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Automated Emerging Cyber Threat Identification and Profiling Based on Natural Language Processing

VENKATESWARLU GOLLA

Assistant Professor, Department of CSE(AIML), CMR ENGINEERING COLLEGE, Medchal Rd, Medchal, Kandlakoya, Seethariguda, Telangana,501401

ABSTRACT :

The time window between the disclosure of a new cyber vulnerability and its use by Cyber criminals has been getting smaller and smaller over time. Recent episodes, such as Log4j vulnerability, exemplifies this well. Within hours after the exploit being released, attackers started scanning the internet looking for vulnerable hosts to deploy threats like cryptocurrency miners and ransomware on vulnerable systems. Thus, it becomes imperative for the cyber security defense strategy to detect threats and their capabilities as early as possible to maximize the success of prevention actions. Although crucial, discovering new threat s is a challenging activity for security analysts due to the immense volume of data and information sources to be analyzed for signs that a threat is emerging. In this sense, we present a framework for automatic identification and profiling of emerging threats using Twitter messages as a source of events and MITRE ATT&CK as a source of knowledge for threat characterization. The framework comprises three main parts: identification of cyber threats and their names; profiling the identified threat in terms of its intentions or goals by employing two machine learning layers to filter and classify tweets; and alarm generation based on the threat's risk. The main contribution of our work is the approach to characterize or profile the identified threats in terms of their intentions or goals, providing additional context on the threat and avenues for mitigation. In our experiments, the profiling stage reached an F1 score of 77% in correctly profiling discovered threats.

I. INTRODUCTION :

As the cyber landscape continues to evolve, the shrinking timeframe between the disclosure of vulnerabilities and their exploitation by threat actors presents a pressing challenge for cybersecurity. Recent incidents, exemplified by the

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Log4j vulnerability, vividly illustrate this trend. Within hours of its disclosure, malevolent entities swiftly initiated attacks, targeting vulnerable systems for deploying ransomware and cryptocurrency miners. This underscores the urgency for cybersecurity strategies to swiftly detect and comprehend emerging threats to maximize preemptive defense actions. Yet, amidst vast volumes of data, identifying nascent threats remains a formidable task for security analysts. To address this challenge, our project introduces a novel framework designed for the automatic identification and profiling of emergent cyber threats, utilizing Twitter as an event source and leveraging MITRE ATT&CK for threat characterization."

"The framework orchestrates three core components: first, the identification of cyber threats and their nomenclature; second, the profiling of these identified threats, discerning their intentions and goals through a sophisticated machine learning architecture; and finally, the generation of alerts based on the risk posed by the identified threats. A significant stride in our work lies in our approach to characterizing these emergent threats, providing contextual insights into their intentions. This added layer of understanding not only facilitates threat identification but also offers avenues for effective mitigation strategies. In our experimental endeavors, the profiling stage exhibited a commendable F1 score of 77%, demonstrating a robust capability in accurately profiling and understanding discovered threats."

"This project stands at the forefront of proactive cybersecurity measures, aiming to equip defenders with a sophisticated system capable of early threat detection and nuanced threat characterization. By leveraging Twitter as a valuable source of event data and employing cutting-edge machine learning techniques, the framework not only identifies threats but also delves deeper into their intentions, providing invaluable insights for proactive defense actions against rapidly evolving cyber threats.

II.MODULES

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as

Login, Train & Test User Profile Data Sets, View User Profile Trained and

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Tested Accuracy in Bar Chart, View User Profile Trained and Tested Accuracy Results, View All Profile Identity Prediction, Find and View Profile Identity Prediction Ratio, View User Profile Identity Ratio Results, Download Predicted Data Sets, View All Remote Users

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once login is successful user will do some operations like register and login,predict profile identification status,view your profile.

III.EXISTING SYSTEM:

Cybersecurity is becoming an ever-increasing concern for most organizations and much research has been developed in this field over the last few years. Inside these organizations, the Security Operations Center (SOC) is the central nervous system that provides the necessary security against cyber threats. However, to be effective, the SOC requires timely and relevant threat intelligence to accurately and properly monitor, maintain, and secure an IT infrastructure. This leads security analysts to strive for threat awareness by collecting and reading various information feeds. However, if done manually, this results in a tedious and extensive task that may result in little knowledge being obtained given the large amounts of irrelevant information. Research has shown that Open Source Intelligence (OSINT) provides useful information to identify emerging cyber threats.

