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DS-Viz: a method for visualising design spaces

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Abstract
Problems, solutions, and design itself have been framed as spaces in design research. Visualising the design space and how designers explore it, can give insight into the design process. This paper reports on a novel method for creating Design Space Visualisations (DS-Viz) that generates 2D and 3D representations of design spaces. We show how DS-Viz can be used to investigate designer behaviour, design processes and outcomes using a game-based design activity as an example. We discuss DS-Viz implications for design research highlighting potential benefits to design education and practice.

Keywords: *design space exploration, design landscapes, design creativity, design search, idea generation*

1. Introduction

For decades, researchers have conceptualised design activities in terms of the "spaces" that are explored. One well known example is Simon's (2019) discussion of the "problem space", which he describes as a representation of a problem, which enables the search for possible solutions, these solutions being part of an "alternatives space". Our main focus here is design creativity research, which also often builds from the "spaces" concept. For example, Jansson and Smith's (1991) description of design fixation suggests that conceptual design takes place in a "concept space", containing ideas and abstractions that are realised in a "configuration space", containing drawings of physical objects. Similarly, both design co-evolution theory (Maher and Poon, 1996) and C-K theory (Hatchuel and Weil, 2009) articulate design as the interplay of distinct but interrelated spaces (Problem and Solution spaces for co-evolution theory; Concept and Knowledge spaces for C-K theory). However, it is not just descriptions of design creativity that are framed in terms of spaces, but also measures of design creativity. In the context of ideation tasks, Shah and colleagues (2003) define metrics such as variety and novelty in terms of designers' explorations and expansions of the "design space".

The "design space" idea is found beyond the boundaries of design research. For example, in public policy development, Nadel and Pritchett (2016) discuss the design space of social programs and their outcome landscape, highlighting how this conceptualisation can inform policy design, and illuminate the challenges of working with multidimensional problems and solutions. Similarly, in the field of molecular biology, researchers have long been discussing the fitness landscape of proteins seeing evolutionary pressures as driving the exploration of the space of possible amino acid sequences (Romero and Arnold, 2009). Such widespread application of the design space concept and its multifaceted use attest to its relevance, both in conducting design work, and in explaining it. However, it also leads to ambiguity on what a design space represents and its relation to other "spaces". In the context of this paper, we define the design space as a particular arrangement of a set of solutions (i.e., solution space) to a given, well-defined, problem (one problem in a possible "problem space"), where the arrangement of the solutions permits visual interpretation of the relative position of ideas and of designers' behaviour.

Despite the interest and importance of the design space concept, both within and beyond design research, there remains an open issue on how we should visualise potentially vast multidimensional design spaces while capturing designers' exploration of those spaces and providing them with feedback on that process. With respect to this issue, we report on the development and use of a systematic method for creating design space visualisations ('DS-Viz') and capturing relevant related metrics.

Our DS-Viz has at least three potential use cases in research and education: (i) reframing the analysis of design activities and their outcomes by using novel metrics derived from space characteristics and designers' explorations, (ii) enabling improved feedback in design training settings, by providing visual representations of design progress, and a consistent terminology surrounding that, and (iii) providing the basis for the development of fitness landscapes and framing designers' explorations of those.

To explain the DS-Viz and illustrate its potential in the first of the three use cases, the paper is divided into five further sections. Section 2 reviews previously published visualisation strategies that can be employed for creating design spaces. Section 3 presents the overview of our DS-Viz method, and Section 4 provides an example of its application to a game-based design problem. Section 5 discusses our methods' premisses, limitations and implications to the broader "space" concepts discussed previously. Section 6 concludes with considerations about generalisability and the potential to adapt and expand the DS-Viz to other issues in design creativity research and beyond.

2. Design space visualisation

Visualising design spaces is a challenging endeavour. Design spaces are complex, vast and multidimensional in nature (Westerlund, 2005), preventing us from simply creating a 2D diagram that encompasses the gamut of available solutions in their full complexity. Visualising designers' paths through the design space is not trivial either: it is a laborious process to manually capture designers' rationales and their meaningful "moves" during a design activity (Goldschmidt, 2006).

