

# The matching polytope has exponential extension complexity

Thomas Rothvoss

Department of Mathematics, UW Seattle

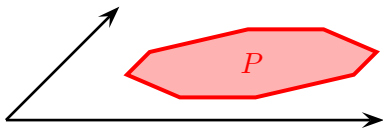


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# Extended formulation

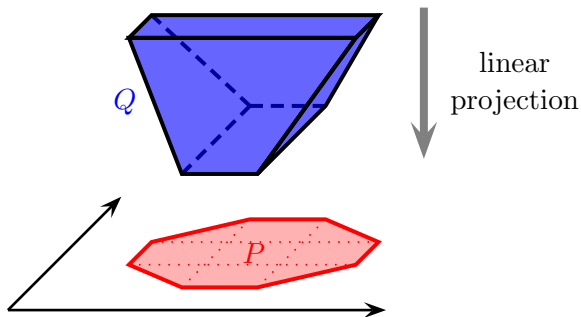
## Extended formulation

- ▶ Given polytope  $P = \{x \in \mathbb{R}^n \mid Ax \leq b\}$



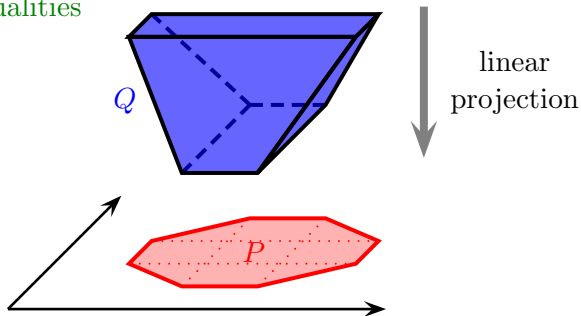
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- ▶ Write  $P = \{x \in \mathbb{R}^n \mid \exists y : Bx + Cy \leq d\}$



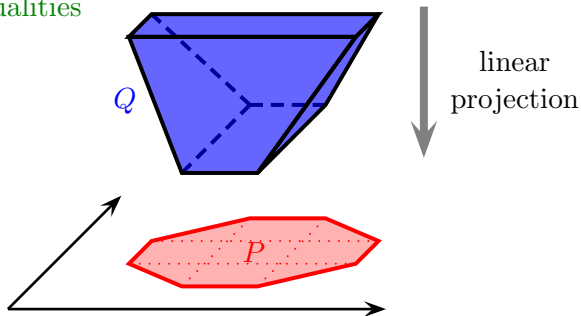
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- ▶ **Extension complexity:**

$$\text{xc}(P) := \min \left\{ \begin{array}{l} \# \text{facets of } Q \mid \\ Q \text{ polyhedron} \\ p \text{ linear map} \\ p(Q) = P \end{array} \right\}$$

# What's known?

## Compact formulations:

- ▶ SPANNING TREE POLYTOPE [Kipp Martin '91]
- ▶ PERFECT MATCHING in planar graphs [Barahona '93]
- ▶ PERFECT MATCHING in bounded genus graphs [Gerards '91]
- ▶  $O(n \log n)$ -size for PERMUTAHEDRON [Goemans '10]  
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**Here:** When is the extension complexity **super polynomial**?



# Lower bounds

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Only **NP**-hard polytopes!!

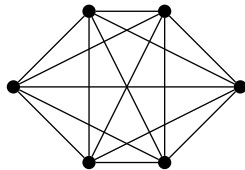
What about poly-time problems?

# Perfect matching polytope



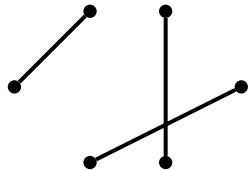
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(complete)



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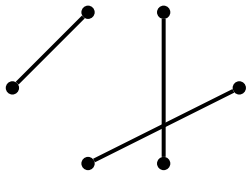


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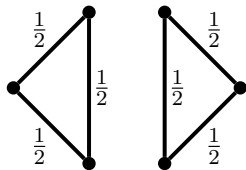


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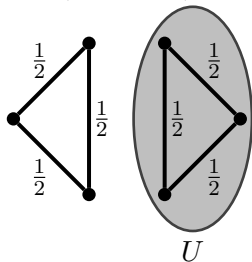


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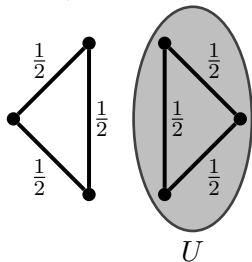
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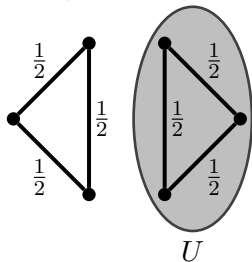
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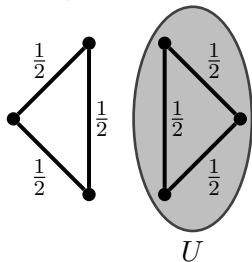
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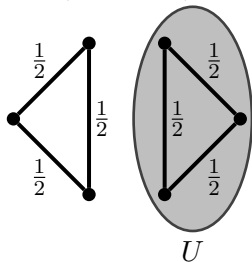
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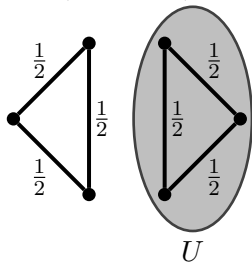
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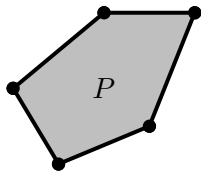
## Theorem (R.13)

$\text{xc}(\text{perfect matching polytope}) \geq 2^{\Omega(n)}$ .

- ▶ Previously known:  $\text{xc}(P) \geq \Omega(n^2)$

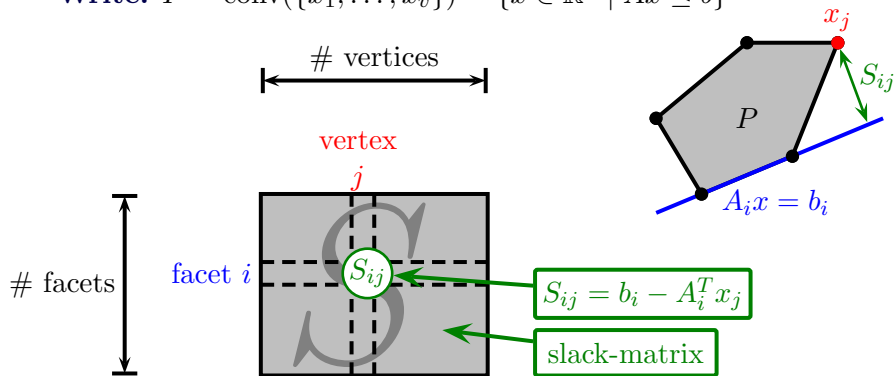
## Slack-matrix

**Write:**  $P = \text{conv}(\{x_1, \dots, x_v\}) = \{x \in \mathbb{R}^n \mid Ax \leq b\}$



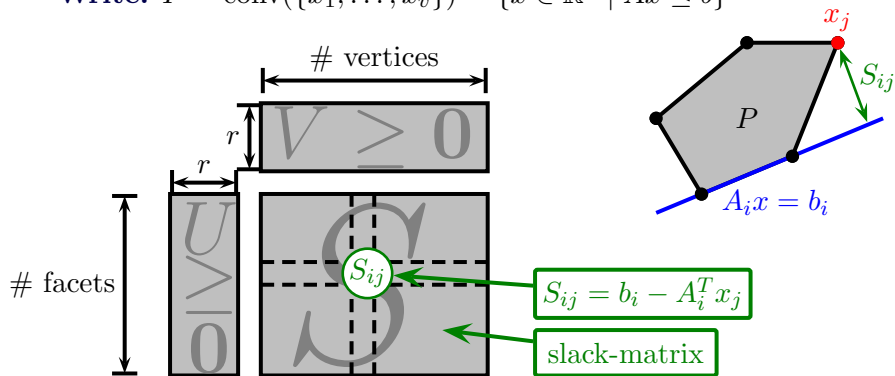
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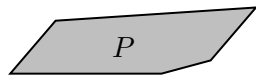
**Non-negative rank:**

