Be the Data: Social Meetings with Visual Analytics

Xin Chen[1], Jessica Zeitz Self[1], Maoyuan Sun[3], Leanna House[2] and Chris North[1]

[1]Department of Computer Science, Virginia Tech
[2]Department of Statistics, Virginia Tech
[3]Computer & Information Science, University of Massachusetts Dartmouth

***Abstract*—Social meetings provide important venues for people to get connected. However, it is challenging to explore reasons of social gathering, identify its key impact factors, and further use it to support people's social activities. In this paper, we present an embodied visual analytics system, which highlights analyzing and displaying social-cluster related information in real time. In the system, each user represents a data point in a high-dimensional dataset, and their positions reflect a 2D projection of the dataset, by using weighted multidimensional scaling. As users move and socialize with others, the 2D projection is dynamically updated, and relevant information of user clusters is visually analyzed and presented through dimension reduction techniques. We conducted informal social meetings with participants who were a mix of strangers and friends. We found that there are 3 stages of social gathering, corresponding to different interactions in the system. Our results also suggest that the system assists social gathering with dimension reduction visualizations.**

***Keywords*—Visualization, Collaboration, Social Interaction, Dimension Reduction.**

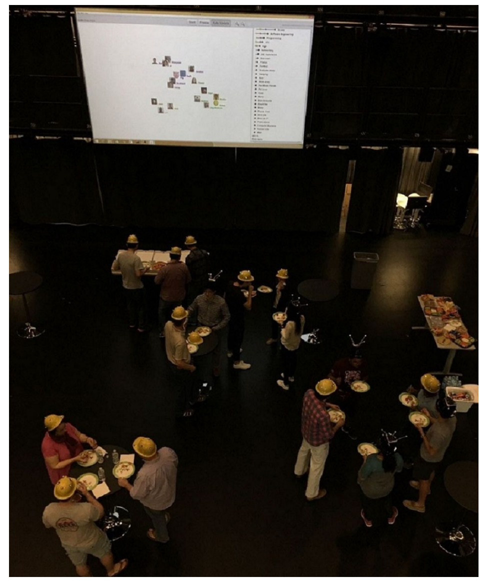


Figure 1. An overview of the system applied in a social meeting. With the system, participants become individual data points of a high-dimensional dataset about themselves. A birds-eye view of their locations in the room is displayed on a large display. The visualization shows participants' head images, name tags, and a dimension chart.

I. Introduction

Social gathering results from certain similarities among people. Individuals have their own characteristics (e.g., age, gender, education, hometown, etc.), which may impact their social activities. For example, people, from the same hometown and attending the same college, are more likely to talk with each other in a social event, since they share similar characteristics. Understanding such similarity among people potentially helps to explain some social phenomena. However, it is not trivial to explore similar characteristics among people in a social event, because it leads to questions in two aspects: data analytics and human-computer interaction. First, considering each individual as a data point with multiple associated attributes (e.g., gender, age, education, etc.), how can we model social gathering and capture the corresponding key attributes? Second, how can we show this computationally modeled information to people in real time and further support their social activities?

We present a new approach to apply embodied interactive visualization to informal social meetings to study peoples' interactions in social gatherings. Specifically, we employed an interactive system called *Be the Data* [2] to track social meeting attendees and provide real-time feedback about social clusters (Figure 1). In this system, each attendee in a physical space is a data point of a high-dimensional dataset that contains attendees' information (Table I). Attendees' quantitative responses to each question are the dimensions of the data points. The positions of attendees in this physical space represent the 2D projection coordinates of their high-dimensional locations. During a social meeting, attendees are free to walk to any other attendees to socialize. While they move, they alter the projections, and receive real-time visual feedback that explains their changes in positions. The visualizations are designed to highlight attributes that characterize social clusters. Also, participants are provided with opportunities to know about other attendees.

The informal social meetings that we arranged were intended to mimic gatherings similar to coffee breaks or receptions, where there is a mix of people who do and do not know each other. The primary focus of this exploratory study is a qualitative evaluation of the *Be the Data* applications deployed during informal social meetings. We attempted to use dimension reduction techniques to explain social behaviors and were interested in how socialization could be mediated by such techniques. The key contributions are:

- The identification of three activities of social gatherings as accompanied by different interactions in the system.
- The demonstrative use of interactive visual analytics meshed with common social meetings.
- The application of dimension reduction techniques to explain social gatherings.

