Ranking the Importance Level of Intermediaries to a Criminal using a Reliance Measure
Pritheega Magalingam*, Stephen Davis, and Asha Rao, Member, IEEE

Abstract—Recent research on finding important intermediate nodes in a network suspected to contain criminal activity is highly dependent on network centrality values. Betweenness centrality, for example, is widely used to rank the nodes that act as brokers in the shortest paths connecting all source and all the end nodes in a network. However both the shortest path node betweenness and the linearly scaled betweenness can only show rankings for all the nodes in a network. In this paper we explore the mathematical concept of pair-dependency on intermediate nodes, adapting the concept to criminal relationships and introducing a new source-intermediate reliance measure. To illustrate our measure, we apply it to rank the nodes in the Enron email dataset and the Noordin Top Terrorist networks. We compare the reliance ranking with Google PageRank, Markov centrality as well as betweenness centrality and show that a criminal investigation using the reliance measure, will lead to a different prioritisation in terms of possible people to investigate. While the ranking for the Noordin Top terrorist network nodes yields more extreme differences than for the Enron email transaction network, in the latter the reliance values for the set of finance managers immediately identified another employee convicted of money laundering.

Index Terms—Shortest path, betweenness, intermediate node, reliance

I. INTRODUCTION

A large number of methods have been proposed to rank the importance of nodes in a network. The betweenness centrality measure is one such measure that attributes importance to intermediate nodes in a path, as these nodes are necessary to retain the flow within the network [7]. In this paper, we present a new measure, the reliance measure, to enable an investigator to identify the intermediate nodes important to a criminal or a suspect, thus helping the investigator to prioritize or narrow down the search to specific targets rather than investigating all the nodes in a sub-network. Our research has the specific aim of aiding the investigation of money laundering crimes, where it is often difficult to identify influential entities with respect to the main source of illegal money by just using data mining techniques [25], [35], [47], [55]. To show the versatility of our measure, we apply it to rank the nodes in the Enron dataset [15] and the Noordin Top Terrorist networks [20].

The betweenness centrality of a node is a measure that computes the number of geodesics (shortest paths) going through that node. The idea of the betweenness centrality of a node was first proposed by Anthonisse [3] in 1971 by taking the highest number of shortest flows through the node in a directed network. Later, in 1977, Freeman [24] defined the betweenness centrality of a node by taking the fraction of the shortest paths passing through the node of interest, from each source to each destination node. Although the concept of betweenness was first introduced by Anthonisse [3], the calculation introduced by Freeman is more widely used in many real world applications such as social network analysis [7], complex route planning [51], computer network analysis [18] etc. In 2001, Brandes proposed a new algorithm using node pair-dependency to compute betweenness centrality for large networks [6].

In a network, the node that appears the most number of times in the shortest paths linking every pair of nodes or components acts as a broker or intermediary [5], [45], and has the highest betweenness centrality value. Researchers have used betweenness centrality to identify the key nodes in a contact network where removal of these nodes could stop the spread of diseases [31], [32], [43], protect the internet function from the failure of an individual router [32] or from a network attack [51]. Cantanese et al. [13] have built in multiple network metrics in their proposed log analysis tool to identify the key members in a criminal network and in particular the betweenness centrality measure in their tool is used to show the communication control of one node on other nodes. Betweenness centrality is also often used in transport networks to propose efficient routing [53], [54]. Some researchers apply recursive calculation of betweenness centrality to find communities [48] and influential people in a network [5], [14], [29].

In 2008, Geisberger et al. [26] introduced a better approximation for betweenness centrality, their main motivation being to apply the betweenness approximation measure on large networks without overestimating the values for the nodes near a pivot or parent node. In [26], Geisberger et al. state that the Brandes’ algorithm [6] overestimates the betweenness values for the nodes near the pivot. To overcome this problem, Geisberger et al. proposed a linearly scaled betweenness method by adding a length function into the aggregation in Brandes’ scheme, thus giving a scaling for each value in the aggregation [25].

Researchers have approached the task of finding influential nodes by combining betweenness with the concept of dependence, where the dependency of node i on node j in a network reflects in some way the total influence of node j on node i [34], [37]. Dependency can be said to exist when there is
information traffic flow between a source and a destination. For example, Shetty et al. [45] explored email connections and set properties of dependency of one email on another. In the sequence of email transactions, the second is said to depend on the first if certain conditions are satisfied, for example, if both appear within the same time frame, if a major part is copied from one email to another, and if that email is forwarded, or if the links in the email are based on a certain event.

