Securing Data Analytics on SGX With Randomization

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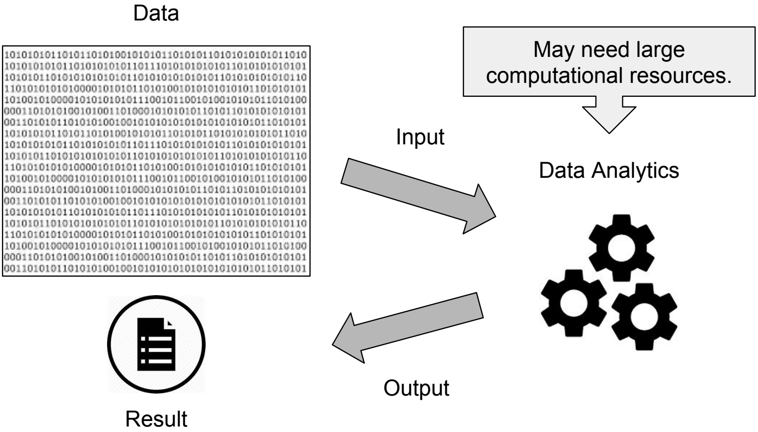
The Problem: Data Analytics in Untrusted Platform



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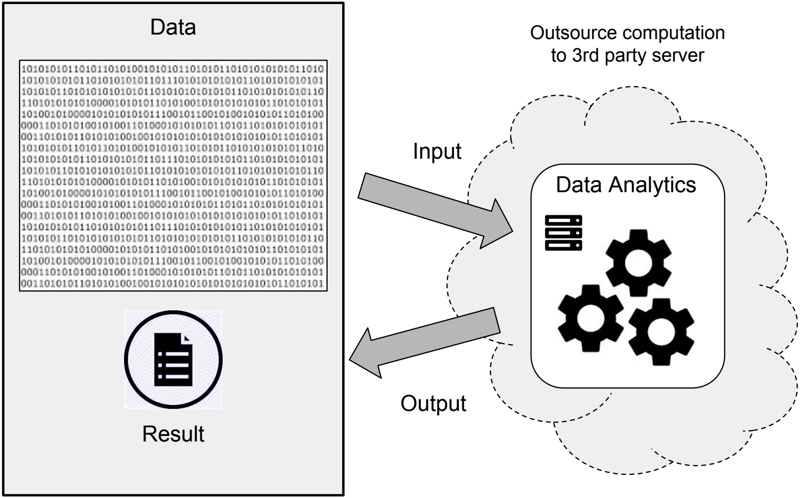

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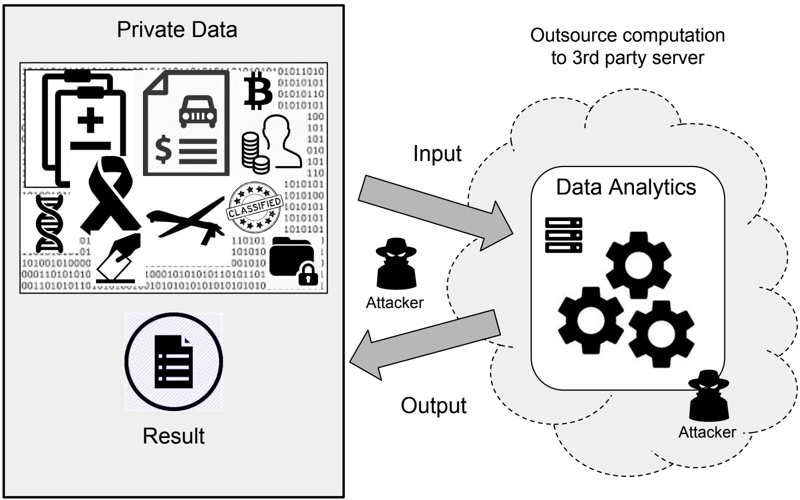

