

A Fraud Detection Visualization System Utilizing Radial Drawings and Heat-maps

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Abstract. We present a prototype system developed in cooperation with a business organization that combines information visualization and pattern-matching techniques to detect fraudulent activity by employees. The system is built upon common fraud patterns searched while trying to detect occupational fraud suggested by internal auditors of a business company. The main visualization of the system consists of a multi-layer radial drawing that represents the activity of the employees and clients. Each layer represents a different examined pattern whereas heat-maps indicating suspicious activity are incorporated in the visualization. The data are first preprocessed based on a decision tree generated by the examined patterns and each employee is assigned a value indicating whether or not there exist indications of fraud. The visualization is presented as an animation and the employees are visualized one by one according to their severity values together with their related clients.

1 Introduction

Internal fraud detection in business organizations gains more and more attention as fraudulent activity appears in ascendant trend during the last years. Fraud is defined as *the intentional misuse or abuse of the assets of a company* and may be committed by employees, clients or other entities [3]. Studies on business fraud schemes show that most of the reported fraud cases have been committed by trusted associates and this is referred to as “occupational or employee fraud”. Occupational fraud can be classified into three main categories: (i) False or fraudulent financial statements, (ii) assets misappropriation and, (iii) corruption [3]. The falsification of financial statements, produces great loss to a company and is mostly committed by employees in senior management or executives. Assets misappropriation is committed by lower-level personnel and due to the fact that produces insignificant losses at an individual level it cannot be easily traced by the auditors. Such schemes may continue for years until fraud is confirmed, producing a huge cost both to the global economy and to the company. As a result of fraud, business reputation, company value, and public and client trust are negatively affected.

Even though advanced information technology has been incorporated into organizations to reduce the risk of internal fraud, monitoring diverse systems that produce textual logs in non-uniform formats is a time-consuming task. Information visualization can be promising since it facilitates the quick identification of fraudulent activity. In this paper, we present a system developed in cooperation with a business organization that exploits the advantages of information visualization and pattern recognition to detect suspicious patterns concerning fraudulent financial statements in systems in which a pair of entities (employee and client) are involved. Towards this direction, the system produces a multi-layer radial drawing (see Figure 1) representing the activity of employees and clients along with other significant information that enable the identification of possible fraud patterns.

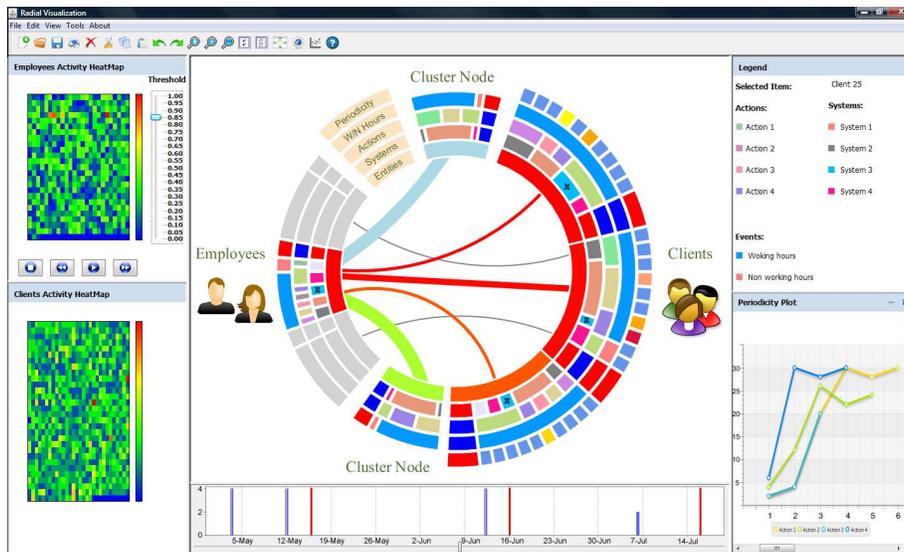


Fig. 1: A snapshot of the interface of the system.

Since occupational fraud schemes are well-hidden in the huge amount of data, we were seeking for an approach that would present to the auditor all the recorded events according to their severity. On the other hand, visualizing large data-sets simultaneously is confusing and inefficient. For this reason, the system measures the similarity of the activity of the employees based on fraud detection patterns (suggested by auditors based on their experience and the framework of the company on internal fraud risk reduction) and appropriate heat-maps are generated and incorporated in the system. The produced visualization is presented as an animation. The system supports supplementary functionalities such as a database log viewer, export log mechanisms, storing and post-processing of data, plots and charts (see Figure 2).

2 Detection Procedure

Fraud detection has been studied enough in the literature. To the best of our knowledge, there exist only few works oriented exclusively on occupational fraud detection. Luell [18] utilizes data-mining and visualization techniques to detect client advisor fraud in a financial institution. Eberle and Holder [12] detect structural anomalies in transactions and processes propagated by employees using a graph representation. SynerScope [23] is an industrial visualization tool for analyzing “Big Data” capable of detecting financial fraud using a visualization scheme similar to ours representing the billing links and relations between the company and other entities. The main difference is that our system is oriented exclusively on occupational fraud detection based on patterns suggested by auditors and, thus, it is equipped with a detection mechanism that preprocesses the data and the visualization conforms to these patterns. We also utilize animations for the detection of fraud schemes to avoid cluttering the visualization. A visualization system based on concentric circles was presented in [2] aiming at identifying periodic events using an algorithm for periodicity detection. Our system extends the one presented in [1] that detects periodic patterns that may conceal occupational fraud in several ways: (i) The visualization of our system provides a complete view of all the examined patterns and the results of the examination on each pattern (in [1], the detection procedure was a “black-box” determining the order of the presentation of the clients in a video representing their activity in which suspicious clients appeared first; partial results of the detection procedure were illustrated in additional plots and charts, which hindered the investigation), (ii) the detection mechanism is based on a decision tree even though we have incorporated most of the patterns presented in [1], (iii) for periodicity detection, we apply a variation of the Longest Common Subsequence algorithm [24] that tackles noisy data, (iv) a parallel coordinates plot has been added to detect unusual employee behavior (unauthorized access to computers, business systems, etc), (v) the system provides a database-viewer to facilitate the investigation procedure.

