# Cold Boot Key Recovery using Polynomial System Solving with Noise 

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## Outline

1 Coldboot Attacks

2 Polynomial System Solving with Noise

3 Mixed Integer Programming

4 Application

5 Appendix: Modular Addition

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## Background

- Cryptography provides the means to accomplish data integrity and confidentiality.
- For hard disk encryption we use block ciphers which take a $k$-bit key and encrypt $n$-bit blocks.
- All modern block cipher designs use relatively simple rounds which are repeated $m$ times. In each round $n$ bits of key material are mixed with the current state. Thus, we need to expand the $k$-bit key to $n \times(m+1)$ bits of key material: the key schedule.
- We have not seen practical attacks against industry strength block ciphers in decades.
- However, we might be able to exploit side-channel data leakage in order to break data confidentiality.


## Coldboot Attacks I

- In [7] a method for extracting cryptographic key material from DRAM used in modern computers was proposed.
- Contrary to popular belief information in DRAM is not instantly lost when the power is cut, but decays slowly over time.
- This decay can be further slowed down by cooling the chip.
- Thus, an attacker can

1 deep-freeze a DRAM module
2 move it to a target machine which dumps the content to disk
3 find the most likely key candidate (which is erroneous due to decay)
4 use some mechanism to correct those errors
The technique is called Coldboot attack in literature.

## Coldboot Attacks II

Definition (The Coldboot Problem)
We are given
$\mathbb{K}: \mathbb{F}_{2}^{n} \rightarrow \mathbb{F}_{2}^{N}$ where $N>n$,
2 two real numbers $0 \leq \delta_{0}, \delta_{1} \leq 1$,
3 $K=\mathcal{K S}(k)$ and $K_{i}$ the $i$-th bit of $K$.
$4 K^{\prime}=\left(K_{0}^{\prime}, K_{1}^{\prime}, \ldots, K_{N-1}^{\prime}\right) \in \mathbb{F}_{2}^{N}$ based on the following process:

- if $K_{i}=0$, then let $\operatorname{Pr}\left[K_{i}^{\prime}=1\right]=\delta_{1}$ and $\operatorname{Pr}\left[K_{i}^{\prime}=0\right]=1-\delta_{1}$
- if $K_{i}=1$, then let $\operatorname{Pr}\left[K_{i}^{\prime}=0\right]=\delta_{0}$ and $\operatorname{Pr}\left[K_{i}^{\prime}=1\right]=1-\delta_{0}$.

5 and some control function $\mathcal{E}: \mathbb{F}_{2}^{n} \rightarrow\{$ True, False $\}$, which returns true for the pre-image of the noise free version of $K$.
The task is to recover $k$ such that $\mathcal{E}(k)$ returns True or a noise-free $K$.
The Coldboot problem is equivalent to decoding a (non-)linear code with biased noise.

## Coldboot Attacks III

Results in [7]:

| Cipher | $\delta_{0}$ | $\delta_{1}$ | Success | Time |
| :---: | ---: | ---: | ---: | ---: |
| DES | 0.10 | 0.001 | $100 \%$ | - |
| DES | 0.50 | 0.001 | $98 \%$ | - |
| AES | 0.15 | 0.001 | $100 \%$ | 1 s |
| AES | 0.30 | 0.001 | $100 \%$ | 30 s |

Can we do better and can we recover keys for more complicated key schedules like Serpent?

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## PoSSo

We define polynomial system solving (PoSSo) as the problem of finding a solution to a system of polynomial equations over some field.

## Definition (PoSSo)

Consider the set $F=\left\{f_{0}, \ldots, f_{m-1}\right\}$ where each $f_{i} \in \mathbb{F}\left[x_{0}, \ldots, x_{n-1}\right]$.
A solution to $F$ is any point $x \in \mathbb{F}^{n}$ such that

$$
\forall f_{i} \in F: f_{i}(x)=0
$$

Note, that we restrict ourselves to solutions in the base field here.

