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A Highly Accurate Query-Recovery Attack against Searchable Encryption using Non-Indexed Documents

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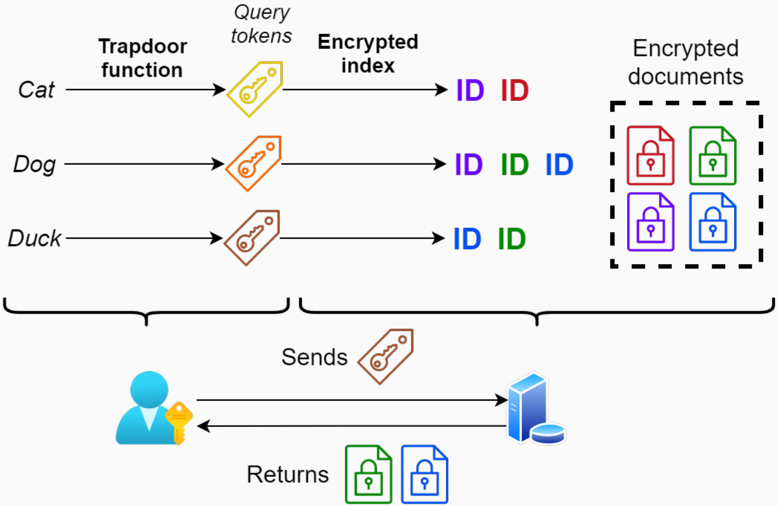
Motivations

Searchable Symmetric Encryption (SSE)



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Related works

- Scope: Passive query-recovery attacks against SSE
- SSE schemes leak the access pattern and the search pattern
- All these attacks exploit this leakage to compute a trapdoor-trapdoor co-occurrence and compare it to a keyword-keyword co-occurrence obtained using documents known by the attacker
- Known-data attacks (when attacker-known documents are indexed) vs. Similar-data attacks (when the documents are only similar, i.e. non-indexed)

Previous attacks

- Islam et al. (2012): Based on optimization problem. Only effective as a known-data attack.
- Cash et al. (2015): Based on a filtering approach. Significantly better than Islam et al.'s attack but still only effective as a known-data attack.
- Pouliot and Wright (2016): Based on optimization problem. Poorly accurate as a similar-data attack. Small queryable vocabularies and long runtime.
- Blackstone et al. (2020): Based on a filtering approach. By construction, can only be used as a known-data attack. Reduce drastically the amount of known documents needed compared to the previous attacks.
- *Summary*: no effective/accurate similar-data attack. Known-data setup can be considered as a strong (unrealistic?) assumption.

Other types of attacks

- Attack using query frequency: Liu et al. (2014), Oya and Kerschbaum (2021)
- Attack with a malicious attacker: Zhang et al. (2016)
- Attack on schemes supporting range queries: Kellaris et al. (2016), Grubbs et al. (2018), Lacharité et al. (2018)
- Other types of attacks exist but are out of scope because they assume a different type of attacker knowledge, a different threat model, a different search scheme, etc.

Our contributions

- A scoring approach to design effective attacks with interpretable results
- Weakening of the attacker assumptions by proposing a highly effective similar-data attack achieving recovery rates of up to 90%
- A proper formalization of the concept of similarity for document sets
- Extensive analysis of our best attack: its qualities and its limitations

Attacker knowledge

- Similar document set: documents similar but different to the indexed documents $\Rightarrow$ extract a vocabulary and a word-word co-occurrence matrix
- Observed queries: the attacker has observed some queries $\Rightarrow$ compute a trapdoor-trapdoor co-occurrence matrix
- Known queries: for a small part of the observed queries, knows the underlying keyword

Score attack

Creating a keyword/trapdoor vector

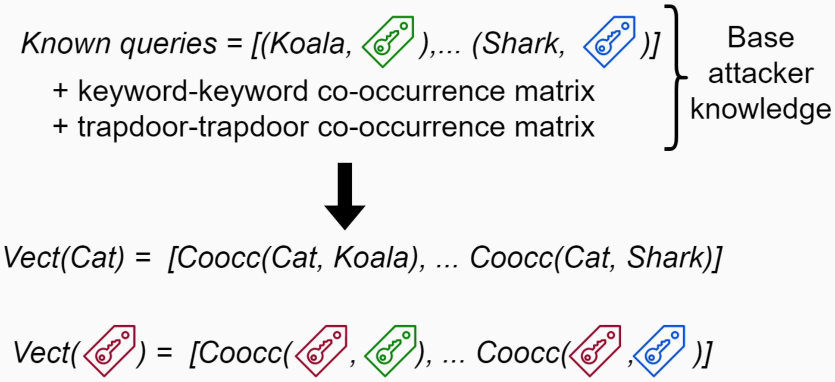

Figure: Attacker knowledge transformation

Scoring function

MatchingScore(Cat, ) = - ln(||Vect(Cat) - Vect()||)

- Using this vectorization, we can directly compare trapdoors to keywords
- The matching score is a logarithmic transformation of a distance between a keyword vector and a trapdoor vector
- Having a score provides a result interpretability: the higher a score is, the more likely a given prediction is

