Multi-Resolution Similarity Hashing

By

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Multi-Resolution Similarity Hashing

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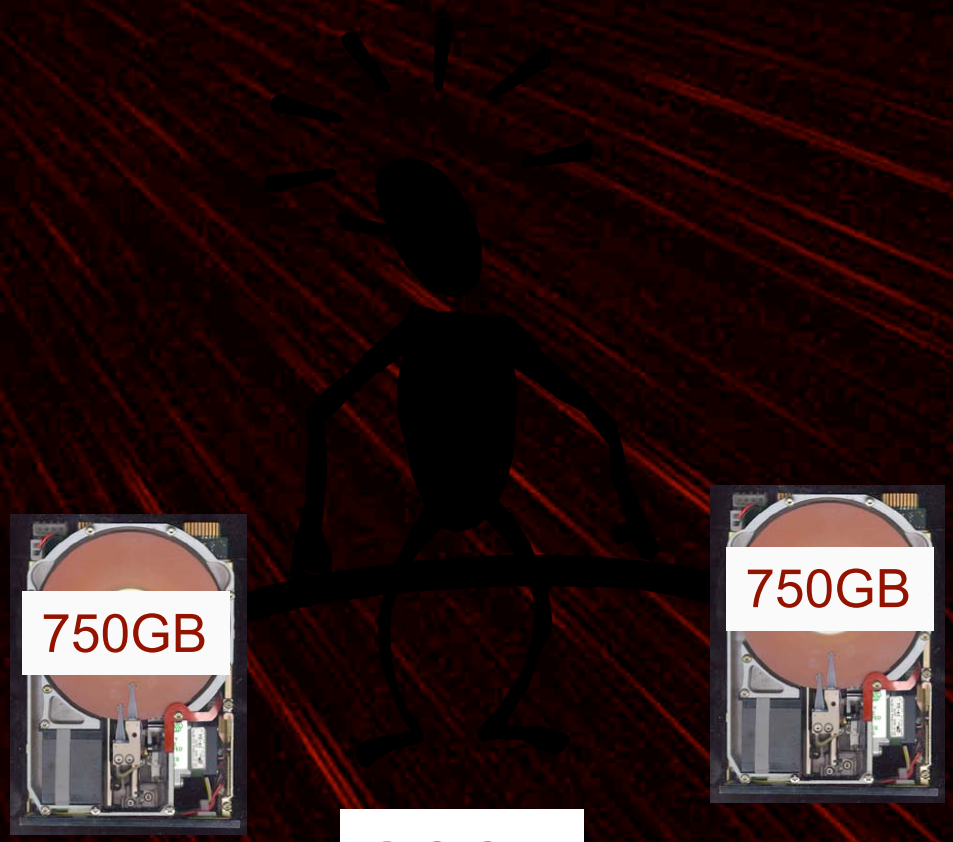
Forensic Challenge #1: Scale



2007

Stream-oriented Tools: MRS Hash

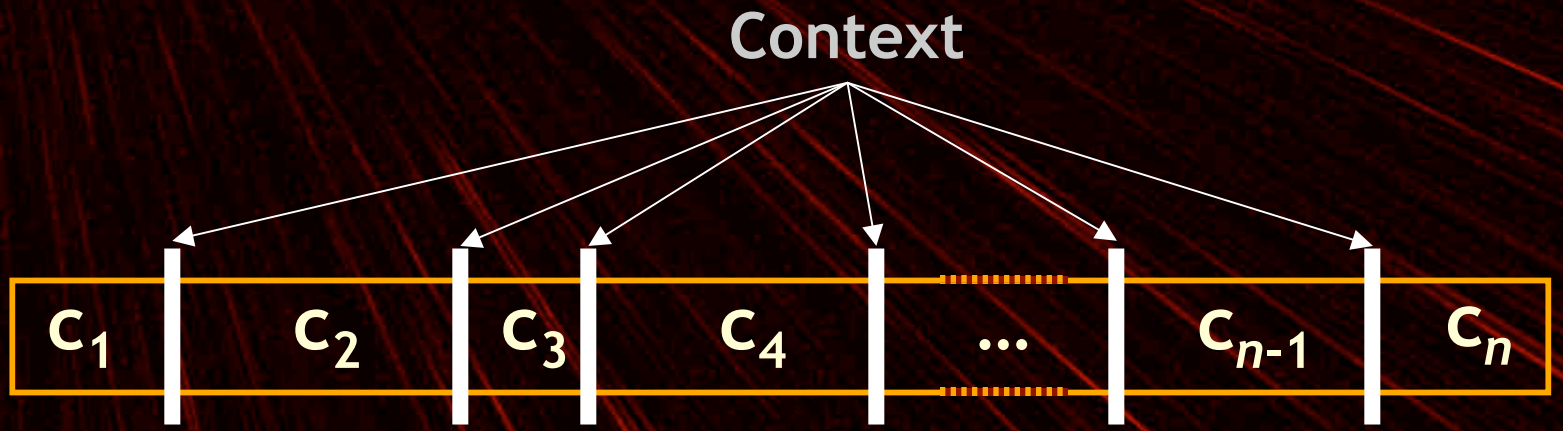
- Observation
  - Cloning a target now is a (necessary) waste of time …
  - … almost nothing is known at the end
- Rationale:
  - Do something useful *while* cloning
- Idea:
  - Generate a similarity hash that can be put to immediate use
  - **M**ulti-**R**esolution **S**imilarity Hash

