Extended Formulations I (Boot Camp)

Thomas Rothvoss

UW Seattle



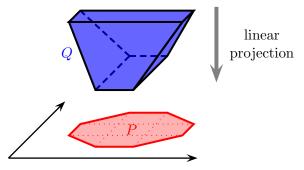
Organization

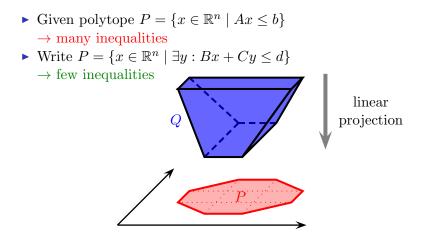
- 1. Thomas Rothvoss (1.x lectures): Introduction to LP Extended Formulations
- 2. Hamza Fawzi (1.x lectures): Introduction to SDP Extended Formulations
- 3. Prasad Raghavendra (1.x lectures): Lower bounds for LP/SDP lifts

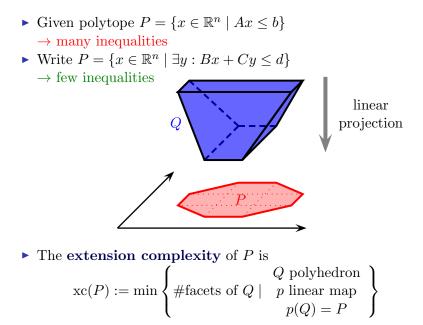
• Given polytope
$$P = \{x \in \mathbb{R}^n \mid Ax \le b\}$$



- Given polytope $P = \{x \in \mathbb{R}^n \mid Ax \le b\}$
- Write $P = \{x \in \mathbb{R}^n \mid \exists y : Bx + Cy \leq d\}$



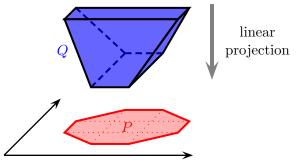




Motivation

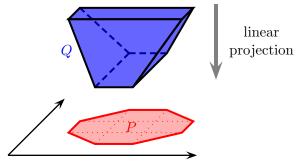
Motivation

▶ $\operatorname{xc}(\operatorname{conv}(\operatorname{Spanning Trees})) \leq O(n^3)$ ⇒ optimize over all Spanning trees with LP of size $O(n^3)$



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In reverse: If xc(P) is high for TSP / MaxCut / Correlation / Matchings, then those problems cannot be solved with a single poly-size LP!

Part I

A NON TRIVIAL EXAMPLE -KNAPSACK

Knapsack

► Input:

- *n* objects with weight $w_i \in \mathbb{Z}_+$
- ▶ profit $p_i \in \mathbb{Q}_+$
- knapsack size $B \in \mathbb{Q}_+$
- ► Goal: Find subset of objects, maximizing the profit and not exceeding the weight bound:

$$OPT = \max_{I \subseteq \{1, \dots, n\}} \left\{ \sum_{i \in I} p_i \mid \sum_{i \in I} w_i \le B \right\}$$

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Known:

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- Pseudo-polynomial time algorithm
- ► FPTAS

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Known:

- ▶ weakly NP-hard
- Pseudo-polynomial time algorithm
- ► FPTAS
- $\operatorname{xc}(\operatorname{conv}\{x \in \{0,1\}^n \mid \sum_{i=1}^n w_i x_i \le B\}) \le O(n \cdot B).$

A dynamic program for KNAPSACK

Lemma

Knapsack can be solved in time $O(n \cdot B)$.

Algorithm

(1) Compute table entries

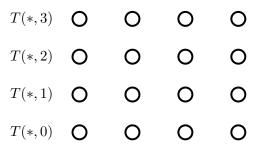
$$T(i, W) = \max_{I \subseteq \{1, \dots, i\}} \left\{ \sum_{j \in I} p_j \mid \sum_{j \in I} w_j = W \right\}$$

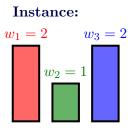
= max. profit of weight W subsets of first

using dynamic programming

$$T(i,W) = \max\left\{\underbrace{T(i-1,W)}_{\text{don't take }i}, \underbrace{T(i-1,W-w_i) + p_i}_{\text{take }i}\right\} \forall i \ \forall W \le B$$

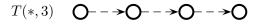
i items





T(0,*) T(1,*) T(2,*) T(3,*)

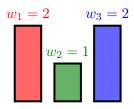
• Create a network with nodes (i, W) and



