

Designing Efficient Span Programs

Robert Špalek



The Google logo is displayed in its characteristic multi-colored font: blue 'G', red 'o', yellow 'o', blue 'g', green 'l', and red 'e'.

joint work with Ben Reichardt

Designing span programs

- **Def:** A span program P is: [Karchmer & Wigderson '93]
 - A target vector t over \mathbf{C} ,
 - Input vectors v_j each associated with a conjunction of literals from $\{x_1, \neg x_1, \dots, x_n, \neg x_n\}$
 - Span program P computes $f_P: \{0, 1\}^n \rightarrow \{0, 1\}$,
 $f_P(x) = 1 \Leftrightarrow t$ lies in the span of $\{ \text{true } v_j \}$
- **Given:** a Boolean function $f: \{0, 1\}^n \rightarrow \{0, 1\}$
Task 1: design a span program P computing f
- Last talk: this gives a bounded-error quantum algorithm for f
[Reichardt & Š, STOC'08]

Efficiency of span programs

- **Def:** *witness size* of P on input x :

length of the shortest vector satisfying certain linear constraint

$$\text{wsize}_S P(x) = \begin{cases} \min_{|w\rangle: A\Pi|w\rangle=|t\rangle} \|S|w\rangle\|^2 & \text{if } f_P(x) = 1 \\ \min_{\substack{|w'\rangle: \langle t|w'\rangle=1 \\ \Pi A^\dagger|w'\rangle=0}} \|SA^\dagger|w'\rangle\|^2 & \text{if } f_P(x) = 0 \end{cases}$$

- S is a diagonal matrix of complexities of the inputs (we typically consider all ones),
- A is the matrix of input vectors of P ,
- Π is the projector onto true columns on input x
- The running time of our quantum alg. is $O(\max_x \text{wsize } P(x))$
- **Task 2:** optimize the witness size of P by tuning its “free coefficients”, ideally to match the lower bound for f
(we use *adversary lower bounds* for comparison [Ambainis'03])

Span programs based on formulas

Using DNF formulas

- Expand the function f as a DNF formula

Ex: $\text{Equal}_n(x_1 \dots x_n) = (x_1 \wedge \dots \wedge x_n) \vee (\neg x_1 \wedge \dots \wedge \neg x_n)$

- Form a span program with 1 row of ones, and with columns corresponding to the clauses, labeled by the conjunctions of the input variables and their negations

target	$x_1 \dots x_n$	$\neg x_1 \dots \neg x_n$
1	1	1

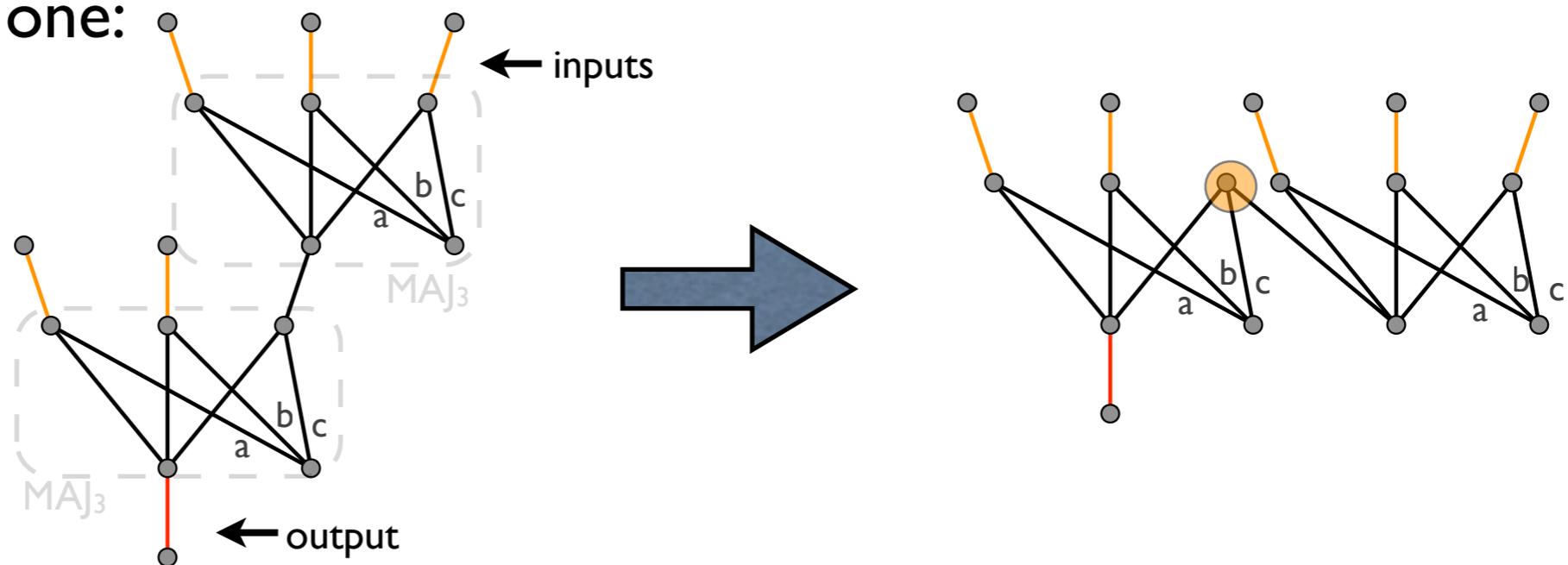
- By definition, this span program evaluates f
- It may not be efficient, but one can optimize its weights.

