To Be or not to Be on Social Media: Analysis Using Tragedy of Commons

Madhura Ranade*
ACA; PhD; MBS; MCom; Symbiosis Institute of International Business; Symbiosis International Deemed University; Pune, India;
Email: madhura.ranade@siib.ac.in

Aniruddha Joshi
PhD; MBS; Department of Management Sciences; SP Pune University; Pune, India Email: joshiag@gmail.com

Neha Patvardhan
PhD; MBA; Symbiosis Institute of International Business; Symbiosis International Deemed University; Pune, India;
Email: neha.patvardhan@siib.ac.in

Paritosh Bedekar
BSc; SP Pune University; Pune, India;
Email: paritosh.bedekar@gmail.com

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Abstract: Social media websites like Twitter and Facebook have become a treasure trove of data. Even today, people have not been able to fully comprehend the consequences, both positive and negative, of being on these websites. We have modeled the risks associated with such websites as a function of the population, i.e., the number of accounts present, along the lines of the tragedy of commons. We have tracked the variations between the average Strogartz Watts local clustering coefficient, the variance of Strogartz Watts local clustering coefficient and the global clustering coefficient as the number of accounts in a database increases. Regarding the average local and global clustering coefficient, researchers observed an initial phase of rapid increase followed by a phase of a continuous relatively smaller increase in their values. The variance of the average local clustering coefficient shows an initial phase of significant variation followed by a phase of continuous reduction in its value. Thus, the increase in the population size increases the transitivity of the network, increasing the risk associated with data being leaked via

* Corresponding Author

the website. The purpose of this research study is to simulate the social media connections and identify the application of the concept of 'tragedy of commons' in the social media domain. The researchers have also tried to look at insights obtained from simulations from a network theory perspective. The scope of this research study is to look at the way the connections are made on social media depending on the common interests of the people who use social media platforms. Using network theory, the researchers have tried to find out the connections structures. The researchers have used a simulation approach using a program that was written in C language on a UNIX system. Additional accounts to a hypothetical database were simulated using this program.

Keywords: Tragedy of Commons, Strogartz Watts Local Clustering Coefficient, Global Clustering Coefficient, Nash Equilibrium

Introduction

"The tragedy of the commons is a situation in a shared-resource system where individual users, acting independently according to their self-interest, behave contrary to the common good of all users, by depleting or spoiling that resource through their collective action. The theory originated in an essay written in 1833 by the British economist William Forster Lloyd." (Hardin,1968, p. 1244). An example of the "tragedy of commons" is the exploitation of pastureland by herders. If a herder increased the number of animals he possessed, they get additional profits, but the pastureland would suffer from overgrazing, affecting the whole community. It has been successfully applied in many fields like traffic congestion (Iaione, 2010), exploitation of fisheries (McWhinnie, 2009), exploitation of the atmosphere (O'Gorman, 2010), etc. A potential field in which the tragedy of commons can be used extensively in the virtual world. Several papers and articles have tried to apply it to virtual objects (Nagle, 2018;Xu et al., 2012;O'Gorman, 2012;Amedie, 2015); however, none of them have focused on social media and investigated it in details with regards to global and local actions and their consequences. The essence of the tragedy of commons is that in situations where profits are privatized but the costs are communal, the resource is vulnerable to overexploitation. This can be applied to social media websites as well, wherein the website is the resource and the account users being the players. The benefit of being on the website is privatized since the act of connecting with other accounts is limited to the accounts involved only. However, the risk is shared communally as the addition of accounts results in the overall increase in the data present on the website, resulting in more chances of the website being attacked by agencies looking to gather data. It is important to note that what is profitable from the point of view of an account user may not be profitable when viewed with regards to the database as a whole. Thus, Strogartz-Watts local clustering coefficient is an effective parameter to judge the privatized benefit while the global clustering coefficient can be used to estimate the communal risk (Holland and Lienhart, 1971). Figure 1 describes different types of triads in directed graphs. A directed graph consisting of nodes and edges is considered with the nodes representing the profiles of users and the edges representing the connections between two users. A triad consists of a group of three nodes and all the edges are connected the nodes. There are sixteen different triads possible based on the configuration of the edges between the nodes of the triad. These are illustrated in figure 1 shown below.

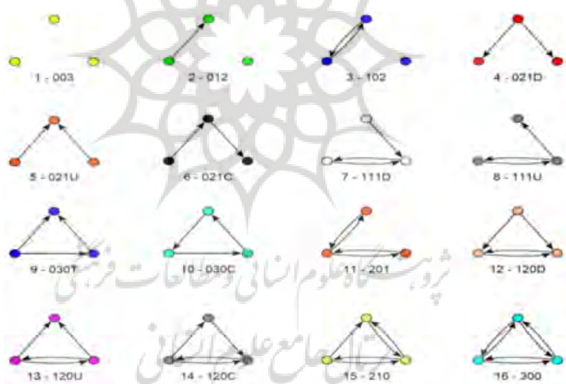

Figure 1: Different types of triads in directed graphs
(Source: Juszczyszyn, Katarzyna & Marcin 2011)

The formulae for the local and global clustering coefficients in directed graphs are-

Strogartz Watts local clustering coefficient Ci = ti / ki (ki -1)

Where ti is the number of triads node i takes part in and ki is the number of edges node i has. Global clustering coefficient C = 3t / ∑ ki (ki -1)

Where t is the total number of triangles triads present in the network and ki is the number of edges node i has.

