

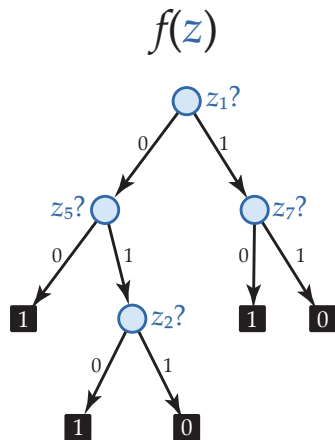


# Query-to-Communication Lifting for BPP

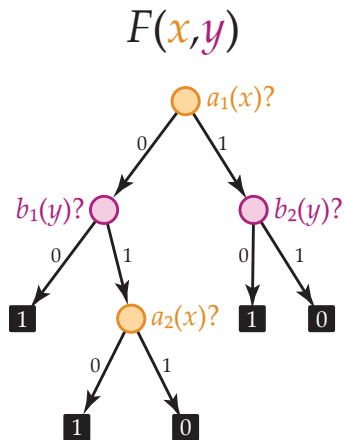
*(incl. a pseudorandomness lemma)*

Mika Göös     *Harvard & Simons Institute*  
Toniann Pitassi     *University of Toronto*  
Thomas Watson     *University of Memphis*

# Query vs. Communication

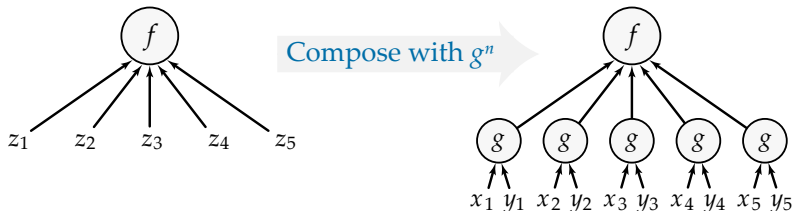


*Decision trees*



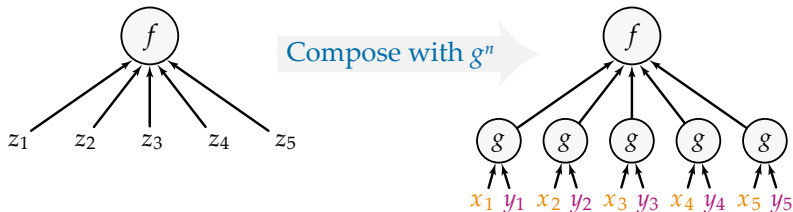
*Communication protocols*

# Composed functions $f \circ g^n$



- Examples:**
- Set-disjointness:  $\text{OR} \circ \text{AND}^n$
  - Inner-product:  $\text{XOR} \circ \text{AND}^n$
  - Equality:  $\text{AND} \circ \neg\text{XOR}^n$

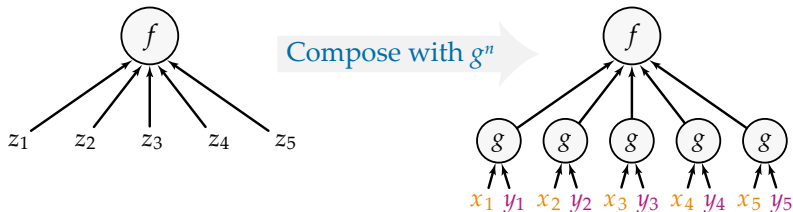
# Composed functions $f \circ g^n$



**In general:**  $g: \{0,1\}^m \times \{0,1\}^m \rightarrow \{0,1\}$  is a small gadget

- **Alice** holds  $x \in (\{0,1\}^m)^n$
- **Bob** holds  $y \in (\{0,1\}^m)^n$

# Composed functions $f \circ g^n$



## Lifting Theorem Template:

$$M^{\text{cc}}(f \circ g^n) \approx M^{\text{dt}}(f)$$

# Composed functions $f \circ g^n$

M	Query	Communication	
P	deterministic	deterministic	[RM99, GPW15, dRNV16, HHL16]
NP	nondeterministic	nondeterministic	[GLM <sup>+</sup> 15, G15]
<i>many</i>	poly degree	rank	[SZ09, She11, RS10, RPRC16]
<i>many</i>	conical junta deg.	nonnegative rank	[GLM <sup>+</sup> 15, KMR17]
P <sup>NP</sup>	decision list	rectangle overlay	[GKPW17]
	Sherali–Adams	LP complexity	[CLRS16, KMR17]
	sum-of-squares	SDP complexity	[LRS15]