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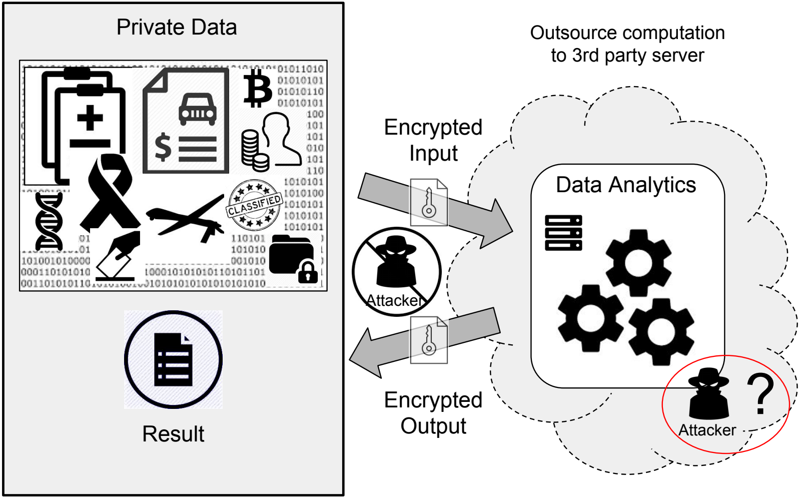

Existing Efforts

Privacy Preserving Analytics

Modifications to data before sharing it to the third-party server [AP08].

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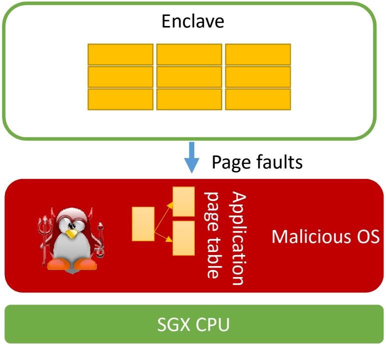
Leveraging Trusted Execution Environment (TEE)

- Recent TEEs: Intel SGX [MAB+13], ARM TrustZone.
- Perform analytics on private data within secure environment, isolated from adversary [SCF+15].

Issues w/ TEE Approaches

Information leakage via (controlled) side-channels harms data privacy



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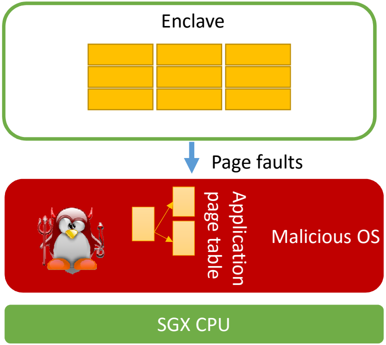

Attacker can use page-fault attack to observe execution flow and guess parameter values [XCP15].

State-of-the-Art

- **Balanced Execution** [SCNS16]: Execute each conditional branch.
- **Data oblivious execution** [OSF+16]: Manipulate execution sequence to be fully data independent.

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Execution overhead impractical for large analytics.

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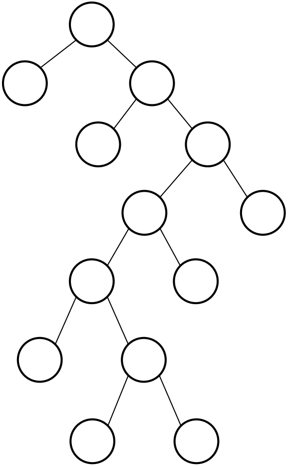
What are large parameters?

- Decision Tree: **Large number of nodes**
- Naive Bayes: **Large domain size**
- K-Means: **Large domain size**

Limtations in State-of-the-Art

Example Decision Tree

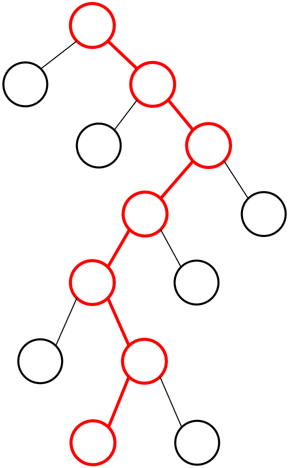
- Given a trained decision tree.



Limtations in State-of-the-Art

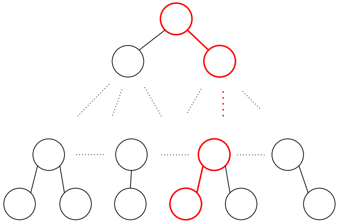
Example Decision Tree

- Given a trained decision tree.
- **Input**: Data instance X for evaluation.



