Thin Slices of Online Profile Attributes

Kristin Stecher & Scott Counts

University of Washington & Microsoft Research
Author(s) Address(es) Go(es) Here in 9 Point Times Roman
Author(s) Address(es) Go(es) Here in 9 Point Times Roman
stech@u.washington.edu, counts@microsoft.com

Abstract

People form consistent impressions of others given surprisingly little information. With the advent of social networks, impressions now may form online rather than in a face-to-face context. This research explores aspects of online impression formation and discusses the crucial role of user profiles in this process. By examining users' decisions in an experimentally controlled social network, we show that users need only a "thin slice" of profile information in order to form impressions of others online. Additionally, specific profile attributes are evaluated for their perceived utility (how much do users choose to view these attributes), predictiveness (how well they serve as a proxy for a full profile), and diagnosticity (their ability to help users choose between online profiles). Findings provide design suggestions for better profile displays when space is restricted.

Introduction

Online social networks and other social applications with networking capabilities like blogs and online personals are growing in size and popularity on the web. Weekly over 100,000 new users join Facebook alone (Geist, 2007). Social networks allow connections and interactions with millions of other users. Many of these interactions occur for the first time in online contexts (Parks & Floyd, 1996). Do people use the same processes online that they use offline to form impressions of one another?

Offline, perceivers are bombarded with a complex interaction of behavioral, facial and environmental information, yet how much of this data do they take into account to form impressions? Accurate impressions are a function not only of the actor's ability to emit a relevant trait but also of the availability of this information to the perceiver, and finally the perceiver's ability to detect and utilize this information (Gosling, Gaddis & Vaizre, 2007; Funder, 1995). Although impressions are a function of complex information, initial impressions often form quickly, on the basis of relatively little information and their effects are long lasting (Ambady & Rosenthal, 1992). These impressions are important because they guide future interactions and relationships. Consensus in offline impression formation is typically high and can be accounted for using only a few important variables such as the attractiveness of the actor and the number of perceivers (Kenny, 1991).

Online, one way that people form impressions of others is through user profiles that, like their offline counterparts, often present a complex description of another person. Effective profiles help others form impressions that are predictive of either the offline personality of the user, or the online content of the user, such as their blog or other media. Challenging the effectiveness of profiles to convey consensual impressions is the fact that impressions are often formed not from a full profile, but from a condensed version of the profile designed to save screen space. The benefits of a complex full profile that allowed a user to represent various aspects of her personality and interests may be lost. Condensed profiles are utilized in online communities, social networking services, and mobile social software systems, and are often seen in listings of people in search results and group memberships. This format enables users to browse through lists of profiles in order to quickly identify interesting individuals. Despite frequent use of condensed profiles, there is little consensus as to what information these condensed profiles should contain: social networking sites like Facebook often include a picture, user name and network information, blogging sites such as Xanga and Windows Live Spaces display a user's picture and "About Me" statement or simply the first attribute fields completed by the individual.

Thus with this research we focus on the process of forming impressions from online profiles, but with a specific focus on how little information is needed for impressions to form. First we test if condensed profiles serve as proxies for full profiles. We then examine how well specific profile attributes help a condensed profile perform this proxy role. Finally, we show which attributes, if shown in condensed profiles, best help users make meaningful decisions in social networks.

Background

We present a brief background of the importance of user profiles, demonstrate the way that people form impressions online, and finally we will use social cognitive theory to argue that there is consensus in the inferences people make from condensed profiles.

Representation through User Profiles

Social network environments provide an obvious opportunity for users to create, control, and modify their online identity. Users are typically presented with various profile fields that they can complete and post to create an online profile. Importantly, different profile fields are not of equal importance. Lampe and colleagues (2007) analyzed the role of profile fields and friendship links within the Michigan State University Facebook network. They found that the completion of certain fields is predictive of more friendship bonds.

Despite variations within profiles, online profiles appear to represent individuals' offline personalities fairly well. Hancock, Toma and Ellison (2007) demonstrated that lying is minimal in online dating contexts. Although, 81% of users were deceptive, these deceptions were minor. Additionally, people are able to form accurate impressions of other users' personalities using their profiles. Perceivers' personality trait ratings of Facebook profiles were strongly correlated with the users' self ratings and friends' ratings (Gosling et al., 2007). In addition, people believe that their Facebook profile represents them well (Lampe, Ellison & Steinfeld, 2006).

This initial evidence suggests that online profiles may represent offline personalities with reasonable fidelity, but several questions remain. First, how much information is needed in order for a profile to remain an accurate portayal of a person's online self-representation? And second, if in fact profile fields can play different roles in the impression formation process, what elements contribute most to an accurate representation?

