

Advanced Algorithms

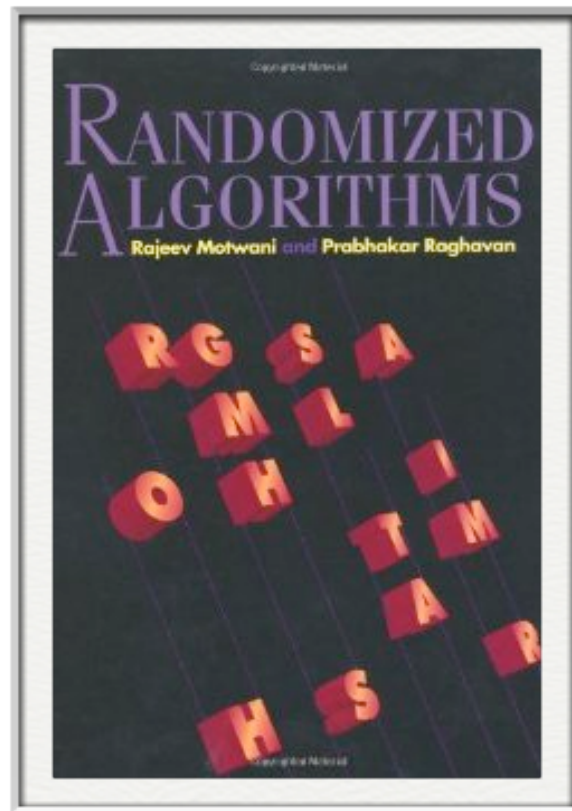
南京大学

尹一通

Course Info

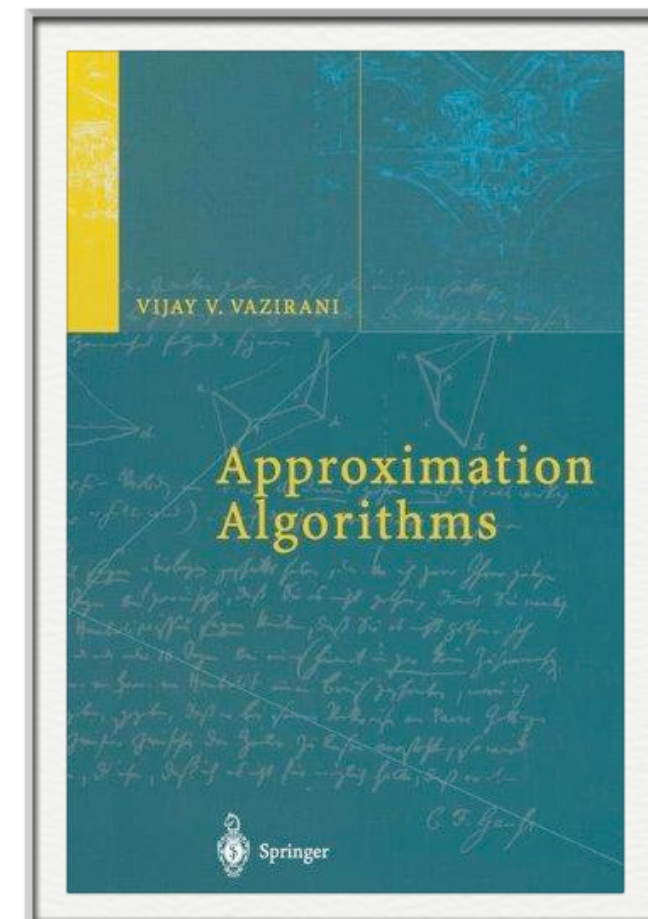
- Instructor: 尹一通、郑朝栋
 - {[yinyt](mailto:yinyt@nju.edu.cn), [chaodong](mailto:chaodong@nju.edu.cn)}@nju.edu.cn
- Office hour: Wednesday, 10am-12pm
 - 804 (尹一通), 302 (郑朝栋)
- course homepage:
 - <http://tcs.nju.edu.cn/wiki/>

Textbooks

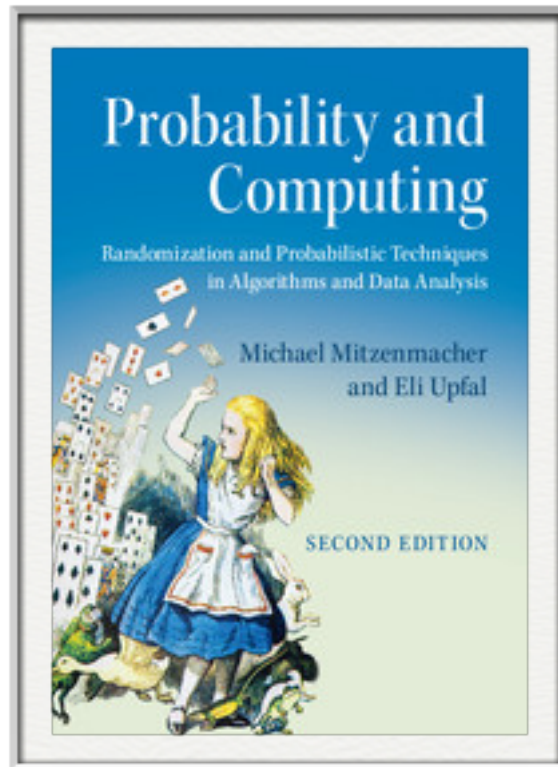


Rajeev Motwani and Prabhakar Raghavan.
Randomized Algorithms.
Cambridge University Press, 1995.

Vijay Vazirani
Approximation Algorithms.
Springer-Verlag, 2001.

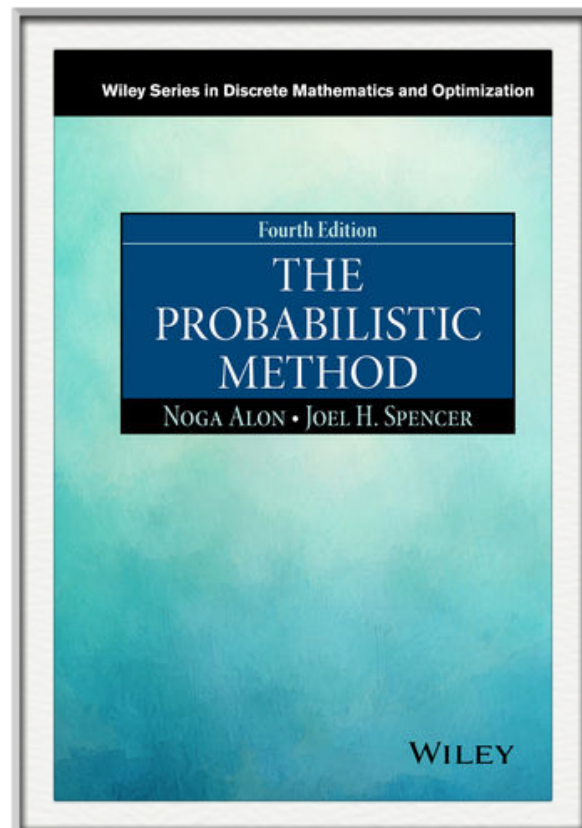
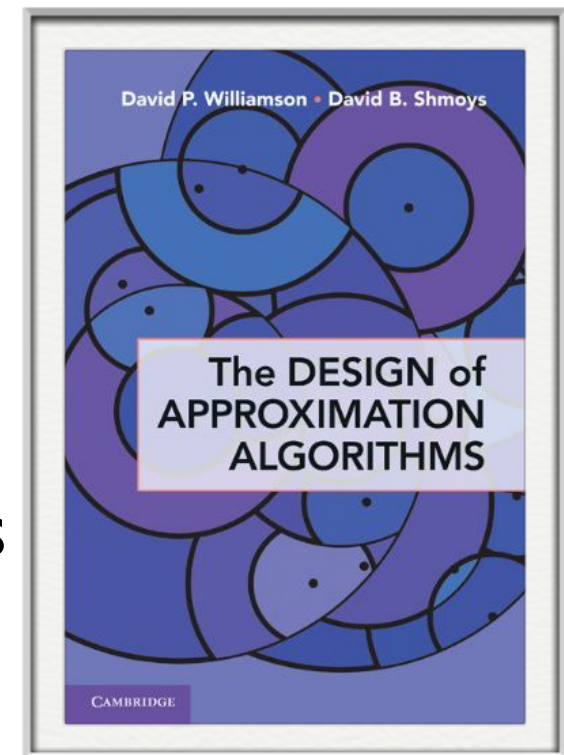


