

Generalized tally-based decoders for traitor tracing and group testing

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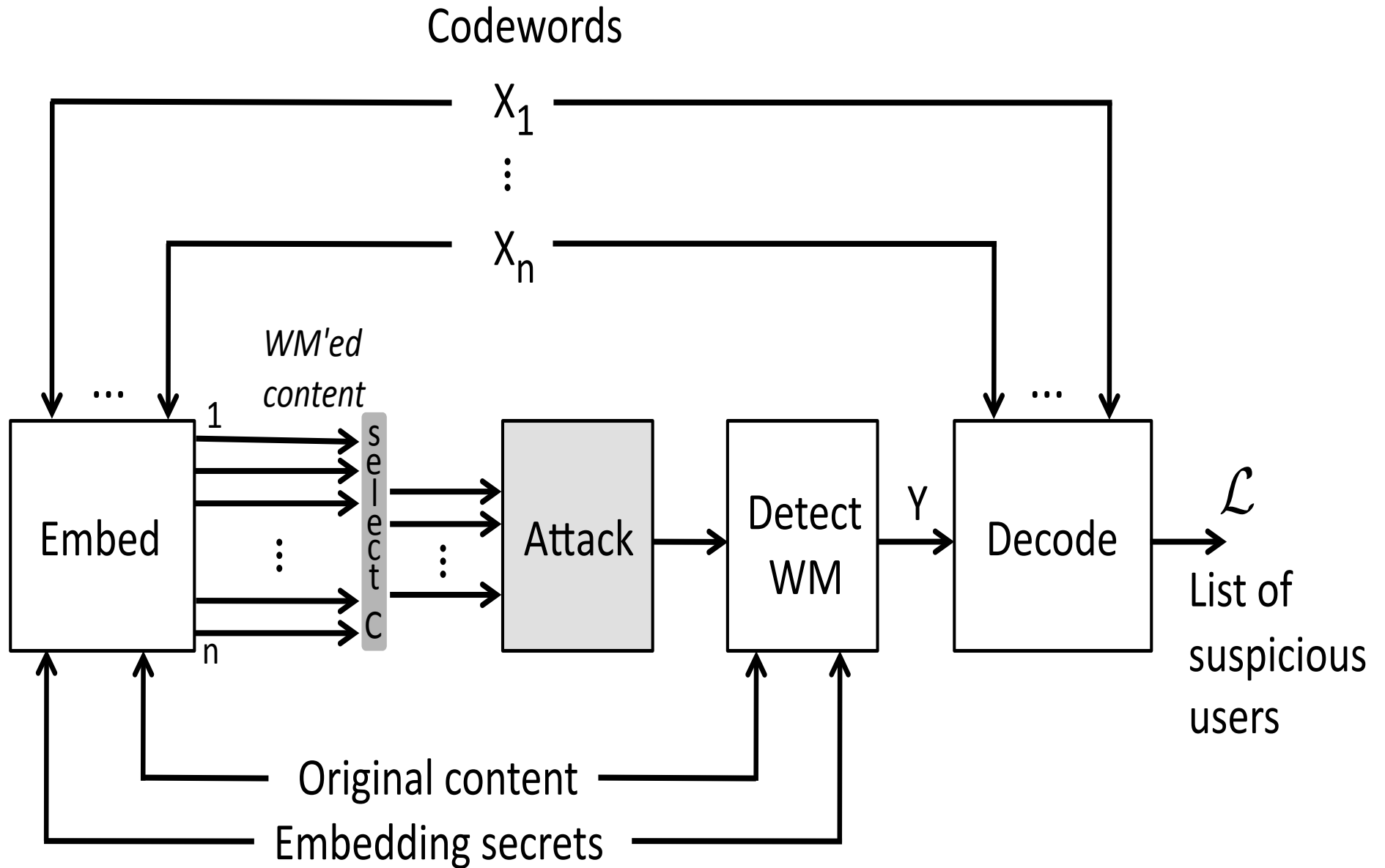


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Outline

- Collusion attacks on watermarks
- Tardos codes
- Attack vs. defense: game theory
- Decoders
 - Neyman-Pearson scores
 - composite symbols
- Group testing

Forensic watermarking



Collusion attacks



"Coalition of pirates"

- Attackers compare their content
- Differences point to watermark
- Try to remove watermark

Collusion-resistant watermarking

Requirements

- Resistance against c_0 attackers
- Low False Positive and False Negative error rate
- small watermark payload!

