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Highlighting Unusual Behavior in Insurance Based on Social Network Analysis

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ABSTRACT

Insurance companies have evolved into a highly competitive market that demands companies to put in place an effective customer behavior monitoring system, both in terms of usage and value. Unusual behavior in insurance can represent distinct business meanings, such as heavy users or suspicious transactions. Social network analysis can be used to raise business knowledge in relation to the average customer's behavior and, therefore, to highlight unexpected usage. Regardless of the reason for high usage in relation to insurance services, high usage substantially impacts the operational cost, either by the claims' expenses or the possible fraud events. SNA can be used to evaluate the different roles assigned to the actors and their relationships, allowing companies to deploy a more effective program to better understand and monitor the claims' transactions.

INTRODUCTION

This paper aims to highlight the benefits from a social network analysis approach. This case study is based on data related to a motor insurance company. This data comprises transactional information about the claims in a real motor insurance operation. The main objective of the social network analysis in this particular case is to highlight unusual behavior in relation to the participants assigned to a claim, such as policy holders, suppliers, repairers, specialists, witnesses and so on. The idea of the social analysis is to identify unexpected relations among the participants, or recognize particular suspicious groups of them. This approach can reveal possible fraudulent connections inside social structures, indicating through the participants the claims which have a significant likelihood to be fraud or exaggerated.

In this case study, a distinguish approach in order to identify suspicious claims based on the network measures is presented, describing the steps in relation to the network building, the metrics computing, and finally the network evaluation. This sort of methodology arises; in terms of social structures and relationships; business knowledge and understanding about participants upon the claims' transactions.

The social network definition in this case study is established upon the claims records. From these records, the participants, and the different roles they can possible play within the claim, are selected, and then their relationships to other participants are settle.

All participants in one particular claim are connected each other in order to create all possible links. For instance, claim 1234 has one policy holder **A**, one claimant **B**, one supplier **C** and one approved recommended repairer **D**. By using this approach, a combination of 3 by 2 should be provided to produce a social structure containing 4 nodes and 6 links

- **Nodes** A, B, C e D, and **Links** A-B, A-C, A-D, B-C, B-D, C-D.

Figure 1 shows the graphical representation about this combination.

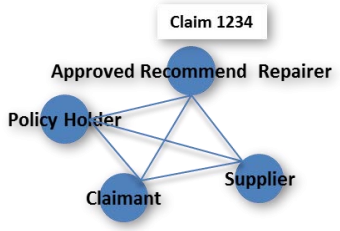

Figure 1. Social links among participants in a claim

In this case study, 22,815 claims were considered in order to produce the social network. All claims' records were aggregated to consider distinct claims with multiple occurrences of participants. Also, the participants were considered based on a smooth match code of their names and addresses, avoiding in this way eventually clear duplicates. From those noticed claims, 41,885 distinct participants were identified comprised in 74,503 relationships. In the social network analysis approach, a participant is considered a node and a relationship is considered a link.

By connecting all participants each other, a huge number of connections among them can be reached. For instance, in the network presented in figure 2, there are two participants which appear simultaneously in two sub-networks. Claims 1234 and 7869 comprise the same supplier, and claims 3256 and 4312 have the same driver third party. This fact makes that all participants in the claims 1234 and 7869 are connected somehow. The same thing happens to the claims 3256 and 4312, where all participants are also connected.

