Exact Soft Analytical Side-Channel Attacks using Tractable Circuits

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Abstract

Detecting weaknesses in cryptographic algorithms is of utmost importance for designing secure information systems. The state-of-the-art *soft analytical side-channel attack* (SASCA) uses physical leakage information to make probabilistic predictions about intermediate computations and combines these "guesses" with the known algorithmic logic to compute the posterior distribution over the key. This attack is commonly performed via loopy belief propagation, which, however, lacks guarantees in terms of convergence and inference quality. In this paper, we develop a fast and exact inference method for SASCA, denoted as ExSASCA, by leveraging knowledge compilation and tractable probabilistic circuits. When attacking the *Advanced Encryption Standard* (AES), the most widely used encryption algorithm to date, ExSASCA outperforms SASCA by more than 31% top-1 success rate absolute. By leveraging sparse belief messages, this performance is achieved with little more computational cost than SASCA, and about 3 orders of magnitude less than exact inference via exhaustive enumeration. Even with dense belief messages, ExSASCA still uses 6 times less computations than exhaustive inference.

1. Introduction

Unifying learning, logical reasoning and probabilistic inference at scale has a wide range of applications, such as error correcting codes, verification and system diagnostics. In particular, *cryptographic attacks* play a central role in defining, analysing and designing cryptographic algorithms, which form the backbone of our modern information society. Specifically, *side-channel attacks* attempt to learn about secret material used in a cryptographic computation by observing implementation artifacts, commonly called *leakages*, such as timing information (Kocher, 1996), electromagnetic emissions (Gandolfi et al., 2001), and power consumption (Kocher et al., 1999). Most contemporary attacks use these leakages to reason about the internal state of a cryptographic algorithm in a probabilistic manner. Specifically, in *template attacks* (Chari et al., 2002) the attacker has access to a clone of the device under attack and can run the algorithm repeatedly with randomly generated keys and plaintexts as inputs. Simultaneously, the attacker also records leakage information during all runs, e.g. the *power trace* of the device. Using this data, the attacker can easily build a set of probabilistic models, predicting distributions of intermediate values conditional on the leakage.

The attacker's goal is now to combine these value distributions ("soft guesses") and the (hard logical) knowledge about the algorithm to infer the posterior distribution of the secret key. A naïve exhaustive computation of this posterior is prohibitive for practical attacks as a single leakage might require hours of compute time. As a remedy, the state-of-the-art *soft analytical side-channel attack* (SASCA) (Veyrat-Charvillon et al., 2014) uses loopy belief propagation (BP) on a factor graph representation of the cryptographic algorithm, to produce an approximate key posterior. However, loopy BP has limited theoretical underpinnings as neither convergence is granted, nor does it guarantee accurate posterior estimates in case of convergence (Knoll, 2022). Consequently, while SASCA *can* detect weaknesses in cryptosystems, an unsuccessful SASCA does *not* imply any certificate that the leakage cannot be exploited further. On the contrary, it is straightforward to construct examples where inference is in fact easy but loopy BP fails catastrophically.

In this paper, we develop a fast and exact inference algorithm for SASCA, denoted as *ExSASCA*, for the *Advanced Encryption Standard (AES)*, the most prominent and widely used encryption algorithm to date. To this end, we build on recent results from knowledge compilation (Darwiche & Marquis, 2002; Darwiche, 2011) and tractable probabilistic circuits (Kisa et al., 2014; Vergari et al., 2020). Similarly as

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in SASCA, we start from a factor graph representation of AES, whose core part, MIXCOLUMNS, is a highly loopy subgraph involving 168 binary variables (bits). While SASCA performs loopy BP, we instead compile MIXCOLUMNS into a compact *(probabilistic) sentential decision diagram* (SDD, PSDD) (Darwiche, 2011; Kisa et al., 2014), a circuit representation allowing a wide range of logic and probabilistic inference routines (Vergari et al., 2020). On a conceptual level, this amounts to replacing MIXCOLUMNS with a *single* factor and reducing the factor graph to a *tree*, on which we can perform exact message passing (Koller & Friedman, 2009), albeit involving a factor with 2^{168} entries. The compiled PSDD is compact, containing only 19,000 sums and products, and allows inference in *polynomial time of the circuit size*.

In particular, for the key posterior we require mainly *factor multiplication* (worst-case quadratic in the circuit size) and *factor summation* (linear in the circuit size), which are readily provided by tractable circuits and have previously been employed in structured Bayesian networks (Shen et al., 2019) and neuro-symbolic approaches (Ahmed et al., 2022). When attacking standard AES, we leverage the fact that the value distributions are typically concentrated on byte values with the same hamming weight, allowing us to work with sparse messages. With this simplification, an out-of-the box implementation of ExSASCA yields an improvement of *31% top-1 success rate absolute* in comparison to conventional SASCA. Here, the required computation for ExSASCA is on the same level as for SASCA, which is *three orders of magnitude* less than for exhaustive enumeration, the only other known exact inference algorithm.

Countermeasures to side-channel attacks, such as *protected* AES implementations, increase the entropy of intermediate algorithmic values and render our sparse-message approach futile. For this case, however, we develop a novel dynamic compilation strategy for SDDs, reducing inference to a weighted model counting problem. The resulting inference machine still requires 6 times less computation than exhaustive inference and substantially outperforms SASCA on all protection levels. Overall, our main contributions are:

- We propose ExSASCA, an exact SASCA implementation, which substantially improves the success rate of attacks on AES, while using far less computational resources than inference by exhaustive enumeration.
- With our method we open a new avenue to study vulnerability in cryptosystems; in the long run our techniques might lead to stronger theoretical guarantees in cryptographic algorithms, for example using results from circuit complexity (de Colnet & Mengel, 2021) for proving the non-existence of a tractable circuit representation of particular cryptographic algorithms.
- We develop a novel dynamic compilation framework for circuit-based inference in large-scale-probabilistic systems, which has a wide range of applications, such as error correcting codes (MacKay, 2003), system verification and structured Bayesian networks (Shen et al., 2019).

2. Background

2.1. Advanced Encryption Standard

In this work, we attack the *Advanced Encryption Standard* (AES) (Daemen & Rijmen, 1998), the most popular symmetric-key block cipher used to date. AES takes an 128-bit *plaintext* $\mathbf{p}$ and a secret b-bit *key* $\mathbf{k}$ as input, and produces a 128-bit *ciphertext* $\mathbf{c}$ as output. In our experiments, we attack AES-128, i.e., $b = 128$. We refer to bytes of the key and plaintext as *input variables* and the bytes of the ciphertext as output variables; besides this, the algorithm also computes several byte-valued *intermediate variables* in the course of computing the ciphertext. AES encryption is performed in 10 iterations (so-called rounds), where each round essentially consists of the functions SUBBYTES, SHIFTROWS, MIXCOLUMNS, and ADDROUNDKEY. Figure 1 illustrates such a round.