Attack model

- Discrete positions with embedded symbols
- **Restricted digit model**: Choice from available symbols only

Bias-based code [Tardos 2003, ŠKC 2007]

Alphabet Q of size q

Step 1:

For each position, generate bias vector $\mathbf{p}=(p_\alpha)_{\alpha \in Q}$. $|\mathbf{p}|=1$ $\mathbf{p} \sim F$

Step 2:

For each position and user, draw watermark symbol: $\Pr[\text{symbol } \alpha] = p_\alpha$.

								p_A											
								p_B											
								p_C											
								p_D											
								A											
								C											
								A											
								B											
								B											
								A											
								D											

code matrix X

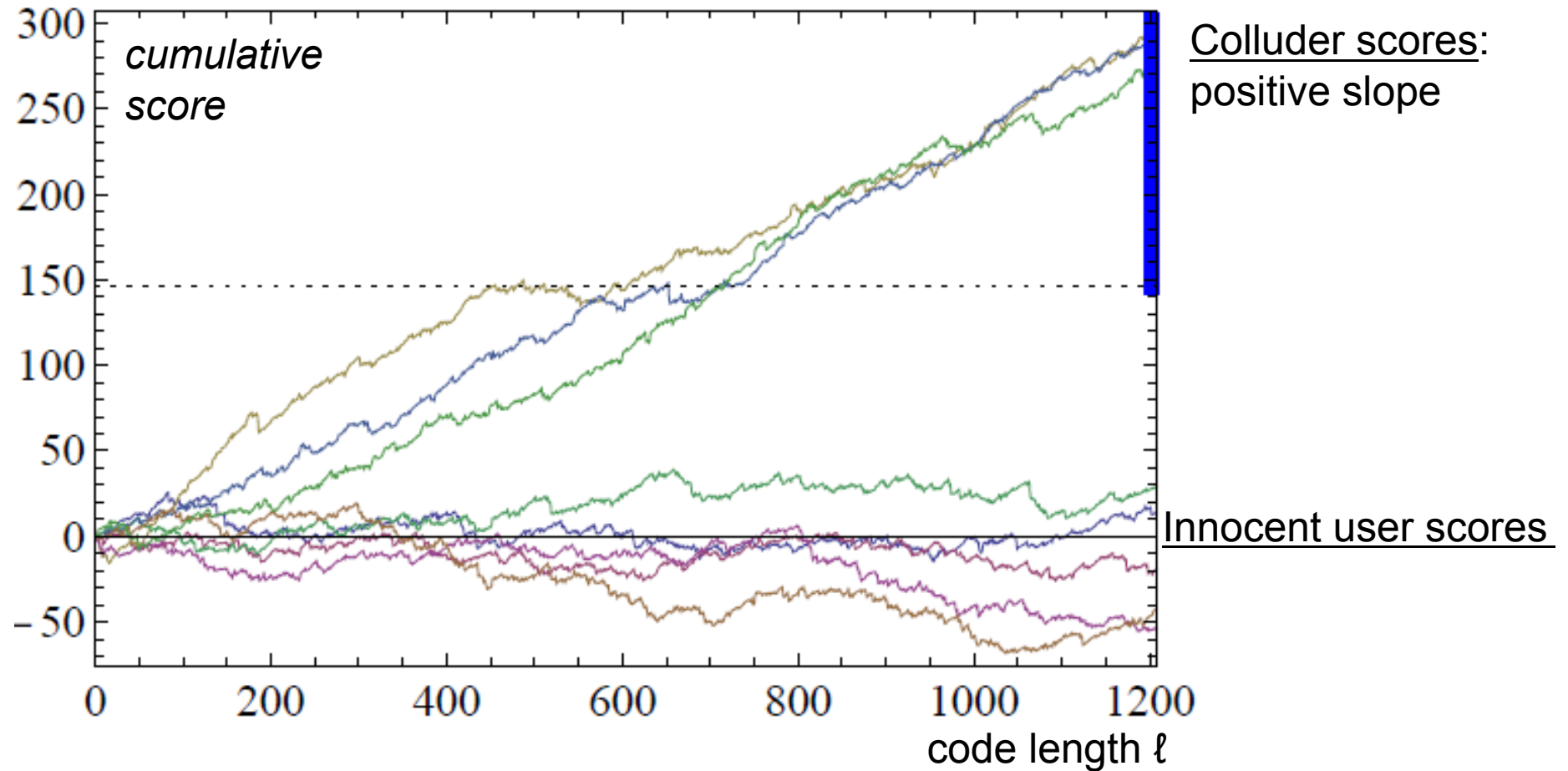
pirated copy carries watermark y

Step 3:

Find attackers based on X and y

**Asymptotically optimal scaling:
code length $\propto c_0^2$**

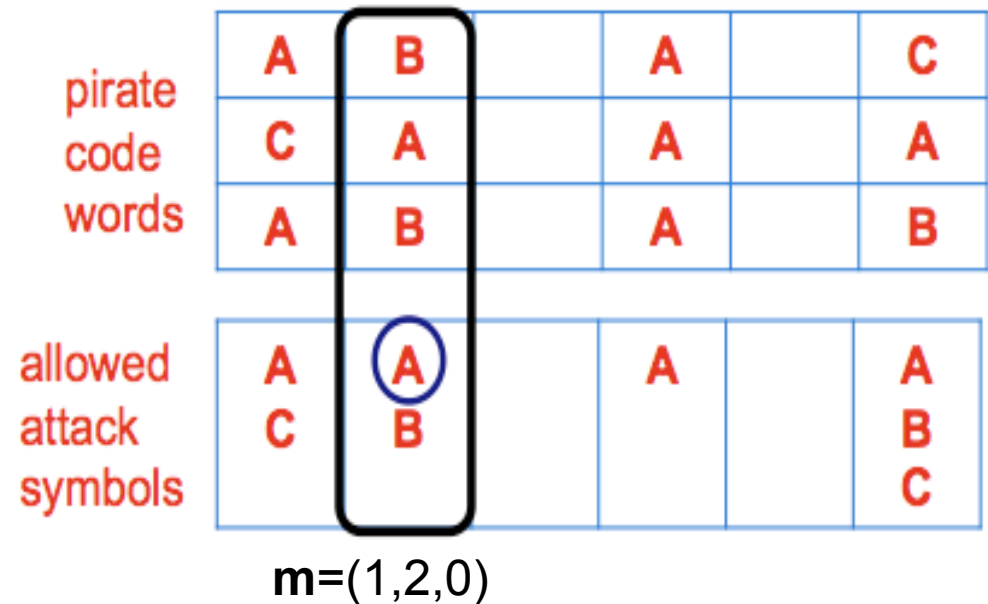
Separating the attackers from the innocents



