InfoTracker:
Pedigree Tracking in the Face of Ancillary Content

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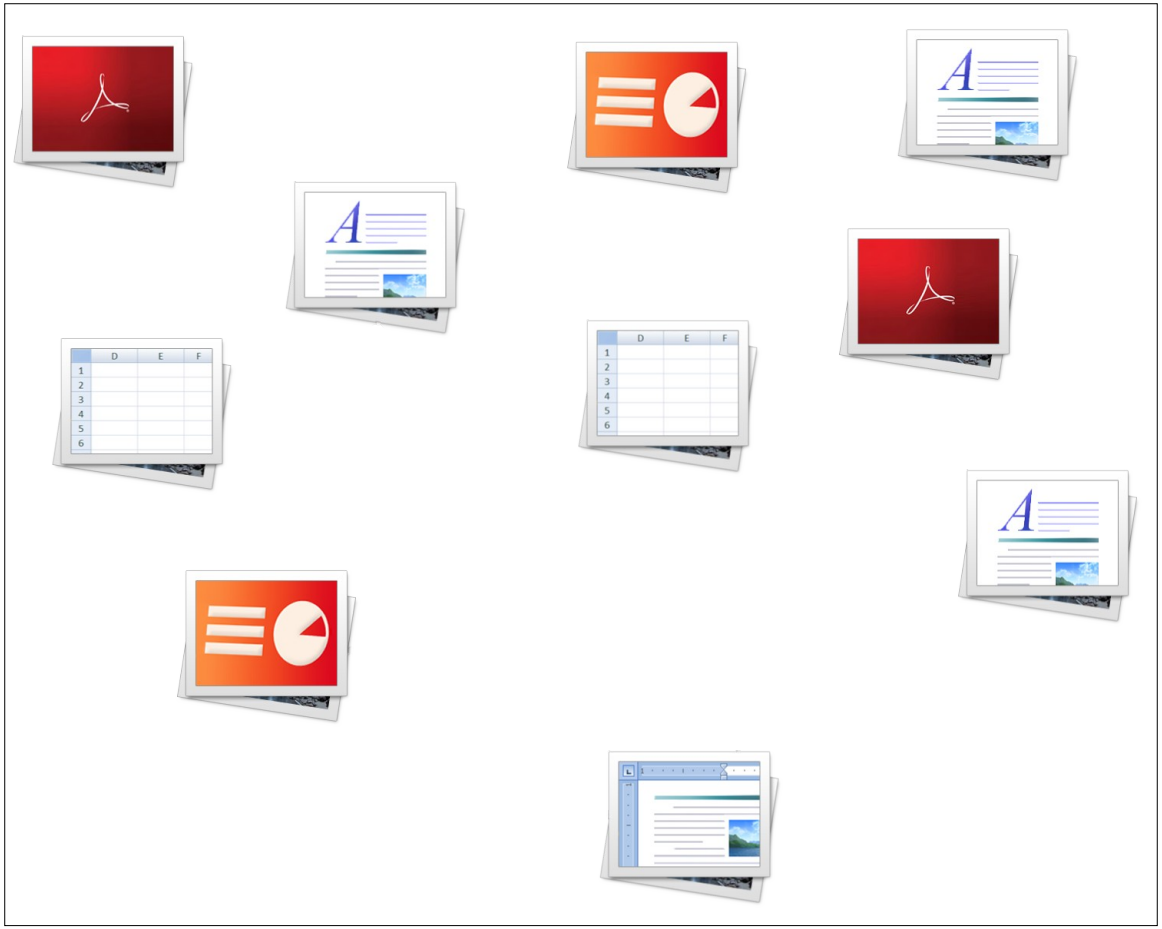
Track Document Pedigree



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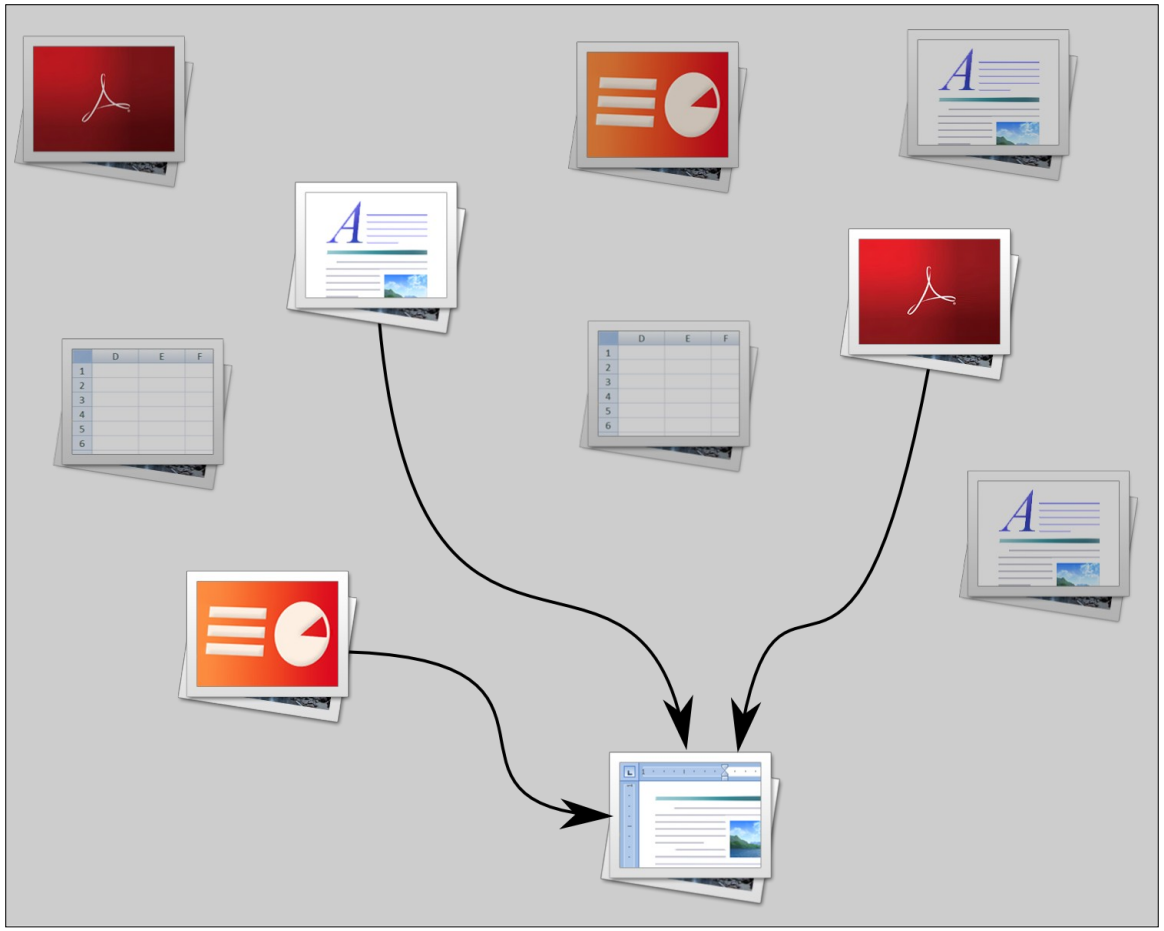

