Sampling lower bounds

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The complexity of distributions

- Leading goal: lower bounds
  for computing a function on a given input

- This talk: lower bounds
  for sampling distributions, given uniform bits

- Several papers, connections,
  still uncharted

The complexity of distributions

- 2-source extractors [Chattopadhyay Zuckerman, …, Ben-Aroya Doron Ta-Shma]
- Data structure lower bounds ?

- This ta s
  for sampling d ons, given uniform bits

- Several papers, connections, still uncharted

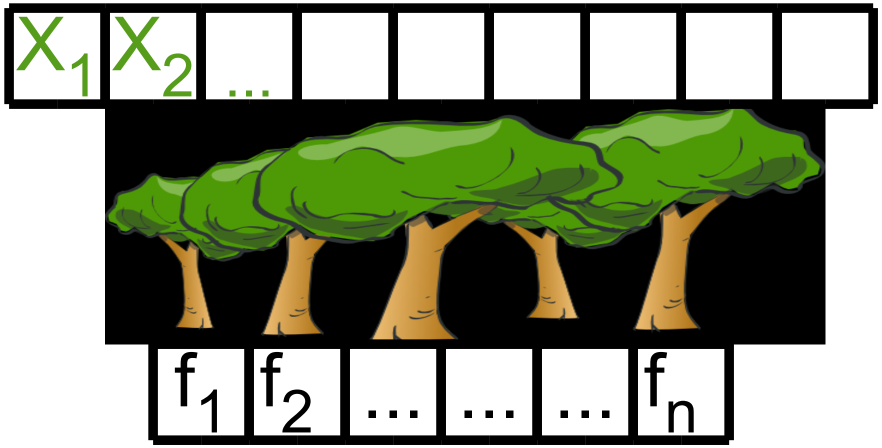
Outline

- A couple of problems for decision trees

- AC^0
  - Upper bounds
  - Lower bounds

Sampling Hamming slices

- S = n uniform bits of weight n/2
- X uniform



- $f : \{0,1\}^* \to \{0,1\}^n$
  depth-d forest

- Statistical distance $\Delta\,(f(X),\, S) \geq$?

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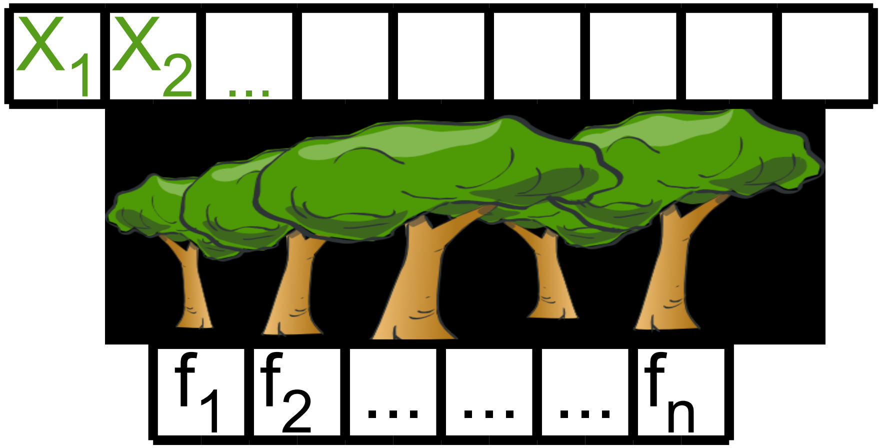