## Lifting Theorem Template:

$$M^{\text{cc}}(f \circ g^n) \approx M^{\text{dt}}(f)$$

# Lifting theorem for BPP

**Index gadget**  $g: [m] \times \{0,1\}^m \rightarrow \{0,1\}$

$$g(x, y) = y_x$$

$\text{BPP}^{\text{dt}}(f)$  = randomised query complexity of  $f$

$\text{BPP}^{\text{cc}}(F)$  = randomised communication complexity of  $F$

## Our result

For  $m = n^{100}$  and every function  $f: \{0,1\}^n \rightarrow \{0,1\}$ ,

$$\text{BPP}^{\text{cc}}(f \circ g^n) = \text{BPP}^{\text{dt}}(f) \cdot \Theta(\log n)$$

# New applications

$$\text{BPP}^{\text{dt}}(f) \gg \text{M}^{\text{dt}}(f)$$



$$\text{BPP}^{\text{cc}}(f \circ g^n) \gg \text{M}^{\text{cc}}(f \circ g^n)$$



# ~~New applications~~

$$\text{BPP}^{\text{dt}}(f) \gg \text{M}^{\text{dt}}(f)$$



$$\text{BPP}^{\text{cc}}(f \circ g^n) \gg \text{M}^{\text{cc}}(f \circ g^n)$$

# ~~New applications~~

## Classical vs. Quantum

- 2.5-th power total function gap [ABK16,ABB<sup>+</sup>16]
- *Conjecture*: 2.5 improves to 3 [AA15]
- exponential partial function gap [Raz99,KR11]

## BPP vs. Partition numbers

- 1-sided (= Clique vs. Independent Set) [GJPW15]
- 2-sided [AKK16,ABB<sup>+</sup>16]

Approximate Nash equilibria [BR17]

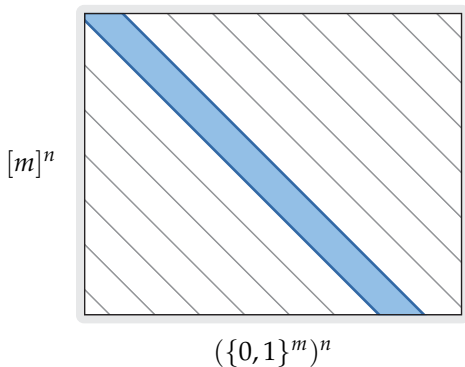
$$\text{BPP}^{\text{cc}}(f \circ g^n) \geq \text{BPP}^{\text{dt}}(f) \cdot \Omega(\log n)$$

*...how to begin?*

# What we actually prove

**Input domain** partitioned into **slices**

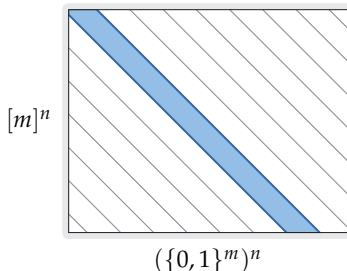
$$[m]^n \times (\{0,1\}^m)^n = \bigcup_{z \in \{0,1\}^n} (g^n)^{-1}(z)$$



# What we actually prove

## Simulation

- $\forall$  deterministic protocol  $\Pi$   
 $\exists$  randomised decision tree of height  $|\Pi|$  outputting a random transcript of  $\Pi$  such that **1**  $\approx$  **2**
- 1** output of randomised decision tree on input  $z$
  - 2** transcript generated by  $\Pi$  on input  $(x, y) \sim (g^n)^{-1}(z)$



