Estimating *g*-leakage via Machine Learning

Marco Romanelli[1,2,3], Konstantinos Chatzikokolakis[4], Catuscia Palamidessi[1,2] & Pablo Piantanida[5,6,7]

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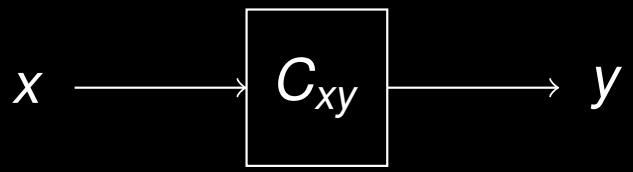
Motivation



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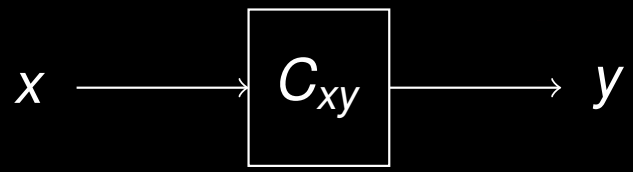

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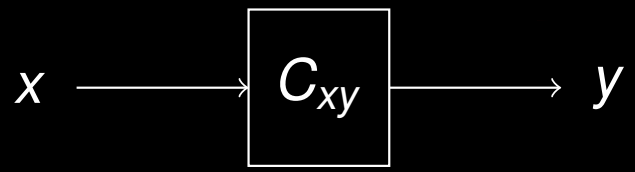

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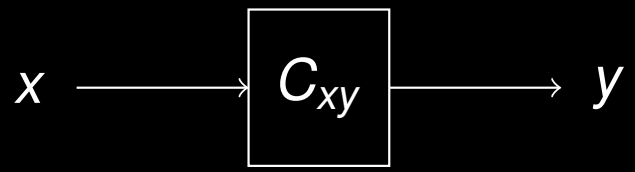

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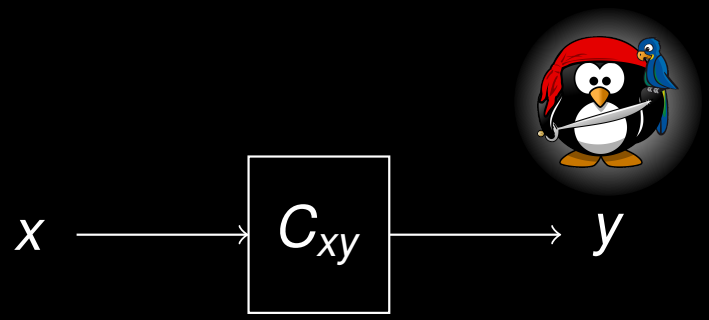

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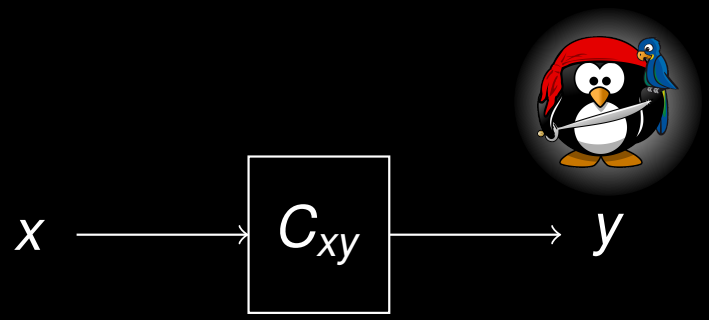

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- Can we use ML to estimate how much information this system leaks?

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F-BLEAU [Cherubin et al., 2019]: introduces the use of ML to model the attacker

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$\Longrightarrow$ We introduce neural network models and ***g*-leakage** estimation.

