Shifting Behaviour of Users: Towards Understanding the Fundamental Law of Social Networks

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Abstract. A significant amount of research has attempted to understand the advertisement of products using social networking websites. Scientists have tried targeting the most influential people in a society to impact the largest possible fraction. But, the reasons for the change in people’s preferences from one product to another have not been understood completely. Inculcating this idea, the paper proposes a model to simulate the behaviour of people’s choices when new products are introduced in the system. Here, we try to analyse the transition of users from one Social Networking Site (SNS) to another. Although many researchers have studied social networking websites, none of them have focussed on how these transitions occur. Our model considers two major factors as pivotal in determining the success of a new SNS. The first being time, we study whether this time that an SNS like Facebook received to monopolise its reach had a distinguishable effect on the transition. The second factor that is considered to determine the success of a new SNS is the set of features showcased. The results of the model are experimentally verified with the aid of the data collected by means of a survey.

Keywords: social networks, diffusive shift, passive engagement, homophily

1 Introduction

Our market is flooded with several new products on a daily basis. Though many of these products begin as luxurious items, they end up becoming an indispensable component of our lives. The success of a product can be attributed to numerous factors, such as its quality, unique features, mass appeal, multi-functionality, price, availability, early bird offers and advertising policies. Exploring the reasons for the success of such efficacious products is an interesting and important line of research on its own.

http://www.forbes.com/sites/kevinharrington/2013/10/08/10-qualities-of-a-successful-product/
Google as a search engine is a very relevant example in this scenario. The phenomenal success of Google can be realised by seeing how the term “googling” has become an official replacement for the act of searching on the web\(^4\). A new search engine will certainly experience a hard time matching Google’s reach and performance. Undoubtedly, Google’s success is primarily attributed to its PageRanking algorithm. Another substantial reason for this could be the attachment and the comfort level that people develop towards a product while using it for a prolonged period of time\(^5\). So, the users always experience a feeling of inertia while experimenting with other products.

While most people prefer using the old product, there are some exceptions. These exceptions are people who either have an urge to try new products or are incentivised for using the new product in the market. Thus, these initial adopters could possess the potential to spearhead everybody to try the new search engine. The principles of homophily and social reinforcement can result in the slow shifting of the entire population towards the new search engine\(^6\). However, whether such a shift occurs or not certainly depends upon the quality and time of arrival of the new search engine, the quality of the existing search engine, and plenty of such factors. In this paper, we address this very question of whether a new product can make a mark when the existing market has been monopolized for a long period of time. Although, the adoption of a product by people and its cascading pattern in the population has been studied\(^2\)\(^3\)\(^4\), the adoption of a SNS requires a different kind of modeling. Shifting from one SNS to another is difficult due to various reasons like connections being lost, having to recreate the same connections, et cetera. Our paper specifically deals with a social networking site as a product.

Social networking sites have a long history. The first major social networking site to hit the internet was SixDegrees, which was launched in May 1996. It was followed by a number of different sites like Napster(1999), Friendster(2002), MySpace(2003), et cetera. In 2004, Orkut and Facebook were launched. The growth of Orkut was dominant initially but this was soon suppressed by Facebook. As a result, Orkut was officially shut down on September 30, 2014. Although Orkut faded, other social networking sites like LinkedIn, Twitter, et cetera continued to grow in parallel not only in terms of number but also in terms of user activity. Google Plus strived to stand collateral with Facebook but could not. The activity of people on Google Plus remains low.

We characterize the shifting behaviour of people from one social networking site to another that happens steadily over a period of time. We propose a model that explains the shift of a person from one social networking site to another in terms of the time spent on the new social networking website in addition to their features. Our model makes provision for the inertia that grows over time and

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\(^4\) http://www.oxforddictionaries.com/definition/english/google

\(^5\) 1. Homophily- Similar kind of people tend to be connected to each other, hence impacting each others’ choices.

2. Social reinforcement:- Multiple exposure of information to a person may lead to them adopting it
the herd-like tendency that humans exhibit. It further provides an insight into
why the efforts made by Google Plus to reach Facebook’s reach were unfruitful,
whereas Facebook was outstandingly successful in overtaking Orkut.
The paper is organised as follows: First, we highlight important work done in
this direction in Section 2 which is followed by Basics in Section 3. The mathem-
atical model is discussed in Section 4. Section 5 gives an overview to the survey
conducted. The paper continues with the Results and Simulations in Section 6
and concludes with Conclusion and Future Work in Section 7.

