

## Pitfalls and Shortcomings for Decompositions and Alignment

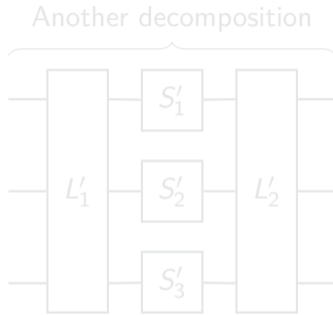
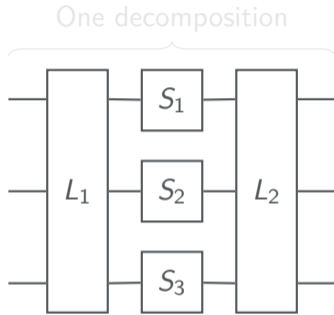
Lyon, April 25

Baptiste Lambin<sup>1,2</sup> Gregor Leander<sup>1</sup> Patrick Neumann<sup>1</sup>

<sup>1</sup>Ruhr-University Bochum

<sup>2</sup>University of Luxembourg

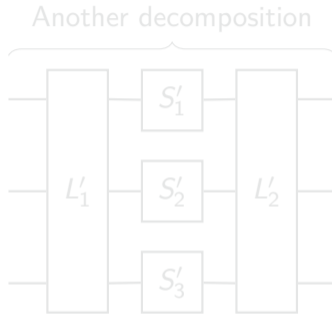
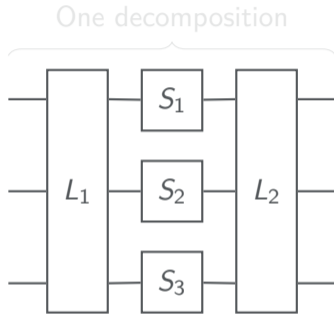
## Decomposition of SPN Round Function



- ▶ Linear layers:  
 $L_1, L_2, L'_1, L'_2$
- ▶ S-boxes:  
 $S_1, S_2, S_3, S'_1, S'_2, S'_3$

- ▶ Security arguments based on decomposition
- ▶ Example: Bound probability of differential characteristic by counting active S-boxes
- ▶ Potential problem: Result may depend on the decomposition
- ▶ Question: When do multiple decompositions exist?