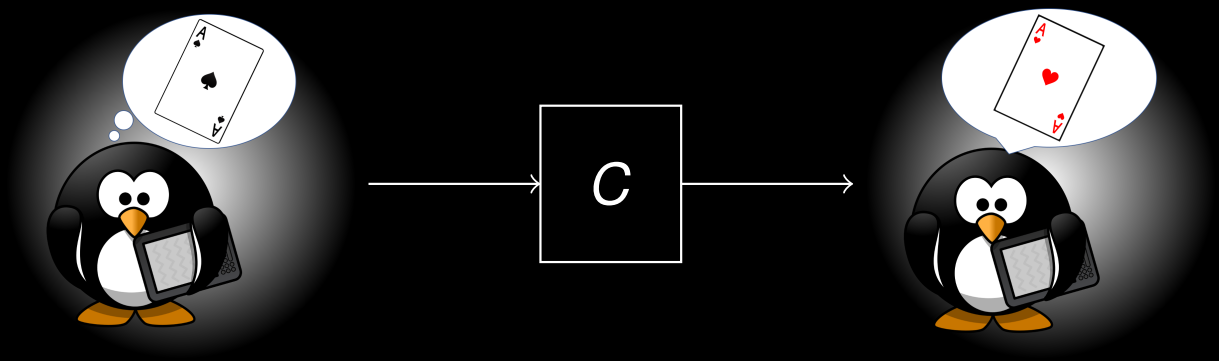
Why *g*-leakage?

set of actions (guesses)

$$= \left\{ w \in \mathcal{W} \; ; \; g : \mathcal{W} \times \mathcal{X} \to [a, b] \text{ with } a, b \in \mathbb{R}^{+} \right\}$$

gain function

Example of attacks: Bayesian attack



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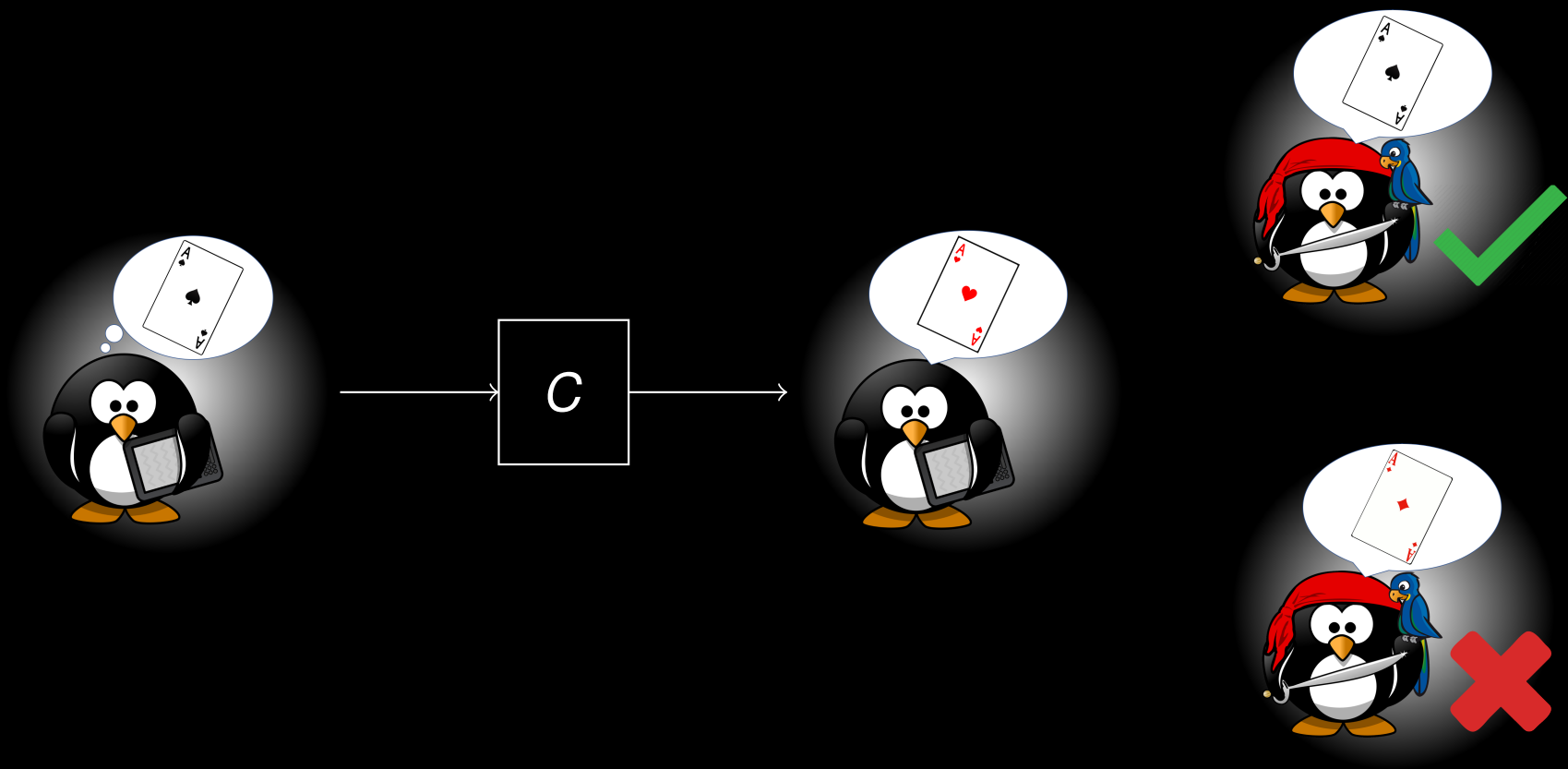

