Networks and Cyber Security

Project

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Contents

Define the problem.

The specific problem we want to solve with our intrusion detection system is to detect and prevent **SQL injection attacks on web applications**. Our target users are web developers and system administrators who are responsible for maintaining the security of their web applications. SQL injection attacks pose a significant threat to web applications as they can result in unauthorized access to sensitive data, alteration or deletion of data, and even complete system compromise.

To address this problem, we will conduct a risk assessment to identify the potential security threats and vulnerabilities that our application might face, such as malicious SQL queries and code injection attacks. We will define our security objectives, which will include preventing unauthorized access to the application and protecting sensitive data from being stolen or modified.

Based on our identified risks and objectives, we will specify the security requirements for our intrusion detection system. These will include the implementation of a neural network model trained on a dataset of SQL injection examples, as well as monitoring and logging of user activity to detect and respond to security incidents. We will evaluate the effectiveness of our security controls through extensive testing and validation to ensure that our system can effectively mitigate the identified security risks.

Data Collected

We used datasets found on Kaggle to train our neural network model. This dataset can be found at https://www.npmjs.com/package/ng2-file-type

Detection method:

The appropriate detection method for this problem is machine learning-based detection, specifically using a neural network trained on SQL injection examples. This method is effective in detecting known and unknown SQL injection attacks by analyzing patterns in the data.

Implement the detection method:

The neural network can be implemented using programming techniques such as Python and TensorFlow. The model can be trained on the SQL injection dataset and then used to classify possible SQL injection alerts in the DVWA logs. Regular expressions can also be used to preprocess the logs and extract relevant information for the neural network.

SQL Injection Detection Model using a Neural Network

```
from keras.models import Sequential
from keras import layers
from keras.preprocessing.text import Tokenizer
```

```
from keras.models import load_model
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
import pandas as pd
from sklearn.metrics import accuracy_score, precision_score, recall_score
from nltk.corpus import stopwords
import nltk

class SQLIModel:

    def __init__(self):
        self.model = None
        self.vectorizer = None

    def create_model(self, input_dim):
        model = Sequential()
        model.add(layers.Dense(20, input_dim=input_dim, activation='relu'))
        model.add(layers.Dense(10,  activation='tanh'))
        model.add(layers.Dense(1024, activation='relu'))
        model.add(layers.BatchNormalization())
        model.add(layers.Dropout(0.5))
        model.add(layers.Dense(1, activation='sigmoid'))

        model.compile(loss='binary_crossentropy',
                      optimizer='adam',
                      metrics=['accuracy'])
        return model

    def train_model(self, csv_file_path, model_file_path):
        # Load dataset
        df = pd.read_csv(csv_file_path, encoding='utf-16')
        nltk.download('stopwords')
        self.vectorizer = CountVectorizer(min_df=2, max_df=0.7,
stop_words='english')
        posts =
self.vectorizer.fit_transform(df['Sentence'].values.astype('U')).toarray()
        transformed_posts = pd.DataFrame(posts,
columns=self.vectorizer.get_feature_names_out())
        df = pd.concat([df, transformed_posts], axis=1)
        X = df[df.columns[2:]]
        y = df['Label']
        # Split dataset into training and testing sets
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
        # Create model
```

```
        input_dim = X_train.shape[1]  # Number of features
        self.model = self.create_model(input_dim)
        # Train model
        classifier_nn = self.model.fit(X_train, y_train,
                                       epochs=10,
                                       verbose=True,
                                       validation_data=(X_test, y_test),
                                       batch_size=15)
        # Make predictions
        y_pred = self.model.predict(X_test)
        y_pred = [1 if p >= 0.5 else 0 for p in y_pred]
        # Evaluate model
        accuracy = accuracy_score(y_test, y_pred)
        precision = precision_score(y_test, y_pred)
        recall = recall_score(y_test, y_pred)
        print("Accuracy: {0:.4f}, Precision: {1:.4f}, Recall:
{2:.4f}".format(accuracy, precision, recall))
        self.model.save(model_file_path)
        return self.model

    def is_sqli(self, sentence, model):
        if not isinstance(sentence, str):
                raise TypeError("sentence must be a string")
        if not self.vectorizer:
            raise ValueError("model must be trained first")
            sentence = pd.Series(sentence)
            sentence = self.vectorizer.transform(sentence).toarray()
        if not self.model:
            raise ValueError("model must be trained first")

        return self.model.predict(sentence)[0][0] >= 0.5
```

Introduction:

The SQL Injection (SQLI) is a type of security attack where an attacker can execute malicious SQL statements in a web application's database. To detect SQLI attacks, we can use machine learning techniques. In this project, we are building a neural network model to detect SQLI attacks using a dataset obtained from Kaggle.

Dataset:

The dataset used in this project is obtained from Kaggle, containing around 50,000 labeled instances of SQL injection and non-SQL injection sentences. Each instance is labeled either as SQLI or non-SQLI. We used pandas library to read and process the dataset.

Preprocessing:

We used CountVectorizer from Scikit-learn library to tokenize and create the bag of words for each sentence. We also removed stop words using the NLTK library.

Model:

We created a sequential neural network with three hidden layers: two dense layers with 20 and 10 neurons respectively and a dense layer with 1024 neurons. We used ReLU activation for the first two layers, tanh activation for the third layer, and sigmoid activation for the output layer. We also added Batch Normalization and Dropout layers to prevent overfitting.

Training:

We split the dataset into training and testing sets using 80/20 ratio. We used binary cross-entropy loss function and Adam optimizer for training the model. We ran 10 epochs and used a batch size of 15.

Evaluation:

We used the testing set to evaluate the model performance. We calculated accuracy, precision, and recall scores using Scikit-learn metrics library. The model was able to achieve an accuracy of 0.9961, precision of 0.9988, and recall of 0.9929.

Saving the Model:

We used Keras to save the trained model to a file.

Usage:

We created a class named SQLIModel with methods to train the model and to predict whether a given sentence is SQLI or not. The is_sqli() method takes a sentence as input and returns a boolean value indicating whether the sentence is SQLI or not.

Conclusion:

In this project, we demonstrated the effectiveness of using a neural network model to detect SQLI attacks. The model achieved high accuracy, precision, and recall scores on the testing set. This model can be used to provide an extra layer of security for web applications against SQLI attacks.

Test the system:

To test the intrusion detection system, a test environment can be set up with simulated attack scenarios, such as injecting malicious SQL queries into the DVWA web application. Metrics such as false positives and false negatives can be used to evaluate the system's performance and adjust the neural network model if necessary.

IP Address	Payload	Timestamp	Method
192.168.0.1	SELECT * FROM users WHERE id=1; DROP TABLE users;	2023-05-07 14:30:00	POST
192.168.0.2	SELECT * FROM orders WHERE customer_name='John Doe';	2023-05-07 14:30:05	GET
192.168.0.3	INSERT INTO customers (name, email) VALUES ('Jane Smith', 'jane@example.com');	2023-05-07 14:30:10	POST