Measuring the Security of Blackbox Systems via Machine Learning

Part I - The quest for Machine Learning optimality

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EPFL

ForMal 2019

EPFL

Spoiler: Our final goal

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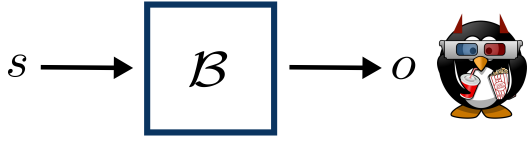

Tutorial outline

Two parts ($\sim$ 2h, including 10' break):

1. Optimality in ML, asymptotically optimal rules, impossibility results
2. Applying these results for measuring the information leakage of generic systems

Outline

- Quick review of supervised learning
- Optimality: Bayes classifier
- Asymptotic properties of NN and k_n-NN, and universally consistent rules
- Impossibility results
- Features and convergence

Supervised learning

- "Nature" gives us n examples (object-label pairs) $(x_1, y_1), ..., (x_n, y_n)$, sampled independently from the same distribution μ on $\mathcal{X} \times \mathcal{Y}$, finite $\mathcal{Y}$.

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$$R^g = \mathbb{E}(I(g(x) \neq y)) = P(g(x) \neq y)$$

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We call **learning rule** a sequence of classifiers $\{g_n, n \geq 1\}$.

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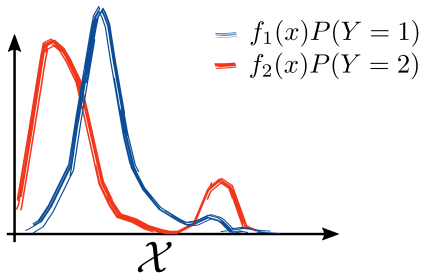

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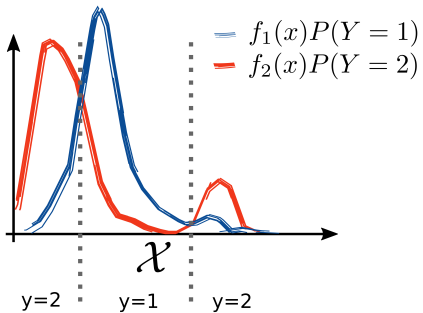

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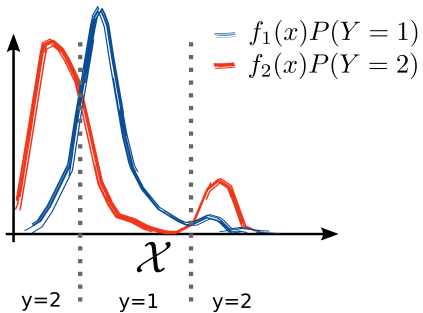

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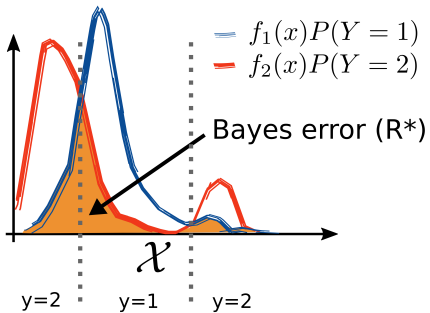

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The Bayes classifier

Remark: **Bayes classifier $\neq$ Naïve Bayes classifier**

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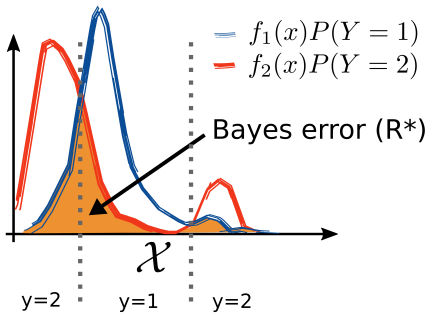

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Bayes error
An example

Consider finite space X. The Bayes risk is:

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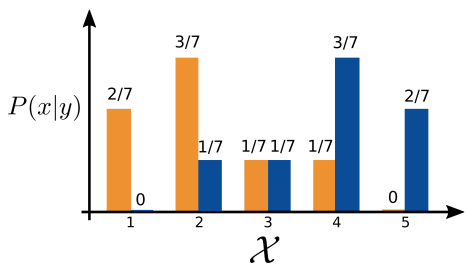
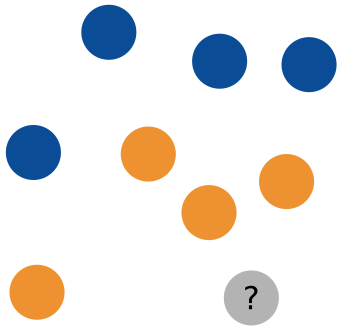


But...

