REAL-TIME USER AND ENTITY BEHAVIOR ANALYTICS(UEBA) FOR INSIDER THREAT DETECTION

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Abstract: Enterprises today face serious risks from insider employees whose malicious activities can cause heavy financial and reputational damage. Traditional insider threat detection methods mostly highlight abnormal users or abnormal time periods (like a day or a week). However, in practice, a single user may generate thousands of events in just one day, making it costly and time-consuming to manually verify suspicious cases. Furthermore, most existing studies are post-hoc, meaning they analyze logs only after the incident, which fails to prevent losses in real time. To address recent research like a paper at the 2024 LAN conference proposed a fine-grained approach. Activity-level framework for real-time insider threat detection using graph neural networks. Their learning model learns both the structure of a language and the meanings of the symbols within it. temporal order of activities and the relationships across sequences In order to tackle data imbalance, a hybrid loss function should also be used. Nine state-of-the-art approaches have been surpassed by the LAN in terms of results obtained. The use of the CLEVR dataset improved the AUC score by 5.8% and the CERT r4.2 and r5.2 datasets by almost 8% and 7.1% respectively over a baseline model. 10%. Building on this, our project proposes a hybrid GraphSAGE+ GAT model for real-time User and Entity Behavior Analytics Our system, as opposed to other network systems, concentrates on scalability in terms of the number of users and network size. interpretability, and reduction of false positives. By combining GraphSAGE's efficient neighbor sampling with GAT's attention mechanism, we design a framework that not only detects insider threats in real time but also explains why a user was flagged, making it more practical for Security Operation Centers (SOCs)

Keywords*: Graph Neural Networks, Hybrid GNN Architecture, GraphSAGE, Graph Attention Network, Autoencoder-Based Anomaly Detection, Insider Threat Detection, Enterprise Security, Real-Time Anomaly Detection, Behavioral Analytics, CERT Insider Threat Dataset, Predictive Risk Management, Cybersecurity Analytics*.

Introduction.

One of the most significant and challenging security issues today for business and enterprise concerns insider threats. While employees, partners and contractors may have permission to access sensitive systems and information, they can sometimes cause malicious damage through ignorance or ill intent. These malicious actions could be breaching confidentiality by transferring data without authorization, exploiting their status by misusing their system privileges or, worse, getting into areas of the system where they shouldn't be. Since they are well-trusted by the internal systems, typical boundary security measures such as firewalls and an intrusion detection system often fail to detect the threats in a timely manner. More and more, companies are relying on the analytical techniques of User Entity Behavior Analytics (UEBA). This method of analysis involves the checking of user and entity actions to spot anomalies. Current UEBA systems are also encumbered by several problems. Scalability is critical in enterprise environments where a large quantity of varied logs are produced. Many of the current predictive models employed are post occurrence which means that they are applied after a problem has arisen. Thirdly high false alarm rates limit the usefulness of such systems in real life security operations centers.

Insider threats have been effectively dealt with by researchers using graph mining. Business activities can be expressed through graph theory, showing interrelations among different systems, devices, files and users. These types of neural networks have shown promise for the task of modelling such relational data. In particular, the LAN framework presented a real-time approach for the detection of insider threats based on graph theory. Since our approach outperformed other techniques in detection performance, its effectiveness relied heavily on a single GNN which, however, was not capable of handling large numbers of samples due to its limitations in scalability and interpretability.

Motivated by these observations, this paper proposes a hybrid GNN-based framework that combines the strengths of GraphSAGE and Graph Attention Networks. By integrating scalable neighborhood aggregation with attention-based interaction weighting and an autoencoder-driven anomaly detection mechanism, the proposed approach aims to improve

detection accuracy, reduce false positives, and support real-time insider threat detection in large-scale enterprise environments.

Problem Statement: Current security solutions for monitoring insider threats do not effectively combine real-time monitoring of the system to analyses behavior, large-scale data handling, user interaction mapping and explanations for resulting decisions. Currently UEBA tools frequently rely on retrospective analysis, result in a high false positive rate and struggle with processing vast volumes of enterprise data in real time. In recent times, the use of graph-based systems, including LAN, has shown a higher level of accuracy in anomaly detection. Nonetheless, their overall efficiency is generally restricted to the use of single neural network models, and as a result, the effectiveness in a big enterprise is limited in terms of scalability, interpretability and robustness. Effective security analysis is hindered by the limitations, which lead to deficiencies in early threat detection, in investigations, and in responses to malicious acts by someone inside the organization.