# What we actually prove

## Simulation

$\forall$  deterministic protocol  $\Pi$   
 $\exists$  randomised decision tree of height  $|\Pi|$  outputting a random transcript of  $\Pi$  such that **1**  $\approx$  **2**

**1** output of randomised decision tree on input  $z$

**2** transcript generated by  $\Pi$  on input  $(\mathbf{x}, \mathbf{y}) \sim (g^n)^{-1}(z)$

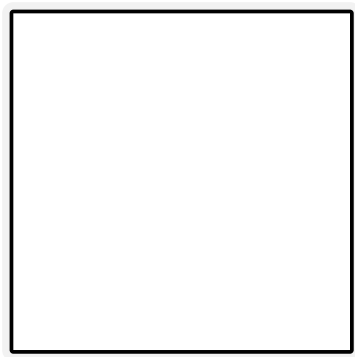
- Main theorem:**
1. pick  $\Pi \sim \Pi$
  2. simulate  $\Pi$  via query access to  $z$
  3. output value of leaf

$$\mathbb{E}_{(\mathbf{x}, \mathbf{y}) \sim (g^n)^{-1}(z)} \overbrace{\Pr_{\Pi}[\Pi(\mathbf{x}, \mathbf{y}) \text{ correct}]}^{> 2/3} = \mathbb{E}_{\Pi \sim \Pi} \Pr_{(\mathbf{x}, \mathbf{y}) \sim (g^n)^{-1}(z)}[\Pi(\mathbf{x}, \mathbf{y}) \text{ correct}]$$

# Goal in pictures

**Goal:** **1**  $\approx$  **2**

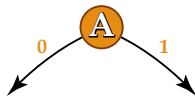
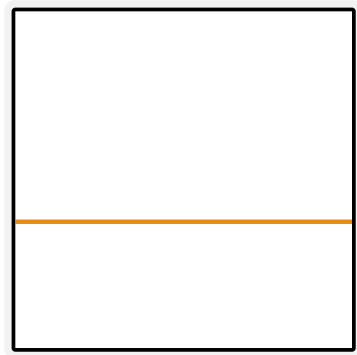
- 1** output of randomised decision tree on input  $z$
- 2** transcript generated by  $\Pi$  on input  $(x, y) \sim (g^n)^{-1}(z)$



# Goal in pictures

**Goal:** 1  $\approx$  2

- 1 output of randomised decision tree on input  $z$
- 2 transcript generated by  $\Pi$  on input  $(x, y) \sim (g^n)^{-1}(z)$

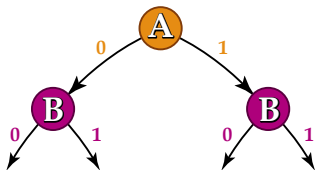
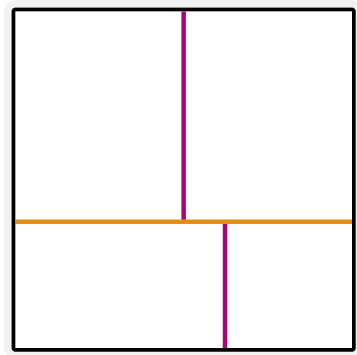




# Goal in pictures

**Goal:** 1  $\approx$  2

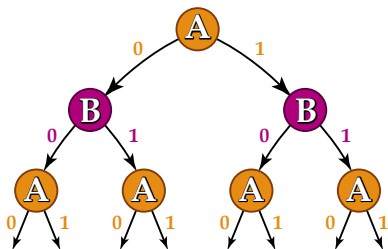
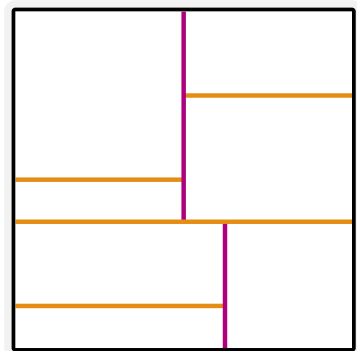
- 1 output of randomised decision tree on input  $z$
- 2 transcript generated by  $\Pi$  on input  $(x, y) \sim (g^n)^{-1}(z)$



