ABSTRACT

NLP is a form of artificial intelligence and machine learning concerned with a computer or machine’s ability to understand and interpret human language. Language models are crucial in text analytics and NLP since they allow computers to interpret qualitative input and convert it to quantitative data that they can use in other tasks.

In essence, in the context of transfer learning [1], language models are typically trained on a large generic corpus, referred to as the pre-training stage, and then fine-tuned to a specific underlying task. As a result, pre-trained language models are mostly used as a baseline model that incorporates a broad grasp of the context and may be further customized to be used in a new NLP task.

The majority of pre-trained models are implemented using corpora from general domains, such as Twitter, newswire, Wikipedia, and the Web. Given that language is typically domain-specific; for example, healthcare documents use terminology that is significantly different than that used in a vulnerability report, off-the-shelf natural language processing models trained on general text may be inaccurate and unreliable in specialized fields. Thus, building a domain-specific language model can considerably increase the performance and efficacy.

In this paper, we propose a cybersecurity language model called SecureBERT, which is able to capture the text connotations in the cybersecurity domain, and therefore could further be used in automation for many important cybersecurity tasks that would otherwise rely on human expertise and tedious manual efforts. SecureBERT is trained on a large corpus of cybersecurity text collected and preprocessed by us from a variety of sources in cybersecurity and the general computing domain. Using our proposed methods for tokenization and model weights adjustment, SecureBERT is not only able to preserve the understanding of general English as most “off-the-shelf” language models can do, but also effective when applied to text that has cybersecurity implications. We conducted comparative evaluations of SecureBERT using the industry-standard Masked Language Model (MLM) test to demonstrate its efficacy in processing cybersecurity text, as well as two downstream tasks to prove how well it retains general English language understanding.

NOTE: This is the initial draft of this work and it may contain errors and typos. The revised complete version has already been submitted to a venue. Following the publication of the paper, the full version would be updated and the corpus and the pre-trained model will be made available on GitHub.

Keywords cyber automation, cyber threat intelligence

1 Introduction

Security automation technology use has climbed year over year. The cyber security market is flooded with solutions that safeguard users from malicious sources, protect mission-critical servers, and secure personal information, healthcare data, intellectual property, and sensitive financial data. Businesses invest in technology to handle such security solutions,
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often aggregating a massive quantity of data into a single system to aid in organizing and accessing important information with the purpose of better identifying where they confront risk or where specific traffic originates or terminates.

Recently, as social networks and ubiquitous computing have grown in popularity, the overall volume of digital text content has increased. This text content spans a range of domains, from a simple tweet or news blog article to more sensitive information such as a medical record [2,3] or financial transaction. In cybersecurity context, security analyst's analyze relevant data to detect cyber threat-related information, such as vulnerabilities, in order to monitor, prevent, and control potential risk. Each year, cybersecurity agencies such as MITRE, NIST, CERT, and NVD invest millions of dollars in human expertise to analyze, categorize, prioritize, publish, and fix disclosed vulnerabilities. This time-consuming and inefficient manual approach is costly. As the number of products grows, and therefore the number of vulnerabilities increases, it is critical to have an automated system that can identify vulnerabilities and promptly deliver an effective defensive plan.

Natural language processing (NLP) has been extensively used to automate text analytic tasks in a range of sectors, including cybersecurity, by enabling machines to rapidly build or synthesis human language. Language models play important roles in NLP applications by allowing the computers to interpret qualitative data and transform it to quantitative data, that the machines may then employ for different underlying tasks.

There are several well-known and well-performing language models, such as ELMO [4], GPT [5], and BERT [6], trained on general English corpora and used for a variety of NLP tasks such as machine translation, named entity recognition, text classification, and semantic analysis. There is continuous discussion in the research community over whether it is beneficial to employ these off-the-shelf models as a baseline, and then fine-tune them through domain-specific tasks. The assumption is that the fine-tuned models will retain the basic linguistic knowledge in general English and meanwhile develop "advanced" knowledge in the domain while fine tuning [7].

