# Evaluation of Geometric Similarity Metrics for Structural Clusters Generated using Topology Optimization

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**Research article**

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# Abstract

In an engineering design process, multitudes of feasible designs can be automatically generated using structural optimization methods by varying the design requirements or user preferences for different performance objectives. Design exploration of such potentially large datasets is a challenging task. An unsupervised data-centric approach for exploring designs is to find clusters of similar designs and recommend only the cluster representatives as designs for review. Similarity can be defined on a purely functional level but also based on the geometric properties, such as size, shape, and topology, which are important at the early stages of design engineering. Different metrics exist to measure geometrical differences, e.g., voxel distance, chamfer distances, or Euclidean distance in the reduced representation of the high-dimensional 3D geometric data. It is not clear which of the numerous metrics is best suited for exploring designs obtained in structural optimization. For example, chamfer distance intuitively measures the geometrical differences but is expensive. Euclidean distance with low-dimensional geometric features, when meaningful, provides features that can be associated with designs, which eases the visualization and exploration of a design dataset. To evaluate different metrics in the context of design exploration, we propose a novel approach to quantify certain useful properties of a metric such as the ability to capture intuitive geometrical differences and to identify similar designs in topologically-complex synthetic datasets using clustering, an unsupervised machine learning method. From our results, we conclude that dimensionality reduction techniques, namely, UMAP (Uniform Manifold Approximation and Projection), and PCAE (Pointcloud Autoencoder) are promising in encoding geometric features that enable us to integrate geometrical properties with performance attributes.


# Full Text

Due to technical limitations, full-text HTML conversion of this manuscript could not be completed. However, the latest manuscript can be downloaded and accessed as a PDF.

# Figures

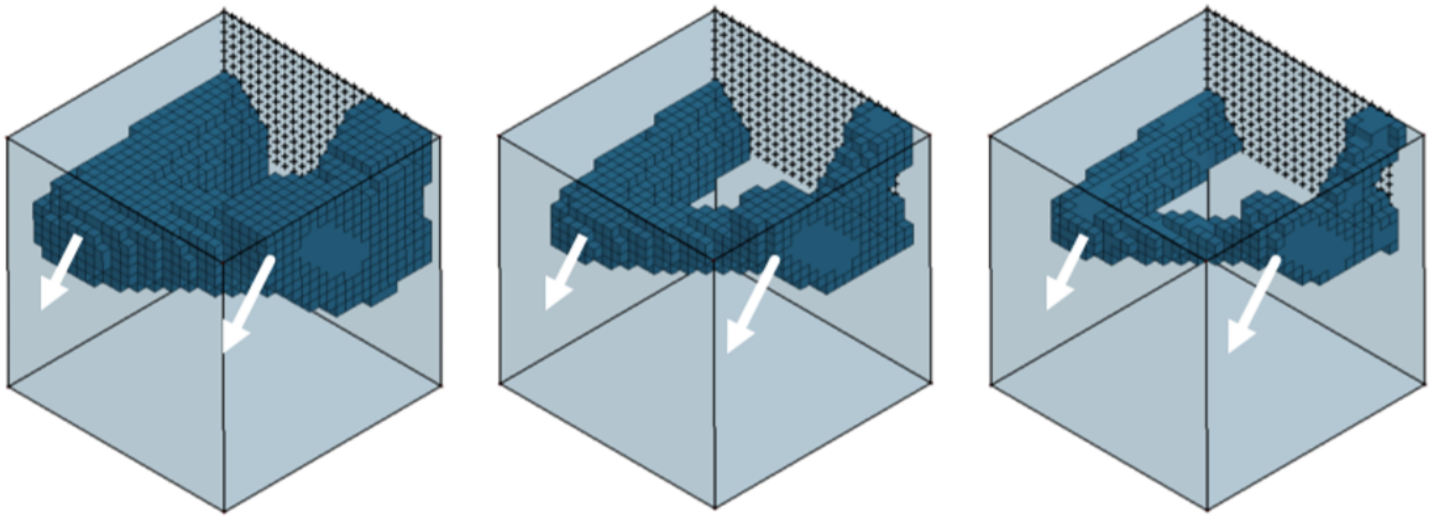


**Figure 1**

TO designs optimized for structural compliance and constrained to different volume fractions in the cubic design space. The optimization objective is structural compliance of the design under two fixed loads, shown by white arrows, with a fixed boundary. The allowed volume fraction is ranging from 0.3 to 0.1, from left to right.