In this paper, we adapt the betweenness centrality formulae by Brandes and Geisberger et al. and propose a new dependency formula to calculate the dependency of a source node on an intermediate node. We name this dependency, reliance. The reliance formula is used as a tool to build a source-intermediate node reliance measure algorithm that can measure the suspicious sub-network that contains the criminals or suspects and their associates. The reliance values are used to rank the nodes upon which a criminal or a crime suspect relies. The commonly deployed centrality measures for example degree centrality, closeness centrality, eigenvector centrality, etc. compute the central value of a node by summing the values for all source nodes in a network. Our reliance formula focuses only on the intermediate nodes in the shortest paths from a particular source node to every end node in a network. Our interest is in the relationship between a specific set of source nodes (either criminals or suspects) and their intermediate nodes because the intermediary that carries the information tends to hide illicit activity either on purpose or unknowingly [12], [41].

We illustrate the use of our reliance measure by applying it to the Enron email transactions [15], obtaining a reliance sub-network to aid a money laundering criminal investigation. History shows that some high officials of Enron were involved in accounting irregularities [1] that led to an investigation on various internal business and financial activities including the partnerships set up by some finance managers. This was followed in early January 2002 by an inquiry into other criminal activities leading to an investigation of many Enron executives [17], and finally to the conviction of 10 individuals of money laundering crimes [8]. In [39], we built a shortest path network search algorithm (SPNSA) using shortest paths combined with two centrality measures, eigenvector centrality and betweenness centrality. We applied this SPNSA [38], [39] to the Enron dataset, and it was able to extract a sparse and more manageable network of people for further criminal investigation. The method begins by identifying a list of suspects (the algorithm feed) to form a network. Here we use the new reliance measure proposed in this paper to calculate the reliance values and rank each intermediate node of each suspect in the extracted network. The intermediate nodes with the highest reliance value are gathered and called the crime priority nodes. For the purpose of illustration, we compare our reliance ranking with some other ranking measures for example Google PageRank and Markov centrality.

The rest of the paper is organised as follows: section II contains the definitions and mathematical terms used, while section III describes the proposed method of calculating the reliance of source nodes on the intermediate nodes. In the section following this, we compare the pair-dependency formula given by Brandes, Freeman, Geisberger et al. with our reliance method as well as quantifying the difference between the reliance measure and Geisberger et al.’s formula. Section IV describes the two datasets; the Enron email transactions and Noordin Top Terrorist networks that we use for our experiments. In section V, VI we rank the nodes from these two datasets using the reliance and the Brandes and Geiseberger et al. measures. We further illustrate the novelty of the reliance measure by comparing the rankings found with the Markov walk-path and the Google Pagerank algorithm. Section VII details the prioritisation of nodes for the purpose of a criminal investigation. Finally we give the conclusion.

II. Preliminaries

This section includes the graph-theoretic terminology [28] for defining the betweenness centrality measure introduced by Freeman [24], Brandes [6] and Geisberger et al. [26]. Our research focuses on these three main definitions; for broader explanation and analysis, see Brandes [7] and Newman [42].

Let \( G = (V, E) \) be a graph where \( V \) is the set of vertices \( V = \{v_1, v_2, \ldots\} \) (also called nodes) and \( E \) the set of edges \( E = \{e_1, e_2, \ldots\} \) (representing the connections between the vertices), with the total number of vertices and edges given by \( |V| = n \) and \( |E| = m \), respectively. An edge that has the same start node and end node is called a self-loop or a loop. If more than one edge is associated with a pair of nodes, these are called multiple edges. For our purpose, we exclude all self-loops and the multiple edges are considered as one edge.

A path is a sequence of edges that connects multiple nodes [42]. Given a path \((s, t)\), we call \(s\) the source node and \(t\) the destination, end node or target node. In between the source and the target, lies the alternating sequence of nodes and edges, for instance, \(s, e_1(s, v_1), v_1, e_2(v_1, v_2), v_2, \ldots, e_t(v_t, t)\). Here \(e(u, v)\) denotes the edge connecting nodes \(u\) and \(v\). In the graph \(G\), the length of an \((s, t)\)-path is the number of edges it contains, and the distance, \(\mu(s, t)\), from \(s\) to \(t\) is defined as the minimum length of any \((s, t)\)-path if one exists and undefined otherwise [7]. Let the number of shortest paths from \(s\) to \(t\) be given by \(\sigma_{st}\), and let \(\sigma_{st}(v)\) be the number of shortest paths from \(s\) to \(t\) that pass through \(v\).