Collusion channel (in Restricted Digit Model)

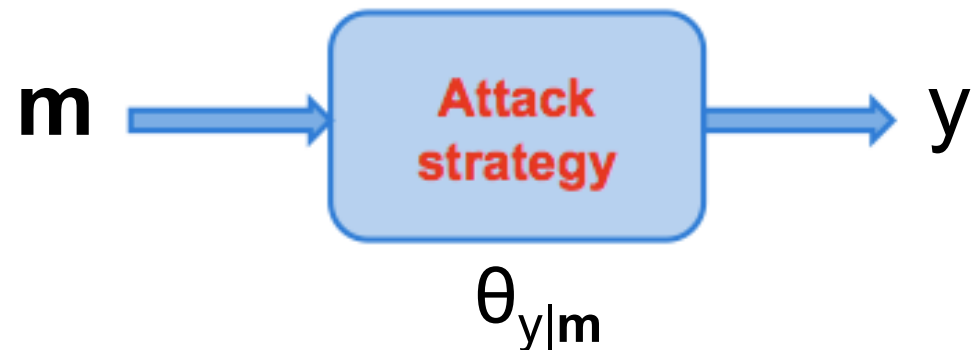
"Tally" vector \mathbf{m} :

- #colluders = c
- $m_\alpha = \#\alpha$ received by colluders
- $|\mathbf{m}| = c$



Attack:

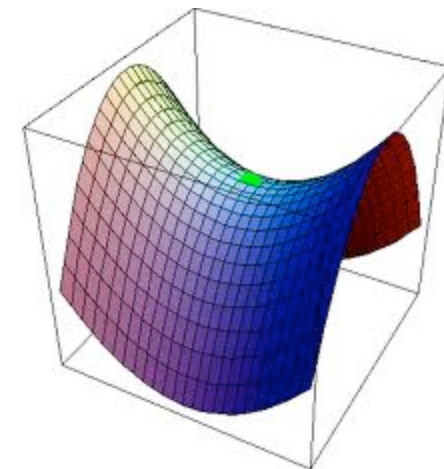
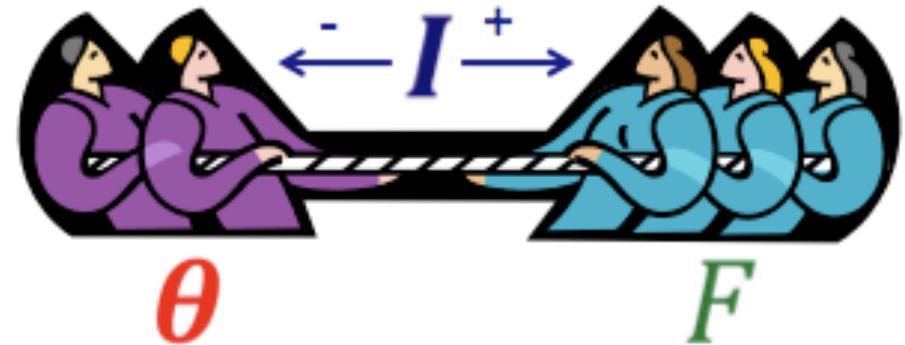
- Same strategy in each position (asymptotically strongest)
- Choose y as a function of \mathbf{m} :
 $\theta_{y|\mathbf{m}} = \text{Prob}[\text{output } y \text{ given } \mathbf{m}]$



- Collusion attack is "malicious noise".
- Use techniques from channel coding!
 - How much does Y reveal about \mathbf{M} ? (\mathbf{M} is equivalent to colluder identities)
 - *Mutual information* $I(\mathbf{M}; Y)$

Game theory:

- Pay-off function $I(\mathbf{M}; Y | \mathbf{P})$
- Tracer chooses bias distribution $F(\mathbf{p})$
- Colluders choose strategy θ



Fingerprinting capacity

$$C = \frac{1}{c} \max_F \min_{\theta} I(\mathbf{M}; Y | \mathbf{P})$$

saddle point

Asymptotic saddlepoint

[Huang+Moulin 2012]

q-ary alphabet.