This way, for example, one gets an optimal $O(\sqrt{n})$ algorithm for {AND, OR} formulas of size n

[Ambainis, Childs, Reichardt, Š & Zhang, FOCS'07]

Formulas that are not in DNF

- If the formula consists of more complicated sub-formulas, we can use composition of their corresponding span programs
- Connect the output edge of one gadget with an input edge of another one:



- The span program then looks like this:

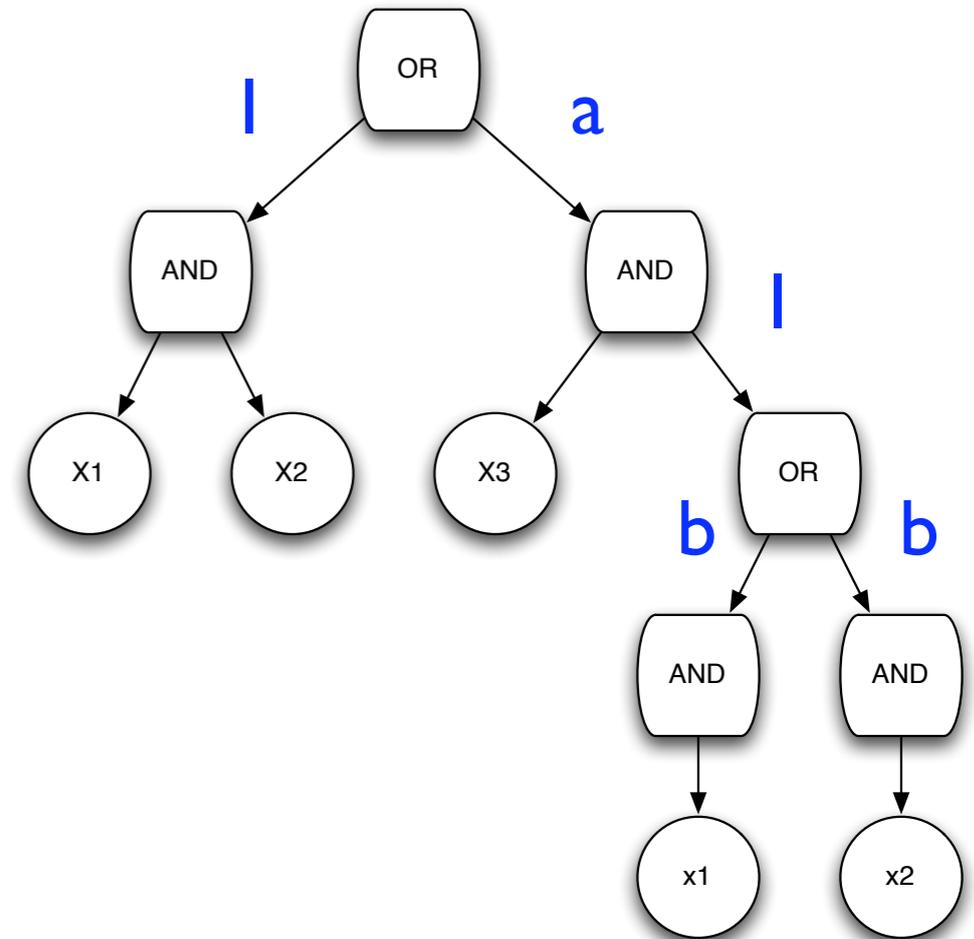
\underline{t}	x_1	x_2	1	x_3	x_4	x_5
1	1	1	1	0	0	0
0	a	b	c	0	0	0
0	0	0	1	1	1	1
0	0	0	0	a	b	c

Running example: Majority of 3

- $\text{Maj}_3(x_1, x_2, x_3) = (x_1 \wedge x_2) \vee ((x_1 \vee x_2) \wedge x_3)$
- Since this is not in a DNF form, we need to compose two span programs, one for $(x_1 \wedge x_2)$ and one for $((x_1 \vee x_2) \wedge x_3)$.
- If we set the weights according to [ACRŠZ'07], we get witness size $\sqrt{5}$.
- These weights would be optimal if the formula was a **read-once** formula on bits, i.e. $(x_1 \wedge x_2) \vee ((x_4 \vee x_5) \wedge x_3)$.

However, we are promised that $x_4 = x_1$ and $x_5 = x_2$, so some inputs don't appear.

- If we optimize the weights under this promise, the witness size is $\sqrt{3 + \sqrt{2}} < \sqrt{5}$.



