CLAASP: a Cryptographic Library for the Automated Analysis of Symmetric Primitives

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Abstract. This paper introduces CLAASP, a Cryptographic Library for the Automated Analysis of Symmetric Primitives. The library is designed to be modular, extendable, easy to use, generic, efficient and *fully* automated. It is an extensive toolbox gathering state-of-the-art techniques aimed at simplifying the manual tasks of symmetric primitive designers and analysts. CLAASP is built on top of Sagemath and is open-source under the GPLv3 license.
The central input of CLAASP is the description of a cryptographic primitive as a list of connected components in the form of a directed acyclic graph. From this representation, the library can automatically: (1) generate the Python or C code of the primitive evaluation function, (2) execute a wide range of statistical and avalanche tests on the primitive, (3) generate SAT, SMT, CP and MILP models to search, for example, differential and linear trails, (4) measure algebraic properties of the primitive, (5) test neural-based distinguishers. We demonstrate that CLAASP can reproduce many of the results that were obtained in the literature and even produce new results.
In this work, we also present a comprehensive survey and comparison of other software libraries aiming at similar goals as CLAASP.

Keywords: Cryptographic library · Automated analysis · Symmetric primitives

1 Introduction

The security targets for cryptographic primitives are well-defined, and relatively stable, after decades of cryptanalysis. In particular, a symmetric cipher should behave like a random keyed permutation, a hash function should behave like a random function, and a MAC scheme should be unforgeable. Testing a cryptographic primitive for these properties is, on the other hand, a vastly difficult task that relies on testing for known weaknesses. Such a process generally involves determining the most likely differential or linear characteristic, evaluating the resistance of the primitive to various cryptanalysis techniques such as integral attacks, and running generic randomness tests. Fortunately, automatic techniques

exist to help designers and cryptographers run such evaluations; for instance, SAT/SMT, Mixed Integer Linear Programming (MILP) or Constraint Programming (CP) are frequently used to find optimal differential and linear characteristics. These tools have, over time, become more accessible to non-experts, through libraries such as [45], that generate models (in this case, SMT) automatically from a description of the cipher. However, such tools generally focus on a single aspect, such as generating models in a given paradigm, and there is currently no single-stop toolkit that combines automated model generation, statistical testing and machine learning based analysis. We aim to fill this gap with CLAASP, a Cryptographic Library for the Automated Analysis of Symmetric Primitives. This paper introduces the first public version of CLAASP; the ambition of the project is to keep adding analysis tools in line with the state of the art, to provide cryptanalysts with a click-of-a-button solution to run all the standard analysis tools and gain an overview of the security of a given primitive.

The library's source code has been made available to the wider community and is publicly accessible at Github: https://github.com/Crypto-TII/claasp. Also, in Github: https://github.com/peacker/claasp_white_paper, you can find the scripts used to accompany this paper.

We first present existing cryptanalysis libraries in Section 1.1, before introducing the building blocks of CLAASP: the cipher object in Section 2, and the evaluators in Section 3. We then present the battery of tests and tools implemented in CLAASP in Section 4, and finish with a comparison with other cryptographic libraries in Section 5.

1.1 Related works

Automated tools to support cryptanalysts have become a cornerstone for the design of new primitives. Over time, such tools were made more generic and gathered into libraries; we describe the most prominent ones in this section.

The lineartrails library [22] is dedicated to the search for linear characteristics on SPN ciphers. ARX toolkit [32,33] and YAARX [58] focus on ARX ciphers, the former testing conditions for trails to be possible, and the latter performing various analysis techniques on the components.

On the algebraic cryptanalysis side, the Automated Algebraic Cryptanalysis tool [53] tests properties of block and stream ciphers; in particular, it evaluates the randomness of a cipher through Maximum Degree Monomial tests [54].

Autoguess [27] is a tool to automate the technique guess-and-determine. This technique involves making a calculated guess of a subset of the unknown variables, which enables the deduction of the remaining unknowns using the information obtained from the guessed variables and some given relations. In order to automate this technique, SAT/SMT, MILP, and Gröbner basis solvers are used and several new modeling techniques to exploit these solver proposed. For instance, the authors of the library introduce new encodings in CP and SAT/SMT to solve the problem of determining the minimal guess, i.e., the subset of guessed variables from which the remaining variables can be deduced. Autoguess also

allows to automate the key-bridging technique. This technique is utilized in key-recovery attacks on block ciphers, wherein the attacker seeks to determine the minimum number of sub-key guesses needed to deduce all the involved sub-keys through the key schedule. The significant contribution of this work lies in integrating key-bridging techniques into tools that were previously only capable of searching for distinguishers. As a result, these enhanced tools can now be utilized as fully automatic methods for recovering keys.

CryptoSMT [55] is the first large-scale solver-based library dedicated to cryptanalysis. Based on SMT and SAT solvers, it provides an extensive toolkit, permitting the search for optimal differential and linear trails, the evaluation of the probability of a differential, the search for hash function preimages, and secret key search.

The study described in [28] presents an innovative approach to explore differentials and linear approximations. Different from methods that rely on SAT or MILP techniques, this approach transforms the search for differential and linear trails into a problem of identifying multiple long paths within a multi-stage graph. A practical implementation of this research, called CryptaGraph, is available in [29]. One notable feature of CryptaGraph is its automatic conversion capability, enabling C or Rust implementations of ciphers to be transformed into models for searching differentials or linear approximations using the graph-based approach mentioned earlier. An improvement of [28] can be found in [30] and its implementation was named PathFinder.

Another SMT-based library, based on ArxPy [45] is the CASCADA framework [46], which also implements techniques to search for rotational-XOR differentials, impossible-rotational-XOR, but also related-key impossible-differentials, linear approximations, and zero-correlation characteristics. The generated SMT models are expressed through the theory of bit-vectors [5], and follow the general methodology of Mouha and Preneel [40] for differential properties, Sasaki's [50] technique for impossible differentials, an SMT-based miss-in-the middle search for related-key impossible differentials of ARX ciphers [4], and a novel method proposed for zero-probability global properties. If a search can not use the previous methods, then a generic method, based on the constructions of statistical tables, such as the Differential Distribution Table (DDT), is used. Depending on the sizes of the inputs of the block cipher, these generic models could be costly, so they also proposed heuristic models by relaxing the accuracy of their properties; they called them weak models. Finally, their framework implements methods to check the properties mentioned above experimentally.

Finally, TAGADA [34] is a tool which generates Minizinc [42] models for the search for differential properties on word-based SPN ciphers, such as the AES. The search for such ciphers is typically divided into two steps, one where the word variables are abstracted as boolean values denoting the presence or absence of a difference, and one where the abstracted solutions from step 1 are instantiated to word values, when possible. The models generated by TAGADA implement the first step, including optimisations based on inferred equalities through XOR operators, in order to drastically reduce the number of incorrect solutions to

be passed to step 2. Such constraints are deduced naturally from a Directed Acyclic Graph (DAG) representation of the cipher under study. The genericity of Minizinc models enables solving with a range of CP, SAT and SMT solvers, in particular, the ones participating in the MiniZinc competition, that provide an interface to MiniZinc. On the other hand, solver-specific optimisations and perks are abstracted away by the Minizinc interface, compared to models developped in the native language of a solver.

A summary of the functionalities of these libraries is presented in Table 1.

