Transformer-Boosted Anomaly Detection with Fuzzy Hashes

Frieder Uhlig*1, Lukas Struppek*1, Dominik Hintersdorf*1, and Kristian Kersting1,2,3

1Department of Computer Science, Technical University of Darmstadt, Germany
2Centre for Cognitive Science, Technical University of Darmstadt
3Hessian Center for AI (hessian.AI)

Abstract

Fuzzy hashes are an important tool in digital forensics and are used in approximate matching to determine the similarity between digital artifacts. They translate the byte code of files into computable strings, which makes them particularly interesting for intelligent machine processing. In this work, we propose deep learning approximate matching (DLAM), which achieves much higher accuracy in detecting anomalies in fuzzy hashes than conventional approaches. In addition to the well-known application for clustering malware, we show that fuzzy hashes and deep learning are indeed well-suited to classify files according to the presence of certain content, e.g., malware. DLAM relies on transformer-based models from the field of natural language processing and outperforms existing methods. Traditional fuzzy hashes like TLSH and ssdeep have a limited size and fail to detect file anomalies if they are relatively small compared to the overall file size. DLAM, however, enables the detection of such file correlations in the computed fuzzy hashes of TLSH and ssdeep, even for anomaly sizes of less than 15%. It achieves comparable results to state-of-the-art fuzzy hashing algorithms while relying on more efficient hash computations and can, therefore, be used at a much larger scale.

1 Introduction

Digital forensics comprises the analysis and interpretation of digital material. One of the biggest challenges facing digital forensic investigation is coping with the vast number of files to be processed. Hashing algorithms have become an indispensable part of computer science, since the computed hashes can be used as unique identifiers to compare digital artifacts. For traditional cryptographic hashes, such as MD5 and SHA-2, even changing a single bit already alters the hash value significantly. This so-called cryptographic diffusion obscures the relationship between ciphertext and plaintext, as it is intended for one-way functions. Cryptographic hashes are therefore unsuitable for recognizing similar artifacts. Fuzzy hashing, on the other hand, breaks the cryptographic diffusion and still hides the relationship between the original image and the hash. Through approximate matching, the similarity of two fuzzy hashes can be determined.

A recent survey by Singh [24] shows that 65% of digital forensic investigators are actively using fuzzy hashes during their investigation processes. Fuzzy hashing is primarily used to identify related documents, but they are also used in other contexts which are based on similarity search. Examples are data loss prevention [8], IoT device identification [3, 9], genome sequencing [11] or biometric template protection [18]. However, one primary application for fuzzy hashes remains malware detection and analysis [6, 15], for example, as used in Google’s VirusTotal [23].

Traditional approaches compute similarity scores between fuzzy hashes to identify shared anomalies of different files. However, such similarity scores are limited in their expressiveness and frequently fail to detect shared anomalies or even state misleading similarities. The fact that fuzzy hashes translate bytes into computable strings makes them especially interesting for processing them using machine learning techniques. With our approach, named Deep Learning Approximate Matching (DLAM), we intend to build a bridge between recent advances in deep learning and fuzzy hashing and demonstrate large performance improvements for the task of anomaly detection by combining both concepts. More specifically, we introduce a transformer-based approach to detect parts of file anomalies in their corresponding fuzzy hashes. We empirically show that DLAM improves anomaly detection in fuzzy hashes produced by ssdeep [14] and TLSH [17], whereas traditional similarity measures fail to detect the anomalies. In contrast to state-
of-the-art fuzzy hashing algorithms and other deep learning approaches, DLAM consistently classifies the anomalies with an accuracy of over 90% on multiple file types.

Our contributions can be summarized as follows:

- We introduce deep learning approximate matching (DLAM) that combines efficient fuzzy hashing algorithms with transformer models from natural language processing.
- We show that DLAM beats conventional approximate matching with fuzzy hashes, such as ssdeep and TLSH. DLAM works even for small anomaly sizes, for which the traditional similarity measurements completely fail.
- We further demonstrate that DLAM for anomaly detection achieves comparable results to state-of-the-art multi-resolution fuzzy hashing algorithms.

2 Background and Related Work

In the following, we introduce fuzzy hashing, including TLSH and ssdeep as standard fuzzy hashing algorithms on which DLAM is based. We further describe transformer networks, which build the foundation of our approach.