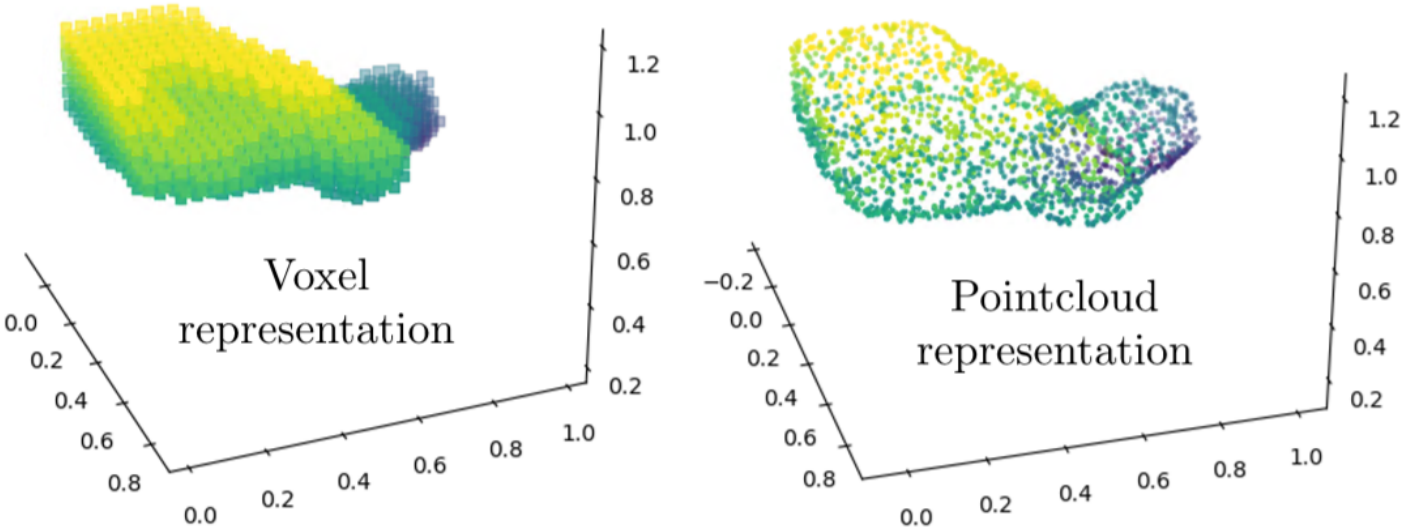



**Figure 2**

Geometric representations

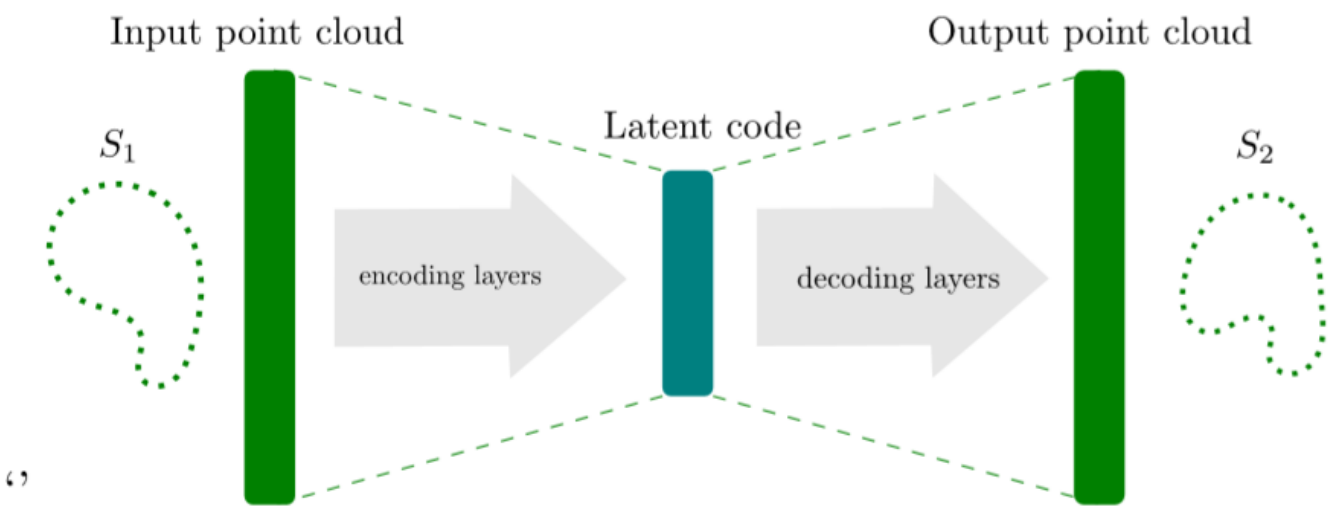



**Figure 3**

Pointcloud Autoencoder

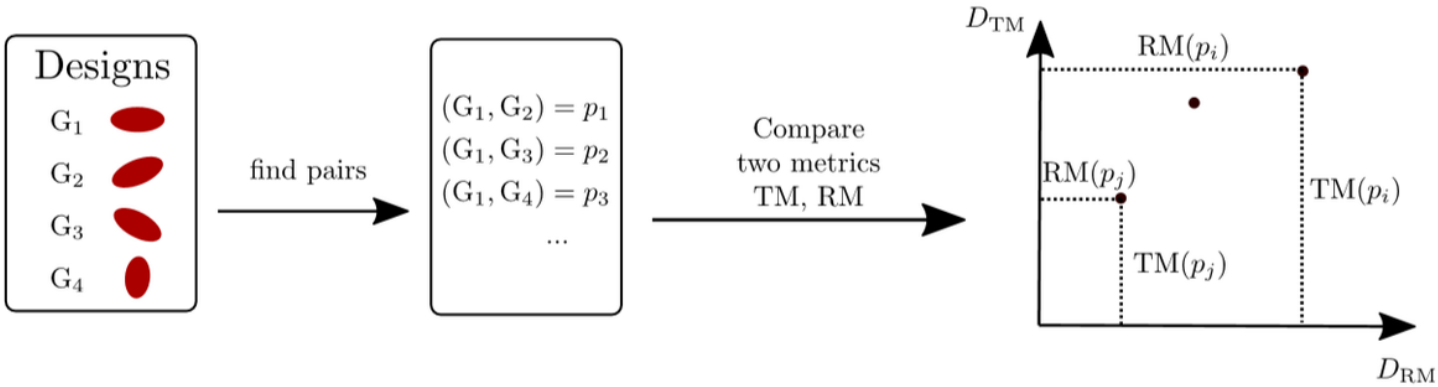



**Figure 4**

Workflow to measure similarity between two metrics RM and TM. Identify different possible pairs of geometries in the dataset. For each pair pi, each metric gives a distance value. Two metrics will yield a tuple of values shown as a point in the comparison graph. A high correlation between x- and y-values indicates that the metrics are similar.

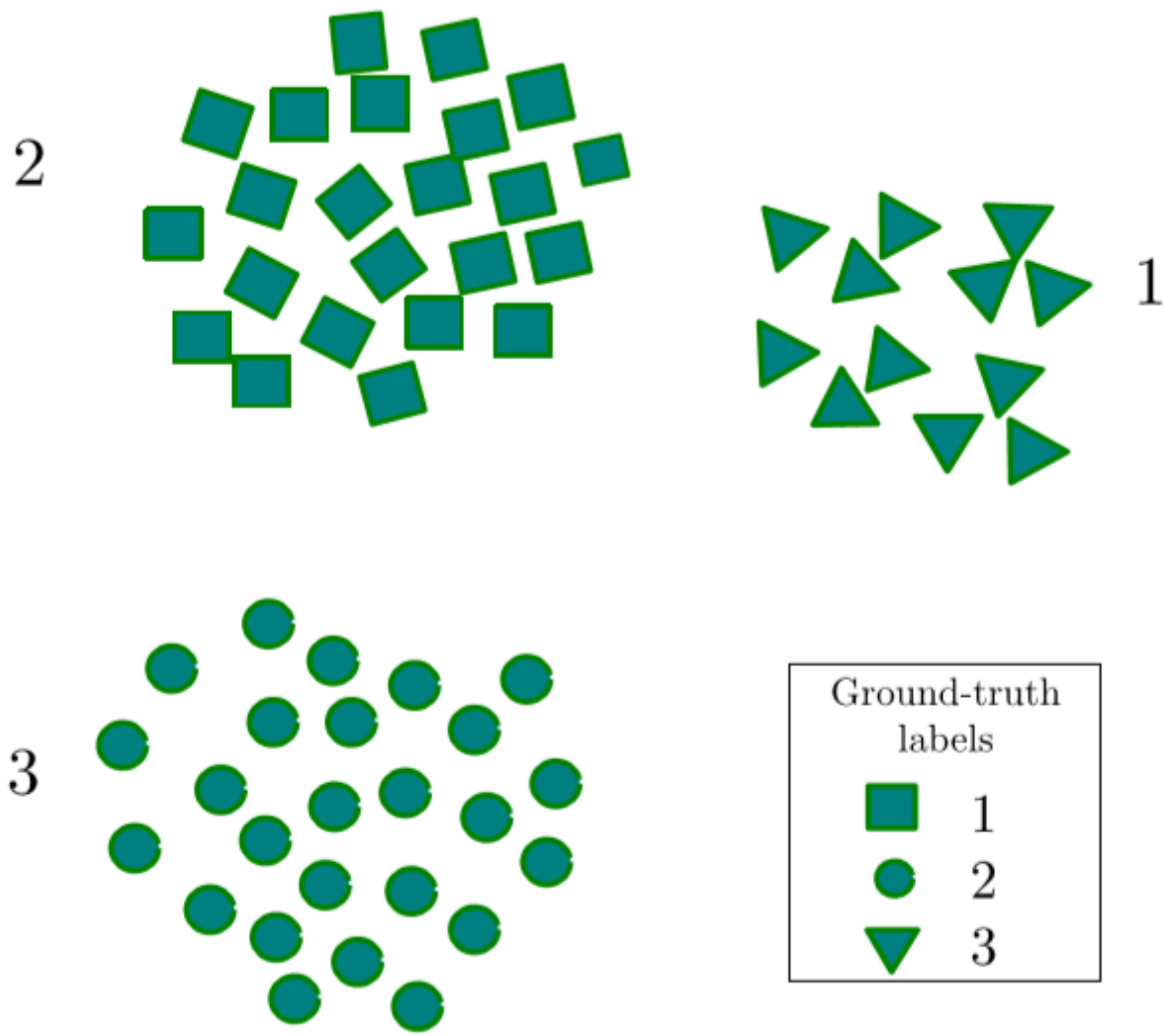



**Figure 5**

Clusters of designs: Ground-truth labels are different from labels (shown beside clusters) obtained by clustering. The label matching method maps the ground-truth labels 1,2,3 with cluster labels 2,3,1 respectively.

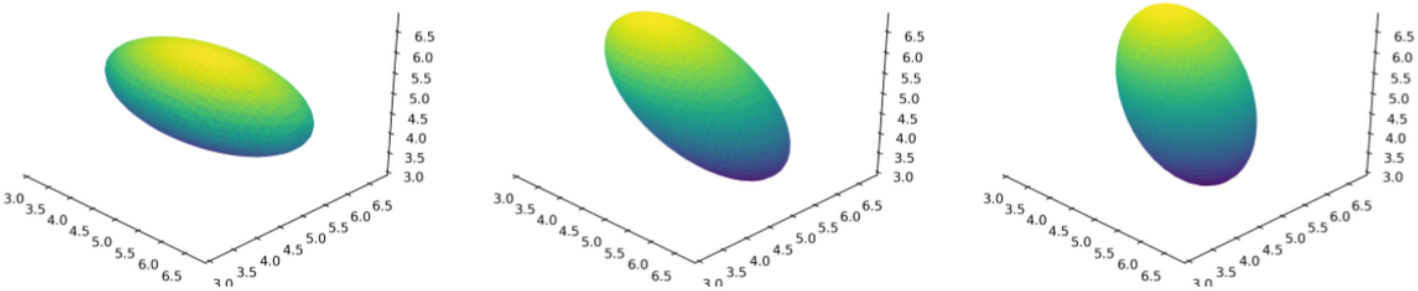


**Figure 6**

Beam-rotation dataset: A beam is rotated by different angles to create different designs.

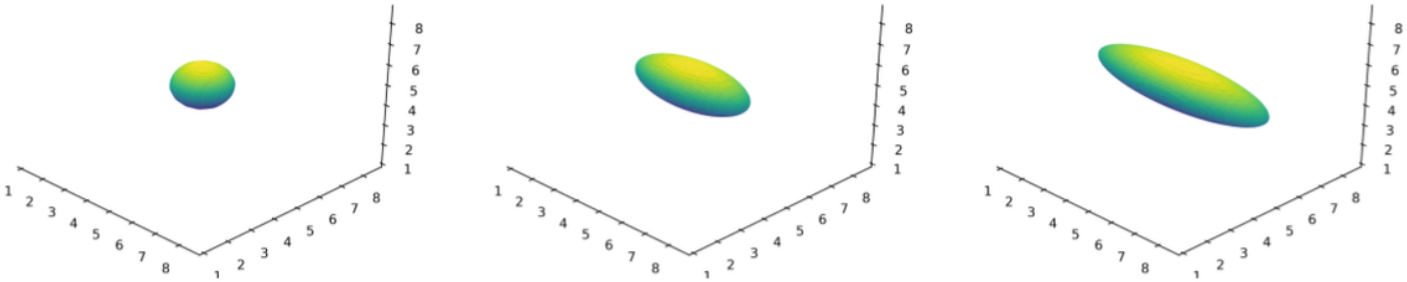


**Figure 7**

Beam-elongation dataset: A beam is elongated to different lengths to create different designs.