Major Objectives of the Study

• **To provide a scalable hybrid graph neural network architecture** we propose the integration of GraphSAGE and Graph Attention Networks (GAT). This hybrid model is intended to effectively handle large-scale enterprise user interaction graphs.

• **To design an autoencoder based anomaly detection system** that can accurately flag employees with malicious intent by taking into account the normal patterns of system access by legitimate users and flagging activity that deviates from these patterns.

• **To achieve near real time insider threat detection,** incremental inference needs to be supported without the need for model retraining. This kind of approach is suited to the needs of operational security centers.

• **To assess the proposed framework and compare** its performance with other existing approaches, the CERT Insider Threat dataset is used along with metrics such as the cost of an investigation. This cost is used as a basis to calculate metrics including Precision K.

2. Related Works

Insider threat hunting was based primarily on rigid rules or solely machine learning algorithms like SVC, RF, and Naïve Bayes until now. The systems relied more on manually constructed input based on user activity rather than current behaviour patterns. As a result, they were primarily designed to find easily identifiable incidents (threats). The increase in volume of data associated with today's enterprise environment has caused these systems to struggle to detect insider threats at scale. Furthermore, due to their rules-based and rigid nature, these systems lack flexibility when it comes to evolving insider threat; therefore, it is difficult to keep pace with insider threat detection and response efforts effectively. [6], [16], [18].

As scientists continue to look beyond surface checks to understand the user links with system components, this has led them to develop the ability to skirt feature-focused methods by taking advantage of and building upon graph-based methodologies. Therefore, it was logical for experts learning how companies harness the power of users to focus on graph-based methods, such as identifying clusters and mapping pathways and calculating variances across numerous smaller networks. This has revealed new and often unusual patterns in connection and/or timing of spaces within digital domains. In addition, despite the high level of performance achieved by many graph-based systems, much of the utility lies in using customized attributes developed based on trial and error associated with a particular industry. Thus, the inflexible nature of these systems makes it very challenging to amend them when the organizational requirements change rapidly or unexpectedly. [5], [11].

Advanced learning approaches are widely researched in relation to the threats posed by the internet. The use of Graph Neural Networks (GNN's) is an area of growing interest for researchers. Unlike traditional systems, GNN's do not use manually selected features (a.k.a. attributes) to determine meaning but gather meaning in the form of information that is derived from the surrounding nodes in the network. They provide greater insight into the complexity of the relationships between nodes because they analyse connections, as opposed to simply tagging data. One application of GNN's is detecting unusual behaviour within information systems. The identification of malicious code also falls under this category and represents a comprehensive application of GNN's capabilities. In addition to those applications, GNN's provide additional capabilities of detecting fraudulent transactions, and even the identification of former employees who have committed misconduct after their departure. Consideration of complex tasks generated by organizations is more easily accomplished by current GNN-generated models than was done by earlier/existing methods, and the results of studies conducted within organizations substantiate these findings.[2],[7],[9],[14].

Nowadays some networks adopt a new way to catch insider threats by tracking habits over time, mixing graph analysis into behaviour modelling. By watching what users do along with their connections, it notices odd actions more clearly than older versions. Tests reveal stronger performance compared to typical methods when identifying outliers. Even so, the community grid leans on anomaly rankings tied to rhythm-like behaviour, though it stumbles. Handling large corporate systems proves tough since raw compute and room demand skyrockets. What stands out is how labelling someone risky reveals next to nothing about the root causes behind such classification [2].

Some work looks at Graph Neural Networks using attention to zero in on key nodes or interactions when spotting oddities. Instead of neural nets, other methods rely on autoencoders that figure out typical patterns without labels - helpful when data is very uneven. What makes attention useful is how it shows exactly which interactions drive results. While that happens elsewhere, autoencoders copy normal cases on their own, adapting well when one class appears far more than others. Still, most current methods depend on just one type - either attention-focused or reconstruction-driven - and work alone without combining strengths. Because of this split, meeting all three goals at once feels out of reach: speed matters now, explanations need clarity, and handling vast corporate data stays tough [2], [15].