References



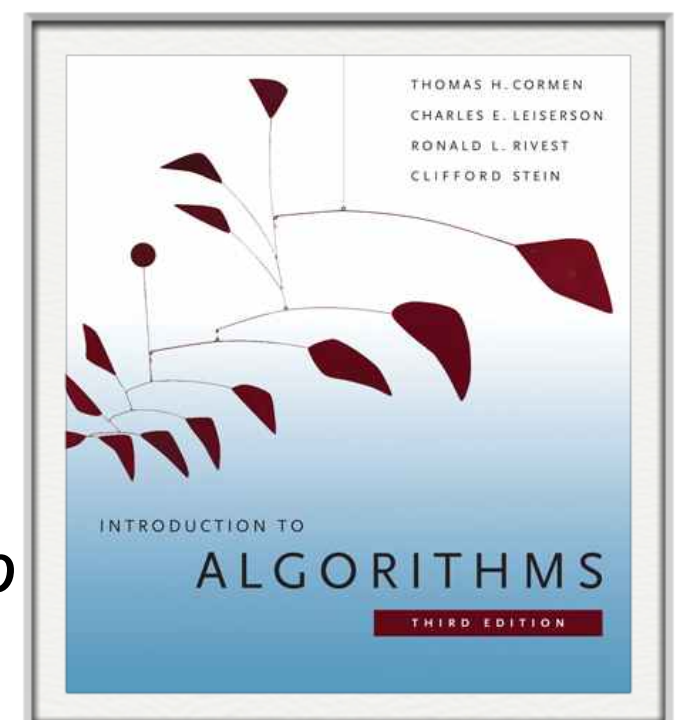
Mitzenmacher and Upfal.
Probability and Computing,
2nd Ed.

Williamson and Shmoys
*The Design of
Approximation Algorithms*



Alon and Spencer
The Probabilistic Method,
4th Ed.

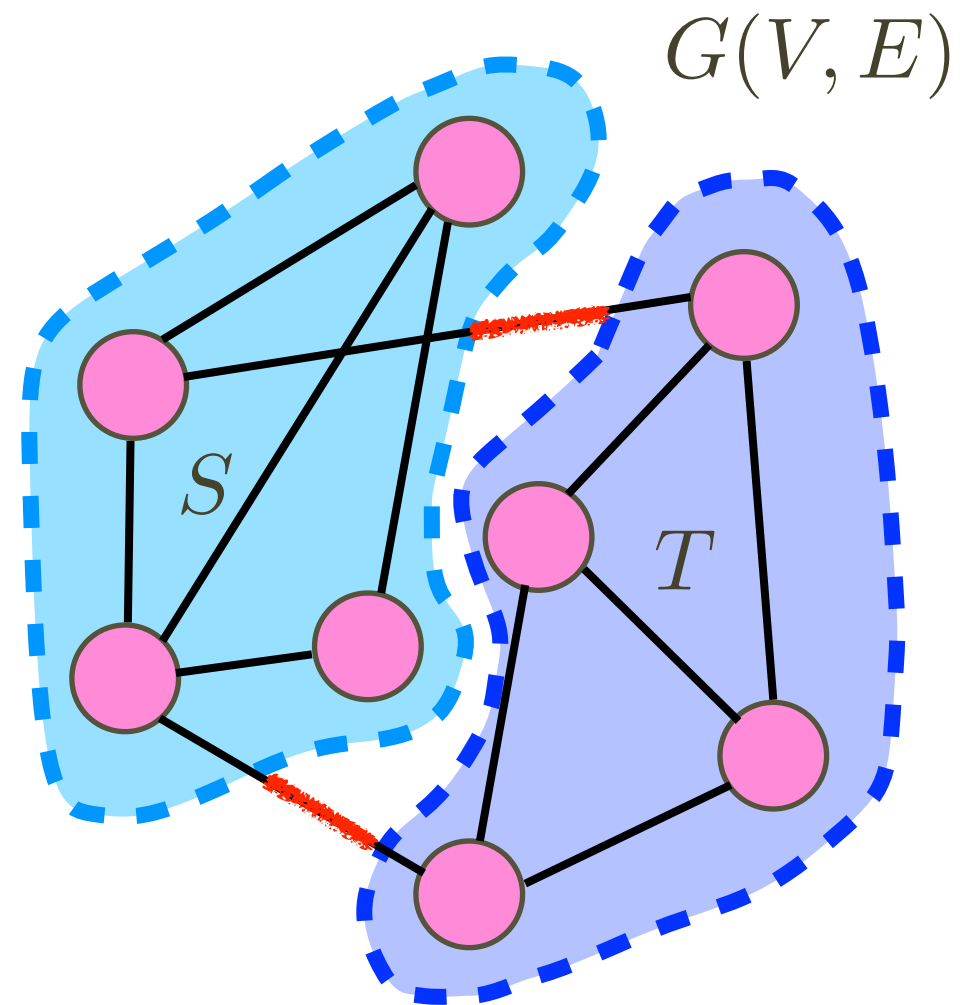
CLRS
*Introduction to
Algorithms*



“Advanced” Algorithms

Min-Cut

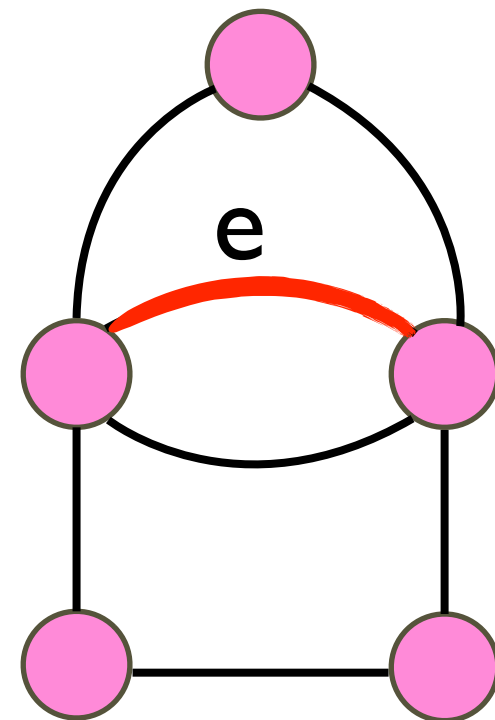
- **Partition** V into two parts:
 S and T
- **Minimize** the **cut** $E(S, T)$
- deterministic algorithm:
 - max-flow min-cut
 - best known upper bound:
 $O(mn + n^2 \log n)$



