Efficient and Robust Data Aggregation Using Untrusted Infrastructure

Marek Klonowski, Michał Koza, Mirosław Kutyłowski

Wrocław University of Technology

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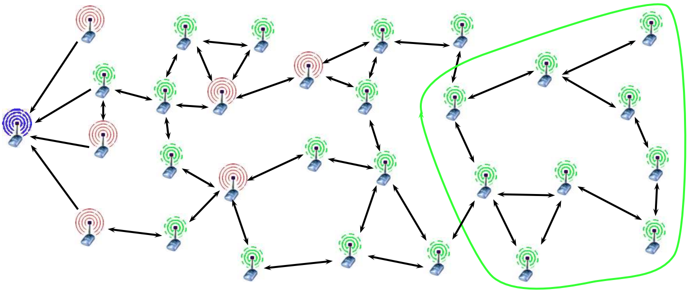
- or sending directly is not efficient (energy necessary for sending for distance r is $\sim r^{\nu}$ and $\nu > 1$)
  $\Rightarrow$ the subnetwork has to use extraneous stations.



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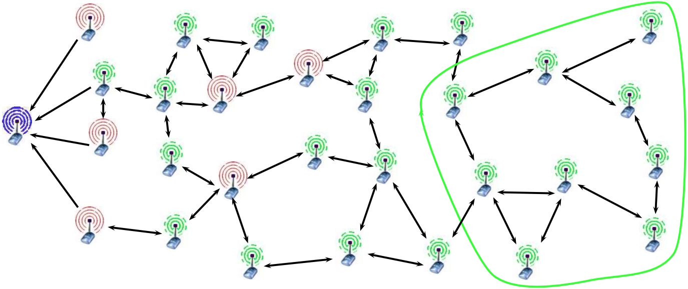

Green – trusted stations, try to deliver their values to the sink. Blue – the sink. Red – extraneous stations, used for data transmission.

Problem Statement - cd

Trust model

Extraneous nodes

- Extraneous nodes are untrusted (adversarial).
- They may aim at:
  - changing the result of data aggregation (even blindly);
  - learning the (partial) result encoded in transmitted data.

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- Legitimate stations can add any element.
- Extraneous nodes cannot manipulate the representation. Every manipulation is **detected** with high probability.
- Protocol supports **idepotence** and **commutativity**. $\Rightarrow$ no synchronization is needed, multi-route processing is possible.
- Only the sink can learn (even the partial) the result.

Our protocols

RCC - Robust Cryptographic Counter

- Better size/security trade-off
- ”Aggregation“ limited to some functions (sum, maximum ...)
- Protocol supports **commutativity** but not **idepotence.**

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- We can check if a given element is in the set represented by BF
  - if is, the answer is always TRUE.
  - FALSE positive is possible with some small, **controllable** probability.

Bloom Filter - II

Construction

- depends on two parameters n, l
- a table of n bits; at the beginning all are 0.
- l hash functions $H_1, H_2, \ldots, H_l : \{0,1\}^* \rightarrow \{1, \ldots, n\}$

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Adding element x to BF

1. We compute $\{H_i(x)\}_{i=1}^{l}$
2. $H_i(x)$-th bit of the table is set to 1 for all $1 \leq x \leq l$.

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Bound for false positive error

$$< \left(1 - \exp\left(\frac{-l(n + 0.5)}{k - 1}\right)\right)^l .$$

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- ElGamal (some other as well).

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- trick one - every single bit of BF is represented by a ciphertext of 0 or 1 (homomorphic encryption), called **block**.
- trick two - we add a m “dummy blocks”- ciphertexts of a fixed value ζ.
  They are randomly permuted with regular blocks.
  Adversary cannot distinguish them. If the dummy block is changed - the sink can detect it.
  $\Rightarrow$ The final result is considered **corrupted**.

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- Only stations from the subset knows positions of dummy blocks.
- Such construction (collection of blocks) is traversing the network and **all** blocks are recoded after visiting any "green" station. Moreover the station can add its element to BF (homomorphic property).

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- Some details are skipped.

Analysis

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Used techniques

Combinatorial observations, Chernoff bound ...

Analysis
Real values

Weaker

For $k = 60$ elements, size of BF $n + m = 1200 + 600$ and $l = 20$ hash functions

- false positive < 0.00003;
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Stronger

For $k = 100$ elements, size $n + m = 10000 + 5000$ and $l = 70$ hash functions

- false positive $< 3 \cdot 10^{-16}$;
- prob. of successful attack $< 1.8 \cdot 10^{-10}$ if adversary can compute $< 10^{17}$ values of hash functions.

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- The same tricks used in construction.
- We need less blocks (in **some** cases the difference is exponential).
- “Aggregation” is reduced to computing restricted functions e.g. sum or maximum of values.

Thank you for your attention!

marek.klonowski@pwr.wroc.pl