Beyond CPM and CPC: Determining the Value of Users on OSNs

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ABSTRACT

Not all of the over one billion users of online social networks (OSNs) are equally valuable to the OSNs. The current business model of monetizing advertisements targeted to users does not appear to be based on any visible grouping of the users. The primary metrics remain CPM (cost per mille—i.e., thousand impressions) and CPC (cost per click) of ads that are shown to users. However, there is significant diversity in the actions of users—some users upload interesting content triggering additional views and comments leading to further cascades of action. Beyond direct impressions, a user's action can generate indirect impressions by actions induced on friends and other users. Identifying the valuable user segments requires examination of profile data, friendships, and most importantly, their activity. Here we explore an alternate approach for measuring the value of users in OSNs by proposing a framework from the viewpoint of a popular OSN. Using a real dataset on the social network and activities of users, we show that a small subset of actions are likely to be key indicators of a user's value. Additionally, by examining the current targeting demographics available in Facebook, we are able to explore the relative (monetary) value that different users represent to the OSN.

Categories and Subject Descriptors

I.6 [**Simulation and Modeling**]: Applications; J.4 [**Social and Behavioral Sciences**]: Sociology; H.3.5 [**Information Storage and Retrieval**]: Online Information Services—*Web-based services.*

General Terms

Theory, Measurement, Economics.

Keywords

Online advertising, online social networks, user value.

COSN'14, October 1–2, 2014, Dublin, Ireland.

http://dx.doi.org/10.1145/2660460.2660477.

1. INTRODUCTION

Online advertising underlies much of the economic basis of the Web today; many sites provide free services supported by advertising. Google—far and away the largest advertising network on the Web—reported over $50 billion in 2013 [15] in advertising revenue alone. Typically, advertisers place ads on Google by specifying keywords of interest; different keywords have different values with their market price determined via a dynamic auction. The cost to advertisers when using networks like Google is generally expressed in terms of CPM (Cost per Mille, or the cost of 1,000 ad impressions) or CPC (Cost per Click, or the cost to receive a single ad click independent of the number of impressions).

Recently, online social networks (OSNs) such as Facebook have also seen an advertising market develop. For example, Facebook's most recently quarterly report indicated advertising revenue of over $7.8 billion in 2013 [12]. Advertising on OSNs works in a manner similar to advertising on Google: advertisers specify targeting parameters (i.e., attributes that the advertisers desire users to have) and a CPM/CPC bid price, and the OSN ranks the ads to select the ones to be shown. The ranking is typically based on the bids and the click-through-rate (CTR) of the ad.

The strong similarity between advertising on the Web and OSNs is surprising given that OSNs are significantly different from a typical website or a search engine answer page. On Web-search-based ads such as Google, the ad network, by default, knows relatively little about the user. Instead, the network must track users using cookies and other techniques, extracting more information about users through data mining. For example, Google provides a significant number of services (e.g., email, calendar, etc.) to users, presumably to be able to gather additional information. However, in the case of OSN-based ads, users must have an account and be logged in, in order to even see ads. As part of participating in the OSN, users provide information about themselves in profiles (interests, identities of friends, demographics, educational history, etc.) and through interactions with the site (posting updates, "checking in", installing applications, etc.). Moreover, because the OSN is run by a single centralized entity, the OSN observes all user actions on the site.

We posit that users on OSNs have sharply different values—in terms of the revenue they generate through ad impressions—to both the OSN itself and advertisers. For example, influential users often have many friends, post significant amounts of content, and have their posts forwarded to many others; these users are likely to be more valuable than the average user. Such users are likely to bring more value to the OSN itself (as they afford more advertising opportunities) and to advertisers as well (as their activities offer more opportunities for the advertiser's message to be spread). However, little work has gone into studying how the value of users in OSNs varies, and determining the extent to which users' value contributions can be extracted, quantified, and presented to advertisers. Moreover, no one has come up with a framework for assigning different values to individual users; the focus is typically on aggregate user values.

