

Formal Security Proofs via Doebelin Coefficients

Optimal Side-channel Factorization from Noisy Leakage to Random Probing

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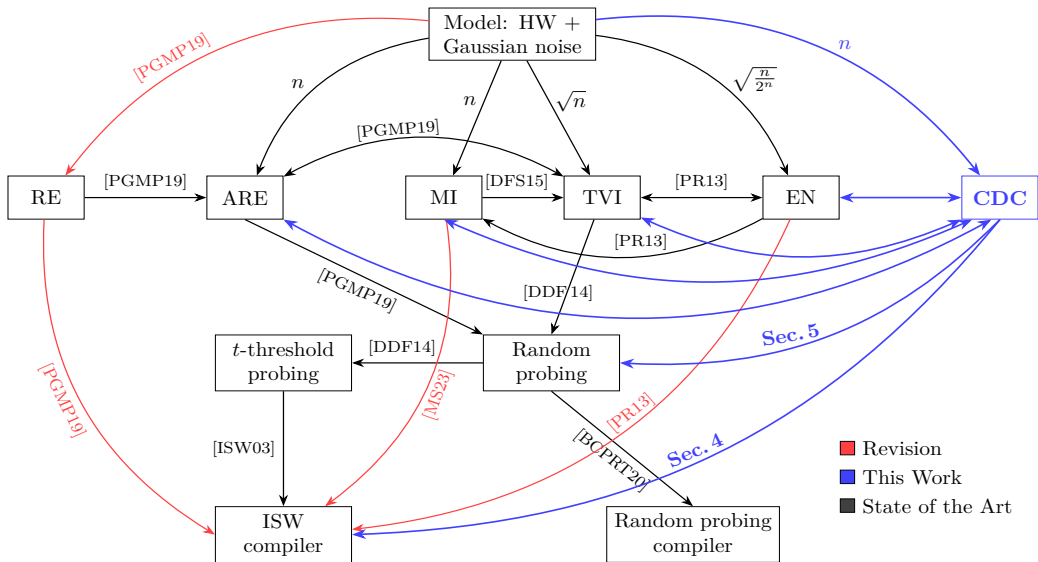
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- **Our work** : Complementary Doeblin Coefficient : **optimal** reduction from **noisy leakage** to **random probing** model; direct proof (PR'13) and indirect proof (DDF'14) + **points several flaws** in previous derivations from PR'13, DDF'14, DFS'15, PGMP'19 and MS'23.

Context



Adversary's Model

Let K be the secret. Adversary obtains side information (Y_1, \dots, Y_l) about sensitive values (X_1, \dots, X_l) through $\varphi_i = (X_i \rightarrow Y_i)$, $i = 1, \dots, l$. $\varphi = (\varphi_1, \dots, \varphi_l)$ is restricted to limit the adversary's abilities :

- **t -threshold probing** : t identity channels and opaque channels otherwise ;
- **$\bar{\mathcal{E}}$ -random probing** : \mathcal{E} -erasure channels ;
- **δ -noisy** : δ -noisy channels with respect to \mathcal{D} i.e. $\mathcal{D}(X; Y) \leq \delta$ where X is uniformly distributed and Y is the output of the side-channel $X \rightarrow Y$;
- **(σ, f) -additive** : channels $X \rightarrow Y \triangleq f(X) + \sigma N$.

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Let $\text{rank}(K|Y)$ be the rank of the correct key in the ranking produced by the adversary upon observation Y . The performance of the attack is usually assessed using :

1. **Success rate of order o** , $(SR_o) : \mathbb{P}_{s,o}(K|Y) \triangleq \mathbb{P}(\text{rank}(K|Y) \leq o)$
2. **Guessing entropy (GE)** : $G(K|Y) \triangleq \mathbb{E}\{\text{rank}(K|Y)\}$