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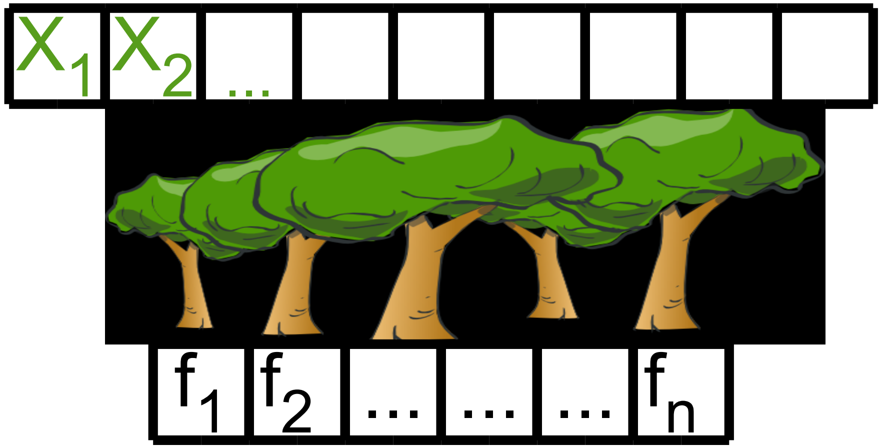

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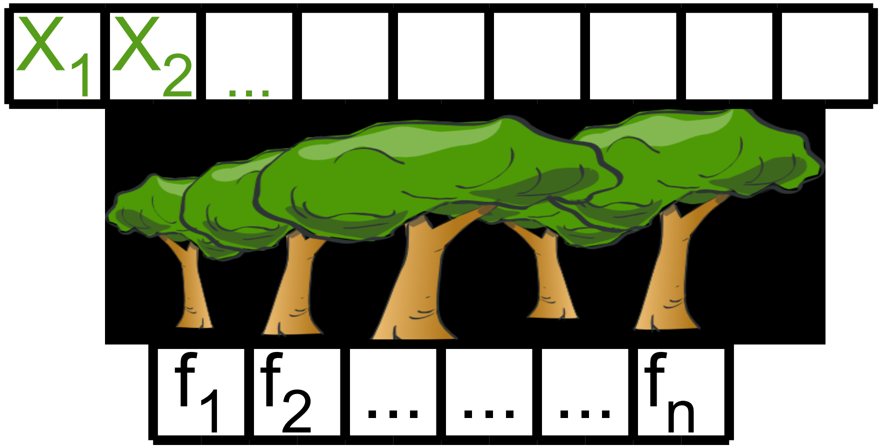

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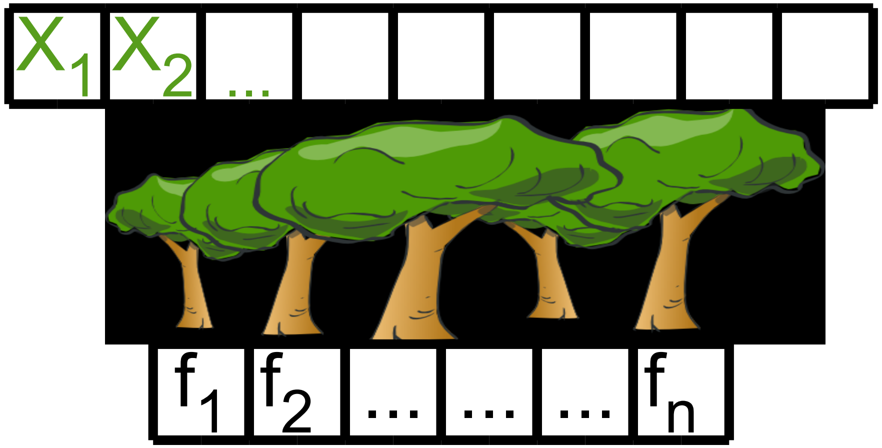
- Open: $\Delta\,(f(X), S)$ for $d = O(1)$?

Sampling permutations

- $\prod$:= uniform permutations of $[n]$

- $f : [n]^* \rightarrow [n]^n$

  depth-2 forest



- Statistical distance $\Delta\,(f(X), \prod) \geq$?