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

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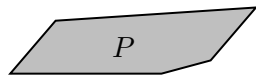
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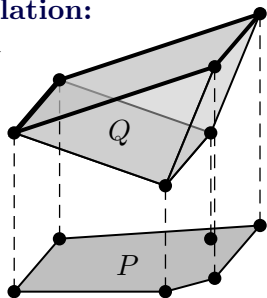
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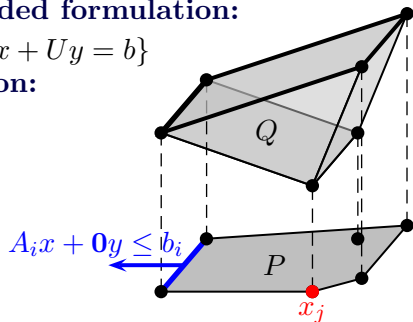
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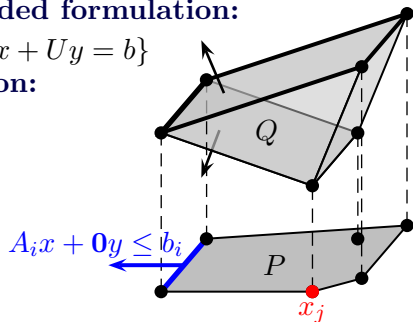
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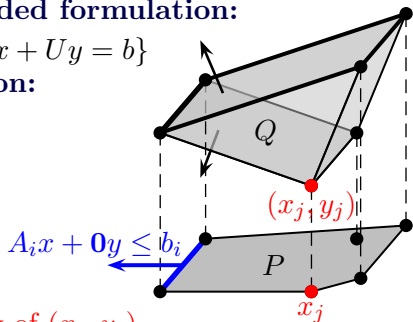
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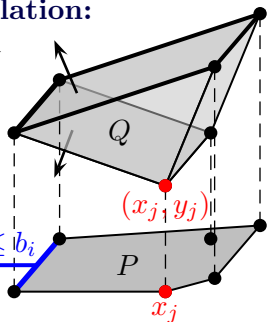
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$$\langle u(i), v(j) \rangle = \underbrace{u(i)^T d}_{=b_i} - \underbrace{u(i)B}_{=A_i} x_j - \underbrace{u(i)C}_{=0} y_j = S_{ij}$$



# Rectangle covering lower bound

Observation

$$\text{rk}_+(S) \geq \text{rectangle-covering-number}(S).$$

## Rectangle covering lower bound

$$\begin{array}{c} V \\ \begin{array}{|c|c|c|c|c|} \hline 0 & 0 & 2 & 1 & 0 \\ \hline 0 & 2 & 2 & 0 & 3 \\ \hline \end{array} \\ \\ \begin{array}{c} U \\ \begin{array}{|c|c|} \hline 3 & 2 \\ \hline 1 & 1 \\ \hline 0 & 2 \\ \hline 0 & 0 \\ \hline 2 & 0 \\ \hline \end{array} \end{array} \begin{array}{|c|c|c|c|c|} \hline 0 & 4 & 10 & 3 & 5 \\ \hline 0 & 2 & 4 & 1 & 3 \\ \hline 0 & 4 & 4 & 0 & 6 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 4 & 2 & 0 \\ \hline \end{array} S \end{array}$$

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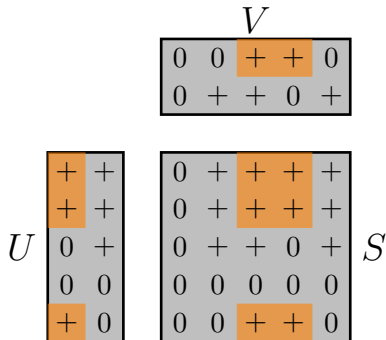
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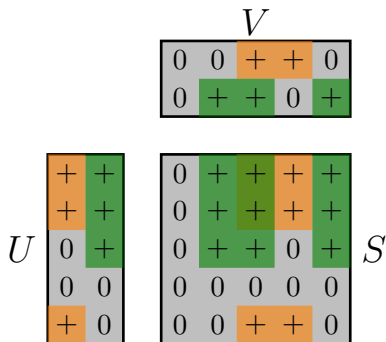


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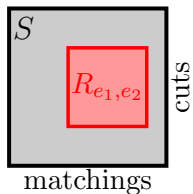
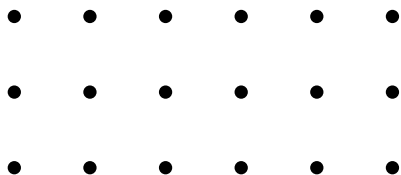
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# Rectangle covering for matching

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Rect-cov-num(matching polytope)  $\leq O(n^4)$ .

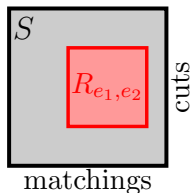
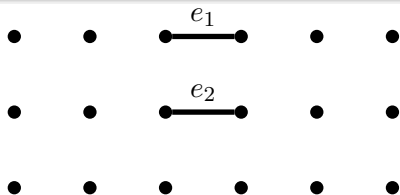


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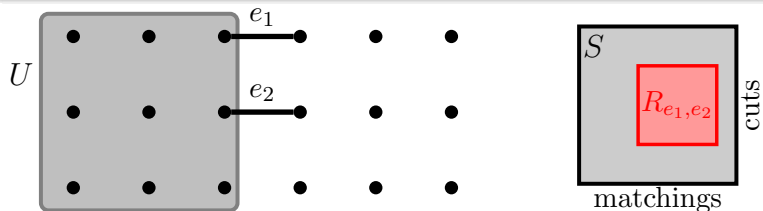
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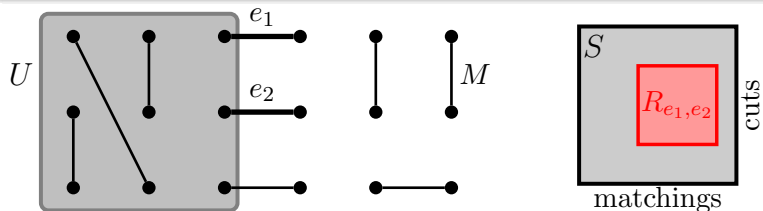
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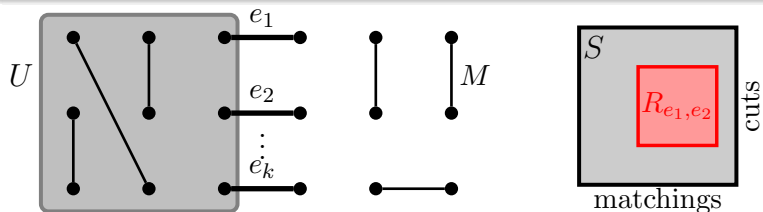
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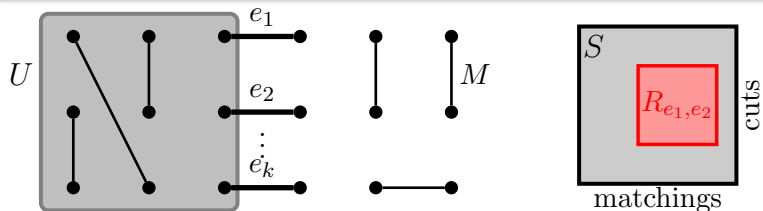
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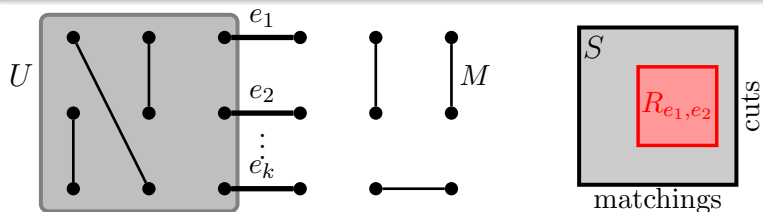
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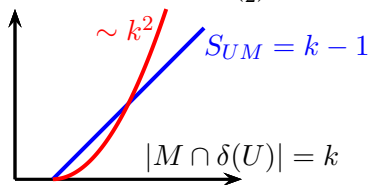
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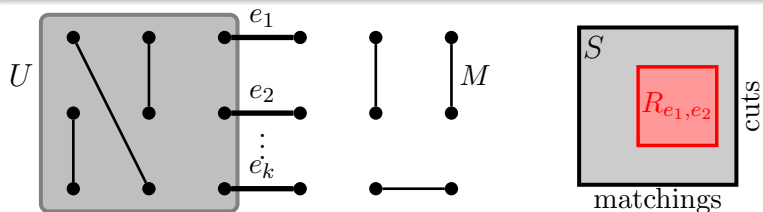


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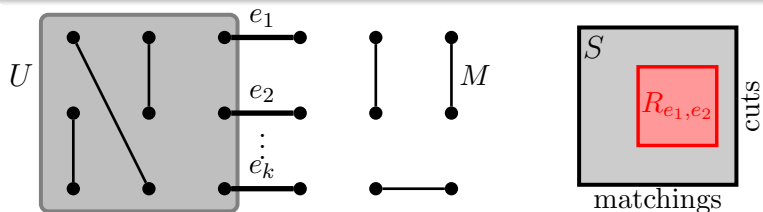
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Does every rectangle covering  
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# Hyperplane separation lower bound [Fiorini]

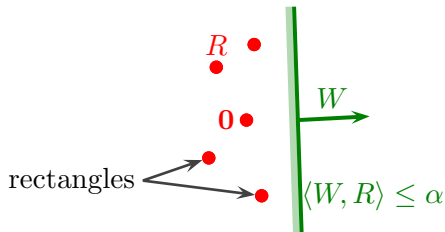
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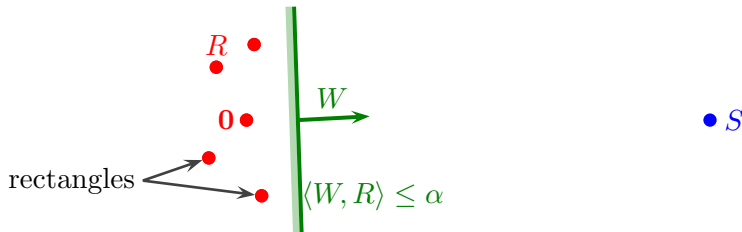