II. Related Work

A. Augment physical social space

Researchers haven already attempted to make use of physical spaces to promote social interactions among people. Proactive displays are a means to augment public physical social spaces; they are normally large public displays coupled with motion sensors. The displays are able to detect and respond to people standing nearby. For example, Ticket2Talk [8] is a proactive display designed to bring up interesting topics during coffee breaks in academic conferences. An attendee is able to intentionally move closer to the display, so that the display will show his interest to bring up discussions. Another example of proactive display is AutoSpeakerID [8] used during a question and answer session following a paper/panel presentation. The display will show the name, affiliation, and photo (if provided) of the person who approaches the display in order to ask the speaker questions. It provides a quick and brief background of the questioner to facilitate future follow-ups of speaker or audience with the questioner.

Interactive technologies have been extended beyond the proactive displays to maximize the use of larger physical spaces. Wearable and hand-held devices haven been applied to augment physical social spaces during academic conferences. These devices take advantage of sensor technology (e.g., radio frequency) to provide location-based services. They are often made small enough to be carried on (e.g., a conference badge or a cellular device), such as IntelliBadge [4], CharmBadge (www.charmed.com), Meme Tags [1], and SpotMe(www.spotme.ch). Some of these devices facilitate the one-on-one or person-finding activities. For example, the Meme Tags (a badge with small LED displays) allows people to share memes in person-to-person transactions [1]. Some of these devices focus on the aggregated data of all attendees to create dynamic visualizations for pubic views. For example, the IntelliBadge system tracks conference attendees and provides real-time snapshot of the conference events attendance [4].

The *Be the data* application differs from the tools described above both in terms of the motion tracking technology and more importantly in terms of end-user information analysis techniques. First, the *Be the data* system uses an OptiTrack motion tracking system to collect and process motion capture data from 24 motion cameras. Second, in addition to simple aggregated statistics to summarize attendees, the *Be the Data* system coupled the Weighted-Multidimensional Scaling (WMDS) techniques with a prior knowledge about the attendees to interpret dynamic social clusters in real time visualizations. For example, as Figure 2 a shows, attendees clustered in pink seem to share the similarity of having more friends on Facebook than attendees in other clusters; attendees clustered in yellow seem not using Facebook. As a probe of context-aware technology for the space that "comes into being through interaction" [12], the *Be the Data* system intends to augment the physical social space with such interactive technologies. In turn, the attendees are able to observe and react to the dynamics of social clusters.

B. Social Computing

Social computing is concerned with incorporating social context into the design of interactive systems [5]. Driven by the needs for computerizing aspects of social behaviors to promote communication and interaction among groups of people [13], social computing seeks to integrate technologies with humans' interactions, improvised naturally in real time and real space [5]. It has been increasingly influenced by social and psychological theories as an analytical perspective to understand interaction and the use of interactive tools [5]. Social computing denotes a collaborative status where users work collectively to construct understanding [9]. One of the most influential applications of social computing is the development of the field of Computer-Supported Cooperative Work (CSCW) [5]. Our application is an attempt of social computing within regular social meetings to trigger and respond to users' social reactions.

Embodied interaction is extended from the work of social computing [5]. Paul Dourish [5] describes embodied interaction as "the creation, manipulation, and sharing of meaning through engaged interaction with artifacts." He further explained it as an attempt to integrate physical and social reality of our everyday world into computing. People have developed sophisticated perceptions and skills acting in the world. However, they are rarely embraced for visual analytics to facilitate social interaction in an intentional and natural way. Therefore in this study, we present an application of the embodied system to mesh natural embodied social interactions with visual analytics. With the *Be the Data* system, we highlight how people naturally interpret the relative distance in the physical space (i.e., the "near is similar, far is dissimilar" metaphor) to comprehend clustering information. While people socialize with others, they embody their virtual data points to manipulate the underlying mathematical model. The real world social experiences is unified with the computational experience in a seamless way.

III. System Overview

The system [2] exploits a multi-media high-tech room called the Cube, which includes a large overhead display, a motion tracking system, and the backbone software adapted from Andromeda [11], [10] based on the system described in [2] for direct manipulation of virtual high-dimensional data models.