- $\Delta \geq 1-o(1)$ ➔ data structure lower bound

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  - Some upper bounds

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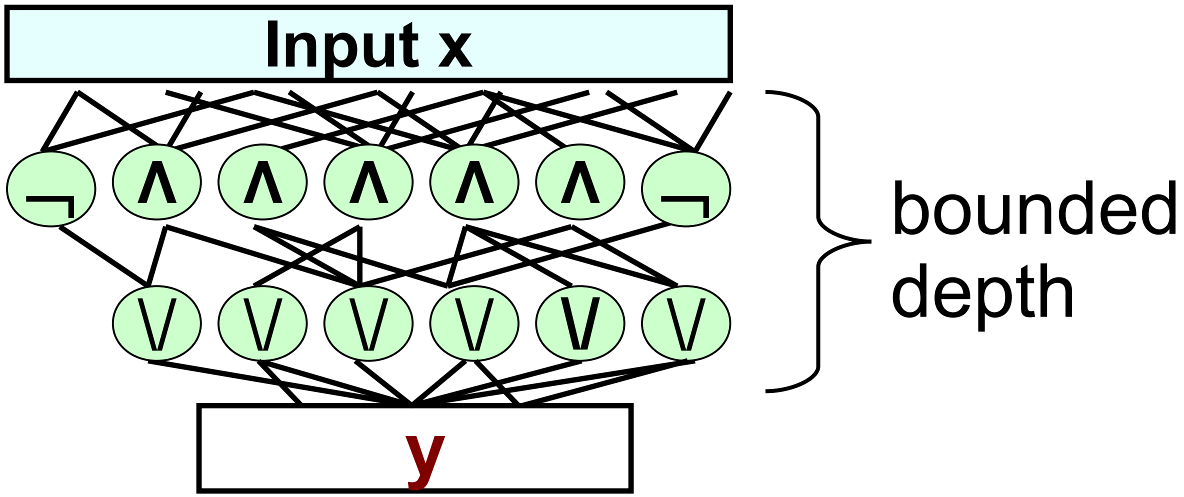
Bounded-depth circuits (AC^0)



∨ = or
∧ = and
¬ = not

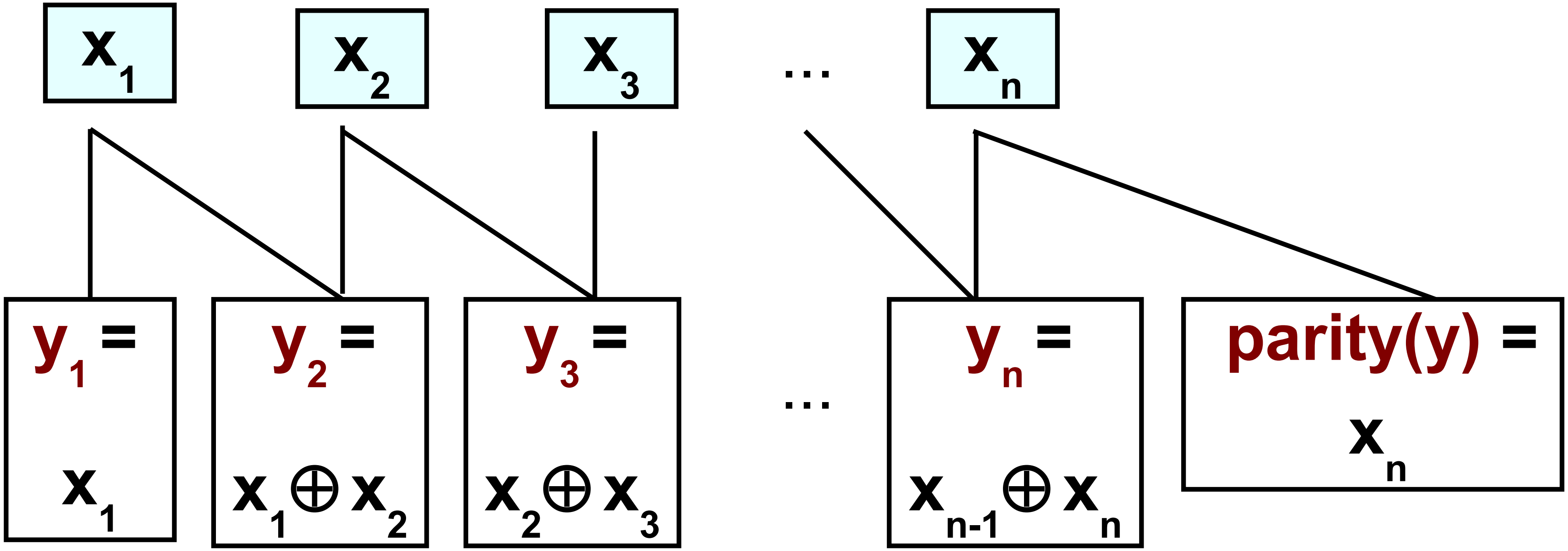
- AC^0 cannot compute parity
  [1980's: Furst Saxe Sipser, Ajtai, Yao, Hastad, ….]

