Using a Social Media Platform to Explore How Social Media Can Enhance Primary and Secondary Learning

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ABSTRACT

The growing set of Social Media tools such as Twitter, Facebook, Instagram, and Google Docs has the potential to enhance primary and secondary learning. To collect and evaluate suggestions for novel applications of social media to learning from online participants, we created a version of our Collective Discovery Engine. Over 155, educators, engineers, and social scientists responded to our emailed invitations to participate. In this paper we summarize the experiment, the data collected, and the responses. Suggestions were broadly classified into three categories: collaboration, diversity, and evaluation. We report on demographic correlations and present the suggestions that participants collectively considered most valuable (effective and/or novel). The interface is available online at:

http://opinion.berkeley.edu/learning

1. Introduction

The Collective Discovery Engine (CDE) is an interactive visual and social environment designed to allow participants to collaboratively generate, and evaluate ideas around topics of interest. CDE was developed as a part of the Opinion Space project [11] at University of California Berkeley, and has been applied to many different discussion topics.

On July 15, 2012, we launched a project to brainstorm ideas on how Social Media could be used to enhance primary and secondary learning. Our primary goal was to connect a diverse group of educators, engineers, and social scientists. The project ended December 15, 2012. We analyzed the textual responses collected, a profile of the participants, and how participants evaluated the response of others.

2. Related work

In 2012, MMS conducted a study on Social Media and K-12 educators [49]. About 82% of K-12 educators are members of social networks, which show a growth of

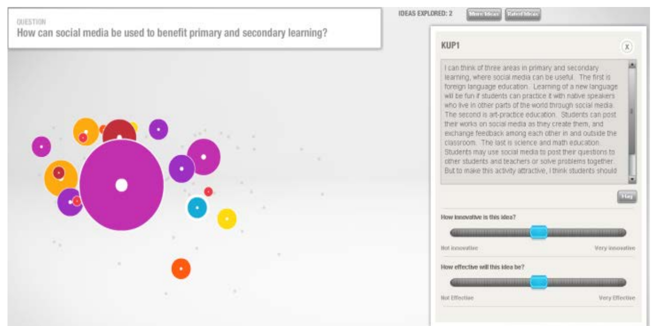

Figure 1: The Collective Discovery Engine interface where each participant and textual responses is represented by a circular "bloom" on the left. The position of each bloom is determined by dimensionality reduction of an 8-dimensional continuous space, and the size of each bloom is based on the reputation of the textual comment as determined by other participants.

34% from the previous survey in 2009. The study also listed two concerns of educators: privacy (84%) and information overload (65%). These quantitative results complement our qualitative results from participants, and also re-iterate CDE's critique of the data deluge in Social Media.

Self-organizing collective systems, like CDE, have also been explored in the context of education. In a 2002 education journal, Wiley and Edwards described the future of distance learning as one with Online Self-Organizing Social Systems [44]. In 2005, Squire [41] argued that collaborative games are a powerful part of learning and knowledge creation, and notes the interesting self-organizing behavior of these games. Our work takes advantage of both the phenomenon described in these publications and combines self-organizing social learning with aspects of gameplay. Recently, research has looked into interfaces for MOOCs (Massive Open Online Courses), such as Coursera and edX. Daniel [9] argues that researchers have not settled on an interface paradigm for these systems. Using ideas from Machine Learning and Information Retrieval is an active area of research [48].

Lave and Wenger argue that learning is not merely a knowledge transmission, but a social process where individuals participate in a “community of practice” where the knowledge is collectively constructed [21]. In addition, Sugata Mitra, the winner of TED Prize at TED2013, proposes the notion of learning as “self-organizing organism” where people learn in self-driven learning environments in their own lives. This resonates “peer-based self-directed learning online” reported by Ito et al. [28].

Woolley et al. describe “collective intelligence systems” like the CDE. They argue that diverse groups can address tasks better than any individual member [45]. Political scientists have long praised public opinion polling as “inclusive” democracy. Berinsky [4] argues that polling is one of the most inclusive means for participating in political discussions. An alternate form of public opinion polls first proposed by Fishkin in 1991 [12], deliberative polling, is where participants are first polled on a set of issues, allowed to deliberate for a period of time, and then polled once more. Online deliberation has since been extensively studied [8].