2 Related Work

Our work derives its theme from two lines of research in Social Network Analy-
sis: 1) Study of the cascading pattern of a meme on a social networking site and
2) Temporal evolution of Social Networking Sites.
One of the most widely studied problem in Social Network Analysis is under-
standing the spreading pattern of a meme on an online social network [2,3,4]. A
meme can carry any kind of information: a joke, a rumour, an advertisement
of a product etc. People tend to share memes on SNS because of interest or
altruism. The spread of such memes on a network has been studied extensively.
Many researchers have tried predicting the virality of a meme or a product by
analyzing its content and the initial pattern of spreading in a SNS [5,6,7]. One
of the most important applications of SNSs lies in digital advertising [8]. Today,
social networking sites turn out to be the most widely used platforms for the
advertisement of a wide variety of products. Most of the population is online
and hence triggering a group of people to adopt a product may result in the
product being globally popular due to a large cascade. Kleinberg et al. gave an
approximation algorithm for choosing the right set of seed nodes that results
in the largest cascade over a given network [9]. Ugander et al. observed the
cascading process at a local level. He extrapolated the linear threshold model
theory to include the diversity of a node’s neighbours in addition to their num-
ber. Here, the diversity is quantified by the number of connected components
in the induced subgraph on its neighbours [10]. Watts conducted an experiment
[11] to prove the increase in the unpredictability of the success of a product in
an environment with increasing social influence. Another similar paradox, that
of a globally sparse phenomenon giving you an illusion of being globally viral
was discussed in [12].
Extensive research has been done towards understanding the growth of online
social networks. Leskovec et al. proposes a model for the evolution of a social
network over time [13]. This model is based on the data collected from different
social networking sites like Flickr, LinkedIn, Delicious and Answers. Kumar et
al. explains the process of a SNS evolution by categorising the nodes of the net-
work into 3 types [14]: Passive, Linker and Inviter. Mislove et al. observed a
proximity bias in new links that are being created [15]. Kairam et al. [16] have
studied the life and death of online groups in different Ning communities. They
proposed two ways for the growth of a new group: Diffusion and Non-Diffusion.
Anderson et al. observed homophily in cascading invitations after analysis of LinkedIn sign up cascades [17]. Benevenuto et al. [18] experimentally analyzed user behaviour on different social networking sites and observed that people used to spend maximum amount of time on Orkut. Wilson et al. [19] and Viswanath et al. [20] emphasized the importance of the level of interaction between 2 nodes in a social graph. They also studied the evolution of these interactions with time on the Facebook network. Our work proposes a model that demonstrates transition/no transition of people from one social networking website to another based on a number of parameters. To the best of our knowledge, this kind of modeling is the first of its kind.

3 Basics

Modeling the shifting phenomenon of users from one SNS to another requires us to concretely define a social networking site (SNS). There have been earlier attempts to define a SNS [21], but for the ease of modeling, we adopt a slightly modified definition compared to those already proposed. A social networking site $S$ act as a platform for people sharing common interests, beliefs, ideas and hobbies to communicate and socialise with each other. In today’s world, a SNS provides us an opportunity to constantly stay connected with our friends, majorly though passive engagement [22][18]. In addition, a SNS can be characterized by the following attributes:

- Set of all features available ($F(S)$)
- User-Interface of the website (excluding the UI of features)
- Latency

A feature $(f)$ on a SNS $S$ is identified by its functionality, volatility, UI, etc. A feature $f$ on a SNS is considered to be important for the website if it consumes a large amount of time of its users. To quantify the same, we introduce a new parameter $\phi(f,u)$ for a feature $f$ and a user $u$, which is defined as follows:

$$\phi(f,u) = \frac{\text{time spent by the user } u \text{ on feature } f \text{ in a day}}{\text{total time spent by the user } u \text{ on social networking sites in a day}}$$

Throughout the paper, a day is considered as one unit of time. Each SNS has an underlying explicit network, with nodes of the graph being the users of the SNS and the links between them representing a type of connection between them. For example, on Facebook, the connections represent friendship links whereas on Twitter it represents follower-followee relationship.