Sampling (Y, parity(Y))

- Theorem [Babai '87; Boppana Lagarias '87]

There is f : $\{0,1\}^n \rightarrow \{0,1\}^{n+1}$, in AC^0

Distribution $f(X) \equiv$ (Y, parity(Y)) (X, Y $\in \{0,1\}^n$ uniform)



AC^0 can sample

- (Y, Inner-Product(Y)) [Impagliazzo Naor]

- Permutations (error 2^{-n}) [Matias Vishkin, Hagerup]

- (Y, f(Y)), any symmetric f (error 2^{-n}) [V]

  e.g. f=Majority

- Open: (Y, Majority(Y)) with error 0?

AC^0 can sample

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Sampling permutations in AC^0

- Dart throwing Place i = 1..n in A[1..n] uniformly

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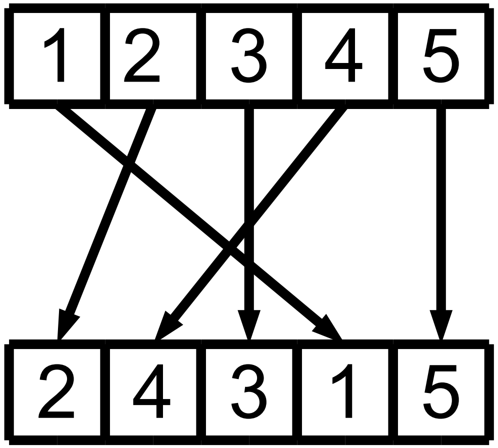


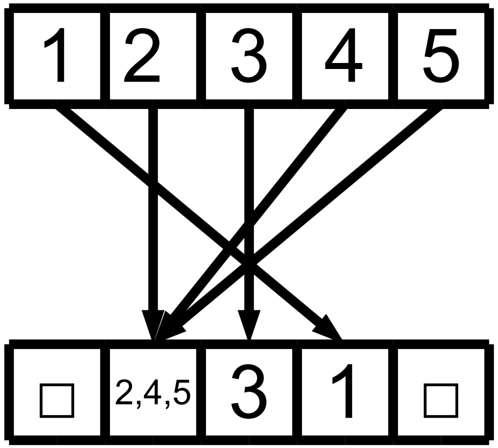
1	2	3	4	5
2	4	3	1	5

Sampling permutations in AC^0

- Dart throwing Place i = 1..n in A[1..n] uniformly

- ~~If no collisions, done~~

  There will be collisions



1 2 3 4 5

□ 2,4,5 3 1 □

Sampling permutations in AC^0

- Dart throwing Place i = 1..n in A[1..m] uniformly

- Enlarge A.

  No collisions,

  and I just need

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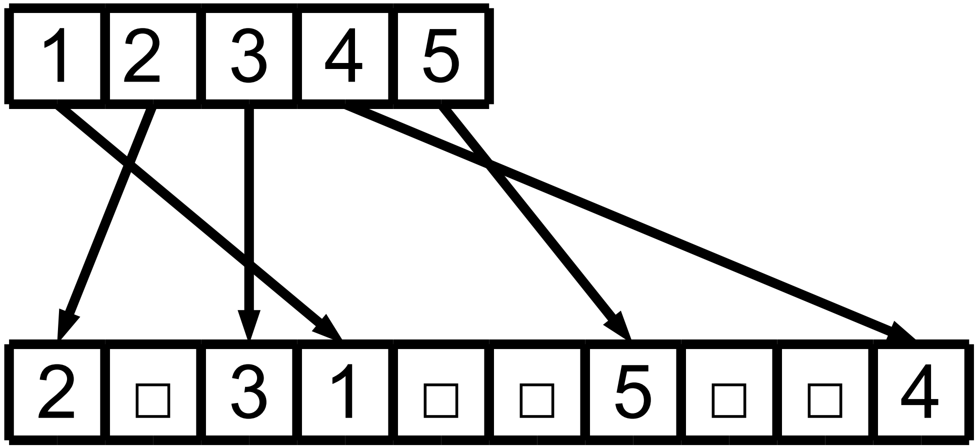