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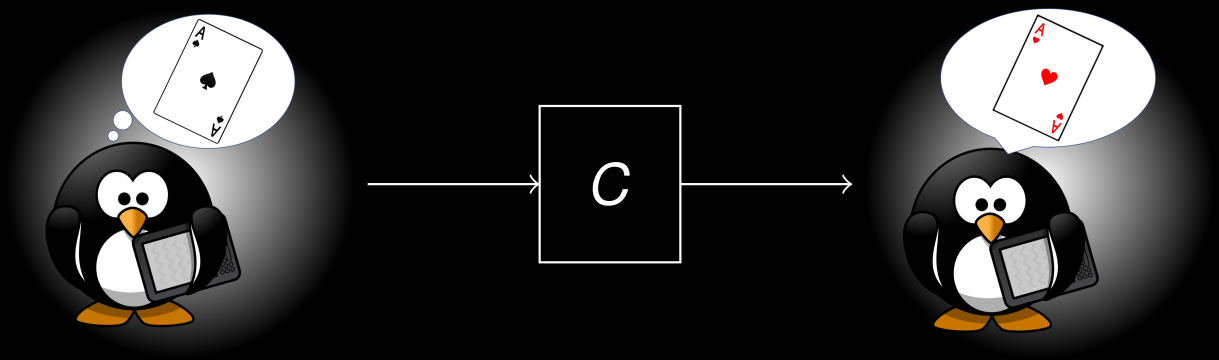

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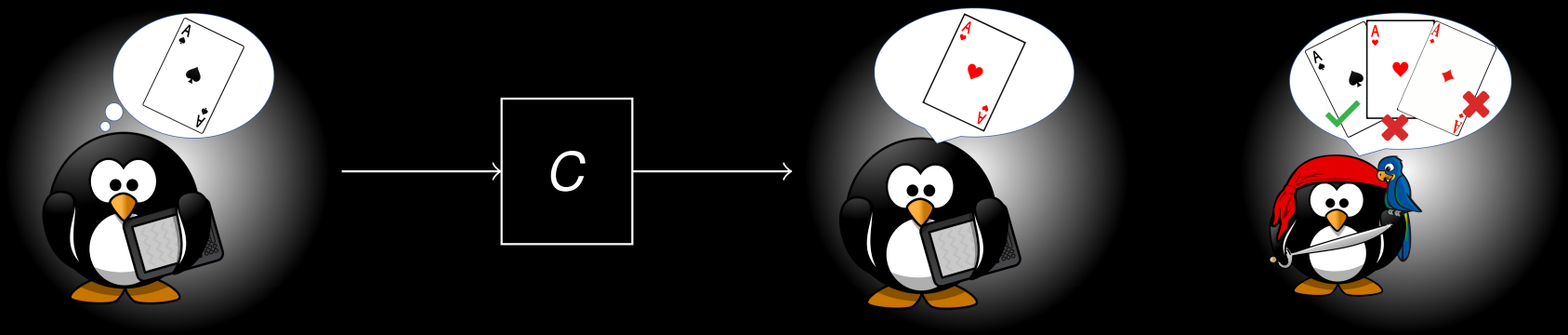

