Template Attack vs. Bayes Classifier

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Outline

1. Introduction
2. Machine Learning
3. Profiled SCA
4. Experimental Evaluation
5. Observations
6. Conclusions
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Implementation attacks

Implementation attacks do not aim at the weaknesses of the algorithm itself, but on the actual implementations on cryptographic devices.

- Implementation attacks can be categorized on **active** and **passive** attacks.
- In passive attacks, the device operates within its specification and the attacker just reads hidden signals.
- **Side-channel attacks** (SCA) belong into passive, non-invasive attacks.
- Side-channel attacks represent one of the most powerful category of attacks on cryptographic devices.
Profiled Attacks

- Profiled attacks have a prominent place as the most powerful among side channel attacks.
- Within profiling phase the adversary estimates leakage models for targeted intermediate computations, which are then exploited to extract secret information in the actual attack phase.
- Template Attack (TA) is the most powerful attack from the information theoretic point of view.
- TA efficiency can only be guaranteed when the template estimates are provided with a reasonable amount of traces in the profiling phase.
- Some machine learning (ML) techniques also belong to the profiled attacks.
Motivation

- When working with ML, methods used up to now belong to more powerful ML techniques.
- However, when using such powerful methods, space and time complexity grows significantly.
- Tuning phase is a long process where one cannot be sure in the results.
- It is difficult to explain on an intuitive level what is happening.
- Finally, it becomes very difficult to follow some more theoretical framework.
- Accordingly, our goal is to explore some simpler ML techniques where there is also a clear connection between those methods and TA.
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Introduction to ML

- **Machine learning** (ML) is a subfield of computer science that evolved from the study of pattern recognition and computational learning theory.
- Algorithms extract information from data, however, they also learn a model to discover something about the data in the future.
- Today, there exists a plenitude of ML algorithms when could choose from.

**Machine Learning**

A computer program is said to learn from experience $E$ with respect to some task $T$ and some performance measure $P$, if its performance on $T$, as measured with $P$, improves with experience $E$. 
Types of ML on a Basis of Feedback

- Supervised learning - available data also include information how to correctly classify at least a part of data.
- Unsupervised learning - input data does not tell the algorithm what the clusters should be.
- Reinforcement learning.
- Active learning.
What can we do with ML

- Regression.
- Feature selection.
- Prototyping.
- Classification.
- Clustering
What can we do with ML

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No Free Lunch

There exists no single model that works best for every problem.

- To find the best model for a certain problem, numerous algorithms and parameter combinations should be tested.
- Not even then we can be sure that we found the best model, but at least we should be able to estimate the possible trade-offs between the speed, accuracy, and complexity of the obtained models.
ML model

- Training set consists of pairs \((x, y)\) called training examples.
- \(x\) is a feature vector, \(y\) is a label (classification value for \(x\)).
- Objective is to find function \(y = f(x)\).
- if \(y\) is a real number \(\rightarrow\) regression.
- \(y\) is a Boolean variable \(\rightarrow\) binary classification.
- \(y\) is member of a finite set \(\rightarrow\) multiclass classification.
ML architecture
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We are particularly interested in multivariate leakage $\mathbf{X} = X_1, \ldots, X_D$, where $D$ is the data dimensionality (i.e., the number of time samples per measurement trace).

In order to guess the secret key an attacker chooses a model $Y$ depending on a key guess $k$ and on some known text $T$.

Considering a powerful attacker, a set of $N$ profiling traces $\mathbf{X}_1, \ldots, \mathbf{X}_N$ is used in order to estimate the leakage model beforehand, which can then be used in the attacking phase with $\mathbf{X}_1, \ldots, \mathbf{X}_Q$ traces.
Template Attack

- Given $\vec{X}_1, \ldots, \vec{X}_N$ measurements in the profiling phase the template attack (TA) consists in estimating

$$\hat{P}(\vec{X}|Y = y)$$

for all possible values of $y$.

- In the attack phase the attacker uses a new set of measurements $\vec{X}_1, \ldots, \vec{X}_Q$ and decides for a key $\hat{k}$ given by

$$\hat{k} = \arg \max_{k \in \mathcal{K}} \prod_{\vec{X}_1, \ldots, \vec{X}_Q} \hat{P}(\vec{X}|Y(k)).$$
Naive Bayes

- Naive Bayes is a method based on the Bayesian rule, but it works under a simplifying assumption that the predictor attributes (measurements) are mutually independent among the $D$ features given the target class.