OSINT is the collection, analysis, and use of data from openly available sources for intelligence purposes [21]. Examples of sources for OSINT are public blogs, dark and deep websites, forums, and social media. In such platforms, any person or entity on the Internet can publish, in real-time, information in natural language related to cyber security, including incidents, new threats, and vulnerabilities. Among the OSINT sources for cyber threat intelligence, we can highlight the social media Twitter as one of the most representative [22]. Cyber security experts, system administrators, and hackers constantly use Twitter to discuss technical details about cyber attacks and share their experiences [4].

Utilization of OSINT to automatically identify cyber threats via social media, forums and other openly available sources using text analytics was proposed in different researches [1], [23], [7], [24], [25], [26], [13], [27] and [28]. However, most proposals focus on identifying important events related to cyber threats or vulnerabilities but do not propose identifying and profiling cyber threats.

Amongst research, [13] proposes an early cyber threat warning system that mines online chatter from cyber actors on social media, security blogs, and dark web forums to identify words that signal potential cyber-attacks. The framework is comprised by two main components: text mining and warning generation. The text mining phase consists on pre-processing the input data to identify potential threat names by discarding ‘‘known’’ terms and selecting repeating ‘‘unknown’’ among different sources as they potentially can be the name of a new or discovered cyber threat. The second component, warning generation, is responsible for issuing alarms for unknown terms that meet some requirements, like appearing twice in a given period of time. The approach presented in this research uses keyword filtering as the only strategy to identify cyber threat names, which may result in false positives as unknown words may appear in tweets or other content not necessarily related to cyber security. Additionally, this research does not profile the identified cyber threat.

In [26] an identification and classification approach of cyber threat indicators in the Twitter stream is presented. The research proposes a data-driven approach for

modeling and classification of tweets using a cascaded Convolutional Neural Network (CNN) architecture to both classify tweets as related or not to cyber security and classify the cyber-related tweets into a fixed listed of cyber threats. The proposed solution includes a pre-processing phase that uses IBM’s Watson Natural Language API to identify tweets related to cyber security according to Watson classification results. Additionally, in the pre-processing phase, there is a pre-labeling step performed by simple string matching on the pure tweet text. The threat types considered were: ‘‘vulnerability’’, ‘‘DDoS’’,

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''ransomware'', ''botnet'', ''data leak'', ''zero-day'' and ''general''. Further, the proposed approach uses CNN models trained to classify each tweet as relevant or irrelevant to cyber security. The relevant tweets are passed to a second CNN layer to be classified as one of the 8 different threat types mentioned above. There are important differences of our proposal compared to this one.

First, the proposed approach does not name the identified threat. Naming the threat is an important step to cyber threat intelligence
as it may allow analysts to identify and mitigate campaigns based on the historic modus operandi employed by a given threat or group.

Second, the proposed approach relies on an external component to classify tweets as related or not to cyber security as opposed to our approach that proposes a component to classify tweets using machine learning trained with the evolving knowledge from MITRE ATT&CK. Third, instead of using a keyword match to pre-filter threats and a fixed list of threat types, we present an approach to profile the identified cyber threat to spot in which phase of phases of the cyber kill chain the given threat operates in. This is important for a cyber threat analyst as he or she may employ the necessary mitigation steps depending on the threat profile.

