

# Connections between g-leakage and the Dalenius desideratum

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# I. Concepts of Quantitative Information Flow (QIF)

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- We wish to **quantify** the leakage of a secret input  $X$  to an observable output  $Y$  caused by a probabilistic channel  $C$ .
  - Example:  $Y = X \& 0x1ff$  leaks 9 bits of  $X$ , intuitively.
- The possible values of  $X$  and  $Y$  are given by finite sets  $\mathcal{X}$  and  $\mathcal{Y}$ .
- There is a **prior distribution**  $\pi$  on  $\mathcal{X}$ .
- Both  $\pi$  and  $C$  are assumed known by the adversary  $\mathcal{A}$ .
- Then the (information-theoretic) essence of  $C$  is a mapping from **priors**  $\pi$  to **hyper-distributions**  $[\pi, C]$ .

# Example

Prior

$\pi$
3/8
3/8
1/4

Channel matrix

C	$y_1$	$y_2$
$x_1$	2/3	1/3
$x_2$	2/3	1/3
$x_3$	1/4	3/4

Multiply each row by prior probability.

Joint matrix

J	$y_1$	$y_2$
$x_1$	1/4	1/8
$x_2$	1/4	1/8
$x_3$	1/16	3/16

Abstractly, channel C is a mapping from priors to hyper-distributions.

Add up each column.

Distribution on Y

$p_y$	9/16	7/16
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Hyper-distribution on X

	9/16	7/16
$x_1$	4/9	2/7
$x_2$	4/9	2/7
$x_3$	1/9	3/7

Normalize columns of joint matrix.

Posterior distributions

	$p_{x y_1}$	$p_{x y_2}$
$x_1$	4/9	2/7
$x_2$	4/9	2/7
$x_3$	1/9	3/7

Forget about column labels.

# Vulnerability and min-entropy leakage

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- [Smith09] proposed to measure leakage based on  $X$ 's **vulnerability** to be guessed by  $\mathcal{A}$  in one try.
- Prior vulnerability:  
 $V[\pi] = \max_x \pi_x$
- Posterior vulnerability:  
 $V[\pi, \mathcal{C}] = \sum_y p(y) V[p_{X|Y}]$ 
  - $V[\pi, \mathcal{C}]$  is the average vulnerability in the hyper-distribution.
  - $V[\pi, \mathcal{C}]$  is the complement of the **Bayes risk**.
- **Min-entropy leakage**:  
 $\mathcal{L}(\pi, \mathcal{C}) = \lg (V[\pi, \mathcal{C}] / V[\pi])$

# Operational significance of vulnerability

- $V[\pi]$  is an optimal adversary  $\mathcal{A}$ 's probability of winning the following game:

$$x \stackrel{\$}{\leftarrow} \pi$$

$$w \stackrel{\$}{\leftarrow} \mathcal{A}(\pi)$$

if  $w = x$  then **win** else **lose**

- $V[\pi, C]$  is an optimal adversary  $\mathcal{A}$ 's probability of winning the following game:

$$x \stackrel{\$}{\leftarrow} \pi$$

$$y \stackrel{\$}{\leftarrow} C_{x,-}$$

$$w \stackrel{\$}{\leftarrow} \mathcal{A}(\pi, C, y)$$

if  $w = x$  then **win** else **lose**

# Generalizing to $g$ -vulnerability [ACPS12]

- Finite set  $W$  of guesses about  $X$  (or “actions”).
- Gain (or “scoring”) function  $g : W \times \mathcal{X} \rightarrow [0, 1]$ 
  - $g(w, x)$  gives the value of  $w$  if the secret is  $x$ .
  - Can model scenarios where the adversary benefits by guessing  $X$  **partially, approximately, in  $k$  tries, ...**
- Note: (Ordinary) vulnerability implicitly uses
$$g_{\text{id}}(w, x) = \begin{cases} 1, & \text{if } w = x \\ 0, & \text{otherwise} \end{cases}$$
- **Prior  $g$ -vulnerability:**  $V_g[\pi] = \max_w \sum_x \pi_x g(w, x)$
- **Posterior  $g$ -vulnerability:**  $V_g[\pi, \mathcal{C}] = \sum_y p(y) V_g[p_{X|Y}]$

