Problem Solving in User Networks: Complex Communication Issues and Item-to-Item Collaborative Filtering

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ABSTRACT
This paper argues that online communication products should employ item-to-item collaborative filtering algorithms to equip readers with the best potential sets of information that fits their specific contexts. Many online resources are utilizing item-to-item collaborative filtering algorithms which harness the decisions of users to affect their experience. Examples include the recommendation engine used by Amazon.com to help steer customers to products they might enjoy, the "Music Genome Project" used by the internet radio platform, Pandora, and various user interfaces that quickly determine the best user experience to present each individual user.

Categories and Subject Descriptors
H.0 Information Systems: General

General Terms
Documentation, Design, Human Factors, Theory

Keywords
Recommendation Engines, Item-to-item Collaborative Filtering, User Experience, Algorithm, User Generated Documentation, Crowdsourcing, Interface Design, Information Design

INTRODUCTION
We live in a world where information consumers, the users of technology, are shaping the information they receive. They are no longer reliant on organizations to provide answers and solutions – they provide their own answers, they create their own solutions. They do this both knowingly and unknowingly. They knowingly provide content in the form of reviews, comments, forum posts and videos. But they also unknowingly refine decision-making algorithms by clicking certain links and not others, by choosing one website exit over another, or by responding to certain content above similar content (for further discussion about Data Mining see Tavani, 1999).

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Information consumers in essence have become a collective force. As individuals they really have limited power, but when the sum total of all of their clicks and comments, posts and selections are taken into account, they are a very powerful network that has the ability to quickly solve complex and time-consuming problems.

These networks are only recently facilitated by interactive web technologies, but online user forums that have allowed information consumers to band together into informal or formal networks have been around for at least two decades (Lakhani, & von Hippel, 2000). However, social networking platforms now create engagement mechanisms between various users where private or public networks are quickly and conveniently formed. These networks may focus on a particular topic (fans of brands, products, etc.), or social relationship (personal networks of friends and family members).

Aimed at a particular purpose and these networks of online users have immense problem solving potential.

None of this, of course, is ground breaking. Researchers and professionals have known for years about the problem solving potential of the crowd, the term we will use for the network of users aimed at a single goal. In the aftermath of the earthquake that devastated Haiti in 2010, for example, disaster relief volunteers began using social media platforms to monitor where supplies were needed and where emergencies were occurring (Barbier & Gao, 2011). Similarly, non-governmental organizations used information provided by the crowd on social networks to aid in relief logistics after the East Japan earthquake and tsunami of 2011 (Peary, Shaw & Takeuchit, 2012).

Networks of users then – the crowd – can be quite effective in solving large, complex problems that demand coordination and a wealth of data points and variables. But as yet, few solutions based on networks of users have been created to help understand and mediate problems in communicating complex information. However, such solutions hold a wealth of potential for helping information and communication designers in the future.

This paper enters this discussion by first presenting a current and relevant example of how the crowd is used to provide solutions to two complex problems. It then discusses the specific model used in these cases and further how it can be replicated it in contexts more relevant to communication. Finally, this paper questions the very idea of using the combined decisions made by users as a tool for problem solving without the users' knowledge (which is the basis for this model). Is this ethical? What do the users get in return?

By better understanding how users' actions drive problem solving mechanisms, I believe we can more effectively deliver online solutions (in a variety of areas) to users. I specifically feel that more useful communication products would be the result of this understanding.

The next section discusses two platforms that use the actions of crowds to help them determine what services to provide individual users, but which do so in very different ways. These platforms are the e-commerce website, Amazon.com and the internet radio platform, Pandora.

HOW AMAZON.COM AND PANDORA MAKE YOU HAPPY

The e-commerce website, Amazon.com was founded in 1995 as primarily a web-based bookstore. Since its initial creation it has since expanded to sell virtually anything that a consumer might want or need. It still sells books, of course, but also toys, electronics, clothes and even groceries.

Either as an indicator of its growth or a catalyst for it, Amazon has invested heavily in cutting edge technology to make its processes more efficient. In advance of the 2014 holiday season, for example, Amazon showed off an army of robots in its Tracy, California fulfillment center. These small robots travel through its warehouse to deliver specific products to human workers just at the moment they are filling packages requiring these same products. The robots shave off minutes during the packaging process because the human workers no longer have to wander about the warehouse to fetch an ordered item. Instead the robot does it for them in advance of the humans even knowing they need it yet (Wohlsen, 2014).