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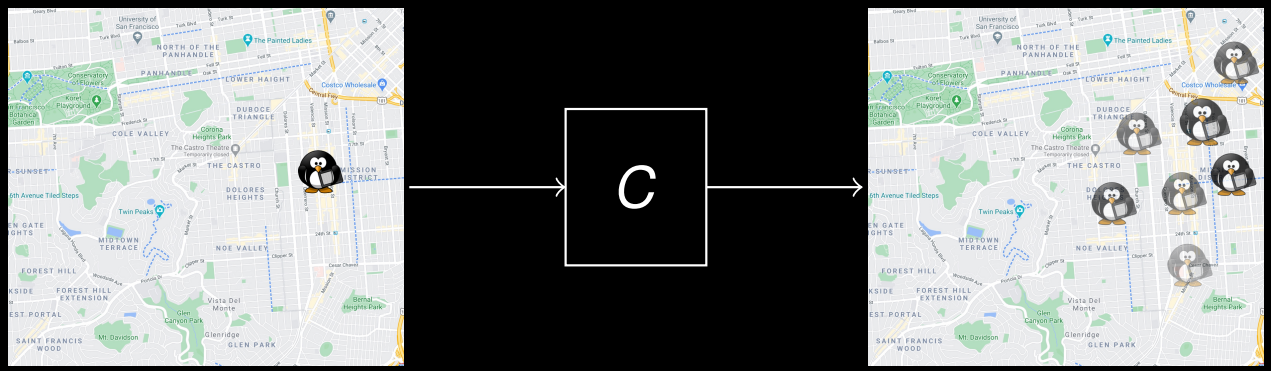

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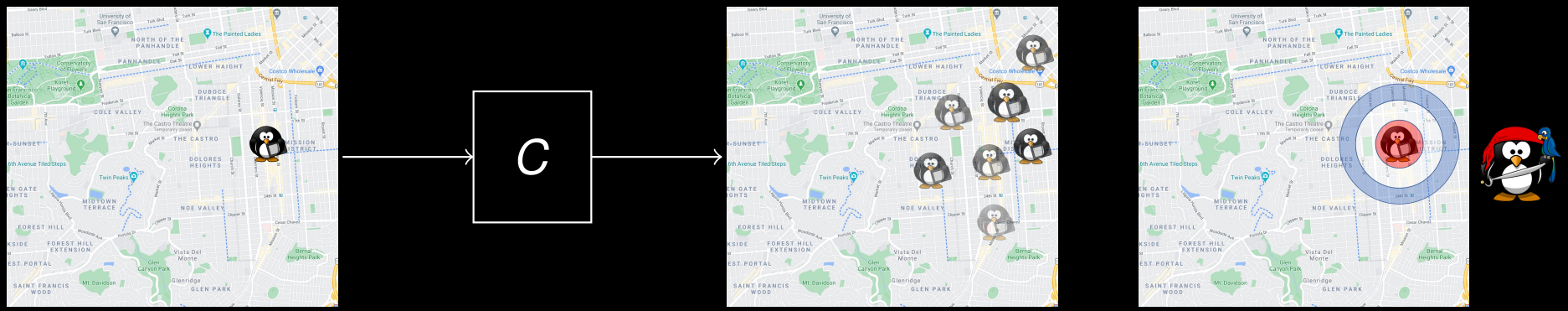
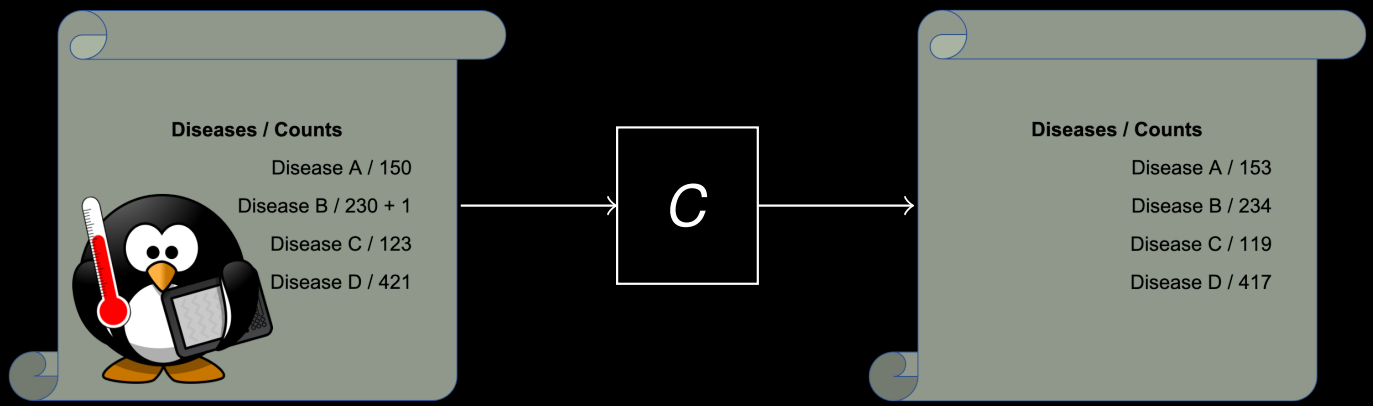