Requirements

- Performance
  - Work at line speed (or at least at block hash rates)
- Scalability
  - Work for any size target
  - Compare the tiny and the **ENORMOUS**
- Efficiency
  - Space efficiency (low overhead)
  - Processing efficiency (quick comparison)
- Ease of use/standardization
  - Must work out of the box

Basic Idea

- Repeatedly find a ***context***
- Hash chunks in between contexts
- Compose hashes



$$\text{Hash} = h(c_1) \cdot h(c_2) \cdot \ldots \cdot h(c_n)$$

Rationale

- Block hashes are fragile:
  - Insert/delete at the beginning
  - Reordering
- Context-based hashes are resilient:
  - Insert/delete have only local effect

  ➔ We can discover 'versions'
    - » Modified file
    - » Piece-to-whole correlation
    - » Common pieces

Design/Implementation Options

- Each step offers many choices:
  - Context:
    - » length, discovery algorithm
  - Hashing:
    - » hash function(s), granularity
  - Composition
    - » sequence vs. set
    - » fixed vs. variable size
  - Comparison semantics

Example: *ssdeep*

- Context discovery:

ssdeep (2)

- Chunk hashing
  - FNV-derivative, LSB6
    - » 6 bits of hash/chunk
- Hash composition
  - Base64 string concatenation
  - Fixed size hash
- Comparison
  - Edit distance

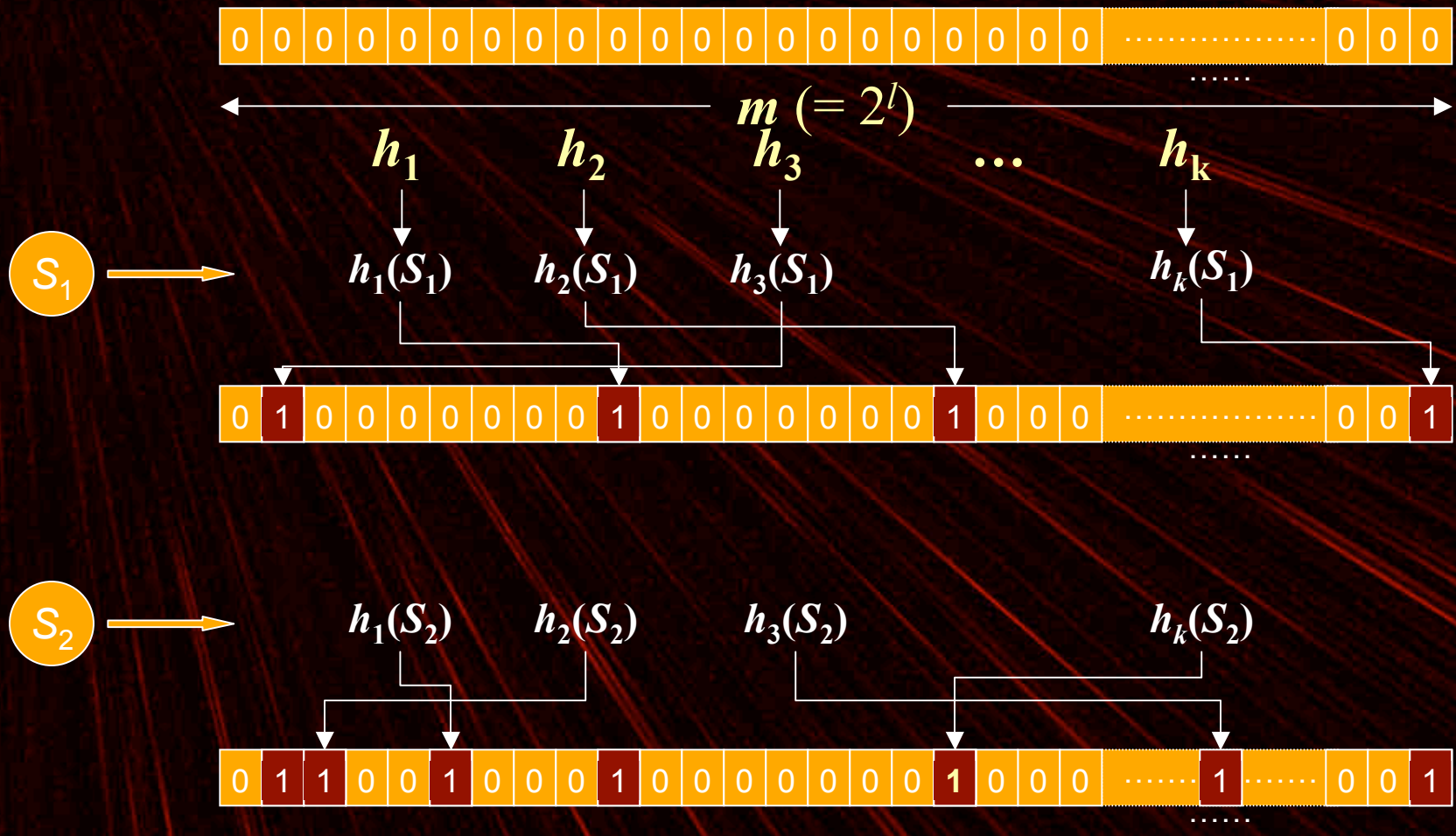
ssdeep (3)