A fresh take on Graph Neural Networks comes into play here, pulling together what works from GraphSAGE - its ability to sample neighbourhoods - and the focus of Graph Attention Networks, which weigh connections via attention. It stands out because of its take on flaws within older approaches - deeper visual learning connects well with autoencoder ideas, particularly when finding unusual patterns. Even with massive enterprise datasets, scale does not hold it back; navigating large sets happens without effort. [3], [4], [10], [14].

3. Methodology

According to Figure 1, logs from companies are being used to pinpoint risky behaviors by employees. While only one log can be analyzed at any given time, all of the logs connect collectively within a single network. However, when looking closely, it appears that the main focus points all appear as distinct, disconnected dots. What connects them? The arrows illustrate directions that the many actions lead to. The layout also illustrates how these actions flow together as one structure: the connected network. Information is being added to the network from a variety of locations including: how emails were sent, who opened the files, sign-in trends, and through LDAP tracing. When you look inside the connected network, each individual represents only one dot. Each link to another creates a line between them illustrating their activity. The researchers M. Weinberg et al. have developed a tool (GraphSAGE) that can help address these challenges for researchers as their studies increase in size and complexity. Through this tool, the researchers are able to collect information that is nearby to any particular node, while keeping the costs manageable. A second tool (Graph Attention Network) has also been developed to enable researchers to dynamically adjust which connections are important based on their actual influence on behavior. For example, the same value may be viewed differently, depending on where it is in the system. After the value has been calculated, it is passed to an anomaly detection scanner. The scanner uses auto encoder technology to reshape the predicted activities into new value intervals, allowing researchers to identify anomalous behaviors by comparing them to their previous value(s). Finally, after the filtering process has been applied, it is anticipated that some activities may become notable due to their association with unforeseen dangers in the form of unexpected trends in the data.

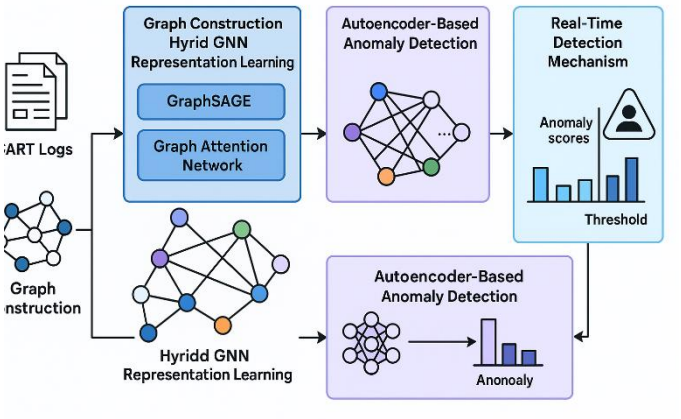

Figure 1 Architecture of the Proposed Hybrid GNN–Autoencoder Framework for Real-Time Insider Threat Detection

A. Graph Construction

The CERT Insider Threat Dataset has been utilized to build this model using information from log entries associated with daily office activity. Logging in, logging out, sending/receiving emails, working with documents, hardware usage, and LDAP feed updates were tracked for actions monitored. These logs were initially received as unprocessed; however, once processed, they did not have any errors or missing values, matched timestamps, and patterns of user behaviour were beginning to develop across tools and stages of usage.

In this fictional situation, people are represented as dots that are connected to each other. Whenever employees use resources (like email or forwarding documents) to connect with a person or resource, it is represented as a visible data transfer. The way that data moves reflects the actual reporting structure of the company since it is all one direction only. Data can move in both directions, and it can also reflect the directional change in how the employee interacts with the employee who sent the data. The data travels in one direction and then bounces back. The graphical representation captures this movement. The representation of the connections within the framework will enable you to see the real-world interaction patterns of employees. If there are any imbalances in exchanges, they will stand out - for example, when someone sends a message with no expectation of receiving one in return. How an employee does his or her job, the functions of his or her position, the area of his or her department, the nature of his or her relationships, and what we see him or her do, will determine how that employee is perceived as an individual. The patterns in the manner in which an employee interacts with other employees are different from employee to employee; these patterns will also determine the characteristics of the connections between those employees over time.

