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USING SNA VISUALIZATIONS TO DEPICT SUSPICIOUS SOCIAL MEDIA USERS: A FORAGE FOR LAW ENFORCERS

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ABSTRACT: The evident increase in the sophistication of cyber criminals has a significant impact that can threaten the national security if it goes unabated. Presently, use of social media in mining crucial digital or forensic evidence by law enforcement bodies in Kenya is a novel idea that needs to be explored and implemented. The study's objective was to demonstrate how Social Network Analysis (SNA) can be used as an investigative tool to mine, analyse data from selected online social media users and present digital forensic evidence to aid law enforcement in Kenya. Particularly, the study aimed at identifying high degree nodes in the network and profiling them using visualizations. NodeXL software was used to mine and analyse data. Computation of centrality measures, network clusters, cliques were presented using both infographic visualizations and centrality metrics of the respondents on egocentric networks focal communication paths through which information flows in the network were also depicted. The discoveries of this study indicated that Social Network Analysis is an essential and supplementary tool that can be employed by law enforcement agencies and related stakeholders to mine, analyse and present court accepted digital forensic evidence. The findings presented in this research illustrates how social network analysis can be used to determine the interpersonal connections, importance of actors in a given social network and detect communities of people and principally how law enforcement agencies can utilize this technique in identifying and tracking suspicious characters and ultimately help in maintaining law and order. SNA ought to be embraced as a supplement of conventional investigation, not necessarily replacing it.

KEYWORDS: *Social Media, visualizations Social Network Analysis, actor(s), node(s)*

Background of the study

Social network analysis regards social interactions from the perspective of network theory comprising of nodes and links (also called ties, edges, or connections). Nodes in this case are the persons within the social networks, whereas the ties are the associations between these persons. The resultant graphical structures are mostly quite intricate(Passmore, 2011)

The increasing availability of large-scale, real-world sociographic data derived from social media, web pages and datasets has led, among other things, to a renaissance of Social Network Analysis and its

application in new fields of enquiry. Social network analysis allows one to measure, map and explain everything pertaining social network and its elements (Gupta & Brooks, 2015).

According to a report by PewResearch Center (2014), social media include the various ways and means people hook with one another through online interactions. Mobile devices, social networks, email, texting, micro-blogging and location sharing are just a few of the many ways people engage in computer-mediated collective action. As people connect, like, follow, friend, reply, retweet, comment, tag, rate, review, edit, update, and text one another they form collections of connections. These set of connections develops into network formations that can be mined, investigated and the results depicted using various ways and techniques. The result can give a new understanding of into the structure, size, and key positions in these networks.

Latent Social Security Information

Nouh and Nurse (2015) corroborated these findings by observing that not only does social media platforms provide a new unexploited fountain of mining intelligence for law enforcement community, but it also gives an insight of understanding behavioural patterns of covert groups.

According to Global Justice Initiative report (2013), various social network platforms are progressively exploited to initiate or carry out unlawful acts and therefore law enforcement agencies ought to comprehend the idea and purpose of these platforms. They also need to understand the way social media forensic apparatus and resources can be used to thwart, lessen, act in response to, and probe illegal actions. Although the advent of social media has created new investigatory opportunities for law enforcement, it also presents ethical, legal, and technical challenges. Depending on the country in which the investigation takes place, it may be illegal to gather information on social media if a user's profile is not public (Rice & Parkin, 2016).

Social Network analysis in law enforcement

In his quest to find out how law enforcers utilize social media platforms to covertly examine unlawful movements, Wyllie (2015) established that law enforcement agencies are employing the use of popular social media platforms such as Facebook and Twitter in various ways to assist in combating offences and give services to their societies. More significantly is the fast growing application of social media investigating means to uncover evidence of criminal activity which the lawless individuals on their own volition frequently place to the online network habitually paving way for swift apprehension of themselves and impending likely sentence. Detectives can use social media platforms as an investigative tool by creating undercover pseudo accounts in order to use to harvest intelligence on crimes and suspects or get the identity and movements of suspects (Murphy & Fontecilla, 2013).

Statement of the Problem

This paper revolved around an ego. The egocentric analysis entails the examination of a single node within a given social network platform including all the actors the node is linked to. Social theorist postulates that influence between social network friends goes up to three degrees or three intermediary levels. In criminology and law enforcement, Social network analysis has been proved to be a powerful tool to learn the structure of a criminal network notably in social media platforms. It allows researchers to understand the structural relevance of single actor and his/her connections amongst members of a given social network by defining the key concepts to characterize network structure and roles.

Purpose of the Study

To perform experiments on real life social networks available in commonly used types of popular social services such as Facebook and Twitter in quest to demonstrate how Social Network Analysis as an invaluable tool can be employed to extract latent knowledge or information from networks encountered in nature, especially networks formed by people.

Specific Objective of the Study

The objective of the paper was to visualize social networks and clusters to uncover the patterns of the social relationships of people in investigating crimes committed over selected popular social media platforms in Kenya.

Research Design and Methodology

Social Network Analysis experimental research design was employed in this study. Initially, selected respondents treated as focus groups were subjected to a brief interview and thereafter persuaded to create pseudo-online accounts in specified social media platforms which were used to perform online mining of the selected respondents to obtain data that ultimately aided in social network analysis.

Discussion and Evaluation

From the initial seed of 94 respondents selected for the study, the social network expanded exponentially to 29295 over the three months of study.

Unearthing Key Social Network Actors Using Visualizations and Clusters

NodeXL was employed by the researcher in the analysis to visualize and identify subgroups (clusters), generate set of graph metrics using various actors' interactions using either force directed algorithms such as Harel- Koren fast multiscale or Fruchterman –Reingold or using geometrical algorithms such as spiral, vertical, grid, horizontal or circle. Therefore, social networks was depicted differently over time due to structural changes as a result of increase or decrease of network membership

In essence, ties between actors was analysed and visualized using various social network analysis metrics.

The researcher employed the use of visualization and clusters so as to aid in focusing and identifying individual nodes that exhibit important network properties to the rest of the network. Use of network visualizations is crucial because it reveals patterns that are otherwise invisible by other means of analysis or investigations of a network setup.