$x_1 x_2$	x_3	x_1	x_2
1	a	0	0
0	1	b	b

$$a = \sqrt{\frac{1 + \sqrt{2}}{2}} \quad b = \frac{1}{\sqrt[4]{2}}$$

Going beyond formulas

and respecting function symmetries

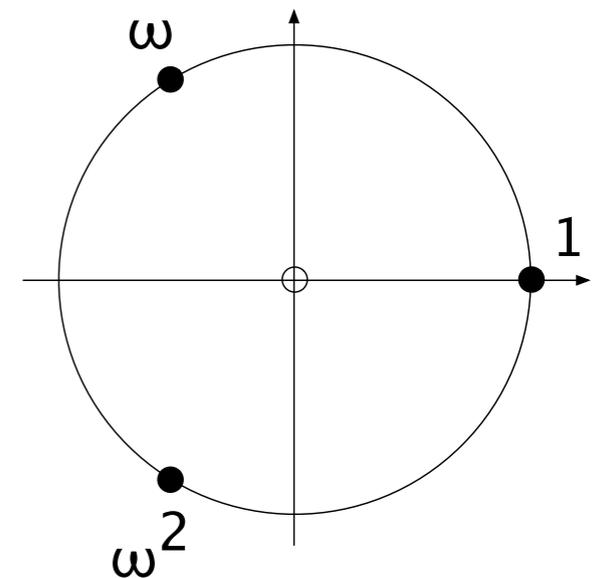
Symmetric span program for Maj_3

- Maj_3 is a *symmetric function*: one can permute the input bits any way and the function value stays the same. However, the span program doesn't treat the input bits symmetrically.

- Consider span program:

target	x_1	x_2	x_3
1	1	1	1
0	1	ω	ω^2

$$\omega = e^{2\pi i/3}$$



- If any two input bits are one, we get the same true column vectors $(1, 1)$, $(1, \omega)$, modulo a unitary transform. The program is symmetric with respect to all minimal 1-inputs.
- Simple computation shows that witness size of this span program is 2, matching the adversary bound, and hence it is optimal

Automorphisms of Maj₃

- *Automorphism* = combination of a permutation and bit-flip of some input bits, preserving the function value

Automorphism group = group of all automorphisms

- The automorphism group of Maj₃ is **S₃**.
 - Since we are permuting bits which can only have one of two values {0, 1}, in each input string there will always exist two bits of the same value (pigeonhole principle).
 - We don't care whether these two equal bits are swapped ⇒ we can apply an extra transposition to each permutation σ from S_3 to make σ **even**, with no effect to the input.
 - Therefore the “*symmetry group*” of our interest isn't S_3 , but **A₃=Z₃**, i.e. one can get to any input string with the same number of ones by using just rotation.

Using representation theory

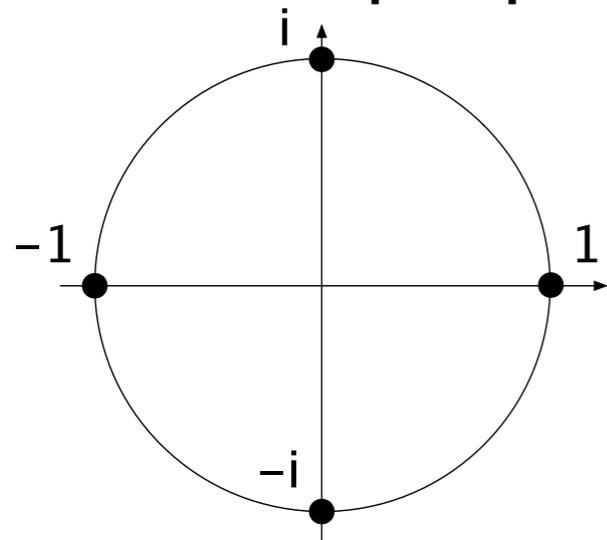
- The optimal span program for Maj_3 is

target	x_1	x_2	x_3
1	1	1	1
0	1	ω	ω^2

- Note that it consists of two *representations of \mathbb{Z}_3* , 1 and ω^i , one in each row
- **Q:** Is this a coincidence or can we find a similar pattern for more interesting functions?

Threshold 2 of 4

- Generalization of Maj_3 to more input bits
- A natural span program is



target	x_1	x_2	x_3	x_4
1	1	1	1	1
0	1	i	-1	-i

- However, this span program is not symmetric, because the sub-matrix corresponding to input 1100 is very different from the sub-matrix for input 1010.

Indeed, its witness size is $\sqrt{8} > \sqrt{6}$

- Need to go to **higher dimensions** to achieve symmetry

Using different rings than \mathbf{C}

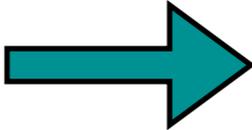
- A complex number $a+bi$ can be thought of as a pair of real numbers (a, b) , or as a 2×2 matrix

a	$-b$
b	a

This matrix representation preserves summation and multiplication.