- Some (constructive) critique:
  - Optimal context == ???
  - Adler32 & FNV are weak hashes
    - » Can lead to skewed distributions of chunk sizes
    - » Low-entropy data is a problematic
  - Hash concatenation
    - » Do we really want to pay for sequence-based composition?
      - – Requires 6-8 times more space than a set-based one
  - Fixed size
    - » Causes repeated hash calculations (1.33 for html, 2.0 for doc/xls)
    - » Catastrophic loss of accuracy for larger targets
  - Comparison
    - » Edit distance—what does it tell us for binary data?

Building a Better Mousetrap

- Context discovery
  - Size of 7 bytes appears reasonable
  - Hash:
    - » `Adler32` is probably ok
    - » We picked `djb2` which works as well as `md5`
  - Optimal t = ?
    - » Optimal t ⇔ average chunk size ~ 2^t
    - » NB: To compare f_1 & f_2, we **must** ensure t_1 == t_2!
      - – *ssdeep* cannot do this for arbitrary files
    - » Assume t = 8 (for now)

Hash Composition: Bloom Filters



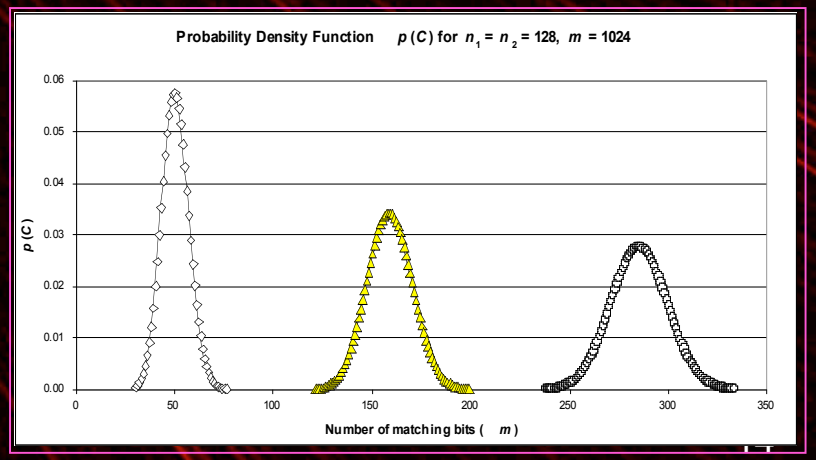
Bloom Filters: False Positive Rates

		k					
		2	4	6	8	12	16
m / n	16	0.0138	0.0024	0.0009	0.0006	0.0005	0.0007
	14	0.0177	0.0038	0.0018	0.0013	0.0013	0.0022
	12	0.0236	0.0065	0.0037	0.0032	0.0041	0.0075
	10	0.0329	0.0118	0.0085	0.0085	0.0136	0.0272
	8	0.0490	**0.0240**	0.0216	0.0255	0.0484	0.0979
	4	0.1549	0.1598	0.2201	0.3128	0.5423	0.7444

Comparing Bloom Filters

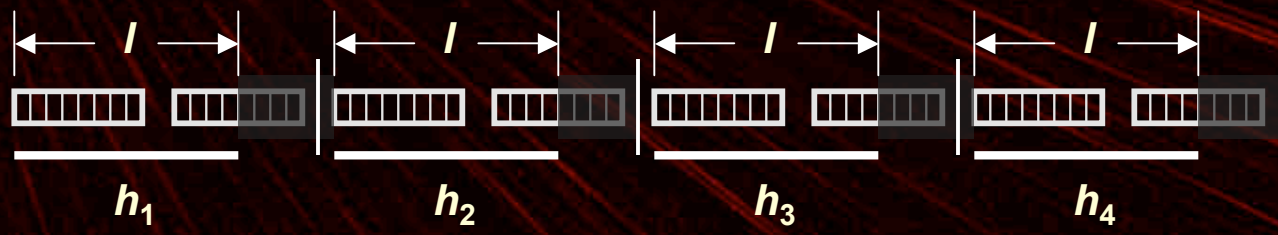
- Filters: f_1, f_2
  - $f_{12} = f_1 \cdot f_2$ (bitwise AND)
  - Number of zeroes: Z_1, Z_2, Z_{12}
  - $lz = \log[(Z_1 + Z_2 - Z_{12})/(Z_1 Z_2)]$
  - $\log(1/2^{11}) \leq lz \leq \log(1/Z_1)$