2.1 Fuzzy Hashing and Approximate Matching

Fuzzy hashing was first introduced in the mid-2000s in order to perform altered document and partial file matching [14]. Generally, fuzzy hashing algorithms $H$ are functions that compute a dense hash representation $H(x)$ of a file $x$. The goal is to provide similar hashes, which are also called digests, for similar inputs: $H(x) \approx H(y) \iff x \approx y$. This property distinguishes them from traditional cryptographic hashes for which small input changes lead to strong output changes, also known as cryptographic diffusion or avalanche effect. Then a similarity function $\text{sim}(H(x), H(y))$ is applied, which computes the similarity between two files $x$ and $y$ based solely on their fuzzy hashes. This procedure of finding files with similar artifacts or patterns is known as approximate matching. Approximate matching algorithms all work in a three-step manner: they first select features from a digital artifact and then generate a hash-digest from these features, which then can be compared to other hashes in a third step. As for the comparison step, there are three ways in which current algorithms achieve their goal: either based on plain byte, syntactic or semantic commonalities. The matching mechanism is chosen based on the digital artifact that must be processed. Malware developers often obfuscate their payload deliberately to prevent detection. Benign files might have further been compressed or rearranged through software, which makes it hard to distinguish between obfuscated malware and benign files.

To deal with these issues, approximate matching research has come up with two approaches: The first approach is to create new algorithms that are more resilient and attest the similarity on a more granular level [1]. The other approach is to pre-process the artifacts before hashing them and focusing on selected parts that hold vital information [23]. With our work, we propose a third option and detect shared commonality in fuzzy hashes using machine learning approaches. We note that Microsoft [15] pursues
a similar direction, however, this direction has so far only barely been formalized in academic research. Fig. 1 illustrates how conventional approximate matching and this new combination of fuzzy hashes and machine learning tackle the challenge of anomaly detection.

Overall, the combination of fuzzy hashes and machine learning is still in its early stages. Raff et al. [21] first proposed to train neural networks for malware detection from raw byte sequences. However, training networks with sufficient capacity on entire files is time- and resource-consuming. Peiser et al. [20] used simple feed-forward neural networks to detect malware in JavaScript files through static analysis based on features computed by fuzzy hashing algorithms and compared their results with conventional JavaScript malware classifiers, none of which rely on fuzzy hashes. The authors showed that simple models, trained on a small dataset with only 5,000 samples, already achieved a high detection accuracy. However, Peiser et al. [20] limited their investigation to JavaScript malware detection and only trained their models on JavaScript files that either contained malware or not.

In our work, we take a more holistic view and contextualize the fusion of deep learning and digital forensics based on fuzzy hashing. We further evaluate our approach on a set of different file types by injecting synthetic anomalies into real-world files. DLAM relies on the fuzzy hashes of TLSH and ssdeep, both of which we introduce next in more detail.

**TLSH** (Trend Micro Locality Sensitivity Hash) is a hashing algorithm first presented by Oliver et al. [17]. It is specifically intended for malware detection and clustering. TLSH scans the byte code of a file with a sliding window and combines 5 bytes at a time into a unit using the Pearson hash function [19], a fast non-cryptographic hashing procedure. These units are then mapped into an array of so-called buckets. Next, the digest body, a hexadecimal-string, is constructed from the array of buckets by dividing it into 3 distinct quartiles q1, q2 and q3. The first three bytes of the hash are the digest header, which primarily consists of check sums, and forms together with the body a 70 character hexadecimal string. The final TLSH hash is a fixed length 72 character long string. To compare two hashes, TLSH calculates an approximation to the hamming distance between two digest bodies. The relation of two artifacts is expressed through a distance score between 0 (very similar) and 1000 (not similar).

**ssdeep** was introduced by Kornblum [14]. The algorithm breaks a file up into pieces using a rolling hash function, which hashes an input in a sliding window approach. Then, a non-cryptographic hash function is used to hash every piece that has been created by the rolling hash function. These smaller hashes are concatenated and form the hash signature for the whole input file. To compare two hashes, a distance measure is used that determines the correlation between the two hashes. The similarity is indicated by a score between 0 (not similar) and 100 (very similar). As the produced hashes can vary in size, the final hash contains information about the total size at the beginning of the hash. Even though the overall hash is variable in its length, the size is bounded to 148 encoded characters.
2.2 Language Processing With Transformers

To perform similarity analyses on fuzzy hashes, we interpret the binary strings as a language representation and process these strings using transformers. Since their introduction in 2017 by Vaswani et al. [25], transformers are the dominating architecture for natural language processing. Unlike previous state-of-the-art models for sequence modelling, transformers rely on the attention mechanism and remove the recurrent components of previous approaches. More specifically, they rely on the multi-head self-attention mechanism, which enables the models to process different representations at different positions by running an attention mechanism several times in parallel. Since detecting relations between different positions in the hashes is essential for anomaly detection, transformers are a natural architecture choice for this task.

