Detecting malicious logins as graph anomalies

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Abstract—Authenticated lateral movement via compromised accounts is a common adversarial maneuver that is challenging to discover with signature- or rules-based intrusion detection systems. In this work a behavior-based approach to detecting malicious logins to novel systems indicative of lateral movement is presented, in which a user’s historical login activity is used to build a model of putative “normal” behavior. This historical login activity is represented as a collection of daily login graphs, which encode authentications among accessed systems. Each system, or graph vertex, is described by a set of graph centrality measures that characterize it and the local topology of its login graph. The unsupervised technique of non-negative matrix factorization is then applied to this set of features to assign each vertex to a role that summarizes how the system participates in logins. The reconstruction error quantifying how well each vertex fits into its role is then computed, and the statistics of this error can be used to identify outlier vertices that correspond to systems involved in unusual logins. We test this technique with a small cohort of privileged accounts using real login data from an operational enterprise network. The ability of the method to identify malicious logins among normal activity is tested with simulated graphs of login activity representative of adversarial lateral movement. We find that the method is generally successful at detecting a broad range of lateral movement for each user, with false positive rates significantly lower than those resulting from alerts based solely on login novelty.

Index Terms—intrusion detection, lateral movement, graph anomaly detection

I. INTRODUCTION

A healthy mindset in cybersecurity is that your network will eventually be breached, that it is only a matter of time before your perimeter defenses and endpoint protections fail and the adversary gains access to your enterprise. Once inside the network, the adversary will get quiet—they will live off the land stealing credentials and moving between systems via authenticated access rather than launching noisy exploits or deploying malware that could trigger alarms. They will do their best to look like authorized users doing legitimate things. The healthy mindset is therefore not to expend all one’s efforts securing the outer walls, but to also invest in shoring up internal defenses. The challenge is that, while commercial solutions abound for perimeter and endpoint security, the few offerings that tackle the problem of lateral movement tend to take considerable time to configure and test, and are often proprietary black boxes (e.g. Windows ATA or FireEye TAP). That’s not to say that organizations don’t have effective defensive strategies making use of internal sensor data and logs, but these tend to involve rule-based indicators. The trouble with static rules is that they apply to known, explicit patterns of activity, that is, the threat indicators must have been previously observed. Furthermore, there is a sort of selection bias at play in which only those threat activities that possess stable and recognizable signatures are ever even considered for detection. Alas, authenticated lateral movement does not follow an explicit or recurrent pattern: the sequence and tempo of accesses, and the tools used and the systems targeted, vary according to the whims, tactics, and plans of the adversary.

Lateral movement via compromised accounts does have a common tell: the adversary’s pattern of accesses need not include systems visited very often, if ever, by the compromised account. Such novel logins might be a sign that a credential has been stolen or an authorized user is up to no good. But for privileged accounts with broad access like network administrators, novel logins might also be normal and common. Since such accounts are precisely those most often targeted by attackers, this particular indicator will generate many false positives, potentially swamping a true signal of adversarial activity. The difficulty here is that novelty does not imply malice.

Given that the adversary is a rational agent intent on achieving some objective in an orderly, stealthy manner, we expect that there are patterns in lateral movement, but they are not known a priori by defenders. Instead, they must be inferred from observed activities—the problem is that data on generic adversarial lateral movement is hard to come by in sufficient quantities. On the other hand, organizations do have lots of data tracking and characterizing normal activities on their networks. Appropriate paradigms for cybersecurity analytics are therefore unsupervised and one-class learning, in which a sample of data describing normal activities is used to generalize and model it: anything that deviates significantly from what the model considers normal is deemed anomalous. By carefully selecting data sources and features, these anomalies are more than simple novelties—they are sophisticated patterns of atypical activity relative to the user’s baseline behavior—with consequently much lower false positive rates than the alternatives.

In this paper, we explore the application of unsupervised learning to the detection of malicious authenticated logins indicative of adversarial lateral movement. The method identifies malicious logins as anomalies in login graphs of a given user’s authentication activity over some historical period. A login graph is a weighted, directed graph depicting all of the user’s remote login activity over a 24-hour period: vertices are systems and directed edges are logins between them. The historical period typically spans several weeks, and so is comprised of dozens of login graphs. Each vertex is summarized in terms of a set of graph centrality and topology measures, and then the set of all vertices are taken together and transformed by the method of non-negative matrix factorization. The purpose of this transformation is to assign each vertex to one of a small set of roles, and then measure how well each fits into its role using the transformation’s reconstruction.