Accounting for different types of data generated and manipulated throughout the design process (e.g., verbalisations, sketches) adds yet another layer of complexity to the analysis (Goldschmidt, 2006). Existing computational approaches are usually restricted to numerical variables manipulated automatically via a guiding set of inequalities that define the design problem (Agrawal and McComb, 2022). Despite these challenges, many attempts have been made to create design space visualisations. We briefly review here the most notable examples: (a) parallel coordinates plots (Fischer et al., 2014), (b) computationally-derived design spaces (Agrawal and McComb, 2023; Danhaive and Mueller, 2021), (c) set-based design spaces (Nickel et al., 2022) (d) genealogy trees (Bayırlı and Börekçi, 2022; Shah et al., 2003), and (e) conceptual design spaces (Gero and Milovanovic, 2022), which are illustrated in Figure 1.

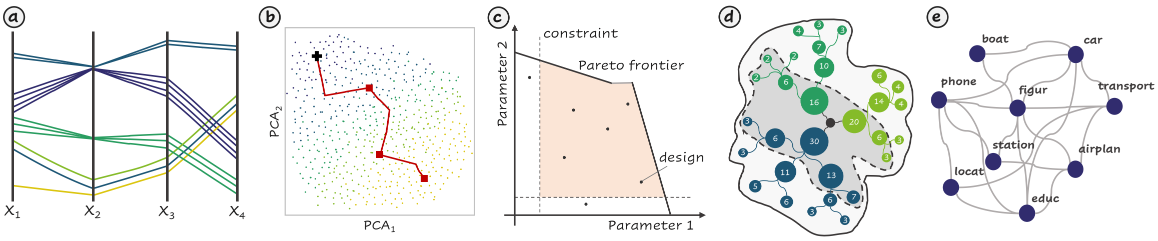

Figure 1. Schematic representation of different design space visualisation approaches

Parallel coordinates plots (PCP) are a traditional method for visualising multidimensional data, and they have been widely used in design optimisation contexts for supporting the investigation of Pareto front solutions and identifying clusters in the data (e.g., Fischer et al. 2014). When employed as a design space representation, each relevant design variable (usually in numerical scale) are plotted as parallel vertical axes and the different solutions are lines that cut across each axis at given values — see Figure 1(a). Among the limitations of using PCPs, Munzner (2014) highlights that the need to order the axes influences the behaviour of the lines and that it is virtually impossible to explore all orderings as they grow exponentially with the number of variables. Some of these limitations can be addressed through introducing diagram interactivity and using scatter plots focused on pairs of variables for detailed

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analysis. While categorical data variants of PCPs exist (e.g., parallel categories diagram), the ordering issue is exacerbated as now both vertical axes and their individual categories can be reordered at will, impacting the visualisation and exploration of the underlying design space.

Computationally derived design spaces rest on the premise that one is able to reduce a design problem to a set of variables governed by known or derived relationships, usually in the form of a mathematical formulation. In this approach, the design space can be constructed by programmatically changing the values of the variables and observing the resulting outcomes, potentially employing dimensionality reduction techniques to represent individual solutions as points in 2D or 3D space embeddings. Agrawal and McComb (2023) report that such a space can be explored by machine learning agents (see Figure 1(b)) and Danhaive and Mueller (2021) discuss how design landscapes can support parametric design. The core limitation of creating design spaces in this way is related to the design problem formulation that must be amenable to a mathematical parametrisation. This could hinder its application to a broader class of open-ended, ill-defined or wicked problems, and disregards the possibility of problem reformulation, evolution and co-evolution.

Going beyond a formal elaboration of design problems, the **set-based design space** proposed by Nickel et al. (2022) relies on the designers' choice of parameter to create the design space. This approach incorporates parameters that are related to the formulation of both the problem and solution, acknowledging that a design problem may have different design spaces associated with it due to its parametrisation. The visualisation of the design space offered by Nickel et al. (2022) is based on 2D and 3D Cartesian schematic visualisations, in which the axes represent specific parameters (variables) that are being manipulated and each combination leads to a point in the space — see Figure 1(c). The design space is further delimited by parameter constraints and Pareto frontiers that effectively define a feasible subset of the space. Those can evolve through time as designers manipulate both parameters and constraints. However, if multiple design parameters have to be considered at the same time, the usual limitations of visualising multidimensional space in Cartesian graphs still apply (Nickel et al. 2022).