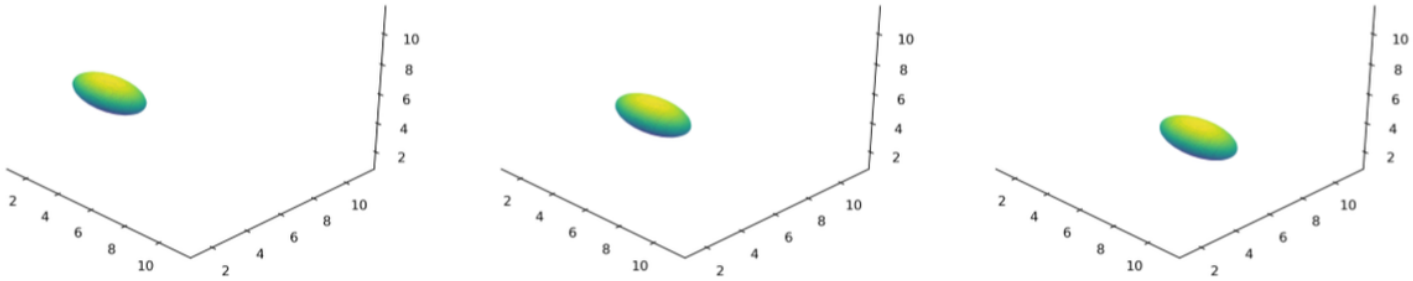


**Figure 8**

Beam-translation dataset: A beam is translated by different amounts to create different designs.

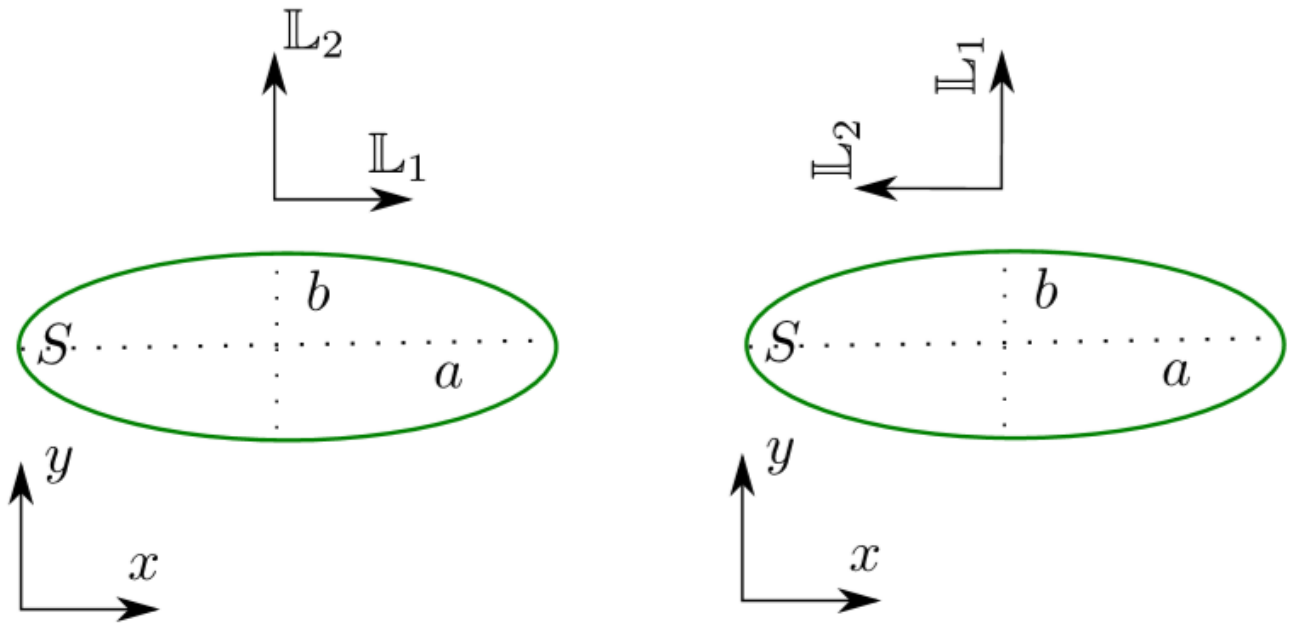



**Figure 9**

Redundancy of MMC parametrization illustrated in 2D. Let an MMC in 2D be parametrized by (l1,l2,θ°) where l1,l2 are the lengths along the two principal axes L1,L2, and a rotation angle θ between L1 and x axes. Now S can be parametrized in two ways: (1) S = (a,b,0°) and (2) S = (b,a,90°), i.e., the principal axes are reversed.

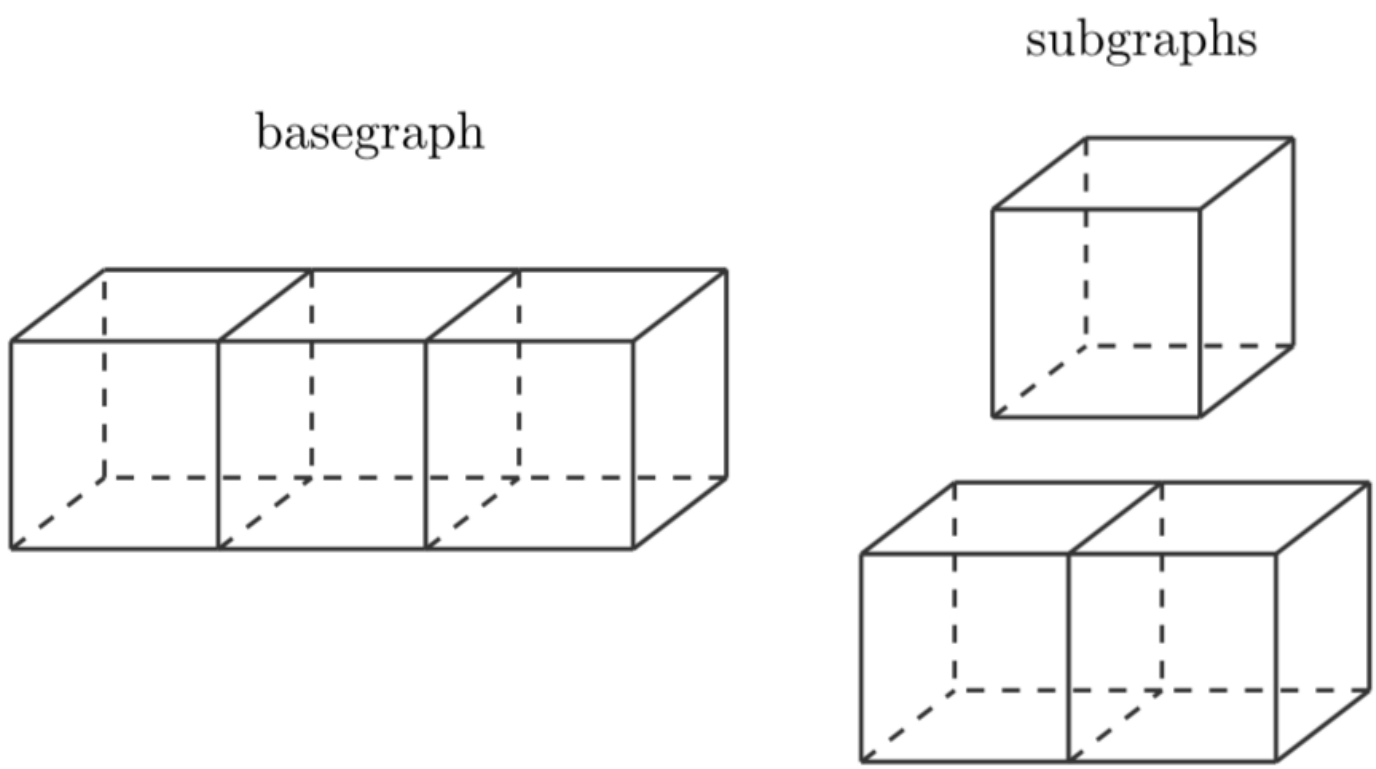



**Figure 10**

Three cube basegraph and subgraphs: Each subclass of designs is restricted to a subgraph of the basegraph. Hidden edges in the basegraph are shown as dashed lines in the basegraph and subgraphs.