# g-leakage

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- g-leakage is defined based on the prior and posterior g-vulnerability.
- But there are a number of plausible definitions:
  - “logged” multiplicative:  $\lg (V_g[\pi, C] / V_g[\pi])$
  - additive:  $V_g[\pi, C] - V_g[\pi]$
  - multiplicative:  $V_g[\pi, C] / V_g[\pi]$
- Fortunately, if we just want to **compare** the leakage of two channels, these all give the same result!
- We always get
$$\mathcal{L}_g(\pi, A) \leq \mathcal{L}_g(\pi, B) \quad \text{iff} \quad V_g[\pi, A] \leq V_g[\pi, B].$$

## II. "Dalenius's Desideratum"

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- [Dwork11]: "In 1977...Tore Dalenius articulated an 'ad omnia' (as opposed to ad hoc) privacy goal for statistical databases: **Anything that can be learned about a respondent from the statistical database should be learnable without access to the database.**"
- "...The last hopes for Dalenius's goal evaporate in light of the following parable..."
- "Given the auxiliary information **'Turing is two inches taller than the average Lithuanian woman'**, access to the statistical database teaches Turing's height."
- (Actually, Dwork's account appears to be completely unfair to Dalenius...)



# A "Dalenius" QIF scenario

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- Imagine a secret  $X$  with prior  $\pi$ .
- Suppose adversary  $\mathcal{A}$  is interested in learning  $X$ , measuring knowledge with a gain function  $g$ .
- Now imagine a channel  $C$  from  $Y$  to  $Z$ , apparently having **nothing** to do with  $X$ .
- But suppose there is an interesting joint matrix  $J$  on  $(X, Y)$ , expressing a **correlation** between  $X$  and  $Y$ .
  - ( $J$  must give marginal distribution  $\pi$  to  $X$ .)
- Can we see  $C$  as leaking information about  $X$ ?

# The Dalenius scenario with $g$ -leakage

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- Given channel  $C$  from  $X$  to  $Y$ , we can construct  $C^*$  from  $(X,Y)$  to  $Z$ :
  - $C^*_{(x,y),z} = C_{y,z}$
  - $C^*$  ignores  $X$ .
- Given gain function  $g$  from  $W$  to  $X$ , we can construct  $g^*$  from  $W$  to  $(X,Y)$ :
  - $g^*(w,(x,y)) = g(w,x)$
  - $g^*$  ignores  $Y$ .
- Hence  $\mathcal{L}_{g^*}(J, C^*)$  can be seen as the leakage about  $X$  caused by  $C$ , given the correlations in  $J$ .

# A neater formulation

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- The joint matrix  $J$  can of course be converted into the prior  $\pi$  on  $X$  and a channel matrix  $B$  from  $X$  to  $Y$ .
- We can **cascade**  $B$  and  $C$  to get a channel  $BC$  from  $X$  to  $Z$ .
- And it turns out (a bit mysteriously, to me) that  $\mathcal{L}_g(\pi, BC) = \mathcal{L}_g^*(J, C^*)$ .
- One nice consequence (thanks to theorems about cascading) is that this “Dalenius” leakage of  $X$  cannot exceed the **capacity** of  $C$ , no matter what correlations  $J$  may ever be discovered to exist!

### III. Another application of Dalenius scenarios

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- Given channels  $A$  and  $B$  on input  $X$ , the question of **which leaks more** will ordinarily depend on  $\pi$  and  $g$ .
- Is there a **robust** ordering?
- Yes!
- **Coriaceous Theorem:**  
A **never leaks more** than  $B$ , regardless of  $\pi$  and  $g$   
iff  
A **can be factored** into  $BR$ , for some channel  $R$ .
- Proved in [MMSEM14], but proved in the early 1950s by statistician David Blackwell.

# Example

$$A =$$

	$z_1$	$z_2$
$x_1$	$2/3$	$1/3$
$x_2$	$2/3$	$1/3$
$x_3$	$1/4$	$3/4$

$$B =$$

	$y_1$	$y_2$	$y_3$
$x_1$	$1/2$	$1/2$	$0$
$x_2$	$1/2$	$0$	$1/2$
$x_3$	$0$	$1/2$	$1/2$

- $A$  **cannot be factored** into  $BR$ , for any  $R$ .
- Yet under ordinary vulnerability (min-entropy leakage),  $A$  **never leaks more** than  $B$ , regardless of  $\pi$ .
- But suppose that  $x_1$  and  $x_2$  are **male** and  $x_3$  is **female**, and the adversary uses a gain function that cares only about the **gender** of the secret.
- In that case  $A$  leaks more than  $B$ .