Each user has only certain stipulated amount of time which she spends on SNSs. We define $\Delta(u)$ to signify this time span of a user $u$. For the sake of simplicity, we assume the distribution of $\Delta(u)$ to be uniform i.e. each user spends equal amount of time on SNSs. Therefore, $\Delta(u) = \Delta$ for all users $u$. We support our assumption with the help of a survey we conducted, the details of which are discussed in section 6.
Since most of the users on a social networking site have a large number of friends, it is impossible for a user to explicitly devote time to each of her friends. Therefore, features that allow passive engagement of the user are more popular. Most features act as a platform for all users to participate as a group and are not one-to-one. Therefore, a user’s time span is distributed across the features of SNSs and not across her friends. This claim can be supported by the clickstream analysis done in [18], very less percent of net time spent by users is on features supporting passive engagement.

For better visualization of how the feature sets of different SNSs intersect, we introduce the concept of a feature space (FS). We introduce it with the help of an example, shown in Figure 1. Let $u^*$ be a hypothetical user who uses all three SNSs $S_1$, $S_2$ and $S_3$, then

\[ x_1 = 10\% = \text{percent of time span } \Delta \text{ spent by the user } u^* \text{ on features which are unique to } S_1 \]
\[ x_{2,3} = 8\% = \text{percent of time span } \Delta \text{ spent by the user } u^* \text{ on features which are present precisely on } S_2 \text{ and } S_3 \]
\[ x_{1,2,3} = 40\% = \text{percent of time span } \Delta \text{ spent by the user } u^* \text{ on features which are present on all three SNSs} \]

Although, we can calculate quantities like $x_1$, $x_{2,3}$ and $x_{1,2,3}$ with the help of a FS, it does not provide us complete information regarding the distribution of $u$’s time across the three SNSs $S_1$, $S_2$ and $S_3$.

In general, consider a system with SNSs $S_1$, $S_2$, $\ldots$, $S_m$. Then, $x(S_{a_1}, S_{a_2}, S_{a_3}, \ldots, S_{a_k})$ represents the percent of time span $\Delta$ spent by the user $u^*$ on features which are available precisely on $S_{a_1}$, $S_{a_2}$, $S_{a_3}$, $\ldots$, $S_{a_k}$, which is equal to

\[ \left( 100 \times \sum_{f \in F'} \phi(f, u^*) \right) \]

where $F' = \bigcup_{i=1}^{k} F(S_i) - (F - \bigcup_{i=1}^{k} F(S_i))$. 

**Fig. 1.** An example of feature space
4 Model

Consider a system where only one SNS $S_1$ is present, which consists of $n$ users. Therefore, each of these users spend their entire time span $\Delta$ on $S_1$. Let the underlying graph of $S_1$ be represented by $G_1$. Now, a new SNS $S_2$ is introduced into the system.

When the new SNS $S_2$ is launched, some people are attracted towards it probably because of an internal urge or explicit incentive as stated earlier. Even if an individual starts using $S_2$, they do not stop using the SNS $S_1$ completely. This is largely attributed to the attachment and trust factor associated with the old site $S_1$ [18]. It is also illogical to betray one’s social networking site altogether and try another one, since the user will be risking his means to socialize online. Also, we assume that a user will only start using the SNS $S_2$ to check out the new features that it offers, which is generally the case observed. Another important point to note is that $S_2$ can have certain features common with $S_1$. We further assume that during the transition phase i.e. around the time when $S_2$ was introduced, the common features are used only on $S_1$. However, gradually people may start using the common features on $S_2$, but in this study, we focus only at the transition stage. All the assumptions mentioned above are supported by the survey results in section 5.

To understand the cascading phenomenon from one SNS to another, one needs to have a microscopic view of the underlying graph $G_1$. We look at an exclusive user of $S_1$ and examine the reasons which can incentivize her to use $S_2$ as well. Similar to the concept given in [16], we propose two mechanisms through which a user can be encouraged to use $S_2$.

1. Non-Diffusive Shift is the process in which a user shifts from one social networking site to another as a result of marketing strategies used by $S_2$ and is independent of the network structure of $S_1$ and $S_2$, i.e. independent of which social networking sites her friends are using. To account for this in our model, we associate a small probability $p$ with which an exclusive user of $S_1$ starts using $S_2$ at a given point in time. Since we have chosen a day as our unit of time, $p$ is the non-diffusive infection probability per unit day.