# Goal in pictures

**Goal:** 1  $\approx$  2

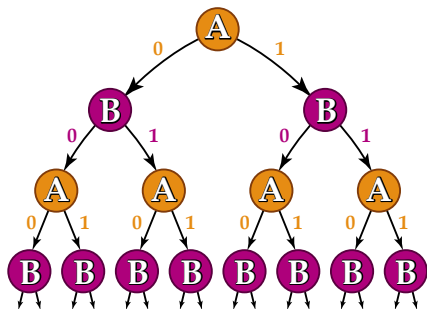
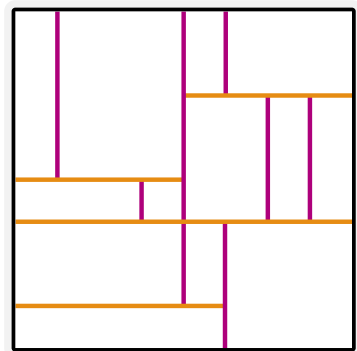
- 1 output of randomised decision tree on input  $z$
- 2 transcript generated by  $\Pi$  on input  $(x, y) \sim (g^n)^{-1}(z)$



# Goal in pictures

**Goal:** 1  $\approx$  2

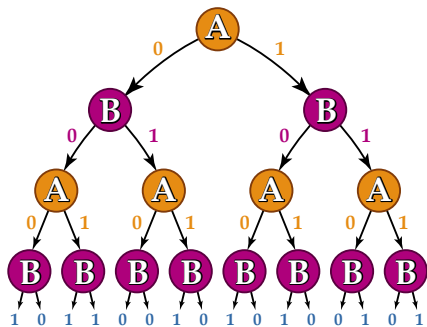
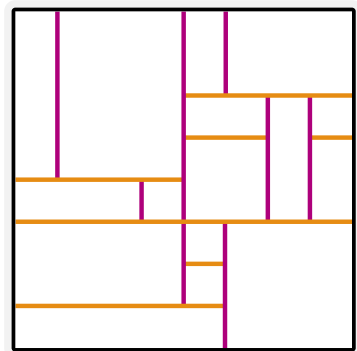
- 1 output of randomised decision tree on input  $z$
- 2 transcript generated by  $\Pi$  on input  $(x, y) \sim (g^n)^{-1}(z)$



# Goal in pictures

**Goal:** 1  $\approx$  2

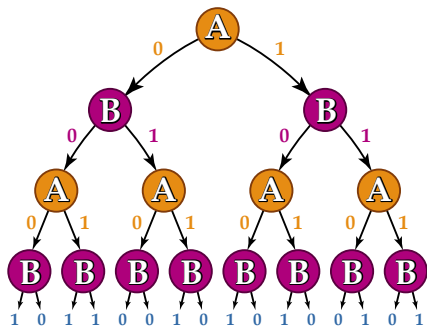
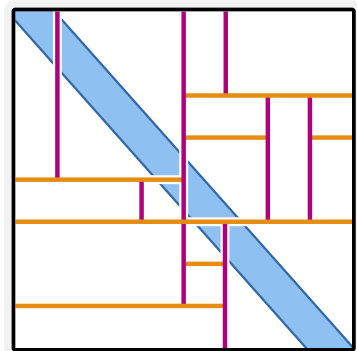
- 1 output of randomised decision tree on input  $z$
- 2 transcript generated by  $\Pi$  on input  $(x, y) \sim (g^n)^{-1}(z)$



