F-BLEAU: Fast Black-box Leakage Estimation

via Machine Learning

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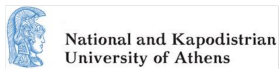
IEEE Symposium on Security&Privacy
21 May, 2019



A black-box

Assume no knowledge of system's internals

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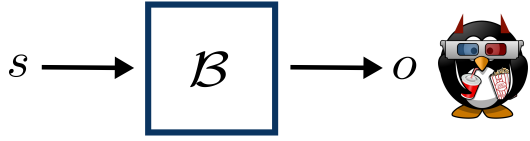

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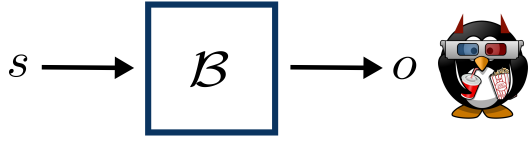

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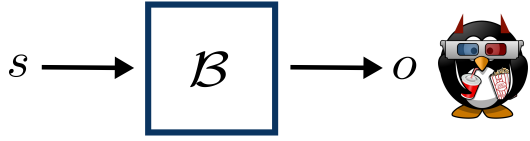

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- how much o leaks about s?

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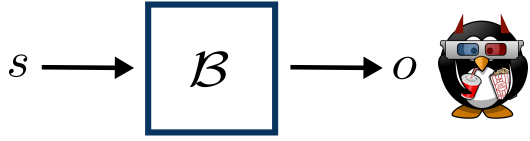


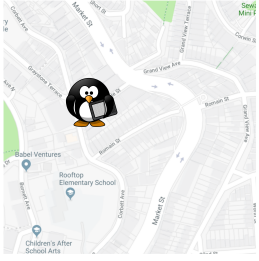
Assume no knowledge of system's internals

How can we measure:

- how much o leaks about s?
- how hard is it to predict s given o?

Application Examples

Location privacy



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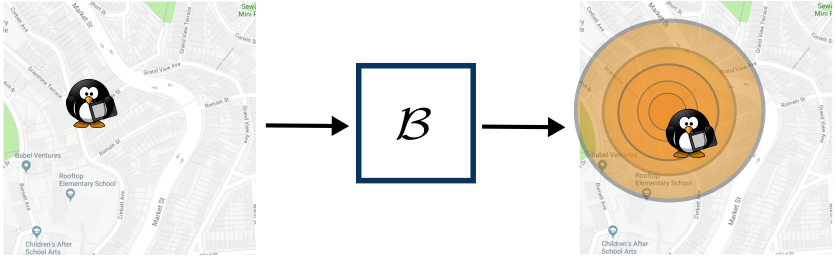
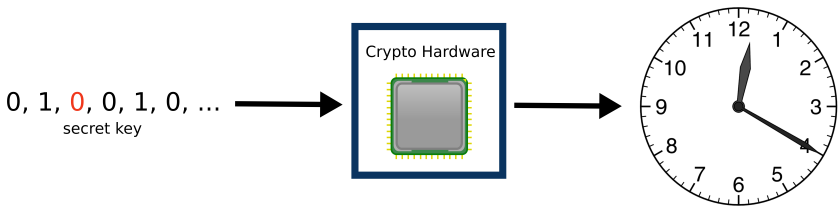


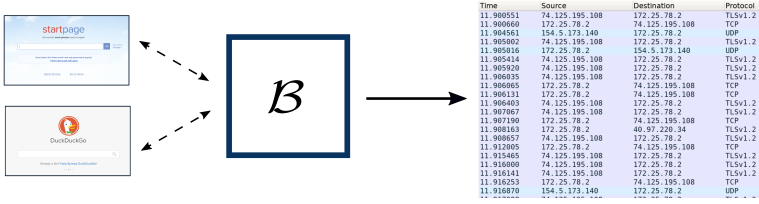
Application Examples

Side channels in crypto primitives' implementation



Application Examples

Network traffic analysis (e.g., Website Fingerprinting)



Time	Source	Destination	Protocol
11.900551	74.125.195.108	172.25.78.2	TLSv1.2
11.900660	172.25.78.2	74.125.195.108	TCP
11.904561	154.5.173.140	172.25.78.2	UDP
11.905002	74.125.195.108	172.25.78.2	TLSv1.2
11.905016	172.25.78.2	154.5.173.140	UDP
11.905414	74.125.195.108	172.25.78.2	TLSv1.2
11.905920	74.125.195.108	172.25.78.2	TLSv1.2
11.906035	74.125.195.108	172.25.78.2	TLSv1.2
11.906065	172.25.78.2	74.125.195.108	TCP
11.906131	172.25.78.2	74.125.195.108	TCP
11.906403	74.125.195.108	172.25.78.2	TLSv1.2
11.907067	74.125.195.108	172.25.78.2	TLSv1.2
11.907190	172.25.78.2	74.125.195.108	TCP
11.908163	172.25.78.2	40.97.220.34	TLSv1.2
11.908657	74.125.195.108	172.25.78.2	TLSv1.2
11.912005	172.25.78.2	74.125.195.108	TCP
11.915465	74.125.195.108	172.25.78.2	TLSv1.2
11.916000	74.125.195.108	172.25.78.2	TLSv1.2
11.916141	74.125.195.108	172.25.78.2	TLSv1.2
11.916253	172.25.78.2	74.125.195.108	TCP
11.916870	154.5.173.140	172.25.78.2	UDP