**Definition 1** (Freeman [24]). The pair-dependency \(\delta_{st}(v)\) of a pair of nodes \(s\) and \(t\) on an intermediate node \(v\) is the proportion of the shortest paths from \(s\) to \(t\) that contain \(v\), that is:

\[
\delta_{st}(v) = \frac{\sigma_{st}(v)}{\sigma_{st}}
\]

The betweenness centrality of \(v\) is then the sum of all such pair-dependencies [24]:

\[
BC(v) = \sum_{s \neq v \neq t \in V} \delta_{st}(v)
\]

In 2001, Brandes [6] introduced an algorithm for computing betweenness centrality, called the Brandes’ algorithm.
**Definition 2** (Brandes [6]). The dependency of $s$ on an intermediate node $v$ is given by:

\[
\delta_{s,v}(v) = \sum_{w:w \in P_s(w)} \frac{\sigma_{sw}}{\sigma_{sw}} (1 + \delta_{s,w}(w)) \quad (3)
\]

Here \( \{w : v \in P_s(w)\} \) is the set of all nodes $w$ where $v$ is an immediate predecessor of $w$ in a shortest path from $s$ to $w$, that is $v \in P_s(w)$.

According to Brandes [6], $\delta_{s,v}(v)$, the dependency of $s$ on $v$ is positive, that is $\delta_{s,v}(v) > 0$ only when $v$ lies on at least one shortest path from $s$ to $t$ and on any such path there is exactly one edge \( \{v, w\} \) with $v \in P_s(w)$. The Brandes’ algorithm has been used by researchers to measure the centrality of words from a group of texts [6].

In 2008, Geisberger et al. applied a linear scaling to Brandes’ algorithm by introducing the length function (unit edge weight) [26].

**Definition 3** (Geisberger et al. [26]). Given a shortest path from source $s$ to a node $w$ with node $v$ a predecessor of $w$ on this path, the length function is the ratio of the distance $\mu(s,v)$ of $v$ from $s$ to the distance of $w$ from $s$, $\mu(s,w)$. Thus Brandes’ algorithm changes to:

\[
\delta_{s,v}(v) = \sum_{w:w \in P_s(w)} \frac{\mu(s,v)}{\mu(s,w)} \left[ \frac{\sigma_{sv}}{\sigma_{sw}} \times (1 + \delta_{s,w}(w)) \right] \quad (4)
\]

With this change to Brandes’ algorithm, Geiseberger et al., could apply betweeness centrality to real world situations such as choosing improved highway-node routings [26], [27]. While Brandes gives good exact results for small networks, often it is not possible to get exact results in reasonable running time for large networks. The Geisberger et al. formula gives better approximations in relation to large networks such as dynamic highway-node routing.

### III. The Reliance Measure

In our proposed reliance formula, we start with a specific set of source nodes \( \{s_1, s_2, \ldots\} \) and calculate the reliance (a.k.a. “dependency”) value for each intermediary node $v$ that occurs on paths starting from each $s_t$ to all possible end nodes $t$. Thus, we consider all shortest paths from a particular source $s$ to all possible end nodes $t$ where $v \neq t$. In the first part of our formula, we calculate the proportion of the shortest paths linking source $s$ to all nodes $t$ that contain $v$.

**Definition 4** (Importance Rate). Given a graph $G = (V,E)$, $s$ a source node and $v$ an intermediate node on some path $(s,t)$ from $s$ to an end node $t$, the importance rate $IR_{(s,t)}(v)$ measures the importance of $v$ to $s$ such that $s$ may continue communicating with $t$ and is given by:

\[
IR_{(s,t)}(v) = \delta_{s,t}(v) \quad (5)
\]

Here, $\delta_{s,t}(v)$ is the pair dependency of $s$ and $t$ on $v$ as given in Equation (1).

We name this pair dependency as the importance rate of $v$ as it indicates how often the node $v$ is relied on to complete a path to reach the destination $t$ in proportion to all paths from $s$ to $t$. The second part of our formula gives a trust value that the source $s$ places on $v$ to pass messages to any $t$ along the shortest paths.

**Definition 5** (Trust). Given a graph $G = (V,E)$, $s$ a source node and $v$ an intermediate node on some path $(s,t)$ from $s$ to an end node $t$, the trust of $s$ on $v$, relative to the path $(s,t)$ denoted by $T_{(s,t)}(v)$, is given by:

\[
T_{(s,t)}(v) = \frac{\mu(s,v)}{\mu(s,t)}, \text{ for } t \neq s, s \neq v \neq t \quad (6)
\]

where $\mu(s,u)$ is the minimum length from $s$ to $u$ along the path $(s,t)$, $u \in V$, if one exists and undefined otherwise.

This trust concept is illustrated with an example. Figure 1 shows a small network.

![Small network](image)

**Fig. 1: A small network.** This network has 8 nodes and 8 edges. The floating-point numbers near to each node represent the trust value of source node 1 on each intermediate node \( \{2,3,5,7\} \) in the path 1 \( \rightarrow 2 \rightarrow 3 \rightarrow 5 \rightarrow 7 \rightarrow 8 \).