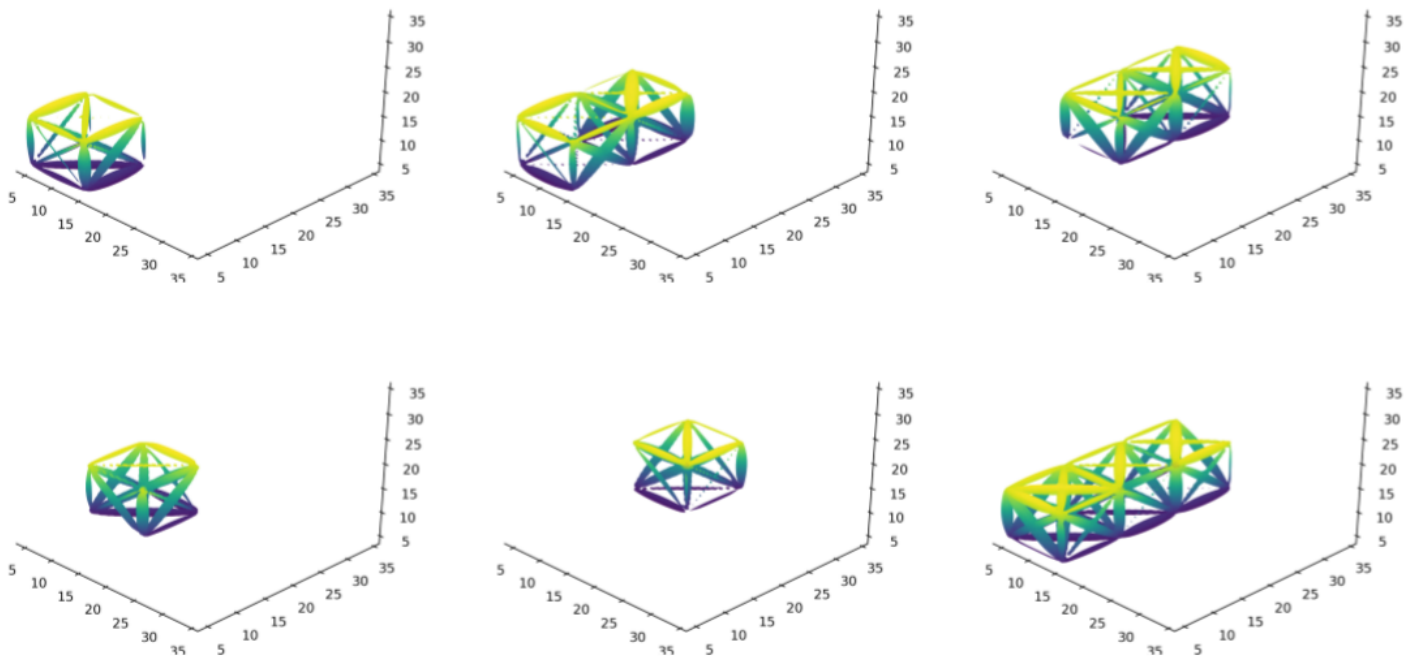
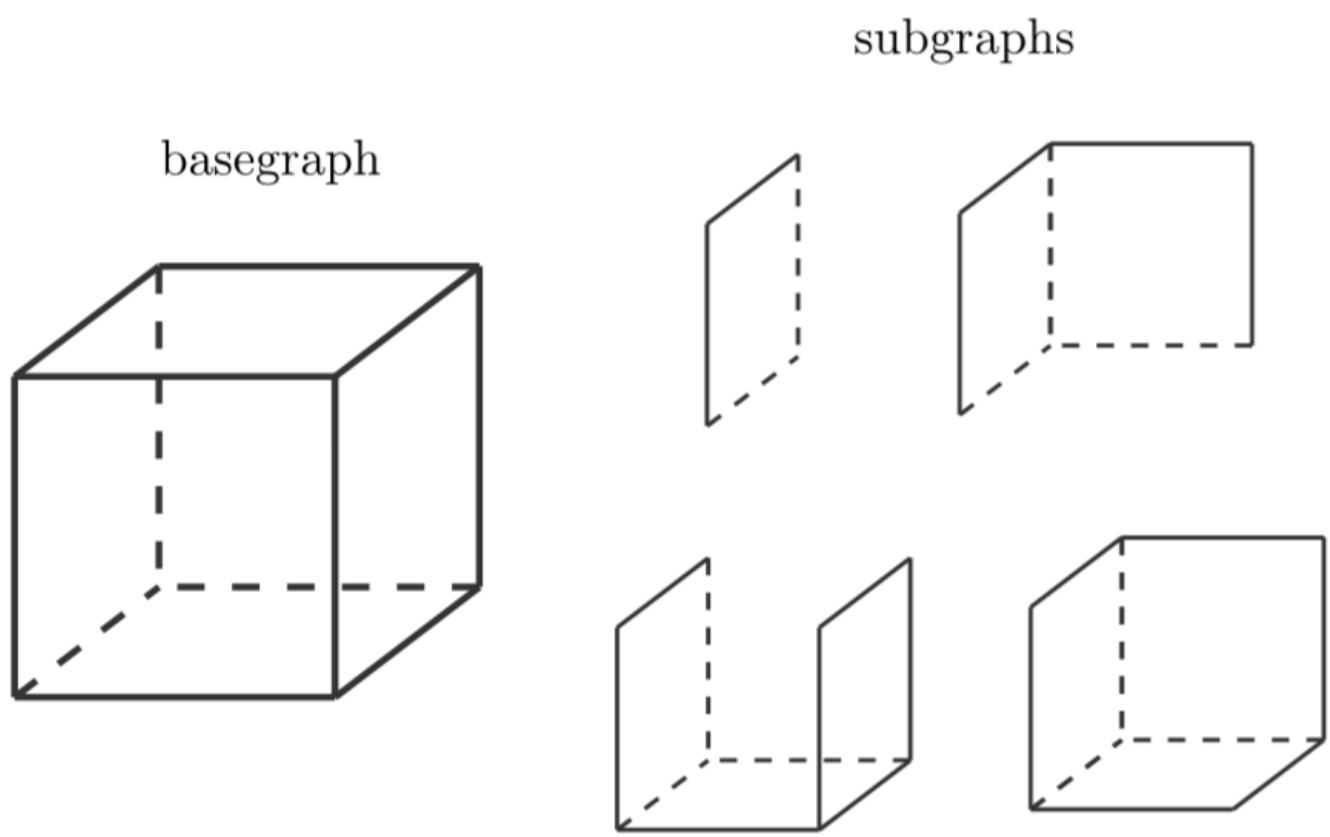


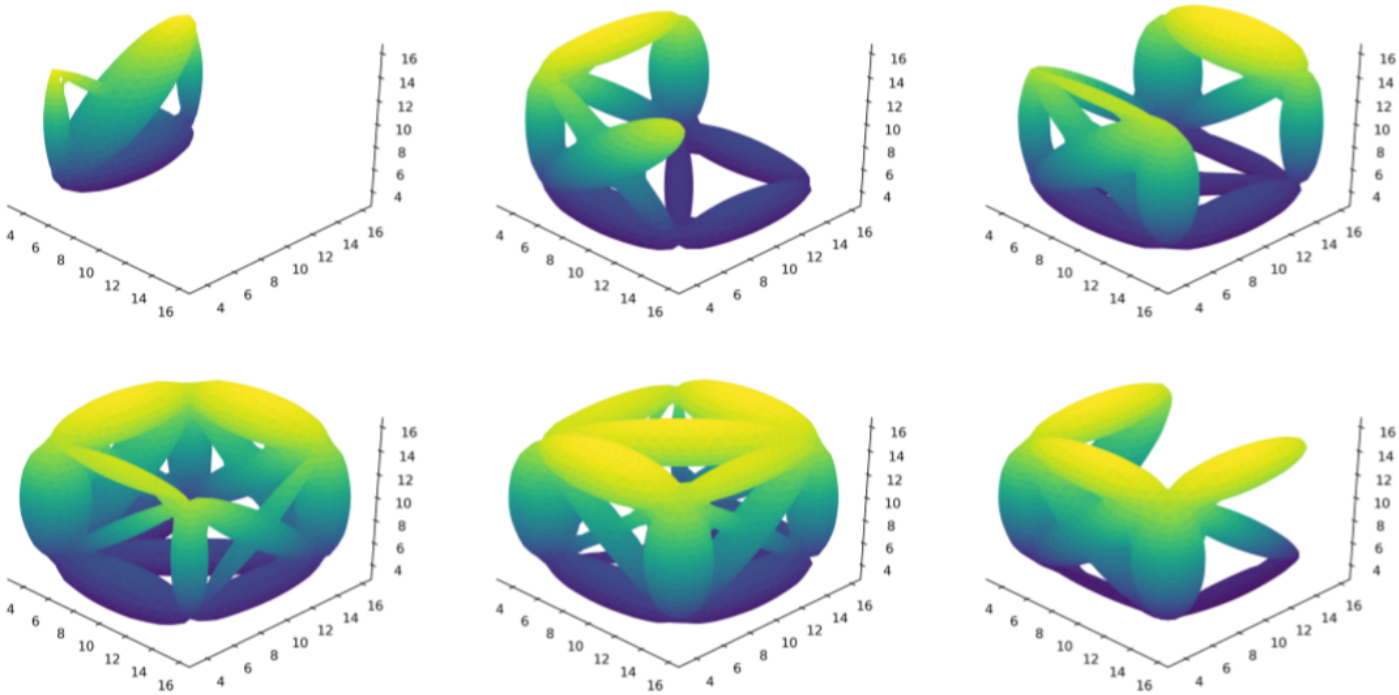
**Figure 11**

Three cube truss dataset: Samples from 6 different subclasses are shown.



