

# The Anatomy of the Facebook Social Graph

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## Abstract

We study the structure of the social graph of active Facebook users, the largest social network ever analyzed. We compute numerous features of the graph including the number of users and friendships, the degree distribution, path lengths, clustering, and mixing patterns. Our results center around three main observations. First, we characterize the global structure of the graph, determining that the social network is nearly fully connected, with 99.91% of individuals belonging to a single large connected component, and we confirm the ‘six degrees of separation’ phenomenon on a global scale. Second, by studying the average local clustering coefficient and degeneracy of graph neighborhoods, we show that while the Facebook graph as a whole is clearly sparse, the graph neighborhoods of users contain surprisingly dense structure. Third, we characterize the assortativity patterns present in the graph by studying the basic demographic and network properties of users. We observe clear degree assortativity and characterize the extent to which ‘your friends have more friends than you’. Furthermore, we observe a strong effect of age on friendship preferences as well as a globally modular community structure driven by nationality, but we do not find any strong gender homophily. We compare our results with those from smaller social networks and find mostly, but not entirely, agreement on common structural network characteristics.

## Introduction

The emergence of online social networking services over the past decade has revolutionized how social scientists study the structure of human relationships [1]. As individuals bring their social relations online, the focal point of the internet is evolving from being a network of documents to being a network of people, and previously invisible social structures are being captured at tremendous scale and with unprecedented detail. In this work, we characterize the structure of the world’s largest online social network, Facebook, in an effort to advance the state of the art in the empirical study of social networks.

In its simplest form, a social network contains individuals as vertices and edges as relationships between vertices [2]. This abstract view of human relationships, while certainly limited, has been very useful for characterizing social relationships, with structural measures of this network abstraction finding active application to the study of everything from bargaining power [3] to psychological health [4]. Moreover, social networks have been observed to display a broad range of unifying structural properties, including homophily, clustering, the small-world effect, heterogeneous distributions of friends, and community structure [5, 6].

Quantitative analysis of these relationships requires individuals to explicitly detail their social networks. Historically, studies of social networks were limited to hundreds of individuals as data on social relationships was collected through painstakingly difficult means. Online social networks allow us to increase the scale and accuracy of such studies dramatically because new social network data, mostly from online sources, map out our social relationships at a nearly global scale. Prior studies of online social networks include research on Twitter, Flickr, Yahoo! 360, Cyworld, Myspace, Orkut, and LiveJournal among others [7–11].

The trend within this line of research is to measure larger and larger representations of social networks,

including networks derived from email [12], telephony [13], and instant messaging [14] traces. Two recent studies of Renren [15] and MSN messenger [14] included 42 million and 180 million individuals respectively. Network completeness is especially important in the study of online social networks because unlike traditional social science research, the members of online social networks are not controlled random samples, and instead should be considered biased samples. While the demographics of these networks have begun to approach the demographics of the global population at large [16], the most accurate representation of our social relationships will include as many people as possible. We are not there yet, but in this paper we characterize the entire social network of active members of Facebook in May 2011, a network then comprised of 721 million active users. To our knowledge, this is the largest social network ever analyzed.

Facebook has naturally attracted the attention of researchers in the past. Some of this research has been devoted towards understanding small subsets of the Facebook population, including in particular the social networks of university students [17–19]. Other studies have analyzed communication patterns and activity amongst segments of the user population [20,21]. Then another thread of research has measured some large-scale network properties of the Facebook graph through sampling, crawling, and other methods to collect network data [22,23]. Notably, these methodologies have no way of distinguishing between active and stale accounts. Unlike these studies, we analyze the entire Facebook graph in anonymized form and focus on the set of active user accounts reliably corresponding to people.

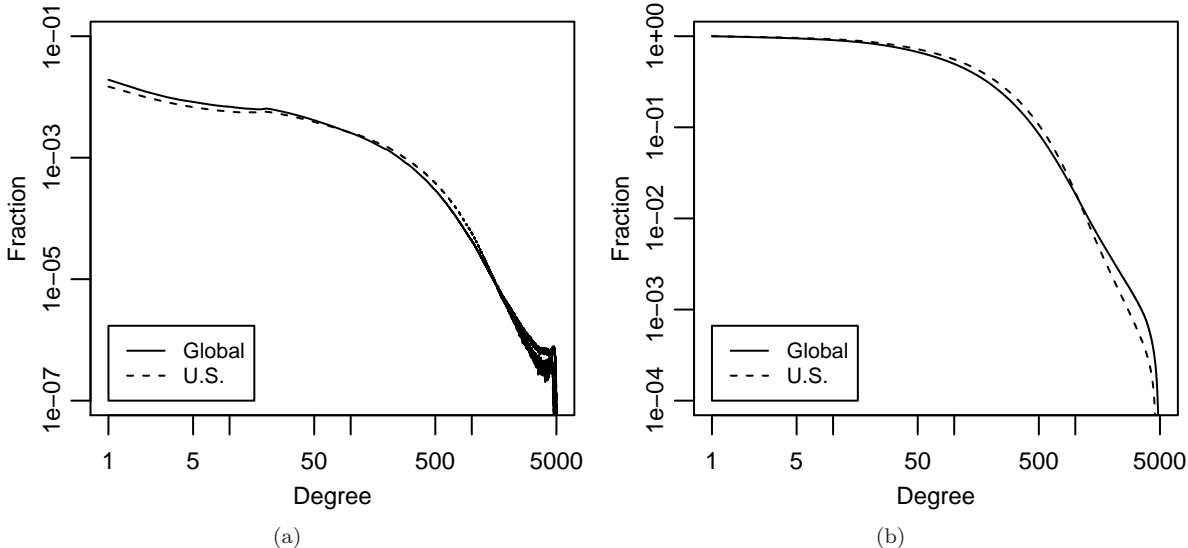
We defined a user of Facebook as an active member of the social network if they logged into the site in the last 28 days from our time of measurement in May 2011 and had at least one Facebook friend. We note that this definition is not precisely Facebook’s ordinary definition of active user, and therefore some of our statistics differ slightly from company statistics. According to our definition of active, the population of active Facebook users consisted of around  $n = 721$  million individuals at the time of our measurements. For comparison, estimating that the world’s population was around 6.9 billion people in May 2011 means that the network includes roughly 10 percent of the world’s population. Restricting the comparison to individuals age 13 or more and with access to the internet (the set of individuals eligible to have Facebook accounts) would put this percentage significantly higher. There were 68.7 billion friendship edges at the time of our measurements, so the average Facebook user in our study had around 190 Facebook friends. Our analysis predated the existence of ‘subscriptions’ on Facebook, and in this work we study only reciprocal Facebook friendships.