# Goal in pictures

Goal: 1  $\approx$  2

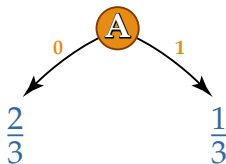
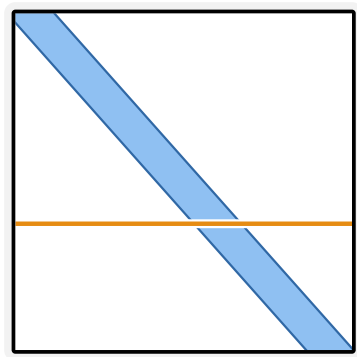
- 1 output of randomised decision tree on input  $z$
- 2 transcript generated by  $\Pi$  on input  $(x, y) \sim (g^n)^{-1}(z)$



# Goal in pictures

**Goal:** 1  $\approx$  2

- 1 output of randomised decision tree on input  $z$
- 2 transcript generated by  $\Pi$  on input  $(x, y) \sim (g^n)^{-1}(z)$



Idea:

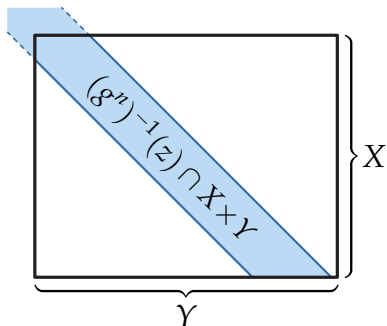
Pretend marginals are uniform!

# Pseudorandomness

## Uniform Marginals Lemma:

Suppose  $X \subseteq [m]^n$  is **dense**  
 $Y \subseteq (\{0,1\}^m)^n$  is “large”

Then  $\forall z \in \{0,1\}^n$  the uniform distribution on  $(g^n)^{-1}(z) \cap X \times Y$  has both marginal distributions close to uniform on  $X$  and  $Y$

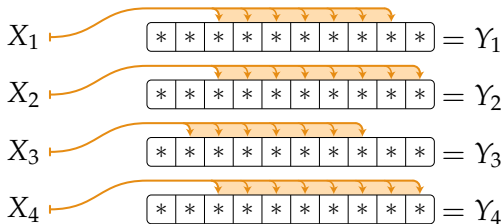


**Dense:**  $H_\infty(\mathbf{X}_I) \geq 0.9 \cdot |I| \log m$  for all  $I \subseteq [n]$   
[GLMWZ15]

# Simulation

When **density** is lost, restore it!

- 1 Compute partition  $X = \cup_i X^i$  where each  $X^i$  [GLMWZ15] is fixed on some  $I \subseteq [n]$  and **dense** on  $\bar{I}$
- 2 Update  $X \leftarrow X^i$  with probability  $|X^i|/|X|$
- 3 Query  $z_I \in \{0,1\}^I$
- 4 Restrict  $Y$  so that  $g^I(X_I, Y_I) = z_I$
- 5 Update  $Y \leftarrow Y_{\bar{I}}$  and  $X \leftarrow X_{\bar{I}}$  (which is **dense**)

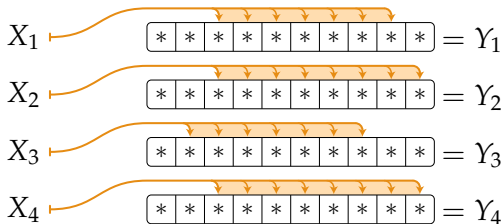




# Simulation

When **density** is lost, restore it!

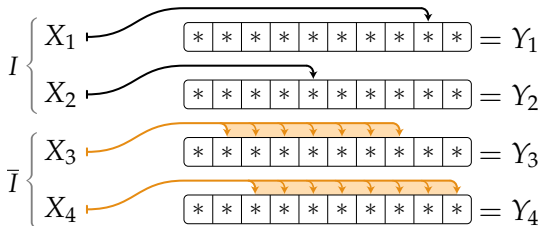
- 1 Compute partition  $X = \cup_i X^i$  where each  $X^i$  is fixed on some  $I \subseteq [n]$  and **dense** on  $\bar{I}$  [GLMWZ15]
- 2 Update  $X \leftarrow X^i$  with probability  $|X^i|/|X|$
- 3 Query  $z_I \in \{0,1\}^I$
- 4 Restrict  $Y$  so that  $g^I(X_I, Y_I) = z_I$
- 5 Update  $Y \leftarrow Y_{\bar{I}}$  and  $X \leftarrow X_{\bar{I}}$  (which is **dense**)



# Simulation

When **density** is lost, restore it!