2.2. Side-Channel Attacks

Although a cryptographic algorithm may be secure conceptually, its implementation may be not: Side-channel attacks exploit the fact that physical implementations of an algorithm unintentionally leak information about the processed data (Spreitzer et al., 2018). For example, since the power usage of CMOS transistors depends on the switching activity during the computation, the power consumption of the device performing the encryption is data dependent (Standaert, 2010). It has been frequently shown that side-channel attacks are more efficient than the best-known cryptanalytic attacks, which consider the system under attack as an idealized, mathematical model (Standaert, 2010). While adversaries can exploit various side channels such as timing of operations (Kocher, 1996) and electromagnetic emanation (Gandolfi et al., 2001), this work focuses on power traces.

2.2.1. TEMPLATE ATTACKS

In a template attack the adversarial has access to a *clone* of the target device (e.g., a smart card). First, in the so-called *profiling phase*, the attacker queries the clone device with a large number of random inputs, i.e. key and plaintext in case of AES, and records side-channel leakage of their choice. Let v be an arbitrary byte-valued variable involved in AES (input, intermediate variable, or output). The profiling phase yields a dataset $\{(\boldsymbol{\ell}^{(i)}, v^{(i)})\}_{i=1}^{n}$, where n is the number of profiling runs and $\boldsymbol{\ell} \in \mathbb{R}^d$ denotes the leakage. This

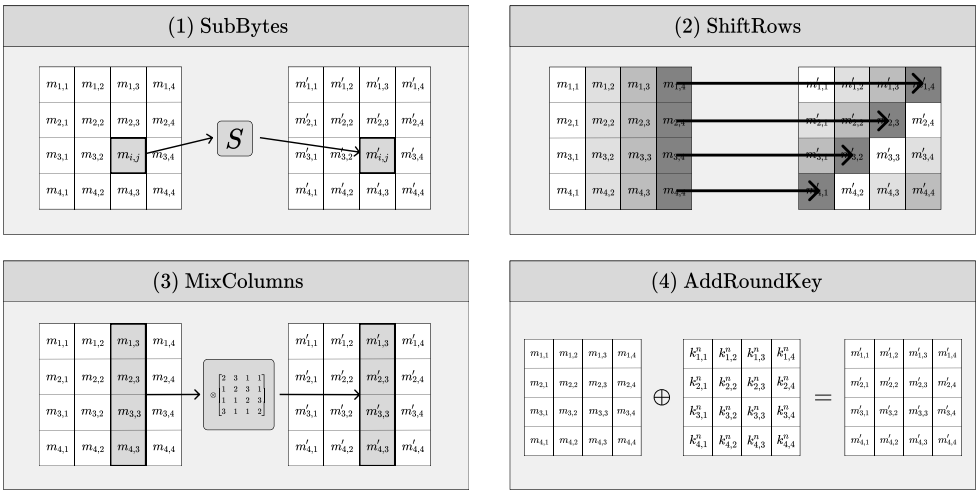

Figure 1. A round of AES takes a 4×4-byte matrix $\mathbf{M}$ and computes a series of functions: (1) SUBBYTES applies a non-linear bijection S to each byte individually, (2) SHIFTROWS shifts the rows of the input matrix to the left, (3) MIXCOLUMNS computes a linear function which takes each input column and performs a matrix-vector product in the Galois field of characteristic 256 ($\mathbb{F}_{256}$) and (4) ADDROUNDKEY, a byte-wise XOR operation with the "round key" (which is just the key in the first round).

data is then used to construct a likelihood model $p(\boldsymbol{\ell} \mid v)$, a so-called *template*. A common choice are multivariate Gaussians with mean $\boldsymbol{\mu}_v$ and covariance $\boldsymbol{\Sigma}_v$, i.e., $p(\boldsymbol{\ell} \mid v) = \mathcal{N}(\boldsymbol{\ell}; \boldsymbol{\mu}_v, \boldsymbol{\Sigma}_v)$ for each value $v \in \{0, \dots, 255\}$. Hence, n is typically at least a few thousand, to make sure that for each value there are sufficiently many leakage samples.

Since the leakages $\boldsymbol{\ell}$ are high-dimensional (e.g., $d \approx 10^5$ for power traces), one usually first applies some dimensionality reduction. We adopt the approach from (Bronchain et al., 2021), using a combination of interest point detection in $\boldsymbol{\ell}$ and linear discriminant analysis. We also experimented extensively with various neural network architectures to construct more expressive templates, which, however, consistently performed worse than (Bronchain et al., 2021). Finally, in the attack phase, only the leakage $\boldsymbol{\ell}$ is observed. Using Bayes' law and a uniform prior $p(v)$, we get a *local distribution* (*belief*) for v, conditional on the leakage:

$$p(v \mid \boldsymbol{\ell}) = \frac{p(\boldsymbol{\ell} \mid v)}{\sum_{v'=0}^{255} p(\boldsymbol{\ell} \mid v')} \tag{1}$$

The procedure above, explained for a generic value v, is done for several byte variables $v_1, \dots, v_k$ computed in AES. Usually, one selects variables which are "close to the key" in the computational path, as these will typically be more correlated with the secret key than variables "further away."

2.2.2. SOFT ANALYTICAL SIDE-CHANNEL ATTACKS

After obtaining distributions $p(v_1 \mid \boldsymbol{\ell}), \dots, p(v_k \mid \boldsymbol{\ell})$ for all variables of interest, the attacker aims to aggregate them into a posterior distributions over the *key bytes*. Intuitively, the beliefs about intermediate variables, which depend operationally and logically on the secret key, should be propagated backwards and combined into beliefs about the key. This is naturally expressed using a *factor graph* (Kschischang et al., 2001; Veyrat-Charvillon et al., 2014), where variable nodes (circles) correspond to the byte-valued variables and factors (black squares) represent indicator functions that model the logical relationship between variables.

Figure 2 (left) shows the factor graph for part of the first round of AES, consisting of ADDROUNDKEY, SUBBYTES and one column multiplication of MIXCOLUMNS. We do not model the SHIFTROWS operation since it merely corresponds to a fixed re-labeling of the input bytes and does not affect probabilistic inference. Note that the nodes representing the plaintext are shaded, meaning that they are observed, which is a common assumption in this type of attacks (Veyrat-Charvillon et al., 2014). While the hardware implementation of the SBOX also leaks information in practice, we simply abstract it as a 256×256-dimensional binary factor (i.e., a lookup table).

