

SySeVR: A Framework for Using Deep Learning to Detect Software Vulnerabilities

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Abstract—The detection of software vulnerabilities (or vulnerabilities for short) is an important problem that has yet to be tackled, as manifested by many vulnerabilities reported on a daily basis. This calls for machine learning methods to automate vulnerability detection. Deep learning is attractive for this purpose because it does not require human experts to manually define features. Despite the tremendous success of deep learning in other domains, its applicability to vulnerability detection is not systematically understood. In order to fill this void, we propose the *first* systematic framework for using deep learning to detect vulnerabilities. The framework, dubbed **Syntax-based, Semantics-based, and Vector Representations (SySeVR)**, focuses on obtaining program representations that can accommodate syntax and semantic information pertinent to vulnerabilities. Our experiments with 4 software products demonstrate the usefulness of the framework: we detect 15 vulnerabilities that are not reported in the National Vulnerability Database. Among these 15 vulnerabilities, 7 are unknown and have been reported to the vendors, and the other 8 have been “silently” patched by the vendors when releasing newer versions of the products.

Index Terms—Vulnerability detection, security, deep learning, program analysis, program representation.

I. INTRODUCTION

SOFTWARE vulnerabilities (or vulnerabilities for short) are a fundamental reason for the prevalence of cyber attacks. Despite academic and industrial efforts at improving software quality, vulnerabilities remain a big problem. This can be justified by the fact that each year, many vulnerabilities are reported in the Common Vulnerabilities and Exposures (CVE) [1].

Given that vulnerabilities are inevitable, it is important to detect them as early as possible. Source code-based static analysis is an important approach to detecting vulnerabilities, including *code similarity-based* methods [2], [3] and *pattern-based* methods [4], [5], [6], [7], [8], [9], [10]. Code similarity-based methods can detect vulnerabilities that are incurred by code cloning, but have high false-negatives when vulnerabilities are not caused by code cloning [11]. Pattern-based methods may require human experts to define vulnerability features for representing vulnerabilities, which makes them error-prone and laborious. Therefore, an ideal method should

be able to detect vulnerabilities caused by a wide range of reasons while imposing as little reliance on human experts as possible.

Deep learning — including Recurrent Neural Networks (RNN) [12], [13], [14], [15], [16], Convolutional Neural Networks (CNN) [17], [18], and Deep Belief Networks (DBN) [19], [20] — has been successful in image and natural language processing. While it is tempting to use deep learning to detect vulnerabilities, we observe that there is a “domain gap”: deep learning is born to cope with data with natural *vector representations* (e.g., pixels of images); in contrast, software programs do not have such vector representations. Recently, we proposed the *first* deep learning-based vulnerability detection system VulDeePecker [11] with the capability of pinning down the locations of vulnerabilities. While demonstrating the feasibility of using deep learning to detect vulnerabilities, VulDeePecker has a range of weaknesses: (i) It considers only the vulnerabilities that are related to library/API function calls. (ii) It leverages only the semantic information induced by *data dependency*. (iii) It considers only the particular RNN known as Bidirectional Long Short-Term Memory (BLSTM). (iv) It makes no effort to explain the cause of false-positives and false-negatives.

Our contributions. In this paper, we propose the *first* systematic framework for using deep learning to detect vulnerabilities. The framework is centered at answering the following question: *How can we represent programs as vectors that accommodate syntax and semantic information that is suitable for vulnerability detection?* In order to answer this question, we introduce and define the notions of Syntax-based Vulnerability Candidates (SyVCs) and Semantics-based Vulnerability Candidates (SeVCs), and design algorithms for computing them. Intuitively, SyVCs reflect vulnerability syntax characteristics, and SeVCs extend SyVCs to accommodate the semantic information induced by data dependency and control dependency. Correspondingly, the framework is called Syntax-based, Semantics-based, and Vector Representations, or SySeVR for short. As a piggyback, this study overcomes the aforementioned weaknesses (i)-(iv) of [11].

In order to evaluate SySeVR, we produce a dataset of 126 types of vulnerabilities caused by various reasons from the National Vulnerability Database (NVD) [21] and the Software Assurance Reference Dataset (SARD) [22], while noting that the dataset published by [11] is not sufficient for our purpose because it contains only 2 types of vulnerabilities. Our dataset is of independent value, and has been made publicly available at <https://github.com/SySeVR/SySeVR>.

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Equipped with the new dataset, we show that SySeVR can make deep learning detect vulnerabilities. Some findings are: (1) SySeVR can make multiple kinds of deep neural networks detect various kinds of vulnerabilities. SySeVR makes Bidirectional RNNs, especially the Bidirectional Gated Recurrent Unit (BGRU), more effective than CNNs, and makes CNNs more effective than DBNs. Moreover, SySeVR renders deep neural networks (especially BGRU) much more effective than the state-of-the-art vulnerability detection methods. (2) In terms of explaining the cause of false-positives and false-negatives, we find that the effectiveness of BGRU is substantially affected by the training data. If some syntax elements (e.g., tokens) often appear in vulnerable (vs. not vulnerable) pieces of code, then these syntax elements may cause high false-positives (correspondingly, false-negatives). (3) It is better to use deep neural networks that are tailored to specific kind of vulnerabilities than to use a single deep neural network to detect various kinds of vulnerabilities. (4) The more semantic information accommodated for learning deep neural networks, the higher vulnerability detection capability the learned neural networks. For example, semantic information induced by control dependency can reduce the false-negative rate by 19.6% on average. (5) By applying SySeVR-enabled BGRU to 4 software products (Libav, Seamonkey, Thunderbird, and Xen), we detect 15 vulnerabilities that have not been reported in NVD [21]. Among these 15 vulnerabilities, 7 are unknown to exist in these software despite that similar vulnerabilities are known to exist in other software; for ethical reasons, we do *not* release their precise locations, but we have reported them to the respective vendors. The other 8 vulnerabilities have been “silently” patched by the vendors when releasing newer versions of the products.

Paper outline. Section II presents the SySeVR framework. Section III describes experiments and results. Section IV discusses limitations of the present study. Section V reviews related prior work. Section VI concludes the paper.

II. THE SYSEVR FRAMEWORK

A. The Domain Gap

Deep learning is successful in the domain of image processing and other applications, which is however different from the domain of vulnerability detection. In order to clearly see the gap between these domains (i.e., the “domain gap”), let us consider the example of using deep learning to detect human in an image. As illustrated in Fig. 1(a), this can be achieved by using the notion of *region proposal* [23], [24] and leveraging the structural representation of images (e.g., texture, edge, and color). Multiple region proposals can be extracted from one image, and each region proposal can be treated as a “unit” for training neural networks to detect objects (i.e., human in this example). When using deep learning to detect vulnerabilities, there is *no* natural structural representation for programs like what region proposal is to images. This means that deep learning cannot be directly used for vulnerability detection.

B. The Framework

Overview. In order to bridge the domain gap, one may suggest treating each *function* in a program as a region proposal in image processing. However, this is too coarse-grained because vulnerability detectors not only need to tell whether a function is vulnerable or not, but also need to pin down the locations of vulnerabilities. That is, we need finer-grained representation of programs for vulnerability detection. On the other hand, one may suggest treating each *line of code* (i.e., *statement* — the two terms are used interchangeably in this paper) as a unit for vulnerability detection. This treatment has two drawbacks: (i) most statements in a program do not contain any vulnerability, meaning that few samples are vulnerable; and (ii) multiple statements that are semantically related to each other are not considered as a whole.

Inspired by the notion of region proposal in image processing, we propose dividing a program into smaller pieces of code (i.e., a number of statements), which may exhibit the *syntax* and *semantics* characteristics of vulnerabilities. This explains, as highlighted in Fig. 1(b), why the framework seeks SyVC, SeVC, and vector representations of programs.

Running example. In order to help understand the details of SySeVR, we use Fig. 2 to highlight how SySeVR extracts SyVCs, SeVCs, and vector representation of SeVCs. At a high level, a SyVC, highlighted by a box in Fig. 2, is a code element that may or may not be vulnerable according to some syntax characteristics of known vulnerabilities. A SeVC extends a SyVC to include statements (i.e., lines of code) that are semantically related to the SyVC, where semantic information is induced by control dependency and/or data dependency; this SyVC→SeVC transformation is fairly involved and therefore elaborated in Fig. 3. Each SeVC is encoded into a vector for input to deep neural networks.