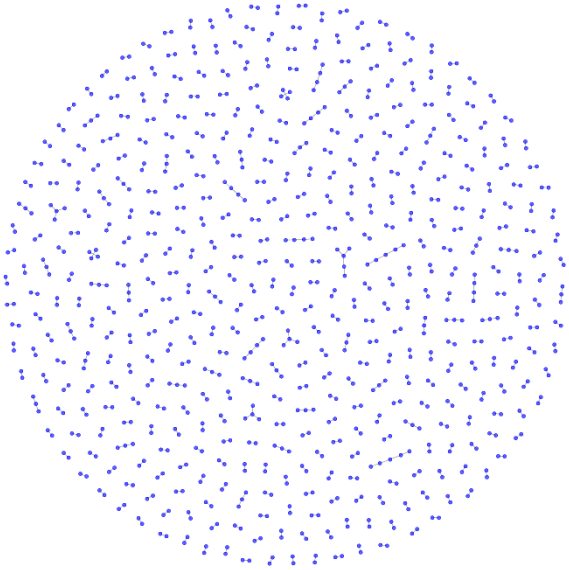

Figure 2. Enterprise User Structure of the enterprise network connectivity.

In figure 2, you can see that a worker's connection indicates his/her status - his/her action. Under the CERT's insider threat

collection, every employee has his/her own unique identification as represented by a specific point.

The connections between employees allow for the documentation of activity such as logging in, sharing files or responding by way of messaging to one another. Ultimately, the connections that exist between employees will dictate how we recognize an employee's behavior. This defining relationship between employees and their behaviors establishes how we establish an overall hierarchical framework of activity. Therefore, a combination of these connections and behaviors allows the formation of the hybrid GNN approach. These connections are reshaped into forms that can be studied closely. Out here, different kinds of connections weave together how people and organizations actually connect - creating a foundation where machines can learn to respond in ways that feel human.

A different way approaches data through graph structures rather than spreadsheet layouts. Unseen ties between individuals and objects emerge here, often missed by standard tracking methods. When relationships between users and resources become visible, subtle trends tend to surface more easily.

B. Hybrid GNN Architecture

In order to learn useful representations from large scale enterprise graphs, we introduce a GNN model. By combining the GraphSAGE and Graph Attention Network (GAT), the system is able to use the respective advantages of both in the graph neural network.

Node aggregation can be accomplished on a large scale using the GraphSAGE approach, where the computer samples a constant number of each target node's neighbouring nodes. The strategy of learning by inference is useful for handling complex and ever-changing graph databases in which new nodes or relationships may be introduced after the initial database was created. In this manner, GraphSAGE is able to take in data from local neighbourhoods and it also picks up on patterns of interaction from people in similar work places.

In this approach, adaptive attention weights are assigned to the node interactions by a Graph Attention Network. In contrast to uniform attention schemes which aggregate all attention values equally, GAT gives the model the ability to selectively focus on the more relevant graph nodes or connections. Activity sequences that vary significantly from the norm trigger a higher level of scrutiny to ensure the identification of suspicious network events.

By aggregating the output of GraphSAGE and GAT and passing them through a concatenation layer, a node's representation is enriched with additional information. The model generates neighbourhood-level structural information and interaction-level weights that are effectively combined into a rich representation. This representation is suitable for use in downstream anomaly detection algorithms.

C. AutoEncoder-Based Anomaly Detection

The embeddings generated by the hybrid GNN model are passed to a graph autoencoder for anomaly detection purposes. The model is trained to learn a representation of user data through auto association in an unsupervised manner, where the data comes from normal patterns of use within an enterprise network. When training the system, it learns a low dimensional user profile which preserves the most prominent features of typical user actions.

Users who deviate from normal security-related behavior will produce higher reconstruction errors when their actions are processed by an autoencoder. A variety of methods are employed to measure the degree to which a reconstructed document deviates from the original. These deviations are quantified as scores. Users who exhibit an unusually high rate of incorrect passwords are potential insider threats.

