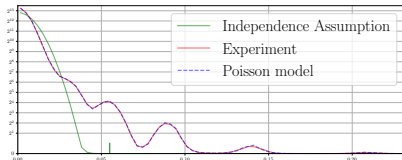


# Rigorous Foundations for Dual Attacks in Coding Theory

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TCC 2023



# Dual attacks in codes and lattices

## Dual attacks solve

Decoding Problem in Codes and Lattices

→ Heart of security of cryptographic primitives

Lattices : Dual attacks would impact Kyber (NIST standard)

**Independence** assumptions to analyze dual attacks

Not valid

Codes

Carrier, Debris-Alazard, Meyer-Hilfiger,  
Tillich. 2022 : "Statistical decoding  
2.0"



Notice experimental differences

Lattices

Ducas, Pulles. 2023 : "Does the  
Dual-Sieve Attack on Learning with  
Errors even Work?"



Seriously question dual attacks

## Contributions of the paper

- Explain why independence assumptions does not hold
- Give rigorous foundations for analyzing dual attacks ← **This talk**
- Show that dual attacks in coding theory work

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1 Dual attacks and their analysis

2 Contribution : The distribution of the the bias

# Setting for **Dual** attacks in Coding Theory

## Linear code

$\mathcal{C}$  a binary  $[n, k]$  linear code: linear subspace of  $\mathbb{F}_2^n$  of dimension  $k$ .

## Decoding problem at distance $t$ (small)

- **Input:**  $\mathbf{y} \in \mathbb{F}_2^n$  where  $\mathbf{y} = \mathbf{c} + \mathbf{e}$  with  $\mathbf{c} \in \mathcal{C}$  and  $|\mathbf{e}| = t$
- **Output:**  $\mathbf{e} \in \mathbb{F}_2^n$  such that  $|\mathbf{e}| = t$  and  $\mathbf{y} + \mathbf{e} \in \mathcal{C}$ .

$|\mathbf{x}|$  is Hamming weight of  $\mathbf{x}$ : number of non-zero coordinates.

## Dual code

$\mathcal{C}^\perp = \{\mathbf{h} \in \mathbb{F}_2^n : \langle \mathbf{h}, \mathbf{c} \rangle = 0 \quad \forall \mathbf{c} \in \mathcal{C}\} \rightarrow \mathcal{C}^\perp$  is  $[n, n - k]$  linear code

$\langle \mathbf{x}, \mathbf{z} \rangle \in \mathbb{F}_2$  usual inner product for  $\mathbb{F}_2^n$

## Idea of Dual attacks (Al-Jabri, 2001)

- $\mathbf{h} = \boxed{\phantom{w}} \in \mathcal{C}^\perp$

- $\langle \mathbf{y}, \mathbf{h} \rangle = \langle \mathbf{c}, \mathbf{h} \rangle + \langle \mathbf{e}, \mathbf{h} \rangle = \langle \mathbf{e}, \mathbf{h} \rangle = \sum_{i=1}^n e_i h_i \rightarrow$  Biased toward 0

Distinguisher

( $\mathbf{y}$  random v.s  $\mathbf{y} = \mathbf{c} + \mathbf{e}$ )

- Compute all parity-checks of weight  $w$

$$\mathcal{C}_w^\perp \triangleq \{\mathbf{h} \in \mathcal{C}^\perp : |\mathbf{h}| = w\}$$

- Compute **bias**

$$\text{bias}_{\mathcal{C}_w^\perp}(\mathbf{y}) \triangleq \frac{1}{|\mathcal{C}_w^\perp|} \sum_{\mathbf{h} \in \mathcal{C}_w^\perp} (-1)^{\langle \mathbf{y}, \mathbf{h} \rangle} \in [-1, 1]$$

- Make decision:

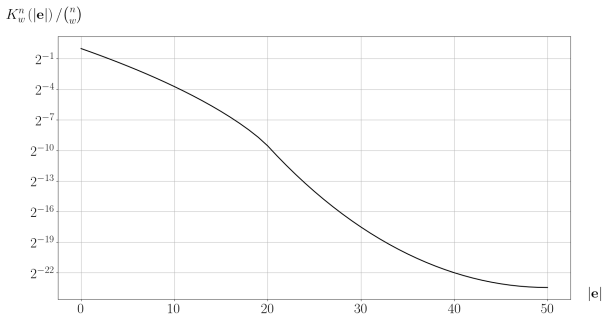
$\text{bias}_{\mathcal{C}_w^\perp}(\mathbf{y})$  is **big** enough  $\rightarrow$  decide  $\mathbf{y} = \mathbf{c} + \mathbf{e}$

# Estimate of $\text{bias}_{\mathcal{C}_w^\perp}(\mathbf{y})$ ( $\mathbf{y} = \mathbf{c} + \mathbf{e}$ , w.t. $|\mathbf{e}|$ small)

## Theorem [CDMT22]

Under certain conditions:

$$\text{bias}_{\mathcal{C}_w^\perp}(\mathbf{y}) \approx \frac{K_w^{(n)}(|\mathbf{e}|)}{\binom{n}{w}} \quad (K_w^{(n)} \text{ Krawtchouk polynomial})$$



## Idea of Dual Attacks 2.0 [CDMT, 2022]

- Split support in arbitrary complementary part  $\mathcal{P}$  and  $\mathcal{N} \rightarrow$  Recover  $\mathbf{e}_{\mathcal{P}}$ ?