In practice, underlying distribution is unknown $\Longrightarrow$ we can't use Bayes classifier

Nearest neighbour

Nearest neighbour



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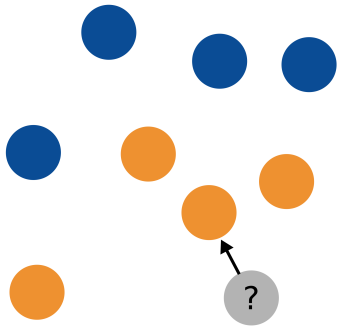


Nearest neighbour
Asymptotic convergence [CH'67]

Theorem

Let $|\mathcal{Y}| = 2$. Consider a separable metric space $\mathcal{X}$ with (arbitrary) metric d.
As $n \to \infty$, the error of the Nearest Neighbour (NN) classifier is at most twice the Bayes risk:

$$R^{NN} \leq 2R^*(1 - R^*)$$

($\mathcal{X}$ must be separable metric space, with (any) metric d. Minor continuity assumption on density functions omitted.)

Nearest neighbour

Asymptotic convergence - Proof idea

Consider training data $(x_1, y_1), ..., (x_n, y_n)$, and a new object to predict x.
Let x'_n be the closest training object to x.

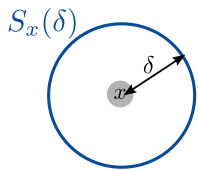
Two steps:

1. (Lemma) Show that $x'_n \to x$ as $n \to \infty$;
2. (Theorem) A posteriori distribution on x'_n converges to that of x. Some calculations for the bound.

Nearest neighbour

Asymptotic convergence - Lemma: $x'_n \to x$

Consider the δ-sphere centered in x:



Pf. intuition: Work on x such that $\forall \delta > 0$ every sphere $S_x(\delta)$ has nonzero probability measure. (Indeed, the set of points without this property has probability 0.)

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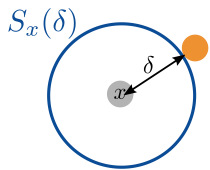

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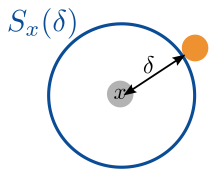

Pf. intuition: Work on x such that $\forall \delta > 0$ every sphere $S_x(\delta)$ has nonzero probability measure. (Indeed, the set of points without this property has probability 0.)
As $n \to \infty$, it becomes more and more unlikely that at least one training point is not in the δ-ball, for any chosen $\delta > 0$.

$$P(d(x, x'_n) > \delta) = P(x'_n \notin S_x(\delta)) = (1 - P(S_x(\delta))^n \to 0$$

Nearest neighbour

Asymptotic convergence - Main theorem

Let $\mathcal{X}$ separable metric space. Assume f_1 and f_2 are s.t. w.p 1, x either: i) continuity point of f_1 and f_2, or ii) point of nonzero probability measure.
Then:

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- $r(x) = 2r^*(x)(1 - r^*(x))$
- Take expectation, $R^{NN} = \lim_{n\to\infty} \mathbb{E}(r(x, x'_n))$, conclude that $R^{NN} \leq 2R^*(1 - R^*)$

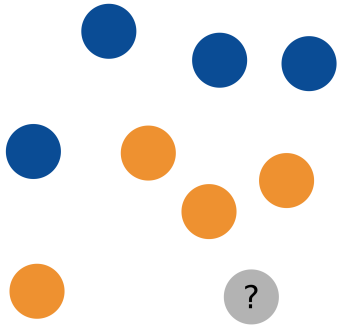
Nearest neighbour

Asymptotic convergence - General bound

Let $L = |\mathcal{Y}|$. Then:

$$R^{NN} \leq R^* \left(2 - \frac{L}{L-1} R^*\right)$$

k-Nearest Neighbour



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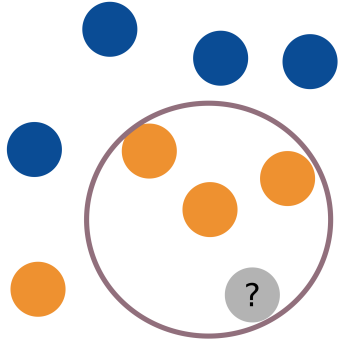


k-Nearest Neighbour

Asymptotic optimality [S'77]