Every variable (blank node) in the factor graph is equipped with a local distribution derived via a template attack, as described in Section 2.2.1. Note that the figure shows only one of the four parallel branches of the first AES round; the other three branches are of identical structure and can be treated independently. In this work we attack, as common in literature (Veyrat-Charvillon et al., 2014), only the first round of AES; attacking later rounds is doable, but is of diminishing return.

The desired posterior over the key bytes is now simply given as a *factor product* of all involved factors, followed by a summation over all unobserved variables, except for the

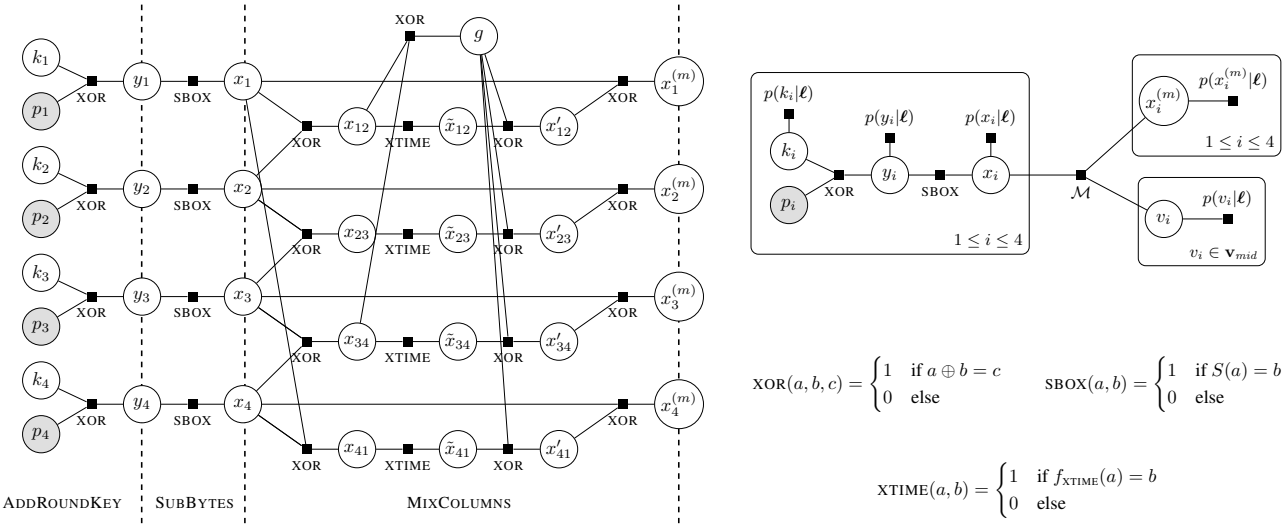

Figure 2. (left) Factor graph over the first four key bytes and plaintext bytes and their operations in AES. Black squares denote logical factors that represent AES operations. For example, an XOR-factor is 1 if and only if the variable on its right is the *bit-wise exclusive or* of the two variables on its left and 0 otherwise. Similarly, SBOX encodes a bijection S between byte-values and XTIME encodes a multiplication with 2 in the Galois field of characteristic 256 (abstracted as f_{XTIME}). Every unobserved (blank) variable node has an additional factor $p(v \mid \boldsymbol{\ell})$ (omitted for sake of visual clarity). Shaded variable nodes are observed. (right) The same factor graph, but where the loopy MixColumns part has been summarized in a single high-dimensional factor $\mathcal{M}$ (represented by a PSDD). We use plate notation to illustrate structurally identical parts. The set $\mathbf{v}_{mid}$ contains all intermediate variables in the MixColumns function.

key bytes (Kschischang et al., 2001). Evidently, a naïve implementation is infeasible, since the total factor product is of size 2^{232} (involving 29 bytes). However, exploiting the fact that the factor graph encodes an algorithm and that all variables deterministically follow from the key (and plaintext), one actually just needs to enumerate the values of the 4 key bytes and evaluate the factor graph for each of these 2^{32} combinations. The desired key posterior is then given by re-normalizing the computed factors.

As inference by exhaustive key enumeration is computationally expensive, the *soft analytical side-channel attack* (SASCA) (Veyrat-Charvillon et al., 2014) applies loopy belief propagation (BP) (Kschischang et al., 2001) to approximate the desired conditional distribution over key bytes $p(k_i \mid \boldsymbol{\ell})$. Loopy BP requires about three orders of magnitude less compute than exhaustive inference and is thus considered a practically relevant attack.

However, while SASCA *might* detect weaknesses in a cryptoalgorithm, an unsuccessful application of SASCA is no certificate towards security of the attacked system. In particular, loopy BP is notoriously unpredictable, as neither convergence is granted, nor does convergence imply that the posterior has been successfully approximated (Knoll, 2022). In fact, it is straightforward to design easy inference problems where loopy BP fails catastrophically.

3. Exact Soft Analytical Side-Channel Attacks

In this paper, we develop the first exact attack on AES-128 which substantially improves over SASCA and uses far less computational resources than exhaustive enumeration. Our high-level strategy is to reduce the problem to a tree-shaped factor graph, for which BP becomes an exact inference algorithm (Kschischang et al., 2001; Koller & Friedman, 2009). Note that the central problem in Figure 2 (left) is the sub-graph corresponding to MixColumns, which involves 21 byte-valued variables and has many loops. We can now summarize this part into a *single* logical factor $\mathcal{M}(\mathbf{v})$ as shown in Figure 2 (right), where $\mathbf{v}$ contains all 21 variables. Thus, $\mathcal{M}(\mathbf{v})$ is a binary function evaluating to 1 if and only if $\mathbf{v}$ corresponds to variable assignment consistent with the entire MixColumns computation.

Running BP in the resulting tree-shaped factor graph yields the exact marginals, by propagating messages from $\mathcal{M}$ to the input bytes x_i, computed as (Kschischang et al., 2001),

$$\mu_{\mathcal{M}\to x_i}(x_i) = \sum_{\mathbf{v}\setminus x_i} \mathcal{M}(\mathbf{v}) \cdot \prod_{v_j \in \mathbf{v}\setminus x_i} p(v_j|\boldsymbol{\ell}) \qquad (2)$$

which requires only two operations, namely *factor multiplication* and *factor summation*. However, naïvely computing these messages requires enumerating all 2^{168} possible assignments for $\mathbf{v}$, which is clearly intractable.

