Ranking Algorithms for Digital Forensic String Search Hits

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Overview

• Background
  – Information overload problem with string search results
  – Why ranking algorithms are possible solution

• Research
  – Identification of relevancy ranking features
  – Ranking algorithm development
    • Machine learning model building and ranking functions
  – Empirical results
    • Relevant/non-relevant (class) prediction accuracies
    • Relevancy ranked list (score) precision, recall, average precision
    • Feature significance analysis

• Conclusions, software, next steps
BACKGROUND
Motivation

• String searching nearly infeasible, yet still worthwhile
  – Much info/evidence sought is textual in nature
  – Extremely low signal to noise ratio (<5%)
  – Millions+ hits for reasonably small queries
  – Resource constraints favor other search techniques

• Current attempts to solve the problem
  – State of the art DF tool features adding to noise
  – Cluster-based platforms for increased compute power
  – Hit sorting (query, data type, allocation status)
  – Some improvement via grouping by object type
• Hit grouping
  Query based, Data type, File type/item
What We Want...

DIGITAL FORENSIC STRING SEARCH OUTPUT

34 million Search Hits ... in 2010
>250M in 2013

Engine is useful because search hits are ranked

About 34,000,000 results (0.27 seconds)
In short...

What would “Googling” be like without ranking algorithms?

... Ask a digital forensic analyst!
Problem is only getting worse...

Problem is only getting worse... = data overload
Search Hit Ranking

Simulated Digital Forensic Text String Search Hit Output:

<table>
<thead>
<tr>
<th>Search Hit</th>
<th>Rank Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>I plan to kill her after dark tonight...</td>
<td>3.5</td>
</tr>
<tr>
<td>...kill killed killer killing...</td>
<td>1.4</td>
</tr>
<tr>
<td>kill -9 3303</td>
<td>0.8</td>
</tr>
</tbody>
</table>

So... just “Google” it.

If it were only that simple...
- We need to identify appropriate ranking features for this domain.
- Few of Google’s 200+ features apply in the digital forensics context.
THE RESEARCH
1. Theorized 18 quantifiable characteristics (AKA ranking features)

2. Trained a support vector machine (SVM) to generate ranking functions
   – Binary class SVM feature weights can be used in a weighted, linear ranking function

3. Empirically tested ranking functions
   – Achieved 81.02%-85.97% prediction accuracies
   – Significant improvement in average precision over unranked lists (0.82 & 0.90 vs. 0.50*)

*artificially high, due to balanced data set—equal number of relevant & non-relevant hits
STEP 1: Feature Identification

• Theorized quantifiable characteristics (ranking features)
  – of allocated files and unallocated clusters containing hits
  – of the string search hits themselves
  – believed pertinent to hit relevancy determination
  – based on past ranking research, existing ranking applications, and investigator experience
# Ranking Feature Specifics

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
<th>Operationalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recency-Created</td>
<td>Temporal proximity of an allocated file’s creation to a reference point</td>
<td>Data extracted from the $STANDARD_INFORMATION attribute from $MFT records; difference between date/time stamp and a reference point (specified as date of forensic analysis in this case, but may differ in other cases); normalized by maximum time difference in corpus (difference between oldest date/time stamp and reference point); continuous feature with range f={0…1}, with lower values being closer to reference point</td>
</tr>
<tr>
<td>Recency-Modified</td>
<td>Temporal proximity of an allocated file’s modification to a reference point</td>
<td></td>
</tr>
<tr>
<td>Recency-Accessed</td>
<td>Temporal proximity of an allocated file’s access to a reference point</td>
<td></td>
</tr>
<tr>
<td>Recency-Average</td>
<td>Average MAC temporal proximity to a reference point</td>
<td></td>
</tr>
<tr>
<td>Filename-Direct</td>
<td>Hit exists in a file/path name</td>
<td>Simple pattern match operation for the hit’s search expression in the file’s path/filename; binary feature with f={0</td>
</tr>
<tr>
<td>Filename-Indirect</td>
<td>Hit is contained in the content of an allocated file, whose file/path name contains a different search term.</td>
<td>Simple pattern match operation for other search expressions in the file’s path/filename; binary feature with f={0</td>
</tr>
<tr>
<td>User Directory</td>
<td>Hit is contained in an allocated file found in a non-system directory</td>
<td>Specified standard Windows system directories and defined user directories as all non-system directories; binary feature with f={0</td>
</tr>
</tbody>
</table>