Limtations in State-of-the-Art
Example Decision Tree

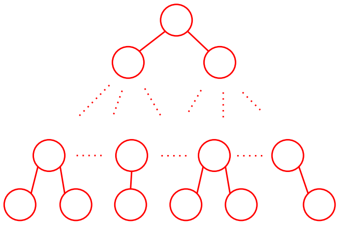
- Given a trained decision tree.
- **Input**: Data instance X for evaluation.
- **Defense**: Hide structure using dummy nodes.



Limtations in State-of-the-Art

Example Decision Tree

- Given a trained decision tree.
- **Input**: Data instance X for evaluation.
- **Defense**: Hide structure using dummy nodes.
- But, evaluation of X will explore all branches causing computational bottleneck.



Intel SGX

Intel Software Guard Extension (SGX)

Capabilities

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Assumptions

- All privileged software (kernel, hypervisor) is malicious.

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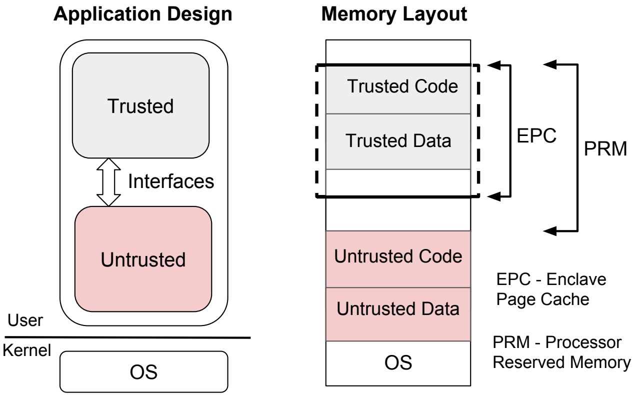
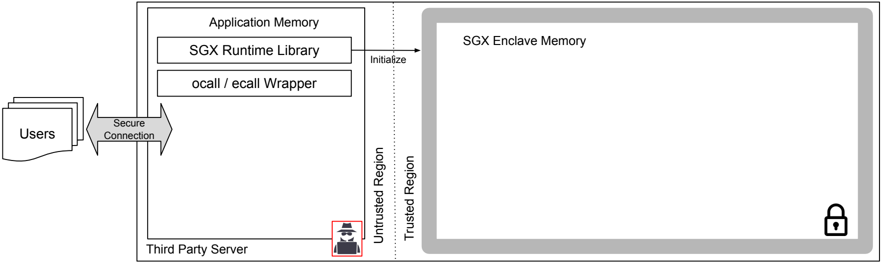


SGX-Rand: Secure Data Analytics

Architecture and the Threat Model



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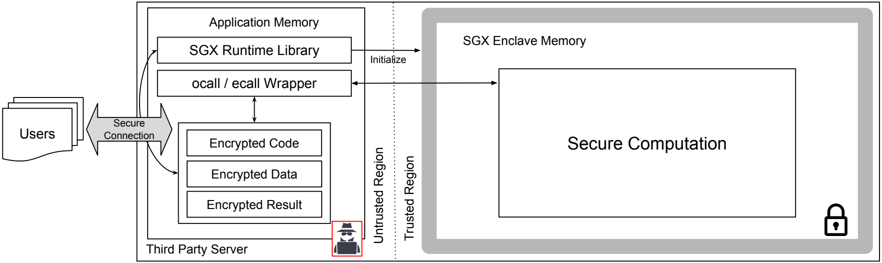

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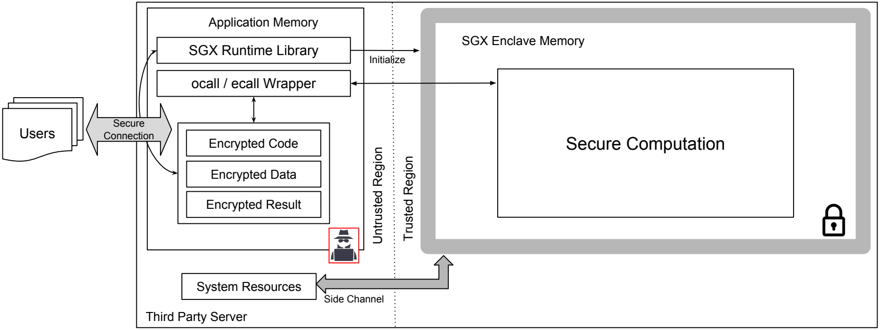