➔ **0 ≤ *Z*-score ≤ 1**



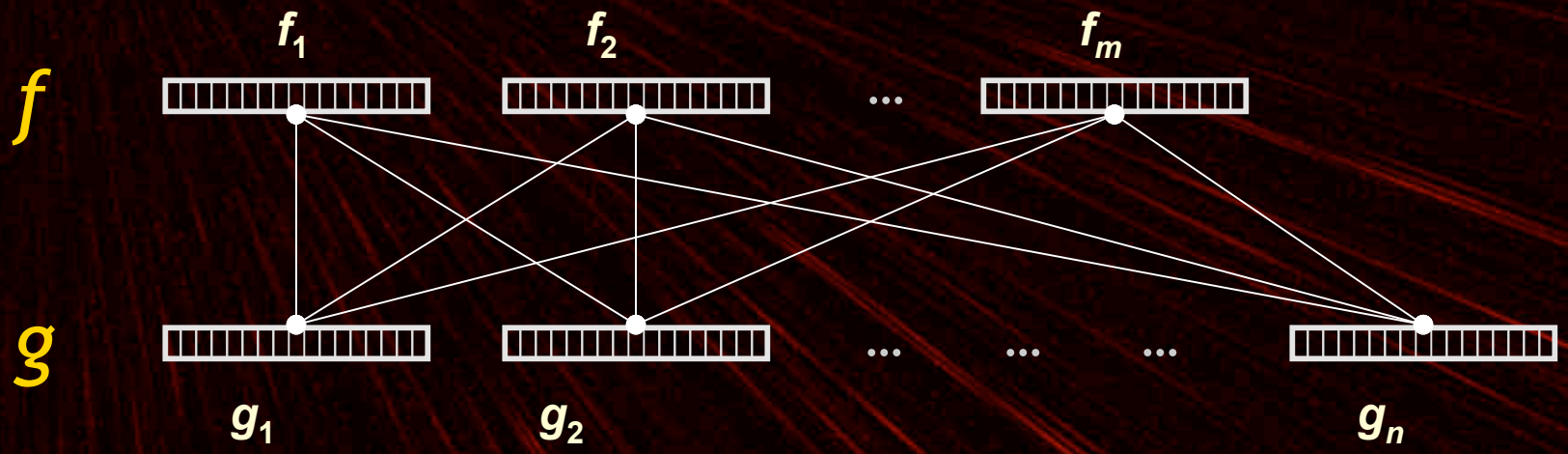
Bloom **Filters as Composite Hashes**

- md5 the chunks and place in a BF:



- Example:
  - $l = 11$ ➔ $m = 2^l = 2048$ bits = 256 bytes
  - $k = 4$, $n = 256$ ($m/n = 8$)
  - Recall that $t = 8$
  - Expected coverage per BF:
    - » $n \times 2^t = 256 \times 256 = 64KB$

Comparing Similarity Hashes



Resolution & Scalability

- Z-score has quadratic complexity: O(nm)
- For t = 8, exp. coverage: 256 x 2^8 = 64 KB :
  - 64KB vs. 64KB ➔ ~ 1 comparison
  - 64KB vs. 64MB ➔ ~ 1,000 comps
  - 64MB vs. 64MB ➔ ~ 1 mln comps
  - …
  - 64 GB vs. 64 GB ➔ ???
- For t = 12 ➔ exp. coverage: 256 x 2^{12} = 1 MB
  - 64 MB vs. 64 MB ➔ ~ 3,600 comps
  - 64 GB vs. 64 GB ➔ ~ 4.300 bln comps
- For t = 16 ➔ exp. coverage: 256 x 2^{16} = 16 MB
  - 64 GB vs. 64 GB ➔ ~ 4.3 mln comps

…

Multi-Resolution Similarity Hash

- Q: Optimal ***t*** ?
- A: No single value will work
- Q: Solution?
- A: Take multiple resolutions
- Q: Which ones?
- A: Pick a "reasonable" **standard** set of numbers:
  - t = 8, 12, 16, 20, 24, 28, 32
  - Note: for t = 32, coverage is 2^{40}/BF = 1TB (!)
  - Note: not all hashes will have all resolutions
    - » We set a minimum of 16 BF elements

MRS Hash: Raw Performance

- Hash generation: > 20MB/s
  - Pentium D 2.8GHz
  - Dominant cost
  - Comparable to 512-block MD5
  - Alpha version:
    - » single thread
    - » almost no optimizations
    - » it's "embarrassingly" parallelizable
- Storage requirements:
  - < 0.5% of target, i.e. 500GB → 2.5GB

MRS Hash: What does it mean?