Another design space visualisation approach employs the **genealogy tree** strategy exemplified by Shah et al. (2003). The genealogy tree provides the basis to assess the variety and novelty of individual ideas across different levels (from physical and working principles to embodiment and detail). The creation of a genealogy tree requires counting how many ideas exist for each of the levels for each relevant function of the design. While we focus on the genealogy trees, different tree representations have also been employed elsewhere, such as the tree-like structure used to describe the "concept space" in C-K theory (Hatchuel and Weil, 2009). Genealogy trees can be graphically manipulated to create visual representations of the "design solution space" (Bayırlı and Börekçi, 2022) — see Figure 1(d). Here, idea categories and their frequency are represented as circles of differing sizes, but their relative positioning and distances convey no meaning as it is a visual re-arrangement of the genealogy tree.

For the **conceptual design spaces**, Gero and Milovanovic (2022) employed a semi-automatic method that creates a space of the concepts formulated by designers throughout a design activity — see Figure 1(e). The method creates team-specific networks from verbal transcripts, where concepts are represented as nodes and the edges are the syntactic connections between the concepts. This verbal concept design space enables comparisons between the spaces of different designers, and investigation of how they explored the space, potentially deriving network metrics that could reveal designer behaviour (Gero and Milovanovic, 2022). However, the concept design space is limited to the type of input it can deal with (e.g., transcripts from verbalisations in design sessions) and is distinct from the more concrete notion of a design space of the *solutions* created for a problem.

The brief overview given here highlights that the design research community is searching for and developing different visualisations of design spaces. This is despite the challenges of dealing with multidimensional problems and solutions, and of accommodating different data modalities. In an attempt to address these challenges, we present the DS-Viz method, which provides a streamlined process that enables researchers to analyse traditional design outputs (e.g., sketches, 3D models). This method takes into account the multidimensional characteristics of the data, to create 2D spaces and 3D landscapes representing different solutions, their similarity or dissimilarity and their performance.

3. The DS-Viz method

The preceding discussion of different approaches to design space visualisation suggests the following requirements for the development of a method to create such visualisations:

- Data – the method should be able to parse both quantitative and qualitative data derived from traditional design outcomes (e.g., sketches, diagrams, 3D models, verbalisations).
- Dimensionality – the method should include or accommodate the high dimensionality of data into the creation of the design space.
- Visualisation – the method should enable the creation of 2D representations of the design space and 3D visualisations (when taking into account performance metrics for the solutions).
- Represented elements – the method should represent distinct solutions as points in space; similar solutions should be closer together and distinct solutions farther apart.
- Metrics – the method should output relevant metrics of design space exploration (design process focus), such as distances and areas as well as metrics for the individual solutions (design outcome focus).
- Reproducibility – the method should be reproducible, and each of its steps should be adaptable for specific contexts and problems, as well as being complementary to traditional methods.

This set of requirements guided the development of the DS-Viz method which enables the creation of design space visualisations from the analysis of design outcomes. The DS-Viz method outlined in Figure 2(A) was implemented in Python (3.10) and is available online (see Acknowledgements section).