TABLE I. A portion of the high-dimensional dataset resulted from participants' quantitative responses to a list of questions in the pre-survey. Each participant is a data point and each question is a dimension. The example in this table shows 3 participants and 7 (out of 26) dimensions. Questions for the above dimensions were asked as below:
Age Your age?
Beer How much do you like beer? 1=I don't drink it at all; 100=I have it every day; 50=don't care.
Countries How many different countries have you visited in your lifetime?
Facebook How many FaceBook Friends and/or Google+ friends do you have? 0=i don't use Facebook/Google+
HCI On a scale of 1-100, my study (research) is related with human computer interaction (HCI). 0=not relevant; 100=I'm a HCI researcher; 50=ok or don't care.
Math Do you like math? 1=hate; 100=love; 50=ok or don't care.
Networking On a scale of 1-100, my study (research) is related with networking. 0=not relevant; 100=I'm a HCI researcher; 50=ok or don't care.

Name	**Age**	**Beer**	**Countries**	**Facebook**	**HCI**	**Math**	**Networking**
ID1	26	50	1	100	0	100	50
ID2	21	75	8	646	65	80	15
ID3	26	100	2	0	50	100	0

To use the system, participants enter the Cube and embody their virtual data points by wearing a trackable hat so that their positions in the room will be detected (Figure 1). Food tables and stand tables are randomly placed in the Cube. There is a large overhead display to show the interactive visualization (Figure 2). The visualization includes two essential parts: a scatter plot and a dimension chart, organized left and right respectively on the large display. The scatter plot reflects participants' current physical layout in the Cube (from a birds eye view). Dots are colored according to its 2D spatial clustering. Colors are randomly assigned by the system to differentiate clusters. The dimension chart lists the dimensions and reveals their current weight values. Centralized cluster values (i.e. the mean value for a given dimension of all the data points in the cluster) are calculated and visualized on some of the dimensions that are highly weighted. The dimension chart is sorted based on their weights (high to low) for easy identification of cluster distributions that characterize the clustering.

The underlying algorithm of visualizations relies on Weighted Multi-Dimensional Scaling (WMDS) [6]. WMDS visually plots the data in 2D Euclidean space to represent how the data spread in the high-dimensional space. The system takes advantage of the inverse WMDS algorithm [7] so that we can map any layout changes to new values of weights. That is, the inverse algorithm solves weight ω given adjusted low-dimensional coordinates $r*$,

$$\omega = \min_{\omega_1,\ldots\omega_p} \sum_{i=1}^{n} \sum_{j>i}^{n} |dist_L(r_i^*, r_j^*) - dist_H(\omega, d_i, d_j)|, \quad (1)$$

where $dist_L(r_i^*, r_j^*)$ is 2D Euclidean distance and $dist_H(\omega, d_i, d_j)$ is p-dimensional weighted Euclidean distance.

The default layout in the WMDS plot is set by considering all the dimensions equally weighted. As participants move around, they adjust the two dimensional coordinates. In turn, they are provided with real time feedback (i.e., a new set of weights) that best describes their current layout. For example, in Figure(2) a, clusters of participants were considered more similar in up-weighted dimensions, such as Facebook, Networking, Beer and more. The yellow cluster ranks lowest on the Facebook dimension, suggesting that these people rarely used Facebook as compared to people in the pink cluster.

IV. Evaluation

We conducted two informal social meetings to explore how participants deployed interactive visual analytics to socialize with others. Specifically, we seek to answer a key question: how does the system explain and support social gathering?

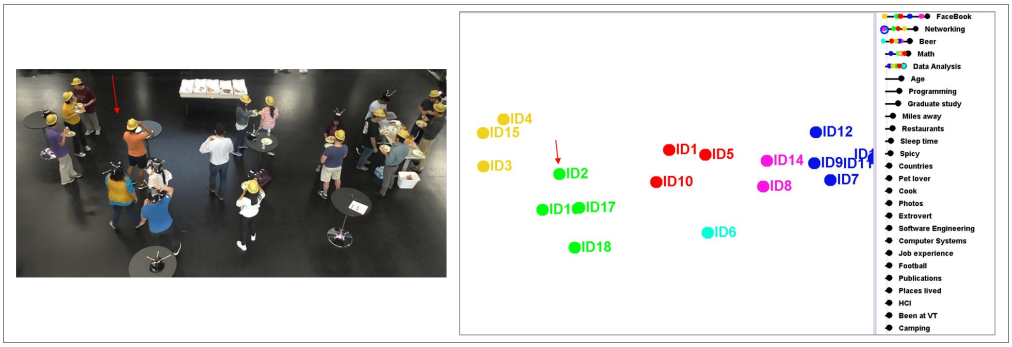
A. Participants

We recruited 35 participants to attended two informal social meetings for our study. 17 of them participated in the first meeting, and 18 participants joined the second one. Participants are a mix of people who did or did not know each other. They were from various departments, including Computer Science, Statistics, Industrial Engineering, and some other disciplines.