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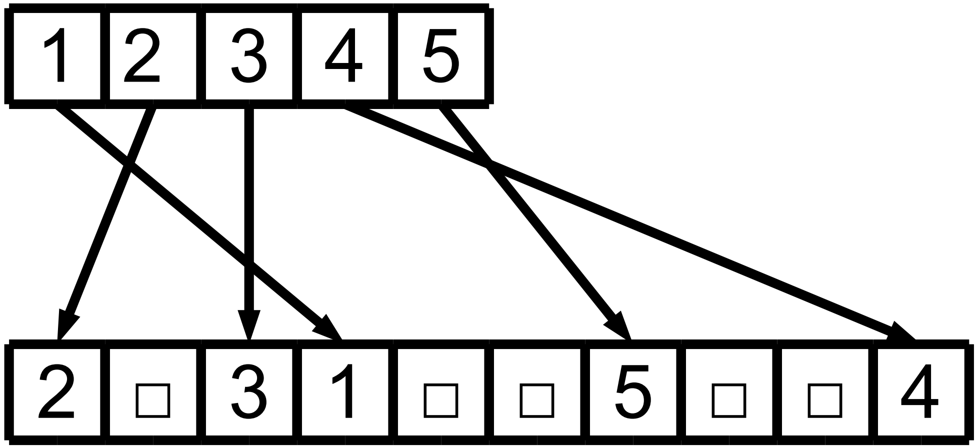
impossible



Sampling permutations in AC^0

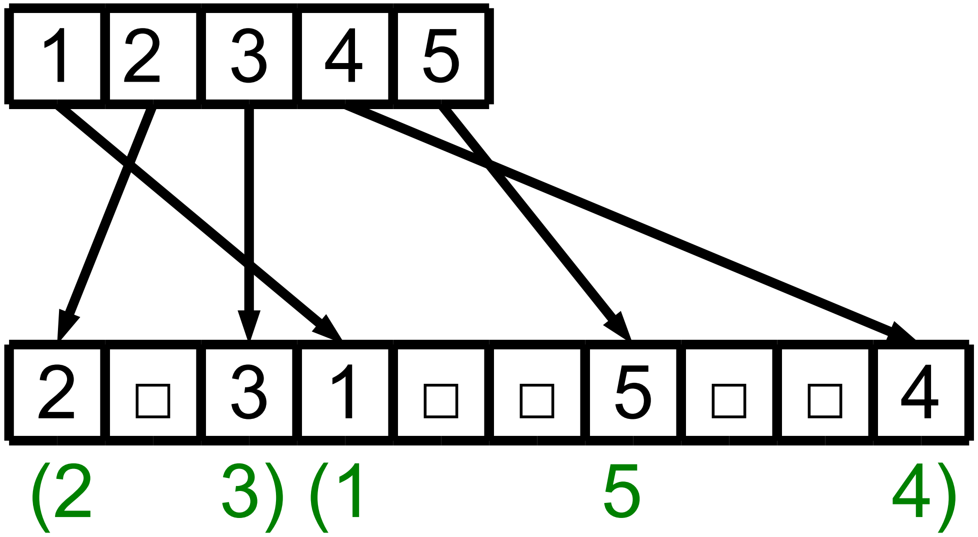
- Dart throwing Place i = 1..n in A[1..m] uniformly

- Cycle format.

  Each cycle starts with

  least element.

  Least elements sorted.



