

# Optimization of LPN Solving Algorithms

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# Motivation

- LPN can be defined as a noisy system of linear equations in the binary domain

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- used in authentication protocols and cryptosystems
- special case of LWE, but its hardness is not proven so far

Best way to study its hardness is by improving the algorithms that solve it



# Our Results

- analyse the existing LPN algorithms and study its building blocks
- improve the theory behind the covering code reduction
- optimise the order and the parameters used in LPN solving algorithms
- improve the best existing algorithms from ASIACRYPT'14 and EUROCRYPT'16

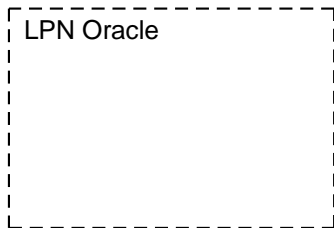
# Outline

- 1 LPN
- 2 Code Reduction
- 3 Our Algorithm
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LPN Oracle

secret random vector  $s$

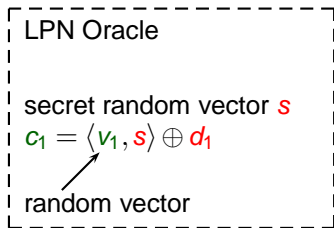
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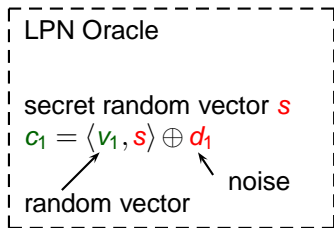
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$$c_1 = \langle v_1, s \rangle \oplus d_1$$

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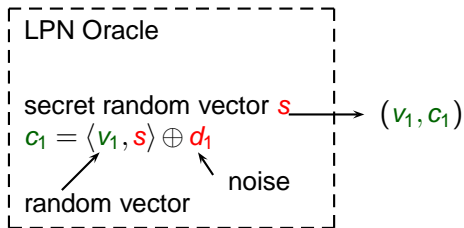


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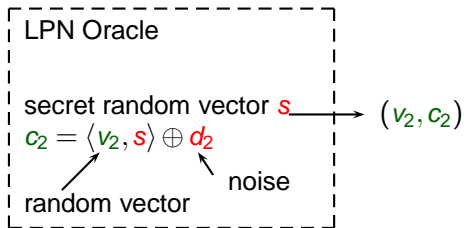




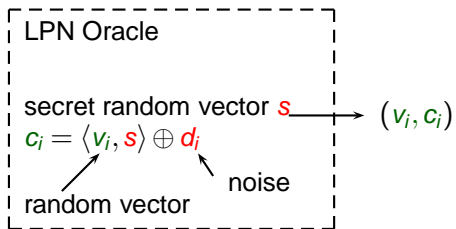
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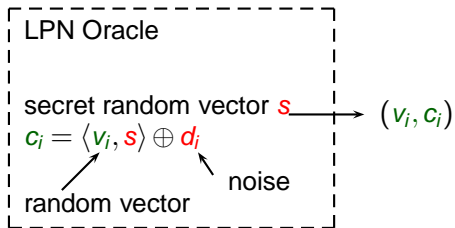
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## Definition (LPN)

Given independent queries from the LPN oracle, find the secret  $s$ .

# LPN Solving Algorithm

## Definition (LPN solving algorithm)

We say that an algorithm  $\mathcal{M}$  solves the LPN problem if

$$\Pr[\mathcal{M} \text{ recovers the secret } \mathbf{s}] \geq \frac{1}{2},$$

The performance of  $\mathcal{M}$  is measured by the running time  $t$ , memory  $m$  and **number of queries**  $n$  from the LPN oracle

Define  $\delta = \Pr[d_i = 0] - \Pr[d_i = 1]$  as the **noise bias**

# General Structure

To recover a secret  $s$  of  $k$  bits:

- reduce to a secret  $s'$  of  $k' \leq k$  bits
- recover the secret  $s'$
- update the queries & repeat the steps

# General Structure

To recover a secret  $s$  of  $k$  bits:

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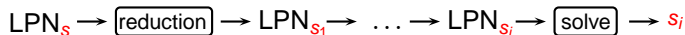
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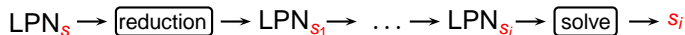
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## Optimise the use of the reduction techniques