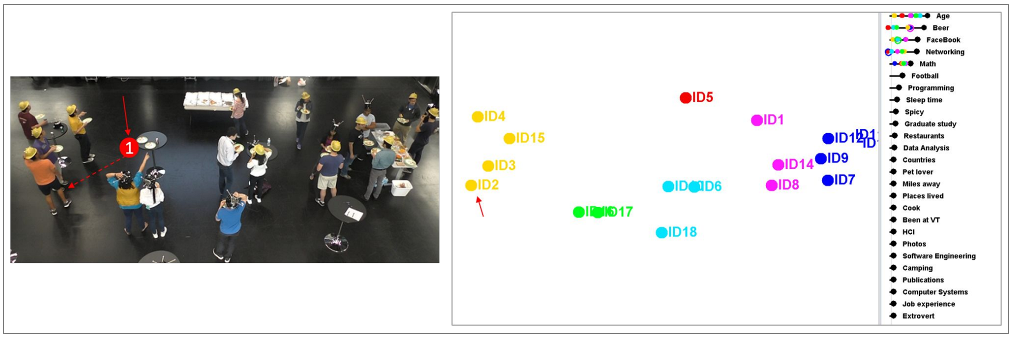
B. Procedure

The study includes three parts. First, participants were asked to answer a list of questions about themselves upon their arrival. Those questions are phrased to require a quantitative answer (e.g., Do you like to cook? 1 = I'd rather starve; 100 = I will be on the next Chef Wars TV show; 50 = Don't care). The numeric responses were turned into a high-dimensional data set (Table I) and used to generate interactive visualizations.

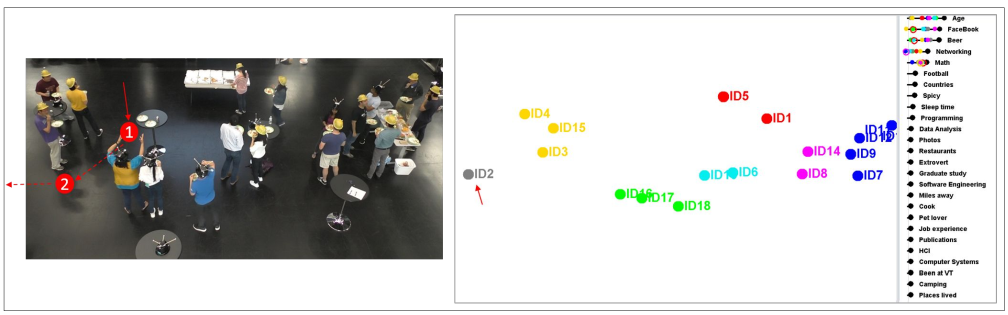
Second, participants socialize with others. The social meeting starts with a short introduction about how to use the system. The research team introduces that the interactive visualizations on the screen were generated by a high-dimensional dataset created from their responses to the pre-survey. Each participant represents a data point in the data set and responses



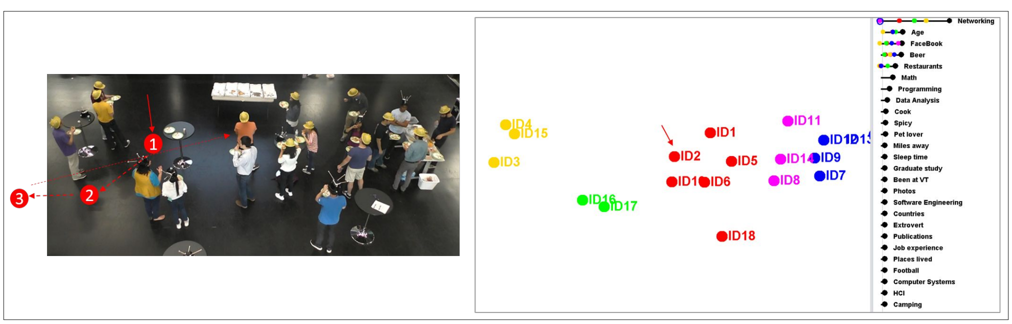
(a) ID2 starts from a random position where he was clustered with three other participants behind him.