- One can represent a complex span program by a real one with the same witness size. For example, for Maj_3 :

target	x_1	x_2	x_3
1	1	1	1
0	1	ω	ω^2



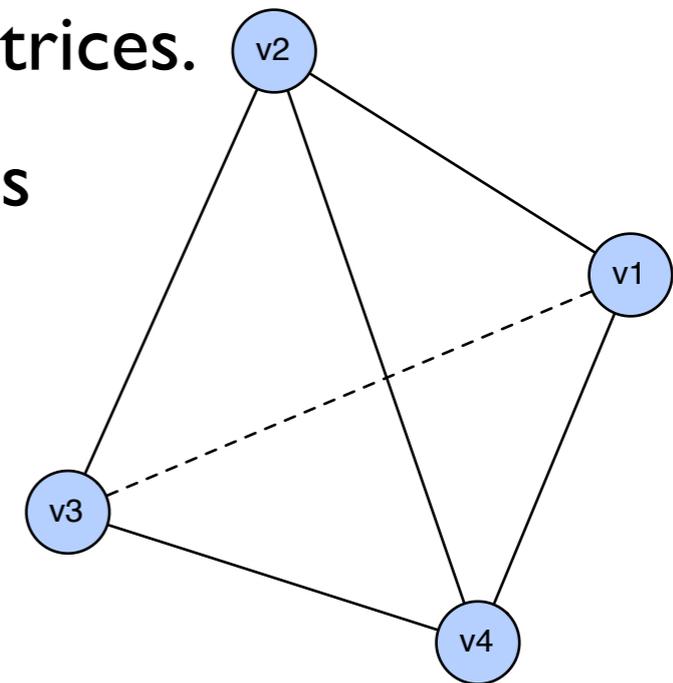
target	x_1	x_1	x_2	x_2	x_3	x_3
1	1	1	1	1	1	1
0	1	0	$-1/2$	$-\sqrt{3}/2$	$-1/2$	$\sqrt{3}/2$
0	0	1	$\sqrt{3}/2$	$-1/2$	$-\sqrt{3}/2$	$-1/2$

- Can we do the opposite, i.e. extend \mathbf{C} ? Yes.

Simplex with 4 vertices

- In 3 dimensions, we can take 4 vertices of the regular tetrahedron. All its edges are symmetric to each other.
- How to embed such a simplex into a span program?
- We go from the ring \mathbf{C} of complex numbers into an extension ring of quaternions/unitary matrices.
- In this extension ring, the span program is

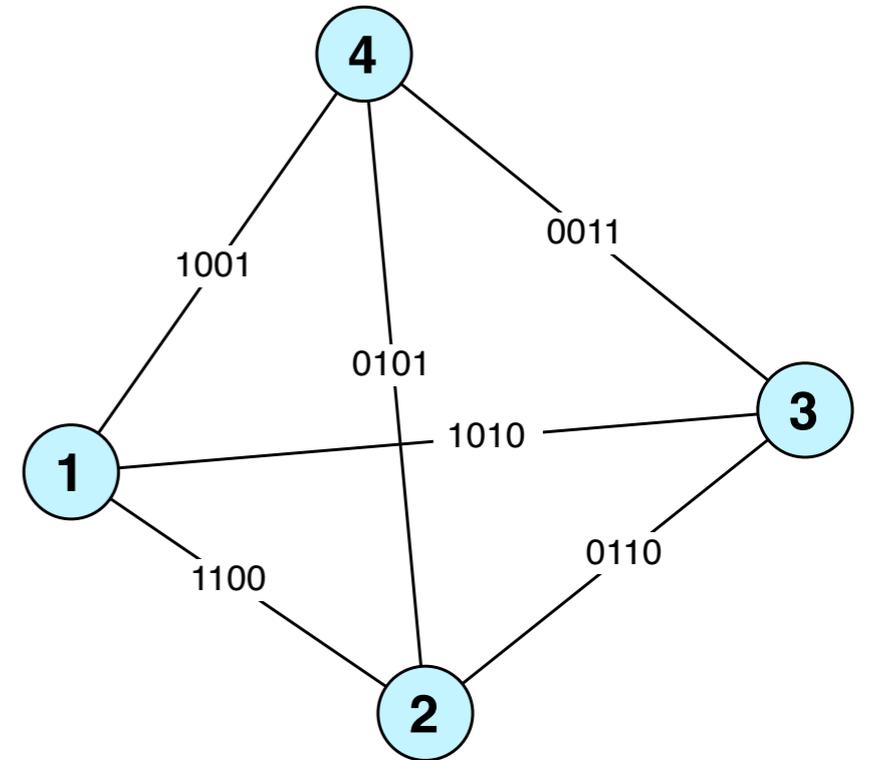
target	x_1	x_2	x_3	x_4
1	1	1	1	1
0	v_1	v_2	v_3	v_4



where v_1, v_2, v_3, v_4 are elements of the extension ring corresponding to the vertices of the simplex.

Constructing the extension ring

- The automorphism group of Thr_2 of 4 is S_4 , and we can again restrict our attention to A_4 , the subgroup of even permutations
- This is the group of orientation-preserving symmetries of tetrahedron. Its generators are:
 - Define a clock-wise rotation “around” each vertex, labeled by the fixed input bit.
 - Represent the rotations in $SO(3) \subseteq SU(2)$.



