Automated Digital Evidence Target Definition Using Outlier Analysis and Existing Evidence

By

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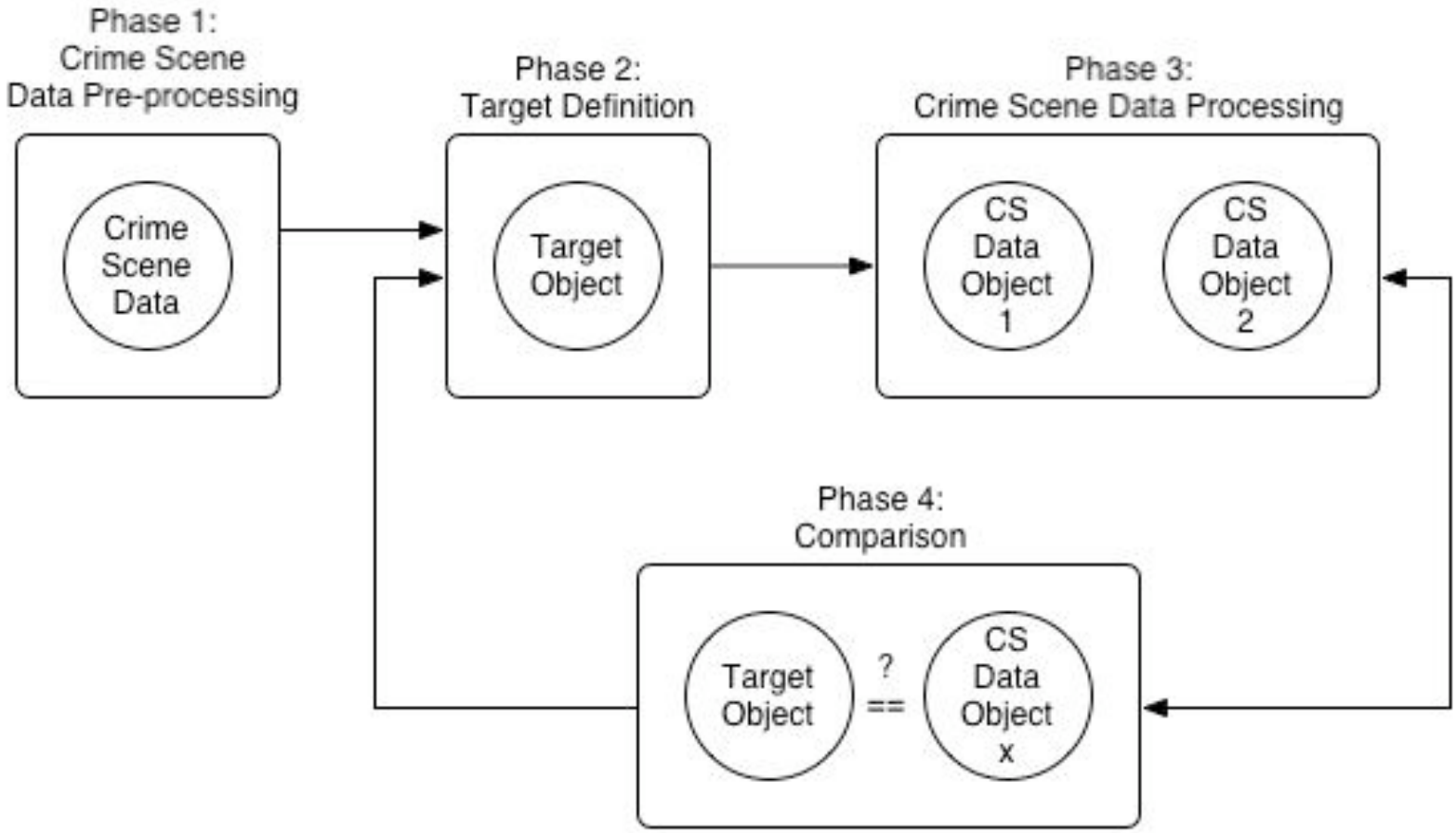
Searching Phases

1. Crime Scene Data Preprocessing

2. Target Definition
   - For what are we looking?
3. Crime Scene Data Processing
   - Process abstraction layers
4. Comparison
   - Are the crime scene data and the target similar?

Searching Phases



How Do We Define Target Objects?

- Develop a hypothesis
  - Experience and training
  - Existing evidence
- Determine what evidence would support or refute hypothesis
- Define the attributes in a target object

Existing Evidence Automation in Autopsy

1. Investigator identifies “evidence”
2. Tool makes suggestions for future searches
3. Tool saves approved searches
4. Investigator selects suggested searches

Suggested Targets

- Files in same parent directory
- Files with same temporal data
- Files with similar names
- Files with same application type
- Files with file name in content
- Files with similar content

Case Study Results

- Honeynet Forensic Challenge
- We find `/dev/ptyp` using experience
- Autopsy suggests similar times, name in content etc.
- Finds `/bin/ps` file and `/usr/man/.Ci` directory

New Topic: File Hiding Techniques

- Change MAC times
- Use similar names
- Pad data to maintain size or CRC
- Make “innocent looking” directory
- Special characters