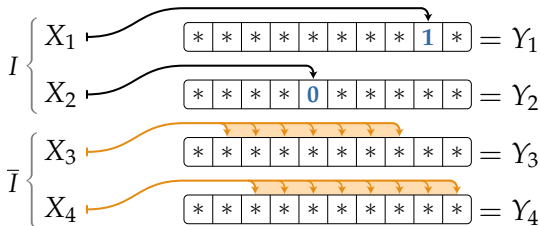
- 1 Compute partition  $X = \cup_i X^i$  where each  $X^i$  [GLMWZ15] is fixed on some  $I \subseteq [n]$  and **dense** on  $\bar{I}$
- 2 Update  $X \leftarrow X^i$  with probability  $|X^i|/|X|$
- 3 Query  $z_I \in \{0,1\}^I$
- 4 Restrict  $Y$  so that  $g^I(X_I, Y_I) = z_I$
- 5 Update  $Y \leftarrow Y_{\bar{I}}$  and  $X \leftarrow X_{\bar{I}}$  (which is **dense**)



# Simulation

When **density** is lost, restore it!

- 1 Compute partition  $X = \cup_i X^i$  where each  $X^i$  is fixed on some  $I \subseteq [n]$  and **dense** on  $\bar{I}$  [GLMWZ15]
- 2 Update  $X \leftarrow X^i$  with probability  $|X^i|/|X|$
- 3 Query  $z_I \in \{0,1\}^I$
- 4 Restrict  $Y$  so that  $g^I(X_I, Y_I) = z_I$
- 5 Update  $Y \leftarrow Y_{\bar{I}}$  and  $X \leftarrow X_{\bar{I}}$  (which is **dense**)



# Simulation

When **density** is lost, restore it!

- 1 Compute partition  $X = \cup_i X^i$  where each  $X^i$  is fixed on some  $I \subseteq [n]$  and **dense** on  $\bar{I}$  [GLMWZ15]
- 2 Update  $X \leftarrow X^i$  with probability  $|X^i|/|X|$
- 3 Query  $z_I \in \{0,1\}^I$
- 4 Restrict  $Y$  so that  $g^I(X_I, Y_I) = z_I$
- 5 Update  $Y \leftarrow Y_{\bar{I}}$  and  $X \leftarrow X_{\bar{I}}$  (which is **dense**)

## Correctness

- 1 #queries  $\leq |\Pi|$  (whp)
- 2 Resulting transcript is close to that generated by random input from  $(g^n)^{-1}(z)$


# *Some problems*

## Maybe doable

- Lifting for BQP?
- Lifting using **constant-size** gadgets?

[ABG<sup>+</sup>17]

## Challenges

- Disprove the log-rank conjecture 
- Explicit lower bounds against  $\text{PH}^{\text{cc}}$ ?  
Or even  $\text{SZK}^{\text{cc}} \subseteq \text{AM}^{\text{cc}} \subseteq \Pi_2\text{P}^{\text{cc}}$ ?


[BCHTV16]

## Maybe doable

- Lifting for BQP?
- Lifting using **constant-size** gadgets?

[ABG<sup>+</sup>17]

## Challenges

- Disprove the log-rank conjecture 
- Explicit lower bounds against  $\text{PH}^{\text{cc}}$ ?  
Or even  $\text{SZK}^{\text{cc}} \subseteq \text{AM}^{\text{cc}} \subseteq \Pi_2\text{P}^{\text{cc}}$ ?

[BCHTV16]

# Cheers!