Hax: Visualizing Targeted Audiences

Saiph Savage, Angus Forbes, Carlos Toxtli, Grant McKenzie, Shloka Desai, and Tobias Hollerer

Universidad Nacional Autonoma de Mexico
University of California, Santa Barbara
University of Arizona
{saiph@cs.,grant.mckenzie@geog.,holl@cs.}ucsb.edu
{angus.forbes@sista.,shlokadesai@email.}arizona.edu
{ctoxtli}@fi-b.unam.mx
http://www.springer.com/lncs

Abstract. Users are passionate about sharing their political convictions, art projects, or businesses. Many times they also want to direct social interactions to certain people to start collaborations, or to raise awareness of their causes. However, users have scattered unstructured information about the characteristics of their audiences, making it difficult to deliver the right messages or interactions to the right people. Existing audience targeting tools often only allow people to select potential candidates based on long predefined lists, which provide few insights about audience candidates. We explore instead the idea of using data visualizations to help people dynamically identify audiences for their different sharing efforts. In this paper, we introduce the motivations behind visualizing online audiences, and describe a research implementation we have designed to experiment with the concept in the setting of targeting audiences in an online community. We provide the results of a preliminary empirical evaluation which shows the strength of the idea and areas for future research.

Key words: targeted audiences, targeted sharing, online audience, selective sharing, social networks, online community, Facebook

1 Introduction

People are the main driving force behind fostering healthy and successful collaborations and interactions [5]. Through different actions, people can create favorable collaborative environments. For example, they can start conversations; encourage contributions, advertise their projects [7], among other related activities.

People get participation and action from others via postings in an online community. For example, they can create posts to request attention to interesting shared content [20]. By making posts in a large community, people potentially increment their number of responses. Yet, communication research has found that online users receive less replies when they share content with their entire

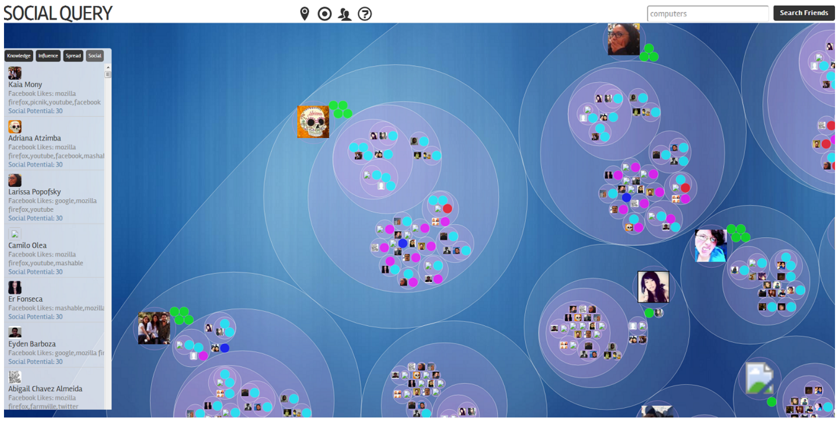

Fig. 1. Screen shots of *Hax's* social spread interface which lets users view the social groups of their potentially interested audiences.

network, than with a small targeted audience [4, 15]. Sociological theory on disclosures, also establishes that when a person feels signaled out due to her unique traits, the more likely the person is to be responsive [16].

Many proficient users sometimes use different online sharing mechanisms to engage in *selective sharing*, directing content to specific predefined audiences [13]. These users define collections of people, and then post content to each of these lists.

But, maintaining up-to-date user collections can be difficult and time-consuming. This model is especially unsuitable for more dynamic collections, such as those based on the location, social affiliations, or popularity of the targeted users. For example, the administrators of an online group might want to target only the most influential users in the women's rights movement for promoting their group's cause; the organizer of a social rally might only want to target those community members who are in town next weekend. In these cases, predefined collections of users might be too coarse or irrelevant.