However, some domains like cybersecurity are sensitive, dealing with critical data and any error in the process can expose the entire infrastructure to the cyber threats. Cybersecurity contains unique terminology that rarely appear in general English, such as ransomware, API, OAuth, exfiltrate, and keylogger; or carry different meaning in other domains, like run, honeypot, patch, handshake, and worm. This existing gap in language structure and semantic contexts complicates text processing and indicates that the generic English language model is unable to accommodate the vocabulary of cybersecurity texts, and have limited comprehension of cybersecurity implications.

In this work, we address this critical cybersecurity issue by introducing a language model called SecureBERT utilizing the state-of-the-art NLP architecture BERT [6], which is able to effectively process texts that have cybersecurity implications. In addition, SecureBERT is generic enough to be applied in other cybersecurity tasks, such as phishing detection [8], code and malware analysis [9], intrusion detection [10], etc. SecureBERT is a pre-trained cybersecurity language model that have the fundamental understanding of both the word-level and sentence-level semantics, which is an essential building block for any cybersecurity report. In this context, we collected, curated, and preprocessed a large corpus with 1.1 billion words from a variety of cybersecurity text resources, such as news, reports, textbooks, etc. We designed a subword-based tokenization and a model weight adjustment approach in our proposed language model called SecureBERT, through which the general English vocabulary is retained as much as possible while new words or words with different meanings in cybersecurity are accommodated effectively. We evaluated the performance of SecureBERT with a standard Masked Language Model (MLM) test and other standard NLP tasks such as sentiment analysis and named entity recognition.

section Overview of BERT

Language Model BERT (Bidirectional Encoder Representations from Transformers) [6] is a transformer-based neural network technique for natural language processing pre-training. BERT can train language models based on the entire set of words in a sentence or query (bidirectional training) rather than the traditional way of training on the ordered sequence of words (left-to-right or combined left-to-right and right-to-left). BERT allows the language model to learn word context based on surrounding words rather than just the word that immediately precedes or follows it.

BERT leverages Transformer, an attention mechanism that can learn contextual relations between words and sub-words in a sequence. The Transformer includes two separate mechanisms, an encoder that reads the text inputs and a decoder that generates a prediction for the given task. Since BERT's goal is to generate a language model, only the encoder mechanism is necessary [11]. This transformer encoder reads the entire data at the same time instead of reading the text in order.

Building a BERT model requires two steps: pre-training and fine-tuning. In pre-training stage, the model is trained on unlabeled data over different pre-training tasks, namely Masked LM (MLM) and Next Sentence Prediction (NSP). MLM masks some percentage of the input tokens (15%) at random and then predicts them through a learning procedure. In this case, the final hidden vectors corresponding to the mask tokens are fed into an output softmax over the vocabulary. NSP is mainly designed to understand the relationship between two sentences, which is not directly captured by language
SecureBERT

modeling. In order to train a model that understands sentence relationships, it trains for a binarized next sentence prediction task that can be trivially generated from any monolingual corpus, in which it takes a pair of sentences as input and in 50% of the times in replaces the second sentence with a random one from the corpus.

For fine-tuning, the BERT model is initialized with the pre-trained parameters, and all of the parameters are fine-tuned using labeled data from the downstream tasks, in which every downstream task has separate fine-tuned models. BERT model has a unified architecture across different tasks, and there is a minor difference between pre-trained and final downstream architecture, as mentioned above. BERT pre-trained model used Books Corpus (800M words) and English Wikipedia (2,500M words) and improved the state-of-the-art for eleven NLP tasks such as getting a GLUE [12] score of 80.4%, which is 7.6% of definite improvement from the previous best results, and achieving 93.2% accuracy on Stanford Question Answering Dataset (SQuAD) [13].

Later on there is a variant of BERT, called RoBERTa [14]. It is claimed to be a robustly optimized version of BERT with certain modifications in the tokenizer and the network architecture. RoBERTa extends BERT’s MLM, where the model intentionally learns to detect the hidden text part inside otherwise unannotated language samples. With considerably bigger mini-batches and learning rates, RoBERTa changes important hyperparameters in BERT training, enabling it to noticeably improve on the masked language modeling task and accordingly the overall performance.

