

Iterative Randomized Rounding

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Cargèse 2011

Joint work with Jarosław Byrka,
Fabrizio Grandoni and Laura Sanità



**Massachusetts
Institute of
Technology**

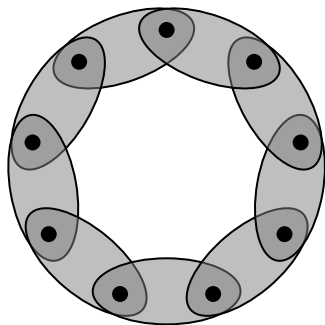


Alexander von Humboldt
Stiftung/Foundation

What is Iterative Randomized Rounding?

Set Cover:

- ▶ Input: Sets S_1, \dots, S_m over elements $1, \dots, n$; cost $c(S_i)$
- ▶ Goal: $\min_{I \subseteq [m]} \{ \sum_{i \in I} c_i \mid \bigcup_{i \in I} S_i = [n] \}$



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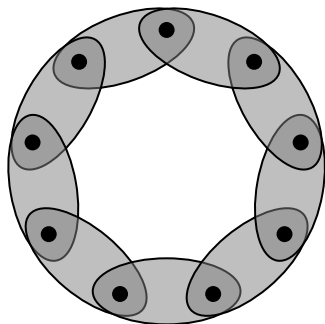
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Standard LP:

$$\min \sum_{i=1}^m c(S_i) \cdot x_i$$

$$\sum_{i:j \in S_i} x_i \geq 1 \quad \forall j \in [n]$$

$$x_i \geq 0 \quad \forall i \in [m]$$



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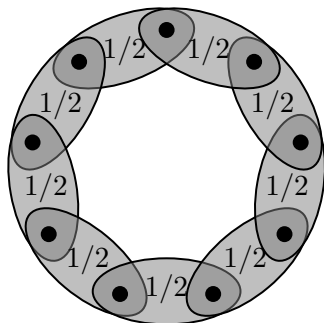
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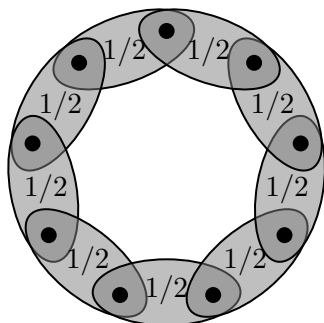
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Known:

- ▶ Integrality gap is $\Theta(\ln n)$

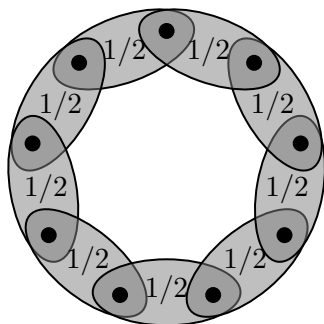
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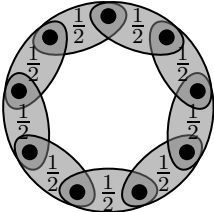
- ▶ Integrality gap is $\Theta(\ln n)$
- ▶ Suppose $|S_i| \leq k$. Then gap is $\Theta(\ln k)$.

Iterative randomized rounding algorithm:

- (1) FOR $t = 1$ TO ∞
- (2) Solve LP $\rightarrow x$
- (3) FOR ALL i : Buy S_i with prob. x_i (remove covered el.)
- (4) IF no element left THEN RETURN all bought sets

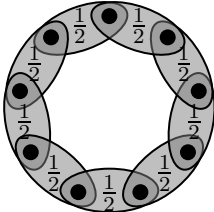
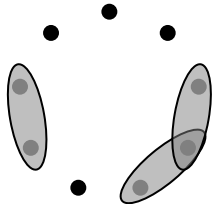
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bought sets		

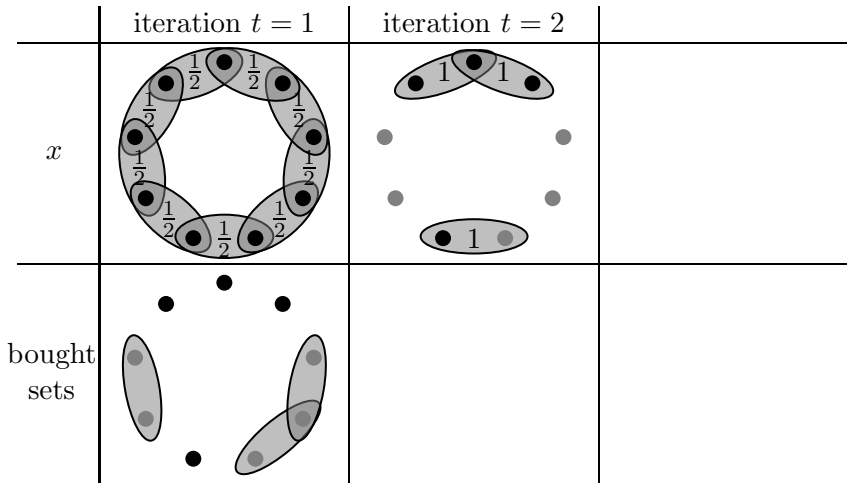
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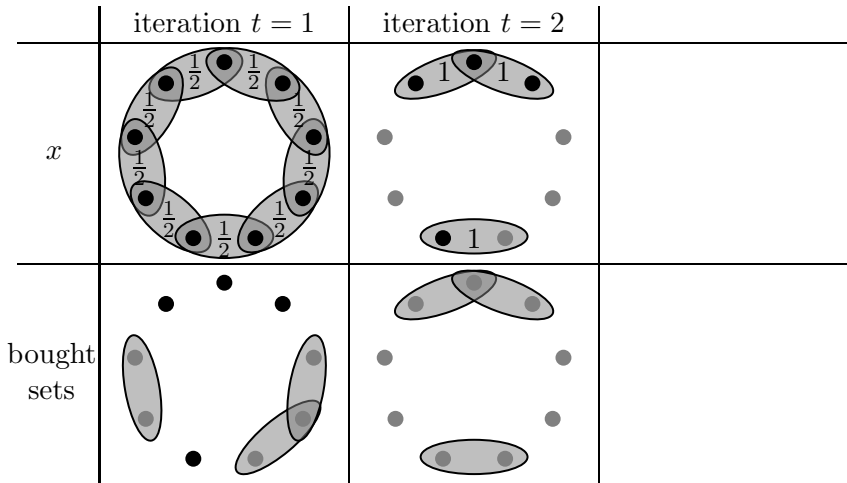
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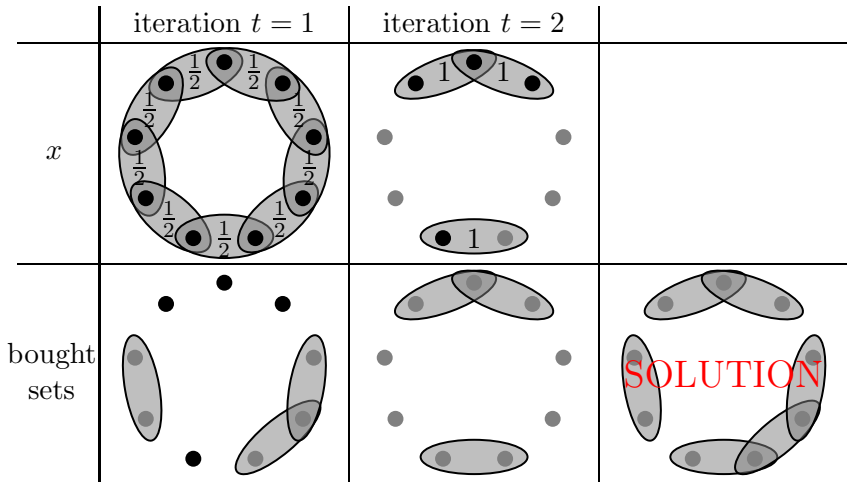
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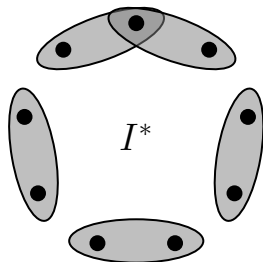
Analysis