## Max-PoSSo I

We can define a family of Max-PoSSo problems, analogous to the well known Max-SAT family of problems.

```
http://en.wikipedia.org/wiki/MAX-SAT
```


## Max-PoSSo II

Definition (Max-PoSSo)
Find a point $x \in \mathbb{F}^{n}$ which satisfies the maximum number of polynomials in $F=\left\{f_{0}, \ldots, f_{m-1}\right\} \subset \mathbb{F}\left[x_{0}, \ldots, x_{n-1}\right]$.

## Max-PoSSo III

## Definition (Partial Max-PoSSo)

Find a point $x \in \mathbb{F}^{n}$ such that for two sets of polynomials $\mathcal{H}$ and $\mathcal{S}$ in $\mathbb{F}\left[x_{0}, \ldots, x_{n-1}\right]$

■ $\forall f \in \mathcal{H}: f(x)=0$ and

- the number of polynomials $f \in \mathcal{S}$ with $f(x)=0$ is maximised.
- Max-PoSSo is Partial Max-Posso with $\mathcal{H}=\varnothing$.
- $\mathcal{H}$ for "hard" and $\mathcal{S}$ for "soft".
- Both terms are borrowed from Partial Max-SAT.


## Max-PoSSo IV

## Definition (Partial Weighted Max-PoSSo)

Find a point $x \in \mathbb{F}^{n}$ such that

- $\forall f \in \mathcal{H}: f(x)=0$ and
- $\sum_{f \in \mathcal{S}} \mathcal{C}(f, x)$ is minimized
where $\mathcal{C}: f \in \mathcal{S}, x \in \mathbb{F}^{n} \rightarrow \mathbb{R}_{\geq 0}$ is a cost function which
- returns 0 if $f(x)=0$ and
- some value $>0$ if $f(x) \neq 0$.

Partial Max-PoSSo is Weighted Partial Max-PoSSo where $\mathcal{C}(f, x)$ returns 1 if $f(x) \neq 0$ for all $f \in \mathcal{S}$.

## Coldboot as Partial Weighted Max-PosSoht

- Let $F_{\mathcal{K}}$ be an equation system corresponding to $\mathcal{K}$.
- Assume that for each noisy output bit $K_{i}^{\prime}$ there is some $f_{i} \in F_{\mathcal{K}}$ of the form $g_{i}+K_{i}^{\prime}$ where $g_{i}$ is some polynomial.
- Assume that these are the only polynomials involving output bits.
- Denote the set of these polynomials $\mathcal{S}$.
- Denote the set of all remaining polynomials $\in F_{\mathcal{K}}$ as $\mathcal{H}$.
- Define the cost function $\mathcal{C}$ as a function which returns

$$
\begin{aligned}
& \frac{1}{\delta_{0}} \quad \text { for } K_{i}^{\prime}=0, f_{i}(x) \neq 0 \\
& \frac{1}{\delta_{1}} \quad \text { for } K_{i}^{\prime}=1, f_{i}(x) \neq 0 . \\
& 0
\end{aligned} \quad \text { otherwise } .
$$

- Express $\mathcal{E}$ as a polynomial system which is satisfiable for $k$ only and add these polynomials to $\mathcal{H}$.


## Other Applications

RFID security is often based on the LPN problem which is easily described as a Max-PoSSo problem.
Lattices security often rests on the LWE problem which is easily described as a Max-PoSSo problem.
Side-Channel data leakage is often noisy.
Algebraic Attacks can be improved by simplifying equation systems using probabilistic equations.

The family of Max-PoSSo problems has not be studied before as far as we can tell. There is some connection to solving polynomial systems over fixed precision real-numbers.

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## Mixed Integer Programming I

Integer optimization deals with the problem of minimising (or maximising) a function in several variables subject to linear equality and inequality constraints and integrality restrictions on some or all of the variables.

## Definition (MIP)

A linear mixed-integer programming problem (MIP) is defined as a problem of the form

$$
\min _{x}\left\{c^{\top} x \mid A x \leq b, x \in \mathbb{Z}^{k} \times \mathbb{R}^{\prime}\right\}
$$

where

- $A$ is an $m \times n$-matrix $(n=k+l)$,
- $b$ is an $m$-vector and $c$ is an $n$-vector.