In traditional formulations of the tragedy of commons, there is a linear relationship between additional costs incurred and population size. Hence, it is always profitable for players to increase their profits as the additional costs will increase linearly and always be shared by the community, thus never manage to catch up to the increase in profits. However, in the case of social media websites, we expect the relationship to be non-linear. Since most linked accounts have some field in common (as people connect virtually with people they know in real life), regions of high transitivity will be formed (Dieckert, 2012). This would result in an efficient data harvest using probability and statistics even if a small region of the database was compromised. Also, traditional formulations consider a herder who can add cows, while here, we consider several agents that can choose to access the resource or not. The traditional formulation does not possess a Nash equilibrium (Estrada, 2015). The interactions between the players can be divided into two types based on the proximity of the users concerned. The payoffs in both cases are-

Table 1. Payoffs for proximal users; y>x, x>0

User 1 / User 2	Being on social media	Not being on social media
Being on social media	(y, y)	(0,x)
Not being on social media	(x,0)	(0,0)

Table 2. Payoffs for distant users; x>0 (Source: Developed by the researcher)

User 1 / User 2	Being on social media	Not being on social media
Being on social media	(x, x)	(0,x)
Not being on social media	(x,0)	(0,0)

Table 1 and 2 explain the payoffs for proximal and distant users, respectively. If the users are proximal, then both will derive an additional benefit by being on the website. Thus, in that case, the payoff will be greater in this case (y>x). Hence, in this case, both being on social media is the Nash equilibrium of this scenario. If the two users are distant, they will not receive any additional benefit if the other individual is using social media. Despite that, the Nash equilibrium of this case would also be being on social media.

We have studied the variations in the average local clustering coefficient, the variance of the average local clustering coefficient and the global clustering coefficient as the population size increases to understand the possibility of this scenario and its application.

Considering the seriousness of social media (Xu et al., 2012) websites and the underlying concept of the tragedy of commons, the researchers have tried to create a simulation model of social media connections. Researchers have also tried to address the application of the concept of 'tragedy of commons' in the social media domain through a simulation approach. The researchers have also tried to look at insights obtained from simulations from a network theory perspective.

Review of Literature

Referring to the literature on the subject, the researcher has found a few papers which talk about the theory of the tragedy of commons and its applications (O'Gorman, 2012). Even though the theory on "Tragedy of Commons" was initiated by William Forster Lloyd in 1833, it was further extended by G. Hardin (1998). In his article on the "Extensions of the Tragedy of Commons," Gerrett Hardin threw light on the consequences of individual freedom on resources and society. Individual freedom is limited by the number of resources available. The problem of the tragedy of commons goes beyond the conceptual sphere of fields of biology, economics and philosophy; and, there is the need to have a holistic approach towards finding a solution to this problem.

This theory can be applied when the resource under consideration is digital. The expansion of digital commons has affected various fields like law, sociology, commerce and medicine. Few papers talk about the opportunities created by the digital commons and how it has allowed members of the underprivileged communities to access facilities that may have been otherwise inaccessible for them. The paper calls for better regulation and policing of the digital commons to ensure that this resource is used for the benefit of humankind.

As the sociology field is also impacted, social media needs to be assessed from this perspective (Nagle, 2018). Overexploitation of resources can be controlled by government restrictions and regulations. The problem in the depletion of resources lies in the natural selection of resources by any person at an individual level without considering sustainability (Jouni, 2011). The theory of "Tragedy of Commons is also applicable to the security aspects of the internet. An individual's role in the process of spamming and hacking is very complex. Ultimately an individual will involuntarily end up contributing to the hacking and spamming via possessing compromised machines. A research paper was written on "Reconceptualizing the role of security user," which states the security guidelines for an individual, which can help the users to restrain the hackers (Liaropoulos, 2016). "Markov Perfect Equilibrium (MPE) strategies" are always sub-optimal and lead to the creation of tragedy.

A paper on "Depleted Trust in the Cyber Commons" has analyzed the problems in regulating the digital commons, especially when there are two or more governments concerned. It states the role played by various governments to create a global framework to regulate this resource. It applies the tragedy of Commons to the digital resource, considering organizations as agents and identifies the creation and evolution of the tragedy. It also considers the variations in the tragedy with various aspects of the digital commons like the size of the resource. The tragedy of Commons has different effects when it is applied to physical and digital resources. "Theory of Tragedy of commons" can deal with the legal and intellectual complications that arise in cases of digital commons like the internet.

A paper on "The Commons.... and Digital Planetary" has analyzed the differences in the tragedy of commons when applied to physical resources and digital resources. It also deals with the legal and intellectual complications that arise in cases of digital commons like the internet (Elias and Moraru 2015). Hence so far, the theory of Tragedy of Commons is used in various fields like environment, wildlife, nature, ecology, water conservation, biology etc. There are various research papers available where the above theory was applied and the effects were analyzed in the respective fields.

Methodology

A program was written in C language on a UNIX system. Additional accounts to a hypothetical database were simulated using this program. Each account had three fields (geographical, intellectual, and social) associated with it which were generated at random. A representation of the accounts is provided in table 3.