Example of attacks: attack against differential privacy



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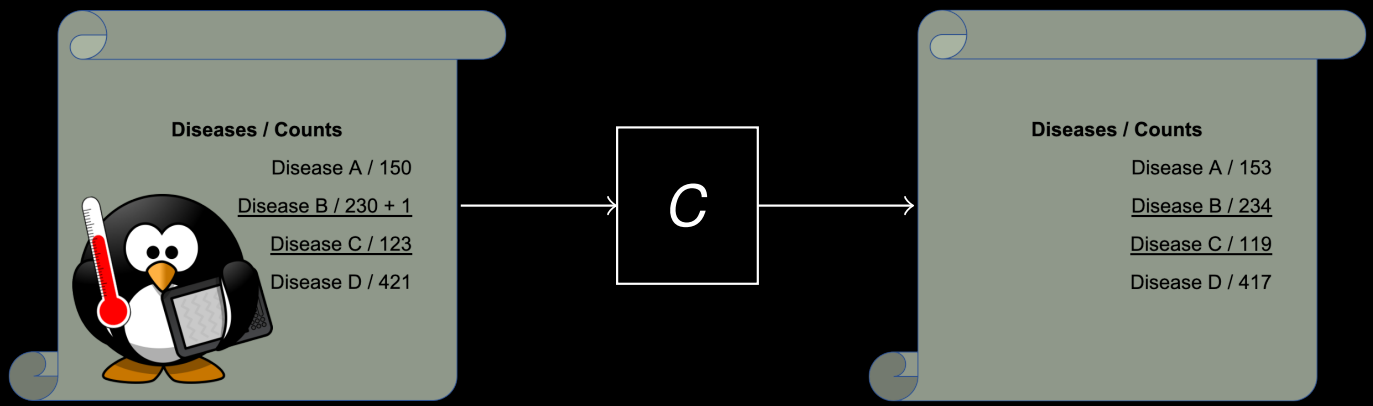

Estimating g-vulnerability from samples

Learnability result: We can upper-bound the expected estimation error

$$\mathbb{E}|V_g - \widehat{V}_n(f^\star_m)|$$

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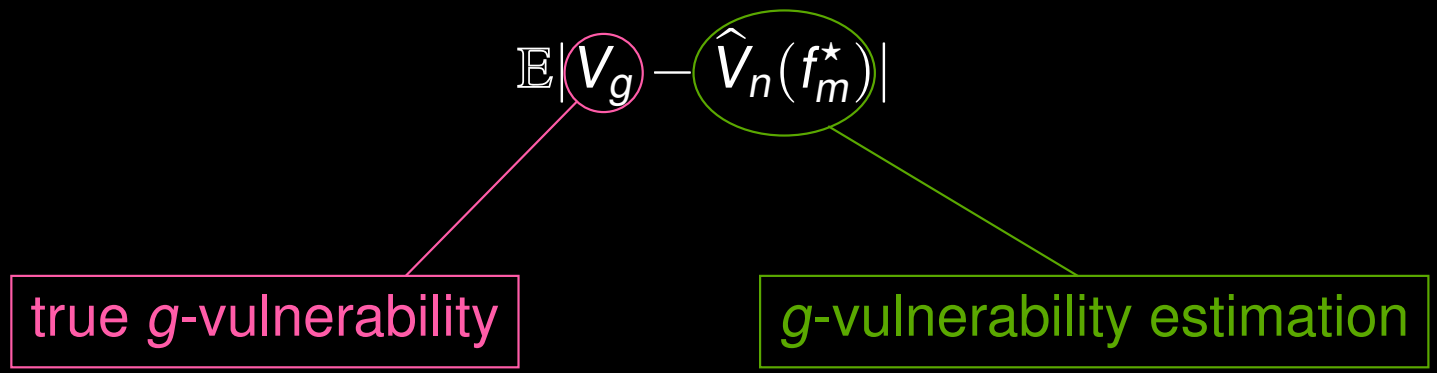

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strongest attacker model with m samples

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g-vulnerability estimation

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$$f : \mathcal{Y} \to \mathcal{W}$$

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How do we obtain the samples we need from the system?