The elements $v_{1..4}$ of the span program will be the 2×2 representations of these rotations.

target	x_1	x_1	x_2	x_2	x_3	x_3	x_4	x_4
1	1	1	1	1	1	1	1	1
0	1	1	1	-1	i	$-i$	i	i
0	i	$-i$	i	i	1	1	1	-1

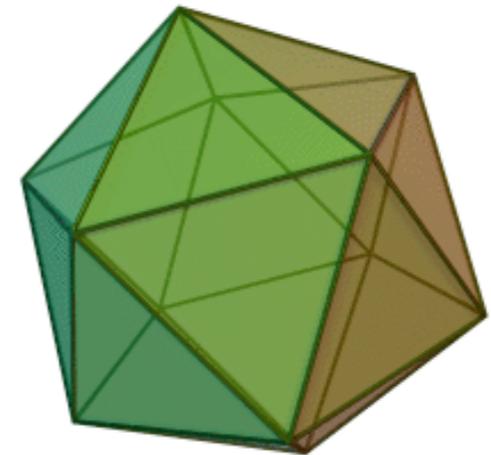
optimal wsize = $\sqrt{6}$

2×2 unitary matrix

Threshold 2 of 5

- Similarly to $\text{Thr}_{2 \text{ of } 4}$, one can use the vertices of a regular 5-simplex in 4 dimensions.
- They can also be represented by 2×2 complex matrices and give an optimal span program with witness size $\sqrt{8}$, of the form

target	x_1	x_2	x_3	x_4	x_5
1	1	1	1	1	1
0	v_1	v_2	v_3	v_4	v_5



- The symmetry group of $\text{Thr}_{2 \text{ of } 5}$ is \mathbf{A}_5 , which is the group of orientation-preserving *symmetries of the icosahedron*. It can also be embedded into $SO(3) \subseteq SU(2)$.
- **Q:** Can we think of the 2×2 matrices corresponding to the 5 vertices of the simplex as generators of this group?

Threshold_M of N

- Span programs for $M=2$ and $N \geq 5$:
 - **Q:** Can we analyze them in a closed form?
- Span programs for $M=3$ and $N=5$:
 - **Q:** Can we get a symmetric span program of the form

target	x_1	x_2	x_3	x_4	x_5
1	1	1	1	1	1
0	v_1	v_2	v_3	v_4	v_5
0	w_1	w_2	w_3	w_4	w_5

where v_i, w_i are 2×2 unitary matrices? What would the pairs of matrices correspond to on the icosahedron?

- **Q:** Can we solve in a closed form the general case?
- **Q:** Do we actually need the smaller “symmetry group” A_n instead of S_n ? It arises very naturally for Maj_3 .

Going beyond permutation symmetry

Automorphism groups with flipping input bits

Ambainis function

- **Def:** $A(x_1, x_2, x_3, x_4)$ is true iff the input bits are sorted, i.e.

$$x_1 \leq x_2 \leq x_3 \leq x_4 \text{ or } x_1 \geq x_2 \geq x_3 \geq x_4$$

- Its automorphism group is generated by

$$A(x_1, x_2, x_3, x_4) = A(x_2, x_3, x_4, \neg x_1)$$

i.e. one can rotate the whole string to the left while flipping the new last bit

- Simplest non-monotone function with unknown witness size.

$$\text{deg}(A)=2, \text{ Adv}(A)=2.5, \text{ Adv}^\pm(A)=2.51353$$

$$\text{wsize}(A) \leq 2.77394 \text{ using optimized weights for formula } (x_1 \wedge ((x_2 \wedge x_3) \vee (\neg x_3 \wedge \neg x_4))) \vee (\neg x_1 \wedge ((\neg x_2 \wedge \neg x_3) \vee (x_3 \wedge x_4)))$$

0- and 1- inputs of the Ambainis function

- If we order both x_i 's and $\neg x_i$'s in one line, then the “symmetry group” of this function is Z_8
- **Idea:** it may be worthy to look at span programs consisting of representations of Z_8 .
- If a span program is generated this way, then it is sufficient to verify just 2 input strings 0000 and 0010. All other inputs are unitarily related due to the rotational symmetry.
- Cannot make it work yet due to some “little” details