In [1], a framework for automatically gathering cyber threat intelligence from Twitter is presented. The framework utilizes a novelty detection model to classify the tweets as relevant or irrelevant to Cyber threat intelligence. The novelty classifier learns the features of cyber threat intelligence from the threat descriptions in the Common Vulnerabilities and Exposures (CVE) database 5 and classifies a new unseen tweet as normal or abnormal in relation to Cyber threat intelligence. The normal tweets are considered as Cyber threat relevant while the abnormal tweets are considered as Cyber threat-irrelevant. The paper evaluates the framework on a data set created from the tweets collected over a period of twelve months in 2018 from 50 influential Cyber security-related accounts. During the evaluation, the framework achieved the highest performance of 0.643 measured by the F1-score metric for classifying Cyber threat tweets. According to the authors, the proposed approach outperformed several
baselines including binary classification models. Also, was analyzed the correctly classified cyber threat tweets and

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discovered that 81 of them do not contain a CVE identifier. The authors have also found that 34 out of the 81 tweets can be associated with a CVE identifier included in the top 10 most similar CVE descriptions of each tweet. Despite presenting a proposal to distinguish between relevant and irrelevant tweets, the proposal does not address the identification of threats and their intentions. Those are important requirements for Cyber Threat Intelligence in formulating defense strategies against emerging threats.

The tool proposed in [23] collects tweets from a selected subset of accounts using the Twitter streaming API, and then, by using keyword-based filtering, it discards tweets unrelated to the monitored infrastructure assets. To classify and extract information from tweets the paper uses a sequence of two deep neural networks. The first is a binary classifier based on a Convolutional Neural Network (CNN) architecture used for Natural Language Processing (NLP) [29]. It receives tweets that may be referencing an asset from the monitored infrastructure and labels them as either relevant when the tweets contain security-related information, or irrelevant otherwise.

Relevant tweets are processed for information extraction by a Named Entity Recognition (NER) model, implemented as a Bidirectional Long Short-Term Memory (BiLSTM) neural network [30]. This network labels each word in a tweet with one of six entities used to locate relevant information. Furthermore, the authors chose to use the application of deep learning techniques because of its advantages in the NLP domain [31]. Thus, they propose an end-to-end threat intelligence tool that relies on neural networks with no feature engineering.

Disadvantages

- An existing system never implemented Multi-Class machine learning (ML) algorithms - the next steps in the pipeline.
- An existing system didn't implement the following method process identified and classified threats.

IV.PROPOSED SYSTEM

The overall goal of this work is to propose an approach to automatically identify and profile emerging cyber threats based on OSINT (Open Source Intelligence) in order to generate timely alerts to cyber security engineers. To achieve this goal, we propose a solution whose macro steps are listed below.

1) Continuously monitoring and collecting posts from prominent people and companies on Twitter to mine unknown terms related to cyber threats and malicious campaigns;
2) Using Natural Language Processing (NLP) and Machine Learning (ML) to identify those terms most likely to be threat names and discard those least likely;
3) Leveraging MITRE ATT&CK techniques' procedures examples to identify most likely tactic employed by the discovered threat;
4) Generating timely alerts for new or developing threats along with its characterization or goals associated with a risk rate based on how fast the threat is evolving since its identification.

Advantages

To conduct a cyber-attack, malicious actors typically have to
1) Identify vulnerabilities,
2) acquire the necessary tools and tradecraft to successfully exploit them,
3) choose a target and recruit participants,
4) Create or purchase the infrastructure needed, and
5) Plan and execute the attack. Other actors— system administrators, security analysts, and even victims— may discuss vulnerabilities or coordinate a response to attacks

Decision tree classifiers

Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing descriptive decision making knowledge from the supplied data. Decision tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes C1, C2, …, Ck is as follows:

Step 1. If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class

Step 2. Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,… Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by invoking the same procedure recursively on the set Si.

Gradient boosting

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Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision trees.[1][2] When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms random forest.A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

Logistic regression Classifiers

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name *logistic regression* is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name *multinomial logistic regression* is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar.

Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does.

This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

Naïve Bayes

The naive bayes approach is a supervised learning method which is based on a simplistic hypothesis: it assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature .

Yet, despite this, it appears robust and efficient. Its performance is comparable to other supervised learning techniques. Various reasons have been advanced in the literature. In this tutorial, we highlight an explanation based on the representation bias. The naive bayes classifier is a linear classifier, as well as linear discriminant analysis, logistic regression or linear SVM (support vector machine). The difference lies on the method of estimating the parameters of the classifier (the learning bias).