2 Data Collection

We collected a large number (98,411) of online cybersecurity-related text data including books, blogs, news, security reports, videos (subtitles), journals and conferences, white papers, tutorials, and survey papers, using our web crawler tool[1]. We created a corpus of 1.1 billion words splitting it to 2.2 million documents each with average size of 512 words using the Spacy[2] text analytic tool. Table 1 shows the resources and the distribution of our collected dataset for pre-training the SecureBERT.

| Type                      | No. Documents |
|---------------------------|---------------|
| Articles                  | 8,955         |
| Books                     | 180           |
| Survey Papers             | 515           |
| Blogs/News                | 85,953        |
| Wikipedia (cybersecurity) | 2,156         |
| Security Reports          | 518           |
| Videos                    | 134           |
| **Total**                 | **98,411**    |

Vocabulary size 1,674,434 words
Corpus size 1,072,798,637 words
Document size 2,174,621 documents (paragraphs)

Table 1: The details of collected cybersecurity corpora for training the SecureBERT.

This corpora contains various forms of cybersecurity texts, from basic information, news, Wikipedia, and tutorials, to more specialized texts such as CTI, research articles, and threat reports. When aggregated, this collection offers a wealth of domain-specific connotations and implications that is quite useful for training a cybersecurity language model. The table ?? lists the web resources from which we obtained our corpus.

3 Methodology

We present two approaches in this section for refining and training our domain-specific language model. We begin by describing a strategy for developing a customized tokenizer on top of the pre-trained generic English tokenizer, followed by a practical approach for biasing the training weights in order to improve weight adjustment and therefore a more efficient learning process.

1Sample data: dropbox.com/sh/jg45zvfl7iek12i/AAB7bFghED9GmkO5YxpPLJuma?dl=0
2https://spacy.io/usage
3.1 Customized Tokenizer

A word-based tokenizer primarily extracts each word as a unit of analysis, called a token. It assigns each token a unique index, then uses those indices to encode any given sequence of tokens. Pre-trained BERT models mainly return the weight of each word according to these indices. Therefore, in order to fully utilize a pre-trained model to train a specialized model, the common token indices must match, either using the indices of the original or the new customized tokenizer.

For building the tokenizer, we employ a byte pair encoding (BPE) [15] method to build a vocabulary of words and subwords from the cybersecurity corpora. Our objective is to create a vocabulary that retains the tokens already provided in RoBERTa’s token language while also incorporating additional unique cybersecurity-related tokens. In this context, we extract 50, 265 tokens from the cybersecurity corpora to generate the initial token vocabulary \( \Psi_{Sec} \). We intentionally make the size of \( \Psi_{Sec} \) the same with that of the RoBERTa’s token vocabulary \( \Psi_{RoBERTa} \) since we intended to imitate original RoBERTa’s design. Character based encoding allows for the learning of a small subword vocabulary that can encode any input text without introducing any "unknown" tokens [16].

If \( \Psi_{Sec} \) represents the vocabulary set of SecureBERT, and \( \Psi_{RoBERTa} \) denotes the vocabulary set of original RoBERTa, both with size of 50, 265, \( \Psi_{Sec} \) shares 32, 592 mutual tokens with \( \Psi_{RoBERTa} \) leaving 17, 673 tokens contribute uniquely to cybersecurity corpus, such as "firewall", "breach", "crack", "ransomware", "malware", "phishing", "mysql", "kaspersky", "obfuscated", and "vulnerability", where RoBERTa’s tokenizer analyzes those using byte pairs:

\[
\begin{align*}
V_{mutual} &= \Psi_{Sec} \cap \Psi_{RoBERTa} \rightarrow 32,592 \text{ tokens} \\
V_{distinct} &= \Psi_{Sec} - \Psi_{RoBERTa} \rightarrow 17,673 \text{ tokens}
\end{align*}
\]

Studies [2] shows utilizing complete words (not subwords) for those are common in specific domain, can enhance the performance during training since alignments may be more challenging to understand during model training, as target tokens often require attention from multiple source tokens. Hence, we choose all mutual terms and assign their original indices, while the remainder new tokens are assigned random indices with no conflict, where the original indices refers to the indices in RoBERTa’s tokenizer, to build our tokenizer. Ultimately, we develop a customized tokenizer with a vocabulary size similar to that of the original model, which includes tokens commonly seen in cybersecurity corpora in addition to cross-domain tokens. Our tokenizer encodes mutual tokens \( V_{mutual} \) as original model, ensuring that the model returns the appropriate pre-trained weights, while for new terms \( V_{distinct} \) the indices and accordingly the weights would be random.