Egocentric Seed Network

Figure 1 depicts the egocentric network of the seed actor whose pseudo-name was "samsonpeter9252" (*this name has been by truncated as "sams~"in this study*) is visualized and positioned at the epicentre of the social network. The seed actor's initial connections to the selected respondents are illustrated by the arrows pointing outwards and inwards the main or seed node. Hence it is a directed graph. The graph's vertices were grouped by cluster using the Clauset-Newman-Moore cluster algorithm while the graph was laid out using the Harel-Koren Fast Multiscale layout algorithm. The findings illustrates that at a 1-degree egocentric network comprising of the initial 55 seed correspondences out of the targeted study sample size of 94.

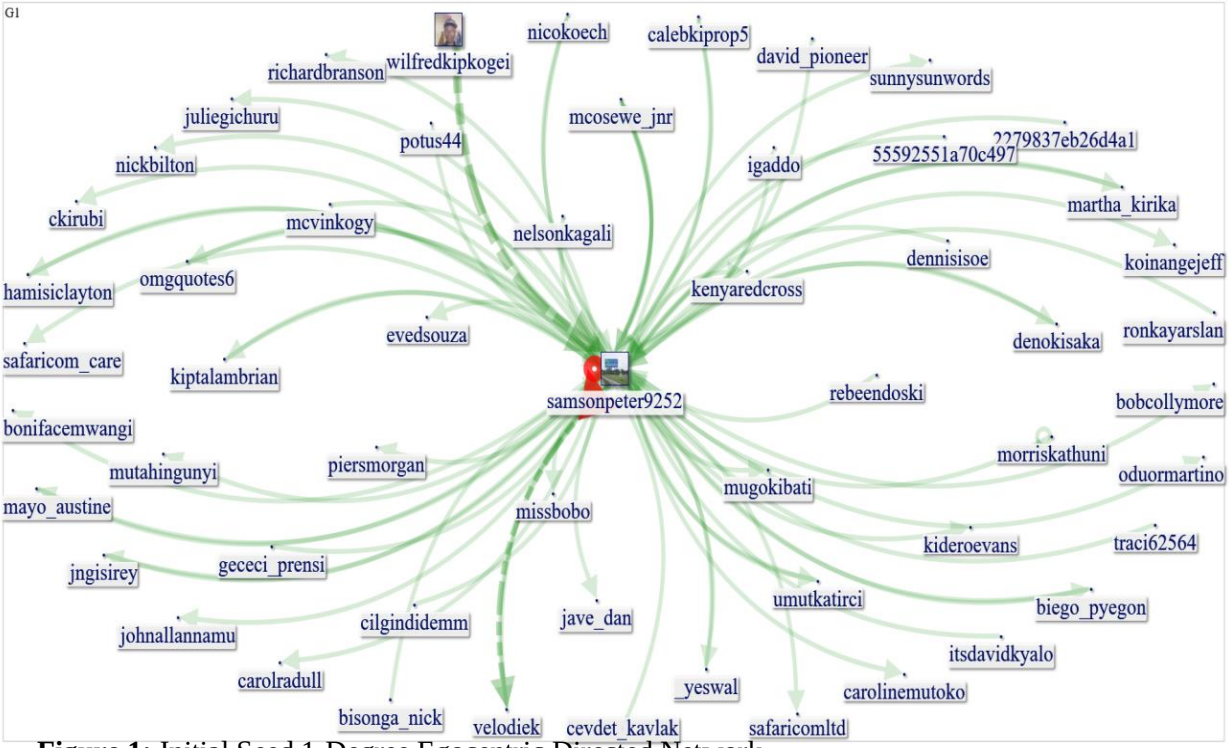

Figure 1: Initial Seed 1-Degree Egocentric Directed Network

Source: *Researcher*

Identifying Communities

The visualizations result in Figure 2 shows how respondents have regrouped themselves into three distinct communities (labelled C1, C2 and C3). This is an important findings which was achieved by employing the force directed algorithm in the visualization so that the connected actors draw to every other while non-connected actors are separated. This means that the highly linked actors are drawn towards the epicentre of the graph. Evidentially, the findings clearly portrays that in the three communities detected, there is one main influential node in each community. Their pseudo-names are velo~(*velodiek*), wilf~(*wilfredkipkos)* and deno~(*denokisaka*). The results are closely related to study done by Staudt, Marrakchi and Meyerhenke (2014) on detecting communities. In each community, the primary distributors of information were identified. In conformity, Yang, Liu and Sageman (2006) underscores that identifying groups such as this assists a detective to quickly unearth the associated criminals when a small number of suspicious characters are known.

Markedly, in these aforementioned detected communities, respondent velo~ has the highest degree centrality, followed by respondents wilf~ and deno~ in that order. This means that the three actors are not only powerful in the network, but it also shows that have great access to information in their respective communities. These findings are in conformity with that of Wu, Carleton and Davies (2014) which advises that in a terror network, investigators usually go for actors with the highest degree centrality scores because they are the most connected and possibly the most influential nodes in the entire network and that one can easily identify a subgroup of a network communities that particular nodes belongs to by visually assessing the links amongst network actors. In a rejoinder, Perliger and Pedahzur (2011) stressed that discovering the communities enables the investigators to identify the various roles of the nodes in the network such as leadership or brokers and how information flows in the entire network.

Besides examining the roles of several members of the network, investigators ought to concentrate on specific subgroups in order tell their particular duty. Usually, network members come together with an obligation of accomplishing their heinous acts and therefore identifying the subgroups who are interconnected could enhance the chance of detectives comprehending the intention of the entire network. In an investigation scenario, the objective of identifying communities in a suspicious network is to detect their groups and social structures they belong. In Faustand Fitzhugh (2012) Social Network Analysis techniques helps to comprehend network communities by mapping the relations that link them as a network and thereafter determine key players or groups and ties between the nodes.