Applications

- **Plagiarism**
- **Information Flow**
- **Security Policies**

The Challenge

Common content confuses comparisons

determines the degree of extremity required of the outliers. N can be used to shift the balance between precision and recall. For example, the full 116 data points of the results in Table 2 have a lower quartile of 1.837 (Q_1) and an upper quartile of 47.250 (Q_3), indicating that 29 data points have scores under 1.837 and 87 data points have scores under 47.250. With $N = 6$, the threshold is set to 319.728, and only the top seven results are retained.

The experiment described in Section 4.2 was run with varying values of N from the range [0–6]. Low values of N represent very conservative estimates of the distribution of unrelated documents, and sets a low threshold for outliers. Each full-unit increment increases the threshold by an amount equal to the inter-quartile range, trimming the query results more aggressively. The full test corpus of 38 query documents was run on each successive value of N and the average number of results, average precision, and average recall are recorded in Table 3.

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Table 3 clearly shows the control available over the balance between precision and recall, and demonstrates the amount of result trimming that can safely be applied for a desired level of recall. Even the most minimal trimming attempted shortened the results list by over 60% (compared to the initial minimum size of 106 results) yet only reduced average recall by 1% compared to the case where no trimming was done.

5 CONCLUSIONS AND FUTURE WORK

During the execution of this project, we have identified a number of directions to pursue in the future:

Evaluate in an Active Learning scenario: Foremost in our future goals is to perform an exhaustive evaluation of the InfoTracker prototype in a scenario that takes advantage of Active Learning to identify and mark boilerplate content while the system is in use.

Incorporate time stamps: The current approach does not take the temporal aspect of document authoring and reuse into account when determining pedigree. Therefore, if a query document shares a source with a historical document, then both the source and the sibling document are likely to be returned in the list of results. These false–positive results can be reduced by considering the dates that the returned documents are authored, possibly presenting the results hierarchically, or only returning either the youngest or oldest sources.

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Related Work

- **Suffix Tree Document Models**
- **Fuzzy Fingerprints**
- **Hoad & Zobel's Fingerprints**

Solution

Ignore the ancillary content

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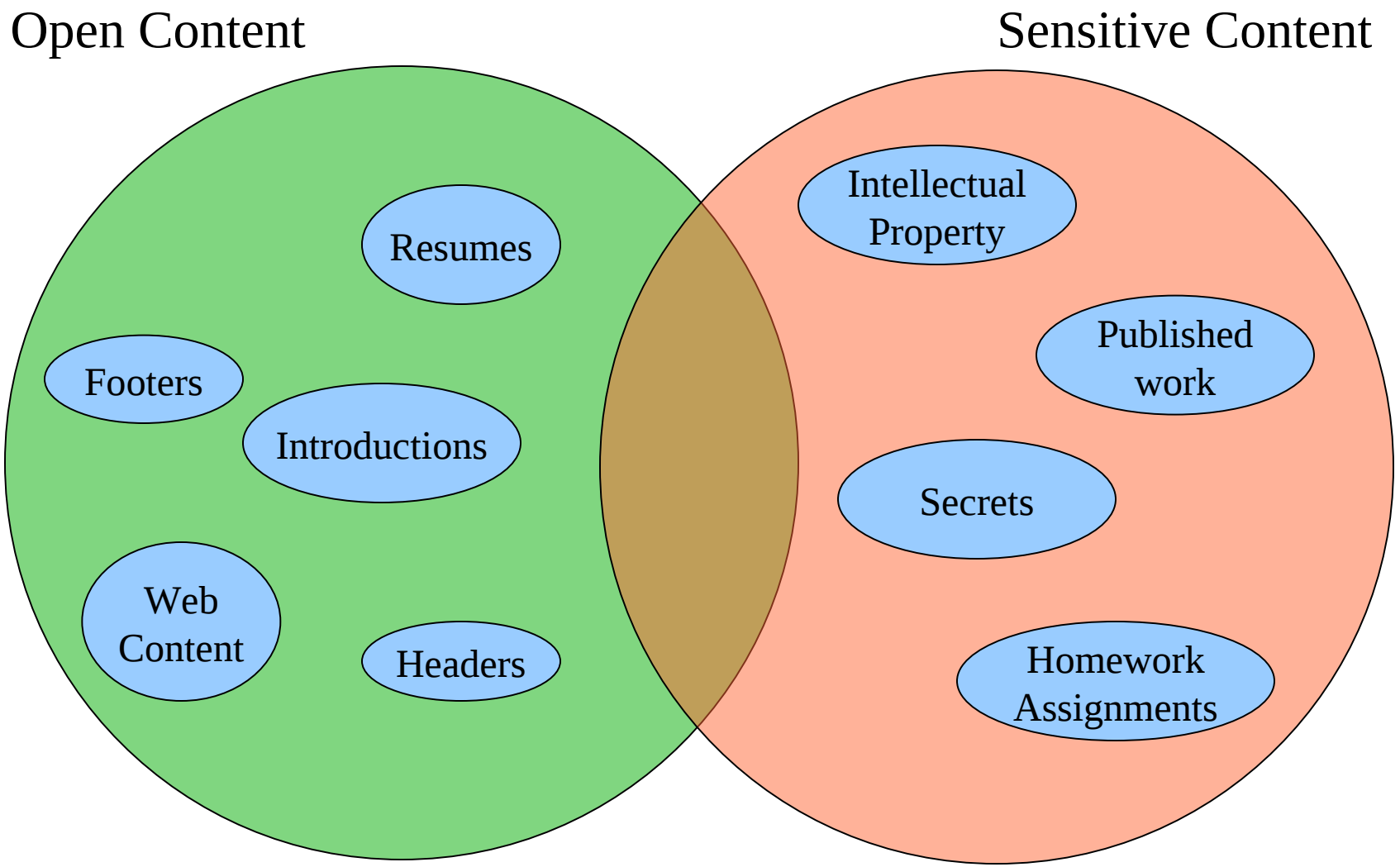
How?

