FRASHER -- A Framework for Automated Evaluation of Similarity Hashing

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FRASHER - A Framework for Automated Evaluation of Similarity Hashing

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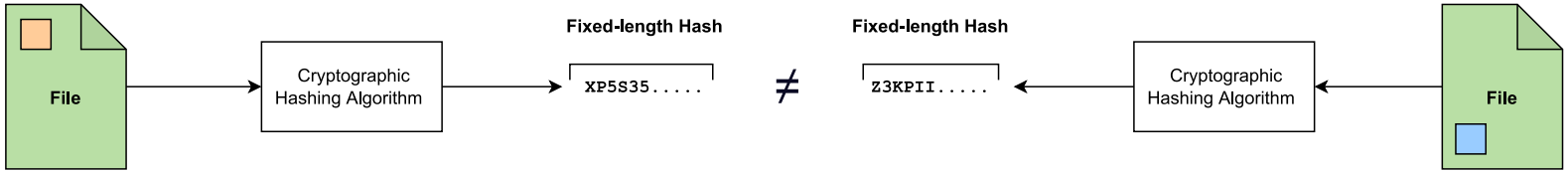
Background

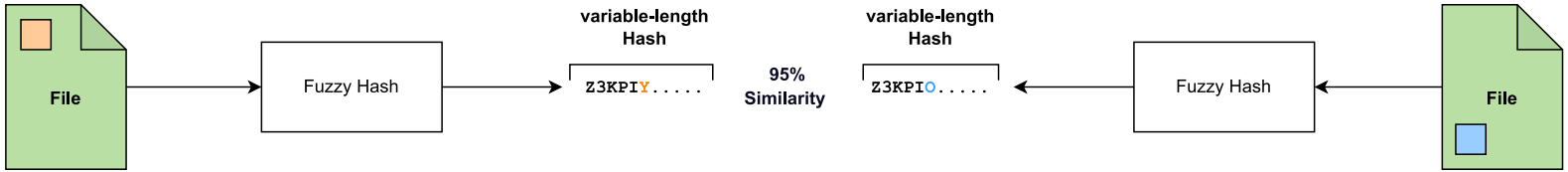
Cryptographic Hashes

- Deterministic, Collision resistant etc.
- Used to verify integrity
- Concise unique representation of a digital artifact

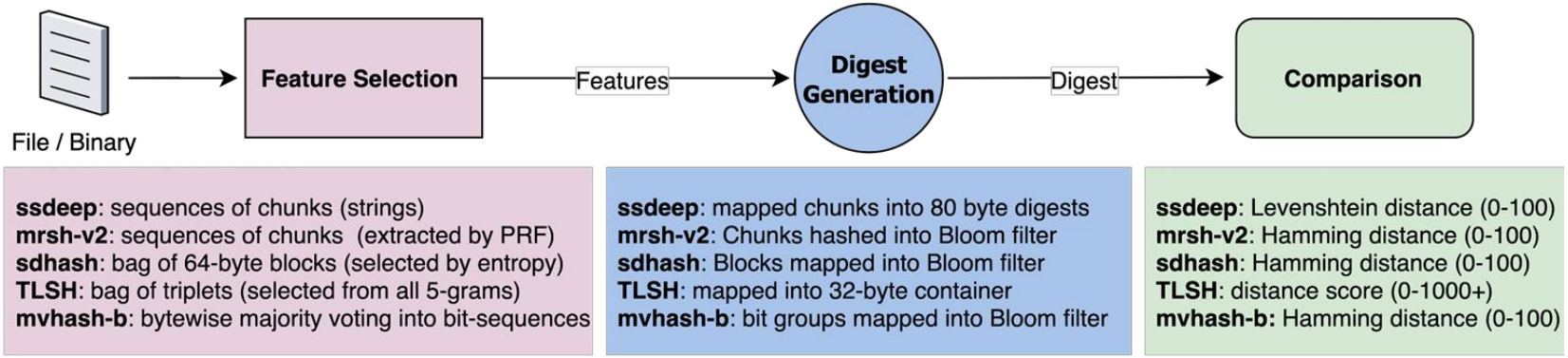


Fuzzy Hashes

- Non-cryptographic hashes (not collision resistant etc.)
- Used to determine similarity
- Concise similarity preserving representation of a digital artifact

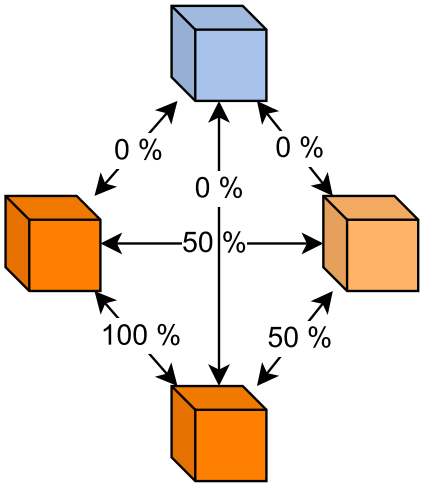


Fuzzy Hashing Schemes



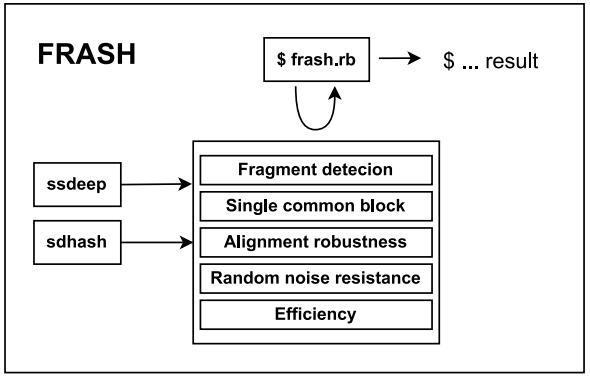
Uses of Fuzzy Hashes – Approximate Matching

