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UNDERSTANDING BRAINSTORMING THROUGH TEXT VISUALIZATION

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ABSTRACT

Automated content analysis software tools have significantly aided in the study of design processes in the recent past. However, they suffer from the lack of domain knowledge and insight that a human expert can provide. In this paper, we adopt the use of text visualization techniques that help in gaining insights and identifying relevant patterns from the results obtained through a content analysis software. We motivate our approach with the observation that examining overall patterns in data aids us significantly in identifying interesting and relevant details concerning specific contexts in the data. We use the proposed approach to study the effect of adopting Laseau's "design funnel" of alternating divergent and convergent design processes among student teams in a toy design course, and compare it to student teams that follow a free brainstorming process. We demonstrate the application of lexical dispersion plots and text concordances as a means to further examine the output of a conventional content analysis tool, and use these techniques to separate patterns from anomalies. We identify cases of concept consistency across teams using the dispersion plots, and identify cases of multiple word senses through text concordances. Finally, we present insights that were obtained through these visualizations and propose contexts for further studies of the data.

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1 Introduction

The balance between creative thinking and analytical thinking in design has been emphasized by many [1, 2, 3]. Over the last thirty years, several methods have been proposed that enable designers to achieve this balance, the most famous being Pugh's method of controlled convergence [4]. An early graphical model to this end was provided by Laseau [5, p. 91], who illustrated his model as a combination of two funnels, an expanding funnel of elaboration or "opportunity-seeking", and a contracting funnel of reduction or "decision-making". Recent years have seen developments in the study of cognitive aspects of the design process from the point of view of design education. Content analysis and protocol analysis have become widely-used methods in such studies. Studying the effects of design processes in an educational setting has two advantages: the larger body of student designers improves the robustness and repeatability of a study, and the results of the study could potentially have a more direct impact on design education. However, the large volume of textual data generated in such studies becomes challenging, primarily when identifying critical information in the data.

Textual analysis has benefited greatly from the developments in Natural Language Processing (NLP) [6], and can thus be used with large bodies of text. However, completely automated content analysis has its pitfalls [7], especially when classifying domain-specific information. Techniques that would allow analysts to vet the results from a content analysis tool, and allow them to "zoom in" to details and examine the data in its more basic form would mitigate these potential pitfalls. With this in mind, we propose a visualization-driven approach towards the required structured analysis of information present in voluminous unstructured data.

The motivating aspect of visualization in our work is that it combines the advantages of computational capabilities for processing large datasets and those of humans in separating meaningful data from "noise", identifying patterns and anomalies, and understanding specific contexts of data. By observing visually encoded data, domain experts can use their knowledge to understand the meaning behind discovered patterns and gain useful insights. While there are several existing techniques of text visualizations in various domains, it has, to the best of our knowledge, yet to find application in research in design studies.

In this paper, we demonstrate the investigation of a domain-specific design process by augmenting automated content analysis with text visualization techniques. We perform a study that compares free brainstorming to an alternating divergent-convergent brainstorming process, or two passes through Laseau's funnel. We perform a content analysis on text collected in the form of transcribed team conversations, sketch annotations, and student reports, and extract prominent concepts from the text. We then use text visualization techniques to examine these concepts in relation to the text corpora, and report our insights gained.

2 Background

The focus of our work is two-fold: (1) we study the effect of two different approaches to concept generation in a toy design course, and (2) we adopt text visualization methods for analyzing relevant text data generated by the participants to gain further insights into patterns of concept generation, collaborative learning, shared representations of knowledge, and reflective learning. To establish a clear background and motivation for this study, we will look at two main areas: Analysis of Design Processes, and developments in text visualization techniques.

2.1 Analysis of Design Processes

Recent studies on design cognition has drawn significant attention towards the design processes and on how knowledge and understanding of the designer is affected by design processes and interaction among teams. Stempfle and Badke-Schaub [8] propose a generic model of design activity in teams based on the four basic operations of generation, exploration, comparison and selection, and apply it in their study of design teams. They report that traditional focus of design methodology needs to focus not only on the solution concept, but also on the time and cognitive effort to generate the solution. Mumford et al. [9] in their extensive review of methods in creativity research posit that creativity is "a product of work on a particular type of problem" which is: (1) ill-defined, (2) novel, (3) demanding, (4) complex, and (5) exploitable. They recommend that studies of creativity and innovation require a multi-method, multi-measure approach. Gero et al. [10] through their protocol studies on engineering students following three concept generation techniques of brainstorming, morphological analysis and TRIZ conclude that using structured methods tend to help students focus better on the structure of a solution. Jin and Chuslip [11] focus on the issue of "mental iteration" in engineering design, defined as "a goal-directed problem solving process", modeled as a "sequence of transition behaviors between information processing and decision-making". They studied the process of iterative thinking in designers and identify three distinctive "global iteration loops": problem definition loop, idea stimulation loop, and concept reuse loops. They further conclude that "creative design involves more iterations than routine design". This idea of iteration promoting more creative thinking has been empirically suggested, and it could even be argued that this to an extent explains the design expert's emphasis on early design having alternating cycles of divergence and convergence.