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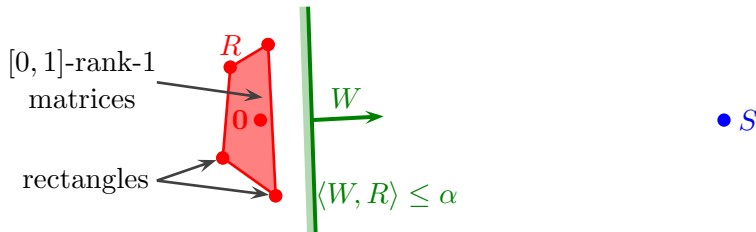
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- **Proof:** Write  $S = \sum_{i=1}^r R_i$  with  $\text{rk}_+(R_i) = 1$ . Then

$$\langle W, S \rangle = \sum_{i=1}^r \|R_i\|_\infty \cdot \underbrace{\left\langle W, \frac{R_i}{\|R_i\|_\infty} \right\rangle}_{\leq \alpha} \leq \alpha \cdot \sum_{i=1}^r \underbrace{\|R_i\|_\infty}_{\leq \|S\|_\infty} \leq \alpha \cdot r \cdot \|S\|_\infty.$$



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## Lemma

For  $k$  large, any rectangle  $R$  has  $\langle W, R \rangle \leq 2^{-\Omega(n)}$ .

## Applying the Hyperplane bound (II)

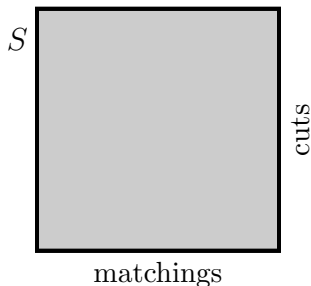
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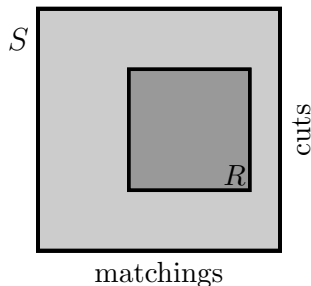


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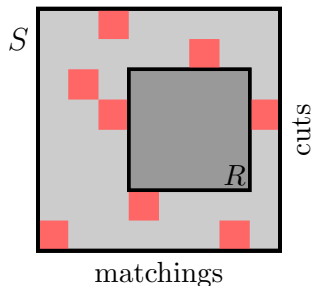


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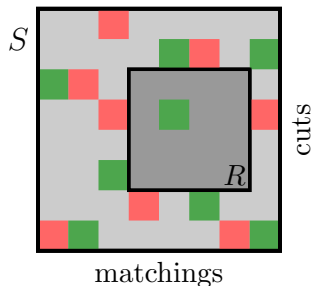


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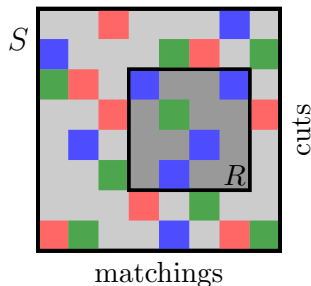


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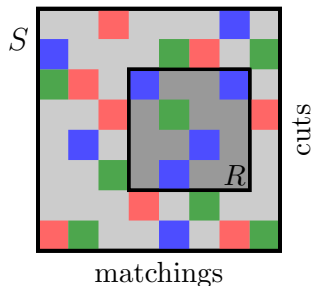