Make file characteristics “fit in”

Spatial Outlier

- Outliers objects are “grossly different” from all other objects
- Spatial outliers are “grossly different” from local objects
- Hypothesis: Hidden files could be spatial outliers in their parent directory

Variant of Iterative Z Algorithm

Lu, Chen, & Kou - 2003 IEEE CDM

1. Compute average attribute value (g) for each directory
2. Compute distance (h_i) from each file to g
3. Compute mean (μ) and std dev (σ) of h_i
4. Standardize each h_i :

$$y_i = \left| \frac{h_i - \mu}{\sigma} \right|$$

- If largest y_i is > θ (2 or 3), it is an outlier

Single Attribute Results

	/ partition			/usr/ partition		
Attribute	**Hits**	**Accuracy**	**Comp**	**Hits**	**Accuracy**	**Comp**
App Type	1.01%	10.00%	14.00%	9.15%	3.08%	18.58%
Block	6.93%	6.22%	60.00%	3.96%	2.97%	7.74%
C-time	2.24%	26.92%	84.00%	1.27%	54.44%	45.51%
M-time	0.75%	5.77%	6.00%	8.26%	7.63%	41.49%
Size	4.78%	2.41%	16.00%	5.84%	3.22%	12.38%

	Combined		
Attribute	**Hits**	**Accuracy**	**Comp**
App Type	7.14%	3.33%	17.96%
Block	4.69%	4.15%	14.75%
C-time	1.51%	44.37%	50.67%
M-time	6.41%	7.58%	36.73%
Size	5.58%	3.05%	12.87%

/: 6,951 files and 50 (0.72%) involved

/usr/: 21,267 files and 323 (1.49%) involved

Results Summary

- Trojan exec on `/` not found, but was found on `/usr/` because of starting block
- Many false positives were obvious: README files
- Generic Windows System:
  - 2.58% files identified (5.07% on honeypot)
  - 100% false positive rate

Multiple Attributes

1. Standardize all attributes
2. Compute average attribute for each directory (g) and distance for each file (hi)
3. Compute directory mean and variance-covariance

$$\mu_S = \frac{1}{|NN(x_i)|} \sum_{x \in NN(x_i)} h(x)$$

$$\Sigma_s = \frac{1}{|NN(x_i)|} \sum_{x \in NN(x_i)} [h(x) - \mu_s][h(x) - \mu_s]^T$$

Multiple Attributes (2)

4. Compute Mahalonobis distance for each file:

$$a_i = (h(x_i) - \mu_s)^T \Sigma (h(x_i) - \mu_s)$$

5. Standardize distances and determine if largest is > 3

- Lu, Chen, Kou - 15th IEEE Conference on Tools with AI

Multiple Attribute Results

	/ partition			/usr/ partition		
Attribute	**Hits**	**Accuracy**	**Comp**	**Hits**	**Accuracy**	**Comp**
C- and M-time	0.30%	85.71%	36.00%	0.56%	23.33%	8.67%
C-, M-time, and Size	0.22%	53.33%	16.00%	0.32%	43.28%	8.98%
C-, M-time, Size, and Block	0.22%	53.33%	16.00%	0.22%	31.91%	4.64%
C-, M-time, Size, Block and App Type	0.10%	57.14%	8.00%	0.15%	38.71%	3.72%

	Combined		
Attribute	**Hits**	**Accuracy**	**Comp**
C- and M-time	0.50%	32.62%	12.33%
C-, M-time, and Size	0.29%	45.12%	9.92%
C-, M-time, Size, and Block	0.22%	37.10%	6.17%
C-, M-time, Size, Block and App Type	0.13%	42.11%	4.29%

Clean Windows:

C&M: 0.63%

C,M,&S: 0.54%

Hidden Directories

- Calculate average attribute value for files in a directory
- Compare with other directories at same “level”
- Detect outliers using “iterative Z”

Directory Outlier Results

	/ partition			/usr/ partition		
Attribute	**Hits**	**Accuracy**	**Comp**	**Hits**	**Accuracy**	**Comp**
App Type	0.00%	0.00%	n/a%	7.44%	0.00%	0.00%
C-time	2.25%	0.00%	n/a%	1.65%	0.00%	0.00%
M-time	1.12%	0.00%	n/a%	1.38%	0.00%	0.00%
Size	1.12%	0.00%	n/a%	3.77%	0.00%	0.00%

	Combined		
Attribute	**Hits**	**Accuracy**	**Comp**
App Type	6.88%	0.00%	0.00%
C-time	1.70%	0.00%	0.00%
M-time	1.36%	0.00%	0.00%
Size	3.57%	0.00%	0.00%

- `/` had 89 and 0 hidden directories
- `/usr/` had 1,088 and 1 hidden directory
- Was found when $\theta = 2$
- 0.78% on Windows System

Conclusions

- Implemented a tool to suggest and save searches
- Implemented outlier analysis algorithms to find hidden & new files

- What is human error rate?
- Honeypot is not an ideal case study (little user activity before and after incident)

Future Work

- Investigate human error rate
- Identify which techniques work better with different types of incidents
- Incorporate data mining with other analysis techniques - keyword searching, hashes etc.

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