Other techniques are selecting on the fly individuals to target, and only to them sharing the content or message. This type of behavior allows for a more dynamic selective sharing experience that is more context-driven. We will refer to this practice as *targeted sharing*.

But, finding the right people at the right time is hard. Especially in large communities where users may not have a notion of everyone's traits. Previous work in social recommenders have created list-based interfaces where the system recommended users with a certain expertise or skill set [6, **?**]. These systems however, do not allow people to easily explore and compare the different characteristics of the recommended individuals. Yet, those characteristics can play an important role in people's decision for collaborating or interacting with someone [26].

We explore how data visualizations transform (or not) people's audience selection activity. Our belief is that data visualizations prompt people to learn about their audience. This empowers people to target audiences that capture their different sharing needs.

To explore these ideas, we designed *Hax* [1] — a tool that provides a query interface and many visualizations, to support users in dynamically choosing audiences for their targeted sharing tasks. Fig. 1 presents a screen shot of one of Hax's visualizations for targeting audiences. We set to study how users engaged with such a tool in the context of sharing and connecting with an audience in a Facebook group. Facebook designed groups to ease online community-building. We can consider each group to be an online community of its own [1].

The contributions of this work are:

- A novel system for discovering and visualizing the shared interests of an online group or community;
- A novel system for visualizing the spatial-temporal constraints of people;
- a novel system for visualizing the social spread of people;
- A novel system for targeting audiences on the fly based on a thematic task or project.
- A better understanding of the way data visualizations transform users' audience selection activity.

2 Motivation

One of the challenges in identifying community audiences to collaborate or share content is the fact we have dynamic sharing and collaboration needs. For instance, a person might have just gotten a parking ticket and would like to discuss with legal experts ways of fighting the ticket; or a person would like to share with interested folks a popular news piece she just read. These ever-changing needs affect in subtle ways who we want to exchange information with, or simply interact. As a result, social media tools need to offer dynamic mechanisms that let users easily find the people or audience that on-demand can cover their necessities.

We believe that the data modelling techniques that work for content categorization and information retrieval can be adapted to mine people's interests, and retrieve audiences relevant to users' diverse needs. But, while data modelling algorithms are specialized at correctly categorizing data, they rarely fully capture humans' ever-changing decision process for selecting with whom to interact. We therefore opt to integrate data visualizations that help put humans in the loop, and let them make the final decision.

We designed different data visualizations highlighting specific social signals (traits) of relevant community members to aid users to select their audience. Our exploration begins with the three social signals listed below. We briefly explain the signal, and the reasons for considering it. Note that other signals

[1] Mayan for *exclusive*. This references it is a tool to select people for a task.

could have been contemplated, but we decided to begin with these as previous work identified they played an important role in targeting audiences [7, 27]:

1. **shared interests:** this signal captures the personal thematic interests of each community member. Many researchers and practitioners view collaborations as a process that aggregates personal interests into collective choices through self-interested bargaining [27]. We believe this bargaining process can be facilitated by making users aware of the personal interests of others, and how they relate to the collaboration task they are promoting.
2. **location:** this signal holds information about the countries, states, and cities where community members live. Collaborations supported by computers have traditionally provided users with the luxury of interacting with others without having to worry about their location [2]. However, location does play an important role when interacting and organizing events within the physical world [23] (e.g., a social rally,) as others' spatial-temporal constraints can determine how much a person will engage in the activity [24].
3. **social connectivity:** this signal holds information about the type of friends and social ties community members have. This signal is important because it can aid members to recognize prospective newcomers, who can help keep the community alive and active [7]. Additionally, the social connections of a member can also help in the spread of the community's messages and visions. Members could thus use this signal to identify the users whose social connectivity would help them the most in distributing certain content.