- $T(*,2) \quad \mathsf{O} {-} {-} {\rightarrow} \mathsf{O} {-} {-} {\rightarrow} \mathsf{O} {-} {-} {\rightarrow} \mathsf{O}$
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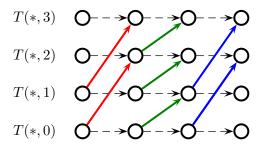
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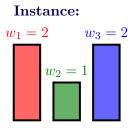




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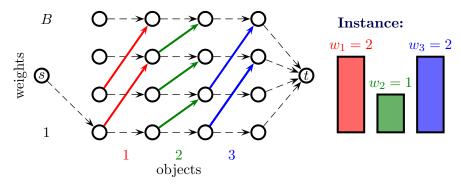
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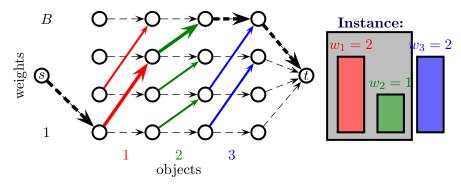
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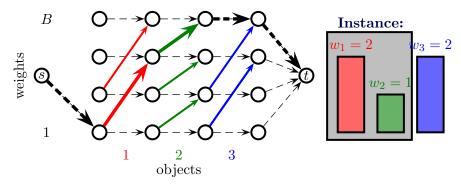
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- max cost s-t path = max profit packing

- Let G = (V, E) be network.
- Let $E_i = \{ \text{take item } i \text{ edges } \}$

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Observation

The Knapsack polytope is the projection of ${\cal Q}$ with

$$x_i = \sum_{e \in E_i} y(e) \quad \forall i \in [n]$$
$$y(\delta^+(v)) - y(\delta^-(v)) = \begin{cases} 1 & v = s \\ -1 & v = t \\ 0 & \text{otherwise} \end{cases} \quad \forall v \in V$$
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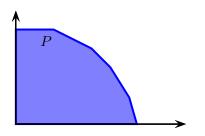
Corollary

 $\operatorname{xc}(\operatorname{Knapsack} \operatorname{polytope}) \leq O(n \cdot B).$

Open problem

Consider a Knapsack polytope

$$P = \operatorname{conv} \Big\{ x \in \{0, 1\}^n \mid \sum_{i=1}^n w_i x_i \le B \Big\}.$$



Open problem

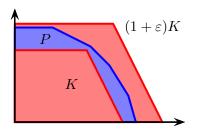
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Is there is always a polytope ${\cal K}$ with

$$\blacktriangleright K \subseteq P \subseteq (1 + \varepsilon)K$$

•
$$xc(K) \le \operatorname{poly}(n, \frac{1}{\varepsilon})?$$



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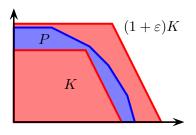
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Known:

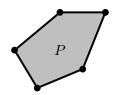
• $\operatorname{xc}(K) \le n^{O(1/\varepsilon)}$ possible (Bienstock)



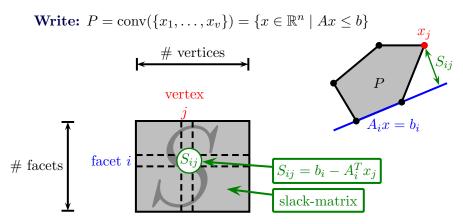
Part II

SLACK-MATRICES, YANNAKAKIS' THEOREM AND COMMUNICATION COMPLEXITY Slack-matrix

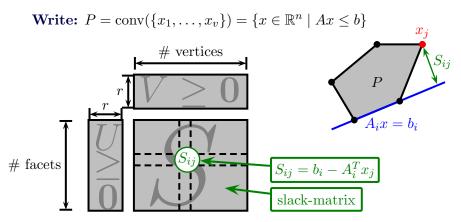
Write:
$$P = \operatorname{conv}(\{x_1, \ldots, x_v\}) = \{x \in \mathbb{R}^n \mid Ax \le b\}$$



Slack-matrix



Slack-matrix



Non-negative rank:

$$\operatorname{rk}_{+}(S) = \min\{r \mid \exists U \in \mathbb{R}_{\geq 0}^{f \times r}, V \in \mathbb{R}_{\geq 0}^{r \times v} : S = UV\}$$

Theorem (Yannakakis '88)

If S is the **slack-matrix** for $P = \{x \in \mathbb{R}^n \mid Ax \leq b\}$, then $\operatorname{xc}(P) = \operatorname{rk}_+(S)$.

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• Let $P = \{x \in \mathbb{R}^n \mid \exists y \ge \mathbf{0} : Ax + Uy = b\}$

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• For vertex
$$x^j$$
: $A_i x^j + U_i V^j = b_i$.