$$E(S, T) = \{uv \in E \mid u \in S, v \in T\}$$

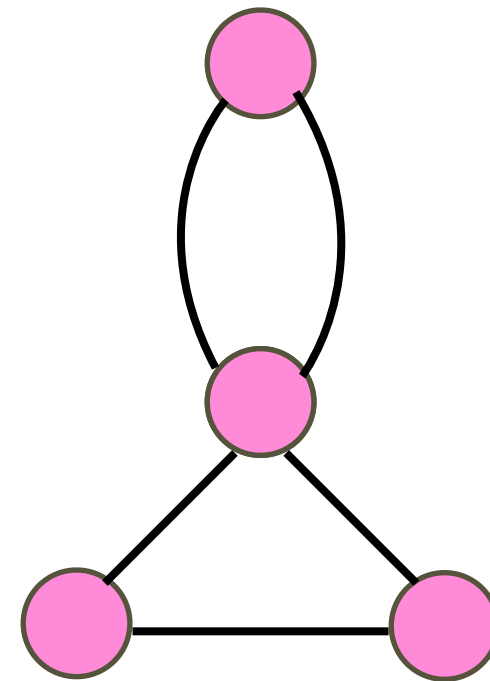
Contraction

- **multigraph** $G(V, E)$
- **multigraph**: allow parallel edges
- for an edge e , **contract**(e) merges the two endpoints.



Contraction

- multigraph $G(V, E)$
- multigraph: allow parallel edges
- for an edge e , $\text{contract}(e)$ merges the two endpoints.



Karger's min-cut Algorithm

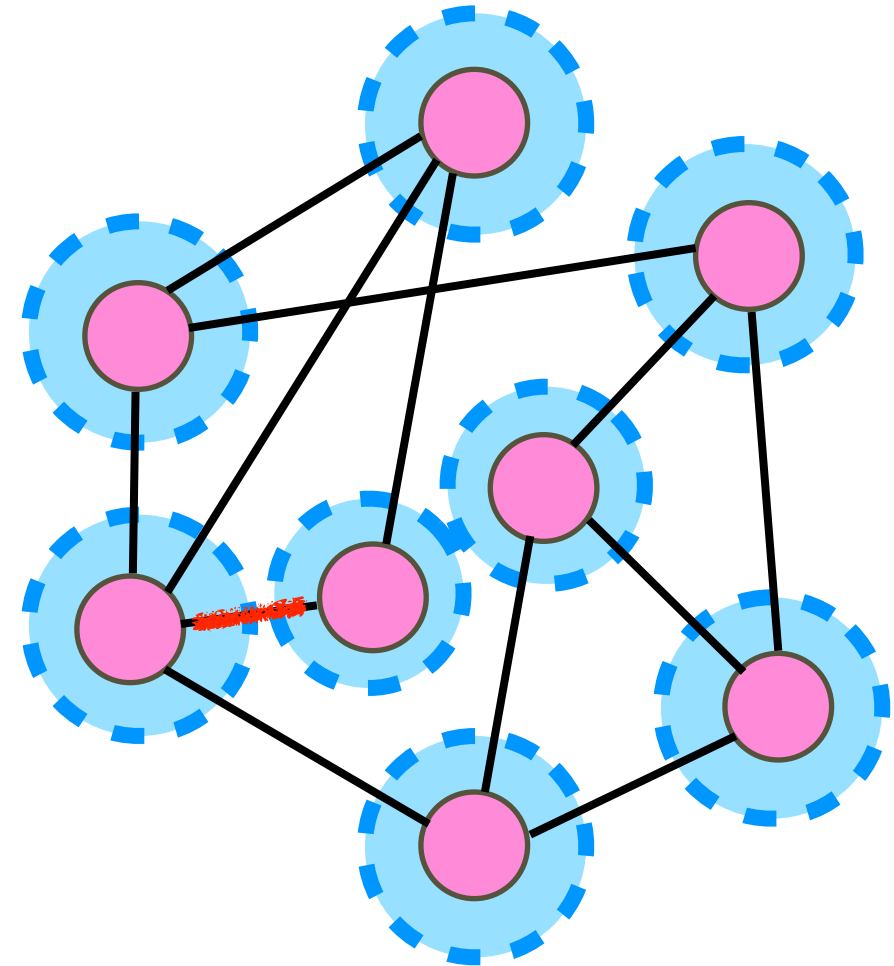
MinCut (multigraph $G(V,E)$)

while $|V| > 2$ do

 choose a **uniform** $e \in E$;

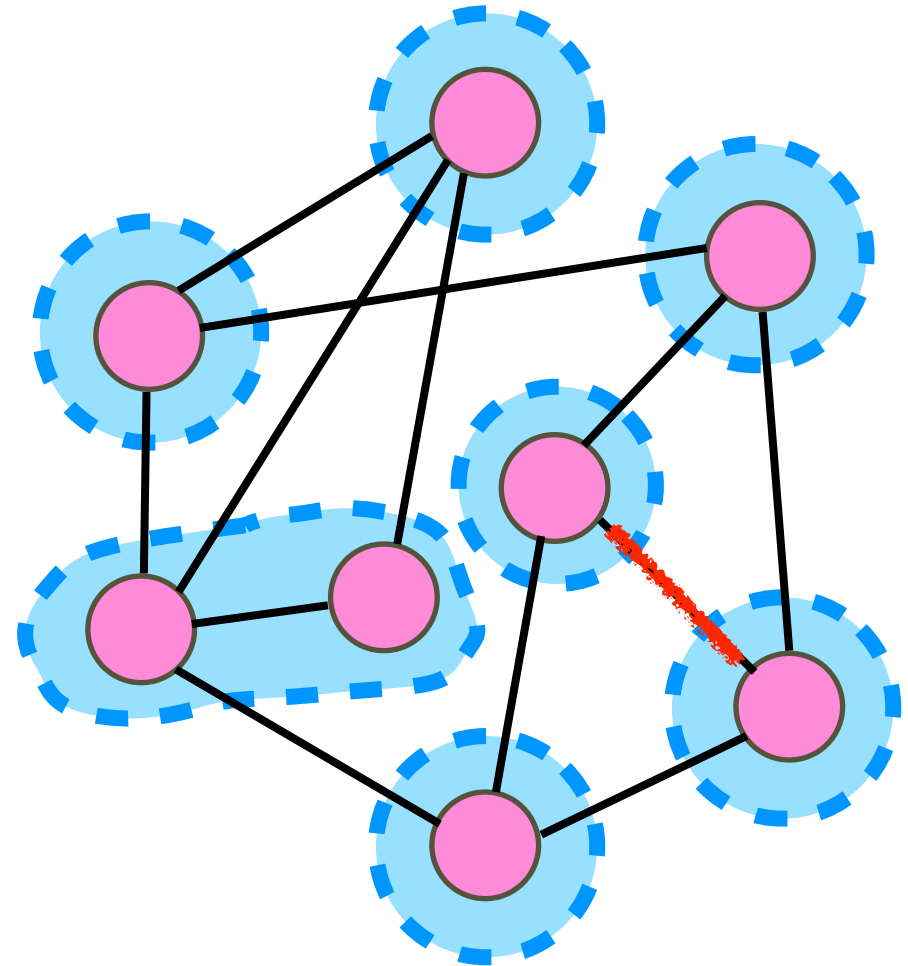
contract(e);

return remaining edges;



Karger's min-cut Algorithm

```
MinCut ( multigraph  $G(V,E)$  )  
while  $|V| > 2$  do  
  choose a uniform  $e \in E$  ;  
  contract( $e$ );  
return remaining edges;
```