Many of the existing publications that deal with fraud detection in general, use of data-mining techniques [4], [17], [19]. The Financial Crimes Enforcement Network AI System [14], [21] is a system that correlates and evaluates all reported transactions for indications of money laundering using pattern-matching techniques. The NASD Regulation Detection System [16], [20] identifies patterns of violative activity in the Nasdaq stock market by combining pattern matching and data mining techniques and provides visualizations of the results. The Link Analysis Workbench [25] searches for criminal activity and terrorism in noisy and incomplete data also utilizing pattern matching techniques. Visualization techniques have been also proposed for financial fraud detection. 3D-treemaps have been used to monitor the real-time stock market performance and to identify a stock that may represent an unusual trading pattern [15]. “WireVis” [7] is a system that provides interactive visualizations of financial wire transactions and aims to detect financial fraud. A system that correlates data and discovers complex networks of po-

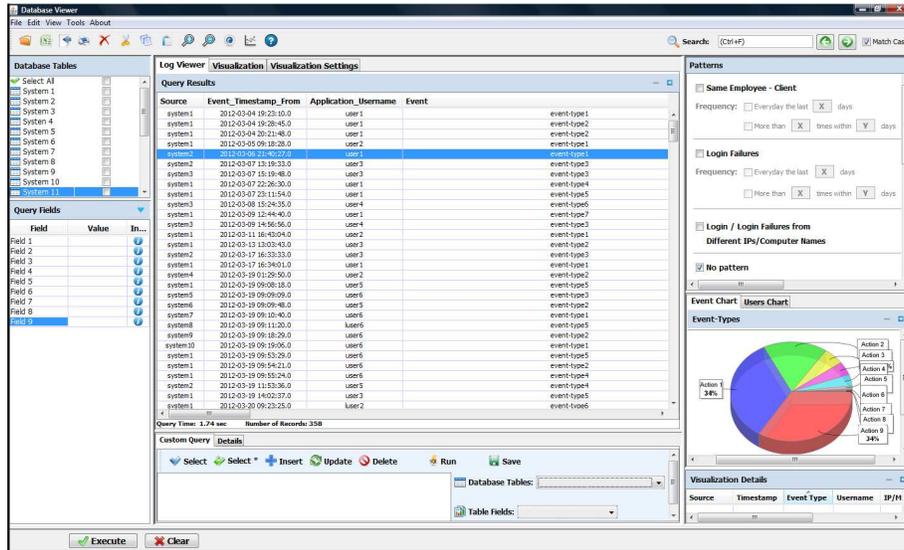


Fig. 2: The startup screen of the system. Custom queries can be performed and results are presented in the log viewer. The data have been anonymized for security and data privacy reasons.

tentially illegal financial activities based on visualization techniques was presented in [13]. “VISFAN” [10] has been developed for the visual analysis of financial activity networks that tries to discover financial crimes, like money laundering and frauds. “VIS4AUI” [9] is a system that tries to detect money laundering and financial crimes by collecting financial information related to ongoing bank relationships and high value transactions. Radial drawings are widely used for the visualization of large data-sets, especially in bioinformatics [8], [11] and social networks [6], where a large portion of information has to be visualized simultaneously. This paper is structured as follows: In Section 3, we describe the detection procedure. In Section 4, we present the features of the visualization of the system. Section 5 presents a case-study based on real data. We conclude in Section 6 with open problems and future work.

3 Overview of the Detection Procedure

As input, the system takes log files from diverse control systems that are appropriately parsed and stored in a database using a uniform format. Records generated by systems involving an employee and a client consist (among other secondary fields) of a time-stamp, an employee ID, a client ID and an action. An event, say e , is defined as a 4-tuple (t, u, c, a) , where: (i) t corresponds to the time-stamp of the occurrence of e , (ii) u corresponds to an employee, (iii) c represents a client, and (iv) a is the action taken by the employee. For an event $e = (t, u, c, a)$, we say that

client c is related to e and is also related to employee u . For a pair of employee-client (u, c) , an event-series $T_{u,c} = \{e_{(u,c)}^1, e_{(u,c)}^2, \dots\}$ is a sequence of events $e_{(u,c)}^i = (t_i, u, c, a_i)$ related to client c and employee u .

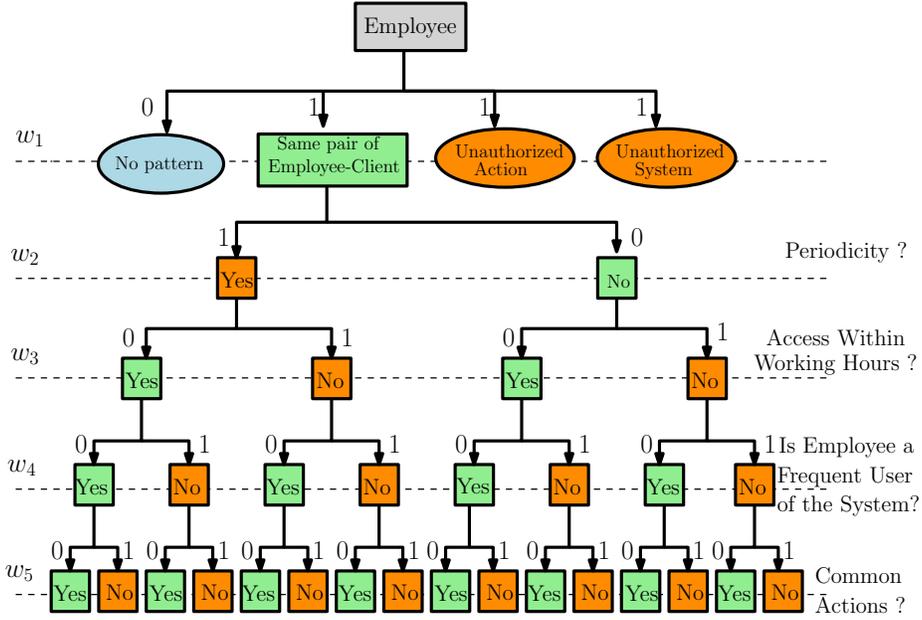


Fig. 3: The decision tree based on which the event-series of the employees are assigned a severity value.