2.2 Developments in Text Visualization

Two of the early text visualization schemes found in literature are lexical dispersion plots [12, p. 120] and text concordances [13, p. 31], both developed as NLP techniques. Recent developments in text visualization have been used to analyze large bodies of text such as parallel tag clouds [14] and Docuburst [15] for providing a quick overview of document content, while visualizations such as FeatureLens [16] and Arc Diagrams [17] were developed for providing an overview of patterns throughout a document. Visualizations such as Word Trees [18] and Tag Clouds[1] focus on repetition in context in large documents. Glyph techniques like Starstruck [19] are used to provide synoptic visualizations of documents and abstract document similarities to shape similarities between the generated glyphs which can be visually compared. The visualization techniques used in our work involve more basic visualizations: lexical dispersion plots [12, p. 120] for abstract representations of usage patterns of a word or phrase in a document, and text concordances [13, p. 31] for representing the "raw" text data to examine the usage in context of these words or phrases.

3 Study

Our study was conducted in the context of a toy design course offered as a senior elective to undergraduate engineering students. The course includes lectures that all students attend at the same time, and lab sessions, where the class is split into two batches. This batch assignment is based on a first-come, first-served basis at the time of enrollment. We used this division of batches for our between-groups study. The course includes

[1] http://www.wordle.net/

a team project to design, model, and prototype an action toy. Students are split into teams of 4 for the project, for which we performed a random assignment to reduce the chances of performance outliers. Before they begin this project, the students are taught idea generation techniques like SCAMPER and "combining things" [20, p. 72, 332], trained on sketching as a way of visual thinking [21], and given an understanding of play value [22]. Equipped with these tools and techniques, the students are expected to start their project with a brainstorming session. We conducted this brainstorming session under a controlled environment in a classroom, where we gave one batch guidelines for "free" brainstorming, and guidelines for an alternating divergent-convergent brainstorming to the other. We then recorded the team discussions and the concepts generated in the session.

3.1 Participants

We recruited 70 participants (68 male, 2 female), who formed the entirety of the mentioned toy design course. All participants were undergraduate engineering students in their senior year.

3.2 Experiment Design

We used a lab session to conduct the brainstorming, so we could perform a between-groups study, with the groups comprising of the two lab batches. By conducting both sessions with a space of only ten minutes between them, we reduced the possibility of communication between the two batches. We conducted the session in a room where the seating arrangement was modified to allow students in each team to sit facing their teammates, and each team was provided with a tack board for putting up their sketches or notes for discussion. Teams brought their own sketching instruments, and were provided with sheets of paper marked with their team numbers for later identification.

3.3 Tasks

We gave both batches the same problem statement: "Design a toy that exhibits a creative, non-trivial motion". Both batches had the same required outcome: a two-point perspective sketch of their final concept, with annotations and notes describing the toy and the target customer, and profile sketches of the concept showing salient features. We gave both batches 90 minutes to brainstorm and arrive at this final concept.

Each team was then provided with different procedures to follow:

Batch 1 teams were provided with sheets of paper marked with their corresponding team numbers, and were allowed to brainstorm with relative freedom, as shown in their instructions below:

1. Brainstorm and generate multiple ideas
2. Put the ideas up on the tack board
3. Discuss and develop the ideas
4. Discuss and select ideas that the team likes
5. Select a final concept and develop it to detail

Batch 2 teams were provided with two kinds of sheets of paper: sheets marked with red dots, and sheets marked with blue dots. All sheets of paper were marked with the corresponding team numbers. The batch was told to follow a two cycles of alternating divergent and convergent brainstorming. They were advised to do the following:

1. Brainstorm and generate concepts (as many as you like, roughly in the two digit range) as a team and sketch them on the sheets of paper marked with the red dots.
2. Put the ideas up on the wall
3. Discuss and select concepts (preferably in the single-digit range) that best appeal to you
4. Mark the sheets with the concepts as "selected"
5. Use further brainstorming and "crossing products" [20] to take features from the selected ideas and develop them to concepts (again, preferably in the two-digit range). Use the sheets marked with the blue dots.
6. Select the one concept that holds the most promise.

