Looking for non-compliant documents using error messages from multiple parsers

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***Abstract*—Whether a file is accepted by a single parser is not a reliable indication of whether a file complies with its stated format and presents minimal risk to the user. Bugs within both the parser and the format specification mean that a compliant file may fail to parse, or that a non-compliant file might be read without any apparent trouble. The latter situation presents a significant security risk, and should be avoided. This paper suggests that a better way to assess format specification compliance is to examine the set of error messages produced by a set of parsers rather than a single parser. If both a sample of compliant files and a sample of non-compliant files are available, then we show how a statistical test based on a pseudo-likelihood ratio can be very effective at determining a file's compliance and safety. Our method is format agnostic, and does not directly rely upon a formal specification of the format. Although this paper focuses upon the case of the PDF format (ISO 32000-2), we make no attempt to use any specific details of the format. Furthermore, we show how principal components analysis can be useful for a format specification designer to assess the quality and structure of these samples of files and parsers. While these tests are absolutely rudimentary, it appears that their use to measure file format variability and to identify non-compliant files is both novel and surprisingly effective.**

I. Introduction

Modern file formats are often quite complex, yet the formal specifications for some common formats can be ambiguous or confusing. A single parser is therefore not a reliable arbiter of file format compliance: it may incorrectly deem a compliant file as non-compliant, or conversely it may parse a non-compliant file (perhaps with disastrous consequences). For widely used file formats, there are usually several readily available parsers. It is natural to ask if a statistical approach that leverages multiple existing parsers – but is otherwise format agnostic – might suffice to discriminate between compliant and non-compliant files.

This paper describes an exploratory technique and a statistical test for identifying files whose parser behavior is unusual. The techniques presented perform no direct inspection of the contents of any file. Certainly the content of a given file plays an important role in its usage, but the techniques of this paper only "see the content" through the lens of an ensemble of parsers. Our techniques are therefore also well-suited to assessing the background variability of parser behavior on different classes of files. Since our approach aims to leverage existing parsers in their unmodified, uninstrumented state, the statistical techniques could be used on many different file formats without much alteration.

For the purpose of this paper, a *file format* consists of a set of compliant files with no explicitly malicious content and a set of files that are either non-compliant or malicious (or both). Formal specifications specify properties that compliant files must have, but formal specifications need not be present for there to be an agreed-upon file format. Furthermore, formal specifications may have limited utility in determining whether a file is safe to use. This paper presents a new statistical test, which we call *the Bernoulli misclassification test*, that determines whether a given file is more representative of the compliant and benign files or of the non-compliant files. In order to perform such a test, we require *samples* of both sets: namely a sample of files that are both benign and compliant, and a sample of files which are either non-compliant or not benign. For brevity, we we usually say "compliant" instead of "benign and compliant", and use "non-compliant" in a similar way.

Because realistic samples of files are large and difficult to curate, the sample of compliant files may be contaminated with files that should not be considered as compliant. Conversely, there may be some files in our sample that are erroneously marked as non-compliant. Our statistical test is designed to identify these *misclassified* files.

The foundation of any statistical approach necessarily relies on both data coverage and sufficient sampling to ensure good estimation of the relevant governing parameters. Our approach here is no different, as the basis of the statistical test relies upon parameters estimated from the data in order to be effective. Given that our approach is format agnostic, it is reliant upon not only a good sample of files but also a good sample of parsers.

To test our approach, this paper presents a case study using the PDF specification (ISO 32000-2), because there are many extant open source parsers with distinct underlying codebases. The test data presented in this paper were developed by an independent test and evaluation team in support of the "DARPA SafeDocs Evaluation 2" exercise. (See the Acknowledgments section for a reference to the data curators.) The data consist of two datasets corresponding to the samples explained above: a sample of largely compliant files and a sample of largely non-compliant files. Each of the files (in both samples) was manually tested for compliance, so that the performance of our statistical test could be determined. While the fraction of misclassified files in the two datasets differ, the two datasets were sufficiently clean so as to allow reliable enough parameter estimation for our statistical test.

While the statistical methods discussed in this paper are absolutely rudimentary, they did locate files that were truly misclassified with surprising effectiveness. Although these statistical methods surely do not suffice on their own for all purposes, they are easy to deploy and understand. We suggest that they ought to be part of the format hacker's toolbox. Specifically, an organization that has to scan many PDF documents for potential issues could use the Bernoulli misclassification test with a fixed collection of parsers. The renderings, text extractions, and the like can be discarded without further examination. Based on the error message outputs from the set of parsers, our Bernoulli misclassification test gives a "safety score" that determines whether the file should be passed or flagged as potentially dangerous. Because the renderings are not required, nor are error messages interpreted, the testing can be completely sandboxed aside from `stderr`. As a result, many of the potential security exploits are blocked as a matter of course.

II. Historical context

There appears to be very little work in analyzing file format compliance using statistical tools. In contrast to what we present here, most format compliance assessment that the author is aware of is performed using techniques common in compiler theory. For instance, [1], [2] explain the typical approaches.

The closest connections to this paper appear to be various techniques for identifying malware using the structure of file *contents* rather than responses to those contents. For instance [3] looked for statistical features characteristic of malware present in headers of executable files. Using the structure of file contents, ransomware can be classified statistically [4], [5]. Similar to our use of error messages on files, the distribution of API calls can be useful in identifying malware as it executes [6]. Other behavioral indicators, such as performance counters [7] can be useful as well. However, it appears that the use of statistical tools to determine file format compliance is completely unanticipated and novel.

In a few cases, statistical methods are useful in identifying file formats that might be difficult to archive or curate [8]–[10].