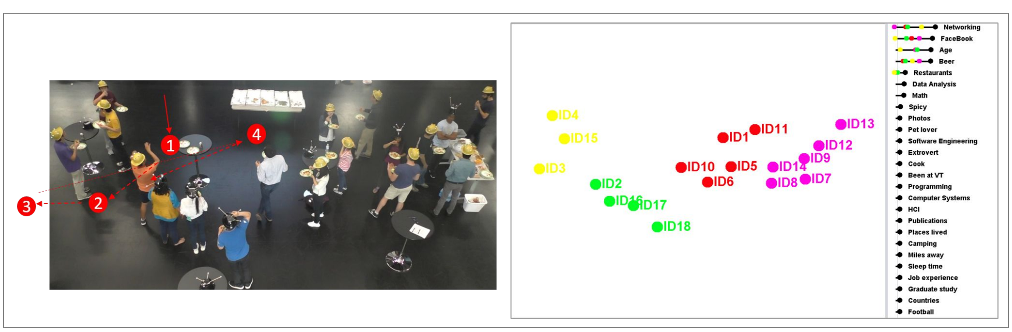
(b) ID2 moves to a cluster on his left.



(c) ID2 left the leftmost cluster and identified himself as a own cluster.



(d) ID2 walked back.



(e) ID2 joined a new cluster.

Figure 2. Participant ID2 experimented with the system. Names and head images were removed from the visualization for anonymous purposes.

