Simplification of Design Space Exploration: A Critical Analysis of Interfaces for Generative Design

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Abstract. Managing the extensive design spaces available through generative design workflows poses a significant cognitive challenge, requiring effective tools for navigating and evaluating alternatives. Although multiple approaches, such as clustering, dimensionality reduction, and user-driven grouping, have been proposed to simplify making alternatives more accessible, we have yet to see the effective application of these approaches to design interfaces. We argue that this is due to issues surrounding how such approaches are presented to designers (e.g., unfamiliar and in black-box modes) or the limited interactions afforded to their representation (unintegrated and inflexible). To develop insight for tool development, we investigated eight design space exploration interfaces and two general-purpose visualization systems through criteria that are based on a literature review. As a contribution, we propose interface guidelines to streamline design exploration with integrated simplification methods.

Keywords: Design Analytics, Data Visualization, Design Space Exploration, Generative Design, Simplification.

1 Introduction

Several Design Space Exploration (DSE) systems have been proposed over the last decade, such as Cupid (Beham et al., 2014), Dream Lens (Matejka et al., 2018), Fuchkina et al. (2018), D.Star (Mohiuddin and Woodbury, 2020), Refinery (Autodesk, Project Refinery Beta), Design Explorer and Thread (CORE Studio, 2024), and DesignSense (Abuzuraiq and Erhan, 2020). Such DSE systems combine interactive visualizations of design data with 2D or 3D geometries in varying degrees of coupling to reveal and filter the design space. However, despite the effectiveness of data visualization at filtering, designers often face cognitive overload due to large sets of alternatives and their corresponding performance and form data (Shireen et al., 2019). To address this challenge, ‘simplification’ or ‘segmentation’ approaches are proposed, relying on clustering or dimensionality reduction followed by presentation of the results to designers.

Simplification, in our context, refers to reducing the complexity of the design space exploration by considering the structure of a design space, exploration tasks, and views of the structures so that designers can make sense of the generated ideas. Abuzuraiq and Erhan (2020) showed that simplification has been used to alleviate the choice overload, create visual overviews of the design space, and open new venues for interrelating design forms and data. They further argued for a flexible and integrated simplification of the exploration process. The challenge lies in effectively presenting the simplification results so that they are visual and intuitive to designers with no expertise in data analysis. However, as we see from the literature, simplification features have yet to be widely adopted in the tools used in practice.

In this study, we analyze existing tools to question how to effectively integrate simplification (or segmentation) into DSE and inquire about the qualities of effective and usable simplification in DSE interfaces. We present a review of DSE interfaces that feature a simplified representation of the design space via clustering, grouping or dimensionality reduction. The review is based on the literature on simplification, guidelines from information visualization, and studies on designers' behaviours. Our methodology is grounded in a literature review and analysis of the select tools through their documentation. Next, we draw the evaluation criteria from the relevant literature in computational design, visual analytics, interactive data visualizations, and cognitive studies. In addition to this analysis of the DSE interfaces, our contributions include a set of design guidelines and design considerations for creating interactive and effective visualizations for simplification of design spaces through novel DSE interface features.

2 Design Space Simplification

Design space simplification methods, primarily clustering and Dimensionality Reduction (DR), reduce the cognitive load of exploring large design spaces by aggregating data. DR is a set of techniques used to project high-dimensional data into spaces of lower dimensions, using techniques like self-organizing maps and principal component analysis. Munzner (2015) classifies DR as “attribute aggregation” in that it reduces the amount of data and simplifies visualization complexity. Design data is often multi-dimensional, and a typical generative design process includes a handful of input and output parameters. Clustering groups alternatives based on their similarity distances derived from parameters, performance metrics or geometric features (Abuzuraiq and Erhan, 2020). Common examples of clustering techniques include K-Means and Hierarchical Clustering.

2.1 Empirical Data on Managing Design Space

Experiments by Erhan et al. (2015; 2017) and Sheerin et al. (2019) emphasize the need for simplification in large design spaces. In particular, the researchers discovered that when faced with a large set of design alternatives, designers tend to categorize and manage them by creating coherent collections predicated on predetermined design criteria or the ones that emerge during the exploration process. However, these studies focused solely on design forms and didn’t represent performance data.

A deeper analysis of the experiment's outcome (Shireen et al., 2020) reveals a gap between designers’ tasks when navigating generated alternatives and existing DSE system features. Designers divided alternatives into collections, each reflecting a criterion. The collections can, as the designers’ criteria evolve. The designers also divided their workspace into dynamic zones to manage collections. They ‘placed’ alternatives to arrange, sort, scan, and compare to evaluate design alternatives. Finally, they referred to marking for indicating alternatives with bookmark, tag, rate, rank and annotate to enhance the designers’ selection process. Therefore, divide, place, and mark actions manifest design space simplification goals.