- Observation:
  - Our comparison is purely syntactic, and
  - Can be applied to *any* data.
  - ➔ We cannot predict what it means!
- Q: How do we know it's useful?
- A: Empirical study
  - Shows how the Z-score should be interpreted
  - Demonstrates possible uses

MRS Hash: Empirical Study

- Corpus: downloaded internet files (Yahoo!)
  - File types: doc, xls, pdf, jpg, (html)
  - 10 files per (generic) topic per type
  - Data cleaned up manually
- Scenarios (for each type)
  - 'All-pairs': compare all file pairs
  - 'Half-directory':
    - » Place (random) half of file in an uncompressed zip
    - » Compare **all** files to the zip file

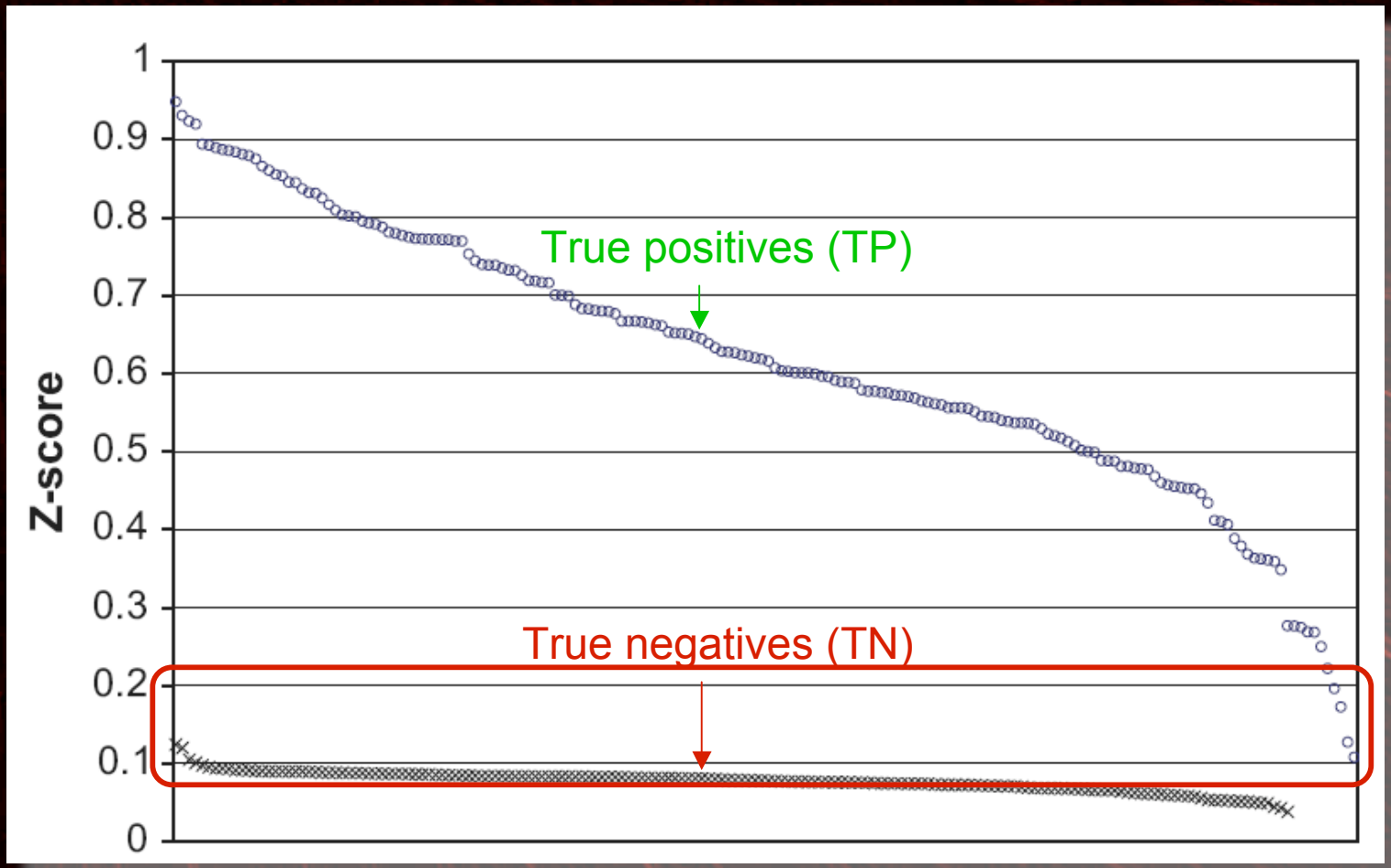
Q: Can Z-score split true positive & true negatives?

