Planetary-Scale Views on a Large Instant-Messaging Network

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ABSTRACT

We present a study of anonymized data capturing a month of high-level communication activities within the whole of the Microsoft Messenger instant-messaging system. We examine characteristics and patterns that emerge from the collective dynamics of large numbers of people, rather than the actions and characteristics of individuals. The dataset contains summary properties of 30 billion conversations among 240 million people. From the data, we construct a communication graph with 180 million nodes and 1.3 billion undirected edges, creating the largest social network constructed and analyzed to date. We report on multiple aspects of the dataset and synthesized graph. We find that the graph is well-connected and robust to node removal. We investigate on a planetary-scale the oft-cited report that people are separated by "six degrees of separation" and find that the average path length among Messenger users is 6.6. We also find that people tend to communicate more with each other when they have similar age, language, and location, and that cross-gender conversations are both more frequent and of longer duration than conversations with the same gender.

Categories and Subject Descriptors: H.2.8 Database Management: : Database applications – Data mining

General Terms: Measurement; Experimentation.

Keywords: Social networks; Communication networks; User demographics; Large data; Online communication.

1. INTRODUCTION

Large-scale web services provide unprecedented opportunities to capture and analyze behavioral data on a planetary scale. We discuss findings drawn from aggregations of anonymized data representing one month (June 2006) of high-level communication activities of people using the Microsoft Messenger instant-messaging (IM) network. We did not have nor seek access to the content of messages. Rather, we consider structural properties of a communication graph and study how structure and communication relate to user demographic attributes, such as gender, age, and location. The data set provides a unique lens for studying patterns of human behavior on a wide scale.

*Jure Leskovec performed this research during an internship at Microsoft Research.

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We explore a dataset of 30 billion conversations generated by 240 million distinct users over one month. We found that approximately 90 million distinct Messenger accounts were accessed each day and that these users produced about 1 billion conversations, with approximately 7 billion exchanged messages per day. 180 million of the 240 million active accounts had at least one conversation on the observation period. We found that 99% of the conversations occurred between 2 people, and the rest with greater numbers of participants. To our knowledge, our investigation represents the largest and most comprehensive study to date of presence and communications in an IM system. A recent report [6] estimated that approximately 12 billion instant messages are sent each day. Given the estimate and the growth of IM, we estimate that we captured approximately half of the world's IM communication during the observation period.

We created an undirected *communication network* from the data where each user is represented by a node and an edge is placed between users if they exchanged at least one message during the month of observation. The network represents accounts that were active during June 2006. In summary, the communication graph has 180 million nodes, representing users who participated in at least one conversation, and 1.3 billion undirected edges among active users, where an edge indicates that a pair of people communicated. We note that this graph should be distinguished from a buddy graph where two people are connected if they appear on each other's contact lists. The buddy graph for the data contains 240 million nodes and 9.1 billion edges. On average each account has approximately 50 buddies on a contact list.

To highlight several of our key findings, we discovered that the communication network is well connected, with 99.9% of the nodes belonging to the largest connected component. We evaluated the oft-cited finding by Travers and Milgram that any two people are linked to one another on average via a chain with "6-degrees-of-separation" [17]. We found that the average shortest path length in the Messenger network is 6.6 (median 6), which is half a link more than the path length measured in the classic study. However, we also found that longer paths exist in the graph, with lengths up to 29. We observed that the network is well clustered, with a clustering coefficient [19] that decays with exponent -0.37. This decay is significantly lower than the value we had expected given prior research [11]. We found strong *homophily* [9, 12] among users; people have more conversations and converse for longer durations with people who are similar to themselves. We find the strongest homophily for the language used, followed by conversants' geographic locations, and then age. We found that homophily does not hold for gender; people tend to converse more frequently and with longer durations with the opposite gender. We also examined the relation between communication and distance, and found that the number of conversations tends to decrease with increasing geographical distance between conversants. However, communication links spanning longer distances tend to carry more and longer conversations.

2. INSTANT MESSAGING

The use of IM has been become widely adopted in personal and businesss communications. IM clients allow users fast, near-synchronous communication, placing it between synchronous communication mediums, such as real-time voice interactions, and asynchronous communication mediums like email [18]. IM users exchange short text messages with one or more users from their list of contacts, who have to be online and logged into the IM system at the time of interaction. As conversations and messages exchanged within them are usually very short, it has been observed that users employ informal language, loose grammar, numerous abbreviations, with minimal punctuation [10]. Contact lists are commonly referred to as *buddy lists* and users on the lists are referred to as *buddies*.

2.1 Research on Instant Messaging

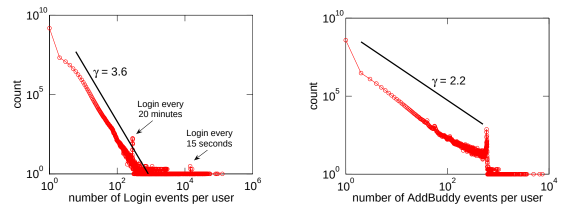
Several studies on smaller datasets are related to this work. Avrahami and Hudson [3] explored communication characteristics of 16 IM users. Similarly, Shi et al. [13] analyzed IM contact lists submitted by users to a public website and explored a static contact network of 140,000 people. Recently, Xiao et al. [20] investigated IM traffic characteristics within a large organization with 400 users of Messenger. Our study differs from the latter study in that we analyze the *full* Messenger population over a one month period, capturing the interaction of user demographic attributes, communication patterns, and network structure.

2.2 Data description

To construct the Microsoft Instant Messenger communication dataset, we combined three different sources of data: (1) user demographic information, (2) time and user stamped events describing the presence of a particular user, and (3) communication session logs, where, for all participants, the number of exchanged messages and the periods of time spent participating in sessions is recorded.

We use the terms *session* and *conversation* interchangeably to refer to an IM interaction among two or more people. Although the Messenger system limits the number of people communicating at the same time to 20, people can enter and leave a conversation over time. We note that, for large sessions, people can come and go over time, so conversations can be long with many different people participating. We observed some very long sessions with more than 50 participants joining over time.

