

# A Tight Lower Bound for Entropy Flattening

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# Agenda

- ① Problem Definition / Model
- ② Cryptographic Motivations
- ③ Proof Techniques

## Definition (Entropies)

Let  $X$  be a distribution over  $\{0, 1\}^n$ . Define the **surprise** of  $x$  to be  $H_X(x) = \log(1/\Pr[X = x])$ .

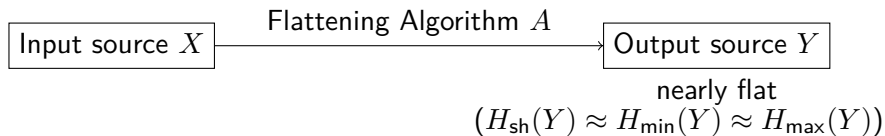
$$H_{\text{sh}}(X) \stackrel{\text{def}}{=} \mathbb{E}_{x \sim X} [H_X(x)],$$

$$H_{\text{min}}(X) \stackrel{\text{def}}{=} \min_x H_X(x),$$

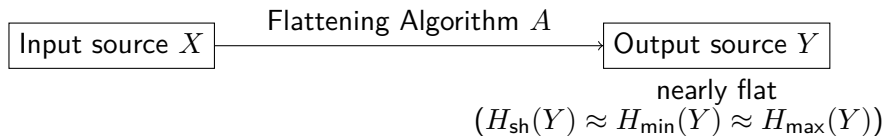
$$H_{\text{max}}(X) \stackrel{\text{def}}{=} \log |\text{Supp } X| \leq \max_x H_X(x).$$

- $H_{\text{min}}(X) \leq H_{\text{sh}}(X) \leq H_{\text{max}}(X)$  (The gap can be  $\Theta(n)$ .)
- A source  $X$  is **flat** iff  $H_{\text{sh}}(X) = H_{\text{min}}(X) = H_{\text{max}}(X)$ .

# Entropy Flattening

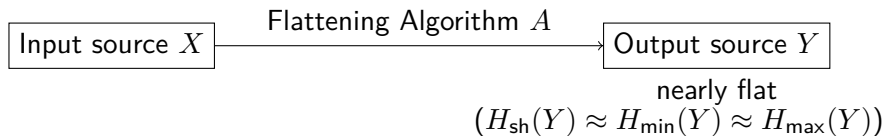


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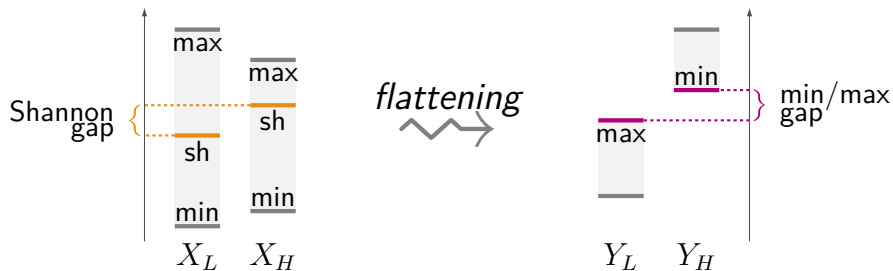


- Entropies of the output and input sources are monotonically related.

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# Entropy Flattening

## Entropy Flattening Problem

Find an flattening algorithm  $A$ :

- If  $H_{\text{sh}}(X) \geq \tau + 1$  , then  $H_{\text{min}}^{\epsilon}(Y) \geq k + \Delta$ .
- If  $H_{\text{sh}}(X) \leq \tau - 1$  , then  $H_{\text{max}}^{\epsilon}(Y) \leq k - \Delta$ .

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## Smooth Entropies

- $H_{\text{min}}^{\varepsilon}(Y) \geq k$  if  $\exists Y'$  s.t.  $H_{\text{min}}(Y) \geq k$  and  $d_{\text{TV}}(Y, Y') \leq \varepsilon$ .
- $H_{\text{max}}^{\varepsilon}(Y) \leq k$  if  $\exists Y'$  s.t.  $H_{\text{max}}(Y) \leq k$  and  $d_{\text{TV}}(Y, Y') \leq \varepsilon$ .