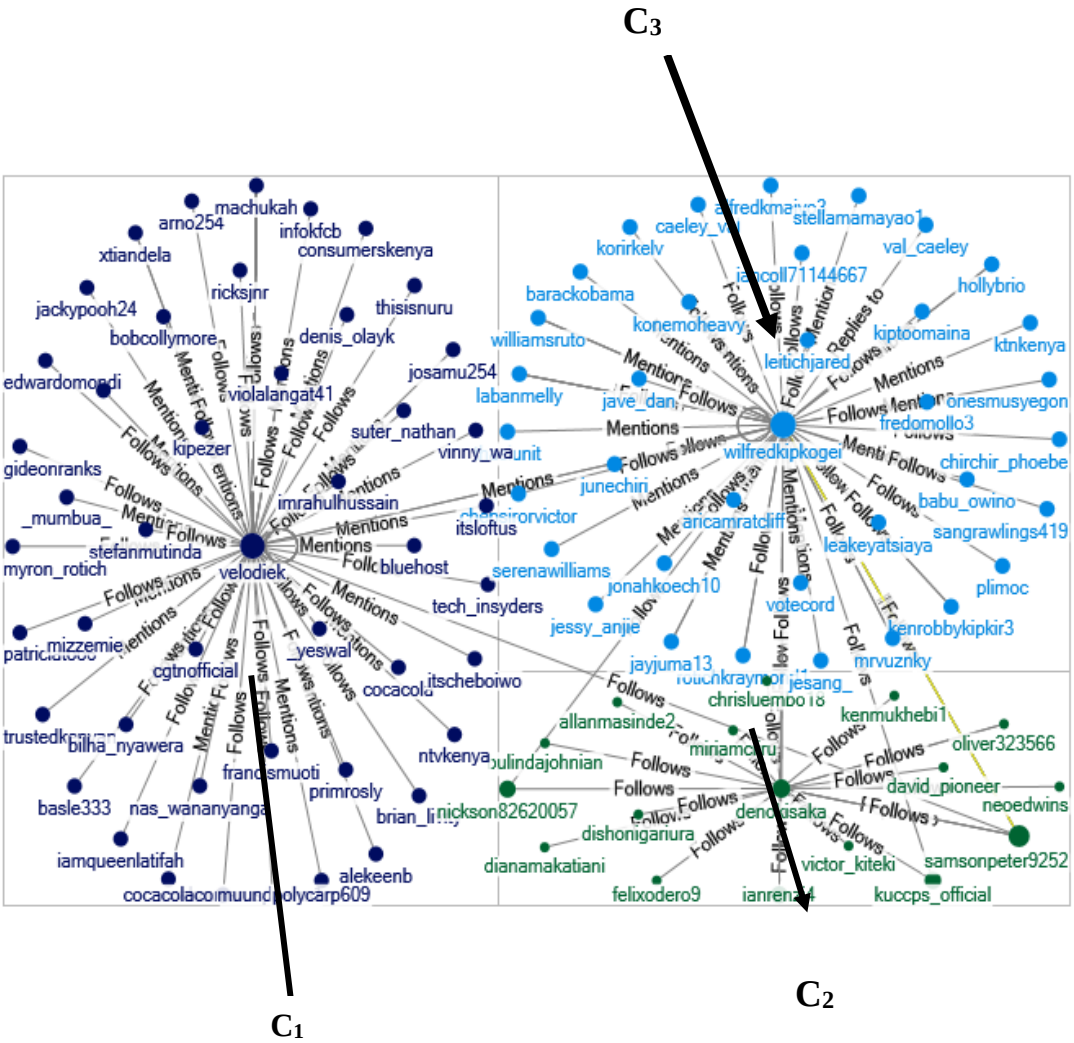

Figure 2: Identifying Communities and their Main Actors

Source: *Researcher*

Community Densities

The findings in Figure 3 shows varying densities of six communities or subgroups densely connected in one network, each identified by label codings D_1 to D_6. Necessitated by the need to portray the insight phenomenal of how information visually diffuses amongst the actors in the network, researcher employed the Wakita-Tsurumi algorithm to generate the network densities of the detected communities. A similar approach was employed by Waskiewicz (2012). The research findings indicates that as the size of the network exponentially increased over time, the density of the network expanded but not uniformly for each community.

More specifically, the study results in Figure 3 revealed that relationship or links exist between the detected communities. Notably, the densities of D_2, D_3 and D_6 communities are visually more or less

equal which implies that members of these three aforementioned communities communicate more frequently about an issue(s) they are all familiar with and probably know one another most. However, the density is slightly higher for the D1 community in the entire network and visibly has a node with the high degree centrality score.

Borrowing from Krebs (2002), a dense cluster having numerous interactions is suspicious and warrants investigations to unearth or discover more information about the group. Last but not least, the D4 and D5 community members are scattered and also depicted the least density in the whole network. These results closely relates to the study done by Staudt, Marrakchi and Meyerhenke (2014) on community detection in quest of revealing structures or patterns of interactions between nodes in a network. Furthermore, the findings conforms with (Hansen, Shneiderman & Smith, 2011) comparative analysis on determining communities that are highly related or sparsely connected. Density metrics helps to predict the flow of information between nodes of a given network and it indicates homogeneousness of a community and nodes' interactions with one another (Martino & Spoto, 2006). By employ the density measure, detectives are able to a holistic understanding structure of the entire network under scrutiny.