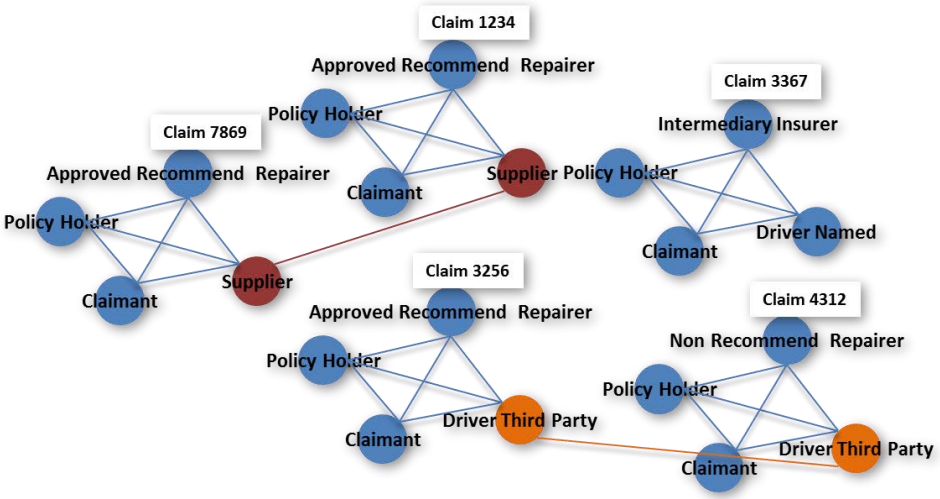

Figure 2. Social structure considering same participants within distinct claims

In order to analyze the entire network structure and all correlations among the nodes, the social network approach considers all types of roles within the claims, but performs distinct analyses according to them. The network measures are computed based on the entire network, considering all nodes and links, regardless the participants' roles. Then, all metrics assigned to the *individual* nodes are evaluated. The same approach is performed to the *organization* nodes. Distinct analyses could be take place according to the participant's roles, such as policy holder, third party driver, repairer, and so on. These detailed analyses tend to highlight easily the unusual behavior in relation to each type of participant. A particular repairer could be an outlier according to its network metrics when just the category *repairers* are considered, but do not when all types of participants, including the category *approved recommended repairer*, are included into the analysis. Figure 3 presents the network with nodes as *individual* colored and nodes as *organization* faded. This is the way the network could be viewed in terms of analysis rather than in terms of building.

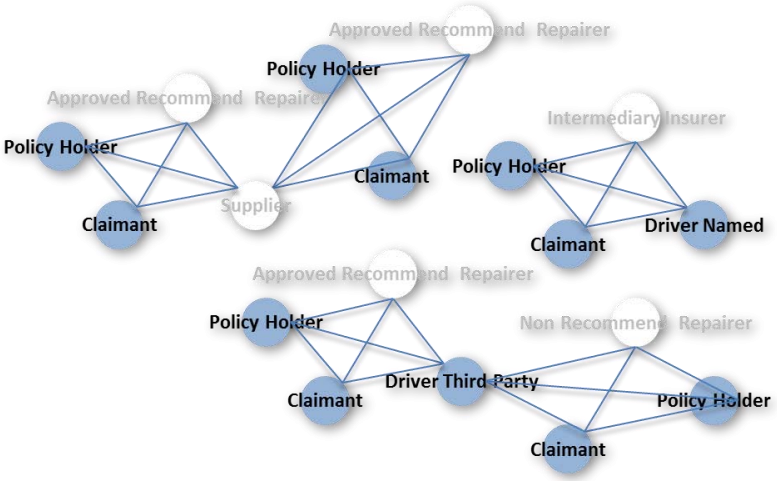

Figure 3. Distinct social network analyses due to different roles of participants

The analytical methodology deployed in this case study combines a social network analysis to build and compute the network metrics and a subsequently exploratory analysis aiming to seek for unusual behavior, based on occurrences

of outliers' observations, either in terms of nodes or links. The outliers' occurrences are highlighted by running univariate, principal component and clustering analyses over the network measures.

In order to perform an analysis over the *individual* participants, a categorization was established based on the participants' names. Once again, the network measures were computed over the entire network and the exploratory analysis was performed considering just the *individual* participants. Figure 3 presents graphically this approach. All links in the network and all participants classified as individual are highlighted, and all participants classified as organization are faded.

