

MDS Matrices with Lightweight Circuits

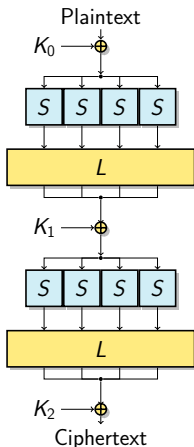
Sébastien Duval

Gaëtan Leurent

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SPN Ciphers



Shannon's criteria

1 Diffusion

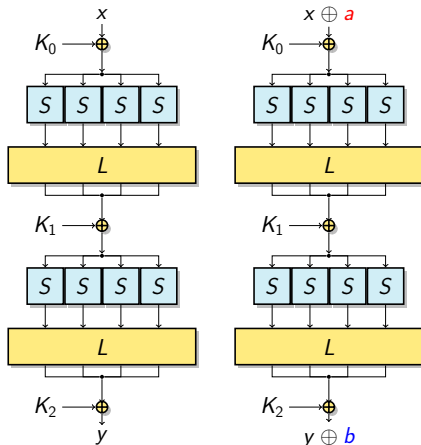
- Every bit of plaintext and key must affect every bit of the output
- We usually use **linear** functions

2 Confusion

- Relation between plaintext and ciphertext must be intractable
- Requires **non-linear** operations
- Often implemented with tables: **S-Boxes**

Example: Rijndael/AES [Daemen Rijmen 1998]

Block Cipher Security Analysis



Differential Attacks [Biham Shamir 91]

- ▶ Attacker exploits (a, b) such that

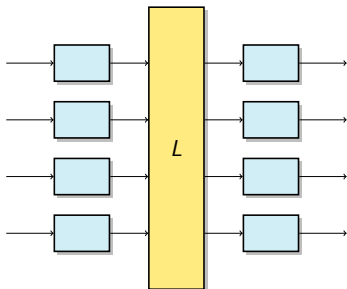
$$E_K(x) \oplus E_K(x \oplus a) = b$$

with high probability

- ▶ Maximum of the probability over all (a, b) bounded by

$$\left(\frac{\delta(S)}{2^n} \right)^{B_d(L)} - 1$$

MDS Matrices



L linear permutation
on k words of n bits.

Differential Branch Number

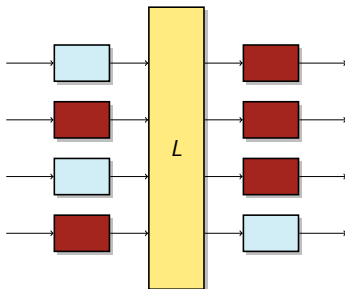
$$\mathcal{B}_d(L) = \min_{x \neq 0} \{w(x) + w(L(x))\}$$

where $w(x)$ is the number of non-zero n -bits words in x .

Linear Branch Number

$$\mathcal{B}_l(L) = \min_{x \neq 0} \{w(x) + w(L^\top(x))\}$$

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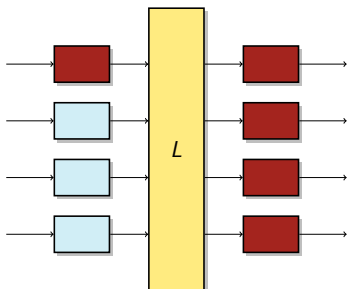
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$$\mathcal{B}_l(L) = \min_{x \neq 0} \{w(x) + w(L^T(x))\}$$

Maximum branch number : $k + 1$
Equivalent to MDS codes.

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Matrices and Characterisation

$$\begin{bmatrix} 2 & 3 & 1 & 1 \\ 1 & 2 & 3 & 1 \\ 1 & 1 & 2 & 3 \\ 3 & 1 & 1 & 2 \end{bmatrix}$$

AES MixColumns

Usually on finite fields:

x a primitive element of \mathbb{F}_2^n

Coeffs. $\in \mathbb{F}_2[x]/P$, with P a primitive polynomial

$2 \leftrightarrow x$

$3 \leftrightarrow x + 1$

Characterisation

L is MDS iff its minors are non-zero

Previous Works

Recursive Matrices [Guo *et al.* 2011]

A lightweight matrix

A^i MDS

Implement A , then iterate A i times.

Optimizing Coefficients

- ▶ Structured matrices: restrict to a small subspace with many MDS matrices
- ▶ More general than finite fields: inputs are binary vectors, matrix coeffs. are $n \times n$ matrices.
⇒ less costly operations than multiplication in a finite field

Cost Evaluation

“Real cost”

Number of operations of the best implementation.

