D-Graph: AI-Assisted Design Concept Exploration Graph

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Abstract

We present a pilot study of an AI-assisted search tool, the "Design Concept Exploration Graph" ("D-Graph"). It assists industrial designers in creating an original design-concept phrase (DCPs) using a ConceptNet knowledge graph and visualizing them in a 3D graph. A DCP is a combination of two adjectives that conveys product semantics and aesthetics. The retrieval algorithm helps in finding unique words by ruling out overused words on the basis of word frequency from a large text corpus and words that are too similar between the two in a combination using the cosine similarity from ConceptNet Numberbatch word embeddings. Our pilot study with the participants suggested the D-Graph has a potentially positive effect, though we need to improve the UI to help users adhere to the use of the algorithms in the intended ways.

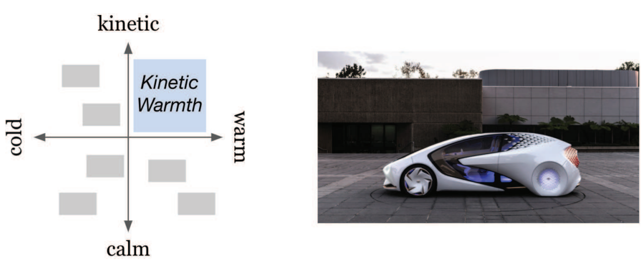


Figure 1: Left: character space for "kinetic warmth." Right: design derived from "kinetic warmth" (© 2021 Toyota Motor Sales, U.S.A., Inc.).

Introduction

We present a pilot study of an AI-assisted search tool, the "Design Concept Exploration Graph" ("D-Graph"). It assists industrial designers in creating an original design-concept phrase (DCPs) using a ConceptNet knowledge graph and visualizing them in a 3D graph. A DCP is a combination of two adjectives that conveys product semantics and aesthetics. The retrieval algorithm helps in finding unique words by ruling out overused words on the basis of word frequency from a large text corpus and words that are too similar between the two in a combination using the cosine similarity from ConceptNet Numberbatch word embeddings. Our pilot study with the participants suggested the D-Graph has a potentially positive effect, though we need to improve the UI to help users adhere to the use of the algorithms in the intended ways.

Designers are in charge of creating the meanings and characters attached to their designs and communicating them with other stakeholders in both visual and verbal modes (Chiu and Shu 2012; Koch et al. 2019; Kita and Rekimoto 2018). We define a design-concept phrase ("DCP") as a combination of two adjectives that conveys product aesthetics. For example, "kinetic warm" was created by the designers at Toyota's North American design studio for Concept-i (Fig. 1-right). This unorthodox DCP was created and communicated using a "character space (CS),"(Fig. 1-left). A character space explains design concepts in terms of how and by which attributes they differ and what already exists or what is to be avoided (Krippendorff 2005). While this approach is common in design practice, there's little computational support for such tasks.

In this study, we focus on two key features: word frequency and cosine similarity between words. Setchi et al.(2011) demonstrated a term with a low document frequency in a corpus could support richer inspiration and creativity for designers. Han et al. (2019; 2018) analyzed the conceptual distances between two ideas expressed in word combinations and concluded that good design concepts have a certain distance between two ideas.

Also, among different language models, the concept distances measured by ConceptNet best agreed with human experts' judgment on concept distance(Han et al. 2020). In D-Graph, we use ConceptNet to measure the cosine similarity of two words. Our method uses it to control the quality of the combinational adjectives that express the design concepts.

Methods

The D-Graph searches for and filters adjectives that are related to users' queries by using a ConceptNet knowledge graph (Speer, Chin, and Havasi 2017).