Multiple Leakage Measures

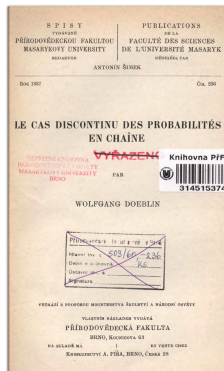
- **Mutual Information** : $I(X; Y) = D_{\text{KL}}(p_{XY} \| p_X p_Y) = \int p_{XY}(x, y) \log \frac{p_{X,Y}(x,y)}{p_X(x)p_Y(y)}$.
- **Total Variation Information** : $\Delta(X; Y) = D_{\text{TV}}(p_{XY} \| p_X p_Y) = \frac{1}{2} \|p_{XY} - p_X p_Y\|_1$.
- **Maximal Leakage** : $\mathcal{L}(X \rightarrow Y) = \log \int_y \sup_x p_{Y|X}(y|x)$.
- **Euclidean Norm bias** : $\beta(X; Y) = \mathbb{E}_Y \|p_{X|Y}(\cdot|Y) - p_X\|_2$.
- **Relative Error** : $RE(X; Y) = \sup_{x,y} \left| \frac{p_{X|Y}(x|y)}{p_X(x)} - 1 \right|$.
- **Average Relative Error** : $ARE(X; Y) = \mathbb{E}_Y \left[\sup_x \left| \frac{p_{X|Y}(x|Y)}{p_X(x)} - 1 \right| \right]$.
- **Complementary Doeblin Coefficient** :

$$\bar{\mathcal{E}}(X \rightarrow Y) = 1 - \int_y \inf_x p_{Y|X}(y|x) = \mathbb{E}_Y \left[\sup_x \left(1 - \frac{p_{X|Y}(x|Y)}{p_X(x)} \right) \right].$$

Wolfgang Doeblin (Vincent Döblin)



*Here
died at the age of 25
on June 21, 1940
Vincent Döblin
mathematical genius*



The discontinuous
case of probability
chains (1937)



Wolfgang Döblin,
ca. 1935

Erasure Channel

Definition (Erasure Channel)

The channel

$$X \rightarrow \boxed{\text{EC}_{\varepsilon}^{\perp}} \rightarrow Y \quad (1)$$

is said to be an erasure channel with erasure probability $\varepsilon \in [0, 1]$ and special erasure symbol \perp if on input x , $\text{EC}_{\varepsilon}^{\perp}$ outputs x with probability

$$\bar{\varepsilon} = 1 - \varepsilon \quad (2)$$

and the special erasure symbol \perp otherwise (with probability ε). That is

$$\begin{cases} p_{Y|X}(\perp|x) = \varepsilon \\ p_{Y|X}(x|x) = \bar{\varepsilon} \end{cases} \quad (\forall x \neq \perp). \quad (3)$$

Optimal Reduction from Noisy Leakage to Random Probing

Theorem (Optimal Reduction)

Any channel $X \rightarrow \boxed{P_{Y|X}} \rightarrow Y$ is a stochastically degraded erasure channel :

$$X \rightarrow \boxed{\text{EC}_{\varepsilon}^{\perp}} \rightarrow X' \rightarrow \boxed{P_{Y|X'}} \rightarrow Y \quad (4)$$

with *maximum* erasure probability given by the *Doeblin Coefficient*

$$\varepsilon(X \rightarrow Y) = \int_Y \inf_{x \in \mathcal{X}} p_{Y|X}(y|x). \quad (5)$$

Proof : Achievability

1. Consider a channel $X \rightarrow \boxed{P_{Y|X}} \rightarrow Y$ with a given Doeblin coefficient

$$\varepsilon = \int_Y \inf_{x \in \mathcal{X}} p_{Y|X}(y|x).$$

2.

$$\begin{cases} p_{Y|X'}(y|\perp) = \varepsilon^{-1} \inf_{x \in \mathcal{X}} p_{Y|X}(y|x) \\ p_{Y|X'}(y|x) = \bar{\varepsilon}^{-1} \left(p_{Y|X}(y|x) - \inf_{x \in \mathcal{X}} p_{Y|X}(y|x) \right) \end{cases}$$

is such that

$$\left(X \rightarrow \boxed{P_{Y|X}} \rightarrow Y \right) = \left(X \rightarrow \boxed{EC_\varepsilon} \rightarrow X' \rightarrow \boxed{P_{Y|X'}} \rightarrow Y \right).$$

Proof : Converse

1. Assume that there exists $\varepsilon \in [0, 1]$ such that

$$\left(X \rightarrow \boxed{P_{Y|X}} \rightarrow Y \right) = \left(X \rightarrow \boxed{EC_\varepsilon} \rightarrow X' \rightarrow \boxed{P_{Y|X'}} \rightarrow Y \right).$$