1) *Extracting SyVCs:* We observe that most vulnerabilities exhibit some simple *syntax characteristics*, such as function call and pointer usage. Therefore, we propose using syntax characteristics to identify SyVCs, which serve as a starting point (i.e., SyVCs are *not* sufficient for training deep learning models because they accommodate *no* semantic information of vulnerabilities). In order to define SyVC, we first define:

Definition 1 (*program, function, statement, token*): A program P is a set of functions f_1, \dots, f_η , denoted by $P = \{f_1, \dots, f_\eta\}$. A function f_i , where $1 \leq i \leq \eta$, is an ordered set of statements $s_{i,1}, \dots, s_{i,m_i}$, denoted by $f_i = \{s_{i,1}, \dots, s_{i,m_i}\}$. A statement $s_{i,j}$, where $1 \leq i \leq \eta$ and $1 \leq j \leq m_i$, is an ordered set of tokens $t_{i,j,1}, \dots, t_{i,j,w_{i,j}}$, denoted by $s_{i,j} = \{t_{i,j,1}, \dots, t_{i,j,w_{i,j}}\}$. Note that tokens can be identifiers, operators, constants, and keywords, and can be extracted by lexical analysis.

Defining SyVCs. Given a function f_i , there are standard routines for generating its abstract syntax tree, which is denoted by T_i . On T_i , the root corresponds to function f_i , a leaf node corresponds to a token $t_{i,j,g}$ ($1 \leq g \leq w_{i,j}$), and an internal node corresponds to a statement $s_{i,j}$ or multiple consecutive tokens of $s_{i,j}$. Intuitively, a SyVC is one token (corresponding to a leaf node) or consists of multiple consecutive tokens (corresponding to an internal node). Formally,

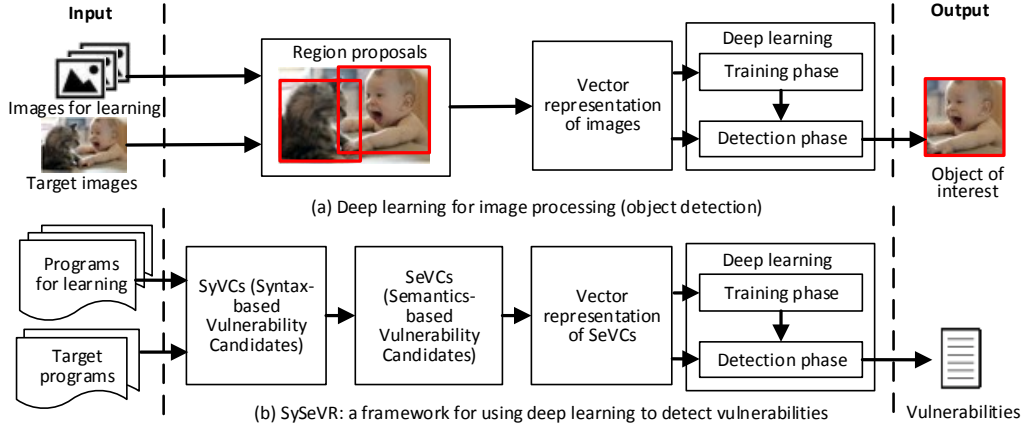


Fig. 1. (a) The notion of region proposal in image processing. (b) The SySeVR framework inspired by the notion of region proposal and centered at obtaining SyVC, SeVC, and vector representations of programs.

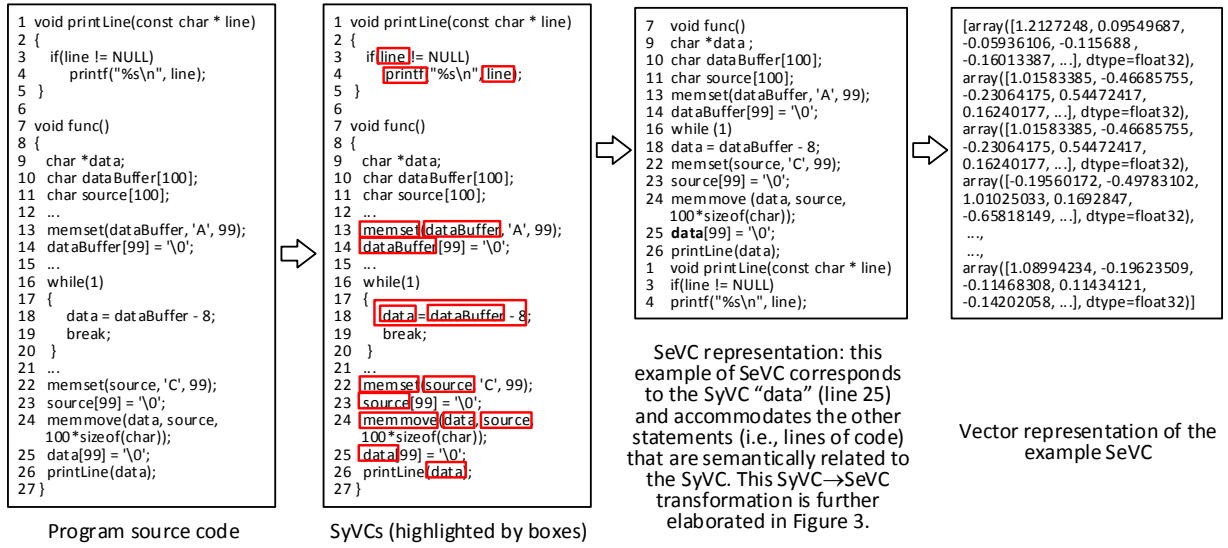


Fig. 2. An example illustrating SyVC, SeVC, and vector representations of program, where SyVCs are highlighted by boxes and one SyVC may be part of another SyVC. The SyVC→SeVC transformation is elaborated in Fig. 3.

Definition 2 (SyVC): Consider a program $P = \{f_1, \dots, f_\eta\}$, where $f_i = \{s_{i,1}, \dots, s_{i,m_i}\}$ with $s_{i,j} = \{t_{i,j,1}, \dots, t_{i,j,w_{i,j}}\}$. Given a set of vulnerability syntax characteristics, denoted by $H = \{h_k\}_{1 \leq k \leq \beta}$ where β is the number of syntax characteristics, a *code element* $e_{i,j,z}$ is composed of one or multiple consecutive tokens of $s_{i,j}$, namely $e_{i,j,z} = (t_{i,j,u}, \dots, t_{i,j,v})$ where $1 \leq u \leq v \leq w_{i,j}$. A code element $e_{i,j,z}$ is called a *SyVC* if it matches some vulnerability syntax characteristic h_k .

Note that different kinds of vulnerabilities would have different syntax characteristics. For example, vulnerabilities related to library/API function calls have the following syntax characteristic: a function on T_i is a “callee” (indicating a function call). In Section III, we will show how to extract vulnerability syntax characteristics and determine whether a code element matches a syntax characteristic or not.

Algorithm for computing SyVCs. Given a program $P = \{f_1, \dots, f_\eta\}$ and a set $H = \{h_k\}_{1 \leq k \leq \beta}$ of vulnerability syntax characteristics, Algorithm 1 extracts SyVCs from P as follows. First, Algorithm 1 uses a standard routine to

Algorithm 1 Extracting SyVCs from a program

Input: A program $P = \{f_1, \dots, f_\eta\}$; a set $H = \{h_k\}_{1 \leq k \leq \beta}$ of vulnerability syntax characteristics
Output: A set Y of SyVCs

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1:  $Y \leftarrow \emptyset$ ;
2: for each function  $f_i \in P$  do
3:   Generate an abstract syntax tree  $T_i$  for  $f_i$ ;
4:   for each code element  $e_{i,j,z}$  in  $T_i$  do
5:     for each  $h_k \in H$  do
6:       if  $e_{i,j,z}$  matches  $h_k$  then
7:          $Y \leftarrow Y \cup \{e_{i,j,z}\}$ ;
8:       end if
9:     end for
10:  end for
11: end for
12: return  $Y$ ; {the set of SyVCs}
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generate an abstract syntax tree T_i for each function f_i . Then, Algorithm 1 traverses T_i to identify SyVCs, namely the code elements that match some h_k . We defer the details to Section III-B1, because different vulnerability syntax characteristics need different matching methods.

Running example. In the second column of Fig. 2, we use boxes to highlight all of the SyVCs that are extracted from the program source code using the vulnerability syntax characteristics that will be described in Section III-B1. We will elaborate how these SyVCs are extracted. It is worth mentioning that one SyVC may be part of another SyVC. For example, there are three SyVCs that are extracted from line 18 because they are extracted with respect to different vulnerability syntax characteristics.

2) *Transforming SyVCs to SeVCs:* In order to detect vulnerabilities, we propose transforming SyVCs to SeVCs, or SyVC→SeVC transformation, to accommodate the statements that are semantically related to the SyVCs in question. For this purpose, we propose leveraging the *program slicing* technique to identify the statements that are semantically related to SyVCs. In order to use the program slicing technique, we need to use *Program Dependency Graph* (PDG). This requires us to use *data dependency* and *control dependency*, which are defined over *Control Flow Graph* (CFG). These concepts are reviewed below.