The top section of the web UI (Fig. 2) has a design brief and a search window. The large space below the design brief is allocated to a "playground," in which graphs of explored words are visualized in 3D hub-and-spoke style. When the user expands the search by clicking words, new clusters are shown in different colors so that users can visually track-

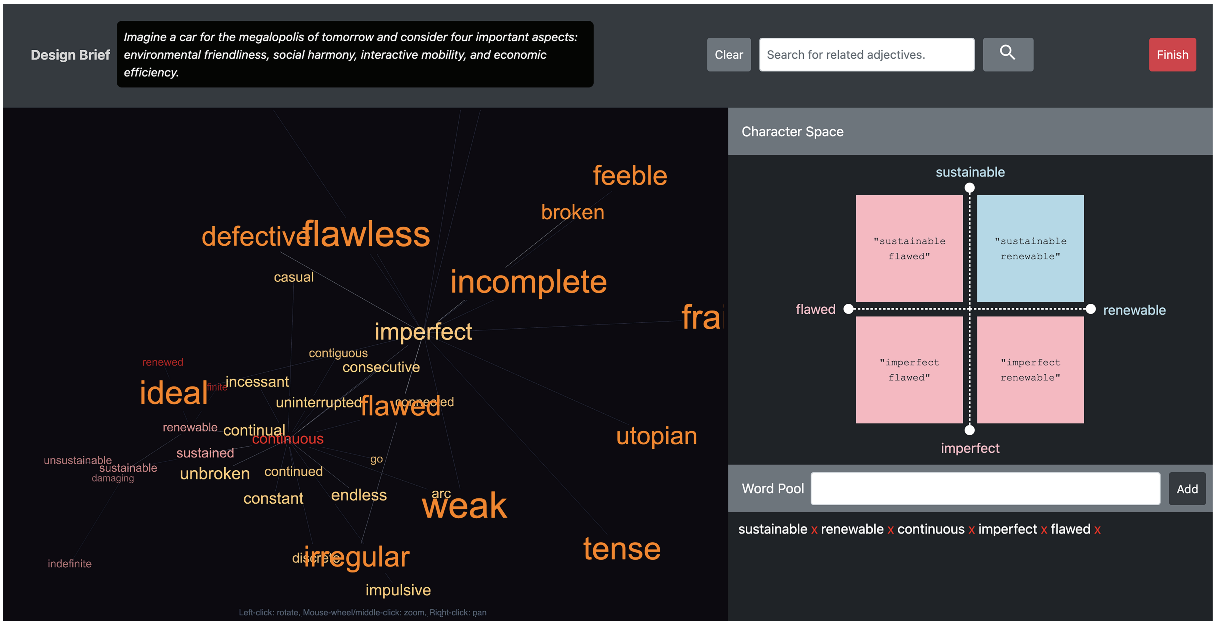


Figure 2: D-Graph web UI (experiment). The baseline tool has Merriam-Webster online thesaurus instead of D-Graph in the playground. All the other UIs are the same for both tools.

back to previous explorations. The lower-right section is a "word pool" where users can store candidate words for design concept phrases. Every time the user puts a query in the search window, clicks on a word on the D-Graph, or drags & drops words from the D-Graph to the word pool, those words are stored in the word pool. Finally, the right-middle section is the CS, which is completed when all four ends on the axes are defined as w_1 through w_4. The words on the CS can be set by dragging & dropping words either from the word pool or directly from the D-Graph. The upper-right quadrant, represented by the combination of w_1 and w_2, is the target design-concept phrase. All the other quadrants are contrasting concepts to be used by the users to explain what are not the target design concepts.

Search and filter algorithms

D-Graph directs users to set words on the CS in a predetermined order (w_1, w_2, w_3, then w_4). This strategy mandates that users first establish the target design concept, represented by the upper-right quadrant (blue square shown in Fig.2) defined by w_1 and w_2, followed by all the other quadrants.