Karger's min-cut Algorithm

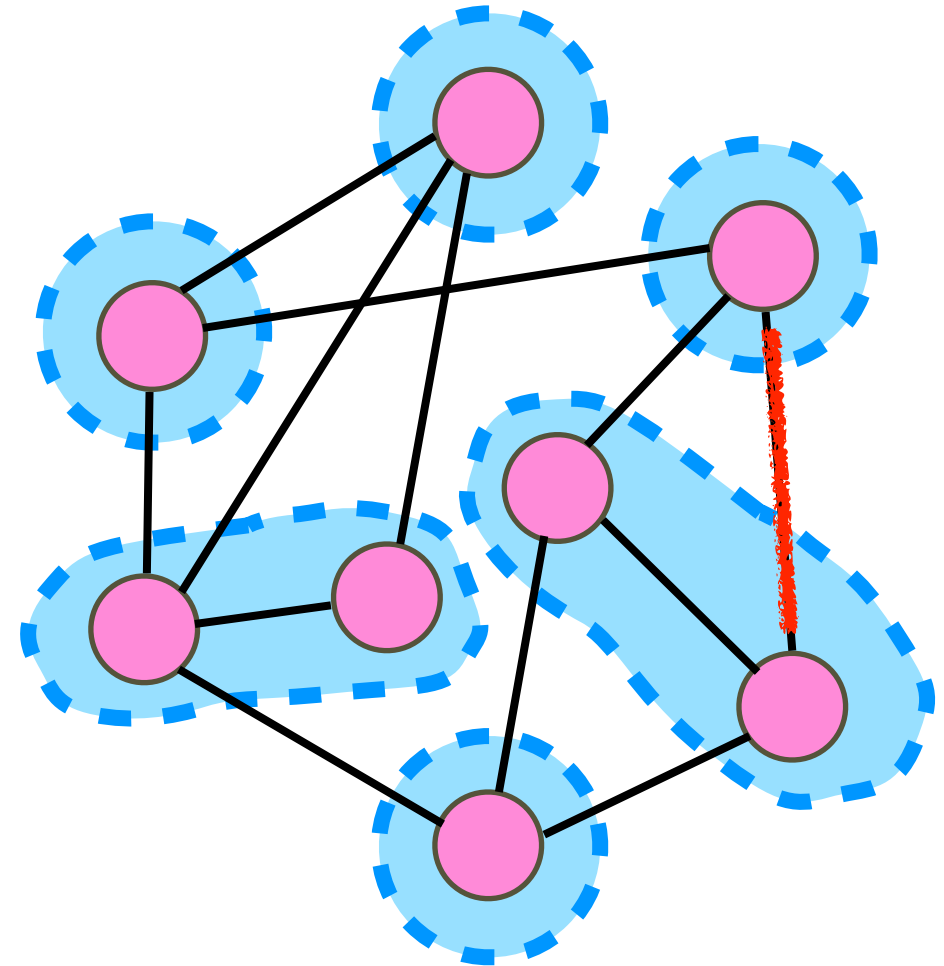
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Karger's min-cut Algorithm

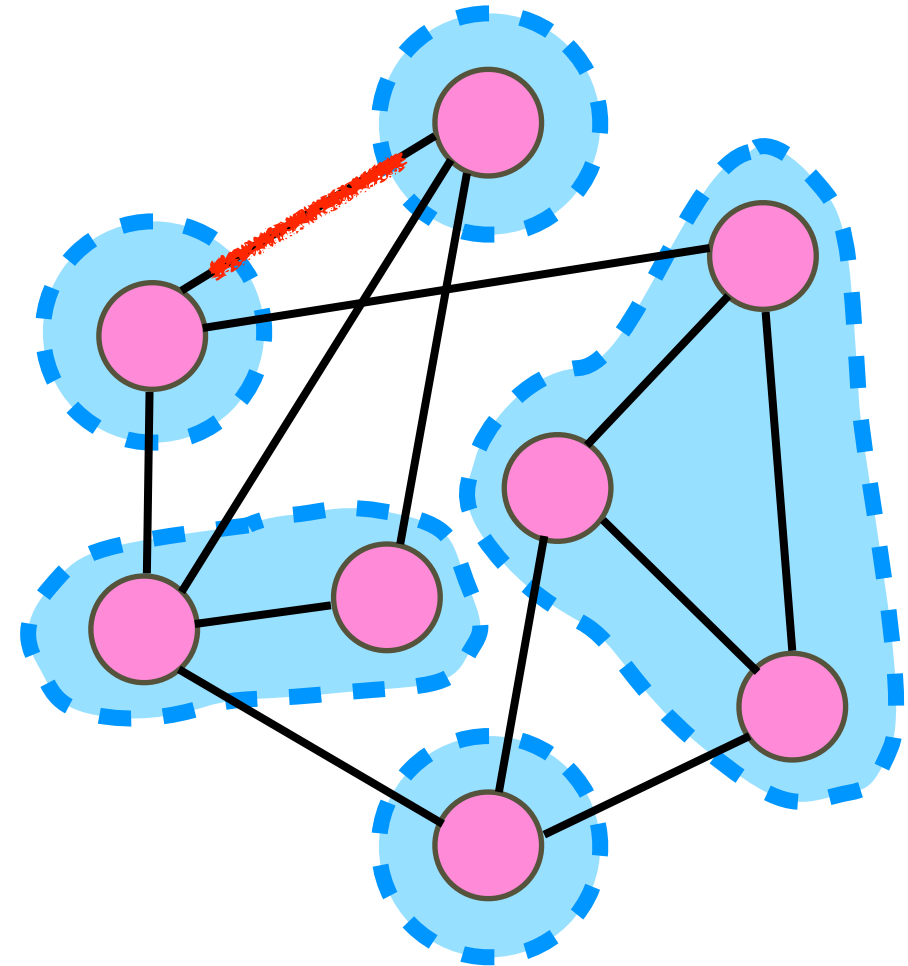
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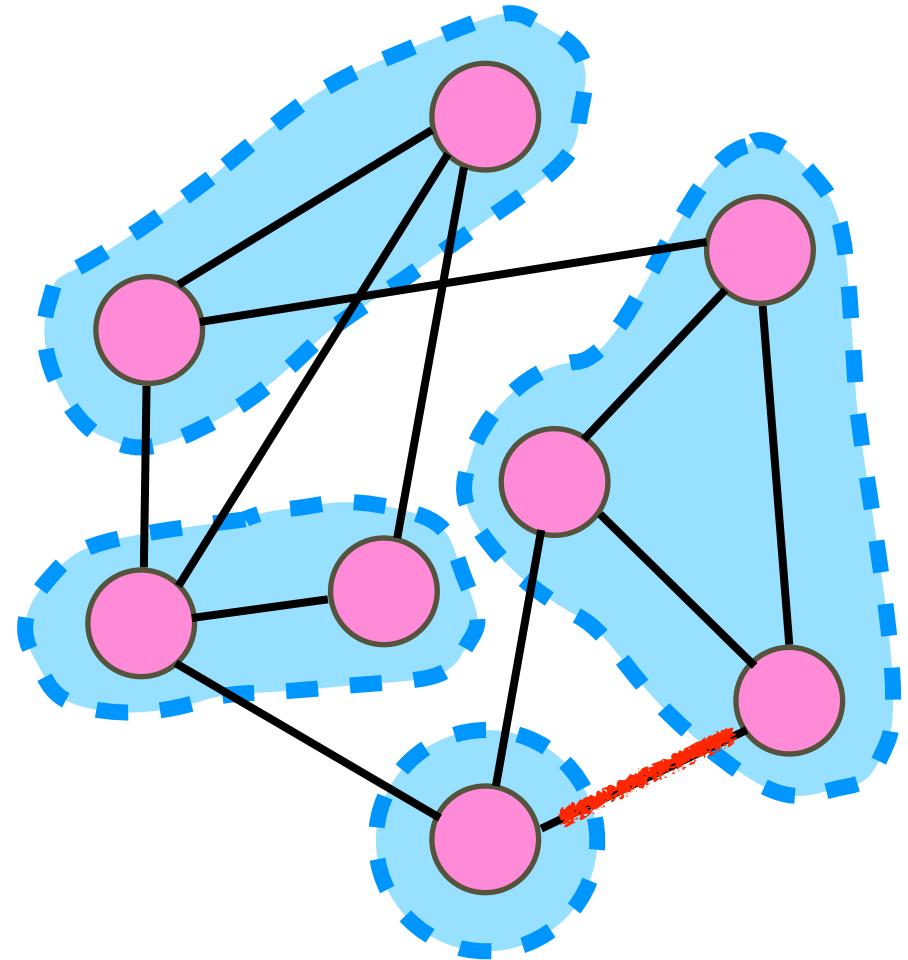
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Karger's min-cut Algorithm