CDE also draws from many recent research and commercial projects such as All Our Ideas [39], Debategraph [3], Sidelines [29], BALANCE [30], SpigIt, IdeaScale, Innocentive, and BrightIdea.

Visualization in Social Media has been extensively researched [6][34], and many different projects have addressed scalable interactive visualization. Freeman [13] surveys the work in social network visualization. Viegas and Donath [42] explore visualizations based on emails: graph-based visualization and visualization of temporal patterns. They argue that visualization should go past the standard graph-based approach. Morningside Analytics visualizes online communities through textual and content analysis. Sack presents the Conversation Map interface that has a graphical display of links between message content [38]. Other visualization interfaces include SocialAction, which, like CDE, allows for the visualization of social network based on similarity measures [29]. Vizster is also a system for visual search and structure analysis [16]. We The Data (http://wethedata.org/) visualizes the network structure of topics and questions. One focus of the Stanford SNAP project (snap.stanford.edu) is visualization. In addition it has publicly posted social network datasets which have led to a series of analysis and visualization projects.

As a part of our projects, we have explored the role of incentives and scores in encouraging participation. Addressing incentives for information sharing is an active field of research [36][37]. In addition, the problem of assigning scores has had interest. Altman and Tennenholtz [1][2] lay the axiomatic foundation for analyzing ranking systems. Such systems have been evaluated for resistance against manipulation [14][47], and have even been framed as dimensionality reduction problems [20]. Furthermore, work in collaborative filtering has addressed the problem of preferential attachment, or a rich-get-richer effect, seen in many recommender systems [15][46].

The CDE asks participants to express their opinions using both the Visual Analog Scale and textual input boxes. Continuous scales have been applied in many applications [27][43]. In fact, some of the original work in dimensionality reduction was in psychometrics [19].

We also draw heavily from the field of collaborative filtering, opinion mining and recommender systems. Pang and Lee [31] extensively surveyed the field of Opinion Mining, and extracting data from Social Media systems. Like CDE, many of these systems rely on low-rank approximations and dimensionality reduction [35]. Our project also tries to highlight diversity which is a popular research topic in recommender systems [32][26].

3. System description

CDE is a social media tool with novel visual interface that allows participants to interact with textual responses on an interactive graphical map. CDE combines ideas from deliberative polling, dimensionality reduction, and collaborative filtering, to highlight particularly insightful ideas. In an initial controlled (laboratory) user study comparing this interface with list-based interfaces, participants read a similar diversity of responses. Participants were significantly more engaged and they had significantly higher agreement with and respect for the responses they read [7][8].

CDE instances are focused on a specific discussion question. In this project the main question was:

“**How can Social Media be used to benefit primary and secondary learning?**”

To position their point, participants entering the space first express their opinion on the following profile questions using Visual Analog Scales [27] (from strongly disagree to strongly agree):