2. Then for any pair x, y :

$$p_{Y|X}(y|x) = \bar{\varepsilon} p_{Y|X'}(y|x) + \varepsilon p_{Y|X'}(y|\perp) \geq \varepsilon p_{Y|X'}(y|\perp).$$

3. Since it is true for all x :

$$\inf_x p_{Y|X}(y|x) \geq \varepsilon p_{Y|X'}(y|\perp).$$

4. Since $\sum_{y \in Y} p_{Y|X}(y|\perp) = 1$:

$$\sum_{y \in Y} \inf_{x \in X} p_{Y|X}(y|x) \geq \varepsilon.$$

Example with BSC and Z-channel

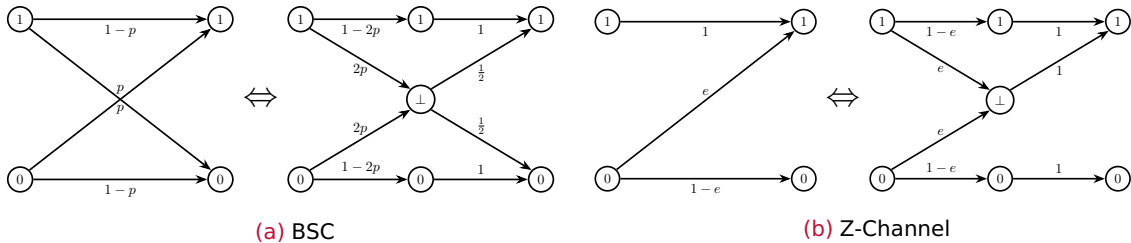


Figure – Illustration of the Theorem

Many Good Properties !

1. **Strengthened-DPI** For any $X \rightarrow Y \rightarrow Z$, CDC satisfies the following strengthened-DPI

$$\overline{\mathcal{E}}(X \rightarrow Z) \leq \overline{\mathcal{E}}(X \rightarrow Y)\overline{\mathcal{E}}(Y \rightarrow Z) \quad (6)$$

2. **Adaptive Single Letterization**

$$\overline{\mathcal{E}}(K \rightarrow Y_1, \dots, Y_q) \leq 1 - (1 - \overline{\mathcal{E}})^q \leq q\overline{\mathcal{E}} \quad (7)$$

3. **Fano's Inequality** The adversary's advantage is bounded as follows :

$$\begin{array}{l} 0 \leq \mathbb{P}_{S,o}(K|Y) - \mathbb{P}_{S,o}(K) \leq \overline{\mathcal{E}}(K \rightarrow Y)\lambda_{SR_o} \\ 0 \leq G(K) - G(K|Y) \leq \overline{\mathcal{E}}(K \rightarrow Y)\lambda_{GE} \\ 0 \leq \Delta(K; Y) \leq \overline{\mathcal{E}}(K \rightarrow Y)\lambda_{TVI} \end{array} \quad \left\| \begin{array}{l} \lambda_{SR_o} = (1 - \mathbb{P}_{S,o}(K)), \\ \lambda_{GE} = (G(K) - 1), \\ \lambda_{TVI} = (1 - \exp(-H_2(K))), \end{array} \right.$$

Subsequence Decomposition

For typical block ciphers like the AES, featuring substitution boxes, Prouff and Rivain (EuroCrypt'13) decompose the computations in four different types of subsequences :

- Type 1** $(z_i \leftarrow g(x_i))_i$ where g is a linear function (of the block cipher)
- Type 2** $(x_i \leftarrow g(y_i))_i$ where g is an affine function (of Sbox evaluation)
- Type 3** $(v_{i,j} \leftarrow a_i b_j)_{i,j}$ (First step of non-linear secure multiplication)
- Type 4** $(t_{i,j} \leftarrow t_{i,j-1} + v_{i,j})_{i,j}$ (Last step of non-linear secure multiplication)

Explicit Algorithm in AES (from MS'24 article)

Algorithm 1 Linear gadget in Prouff & Rivain's proof.

Require: \mathbf{A} : $(d+1)$ -sharing of A , \mathbf{C} : elementary calculation linear with its input.