We explore an alternate approach for measuring the value of users in OSNs such as Facebook via a framework for estimating their relative value. We do so from the perspective of the OSN operator, who both runs the advertising network and the OSN site. However, our analysis is constrained by the (very) limited visibility we have into the OSN's revenue (i.e., we are typically unable to know how many ad impressions each user receives, or how often they click on ads). Thus, we rely on the data available to us to parametrize our model, with the knowledge that the OSN operator likely has significantly better data available; this more accurate data could be used to further refine our model and the resulting predictions. It is worth noting that our goal is not to validate a specific model, but rather to propose a potential model and explore its feasibility given the limited data available to external observers.

We examine the wealth of information that the OSN operator receives about user activity on their site and present a methodology for reasoning about how different user actions correspond to revenue. We argue that a user's value can be divided into direct impressions (advertising opportunities that a user provides by browsing OSN site pages) and indirect impressions (advertising opportunities that a user provides by enticing others to browse OSN site pages). Indirect impressions can *cascade* via the network, where a user's actions ultimately cause other users to visit the OSN. For example, after one user uploads a photo, this action may cause her friends to log in to the OSN and view it (potentially causing more users to log in, etc.).

Having a proper understanding of the economic value of different users benefits both the OSN and advertisers. OSNs can enable targeting of such "more valuable" users, increasing revenues and making their advertising platform more attractive to advertisers. Additionally, uncovering the value of users will also benefit the users themselves, as they become aware of their relative value. In other types of networks, understanding which nodes are most central has proven quite valuable. For example, on the AS-level Internet topology, the peerings and traffic details of Internet Exchange Points (IXPs) were not widely known until recently [3]. It was revealed that each of largest European IXPs handles on a daily basis as much traffic as some of the global Tier-1 ISPs and supports a peering fabric that consists of more peering links than were previously believed to exist Internet-wide [32]. Locating high value users may likewise uncover a different microcosm in the OSN.

We explore our framework by leveraging a detailed data set from Facebook covering 90,269 users in the New Orleans metropolitan area [29]. We estimate the number of impressions attributable to users via activity, and show that users from our data set are likely to have sharply different values. We also show that our model can be extended to represent the user value in monetary terms beyond just the number of advertising impressions. We collect data from the Facebook Ads platform for each of the New Orleans users who have filled in basic demographic information, and use this as a basis for estimating revenue per user.

2. BACKGROUND

We now provide background on OSN advertising and cover work related to this study.

Facebook's Advertising Model. To study current advertising models in OSNs, we focus on Facebook, as it is the largest and most mature OSN. Facebook offers targeting parameters—such as location, gender, interests—and advertisers pay either per click or per impression for users who match the advertiser's specified targeting parameters. Although the parameters are quite detailed in terms of different demographics and interests, they currently do not relate directly to the target user's popularity or level of activity within the OSN (e.g., there is generally no mechanism for directly targeting "users who are influential").

The CPM and CPC ad prices are set through an auction, where each advertiser bids the maximum that she is willing to pay for impressions or clicks. Facebook selects the "best" ads to present to the user; while the ad selection algorithms are secret, the OSNs presumably use the highest bids in the case of CPM, or the highest expected revenues in the case of CPC (similar to the popular approach used in sponsored search advertisement auctions [17]). Thus, targeting parameters that are popular with advertisers are expected to have higher winning auction prices.

Information Diffusion. Much work has studied "influential" users in social networks; but deciding where to "seed" ads to reach the biggest possible audience remains a challenge. Social contagion has been studied from different angles: finding the set of users that maximize the probability of spreading [11], discovering topical authorities [31] or identifying trendsetters [26]. Other roles in the diffusion process include promoters [7], early adopters and imitators [5].

Beyond social contagion, cascading behavior is common in OSNs [9], and although the user's popularity does not necessarily create cascades [10], being popular is essential for direct influence [4] (popular users broadcast to a broader audience). Moreover, if we consider that cascades tend to be wider than deeper [25], the size of a user's audience (i.e., node in-degree) is key to estimating their value.