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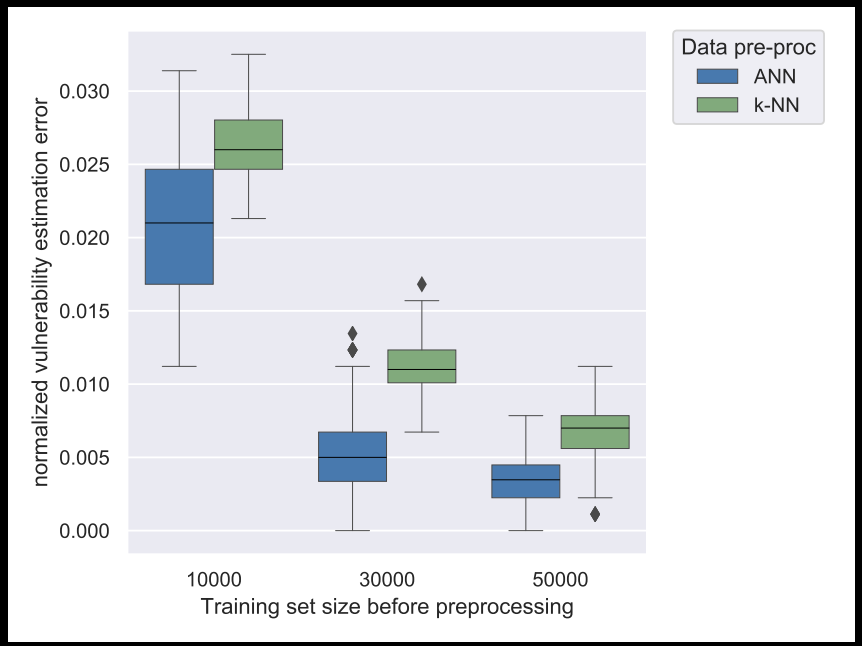
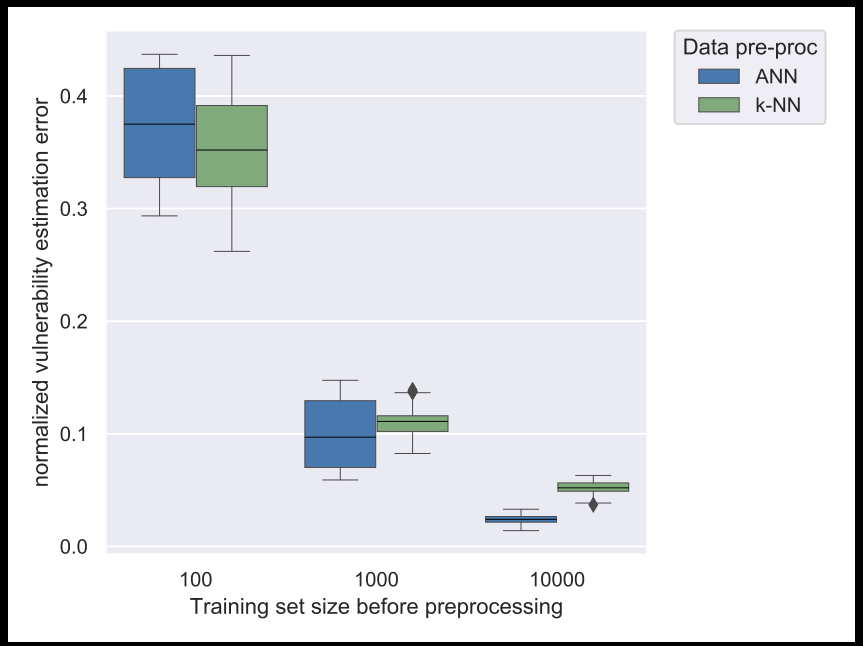


(a) Multiple guesses



(b) Location privacy: Gowalla dataset

Figure: Normalized estimation error between V_g and the estimation $\widehat{V}_n(f_m)$.

