Co-Creating Dimensions and Examples Using Design Space Gaps

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Abstract

A design space is a tool used in design and problem solving when a user is considering many different aspects of a problem, and there are many possible options to consider for each aspect. In this paper, we discuss what design spaces are, how they are constructed by users and how a computational agent may be able to work with a user to suggest areas in the design space to consider. We propose a mixed-initiative system for the co-creation and exploration of design spaces.

Introduction

Designers and researchers attack open-ended problems that require creative ideation, iteration and evaluation. The problems, by nature, do not have a single, fixed solution, but many possible solutions. Design fixation is a result of working towards a local maxima within a multi-dimensional problem space, though designers and researchers may not think of fixation in such a mathematical fashion. Design fixation occurs when focusing on a few related solutions or dimensions without exploring the vast set of possible solutions or dimensions that are less related to the current one under consideration.

While some designers and researchers naturally think in terms of the dimensions of a problem and may even draw tabular or other representations of the dimensions and solutions under consideration, our research has shown that such thinking does not come naturally to everyone (MacNeil, Okerlund, and Latulipe 2017). And yet the hard work of thinking through a problem and creating a dimensional representation can be very rewarding. A dimensionalized design space that can be explored offers benefits to users in being able to see how different possible solutions are related to one another. More importantly, a dimensionalized space can allow users to see what areas within the space are under-explored and ripe for consideration.

One of the challenges with dimensionalized design spaces is that it can be difficult to define dimensions and to populate these spaces with relevant examples. Considering the bounds of the space and all of the potential points that exist within, it can be cognitively demanding and users settle for adding obvious dimensions and a homogeneous set of example points that exist along these dimensions. Our work proposes to address this challenge by co-constructing spaces.

In this workshop paper, we present a web-based tool, the Design Space Explorer, that we have created for helping users to build, visualize, and explore dimensionalized design spaces. Our tool does not currently have a computational agent to help users construct the space, but that is the next step for this system and we present here some initial ideas for how this agent might interact with the user to help the user explore the design space, reflect more effectively on the interesting parts of the space, and fill it with more diverse and comprehensive dimensions and examples. Our tool has the potential to support ideation and exploration, but it is necessary to first construct a comprehensive space. Construction and curation is the main focus of this work.

Background

Dimensionalization and thinking about high-dimensional spaces are cognitively demanding tasks that humans are not naturally good at. Providing tools to help users externalize high-dimensional problem spaces can be helpful, but even the process of defining dimensions can be difficult (MacNeil, Okerlund, and Latulipe 2017). Research has shown that understanding the different dimensions in a space and considering the less common, obscure dimensions help a user to consider more unique solutions (McCaffrey and Spector 2012). This work has also shown that such obscure features are hardest for people to generate.

For concept generation and problem solving, design analogues aid in the process of transferring ideas from one domain to another (Mednick 1962). In the same way that considering obscure dimension can lead to more creative ideas, far analogues are often harder to think of than near analogues (Gentner, Rattermann, and Forbus 1993), but they can lead to more original concepts than near analogues (Chan et al. 2011). In both cases, obscure dimensions and distant examples are the hardest for people to generate on their own, but are also the most useful for ideation.

Design spaces are used to illuminate design decisions and enumerate the possible options for each decision. As in the case of the Question-Option-Criteria (QOC) method, the design space provides design rationale. The QOC method lists questions, the options for each question, and criteria that need to be satisfied (MacLean et al. 1991). Morphological analysis uses a matrix-based representation that helps designers eliminate infeasible designs as they specify values for options along each dimension (Zwicky 1967; 1969). A schema-based interpretation of design spaces has aspects as table headers and options for each aspect as rows within that column (Biskjaer, Dalsgaard, and Halskov 2014; Dalsgaard, Halskov, and Nielsen 2008). These approaches parameterize design and problem solving. While useful, they focus on mostly on guiding design decisions rather than on understanding the space in terms of patterns, clusters, or gaps. Parameterized design is useful, but only if the parameters are well understood. In this work, we focus on co-defining such parameters (dimensions) and selecting heterogenous design analogues (examples).

