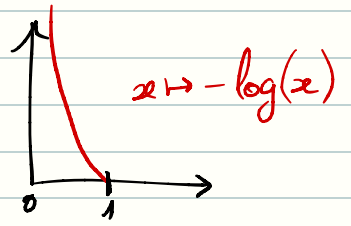


### III) The g-leakage

#### 1) Min-entropy leakage

Given a random variable  $X$ , the min-entropy is defined as:

$$H_{\infty}(X) = -\log(\max_x P(X=x))$$



The bigger it is, the harder the guessing is.

Let consider  $X$  and  $Y$ , two random variables, the the conditional min-entropy is given by:

$$H_{\infty}(X|Y) = -\log(\max_x P(X=x|Y))$$

Take the average over all possible values of  $y$ .

Knowing  $Y$ , it should be easier for the attacker to guess the correct value of  $X$ . Therefore  $H_{\infty}(X) \geq H_{\infty}(X|Y)$ .

The min-entropy leakage is finally defined by:

$$L_{\infty}(X, Y) = H_{\infty}(X) - H_{\infty}(X|Y)$$

Remark:  $H_{\infty}$  has some entropy properties: the flatter the distribution is, the bigger  $H_{\infty}$  is. It measures the randomness by considering the best 1-try possible attacker.

Min-entropy leakage can be written as:

$$L_{\infty}(X, Y) = \log\left(\frac{\max_x P(X=x|Y)}{\max_x P(X=x)}\right)$$

## 2) The main problem with min-leakage

Example: Let  $X$  contain 1000 different passwords 10-bits long.

Let  $Y$  be one of these 1000 passwords.

$$L_{\infty}(X, Y) = 10 \text{ bits}$$

We now consider a user having one of these 1000 passwords. We want to measure how this user is in trouble. The probability of guessing it is  $2^{-10}$  without the leak, and  $0,001 + 0,999 \cdot 2^{-10} = 0,00198 \dots$

$$\text{Then } L_{\infty}(X_{\text{user}}, Y) = \log\left(\frac{0,00198}{2^{-10}}\right) \approx 1,016 \text{ bits}$$

But a whole password has been completely leaked! *And the attacker might be very happy!* Min-entropy is not sufficient for this type of threats. The *g-leakage* is a generalization of the min-entropy leakage.

## 3) The g-function

Let  $(X, Y, P_{Y|X})$  be a channel. We call  $\pi := P_X$  the prior, and the posterior is given by  $\pi(x)P_{Y|X}(y, x)$ . The prior vulnerability is given by  $V(X) = \max_x \pi(x)$ , and the posterior vulnerability is written  $V(X|Y) = \sum_{y \in \mathcal{Y}} \max_x \pi(x)P_{Y|X}(y, x)$ .

As a reminder,  $H_{\infty}(X) = -\log(V(X))$ ,  $H_{\infty}(X|Y) = -\log(V(X|Y))$  and  $L_{\infty}(X, Y) = \log \frac{V(X|Y)}{V(X)}$ .

The *min-capacity* is then defined as  $ML_{\infty}(P_{Y|X}) = \sup_{P_X} L_{\infty}(X, Y)$ , realized for the uniform prior.

Let  $x \in X$  be the secret. Given a guess  $w \in X$ , we define between 0 and 1 how much is the attacker happy with  $w$  by the *gain function*  $g: X^2 \rightarrow [0, 1]$ .

Example: In the min-entropy case,  $g$  is defined by  $g: (w, x) \mapsto \begin{cases} 1 & \text{if } x=w \\ 0 & \text{otherwise} \end{cases}$

This is called the identity  $g$  function,  $g_{\text{id}}$ .

This is better for clarity if we use  $W$  for the space of guesses instead of  $\mathcal{X}$  but this doesn't change the core idea. Formally,  $g: W \times \mathcal{X} \rightarrow [0, 1]$ .

- The **prior  $g$ -vulnerability** is defined by  $V_g(X) = \max_w \mathbb{E}[g(w, X)]$ .
- The **posterior  $g$ -vulnerability** is defined by  $V_g(X|Y) = \mathbb{E}_{\hat{Y}}[V_g(X|Y=\hat{Y})]$ .

Other forms are shown on the paper but this one makes the link with PML. ↗

$$\begin{aligned}
 V_g(\pi, C) &= \sum_{y \in \mathcal{Y}} \max_{w \in W} \sum_{x \in \mathcal{X}} \pi[x] C[x, y] g(w, x) \\
 &= \sum_{y \in \mathcal{Y}} \max_{w \in W} \sum_{x \in \mathcal{X}} p(x, y) g(w, x) \\
 &= \sum_{y \in \mathcal{Y}} p(y) \underbrace{V_g(p_{X|Y=y})}_{\text{Dynamic posterior vulnerability } V_g(X|Y=y)} \\
 &\quad \text{Dynamic } g\text{-leakage } \log \frac{V_g(X|Y=y)}{V_g(X)}.
 \end{aligned}$$

- The  **$g$ -entropy** is defined by  $H_g(X) = -\log(V_g(X))$
- The  **$g$ -leakage** is defined by  $L_g(X, Y) = H_g(X) - H_g(X|Y)$ .
- The  **$g$ -capacity** is defined by  $ML_g(P_{Y|X}) = \sup_{P_X} L_g(X, Y)$ .

Theorem:

$\forall w \in \{\text{vulnerability, entropy, leakage, capacity}\}$ ,  $g$ - $w$  coincides with  $\min$ - $w$ .

#### 4) Special $g$ -functions

Let  $d: \mathcal{X} \rightarrow \mathbb{R}_+$  be a distance. Since  $\mathcal{X}$  is finite, let  $d^* = \max_{c \in \mathcal{X}} d(c)$ .

A gain function induced from  $d$  could be  $1 - \frac{d(x, y)}{d^*}$ , or  $e^{-d(x, y)}$ .

Let  $W \subseteq \mathcal{P}(\mathcal{X})$  be the set of possible guesses. Then it is usual that  $W$  is a **partition** of  $\mathcal{X}$  and that we want to know on which set the secret  $x$  is.

Let  $k \in \mathbb{N}^*$ . We then define  $\mathcal{W} = \{w \in \mathcal{S}(X) \mid |w| = k\}$ . Let us compute the prior of  $g_w$ -vulnerability:  $\max_w E[g_w(w, X)] = \max_{x_0 \neq x_1 \neq x_2} \pi(x_0) + \pi(x_1) + \pi(x_2)$ .

This is exactly what we expect of a prior vulnerability within  $k$  tries!

We then easily define:

- the  $k$ -tries prior vulnerability
- the  $k$ -tries posterior vulnerability
- the  $k$ -tries min-entropy
- the  $k$ -tries min-leakage
- the  $k$ -tries min-capacity

Going further:

IV. MATHEMATICAL PROPERTIES OF  $g$ -VULNERABILITY  
AND  $g$ -LEAKAGE

V. RESULTS ON CHANNEL CAPACITY

VI. COMPARING CHANNELS

VII. RELATED WORK