**Note:** These features are only applicable to hits found in allocated space; Driving the need for separate allocated vs. unallocated ranking functions.
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</tr>
</thead>
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<tr>
<td>High Priority Data Type</td>
<td>Hit is contained in a high priority data type</td>
<td>Specified high-medium-low data type tables; used file signatures of allocated files for type identification; used Sceadan, a naïve statistical data type classifier, for data type classification of unallocated blocks; binary feature with f={0</td>
</tr>
<tr>
<td>Medium Priority Data Type</td>
<td>Hit is contained in a medium priority data type</td>
<td></td>
</tr>
<tr>
<td>Low Priority Data Type</td>
<td>Hit is contained in a low priority data type</td>
<td></td>
</tr>
<tr>
<td>Search Term TF-IDF</td>
<td>Term frequency moderated by inverse document frequency of the search term in the corpus</td>
<td>Used normalized, logarithmic, corpus level term frequency, moderated by inverse document frequency (see Eq. 2); continuous feature with range f={0...1}</td>
</tr>
<tr>
<td>Block-level hit frequency</td>
<td>Count of instances of the search hit term in an allocated file or cluster</td>
<td>Measured by the term frequency (TF) of the search expression in the file or unallocated cluster; normalized by the highest TF returned; continuous feature with range f={0...1}</td>
</tr>
<tr>
<td>Cosine-Similarity</td>
<td>Traditional cosine similarity between query and file/cluster vector</td>
<td>Measured by the traditional IR cosine similarity measure between the document and the query; normalized by the highest cosine similarity measure returned; continuous feature with range f={0...1}</td>
</tr>
</tbody>
</table>
### Ranking Feature Specifics

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</thead>
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<tr>
<td>Search Hit Adjacency</td>
<td>Byte-level logical offset between adjacent hits (next nearest neighbor)</td>
<td>Distance (in bytes) between search expression and the most proximally located search hit for a different search expression; measured via file offset to account for fragmentation effects on distance; normalized the largest adjacency distance returned; continuous feature with range ( f = {0...1} )</td>
</tr>
<tr>
<td>Search Term Block Offset</td>
<td>Distance from start of file or unallocated cluster</td>
<td>Measured by file offset of the search expression from the start of the file or cluster; normalized by largest search term block offset value returned; continuous feature with range ( f = {0...1} )</td>
</tr>
<tr>
<td>Proportion of Search Terms in Block</td>
<td>How many different search terms appear in the file or cluster</td>
<td>Total number of search expressions that exist in the file or cluster; normalized by the maximum number of search expressions per block returned; continuous feature with range ( f = {0...1} )</td>
</tr>
<tr>
<td>Search Term Length</td>
<td>Byte length of search term</td>
<td>Search expression’s length in bytes; normalized by maximum length of any search expressions; continuous feature with range ( f = {0...1} )</td>
</tr>
<tr>
<td>Search Term Priority</td>
<td>User ranked priority of search term</td>
<td>Measured by rank-ordering of the search expressions by the user; normalized by the highest numeric rank returned; continuous feature with range ( f = {0...1} )</td>
</tr>
</tbody>
</table>
STEP 2: Ranking Function Development

• Trained a binary class (relevant/non-relevant), linear kernel, support vector machine (SVM)
  – Generate SVM model with feature weights
  – Use binary class feature weights as coefficients in ranking functions (fast linear discriminant functions)

\[ R_{hit} = \sum_{n=1}^{18} w_n f_n \]

  – Traditional SVM would assign threshold for class prediction
  – Linear discriminant function approach facilitates continuous scale relevancy rank score
Data Set & Sampling

- M57 Patents case ("police seizure images")
  - [http://digitalcorpora.org](http://digitalcorpora.org)
  - 4 user workstations imaged on last day of scenario
- Executed 36-term search query
  - 2.6M search hits in 46.9K files/clusters
  - 4.24% relevancy rate (determined by human analyst*)
- Search hit sample selection
  - All relevant hits
  - Random sample of non-relevant hits to create balanced sample (equal number of relevant and non-relevant)

*Some inferences made; see paper
Model Building

• **Used** `libsvm` and `liblinear`

• Experimentally selected linear kernel
  – Experimentally selected optimal solver, parameter values

• Used 60%:40% train:test ratio during model building & testing (random sampling without replacement)

• Trained two classifiers – allocated & unallocated
  – Since not all features are applicable to unallocated
STEP 3: Empirical Testing