Ensure: \mathbf{B} : $(d+1)$ -sharing of $C(A)$.

```
1: for  $i = 0, \dots, d$  do
2:    $B_i \leftarrow C(A_i)$                                 ▷ Type 1 or 2
3: end for
4:  $\mathbf{B} \leftarrow \text{Refresh}(\mathbf{B})$                         ▷ Assumed to be leak-free
5:  $\mathbf{A} \leftarrow \text{Refresh}(\mathbf{A})$                         ▷ Only if  $A$  used subsequently.
```

Algorithm 2 Multiplication gadget in Prouff & Rivain's proof.

Require: \mathbf{A}, \mathbf{B} : $(d+1)$ -sharing of A, B .

Ensure: \mathbf{C} : $(d+1)$ -sharing of $A \times B$.

```
1: for  $i = 0, \dots, d$  do
2:   for  $j = 0, \dots, d$  do
3:      $V_{i,j} \leftarrow A_i \times B_j$                     ▷ Cross products (type 3)
4:   end for
5: end for
6:  $\mathbf{V} \leftarrow \text{Refresh}(\mathbf{V})$                         ▷ Assumed to be leak-free
7: for  $i = 0, \dots, d$  do
8:    $C_i = 0$ 
9:   for  $j = 0, \dots, d$  do
10:     $C_i \leftarrow C_i \oplus V_{i,j}$                     ▷ Compression (type 4)
11:   end for
12: end for
13:  $\mathbf{C} \leftarrow \text{Refresh}(\mathbf{C})$                         ▷ Assumed to be leak-free
14:  $\mathbf{A}, \mathbf{B} \leftarrow \text{Refresh}(\mathbf{A}), \text{Refresh}(\mathbf{B})$   ▷ Only if  $A, B$  used subsequently.
```

Mrs. Gerber's Lemma for CDC, Type 1 & 2 Subsequences

Let $\mathbf{G} = (G_i)_{i=0}^d$ be a d -th order encoding of $G = g(X)$ where g is a given function. Each share leaks independently through the side-channels $(G_i \rightarrow Y_i)_{i=0}^d$.

$$\overline{\mathcal{E}}(X \rightarrow \mathbf{Y}) \leq \prod_i \overline{\mathcal{E}}(G_i \rightarrow Y_i).$$

Intuition : A shared sensitive value is probed if and only if all of its shares are probed.

Type 3 subsequences

Definition (Rook Domination Polynomial)

Let $(E_{i,j})_{0 \leq i,j \leq d}$ be a collection of independent events with respective probabilities $((\bar{\epsilon}_{i,j})_{0 \leq i,j \leq d})$. Let

$$\Upsilon((\bar{\epsilon}_{i,j})_{0 \leq i,j \leq d}) \triangleq \mathbb{P} \left((\cap_{i=0}^d \cup_{j=0}^d E_{i,j}) \cup (\cap_{j=0}^d \cup_{i=0}^d E_{i,j}) \right). \quad (9)$$

For short $\Upsilon_d(\bar{\epsilon}) \triangleq \Upsilon((\bar{\epsilon}_{i,j})_{0 \leq i,j \leq d})$ when for all i, j we have $\bar{\epsilon}_{i,j} = \bar{\epsilon}$.

Lemma (Type 3 Subsequences)

Consider the channels $((G_i, H_j) \rightarrow Y_{i,j})_{0 \leq i,j \leq d}$ and let $\mathbf{Y} \triangleq (Y_{i,j})_{0 \leq i,j \leq d}$. Then one has

$$\bar{\epsilon}(X \rightarrow \mathbf{Y}) \leq \Upsilon((\bar{\epsilon}((G_i, H_j) \rightarrow Y_{i,j}))_{0 \leq i,j \leq d}). \quad (10)$$

Type 4 subsequences

Let $(V_{i,j})$ be an encoding in $(d + 1)^2$ shares of $f(X)$ where f is a given function. Let

$$\begin{cases} T_{i,0} = V_{i,0} \\ T_{i,j} = T_{i,j-1} \oplus V_{i,j}. \end{cases} \quad \text{In particular } (T_{i,d})_{i=0}^d \text{ is a } d\text{-th order encoding of } f(X).$$

Lemma (Type 4 Subsequences)

