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FORENSICS @ NIST

#NISTForensics

Approximate Matching: Testing how well matchers work

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Motivation

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- In today's world everything is going digital.
  - Conventional books have been converted to eBooks.
  - Letters have been converted to emails.
  - Images have been digitized (jpeg, png).
  - Compact cassettes and video cassettes have been converted to mp3 and mp4s.

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  - Compact cassettes and video cassettes have been converted to mp3 and mp4s.
- It is an enormous volume of data for a forensic investigator to manually examine in a reasonable period of time.

Motivation

1 terabyte 1 terabyte of digital text is (approximately) equal to:

- 1 trillion characters: 1 character = 1 byte.
- 220 million pages: 1 page = 5000 characters.
- 21 years of printing time: 20 sheets per minute.
- 1 million kg of paper: onesided printed.
- Paper stack of 22 km height: bulk of 0.1 mm.

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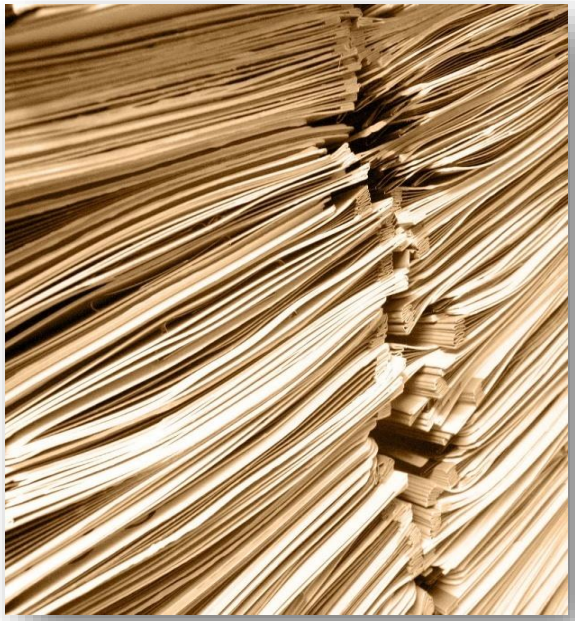
Motivation

A major requirement of modern digital forensic investigations is an ***automatic filtering*** of the correlated/relevant data, that otherwise requires a manual examination by the investigator.



Automatic Filtering

Motivation

Filtering can be of following types:

- Whitelisting
  - The process filters out files by matching them with the database of already ***known to be good*** files.
  - Matched files do not require manual investigation by the investigator.
- Blacklisting
  - The process filters out files by matching them with the set of already ***known to be bad*** files.
  - Matched files are malicious files that the investigator needs to examine further.

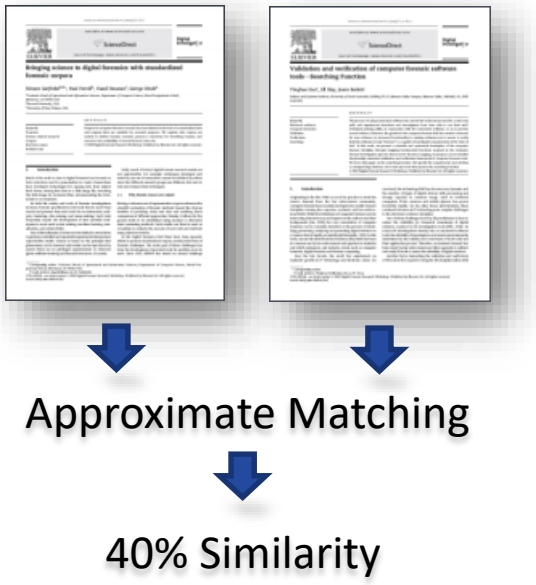
Motivation

The Cryptographic hash functions in digital forensics

- Identify exact duplicates.
- However, they fail to detect similarity.
  - If the input of the hash function is changed slightly (say, the flip of a single bit), the output changes significantly (half of the output bits would get flipped).
- The investigators need robust algorithms that allow similarity detection.