Definition 3 (CFG [25]): For a program $P = \{f_1, \dots, f_\eta\}$, the CFG of function f_i is a graph $G_i = (V_i, E_i)$, where $V_i = \{n_{i,1}, \dots, n_{i,c_i}\}$ is a set of nodes with each node representing a statement or control predicate, and $E_i = \{\epsilon_{i,1}, \dots, \epsilon_{i,d_i}\}$ is a set of direct edges with each edge representing the possible flow of control between a pair of nodes.

Definition 4 (data dependency [25]): Consider a program $P = \{f_1, \dots, f_\eta\}$, the CFG $G_i = (V_i, E_i)$ of function f_i , and two nodes $n_{i,j}$ and $n_{i,\ell}$ in G_i where $1 \leq j, \ell \leq c_i$ and $j \neq \ell$. If a value computed at $n_{i,\ell}$ is used at $n_{i,j}$, then $n_{i,j}$ is *data-dependent* on $n_{i,\ell}$.

Definition 5 (control dependency [25]): Consider a program $P = \{f_1, \dots, f_\eta\}$, the CFG $G_i = (V_i, E_i)$ of function f_i , and two nodes $n_{i,j}$ and $n_{i,\ell}$ in G_i where $1 \leq j, \ell \leq c_i$ and $j \neq \ell$. It is said that $n_{i,j}$ *post-dominates* $n_{i,\ell}$ if all paths from $n_{i,\ell}$ to the end of the program traverse through $n_{i,j}$. If there exists a path starting at $n_{i,\ell}$ and ending at $n_{i,j}$ such that (i) $n_{i,j}$ *post-dominates* every node on the path excluding $n_{i,\ell}$ and $n_{i,j}$, and (ii) $n_{i,j}$ does not post-dominate $n_{i,\ell}$, then $n_{i,j}$ is *control-dependent* on $n_{i,\ell}$.

Based on data dependency and control dependency, we can define PDG.

Definition 6 (PDG [25]): For a program $P = \{f_1, \dots, f_\eta\}$, the PDG of function f_i is denoted by $G'_i = (V_i, E'_i)$, where V_i is the same as in CFG G_i , and $E'_i = \{\epsilon'_{i,1}, \dots, \epsilon'_{i,d'_i}\}$ is a set of direct edges with each edge representing a data or control dependency between a pair of nodes.

Given PDGs, we can extract the *program slices* of SyVCs, which may go beyond the boundaries of individual functions. We consider both forward and backward slices because (i) the SyVC may affect some subsequential statements, which may therefore contain a vulnerability; and (ii) the statements affecting the SyVC may render the SyVC vulnerable. Formally,

Definition 7 (forward, backward, and program slices of a SyVC): Consider a program $P = \{f_1, \dots, f_\eta\}$, PDGs $G'_i = (V_i, E'_i)$ of functions f_i , and a SyVC, $e_{i,j,z}$, of statement $s_{i,j}$ in G'_i .

- The *forward slice* of SyVC $e_{i,j,z}$ in f_i , denoted by $fs_{i,j,z}$, is defined as an ordered set of nodes $\{n_{i,x_1}, \dots, n_{i,x_{\mu_i}}\} \subseteq V_i$ in G'_i , where n_{i,x_p} , $1 \leq x_1 \leq x_p \leq x_{\mu_i} \leq c_i$, is reachable from $e_{i,j,z}$ in G'_i . That is, the nodes in $fs_{i,j,z}$ are from all paths in G'_i starting at $e_{i,j,z}$.
- The *interprocedural forward slice* of SyVC $e_{i,j,z}$ in program P , denoted by $fs'_{i,j,z}$, is a forward slice going beyond function boundaries (caused by function calls).
- The *backward slice* of SyVC $e_{i,j,z}$ in f_i , denoted by $bs_{i,j,z}$, is defined as an ordered set of nodes $\{n_{i,y_1}, \dots, n_{i,y_{\nu_i}}\} \subseteq V_i$ in G'_i , where n_{i,y_p} , $1 \leq y_1 \leq y_p \leq y_{\nu_i} \leq c_i$, from which $e_{i,j,z}$ is reachable in G'_i . That is, the nodes in $bs_{i,j,z}$ are from all paths in G'_i ending at $e_{i,j,z}$.
- The *interprocedural backward slice* of SyVC $e_{i,j,z}$ in program P , denoted by $bs'_{i,j,z}$, is a backward slice going beyond function boundaries (caused by function calls).
- Given an interprocedural forward slice $fs'_{i,j,z}$ and an interprocedural backward slice $bs'_{i,j,z}$, the (interprocedural) *program slice* of SyVC $e_{i,j,z}$, denoted by $ps_{i,j,z}$, is defined as an ordered set of nodes (belonging to the PDGs of functions in P) by merging $fs'_{i,j,z}$ and $bs'_{i,j,z}$ at the SyVC $e_{i,j,z}$.

Defining SeVCs. Having extracted the program slices of SyVCs, we can transform them to SeVCs according to:

Definition 8 (SeVC): Given a program $P = \{f_1, \dots, f_\eta\}$ and a SyVC $e_{i,j,z}$ in statement $s_{i,j}$ of function f_i , the SeVC corresponding to SyVC $e_{i,j,z}$, denoted by $\delta_{i,j,z}$, is defined as an ordered subset of statements in P , denoted by $\delta_{i,j,z} = \{s_{a_1,b_1}, \dots, s_{a_{u_{i,j,z}},b_{u_{i,j,z}}}\}$, where a data dependency or control dependency exists between statement s_{a_p,b_p} ($1 \leq p \leq u_{i,j,z}$ and $1 \leq q \leq v_{i,j,z}$) and SyVC $e_{i,j,z}$. In other words, a SeVC, $\delta_{i,j,z}$, is an ordered set of statements that correspond to the nodes of (interprocedural) program slice $ps_{i,j,z}$.

Algorithm for computing SeVCs and running examples.

Algorithm 2 summarizes the preceding discussion in three steps: generating PDGs; generating program slices of the SyVCs output by Algorithm 1; and transforming program slices to SeVCs. In what follows we elaborate these steps and using Fig. 3 to illustrate a running example. Specifically, Fig. 3 elaborates the SyVC→SeVC transformation of SyVC “data” (related to pointer usage) while accommodating semantic information induced by data dependency and control dependency.

Step 1 (lines 2-4 in Algorithm 2). This step generates a PDG for each function. For this purpose, there are standard algorithms (e.g., [26]). As a running example, the second column of Fig. 3 shows the PDGs respectively corresponding to functions *func* and *printLine*, where each number represents the line number of a statement.

Step 2: (lines 6-9 in Algorithm 2). This step generates the program slice $ps_{i,j,z}$ for each SyVC $e_{i,j,z}$. The interprocedural forward slice $fs'_{i,j,z}$ is obtained by merging $fs_{i,j,z}$ and the forward slices from the functions called by f_i . The interprocedural backward slice $bs'_{i,j,z}$ is obtained by merging $bs_{i,j,z}$ and the backward slices from both the functions called by f_i and the functions calling f_i . Finally, $fs'_{i,j,z}$ and $bs'_{i,j,z}$ are merged into a program slice $ps_{i,j,z}$.

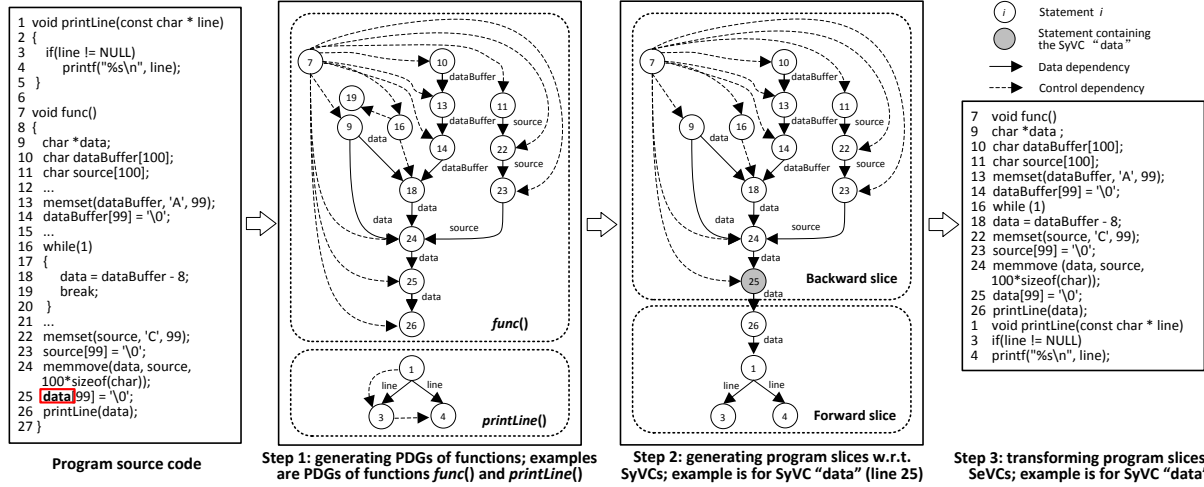


Fig. 3. Elaborating the SyVC→SeVC transformation in Algorithm 2 for SyVC “data”, where solid arrows (i.e., directed edges) represent data dependency, and dashed arrows represent control dependency.

