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Leveraging Large Language Models for Multi-Domain Malware and Vulnerability Detection

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Abstract

This study presents the application of deep learning methodologies, particularly leveraging GPT-2, to enhance various aspects of cybersecurity, including source code vulnerability detection, malware detection, and mobile malware security. The first part introduces a method for identifying security vulnerabilities in C/C++ source code by fine-tuning a GPT-2 model on diverse open-source code datasets. The results show that the GPT-2 model, using default tokenizers and encoders, performs comparably to other deep learning methods in vulnerability detection. The second part explores the use of GPT-2 for improving malware detection, proposing a novel approach that classifies malware through opcode snippets and textual features. Fine-tuning GPT-2 on a diverse dataset of malware and benign software demonstrates enhanced detection accuracy and reduced false positives. Lastly, the study investigates mobile malware detection, proposing a framework that combines static and dynamic analysis using deep learning to detect unseen malware variants. The framework is evaluated on a comprehensive dataset, showing improved accuracy and fewer false positives than traditional methods. This integrated approach highlights the potential of deep learning, particularly GPT-2, to address the challenges of modern cybersecurity, offering robust solutions across multiple domains.

A. Introduction

The growing complexity and frequency of cyber threats have made the detection and mitigation of software vulnerabilities and malware essential to cybersecurity efforts. Traditional methods, such as signature-based and heuristic approaches, have long been relied upon but struggle to keep pace with rapidly evolving threats, particularly with the rise of polymorphic malware and sophisticated attack strategies (Moser et al., 2007; Grier et al., 2010). These limitations highlight the need for more advanced, adaptive solutions. Recently, deep learning models, particularly those leveraging natural language processing (NLP) architectures like GPT-2, have emerged as promising tools for addressing these challenges. These models have demonstrated their ability to learn complex patterns from large datasets, making them suitable for detecting vulnerabilities in source code and malicious activity in both traditional and mobile environments (Wu et al., 2017; Radford et al., 2019).

The application of deep learning, specifically transformer-based models such as GPT-2, for cybersecurity tasks, such as vulnerability detection and malware classification, has garnered significant interest. GPT-2, although initially designed for text generation, can be adapted to analyze the semantic structures of source code or opcode sequences, enabling it to identify patterns indicative of vulnerabilities or malicious behavior (Mazuera-Rozo et al., 2021; Guo et al., 2021). By fine-tuning such models on specialized datasets, it becomes possible to improve detection accuracy, reducing false positives and enhancing the resilience of systems against cyber threats. This paper explores the application of GPT-2 for malware detection and vulnerability analysis, evaluating its potential to provide more automated, adaptive, and accurate solutions for modern cybersecurity challenges (Zhang et al., 2019; Shahzad, 2024).

B. Related Works

The increasing number of software vulnerabilities has driven the development of various approaches for vulnerability detection, including traditional methods like manual code reviews, static and dynamic code analysis, and newer machine learning techniques (Yamaguchi et al., 2014; Perl et al., 2015; Stuckman et al., 2017). Deep learning methods initially focused on feature extraction, using code "gadgets" to detect vulnerabilities (Russell et al., 2018; Zhen et al., 2018). However, to address the limitation of detecting only those vulnerabilities within function calls, frameworks such as the muVuldeePecker (MVD) dataset were developed, enabling detection across broader source code structures (Zou et al., 2021). Recent advancements in transformer-based models, particularly BERT and its variations (e.g., RoBERTa, CodeBERT), have significantly improved detection accuracy by learning complex patterns within source code (Devlin et al., 2018; Liu et al., 2019; Feng et al., 2020). Furthermore, models like C-BERT and VulBERTa have achieved notable success in vulnerability detection tasks by incorporating Abstract Syntax Trees (AST) and custom tokenization techniques (Buratti et al., 2020; Hanif et al., 2022). Recent research has also explored the application of language models, such as GPT-2, for generating and analyzing malware samples, enhancing the robustness of machine learning models (Khan et al., 2022; Buratti et al., 2020). In addition, traditional malware detection has shifted from signature-based to more adaptive machine learning techniques, such as CNNs and RNNs, which offer improvements in analyzing complex malware behaviors (Yin et al., 2018; Zhang et al., 2021). Although deep learning methods provide substantial improvements, challenges such as the need for large datasets and computational resources persist (Zhou et al., 2021).

C. Methodology

This study utilized the GPT-2 model for pre-training, fine-tuning, and evaluating the detection of vulnerabilities in C/C++ code, leveraging a range of datasets for both training and evaluation. The hardware setup included a 2019 Apple Mac Pro with an Intel Xeon W-3265M processor, dual AMD Radeon Pro W6800X GPUs (each with 32GB VRAM), and 192GB RAM, operating on macOS Sonoma and utilizing tools such as Python 3.11.5, PyTorch 2.1.2, and Transformers 4.32.1. Pre-training was conducted on a variety of datasets, including Devign and GitHub, to train the model on C/C++ source code, dividing data into 80% training, 10% validation, and 10% testing. Fine-tuning then tailored the model to vulnerability detection, using datasets such as D2A, FormAI, and muVulDeePecker. Evaluation was conducted using datasets like REVEAL, Draper, and VulDeePecker to assess the model's accuracy in detecting vulnerabilities.

To optimize performance, the study employed parallel computing via dual GPUs connected with an AMD Infinity Fabric Link, enhancing data transfer speeds for efficient model training. The PyTorch framework, utilizing the Metal Performance Shaders (MPS) backend, provided GPU acceleration, with the DataParallel class managing simultaneous data processing across GPUs. The evaluation process followed a similar structure to training, excluding backpropagation and gradient descent to focus on prediction accuracy. By combining pre-existing libraries and optimizing hardware resources, the study aimed to maximize both the vulnerability detection accuracy and computational efficiency.

D. Results

Table 1. Model Accuracy. Accuracy is the proportion of correct predictions out of the total predictions made

Source Code Vulnerability Dataset	**GPT-2 Model Accuracy (%)**
REVEAL	90
Draper	91
VulDeePecker	99

Table 2. GPT-2 Model Results. Accuracy is the proportion of correct predictions out of the total predictions made

Dataset	Accuracy (%)
DasMalwerk	93
MalwareFeed	92
Wolfvan	97

Table 3. GPT-2 and CNN Model Results. Accuracy is the proportion of correct predictions out of the total predictions made

Dataset	Accuracy (%)
AndroZoo	90
X2C2 (Transformer)	95
X2C2 (CNN)	97

E. Conclusion

In conclusion, this research highlights the potential of advanced machine learning models, such as GPT-2 and deep learning techniques, in enhancing cybersecurity, particularly in source code vulnerability analysis, malware detection, and mobile device security. The study demonstrated that a pre-trained and fine-tuned GPT-2 model, despite not relying on customized tokenizers, effectively captures the syntactic and semantic intricacies of source code, making it suitable for vulnerability analysis. Moreover, the use of GPT-2 in malware detection significantly outperformed traditional methods, showcasing its ability to distinguish between malicious and benign software with high accuracy while minimizing false positives. Similarly, the integration of convolutional and recurrent neural networks (CNNs and RNNs) for mobile malware detection further advanced detection capabilities, enabling the identification of novel and polymorphic threats. However, challenges such as the need for large labeled datasets, computational demands, and the evolving nature of threats remain. Future research should focus on improving model efficiency, incorporating new learning techniques like transfer learning and adversarial training, and enhancing model robustness to address these challenges and further strengthen cybersecurity frameworks (Goodfellow et al., 2014; Brown et al., 2020; Malik et al., 2020; Rajkumar et al., 2021).

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