

DCSRP Award 2021

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

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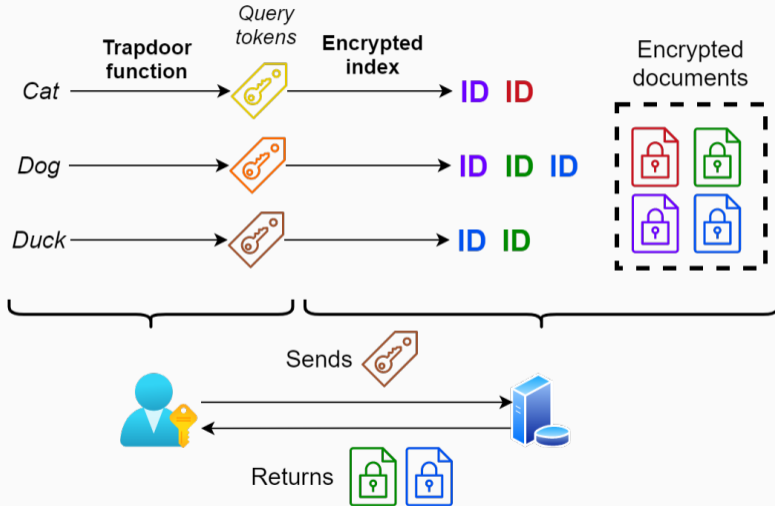
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# 1. Motivations

2. Score attack

3. Refined score attack

# Searchable Symmetric Encryption (SSE)



## SSE attacks

- **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 co-occurrence and compare it to a keyword co-occurrence obtained using documents known by the attacker
- **Known-data attacks** (attacker-known documents are indexed) vs. **Similar-data attacks** (the documents are only similar  $\iff$  non-indexed)

- Islam et al. (2012), Cash et al. (2015), Blackstone et al. (2020): only effective results as known-data attack / Pouliot and Wright (2016): low accuracy as a similar-data attack
- ⇒ **No accurate similar-data attack**
- Known-data setup can be considered as a strong (unrealistic?) assumption

## Our contributions

- A **scoring approach** to design efficient 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

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



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## Creating a keyword/trapdoor vector

*Known queries* = [(Koala, ) , ... (Shark, ) ]

+ keyword-keyword co-occurrence matrix  
+ trapdoor-trapdoor co-occurrence matrix

} Base attacker knowledge



$Vect(Cat) = [Coocc(Cat, Koala), \dots Coocc(Cat, Shark)]$

$Vect(\img alt="red key icon" data-bbox="225 630 275 710"/>) = [Coocc(\img alt="red key icon" data-bbox="405 630 455 710"/>, \img alt="green key icon" data-bbox="460 630 510 710"/>) , \dots Coocc(\img alt="red key icon" data-bbox="630 630 680 710"/>, \img alt="blue key icon" data-bbox="685 630 735 710"/>) ]$

Figure: Attacker knowledge transformation

$$\text{MatchingScore}(\text{Cat}, \text{Trapdoor}) = -\ln(\|\text{Vect}(\text{Cat}) - \text{Vect}(\text{Trapdoor})\|)$$

- 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

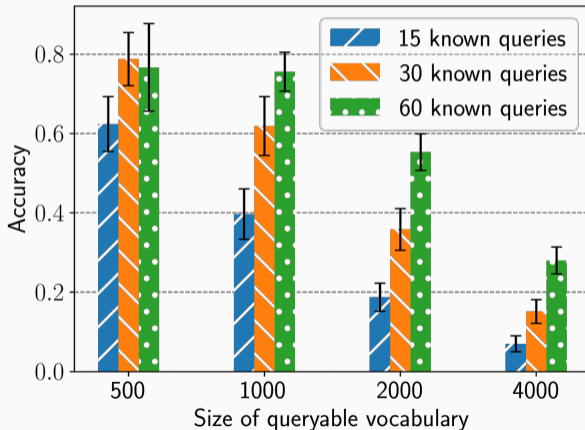
- Compute the matching score of each trapdoor-keyword pair and return the keyword providing the highest score for each trapdoor
- **Very fast:** few seconds
- **Exploitable prediction scores:** can be used to design improvement strategies (e.g. refinement and clustering presented in the paper)