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error. By analyzing the statistics of the reconstruction errors in the sample, outlier vertices can be identified, corresponding to systems that are accessed in ways atypical of the user in question.

We test this approach against a small cohort of six high-privilege users—Domain Administrators on a large, operational enterprise network. Login data is obtained from authentication logs collected for each user over a period of eight weeks and used to model the login behavior of each user. When a novel system is seen in a user’s daily login activity, it is tested by the model. A false positive occurs when a normal novel login is found to be anomalous. We find generally low false positive rates (FPR) across the cohort: two users with FPR = 5% and the rest with FPR < 2%. In comparison with a detection process that alerts on all novel daily logins, these results are better by at least an order of magnitude for these users.

Since the historical data used to construct the model is presumed normal, the models must be validated on data indicative of malicious activity. We therefore generate a varied set of adversarial login graphs, which are devised to be representative of a threat’s lateral movement tactics for two use-cases: when the threat moves solely between novel systems, and when they move between known and novel systems. True positive rates (TPR) for the novel-to-novel case are, with few exceptions, greater than 95% across the full range of adversarial graphs for all users in the cohort. The second use-case is more challenging, but with TPR still in excess of 90% for most users across most adversarial graphs.

II. RELATED WORK

The problem of lateral movement detection has attracted many attempts at solution, including rules- and behavior-based approaches. As an adaptive method based on learning user behaviors, we contrast the present work with other behavior-based approaches. These approaches tend to target either host-based activities or network behaviors. Host-based activities indicative of lateral movement might include suspicious use of certain programs [1], system calls [2], [3], [4], [5], or terminal commands [6], [7], [8], [9], [10].

In contrast to these approaches, this work seeks to detect lateral movement solely by the patterns of adversarial access across the network, independently of underlying method. This approach is fundamentally graph-based, as are several other related studies. The work of [11] makes use of login graphs which are characterized in terms of a set of global measures, like the number of vertices, number of arcs, and graph diameter. Logistic regression was then used to compare the login graphs of a given user at different times to look for changes that might suggest account compromise. The accuracy of the regression model is comparable to the models developed in this paper; however, their method employed supervised learning on normal and sample attack data, and login graphs spanned several weeks. In contrast, in this work we seek a method that can find anomalies relative to normal data only, on time scales of hours or days so that alerts are actionable.

In [12], combined login graphs of groups of users are constructed and intruders are sought by removing users one-by-one and comparing the similarities of the resulting subgraphs. This approach has applications to collaborative information systems, for which groups of users are expected to assume common roles. In contrast, our work is focused on ascertaining anomalous login behavior by comparing events with a single user’s historical activity, not through comparisons with collective or group behaviors since the users of interest might not form such groups.

The work of [13] looks for anomalies in login graphs indicative of malicious insider activity. Three types of anomalies are considered: modifications, insertions, and deletions. In contrast to our work, which looks for anomalous vertices, this analysis is at the level of the login graph itself. Given the potentially large daily variability of user’s login graphs (see Figures 2 and 3), the anomaly tests of [13] would be expected to yield many false positives for our application. This highlights the challenge of the current project—to find potentially subtle but unusual characteristics of individual vertices in login graphs with widely varying global properties across the historical record.

To this end we explore methods of graph anomaly detection that focus on more localized characteristics of graph vertices. The field of graph-based anomaly detection [14], [15] is expansive with methods covering virtually any application. The most relevant techniques to our case are those that characterize vertices using local and neighborhood metrics, and then apply outlier detection to collections of these vertices [16], [17], [18]. The application of [18] is not lateral movement, but more general intrusion detection: graphs are formed from entities (like IP addresses or users) present in various sensors and detection logs, and edges connect those entities that appear together in at least one alert. These vertices are then evaluated in terms of recurrent graph measures [19], assigned roles using non-negative matrix factorization (following [20]), and the roles of each vertex are tracked over time for anomalous changes. This is the kind of local, graph-based detection we are interested here, but the novel logins we seek to examine have no history and so a time series analysis is not appropriate. Our use of non-negative matrix factorization is therefore rather different: it is not for assigning roles that can monitored over time, but for assigning roles simultaneously to all vertices in the historical sample, and identifying those that don’t fit well into any role.