- Many names – one concept (Fuzzy hashing, Approximate matching, Similarity digest comparison, Locality Sensitive Hashing)
- Powerful concept to determine relations
  - Based on text
  - Based on raw bytes



FRASH Framework

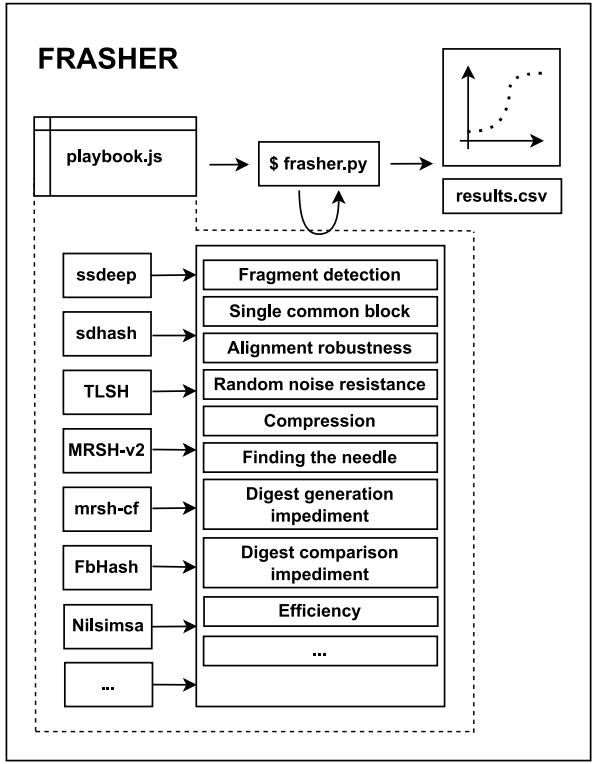
- Framework to test algorithms of similarity hashing
- Offers the following features:
  - 2 fuzzy hashing algorithms
  - 5 test cases
  - Written in Ruby



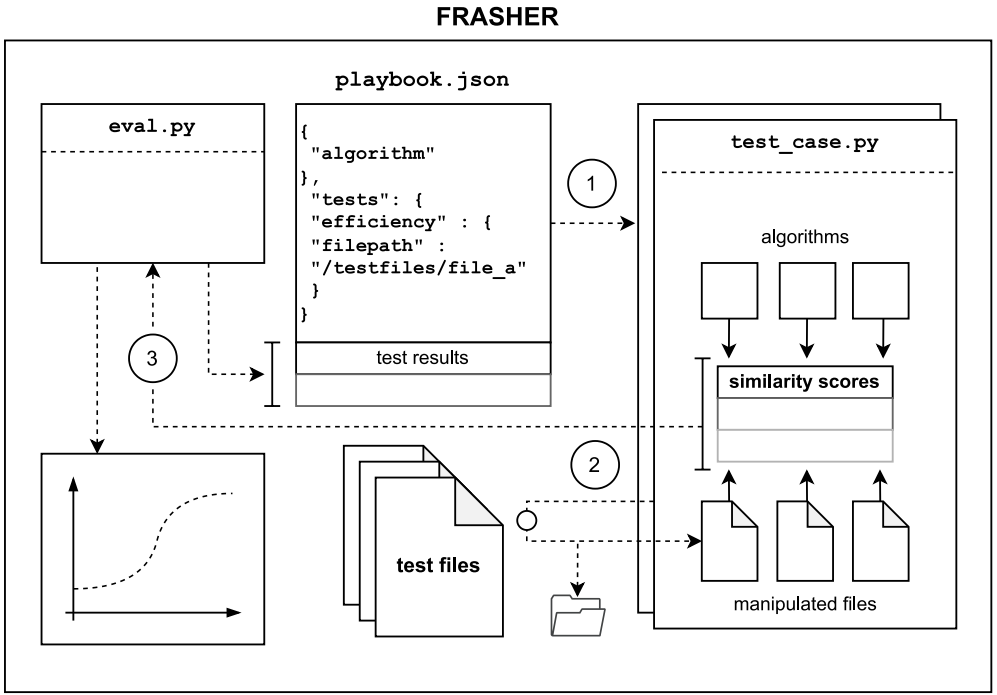
[8] Breitinger, F., Stivaktakis, G., & Baier, H. (2013). FRASH: A framework to test algorithms of similarity hashing. Digital Investigation, 10 , S50–S58. doi:10.1016/j.diin.2013.06.006. The Proceedings of the Thirteenth Annual DFRWS Conference.