Table 3: Sample representation of accounts
(Source: Developed by the researcher)

Account Number	Field A	Field B	Field C
1	8	4	2
2	5	6	1
3	8	7	9

Account number one has a triplet (8,4,2) that represents the entries in the three fields for this account. Every account has a unique triplet associated with it.

The first field represented geographical proximity as having the same workplace or being from the same school. The second field represented having common interests and similar likes and dislikes. The third field represented proximity due to familial relations. Social media like Facebook (figure 2) possess features like entering one's school, residence, workplace, etc., allowing geographical proximity to be known. The pages that are liked by the user can reveal the interests of the user. The third field can be identified by filtering investigating accounts that possess similar names and cross-referencing them with fields that describe addresses and other such parameters. The more similar values in the fields, the greater the probability of the accounts forming a connection.

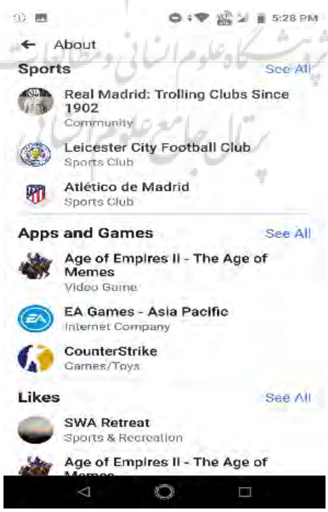

Image 1. Fields present on Facebook

Image 1 shows a screenshot from the Facebook account for the fields of interest.

We varied two factors during the simulation, the number of accounts that were added to the database and the ratio of possible entries in the field to the number of total accounts being added. Variations in average local clustering coefficient, the variance of local clustering coefficient, and global clustering coefficient were tracked as accounts were added to the database.

Results and Discussion:

The table illustrates the quantities plotted in the graphs. The number of accounts added to the database was varied in Figures 1 A, 1 B, 1 C, 2 A, 2 B, 2 C, 3 A, 3 B and 3 C while keeping the number of accounts to a range of field values ratio constant (1: 10). The range of field values was varied in Figures 1 D, 1 E, 1 F, 2 D, 2 E, 2 F, 3 D, 3 E and 3 F while keeping the number of accounts added to the database constant.

Table 4. Simulation Results; Source: Developed by the researcher

Figure	Quantity considered	Number of accounts simulated	Range of field values
1 A	Local clustering coefficient	50	1 to 5
1 B	Local clustering coefficient	100	1 to 10
1 C	Local clustering coefficient	150	1 to 15
1 D	Local clustering coefficient	100	1 to 10
1 E	Local clustering coefficient	100	1 to 20
1 F	Local clustering coefficient	100	1 to 50
2 A	The variance of local clustering coefficient	50	1 to 5
2 B	The variance of local clustering coefficient	100	1 to 10
2 C	The variance of local clustering coefficient	150	1 to 15
2 D	Variance of local clustering coefficient	100	1 to 10
2 E	Variance of local clustering coefficient	100	1 to 20
2 F	Variance of local clustering coefficient	100	1 to 50

Figure	Quantity considered	Number of accounts simulated	Range of field values
3 A	Global clustering coefficient	50	1 to 5
3 B	Global clustering coefficient	100	1 to 10
3 C	Global clustering coefficient	150	1 to 15
3 D	Global clustering coefficient	100	1 to 10
3 E	Global clustering coefficient	100	1 to 20
3 F	Global clustering coefficient	100	1 to 50

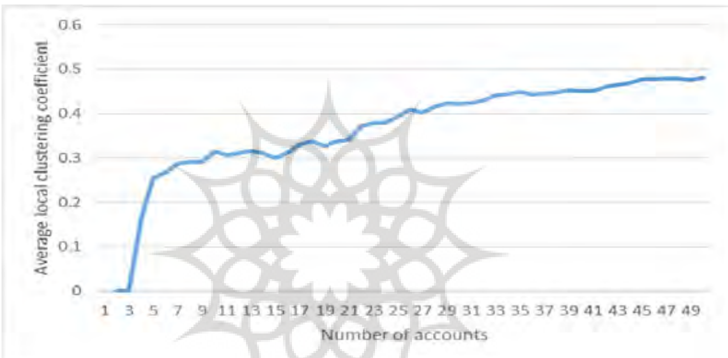

Figure 1A. (Local clustering coefficient with 50 accounts and the range of field values is 1 to 5 Source: Simulated by the researcher)

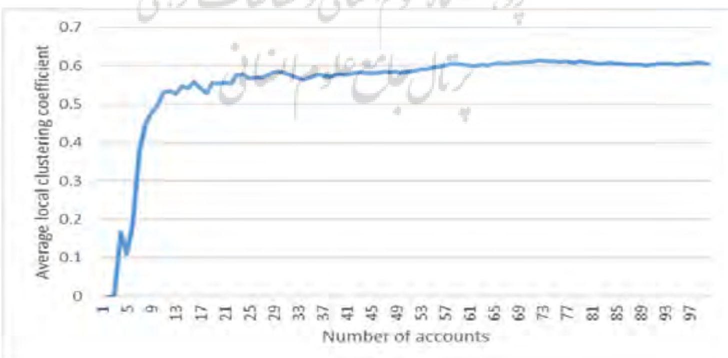

Figure 1B. (Local clustering coefficient with 100 accounts and the range of field values is 1 to 10 Source: Simulated by the researcher)