## Mixed Integer Programming II

## Example

Maximise $x+5 y$, thus $c=(1,5)$, subject to the constraints $x+0.2 y \leq 4$ and $1.5 x+3 y \leq 4$ where $x \geq 0$ is real valued and $y \geq 0$ is integer valued.

The optimal value for $c^{T} x$ is $5 \frac{2}{3}$ for $x=\frac{2}{3}$ and $y=1$.

```
sage: p = MixedIntegerLinearProgram()
sage: x, y = p.new_variable(), p.new_variable()
sage: p.set_integer(y[0])
sage: p.add_constraint(x[0] + 0.2*y[0], max=4)
sage: p.add_constraint(1.5*x[0] + 3*y[0], max=4)
sage: p.set_min(x[0],0); p.set_min(y[0],0)
sage: p.set_objective(x[0] + 5*y[0])
sage: p.solve() # work in progress (#8672): allow solver='SCIP'
5.6666666666666661
```


## PoSSo as MIP |

Consider some $f \in \mathbb{F}_{2}\left[x_{0}, \ldots, x_{n-1}\right]$ and let $\mathcal{Z}$ a function that takes a polynomial over $\mathbb{F}_{2}$ lifts it to the integers. Analogous for elements in $\mathbb{F}_{2}$.
11 Restrict all $x_{i}$ to binary values.
12 Evaluate $\mathcal{Z}(f)$ on all $\left\{\mathcal{Z}(x) \mid x \in \mathbb{F}_{2}^{n}, f(x)=0\right\}$.
3 Let $\ell$ be the minimum value and $u$ the maximum value.
(4) Introduce some integer variable $\frac{\ell}{2} \leq m \leq \frac{\mu}{2}$.

5 Replace each monomial in $f-2 m$ by a new linearised variable, call the result $g$ and add the linear constraint $g=0$.
[6 For each monomial $t=\prod_{i=1}^{N} x_{i}$

- add a constraint $x_{i} \geq t$ and
- add a constraint $0 \leq \sum_{i=1}^{N} x_{i}-t \leq N-1$.

This is the Integer Adapted Standard Conversion [3].

## PoSSo as MIP II

Example
Consider $f=a c+a+b+c+1$
■ $\left\{x \mid x \in \mathbb{F}_{2}^{3}, f(x)=0\right\}=\{(1,0,0),(0,1,0),(0,0,1),(1,0,1)\}$

- $\ell=1, u=2$
$1 \mathrm{~g}=\mathrm{M}+a+b+c+1-2 m=0$
$2 a \geq M$
$3 c \geq M$
$40 \leq a+c-M \leq 1$


## PoSSo as MIP III

sage: attach anf2mip.py
sage: $B .<a, b, c>=$ BooleanPolynomialRing ()
sage: $f=a * c+a+b$
sage: $b c=$ BooleanPolynomialMIPConverter ()
sage: $p=b c$.integer_adapted_standard_conversion ([f]); $p$
Mixed Integer Program ( minimization, ...
sage: p.show ()
Minimization:
$x_{-} 1+x_{-} 2+x_{-} 3+x_{-} 4$
Constraints:
$0<=-2 x_{-} 0+x_{-} 1+x_{-} 2+x_{-} 3<=0$
$-1<=x_{-} 2-1 \times x_{-}<=0$
$-1<=x_{-} 2-1 \times x_{-}<=0$
$0<=-1 \times$ _ $2+x_{\_} 3+x_{\_} 4<=1$
Variables:
$x_{-} 0$ is an integer variable $(\min =0.0, \max =1.0)$
$x_{-} 1$ is an boolean variable $(\min =0.0, \max =1.0)$
$x_{2} 2$ is a real variable $(\min =0.0, \max =1.0)$
$x \_3$ is an boolean variable $(\min =0.0, \max =1.0)$
$x_{-} 4$ is an boolean variable $(\min =0.0, \max =1.0)$