How? Use Contrasting Corpora



Algorithm

Index Both Corpora with one Suffix Tree

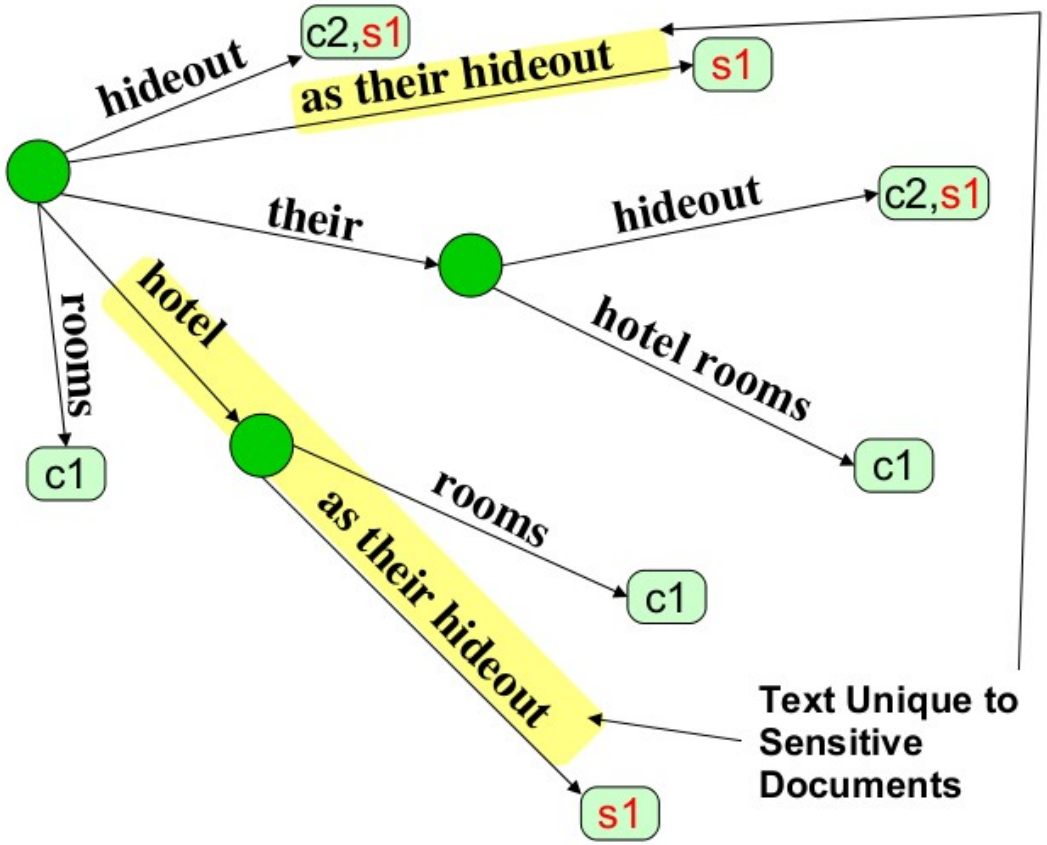
Widely-Used/Common Text
c1="their hotel rooms"
c2="their hideout"

Sensitive Documents
s1="hotel as their hideout"

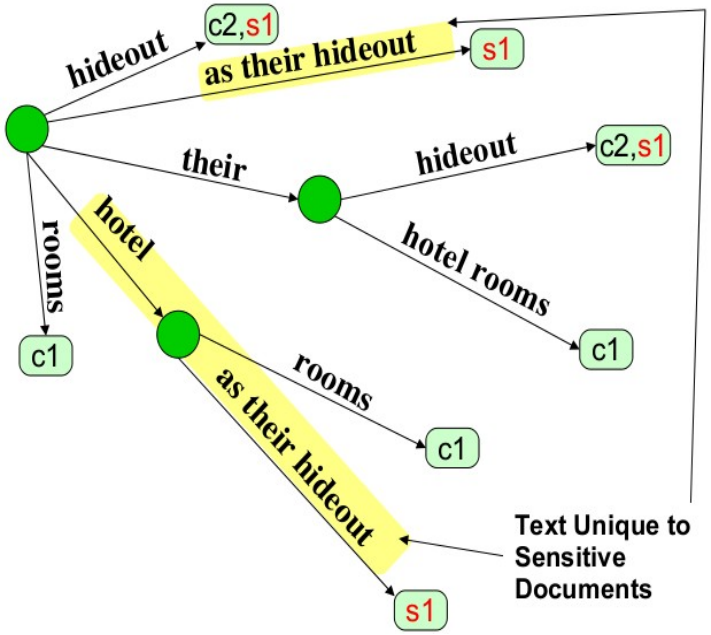
Suffixes: c1
rooms
hotel rooms
their hotel rooms

Suffixes: c2
hideout
their hideout

Suffixes: s1
hideout
their hideout
as their hideout
hotel as their hideout

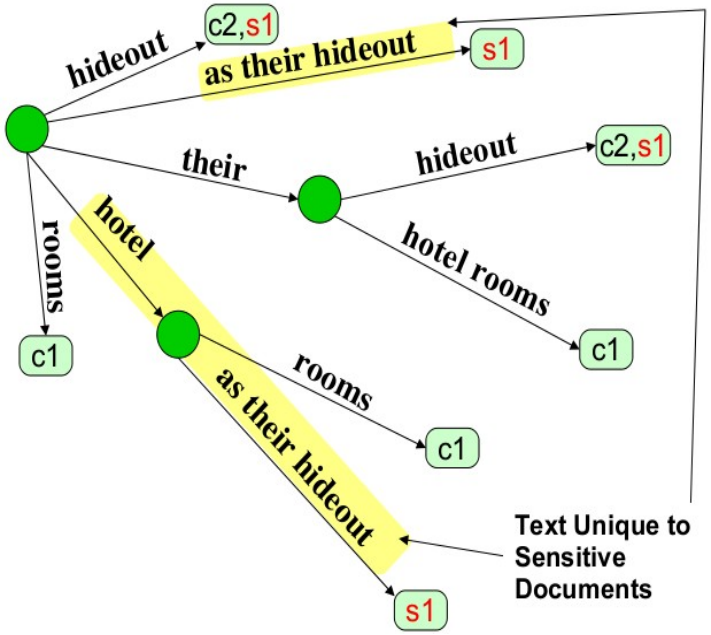


Search for a document



Query: “Hotel rooms as their hideout”