FRASHER Framework (1/2)

- 7 fuzzy hashing algorithms available
  - `ssdeep`, `sdhash`, `TLSH`, `MRSH-v2`, `mrsh-cf`, `FbHash`
  - `Nilsimsa` was not evaluated (slow speed)
  - `TLSH`'s similarity score was capped at 300 and inversed
- 9 test cases so far
- Modular framework architecture (i.e., extensible in test cases, algorithms, visualization, etc.)
- Graphical representation of results
- Tests are repeatable and can be adapted
- Written in Python, runs on Linux Ubuntu 21.04



FRASHER Framework (2/2)



Efficiency

- **Generation Efficiency**
  - How *fast* can an algorithm generate a hash from a given file?
  - Algorithms have to hash the *t5-corpus* (1.9 GB, various file types)
- **Comparison Efficiency**
  - How fast can an algorithm compare given files?
  - Algorithms must compare the entire *t5-corpus* with itself (*all-vs-all*)
  - Algorithms must compare a single file with entire *t5-corpus* (*one-vs-all*)
- **Compression Efficiency**
  - How *effective* can an algorithm compress a given input?
  - Algorithms must hash the entire *t5-corpus*

Efficiency

Generation Efficiency & Comparison Efficiency

Algorithm	Digest generation (sec)	Comparison (all-vs-all) (sec)	Comparison (one-vs-all w/ t5/000001.doc) (sec)
MRSH-v2	9.084s	144.746s	1.086s
sdhash	6.393s	110.592s	0.298s
TLSH	14.791s	2.617s	0.01s
FbHash	1838.597s	NA	463.721s
mrsh-cf	10.771s	12.569s	0.507s
ssdeep	15.576s	22.688s	0.01s

Table 4: *Generation efficiency* and *Comparison efficiency* in case of All-vs-All and One-vs-All comparisons; carried out 10 times each and averaged.

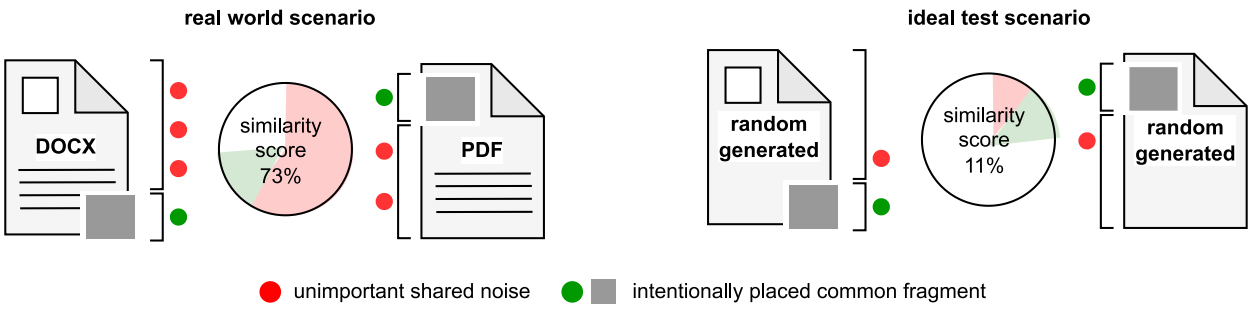
Compression Efficiency

Algorithm	Digest file size (bytes)	Compression ratio (%)
MRSH-v2	28.67 MB	1.500%
sdhash	61.52 MB	3.218%
TLSH	394.11 KB	0.021%
FbHash	19.81 GB	1036.087%
mrsh-cf	33.55 MB	1.755%
ssdeep	485.45 KB	0,025%

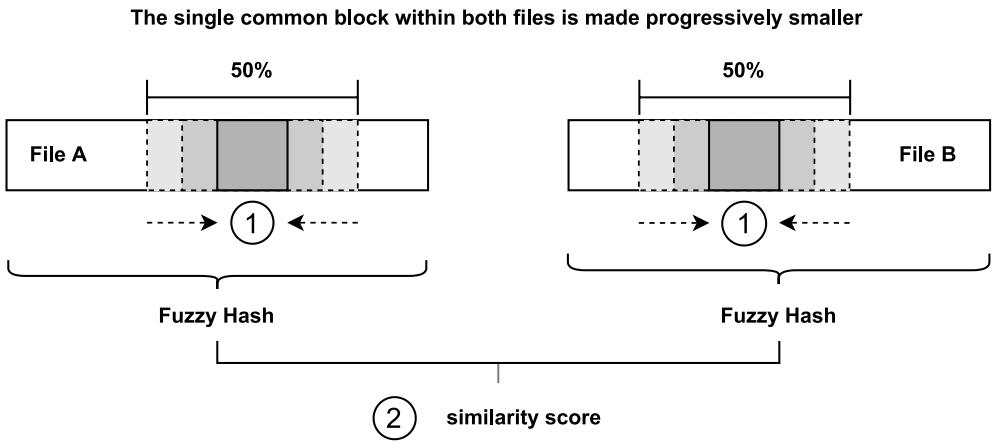
Table 5: *Compression efficiency* of tested algorithms using *t5-corpus* with total size of 1911.81 MB.