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MinCut ( multigraph  $G(V,E)$  )  
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Karger's min-cut Algorithm

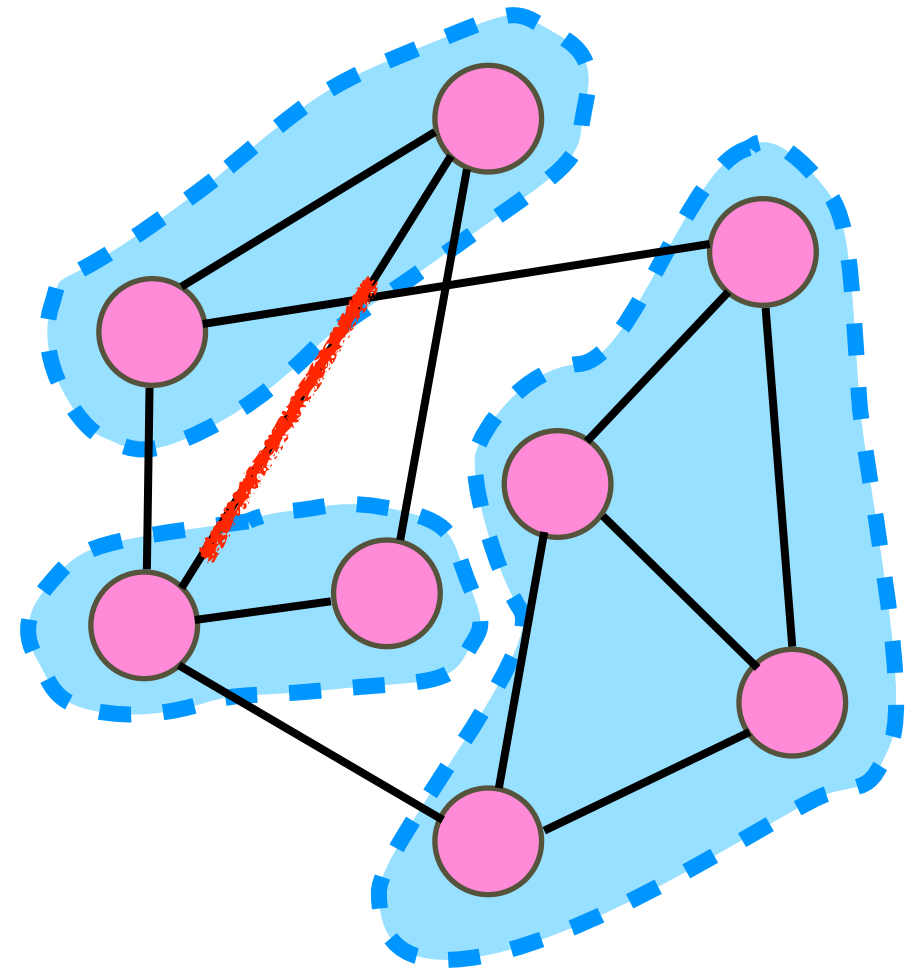
MinCut (multigraph $G(V,E)$)

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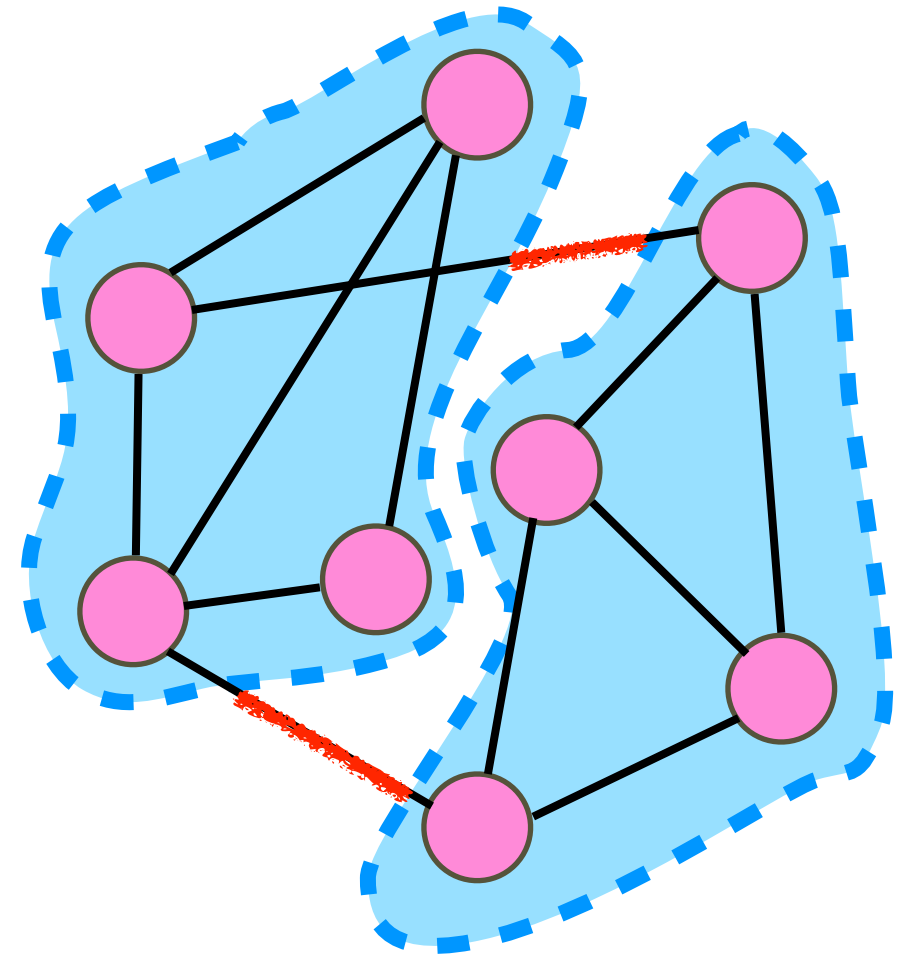
contract(e);

return remaining edges;



Karger's min-cut Algorithm

```
MinCut ( multigraph  $G(V,E)$  )  
while  $|V| > 2$  do  
  choose a uniform  $e \in E$  ;  
  contract( $e$ );  
return remaining edges;
```



edges returned

MinCut (multigraph $G(V,E)$)

while $|V| > 2$ do

 choose a **uniform** $e \in E$;

contract(e);

return remaining edges;

