## **Essentially Conditional Information Inequalities**

## Tarik Kaced

(part of this work is joint work with Andrei Romashchenko)

Post-doctoral fellow at the Institute of Network Coding The Chinese University of Hong Kong

April 17, 2013

First Workshop on Entropy and Information Inequalities



香港中文大學 The Chinese University of Hong Kong



## The "Messy" Part

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- **1** Information Inequalities
- 2 Equivalence of Two Proofs Systems
- **3** Essentially Conditional Inequalities
- Going further

## Information Inequalities

# Shannon's Information Measures

#### **Conditional Entropy:**

$$H(X|Y) = H(XY) - H(Y)$$

#### Mutual Information:

$$I(X:Y) = H(X) + H(Y) - H(XY)$$

#### **Conditional Mutual Information:**

$$I(X:Y|Z) = H(XZ) + H(YZ) - H(XYZ) - H(Z)$$

#### **Conditional Entropy:**

$$H(X|Y) = H(XY) - H(Y) \ge 0$$

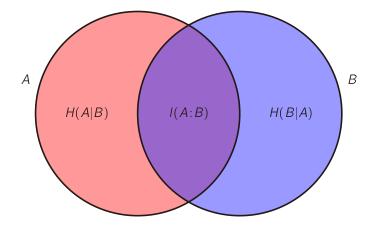
Mutual Information:

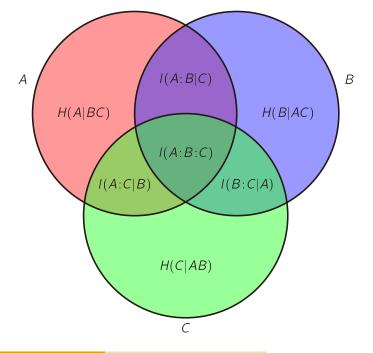
$$I(X:Y) = H(X) + H(Y) - H(XY) \ge 0$$

#### **Conditional Mutual Information:**

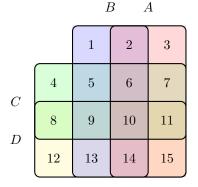
$$I(X:Y|Z) = H(XZ) + H(YZ) - H(XYZ) - H(Z) \ge 0$$

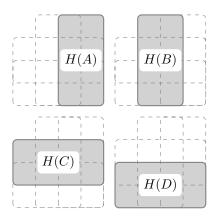
#### Shannon's Basic Inequality

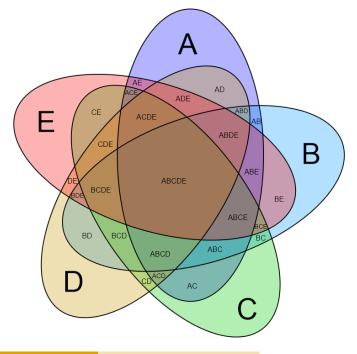


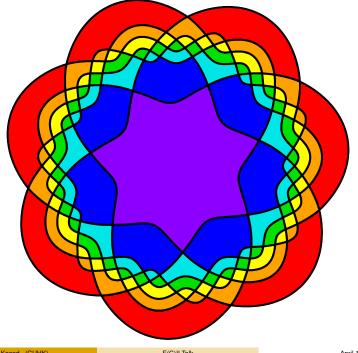


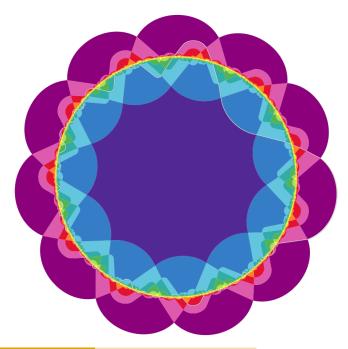
## 4-Information Diagram

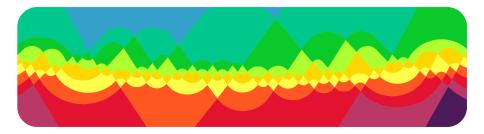












## Linear information inequalities

Pippenger (1986): "What are the laws of Information Theory?"