The Design Space Explorer

The Design Space Explorer is a web-based system that walks users through a process of dimensionalization, population and exploration. The user begins by creating a design space and giving it a name, for example Plant-Based Interactive Art Installation. Then the user can go to the first step of the process, which is defining dimensions.

Defining Dimensions

In the defining dimensions step, the user can define as many dimensions as they want. Each dimension is given a name, an optional description and a type. The types of dimensions currently supported are numeric, categorical and boolean. Once the type of the dimension is set, the user must specify additional information about the dimension as noted:

Categorical: The name for each category.

Numerical: Minimum and maximum values in the range.

Boolean: A conditional statement (T/F).

Examples of dimensions for plant-based interactive art might include the categorical dimensions: type of sensor, interaction modality; the numerical dimension: number of sensors; and the boolean dimension: continuously or periodically responsive.

When the user feels they have created enough dimensions to define their space, they can move on to populating the design space with potential or existing solutions. Note that the user is able to go back later and edit or add dimensions, as design space creation is often an iterative process.

Populating with Examples

With dimensions defined, the user can populate the design space with examples. To create an example, the user gives a name for the example and then is walked through the process of defining how the example fits along each dimension. For the interactive plant-based art design space, if a user wants to add "Botanicus Interactus" as an example (Poupyrev et al. 2012), they would type in that name and then be presented with dimensional widgets. By interacting with these widgets they can define values for each dimension. They would choose *capacitive sensing* for the type of sensor and *gesture* for the type of interaction modality. For the number of sensors they would choose one and for the boolean dimension, continuously or periodically responsive, they would choose *continuously*. After adding this example, they could add other examples of plant-based interactive art.

As users add examples, they might find that there are aspects of the examples that are not captured by their specified dimensions, and so they may have to go back and add more dimensions or refine the options of the existing dimensions.

Exploring

Once the user has added existing examples or ideas to the design space they are ready to explore the space. We currently provide a parallel coordinates visualization. Many visualizations are designed for visualizing data sets with millions of data points. Design spaces are interesting because they are not 'big data', they are small data sets with high dimensionality, and typically the number of dimensions is larger than the number of data points. Thus, the space is naturally sparse. Figure 1 shows an example of a visualized design space from our prior work (MacNeil, Okerlund, and Latulipe 2017). For parallel coordinates the ordering of the dimensions can over-emphasize certain dimensions and under-emphasize others. Our tool supports dimensional reordering and other interaction techniques to improve usability.

Consider the plant-based interactive art design space. Even with only the four dimensions described above the number of possibilities is vast. There might be 3 sensor types, up to 6 modalities, up to 10 sensors and continuous vs. periodic options, that is $3 * 6 * 10 * 2 = 360$. With just this very limited set of dimensions there are 360 possible designs. It is unlikely that a user wants to consider each of these possibilities, but design fixation occurs when the user only considers new solutions that are very similar to solutions already in the space. Dimensional reduction techniques, such as Principal Component Analysis (PCA), may help but they may also make it harder both to understand the relationships between dimensions and to reflect on the space holistically. Such techniques would be useful when using the tool for constrained-based exploration but may be less useful for constructing and reflecting on the space.

Mixed Initiative Interaction

In order to help the user make the most of the externalized representation that the Design Space Explorer offers and to explore distant possibilities, a computational agent could propose areas of the multi-dimensional space to consider. There are a number of issues that have been considered in designing an interactive agent:

initiation: should the agent begin interacting as soon as the user has added some dimensions and examples? If so how many dimensions and how many examples? Or should the user be the one to signal that they are ready to interact?

clustering and gap detection: which gaps are most relevant in sparsely populated, high-dimensional spaces that likely contain many gaps?

interest definition: is it possible to create rules that would help an agent determine what combinations of dimension options are likely to be interesting? if so, what are the criterion that lead to interesting combinations?