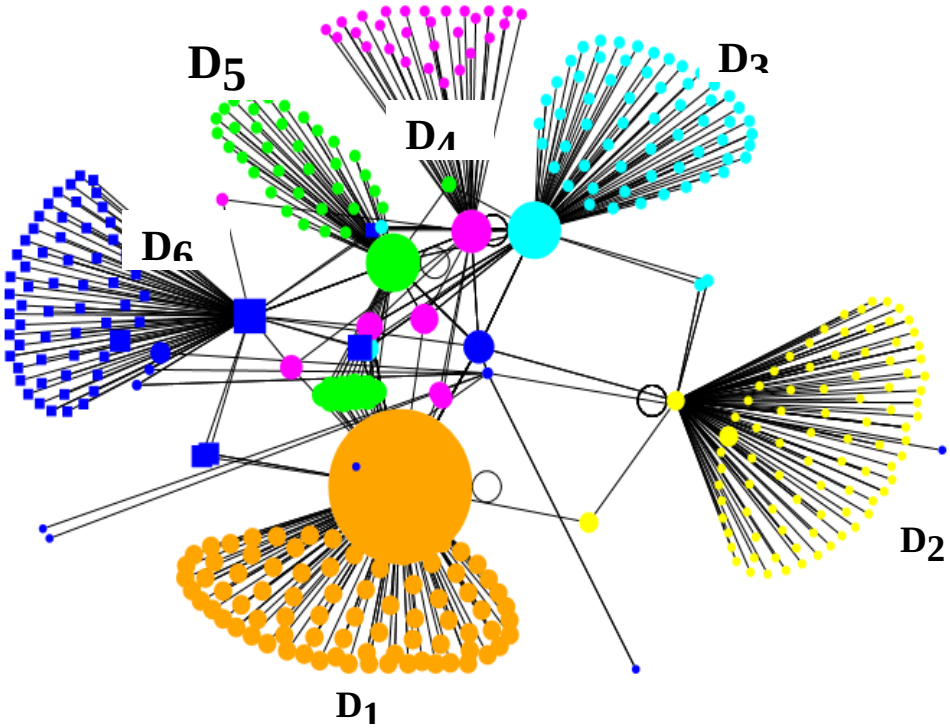

Figure 3: Network Density Isolation
Source: *Researcher*

Therefore, the visualization of network community densities has not only helped to portray the interconnections of individuals and subgroups in a social network, but also it has also aided to expose communities who possibly dominate several ranks in the network are likely to be influential or close and bonded than others in the network. These illustrations concurs with Mulazzani, Huber and Weippl (2012)

that visualizations can be a very effective tool in law enforcement agencies investigating social networks because it enables them understand the behaviour of social media users and they can predict criminal activities by monitoring connections between suspects, understand the dynamics such as discovering the leaders, followers and new individuals being integrated into a group. The techniques of detecting and identifying communities helps to know groups of nodes densely connected than other in the entire network (Tayebi & Glässer, 2016). In a rejoinder, Faust (2006) outlined that the density of a network is proportional to the probable number of connections in that network. A conspicuously dense community is susceptible and exposed to law enforcement officers for further scrutiny and identification of the main actors who are most likely to be the leaders of a particular cohort of felons (Xu, Marshall, Kaza & Chen, 2004).

Detecting Clusters of Communities

Figure 4 shows the generated visualizations results of six distinct interconnected clusters equivalent to the number of network communities (*the clusters are labelled S1 to S6*). The size of the visuals indicates how active a node is in the cluster or the entire network. Evidently, S4 community cluster density is the highest and its members are seemingly well connected and active too, hence the tight bonding visuals. Voigt, Hinz and Jansen (2013) outlined that the characteristics of clusters presenting high density scores are usually attributed to few interrelated or connected nodes. The cluster labelled S6 is the second highly active group in the network although it slightly scattered to vaguely overlap S5 cluster in the network. Except for one isolated member, all members of S3 cluster are dependent on one actor who connects them to the rest of others in the network. By employing such Social Network Analysis visualization techniques, there is a possibility to detect clusters, identify the most important actors and their roles and unveil interactions between nodes (Mena, 2003). The findings can be related to Hoppe and Reinelt (2010) observation that clustering helps to unearth important communities of a network that were not known previously. This was corroborated by Xu *et al* (2004) in cluster analysis as a way of detecting not only network subgroups but also the central actors and how they interact with other communities.

If a network community depicts a strong connection between its members, then it can aid to know the associates that belong to that network community Krebs (2002). This way, detectives can narrow down the list of suspicious characters under investigation. Moreover, identification of gatekeepers connecting to a particular subgroup (community) is also important in unearthing specific dubious characters. In Zhu, Watts and Chen (2010), network clustering helps detectives to narrow down their investigations to a specific subgroup or community.

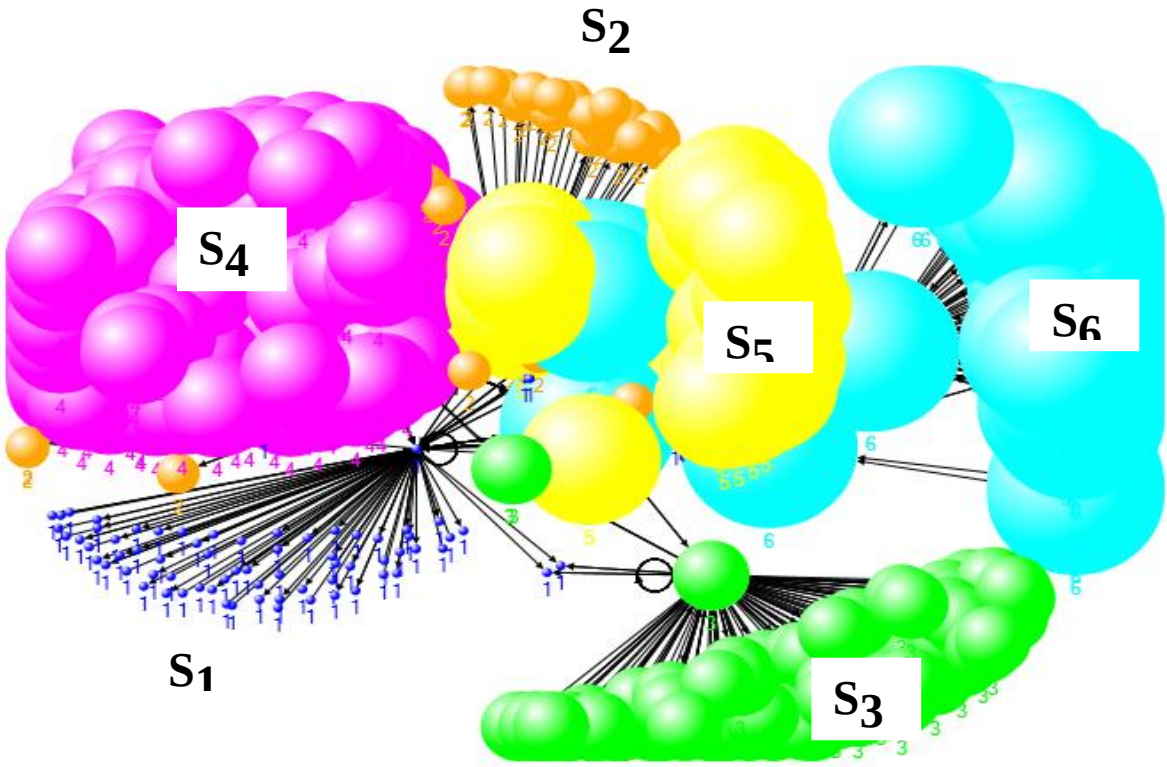

Figure 4: Clustering Network Communities

Source: *Researcher*

Degree Centrality Distributions

Betweenness Centrality Visualizations

Figure 5 shows the corresponding degree distributions of the network actors under study. It clearly illustrates that actor wilf~ has highest degree and betweenness centrality and therefore is the most influential person in the entire network. This implies that respondent wilf~ probably knows what is going on in multiples social clusters of the entire network. Identifying the actors with the highest betweenness centrality in a suspicious network helps detectives to focus their attention and resources in profoundly investigating those nodes in the entire network (Kirchner & Gade, 2011).