Theorem

If we let $k_n \to \infty$ and $k_n/n \to 0$ as $n \to \infty$, then:

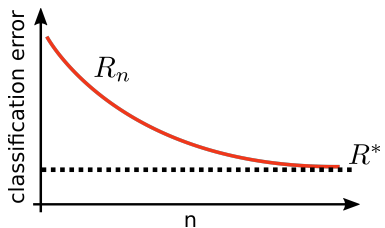
$$R^{k_n\text{-NN}} \to R^*$$

E.g.: $k_n = \log n$ or $k_n = \sqrt{n}$.

Universally consistent rules

Definition

A learning rule $g_n(x)$ is **universally consistent** if for every distribution μ on $\mathcal{X} \times \mathcal{Y}$ its expected error converges to R^* as $n \to \infty$.



Impossibility results

No convergence rate results [A+]

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Nope In the general case, for every rule $g_n(x)$ we can find a distribution for which $g_n(x)$ converges arbitrarily slowly.

Impossibility results
No Free Lunch (NFL)

In the finite sample, is there a rule $g_n^+(x)$ which is “often” better than the others?

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Takeaway Try as many learning algorithms as you can.*

Improving convergence

Features!

x : “anything” physically measurable

y : will the car make it to the other side?

Improving convergence

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y : will the car make it to the other side?

Features:

- speed
- acceleration
- bridge status...

Features

Basic results:

- features can improve the finite sample convergence

Features

Basic results:

- features can improve the finite sample convergence
- BUT they cannot improve the asymptotic behaviour (trivially, the Bayes risk based on feature information cannot be smaller than the Bayes risk based on full information).

Summary

- Bayes classifier is optimal, but we generally cannot use it
- NN classifier offers a good approximation (bound)
- Universally Consistent rules (e.g., k_n-NN) approximate the Bayes classifier asymptotically
- There's no free lunch (well, we're having one at 12:00 today, but free lunches are rare)
- Features

What's next We'll use all this beautiful theory to solve real! world! problems!
Spoiler: `https://github.com/gchers/fbleau`

Bibliography

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Measuring the Security of Blackbox Systems via Machine Learning

Part II - Measuring security with ML

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Based on

- G. Cherubin, *Bayes, not naïve: Security bounds on website fingerprinting defenses*, PETS 2017.
- G. Cherubin, K. Chatzikokolakis, C. Palamidessi, *F-BLEAU: Fast Black-box Leakage Estimation*, IEEE S&P 2019.

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

`https://giocher.com/projects/bayes`

Outline

- A black-box
- Application examples
- Current estimation paradigm (frequentist approach)
- Analogy between ML and Black-box security
- Feature-based security notions
- Infinite secret space

A black-box

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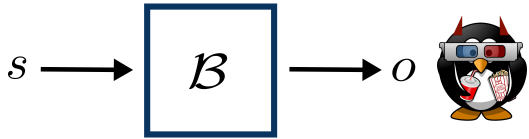

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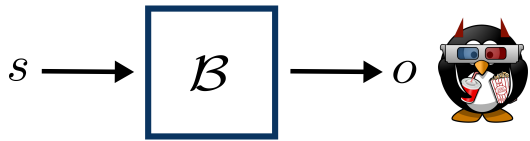

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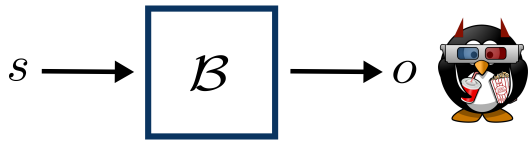

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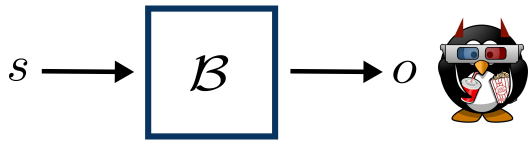

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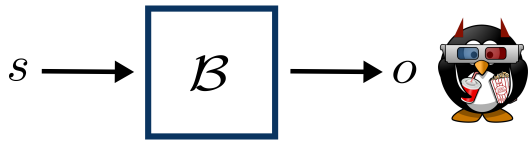
- Informal questions:

A black-box



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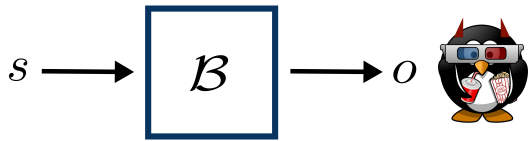

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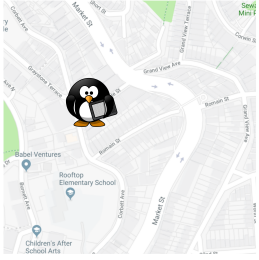
  - how hard is it to predict s given o.