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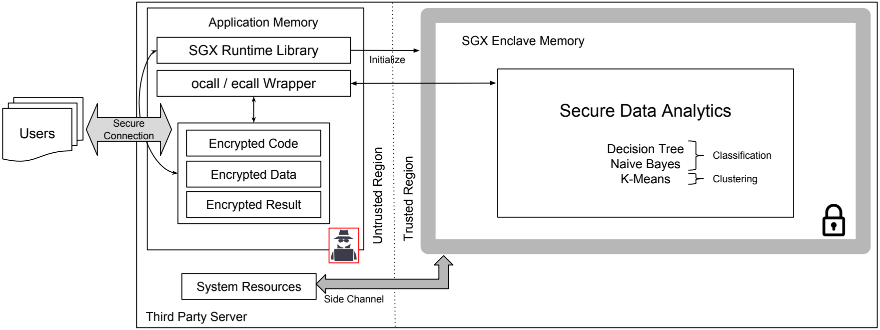

SGX-Rand: Secure Data Analytics

Objective: reduce leakage of private information during execution of analytic algorithms

What should we secure?

Model and data specific to each analytics

- **Trained parameters** such as posterior probability in Naive Bayes or internal node values in decision tree.
- **Learned structure** such as decision tree.

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What need not be secure?

Public information in Analytics.

- Number of data instances.
- Total number of class labels.
- User-defined parameters such as number of clusters in K-Means clustering.

SGX-Rand

Key Idea

How to reduce computational cost?

- Create **dummy data instances**, equivalent to input data.
- **Randomly mix dummy data instances** with input test instances to form a contaminated test dataset.
- Evaluate with the **newly generated dataset**
- **Obliviously ignore** results from dummy data instances.

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Attacker's perspective

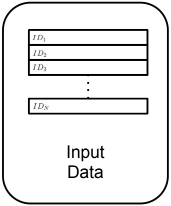
- Obtain traces from **side-channel** during evaluation.
- **Cannot distinguish traces** corresponding to **real vs. dummy** data instances.

SGX-Rand

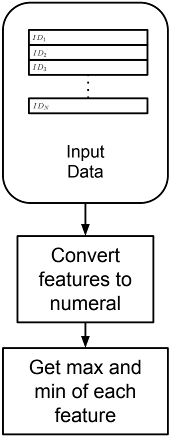
Two Key Primitives

1. **Dummy data generation**
2. **Data oblivious methods**
   - shuffling dummy data with input data to create contaminated dataset.
   - ignoring results of dummy data.

SGX-Rand: **Dummy Data Generation** Primitive



SGX-Rand: **Dummy Data Generation** Primitive



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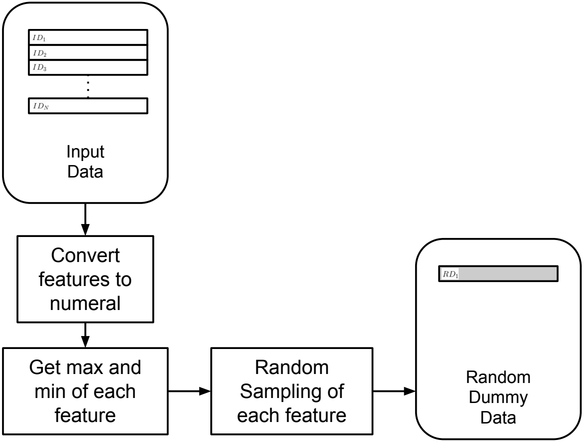

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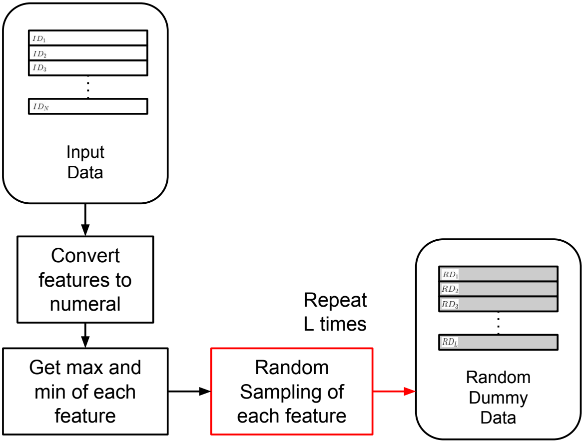