The research findings further portrays that respondent wilf~ act as gatekeeper by connecting the cluster that he belongs to the entire network because communications emanating from other clusters from the rest of entire network must pass through him. This means that actor wilf~ is capable of influencing the entire network but he is more susceptible to detection. Besides node wilf~ other actors namely 2279837eb26d4a1, velo~, nico~, deno~ and kiptal~ scored considerably higher degree and betweenness centralities after wilf~ from second to sixth positions respectively in the entire network but first in their clusters. This implies that these main actors are leaders or hubs of their respective subgroups in the social network. Intuitively therefore, the six actors act as intermediaries in their network subgroups because information must flow through them. The findings concurs with advice of Xu, Marshall, Kaza and Chen

(2004) that while carrying out an investigation, one needs to know which nodes other actors have to connect to in order to link to the entire network and gather other valuable leading information. Nodes acting as bridges to their subgroups create structural holes which help investigators to easily detect friends of the influential nodes (Hanneman & Riddle, 2005).

Boundary Spanners Visualizations

It was also necessary to establish the boundary spanners in the network. By doing so, the researcher was able to know the actors that connect several other clusters as this will imply that they are more central in the entire network. Accordingly, Figure 5 further reveals the boundary spanners as actors wilf~, 2279837eb26d4a1, velo~, nico~, deno~ and kiptal~ who bridge their respective clusters and therefore are strategically placed to get information from other clusters. Furthermore, these actors are able to integrate concepts and information from other clusters. The results are closely consistent with Long, Cunningham and Braithwaite (2013) that the boundary spanners act as conduit of information flow between network nodes or individuals who cannot communicate directly or have no or little trust to each other.

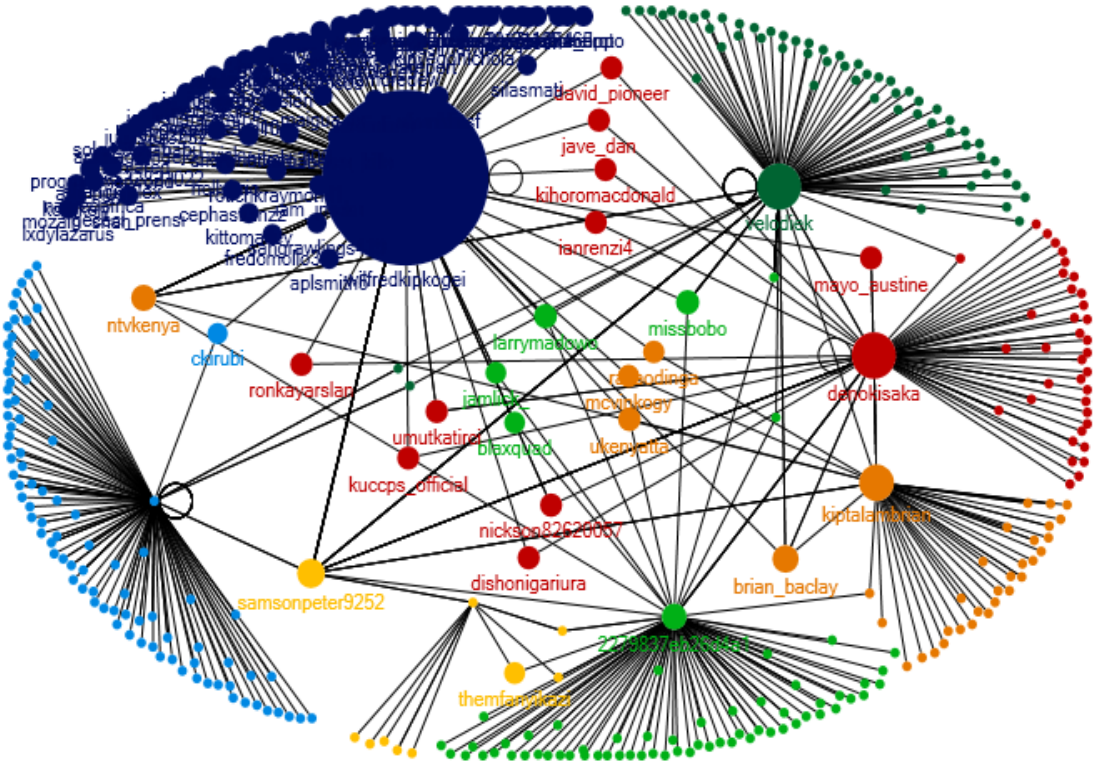

Figure 5: Degree Distributions

Source: *Researcher*

Closeness Centrality Visualizations

Figure 5 visualization results also indicates that actors sams~,wilf~, deno~, velo~, kipatal~, ntvk~ and 2279837eb26d4a1 had almost equal and similar pattern of closeness centrality measures in the entire network. Connections with nodes having high closeness scores when put together with nodes having low degree centrality values can have indirectly impact on the behaviour of the other nodes in that network (Wasserman & Faust, 1994). This implies that the aforementioned respondents were highly connected to other individuals in the network. It is important to note that the thicker the edge the higher the frequency interaction between any given actors in a network.

Regarding structural similarity, the researcher attempted to depict and find actors who are linked to more other nodes connected to the influential actor in the network. This implies that if two or more actors have similar friends, then this implies that all of them are friends in real world. Actors 2279837eb26d4a1, velo~, nico~, deno~ and kiptal~ was found to have structural similarity because they largely share a number of friends as shown by the edges in the diagram and also they are leaders of their respective clusters too. This agrees with McPherson, Smith-Lovin & Cook (2001) similarity yields interconnections between nodes with structural similarity.

Information Flow between Network Actors

It was also imperative for the researcher to visually depict how information flows in a network between actors/respondents under study.