Application Examples

Location privacy



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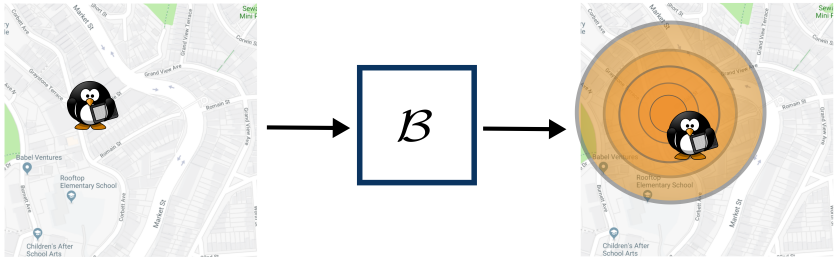
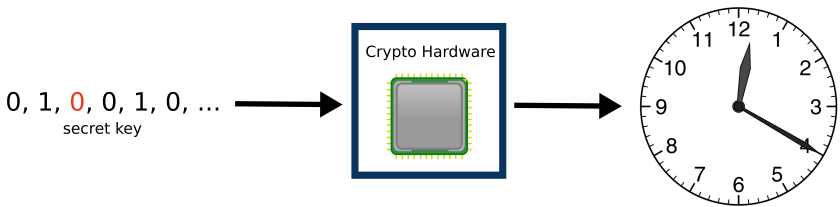


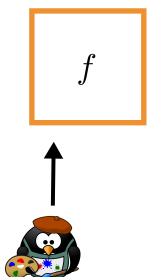
Application Examples

Side channels in crypto primitives' implementation [B+'08]



Application Examples
Membership Inference [S+'17]

Consider a classifier $f : \mathcal{X} \mapsto [0,1]^L$ trained on data (X, Y).



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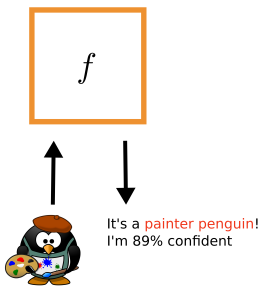

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Membership Inference [S+'17]

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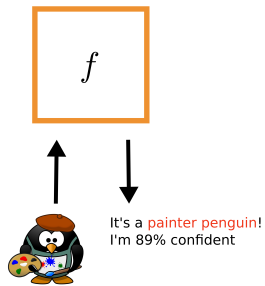
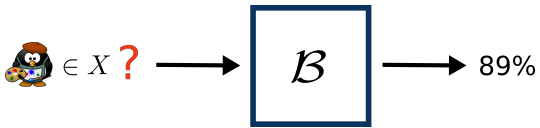


 wants to guess if the object $x =$  was in the training data (X, Y).

Application Examples

Membership Inference in the Black-box setting



Bayes risk and security measures

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

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

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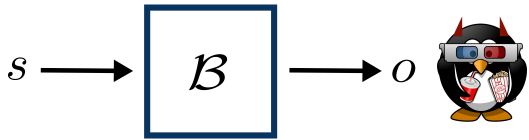
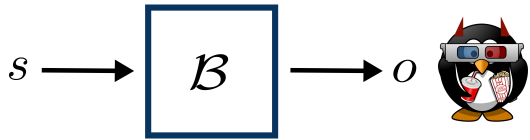
On its basis we can compute **leakage measures** (e.g., Min-entropy, multiplicative/additive leakage). We write $\lambda(R^*)$ for a generic leakage measure.

Black-box estimates



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

Black-box estimates



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

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

Desiderata

Leakage estimate should:

- Given enough queries, converge to the true value (**asymptotic optimality**)

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- Given enough queries, converge to the true value (**asymptotic optimality**)
- Require few queries (i.e., it should **converge quickly**)

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

Black-box security and Machine Learning

An equivalence [C'17, C+'19]

Idea! We can use ML techniques (e.g., UC rules/bounds) for estimating the security of a system.