$(V_{i,0}, \dots, V_{i,d})$ is a d -th order sharing of $T_{i,d}$. Consider $((T_{i,j-1}, V_{i,j}) \rightarrow Y_{i,j})_{0 \leq i,j \leq d}$ and let $\mathbf{Y} = (Y_{i,j})_{0 \leq i,j \leq d}$ then,

$$\bar{\mathcal{E}}(X \rightarrow \mathbf{Y}) \leq \prod_{i=0}^d \bar{\mathcal{E}}((T_{i,d-1}, V_{i,d}) \rightarrow Y_{i,d}). \quad (11)$$

Theorem : Direct Security Proof

Consider an implementation with n_i subsequences of type i and a $\bar{\epsilon}$ -noisy with respect to CDC adversary with q queries.

$$0 \leq \bar{\epsilon}(K \rightarrow \mathbf{Y}) \leq 1 - \left((1 - \bar{\epsilon}^{d+1})^{n_1+n_2+n_4} (1 - \Upsilon_d(\bar{\epsilon}))^{n_3} \right)^q \leq 1. \quad (12)$$

(12) is asymptotically equivalent to

$$\bar{\epsilon}(K \rightarrow \mathbf{Y}) \leq q (n_1 + n_2 + (2(d+1)^{d+1} - (d+1)!) n_3 + n_4) \bar{\epsilon}^{d+1}. \quad (13)$$

(12) can be weakened to

$$\bar{\epsilon}(K \rightarrow \mathbf{Y}) \leq q ((n_1 + n_2 + n_4) + 2n_3(d+1)^{d+1}) \bar{\epsilon}^{d+1}. \quad (14)$$

Theorem : Lower Bound on the Number of Queries

Let

$$\lambda(\bar{\mathcal{E}}, d) = (\ln((1 - \bar{\mathcal{E}}^{d+1})^{n_1+n_2+n_4} (1 - \Upsilon_d(\bar{\mathcal{E}}))^{n_3}))^{-1} \quad (15)$$

$$= ((n_1 + n_2 + n_4) \log(1 - \bar{\mathcal{E}}^{d+1}) + n_3 \log(1 - \Upsilon_d(\bar{\mathcal{E}})))^{-1} \quad (16)$$

$$\approx ((n_1 + n_2 + n_4 + n_3(2(d+1)^{d+1} - (d+1)!)) \bar{\mathcal{E}}^{d+1})^{-1}. \quad (17)$$

Number of queries to achieve $\mathbb{P}_{s,o}(K|\mathbf{Y}) = \mathbb{P}_{s,o}$, $G(K|\mathbf{Y}) = G$ or $\Delta(K; Y) = \Delta$ is at least :

$$\begin{aligned} q_{sr} &\geq \lambda(\bar{\mathcal{E}}, d) \ln((1 - \mathbb{P}_{s,o})^{-1} \lambda_{SR_o}), \\ q_{ge} &\geq \lambda(\bar{\mathcal{E}}, d) \ln((G - 1)^{-1} \lambda_{GE}), \\ q_{tvi} &\geq \lambda(\bar{\mathcal{E}}, d) \ln(\Delta^{-1} \lambda_{TVI}). \end{aligned} \quad (18)$$

Theorem : Indirect Security Proof

Circuit Γ decomposed into $|\Gamma|$ regions with (l_i) wires. Any set of at most t (probed) wires in each region of the circuit is independent with the secret key. Let \mathcal{A} be a $\bar{\epsilon}$ -noisy adversary with respect to CDC with q queries.

$$\bar{\epsilon}(K \rightarrow \mathbf{Y}) \leq \text{fail}(t, (l_i), \bar{\epsilon}, q) \triangleq 1 - \prod_{i=1}^{|\Gamma|} \left(1 - Q_B(t, l_i, \bar{\epsilon})\right)^q \leq q \sum_{i=1}^{|\Gamma|} Q_B(t, l_i, \bar{\epsilon}). \quad (19)$$

Thank you ! Questions ?

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Optimal Masking Order?