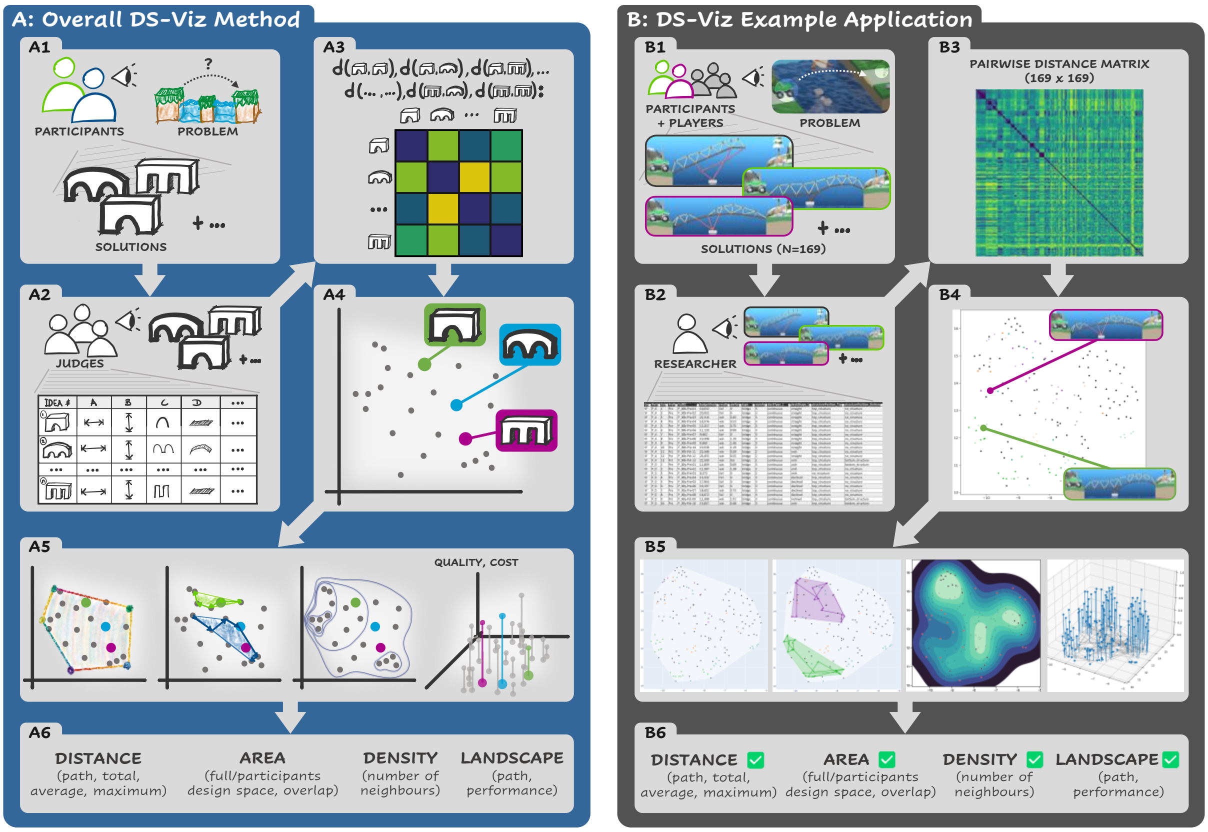

Figure 2. Schematic overview of the DS-Viz method (A) and application of the method (B)

3.1. Problem identification

The first step of the DS-Viz method is to identify a relevant design problem and existing solutions for it. In design creativity research, it is quite typical to conduct laboratory-based studies in which participants are tasked with creating solutions to a problem. The design outputs from such experiments (e.g., sketches) or the results of other ideation tasks are the first input for the DS-Viz.

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The problem and its solutions do not need to originate from researchers' own studies. They could use existing datasets that are available online, e.g., the dataset collated by Hay et al. (2020) or even gather secondary data from repositories of 3D models, relevant design games, or video and image platforms that document design activity, among other sources. There is no restriction on how structured or open-ended the problem and its solutions should be, as long as it is possible to identify relevant problem characteristics and analyse the solutions. This step is illustrated in Figure 2(A1), in which participants were tasked with creating solutions to permit an object to cross to the other side of a river.

3.2. Characterising solutions

Once the problem is defined and solutions are collected, the next step is to characterise the solutions. Different approaches are possible, from the traditional qualitative analysis that identifies the core functions of the solutions, relying on consensual assessment from expert judges (e.g., Bayırlı and Börekçi, (2022) and Shah et al., (2003)) to the use of design space schemas (Halskov and Lundqvist, 2021) that list relevant "aspects" and the available "options" across the set of solutions analysed. Alternatively, algorithms could be used to characterise both 3D models and semantic description of solutions (Kyriakou et al., 2022),1 as well as machine learning algorithms for image recognition.
The output of this step could be a list of all the solutions available being analysed across a set of characteristics (dimensions), either qualitative or quantitative in nature (or a mix of both). Attention has to be paid to the data type of each dimension (numerical, categorical, Boolean, etc.) as it will influence the distance metric's selection and calculation in the next steps. In Figure 2(A2) we illustrate this step by indicating that judges would then analyse the bridge-like solutions created by participants across the identified core dimensions (e.g., length, height, span type, span shape, deck shape, etc.).