		TAGADA	CASCADA	CryptoSMT	lineartrails	YAARX	Autoguess	CLAASP
Cipher types		SPN	All	All	SPN	ARX	All	All
Cipher representation		DAG	Python code	Python code	C++ code	C code	Algebraic representation	DAG
Statistical/Avalanche tests		-	-	-	-	-	-	Yes
Continuous diffusion tests		-	-	-	-	-	-	Yes
Components analysis tests		-	-	-	-	-	-	Yes
Constraint solvers	Differential trails	Truncated	Yes	Yes	-	Yes	-	Yes
	Differentials	-	Yes	Yes	-	Yes	-	Yes
	Impossible differential	-	Yes	-*	-	-	-	Yes
	Linear trails	-	Yes	Yes	Yes	-	-	Yes
	Linear hull	-	-*	-*	-	-	-	Yes
	Zero correlation approximation	-	Yes	-*	-	-	-	Yes
	Supported solvers	CP, (MiniZinc)	SMT	SMT	-	-	SAT, SMT, MILP, CP, Groebner basis	SAT, SMT, MILP, CP, Groebner basis
	Supported Scenarios	single-key related-key	single-key related-key	single-key related-key	single-key	single-key	single-key related-key single-tweak related-tweak	single-key related-key single-tweak related-tweak
Algebraic tests		-	-	-	-	-	-	Yes**
Neural-based tests		-	-	-	-	-	-	Yes
State Recovery		-	-	-	-	-	Yes	-
Key-bridging		-	-	-	-	-	Yes	-

Table 1: Comparison of cryptanalysis libraries features with CLAASP. -* means that the functionality is not supported, but could easily be added from the existing code. ** means the algebraic tests works on algebraic model for cipher preimages.

1.2 Our contribution

We introduce CLAASP, a Cryptographic Library for the Automated Analysis of Symmetric Primitives. CLAASP has been designed to simplify the manual tasks of symmetric cipher designers and analysts. CLAASP has been designed with the following goals:

- Be *open-source* with a GPLv3 licence.
- Be *modular*. For this reason it is built on top of Sagemath, thus inheriting Python modularity.

- Be *extendable*. The Python/Sagemath environment allows to easily integrate other powerful libraries: constraint solvers such as Cryptominisat, Cadical or Gurobi, machine learning engines such as Tensorflow, Grobner basis solvers, parallelization packages such as NumPy, etc..
- Be *usable*. Much effort has been dedicated to provide a smooth user experience for both designing and analyzing a cipher. This includes a comprehensive documentation for users and developers, and a Docker image to easily start with the library without the need of installing all the dependencies.
- Be *generic*. The wide range of pre-defined components, allows to implement a wide range of iterated symmetric ciphers, ranging from block ciphers (possibly with a tweak), cryptographic permutations, hash functions, and covering several design types such as Feistel, SPN, ARX, etc..
- Be *automated*. The concept of the library revolves around providing a cipher design as the input and getting an analysis of the cipher design as the output with respect to some desired property.
- Be *efficient*. In spite of being the most generic and fully automated tool of its kind, this library is competitive in terms of efficiency with similar tools targeting specific sectors.

The central objects of CLAASP are symmetric ciphers. They are described as directed acyclic graphs whose nodes are components (S-Boxes, linear layers, constants, Input/Output, etc.) and whose edges are input/output component connections. From this representation, the library can automatically:

1. generate the Python or C code of the evaluation function;
2. execute a wide range of statistical and avalanche tests on the primitive, including continuous diffusion tests;
3. generate a report containing the main properties of the cipher components (e.g. S-Box differential uniformity or algebraic degree, linear layer order or branch number, etc.);
4. generate SAT, SMT, CP and MILP models and feed them to most open-source and commercial solvers, in order to search, for example, differential and linear trails;
5. measure algebraic properties of the primitive;
6. test neural-based distinguishers.

We demonstrate that CLAASP can reproduce many of the results that were obtained in the literature: in terms of differential cryptanalysis, we retrieve similar results to CASCADA for the 1 to 7 rounds of SPECK32, 64, and LEA128. Furthermore, we were able to find an optimal differential trail for Speck128-128 reduced to 10 rounds. To the best of our knowledge, optimal trails for this specific version of Speck were only known for up to 9 rounds. This achievement was made possible by seamlessly integrating a Parallel SAT solver into CLAASP. In particular, we successfully incorporated ParKissat, the winner of the SAT competition 2022 (parallel track) [59], into the SAT module of CLAASP. In addition, we show how to use CLAASP to retrieve the known 17-rounds impossible differential on HIGHT, as well as 6-round impossible differentials on

SPECK32. Regarding linear cryptanalysis, we obtain a linear trail of Salsa with better correlation than the one reported in [16]. This discovery has the potential to enhance the correlation of the differential-linear distinguisher against Salsa reduced to 8 rounds presented in the aforementioned paper. Finally, in terms of neural cryptanalysis, CLAASP implements (and can reproduce the results of) [9], in addition to the seminal results of [26]. In addition, researchers willing to apply neural cryptanalysis to new ciphers using the techniques from [9] can do so in a straight-forward manner using the library functions.

Besides the presentation of the library, important contributions of this work are a survey and a comparison (where possible) of the main software tools trying to achieve the same goals as CLAASP.

2 Symmetric primitives in CLAASP

In this section, we describe how a symmetric primitive is represented in CLAASP. We also present the main pre-implemented primitives that are available for testing and give some indications on how to build a custom cipher.

2.1 The Component class

Informally, in CLAASP, a symmetric cipher is represented as a list of "connected components". By the term *cipher component* (or simply *component*) we refer to the building blocks of symmetric ciphers (S-Boxes, linear layers, word operations, etc.). Two components are *connected* when the output bits of the first component become the input bits of the second component, in a one-to-one correspondence. The library supports the following *primitive* components: the S-Box component, linear layer components (fixed and variable rotation, fixed and variable shift, bit and word permutation, multiplication by a binary or word matrix), word operations components (NOT, AND, OR, XOR, modular addition and subtraction), and the constant component. It also supports *composite* components, which are a combination of primitive components: the sigma function used in ASCON, the theta function used in Keccak, and the theta function used in Xoodoo. For example, the linear layer in ASCON can be presented by the combination of several XOR and ROTATE components, or as a composite component. Composite components can also be created at a user level.

Finally, some special components are used to represent the inputs of the cipher, and cipher intermediate and final outputs.

In CLAASP, each component requires the following minimal information to be defined: a unique component ID (e.g. "sbox_0_0"); a component type (e.g. "sbox", "word_operation", "linear_layer", etc.); the input and output bit size of the component; a list of the components that are connected to the input of the component (a list of IDs); a list of lists of bits positions specifying which output bits of the input components are connected to the component; a description containing the necessary information to finalize the definition of the component

(e.g., the list of integers defining an SBox, the binary matrix defining a linear layer, the amount of a rotation, etc.).

More precisely, in CLAASP, a component is represented as a Python class.

2.2 The Cipher class

Ciphers as directed acyclic graphs In CLAASP, a symmetric cipher is represented as a list of connected components, forming a directed acyclic graph, and a list of basic properties, listed in Table 2.

Property	Description
id	unique identifier of the cipher, composed by cipher name and parameters
family_name	name of the cipher family, such as AES ASCON, etc.
type	type of the cipher (block cipher, permutation, hash or stream cipher)
inputs	inputs of the cipher, such as key and plaintext.
inputs_bit_size	list of number of bits of each input parameters.
output_bit_size	number of bits of the cipher output
number_of_rounds	number of rounds in the cipher
rounds	list of rounds each containing a list of components
reference_code	[optional] Python reference code (as a string) of the cipher evaluation function, used to verify the cipher correctness.

Table 2: Parameters that are used to define a cipher in CLAASP.

CLAASP supports *iterated symmetric ciphers*, based on the composition of several round functions, which are themselves a list of connected components; each cipher must have at least one round. The round decomposition is useful and common in symmetric cipher design and cryptanalysis; in most tests, a given property is studied round by round.

CLAASP natively implements a range of well-known block ciphers (AES TEA, DES, XTEA, LEA, Twofish, LowMC, Threefish, Midori, HIGHT, PRESENT, SKINNY, Raiden, Sparx, SIMON, SPECK), permutations (ASCON, Xoodoo, ChaCha, Spongent-π, GIFT-128, TinyJAMBU, GIMLI, Grain core, KECCAK-p, PHOTON, SPARKLE) and hash functions (SHA-1, SHA-2, MD5, BLAKE, BLAKE2). This list is meant to be expanded over time.

How to create the cipher object While native support for more primitives will be added over time, CLAASP exposes a simple interface for users to add new ones as well. This process is illustrated through a toy example of a 2-rounds cipher with 6-bit block, 6-bit key injected in every round with a XOR operation, 2 3-bit S-boxes, and a linear layer made of a left rotation of 1 bit, shown in Figure 2, and the corresponding CLAASP implementation in Figure 1.