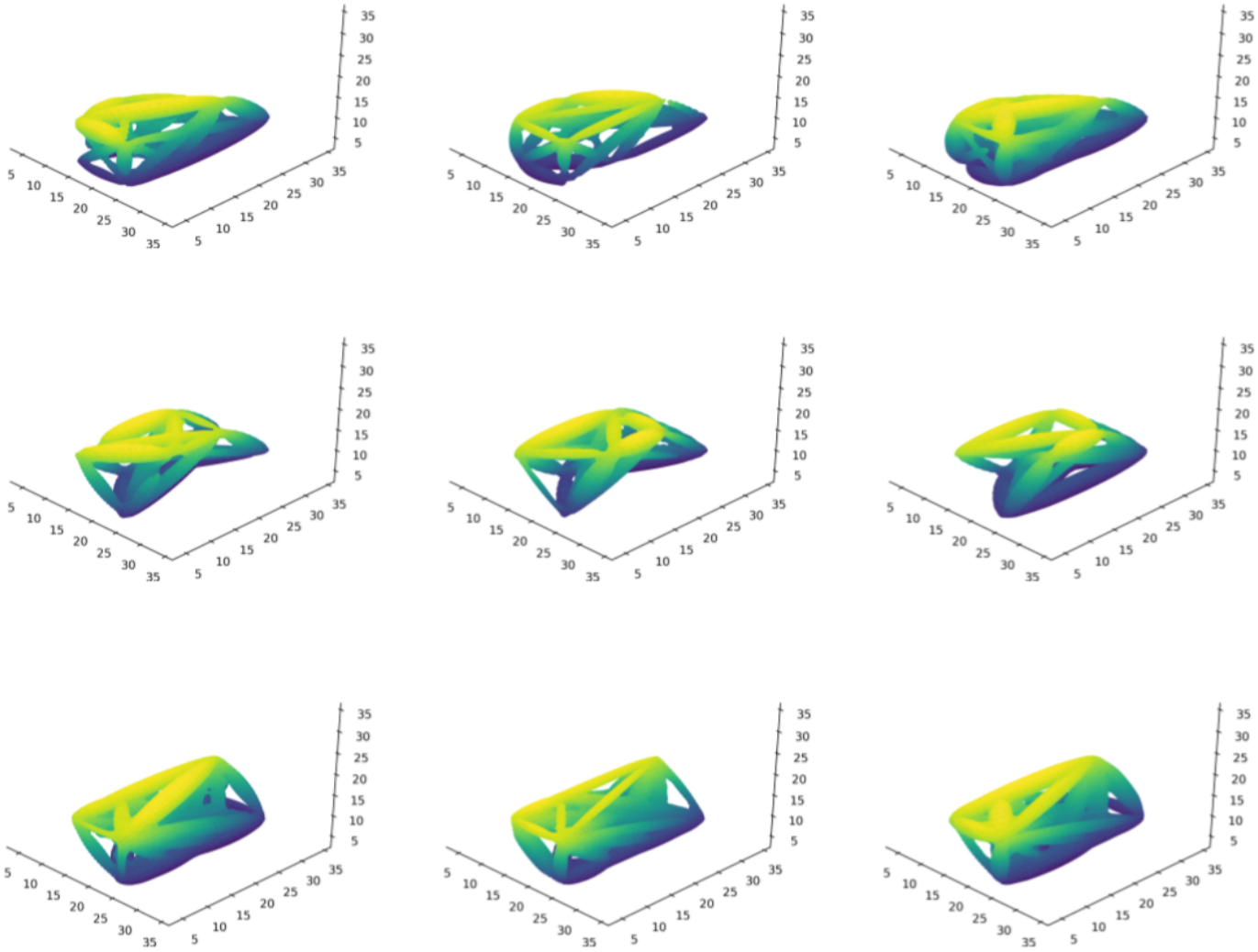
## Figure 12

Single cube basegraph and subgraphs: Each subclass of designs is restricted to a subgraph of the basegraph. Hidden edges in the basegraph are shown as dashed lines in the basegraph and subgraphs.



## Figure 13

Single cube truss dataset: Samples from 6 different subclasses are shown.



## Figure 14

Randomized topologies: Each row shows designs from a subclass. With low probability, beams are cut or/and removed.

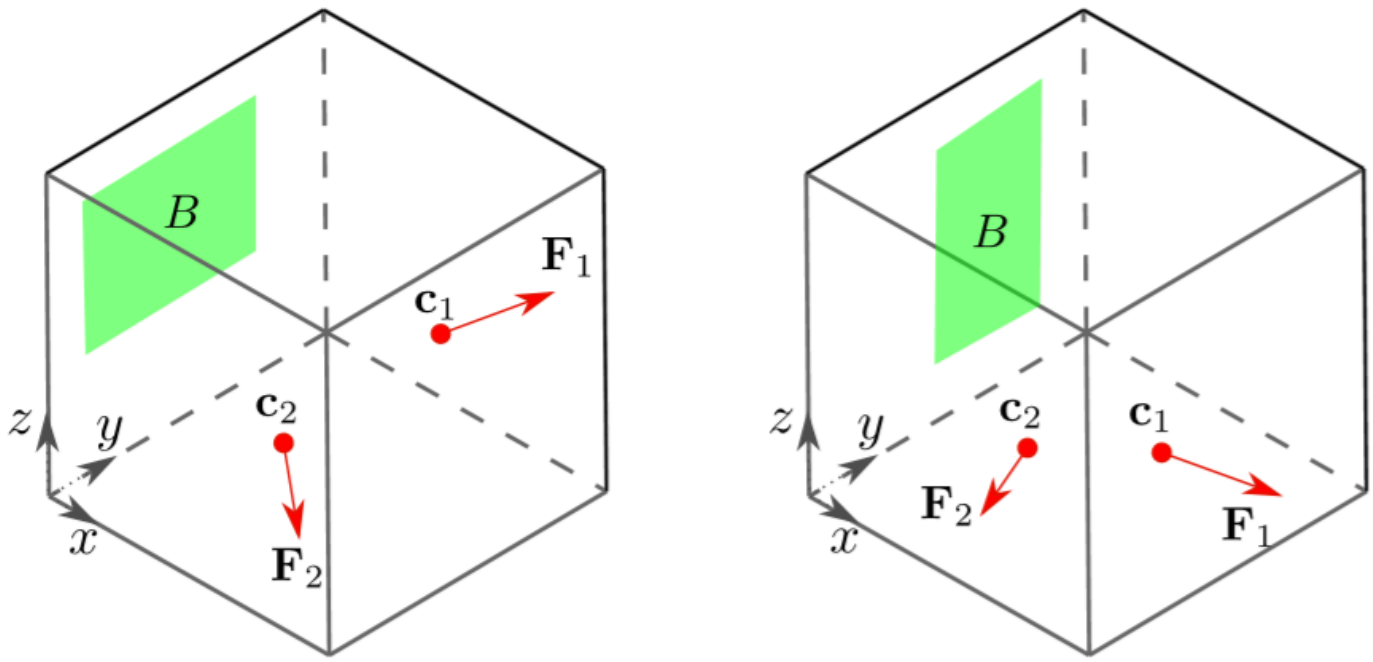
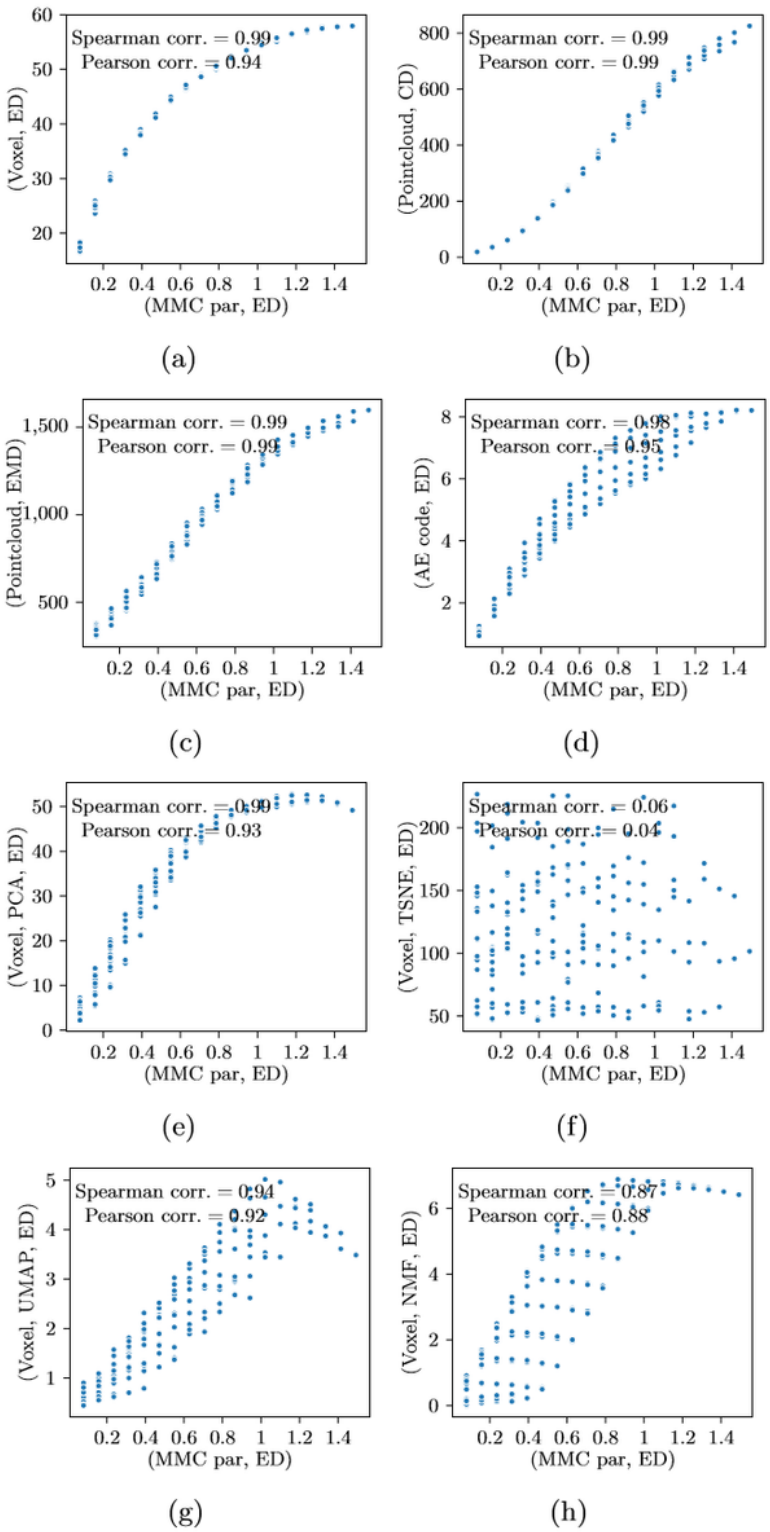