III. LOGIN GRAPHS AND FEATURES

In this work we seek to characterize the authentication behaviors of individual users. The behavioral profile is established over a chosen time period and is derived from historical login records collected over this time period. From this record, each system remotely accessed by the user in each 24-hour period is evaluated according to a set of features that characterize the user’s login behavior with respect to that system. The behavioral profile is then the set of these feature vectors.

A. Login graphs

The basic data structure used in this analysis is the daily login graph of a particular user, Figure 1. It is a weighted,
directed graph depicting all the user’s remote login activity over a 24-hour period. The vertices are information systems and a directed edge \((u, v)\) between vertices \(u\) and \(v\) represents successful authentication from system \(u\) to system \(v\). The edges are weighted according to the number of logins that occur over the time period covered by the login graph. This graph can be generated using any authentication log that includes source and destination systems and a timestamp of the login\(^1\).

We next decide on the time period over which we wish to model the user’s login behavior, which should be long enough such that the model is stable and accurate\(^2\). In this work, we find that eight weeks is a sufficient amount of time to construct reliable models of the cohort of six users considered in our analysis.

From day to day, a given user’s login activity can vary greatly. In Figure 2, seven consecutive days of login graphs of the same user are shown: they vary considerably in the number of vertices, edges, and general topology. This variability can be quantified in terms of the \textit{graph edit distance},

\[
\text{GED}(g_1, g_2) = |V_1| + |V_2| - 2|V_1 \cap V_2| + |E_1| + |E_2| - 2|E_1 \cap E_2|, \tag{1}
\]

where \(V_i\) and \(E_i\) are the vertex and edge sets of \(g_i\) and vertical bars denote cardinality. The GED provides a measure of the difference between two graphs, reflecting the changes in their vertex and edge sets. To get a quantitative sense of the variability of login activity of the user cohort over time, we apply the GED to each user’s consecutive login graphs, Figure 3.

Most users exhibit dramatic daily variability, suggesting that global measures of graph similarity, like the GED, are not useful for graph anomaly detection in this domain. Instead, we consider a more local assessment of anomalous activity—at the level of individual vertices and their local neighborhoods in a login graph.

\(^1\)On Windows systems, successful authentications are recorded as event type 4624 in Windows Event Logs.

\(^2\)As assessed via a process akin to cross-validation; we describe this process later.

### B. Graph measures

We consider a variety of features that characterize the centrality and local neighborhood topology of individual graph vertices, \(v\), including: in degree \((k_{in})\), out degree \((k_{out})\); in weight \((w_{in})\); out weight \((w_{out})\); left Katz centrality,

\[
e_K(v) = \sum_s A_{vs} e_k(s) + \beta, \tag{2}
\]

where \(\alpha\) is an attenuation factor, \(\beta\) is an initial centrality given to all vertices, and \(A\) is the graph adjacency matrix; local clustering coefficient,

\[
e(v) = \frac{2T(v)}{k(v)(k(v)-1)} \tag{3}
\]

where \(T(v)\) is the number of triangles through \(v\) and \(k(v)\) is its degree; total degree of \(v\)’s egonet, that is, the subgraph formed from \(v\) and its neighboring nodes,

\[
E(v) = k(v) + \sum_{s \in N} k(s) \tag{4}
\]

where the sum is taken over all nodes in \(v\)’s neighborhood, \(N\); and eccentricity, \(\epsilon\), which is the longest directed path from the vertex. We also consider a few quantities derived from these base measures, including degree \(k = k_{in} + k_{out}\), two kinds of “reduced” eccentricity: \(\epsilon/(E + 1)\) and \(\epsilon/(w_{out} + 1)\), and two rescaled degree measures: \(k_{in}/(w_{in} + 1)\) and \(k_{out}/(w_{out} + 1)\). The full collection of graph metrics is given in Table I.