$$E[APX] = \sum_{t \geq 1} E[OPT_f \text{ in step } t]$$

Analysis

- ▶ Let I^* be optimal SET COVER solution.

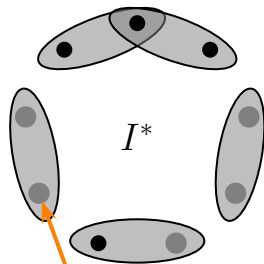
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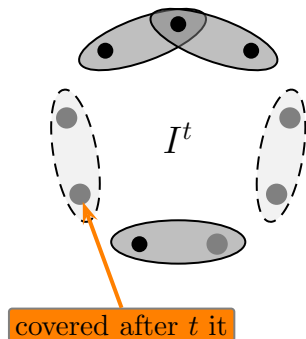


covered after t it

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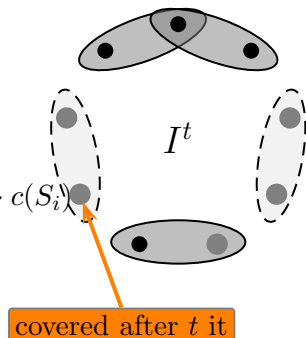
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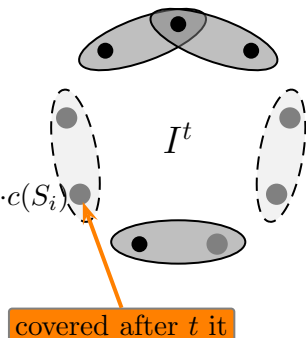
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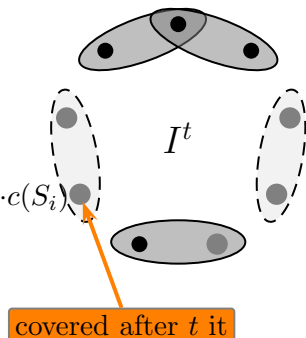
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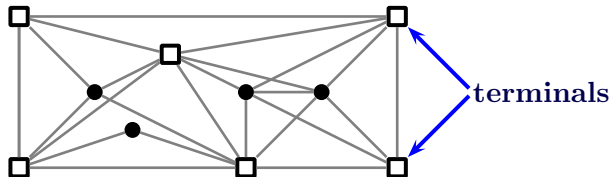
Steiner Tree

Given:

- ▶ undirected graph $G = (V, E)$
- ▶ cost $c : E \rightarrow \mathbb{Q}_+$
- ▶ terminals $R \subseteq V$

Find: Min-cost Steiner tree, spanning R .

$$OPT := \min\{c(S) \mid S \text{ spans } R\}$$



W.l.o.g.: c is metric.

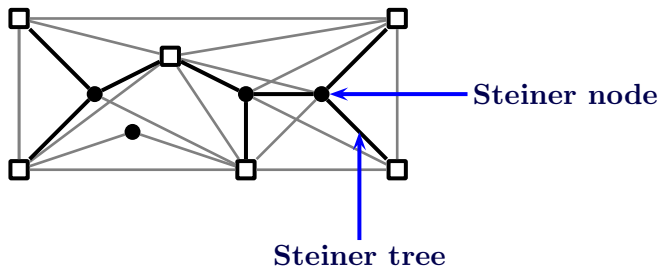
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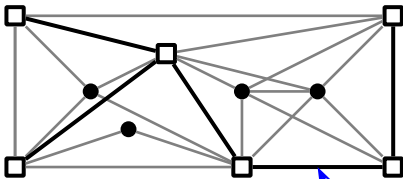
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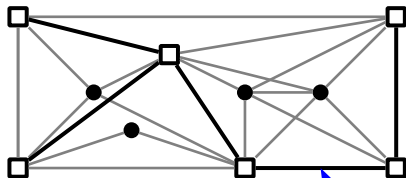
Spanning tree



terminal spanning tree

Min-cost terminal spanning tree (MST):

Spanning tree

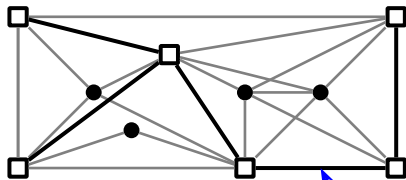


terminal spanning tree

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Spanning tree



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- ▶ Can be computed in poly-time.
- ▶ Costs $\leq 2 \cdot OPT$.

Known results for Steiner tree:

Approximations:

- ▶ 2-apx (*minimum spanning tree heuristic*)
- ▶ 1.83-apx [Zelikovsky '93]
- ▶ 1.667-apx [Prömel & Steger '97]
- ▶ 1.644-apx [Karpinski & Zelikovsky '97]
- ▶ 1.598-apx [Hougardy & Prömel '99]
- ▶ 1.55-apx [Robins & Zelikovsky '00]

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Hardness:

- ▶ **NP**-hard even if edge costs $\in \{1, 2\}$ [Bern & Plassmann '89]
- ▶ no $< \frac{96}{95}$ -apx unless **NP** = **P** [Chlebik & Chlebikova '02]

Our results:

Theorem

There is a polynomial time 1.39-approximation.

- ▶ LP-based! (*Directed-Component Cut Relaxation*)
- ▶ Algorithmic framework: *Iterative Randomized Rounding*

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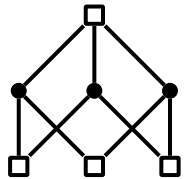
- ▶ LP-based! (*Directed-Component Cut Relaxation*)
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Theorem

The Directed-Component Cut Relaxation has an integrality gap of at most 1.55.