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**Basic** inequality:

$$\begin{aligned} H(AB) &\leq H(A) + H(B) & [I(A:B) \geq 0] \\ H(ABC) + H(C) &\leq H(AC) + H(BC) & [I(A:B|C) \geq 0] \end{aligned}$$

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Shannon-type inequalities: any positive combination of basic ineq., e.g.,

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Non-Shannon-type inequalities, e.g., [Z. Zhang, R. W. Yeung, 1998] :

 $I(C:D) \le 2I(C:D|A) + I(C:D|B) + I(A:B) + I(A:C|D) + I(A:D|C)$ 

# How to prove non-Shannon inequalities?

## Sautéed ZY98 à la DFZ

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## $I(C:D) \le I(C:D|A) + I(C:D|B) + I(A:B) +$ + I(C:D|Z) + I(Z:C|D) + I(Z:D|C) ++ 9811I(Z:AB|CD)

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**IDEA:** Take Z to be a *B*-copy of A over *CD*:

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**IDEA:** Take Z to be a common information between C and D

$$H(W|C) = H(W|D) = 0$$
$$H(W) = I(C:D)$$

$$\begin{aligned} H(Z) &\leq I(C:D|A) + I(C:D|B) + I(A:B) + 2H(Z|C) + 2H(Z|D) \\ H(Z) &\leq H(Z|A) + H(Z|B) + I(A:B) \\ H(Z|A) &\leq H(Z|C) + H(Z|D) + I(C:D|A) \end{aligned}$$

 $H(Z|B) \le H(Z|C) + H(Z|D) + I(C:D|B)$ 

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H(W|C) = H(W|D) = 0H(W) = I(C:D)

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**IDEA:** Take Z to be a common information between C and D

H(W|C) = H(W|D) = 0H(W) = I(C:D)

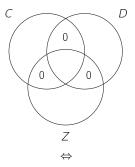
$$I(C:D) \le I(C:D|A) + I(C:D|B) + I(A:B)$$

Wait...Such a common information does not exist in general!

## Common Information vs. Mutual Information 1/2

## **Extractability Criterion for Triples**

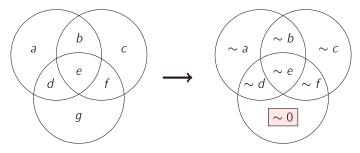
(Romashchenko)



There is a common information W for the random variables C, D, Z.

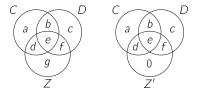
## Common Information vs. Mutual Information 2/2

We can still "approximately" extract mutual information. (indep. by Ahlswede/Gacs/Korner, Wyner rediscovered by Zhang, Romashchenko, Chan...)



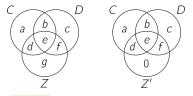
- From the diagram on the left, we can get the diagram of the right up to any given precision.
- Can be generalized to *n* variables.

 $H(Z) \le I(C:D|A) + I(C:D|B) + I(A:B) + 2H(Z|C) + 2H(Z|D)$ 



IDEA: Take Z' as in diagram

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# Equivalence of Two Proofs Systems

## Inference Rules 1/2

## Rule ZY

(A) Let f and g be linear maps on entropies such that

$$f(X_{\mathcal{N}}, Y_{\mathcal{M}}) + g(Y_{\mathcal{M}}, Z) + \alpha I(Z; X_{\mathcal{N}}|Y_{\mathcal{M}}) \geq 0,$$

for some  $\alpha \geq 0$ ;

(B) then the following (stronger) inequality is also valid:

 $f(X_{\mathcal{N}}, Y_{\mathcal{M}}) + g(Y_{\mathcal{M}}, Z) \geq 0.$ 

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I(C:D|A) + I(C:D|B) + I(A:B) +

+ I(C:D|Z) + I(Z:C|D) + I(Z:D|C) - I(C:D) +

 $+ 3I(Z:AB|CD) \ge 0$ 

### Inference Rules 2/2

#### Rule MMRV

(A) Let f and g be linear maps on entropies such that

$$f(X_{\mathcal{N}},Y_{\mathcal{M}}) + g(Y_{\mathcal{M}},Z) \geq 0;$$

(B) then the following (stronger) inequality is also valid:

$$f(X_{\mathcal{N}},Y_{\mathcal{M}}) + g(Y_{\mathcal{M}},Z) - r_Z H(Z|Y_{\mathcal{M}}) \geq 0,$$

where  $r_Z$  is the sum of coefficients invoving Z.