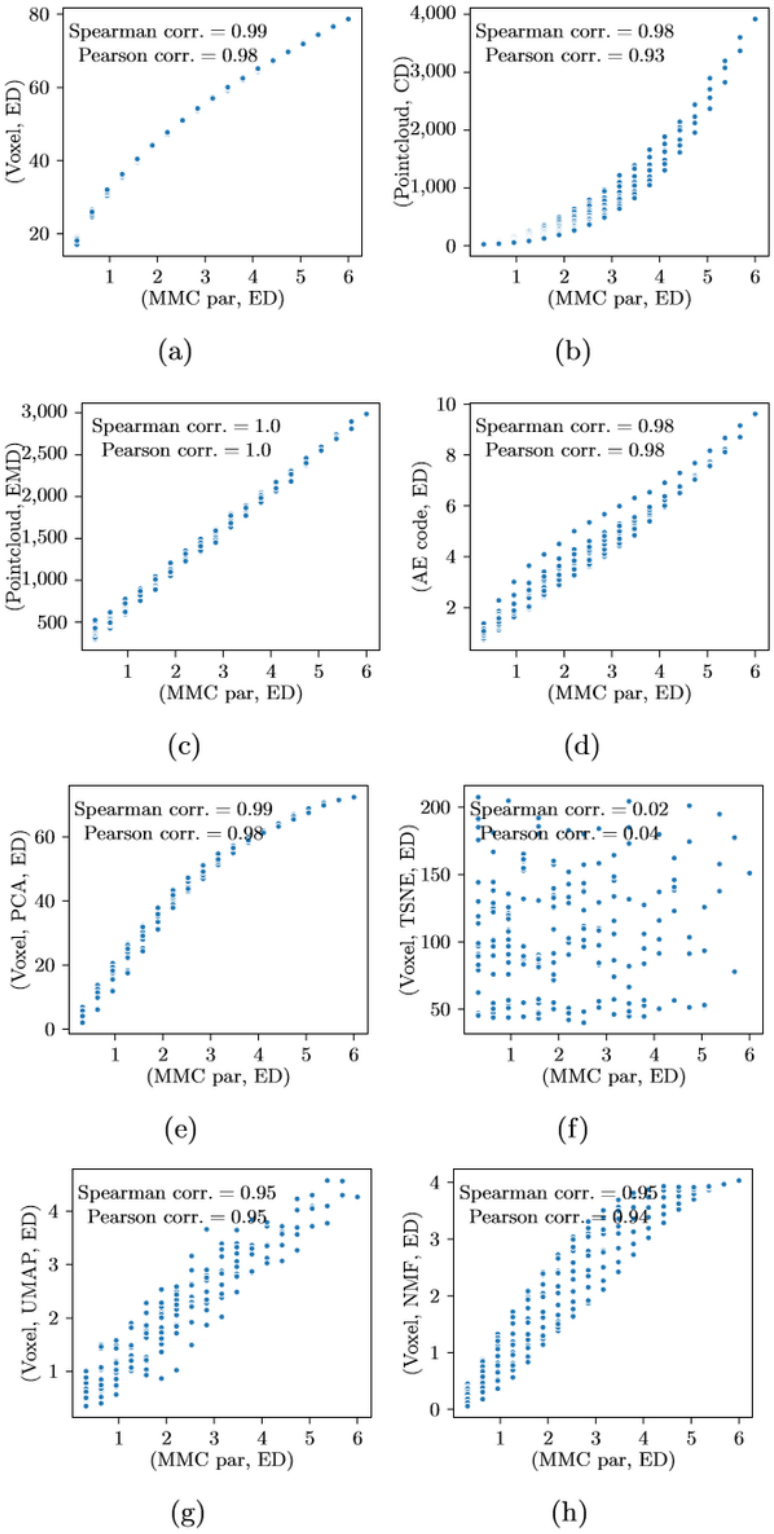

**Figure 15**

TO in a unit cube: Two possible configurations of boundary conditions. The objective is to minimize structural compliance under radial loads F1 and F2 (centered around the points c1 and c2) given an arbitrary rectangular boundary patch B in a fixed face.



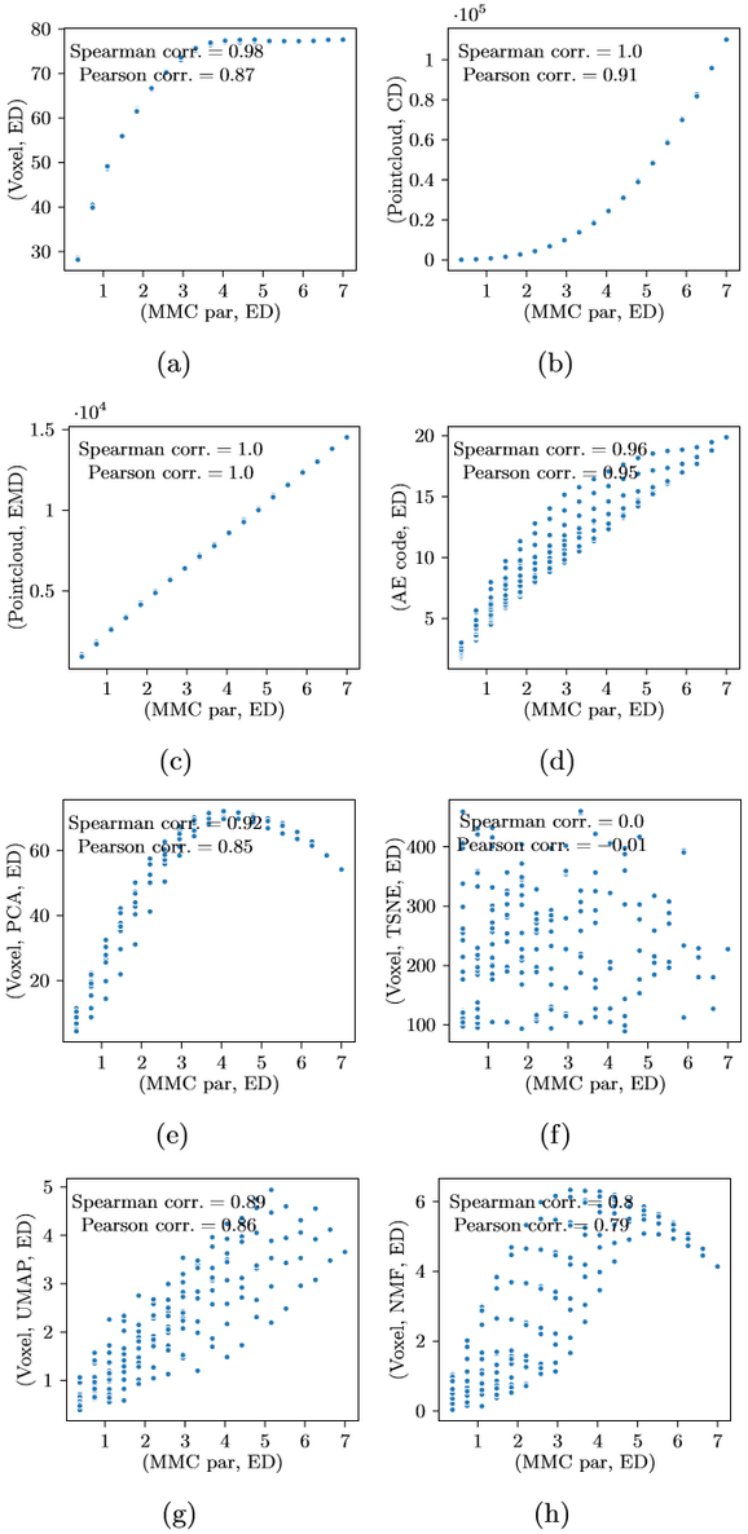

## Figure 16

Metric correlations for the beam-rotation dataset: Voxel distance and Pointcloud based metrics correlate well with differences in orientation.




## Figure 17

Metric correlations for the beam-elongation dataset: Voxel distances and Pointcloud based metrics correlate well with differences in design length.




## Figure 18

Metric correlation for beam-translation dataset: Pointcloud based metrics correlate well with differences in position.