All of our data was anonymized; we had no access to personally identifiable information. Also, we had no access to text of the messages exchanged or any other information that could be used to uniquely identify users. We focused on analyzing high-level characteristics and patterns that emerge from the collective dynamics of 240 million people, rather than the actions and characteristics of individuals. The analyzed data can be split into three parts: *presence data*, *communication data*, and *user demographic information*:



(a) Login (b) AddBuddy

Figure 1: Distribution of the number of events per user. (a) Number of logins per user. (b) Number of buddies added per user.

- **Presence events:** These include login, logout, first ever login, add, remove and block a buddy, add unregistered buddy (invite new user), change of status (busy, away, be-right-back, idle, etc.). Events are user and time stamped.
- **Communication:** For each user participating in the session, the log contains the following tuple: session id, user id, time joined the session, time left the session, number of messages sent, number of messages received.
- **User data:** For each user, the following self-reported information is stored: age, gender, location (country, ZIP), language, and IP address. We use the IP address to decode the geographical coordinates, which we then use to position users on the globe and to calculate distances.

We gathered data for 30 days of June 2006. Each day yielded about 150 gigabytes of compressed text logs (4.5 terabytes in total). Copying the data to a dedicated eight-processor server with 32 gigabytes of memory took 12 hours. Our log-parsing system employed a pipeline of four threads that parse the data in parallel, collapse the session join/leave events into sets of conversations, and save the data in a compact compressed binary format. This process compressed the data down to 45 gigabytes per day. Processing the data took an additional 4 to 5 hours per day.

A special challenge was to account for missing and dropped events, and session "id recycling" across different IM servers in a server farm. As part of this process, we closed a session 48 hours after the last leave session event. We closed sessions automatically if only one user was left in the conversation.

3. USAGE & POPULATION STATISTICS

We shall first review several statistics drawn from aggregations of users and their communication activities.

3.1 Levels of activity

Over the observation period, 242,720,596 users logged into Messenger and 179,792,538 of these users were actively engaged in conversations by sending or receiving at least one IM message. Over the month of observation, 17,510,905 new accounts were activated. As a representative day, on June 1 2006, there were almost 1 billion (982,005,323) different sessions (conversations among any number of people), with more than 7 billion IM messages sent. Approximately 93 million users logged in with 64 million different users becoming engaged in conversations on that day. Approximately 1.5 million new users that were not registered within Microsoft Messenger were invited to join on that particular day.

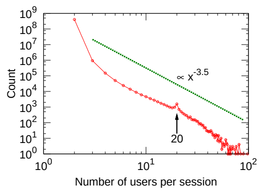


Figure 2: (a) Distribution of the number of people participating in a conversation. (b) Distribution of the durations of conversations. The spread of durations can be described by a power-law distribution.

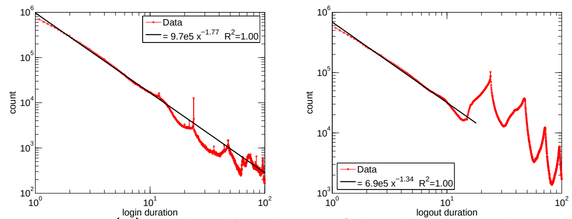


Figure 3: (a) Distribution of login duration. (b) Duration of times when people are not logged into the system (times between logout and login).

We consider event distributions on a per-user basis in Figure 1. The number of logins per user, displayed in Figure 1(a), follows a heavy-tailed distribution with exponent 3.6. We note spikes in logins at 20 minute and 15 second intervals, which correspond to an auto-login function of the IM client. As shown in Figure 1(b), many users fill up their contact lists rather quickly. The spike at 600 buddies undoubtedly reflects the maximal allowed length of contact lists.

Figure 2(a) displays the number of users per session. In Messenger, multiple people can participate in conversations. We observe a peak at 20 users, the limit on the number of people who can participate simultaneously in a conversation. Figure 2(b) shows the distribution over the session durations, which can be modeled by a power-law distribution with exponent 3.6.

Next, we examine the distribution of the durations of periods of time when people are logged on to the system. Let (ti_j, to_j) denote a time ordered $(ti_j < to_j < ti_{j+1})$ sequence of online and offline times of a user, where ti_j is the time of the jth login, and to_j is the corresponding logout time. Figure 3(a) plots the distribution of $to_j - ti_j$ over all j over all users. Similarly, Figure 3(b) shows the distribution of the periods of time when users are logged off, *i.e.* $ti_{j+1} - to_j$ over all j and over all users. Fitting the data to power-law distributions reveals exponents of 1.77 and 1.3, respectively. The data shows that durations of being online tend to be shorter and decay faster than durations that users are offline. We also notice periodic effects of login durations of 12, 24, and 48 hours, reflecting daily periodicities. We observe similar periodicities for logout durations at multiples of 24 hours.

3.2 Demographic characteristics of the users

We compared the demographic characteristics of the Messenger population with 2005 world census data and found differences between the statistics for age and gender. The visualization of this comparison displayed in Figure 4 shows that users with reported ages in the 15–35 span of years are

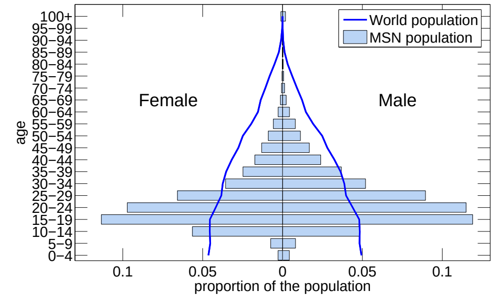


Figure 4: World and Messenger user population age pyramid. Ages 15–30 are overrepresented in the Messenger population.

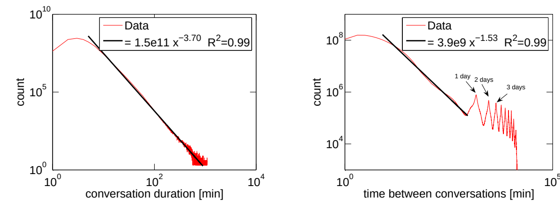


Figure 5: Temporal characteristics of conversations. (a) Average conversation duration per user; (b) time between conversations of users.