Such technological advancements in seemingly mundane areas have helped Amazon to indirectly grow their customer base. However, another very visible mechanism has directly had much more of an impact to the company's sales: recommendations.

Amazon.com has been using some form of recommendation mechanism (see figure 1) for well over 15 years. In 2000 they were granted a patent for a recommendation algorithm they called, BookMatcher. This mechanism used a limited number of variables to help match customers with books the algorithm has determined the customer may enjoy. It was initially simple and was based on books similar to the books a customer may have purchased (Keating, 2000).

The mechanism worked well at first, as the technology was young and buyers had not yet been exposed to the swath of similar mechanisms on other e-commerce websites. However, Amazon.com felt the technology could be refined and so has since vastly improved its recommendation system. In a 2003 article they called this recommendation mechanism "item-to-item collaborative filtering." (Linden, Smith & York, 2003)

Essentially, Amazon.com added many more variables into its algorithm including not only what customers have previously bought, but also how they have rated and ranked other items, what else they have viewed in the store, and what other people (similar buyers) have viewed and bought as well (figure 2).

The "other people" variables increased the available data exponentially. If a customer buys a certain product and the algorithm only looks at that customer, then the data is limited. If however the algorithm also considers other buyers of the same product, then it can also consider the likes, dislikes, ratings, rankings, views and reviews of those other customers as well.

In terms of the algorithm used, this group of other customers with similar purchases is called a "neighborhood," the formation of which is based on what is called, "proximity." According to the theoretical foundation underlying the algorithm, the closer two items or customers might be the more likely they will have similar tastes and desires (Sarwar, Karypis, Konstan, & Riedl, 2001). The algorithm measures the proximity between items bought and/or customers who have bought them and then creates this neighborhood. The recommendations are then based on what "neighbors" might have also bought.

In a computer operation the algorithm may look something like figure 3.

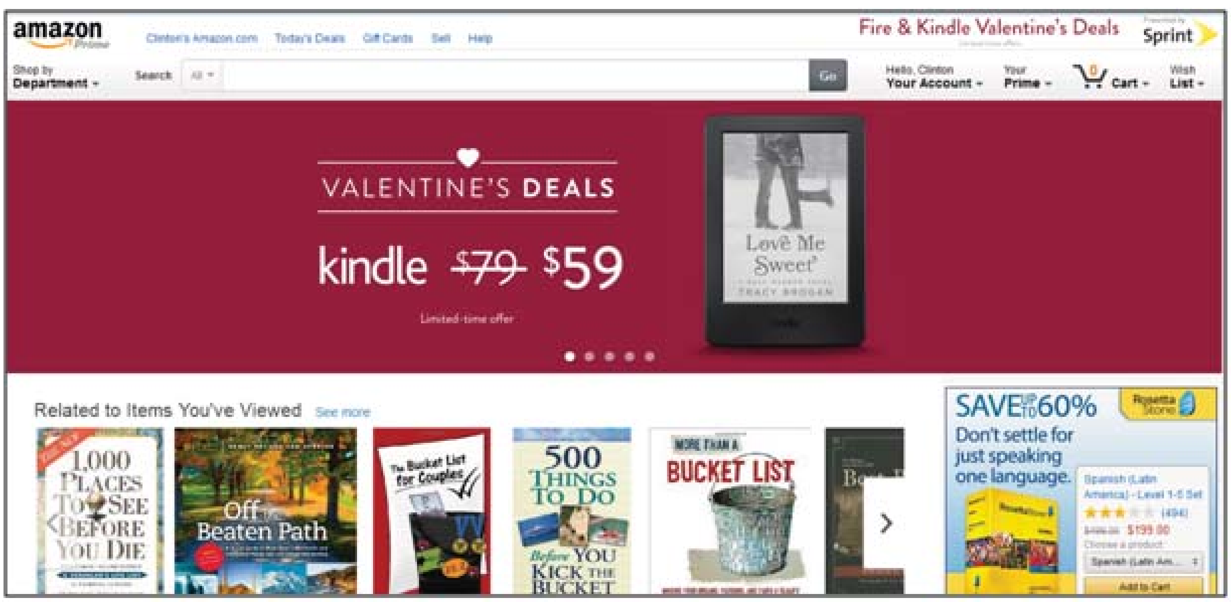

Figure 1. Amazon.com's recommendations for items similar to items the customer has viewed/purchased before.