Auction mechanisms. Online advertising has been extensively studied due to its popularity and data availability [16, 30]. Researchers have studied the properties of advertisers [19, 23], and techniques for online advertisers to maximize their revenue [24]. Barford et al. [6] studied the features, mechanisms and dynamics of display advertising on the Web, demonstrating that a user's profile (i.e., browser and cookies) can have a significant impact on which ads are shown. Moreover, they demonstrated that the specific types of ads delivered generally correspond with the details of user profiles. Our work is complementary to these, as we focus on differentiating between more- and less-valuable users, rather than ad auctions or targeting. Beyond CPC and CPM [21, 22], there are other proposed pricing models [13, 14] that combine both (called impression-plus-click pricing). Other work has explored predicting the number of clicks—effectively, the CTR—for new ads [2, 18].

3. USER VALUE FRAMEWORK

Each page on the OSN that the user visits gives an opportunity to the OSN provider to show advertisements. As discussed above, the value of a user in an OSN is directly proportional to the number of advertising impressions and clicks that the user generates by their actions. The actions may be visible (such as uploading content or commenting on a friend's content) or invisible (such as visiting a friend's profile or browsing a friend's photos without commenting).

We call the advertisements shown directly to the user *direct impressions*. Thus, users who browse the OSN frequently are likely to generate many direct impressions. When a user perform actions that have effects visible to others in the OSN, the user has the potential to also generate *indirect impressions*. For example, a user commenting on a friend's photo may trigger other users to return to the OSN (thereby generating additional, indirect impressions). Thus, when more people browse the OSN as a result of one user's action, more impressions can be attributed to the action.

We argue that different user actions are likely to generate different numbers of impressions. The "place" where the action has been done (e.g., in the user's profile, friends' profiles, or on group/community pages) can result in generating different numbers of impressions.

Below, we propose a potential framework that considers all these factors and uses them to compute a user's value (in terms of the advertising revenue of the OSN that can be attributed to the user). First, we analyze why different actions produce different numbers of indirect impressions and how external observers or the OSN provider can measure this. Next, we show how users' characteristics and the places where they perform their actions affect their value. Finally, we propose a comprehensive methodology for computing users' values that can be applied to many OSNs.

3.1 The Value of Actions

Consider an OSN where the most common action is to browse photos of friends, but articles posted by friends are rarely read. In such an OSN, when a user uploads a photo, the user is generating more indirect impressions than by posting an article. The value of an action is thus related to the new actions triggered.

The primary challenge in measuring the value of actions is that many of the impressions cannot be directly observed; only the OSN knows when they occur and few OSNs provide visibility into how often other users browse content. An external observer, however, can estimate invisible actions, for example, by considering visible actions as a proxy for invisible actions [33]. Another option is to extrapolate this information from previous studies that have access to (private) invisible actions and show that most user activities on OSNs consist of visiting friend profiles and photos. We take this approach and use two studies [8, 28] that examined user's actions on popular OSNs. Each of these studies relied on clickstream data (e.g., records of requests to the OSN) in order to study how users spend their time in OSNs. Table 1 shows activity distribution of a large number of users in three different OSNs in these two studies. Although the actual distribution of user activities may vary with the OSN, we show in Section 4 that small variations in action value assignment are not likely to dramatically impact the final user value.

Facebook		**Orkut**		**Hi5**	
Category	Share	Category	Share	Category	Share
Home	35 %	Profile,Friends	41%	Photos	45%
Profile	16 %	Photos	31%	Profile	20%
Photos	16 %	Scrapbook	20%	Home	13%
Friends	4.7 %	Other	3%	Friends	13%
Groups	3 %	Communities	1%	Groups	1%

Table 1: Comparison of popular user activities across three OSN sites [8, 28].

3.2 Users Characteristics and Interactions

We next consider the information that external observers can collect to help estimate the value of users. Many OSN services make basic personal information provided by each user (gender, age, location, interests) public by default. It is also generally possible to obtain some information about the social graph, such as the number of friends and their identities. While the basic information is useful for targeting (e.g., an advertiser is targeting 30-year-old men in Barcelona), the latter is useful to estimate the indirect impressions. For example, when a user with thousands of friends posts an update, the user is broadcasting information to a wider audience than a user with only a few friends. As a user's friends tend to be similar in demographics and tastes to the user [1], it is conceivable that most of the indirect impressions would be shown to a similar target group.