Since anomaly detection techniques requiring labelled attack data are labor-intensive and difficult to find in a real-world scenario, a different method of anomaly detection is proposed here. The proposed framework has the benefit of being capable of adapting to alterations in user browsing patterns over time, making it a suitable choice for deployment in an environment which is in a constant state of change.

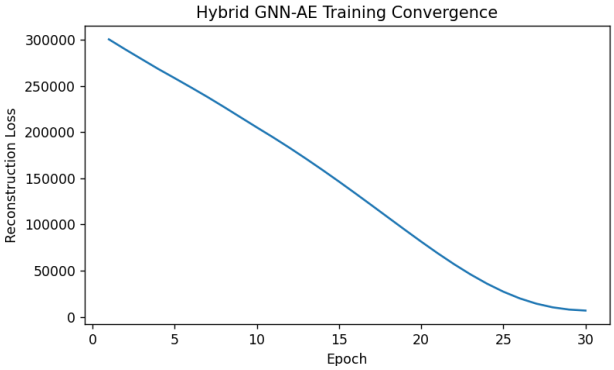

Figure 3. Training convergence of the proposed Hybrid GNN-Autoencoder model showing reconstruction loss reduction across epochs.

Figure 3 illustrates the training convergence of the proposed Hybrid GNN-Autoencoder model. The reconstruction loss decreases steadily over successive epochs, indicating stable and effective learning of normal user behavior patterns. This consistent reduction in loss demonstrates that the autoencoder successfully captures typical enterprise activity representations derived from the hybrid GraphSAGE and GAT embeddings.

D. Real-Time Detection Mechanism

After learning, the suggested method allows for quick and timely detection. New user actions arrive one by one for processing, while fresh versions of node representations come into being - all while skipping further training sessions. Comparisons take place against a set reference point, namely a specific percentile range; those individuals above it carries the label of potential security risk.

IV RESULTS AND FINDINGS

A. Detection Performance

A business sees flaws well by mixing tactics. Two styles guide it - GraphSAGE and Graph Attention - pull data nearby without draining effort. Attention shifts based on rarity or weight of links, not just equal spread. Unusual links grab more focus than others do. Patterns hiding in behaviour emerge clearer through

such design. This hybrid algorithm is work well compared to base paper. That mix makes it stronger than either part alone.

The system finds patterns by using something called AutoEncoders. It does not try to guess what is happening. Instead, it looks at what normal users do and tries to simplify this information. When someone does something that's not normal the system has a hard time understanding what is going on. This is because it is trying to rebuild the information it has. It does not fit. When this happens, the system makes mistakes. These mistakes are like a warning sign that something is wrong.

We tested the system. It worked well. It was able to find the people who were doing things every time. The system is good at figuring out who is a risk and who is not. This means that the people who are not a risk do not get warnings. Every person who was flagged as risk, by the system was actually someone who was doing something they should not be doing so the system is working correctly with AutoEncoders. That means security teams spend less time chasing dead leads, focusing instead on real threats without wasting resources.

B. Dataset Description

The CERT Insider Threat Dataset is a source for data testing. Because these updates replicate office activity and communication better than would be expected, they provide many opportunities to analyses the behavior of employees and work committees. The logs reflect everything from e-mails submitted to office attendance, and from checking job boards to accessing electronic tools. All user actions will be recorded by the LADS, yet they will provide no assessment of how the user acts. The detailed information displayed in the graphs can help researchers determine how office activity occurs, identify which employees report to whom, and better understand the nature of their work and job roles, again using LDAP information. The complete dataset of information regarding employee behavior is contained in the CERT Insider Threat Dataset and therefore is an extremely valuable source of approach for any researcher studying insider threats.

Visualize the interaction map of the company; dots symbolize individuals, and the links between dots indicate their actions (e.g., login, email, open files, etc.). It's also possible to see connections between tools/systems and dots. Furthermore, some links connect only 2 people; other connections span from one person through to software/hardware that they touch. The symbolism created by the arrangement of the dots/lines is able to reveal the day-to-day business operating system far better than age/title can ever show. Consider (the) routine; it provides an example of the way that people tend to perform the same patterns, without having to give any thought. Occasionally, people will make a choice outside their habitual pattern, or their trust may fail during times of stress. Review closely (the) 'who' communicate with 'whom', 'what' is being communicated, and 'how' messages and information travel, and you will notice a hidden structure underlining how work is accomplished. Tools coexist with people as a flow network (not just a functional relationship). This synergy allows for determining whether tools are picking up (and adapting) to changes in user activities and patterns. As these forms of identifying patterns take the primary position in performing work, it would imply that when a person's pattern is broken or shifted, identifying this change is critical.