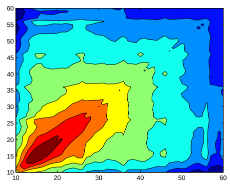
strongly overrepresented in the active Messenger population. Focusing on the differences by gender, females are overrepresented for the 10–14 age interval. For male users, we see overall matches with the world population for age spans 10–14 and 35Ů39; for women users, we see a match for ages in the span of 30–34. We note that 6.5% of the population did not submit an age when creating their Messenger accounts.

4. COMMUNICATION CHARACTERISTICS

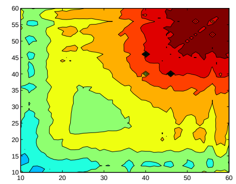
We now focus on characteristics and patterns with communications. We limit the analysis to conversations between two participants, which account for 99% of all conversations.

We first examine the distributions over conversation durations and times between conversations. Let user u have C conversations in the observation period. Then, for every conversation i of user u we create a tuple $(ts_{u,i}, te_{u,i}, m_{u,i})$, where $ts_{u,i}$ denotes the start time of the conversation, $te_{u,i}$ is the end time of the conversation, and $m_{u,i}$ is the number of exchanged messages between the two users. We order the conversations by their start time $(ts_{u,i} < ts_{u,i+1})$. Then, for every user u, we calculate the average conversation duration $\bar{d}(u) = \frac{1}{C}\sum_i te_{u,i} - ts_{u,i}$, where the sum goes over all the u's conversations. Figure 5(a) shows the distribution of $\bar{d}(u)$ over all the users u. We find that the conversation length can be described by a heavy-tailed distribution with exponent -3.7 and a mode of 4 minutes.

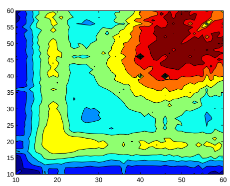
Figure 5(b) shows the intervals between consecutive conversations of a user. We plot the distribution of $ts_{u,i+1} - ts_{u,i}$, where $ts_{u,i+1}$ and $ts_{u,i}$ denote start times of two consecutive conversations of user u. The power-law exponent of the distribution over intervals is -1.5. This result is similar to the temporal distribution for other kinds of human communication activities, *e.g.*, waiting times of emails and letters before a reply is generated [4]. The exponent can be explained by a priority-queue model where tasks of different



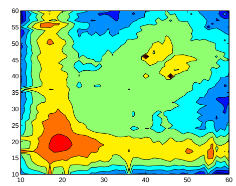
(a) Number of conversations



(b) Conversation duration



(c) Messages per conversation



(d) Messages per unit time

Figure 6: Communication characteristics of users by reported age. We plot age vs. age and the color (z-axis) represents the intensity of communication.

priorities arrive and wait until all tasks with higher priority are addressed. This model generates a task waiting time distribution described by a power-law with exponent -1.5.

5. COMMUNICATION DEMOGRAPHICS

Next we examine the interplay of communication and user demographic attributes, *i.e.*, how geography, location, age, and gender influence observed communication patterns.

5.1 Communication by age

We sought to understand how communication among people changes with the reported ages of participating users. Figures 6(a)-(d) use a heat-map visualization to communicate properties for different age–age pairs. The rows and columns represent the ages of both parties participating, and the color at each age–age cell captures the logarithm of the value for the pairing. The color spectrum extends from blue (low value) through green, yellow, and onto red (the highest value). Because of potential misreporting at very low and high ages, we concentrate on users with self-reported ages that fall between 10 and 60 years.

Let a tuple (a_i, b_i, d_i, m_i) denote the ith conversation in the entire dataset that occurred among users of ages a_i and b_i. The conversation had a duration of d_i seconds during which m_i messages were exchanged. Let $C_{a,b} = \{(a_i, b_i, d_i, m_i) : a_i = a \wedge b_i = b\}$ denote a set of all conversations between users of ages a and b, respectively.

Figure 6(a) shows the number of conversations among people of different ages. For every pair of ages (a, b) the color indicates the size of set $C_{a,b}$, *i.e.*, the number of different conversations between users of ages a and b. We note that, as the notion of a conversation is symmetric, the plots are symmetric. Most conversations occur between people of ages 10 to 20. The diagonal trend indicates that people tend to talk to people of similar age. This is true especially for age groups between 10 and 30 years. We shall explore this observation in more detail in Section 6.

Figure 6(b) displays a heat map for the average conversation duration, computed as $\frac{1}{|C_{a,b}|}\sum_{i \in C_{a,b}} d_i$. We note that older people tend to have longer conversations. We observe a similar phenomenon when plotting the average number of exchanged messages per conversation, computed as $\frac{1}{|C_{a,b}|}\sum_{i \in C_{a,b}} m_i$, displayed in Figure 6(c). Again, we find that older people exchange more messages, and we observe a dip for ages 25–45 and a slight peak for ages 15–25. Figure 6(d) displays the number of exchanged messages per unit time; for each age pair, (a, b), we measure $\frac{1}{|C_{a,b}|}\sum_{i \in C_{a,b}} \frac{m_i}{d_i}$. Here, we see that younger people have faster-paced dialogs, while older people exchange messages at a slower pace.

We note that the younger population (ages 10–35) are strongly biased towards communicating with people of a similar age (diagonal trend in Figure 6(a)), and that users who report being of ages 35 years and above tend to communicate more evenly across ages (rectangular pattern in Fig. 6(a)). Moreover, older people have conversations of the longest durations, with a "valley" in the duration of conversations for users of ages 25–35. Such a dip may represent shorter, faster-paced and more intensive conversations associated with work-related communications, versus more extended, slower, and longer interactions associated with social discourse.

(a)	U	F	M
U	1.3	3.6	3.7
F		21.3	49.9
M			20.2

(b)	U	F	M
U	277	301	277
F		275	304
M			252

(c)	U	F	M
U	5.7	7.1	6.7
F		6.6	7.6
M			5.9

(d)	U	F	M
U	1.25	1.42	1.38
F		1.43	1.50
M			1.42

Table 1: Cross-gender communication, based on all two-person conversations during June 2006. (a) Percentage of conversations among users of different self-reported gender; (b) average conversation length in seconds; (c) number of exchanged messages per conversation; (d) number of exchanged messages per minute of conversation.