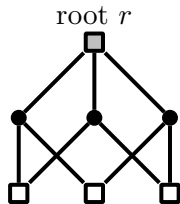
- ▶ First < 2 bound for *any* LP-relaxation.

Bi-directed cut relaxation



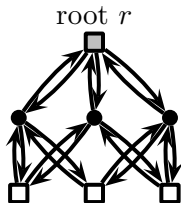
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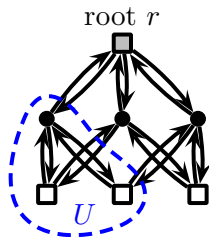
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$$\min \sum_{e \in E} c(e) z_e \quad (\text{BCR})$$

$$\sum_{e \in \delta^+(U)} z_e \geq 1 \quad \forall U \subseteq V \setminus \{r\} : U \cap R \neq \emptyset$$

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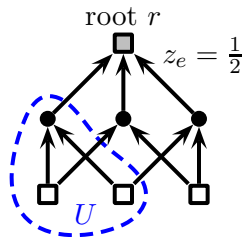
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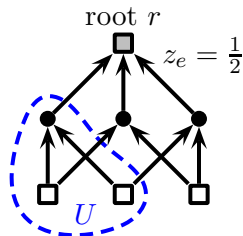
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Theorem (Edmonds '67)

$R = V \Rightarrow \text{BCR integral}$

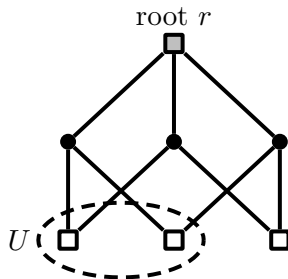
- ▶ Integrality gap $\leq 4/3$ for quasi-bipartite graphs
[Chakrabarty, Devanur, Vazirani '08]
- ▶ Integrality gap $\in [1.16, 2]$

Directed component cut relaxation

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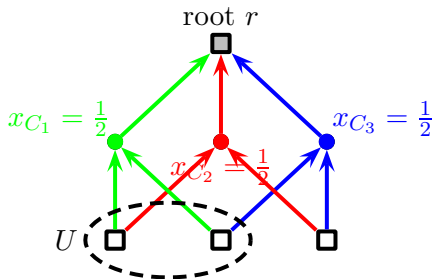


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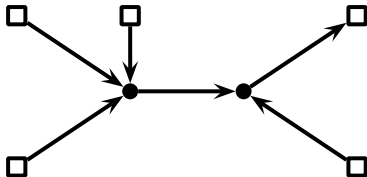
Properties:

- ▶ Number of variables: **exponential**
- ▶ Number of constraints: **exponential**
- ▶ **Approximable within $1 + \varepsilon$** (we ignore the ε here).

Solvability of the LP

Lemma

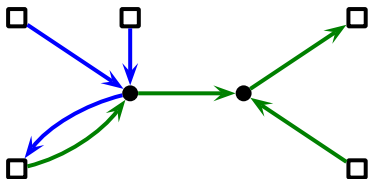
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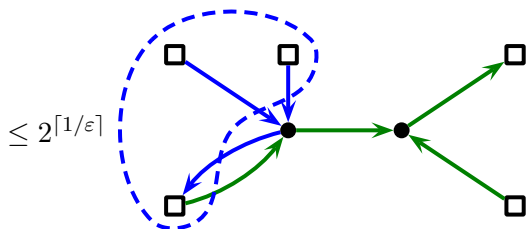


- ▶ Use only components of size $2^{\lceil 1/\varepsilon \rceil} = O(1)$
[Borchers & Du '97]: Increases cost by $\leq 1 + \varepsilon$
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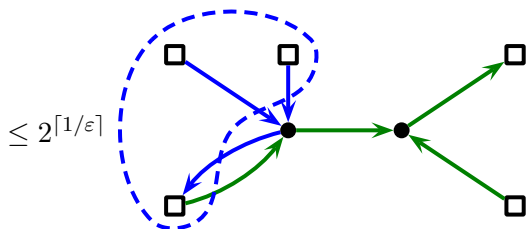


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→ # variables **polynomial**
- ▶ Compact flow formulation → # constraints **polynomial**
(or solve with ellipsoid method).



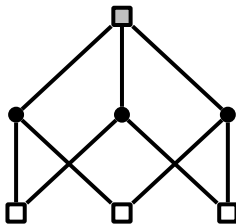
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- (1) FOR $t = 1, \dots, \infty$ DO
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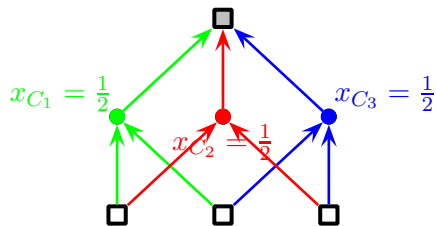
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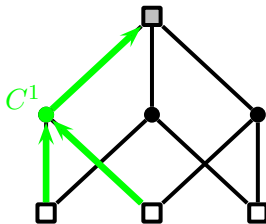
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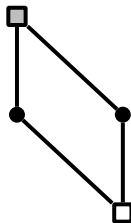
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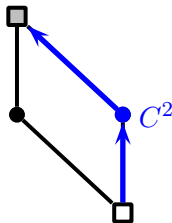
An iterative randomized rounding algo

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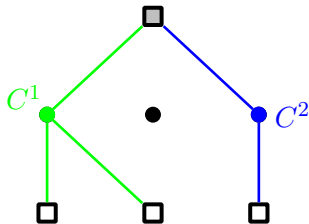
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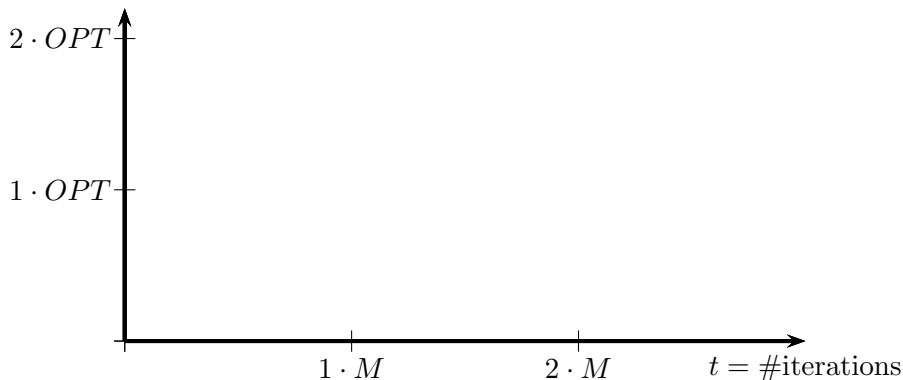
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- W.l.o.g. $M := \mathbf{1}^T x$ invariant