Variables Used

Buyer's previous purchases

Buyer's ratings on previous purchases

Buyer's product views (not purchased)

Similar buyer's previous purchases

Similar buyer's ratings on previous purchases

Similar buyer's product views (not purchased)

Figure 2. Potential variables used in Amazon.com recommendation engine.

Apparently the mechanism works well. According to a Fortune Magazine report, the recommendation engine itself is primarily credited with driving Amazon.com's 2012 sales to increase by almost 30% (Mangalindin, 2012). The assumption is that item-to-item collaborative filtering can help consumers find products they may be interested or want without the consumer doing any extra work for that information.

Another platform that uses a similar filtering algorithm, but which has an entirely different purpose, is the online radio station, Pandora.

Pandora (figure 4), founded in 1999, streams music according to the tastes of the listener. It was created by a musician, Tim Westergren, who saw an opportunity to deliver music to people via the internet. However, he wanted people to find new and interesting music, songs and musicians that they may never have heard of before, but which perfectly match the listener's musical tastes.

His solution was what he referred to as the "Music Genome Project."

As the name implies, Westergren approached music as a genome, which can be mapped according to its protein pairs. Just as a certain sequence of protein pairs makes up the genomes for any specific organism, Westergren suggested that every piece of music could also be determined according to its sequence of very specific variables (Clifford, 2007).

With this in mind he generated a list of 400 variables that could map the genome of a song or music track. The algorithm he developed measures such variables as genre, tone, instruments, mood, style, virtuosity, harmony, and lyrical content.

Each song in Pandora's database is analyzed by a human (who is a trained professional musician) and a measurement for each variable is assigned. Once in the database the song and corresponding variables can be compared to other songs and then included or excluded from a user's radio station depending on the tastes of that user.

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For each item in product catalog, I1
    For each customer C who purchased I1
        For each item I2 purchased by
            customer C
        Record that a customer purchased I1
            and I2
    For each item I2
        Compute the similarity between I1 and I2
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Figure 3. Potential computer operation of item-to-item collaborative filtering (Linden, Smith and York, 79).

And while recommendations are made for Amazon.com's customers based on a neighborhood of collaborative customers and their proximal actions, Pandora's recommendations are based on a "seed" entered by the user. That "seed" is either a song or an artist entered into a station creation text field. It subsequently tells Pandora what the user's preferences are at that moment and thereby gives it a starting point for measurement against other songs and artists in its database.

Though users do not necessarily collaborate with other users, they are collaborating with those humans who mapped the song's genome. Further, a neighborhood is similarly formed amongst the user's original "seed" and other songs and artists in the database instead of among the user and other users (Song, Dixon, & Pearce, 2012).

Users also (typically unknowingly) refine the results of the recommendation engine through selecting a "thumbs up" or a "thumbs down" on the interface for different songs or music tracks. In the case of a "thumbs up", every time users indicate they like a song, the algorithm changes to find more music that more closely matches that particular song or track. If users give certain selection a "thumbs down" then the algorithm excludes songs or tracks that closely resemble that selection.

In both cases the algorithm model is item-to-item collaborative filtering. This model, I believe has an amazing amount of potential for communication work, especially in delivering specialized communication products to online users.

ITEM-TO-ITEM COLLABORATIVE FILTERING VERSUS CROWDSOURCING

Before moving on it is important here to distinguish between item-to-item collaborative filtering as a collaborative mechanism and a similar mechanism that also uses a network of user's and their choices and decisions: crowdsourcing. While the type of collaborative problem-solving Amazon and Pandora employs is carried out through algorithms completely transparent to the user, crowdsourcing on the other hand "harnesses the creative solutions of a distributed network of individuals through what amounts to an open call for proposals." (Brabham, 2008)

In other words, in contrast to item-to-item collaborative filtering, crowdsourcing is an explicit act undertaken by the user for solving a problem proposed by someone or something else. Amazon.com users may rarely understand that while taking virtually any action in the website they are in fact feeding the recommendation algorithm. Likewise, Pandora listeners most likely do not notice the degree to which their original seed song is similar to a particular song they may be currently listening to, instead they simply enjoy the music (in the best case scenario, anyway).