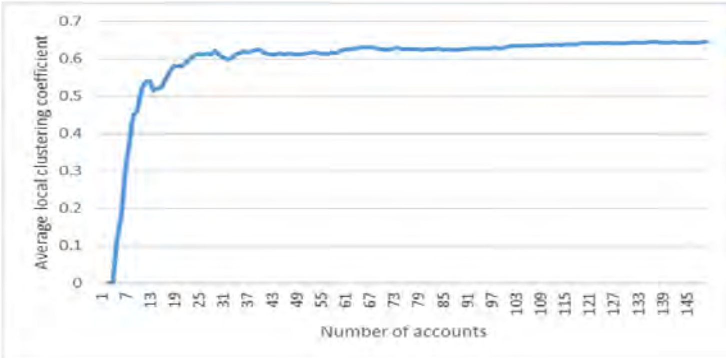

Figure 1C. (Local clustering coefficient with 150 accounts and the range of field values is 1 to 15 Source: Simulated by the researcher)

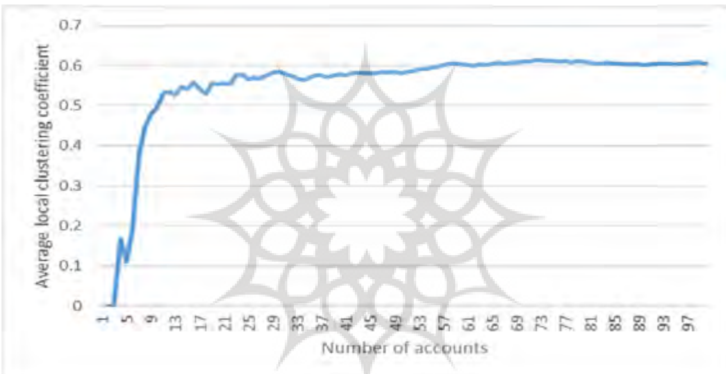

Figure 1D. (Local clustering coefficient with 100 accounts and the range of field values is 1 to 10. Keeping the number of accounts fixed and varying the number of fields Source: Simulated by the researcher)

Figure 1E. (Local clustering coefficient with 100 accounts and the range of field values is 1 to 20. Keeping the number of accounts fixed and varying the number of fields Source: Simulated by the researcher)

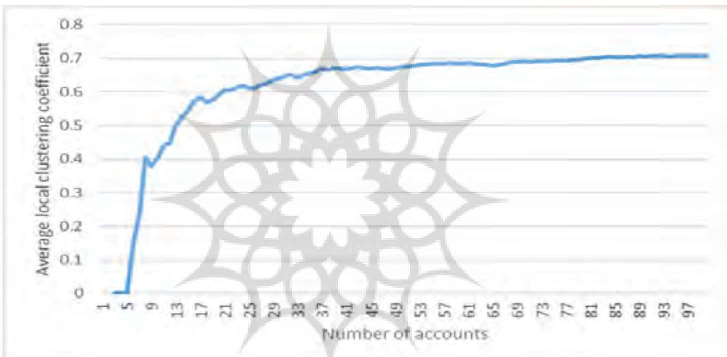

Figure 1F. (Local clustering coefficient with 100 accounts and the range of field values is 1 to 50. Keeping the number of accounts fixed and varying the number of fields Source: Simulated by the researcher)

During the initial stages, there is a sharp increase in the values followed by a stage of relatively moderate but continuous increase (Figure 3: A, B, C and Figure 4: A, B, C). In the initial stages, the addition of each account leads to the addition of new information to the database. This happens as new accounts bring new profiles that are not shared with any account already present in the database. Thus, local clustering is low (reflected by the values in the graph (Figure 3: A, B, C and Figure 4: A, B, C), and the formation of a connection in between has a significant impact on the average local clustering coefficient. Eventually, there comes the point when the addition of new accounts doesn't result in the addition of new information to the database since new accounts do not possess information that is unique to them.

At this point, local clustering is fairly high, and thus, the formation of connections does not have a significant impact on the average clustering coefficient. Hence, there is a continuous but moderate increase in the value of the average local clustering coefficient. Since new accounts will always join an existing local cluster and not form a new one beyond this stage, as the number of accounts tends to infinity, the value of the average local clustering coefficient will tend to one. When the field-toaccount ratio is kept constant, increasing the number of accounts results in a higher value of the average local clustering coefficient. Also, the length of the initial stage (of rapid increase) is observed to be proportional to the number of accounts being added to the database while the increase of the average local clustering coefficient during the next stage is inversely proportional to the number of accounts (Figure 3: A, B, C and Figure 4: A, B, C). This can be explained by the fact that if the field-to account ratio is kept constant, the number of accounts sharing the same fields is proportional to the total number of accounts being added. Thus, when the number of accounts is low, each account has a more pronounced impact on local clustering (since there is a smaller number of accounts sharing the same field present in the database) during the moderate stage. The initial stage is reduced due to the fact that there are fewer accounts per cluster, thus reducing the time required to fill up the cluster. Varying the field to account ratio increases local clustering due to the presence of more local clusters but does not have a pronounced effect on the time period of the initial stage.

