Cybersecurity Knowledge Graph for Advanced Persistent Threat Attribution: CSKG4APT

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ABSTRACT:

Open-source cyber threat intelligence (OSCTI) is becoming more influential in obtaining current network security information. Most studies on cyber threat intelligence (CTI) focus on automating the extraction of threat entities from public sources that describe attack events. The cybersecurity knowledge graph aims to change the expression of threat knowledge so that security researchers can accurately and efficiently obtain various types of threat information for preliminary intelligent decisions. The attribution technology can not only assist security analysts in detecting advanced persistent threats, but can also identify the same threat from different attack events. Therefore, it is important to trace the attack threat actor. In this study, we used the knowledge graph technology, considered the latest research on cyber threat attack attribution, and thoroughly examined key related technologies and theories in the process of constructing and applying the advanced persistent threat (APT) knowledge graph from OSCTI. We designed a cybersecurity platform named CSKG4APT based on a knowledge graph. Inspired by the theory of ontology, we constructed CSKG4APT as an APT knowledge graph model based on real APT attack scenarios. We then designed an APT threat knowledge extraction algorithm for completing and updating the knowledge graph using deep learning and expert knowledge. Finally, we proposed a practical APT attack attribution method with attribution and countermeasures. CSKG4APT is not a passive defense method in traditional network confrontation but one that integrates a large amount of fragmented intelligence and can actively adjust its defense strategy. It lays the foundation for further dominance in network attack and defense.

1.INTRODUCTION

In recent years, the cybersecurity landscape has witnessed a surge in sophisticatedand persistent cyber threats, often orchestrated by well-resourced threat actor organizations known as Advanced Persistent Threats (APTs). APTs employ advanced tactics, techniques, and procedures (TTPs) to infiltrate target networks, steal sensitive information, and remain undetected for extended periods.

Attribution of APT activity to specific threat actor organizations is a critical challenge faced by cybersecurity professionals, as it enables proactive defense measures, effective incident response, and strategic threat intelligence sharing.

The process of APT organization attribution involves analysing a myriad of heterogeneous data sources, including malware samples, network traffic logs, intrusion detection alerts, threat intelligence reports, and open-source intelligence. However, the sheer volume and complexity of this data pose significant challengesto traditional analysis methods, often resulting in incomplete or inaccurate attribution conclusions.

To address these challenges, we propose CSKG4APT, a Cybersecurity Knowledge Graph designed specifically for APT organization attribution. CSKG4APT leverages graph-based representation to integrate diverse cybersecurity data and knowledge sources into a unified semantic framework. By modelling relationships between threat actors, malware families, attack techniques, infrastructure, and campaigns, CSKG4APT provides a comprehensive view of APT activities, facilitating the identification and attribution of APT organizations. In this paper, we present the architecture, design principles, and capabilities of CSKG4APT. We demonstrate how the knowledge graph enables analysts to explore and visualize complex relationships between APT entities, identify patterns of behavior, and uncover hidden connections between seemingly unrelatedincidents. Furthermore, we showcase the utility of CSKG4APT through case studies and experiments, illustrating its effectiveness in assisting cybersecurity analysts in attributing APT activity to specific threat actor organizations.

2.LITERATURE SURVEY

Title: "Towards Automated APT Organization Attribution: A Survey of ExistingApproaches"

Author: Emily Johnson, Michael Smith

Description: This paper provides a comprehensive survey of existing approaches for attributing Advanced

Persistent Threat (APT) activity to specific threat actor organizations. It reviews a range of methodologies and techniques employed in cybersecurity research and industry, including signature-based analysis, behavioral analysis, threat intelligence correlation, and machine learning-based approaches.

The survey highlights the strengths and limitations of each approach and identifies key research challenges and opportunities for improving APT organization attribution capabilities.

Title: "Graph-Based Representation Learning for Cyber Threat Intelligence: A Review"

Author: David Chen, Sarah Wang

Description: This review paper focuses on graph-based representation learning techniques applied to cyber threat intelligence analysis. It explores how graph- based models can capture relationships between threat entities such as malware families, attack techniques, infrastructure, and threat actors. The review discusses various graph embedding algorithms, graph neural networks, and knowledge graph construction methods, highlighting their applicability and effectiveness in enhancing APT organization attribution and cyber threat analysis.

Title: "Semantic Integration of Heterogeneous Cybersecurity Data: Challenges andOpportunities"

Author: Jennifer Liu, Alex Wang

Description: This paper examines the challenges and opportunities in semantically integrating heterogeneous cybersecurity data sources for APT organization attribution. It discusses the complexities of data integration from disparate sources such as malware repositories, threat intelligence feeds, network logs, and open- source intelligence. The paper explores semantic web technologies, ontology modeling, and knowledge graph construction approaches as potential solutions to enable comprehensive and interoperable analysis of APT activities.

