

Fast MILP Models for Division Property

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Division Trails

Target: $f = f_n \circ f_{n-1} \circ \dots \circ f_1 \circ f_0$

- Search for division trails through f
- Decompose f into smaller layers (e.g. small Sboxes, linear layer, AND, XOR, Copy, ...)
- Valid transitions known for each layer

Accuracy

- $f_0(x, y, z, t) = (xt \oplus y, xt \oplus z)$, $f_1(u, v) = (u \oplus v)$
- Division trail $(1, 0, 0, 1) \rightarrow (1)$ (i.e. $f_1 \circ f_0$ may depend on xt)
- **XOR might lead to accuracy issue**

Searching for Division Trails

Increase accuracy → handle larger layers

- **[Xia+16]**: **Convex Hull** (CH) to describe transitions through Sboxes (practical up to 6 bits)
- **[ZR19]**: exact modelization for **any linear layer**, practical for binary matrices on a field extension
- **[HWW20]**: quadratic constraints to modelize any linear layer → **SMT** solver
- **[DF20]**: propagation table of SuperSboxes (16 bits) → **ad-hoc** algorithm
- **[Udo21]**: modelize propagation table of SuperSboxes with thousands of logical constraints → **SAT** solver

All recent works abandoned MILP solver for either ad-hoc algorithm or SAT/SMT solvers!

MILP Models

- A **mixed-integer program** (MIP) is an optimization problem of the form:

$$\begin{array}{ll} \textit{Minimize} & c^T x \\ \textit{Subject to} & Ax = b \\ & l \leq x \leq u \\ & \text{some or all } x_j \text{ integer} \end{array}$$

MILP Models

- A **mixed-integer program** (MIP) is an optimization problem of the form:

How to improve MILP models?

- Reduce the number of variables
- Reduce the number of inequalities
- Add dedicated branching strategy
- Solve easier problems
- ...

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 \textit{Subject to} & Ax = b \\
 & l \leq x \leq u \\
 & \text{some or all } x_j \text{ integer}
 \end{array}$$

An Important Property

2-subset bit-based division property

A transition $u \xrightarrow{f} v$ through a function f is valid if and only if x^u divides at least one monomial of $f(x)^v$.

A direct consequence for the search of division trails through a cipher is that for all $u' \prec u$ and $v' \succ v$, the transition $u' \xrightarrow{f} v'$ can be safely **added to or removed from** the model.

- Originally used to keep minimal transitions only
- But actually, **adding such "false/unnecessary" transitions does simplify the constraints**

Modelisation of AND and ADDMOD

Operation	<i>AND</i>	<i>ADDMOD</i>
Trail	$(a_1, a_2, \dots, a_m) \rightarrow b$	$(a_1, \dots, b_1, \dots) \rightarrow (y_1, \dots, c_1, \dots)$
Constraints	$a_1 + \dots + a_m \geq b$ $a_1 + \dots + a_m \leq mb$	$-a_i - b_i - c_i + 2c_{i+1} + y_i \geq 0$ $a_i + b_i + c_i - 2c_{i+1} - 2y_i \geq -1$

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- Inequalities in **red** can be safely removed from models

Classical Problem

- Let assume the following values for (x, y, z, t) are impossible

$(0, 0, 1, 1)$ $(0, 1, 1, 1)$ $(1, 0, 1, 1)$ $(0, 0, 0, 1)$ $(0, 0, 1, 0)$ $(0, 0, 0, 0)$

- Discarding those 6 values from a MILP model can be done with the 6 inequalities:

$$x + y + (1 - z) + (1 - t) \geq 1$$

$$x + (1 - y) + (1 - z) + (1 - t) \geq 1$$

$$(1 - x) + y + (1 - z) + (1 - t) \geq 1$$

$$x + y + z + (1 - t) \geq 1$$

$$x + y + (1 - z) + t \geq 1$$

$$x + y + z + t \geq 1$$

Use Quine-McCluskey algorithm to reduce the number of inequalities

Quine-McCluskey Algorithm

- Search for **cosets of bit-aligned** vector spaces of impossible values
- Example: assume the following values for (x, y, z, t) are impossible

$(0, 0, 1, 1)$ $(0, 1, 1, 1)$ $(1, 0, 1, 1)$ $(0, 0, 0, 1)$ $(0, 0, 1, 0)$ $(0, 0, 0, 0)$

- The QM algorithm aims at identifying pairs of impossible values that **differ in only one bit**

$(0, 0, *, *)$ $(*, 0, 1, 1)$ $(0, *, 1, 1)$

- Number of inequalities **reduced** to 3:

$$x + y \geq 1$$

$$y + (1 - z) + (1 - t) \geq 1$$

$$x + (1 - z) + (1 - t) \geq 1$$

Going Further

- Number of inequalities reduced to 3:

$$x + y \geq 1$$

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- Quine-McCluskey algorithm solves a **NP-complete** problem (complexity: $O(3^n/\sqrt{n})$)
- Adding non-minimal transitions **removes the saturation step** of QM algorithm → only need to find a minimal cover

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- **Merge** the two last inequalities:

$$x + y \geq 1$$

$$x + y + 2((1 - z) + (1 - t)) \geq 2$$

Modélisation Techniques

- Sbox:
 - COPY-AND-XOR (Lossy)
 - Convex Hull (Exact)
 - QM (Exact)

