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Seminar report on

"Machine Learning for SQL Injection Prevention on Server-Side Scripting"

Submitted by

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Certificate for Approval of Seminar Report

This is to certify that Mr. AJAYKUMAR MAJUKAR bearing 2KL15CS005 has satisfactorily completed the Seminar **"**Machine Learning for SQL Injection Prevention on Server-Side Scripting**"** for partial fulfillment of Seminar of VIII Semester B.E Computer Science and Engineering of the Visvesvaraya Technological University, Belagavi for the year 2018-2019.

GUIDE SEMINAR COORDINATOR HOD

Table of Contents

ABSTRACT

SQL injection is the most common web application vulnerability. The vulnerability can be generated unintentionally by software developer during the development phase. To ensure that all secure coding practices are adopted to prevent the vulnerability. The framework of SQL injection prevention using compiler platform and machine learning is proposed. The machine learning part will be described primarily since it is the core of this framework to support SQL injection prediction by conducting 1,100 datasets of vulnerabilities to train machine learning model. The results indicated that decision tree is the best model in term of processing time, highest efficiency in prediction.

CHAPTER 1

INTRODUCTION

The most common web application vulnerability found in the National Security Agency (NSA) report is SQL injection [1]. An attacker uses specifically crafted inputs that are considered as database queries to gain unauthorized access and execute SQL database via a web application. As the results, an intruder can alter data, reveal confidential information, and attack the internal database. Typically, web application developers try to prevent SQL injection by implementing input sanitization or use personal expertise on coding. However, web application is still vulnerable if the input sanitization or filtering is not being able to either fulfil or predict the trend of vulnerability over the web application code. Lee demonstrated the types of SQL injection attacks and examples in SQL Injection commands [2] as follows:

A. Illegal/Logically Incorrect Queries

This attack derives the CGI tier replies error message by inserting a crafted SQL commands such as query 1.

- Query 1:
  SELECT * FROM user WHERE id= ‘1111’ AND

  password= ‘1234’ AND CONVERT (char, no) --;

B. Union Queries

This type of SQL injection uses the ‘‘Union’’ operator which performs unions between two or more SQL queries. The attack performs unions of malicious queries and a normal SQL query with the ‘‘union’’ operator. Query 2 shows an example.

- Query 2
  SELECT * FROM user WHERE id= ‘1111’ UNION

  SELECT * FROM member WHERE id= ‘admin’--’

AND password= ‘1234’;

All subsequent strings after -- are recognized as comments, and two SQL queries are processed in this example. The result of the query process shows the administrator’s information in the DBMS.

C. Piggy-Backed Queries

This attack inserts malicious SQL queries into a normal SQL query. It is possible because many SQL queries can be processed if the operator ‘‘;’’ is added after each query. Query 3 is an example. Note that the operator ‘‘;’’ is inserted at the end of query.

- Query 3:
  SELECT * FROM user WHERE id= ‘admin’ AND

  password= ‘1234’; DROP TABLE user; --;

The result of query 3 is to delete the user table.

- Query 4:
  CREATE PROCEDURE DBO @userName varchar2,

  @pass varchar2, AS EXEC ("‘SELECT * FROM user

  WHERE id=’" + @userName + " ‘and password=’" +

  @password + "’); GO

Query 4 is also vulnerable to attacks such as Piggy-backed queries. However, the vulnerability in stored procedures is not tested in this study. Typically, the vulnerability can be produced unintentionally by software developers under a web application development phase using unsecured coding practices [3]. To guarantee that all secure coding practices are adopted to prevent the vulnerability, before they are unintentionally added into the production code, the framework of SQL injection prevention in Illegal/Logically Incorrect Queries, Union Queries, and Piggy-backed Queries on server- side scripting using compiler platform and machine learning is proposed. The machine learning part will be described primarily in this paper.

CHAPTER 2

LITERATURE SURVEY

A. SQL injection and cross-site scripting vulnerabilities prediction and detection

Shar and Tan have found the vulnerability detection approaches based on static and dynamic taint analysis techniques produce too many false alarms and too complex in commercialization perspective [4]. Therefore, Shar and Tan proposed the framework called "PhpMinerI" for SQL injection (SQLI) and cross site scripting (XSS) vulnerabilities prediction in PHP server-side script using machine learning [4].

C4.5, Naïve Bayes (NB), and Multi-Layer Perceptron (MLP) were used as the machine learning models in the framework to predict and detect the vulnerabilities on eight PHP standard open-source web applications to evaluate efficacy of detection and prediction in the vulnerabilities. The benchmark of each machine learning model revealed the best machine learning model due to indication of the highest accuracy and lowest false alarm is MLP for prediction SQL injection and XSS on average probability of detection in SQL injection at 93%, probability of false alarm in SQL injection at 11%, probability of detection in XSS at 78%, and probability of false alarm in XSS at 6% [4].

MLP is one of machine learning algorithms which is supposed to be more effective than traditional testing if the model in machine learning is effectively trained [2].

