SAFE-PDF: Robust Detection of JavaScript PDF Malware With Abstract Interpretation

Alexander Jordan\textsuperscript{1}, François Gauthier\textsuperscript{1}, Behnaz Hassanshahi\textsuperscript{1}, and David Zhao\textsuperscript{1,2}

\textsuperscript{1}Oracle Labs, Brisbane, Australia
\{firstname.lastname\}@oracle.com
\textsuperscript{2}University of Sydney, Sydney, Australia
d-z@outlook.com

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Abstract

The popularity of the PDF format and the rich JavaScript environment that PDF viewers offer make PDF documents an attractive attack vector for malware developers. PDF documents present a serious threat to the security of organizations because most users are unsuspecting of them and thus likely to open documents from untrusted sources.

We propose to identify malicious PDFs by using conservative abstract interpretation to statically reason about the behavior of the embedded JavaScript code. Currently, state-of-the-art tools either: (1) statically identify PDF malware based on structural similarity to known malicious samples; or (2) dynamically execute the code to detect malicious behavior. These two approaches are subject to evasion attacks that mimic the structure of benign documents or do not exhibit their malicious behavior when being analyzed dynamically. In contrast, abstract interpretation is oblivious to both types of evasions. A comparison with two state-of-the-art PDF malware detection tools shows that our conservative abstract interpretation approach achieves similar accuracy, while being more resilient to evasion attacks.

1 Introduction

The Portable Document Format (PDF) allows for the embedding of interactive elements written in JavaScript.\textsuperscript{1} JavaScript in PDFs allows document creators

\textsuperscript{1}While the major parts of the PDF format are standardized as ISO 32000-1 [1], the specification of some advanced features supported by Adobe’s PDF software remains proprietary technology, and is referenced only by the ISO standard. The proprietary parts include JavaScript support and APIs available in Adobe’s PDF software. Adobe provides an informal specification for this JavaScript part in their public documentation [3, 4].
to support input validation in forms and to offer convenient shortcuts for common actions such as printing. More elaborate use cases of PDF JavaScript include controlling embedded multimedia objects and interacting with the file system or network. However, this rich and complex PDF JavaScript environment can also be used for illegitimate purposes. Indeed, previous work has shown that JavaScript is the vector of choice for PDF malware because: (1) implementation bugs in the PDF JavaScript extensions can be exploited to deliver and execute malicious payloads; (2) bugs in the JavaScript runtime and/or sandbox can be triggered with JavaScript code; and (3) JavaScript can be used as a facilitator to exploit vulnerabilities outside the JavaScript environment through techniques like heap spraying [28, 16].

In 2008, the number of PDF-based attacks increased sharply. Then, in 2009, the number of Common Vulnerabilities and Exposures (CVEs) reported against the Adobe Reader rose alarmingly. Previous work showed how the vast majority of PDF malware uses JavaScript in one way or another [11, 28, 16]. The histogram in Figure 1 shows how the number of CVEs reported against Adobe Reader is still at all time highs, with 39 CVEs already reported at the time of writing (May 2018), despite the introduction of sandboxing for increased safety in Adobe Reader X.

To lower the risk to users posed by PDF malware, several well-known techniques are available. These techniques are either employed in the PDF viewer software or implemented as (part of) stand-alone software products, such as anti-virus or anti-malware scanning tools.

We found, however, that existing tools to detect PDF malware (both in industry and research), are vulnerable to various kinds of evasion attacks. Indeed, simple static malware detectors (e.g. anti-virus tools) that rely on a signature
database that contains known patterns of exploit code are subject to code obfuscation attacks. More recent and advanced approaches that use machine learning to automatically capture structural patterns of malware are vulnerable to mimicry attacks where the malware emulates the structure of benign documents to avoid detection. Finally, approaches that attempt to statically isolate and analyze PDF JavaScript code are typically vulnerable to parser confusion attacks, where the malware is embedded in non-standard, or poorly documented PDF constructs that are meant to trip up code extractors.

Dynamic (runtime) malware detection tools, on the other hand, rely on executing code under analysis in a special environment (a sandbox) to detect suspicious behaviors (e.g., network traffic, execution of known exploit code). However, dynamic approaches are susceptible to sandbox evasion attacks where the malicious code avoids detection by probing its environment to detect if it is running in a sandbox environment [17]. Dynamic approaches also typically load suspicious PDFs in a limited number of viewer applications, which makes them fail to identify malware that checks the version of the viewer before picking a vulnerability to exploit. More importantly, dynamic approaches are underapproximative by nature, e.g., they may miss any malicious behavior that does not manifest itself by loading the document only, but is rather triggered by user interaction.

To address the limitations of signature-based, machine learning, and dynamic tools, we introduce SAFE-PDF, an abstract interpretation-based JavaScript malware detector for PDF documents. Abstract interpretation is a powerful framework for static program analysis that computes a sound over-approximation of all possible program behaviors. In other words, abstract interpretation allows us to check if a JavaScript program can ever exhibit malicious behavior under any possible execution and viewer version. Furthermore, we address the main limitation of existing static analysis approaches by developing one of the most robust PDF JavaScript code extractors to date and validating it against 2952 documents that are known to cause issues in existing code extractors [16]. We also complement abstract interpretation with a model of the JavaScript environment available to programs embedded in a PDF document, and a whitelist policy that does not allow malicious behavior (e.g., calls to vulnerable APIs, heap spraying) to go undetected. The model and whitelist are easy to understand and maintain, especially when compared to opaque machine learning classifiers. Used together with our analysis in a conservative manner, obfuscation, mimicry, and sandbox evasion attacks are no longer effective.

This prompted us to design the SAFE-PDF tool for high recall[2] and robustness to evasion attacks. At the same time, SAFE-PDF (due to its straightforward model and whitelist) is flexible enough to be quickly adapted to changes in the threat landscape, because it does not require training or tuning of parameters. In this paper, we show how SAFE-PDF achieves comparable precision[3] and recall to state-of-the-art tools, while being oblivious to evasion strategies.

\[2\] ratio of true positives to total number of malware in a given set of documents
\[3\] ratio of true positives to total number of reports
that affect existing approaches. To summarize, we make the following contributions:

- We present a practical conservative abstract interpretation approach that efficiently detects PDF malware by statically analyzing all possible behavior of its embedded JavaScript code in less than 4 seconds on average.

- We develop one of the most robust PDF JavaScript code extractors to date, by addressing all known limitations of existing extractors and testing our tool on PDF documents with hard-to-extract JavaScript code [16].

- We compare SAFE-PDF against two state-of-the-art PDF malware detection tools: PDF Malware Slayer [31], and Hidost [46], and show how SAFE-PDF achieves comparable precision and recall while capturing malware that evade other tools.