In this paper, we therefore build on recent results from knowledge compilation (Darwiche & Marquis, 2002; Dar-

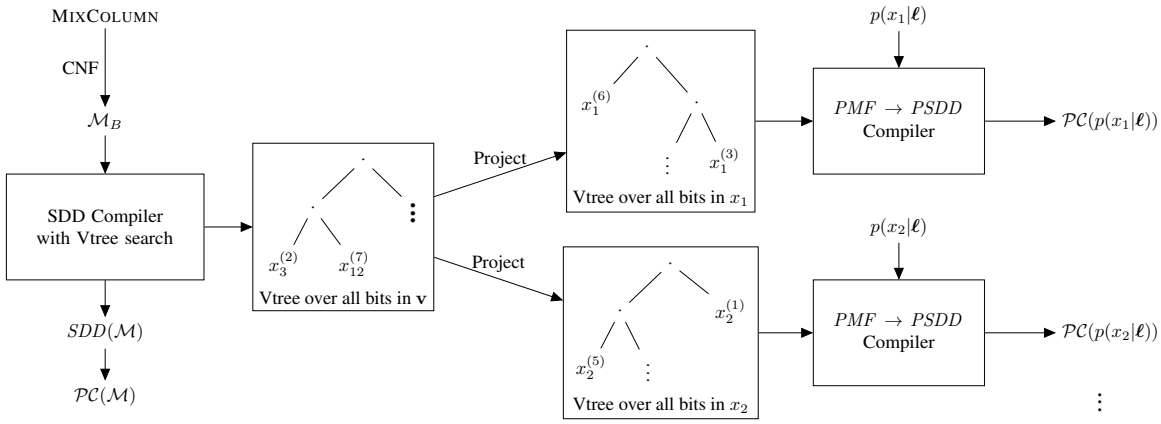

Figure 3. Given the algorithmic description of MIXCOLUMN ($\mathcal{M}$) and the local beliefs $p(v \mid \boldsymbol{\ell}), v \in \mathbf{v}$ as inputs to our compilation pipeline, we yield a PSDD representations of all input distributions, denoted $\mathcal{PC}(p(v \mid \boldsymbol{\ell}))$. Moreover, all PSDDs are pairwise *compatible* for downstream circuit multiplication tasks.

wiche, 2011) and tractable probabilistic circuits (Vergari et al., 2020; Choi et al., 2020; Peharz et al., 2020). The aim of *knowledge compilation* (Darwiche & Marquis, 2002) is to convert a logical formula, e.g. given in conjunctive normal form (CNF), into a different target representation that can tractably (i.e., in polynomial time) answer certain queries (e.g., the SAT problem). In our context, the relevant formula is the boolean factor $\mathcal{M}$ for MIXCOLUMNS.

Specifically, we compile $\mathcal{M}$ into a *sentential decision diagram* (SDDs) (Darwiche, 2011) which is subsequently converted into its probabilistic extension, *probabilistic SDDs* (PSDDs) (Kisa et al., 2014). PSDDs are a special case of probabilistic circuit, a structured representation of high-dimensional probability distributions allowing a wide range of tractable probabilistic inference routines (Vergari et al., 2020). Our constructed PSDD represents the uniform distribution over all $\mathbf{v}$ which are consistent with MIXCOLUMNS, while inconsistent $\mathbf{v}$ are assigned probability 0.

PSDDs allow both factor multiplication and factor summation in polynomial time (Vergari et al., 2020; Choi et al., 2020), as required in (2). Furthermore, they also allow to compute a *most probable evidence* (MPE), i.e. a probability maximizing assignment. These tractable routines are the key routines we require for attacking AES. Before proceeding with implementation details, we review the required background on tractable circuits, in particular SDDs and PSDDs. At their core, SDDs are hierarchical and structured decompositions of Boolean functions, defined by so-called *compressed partitions*.

Definition 3.1 (Compressed Partition (Darwiche, 2011))**.** Let $f(\mathbf{x}, \mathbf{y})$ be a Boolean function over disjoint sets of binary variables $\mathbf{x}$ and $\mathbf{y}$. Any such f can be written as $f = (p_1(\mathbf{x}) \wedge s_1(\mathbf{y})) \vee \cdots \vee (p_k(\mathbf{x}) \wedge s_k(\mathbf{y}))$, where p_i (*primes*) and s_i (*subs*) are Boolean functions over $\mathbf{x}$ and $\mathbf{y}$, respectively. Moreover, this decomposition can be constructed such that $p_i \wedge p_j = \bot$ for $i \neq j$, $p_1 \vee \cdots \vee p_k = \top$, and $p_i \neq \bot$ for all i. Further, we restrict the subs to be distinct, i.e., $s_i \neq s_j$ for all $i \neq j$. Then we call $\{(p_1, s_1), \ldots, (p_k, s_k)\}$ a *compressed* $\mathbf{x}$*-partition* of f.

A structure-defining notion of SDDs are *vtrees*.

Definition 3.2 (Vtree (Pipatsrisawat & Darwiche, 2008))**.** A *vtree*, or *variable tree*, over a set of binary variables $\mathbf{z}$ is a full, rooted binary tree whose leaves are in a one-to-one correspondence to the variables in $\mathbf{z}$.

Definition 3.3 (Sentential Decision Diagram (Darwiche, 2011))**.** Let v be a vtree over binary variables $\mathbf{z}$. A *sentential decision diagram* (SDD) is a logical circuit where each internal node is either an *or*-node ($\vee$) or an *and*-node ($\wedge$), while leaf nodes correspond to variables, their negation, $\top$, or $\bot$. W.l.o.g., we demand that every *or*-node n has $k \geq 1$ $\wedge$-nodes as children, denoted $n_1, \ldots, n_k$. Each n_i has exactly two children, denoted p_i, s_i. Then, n represents a boolean function $g_n(\mathbf{x}, \mathbf{y})$ (where $\mathbf{x}, \mathbf{y}$ are disjoint sets of binary variables) such that $\{(p_i, s_i)\}_{i=1}^{k}$ is a compressed $\mathbf{x}$-partition of g_n. Further, there exists a node v' in the vtree v such that $\mathbf{x} = v'_l, \mathbf{y} = v'_r$ where v'_l, v'_r denote the set of variables mentioned in the left and right subtree of v', respectively. We say that n is *normalized* w.r.t. v'. Moreover, we say that an SDD *respects* a vtree v iff every *or*-node n in the SDD is *normalized* w.r.t. a vtree node in v.

Hence, an SDD is a representation of a Boolean function; due its structural constraints it allows a wide range of logical operations (Darwiche, 2011). As mentioned above, we can also think of an SDD as an unnormalized uniform distribution over all satisfying assignments $\mathbf{z}$. It is straightforward to turn an SDD into a proper probability distribution, a so-called PSDD (Kisa et al., 2014).

Definition 3.4 (Probabilistic SDD)**.** Given an SDD, the corresponding PSDD is obtained by replacing all *and*-nodes with *product* nodes and all *or*-nodes with *sum* nodes. A *product* node computes the product of its inputs while a *sum* node computes a convex combination of its inputs.