In the graph in Figure 1 let 1 be the source node and 8 the destination or end node. A path from source 1 to destination 8 is:

1 \( \rightarrow 2 \rightarrow 3 \rightarrow 5 \rightarrow 7 \rightarrow 8 \)

Verbiest et al. [29], [50] in their research incorporating path length and trust aggregation mention that the shorter the distance from source $s$ to $v$, the more the source $s$ trusts $v$. De Meo et al. [19] have designed an algorithm to compute edge centrality using k-path length with the assumption that the influence between two nodes reduces when the distance between them increases. Indeed, a common way to start a criminal investigation process is to identify the closest node to a criminal or source because the shorter the distance from the source, the higher the chances the node is the source’s subordinate [40]. We claim that the longer the distance from a source to an intermediate node, the more the source needs to trust that node to pass on a message. Thus, if node 1 in Figure 1 is the source node, then the trust of source node 1 on node 7 to pass the message to destination node 8, \( T_{(1,8)}(7) = \frac{1}{2} \) at distance 4 from node 1 is higher than the trust on node 3, \( T_{(1,3)}(3) = \frac{1}{2} \) at distance 2.
Figure 1 could represent the layering of illegal money within a money laundering syndicate, with node 1 the money laundering suspect. The layering process involves multiple transactions of money through various channels [4], [44]. In such a money layering process, money below the threshold is distributed to different financial institutions or accounts. This contributes to the growth in the length of the paths that are used to transport the money from a source to a destination. The source uses longer sequences of channels to divide and distribute smaller amounts of money making it more difficult for law enforcement authorities to identify the influential people [4], [44]. We propose a method to identify key people within a money laundering syndicate, with node 1 the money laundering suspect. The layering process involves multiple nodes that contains 8 as an intermediate node. The biggest pattern of Geisberger et al.’s technique and our reliance model is compared to the other dependency values.

Figure 2 shows the dependency or the reliance value of node 1 on node 3. Freeman and Brandes’ methods show that node 1 relies more on node 3 than on node 2. The network graph shown in Figure 1 is undirected and node 3 is at the crucial position of separation between two groups. Removing node 3 cuts the information flow from node 1 and node 2 to other nodes. Thus, based on the position of the nodes, the dependency or the reliance value of node 1 on node 3 should be intuitively higher.

Geisberger et al., through their experiments in [26], also show that their technique gives a better estimation of betweenness value when compared to Brandes’ algorithm. The ranking pattern of Geisberger et al.’s technique and our reliance model is the same and the dependency or the reliance value of node 1 on node 3 is the highest. Although the ranking is the same, the technique by Geisberger et al. is different from our reliance formula as the reliance calculation focuses on the reliance of a specific source on other nodes. Another difference is the dependency estimation value of Geisberger et al.’s technique gets higher than our reliance model when the graph gets bigger.

Definition 6 (Reliance). Given a graph \( G = (V, E) \), with \(|V| = n\), a source node \( s \), and an intermediate node \( v \), on some path from \( s \) to an end node \( t \), the reliance of \( s \) on \( v \) along the path \((s,t)\), \( r_{s,t}(v) \) for \( v \in (s,t), t \neq s, s \neq v \neq t \), is the product of the importance rate \( IR_{s,t}(v) \) and the trust \( T_{s,t}(v) \):

\[
r_{s,t}(v) = \delta_{st}(v) \times \frac{\mu(s,v)}{\mu(s,t)} \tag{7}
\]

Finally, the total reliance of source \( s \) on \( v \) over all paths from \( s \) to all possible end nodes \( t \), is:

\[
R_s(v) = \sum_{v \in (s,t), t \neq s, s \neq v \neq t} \frac{r_{s,t}(v)}{(n-2)} \tag{8}
\]

Here, \(|V| = n\), that is, there are \( n \) vertices in the graph, and since the start node \( s \) and the intermediate node \( v \) are fixed and \( \delta_{st}(v) \) is taken for all \( t \neq s, s \neq v \neq t \), there are \((n-2)\) possible values for \( t \). Thus, we normalise the reliance value, \( R_s(v) \) with \((n-2)\).

IV. COMPARISON BETWEEN DIFFERENT DEPENDENCY TECHNIQUES

Our reliance model is compared to the dependency techniques of Freeman [24], Brandes [6] and Geisberger et al. [26]. The graph in Figure 2 shows the dependency or the reliance value of node 1 on other intermediate nodes of the network in Figure 1.