### IV. OUTLIERS FROM NMF RECONSTRUCTION ERROR

Non-negative matrix factorization (NMF) is primarily a dimensionality reduction technique (see |21| for a nice review). It has found success in a range of applications, including image segmentation and text mining, for its ability to find efficient, sparse representations of high-dimensional feature spaces. From \(n\) data points \(x_i \in \mathbb{R}^p\), the matrix \(X \in \mathbb{R}^{p \times n}\) is formed. The objective of NMF is to find two non-negative matrices \(G\) and \(F\) such that

\[
X_{np} \approx G_{np}F_{rp}, \tag{5}
\]

where \(r < \min(p, n)\) is the number of \textit{roles}, or the dimensionality of the reduced set of basis elements. Since each data point \(x_i\) will generally have non-zero components along each of the \(r\) directions, it will belong to a mixture of roles. The

| Index | Metric |
|-------|--------|
| 0     | out degree, \(k_{out}\) |
| 1     | out degree (rescaled), \(k_{out}/(w_{out} + 1)\) |
| 2     | in degree, \(k_{in}\) |
| 3     | in degree (rescaled), \(k_{in}/(w_{in} + 1)\) |
| 4     | local clustering, \(\epsilon\) |
| 5     | Katz centrality, \(e_K\) |
| 6     | ego degree, \(E\) |
| 7     | out weight, \(w_{out}\) |
| 8     | in weight, \(w_{in}\) |
| 9     | degree, \(k\) |
| 10    | eccentricity (ego-reduced), \(\epsilon/(E + 1)\) |
| 11    | eccentricity (weight-reduced), \(\epsilon/(w_{out} + 1)\) |
| 12    | eccentricity, \(\epsilon\) |

**Fig. 1:** Daily login graph of a user. Vertices are systems and directed edges indicate logins. Edges are weighted according to number of logins occurring over the 24-hour period.
Fig. 2: Seven consecutive days of a user’s login activity. There is considerable variability in the number of systems accessed and the topology of the login graph.

Fig. 3: GED of six users applied to consecutive login graphs over the course of 40 days.

The factorization is found by minimizing the Frobenius norm of the error,

$$||X - GF||^2_F = \sum_{i,j} (X - GF)^2_{ij},$$

with $G > 0$ and $F > 0$. NMF is a non-convex optimization problem, and so a single matrix $X$ can have many possible factorizations. For this study, we employ coordinate descent for the optimization and initialize with the singular value decomposition of $X$ to enforce sparsity of the factorization, that is, to ensure that points tend to map into single roles. With sparse representations and/or those with fewer roles than the dimension of the original feature space, NMF results in a compression of the original data that necessarily involves the loss of information. The amount of information lost is quantified in terms of the transformation’s reconstruction error.

We propose the NMF reconstruction error of a datapoint, $x_i$, as an outlier measure,

$$\delta_{x_i} = \sum_{j,k} (X_{ij} - G^j F^k)^2.$$  \hspace{1cm} (7)

Similar to other reconstruction error-based outlier detection schemes, like principal component analysis or autoencoders, the transformation to the reduced basis set is largely informed by the bulk of normal points in the sample. If outliers are few and sufficiently different, they will not fit well into the available roles—they will not be well reconstructed by the transformation—and the error Eq. (7) will be relatively large. To find anomalous points, we simply apply a threshold to the reconstruction scores and take the outliers.

As an unsupervised anomaly detection method, there is no model training. All that is required is a store of putatively “normal” historical data against which to compare the new data to be tested. Suppose we wish to test each user’s daily login activity. In this work, we use the prior eight weeks of the user’s historical login data, including the day to be tested, compiled into daily (24-hour) login graphs. Days with no login activity lack corresponding graphs. A selected set of graph metrics from Section III are evaluated for each system on each day and the matrix $X$ is formed, where each row is indexed by hostname and day. Next, NMF is applied to $X$ and the reconstruction error is computed—those vertices corresponding to novel systems from the test day lying outside a chosen confidence limit of the resulting distribution are considered anomalous.