We denote the PSDD representation of a Boolean function f as $\mathcal{PC}(f)$. A PSDD is a type of *Probabilistic Circuit* (PC) (Choi et al., 2020) with particular properties, allowing (i) *arbitrary factor summation (marginalization)* in time linear in the circuit size; (ii) *circuit multiplication* of two circuits respecting the same vtree, yielding a PSDD whose size is in the worst-case the product of the sizes of the involved circuits; (iii) computing a *most-probable-explanation*, i.e. a probability maximizing variable assignment in time linear in the circuit size. Hence, PSDDs provide, among others, the operations required for exact message passing (Equation 2). The crucial first step is to compile $\mathcal{M}$.

3.1. Compiling MixColumn into an SDD

In order to compile MIXCOLUMN (Algorithm 2) to an SDD, we represent it as a Boolean function over 168 binary variables by replacing all variable assignments with equivalence constraints. Represented in conjunctive normal form (CNF), $\mathcal{M}$ consists of 648 clauses with an average of 3.09 literals within a clause. To compile the CNF into an SDD representation $SDD(\mathcal{M})$, we leverage the bottom-up SDD compiler introduced in (Choi & Darwiche, 2013). Initializing the vtree to be left-linear and using dynamic vtree minimization (Choi & Darwiche, 2013), we find that the resulting SDD contains $19k$ sums and products and takes ≈ 30 seconds to compile on a modern laptop CPU.

Further, to tractably compute the BP message in (2), we need to represent the product $\mathcal{M}(\mathbf{v}) \cdot \prod_{v_j \in \mathbf{v} \setminus x_i} p(v_j|\boldsymbol{\ell})$ as a circuit. We present two methods for this task, namely (i) an "out-of-the-box" implementation, compiling the mass functions $p(v_j|\boldsymbol{\ell})$ upon observing $\boldsymbol{\ell}$ into PSDDs and computing a sequence of circuit products, described in Section 3.2, and (ii) compiling the product symbolically and reducing the problem to *weighted model counting* (WMC) (Chavira & Darwiche, 2008), described in Section 3.3. The first techniques makes a slight simplifying sparseness assumption on the variable beliefs, while the second method is exact and can work with arbitrary messages.

3.2. PSDD Multiplication Chain

First, we convert the SDD representation of MIXCOLUMN into a PSDD $\mathcal{PC}(\mathcal{M})$. Given the vtree of $\mathcal{PC}(\mathcal{M})$ (ranging over 168 binary variables), we compute a vtree projection (Shen et al., 2016) for each byte v in $\mathbf{v}$, where each projection ranges over the 8 bits that make up v. It is then straightforward to compile $p(v|\boldsymbol{\ell})$ into a PSDD that respects the projected vtree. This technique ensures that all pairs of circuits in $\{\mathcal{PC}(\mathcal{M})\} \cup \{\mathcal{PC}(p(v_j|\boldsymbol{\ell}))\}_{j=1}^{21}$ are compatible and can be multiplied on the circuit level. Thus, the message in Equation 2 can be computed by a tractable marginal query in the circuit product $\mathcal{PC}(\mathcal{M}(\mathbf{v})) \cdot \prod_{v_j \in \mathbf{v} \setminus x_i} \mathcal{PC}(p(v_j|\boldsymbol{\ell}))$. In practice, computing this product is infeasible as the circuit size grows in the worst exponentially in the number of multiplied circuits (i.e. quadratic for two circuits, cubic for three, etc.), and the total number of involved circuits is 22.

However, when attacking vanilla AES, some of local beliefs $p(v|\boldsymbol{\ell}), v \in \mathbf{v}$ will typically have *low entropy*, i.e., the probability mass is concentrated on only a few values, often sharing the same hamming weight. Thus, we can work with *sparse* distributions by setting very small values in the mass functions to 0: Given $p(v|\boldsymbol{\ell})$ and a hyperparameter $0 \leq \varepsilon < 1$, we sort the probabilities in ascending order and find the largest k such that the sum of k smallest probabilities is $\leq \varepsilon$. We then clamp the k smallest probabilities to 0 and re-normalize the mass function. Empirically, we find that even for values of ε as small as 10^{-8}, the runtime of computing this circuit product is comparable to SASCA, while substantially outperforming it.

During compilation, this method can readily leverage sparse probability distributions. However, since we fix the vtree after the initial SDD compilation we cannot perform dynamic vtree optimization (Choi & Darwiche, 2013) during the PSDD multiplication chain. Since dynamic compilation is key to achieve small circuits, this out-of-the-box method is computationally infeasible when dropping the low entropy assumption. This is in particular the case for protection techniques which add noise to the leakage signals.

3.3. SDD with Auxiliary Byte Indicators

Our second strategy is to perform *symbolic* circuit multiplication, which can take use of dynamic vtree optimization (Choi & Darwiche, 2013). Specifically, we take the SDD representation of $SDD(\mathcal{M})$ modelling *bit interactions* and, akin to previous work on SDD compilation (Choi et al., 2013), successively add auxiliary variables that represent the values of *bytes*. For example, let v be a byte that consists of the bits $v^{(1)}, \ldots, v^{(8)}$. For each byte variable v in MIXCOLUMN, we create 256 auxiliary boolean variables $b_{v=0}, \ldots, b_{v=255}$ that indicate the state of v. After adding these *byte indicator variables* to the vtree, we conjoin the following constraint to the current SDD:

$$\left(b_{v=0} \Leftrightarrow \left(\neg v^{(1)} \wedge \cdots \wedge \neg v^{(8)}\right)\right) \wedge \ldots$$
$$\left(b_{v=255} \Leftrightarrow \left(v^{(1)} \wedge \cdots \wedge v^{(8)}\right)\right)$$

To efficiently encode this into an SDD, we follow the method proposed in (Choi et al., 2013) and compute a base

SDD α that represents $\neg b_{v=0} \wedge \cdots \wedge \neg b_{v=255}$ that we can re-use throughout the compilation.

When compared to the PSDD multiplication chain, the advantage of this approach is that we can utilize dynamic vtree optimization (Choi & Darwiche, 2013) *throughout the entire compilation procedure*. In the SDD with byte indicators, computing the BP messages defined in Equation 2 is effectively a series of weighted model counting (WMC) problems: Let $w(l)$ denote the weight of a literal l. To compute $\mu_{\mathcal{M}\to x_i}(x_i = x)$, we set $w(b_{x_i=x}) = 1$, $w(\neg b_{x_i=x}) = 0$, and the weight of all other byte indicators to $w(b_{v=x}) = p(v = x|\boldsymbol{\ell})$ and $w(\neg b_{v=x}) = 1$ $\forall x \in \{0,\dots,255\}, \forall v \in \mathbf{v} \setminus x_i$, while we set $w(l) = 1$ for all non-auxiliary literals l. Naïvely, this entails that computing $\{\mu_{\mathcal{M}\to x_i}\}_{i=1}^{4}$ requires $4 \cdot 256$ WMC executions. However, it is known that all marginals (i.e., messages) can be computed using a *single WMC computation and its derivative* (backward pass) (Darwiche, 2000; Peharz et al., 2015). We thus assume that the number of operations needed to compute all messages is approximately twice the number of operations needed for a bottom-up circuit evaluation.