III. Data description

This paper focuses on the analysis of PDF files, whose format is determined by the PDF specification (ISO 32000-2). It is recognized that the specification is ambiguous in places, and that there are many proprietary extensions to the specification. Furthermore, the standard does not endorse a reference implementation, even though the Adobe PDF viewer is commonly taken as such. Because of this, many "PDF files" may not be completely compliant or may be close enough to compliance to parse correctly. On the other hand, bugs within the parsers may cause them to accept non-compliant files.

To explore these issues, the test and evaluation team collected a corpus of "PDF files" into two datasets: `internet_sourced` and `dangerous` comprising a total of 10000 files. The `internet_sourced` set is a subset of Common Crawl [11], while the `dangerous` set is a hand-curated collection of various non-compliant files found in the wild (from Common Crawl), malicious files created by the test and evaluation team, and non-malicious non-compliant files created by the test and evaluation team.

Within each dataset, the files were manually determined to be either "valid", that is that they are compliant with the PDF specification and are harmless, or "rejected", which means that they fail to comply with the specification or contain malicious aspects. Therefore, there were two stages to the data curation: (1) the automated process of selecting files for the two sets, followed by (2) an extensive manual marking of each file individually by an expert as benign and compliant ("valid" in what follows), or non-compliant or malicious (both are "rejected" in what follows). Due to the complexity of the PDF format specification, a panel of experts was convened to adjudicate a handful of difficult-to-classify files that were discovered during stage 2 (the manual marking process). In total, there were around two dozen such contentious files considered by the panel. Each contentious file was discussed individually by the panel, and its contents were examined at the byte level (if necessary) to verify its marking. This manual marking process is essential because some of the malicious files turned out to be judged as harmless by the experts. Although these files were apparently intended to be malicious by their authors, they were judged by the experts to be ineffective in their malicious goals. Conversely, some files listed in the `internet_sourced` set were judged to be "rejected" by the experts.

In this paper, we use the term *misclassification* to refer to files that received different determinations between the two stages of curation. Specifically, a missclassified file in `internet_sourced` is one which is "rejected", while conversely a misclassified file in `dangerous` is one which is "valid".

It is worth mentioning that there are policy implications for the choice to mark a benign, non-compliant file as "rejected". Indeed, many parsers will attempt to repair non-compliant files so that they can be rendered. Marking these files as "rejected" cautions that this is potentially dangerous from a security standpoint unless the standard dictates how the repairs should be made. Absent this guidance, different parsers may perform different repairs, resulting in different behaviors. Because a malicious file can be crafted to exploit these differences, it was deemed safer to mark all such files as "rejected".

In this paper, we treat the "valid" or "rejected" determinations as experimental *ground truth* for the files. Since our Bernoulli misclassification test did not use these determinations, we were able to use them to estimate the test's accuracy (discussed in Section V). The overall statistics of

TABLE I
COUNTS OF FILES IN THE internet_sourced AND dangerous DATASETS

Dataset	Valid	Rejected	Total
internet_sourced	7206	1794	9000
dangerous	488	516	1000
Totals	7694	2306	10000

both datasets are shown in Table I. A standard χ^2 test reveals that the differences in compliance between the two datasets is statistically significant ($p < 0.0001$). Although it is far from true, we took the internet_sourced set to be our sample of predominantly compliant files, and we took the dangerous set to be our sample of predominantly non-compliant files. The significant difference between the two sets of files is precisely what our misclassification test leverages in order to find misclassified files.

Rather than looking at the contents of each file, we reasoned that there are already many extant parsers that do just that. Since PDF renderings can differ in many irrelevant ways, it seemed wise to simply focus on the textual output from the parsers. This enables a uniform, standardized way to collect information from parsers rather than relying on potentially subjective metrics on the rendered output.

Therefore, we ran each file through each of a large collection of parsers shown in Table II. Since several of the parsers can be run with different options, Table II lists a distinct row for each of these sets of options. For instance, there are three different modes for caradoc that we chose to use, namely

1) `caradoc extract` *file.pdf*
2) `caradoc stats` *file.pdf*
3) `caradoc stats --strict` *file.pdf*

These appear as the first three rows in Table II. The number of distinct messages captured from each parser is shown as the last column of Table II. Moreover, as described below, the distinct messages produced by each parser correspond to rows of the matrices shown in Figure 1. The second and third columns of Table II associate rows in Figure 1 with each of the parsers. So for instance, the dark horizontal bands at row 700 in Figure 1 correspond to the output of pdfminer.

We selected these parsers based on their easy availability and with the understanding that many of them do not share code. This latter fact ensures that places within the PDF specification that are ambiguous may receive several interpretations by different parsers. The output to stderr from each parser was collected for each file, and a set of 955 regular expressions were used to identify which error messages had occurred for each parser-file pair (see Table II). Many parsers write to stderr while continuing to process a file, making it straightforward to collect all of its output regardless of its exit status. Furthermore, failure of a parser to terminate within a reasonable amount of time (several minutes) was recorded as the presence of a distinct timeout message.

As an example, the 1000-th file in the internet_sourced dataset was considered "valid," yet produced 7 distinct messages:

58	`caradoc_extract: Type error : Invalid variant type`,
254	`caradoc_stats: Type error : Invalid variant type`,
393	`caradoc_stats_strict: PDF error : Syntax error`,
589	`hammer`: uncategorized error,
683	`pdfium`: uncategorized error,
910	`xpdf_pdfinfo`: uncategorized error, and
911	`xpdf_pdftops`: uncategorized error.

It is important to recognize that our method *makes no attempt to interpret* the semantic meanings of these error messages. Instead, we are merely interested in the statistics of the co-occurrence of these messages.