Theorem (Karger 1993):

$$\Pr[\text{a min-cut is returned}] \geq \frac{2}{n(n-1)}$$

repeat independently
for $n(n-1)/2$ times
and return the smallest cut

$\Pr[\text{fail to finally return a min-cut}]$

$$= \Pr[\text{fail to construct a min-cut in one trial}]^{n(n-1)/2}$$

$$\leq \left(1 - \frac{2}{n(n-1)}\right)^{n(n-1)/2} < \frac{1}{e}$$

MinCut (multigraph $G(V,E)$)

while $|V| > 2$ do

choose a **uniform** $e \in E$;

contract(e);

return remaining edges;

suppose e_1, e_2, \dots, e_{n-2}
are contracted edges

initially: $G_1 = G$

i -th round:

$G_i = \text{contract}(G_{i-1}, e_{i-1})$

$\left. \begin{array}{l} C \text{ is a min-cut in } G_{i-1} \\ e_{i-1} \notin C \end{array} \right\} \Rightarrow C \text{ is a min-cut in } G_i$

C : a min-cut of G

$\Pr[C \text{ is returned}] \geq \Pr[e_1, e_2, \dots, e_{n-2} \notin C]$

chain rule: $= \prod_{i=1}^{n-2} \Pr[e_i \notin C \mid e_1, e_2, \dots, e_{i-1} \notin C]$

suppose e_1, e_2, \dots, e_{n-2} are contracted edges

initially: $G_1 = G$ **i -th round:** $G_i = \text{contract}(G_{i-1}, e_{i-1})$

C is a min-cut in G_{i-1} } $e_{i-1} \notin C$ \Rightarrow C is a min-cut in G_i

C : a min-cut of G

$$\Pr[C \text{ is returned}] \geq \prod_{i=1}^{n-2} \Pr[e_i \notin C \mid e_1, e_2, \dots, e_{i-1} \notin C]$$

\Downarrow
 C is a min-cut in G_i

C is a min-cut in $G(V, E)$
 $\Rightarrow |E| \geq \frac{1}{2} |C| |V|$

Proof:

min-degree of $G \geq |C|$

$$\begin{aligned} &\geq \prod_{i=1}^{n-2} \left(1 - \frac{2}{(n-i+1)} \right) \\ &= \prod_{i=1}^{n-2} \frac{n-i-1}{n-i+1} = \frac{2}{n(n-1)} \end{aligned}$$

MinCut (multigraph $G(V,E)$)

while $|V| > 2$ do

 choose a **uniform** $e \in E$;

contract(e);

return remaining edges;

Theorem (Karger 1993):

For any min-cut C ,

$$\Pr[C \text{ is returned}] \geq \frac{2}{n(n-1)}$$

running time: $O(n^2)$

repeat *independently* for $O(n^2 \log n)$ times

returns a min-cut with probability $1 - O(1/n)$

total running time: $O(n^4 \log n)$

Number of Min-Cuts

Theorem (Karger 1993):

For any min-cut C ,

$$\Pr[C \text{ is returned}] \geq \frac{2}{n(n-1)}$$

Corollary

The number of distinct min-cuts
in a graph of n vertices is at most $n(n-1)/2$.

An Observation

MinCut (multigraph $G(V,E)$)

while $|V| > t$ do

 choose a uniform $e \in E$;

 contract(e);

return remaining edges;

C : a min-cut of G

$$\begin{aligned} \Pr[e_1, \dots, e_{n-t} \notin C] &= \prod_{i=1}^{n-t} \Pr[e_i \notin C \mid e_1, \dots, e_{i-1} \notin C] \\ &\geq \prod_{i=1}^{n-t} \frac{n-i-1}{n-i+1} = \frac{t(t-1)}{n(n-1)} \end{aligned}$$

only getting bad when t is small

Fast Min-Cut

MinCut (multigraph $G(V,E)$)

while $|V| > t$ do

 choose a uniform $e \in E$;

 contract(e);

return remaining edges;

FastCut (G)

if $|V| \leq 6$ then return a min-cut by brute force;

else: (t to be fixed later)

$G_1 = \text{Contract}(G, t);$

$G_2 = \text{Contract}(G, t);$

(independently)

return $\min\{\text{FastCut}(G_1), \text{FastCut}(G_2)\};$

FastCut (G)

if $|V| \leq 6$ then return a min-cut by brute force;

else: (t to be fixed later)

$G_1 = \text{Contract}(G, t);$
 $G_2 = \text{Contract}(G, t);$ (independently)

return $\min\{\text{FastCut}(G_1), \text{FastCut}(G_2)\};$

C : a min-cut in G

A : no edge in C is contracted during $\text{Contract}(G, t)$

$$\begin{aligned} \Pr[A] &= \prod_{i=1}^{n-t} \Pr[e_i \notin C \mid e_1, \dots, e_{i-1} \notin C] \\ &\geq \prod_{i=1}^{n-t} \frac{n-i-1}{n-i+1} \geq \frac{t(t-1)}{n(n-1)} \geq \left(\frac{t-1}{n-1} \right)^2 \end{aligned}$$

FastCut (G)

if $|V| \leq 6$ then return a min-cut by brute force;

else: (t to be fixed later)

$G_1 = \text{Contract}(G, t);$

$G_2 = \text{Contract}(G, t);$

(independently)

return $\min\{\text{FastCut}(G_1), \text{FastCut}(G_2)\};$

C : a min-cut in G **set** $t = \left\lceil 1 + \frac{n}{\sqrt{2}} \right\rceil$

A : no edge in C is contracted during $\text{Contract}(G, t)$

$$\Pr[A] \geq \left(\frac{t-1}{n-1} \right)^2 \geq \frac{1}{2}$$

$$p(n) = \min_{G: |V|=n} \Pr[\text{FastCut}(G) \text{ returns a mincut in } G]$$

succeeds

$$\geq 1 - (1 - \Pr[A] \Pr[\text{FastCut}(G_1) \text{ succeeds} \mid A])^2$$

$$\geq 1 - \left(1 - \left(\frac{t-1}{n-1} \right)^2 p(t) \right)^2 \geq p\left(\left\lceil 1 + \frac{n}{\sqrt{2}} \right\rceil\right) - \frac{1}{4} p\left(\left\lceil 1 + \frac{n}{\sqrt{2}} \right\rceil\right)^2$$

FastCut (G)

if $|V| \leq 6$ then return a min-cut by brute force;

else: **set** $t = \left\lceil 1 + \frac{n}{\sqrt{2}} \right\rceil$

$G_1 = \text{Contract}(G, t);$

$G_2 = \text{Contract}(G, t);$

(independently)

return $\min\{\text{FastCut}(G_1), \text{FastCut}(G_2)\};$

$$p(n) = \min_{G: |V|=n} \Pr[\text{FastCut}(G) \text{ returns a mincut in } G]$$

$$\geq p\left(\left\lceil 1 + \frac{n}{\sqrt{2}} \right\rceil\right) - \frac{1}{4}p\left(\left\lceil 1 + \frac{n}{\sqrt{2}} \right\rceil\right)^2$$

by induction: $p(n) = \Omega\left(\frac{1}{\log n}\right)$

running time: $T(n) = 2T\left(\left\lceil 1 + \frac{n}{\sqrt{2}} \right\rceil\right) + O(n^2)$

by induction: $T(n) = O(n^2 \log n)$

FastCut (G)

if $|V| \leq 6$ then return a min-cut by brute force;

else: **set** $t = \left\lceil 1 + \frac{n}{\sqrt{2}} \right\rceil$

$G_1 = \text{Contract}(G, t);$

$G_2 = \text{Contract}(G, t);$

(independently)

return $\min\{\text{FastCut}(G_1), \text{FastCut}(G_2)\};$

Theorem (Karger-Stein 1996):

FastCut runs in time $O(n^2 \log n)$ and
returns a min-cut with probability $\Omega(1/\log n)$.