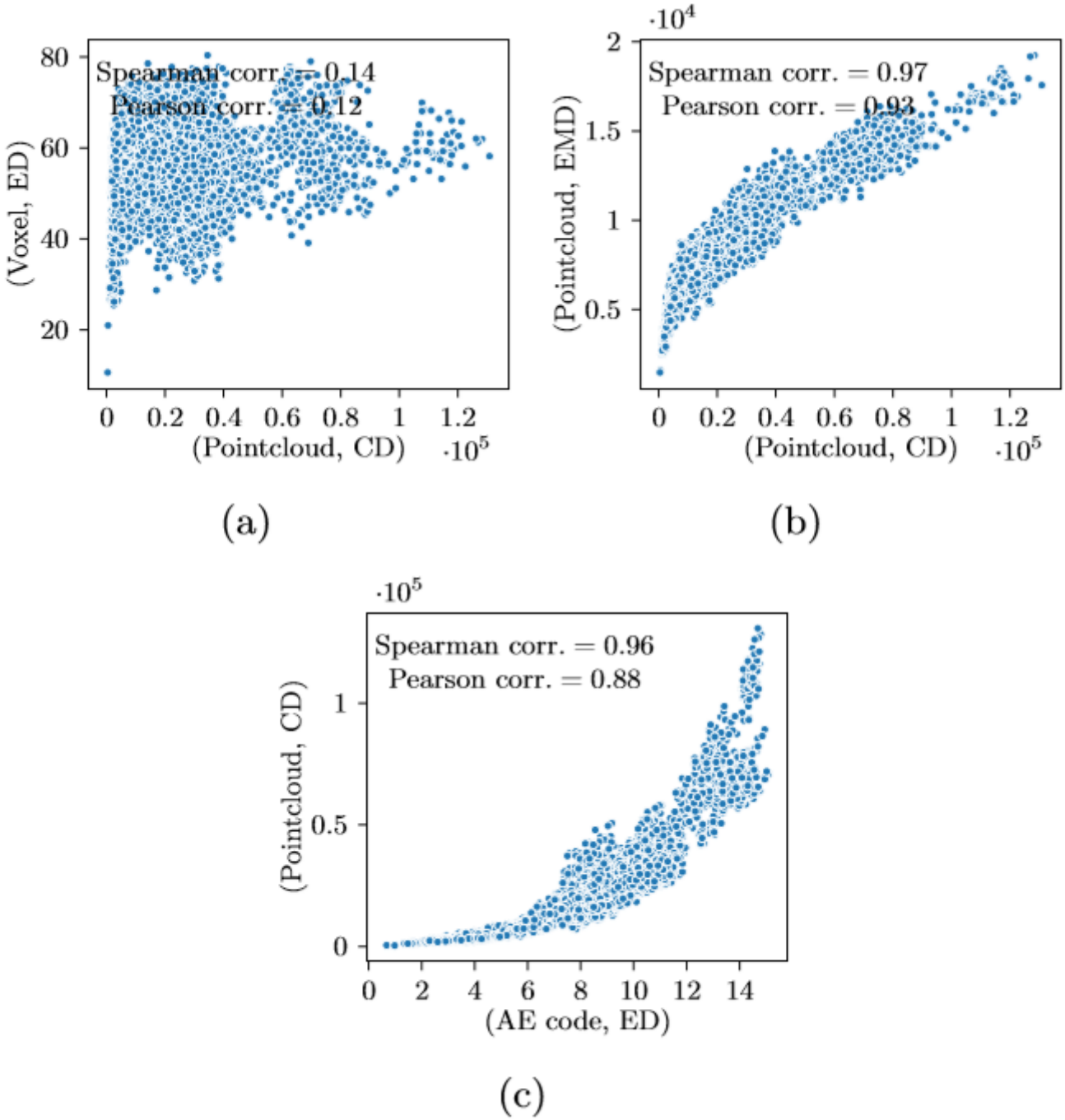



**Figure 19**

Metric correlation for single cube truss dataset

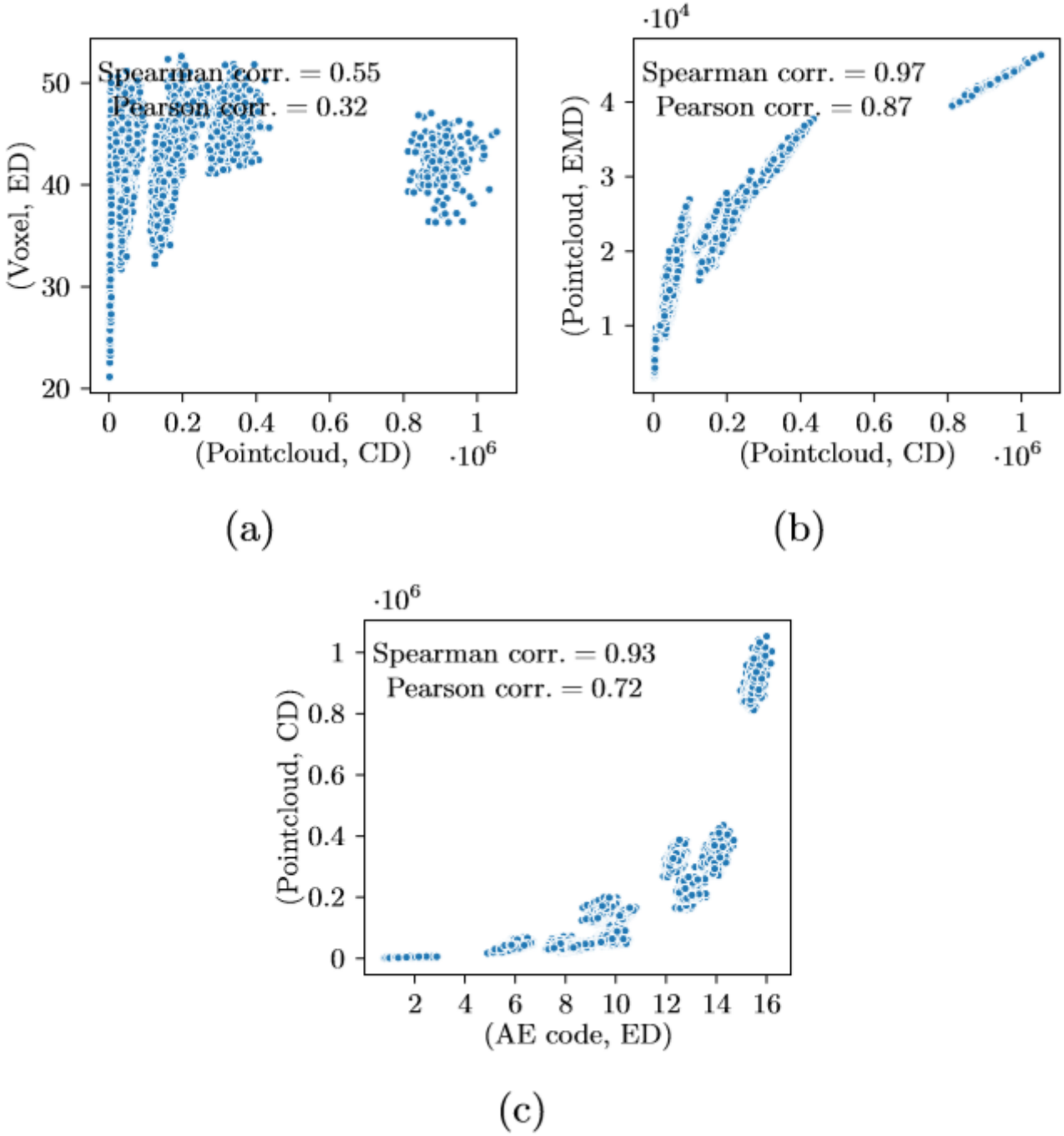
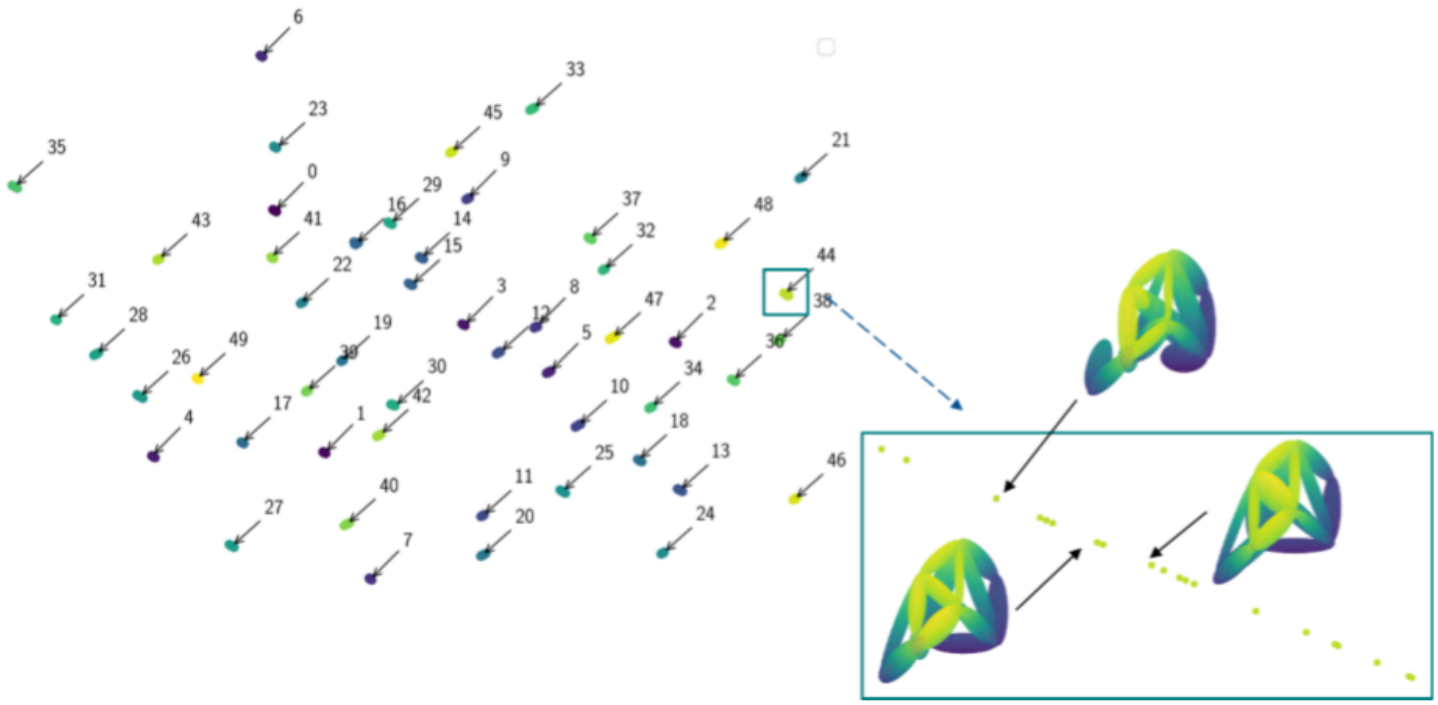



**Figure 20**

Metric correlation for three cube truss dataset




## Figure 21

Visualizing design clusters in the AE code data using UMAP. Each cluster is a set of 2D points with each point representing a design. The dataset contains 50 clusters, numbered from 0 to 49. The inset shows the 44th cluster and three sample designs in it.