Empirical Study: doc **(all-pairs)**

- 355 files, 64kB - 10MB, 298MB total
- All-pairs:
  - 62,835 pairs (ps)
  - 57 ps (<0.1%) with z-score > 0.1
  - 18 ps with z-score > 0.2:
    - » 16 TP (true positives)
    - » 2 FP (false positives)
  - 29 ps b/w 0.1 & 0.2:
    - » 1 TP
    - » 28 TN

  ➔Threshold of 0.2 yields: 2 FP, 1 FN!
  - File versions found: XBRL 2.1 (92/99p), manual (53/54)

Empirical Study: doc (half-dir)



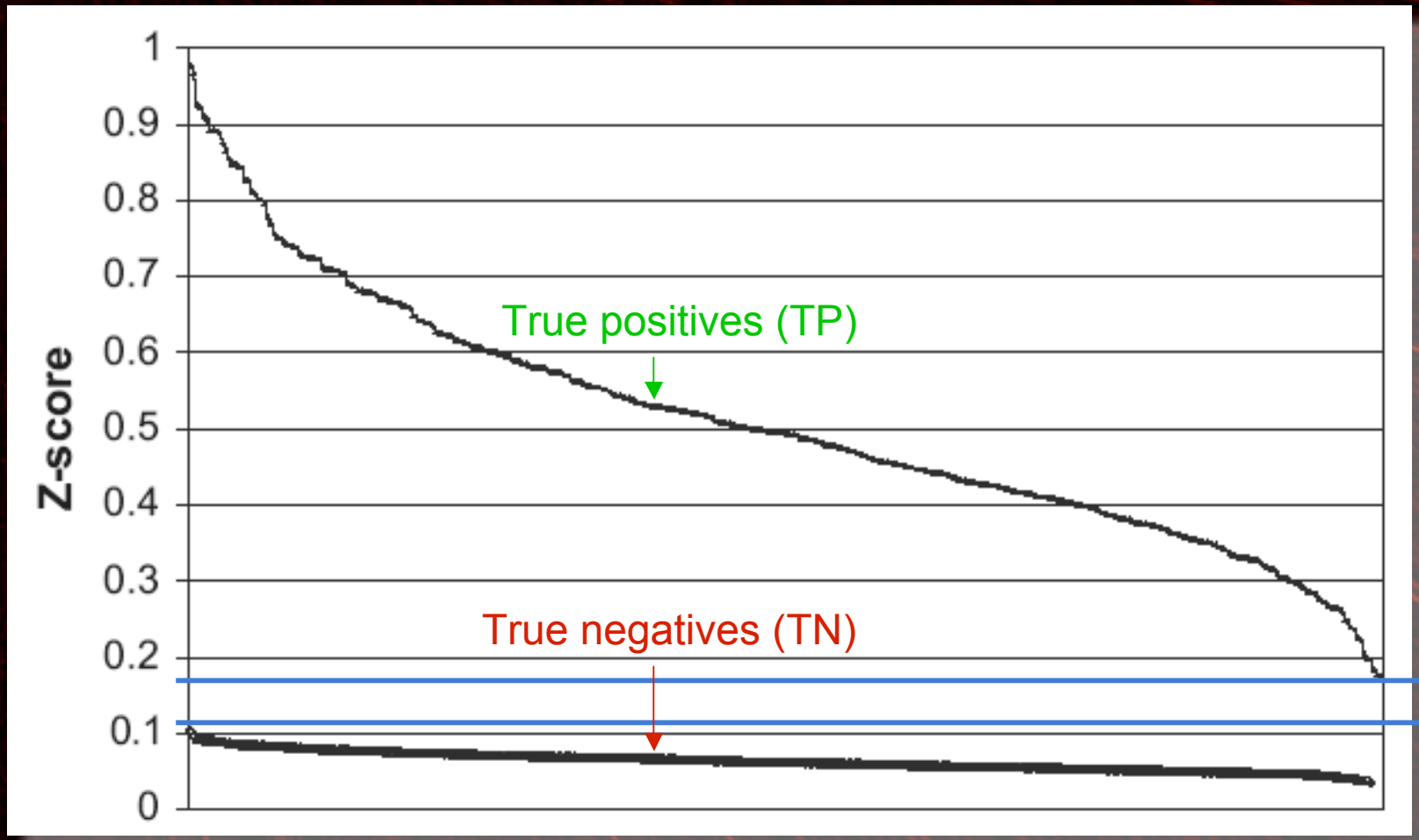
- Note: all known similar files have been removed

Empirical Study: xls (all-pairs)

- 415 files, 64kB - 7MB, 257MB total
- All-pairs:
  - 85,905 pairs (ps)
  - 26 ps (<<0.1%) with z-score > 0.1