After the session, all the teams were given three days to prepare a report that reflected on the process they followed and the product that they developed. This was to include the process they followed to generate ideas, how they balanced quantity and quality, and the rationale they used to select ideas that they found promising. They were also asked to include their feedback on the process they followed, and then discuss aspects that they found effective and those they found ineffective. The product section of the report was to include the number of initial concepts generated, a description of the final concept, its play value, and its features that customers would value. In addition, the teams were also to identify the underdeveloped features of their concept and explain what they would do to improve them. Finally, they were asked to list other concepts that they had liked, but had discarded in favor of their selected concept, and explain why.

3.4 Data Collection

Our intent was to study three main aspects of the brainstorming process, namely (1) concept discussion, which focuses on the conversations that occur within teams during brainstorming, (2) concept representation, which focuses on the sketches and annotations that the teams generate during the session, and (3) concept reflection, which focuses on what the students think in retrospect about both the session and their concept. To this end, we made three corresponding categories of data:

Concept Discussion: We recorded the brainstorming discussions of each team on individual audio recorders placed on their desks. Each individual audio recording was then

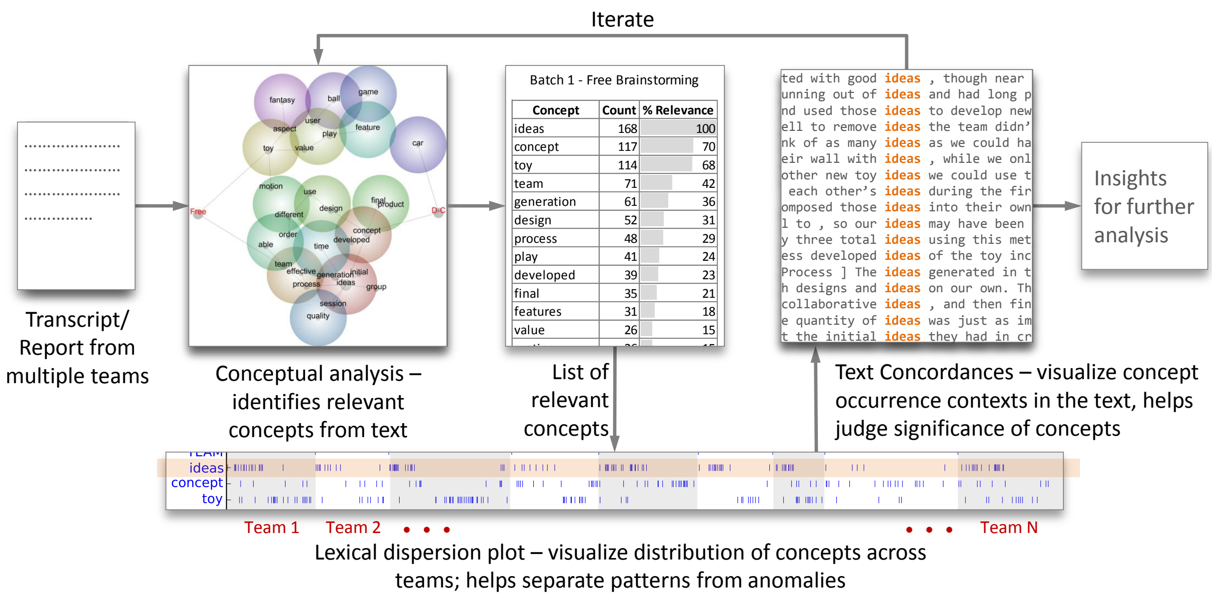


FIGURE 1. FLOWCHART OF THE ANALYSIS PERFORMED ON TEXT CORPORA FROM THE DISCUSSIONS, REPRESENTATIONS, AND REPORTS FROM STUDENT BRAINSTORMING SESSIONS.

transcribed, into text documents. A total of 41690 words were obtained as conversation records from the Free batch, and 40170 words from the D-C batch. In addition, two teams from each batch were arbitrarily chosen for video recording as well.

Concept Representation: We collected and scanned all the sketches made by the teams, and further transcribed all sketch annotations into a text file for every team. A total of 1580 words were recorded as sketch annotations from the Free batch, while the D-C batch used 1470 words in total.

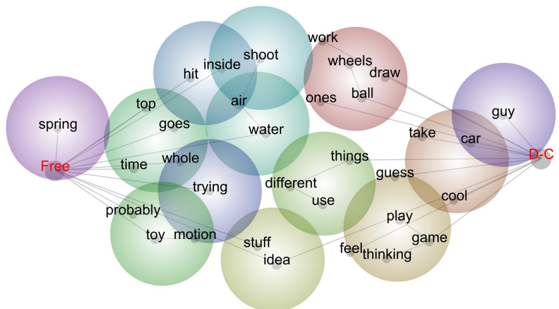
Concept Reflection: We collected soft copies of the reports the teams prepared on their process and their product.

We tagged all the above information with the corresponding team names. Data from teams in batch 1 (free) were then combined to one text corpus each for concept discussion, concept representation, and concept reflection. A similar process was carried out for data from teams in batch 2 (D-C) as well.