Pay-off function $I(\mathbf{M}; Y | \mathbf{P})$.

$$F(\mathbf{p}) \propto \prod_{\alpha \in Q} p_{\alpha}^{-1/2}$$

With increasing c ,

- optimal bias distribution gets closer to **Jeffreys prior**.
- optimal attack gets closer to **Interleaving attack**.

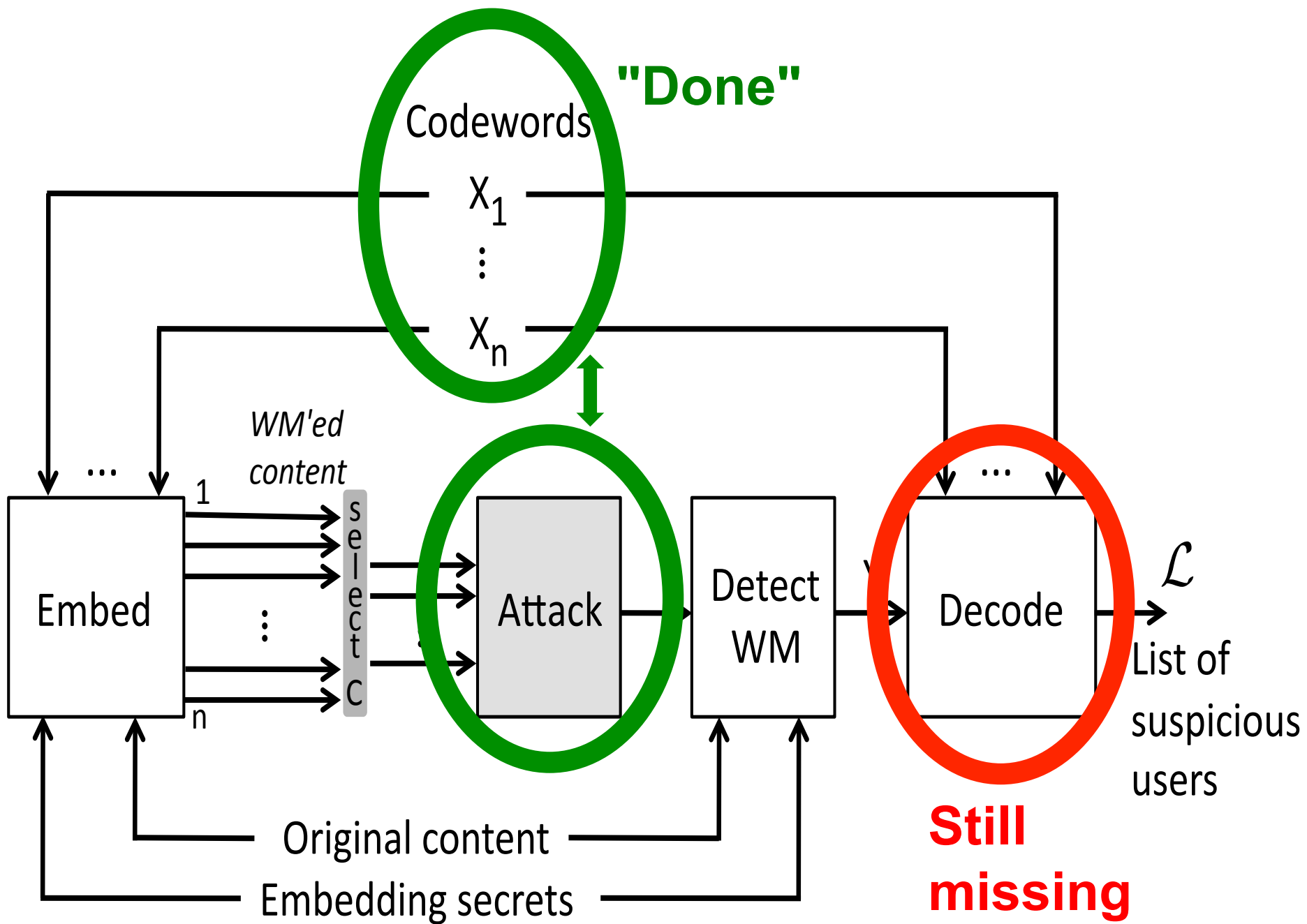
$$\theta_{y|m} = \frac{m_y}{c} \quad (\text{pick random attacker})$$