Bayes risk

$$Pr\left(\text{  }(o) \neq s\right)$$

Bayes risk

$$R^* = \min_{\text{  }} \{ Pr\left(\text{  }(o) \neq s \right) \}$$

Bayes risk

Bayes risk R^* is the probability of error of the **optimal** adversary:

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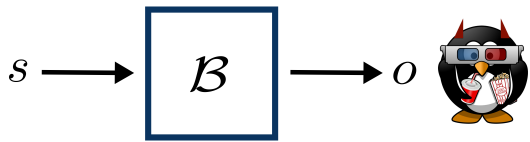
On its basis we can compute **leakage measures** (e.g., Min-entropy, multiplicative/additive leakage)

Black-box estimates



We wish to measure leakage based on queries we make to the system:

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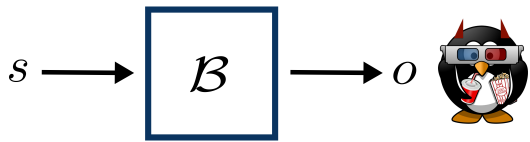

We wish to measure leakage based on queries we make to the system:

$$(s_1, o_1), (s_2, o_2), \ldots, (s_n, o_n)$$

Frequentist paradigm [C+'10]

(E.g., `leakiEst`, `LeakWatch`)

Suppose adversary observed data:

$$(s, 0.4), (s, 0.7), (s, 1.2), (s, 0.4), (s, 0.4)$$

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Suppose adversary observed data:

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$\text{Freq}\left(0.4\right) =$

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- Does not work for **continuous** output space
- Does not scale to **large** systems (needs at least one example per output value)

Nearest Neighbor

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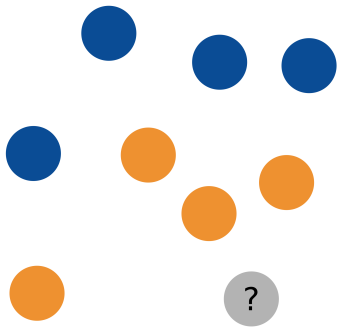

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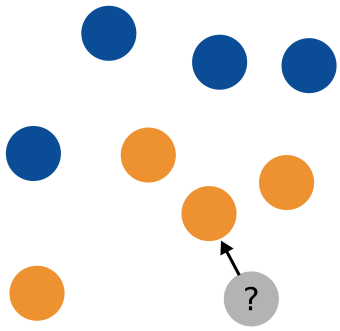

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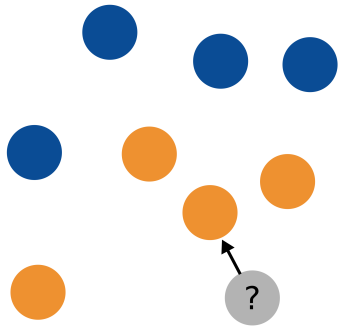

With minor modifications NN is leakage estimator

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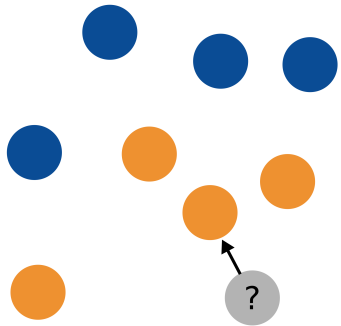
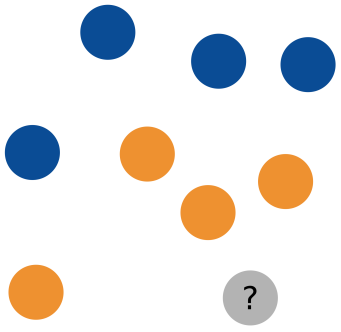


With minor modifications NN is leakage estimator (when o from finite set).

k-Nearest Neighbour [S'77]



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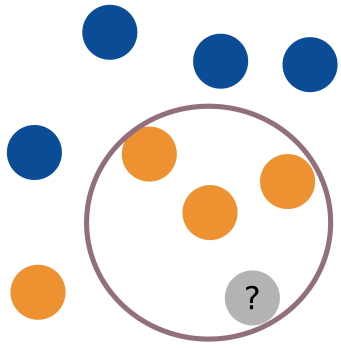

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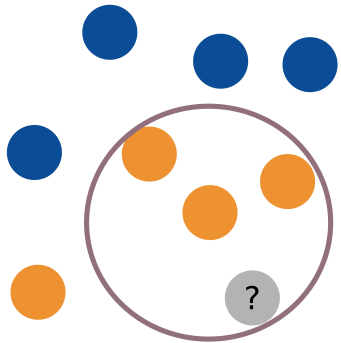

If we choose $k/n \to 0$ and $k \to \infty$ as $n \to \infty$, then k-NN is leakage estimator.

