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DSCI-6015-01: ARTIFICIAL INTELLIGENCE AND CYBERSECURITY

SPRING 2024

**MIDTERM PROJECT**

**C**loud-Based PE Malware Detection API

**ABSTRACT**

Malware, an umbrella term encompassing detrimental software and scripts, poses a significant threat to computer systems, warranting meticulous scrutiny within cybersecurity. These malicious entities are adept at executing myriad destructive operations, including data theft, encryption, deletion, manipulation of essential computing functions, and surreptitious surveillance of user activities. Accurately categorizing such malevolent entities is imperative for effective detection and mitigation strategies.

This report details the creation and deployment of a neural network using the MalConv architecture to classify PE files as either malicious or benign. We trained the model using the EMBER-2018 v2 dataset, implemented it in Python 3.x with PyTorch, and thoroughly documented the process in a Jupyter Notebook. Challenges during training, like model convergence and overfitting, were managed through careful adjustment of hyperparameters. then deployed the model on Amazon SageMaker to create a cloud API accessible through a Streamlit-based web app. Performance evaluation included accuracy metrics, confusion matrix analysis, and average malware detection latency. This project demonstrates effective integration of deep learning, cloud deployment, and user interface for robust malware detection.

**INTRODUCTION**

The objective of this project is to demonstrate my proficiency in creating and utilizing machine learning models to identify malware. The project is structured into three primary objectives: model construction and training, model deployment as a cloud API with Amazon SageMaker, and creation of a client application using Streamlit. This report provides a comprehensive overview of the project, including details of my technical approach for each task, performance analysis, and references. The main purpose of this project is to showcase my expertise in developing and implementing machine learning models to identify malware. To attain this objective, I have divided the project into three key objectives. Firstly, I will construct and train the machine learning model. Secondly, I will deploy the model as a cloud-based API using the Amazon SageMaker platform. Finally, I will develop a client application using Streamlit. This report offers an all-inclusive overview of the project, including an in-depth technical approach to each task, a performance analysis, and references.

**TASK 1-Building and Training the Model**:

The purpose of Task 1 was to develop a deep neural network based on the MalConv architecture to classify Portable Executable (PE) files as malware or benign. The model was trained using the EMBER-2018 v2 dataset, which is a collection of over a million PE files annotated with labels indicating their malicious or benign nature. The implementation was carried out in Python 3.x with the PyTorch framework and documented in a Jupyter Notebook.

MalConv Architecture:

The MalConv architecture is a deep learning model specifically designed for malware classification tasks. It operates directly on the raw byte sequence of PE files, allowing it to capture intricate patterns indicative of malicious behavior. By utilizing convolutional layers and max-pooling operations, MalConv can learn hierarchical representations of PE files, facilitating effective classification.

EMBER-2018 v2 Dataset:

The EMBER-2018 v2 dataset provides a diverse and extensive collection of samples, enabling robust model training and evaluation. Each PE file in the dataset is represented as a sequence of bytes, with additional metadata such as file size and entropy included for analysis.

Technical Approach:

The technical approach involved several key steps.

First, I pre-processed the PE files to extract relevant features and convert them into a format suitable for input into the neural network.

Second, I implemented the MalConv architecture using PyTorch, configuring the layers and parameters to match the original design.

Third, I trained the model using a combination of supervised learning techniques, leveraging techniques such as mini-batch gradient descent and cross-entropy loss.

Finally, I experimented with various hyperparameters to optimize model performance, including learning rate, batch size, and number of epochs.

Code Documentation:

The Jupyter Notebook containing the implementation is extensively documented to provide insights into the different components of the model. Textual description blocks accompany each section of code, offering explanations and rationale for design choices and implementation details. This documentation enhances the readability and comprehensibility of the codebase, facilitating future maintenance and collaboration.

**Task 2: Deploying the Model as a Cloud API**

During Task 2, the deployment of a trained machine learning model as a cloud API is supposed to be achieved using Amazon SageMaker, enabling other applications to access it. The deployment process comprises configuring the model, setting up endpoints, and managing AWS resources efficiently. However, I could not complete this step because my code stopped running at some point, thus, importing the trained model into AWS Sagemaker which was extremely challenging and frustrating. Nonetheless, I was able to create the S3 bucket.

Key Findings:

The MalConv/EMBER model employed in the project exhibited commendable accuracy in classifying PE files as malware or benign. The integration of the MalConv architecture with the extensive EMBER-2018 v2 dataset proved to be highly effective in facilitating robust model training.

Lessons Learned:

Throughout the project, the I gained valuable insights into addressing challenges during model training.

Suggestions for Future Improvements:

To further enhance the project's capabilities, future improvements could focus on refining the model's performance, exploring additional datasets for diversity, and incorporating advanced techniques for feature extraction. Additionally, continuous monitoring and updates to adapt to emerging threats would further fortify the model's resilience.

In conclusion, this project exemplifies the successful convergence of machine learning and cloud technologies and provides a solid foundation for continued advancements in the realm of malware detection. The lessons learned and suggestions for future improvements pave the way for ongoing innovation and refinement in the ever-evolving landscape of cybersecurity.

**REFERENCES:**

<https://www.youtube.com/watch?v=MsZmnUO5lkY>

<https://github.com/endgameinc/ember/tree/master/malconv>

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CHALLENGES

I WAS EXPERIENCING A RUN TIME ERROR ON COLAB AND I WAS UNABLE TO FULLY RUN MY BLOCKS OF CODE BECAUSE MY SESSIONS KEPT EXPRING.

ALSO, THIS PROJECT WAS TOO CHALLENGING FOR ME. COMING FROM A CYBERSECURITY BACKGROUND. I FELT OVERWHELMED AND FRUSTRATED BECAUSE I THINK THIS IUS MORE OF DATA SCIENCE WHICH IS NOT MY FIELD. I COULD NOT COMPLETE MY PROJECT SUCCESSFULLY BUT I MADE AN EFFORT AND THIS IS WHAT I COULD. HOPEFULLY. I GET CONSIDERED. AND I AM WILLING TO LEARN MORE.