Xor count (naive cost)

Hamming weight of the binary matrix. Cannot reuse intermediate values.

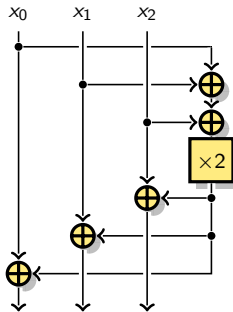
Intermediate values

- ▶ *Local optimisation*: LIGHTER [Jean *et al.* 2017]
cost of matrix multiplication = number of XORs + cost of the mult. by each coefficient.
- ▶ *Global optimisation*:
 - ▶ Hardware synthesis: straight line programs [Kranz *et al.* 2018].
Heuristics to implement binary matrices.
 - ▶ Our approach: Number of operations of the best implementation **using operations on words**.

Metrics Comparison

$$\begin{bmatrix} 3 & 2 & 2 \\ 2 & 3 & 2 \\ 2 & 2 & 3 \end{bmatrix}$$

Xor Count: $\begin{cases} 6 \text{ mult. by } 2 \\ 3 \text{ mult. by } 3 \\ 6 \text{ XORS} \end{cases}$

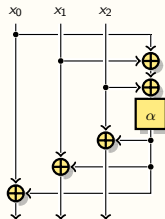


Our approach: $\begin{cases} 1 \text{ mult. by } 2 \\ 5 \text{ XORS} \end{cases}$

Formal Matrices

Formal matrices

- ▶ Optimise in 2 steps:
 - 1 Find $M(\alpha)$ for α an undefined linear mapping.
 - 2 Instantiate with the best choice of α
- ▶ Not necessarily a finite field.
- ▶ Then coeffs. are polynomials in α .

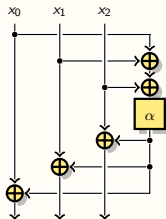


$$\begin{bmatrix} \alpha+1 & \alpha & \alpha \\ \alpha & \alpha+1 & \alpha \\ \alpha & \alpha & \alpha+1 \end{bmatrix}$$

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Characterisation of formally MDS matrices

- ▶ Objective: find $M(\alpha)$ s.t. $\exists A, M(A)$ MDS.
- ▶ If a minor of $M(\alpha)$ is null, then impossible.
- ▶ Otherwise, there always exists an A .

Characterisation possible on $M(\alpha)$.

Search Space

Search over circuits

Search Space

Operations:

- ▶ word-wise XOR
- ▶ α (generalization of a multiplication)
- ▶ Copy

Note: Only word-wise operations.

r registers:

one register per word (3 for 3×3)

+ (at least) one more register \rightarrow more complex operations

Implementation: Main Idea

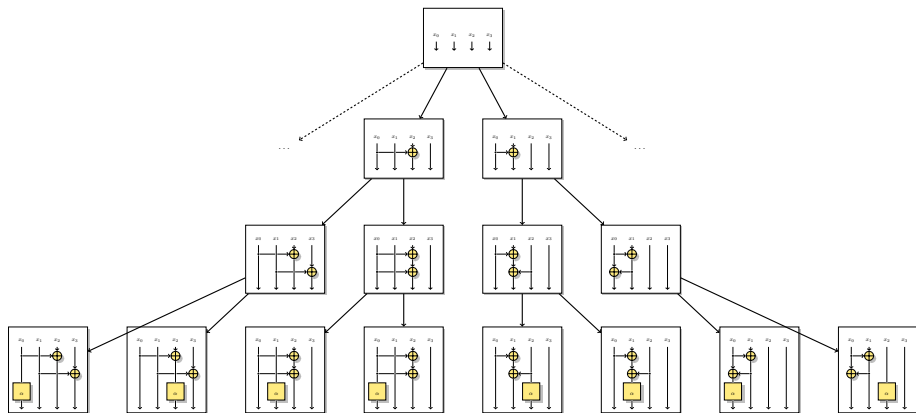
Tree-based Dijkstra search

- ▶ Node = matrix = sequence of operations
- ▶ Lightest circuit = shortest path to MDS matrix
- ▶ When we spawn a node, we test if it is MDS

Search results

- ▶ $k = 3$ fast (seconds)
- ▶ $k = 4$ long (hours)
- ▶ $k = 5$ out of reach
- ▶ Collection of MDS matrices with trade-off between cost and depth (latency).

Scheme of the Search



Optimization: A^*

A^*

Idea of A^*

- ▶ Guided Dijkstra
- ▶ $\text{weight} = \text{weight from origin} + \text{estimated weight to objective}$

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Our estimate:

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Our estimate:

- ▶ Heuristic
- ▶ How far from MDS ?