1. Google Docs can help students learn math by enabling them to work together to solve problems.

2. Social Media games like "Words with Friends" can teach students about collective problem solving.

3. Twitter can expose students to new perspectives on topics they are studying.

4. Facebook can improve student's social skills.

5. A degree from an on-line school like Khan Academy is equivalent to a high-school diploma.

6. Nothing can replace a pencil and paper for learning.

7. Facebook causes distraction for primary and secondary students.

8. Video lectures are better than traditional lectures as they free up class time for group discussions.

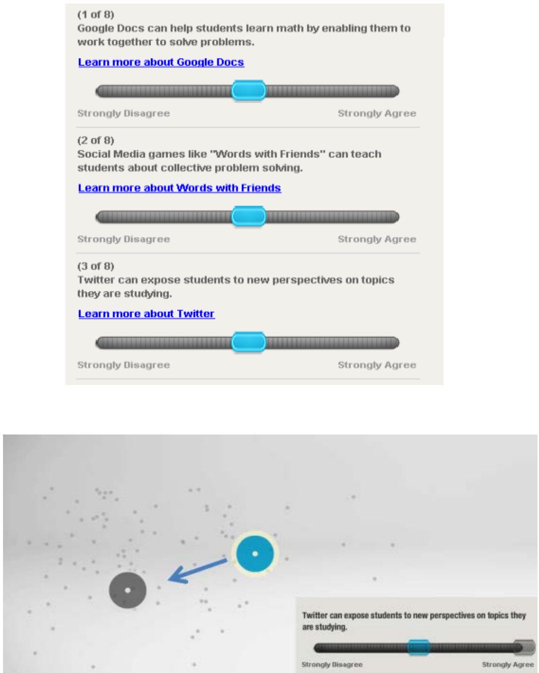

Figure 2: Participants enter responses on a visual analog scale. Their responses are visualized with a 2D projection as they move the scale.

The numerical responses to these questions define a vector in a multi-dimensional space. We apply Principal Component Analysis (PCA) [33] to project the vector onto a two-dimensional plane for visualization and navigation. This places all participants onto one level playing field. Points far apart correspond to participants with very different opinions, and participants with similar opinions are proximal. The arrangement of points is statistically optimized to convey the underlying distribution of opinions and does not correspond to conventional left/liberal and right/conservative polarities.

After placing their point, participants contribute a textual response to the primary discussion question. Participants can view and rate responses of others by clicking on the associated points in the visualization. When a point is selected, a window displays the response entered by the corresponding participant with two prompts, each accompanied by additional sliders (visual analog scales):

1. **"How effective will this idea be?"**
2. **"How innovative is this idea?"**

Participants are assigned an Author and Reviewer scores based on how others evaluate their response and how they evaluate the responses of others.

4. Results

The project launched on July 15th, 2012 and ran until December 15th, 2012. In the course of these five months, 552 unique visitors arrived, of these 155 registered and completed the profile questions. The system collected 118 suggestions from those 155 participants. The 118 textual responses collectively received 751 ratings of efficacy and 783 ratings on innovativeness. The system attracted participants from many different age groups and locations. 67% of the participants self-reported their location as the United States, with China (8%) and Japan (7%) as the next largest sources.

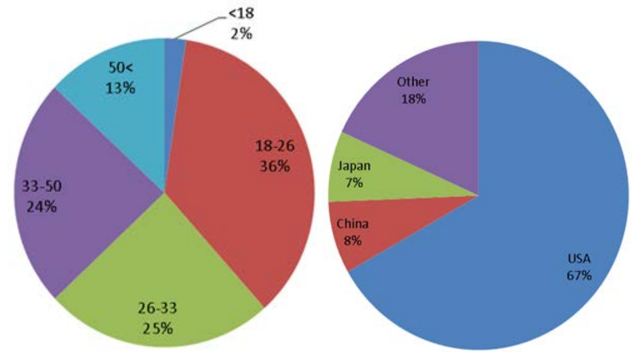

Figure 3: Participants were asked to self-report their age and current location. Most of the participants were 18-26 and from the United States.

4.1. Analysis of participant profile data (quantitative data)

From the profile question responses, we found that most participants agreed that Facebook was a distraction for students and were skeptical about equating the Khan Academy with a high-school diploma. The most contentious question was whether a "Pencil and Paper" education could not be replaced. Surprisingly, the question about Twitter was more positively received than the questions about Facebook.

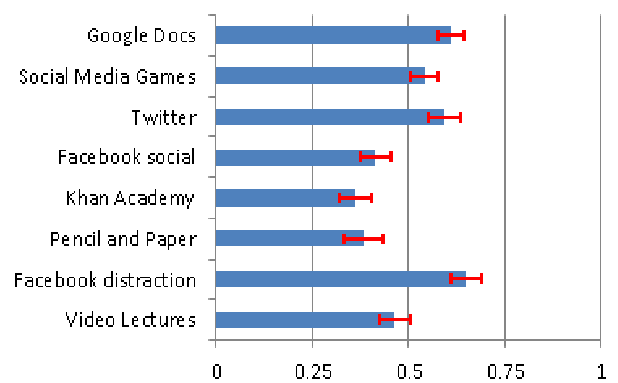

Figure 4: For each profile question, we calculated the average response and the standard deviation in responses. Most felt that Facebook was a distraction to students and the most disagreement was on the question about Pencil and Paper education.