2. Diffusive Shift can be defined as the process in which a user starts using the new social networking site due to the influence from her friends, mainly by the principles of social reinforcement and homophily. Diffusive shift can be catalyzed using various techniques, few of which are mentioned below:

   - Reduction in the time spent by a user $u$’s neighbors on $S_1$.
   - Invitations to join $S_2$ from neighbors of $u$ who are present on $S_2$.
   - Word of mouth advertisements.

   Figure 2 illustrates both these phenomena.

Consider a user ($u$) who is an exclusive user of $S_1$ having $d$ neighbours. Out of these, $d_1$ neighbours are the exclusive users of $S_1$ whereas $d_2$ of them uses $S_1$ and $S_2$ simultaneously. Let $T_1$ and $T_2$ be the net time spent by the neighbours of user $u$ on SNS $S_1$ and $S_2$ respectively.
Lemma 1. $T_1 = \Delta(d - d_2x_2)$

Proof. $d_1$ friends of user $u$ spend their entire time span $\Delta$ on $S_1$. From the definition of a Feature Space and the assumption involved that common features are used by the users on $S_1$, $d_2$ friends of $u$ spend $(1 - x_2)$ fraction of their time
span on S1. Therefore,

\[ T_1 = \Delta(d_1) + \Delta(1-x_2)(d_2) = \Delta(d-d_2) + \Delta(1-x_2)(d_2) = \Delta(d-d_2 + d_2 - x_2 d_2) = \Delta(d-d_2 x_2) \]

\[ \tag*{\Box} \]

**Lemma 2.** \( T_2 = \Delta d_2 x_2 \)

**Proof.** Follows from Lemma 1 \( \tag*{\Box} \)

Almost all of the features of a SNS are valued only because of the presence of users. For example: NewsFeed, Groups, etc. Hence, even if a feature \( f \) may have attracted user \( u \) initially with its novelty and UI, for it to be a feature where the user \( u \) spend time regularly, the feature must also be used by the friends of \( u \). Therefore, if most of user \( u \)'s friends start using \( S_2 \), \( T_1 \) would reduce, and at some stage will incentivize user \( u \) to start using \( S_2 \) as well. We introduce a new parameter \( \epsilon \) to determine the threshold for diffusive shift. A user \( u \) starts using \( S_2 \) iff \( T_2 > \epsilon(T_1 + T_2) \) i.e. once the time spent by friends of \( u \) on \( S_1 \) fall below a fraction of their net time span on SNSs, user \( u \) starts using \( S_2 \). This constant \( \epsilon \) is called the attachment factor of SNS \( S_1 \). The attachment factor always lies between 0 and 1. It accounts for the attachment that the users develop towards a SNS over time. It is an abstract quantity that represents the stability of a SNS. We tend to believe that this factor is low when a site is just launched and it increases over time. Thus, lower is the value of \( \epsilon \), easier is it for the cascade to occur, and higher the value of \( \epsilon \), tougher it will be for the diffusive shift. From [1], with time the attachment factor increases. The detailed study of the attachment factor is out of the scope of this paper.

**Theorem 3.** If \( \epsilon \geq x_2 \), diffusive shift can never occur.

**Proof.** Consider a user \( u \) with \( \text{deg}(u) = d = d_1 + d_2 \) where \( d_1 \) = number of friends of \( u \) who exclusively use \( S_1 \)

\[ \Delta d_1 \geq \Delta d_2 x_2 \quad \text{(From the given condition)} \]

\[ \Delta d_2 \geq \Delta d_2 x_2 \quad \text{(Since } d_2 \leq d) \]

\[ (T_1 + T_2) \epsilon \geq T_2 \quad \text{(from lemma 1 and 2, } (T_1 + T_2) = \Delta d) \]

\[ \tag*{\Box} \]

Therefore, the user \( u \) can never start using \( S_2 \) with the help of diffusive shift. Since we picked an arbitrary user \( u \), no node in \( G_1 \) can be diffused to the other SNS.