- Linear layer:
 - COPY-XOR (Lossy)
 - ZR (Exact)

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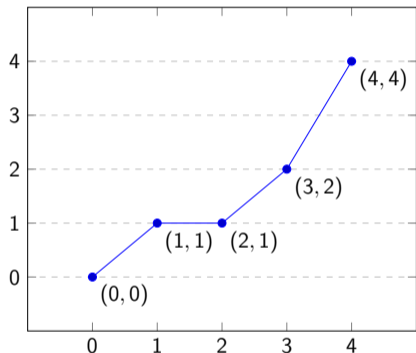


Figure: Piecewise linear function

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- For most of Sboxes used in practice, the following constraints are quite accurate to describe valid transitions $u \xrightarrow{S} v$:

$$\text{hw}(v) = \begin{cases} 0 & \text{if } \text{hw}(u) = 0 \\ n & \text{if } \text{hw}(u) = n \text{ (for a } n\text{-bit Sbox)} \\ 1 & \text{otherwise} \end{cases}$$

Modelisation Techniques

- Sbox:
 - COPY-AND-XOR (Lossy)
 - Convex Hull (Exact)
 - QM (Exact)
 - Piecewise modelisation (Lossy)
- Linear layer:
 - COPY-XOR (Lossy)
 - ZR (Exact)
 - Weight equality (Lossy)

$u \xrightarrow{L} v$ valid iff the minor is invertible
 $\implies \text{hw}(u) = \text{hw}(v)$

Modelisation Techniques

- Sbox:
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 - QM (Exact)
 - Piecewise modelisation (Lossy)
- Linear layer:
 - COPY-XOR (Lossy)
 - ZR (Exact)
 - Weight equality (Lossy)
 - Local ZR (Exact)

if the minor is not invertible

1. find a linear combination of rows equals to 0
2. compute the same linear combination of rows on the **full** matrix
3. look at columns with a non-zero coefficient
4. add a constraint to ensure that if those lines are selected, at least one of the columns is selected as well

Use **Callbacks** to remove false-positive trails

Running Times

Cipher	Rounds	Type of Result	Word Size	Our Time	Previous Time
AES	5	No Ext. Dist.	8-bit	13min	31min [EY21] [†]
ARIA	5	No Ext. Dist.	8-bit	5h	≥ 24h [EY21] [†]
CRAFT	13	Conv. Dist.	-	3.6s	-
	14	No Ext. Dist.	16-bit	11min	-
HIGHT	20	Ext. Dist.	16-bit	12min	13 days [DF20]
	21	No Ext. Dist.	16-bit	14min	-
LED	8	No Ext. Dist.	16-bit	3h*	16h [Udo21]
Skinny	11	Ext. Dist.	16-bit	9min	22min [DF20]
	12	No Ext. Dist.	16-bit	80s	4min [DF20]
Camellia	7	Conv. Dist.	-	30s	99min [HWW20]
CLEFIA	10	Conv. Dist.	-	23min	82min [HWW20]
LEA	8	Conv. Dist.	-	20s	30min [Sww17]

Best Strategies

Cipher	Rounds	Modeling	LC-S-box	LC-Lin	LC-SSB
AES	4	PWL + WE	0	0	-
	5	QM + WE	-	60	-
ARIA	4	PWL + WE	0	0	-
	5	QM + CX	-	91	-
CRAFT	13	QM/CH + QM/CH	-	-	0
	14	QM/CH + CX	-	0	314
HIGHT	20	CX	-	6	0
	21	CX	-	21	0
LED	8	QM/CH + WE	-	107	54
Skinny	11	QM/CH + QM/CH	-	-	7
	12	QM/CH + QM/CH	-	-	93
Camellia	7	PWL + WE	0	0	-
	8	QM + CX	-	31	-
CLEFIA	10	PWL + WE	0	0	-
	11	QM + CX	-	9	-

About Weight Equality

What is the probability for a minor of an invertible matrix to be invertible?

- A random binary matrix is invertible with probability between 30 and 50%
- But matrices used in block ciphers are (most often) not random!
- Percentage of invertible minors for AES MixColumns matrix:

1 : 15.9%	5 : 1.4%	9 : 1.9%	13 : 3.5%	17 : 5.1%	21 : 12.3%	25 : 18.6%	29 : 26.3%
2 : 6.4%	6 : 0.9%	10 : 1.3%	14 : 3.6%	18 : 6.0%	22 : 13.0%	26 : 18.7%	30 : 31.5%
3 : 2.9%	7 : 0.6%	11 : 1.6%	15 : 3.4%	19 : 7.5%	23 : 15.3%	27 : 20.5%	31 : 44.5%
4 : 1.9%	8 : 1.8%	12 : 1.9%	16 : 3.8%	20 : 11.4%	24 : 17.5%	28 : 22.5%	32 : 100%

Conclusion

- **New modelisation techniques** for 2-subset division property
- Much better to **not add** all constraints into the model → use callbacks!
- Considering SuperSboxes not as useful as expected
- Optimizing models is important
- Code: <https://github.com/FastMILPDivisionProperty/FastMILPDivision>

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Thank you for your attention!