3.5 Analysis

We subjected the text corpora from concept discussion and concept reflection to a (textual) conceptual analysis, is based on the frequency of certain word co-occurrences, and a relational analysis, based on relationship between these textual concepts in the structure of the text. We adopted a visualization pipeline as shown in figure 1 that consisted of three main representations:

Concept Maps: We used Leximancer [23] to conduct the conceptual and relational analysis, the results of which are then displayed as a "concept map". An example use of Leximancer techniques can be seen in [24]. Leximancer uses computational linguistics and machine learning to extract "textual concepts" based on word co-occurrence statistics. These concepts are ranked based on their relevance to the most occurring concept, as shown in the tables on the left and the right in figure 2. The most occurring concept thus has a relevance of 100%. The relational analysis uses a concept-mapping algorithm based on a variant of Chalmers & Chiston's spring-force model [25] to identify relationships between these textual concepts. The output is the concept map, which consists of a graph with nodes as concepts and edges as relations between concepts. The concepts are further clustered into groups called "themes". The concept map represents (1) *concept frequency* through brightness of a cluster of concepts, (2) inter-concept *relative co-occurrence frequency* through the intensity of edges connecting related concepts, (3) total concept connectedness through hierarchical order of appearance on the map, and (4) a representation of direct and indirect inter-concept co-occurrence through proximity of the concepts on the map. Further, Leximancer allows manual tagging of a text corpus, which is then represented on the concept maps as a category [26]. The final concept map then clusters the discovered textual concepts around the specified tag categories, as shown in figure 3. However, in this representation, the discovered concepts do not characterize the whole text: they are specific to the tag categories and do not cover the major themes of the whole data set. Relevance here is then calculated as the probability of a concept occurring in a specified category, i.e., one of the two batches in



Batch 1 - Free Brainstorming

Concept	Count	% Relevance
idea	308	100
toy	228	74
ball	154	50
water	132	43
draw	127	41
car	123	40
things	109	35
time	104	34
motion	101	33
goes	98	32
different	91	30
use	91	30
stuff	88	29
top	82	27
probably	78	25
game	75	24
spring	72	23
thinking	70	23
play	67	22
guess	67	22
boat	66	21
hit	65	21
air	61	20
inside	60	19
ones	55	18
whole	41	13
cause	41	13

Proximity Analysis (between batches)

Concept	Count	% Relevance
idea	597	6
toy	372	3
car	362	3
ball	347	3
cool	299	3
draw	272	3
water	262	2
use	247	2
shoot	245	2
things	238	2
wheels	218	2
game	191	2
different	185	2
play	184	2
motion	183	2
goes	173	2
work	172	2
stuff	171	2
time	169	2
thinking	160	2
guess	158	1
take	131	1
top	129	1
hit	128	1
probably	128	1
air	116	1
guy	116	1
ones	112	1
trying	108	1
inside	102	1
spring	102	1
feel	99	1
whole	72	1

Batch 2 - D-C Brainstorming

Concept	Count	% Relevance
idea	287	100
car	214	75
ball	194	68
cool	176	61
draw	143	50
water	130	45
things	129	45
use	125	44
toy	121	42
wheels	105	37
game	103	36
play	99	34
different	92	32
guess	91	32
thinking	90	31
work	86	30
stuff	83	29
motion	79	28
take	77	27
guy	76	26
goes	75	26
time	65	23
people	59	21
air	54	19

Legend
Common concepts
Unique to D-C
Unique to Free
Unique to common corpus

FIGURE 2. RELEVANT CONCEPTS EXTRACTED FROM BATCH-WISE BRAINSTORMING TRANSCRIPTS, COLORED ACCORDING TO THEIR UNIQUENESS TO EACH BATCH. THE PROXIMITY CONCEPT MAP ON TOP SHOWS CONCEPTS CLUSTERED NEARER THE GROUPS THEY ARE RELATED TO. WARMER HUES OF CONCEPT CLUSTERS INDICATE HIGHER FREQUENCY OF OCCURRENCE.

this study. Thus the concept with the highest occurrence in both categories does not have a relevance of 100%, as shown in the central table marked "Proximity Analysis" in figure 2. This visualization of the concept map in relation to the tagged categories is then useful for a comparative analysis, in our case, between batch 1 and batch 2.