## Experimental setup

- Dataset: **Enron** (i.e. documents = 30K emails)
- Attacker knowledge generation: indexed document set and attacker document set are **disjoint**
- The keyword universe (i.e. "queryable" vocabulary) is composed of the  $m$  most frequent keywords of the indexed document set.

## Experimental results

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



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**Goal:** reduce drastically the number of known queries needed.

We iteratively impute new known queries to refine our predictions:

1. Use the base score attack on the unknown queries.
2. Sort the predications based on their respective score.
3. Add the  $k$  most certain queries to the known query set. Go to step 1.

# Experimental results

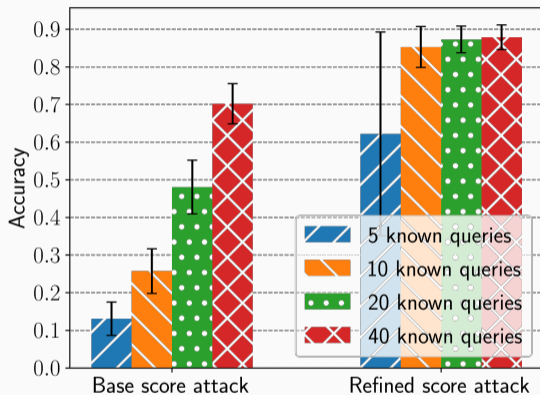
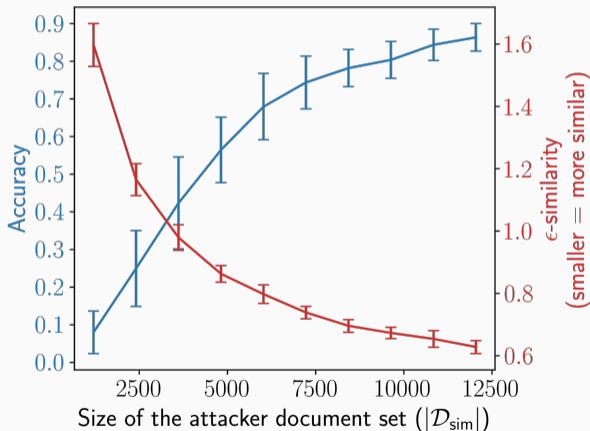


Figure: Score attack vs. Refined score attack

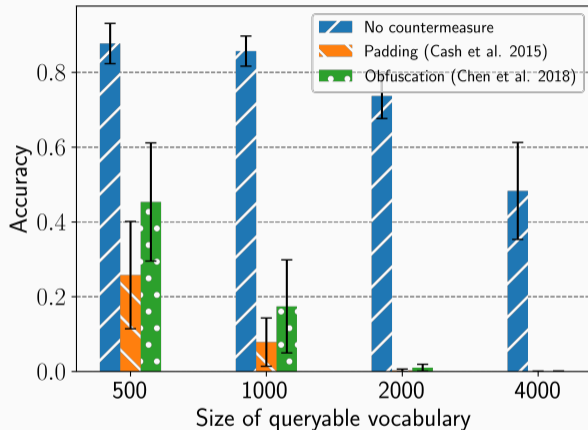


## Similarity analysis

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



## Refined score attack: Mitigation



## Conclusion

- **Highly accurate attacks** using non-indexed documents are possible (i.e. Score and Refined Score attacks)... but can be mitigated
- Our attacks work under **weaker assumptions** on the attacker knowledge than previous attacks and move toward realistic attack situations
- **Future work:** understanding the real-life impact of SSE attacks

# Thank you for your attention!

**Source code:** <https://github.com/MarcT0K/Refined-score-atk-SSE>

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