# A less convincing example

$$A =$$

	$z_1$	$z_2$	$z_3$
$x_1$	0.2	0.22	0.58
$x_2$	0.2	0.4	0.4
$x_3$	0.35	0.4	0.25

$$B =$$

	$y_1$	$y_2$	$y_3$	$y_4$
$x_1$	0.1	0.4	0.1	0.4
$x_2$	0.2	0.2	0.3	0.3
$x_3$	0.5	0.1	0.1	0.3

- Again,  $A$  **cannot be factored** into  $BR$ , for any  $R$ .
- Here's a gain function that makes  $A$  leak more than  $B$ :

$g$	$x_1$	$x_2$	$x_3$
$w_1$	153/296	0	1/2
$w_2$	0	289/296	63/296
$w_3$	21/148	1	0

- Why should we care about such **weird** gain functions?

# The trace formulation of $g$ -vulnerability

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- Recall that we can express  $g$ -vulnerability as a **trace**.
- The **trace** of a square matrix is the sum of its diagonal entries.
- $V_g[\pi, C] = \max_S \text{tr}(D_\pi C S G)$ 
  - $D_\pi$  (indexed by  $X, X$ ) is a diagonal matrix of the prior
  - $C$  (indexed by  $X, Y$ ) is the channel matrix
  - $S$  (indexed by  $Y, W$ ) is the strategy for choosing guess  $w$  from output  $y$
  - $G$  (indexed by  $W, X$ ) is the gain function

# Gain functions as Dalenius scenarios

- Amazingly, trace satisfies a **cyclic property**:  
 $\text{tr}(ABC) = \text{tr}(BCA) = \text{tr}(CAB)$
- Hence we have  
$$\begin{aligned} V_g[\pi, C] &= \max_S \text{tr}(D_\pi CSG) \\ &= \max_S \text{tr}(GD_\pi CS) \\ &= \max_S \text{tr}((GD_\pi)CSI) \end{aligned}$$
- $I$  (identity matrix) gives ordinary vulnerability.
- And note that  $GD_\pi$  can always be normalized to a **joint matrix  $J$**  between  $W$  and  $X$ !
- Hence we can see the  **$g$ -leakage of  $X$**  caused by  $C$  as the **min-entropy leakage of  $W$**  caused by  $C$  when  $W$  and  $X$  are correlated according to  $GD_\pi$ .



# Example, revisited

A	$z_1$	$z_2$	$z_3$
$x_1$	0.2	0.22	0.58
$x_2$	0.2	0.4	0.4
$x_3$	0.35	0.4	0.25

B	$y_1$	$y_2$	$y_3$	$y_4$
$x_1$	0.1	0.4	0.1	0.4
$x_2$	0.2	0.2	0.3	0.3
$x_3$	0.5	0.1	0.1	0.3

g	$x_1$	$x_2$	$x_3$
$w_1$	153/296	0	1/2
$w_2$	0	289/296	63/296
$w_3$	21/148	1	0

- With a uniform prior, **A's g-leakage of X exceeds B's.**
- And if W is regarded as a secret, and it is correlated with X according to g, then **A's min-entropy leakage of W exceeds B's.**
- So if we care about min-entropy leakage under arbitrary correlations **then** we also need to care about g-leakage for all g, no matter how weird!

# IV. [Dalenius77]

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- The apparent source of Dwork's characterization of the "Dalenius Desideratum":

"If the release of statistics  $S$  makes it possible to determine the value  $D_K$  more accurately than is possible without access to  $S$ , a disclosure has taken place."
- But Dalenius does not make this a **desideratum**!
- On the contrary:

"A reasonable starting point is to discard the notion of **elimination** of disclosure."  
"It may be argued that elimination of disclosure is possible only by elimination of statistics."  
"[This] is the reason for our use of the term 'statistical disclosure **control**' rather than 'prevention' or 'avoidance'. "  
"More specifically, we need two measures:  $M$  = the amount of disclosure associated with the release of some statistics; and  $B$  = the benefit associated with the statistics."

# Questions?

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