  ➔Threshold of 0.2 yields: 1 FP, 1 FN
  - Found: different drafts of an environment form

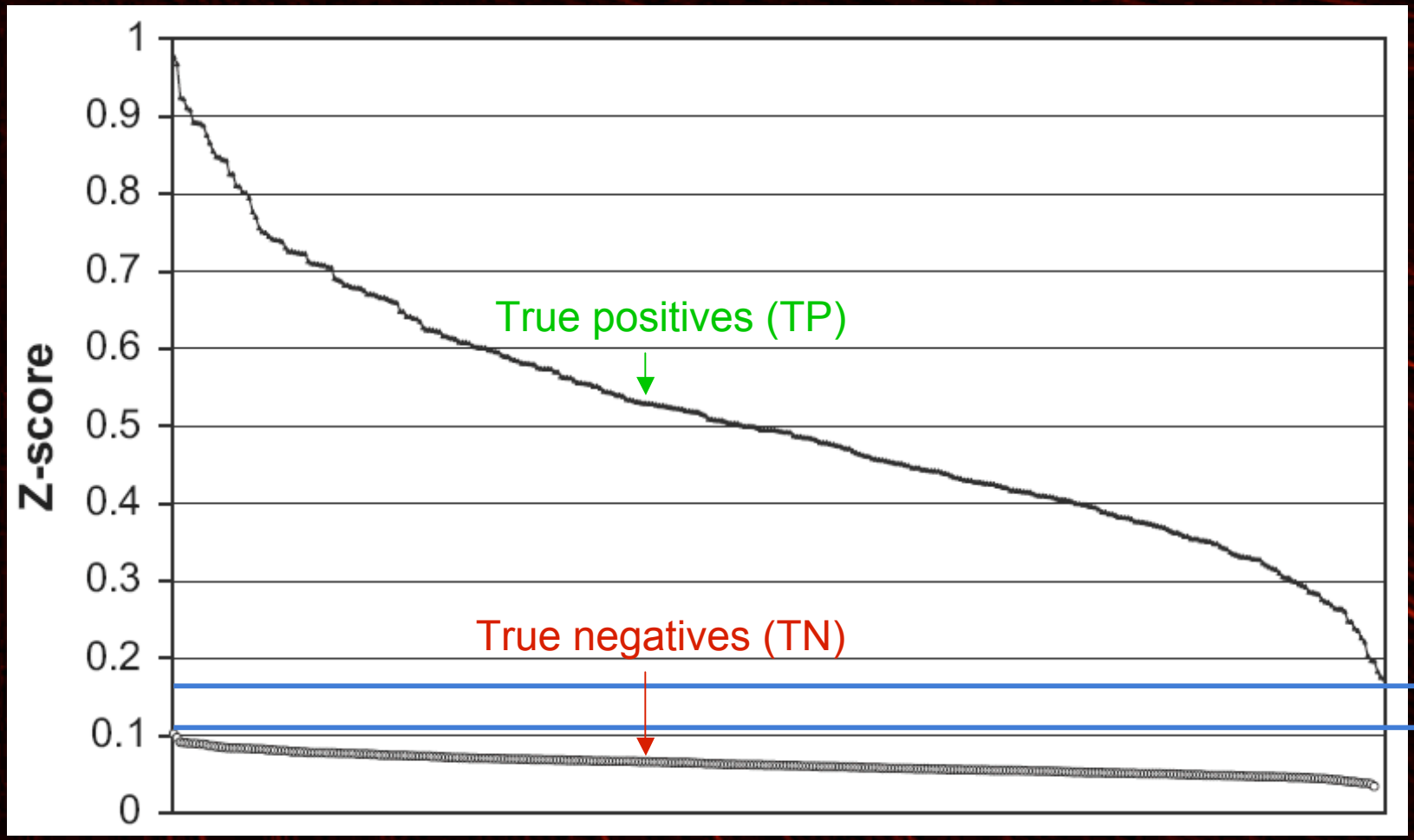
Empirical Study: xls (half-dir)



Empirical Study: jpeg (all-pairs)

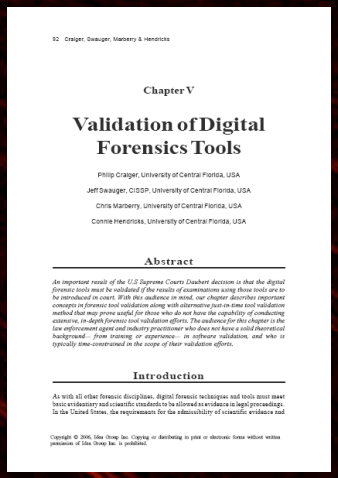
- 737 files, 64kB - 5MB, 121MB total
- All-pairs:
  - 273,370 ps
  - 46 ps (<0.01%) with z-score > 0.1
    - » 4 TP (0.214, 0.166, 0.136, 0.121) among top 5
    - » Example?

