

# Template Attacks

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# Profiled Side-Channel Attacks (SCAs)

## Overview

- A powerful class of SCAs designed to attack targets with minimal measurements (even down to a single one).
- Overcome countermeasures that restrict the number of measurements an attacker can acquire.
- Involve two main phases:
  - ① **Profiling Phase:** Attacker builds an accurate model of the device's side-channel behavior.
  - ② **Exploitation Phase:** The model is used to extract the unknown key from the target device.

# Profiled SCAs: The Template Attack Advantage

## The Profiling Advantage

- Performed on a device *identical* to the target, but fully controlled by the attacker.
- This allows setting the secret key value at will and performing unlimited measurements.
- Enables deriving a "perfect" side-channel behavior or "profile" for every possible value of the key bits.

## Core Idea of Template Attacks

- TAs are considered the **most effective profiled attack** in an information-theoretic sense.
- They can, in principle, defeat masking and hiding countermeasures if enough measurements are collected during profiling.

## Modeling Side-Channel Traces

- Each side-channel measurement trace is assumed to be affected by **additive Gaussian noise**.
- Each trace  $\hat{T}^{(k_i)}$  (for a specific key bit  $k_i$ ) is modeled as a random vector variable  $T^{(k_i)}$ .
- $T^{(k_i)}$  is assumed to follow a **multivariate Gaussian distribution**:  $\mathcal{N}(\mu^{(k_i)}, \Sigma^{(k_i)})$ .
  - $\mu^{(k_i)}$ : Mean vector (average trace for key  $k_i$ ).
  - $\Sigma^{(k_i)}$ : Covariance matrix (describes how data points vary together for key  $k_i$ ).
- The mean vector ( $\mu$ ) and covariance matrix ( $\Sigma$ ) are computed over selected **points of interest** (POIs) in the trace, where significant leakage occurs.

## The Probability Density Function (PDF)

For a trace  $x$  (composed of selected POIs) belonging to a key hypothesis  $k_i$ , its probability density function is given by:

$$\Pr(T^{(k_i)} = x) = \frac{\exp\left(-\frac{1}{2}(x - \mu^{(k_i)})^T (\Sigma^{(k_i)})^{-1} (x - \mu^{(k_i)})\right)}{\sqrt{(2\pi)^n \det(\Sigma^{(k_i)})}}$$

- $n$ : Number of selected points of interest (dimension of the trace vector  $x$ ).
- $\mu^{(k_i)}$ : Mean vector for key hypothesis  $k_i$ .
- $\Sigma^{(k_i)}$ : Covariance matrix for key hypothesis  $k_i$ .

## Generating Templates

- The attacker, on their controlled device, sets a specific key bit value  $k_i$  (e.g.,  $k_i = 0$  or  $k_i = 1$ ).
- For each possible value of  $k_i$ , a large number of side-channel traces are collected (from the POIs).
- From these measurements, *sample estimates* of the mean vector ( $\hat{\mu}^{(k_i)}$ ) and covariance matrix ( $\hat{\Sigma}^{(k_i)}$ ) are derived.
- These statistical models ( $\hat{\mu}^{(k_i)}, \hat{\Sigma}^{(k_i)}$ ) form the **templates** for each key bit value.



# Template Attack: Profiling Phase

## Example: Targeting a Key Portion

- If targeting an 8-bit key byte, an attacker might build  $2^8 = 256$  templates (one for each possible byte value).
- Alternatively, using a divide-and-conquer approach, they could target each bit individually, building two templates (for '0' and '1') for each bit.

# Template Attacks: Matching Phase

## Key Recovery Steps

- A single (or few) side-channel trace(s)  $\hat{T}$  is acquired from the target device, where the key value is unknown
- Measurement conditions must be identical to the profiling phase
- For each possible key bit value, the likelihood of the acquired trace  $\hat{T}$  belonging to that template's distribution is evaluated
- This is done by calculating the **a-posteriori probability**  $\Pr(k_i|\hat{T})$ , typically using Bayes' theorem:

$$\Pr(k_i|\hat{T}) = \frac{\Pr(\hat{T}|k_i) \cdot \Pr(k_i)}{\sum_j \Pr(\hat{T}|k_j) \cdot \Pr(k_j)}$$

- The key bit value  $k_i$  that maximizes this a-posteriori probability is selected as the most likely secret key bit.

## Statistical Efficacy

- The assumption of multivariate Gaussian distributions for power consumption has proven to be a very good practical approximation.
- Statistical tests are used to determine the "goodness of fit" of a model to the actual device behavior, accounting for noise.

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## Beyond Statistical Templates

- Machine Learning (ML) techniques offer an alternative to traditional Template Attacks.
- Instead of calculating probabilities, ML uses a **classification step** to identify the secret information
- A key advantage: ML provides a **nonparametric and data-driven approach**, removing assumptions about the statistical distribution of the leakage (like the Gaussian assumption in TAs)

## Support Vector Machines (SVMs)

- SVMs are a widely used and effective choice for profiled side-channel attacks.
- Their goal is to find an optimal hyperplane that best separates data points belonging to different classes (e.g., traces for key bit '0' vs. key bit '1')
- This hyperplane acts as a decision boundary

## Profiling Phase (Training)

- Using the controlled device, the attacker collects many labeled side-channel traces (traces paired with their known key bit values)
- The SVM algorithm learns from this labeled data to compute the optimal hyperplane
- This process involves mapping the traces into a (potentially) higher-dimensional space where they become linearly separable, making it easier to find the separating hyperplane

## Classification Phase

- A new, unlabeled side-channel trace is acquired from the target device (where the key is unknown)
- This new trace is then input into the trained SVM model
- The SVM classifies the trace by determining which side of the learned hyperplane it falls on, thereby predicting the most likely key bit value



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# Feature Selection: A Crucial Preprocessing Step

## Why Feature Selection is Needed

- Side-channel traces can contain hundreds or thousands of samples (time points)
- Too many samples can introduce noise, increase computational complexity, and lead to numerical instability, especially for machine learning algorithms and covariance matrix inversion in Template Attacks

# Feature Selection: Common Techniques

## Common Techniques

- Feature selection aims to select a subset of trace samples that contain the most sensitive leakage information, often explicitly identifying them as **Points of Interest (POIs)**, or to transform the data into a smaller, more meaningful set of **features**
- This process helps to filter out redundant or uncorrelated information, making the profiling and exploitation phases more efficient and effective.
  - **Maximum Variance:** Selecting samples that show the most variation across traces
  - **Sum of Squares of t-difference (SOST):** Identifies samples where the difference in means between classes (e.g., key hypotheses) is most statistically significant
  - **Principal Component Analysis (PCA):** A dimensionality reduction technique that transforms original, correlated variables into a new set of uncorrelated variables (principal components), ordered by the amount of variance they explain