3 Background and Related Work

Audience Targeting Practices
Traditionally, editors were in charge of publishing and distributing content [10]. Editors invested resources in marketing consultants. Consultants provided them with a clear picture of who their best audience was [10]. Yet, the Internet has transformed this pattern. Anyone, can now author, share, and distribute content. But, unlike editors, users typically don't have a clear image of their audience [3]. Yet understanding their audience and adequately targeting it, can bring faster and better responses [19].

To overcome the lack of marketing knowledge, people rely on cues to estimate the traits of their online audiences. But, few cues are available [3]. For example, a person might remember she friended her co-workers, and they are thus now in her audience. Yet, it might be unclear to the person exactly what these people, care about [14].

In this work, we explore how we can make audience cues more readily available for people. We study the impact these audience cues can have on users' audience selection process.

Expert Search Tools
Hax, the tool we developed based on our qualitative study, helps users of targeted sharing find a suitable audience for their content. This task is related to expert

search in social networks in that the problem is finding a set of contacts that satisfy certain criteria with regard to their knowledge, traits, or social status.

Perer et al. [21] present SaNDVis, a tool for visual social network analysis inside of an enterprise that also supports expertise location. In their usage study, they found that their tool helps users find authorities on certain topics, also taking their location into account. Similarly, ContactMap [28] visualizes contacts along with their attributes and location. In their algorithm, Chen et al. [8] add strong social links as a requirement for finding experts on a topic.

Systems that support *social question asking* help users direct questions at people from their social network that are most likely to know an answer [6, 9, 17, 19].

In summary, these works show interesting parallels to understanding and supporting targeted sharing. Yet, they focus either on user goals or audience characteristics that are distinctly different from those of targeted sharing.

3.1 Facebook Graph Search

Facebook's *Graph Search*[2] offers a natural language interface for searching one's social network. Queries may consider several social variables: an example query is *"TV shows liked by people who study computer science."* A search returns a ranked list of relevant Facebook users with some of their characteristics — such as the city where they live, music they like, number of friends on the site, and others.

However, it is doubtful whether the design of Graph Search was influenced by the requirements of users employing targeted sharing. The attributes and interactions modes it supports — presenting a long list of matching users — are limited. The task specificity and the richer interaction modes of the tool presented in this work should make it more useful and accessible to our target group.

While these works provide means to find users to direct content to, none of them necessarily cover the needs of our target group of normal everyday users.

3.2 Facebook Advertisment Targeting Options

Facebook offers advertisers options[3] for ensuring that their ad will reach a targeted relevant audience. Facebook allows advertisers to target audiences based on users' location, age, zodiacal sign, interest, education, as well as whether they have liked their particular product in the past, or their friends have.

Facebook's targeting options assume that the end-user has a crisp image of who their desired audience is. While this design consideration can be effectively true for advertisers who have previously conducted market studies and identified the demographics of their clients, it is not necessarily valid for community members who engage in targeted sharing.

[2] `https://www.facebook.com/about/graphsearch`
[3] `https://www.facebook.com/help/www/131834970288134?rdrhc`

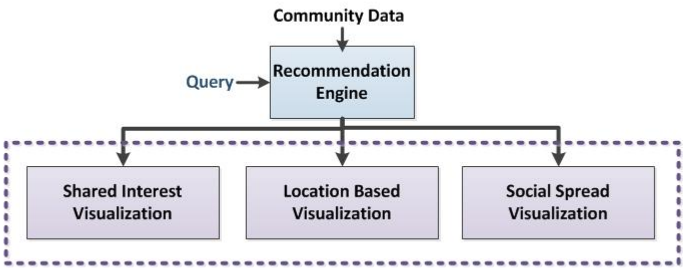

Fig. 2. The components of the *Hax* system.

Bernstein et al. [3] identified that social media users consistently underestimate the audience size for their posts, guessing that their audience is just 27% of its true size. It is therefore likely, that community members also will not have a clean-cut notion of the characteristics and traits of their most relevant audience for a given post. This leaves space for the creation of online tools that help end-users better visualize and understand their different audiences and their characteristics.