Sensitivity & Robustness Tests

- How **resilient** and **robust** are the fuzzy hashes?
- Performed with random generated data
  - Lowers the risk of unintended commonalities distorting the similarity score
  - Idealized but important setting

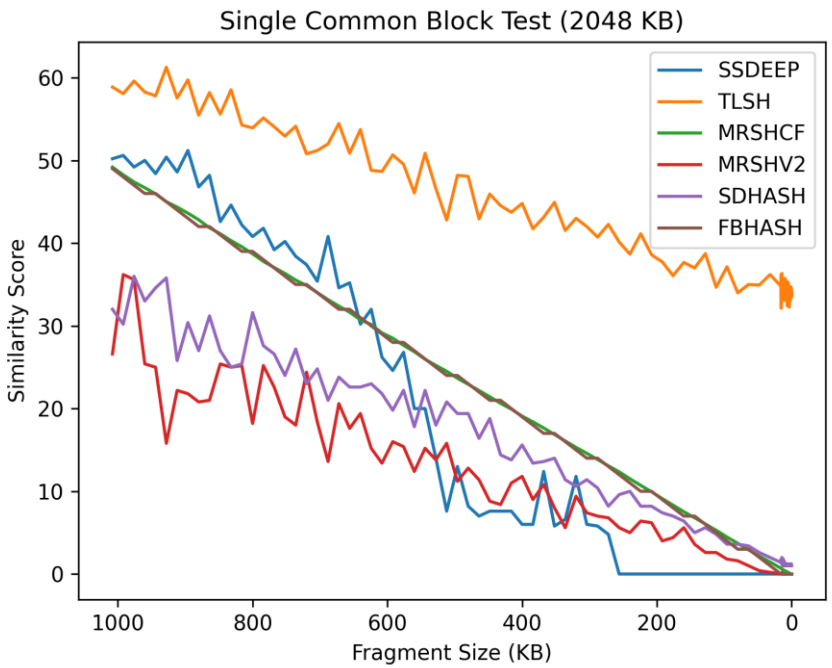


Single Common Block Test

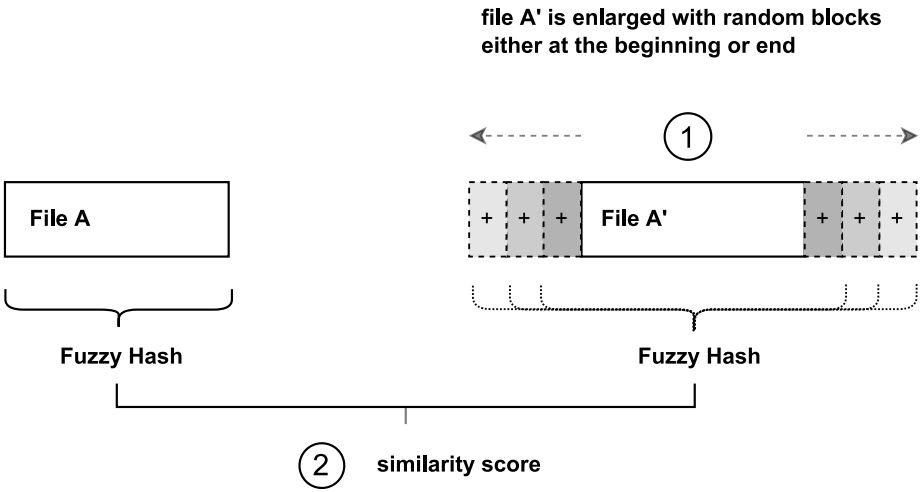


Sensitivity & Robustness

Single Common Block Test

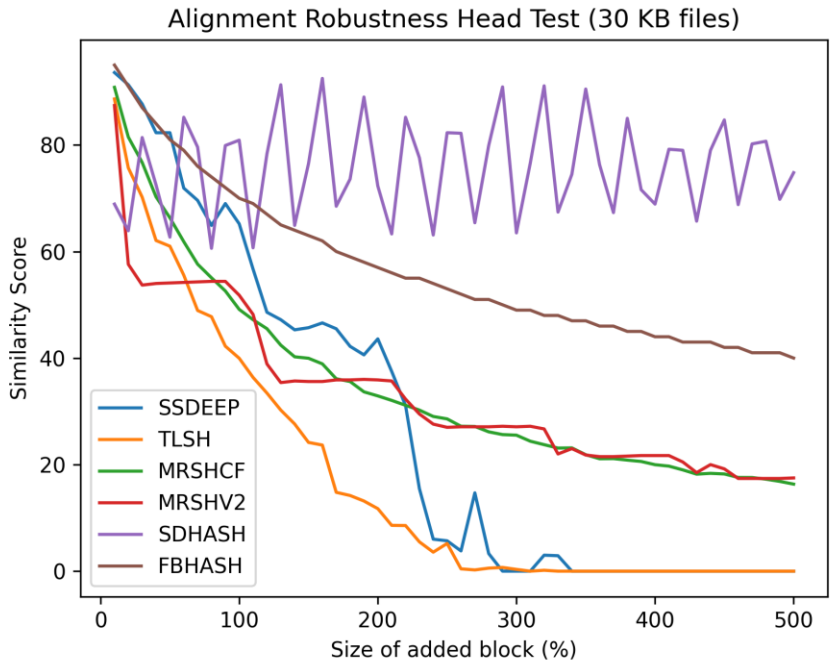


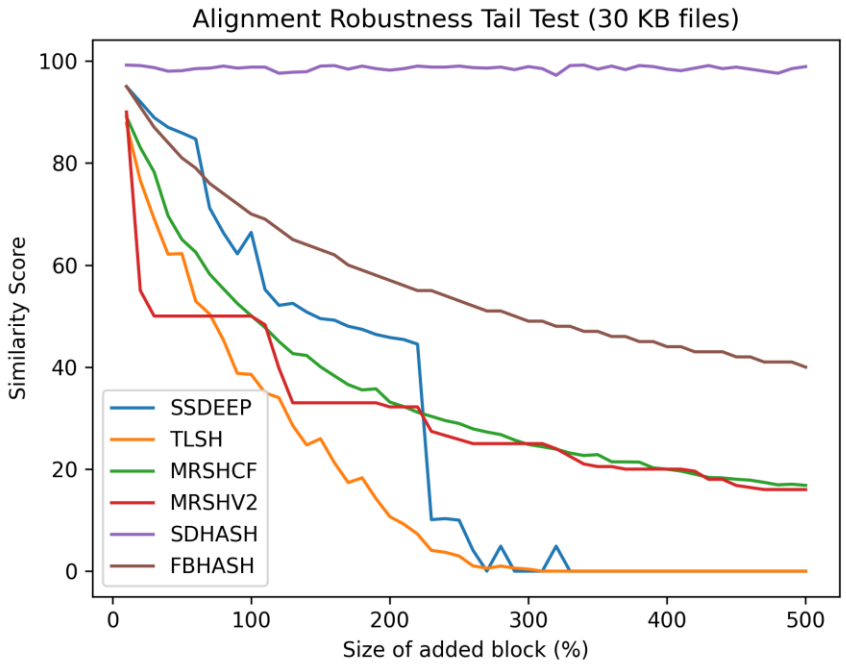
Alignment Robustness Test



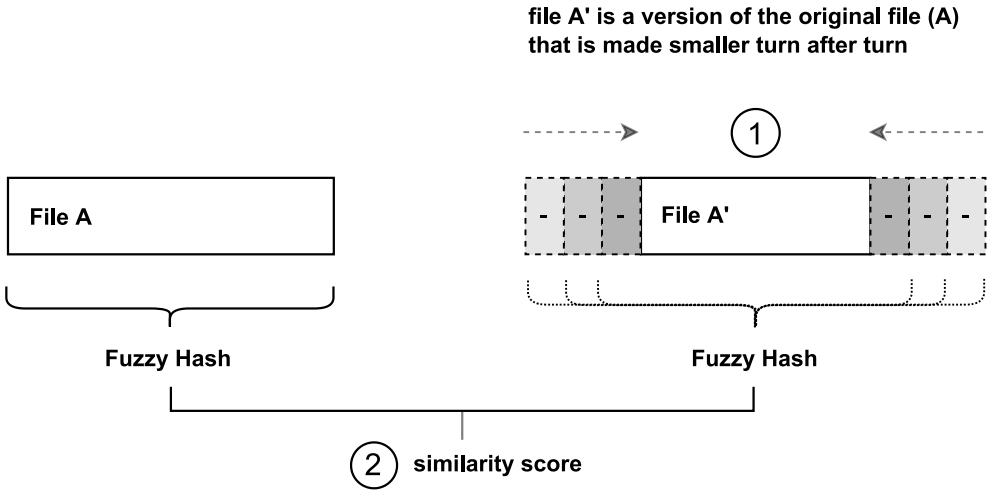
Sensitivity & Robustness

Alignment Robustness Test

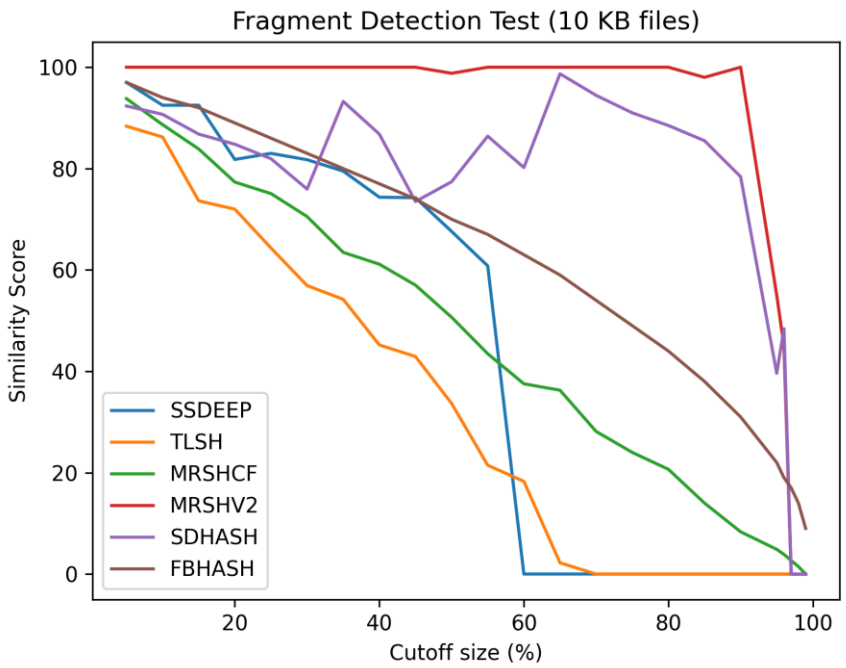




Fragment Detection Test



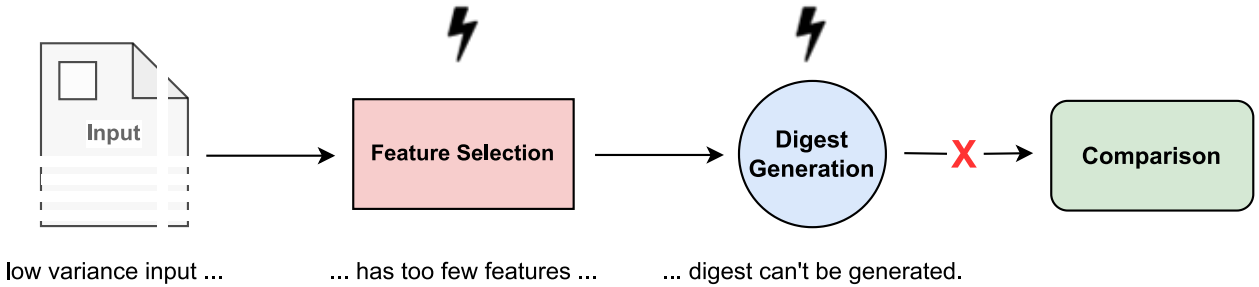
Fragment Detection Test



Adversarial Resilience Test