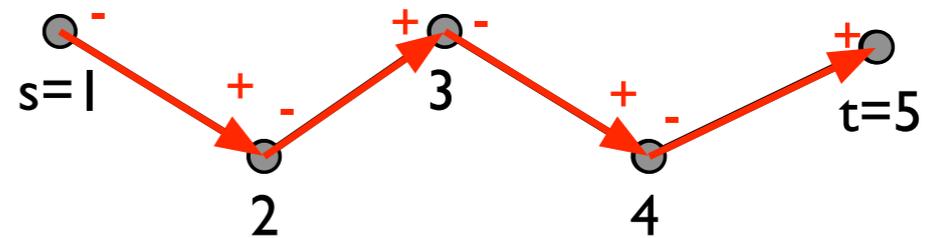
	x_1	x_2	x_3	x_4	$\neg x_1$	$\neg x_2$	$\neg x_3$	$\neg x_4$
0000					✓	✓	✓	✓
0001				✓	✓	✓	✓	
0011			✓	✓	✓	✓		
0111		✓	✓	✓	✓			
1111	✓	✓	✓	✓				
1110	✓	✓	✓					✓
1100	✓	✓					✓	✓
1000	✓					✓	✓	✓
0010			✓		✓	✓		✓
0101		✓		✓	✓		✓	
1011	✓		✓	✓		✓		
0110		✓	✓		✓			✓
1101	✓	✓		✓			✓	
1010	✓		✓			✓		✓
0100		✓			✓		✓	✓
1001	✓			✓		✓	✓	

Non-constant size span programs

Examples of large span programs

- **Ex:** Undirected s-t connectivity
 - G a graph with marked source and sink vertices
 - $|t\rangle = |\text{sink}\rangle - |\text{source}\rangle$
 - $|v_{(i,j)}\rangle = |i\rangle - |j\rangle$

t	e(1,2)	e(2,3)	e(3,4)	e(4,5)	e(1,3)	e(1,4)	...
-1	-1	0	0	0	-1	-1	
0	1	-1	0	0	0	0	
0	0	1	-1	0	1	0	...
0	0	0	1	-1	0	1	
1	0	0	0	1	0	0	

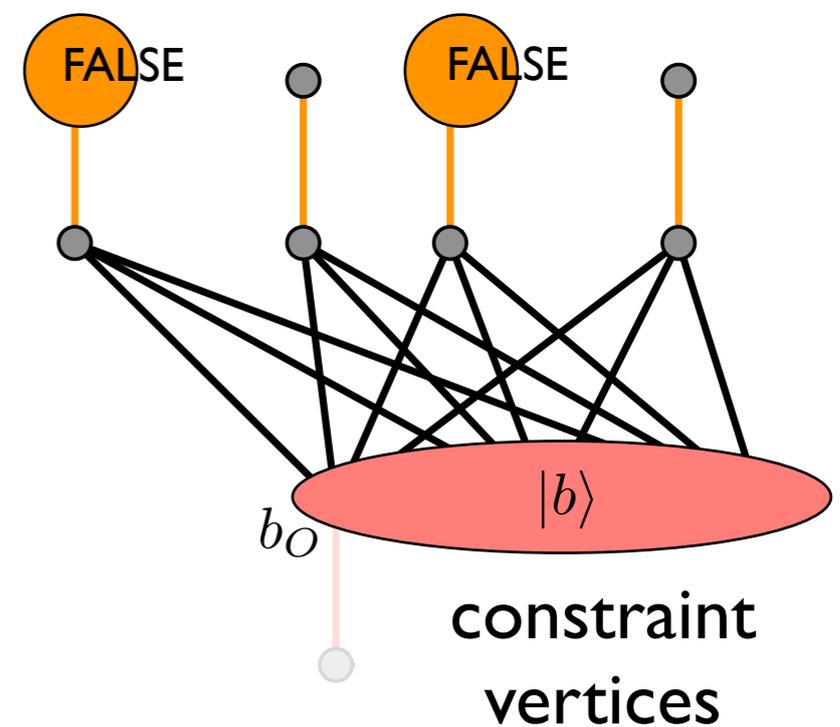
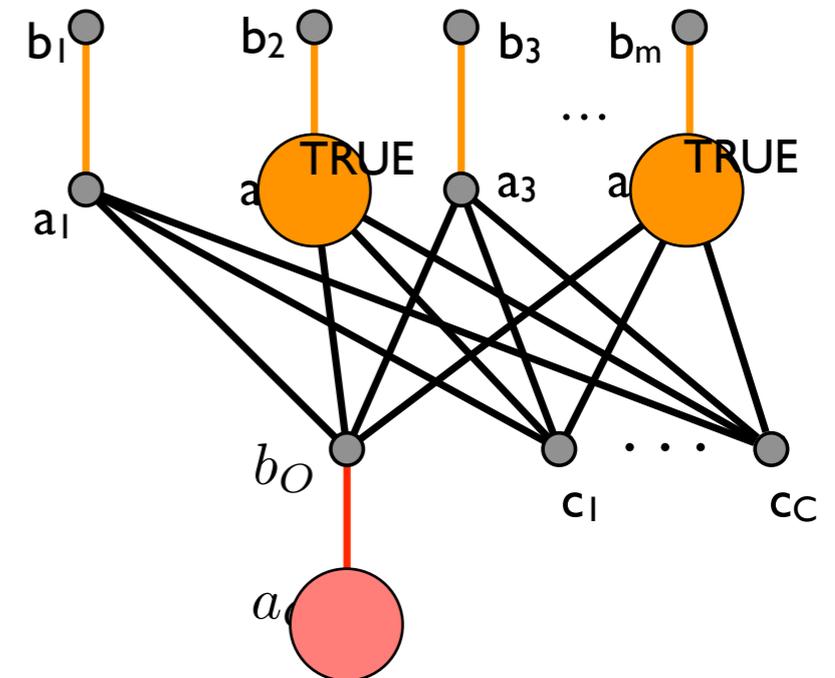


Linear combinations of the edge vectors correspond to paths in the graph.