The visualization may be generated either based on the whole data-set of the database or on queries performed by the auditor in the startup screen of the system (see Figure 2). As mentioned above, data have to be preprocessed before producing the visualization such that employees with strong indication of fraud are distinguished. For this reason, for a given employee u , the event-series with each client related to u will be evaluated based on possible fraud patterns and a value indicating the severity of the related events (within range $[0, 1]$) will be assigned first to the event-series and then, to the employee. If several fraud patterns are identified, employee u is assigned the maximum severity value of the already calculated event-series related to u . The evaluation is performed based on a decision tree generated by the following patterns suggested by the auditors (see Figure 3): (i) There exist more than X events related to employee u and client c within a time interval of Y days/months where X, Y are configurable by the auditor (refer to the green rectangle node of the first layer below the root of the decision tree in Figure 3), (ii) the employee has performed unauthorized actions (based on a list of actions provided by the auditors) and, (iii) the employee operated in

systems that she is not authorized to use. In the case where patterns (ii) or (iii) occur, the event-series of the employee is assigned the maximum value (i.e., value 1) such that the employee is definitely distinguished in the visualization. However, in the case where pattern (i) occurs, the investigation has to proceed further. The patterns that are taken into consideration in this case include the following:

- **Event-series periodicity:** A common pattern while examining such fraud schemes is the occurrence of the events in regular time basis. For instance, an employee modifies intentionally the account of a client every month within the billing cycle of the account and more precisely, before its billing date. Assuming that event-series $T_{u,c}$ related to employee u and client c is ordered according to the timestamps of the events, the system aims to detect similarities between pattern time-series based on a variation of Longest Common Subsequence (LCSS) algorithm for time-series [24] which is robust under noisy conditions. The pattern time-series include the ideal time-series if the events between the entities appear in time intervals that equal exactly to 1, 7, 15, 30 days and other time-series identified in the past as fraud patterns. In the case where similarity with any of the above time-series is detected, we consider the event-series of the employee to be periodical.
- **Events occurring outside working hours:** Fraudulent activities usually occur outside working hours, on weekends, on holidays or at the end of the employee’s shift. For this reason, if such events occur they have to be taken under consideration.
- **Employee frequency in recorded systems:** Each employee according to her responsibilities operates in specific business systems. If this is not the case, then the employee has to justify the recorded event. Also, in several systems such as fraud management systems (FMS), it is expected that an employee monitors the activity of a suspicious client. Hence, events stemming from these systems have to be given smaller weight.
- **Actions taken by the employee:** Similarly to the previous case, there exist some actions that an employee is unlikely, but not unauthorized to perform since they do not conform to her responsibilities.

The idea behind the decision tree was to correspond to each layer one fraud pattern and create a path according to the result of the examination on each pattern. We consider the importance of patterns based on their corresponding layer in the decision tree, such that the higher ones (closer to the root) are more important. Let $x = [x_1, x_2, x_3, x_4, x_5]$ be the pattern vector examined (e.g., $x = [0, 0, 0, 0, 0]$ corresponds to non-fraudulent activity) and let $y = [y_1, \dots, y_5]$ be the vector resulting from the traversal of the decision tree from its root to its leaves according to the evaluation of the events of pair (u, c) on each factor. If the examination of the events leads to “Unauthorized action” or “Unauthorized system” the event-series is directly assigned value 1. Else, each tree layer i is assigned a weight, say $w_i, i = 1, \dots, 5$, based on the formula presented in [22] such that dissimilarities between the two vectors that occur at higher levels of the tree will be more important. For this reason, the distance between vectors x, y , say $d(x, y)$, representing the dissimilarity by the pattern vector,

is calculated by applying the normalized Weighted Euclidean Distance metric formula $d(x, y) = \sqrt{\sum_{i=1}^5 (x_i - y_i)^2 * w_i} / \sqrt{\sum_{i=1}^5 w_i}$. This value (or the maximum of the already calculated values, if more than one fraud patterns exist) corresponds to the severity value of the event-series of employee u , which is the value finally assigned to the employee. Based on these values the system generates a heat-map representing all employees by rectangular nodes and gradient colors from blue to red (refer to the upper-left heat-map of Figure 1), such that nodes with color close to color-red represent employees with strong indications of fraud, whereas blue colored nodes employees with no suspicion of fraud. Similarly to the severity calculation of the event-series of employees, the system assigns also a severity value to clients based on the above patterns. The only difference is that for a given client c , the severity value is calculated on all the events related to c (not only the ones that concern a specific employee). In this manner, a client involved in suspicious activity with two or more employees will be distinguished.

4 Description of the System

The visualization window³ consists of two heat-maps representing the severity of the activity of employees and clients (refer to the upper-left and the bottom-left panels of Figure 1). Although a great deal of research has focused on the deficiencies of rainbow color maps [5], they are still widely used in the visualizations, since their effectiveness depends on the nature of the data. In our data-sets, it was necessary to have three colors (red, green, blue) representing clearly the severity value of the examined entities (high, medium, low, resp), and thus, we have chosen this type of color map. We have tried different types of color maps, but the result was more misleading during the investigation. The particular selection of colors was not confusing to the auditors since fraud cases appear rarely in a company which implies that few red-colored rectangles appear eventually in the heat-maps.

At startup only the heat-map representing the activity of the employees is generated. The auditor selects a threshold value that determines the employees that will be presented based on their severity values. The visualization is animated and each time an employee together with her related clients is illustrated. Before an employee is presented, the heat-map that corresponds to the activity of related clients is generated.

The main visualization of the system is a multi-layer radial drawing where each layer L_1, \dots, L_5 (see Figure 4) represents a different aspect of the audit data (systems, actions, within working hours or not, periodicity) and each circular sector corresponds to an entity (employee, client or cluster). Then, a graph is generated; its nodes correspond to each of the above entities, whereas its edges correspond to the connections among them. The innermost layer of the visualization (layer L_1 of Figure 4) accommodates the nodes of the graph (drawn as portions of a ring).

³ The reader is suggested to print the paper in color.