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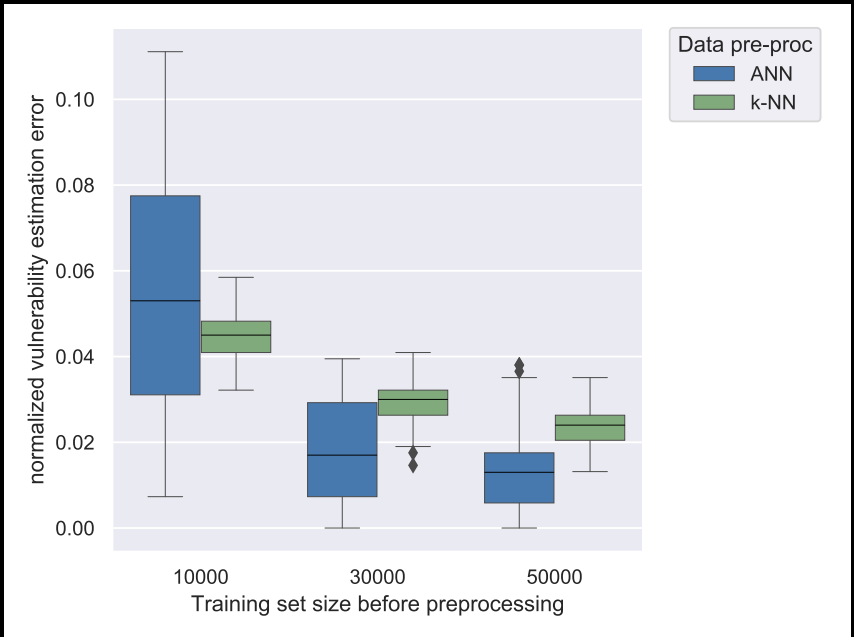
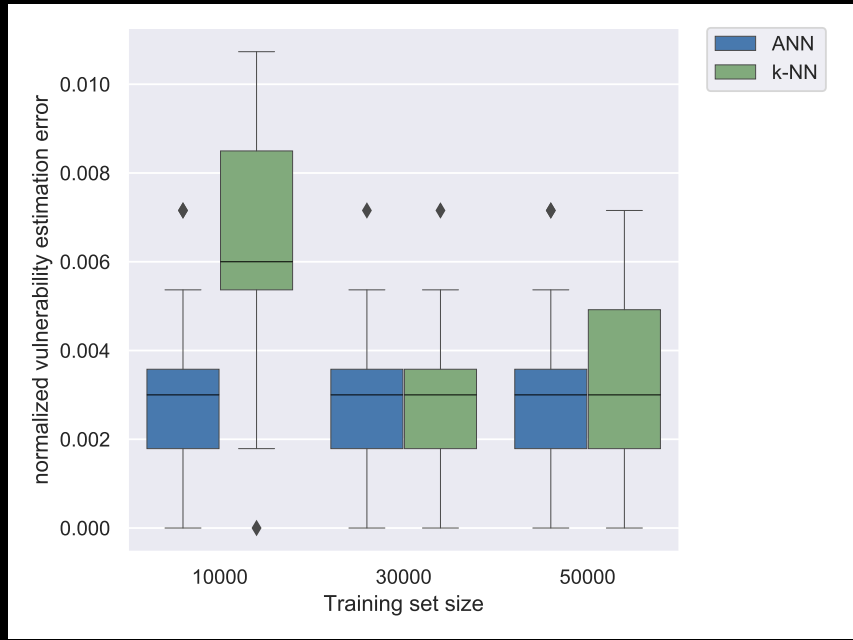


(a) Differential privacy: Cleveland heart desease dataset



(b) Side channel attack

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- We have introduced two **pre-processing** methods to obtain samples that can be used to model several different attackers applying state-of-the-art ML algorithms.
- We have applied our framework to many different scenarios, analyzing its performance and showing favorable results.

Thank you.

Some elments in the pictures are courtesy of https://www.stockio.com/