Roadmap

- ▶ In one iteration t :

$$E[c(\text{comp. sampled in it. } t)] = \sum_C \frac{x_C}{M} \cdot c(C) \leq \frac{1}{M} \cdot OPT \text{ in it } t$$



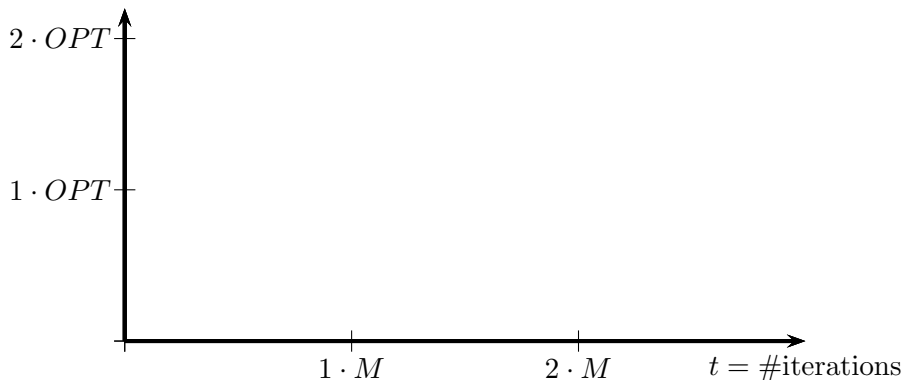
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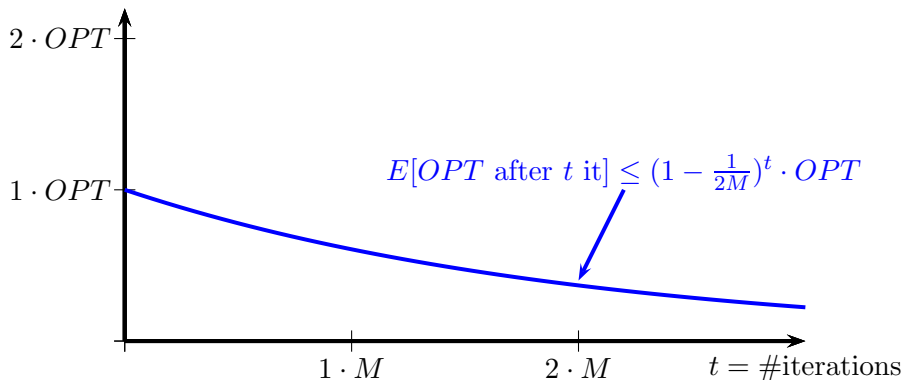
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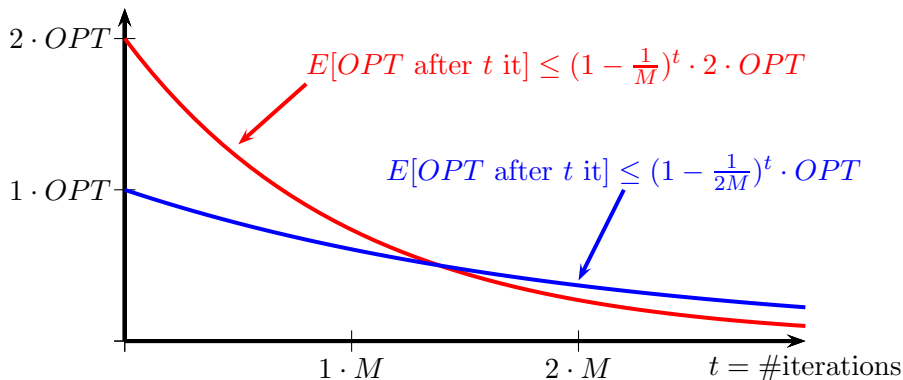
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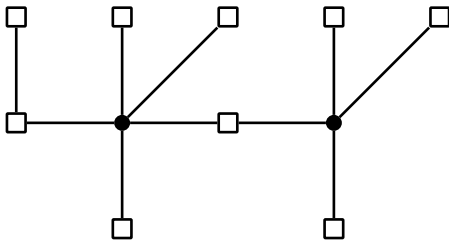
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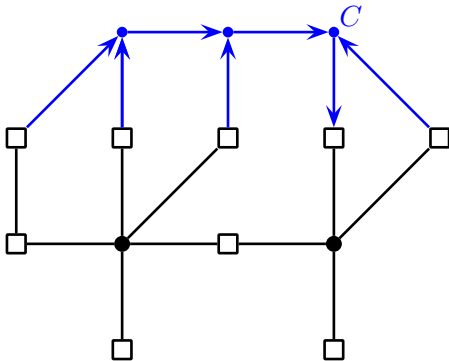
Bridges

- ▶ Let S be Steiner tree



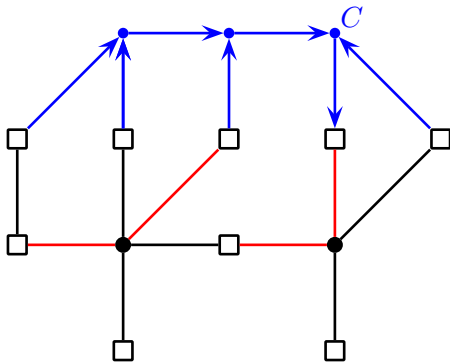
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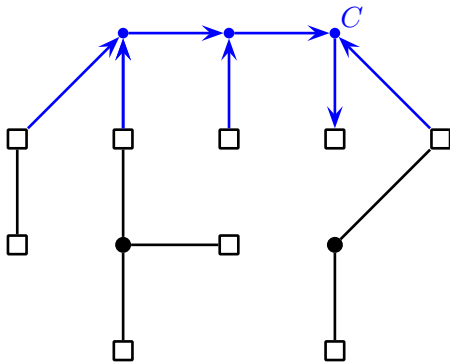


- ▶ **Bridges:**

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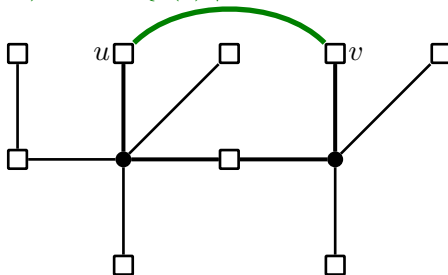
The saving function

Definition

For a Steiner tree S , the **saving function** $w : E \rightarrow \mathbb{Q}_+$ is defined as

$$w(u, v) := \max\{c(e) \mid e \text{ on } u - v \text{ path in } S\}.$$

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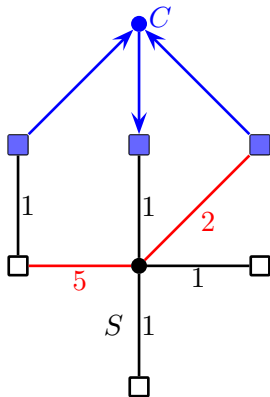