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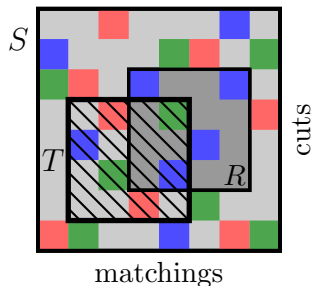
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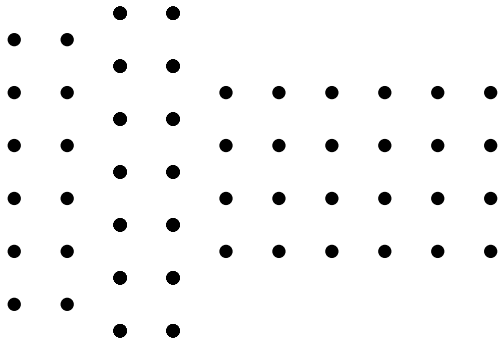
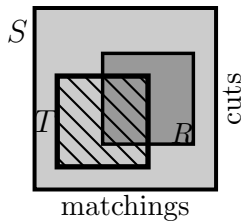
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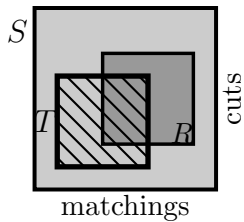
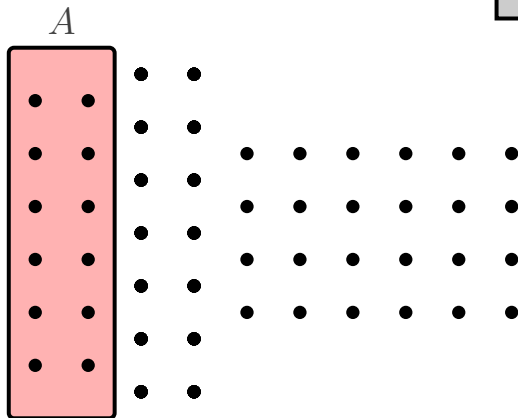
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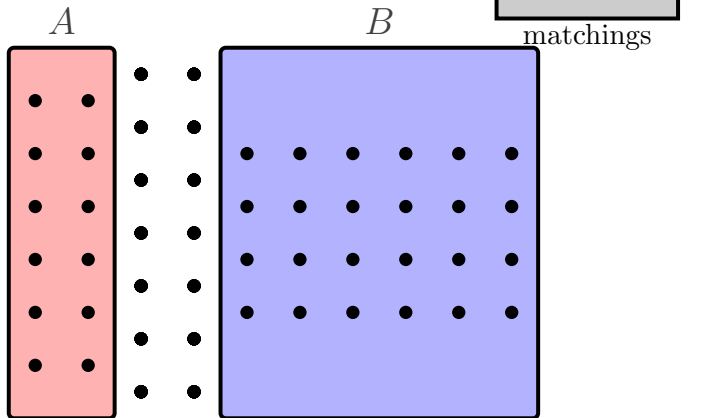
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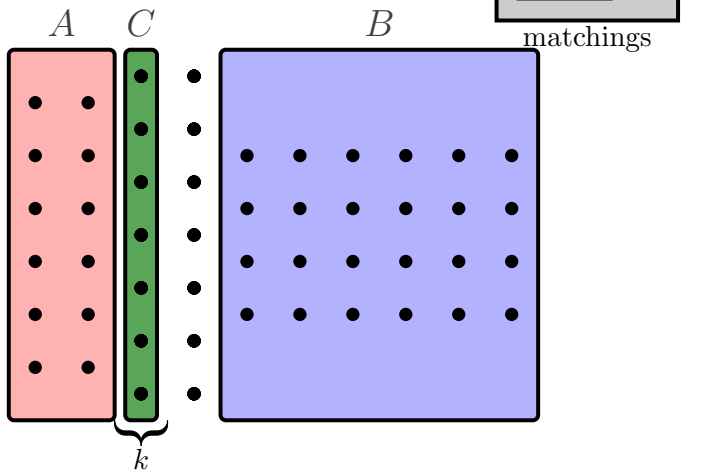
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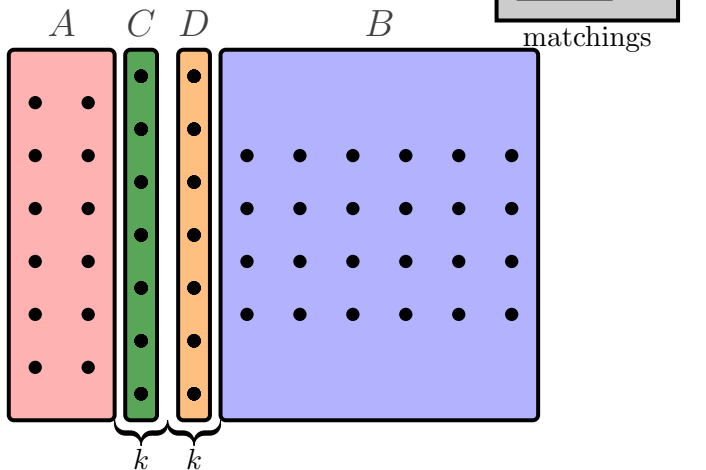
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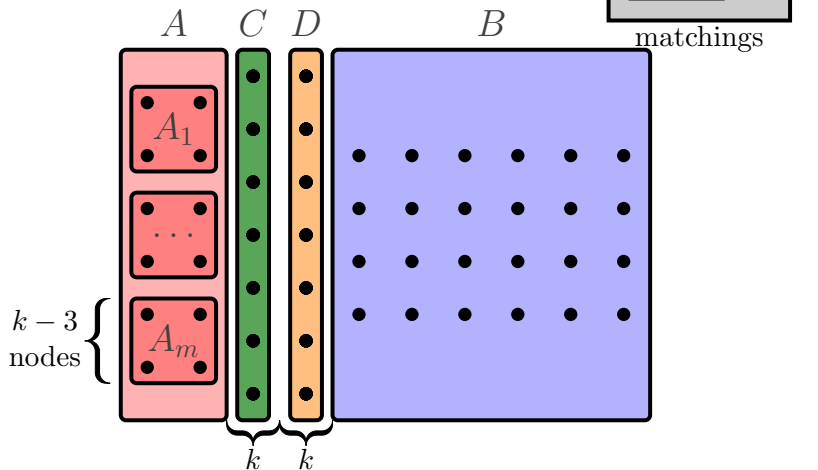
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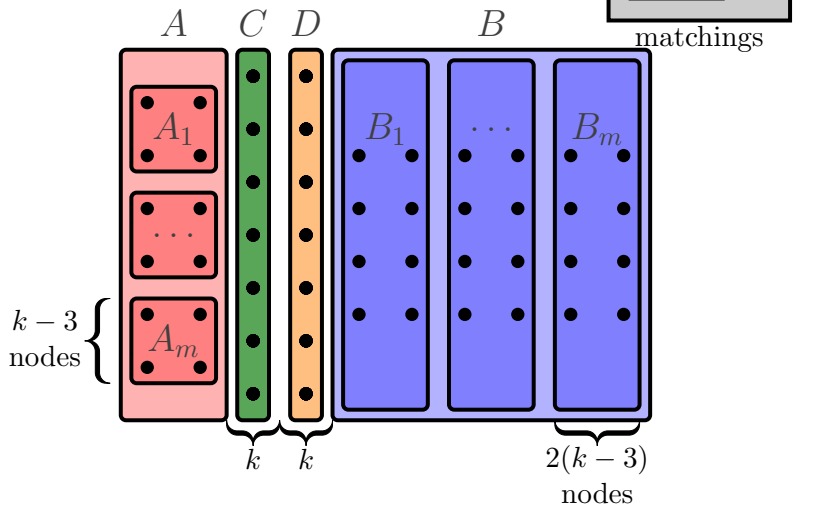
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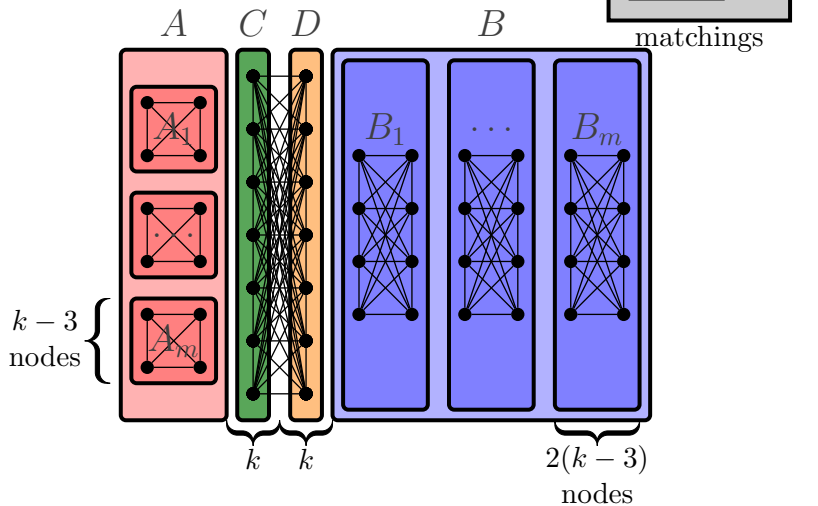
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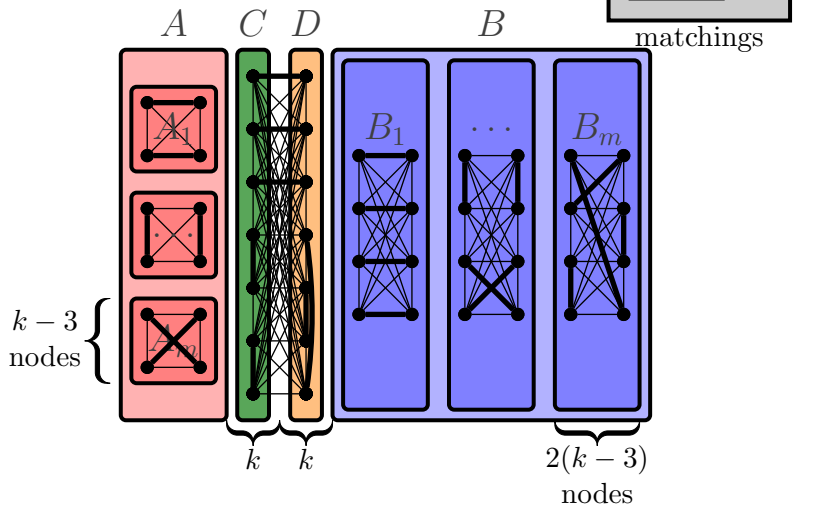
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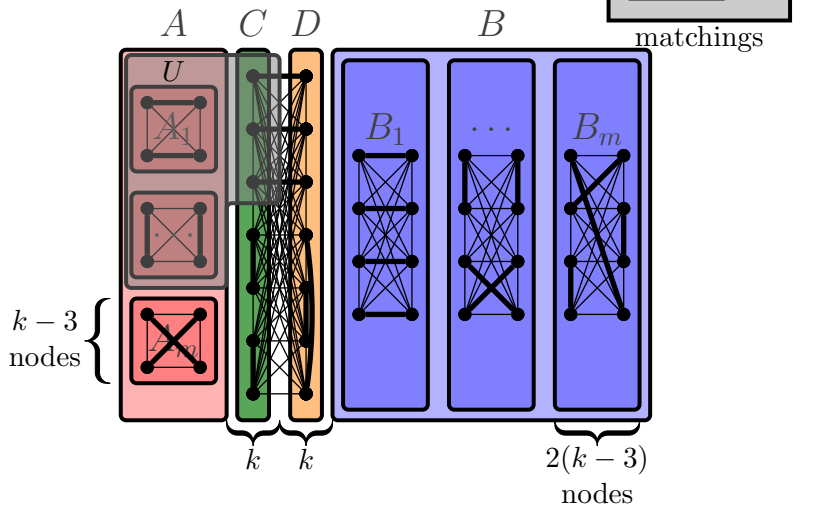
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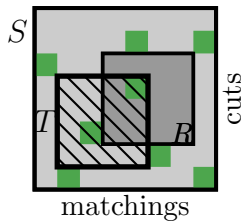
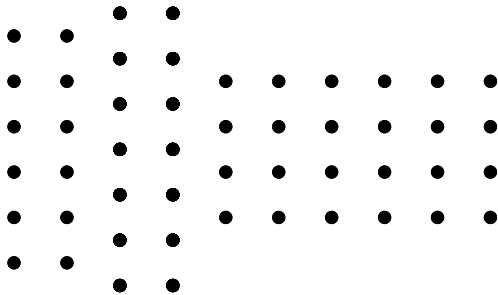
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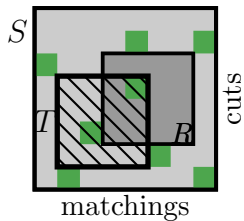
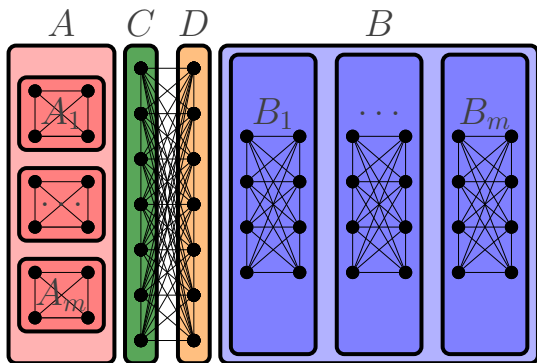
Rewriting  $\mu_3(R)$



Randomly generate  $(U, M) \sim Q_3$ :

$$\mu_3(R) =$$

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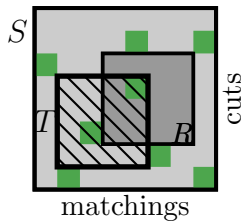
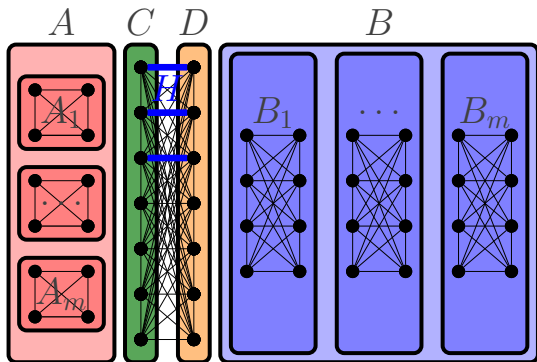