The data can be tabulated as an integer *relation matrix*, in which each row corresponds to a particular regular expression (an *error message* in what follows) and each column corresponds to a particular file. Each entry records the number of times a given error message occurred for each file. Return values to the operating system were not collected, though if desired these could have simply been added as additional "messages" as rows in the relation matrix.

We constructed two relation matrices, one for internet_sourced (Figure 1(a)) and one for dangerous (Figure 1(b)). Each relation matrix has the same rows (955 distinct error messages, as shown in Table II) but different numbers of columns (9000 for internet_sourced and 1000 for dangerous).

Continuing our example of the 1000-th file in internet_sourced, this file corresponds to the 1000-th column of the relation matrix in Figure 1(a), and has 1s in rows 58, 254, 393, 589, 683, 910 and 911, because each of these messages occurred exactly once. It has 0s in all other entries in that column.

The horizontal dark bands present in both relation matrices shown in Figure 1 correspond to error messages that could not be categorized easily: not syntax errors or other specific malformations. Some parsers produce these kind of messages more frequently than others, which explains why some portions of the matrices show a greater prevalence of dark horizontal bands than others.

Although there is some apparent structure visible in Figure 1, namely the dark horizontal bands, it is difficult to discriminate any column-by-column differences. These differences are indeed present, but require more sophistication to extract. That statistical analysis forms the basis of most of this paper.

IV. PRINCIPAL COMPONENTS ANALYSIS

To build some intuition about the structure of the relation matrices, let us develop a dimension-reduced visualization of the columns (files) of both relation matrices shown in Figure 1. While there are many possible techniques for dimension reduction, principal components analysis is generally the easiest to construct and to interpret. To better understand the structure of the data, we will incorporate the ground truth as part of the

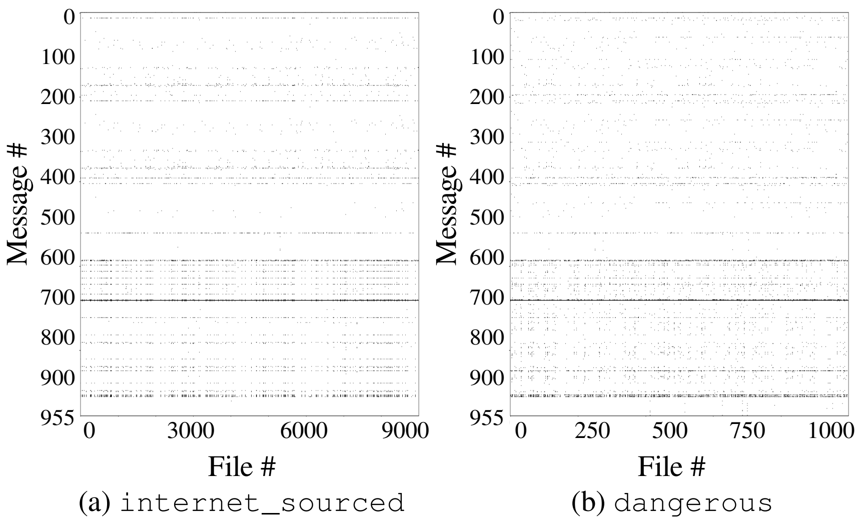


Fig. 1. The relation matrix for (a) internet_sourced, (b) dangerous. Rows correspond to the error messages listed in Table II. Columns correspond to files. In each matrix entry, white indicates no error, black indicates error.

visualization. This will help explain the performance of the Bernoulli misclassification test statistic in the next section.

Principal components analysis is a way to render a high dimensional data set that shows the "most important" dimensions and suppresses the rest. It is therefore a convenient way to visualize data that are formatted as a set of points in $\mathbb{R}^n$ where n is large. The output of principal components analysis is a scatter plot in which the axes are chosen as the linear combinations of rows yielding the largest variance. These axes are called the principal vectors, and are sorted from largest variance to least variance. In our analysis, the largest three principal vectors were used because they represented the majority of the variance in the data.

To apply principal components analysis, we reinterpret our tabular data as a discrete subset of $\mathbb{R}^n$ (a point cloud) in which columns (files) are points, rows (messages) are components of the coordinates for each point. In both datasets, there are $n = 955$ messages. Because a file exhibits an error or not, the components are all either 0 or 1. Although one might argue that this could result in quantization error, many interesting features are nevertheless visible in the two datasets. A look at the last column of Table II indicates that a small minority of the parsers contribute an outsized proportion of the error messages. Principal components analysis normalizes against this disparity as a first step, so it need not concern us further.

Figure 2 shows the principal components analysis plots for both datasets. Points in both plots are colored according to the ground truth so that a point corresponding to a "valid" file is black, and a point corresponding to a "rejected" file is gray. The most striking difference in the principal components analysis plots is that the internet_sourced dataset is apparently much more "clumpy" than the dangerous dataset. The three dense clusters in Figure 2(a) consist entirely of "valid" files, with most of the "rejected" files in the internet_sourced data appearing as a "haze" of files outside of those clusters. Although the cause of these three dense clusters of "valid" files cannot be determined solely from the relation matrix – which files are accepted by which parsers – we hypothesize that these clusters correspond to popular tool chains for creating PDF files.