3.2 Weight Adjustments

The RoBERTa model already stores the weights for all the existing tokens in its general English vocabulary. Many tokens such as "email", "internet", "computer", and "phone" in general English convey similar meanings as in the cybersecurity

| Websites |
|------------------|
| Trendmicro, NakedSecurity, NIST, GovernmentCIO Media, CShub, Threatpost, Techopedia, Portswigger, Security Magazine, Sophos, Reddit, FireEye, SANS, Drizgroup, NETSCOUT, Imperva, DANIEL MIESSLER, Symantec, Kaspersky, PacketStorm, Microsoft, RedHat, Tripwire, Krebs on Security, SecurityFocus, CSO Online, InfoSec Institute, Enisa, MITRE |

| Security Reports and Whitepapers |
|---------------------------------|
| APT Notes, VNote, CERT, Cisco Security Reports, Symantec Security Reports |

| Books, Articles, and Surveys |
|-------------------------------|
| ACM CCS: 2014-2020, IEEE NDSS (2016-2020), IEEE Oakland (1980-2020), ACM Security and Privacy (1980-2020), Arxiv, Cybersecurity and Hacking books |

| Videos (YouTube) |
|------------------|
| Cybersecurity courses, tutorial, and conference presentations |

Table 2: The resources collected for cybersecurity textual data.
domain. On the other hand, some other homonyms such as adversary, virus, worm, exploit, and crack carry different meanings in different domains. Using the weights from RoBERTa as initial weights for all the tokens, and then retraining against the cybersecurity corpus to update those initial weights will in fact not updating much leading to overfitting condition in training on such tokens because the size of the training data for RoBERTa (16 GB) is 25 times larger than that for SecureBERT. When a neural network is trained on a small dataset, it may memorize all training samples, resulting in overfitting and poor performance in evaluation. Due to the unbalance or sparse sampling of points in the high-dimensional input space, small datasets may also pose a more difficult mapping task for neural networks to tackle.

One strategy for smoothing the input space and making it simpler to learn is to add noise to the model during training to increase the robustness of the training process and reduces generalization error. Referring to previous works on maintaining robust neural networks \[17\] \[18\] \[19\], incorporation of noise to an unstable neural network model with a limited training set can act as a regularizer and help reduce overfitting during the training. It is generally stated that introducing noise to the neural network during training can yield in substantial gains in generalization performance in some cases. Previous research has demonstrated that such noise-based training is analogous to a form of regularization in which an additional term is introduced to the error function \[20\]. This noise can be imposed to either input data or between hidden layers of the deep neural networks. When a model is being trained from scratch, typically noise can be added to the hidden layers at each iteration, whereas in continual learning, it can be introduced to input data to generalize the model and reduce error \[21\] \[22\].

For training SecureBERT as continual learning process, rather than using the initial weights from RoBERTa directly, we introduce a small "noise" to the weights of the initial model for those mutual tokens, in order to bias these tokens to "be a little away" from the original tokens meanings in order to capture their new connotations in a cybersecurity context, but not "too far away" from standard language since any domain language is still written in English and still carries standard natural language implication. If a token conveys a similar meaning in general English and cybersecurity, the adjusted weight during training will converge to the original weight as the initial model. Otherwise, it will deviate more from the initial model to accommodate its new meaning in cybersecurity. For those new words introduced by the cybersecurity corpus, we use the Xavier weight initialization technique \[23\] to assign weights for each of them.

We instantiated the SecureBERT by utilizing the architecture of pre-trained RoBERTa-base model, which consists of twelve hidden transformer and attention layers and one input layer. We adopted the base version for a variety of reasons, the most important of which are its efficiency and usefulness. Smaller models are less expensive to train, and the cybersecurity domain has far less diversity of corpora than general language, implying that a compact model would suffice. The model’s size is not the only factor to consider; usability is another critical factor to consider when evaluating a model’s quality. Since large models are difficult to use and expensive to maintain, it is more convenient and practical to utilize a smaller, and more portable architecture.

