

# The complexity of distributions:

# boolean average-case lower bounds

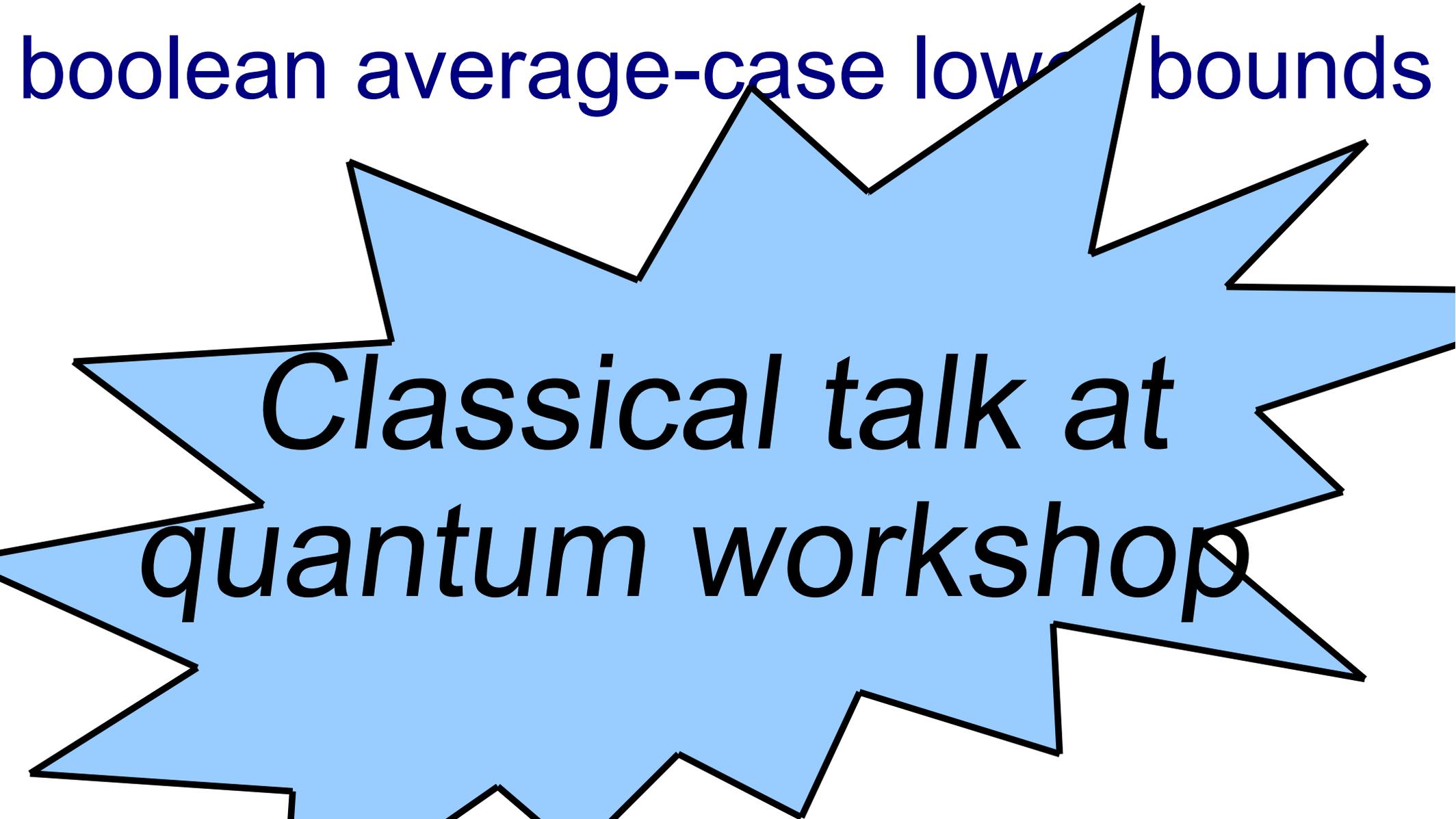
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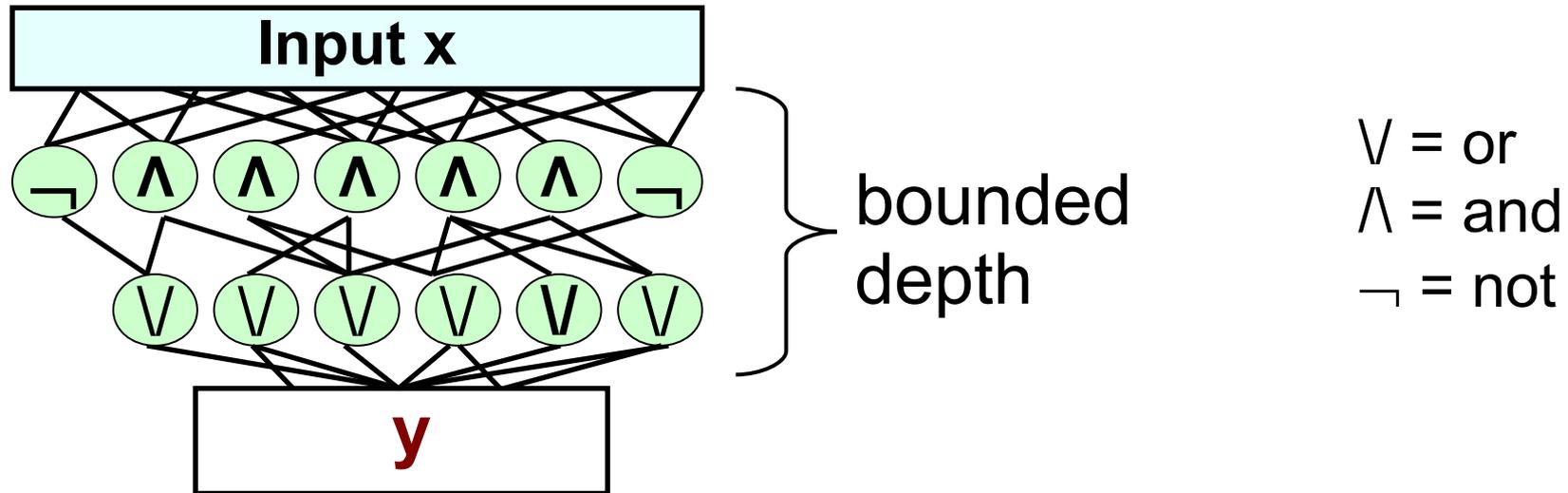
*Classical talk at  
quantum workshop*