We also analyzed the subgraph of 149 million U.S. Facebook users. Using population estimates from the U.S. Census Bureau for 2011, there are roughly 260 million individuals in the U.S. over the age of 13 and therefore eligible to create a Facebook account. Within the U.S., the Facebook social network therefore includes more than half the eligible population. This subpopulation had 15.9 billion edges, so the average U.S. user was friends with around 214 other U.S. users. This higher average value may reflect Facebook’s deeper adoption in the U.S. as of May 2011.

Our goals with characterizing Facebook’s social network are two-fold. First, we aim to advance the collective knowledge of social networks and satisfy widespread curiosity about social relationships as embodied in Facebook. Second, we hope to focus the development of graph algorithms and network analysis tools towards a realistic representation of these relationships. Towards these goals, we provide an accurate description of Facebook’s social network here.

## Results

In this section, we apply a wide variety of graph measures to the Facebook social network. As the network is truly enormous, we utilize extensive computational resources to perform these measurements. However, the focus of this paper is on the results of these measurements, and therefore we relegate discussions of our techniques to the Methods.



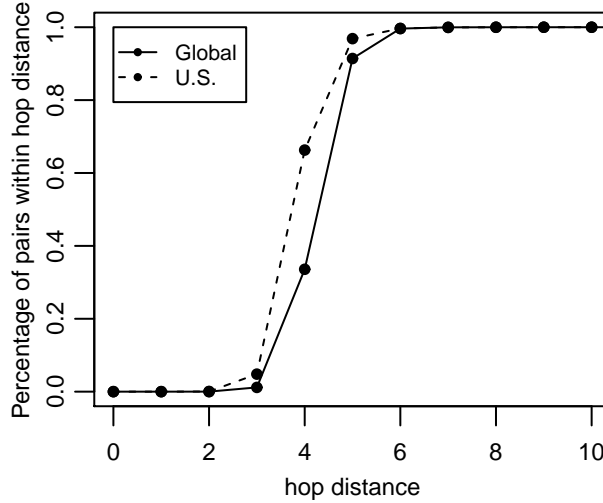
**Figure 1. Degree distribution  $p_k$ .** (a) The fraction of users with degree  $k$  for both the global and U.S. population of Facebook users. (b) The complementary cumulative distribution function (CCDF). The CCDF at degree  $k$  measures the fraction of users who have degree  $k$  or greater and in terms of the degree distribution is  $\sum_{k' \geq k} p_{k'}$ . For the U.S., the degree measures the number of friends also from the United States.

## The Facebook Graph

**Degree distribution.** A fundamental quantity measured repeatedly in empirical studies of networks has been the *degree distribution*  $p_k$ . The degree  $k$  of an individual is the number of friends that individual has, and  $p_k$  is the fraction of individuals in the network who have exactly  $k$  friends. We computed the degree distribution of active Facebook users across the entire global population and also within the subpopulation of American users. The global and U.S. degree distributions are shown in Fig. 1, displayed on a log-log scale.

Because the distribution for the U.S. is quite similar to that of the entire population, we focus our attention on the global degree distribution. The distribution is nearly monotonically decreasing, except for a small anomaly near 20 friends. This kink is due to forces within the Facebook product to encourage low friend count individuals in particular to gain more friends until they reach 20 friends. The distribution shows a clear cutoff at 5000 friends, a limit imposed by Facebook on the number of friends at the time of our measurements. Note that since 5000 is nowhere near the number of Facebook users, each user is clearly friends with a vanishing fraction of the Facebook population. Reflecting most observed social networks, our social relationships are sparse.

Indeed, most individuals have a moderate number of friends on Facebook, less than 200, while a much smaller population have many hundreds or even thousands of friends. The *median* friend count for global users in our study was 99. The small population of users with abnormally high degrees, sometimes called *hubs* in the networks literature, have degrees far larger than the average or median Facebook user. The distribution is clearly right-skewed with a high variance, but it is notable that there is substantial curvature exhibited in the distribution on a log-log scale. This curvature is somewhat surprising, because empirical measurements of networks have often claimed degree distributions to follow so-called power-



**Figure 2. Diameter.** The neighborhood function  $N(h)$  showing the percentage of user pairs that are within  $h$  hops of each other. The average distance between users on Facebook in May 2011 was 4.7, while the average distance within the U.S. at the same time was 4.3.

laws, represented mathematically by  $p_k \propto k^{-\alpha}$  for some  $\alpha > 0$  [24, 25]. Power-laws are straight lines on a log-log plot, and clearly the observed distribution is not straight. We conclude, like Ref. [23], that strict power-law models are inappropriate for Facebook’s degree distribution. It is not our intent, though, to determine which parametric form best models the distribution. The relevant results are the monotonicity and curvature of the degree distribution, the degrees of typical users, the large variance in degrees, and the network’s sparsity.

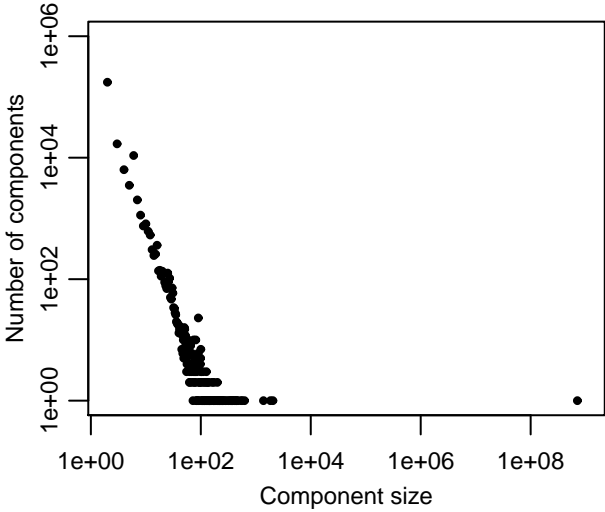
The sparsity of the network does not, however, imply that users are far from each other in Facebook’s network. While most pairs of users are not directly connected to each other, practically all pairs of users are connected via paths of longer lengths. In the next section, we measure the distances between users in the social graph.