Put simply, crowdsourcing participants know the goal they are working for and for which organization they are solving the problem. Further, those who attempt to solve the problem often do so because they are rewarded with some type of compensation.

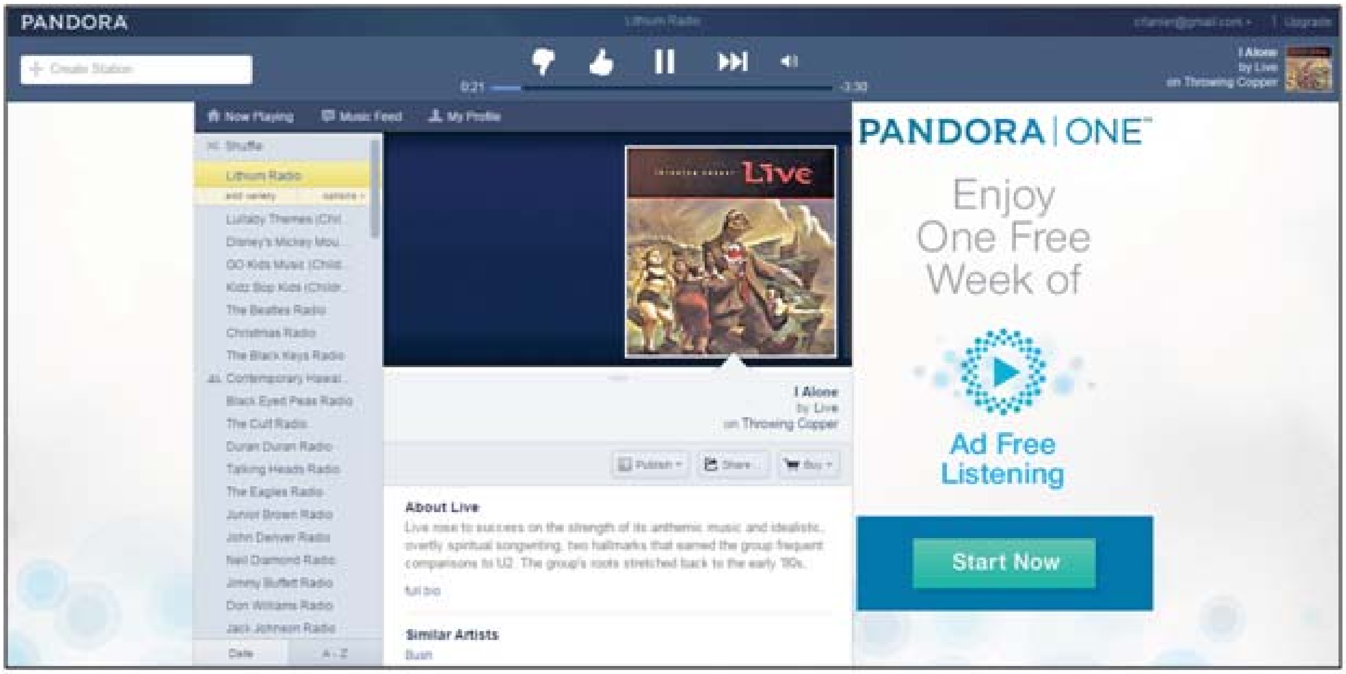

Figure 4. Pandora.com interface with music selected by algorithm based on "seed" song, artist or style.

One example is in the case of the e-commerce company called Threadless. Threadless sells tee shirts with original designs that are created by customers of the company. These customers can submit designs in a contest-like scenario, and then Threadless allows other customers to vote and determine which design is best. The design that is chosen is then printed on a tee shirt and sold (thus rewarding the "crowd" that chose the design), and the designer who submitted the original design is given a small monetary award (Brabham).

Typically, in item-to-item collaborative filtering there is no reward for the user and, as mentioned already, users also have little idea they are contributing to any sort of solution at all (which they are; recommendations in the case of our two current examples). Rather than pursuing any particular course for change, users are simply interacting with online mechanisms and in the course of this interaction they are creating variables added to the algorithm.

ITEM-TO-ITEM COLLABORATIVE FILTERING IN INFORMATION DESIGN AND COMMUNICATION

While the focus is typically on its commercial applications, item-to-item collaborative filtering could be useful in many other contexts, including (and more specifically important for this discussion) interface design and communication.