Analogously to any traditional exploratory analysis the occurrences of outliers and the unusual behavior are able to raise a set of rules and thresholds in relation to the suspicious events of claims. However, in the social network analysis approach, the unusual behavior and the occurrences of outliers are raised based on the relationship instead the individual attributes. A high number of similar addresses or participants involved in different claims can trigger an alert about the participants, and therefore, about the claims involved. Different analytical methods raise distinct set of rules based on network measures thresholds. A combined approach to catch suspicious events should take into consideration all set of rules.

The social network analysis approach deployed in this case study aims to raise suspicious participants, or participants with unusual or outlier relationship behavior, considering the network connections under the claims transactions. Traditionally, if several claims have average values for their attributes, such as total amount, number of participants, number of roles, addresses and so on, neither those claims would be raised as suspicious, or flagged to be monitored and investigated by using the traditional analysis approaches. However, if a particular participant, such as a supplier or a claimant, is involved in all those claims, its relationship level could be considered as too high and an alert would be raised in order to highlight it to be tracked. The individual values in relation to the claims, in a transaction basis, are all normal or expected, but the strength of the connections are much higher than the normal values expected when a network structure is considered. Due to this, an alarm could be triggered for further investigation.

This approach does not discard any traditional method at all. Business rules, based on previous experience, and individual thresholds due to any relevant attribute are always quite effective and should be put in place in parallel. The main gain in the social network analysis approach is the possibility to raise unusual behavior according to the relationship perspective rather than the unique attributes one. The most suitable approach to monitor transactions in a fraud perspective is therefore by combining as much distinct methodologies as possible. Each analytical method is more or less suitable to catch a particular type of suspicious event, and then a combination of distinct approaches makes it possible to track a wide range of different types of risk occurrences.

OVERALL FIGURES IN RELATION TO THE PARTICIPANTS NETWORK

One of the most important outcomes from a social network analysis is the measures in relation to the participants' network. How the participants relate each other, in which frequency, and how relevant are their relationships. From the network analysis some suspicious relationships could be raised and hence some participants.

The network measures are in respect to the overall network, considering all relations of a particular node, and also some individual attributes of them.

The measures presented onward depict the network' structure, its topology, and the overall characteristics considered by the deployment of the social network analysis approach in this motor insurance case study. From the 41,885 nodes within the social structure analyzed, 30,428 are *individual*, and 4,423 are *organization*. In addition to the distinct analyses due to the participant's role; individual and organization; a set of analyses were performed in order to highlight unusual groups of participants, either in terms of nodes or links. There are some different types of group analysis which can be performed within the social network analysis approach, such as community, cluster, connected components and bi-connected components, as presented afterward.

GROUP ANALYSIS

There are some relevant concepts in relation to the social network analysis approach, which describes the importance of some particular nodes, links, and also the overall structure of the network. These concepts can be used to highlight suspicious groups of nodes, or participants, and hence the claims assigned to them. There are some distinct methods to identify groups of nodes based on similarity, distance, or the internal paths inside the sub-networks.

Connected components

When there is a group of nodes, where each node can reach any other, even undergoing by more than one node, this group of nodes are named as connected components. The connected components can be understood as a very close group of nodes, separated of the rest of the network, but each node being reachable by any other one within

this sub-graph. The network of this particular case study comprises 6,263 connected components. It is quite important to notice that during the data cleansing some particular entities were removed from the network. There are some participants within the claims which are very frequently, such as government agencies and some insurers, among other. By including these participants the entire network should be all connected once they appear in almost every claim.

Bi-connected components

One another important concept in relation to the social network analysis approach is the bi-connected components. When there is a connected component which comprises a particular node who if is removed it splits this connected component into two distinct connected components, this original connected component can be considered as a bi-connected component, and that particular node, who if is removed splits the original connected component into two is called as articulation point.

In the network studied 15,734 bi-connected components and 2,307 articulation points were identified. Analogously to the connected components, the articulation point can be highlighted to be further investigated. Also, from those 2,307 articulation points, 984 of them are participants as *individual*, which is even more suspicious.