Lexical Dispersion Plots: The text corpus for each batch contains content from nine teams. Thus, it becomes important to examine the distribution of the most occurring concepts. A concept cannot be said to characterize a batch unless it is fairly uniformly distributed across most teams in the batch. While it is possible to construct proximity maps with each team as a category to identify if some of the concepts are skewed toward certain teams, the human readability of such maps becomes difficult with increasing number of teams. A *lexical dispersion plot* [12, p. 120] offers a more visually preattentive way to represent concept distribution. The plot indicates locations in the text corpus where a particular concept occurs, and therefore can offer the following visual representations:

1. In analysis of transcribed meetings and discussions, it can show temporal patterns in the occurrences of concepts within and among teams.
2. It provides a visual representation of document structure with respect the concepts of interest.
3. It provides a means of visually comparing concept occurrence counts, which can be used to evaluate annotations on sketches to identify common or unique ideas among teams.

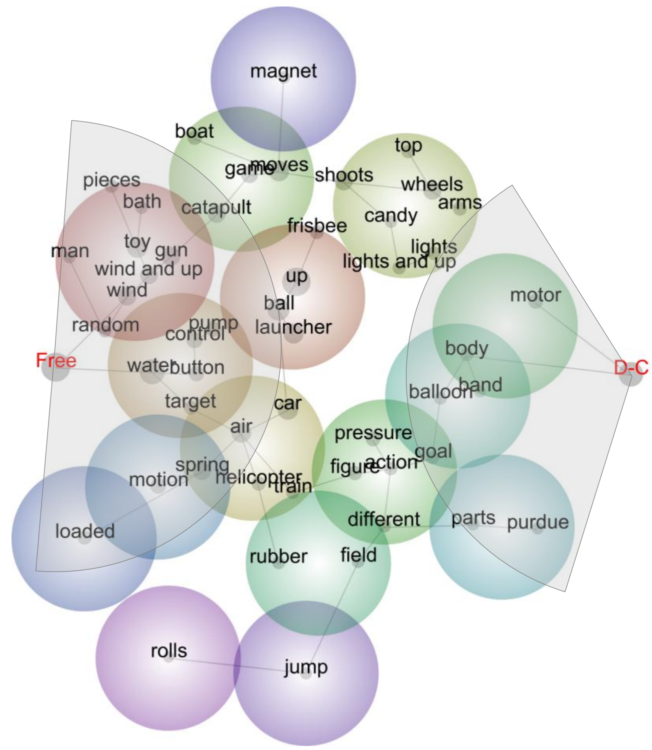


FIGURE 3. PROXIMITY DIAGRAM FOR CONCEPT REPRESENTATION. THE GREY CIRCULAR SECTORS ARE CENTERED ON THE FREE AND D-C CATEGORIES, AND ARE OF THE SAME RADIUS. THE HIGHER CLUSTERING AROUND FREE INDICATES A HIGHER NUMBER OF CONCEPTS FROM THE CORRESPONDING TEAMS.

The lexical dispersion plot in our study was generated using the Python Natural Language ToolKit (NLTK) [27].

Concordances: In addition to consistent distribution of a concept's occurrences across teams, its significance is also determined by its usage in context. For example, frequent occurrences of the word "feel" in a design discussion could indicate that participants are discussing user experience, or are using the word to voice their opinion. A *Key Word In Context* (KWIC) concordancing program [13, p. 31] is used in Natural Language Processing (NLP) to display all occurrences of a word of interest, along with their surrounding words to establish context. The word in question is aligned vertically to provide a visual reference for the user to identify patterns in the preceding and succeeding words. Figure 5 shows an output of such a concordancing program. In addition to providing a means to visually determine the context of a concept, concordances are also useful in identifying compound concepts: groups of words that carry a meaning different from that of the words that make it up, such as "remote control". Concordances were thus used to (1) further vet the concepts for significance, and gain insight into the sense in which the concept was used (2) To disambiguate word senses visually, and (3) to identify compound concepts and further iterate over the conceptual analysis with Leximancer. The KWIC concordancing program used in our study was again from Python's NLTK.

4 Results and Discussions

We sought to study the effects of two different approaches to brainstorming among student teams, and to identify any patterns in their discussion, representation, and reflection that may be attributed to the process they followed. Our results are thus structured under the three heads of Concept Discussion, Concept Representation, and Concept Reflection. Under each of these heads, we discuss our findings from the content analysis, and explain the visual representations generated using the lexical dispersion plots and KWIC concordances, which allowed us to drill down to details and gain further insights.

4.1 Concept Discussion

The conceptual analysis of each batch revealed 27 concepts for the Free batch, and 24 concepts for the D-C batch. The proximity analysis of both batches revealed 33 concepts, 7 of which were unique to the Free batch and 5 to the D-C batch. A complete list of the concepts color coded according to uniqueness to the two batches is shown in figure 2.

Concepts closest to the "Free" and "D-C" categories on the proximity map were then considered as potentially significant concepts. Dispersion plots of these selected concepts in their corresponding text corpora revealed that "top", "probably", "time", and "motion" were both relevant to and consistent within the Free batch. Similarly, "guy", "cool", "game", "play", "take", and "draw" were selected as potentially significant concepts for the D-C batch.