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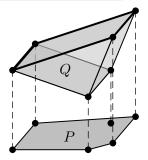
$$\bullet A_i x > b_i \Longrightarrow A_i x + \underbrace{U_i y}_{>0} > b_i.$$

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Extended form. \Rightarrow factorization:

• Given an extension $Q = \{(x, y) \mid Bx + Cy \le d\}$

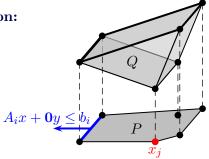


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• Given an extension $Q = \{(x, y) \mid Bx + Cy < d\}$



 S_{ij}

$$\langle u(i), v(j)
angle =$$

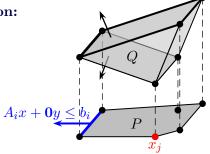
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u(i) := conic comb of i

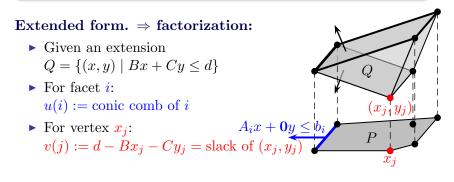


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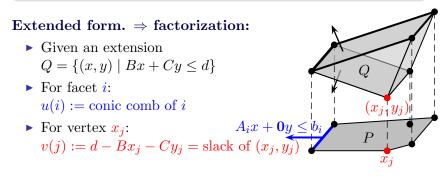
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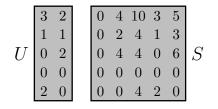
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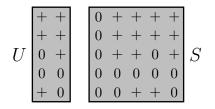


$$\langle u(i), v(j) \rangle = \underbrace{u(i)^T d}_{=b_i} - \underbrace{u(i)B}_{=A_i} x_j - \underbrace{u(i)C}_{=\mathbf{0}} y_j = S_{ij}$$

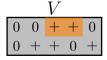
Observation $rk_+(S) \ge rectangle-covering-number(S).$

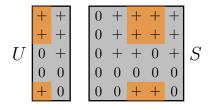


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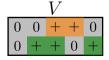


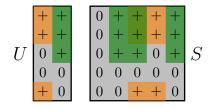
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• Function $f: X \times Y \to \mathbb{R}$



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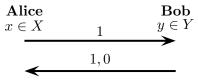
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Alice	Bob
$x \in X$	$y \in Y$

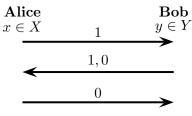
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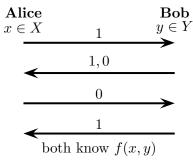
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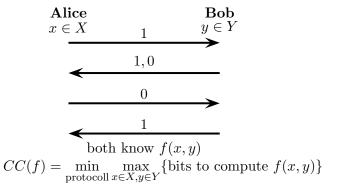
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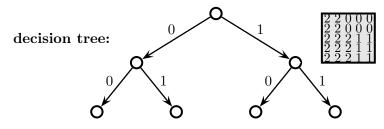


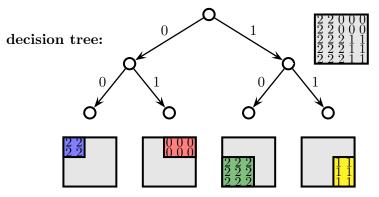
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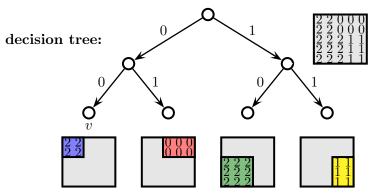


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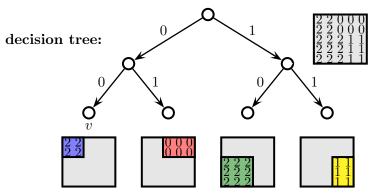






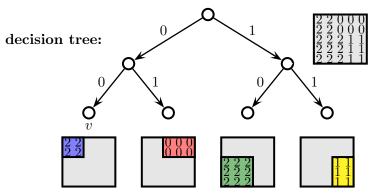
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 xc(polytope) ≤ 2^{CC(slack matrix)}