2.2 Why is Simplification Not Common in the DSE Tool?

Similarity-based clustering offers a promising approach for managing and exploring design alternatives (Erhan et al., 2015), as it helps designers gain insights into patterns and relationships within the design space. This process involves computing the similarity between design alternatives and clustering them accordingly. However, in a survey by Garcia and Leitao (2022), it was observed that two tools used in practice, namely DesignExplorer (CORE Studio, 2024) and Refinery (Autodesk, Project Refinery Beta 2024), do not employ clustering or grouping. Similarly, more recent commercial DSE tools like Thread (CORE Studio, 2024), and Fusion 360 (Autodesk, 2024) do not feature clustering.

On the other hand, simplification and clustering are evident in some research systems. Consequently, the question arises: why aren’t simplification approaches, such as clustering, grouping and dimensionality reduction, adopted by DSE interfaces in practice? And what hinders their adoption? We speculate that possible reasons include:

1. *Clustering Not Integrated to Design Process:* DSE interfaces may not incorporate clustering as a navigation method if there is uncertainty about how effectively it supports designers’ workflows in the design process.

2. *Lack of Transparency:* Some interfaces might not incorporate clustering due to its perceived "black box" nature, where designers find the underlying processes unclear and complex.
3. *Inflexibility:* Even with transparency, designers would still need flexible and customizable clustering options.
4. *Representation Challenges:* If interfaces struggle to represent clustering results in familiar and easy-to-understand representations effectively, designers may be less inclined to adopt clustering as a navigation method.

From a user experience perspective (Hutchins et al., 1985), the lack of transparency and unfamiliar representations widens the ‘gulf of evaluation,’ making it harder for designers to understand the system's state. Additionally, the limited customization and integration increase the ‘gulf of execution,’ i.e., the effort needed to take action to accomplish user goals based on the system's current state. To determine the validity of these four hypotheses, we select eight DSE interfaces that employ grouping and clustering to manage the design space and analyze them based on criteria derived from these hypotheses.

3 Interfaces for Design Exploration

In this section, we analyze eight DSE tools that use clustering and grouping and show the results in various visualizations and interactions.

Abuzuraiq and Erhan (2020) in DesignSense integrated design exploration and data analytics through coordinated visualization of form and performance data. They use hierarchical clustering to simplify the design space, providing a structured hierarchy of choices. Users select hierarchical clustering to define different aspects for segmentations so that the clusters can vary in other aspects. The dashboard uses coordinated views of a scatterplot, a parallel coordinates plot, and a thumbnail grid for form view. Also, the interface uses k-means clustering with thumbnails and sets operations part (Abuzuraiq, 2020).

Erhan et al. (2015) studied how design spaces could narrow through “similarity-based” exploration utilizing techniques such as similarity matrices, hierarchal clustering and self-organized maps (SOM). Their prototype system involved four steps: (a) setting parameters, (b) selecting a similarity algorithm, (c) generating and visualizing a similarity matrix, and (d) creating subsets in clusters using SOM. They use dendrograms for visualization of clustering. Also, a hexagon topology mapping to clusters was generated in which cells represent the number of design alternatives in each set, and their proximity indicates the distance between clusters.

Beham et al. (2014) identified three tasks for analyzing the geometry generator and narrowing it down through their interface: (a) Finding the corresponding parameters for similar 3D shapes, (b) Identifying implausible 3D shapes, and (c) Finding the influence of parameters on results. Based on these three tasks, they introduce a visualization interface called Cupid to explore the results of a geometry generator. The 3D shapes are hierarchically clustered based on their shape similarity and are visualized by a radial tree. The 3D shapes are then nested within a “composite” parallel coordinate visualization, allowing users to narrow into sub-clusters for detailed analysis selectively.

Shireen et al. (2019) investigated how designers manage large sets of design alternatives within their work environment. Their study observed designers as they eliminated and categorized hundreds of designs. They noted that when designers are confronted with over a thousand designs, their initial step is categorizing, finding patterns, and analyzing the alternatives through sets to comprehend the problem space and establish their criteria. The researchers translated the findings into an interface prototype that allows designers to sort and group alternatives based on their criteria.