1	2	3	4	5

2	□	3	1	□	□	5	□	□	4

(2 3) (1 5 4)

- Next element in cycle computable in AC^0

Qed

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- A couple of problems for decision trees

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  - Lower bounds

AC^0 cannot sample

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- Error-correcting codes [Lovett V 2011, Beck Impagliazzo Lovett]

  Z = uniform on good binary code $\subseteq \{0,1\}^n$

  AC^0 circuit $C : \{0,1\}^* \to \{0,1\}^n$

  ➔ Statistical-Distance(Z, $C(X)$) $\geq 1 - \exp(-n^{0.1})$

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- (Y, f(Y)) for bit-block extractor $f : \{0,1\}^n \to \{0,1\}$

  Statistical-Distance((Y, f(Y) ,C(X)) > 0 [V 2011]

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  $> 1/2 - 1/n^{\omega(1)}$ [now]

"Cannot compute f better than tossing a coin, even if you can sample the input yourself"

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"Cannot compute f better than tossing a coin, even if you can sample the input yourself"

- Theorem: AC^0 circuit C

  min-entropy $C(X) \geq k$ ($\forall\, a$, $\Pr[C(X) = a] \leq 2^{-k}$)

  ➔ C(X) close to convex combination of bit-block sources

  with min-entropy $\geq k^2/n^{1.01}$

- Bit-block source: each bit is either constant or literal

  Example: $(0, 1, z_5 , 1\text{-}z_3 , z_3 , z_3 , 0 , z_2)$

- Corollary: f bit-block extractor ➔ $C(X) \neq (Y, f(Y))$

- Proof:

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- Proof: $C(X) = (Y, f(Y))$ ➔ min-entropy $C(X) \geq |Y| = n$
  ➔ convex combination high min-entropy bit-block sources
  can fix "f(Y)" bit leaving high min-entropy
  contradicts extractor property QED

- Theorem: AC^0 circuit C

  min-entropy C(X) ≥ k (∀ a, Pr[C(X) = a] ≤ 2^{-k})

  ➔ C(X) close … sources

  with min-en…

Heads up:

Rules out Statistical-Distance 0, but not 0.1

Example later

- Bit-block sour… …eral

  Example: (0, 1, …

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- Proof:

  (1) Prove when C is d-local (each output bit depends on d input bits)

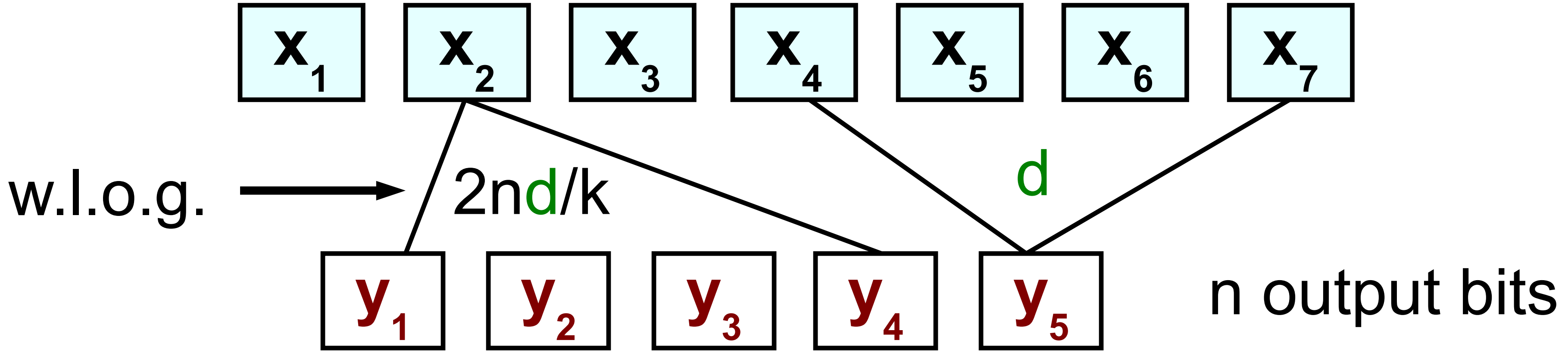
  (2) For AC^0 use random restrictions

  - switching lemma collapses AC^0 to d-local

  - New: entropy is preserved

Proof

- d-local n-bit source min-entropy k: convex combo bit-block



- Output entropy > $\Omega(k)$ ➔ $\exists\ \mathbf{y}_i$ with variance > $\Omega(k/n)$
- Isoperimetry ➔ $\exists\ \mathbf{x}_j$ with influence > $\Omega(k/nd)$
- Set uniformly $N(N(\mathbf{x}_j)) \setminus \{\mathbf{x}_j\}$ (N(v) = neighbors of v)