Approximate Matching

The approximate matching is a generic term describing any technique designed to identify similarity between two digital artifacts.



Approximate Matching

- Standard definition, terminology and essential requirement of an Approximate Matching algorithm has been defined by NIST (January 2014).
  - DRAFT NIST SPECIAL PUBLICATION 800-168 "APPROXIMATE MATCHING: DEFINITION AND TERMINOLOGY"
- Not much security analysis of the existing algorithm has been done.

Approximate Matching

Existing Schemes:

- dcfldd (Nicholas Harbour, 2002)
- ssdeep (Jesse Kornblum, 2006)
- sdhash (Vassil Roussev, 2010)
- bbHash(Frank Breitinger 2012)
- mvHash-B(Frank Breitinger 2013)
- mrsh-v2(Frank Breitinger 2013)

Evaluation Framework

To develop a suitable evaluation framework, based on which the evaluation of existing approximate matching algorithms and upcoming schemes can be performed.

Use Cases:

An approximate matching algorithm should address at least one of the following problems:

- **Embedded Object Identification**
- **Fragment Identification**
- **Related Document Detection**
- **Code Version Identification**

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An approximate matching algorithm should address at least one of the following problems:

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- **Related Document Detection**
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- **Code Version Identification**
  - Software version, malware detection

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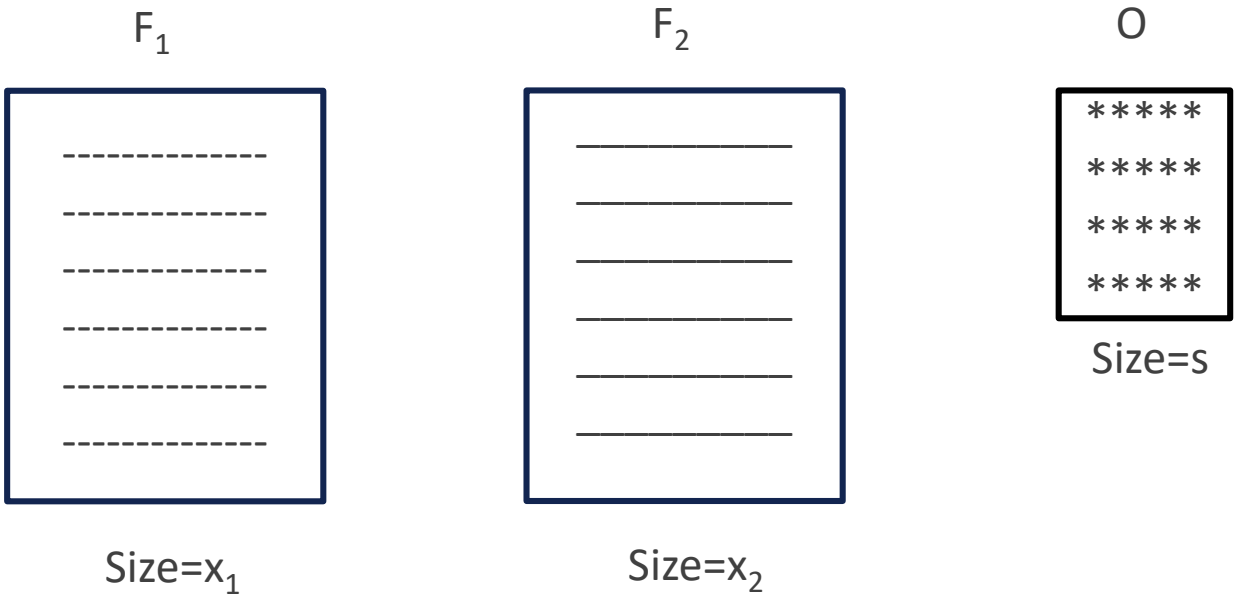
    - Encase
    - FTK
    - X-Ways