Impression Formation

We know that perceivers are motivated to form accurate impressions of their interaction partners and this goal is especially salient online (Fiore, 2002). The anonymity of online interactions may incentivize users to form accurate impressions. Donath (1999) explored identity maintenance and deception in Usenet communities and found that perceivers become attuned to useful cues such as user name, signature and even writing style in order to pick up on deception. Although the anonymity of online interactions causes users to fear deception, even in online dating contexts where the incentive for deception is higher, deception is relatively rare (Hancock et al., 2007).

One way that users may verify personal information is through "warrants", cues that link offline and online identities (Walther & Parks, 2002). In social networks even friendship links can serve as warrants or signals to other users that target individuals can be trusted (Parks & Floyd, 1996).

However, errors in perception can occur even in the absence of deception. How can user profiles be structured to allow for more accurate inferences? Preliminary research identifies the profile attributes users find informative in social networks. Riegelsberger, Counts, Farnham & Phillips (2007) examined attributes gamers use to select partners and identified that gamers found voice information more disambiguating than photos. In dating contexts, men and women weight profile factors differently (Fiore, 2002). Although we know the importance of profile attributes, we do not know why these attributes are important or how they facilitate the impression formation processes. In order to understand these questions, it is necessary to uncover the social cognitive factors behind this process.

Social Cognitive Factors

Psychologists are uncovering the overwhelming extent that our behaviors are governed by automatic processes (Bargh, Chen & Burrows, 1996). People automatically evaluate other people's personalities when they first meet them (Uleman, 1999). We rely heavily on prior experiences, and seem hardwired to behave based on very little information.

One process that is particularly hardwired is our ability to form quick, meaningful impressions of others on the basis of very little information. In fact, after viewing two seconds of an offline interaction, people are apt to form the same impression that they will form after an entire interview with a job candidate or after an entire quarter with a teaching assistant (Ambady & Rosenthal, 1993). This is true even when sound is stripped from the interaction. Ambady and her colleagues have labeled our ability to form consensual impressions from very little behavioral information "thin slicing". Impressions after a "thin slice" of behavior are said to be "accurate" if: 1) they match impressions formed after more detailed behavioral information and 2) if raters agree in their judgments. (See Ambady, Bernieri & Richeson, 2000 for a review).

When we form first impressions of other people online, we do not typically view their behaviors. Instead, we view

Table 1. Attributes- Percentage completed

Attribute	Complete	Attribute	Complete
About Me	73%	Last Updated	23%
Activities	83%	Looking For	23%
Birthday	97%	Movies	87%
Books	83%	Music	93%
College	90%	Name	100%
Concentration	80%	Networks	100%
Current Town	53%	Number of Friends	100%
Employer	53%	Number of Groups	100%
Full Name	100%	Photo	100%
Gender	97%	Political Views	73%
High School	83%	Quotes	67%
Hometown	93%	Relationship Status	77%
Interested In	66%	Religious Views	43%
Interests	77%	Status	23%
		TV Shows	87%

their personal profiles which are conveniently categorized into discrete, measurable attributes. In this context, thin slicing occurs naturally when users view a condensed profile, as described above. Can users synthesize information from a condensed profile quickly and efficiently to form a predictive impression of the target individual? Do condensed profiles represent a type of thin slice even though they contain information that is discrete rather than continuous like behavioral information? Walther (1996) suggests that people form impressions online and offline in similar ways, but online impression formation may be more carefully crafted and therefore may occur more slowly. More research is needed to determine whether people form accurate impressions of those they meet online after a very small slice of their profile. And, if this is so, how small can this slice be before it is no longer accurate?

Empirical Studies

Stimuli: Target Profiles

Facebook profiles served as the profile stimuli. Facebook is a social networking tool created with more restrictive profile fields than both MySpace and Friendster, other prominent social networking tools. Facebook is also unique because it allows users more control and privacy. Portions of Facebook profiles can be revealed and hidden from friend groups and other users as the user desires. Because of the popularity and the uniform look and content of Facebook profiles we obtained consent to use the profiles of 30 Facebook users as stimuli for both studies.

Attribute fields. A profile attribute is defined as any field within a Facebook profile. Because we were interested in effects of individual profile attributes on impression formation, we needed to determine which Facebook profile attributes to include in our studies. Here we describe our process for selecting profile attributes of interest. Twenty-nine important attributes were analyzed within each target profile. We specifically analyzed attributes determined important to users by previous research (Lampe et al., 2007). Additional fields were added due to recent Facebook updates. Other fields (such as contact information) were not analyzed due to privacy concerns.

Although 29 attribute fields were analyzed, not all of these fields were complete in every stimulus profile. On average 72% of this content was completed. The amount of content in our sample population is representative of Facebook profiles at large. In a sample of over 30,000 profiles, 59% of the profile fields were completed (Lampe et al., 2007). In our sample we included several extra attributes that participants did not actually complete such as Number of Groups. Controlling for these attributes, participants completed 64% of the content. Table 1 displays the profile fields we included in our study and the percentage likelihood that each profile field was completed.