2 Overview

2.1 Motivation

PDF malware frequently depends on embedded JavaScript code. While disabling JavaScript in the PDF viewer and removing it from documents is the most obvious and effective defense against JavaScript PDF malware, we think that such measures impose an unnecessary loss of functionality on users. Indeed, blind removal of JavaScript code breaks several harmless PDF documents and prevents users from using very common and useful features such as form input validation.

SAFE-PDF thus aims at enabling JavaScript use in benign documents while conservatively and robustly filtering out malicious documents.

JavaScript malware in PDF documents seeks to exploit bugs in PDF viewer applications. As a result, an attacker is able to disrupt operation or gain control of the targeted host system. The most frequently exploited vulnerabilities in PDF viewer applications have shown to be: (1) lack of user input validation and the allowing of arbitrary and unsafe operations outside the scope of the document; (2) unintended side effects of otherwise legitimate operations (e.g. file creation, or network access); and (3) memory corruption bugs in PDF JavaScript extensions or in the runtime itself.

2.2 Existing approaches to PDF malware detection

The most common way for anti-virus software to identify PDF malware is to search files for signatures or patterns of known malware. While cheap and fast, signature-based methods are easily evaded through simple obfuscations.

Indeed, all examples of PDF malware we examined obfuscate their JavaScript code to avoid detection by matching the code’s textual representation against a signature (or pattern). While the vulnerable APIs that malware seeks to exploit might be well known, detecting them syntactically can ultimately be prevented
try {
    eval("thi" + "s.f" + "ea" + "tu" + "re" + "A.n" + "ew" + "Ob" + "je" + "ct" + "n" + "ull");
}

Listing 1: Artificial malware example: evaluating string with simple obfuscation of call to featureA.newObject(size)

function start(foo, bar) {
    // bar = reference to featureB object
    // encoded property = "sendMessage"
    bar["\x73\x6e\x64\x4d\x65\x73\x73\x61\x67\x65"]({
        data: /* ... */
    });
}

Listing 2: Artificial malware example: obfuscated call to exploitable function featureB.sendMessage() through obfuscation. Code obfuscation in JavaScript can be achieved easily using the language's built-in support for string manipulation, reflection, and different character-encoding. Listings 1 to 3 give examples of PDF malware using different methods of obfuscation. The first two examples use string concatenation and string encoding to cloak the code they would execute and property name they seek to access. Both of these obfuscations are simple enough to undo. The example in Listing 3 is more complicated. It aliases and composes function objects, uses string replacement, and the built-in unescape function to decode its malicious payload. Through these powerful means of obfuscation, exploit code can be rewritten (manually or automatically) in countless ways, and its detection requires the signature database of anti-virus software to be updated continuously and promptly. However, to reason about such complex code, more advanced techniques are needed.

To overcome the limitations of signature-based techniques, metadata [43] and structure-based [34, 46] learning approaches have been proposed. Both types of approaches mainly differ in feature extraction. While metadata-based approaches distinguish between benign and malicious documents based on features such as file size, number of JavaScript components, or number of embedded fonts, structure-based approaches classify documents based on paths in the PDF document tree. Because simple obfuscation techniques do not alter the metadata or structure of PDF documents, such approaches proved to be very efficient at detecting PDF malware. However, because metadata and structural features do not cause malicious behavior, metadata and structure-based approaches learn only what features are correlated to malicious behavior. For this reason, they can be easily evaded through mimicry [45] and reverse mimicry attacks [33] that...
function urpl(sc) {
    var keyu = "%u";
    var re = /XY/g;
    sc = sc.replace(re, keyu);
    return sc;
}

var unes = unescape
var pGvRIJZpqdN
for (i = 0; i < 18000; i++)
    pGvRIJZpqdN = pGvRIJZpqdN + 0x77;
var s = "XY104CXY106FXY1072XY1065XY1020XY" +
    "1069XY1070XY1073\x75XY106DXY1020XY1064" +
    "XY106FXY106CXY106FXY1072XY1020XY1065XY" +
    "1069XY1074XY1020XY1061XY106DXY1065XY10" +
    "74\x25XY1020XY1063XY106FXY106EXY1073XY" +
    "1065XY1063XY1074XY1065XY1074\x75XY1072" +
    "XY1020XY1061XY1064XY1069XY10...";
    pGvRIJZpqdN = unes(urpl(s));

Listing 3: Artificial malware example: obfuscated binary payload

hide malicious payloads in files exhibiting metadata and structural properties
of benign files.

var curDate = new Date();
var day = util.printd("ddd dd", curDate);
if (app.viewerVersion < 8.0) {
    /* trigger exploit */
}

Listing 4: Artificial malware example: exploit code active only on PDF viewers
with a version less than 8.0

JavaScript-based detection approaches search for signs of malware closer to
the source of the problem, by targeting the JavaScript code embedded in PDF
documents. JavaScript-based detection approaches vary from fully static ma-
chine learning approaches \[28, 49\] to hybrid static and dynamic techniques \[31, 48, 32\]. On the one hand, all the JavaScript-based machine learning approaches
we are aware of perform lexical analysis of the JavaScript code and thus capture
only lexical features of malicious PDFs, making them susceptible to mimicry
attacks. Dynamic approaches (including the dynamic component of a hybrid
approach), on the other hand, partly rely on either an instrumented PDF viewer
or a special JavaScript runtime environment to dynamically detect malicious
behavior. Any dynamic approach, however, is inherently limited by the fact that
they target a specific runtime environment only. They may miss malicious be-
navior due to simple checks that probe the environment, such as the one shown
As PDF viewers evolve and as vulnerabilities get fixed, dynamic (and hybrid) approaches quickly become outdated unless significant effort is invested in maintaining the analysis runtime environment.

2.3 Our approach: SAFE-PDF

We propose the use of conservative abstract interpretation of JavaScript as a static analysis to detect malware in PDF documents. By means of abstract interpretation, SAFE-PDF hits a sweet spot in the analysis landscape where it can statically consider all possible executions of the JavaScript code, and detect malicious behavior without relying on a special runtime environment or requiring any user interaction. For example, during abstract interpretation, all event listeners (e.g., Keystroke, Mouse Down, Mouse Enter) are automatically triggered and analyzed. Because it reasons about the runtime behavior of the JavaScript code instead of its structure or syntax, abstract interpretation is oblivious to mimicry attacks. On the other hand, because it is not tied to a specific runtime environment, SAFE-PDF requires less maintenance than its dynamic analysis counterparts, and is not subject to sandbox evasion attacks.

By conservative, we mean that when in doubt, our analysis will err on the safe side. In other words, we are willing to accept that our analysis may regard a harmless PDF as malicious (i.e., a false positive), but we do not accept the opposite (i.e., a false negative). Abstract interpretation considers all possible behavior of the code under analysis without directly executing it. Based on its result, we use a whitelisting mechanism to allow only safe behavior (e.g., restricting the use of JavaScript APIs to a known safe subset) and reject everything else as malware.