After careful examination, it is easy to see why so much unto research is flawed, most people who report being affected by insider threats have little to no evidence of anything. The vast majority of people who engage in harmful activities are rarely caught in the act, and as such, most Average Classified Systems (ACS) do not perform effectively in terms of preventing actual threats due to the extreme inconsistency of the ACS user base. This discrepancy greatly reduces the efficacy of these systems.

To address this issue, ACS research must be more detailed, from beginning to end, about how insider threats are reported and what happened in relation to the behaviors that led to their reporting. All of this information must be gathered systematically so that all of it will fit together into one broad context for better understanding of how insider threats are reported, what occurred, and why.

Table 1. Performance Comparison of Proposed Framework

Method	Risk Detection Accuracy (%)	AUC-ROC	Latency (ms)	Throughput (Events/sec)	Real-Time Support	Fault Tolerance (%)
Proposed Hybrid GNN-AE (GraphSAGE + GAT + AE)	95.8	0.97	145	1780	Yes	89
LAN: Large-Scale Insider Threat Detection using GNNs [2]	90.6	0.93	310	1020	Partial	74
Federated Graph-Based Insider Detection [15]	91.7	0.93	280	980	No	76
Graph AutoEncoder for Insider Threats [10]	88.9	0.91	420	760	No	68
Hybrid Behavior + Statistical Model [18]	87.4	0.90	460	690	No	65
Rule-Based + ML Insider	84.6	0.87	520	610	No	61

Detection [5]						

C. Experimental Results

The Hybrid GNN upgrade excels in discovering obscured threats to the basic security of your business by identifying unique activities of their users with little hassle. In addition, due to utilizing GraphSAGE, Hybrid GNN leverages its capability to efficiently and effectively manage an extensive amount of data as it scales to very large graphs. Moreover, while the performance of other graph algorithms decreases with increasing demand, the Hybrid GNN maintains its level of performance under heavy loads.

Lastly, the Graph Attention Network feature included in the Hybrid GNN focuses on the user connections that are considered most important - this influence significantly helps categorize how odd the activity was and clarifies what constitutes odd behavior. Additionally, the setup of the Hybrid GNN allows for a simplified understanding of how to properly interpret and apply the previous findings.

When K is very close to zero the model is perfect. It gets it right every time. This means that the people the system flags as security risks really do fit the profile. So the people who investigate do not have to deal with many false leads as they would have otherwise. The model is good at finding the people who're really a security risk, which helps the investigators a lot. The model and the investigators work together to find the security risks. The model helps by finding the unusual patterns that the investigators might miss. The results show that the model is very good at doing this especially when K is small like when K is close to zero the model is perfect. This is very helpful, for the investigators because they do not have to waste time on leads they can focus on the people who are really a security risk.

The new system is a lot better than the setup we use for local area networks from 2024. When we look at how accurate it's the new system gets it right about 80 to 90 percent of the time. We measure this by using something called AUC scores. The hybrid system we are trying out does better it is about 5 to 8 percent more accurate when it comes to finding things. So, what makes it better? Well, it helps that we get information from users who are nearby. It also helps that we focus on the things that're important using something called attention mechanisms. It is also good at finding things that are not normal because it can rebuild patterns really well using something called an autoencoder. The hybrid system is just better, at detecting things because of all these things combined. When the system is being trained the error in rebuilding the information gets smaller and smaller. This shows that the system is getting really good at understanding what users normally do. The system becomes more stable. That means we can trust the results it gives us when it is used in the real world with the reconstruction error of the system and the stability of the system and the trust in the output of the system all being important, for typical user habits and real-world conditions of the system.