Large overhead of span programs

- On true inputs, the span program has negligible *overhead*, because all amplitude of 0-eigenvalue eigenvectors is put on the true inputs and on the output vertex
- **Problem:** On false inputs, the span program puts amplitude also on its *constraint vertices*, and hence it decreases the overlap of the eigenvector with the root vertex.

This is negligible for span programs with $O(1)$ constraints, but may not be for larger ones.



The trouble of unbalanced inputs

3-bit functions

Fully solved for balanced inputs

Gate	Adversary lower bound
0	0
x_1	1
$x_1 \wedge x_2$	$\sqrt{2}$
$x_1 \oplus x_2$	2
$x_1 \wedge x_2 \wedge x_3$	$\sqrt{3}$
$x_1 \oplus x_2 \oplus x_3$	3
$x_1 \oplus (x_2 \wedge x_3)$	$1 + \sqrt{2}$
$x_1 \vee (x_2 \wedge x_3)$	$\sqrt{3}$
$(x_1 \wedge x_2) \vee (\overline{x_1} \wedge x_3)$	2
$x_1 \vee (x_2 \wedge x_3) \vee (\overline{x_2} \wedge \overline{x_3})$	$\sqrt{5}$
$\text{MAJ}_3(x_1, x_2, x_3) = (x_1 \wedge x_2) \vee ((x_1 \vee x_2) \wedge x_3)$	2
$\text{MAJ}_3(x_1, x_2, x_3) \vee (\overline{x_1} \wedge \overline{x_2} \wedge \overline{x_3})$	$\sqrt{7}$
$\text{EQUAL}(x_1, x_2, x_3) = (x_1 \wedge x_2 \wedge x_3) \vee (\overline{x_1} \wedge \overline{x_2} \wedge \overline{x_3})$	$3/\sqrt{2}$
$(x_1 \wedge x_2 \wedge x_3) \vee (\overline{x_1} \wedge \overline{x_2})$	$\sqrt{3 + \sqrt{3}}$

The highlighted functions require span programs.

The rest follows from composition.

<http://www.ucw.cz/~robert/papers/gadgets/>

Partially unbalanced inputs

- Assume the input complexities of 2 inputs are equal and the third one is arbitrary

Ex: $\text{Maj}_3(x_1, x_2, y_1 \vee y_2)$

- Maj_3 is relatively easy to compute and is optimal

target	x_1	x_2	x_3
1	α	α	$\sqrt{(1/2 + \beta\alpha^2)}$
0	i	$-i$	2α

$$\beta = \frac{\text{wsize}(x_3)}{\text{wsize}(x_1)}$$

$$\alpha = \frac{1}{2\sqrt{2}} \sqrt{\sqrt{8 + \beta^2} - \beta}$$

$$\text{wsize}(P) = \frac{1}{2} (\sqrt{8 + \beta^2} + \beta) \text{wsize}(x_1)$$

- Equal_3 needs to be solved separately in 3 intervals of β . One gets 3 different expressions that smoothly connect. The solution is optimal, too.

$$\left\{ \beta + \sqrt{2 - \beta^2}, \quad \sqrt{\frac{3}{2}(2 + \beta^2)}, \quad 1 + \beta \right\}$$

$$\sqrt{2/5} \qquad \qquad \qquad 2$$

Partially unbalanced inputs

- **Def:** If-then-else: $(x_1 \wedge x_2) \vee (\neg x_1 \wedge x_3)$
- If $\text{wsize}(x_2) = \text{wsize}(x_3)$, then there exists a natural optimal span program with witness size $\text{wsize}(x_1) + \text{wsize}(x_2)$
- Otherwise one can easily prove obvious bounds on wsize
 - upper bound $\text{wsize}(x_1) + \max(\text{wsize}(x_2), \text{wsize}(x_3))$
 - lower bound $\text{wsize}(x_1) + \min(\text{wsize}(x_2), \text{wsize}(x_3))$
- For input complexities $(1, 1, \sqrt{2})$, we only know

min	Adv	Adv \pm	wsize	max
2	2.18398	2.20814 < 2.22833		2.41421

Completely unbalanced inputs

- **Ex:** $\text{Maj}_3(x_1, x_2 \vee x_3, x_4 \oplus x_5)$ or, more generally, $\text{Maj}_3(x_1, x_2, x_3)$ with input complexities $(1, \alpha, \beta)$
- We don't know their witness size
 - The exact solution of the adversary bound leads to a cubic polynomial.
 - We don't have a candidate solution of the span program yet.