Estimation tools

Method	Guarantee	Space $\mathcal{X}$	Assumptions
Frequentist [C+'10]	$\to R^*$	finite	
k_n-NN	$\to R^*$	infinite	
NN Bound: $\frac{\lvert\mathcal{S}\rvert-1}{\lvert\mathcal{S}\rvert}\left(1-\sqrt{1-\frac{\lvert\mathcal{S}\rvert}{\lvert\mathcal{S}\rvert-1}R^{NN}}\right)$	$\leq R^*$	infinite	$(d,\mathcal{X})$ separable
NN	$\to R^*$	finite	
SVM-RBF	$\to R^*$	infinite	$\mathcal{X}$ compact subset of $\mathbb{R}^m$

(Under certain parameter choices.)

Bayes Error estimates in Practice

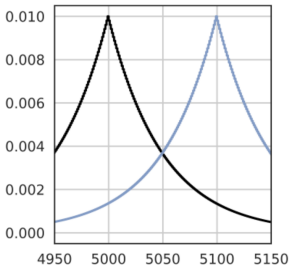
UC rules give guarantees: i) for $n \to \infty$ and ii) w.r.t. their expected error.

In practice, we only have access to a finite number of examples.
Options:

- training + held-out sets
- k-fold CV

Results

Geometric



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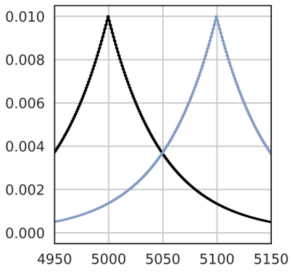

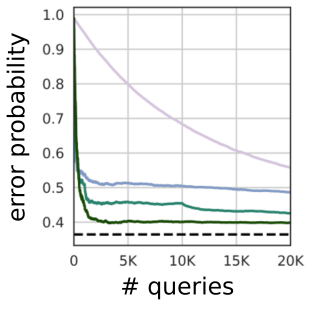

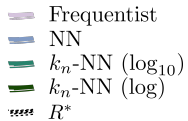

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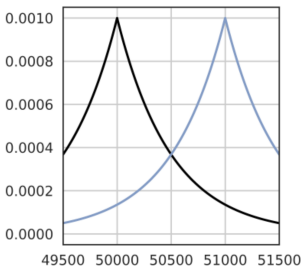
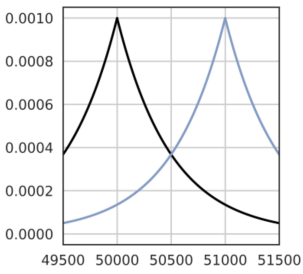
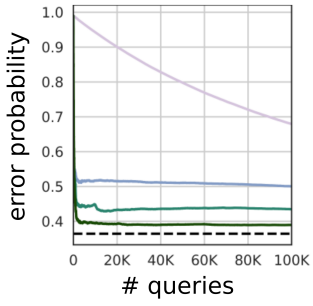


Frequentist
NN
k_n-NN ($\log_{10}$)
k_n-NN (log)
R^*

Results

Geometric





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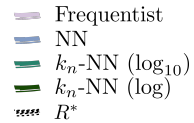

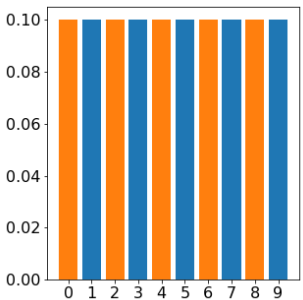

2 secrets, 10K observable values

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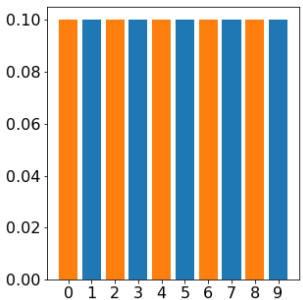

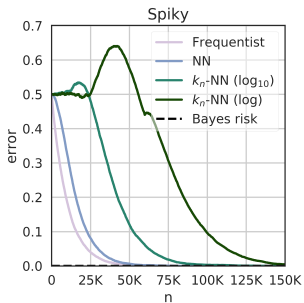

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Location privacy

Defense mechanisms:

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

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

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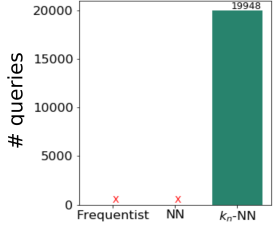