3.4. Merging Trick and Conditioning

Even when using modern knowledge compilers, constructing the SDD described above is prohibitively expensive. Hence, we aid the SDD compiler by performing a number of pre-processing steps. First, we apply a known technique in the SCA literature, called the *merging trick* (Guo et al., 2020): For example, in the SASCA factor graph (Figure 2), x_{12} and $\tilde{x}_{12}$ are connected via a deterministic bijection $f_{\text{XTIME}}(x_{12}) = \tilde{x}_{12}$. Thus, when computing key marginals, there is no need to model both variables in the factor graph—instead, we aggregate the leakage distributions of these variables by updating the local beliefs $p(x_{12} = x|\boldsymbol{\ell}) \leftarrow p(x_{12} = x|\boldsymbol{\ell}) \cdot p(\tilde{x}_{12} = f_{\text{XTIME}}(x)|\boldsymbol{\ell})$ for all $x \in \{0,\dots,255\}$. We remove the node $\tilde{x}_{12}$ from the factor graph and omit introducing byte indicator variables for it (or multiplying the PSDD that represents $p(\tilde{x}_{12}|\boldsymbol{\ell})$). We repeat this trick to remove $\tilde{x}_{23}, \tilde{x}_{34}$, and $\tilde{x}_{41}$.

Moreover, notice that if we condition on g, all XOR factors connected to g become indicator functions $\text{XOR}_g(x, x')$ that evaluate to 1 iff $x \oplus g = x'$. Thus, we can leverage the merging trick to remove $x'_{12}, x'_{23}, x'_{34}, x'_{41}$ by combining their local beliefs with the distributions of their corresponding left neighbors $\tilde{x}_{12},\dots,\tilde{x}_{41}$. In the same way, we remove x_{34}, x_{41} by updating the beliefs of x_{12} and x_{23}, respectively. As this simplifies the inference problem drastically, we condition $SDD(\mathcal{M})$ on a fixed $g \in \{0,\dots,255\}$ and only add byte indicator variables for 10 bytes in total (corresponding to 2560 auxiliary byte indicators). In the general case, we can compile a conditional SDD for each value of g (resulting in 256 SDDs) and easily combine them into a larger SDD by connecting them to an *or*-node.

However, due to the linearity of MIXCOLUMN, it suffices to compile a *single* conditional SDD (with arbitrary, fixed $g \in \{0,\dots,255\}$), as we can also run inference queries for different $g' \neq g$ by simply permuting some of the weight functions. This novel technique (1) reduces the time and space complexity of SDD compilation by a factor of ≈ 256, and (2) opens up the possibility for highly-parallel GPU-centric inference implementations. A more detailed exposition of this technique can be found in Appendix A.

Using these techniques, compiling $SDD(\mathcal{M})$ takes about 7 hours on a Intel Xeon E5-2670 CPU and the resulting circuit consists of $\approx$ 20M nodes and needs 17.4M sums and 37.2M products for a bottom-up evaluation. When evaluated 256 times, this amounts to 6 times less computations for MPE queries in the corresponding PSDD, and 3.5 times less computations when computing all marginals.

3.5. Implementation

While our approach involves a rather sophisticated compilation and inference pipeline, our implementation makes heavy use of existing software packages for both knowledge compilation and probabilistic inference. Most notably, we leverage `pysdd` (Meert, 2017), a Python interface for the `sdd`[1] software package, which allows us to easily construct, manipulate and optimize SDDs and their associated vtrees. This allows us to implement many components of our pipeline (e.g., the "merging trick") in a relatively straightforward way. Our implementation can be found at `https://github.com/wedenigt/exsasca`.

4. Experiments

To evaluate our method, we use asynchronously captured power traces from an SMT32F415 (ARM) microcontroller (Bursztein & Picod, 2019) that performs encryption using AES-128. The data $\mathcal{D} = \{(\boldsymbol{\ell}^{(i)}, \mathbf{k}^{(i)}, \mathbf{p}^{(i)})\}_{i=1}^{n}$ contains $n = 131{,}072$ samples, each of which consists of a high-dimensional power trace $\boldsymbol{\ell} \in \mathbb{R}^{20{,}000}$, and 16 byte key and plaintext vectors $\mathbf{k}, \mathbf{p}$, with 512 unique keys $\mathbf{k}$. For each unique key, the dataset contains 256 elements, each with a different plaintext $\mathbf{p}$. During the attack phase, we assume the plaintext to be known (*known plaintext attack*). We use 20% of $\mathcal{D}$ as a test set $\mathcal{D}_{\text{test}}$, while the remaining 80% of $\mathcal{D}$ are again split into a training set $\mathcal{D}_{\text{train}}$ (82.5% of $\mathcal{D} \setminus \mathcal{D}_{\text{test}}$) and a validation set $\mathcal{D}_{\text{val}}$ (17.5% of $\mathcal{D} \setminus \mathcal{D}_{\text{test}}$). The set of unique keys in $\mathcal{D}_{\text{train}}, \mathcal{D}_{\text{test}}, \mathcal{D}_{\text{val}}$ are non-overlapping, i.e., when validating and testing a side-channel attack, it must reason about keys $\mathbf{k}$ it has never seen during profiling/training.

[1] `http://reasoning.cs.ucla.edu/sdd/`

Table 1. Top-1 success rate of different inference methods, measured on the validation dataset $\mathcal{D}_{\text{val}}$. ε controls the level of sparsity in the approximated distributions, where $\varepsilon = 0$ means no approximation (utilizing the method in Section 3.3).

Inference Method	Top-1 Success Rate		
	$\varepsilon = 10^{-2}$	$\varepsilon = 10^{-8}$	$\varepsilon = 0$
Baseline	0.10%	0.10%	0.10%
SASCA (3 iters)	0.52%	0.52%	0.52%
SASCA (50 iters)	32.34%	33.81%	33.76%
SASCA (100 iters)	34.25%	36.04%	35.84%
ExSASCA + MAR	57.36%	67.37%	67.37%
ExSASCA + MPE	**57.51%**	**67.60%**	**67.61%**

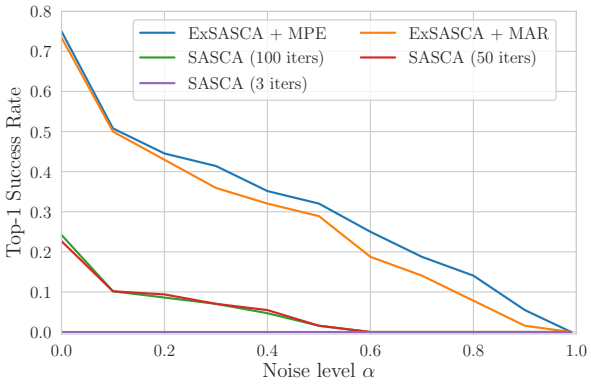

Figure 4. Top-1 success rate of different inference methods when using corrupted beliefs $\tilde{p}_\alpha(v \mid \boldsymbol{\ell})$, computed on a batch of 128 traces in $\mathcal{D}_{\text{val}}$ ($\varepsilon = 0$). As $\alpha \to 1$, the local beliefs become increasingly uninformative.

