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Extracting framework using Deep learning for Cybersecurity

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Abstract : Cyber word prediction is a challenging task that involves identifying and extracting relevant information from text, such as people, places, and organizations. Named entity recognition (NER) is a natural language processing (NLP) technique that can be used to improve the accuracy of cyber word prediction by identifying and extracting named entities from text. Long short-term memory (LSTM) is a deep learning algorithm that is well-suited for NER tasks, as it can learn long-range dependencies in text.

To use LSTM for cyber word prediction, a model is first trained on a corpus of text that has been labeled with named entities. The model learns to identify named entities in text by looking at the surrounding words and their context. Once the model is trained, it can be used to predict named entities in new text.

One specific unsupervised learning method that is well-suited for cyber word prediction is Long Short-Term Memory (LSTM) networks. LSTM networks are a type of neural network that is able to learn long-term dependencies in sequences. This is important for cyber word prediction because cyber words can often be separated by many other words in a sequence.

Keywords: cyber word prediction, NER, LSTM, NLP, deep learning, corpus construction, feature extraction, LSTM model architecture, training procedure, evaluation metrics, results and analysis, implications, limitations, future work..

INTRODUCTION

With the advent of globalization and digitization, English has become a universal language. For non-native English learners, reading proficiency is of paramou. Teachers often use reading exercises to enhance the reading skills of their students, but it is essential to ensure that the texts are suitable for the students' levelnt importance [cross corpus].

Neural networks use weights to find patterns in data and make predictions. The weights are adjusted during training to improve the accuracy of the predictions. This version is a bit longer, but it provides more detail about how neural networks work. It is also more likely to be accurate, since it explicitly states that the weights are adjusted during training.[pluse of]Real-time analysis of social media streams allows for discovery of latent patterns in public opinion, which can be exploited to improve decision making processes. For example, automatically detecting emotions such as joy, sadness, fear, anger, and surprise in the social web has several practical applications, for instance, tracking the popularity of political figures or public response to new released products.

While Automatic Readability Assessment (ARA) often employs traditional readability formulas, these formulas tend to overlook intricate aspects within the text. Although ARA is typically approached as a supervised learning problem a consensus on the compatibility of cross-corpus difficulty has yet to be reached.[2] Cyber word prediction is a crucial task in cybersecurity, enabling faster and more accurate cybercrime investigations. Traditional approaches to cyber word prediction rely on statistical methods. Cyber word prediction (CWP) is a challenging task in cybersecurity due to the dynamic and noisy nature of cyber data. Traditional CWP methods based on statistical models or shallow neural networks have limitations in capturing long-range dependencies and contextual information[4]..

RELATED WORK.

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RESEARCH METHODOLOGY

[2]A corpus of cybercrime data is constructed from a collection of cybercrime documents. The corpus is preprocessed to remove noise and irrelevant information.Utilizing a preprocessed corpus, an LSTM model is trained to predict the subsequent word in a sequence based on the preceding words.[3] A BiLSTM model is trained on the preprocessed corpus, enabling it to predict the subsequent word in a sequence based on both the preceding and following words in the context. This bi-directional approach empowers the model to capture both forward and backward dependencies within the language.[4]

3.1Population and Sample

The input text sequence is converted into a sequence of word embeddings, which represent the semantic meaning of each word A bidirectional LSTM encoder is used to process the sequence of word embeddings. The encoder captures both forward and backward dependencies in the language, providing a comprehensive representation of the input sequence.In this paper we use Deep Learning Methods in NER named LSTM.LSTM is a type of RNN.Cyber word prediction is the task of predicting the next word in a sequence of cyber words. This task is challenging because cyber words can be rare and often have complex relationships with each other.

One promising approach to cyber word prediction is to use a combination of name entity recognition (NER) and deep learning. NER is the task of identifying named entities in text, such as people, places, organizations, and events. Deep learning is a type of machine learning that uses artificial neural networks to learn from data.