The flowchart in Figure 2 highlights the main steps of SAFE-PDF, our PDF malware detection tool. SAFE-PDF starts by extracting the JavaScript code from the input document. Then, it complements the extracted code with a model of the JavaScript runtime environment inside a PDF viewer following Adobe’s specification, hereafter called the PDF-JS model, and performs abstract interpretation. If abstract interpretation does not complete (i.e., it cannot reach a fixpoint) within a certain time, the document is immediately reported as malicious. If abstract interpretation terminates, SAFE-PDF then checks if the document exhibits potentially malicious behavior. If so, the document is reported as malicious. Otherwise, it is reported as benign.

2.4 Background: Abstract Interpretation

Abstract interpretation is a mathematically well-founded framework for static analysis introduced by Cousot and Cousot in 19. It addresses the challenge of computing non-trivial properties of a program, which is known to be undecidable when the concrete language semantics is used (c.f., Rice’s theorem [23, chapter 9]). When concrete values and operations are approximated with abstract values and abstract operations, however, such an abstract interpretation of a program becomes computable. This comes at the cost of losing precision.
Figure 2: Overview of our malware detection analysis
Figure 3: SAFE’s string abstract domain. It keeps track of sets of at most $k$ different (number-) strings before approximating them as $Number$ or $NotNumber$. ($k = 2$ in this figure.)

for some properties of a program due to the abstraction (approximation) that is applied. In the context of static analysis, such a (partially) imprecise result means that some of our questions about a program (e.g., “is it malicious?”) have to be answered with “We don’t know” for the analysis to be sound. In the following paragraphs we explain some of the concepts behind abstract interpretation that are required later on, and we give a step-by-step example. A formal introduction to abstract interpretation can be found in [35, chapter 4].

From a program analysis point of view, abstract interpretation gives us the ability to statically (i.e., without running the program) build an abstract state for every point in the program. These states capture information about possible concrete executions and we can use them to validate assertions or find problems in the programs we want to analyze. It is up to us, as the designer of the abstract interpretation analysis, to choose an appropriate abstraction. An abstraction consists of (1) abstract domains and (2) abstract semantics. The abstract domains capture the program states in our analysis as abstract values. It is important to note that an abstract value must be able to represent more than one concrete value at a time. A domain maintains information in the form of a lattice, which may have up to infinite elements and infinite height. (See Figure 3 for an example of the abstract domain for string values used by SAFE-PDF; this is a simple powerset lattice ordered by set inclusion.) Depending on the abstraction function, a domain can capture information about possible concrete values using wide approximations. For example, if we were interested only to find out whether a numeric value can be negative, we could abstract an integer value as its sign; or we abstract it as a set or a range of concrete integer values. We also need to encode the semantics of abstract operations, which approximates concrete operations on abstract values. Given an abstraction, we compute a fixpoint for a program in the abstraction. Note that in practice, analysis might not reach a fixpoint for all programs within feasible time and memory bounds.
var msg = "hello world";
// local: msg := "hello world"
var arr = [
  function(s) { console.println(s); },
  function(s) { doc.getField("msgField").value = s; }
];
// heap: #1 := Func
// #2 := Func
// #3 := Obj { "0" := #1, "1" := #2, length := 2 }
// local: arr := #3, msg
var i = doc.getField("inputField");
// local: arr, i := ⊤String, msg
var n = Number.parseInt(i);
// local: arr, i, msg, n := ⊤Number
var fn = arr[n];
// local: fn := {#1, #2, undefined}
if (fn === undefined)
  // local: fn := {undefined}
  app.alert("Unexpected input: " + i);
  // calls app.alert()
else
  // local: fn := (#1, #2)
  fn(msg);
  // calls either #1 or #2

Listing 5: PDF JavaScript snippet with abstract interpretation state in comments

Abstract interpretation example We present a simple JavaScript code snippet in Listing 5. Lines that start with // show updates to the abstract state after every instruction. The var keyword at line 1 creates a local variable, which our abstract state stores directly, together with the right-hand side string-value, in the current local scope. The array arr (created at line 3) contains two function objects, which are stored in the abstract heap at address #1 and #2 respectively. The abstract array object itself is stored at address #3 and referenced by a new variable in local. The arr object contains three properties: “0” and “1” point to the function objects at their respective addresses; the internal length property approximates the number of items contained in an array (or any JavaScript object). The next two instructions (lines 11 and 13) call a PDF API and JavaScript built-in function respectively. The call to getField returns a user input that cannot be known statically. But based on the specification of getField, our abstract interpretation can approximate the returned value with the abstract value ⊤String, which represents any string. This value is then passed to parseInt (l. 13), for which our analysis has a semantic model: it returns an integral number if the string argument can be parsed and NaN otherwise. In this case, for any string as input, it returns ⊤Number, i.e., any
number. The resulting value stored in n is then used in a property lookup on
the array object arr (l.15). The information in our abstract state at this point
is precise enough to give a close approximation for the lookup with a key value
of $\top_{\text{Number}}$, which is converted to a string value during lookup according
to JavaScript semantics. Consequently, the values with property names “0” and
“1” match the lookup because they are number strings, and are thus returned
as results to fn. The value undefined is also returned because $\top_{\text{Number}}$ includes
numbers that are not in arr (e.g., 2, 42, 3, ...). Note, however, that because
$\top_{\text{Number}}$ matches number strings only, the lookup does not match length or
any of the internal array functions (e.g. find()), which can be accessed from a
JavaScript array object by following its prototype chain. To approximate the
control-flow behavior of the if-statement starting in line 17, we perform its test
against our abstract state. Abstract interpretation determines that because fn
may be undefined, the then-branch (l.19) can be taken, and the call to app.alert
may be executed. In the else-branch (also reachable due to the abstract value
of fn), abstract interpretation can remove undefined from the possible values of
fn (before reaching line 23) because it contradicts the if-condition. This proves
that the call to the function object fn, can invoke only the two functions defined
inside arr. It cannot call any other function, and cannot fail due to fn not being
a function object.

3 Malware Detection

In this section we describe in detail how to detect malicious JavaScript in PDF
files using conservative abstract interpretation and how we overcome parser
confusion attacks that plague existing PDF JavaScript code extractors. Our
description of processing steps follows the flowchart in Figure 2.