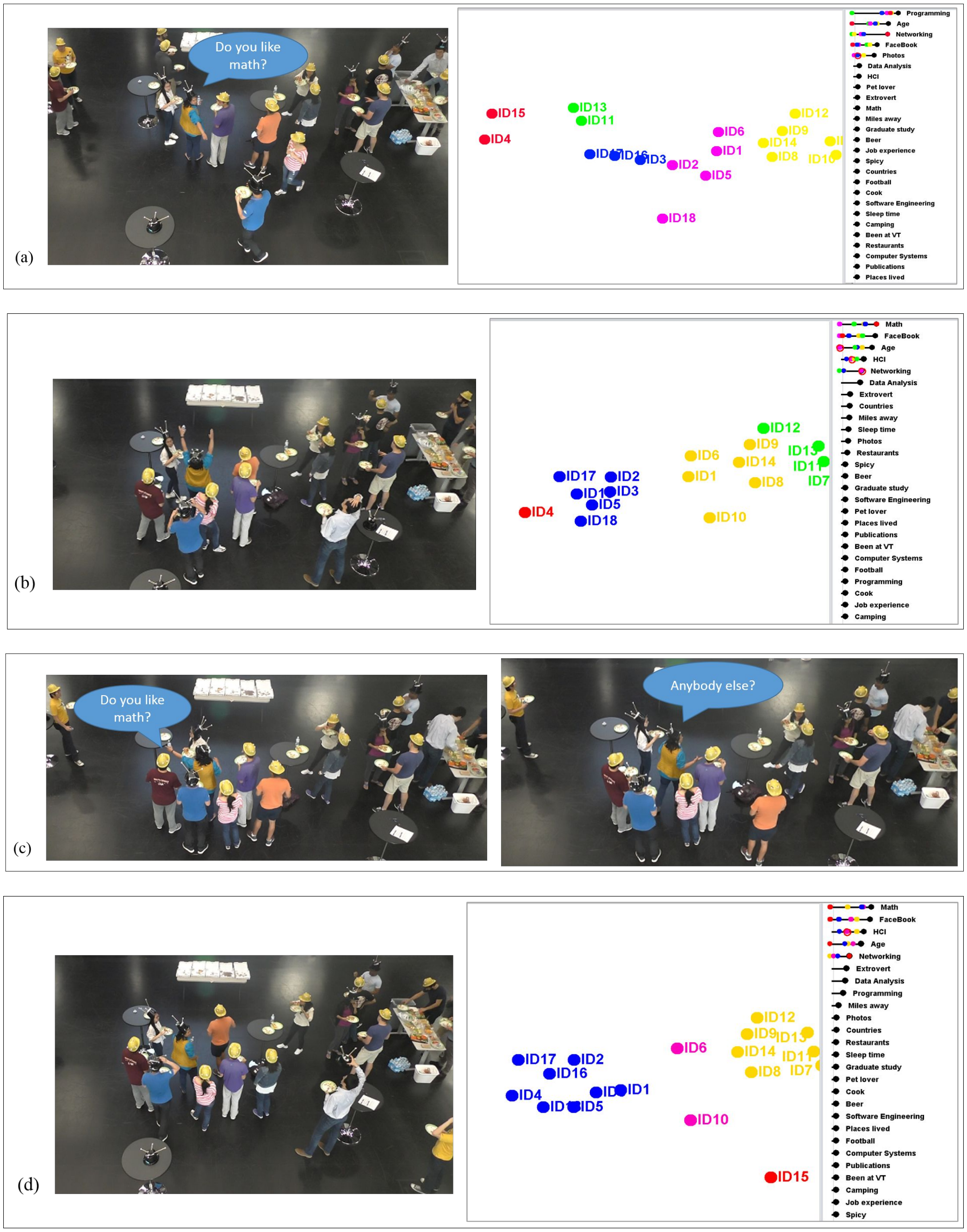


Figure 3. Participants collaborated on a specific category (e.g., math) of their interest. Names and head images were removed from the visualization for anonymous purposes

to different questions are values in different dimensions of in the data. The research team also explains the near-far metaphor and weight changes in dimensions to interpret the visualizations. After the introduction, participants start social activities. There is no specific required task for participants to complete during the study. Participants move in the Cube to talk with others on a completely voluntary basis.

Third, participants answer a post-survey probing their experiences with the visualized social meeting.

C. Data Collection and Analysis

To answer the research questions, we collected qualitative data from a post-survey and a recorded video of the meeting. The post-survey includes short answer questions probing participants' experiences and reflections about using the system to socialize. The video documented participants' movement and social clusterings during the meeting.

To analyze qualitative data from surveys' open-ended questions, two authors encoded the data independently and compared their codes to draw interpretations. To analyze qualitative data from recorded videos, two authors watched the replay and collaboratively identified important social strategies participants used.

V. Results

A. The activities of social gathering, corresponding to different interactions in the system

The proposed system supports two key types of interaction: human-computer interaction (*HC*) and human-human interaction (*HH*). One typical example of the former is the dynamic layout updating as users move around in the physical space, while the latter refers to human communications (e.g., talking to each other). During the process of social gathering, potentially three possible ways of interactions may appear: *HC-only*, *HH-only* and *HC+HH*. The *HC-only* interaction indicates that individual users play with the system but does not explicitly communicate with others (e.g., never talking with others). The *HH-only* interaction reveals that users focus on talking to each other without paying much attention to the system (e.g., never looking at the display). The *HC+HH* interaction appears when users pay attention to the system (e.g., looking at the displayed information when they moving around) and also talk with others.

We find three key activities occurred through out the social interaction: *group exploration*, *group formation* and *group preservation*, respectively, corresponding to the three possible ways of interactions: *HC-only*, *HC+HH* and *HH-only*. The three activities reveal social gathering from a dynamic process perspective, starting from individuals and ending by some social clusters.

1) Group Exploration facilitated by HC-only interaction: In the process of group exploration, participant employed the *HC-only* interaction. Rather than talk to anyone, they merely interacted with the system using body movement. By referring to the displayed information, participants attempted to find a group and finally joined in it.

We observed 12 participants conduct *HC-only* interaction to find their groups. For example, Figure 2 shows the group exploration process of the participant ID2 (henceforth, P2), who interacted with the system. Initially, he stood isolatedly around a table, while the system grouped him into a yellow cluster with other three participants behind him. After looking at the results, he seemed unsatisfied with his isolation, so he decided to move (Figure 2 a). He intentionally walked toward people on his left. This led to the system changing his color (Figure 2 b). He moved further left which resulted in the system identifying him as a independent cluster (Figure 2 c). As he moved, he observed the changes of dimension weights and clusters shown on the display. Then, he came back, joined a new group (Figure 2 d), and finally talked with the person in this group (Figure 2 e).

2) Group Formation facilitated by HC + HH interaction: We observed 25 participants who applied *HC + HH* interactions to form a group. The *HC* interaction enabled them to see the potentially emphasized topic (e.g., top dimensions and their distribution on these dimensions). The *HH* interaction helped them to justify the learned information from the *HC* interaction, so that they could finally decide to join the group or stay away from it.