5.2 Communication by gender

We report on analyses of properties of pairwise communications as a function of the self-reported gender of users in conversations in Table 1. Let $C_{g,h} = \{(g_i, h_i, d_i, m_i) : g_i = g \wedge h_i = h\}$ denote a set of conversations where the two participating users are of genders g and h. Note that g takes 3 possible values: female, male, and unknown (unreported).

Table 1(a) relays $|C_{g,h}|$ for combinations of genders g and h. The table shows that approximately 50% of conversations occur between male and female and 40% of the conversations occur among users of the same gender (20% for each). A small number of conversations occur between people who did not reveal their gender.

Similarly, Table 1(b) shows the average conversation length in seconds, broken down by the gender of conversant, computed as $\frac{1}{|C_{g,h}|}\sum_{i \in C_{g,h}} d_i$. We find that male–male conversations tend to be shortest, lasting approximately 4 minutes. Female–female conversations last 4.5 minutes on the average. Female–male conversations have the longest durations, taking more than 5 minutes on average. Beyond taking place over longer periods of time, more messages are exchanged in female–male conversations. Table 1(c) lists values for $\frac{1}{|C_{g,h}|}\sum_{i\in C_{g,h}} m_i$ and shows that, in female–male conversations, 7.6 messages are exchanged per conversation on the average as opposed to 6.6 and 5.9 for female–female and male–male, respectively. Table 1(d) shows the communication intensity computed as $\frac{1}{|C_{g,h}|}\sum_{i\in C_{g,h}} \frac{m_i}{d_i}$. The number of messages exchanged per minute of conversation for male–female conversations is higher at 1.5 messages per minute than for cross-gender conversations, where the rate is 1.43 messages per minute.

We examined the number of *communication ties*, where a tie is established between two people when they exchange at least one message during the observation period. We computed 300 million male–male ties, 255 million female–female ties, and 640 million cross-gender ties. The Messenger population consists of 100 million males and 80 million females by self report. These findings demonstrate that ties are not heavily gender biased; based on the population, random chance predicts 31% male–male, 20% female–female, and 49% female–male links. We observe 25% male–male, 21% female–female, and 54% cross-gender links, thus demonstrating a minor bias of female–male links.

The results reported in Table 1 run counter to prior studies reporting that communication among individuals who resemble one other (same gender) occurs more often (see [9] and references therein). We identified significant heterophily, where people tend to communicate more with people of the opposite gender. However, we note that link heterogeneity was very close to the population value [8], *i.e.*, the number of same- and cross-gender ties roughly corresponds to random chance. This shows there is no significant bias in linking for gender. However, we observe that cross-gender conversations tend to be longer and to include more messages, suggesting that more effort is devoted to conversations with the opposite sex.

5.3 World geography and communication

We now focus on the influence of geography and distance among participants on communications. Figure 7 shows the geographical locations of Messenger users. The general location of the user was obtained via reverse IP lookup. We plot all latitude/longitude positions linked to the position of servers where users log into the service. The color of each dot corresponds to the logarithm of the number of logins from the respective location, again using a spectrum of colors ranging from blue (low) through green and yellow to red (high). Although the maps are built solely by plotting these positions, a recognizable world map is generated. We find that North America, Europe, and Japan are very dense, with many users from those regions using Messenger. For the rest of the world, the population of Messenger users appears to reside largely in coastal regions.

We can condition the densities and behaviors of Messenger users on multiple geographical and socioeconomic variables and explore relationships between electronic communications and other attributes. As an example, harnessed the United Nations gridded world population data to provide estimates of the number of people living in each cell. Given this data, and the data from Figure 7, we calculate the number of users per capita, displayed in Figure 8. Now we see transformed picture where several sparsely populated regions stand out as having a high usage per capita. These regions include the center of the United States, Canada, Scandinavia, Ireland, Australia, and South Korea.

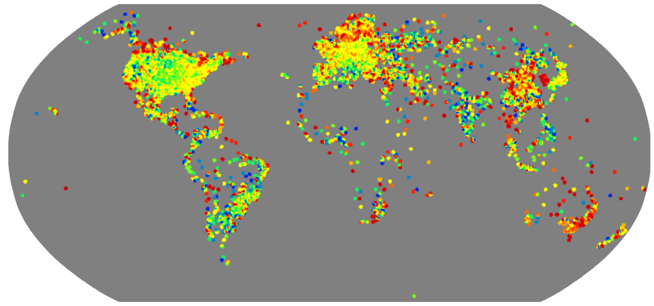


Figure 7: Number of users at a particular geographic location. Color of dots represents the number of users.

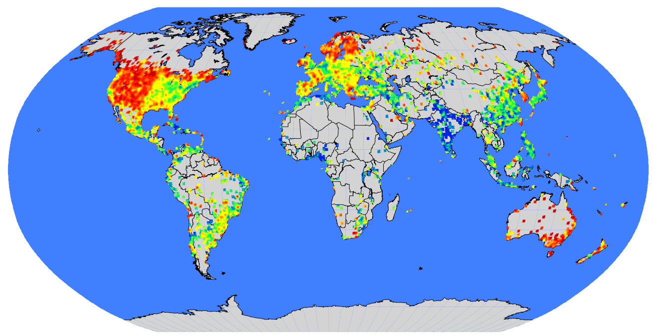


Figure 8: Number of Messenger users per capita. Color intensity corresponds to the number of users per capita in the cell of the grid.

Figure 9 shows a heat map that represents the intensities of Messenger communications on an international scale. To create this map, we place the world map on a fine grid, where each cell of the grid contains the count of the number of conversations that pass through that point by increasing the count of all cells on the straight line between the geo-locations of pairs of conversants. The color indicates the number of conversations crossing each point, providing a visualization of the key flows of communication. For example, Australia and New Zealand have communications flowing towards Europe and United States. Similar flows hold for Japan. We see that Brazilian communications are weighted toward Europe and Asia. We can also explore the flows of transatlantic and US transcontinental communications.