Research on interface design has already determined a need for more personalized user experiences. A project (called, SUPPLE) carried out by researchers at Harvard University and the University of Washington has, for the past ten years, been experimenting with such interface personalization. SUPPLE's algorithm defines a variety of parameters, such as device size and constraints (for various shaped and sized screens), user-movement ability (for motor impairment), and "jittery" movements (as if using a mobile device on a bus), and then reacts to create an interface best suited for the context (Gajos, Weld, & Wobbrock, 2010).

Taking each variable into account the algorithm creates a personalized interface in less than a second that, according to researchers, is optimal in every instance considering its parameters (figure 5). This not only includes the size of the display, but also the magnification of the material within the interface (such as text or images), and the dynamics of any interactions (such as cursor control). Studies have found that this type of interface makes online interactivity easier for people with certain disabilities or restrictions, and decreases the amount of time it takes them to achieve tasks online (Gajos, Weld, & Wobbrock, 2008).

The algorithm that drives this interface is almost identical to the type that drives the recommendation engines of both Amazon.com and Pandora. It essentially looks at each variable and creates a neighborhood of proximal factors and then reacts, building the personalized interface in an instant that best meets the needs of the user (according to said algorithm, that is). What is missing in personalized interfaces is the human element. Users really do not have a say in the interface's eventual look or feel.

An alternative is an Adaptive User Interface (AUI). Where the mechanism in a program like SUPPLE makes the decision for the user based on what we can call contextual factors, an AUI system instead gathers information about the user and applies that to the interface experience (source). In one case researchers based the interface design on how much knowledge users have about the technology. Those more knowledgeable about the technology are presented with an interface free from information that will otherwise help a novice user (think command line versus menu system) (Benyan, 1993).

Interfaces following the AUI design could potentially use feedback from the user's experience with the interface to further shape the experience of that user or similar users. In other words the program creates a neighborhood of proximal characteristics and then shapes further experiences for other users. Likewise it could take feedback from those users and again shape experiences in a recursive, never