A saving lemma

Lemma

For any component C , \exists *saving tree* spanning the terminals of C with

$$c(Br_S(C)) = w(\textit{saving tree})$$

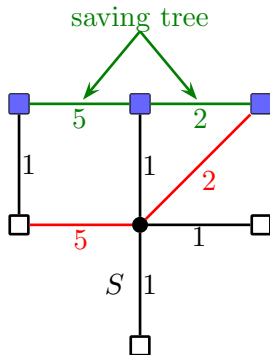


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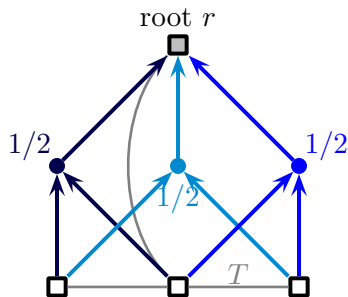


The Bridge Lemma (1)

Lemma (Bridge Lemma)

For T terminal spanning tree, x LP solution:

$$E \left[c \left(\begin{array}{l} \text{terminal spanning tree} \\ \text{after 1 sampling step} \end{array} \right) \right] \leq \left(1 - \frac{1}{M} \right) \cdot c(T)$$

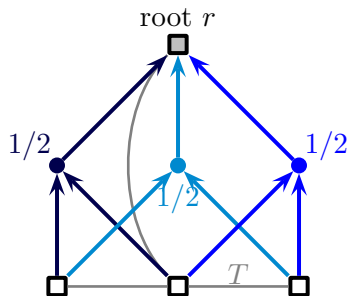


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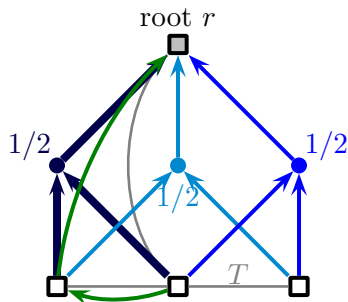
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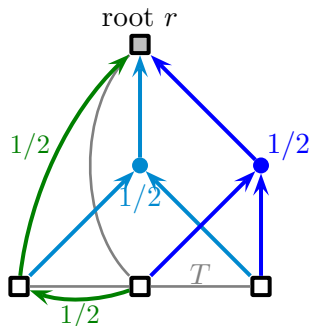
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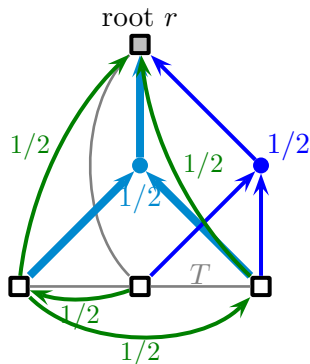
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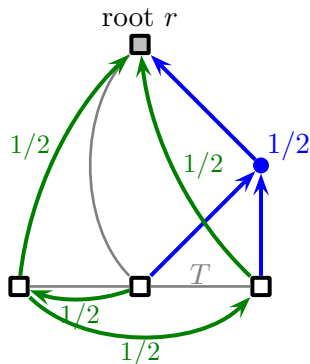
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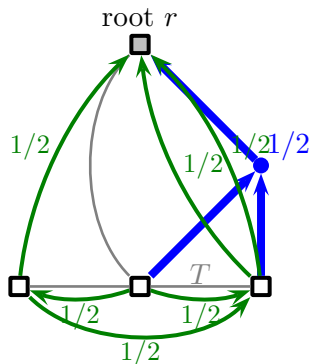
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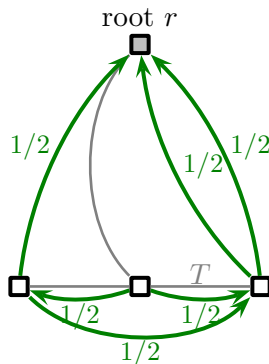
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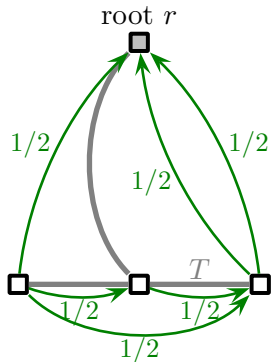
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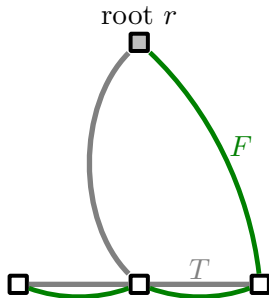
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The Bridge Lemma (2)

Edmonds Thm

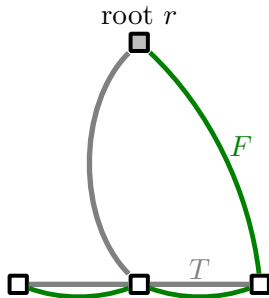
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Edmonds Thm Cycle rule



A 1st bound on OPT

Lemma

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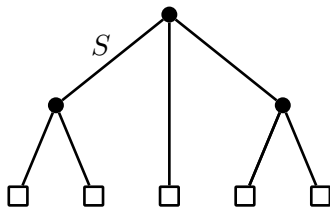
A 2nd bound on OPT

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$$E[\text{new } OPT] \leq \left(1 - \frac{1}{2M}\right) \cdot \text{old } OPT$$

- ▶ Let S be opt. Steiner tree



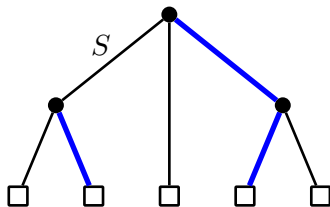
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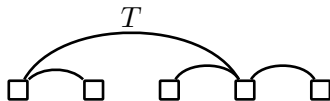
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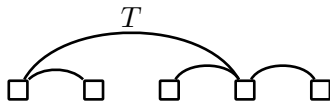
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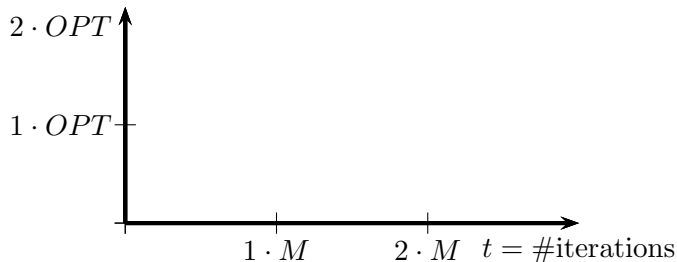
$$E[\text{save on } S] \geq E[\text{save on } T] \stackrel{\text{Bridge Lem}}{\geq} \frac{1}{M} \cdot \underbrace{c(T)}_{\geq \frac{1}{2}c(S)} \geq \frac{1}{2M} \cdot c(S)$$