We also considered the role that age played in the way that participants responded to the profile questions. We also found that age groups roughly agreed on most of the questions. After running a statistical significance test, we find that two only sets of responses have a statistically significant correlation with age (Video Lectures, and Pencil and Paper). Older participants valued video lectures more than younger ones did, and were also more likely to accept alternatives to “pencil and paper” learning.

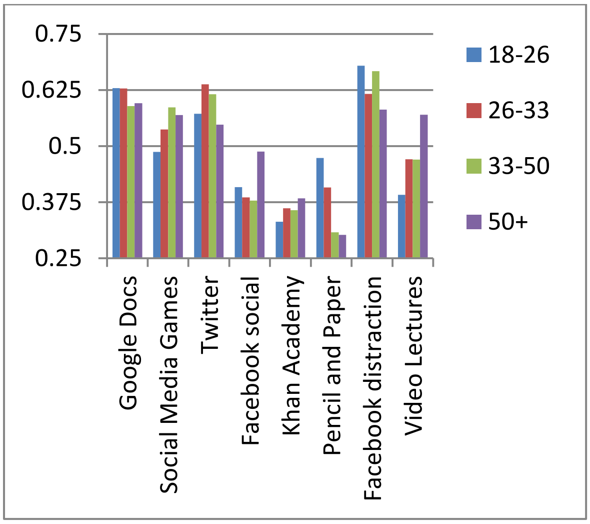

Figure 5: Mean ratings conditioned on age. We found that age groups roughly agreed on most questions, except for the questions about “pencil and paper education” and “video lectures”.

4.2. Ranking textual responses

We ranked the textual responses based on the two categories: innovation and effective. We found that these two axes were strongly positively correlated. In addition, on the whole ideas were rated very positively. That said, this audience did have disagreements over ratings, and the mean standard deviations of effective ratings was .2056.

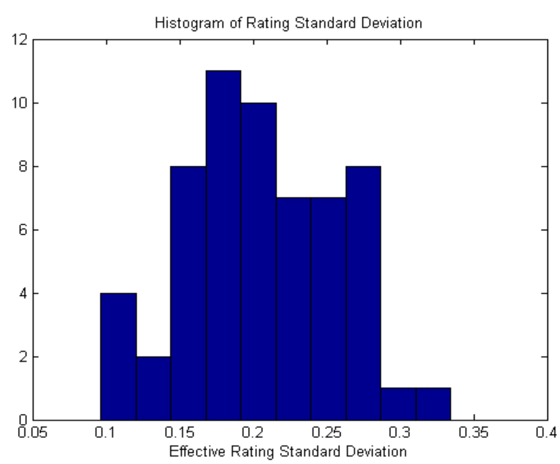

Figure 6: For each textual response’s effective ratings we found that there was a relatively high disagreement among raters with an average standard deviation of .23.

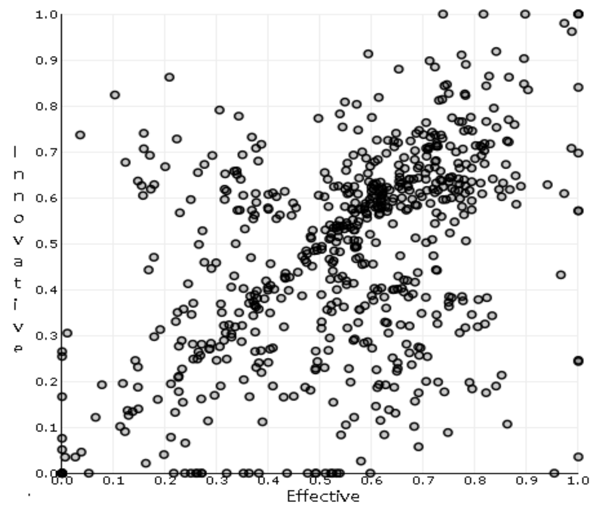

Figure 7: A scatter plot of effective and innovative rating pairs. We find that the two ratings are strongly positively correlated with many ratings falling on the diagonal.