Example 1. Difference between dependency techniques and reliance formula

Example 2. Difference between the reliance formula and Geisberger et al.’s formula.
Our SPNSA implementation in [39] was based on the number of BCC recipients needed to identify a trust network, where the focus was on emails that contained one or two recipients bcc-ed. By its very nature, ‘BCC’ email transactions contains recipients that are kept secret [21]. In [38], our experiment results showed that the undirected BCC email transactions have most number of criminals in the shortest paths network, thus further analysis was conducted using BCC email transactions. In this paper, both the ‘TO/CC’ and ‘BCC’ undirected email transaction networks are used to produce the reliance sub-networks for all suspects. Through dividing the email transactions, we are able to compare the important nodes that a suspect relies on, whether or not the connection (email) is kept secret (bcc-ed). To form an undirected network, we make the broad assumption that an email sent from A to B or from B to A implies an undirected relationship between A and B.

The majority of email transactions in the Enron dataset, 87.3% use the fields ‘TO/CC’, while 12.7% are ‘BCC’ email transactions. The email transactions in this dataset comprise of external and internal email addresses where the external email addresses refer to emails that do not have ‘@enron’ while the internal emails do. The email addresses are the nodes and we give more importance to the sequence of emails exchanged by the nodes rather than the content of the emails. Similar to [38], [39], in this paper, Enron managers that comprise of the Enron finance managers and a few others who hold top posts are used as the suspects or source nodes. The employees of Enron have been selected based on the possibility of being involved in money laundering and are henceforth called suspects. These suspects were used as feed to the SPNSA algorithm in [39]. In this paper, the first set of suspects consists of the Enron finance managers [2] while a second larger list comprises of all managers [2] including the finance managers. These lists of Enron managers were collected from a report on the chronology of events related to the collapse of Enron [2].

A manager may be indexed by more than one node if he or she has more than one email account. Both the email transaction groups, the ‘TO/CC’ and ‘BCC’, have distinct ID sets for the different email addresses and this is designed as such because, somewhat surprisingly some nodes that exist in the ‘BCC’ group do not exist in the ‘TO/CC’ group. The network formed using the ‘BCC’ email transaction subsets has 19,716 nodes and 65,532 edges while the network formed using the ‘TO/CC’ email transaction subsets has 26,027 nodes and 252,863 edges. All self-loops and multiple edges have been removed from these networks.

**B. The Noordin Top Terrorist Network**

The second dataset that we use to compare rankings is the Noordin Top terrorist network [20]. This dataset is small and consists of different types of connections. The first group of connections gives the terrorists’ affiliations such as terrorist organisations, educational institutions, business and religious institution. The second group contains relationship information such as classmates, kin, friends and the third group comprises of individuals that provided logistical support or participated
in training events, terrorist operations, and meetings [20]. We take 2 different subsets from this dataset for our analysis. These are terrorist-friendship and terrorist-classmates.

Terrorists in this dataset have been ranked using particular key node ranking techniques [10], [11], [22], [23], [36]. Key players in this dataset were predicted by Butt et al. [11], incorporating certain centrality measures (degree, betweenness, closeness centrality and eigenvector) with some classifying techniques; k-nearest neighbours (KNN), Gaussian mixture model (GMM) and support vector machine (SVM). Liebzig and Rao [35] use a bipartite clustering coefficient to find important nodes in this multi structured terrorist network. Brown [10] in his thesis project finds key players of this terrorist network by integrating some centrality measures (betweenness, closeness, and total degree) into network fragmentation and diffusion processes.

In our experiment, we rank the terrorists using source-intermediate reliability value. Since it is a small sub-network, we do not extract any terrorist sub-network using SPNSA [39] instead using the terrorist-friendship and terrorist-classmates network as it is.

VI. RANKING IMPORTANT NODES USING THE RELIANCE MEASURE

In subsection VI-A for the purpose of illustration, we compare the ranking of the nodes in the Enron ‘BCC’ network using betweenness centrality and the reliance formula.

We also compare the reliance value ranking with the rankings obtained using a Markov centrality score and the Google PageRank method. Random walks are used to calculate Markov centrality scores [52]. The centrality score of a node is calculated by first taking the average path length of a random walk starting at that node and arriving (for the first time) at some other node, averaged over all other nodes. Markov centrality of the node is then the inverse of the average distance between it and every other node [16], [52]. The PageRank algorithm, used by Google to rank important web pages, uses the assumption that a page is important when it is linked by many pages or if it is linked to many other important pages [9], [33]. The mathematical equivalent of this concept is the eigenvector centrality measure [33].

For the Noordin Top terrorist network, in section VI-B we use these measures to rank a terrorist, his friends and classmates to see if there are any differences between reliance ranking to other measures.

A. Comparing node ranking using betweenness centrality, Markov centrality and PageRank with the reliance value in the Enron network

We first compare the node ranking results of betweenness centrality proposed by Brandes and Geisberger et.al with the results produced using the reliance measure on the Enron ‘BCC’ network. The total reliance of all finance managers and all managers on each $v$ in the Enron finance manager and manager BCC sub-networks is used for this comparison. The nodes are ranked based on the descending order of betweenness centrality (Brandes’ and Geiseberger et. al) values.