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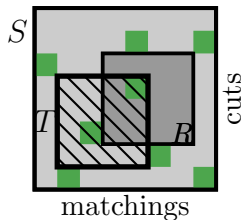
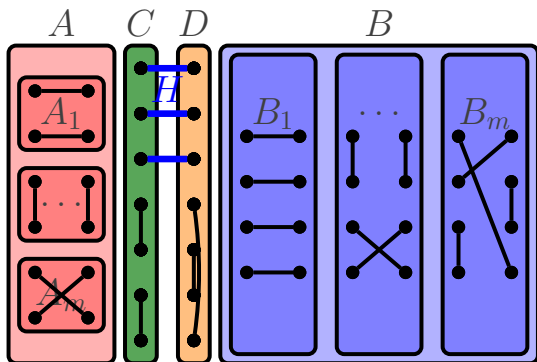


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1. Choose  $T$
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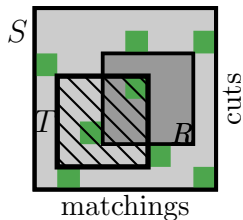
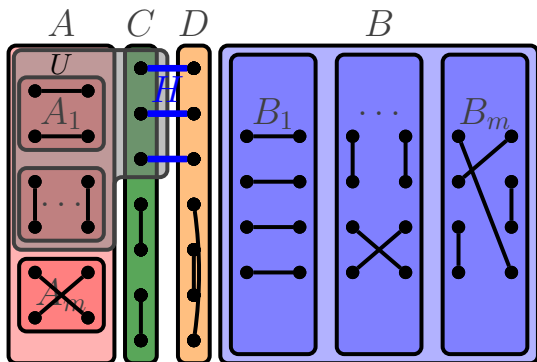


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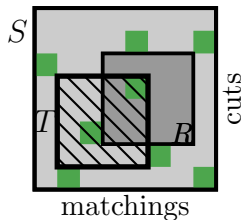
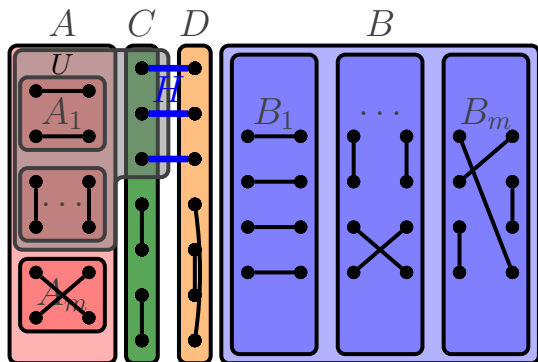


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$$\mu_3(R) = \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ \Pr[(U, M) \in R \mid T, H] \right] \right]$$

# Rewriting $\mu_3(R)$

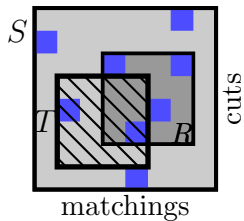
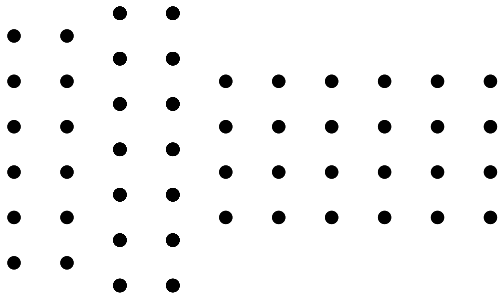


Randomly generate  $(U, M) \sim Q_3$ :

1. Choose  $T$
2. Choose 3 edges  $H \subseteq C \times D$
3. Choose  $M \supseteq H$  (not cutting any other edge in  $C \times D$ )
4. Choose  $U$  cutting  $H$  (not cutting any  $A_i$ )

$$\mu_3(R) = \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ \Pr[U \in R \mid T, H] \cdot \Pr[M \in R \mid T, H] \right] \right]$$

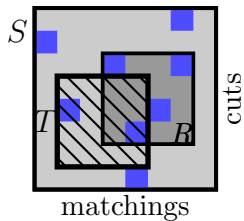
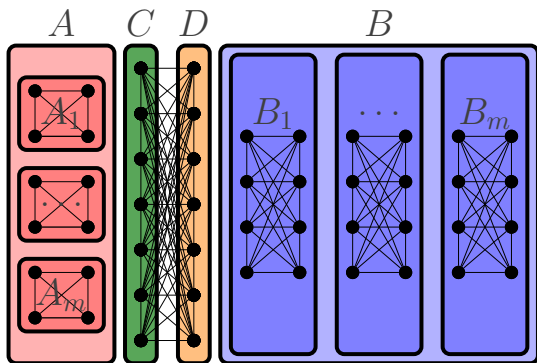
Rewriting  $\mu_k(R)$



Randomly generate  $(U, M) \sim Q_k$ :

$$\mu_k(\mathcal{R}) =$$

# Rewriting $\mu_k(R)$



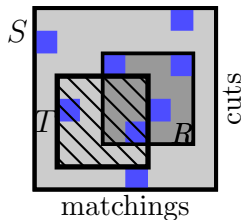
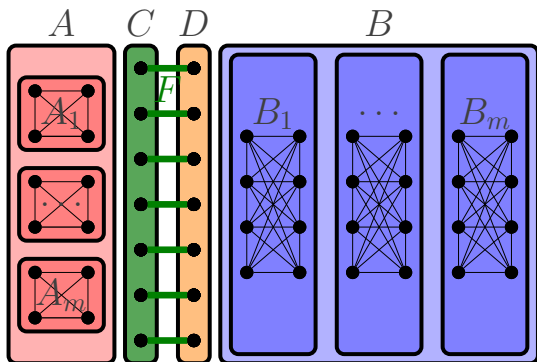
Randomly generate  $(U, M) \sim Q_k$ :

1. Choose  $T$

$$\mu_k(\mathcal{R}) = \mathbb{E}_T \left[ \quad \right]$$



# Rewriting $\mu_k(R)$

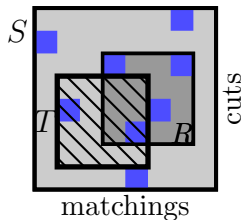
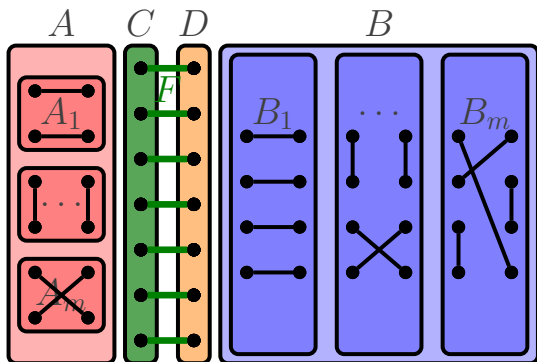


Randomly generate  $(U, M) \sim Q_k$ :

1. Choose  $T$
2. Choose  $k$  edges  $F \subseteq C \times D$

$$\mu_k(\mathcal{R}) = \mathbb{E}_T \left[ \mathbb{E}_{|F|=k} \left[ \right] \right]$$

# Rewriting $\mu_k(\mathcal{R})$

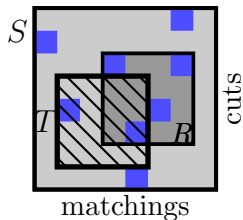
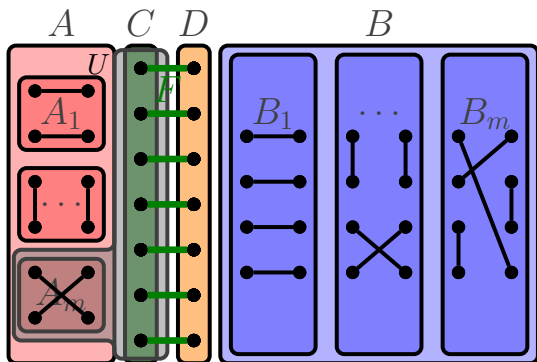


Randomly generate  $(U, M) \sim Q_k$ :

1. Choose  $T$
2. Choose  $k$  edges  $F \subseteq C \times D$
3. Choose  $M \supseteq F$

$$\mu_k(\mathcal{R}) = \mathbb{E}_T \left[ \mathbb{E}_{|F|=k} \left[ \Pr[M \in \mathcal{R} \mid T, H] \right] \right]$$

# Rewriting $\mu_k(R)$



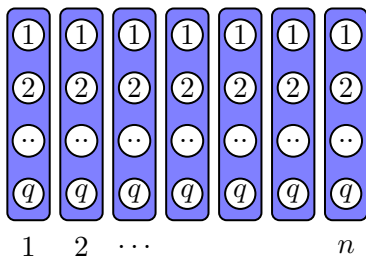
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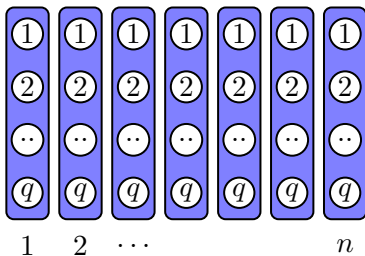
# Pseudorandom-behaviour of large sets

- ▶ Consider vectors  $X \subseteq [q]^n$ .