Text concordance of these concepts revealed no unique use of "probably", "time", and "motion". However, there were 8 instances of the mention of "top" as a toy by four teams in the Free batch, but none in the D-C batch. The D-C batch showed relatively higher incidences of the word "guy" in the specific context of an action figure, and lower occurrences of the term "play value" than the Free batch.

The analysis of concept discussion does not reveal much information, and one of the main reasons can be seen in the ranked concept list from the proximity analysis, shown in the central table of figure 2. The percentage relevance of the top concept, "idea", is 6%. As mentioned earlier, this number indicates the percentage incidence of the concept in the text corpora from either of the batches. A cursory reading of the transcripts shows a significant amount of banter among team members, which dilutes the occurrences of discussions meaningful to the brainstorming exercise. A possible solution could be to manually excise non-relevant discussions from the transcripts, but this may result in the loss of information that could potentially contain records of "chance encounters" [28]. A more challenging but fruitful approach would be to manually identify the presence of such instances of creativity that come from chance encounters with new content, stories, or recall of past experiences. The visualization pipeline used in this work may not be sufficient for this task, but a more hierarchical visualization of broad-level concepts from text [15] could perhaps aid discovery.

4.2 Concept Representation

As mentioned in section 3.5, the text corpora from concept representation consisted of annotations made on sketches. These were isolated words and phrases, and the proximity of these words on the transcribed text file might have meaning only if they were from the same sketch. Thus the results of the conceptual analysis had to be interpreted with care. The concept clusters were unlikely to have any thematic meaning, but the proximity of the concepts to the manually-assigned categories of "Free" and "D-C" was still meaningful. Figure 3 shows the proximity diagram for concept representation, with circular sectors of the same radius drawn centered at the "Free" and "D-C" categories to show the variation in clustering density. It was immediately evident from the diagram that concepts were more heavily clustered around the Free batch, and those clustered around the D-C batch occurred less frequently. This was also evident in an examination of the ranked concepts from individual analyses of text from each batch: concepts unique to the Free batch were more frequent in the the combined proximity analysis than those unique to the D-C batch. Lexical dispersion plots of selected concepts helped discard the concepts "catapult" and "parts" from

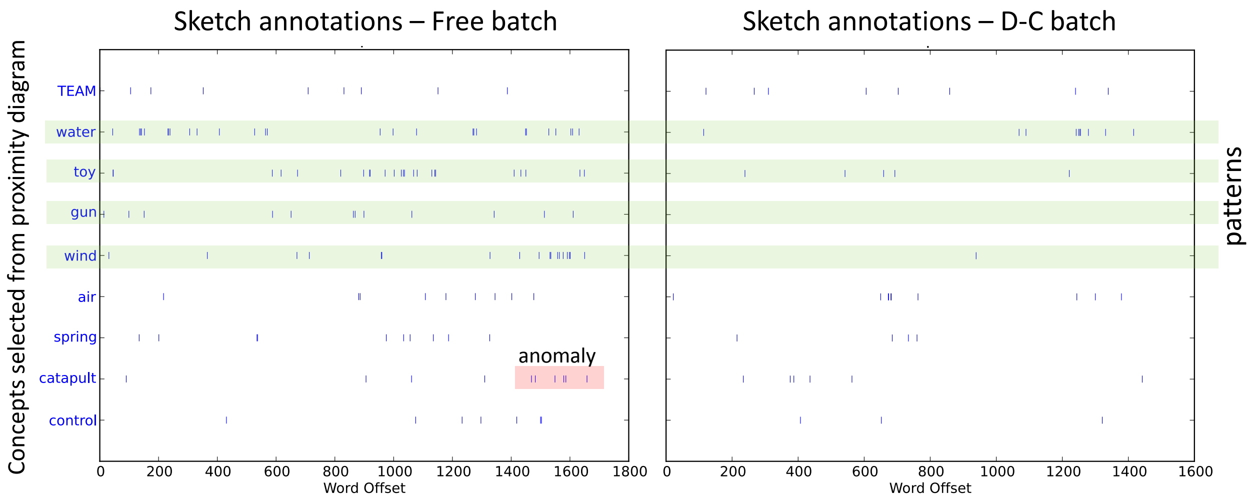


FIGURE 4. TEXT DISPERSION PLOTS OF SELECTED CONCEPTS FROM SKETCH ANNOTATIONS AID THE IDENTIFICATION OF PATTERNS AND ANOMALIES

both batches, while "water", "toy", "gun", "wind" were selected for examination in the Free batch. "Motor" and "body" were concepts relevant to the D-C batch that were selected for further analysis. Some of these dispersion plots are shown in figure 4.