4.1. Evaluation

As usual in literature, we model only the first round of AES, thus we can independently attack all 4 branches of MIXCOLUMN and reason about the corresponding 4-byte subkeys independently. For a given leakage $\boldsymbol{\ell}$, we utilize the template attack described in (Bronchain et al., 2021) to obtain a set of local beliefs $p(v \mid \boldsymbol{\ell})$ for all bytes $v \in \mathbf{v}$ and for each call to MIXCOLUMN. Using these beliefs, SASCA and ExSASCA + MAR compute marginal posterior distributions $p(k_1 \mid \boldsymbol{\ell}), \ldots, p(k_{16} \mid \boldsymbol{\ell})$ and then define the joint key posterior to be $p(\mathbf{k}|\boldsymbol{\ell}) = \prod_{i=1}^{16} p(k_i|\boldsymbol{\ell})$. On the other hand, ExSASCA + MPE does *not* make this conditional independence assumption and directly computes $\operatorname{argmax}_{\mathbf{k}} p(\mathbf{k} \mid \boldsymbol{\ell})$, i.e., the MPE in the *true joint key posterior* according to our probabilistic model $p(\mathbf{k} \mid \boldsymbol{\ell}) = p(\mathbf{k}_{1:4} \mid \boldsymbol{\ell}) \cdots p(\mathbf{k}_{13:16} \mid \boldsymbol{\ell})$, where $\mathbf{k}_{i:j} = (k_i, k_{i+1}, \ldots, k_j)$ denotes a subkey.

To simulate *protected* AES implementations, we experiment with corrupting the local belief distributions: For $\alpha \in [0, 1]$ and for all bytes $v \in \mathbf{v}$, we compute

$$\tilde{p}_\alpha(v = x \mid \boldsymbol{\ell}) = (1 - \alpha)p(v = x \mid \boldsymbol{\ell}) + \alpha \frac{1}{256}$$

for all $x \in \{0, \ldots, 255\}$ and use the set of corrupted beliefs $\tilde{p}_\alpha(v \mid \boldsymbol{\ell})$ as inputs to different inference methods. In this scenario, we cannot effectively leverage sparse approximations and thus, choose $\varepsilon = 0$ in this experiment.

For evaluation we use *top-1 success rate*: Given a single leakage $\boldsymbol{\ell}$ and the corresponding 16-byte key $\mathbf{k}^*$ and plaintext $\mathbf{p}$, we define an attack to be *successful* if $\mathbf{k}^* = \operatorname{argmax}_{\mathbf{k}} p(\mathbf{k}|\boldsymbol{\ell})$, i.e., the true key has the highest probability in the joint key posterior. The *top-1 success rate* is the fraction of successful attacks.

4.2. Results

While SASCA always computes approximate marginals over key bytes, we can use our circuit to compute both (1) exact key marginals (ExSASCA + MAR) and (2) exact most probable evidence assignments directly in the joint key posterior (ExSASCA + MPE). As a baseline, we run BP only in the acyclic factor graph given by the ADDROUNDKEY and SUBBYTES routines, i.e., we neglect all local beliefs over bytes involved in the computation of MIXCOLUMN.

The results in Table 1 show that (1) both ExSASCA variants systematically and substantially outperform all SASCA runs—even when ExSASCA uses sparse approximations and SASCA does not, and (2) directly computing the MPE in the joint key posterior yields a slightly higher success rate. Moreover, Figure 4 demonstrates empirically that as the local beliefs become less informative (e.g. due to noise), SASCA effectively fails to attack the system while the ExSASCA variants still show success rates of about 20%.

4.3. Computational Complexity

When $\varepsilon > 0$, the computational cost of ExSASCA depends on both ε and the entropy of the distributions $p(v \mid \boldsymbol{\ell})$. In our experiments, we find that the runtime of ExSASCA with $\varepsilon \geq 10^{-8}$ is still very competitive to a high-performance implementation of SASCA (Cassiers & Bronchain, 2023): For a single trace, a SASCA takes tens to hundreds of milliseconds on a modern laptop CPU, while our PSDD multiplication chain takes hundreds of milliseconds for $\varepsilon = 10^{-2}$ and seconds for $\varepsilon = 10^{-8}$. In this regime, both SASCA and ExSASCA need three orders of magnitudes less compute than the naïve exhaustive inference routine. Even without approximations ($\varepsilon = 0$), ExSASCA + MPE can perform exact inference with 6 times less operations than its exhaustive counterpart, while ExSASCA + MAR needs 3.5 times less operations.

4.4. Extensions to Larger Inference Problems

In principle, ExSASCA can also be used to attack more than a single AES round:[2] When neglecting the functional relationship between the key and the so-called "round keys", the resulting factor graph is still acyclic (given that MIXCOLUMNS is represented as a high dimensional factor). However, in this scenario, the usefulness of attacking multiple rounds heavily depends on the beliefs over the round key bytes. Since our dataset does not contain traces for all round key byte values, we cannot learn probabilistic models in the same way as in the single-round attacks and thus, we do not report empirical evaluations of attacking multiple rounds.

5. Conclusion

In this work, we introduce ExSASCA, a fast and exact probabilistic inference algorithm for SASCA and demonstrate that ExSASCA substantially outperforms SASCA when attacking the Advanced Encryption Standard (AES). While SASCA uses loopy belief propagation to compute approximate marginal posteriors over the key bytes, we instead choose to represent the loopy part of the factor graph as a high-dimensional factor, which—conceptually—allows us to perform message passing on a tree.

To efficiently compute messages which involve this factor, we compile it into a tractable probabilistic model that allows us to compute marginals and most probable evidence (MPE) queries in polynomial time of the circuit size. In particular, we develop two distinct approaches for compilation: (i) leveraging sparsity in the beliefs about intermediate computations during compilation, we frame the task as a combination of an off-line compilation phase and an on-line sequence of PSDD multiplications. (ii) for dense belief distributions, we present a novel dynamic compilation pipeline that produces an SDD that can perform exact inference with 6 times less operations than exhaustive enumeration. We posit that our method opens a new avenue for studying both side-channel attacks and cryptanalysis using the framework of tractable (probabilistic) models and may lead to stronger theoretical guarantees in cryptographic systems.