Communities

The third relevant concept in relation to the social network analysis approach is regarded to the communities. There are some techniques which are put in place in order to identify communities inside the entire network. Differently of the connected components, which are isolated from the rest of the network, a community can holds some nodes which have connections outside the community, as branches or arms outside the internal community. In this way, a community can be connected with other communities, though more than one node. Communities inside networks can be understood as clusters inside populations. The study of the communities can raise some important knowledge in relation to the network's behaviors allowing particular analyses in terms of suspicious individuals inside them.

In the network studied 13,279 communities were identified, considering all nodes, regardless if they were classified as *individual* or *organization*.

METHODOLOGY TO DETECT OUTLIERS INSIDE THE SOCIAL NETWORK

The next phase in this analytical approach based on social network analysis is to consider the overall measures against to the individual ones. This approach raises relevant aspects in relation to the components of particulars social structures within the network. In order to perform this sort of analysis, the entire network was considered to compute the individual measures. These measures are assigned to each node and link inside the network. The second step is to compare the individual measures (nodes and links) against to the average metrics, in relation to the entire network, or in relation to some particular categories, such as *individual*, *organization*, *policy holder*, *repairer*, and so on. Unusual and unexpected behaviors in relation to nodes and also to links can be arisen through this comparison process. This paper is covering the analysis for participants as *individual*, but the method for the participants as *organization* or any other category is analogous and straightforward.

There are several measures to be calculated in relation to social network analysis. In this particular approach, six measures were taken into consideration.

Degree: represents the number of connections a particular node has. In a directed graph, where the direction of the node is relevant, there is a differentiation between the in-degree; the number of links a particular node receives, and the out-degree; the number of links a particular node sends. The sum of in-degree and the out-degree gives the degree measure. In insurance, this metric is usually considered as undirected, and it can be straightforward computed.

Eigenvector: represents the measure of the importance in relation to a particular node inside the network. Relative scores for all nodes are computed based on their connections, considering frequency and strength for instance. Eigenvector is assigned to a recursive algorithm in order to calculate the importance of a particular node considering the importance of all nodes and all connections within the network.

Closeness: represents the mean of the geodesic distances (shortest path in the social network perspective) between some particular node and all other nodes connected with it. This measure describes the average distances between one node and all other nodes connected with it. It can be understand as how long a message will take to spread inside the network from a particular node.

Betweenness: represents how many shortest paths a particular node makes part. Nodes that occur on many shortest paths between other nodes have higher betweenness than those that do not. It can be understand as how central a node is considering the entire network and all connections it has.

Influence 1: represents the first order centrality for a particular node, which means how many other nodes it is straight connected. This measure can be understood as how many "friends" I have. It describes how many nodes can be possible straight influenced by some particular node.

Influence 2: represents the second order centrality for a particular node, which means how many nodes the nodes it is straight connected are connected. This measure can be understood as how many "friends" my "friends" have. It describes how many nodes can be indirect influenced by some particular node.

All these measures were taken into account to highlight the outliers within the social structure studied. Distinct processes to trigger the outliers' thresholds were applied, such as univariate, principal component and clustering analyses. These techniques were applied over the measures in relation to nodes and links.

OUTLIER ANALYSIS OVER THE SOCIAL NETWORK MEASURES

In order to identify unusual events, an outlier analysis was performed over the network measures. The outlier analysis approach takes into account the average measures for the entire network, and therefore compares these measures with the metrics assigned to the individual nodes and links.

Distinct approaches to highlight the occurrences of outliers were put in place over the network metrics assigned to individual nodes and links. Based on univariate, principal component and clustering analyses, a set of distinct conjunction rules was established, one for each of these techniques. All of them were deployed considering the entire network and compared upon the *individual* participants' relationships.