## Solution: Repetition

### Theorem ([HILL99, HR11])

- $X$ : a distribution over  $\{0, 1\}^n$ .
- Let  $Y = (X_1, \dots, X_q)$  where  $X_i$ s are i.i.d. copies of  $X$ .

$$H_{\min}^{\varepsilon}(Y), H_{\max}^{\varepsilon}(Y) \in H_{\text{sh}}(Y) \pm O\left(n\sqrt{q \log(1/\varepsilon)}\right) \\ q \cdot \left( H_{\text{sh}}(X) \pm O\left(n\sqrt{\frac{\log(1/\varepsilon)}{q}}\right) \right)$$

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- $q = O(n^2)$  is sufficient for the constant entropy gap.
- $q = \Omega(n^2)$  is needed due to anti-concentration results. [HR11]

# Query Model

The Model:

- **Input source:** encoded by a function  $f : \{0, 1\}^n \rightarrow \{0, 1\}^m$  and defined as  $f(U_n)$ .
- **Flattening algorithm:** oracle algorithm  $A^f : \{0, 1\}^{n'} \rightarrow \{0, 1\}^{m'}$  has query access to  $f$ .
- **Output source:**  $A^f(U_{n'})$ .
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- $H_{\text{sh}}(f(U_n)) \geq \tau + 1 \quad \Rightarrow \quad H_{\text{min}}^\varepsilon(A^f(U_{n'})) \geq k + \Delta$
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More powerful:

- Querying correlated positions or even in an adaptive way.
- Computation on the query inputs. e.g., hashing

# Main Theorems

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Flattening algorithms for  $n$ -bit oracles  $f$  require  $\Omega(n^2)$  oracle queries.

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## Def: SDU Algorithm

- $H_{\text{sh}}(f(U_n)) \geq \tau + 1 \Rightarrow d_{\text{TV}}(A^f(U_{n'}), U_{m'}) < \varepsilon.$
- $H_{\text{sh}}(f(U_n)) \leq \tau - 1 \Rightarrow \text{Supp}(A^f(U_{n'}))/2^{m'} \leq \varepsilon.$

Flattening Algorithm  $\iff$  SDU Algorithm  
(Reduction between two NISZK-complete problems [GSV99])

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## Connection to Cryptographic Constructions

**Example:** OWF  $f \rightarrow$  PRG  $g^f$  ([HILL90, Hol06, HHR06, HRV10, VZ13]):

- 1 Create a gap between “pseudoentropy” and (true) entropy.
- 2 Guess the entropy threshold  $\tau$  (or other tricks).
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- Overall, the best PRG makes  $\tilde{O}(n^3)$  queries to the one-way function [HRV10, VZ13].
  - From regular one-way function, Step 3 is unnecessary, and so  $\tilde{O}(n)$  query is sufficient. [HHR06]

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Can we do better in the entropy flattening step?

# Overview of the Proof

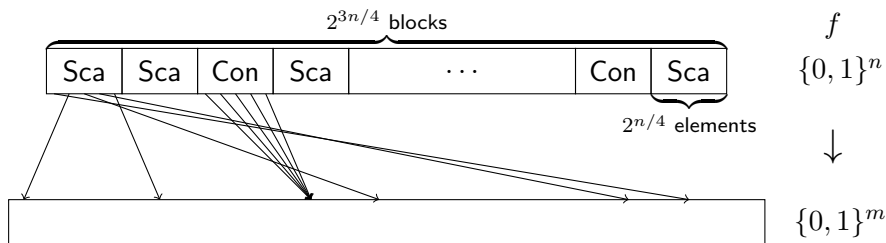
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- 1 Construct distributions  $\mathcal{D}_H$  and  $\mathcal{D}_L$ :
  - Sample  $f$  from  $\mathcal{D}_H$ , then  $H_{\text{sh}}(f(U_n)) \geq \tau + 1$  w.h.p.
  - Sample  $f$  from  $\mathcal{D}_L$ , then  $H_{\text{sh}}(f(U_n)) \leq \tau - 1$  w.h.p.
- 2  $A$  cannot “behave very different” on both distributions by making only  $q = o(n^2)$  queries.

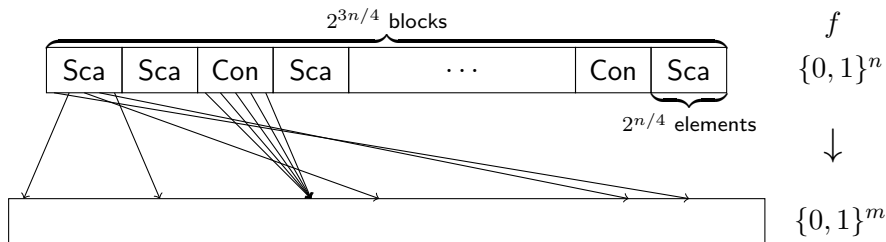
# Construction of $f$

- Partition the domain into  $s$  blocks, each with  $t$  elements ( $s \cdot t = 2^n$ )
  - Concentrated: map to the same element.
  - Scattered: map to all distinct elements.