Analyzing candidate span programs

Software packages for computing the witness size and the adversary bound

Adversary bound

- Matlab program using SeDuMi finds the optimal adversary bound using semidefinite programming

<http://www.ucw.cz/~robert/papers/adv/>

- Works with non-Boolean inputs and promise functions
- **Input:** list of 0- and 1-inputs, and the input complexities
- **Output:** Adv and Adv[±], and the adversary matrices
- **Ex:** Maj₃
 - $X = [0, 0, 0; 0, 0, 1; 0, 1, 0; 1, 0, 0]$
 - $Y = [0, 1, 1; 1, 0, 1; 1, 1, 0; 1, 1, 1]$
 - $\text{costs} = [1, 2, 3]$
 - $[\text{Gamma}, D] = \text{madv}(X, Y, \text{costs})$
 - $\text{Gamma}1 = \text{Gamma} .* \text{mat}(D(:, 1))$
 - $\text{norm}(\text{Gamma}) / \text{norm}(\text{Gamma}1)$

Witness size

- Mathematica module computes the witness size of a given span program. It can also perform limited optimization of the program.
- **Input:**
 - span program template
 - target vector
 - input vectors, possibly with some coefficients as free variables
 - (conjunctions of) input bits corresponding to the vectors
- **Output:**
 - which function is computed by this program
 - the witness size for each input
 - the best assignment of the weights.
Both symbolical and numerical optimization are available (the latter being much faster).

Witness size

Ex: Maj₃ using NAND formula

$n = 3;$
 $\text{inputs} = \{\{y\}, \{x_1, x_2\}, \{x_3\}, \{x_1\}, \{x_2\}\};$
 $m = \{\{A, 1, w_1, 0, 0\},$
 $\quad \{0, 0, w_2, w_3, w_3\}\};$

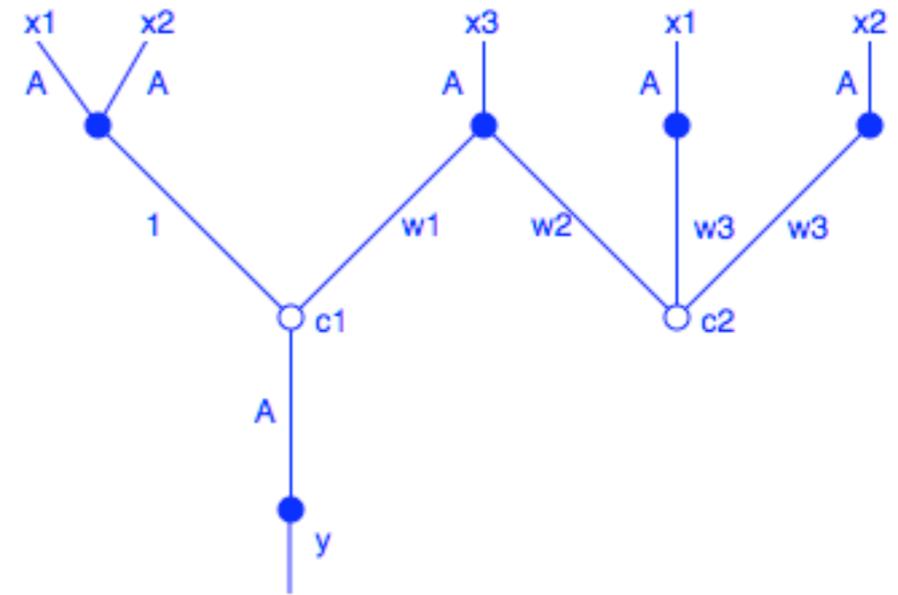
$r_{\text{out}} = \text{computeSolution}[m, \text{inputs}];$
 $\text{evaluations} = \text{evaluateInputs}[];$
 $\text{evaluations} // \text{MatrixForm}$

$\text{optimizeWeights}[\text{evaluations}, \{w_1, w_2, w_3\}]$

Function computed is 831

$$\begin{pmatrix} 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 \\ \frac{w_2^2 + 2(1 + 2w_1^2)w_3^2}{2A^2(w_2^2 + 2w_3^2)} & \frac{w_2^2 + 4w_1^2w_3^2}{2A^2w_2^2} & \frac{1 + w_1^2}{A^2} & \frac{A^2(w_2^2 + w_3^2)}{w_1^2w_3^2} & \frac{1 + w_1^2}{A^2} & \frac{A^2(w_2^2 + w_3^2)}{w_1^2w_3^2} & 2A^2 & \frac{2A^2(w_2^2 + 2w_3^2)}{w_2^2 + 2(1 + 2w_1^2)w_3^2} \end{pmatrix}$$

$$\left\{ \left\{ \sqrt{3 + \sqrt{2}}, 2.101002989615459 \right\}, \left\{ w_1 \rightarrow -\sqrt{\frac{1}{2}(1 + \sqrt{2})}, w_2 \rightarrow 1, w_3 \rightarrow \frac{1}{2^{1/4}} \right\} \right\}$$



Summary

1. Span programs design
 - based on formulas
 - based on the “symmetry group”
 - using extension rings
 - using representation theory
 - symmetry group with allowed bit flips
2. Non-constant size span programs
3. Trouble with unbalanced inputs
4. Our software packages

Q&A