A link analysis was performed in order to identify outliers' links and therefore highlight the nodes which are comprised into those links.

In terms of group analysis, a comparison was performed upon the social structures within the network in order to highlight the outliers' occurrences of connected components, bi-connected components and communities, and therefore identify the nodes which are comprised on them. Particularly in relation to the bi-connected components, the articulation points were deeply analyzed once they are very relevant in terms of connections, associating two or more connected components. The fact of an *individual* node play a role of articulation point could be suspicious, and hence susceptible for further tracking.

RULES AND THRESHOLDS BASED ON UNIVARIATE ANALYSIS

The univariate analysis evaluates the network's measures and defines a set of ranges of observations according to predefined percentiles. All observations that, in conjunction, satisfied the established rules assigned to the outlier's percentile should be highlighted for further tracking and monitoring.

For instance, in this particular case study, considering the individual network's measures, when the degree is greater than 9, the eigenvector is greater than 6.30E-03, the closeness is greater than 1.46E-01, the betweenness is greater than 1.12E-04, the influence 1 is greater than 2.32E-04, and the influence 2 is greater than 1.44E-01, then the node is considered a outlier and should be flagged for further investigation.

According to the univariate analysis, there are 331 nodes considered as outliers. The average behavior of these 331 nodes creates the thresholds previously presented, which when applied onto the production environment raise 21 participants from the transaction's database.

RULES AND THRESHOLDS BASED ON PRINCIPAL COMPONENT ANALYSIS

The principal component analysis evaluates the network's measures reducing the dimensionality of the variables. All measures in relation to the network are comprised then into a single attribute which can represent the original characteristics of the nodes. Similarly, the outlier's observations are identified according to the high values among the set of observations.

Considering the individual network's measures, when the degree is greater than 13, the eigenvector is greater than 3.65E-03, the closeness is greater than 1.42E-01, the betweenness is greater than 9.10E-05, the influence 1 is greater than 3.22E-04 and the influence 2 is greater than 8.48E-02, then the node is considered an outlier observation and should be flagged for further investigation.

According to the principal component analysis, there are 305 nodes considered as outliers. The average behavior of these 305 nodes creates the thresholds previously presented, which when applied onto the production environment raise 23 participants from the transaction's database.

RULES AND THRESHOLDS BASED ON CLUSTERING ANALYSIS

The clustering analysis evaluates the network's measures creating distinct group of nodes according to their similarities. These similarities could be based on the network's metrics such as degree, eigenvector, closeness, betweenness and influences. The outliers' observations are identified not based on buckets or percentiles but instead according to unusual clusters. The vast majority of the clusters identified within the network hold usually several nodes. Based on that, when particular clusters hold a few amount of members they are defined as uncommon, and therefore as outliers groups of nodes. As consequence, all nodes comprised in these uncommon clusters would be considered as outliers as well.

The averages network's measures for the outliers' clusters establish the thresholds in order to highlight which nodes within the network would be considered as outliers. According to the clusters' thresholds, when a degree is greater than 36, the eigenvector is greater than 1.04E-02, the closeness is greater than 1.45E-01, the betweenness is greater than 6.50E-04, the influence 1 is greater than 9.35E-04 and influence 2 is greater than 1.49E-01, then the node is considered as outlier and should be flagged for further investigation.

According to the clustering analysis, 3 clusters were considered as outliers, comprising respectively 18, 2 and 3 nodes. In summary, these 3 outliers' clusters contain 23 nodes as outliers. The average behavior of these 23 nodes creates the thresholds previously presented, which when applied onto the production environment raise just 2 participants from the transaction's database.