The main concern of a user implementing a primitive is to correctly link the components at a bit level, and mark which component or group of components need to be reported in the output of the tests. This is because a user might be interested not only in getting reports at every round, but, for example, after the linear and the nonlinear layer of an SPN.

```
from claasp.cipher import Cipher

class ToySPN(Cipher):
  def __init__(self):
    super().__init__(family_name="toyspn",
      cipher_type="block_cipher",
      cipher_inputs=["plaintext", "key"],
      cipher_inputs_bit_size=[6, 6],
      cipher_output_bit_size=6)

    sbox = [0, 5, 3, 2, 6, 1, 4, 7]
    self.add_round()
    xor = self.add_XOR_component(["plaintext", "key"
          ↪ ],[[0,1,2,3,4,5],[0,1,2,3,4,5]],6)
    sbox1 = self.add_SBOX_component([xor.id], [[0, 1,
          ↪ 2]], 3, sbox)
    sbox2 = self.add_SBOX_component([xor.id], [[3, 4,
          ↪ 5]], 3, sbox)
    rotate = self.add_rotate_component([sbox1.id,
          ↪ sbox2.id],[[0, 1, 2], [0, 1, 2]], 6, 1)
    self.add_round_output_component([rotate.id], [[0,
          ↪ 1, 2, 3, 4, 5]], 6)

    self.add_round()
    xor = self.add_XOR_component([rotate.id, "key"
          ↪ ],[[0,1,2,3,4,5],[0,1,2,3,4,5]],6)
    sbox1 = self.add_SBOX_component([xor.id], [[0, 1,
          ↪ 2]], 3, sbox)
    sbox2 = self.add_SBOX_component([xor.id], [[3, 4,
          ↪ 5]], 3, sbox)
    rotate = self.add_rotate_component([sbox1.id,
          ↪ sbox2.id],[[0, 1, 2], [0, 1, 2]], 6, 1)
    self.add_cipher_output_component([rotate.id], [[0,
          ↪  1, 2, 3, 4, 5]], 6)

toyspn = ToySPN()
hex(toyspn.evaluate([0x3F,0x3F]))
```

Fig. 1: ToySPN class definition.

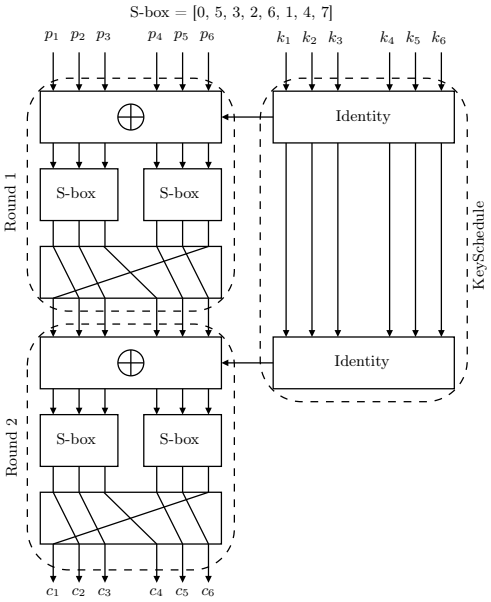

Fig. 2: ToySPN diagram.

Cipher inputs It is important to notice that, in order to be generic, the library has been designed to accept multiple inputs which can be labeled with different names: for example, a key, a plaintext and a tweak, or a message and a nonce. On the other hand, to better exploit the features of some tests, a naming convention has been introduced for inputs such as "key" or "plaintext".

The *cipher representation* is not unique The *cipher representation* as a list of connected components is *not* unique. For example, the nonlinear layer of ASCON permutation can be represented as a circuit made of word operation components (XOR, AND and NOT) or with a layer of parallel S-boxes. This is detailed in Appendix A.

Different *cipher representations* may affect the output of tests; for instance, a differential cryptanalysis model built for an ASCON implementation using the circuit representation is less accurate than one using a S-Box representation. In general, the circuit model is useful when a user wishes to monitor the action of every gate (i.e. word operation) on a single bit. On the other hand an S-Box-based model often allows a faster evaluation function, and more precise automated search for differential and linear trails for some constraint solvers such as CP, where the search can have a preliminary filter to identify all possible active S-Boxes configurations. Another example of different representation is the use of binary matrices as opposed to word-based matrices in linear layers.

To test the properties mentioned above, CLAASP already contains some primitives with both circuit and S-Box-based representation, such as ASCON, Xoodoo, Keccak and Gimli, as well as the bit-based and word-based such as TinyJambu representations.

3 Library: evaluation modules

The most basic functionality of CLAASP is to evaluate a cryptographic primitive on a given input. This can be easily achieved in few lines of Python code. However, some statistical tests require the evaluation of millions of inputs, and looping over all inputs is not practical, due to Python's well-known sluggishness with loops. In CLAASP, this issue is tackled through different options, namely Python vectorized implementations, and C code generation. A further speedup, to appear in future versions, is CUDA-based parallel evaluation with GPUs.

3.1 Base Evaluator in Python and C

One essential functionality for a cryptographic primitive is being able to evaluate it over some input. In CLAASP, users can create a cipher object and call an evaluation method to evaluate a particular input. This functionality is also used internally in CLAASP by some of the modules, to run, for example, avalanche or statistical tests. By inserting output components in the cipher, users may also intercept and visualize the intermediate output of any desired component or group of components during the evaluation. Both the Python code or the C code[3] to evaluate a cipher are generated automatically by scanning the list of the cipher components, generating the corresponding block of code and linking each block in the correct order. The automatically generated code is not optimized. However, it provides an easy way for users to export the code for quick prototyping. The optimization of the automatically generated code is planned for future versions of the library.

3.2 Vectorized Implementations

A *vectorized* implementation of a function handles multiple inputs, presented as a vector, at the same time. In Python, the NumPy library allows to parallelize function evaluations, by running the function on an *array* of inputs, rather than a single input. NumPy arrays are typed and homogeneous, which, combined with NumPy's optimisations, enables significant performance gains compared to Python native lists.

The cipher object provides the NumPy-based *evaluate_vectorized* function, which can be used for the fast evaluation of an array of inputs. The inputs are specified as NumPy arrays, of 8-bit unsigned integer values, arranged as one

[3] When possible a word-oriented implementation is used, opposed to a slower bit-oriented implementation for primitives with mixed type of components.

column per data point. The return value is encoded as a list containing a single NumPy array of 8-bit unsigned integer values, this time arranged as one row per data point. The choice of using bytes stems from NumPy's lack of support for integers over 64 bits, and the ease to generate such format automatically.

3.3 Performance Evaluation

The performance of the primitives' evaluators are compared in Table 3. Note that, since the code are auto-generated and not optimized, the table does not indicate the efficiency of the specified primitives. Interestingly, single evaluation in NumPy is usually faster than the single evaluation using Python or even C. Yet, it is convenient to keep Python and C for very few evaluations as the input/output format is more intuitive as it is represented by an integer. Finally note that the time reported for C also include the time to compile the C program.