Asymptotic
capacity
result

$$\ell_{\text{sufficient}} = \frac{2c^2}{q-1} \ln \frac{n}{P_{\text{FP}}}$$

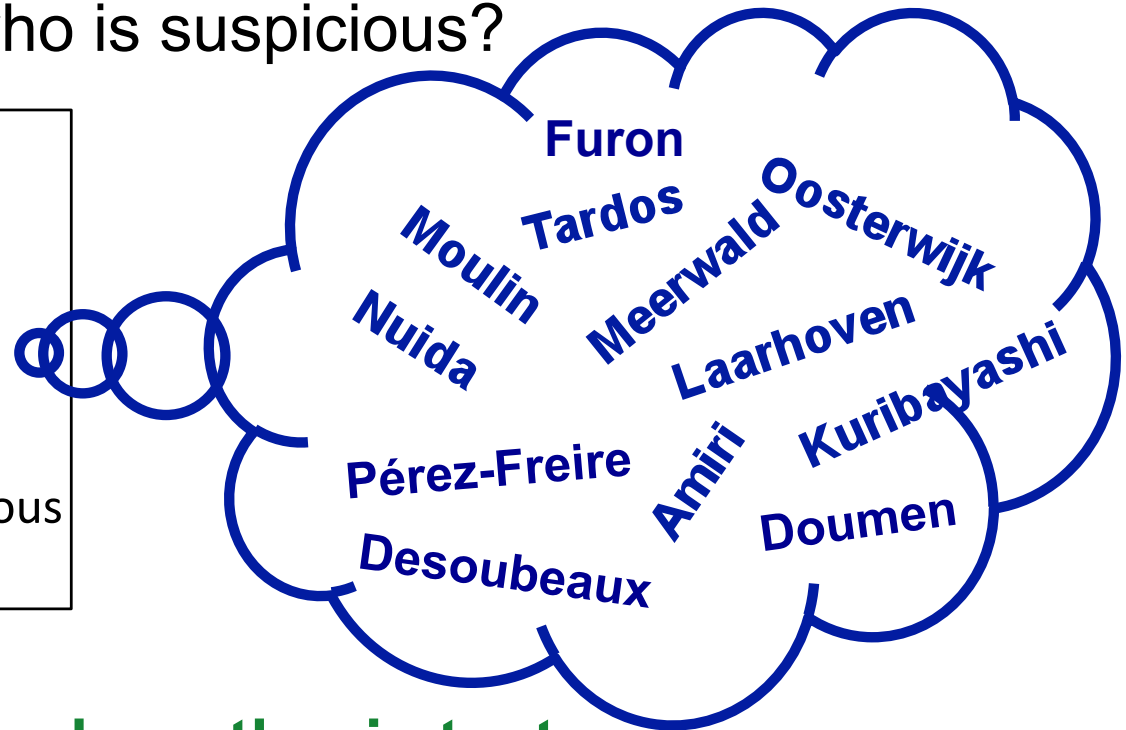
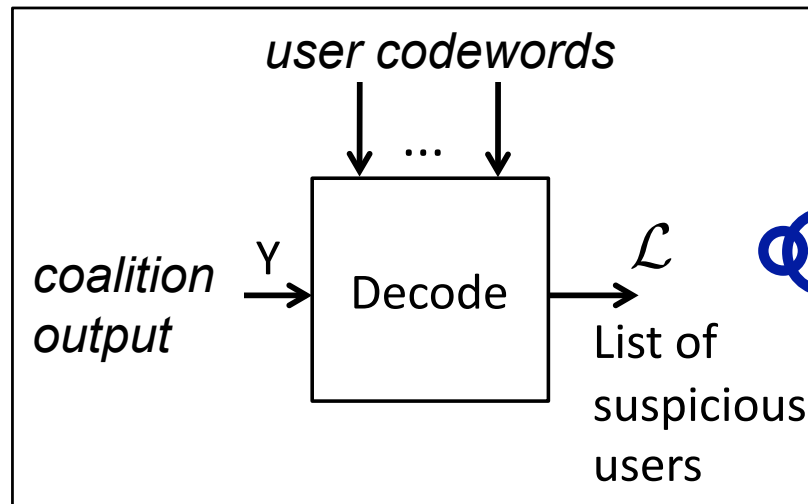
Larger q is better

[Boesten+Škorić 2011]



Decoding

- Capacity analysis says nothing about the decoder!
- How do you decide who is suspicious?



Idea: Neyman-Pearson hypothesis test.

- best P_{FN} at given P_{FP}
- best P_{FP} at given P_{FN}

Neyman-Pearson scores

Hypothesis H_j : "j is part of the coalition".

Neyman-Pearson score:

$$S_j = \frac{\Pr[H_j \mid \text{evidence}]}{\Pr[\neg H_j \mid \text{evidence}]}$$

If $S_j >$ threshold Z , then consider j to be guilty.

Assume colluder symmetry and position symmetry:

S_j equivalent to $\ln \frac{\mathbb{E}_{\bar{M} \mid x, j \in \mathcal{C}} \prod_{i \in [\ell]} \theta_{y_i \mid M_i}}{\mathbb{E}_{\bar{M} \mid x, j \notin \mathcal{C}} \prod_{i \in [\ell]} \theta_{y_i \mid M_i}}$

1. **Score depends on (unknown) strategy θ .**
2. Expectation $\mathbb{E} \dots$ means: **sum over all possible coalitions of size c .**

Neyman-Pearson scores (2)

Problems:

1. Score depends on (unknown) strategy θ .
2. Expectation E_{\dots} : sum over all possible coalitions of size c .

Solutions:

1. Theorem by Abbe and Zheng (2010): $\theta_{\text{saddlepoint}}$ gives *Universal Decoder*.
 - insert the Interleaving attack
2. "Forget" part of the evidence. "Remember" only x_j and
 - biases \mathbf{p} (Laarhoven 2014)
 - symbol tallies (Škorić 2014)
 - composite-symbol tallies. **NEW!**