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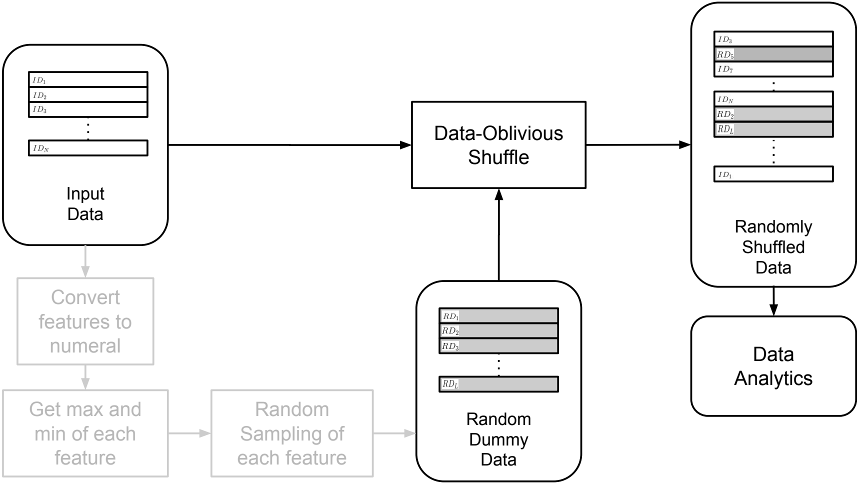

SGX-Rand: **Data Oblivious Comparison** Primitives

- Example function foo.
- Call function bar on different variables depending on condition.

```
int foo(int x, int y)
{
    ...
    if (x > y) {
          bar(x);
    } else {
          bar(y);
    }
    ...
}
```

SGX-Rand: **Data Oblivious Comparison** Primitives

- Example function `foo`
- Call function bar on different variables depending on condition
- Instead, we **define a temporary variable (t) to capture condition**
- Use it to pass appropriate value to bar, making the function **data oblivious**

```
int foo(int x, int y)
{
    ...
    int t;
    if (x > y) {
            t=1;
    } else {
            t=0;
    }
    bar(t*x + (1-t)*y);
    ...
}
```

SGX-Rand: Secure Data Analytics

How to Use SGX-Rand

- Train model using confidential training data.
- Provide input to third-party server
  - Trained model
  - Unknown data set for evaluation.
- Obtain output from third-party server.
- Discard dummy output.

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Securing popular analytics during evaluation

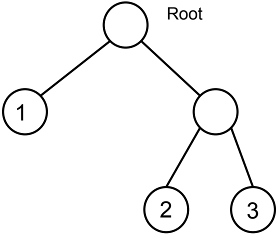
- Classification
  - **Decision Tree**
  - Naive Bayes
- Clustering
  - K-Means

Case-Study: Securing Decision Tree

Private Information	Public Information
Tree Structure Node values Data distribution	Number of input data instances. Number of class labels.

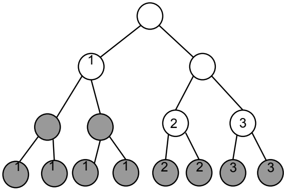
Case Study: Securing Decision Tree

- Train a decision tree offline.



Case Study: Securing Decision Tree

- Train a decision tree offline.
- Balance the tree with **dummy nodes** such that leaf has same label as real-tree parent leaf. (extra step to secure tree structure).
- Load it into SGX enclave.



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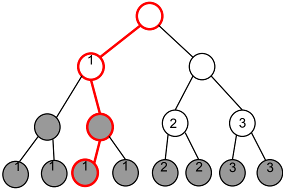

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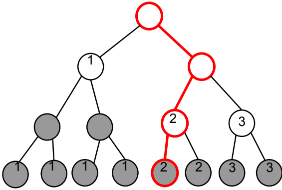
- Obliviously ignore results from dummy data instances.
- Attacker cannot differentiate between 2 traces.