Study 1

Hypotheses.

1) "Thin slicing": Users can make predictive inferences using condensed profiles.

2) Certain attributes contribute more to these condensed profiles than others.

Participants. Forty-four participants took part in our study. Thirty-one participants were male, eleven were female and two did not complete the demographic questionnaire. Participants were recruited using an email procedure and were not known to experimenters. The average age was 48, ranging from 23-70. Note that the average age is older than a typical college Facebook demographic, although there appeared to be no effect of age on study results (see below). Nine participants reported having specific experience with Facebook, and 19 participants reported using MySpace. Twenty-nine participants reported using some social network. In order to assess familiarity with condensed profiles we measured mobile social software use and community participation. Ten participants use mobile social software and 26 participants use the community feature of social networks.

Procedure. Participants were told that they were entering a social network and that their task was to select a friend within the network.

Phase I. In Phase I of our study, participants were asked to compare ten sets of three profiles. Initially no profile information was provided. Figure 1a displays the empty profiles that the participants first encountered.

Step 1: Choose Attributes to Reveal. Participants selectively revealed profile information of their choosing by selecting from the 29 attributes presented on the side of the screen. When an attribute was selected, it was revealed for all three profiles. Figure 1b depicts three profiles with one attribute revealed.

Step 2: Rank Profiles. After each attribute was revealed, participants were asked to rank all three profiles from 1 (favorite) to 3 (least favorite). Forced ranking controlled for possible ceiling or floor effects. For each set of three profiles, participants revealed 5 attributes one at a time, completing a ranking of the three profiles after each attribute revelation. Therefore, for each set of profiles, participants only saw 5 of 29 attributes, in essence creating their own condensed profile. Instructions indicated to participants that their rankings should account for all the attributes revealed not just the most recent attribute.

Step 3: Rate Profiles. After all five attributes were revealed and the profiles were ranked for the fifth time, participants were asked to give each profile a 1-100 rating indicating how much they would like to be friends with this person. Figure 1c is a final screenshot after all five profile attributes were revealed and the profiles were ranked and rated. Participants completed this entire task ten times before moving on to Phase II.

Phase II.

Full Profile Ratings. Participants rated the target persons again in Phase II. However Phase II contained screenshots of the targets' Facebook profiles rather than selected attributes. Again, the same target persons were presented to the participants, but in this phase of the experiment participants used the entire profile to make overall profile ratings. Participants viewed the profile screenshots paired again in the same groups of three and rated the profiles from 1-100. Profile ratings were completed for all ten comparisons. Participant ratings of the full Facebook profiles served as the measure of predictiveness for the condensed profiles in Phase I.

Results

Hypothesis 1, "thin slicing": Users can make predictive inferences using condensed profiles. We examined correlations between participants' profile ratings (1-100) at the end of Phase I (condensed profiles), and their ratings at Phase II (full profiles). Profile ratings from Phase I correlated with those from Phase II at $r=0.404$, $p<0.01$.

Additionally, we examined the consensus between participant ratings of the profiles at Phase I. Even after only viewing five attributes, ratings of the profiles were significantly intercorrelated ($r=0.35$, $p<0.001$). In other words, the participants liked and disliked the same profiles. Finally, because our participants were older than the typical Facebook demographic, we checked for but found no relationship between age and the Phase 1-Phase II correlation ($r=-0.04$, $p=0.77$).

Hypothesis 2: Certain attributes contribute more meaningfully to these profiles than others. We identified

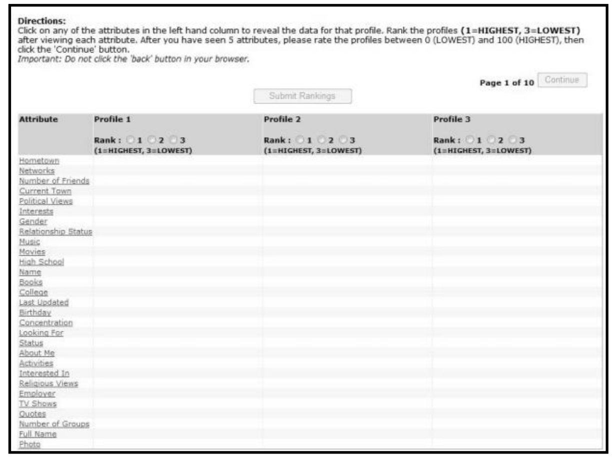

Figure 1a. No attributes revealed.