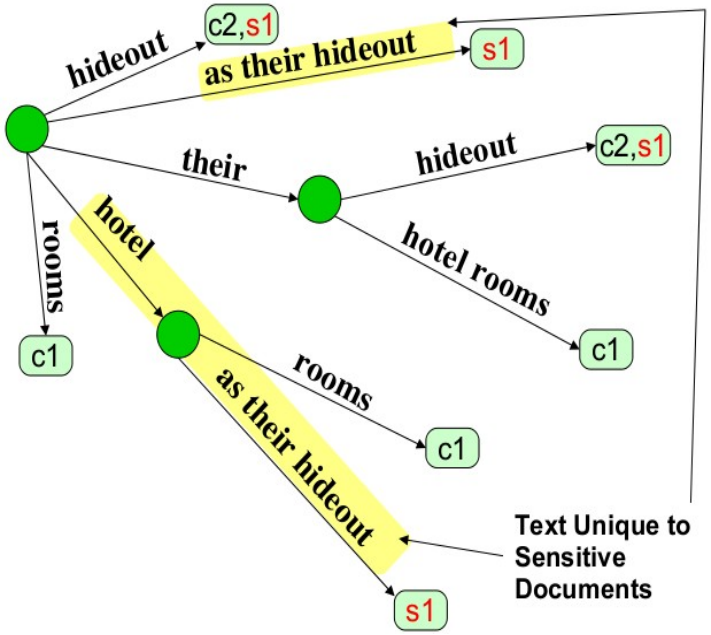
Search for a document



Query: “Hotel rooms as their hideout”

Open: “Hotel rooms”

Search for a document

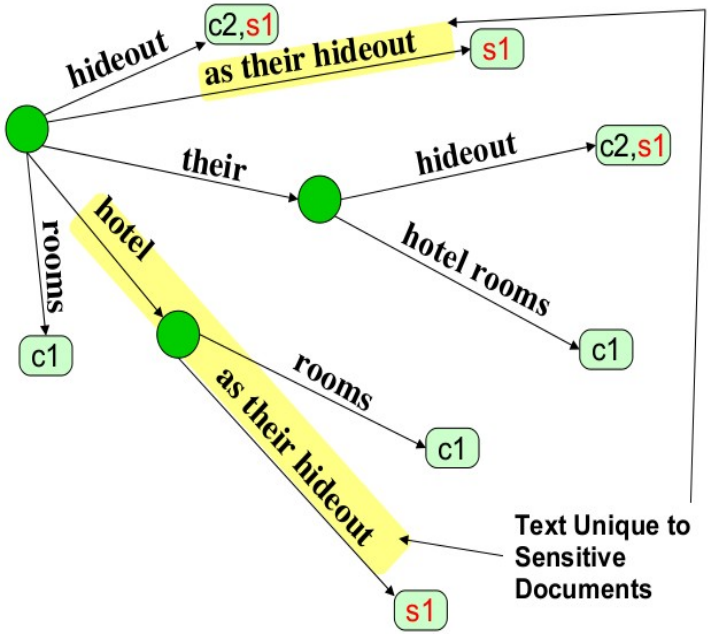


Query: “Hotel rooms as their hideout”

Open: “Hotel rooms”

Open: “rooms”

Search for a document



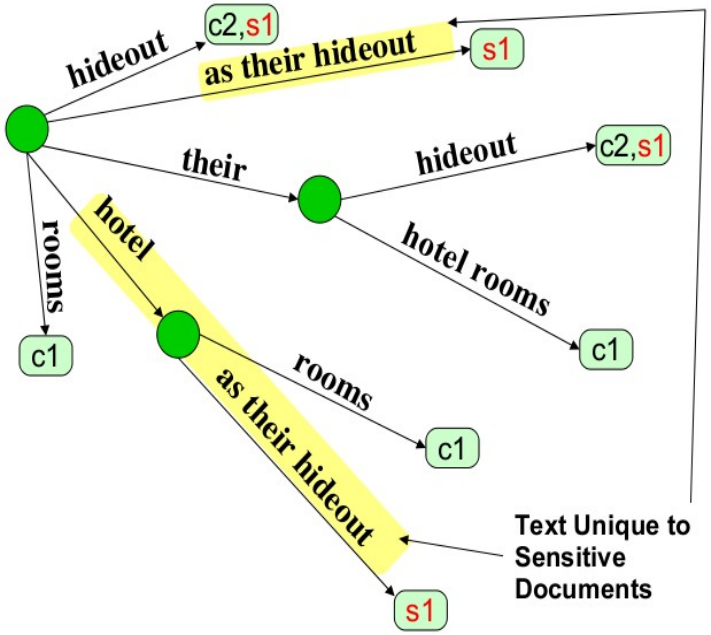
Query: “Hotel rooms as their hideout”

Open: “Hotel rooms”

Open: “rooms”

Sensitive: “as their hideout”

Search for a document



Query: “Hotel rooms as their hideout”

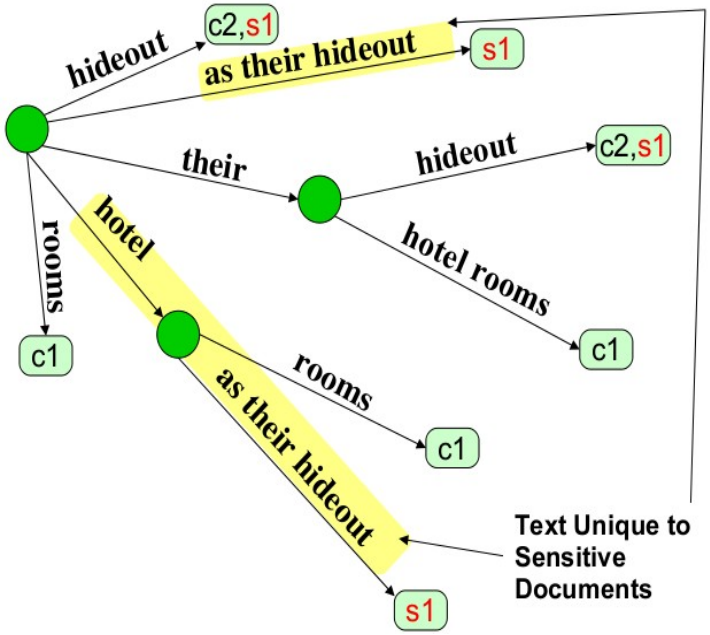
Open: “Hotel rooms”