Each input token is represented by an embedding vector with a dimension of 768 by pre-trained RoBERTa. Our objective is to manipulate these embedding vector representations for each of the 50,265 tokens in the vocabulary by adding a small symmetric noise. Statistical symmetric noise with a probability density function equal to the normal distribution is known as Gaussian noise. We generate this noise by applying a random Gaussian function to the weight vectors. Therefore, for any token \(t\), let \(\bar{W}_t\) be the embedding vector of token \(t\) as follows:

\[
\bar{W}_t = [w^1_t, w^2_t, ..., w^{768}_t]
\]  \hspace{1cm} (1)

where \(w^k_t\) represents the \(k\)th element of the embedding vector for token \(t\).

Let notation \(\mathcal{N}(\mu, \sigma)\) be normal distribution where \(\mu\) denotes the mean and \(\sigma\) the standard deviation. For each weight vector \(\bar{W}_t\), the noisy vector \(\bar{W}_t'\) is defined as follows:

\[
\bar{W}_t' \leftarrow \bar{W}_t \oplus (\bar{W}_t \odot \epsilon), \epsilon \sim \mathcal{N}(\mu, \sigma)
\]  \hspace{1cm} (2)

where \(\epsilon\) represents the noise value, and \(\oplus\) and \(\odot\) means element-wise addition and multiplication, respectively.

The SecureBERT model is designed to emulate the RoBERTa’s architecture, as shown in \[1\] To train SecureBERT for a cybersecurity language model, we use our collected corpora and customized tokenizer. SecureBERT model contains 12 hidden layers and 12 attention heads, where the size of each hidden state has the dimension of 768, and the input embedding dimension is 512, the same with RoBERTa. In RoBERTa (768 \times 50265 elements), the average and variance of the pretrained embedding weights are \(-0.0125\) and \(0.0173\), respectively. We picked \(mu = 0\) and \(sigma = 0.01\) to generate zero-mean noise value since we want the adjusted weights to be in the same space as the original weights. We replace the original weights in the initial model with the noisy weights calculated using Eq. 2.
4 Evaluation

We trained the model against MLM using dynamic masking using RoBERTa’s hyperparameters running for 500,000 training steps for 150 hours on 8 Tesla V100 GPUs with \( \text{Batch size} = 18 \). We evaluate the model on cybersecurity masked language modeling and other more general purpose underlying tasks including sentiment analysis and named entity recognition to further show the performance and efficiency of SecureBERT in processing the cybersecurity text as well as reasonable effectiveness in general language.

4.1 Masked Language Model (MLM)

In this section, we evaluate the performance of SecureBERT in predicting the masked word in an input sentence, known as the standard Masked Language Model (MLM) task.

Owing to the unavailability of a testing dataset for the MLM task in the cybersecurity domain, we create one. We extracted sentences manually from a high-quality source of cybersecurity reports - MITRE technique descriptions. Rather than masking an arbitrary word in a sentence, as in RoBERTa, we masked only the verb or noun in the sentence because a verb denotes an action and a noun denotes an object, both of which are important for understanding the sentence’s semantics in a cybersecurity context. Our testing dataset contains 17,341 records, with 12,721 records containing a masked noun (2,213 unique nouns) and 4,620 records containing a masked verb (888 unique masked verbs in total).

Figure 2a and 2b show the MLM performance for predicting the masked nouns and verbs respectively. Both figures present a cumulative accuracy if the masked word exist in top\(N\) model prediction. SecureBERT constantly outperforms RoBERTa-base, RoBERTa-large and SciBERT even thought the RoBERTa-large is a considerably large model trained on a massive corpora with 355\(M\) parameters.

Our investigations show that RoBERTa-large is pretty powerful language model in general cybersecurity language. However, when it comes to advance cybersecurity context, it constantly fails. For example, three cybersecurity sentences are shown in Fig. 3 each with one word masked. Three terms including reconnaissance, hijacking, and DdoS are commonly used in cybersecurity corpora. SecureBERT is able to understand the context and properly predict these masked words, while RoBERTa’s prediction is remarkably separate. When it comes to cybersecurity tasks including cyber threat intelligence, vulnerability analysis, and threat action extraction [24, 25], such knowledge is crucial and utilizing a model with SecureBERT’s properties would be highly beneficial. The models do marginally better in predicting verbs than nouns, according to the prediction results.