3.1 Pre-processing step: extraction

Our approach requires JavaScript code to be extracted from PDF documents
before it can be analyzed. While conceptually simple, the PDF format makes
extraction extremely tricky. Indeed, JavaScript code can be embedded in differ-
ent PDF constructs, encoded with various uncommon encodings, compressed,
and encrypted, meaning that JavaScript code extraction requires a full-fledged
PDF parser. Moreover, Carmony et al. [16] showed that PDF viewers often
deviate from the specification, in an attempt to “just work”, and that existing
open-source and commercial JavaScript code extractors all fail to extract code
from various PDF documents. As a result of their work, they compiled a set
of 2952 PDF documents that are known to cause extraction issues in one or
more JavaScript code extractors. Starting from those documents with hard-
to-extract JavaScript code, we extended an existing commercial extractor [7]
until it could successfully extract JavaScript code from all documents in the
set. Because static code extraction can reach code that might not be loaded
dynamically (e.g. form actions that are only triggered when interacting with the
Table 1: Extractor limitations and associated PDF constructs

| Extractor limitation | Problematic PDF construct                          |
|----------------------|---------------------------------------------------|
| Implementation Bugs  | Comment in document trailer                        |
|                      | Comment in dictionary object                       |
|                      | Trailing whitespace in stream data                 |
|                      | **Null object reference**                          |
|                      | Security handler revision 5 hex encoded encryption data parsing |
|                      | Security handler revision 3, 4 encryption key computation |
|                      | Hexadecimal string literal in encoded objects      |
| Design Errors        | Use of orphaned encryption objects                 |
|                      | Security handler revision 5 key computation with clear metadata |
| Omissions            | No XFA support                                    |
|                      | No security handler revision 5 support            |
|                      | No security handler revision 6 support            |
| Ambiguities          | Invalid object keywords                            |
|                      | No cross-reference table                           |
|                      | **Wrong or missing entries in the cross-reference table** |
|                      | **Partially broken compressed streams**            |

document), we claim that our approach analyzes a strict superset of the code that can be extracted by dynamically loading a PDF document in a sandbox.

In the following paragraph, we briefly introduce the PDF format, focusing only on elements that are relevant to code extraction. We refer the interested reader to [22] for an extensive description of the Portable Document Format (PDF). For code extraction purposes, the four most important elements of the PDF syntax are: (1) direct objects, which are the basic building blocks of a PDF; (2) indirect objects, which are uniquely identified, and can be referenced from elsewhere in the document; (3) cross-reference tables, which contain the positions of objects in the file; and (4) content streams, which store various parts of the document content. Content streams are composed of two parts: a stream that is an optionally compressed and encrypted byte sequence, and a metadata dictionary object that carries information about the stream’s encoding and how to uncompress it. Because Adobe Reader can cope with partially broken compressed streams, and unspecified encodings, we extended our extractor with
the same capabilities.

Furthermore, because JavaScript code in PDF documents is usually broken into snippets and spread across several content streams, a code extractor must not only extract the various snippets from streams, it must also parse the document in order to recover its structure and re-assemble the snippets into a semantically valid program. In [10], the authors list several constructs that are known to cause PDF parser failures and extraction errors. We report those constructs in Table 1 along with additional problematic constructs we addressed in our extractor (in bold). In Table 1, security handlers refer to various encryption algorithms that can be used to encrypt streams, and XFA refers to the XML Forms Architecture, which is supported by the PDF specification, and that allows the embedding of JavaScript actions in XML forms. After meticulous extensions, our extractor now supports all constructs listed in Table 1 and extracts JavaScript code from all of the original 2952 PDF documents with hard-to-extract JavaScript code that contain non-empty JavaScript code and that do not cause our extractor to fail. Indeed, during manual investigation of the documents with no extracted JavaScript, we observed that all of them contain an empty JavaScript string (e.g. `/JS()/S/JavaScript`). We believe that because the approach in [10] detects JavaScript code by monitoring loads of the EScript.api module, which would be triggered by the `/JavaScript` keyword, it mistakenly tags those files as containing JavaScript code. We also observed that most of the hard-to-extract files that cause extraction failure are so broken that they cannot be opened with Acrobat Reader DC 2018.011. Hence, we are highly confident that our extractor retrieves all the JavaScript code that can be extracted.

3.2 Main analysis step: abstract interpretation

During the main analysis step, we perform abstract interpretation of the extracted JavaScript code. As secondary input, we provide a model of the JavaScript runtime environment emulating that of a concrete PDF viewer, which we refer to as our PDF-JS model. The role of the PDF-JS model is to provide extracted JavaScript code with an abstract environment for analysis emulating that of a PDF viewer application. It thus captures (a subset of) the PDF-JavaScript specification [4, 3]. For example, the global static objects `app` and `doc` are made available as part of the JavaScript environment according to Adobe’s documentation. Unlike a concrete JavaScript-based environment, which would be used for dynamic analysis, our model can make use of abstract semantics (i.e. not all API functions must provide concrete results), as long as it remains conservative, i.e., it must not under-approximate the behavior of the JavaScript API. We present the PDF-JS model in detail in Section 3.4.

To support JavaScript code in XFA and its interactions with objects specified as XML entities, we provide additional modeling. In accordance with available documentation [5], the analysis extracts and dynamically models XFA entities as JavaScript objects and, using the same principles as the PDF-JS model, provides an environment to analyze XFA JavaScript code.
The result we receive from this analysis step must represent an over-approximation of the JavaScript code’s behavior. In situations where abstract interpretation cannot reach a fixpoint, no valid over-approximation is available, and thus the analysis immediately reports a potential malware. Causes for not reaching a fixpoint are: (1) the analysis reaching a timeout or exhausting the available memory; and (2) syntactic or semantic errors in the extracted JavaScript code causing the analysis to fail. Only if the analysis reaches a fixpoint, we pass on the result of abstract interpretation to the final whitelisting step.

### 3.3 Post-processing step: semantic whitelist

The last step of our static analysis classifies the extracted JavaScript as either safe or malicious. This is done by inspecting the result of abstract interpretation from the previous step. For our analysis to be conservative, SAFE-PDF has to reject a PDF document as malicious if the result of performing abstract interpretation on its extracted JavaScript code cannot prove the absence of all of the following:

1. a call to a vulnerable API method
2. a potentially malicious program behavior
3. an unknown behavior

We detect the use of vulnerable APIs \[1\] by building a PDF-JS model (see Section \[3.4\]), which, through semantic modeling, selectively whitelists those API methods known not to be vulnerable. As a result, any call to a non-whitelisted method is detected as malicious. To detect the second class of malware \[2\] that typically performs heap spraying to exploit memory corruption in the language runtime, we detect the creation of large values. Specifically, our semantic whitelisting detects the following potentially malicious program behavior:

- string length exceeding a predefined limit;
- object (array) size exceeding a predefined limit.