Algorithm 2 Transforming SyVCs to SeVCs

Input: A program $P = \{f_1, \dots, f_n\}$; a set $Y = \{e_{i,j,z}\}$ of SyVCs generated by Algorithm 1

Output: The set of SeVCs

- 1: $C \leftarrow \emptyset$;
- 2: **for each** $f_i \in P$ **do**
- 3: Generate a PDG $G'_i = (V_i, E'_i)$ for f_i ;
- 4: **end for**
- 5: **for each** $e_{i,j,z} \in Y$ **in** G'_i **do**
- 6: Generate forward slice $fs_{i,j,z}$ & backward slice $bs_{i,j,z}$ of $e_{i,j,z}$;
- 7: Generate interprocedural forward slice $fs'_{i,j,z}$ by interconnecting $fs_{i,j,z}$ and the forward slices from the functions called by f_i ;
- 8: Generate interprocedural backward slice $bs'_{i,j,z}$ by interconnecting $bs_{i,j,z}$ and the backward slices from both the functions called by f_i and the functions calling f_i ;
- 9: $ps_{i,j,z} \leftarrow fs'_{i,j,z} \cup bs'_{i,j,z}$; {throughout this algorithm, “set \cup ” means ordered set union; see text for explanations}
- 10: **for each** statement $s_{i,j} \in f_i$ appearing in $ps_{i,j,z}$ as a node **do**
- 11: $\delta_{i,j,z} \leftarrow \delta_{i,j,z} \cup \{s_{i,j}\}$, according to the order of the appearance of $s_{i,j}$ in f_i ;
- 12: **end for**
- 13: **for two** statements $s_{i,j} \in f_i$ and $s_{a_p,b_q} \in f_{a_p}$ ($i \neq a_p$) appearing in $ps_{i,j,z}$ as nodes **do**
- 14: **if** f_i calls f_{a_p} **then**
- 15: $\delta_{i,j,z} \leftarrow \delta_{i,j,z} \cup \{s_{i,j}, s_{a_p,b_q}\}$, where $s_{i,j} < s_{a_p,b_q}$;
- 16: **else**
- 17: $\delta_{i,j,z} \leftarrow \delta_{i,j,z} \cup \{s_{i,j}, s_{a_p,b_q}\}$, where $s_{i,j} > s_{a_p,b_q}$;
- 18: **end if**
- 19: **end for**
- 20: $C \leftarrow C \cup \{\delta_{i,j,z}\}$;
- 21: **end for**
- 22: **return** C ; {the set of SeVCs}

As a running example, the third column in Fig. 3 shows the program slice of SyVC “data”, where the backward slice corresponds to function *func* and the forward slice corresponds to functions *func* and *printLine*. It is worth mentioning that for obtaining the forward slice of a SyVC, we leverage only data dependency for two reasons: (i) statements affected by a SyVC via control dependency would not be vulnerable in most cases and (ii) utilizing statements that have a control dependency on a SyVC would involve many statements that have little to do with vulnerabilities. On the other hand, for obtaining the backward slice of a SyVC, we leverage both data dependency and control dependency.

Step 3 (lines 10-19 in Algorithm 2). This step transforms

program slices to SeVCs as follows. First, the algorithm transforms the statements belonging to function f_i and appearing in $ps_{i,j,z}$ as nodes to a SeVC, while preserving the order of these statements in f_i . As a running example shown in Fig. 3, 13 statements belong to function *func*, and 3 statements belong to function *printLine*. According to the order of these statements in the two functions, we obtain two ordered sets of statements: lines $\{7, 9, 10, 11, 12, 14, 16, 18, 22, 23, 24, 25, 26\}$ and lines $\{1, 3, 4\}$.

Second, the algorithm transforms the statements belonging to different functions to a SeVC. For statements $s_{i,j} \in f_i$ and $s_{a_p,b_q} \in f_{a_p}$ ($i \neq a_p$) appearing in $ps_{i,j,z}$ as nodes, if f_i calls f_{a_p} , then $s_{i,j}$ and s_{a_p,b_q} are in the same order of function call, that is, $s_{i,j} < s_{a_p,b_q}$; otherwise, $s_{i,j} > s_{a_p,b_q}$. As a running example shown in Fig. 3, the SeVC is $\{7, 9, 10, 11, 13, 14, 16, 18, 22, 23, 24, 25, 26, 1, 3, 4\}$, in which the statements in function *func* appear before the statements in function *printLine* because *func* calls *printLine*. The fourth column in Fig. 3 shows the SeVC corresponding to SyVC “data”, namely an order set of statements that are semantically related to SyVC “data”.

3) *Encoding SeVCs into Vectors:* Algorithm 3 encodes SeVCs into vectors in three steps.

Step 1 (lines 2-6 in Algorithm 3). Each SeVC $\delta_{i,j,z}$ is transformed to a *symbolic representation*. For this purpose, we propose removing non-ASCII characters and comments, then map variable names to symbolic names (e.g., “V1”, “V2”) in a one-to-one fashion, and finally map function names to symbolic names (e.g., “F1”, “F2”) in a one-to-one fashion. Note that different SeVCs may have the same symbolic representation.

Step 2 (lines 8-13 in Algorithm 3). This step is to encode the symbolic representations into vectors. For this purpose, we propose dividing the symbolic representation of a SeVC $\delta_{i,j,z}$ (e.g., “V1=V2-8;”) into a sequence of symbols via a lexical analysis (e.g., “V1”, “=”, “V2”, “-”, “8”, and “;”). We transform a symbol to a fixed-length vector. By concatenating the vectors, we obtain a vector $R_{i,j,z}$ for each SeVC.

Step 3 (lines 14-22 in Algorithm 3). Because (i) the number of symbols (i.e., the vectors representing SeVCs) may be