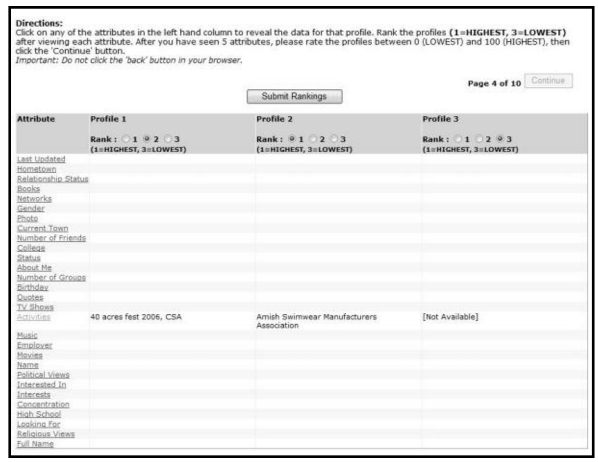

Figure 1b. 1 of 5 attributes revealed, profiles ranked.

Figure 1c. 5 of 5 attributes revealed, profiles ranked and rated.

and measured three aspects of profile attributes: Perceived utility, diagnosticity and predictiveness.

Perceived Utility- Frequencies. First, we calculated the frequency that each attribute was selected and viewed in Phase I. The frequency is the percentage likelihood that a given attribute was one of the five attributes selected by a participant in any trial. The frequencies are reported in Table 2 (column 1). This measure indicates how helpful participants anticipate each attribute will be for their friendship decisions, or the "perceived utility".

Diagnosticity- Change (Part I Ranking) x Attribute. We also calculated the total amount of change in rankings (1-3) generated after each attribute was selected in Phase I. These scores range from 0-4 because 3 profiles are compared at once and each can move 2 places in rank. This change measure assesses the attributes that allow participants to distinguish between profiles and therefore is a measure of "diagnosticity". For example, if a participant revealed the Movies attribute and then significantly reordered her profile rankings by switching the profiles that previously were ranked #1 and #3, the Movies attribute would receive a 4 change score for that trial and would be considered highly diagnostic. The average amount of change generated by each attribute is also presented in Table 2 (column 2).

Table 2. Study 1 attributes. Top five highlighted for each category. (Low differences scores mean high accuracy).

	Perceived Utility	Diagnos-ticity	Accuracy
About Me	26.4%	1.92	50.1
Activities	24.5%	2.14	49.7
Birthday	8.0%	2.39	52.4
Books	18.2%	2.33	54.6
College	13.0%	2.75	56.6
Concentration	12.7%	2.00	55.7
Current Town	11.1%	2.15	52.6
Employer	18.9%	2.40	52.7
Full Name	13.0%	2.07	53.1
Gender	15.7%	2.47	47.2
High School	6.6%	1.98	45.0
Hometown	10.7%	2.40	51.1
Interested In	28.9%	2.34	52.8
Interests	29.1%	2.37	50.1
Last Updated	9.5%	2.09	63.3
Looking For	22.5%	2.61	53.2
Movies	21.4%	2.54	53.6
Music	16.4%	2.66	56.3
Name	9.3%	1.71	44.6
Networks	9.3%	2.58	56.9
Number of Groups	6.1%	1.89	48.3
Number of Friends	10.5%	2.37	50.5
Photo	31.8%	2.12	47.7
Political Views	25.7%	2.40	53.2
Quotes	19.8%	2.35	59.2
Relationship Status	13.9%	2.27	56.2
Religious Views	21.4%	2.41	56.7
Status	12.7%	2.02	47.7
TV Shows	16.6%	2.70	61.8

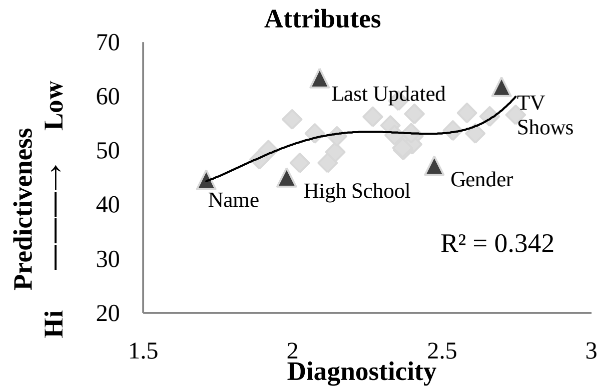

Figure 3. Attributes scatterplot, social networks

Predictiveness- Difference (Phase I-Phase II Rating) x Attribute. Earlier analyses established that participants rated target profiles similarly given condensed profiles (Phase I ratings) or full profiles (Phase II ratings). What attributes drive this relationship? By measuring the difference between Phase I ratings (1-100) and Phase II ratings (1-100) when an attribute had been selected in Phase I, we isolated which attributes are predictive after just five attributes. If the difference scores are small, this indicates similar Phase I and Phase II ratings. If the differences scores were large, then the attribute was not helpful. Average difference scores for each attribute are also presented in Table 2 (column 3).