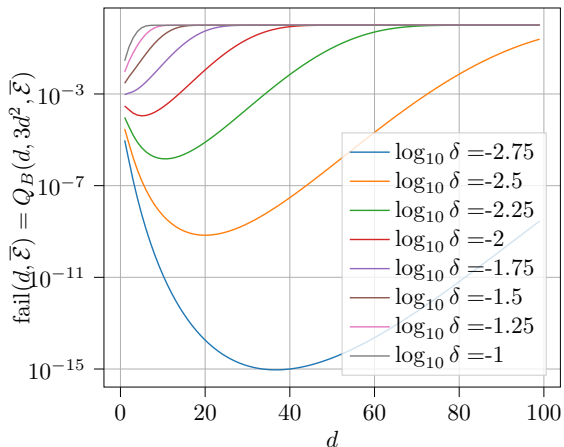


Figure – Bound for a Quadratic Gadget

Lemma : Practical Evaluation

$Y = f(X) + Z$ where Z is a radially symmetric decreasing with survival function S . Then

$$\varepsilon(X \rightarrow Y) = 2S \left(\frac{\sup_{x \in \mathcal{X}} f(x) - \inf_{x \in \mathcal{X}} f(x)}{2} \right). \quad (20)$$

If $f(X) = \sum_{i=1}^n a_i X_i$,

$$\varepsilon(X \rightarrow Y) = 2S \left(\frac{\|\mathbf{a}\|_1}{2} \right). \quad (21)$$

If $Z \sim \sigma \mathcal{N}(0, 1)$,

$$\bar{\varepsilon}(X \rightarrow Y) = 1 - 2Q \left(\frac{\|\mathbf{a}\|_1}{2\sigma} \right) \stackrel{\sigma \rightarrow \infty}{\approx} \frac{\|\mathbf{a}\|_1}{\sqrt{2\pi}} \frac{1}{\sigma} + O(\sigma^{-3}). \quad (22)$$

Lemma : Comparison with Other Leakage Measures

$$\left. \begin{array}{l} \frac{I(X;Y)}{\log |\mathcal{X}|} \leq \frac{I(X;Y)}{H(X)} \\ \frac{ARE(X;Y)}{2\gamma_X \lambda_{TVI}} \\ \frac{\beta(X;Y)}{2\lambda_{TVI}} \\ \frac{\exp(\mathcal{L}(X \rightarrow Y)) - 1}{|\mathcal{X}| - 1} \end{array} \right\} \leq \frac{\Delta(X;Y)}{\lambda_{TVI}} \left. \vphantom{\frac{I(X;Y)}{\log |\mathcal{X}|}} \right\} \leq \bar{\mathcal{E}}(X \rightarrow Y) \leq \left\{ \begin{array}{l} ARE(X;Y) \leq RE(X;Y) \\ \gamma_X \beta(X;Y) \\ \gamma_X \Delta(X;Y) \leq \gamma_X \left(\frac{I(X;Y)}{2 \log e} \right)^{\frac{1}{2}} \\ (|\mathcal{X}| - 1)(\exp(\mathcal{L}(X \rightarrow Y)) - 1) \end{array} \right. \quad (23)$$

where H is Shannon entropy, H_2 is the collision entropy, $\lambda_{TVI} = 1 - \exp(-H_2(X))$ and $\gamma_X \triangleq \left(\inf_{x \in \mathcal{X}} p_X(x) \right)^{-1}$. If $X \sim \mathcal{U}(\mathcal{X})$ then $\gamma_X = |\mathcal{X}|$ and $\lambda_{TVI} = 1 - \frac{1}{|\mathcal{X}|}$.

Definition (Kullback-Leibler Divergence and Total Variation Distance)

Let P, Q be two probability distributions with respective pdf or pmf p, q defined over \mathcal{X} . The Kullback–Leibler (KL) divergence between P and Q is

$$D_{\text{KL}}(P\|Q) \triangleq \int_{\mathcal{X}} p \log \frac{p}{q} \quad (24)$$

and the total variation distance (TV) between P and Q is

$$D_{\text{TV}}(P\|Q) = \frac{1}{2} \int_{\mathcal{X}} |p - q| = \frac{1}{2} \|p - q\|_1. \quad (25)$$

Proof I

Let

$$X \rightarrow \boxed{f} \rightarrow G \rightarrow \boxed{\text{Mask}_d} \rightarrow \mathbf{G} \rightarrow \boxed{\prod_{i=0}^d p_{Y_i|G_i}} \rightarrow \mathbf{Y}. \quad (26)$$