Discussion

SecureBERT successfully outperforms the current language models in predicting cybersecurity related masked tokens in texts which demonstrates its ability to digest and process in-domain texts. We have utilized particular strategies including the creating of specialized tokenizer and weight adjustment to boost its performance and to preserve general
SecureBERT introduces a novel weight adjustment employing an imposed noise that allows the model to better fit with cybersecurity context. In MLM, the model outperforms the other models without the addition of noise. However, homonyms are important, and the model’s predictions may be incorrect or inaccurate depending on the context. The token is placed in a deviated space as a result of the noise, which allows the model to adjust embedding weights more effectively. For example, as depicted in Fig. 4 to predict the masked token in input "Virus is a type of <mask>.", different versions of SecureBERT (with and without weight adjustment) perform slightly different. As depicted in this figure, weight adjustment helps better learning of the cybersecurity context. In this example, off-the-shelf RoBERTa predicts the masked word in a very general way. However, Virus has a different meaning in cybersecurity context that is a malware which is a type of security threat. The word Threat which is predicted as the first word by unmodified version of SecureBERT has broader meaning than the Malware which conveys more to cybersecurity implication.

In addition, such model modifications helps in preserving the general language understanding making the SecureBERT more effective since the cybersecurity language is still English and many of the terminologies and roles is applicable.
To further proof the performance of SecureBERT in handling the general NLP tasks, we conduct two training experiments including sentiment analysis as well as named entity recognition (NER).

In the first task, we used publicly available Rotten Tomatoes dataset[^1] that contains corpus of movie reviews used for sentiment analysis. Socher et al. [] used Amazon’s Mechanical Turk to create fine-grained labels for all parsed phrases in the corpus. The dataset is comprised of tab-separated files with phrases from the Rotten Tomatoes dataset. Each Sentence has been parsed into many phrases by the Stanford parser. Each phrase has a "Phrase Id" end each sentence has a "Sentence Id" and there is no duplicated phrase included in the dataset. Phrases are labeled with five sentiment impressions including negative, somewhat negative, neutral, somewhat positive, and positive. We build a single layer MLP on top of the four models as classification layer to classify the phrases to the corresponding label. We trained two version of the SecureBERT called raw SecureBERT and modified SecureBERT. The former model is the version of our model in which we utilized specialized tokenizer and the weight adjustment method, while the latter is the original RoBERTa model trained as is using the collected cybersecurity corpora. We trained the model for 1,500 steps with learning rate $1 \times 10^{-5}$ and batchsize $=32$, to minimize the error of CrossEntropy loss function using Adam optimizer and Softmax as the activation function in the classification layer.

In Table 3, we show the performance of both models and compared it with original RoBERTa-base and SciBERT, fine-tuned on Rotten Tomatoes dataset. As illustrated, despite the fact that SciBERT is trained on a broader range of domains (biomedical and computer science), both SecureBERT versions perform quite similarly to SciBERT. In addition, the 2.23% and 2.02% difference in accuracy and F1-score with RoBERTa-base demonstrates the effectiveness of SecureBERT in analysing the general English language as well. Furthermore, the modified model perform slightly better than the raw version by 0.34% accuracy and 0.71% F1-score improvement.

| Model Name           | Error | Accuracy | F1-Score |
|----------------------|-------|----------|----------|
| RoBERTa-base         | 0.733 | 69.46    | 69.12    |
| SciBERT              | 0.768 | 67.76    | 67.08    |
| SecureBERT (raw)     | 0.788 | 66.89    | 66.39    |
| SecureBERT (modified)| 0.771 | 67.23    | 67.10    |

Table 3: Shows the performance of different models on general English sentiment analysis task

In the second task, we fine-tune the SecureBERT to conduct cybersecurity-related name entity recognition (NER). NER is a special task in information extraction that focuses on identifying and classifying named entities referenced in unstructured text into predefined entities such as person names, organizations, places, time expressions, etc.