Figure 3 shows such an example. In this example, participants collaboratively bring people with common interest (i.e., math) together. The group forming process was initiated by P16, who was interested in math and wanted to get people with the similar interests together. She explicitly asked P18 whether he liked math when he passed by (Figure 3 a). P4 also heard the call. Both P4 (math = 100) and P18 (math = 80) joined the group. P5 (math = 80) also walked closer to the center of this group. This led to the system moving the *math* dimension to the top and they seemed excited about it (Figure 3 b). After this, P16 asked others to join this group (Figure 3 c). P1 joined after she talked with P6. P15 (math = 50) said that he did not like math, so he moved to the right-bottom corner of the room and stayed away from this social cluster.

3) Group Preservation facilitated HH-only interaction : We observed that 29 participants focused on *HH-only* interaction after they formed a social group. This potentially helped to preserve the group. A typical example is shown as the group of people on the right side in Figure 3. They seldom looked at the display but kept talking with others. Moreover, most of them did not move their positions. The group preservation formed the last stage of a social gathering cycle. After it, some participants left their current group, and started a new cycle to find a new group.

B. Common Ground Promotion

The proposed system assists social gathering by promoting common ground. Common ground [3] facilitates communication with established mutual understanding, which potentially reduces effort for communication with grounded information. In the context of social gathering, we find that the proposed system can promote common ground in two aspects: *offering conversational topic candidates*, and *revealing top ranked dimensions.*

Participants gained conversation topics from visualizations and learned their similarity by referring to top ranked dimensions. For instance, instead of common topics (e.g., weather, sports or local news), one group started a conversation with "*do you also like spicy food?*" This was resulted from the spicy dimension up-weighted (visually revealed as a longer bar), as one participant joined the group. As indicated in 29 participants' returned surveys, over 50% of them claimed that the learned common interests helped them to start conversations with others, and 25 participants mentioned that they learned about other attendees from the visualizations.

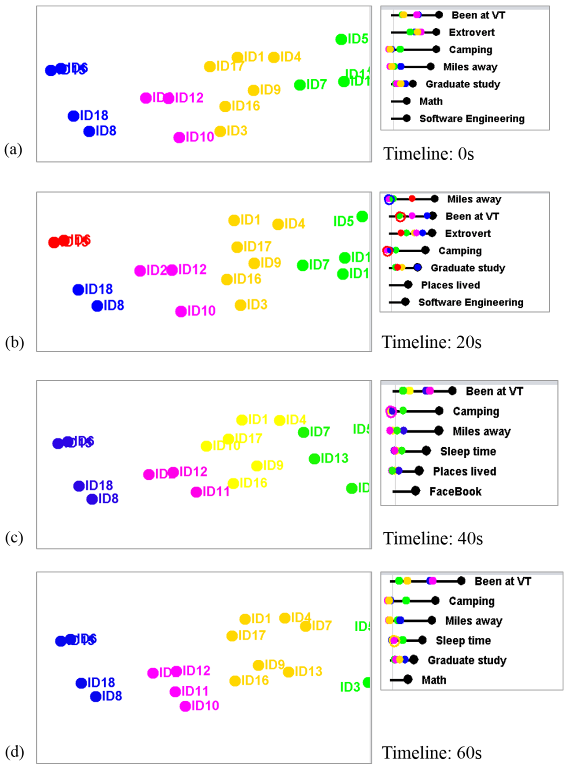


Figure 4. An example of social gathering explained by the WMDS model.

Participants tried to break out their the modes in social gathering. As indicated in 29 participants' returned surveys, 13 participants said that they talked with someone they would normally not talk, and 10 participants particularly mentioned that they did something different to socialize. One participant explained that he/she was trying to find what he/she had in common with other people by moving closer. One participant said that he/she introduced him more new people because he/she was curious about how the system would react when he/she approached to a new person.

C. Social Gathering Modeled by Dimension Reduction

Our application suggested that the dimension reduction techniques in *Be the Data* were able to explain people's gatherings. For example, in the beginning of the meeting, it was common to see participants gathered by their pre-existing relationships. In the beginning of the meeting, we observed participants at the similar grade level (e.g., in Figure 4 d, ID12, ID11, and ID10 in pink had been in this university for 5-7 years while ID1, ID4, and ID17 in yellow had been in this university for only 1 year.) or from the same countries (e.g., in Figure 4 b, ID6 and ID15 in red were from China while ID2 and ID12 in pink were from the United States) socialized together. We inferred from our model captured and calculated that participants clustered due to their previous class relationships (reflected as dimensions that measured the amount of time of "Been at VT" and "Graduate Study" dimensions) and nationality (reflected as dimensions that measured the "Miles away" from United states and number of "Places lived") (Figure 4). During the activity, the model also captured specific groups. For example, when the math people got together, the model increased the dimension about Math, as shown in Figure 3.