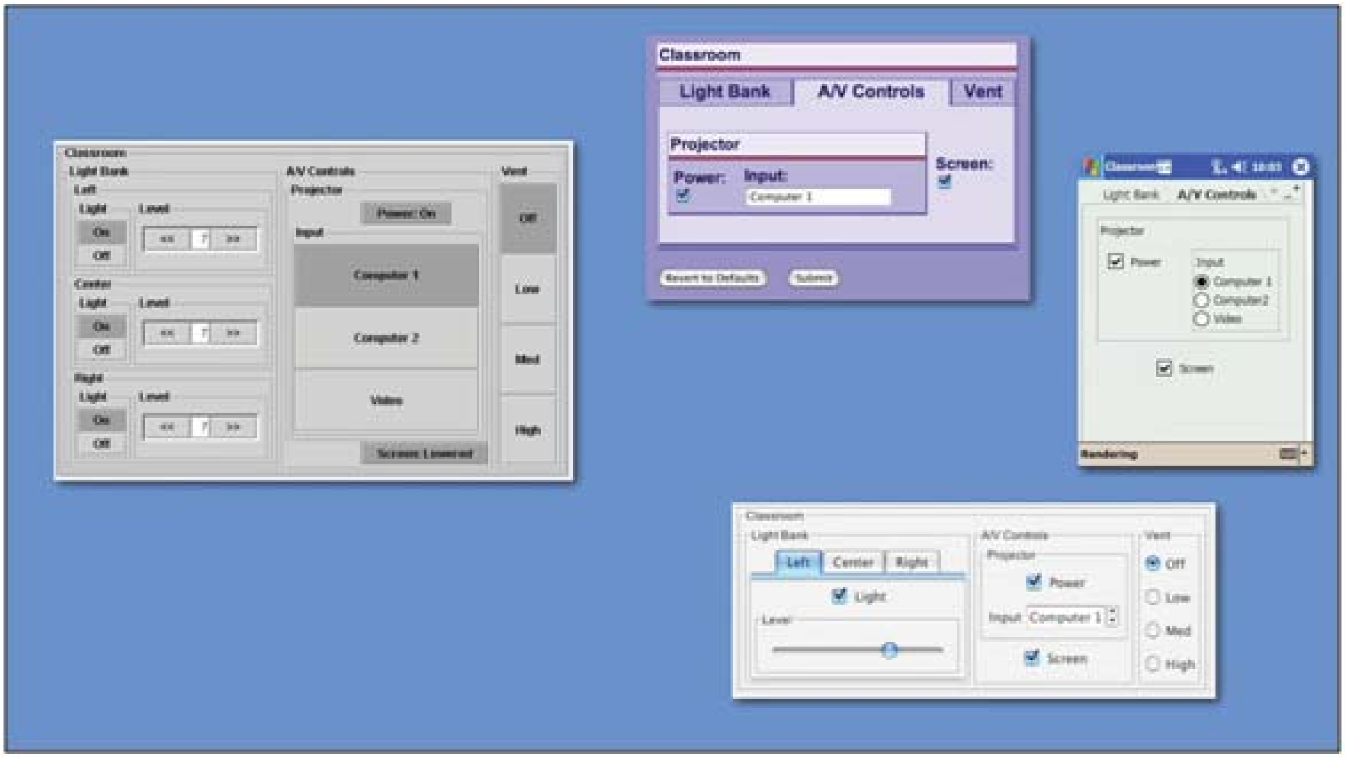

Figure 5. Examples of SUPPLE adjusting the interface to fit various devices (from http://www.eecs.harvard.edu/~kgajos/research/supple/).

ending design system.

Imagine the possibilities of such interfaces, especially for international information sharing. Such an interface could adapt quickly to the cultural-rhetorical differences between users around the world. Instead of creating multiple interfaces for multiple audiences, single interfaces could be produced that provide successful experiences to a wide variety of audiences. And these interfaces could further adapt quickly to the environment –the context – in which they are found, whether that be on a jittery bus ride on a tablet, or at a bus stop on your smart phone.

The upshot is that ultimately, users of technology have a collaborative and shared influence – knowingly or otherwise – over things like their streamed music, their shopping and even their interface experiences.

However, missing from these examples are instances of communication, especially technical communication, which adapts to the preferences of the users. Though there has been past discussion about professional communication products generated by or affected by users rather than by organizations, none consider a type of filtering mechanism.

Warnick, for example, discussed the use of wikis and other “digital texts” in technical communication, and suggested that they presented an ideal space for users to create their own documentation for products (Warnick, 2005). Such a case is more akin to crowdsourcing, because users are asked explicitly to share in creating the solution. Further, obviously users also understand that they have a role in creating and delivering this solution.

Forums, where users can ask and answers questions about technology products, have been similarly viewed as user-generated texts. And forums in particular have been noted as particularly helpful for users who have questions about their technology products in action (Lanier, 2011). Again, however, as in the case of wikis, users understand they have a role in the creation of knowledge. They ask or answer questions as a function of the mechanisms (in the case, the forum) they are in.

These examples of user-generated technical communication are becoming more prevalent as mobile technology with access to the internet become more pervasive. Users seek information to help them with specific tasks in real time. Forum posts and wiki entries are curated and indexed by search engines and at the ready when users need them.

Forums in particular were the recent focus of Swarts, who discussed them in terms of their ability to give direct, in-the-moment help to users that traditional user documentation could not provide (Swarts, 2014). He points out that traditional documentation cannot possibly account for all the potential contexts in which a product will be used, nor can it account for the different possible problems that users will have to solve.

Instead he seems to suggest that users themselves are best suited to identify and solve these outlying variables of context, use and problem-solving. He brings this potential back to forums, and discusses them as spaces that facilitate such a purpose. If the information is currently there in the forum’s repository or archive, then it is simply a matter of searching through it (or through larger search engines that have the forum indexed) to find the specific information needed. If the information is not there, then it is simply a matter of creating a forum topic and asking other users for that information.

Such information gathering mechanisms are becoming more commonly used by online technology users. At the same time, those in communication professions are wondering how user-generated information will affect communication professionals of the future. Some have sought to find a place in forums for technical writers, for example, suggesting they could act as moderators or curators of information, virtually guiding users to the correct forum posts to ensure they get the information they are looking for (an occupation made moot as search engines get more precise) (Frith, 2014).

But rather than a future where communication professionals point users to relevant information, I think we are more likely to see one where item-to-item collaborative filtering algorithms create better, more precise user-assistance experiences. If, for example, an algorithm tracks your requests in a forum, and then creates a neighborhood of users who have similar requests, it could anticipate proximal information needs based on other requests your neighbors have made.