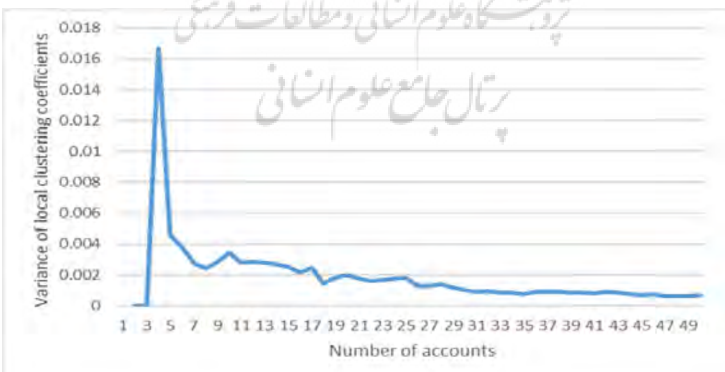

Figure 2A. (variance of Local clustering coefficient with 50 accounts and the range of field values is 1 to 5 Source: Simulated by the researcher)

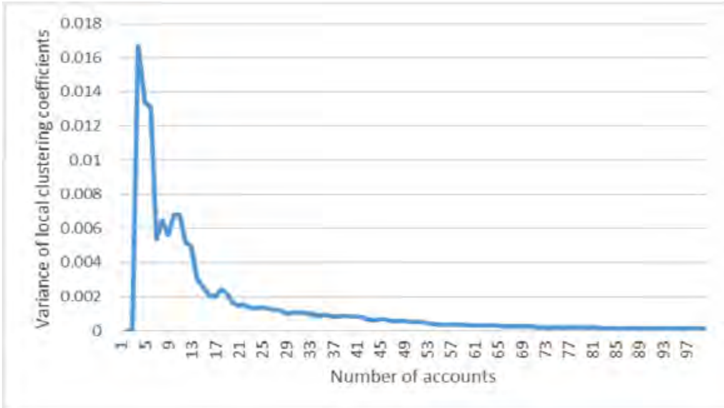

Figure 2B. (Variance of Local clustering coefficient with 100 accounts and the range of field values is 1 to 10 Source: Simulated by the researcher)

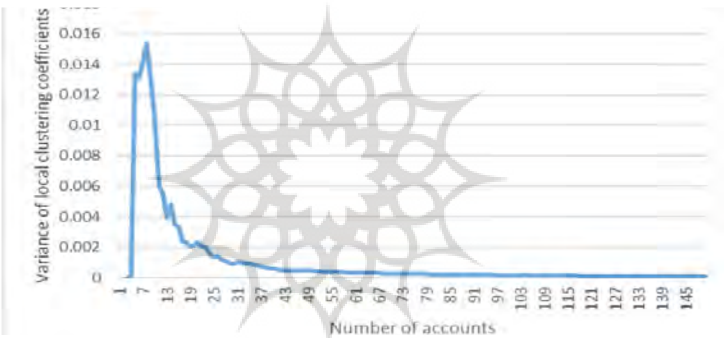

Figure 2C. (Variance of Local clustering coefficient with 150 accounts and the range of field values is 1 to 15 Source: Simulated by the researcher)

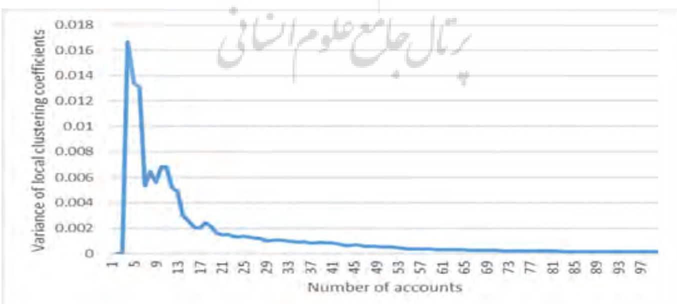

Figure 2D. (variance of Local clustering coefficient with 100 accounts and the range of field values is 1 to 10. Keeping the number of accounts fixed and varying the number of fields Source: Simulated by the researcher)

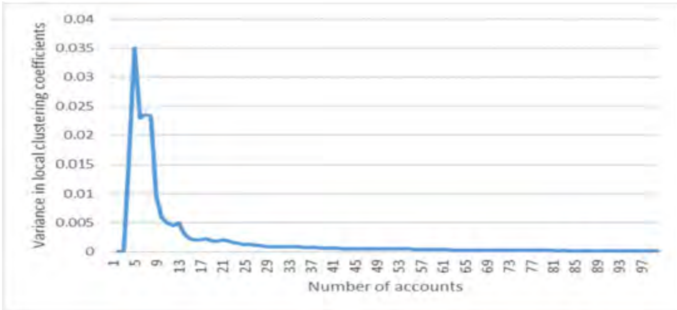

Figure 2E. (variance of Local clustering coefficient with 100 accounts and the range of field values is 1 to 20. Keeping the number of accounts fixed and varying the number of fields Source: Simulated by the researcher)