Attack algorithm

- Compute the matching score of each trapdoor-keyword pair and return the keyword providing the highest score for each trapdoor
- Very fast (few seconds) and deterministic
- Exploitable prediction scores. Can be used to design improvement strategies (e.g. refinement and clustering presented in the paper)

Experimental setup

- Each result is the average accuracy over 50 experiments
- The indexed document set and the attacker document set are two ramdonly picked **disjoint** subsets of the Enron document set
- The attacker does not know the queryable vocabulary contrary to the previous attack papers
- The vocabulary is the *m* most frequent keywords of the indexed document set. By default, we use $m = 1K$
- The queries are uniformly picked among the queryable vocabulary. By default, the query set size is 15% of the vocabulary size
- In the paper, we test different sizes for the vocabulary, the query set, etc

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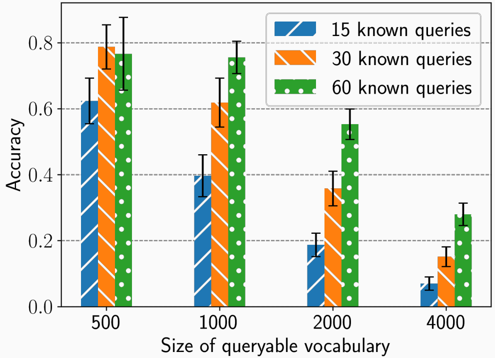
Experimental results



Comment: improves the state-of-the-art but still impractical (no. of known queries needed too high).

Refined score attack

Refinement strategy

Goal: reduce drastically the number of known queries needed.

We iteratively impute new known queries. Three steps per iteration:

1. Remove all (attacker-)known queries from the queries to be recovered
2. Use the base score attack to find a candidate for each unknown query/trapdoor. Use the score to evaluate each prediction ”certainty”
3. If there are more than k remaining unknown queries, add the k most certain queries to the known query set. Otherwise, stop the algorithm and return the predictions

Experimental results

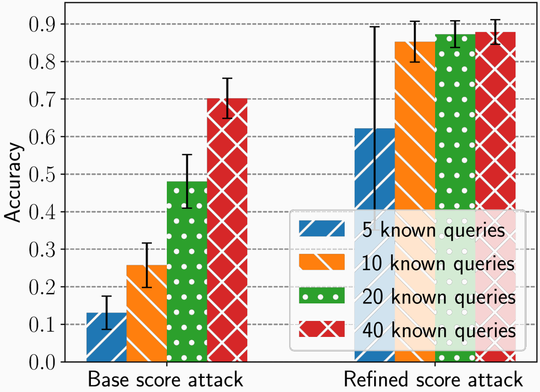
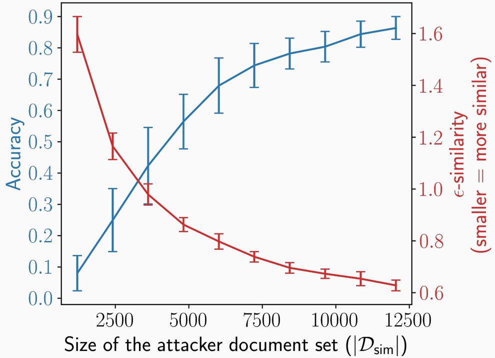


Figure: Score attack vs. Refined score attack

Similarity analysis



We propose a similarity metric ϵ to compare document sets. The attacker assumes that $\mathcal{D}_{\text{real}}$ and $\mathcal{D}_{\text{sim}}$ are ϵ-similar, with ϵ sufficiently small.

Refined attack mitigation

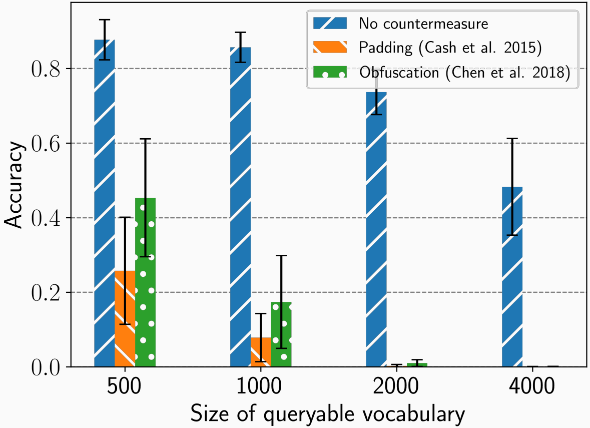


Figure: Comparison of the accuracy for two countermeasures.

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Conclusion

- Highly accurate attacks using non-indexed documents are possible (Score and Refined Score attacks being two examples)
- Our attacks work under weaker assumptions on the attacker's background knowledge than previously published attacks and move toward realistic and practical attack situations
- Despite the accuracy of the Refined Score attack, even the simplest countermeasures can be effective (at the cost of some overheads)

Thank you for your attention!

Code available: `https://github.com/MarcT0K/Refined-score-atk-SSE`

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