4 Designing Hax

Hax is a web-based tool that supports targeted sharing on Facebook. The user first enter a query that determines the topic they are interested in posting content about, such as *"women's rights"*. Hax includes a **recommendation engine** that accepts and processes such queries to produce a list of relevant community members based on their *Likes*. For each returned member, the recommendation engine includes their signals — e.g., their *Likes*, hometown, or number of friends — and a weighting. At this point, the **visualization engine** provides three different presentations for the recommendations. Fig. 2 presents an overview of the Hax components. We now briefly describe these two modules.

4.1 Recommendation Engine

The recommendation engine models the interests of community members based on their profile information. It then identifies those members whose interests are the most relevant to a user's search query.

We model the general interests of community members through their Facebook Likes. A Facebook Like typically has a name, a label and a definition. For example, the Like *"Everyday Feminism"* might have the name *"Everyday Feminism"*, the label *"Community Organization"*, and the definition *"Everyday Feminism strives to stop the everyday violence, dominance, and silencing used against women"*.

We found that Facebook's existing curated labeling to categorize interests was very general, and did not enable an exploration of the data on various levels. To counter this effect, we use topic models [22] to model the community's shared interests.

Given the nature of the data, we used a labeled latent dirichlet allocation approach (labeled LDA) [22], similar to that proposed by Forbes et al. [12]. The discovered LDA topics correspond to the community's shared interests, labels correspond to the ones Facebook assigns to Likes, and each document corresponds to a Like with its definition. Specifically, we use a generative process to discover the interests shared by the community members. The process first detects the K number of unique labels associated to the community's Likes. This sets the initial number of shared interests that will be considered. For each shared interest, a unique Like and its associated data is drawn with a Dirichlet distribution α. A multinomial mixture distribution θ^d over all K shared interests is drawn for each community member with a Dirichlet prior α_ϕ. Now, using information about the labels associated with the Likes of the user, we restrict the definition of θ^d to be defined only to the shared interest associated with the labels present in their Likes. After this step, each community member is represented as a mixture over shared interests. An end user's query is also modeled as a mixture over shared interests, except that because it does not have any explicit labels, θ^d is not restricted. The community members who exhibit a shared interest mixture similar to that of the query are presented to the user via the interactive visualizations. We use L_1 norm as our similarity metric.

Our experimental experience as well as related work in modeling micro blog conversations and users via topic models suggest that using topic models to mine a community's shared interests is a feasible approach [18].

Given a search query, the recommendation engine first identifies the community's shared interest most relevant to the query. It then finds the community members that have Facebook Likes most relevant to the query, weighting each of them based on their number of relevant Likes. This list of weighted members, and most relevant shared interest is handed over to the visualization engine.

4.2 Visualization Engine

The visualization engine displays the list of recommended members with their weighted social signals. This allows users to consider these signals directly in her targeted sharing decision process.

Our tool provides three different interactive visualizations, each emphasizing different social signals. Following the visualization mantra [25], every visualization lets the user (a) obtain an overview of the community's social signals; (b) zoom into particular groups of members; and (c) obtain details of a desired user's social signals.

This rich interaction is not possible with a list-based interface. List-based interfaces do not allow the user to easily obtain overviews and summaries of the data. Given that community users are many times organizing things for the entire community, providing overviews of the members' interests can help users remain relevant. Tooltips could potentially be used for offering these data