While the Naive Bayes classifier is widely used in the research world, it is not widespread among practitioners which want to obtain usable results. On the one hand, the researchers found especially it is very easy to program and implement it, its parameters are easy to estimate, learning is very fast even on very large databases, its accuracy is reasonably good in comparison to the other approaches. On the other hand, the final users do not obtain a model easy to interpret and deploy, they does not understand the interest of such a technique.

Thus, we introduce in a new presentation of the results of the learning process. The classifier is easier to understand, and its deployment is also made easier. In the first part of this tutorial, we present some theoretical aspects of the naive bayes classifier. Then, we implement the approach on a dataset with Tanagra. We compare the obtained results (the parameters of the model) to those obtained with other linear approaches such as the logistic regression, the linear discriminant analysis and the linear SVM. We note that the results are highly consistent. This largely explains the good performance of the method in comparison to others. In the second part, we use various tools on the same dataset (Weka 3.6.0, R 2.9.2, Knime 2.1.1, Orange 2.0b and RapidMiner 4.6.0). We try above all to understand the obtained results.

Random Forest

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output

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of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance.

The first algorithm for random decision forests was created in 1995 by Tin Kam Ho[1] using the random subspace method, which, in Ho's formulation, is a way to implement the "stochastic discrimination" approach to classification proposed by Eugene Kleinberg.

An extension of the algorithm was developed by Leo Breiman and Adele Cutler, who registered "Random Forests" as a trademark in 2006 (as of 2019, owned by Minitab, Inc.).The extension combines Breiman's "bagging" idea and random selection of features, introduced first by Ho[1] and later independently by Amit and Geman[13] in order to construct a collection of decision trees with controlled variance.

Random forests are frequently used as "blackbox" models in businesses, as they generate reasonable predictions across a wide range of data while requiring little configuration.

SVM

In classification tasks a discriminant machine learning technique aims at finding, based on an *independent and identically distributed* (*iid*) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point x and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space.

SVM is a discriminant technique, and, because it solves the convex optimization problem analytically, it always returns the same optimal hyperplane parameter—in contrast to *genetic algorithms* (*GAs*) or *perceptrons*, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training, which will translate into several hyperplanes' meeting this requirement.

WORKING :

Data Collection:

Collect and aggregate textual data from various sources such as social media platforms, forums, security feeds, news articles, blogs, and security reports. Focus on cyber threat-related discussions, incidents, or reports.

Preprocessing:

Preprocess the collected data by cleaning, tokenizing, and normalizing the text. Remove noise, irrelevant information, and perform tasks like stemming, lemmatization, and removing stop words to prepare the text for analysis.

MITRE ATT&CK Integration:

Integrate MITRE ATT&CK framework to enhance threat characterization and mapping. Leverage ATT&CK's structured knowledge base to correlate identified threats with known attack patterns, tactics, techniques, and procedures.

Continuously evaluate prediction models' performance using validation techniques and refine them based on feedback and new data to improve predictive accuracy.

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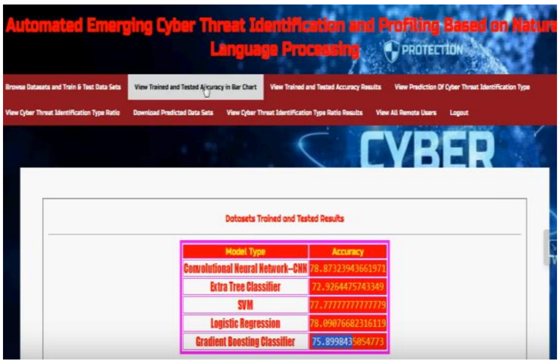
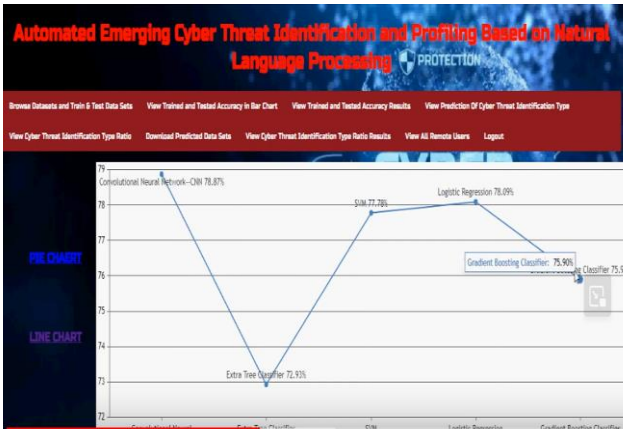
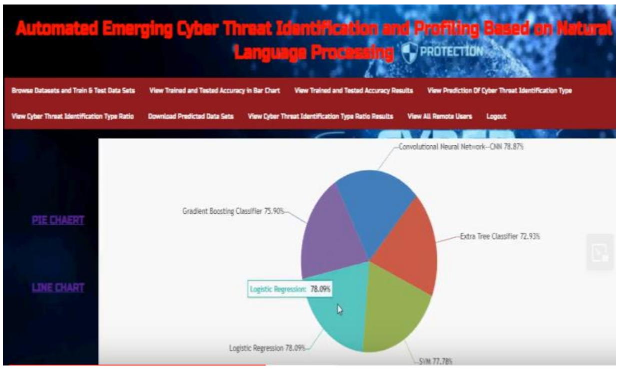