3.3. Distance metric calculation

The distance calculation step aims to operationalise the premise that in a design space, similar solutions should be close to each other. At the same time, it must account for the high dimensional characteristics of the solutions (i.e., the multiple dimensions identified in previous steps). The metric calculation must account for the type of the data available (the values for each dimensions), and suitable metrics should be employed accordingly. Note that merely assigning numbers to categories for the calculation of the traditional Euclidean distance (e.g., for the deck shape dimension of the bridge solutions: arch = 1, straight = 2, double arch = 3, …) would lead to a violation of the premise that similar solutions should be close (as the arch shape should be closer to the double arch than to the straight deck shape). As such, the distance metric decision must be taken with care, considering a range of possible metrics. For instance, the Gower distance could be used for mixed-type data (Hummel et al., 2017), the Jaccard distance for set-based distance (Kosub, 2016), semantic distance (Beaty et al., 2022) when evaluating words, etc. In this step, researchers can fine tune the importance of each dimension by assigning weights to each dimension when calculating the distance between the solutions.
The outcome of this step is a pairwise distance matrix, i.e., a square matrix that contains the distance values between each pair of solutions. In such a matrix the diagonal is always zero, since it represents the distance between a solution and itself. This is a crucial step for the DS-Viz method and one that can be validated (e.g., by the varying weights assigned to each dimension and evaluating the impact on the visualisations generated). Eventually, depending on the data types, researchers could skip the explicit calculation of the distance metric in this step and use the dimensionality reduction algorithms metric computation. However, the understanding of how solutions have been compared and the distances calculated remains crucial as it provides the basis for the next steps of the method. Figure 2(A3) illustrates the pairwise distance calculation and the visualisation of the distance matrix as a heatmap (darker colours indicate pairs of similar solutions; brighter colours indicate dissimilar pairs).

3.4. Creating the 2D embedding of the solutions

Once the pairwise distance matrix for the solutions has been calculated, it becomes possible to create a 2D embedding of the solutions using dimensionality reduction techniques which include, among others, the Principal Component Analysis (PCA), the Uniform Manifold Approximation and Projection

(UMAP), and the t-distributed Stochastic Neighbor Embedding (t-SNE) which are among the ones compared in Agrawal and McComb (2022) design space exploration with reinforcement learning agents. The idea behind these approaches is to infer how the different solutions are spread out in the higher dimensional space and then project those relationships onto a lower dimensional embedding (usually 2D), while (trying) to preserve local and global characteristics of the data. Each of these techniques for dimensionality reduction has a set of parameters that allows fine-grained control over the embedding. The details of loss functions and the transformation of the high dimensional spaces into the lower dimensional embedding is outside the scope of the current discussion as it is well documented elsewhere (e.g., Huang et al., 2022). The DS-Viz method employs the UMAP technique for the dimensionality reduction as it is widely used (for an application in genetics, see Becht et al. (2019)), well documented and flexible in terms of input data (i.e., it can receive a precomputed distance matrix).
The outcome of the dimensionality reduction is a set of coordinates for each solution finally, enabling their visualisation in a 2D plane and accounting for the distinct dimensions and features identified in the preceding steps. Given the different parameters of the algorithm and the "approximate" nature of the technique, there will always be some distortion associated with representing high dimensional data in a low dimensional way, such as in 2D representations. Consequently, validation routines can be employed to compare the embedding distances and the original, high dimensional ones as well as running multiple sets of embeddings with distinct values to see the differences and verify the robustness of the method. Figure 2(A4) illustrates the lower dimensional embedding represented as a scatter plot. Note that the axes are not labelled: after dimension reduction the axes do not refer to particular dimensions or parameters of the solutions, they are abstract compilations of all the dimensions evaluated.