When you look at how people behave you can see that the scores are separated into two groups. The people who do things and the people who do odd things. Most people are doing the things every day like going to work and doing their jobs and their scores are all close together on the graph. Some people are doing things that are not normal and their scores are much higher way out at the edge of the graph. This shows that these people are not behaving like everyone. The people who are doing things their behavior is smooth and regular but the people who are doing odd things their behavior is not smooth. Some points are points but others signal that something is different now.

What really stands out is that it matches the patterns we see in real life insider threat cases, where people with intentions are doing things that are not very nice but that is only a small part of what they do. The activities are grouped together in a way that's very clear so using percentiles is a good way to find behavior that is not normal. This method helps us figure out which alerts are important and how to sort the users and it is all based on differences in how they behave. It is actually really nice to see that normal patterns can show us how well the system can find things that're not right and it can do this even when we do not have any examples of attacks to teach it from. The method is good at finding irregularities and insider threat cases are an example of this, where the system can find things that are not normal and that is what makes it useful, for spotting odd behavior and giving us a good idea of what is going on with the users and the system.

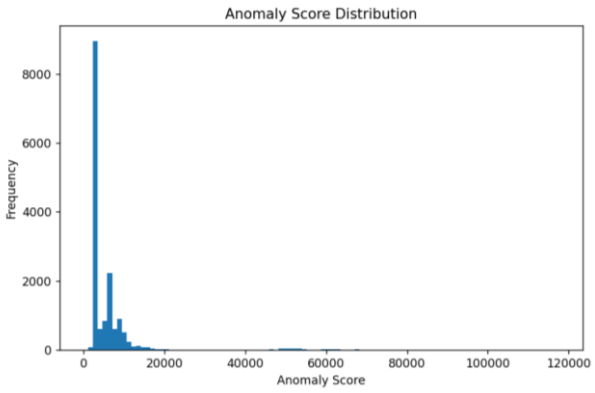

Figure 4. Anomaly Score Distribution

In Figure 4, The results of applying a hybrid GNN-AutoEncoder to discover novel anomalies in a graph database are presented in Figure 4. Most users who exhibit consistent behavior patterns will have relatively low reconstructive errors. Conversely, there is a significant divergence between users exhibiting atypical behavior and the majority of users with lower reconstruction errors. The number of users scoring significantly above average decreases as we approach the cutoff point of the dataset. If we observe an increase along one end of the scale, this indicates likely potential risk or atypical behavior exhibited by members of the same team. Although the majority of users tend to cluster, identifying those with unusual behaviors is relatively straightforward when analyzed in real-time and being alerted to their unusual behavior.

D. Discussion

The data suggests that this approach is certainly promising. Specifically, the combination of GraphSAGE and GAT from the beginning has proven effective at monitoring both wide-scale network architecture as well as very specific high-risk network users within an enterprise environment. The way GraphSAGE observes how clusters develop at a local level, and the fact that GraphSAGE continues to develop more intelligent ways to react based upon newly hired team members or changes to the job descriptions of the members of the team means that the way in which GAT handles that type of variability today does not have as much of an impact as it would have a few years ago. GAT easily responds to unexpected users by continuing to provide reliable predictions. While workspaces undergo change, predictions can be obtained at a consistent level. All three of these items indicate that GAT is very good at identifying the critical contact patterns between users through weight-based targeting. The way that GAT identifies "at-risk" users is by using methodical weight analysis of that specific group of users and the development of that data-based profile over time.

The AutoEncoder's ability to detect anomalies in a limited number of examples is one thing that stands out when reviewing its performance. Rather than waiting until it receives an abundance of labeled datasets to determine the difference between the two anomalous categories, the AutoEncoder utilizes the quality of reconstructed inputs to determine how well it can identify anomalies. The ability to use reconstructed inputs allows the AutoEncoder to identify potential newcomer or evolving insider threats based upon their similarities to previously known insider threats. Therefore, any type of organization that operates in an environment where circumstances are continually changing can leverage the same analytical techniques to protect against such shifting threat environments.