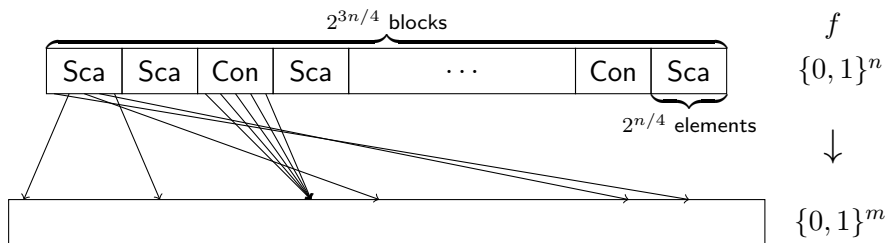
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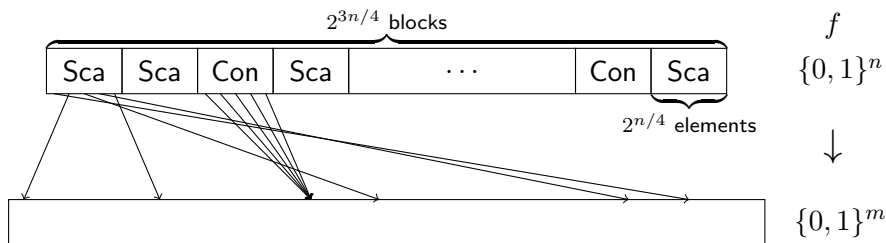
- $\geq s \cdot (1/2 + 4/n)$  blocks are scattered  $\Rightarrow H_{\text{Sh}}(f) \geq 7n/8 + 1$
- $\leq s \cdot (1/2 - 4/n)$  blocks are scattered  $\Rightarrow H_{\text{Sh}}(f) \leq 7n/8 - 1$

# $\mathcal{D}_H$ and $\mathcal{D}_L$



- 1 Randomly partition  $\{0, 1\}^n$  into  $2^{3n/4}$  blocks.

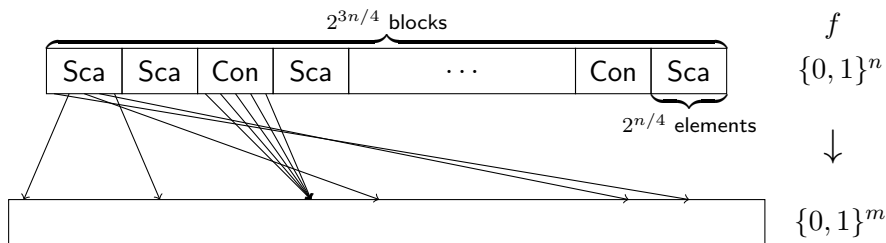
# $\mathcal{D}_H$ and $\mathcal{D}_L$



- 1 Randomly partition  $\{0, 1\}^n$  into  $2^{3n/4}$  blocks.
- 2 Decide each block to be scattered or concentrated.
  - $\mathcal{D}_H$ : scattered with probability  $(1/2 + 5/n)$ ,  
then w.h.p.  $\geq s \cdot (1/2 + 4/n)$  blocks are scattered
  - $\mathcal{D}_L$ : scattered with probability  $(1/2 - 5/n)$ ,  
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- 3 Random mapping:
  - Randomly map each element in a *scattered* block.
  - Map all  $t$  elements in a *concentrated* block to a *random* target.

## Intuitions for the Hard Distributions

Fix an SDU algorithm  $A^{(\cdot)}$ . An input  $w$  is **block-compatible** (B.C.) for  $f$  if each block is queried (when evaluating  $A^f(w)$ ) at most once.

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Why random partition?

- Hard to make correlated queries.
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Why random mapping?

- Conditioning on B.C., an algorithm cannot distinguish scattered or concentrated blocks.
- $O(n)$  queries is sufficient if the algorithm knows the block is scattered or concentrated!

## Proof Overview

We will focus on the event  $\left[ \exists \text{B.C. } w, A^f(w) = z \right]$ .