### Inference Rules 2/2

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 $I(C:D|A) + I(C:D|B) + I(A:B) + \frac{2H(Z|C) + 2H(Z|D) - H(Z)}{2} \ge 0$ 

#### Definition

A *proof system* (for inequalities) consists of a *pool P* of inequalities and a rule T. A (computation) *step* in a proof system is described as follows:

- **1** Pick an inequality (*A*) from the convex closure of *P*;
- 2 Apply rule T to (A) and infer inequality (B);
- **3** Add (B) to the pool P.

A *derivation* is a sequence of valid steps in a system. An inequality  $(\mathcal{I})$  is *provable in system S* if it belongs to the convex closure of the pool of *S* after some derivation.

- SYSTEM ZY: the system using RULE ZY.
- SYSTEM MMRV: the system using RULE MMRV.

### More on Information Inequalities

### Theorem (Balanced Inequalities, Chan)

1 The inequality

$$\sum_{\emptyset \neq J \subseteq \mathcal{N}} c_J H(X_J) \ge 0$$

is a valid information inequality.

2 The inequality

$$\sum_{\substack{M \neq J \subseteq \mathcal{N}}} c_J H(X_J) - \sum_{i \in \mathcal{N}} r_i H(X_j | X_{\mathcal{N}-i}) \ge 0,$$

where  $r_j$  is the sum of all  $c_j$  involving j, is a valid balanced information inequality.

In other words, we can always assume that

$$\forall i \in \mathcal{N}, r_i = \sum_{i \in J \subseteq \mathcal{N}} c_J = 0.$$

### Balanced Shannon-type Inequalities

Toy example:

Proposition

The basic inequality

 $I(X_I:X_J|X_K) \ge 0$ 

is balanced iff  $I \cap J \subset K$ .

Any instance can be put in balanced form as a some of two other instances.

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The basic inequality

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Any instance can be put in balanced form as a some of two other instances.

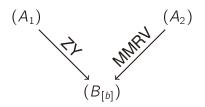
- Simpler and direct proof that Shannon-type inequalities can be "balanced".
- Note: The elemental inequality  $H(X_i|X_{N-i}) \ge 0$  is not balanced.

### Theorem (informal)

SYSTEM ZY and SYSTEM MMRV prove the same balanced inequalities

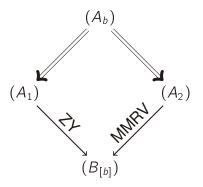
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# Essentially Conditional Inequalities

For *n* random variables, there  $2^n - 1$  possible entropies. When n = 3, there are 7 possible joint entropies:

 $(H(A), H(B), H(C), H(AB), H(AC), H(BC), H(ABC)) \in \mathbb{R}^7$ 

Such a vector of entropies is called an **entropic point**. An **almost entropic point** is the limit of a sequence of entropic points.

Disclaimer: This notation is handy so we (ab)use it and use, e.g., H(AB) for the corresponding value of an almost entropic vector (even if it does not correspond to any distribution entropy)

### Story / Motivation

- Closed pointed convex cones
- Points inside the cone are entropic, *i.e.* the difference is at the boundary.
- How much difference?
- Hard: The difference can be significant
- Simpler: What do the faces looks like?

What are the valid (conditional) inequalities on faces (subcone)?

If [some linear constraints for entropies] then [a linear inequality for entropies].