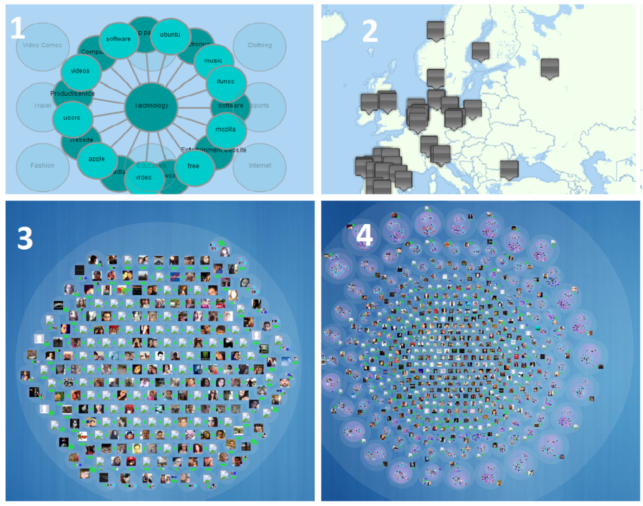

Fig. 3. Overviews given by each visualization: (1) shared interest, (2) location-based interfaces; (3, 4) social spread interface.

summaries. However, they do not allow users to zoom in, and explore particular aspects of the data.

We provide a short description of each view below. Fig. 3 presents the type of overviews each interface provides. Fig. 4 shows a screen shot of all three visualizations with their zoomed-in view.

Shared Interest Interface Initially, the Shared Interest Interface presents an overview of all of the discovered shared interests of the community (Fig. 3.1). Shared interests are displayed as nodes on a grid. Each node has in its center the keyword most representative of the shared interest. Mousing over a shared interest displays in light green its most representative keywords, and in dark green its most representative Facebook labels. This view allows users to quickly identify the general interests of their community, as well as some of the most popular specific related interests.

When the user queries the system, a list of relevant members is displayed along with the community's shared interest topic most correlated to that query (Fig. 4, middle). Relevant members are visualized as a list of nodes on the right hand side of the interface.

A large node in the center represents the most relevant shared interest topic; other shared interests are shown on the left for reference. Mousing over a member or a shared interest provides more information, e.g. the Likes of a member that correlate to the query, the description of a Like, or the Facebook labels associated with a shared interest.

The shared interest interface thus allows a user to quickly see the members that are likely to be interested or knowledgeable about a particular shared inter-

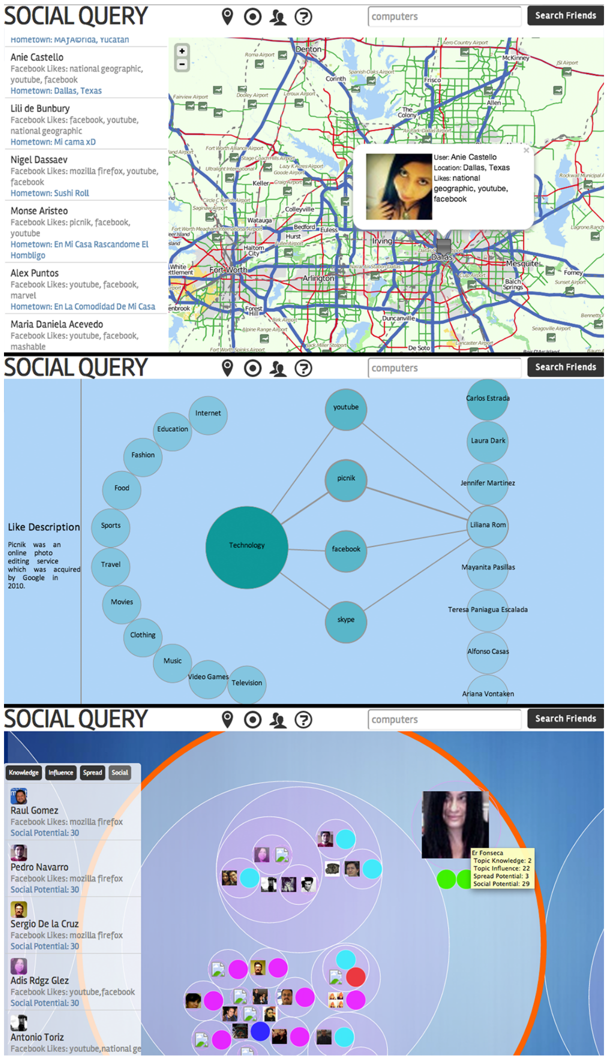

Fig. 4. Screen shots of a zoomed-in version of the different visualizations in *Hax* (top to bottom): location-based, shared interest, and social spread interfaces.

est related to the query. By letting the user investigate the connections between members, Likes, labels, and shared interest, it moreover allows the user to explore the algorithm's rationale.