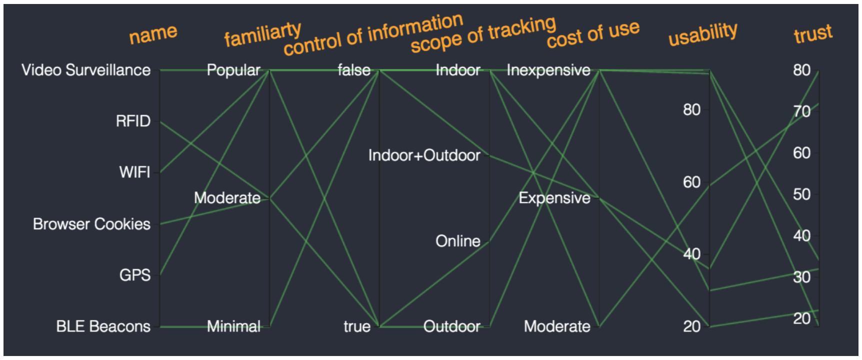

Figure 1: An example design space visualized as a parallel coordinate chart.

nonsensical combinations: if the agent suggests a solution that consists of combinations of dimensional options that make no sense, what is the best way for the user to communicate this, and can the user then be asked to delimit the range of the nonsense in some way?

reinforcement: if the user responds positively to a solution suggested by the agent, how can the agent learn from that, and what is the appropriate way for the agent to generalize that knowledge across the multi-dimensional space?

closure: when and how should the interaction between the user and the agent end?

interaction history: how should the interaction history between the agent and the user be stored and presented so that the user can revisit agent suggestions at a later time?

We're considering these issues as we think about how to create an agent that can help a user identify interesting gaps in a design space. As users construct and explore their space they may be overwhelmed by the options within that space; however, in practice these spaces are often sparsely populated (MacNeil, Okerlund, and Latulipe 2017). Given that people often struggle to think of far design analogues or obscure dimensions (McCaffrey and Spector 2012; Gentner, Rattermann, and Forbus 1993), a computational agent might be best suited to guide users to populate the space and reflect on the dimensions and examples. Such an agent could prompt users to contribute either examples or dimensions. To do this, the agent might fill out the dimensions for a theoretical example and then ask the user if they can think of a specific example that meets the criteria. Similarly for dimensions, the agent would identify two examples that are very similar along each dimension and ask the user to define a new dimension that differentiates the two examples.

In the case of co-creating examples, the agent would perform a modified outlier detection to identify a multi-dimensional point that is most distant from other points and maximizes the coverage of the space. An information theoretic model could choose the outlier based on increasing the overall complexity of the space (Lee and Xiang 2001). The chosen point would represent a point that is most distant from the points the user has already created. The associated values for this point are implied. If the user can think of no existing examples that fit these dimensional values, the user could consider this an "ideation prompt" and try to imagine what a solution that fits these values would look like. This might lead to a novel idea that they could try themselves. After naming the point, it would be added to the design space.

In the case of co-creating dimensions, the agent would need to find the two points that are most similar, as measured by the proximity to each other in the multidimensional space. By computing the distances between all points, the points with the minimum distance would be recommended to the user. The user would be asked to think of a dimension that distinguishes them. The user would be prompted to identify how existing examples fit within this new dimension. The agent could provide feedback about how much the new dimension improved coverage in terms of distances between the points in the space.

While co-creating dimensions and examples may lead to more comprehensive design spaces and opportunities for ideation, each approach this in complimentary ways. The goal for co-creating examples is to improve the coverage within the design space and is convergent in nature. On the other hand, co-creating dimensions opens up the space with more possible ways to categorize each example, leading the user to consider the space more holistically. These opportunities for both convergent and divergent thinking can lead to more creative ideas (Guilford 1956; Cropley 2006). Of these two ways of co-creating, co-creating examples is most similar to Yannakakis et al.'s view of Mixed-Initiative Co-creation (Yannakakis, Liapis, and Alexopoulos 2014).

Conclusion

We have presented the Design Space Explorer and a theoretical co-creation agent that would guide users to create more comprehensive design spaces. As shown in previous work, thinking of relevant examples, dimensions, and actually constructing the design space itself are cognitively demanding. Therefore, a co-creation agent may be one way to support users as they grapple with dimensional reasoning and design space construction; leading to more comprehensive spaces that are more interesting to explore.

Acknowledgments

We would like to thank Jim Davies for his helpful feedback.

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