Future work includes various interesting directions. In this work we used the hand-designed template attacks proposed by (Bronchain et al., 2021), but these might be replaced with a deep neural nets in combination with PCs similar as in (Stelzner et al., 2019; Tan & Peharz, 2019; Shao et al., 2020; Ahmed et al., 2022; Gala et al., 2024).[3]

[2]Attacking multiple rounds is also necessary if the key is longer than 128 bits (e.g., 192 or 256 bits).

[3]Our preliminary experiments for this paper were actually using deep learning templates, which however under-performed in comparison to (Bronchain et al., 2021), indicating that designing "deep templates" might require some additional engineering effort.

Moreover, while our central effort in this paper is to detect weaknesses in cryptographic systems, the developed techniques might well be used in other application requiring large-scale integration of probabilistic and logical reasoning, such as system verification and error correcting codes.

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Impact Statement

This paper presents work whose goals are to advance the field of Machine Learning, specifically the area of exact inference and tractable models, and the field of Cryptography, by providing new tools to analyse weaknesses in cryptographic algorithms via cryptographic attacks. Hence, our work has a hypothetical potential of dual use. However, this potential for dual use is very limited, since (i) we do not provide a new attack, but rather a novel inference method to perform an established attack, and (ii) this established attack is technically challenging. Moreover, by publishing this improved method we ensure that the scientific and general public is aware of and can react to the connected risks.

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Algorithm 1 Simplified Beginning of AES-128

Input: Key bytes $k_1, \ldots, k_{16}$, Plaintext bytes $p_1, \ldots, p_{16}$
for i **in** $1, \ldots, 16$ **do**
  $y_i \leftarrow k_i \oplus p_i$
  $x_i \leftarrow S(y_i)$
end for
for i **in** $0, 4, 8, 12$ **do**
  $x_{i+1}^{(m)}, \ldots, x_{i+4}^{(m)} \leftarrow \text{MIXCOLUMN}(x_{i+1}, \ldots, x_{i+4})$
end for

Algorithm 2 MIXCOLUMN

Input: Input bytes $x_1, \ldots, x_4$
$x_{12},\ x_{23},\ x_{34},\ x_{41} \leftarrow (x_1 \oplus x_2), (x_2 \oplus x_3), (x_3 \oplus x_4), (x_4 \oplus x_1)$
$g \leftarrow x_{12} \oplus x_{34}$
$\tilde{x}_{12},\ \tilde{x}_{23},\ \tilde{x}_{34},\ \tilde{x}_{41} \leftarrow \text{XTIME}(x_{12}), \text{XTIME}(x_{23}), \text{XTIME}(x_{34}), \text{XTIME}(x_{41})$
$x'_{12},\ x'_{23},\ x'_{34},\ x'_{41} \leftarrow (\tilde{x}_{12} \oplus g), (\tilde{x}_{23} \oplus g), (\tilde{x}_{34} \oplus g), (\tilde{x}_{41} \oplus g)$
$x_1^{(m)},\ x_2^{(m)},\ x_3^{(m)},\ x_4^{(m)} \leftarrow (x_1 \oplus x'_{12}), (x_2 \oplus x'_{23}), (x_3 \oplus x'_{34}), (x_4 \oplus x'_{41})$
Return: $x_1^{(m)},\ x_2^{(m)},\ x_3^{(m)},\ x_4^{(m)}$

A. Single-Circuit Compilation

As detailed in Section 3.4, we compile $\mathcal{M}$ conditioned on some arbitrary, but fixed $g \in \{0, \ldots, 255\}$, denoted $SDD(\mathcal{M} \mid g)$. Consider the set of models $\mathcal{X}_g = \{\mathbf{v} \text{ s.t. } (\mathcal{M} \mid g)(\mathbf{v}) = 1\}$. Since $g = x_1 \oplus x_2 \oplus x_3 \oplus x_4$, it is easy to see that g partitions the set of *all* models into equally sized sets, i.e., $|\mathcal{X}_g| = |\mathcal{X}_{g'}|$ for all byte-valued g, g'. Thus, there exists a *bijection* $\phi_{g \to g'} : \mathcal{X}_g \to \mathcal{X}_{g'}$ that maps a model from $\mathcal{X}_g$ to a model in $\mathcal{X}_{g'}$. Importantly, due to the linear structure of MIXCOLUMN, we can define such a bijection by *independently* mapping the individual bytes $v \in \mathbf{v}$:

$$\left(\phi_{g \to g'}(\mathbf{v})\right)_i = \phi_{g \to g'}^{v_i}(v_i) \tag{3}$$

Let $\mathbf{v}_g \in \mathcal{X}_g$. Since we can use the merging trick detailed in Section 3.4, it suffices to consider the subset of bytes in $\mathbf{v}_g$, namely $\hat{\mathbf{v}}_g = (x_1, x_2, x_3, x_4, x_{12}, x_{23}, x_1^{(m)}, x_2^{(m)}, x_3^{(m)}, x_4^{(m)})^\top$. To map this to some $\hat{\mathbf{v}}_{g'}$, we set

- $\phi_{g \to g'}^{x_4}(x_4) = x_4 \oplus g \oplus g'$
- $\phi_{g \to g'}^{x_1^{(m)}}(x_1^{(m)}) = x_1^{(m)} \oplus g \oplus g'$
- $\phi_{g \to g'}^{x_2^{(m)}}(x_2^{(m)}) = x_2^{(m)} \oplus g \oplus g'$
- $\phi_{g \to g'}^{x_3^{(m)}}(x_3^{(m)}) = x_3^{(m)} \oplus f_{\text{XTIME}}(g \oplus g')$
- $\phi_{g \to g'}^{x_4^{(m)}}(x_3^{(m)}) = x_3^{(m)} \oplus f_{\text{XTIME}}(g \oplus g') \oplus g \oplus g'$

and $\phi_{g \to g'}^{v}(v) = v$ for all remaining bytes $v \in \hat{\mathbf{v}}_g$. Consequently, we can exploit this fact to compute a weighted model count over $\mathcal{X}_{g'}$ using $SDD(\mathcal{M} \mid g)$ with $g' \neq g$ by (1) performing the merge trick with g' instead of g, and (2) by constructing a new weight function w' that first applies the corresponding byte-wise bijection before invoking the original weight function w, i.e., $w'(v) = w\left(\phi_{g \to g'}^{v}(v)\right)$. Thus, we keep the circuit $SDD(\mathcal{M} \mid g)$ fixed and compute the weighted model count 256 times, where each computation is performed with a different weight function.