As Swarts points out, the primary stumbling block to comprehensive user-assistance may be the necessary limitation of the rhetorical situations accounted for in traditional user documentation (and other user-assistance products). In other words, because any particular piece of complex technology can be used in a variety of ways and contexts and for such a variety of purposes, we will never be able to communicate everything that a user may need to know. And if this is the case then harnessing the assistance requests from thousands of other users to filter out what is most helpful for any individual user may be the absolute best method to truly achieve user assistance.

One example of a potential use in user documentation design is illustrated in the following model.

1. User enters a search in the forum's search engine, or arrives at a forum thread based off of the results of an internet search. This initial search serves at the "seed" parameter for the algorithm.
2. The algorithm matches the seed against users who have entered a similar seed as part of their search for information.
3. The algorithm creates a series of proximal threads that share a close relationship with the seed thread. These proximal threads are weighted for distance and the closer threads are put into neighborhoods.
4. Finally, these neighborhoods are suggested to the user as potential solutions to the problem.

This is only one model and, as in the case of both Pandora and Amazon, the more information shared the more fine-honed the solutions can be. If the user shares, for example, a software product that more information is needed about this will dramatically narrow the number of potential neighbors that the algorithm includes.

Likewise, presenting the user with a feedback mechanism (such as, "was the answer helpful") will further aid the mechanism better fine-tune the potential threads or solutions it recommends.

Before closing I want to point out that the particular algorithm model I use here – item-to-item collaborative filtering – is only one model in use today. Other models for example measure only the similarities of two or more users instead of specific items (products, songs or answers in the examples here) that those users are interested in.

The point is not so much which model is used, but only that some type of mechanism be tested and used to better help online users find answers to their questions. It is quite obvious that technology is heading in the direction of do-it-yourself models (look, for example, at 3D printing, website design and even publishing), so it is a fair assumption to say that user-assistance is on a similar path. Understanding how to integrate mechanisms that allow users to better help themselves and each other is crucial to the future of better information and communication design.

CONCLUSION

Ultimately, users are creating for themselves their own technical communication products (Warnick, 2005), and perhaps rightly so. Over 20 years ago Johnson-Eilola and Selber argued that the organizations using hypertextual documents and technology for technical communication were simply reinforcing existing corporate structures – creating and delivering communication products became faster and cheaper, but not necessarily better (Johnson-Eilola & Selber, 1994). Faced with the technology to create, publish and distribute information products themselves, it almost seems destiny that users do so.

Studies of motivation, however, suggest that even for the users there are few altruistic motives behind creating technical documentation for other users. In forums those users who provide the best and most successful answers to problems (in the eyes of other users as decided by ratings or votes) establish some type of social capital (Bourdieu, 1986; Lerner & Tirole, 2002). Below their username are words like "Apprentice," "Guru" or "Expert" followed by the number of posts they may have written.

Similarly, users who upload content to platforms like YouTube have the option to "monetize" their content through advertising. They are, in effect, selling the solutions or knowledge they provide other users. In fact, technical forums also display a number of advertisements throughout their sites, and realize a return on effort put into the forums through the advertising revenue they generate. Content may be free, but there is still a cost associated with access to it. And while some argue that it is perfectly acceptable (see Anderson, 2009), others suggest the current model is wholly unethical (see Lanier, 2014).

But is there an ethical question in terms of item-to-item collaborative filtering? Should the users be made aware that their actions get fed into a recommendation algorithm to help the mechanism perform better? In such a situation, perhaps it is crowdsourcing that is the more ethical of the two approaches. After all, crowdsourcing requires as its foundation, that the user understand the goals and rewards for any effort put forth.

In collaborative filtering, however, users do not necessarily know the affect they have on outcomes for either themselves or other users. After all, not only are they affecting the results they get, but they are also affecting the results that you or I get as well. What if the information to be communicated was direly important? What if the consequences of finding the right information were a matter of life or death? How important would it be for users to know their place within the algorithm; to know that their decisions affect the outcome of other people's search for information?

These questions are not easily answered, but they do need to be asked and discussed before these types of mechanism are put into place in information communication settings. It is really only a matter of time before a mechanism as described here is created, after all, so confronting the ethical dilemmas well ahead of time would certainly create more ethical mechanisms later.

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