D. Usability Issues

The proposed system was fast learned. After the researcher's 1-minute short introduction, participants learned to engage each other through the interactive visualizations and used it as part of their social activities.

We evaluated participants' overall impression about whether the system helped or hindered their socialization in their post-surveys. From 27 responses to this question out of 29 returned surveys, 14 attendees believed that it helped, 3 felt that it hindered their socialization, and 10 thought it neither helped nor hindered or depends on different situations.

Of the Participants who answered "helped", 7 participants indicated that the system, especially the colored groups, motivated them to join different groups and understand their characteristics. One participant emphasized that he/she was encouraged to talk because "*people nearby were in the same color, a feeling of being related with others*." One participant mentioned that the system fostered discussion with extra conversational topics.

The participants who answered "hindered" had different opinions. Two participants thought the visualizations were distracting. They complained about spending a long time to look at the screen to check the system's updates, which disrupted their normal routine of socializing. One participant was not satisfied with the physical conditions (light, ceiling) of the Cube for social activities.

Of the participants who answered "neither" or "depends", one participant explained that the system could be more helpful when attendees know fewer people because it provided a starting point of question to talk about. However, these conversations might not last long because people were busy to check system updates. One participant indicated that the visualization could be a distraction that hindered the existing relationship among attendees.

We observed two limitations of the system's accuracy. First, the system was limited in its single metric (i.e., the relative distance) to interpret social gatherings. Proximity is not necessarily reflecting social interactions. For example, in Figure 2e, while ID10 was playing and moving the hat on his own, the system classified him into the pink cluster with two other participants. Moreover, participants who simply gathered around the food table to get food (not for socializing purpose) had an effect on the visualization results. Second, the system was limited in using the dimensions we had in the survey to interpret social gatherings. It was possible that participants gathered because of other characteristics.

We observed some usability problems. The dimension chart needed to be resized according to the display size and distance. Four participants complained that dimension names and the distribution of clusters along those weight bars were not clear enough. The trackable hats ran small and were uncomfortable for some participants. Thankfully, those who chose to carry the hats did not affect the tracking or the visualization. The head gear fitting problem could be fixed by employing elastic bands to fit a larger range of head sizes securely.

VI. Discussion

It was our goal to explore how socialization could be explained and mediated by interactive visual analytics using dimension reduction. We focused on an exploratory qualitative analysis of how participants used the *Be the Data* system to socialize. *Be the Data* was able to be implemented into regular social meetings with minimal required actions from attendees. Our results suggested that participants' three activities of social gatherings were corresponding to different interactions in the system. The dimension reduction techniques were able to characterize social gatherings.

Be the Data might be more useful when most attendees do not know each other. From our observations, participants who had strong per-existing relationships (e.g., classmates, co-workers) tended to by-pass the group exploration and formation stages, and directly got engaged in a steady group. It is known that in regular social meetings, people who know each other stick to a group and strangers find it difficult to join the group [1]. When participants were mostly strangers, they tended to refer to the visualization more frequently, and use the visualization information to set up new connections.

This study has three limitations. Although we found insightful, notable advantages of visualizing social meetings, our findings rely on a single metric (the relative distance among people) to interpret social interactions. Additional metrics could be useful to summarize the clusters where people are socializing with each other. In addition, this study did not quantify the level of different interactions in the system as related with the three stages of social gathering. We are interested in how to measure levels of interactions and further examine the trade-offs of different levels. Moreover, the current study did not have a control group to compare the social activities with static prior information (e.g., in excel). More work is needed to understand how participants use the prior information differently without the aid of the *Be the Data* system. However, this research is valuable in applying dimension reduction methods to explain social gatherings, as accompanied by attendees' identified usage scenarios that employed different interactions in the system. A comparison to the control is beyond the scope of this paper.

Current applications for social meetings could be improved in at least two ways to guide and facilitate user social activities. Checking both graph and cluster values is not user friendly, since users have to switch their focus from left to right to learn information from both. To reduce such effort, theme labels near clusters of dots offer a potential solution. Also, the system could provide personal-level information, besides current cluster-level information, possibly by using individual hand-held devices.

VII. Conclusion

We brought *Be the Data* into normal social meetings to analyze and display social-cluster related information in real time. We demonstrated its usage in two informal social meetings at our institution. Our results suggested that *Be the Data* was able to explain and facilitate social gatherings with different interactions in the system.

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