Non-diffusion is generally a less important cascading factor as compared to diffusion [16]. Therefore, from the previous theorem, If \( \epsilon \geq x_2 \), a new SNS will
never be able to uproot the existing SNS. The condition in theorem 1 is very strong, even if $\epsilon$ and $x_2$ are close by, diffusive shift does not propagate for large distances in the network. Since, with time the attachment factor $\epsilon$ increases, it will keep becoming tougher for a newcomer to overtake the current popular SNS. This theorem also gives a lower bound on the novelty that $S_2$ must have ($x_2$) if it wants to have any chance of beating the current favourite SNS.

5 Survey

We consider as a case study, the shift of users from Orkut to Facebook and Facebook to Google Plus. Due to lack of availability of actual data for the cascade, we conducted an online survey asking our participants a plethora of questions. The participants belonged to a wide age group. 189 of these participants were between 17 to 25 years of age. Out of the remaining, 27 belonged to the age group 25-40. A very small fraction of participants were between 13 -17 or more than 40 years old. This has been shown in figure 4. The survey comprised of a wide variety of questions ranging from their reason of shifting to other SNSs to the amount of time they spend on the features of various social networking sites. Other information asked from the participants was:

- the time they spent on different social networking sites
- the features they look for and use on a social networking site
- the sites they currently use and their distribution of time span across these websites
- The reason for their inactivity on Google Plus (Which was observed to be the case with most survey participants)

In total, 222 responses were reported. The survey has been described in detail in the appendix. But, the major observations made from the survey are described below.
97% of the participants used Facebook, 29.7% of them used Twitter (mostly along with Facebook) and 32% of them used Google Plus (mostly along with Facebook). The average time spent on Facebook is 43.8 minutes which is relatively much higher than that spent on Twitter (8.71 minutes) and Google Plus (9.66 minutes). This shows that a majority of the people are bound to use the more popular social networking sites, both in terms of number of users and also the time spent by the users of the site on it. Both these statistics are in favour of our model. The participants were further asked to rate the features of Facebook, Google Plus and Orkut based on the time spent on it: (5) if they spent most of their time on that social networking site using that particular feature and (0) if they don’t use that feature at all. Based on these ratings, we calculated $\phi(f, u^*)$ for each feature $f$, where $u^*$ is a hypothetical user who used all SNSs in the system. Further using these values we developed the feature spaces for both the systems under consideration, as shown in figure 6. Similarly, the values for Orkut and Facebook were calculated. This is displayed in figure 7.

6 Results and Simulations

Using the survey we initially calculated the feature set of Facebook, Google Plus and Orkut, using which we constructed the feature spaces shown in figures 6 and 7. Next, using the SNAP Facebook data set and the information gathered by our survey we try and understand the dynamics of diffusive and non-diffusive shifts on real world graphs. We perform two simulations: 1) initially assume all nodes to be present on Orkut, and then we try and shift nodes to a new SNS Facebook using the model we developed and 2) assume all nodes to be present on Facebook, and then we shift nodes to a new SNS Google Plus. We plot the net cascade of the network to the new SNS as a function of time. We also vary the attachment factor ($\epsilon$) for a better understanding of this parameter. The non-diffusion probability ($p$) is kept as low.
as 0.001, since our major focus is to observe the impact of diffusive shift. The results of this simulation is available in figure 8. It can be observed from the plots that as $\epsilon$ increases, the number of time steps required to completely shift the entire population in the network also increases. This is the proof that increasing $\epsilon$ is an indication of the network being less susceptible to change. Also, it can be observed from the plots that, the transition/cascade from Orkut to Facebook was way faster when compared to the percent cascade from Facebook to Google Plus, this observation can be clearly accounted for by looking at the feature spaces of both the systems. Therefore, we can conclude that the two major factors which
can drive the success of a new SNS is the amount of novelty it possess and the
time at which it was launched (the sooner the better).

The results are shown in the figure 8.

\[ \epsilon = 0.5 \]

\[ \epsilon = 0.3 \]

\[ \epsilon = 0.1 \]

Fig. 8. Shifting behaviour of nodes

7 Conclusion and Future Work

The paper proposes a model to simulate the shifting behaviour of population
across social networking websites. The proposed model provides an insight in
understanding the factors that leads people to shift from one social networking
site to another. The key elements of the model considered are the amount
of novelty in the new website and the attachment factor associated with the pre-
vious website. Although our model is to understand the transition in SNSs, it
can be applied to other scenarios as well. In other transitions, there might not
always exist an explicit graph as in this case of a social networking site.
In this paper, we study the characteristics of a social networking site at a fun-
damental stage, where we define it as a set of features. Further, we study the
different properties and types of features present on SNSs, and discovered that
the features attracting user-time were those that provided users to passively in-
teract. Also, our model only considers the progressive case, wherein a user does
not stop using the new site and return to the first site again. The non-progressive state will be further explored in future work.