- Compute  $\mathbf{h} = \underbrace{\text{[hatched box]}}_{\mathcal{P}} \underbrace{\text{[white box with } w \text{ (small)]}}_{\mathcal{N}} \in \mathcal{C}^{\perp}$

$$\langle \mathbf{y}, \mathbf{h} \rangle = \langle \mathbf{e}, \mathbf{h} \rangle = \langle \mathbf{e}_{\mathcal{P}}, \mathbf{h}_{\mathcal{P}} \rangle + \langle \mathbf{e}_{\mathcal{N}}, \mathbf{h}_{\mathcal{N}} \rangle$$

$$\langle \mathbf{y}, \mathbf{h} \rangle + \langle \mathbf{e}_{\mathcal{P}}, \mathbf{h}_{\mathcal{P}} \rangle = \langle \mathbf{e}_{\mathcal{N}}, \mathbf{h}_{\mathcal{N}} \rangle \rightarrow \text{biased toward 0}$$

Algorithm : return  $\mathbf{x}$  s.t  $\langle \mathbf{y}, \mathbf{h} \rangle + \langle \mathbf{x}, \mathbf{h}_{\mathcal{P}} \rangle$  most biased tower 0

- Compute set of parity-checks  $\mathcal{C}_w^{\perp} \triangleq \{\mathbf{h} \in \mathcal{C}^{\perp} : |\mathbf{h}_{\mathcal{N}}| = w\}$
- Compute **bias** for each  $\mathbf{x}$

$$\text{bias}_{\mathcal{C}_w^{\perp}}(\mathbf{x}) \triangleq \frac{1}{|\mathcal{C}_w^{\perp}|} \sum_{\mathbf{h} \in \mathcal{C}_w^{\perp}} (-1)^{\langle \mathbf{y}, \mathbf{h} \rangle + \langle \mathbf{x}, \mathbf{h}_{\mathcal{P}} \rangle} \in [-1, 1]$$

- Return  $\mathbf{x}$  such that  $\text{bias}_{\mathcal{C}_w^{\perp}}(\mathbf{x})$  maximum  $\rightarrow$  Hope max given by  $\mathbf{e}_{\mathcal{P}}$



## Analysis of Dual Attack 2.0

Recall  $\mathbf{bias}_{\mathcal{C}_w^\perp}(\mathbf{x}) \triangleq \frac{1}{|\mathcal{C}_w^\perp|} \sum_{\mathbf{h} \in \mathcal{C}_w^\perp} (-1)^{\langle \mathbf{y}, \mathbf{h} \rangle + \langle \mathbf{x}, \mathbf{h} \rangle}$

Study probability that  $\mathbf{bias}_{\mathcal{C}_w^\perp}(\mathbf{e}_{\mathcal{P}}) > \mathbf{bias}_{\mathcal{C}_w^\perp}(\mathbf{x})$  for all  $\mathbf{x} \neq \mathbf{e}_{\mathcal{P}}$

### **bias** for $\mathbf{e}_{\mathcal{P}}$ : Theorem [CDMT22]

Under certain conditions:

$$\mathbf{bias}_{\mathcal{C}_w^\perp}(\mathbf{e}_{\mathcal{P}}) \approx \frac{K_w^{(|\mathcal{N}|)} (|\mathbf{e}_{\mathcal{N}}|)}{\binom{|\mathcal{N}|}{w}}$$

### **bias** for others $\mathbf{x} \neq \mathbf{e}_{\mathcal{P}}$

#### Independence Assumption



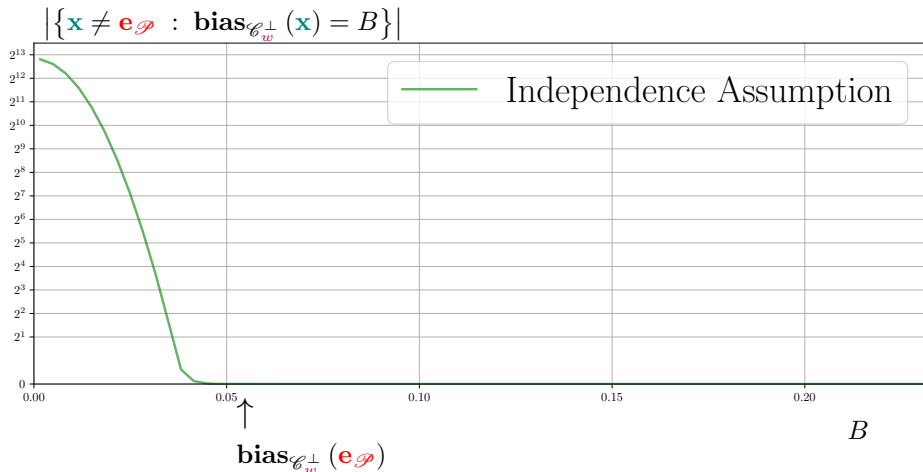
$\langle \mathbf{y}, \mathbf{h} \rangle + \langle \mathbf{x}, \mathbf{h} \rangle \sim \text{Bernoulli}(1/2)$        $\mathbf{h}$  sampled in  $\mathcal{C}_w^\perp$  and  $\mathbf{x} \neq \mathbf{e}_{\mathcal{P}}$