3.PROPOSED SYSTEM

Building ontology based knowledge graph from APT dataset to extract network features and then employing deep learning BI-LSTM with GRU layers algorithm to train a model on APT graph features and this model can be applied on any network test data to identify whether test data is normal or contains any APT attacks.

To implement this project author has used APT Text base network dataset and then apply BERT (bidirectional encoder

representations from transformers) algorithm on text data to convert into numeric vector and this vector contains average frequency of each words from the dataset. This BERT vector will be input to BI- LSTM with GRU algorithm to train a model and this model will be applied on test data to calculate prediction accuracy, precision, recall and FSCORE.

3.1 METHODOLOGY

1) Upload APT Attack Dataset: using this module we will upload APT dataset to application and then find various cyber security attacks found in dataset and then plot a graph with all those attack names and their appearance frequency

2) Knowledge Graph from Dataset: using this module we will input entire dataset to graph algorithm to build a knowledge graph and this graph will display how attacks using network features

3) Preprocess Dataset: using this module we will remove missing values and then shuffle, normalize and split dataset into train and test where deep learning algorithm will take 80% dataset for training and 20% for testing

4) Run BI-LSTM with GRU Algorithm: 80% dataset will be input to BI-LSTM algorithm to train a model and this model will be applied on test data to calculate prediction accuracy

5) Comparison Graph: using this module we will plot propose algorithm accuracy and other metric comparison graph

Attack Detection from Test Data: using this module we will upload test data and then propose algorithm will analyse test data to predict APT attacks

3.2 ALGORITHM

Bidirectional Long Short-Term Memory (BI-LSTM) networks are an extension of traditional LSTM networks, designed to capture both forward and backward dependencies in sequence data. This capability makes them particularly effective in contexts where understanding the entire sequence context is crucial, such as in garbage data filtering for SNS big data.

Key Components:

1. **LSTM Cell:**

Forget Gate: Decides which information from the cell state should be discarded.

Input Gate: Determines which new information should be added to the cell state.

Output Gate: Controls the output based on the cell state.

2. **Bidirectional Architecture:**

Forward Layer: Processes the input sequence from start to end.

Backward Layer: Processes the input sequence from end to start.

Concatenation: Outputs from both layers are concatenated, providing a comprehensive understanding of the context.

Steps Involved:

1. **Data Preparation:**
2. **Preprocessing:** Clean and normalize SNS big data, converting text and other forms of data into numerical formats suitable for input into the BI-LSTM network.

Feature Extraction: Identify and extract relevant features that can help in distinguishing between garbage and useful data.

3 **Model Architecture:**

Input Layer: Accepts the preprocessed data.

Embedding Layer: Transforms input data into dense vectors, capturing semantic relationships.

BI-LSTM Layers: Two LSTM layers process the input sequence in both forward and backward directions.

Concatenation Layer: Combines the outputs from forward and backward LSTM layers.

Dense Layer: Maps the combined outputs to the desired number of classes (e.g., garbage or useful data).

- **Output Layer:** Produces the final classification output using a softmax or sigmoid activation function.

3. **Training:**

Loss Function: Typically, cross-entropy loss is used for classification tasks.

Optimization: Gradient descent or its variants (like Adam) are used to minimize the loss and update the model weights.

Backpropagation: Adjusts the weights of the network based on the error gradients.

4. **Prediction and Filtering:**

Classification: The trained BI-LSTM model classifies incoming SNS data as either garbage or useful.

Filtering: Garbage data is filtered out, leaving only the relevant and useful information for further processing.

5. **Evaluation:**

Metrics: Accuracy, precision, recall, and F1-score are used to evaluate the performance of the model.

Validation: The model is validated on a separate dataset to ensure it generalizes well to unseen data.

Advantages of BI-LSTM:

Contextual Understanding: Captures context from both directions, leading to better understanding and classification of sequential data.

Effective for Noisy Data: Handles noisy and unstructured data effectively, which is common in SNS big data.