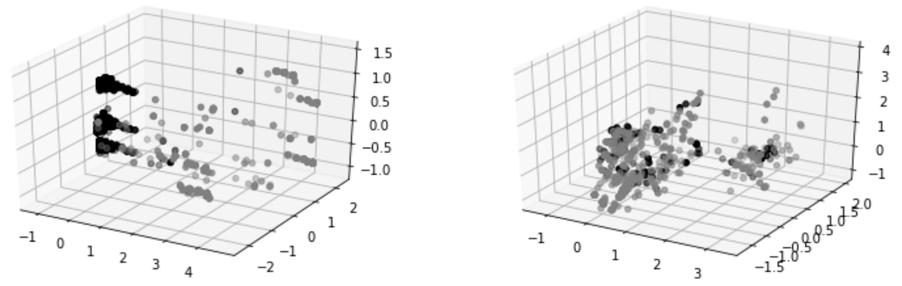
In stark contrast, the dangerous set shown in Figure 2(b) contains two loose clusters that are mixed "valid" and "rejected" files. Intuitively, if one is looking to identify "valid" files, one would have a much harder time doing this with the dangerous set, so we might argue that the apparent signal-to-noise ratio is much lower in the dangerous set.

Principal components analysis can be misleading if only a small fraction of the overall variance in the data is explained by the first few principal vectors. It is easy to determine if this problem is occurring – simply plot the variance in the data explained by each principal vector. This is called a Scree plot [12], and is shown in Figure 3. In both datasets, the Scree plots decrease quite rapidly over the first few principal vectors. This shows that principal components analysis reliably represents the data.

We can conclude that if one is generally working with files that are naturally occurring (like the internet_sourced set), one probably does not need to dig too deeply to determine whether a given file is valid or not. The rest of this paper buttresses this claim by providing a statistical test that does just that. On the other hand, if one is routinely handling files that test the limits of their format (like the dangerous set), statistical analysis alone will likely be insufficient to determine which files are valid. A deeper format-aware analysis would be necessary in that case.

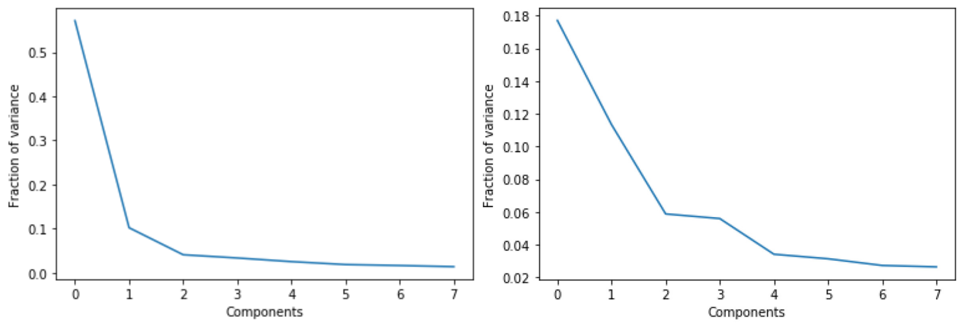
V. Bernoulli likelihood ratio misclassification test statistic

In order to determine file validity implicitly – by consulting parser behavior rather than the specification itself – we need



(a) `internet_sourced` (b) `dangerous`

Fig. 2. Principal components plots for (a) `internet_sourced` and (b) `dangerous`. Black indicate “valid”, and gray indicates “reject”. The axes correspond to the three principal vectors, and so are not plotted on the same scale.



(a) `internet_sourced` (b) `dangerous`

Fig. 3. Scree plots for (a) `internet_sourced` and (b) `dangerous`.

exemplars of parser behavior on typical compliant and non-compliant files. We propose to use the fact that the two datasets have rather different statistics (Table I) with the majority of files in `internet_sourced` being “valid” while a (slim) majority of files in `dangerous` are “rejected”. We can attempt to identify files in `internet_sourced` that exemplify the parser behavior present in the `dangerous` dataset – these files probably should be treated with suspicion, and are perhaps not “valid.” Conversely, files within the `dangerous` set that behave more like those in `internet_sourced` may well be “valid.”

A file is *misclassified* if the set of messages it produces is more characteristic of the other dataset but not the one in which it is presently found. Given our experiemtnal design, this is quite simply to state by reference to Table I. There are 1794 misclassified files in the `internet_sourced` set and 488 misclassified files in the `dangerous` set. Our task is simply a matter of identifying these! We suspect that such a misclassified file will have a collection of error messages that is unusual when compared to the others in that dataset. We estimate the probability that each error message occurs in each dataset, and estimate a likelihood for each file assuming the error messages are independent. Since both datasets have the same error messages, we can *also* estimate the likelihood that the file came from the other dataset. A likelihood ratio statistic can thereby detect when a file is misclassified, because it is more likely to belong to the other dataset.

Since we cannot assume that the occurrence of any given set of error messages is statistically independent, it is difficult to write a proper likelihood function. To that end, we use a *pseudo-likelihood*, which makes the incorrect assumption that error messages are statistically independent [13]. On the other hand, this assumption merely reduces the sensitivity of the test without producing extra outliers. The pseudo-likelihood assumption trades *recall* to get better *precision*. As such, pseudo-likelihoods are useful for classification but not for uncertainty quantification.

For the Bernoulli misclassification test, we assume each error message is governed by a Bernoulli distribution, which means that it either occurs or does not occur. Multiple instances of the same error are ignored. The test assumes that each error message occurs with a probability that depends on the dataset (either `internet_sourced` or `dangerous`). When a parser processes a given file, sometimes it produces multiple copies of the same error message. This can happen if the parser attempts to repair a slightly non-compliant file as it proceeds, for instance. If this happens, then the Bernoulli distribution is no longer valid because it assumes at most one instance of a given error message. Ultimately, the performance of the Bernoulli misclassification test was good even though