Universally Consistent rules

Main result

We can use Machine Learning techniques for measuring the leakage.

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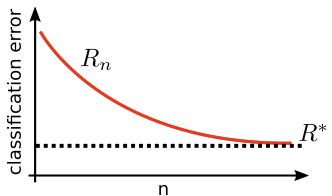
Definition An ML rule is universally consistent if its error R_n converges to R^* as the size of the training data $n \to \infty$



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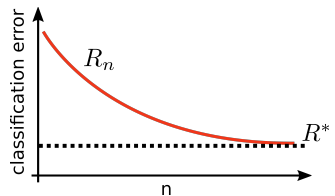

E.g., NN (finite case), k-NN, SVM and Neural Networks (some param. choices)

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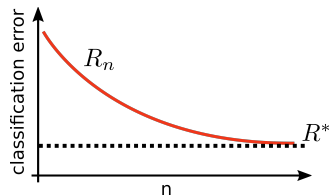

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Results
Location privacy

Defense mechanisms:

- **Geometric**
- Laplacian
- Blahut-Arimoto [O+'17]

Gowalla dataset: users' location data, $100K$ examples.

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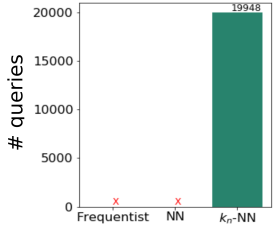

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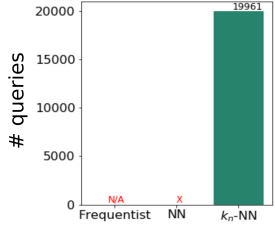

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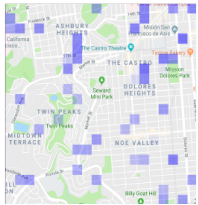

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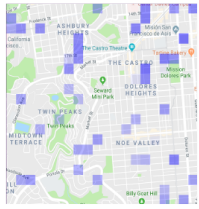

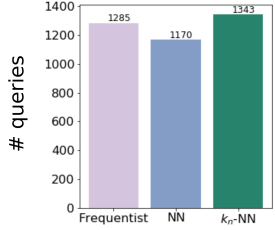

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Synthetic experiments

- Scale to large systems & excel when there's a metric on the output
- When no metric: equivalent to Frequentist
- However, may converge slowly for maliciously crafted systems

Quick convergence?
No Free Lunch [W'96]

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Takeaway Always try several estimators and select the one converging faster.

`fbleau` based on this idea

TL;DL + future ideas

- Several applications: location privacy, side channels, traffic analysis, ...
- We can use ML (UC) rules: they **scale** to large problems, and tend to converge faster (or equivalently to) frequentist approach

\+ More applications (e.g., side channels, attacks to ML models)

fbleau: `https://github.com/gchers/fbleau`

Takeaway Black-box security and ML are solving similar problems: let's bridge them.

References

Applications

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Black-box security

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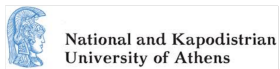
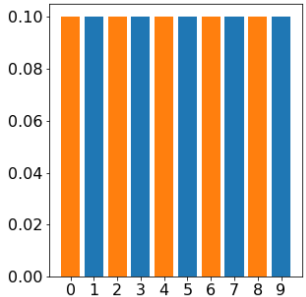


Spiky channel



2 secrets, 10K observable values

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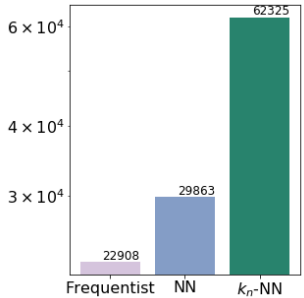

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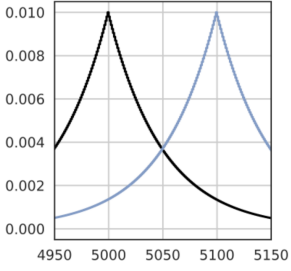
Geometric distribution



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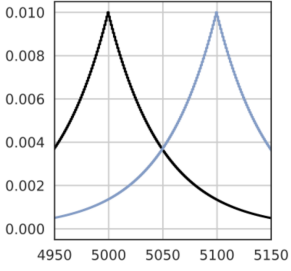
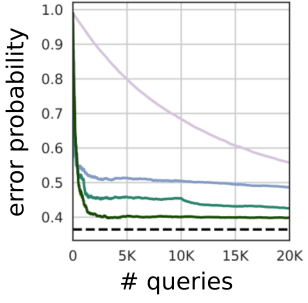
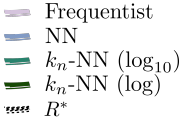
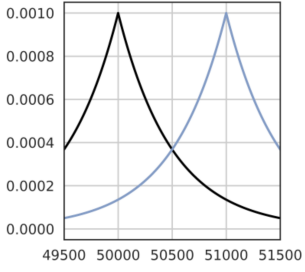


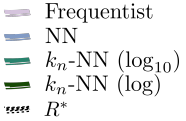




Results

Geometric distribution





Results

Geometric distribution