However, Shar and Tan did not specify the types of SQL injection that their research can resolve.

B. A novel method for SQL injection attack detection based on removing SQL query attributes values

Lee proposed a method to remove the attribute values of SQL queries at runtime using dynamic method and compares them with the SQL queries analysed in advance of using static method [2]. The result is rule-based method to remove the attribute in SQL queries for SQL injection analysis. However, the method cannot validate SQL syntax before detecting SQL injection.

C. Microsoft Azure Machine Learning

Microsoft Azure Machine Learning is cloud based predictive service that provides full-managed model predictive analytics and predictive models as web services [10].

Microsoft Azure Machine Learning provides tools for creating predictive analytics solutions by creating analytics workflow module. Data can retrieve from the various type of data sources to build analytics and predictive models. Finally, the validated analytics and predictive models are deployed as web services which can connect to applications or websites, or provide insights in business intelligence [10].

CHAPTER 3

SCOPE AND OBJECTIVES

SCOPE: Proposed framework can be used in prevention of SQL injection in Illegal/Logically Incorrect Queries, Union Queries, and Piggy-backed Queries on server-side scripting using compiler platform and machine learning.

OBJECTIVES:

- To guarantee that all secure coding practices are adopted to prevent the vulnerability, before they are unintentionally added into the production code.
- To design the framework such that the input attribute is marked for extraction of SQL commands datasets.

CHAPTER 4

EXPLANATION OF THE PAPER

The framework is designed for SQL commands datasets extraction to mark as input attribute. The input attribute will be sent to the machine learning models as well as prediction of SQL injection is reported. To explain the overview of the framework, Figure 1. Demonstrate overview of the framework

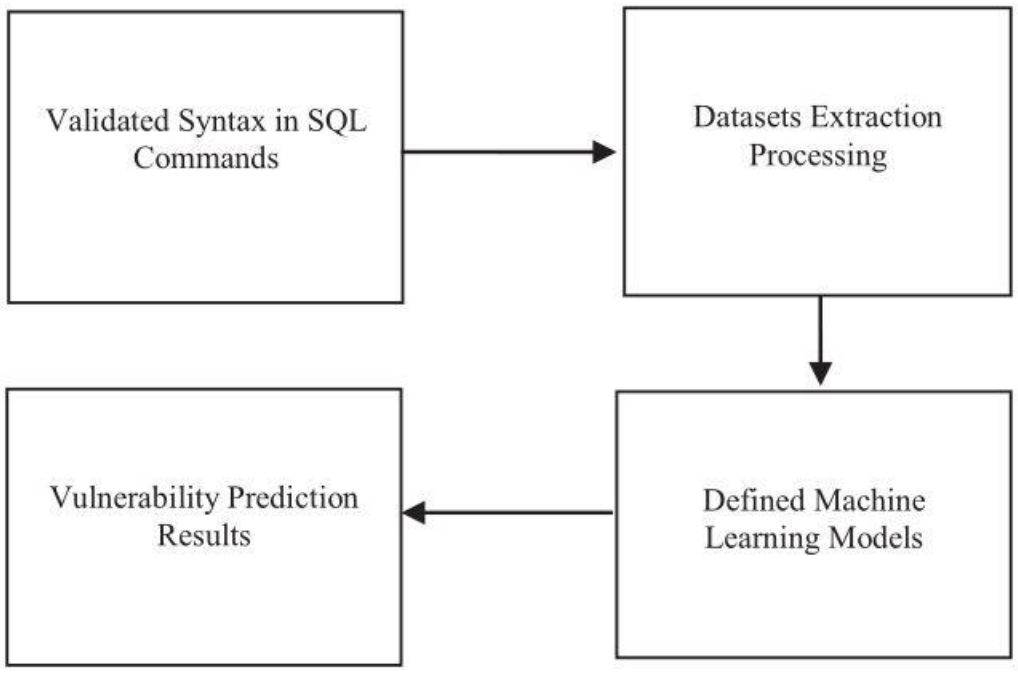

Fig 1. Overview of the framework

This section explains the methodologies used for building the proposed framework in machine learning part. The framework is designed to support the ability to validate SQL syntax, detect, and predict SQL injection in web application development. The techniques used for SQL injection detection and prediction, e.g., machine learning models, research methods, and plan are described.

A. SQL Injection Commands Datasets Extraction

SQL commands consist of variables that can be classified into 2 categories:

- Fixed variable
  A fixed variable is a variable that receives value internally within server-side scripts. This type of variable does not directly involve with SQL injection.
- Dependent variable
  A dependent variable is a variable that receives value from user input, thus, there is a possibility that SQL injection could happen as shown in a demonstration of dependent variable in SQL command in below.

*"SELECT * from db_user where username =*

'$input_username' and password = '$input_password'"

This command receives two variables from the user:

$input_username and $input_password.

If the user injects the command:

$input_username = "krit"

$input_password = " " ; drop table users --

Then, these SQL commands will be included into:

*SELECT * from db_user where username = 'krit' and*

password = '_'; drop table users --

Finally, the code has been injected by another SQL command.