3.5. Creation of the design space visualisations

The 2D embedding of the solutions as points in the space is the basis for the design space visualisations presented here. We propose that the convex hull (the smallest convex polygon that contains all points in a set) that envelops all available solutions in the 2D embedding is the visualisation of the "full design space" that is known, see Figure 2(A5, leftmost). Similarly, if we record which participants generated which solutions in a temporal order, we can visualise the participants' individual convex hulls and their trajectory during the design process, see Figure 2(A5, second illustration from the left).
Given the distribution of the points (solutions) in the space it is possible to visualise the most visited areas in the space using contour and density plots, as shown in Figure 2(A5, third illustration from the left). Furthermore, if we have performance metrics for the solution or a quality metric, we can add this as a third dimension, effectively creating design landscapes (when the data is continuous) or 3D scatter plots (when continuity in the design space is ambiguous), shown in Figure 2(A5, rightmost illustration). Based on the data available other visualisations are possible, including clustering and network representations of the solutions which can also be derived from UMAP outputs. Ultimately these visualisations enable a deeper understanding of the design space for the given problem. The DS-Viz also provides an interactive manipulation of the visualisations for further exploration and analysis.

3.6. Calculation of relevant metrics

From the design space visualisations, it becomes possible to extract relevant metrics for design space expansion and exploration. Tracking the exploration path of a designer through the space allows us to extract distance metrics (total distance covered, average and maximum distances between solutions created) that give clues to how the participant navigated through the space. Similarly, computing the area of the convex hull for each participant's set of ideas allows us to assess how much of the full area of the design space they have covered. Furthermore, tracing participants' exploration path on the design landscape allows for the identification of strategies like hill-climbing or of behaviours like the exploration of local maxima. In terms of solution-specific metrics, from the distribution of the points and the ensuing density distribution it is possible to evaluate the density value at each solution coordinate. Drawing from Shah et al.'s (2003) discussion of how novelty can be interpreted as "points that are initially not perceived to be in the design space" we propose novelty metrics derived from the density of the points' distribution (i.e., popular areas are less novel) or from neighbourhood evaluation (i.e., points with few neighbours are more novel). These metrics can also be interpreted in terms of the

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variety of their spatial distribution as a proxy for the expansion of the known design space boundaries. Validating the metrics and performing sensitivity analyses to evaluate how the different DS-Viz parameters impact the measurements is necessary for assessing the method's robustness.

3.7. Validation and verification of the method

The final step of the DS-Viz method entails the validation and verification of the visualisations and metrics calculated. The main steps that need to be validated and verified are the distance metric calculation, dimensionality reduction for 2D embedding creation and the metrics calculation (determined by the design space visualisations). Several validation and verification routines have been implemented in the method assessing the following: influence of different weightings on the distance between solutions, distortion of 2D embedding distances compared to high dimensional distances, influence of UMAP parameters on sensitivity analysis on solutions' embedding among others.

Through the validation and verification steps devised in DS-Viz we are able to identify potential issues with dimensionality reduction, refine the parameters for each different step and record with transparency the process undertaken for the creation of design space visualisation. Examples from the validation outcomes are discussed in the following section.

4. Example application: a game-based design problem

In order to demonstrate the application of the DS-Viz, we analyse a subset of data collected during a game-based design creativity study. The detailed experimental design can be found in a pre-registration report by Paravizo and Crilly (2023). For this example application, the problem presented to participants was a level of the game Poly Bridge 2, which prompted participants to create solutions to get a vehicle across a gap to reach a flag — Figure 2(B1). The data reported here was collected from four participants who participated in the experiment but were excluded from the final sample because they had previous experience with the game. In addition to the solutions created by the participants, 100 solutions created by the general player population were collected from the game's online gallery. Thus, a total of 169 solutions were analysed (69 from the participants, 100 from the gallery) — Figure 2(B1).

The next step of the method is the analysis of the solutions. In this step, the first author constructed a template for the analysis of the solutions, deriving 37 dimensions from domain-specific concepts (e.g., structure, deck type) and problem-specific concepts (e.g., number of anchor points used, materials employed, etc.). For example, a solution was classified as a "bridge-like" solution if it had supports on both sides of the gap. If it had supports only on one side of the gap and in the middle anchor point, it would be characterised as a "ramp"-like solution. The same process was applied to the other dimensions, which yielded a mixed-type dataset, characterising each solution — see Figure 2(B2). If all combinations of all possible values for the 37 dimensions were considered, the scale of the overall design space would be in the order of 10^{18} solutions.