- Existence of highly-correlated attributes in a dataset can thus influence the learning process and reduce the number of successful predictions.

$$p(Y = y | X = x) = p(Y = y) \prod_{i=1}^{D} p(X_i = x_i | Y = y).$$
A0DE

- If the assumption of independence is violated, Naive Bayes may result in high precision loss.
- In Averaged One-Dependence Estimators there is a Super-Parent One-Dependence Estimate that relaxes the assumption of independence by making all other attributes independent given the class and one privileged attribute called the super-parent $x_\alpha$.
- Since this is a weaker assumption, the bias of this model should be lower, while the variance should be higher since it is derived from higher-order probability estimates.

$$p(Y = y|X = x) = p(Y = y, x_\alpha) \prod_{i=1}^{D} p(X_i = x_i|Y_i = y_i, x_\alpha).$$
AnDE

- AnDE algorithm works by learning an ensemble of $n$-dependence classifiers where the prediction is obtained by aggregating the predictions of all classifiers.

- $n$-dependence estimator means that the probability of an attribute is conditioned by the class variable and at most $n$ other attributes.

- In AnDE algorithm, an $n$-dependence classifier is constructed for every combination of $n$ attributes where those $n$ attributes are set as parents to all other attributes.

$$p(Y = y | X = x) = \sum_{s \in S^n} p(Y = y, x_s) \prod_{i=1}^{D} p(X_i = x_i | Y_i = y_i, x_s) / \binom{D}{n},$$
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Datasets

- Datasets with 5,000, 10,000, 20,000, 30,000, 50,000, and 100,000 measurements which are randomly selected from the whole data sets.
- 2/3 of the data is for training and 1/3 for testing.
- The number of features equals 50 and the model consists either of 256 uniformly distributed classes (S-box output) or 9 binomial distributed classes (HW of the S-box output).
- DPAcontest v2 → provides measurements of an AES hardware implementation.
- DPAcontest v4 → provides measurements of a masked AES software implementation.
DPAnest v2
DPAContest v4
A1DE Tuning

Table: Parameter tuning

<table>
<thead>
<tr>
<th>freq/m</th>
<th>DPAcontest</th>
<th>0.1</th>
<th>0.2</th>
<th>0.5</th>
<th>0.8</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
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<tbody>
<tr>
<td>1 v4</td>
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<td></td>
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<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td>83.22</td>
<td>83.33</td>
<td>83.35</td>
<td>83.34</td>
<td>83.36</td>
<td>83.39</td>
<td>83.3</td>
<td>83.29</td>
<td></td>
</tr>
<tr>
<td>1 v2</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>27.86</td>
<td>27.86</td>
<td>27.86</td>
<td>27.86</td>
<td>27.86</td>
<td>27.86</td>
<td>27.86</td>
<td>27.86</td>
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</tr>
<tr>
<td>1 v4</td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td>22.68</td>
<td>22.67</td>
<td>22.76</td>
<td>22.77</td>
<td>22.67</td>
<td>22.22</td>
<td>22.02</td>
<td>21.85</td>
<td>21.78</td>
</tr>
<tr>
<td>1 v2</td>
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<td></td>
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<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
</tr>
</tbody>
</table>

The frequency limit \( \text{freq} \) parameter denotes that all features with a frequency in the train set below this value are not used as parents, weight parameter \( m \) sets the base probabilities with \( m \)-estimation.
## Verification of Results for 9 classes

**Table:** Testing results for 9 classes (ACC/F-Measure/AUC)

<table>
<thead>
<tr>
<th>Size</th>
<th>Naive Bayes</th>
<th>A1DE</th>
<th>TA</th>
<th>TA (pooled)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 000</td>
<td>65.52/65.5/91.3</td>
<td>78.12/78.1/96.3</td>
<td>19.49</td>
<td>62.07</td>
</tr>
<tr>
<td>10 000</td>
<td>67.01/67.1/91.5</td>
<td>81.26/81.3/97.2</td>
<td>52.14</td>
<td>76.54</td>
</tr>
<tr>
<td>20 000</td>
<td>68.25/66.7/91.3</td>
<td>83.39/83.4/97.7</td>
<td>75.43</td>
<td>77.78</td>
</tr>
<tr>
<td>30 000</td>
<td>67.66/67.7/91.7</td>
<td>84.25/84.3/97.9</td>
<td>75.43</td>
<td>78.09</td>
</tr>
<tr>
<td>50 000</td>
<td>67.19/67.2/91.5</td>
<td>84.93/84.9/98</td>
<td>78.71</td>
<td>77.85</td>
</tr>
<tr>
<td>100 000</td>
<td>67.29/67.3/91.7</td>
<td>85.55/85.6/98.1</td>
<td>79.91</td>
<td>77.83</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Size</th>
<th>Naive Bayes</th>
<th>A1DE</th>
<th>TA</th>
<th>TA (pooled)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 000</td>
<td>10.06/10.5/50.1</td>
<td>25.76/10.6/50</td>
<td>1.29</td>
<td>10.07</td>
</tr>
<tr>
<td>10 000</td>
<td>10.94/9.9/50.1</td>
<td>26.06/10.8/50</td>
<td>1.73</td>
<td>8.74</td>
</tr>
<tr>
<td>20 000</td>
<td>7.88/9.2/50.5</td>
<td>27.1/11.6/50</td>
<td>15.48</td>
<td>7.64</td>
</tr>
<tr>
<td>30 000</td>
<td>8.81/10.4/50.3</td>
<td>25.6/15.5/51.7</td>
<td>17.66</td>
<td>6.66</td>
</tr>
<tr>
<td>50 000</td>
<td>10.21/11.6/50.4</td>
<td>24.3/15.8/51.2</td>
<td>15.99</td>
<td>5.88</td>
</tr>
<tr>
<td>100 000</td>
<td>12.44/14.1/50.6</td>
<td>23.79/16.3/50.5</td>
<td>13.20</td>
<td>5.98</td>
</tr>
</tbody>
</table>
## Verification of Results for 256 classes