  with prob. > $\Omega(k/nd)$, $N(\mathbf{x}_j)$ non-constant block of size 2nd/k
- Repeat $\Omega(k) / |N(N(\mathbf{x}_j))|$ times ➔ expect $\Omega(k^3/n^2d^3)$ blocks

♦

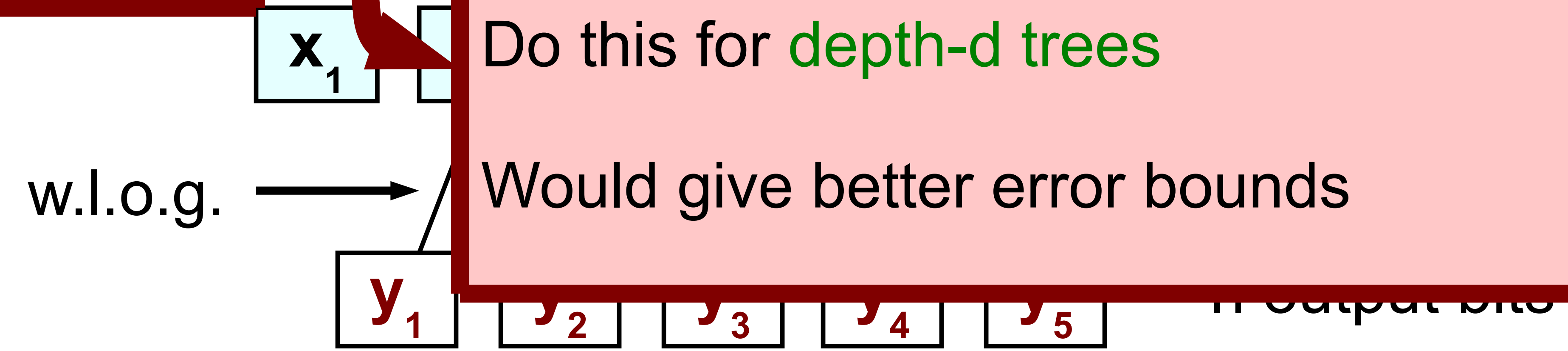
Proof

- d-local n-bit sc

Open problem:

Do this for depth-d trees

Would give better error bounds



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(2) For AC^0 use random restrictions
- switching lemma collapses AC^0 to d-local
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The effect of restrictions on entropy

- Theorem $f : \{0,1\}^* \to \{0,1\}^n$: $f(X)$ has min-entropy k

  Let R be random restriction with $\Pr[*] = p$

  W.h.p. $f|_R(X)$ has min-entropy $\Omega(pk)$

- Proof:
- Bound collision probability $\Pr[\, f|_R(X) = f|_R(X)\,]$

- Isoperimetric inequality for noise [Lovett V]

  $\forall A \subseteq \{0,1\}^L$ of density α, uniform X, p-noise vector N :

$$\alpha^2 \leq \Pr[X \in A \wedge (X+N) \in A] \leq \alpha^{1+p}$$

Proof of isoperimetric inequality

- $\forall A \subseteq \{0,1\}^L$ of density α random X, p-noise vector N :
  $\Pr[X \in A \wedge (X+N) \in A] \leq \alpha^{1+p}$

- Proof:
  $f := 1_A$
  $E_{X,N}[\ f(X) \bullet f(X+N)\ ]$
  $= E_X[\ f(X) \bullet E_N[f(X+N)]\ ]$