**Path lengths.** When studying a network’s structure, the distribution of distances between vertices is a truly macroscopic property of fundamental interest. Here we characterize the *neighborhood functions* and the *average pairwise distances* of the Facebook and U.S. networks.

Formally, the neighborhood function  $N(h)$  of a graph describes the number of pairs of vertices  $(u, v)$  such that  $u$  is reachable from  $v$  along a path in the network with  $h$  edges or less. Given the neighborhood function, the diameter of a graph is simply the maximum distance between any pair of vertices in the graph. The diameter is an extremal measure, and it is commonly considered less interesting than the full neighborhood function, which measures what percentile of vertex pairs are within a given distance. The exact diameter can be wildly distorted by the presence of a single ill-connected path in some peripheral region of the graph, while the neighborhood function and its average are thought to robustly capture the ‘typical’ distances between pairs of vertices.

Like many other graphs, the Facebook graph does not have paths between all pairs of vertices. This does not prevent us from describing the network using the neighborhood function though. As we shall see in the next section, the vast majority of the network consists of one large connected component and therefore the neighborhood function is representative of the overwhelming majority of pairs of vertices.

Figure 2 shows the neighborhood function computed for both the graph of all Facebook users as well as the graph of U.S. Facebook users, as of May 2011, using the recently developed HyperANF



**Figure 3. Component size distribution.** The fraction of components with a given component size on a log-log scale. Most vertices (99.91%) are in the largest component.

algorithm [48]. We find that the average distance between pairs of users was 4.7 for Facebook users and 4.3 for U.S. users. Short path lengths between individuals, the so-called “six degrees of separation” found by Stanley Milgram’s experiments investigating the social network of the United States [26], are here seen in Facebook on a global scale. As Figure 2 shows, fully 92% of all pairs of Facebook users were within five degrees of separation, and 99.6% were within six degrees. Considering the social network of only U.S. users, 96% were within five degrees and 99.7% were within six degrees. For the technical details behind these calculations, we refer the interested reader to a separate paper concerning the compression and traversal of the Facebook graph [27].

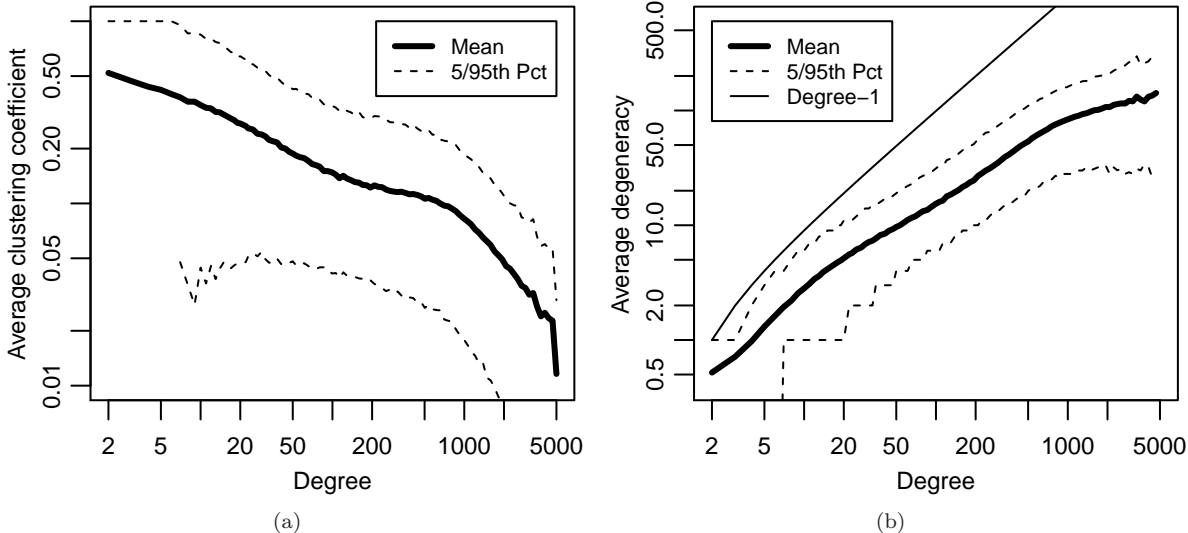
In order to show that these path length results are representative of the entire Facebook network, we now investigate the component structure of the graph.

**Component sizes.** Our conclusion from the previous section that the network has very short average path lengths relies on the existence of such paths between most pairs of vertices, a fact which we shall confirm in this section. We do so by finding the *connected components* of the social network, where a connected component is a set of individuals for which each pair of individuals are connected by at least one path through the network. Our neighborhood function calculations only computed distances between pairs of users within connected components because these are the only users actually connected via paths. In order for the results from the previous section to be interpreted as describing the diameter, we require that most, if not all, of the network be in one large connected component.

In Fig. 3, we show the distribution of component sizes on log-log scales, found exactly using an algorithm described in the Methods. While there are many connected components, most of these components are extremely small. The second-largest connected component only has just over 2000 individuals, whereas the largest connected component, the outlier all the way on the right-hand side of the figure, consists of 99.91% percent of the network. This component comprises the *vast* majority of active Facebook users with at least one friend. So not only are the average path lengths between individuals short, these social connections exist between nearly everyone on Facebook.

The path lengths and component structure of the network give us a view of the network at a macroscopic scale, and we now continue our investigation by examining more local properties of the network.

**Clustering coefficient and degeneracy.** Earlier we characterized the number of friends per user by



**Figure 4. Local clustering coefficient and degeneracy.** The clustering coefficient (a) and the degeneracy (b) as a function of degree on log-log scales. The means are shown as solid lines and the dashed lines display the 5/95th percentiles. An upper-bound on the degeneracy given by degree minus 1 is also shown as the thin solid line for comparison.

computing the degree distribution, and we now perform a closer analysis of the social graph neighborhoods of users. The *neighborhood graph* for user  $i$ , sometimes called the *ego graph* or the *1-ball*, is the vertex-induced subgraph consisting of the users who are friends with user  $i$  and the friendships between these users. User  $i$  is not included in their own neighborhood.