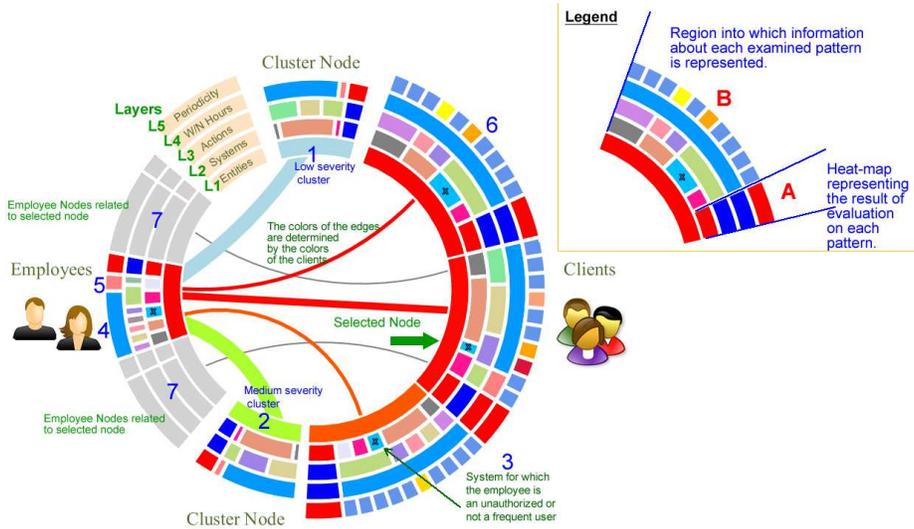


Fig. 4: Description of the main-visualization of the system. “Fat” edges (unless referring to cluster nodes) and in particular, the red-colored ones may be indications of fraud that have to be further examined.

Nodes representing employees are drawn to the left-part of the visualization where the ones representing their related clients to the right part. To avoid cluttering the visualization with nodes representing clients with no indication of fraud, the auditor can specify thresholds that split clients in one or two clusters (low-severity cluster and/or medium-severity cluster) according to their severity values. These nodes are accommodated on top and to the bottom part of the visualization. The color of the nodes (apart from the ones representing clusters and the gray-colored ones that will be explained later) follows the color of the corresponding entities in the heat-maps. The light-blue (green, resp) colored cluster-node corresponds to the low (medium, resp) severity cluster (refer to reference points 1 and 2 of Figure 4, resp.). Regarding the edges of the drawing, the system supports either circular arc edges or straight-line edges. The thickness of an edge is proportional to the number of connections between the employee and the client while its color is determined by the color of the client. In a fraud context, “fat” edges (unless referring to cluster nodes) and in particular, the red-colored ones will be indications of fraud that have to be further examined.

Subsequent layers (i.e., layers $L_2 - L_5$) represent the patterns described in Section 3 and are split into two regions *A* and *B* (refer to Figure 4). Region *A* represents a heat-map indicating the result of the examination of the entity in the specific pattern. Red color indicates identification of suspicious pattern. Region *B* illustrates information about each corresponding examined pattern. In layer L_2 , the different business systems related to the each of the entities are represented. Each such system is

characterized by a specific color and occupies space proportional to the corresponding aggregate percentage of use by the entity. For each employee, this percentage is calculated based on the aggregated percentage of use on all clients that are currently drawn in the visualization, whereas for each client based on the percentage of use by the employee currently visualized (unless more than one employees related to a client are drawn simultaneously in the visualization). Similarly, for cluster nodes the aggregated percentage of use for all clients that belong to the cluster is calculated. Systems for which the employee is an unauthorized or not a frequent user are marked by an X (refer to reference point 3 of Figure 4). Layer L_3 corresponds to the actions reported for each entity, and are drawn in a similar manner as the ones in layer L_2 . Again unauthorized or suspicious actions are marked with an X . Layer L_4 represents the percentage of events that occur within or outside working hours. The light-blue colored parts represent events occurring within working hours, whereas the light-red colored parts indicate the existence of events occurring outside working hours (e.g., see reference points 4 and 5 of Figure 4, resp). For each client node there exists an additional layer (refer to L_5 of Figure 4, e.g., see reference point 6) that indicates whether or not the event-series of the client is periodical. The event-series is compared with the pattern time-series currently stored in the system and a heat-map is generated indicating the degree of similarity with each pattern. Again, light-red colors indicate suspicious cases.

Regarding the investigation procedure, as already mentioned, the auditor specifies a threshold and the employees with assigned severity value above the threshold are presented in the visualization one by one, together with their related clients. The auditor is able to start, pause or stop the video and process the visualization. In the case where a client node is selected, additional employees related to the client can be added to the visualization which facilitates the possible identification of two or more employees that may cooperate in committing fraud (the case where an employee node is selected is treated similarly). In Figure 4, gray colored nodes (see reference point 7) represent nodes added during post-processing when a client node is selected (refer to the node pointed by the green arrow of Figure 4). In the case where more than one node representing employees exist simultaneously in the visualization, the auditor is able to select one of them and add the related clients to the visualization. Gray-color is utilized for non-selected employee nodes together with their edges and related clients (if they are not related also to the selected employee) to avoid distracting the auditor.

Since it is possible to switch between employees during the investigation, if the post-processing of a case is completed, the animation resumes from the last visualized employee before pausing the animation. In the case where a cluster node is selected, the corresponding rectangles in the heat-map representing clients are marked with an X such that they can be added (if desired) to the visualization. However, the system permits a specific number of additions of employee or client nodes in order to avoid cluttering the visualization area. If this number is exceeded, the system optionally is able to produce a visualization where only the inner-most layer of the radial drawing (i.e., the one corresponding to the clients and

employees) is drawn along with the relations between them. Again, the width of the edges is proportional to the number of events that relate two entities. In the case where further investigation is needed the auditor selects the desired node (which becomes larger) and the other layers of the radial drawing (i.e., $L_2 - L_5$) that correspond to the particular node appear in the visualization. In this manner, the system is able to visualize simultaneously a larger set of entities and reveal the relations between them. However, this may slow down the investigation process and for this reason, we adopted both the animation approach and the simultaneous visualization of all layers for each node.

The ordering of the nodes representing the employees is performed according to their severity value (the more suspicious nodes are presented first in the animation). The clients appear in arbitrary order since no crossings between edges connecting a particular employee with her related clients can exist. The only crossings that may occur are caused by gray-colored employees related to clients already visualized and since these edges are also gray-colored, they do not confuse the auditor (see Figure 4). The gray-colored employees that are added in the visualization are placed either on the top or to the bottom of the already placed employee-nodes to retain the relative positions of the already placed nodes. We also have chosen not to apply crossing minimization heuristics since, the addition of new nodes to the visualization may imply a rearrangement of the positions of the already placed nodes, disturbing the underlying mental map.