TABLE II
ERROR MESSAGE COUNTS AND ROWS PER PARSER

Parser	First row	Last row	Total messages
caradoc_extract	1	196	196
caradoc_stats	197	392	196
caradoc_stats_strict	393	588	196
hammer	589	589	1
mutool_show	590	635	46
mutool_clean	636	681	46
origami_pdfcop	682	682	1
pdfium	683	683	1
pdfminer_dumppdf	684	703	20
pdfminer_pdf2txt	704	723	20
pdftk_server	724	724	1
pdftools_pdfid	725	729	5
pdftools_pdfparser	730	734	5
peepdf	735	735	1
poppler_pdfinfo	736	792	57
poppler_pdftocairo	793	849	57
poppler_pdftops	850	906	57
qpdf	907	907	1
verapdf_greenfield	908	908	1
verapdf_pdfbox	909	909	1
xpdf_pdfinfo	910	910	1
xpdf_pdftops	911	911	1
caradoc_extract	912	913	2
caradoc_stats	914	915	2
caradoc_stats_strict	916	917	2
hammer	918	919	2
mutool_clean	920	921	2
mutool_show	922	923	2
origami_pdfcop	924	925	2
pdfium	926	927	2
pdfminer_dumppdf	928	929	2
pdfminer_pdf2txt	930	931	2
pdftk_server	932	933	2
pdftools_pdfid	934	935	2
pdftools_pdfparser	936	937	2
peepdf	938	939	2
poppler_pdfinfo	940	941	2
poppler_pdftocairo	942	943	2
poppler_pdftops	944	945	2
qpdf	946	947	2
verapdf_greenfield	948	949	2
verapdf_pdfbox	950	951	2
xpdf_pdfinfo	952	953	2
Total			955

we ignored duplicate error messages.

Let us consider the internet_sourced dataset first. It is straightforward to compute the probability p_k of error message k occurring from the relation matrix: simply take the average value of row k in the relation matrix shown in Figure 1(a). The resulting probabilities for both datasets are shown in Figure 4. Said another way, if file f is drawn from the internet_sourced dataset, then the probability that f produces error message k is p_k. Conversely, the probability that f does *not* produce this error message is $(1 - p_k)$. If we let $f_k = 0$ if the file f did not produce error k and $f_k = 1$ if the file did produce error k, then the probability that f is from the internet_sourced dataset is

$$p_k f_k + (1 - p_k)(1 - f_k),$$

if we only consider error message k.

Since we have many error messages available for analysis, the pseudo-likelihood that file f (column in the relation matrix) is correctly classified is simply the product of each of these individual probabilities, namely

$$L_{\texttt{internet\_sourced}}(f) = \prod_{k=1}^{955} (p_k f_k + (1 - p_k)(1 - f_k)).$$

We define $L_{\texttt{dangerous}}(f)$ similarly using the error message probabilities p'_k from the dangerous set instead,

$$L_{\texttt{dangerous}}(f) = \prod_{k=1}^{955} (p'_k f_k + (1 - p'_k)(1 - f_k)).$$

We define the *Bernoulli misclassification test statistic* to be the ratio of these two pseudo-likelihoods,

$$\lambda_{\texttt{internet\_sourced}}(f) = \frac{L_{\texttt{dangerous}}(f)}{L_{\texttt{internet\_sourced}}(f)}.$$

If f is a file drawn from the internet_sourced dataset, then we generally expect that $L_{\texttt{internet\_sourced}}(f)$ will be larger than $L_{\texttt{dangerous}}(f)$, which implies that $\lambda_{\texttt{internet\_sourced}}(f) < 1$. Conversely, if a file is drawn from the dangerous dataset, which means it is a misclassification if it actually is present in internet_sourced, we would expect that $\lambda_{\texttt{internet\_sourced}}(f) > 1$. The intuition is that since files in the dangerous set are likely to be invalid, a high value of $\lambda_{\texttt{internet\_sourced}}(f)$ is an indication that the file f is not compliant. A histogram of $\lambda_{\texttt{internet\_sourced}}$ is shown in Figure 5(a).

Conversely, we can define

$$\lambda_{\texttt{dangerous}}(g) = \frac{L_{\texttt{internet\_sourced}}(g)}{L_{\texttt{dangerous}}(g)}$$

for each file g in the dangerous set. The intuition in this case is that a high value of $\lambda_{\texttt{dangerous}}(g)$ is an indication that g is compliant, since it is likely to be a misclassification. The histogram of values of $\lambda_{\texttt{dangerous}}(g)$ is shown in Figure 5(b).

Since there is some variability (or noise) present within the data, we should not use the value of $\lambda = 1$ as the cutoff for detecting misclassifications. Although the intersections between the histogram curves and the red lines $\lambda = 1$ in both frames of Figure 5 are close to the true fraction of misclassifications in both datasets (80% for internet_sourced and 48% for dangerous), they are not exactly correct. This suggests using a different threshold T instead, so that all files whose statistic λ is greater than T will be deemed to be misclassified.

Let us now use the ground truth, which specifies whether a given file is "valid" or "rejected", to determine the performance of the Bernoulli misclassification test statistic. A misclassified file in internet_sourced is one that is "rejected", while a misclassified file in dangerous is one that is "valid".

In the case of either dataset, for a given threshold T, the *probability of detection* is the probability that a truly misclassified file f will have a statistic $\lambda(f) > T$. On the other hand, the *probability of false alarm* is the probability

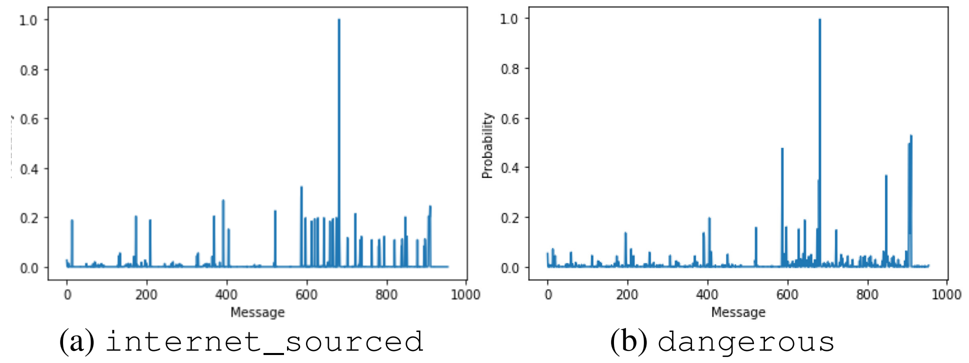


Fig. 4. Error probability for (a) `internet_source` and (b) `dangerous`.