- **Digest Generation Impediment**
  - Could an attacker generate low variance content that cannot be hashed?
    - Text files (same length) but with varying levels of input characters are hashed (up to 100 ASCII chars)
  - What is the smallest input size for fuzzy hashes to process?
    - Minimum file size 10 bytes, maximum 3000 bytes
- **Digest Comparison Impediment**
  - Can fuzzy hashing deal with repetitive content?
    - 5000 bytes randomly generated content are chained together multiple times

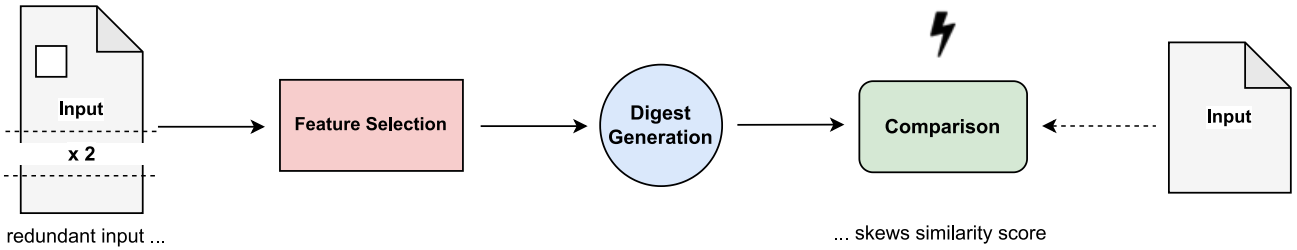
Digest Generation Impediment



Digest Generation Impediment

Algorithms	Limitations
ssdeep & mrsh-cf	Any input > 10 bytes (minimum file size in test)
TLSH	Minimum 50 bytes and more than 2 characters variance