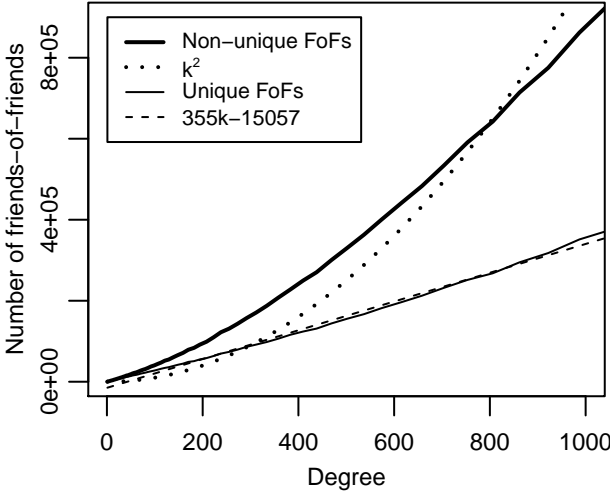
We first computed the average *local clustering coefficient* for users as a function of degree, which for a vertex of degree  $k$  measures the percentage of possible friendships between their  $k$  friends (at most  $k(k-1)/2$ ) are present in their neighborhood graph. This result is shown in Figure 4a, where we note that the axes are log-log.

We see that the local clustering coefficient is very large regardless of the degree, compared to the percentage of possible friendships in the network as a whole, and more importantly, compared to measurements of other online social networks. For example, for users with 100 friends, the average local clustering coefficient is 0.14, indicating that for a median user, 14% of all their friend pairs are themselves friends. This is approximately *five times greater* than the clustering coefficient found in a 2008 study analyzing the graph of MSN messenger correspondences, for the same neighborhood size [14].

Meanwhile, our analysis also shows that the clustering coefficient decreases monotonically with degree, consistent with the earlier MSN messenger study and other studies. In particular, the clustering coefficient drops rapidly for users with close to 5000 friends, indicating that these users are likely using Facebook for less coherently social purposes and friending users more indiscriminately.

Having observed such large clustering coefficients in local neighborhoods, we chose to study the sparsity of the neighborhood graphs further by measuring their *degeneracy*. Formally, the degeneracy of an undirected graph  $G$  is the largest  $k$  for which  $G$  has a non-empty  $k$ -core [28]. Meanwhile, the  $k$ -core of a graph  $G$  is the maximal subgraph of  $G$  in which all vertices have degree at least  $k$ , or equivalently, the subgraph of  $G$  formed by iteratively removing all vertices of degree less than  $k$  until convergence.

The maximal  $k$ -core of a graph  $G$  bears conceptual resemblance to the maximal  $k$ -clique of  $G$ , but



**Figure 5. Friends-of-friends.** The average number of unique and non-unique friends-of-friends as described in the text as a function of degree. Degree squared and a linear fit of the unique friends-of-friends are shown for comparison as the dotted and dashed lines.

it is important to note that a  $k$ -core is not necessarily a  $k + 1$ -clique, unless the  $k$ -core contains exactly  $k + 1$  vertices. The  $k$ -core however offers a readily computable and robust indication of how tightly-knit a community exists within a given graph.

We report the average degeneracy as a function of user degree in Figure 4b, again plotted on a log-log scale. Within the neighborhood graphs of users, we find that the average degeneracy is an increasing function of user degree. This should be considered consistent with our expectations: the more friends you have, the larger a tight-knit community you are typically embedded within. What is however surprising is how dense these neighborhoods in fact are: for a user with 100 friends, the average degeneracy of their neighborhood is 15. Furthermore, for users with 500 friends, their average degeneracy is 53, meaning that they have at least 54 friends who all know 53 of their other friends. In contrast, Eppstein and Strash recently examined the degeneracy of several graphs, both social and non-social, and found that across the entire graphs (not examining only neighborhoods), the degeneracies were much more modest [29]. For the 36,692 vertex graph of Enron email communication, the degeneracy was only 43. For the 16,706 vertex graph of arXiv astro-ph collaborations, the degeneracy was only 56. In contrast, we find comparable degeneracies simply by considering the neighborhood of an average user with 500 friends.

This suggests that even though the Facebook graph is sparse as a whole, when users accumulate sizable friend counts their friendships are far from indiscriminate, and instead center around sizable dense cores. We now consider the neighborhood of a vertex out to greater distances by examining the friends-of-friends of individual users.

**Friends of Friends.** An important property of graphs to consider when designing algorithms is the number of vertices that are within two hops of an initial vertex. This property determines the extent to which graph traversal algorithms, such as breadth-first search, are feasible. In Figure 5, we computed the average count of both unique and non-unique friends-of-friends as a function of degree. The non-unique friends-of-friends count corresponds to the number of length-two paths starting at an initial vertex and not returning to that vertex. The unique friends-of-friends count corresponds to the number of unique vertices reachable at the end of a length-two path.

A naive approach to counting friends-of-friends would assume that a user with  $k$  friends has roughly

$k^2$  non-unique friends-of-friends, assuming that their friends have roughly the same friend count as them. This could also be considered a generous naive estimate of the number of unique friends-of-friends, generous because we saw above that a significant fraction of your friends’s friends are your friends. In reality, the number of non-unique friends of friends grows only moderately faster than linear, and the number of unique friends-of-friends grows very close to linear, with a linear fit producing a slope of 355 unique friends-of-friends per additional friend.

While the growth rate may be slower than expected, until a user has more than 800 friends, it’s important to observe from the figure that the absolute amounts are unexpectedly large: a user with 100 friends has 27,500 unique friends-of-friends and 40,300 non-unique friends-of-friends. This is significantly more than the  $100 * 99 = 9,900$  non-unique friends-of-friends we would have expected if our friends had roughly the same number of friends as us. This excess is related to a principle which we will discuss at length below, where we show the extent to which ‘your friends have more friends than you’, an established result from prior studies of social networks [30].