Figure 6 was generated using geometric spiral algorithm. It clearly illustrates the flow of information in the entire network between actors. At the epicentre of the information flow is the subgroup members labelled A_3, spreading to the second layer. It is densely surrounded by the A_1 subgroup members. This implication here is that the network members of both A_1 and A_3 could be sharing similar information or have same interests with each other. The A_2 subgroup members are somewhat spreading to the hub of the communication flow of the network and also found at the periphery of the communication labyrinth. The results resonates with Nagl, Amos, Sewall and Petraeus (2008) reasoning that nodes on the periphery receive very low centrality scores and are often connected to networks that are not currently mapped but they are important links since they may be resource gatherers or individuals with their own network outside their isolated group. These characteristics make them very important resources for fresh information not available inside their isolated group.

Equally significant is the A_6 and A_4 subgroups, though a little blurred, they are also similarly positioned at the hub of the communication flow and spread heavily to the second layer after epicentre to the periphery. Cluster A_3 is diminutively encircled halfway by subgroup A_6 which spreads heavily to periphery. This conforms with Arnaboldi, Conti, Passarella and Pezzoni(2013) observation that the innermost circle signifies a more stronger social relations of the ego while the outermost circle are typified by fluctuating level of friendliness (also called sympathy or active network groups).

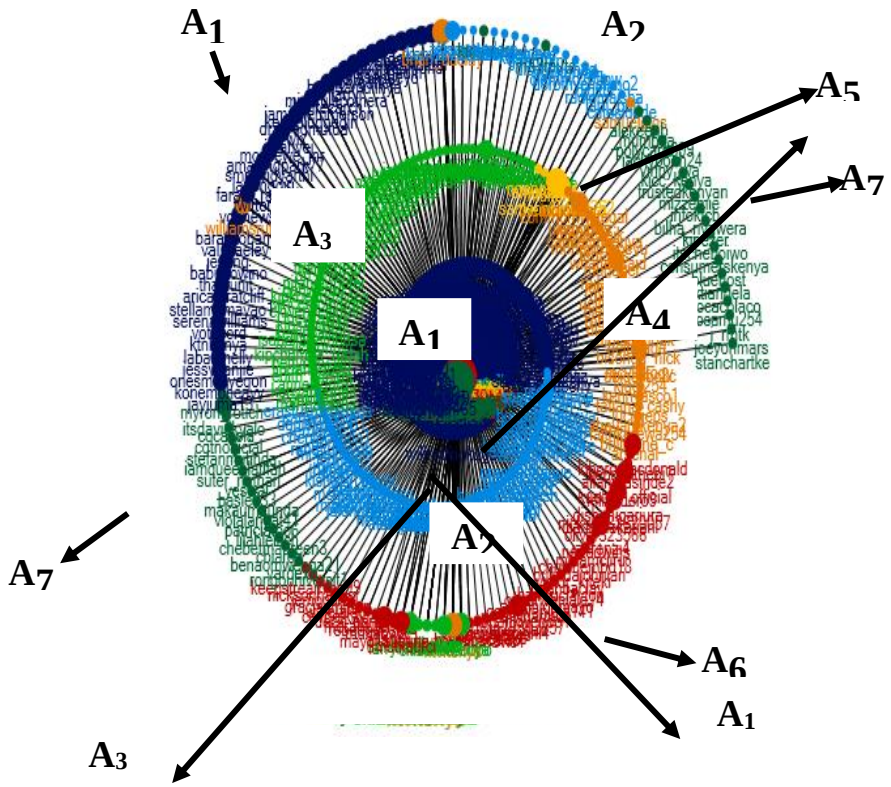

Figure 6: NetworkConcentricInformation Flow

Source: *Researcher*

The A_7 clusters, on the periphery of these visualisations are the isolates in the communication flow. Heeding the advice of Granovetter (1973), that the important channels of communication to be closely monitored are the ones that are rarely utilized and usually located at the network's periphery, cluster A_7 members elicits more scrutiny.

They seem to be recipient of the information from the entire network or they only share information specific to themselves and their interests. This visualization results correlate with Sharma and Strategy (2008) that although nodes at the periphery have less interactions with the entire network, they may be having links beyond the network and as result they can be a reservoir of new information.

Drawing and concluding from Figure 7 therefore, it is apparently evident that A1, A3, A6 and A5 subgroups are the most influential actors over others in this network. This concurs with Ferrara, De Meo, Catanese and Fiumara (2014) that by analysing the flow of information pattern in a given network, one can unearth actors that play key role in a criminal network or have connections to different clusters. Visualizing and identifying subgroups of a network enables investigators to unravel rich information pertaining the nodes, network recruitments paths, operational characteristics and patterns of flow of information (Bonacich, 1972). Hence, an investigator can narrow down his/he probe to those aforementioned subgroups to gather more valuable information and reveal their activities.

Network Communication Channels

The visualization results in Figure 8 shows the channels of communication between the various subgroups of the entire network under study. Notice that group one (denoted G1) and some members of group 4 (G4) have two major common communication links between themselves. This implies that some members in G4 who may not be prominent in that cluster knows each with the most influential member of G1. The two groups (G1 and G4) also share some influential or common actor in cluster G5. However, the influential node in G1 is conspicuously in touch with periphery members of cluster G6. Noticeably, G1 has the most members while G6 has the least. Nodes that are located at the terminals of the communication channels are likely to influence others whereas those found in-between the channels of communication paths are likely to be information conveyance belts (Waskiewicz, 2012).

In Figure 7 the findings also showed that nodes in various clusters frequently communicate with actors within their clusters than with those outside their clusters. By deriving such information, investigators can easily identify cohesive clusters and ultimately establish part of the network where information moves faster and also which cluster(s) closely keeps information to themselves.