Transformers usually need large amounts of data to be trained on, and pre-training plays a crucial role in their performance. Devlin et al. [5] introduced bidirectional encoder representations from transformers, or BERT in short, which proposes a novel pre-training procedure. The novel masked language model pre-training objective masks a random selection of input tokens and trains the model to predict the vocabulary ID of the masked tokens based on the given context. A pre-trained model can then be fine-tuned with only a single additional output layer added.

3 Transformer-Boosted Anomaly Detection

Common fragment detection in fuzzy hashes is similar to anomaly detection. In anomaly detection, the model should learn what constitutes a regular file and what constitutes a file containing a particular element we want to detect. In this work, we introduce deep learning approximate matching (DLAM). Our approach consists of two steps. For each input file \( x \) to check for an anomaly, we first compute a dense hash representation \( H(x) \) using a fuzzy hash algorithm \( H \). The fuzzy hashes serve in this case as an intermediate representation of the files. The hashes reduce the complexity and length of the original files and make them processable by deep learning models.

The hashes and binary labels, which indicate whether an anomaly was hidden in the input file nor not, are then provided to a deep learning model, usually a transformer, for training. Since the hashes are in a byte string representation, they are tokenized and interpreted as a sequence to train the model on. Because the order of the bytes is crucial to the classification task, we added a simple absolute positional encoding to the sequence to indicate the sequence order to the transformer model after tokenizing the hash strings.

As stated in Sec. 2.1 ssdeep produces hashes of variable length. As Fig. 2b illustrates, all hashes produced by ssdeep are padded with zeros to allow parallel training of the models, and attention masking is applied to train the transformer model. Attention masking is used to prevent the model from attending to the padding tokens and only paying attention to the informative tokens of the hash values.

3.1 Experimental Protocol

In the following, we will describe the experimental setting we used to evaluate our approach. The pipeline for our experiments is visualized in Fig. 3.

Fuzzy Hashing Algorithms: We focus our analyses on ssdeep and TLSH, as both are widely used and form the de-facto standard for malware detection. The feature extraction pipeline for both fuzzy hashes is visualized in Fig. 2. According to Peiser et al. [20], when using a rolling-window approach for tokenizing the fuzzy hashes produced by TLSH, the classification accuracy is increased with a feed-forward network. In our experiments, the rolling-window approach did not influence the classification accuracy with a transformer. However, to ensure comparability to Peiser et al. [20], we still used a rolling-window approach for tokenizing the fuzzy hashes produced by TLSH.

Contrary to the findings of Peiser et al. [20], who used a similar rolling window approach on ssdeep as well, we could not confirm that such an approach improved the classification performance of the models when working with ssdeep. Therefore, we applied a simple per-char integer encoding on the ssdeep hash, as can be seen in Fig. 2b. We also removed the chunk size and colons from the ssdeep hashes, regardless of the model architecture. Our experiments showed that the retention of these elements leads to a worse classification accuracy by the models.

Data Selection: To investigate the extent to which the classification performance of the models depends on the type of input file, we selected common file types, namely JavaScript, PDF and XLSX, for training and evaluation. Göbel et al. [8] showed that the accuracy of approximate matching indeed varies depending on the file type. Therefore, we trained and evaluated one model per file type. Since no single file corpus exists that is big enough to allow for training and evaluation of models on all file types, multiple corpora were used. We combined the Govdocs corpus [7], SRILabs JavaScript corpus [22] and the FUSE corpus [2] and used 100,000 samples for each of the file types. This number of samples per file type represents the maximum amount of files that could be assembled with a reliable provenience, meaning that they originate from corpora that have been screened for duplicates and are balanced in size.