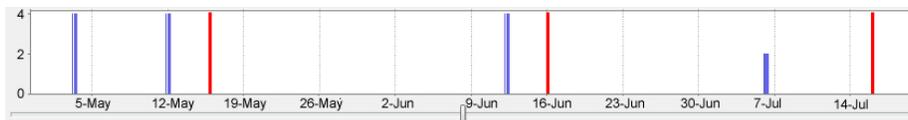


Fig. 5: A time-line plot representing the event-series for the selected pair of entities.

Figure 5 accommodates a time-line plot representing the event-series for the selected pair of entities (refer to the blue series) where the x -axis corresponds to the date of the occurrence of each event and the y -axis to the number of events occurred during the specific date. The red drawn columns represent the billing dates of the account of the specific client. This plot facilitates the identification of possible periodic activity especially close to the billing date of the account of the client. In employee fraud schemes, it is also possible that the event-series related to a pair of entities is periodical only based on a specific action. For this reason, we have incorporated in the system a second plot (refer to Panel #5 of Figure 6) that presents all reported actions by distinct series. In this plot, the y -axis corresponds to the day of the month that event x related to a specific action occurred (e.g., the first event related to an action that occurred on the 15th day of a month will be drawn on point (1, 15)). For this case, we ignore multiple occurrences of events related to the same action occurred the same day of the month. In the case where periodicity

occurs for a specific action, the corresponding series will have part (or the whole series) almost parallel to x -axis.

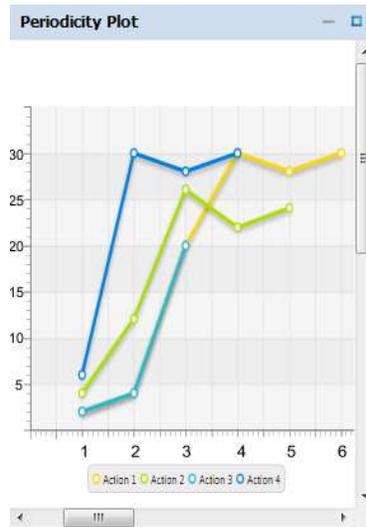


Fig. 6: A periodicity-plot that presents all reported actions by distinct series for the selected pair of entities.

The system supports mechanisms to detect patterns of unusual employee behavior such as unauthorized access to computers, business systems and accounts of employees or clients by producing a parallel coordinates plot (see Figure 7). Each record consists of an employee, a time-stamp, an IP indicating the address of the employee's computer, a computer name and an action (i.e., login, login failure, etc). The size of the nodes and the edges is proportional to the number of their occurrences in the database. The nodes on each layer are ordered by their number of occurrences in the data-set. The patterns used in this scenario include the following: (i) More than X failed login attempts within a time interval of Y days/months, where X, Y are configurable by the auditor, and (ii) Login attempts or failed login attempts occurring from different IPs and/or computer names. The visualization of Figure 4 can also be adapted to this scenario -either with or without the preprocessing step (since the number of employees and actions is manageable in a radial drawing)- by substituting the nodes representing the clients by nodes that represent actions.

5 Case Study

In this section, we present the results of the evaluation of the system on real data-sets stemming from two control systems of a telecommunication

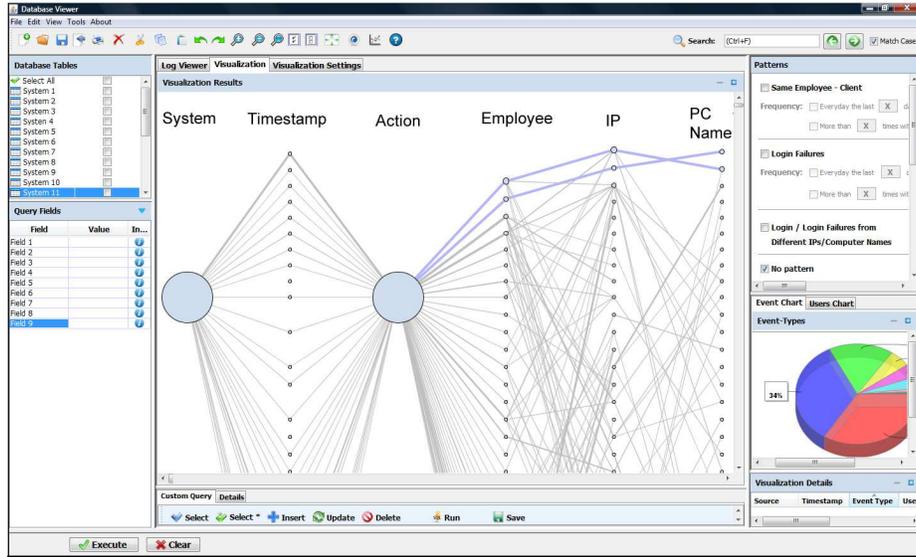


Fig. 7: A parallel coordinates plot to monitor failed login attempts in a specific system.

company. All data provided to us were anonymous for security and data privacy reasons. The data-set consists of approximately 180.637 entries lying within a time interval of six months. The data-set consists of 710 distinct employees and 83.030 distinct clients. In the data-set, 66.2% of clients had only one occurrence, 31.6% between 2 and 5, 1.4% between 5 and 10 while the remaining ones (i.e., 0.8%) had more than 10 occurrences. The auditors have also included a set of entries corresponding to a “fictional” fraud case scenario where an employee modifies the account of a client. However, we were not communicated any information regarding the billing date of the accounts of the clients.

Since one of the data-sets stems from a fraud management system, it is expected that reoccurring activity between the same pair of employee and client will occur (a “suspicious” client reported by a fraud management system is expected to be supervised by an employee). For this reason, we concentrated our study in identifying pairs of employees and clients that appear to have more that 10 related events. The system identified 41 employees (5.8% of the total number of employees) that were related with the same client with more than 10 events (refer to the orange and red colored rectangles of the heat-map of Figure 8).