3.3 Measuring User Value

We now present a framework for measuring the relative values of users, and begin by defining the value of user characteristics, activities, and friends' activities:

User characteristics (u_c): This term measures individual user characteristics and is composed of two elements: the targeting parameters t and the number of friends d (i.e., the user's degree). We can tailor t to a given target group; if the advertiser is seeking older demographics, t could be defined as being proportional to the age. If the target is related to a geographical location, t would be inversely proportional to (e.g., the logarithm of) the distance. All such targeting parameters can be combined depending on the advertiser requirements. Precision and granularity of targeting will depend on user's demographic information available on each OSN (for example gender, countries GDP, etc.). The second parameter d reflects the amplification of an action as a result of the direct audience reached by each user. To be conservative, we define d as the logarithm of the user's degree (as studies have shown that the fraction of a user's friends who the user interacts with is not a linear function of their degree [33]). Hence

$$u_c \propto t \cdot d \propto t \cdot \log(\#friends + 1) \tag{1}$$

Notice that this only captures the first hop on an activity cascade. The next hop will be captured by the activities of the users influenced by this user.

User activity in her own profile ($u_{a_{self}}$): This is a weighted sum of u actions (such as number of photos uploaded, number of articles posted, etc.) done by u in her own profile or home page.

$$u_{a_{self}} \propto \sum_i w_i \ \#action_i \tag{2}$$

where w_i is a weight proportional to the action value. Most likely, activities in a user's profile correspond to direct impressions.

Friends activity in a user's profile ($u_{a_{friends}}$): For all the users v that are friends with u, we measure their activity in u's profile. Given that each time v performs an action in u's profile this information is sent both to u and v friends by default (this can be changed through privacy settings but is rarely done), we weight all these actions by v's individual characteristics v_c:

$$u_{a_{friends}} \propto \sum_{v \in |u|} v_c \sum_i w_i \ \#action_i \tag{3}$$

As discussed earlier, most actions are reactive and thus most of them will correspond to indirect impressions.

User activity in their friends' profiles ($u_{a_{visitor}}$): When u carried out an action in her friends' profiles:

$$u_{a_{visitor}} \propto \sum_{v \in |u|} v_c \sum_i w_i \ \#action_i \tag{4}$$

As in the previous case, most of these activities will likely correspond to indirect impressions.

If we are targeting all users in the same way (that is, $t = 1$), then the final formula for the u_{value} is a function of her activity and her friends:

$$u_{value} \propto (u_{a_{self}} + u_{a_{friends}} + u_{a_{visitor}}) \ u_c \tag{5}$$

In Section 5, we analyze the case of the value of different users as per their different interests. Overall, the first weight captures mainly direct impressions while the other two capture mainly indirect impressions.

This simple definition could be extended to include different weights for friends based on tie strength (closer friends are more likely to see our actions and generate more impressions), privacy settings, and "circles" (groups of users see only partial information about our actions depending on our privacy configuration). Groups or community activity could also be included. However, an easy way to add group activity, is to consider the group as a friend, where all the group members would be friends of friends. Then, group activities can be included in the terms $u_{a_{friends}}$ and $u_{a_{visitor}}$.

4. APPLYING USER VALUE

Having defined a framework for reasoning about the value of users to the OSN, we now apply our model on a real OSN dataset. The goal is to explore how the relative value is distributed by our model across users, and how different strategies to measure invisible actions affect these results.

4.1 Dataset Description

We use a 2009 dataset collected from Facebook covering users in New Orleans [29]. We only consider the 50,564 users with public profiles out of the 90,269 users. As we are interested in classifying users by their interests and demographics, we use only those who share their age and gender, have at least one interest, and have at least one "post" on their wall. Most of the users divulge gender and age but only 23,950 users have at least one interest and an even smaller number (7,054) users have any posts.