For evaluation of the models, 5,000 Samples for each file type from the NapierOne corpus [4] were used. For
Figure 3: The three stages of our training and evaluation pipeline.

|                  | mrsh-cf | MRSH-v2 | ssdeep | TLSH | ssdeep (FF) | TLSH (FF) | ssdeep (TF) | TLSH (TF) |
|------------------|---------|---------|--------|------|-------------|-----------|-------------|-----------|
| JS Accuracy (%)  | 81.54   | 67.38   | 50.02  | 50.02| 92.70       | 82.08     | 92.70       | 87.90     |
| JS FPR (%)       | 0.00    | 0.05    | 0.00   | 0.00 | 0.01        | 0.11      | 0.01        | 0.08      |
| JS FNR (%)       | 0.37    | 0.17    | 1.00   | 1.00 | 0.14        | 0.25      | 0.14        | 0.16      |
| PDF Accuracy (%) | 97.3    | 95.44   | 50.04  | 49.98| 79.10       | 78.42     | 94.34       | 82.60     |
| PDF FPR (%)      | 0.00    | 0.02    | 0.00   | 0.00 | 0.16        | 0.17      | 0.04        | 0.17      |
| PDF FNR (%)      | 0.05    | 0.07    | 1.00   | 1.00 | 0.25        | 0.26      | 0.07        | 0.17      |
| XLSX Accuracy (%)| 96.78   | 88.22   | 52.54  | 51.17| 93.80       | 90.28     | 97.36       | 90.74     |
| XLSX FPR (%)     | 0.00    | 0.00    | 0.00   | 0.04 | 0.01        | 0.08      | 0.01        | 0.11      |
| XLSX FNR (%)     | 0.06    | 0.23    | 0.95   | 0.97 | 0.11        | 0.11      | 0.04        | 0.08      |

Table 1: Comparison of our results for anomaly detection in JavaScript (JS), PDF, and XLSX files for traditional similarity-based fuzzy hashing algorithms and DLAM with feed-forward (FF) and transformer (TF) models. Whereas traditional similarity metrics fail for TLSH and ssdeep fail, our DLAM approaches significantly increase the performance and are even more accurate than state-of-the-art fuzzy hashing algorithms for JavaScript and XLSX files.

both, training and evaluation, only files that were large enough to be hashed by TLSH were selected. Since the files for training and evaluation were collected from different sources, the risk of having duplicate files in the training and test sets is minimal.

**Training Setup:** The architecture of the transformer model relies on the TinyBERT architecture by Jiao et al. [12]. This model has a sufficient size for our purposes, as it needs less training data than other transformer sizes. We further used a TinyBERT model pretrained on natural language, and found that it boosts the performance when fine-tuning it on abstract hashes compared to training a randomly initialized model from scratch. For comparison reasons, we also trained a simple feed-forward neural network, whose architecture is inspired by the work of Peiser et al. [20].

We trained all networks using the Adam optimizer [13] with a fixed learning rate and a batch size of 1,024 for our transformer model (BERT) and a smaller batch size of 512 for the feed-forward network. We further used 15% of the training data as a validation set and stopped training after the validation loss started to increase. A simple binary cross-entropy loss function was used for optimization.

All models were trained on 85,000 files per test case. Into half of the training and evaluation files, an anomaly in the shape of a randomly generated byte sequence was inserted. Even though the same randomly generated byte sequence was used for creating all the files containing an anomaly, the specific elements that were copied were chosen at random. In addition, the inserted anomaly could occupy between 1% and 99% of the original size of the file.

To investigate how traditional fuzzy hashes perform the anomaly detection task without the help of machine learning, the common fuzzy hashing algorithms (ssdeep, TLSH, mrsh-cf, MRSH-v2) had to compare each evaluation file with the entire randomly generated anomaly sequence. If their resulting similarity score was greater than zero, this was considered a positive prediction. If the similarity score was zero, this is considered a negative prediction.

**Evaluation Metrics:** We used various standard metrics for evaluating our experimental results. We measured the accuracy (Acc), the false-positive rate (FPR), and the
false-negative rate (FNR). Regarding the application of our approach in digital forensics for malware or sensitive file detection, false-positive and false-negative predictions are the most relevant performance indicators. False-negative predictions represent all files that a filter failed to detect. Any false-negative prediction can mean a compromise of systems with potentially devastating consequences. False-positive predictions, in turn, are fatal misclassifications in the context of malware detection because they impair processes for no reason and lead to a sustained loss of confidence in the technology by the users.