5.4 Communication among countries

Communication among people within different countries also varies depending on the locations of conversants. We examine two such views. Figure 10(a) shows the top countries by the number of conversations between pairs of countries. We examined all pairs of countries with more than 10 million conversations per month. The width of edges in the figure is proportional to the logarithm of the number of conversations among the countries. We find that the United States and Spain appear to serve as hubs and that edges appear largely between historically or ethnically connected countries. As examples, Spain is connected with the Spanish speaking countries in South America, Germany links to Turkey, Portugal to Brazil, and China to Korea.

Figure 10(b) displays a similar plot where we consider country pairs by the average duration of conversations. The

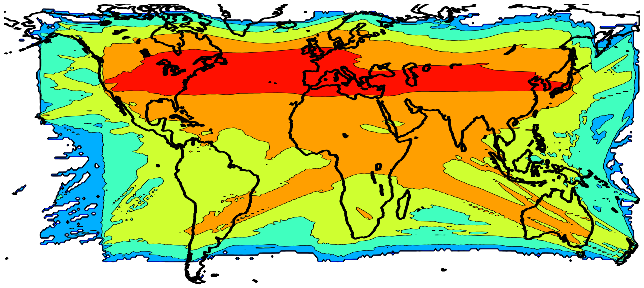


Figure 9: A communication heat map.

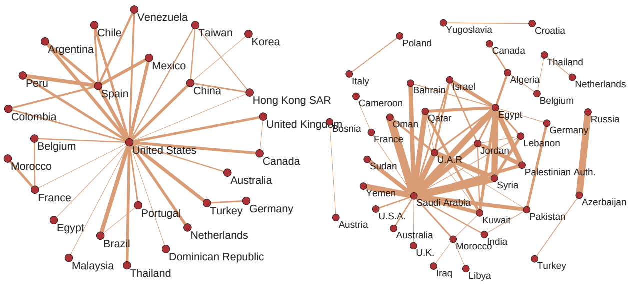


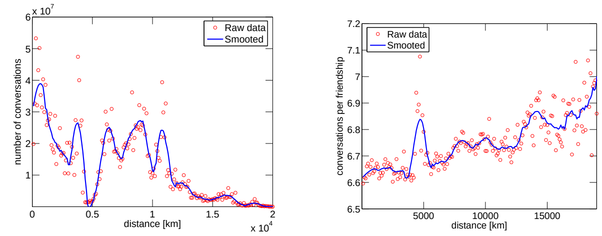
Figure 10: (a) Communication among countries with at least 10 million conversations in June 2006. (b) Countries by average length of the conversation. Edge widths correspond to logarithms of intensity of links.

width of the edges are proportional to the mean length of conversations between the countries. The core of the network appears to be Arabic countries, including Saudi Arabia, Egypt, United Arab Emirates, Jordan, and Syria.

5.5 Communication and geographical distance

We were interested in how communications change as the distance between people increases. We had hypothesized that the number of conversations would decrease with geographical distance as users might be doing less coordination with one another on a daily basis, and where communication would likely require more effort to coordinate than might typically be needed for people situated more locally. We also conjectured that, once initiated, conversations among people who are farther apart would be somewhat longer as there might be a stronger need to catch up when the less-frequent conversations occurred.

Figure 11 plots the relation between communication and distance. Figure 11(a) shows the distribution of the number of conversations between conversants at distance l. We found that the number of conversations decreases with distance. However, we observe a peak at a distance of approximately 500 kilometers. The other peaks and drops may reveal geographical features. For example, a significant drop in communication at distance of 5,000 km (3,500 miles) may reflect the width of the Atlantic ocean or the distance between the east and west coasts of the United States. The number of links rapidly decreases with distance. This finding suggests that users may use Messenger mainly for communications with others within a local context and environment. We found that the number of exchanged messages and con-



(a) Number of conversations (b) Conversations per link

Figure 11: Communication with the distance.

Attribute	Correlation Rnd	Correlation Comm	Probability Rnd	Probability Comm
Age	-0.0001	0.297	0.030	0.162
Gender	0.0001	-0.032	0.434	0.426
ZIP	-0.0003	0.557	0.001	0.23
County	0.0005	0.704	0.046	0.734
Language	-0.0001	0.694	0.030	0.798

Table 2: Correlation coefficients and probability of users sharing an attribute for random pairs of people versus for pairs of people who communicate.

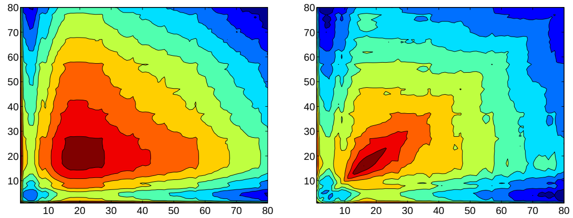
versation lengths do not increase with distance (see plots in [7]). Conversation duration decreases with the distance, while the number of exchanged messages remains constant before decreasing slowly. Figure 11(b) shows the communications per link versus the distance among participants. The plot shows that longer links, *i.e.*, connections between people who are farther apart, are more frequently used than shorter links. We interpret this finding to mean that people who are farther apart use Messenger more frequently to communicate.

In summary, we observe that the total number of links and associated conversations decreases with increasing distance among participants. The same is true for the duration of conversations, the number of exchanged messages per conversation, and the number of exchanged messages per unit time. However, the number of times a link is used tends to increase with the distance among users. This suggests that people who are farther apart tend to converse with IM more frequently, which perhaps takes the place of more expensive long-distance voice telephony; voice might be used more frequently in lieu of IM for less expensive local communications.