$\mathbf{bias}_{\mathcal{C}_w^\perp}(\mathbf{x}) \approx \text{centered Normal}$

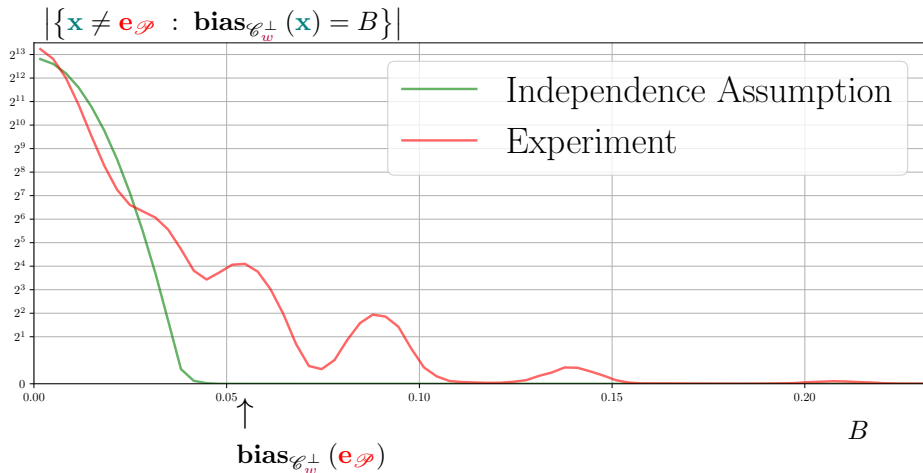
# Sum up in a plot!

Under Independence assumption:



# Sum up in a plot!

Under Independence assumption:



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# A dual expression for $\text{bias}_{\mathcal{C}_w^\perp}(\mathbf{x})$

## Theorem

$$\text{bias}_{\mathcal{C}_w^\perp}(\mathbf{x}) \approx \sum_i N_i \frac{K_w(i)}{\binom{|\mathcal{N}|}{w}}$$

- $N_i$  is number of word of  $\mathcal{C}_x$  at distance  $i$  of  $\mathbf{e}_{\mathcal{N}}$
- $\mathcal{C}_x \triangleq \{\mathbf{c}_{\mathcal{N}} : \mathbf{c} \in \mathcal{C} \text{ and } \mathbf{c}_{\mathcal{P}} = \mathbf{x} + \mathbf{e}_{\mathcal{P}}\}$

**Proof:** Poisson formula

→ Dominated by lowest term  $i$  s.t.  $N_i \neq 0$

## Model for the $N_i$

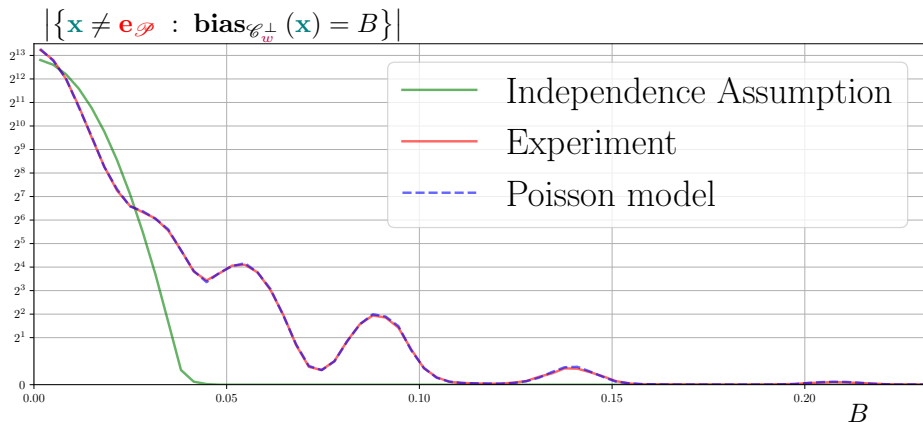
### Poisson model

$$N_i \sim \text{Poisson} ( \mathbb{E} [N_i] )$$

→ The expression of  $\mathbb{E} [N_i]$  is known

# Experimental Results

Under Poisson model:



# Conclusion

- This model can be used to analyze dual attacks
- [CDMT22] with a tweak  $\rightarrow$  originally claimed complexities!  
 $\rightarrow$  **Dual attacks in Coding Theory work!**
- Can be adapted to Lattices

Thank you!