Open: “rooms”

Sensitive: “as their hideout”

Open: “their hideout”

Search for a document



Query: “Hotel rooms as their hideout”

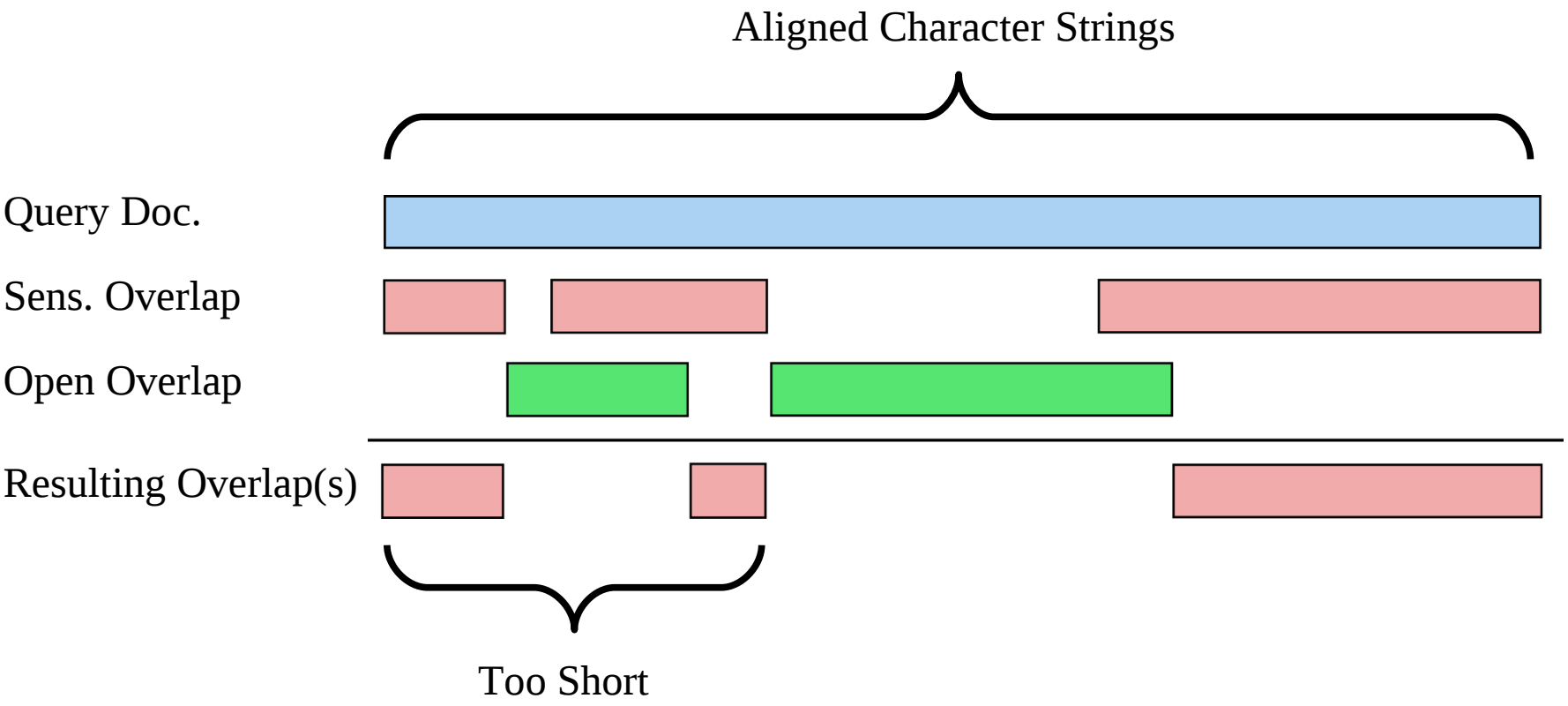
Open: “Hotel rooms”

Open: “rooms”

Sensitive: “as their hideout”

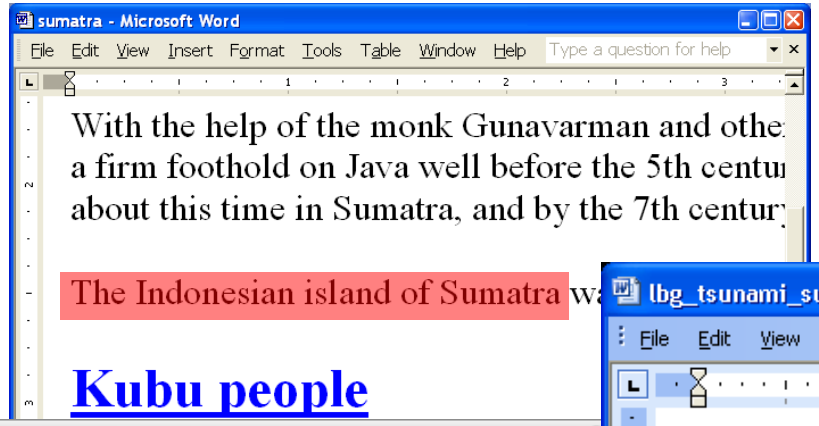
Open: “their hideout”