Embedded Object Identification

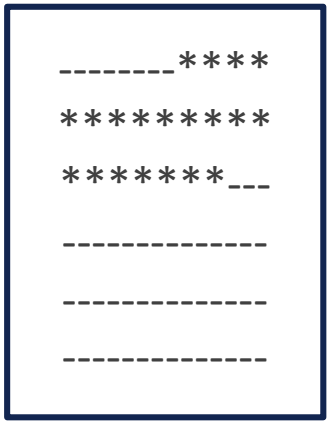
Dataset Generation:

- Dataset type: DOCX, PPTX
- Embedded Object: jpeg, bmp, gif, tiff
- Procedure:
  - Embed each object one by one in each target file at randomly chosen position.
  - For example:
  - User provide 10 docx files(target file) and 10 jpeg (object)
  - Generated embedded file: 100

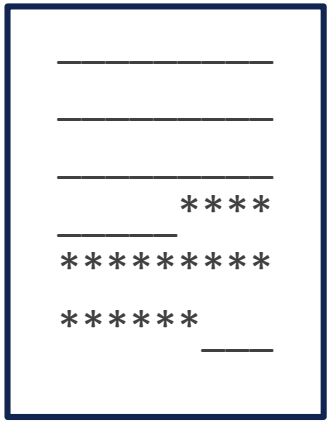
Embedded Object Identification



Embedded Object Identification



Size=x_1+s



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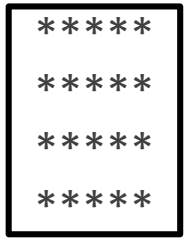

Size=s

Embedded Object Identification

Sub Test cases:

- **Embedded Object Detection**

  Identify a given object inside a file.

- **Single Common Object Identification**

  Identify files that share a common object (cross object identification)

Embedded Object Identification

Measures:

- True Positive
- True Negative
- False Positive
- False Negative
- False positive rate (FPR)
- False negative rate (FNR)
- **Precision** : A perfect precision score of 1.0 means that every result retrieved by a search was relevant.
- **Recall** : A perfect recall score of 1.0 means that all relevant documents were retrieved by the search.
- **F-score** : A measure of a test's accuracy (best value at 1 and worst at 0)
- **MCC** : A measure of the quality of Test(best value at 1 and worst at -1)

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Embedded Object Identification

Fragment Identification

Dataset Generation:

- Dataset type: Text, Docx
- Fragment size:
  95%,90%,85%,80%,……5%,4%,3%,2%,1%.

Fragment Identification

Dataset Generation:

- It sequentially cuts X% of the original input length and generates the match score where X = 5 by default.
- For example file size= 100,000 bytes

A s d f g h j . . . k l p o I u y t r e . . . v b n m x z . . . . a s l k j h . . . s a q w e r t y u l o g . . . h j j k l p

Fragment Identification

Dataset Generation:

- Maximum cuts: $\lceil \frac{100}{x} \rceil$-1
- So for a 100000 bytes long document there will be total 19 cuts of 5000 bytes.

Fragment Identification

Dataset Generation:

- In case that the algorithm still identifies similarity we continue with a further reduction in 1% steps until only 1% of the input is left.
- So the algorithm continues cutting in 1000 byte long pieces until only 1% of the input is left.

Fragment Identification

Dataset Generation:

- **Random fragment** is the first mode. The framework randomly decides whether to start cutting at the beginning or the end of an input and then continues randomly.
- **Sequential Fragment** is the second mode and only cuts blocks at the beginning of an input.

Fragment Identification

Test cases:

- **Fragment detection** identifies similarity tools ability to correlate a an input and a fragment.
- **Smallest Fragment Correlation test** identifies what is the smallest piece or fragment, for which the similarity tool reliably correlates the fragment to the original file?

Fragment Identification

- **Measures:**
  - True Positive
  - True Negative
  - False Positive
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Fragment Identification

Thank You ☺

We are also doing a demo during the poster session. Please stop by if you want to know more about our tool.