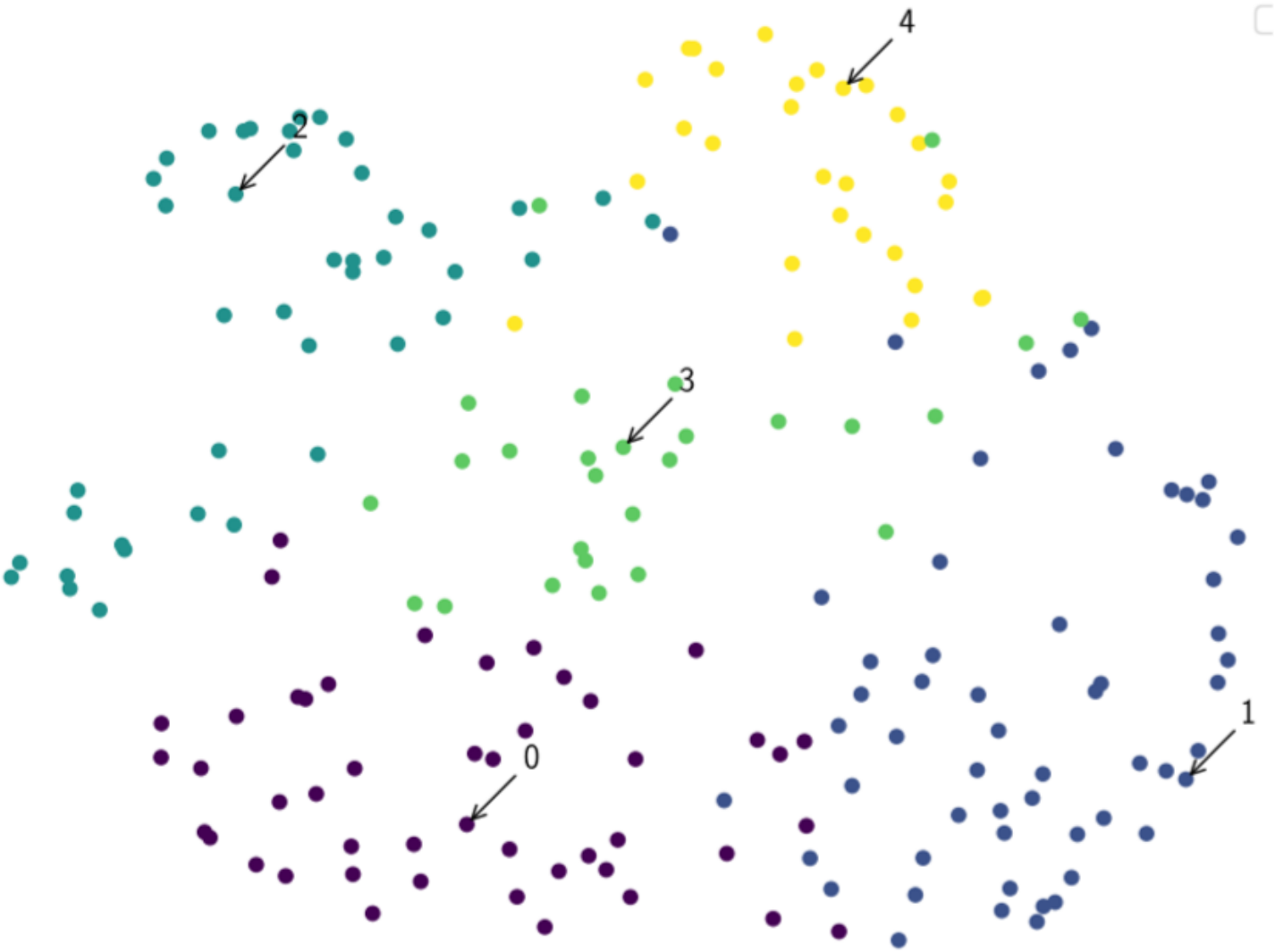



**Figure 22**

Visualizing clusters in TO designs using UMAP. The k-means clustering algorithm identifies the 5 clusters, numbered 0-4, based on the AE code. The cluster label points to the medoid of the cluster. k-means allows identifying subclasses of designs, even if they are not clearly separated, which is often the case with sparse data.

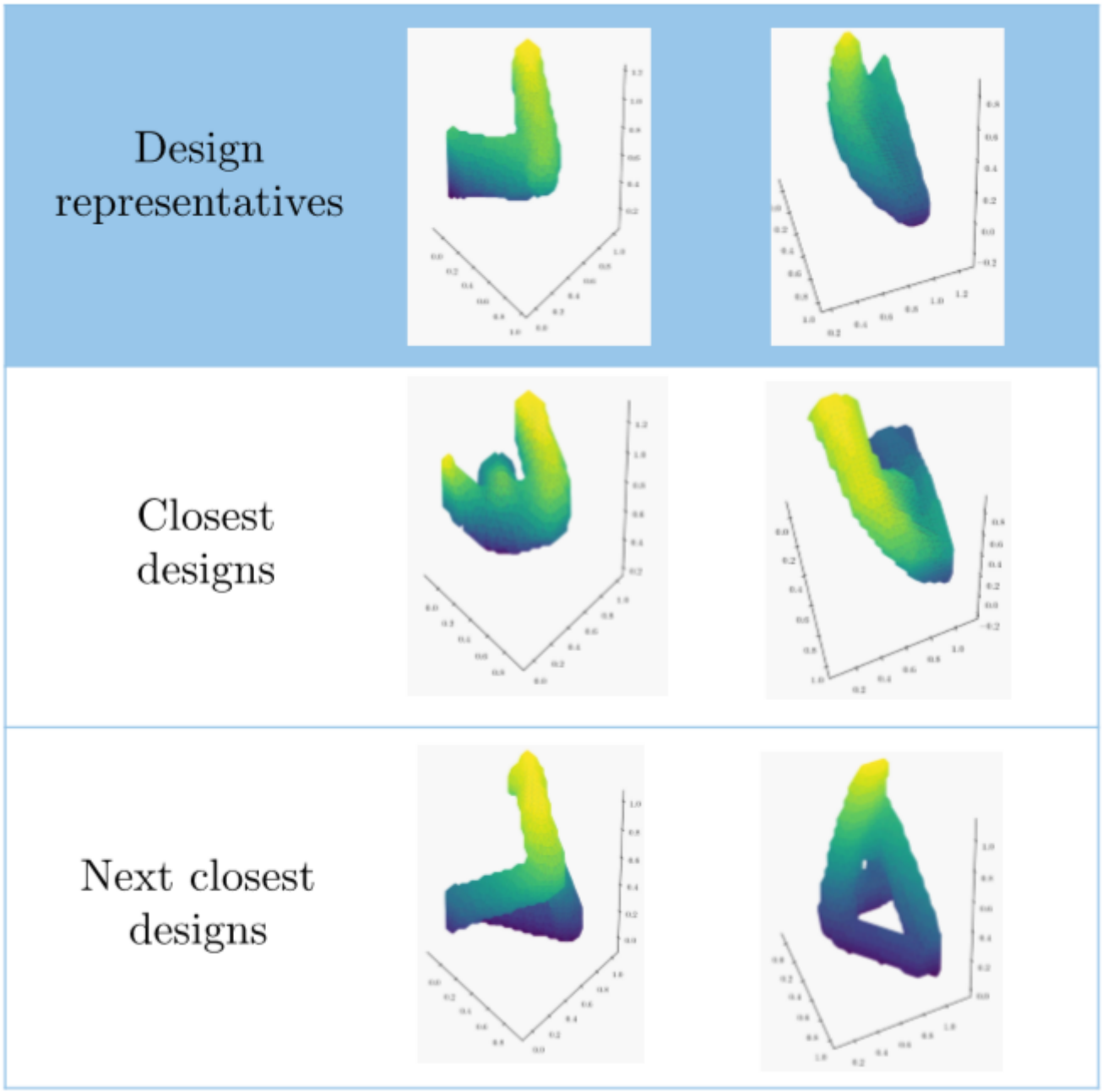



**Figure 23**

Designs similar to representatives: Geometric features extracted by PCAE are used to measure similarity. Two design representatives are shown in the top row. Two designs similar to these designs are shown below (column-wise).