We pick 5 Enron employees who worked as finance managers with the Enron company between the years 1990-2001 as the SPNSA’s [39] feed. The finance managers [2] that are used as the algorithm feed are Andrew Fastow (686, 687), Sherron Watkins (16929), Ben Glisan (1369), Rick Causey (15077) and Jeff McMahon (8071). This sub-network is named as the Enron Finance Manager BCC sub-network and has 30 nodes and 53 edges. The betweenness centrality measures by Brandes and Geisberger et al. calculates the centrality value from all sources on $v$. Thus, to compare the reliance value with the betweenness centrality measures, we take the total reliance of all finance managers or managers on each $v$ in the respective BCC sub-network. The comparison of node ranking is depicted in Figure 4 for nodes that the finance managers rely on and Figure 6 for nodes that the managers rely on.

![Fig. 4: The Enron finance manager BCC sub-network node ranking](image)

Highly ranked nodes can be important nodes for a primary investigation. To compare the results with the reliance measure, we normalise both sets of the betweenness centrality results of Brandes and Geisberger et al. by dividing each node’s betweenness value with the maximum value in each set respectively. In Figure 4 all three measures identified the same node as having the highest value. The interesting point is to note that some of the nodes (for example, 11010, 12935 etc.) ranked lower by the betweenness centrality measures, are ranked as being more important by the reliance measure. One node in this list, node 11010 (lfastow@pop.pdq.net) belongs to Lea Fastow who was convicted as an Enron money laundering criminal [8], [39].

Reliance ranking is also compared with the other two ranking methods; PageRank and Markov centrality. The results are shown in Figure 5. The nodes are ranked based on the descending order of PageRank scores.
Fig. 5: The Enron finance manager BCC sub-network node ranking. The total reliance of all finance managers on each node in the Enron Finance Manager BCC sub-network is used for this comparison. The nodes are ranked based on the descending order of PageRank values. There is a clear difference in node ranking using these three different methods. For example, nodes 3945, 3973, 10917 and 7974 have the same ranking value using Markov centrality and Pagerank method but these nodes are ranked differently using reliance value.

The bar chart in Figure 5 shows the differences in node ranking using Markov centrality, PageRank and the reliance measure. Some nodes (3983, 687 and 15077) are valued by Markov centrality and PageRank but not relied on at all by the finance managers (See figure 5 towards the end of the bar chart). Similar to the betweenness centrality measures in Figure 4, PageRank and Markov centrality ranking were not able to pick 11010 (Lea Fastow), who is not in the finance manager list, as important, in contrast to the reliance formula. Next, the same method is repeated for all the Enron managers; a larger algorithm feed to see again if there is a difference in ranking. A shortest paths sub-network is formed using all the managers and it is named as the Enron Manager BCC sub-network. This is an undirected graph with 121 nodes and 314 edges. First the nodes are ranked based on the descending order of betweenness centrality (Brandes) values.

Fig. 6: The Enron manager BCC sub-network node ranking. Three different methods, betweenness centrality by Brandes, by Geisberger et al. and reliance value using reliance measure are used to show the difference between node (Enron manager) ranking. Note that only the nodes with positive reliance value are displayed here.

Even more than in Figure 4, Figure 6 shows the difference in the ranking between the betweenness centrality measures and the reliance measure; the node (17697) picked as the most important one by the reliance formula is different from the one (15932) valued highest by Brandes and Geisberger et al. with latter node (15932) being one of the least scored nodes as per the reliance measure. Moreover, the betweenness centrality values for nodes 348, 441 and 9395 are almost the same whereas the reliance measure shows a different ranking. These differences may allow an investigator to pick suitable people for further investigation.

Next we applied Markov centrality and PageRank to compare with the Enron managers’ node reliance ranking. The result is shown in Figure 7. The nodes are ranked based on the descending order of PageRank values.

Fig. 7: The Enron manager BCC sub-network node ranking.

The total reliance of all managers on each node in the Enron Manager BCC sub-network is used for this comparison. The nodes are ranked based on the descending order of PageRank values. There is a clear difference in node ranking using the three different methods. For example PageRank, Markov centrality and the reliance measure rank nodes 19075, 6673 and 17697 as having the highest value respectively.

It is clear that an investigation using either the betweenness centrality, the PageRank or the Markov centrality ranking, as opposed to the reliance ranking, will lead to a different outcome in terms of possible people to investigate. For example, note that Lea Fastow is not in the algorithm feed for the experiment using all managers or finance managers but Figure 4 shows that Lea Fastow, the wife of Andrew Fastow and a convicted money laundering criminal, is heavily relied on by the finance managers.