Comparison of Change and Difference Measures. The ranking (1-3) change during Phase I generated by the selection of the attribute, and the difference between the Phase I and Phase II ratings (1-100) allow us to isolate important attributes along the aforementioned dimensions of diagnosticity and predictiveness. However these measures assess very different criteria. The first measure of change reveals attributes that helped participants distinguish between profiles. The second measure of difference assesses the attributes that allow participants to make predictive thin slices in Phase I. We created a scatterplot to chart the relationship between these two variables (See Figure 2). The best fit for the data was a quadratic equation, y = 95.77x4 - 804.0x3 + 2490.x2 - 3360.x + 1709 ($R^2 = 0.342$). Several key attributes that drive the quadratic relationship between predictiveness and diagnosticity are labeled on the scatterplot.

Discussion

Our first hypothesis was confirmed: Ratings after five attributes were strongly correlated with ratings after full profiles were revealed. Since participants completed over 190 total decisions in Phase I & II, we do not think that these effects are due to the participants simply repeating a remembered rating. In fact, in less than 1% of the trials did participants use the same rating in Phase I and Phase II. These ratings were correlated but not the same. It is also worth noting that the ability to thin slice was not related to age.

In their meta-analysis, Ambady and Rosenthal (1992) found that behavioral thin slices of five minutes or less predict the behavioral criterion of accuracy with a correlation of r=0.39. This means that small observations of behavior led to impressions consistent with those after larger behavioral observations. In our study, the thin slices were informational in that they consisted of smaller amounts of information about another person. We found that these online informational thin slices (condensed profiles) predicted our measure of predictiveness or "accuracy" (full profiles) with a correlation of r=0.40. Thus online informational thin slicing led to the same degree of thin slicing as behavioral thin slicing offline. This suggests that the way participants form impressions online and offline is remarkably similar. These findings support the theory that computer mediated contexts are hyperpersonal, and that users make inferences even from lean cues (Walther et al., 2002).

Consensus among our raters was relatively high after a thin slice of only five behaviors (interrater response r=0.35). A meta-analysis of behavioral thin-slicing found a correlation coefficient of r=0.20 in personality domains and r=0.27 in relationship domains (Ambady et al., 2000). Again this indicates that participants draw predictive inferences from condensed profiles and that online impressions formed from informational thin slices are similar to offline impressions formed from behavioral thin slices.

Our second hypothesis was also confirmed: We were able to identify certain attributes as more meaningful than others. The first measure of attribute importance was the frequency that the attribute was selected. High frequency scores indicated that this attribute had high perceived utility and participants expected this attribute would help them distinguish between profiles. Photo, Interested In, Interests, About Me and Political Views were revealed most frequently.

Meaningful attributes were also identified by assessing the amount of change in profile rankings generated when that particular attribute was revealed. Attributes with high change scores were diagnostic attributes that allowed participants to discriminate between target profiles. College, TV Shows, Networks, Music and Looking For, best allowed users to discriminate between profiles.

One focus of this study was to identify the attributes included in condensed profiles that lead to predictive impressions of full profiles. By measuring the difference between Phase I and Phase II ratings for each attribute selected, we isolated the attributes that allowed participants to take accurate thin slices of profiles. When participants included Photo, Name, Status, High School and/or Gender in their condensed profiles, this helped them form predictive impressions.

The attributes that caused participants to change their rankings and the attributes that assisted thin slicing were not necessarily the same. This is because predictiveness and diagnosticity are not the same measurement but are uniquely related. In order to understand this relationship, we plotted these attributes on a scatterplot. The relationship between predictiveness and diagnosticity is not linear but is best represented with a quadratic equation. As can be seen in Figure 3, as diagnosticity increases, predictiveness moves up and down, with a slight overall upward trend. Although further investigation into this wavelike pattern is warranted, it is worth keeping in mind that any given attribute can be diagnostic, predictive, both, or neither. For instance, the TV Shows attribute was diagnostic but did not help users form accurate impressions.

Study 2

Depending on the context, users set different social goals. These goals serve to motivate social behavior. Study 1 was set up to simulate a social networking environment and participants were given the goal of finding a friend within this network. Users in friendship networks have one set of goals, but do users in other types of social networks with different goals form impressions in the same way? In order to generalize these findings, it was important to apply this technique to another domain where users form initial impressions. In Study 2, we applied this technique to the blogging domain. We expect that manipulating user goals will not influence the impression formation process, but it will influence the specific content utilized.

Hypothesis 1: "Thin Slicing". People will make predictive inferences from condensed profiles given various processing goals.