MRSH-v2	Files smaller than 2900 bytes must contain more than 100 characters
sdhash	Minimum 512 bytes to be hashed, and at least 8 characters variance < 750 bytes
FbHash	Minimum 3 characters variance for any input size

Digest Comparison Impediment



Adversarial Resilience

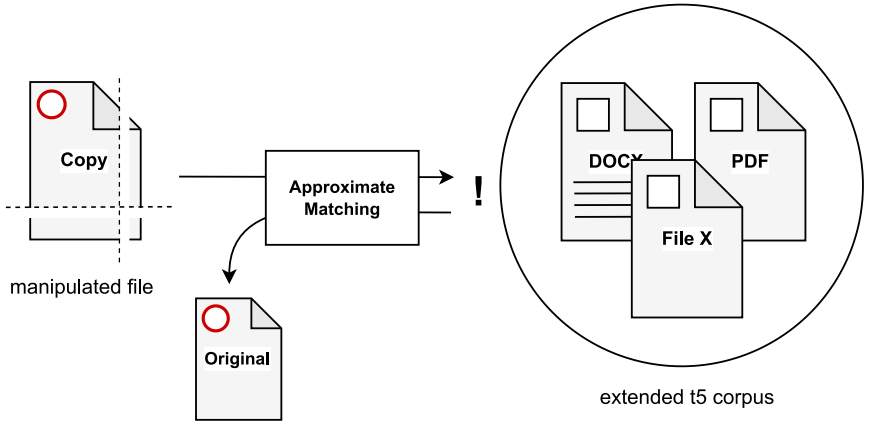
Digest Comparison Impediment

	Similarity scores					
Multiplication factor	ssdeep	TLSH	mrsh-cf	MRSH-v2	sdhash	FbHash
x 1 (5 KB)	100	100	100	100	100	100
x 2 (10 KB)	69	67	96.3	100	100	99
x 4 (20 KB)	0	39	94.3	100	100	99
x 8 (40 KB)	0	11	93.3	100	100	99
x 16 (80 KB)	0	0	92.8	100	100	99
x 32 (160 KB)	0	0	92.6	100	100	99

Table 6: Similarity scores for the same 5000 bytes of randomly generated data; concatenated several times; averaged over 10 test runs.