4.3. Classification of textual responses

From the top rated responses, we find that three broad topics resonated with our participants: diversity, collaboration, and evaluation. We went through all 118 of the textual responses, manually segregating them into one of the broad categories, or other if it was sufficiently different. Surprisingly, nearly 68% of the suggestions could be interpreted as describing one of these common themes.

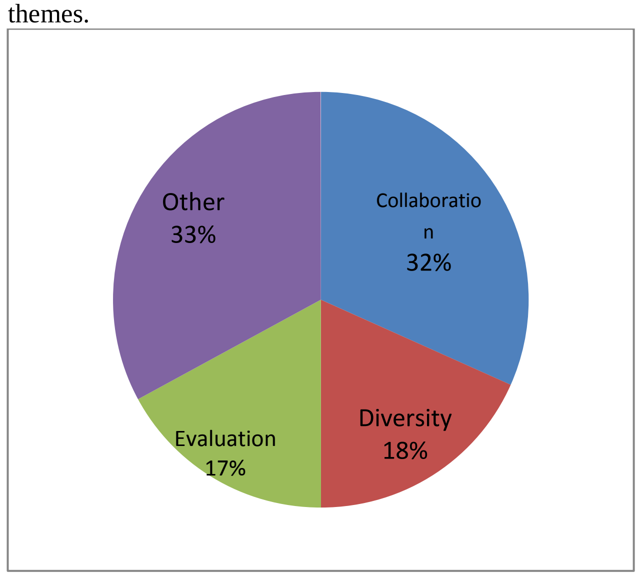

Figure 8: Manual categorization of textual response into a topic. Using social media for collaboration was the most popular topic.

Furthermore, we found that topic of “collaboration” was strongly correlated with age.

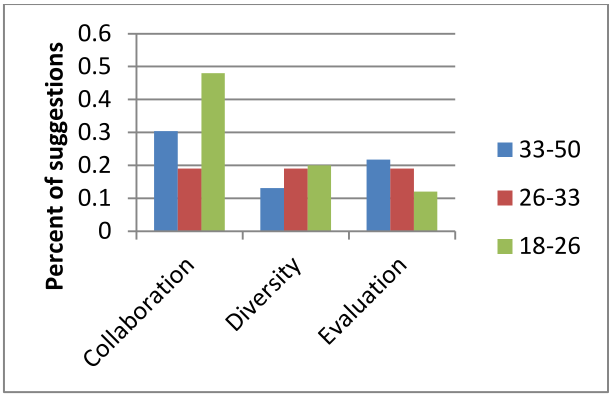

Figure 9: Correlation between age and topic choice. Younger participants were more likely to discuss collaboration, collaboration software, and the benefits of student collaborating.

Many more of the younger participants suggested Social Media a collaboration tool compared to other age groups. Diversity and Evaluation did not have statistically significant relationships with age. Unexpectedly, geographic location was uncorrelated with all of these three topics.

4.4. Profile qustions correlations

Responses to the eight initial profile questions were correlated, and we found interesting correlation relationships between the questions. The CDE visualization illustrates these relationships when a participant responds to a profile question, and the visualization moves their point along a PCA axis.