V. FINDING UNUSUAL logins BETWEEN NOVEL SYSTEMS

When a privileged account is compromised, it is possible that the adversary will use the stolen credentials to authenticate to systems that the compromised account has not previously accessed. Any such novel login is of potential interest to network defenders because it marks a clear deviation from the established authentication behavior of the user in question. Yet, given that this behavior is derived from a finite set of historical data (here, several weeks worth), any system that is legitimately accessed less frequently than the duration of the historical record is effectively novel. An anomaly detection system looking for this kind of novelty will generate false alarms, especially for users that do this frequently.

The approach developed here is designed to only flag novel logins if they are unusual with respect to how the user tends to login to systems. In short, it’s not the novelty but the nature of the login: how often the novel system is accessed, whether and what kinds of other systems are accessed from it, what kinds of systems it is accessed from, and so on. The graph metrics presented in Section III were selected to provide this kind of characterization.

To demonstrate the approach and introduce our experimental procedure, we apply it to a simple but relevant situation: logins between novel systems; that is, between two or more systems not previously accessed over the course of the user’s historical record. In the next section we will consider logins between novel and known systems.

To build a model of a user’s historical login behavior, we must select a set of graph metrics, $m = \{m_1, m_2, ..., m_i\} \in$
The first rule is that the adversary never “doubles back”, that is, if they login to system $v$ from system $u$, they will never login to system $u$ from $v$. This is because access to the originating system, in this case $u$, is assumed to be preserved throughout the course of the intrusion. Second, the adversary never accesses a system $u$ from more than one other system, since a single access should be sufficient to establish a foothold on that system and multiple logins from distinct systems might arouse suspicion. For logins among novel systems, a subgraph generated by these rules is always a separate component in its login graph. These rules imply that each subgraph has a single root vertex with $k_{\text{in}} = 0$; this is the system from which the adversary originates further access.

In this study, we allow the number of systems in a subgraph to vary between 2 and 5. This corresponds to an expected rate of compromise of up to five systems in 24 hours. It is then possible to enumerate all possible subgraphs with $n \leq 5$ that obey the above two rules: there are 16 possible subgraphs (distinct up to isomorphism), Figure 6. For example, there is one possible subgraph with two systems, namely the edge $(u,v)$. There are two possible subgraphs with three systems, namely $\{(u,v), (v,w)\}$ and $\{(u,v),(u,w)\}$.

To measure a model’s TPR, we proceed as did for the FPR determination by repeatedly shuffling and splitting the set of login graphs, but this time an adversarial subgraph is included as part of a randomly selected login graph. If any of the adversarial subgraph’s vertices are detected as outliers, that iteration is considered a true positive. The TPR is then the number of iterations with detections divided by the total number of iterations (here, 25). The TPR is computed in terms of iterations rather than vertices (like FPR) since the detection of a single login is sufficient to discover the adversary on that day (iteration). By including the adversarial subgraph in a different randomly selected login graph each iteration, we are testing the model’s ability to detect that type of subgraph over a range of possible 6.5 week histories. A separate set of iterations is performed for each adversarial subgraph type, $i$, and for each type the TPRs are averaged over the iterations, $\text{TPR}_i$. This algorithm is provided in Figure 5.

Now that we’ve described how to measure the FPR and TPR of a prospective model, we next discuss how to find well-performing models. We demonstrate this approach in detail for
Fig. 6: The complete set of 16 possible adversarial subgraphs including between 2 and 5 vertices.

Fig. 7: (a) True positive rates (TPR) and false positive rates (FPR) of models with a variety of parameterizations for Admin1. Black points are the results of single models parameterized as labeled, and red squares are the results of combining the two models in the label as an ensemble. (b) True positive rate vs. adversarial subgraph type for the best performing ensemble (red dashed), \((1, 6) + (7, 11)\), together with each model separately: \((1, 6)\) (black) and \((7, 11)\) (blue).
one user in the cohort, hereafter referred to as Admin1, and later summarize results for all others. A model is determined by the set of graph metrics, m, and the number of roles, r, used in the NMF transformation. The minimum size of the set m is two elements, and NMF requires that $r \leq |m|$. Starting with $|m| = 2, r = 1$, we perform a grid search over all $\binom{13}{2} = 78$ two-parameter combinations of the 13 graph measures of Table I. With the significance level, $\alpha$, fixed (here, $\alpha = 0.05$), FPR and TPR are computed for each combination. This search is repeated for $r = 2$. Then, a grid search over all $\binom{13}{3} = 286$ combinations of three graph measures is performed for $r$ between 1 and 3. Exploring models with $|m| > 3$ becomes prohibitive to do exhaustively, but happily this is unnecessary since well-performing models are found with $|m| < 3$ for all users.