*SELECT * from db_user where username = 'krit' and*

password = '_'; drop table users –

Input code attributes will be marked manually and extracted for machine learning model analysis which will form the characteristics of the input. Thus, the attributes of vulnerable SQL commands are proposed by 20 input attribute types showing in the TABLE I. in below.

TABLE 1. INPUT ATTRIBUTE TYPES

No.	Attribute	Description
1.	Single Line Comment	Single line comment. Ignores the remainder of the statement.
2.	Semicolon	A query termination.
3.	Three Single quote	Three single quote (''') in SQL query
4.	Two Single Quotes	Two Single Quotes ('') in SQL query
5.	Separated Two Single Quotes	Separated Two Single Quotes (' ') in SQL query.
6.	Number equals to the same number, e.g., 0=0	Condition which is always return true.
7.	Number equals to the same number, e.g., 1=1	Condition which is always return true.
8.	Character equals to the same character, e.g., 'x'= 'x'	Condition which is always return true.
9.	Variable equals to the same variable, e.g., a=a	Condition which is always return true.
10.	Character equals to the same character, e.g., 'a'= 'a'	Condition which is always return true.
11.	Double quote	Double quote (") in SQL query.
12.	Comment delimiter	Comment delimiter (/*) in SQL Query. Text within comment delimiters is ignored
13.	Semicolon and SET IDENTITY_INSERT commands	; SET IDENTITY_INSERT commands in SQL query
14.	Semicolon and TRUNCATE TABLE commands	; TRUNCATE TABLE commands in SQL query
15	Semicolon and DROP TABLE command	; DROP TABLE commands in SQL query
16.	Semicolon and UPDATE command	; UPDATE commands in SQL query
17	Semicolon and INSERT INTO command	; INSERT INTO commands in SQL query
18	Semicolon and DELETE command	; DELETE command in SQL query
19	UNION command	UNION commands in SQL query
20	PiggyBackedQuery or IllegalQuery or UnionQuery	To indicate type of SQL injection, e.g., Illegal query, Union query, and Piggy-backed query

The attributes are collected from HTML code and SQL code in existing CMS applications, e.g., WordPress, Drupal, Joomla, and Simple Machine Forum. Finally, vulnerable SQL commands are extracted to the dataset. 0 and 1 stand for availability of each attribute in sample SQL query, 1 means available attribute and 0 means unavailable attribute. The samples of dataset in each vulnerability type are performed as Figure 1. below:

TABLE 2.a SQL QUERY SAMPLES

SL.No	SQL Query
1	SELECT * from test.members where username=’ ’ or 0=0 #’
2	SELECT * FROM customers WHERE user_name =’’; INSERT into Username (usename, password, user_type) value (‘admin2’, 'admin2’,’1’); --' and password =’
3	SELECT * FROM product WHERE PCategory=''; DROP table Username --'
4	SELECT *FROM newsletter WHERE email = "sqlvuln'
5	SELECT * from test.members where user_name= ‘1’ AND non_existant_table =’1’

TABLE 2.b SAMPLE OF DATASET

SingleLine Comment	Semicolon	Three Single Quote	Two Single Quote	Seperated Two Single Quote	True Case Zero	True Case One	True Case CharX	True Case VarA	True Case charA	Double Quote	Multiple Line Comment	SET IDENTITY_ INSERT	TRUNCATE TABLE	DROP table	UPDATE	INSERT into	DELETE	union	Union Query
0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
1	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The selected models will be analysed and compared to find the model that can produce high accuracy and low false alarm in web vulnerabilities prediction and detection. The models will be analysed through static code analysis to identify a potential design, globalization, interoperability, performance, security, and other categories of potential problems.

The analysis measures the prediction model's performance as follows:

- Probability of detection (Pd) = tp / (tp + fn).
- Probability of false alarm (Pf) = fp / (fp + tn).
- Precision (Pr) = tp / (tp + fp).
- Accuracy (Acc) = (tp + tn) / (tp + fp + fn +tn).
- Processing time

Pd measures efficacy of prediction model in finding the actual vulnerability. Pr measures the correctness of actual vulnerabilities which are predicted in percentage. Pf measures the possibility of false alarm. Acc measures the number of correctness that the models predict the vulnerabilities correctly. Processing time indicates how long each model computes in seconds.

CHAPTER 5

CONCLUSIONS

The goal was to design a framework of SQL injection prevention in Illegal/Logically Incorrect Queries, Union Queries, and Piggy-backed Queries on server-side scripting using compiler platform and machine learning. The machine learning part is described primarily in this paper since it is main core for SQL injection prediction part. 1,100 samples of vulnerable SQL commands are taken into consideration. The conduction of future experiment will be reflected to build the compiler platform on Integrated Development Environment (IDE) which should be able to validate the SQL syntax as well as support prediction and detection the SQL injection using Machine Learning application in server-side scripts within the development phase.

REFERENCES

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