Location-Based Interface The *location-based interface* lets users visualize the geographical locations of the members relevant to their search query. This information can be important when targeting members for activities that take place in the physical world, such as meetings or rallies. In addition, location also provides a sense of cultural context.

The interface shows recommended members on a geographic map, based on the city or place the member listed in their profile. At a first glance, the interface allows users to easily identify the geographical regions where the majority of the members interested in a particular topic reside (Fig. 3.2).

Users can also zoom in on any member, which will show a list of their relevant Likes, their profile photo, and a more detailed map of the area (Fig. 4, top). Since not every member lists their location, this interface only includes recommended members who have shared this information.

Facebook's targeting options for brands offers a filtering based on location. It is assumed that end-users have a good notion of the cities where their targeted audience live. However, given that users may share diverse and dynamic content with their group, it can be difficult for them to have a clear picture upfront of who their most relevant audience members are, or where they live.

We argue that location-based interfaces for targeting of audiences should allow users to obtain overviews of where their audiences are physically located, and then enable end-users to further explore the map on multiple levels. This enables users to consider community members' different physical affordances [24] in their decision process. Knowing others' physical affordances is important, as it can influence their decisions for participating in an event [24].

Social Spread Interface The *social spread interface* helps users identify the members with interests related to their query who at the same time have the most contacts or friends with relevant interests.

This interface finds members that are not just potentially interested in certain content, but rather potentially interested members whose connections help them distribute or "spread" content to large audience. These are the people who bring value to the content not necessarily by the comments they provide to the content, but by lending their social contacts.

From the recommendation engine, the social spread interface receives the list of recommended community members. For each member, the recommendation engine includes a list of her Facebook Likes relevant to the user's query and a list of the member's Facebook friends who also have relevant Facebook Likes.

The visualization first structures the members based on their amount of relevant social connections. Members are structured in a spiral form (cf. Fig. 3.4). The outer rings of the spiral present the members who have the most friends with the most interests related to the user's query. The center of the spiral contains the members who have the least friends with relevant interests. When all interested members exhibit approximately the same number of interested social contacts, members are arranged in a planar circle from left to right, top to bottom, based on their amount of relevant Likes (cf. Fig. 33).

Each node in the spiral or circle represents a community member. Each member is presented with their relevant Likes, photo, and relevant contacts. Each of these contacts is displayed with their own relevant Likes and photo. Contacts are grouped and color-coded based on the Likes they have in common with the community member and their relationship with the community itself. The more Likes a community member has in common with a contact, the closer they both appear in the interface.

Contacts with a light blue circle next to them are contacts that have no other connection with the community than their friendship to that particular member. Dark blue circles denote contacts that have one or more other friends who are also community members. Purple circles denote contacts that have friends who are friends with community members.

From this view, users can thus quickly identify the overall type of social connections the community reveals for different topics; they can also zoom in and inspect particular members and their relevant social contacts. This enables end-users to easily adjust their messages, and who they mention, to content that can have a larger reach and impact. It also allows users to share content with members whose social contacts could be supportive to their cause.

The design of the visualization, i.e., the structuring via a spiral, was inspired from the work of Katayoon et al. [11] In their research it was found that visualizations of hierarchical data, such as community memberssobad, ordered based on their relevant Likes and contacts, can become overcrowded. It can also be difficult to see details about specific nodes. The work thus proposed layouts focused on a node of interest that make use of phyllotactic patterns (spirals) via nested circles that are centered on the node of interest. This type of layout is designed to provide more space than traditional hierarchic visualizations. Given the overwhelming amount of possible members of an online community, and the large amount of relevant contacts each member can have, space-saving designs become important.