**Degree correlations.** The number of friendships in your local network neighborhood depends on the number of friends, the degree, of your friends. In many social networks, online and offline, it has been noticed that your neighbor’s degree is correlated with your own degree: it tends to be large when your degree is large, and small when your degree is small, so-called *degree assortativity*. We can quantify these degree correlations by computing the Pearson correlation coefficient  $r$  between degrees at the end of an edge [31,32]. For the Facebook network,  $r = 0.226$ , displaying positive correlations with similar magnitude to other social graphs. This value is consistent with earlier studies of smaller networks including academic coauthorship and film actor collaborations, where values of  $r$  range from 0.120 to 0.363 [31]. Another more detailed measure  $\langle k_{nm} \rangle(k)$ , the average number of friends for a neighbor of an individual with  $k$  friends [33], is shown as the solid line in Fig. 6a. (We use the notation  $\langle x \rangle$  to represent an average of a quantity  $x$ ). The expected number of friends at the end of a randomly chosen edge,  $\langle k^2 \rangle / \langle k \rangle = 635$ , is shown as a horizontal dotted line. Unlike this constant value — which is our expectation if there were no degree correlations — the solid line increases from near 300 for low degree individuals to nearly 820 for individuals with a thousand friends confirming the network’s positive assortativity. (The measurements become noisy past 1000 and we cut the figure off at this point for clarity.)

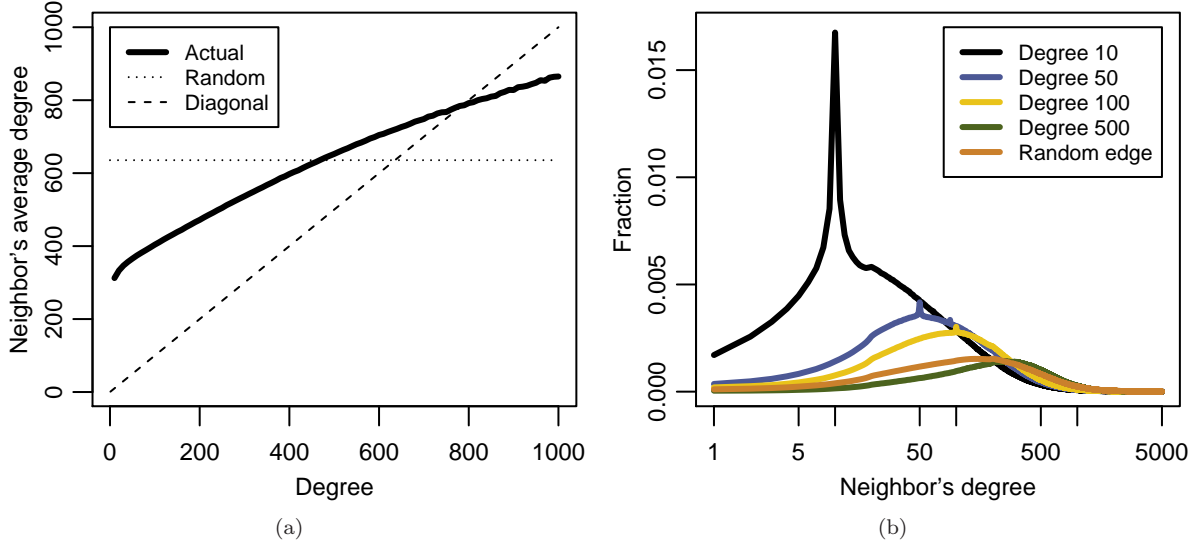
Comparing the solid line to the diagonal dashed line shows that until you have nearly 700 friends, your (average) neighbor has more friends than you. This phenomena has been discussed at length by Feld [30], and Facebook displays the effect on a grand scale. The fact that our average neighbors have so many more friends also explains why our naive friend-of-friend estimates in the previous section were far too low.

Feld’s observation that ‘your friends have more friends than you’ is an important psychological paradox, applying to friendship as well as sexual partners. When people compare themselves to their friends, it is conceptually more appropriate to frame the comparison relative to the median of their friends, psychologizing the question as a matter of asking what one’s ‘class rank’ is amongst one’s peers [34]. Our finding with regard to the median is therefore perhaps more significant: we observe that 83.6% of users have less friends than the median friend count of their friends. All these individuals experience that more than half of their friends have more friends than they do. For completeness, we also note that 92.7% of users have less friends than the average friend count of their friends.

However, we can do more than measure these simple statistics and we characterize the conditional probability  $p(k'|k)$  that a randomly chosen friend of an individual with degree  $k$  has degree  $k'$  [35]. We computed this for evenly spaced values of  $k$ , all multiples of ten, and show the distribution for a few example values of  $k$  in Fig. 6b, along with the distribution if there were no degree correlations, i.e. the distribution of degrees found by following a randomly selected edge.

First, note that the horizontal axis is log while the vertical axis is linear. Agreeing with Fig. 6a, the mean of these distributions is clearly less than the mean of the orange distribution which represents following a random edge in the network, except for the green line denoting  $k = 500$ . Again, the distributions