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• Example 1 (trivial): If I(B:C) = 0, then  $H(A) \le H(A|B) + H(A|C)$ . Explanation:

 $H(A) \leq H(A|B) + H(A|C) + I(B|C).$ 

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- Example 2 (trivial): If I(C:D|E) = I(C:E|D) = I(D:E|C) = 0, then  $I(C:D) \le I(C:D|A) + I(C:D|B) + I(A:B)$ .

Explanation:

 $I(C:D) \le I(C:D|A) + I(C:D|B) + I(A:B) + I(C:D|E) + I(C:E|D) + I(D:E|C).$ 

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- Example 3 (nontrivial) [Zhang–Yeung 1997]: If I(A:B) = I(A:B|C) = 0, then  $I(C:D) \le I(C:D|A) + I(C:D|B)$ .

Any explanation???

#### Theorem (Matus)

$$\begin{split} I(C:D) &\leq I(C:D|A) + I(C:D|B) + I(A:B) \\ &+ I(A:C|E) + I(A:E|C) + \frac{1}{k}I(C:E|A) + \frac{k-1}{2}[I(A:D|C) + I(A:C|D)]. \end{split}$$

#### Corollary

If I(A:C|D) = I(A:D|C) = 0 then

 $I(C:D) \le I(C:D|A) + I(C:D|B) + I(A:B) + I(A:C|E) + I(A:E|C).$ 

This conditional inequality hold (not only for entropic but also) for almost entropic points.

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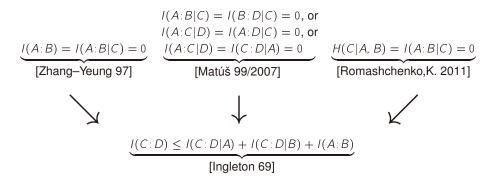
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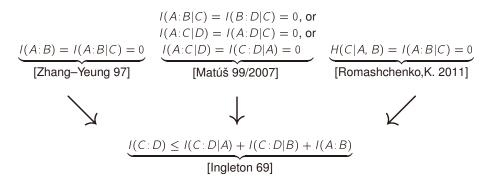
If I(A:C|D) = I(A:D|C) = 0 then

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This conditional inequality hold (not only for entropic but also) for almost entropic points.

Two 4-variable conditional inequalities are valid for all almost entropic points





Theorem (Romashchenko, K. 2011/2012)

All of these statements are essentially conditional inequalities.

• Z. Zhang, R. W. Yeung 97:

if I(A:B) = I(A:B|C) = 0, then  $I(C:D) \le I(C:D|A) + I(C:D|B)$ .

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• **Theorem** [Romashchenko, K. 2011] This inequality is *essentially conditional*, i.e., for all  $\kappa_1, \kappa_2$  the inequality:

 $I(C:D) \leq I(C:D|A) + I(C:D|B) + \kappa_1 I(A:B) + \kappa_2 I(A:B|C)$ 

is not valid.

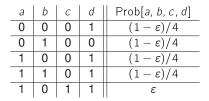
**Claim:** For any  $\kappa_1$ ,  $\kappa_2$  there exist (*A*, *B*, *C*, *D*) such that:

 $I(C:D) \not\leq I(C:D|A) + I(C:D|B) + \kappa_1 I(A:B) + \kappa_2 I(A:B|C)$ 

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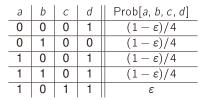
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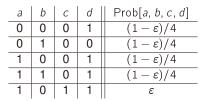
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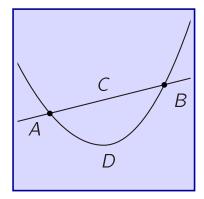
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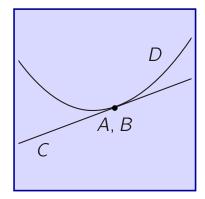
 $I(C:D) \not\leq I(C:D|A) + I(C:D|B) + \kappa_1 I(A:B) + \kappa_2 I(A:B|C)$ 

 $\Theta(\varepsilon) \leq 0 + 0 + O(\kappa_1 \varepsilon^2) + 0$ 

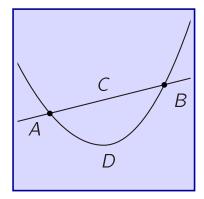
- 1 Pick a random a non-vertical line C.
- 2 Pick two random points A and B on C.
- Original Pick a random non-degenerate parabola D intersecting C exactly at A and B.