RULES AND THRESHOLDS BASED ON LINK ANALYSIS

The previous rules and thresholds were raised based on the analysis of outliers considering the individual nodes measures. Although the clustering analysis takes into consideration a group of nodes, the individual nodes' measures are computed to establish the thresholds. However, in terms of social network analysis is also possible to analyze the behavior of the links among the nodes. The link analysis might highlight the outliers' occurrences of links and therefore identifying the nodes assigned to these particular outliers' links. Somehow similar to the clustering analysis where an uncommon group of nodes are considered outlier, and therefore its individual nodes, the link analysis consider uncommon connections among the nodes in order to point out the uncommon individual nodes.

In relation to the links' features, there is a measure which identifies the geodesic distance among the nodes, or the shortest paths assigned to them. The link betweenness represents how many shortest paths a particular links partakes in. Analogously to the nodes measures, links which take part on many shortest paths have higher link betweenness than those do not. The nodes comprised in those outliers' links are also considered as uncommon, and therefore in this approach, as outliers nodes.

The averages network's measures for the outliers' links establish the thresholds in order to highlight which nodes within the network would be considered as outliers according to their uncommon links. Based on the links' thresholds, when the degree is greater than 9, the eigenvector is greater than 4.30E-03, the closeness is greater than 1.41E-01, the betweenness is greater than 2.32E-04, the influence 1 is greater than 2.26E-04 and the influence 2 is greater than 9.37E-02, then the node is considered as outlier and should be flagged for further investigation.

According to the link analysis, 300 links were identified as outliers' connections, comprising 199 nodes. The average behavior of these 199 nodes creates the thresholds previously presented, which when applied onto the production environment raise 18 participants from the transaction's database.

RULES AND THRESHOLDS BASED ON THE BI-CONNECTED COMPONENT ANALYSIS

The social structure in this case study contains 15,734 bi-connected components. Interconnecting these bi-connected components there are 2,307 articulation points, which 984 are participants classified as *individual*. The articulation point is an individual which binds two connected components. The claims in insurance supposed to have not too much individual participants connecting them. Companies can appear several times in the claims, once they are suppliers, repairers or insurers. However, individuals appearing several times, connecting distinct claims might be suspicious and should be sent for further analyses.

There are two different ways to use the articulation points' approach. The first one is highlight them straightforward. The second one is to collect their average behavior, as done in the other approaches, and identify all nodes which match with this criterion.

The averages network's measures for the articulation points would therefore establish the thresholds to highlight the outlier nodes. Based on this, when the degree is greater than 20, the eigenvector is greater than 5.05E-03, the closeness is greater than 1.43E-01, the betweenness is greater than 4.27E-04, the influence 1 is greater than 5.00E-04 and the influence 2 is greater than 1.03E-01, then the node is considered as outlier and should be flagged for further investigation.

According to the bi-connected component analysis, 99 articulation points were identified as outliers' observations. The average behavior of these 99 nodes creates the thresholds previously presented, which when applied onto the production environment raise 15 participants from the transaction's database.

CONNECTED COMPONENTS ANALYSIS FOR THE ENTIRE NETWORK

Connected components hold a strong concept of relationship among the nodes. All nodes can reach each other, no matter the path required to do that. A connected component analysis was performed over the entire network. Differently than as proceeded for the previous analyses, where the evaluation considered just participants classified as *individual*, the connected components approach to identify outliers took into account all nodes, both *individual* and *organization*.

Additional information in terms of number of nodes, number of *individual* and *organization* nodes, and also, the total amount of the claims where the connected component's nodes are involved were taken into consideration to this new analysis.

A principal component analysis was performed over the network and business's measures for the connected components, such as the average values for degree, eigenvector, closeness, betweenness, influence 1 and 2, and also, the number of nodes within the connected components. Additional business information such as total ledger, amount claimed, number of vehicles involved, number of participants, and others, were included into the analysis.

The averages network's measures for the nodes comprised into the outliers' connected components would therefore establish the thresholds to highlight the overall outlier nodes. Based on this, when the degree is greater than 7, the eigenvector is greater than 6.97E-17, the closeness is greater than 8.33E-02, the betweenness is equal 0.00E-00, the influence 1 is greater than 1.89E-04 and the influence 2 is greater than 1.50E-03, then the node is considered as outlier and should be flagged for further investigation.