A concordance analysis showed that "water" continued to be of significant importance: eight teams from the Free batch discussed ideas for water toys or games, while only three teams discussed water-based ideas for toys. The word "wind" was used in the sense of "wind up" (wind-up toys) in almost every occurrence in the Free batch, while it appeared only once in the D-C batch, in the context of "wind powered". The word "toy" was five times more frequent in the Free batch than the D-C batch. In terms of sketch annotation, this could be significant: it could mean that the Free batch concentrated more on types of toys, without getting too much into detail, while the D-C batch showed a higher tendency to get into detail. This inference is further supported by the higher frequency of use of the terms "motor" and "body" in the D-C batch. Text concordances of both concepts revealed that they referred to components of the toys, thus showing a greater focus on how they worked. Some representative concordances are shown in figure 5.

The inferences from the sketch annotations section were more or less what was expected: the alternating divergent-convergent process requires, in the second cycle, to concentrate on features of the design, and helps the designers focus on detail. The next question that came up was, which approach is better? The Free brainstorming batch came up with more kinds of toys, which is beneficial for initial idea generation, while the D-C batch focused on details, which is beneficial for better quality and evaluation of ideas. The question of duration also comes into the picture: did the D-C batch focus on details "too quickly"? Is it better to perform an alternating divergent-convergent brainstorming session in one go, or is it better to have a gap between each cycle to allow for reflection? These could form the topic of future research.

4.3 Concept Reflection

The proximity diagram for concept reflection, shown in figure 6 indicates a higher incidence of shared concepts between the two batches, shown in the higher clustering in the middle of the "Free" and "D-C" categories. As with concept reflection, circular sectors of equal radii centered on the category nodes and overlaid on the diagram helped isolate concepts that were closest to each category. A lexical dispersion plot of the selected concepts helped eliminate "car", which was concentrated on two teams in the D-C batch, and also helped draw attention to "team", which had a higher occurrence in the Free batch, and "group" and "feature", which seemed to have a higher occurrence in the D-C batch. While "toy" had high occurrences in both batches, it seemed relatively higher in the D-C batch. An interesting observation here was that the occurrences of "toy" were concentrated in the latter half of each team's report. This was consistent with our requirement which stated that the reports should have a separate sections for the process and the product: "toy" would occur more in the section discussing the product. This structure being revealed by the lexical dispersion plot highlights its characteristics discussed in section 3.5.

Text concordances of the selected concepts revealed that the D-C teams discussed more about the features of the toy than the Free batch, which is consistent with the results of the concept representation. The use of "group" and "team" were revealed to be synonymous to each other, and combining the two revealed that reports from the Free batch discussed more about

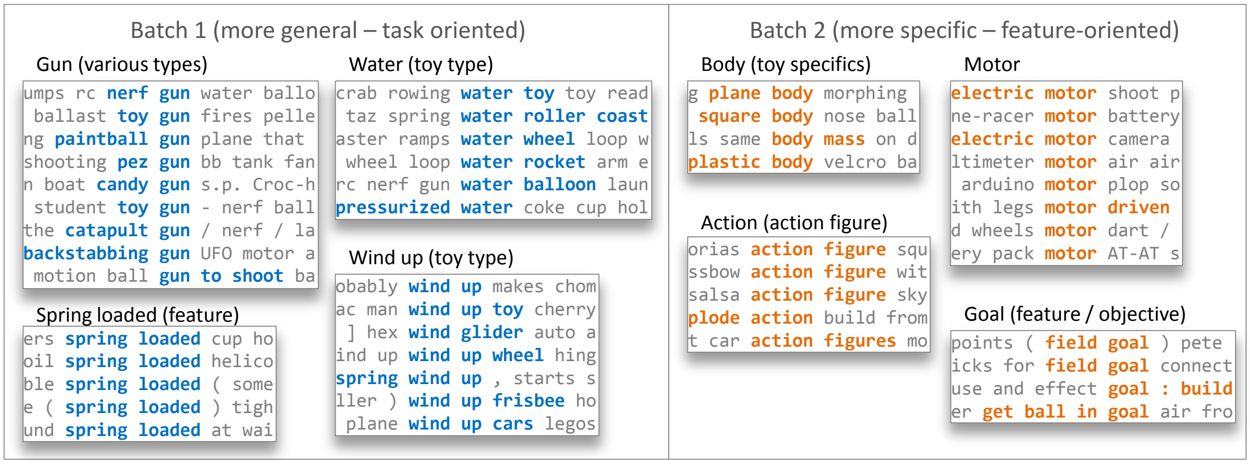


FIGURE 5. TEXT CONCORDANCES FROM CONCEPT REPRESENTATIONS. EXAMINING THE USAGE OF THE IDENTIFIED CONCEPTS HELPS DEVELOP INSIGHT INTO SIGNIFICANCE OF CONCEPTS.