Algorithm 3 Transforming SeVCs to vectors

Input: A set C of SeVCs generated by Algorithm 2;
a threshold θ

Output: The set of vectors corresponding to SeVCs

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1:  $R \leftarrow \emptyset$ ;
2: for each  $\delta_{i,j,z} \in C$  do
3:   Remove non-ASCII characters in  $\delta_{i,j,z}$ ;
4:   Map variable names in  $\delta_{i,j,z}$  to symbolic names;
5:   Map function names in  $\delta_{i,j,z}$  to symbolic names;
6: end for
7: for each  $\delta_{i,j,z} \in C$  do
8:    $R_{i,j,z} \leftarrow \emptyset$ ;
9:   Divide  $\delta_{i,j,z}$  into a set of symbols  $S$ ;
10:  for each  $\alpha \in S$  in order do
11:    Transform  $\alpha$  to a fixed-length vector  $v(\alpha)$ ;
12:     $R_{i,j,z} \leftarrow R_{i,j,z} || v(\alpha)$ , where  $||$  means concatenation;
13:  end for
14:  if  $R_{i,j,z}$  is shorter than  $\theta$  then
15:    Zeroes are padded to the end of  $R_{i,j,z}$ ;
16:  else if the vector corresponding to  $fs_{i,j}$  is shorter than  $\theta/2$  then
17:    Delete the leftmost portion of  $R_{i,j,z}$  to make  $|R_{i,j,z}| = \theta$ ;
18:  else if the vector corresponding to  $bs_{i,j}$  is shorter than  $\theta/2$  then
19:    Delete the rightmost portion of  $R_{i,j,z}$  to make  $|R_{i,j,z}| = \theta$ ;
20:  else
21:    Delete almost the same length from the leftmost portion and the
    rightmost portion of  $R_{i,j,z}$  to make  $|R_{i,j,z}| = \theta$ ;
22:  end if
23:   $R \leftarrow R \cup R_{i,j,z}$ ;
24: end for
25: return  $R$ ; {the set of vectors corresponding to SeVCs}
  
```

different and (ii) neural networks take vectors of the same length as input, we use a threshold θ as the length of vectors for the input to neural network. When a vector is shorter than θ , zeroes are padded to the end of the vector. When a vector is longer than θ , we consider three scenarios. (i) If the portion of the vector corresponding to the forward slice $fs_{i,j}$ is shorter than $\theta/2$, we delete the leftmost portion of $R_{i,j,z}$ to make $|R_{i,j,z}| = \theta$. (ii) If the portion of the vector corresponding to the backward slice $bs_{i,j}$ is shorter than $\theta/2$, we delete the rightmost portion of $R_{i,j,z}$ to make $|R_{i,j,z}| = \theta$. (iii) Otherwise, we delete almost the same length from the leftmost portion and the rightmost portion of $R_{i,j,z}$ to make $|R_{i,j,z}| = \theta$.

4) *Labeling SeVCs and Corresponding Vectors:* In order to learn a deep neural network, we label the vectors (i.e., the SeVCs they represent) as vulnerable or not as follows: A SeVC (i.e., the vector representing it) containing a known vulnerability is labeled as “1” (i.e., vulnerable), and “0” otherwise (i.e., not vulnerable). A learned deep neural network encodes vulnerability patterns and can detect whether given SeVCs are vulnerable or not.

C. Evaluation Metrics

The effectiveness of vulnerability detectors can be evaluated by the following 5 widely-used metrics [27]: *false-positive rate* (FPR), *false-negative rate* (FNR), *accuracy* (A), *precision* (P), and *F1-measure* ($F1$). Let TP denote the number of vulnerable samples that are detected as vulnerable, FP denote the number of samples are not vulnerable but are detected as vulnerable, TN denote the number of samples that are not vulnerable and are detected as not vulnerable, and FN denote the number of vulnerable samples that are detected as not vulnerable. Table I summarizes their definitions.

TABLE I
EVALUATION METRICS.

Metric	Formula	Meaning
False-positive rate	$FPR = \frac{FP}{FP+TN}$	The proportion of false-positive samples in the total samples that are not vulnerable.
False-negative rate	$FNR = \frac{FN}{TP+FN}$	The proportion of false-negative samples in the total samples that are vulnerable.
Accuracy	$A = \frac{TP+TN}{TP+FP+TN+FN}$	The correctness of all detected samples.
Precision	$P = \frac{TP}{TP+FP}$	The correctness of detected vulnerable samples.
F1-measure	$F1 = \frac{2 \cdot P \cdot (1-FNR)}{P+(1-FNR)}$	The overall effectiveness considering both precision and false-negative rate.

III. EXPERIMENTS AND RESULTS

A. Research Questions and Dataset

Research questions. Our experiments are geared towards answering the following Research Questions (RQs):

- RQ1: Can SySeVR make BLSTM detect multiple kinds (vs. single kind) of vulnerabilities?
- RQ2: Can SySeVR make multiple kinds of deep neural networks to detect multiple kinds of vulnerabilities? Can we explain their (in)effectiveness?
- RQ3: Can accommodating control-dependency make SySeVR more effective, and by how much?
- RQ4: How more effective are SySeVR-based methods when compared with the state-of-the-art methods?

In order to answer these questions, we implement the following 6 deep neural networks in Python using Theano [28]: CNN [29], DBN [30], and RNNs (including LSTM, GRU, BLSTM, and BGRU [31], [32], [33]). The computer running experiments has a NVIDIA GeForce GTX 1080 GPU and an Intel Xeon E5-1620 CPU running at 3.50GHz.

Vulnerability dataset. We produce a vulnerability dataset from two sources: NVD [21] and SARD [22]. NVD contains vulnerabilities in production software and possibly `diff` files describing the difference between a vulnerable piece of code and its patched version. SARD contains production, synthetic and academic programs (also known as *test cases*), which are categorized as “good” (i.e., having no vulnerabilities), “bad” (i.e., having vulnerabilities), and “mixed” (i.e., having vulnerabilities whose patched versions are also available).

For NVD, we focus on 19 popular C/C++ open source products (same as in [11]) and their vulnerabilities that are accompanied by `diff` files, which are needed for extracting vulnerable pieces of code. As a result, we collect 1,592 open source C/C++ programs, of which 874 are vulnerable. For SARD, we collect 14,000 C/C++ programs, of which 13,906 programs are vulnerable (i.e., “bad” or “mixed”). In total, we collect 15,592 programs, of which 14,780 are vulnerable; these vulnerable programs contain 126 *types* of vulnerabilities, where each type is uniquely identified by a Common Weakness Enumeration Identifier (CWE ID) [34]. The 126 CWE IDs are published with our dataset.

B. Experiments

The experiments follow the SySeVR framework, with elaborations when necessary.

1) *Extracting SyVCs*: In what follows we will elaborate the two components in Algorithm 1 that are specific to different kinds of vulnerabilities: the extraction of vulnerability syntax characteristics and how to match them.

Extracting vulnerability syntax characteristics. In order to extract syntax characteristics of known vulnerabilities, it would be natural to extract the vulnerable lines of code from the vulnerable programs mentioned above, and analyze their syntax characteristics. However, this is an extremely time-consuming task, which prompts us to leverage the C/C++ vulnerability rules of a state-of-the-art commercial tool, **Checkmarx** [6], to analyze vulnerability syntax characteristics. As we will see, this alternate method is effective because it covers 93.6% of the vulnerable programs collected from SARD. It is worth mentioning that we choose Checkmarx over open-source tools (e.g., Flawfinder [4] and RATS [5]) because the latter have simple parsers and imperfect rules [35].

Our *manual* examination of Checkmarx rules leads to the following 4 syntax characteristics (each accommodating many vulnerabilities).

- **Library/API Function Call (FC for short)**: This syntax characteristic covers 811 library/API function calls, which are published with our dataset. These 811 function calls correspond to 106 CWE IDs.
- **Array Usage (AU for short)**: This syntax characteristic covers 87 CWE IDs related to arrays (e.g., issues related to array element access, array address arithmetic).
- **Pointer Usage (PU for short)**: This syntax characteristic covers 103 CWE IDs related to pointers (e.g., improper use in pointer arithmetic, reference, address transfer as a function parameter).
- **Arithmetic Expression (AE for short)**: This syntax characteristic covers 45 CWE IDs related to improper arithmetic expressions (e.g., integer overflow).

Fig. 4 shows that these 4 syntax characteristics overlap with each other in terms of the CWE IDs they cover (e.g., 39 CWE IDs exhibit all of the 4 syntax characteristics, but $|FC \cup AU \cup PU \cup AE| = 126$).

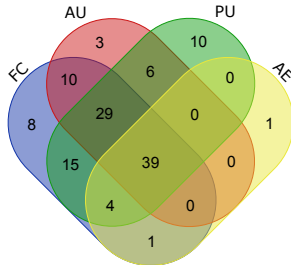


Fig. 4. Venn diagram of the FC, AU, PU, and AE in terms of the CWE IDs they cover, where $|FC| = 106$, $|AU| = 87$, $|PU| = 103$, and $|AE| = 45$.

