Automatic Event Log Abstraction to Support Forensic Investigation

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Outline

- Introduction
- Existing Methods
- The Proposed Method
    - Event Log Preprocessing
    - Grouping based on Word Count
    - Graph Model for Log Messages
    - Grouping with Automatic Graph Clustering
    - Extraction of Event Log Abstraction
- Experimental Results
- Conclusion and Future Work

Introduction

- Abstraction of event logs is the creation of a template that contains the most common words representing all members in a group of event log entries
- Abstraction helps the forensic investigators to obtain an overall view of the main events in a log file

Input log file: auth.log
Output abstractions:
#1 Mar * * nssal * removing removable location: *
#2 Mar 8 * nssal * Invalid user * from *
#3 Mar 8 * nssal * Failed password for * from * port * ssh2
...

Existing Methods

Existing log abstraction methods require user input parameters. It is time consuming due to the need to identify the best parameters.

- SLCT (Vaarandi, 2003): one mandatory parameter and 14 optionals
- LogCluster (Vaarandi and Pihelgas, 2015): one mandatory parameter 26 optionals
- IPLoM (Makanju et al., 2012): five mandatory parameters
- LogSig (Tang et al., 2011): one mandatory parameter
- Drain (He et al., 2017): three mandatory parameters
- Model training (Thaler et al., 2017)

The Proposed Method

Raw event logs

↓

Automatic log preprocessing

↓

Grouping based on word count

↓

Refine grouping with automatic graph clustering

↓

Get the event log abstraction per cluster

Event Log Preprocessing

- We parse the log files using the nerlogparser, a log parsing tool based on named entity recognition
- It supports fully automatic parsing because it provides a pre-trained model
- We then extract unique messages from the log entries

Input:
Jan 18 09:31:32 victoria dhclient: DHCPACK from 10.0.2.2

Process: automatic parsing with the nerlogparser tool

Output:
timestamp: Jan 18 09:31:32
hostname: victoria
service: dhclient
message: DHCPACK from 10.0.2.2

Grouping based on Word Count

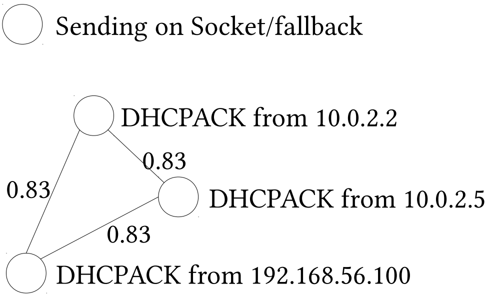
- We split the discovered unique messages based on space character then count the word length
- An abstraction is extracted from the always-occurring word in a group of log entries having the same length

```
Cluster #1:
Jan 18 09:31:32 victoria dhclient: DHCPACK from 10.0.2.2
Jan 18 10:56:40 victoria dhclient: DHCPACK from 10.0.2.2
Feb  6 13:31:12 victoria dhclient: DHCPACK from 10.0.2.5

Abstraction #1:
*   * *      victoria dhclient: DHCPACK from *

Cluster #2:
Feb  6 12:56:48 victoria init: Switching to runlevel: 0
Jan 18 17:13:49 victoria init: Switching to runlevel: 6
Feb  6 13:03:53 victoria init: Switching to runlevel: 6

Abstraction #2:
*   * *      victoria init: Switching to runlevel: *
```

Graph Model for Log Messages

The log entries have very diverse vocabularies, so we need to refine discovered groups based on the string similarity

- We use an automatic graph-based clustering
- Vertex: a unique message, edge: the weighted Hamming similarity



Grouping with Automatic Graph Clustering

Algorithm 1: The proposed automatic graph clustering.

```
Input: graph
Output: best_cluster
Procedure GetClusters(graph):
    best_cluster ← dict()
    max_modularity ← -1
    clusters ← GirvanNewman(graph)
    for cluster in clusters do
        modularity ← get_modularity(cluster, graph)
        if max_modularity < modularity then
            max_modularity ← modularity
            best_cluster ← cluster
        end
    end
End Procedure
```

Building Micro-clusters

Algorithm 2: Building micro-clusters automatically.

```
Input: graph
Output: final_clusters
Procedure AutomaticClustering(graph):
    clusters ← GetClusters(graph)
    final_clusters ← dict()
    for cluster in clusters do
        if len(cluster) ≤ micro-cluster size then
            final_clusters.update(cluster)
        else
            AutomaticClustering(cluster) // recursion
        end
    end
End Procedure
```

Extraction of Abstraction: Merging Abstractions

- We extract an abstraction from each micro-cluster
- Merging is needed because an abstraction from each micro-cluster has a possibility to be very similar with others
    - We find pair combinations (A_i, A_j) from all abstractions to be compared.
    - Two abstractions A_i and A_j will continue to be checked for merging if there is a weighted Hamming similarity between them.