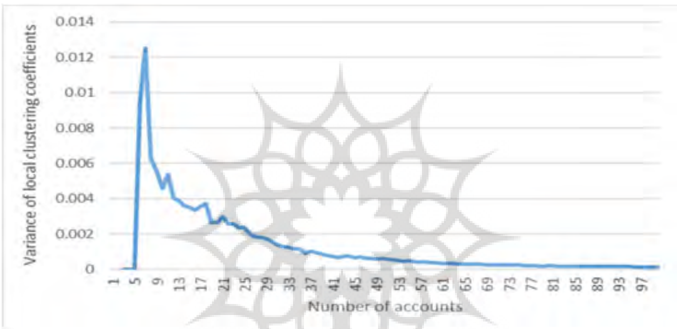

Figure 2F. (variance of Local clustering coefficient with 100 accounts and the range of field values is 1 to 50. Keeping the number of accounts fixed and varying the number of fields Source: Simulated by the researcher)

As mentioned earlier, during the initial stages, the variance of the clustering coefficient is high due to the nature of the network at that point. The addition of a new account result in a significant change to the database and thus has a huge impact on the variance of the local clustering coefficient (Figure 5: A, B, C and Figure 6: A, B, C). The increase in the population of the database is perfectly represented by the harmonic series. The harmonic series is given by-

1 + ½ + 1/3 + ¼ + 1/5 + 1/6………..

The addition of the first account results in the addition of some data to an empty database (+1). The addition of the second account increases the data present in the database by 2; thus, half of the total is contributed by the second account, one-third by the third account and so on, thus forming a harmonic series.

The initial additions cause a much larger fluctuation due to the small size of the database at that point, while the later additions can be compared to the addition of drops to an ocean. This is evident from the graph as the variance is continuously reducing after the initial stage is over. Changes in the parameters do not seem to have a significant impact except in the case of the field-to-account ratio 2:10, in which the peak variance is significantly higher than that seen in all other graphs.

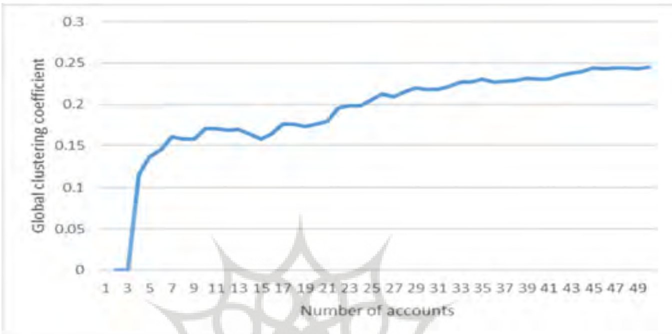

Figure 3A. (Global clustering coefficient with 50 accounts and the range of field values is 1 to 5 Source: Simulated by the researcher)

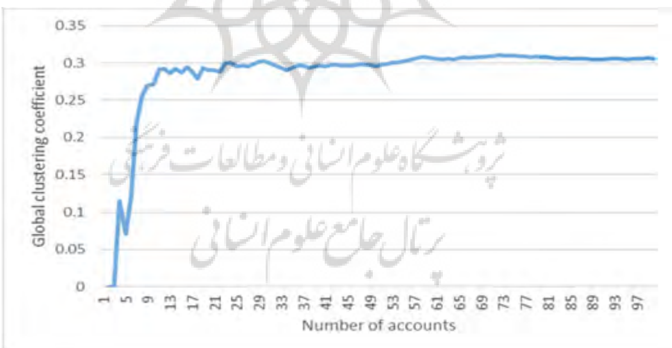

Figure 3B. (Global clustering coefficient with 100 accounts and the range of field values is 1 to 10 Source: Simulated by the researcher)

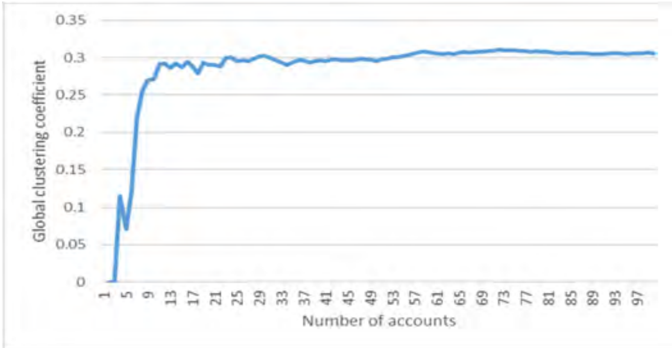

Figure 3C. (Global clustering coefficient with 150 accounts and the range of field values is 1 to 15 Source: Simulated by the researcher)

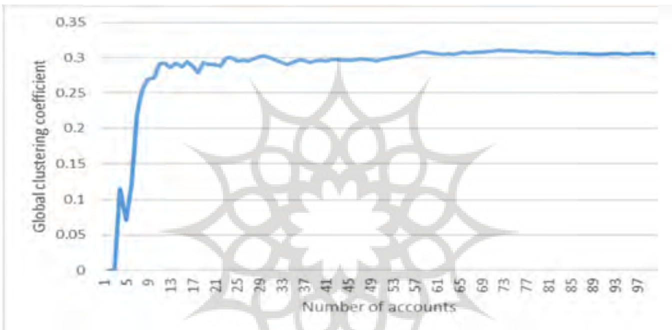

Figure3D. (Global clustering coefficient with 100 accounts and the range of field values is 1 to 10 keeping the number of accounts fixed and varying the number of fields. Source: Simulated by the researcher)