Matching syntax characteristics. In order to use Algorithm 1 to extract SyVCs, we need to determine whether or not a code element $e_{i,j,z}$, which is on the abstract syntax tree T_i of function f_i in program P , matches a vulnerability syntax characteristic. Note that T_i can be generated by using Joern [36]. The following method, as illustrated in Fig. 5 via the example program shown in Fig. 2, can automatically

decide whether or not code element $e_{i,j,z}$ matches a syntax characteristic.

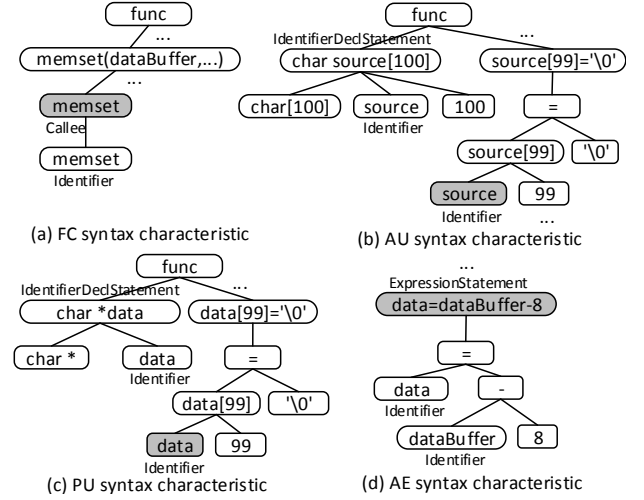


Fig. 5. Examples for illustrating the matching of syntax characteristics, where a highlighted node matches some vulnerability syntax characteristic and therefore is a SyVC.

- As illustrated in Fig. 5(a), we say code element $e_{i,j,z}$ (i.e., “memset”) matches the FC syntax characteristic if (i) $e_{i,j,z}$ on T_i is a “callee” (i.e., the function is called), and (ii) $e_{i,j,z}$ is one of the 811 function calls mentioned above.
- As illustrated in Fig. 5(b), we say code element $e_{i,j,z}$ (i.e., “source”) matches the AU syntax characteristic if (i) $e_{i,j,z}$ is an identifier declared in an identifier declaration statement (i.e., IdentifierDeclStatement) node and (ii) the IdentifierDeclStatement node contains characters ‘[’ and ‘]’.
- As illustrated in Fig. 5(c), we say code element $e_{i,j,z}$ (i.e., “data”) matches the PU syntax characteristic if (i) $e_{i,j,z}$ is an identifier declared in an IdentifierDeclStatement node and (ii) the IdentifierDeclStatement node contains character ‘*’.
- As illustrated in Fig. 5(d), we say code element $e_{i,j,z}$ (“data=dataBuffer-8”) matches the AE syntax characteristic if (i) $e_{i,j,z}$ is an expression statement (ExpressionStatement) node and (ii) $e_{i,j,z}$ contains a character ‘=’ and has one or more identifiers on the right-hand side of ‘=’.

Extracting SyVCs. Now we can use Algorithm 1 to extract SyVCs from the 15,592 programs. Corresponding to the 4 syntax characteristics, we extract 4 kinds of SyVCs:

- **FC-kind SyVCs**: We extract 6,304 from NVD and 58,099 from SARD, or 64,403 in total.
- **AU-kind SyVCs**: We extract 9,776 from NVD and 32,453 from SARD, or 42,229 in total.
- **PU-kind SyVCs**: We extract 73,856 from NVD and 217,985 from SARD, or 291,841 in total.
- **AE-kind SyVCs**: We extract 5,264 from NVD and 16,890 from SARD, or 22,154 in total.

Putting them together, we extract 420,627 SyVCs, which cover 13,016 (out of the 13,906, or 93.6%) vulnerable programs collected from SARD; this coverage validates our idea of using

Checkmarx rules to derive vulnerability syntax characteristics. Note that we can compute the coverage 93.6% because SARD gives the precise location of each vulnerability; in contrast, we cannot compute the coverage with respect to NVD because it does not give precise locations of vulnerabilities. The average time for extracting a SyVC is 270 milliseconds.

2) *Transforming SyVCs to SeVCs*: When using Algorithm 2 to transform SyVCs to SeVCs, we use *Joern* [36] to extract PDGs. Corresponding to the 420,627 SyVCs extracted from Algorithm 1, Algorithm 2 generates 420,627 SeVCs (while recalling that one SyVC is transformed to one SeVC). In order to see the effect of semantic information, we actually use Algorithm 2 to generate two sets of SeVCs: one set accommodating semantic information induced by data dependency only, and the other set accommodating semantic information induced by both data dependency and control dependency. In either case, the second column of Table II summarizes the numbers of SeVCs categorized by the kinds of SyVCs from which they are transformed. In terms of the efficiency of the SyVC→SeVC transformation, on average it takes 331 milliseconds to generate a SeVC accommodating data dependency and 362 milliseconds to generate a SeVC accommodating data dependency and control dependency.

TABLE II
THE NUMBER OF SEVCs, VULNERABLE SEVCs, AND NOT VULNERABLE SEVCs FROM THE 15,592 PROGRAMS.

Kind of SyVCs	#SeVCs	#Vul. SeVCs	#Not vul. SeVCs
FC-kind	64,403	13,603	50,800
AU-kind	42,229	10,926	31,303
PU-kind	291,841	28,391	263,450
AE-kind	22,154	3,475	18,679
Total	420,627	56,395	364,232

3) *Encoding SeVCs into Vector Representation*: We use Algorithm 3 to encode SeVCs into vector representation. For this purpose, we adopt *word2vec* [37] to encode the symbols of each SeVC into fixed-length vectors. Then, each SeVC is represented by the concatenation of the vectors representing its symbols. We set each SeVC to have 500 symbols (padding or truncating if necessary, as discussed in Algorithm 3) and the length of each symbol is 30, meaning $\theta = 15,000$.

4) *Generating Ground Truth Labels of SeVCs*: For SeVCs extracted from NVD, we examine the vulnerabilities whose *diff* files involve line deletion; we do not consider the *diff* files that only involve line additions because in these cases the vulnerable statements are not given by NVD. We generate the ground truth labels in 3 steps. **Step 1**: Parse a *diff* file to mark the lines that are prefixed with a “-” and are deleted/modified, and the lines that are prefixed with a “-” and are moved (i.e., deleted at one place and added at another place). **Step 2**: If a SeVC contains at least one deleted/modified statement that is prefixed with a “-”, it is labeled as “1” (i.e., vulnerable); if a SeVC contains at least one moved statement prefixed with a “-” and the detected file contains a known vulnerability, it is labeled as “1”; otherwise, a SeVC is labeled as “0” (i.e., not vulnerable). **Step 3**: Check the SeVCs that are labeled as “1” because Step 2 may mislabel some SeVCs that are not vulnerable as “1” (while noting that it is not possible to mislabel a vulnerable SeVC as “0”). Among

the preceding 3 steps, the first two are *automated*, but the last one is *manual*.

For SeVCs extracted from SARD, a SeVC extracted from a “good” program is labeled as “0”; a SeVC extracted from a “bad” or “mixed” program is labeled as “1” if the SeVC contains at least one vulnerable statement, and “0” otherwise.

In total, 56,395 SeVCs are labeled as “1” and 364,232 SeVCs are labeled as “0”. The third and fourth columns of Table II summarize the number of vulnerable vs. not vulnerable SeVCs corresponding to each kind of SyVCs. The ground-truth label of the vector corresponding to a SeVC is the same as the ground truth label of the SeVC.

C. Experimental Results

For learning a deep neural network, we use 80% of the programs respectively and randomly selected from NVD and SARD for training (*training programs*), and use the rest 20% for testing (*testing programs*).

1) *Experiments for Answering RQ1*: In this experiment, we use BLSTM as in [11] and the SeVCs accommodating semantic information induced by data and control dependencies. We randomly choose 30,000 SeVCs extracted from the training programs as the training set (12.7% of which are vulnerable and the rest 87.3% are not) and 7,500 SeVCs extracted from the testing programs as the testing set (12.2% of which are vulnerable and the rest 87.8% are not). Both sets contain SeVCs corresponding to the 4 kinds of SyVCs, proportional to their amount as shown in the second column of Table II. For fair comparison with VulDeePecker [11], we also randomly choose 30,000 SeVCs corresponding to the FC-kind SyVCs extracted from the training programs (22.8% of which are vulnerable and the rest 77.2% are not) as the training set, and randomly choose 7,500 SeVCs corresponding to the FC-kind SyVCs extracted from the testing programs as the testing set (22.0% of which are vulnerable and the rest 78.0% are not). These SeVCs only accommodate semantic information induced by data dependency (as in [11]).

The main parameters for learning BLSTM are: dropout is 0.2; batch size is 16; number of epochs is 20; output dimension is 256; minibatch stochastic gradient descent together with ADAMAX [38] is used for training with a default learning rate of 0.002; dimension of hidden vectors is 500; and number of hidden layers is 2.

TABLE III
EFFECTIVENESS OF VULDEEPECKER [11] VS. EFFECTIVENESS OF BLSTM IN THE SYSEVR FRAMEWORK.

Kind of SyVC	FPR (%)	FNR (%)	A (%)	P (%)	F1 (%)
VulDeePecker w/ FC-kind	4.1	21.7	92.0	84.0	81.0
SySeVR-BLSTM w/ FC-kind	3.8	9.6	94.9	87.3	88.8
SySeVR-BLSTM w/ AU-kind	6.3	11.7	92.4	82.5	85.3
SySeVR-BLSTM w/ PU-kind	2.1	13.6	96.9	80.2	83.2
SySeVR-BLSTM w/ AE-kind	1.5	12.5	97.3	87.5	87.5
SySeVR-BLSTM w/ all-kinds	2.9	12.1	95.9	82.5	85.2

Table III summarizes the results. We observe that SySeVR-enabled BLSTM (or SySeVR-BLSTM) with FC-kind SyVCs leads to the lowest FNR (9.6%), but its FPR is higher than that of PU- and AE-kind SyVCs. The other 3 types of SyVCs lead

to, on average, a FPR of 3.3% and a FNR of 12.6%. Overall, SySeVR makes BLSTM achieve a lower FPR (0.3% lower) and a lower FNR (12.1% lower) than VulDeePecker for the same kind of vulnerabilities. This leads to:

Insight 1: SySeVR-BLSTM detects various kinds of vulnerabilities, and can reduce FNR by 12.1%.

2) *Experiments for Answering RQ2:* In order to answer RQ2, we train 1 CNN, 1 DBN, and 4 RNNs (i.e., LSTM, GRU, BLSTM, and BGRU) using the same dataset as in Section III-C1. Table IV summarizes the results. We observe that when compared with unidirectional RNNs (i.e., LSTM and GRU), bidirectional RNNs (i.e., BLSTM and BGRU) can reduce FNR by 3.1% on average, at the price of increasing FPR by 0.3% on average. This phenomenon might be caused by the following: Bidirectional RNNs can accommodate more information about the statements that appear before and after the statement in question. In summary,

Insight 2: SySeVR-enabled bidirectional RNNs (especially BGRU) are more effective than CNNs, which in turn are more effective than DBNs. Still, their FNRs are consistently much higher than their FPRs.

TABLE IV
COMPARISON BETWEEN 6 NEURAL NETWORKS.

Neural network	FPR (%)	FNR (%)	A (%)	P (%)	F1 (%)
CNN	2.1	16.3	95.9	86.5	85.0
DBN	11.0	83.6	78.8	19.4	17.8
LSTM	2.5	15.9	95.7	83.7	83.9
GRU	2.5	14.7	95.9	84.9	85.1
BLSTM	2.9	12.1	95.9	82.5	85.2
BGRU	2.7	12.3	96.0	84.1	85.9

Towards explaining the effectiveness of BGRU in vulnerability detection. It is important, but an outstanding open problem, to explain the effectiveness of deep neural networks. Now we report our initial effort along this direction. In what follows we focus on BGRU because it is more effective than the others.

In order to explain the effectiveness of BGRU, we review its structure in Fig. 6. For each SeVC and each time step, there is an output (belonging to $[0, 1]$) at the activation layer. The output of BGRU is the output of the last time step at the activation layer; the closer this output is to 1, the more likely the SeVC is classified as vulnerable. For the classification of a SeVC, we identify the tokens (i.e., the symbols representing them) that play a critical role in determining its classification. This can be achieved by looking at all pairs of tokens at time steps $(t', t' + 1)$. We find that if the activation-layer output corresponding to the token at time step $t' + 1$ is substantially (e.g., 0.6) greater (vs. smaller) than the activation-layer output corresponding to the token at time step t' , then the token at time step $t' + 1$ plays a critical role in classifying the SeVC as vulnerable (correspondingly, not vulnerable). Moreover, we find that many false-negatives are caused by the token “if” or the token(s) following it, because these tokens often appear in SeVCs that are not vulnerable. We also find that many false-positives are caused by the token(s) related to library/API function calls and their arguments, because these tokens often appear in SeVCs that are vulnerable. In summary, we have

Insight 3: The effectiveness of BGRU is substantially influenced by the training data. If some syntax elements often

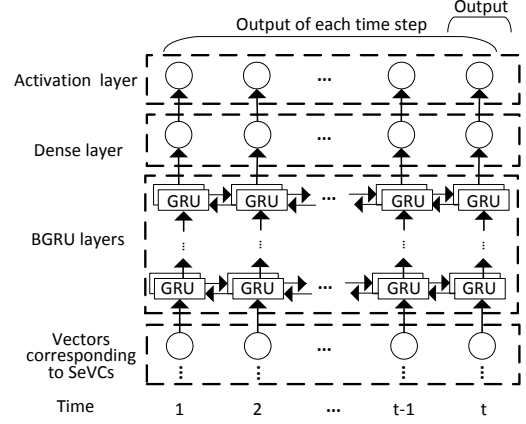


Fig. 6. The structure of BGRU.

appear in SeVCs that are vulnerable (vs. not vulnerable), then these elements may cause false-positives (correspondingly, false-negatives).

Using tailored or universal vulnerability detectors? In practice, we often deal with multiple kinds of vulnerabilities (or SyVCs). This raises a new question: should we use multiple neural networks (one for each kind of SyVCs) or a single neural network (accommodating 4 kinds of SyVCs) to detect vulnerabilities? In order to answer this question, we conduct the following experiment. For FC-, AU- and PU-kind SyVCs, we randomly choose 30,000 SeVCs extracted from the training programs as the training set and 7,500 SeVCs extracted from the testing programs as the testing set, where the SeVCs accommodate semantic information induced by data dependency and control dependency. For the much fewer AE-kind vulnerabilities, we use all of the 20,336 SeVCs extracted from the training programs for training (15.9% of which are vulnerable and the rest 84.1% are not), and all of the 1,818 SeVCs extracted from the testing programs for testing (12.0% of which are vulnerable and the rest 88.0% are not).

TABLE V
EFFECTIVENESS OF TAILORED VS. UNIVERSAL BGRU.

Kind of SyVC	FPR (%)	FNR (%)	A (%)	P (%)	F1 (%)
FC-kind	3.1	7.6	95.9	89.5	90.9
AU-kind	3.0	10.2	95.2	90.6	90.2
PU-kind	1.7	22.7	96.2	83.2	80.1
AE-kind	1.4	3.8	98.2	93.7	94.9
All-kinds	2.7	12.3	96.0	84.1	85.9

Table V summarizes the experimental results. We observe that using BGRU specific to each kind of SyVCs is more effective, except for PU, than using a single BGRU to detect vulnerabilities related to 4 kinds of SyVCs. This does not hold for PU likely because as shown in Table II, the ratio of vulnerable vs. not vulnerable SeVCs in PU-kind of SyVCs is 1:9, which is much smaller than the average ratio of 1:4 in the other 3 kinds of SyVCs. As a consequence, the resulting BGRU would be biased for SeVCs that are not vulnerable, leading to a high FNR. In summary,

Insight 4: It is better to use BGRU tailored to specific kind of vulnerabilities than to use a single BGRU for detecting multiple kinds of vulnerabilities.

3) *Experiments for Answering RQ3:* We use experiment to compare the effectiveness of (i) the 6 neural networks learned

from the SeVCs that accommodate semantic information induced by data dependency and (ii) the 6 neural networks learned from the SeVCs that accommodate semantic information induced by data dependency and control dependency. In either case, we randomly choose 30,000 SeVCs extracted from the training programs as the training set and 7,500 SeVCs extracted from the testing programs as the testing set. All of these training and testing sets correspond to the 4 kinds of SyVCs, proportional to their amount as shown in the second column of Table II.

TABLE VI

EFFECTIVENESS OF SEMANTIC INFORMATION INDUCED BY DATA DEPENDENCY (“DD” FOR SHORT) VS. SEMANTIC INFORMATION INDUCED BY DATA DEPENDENCY AND CONTROL DEPENDENCY (“DDCD” FOR SHORT).

Neural network	Kind of SeVC	FPR (%)	FNR (%)	A (%)	P (%)	F1 (%)
CNN	DD	1.8	38.8	93.2	83.8	70.7
	DDCD	2.1	16.3	95.9	86.5	85.0
DBN	DD	10.9	86.3	79.0	16.3	14.9
	DDCD	11.0	83.6	78.8	19.4	17.8
LSTM	DD	5.3	39.6	90.2	64.0	62.2
	DDCD	2.5	15.9	95.7	83.7	83.9
GRU	DD	2.5	37.4	92.8	79.2	69.9
	DDCD	2.5	14.7	95.9	84.9	85.1
BLSTM	DD	2.9	38.5	92.3	76.7	68.3
	DDCD	2.9	12.1	95.9	82.5	85.2
BGRU	DD	3.1	31.9	93.0	77.2	72.3
	DDCD	2.7	12.3	96.0	84.1	85.9

Table VI summarizes the results. We observe that accommodating semantic information induced by data dependency and control dependency can improve the vulnerability detection capability in almost every scenario, and reduce the FNR by 19.6% on average. This can be explained by the fact that control dependency accommodates extra information useful to vulnerability detection.

Insight 5: The more semantic information is accommodated for learning neural networks, the higher vulnerability detection capability of the learned neural networks.

4) *Experiments for Answering RQ4:* We consider BGRU learned from the 341,536 SeVCs corresponding to the 4 kinds of SyVCs extracted from the training programs and the 79,091 SeVCs extracted from the testing programs, while accommodating semantic information induced by data dependency and control dependency. We compare our most effective model BGRU with the commercial static vulnerability detection tool Checkmarx [6] and open-source static analysis tools Flawfinder [4] and RATS [5], because (i) these tools arguably represent the state-of-the-art static analysis for vulnerability detection; (ii) they are widely used for detecting vulnerabilities in C/C++ source code; (iii) they directly operate on the source code (i.e., no need to compile the source code); and (iv) they are available to us. We also consider the state-of-the-art system VUDDY [2], which is particularly suitable for detecting vulnerabilities incurred by code cloning. We further consider VulDeePecker [11], and we consider all 4 kinds of SyVCs and data as well as control dependency for SySeVR.

Table VII summarizes the experimental results. We observe that SySeVR-enabled BGRU substantially outperforms the state-of-the-art vulnerability detection methods. The open-source Flawfinder and RATS have high FPRs and FNRs.

TABLE VII
COMPARING BGRU IN THE SYSeVR FRAMEWORK AND STATE-OF-THE-ART VULNERABILITY DETECTORS.

Method	FPR (%)	FNR (%)	A (%)	P (%)	F1 (%)
Flawfinder	21.6	70.4	69.8	22.8	25.7
RATS	21.5	85.3	67.2	12.8	13.7
Checkmarx	20.8	56.8	72.9	30.9	36.1
VUDDY	4.3	90.1	71.2	47.7	16.4
VulDeePecker	2.5	41.8	92.2	78.0	66.6
SySeVR-BGRU	1.4	5.6	98.0	90.8	92.6