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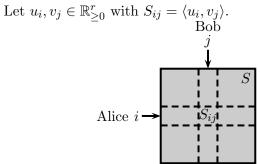
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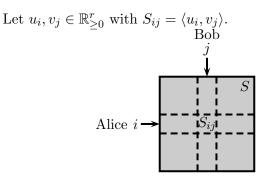
Let $CC_{RAND}(S)$ be min. # bits. Then

$$xc(polytope) = 2^{CC_{RAND}(slack matrix S)}$$

An exact model (2) Let $u_i, v_j \in \mathbb{R}^r_{\geq 0}$ with $S_{ij} = \langle u_i, v_j \rangle$. Bob *j* Alice $i \rightarrow \bigcup_{i \in I_{ij}}^{I}$

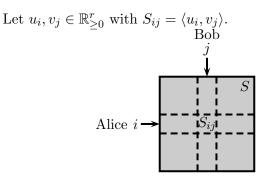


Protocoll with $\log_2(r)$ **bits:**



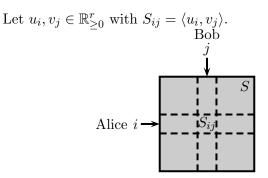
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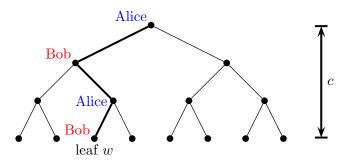
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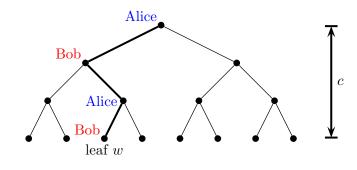
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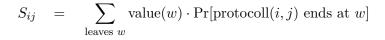
$$\mathbb{E}[\operatorname{protocoll}(i,j)] = \sum_{k=1}^{r} v_i(k) \cdot u_j(k) = \langle u_i, v_j \rangle$$

Consider depth c protocoll tree:

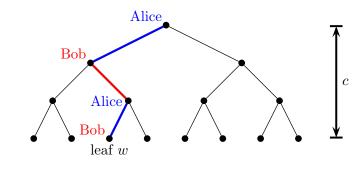


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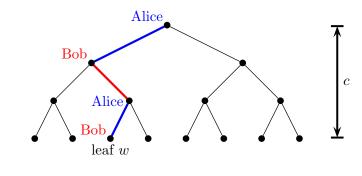


 $S_{ij} = \sum_{\text{leaves } w} \text{value}(w) \cdot \Pr[\text{protocoll}(i, j) \text{ ends at } w] =$

 $\sum_{\text{leaves } w} \underbrace{\text{value}(w)}_{\geq 0} \cdot \Pr[\text{Alice stays on } w \text{ path } | i] \cdot \Pr[\text{Bob stays on } w \text{ path } | j]$

An exact model (3)

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 $\Rightarrow 2^c$ -size non-neg factorization

Part III

The Lower Bound on the Correlation Polytope

The correlation polytope is

 $COR = \operatorname{conv}\{bb^T : b \in \{0,1\}^n\}$

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Observation: The polytope is **NP**-hard. For graph G = ([n], E) with adjacency matrix A_G maxcut $(G) = \max_{(G) \in I} (D_G - A_G) \bullet xx^T = \sum_{(x_i) \in I} (x_i + x_j - 2x_i x_j)$

$$x \in \{0,1\}^n \qquad (i,j) \in E \quad =1 \text{ if } x_i \neq x_j, 0 \text{ o.w.}$$

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Theorem (Fiorini, Massar, Pokutta, Tiwary, de Wolf '12) $xc(COR) \ge 2^{\Omega(n)}.$

▶ Here: Simplified proof by Kaibel and Weltge

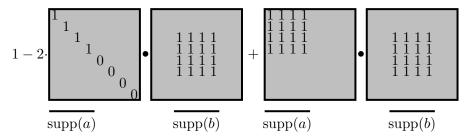
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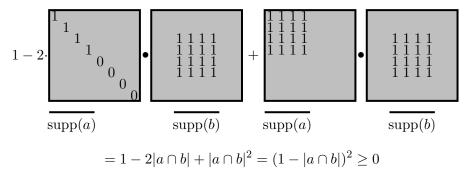
• Suffices to check slack for $Y = bb^T$.