We find that in no single model (choice of $m$ and $r$) performs strongly across the full range of 16 adversarial subgraph types for any of the users in the cohort. Focusing on Admin1, in Figure 7 (a) we show FPR vs TPR, for a collection of two-parameter models with $r = 1$ (black dots). Some models, like $m = (1,6)$, perform well generally but struggle against a few subgraphs, Figure 7 (b). Meanwhile, the model $m = (7,11)$ performs only moderately-well overall, with TPR$_i \approx 62\%$, but it does particularly well against precisely those subgraphs that challenge the model $m = (1,6)$. Combining individual models into ensembles by taking the logical OR of their detections results in a generally improved TPR$_i$, as illustrated in Figure 7 (b), though generally at the expense of an increased FPR. We therefore attempt to build well-performing ensembles out of individual models, with an eye towards keeping FPR low.

Ensembles are formed by computing the Pearson correlation between each model’s TPR$_i$ vector (for this analysis, only models with the same $|m|$ and $r$ were compared in this way: though not a necessary restriction, it is more efficient and still results in well-performing models). Anti-correlated models have complementary detection capability but there is no guarantee that an ensemble formed from them will have high TPR$_i$ for all $i$ or a sufficiently low FPR. Furthermore, there is no unique and rigorous way to identify the “best” performing model out of a group—it is a firmly subjective process. For example, perhaps we are willing to accept poor performance against one or two types of adversarial subgraphs in exchange for a lower FPR than a model that performs well against all subgraphs. Therefore, selecting the “best” model for each user is ultimately a manual process that lacks rigid criteria: in selecting the models presented in this section, we have indulged a preference for models with low FPR even if that entails sacrificing performance against one or two adversarial subgraph types.

The performance of each user’s selected model finds mixed but generally positive results, Figure 8. These models all have $m = 2$ and $r = 1$. All users achieve greater than 95% true positive rates on most subgraph types, with false positive rates given in Table II. The notable exception is user Admin6, whose model does very poorly against subgraph types 1 and 3, which are of the form $v_1 \rightarrow v_2$ and $v_1 \rightarrow v_2 \rightarrow v_3$. This user routinely logs in to novel systems from novel systems, perhaps as part of remote administrative tasks, and so this kind of authentication is not considered anomalous by the model. A model with $m = 2$ and $r = 2$ was found for Admin6 that achieved a TPR > 80% for subgraph types 1 and 3 but at the cost of an increase in FPR to 6%.

For comparison, we include in Table II the FPR (denoted FPR$_{\text{new}}$) that would result from a detection system configured to alert on any novel login, that is, systems with no logins over the course of the historical record, FPR$_{\text{new}} = n_{\text{new}}/N$. While such an approach would catch all malicious authentications, it comes at the price of a very high FPR. Note that each user has a different best-performing model, suggesting distinct login behaviors across users. And the lesson drawn from Admin6 is that a model’s ability to detect malicious activity is shaped and limited by the user’s normal activity.

### Table II: Average false positive rates (FPR) of users in cohort with parameterization of best-fitting ensemble for logins between novel systems.

| User   | Parameters       | FPR  | FPR$_{\text{new}}$ |
|--------|------------------|------|--------------------|
| Admin1 | (1,6) + (7,11)   | 0.00 | 0.1                |
| Admin2 | (3,11) + (3,10)  | 0.02 | 0.6                |
| Admin3 | (1,4) + (8,10)   | 0.004| 0.4                |
| Admin4 | (1,9) + (6,11)   | 0.02 | 0.8                |
| Admin5 | (1,6) + (0,5)    | 0.01 | 0.3                |
| Admin6 | (1,8) + (1,12)   | 0.006| 0.6                |

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3After comparing across models with fixed $\alpha$, the receiver operating characteristic curve can be obtained for those of interest by varying $\alpha$.