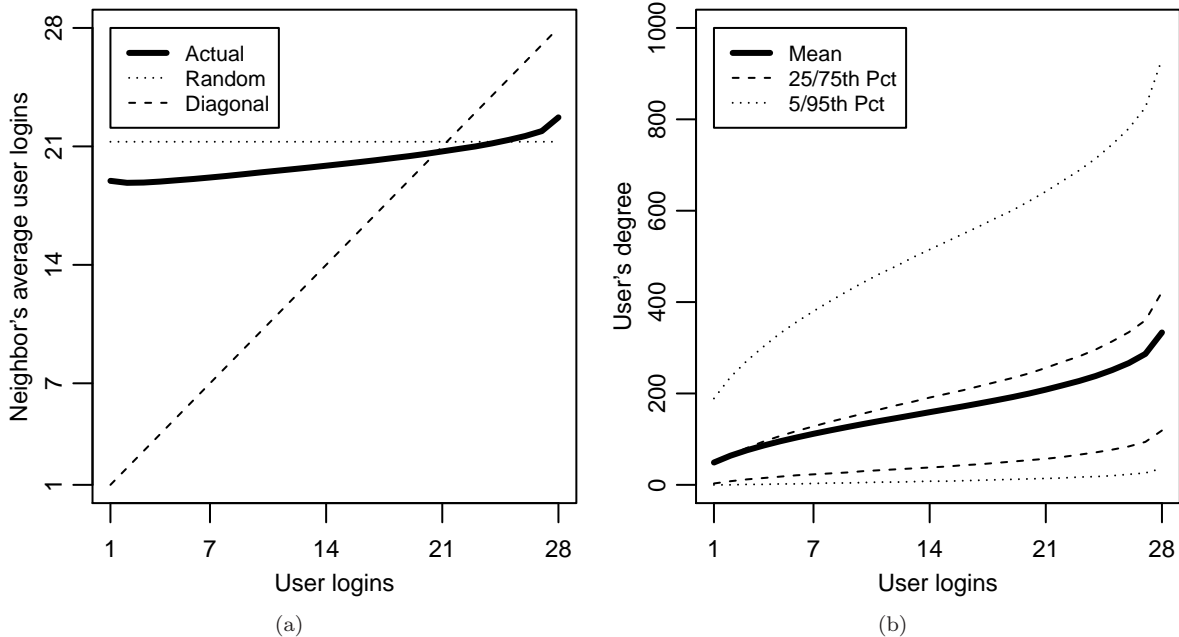
**Figure 6. Degree correlations.** (a) The average neighbor degree of an individual with degree  $k$  is the solid line. The horizontal dashed line shows the expected value if there were no degree correlations in the network  $\langle k^2 \rangle / \langle k \rangle$ , and the diagonal is shown as a dashed line. (b) The conditional probability  $p(k'|k)$  that a randomly chosen neighbor of an individual with degree  $k$  has degree  $k'$ . The solid lines, on the linear-log scale, show the measured values for four distinct degrees  $k$  shown in the caption. The orange line shows the expected distribution,  $\frac{k' p_{k'}}{\langle k \rangle}$ , if the degrees were uncorrelated.

shift to the right as  $k$  increases demonstrating the degree assortativity. Furthermore, barring any strange non-smooth behavior between the sampled values of  $k$ , the median for  $p(k'|k)$  is greater than  $k$  up until between 390 and 400 friends, confirming that the behavior of the mean in Fig. 6a was not misleading. Another observation from the figure, and data for other values of  $k$  not shown, is that the modal degree of friends is exactly equal to  $k$  until around  $k = 120$ . So while your friends are likely to have more friends than you on average, the most likely number of your neighbor's friends is the same as your degree for low to moderate degree users.

**Site engagement correlation.** Besides for degree correlations, we also examined correlations amongst traits of individuals and network structure [36]. We now repeat our correlation calculations using the number of days users logged in during the 28-day window of the study, instead of degree, seen in Fig. 7a. Again, we provide the average value at the end of a randomly selected edge and the diagonal line for comparison.

Unlike the degree case, here there is an ambiguity in defining a random neighbor and hence the average number of neighbor logins. Our definition of random neighbor of vertices with trait  $x$  is to first select a vertex with trait  $x$  in proportion to their degree and then select an edge connected to that vertex uniformly at random. In other words, we give each edge connected to vertices with trait  $x$  equal weight. So a vertex who is connected to 5 vertices with trait  $x$  is given 5 times as much weight in the average as a vertex who connects to a single vertex with trait  $x$ .

Like the degree, your neighbor's site engagement is correlated with your site engagement, but the average number of neighbor logins is better represented by the horizontal random expectation than what was seen in the degree case. The more interesting observation, though, is that the solid value is far larger than the diagonal value over most of the range from logging in 0 to 20 times in the past 28 days. So by



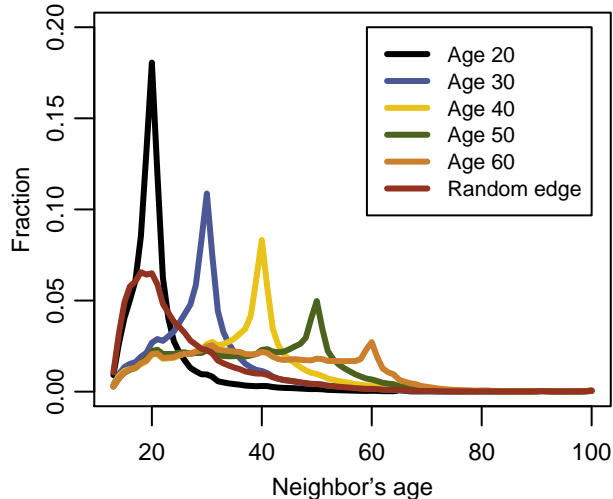
**Figure 7. Login correlations.** (a) Neighbor’s logins versus user’s logins to Facebook over a period of 28 days. The solid line shows the actual mean values and the horizontal line shows the average login value found by following a randomly chosen edge. The dashed line shows the diagonal. (b) A user’s degree versus the number of days a user logged into Facebook in the 28 day period. The solid line shows the mean user degree, the dashed lines the 25/75 percentiles, and the dotted lines the 5/95th percentiles.

the same line of reasoning for the degree case, up until you log in around 70 percent of days in a month, on average, your friends log into Facebook more than you do.

We can understand this phenomena by examining the correlation between an individual’s degree and logging into Facebook. A Facebook user provides and receives content through status updates, links, videos, and photos, etc. to and from their friends in the social network, and hence may be more motivated to log in if they have more friends. Such a positive correlation does exist between degree and logins, and we show that in Fig. 7b. A user who logs in more generally has more friends on Facebook and vice versa. So since your friends have more friends than you do, they also login to Facebook more than you do.

**Other mixing patterns.** There are many other user traits besides logging into Facebook that can be compared to the network structure. We focus on three other such quantities with essentially complete coverage for Facebook’s users; age, gender, and country of origin, and characterize their homophily [36] and mixing patterns [32].