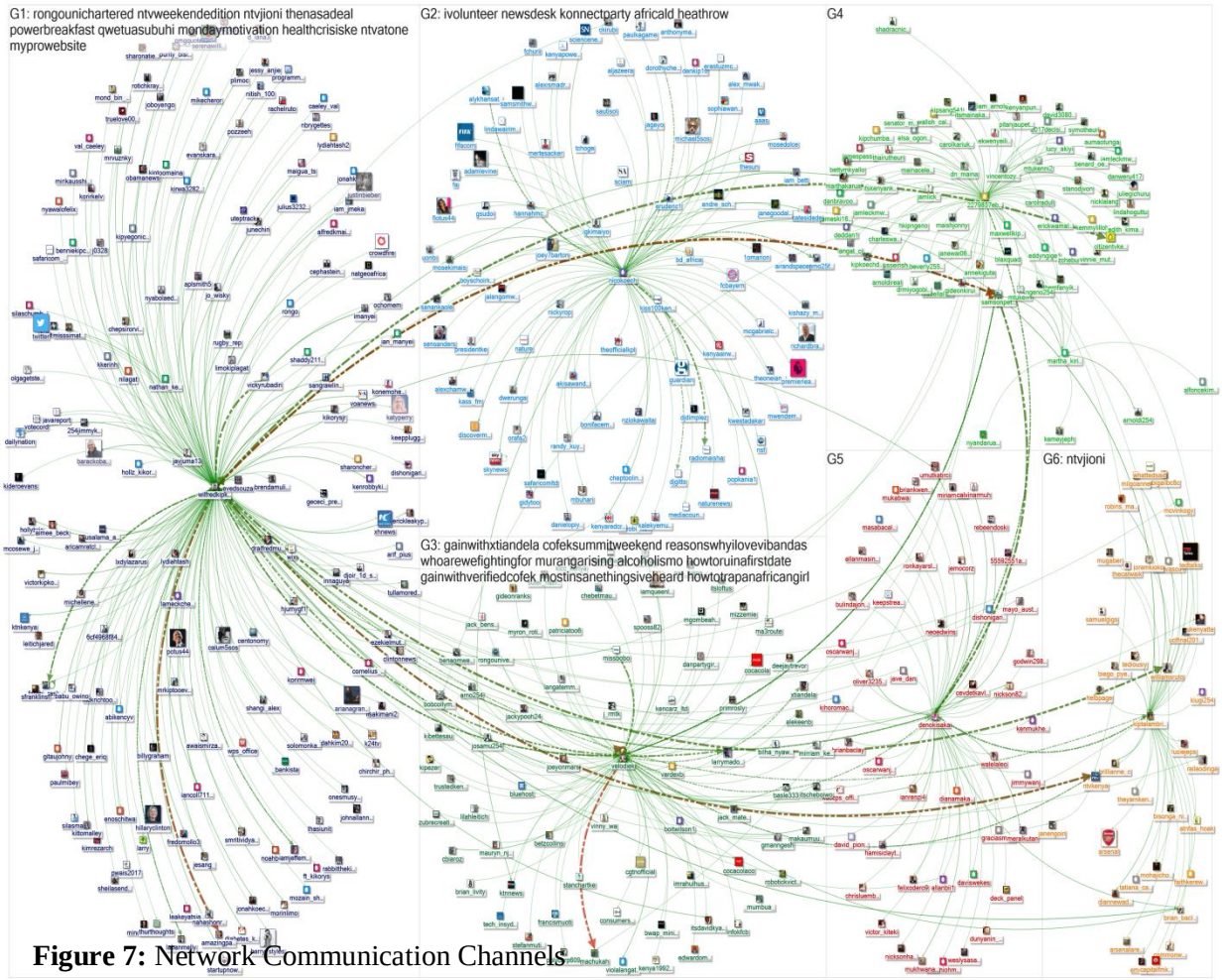

Figure 7: Network Communication Channels

Source: *Researcher*

Network Cliques

In quest of gaining deeper insight into the network, the researcher generated a complex network visualization shown in Figure 8 depicting how actors of a network over time, can ultimately fragment into interesting groups called cliques. Thus Figure 8 shows the visualization findings of network cliques generated from the now complex network. Notice that the network has now fragmented into subgroups of cliques (*denoted as G1, G2, G3,……up to G23*) and each clique is labelled with the topics they frequently discuss. The Clauset-Newman-Moore grouping algorithm identified 23 cliques within this network. However, some cliques such as G1, G2, G3, G4 and G19 have further but minute fragments within the respective cliques. These findings indicate the nodes in the entire network are highly diverse. This implies that as time elapses, network users tend to slowly degenerate into fragmented interactions and eventually form their own cliques according the nature of information exchanged between themselves as well as interests.

Stemming from these findings, the results are consistent with Bonacich (1972) on the painstaking examination of characteristics of such cliques for homogeneous ideologies and the strength of their cohesion with that network, as well as how this influences the activities and development of the

unlawful network. This way, such information can assist an investigator to tell if they are still an healthy communication or leadership roles have been changed and splinter groups emerged. Thus, the graph was generated not only to depict the number of cliques in the network but also to utilize the visual properties to map the attributes of the network showing the interaction of the actors.

The network visualizations depicted in the findings so far discussed above, underscored how important Social Network Analysis visualizations is to law enforcement agencies in unearthing leading information from a large set of data, which could otherwise been difficult or impossible to tell using conventional methods of investigations. While backing up the use of Social Network Analysis, Rahim, Amalina and Sulaiman (2015) emphasized that visualisation methods are crucial because it helps scholars to comprehend social interaction or patterns of online relations and who communicates with who more or less frequently. Hence cannot comprehend the trends and concepts of social networks without employing the use of computerized visualizations as presented in this thesis.

In an investigation scenario, the detectives ought to concentrate their probe efforts to specific actor under scrutiny then traverse the network as they examine for crucial leads. Visualizations makes this investigation process much forthright because it enables the discovery of unknown interactions and relationships that exists between actors.