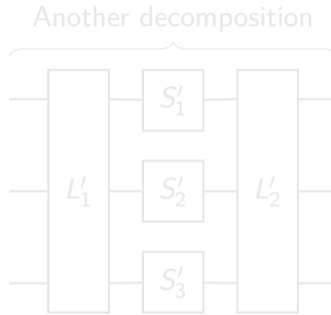
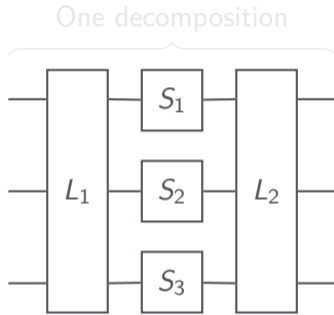
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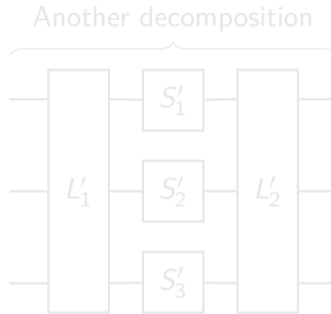
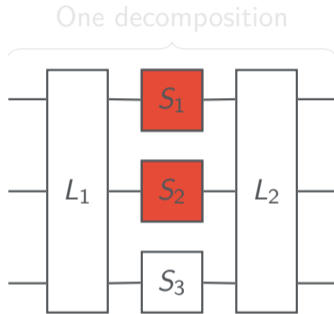
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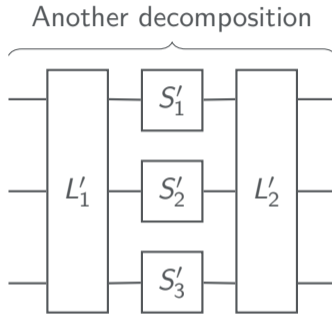
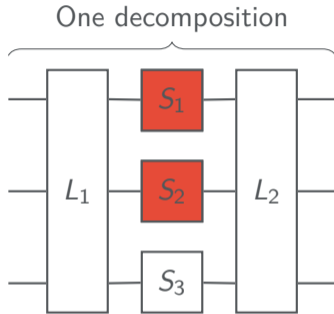
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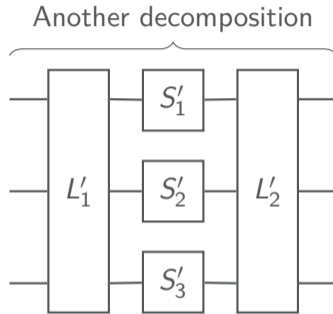
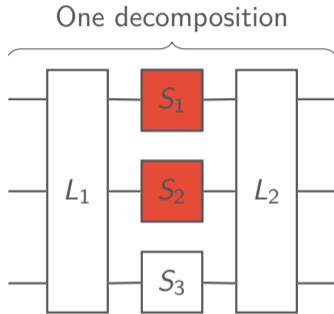
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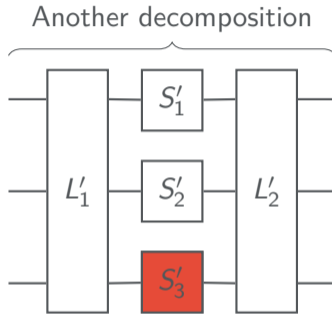
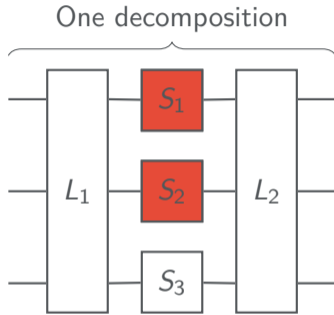
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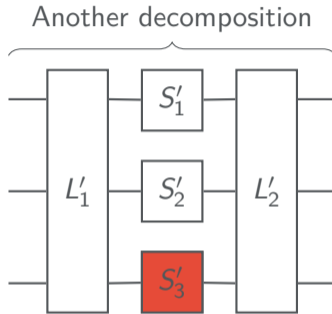
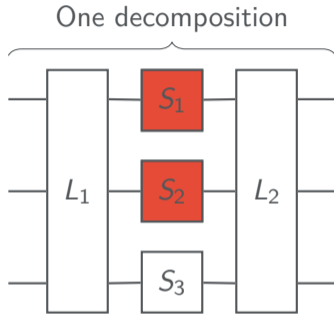


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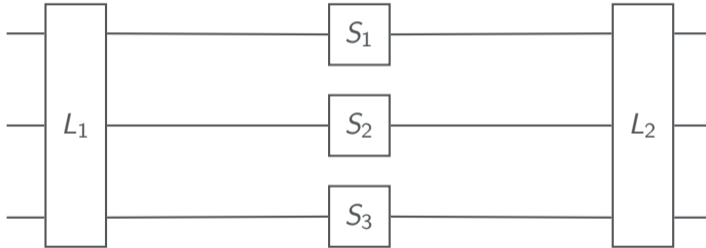


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## Uniqueness of Decompositions

- ▶ Well knows limitations to uniqueness
  - ▶ Reordering the  $S$ -boxes
  - ▶ Linear equivalence of the  $S$ -boxes
  - ▶ Combining  $S$ -boxes

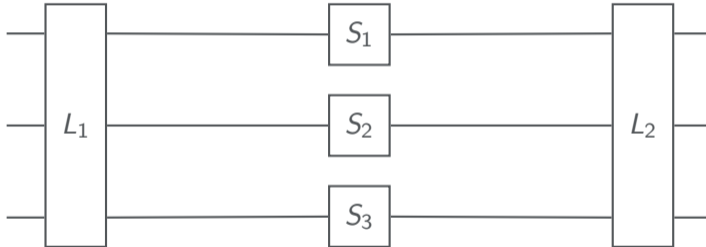


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*When is a decomposition unique (up to those limitations)?*

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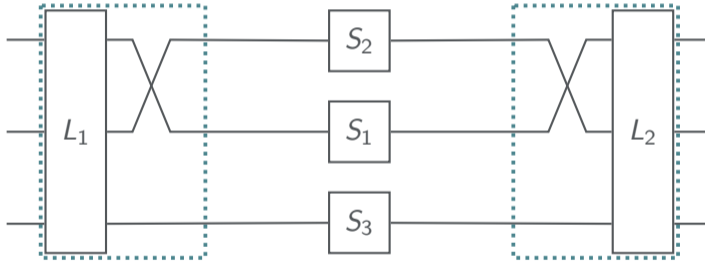