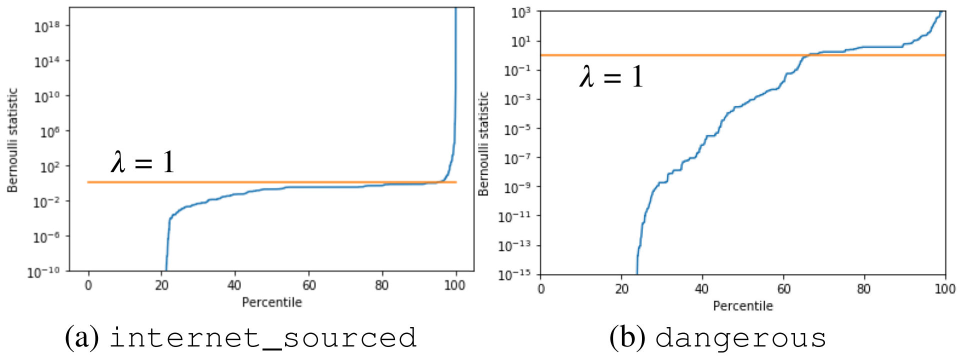


Fig. 5. Histogram of Bernoulli misclassification test statistic for (a) `internet_sourced` and (b) `dangerous`. The horizontal line marks a value of $\lambda = 1$.

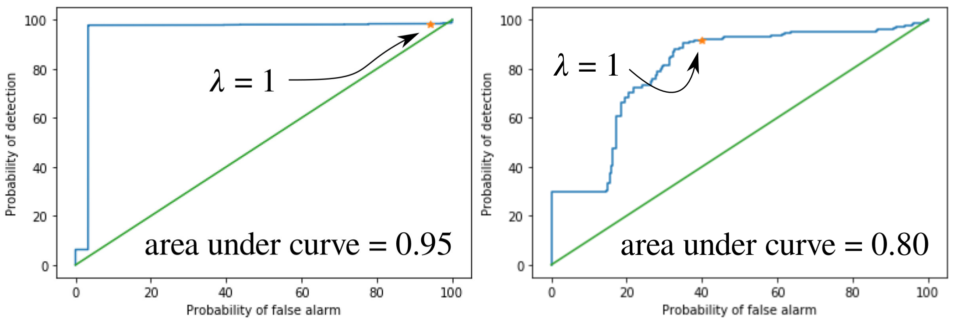
that a correctly classified file f will have a statistic $\lambda(f) > T$. Ideally, the probability of detection will be close to 1, while simultaneously the probability of false alarm will be close to 0.

The plot of probability of detection versus false alarm for all thresholds is shown in Figure 6. Better misclassification detectors have plots further to the upper left, away from the diagonal. Since the curve plotted is far above the diagonal for `internet_sourced` in Figure 6(a), we conclude that the Bernoulli likelihood ratio misclassification statistic is a very accurate detector of misclassified files in `internet_sourced`. Additionally, since the plot in Figure 6(b) is above the diagonal, this indicates that the Bernoulli likelihood ratio misclassification statistic also performs well on the `dangerous` dataset set. The sharp plateau in Figure 6(b) is due to a number of instances in which $L_{\texttt{internet\_sourced}}$ took the value 0 on some files in `dangerous`. These happen to be truly non-compliant files! These qualitative assessments are confirmed by the areas under the curves in Figure 6. A perfect misclassification detector will have an area of 1 under the curve, while a detector that randomly decides misclassifications would have area 0.5 under the curve. We obtained 0.95 for $\lambda_{\texttt{internet\_sourced}}$ and 0.80 for $\lambda_{\texttt{dangerous}}$ for areas under the curve, which we deem to be surprisingly good given the fact that the file contents were not directly inspected by our method.

VI. Parser redundancy analysis

The Bernoulli misclassification statistic relies upon the diversity of responses to each file in order to make reliable decisions. It is impractical to use quite so many parsers as we used, so it is useful to assess whether we could get good performance with fewer parsers. The easiest way to do this is to measure the correlation between the typical error message distributions produced by different parsers across all files. In the following analysis, we combined both `internet_sourced` and `dangerous` into a single dataset, whose relation matrix consists of the horizontal concatenation of both matrices shown in Figure 1. That is, the rows are the same as before, but the columns consist of the union of the columns from both matrices. Error messages (rows) that never occur were removed from the analysis, since they contribute no information.

The data can also be visualized using principal components analysis, much as was done in Section IV, but instead we use the error counts across files as coordinates for each parser. Since specific error messages cannot be enabled or disabled individually, it makes sense to aggregate the error messages into parsers by taking the total number of error messages for a each parser on a given file. Principal components analysis places the parsers according to the plot shown in Figure 7. There is one large cluster (in the lower left of Figure 7) of parsers which have similar behaviors. There are quite a few outliers, most notably `caradoc_extract` and `poppler_pdfinfo`. The



(a) `internet_sourced` (b) `dangerous`

Fig. 6. Receiver operating curves for Bernoulli likelihood ratio misclassification statistic for (a) `internet_sourced` and (b) `dangerous`.