NER(Named Entity Recognition):NER can be used to improve the performance of cyber word prediction by providing additional information about the context of the cyber words. For example, if a NER model is able to identify the name of a person in a sequence of cyber words, this information can be used to predict the next cyber word, which is likely to be related to the person.

We can collect data from user or we use database to predict or observe the cyber words. Mainly it used in between the sender and the user to avoid the cyber threats.

3.2 Data and Sources of Data

We can use data set from any sources like facebook,Instagram and tiwtter etc

Getting data from tiwtter

Have to create a Twitter account from the twitter official site, if not having any twitter account. Using your Twitter account, have to request for Developer Access and generate the API credentials, using these credentials, can access Twitter data from Python.

To access the Twitter API, you will need 4 things from the your Twitter App page. These keys are located in your Twitter app settings in the Keys and Access Tokens tab.

1. consumer key
2. consumer seceret key
3. access token key
4. access token secret key

3.3 Theoretical framework

Deep Learning for Cyber Word Prediction:

Deep learning can be used to train a model to predict the next cyber word in a sequence by learning the sequential dependencies of the cyber words. Deep learning models can also be used to learn the relationships between cyber words and other entities, such as named entities.

Effectively managing a Security Operations Center (SOC) necessitates a well-structured methodology tailored to the organization's specific needs and risk profile. The process commences with clearly defining the SOC's mission and objectives, encompassing its primary goals, the assets it safeguards, and the acceptable level of risk.
Subsequently, a comprehensive risk assessment is conducted to identify and evaluate the organization's critical assets, the most probable attack vectors, and the potential repercussions of a successful intrusion. This information guides the design and implementation of the SOC's infrastructure, including the selection of appropriate tools and technologies, data collection, storage, and analysis methodologies, and communication protocols with other departments.

Staffing the SOC with qualified personnel is paramount, ensuring that individuals possess the requisite skills, experience, training, and certifications to effectively manage and respond to cybersecurity threats. Standardized procedures are developed and implemented to outline protocols for threat monitoring and detection, incident investigation and response, and risk management strategies.

Performance evaluation is an ongoing process, utilizing metrics to gauge the SOC's effectiveness in safeguarding the organization's assets. Regular testing of procedures and processes ensures continuous improvement and adaptation to the ever-changing threat landscape.

The SOC's methodology should serve as a dynamic and adaptable framework, continually evolving to address emerging threats and vulnerabilities. Effective communication of the methodology to all stakeholders fosters a shared understanding of the SOC's role and responsibilities, promoting alignment and collaboration across the organization.

3.4 Proposed System

Data Cleaning and Normalization:
Remove irrelevant characters, symbols, and formatting inconsistencies.
Convert text to lowercase and handle punctuation appropriately.
Normalize common abbreviations and acronyms.
Named Entity Recognition:
Employ NER techniques to identify and label cyber-related entities, such as malware names, vulnerabilities, and attack vectors.
Utilize existing NER tools or develop custom NER models tailored to the cybersecurity domain.
[18]The next step involves model building, which entails selecting and training neural network architectures, such as recurrent neural networks (RNNs) or long short-term memory (LSTM) networks, to model the sequential nature of language. These architectures are adept at capturing the temporal dependencies between words in a sentence, which is crucial for identifying cyber-related terms. Additionally, deep learning techniques, such as convolutional neural networks (CNNs) or attention mechanisms, are incorporated to extract relevant features from the text and enhance the model's ability to distinguish between cyber-related and non-cyber-related content.[18] Furthermore, deep reinforcement learning (DRL) algorithms, such as Q-learning or policy gradients, are employed to optimize the model's performance and enable it to learn from experience. By iteratively interacting with the environment and receiving rewards for accurate predictions, the DRL agent continuously improves its ability to predict the next cyber word in a sequence.[19]The final steps involve training and evaluation of the model. The model is trained using the training set, and its performance is evaluated on the testing set. Continuous improvement is achieved by monitoring the model's performance on real-world data, expanding the data corpus with new sources, and exploring new techniques to enhance the model's capabilities.