3.2 Experimental Results

We now want to empirically investigate the following research questions:

Q1: Can DLAM detect file anomalies more precisely than traditional approximate matching? Q2: Has the type of the file carrying the anomaly an impact on the detection with DLAM? Q3: Does DLAM based on transformers perform better than based on simple neural networks? Q4: Can DLAM compensate for weaknesses in conventional approximate matching?

Q1: DLAM meets accuracy of state-of-the-art fuzzy hashing algorithms. In Tab. 1 the accuracy, false-positive rate, and false-negative rate of our approach are compared to common and state-of-the-art fuzzy hashing algorithms. While ssdeep and TLSH completely fail in detecting the anomalies in all file types, the state-of-the-art hashing algorithms mrsh-cf and MRSH-v2 are able to reliably identify the anomalies in most cases. This is especially interesting since the files to be classified have the same length as the anomaly, which in theory is an easy setting for ssdeep and TLSH as was shown by Martínez et al. [16]. Unlike ssdeep and TLSH, mrsh-cf and MRSH-v2 are multi-resolution hashes, which can map many more features into the hashes. As a result, the length of the hashes is not limited to a maximum size, which increases accuracy for similarity matching since less information about the files is lost.

As for the deep learning approaches, our approach is on par with the feed-forward model of Peiser et al. [20] for JavaScript files and significantly outperforms the feed-forward model on PDF and XLSX files by 15.24% and 3.56%, respectively. Our transformer-based approach performs better when using the hashes of ssdeep than with using the TLSH hashes. The superiority of ssdeep over TLSH for approximate matching with real-world file types was also pointed out by Göbel et al. [10].

Our approach also outperforms the state-of-the-art multi-resolution fuzzy hashing functions mrsh-cf and MRSH-v2 on the JavaScript files. While the accuracy of the approach of [20] is 18.2% lower than the state-of-the-art hashes, the accuracy of our approach is only 2.96% below the mrsh-cf hash on PDF files. On XLSX files, the transformer based DLAM approach even outperforms the mrsh-cf hash and achieves an accuracy of 97.36%. This is especially interesting since our transformer-based approach enables anomaly detection based on fuzzy hashes like ssdeep and TLSH, which scale much better than the mentioned multi-resolution hashes with only moderate accuracy losses when using DLAM.

Fig. 4a and Fig. 4b show the false negatives (as blue bars) and the true positives (yellow bars). The height of the bars represents the proportion of the anomaly in the total file. In both figures, the accumulation of blue bars in the left half of the graphs shows that the smaller the proportion of anomalies in a file, the higher the risk of a false-negative classification by the model.

With ssdeep, the model detects the anomalies in the hashes much more consistent, even for small anomaly sizes. The red line in Fig. 4a is an approximation of the minimum amount of similarity that two files need to have in common, in order for ssdeep to approximately match them. Göbel et al. [10] discovered that between 9 and 13% was the minimum amount of common content that two randomly generated files of size 2048 kB needed to possess in order for ssdeep to find any relation. Even though this minimum was
never confirmed for PDF files specifically, our experimental results support this theory.

The fact that almost 87% of all false negatives have a smaller anomaly than 13% means that the smaller the anomaly, the less likely it is to be classified correctly. The false negatives in Fig. 4B are more widespread and cannot primarily be attributed to a small anomaly size, as for ssdeep in Fig. 4A.

Göbel et al. [10] stated that TLSH was less precise than ssdeep when tested on various file types in their needle in a haystack test case. An observation that we could confirm with our tests. The classification accuracy of any model was consistently lower for TLSH than that of ssdeep. Our experiments show that working consciously with DLAM and ssdeep within these boundaries – only classifying files with anomalous content of more than 13% – even leads to a higher classification accuracy than with mrsh-cf or MRSH-v2.

Q2: DLAM reliably detects anomalies for all file types. Our results in Tab. 1 further illustrate that the accuracy with which DLAM detects anomalies in files seems to be more stable in face of different file types. Using a feed-forward network leads to highly fluctuating accuracy values for each file type. The same can be seen for the multi-resolution hashes. Even though their accuracy is very high on PDF and XLSX files, there is a high loss of accuracy on JavaScript files, indicating that the file types have a high impact on the performance of state-of-the-art fuzzy hashes. Our transformer-based DLAM approach, on the other hand, is much more stable and the accuracy for the anomaly detection is consistently above 90% for all three file types when using ssdeep hashes.