	block size	round	Python		C		Vectorized		
			1	10^3	1	10^3	1	10^3	10^6
SKINNY	128	40	4.32	3546.98	2.87	1545.29	1.22	1.10	14.27
AES	128	10	0.80	739.26	1.59	765.86	0.27	0.28	2.79
HIGHT	64	32	0.83	848.06	1.53	627.53	0.11	0.22	1.33
LEA	128	24	1.51	1391.93	1.70	771.62	0.08	0.08	4.77
LowMC	128	20	3.05	2922.92	2.50	1710.59	1.80	2.24	907.42
Midori	128	20	1.53	2093.48	2.24	1204.19	0.64	0.80	105.55
SIMON	128	68	3.19	3163.11	1.37	755.87	0.09	0.10	8.18
Speck	128	32	1.46	1467.64	0.95	432.67	0.05	0.06	6.09
Raiden	64	16	0.78	770.91	0.94	433.65	0.05	0.08	7.75
Sparx	128	8	1.68	1726.98	1.24	810.48	0.22	0.24	5.89
TEA	64	32	1.12	1127.31	0.99	439.49	0.09	0.09	8.66
XTEA	64	32	1.00	1052.29	0.94	443.84	0.06	0.07	7.20
Threefish	256	72	3.76	3883.64	0.84	778.91	0.19	0.19	29.57
ASCON	320	12	3.05	2050.94	7.23	416.29	0.17	0.07	4.25
Gift	128	40	1.85	1565.64	1.40	799.74	0.17	0.18	8.38
Keccak	200	18	2.20	1989.07	1.63	605.79	0.26	0.24	2.80
PHOTON	256	12	1.18	942.26	1.28	703.64	0.31	0.28	22.46
Spongent-π	160	80	7.77	7916.27	3.97	3715.62	5.07	6.80	2300.32
TinyJAMBU	128	32	0.43	411.65	1.02	533.11	0.08	0.07	3.51
Xoodoo	384	12	2.06	2096.78	1.23	701.80	0.20	0.20	4.32
SPARKLE	256	10	1.75	1874.37	1.38	780.80	0.09	0.09	6.05
GIMILI	384	24	3.31	3053.50	1.03	558.23	0.17	0.16	7.05
Grain core	80	160	0.93	909.32	1.57	847.19	0.23	0.22	11.03
ChaCha	512	20	1.19	1144.58	1.19	517.94	0.06	0.07	5.42
SHA-1	160	80	2.14	1926.06	1.34	418.85	0.12	0.13	10.45
SHA-2	256	65	4.20	4515.25	0.97	545.93	0.18	0.20	20.68
MD5	64	64	1.36	1453.34	1.11	610.73	0.08	0.09	7.27
BLAKE	512	28	5.26	4651.17	1.62	545.44	0.32	0.31	22.79
BLAKE2	1024	12	5.49	5719.36	0.90	528.41	0.27	0.32	39.54

Table 3: Primitives evaluator performance in CLAASP with 1, 10^3 and 10^6 inputs. The timings are in seconds.

4 Library: test modules

In this section, we describe all automated analysis modules that are currently supported in CLAASP. Many of the analysis tools presented here are derived from differential and linear cryptanalysis [12], the cornerstones of modern symmetric primitives evaluation. Let $S_K(X)$ be a symmetric primitive; differential cryptanalysis focuses on the probability, over all inputs, for a difference δ to propagate to γ, *i.e.,* X, $Pr[S_k(X) \oplus S_K(X \oplus \delta)] = \gamma$. Conversely, linear cryptanalysis focuses on the correlation for a linear mask Γ_0 to propagate to Γ_1, $Pr[S_k(X) \cdot \Gamma_1 = X \cdot \Gamma_0]$. In both cases, the cryptographer is interested in finding *differences* (resp. *masks*) for which this probability (resp. correlation) is high.

4.1 Component analysis

This module allows the visualization of the "quality" of certain properties of the components used in a cipher, by means of radar charts. These properties include: Boolean function properties (number of terms, algebraic degree, number of variables, whether the Boolean function is APN or balanced), vectorial Boolean function properties (differential uniformity, boomerang uniformity, nonlinearity, etc.), linear layer properties (order, linear and differential branch number).

More precisely, this module allows to retrieve the list of the components used in the cipher, the number of occurrences of each component, and the corresponding properties. For example, for 2 rounds of AES-128, the user will notice that a XOR operation between 2 inputs of 128 bits each occurs 3 times. If one considers XOR output bits expressed as a Boolean function, then each of these XOR components has an algebraic degree of 1 with 2 terms, and 2 variables.

For a better visualization, this module can also plot the results of the observation in a radar chart, such as the one presented in Figure 3 for the S-Box of AES. A full list of the radar charts of the components of 2 rounds of AES is given in the Appendix C.

4.2 Statistical and avalanche tests

Statistical tests Statistical tests aim at evaluating the randomness of a set of bit strings. Such tests were applied to evaluate AES candidates [51,52,7] through the NIST Statistical Test Suite (NIST STS) [48,6]. In addition, tools such as Diehard [37], or its successor Dieharder [15], provide additional statistical tests. CLAASP integrates both the NIST STS and Dieharder suites within the statistical test module. The statistical test process is divided into two phases, dataset generation and analysis.

Dataset generator The datasets used in CLAASP which covers keyed primitives are defined in [51]. Keyless primitives datasets are somehow special cases of the keyed ones. As an example, the illustration of the avalanche dataset generator is shown in Appendix B. The dataset generator, which returns a set of bit strings, is based on CLAASP's vectorized evaluation method.

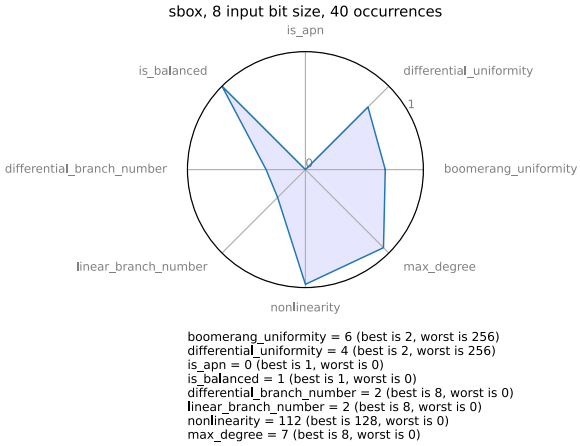

Fig. 3: Observation of the open-source of AES as a radar chart

Statistical test tools The results of NIST STS and Dieharder are exported into a file and additionally returned as a Python dictionary for easy integration into scripts. CLAASP also features visualization of the results, as shown in Figure 4.

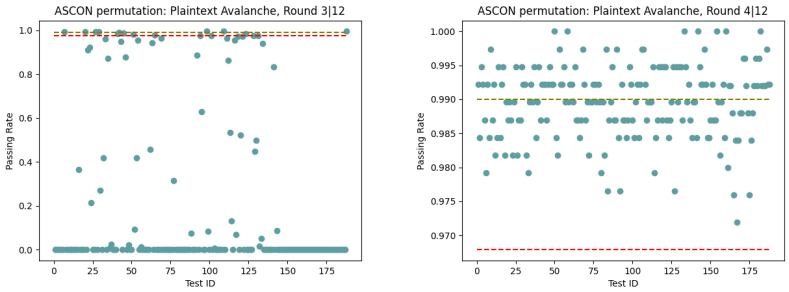

Fig. 4: CLAASP plot for the 188 NIST statistical tests pass rate of ASCON round 3 and round 4.

Performance and experiments To generate the plaintext avalanche test for all supported primitives (191 Gigabits), it takes 4 hours. For a 100 Mbits dataset, it takes around 30 minutes to finish the NIST statistical tests. Figure 5 shows the number of tests that pass for each round of ASCON (left) and the percentage of the rounds needed to pass all statistical tests with respect to the 9 possible datasets for several primitives.

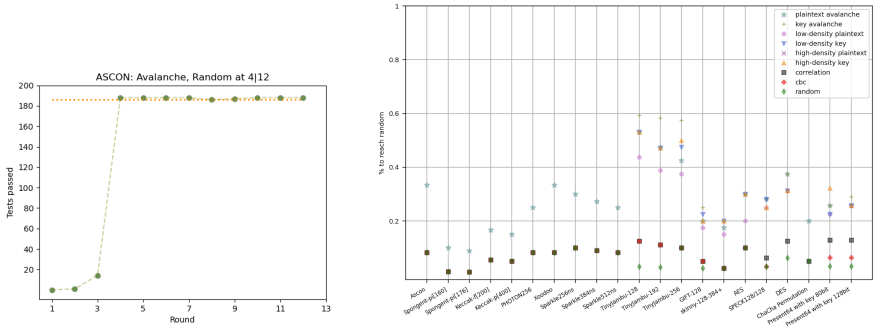

Fig. 5: Randomness graphs of ASCON generated by CLAASP. Left side is the statistical test result of avalanche dataset. Right side are all the statistical results of ASCON compared with other primitives.