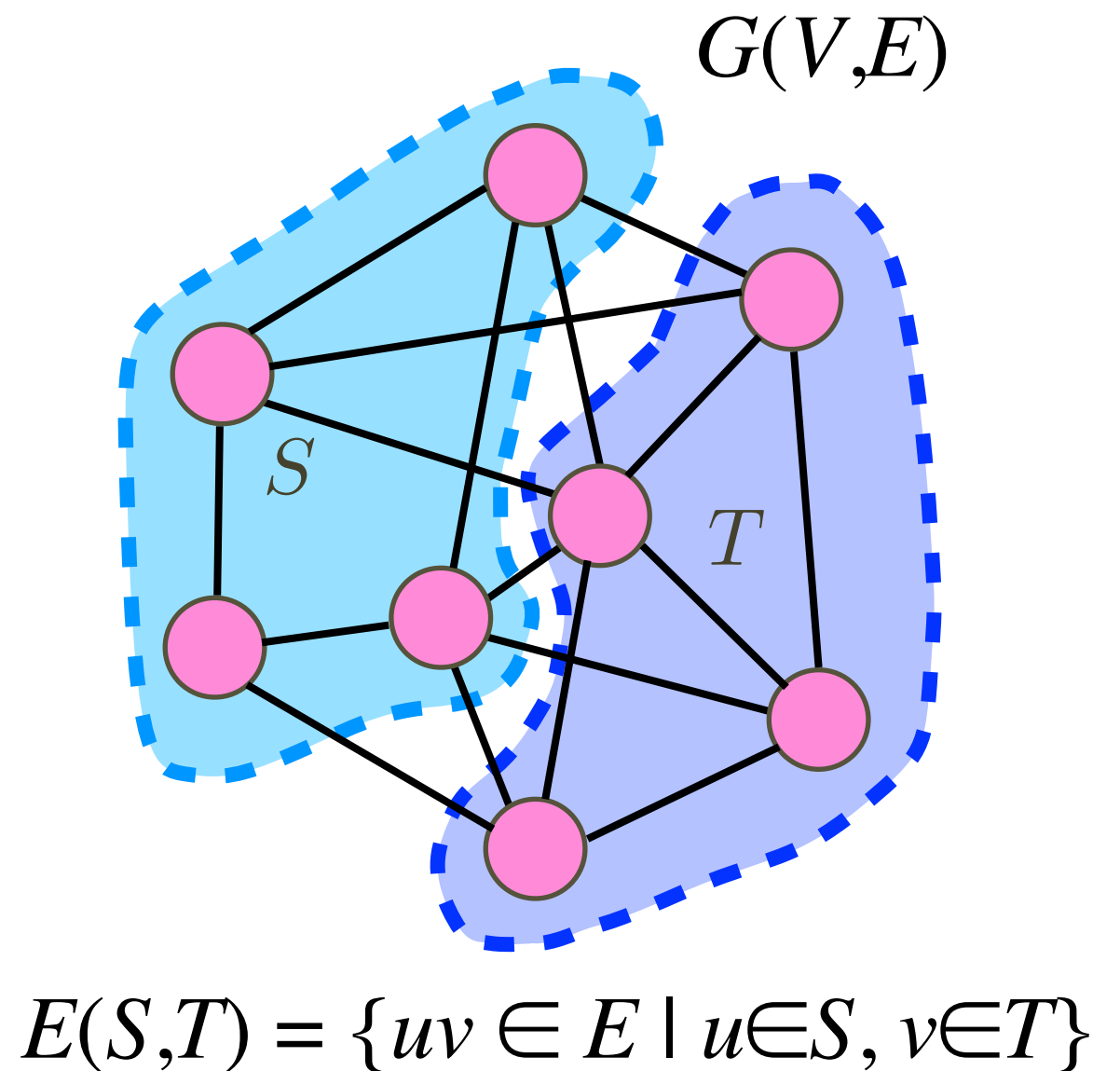
repeat *independently* for $O((\log n)^2)$ times

total running time: $O(n^2 \log^3 n)$

returns a min-cut with probability $1 - O(1/n)$

Max-Cut

- **Partition** V into two parts:
 S and T
- **Maximize** the **cut** $E(S,T)$
- **NP-hard**
 - one of Karp's 21 NP-complete problems
- **Approximation algorithms?**



