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DEEPVD: Toward Class-Separation Features for Neural Network Vulnerability Detection

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Jiyuan Zhang Computer Science Department University of Illinois Urbana-Champaign <u>Aashish Yadavally</u> Computer Science Department The University of Texas at Dallas Vulnerability detection is the task of analyzing a given code example to predict whether it is vulnerable (i.e., possesses vulnerabilities such as Denial of Service, Memory Corruption, etc.), or benign.

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 - 3. Inadequate Model Capabilities
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Non-vulnerable code is much more frequent than vulnerable one!

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 - Duplication across training/testing splits.

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Treat code as sequence of tokens and DO NOT consider semantic dependencies..

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Training Process & Model Design

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We focus on identifying "Class-Separation" features

Figure 1. CVE-2020-18899: Denial of Service (DoS) from an Uncontrolled Memory Allocation in Exiv2 0.27

```
void Jp2Image::printStructure(...) {
1
2
     subBox.length=getLong((byte*)&subBox.length,bigEndian);
3
     subBox.type=getLong((byte*)&subBox.type,bigEndian);
 4
    // subBox.length makes no sense if it is larger than
5
          the rest of the file
    if (subBox.length > io_->size() - io_->tell()) {
 6
7
       throw Error(kerCorruptedMetadata);
8
     }
9
    DataBuf data(subBox.length - sizeof(box));
    io_->read(data.pData_,data.size_);
10
11 }
```

```
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     . . .
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3
     subBox.type=getLong((byte*)&subBox.type,bigEndian);
4
5
    // subBox.length makes no sense if it is larger than
         the rest of the file || 0
    if (subBox.length == 0 ||
6
         subBox.length > io_->size() - io_->tell()) {
7
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    DataBuf data(subBox.length - sizeof(box));
                                                                           }
    io_->read(data.pData_,data.size_);
                                                                      10
                                                                           DataBuf data(subBox.length - sizeof(box));
10
                                                                           io ->read(data.pData ,data.size );
11 }
                                                                      11
                                                                      12 }
```

Value of 0 for subBox.length results in Integer Overflow

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We can observe a data dependency (red) from line 3 to line 6, and a control dependency (blue) from line 6 to line 7.

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Observation 1

A model could investigate the data and control flows toward the exception/error-handling points to detect a potential vulnerability.

Figure 2. CVE-2020-19155: Improper Access Control in Jfinal

```
1 public JSONObject rename() {
 2 String oldFile = this.get.get("old");
 3 String newFile = this.get.get("new");
 4 oldFile = getFilePath(oldFile);
 5 ...
 6
    String path = oldFile.substring(0, pos + 1);
   File fileFrom = null;
 7
 8 File fileTo = null;
9 try {
    fileFrom = new File(this.fileRoot + oldFile);
10
    fileTo = new File(this.fileRoot + path + newFile);
11
12
    if (fileTo.exists()) {
13
    if (fileTo.isDirectory()) {
14
    this.error(sprintf(lang("DIRECTORY_ALREADY_EXISTS");
15
    error = true;
    } else { // fileTo.isFile
16
17
      this.error(sprintf(lang("FILE_ALREADY_EXISTS").));
18
        error = true;
19
     }
20
     } else if (!fileFrom.renameTo(fileTo)) {
21
     this.error(sprintf(lang("ERROR_RENAMING_DIRECTORY"));
22
      error = true;
23
    }
24
    } catch (Exception e) {
25
    if (fileFrom.isDirectory()) {
26
    this.error(sprintf(lang("ERROR_RENAMING_DIRECTORY").;
27
    } else {
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     this.error(sprintf(lang("ERROR_RENAMING_FILE"),..));
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    }
30
     error = true;
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```

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Figure 3. Exception-Flow Graph (EFG) and Post-Dominator Tree (PDT) for vulnerable code example (left).



Key Ideas

Focused on improving *class-separability*, we consider the following:

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Figure 3. Exception-Flow Graph (EFG) and Post-Dominator Tree (PDT) for vulnerable code example (left).

Statement **d** is considered as a *post-dominator* of another statement **s** if all the paths to the exit point of the method starting at **s** must go through **d**.



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Architecture Overview



Approach	Precision	Recall	F-score
VulDeePecker	0.55	0.77	0.64
SySeVR	0.54	0.74	0.63
Russell et al.	0.54	0.72	0.62
Devign	0.56	0.73	0.63
Reveal	0.62	0.69	0.65
IVDetect	0.54	0.77	0.67
DEEPVD	0.70	0.89	0.78

Table 1: Comparison with other DL-Based VD Approaches

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*Overall, DEEPVD r*elatively improves over the baseline models from <u>13%– 29.6%</u> in Precision, from <u>15.6%–28.9%</u> in Recall, and from <u>16.4%–25.8%</u> in F-score.

Figure 4. CVE-2019-1563: A vulnerable code example in OpenSSL.

```
1 BIO *PKCS7_dataDecode(PKCS7 *p7, EVP_PKEY *pkey, BIO
        *in_bio, X509 *pcert) {
 2
     . . .
    if (evp_cipher != NULL) {
 3
 4
      . . .
     if (pcert == NULL) {
 5
     for (i = 0; i < sk_PKCS7_RECIP_INFO_num(rsk); i++) {</pre>
 6
      ri = sk_PKCS7_RECIP_INFO_value(rsk, i);
 7
         if (pkcs7_decrypt_rinfo(&ek, &eklen, ri, pkey) < 0)</pre>
 8
 9
           goto err;
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        }
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         if (pkcs7_decrypt_rinfo(&ek, &eklen, ri, pkey) < 0)</pre>
 8
 9
            goto err;
          ERR_clear_error();
10
111
        3
     } else {...}
12
13 }
```

- Has 186 lines of code after removing comments and empty lines.
- PDG with 145 nodes and 477 edges, and the CPG with 622 nodes and 1,393 edges.
- In contrast, EFG + PDT has 145 nodes and 295 edges.

	Vulnerability Type	TN	FP	FN	TP	Total	Precision	Recall	F-score
1	Denial Of Service	424	490	64	658	1,636	0.57	0.91	0.70
2	Overflow	225	371	28	340	964	0.48	0.92	0.63
3	Execute Code	129	279	11	202	621	0.42	0.95	0.58
4	Memory corruption	102	190	9	162	463	0.46	0.95	0.62
5	Obtain information	63	45	7	76	191	0.63	0.92	0.75

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Leveraging EFG+PDT particularly also helped with identifying the popular **<u>DOS-based</u> <u>vulnerabilities</u>**, that are majorly identified with improper exception/error-handling.





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- automated vulnerability detection.

However, Chakraborty et al. [1] reported four key-issues with these approaches:

2. Data Duplication 3. Inadequate Model Capabilities 4. Learning Irrelevant Features



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exception/error-handling points to detect a potential vulnerability.

Figure 1. CVE-2020-18899: Denial

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10 11 12

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Empirical Evaluation

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Overall, DEEPVD relatively improves over the baseline models from 13%-29.6% in Precision, from 15.6%-28.9% in Recall, and from 16.4%-25.8% in F-score.



Link: https://tinyurl.com/4z56haa3



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