4.2 Choosing Weights

Facebook's users can share different types of posts (status updates, posts, URLs, etc.), upload multimedia content (photos, videos), and perform actions within communities (join a group, event, fan page, etc.). To simplify our analysis, we group all these actions in three categories: posts, multimedia, and communities. We need a way to define the weights w_i described in Section 3 for each of these groups. This is difficult because the invisible actions (e.g. watching a video without leaving any comments) are unknown to external observers. Of course, the OSN operator is privy to much more detailed information and could likely derive many of the weights from the traces of user activity. Instead, we rely on externally-visible information in order to estimate the rough values of the weights.

Previous studies (see Table 1) have shown that visiting friend's profiles (corresponding to our "posts" category) is the most frequent activity, followed by browsing photos (multimedia), while group or community actions are infrequent. Although this ordering is consistent among different OSNs, the percentage of time spent in each category varies (e.g people spent 45% browsing photos in Hi5 vs only 16% on Facebook). Thus, we need to study the sensitivity of u_{value} to different w_i values. To understand how these weights affect the results, we can check to see if correlation among these three groups of actions is high, indicating that the weights are less important. If user's activities are equally distributed, weights are less important, because the numbers of actions ($\#action_i$) will be proportional.

We found a strong correlation between posts and multimedia actions but a lower correlation between multimedia and communities. Users uploading significant multimedia content are thus also creating many "wall posts" but do not necessarily engage in group activities. Thus, we normalize by the three categories of actions and group "home", "profile" and "friends" activities in the posts category; we then assign weights of 0.75 for posts, 0.21 for multimedia, and 0.04 for communities.

4.3 Value Distributions

Next, we want to study how value is distributed among users after applying our model and how they are related to user attributes (age, gender, and interests). Our hypothesis is that the number of impressions (i.e. value) generated by each user varies over a wide range. We expect a small fraction of users to create a lot of impressions and many users generating only a handful.

To test our hypothesis, we first compute the value for each user in our dataset. Next, we normalize these values, with 1 being the most valuable user. Not too surprisingly, we found users' value distribution is Zipfian, confirming our hypothesis that a small subset generates most of the impressions.

Next, we identify the high value users. In our experiment, we are considering all the users in our New Orleans dataset as the target group. Thus, t in equation 1 does not depend on age, gender or interests and so u_c only depends on the number of friends. We want to compute a generic value that allows us to compare the impressions generated by different demographic groups. For example, do women generate more

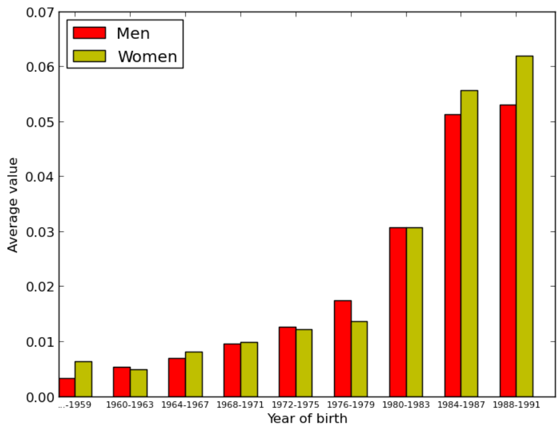

Figure 1: Users' relative value predicted by our model, broken down by age and gender. Younger users appear to be significantly more valuable, largely due to their higher level of activity.