6. HOMOPHILY OF COMMUNICATION

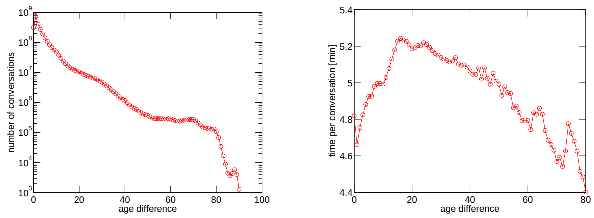
We performed several experiments to measure the level at which people tend to communicate with similar people. First, we consider all 1.3 billion pairs of people who exchanged at least one message in June 2006, and calculate the similarity of various user demographic attributes. We contrast this with the similarity of pairs of users selected via uniform random sampling across 180 million users. We consider two measures of similarity: the correlation coefficient and the probability that users have the same attribute value, *e.g.*, that users come from the same countries.

Table 2 compares correlation coefficients of various user attributes when pairs of users are chosen uniformly at random with coefficients for pairs of users who communicate. We can see that attributes are not correlated for random pairs of people, but that they are highly correlated for users



(a) Random (b) Communicate

Figure 12: Numbers of pairs of people of different ages. (a) Randomly selected pairs of people; (b) people who communicate. Correlation between age and communication is captured by the diagonal trend.



(a) Number of conversations (b) Conversation duration

Figure 13: Communication characteristics and age difference between conversants.

who communicate. As we noted earlier, gender and communication are slightly negatively correlated; people tend to communicate more with people of the opposite gender.

Another method for identifying association is to measure the probability that a pair of users will show an exact match in values of an attribute, *i.e.*, identifying whether two users come from the same country, speak the same language, etc. Table 2 shows the results for the probability of users sharing the same attribute value. We make similar observations as before. People who communicate are more likely to share common characteristics, including age, location, language, and they are less likely to be of the same gender. We note that the most common attribute of people who communicate is language. On the flip side, the amount of communication tends to decrease with increasing user dissimilarity. This relationship is highlighted in Figure 11, which shows how communication among pairs of people decreases with distance.

Figure 12 further illustrates the results displayed in Table 2, where we randomly sample pairs of users from the Messenger user base, and then plot the distribution over reported ages. As most of the population comes from the age group 10–30, the distribution of random pairs of people reaches the mode at those ages but there is no correlation. Figure 12(b) shows the distribution of ages over the pairs of people who communicate. Note the correlation, as represented by the diagonal trend on the plot, where people tend to communicate more with others of a similar age.

Next, we further explore communication patterns by the differences in the reported ages among users. Figure 13(a) plots on a log-linear scale the number of conversations in the social network with participants of varying age differences. Again we see that links and conversations are strongly correlated with the age differences among participants. Figure 13(b) shows the average conversation duration with the age difference among the users. Interestingly, the mean conversation duration peaks at an age difference of 20 years between participants. We speculate that the peak may correspond roughly to the gap between generations.

The plots reveal that there is strong homophily in the communication network for age; people tend to communicate more with people of similar reported age. This is especially salient for the number of buddies and conversations among people of the same ages. We also observe that the links between people of similar attributes are used more often, to interact with shorter and more intense (more exchanged messages) communications. The intensity of communication decays linearly with the difference in age. In contrast to findings of previous studies, we observe that the number of cross-gender communication links follows a random chance. However, cross-gender communication takes longer and is faster paced as it seems that people tend to pay more attention when communicating with the opposite sex.

Recently, using the data we generated, Singla and Richardson further investigated the homophily within the Messenger network and found that people who communicate are also more likely to search the web for content on similar topics [14].

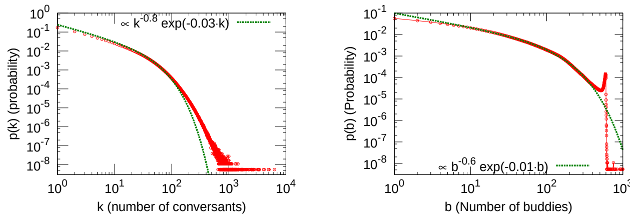
7. THE COMMUNICATION NETWORK

So far we have examined communication patterns based on pairwise communications. We now create a more general communication network from the data. Using this network, we can examine the typical *social distance* between people, *i.e.*, the number of links that separate a random pair of people. This analysis seeks to understand how many people can be reached within certain numbers of hops among people who communicate. Also, we test the transitivity of the network, *i.e.*, the degree at which pairs with a common friend tend to be connected.

We constructed a graph from the set of all two-user conversations, where each node corresponds to a person and there is an undirected edge between a pair of nodes if the users were engaged in an active conversation during the observation period (users exchanged at least 1 message). The resulting network contains 179,792,538 nodes, and 1,342,246,427 edges. Note that this is not simply a *buddy network*; we only connect people who are buddies *and* have communicated during the observation period.

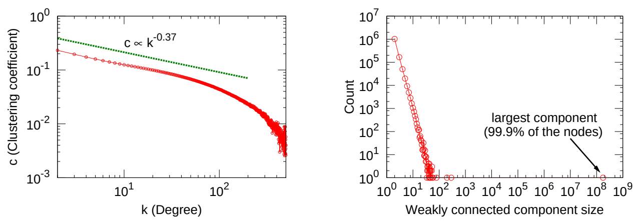
Figures 14–15 show the structural properties of the communication network. The network degree distribution shown in Figure 14(a) is heavy tailed but does not follow a power-law distribution. Using maximum likelihood estimation, we fit a power-law with exponential cutoff $p(k) \propto k^{-a}e^{-bk}$ with fitted parameter values $a = 0.8$ and $b = 0.03$. We found a strong cutoff parameter and low power-law exponent, suggesting a distribution with high variance.

Figure 14(b) displays the degree distribution of a buddy graph. We did not have access to the full buddy network; we only had access to data on the length of the user contact list which allowed us to create the plot. We found a total of 9.1 billion buddy edges in the graph with 49 buddies per user. We fit the data with a power-law distribution with exponential cutoff and identified parameters of $a = 0.6$ and $b = 0.01$. The power-law exponent now is even smaller. This model described the data well. We note a spike at 600 which is the limit on the maximal number of buddies imposed by the Messenger software client. The maximal number of buddies was increased to 300 from 150 in March



(a) Communication (b) Buddies

Figure 14: (a) Degree distribution of communication network (number of people with whom a person communicates). (b) Degree distribution of the buddy network (length of the contact list).