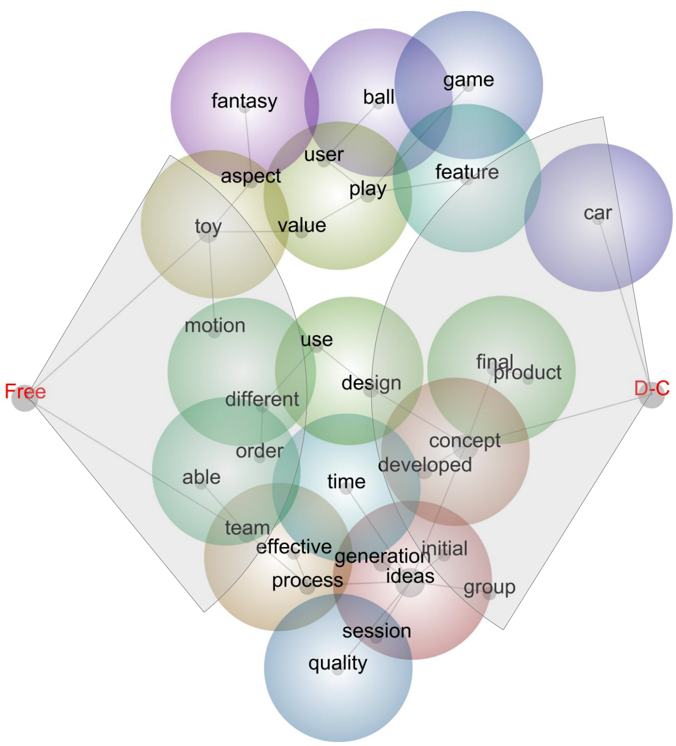


FIGURE 6. PROXIMITY DIAGRAM FOR CONCEPT REFLECTION. THE GREY CIRCULAR SECTORS ARE CENTERED ON THE FREE AND D-C CATEGORIES, AND ARE OF THE SAME RADIUS.

their teams. Closer examination of the occurrence patterns of "group" and "team" did not show a clear concentration of occurrences in either section of the report. The D-C batch also had higher instances of the term "final" which was used in the context of "final concept" or "final design" in both batches. This could perhaps be due to the emphasis on the selection process that is placed due to the alternating divergent-convergent processes, and merits further study. A concordance of all concepts from the proximity diagram also revealed that the D-C batch showed 25 instances of the term "game", while the Free batch showed 5. A preliminary inference that could be drawn from this is that the D-C batch tended to reflect more on the use of their toy, and how it would be played with. However, more teams from the Free batch reported on the play value [22] of their toy, while the term "customers will value" was used uniquely (but not very frequently) in the reports from the D-C batch. This could reinforce the inference of the D-C teams reflecting more on the user experience, if one thinks of "play value" as a feature. A further study on concept discussion focusing more on terms related to the experience of using the toy could reveal more about how the two processes might influence consideration towards the user experience.

5 Conclusions and Future Work

In this paper, our key contribution is a visualization-driven approach to augment automated content analysis tools in order to enable a domain expert to observe patterns, identify anomalies from an overview of data, while also enabling a closer examination of data in context to gain deeper insights. Our primary motivation was to enable the analysis of large bodies of unstructured text obtained from brainstorming sessions of student groups. To the best of our knowledge, this integration has not been attempted in previous literature. Our primary goal was to understand the difference between the effects of two distinct modes of brainstorming, embedded in the context of a toy design course. To this end we concretely investigated our approach through the study of discussion, representation, and reflection of concepts generated during two independently conducted sessions: free brainstorming, and alternating divergent-convergent brainstorming. The visualization techniques used were lexical dispersion plots, which helped evaluate the consistence of concepts identified by the content analysis tool, and text concordances, which helped observe the use of these concepts in the original text body. These visualizations helped separate the relevant concepts from anomalies, and verify the significance of the usage of these concepts, leading to insights that would guide further studies.

We observe that the study of brainstorming design processes can be as subjective as the processes themselves due to the inevitable involvement of several modes of communication and expression distributed across several individuals in a group. This poses a very unique challenge in terms of both the data acquired from the brainstorming sessions in different forms as well as the final concepts generated which cannot be objectively evaluated due to absence of details. With this in view, we appreciate the importance of more in-depth studies using our proposed approach towards conclusive and insightful results. Our next steps would involve a more focused analysis of team orientation towards trends observed in this study such as user experience and reflection on team processes. We posit that a protocol analysis of the video recordings would reveal behavioral aspects of participants and their relation to tendencies observed in this study. We believe that a visualization-driven approach has immense potential to address many of the issues related to content analysis in design studies and must be investigated and developed further.

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