The approximation guarantee

Theorem

$$E[APX] \leq (1.5 + \varepsilon) \cdot OPT.$$



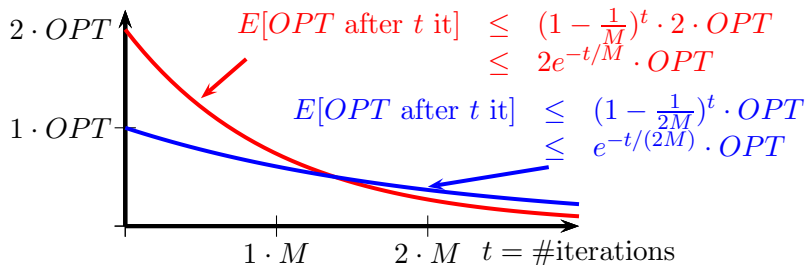
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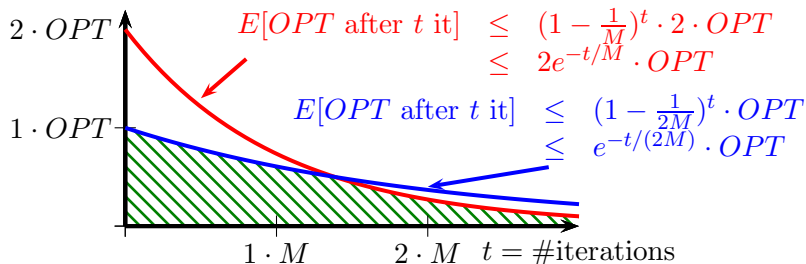
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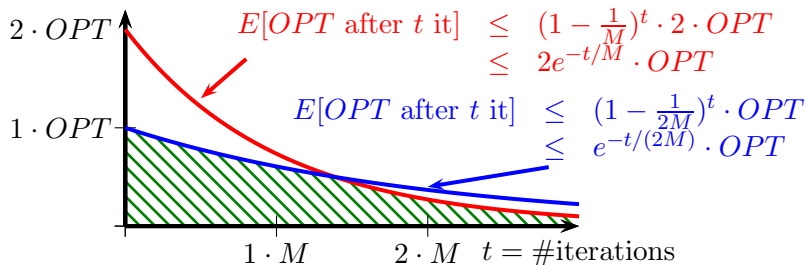
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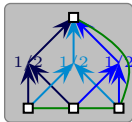


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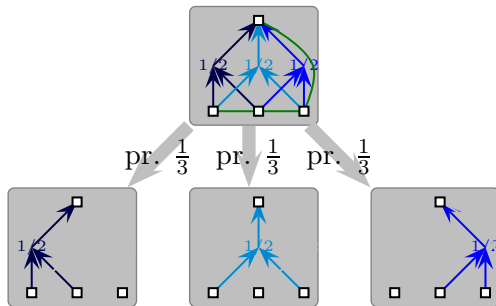
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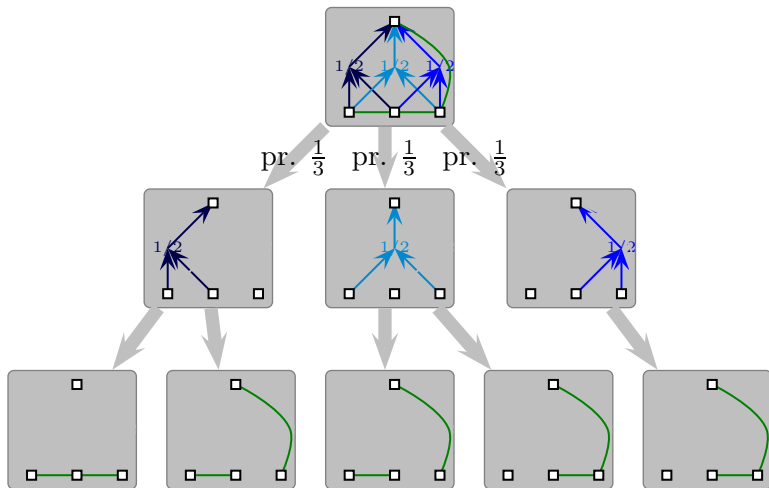
A generalized bridge lemma



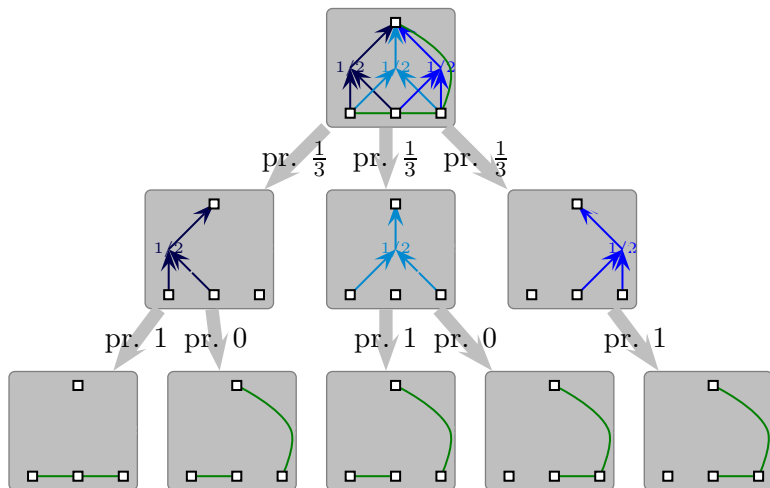
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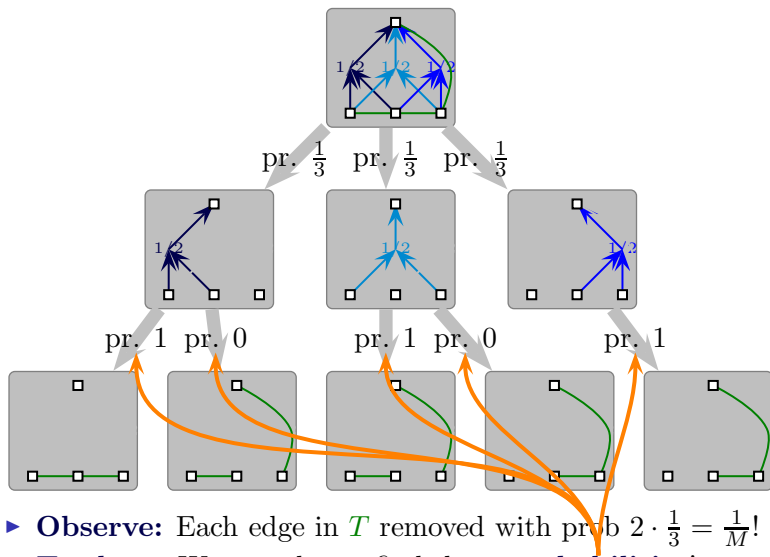


A generalized bridge lemma



► **Observe:** Each edge in T removed with prob $2 \cdot \frac{1}{3} = \frac{1}{M}$!