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- ▶ Column with a 0: cannot be part of MDS matrix
- ▶ Linearly dependent columns: not part of MDS matrix
- ▶ Estimate: $m = \text{rank of the matrix (without columns containing 0)}$
- ▶ Need at least $k - m$ word-wise XORs to MDS

Result: much faster

Methodology of the Instantiation

The Idea

- 1 Input: Formal matrix $M(\alpha)$ MDS
- 2 Output: $M(A)$ MDS, with A a linear mapping (the lightest we can find)

Characterisation of MDS Instantiations

MDS Test

- ▶ Intuitive approach:
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 - ▶ Let I, J subsets of the lines and columns
 - ▶ Define $m_{I,J} = \det_{\mathbb{F}_2[\alpha]}(M_{|I,J})$
 - ▶ $M(A)$ is MDS iff all $m_{I,J}(A)$ are non-singular

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- ▶ With the minimal polynomial
 - ▶ Let μ_A the minimal polynomial of A
 - ▶ $M(A)$ is MDS iff $\forall(I, J), \gcd(\mu_A, m_{I,J}) = 1$

Multiplications in a Finite Field

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Low Cost Instantiation

- ▶ Pick π with few coefficients: a trinomial requires 1 rotation + 1 binary xor

Concrete Choices of A

We need to fix the size

Branches of size 4 bits (\mathbb{F}_2^4)

$$A_4 = \begin{bmatrix} \cdot & 1 & \cdot & \cdot \\ \cdot & \cdot & 1 & \cdot \\ \cdot & \cdot & \cdot & 1 \\ 1 & 1 & \cdot & \cdot \end{bmatrix}$$

(companion matrix of $X^4 + X + 1$ (irreducible))

$$A_4^{-1} = \begin{bmatrix} 1 & \cdot & \cdot & 1 \\ 1 & \cdot & \cdot & \cdot \\ \cdot & 1 & \cdot & \cdot \\ \cdot & \cdot & 1 & \cdot \end{bmatrix}$$

(minimal polynomial is $X^4 + X^3 + 1$)

Branches of size 8 bits (\mathbb{F}_2^8)

$$A_8 = \begin{bmatrix} \cdot & 1 & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & 1 & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & 1 & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & 1 & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & 1 & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & 1 & \cdot \\ 1 & \cdot & 1 & \cdot & \cdot & \cdot & \cdot & 1 \end{bmatrix}$$

(companion matrix of
 $X^8 + X^2 + 1 = (X^4 + X + 1)^2$)

$$A_8^{-1} = \begin{bmatrix} \cdot & 1 & \cdot & \cdot & \cdot & \cdot & \cdot & 1 \\ 1 & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & 1 & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & 1 & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & 1 & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & 1 & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & 1 & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & 1 & \cdot \end{bmatrix}$$

(minimal polynomial is $X^8 + X^6 + 1$)

Comparison With Existing MDS Matrices

Size	Ring	Matrix	Cost			Ref
			Naive	Best	Depth	
$M_4(M_8(\mathbb{F}_2))$	$GL(8, \mathbb{F}_2)$	Circulant	106			(Li Wang 2016)
	$GL(8, \mathbb{F}_2)$	Hadamard		72	6	(Kranz <i>et al.</i> 2018)
	$\mathbb{F}_2[\alpha]$	$M_{4,6}^{8,3}$		67	5	$\alpha = A_8$ or A_8^{-1}
	$\mathbb{F}_2[\alpha]$	$M_{4,4}^{8,4}$		69	4	$\alpha = A_8$
	$\mathbb{F}_2[\alpha]$	$M_{4,3}^{9,5}$		77	3	$\alpha = A_8$ or A_8^{-1}
$M_4(M_4(\mathbb{F}_2))$	$GF(2^4)$	$M_{4,n,4}$	58	58	3	(Jean Peyrin Sim 2017)
	$GF(2^4)$	Toeplitz	58	58	3	(Sarkar Syed 2016)
	$GL(4, \mathbb{F}_2)$	Subfield		36	6	(Kranz <i>et al.</i> 2018)
	$\mathbb{F}_2[\alpha]$	$M_{4,6}^{8,3}$		35	5	$\alpha = A_4$ or A_4^{-1}
	$\mathbb{F}_2[\alpha]$	$M_{4,4}^{8,4}$		37	4	$\alpha = A_4$
	$\mathbb{F}_2[\alpha]$	$M_{4,3}^{9,5}$		41	3	$\alpha = A_4$ or A_4^{-1}