We start by considering friendship patterns amongst individuals with different ages, and compute the conditional probability  $p(t'|t)$  of selecting a random neighbor of individuals with age  $t$  who has age  $t'$ . Again, random neighbor means that each edge connected to a vertex with age  $t$  is given equal probability of being followed. We display this function for a wide range of  $t$  values in Fig. 8. The resulting distributions are not merely a function of the magnitude of the age difference  $|t - t'|$  as might naively be expected, and instead are asymmetric about a maximum value of  $t' = t$ . Unsurprisingly, a random neighbor is most likely to be the same age as you. Less obviously, the probability of friendship with older individuals falls off rapidly, nearly exponentially, from the mode. Below the mode, the distributions also fall off,



**Figure 8.** The distribution  $p(t'|t)$  of ages  $t'$  for the neighbors of users with age  $t$ . The solid lines show the measured distributions against the age  $t$  described in the legend, and the red line shows the distribution of ages found by following a randomly chosen edge in the network.

but then level out to a value that is nearly independent of the user’s age  $t$  (see for example the blue, yellow and green lines). And from the figure we notice that as  $t$  increases the variance in the distribution increases. Roughly speaking, younger individuals have most of their friends within a small age range while older individuals have a much wider range. None of this behavior is evident when comparing to the distribution of ages at the end of a randomly chosen edge, the red line, which is centered around 20. So while it is obvious that age matters to our social relationships, the Facebook social network shows non-trivial asymmetric patterns, consistent across user ages  $t$ .

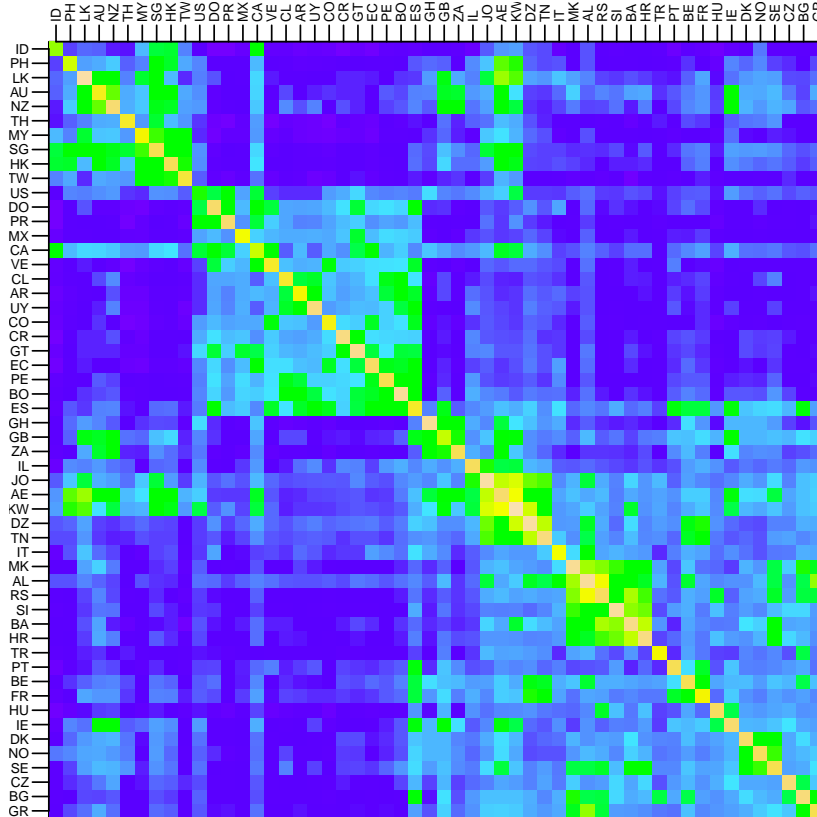
Switching to gender, we compute the conditional probability  $p(g'|g)$  that a random neighbor of individuals with gender  $g$  has gender  $g'$  where we denote male by  $M$  and female by  $F$ . For friends of male users, we find that  $p(F|M) = 0.5131$  and  $p(M|M) = 0.4869$ . For friends of female users, we find that  $p(F|F) = 0.5178$  and  $p(M|F) = 0.4822$ . In both cases, we see that a random neighbor is more likely to be female.

In order to understand this result, we compare to the probability of following a randomly selected edge and arriving at a particular gender. These probabilities are given by  $p(F) = 0.5156$  and  $p(M) = 0.4844$  respectively. The probability is higher for females because the number of edge ends, called stubs in the networks literature, connected to females is higher than for males. While there are roughly 30 million fewer active female users on Facebook, the average female degree (198) is larger than the average male degree (172), resulting in  $p(F) > p(M)$ .

Comparing these quantities, we see that  $p(F|M) < p(F) < p(F|F)$  and  $p(M|F) < p(M) < p(M|M)$ . However, the magnitude of the difference between these probabilities is extremely small and only differs in the thousandths place. So if there is a preference for same gender friendships on Facebook, the effect appears minimal at most.

Lastly, we turn to country of origin, a categorical variable divided into 249 categories according to the ISO 3166-1 country code standard. These labels are attributed to users based on the user’s most recent IP address login source and known correspondences between IP addresses and geographic locations. While imperfect, so-called geo-IP data is generally reliable on a national level.

Intuitively, we expect to have many more friends from our country of origin than from outside that



**Figure 9. Normalized country adjacency matrix.** Matrix of edges between countries with  $> 1$  million users and  $> 50\%$  Facebook penetration shown on a log scale. To normalize, we divided each element of the adjacency matrix by the product of the row country degree and column country degree.

country, and the data shows that 84.2% percent of edges are within countries. So the network divides fairly cleanly along country lines into network *clusters* or *communities*. This mesoscopic-scale organization is to be expected as Facebook captures social relationships divided by national borders. We can further quantify this division using the modularity  $Q$  [37] which is the fraction of edges within communities minus the expected fraction of edges within communities in a randomized version of the network that preserves the degrees for each individual [38], but is otherwise random. In this case, the communities are the countries. The computed value is  $Q = 0.7486$  which is quite large [39] and indicates a strongly modular network structure at the scale of countries. Especially considering that unlike numerous studies using the modularity to detect communities, we in no way attempted to maximize it directly, and instead merely utilized the given countries as community labels.

We visualize this highly modular structure in Fig. 9. The figure displays a heatmap of the number of edges between the 54 countries where the active Facebook user population exceeds one million users and is more than 50% of the internet-enabled population [40]. To be entirely accurate, the shown matrix contains each edge twice, once in both directions, and therefore has twice the number of edges in diagonal elements. The number of edges was normalized by dividing the  $ij$ th entry by the row and column sums, equal to the product of the degrees of country  $i$  and  $j$ . The ordering of the countries was then determined via complete linkage hierarchical clustering.