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$$\Pr_{f \sim \mathcal{D}_H} \left[\exists \text{B.C. } w, A^f(w) = z\right] \geq 1 - \varepsilon \geq \Theta(1)$$

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### Main Technical Lemma

Suppose  $A^f$  algorithm makes  $q$  oracle queries, for most  $z \in \{0, 1\}^{m'}$ ,

$$\begin{aligned} \Pr_{f \sim \mathcal{D}_H} [\exists \text{B.C. } w, A^f(w) = z] \\ \leq 2^{O(\frac{q}{n^2})} \cdot \Pr_{f \sim \mathcal{D}_L} [\exists \text{B.C. } w, A^f(w) = z] + o(\varepsilon) \end{aligned}$$

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which concludes that  $q = \Omega(n^2)$  (or  $\Omega(n^2 \log(1/\varepsilon))$ ).



## Primitive Intuition for Distinguishing $\mathcal{D}_L$ and $\mathcal{D}_H$

We flip coins to decide each block is scattered or concentrated.

$$\mathcal{D}_H : \text{Bern}(1/2 + 5/n) \quad \mathcal{D}_L : \text{Bern}(1/2 - 5/n)$$

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- Conditioning on the “balance” event, the ratio is at most

$$\begin{aligned} & (1 + 20/n)^{q \cdot (1/2+6/n)} \times (1 - 20/n)^{q \cdot (1/2-6/n)} \\ & \leq (1 + 20/n)^{12q/n} \times (1 - 20/n)^{-12q/n} = 2^{O(q/n^2)}. \end{aligned}$$

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- **Warning!** To distinguish two cases in “NISZK”-sense (instead of BPP)  $O(n)$  queries are sufficient.

## Comparison to [Lovett Zhang 17]

Entropy reversal:  $A$  has to make **exponentially** many queries such that

- $f(U_n)$  has high entropy  $\Rightarrow A^f(U_{n'})$  has small support.
- $f(U_n)$  has low entropy  $\Rightarrow A^f(U_{n'})$  is close to uniform

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Lemma (Lemma in [LZ17])

$$\Pr_{f \sim \mathcal{D}_H} [\exists B.C. w, A^f(w) = z] \geq \Pr_{f \sim \mathcal{D}_L} [\exists B.C. w, A^f(w) = z] + \text{negl}$$

Lemma (This work)

$$\Pr_{f \sim \mathcal{D}_H} [\exists B.C. w, A^f(w) = z] \leq 2^{O(\frac{q}{n^2})} \cdot \Pr_{f \sim \mathcal{D}_L} [\exists B.C. w, A^f(w) = z] + \text{negl}$$

## Technical Sketch

Let  $\{w_1, \dots, w_{2^{n'}}\} = \{0, 1\}^{n'}$  .  $W_\ell = \{w_1, \dots, w_\ell\}$ .

$$\Pr [\exists w, A^f(w) = z] = \sum_{\ell} \Pr [w_\ell \text{ is the "first" } w \text{ s.t. } A^f(w) = z]$$



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$$\begin{aligned}\Pr [\exists w, A^f(w) = z] &= \sum_{\ell} \Pr [w_\ell \text{ is the "first" } w \text{ s.t. } A^f(w) = z] \\ &= \sum_{\ell} \Pr [\nexists w \in W_{\ell-1} \text{ s.t. } A^f(w) \neq z \mid A^f(w_\ell) = z] \times \Pr [A^f(w_\ell) = z] \\ &= \sum_{\ell} \left( 1 - \Pr [\exists w, \tilde{A}^f(w) = z \mid A^f(w_\ell) = z] \right) \times \Pr [A^f(w_\ell) = z]\end{aligned}$$

where  $\tilde{A}^f(w) = \begin{cases} A^f(w) & \text{if } w \in W_\ell \\ \perp & \text{Otherwise} \end{cases}$

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- Flattening entropy is an important step in constructing PRG, UOWHF and bit commitment from OWF.
- Is the step necessary?  
If Yes  $\Rightarrow \tilde{\Omega}(n^2)$  query lower bound for OWF  $\rightarrow$  PRG

## Conclusion

- We proved the  $\Omega(n^2)$  lower bound for flattening entropy.
- Flattening entropy is an important step in constructing PRG, UOWHF and bit commitment from OWF.
- Is the step necessary?  
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- Can the lower bound combined with the  $\Omega(n)$  one in [HS12]?  
If Yes  $\Rightarrow \tilde{\Omega}(n^3)$  query lower bound for OWF  $\rightarrow$  PRG (tight!)

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Thanks!