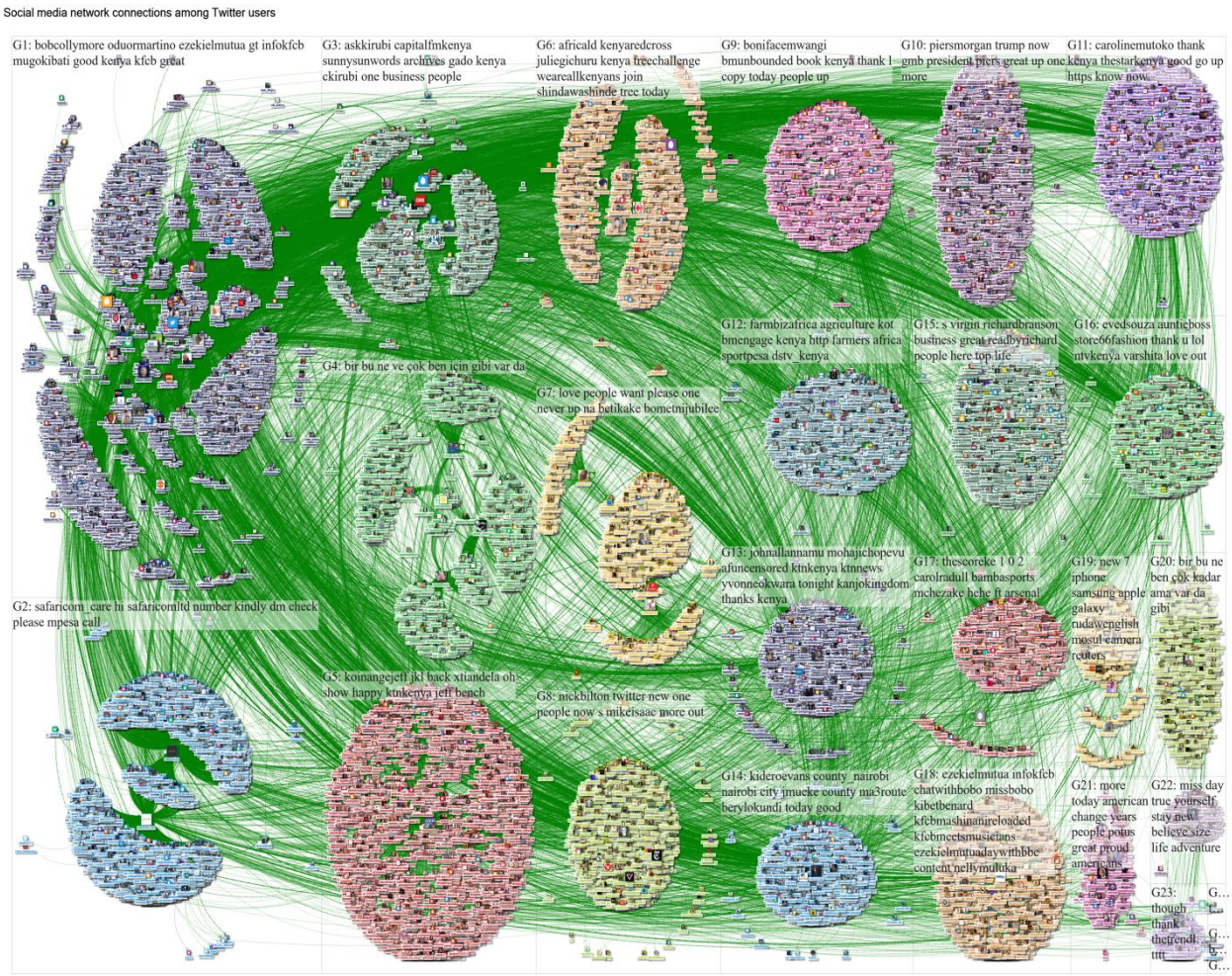

Figure 8: A 2.5 - degree Network Cliques

Source: *Researcher*

Identifying Significant Actors in a Network Using Centrality Metrics

Besides using visualisations to depict interesting patterns of interactions between respondents (actors) of the study, the researcher also employed use Social Network Analysis metrics as buttress of visualizations findings. In this section therefore, centrality measures which are be used to identify crucial actors with the values of closeness, betweenness, degree and eigenvector centralities were computed and tabulated. The network metrics generated has been used to describe either whole network or specific nodes within the network. It is also important to note that the number of vertices and edges kept on growing over time.

Conclusions

The study sought to answer and demonstrate how data obtained from individuals from specific social media can visualized or graph metrics computed as well as harvesting their demographic and related information can aid law enforcement agencies in mining forensic evidence that ultimately lead to arrest of the suspects or arraigning them before a court of law. Through analysis, study noted that there exist numerous ways and measures of determining people that have particular online prominence or influence. Visualizations and graph metric scores supplement one another in the study findings.

The visualizations were used to show fluid relations between nodes in the network and establish the structures of social network connections that exist instead of depending on theoretic or numeric values only. The use visual displays also aided in knowing that a community or network breaks into subgroups based on their interests and other information that captivates specific cohort(s). Thus, Social Network Analysis helps not only to investigate the suspicious characters, but also assist to unearth other dubious nodes that not under probe.

The findings of the study have indicated that the visualizations employed by social network analysis alongside its appropriate software can depict interesting information about the social media users interaction. It is believed that ways and means in which patterns of particular nodes were discovered using visualization will aid the law enforcement officers with ways and techniques of investigating and possibly apprehending online criminal.

Thus, when law enforcement officers employ Social Network Analysis automated tools or techniques to visualize and expose the nature of interactions or structures of suspected criminals using reliable online

information, they can remarkably help to stop them from unleashing their heinous acts to the unsuspecting populace. Thus, graph properties of the visualizations employed in this study helped the researcher to know not only the most central nodes in the network but also nodes that were most influential, popular and those who acted as bridges between subgroups of a network.

Recommendations made in the study are hoped to be of great help to the law enforcement agencies in understanding how to can mine, analyse and unearth concealed network elements and patterns between individuals in question. The study has broadened the knowledge on how to apply some Social Network Analysis techniques that is hoped to be of great help to the law enforcement agencies. Kenya's law enforcement community ought to be challenged to keep abreast both procedurally and legally by the findings of this study. Advanced degree of mining or harvesting data is significant with regards to the forensics evidence from social media users

In Kenya, the majority of members of law enforcement seems to unfamiliar with Social Network Analysis techniques and its associated tools for investigating online suspects. Kenya's law enforcement agencies should embrace the use of social media and social networking in various ways or applications, including recovering evidence, locating and apprehending suspects, conducting intelligence collections using social networking to conduct crime analysis and intelligence trend analysis. Hence, an enabling technology and trained law enforcement officers will help mitigate or thwart crimes about to be committed in real world. The outcomes of this thesis could influence law enforcement community by providing them with a new insight of investigation and analysing crimes from a large dataset.

The study also established the limitations of Social network Analysis which comprised of incomplete datasets, not knowing in advance whom to include or exclude and the fact that social network is dynamic and transcends geographical boundaries.

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