Fuchkina et al. (2018) studied how different design space exploration methods can be mixed to support the better management of designs. They proposed a flexible framework for exploring alternatives, allowing designers to work with various possible methods in one environment. They distinguish three conceptual levels: (a) strategy level, where designers define a solution space exploration strategy with a dataflow diagram; (b) processing level, where designers narrow the solution space based on their dataflow diagram using a filtering module, table view, K-Means clustering, parallel coordinates, and self-organizing maps; and (c) instance level, where designers focus on the details of particular design solutions, and compare with each other.

Harding and Brandt-Olsen (2018) proposed Biomorpher, an interactive evolutionary optimization plugin for the Grasshopper-Rhino3D environment, where designers can iteratively select clusters that meet design criteria and preferences. The optimization algorithm favours the user-chosen clusters. Biomorpher’s interface records and displays the evolution history with performance data. Each cluster is represented through the alternative closest to the cluster’s centroid in the parameter’s space.

Muhiaddin et al. (2018) introduced D.Star, which links a parametric modeller with a gallery interface. It allows the interactive organization of alternatives through an interactive gallery and parallel coordinate plot of input and output parameters. The gallery interface enhances user interaction with design thumbnails and a list view of collections. Hovering over thumbnails reveals details where users can tag collections. Designers can iteratively query, retrieve, filter, and investigate alternatives, refining their choices.

van Kastel (2018) introduced a visual analytics DSE system in a game-like 3D environment that enables immersive exploration. Design data is encoded spatially using a 3D self-organizing map, with a hexagonal grid where each cell represents a design alternative using 3D stacked bars. These bars, varying in height and colour, indicate performance metrics and design similarities. Creating custom collections for more systematic design explorations can be challenging despite its features.

In summary, the studies by Abuzuraiq and Erhan (2020), Erhan et al. (2015), and Beham et al. (2015) all use hierarchical clustering to simplify design space, but with different visualizations: dendrogram trees, hexagon topology maps, and radial trees. Only Fuchkina et al. use a flexible framework combining multiple exploration methods. Biomorpher integrates performance optimization with parametric modelling, unlike other dashboards lacking real-time optimization. Muhiaddin et al.'s (2018) D.Star, with a parameter-focused interface, contrasts with van Kastel's (2018) immersive 3D environment, offering varied interaction experiences.

In addition to the above DSE tools, we analyze Tableau (Tableau, 2024) and Power BI (PowerBI, 2023), two data visualization tools commonly used for data analysis, to evaluate how they facilitate clustering and sets and their interaction. The critical difference is that DSE tools present design forms rather than focusing solely on presenting performance data or parameters.

Tableau enables users to create clusters by dragging "Cluster" from the "Analytics" pane and dropping it on the target area. Users can customize clusters and add variables to aggregate data in groups. However, clustering is not available for multidimensional data (note that design data are mostly multidimensional). Users can create a group dimension from results by dragging a cluster into the data pane. However, updating clusters requires an explicit. Clusters are generally shown in spatial maps or scatterplots. Users can also use 'groups' to visualize clusters on customized graphs.

Microsoft *PowerBI* transforms data into dynamic visuals using tools and connectors. In Power BI, the clusters do not update on data refresh, and new data goes into an empty cluster. Users should only cluster data likely to stay the same over time and plan to manually re-do the clustering at regular intervals. Clusters are visualized by scatter plots or a matrix of scatterplots, and users can display clusters in customizable data visualizations.

4 Analysis of DSE Tools for Simplification

After reviewing the tools discussed in the previous section, we compiled a review and design criteria for visualizing clusters and offering set-based operations on selections, clusters, and sets. We grouped the criteria under functional and visualization categories.

4.1 Functional Features

We identified "controllability," "integration in the design process," and "branching and multiple collections" as key functional capabilities of systems supporting DSE tasks. These features help designers control, navigate, and interact with groups and clusters of alternatives, enabling active management of complex design space exploration.

Controllability helps designers steer the exploration by configuring similarity metrics and allowing them to focus on relevant aspects of design alternatives. This includes selecting similarity metrics for meaningful comparisons, employing data simplification techniques like dimensionality reduction, and adjusting clusters in algorithms like K-Means. Designers can choose specific aspects, such as input parameters, performance metrics, and geometric characteristics, and tailor visualizations accordingly.

The non-linear design exploration process allows seamless switching between criteria and tasks as objectives evolve (Shireen et al., 2020). DSE tools *integrate into the design process*, enabling real-time modification of criteria and updates on clusters and groups, supporting diverse exploration styles and tasks without disrupting the designer's flow. *Branching and multiple collections* in systems facilitate branching sets, creating collections that meet existing or emerging criteria and allowing alternatives to appear simultaneously in multiple clusters or groups.