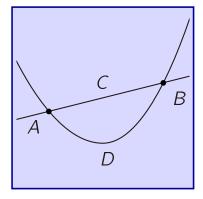
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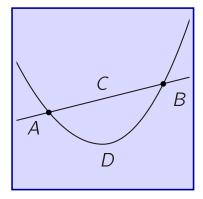


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$$I(C:D) \le \kappa [I(C:D|A) + I(C:D|B) + I(A:B) + I(A:B|C) + H(C|AB)]$$

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- Original Pick a random non-degenerate parabola D intersecting C exactly at A and B.



$$(C:D) \le \kappa [I(C:D|A) + I(C:D|B) + I(A:B) + I(A:B|C) + H(C|AB)]$$
$$1 + \frac{1}{q} \le O\left(\kappa \frac{\log q}{q}\right)$$

$$I(A:B) = I(A:B|C) = 0 \Rightarrow I(C:D) \le I(C:D|A) + I(C:D|B)$$
(ZY97)

In fact we have a stronger result. Let  $\epsilon > 0$ , assume

- $0 < I(A:B) \leq \epsilon$ .
- $0 < I(A:B|C) \leq \epsilon$ .
- 0 < H(ABCD) = const.

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 $\frac{I(C:D)}{I(C:D|A) + I(C:D|B)}$ 

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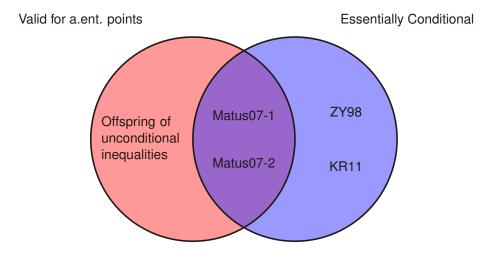
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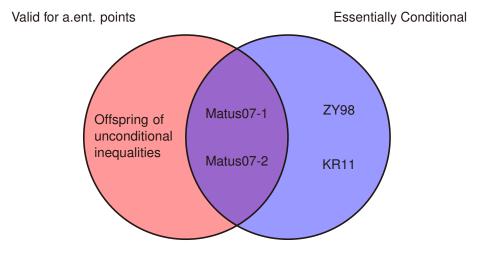
#### Theorem (Romashchenko, K. 2012)

Two essentially conditional inequalities are not valid for all almost entropic points

#### The current essentially conditional zoo



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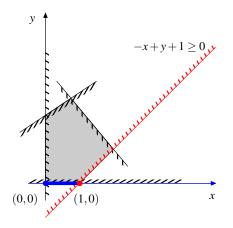
Where does Matus99 belong ?

Convexity has an immensely rich structure and numerous applications. On the other hand, almost every "convex" idea can be explained by a two-dimensional picture.

- Alexander Barvinok

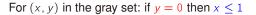
#### Geometric interpretation 1/3

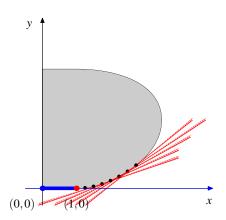
For (x, y) in the gray set: if y = 0 then  $x \le 1$ 



A trivial conditional inequality can be extended to an unconditional one.

#### Geometric interpretation 2/3





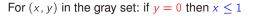
This conditional inequality is implied by an infinite family of tangent half-planes.

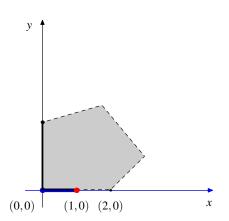
Tarik Kaced (	CUHK)
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**Theorem**: There exist **essentially conditional** inequalities that hold for almost entropic points.