Finally \[3\], because SAFE-PDF is conservative, it needs to report any code as malware that exhibits unknown behavior, which makes it impossible to prove the absence of calls to vulnerable API methods or malicious program behavior. For example, calls to all \texttt{eval}-like functions that allow arbitrary strings to be interpreted as code are causes of unknown behavior. Indeed, the effect of calling an \texttt{eval}-like function is usually statically intractable. Similarly, calls to imprecise function objects (due to aliasing or function lookup using an unknown input value, e.g., a \texttt{⊤String} value) cause unknown behavior as well.
function PDF_Event() {
    this.type = \String
    this.name = \String
    this.change = \String
    this.changeEx = \String
    this.commitKey = \Number
    this.fieldFull = \Bool
    this.keyDown = \Bool
    this.modifier = \Bool
    this.rc = \Bool
    this.selEnd = \Number
    this.selStart = \Number
    this.shift = \Bool
    this.source = PDF_DOM_NODE
    this.target = PDF_DOM_NODE
    this.targetName = PDF_DOM_NODE.name
    this.value = \String
    this.willCommit = \Bool
}

Listing 6: Mock PDF event object used for analysis by SAFE-PDF

3.4 The PDF-JS model

Our analysis depends on a model that emulates the PDF environment during abstract interpretation. In our implementation, this model is based on a set of PDF documents containing benign JavaScript code, while relying on an API reference [3, 4] and being aware of reported vulnerabilities. Because SAFE-PDF is conservative, it always interprets calls to non-whitelisted functions as malicious. As a result, given valid JavaScript code, reducing the false positive rate of SAFE-PDF usually means extending the model. This is a straightforward and incremental process, and we show in Section 4 that it yields very good results in practice.

Unknown inputs can lead to unknown behavior during abstract interpretation, depending on how they are used. This can result in a non-malicious PDF document being classified as malicious (i.e., a false positive). To reduce false positives, we can optionally enrich the PDF-JS model with concrete metadata extracted from the PDF document. Inputs from the user and the host environment, however, cannot be statically known and thus always introduce unknown values during abstract interpretation. Depending on their origin, however, such non-deterministic values can be modeled with different levels of precision. For
example, an input from the user in a free text form field would be conservatively modeled as $\top_{\text{String}}$ while the runtime variable representing the operating system of the user can be modeled as a set of concrete values like $\{\text{‘WIN’}, \text{‘MAC’}, \text{‘UNIX’}\}$. In general, we can start with a model containing many conservative approximations and refine it where necessary.

Similar to JavaScript in web browsers, JavaScript code in PDF documents is largely event-driven, i.e., either triggered by system or user events. While we observed that most malicious code is executed when the PDF document is opened, JavaScript code may be placed in event handlers, where it is executed only on certain user actions (e.g., clicking a form field). Because we cannot exclude the possibility that an event handler might contain malicious code, SAFE-PDF must consider every event handler as an entry point. Moreover, because event handlers can have side effects that alter the computation of other event handlers, SAFE-PDF loops over all handlers and triggers them until a fixpoint is reached, indicating that it computed a suitable over-approximation for the whole program. Because event handlers receive an event object as argument and operate on its properties, our PDF-JS model defines a mock PDF event object that is passed to event handlers at analysis time. Listing 6 shows the mock PDF event object of our PDF-JS model. The right-hand side values $\top_{\text{String}}$, $\top_{\text{Bool}}$, $\top_{\text{Number}}$ represent abstract values. They stand for any string, any Boolean, and any number respectively. The $\text{PDF\_DOM\_NODE}$ abstracts nodes in the PDF Document Object Model (DOM) to which events can be attached.

4 Experimental Evaluation

To assess the effectiveness, and robustness of our technique, we implemented the SAFE-PDF tool, and investigated the following research questions:

**RQ1:** How does the precision, recall and accuracy of SAFE-PDF compare to state-of-the-art malware detection tools?

**RQ2:** How resilient is SAFE-PDF to parser confusion and mimicry attacks compared to state-of-the-art tools?

4.1 Experiment setup

SAFE-PDF is based on version 1.0 of the SAFE abstract interpretation framework for ECMA-Script [29]. We complement the original SAFE framework with (1) malware-specific analyses, (2) our semantic models for the PDF JavaScript and XFA environments, and (3) further modeling of the interactions between XML and JavaScript in XFA forms.

Experiments were conducted on a set of 14 306 benign and 9410 malicious PDF documents. Malicious samples were collected from VirusShare [12], a free online repository of malware samples, Contagio [2], and VirusTotal [13]. The benign benchmark set contains non-malicious PDF documents from Contagio, VirusTotal, PDF attachments from a public email dataset [14], as well as samples collected from the Web (from Google queries targeting PDF documents, e.g.
Table 2: PDF sample benchmarks used in this study

| Benchmark | Source     | #Files |
|-----------|------------|--------|
| Malicious | Contagio   | 7110   |
|           | VirusShare | 1206   |
|           | VirusTotal | 1094   |
| Benign    | Contagio   | 388    |
|           | EDRMv2     | 4434   |
|           | VirusTotal | 2137   |
|           | Web        | 7347   |

 fileType:PDF, test cases for PDF.js, the PDF-rendering engine of Mozilla [9], test cases for PDFium, the PDF-rendering engine of Chrome [8], and interactive documents from the pdfPictures [10] website. The samples from VirusTotal include the hard-to-extract set of documents [4] from [15], which we refer to in Section 3.1. All downloaded PDF documents were confirmed to be non-malicious using VirusTotal. Table 2 lists the different benchmark sets, the number of files they contain, and whether they contain malicious or benign samples.

To extract JavaScript code from PDF documents, we extended version 2015.1.4 of the Clean Content SDK [7], as described in Section 3.1. In the rare cases where a PDF document causes Clean Content to fail with an extraction error, we pre-process the document with a modified version of PDFBox [11] in an attempt to fix structural issues. Also, we syntactically remove one particular nonsensical but benign code fragment, a call to the non-existent jQuery.post method, from the extracted JavaScript code. Instances of this call were introduced into our web-sourced dataset by an obviously broken web-based PDF creator.

For our experimental evaluation, we set a 30 second timeout for the abstract interpretation step, after which SAFE-PDF rejects an input as malware. We run six instances of SAFE-PDF in parallel sharing eight cores of a Xeon E5-2.60GHz with 32GB RAM. On average SAFE-PDF takes less than 4 seconds to perform analysis (i.e., extraction and abstract interpretation) of a single PDF document.

The PDF-JS model in SAFE-PDF was incrementally extended to whitelist the subset of JavaScript functionality used by the benign samples in our benchmarks. Our experience suggests that supporting a new functionality in the PDF-JS model typically requires one to two lines of JavaScript code. In cases where a fine-grained model is needed, however, a developer can use all (sane) features of the JavaScript language.
Table 3: Numbers of true positives (TP), true negatives (TN), false positives (FP), false negatives (FN), and errors per tool

| Tool       | TP   | TN   | FP | FN | Errors |
|------------|------|------|----|----|--------|
| Slayer     | 9125 | 13877| 10 | 72 | 631    |
| Hidost     | 9215 | 14086| 6  | 31 | 377    |
| SAFE-PDF   | 9396 | 13920| 321| 7  | 72     |

Table 4: Precision, recall and accuracy of Slayer, Hidost, and SAFE-PDF

| Tool      | Precision | Recall    | Accuracy |
|-----------|-----------|-----------|----------|
| Slayer    | 95.62     | 99.23     | 97.89    |
| Hidost    | 97.72     | 99.67     | 98.95    |
| SAFE-PDF  | 96.06     | 99.93     | 98.34    |

4.2 RQ1: Comparison to state-of-the-art tools

To determine how SAFE-PDF compares to the state-of-the-art, we compared the detection rate of SAFE-PDF against two other publicly available PDF malware detection tools: PDF Malware Slayer [34], and Hidost [46].