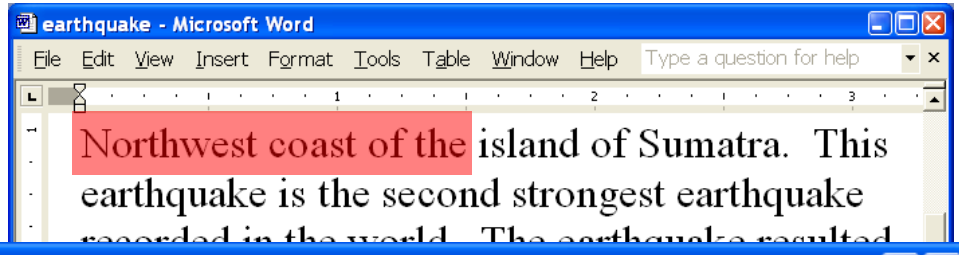
Filter the resulting string overlaps

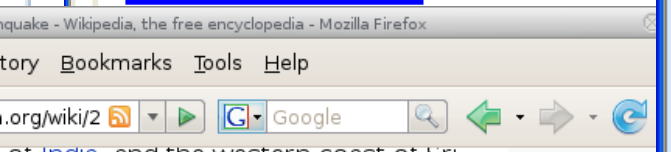


Algorithm > Ranking

Overlap-based Ranking

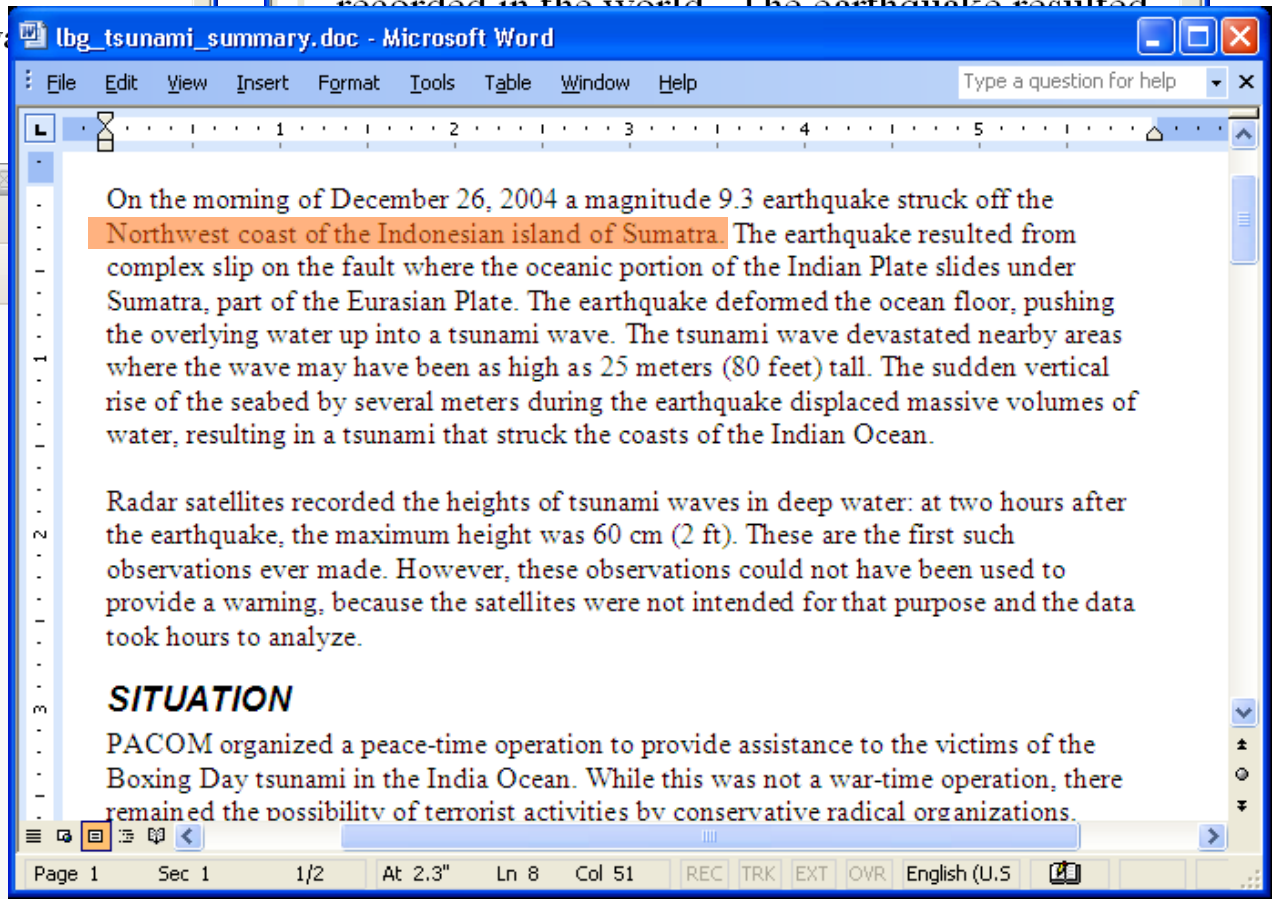




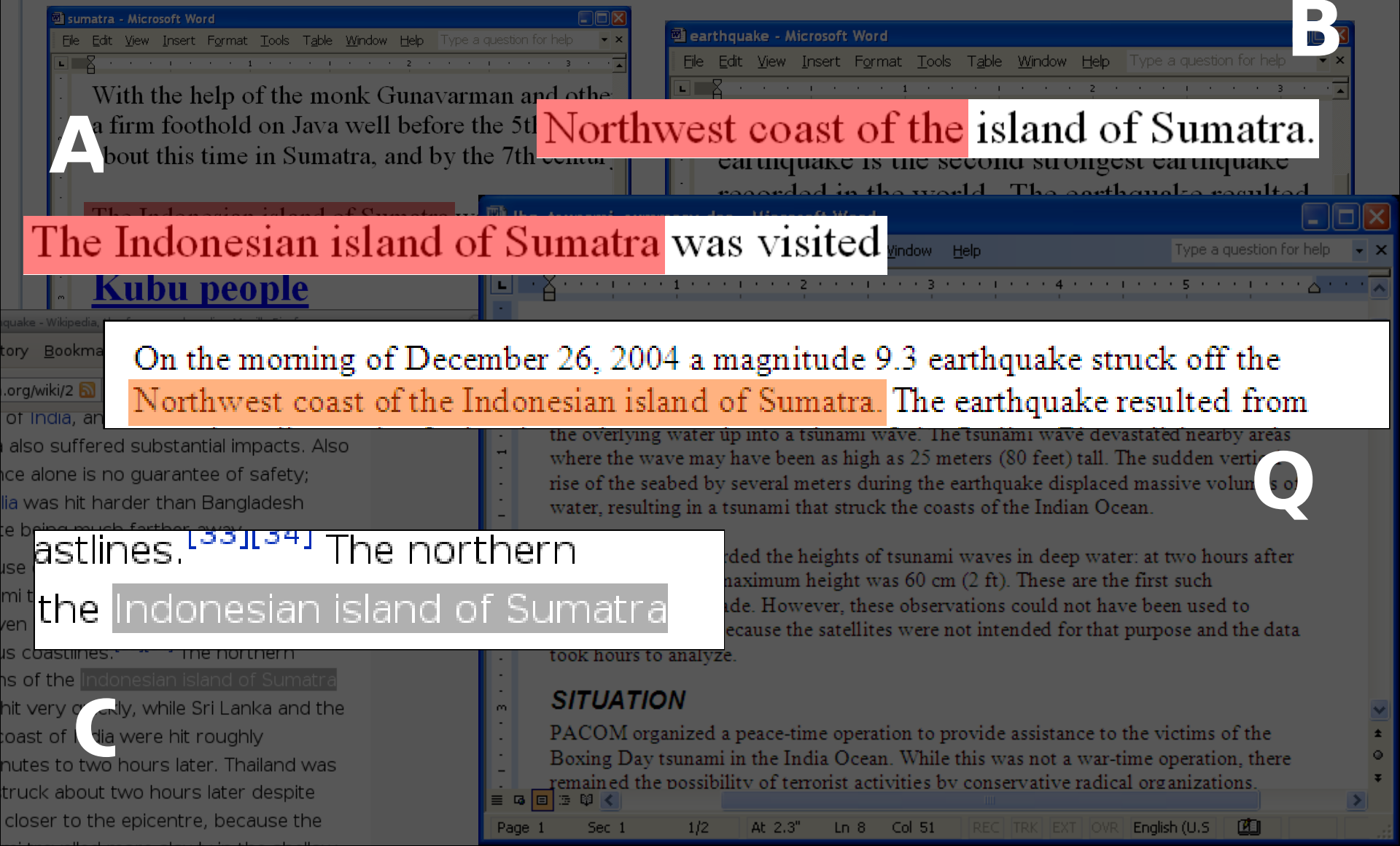


of India, and the western coast of Sri
a also suffered substantial impacts. Also
nce alone is no guarantee of safety;
lia was hit harder than Bangladesh
te being much farther away.

use of the distances involved, the
mi took anywhere from fifteen minutes
ven hours (for Somalia) to reach the
us coastlines.[33][34] The northern
ns of the Indonesian island of Sumatra
hit very quickly, while Sri Lanka and the
coast of India were hit roughly
nutes to two hours later. Thailand was
struck about two hours later despite
closer to the epicentre, because the



Overlap-based Ranking



Overlap Frequency for Ranking

A: the Indonesian island of Sumatra.
B: Northwest coast of the
C: the Indonesian island of Sumatra.

unique text

lower frequency