D-Graph has two types of search and filter algorithms, SEARCH_FOR_RELATED_WORDS and SEARCH_FOR_ANTONYMS . The former gets a new word w' from all nodes inside the edge e, using all 33 relations in ConceptNet, except for "Antonym.". Then, each new word w' from the nodes will be filtered in terms of both the relative word frequency ($Freq$) of w' and the cosine similarity ($cosSim$) between the query word w and the new word w', calculated with ConceptNet Numberbatch word embeddings. We currently set the threshold at ($.05 \leq |cosSim| \leq .5$), according to the results by Han et al. (2020), and ($1 \leq Freq \leq 50$) from several tests. The latter first gets related words with the former algorithm; then, for each new word w', it gets all the nodes in the edge using the "Antonym" relation. All the results are set as labels of the start node and end node and the link between them to render the graph.

Pilot study design

Ten undergraduate/graduate students (mean age of 25.1 years, $\sigma = 4.01$), in an industrial design department, participated the pilot study. The independent variables were two different search tools, D-Graph (Fig.2), using the above mentioned algorithms, and the baseline tool, using Merriam-Webster online thesaurus instead of D-Graph UI.

The participants were asked to perform the same task twice with the baseline and experimental tools with different design briefs in a counterbalanced order. A design brief is a written description of a project that requires some form of design, containing a project overview, its objectives, tasks, target audience, and expected outcomes (Phillips 2004; Koronis et al. 2018). After reading the brief, the participants were prompted to start the task. First, they were asked to find a combination of two words that forms a DCP by determining w_1 and w_2; then, they were asked to find the opposing concept to each of w_1 and w_2 to generate the CS. The session was concluded when the user was satisfied with the design-concept phrase in terms of w_1 and w_2 and comfortable explaining it in contrast to the other three quadrants. They participated in the experiment online using Playbook UX, a usability testing platform that enables screen recordings. Each participant was given a video instruction and a practice time window (2-3 min.) to get familiar with the tools.

Subjective evaluation A post-task questionnaire with self-reported evaluations was administered using a 7-point Likert scale for four measurements: the "breadth" of exploration that they could perform, the "originality" of the DCP, the "relevancy" of the DCP to the design brief, and the "explainability" of the DCP. The participants were asked to write a short explanation of the DCP (upper-right quadrant of the CS), in contrast to the ideas expressed in the other quadrants. "Explainability" was measured by a 7-point Likert scale on how comfortable they were in explaining the DCP.

Computational metrics The relative word frequency ($Freq$) of both w_1 and w_2 for each DCP as well as the cosine similarity ($cosSim$) between them were calculated post-hoc. The duration of the task and the word count in the "word pool," which indicates how many words the participant interacted with in the task, were also retrieved. We further analyzed how the selected participants interacted with the words using spatial mapping based on the word embedding.

Qualitative data

All the DCPs and two other words on the CS and the written explanations were obtained. We also had screen recordings that shows the sequence of users' word explorations.

Results and discussion

All the subjective evaluations on the DCPs with D-Graph were higher than those with the baseline tool, though they were not significant (Table 1). Table 2 shows all the DCPs with the participant ID, the tool used, the mean word frequency ($meanFreq$) of w_1 and w_2, and the cosine similarity ($cosSim$) between them. There were no significant differences ($p = .218$) in mean $cosSim$ between the D-Graph ($.246, \sigma = .195$) and the baseline tool ($.149, \sigma = .124$).

Table 1: Subjective evaluation results

Ratings (N=10)				
Variable		Bsln. (σ)	Exp. (σ)	p
Breadth	Mean	4.7(1.42)	5.9(1.10)	0.126
	Medien	5	6	
	Mode	6	6	
Originality	Mean	5.1(0.99)	5.4(1.43)	0.591
	Medien	5	6	
	Mode	5	7	
Relevancy	Mean	5.5(1.51)	6.1(0.99)	0.217
	Medien	6	6	
	Mode	7	7	
Explainability	Mean	5.4(1.65)	5.9(1.45)	0.427
	Medien	6	7	
	Mode	7	7	