# Reduction Techniques

- *sparse-secret*
- *partition-reduce*( $b$ )
- *xor-reduce*( $b$ )
- *drop-reduce*( $b$ )
- *code-reduce*( $k, k', \text{params}$ )
- *guess-secret*( $b, w$ )

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Keep track of the:

- secret size
- number of queries
- noise bias
- secret bias

# Reduction *sparse-secret*

$V_1$	$\dots$	$C_1$
$V_2$	$\dots$	$C_2$
$V_3$	$\dots$	$C_3$
$V_4$	$\dots$	$C_2$
$V_5$	$\dots$	$C_5$
$V_6$	$\dots$	$C_6$
.....		
$V_{n-2}$	$\dots$	$C_{n-2}$
$V_{n-1}$	$\dots$	$C_{n-1}$
$V_n$	$\dots$	$C_n$

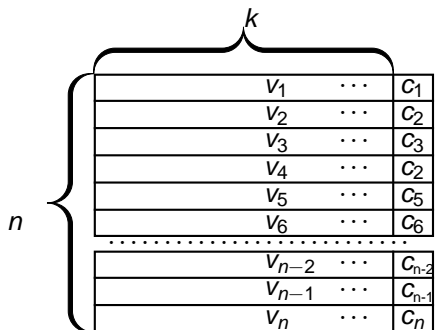
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$n$  {

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.....		
$V_{n-2}$	$\dots$	$C_{n-2}$
$V_{n-1}$	$\dots$	$C_{n-1}$
$V_n$	$\dots$	$C_n$



# Reduction *sparse-secret*



## Reduction *sparse-secret*

n	k		
	$v_1$	$\dots$	$c_1$
	$v_2$	$\dots$	$c_2$
	$v_3$	$\dots$	$c_3$
	$v_4$	$\dots$	$c_2$
	$v_5$	$\dots$	$c_5$
	$v_6$	$\dots$	$c_6$
	.....		
	$v_{n-2}$	$\dots$	$c_{n-2}$
	$v_{n-1}$	$\dots$	$c_{n-1}$
	$v_n$	$\dots$	$c_n$

$$c_i = \langle v_i, s \rangle \oplus d_i$$

# Reduction *sparse-secret*

$n$

$k$									
$n$	1	0	1	0	1	0	1	...	0
	1	1	1	0	1	0	0	...	0
	0	0	0	1	1	1	0	...	0
	0	0	0	0	0	1	0	...	1
	0	0	1	1	0	0	1	...	1
	1	0	1	0	0	1	1	...	0
	...	...	...	...	...	...	...	...	...
	0	0	1	1	0	1	1	...	0
	1	0	1	0	1	1	0	...	1
	1	0	0	1	1	0	0	...	1

$$c_i = \langle v_i, s \rangle \oplus d_i$$

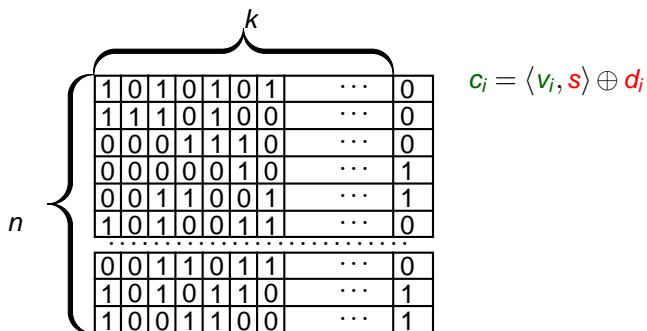
## Reduction *sparse-secret*

1	0	1	0	1	0	1	...	0
1	1	1	0	1	0	0	...	0
0	0	0	1	1	1	0	...	0
0	0	0	0	0	1	0	...	1
0	0	1	1	0	0	1	...	1
1	0	1	0	0	1	1	...	0
...	...	...	...	...	...	...	...	...
0	0	1	1	0	1	1	...	0
1	0	1	0	1	1	0	...	1
1	0	0	1	1	0	0	...	1