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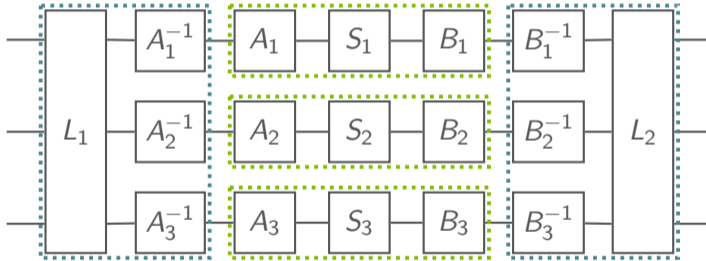


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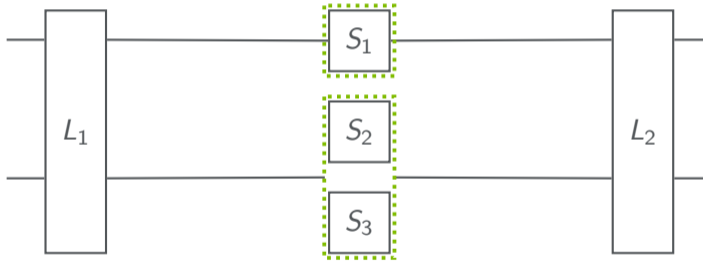


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## Uniqueness of Decompositions

### Definition

*A function  $F$  has maximal differential uniformity if  $F(x) + F(x + \alpha) = \beta$  for some non-zero  $\alpha$ , some  $\beta$  and all  $x$ .*

### Definition

*A function  $F$  has maximal linearity if  $\alpha^T \cdot F$  is affine for some non-zero  $\alpha$ .*

### Main Theorem

*A decomposition is not unique if and only if one S-box has maximal differential uniformity and another one has maximal linearity.*

- ▶ Good, since decomposition is unique for all cryptographically strong S-boxes
- ▶ Easy/efficient to check (for all common S-box sizes)



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## Sketch of Proof

- ▶ Backward direction: If one S-box has maximal differential uniformity and another one has maximal linearity then there exist multiple decompositions

### Lemma

*Functions with maximal differential uniformity are exactly those that are linear equivalent to functions of the form*

$$G \begin{pmatrix} x \\ y \end{pmatrix} = G \begin{pmatrix} x \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ y \end{pmatrix}.$$

### Idea of Proof:

- ▶  $F$  has maximal differential uniformity  $\implies F(x') + F(x' + \alpha) = \beta$  for some  $\alpha \neq 0, \beta$
- ▶ Linearly transform  $F$  to  $G$  such that  $\alpha$  and  $\beta$  correspond to last bit  $y$

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*Functions with maximal linearity are exactly those that are affine equivalent to functions of the form*

$$H \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x \\ h \begin{pmatrix} x \\ y \end{pmatrix} \end{pmatrix}.$$

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- ▶  $F$  has maximal linearity  $\implies \alpha^T \cdot F(x') = \beta^T \cdot x' + c$  for some  $\alpha \neq 0$ ,  $\beta$  and  $c$
- ▶ Add  $F(0)$  to  $F$ , as  $\alpha^T \cdot (F + F(0))$  is linear
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## Sketch of Proof

### Corollary

Functions without unique decomposition are exactly those affine equivalent to ones of the form

$$R \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \left( \begin{array}{c} G \begin{pmatrix} x_1 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ x_2 \end{pmatrix} \\ x_3 \\ h \begin{pmatrix} x_3 \\ x_4 \end{pmatrix} \end{array} \right) \left. \begin{array}{l} \vphantom{\begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix}} \\ \vphantom{\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}} \\ \vphantom{\begin{pmatrix} x_3 \\ x_4 \end{pmatrix}} \end{array} \right\} \begin{array}{l} S\text{-box}(es) \\ \cdot \\ S\text{-box}(es) \end{array} .$$

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- ▶ Other direction: See paper

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## Uniqueness of Decompositions