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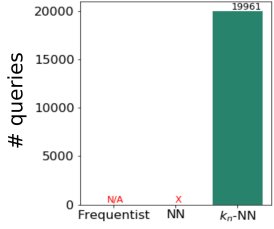

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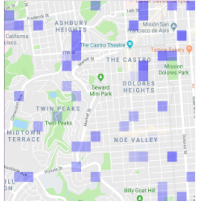

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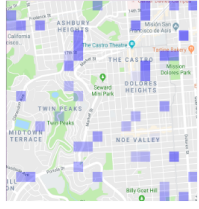

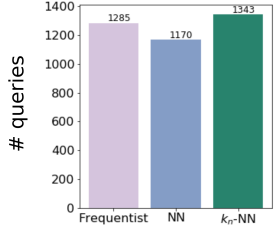

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fbleau: `https://github.com/gchers/fbleau`

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Recall that features may allow us to obtain faster convergence.

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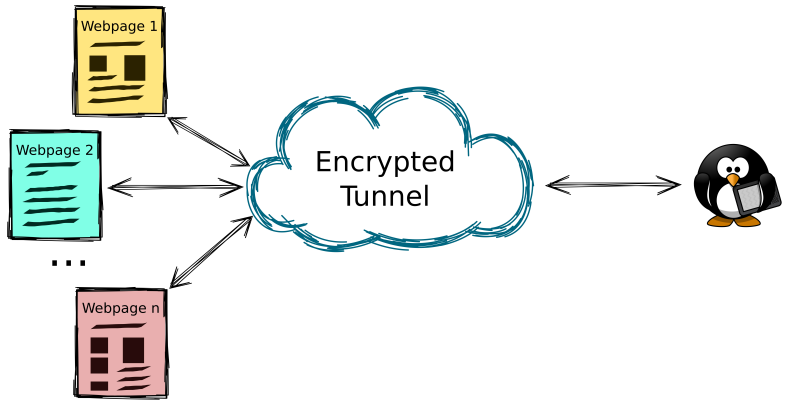
- But, weaker security definition.

Application Example

Website Fingerprinting [C'17]



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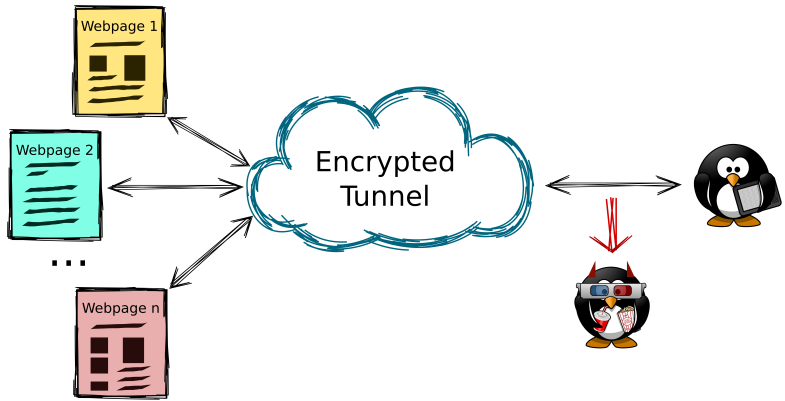
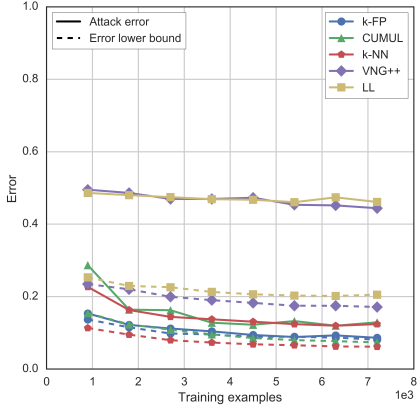


Website Fingerprinting
Results

Results on undefended Tor traffic



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- 0-1 risk notion does not apply. Use for example $\ell(s, \hat{s}) = (s - \hat{s})^2$
- Use an UC regressor; for example, the k_n-NN regressor is UC under some conditions.

Summary

- With Black-box security we can model several attacks: location privacy, side channels, traffic analysis, …
- Frequentist paradigm doesn't scale & not applicable to continuous
- We can use ML results to scale to large/complex systems
- If needed, we can use features for scaling to even more complex problems (albeit achieving weaker security notions)

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

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