After the characterisation of the solutions, the next step of the DS-Viz method is the distance metric calculation. Due to the mixed-type nature of the data, the distance metric employed for assessing the dissimilarity of the solutions was a combination of the Gower distance (Hummel et al., 2017) and the Jaccard distance (Kosub, 2016). The pairwise distances were calculated for the given input dataset, and the resulting 169 x 169 distance matrix is represented in Figure 2(B3). All dimensions were given the same weight for the metric calculation; weight choice is further discussed in the validation step.

With the distance matrix calculated, the next step of the method is the creation of the 2D embedding using the UMAP technique. The list of (x, y) coordinates for each solution was then drawn in a scatter plot, as seen in Figure 2(B4). The different weights and parameters for the UMAP embedding were evaluated in the validation step, which supported the decision of setting the number of neighbours as 60 and the minimum distance as 0.25. Furthermore, a distance matrix was created based on the embedding for the comparison with the high dimensional distance matrix as discussed in the validation step.

With the 2D embedding created, the next step of the method is generating the design space visualisations. Figure 2(B5) shows, from left to right, the convex hull for all of the solutions (i.e., the full design space), the convex hull and exploration path (arrows) for two participants, the density plot for the full set of solutions with marks added for calculated novelty scores (most novel = red crosses; least novel = black "x") and the 3D landscape, shown as a 3D scatterplot with the z-axis value given by

a performance metric calculated from the budget used and result obtained (success or failure) when simulating the solution. The metrics listed in Figure 2(B6) were obtained from the visualisations created supporting the comparison of participants' outcomes and a better understanding of the space itself.
The final step of the DS-Viz requires the validation and internal robustness checks. Figure 3 (left panel) shows a heatmap for the high-dimensional (left) and embedded (right) distance matrices, which are clearly different. To verify the extent of this difference, we calculated the Pearson correlation coefficient for over 2,100 combinations of different parameters' values for the UMAP and the weights for the dimensions. For the defined parameters (equal weights to all dimensions, number of neighbours 60 and minimum distance as 0.25) we obtained a Pearson correlation coefficient of 0.501, which is even better than the best performing algorithm for dimensionality reduction analysed by Agrawal and McComb (2022). This analysis indicates that although there is a distortion between the high-dimensional and embedded distances across the solutions, those seem to be in line with other approaches in the field and can be seen as acceptable for the current application.
The validation of the method's robustness is illustrated in Figure 3 (centre). Four solutions are highlighted in embeddings that originate from distance metrics calculated using different weightings. Despite the change in the weights for the distance metric calculation, the relative positioning across the solutions is maintained indicating that the method is internally robust. Similar analysis can be performed varying UMAP parameters with similar results. Further investigation of the robustness can be achieved by comparing the actual distances across specific solutions or identifying solutions at specific distances. Routines for those were also implemented in the DS-Viz method.
The diagram in Figure 3 (right) shows the sensitivity analysis of the areas covered by each participant (area of the convex hull for each participant) for different weights. There is some variation stemming from the weights assigned for the metrics calculation step which can be partially explained by the convex hull being a geometric construct. A convex hull is determined by the most extreme points of a given set — any variation on those perimeter points (however small) may have larger impact on the area of the region they define. Nonetheless, having the guidance for the selection of the parameters from the other validation calculations and the ability to assess the sensitivity allows a deeper understanding of data and method. For the current example despite the variation that is present, the separation of participants in two groups (larger area explored; participants B and D, and smaller area explored; participants A and C) is clearly maintained. The DS-Viz method developed and illustrated here provides unique opportunities for design creativity research enabling researchers to precisely characterise a design space given a set of solutions for a problem.