Avalanche tests This module focuses on the avalanche properties, presented in [19], of a symmetric iterated primitive. These tests evaluate the cipher with respect to three different metrics that represent what usually the literature calls *full diffusion*, *avalanche* and *strict avalanche* criteria. The goal of the tests is to compare how these metric evolve with respect to the computational cost of the round function; each metric is expected to satisfy a certain criterion (namely to pass a threshold) after a few rounds.

Measure avalanche criteria The results of the avalanche tests allow a user to: check if a criterion is satisfied at a certain round for a specific input bit difference; obtain the worst input bit differences, that are the input bit differences for which the criterion is satisfied after more rounds than the rest of the input bit differences; obtain the value of the criterion for a specific round and a specific input bit difference; obtain the average value of the criterion among all the input bit differences for a specific round.

For better visualization, CLAASP can generate a heatmap graph of the output returned by the avalanche tests. This is illustrated for 5 rounds of ASCON320 in Appendix D, which represents the heatmap graphs for the entropy criterion when the input bit difference has been injected in position 0. Each cell of this figure has a lighter shade of green if the entropy based on the probability of flipping of the underlying bit is close to 1, with a darker shade of red otherwise.

Performance Figure 6 reports the timings of the avalanche tests for 5 rounds of some popular ciphers, using the vectorized evaluation function, up to 50,000 samples; all tests run globally in less than 5 minutes.

Truncated Differential Search This module offers a range of features, including the ability to easily discover truncated differentials with only one active bit in both the input and output states. Such differentials, when paired with linear

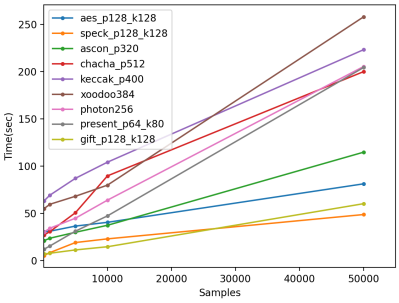

Fig. 6: Timings of the avalanche tests for five rounds of popular ciphers

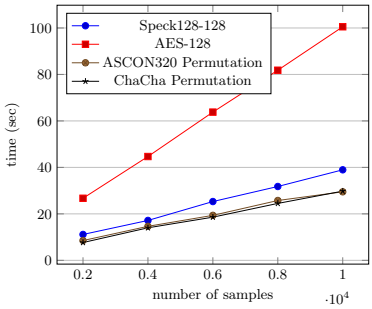

Fig. 7: Time comparison of the CAF computation for Speck128-128, AES-128, the iterated permutation in ASCON320 cipher, and the iterated permutation in ChaCha cipher, fixed to 5 rounds each for several random samples.

approximations, can be very useful for increasing the correlations of differential-linear distinguishers. For instance, we successfully used this module to rediscover the truncated differential outlined in [3], which has been cited and studied extensively in various papers (such as [21]). To view the script we used to rediscover this differential, you can refer to the accompanying repository for this paper.

4.3 Constraint Solvers for Differential and Linear Cryptanalysis

The search for strong differential or linear properties often relies on *trails*, *i.e.*, round by round propagation of the property under study; the final probability of the trail, under the Markov assumption that all round keys are independent, is computed as the product of the probabilities of each round. Finding such trails is a difficult combinatorial problem, traditionally handled with Matsui's algorithm [38] variations. In recent years, the use of automatic solvers, such as Mixed Integer Linear Programming (MILP), SAT, SMT, and more recently Constraint Programming (CP), have become a simpler alternative. These tools have the benefit of being extensively studied and optimized by the AI and OR communities, so that the focus shifts from implementing a search algorithm to modeling the problem properly. CLAASP can automatically generate MILP, SAT, SMT and CP models for differential and linear cryptanalysis, from a primitive's description.

Differential and Linear Models for ARX Ciphers In order to implement the search for differential and linear trails on ARX ciphers, we utilized the techniques outlined in [18] and in [35]. Specifically, we implemented the MILP constraints described in those papers for the ARX components and were able to

successfully replicate the trails reported therein. In addition to the MILP constraints described there, we also implemented SAT, CP, and SMT equivalent constraints not only for ARX ciphers but also for SPN ciphers. To accelerate the search for trails using SAT techniques, we implemented the sequential encoding method presented in [56] on CLAASP. Moreover, through modeling the cipher evaluation process (as discussed in Section 3) using MILP, SAT, CP, and SMT, we were able to implement the techniques outlined in [49]. Those techniques aimed to verify the validity of differential trails. In particular, by using those techniques, their authors reported some invalid trails presented in [36]. The scripts accompanying this paper demonstrate how we used CLAASP to verify differential trails.

For linear trails on ARX ciphers, we were able to rediscover trails presented in recent papers, such as those presented for two well-studied ciphers, such as Speck and ChaCha. Specifically, we rediscover the linear trails presented at [16] and the linear trails outlined in [8]. The former presents the best attacks against ChaCha reduced to 7 rounds, while the second is a recent paper attacking Speck. Again, the scripts accompanying this paper demonstrate how we used CLAASP to verify these linear trails.

New results Our library supports a range of SAT solvers, including parallel solvers, which we believe is a unique feature not found in other cryptanalysis libraries. By utilizing the CLAASP interface, we were able to search for differential and linear trails using parallel SAT solvers. We managed to find an optimal differential trail for 10 rounds of Speck128-128. This accomplishment was made possible by utilizing the power of 125 AMD EPYC 7763 cores on a Ubuntu machine with 1TB of memory. To confirm the optimality of this trail, we used CLAASP in conjunction with ParKissat [59] to search for a 10-round trail of this version of Speck with a probability weight of 48. It took approximately 2.23 days to obtain as output UNSAT. The script accompanying this paper contains the details of this finding.

Regarding linear cryptanalysis, we obtain a linear trail for Salsa with better theoretical correlation than the one reported in [16]. We start from the same input bit mask described in Lemma 10 and Lemma 11 of [16]. Specifically, we found a trail with a theoretical correlation of 2^{-31} instead of 2^{-34} as described in [16]. This accomplishment was made possible by utilizing the SAT module of CLAASP. We use only 1 AMD EPYC core, and the trail was found in less than 1 minute. We attempt to find a trail with a theoretical correlation of 2^{-30}, but the solver outputs UNSAT. This discovery has the potential to enhance the correlation of the differential-linear distinguisher against Salsa reduced to 8 rounds presented in the aforementioned paper. The reader can reproduce the trail by using the script accompanying this paper.

Differential and Linear Models for SPN Ciphers SPN ciphers use Substitution Boxes (SBoxes) as their non-linear component. In addition, their linear layers can typically be expressed as a matrix multiplication. The representation

of SBoxes in differential search models typically uses its *Differential Distribution Table*, or DDT. The DDT is a 2 dimensional object such that $\texttt{DDT}_{\delta,\gamma} = \frac{\#\{x \in \mathbb{F}_2^n : x \oplus y = \delta, SB[x] \oplus SB[y] = \gamma\}}{2^n}$. Models for linear trails use the Linear Approximation Table (LAT) built in a similar fashion instead. To represent the DDT in SAT, SMT or MILP, a constraint to forbid each invalid triplet $(\delta, \gamma, Pr[\delta \rightarrow \gamma])$ is typically introduced [57]. Techniques such as the Quine-McCluskey algorithm [43,44,39] or the heuristic *Espresso* are used to reduce the number of generated equations. In the case of Constraint Programming (CP), *table constraints* permit to directly enforce the constraint $(\delta, \gamma, Pr[\delta \rightarrow \gamma]) \in \texttt{DDT}$, where DDT is the set of valid tuples [25]. These techniques are implemented in CLAASP.

Differential and Linear Trails Search CLAASP exposes functions to generate, for either paradigm among SAT, SMT, MILP or CP, a model for the search of differential or linear trails. More specifically, CLAASP implements the generation of models to find: (1) One optimal (highest objective value) trail; or (2) All trails for which the objective value is within a fixed range. The functions generating these models take, as an additional parameter, a list of variables for which the values are to be fixed, and the corresponding values. Single-key trails are found by setting the key variables to zero, while related-key trails are found by placing no restrictions.