Q3: Transformers outperform simple neural networks for anomaly detection. As can be seen in Tab. 1 our DLAM approach with ssdeep consistently outperforms the neural networks with TLSH hashes. Using TLSH, the model produces more false-negatives than with ssdeep, as can be seen in Fig. 4B and Fig. 4A. The results in Tab. 1 also show that a combination of transformers and ssdeep consistently outperforms all approaches which are based on simple feed-forward networks.

However, even if feed-forward networks perform worse than transformer models in most cases, they still achieve a decent performance. Consequently, for applications with limited computational power available, feed-forward networks might still be a reasonable architecture to choose.

Q4: DLAM increases the robustness when working with fuzzy hashes. Concatenating the same file multiple times and then calculating the hashes for the composed file, Tab. 2 demonstrates that the use of DLAM can compensate for the known low resilience against repetitive content.

The accuracy is very stable throughout multiple repetitions of the same file. Göbel et al. [10] showed that the similarity scores of ssdeep and TLSH could be lowered to 0 when comparing a single instance of a file with another file that consisted of multiple concatenations of the first one. In the case of TLSH, a 16-fold concatenation of the same 5,000 bytes was sufficient to lower the similarity score to 0. Tab. 2 on the other hand, shows that TLSH, in combination with a transformer network, is still able to classify anomalous and benign files with higher accuracy than mrsh-cf and MRSH-v2 in face of a multifold repetition.

4 Discussion and Limitations

With this work, we demonstrated the large potential that lies in the combination of traditional fuzzy hashing algorithms and recent advances in deep learning. For the task of anomaly detection, our DLAM approach achieves accuracy values close to those of multi-resolution. Furthermore, the underlying fuzzy hashes ssdeep and TLSH are far more scalable due to more effective compression procedures. For example, an unbounded MRSH-v2 hash compresses 68x worse than a ssdeep hash bounded to 148 bytes length. With our DLAM, a comparatively small hash length can then still
be classified with high accuracy, comparable to conventional approximate matching with mrsh-cf and MRSH-v2. For the anomaly detection in JavaScript, DLAM achieves even higher accuracy values than all state-of-the-art mrsh-cf and MRSH-v2. Furthermore, DLAM also increases the resilience against repetition, as we demonstrated in Tab.2.

Based on our empirical results, we recommend ssdeep over TLSH, since ssdeep’s weaknesses can be narrowed down much more precisely. Similarities smaller than 15% are no longer detectable and should therefore be avoided when classifying with DLAM and ssdeep. TLSH, on the other hand, is generally less precise, and possible false predictions are much more difficult to predict.

We limited our analyses to algorithms that produce hashes with a fixed-sized (TLSH) or a maximum length (ssdeep). Other algorithms, such as Mrsh-v2, produce large hashes with potentially infinite length. We expect our approach to be easily adjustable to such cases in practice, but leave the realization open for future research. The application of other model architectures for DLAM are a promising future direction. These would also open other avenues of working with fuzzy hashes, beyond the binary classification of anomalies, which we explored in this work.

5 Conclusion

The goal of our work is to open up the research on machine learning and fuzzy hashes to the broader scientific community. With deep learning approximate matching, or DLAM in short, it is now possible to contextualize a promising fusion of the two research areas of deep learning and digital forensics based on fuzzy hashing. Our application of transformer models in this context leads to higher classification accuracy than other current approaches. More precisely, we empirically demonstrated that applying DLAM to efficient standard fuzzy hashes, such as ssdeep and TLSH, creates a powerful application that rivals the best performing fuzzy hashes MRSH-v2 and mrsh-cf in terms of file anomaly detection. Through adjusting the size of the anomaly and the file type, we were able to show the impact of these two factors, both of which are important when using DLAM in practical applications for data loss prevention or malware detection. The full potential that DLAM offers for digital forensics and cybersecurity becomes even more apparent, recalling that ssdeep and TLSH are very compact and many times smaller than multi-resolution hashes. This paper proves that machine learning is a powerful enabler that enhances the practical applications of fuzzy hashes well beyond the attention of similarity.