By optimal reduction theorem,

$$(G_i \rightarrow \boxed{P_{Y_i|G_i}} \rightarrow Y_i) = (G_i \rightarrow \boxed{\text{EC}_{\mathcal{E}_i}^{\perp}} \rightarrow G'_i \rightarrow \boxed{P_{Y_i|G'_i}} \rightarrow Y_i) \quad \text{where} \quad \mathcal{E}_i = \mathcal{E}(G_i \rightarrow Y_i). \quad (27)$$

$$G \rightarrow \boxed{\text{Mask}_d} \rightarrow \boxed{\prod_{i=0}^d \text{EC}_{\mathcal{E}_i}^{\perp}} \rightarrow \mathbf{Y}' \rightarrow \boxed{\prod_{i=0}^d p_{Y_i|G_i}} \rightarrow \mathbf{Y}. \quad (28)$$

By DPI,

$$\bar{\mathcal{E}}(X \rightarrow \mathbf{Y}) \leq \bar{\mathcal{E}}(G \rightarrow \mathbf{Y}) \leq \bar{\mathcal{E}}(G \rightarrow \mathbf{Y}').$$

Proof II

By definition,

$$\bar{\mathcal{E}}(\mathbf{G} \rightarrow \mathbf{Y}') = \mathbb{E}_{Y'_0, \dots, Y'_d} \left[\sup_{g \in f(\mathcal{X})} \left(1 - \frac{p(g|Y'_0, \dots, Y'_d)}{p(g)} \right) \right]. \quad (30)$$

If $\exists i$ s.t. $y'_i = \perp_i$ then $p(g|y'_0, \dots, y'_d) = p(g)$,

$$\sup_{g \in f(\mathcal{X})} \left(1 - \frac{p(g|y'_0, \dots, y'_d)}{p(g)} \right) = 0. \quad (31)$$

Otherwise,

$$\begin{cases} p(g|y'_0, \dots, y'_d) = 1 & \text{if } g = y'_0 + \dots + y'_d \\ p(g|y'_0, \dots, y'_d) = 0 & \text{if } g \neq y'_0 + \dots + y'_d \end{cases} \quad (32)$$

Proof III

So that,

$$\sup_{g \in f(\mathcal{X})} \left(1 - \frac{p(g|y'_0, \dots, y'_d)}{p(g)} \right) = \sup \left(1, 1 - \frac{1}{p(y'_0 + \dots + y'_d)} \right) = 1. \quad (33)$$

As a consequence,

$$\bar{\mathcal{E}}(G \rightarrow \mathbf{Y}') = \mathbb{E}_{Y'_0, \dots, Y'_d} \left[\mathbb{1}_{Y'_0 \neq \perp_0, \dots, Y'_d \neq \perp_d} \right] = \mathbb{P}(Y'_0 \neq \perp_0, \dots, Y'_d \neq \perp_d) = \prod_{i=0}^d \bar{\mathcal{E}}_i. \quad (34)$$

Comparison Leakage Metrics

	$I(X; Y)$	$\Delta(X; Y)$	$\mathcal{L}(X \rightarrow Y)$	$\beta(X; Y)$	$RE(X; Y)$	$ARE(X; Y)$	$\bar{\mathcal{E}}(X \rightarrow Y)$
T	$\frac{ \mathcal{X} \log \mathcal{X} }{\sqrt{2 \log e} I(X; Y)}$	$ \mathcal{X} - 1$	$(\mathcal{X} - 1)^2$	$2(\mathcal{X} - 1)$	$+\infty$	$2(\mathcal{X} - 1)$	1
M	$\log \mathcal{X} $	$1 - \frac{1}{ \mathcal{X} }$	$\log \mathcal{X} $	$\sqrt{1 - \frac{1}{ \mathcal{X} }}$	$ \mathcal{X} - 1$	$ \mathcal{X} - 1$	1
H	$\frac{n \log e}{8} \frac{1}{\sigma^2}$	$\frac{\sqrt{n}}{2\pi\sigma}$	$\frac{n \log e}{\sqrt{2\pi}\sigma}$	$\sqrt{\frac{n}{2\pi 2^n}} \frac{1}{\sigma}$	$2^n - 1$	$\frac{n}{\sqrt{2\pi}\sigma}$	$\frac{n}{\sqrt{2\pi}\sigma}$