(a) Clustering (b) Components

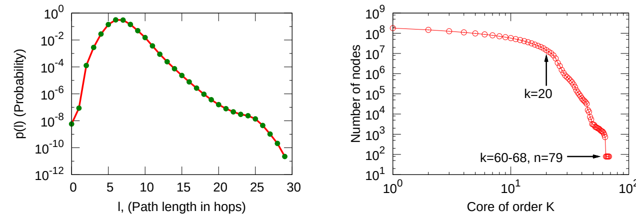
Figure 15: (a) Clustering coefficient; (b) distribution of connected components. 99.9% of the nodes belong to the largest connected component.

2005, and was later raised to 600. With the data from June 2006, we see only the peak at 600, and could not identify bumps at the earlier constraints.

Social networks have been found to be highly transitive, *i.e.*, people with common friends tend to be friends themselves. The clustering coefficient [19] has been used as a measure of transitivity in the network. The measure is defined as the fraction of triangles around a node of degree k [19]. Figure 15(a) displays the clustering coefficient versus the degree of a node for Messenger. Previous results on measuring the web graph as well as theoretical analyses show that the clustering coefficient decays as k^{-1} (exponent -1) with node degree k [11]. For the Messenger network, the clustering coefficient decays very slowly with exponent -0.37 with the degree of a node and the average clustering coefficient is 0.137. This result suggests that clustering in the Messenger network is much higher than expected—that people with common friends also tend to be connected. Figure 15(b) displays the distribution of the connected components in the network. The giant component contains 99.9% of the nodes in the network against a background of small components, and the distribution follows a power law.

7.1 How small is the small world?

Messenger data gives us a unique opportunity to study distances in the social network. To our knowledge, this is the first time a planetary-scale social network has been available to validate the well-known "6 degrees of separation" finding by Travers and Milgram [17]. The earlier work employed a sample of 64 people and found that the average number of hops for a letter to travel from Nebraska to Boston was 6.2 (mode 5, median 5), which is popularly known as the "6 degrees of separation" among people. We used a population sample that is more than two million times larger than the group studied earlier and confirmed the classic finding.



(a) Diameter (b) k-cores

Figure 16: (a) Distribution over the shortest path lengths. Average shortest path has length 6.6, the distribution reaches the mode at 6 hops, and the 90% effective diameter is 7.8; (b) distribution of sizes of cores of order k.

Figure 16(a) displays the distribution over the shortest path lengths. To approximate the distribution of the distances, we randomly sampled 1000 nodes and calculated for each node the shortest paths to all other nodes. We found that the distribution of path lengths reaches the mode at 6 hops and has a median at 7. The average path length is 6.6. This result means that a random pair of nodes in the Messenger network is 6.6 hops apart on the average, which is half a link longer than the length measured by Travers and Milgram. The 90th percentile (effective diameter [16]) of the distribution is 7.8. 48% of nodes can be reached within 6 hops and 78% within 7 hops. So, we might say that, via the lens provided on the world by Messenger, we find that there are about "7 degrees of separation" among people. We note that long paths, *i.e.*, nodes that are far apart, exist in the network; we found paths up to a length of 29.

7.2 Network cores

We further study connectivity of the communication network by examining the k-cores [5] of the graph. The concept of k-core is a generalization of the giant connected component. The k-core of a network is a set of vertices K, where each vertex in K has at least k edges to other vertices in K. The distribution of k-core sizes gives us an idea of how quickly the network shrinks as we move towards the core.

The k-core of a graph can be obtained by deleting from the network all vertices of degree less than k. This process will decrease degrees of some non-deleted vertices, so more vertices will have degree less than k. We keep pruning vertices until all remaining vertices have degree of at least k. We call the remaining vertices a k-core.

Figure 16 plots the number of nodes in a core of order k. We note that the core sizes are remarkably stable up to a value of $k \approx 20$; the number of nodes in the core drops for only an order of magnitude. After $k > 20$, the core size rapidly drops. The central part of the communication network is composed of 79 nodes, where each of them has more than 68 edges inside the set. The structure of the Messenger communication network is quite different from the Internet graph; it has been observed [2] that the size of a k-core of the Internet decays as a power-law with k. Here we see that the core sizes remains very stable up to a degree ≈ 20, and only then start to rapidly degrease. This means that the nodes with degrees of less than 20 are on the fringe of the network, and that the core starts to rapidly decrease as nodes of degree 20 or more are deleted.

7.3 Strength of the ties

It has been observed by Albert et al. [1] that many real-world networks are robust to node-level changes or *attacks*. Researchers have showed that networks like the World Wide Web, Internet, and several social networks display a high degree of robustness to random node removals, *i.e.*, one has to remove many nodes chosen uniformly at random to make the network disconnected. On the contrary, targeted attacks are very effective. Removing a few high degree nodes can have a dramatic influence on the connectivity of a network.

Let us now study how the Messenger communication network is decomposed when "strong," *i.e.*, heavily used, edges are removed from the network. We consider several different definitions of "heavily used," and measure the types of edges that are most important for network connectivity. We note that a similar experiment was performed by Shi et al [13] in the context of a small IM buddy network. The authors of the prior study took the number of common friends at the ends of an edge as a measure of the link strength. As the number of edges here is too large (1.3 billion) to remove edges one by one, we employed the following procedure: We order the nodes by decreasing value per a measure of the *intensity of engagement* of users; we then delete nodes associated with users in order of decreasing measure and we observe the evolution of the properties of the communication network as nodes are deleted.

We consider the following different measures of engagement:

- Average sent: The average number of sent messages per user's conversation
- Average time: The average duration of user's conversations
- Links: The number of links of a user (node degree), *i.e.*, number of different people he or she exchanged messages with
- Conversations: The total number of conversations of a user in the observation period
- Sent messages: The total number of sent messages by a user in the observation period
- Sent per unit time: The number of sent messages per unit time of a conversation
- Total time: The total conversation time of a user in the observation period

At each step of the experiment, we remove 10 million nodes in order of the specific measure of engagement being studied. We then determine the relative size of the largest connected component, *i.e.*, given the network at particular step, we find the fraction of the nodes belonging to the largest connected component of the network.