PDF Malware Slayer first identifies keywords that are characteristic of benign and malicious documents from sets of benign and malicious PDFs. It then trains a Random Forests classifier on feature vectors obtained by computing the frequency of characteristic keywords in each document. To measure the precision, recall, and accuracy of PDF Malware Slayer, we perform a 10-fold cross-validation experiment with default parameters and report averaged results.

Hidost also uses a Random Forests classifier to identify malicious PDFs. Hidost mainly differs from PDF Malware Slayer in the way it extracts feature vectors from PDFs. Hidost builds feature vectors by extracting structural paths from PDF documents, where structural paths capture the embedding of PDF components. Because Hidost was initially trained and tested on a very large dataset, comprising more than 400,000 documents, it considers only structural paths present in at least 1000 documents by default. To accommodate our smaller dataset, we reduced this threshold to 200. Because Hidost also uses a random classifier, we perform a 10-fold cross-validation experiment and report averaged results.

Table 3 summarizes the output of PDF Malware Slayer, Hidost and SAFE-PDF on our benchmarks. In Table 3, the last column counts “errors”, i.e., when the tool failed to analyze a PDF document, either by failing silently, ignoring

[jQuery.post(Drupal.settings.basePath + 'jstats.php', {...})]

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Table 5: Parser confusion and reverse mimicry attacks

| Obfuscation                                                                 | Slayer | Hidost | SAFE-PDF |
|-----------------------------------------------------------------------------|--------|--------|----------|
| None                                                                        | ✓      | ✓      | ✓        |
| Flate compression, obj streams                                             | ✗      | ✓      | ✓        |
| Flate compression, R5 security handler                                     | ✗      | ✓      | ✓        |
| Flate compression, R5 security handler, obj streams                         | ✗      | ✗      | ✓        |
| Flate compression, R6 security handler                                     | ✗      | ✗      | ✓        |
| Flate compression, R6 security handler, obj streams, comment in trailer    | ✗      | ✗      | ✓        |
| JS encoded as UTF-16BE in hex string                                       | ✓      | ✓      | ✓        |
| JS encoded as UTF-16BE in hex string, flate compression, obj streams        | ✓      | ✓      | ✓        |
| JS encoded as UTF-16BE in hex string, flate compression, R5 security handler, obj streams, comment in trailer | ✗      | ✓      | ✓        |

Reverse mimicry attack + parser confusion                                    | ✗      | ✗      | ✓        |

it, or by exiting with an error. The errors in SAFE-PDF all stem from heavily broken PDF documents that cause our code extractor to fail.

Table 4 lists the precision, recall, and accuracy of all of the investigated tools. Equations (1) to (3) show the corresponding formulas, where $TP$, $FP$, $TN$ and $FN$ stand for true positive, false positive, true negative and false negative respectively.

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (1)
\]
\[
\text{Recall} = \frac{TP}{TP + FN} \quad (2)
\]
\[
\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (3)
\]

All of the evaluated tools failed to analyze some PDF documents, either through silent failure (e.g., not analyzing the document) or by exiting with an error. Because SAFE-PDF is conservative, we treat any extraction failure as an indication that the document is malicious. To perform a fair comparison, we treat errors in other tools as malicious reports too.

Going back to our initial research question, the metrics presented in Table 4 show that SAFE-PDF achieves comparable precision, recall and accuracy with state-of-the-art PDF malware detectors.
4.3 RQ2: Resilience to evasion attacks

To evaluate the resilience of SAFE-PDF to evasion, we evaluated SAFE-PDF on malicious PDF documents that were specifically designed by the authors of [16] to evade detection by performing parser confusion and reverse mimicry attacks [33]. Table 5 shows how many evasive variants were detected by Slayer, Hidost, and SAFE-PDF. Interestingly, while parser confusion attacks were designed to primarily target approaches that rely on JavaScript code extraction, Table 5 shows how tools that rely on structural PDF features are also affected. Indeed, all malicious documents containing R5 handlers evaded Slayer, while documents containing R6 security handlers evaded both Slayer and Hidost. SAFE-PDF caught all evasive variants based on parser confusion.

Furthermore, because SAFE-PDF statically analyzes program behavior, it is oblivious to reverse mimicry attacks, which are known to be very effective against structure-based approaches [33, 45, 50]. Indeed, as shown in Table 5, SAFE-PDF could detect the malicious payload, even in the presence of both reverse mimicry and parser confusion attacks.

5 Discussion

In this section, we discuss open challenges for JavaScript-based PDF malware detectors and present a threat model for SAFE-PDF together with possible attacks.

5.1 JavaScript-based malware detection

All JavaScript-based PDF malware detectors need to extract the JavaScript code from the PDF document either dynamically through an instrumented PDF viewer or statically using a stand-alone extractor. As highlighted in [16], however, because the PDF specification is very complex, extracting JavaScript code from PDF documents is far from trivial. While we addressed all known limitations of existing extractors, static analysis of JavaScript remains very difficult. In the following paragraphs, we discuss the challenges that SAFE-PDF faced during analysis of our benchmark set.

First, because SAFE-PDF is designed for high recall, we manually investigated the 7 false negatives reported in Table 3 and confirmed that all of them stem from documents that contain benign JavaScript only. Specifically, 4 PDFs trigger a JavaScript alert message that encourages the user to open a malicious file attachment, 2 PDFs contain benign form manipulation code only, and 1 PDF contains a malicious payload that is embedded in a JavaScript function that is never called.

Next, we investigated the causes of malware reports in the benign and malicious benchmark sets to learn what causes the analysis to classify a sample as malware. Table 5 breaks down the causes and shows their proportions relative to all malware reports in each of the two sets.
Table 6: Causes of malware reports by SAFE-PDF

| Benchmark | Report Cause        | Count | Percentage |
|-----------|---------------------|-------|------------|
| Benign    | Unexpected behavior | 145   | 37.56%     |
|           | Malicious behavior  | 129   | 33.42%     |
|           | Extraction error    | 65    | 16.84%     |
|           | JS parsing error    | 41    | 10.62%     |
|           | Fixpoint not reached| 6     | 1.55%      |
| Malicious | Malicious behavior  | 8510  | 91.20%     |
|           | Unexpected behavior | 564   | 6.04%      |
|           | JS parsing error    | 172   | 1.84%      |
|           | Fixpoint not reached| 78    | 0.84%      |
|           | Extraction error    | 7     | 0.08%      |

```plaintext
1. `qwe = ('nhsthn', 'ntrht').substr;
2. `var g = qwe();
```

Listing 7: Example of unexpected behavior exhibited by malware (excerpt)

“Malicious behavior” refers to a whitelist violation, e.g., creation of a large object, or a call to a vulnerable API method or to `eval`. As expected, it is the top cause for identifying *true positives* in the “Malicious” benchmark set. In the “Benign” set, “Malicious behavior” indicates the use of a (historically) vulnerable API in a non-malicious way and such cases are responsible for approximately a third of *false positive* reports. We plan to address some of these false reports in the next version of SAFE-PDF by inspecting the abstract values that reach vulnerable APIs. I.e., we will not report PDFs where abstract interpretation can prove the absence of a malicious payload reaching a vulnerable API.