For each of the above employees we had to calculate the similarity of the event-series with pattern time-series (see Section 3) in order to detect periodicity. In particular, the auditors were interested for periodic events that occur monthly (i.e., periodicity of 28 up to 30 days). Thus, we could consider only the pattern time-series (refer to Section 3) that corresponds to monthly activity. However, we decided to calculate the severity values based on all pattern time-series in order to distinguish any reoccurring activity and decide afterwards through the visualization

if suspicious activity really exists. Even though, this approach creates more false positives that have to be investigated, it ensures that other possible periodic events will not be omitted. Among these 41 employees that were related with the same client with more than 10 events, 17 of them (2.4% of the total number of employees) appear to have periodic activity and events occurring outside working hours (refer to the red-colored rectangles of Figure 8), while the remaining ones (24 employees; 3.4% of the total number of employees) had events occurring outside working hours (refer to the orange-colored rectangles of Figure 8). Also, no employee had performed unauthorized access to systems or had used unauthorized actions, whereas only one employee had used non common actions. The results were communicated to the auditors who investigated whether there exist real indications of fraud.

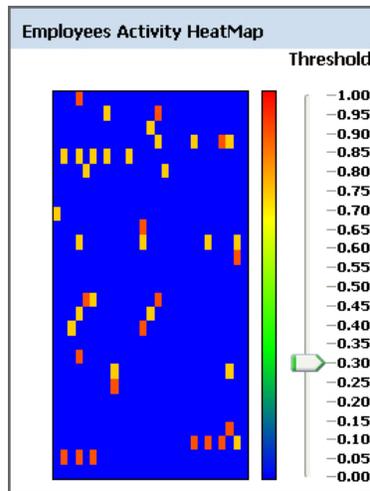


Fig. 8: A heat-map indicating the severity values for the employees participated in the case study.

In the following, we present some of the first frames of the animation in order to describe the investigation procedure. Figure 9 indicates a highly-ranked employee (i.e., Employee-29). Employee-29 was related to four clients, i.e., Client-1, Client-2, Client-3 and Client-4, more than 10 times using one system for which the employee was a frequent user and common actions (see reference points 1 and 2 of Figure 9; the parts representing the systems and the actions are not marked by an X, which implies that the user was frequent for the specific systems or had performed common actions, and the corresponding heat-maps are blue-colored; see reference points 3 and 4 of Figure 9). All other clients related to Employee-29, were placed in the low-severity cluster, whereas no client was placed in the medium-severity cluster (see reference points 5 and 6 of Figure 9, resp.). Most of the events related to Employee-26 (see reference point 7

of Figure 9). The layer of the visualization which accommodates the actions that Employee-26 has performed, is split in two parts representing “Action 6” and “Other”. In the “Other” action, we have clustered actions whose percentage of use was too small ($< 0.1\%$) to be visualized. The problem was caused by the large number of possible actions in this particular system which does not permit the simultaneous visualization of all actions. However, if one of the clustered actions is not common for a particular employee, the red-colored heat-map in the corresponding layer and the X marking in the part representing the “Other” action would reveal the problem to the auditor.

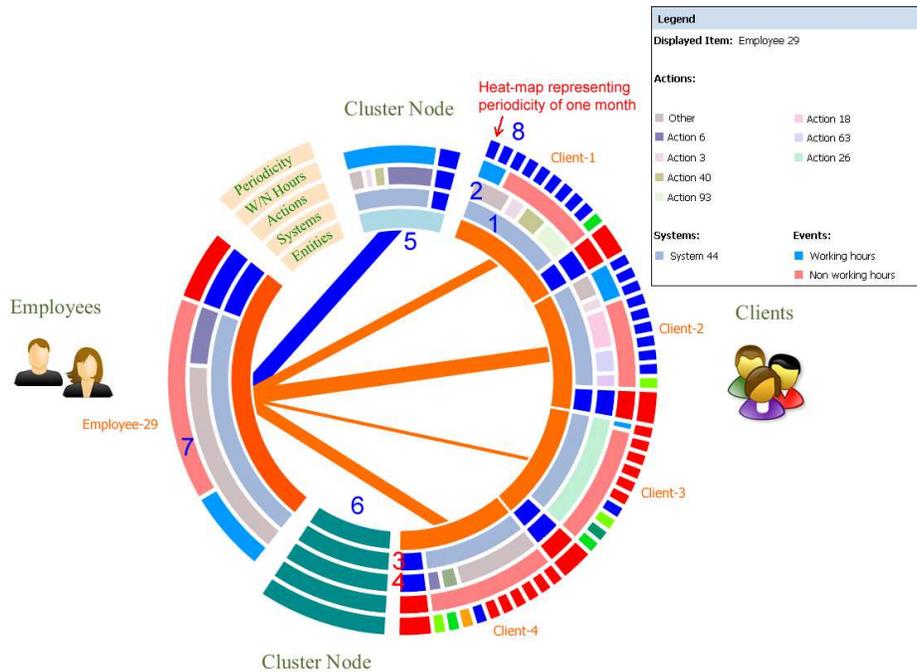


Fig. 9: A frame of the animation indicating the activity of highly-ranked Employee-26.

We will now proceed to describe the investigation procedure for each of the four clients. Client-1 and Client-2 have the majority of the events that relate them with Employee-29 occurring outside working hours (refer to the corresponding layer of Client-1 and Client-2). However, they appear to have a small similarity (less than 50%) with only one fraud pattern time-series. Note that, the pattern time-series that corresponds to periodicity of one month corresponds to the first heat-map of the each periodicity layer (see e.g., reference point 8 of Figure 9). Since the auditors were interested in events that occur monthly, these clients were not considered suspicious. Regarding Client-3 and Client-4, they have also the majority of the events that relate them with Employee-29 occurring

outside working hours but, they appear to have strong periodic activity. In particular, there exist six heat-maps indicating strong similarities with pattern time-series including the one that represents monthly periodic activity. For this reason, these clients have to be further investigated.