Hypothesis 2. Important attributes will vary based on user specific (social) goals.

Participants

73 participants took part in Study 2. Participants were recruited using the same process as Study 1. Participants in this study were younger, M=32.3, although there was a large age range, (19-65). Forty-two males and 30 females took part in the study. One participant did not complete demographic information. Sixty-eight participants reported use of some social network, 56 participants use MySpace, and 34 participants use Facebook (non-exclusively). Forty-nine participants participate in blogging communities either by reading or writing in blogs.

Procedure

Study 2 replicated Study 1, except participant goals were manipulated through the instruction set. Participants were told that they were entering a blogging network and that their task was to find another blogger whose blog they wanted subscribe to.

Target profiles from Study 1 were utilized. Participants were told that these profiles represented bloggers. Phase I and Phase II of the study were a direct replication of Study I. Only the instruction set was manipulated.

Results

Hypothesis 1. People will make predictive inferences from condensed profiles given various processing goals.Again we examined the correlations between participants' ratings after Phase I (five attributes), and their profile ratings in Phase II (full profiles). Ratings after the full profiles served as our criterion of predictiveness. Profile ratings in Phase I were moderately correlated with Phase II ratings ($r=0.301$, $p<0.01$). Again age was not a factor, as reflected by the lack of correlation between participant's age and their Phase I - Phase II thin slicing correlation ($r=-0.04$, $p=0.974$).

The intercorrelation between participant ratings at Phase I describes the agreement about the profiles after a thin slice. Even after only viewing five attributes, participants' ratings for the profiles were significantly intercorrelated, ($r=0.40$, $p<0.001$).

We compared the correlations between Phase I and Phase II for the blogging participants and for the social network participants. Participants did not exhibit significantly different amounts of thin slicing depending on if they received social networking instructions or blogging instructions, $F(1,114)=2.11$, $p=0.156$.

Hypothesis 2: Important attributes will vary based on network specific goals. The same three measures of attribute importance were used: frequency (predicted utility), change in rankings (diagnosticity) and difference in ratings (predictiveness). Scores on each measure are presented in Table 3.

Comparison of Change and Difference Measures. Different attributes brought about diagnosticity than those that brought about predictiveness. As in Study 1, the relationship between these variables fit a quadratic pattern. The data was best fit to the equation $y = 612.1x4 - 5417x3 + 17885x2 - 26106x+14264$, $R^2 = 0.203$. Key attributes driving this relationship within blogging contexts are highlighted on the scatterplot (See Figure 3).

Discussion

These results support our first hypothesis that users have the ability to use thin slices of profiles in domains beyond social networks, including weblog communities. Even when given the alternate instruction set to find people whose blog they would subscribe to, participants rated profiles similarly when they were given five attributes and when they were given full online profiles. In addition, participants' ratings agreed after only five attributes, meaning participants exhibited a high degree of interrater consensus on which users' blogs they would or would not like to read. This has implications for user testing and marketing. For example, a smaller participant sample can be used with fewer trials.

Our second hypothesis was also supported and we identified the attributes that varied based on user goals. Those picking bloggers and those picking friends in social networks choose to view largely similar attributes; therefore their perceived utility for the attributes was similar. Photo, About Me, Activities and Interests were identified as important both when participants were searching for a friend and searching for a blog. Those searching for a blog also identified TV Shows as important.

Table 3. Study 2 blog attributes. Top 5 highlighted for each category.

	Perceived Utility	Diagno-sticity	Predictive-ness
About Me	34.9%	2.08	56.7
Activities	25.6%	2.16	56.5
Birthday	9.0%	2.30	64.3
Books	21.1%	2.27	57.0
College	14.1%	2.17	63.3
Concentration	15.1%	2.33	63.4
Current Town	11.1%	2.46	56.2
Employer	17.4%	2.62	54.0
Full Name	9.0%	2.05	60.6
Gender	12.3%	1.89	62.5
High School	7.3%	2.32	67.1
Hometown	8.1%	2.19	55.0
Interested In	22.9%	2.02	63.0
Interests	35.5%	2.04	54.8
Last Updated	8.5%	2.31	62.4
Looking For	12.5%	1.85	71.7
Movies	24.1%	2.09	56.2
Music	23.6%	2.04	61.3
Name	7.4%	1.99	68.5
Networks	11.5%	1.99	59.9
Number of Friends	5.6%	2.26	64.4
Number of Groups	7.1%	2.37	69.3
Photo	55.6%	2.55	53.4
Political Views	18.2%	2.34	63.2
Quotes	21.0%	2.19	63.2
Relationship Status	12.2%	1.75	63.6
Religious Views	14.5%	2.78	69.1
Status	8.6%	1.86	66.3
TV Shows	26.2%	2.35	58.2