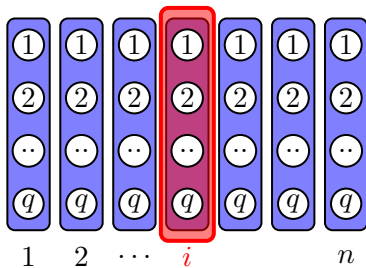
# Pseudorandom-behaviour of large sets

- ▶ Consider vectors  $X \subseteq [q]^n$ .
- ▶ Draw  $x \sim X$ .



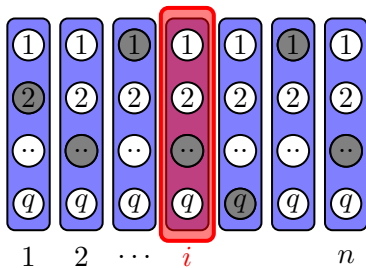
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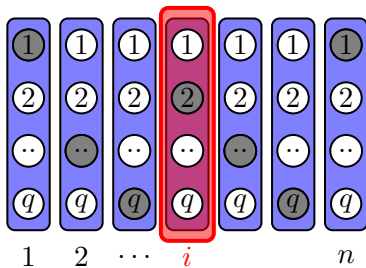
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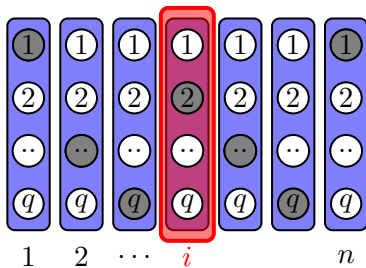


# Pseudorandom-behaviour of large sets

- ▶ Consider vectors  $X \subseteq [q]^n$ .
- ▶ Draw  $x \sim X$ .

Lemma

$|X|$  large  $\Rightarrow$  for most indices  $x_i$  is **approx. uniform**

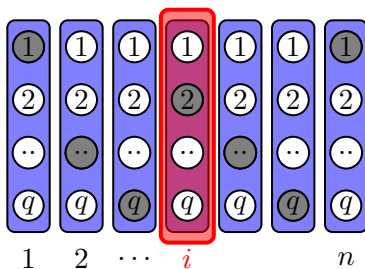


# Pseudorandom-behaviour of large sets

- ▶ Consider vectors  $X \subseteq [q]^n$ .
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## Lemma

$\varepsilon n$  **biased** indices  $\Rightarrow \frac{|X|}{q^n} \leq 2^{-\Omega(n)}$ .



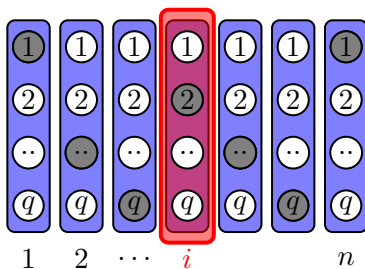
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$$\log_2(|X|) = H(x)$$



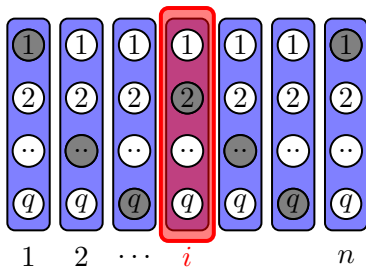
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$$\log_2(|X|) = H(x) \leq \sum_{i=1}^n H(x_i)$$



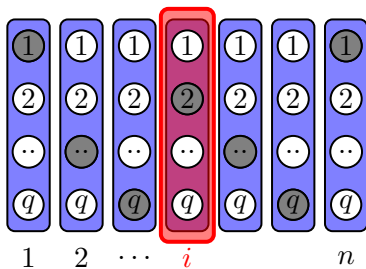
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$$\log_2(|X|) = H(x) \leq \sum_{i \text{ biased}} H(x_i) + \sum_{i \text{ unbiased}} H(x_i)$$



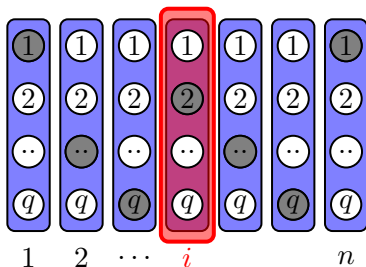
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$$\log_2(|X|) = H(x) \leq \sum_{i \text{ biased}} \underbrace{H(x_i)}_{\leq \log_2(q) - \Theta(1)} + \sum_{i \text{ unbiased}} \underbrace{H(x_i)}_{\leq \log_2(q)}$$



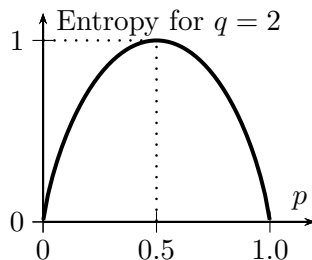
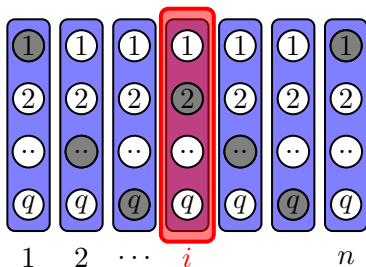
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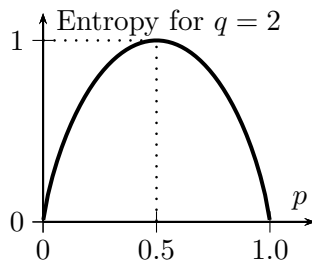
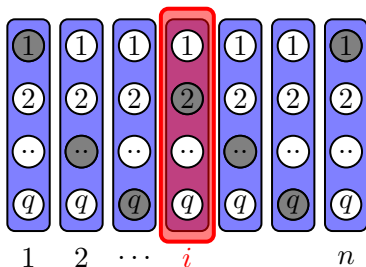
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## Corollary

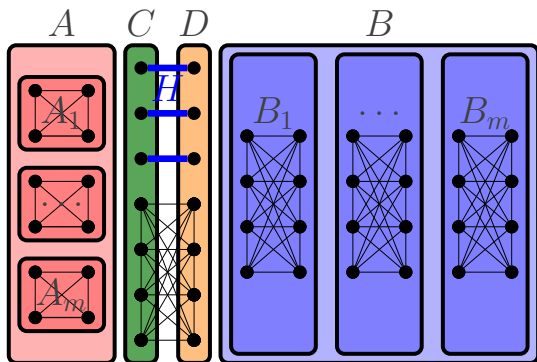
If  $X$  large, then for most  $i$

$$\Pr_{x \sim [q]^n} [x \in X] \approx \Pr_{x \sim [q]^n} [x \in X \mid x_i = j]$$

# $M$ -good

## Definition

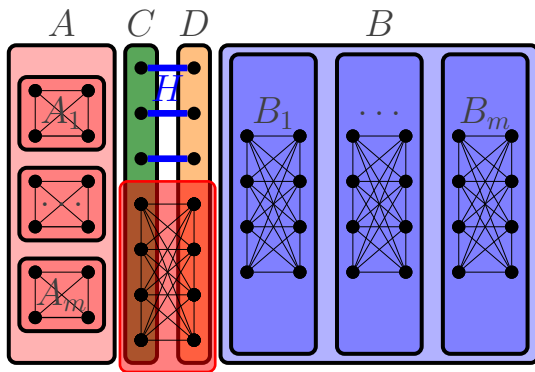
$(T, H)$   $M$ -good if  $M \sim \{M \in R \mid H \subseteq M \subseteq E(T)\}$  is  $\varepsilon$ -uniform on  $(C \cup D) \setminus V(H)$ .



# $M$ -good

## Definition

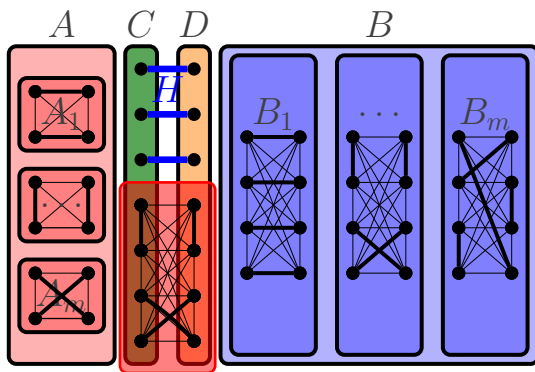
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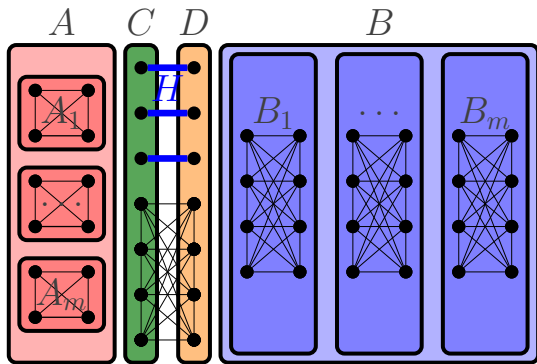
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## Definition

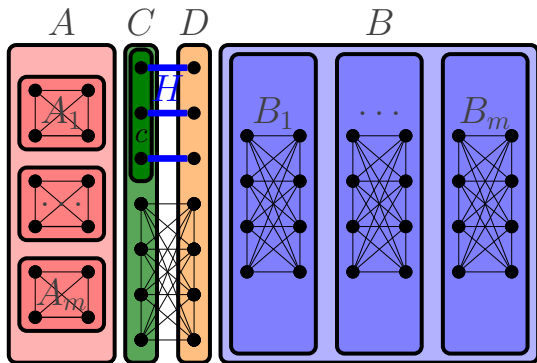
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$U$ -good