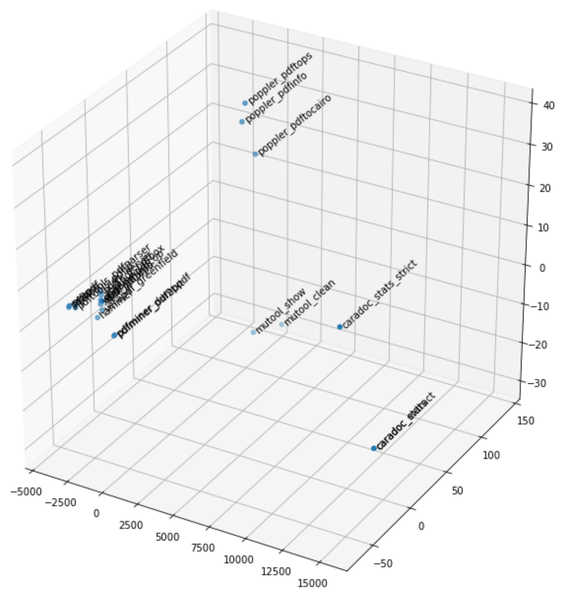


Fig. 7. Parsers placed in three dimensions according to principal components analysis of the union of `internet_sourced` and `dangerous`.

reader is cautioned that the apparent density of the large cluster is a bit misleading, because the ranges of the axes are quite different. In any event, the wide spread of parsers across the plot indicates that having a large number of parsers is quite valuable.

Although principal components analysis is useful, we can obtain a ranking of parsers by their redundancy, so that we can prioritize more informative parsers. We computed Pearson's correlation coefficient between all pairs of error messages (rows), to form a fairly large correlation matrix (not shown). Different error messages that occur on exactly the same set of files have a correlation coefficient of 1. In that case, one of those error messages is redundant. Errors were then grouped by parser, and for each pair of parsers we stored the median correlation from each of their pairwise message correlations. The result of this aggregation is the matrix shown in Figure 8. Whiter colors indicate higher correlation – more redundancy – while darker colors indicate lower correlation. Most of the matrix is fairly dark, which indicates low redundancy overall. The bright off-diagonal entries indicate trade-offs: one needs only run one of the two parsers indicated. The bright bands for `pdftools_pdfid` occurred because that parser did not correlate with any of the others at all. The reader is cautioned that Figure 8 is *not* a correlation matrix itself, because of the median grouping operation. Therefore, it is not surprising that the diagonal blocks are not all ones. Specifically, the diagonal blocks report the median correlation between all pairs of error messages emitted by a given parser. Since a given parser will typically emit only one error message on a given file, the correlation between error messages from the same parser is typically zero.

The clusters visible in the Figure 7 can be confirmed by sorting the parsers based on their median correlation. The rows and columns shown in Figure 8 are sorted in this way. This indicates which parsers are individually most informative, because they form an approximate spanning set for the data. The obvious block in the lower right suggests that parsers should be grouped into two categories based on their informativeness: high and low. The rows and columns of the block in Figure 8 suggest that the boundary between the high and low categories appears to be fairly sharp, with all parsers to the left of `origami_pdfcop` being highly informative.

Based on the approximate spanning property of the highly informative category, which covers most of the variability visible in Figure 7, one should always run the parsers in the high category, with the other parsers in the low informative category parser treated as increasingly optional as one moves to the lower right of Figure 8. Notice that the parsers near the lower right of Figure 8 all come from the cluster in the lower left of Figure 7. Although it is difficult to see from the projection shown in Figure 7, least informative parsers are on the *inside* of the cluster, while the parsers in the same cluster that are on the outer edges of the cluster are more informative.