Neyman-Pearson scores (3)

Laarhoven score:

$$\delta_{xy} \ln\left(1 + \frac{1}{c-1} \cdot \frac{1}{p_y}\right)$$

Škorić 2014:

$$\delta_{xy} \ln\left(1 + \frac{1}{c-1} \cdot \frac{n-1}{t_y-1}\right)$$

(s=1)

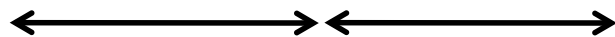
Global tally $t_y = \#$ users who received symbol y

p	p	p	p	p	p
A	A	A	C	D	A
C	C	B	B	B	C
A	D	B	A	B	C
B	C	A	B	A	D
B	D	B	B	C	C
A	C	B	A	C	B
D	B	C	C	B	C

NEW IDEA:

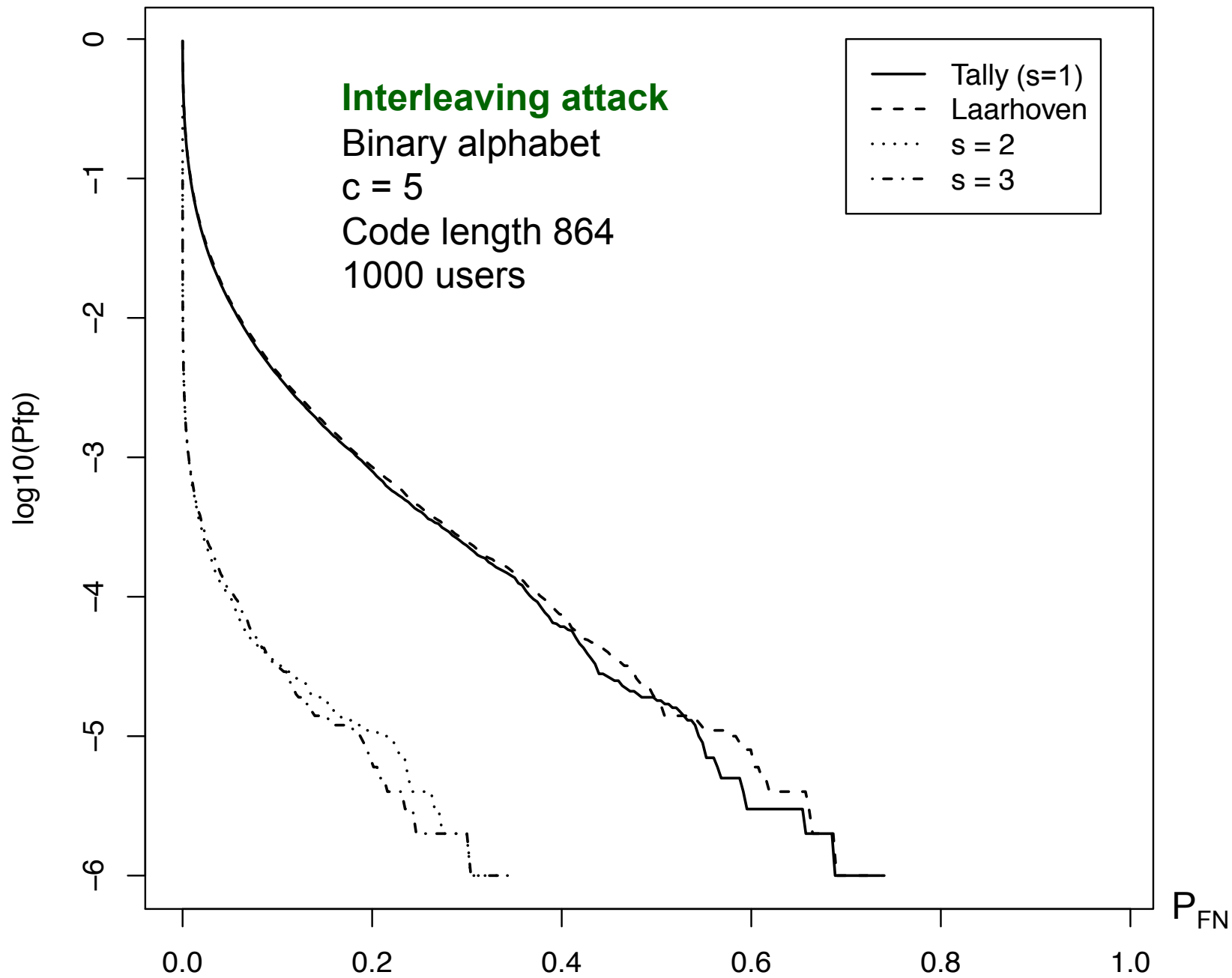
Use more info by combining columns

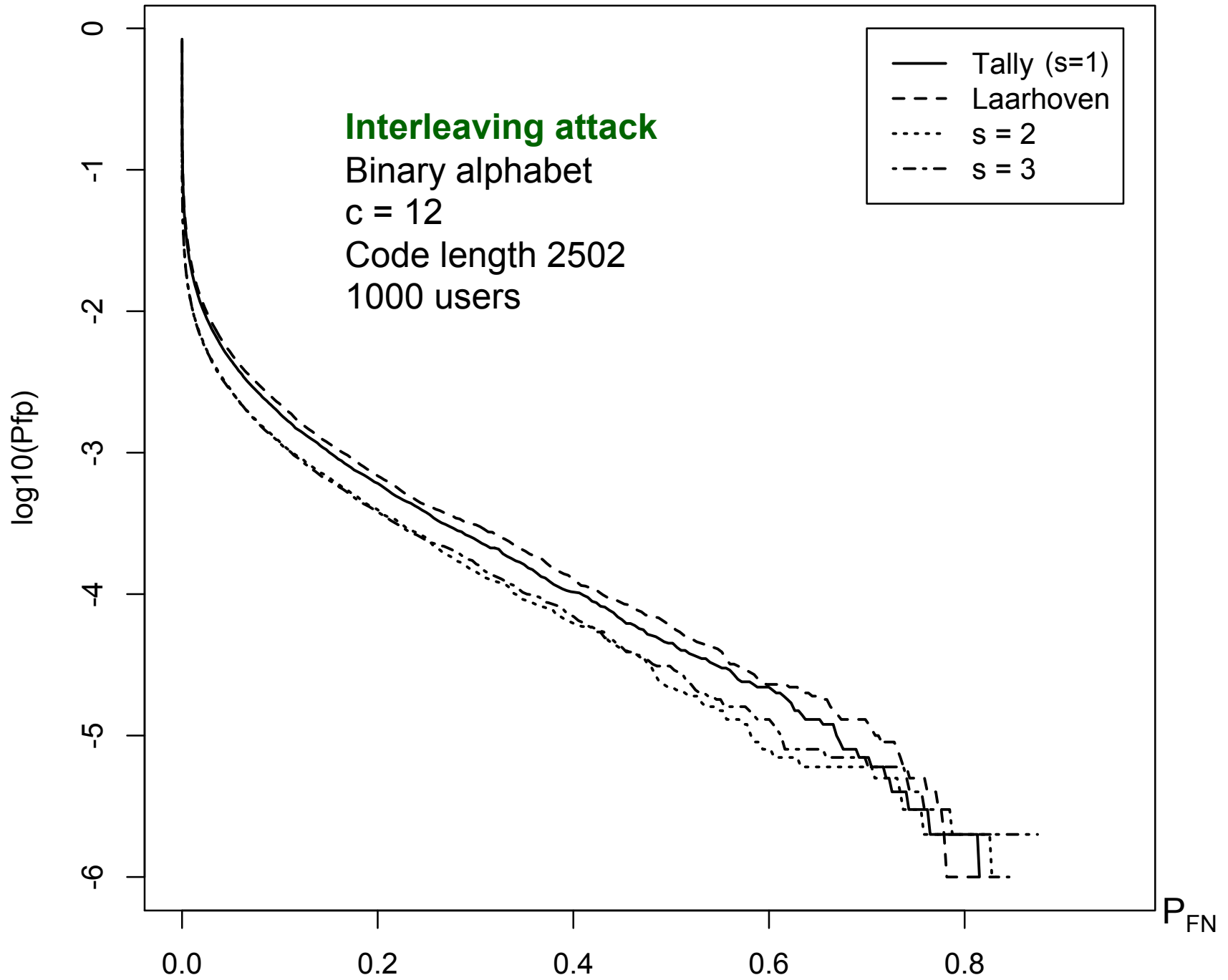
composite symbols "DBC", "CBC"