# The complexity of distributions

- Leading goal of computational complexity: lower bounds for computing a function on a given input
- Since 2009 have advocated lower bounds for sampling distributions, given uniform bits
- Several papers, connections, still uncharted



# Bounded-depth circuits ( $AC^0$ )



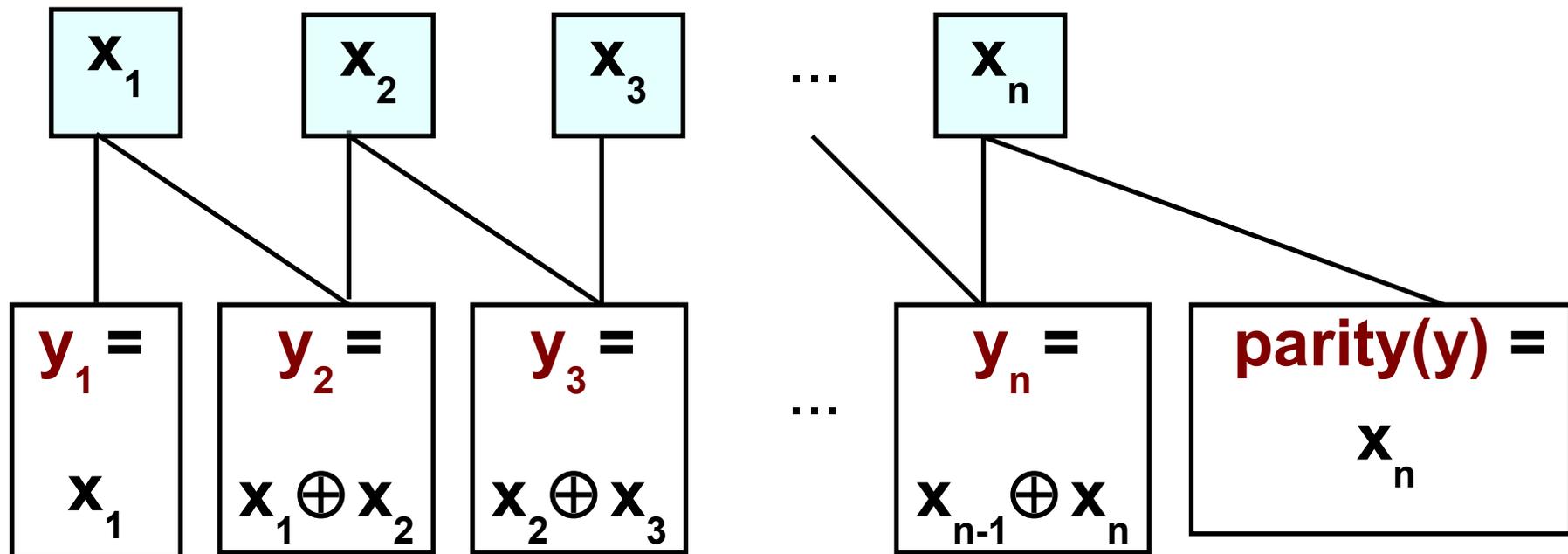
- $AC^0$  cannot compute parity  
[1980's: Furst Saxe Sipser, Ajtai, Yao, Hastad, ....]