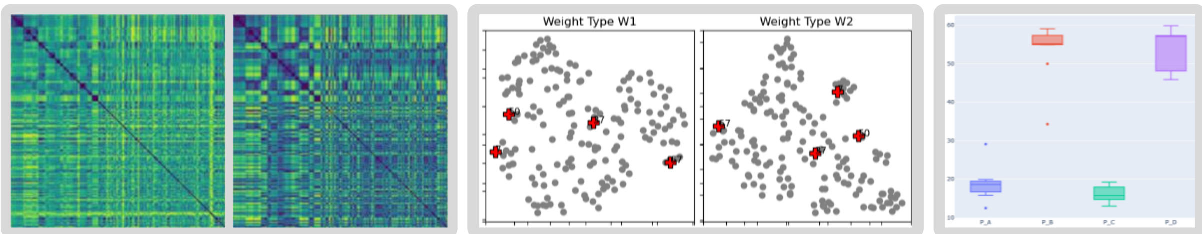

Figure 3. Left to right: visualisation comparing the distances in the high dimensional and low2D space; solution relative positioning given different weights for the metric calculation; sensitivity analysis of the participants' convex hull areas for different weights

5. Discussion

The DS-Viz is a unique approach that proposes a streamlined process to analyse design outcomes and create 2D and 3D design space representations. The underlying requirements for the method outlined on Section 3 have been respected: the DS-Viz is capable of handling mixed-type data, representing distinct solutions as points in a 2D or 3D space, allowing the creation of different visualisations and extraction of relevant metrics. Internal consistency of the method can be checked across a range of validation routines and reproduced by others as the scripts and dataset are available online.
Fundamentally, the DS-Viz is a method created to support design creativity research and education. While drawing inspiration from design optimisation approaches, it departs from the visualisation of

multidimensional data using PCPs to allow the (extensive) use of categorical and mixed type data coupled with the spatial reasoning that the 2D and 3D Cartesian plots allow. Furthermore, while optimisation approaches usually have well-defined problems, modelled as mathematical equations, this is not usually the case in design creativity tasks. As such, we prioritise the creation of a single visualisation that encompasses all underlying dimensions that characterise the solutions. Nonetheless, different representations such as parameter versus parameter Pareto frontier graphs or performance charts using PCPs can still be employed together with the visualisations created with DS-Viz.

Overall, the method is highly modular and customisable. We expect it can be adapted to different problems and contexts (including open-ended ones). The control over the different visualisations and metrics that are generated is also a potential benefit — they can be further refined and adjusted given the experimental design setting or problem definition. Interactive features that would enhance exploration of the design space are also possible and are implemented as a demo in the DS-Viz code.

The DS-Viz approach engages with current discourse on the nature and creation of design spaces (Goldschmidt, 2006; Halskov and Lundqvist, 2021; Nickel et al., 2022; Westerlund, 2005). Ultimately, the DS-Viz builds from rich discussion and debate in the design field, and from other fields. As discussed above, the design space visualisations created by the method are all contingent on researchers' decisions: we agree with Westerlund (2005) and Nickel et al. (2022) that multiple design spaces exist for the same problem. What the DS-Viz brings to the table is the ability to systematically inquire and extract information about (an interpretation of the) space itself, the exploration patterns, and behaviours of designers. It also reframes how we interpret ideation metrics, such as novelty and variety.

The DS-Viz approach can have clear benefits in educational contexts, both as a feedback modality that educators can use to explain where designers (or design students) are in the design space, how expansive (or not) their solutions are and how that compares to the full space. Similarly, this approach could be eventually incorporated in CAD software as a real time feedback modality when knowledge of the solution space is available. The method could then provide designers with information on how far from previous solutions they have moved and how their current solution compares with a pool of similar solutions available on 3D models repositories online.

6. Conclusion

This paper reported the development of DS-Viz, a novel method to systematically create and analyse rich visualisations of design spaces and their exploration. We highlight the core premises of the method and discuss how those impact its overall outcomes and metrics, showing that the DS-Viz is internally consistent and robust. Further testing of the method with larger datasets and problems of different natures (open-ended problems, constrained problems) should be pursued to validate the applicability of the DS-Viz to a range of contexts. The method is packaged and distributed as a collection of Python scripts so researchers can adapt and further refine it for their own data and research questions.

The novel visualisations and metrics that can be created from the DS-Viz method could unlock new and distinctive interpretations of designer behaviour and the creative outputs they develop. Further investigation on the metrics consistency when compared to traditional ideation metrics is required to verify its generalisability. This should precede the application of the method into educational and practice-oriented contexts.

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