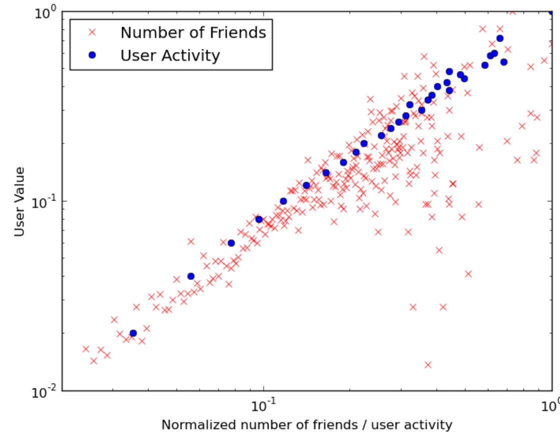

Figure 2: User's value vs. number of friends and activity.

impressions than men? We find that women are more valuable in our model than men, and young people generate more impressions than more mature users (see Figure 1). Given that the difference between the least valuable group (males born after 1959) and the most valuable group (women born between 1989-1991) is less than 10%—with large standard deviation in each group—we can assume that high and low value users are spread across different demographic groups.

A previous study [27] suggests that there is a strong correlation between the number of friends and user activity; users that post/upload more information have more friends. Our experiments show that popular users are more active and valuable (see Figure 2), which is partly a consequence of using friends and activity to compute the user's value. However the correlation is much higher for the activity than for the number of friends; activity produces impressions while the number of friends is only a potential amplifier of activity.

5. FROM VALUE TO REVENUE

The model that we have proposed and evaluated so far has considered ad impressions as the metric for valuing users, as OSNs are typically ad-supported. However, we would also like to be able to reason about the actual (monetary) value of each user so that the OSN provider and advertisers can determine which users are profitable. The mechanism we propose here is only one way of doing so; there may be others that are more attractive if additional data is available.

5.1 Using Ad Auction Data

To map user value to revenue we need to translate ad impressions to monetary revenue. An approach that assumes that all ad impressions provide equal revenue is unrealistic as certain user attributes are likely to be much more valuable (i.e., we know that there are certain demographics that are much more valuable to advertisers, and users in different countries are likely to provide significantly different revenue). Fortunately, Facebook provides advertisers with a "suggested bid" [20] for a given set of targeting parameters; this suggested bid is expressed as a range (min, median, and max) over the current bids for the target demographic. Thus, for a given user, we can determine the current revenue that Facebook receives for each ad impression shown to that user by querying for the suggested bid.

5.2 Collecting Data

To demonstrate this approach in practice, we use the same Facebook New Orleans data set from 2009 from Section 3. For each of the users, we extract as many profile attributes as possible, including basic attributes like gender and age, and free-form attributes like user interests. Recall that we only consider users who provided their age, gender, and at least one interest; leaving us with 7,054 users. We map each of the free-form interests to Facebook's "precise interests"; we found a match to a Facebook-supported interest category 60.4% of the time (4,265 users).

We query Facebook's Ads platform for the suggested bid of each of the 4,265 users, using *all* available targeting parameters [20]. For users with multiple interests that we could match, we queried multiple times (once for each interest).

Examining the bid data, we make two interesting observations. First, the distribution is remarkably even, with the CPC of 99% of users' interests ranging between \$0.62 and \$1.53 and the CPM for 99% of users' interests ranging between \$0.07 and \$0.31. This suggests that there are not specific interests that are significantly more highly valued by advertisers than others. Second, we observe that the prices are quite stable over time (see an example in Figure 3), indicating that our methodology is likely to hold over at least short periods of time.

5.3 Putting It All Together

We demonstrated in the previous section that a user's value (in terms of ad impressions) can be modeled based on the user's actions. Here we showed that these ad impressions can be translated into actual revenue received by the OSN. Now, we use the New Orleans data set to estimate the potential ad revenues brought in by the different users (i.e., we estimate the value of the users to Facebook). To do so, we first use the model of user value to assign credit for ad impressions to different users. Then, we use the advertising revenue for each user, and translate credit for ad impressions to credit for revenue (basically, using a different t per user).