While most of the edges in the figure are on the diagonal, the log-scale clearly highlights further modular structure in friendships between countries. The countries fall into groups, the clearly square-like patterns in the matrix, with preferential friendship patterns amongst citizens of different countries.

The complete list of countries in the order presented in the matrix is shown in Table 1. Many of the resulting country groupings are intuitive according to geography. For example, there are clear groups corresponding to the South Pacific, North and Central America, South America, North Africa and the Middle East, Eastern Europe and the Mediterranean, and to the Nordic countries of Denmark, Sweden, and Norway. Other more curious groupings, not clearly based on geography, include the combination of the United Kingdom, Ghana, and South Africa, which may reflect strong historical ties. The figure clearly demonstrates that not only are friendships predominantly between users within the same country, but that friendships between countries are also highly modular, and apparently influenced by geography. The influence of geographical distance on friendship has been previously discussed [41,42], but earlier work on Facebook has not examined the country-scale structure of friendships [43]. Speculating, some groupings of countries may be better explained by historical and cultural relations than simple geographical distance.

## Discussion

In this paper, we have characterized the structure of the Facebook social graph using many metrics and tools. To our knowledge, our study is the largest structural analysis of a social network performed to date.

We began by characterizing the degree distribution which was shown to be skewed with a large variance in friendship count. Unlike many other networks, a pure power-law was seen to be inappropriate for the degree distribution of Facebook, although hubs certainly exist.

The small-world effect and six degrees of separation were then confirmed on a truly global scale. The average distance between vertices of the giant component was found to be 4.7, and we interpret this result as indicating that individuals on Facebook have potentially tremendous reach. Shared content only needs to advance a few steps across Facebook’s social network to reach a substantial fraction of the world’s population.

We have found that the Facebook social network is nearly fully connected, has short average path lengths, and high clustering. Many other empirical networks, social and non-social, have also been observed with these characteristics, and Watts and Strogatz called networks with these properties ‘small-world networks’ [44].

Because our friends have more friends than we do, individuals on Facebook have a surprisingly large number of friends-of-friends. Further, our friends are highly clustered and our friendships possess dense cores, a phenomena not noticed in smaller social networks. This neighborhood structure has substantial algorithmic implications for graph traversal computations. Breadth-first search out to distance two will potentially query a large number of individuals due to positive degree correlation, and then will follow many edges to individuals already found due to the clustering.

We also performed an exploratory comparison of the network structure with user traits including login behavior, age, gender, and country. We found interesting mixing patterns, including that ‘your friends login to Facebook more than you do’ and a strong preference for friends of around the same age and from the same country.

Community structure was shown to be clearly evident in the global network, at the scale of friendships between and within countries. Countries in turn were seen to themselves exhibit a modular organization, largely dictated by geographical distance. Unlike prior studies of networks, this community structure was discovered without much effort, indicating the significant structural insights that can be derived from basic demographic information.

While our computations have elucidated many aspects of the structure of the world’s largest social network, we have certainly not exhausted the possibilities of network analysis. We hope that this in-

formation is useful both for social science research and for the design of the next-generation of graph algorithms and social network analysis techniques.

## Materials and Methods

Unless otherwise noted, calculations were performed on a Hadoop cluster with 2,250 machines, using the Hadoop/Hive data analysis framework developed at Facebook [45, 46].

For analyzing network neighborhoods, 5,000 users were randomly selected using reservoir sampling for each of 100 log-spaced neighborhood sizes, creating a sample of 500,000 users for which the analysis was performed. The percentiles shown for the clustering coefficient and degeneracy for each neighborhood size are therefore empirical percentiles from this sample population of 5,000 users.

To analyze the component structure of the network, we used the Newman-Zipf (NZ) algorithm [47]. The NZ algorithm, a type of Union-Find algorithm with path compression, records component structure dynamically as edges are added to a network that begins completely empty of edges. When all edges are added, the algorithm has computed the component structure of the network. Crucially for our purposes, the NZ algorithm does not require the edges to be retained in memory. We apply it to the Facebook network on a single computer with 64GB of RAM by streaming over the list of edges.

For path length calculations, neighborhood functions were computed on a single 24-core machine with 72 GB of RAM using the HyperANF algorithm [48], averaging across 10 runs. For the technical details behind this formidable computation, see [27].

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| Country            | ISO code | Country                | ISO code |
|--------------------|----------|------------------------|----------|
| Indonesia          | ID       | United Kingdom         | GB       |
| Philippines        | PH       | South Africa           | ZA       |
| Sri Lanka          | LK       | Israel                 | IL       |
| Australia          | AU       | Jordan                 | JO       |
| New Zealand        | NZ       | United Arab Emirates   | AE       |
| Thailand           | TH       | Kuwait                 | KW       |
| Malaysia           | MY       | Algeria                | DZ       |
| Singapore          | SG       | Tunisia                | TN       |
| Hong Kong          | HK       | Italy                  | IT       |
| Taiwan             | TW       | Macedonia              | MK       |
| United States      | US       | Albania                | AL       |
| Dominican Republic | DO       | Serbia                 | RS       |
| Puerto Rico        | PR       | Slovenia               | SI       |
| Mexico             | MX       | Bosnia and Herzegovina | BA       |
| Canada             | CA       | Croatia                | HR       |
| Venezuela          | VE       | Turkey                 | TR       |
| Chile              | CL       | Portugal               | PT       |
| Argentina          | AR       | Belgium                | BE       |
| Uruguay            | UY       | France                 | FR       |
| Colombia           | CO       | Hungary                | HU       |
| Costa Rica         | CR       | Ireland                | IE       |
| Guatemala          | GT       | Denmark                | DK       |
| Ecuador            | EC       | Norway                 | NO       |
| Peru               | PE       | Sweden                 | SE       |
| Bolivia            | BO       | Czech Republic         | CZ       |
| Spain              | ES       | Bulgaria               | BG       |
| Ghana              | GH       | Greece                 | GR       |

**Table 1.** ISO country codes used as labels in Figure 9.