Checkmarx is better than Flawfinder and RATS, but still has high FPRs and FNRs. VUDDY is known to trade a high FNR for a low FPR, because it can only detect vulnerabilities that are nearly identical to the vulnerabilities in the training programs. SySeVR-enabled BGRU is much more effective than VulDeePecker because VulDeePecker cannot cope with other kinds of SyVCs (than FC) and cannot accommodate semantic information induced by control dependency. Moreover, BGRU learned from a larger training set (i.e., 341,536 SeVCs) is more effective than BGRU learned from a smaller training set (30,000 SeVCs; see Table IV), by reducing 6.7% in FNR. In summary,

Insight 6: SySeVR-enabled BGRU is much more effective than the state-of-the-art vulnerability detection methods.

5) *Applying BGRU to Detect Vulnerabilities in Software Products:* In order to show the usefulness of SySeVR in detecting software vulnerabilities in real-world software products, we apply SySeVR-enabled BGRU to detect vulnerabilities in 4 products: Libav, Seamonkey, Thunderbird, and Xen. Each of these products contains multiple targets programs, from which we extract their SyVCs, SeVCs, and vectors. For each product, we apply SySeVR-enabled BGRU to its 20 versions so that we can tell whether some vulnerabilities have been “silently” patched by the vendors when releasing a newer version.

As highlighted in Table VIII, we detect 15 vulnerabilities that are *not* reported in NVD. Among them, 7 are unknown (i.e., their presence in these products are not known until now) and are indeed similar (upon our manual examination) to the CVE Identifiers (CVE IDs) mentioned in Table VIII. We do not give the full details of these vulnerabilities for ethical considerations, but we have reported these 7 vulnerabilities to the vendors. The other 8 vulnerabilities have been “silently” patched by the vendors when releasing newer versions of the products in question.

IV. LIMITATIONS

The present study has several limitations. **First**, we focus on detecting vulnerabilities in C/C++ program source code, meaning that the framework may need to be adapted to cope with other programming languages and/or executables. **Second**, our experiments cover 4 kinds of SyVCs; future research needs to accommodate more kinds of SyVCs. **Third**, the algorithms for generating SyVCs and SeVCs could be improved to accommodate more syntactic/semantic information for vulnerability detection. **Fourth**, we detect vulnerabilities at the SeVC granularity (i.e., multiple lines of code that are semantically related to each other), which could be improved

TABLE VIII
THE 15 VULNERABILITIES, WHICH ARE DETECTED BY BGRU BUT NOT REPORTED IN THE NVD, INCLUDE 7 UNKNOWN VULNERABILITIES AND 8 VULNERABILITIES THAT HAVE BEEN “SILENTLY” PATCHED.

Target product	CVE ID	Vulnerable product reported	Vulnerability release date	Vulnerable file in the target product	Kind of SyVC	1st patched version of target product
Libav 10.3	CVE-2013-****	Ffmpeg	*/*/*/2013	libavcodec/**.c	AU-kind	–
	CVE-2013-7020	Ffmpeg	12/09/2013	libavcodec/ffv1dec.c	PU-kind	Libav 10.4
	CVE-2013-****	Ffmpeg	*/*/*/2013	libavcodec/**.c	PU-kind	–
	CVE-2014-****	Ffmpeg	*/*/*/2015	libavcodec/**.c	PU-kind	–
	CVE-2014-****	Ffmpeg	*/*/*/2014	libavcodec/**.c	PU-kind	–
Libav 9.10	CVE-2014-9676	Ffmpeg	02/27/2015	libavformat/segment.c	PU-kind	Libav 10.0
Seamonkey 2.32	CVE-2015-4511	Firefox	09/24/2015	.../src/nestegg.c	AU-kind	Seamonkey 2.38
Seamonkey 2.35	CVE-2015-****	Firefox	*/*/*/2015	.../gonk/**.cpp	FC-kind	–
Thunderbird 38.0.1	CVE-2015-4511	Firefox	09/24/2015	.../src/nestegg.c	AU-kind	Thunderbird 43.0b1
	CVE-2015-****	Firefox	*/*/*/2015	.../gonk/**.cpp	FC-kind	–
Xen 4.4.2	CVE-2013-4149	Qemu	11/04/2014	.../net/virtio-net.c	PU-kind	Xen 4.4.3
	CVE-2015-1779	Qemu	01/12/2016	ui/vnc-ws.c	PU-kind	Xen 4.5.5
	CVE-2015-3456	Qemu	05/13/2015	.../block/fdc.c	PU-kind	Xen 4.5.1
Xen 4.7.4	CVE-2016-4453	Qemu	06/01/2016	.../display/vmware_vga.c	AE-kind	Xen 4.8.0
Xen 4.8.2	CVE-2016-****	Qemu	*/*/*/2016	.../net/**.c	PU-kind	–

TABLE IX
SUMMARY OF METHODS FOR DETECTING VARIOUS KINDS OF VULNERABILITIES.

Method	Degree of automation	Vulnerability cause	Kind of SyVC				Model	Granularity	Information uses
			FC-kind	AU-kind	PU-kind	AE-kind			
Code similarity-based methods	Semi-automatic	Code cloning	–	–	–	–	None	Fine/coarse	Code representation
Open source tools (e.g., Flawfinder, RATS)	Manual	Any	✓	✓	✓	✓	None	Fine	Lexical information
Checkmarx	Manual	Any	✓	✓	✓	✓	None	Fine	Data-dependency
Feature-based machine learning	Semi-automatic	Any	–	–	–	–	Machine learning	Coarse	Code metrics
VulDeePecker	More automatic	Any	✓	×	×	×	BLSTM	Fine	Data-dependency
SySeVR (our work)	More automatic	Any	✓	✓	✓	✓	6 deep neural networks	Fine	Data-dependency & control-dependency

to more precisely pin down the *line* of code that contains a vulnerability. **Fifth**, we truncate the vectors transformed from SeVCs when they are longer than a threshold; future research needs to investigate how to cope with varying length of vectors without losing the information caused by the truncation. **Sixth**, our experiments show some deep neural networks are more effective than the state-of-the-art vulnerability detection methods. Although we have gained some insights into explaining the “why” part, more investigations are needed to explain the success of deep learning in this context and beyond [39].

V. RELATED WORK

Prior studies related to vulnerability detection. There are two methods for source code-based static vulnerability detection: *code similarity-based* vs. *pattern-based*. Since code similarity-based detectors can only detect vulnerabilities incurred by code cloning and the present study is a pattern-based method, we review prior studies in the latter method. Table IX summarizes the comparison between SySeVR and previous vulnerability detection methods, which are divided into three categories based on their degree of automation. **(i) Manual methods:** Vulnerability patterns are manually generated by human experts (e.g., Flawfinder [4], RATS [5], Checkmarx [6]). These tools often incur high false-positives and/or high false-negatives [35], as also confirmed by our experiments (Section III-C4). **(ii) Semi-automatic methods:** Human experts are needed to manually define features (e.g., imports and function calls [8]; complexity, code churn, and developer

activity [40]; API symbols and subtrees [10]; and system calls [7]) for traditional machine learning models, such as support vector machine and k-nearest neighbor. Different vulnerabilities are often described by different features (e.g., format string vulnerabilities [41]; information leakage vulnerabilities [42]; missing check vulnerabilities [9]; and taint-style vulnerabilities [43], [44]). This method often detects vulnerabilities at a coarse granularity (e.g., program [7]; component [8]; file [40]; or function [10]), meaning that locations of vulnerabilities cannot be pinned down. **(iii) More automatic methods:** Human experts do not need to define features. Lin et al. [15] presented a method for automatically learning high-level representations of functions (i.e., coarse-grained and not able to pin down locations of vulnerabilities). VulDeePecker [11] is the first system showing the feasibility of using deep learning to detect vulnerabilities while able to pin down locations of vulnerabilities. SySeVR is the first systematic framework for using deep learning to detect vulnerabilities.

Prior studies related to deep learning. Deep learning has been used for program analysis. CNN has been used for software defect prediction [17], malicious URLs, file paths detection, and registry keys detection [45]; DBN has been used for software defect prediction [19], [20]; RNN has been used for vulnerability detection [11], [15], software traceability [12], code clone detection [13], and recognizing functions in binaries [14]. The present study offers the first framework for using deep learning to detect vulnerabilities.

VI. CONCLUSION

We presented the SySeVR framework for using deep learning to detect vulnerabilities. Based on a large dataset of vulnerability we collected, we drew a number of insights, including an explanation on the effectiveness of deep learning in vulnerability detection. Moreover, we detected 15 vulnerabilities that were *not* reported in the NVD. Among these 15 vulnerabilities, 7 are unknown and have been reported to the vendors, and the other 8 have been “silently” patched by the vendors when releasing newer versions.

There are many interesting problems for future research. In particular, it is important to address the limitations discussed in Section IV.

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