B. Comparing node ranking using betweenness centrality, Markov centrality and PageRank with the reliance value in the Noordin Top terrorist network

Four different bar charts are presented here to show the network node importance values calculated using betweenness, Markov centrality, PageRank and the reliance measure. The terrorist-friendship sub-network consists of 61 nodes and 91 edges and the terrorist-classmate sub-network has 39 nodes and 175 edges. We first isolated the highest reliance of each node on the intermediate node in the shortest paths between that node and all other nodes in the sub-network. Then we sum all the reliance values of the same intermediate node and normalise it with the highest value in the list. The results are shown in Figure 8 and 9.
(a) The terrorist-friendship sub-network node ranking using betweenness centrality by Brandes, Geisberger et al. and reliance measure.

(b) The terrorist-classmate sub-network node ranking using betweenness centrality by Brandes, Geisberger et al. and reliance measure.

Fig. 8: The total highest reliance of all nodes in the terrorist-friendship and terrorist-classmate sub-network on each \( v \) is used for this comparison. For figures a and b, the nodes are ranked based on the descending order of Brandes’ betweenness centrality values. In figures a and b, reliance and betweenness values are shown for different subsets of terrorists, that vary in size and membership. For each graph, terrorists with zero reliance and ranked by betweenness (Brandes) values as below the terrorist with the lowest reliance, are not included.

The terrorist node importance level comparison experiment shows that our reliance formula is able to present variations in the importance level of nodes when most nodes that are ranked by the other methods in this paper have similar values. The differences in the rankings for this dataset are even more extreme than for the Enron dataset.

VII. IDENTIFYING CRIME PRIORITY NODES USING THE RELIANCE MEASURE

The experiment hereafter uses only the Enron dataset and the reliance formula to get the persons of interest (a.k.a. “crime priority nodes”) of each finance manager and manager in the ‘BCC’ and ‘TO/CC’ network respectively. The main purpose of the following experiments is to show the important intermediate nodes to the suspects ranked by the reliance measure. At this point, we do not corroborate the persons of interest of the finance managers or the managers that we have obtained with any published articles or past research.

A. Extracting the suspects’ crime priority nodes from the Enron ‘BCC’ email network

We first show the results of identifying the Enron money laundering suspects’s important nodes from the ‘BCC’ email network based on suspect-intermediate reliance value. We start by picking the Enron finance managers as our source nodes. We calculate the reliance of each finance manager on all intermediate nodes \( (v) \) in the path between the finance manager and all other nodes in the Enron Finance Manager BCC shortest paths sub-network. The intermediate node that each finance manager relies on the most was identified. The source-intermediate node reliance measure identifies 2 money laundering criminals [8], [39] who are important to each other; Ben Glisan (1369) had the highest reliance on Andrew Fastow and vice versa.

Next, we change the list of suspects to all managers (including the finance managers) to see if we obtain new people of interest. Unlike the reliance connections in the Enron Finance Manager BCC sub-network, the source-
intermediate criminal to criminal connection does not occur in the Enron Manager BCC sub-network. However, other nodes that are the persons of interest to the managers are retrieved. Some managers also popped up as important intermediate nodes; Greg Whalley (6673), President and Chief Operation Officer, and Lou Pai (11357), CEO of Enron Energy Services. The Enron managers who were convicted of money laundering and who they relied on the most are noted here: Kenneth Rice (9994) relied the most on Rosalee Fleming (rosalee.fleming@enron.com (15932)), Andrew Fastow (686 and 687) relied equally on Rosalee Fleming and Mike Mcconnell (mike.mcconnell@enron.com (12935)), while Ben Glisan (1369) relied on Greg Whalley (greg.whalley@enron.com (6673)).

B. Extracting suspect’s crime priority nodes from the Enron ‘TO/CC’ email network

Using the same method as shown above, we extract the finance managers’ and then all the managers’ crime priority nodes from the ‘TO/CC’ shortest paths sub-network. Note that some employees’ email addresses that exist in the ‘BCC’ network do not occur in the ‘TO/CC’ network, for example email address (andrew.fastow@ljinvestments.com) belonging to Andrew Fastow occurs only in the ‘BCC’ network. Thus, different IDs are used in the ‘TO/CC’ network. The finance managers [2] that are used as the SPNSA algorithm feed are Andrew Fastow (1472), Sherron Watkins (26577), Ben Glisan (2521), Rick Causey (24277) and Jeff McMahon (12919). Ben Glisan (2521) exists only in the ‘BCC’ shortest paths network not in the finance managers’ ‘TO/CC’ shortest paths network. Thus we could not show the person of interest of Ben Glisan for the ‘TO/CC’ shortest paths network. From this finance managers’ ‘TO/CC’ shortest paths network, we obtain one intermediate node (George Wasaff (george.wasaff@enron.com (10351))) that all finance managers rely on the most. Pointing to the same person of interest, is irregular and could be a pointer for further investigation.

