of the box' thinking of the architect. These entries are some of the most provocative, making them different. The ability of machines to identify and emphasize such outliers emphasizes their potential as valuable tools for uncovering unconventional perspectives that may otherwise go unnoticed.

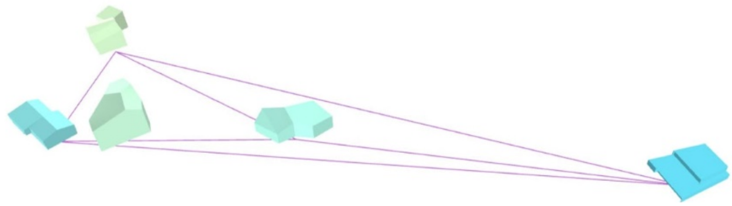

Figure 6. Distinctive formal proposition that sits apart from the other entries in a single competition. The entry's rank is denoted by darkness, where darker colours represent the highest ranking.

The developed platform showcases the capacity of ML algorithms to uncover connections between winning forms, transcending traditional categorizations, and revealing novel perspectives. This can encourage architects and designers to embrace creative thinking and consider alternative formal propositions. The developed platform enables the investigations of these different formal relationships determined by data, sampling strategies, and ML algorithms. Together with conventional architectural metadata, the platform allows for the creation of new relationships from a formal point of view that not only aids in interpreting architectural data but also becomes a catalyst for pushing the creation of new formal architectural vocabularies.

3.2. NAVIGATING ARCHITECTURAL POSSIBILITIES

The machine's latent space enables architecture mapping into a high-dimensional world, breaking the discrete, pre-existing architectural categorization into a single continuous domain (Chaillou, 2022). In contrast to low-dimensional spaces that we experience, so much empty space is created between data points mapped in high-dimensional spaces (Rohlf, 2021). However, our intuition about high-dimensional space is unreliable, and common concepts such as distance and density of data points have little meaning to the reading. Interpolation is one possible method of exploring the voids between data points in the high-dimensional latent space that have been commonly employed in generative ML applications for architectural design (Huang et al., 2021; Mayrhofer-Hufnagl & Ennemoser, 2023).

Therefore, the interpolation function in Arch-form suggests the importance of voids between data points in high-dimensional latent as a medium for navigating architectural possibilities between the winning forms (Fig 7). In conjunction with conventional architectural metadata, latent space interpolation can generate alternative formal propositions given a set of parameters. The challenge is to enable meaningful interpolations that are relevant to architectural context. Much research has been done to investigate the latent space structure of generative models in the visual domain (Asperti & Tonelli, 2022; Liu et al., 2019). This platform is a testing bed for different deep generative models and interpolation techniques in the 3D data domain, particularly for architectural forms.

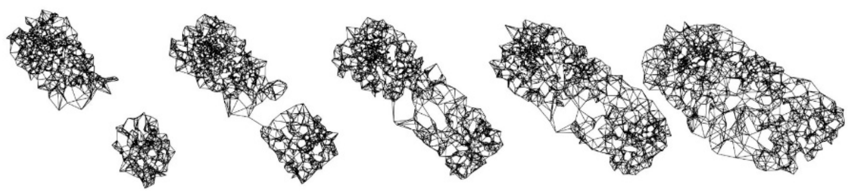

Figure 7: Interpolation of two competition entries.

4. Conclusion and Future Work

This research liberates the use of architectural archives beyond their conventional users, i.e., architectural historians, to the broader audience of practicing architects. By leveraging the ML point cloud to analyze an archive of Swiss school competition data spanning the past 20 years, we seek techniques and methods to reveal the underutilized knowledge valuable for leveraging our understanding of architectural forms. We developed Arch-Form as a platform to enable holistic reading of multiple competition entries compared to conventional individual views of a single competition, allowing the learning of the evolution of form and providing insight into architectural forms that manifest into the cultural zeitgeist and innovations. The developed platform aims to provide a testing bed to map and read the competition differently by coupling traditional architectural competition metadata with ML of architectural forms and visualization techniques. Architectural form is a token of broader architectural data, providing contextual and relational evidence to study the vast repertoire of winning architectural forms. The tools also provide means to generate architectural forms from the learned formal vocabularies through interpolations.

The developed platform suggests several promising future directions of research. In terms of data, the advancement of 3D ML has extended beyond point cloud representation. Finding suitable and robust representations for 3D architectural formats for different scales will advance the proposed platform on a broader scope. The current ML models only learn the point cloud data. The use of multi-modal ML, incorporating metadata like environmental performance, material usage, and urban context, along with LLMs, can leverage the textual information of the competition. This approach provides a more comprehensive understanding of architecture. Furthermore, advanced

3D reconstruction methods from the point cloud can be implemented, involving normal computation and Poisson surface reconstruction for generating new precise forms.

Providing a comprehensive view of architectural forms embodying competition metadata, the interface should allow architects to freely curate, cluster, categorize, and compare different formal qualities of architecture for the design process. Still, humans must carefully compare various ML experiments on visualizations of mapping of formal affinities; there needs to be a way to mathematically and empirically compare the 'strong' forms. The latent space interpolation could also go beyond typical linear interpolation. Research in the visual domain has shown different ways of creating meaningful latent space interpolation given various generative models. The future aim is to extrapolate the research into the 3D architectural domain to enable meaningful exploration of architectural forms.

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