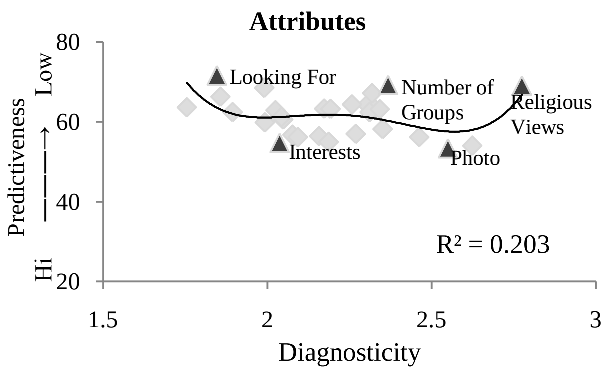

Figure 3. Attributes scatterplot, blog.

However, the other measures of diagnosticity and predictiveness revealed that attributes that help participants choose between people and form accurate impressions in social networking domains are different from those helpful in blog domains. In social network domains, the diagnosticity scores demonstrated that, College, TV Shows, Networks, Music and Looking For drive participants' selections between profiles. Photo, Religious Views Current Town, Employer, and Number of Groups, enabled users searching for bloggers to make more accurate decisions.

Like in Study 1, attributes that helped users form predictive impressions were not necessarily the same attributes that helped them make diagnostic choices between condensed profiles. Again, however, a quadratic relationship between predictiveness and diagnosticity best fit the data (Figure 4). Certain attributes like Religious Views were highly diagnostic, and helped participants discriminate between bloggers, but were not accurate predictors of decisions made when viewing the full profile. Other attributes such as Looking For, a field indicating relationship preference, were not predictive or diagnostic perhaps because they were not appropriate for the blogging domain. The trade-off between these attributes continues to wax and wane in a quadratic pattern similar to that found in the social networking domain.

Conclusion

Based on our findings, we conclude that condensed user profiles are a valid tool for social networks. These profiles are useful because users extract information by forming impressions based on small amounts of information, or the social cognitive process of "thin slicing". Participants in both the social networking and blogging domains were able to extract predictive information from thin slices of online profiles. Findings from these studies are very similar to findings using offline behavioral thin slices (Ambady, LaPlante & Johnson, 2001). This suggests that people are fluid with profile information in a similar way that they are fluid with behavioral information.

However, although users can extract thin slices from condensed profiles, it is important to remember both that the profile attributes presented in a condensed profile affect the impression formed and that these attributes are processed differently based on user goals. In social networking and blogging domains, participants preferentially selected certain attributes over others. This finding allows us to make a reliable recommendation about the content users would like to see across domains. Profiles catering to users' interests should contain an attribute field for Photo, Interests, an About Me statement and Activities in this order of priority.

Although participants in the blogging and social networking domains selected the same attributes to view, these decisions influenced them differently in that attributes that allowed users to accurately thin slice and make diagnostic decisions between profiles were different across domains. We recommend that applications first account for user interests using the first four attributes mentioned above. After accounting for these attributes, applications should take into account the domain specific goals of their users. We provide domain specific suggestions for the creation of profiles that are diagnostic and predictive.

In the social networking domain; College, Music, Networks, Looking For and TV Shows were diagnostic. Users seeking blogging partners used Current Town, Employer, Number of Groups, Photo and Religious Views to distinguish between profiles. These attributes are suggested when users need to choose between others using lists of condensed profiles.

For social networking participants, Photo, Name, Gender, High School and Status best assisted with forming accurate impressions from condensed profiles. That is, when these attributes were revealed in Phase I, participants were able to make ratings that were most similar to ratings made when they had full user profiles. Different attributes assisted the blogging participants. The Photo, Interests, Hometown, Current Town and Employer were helpful. These attributes are useful when users need to make accurate predictions given minimal information such as in a mobile social software environment. It is worthwhile to note that photos are useful for nearly every criterion across domains.

Within social networking and blogging domains, different attributes assisted in predictiveness and diagnosticity. Some attributes allow participants to form more predictive impressions, while others are diagnostic and help them choose among their options. However these attributes are not unrelated. Variables fit together in a unique relationship. Users (and designers) are faced with predictiveness-diagnosticity tradeoffs when they interact with social software. On one hand, the user goal is to choose between people based on condensed profiles, a diagnosticity goal. On the other hand, another user goal is accurately predict other user content using condensed profiles. The tradeoff is important because in a well designed system, once a user has selected a condensed profile for further inquiry, she will have a high likelihood of finding a full profile that matches the impression formed when viewing the condensed profile. Based on our data we can make suggestions to balance predictiveness and diagnosticity needs. For example, in a social network context, attributes such as Movies are both reasonably diagnostic and lead to predictive impressions.