Figure 17 plots the evolution of the fraction of nodes in the largest connected component with the number of deleted nodes. We plot a separate curve for each of the seven different measures of engagement. For comparison, we also consider the random deletion of the nodes.

The decomposition procedure highlighted two types of dynamics of network change with node removal. The size of the largest component decreases rapidly when we use as measures of engagement the number of links, number of conversations, total conversation time, or number of sent messages. In contrast, the size of the largest component decreases very slowly when we use as a measure of engagement the average

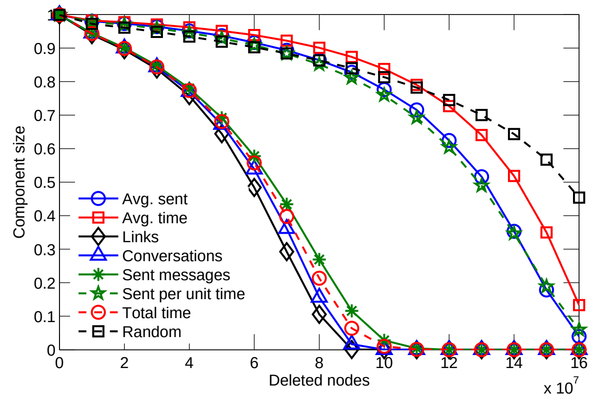


Figure 17: Relative size of the largest connected component as a function of number of nodes removed.

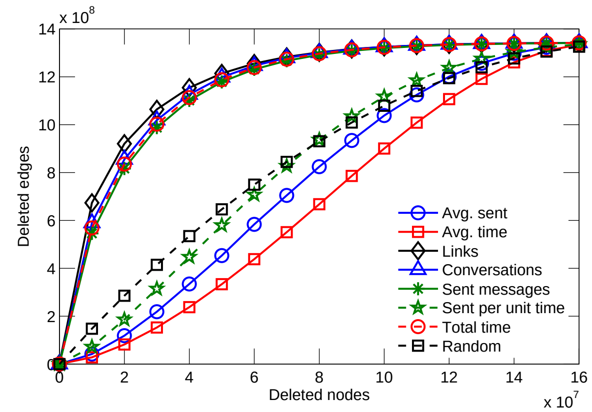


Figure 18: Number of removed edges as nodes are deleted by order of different measures of engagement.

time per conversation, average number of sent messages, or number of sent messages per unit time. We were not surprised to find that the size of the largest component size decreases most rapidly when nodes are deleted in order of the decreasing number of links that they have, *i.e.*, the number of people with whom a user at a node communicates. Random ordering of the nodes shrinks the component at the slowest rate. After removing 160 million out of 180 million nodes with the random policy, the largest component still contains about half of the nodes. Surprisingly, when deleting up to 100 million nodes, the average time per conversation measure shrinks the component even more slowly than the random deletion policy.

Figure 18 displays plots of the number of removed edges from the network as nodes are deleted. Similar to the relationships in Figure 17, we found that deleting nodes by the inverse number of edges removes edges the fastest. As in Figure 18, the same group of node ordering criteria (number of conversations, total conversation time or number of sent messages) removes edges from the networks as fast as the number of links criteria. However, we find that random node removal removes edges in a linear manner. Edges are removed at a lower rate when deleting nodes by average time per conversation, average numbers of sent messages, or numbers of sent messages per unit time. We believe that these findings demonstrate that users with long conversations and many messages per conversation tend to have smaller degrees—even given the findings displayed in Figure 17, where we saw that removing these users is more effective for breaking the connectivity of the network than for random node deletion. Figure 18 also shows that using the average number of messages per conversation as a criterion removes edges in the slowest manner. We believe that this makes sense intuitively: If users invest similar amounts of time to interacting with others, then people with short conversations will tend to converse with more people in a given amount of time than users having long conversations.

8. CONCLUSION

We have reviewed a set of results stemming from the generation and analysis of an anonymized dataset representing the communication patterns of all people using a popular IM system. The methods and findings highlight the value of using a large IM network as a worldwide lens onto aggregate human behavior.

We described the creation of the dataset, capturing high-level communication activities and demographics in June 2006. The core dataset contains more than 30 billion conversations among 240 million people. We discussed the creation and analysis of a communication graph from the data containing 180 million nodes and 1.3 billion edges. The communication network is largest social network analyzed to date. The planetary-scale network allowed us to explore dependencies among user demographics, communication characteristics, and network structure. Working with such a massive dataset allowed us to test hypotheses such as the average chain of separation among people across the entire world.

We discovered that the graph is well connected, highly transitive, and robust. We reviewed the influence of multiple factors on communication frequency and duration. We found strong influences of homophily in activities, where people with similar characteristics tend to communicate more, with the exception of gender, where we found that cross-gender conversations are both more frequent and of longer duration than conversations with users of the same reported gender. We also examined the path lengths and validated on a planetary scale earlier research that found "6 degrees of separation" among people.

We note that the sheer size of the data limits the kinds of analyses one can perform. In some cases, a smaller random sample may avoid the challenges with working with terabytes of data. However, it is known that sampling can corrupt the structural properties of networks, such as the degree distribution and the diameter of the graphs [15]. Thus, while sampling may be valuable for managing complexity of analyses, results on network properties with partial data sets may be rendered unreliable. Furthermore, we need to consider the full data set to reliably measure the patterns of age and distance homophily in communications.

In other directions of research with the dataset, we have pursued the use of machine learning and inference to learn predictive models that can forecast such properties as communication frequencies and durations of conversations among people as a function of the structural and demographic attributes of conversants. Our future directions for research include gaining an understanding of the dynamics of the structure of the communication network via a study of the evolution of the network over time.

We hope that our studies with Messenger data serves as an example of directions in social science research, highlighting how communication systems can provide insights about high-level patterns and relationships in human communications without making incursions into the privacy of individuals. We hope that this first effort to understand a social network on a genuinely planetary scale will embolden others to explore human behavior at large scales.

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