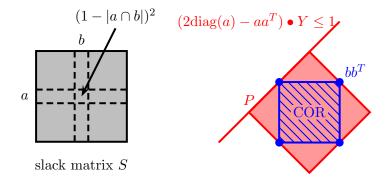


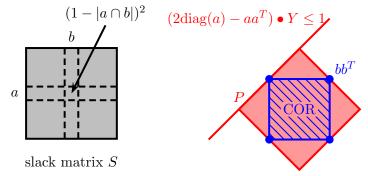
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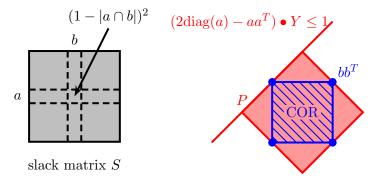






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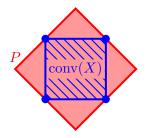
$$S_{ab} = \begin{cases} 1 & |a \cap b| = 0 \\ 0 & |a \cap b| = 1 \end{cases}$$

Incomplete slack matrices

Lemma

For a polytope $P = \{x \mid Ax \leq b\}$ and $X = \{x_1, \ldots, x_v\} \subseteq P$ define a matrix S with $S_{i,j} := b_i - A_i x_j$. Then

 $\operatorname{rk}_{\geq 0}(S) = \min\{\operatorname{xc}(Q) : X \subseteq Q \subseteq \mathbf{P}\}\$

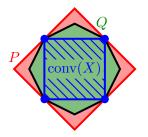


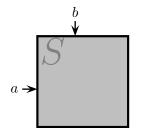
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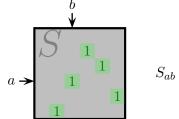
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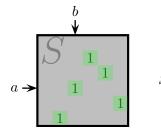


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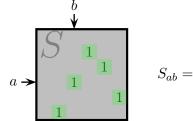
• Define **disjoint pairs** $\mathcal{P}_0 := \{(a, b) : |a \cap b| = 0\}$



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Claim $|\mathcal{P}_0| = 3^n.$



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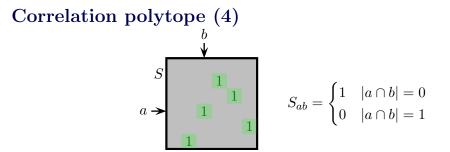
 $\begin{array}{l} \text{Claim} \\ |\mathcal{P}_0| = 3^n. \end{array}$

• For disjoint pair (a, b), for coordinate *i* there are 3 options

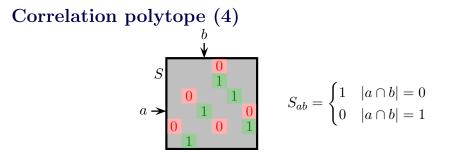
$$\bullet \ a_i = 0, \ b_i = 0$$

▶
$$a_i = 1, b_i = 0$$

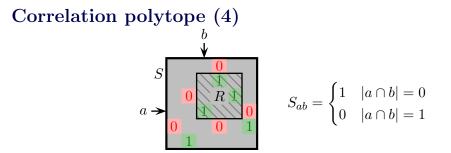
▶
$$a_i = 0, b_i = 1$$



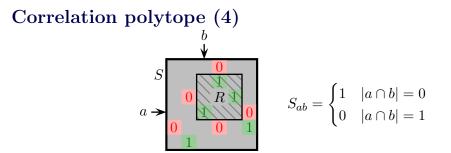
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Lemma

Any rectangle R without forbidden pairs has $|R \cap \mathcal{P}_0| \leq 2^n$.

Correlation polytope (4) S $a \rightarrow 0$ $a \rightarrow 0$ B $a \rightarrow 0$ a

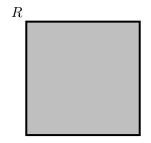
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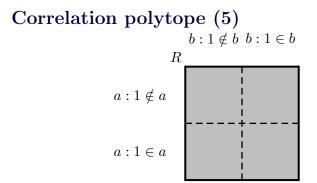
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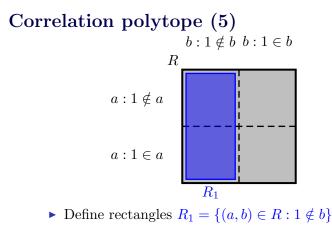
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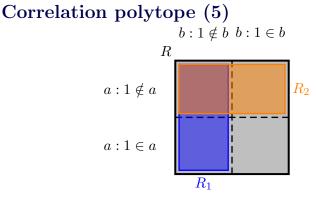
▶ By rectangle covering lower bound

$$\operatorname{xc}(\operatorname{COR}) \ge \frac{|\mathcal{P}_0|}{2^n} = \left(\frac{3}{2}\right)^n$$

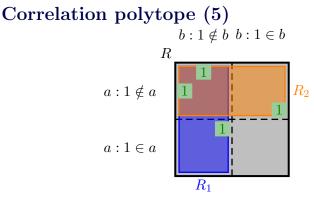








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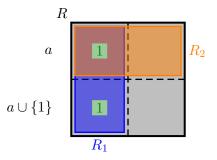
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The end

Thanks for your attention