$$c_i = \langle v_i, s \rangle \oplus d_i$$

Change the distribution of the secret

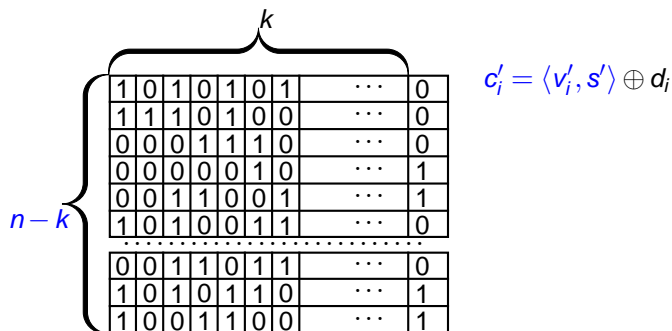
## Reduction *sparse-secret*



Change the distribution of the secret

- from  $s$  being uniformly distributed
- to an  $s$  where each bit has the same distribution as the noise

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- from  $s$  being uniformly distributed
- to an  $s$  where each bit has the same distribution as the noise

Complexity:  $O(\min_{\chi \in \mathbb{N}} (k(n-k) \lceil \frac{k}{\chi} \rceil + k^3 + k\chi 2^\chi))$

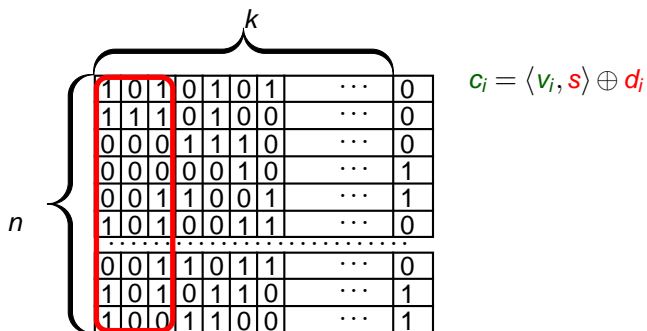
## Reduction *xor-reduce*

k									
n	1	0	1	0	1	0	1	...	0
	1	1	1	0	1	0	0	...	0
	0	0	0	1	1	1	0	...	0
	0	0	0	0	0	1	0	...	1
	0	0	1	1	0	0	1	...	1
	1	0	1	0	0	1	1	...	0
	...	...	...	...	...	...	...	...	...
	0	0	1	1	0	1	1	...	0
	1	0	1	0	1	1	0	...	1
	1	0	0	1	1	0	0	...	1

$$c_i = \langle v_i, s \rangle \oplus d_i$$

Find collisions on a window of  $b$  bits

## Reduction *xor-reduce*



Find collisions on a window of  $b$  bits

- group queries in equivalence classes
- xor each pair of queries from the same equivalence class



## Reduction *xor-reduce*

				$k - b$					
$\frac{n(n-1)}{2^{b+1}}$	0	0	0	0	1	0	1	...	0
	0	0	0	0	1	0	0	...	0
	0	0	0	1	1	1	0	...	0
	0	0	0	0	0	1	0	...	1
	0	0	0	1	0	0	1	...	1
	0	0	0	0	1	1	0	...	0
	0	0	0	...	...	...	...	...	...
	0	0	0	0	0	1	0	...	0
	0	0	0	0	0	1	1	...	1
	0	0	0	1	1	0	0	...	1

$$c_i \oplus c_j = \langle v_i \oplus v_j, s \rangle \oplus d_i \oplus d_j$$

Find collisions on a window of  $b$  bits

- group queries in equivalence classes
- xor each pair of queries from the same equivalence class

Complexity:  $O(k \cdot \max(n, \frac{n(n-1)}{2^{b+1}}))$

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				$k - b$					
$\frac{n(n-1)}{2^{b+1}}$	0	0	0	0	1	0	1	...	0
	0	0	0	0	1	0	0	...	0
	0	0	0	1	1	1	0	...	0
	0	0	0	0	0	1	0	...	1
	0	0	0	1	0	0	1	...	1
	0	0	0	0	1	1	0	...	0
	...	...	...	...	...	...	...	...	...
	0	0	0	0	0	1	0	...	0
	0	0	0	0	0	1	1	...	1
	0	0	0	1	1	0	0	...	1