4Since the full parameter space is not searched, the models found here are not globally optimal; hence the use of the term “well-performing” rather than “best-performing”.

VI. FINDING UNUSUAL LOGINS BETWEEN NOVEL AND KNOWN SYSTEMS

Having introduced our model construction and testing methodology on a rather special use case, we next apply these techniques to the more general situation where the adversary authenticates to novel systems from known systems, and vice versa (hereafter referred to as “novel-to-known” with the understanding that it includes logins from known-to-novel systems as well). We again use the set of 16 adversarial subgraphs as prototypes for validation, but now each subgraph must include a known system as one of its vertices; that is, the subgraphs are no longer separate components in the login graphs. To measure the true positive rate of a model against a particular adversarial subgraph, the procedure described in Section V is used but, this time, one vertex of the subgraph is chosen at random and replaced by a randomly selected known vertex from the randomly selected login graph at each iteration. Because the subgraphs are no longer separate components, the feature vectors of its vertices depend on the nature of the login graph into which it is embedded (in particular, metrics that characterize the local neighborhood of the graph like ego degree, Katz centrality, and eccentricity will vary by login graph). For these kinds of subgraphs, validating over multiple iterations thus does more than just test the generalizability of the model given alternate histories—it
assesses the model’s ability to detect a particular subgraph in a variety of different daily login scenarios.

A grid search over \( m \) and \( r \) is again conducted and we find that no two-model ensemble of any kind is able to reliably detect the full range of adversarial subgraphs. This is likely because the number of subgraphs is effectively much larger than 16 since the subgraph vertices depend on the embedding login graph: the resulting variability is hard for models with so few degrees of freedom to resolve. We therefore adopt the obvious approach—add more models to the ensemble!

Because these ensembles will be constructed from many models, pairwise evaluation of the Pearson correlation is not applicable. Instead, the models are ranked within each subgraph type and an ensemble is formed by selecting the top model from each type. Ranking within each subgraph type is first done by \( \overline{TPR}_i \); then, models within some top percentile (here, 10%) of this ranking are ordered by \( FPR \). To ensure low ensemble \( FPR \), one can exclude models with \( FPR \) above some threshold (here, 5%) from the rankings.

The \( \overline{TPR}_i \) of the best-performing model of each user in the cohort is shown in Figure 8 and \( FPR \)’s are given along with the model parameterization in Table III. There are several items to note: first, the models don’t perform as well when known systems are included in the adversarial subgraphs—that is, it is generally harder to detect the adversary that moves laterally from novel to known systems and vice versa than one that moves laterally solely through novel systems. As before, Admin6 is the worst model in the cohort, but for the other users, apart from a few exceptions, the models give \( TPR > 90\% \) for most subgraph types. Next, models have higher \( FPR \)s than in the novel-to-novel case, but still offer a significant improvement over detections based solely on novelty. Lastly, the best-performing models are built from a wide range of metrics combinations, from a five-combination model (Admin6) to one constructed from 12 combinations (Admin4). All models have \( |m| = 2 \) and \( r = 1 \) except for Admin1, which has \( |m| = r = 3 \).

While we have constructed separate and different models for each user for the novel-to-novel and the novel-to-known cases, in reality each user should have a single model. Ideally, the larger models built for the novel-to-known problem would include the parameters chosen for the novel-to-novel problem, however, this is generally not the case (metric combinations that are in both models are bold-faced in Table III). For example, Admin4, despite the large known-to-novel model, has no combinations in common with its novel-to-novel model and might therefore be expected to perform poorly against that use case. We find, however, that the best-performing known-to-novel models tend to perform as well against the novel-to-novel problem as the two-dimensional models constructed in the last section. This need not be true in general, in which case the known-to-novel model would need to be augmented with the missing metric combination from the novel-to-novel model, possibly at the expense of increased \( FPR \).

Lastly, we note that adversarial subgraphs in which more than a single vertex is replaced by a known system, are in both models are bold-faced in Table III). For example, Admin4, despite the large known-to-novel model, has no combinations in common with its novel-to-novel model and might therefore be expected to perform poorly against that use case. We find, however, that the best-performing known-to-novel models tend to perform as well against the novel-to-novel problem as the two-dimensional models constructed in the last section. This need not be true in general, in which case the known-to-novel model would need to be augmented with the missing metric combination from the novel-to-novel model, possibly at the expense of increased \( FPR \).