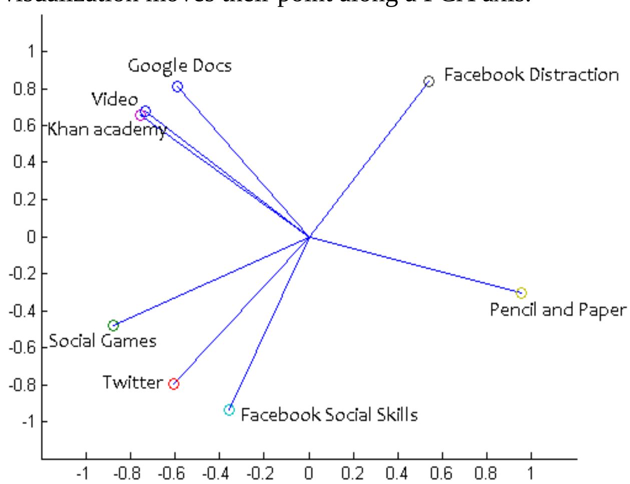

Figure 10: When participants move their sliders to respond to the profile questions, their point moves. The directions in which their point moves for each question is related to the correlation between the questions.

These angles are related to correlations between responses to the questions. The mathematical explanation for this relates to the PCA algorithm. The PCA algorithm tries to find axes that best explain differences between user's responses (i.e. if all excluded). These axes are not necessarily responses to a single question, and are in general linear combinations of the question responses.

When we look at this property in two dimensions (only two axes), questions that are strongly correlated account for the same differences and thus are weighted in a way so that they contribute to same axes. As a result, responding to correlated questions result in "movement" in similar directions. This idea is related to the mathematical concept of Principal Angle (or Canonical Angle), which is the minimum angle between two subspaces.

5. Insights from the textual responses

Combining our analysis of the top responses, profile questions, and demographics, we found the following insights about Social Media and Education:

1. Students can use collaboration software, such as Google Docs and Wikis, for team projects. In addition to facilitating teamwork, these allow teachers to track who has contributed to the project and in what ways.
2. Social networks can help teachers to share materials and ideas. An example would be a Wiki-style platform for teachers to develop curriculums and best practices and share it with others. Similarly, there is a need for a "trusted" network for students, where information from this network is academically acceptable. This conclusion is supported by MMS Education's 2012 study which reports Webinars (48%), document sharing (34%), Wikis (25%) and social networks (20%) as the top four tools among educators [49].
3. Foreign language education can take advantage of an international pen-pal system.
4. Online tools can give a teacher more ways a teacher to measure a student's progress. These tools can also lead to adaptive lessons, and customization of lesson plans.
5. Social media can promote community service and civic involvement, and it can be a conversation starter about current events.
6. Facebook is not a preferred platform for education, and many participants were skeptical about its impact on students. Twitter on the other hand was seen much more positively both in the profile question response and textual responses.
7. Math and Art-practice can benefit from tools such as collaborative equation editors and multi-media message boards.
8. Social media can expose students to other cultures. Students can collaborate with others in different parts of the country.
9. Games, points, or social credits can be part of the evaluation process.
10. Presenting and sharing can go beyond the classroom, where students can share their work with on the internet.

Students can learn by watching other students in different places.

6. Conclusion

We discovered interesting quantitative results such as a perception that Facebook is a distraction for students, that older participants value video lectures, and some skepticism about current online-learning platforms like the Khan Academic. In the textual responses, we found that three broad topics of interest: collaboration, diversity, and evaluation. We discovered that younger participants were more likely to discuss the use of collaboration software such as Wikis, Google Docs, and educational tools like Piazza.

With increasing learning opportunities available through online resources, a new way of conceptualizing learning changes our notion of education to a "process guiding youths' participation in public life" as well [28]. The findings of our experiment also suggest effective alternative teaching processes. Through the use of Social Media, teachers and adults can offer students support in order to prepare them for broader public life.

7. Future work

In future work, we will refine the user interface to make the system easier to use based on user study and data collected from this project. We are also designing an analytics platform to track participation as it involves. In addition, we are exploring the use of spectral methods for large-scale text analysis. This work also includes integrating CDE with the distributed Berkeley Data Analytics Stack. We are also exploring internationalized versions of the software to address discussions in different languages.

This research was funded in part by Fujitsu and the UC Berkeley Data and Democracy Initiative. We thank Siamak Faridani for his help on many aspects of this project.

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