Application to Differential Probability and Linear Hull Evaluation Trails with identical input and output can be combined into a *differential* or a *linear hull* with higher probability than single trails. Observing differentials (or linear hulls), rather than single trails, can result in attacks on more rounds; the gap between the two cases is studied in [1]. CLAASP permits the enumeration of trails with fixed variables, so that the evaluation of the probability of a differential, by enumerating all trails better than a certain weight with a fixed input and output, is straightforward.

Application to Impossible Differential and Zero-correlation Linear Approximation Search Impossible differentials, as well as their counterpart in the linear world, zero-correlation linear hulls, are also of interest to cryptographer. CLAASP implements a technique similar to [18] to find such properties; the main idea is to fix an input and output difference, and to look for a trail with a solver; if no trail is found, then we have an impossible differential.

As an example, we reproduce the 3 impossible differentials for 6 rounds of SPECK32/64 presented in [47] in less than 30 seconds using the SMT model.

4.4 Continuous diffusion tests

In [17], Coutinho *et. al*, describe a framework to construct continuous functions from Boolean ones. Assuming independence, these functions provide the probability or correlation between the output bits being 1 based on an input of real numbers that represent the probability of each input bit being 1. They are also

able to generalize various cryptographic operations, leading to the creation of continuous versions of entire cryptographic algorithms.

Upon these continuous versions of cryptographic algorithms, they construct three metrics, namely Continuous Avalanche Factor (CAF), Continuous Neutrality Measure (CNM), and Diffusion Factor (DF). The CAF is the continuous equivalent of the avalanche factor [20], which measures the proportion of output bits that change for input Hamming distances equal to 1 on average; this proportion is expected to be 0.5 for a random permutation. In the continuous version, since there is no concept of Hamming distance, the Euclidean Distance (ED) is used to evaluate CAF. The idea behind CAF is to measure how much the output of a continuous version of an algorithm changes, on average, when the input bit's probability of being equal to 1 of a chosen random bit is slightly altered by a small real number λ. In other words, we need to evaluate, on average, the behavior of the ED between the outputs $y_0 = f(x_0)$ and $y_1 = f(x_1)$ for $x_0, x_1 \in \mathbb{B}$, when the ED of x_0 and x_1 is lesser than λ. It is expected for "good ciphers" that even with small values of λ, higher values on the ED of the propagation of these alterations, on average. For more information on the other two metrics (CNM and DF), see [17].

Within the continuous diffusion test module, CLAASP implements the continuous versions of several cryptographic operations, following Theorem 1 and Definitions 1 to 12 from [17], which can be combined to obtain the continuous version of entire primitives.

The performance of Speck128-128, AES-128, the iterated permutations in ASCON320 and the iterated permutation in ChaCha with respect to CAF, subject to $\lambda = 0.001$, is presented in Table 4. For the iterated permutation in ChaCha, a single round is equivalent to four half-quarter rounds in the table. Figure 7 displays the timing comparison of these ciphers for various sample sizes used in computing CAF. The experiments were conducted on a Ubuntu 22.04.1 machine equipped with 256 AMD core processors and 1TB of memory.

When comparing Table 4 to Table 2 in [17], we observed slight variations in the CAF values reported in Figure 7 compared to the values presented in [17]. This difference is due to our use of the Python Decimal package to handle small numbers, while the implementation of Table 2 in [17] employed the Relic library [2]. For instance, for five rounds of AES-128, we obtained a value of 0.777, whereas [17] reports 0.734.

4.5 Algebraic module

The objective of this module is to study the algebraic properties of a specified cipher and test if it is secure against algebraic attacks. In algebraic cryptanalysis, breaking a block or stream cipher, essentially involves solving a set of multivariate polynomial equations over a finite field $\mathbb{F}_q$, which often has one or a few solutions in $\mathbb{F}_q$. But solving a system of multivariate random polynomials is generally a hard task.

This module generates a multivariate algebraic polynomial system corresponding to the "sbox", "linear_ layer", "mix_column", and "constant" compo-

Rounds	AES	ASCON	ChaCha	Speck
1 to 4	0	0	0	0
5	0.777	0.008	0	0
6	0.971	0.761	0.019	0
7	0.999	0.962	0.257	0.002
8	-	0.998	0.694	0.067
9	-	0.999	0.939	0.318
10	-	-	0.993	0.613
11	-	-	-	0.828
12	-	-	-	0.941
13	-	-	-	0.98
14	-	-	-	0.997

Table 4: Continuous Avalanche Factor comparison for AES-128, ASCON320 permutation, ChaCha permutation, and Speck128-128 using $\lambda = 0.001$.

nents, together with the "XOR", "AND", "OR", "SHIFT", "ROTATE", and "NOT" operations. It provides a set of polynomials representing the components and operations involved in a particular input cipher along with connection polynomials, which represent the links between the various components. From the polynomial system, it is possible to retrieve its algebraic degree, number of polynomials, and number of variables in order to analyze its algebraic features and the difficulty of solving the system. The security of a cipher (up to a particular number of rounds) against algebraic attacks could be evaluated by solving the corresponding algebraic system up to that many rounds. The module now offers a method to test it by solving the system in a time limit using only the Gröbner basis computation [14] available on the SAGE platform.

The algebraic module is currently in its preliminary stage and will be improved in upcoming releases.

4.6 Neural aided cryptanalysis module

Following Aron Gohr's seminal paper at CRYPTO'19 [26], improving the state-of-the-art differential cryptanalysis result on the SPECK32-64 cipher, neural-based approaches to cryptanalysis have gained traction in the community. In Gohr's approach, a neural network is trained to distinguish, from an input composed of 2 ciphertexts in binary format, whether they correspond to the encryption of two unrelated plaintexts, or of two plaintexts with a given XOR difference. CLAASP implements such approaches, and other neural-based analysis tools.

Single ciphertext approach: Neural Network Black box Distinguisher Tests Differential neural cryptanalysis examines pairs of plaintexts. The black box test implemented by CLAASP takes a step back, and focuses on single ciphertexts. Built from [10], this test investigates whether a neural network can find a relation between the inputs of a primitive and its output. The neural network is trained to label samples $[P, C]$ as 0 (if Y is random) or 1 if Y is the output of a given component of the primitive. This test returns the accuracy of distinguishing a ciphertext coming from an instance of the cipher with a certain key and the output of a random permutation. After a certain amount of rounds,

the accuracy will converge to 0.5, meaning that the black box distinguisher is not able to distinguish the cipher output from random.

Pairs of Ciphertexts: Neural Network Differential Distinguisher Tests This test implements the neural distinguisher described by Gohr in [26], with the simplified training pipeline described in [9], where a depth-1 neural distinguisher trained on n rounds is iteratively retrained for $n+1, \ldots n+t$ rounds, where $n+t$ is the first round where the neural distinguisher fails to learn. Specifically, the neural distinguisher is trained to label samples $[C_0 = E_K(P_0), C_1 = E_K(P_1)]$ as 0 (if $P_0 \oplus P_1$ is random) or 1 if $P_0 \oplus P_1$ is a given, fixed value δ.

Helper Function: Truncated Differential Search For Neural Distinguishers The previous test relies on an input difference with good propagation properties. It has been observed [26] that the input difference that starts the most likely differential does not result in the best neural distinguishers. Further research [11] suggested differential-linear properties, based on highly likely truncated differentials a few rounds before the studied round, may be at play. This assumption was used as the basis to an input difference search technique [9], where a genetic algorithm explores potential input differences and ranks them based on the cumulative biases of the resulting output difference bits. This algorithm is implemented by CLAASP, and can be used to retrieve Gohr's original input difference.

These functions are illustrated in the supplementary material. The script first runs the black box test on 1 round of Speck64, then runs the input difference search for Speck64, and trains Gohr's neural network using the optimal difference returned by the optimizer. Note that the optimizer is not deterministic, and its parameters are adapted for a reasonably fast execution time for demonstration purposes; therefore, it may, in some rare instance, fail to find the optimal input difference $0x00400000$.

5 Benchmark comparison with other libraries

In this section we compare CLAASP to similar libraries.