Greater impact

common text

higher frequency

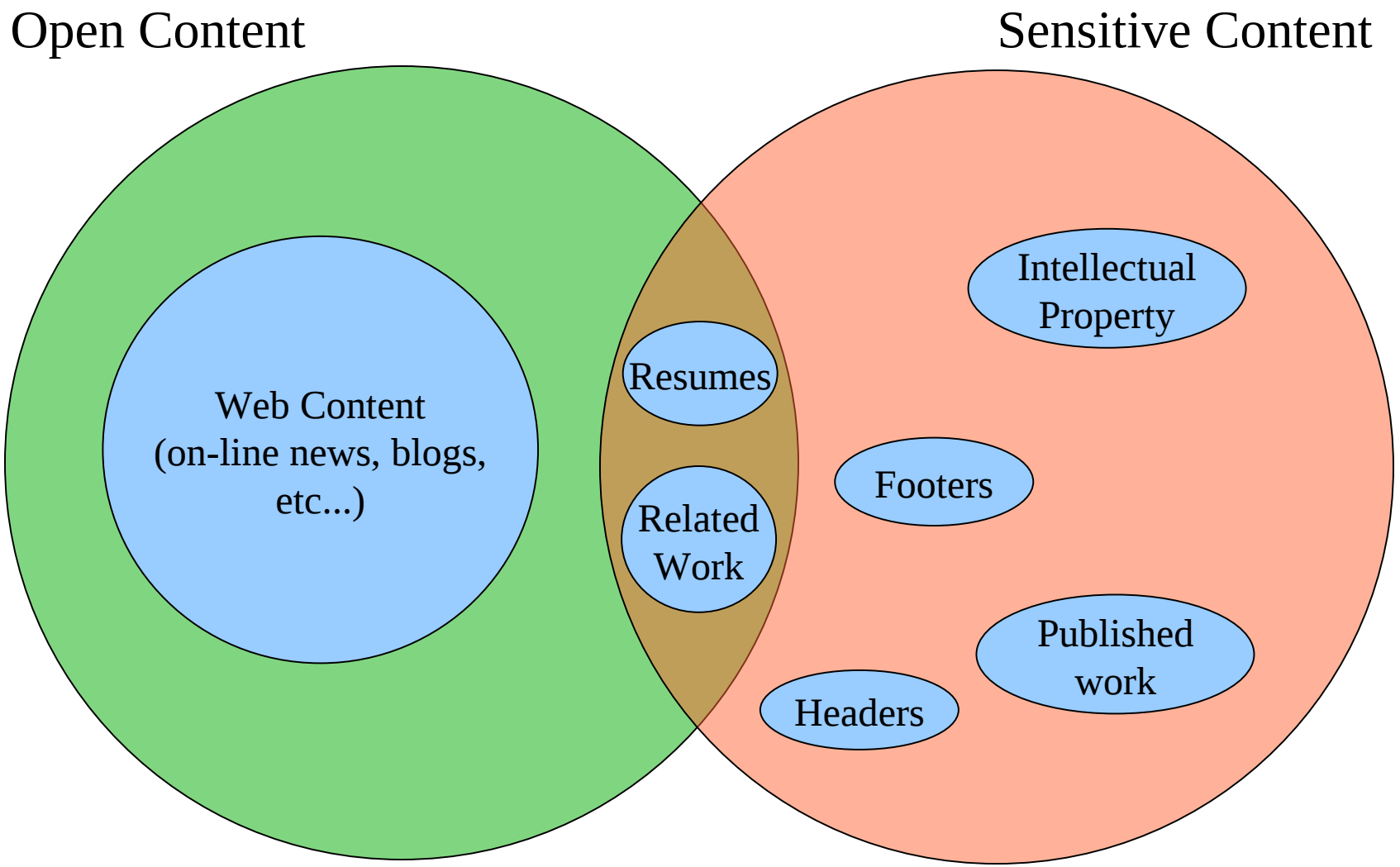
Less impact

Evaluation

InfoTracker was compared to Vector Space

- **Cosine Similarity**
- **TF-IDF weighted vectors**
- **No stop words**

Data Set


Open Content
Sensitive Content
Web Content
(on-line news, blogs, etc...)
Resumes
Related Work
Intellectual Property
Footers
Published work
Headers

Data Set

272 SBIR proposals

234 historical proposals

38 query proposals

Oracle

Image from: http://www.marketoracle.co.uk

Evaluation > Results

InfoTracker improved precision / recall

Algorithm	Precision	Recall
Vector Space	0.119	0.764
InfoTracker	0.167	0.913

Contributions / Future Work

Ancillary content can be managed

Contrasting corpora

Manual/actively learned tags

Detecting document sections

(re)Evaluate on Open data

Compare with differing corpora

The Linux Doc. Project

Algorithmic Improvements

- **Active Learning**
- **Document time stamps**
- **Overlap size / encapsulation**

Questions?