5 Usability Inspection of Hax

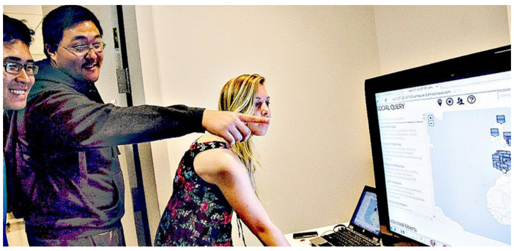

Fig. 5. Hax at a university annual open exhibition which had hundreds of visitors.

We conducted a survey study with users who used Hax as a tool to find relevant audiences for different content sharing tasks. We questioned participants about their experiences using Hax. We used qualitative coding to create from their responses a taxonomy of experiences that emerge from using data visualizations to target audiences. For our study, we worked closely with members of a particular Facebook group for which we were able to recruit participants.

5.1 Participants

Using Facebook's Group Browsers [4] we first identified groups with large number of members, and asked the group administrators whether their group would be interested in participating. We contacted the administrators from 10 different groups, whose members (at least a certain percentage) appeared to be local to us based on information on their Facebook profile. One group accepted the invitation: an activist group organizing social initiatives around the world. Its 2,000+ active members are distributed world-wide. The group covers a wide range of discussions and events, ranging from the philosophy of free software to the coordination of wildlife preservation rallies. We were granted access to the public Facebook profile of all its members. From this data, our system automatically discovered the groups' interests, and produced the three different data visualizations. 15 of the group members agreed to participate in our evaluation: 2 female, 13 male, 4 long-term group members and 11 newcomers (less than one month in the group.) They ranged in age from 19 to 35. Participants came to our laboratory for the study, and receive 10 USD for their time.

5.2 Procedure

During an hour user session each participant completed a series of targeted sharing tasks with Hax using laptops with an Internet connection we provided. We opted for participants to only conduct tasks with Hax because directly comparing with Facebook's native interface would be unfair as it is not particularly designed or tailored for the specific usage of finding relevant online audiences. However, participants were asked to reflect about the benefits and drawbacks of our data visualizations and traditional list-based interfaces. We used qualitative coding based on ground theory for our analysis. In each task, participants were told to identify 10 candidates for targeted sharing.

Each participant was given 15 different tasks that we statistically varied using a Latin square design. Each task came from 5 different scenarios that represented a few of the group's audience targeting needs. Group members not taking part in the evaluation helped edit the tasks and scenarios to reflect real needs. The five scenarios were: 1) Find audiences interested in a certain thematic post; 2) Find audiences to invite to a thematic event, and who are likely to attend; 3)Find audiences to help distribute a thematic article and get others to read it; 4) Find audiences who could help spread news about a thematic event and get others involved; 5) Find audiences who could start a discussion with the group on a certain topic.

[4] `http://www.facebook.com/search.php?type=groups\&q=\%22keyword\%22`

As participants performed the tasks, they were observed by one of the researchers who took notes. After participants completed all tasks, they were asked to complete a questionnaire about their experience with Hax, strategies they adopted to complete the tasks, benefits and drawbacks they saw, and a comparison between Hax and list-based interfaces. The questionnaire is available online[5].

To code responses, the first and second author read every questionnaire response, and identified key concepts about users' perspective on using data visualizations to target audiences. Following grounded theory's coding criteria, we decided that a category would cover a general type of experience that emerges from using data visualizations to target audiences. A total of 4 main categories were identified by this process.

5.3 Results

All participants were able to use Hax to complete all of the tasks assigned to them. Below we discuss each of the 4 categories that emerged from using data visualizations to target audiences. For some of the categories we provide quotes from the questionnaires to help illustrate the core of the category.