The remaining causes for malware reports, are instances of SAFE-PDF being conservative. In both benchmark sets, the majority of conservative reports can be attributed to broken JavaScript code (“unexpected behavior” and JS parsing error) and PDF documents broken beyond repair (“Extraction error”). Looking into the benign documents for which extraction fails, we found that the majority (57) come from the hard-to-extract set, of which 13 were broken during HTTP download (before being submitted to VirusTotal), and only two can be opened with Acrobat Reader DC 2018.011. A small fraction of malware reports is caused by abstract interpretation aborting due to lack of precision or timing out (“Fixpoint not reached”). In all these cases, we cannot safely over-approximate the behavior of JavaScript code and thus have to classify it as malicious.

“Unexpected behavior” refers to cases where SAFE-PDF encounters semantically incorrect JavaScript code, such as property loads from undefined variables, calls to undefined functions, and other behavior that should not occur in a *functionally correct* PDF document.

However, we cannot simply conclude that these are honest mistakes (bugs)
that can safely be ignored, especially not in the context of JavaScript execution, where engines are known for their lenient and non-standard ways of handling errors. Indeed, obvious bugs also occur in malicious code: Listing 7 shows an example of malware being identified through unexpected behavior before its actual malicious behavior is detected. At line 1, the comma operator evaluates each of its operands (from left to right) and returns the value of the last operand [6]. Then, `qwe` is assigned the `substr` function, which is not bound to any receiver object at this point in the program. Next, `qwe` is called at line 2 without a receiver object, resulting in an exception being thrown. SAFE-PDF correctly identifies the call `qwe()` as faulty, and conservatively reports the input as malware. We confirmed that this code snippet raises an exception in recent JavaScript engines (e.g., Node.js v8.1.4).

After manual inspection, we concluded that the high number of “unexpected behavior” in the benign benchmark set is due to semantically incorrect code that either has not been properly tested or maintained or even ended up inside a PDF document by accident (e.g., code that only makes sense in the context of a website). As described in Section 4.1, we handle one frequently occurring instance falling into the last category, but have not addressed all issues of this kind due to time constraints. The existence of such erroneous code can be explained by PDF viewers silently ignoring JavaScript errors.

5.2 Threat model and possible attacks

In this section, we present a realistic threat model and explore potential attacks against SAFE-PDF.

We assume an attacker is trying to have malicious JavaScript code inside a PDF, originally reported as such by SAFE-PDF, misclassified as benign. The attacker can manipulate the PDF document however they want. We further assume that the attacker has black-box access to SAFE-PDF and can observe the outcome report only (e.g., benign or malicious). We also assume that the attacker can submit an unlimited number of PDFs to SAFE-PDF. We further assume that the attacker knows that SAFE-PDF uses abstract interpretation and a model of the PDF viewer runtime environment, but has no access to it. Because we are interested in attacks against SAFE-PDF and not the JavaScript code extractor, we finally assume that all the JavaScript code in the PDF can be extracted without error.

First, because SAFE-PDF analyzes JavaScript code only, it is oblivious to mimicry attacks [33, 45] that alter the structure of the PDF document without altering the malicious behavior of its payload. In [50], the authors showed how they could use genetic algorithms to automatically alter the structure of 500 malware samples so that they successfully evade Hidost [46] and PDFRate [43].

On the other hand, SAFE-PDF might be vulnerable to the following four threats: (1) zero-day vulnerabilities that only exhibit whitelisted behaviors; (2) discrepancies between the concrete semantics of a PDF viewer’s JavaScript engine and the abstract semantics of the SAFE abstract interpreter; (3) unsound approximations in the PDF-JS model; and (4) novel parser confusion attacks.
In the following paragraphs, we explore each threat in more detail.

Obviously, zero-day vulnerabilities that are not exploited using JavaScript are out of scope for SAFE-PDF. Otherwise, for SAFE-PDF to miss a JavaScript-based exploit, the exploit must use a function that has been whitelisted. Indeed, if the vulnerability exploits any function that is not whitelisted, SAFE-PDF will interpret the function call as “unexpected behavior”, and conservatively report the PDF as malware. Hence, to exploit a zero-day vulnerability, the attacker has to find a vulnerability in a whitelisted function, and ensure that the payload that exploits the vulnerability does not exhibit any known malicious behavior (e.g., heap spraying). While not impossible, this attack is very unlikely.

The abstract semantics used in SAFE-PDF is currently based on the ECMAScript 5.1 language specification and thus might differ from the ECMAScript version supported in PDF viewers. However, exploiting discrepancies between the abstract and concrete semantics is far from trivial. First, using language features that are not supported by the abstract semantics of SAFE-PDF will result in undefined behavior and the PDF being reported as malware. Therefore, the attacker must identify semantic discrepancies that are due to either implementation bugs in the viewer or in SAFE-PDF and exploit them. This type of attack is also very unlikely, but not unheard of [47].

Because SAFE-PDF relies on the analysis being conservative, it makes it vulnerable to unsoundness bugs in the PDF-JS model. Indeed, we assume that SAFE-PDF strictly over-approximates all possible runtime execution paths, and every unsoundness bug in the PDF-JS model introduces an opportunity for an attacker to hide malicious behavior behind an under-approximation. Because the PDF-JS model was built manually, it is prone to human errors and makes SAFE-PDF vulnerable to unsoundness bugs. A superior, but far more costly solution would be to automatically infer the PDF-JS model based on a set of concrete PDF viewer applications.

Finally, because the PDF specification is very complex, yet vague, and PDF viewers often deviate from it, an attacker could try to trigger new parser confusion attacks. However, because SAFE-PDF treats extraction errors conservatively, and reports malware on extraction failures, an attacker would have to find a way to hide his payload from the extractor without causing an extraction failure. While such an attack would require a dedicated attacker, we believe it is the most serious threat to SAFE-PDF.

6 Related Work

In this section, we give a brief overview of existing techniques for PDF malware detection (a detailed survey and taxonomy can be found in [36]) and explain how they compare to our analysis approach. We also discuss semantic malware detection and JavaScript static analysis, which are related fields of research.
6.1 Static PDF Malware Detection

The first group of approaches proposed in academic literature that we consider as related work analyzes a PDF document as a whole and does not analyze any embedded JavaScript code. These techniques are categorized as Metadata Analysis in [36]. Three properties of PDF documents are being used to derive a fingerprint: document structure, metadata fields, and document content. The related approaches [43, 34, 33, 37, 46] rely on a set of known malicious PDF documents as training data to identify documents with a similar fingerprint as malware.