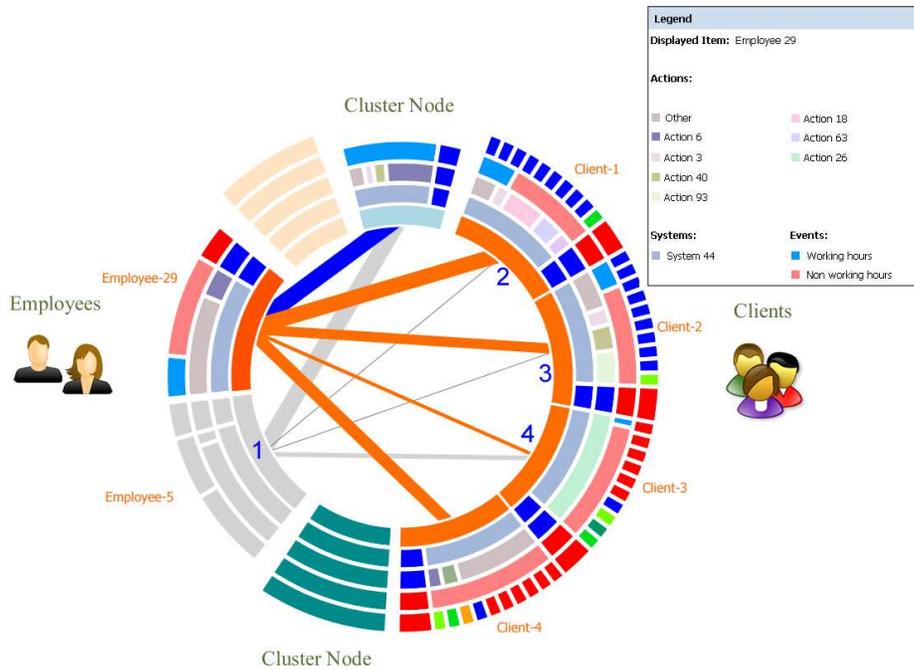


Fig. 10: All employees related to Client-3 are added in the visualization. The gray-colored node corresponds to the new employee added (Employee-5) who surprisingly is related to almost all high-ranked clients of Employee-29.

Client-4 was related to no other employee (when we selected the node that corresponds to Client-4, no other employee was added to the visualization). However, when we selected Client-3, a new employee, referred to as Employee-5 (see the gray-colored node of the visualization; reference point 1 of Figure 10), was added to the visualization. The interesting thing was that Employee-5 was related with the same high-ranked clients as Employee-29 (except for Client-4; see reference points 2, 3 and 4 of Figure 10). There exist two possible explanations for this scenario. Either two employees are both responsible for monitoring the activity of the clients or these employees are accomplice to fraud. Thus, the investigation has to proceed further. The time-line plot of Figure 11a represents the time-stamps of the events relating Employee-29 and Client-3. Obviously, there exists a continuous activity between the two entities. However, this activity according to the auditors resembles more to monitoring activity rather than to a fraud pattern. This assumption is also

reference point 8). In the next step, we examined the time-line plot for the two entities (refer to Figure 13). One can distinguish a monthly periodic activity between June and September (i.e., the actual dates are 22/6, 21/7, 25/9), even with small gaps (no entries in August) and some noisy data (i.e., 7/7). The auditors that examined the case determined that there were no indications of fraud in this particular case mostly because of the actions performed by the employee which were again common monitoring actions. Client-5 was reported by a fraud management system as a suspicious client and thus, Employee-26 was monitored her in regular time basis.

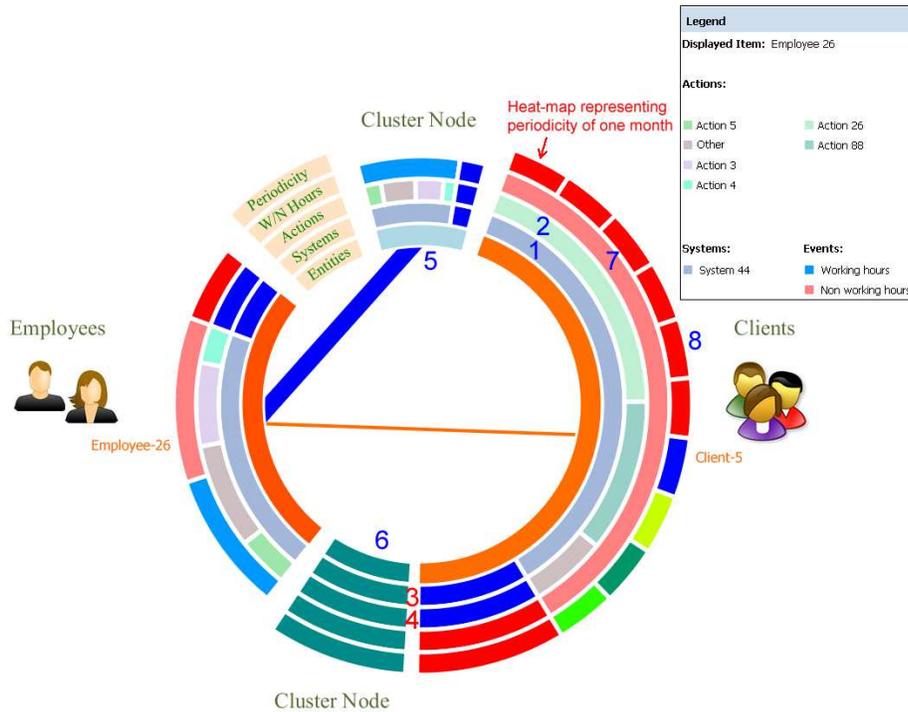


Fig. 12: A frame of the animation indicating the activity of a Employee-26.