Finding the needle

- Real file types
- Finding the original file among many similar one's
- Different manipulation techniques: files are shortened or made bigger, compressed, partially overwritten, mixed up with similar files, etc.
- 10 *needles* in total that challenge the algorithm's ability to find the original file



Finding the needle

Finding the needle – Key takeaways

- **`ssdeep`, `TLSH`** are only usable to a certain extend
- **`MRSH-v2`** performed best followed by **`mrsh-cf`**
- **`FbHash`** is too slow to be used at scale
- **`sdhash`** is ineffective for most file types
- **Multi-Resolution-Hashing** can deal best with gzip file compression

Algorithm	File Type	needle_1	needle_2	needle_3	needle_4	needle_5	needle_6	needle_7	needle_8	needle_9	needle_10
ssdeep	PDF	10/10	10/10	10/10	10/10	2/10	1/10	10/10	10/10	0/10	10/10
	DOC	10/10	10/10	9/10	8/10	2/10	3/10	6/10	7/10	0/10	10/10
	GIF	10/10	10/10	10/10	10/10	2/10	2/10	10/10	10/10	0/10	10/10
	HTML	9/10	10/10	5/10	5/10	0/10	0/10	9/10	9/10	0/10	9/10
	JPG	10/10	10/10	10/10	10/10	5/10	9/10	9/10	9/10	5/10	10/10
	PPT	10/10	10/10	10/10	10/10	8/10	6/10	10/10	10/10	0/10	10/10
	TEXT	10/10	10/10	4/10	9/10	2/10	1/10	10/10	10/10	0/10	9/10
	XLS	10/10	10/10	5/10	6/10	0/10	0/10	8/10	9/10	0/10	10/10
	DOCX	10/10	10/10	10/10	10/10	6/10	8/10	9/10	8/10	1/10	10/10
	XLSX	10/10	10/10	10/10	10/10	7/10	5/10	10/10	8/10	0/10	10/10
	PPTX	10/10	10/10	9/10	10/10	5/10	6/10	9/10	10/10	0/10	10/10
TLSH	PDF	8/10	6/10	9/10	1/10	0/10	0/10	8/10	9/10	0/10	0/10
	DOC	5/10	5/10	5/10	4/10	0/10	0/10	1/10	1/10	0/10	2/10
	GIF	10/10	10/10	10/10	10/10	0/10	0/10	10/10	10/10	2/10	8/10
	HTML	10/10	10/10	7/10	9/10	6/10	5/10	5/10	7/10	0/10	10/10
	JPG	9/10	10/10	10/10	8/10	0/10	0/10	9/10	9/10	4/10	10/10
	PPT	8/10	5/10	10/10	5/10	0/10	0/10	7/10	7/10	5/10	4/10
	TEXT	10/10	10/10	9/10	6/10	0/10	1/10	8/10	7/10	0/10	10/10
	XLS	5/10	8/10	8/10	6/10	1/10	3/10	9/10	9/10	0/10	5/10
	DOCX	10/10	10/10	9/10	9/10	0/10	0/10	5/10	6/10	1/10	9/10
	XLSX	10/10	8/10	10/10	10/10	0/10	0/10	1/10	1/10	0/10	9/10
	PPTX	9/10	9/10	9/10	10/10	0/10	0/10	9/10	7/10	4/10	7/10
mrsh-cf	PDF	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
	DOC	10/10	10/10	10/10	10/10	10/10	10/10	9/10	9/10	4/10	10/10
	GIF	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
	HTML	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
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	XLS	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
	DOCX	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	1/10	10/10
	XLSX	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
	PPTX	10/10	10/10	7/10	10/10	10/10	10/10	9/10	9/10	10/10	10/10
MRSH-v2	PDF	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
	DOC	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	4/10	10/10
	GIF	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
	HTML	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
	JPG	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	3/10	10/10
	PPT	10/10	9/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	8/10
	TEXT	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
	XLS	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
	DOCX	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	1/10	10/10
	XLSX	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	0/10	10/10
	PPTX	10/10	10/10	10/10	10/10	10/10	10/10	10/10	10/10	9/10	10/10
sdhash	PDF	0/10	10/10	0/10	0/10	0/10	10/10	0/10	0/10	0/10	0/10
	DOC	0/10	10/10	0/10	0/10	0/10	10/10	0/10	0/10	0/10	0/10
	GIF	1/10	5/10	0/10	0/10	1/10	7/10	0/10	0/10	0/10	6/10
	HTML	0/10	10/10	0/10	0/10	0/10	10/10	0/10	0/10	0/10	0/10
	JPG	0/10	10/10	0/10	0/10	0/10	10/10	0/10	0/10	0/10	0/10
	PPT	0/10	10/10	0/10	0/10	0/10	10/10	0/10	0/10	0/10	0/10
	TEXT	0/10	10/10	0/10	0/10	0/10	10/10	0/10	0/10	0/10	0/10
	XLS	0/10	10/10	0/10	0/10	0/10	10/10	0/10	0/10	0/10	0/10
	DOCX	0/10	8/10	0/10	0/10	0/10	9/10	0/10	0/10	0/10	0/10
	XLSX	0/10	8/10	0/10	0/10	1/10	10/10	0/10	0/10	0/10	0/10
	PPTX	0/10	10/10	0/10	0/10	0/10	10/10	0/10	0/10	0/10	0/10