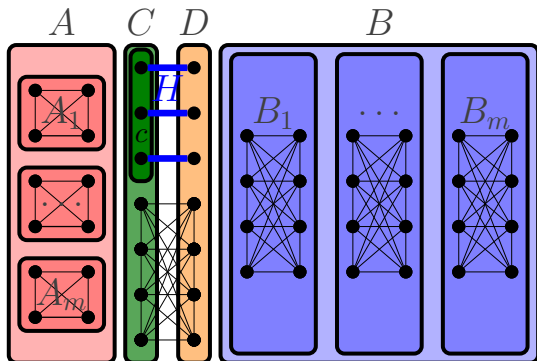
$U$ -good



# $U$ -good

## Definition

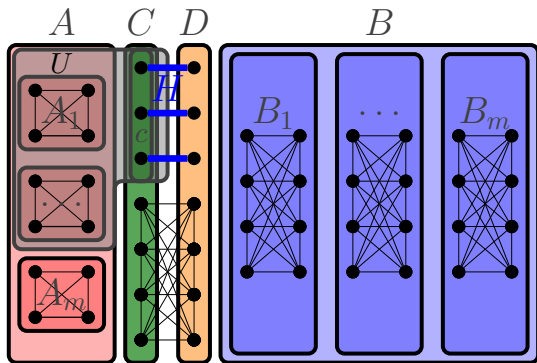
$(T, H)$   $U$ -good if  $U \sim \{U \in R \mid c \subseteq U; \text{doesn't cut any } A_i\}$  has  $\Pr[U \cap C = c] \approx \frac{1}{2} \approx \Pr[U \cap C = C]$ .



# $U$ -good

## Definition

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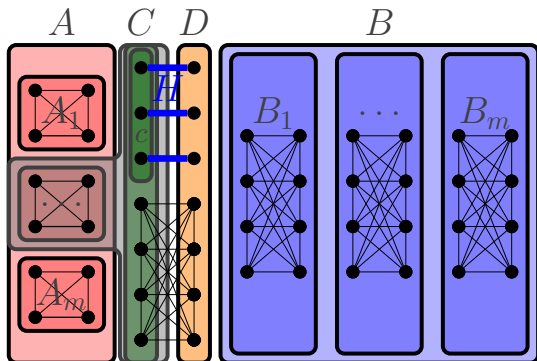




# $U$ -good

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## Splitting $\mu_3(R)$

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$$\mu_3(R) = \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ \Pr[(U, M) \in R \mid T, H] \right] \right]$$

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$$\begin{aligned}\mu_3(R) &= \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ \Pr[(U, M) \in R \mid T, H] \right] \right] \\ &\leq \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ \text{GOOD}(T, H) \cdot \Pr[(U, M) \in R \mid T, H] \right] \right] \\ &\quad + \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ M\text{-BAD}(T, H) \cdot \Pr[(U, M) \in R \mid T, H] \right] \right] \\ &\quad + \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ U\text{-BAD}(T, H) \cdot \Pr[(U, M) \in R \mid T, H] \right] \right]\end{aligned}$$

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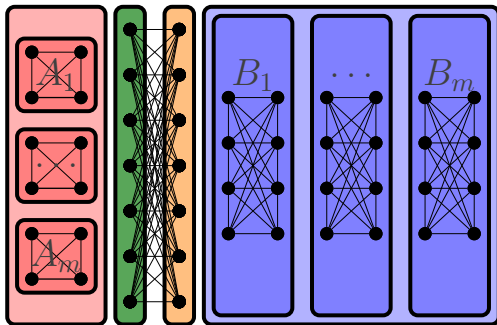
$$\begin{aligned}
 \mu_3(R) &= \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ \Pr[(U, M) \in R \mid T, H] \right] \right] \\
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 &\quad + \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ \leq \varepsilon \cdot \mu_3(R) \Pr[(U, M) \in R \mid T, H] \right] \right] \\
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 \end{aligned}$$

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 &\quad + \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ \leq \varepsilon \cdot \mu_3(R) + 2^{-\Omega(n)} \Pr[(U, M) \in R \mid T, H] \right] \right] \\
 &\quad + \mathbb{E}_T \left[ \mathbb{E}_{|H|=3} \left[ \leq \varepsilon \cdot \mu_3(R) + 2^{-\Omega(n)} \Pr[(U, M) \in R \mid T, H] \right] \right]
 \end{aligned}$$

# Contribution of good partitions

For  $T$

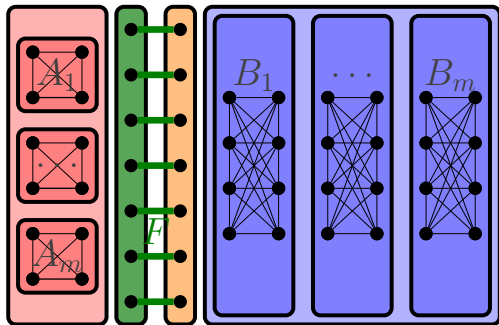




# Contribution of good partitions

For  $T$  and  $F \subseteq C \times D$  with  $|F| = k$  compare:

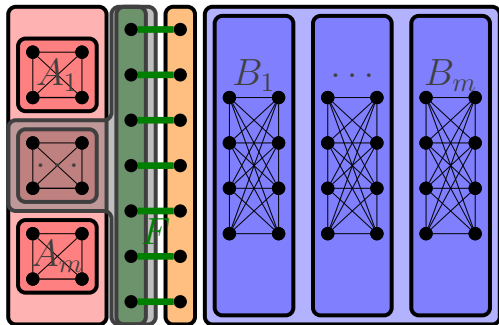
- ▶ Contribution to  $\mu_k(R)$ :



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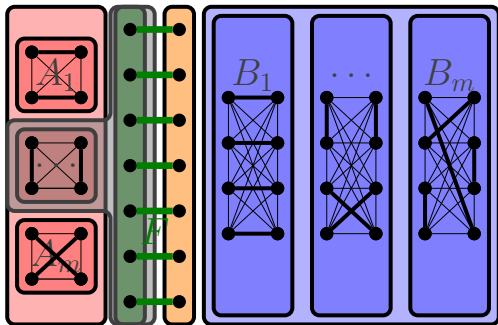
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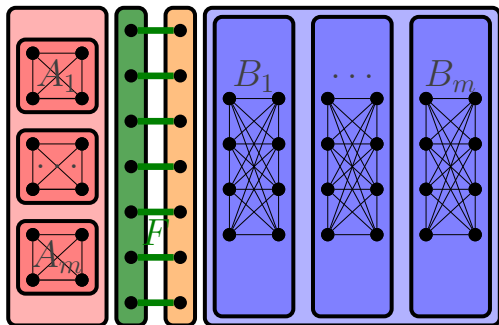
- ▶ Contribution to  $\mu_k(R)$ :  $\Pr[(U, M) \in R \mid T, F]$



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For  $T$  and  $F \subseteq C \times D$  with  $|F| = k$  compare:

- ▶ Contribution to  $\mu_k(R)$ :  $\Pr[(U, M) \in R \mid T, F]$
- ▶ Contribution to  $\mu_3(R)$ :



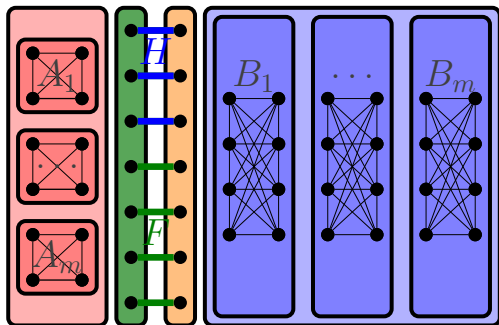
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$$\mathbb{E}_{H \sim \binom{F}{3}} [\text{GOOD}(T, H) \cdot \Pr[(U, M) \in R \mid T, H]]$$

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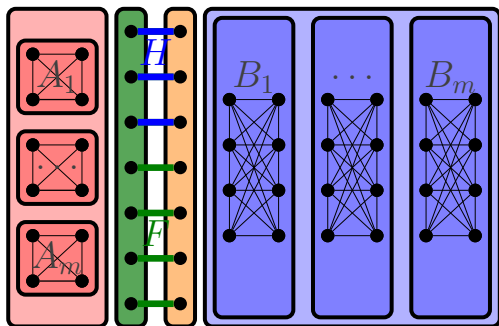
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$$\mathbb{E}_{H \sim \binom{F}{3}} [\text{GOOD}(T, H) \cdot \Pr[(U, M) \in R \mid T, H]] \lesssim \Pr[\dots \mid T, F] \cdot \Pr_{H \sim \binom{F}{3}} [\text{GOOD}(T, H)]$$