According to the connected component analysis, 3 connected components were identified as outliers, comprising 30 nodes in summary. The average behavior of these 30 nodes creates the thresholds previously presented, which when applied onto the production environment raise 555 participants from the transaction's database.

Due to this high number of participants raised by the connected component's rule, this approach can be considered not appropriated to be implemented in a production environment, highlighting a large amount of participants to be further investigated. This particular set of rules and thresholds would be discarded so.

COMMUNITY ANALYSIS FOR THE ENTIRE NETWORK

Analogously to the connected components, the most relevant characteristic of the communities is a sort of relationship among the comprised nodes. As performed previously, additional information in terms of number of nodes, *individuals* and *organizations*, and also, the total amount of the claims where the community's nodes are involved were taken into consideration to accomplish this analysis.

Once again, a principal component analysis was performed over the network and business measures for the communities, such as the average nodes values for degree, eigenvector, closeness, betweenness, influence 1 and 2, and also, the number of nodes within the community. Additional business information such as total ledger, amount claimed, number of vehicles involved, number of participants, among others, were included into the analysis as well.

The averages network's measures for the nodes comprised into the outliers' communities would therefore establish the thresholds to highlight the overall outlier nodes. Based on this, when the degree is greater than 13, the eigenvector is greater than 3.20E-03, the closeness is greater than 1.42E-01, the betweenness is greater than 7.10E-05, the influence 1 is greater than 3.26E-04 and the influence 2 is greater than 8.02E-02, then the node is considered as outlier and should be flagged for further investigation.

According to the community analysis, 13 communities were identified as outliers, comprising 68 nodes in summary. The average behavior of these 68 nodes creates the thresholds previously presented, which when applied onto the production environment raise 24 participants from the transaction's database.

FINDINGS FROM OUTLIER APPROACH OVER THE SOCIAL NETWORK ANALYSIS

The entire process to identify outliers' observations based on the different types of analyses has produced the following figures.

Technique	Individual participants
Univariate Analysis	21
Principal Component Analysis	23
Clustering Analysis	2

Link Analysis	18
Bi-Connected Component Analysis	15
~~Connected Components Analysis~~	~~555~~
Community Analysis	24

Table 1. Amount of outliers' participants based on distinct techniques

Outliers' nodes however might be raised by distinct techniques. The total amount of participants' outliers classified as *individual*, considering all previous techniques is about 33. These participants are involved in 706 claims.

FINAL REMAKRS ABOUT THE SOCIAL NETWORK ANALYSIS OUTCOMES

The analysis of social networks through the calculation of distance paths and frequencies is one of the possible approaches to recognize the pattern in relation to social structures based on relationships. In order to detect unexpected behavior on these social structures a set of exploratory analyses should be put in place. In this case study, univariate analysis, principal component analysis, clustering analysis, as well as group analyses such as bi-connected components, connected components and communities, were performed to highlight possible unusual behavior for nodes and links within social networks. The combination of these two approaches constitutes a distinguish methodology to recognize social patterns and then uncommon events, which might be considered a risk for a set of different industries, like motor insurance presented in this paper.

Individual attributes in regard to claims hold useful information about the particular transactional event in course. However, these attributes might poorly explain correlations in relation to some particular type of event such as fraud or exaggeration. On the other hand, the relationship among the claims can reveals unusual frequency and recency on occurrences of participants within the claims. Social network analysis can possible reveals participants in high distinct number of roles, groups of participants with high average values for some particular business attributes, strong links among a set of participants and so on.

Figure 4 shows an example of a particular doctor specialist who are quite frequent within latest claims above a specific amount of value. He connects a high number of distinct policy holders. The star network describes a node very central holding lots of connections to different nodes. Further analyses showed completely different geographic addresses for these connected nodes. This might be quite uncommon in the motor insurance environment and hence this specialist would be pointed out for further investigation.