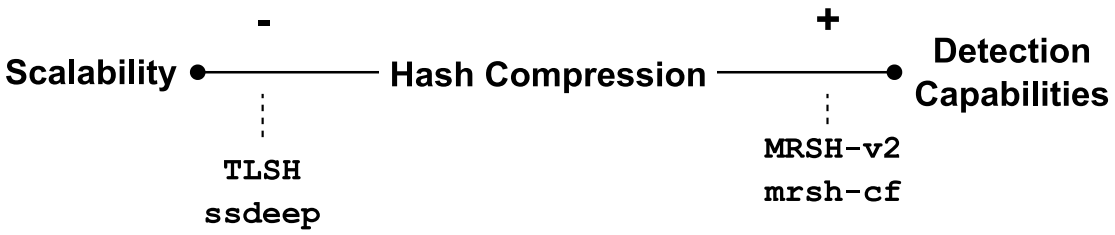
Table 7: Results for different *needle in a haystack* test cases.

A new look on fuzzy hashing

- **`FRASHER`** greatly simplifies the evaluation of byte-wise approximate matching
  - Determining limitations of algorithms and examining their performance with randomly generated files (single-common-block correlation, fragment detection, alignment robustness) or with real-world data (finding the needle test cases)
- **Multi-Resolution-Hashing (`MRSH-v2`, `mrsh-cf`)**
  - Is preferable in digital forensic field work
  - Can detect very small similarities
- **`TLSH` and `ssdeep`**
  - Allow for better integration at scale (effective compression, fast)
  - Users need to be aware of minimum shared content necessary for successful matching
- **`FbHash`** does not compress and is too slow (as of now)
- **`sdhash`** is outperformed in most test cases by newer algorithms

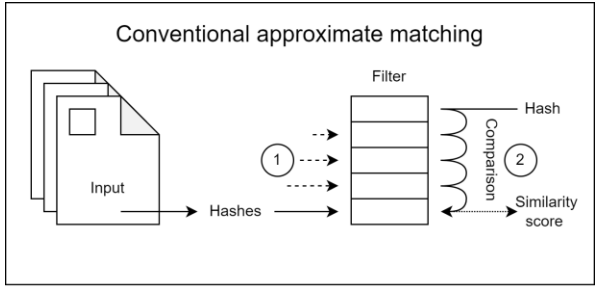
Conclusion

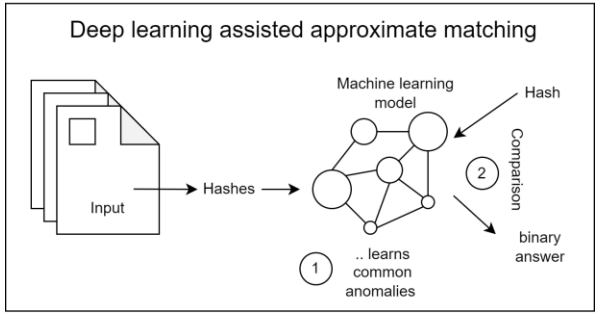
Fuzzy Hashes and their trade-offs



Future research

- **Finding collisions that preserve the information in a file**
- **Deep learning assisted approximate matching:**
  - Hashes are treated like language (NLP)
  - Enables the finding of smaller commonalities
  - **FRASHER** reveals the threats to validity to the machine learning process

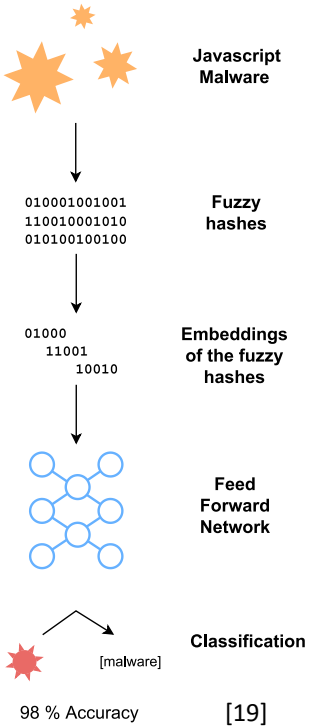




Future Work

Deep learning assisted approximate matching

Current research impressions



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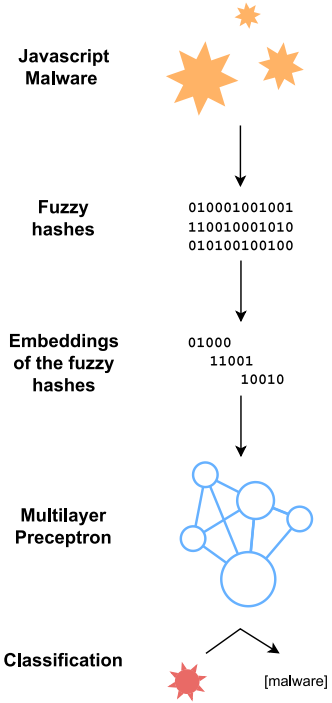

[14]

Microsoft Defender

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FRASHER is available via GitHub:
https://github.com/warlmare/FRASHER