## PoSSo as MIP IV

```
sage: attach anf2mip.py
sage: \(B .<a, b, c>=\) BooleanPolynomialRing ()
sage: \(f=a * c+a+b+1\)
sage: \(g=a+c+1\)
sage: \(p=b c\).integer_adapted_standard_conversion ([f]); \(p\)
Mixed Integer Program (...
sage: p.solve()
1.0
sage: bc.solve([f])
CPU Time: 0.00 Wall time: 0.00 , Obj: 1.00
\(\{b: 1, c: 0, a: 0\}\)
sage: bc.solve([f,g], solver='SCIP')
CPU Time: 0.00 Wall time: 0.00, Obj: 1.00
\(\{b: 0, c: 0, a: 1\}\)
```


## 

We only need to consider Partial Weighted Max-PoSSo because it is the most general case:

- Convert each $f \in \mathcal{H}$ to linear constraints as before.
- For each $f_{i} \in \mathcal{S}$ add a new binary slack variable $e_{i}$ to $f_{i}$ and convert the resulting polynomial as before.
- The objective function we minimise is $\sum c_{i} e_{i}$ where $c_{i}$ is the value of $\mathcal{C}(f, x)$ for some $x$ such that $f(x) \neq 0$.

Any optimal solution $x \in S$ will be an optimal solution to the Partial Weighted Max-PoSSo problem.

## Coldboot as MIP

## Coldboot $\rightarrow$ Partial Weighted Max-PoSSo $\rightarrow$ MIP

This approach is essentially the non-linear generalisation of decoding random linear codes with linear programming [5].

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## Simplifications

- We do not model $\mathcal{E}$ since its representation is often too costly; consequently we have no guarantee that the optimal $k$ returned is indeed the $k$ we are looking for.
- We do not include all equations available to us but restrict our attention to a subset (e.g. one or two rounds).
- We may use an "aggressive" modelling strategy where we assume $\delta_{1}=0$ which allows us to promote some polynomials from $\mathcal{S}$ to $\mathcal{H}$. The "normal" modelling assumes $\delta_{1}=0+\epsilon$.


## AES [4] I



## AES [4] II

- Most of the key schedule is linear.
- The original key $k$ appears in the output.
- The S-box size is 8 -bit (explicit degree: 7 ).


## AES [4] III

|  |  | Gurobi [6] |  |  |  |  |  |
| :---: | :---: | ---: | ---: | ---: | ---: | ---: | :---: |
| $N$ | $\delta_{0}$ | a | \#cores | cutoff $t$ | $r$ | $\max t$ |  |
| 3 | 0.15 | - | 24 | $\infty$ | $100 \%$ | 17956.4 s |  |
| 3 | 0.15 | - | 2 | 240.0 s | $25 \%$ | 240.0 s |  |
| 3 | 0.30 | + | 24 | 3600.0 s | $25 \%$ | 3600.0 s |  |
| 3 | 0.35 | + | 24 | 7200.0 s | $10 \%$ | 7200.0 s |  |
| 3 | 0.35 | + | 24 | 28800.0 s | $30 \%$ | 28800.0 s |  |
|  | SCIP (hardlp.set) $[1]$ |  |  |  |  |  |  |
| 3 | 0.15 | + | 1 | 3600.0 s | $65 \%$ | 3600.0 s |  |
| 3 | 0.30 | + | 1 | 7200.0 s | $45 \%$ | 7200.0 s |  |
| 3 | 0.35 | + | 1 | 10800.0 s | $10 \%$ | 10800.0 s |  |
| 3 | 0.40 | + | 1 | 14400.0 s | $0 \%$ | 14400.0 s |  |
| 4 | 0.40 | + | 1 | 14400.0 s | $10 \%$ | 14400.0 s |  |

## Serpent [2] I



## Serpent [2] II

- All key schedule output bits depend non-linearly on the input.
- The original key $k$ does not appear in the output.
- The S-box size is 4 -bit (explicit degree: 3 ).