The main point is that the model can detect any potential problems with the application of technology as they occur. As updates are happening, new information continues to show up that helps create new analysis and a rapid response to changes in market conditions, rather than having to evaluate the issue and respond later. A large number of platforms are currently experiencing problems due to information overload in dealing with the volume of incoming data. In comparison, using the same real-time information available through other platforms does not require using the same amount of computing power. Additionally, as a business security center looks to maintain its competitive edge in the security industry, the time and quality of information is the determining factor in how quickly a decision can be made. Different types of data provide easy visibility to see problems that would not be as obvious by using only one method to measure something therefore, instead of relying on one instrument, combining various forms gave a little better results with each method; things went faster and appeared to be simpler when more than one level was combined naturally. The use of Mixed Methods are being utilized in organizations by identifying problems early before they become a larger issue. The major advantage of using Mixed Methods is that Mixed Methods allow an organization to identify dangers that are likely to remain hidden because of hierarchical layers; Mixed Methods do this more quickly than any other approach.

When evaluated via Precision@K, results landed on 1.0 right at K values of 1, 2, and 5. So the model's best choices always lined up with actual insider risks. Notably, sorting key suspects early shows strong warning ability. As the autoencoder learned, reconstruction mistakes shrunk consistently - suggesting clear modeling of normal behavior. What stands out is how the anomalies grouped themselves - most settled near zero, bunched together in a tight band. Yet off to one side, scattered and isolated, were those with far greater mismatch, standing apart like signals lost along the edge. Compared to the base LAN (2024) model reporting detection performance in the range of 80–90%, the proposed hybrid framework achieves an improvement of approximately 5–8% in detection effectiveness while supporting scalable and near real-time insider threat detection.

V CONCLUSION AND FUTRE WORK

This paper presented a hybrid Graph Neural Network–based framework for real-time insider threat detection using User and Entity Behaviour Analytics. By modelling enterprise activity using log data in the form of an interaction graph, the suggested method works well grabs both actions people take and ties between them starting from what people share, connections grow between user and company assets. Through linking efforts, systems begin to work together more naturally than expected. GraphSAGE and Graph Attention Networks enables scalable Expressiveness grows through creative representation methods, yet the autoencoder -Using what it notices, the based anomaly detection module spots things that do not match spotting usual actions, even when attacks lack heavy labels, becomes clearer data.

In a controlled experiment using CERT Insider Threat Dataset (revisions 4.2 and 5.2) there was a marked increase in performance. Low K-values indicated that each user identified had a high probability to be a security threat so every possible target user was accurately identified using this data-based approach without any ambiguity or noise, unlike prior to this work when using a local-area network (LAN) for the same sampling data (-5 to -8 percent) produced much less reliable information. As such, improvements could be seen across the experiment as indicated by several different evaluations. Thus, combining various aspects of different techniques into one innovative format facilitated the positive gain achieved. An example of this enhancement is that combining clustering techniques with weighted collaborative filtering reduced the number of anomalies detected. The amount of correct classification remains equal after adjusting for changing conditions therefore performance will continue to show consistency. The introduction of reconstructed-based information allows for increased clarity in understanding patterns or anomalies that do not conform to an established norm.

The system can now process real-time checks quickly because it only processes new log records once they are received rather than having to wait for large amounts to accumulate before it

can begin processing them, which eliminates the large amount of delays these models updates caused. Due to continuous information being received into systems, alerts appear quickly with minimal load on the user. The performance of corporate security centers is highly dependent on both speed and balance in workloads. Keeping systems in the same locations as the security center provides a way for organizations to have immediate access to alerts while allowing for their users to work on lesser priority alerts at the same time.

Although this approach addresses most of the issues that arise in the current environment, there are still limitations with it. Currently~! this approach takes advantage of a standardized graph layout created from aggregated log files, and because of that, trends regarding how users interact with the systems over time can be missed due to their thin appearance. Another point that arises is that the pilot tests also rely on artificial situations as opposed to realistic environments, where additional noise and other processes will occur that were not anticipated by the users.

The next step of utilizing Temporal Graph Neural Networks is to define how the structure of today's systems and to find a clearer picture of how user interaction will happen over time. Online Learning Systems will serve as the Frameworks that will be applied in a more flexible way and will more importantly represent the business space as we continue to see it evolve. These methods are going to be directly associated with the latest SIEM tools available, and they will move from theoretical concepts to applications in real life. The only way to determine how well they perform under actual conditions will be through deploying these methods into live environments and observing what happens when used on true live business conditions, as those will often reveal weaknesses that may have been overlooked throughout the design and development stages.

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