Table 2: Design concept phrases generated by participants

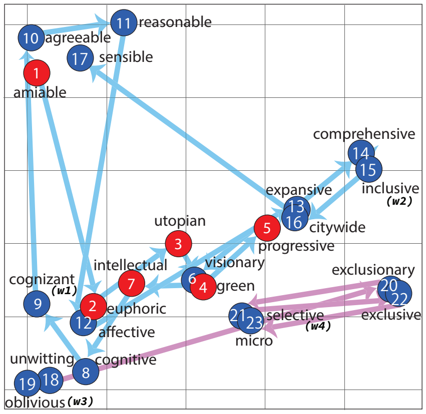
P. ID/Tool	$w_1 + w_2$	$M.Freq$	$cosSim$
1-A/Exp.	"cognizant inclusive"	10.37	0.105
2-A/Exp.	"sustainable renewable"	66.74	0.572
3-A/Exp.	"honest continuous"	26.15	0.123
4-A/Exp.	"futuristic modern"	55.19	0.392
5-A/Exp.	"august renewable"	18.99	0.021
7-B/Exp.	"economical efficient"	31.64	0.551
8-B/Exp.	"affordable neutral"	27.38	0.068
9-B/Exp.	"modular disposable"	5.71	0.162
10-B/Exp.	"empathy transcendent"	1.45	0.240
11-B/Exp.	"utilitarian comfortable"	20.59	0.235
7-A/Bsln.	"efficient functional"	45.45	0.382
8-A/Bsln.	"good-natured safeness"	null	null
9-A/Bsln.	"adventurous lively"	7.01	0.284
10-A/Bsln.	"sustained delightful"	7.41	0.047
11-A/Bsln.	"empathetic minimal"	9.55	0.055
1-B/Bsln.	"protean companionable"	0.13	0.063
2-B/Bsln.	"affordable seamless"	24.26	0.185
3-B/Bsln.	"insensible trustful"	0.18	0.200
4-B/Bsln.	"compact friendly"	28.24	0.121
5-B/Bsln.	"nimble aid"	1.36	0.007

Qualitative results

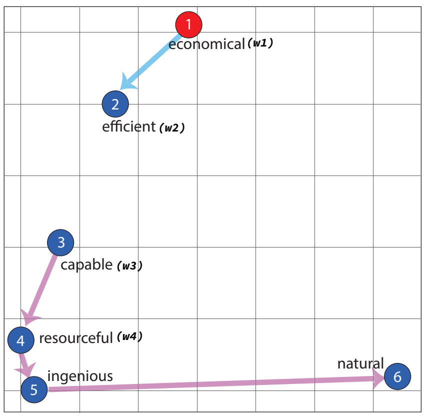
We will present summaries of two cases in this paper. Fig. 3 shows two cases of the participants' exploration process. The words are scatter-plotted according to the ConceptNet Numberbatch word embeddings, whose dimensionality is reduced by principal components analysis (PCA).

Case 1-A: "cognizant inclusive" Fig. 3-(a) was created using a D-Graph with design brief A. It had a $cosSim$ value of 0.105 and the $meanFreq$ was (10.37). The number of words in the word pool was 23, and the task duration was 14 minutes and 58 seconds. The words this participant explored aimed to express "being aware of social issues.". He typed the first word, "amiable," and used the manual search window instead of clicking the words on the graph until he found the sixth word, "visionary,". He opened a new tab on the browser and used an online thesaurus to find the adjective form of "utopia" as the system denied it because "utopia" was not an adjective. He also stated, "desirable for sure, but that's given." When he stored the 16th word in the word pool, he decided to use "cognizant" and "inclusive" for the DCP. He used "oblivious" for w_3. "Inclusive" on w_2 pulled candidates for w_4, but it showed only four words, including the root node. He tried "micro", but did not find anything he liked. Therefore, he went back to "inclusive" and tried "exclusive," which gave him 18 new words. After examining all words there, chose "selective" for w_4. His own ratings for "originality" and "relevancy" were 4 and 7.