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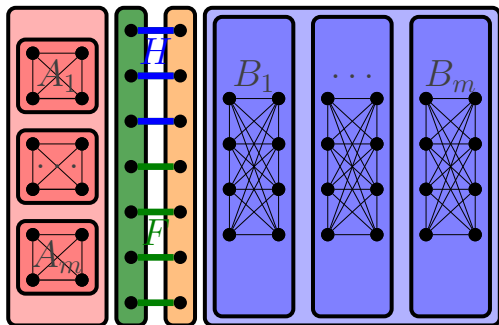
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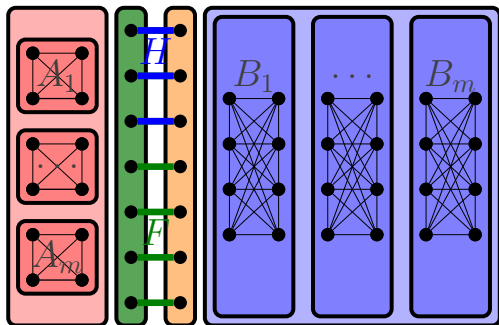
# Contribution of good partitions

For  $T$  and  $F \subseteq C \times D$  with  $|F| = k$  compare:

- ▶ Contribution to  $\mu_k(R)$ :  $\Pr[(U, M) \in R \mid T, F]$
- ▶ Contribution to  $\mu_3(R)$ :

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- ▶ Suffices to show:  $H, H^* \subseteq F$  good  $\Rightarrow |H \cap H^*| \geq 2$





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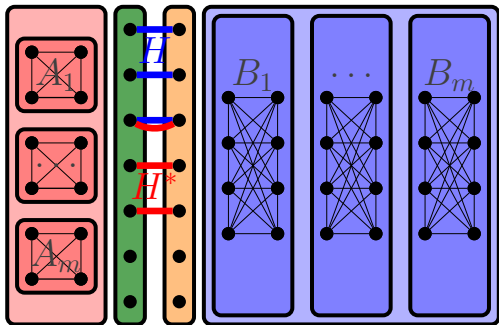
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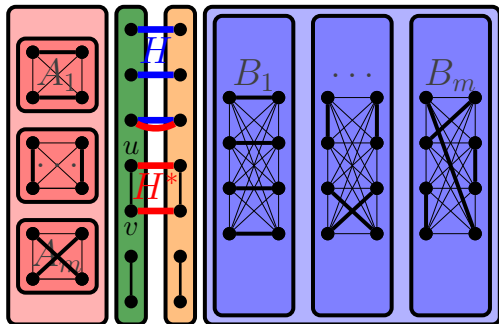
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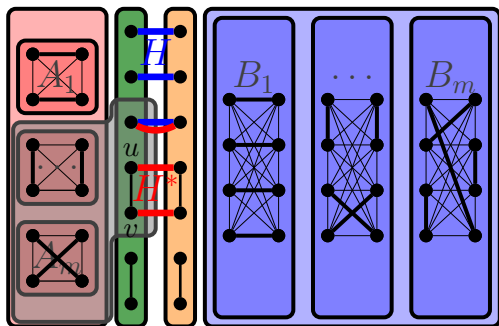
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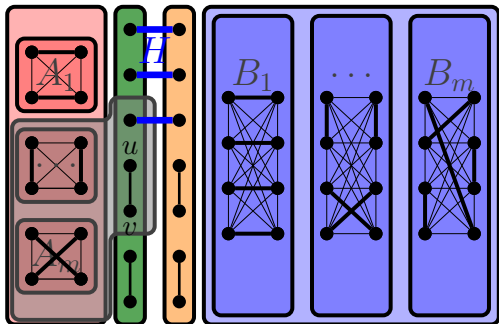
- ▶ Suppose  $|H \cap H^*| \leq 1$

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- ▶  $|\delta(U) \cap M| = 1$

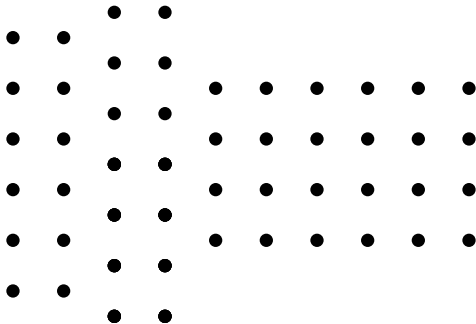
**Contradiction!**



# Most partitions are good

Lemma

$$\Pr[(T, H) \text{ is } M\text{-bad}] \leq \varepsilon$$

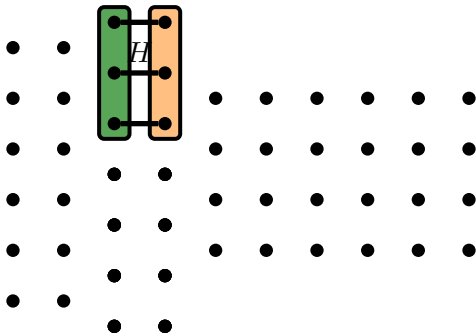


# Most partitions are good

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- ▶ Pick  $H$

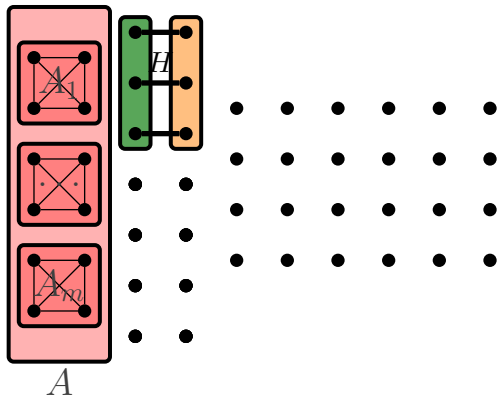


# Most partitions are good

## Lemma

$$\Pr[(T, H) \text{ is } M\text{-bad}] \leq \varepsilon$$

- ▶ Pick  $H, A$

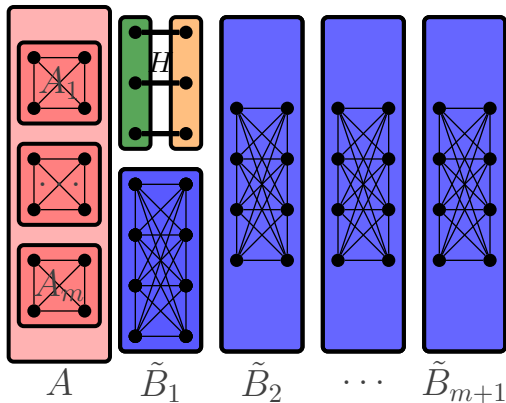


# Most partitions are good

## Lemma

$\Pr[(T, H) \text{ is } M\text{-bad}] \leq \varepsilon$

- Pick  $H, A, \tilde{B}_1, \dots, \tilde{B}_{m+1}$ .



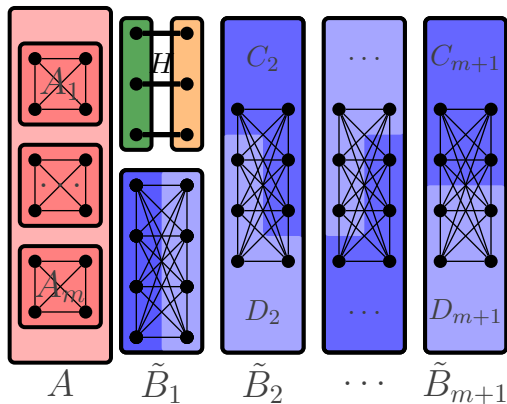


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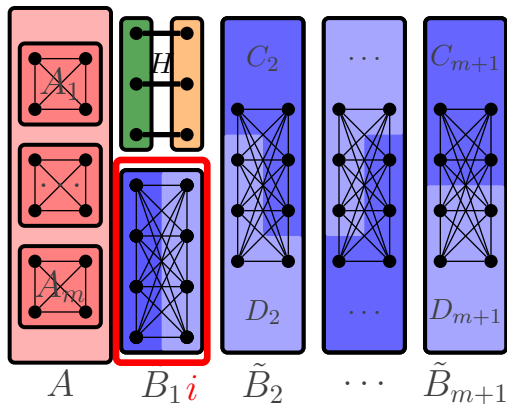


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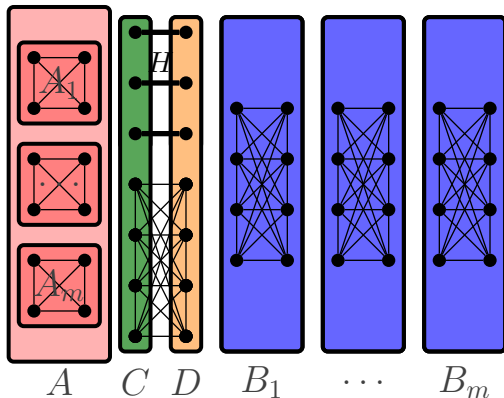


# Most partitions are good

## Lemma

$\Pr[(T, H) \text{ is } M\text{-bad}] \leq \varepsilon$

- ▶ Pick  $H, A, \tilde{B}_1, \dots, \tilde{B}_{m+1}$ . Split  $\tilde{B}_i = C_i \dot{\cup} D_i$ .
- ▶ Pick randomly  $i \in \{1, \dots, m\}$  and let  $C := C_i, D := D_i$



# Open problems

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Show that there is no small **SDP** representing the Correlation/TSP/matching polytope!

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Thanks for your attention