# Sampling ( $Y, \text{parity}(Y)$ )

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

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

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



# AC<sup>0</sup> 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, Mod-3, ...

AC<sup>0</sup> cannot sample

# $AC^0$ cannot sample

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

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

$AC^0$  circuit  $C : \{0,1\}^L \rightarrow \{0,1\}^n$

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

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

$\text{Statistical-Distance}((Y, f(Y)), C(X)) > 0$

[V 2011]

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[V 2011]

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

[V now]

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



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Next

[ $\forall$  2011]

[ $\forall$  now]

“Cannot compute  $f$  better than tossing a coin,  
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- **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  $\geq k$  ( $k/n$ )

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

Example:  $(0, 1, z_5, 1-z_3, z_3, z_3, 0, z_2)$

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

- **Proof:**

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→ convex combination high min-entropy **bit-block sources**  
can fix “ $f(Y)$ ” bit leaving high min-entropy  
contradicts extractor property

QED

- **Theorem:** ACC
- **min-entropy**  $C(X)$
- $\rightarrow C(X)$  close
- with min-ent

Rules out Statistical-Distance 0, but not 0.1

Possible:

Statistical-Distance(  $C(X)$ ,  $(Y, f(Y))$ )  $\leq 0.1$ ,  
but min-entropy  $C(X) = O(1)$

Example next

- **Bit-block source**
- Example:  $(0, 1)$
- **Corollary:**  $f$  bit

- **Proof:**  $C(X) = (Y, f(Y)) \rightarrow$  min-entropy  $C(X) \geq |Y| = n$

$\rightarrow$  convex combination high min-entropy **bit-block sources**  
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# Example

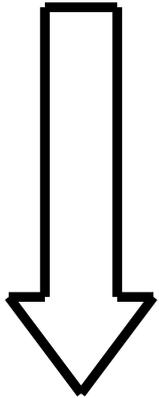
- Circuit C: “On input x:  
If first 4 bits are 0 output the all-zero string  
Otherwise sample  $(Y, f(Y))$  exactly”
- Statistical-Distance(  $C(X)$  ,  $(Y, f(Y))$  )  $\leq 0.1$ ,  
but min-entropy  $C(X) = O(1)$
- Observation: If you fix first 4 bits,  
min-entropy polarizes: either zero or very large  
We show this happens for every  $AC^0$  circuit

# Polarizing min-entropy

- **Theorem:** For every  $AC^0$  circuit  $C : \{0,1\}^L \rightarrow \{0,1\}^n$   
 $\exists$  set  $S$  of  $\exp(n - n^{0.9})$  restrictions such that:
  - (1) preserve output distribution  
 $C|_r(X) \approx C(X)$  for uniform  $r \in S$
  - (2) polarize min-entropy  
 $\forall r \in S, C|_r$  has min-entropy 0 or  $n^{0.8}$
- Note:  $|S| = \exp(n)$  useless and trivial:  
 $S :=$  one input for each of  $\leq 2^n$  outputs, entropy always 0

# Proof steps

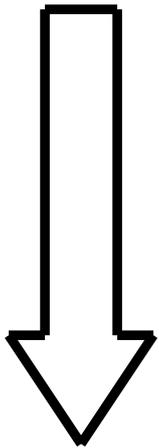
- $AC^0$



- Decision trees

Small set of restrictions that  
(1) preserve output distribution  
hypercontractivity +  
specific concentration of measure

(2) collapse  $AC^0$  to decision trees  
switching lemma



Further restrict  
tree either fixed or has high min entropy

- Polarized decision trees

# Conclusion

- Open problem: Statistical distance  $1/2 - \exp(-n^{0.1})$   
Neither in reduction to bit-block nor entropy polarization

- Much more to chart...