Case 7-B: "economical efficient" Fig. 3-(b) was made using a D-Graph with design brief B. It had a $cosSim$ value of 0.551 and the $meanFreq$ was (31.64). The number of words in the word pool was 6, and the task duration was 7 minutes and 1 second. After reading the design brief, this participant typed "economical" in the search window,



(a) Case 1-A
"cognizant inclusive"



(b) Case 7-B
"economical efficient"

Figure 3: Sequence for word exploration in semantic space. Light blue arrows show searches for DCPs for w_1 and w_2, and pink arrows show searches for antonyms for w_3 and w_4. Red circles are users' query inputs in search window. Blue circles are users' clicks on words.

which showed five words. After clicking on "efficient" and "capable," which pulled another 43 words, he spent 1 minute and 40 seconds rotating the graph, moused-over several words to see the definitions, clicked "efficient" and "capable" twice each, and finally cleared the playground and typed "economical" again, followed by clicking "efficient." Then, he clicked "futile," but this was apparently accidental as he deleted "futile" quickly and cleaned up the playground again. He typed and clicked "efficient" and "capable" for the third time. Before clicking the next one, "resourceful," he carefully examined the definitions of "competent," "thorough," and "resourceful." Then, he spent 20 seconds looking at the definition of 'ingenious" and paused another 10 seconds before clicking "ingenious," followed by "natural" for 15 seconds. He further spent 52 seconds rotating the graph, clicked "capable" and "resourceful" again, then put "economical," "efficient," "capable," and "resourceful" for w_1, w_2, w_3, and w_4, respectively. His own ratings for "originality" and "relevancy" were 6 and 7.

Implications for improvement As described above, the participant in case 1-A chose w_2 from the word pool, so he did not utilize SEARCH_FOR_RELATED_WORDS . Yet, he was able to pick two words that were distant enough. He set w_3 and w_4 with words from the D-Graph, which were output according to w_1 and w_2 using SEARCH_FOR_ANTONYMS . This was how we had assumed users would use D-Graph. However, our video analysis unveiled that there were only two cases (4-A and 5-A) that utilized the former algorithm and three cases (1-A, 4-A, and 5-A) that utilized the latter algorithm to explore the words.

For future development, we will add more clarity on what strategy D-Graph helps the users follow. Some participants pointed out the issues in the transparency of the search process and the system status. For example, it was unclear which of the two search algorithms, SEARCH_FOR_RELATED_WORDS or SEARCH_FOR_ANTONYMS, was running. Another option is to implement more automation. For instance, extracting query words from a design brief can be automated. Such automation would lower the initial barrier to exploration.

Different ways of presenting recommended words should also be explored, as it was not easy for some users to avoid cliché words. For example, showing a ranked list of words according to computational linguistic metrics may be an option. In addition, we could further automate the process of concatenating two adjectives in a way that they maintain a certain distance. Finally, we should be investigating engaging factors (Cherry and Latulipe 2014), which we did not measure.

Conclusion

We created an AI-assisted interactive tool, D-Graph, which aims to help industrial designers explore the semantics and aesthetics of design concepts. We integrated two language-based methodologies to attack the problem. 1. We implemented an interactive UI that supports users in broadly exploring words. 2. We implemented search algorithms, utilizing a ConceptNet knowledge graph, that supports users in creating unique compound phrases using an adjective-adjective formula. Our pilot study with 10 student participants did not show significant differences between D-Graph and the baseline tool, which utilizes a conventional online thesaurus. Our qualitative analysis found several important aspects in how users interact with words in lexico-semantic space when searching for words to create a distinguished design concept.

Acknowledgement

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Author contributions

SS contributed to the conception, design, execution of the study, performing the statistical analysis, writing the first draft, and the final version of the manuscript. SY served as the driving force behind the concept, organized the project, and provided guidance throughout the execution of the project. All authors contributed to manuscript revision, read, and approved the submitted version.

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