5.1 TAGADA

The TAGADA library focuses on the differential cryptanalysis of word-oriented ciphers with an SPN structure. For such ciphers, it is common (e.g, [13]) to divide the search into two steps. The first step aims to find truncated differential characteristics through the minimization of the non-linear operators utilized in this process. The second step enumerates the truncated differential characteristic passing to the minimum number of non-linear operators found in the previous step. It was shown [25] that the filtering of the first step may be insufficient so that too many solutions are left to explore in step 2. More advanced filtering is,

therefore, beneficial and enables scaling to more rounds. This is done through additional constraints that capture linear dependencies between variables during step 1. The TAGADA library generalizes such constraints, making it very efficient for word-based ciphers. These techniques are not, at the moment, included in CLAASP, so TAGADA is expected to perform significantly better on word-based characteristics search. We are planning to include these additional constraints in the next releases of CLAASP.

On the other hand, the basic version of the first step, searching for the minimum number of active SBoxes of SPN ciphers, is implemented in CLAASP. TAGADA implements the option of running the first step search with the basic technique used in CLAASP; we attempted to run the search for 3 and 4 rounds of AES-128, but we were not able to reproduce the known results from [31,41,24] with TAGADA, which reported 2 and 7 SBoxes respectively, rather than the expected 3 and 9. On the other hand, CLAASP returned the expected solution. Note that TAGADA can only generate MiniZinc models, while CLAASP allows to directly write the model in the language supported by the solvers (including a MiniZinc interface).

5.2 CASCADA

We make a comparison between CLAASP and CASCADA by taking the time they spend searching for optimal characteristics in the single-key scenario and in the following ciphers: Speck32-64, Speck64-128 and LEA. Specifically, in Figure 12 (see Appendix E), we show the time spent by CASCADA and CLAASP in the search for an optimal characteristic on across several rounds and using the following SMT solvers: MathSAT, Yices, and Z3. In order to get timings for every round we take the average amount of five repetitions. The experiments were conducted on a machine running Ubuntu 22.04.1, equipped with 256 AMD core processors and 1TB of memory. As observed, while using the Yices solver, the CLAASP library performs similarly to CASCADA. Nevertheless, for MathSAT and Z3, CLAASP exhibits better performance.

In terms of functionalities, CASCADA includes the search for impossible differentials, in particular through the method of [18]. In this method, the variables corresponding to the input and output differences of a differential are fixed to a value that the analyst wants to test, and the solver is run. If the solver finds a solution, then the differential is possible; otherwise, it is impossible. In this method, the analyst usually tests all the pairs of input and output differences of low hamming weight (typically 1). A similar technique can be used for zero-correlation linear approximations. Using this method, CLAASP can for instance retrieve the 17-rounds impossible differential on HIGHT presented in [18] in under 10 minutes on a single core.

6 Conclusion

The fast-paced publication of new cryptanalysis techniques, of improvement of existing ones, makes it crucial to have an efficient way to test a given property

on a large number of primitives; CLAASP aims to fulfill this need. In its current form, it already offers a vast array of cipher analysis techniques, from component analysis, to automatic models building, through neural cryptanalysis. Future releases will add more primitives, as well as further analysis techniques, such as guess-and-determine or meet-in-the-middle techniques. More importantly, the CLAASP team is strongly committed to include new state-of-the-art improvements to automated techniques as it evolves, and provide a one-stop shop to evaluate, compare and experiment with modifications on existing methods. Finally, the open-source status of the library is an invitation to researchers from the community to not only use, but also improve CLAASP as they see fit.

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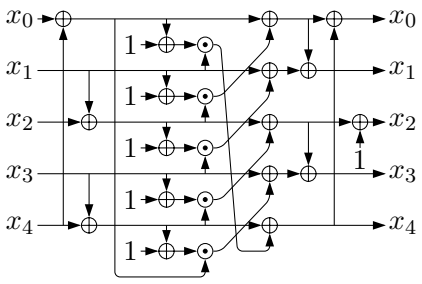
A Two cipher representations of ASCON

The nonlinear layer of ASCON permutation can be represented as circuit made of word operation components (XOR, AND and NOT) or with a layer of parallel S-boxes. This is detailed in Figure 8.




```
ASCON Sbox = [
    0x04, 0x0b, 0x1f, 0x14,
    0x1a, 0x15, 0x09, 0x02,
    0x1b, 0x05, 0x08, 0x12,
    0x1d, 0x03, 0x06, 0x1c,
    0x1e, 0x13, 0x07, 0x0e,
    0x00, 0x0d, 0x11, 0x18,
    0x10, 0x0c, 0x01, 0x19,
    0x16, 0x0a, 0x0f, 0x17
]
```

Fig. 8: Two equivalent cipher representation in ASCON. The left figure is the circuit that represents ASCON S-Box (as stated in [23]). The circuit can be seen as NOT, AND and XOR components acting on 64-bit words. The right side is ASCON 5-bit S-Box as an integer list. The nonlinear layer can be seen as the application of 64 parallel S-Boxes. Both cipher representations are implemented in CLAASP.

B Avalanche dataset generation

Given primitive enc, n-bits plaintext P, key $K = 0$, the mask $mask_i$ with 1 at i-bit and others 0, then the avalanche dataset is the concatenation of $enc_K(P) \oplus enc_K(P \oplus mask_i)$ with different P as shown in Figure 9.

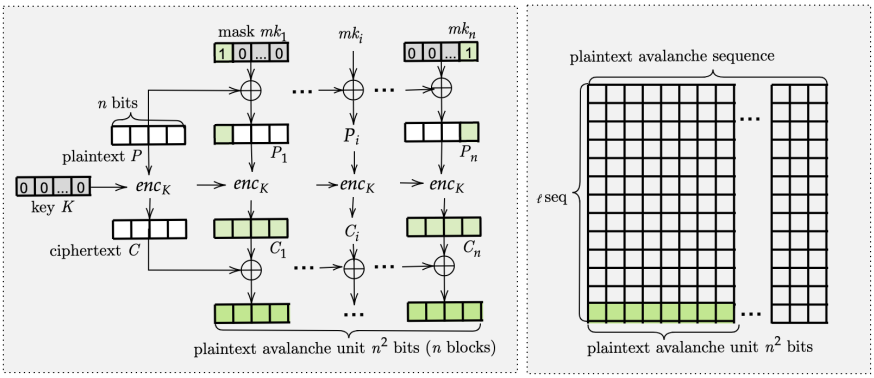


Fig. 9: Illustration of avalanche dataset generation.

C AES as radar charts

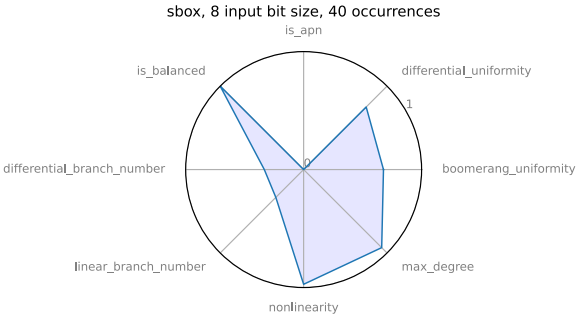
See Figure 10.

D Heatmap of avalanche entropy vectors

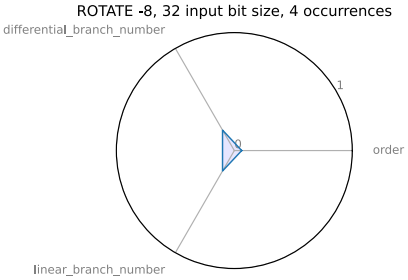
See Figure 11.

E Time comparison CASCADA and CLAASP

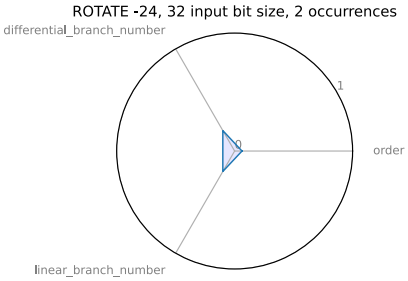
See Figure 12.