Due to lack of experimental data and for the sake of simplicity, we assumed the time span to be constant for all the individuals in the system, which is generally not the case. The model can further be improved by considering the exact distribution of delta across the population. The attachment factor (inertia) that has been left as a blackbox in this paper, is observed to have a direct correlation with time spent on a product over time. There may be some individuals who are relatively new to the SNS compared to others, which implies that the attachment factor varies from individual to individual as well. Most of the SNSs have a plethora of small features, which do not attract a significant chunk of the time span of its users. Their role is vaguely understood, and needs to be explored in future.

Marketing strategies may help in the initial growth of a product's popularity through non-diffusive shift, but the quality of the product is important in making the users stay for longer periods. Also, the marketing strategies must not be too focused on advertising only the new feature being offered. For instance, we discovered that a considerable percentage of participants (14.7%) were not aware of the fact that while using Hangouts, they were indeed using a feature of Google Plus. This may have been the result of emphasizing select features of the site. It appears that the success mantra for a new social networking site is to come up with a lot of new features supporting passive engagement and launch the website in a window of minimum time. The more time it takes to launch, the tougher it becomes to capture people's attention. Don't Wait. Just Do It looks like the most apt and optimal way to increase the odds of an idea becoming successful.

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A APPENDIX

We conducted a survey to determine the amount of time spent by users on different SNSs, the reason for them liking/disliking a particular SNS and their reason for shifting from one SNS to other. The mode used for the survey was a Google Form. The link for the survey is [http://goo.gl/forms/ewa2KG6kGK](http://goo.gl/forms/ewa2KG6kGK). 85% of the survey participants were mostly between 17 to 25 years of age. 12.2% of them belonged to the age group 25-40. And a small fraction 0.9% and 1.8% of them were between 13-17 and more than 40 years old respectively. This has been shown in figure 9.

![Age Group of Survey Participants](image)

Fig. 9. Age group of participants

It was observed that 97% of the participants used Facebook. 29.7% of them used Twitter (mostly along with Facebook) and 32% of them used Google Plus (mostly along with Facebook). This has been shown in figure 10.

![Popularity of Different Social Networking Sites](image)

Fig. 10. Popularity
Previously 63.5% of these individuals used Orkut, while 30.6% of them used none as shown in figure 11. This signifies that most of current Facebook users either used Orkut initially or they joined Facebook directly as their first social networking site. This signals that there was most likely a large cascade from Orkut to Facebook. The users who used Orkut mostly started using Facebook through the concept of Diffusion. And the ones who joined Facebook directly are the ones who either came in through word-of-mouth advertisements or non-diffusion.

![Previously Used Social Networking Sites](image)

**Fig. 11.** Previously used SNSs

62.4% of the participants spent less than an hour on social networking sites (in General) and a very minute fraction of 1.8% used social networking sites for more than 4 hours. This is shown in figure 12. This is a valid explanation for us considering delta as constant for all the users on a SNS. It has been experimentally verified that time spent on SNSs is limited\[18\]. We further enquired the time spent on individual social networking sites and the statistics for them is given in the respective figures.

Next, we give plots for time spent on Facebook, Twitter and Google+ in figures 13, 14 and 15 respectively. Users were asked to rate the feature based on frequency of use, on a scale from 0 to 5. Where 0 implies that they never used that particular feature and 5 meant all her time was on that particular feature of the SNS. This information was further used to calculate the feature space shown in 1 and 2. Which was in turn calculated using the $\phi(f, u^*)$ values for all features $f$, which are depicted in the tables below.