Allocated Model Confusion Matrix

<table>
<thead>
<tr>
<th>True / Predict</th>
<th>Not Relevant</th>
<th>Relevant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not Relevant</td>
<td>75.2%</td>
<td>24.8% (false pos.)</td>
</tr>
<tr>
<td>Relevant</td>
<td>13.2% (false neg.)</td>
<td>86.8%</td>
</tr>
</tbody>
</table>

Unallocated Model Confusion Matrix

<table>
<thead>
<tr>
<th>True / Predict</th>
<th>Not Relevant</th>
<th>Relevant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not Relevant</td>
<td>63.3%</td>
<td>16.7% (false pos.)</td>
</tr>
<tr>
<td>Relevant</td>
<td>5.8% (false neg.)</td>
<td>74.2%</td>
</tr>
</tbody>
</table>

- False positive rate exceeded false negative rate
  - Preferred in this context, to avoid missing relevant evidence
  - Could fine-tune the relevancy ranking threshold if desired
But...What about relevancy score performance?

- Less interested in binary class prediction
  - relevant vs. non-relevant determination
- More interested in relevancy ranking score for ranked list ordering of string search hit output:

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Relevancy Score, Ranked List Performance

- Calculated relevancy rank score ($R_{hit}$) for hits
- Created relevancy rank ordered search hits list
- Measured average precision
- Measured precision & recall at quartile increments

$$\text{Average Precision (AvgP)} = \frac{\sum_{r=1}^{N} P(r) \times \text{rel}(r)}{R}$$

where $r = \text{rank}$

$N = \text{number hits retrieved}$
$\text{rel}(r) = 0 \text{ or } 1$ (relevancy of hit)
$P(r) = \text{total precision up to this point}$
$R = \text{Total number of relevant hits}$
Ranked List Performance

Allocated Model

<table>
<thead>
<tr>
<th>No. Hits Retrieved</th>
<th>Recall</th>
<th>Precision</th>
<th>Average Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>25%</td>
<td>0.42</td>
<td>0.84</td>
<td>0.37</td>
</tr>
<tr>
<td>50%</td>
<td>0.80</td>
<td>0.80</td>
<td>0.68</td>
</tr>
<tr>
<td>75%</td>
<td>0.96</td>
<td>0.64</td>
<td>0.80</td>
</tr>
<tr>
<td>100%</td>
<td>1.00</td>
<td>0.50</td>
<td>0.82</td>
</tr>
</tbody>
</table>

Unallocated Model

<table>
<thead>
<tr>
<th>No. Hits Retrieved</th>
<th>Recall</th>
<th>Precision</th>
<th>Average Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>25%</td>
<td>0.46</td>
<td>0.92</td>
<td>0.43</td>
</tr>
<tr>
<td>50%</td>
<td>0.86</td>
<td>0.86</td>
<td>0.79</td>
</tr>
<tr>
<td>75%</td>
<td>1.00</td>
<td>0.66</td>
<td>0.90</td>
</tr>
<tr>
<td>100%</td>
<td>1.00</td>
<td>0.50</td>
<td>0.90</td>
</tr>
</tbody>
</table>

• Conclusion: Helps analyst find relevant hits faster!
Visualization of Ranked List Performance*

Relevancy of Rank Ordered List

Relevant Hits Presented Earlier

Relevancy of Non-Rank Ordered List

Relevant Hits Sporadically Presented

*different case; for visualization only
Which Features Seem to Matter Most?

• Relative absolute magnitude of feature weight is a measure of feature significance
• Most significant features in both models
  – Search term length
  – Search term priority
  – TF-IDF of search term
  – Proportion of search terms in an object
• Most significant features in the allocated model
  – Filename features
  – User vs. system directory
  – Some date/time stamp features
  – Search term object offset
• Most significant features in the unallocated model
  – Object-level hit frequency
Which Features Seem to Matter Least?

- Some date/time stamp features
- Data type prioritization
- Cosine similarity
- Search hit adjacency
SUMMING IT UP...
Conclusions & Limitations

- Search hit ranking algorithms are feasible
- Search hit ranking algorithms are fast
  - No performance results reported (sorry)
  - Slows down evidence processing slightly, but not much
- Search hit ranking algorithms can save significant analyst time spent wading through non-relevant hits
- Limitations
  - Single, synthetic case
  - Need real-world data to better train/test ranking functions
Current Capability & Next Steps

- Ranking algorithms are currently implemented in open source tool *(Sifter)*

- Currently modifying *Sifter* to collect real-world training data from beta-test volunteers/users

- Plan to validate/improve generic models and create additional case type specific models