We present the results in Figure 4. Recall that for users with multiple interests, we obtained multiple CPM/CPC

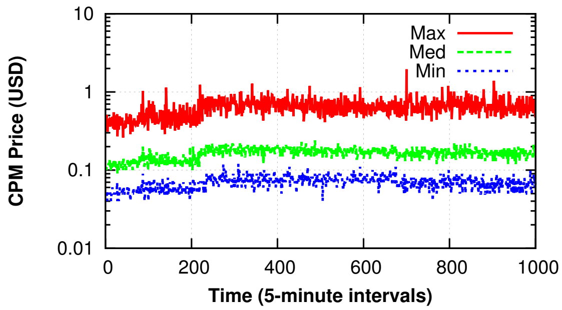

Figure 3: Facebook's suggested CPM bids from one particular set of parameters over three days, showing price stability over time (note y-axis in log-scale).

values (one for each interest). We present two separate means of aggregating these values together for such users: (a) we *average* of all of their interest prices together and (b) we *sum* all of their interest prices together (e.g. the overall potential value of a user). Since most users have only one matched interest, the two cases do not differ significantly.

We observe that there is a surprisingly wide variety in the user value to the OSN. For example, there are users who are over 10,000 times more valuable than other users. In fact, over 95% of the users have a value of less than one-tenth of the most valuable users. This result suggests that the value of different users to the OSN is quite different, and that it would be beneficial for both the OSN and advertisers to focus more on these highly valuable users.

6. CONCLUDING DISCUSSION

Popular OSNs provide "free" access to users in return for revenue generated by advertising impressions shown to them. We explored how different classes of actions result in different advertising impression counts and corresponding revenue. Implicitly, our goal was to demonstrate through our model that users on OSNs have an intrinsic value that varies with the extent of their participation on OSNs. Our two-stage approach first identifies the actions that are key to generating direct and indirect impressions. We then map these actions to actual revenue, showing the feasibility using real-world data sets. Our model is extensible, applicable to other OSNs and adaptable to alternate revenue mapping.

The results of our initial study are intriguing: a small subset of actions on OSNs are responsible for most of the advertising impressions, and a small fraction of users are key to the overall advertising revenue. Identifying these users can benefit OSNs (who may provide more services for such users), advertisers (who can target the more valuable users directly), and users (who will have understand how their actions are actually valued on OSNs). We can imagine an economic *modus vivendi* where there is an explicit trade between user's actions and profile information and the resulting service from the OSN.

Limitations. Our work has several limitations, starting with the heuristic nature of our proposed model and the assignment of parameters. Both of these are due to limited data availability on the actual views and clicks in the OSN. With better data, we could include additional activities and better parametrize the model. Additionally, validating the

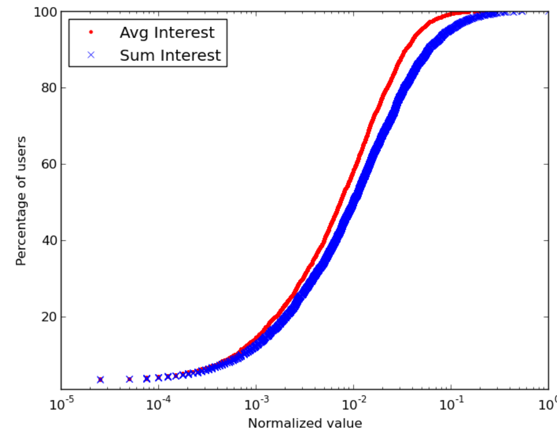

Figure 4: Average and potential (sum) value of users as per their interests and the advertising bids.

proposed model also requires data (such as more detailed breakdowns of the advertising revenue) that is currently in the possession of the OSNs. We leave addressing both of these to future work.

Leveraging user value. While advertisers are clearly interested in the value of users, we believe that it is actually the OSN provider who is best positioned to make direct use of this knowledge. This is due to three reasons: First, the OSN provider is clearly best able to make accurate estimates of user value; the provider observes all user activity, and typically only makes a portion (if any) available to advertisers or other third-parties. Second, the OSN provider is able to encourage "high value" behavior by its users by directly rewarding them or by more prominently featuring the more highly valued friends. By doing this, the OSN increases the value of all users and by proxy the OSN platform itself, and also encourages emulation by other users. Third, the OSN provider is able to charge higher prices for advertising to such users, providing benefits for both advertisers and the provider. Note that users can also benefit by becoming aware of their relative value.

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