$$c_i \oplus c_j = \langle v_i \oplus v_j, s \rangle \oplus d_i \oplus d_j$$

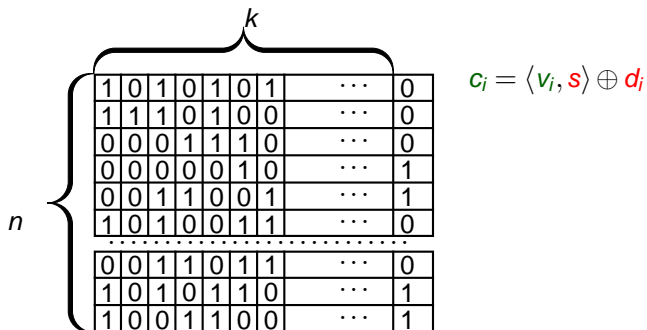
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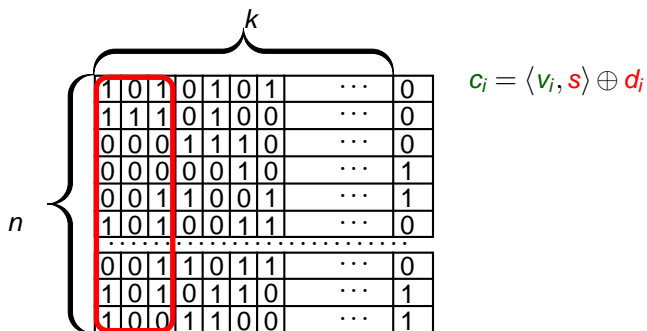
When  $n \approx 1 + 2^{b+1}$ , the number of queries stay constant

## Reduction *drop-reduce*



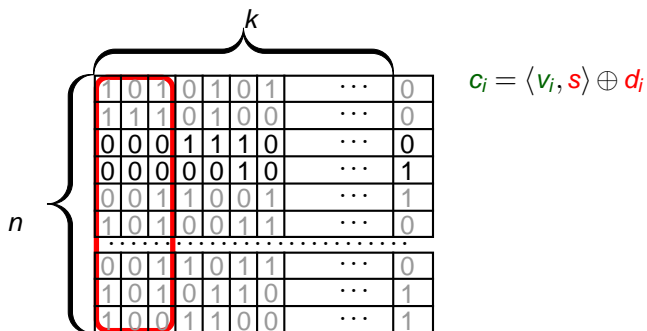
Keep only the queries with 0 on a window of  $b$  bits

## Reduction *drop-reduce*



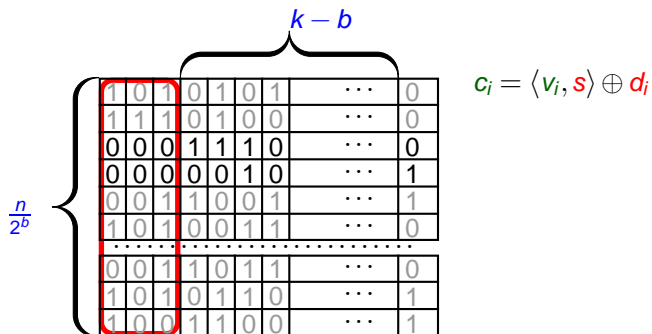
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## Reduction *drop-reduce*



Keep only the queries with 0 on a window of  $b$  bits

# Reduction *drop-reduce*



Keep only the queries with 0 on a window of  $b$  bits

Complexity:  $O(n(1 + \frac{1}{2} + \dots + \frac{1}{2^{b-1}}))$

## Reduction *code-reduce*

1	0	1	0	1	0	1	...	0
1	1	1	0	1	0	0	...	0
0	0	0	1	1	1	0	...	0
0	0	0	0	0	1	0	...	1
0	0	1	1	0	0	1	...	1
1	0	1	0	0	1	1	...	0
.....								
0	0	1	1	0	1	1	...	0
1	0	1	0	1	1	0	...	1
1	0	0	1	1	0	0	...	1

$$c_i = \langle v_i, s \rangle \oplus d_i$$

Introduced at ASIACRYPT'14 [GJL]

Use a linear code  $\mathcal{C}[k, k', D]$  with generator matrix  $G$ , where  $g = g'G \in \mathcal{C}$

Approximate each vector  $v_i$  to the nearest neighbour in the code  $\mathcal{C}$