- ▶ Example without unique decomposition: DEFAULT<sup>1</sup>
- ▶ Have to be careful if S-boxes with maximal differential uniformity and linearity are/can be used!
- ▶ One such case: Alignment
  - ▶ Mysterious property:
    - ▶ Positive & negative cancellations
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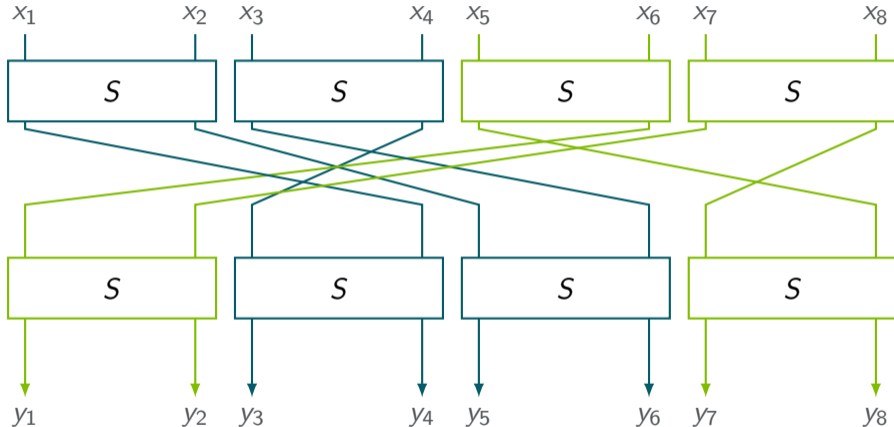
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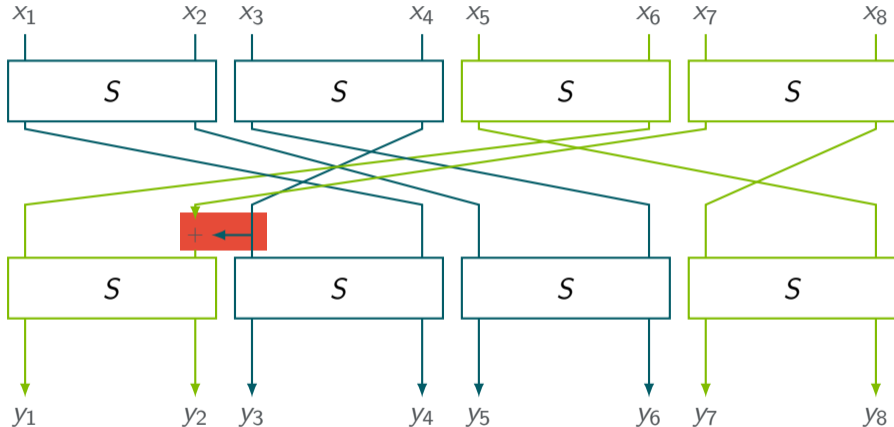
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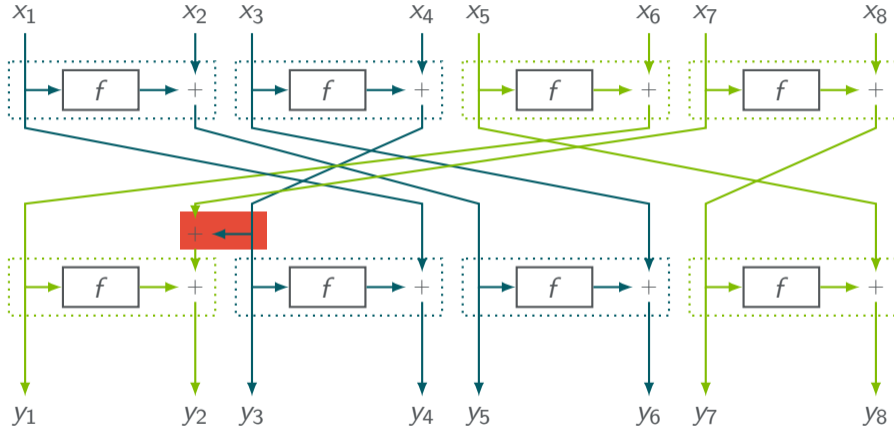
► Function aligned