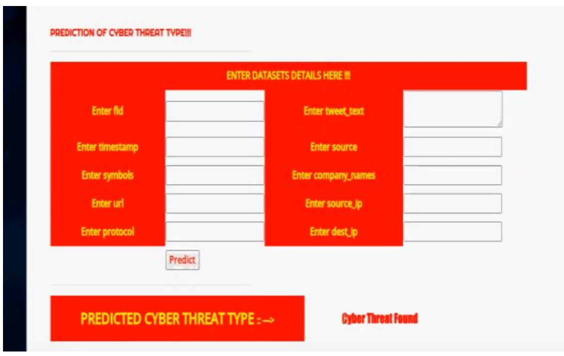
Bar Graph: Represent the distribution of identified threats by type or category, aiding in understanding the prevalence of different threat categories.

Line Charts Graph: Depict the trend of emerging threats over time, showcasing the frequency or intensity of threats detected.





Prediction of cyber threat type:



V.CONCLUSION

Given the dynamism of the cyber security field, with new vulnerabilities and threats appearing at any time, keeping up to date on them is a challenging but important task for analysts. Even following the best practices and applying the best controls, a new threat may bring an unusual way to subvert the defenses requiring a quick response. This way, timely information about emerging cyber threats becomes paramount to a complete cyber security system.

This research proposes an automated cyber threat identification and profiling based on the natural language processing of Twitter messages. The objective is exactly to cooperate with the hard work of following the rich source of information that is Twitter to extract valuable information about emerging threats in a timely manner.

This work differentiates itself from others by going a step beyond identifying the threat. It seeks to identify the goals of the threat by mapping the text from tweets to the procedures conducted by real threats described in MITRE ATT&CK knowledge base. Taking advantage of this evolving and collaborative knowledge base to train machine learning algorithms is a way to leverage the efforts of cyber security community to automatically profile identified cyber threats in terms of their intents.

To put in test our approach, in addition to the research experiment, we implemented the proposed pipeline and run it for 70 days generating online alerts for the Threat Intelligence Team of a big financial institution in Brazil. During this period, at least three threats made the team take preventive actions, such as the Petit Potam case, described in section V. Our system alerted the team making them aware of Petit- Potam 17 days before the official patch was published by Microsoft. Within this period, the defense team was able to implement mitigations avoiding potential exploits and, consequently, incidents.

Our experiments showed that the profiling stage reached an F1 score of 77% in correctly profiling discovered threats among 14 different tactics and the percentage of false alerts of 15%. In future work, we consider it important to advance in tweets selection stages (Unknown Words and One-class), to improve the false positives rate and in the profiling stage, to reach higher accuracy in determining the technique associated with the identified threat. We are working on this way by experimenting with a different NLP approach using the part of speech (POS) algorithm implementation from Spacy29 Python library. The object is to identify the root verb, the subject, and the object of the phrases to select tweets where the action described (the root verb) is referencing the unknown word (the subject).

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