## Reduction *code-reduce*

1	0	1	0	1	0	1	...	0
1	1	1	0	1	0	0	...	0
0	0	0	1	1	1	0	...	0
0	0	0	0	0	1	0	...	1
0	0	1	1	0	0	1	...	1
1	0	1	0	0	1	1	...	0
.....								
0	0	1	1	0	1	1	...	0
1	0	1	0	1	1	0	...	1
1	0	0	1	1	0	0	...	1

$$\begin{aligned}c_i &= \langle v_i, s \rangle \oplus d_i \\ &= \langle g, s \rangle \oplus \langle v_i - g, s \rangle \oplus d_i \\ &= \langle g'G, s \rangle \oplus \langle v_i - g, s \rangle \oplus d_i \\ &= \langle g', sG^T \rangle \oplus \langle v_i - g, s \rangle \oplus d_i\end{aligned}$$

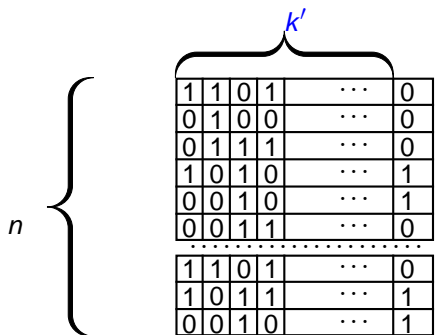
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Use a linear code  $C[k, k', D]$  with generator matrix  $G$ , where  $g = g'G \in C$

Approximate each vector  $v_i$  to the nearest neighbour in the code  $C$

Complexity:  $O(k \cdot n)$

# Solving Technique

Define

$$f(x) = \sum_i 1_{v_i=x} (-1)^{\langle v_i, s \rangle \oplus d_i}$$

and apply the Walsh Hadamard Transform (WHT) to obtain

$$\hat{f}(v) = \sum_x (-1)^{\langle v, x \rangle} f(x) = \sum_i (-1)^{\langle v_i, s+v \rangle \oplus d_i}$$

$|\hat{f}(s)|$  is large; In order to be the largest value in the table of  $\hat{f}$ , we require certain amount of queries

Complexity:  $O(k2^k \frac{\log_2 n+1}{2} + kn)$ , when WHT is applied for a secret of  $k$  bits on  $n$  queries

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## Bias of the Code Reduction

For *code-reduce* we have

$$c_i = \langle v_i, s \rangle \oplus d_i = \langle g', s' \rangle \oplus \langle v_i - g, s \rangle \oplus d_i$$

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$$\begin{aligned} \text{bc} &= E((-1)^{\langle v_i - g, s \rangle}) = \sum_{e \in \{0,1\}^k} \Pr[v_i - g = e] E((-1)^{\langle e, s \rangle}) \\ &= E\left(\delta_s^{\text{HW}(v_i - g)}\right), \end{aligned}$$

where  $\delta_s$  is the secret bias

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We analyse:

- perfect codes
- quasi-perfect codes
- random codes

## Perfect Codes

- Repetition code  $[k, 1, \frac{k-1}{2}]$  with  $k$  odd

$$\text{bc} = \sum_{w=0}^{\frac{k-1}{2}} \frac{1}{2^{k-1}} \binom{k}{w} \delta_s^w$$

- Golay code  $[23, 12, 7]$

$$\text{bc} = 2^{-11} \sum_{w=0}^3 \binom{23}{w} \delta_s^w$$

- Hamming code  $[2^\ell - 1, 2^\ell - \ell, 3]$

$$\text{bc} = 2^{-\ell} \sum_{w=0}^1 \binom{2^\ell - 1}{w} \delta_s^w$$

# Optimal Concatenated Code

Not every code  $\mathcal{C}[k, k', D]$  is perfect or quasi-perfect



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Concatenate codes

Take the  $C[k, k', D]$  code as the concatenation of  $C_1[k - \ell, k' - \ell', D_1]$  and  $C_2[\ell, \ell', D_2]$  with  $bc = bc_1 \cdot bc_2$

# Optimal Concatenated Code

Not every code  $C[k, k', D]$  is perfect or quasi-perfect



Concatenate codes

Take the  $C[k, k', D]$  code as the concatenation of  $C_1[k - \ell, k' - \ell', D_1]$  and  $C_2[\ell, \ell', D_2]$  with  $bc = bc_1 \cdot bc_2$

Computation:

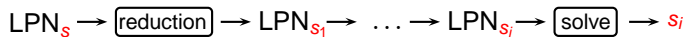
- compute the biases for perfect, quasi-perfect and random codes
- for each  $[k, k', D]$ , check if  $bc[k, k', D] < bc[k - \ell, k' - \ell', D_1] \cdot bc[\ell, \ell', D_2]$

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# LPN Solving Automaton

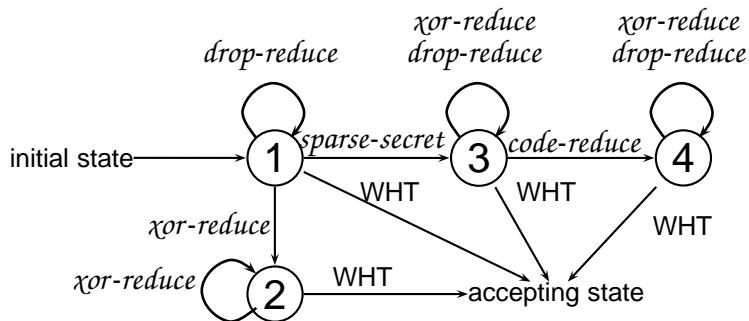
LPN solving algorithms = chains of reductions + WHT



# LPN Solving Automaton

LPN solving algorithms = chains of reductions + WHT

$LPN_s \rightarrow \boxed{\text{reduction}} \rightarrow LPN_{s_1} \rightarrow \dots \rightarrow LPN_{s_i} \rightarrow \boxed{\text{solve}} \rightarrow s_i$



# Graph of Reduction Chains

Construct a graph of all possible reduction chains

- the vertex stores the secret size and the number of queries
- the edge stores the bias change for a reduction

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Construct a graph of all possible reduction chains

- the vertex stores the secret size and the number of queries
- the edge stores the bias change for a reduction

## Find the reductions that optimize the bias

The **time complexity** of a chain is the sum of the complexities of each reduction step + cost of WHT

Use **max-complexity** as an approximation for the time complexity

# Graph of Reduction Chains

Construct a graph of all possible reduction chains

- the vertex stores the secret size and the number of queries
- the edge stores the bias change for a reduction

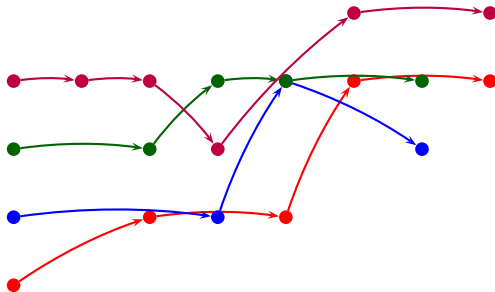
## Find the reductions that optimize the bias

The **time complexity** of a chain is the sum of the complexities of each reduction step + cost of WHT

Use **max-complexity** as an approximation for the time complexity

Find the chain with the smallest max-complexity and compute its total time complexity

# Graph of Reduction Chains



Find the chain with the smallest max-complexity and compute its total time complexity

# Outline

- 1 LPN
- 2 Code Reduction
- 3 Our Algorithm
- 4 Results**

# Results

$(k, \tau)$	ASIACRYPT'14 [GJL]	EUROCRYPT'16 [ZJW]	our results
(512, 0.125)	81.90	80.09	78.84
(532, 0.125)	88.62	82.17	81.02
(592, 0.125)	97.71	89.32	87.57

Table: Logarithmic time complexity to solve LPN (in bit operations)

$k$  - secret size

$\tau$  - noise level

# Results

$\tau$	$k$						
	32	48	64	100	256	512	768
0.05	13.89	14.52	16.04	20.47	36.75	57.77	76.63
0.1	15.04	18.58	21.58	27.61	46.75	73.68	98.97
0.125	15.66	19.29	22.94	28.91	49.90	78.85	105.89
0.2	17.01	21.25	24.42	32.06	56.31	89.04	121.04
0.25	18.42	22.34	26.86	32.94	59.47	94.66	127.35

Table: Logarithmic time complexity to solve LPN

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Table: Logarithmic time complexity to solve LPN



## Conclusion

- Create an algorithm that automatizes the LPN solving algorithms
- Improve the best existing results
- New reduction techniques can be integrated later on

Thank you for your kind attention!