We wish to discover who appears to be the important person to all the money laundering criminals that occur in the ‘TO/CC’ Enron manager shortest paths network. Here we use all managers as the suspects. The nodes that the money laundering criminals (within the list of managers) rely on the most are given here. Kenneth Rice with multiple email addresses; ((kenneth.rice@enron.com (16115)), (ken_rice@enron.com (16069)) and (ken.rice@enron.com (16052)) relies on (rosalee.fleming@enron.com (25079)), (mike.maggi@enron.com (20577)) and (jeff.skilling@enron.com (12946)) respectively. Andrew Fastow (1472) relies on Kelly Johnson (kelly.johnson@enron.com (15959)). Two very senior managers also appear as common persons of interest to some of the suspects (managers). They are Jeff Skillling (jeff.skilling@enron.com (12946)) and Kenneth Lay (kenneth.lay@enron.com (16104)). These persons of interest are important for further investigations. It is possible that more criminal to criminal connections would be identified if an investigator picked the best possible suspects to inspect (based on corroborative information or interviews). The experiments above show that the reliance measure allows an investigator to find people who are close to and heavily relied on by the suspects for further investigation.

VIII. Conclusion

The work presented in this paper introduces a new reliance measure to rank nodes in a network and therefore identify nodes of interest. This reliance measure is different from betweenness centrality because the betweenness centrality measure calculates the centrality value of all sources on a node whereas the reliance measure calculates the reliance of a list of specific sources on a node. We compared the reliance ranking with other centrality measures such as Google PageRank, Markov centrality as well as betweenness centrality. Reliance identifies a very different subset of nodes from those identified by the other measures. The ranking based on the reliance measure can also be used to identify the nodes that particular persons of interest rely on most heavily.

Our SPNSA as described in [39] is able to produce a small and manageable network. In this paper we further our research and analyse the connections between nodes in the network; reliance of one node on another leading possibly to the identification of important nodes. This reliance method could reduce the time for exploring a large network and hence may speed up an investigation process. It is important to note that, prior to the application of the shortest paths network search algorithm [39] and the reliance formula, it is essential to choose the most relevant suspects to a crime. The analysis proposed in this paper could also yield more criminal to criminal connections by choosing the most applicable or appropriate, to a crime incident, algorithm feed.

REFERENCES

[1] (2002) Timeline: Enron’s Rise and Fall. [Online]. Available: http://news.bbc.co.uk/2/hi/business/1759599.stm

[2] J. M. Anderson. (2003, March) Enron: A select chronology of congressional, corporate, and government activities. Congressional Research Service, Library of Congress. [Online]. Available: http://digital.library.unt.edu/ark:/67531/metads4006

[3] J. M. Anthonisse, “The rush in a directed graph,” Stichting Mathematisch Centrum. Mathematische Besliskunde, no. BN 9/71, pp. 1–10, 1971.

[4] AUSTRAC. (2008) Introduction to money laundering. [Online]. Available: http://www.austrac.gov.au/education/index.html

[5] S. P. Borgatti and M. G. Everett, “A graph-theoretic perspective on centrality,” Social networks, vol. 28, no. 4, pp. 466–484, 2006.

[6] U. Brandes, “A faster algorithm for betweenness centrality,” Journal of Mathematical Sociology, vol. 25, no. 2, pp. 163–177, 2001.

[7] ———, “On variants of shortest-path betweenness centrality and their generic computation,” Social Networks, vol. 30, no. 2, pp. 136–145, 2008.

[8] K. F. Brickey, “From Enron to WorldCom and beyond: Life and crime after Sarbanes-Oxley,” Washington University Law Quarterly, vol. 81, pp. 357–402, 2003.

[9] S. Brin and L. Page, “The anatomy of a large-scale hypertextual web search engine,” Computer networks and ISDN systems, vol. 30, no. 1, pp. 107–117, 1998.

[10] J. C. Brown, “Improving nonlethal targeting: a social network analysis method for military planners,” DTIC Document, Tech. Rep., 2012.

[11] W. H. Butt, M. U. Akram, S. A. Khan, and M. Y. Javed, “Covert network analysis for key player detection and event prediction using a hybrid classifier,” The Scientific World Journal, vol. 2014, 2014.

[12] P. B. Campbell, “The illicit antiquities trade as a transnational criminal network: Characterizing and anticipating trafficking of cultural heritage,” International Journal of Cultural Property, vol. 20, no. 02, pp. 113–153, 2013.