Since general purpose NER models may not always function well in cybersecurity, we must employ a domain-specific dataset to train an effective model for this particular field. Training a NER model in cybersecurity is a challenging task since there is no publicly available domain-specific data and, even if there is, it is unclear how to establish consensus on which classes should be retrieved from the data. Nevertheless, here we aim to fine-tune the SecureBERT on a relatively small sized dataset that is related to cybersecurity just to show the overall performance and compare it with the existing models. MalwareTextDB [26] is a dataset containing 39 annotated APT reports with a total of 6,819 sentences. In the

[^1]: https://www.kaggle.com/c/movie-review-sentiment-analysis-kernels-only
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NER version of this dataset, the sentences are annotated with four different tags including:

**Action**: referring to an event, such as "registers", "provides" and "is written".

**Subject**: referring to the initiator of the Action such as "The dropper" and "This module"

**Object**: referring to the recipient of the Action such as "itself", "remote persistent access" and "The ransom note"; it also refers to word phrases that provide elaboration on the Action such as "a service", "the attacker" and "disk".

**Modifier**: referring to the tokens that link to other word phrases that provide elaboration on the Action such as "as" and "to".

In each sentence in addition, all the words that are not labeled by any of the mentioned tags as well as pad tokens will be assigned by a dummy label ("O") in order to ignoring them in calculating performance metrics.

For Named Entity Recognition, we take the hidden states (the transformer output) of every input token from the last layer from SecureBERT. These tokens are then fed to a fully connected dense layer with \( N \) units where \( N \) equals to the total number of defined entities. Since SecureBERT's tokenizer breaks some words into pieces (Bytes), in such cases we just predict the first piece of the word. We trained the model in 3 epochs with \( learningrate = 2e^{-5} \) and \( batchsize = 8 \), to minimize the error of CrossEntropy loss function using Adam optimizer and Softmax as the activation function in the classification layer.

Similar to the previous task, Table 4 shows the performance of both SecureBERT’s version as well as two other models. As depicted, modified SecureBERT outperforms all other models, despite the fact that MalwareTextDB dataset still contains many sentences with general English meaning and is not an cybersecurity-specific corpora.

| Model Name       | Precision | Recall | F1-Score |
|------------------|-----------|--------|----------|
| RoBERTa-base     | 85.05     | 87.48  | 86.25    |
| SciBERT          | 83.32     | 86.85  | 85.05    |
| SecureBERT (raw) | 86.04     | 87.72  | 87.01    |
| SecureBERT (modified) | 86.12    | 88.53  | 87.10    |

Table 4: Shows the performance of different models trained on MalwareTextDB dataset for NER task.

5 Related Works

Beltagy et al. [7] unveiled SciBERT following the exact BERT's architecture, a model that improves performance on downstream scientific NLP tasks by exploiting unsupervised pretraining from scratch on a 1.14M multi-domain corpus of scientific literature, including 18% computer science and 82% biomedical domain. Despite the promising performance of SciBERT in computer science domain, it was unable to outperform SecureBERT in cybersecurity tasks.

In a similar work on biomedical domain, Gu et al. [27] introduced BioBERT focusing particularly on biomedical domain using BERT architecture and publicly available biomedical datasets. This work also creates a benchmark for biomedical NLP featuring a diverse set of tasks such as named entity recognition, relation extraction, document classification, and question answering. ClinicalBERT [28] is another domain adaptation model based on BERT which is trained on clinical text from the MIMIC-III database.

6 Conclusions and Future Works

This study introduces SecureBERT, a transformer-based language model for processing cybersecurity text language based on RoBERTa. We proposed two novel approaches for building a specialized tokenization tool on top of RoBERTa’s tokenizer and adjusting pre-trained weights to develop a successful model for applying to cybersecurity text while preserving general English comprehension. SecureBERT is trained on a corpus of 1.1 billion words gathered from a variety of online cybersecurity resources. SecureBERT has been evaluated using the standard Masked Language Model (MLM) test and demonstrated promising results in comprehending cybersecurity language when compared to available data.

In summary, this paper makes the following contributions:

1. A large and clean cybersecurity corpus with 1.1 billion words from a variety of cybersecurity resources.
2. A tokenization method for a domain-specific language. The idea behind the tokenization method could be generalized to other domains, such as the health, politics, finance, etc.
3. A model weight adjustment method for training a domain-specific language model while retaining the original general English understanding as much as possible.
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4. A benchmark cybersecurity test dataset for evaluating the MLM task performance. We have manually complied 17,341 testing sentences with a focus on the most important words in the sentence from MITRE, a source for high quality cybersecurity written records.

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