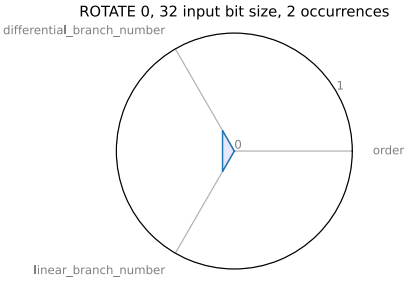
boomerang_uniformity = 6 (best is 2, worst is 256)
differential_uniformity = 4 (best is 2, worst is 256)
is_apn = 0 (best is 1, worst is 0)
is_balanced = 1 (best is 1, worst is 0)
differential_branch_number = 2 (best is 8, worst is 0)
linear_branch_number = 2 (best is 8, worst is 0)
nonlinearity = 112 (best is 128, worst is 0)
max_degree = 7 (best is 8, worst is 0)



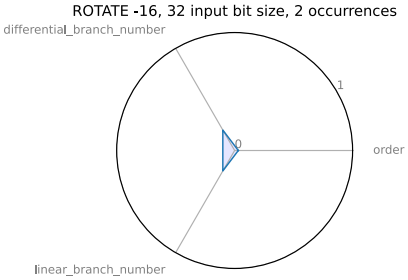
order = 4 (best is 4294967295, worst is 1)
differential_branch_number = 2 (best is 32, worst is 0)
linear_branch_number = 2 (best is 32, worst is 0)



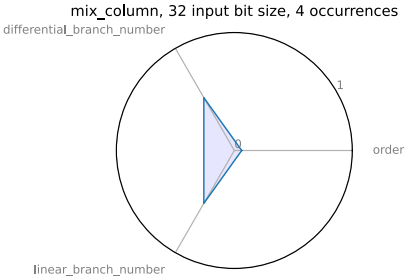
order = 4 (best is 4294967295, worst is 1)
differential_branch_number = 2 (best is 32, worst is 0)
linear_branch_number = 2 (best is 32, worst is 0)



order = 1 (best is 4294967295, worst is 1)
differential_branch_number = 2 (best is 32, worst is 0)
linear_branch_number = 2 (best is 32, worst is 0)



order = 2 (best is 4294967295, worst is 1)
differential_branch_number = 2 (best is 32, worst is 0)
linear_branch_number = 2 (best is 32, worst is 0)



order = 4 (best is 4294967295, worst is 1)
differential_branch_number = 6 (best is 32, worst is 0)
linear_branch_number = 6 (best is 32, worst is 0)

Fig. 10: AES main components as radar charts. The outer region of the radar represents the best value for any property.

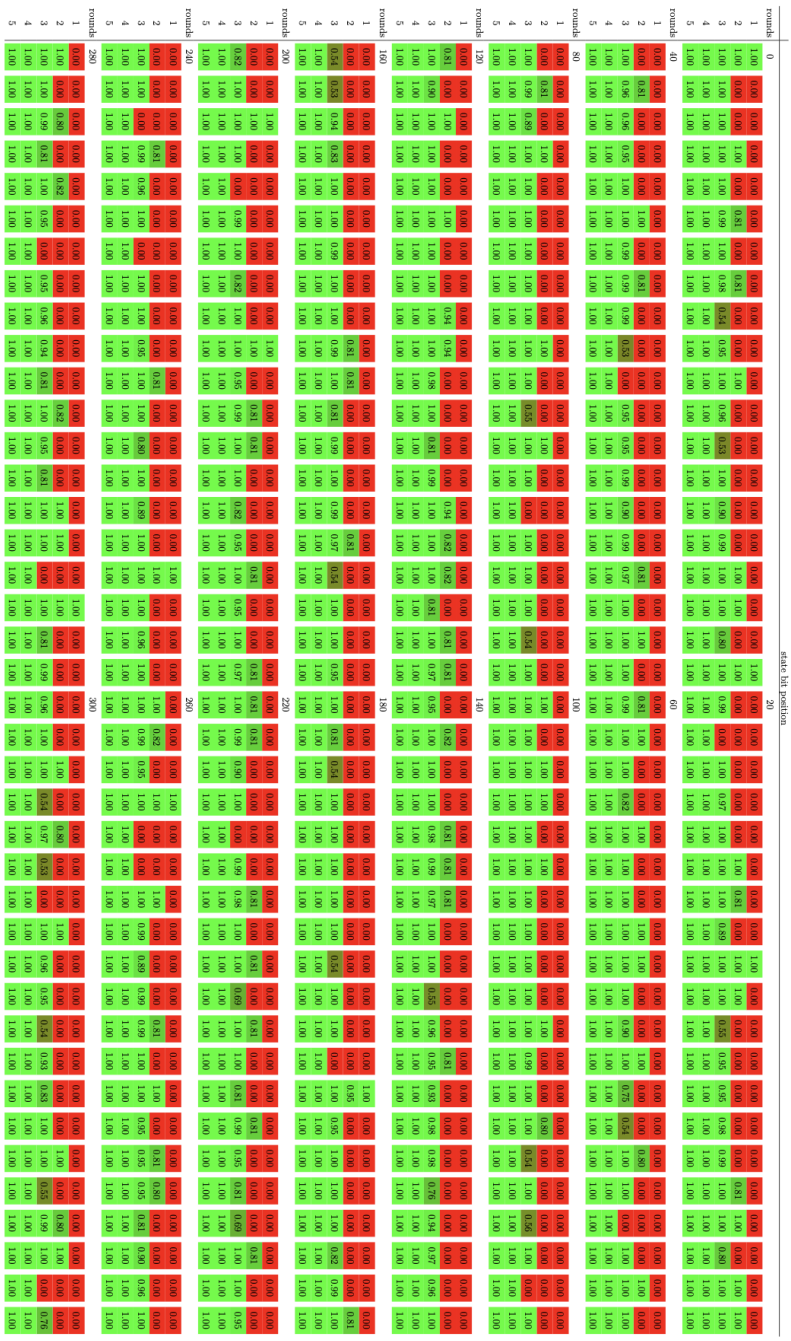


Fig. 11: ASCON320 - avalanche entropy vectors - difference injected in position 0 of plaintext with 10000 samples

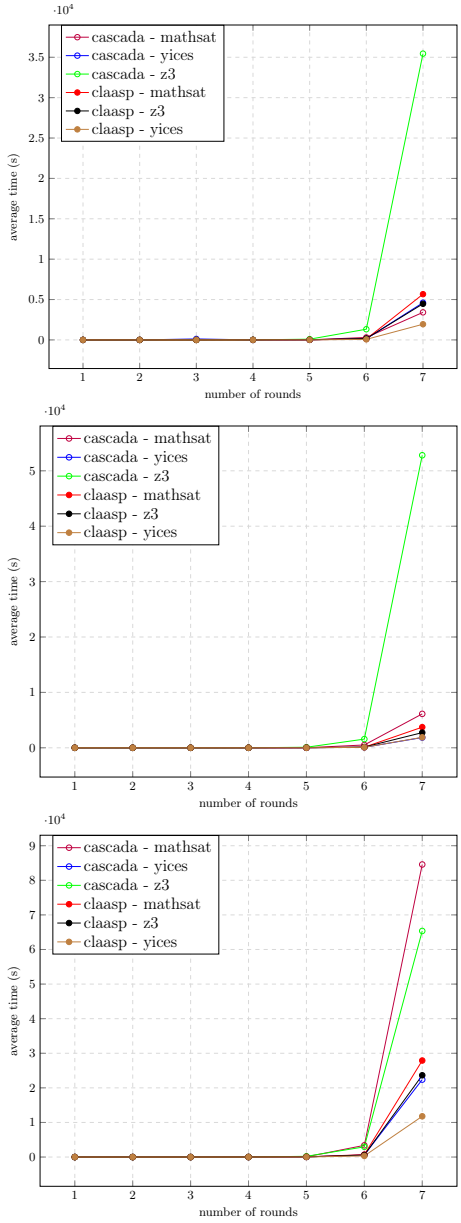


Fig. 12: Time comparison CLAASP vs CASCADA to search for optimal differential characteristics on Speck32-64 (left), Speck64-128 (middle) and LEA128-128(right), using different SMT solvers.