## Alignment and Non-Unique Decompositions



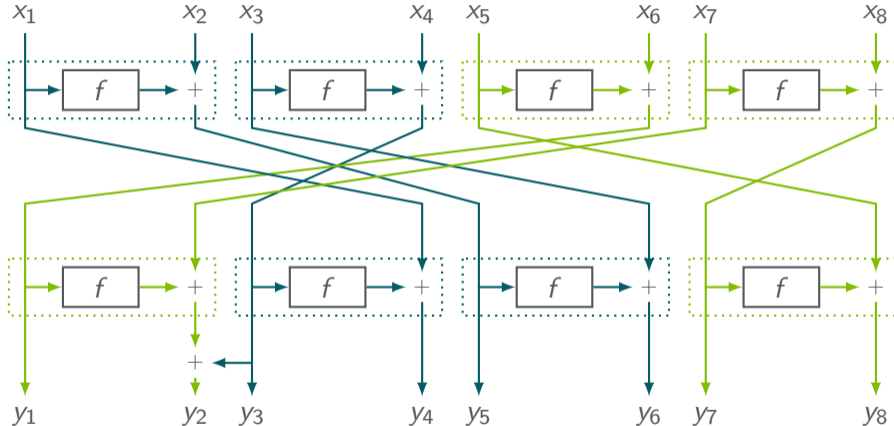
► Function unaligned

## Alignment and Non-Unique Decompositions



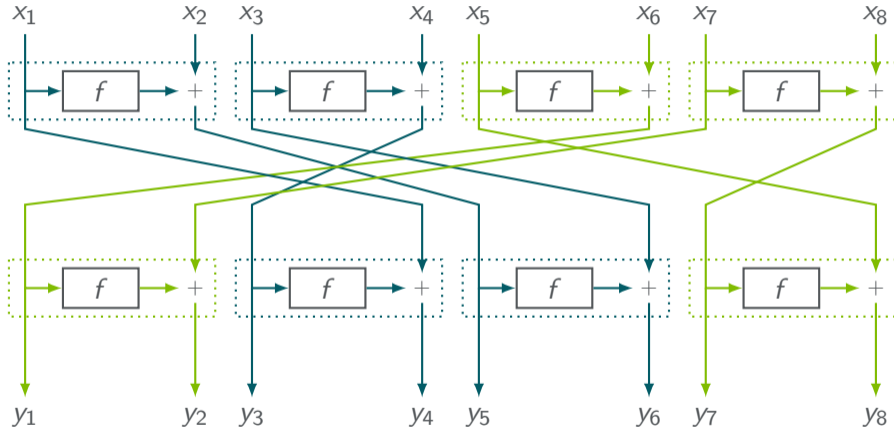
► Function unaligned

## Alignment and Non-Unique Decompositions



► Function unaligned

## Alignment and Non-Unique Decompositions



► Function unaligned, but also aligned?



## Alignment – Impact

- ▶ (CRYPTO'21) compared aligned and unaligned ciphers
- ▶ Infer that alignment might lead to bigger clustering effects
- ▶ Question: Results due to alignment or due to other disparities?
- ▶ Idea: Change bit-permutation of PRESENT
  - ▶ Produce variants that are aligned and ones that are unaligned
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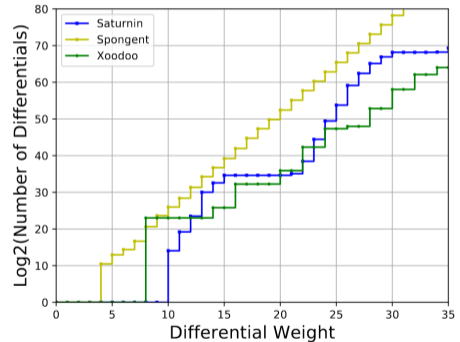
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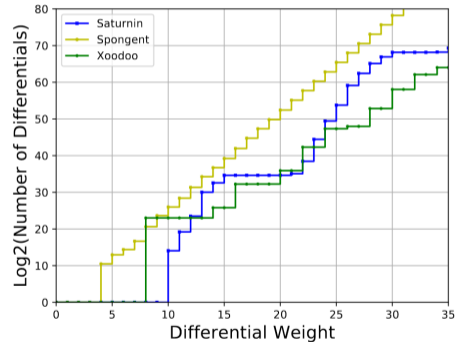


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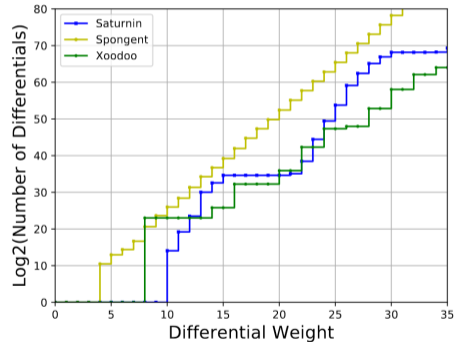