Finally, we suggest that this relationship between accuracy and diagnosticity might extend more broadly across online and offline domains. Those attributes that help us distinguish between people may not be the same attributes that help us form predictive impressions. Traditionally, these may have been difficult to measure in behavioral settings. Because online profiles represent controlled compartmentalized forms of self representation, they may provide more discrete representations of people and thus a more easily quantifiable test bed for studying and understanding phenomena of interpersonal interactions. Thus, the study of these phenomena in the online context may provide insight for those studying more traditional forms of impression formation.

In sum, people form meaningful impressions both offline and online. Predictive impressions form even after very little information. In both social networking and blogging domains users were able to make inferences using condensed profiles. We were also able to identify certain attributes that are useful in different ways. Photo, Interests, About Me and Activities are perceived as useful by users across domains. Users rely on different attributes to make decisions and thin slice based on the domain. Depending on the purpose of the condensed profile, profile fields should reflect these attributes.

REFERENCES

Ambady, N., Bernieri, F., & Richeson, J. A. (2000). Towards a histology of social behavior: Judgmental accuracy from thin slices of behavior, *Advances in Experimental Social Psychology, 32*, 201-271.

Ambady, N., LaPlante, D., & Johnson, E. (2001). Thin slice judgments as a measure of interpersonal sensitivity. In J. Hall & F. Bernieri (Eds.), Interpersonal Sensitivity: Measurement and Applications, NJ: Erlbaum.

Ambady, N., & Rosenthal, R. (1992). Thin slices of expressive behavior as predictors of interpersonal consequences: A meta-analysis. *Psychological Bulletin, 111,* 256-274.

Ambady, N. & Rosenthal, R. (1993). Half a minute: Predicting teacher evaluations from thin slices of nonverbal behavior and physical attractiveness. *Journal of Personality and Social Psychology, 64,* 431-441.

Bargh, J. A., Chen, M., & Burrows, L. (1996). Automaticity of social behavior: Direct effects of trait construct and stereotype priming on action. *Journal of Personality and Social Psychology, 71,* 230-244.

Donath, J.S. (1999) Identity and deception in the virtual community. *Communities in Cyberspace* (Marc Smith & Peter Kollock, eds). London: Routledge..

Gosling, S.D., Gaddis, S. & Vaizre, S. (2007). Personality Impressions Based on Facebook Profiles. ICWSM (2007).

Geist, M. Facing up to Facebook fears. *BBC News.* http://news.bbc.co.uk/2/hi/technology/6639417.stm (2007).

Gross, R. and Acquisti, A., Information Revelation and Privacy in Online Social Networks. in *Workshop on Privacy in the Electronic Society*, (Alexandria, VA,2005), ACM Press.

Fiore, A. Romantic Regressions: An Analysis of Behavior on Online Dating Systems: Program in Media and Cornell (2002) Masters Thesis.

Funder, D.C. (1995). On the accuracy of personality judgment: A realistic approach. *Psychological Review*, 102, 652-670.

Hancock, J.T., Toma, C., & Ellison, N. (2007). The truth about lying in online dating profiles. Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI 2007), 449-452.

Jensen, C., Davis, J. P., & Farnham, S. D., (2002). Finding Others Online: Reputation Systems for Social Online Spaces CHI 2002, ACM Press (2002), 447-454.

Lampe, C., Ellison, N. and Steinfield, C., A Face(book) in the crowd: Social searching vs. social browsing. In *ACM Special Interest Group on Computer-Supported Cooperative Work*, (Banff, Canada, 2006), ACM Press.

Lampe, C., Ellison, N. and Steinfield, C., A familiar Face(book): profile elements as signals in an online social network. SIGCHI 2007, ACM Press (2007), 435-444.

Parks, M. R., & Floyd, K. (1996). Making friends in cyberspace. *Journal of Communication, 46*, 80-97. Also appearing concurrently on-line in the *Journal of Computer-Mediated Communication, 1* (4).

Riegelsberger, J., Counts, S., Farnham, S., & Phillips, B. (2007) Personality Matters: Incorporating detailed user attributes and preferences into the matchmaking process. In Proc. HICSS 2007.

Uleman, J. S. (1999) Spontaneous versus intentional inferences in impression formation. In S. Chaiken & Y. Trope (Eds.), *Dual process theories in social psychology.* New York: Guilford Press.

Walther, J. B. (1996). Computer-mediated communication: Impersonal, interpersonal, and hyperpersonal interaction. Communication Research, 23, 3-4.

Walther, J. B., & Parks, M. R. (2002). Cues filtered out, cues filtered in: Computer-mediated communication and relationships. In M. L. Knapp & J. A. Daly (Eds.), Handbook of interpersonal communication (3rd ed., pp. 529-563). Thousand Oaks, CA: Sage.