Caradoc [22] is an exception to the above. Endignoux et al. focus on weaknesses in the PDF standard related to document structure. These can be exploited to attack the parser implementation of a PDF viewer, e.g., to achieve a denial-of-service attack.

Comparison to our approach When aiming to identify malicious PDF documents that exploit vulnerabilities in the JavaScript runtime of a PDF viewer, our approach is more powerful, since it does not depend on a training set and is not susceptible to mimicry attacks.

6.2 Static PDF-JavaScript Malware Detection

Similar to SAFE-PDF, the related work in this section performs a static analysis of JavaScript code embedded in PDF documents. However, unlike us, but similar to the approaches in Section 6.1, they identify malicious JavaScript based on its similarity to known malicious samples.

PJScan [28] and Vatamau’s approach [49] both perform lexical analysis of the extracted JavaScript code, and use machine learning techniques to classify the code as malicious or non-malicious. In [25], the authors describe of use NiCad, an existing tool for detecting code clones, for the same purpose.

Comparison to our approach The approaches above are always less powerful than our static analysis, because they restrict themselves to lexical analysis of JavaScript code and do not take its semantics into account. Both approaches rely on the similarity of (possibly obfuscated) JavaScript code to known malicious code, and might be defeated by novel obfuscation patterns.

6.3 Dynamic PDF Malware Detection

All approaches in this section rely on the execution of PDF-embedded JavaScript code, either in its native or synthetic runtime environment, for analysis of its behavior.

MDScan [18] and PDF Scrutinizer execute the extracted JavaScript code in a synthetic environment, and aim to detect the presence of malicious payload (so called shell code) in the execution state (as part of strings and variables). PDF Scrutinizer applies further heuristics to identify execution patterns typical of malicious code. Other uses of dynamic analysis proposed in literature do not compare directly to our approach because they are not suitable as stand-alone
analysis tools. For example, MPScan \cite{32} and FCScan \cite{42} propose to integrate with the PDF viewer software, and ShellOS \cite{44} integrates with the underlying operating system to detect attacks (on-the-fly) during runtime.

**Comparison to our approach** Dynamic analysis techniques are prone to miss feasible program behavior, because actual execution depends on inputs and the execution environment. In the context of malware analysis, the malware author can actively target a specific environment, thus preventing the detection of malicious behavior in the analysis environment. For example, the de-obfuscation of exploit code might be triggered only in a specific target environment. This undermines the dynamic analysis-based detection techniques described above. Furthermore, unlike our static analysis-based approach, none of the existing dynamic analyses tries to exhaustively explore all possible behavior of the JavaScript code.

6.4 Semantic-Based Malware Detection

Semantic approaches use techniques from program analysis and formal methods to lift malware detection from syntactic features to the level of program semantics. For example, semantic malware detectors use theorem proving \cite{18} or model checking \cite{26} to match a program, based on its semantic properties (e.g., instruction sequences), against a template derived from actual malware. In general, these approaches are more powerful than signature matching, but still prone to evasion by obfuscation. Preda et al. \cite{40} introduce a theoretical framework for semantic malware detection using abstract interpretation. It assumes the availability of perfect oracles, which return perfect information related to a program’s semantic properties or behavior (e.g., its exact control flow), and shows that whether a detector can overcome a particular obfuscation, depends on the chosen abstract semantics, i.e., the right level of abstraction. More recently, \cite{39} uses statistical analysis of program behavior recorded during dynamic analysis to identify malware. This avoids the difficulty of static reasoning, but introduces the possibility of dynamic analysis missing malicious behavior.

**Comparison to our approach** Our work can be seen as an instance of malware detection based on Preda’s interesting actions [40, Section 5]. However, we use a policy to whitelist acceptable behavior and thus do not have to rely on actual malware as templates for malicious behavior. Furthermore, our conservative strategy enables us to have a practical malware detector in the absence of ”perfect oracles”

6.5 Web JavaScript Malware Detection

The primary vector for JavaScript-based malware remains web browsers. Prominent work in this area includes Nozzle \cite{41}, Zozzle \cite{20}, and Rozzle \cite{27}. Nozzle is a dynamic, in-browser approach that uses heap sampling to detect heap-spraying attacks. Similar to other dynamic approaches, Nozzle requires an instrumented environment, a browser in this case, and induces a performance overhead. Zozzle is a mostly static approach that reduces the performance overhead of Nozzle.
It uses a Naive Bayes classifier, trained on syntactic features of the JavaScript code, to classify programs as benign or malicious. Zozzle relies on the browser’s JavaScript interpreter to de-obfuscate the code before performing feature extraction and classification. Because both Nozzle and Zozzle rely on an instrumented browser environment, both approaches are susceptible to miss malware that exhibits malicious behavior on other environments only. Rozzle addresses this limitation through the use of symbolic execution to emulate different runtime environments in a single instrumented browser.

Comparison to our approach Through the use of abstract interpretation, our work detects heap spraying (like Nozzle), performs de-obfuscation (like Zozzle), and simulates different runtime environments (like Rozzle) entirely statically. Furthermore, SAFE-PDF can statically reason about the runtime behavior of the code, making it more powerful than syntax-based approaches.

6.6 JavaScript Static Analysis

The dynamic nature of JavaScript and its lack of static guarantees make it a difficult target for static analysis. This shortcoming is magnified by the inherent complexity of the most common use of JavaScript, as client-side web application code running inside an equally complex browser environment. At this point in time, state-of-the-art tools based on dataflow analysis [21] or precise abstract interpretation [24, 30] can successfully analyze libraries and small applications, but do not scale to real-world JavaScript code in general.

We are nonetheless successful in using the very same techniques to analyze JavaScript in the context of malware detection. This is due to two reasons: (1) JavaScript code embedded in PDF documents is not as complex as code written for the web; (2) malware detection warrants a conservative strategy where unknown behaviors are interpreted as malicious.

7 Conclusion

We presented a novel approach for detecting malicious JavaScript embedded in PDF documents that uses abstract interpretation—a static program analysis technique—at its core. Using the results of abstract interpretation in a conservative manner, our malware detection is designed for and achieves very high recall. Furthermore, with an average runtime of less than 4 seconds per document, we showed how traditionally “heavy-weight” abstract interpretation tools can be used in practice, given the right abstraction (e.g. the PDF-JS model). By addressing all known limitations of existing PDF JavaScript code extractors, we showed that PDF malware detectors that analyze the embedded JavaScript code can be used in practice. We also showed how SAFE-PDF resists obfuscation, parser confusion, and mimicry evasion attacks that subvert existing malware detector tools. Finally, through comprehensive experimental evaluation, we have shown that our approach achieves almost perfect recall, and comparable precision to state-of-the-art tools.
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