Example of Merging Abstractions

Example 1:
Abstraction #1: Invalid user * from *
Abstraction #2: Invalid user admin from *

Example 2:
Abstraction #1: Invalid user * from 200.27.148.45
Abstraction #2: Invalid user * from *

Extraction of Abstraction: Final Abstractions

- In all previous steps, we consider only the message field in a log entry.
- In the final step, we consider all other fields such as timestamp, host name, and service name.

```
Cluster #1:
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Abstraction #2:
*    * *        victoria init: Switching to runlevel: *
```

Experimental Results: Datasets

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Table 1: List of Public Forensic Datasets

Dataset	# Files	# Lines	# Abs
Digital Corpora (Casper) [7]	15	11,086	3,422
DFRWS 2009 (Jhuisi) [2]	25	11,737	3,488
DFRWS 2009 (Nssal) [2]	40	107,093	5,573
DFRWS 2016 (DF16) [3]	1	3,304	102
Honeynet Challenge 7 (Honey) [1]	12	8,712	2,039

- For all datasets except DFRWS 2016, we recovered the directory `/var/log/` from the forensic disk images
- We retrieved some common log files such as authentication logs, kernel logs, and system logs

Parameter Settings

Table 2: Parameter Settings for Experiments

Method	Parameter settings
Proposed method	none
IPLoM [17]	file support threshold = 0
	partition support threshold = 0
	upper bound = 0.9
	lower bound = 0.25
	cluster goodness threshold = 0.175
LogSig [24]	number of cluster = ground truth cluster
Drain [12]	tree depth = 4
	similarity threshold = 0.4
	maximum child = 100
LogMine [10]	levels of pattern hierarchy = 2
	maximum distance = 0.001
	distance weight = 1
Spell [4]	message type threshold = 0.5

Comparison of Performance

Table 3: F-measure Value Comparison (in %) of The Proposed Method and Five Other Methods

Method	Datasets				
	Casper	Jhuisi	Nssal	DF16	Honey
IPLoM [17]	93.72	87.58	88.15	10.90	89.31
LogSig [24]	77.16	80.33	79.71	12.00	85.50
Drain [12]	90.01	87.49	89.05	17.50	94.12
LogMine [10]	72.06	74.17	66.17	14.60	77.49
Spell [4]	82.00	82.02	79.00	10.80	83.70
Proposed method	**94.94**	**96.32**	**92.11**	**97.10**	**96.26**

- IPLoM shows a good performance because the bijective relationship in a group of log entries can accurately capture the most frequently occurring words
- LogSig' clustering is performed based on a local search algorithm and can lead to local optima. Therefore, it cannot cluster log messages precisely

Comparison of Performance

- Drain performs well because it considers the first few words in a log entry as contributing most significantly to its abstraction. These words are used to construct a fixed-depth tree.
- LogMine performs over-clustering for all datasets because the clustering process is conducted incrementally. If a log entry similarity with an existing cluster representation is less than the given threshold, it will be grouped with that particular cluster.
- Spell employs the longest common subsequence (LCS) technique to obtain the abstractions. LCS cannot capture any potential abstraction that has separate substrings.

Over-clustering vs Under-clustering

- The most important procedure in discovering event log abstractions is the clustering step
- If the clustering is performed well, then good abstractions will be produced
- We need to get the best cluster composition from event logs

Conclusion and Future Work

- This paper proposes an automatic method of event log abstraction
- Being automatic, there is no need for a forensic investigator to supply any parameters
- This is a significant improvement as the existing approaches either need many user inputs or need a model training
- Future work will focus on integrating the automatic abstraction with event reconstruction and anomaly detection

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Thank you

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