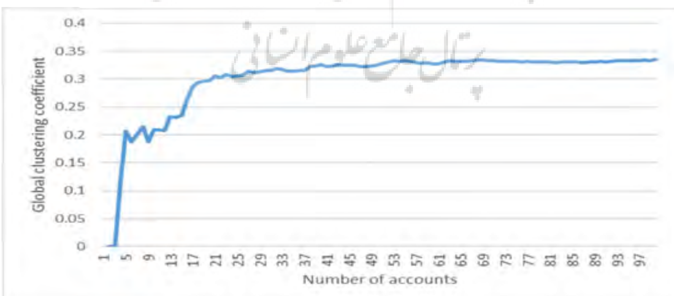

Figure3E. (Global clustering coefficient with 100 accounts and the range of field values is 1 to 20 keeping the number of accounts fixed and varying the number of fields. Source: Simulated by the researcher)

Figure 3F. (Global clustering coefficient with 100 accounts and the range of field values is 1 to 50, keeping the number of accounts fixed and varying the number of fields. Source: Simulated by the researcher)

The trend evident in the graph of average local clustering coefficient is also seen in this graph, albeit with comparatively smaller values (Figure 7: A, B, C and Figure 8: A, B, C). When the addition of new accounts means the addition of new information to the database, the global clustering coefficient shows a sharp increase. Beyond this stage, a continuous, relatively smaller increase is observed. As in the case of the local clustering coefficient, as the number of accounts tends to infinity, the global clustering coefficient will tend to one, provided no new information is added to the database. The trends observed by varying the parameters in the case of the average local clustering coefficient are also observed here. The same explanation is sufficient to understand the reason behind the occurrence of these changes.

No divergence between the average local clustering coefficient and the global clustering coefficient is observed. Thus, structures like the windmill, which result in an increase in local clustering but reduce global clustering, are completely absent or minimal at best in the simulation (Estrada, 2015). Thus, the increase in local clustering, which is beneficial to the individual users, also results in an increase in global clustering. This also increases the transitivity of the network, which is detrimental as it increases the chances of an efficient data harvest by reducing the number of accounts needed to gain complete information possessed by the database. A representation of the phenomenon is given by the figures below. Each circle represents the information shared by the user while signing up for a social media site. The radius of the circle is directly proportional to the amount of information shared by the user. Red areas represent overlapping information, i.e., the information that is contributed by multiple sources.

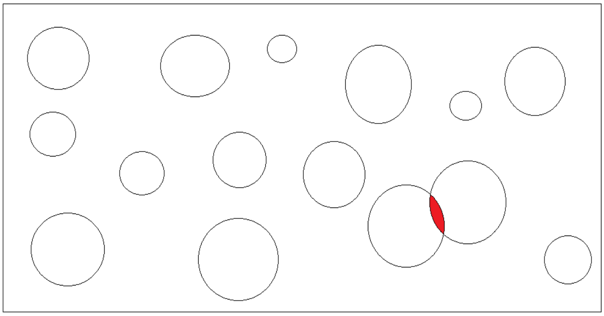

Image 2. A network with low local clustering and low global clustering (Standard Representation)

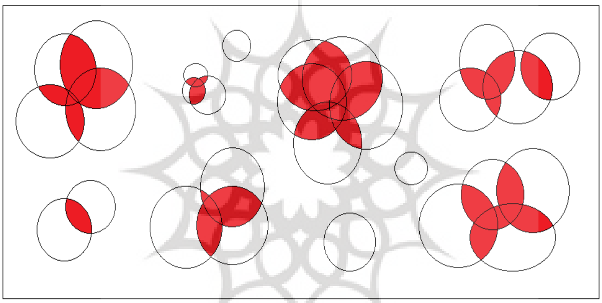

Image 3. network with high local clustering and low global clustering (Source: Developed by the researcher) (Standard Representation)

Figure 4 A network with high local clustering and low global clustering (Source: Developed by the researcher) (Standard Representation)

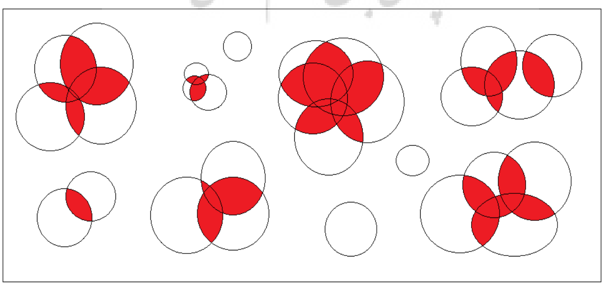

Image 4. A network with low local clustering and high global clustering (Standard Representation)

In situations where the local clustering and global clustering are low, a significant amount of information is exclusive to the user contributing it (less red areas). As local and global clustering increases, the exclusivity of information on the database is lost, and the transitivity of the network increases (more red areas). This loss of exclusivity coupled with the increase in transitivity means that users lose control over the information they have contributed since the same information can be derived from other sources. This results in an increase in the risk faced by the users as the security of their information are dependent on factors beyond their control in cases of high local and/or global clustering. Thus, it is imperative to realize that while digital commons is not limited by carrying capacity, it is limited by the fact that the real world has a finite nature.

It is important to note that the increase in transitivity and local clustering is dependent on in which stage account addition is taking place. When new information is being added to the database, there is a sharp increase in the values of the coefficients. However, the information present in the database is not comprehensive. When the addition of new accounts does not result in the addition of new information to the database, the increase in the values is moderate and continuous, but the information present on the database is comprehensive.