Empirical Study: jpeg (half-dir)



Empirical Study: pdf

- Only 59 files:
  - All-pairs: no FP/FN
  - Half-dir: TN < 0.03, TP > 0.20
- Clustering
  - Added files w/ common format:
  - Cluster #1: 9 book chapters
  - Cluster #2: 5 DFRWS'06 papers
  - Results:
    - » C1: 0.88-0.90, 0.66-0.69, 0.55
    - » C2: 0.12-0.19
    - » All others (2,003 out of 2,046) : < 0.09



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Chapter V

Validation of Digital Forensics Tools

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Jeff Swauger, CISSP, University of Central Florida, USA
Chris Marberry, University of Central Florida, USA
Connie Hendricks, University of Central Florida, USA

Abstract

An important result of the U.S Supreme Courts Daubert decision is that the digital forensic tools must be validated if the results of examinations using those tools are to be introduced in court. With this audience in mind, our chapter describes important concepts in forensic tool validation along with alternative just-in-time tool validation method that may prove useful for those who do not have the capability of conducting extensive, in-depth forensic tool validation efforts. The audience for this chapter is the law enforcement agent and industry practitioner who does not have a solid theoretical background— from training or experience— in software validation, and who is typically time-constrained in the scope of their validation efforts.

Introduction

As with all other forensic disciplines, digital forensic techniques and tools must meet basic evidentiary and scientific standards to be allowed as evidence in legal proceedings. In the United States, the requirements for the admissibility of scientific evidence and

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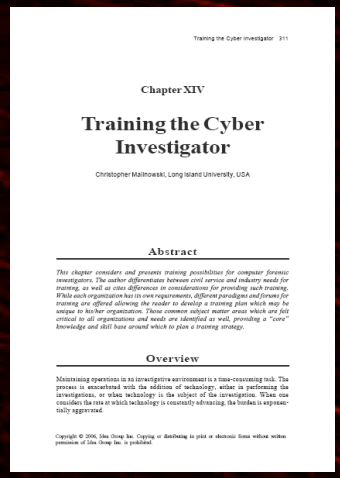

Training the Cyber Investigator 311

Chapter XIV

Training the Cyber Investigator

Christopher Malinowski, Long Island University, USA

Abstract

This chapter considers and presents training possibilities for computer forensic investigators. The author differentiates between civil service and industry needs for training, as well as cites differences in considerations for providing such training. While each organization has its own requirements, different paradigms and forums for training are offered allowing the reader to develop a training plan which may be unique to his/her organization. Those common subject matter areas which are felt critical to all organizations and needs are identified as well, providing a "core" knowledge and skill base around which to plan a training strategy.

Overview

Maintaining operations in an investigative environment is a time-consuming task. The process is encountered with the addition of technology, either in performing the investigations, or when technology is the subject of the investigation. When one considers the rate at which technology is constantly advancing, the burden is exponentially aggravated.

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Digital Investigation

ELSEVIER

A cyber forensics ontology: Creating a new approach to studying cyber forensics

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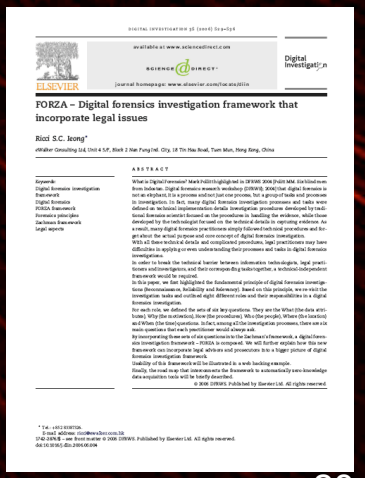
ABSTRACT

1. Introduction

2. Ontological model



Digital Investigation

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FORZA – Digital forensics investigation framework that incorporate legal issues

Ricci S.C. Irong*

ABSTRACT

Conclusions (Req. Review)

- Performance
  - Work at line speed (or at least at block hash rates) ✓
- Scalability
  - Work for any size target ✓
  - Compare the tiny and the **ENORMOUS** ✓
- Efficiency
  - Space efficiency (low overhead) ✓
  - Processing efficiency (quick comparison) ✓
- Ease of use/standardization
  - Must work out of the box ✓

Conclusions (2)

- MRSH can also help you conduct:
  - Efficient searches for files/fragments;
  - Privacy preserving inquiries;
  - Live forensics (taking system signature);
  - Object version discovery;
  - Large-scale target correlation;
  - …

Future Work

- Define serialized format
- Optimize
  - Line speed should be achievable
- Parallelize
  - GPU processing can massively speedup comparisons
- Test for scale
  - Drive-scale testing is necessary
  - Sub-file testing

Thank You!

Questions?