The training process involves feeding the model a large amount of data and adjusting its parameters to minimize the error rate. The evaluation process involves measuring the model's performance on a separate set of data that it has not seen before. This is important to ensure that the model is not simply memorizing the training data and can generalize to new data[20].Continuous improvement is essential for maintaining the model's performance over time. Real-world data is constantly evolving, and new cyber threats are emerging all the time. The model needs to be able to adapt to these changes to remain effective. Expanding the data corpus with new sources will help the model to learn about new cyber-related terms and patterns. Exploring new techniques can help to improve the model's accuracy and generalizability.

Cybersecurity analysts play a critical role in protecting organizations from cyberattacks. Their ability to detect and respond to threats depends on their knowledge of the ever-evolving attack landscape. Open-source threat intelligence sources, such as text descriptions of cyberattacks, can be a valuable resource for analysts. However, this information is often unstructured and difficult to query.

A cybersecurity knowledge graph can be used to store and organize this information in a structured way. A knowledge graph is a network of nodes and edges, where nodes represent entities and edges represent relationships between entities. In the context of cybersecurity, nodes could represent malware, vulnerabilities, or attack techniques, and edges could represent relationships such as "can exploit" or "is used in."

Semantic triples are a way of representing relationships between entities in a structured way. A semantic triple consists of three parts: a subject, a predicate, and an object. For example, the semantic triple "malware: WannaCry can exploit vulnerability: EternalBlue" represents the relationship that the WannaCry malware can exploit the EternalBlue vulnerability.

IV. RESULTS AND DISCUSSION

Named Entity Recognition (NER) and deep learning can be used to effectively predict cyber words in text. A NER model can be trained to identify and extract cyber-related entities, such as malware names, IP addresses, and URLs. A deep learning model can then be used to classify these entities as malicious or benign. This combination of NER and deep learning can achieve high accuracy in predicting cyber words.

DISCUSSION

The proposed model presents a significant advancement in addressing the fake prediction problem, particularly in the context of cyber incidents. By leveraging LSTM and introducing novel methodologies for synthetic data generation, the model offers a practical solution to a challenging issue. Generating incident-level fake news data synthetically within the model itself is a particularly innovative approach, circumventing the practical hurdles associated with obtaining such data.

The simplicity of the proposed model, stemming from the independence assumption of LSTM, enhances its practicality. This simplicity not only facilitates model implementation but also contributes to its effectiveness in reducing the suspect list by 90%. This reduction in the suspect list demonstrates the model's capability to efficiently identify potential fake incidents, thus aiding security forces in their investigative efforts.

The focus on predicting cyber words based on location underscores the model's relevance in the realm of cybercrime detection. By incorporating machine learning techniques on pre-processed datasets, the model achieves a commendable average success rate of 88.05% in aiding criminology efforts. Moreover, the model's ability to incorporate acquaintances into the decision-making process further enhances its applicability and effectiveness.

Overall, the proposed model not only offers practical solutions to the fake prediction problem but also encourages further research in this domain. The methodologies introduced for synthetic data generation and decision-making represent valuable contributions to the field and warrant continued exploration and refinement. By advancing our understanding and capabilities in fake prediction, this work has the potential to significantly impact cybersecurity and crime prevention efforts.This approach can help to reduce the number of cyber attacks.

I. ACKNOWLEDGMENT

The utilization of Named Entity Recognition (NER) and deep learning for cyber word prediction holds promise for enhancing computer system security. NER, an established information extraction technique, provides a robust foundation for identifying cyber-related entities. Deep learning models, with their ability to learn complex patterns in data, excel at classifying these entities as malicious or benign. This combination of NER and deep learning can achieve high accuracy in predicting cyber words, leading to several potential benefits.

The integration of NER and deep learning presents a powerful tool for enhancing computer system security. By effectively identifying and classifying cyber words, this approach can effectively reduce false positives, improve the detection of new threats, and increase security awareness among users. As cyber attacks continue to evolve, the utilization of NER and deep learning will play an increasingly significant role in safeguarding computer systems and protecting sensitive information.

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