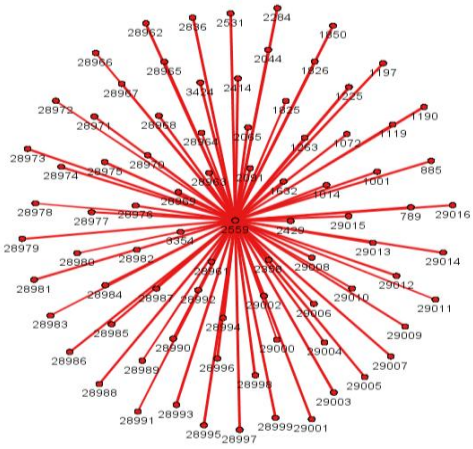

Figure 4. Star network presenting a high central node with lots of distinct connections

Another approach in highlighting unusual behavior is by group analysis, performing analyses over connected components, bi-connected components and communities. Some groups are unexpected by their own network measures, due to the number of nodes or links in relation to the average numbers of the entire social structure. Other groups might be pointed out by business attributes associated to the network measures, such as the amount of claim, the number of distinct roles, cars involved, different addresses, and so on. These business attributes within the groups should be also compared against the average figures of the entire social structure.

Figure 5 show a set of connected components and bi-connected components which are unusual in either in terms of the social network measure or the business attributes.

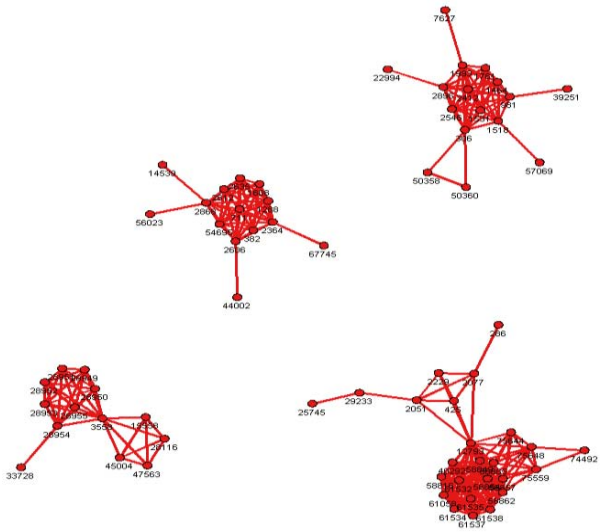

Figure 5. Uncommon groups of participants highlighted through community detection

Distinct approaches can be combined in order to highlight heavy users in the motor insurance environment. In regard to the insurance market, high users in terms of payment claims, fraudsters or even exaggerators are all harmer to companies, jeopardizing the corporate profits and cash flow. All companies currently should maintain operational cost under control, especially the ones in competitive marketplaces such as insurance. Profit on the other hand is quite related to keeping the costs in a low level, which are usually achieved by a thigh monitoring process.

High payments in relation to claims, even though they are not really assigned to fraud can still cause some sort of money leakage to the companies. An exaggeration is a huge problem in most insurance companies, sometimes caused by the customers, some by the suppliers. Hence, not just the fraudsters but mainly the exaggerators might cause the easiest visible financial damage to the companies. All these types of have users should be closely monitored aiming to identify and avoid possible unexpected payment events.

CONCLUSION

As in many industries, motor insurance market is quite dynamic, and some particulars scenarios change very often. When the market changes the data related to it changes as well. A analytical model based on social network analysis should be monitored and assessed to be adapted to new business realities, new scenarios, new regulations, among others.

Even though the motor insurance is a quite dynamic market, social network analysis is a very adaptable analytical model, which fits to different types of changes in data, always pursuing the customer's behavior in terms of actions, usage, consuming and relationships. Finally, this adaptable feature is totally fundamental in a market characterized by high competition.

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