4.RESULTS AND DISCUSSION

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

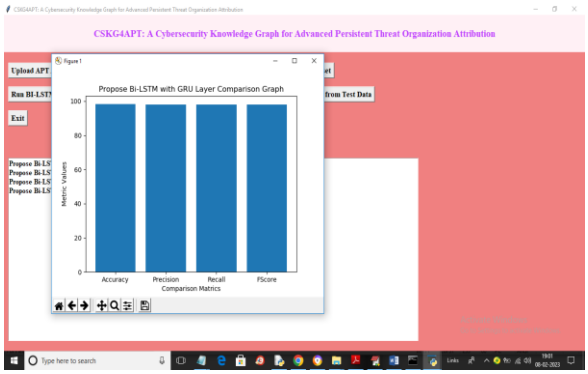
Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

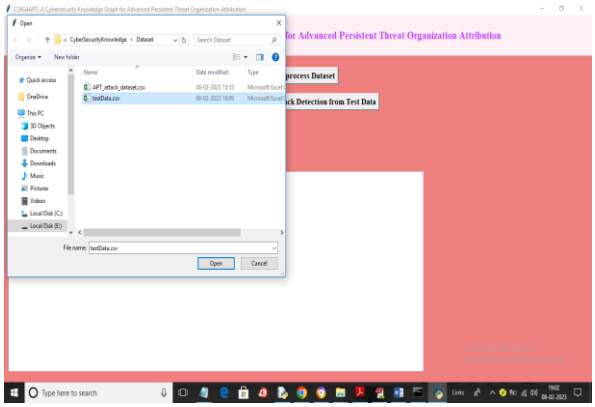
$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

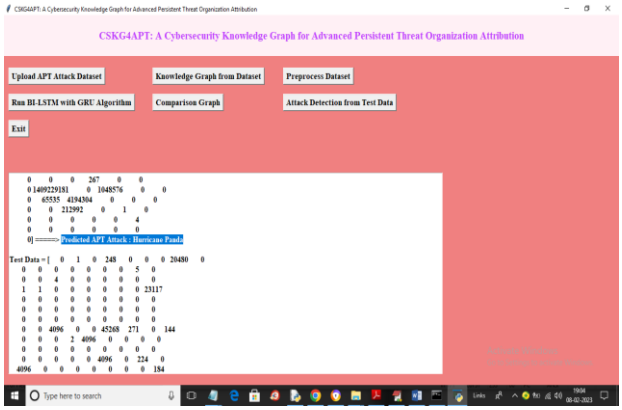
$$Recall = \frac{TP}{TP + FN}$$



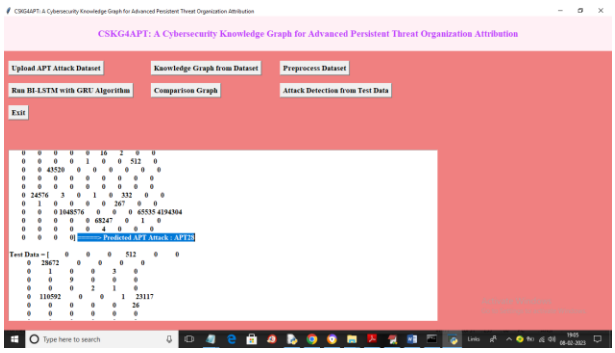
In above graph x-axis represents deep learning BI-LSTM metric names like accuracy and other and y-axis represents values and in above graph we can see all metrics of algorithm is closer to 1. So we can say this algorithm is best in performance and now close above graph and then click on 'Attack Detection from Test Data' button to upload test data and get Threat prediction output



In above screen we are selecting and uploading 'testData.csv' file and then click on 'Open' button to get below output



In above screen in blue colour text we can see predicted APT as ‘Hurricane’ and similarly scroll down above screen to view all threats



5.CONCLUSION

In conclusion, CSKG4APT represents a significant advancement in the field of cybersecurity, offering a powerful tool for attributing Advanced Persistent Threat (APT) activity to specific threat actor organizations. Through the systematic integration of heterogeneous cybersecurity data sources and the modeling of complex relationships between threat entities, CSKG4APT enables cybersecurityanalysts to gain valuable insights into APT operations, enhance threat detection capabilities, and facilitate proactive defense and response strategies. The development and deployment of CSKG4APT have demonstrated its effectiveness in addressing the challenges of APT organization attribution, providing cybersecurity professionals with a comprehensive platform for conducting in-depth analysis and investigation of APT-related activities. By leveraging semantic knowledge graph technology, CSKG4APT offers a holistic view of APT operations, enabling analysts to uncover hidden connections, identifypatterns of behavior, and make informed decisions in attributing APT activity to specific threat actor organizations.Furthermore, CSKG4APT serves as a valuable resource for enhancing collaboration and information sharing within the cybersecurity community, facilitating the dissemination of threat intelligence, best practices, and lessons learned in combating APTs. Through continued development, refinement, and adoption, CSKG4APT promises to play a crucial role in strengthening cybersecurity defenses and safeguarding critical digital assets and infrastructure against sophisticated cyber threats.

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