Lastly, we note that adversarial subgraphs in which more than a single vertex is replaced by a known system are also possible. We don’t test these scenarios explicitly but we expect that adding known systems will further degrade performance of the models. We can infer this by observing, for example, that adding two known systems to the type 2 subgraph will include the type 1 subgraph with one known system, as well as the new graph with a novel system authenticating to two known systems. We might therefore expect performance against type 2 subgraphs with two known systems to be on a par with performance against the type 1 subgraph with one known system, and, in general, performance against type \( n \) subgraphs with two known systems should resemble performance against type \( n - 1 \) subgraphs with one known system.

VII. Conclusions

We have presented a new defense against adversarial authenticated lateral movement that is based on learning individual

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\[^{3}\text{In the novel-to-novel case, the adversarial subgraph was always a separate component and so independent of the login graph into which it was embedded. Not so in the novel-to-known case.}\]
user’s login behaviors over time. Historical login data is converted into daily login graphs, and then each vertex is evaluated according to a set of graph measures that characterize its centrality and local neighborhood topology. This set of feature vectors is then transformed via non-negative matrix factorization (NMF) into a new basis, where each vertex is assigned to a set of roles that characterize how the user tends to login to the corresponding system. Depending on the number of roles used and the sparseness of the new representation, NMF effectively compresses the original feature vectors. The transformation’s reconstruction error is then used to find outlier systems—those vertices that do not “fit” well into the roles identified by the NMF.

This method is applied to the problem of detecting which of a user’s novel logins are potentially malicious. A novel login is an authentication to a system not seen in that user’s historical record: high-value accounts, like network Administrators, can have large numbers of novel logins over the course of days or weeks. Adversaries that compromise such high-value accounts can be expected to access novel systems as well, making the prospects of detecting malicious novel logins a low signal-to-noise endeavor. By applying unsupervised learning to a user’s login behavior encoded as a set of graphs, malicious logins can be identified as vertices with properties that deviate significantly from the bulk. Applied to a user’s novel logins, this approach could be a useful filter to identify logins worth further investigation.

We test this method on a small cohort of six high-value accounts: Domain Administrators from a large, operational enterprise network. Login data from authentication logs is collected over a period of eight weeks for each user. A range of models, consisting of different sets of graph measures, m, and numbers of NMF roles, r, are tested by computing their false positive and true positive rates. False positive rates measure the percentage of systems misclassified as anomalous, and true positive rates are ascertained by testing models against a series of simulated adversarial lateral movement graphs.

We first apply this method to the case of novel-to-novel logins, in which the adversary moves laterally through the network via systems not accessed by the compromised user over the historical period. We find that no single model for any user is capable of detecting the full range of adversarial login types while maintaining an acceptably low false positive rate, but well-performing ensembles can be built by taking the logical OR of individual models. These models achieve greater than 95% true positive rates against the great majority of adversarial login types for all users, with false positive rates below 2%.

Next, the method is applied to the more general case in which the adversary accesses a known system during its intrusion. This a more challenging problem with many more types of adversarial login graphs, though we are able to find moderately well-performing models by building larger ensembles. Apart from a single user in the cohort, these models achieve greater than 90% true positive rates against most adversarial login types; though false positive rates are higher with the larger ensembles, they are still ≤5% and at least an order of magnitude better than rates resulting from a detection scheme based solely on novelty.

Future research could expand this approach in several ways. While the focus on novel logins is motivated by the failure of conventional methods to detect threat activity involving novel systems, it might be possible to use NMF to discover anomalous login behavior of known systems over time. This could take the form of a sequence analysis in which a system’s NMF role is tracked over time, with anomalous behavior manifesting as a change to a new or unlikely role. Another difficulty with the current methodology is the discovery of well-performing models: with such a large parameter space, it is infeasible to search all possible models. A more sophisticated model-search strategy could perhaps be employed to improve results. The present work, absent these potential improvements, nonetheless represents an important first step towards developing a behavior-based, malicious login detection capability.

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