4.2 Visualization Features

Visualization features focus on how the results of design space exploration are presented to the user. They involve the graphical representation of data, clusters, and relationships within the design space. The emphasis is on making the information visually accessible, transparent, and flexible for the user. We identified three visualization features: “Transparency,” “Set Comparison,” and “Marking.” ***Transparency*** refers to the ability of the tools to reveal data and its organization in the exploration process and support informed insight discovery. As such, the decisions on clustering must be transparent to designers for expanding or reviewing the rationales for clustering. ***The set comparison*** allows effective analysis and comparison of sets, providing insights into the relative performance of select or sets of alternatives. The visualization features can be used to ***mark*** by highlighting or symbols on alternative clusters. The marks can be bookmarks, tags, rate, rank, and annotations.

4.3 Results

The results of our analysis of eight DSE and two data visualization tools are summarized in Table 1. First, four of the DSE and both Visual Analytics tools have features to support some level of controllability. DesignSense, Similarity Matrix and Hexagon Map, Design Space Explorer, D.Star, Tableau and PowerBI provide controlling design aspects and dimensions. Second, DesignSense, Cupid, ParaXplore, Design Space Explorer and D.Star use non-linear exploration processes and provide flexibility in considering designers' behaviour. Most allow branching and marking the sets, while only Biomorpher and Cupid enable visual set comparison. Transparency to designers needs further evaluation on each DSE tool.

Table 1. Comparison of design space exploration interfaces.

		Functional			Visualization		
		Controllability	Integrated to Design Process	Branching and Multiple Collections	Transparent to Designers	Set Comparisons	Mark
1	DesignSense (Abuzuraiq and Erhan, 2020)	Y	Y	Y	Y?	Y/N	Y
2	Sim. Matrix and Hexagon Map (Erhan et al., 2015)	Y	N	N	N?	N	N
3	Cupid (Beham et al., 2014)	N	Y	Y	N?	Y	N
4	ParaXplore (Shireen, 2019)	N	Y	Y	Y/N?	N	Y
5	Design Space Explorer (Fuchkina et al. 2018)	Y	Y	Y	Y?	N	Y
6	Biomorpher (Harding and Brandt-Olsen, 2018)	N	N	N	Y/N?	Y	Y
7	D.Star (Muhiaddin et al., 2018)	Y/N	Y	Y	N?	N	Y
8	DSE 3D environment (van Kastel 2018)	N	N	N	N?	N	Y
9	Tableau (2023)	Y	N	Y	N?	Y	Y
10	PowerBI (2023)	Y	N	N	N?	Y	Y

Source: Authors, 2024

5 Reflection and Design Considerations

Based on our analysis, we propose the following guidelines for developing tools to implement simplification on DSE interfaces:

Allow designers to navigate non-linear design processes effortlessly, supporting real-time modifications to criteria and tasks. Shireen et al. (2019) demonstrated the importance of creative flow (Csikszentmihalyi, 1996) in rapidly forming clusters considering current and emerging design criteria. This is consistent with Garcia and Leitao's (2022) suggestion for visual analytics interfaces that support diverse interaction needs.

Allow each alternative to belong to multiple collections simultaneously based on evolving criteria, providing users with a flexible and dynamic exploration experience. In physical space (Erhan et al., 2017), designers are constrained by one representation per alternative. The participants' interaction with analog representations of a large set of alternatives showed that they could position one alternative as part of multiple sets (Shireen et al., 2020). Although analog and simulated task environments could not have afforded this, the new DSE tools using interactive visualizations can address this demand.

Enable user-created collections and clusters for better customization and management of design alternatives. Almost all DSE tools we studied strive to bring design alternatives that are in different ways they should be treated together. This could sometimes be for similarity (Beham et al., 2014; Erhan et al., 2015), sometimes for user-defined grouping, e.g., discarding (Shireen et al., 2020). Muhiddin and Woodbury (2022) supported the creation of clusters by directly interactive interfaces, and Abuzuraiq (2020) provided both algorithmic and interactive collections (sets) definitions.

Develop visualizations that ensure transparent and understandable representations of clusters and groups. Green and Petre (1996) argue that systems should avoid black boxes and hidden dependencies. Although the tools we reviewed provide some clarity in the visible grouping, they should focus more on helping designers recall the clustering purpose or implications for the next navigation moves.