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  $= E_X[\ f(X) \cdot E_N[f(X+N)]\ ]$
  $\leq \sqrt{}\ E_X[\ f^2(X)\ ] \cdot \sqrt{}\ E_X\ [E_N{}^2\ [f(X+N)]\ ]$ Cauchy-Schwarz

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  $\le \sqrt{\ } E_X[\ f^2(X)\ ] \bullet E_X[f^{\ 2-O(p)}\ (X)]^{1/(2-O(p))}$ Hypercontractivity

  $= \sqrt{\ }\alpha\ \bullet \alpha^{\ 1/(2-O(p))}$ Qed

Recap

- Showed high-entropy AC^0 ➔ high-entropy bit-block sources
- Implies sampling lower bounds
- But only Statistical-Distance $\Delta > 0$, not 0.1

Possible:
Δ (C(X), (Y,f(Y)) $\leq$ 0.1, but min-entropy C(X) = O(1)

Example next

Example

- Circuit C: "On input x:

  If first 4 bits are 0 output the all-zero string

  Otherwise sample (Y, f(Y)) exactly"

- Statistical-Distance(C(X) , (Y, f(Y)) ≤ 0.1,

  but min-entropy C(X) = O(1)

- Observation: If you fix first 4 bits,

  min-entropy polarizes: either zero or very large

  We show this happens for every AC^0 circuit

Polarizing min-entropy

- Theorem: For every AC^0 circuit $C : \{0,1\}^* \to \{0,1\}^n$

  $\exists$ set S of $\leq 2^n$ restrictions such that:

  (1) preserve output distribution

  $\Delta(C|_r (X), C(X)) \leq \varepsilon$, for uniform $r \in S$, X

  (2) polarize min-entropy

  $\forall\, r \in S$, $C|_r$ has min-entropy 0 or $n^{0.8}$

- ? ? ? ? ?

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- Trivial:

  $S :=$ one input for each of $\leq 2^n$ outputs, entropy always 0

Polarizing min-entropy

- Theorem: For every AC^0 circuit $C : \{0,1\}^* \rightarrow \{0,1\}^n$

  $\exists$ set S of $\leq 2^{n - n^{0.9}}$ restrictions such that:

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Polarization lemma

- Lemma: For every $f : \{0,1\}^* \to \{0,1\}^n$

  $\exists$ set S of $\leq 2^{n - n^{0.9}}$ restrictions s.t.

  $\Delta(f|_r (X), f(X)) \leq \varepsilon$, for uniform $r \in S$, X

- Proof:
- Pick S randomly with $\Pr[*] = n^{-0.9}$; fix $A = f^{-1}(y)$ of density α

  Show: $\Pr_S\big[\ \Pr_{r,X}[X|_r \in A] < \alpha - \varepsilon 2^{-n}\ \big] < 2^{-n}$

  Note: Deviation $\varepsilon 2^{-n}$ but $|S| < 2^n$

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  Isoperimetric inequality ➔ $\Pr_{r,X}[X|_r \in A]$ “small variance”

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  Isoperimetric inequality ➔ $\Pr_{r,X}[X|_r \in A]$ “small variance”

  Use specific lower-tail concentration bound Qed

Putting things together

- In the end, lower bound for sampling (Y, f(Y))

  $f : \{0,1\}^n \to \{0,1\}$ bit-block extractor

- Given circuit C, statistical distance $1/2 - 1/n^{\omega(1)}$ witness:

  A U B =

  $\{ z : z$ one of those $2^{n - n^{0.9}}$ restrictions s.t. C is constant$\}$

  U $\{ (y,b) : b \neq f(y) \}$

- Proof: Think of C(X) as $C|_r$ (X) for uniform $r \in S$

  $C|_r$ constant ➔ $C|_r (X) \in A$, but (Y, f(Y)) not in A w.h.p.

  else $\Pr[C|_r (X) \in B] > 1/2 - 1/n^{\omega(1)}$, but (Y, f(Y)) never in B

More open problems and conclusion

- Open problem: Statistical distance 1/2 - $\exp(-n^{0.1})$
- Derandomize entropy polarization
- Much more to chart...