### A.1 Calculations for Facebook

This section describes the calculation of various parameters for the features of the Facebook network. Below are the tables for the number of votes and percentage for the different features of Facebook.
| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 13             | 5.9%       |
| 1      | 20             | 9%         |
| 2      | 44             | 19.8%      |
| 3      | 63             | 28.4%      |
| 4      | 38             | 17.1%      |
| 5      | 44             | 19.8%      |

Table 1. Newsfeed

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 33             | 14.9%      |
| 1      | 63             | 28.4%      |
| 2      | 45             | 20.3%      |
| 3      | 39             | 17.6%      |
| 4      | 24             | 10.8%      |
| 5      | 18             | 8.1%       |

Table 2. Chat

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 174            | 78.4%      |
| 1      | 27             | 12.2%      |
| 2      | 10             | 4.5%       |
| 3      | 5              | 2.3%       |
| 4      | 2              | 0.9%       |
| 5      | 4              | 1.8%       |

Table 3. Games

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 169            | 76.1%      |
| 1      | 27             | 12.2%      |
| 2      | 15             | 6.8%       |
| 3      | 7              | 3.2%       |
| 4      | 2              | 0.9%       |
| 5      | 2              | 0.9%       |

Table 4. Groups

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 121            | 54.5%      |
| 1      | 45             | 20.3%      |
| 2      | 34             | 15.3%      |
| 3      | 12             | 5.4%       |
| 4      | 9              | 4.1%       |
| 5      | 1              | 0.5%       |

Table 5. Pokes

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 73             | 32.9%      |
| 1      | 38             | 17.1%      |
| 2      | 7              | 3.2%       |
| 3      | 60             | 27%        |
| 4      | 30             | 13.5%      |
| 5      | 14             | 6.3%       |

Table 6. Notes

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 63             | 28.4%      |
| 1      | 61             | 27.5%      |
| 2      | 55             | 24.8%      |
| 3      | 22             | 9.9%       |
| 4      | 15             | 6.8%       |
| 5      | 6              | 2.7%       |

Table 7. Check-in places

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 13             | 5.9%       |
| 1      | 20             | 9%         |
| 2      | 44             | 19.8%      |
| 3      | 63             | 28.4%      |
| 4      | 38             | 17.1%      |
| 5      | 44             | 19.8%      |

Table 8. Trending

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 63             | 28.4%      |
| 1      | 61             | 27.5%      |
| 2      | 55             | 24.8%      |
| 3      | 22             | 9.9%       |
| 4      | 15             | 6.8%       |
| 5      | 6              | 2.7%       |

Table 9. Events
We calculate the a value for each feature of Facebook by using the following formula:
\[ \sum_{i=1}^{5} \frac{i \times \text{percentage}(i)}{100} \] where the rating for a feature ranges from 1 to 5 and \( \text{percentage}(i) \) depicts the percentage of users giving the feature a rating \( i \).
It is also possible to normalise these values for individual features by the formula:

\[
\text{normalised value of the feature} = \frac{\text{value of the feature}}{\sum_{\text{features}} \text{value of the feature}}
\]

This table for Facebook is shown in table 10.

| Feature   | Score | Normalised Score for Google Plus | Normalised Score for Orkut |
|-----------|-------|----------------------------------|-----------------------------|
| Newsfeed  | 669   | 0.185                            | 0.092                       |
| Chat      | 456   | 0.126                            | 0.63                        |
| Games     | 90    | 0.025                            | 0.012                       |
| Groups    | 271   | 0.075                            | 0.038                       |
| Pokes     | 74    | 0.020                            | 0.010                       |
| Notes     | 96    | 0.026                            | 0.013                       |
| Places    | 190   | 0.052                            | 0.026                       |
| Trending  | 339   | 0.094                            | 0.047                       |
| Events    | 327   | 0.090                            | 0.045                       |

Table 10. Cumulative table for Facebook

A.2 Calculations for Google Plus

This section describes the calculation of various parameters for the features of the Facebook network. Below are the tables for the number of votes and percentage for the different features of Google Plus.

Similar to what we have done for Facebook, we calculate a score for every feature of Google plus also depicting its importance. This has been shown in the table 17. A similar result for Orkut is also shown in table 18.