**Theorem** [Matúš 07] **The cone** of linear information inequalities with 4 random variables **is not polyhedral**, i.e., there exist infinitely many independent linear information inequalities.

#### Geometric interpretation 3/3





For the closure of this set, with the same constraint y = 0 we only have  $x \le 2$ .

# Going further

#### Frameworks with the same underlying inequalities

Framework	Objects	Projection	Quantity
Quantum Entropy	systems	subsystem	Quantum Entropy
Kolmogorov	strings	subtuples	Kolmogorov Complexity
Information Theory	Random variables	subtuples	Shannon Entropy
Group Theory	groups	subgroups	log size
Combinatorial Arrays	Arrays	subarrays	log size
Vector spaces	subspaces	rank dimension	intersection

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• "Reverse mathematics" (philosophical) question:

Is there a common set of axioms that induce these inequalities ?

#### • Question (obvious extension):

Since unconditional inequalities are the same in every framework : What about their conditional inequalities ?

# Kolmogorov Complexity

#### **Counterpart to Kolmogorov Complexity**

Fix an acceptable programming system. For any binary strings x, y:

C(x) = length of a shortest program printing *x*,

C(x|y) = length of a shortest program printing x given input y.

And up to  $O(\log |xy|)$ ,

 $C(x) \ge 0,$   $C(x|y) \ge 0,$  $C(x) + C(y) \ge C(x, y).$ 

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Theorem (Inequalities are the same, Hammer et al)

An inequality is valid for Shannon iff it is valid for Kolmogorov up to an additive logarithmic term

# For Kolmogorov Complexity

### **Conditional Algorithmic Inequalities**

- We cannot say C(a, b) = C(a) + C(b) with exact equality.
- All statements in the Kolmogorov framework are (inherently) asymptotic.
- Need to add a precision for conditions:
- We have "thick" faces of thickness f(N) (where N is the complexity of the tuple of strings)

# For Kolmogorov Complexity

### **Conditional Algorithmic Inequalities**

- We cannot say C(a, b) = C(a) + C(b) with exact equality.
- All statements in the Kolmogorov framework are (inherently) asymptotic.
- Need to add a precision for conditions:
- We have "thick" faces of thickness f(N) (where N is the complexity of the tuple of strings)
- Some conditional inequalities are valid up to O(f(N))
- Some conditional inequalities are valid up to  $\theta\left(\sqrt{Nf(N)}\right)$
- Some conditional inequalities are not valid (*O*(*N*) counterexample)

# Secret Sharing

### New parameters: the leakages.

#### Definition

A perfect secret-sharing scheme for  $\Gamma$  is a tuple of discrete random variables  $(s, p_1, \ldots, p_n)$  such that :

- if  $A \in \Gamma$  then H(s|A) = 0
- if  $B \notin \Gamma$  then I(s:B) = 0

A secret-sharing scheme for  $\Gamma$  is a tuple of discrete random variables  $(s, p_1, \ldots, p_n)$  such that :

• if  $A \in \Gamma$  then  $H(s|A) \leq \varepsilon H(s)$ 



missing information

• if  $B \notin \Gamma$  then  $l(s:B) \leq \delta H(s)$ 

information leak

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missing information

• if  $B \notin \Gamma$  then  $I(s:B) \leq \delta H(s)$ 

 $\underbrace{\delta H(s)}_{\text{information leak}}$ 

#### Parameters of a scheme:

- $\varepsilon$ : missing information ratio.
- $\delta$ : information leak ratio.

$$\rho$$
: information ratio =  $\max_{p} \frac{H(p)}{H(s)}$ .