**Table:** Testing results for 256 classes (ACC/F-Measure/AUC)

<table>
<thead>
<tr>
<th>Size</th>
<th>Naive Bayes</th>
<th>A1DE</th>
<th>TA</th>
<th>TA (pooled)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 000</td>
<td>15.29/14.7/91.6</td>
<td>10.29/8/93.7</td>
<td>0.23</td>
<td>14.89</td>
</tr>
<tr>
<td>10 000</td>
<td>18.26/17.1/93.4</td>
<td>15.65/13.7/95.5</td>
<td>0.32</td>
<td>19.68</td>
</tr>
<tr>
<td>20 000</td>
<td>20.21/18.3/94.5</td>
<td>22.56/21.2/96.9</td>
<td>0.52</td>
<td>23.65</td>
</tr>
<tr>
<td>30 000</td>
<td>20.88/19/94.7</td>
<td>28.19/27.4/97.7</td>
<td>9.44</td>
<td>25.53</td>
</tr>
<tr>
<td>50 000</td>
<td>21.22/19.1/95</td>
<td>32.06/31.5/98.2</td>
<td>15.63</td>
<td>27.47</td>
</tr>
<tr>
<td>100 000</td>
<td>12.44/14.1/50.6</td>
<td>23.71/16.8/51</td>
<td>21.66</td>
<td>29.14</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Size</th>
<th>DPAcontest v2</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 000</td>
<td>0.59/0.1/51</td>
</tr>
<tr>
<td>10 000</td>
<td>0.56/0.2/51.3</td>
</tr>
<tr>
<td>20 000</td>
<td>0.6/0.1/51.2</td>
</tr>
<tr>
<td>30 000</td>
<td>0.63/0.1/50.8</td>
</tr>
<tr>
<td>50 000</td>
<td>0.51/0.1/51.1</td>
</tr>
<tr>
<td>100 000</td>
<td>0.54/0.1/50.9</td>
</tr>
</tbody>
</table>
### Space and Time Complexities

<table>
<thead>
<tr>
<th></th>
<th>Training</th>
<th>Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
<td>$O(kav)$</td>
<td>$O(ta)$</td>
</tr>
<tr>
<td>A1DE</td>
<td>$O(k\binom{a}{n+1}v^{n+1})$</td>
<td>$O(t\binom{a}{n+1})$</td>
</tr>
<tr>
<td>TA</td>
<td>$O(ka^2v)$</td>
<td>$O(ta^2)$</td>
</tr>
</tbody>
</table>

$k$ is the number of classes  
$a$ is the number of features  
$v$ is the average number of values for an attribute  
$t$ is the number of training examples  
$n$ is the number of parent nodes.
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Observations

- Pooled TA has a higher accuracy than TA when the profiling set is rather small.
- With the increase of the profiling set, TA becomes better than the pooled TA.
- NB is worse than pooled TA and TA when the number of measurements is high.
- A1DE is better than TA when working with DPAcontest v4.

**Table:** Testing results for 9 classes with an equal number of measurements.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>v4</th>
<th>v2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naive Bayes</td>
<td>73.76</td>
<td>14.75</td>
</tr>
<tr>
<td>A1DE</td>
<td>80.67</td>
<td>11.76</td>
</tr>
<tr>
<td>TA</td>
<td>63.61</td>
<td>12.53</td>
</tr>
<tr>
<td>TA (pooled)</td>
<td>77.82</td>
<td>13.00</td>
</tr>
</tbody>
</table>
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- Naive Bayes and A1DE give competitive results when compared with TA.
- In general, A1DE is better than Naive Bayes.
- The results seem to be particularly good when the number of measurements is low.
- Furthermore, both space and time complexity work in favor of Naive Bayes (and somewhat less A1DE).
- In our opinion, both NB and A1DE represent a viable choice and a must for the initial assessment of the ML performance.
- Since those methods are simple, also PAC learning is possible!
Conclusions

Questions?

Thanks for your attention!