Empirical Evaluation

Objectives

- At minimum privacy, how much reduction in execution overhead can randomization achieve?
- How much is the trade-off between computation time and privacy-guarantee?

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Dataset

Dataset	Size	Feature	Classes
Arrhythmia (A)	452	280	13
Defaulter (D)	30,000	24	2
ForestCover (F)	50,000	55	7
Synthetic (S)	50,000	71	7

Experiment Setup

Baseline

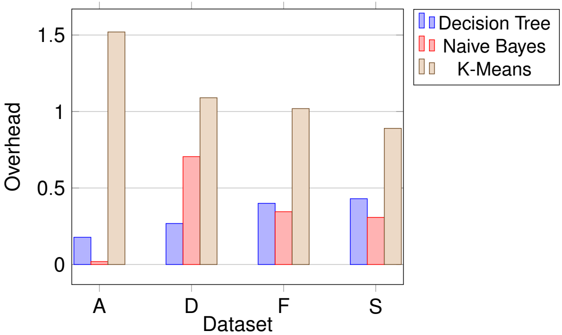
- **SGX**: Analytics within SGX enclave, *without* any defense.
- **SGX+Obliv**: Analytics within SGX enclave, *with* fully data-oblivious defense.
- **SGX+Rand**: Analytics within SGX enclave, *with* our randomization defense.

Measurement

- Execution time $e = \frac{\mathit{time}(SGX+x)}{\mathit{time}(SGX)}$, where $x \in \{\mathrm{Obliv}, \mathrm{Rand}\}$
- Classification accuracy

Results

- With minimum privacy, $L = N$.
- Overhead $o = \frac{e(SGX+Rand)}{e(SGX+Obliv)}$
- Lower o is better, with $o < 1$ is gain in computation time.



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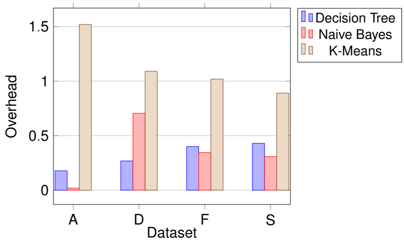

Good

Decision Tree and **Naive Bayes** have significantly large gain in execution time.

Not Good

K-Means for SGX+Rand has larger overhead than SGX+Obliv since every cluster is accessed even for dummy data instances.

Security Evaluation

Objective

- Is there noise in access traces?
- Are traces of input and dummy data instances indistinguishable?

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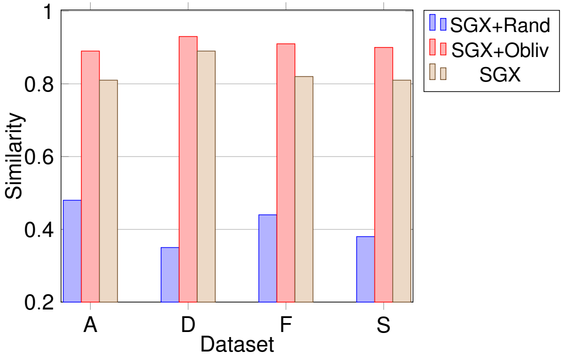
Methodology

- Using Intel PIN to obtain traces during execution.
- Measure **Levenshtein distance** between memory access sequence.
  - Greater distance is dissimilar traces, i.e., less similarity.
  - More similarity is similar traces.

Security Evaluation

Measuring similarity of execution traces obtained from two **independent datasets**



- Smaller value indicates greater randomization.

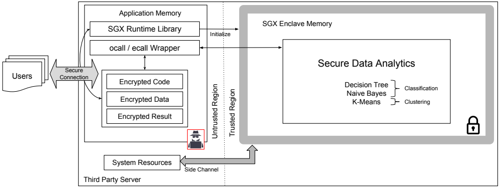
Conclusion

- **Randomization** is effective in reducing execution time overhead in data analytics compared to **fully data oblivious** solution.
- We quantitatively measure privacy and provide a choice in trade-off between privacy and efficiency.
- Our evaluation demonstrates both advantages and disadvantages in employing randomization.

Open-Source

Project code available at `https://github.com/utds3lab/secure-analytics-sgx`

Thank You



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