Acknowledgments. We thank Harald Baier and Thomas Göbel from the Digital Forensics group at CODE of the Universität der Bundeswehr München, Germany for the fruitful discussions and valuable insights. This work was further supported by the German Ministry of Education and Research (BMBF) within the framework program “Research for Civil Security” of the German Federal Government, project KISTRA (reference no. 13N15343). It also benefited from the National Research Center for Applied Cybersecurity ATHENE, a joint effort of BMBF and the Hessian Ministry of Higher Education, Research, Science and the Arts (HMWK).

References

[1] Ari Azarafrooz and John Brock. Fuzzy hashing as perturbation-consistent adversarial kernel embedding. CoRR, abs/1812.07071, 2018.
[2] Titus Barik, Kevin Lubick, Justin Smith, John Slankas, and Emerson R. Murphy-Hill. Fuse: A reproducible, extendable, internet-scale corpus of spreadsheets. In Working Conference on Mining Software Repositories, pages 486–489. IEEE Computer Society, 2015.
[3] Batyr Charyyev and Mehmet Hadi Gunes. Iot traffic flow identification using locality sensitive hashes. In International Conference on Communications (ICC), pages 1–6. IEEE, 2020.
[4] Simon R. Davies, Richard Macfarlane, and William J. Buchanan. Napierone: A modern mixed file data set alternative to govdocs1. Forensic Science International: Digital Investigation, 40:301330, 2022.
[5] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In NAACL-HLT, pages 4171–4186, 2019.
[6] Vincente Diaz. Why is similarity so relevant when investigating attacks. https://blog.virustotal.com/2020/11/why-is-similarity-so-relevant-when.html, 2020. Accessed: 2022-07-20.
[7] Simson L. Garfinkel, Paul F. Farrell Jr., Vassil Roussev, and George W. Dinolt. Bringing science to digital forensics with standardized forensic corpora. Forensic Science International: Digital Investigation, 6 (Supplement):2–11, 2009.
[8] Thomas Göbel, Frieder Uhlig, and Harald Baier. Evaluation of network traffic analysis using approximate
matching algorithms. In *Advances in Digital Forensics XVII*, volume 612, pages 89–108. Springer, 2021.

[9] Thomas Göbel, Frieder Uhlig, and Harald Baier. Find my iot device – an efficient and effective approximate matching algorithm to identify iot traffic flows. In Pavel Gladyshev, Sanjay Goel, Joshua James, George Markowsky, and Daryl Johnson, editors, *Digital Forensics and Cyber Crime*, pages 72–92. Springer International Publishing, 2022.

[10] Thomas Göbel, Frieder Uhlig, Harald Baier, and Frank Breitinger. FRASHER - A framework for automated evaluation of similarity hashing. *Forensic Science International: Digital Investigation*, 42:301407, 2022.

[11] John Healy and Desmond Chambers. Fast and accurate genome anchoring using fuzzy hash maps. In *5th International Conference on Practical Applications of Computational Biology & Bioinformatics*, volume 93 of *Advances in Intelligent and Soft Computing*, pages 149–156. Springer, 2011.

[12] Xiaoji Jiao, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. Tinybert: Distilling BERT for natural language understanding. In *Findings of the Association for Computational Linguistics: EMNLP*, pages 4163–4174, 2020.

[13] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *International Conference on Learning Representations (ICLR)*, 2015.

[14] Jesse D. Kornblum. Identifying almost identical files using context triggered piecewise hashing. *Forensic Science International: Digital Investigation*, 3:91–97, 2006.

[15] Edir Garcia Lazo. Combing through the fuzz: Using fuzzy hashing and deep learning to counter malware detection evasion techniques. https://www.microsoft.com/security/blog/2021/07/27/combing-through-the-fuzz-using-fuzzy-hashing-and-deep-learning-to-counter-malware-detection-evasion-techniques/, 2021. Accessed: 2022-07-20.

[16] Víctor Gayoso Martínez, Fernando Hernández-Alvarez, Luis Hernández Encinas, et al. An improved bytewise approximate matching algorithm suitable for files of dissimilar sizes. *Mathematics*, 8(4):1–37, 2020.

[17] Jonathan Oliver, Chun Cheng, and Yanggui Chen. Tlsh - a locality sensitive hash. *4th Cybercrime and Trustworthy Computing Workshop*, 2013.