Figure 14 illustrates the fictional fraud case which was added by the auditors. In this scenario, Employee-40 is related to Client-6 using two business systems for which she is a frequent user and common actions (see reference points 1, 2, 3 and 4 of Figure 14). All the events occur within working hours (see reference point 5 of Figure 14). However, the event-series of Employee-40 appears to have strong similarity with six fraud pattern time-series, including the one that corresponds to periodicity of one month, which is represented by the first heat-map of the each periodicity layer (see reference point 6 of Figure 14). Also, Client-6

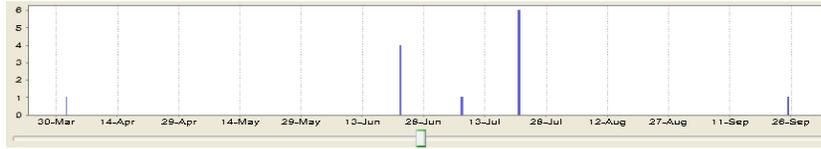


Fig. 13: The corresponding time-line plot for Employee-26 and Client-5.

was not related to any other employee (when selected, no other employee was added to the visualization). All other clients related to Employee-40, where placed in the low-severity cluster, whereas no client was placed in the medium-severity cluster (see reference points 7 and 8 of Figure 14, resp.). Even though, this visualization resembles a lot to the one of Employee-26 (see Figure 12), the time-line plot (see Figure 15) and the periodicity plot (see Figure 16) explain why this case is considered as fraud. The first suspicions according to the auditors, are raised by the fact that there exists activity between the two entities stemming from two business systems (they take also into consideration the type of the systems; an information that was not communicated to us in full detail). The auditors explained to us that the time-line plot (refer to Figure 15) matches to a fraud case scenario according to which there exists some activity at the beginning (between April - May) with no specific periodicity and then, appears periodic activity (from May to September). In the first time interval, the fraudster is trying to plan and organize her fraud by performing a number of actions. Once the fraud is organized, only periodic actions are required. Another suspicious fact in this case is that the events from May to September occur close to the same dates of each month (from 10th to 15th). Of course, there exist some “noisy” data that have to be excluded in order to understand the fraud pattern. These may have been caused either on purpose to cover up the fraud or were part of the duties of the employee.

The above assumption is reinforced by the plot of Figure 16 which reveals the periodic occurrence of each performed action. For instance, “Action 101” (see reference point 1) appears to have periodicity around the 15th day of the month from its second occurrence and later. Also, “Action 107” (see reference point 2) appears to have periodicity around the 11th-13th day of the month from its third occurrence and later. In particular, the vast majority of events are recorded between the 10th and the 15th day of the month. We could be more convinced that this case consists fraud if we knew exactly the billing cycle of the account of the client.

In a similar manner, the frames of the animation illustrating the other highly-ranked employees were investigated. In particular, we were given more attention to the 17 frames of the animation containing periodic events. Since the data-sets provided for the case analysis were sensitive, we were not communicated many details about the final results of the investigation. Fortunately for the company, the only real evidence of fraud existed in the fictional data added by the auditors. However, the auditors had not identified all these cases while examining the data-sets manually and they had to make an additional investigation for them.

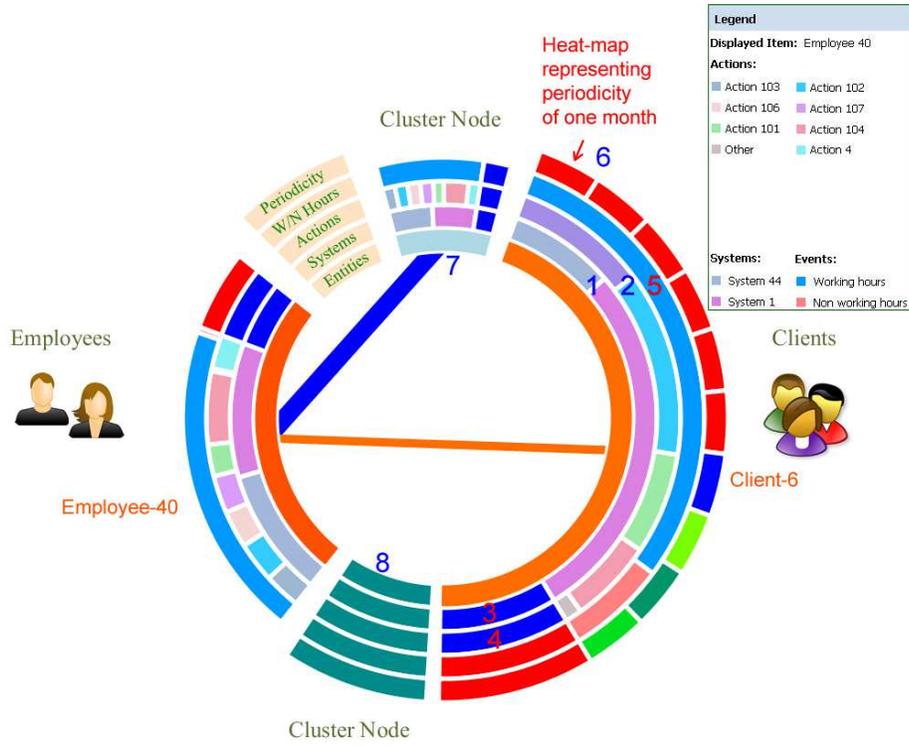


Fig. 14: A frame of the animation illustrating the activity of Employee-40. This case corresponds to a fictional fraud case scenario.

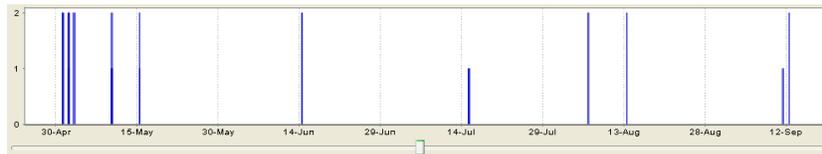


Fig. 15: The time-line plot for Employee-40 and Client-6 indicating an obvious monthly activity.

6 CONCLUSIONS AND FUTURE WORK

We presented an integrated fraud management visualization system that aims to identify patterns that may conceal occupational fraud through a combination of pattern recognition and visualization. Our work opens several aspects for future work such as incorporation of more fraud patterns, use of more statistical methods and, extension of the system in order to identify more complicated fraud schemes (client fraud, telecommunication fraud, etc.) in a wider variety of business systems.

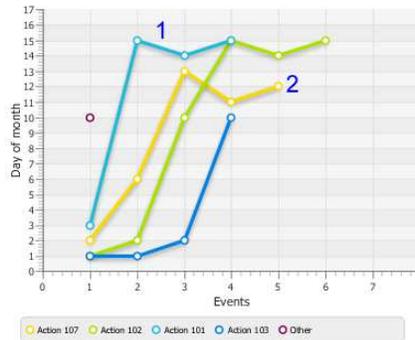


Fig. 16: A plot indicating the periodic pattern for the performed actions of Employee-40 and Client-6.

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