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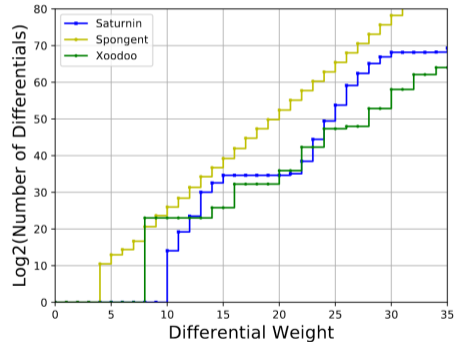


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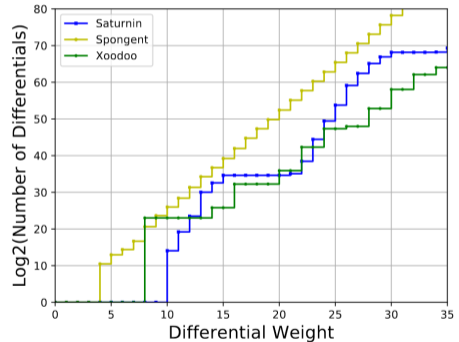


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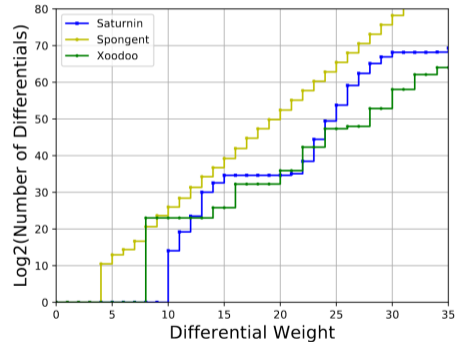


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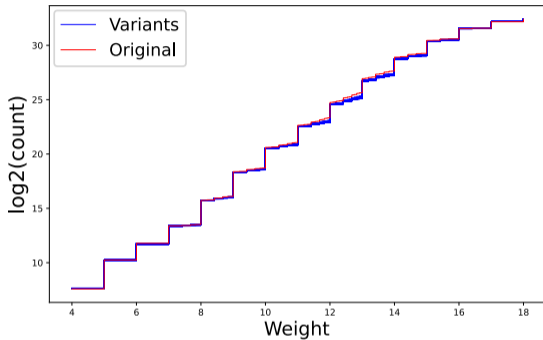
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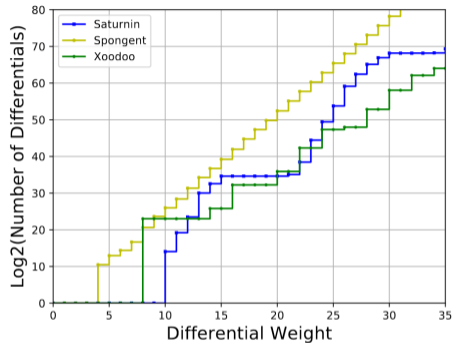
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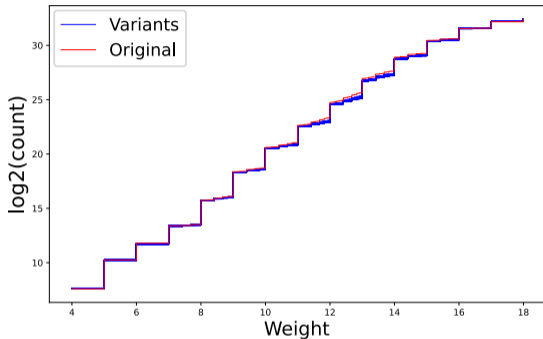
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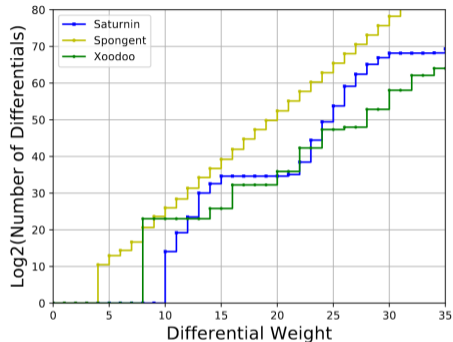
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(CRYPTO'21)

► Overall result: PRESENT variants behave very similar in all aspects

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Saturnin, Spongent and Xoodoo  
(CRYPTO'21)

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- ▶ Still, have to be careful if conditions are not met
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