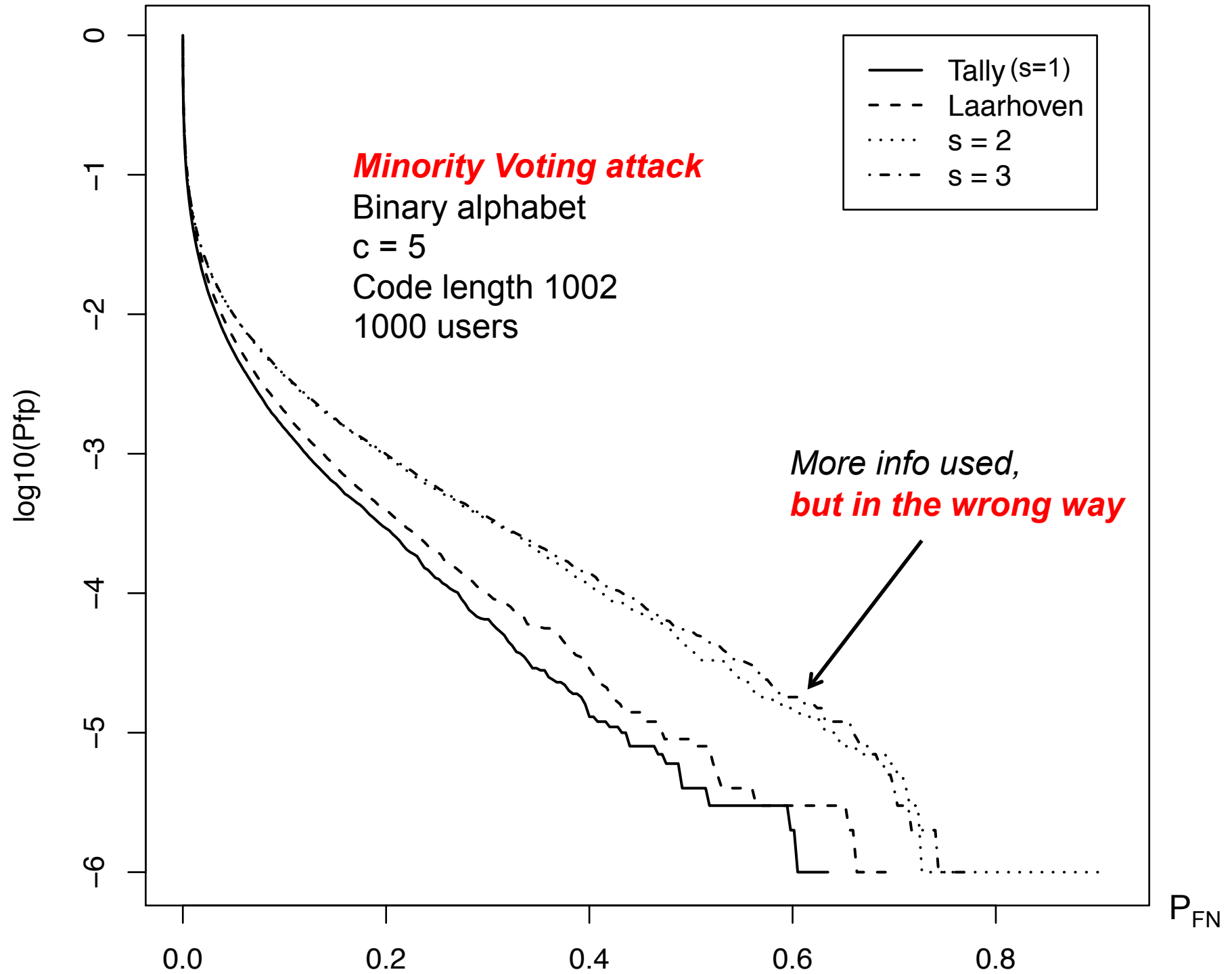


s columns
combined

simulation software: Wouter de Groot







How to combine score functions

Battery of score functions

- The bad decoders cause False Negative, **not False Positive!**
- The good decoders catch the colluders

Group testing

Real-life problem in epidemiology:

- Blood samples from n people
- Expensive test => too few tests
- Long duration => tests in parallel
- Combine blood samples

<i>Traitor Tracing</i>	<i>Group Testing</i>
colluder	infected
symbol 0/1	1 = included in test 0 = not included
code length	number of tests
arbitrary attack θ	θ = All1 attack

Fixed "attack"



The Neyman-Pearson approach to construct score functions is particularly well suited to Group Testing.

Summary

Composite symbol tally:

- Improved Traitor Tracing at "small" c
- Improved Group Testing

Still to be done:

- Further validation
 - simulations, provable bounds, etc.
 - $q > 2$
 - Group Testing numerics etc.
- *Dynamic* scenarios
 - different conditions, different solutions?
- More realistic attack models
 - Combined Digit Model, noisy medical tests, ...



$$g_2(\xi, \lambda, \mathbf{t}) = \ln \left[-1 + \frac{n-2}{n-c} \cdot \frac{(c-1)t_{\lambda[1]}^{\{1\}} t_{\lambda[2]}^{\{2\}} + (n-c)t_\lambda}{(c-1)(t_{\lambda[1]}^{\{1\}} - \delta_{\xi[1]\lambda[1]})(t_{\lambda[2]}^{\{2\}} - \delta_{\xi[2]\lambda[2]}) + (n-1-c)(t_\lambda - \delta_{\xi\lambda})} \right]. \quad (16)$$

$$g_3(\xi, \lambda, \mathbf{t}) = \ln \left[-1 + \frac{n-3}{n-c} \cdot \frac{A_3}{B_3} \right], \quad \text{with} \quad (18)$$

$$\begin{aligned} A_3 &= c^{(3)} t_{\lambda[1]}^{\{1\}} t_{\lambda[2]}^{\{2\}} t_{\lambda[3]}^{\{3\}} \\ &\quad + c^{(2)} (n-c) (t_{\lambda[12]}^{\{1,2\}} t_{\lambda[3]}^{\{3\}} + t_{\lambda[13]}^{\{1,3\}} t_{\lambda[2]}^{\{2\}} + t_{\lambda[23]}^{\{2,3\}} t_{\lambda[1]}^{\{1\}}) \\ &\quad + c(n-c)(n-2c)t_\lambda \end{aligned} \quad (19)$$

$$B_3 = A_3 \text{ with } \mathbf{t} \rightarrow \mathbf{t} - \mathbf{e}_\xi, \quad n \rightarrow n-1 \quad (20)$$