A generalized bridge lemma



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- ▶ **To show:** We can always find these **probabilities!**

A generalized bridge lemma (2)

Lemma

Let T be terminal spanning tree. Sample C from LP solution x .
There are $B \subseteq T$ (dep. on C) s.t.

- ▶ $(T \setminus B) \cup C$ spans all terminals
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- ▶ Suppose system (1) has no non-negative solution.

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$$\begin{aligned} y_C &\geq x_C \cdot c(B) \quad \forall B : T \setminus B \cup C \text{ conn.} \\ \sum_C y_C &< c(T) \end{aligned}$$

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- ▶ **Farkas Lemma:** System (2) has solution $(y, c) \geq \mathbf{0}$

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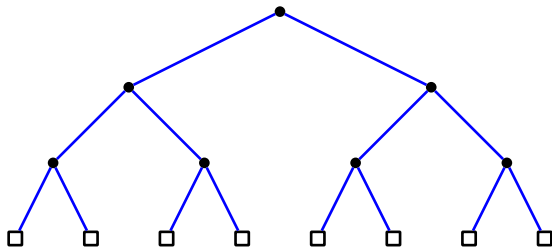
dual

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- ▶ Suppose system (1) has no non-negative solution.
- ▶ **Farkas Lemma:** System (2) has solution $(y, c) \geq 0$
- ▶ **Contradiction** to Bridge Lemma!

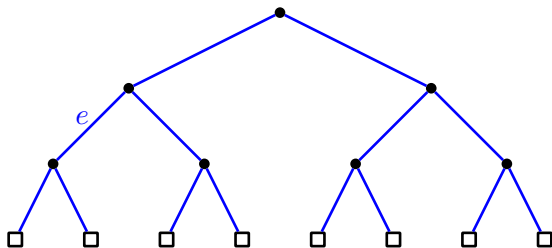


The 1.39 bound



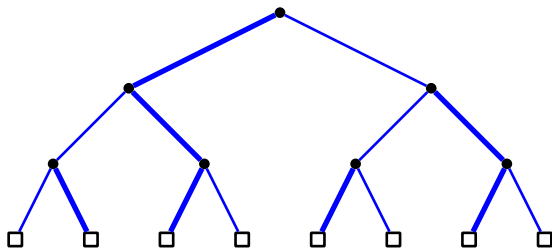
- ▶ Let S^* optimum Steiner tree.

The 1.39 bound



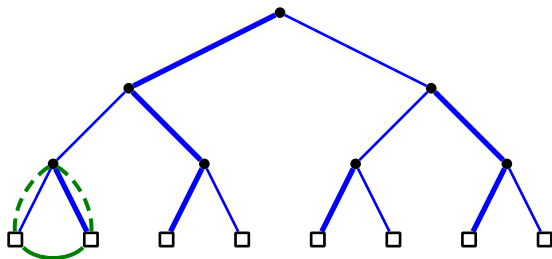
- ▶ Let S^* optimum Steiner tree.
- ▶ **Goal:** Define Steiner tree $S^t \subseteq S^*$ after t iterations with $E[t : e \in S^t] \leq 1.39 \cdot M$.

The 1.39 bound



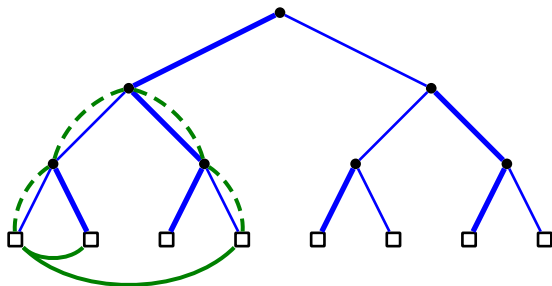
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- ▶ For every internal node in S^* : Mark a random outgoing edge.

The 1.39 bound



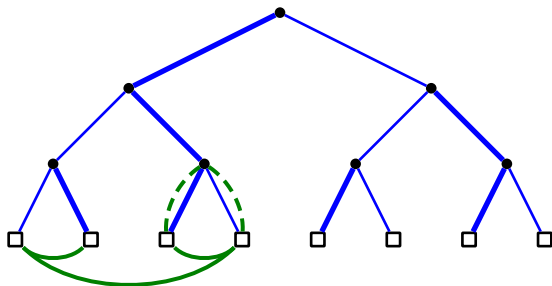
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The 1.39 bound



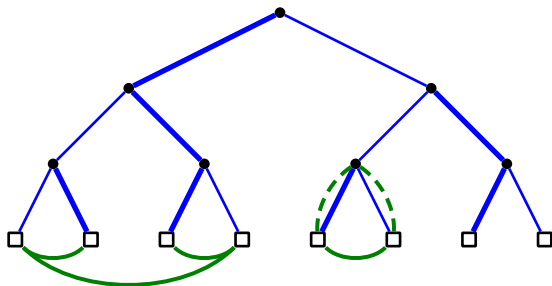
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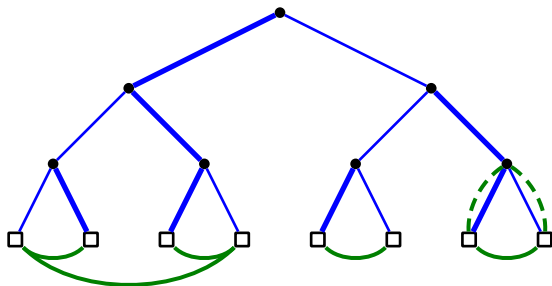
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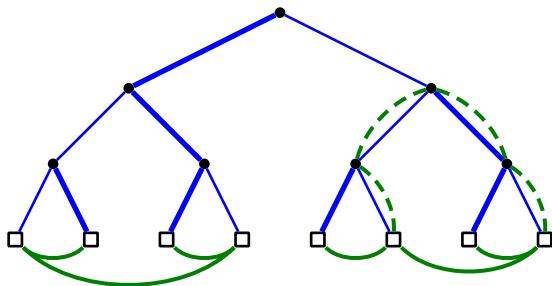
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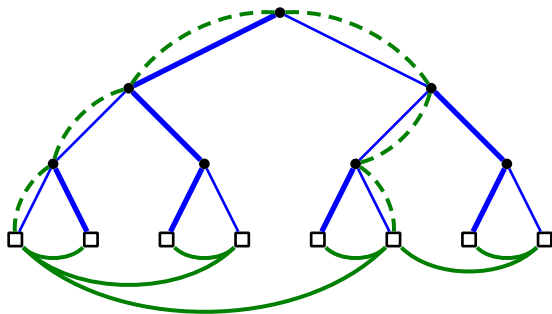
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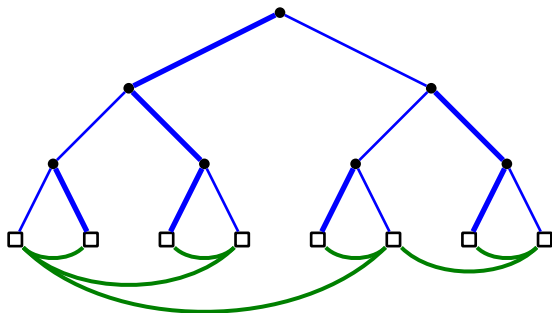
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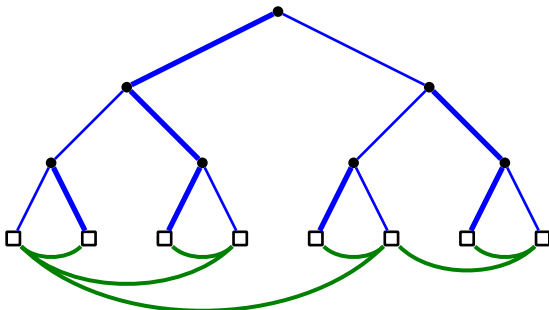
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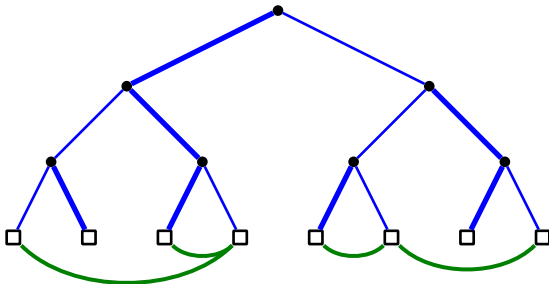
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- ▶ Consider cycles $S^* \cup \{u, v\}$ containing exactly one marked edge.
- ▶ Such edges $\{u, v\}$ induce terminal spanning tree T