Table 5. Payoffs for proximal users, considering the risk involved; y>x, x>0, r>0 (Source: Developed by the researcher)

User 1 / User 2	Being on social media	Not being on social media
Being on social media	(y-cr, y-cr)	(0,x-r)
Not being on social media	(x-r,0)	(0,0)

Table 6. Payoffs for distant users, considering the risk involved; r>0, x>0 (Source: Developed by the researcher)

User 1 / User 2	Being on social media	Not being on social media
Being on social media	(x-r, x-r)	(0,x-r)
Not being on social media	(x-r,0)	(0,0)

Since the increase in the risk of personal data being shared depends on the number of proximal users, the total risk can be considered to be proportional to the summation of the number of proximal users. Thus the Nash equilibrium, in this case, would depend on the values of c, r and x [9]. This feature is a characteristic of the population and thus would vary according to the number of accounts present in the database. However, these changes take place on a globular scale, and it may not be possible to feel its effects at a local level. Studying the relationship between local and global parameters in the case of social media is an interesting avenue. The essence of the problem lies in the fact that the tragedy originates due to the presence of natural selection, which operates at an individual level (Kay, 1997). Thus, it is difficult to motivate the population to voluntarily take action. Rules and regulations defined by the creators of social media or the government and made mandatory for all users seem to be the only way in which the tragedy can be avoided

Hence, it is important to identify the state of the database with respect to the completeness of the knowledge present in the database and transitivity to understand the risks associated with being on the database so that we could be able to counter any threats that may arise. It would also allow the user to better understand the impact social media may have on their lives in terms of the security of private data and allow users to take action to protect their interests (Camp, 2011). Analysis using real datasets would be able to provide a better and more refined model which can be used to increase the cybersecurity of worldwide databases.

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Madhura Ranade

Dr. CA Madhura Ranade is a Chartered Accountant. She has completed her PhD from PUMBA Pune University in Computer Management. She is MCom, PGDBM, MMS, SET and NET. She is currently working as Assistant professor in Symbiosis Institute of International Business, Symbiosis International University. Her area for research interest is economics, Auditing, Financial Analysis. Her research papers include, Future of Virtual Currency in Indian Context, Sustainable financial systems and growth- An enquiry into digitization, The Analytical Study Of Steel Sector Using Altman's Z-Score Method, Sustainable financial systems and growth - An enquiry into digitization.

Aniruddha Joshi

Dr. Aniruddha Joshi, PhD, MMS, MSc, ISO lead auditor. Author is an associate professor at Department of Management Sciences, SP Pune University. He has patents in the area 'Managed Security Services' years: He is working as Sr. Scientist on behavioral studies of snakes as part of Ophiology and a member of Indian Herpetological Society. This activity includes rescuing the snakes and rehabilitating them in appropriate environment. His projects include "Onsite Security Management for 1 year for "Telecom Regulatory Authority of India (TRAI)", New Delhi, Project on Data Analytics for Persistent systems,

Project of technology consultancy to National Credit Guarantee Trusty Company Ltd. (NCGTC) Ministry of Finance, Project on Data Center and Network Design for Shivaji University, Kolhapur, Maharashtra. His research papers cover various areas like, Framework for Issuing, Using, and Validating Identification Documents, Economic and Political Weekly, Use of big data and social media analytics in counter terrorism, Effectiveness of Animal conservation projects using Tools of Information Tech: Indian perspective, Future of Virtual Currency in Indian Context, Possibilities and problems of using autonomic computing in the educational institute's applications and networks.

Neha Patvardhan

Dr. Neha Patvardhan is currently serving as an Assistant Professor in the department of Finance at Symbiosis Institute of International Business, SIDU Pune She has been awarded a Ph.D. degree in the board of management and is also NET qualified. She has received master's degree in management studies (MMS Finance) and has graduated with a Bachelor degree in the field of Pharmacy. To her academic accomplishments include diverse teaching experience of 8+ years in both national and international universities. Her research interests span both corporate financing and Psychological and behavioral aspects related to visually challenged and catering their accessibility requirements. Few Publications-"The analytical study of steel seethe analytical study of steel sector using Altman Z score method (JETIR June 2018) "The Best Way to Improve the Performance of Credit Risk Analytics Model is not to Look for Fancy Tools or Techniques but to Improve Data Quality First"(IJETMAS, July 2017) "Educational outreach: critically important for the beneficiaries to understand the pros and cons of PPP projects"(with special reference to NMC), (IJAR, April 2017) "Green Banking: Management Innovation in India For Sustainable Development"(November 2016) "Public Private Partnership (Ppp) Projects: Reducing Financial Burden And Achieving Sustainable Development (With Special Reference To Nmc)" (IJME, June 2016) "Public Private Partnership (Ppp) Projects: Reducing Financial Burden And Achieving Rapid Infrastructure Development (With Special Reference To Nmc)" (IJMAR, June 2015).

Paritosh Bedekar

Mr. Paritosh Bedekar is a budding biologist who's keen on researching evolution. Paritosh completed his Bachelor's degree in science from Modern College, Pune studying the discipline of biosciences. He is currently pursuing a Master's degree at the University of Melbourne. His research project involves studying the role of temperature in evolution of specialized castes in ants.