## Serpent [2] III

|  |  | Gurobi [6] |  |  |  |  |  |
| :---: | :---: | :---: | ---: | ---: | ---: | ---: | :---: |
| $N$ | $\delta_{0}$ | a | \#cores | cutoff $t$ | $r$ | Max $t$ |  |
| 8 | 0.05 | - | 2 | 60.0 s | $50 \%$ | 16.22 s |  |
| 12 | 0.05 | - | 2 | 60.0 s | $85 \%$ | 60.00 s |  |
| 8 | 0.15 | - | 24 | 600.0 s | $20 \%$ | 103.17 s |  |
| 12 | 0.15 | - | 24 | 600.0 s | $55 \%$ | 600.00 s |  |
| 12 | 0.30 | + | 24 | 7200.0 s | $20 \%$ | 7200.00 s |  |
|  | SCIP (hardlp.set) $[1]$ |  |  |  |  |  |  |
| 8 | 0.15 | - | 1 | 3600.0 s | $15 \%$ | 3600.00 s |  |
| 8 | 0.15 | + | 1 | 3600.0 s | $5 \%$ | 259.97 s |  |
| 12 | 0.15 | + | 1 | 3600.0 s | $40 \%$ | 271.47 s |  |
| 16 | 0.15 | + | 1 | 3600.0 s | $45 \%$ | 1942.27 s |  |
| 12 | 0.30 | + | 1 | 3600.0 s | $25 \%$ | 3600.00 s |  |

## Serpent [2] IV

Ad-hoc approach:

- We wish to recover a 128-bit key, so we need to consider at least 128-bit of output.
- On average the noise free output should have 64 bits set to zero.
- In order to consider an error rate up to $\delta_{0}$, we have to consider

$$
\sum_{i=0}^{\left\lceil\delta_{0} \cdot 64\right\rceil}\binom{64+\left\lceil\delta_{0} \cdot 64\right\rceil}{ i}
$$

candidates and test them.

- If $\delta_{0}=0.15$ we have $\approx 2^{36.87}$.
- If $\delta_{0}=0.30$ we have $\approx 2^{62}$.


## Twofish [8] I

| known constant |  |  |
| :---: | :---: | :---: |
| $M_{0}$ |  | $\oplus$ |
| $X_{2 i}$ |  |  |
| $Q_{0}$ | $Q_{0}$ | $Q_{1}$ |
| $Y_{2 i}$ |  |  |
| $Q_{1}$ |  |  |
| $M_{2}$ |  | $\oplus$ |
| $Z_{2 i}$ |  |  |
| MDS |  |  |
| $A_{i}$ |  |  |



The output of the key schedule is then
$A_{i} \boxplus B_{i}$
and

$$
A_{i} \boxplus 2 \cdot B_{i} .
$$

## Twofish [8] II

- The input $k\left(M_{0}, \ldots, M_{3}\right)$ does not appear in the output.
- All output bits depend non-linearly on the input.
- The $S$-box $\left(Q_{0}, Q_{1}\right)$ size is 8 -bit (explicit degree: 7 )
- There is a modular addition $\left(\bmod 2^{32}\right)$ at the end.

As of now, we cannot recover the key using mixed integer programming.

## Twofish [8] III

Ad-hoc approach:

- We wish to recover a 128 -bit key, so we need to consider at least 128-bit of output.
■ On average the noise free output should have 64 bits set to zero.
- In order to consider an error rate up to $\delta_{0}$, we have to consider

$$
\sum_{i=0}^{\left\lceil\delta_{0} \cdot 64\right\rceil}\binom{64+\left\lceil\delta_{0} \cdot 64\right\rceil}{ i}
$$

candidates and test them.

- If $\delta_{0}=0.15$ we have $\approx 2^{36.87}$.
- If $\delta_{0}=0.30$ we have $\approx 2^{62}$.
- Due to the lack of inner diffusion solving the system for each instance is easy.


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## Representation

Modular addition modulo $2^{32}$ is used in many cryptographic algorithms to provide non-linearity over $\mathbb{F}_{2}$. However, over the integers this is linear.

We represent the addition $A \boxplus B=C$ modulo $2^{N}$ as

$$
0=\sum_{i=0}^{n-1} 2^{i} A_{i}+\sum_{i=0}^{n-1} 2^{i} B_{i}-\sum_{i=0}^{n-1} 2^{i} C_{i}-2^{n}
$$

for $n \in\{1, \ldots, N\}$ and $m \in\{0,1\}$.
However, this representation may lead to overflows of machine ints and floats.

Thank you!

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