To normalizing the scores for simulating the transition from Orkut to Facebook, we take only 50% of the \( \phi(f, u) \) values calculated for Facebooks features \( f \). This change is required because Facebook back then did not have as many
| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 78             | 35.1%      |
| 1      | 24             | 10.8%      |
| 2      | 39             | 17.6%      |
| 3      | 36             | 16.2%      |
| 4      | 13             | 5.9%       |
| 5      | 32             | 14.4%      |

**Table 11.** Hangouts

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 156            | 70.3%      |
| 1      | 30             | 13.5%      |
| 2      | 16             | 7.2%       |
| 3      | 10             | 4.5%       |
| 4      | 4              | 1.8%       |
| 5      | 6              | 2.7%       |

**Table 12.** Stream

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 132            | 59.5%      |
| 1      | 37             | 16.7%      |
| 2      | 33             | 14.9%      |
| 3      | 9              | 4.1%       |
| 4      | 7              | 3.2%       |
| 5      | 4              | 1.8%       |

**Table 13.** Circles

| Rating | Number of Votes | Percentage |
|--------|----------------|------------|
| 0      | 161            | 72.5%      |
| 1      | 23             | 10.4%      |
| 2      | 19             | 8.6%       |
| 3      | 12             | 5.4%       |
| 4      | 4              | 1.8%       |
| 5      | 3              | 1.4%       |

**Table 14.** Communities

| Feature               | Score | Normalised Score |
|-----------------------|-------|------------------|
| Hangouts              | 422   | 0.117            |
| Stream                | 106   | 0.029            |
| Circles               | 187   | 0.051            |
| Communities           | 128   | 0.035            |
| Collections           | 95    | 0.026            |
| Photo editing options | 161   | 0.044            |

**Table 17.** Cumulative table for Google+

| Feature               | Score | Normalised Score |
|-----------------------|-------|------------------|
| Scrapbook             | 196   | 0.100            |
| Communities           | 148   | 0.076            |
| Themes                | 115   | 0.059            |
| Polls                 | 103   | 0.053            |
| Testimonials          | 119   | 0.061            |

**Table 18.** Cumulative table for Orkut
features and the user base it has presently when the survey was conducted. Thus, we make a safe assumption of taking only 50% of the values we calculate.

### A.3 Calculations for feature space values

The common features are: Newsfeed(Stream), Groups(Communities), Explore(Trending), Events. Common Fraction for Facebook is $x_{fb,g+}$: = 0.44 Unique fraction for Facebook $(x_{fb})$ is =0.25. Unique fraction for Google Plus $(x_{g+})$= 0.31. Similarly, we calculated the values for Orkut and Facebook. The Feature Space is described below:

| Facebook Unique Features | Common Features | Google Plus Unique Features |
|-------------------------|-----------------|----------------------------|
| Chat                    | Newsfeed(Stream) | Hangouts                   |
| Check-in Places          | Groups (Communities) | Photo-editing Options     |
| Games                   | Trending         | Circles                    |
| Pokes                   | Events(Events)   | Collections                |
| Notes                   |                 |                            |

Table 19. Feature space for Facebook and Google plus

Common Fraction is $(x_{orkut,fb})$: = 0.076. Unique fraction for Facebook $(x_{fb})$ is =0.651 Unique fraction for Orkut $(x_{orkut})= 0.273$.

Next, we asked them, what was the major cause of their shift from one social networking sites to another. Similarly, the feature space for Facebook and Orkut is shown in table 20

| Orkut Unique Features | Common Features | Facebook Unique Features |
|----------------------|-----------------|--------------------------|
| Scrapbook            | Communities     | Newsfeed                 |
| Themes               | Chat            |                          |
| Polls                | Trending        |                          |
| Testimonials         | Check-in Places, Pokes, Notes, etc. |

Table 20. Feature space for Facebook and Google plus

Common Fraction is $(x_{orkut,fb})$: = 0.076. Unique fraction for Facebook $(x_{fb})$ is =0.651 Unique fraction for Orkut $(x_{orkut})= 0.273$.

### A.4 Reasons for shift and inactivity

The reasons for shifting are shown in figure 16. The reasons for inactivity on Google plus are shown in figure 17. 23.7% of the participants agreed to the fact that there was some sort of attachment to the old site. 52% say that they will
use another social networking site when their friends will start using it. The factors that the participants look for is a combination of Good Content, Good User Interface and never seen before features. It is shown in figure 18. There were a considerable number of users -14.7% who did not know that the never seen before feature of Google Plus: Hangouts was even a part of Google Plus. It is illustrated in figure A.4.
Fig. 18. factors looked upon by participants

Features to look forward to on a new Social Networking Site

Hangouts: A feature of Google Plus?