The 1.39 bound



- ▶ Def S^t : $e \in T$ not deleted \Rightarrow keep edges in corr. cycle in S^*

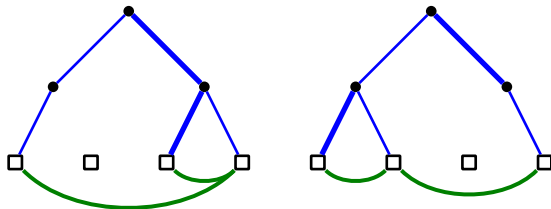
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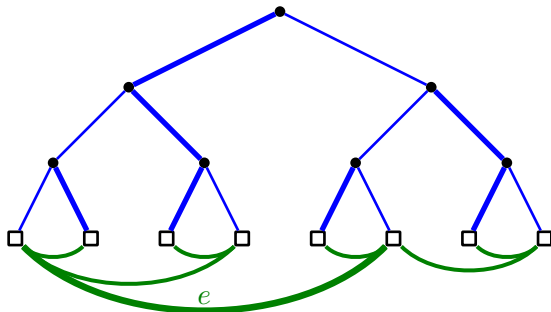
The 1.39 bound

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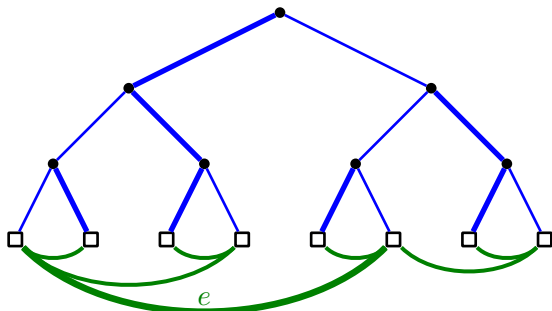
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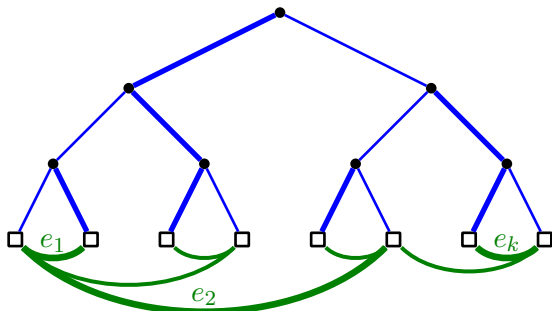
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The 1.39 bound



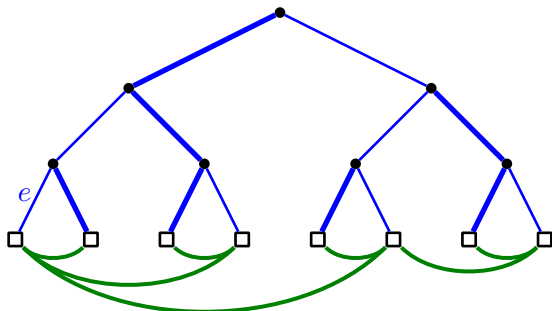
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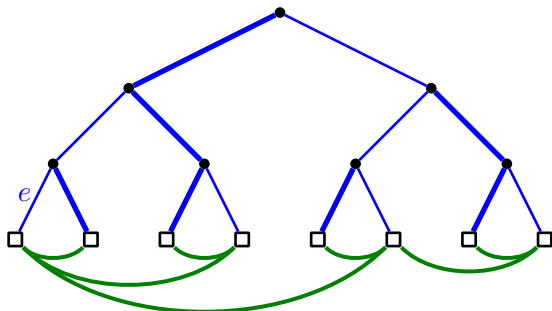
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 \rightarrow **Coupon Collector Theorem**

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 \rightarrow **Coupon Collector Theorem**
- ▶ $E[t : e \text{ deleted}] \leq H(\# \text{cycles through } e) \cdot M$
- ▶ $\Pr[e \text{ in } k \text{ cycles}] = (\frac{1}{2})^k$
 $E[t : e \text{ deleted}] \leq \sum_{k \geq 1} (\frac{1}{2})^k \cdot H(k) \cdot M = \ln(4) \cdot M \approx 1.39 \cdot M. \quad \square$

Open problems

Open Problem I

$1.01 \leq \text{Steiner tree approximability} \leq 1.39$

Open problems

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Open Problem II

Is there an iterative randomized rounding approach for FACILITY LOCATION or k -MEDIAN?

Open problems

Open Problem III

Is there an iterative randomized rounding approach for ATSP?

(1) Solve Held-Karp relaxation:

$$\begin{aligned} \min c^T x \\ x(\delta^+(S)) &\geq 1 \quad \forall \emptyset \subset S \subset V \\ x(\delta^+(v)) = x(\delta^-(v)) &= 1 \quad \forall v \in V \\ x_e &\geq 0 \quad \forall e \in E \end{aligned}$$

(2) Sample a collection of cycles \mathcal{C} from x^* .

(3) Show $E[c(\mathcal{C})] \leq 1000 \cdot OPT$

(4) Show $E[OPT \text{ after contracting } \mathcal{C}] \leq 0.999 \cdot OPT$.

This would yield a $O(1)$ -apx.

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Thanks for your attention