Incorporate interactive features for marking, tagging, rating, ranking, annotating groups and clusters, and individual alternatives. Design space navigation shows the characteristics of creative flow: the moves are rapid or slow depending on the immediate goal. The cognitive limitations (Erhan et al., 2017) should be alleviated using system features that can help designers recall the decisions made in the previous moves. The participants in Shireen et al.'s experiment (2019; 2020) use analog secondary devices (Green and Petre, 1996) to leave 'breadcrumbs' or externalization marks of their choices to be understood by others.

Allow users to perform dynamic set-based operations for comparisons and visualize the results in customizable views. The large design spaces can be managed through cognitive strategies, such as divide-and-conquer or hierarchical goal decomposition. The tools we reviewed, including the visual analytics tools, aim to support seeing the potential of designs in groups by comparing them between chunks called selections, collections, clusters, groups, sets, etc. The set-based operations work on composing such chunks as new insights are developed.

Provide designers with features to dynamically change similarity metrics, simplification techniques, and data dimensions during exploration. Although design requirements may guide the initial exploration, the process may reveal new insights about the solutions to the given design problem (Simon, 1996). Designers can discover and test such insights by simplified metrics definitions and applications on clustering and operations without interrupting the creative flow and exposing extra cognitive load and interrupting their flow (Csikszentmihalyi, 1996).

We also add two more suggestions to the design considerations (Figure 1):

Example-based Exploration: Besides creating similar clusters with similarity metrics, example-based exploration would help find similar designs. For instance, Dtour is an exploratory search tool for web design that allows designers to browse design galleries for inspiration. It features a recommender system with "show more like" and "show less like" interactions (Ritchie et al., 2011). Similar interactions can be integrated by creating clusters or sets.

History-Based Exploration ***for Set Interactions:*** Design tools that utilize history-based modelling offer backtracking and deferral for supporting non-linear design processes, such as OnShape and Rhino. We can use the same approach in the design exploration process, too. Shireen et al. (2020) argue that creating collections can introduce order and direction into the design space.

This process can be stored as exploration history, allowing any part of the design space to be revisited and reused. The Design Exploration system by Fruchkina et al. (2018) allows a gradual narrowing of the solution space based on the data flow diagram, although collections are not visually accessible.

Similar approaches are observed in visual analytic systems like VisFlow (Yu and Claudio, 2016) and DynSpace (El Meseery et al., 2018). These systems facilitate complex multidimensional analysis through multiple workspaces or selection set flows, aiding in organizing analysis and reviewing different paths. The key features to consider based on these examples are:

- Enable branching and merging of different parts of set flows.
- Allow users to bookmark set flows to keep track of insights and reuse different parts.
- Comparing set flows means facilitating the comparison of different scenarios through various comparative visualizations.
- Allow saving collections with specific brush history for easy recall.

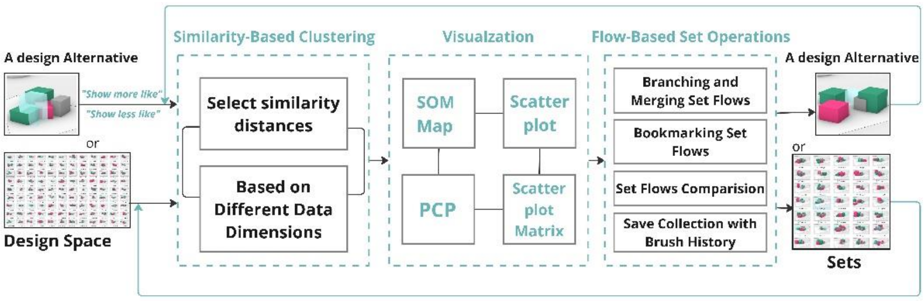

Figure 1. Combining Similarity and Example-based Exploration and Flow-based Set Operations in the Exploration Process. Source: Authors, 2024

6 Conclusions

Recent research highlights the need for novel DSE systems as generative design becomes more popular. Handling large sets of design alternatives necessitates new tools and features. Our review of existing literature and tools revealed that simplifying the design process can help manage these large sets. This simplification involves reducing the complexity of design spaces, the functions operating on them, and the interfaces that visualize these spaces while ensuring transparency, flexibility, and clear representations.

We proposed guidelines for developing future DSE interfaces to help designers make informed decisions in generative design workflows. Our findings were based on available literature, as we couldn't access most tools directly, potentially limiting our understanding of their latest capabilities. Our guidelines are not exhaustive and should be used alongside other relevant visual analytics and computational design literature.

Next, we plan to test our ideas in a case study using one of the analyzed tools and develop new prototype features for simplifying DSE. We also intend to incorporate simplification techniques from data sciences and visual analytics, which address similar challenges across various disciplines.

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