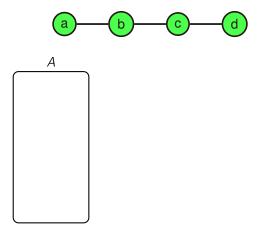
An access structure  $\Gamma$  can be **quasi-perfectly implemented with information ratio**  $\rho$  if there exists a sequence of secret-sharing schemes such that:

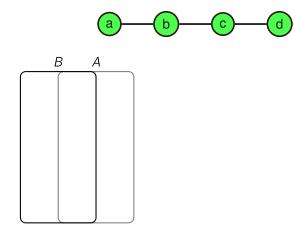
- (1) the lim sup of the information ratio does not exceed  $\rho$ ;
- (2) the missing information ratio tends to zero;
- (3) the information leak ratio tends to zero.

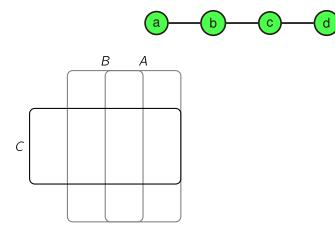
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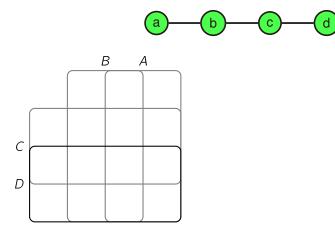
- (1) the lim sup of the information ratio does not exceed  $\rho$ ;
- (2) the missing information ratio tends to zero;
- (3) the information leak ratio tends to zero.
  - Almost entropic version of secret sharing.
  - Closely related to a "Kolmogorovian" Counterpart of Secret Sharing.
  - Question: Can they achieve better information ratios?

#### **Bounds on Perfect Schemes**

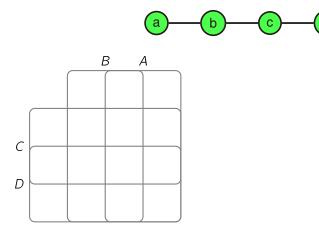




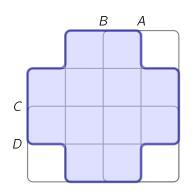




d



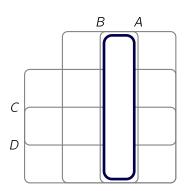




# Cells contained in *B* or *C* represent:

H(BC)

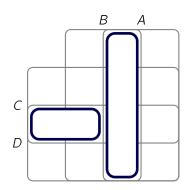




Cells contained in both *A* and *B* represent:

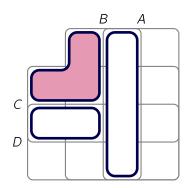
I(A:B)





# Cells contained in both *C* and *D* but not *A* represent:

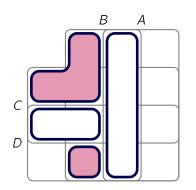




# Cells contained in *B* or *C* but not *A* nor *D* represent:

H(BC|AD)

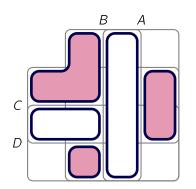




Cells contained in both *B* and *D* but not *A* nor *C* represent:

I(B:D|AC)

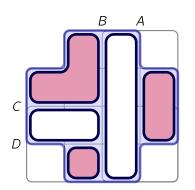




Cells contained in both A and C but not B represent:

I(A:C|B)

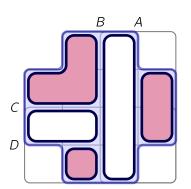




Actually, we just proved an identity without words...

H(BC) = I(A:C|B) + I(B:D|AC) + H(BC|AD) + I(A:B) + I(C:D|A).

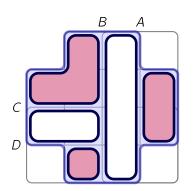




...or an inequality, since all quantities are non-negative.

 $H(BC) \ge I(A:C|B) + I(B:D|AC) + H(BC|AD).$ 

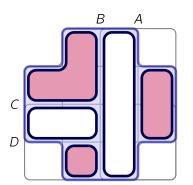




Using the perfect secret sharing requirements, we obtain:

 $H(BC) \ge 3H(S).$ 





# In general this is a HUGELY conditional inequality

#### "secret sharing requirements" $\Rightarrow H(BC) \ge 3H(S)$ .

# Merci de votre attention.

# Des questions?