Calculating Precision / Recall

Rank	Score	File
1	6289.995	Document-92
2	3206.34	Document-21
3	1630.607	Document-13
4	1366.318	Document-46
5	1157.704	Document-1
6	1103.442	Document-43
7	624.2379	Document-114
8	327.5333	Document-67
9	273.6506	Document-74
10	263.0365	Document-48
11	244.4071	Document-10
12	238.4346	Document-113
13	207.32	Document-101
14	134.9912	Document-58
15	131.5204	Document-12
16	118.6787	Document-7
17	97.52703	Document-37
18	89.8972	Document-9
19	89.50462	Document-27
20	81.49963	Document-50
...	...	...

Calculating Precision / Recall

Consider the top 23 results.

(to allow for perfect recall)

Rank	Score	File
1	6289.995	Document-92
2	3206.34	Document-21
3	1630.607	Document-13
4	1366.318	Document-46
5	1157.704	Document-1
6	1103.442	Document-43
7	624.2379	Document-114
8	327.5333	Document-67
9	273.6506	Document-74
10	263.0365	Document-48
11	244.4071	Document-10
12	238.4346	Document-113
13	207.32	Document-101
14	134.9912	Document-58

Ranking Scores Plummet Quickly

Rank	Score	File
1	6289.995	Document-92
2	3206.34	Document-21
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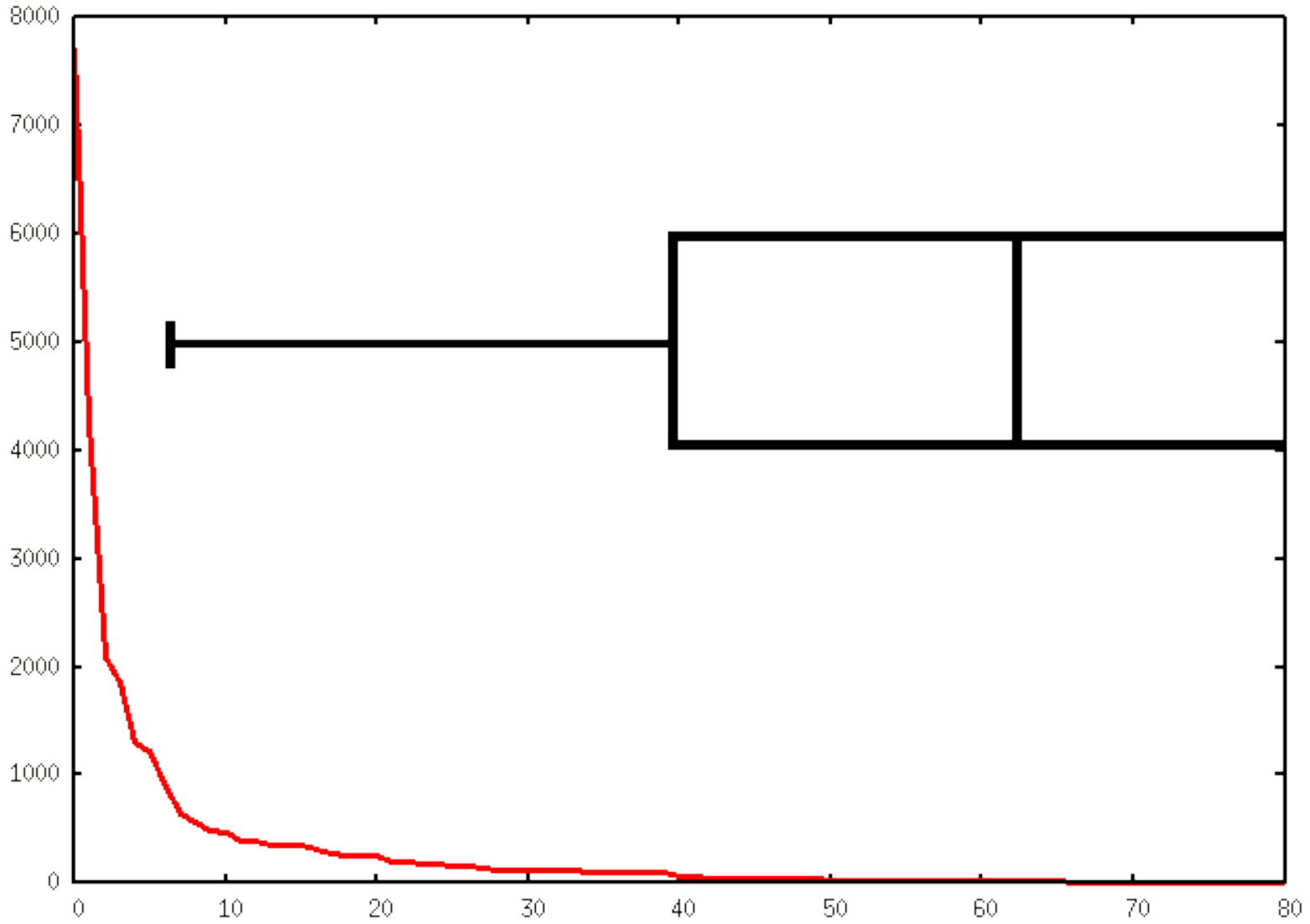
Ranking Scores Plummet Quickly



Trimming improves precision, retains recall

N	Result Count	Precision	Recall
No Trimming	162.53	0.03	0.98
0	40.95	0.11	0.97
0.5	28.71	0.14	0.93
1	22.29	0.16	0.91
1.5	18.92	0.19	0.90
2	15.81	0.21	0.88
2.5	13.47	0.23	0.87
3	11.76	0.24	0.84
3.5	10.50	0.26	0.84
4	9.63	0.27	0.81
4.5	8.82	0.29	0.80
5	8.18	0.31	0.78
5.5	7.55	0.33	0.78
6	7.13	0.36	0.77