Serendipitous Discoveries

This experience is about feeling that data visualizations help one make discoveries about one's targeted audience. All participants reported that Hax prompted them to discover and learn new things about particular group members, and the group in general. Something they felt was not facilitated with traditional list-based interfaces: *"...It was really neat to learn so easy and fast what everyone is into. I never experienced that with Facebook."* Many participants mentioned out loud some of the new discoveries they made with Hax. Additionally, we observed that some started using Hax for their own personal explorations. Dynamic audience visualizations engage users, and facilitate serendipitous discoveries of their social groups. This could help people share better content because they understand their audience more.

Visualizing Diffusion and Participation

This experience is about considering data visualizations to be helpful in finding large pools of people likely to take action in regard to a message, e.g., comment, or attend an invitation.

70% of participants found Hax useful for massively distributing content to audiences who would be engaged with the content. Participants felt list-based targeting tools did not provide such perspective. Participants believed the location-based visualization facilitated finding audiences from big cities who could easily spread messages to large pools of actionable people, e.g., by making announcements on the streets about an event people could walk to. Participants also felt that by visualizing social connections and interests they could distribute content to mass audiences likely of participating in collaborative action afterwards, such as a discussion.

[5] `http://www.surveymonkey.com/s/KND5CGF`

Additionally, the location-based interface helped participants make a connection between the virtual event on Facebook and participation in the physical world, especially selecting an audience who could travel and attend: *"The map really made me think about the actual event, and like really including the person."*

It is interesting to observe how just having a map helped people integrate space in their audience decision process. Our results hint there is value in designing systems that enable users to visualize and explore others' spatial affordances. This signal could provide the perspective needed to make online interactions more realistic, especially compared to list-based interfaces that provide few spatial context.

Audience Diversity

This experience is about feeling that data visualizations bring diversity to one's targeted audience selection process. Participants reported the shared interest visualization helped them find relevant candidates who had different perspectives. Participants also mentioned that the location-based interface let them have more diverse selections: *"I tried to have diversity in who I selected. People who like the same things or are from the same town will have same interests and maybe not that much new to add."*

Audience Verification

This experience is about using data visualizations to verify the recommended audiences. 10% of all participants reported this experience. Participants especially used the shared interest interface to figure out Likes' meanings, and analyse whether it made sense to include certain candidates in their targeted audience: *"There were some brands [Likes] that I didn't know, but the knowledge interface [i.e., shared interest visualization] helped me know what they were about."* Participants particularly enjoyed not having to leave the tool to comprehend the audience the system recommended.

Open Deployment of Hax

Hax was also installed on a large screen display for several hours in a well-attended university open exhibition to further explore how average users experience this open-ended way of selecting audience candidates (cf. Fig. 5.) Without prior notice or any instructions, visitors to the exhibition were able to approach the display and begin interacting with Hax. During the deployment, approximately 150 visitors approached Hax: around 70 visitors interacted with Hax while the rest analysed and studied Hax without interacting. Average interactions times were around 1 min. Hax's visualizations appear to help people intuitively get an idea of what Hax is about and how to use it.

6 Outlook and Discussion

Our results show that users can target their audiences through data visualizations. Data visualizations prompted users to learn more about their peers. They also helped people find diverse audiences for their different sharing tasks. Something people felt was not facilitated with list based interfaces. This type of system design can help to have more cultural sensitivity, fostering better social interactions and collaborations. We see how data visualizations empower users to consider not only others' interests, but also their other traits, such as social, cultural, and spatial signals. This created a much more immerse and realistic sharing experience. We believe there is value in designing systems focused on the visualization of people's traits. Such systems could facilitate serendipitous discoveries, and help users get diversity in their interactions. One threat facing society today is obtaining enough "strangeness." Technology will dictate the type of relationships we will have in the future. It is thus crucial to think about creating digital opportunities where strangers with different opinions can find each other and connect. Social media data mixed with data mining and visualization techniques provide a unique opportunity for giving users diversity. Our results encourage future studies that address audience understanding as the main visualization goals.

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