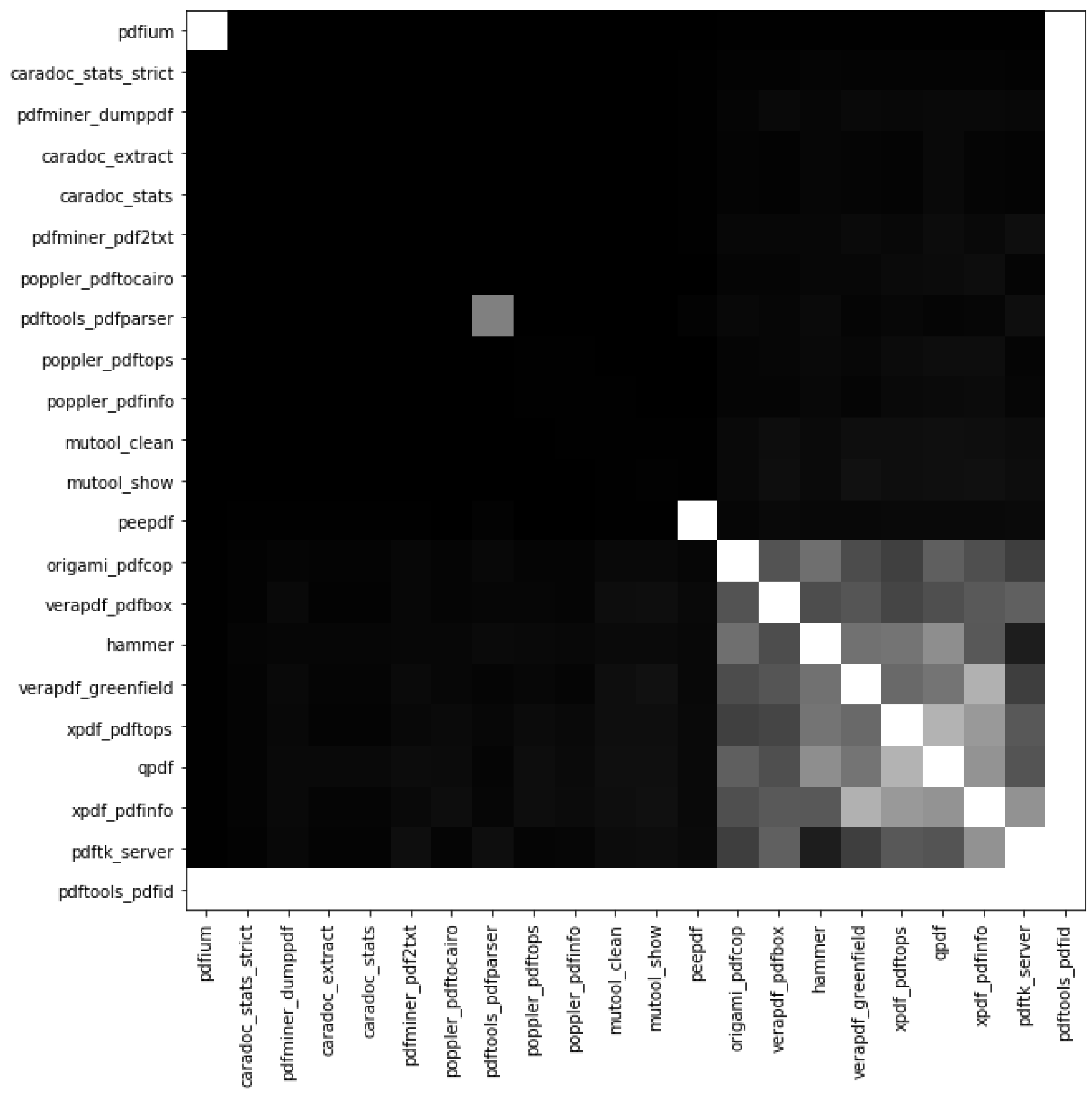


Fig. 8. The matrix of median error message correlations, grouped by parsers. Rows and columns are sorted according to median message correlation. (Note: because medians are reported, the diagonals are not all ones. See the text for more details.)

VII. Conclusion and recommendations

This paper has demonstrated that a given file's compliance with a format specification can be determined from the following three samples: (1) a diverse collection of parsers for the file format, (2) a sample of compliant files, and (3) a sample of non-compliant files. Our methodology is format agnostic, and so could work if a file format is not formally specified. Furthermore, our Bernoulli test for compliance is statistical, so it is both robust to errors in the three samples, yet benefits from richer samples should they be available. We note that the use of the three samples means that this approach is a supervised approach. Under appropriate circumstances, it might be possible to use an unsupervised bootstrapping approach to extract the two samples of files from a single aggregated sample. This requires further investigation.

Principal components analysis is helpful in understanding the variability within a sample of files or parsers, but it holds somewhat less value as an automated analytic tool. Clusters visible within the principal components plots appear to reflect specific tool chains used in the creation of files, with valid files forming several dense clusters. Future studies ought to explore whether this is true by testing the "continuity" of the location of a file in a principal components plot. If one makes a small modification to a given file, do its principal components remain similar? Moreover, if files produced using several distinct versions of a given toolchain are present (perhaps one contains a bugfix), are the corresponding clusters nearby one another?

The Bernoulli likelihood ratio statistic detects non-compliant files by comparing error message prevalence aggregated across all parsers and both samples of files. It relies inherently upon both the coverage and depth of these samples, but we have shown that it can be very effective at its job when these samples are adequate. The datasets discussed in this paper contained fully compliant files, files with "benign" malformations that could be correctd, files that could not be corrected, and some files that were intentionally malicious. Given these datasets, the Bernoulli likelihood ratio statistic was effective at detecting non-compliant files and many of the malicious files.

In the two datasets, we found that finding non-compliant or malicious files against the background of more benign files was an easier task than finding compliant files against the background of problematic files. In the former case, we found a false reporting rate of roughly 5%. Depending on the application, this may or may not be useful in a user-facing tool. It is definitely helpful for identifying files to be queued for further investgation, though. In the latter case, we found a higher false reporting rate of roughly 20%. Again, depending on the application, this may be still be useful for reducing manual effort in determining the validity or safety of a given set of files. Effectively, this higher false reporting rate means that malicious files that are fully compliant with the format are harder to detect than those that cause errors or warnings in some parsers. That said, the fact that even fully compliant files appear to trigger errors or warnings may make crafting such a malicious file quite difficult for an attacker, especially if the attacker does not know the set of parsers being used in advance.

Overall, we found that aside from a few of the parsers that behave relatively similarly, there is not much redundancy present in the behaviors of parsers for the PDF specification. That is to say that the relation matrix contains by far the most information if all parsers are considered, so one ought to use all parsers if possible. Our analysis determined which parsers are individually the most informative, based on pairwise comparisons. While it is entirely reasonable to study different subsets of parsers, we did not perform that analysis here. We refer the interested reader to [14] where such an analysis was performed.

If resources are tight, we found that it is probably not necessary to rerun a given parser with different options. For instance, running only one of `xpdf_tops` and `xpdf_pdfinfo` probably will not change the results too much. Roughly speaking, it appears that the best strategy is "more programmers contributing different code instead of one programmer's code run in many different ways." More research is recommended to determine strategies to better exploit the fact that not all parsers are equally informative.

Our two statistical techniques for analyzing file format compliance are admittedly simple but standard statistical tools, though are apparently not in wide use. They are easy to deploy, easy to interpret, and require little maintenance other than the selection of a single detection threshold. We therefore encourage deeper exploration into and experimentation with statistical methods in the study of file format compliance.

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