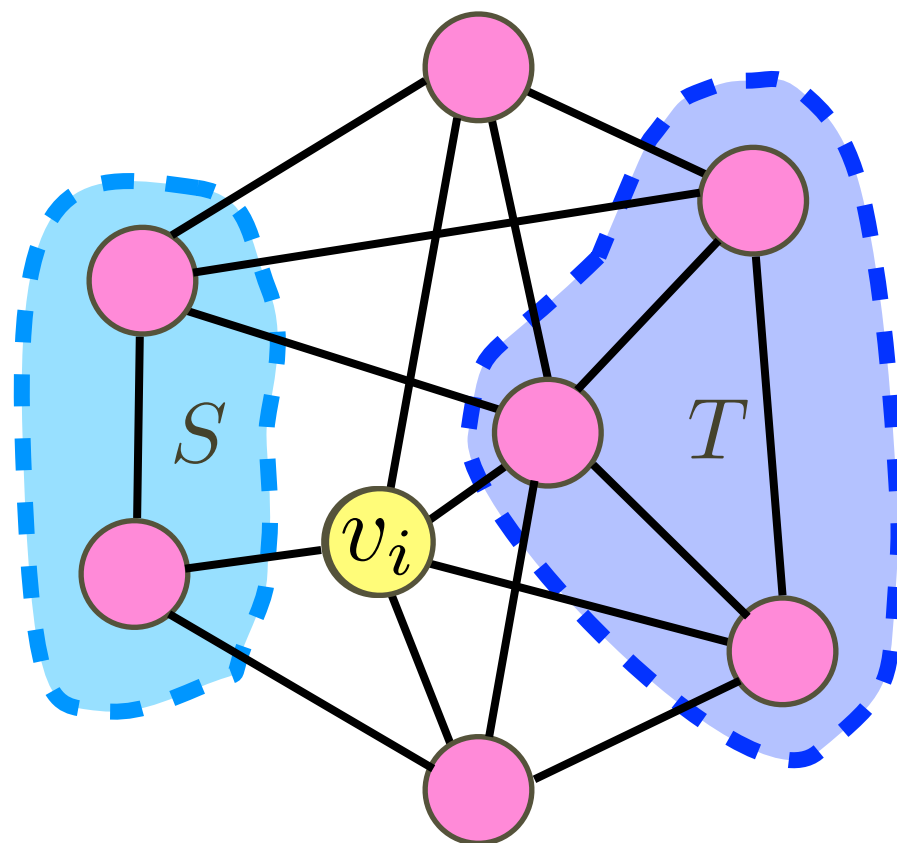
Greedy Heuristics

initially, $S=T=\emptyset$

for $i = 1, 2, \dots, n$

v_i joins one of S, T

to maximize **current** $E(S, T)$



$$E(S, T) = \{uv \in E \mid u \in S, v \in T\}$$

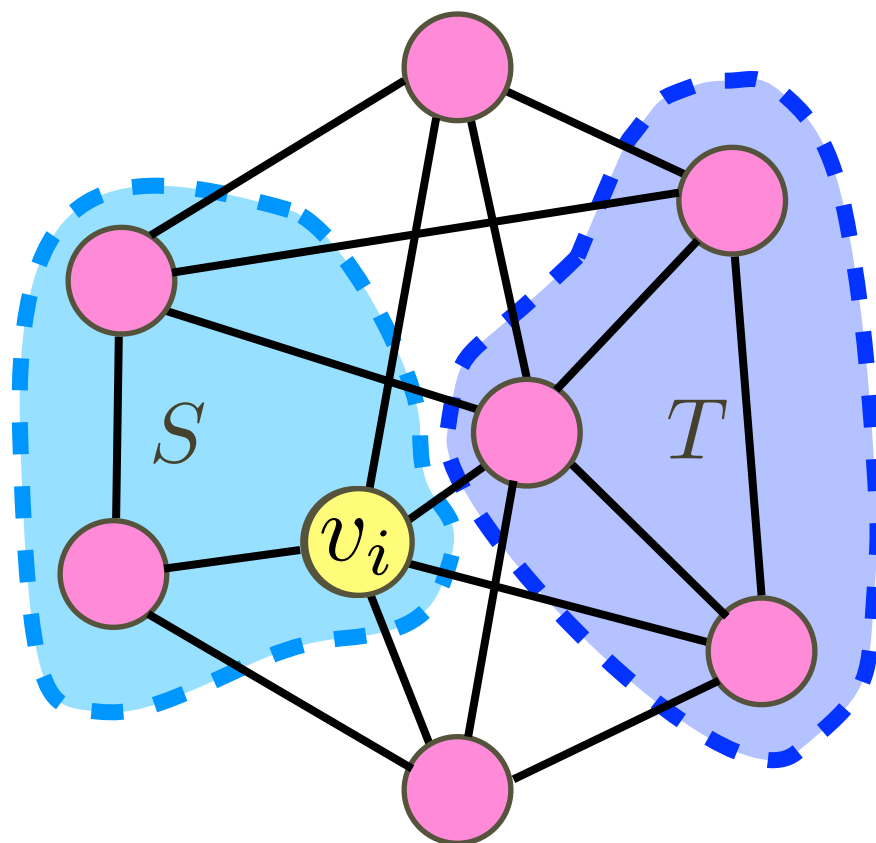
Greedy Heuristics

initially, $S=T=\emptyset$

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v_i joins one of S, T

to maximize **current** $E(S, T)$



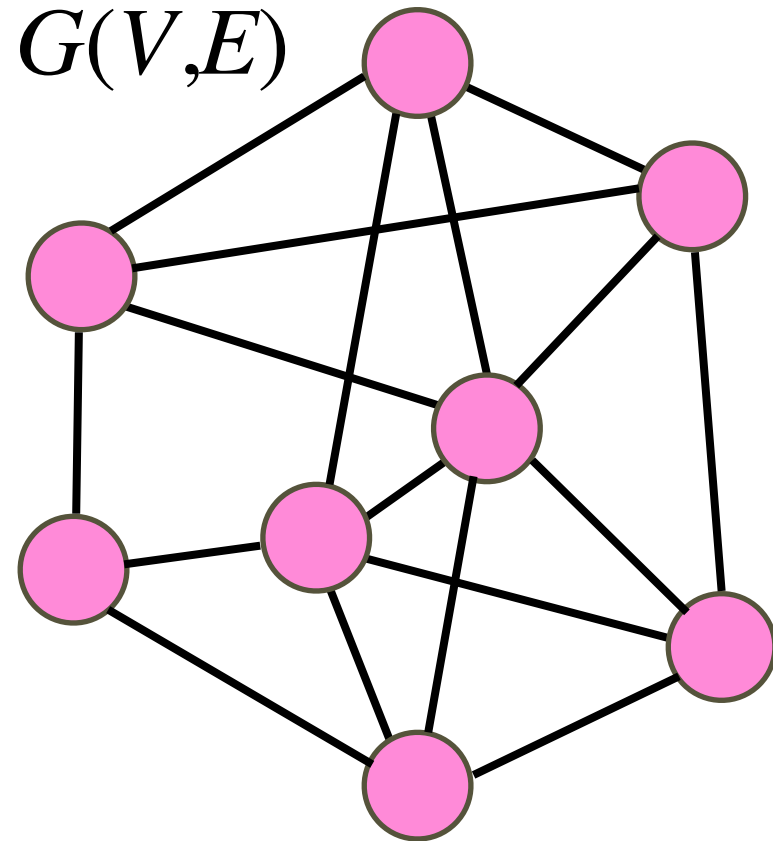
$$E(S, T) = \{uv \in E \mid u \in S, v \in T\}$$

Approximation Ratio

algorithm A :

initially, $S=T=\emptyset$
for $i = 1, 2, \dots, n$
 v_i joins one of S, T
 to maximize **current** $E(S, T)$

instance $G(V, E)$



OPT_G : value of maximum cut of G

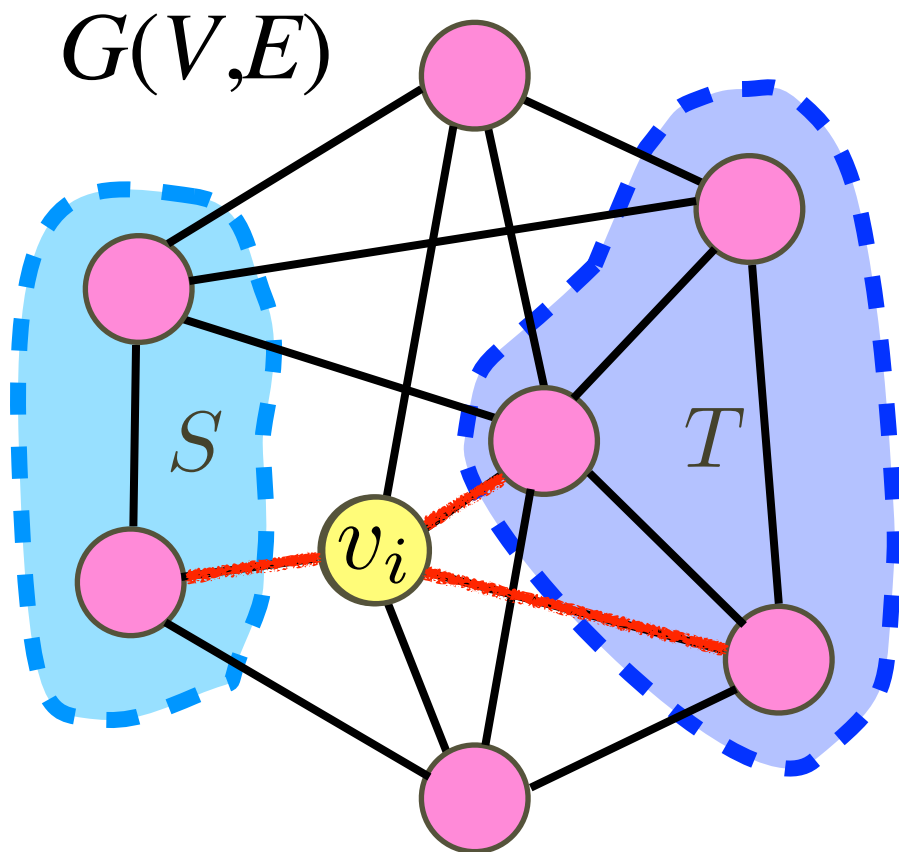
SOL_G : value of the cut returned by algorithm A on G

algorithm A has **approximation ratio** α if

$$\forall \text{ input } G, \quad \frac{\text{SOL}_G}{\text{OPT}_G} \geq \alpha$$

Approximation Algorithm

initially, $S=T=\emptyset$
for $i = 1, 2, \dots, n$
 v_i joins one of S, T
 to maximize **current** $E(S, T)$



$$E(S, T) = \{uv \in E \mid u \in S, v \in T\}$$

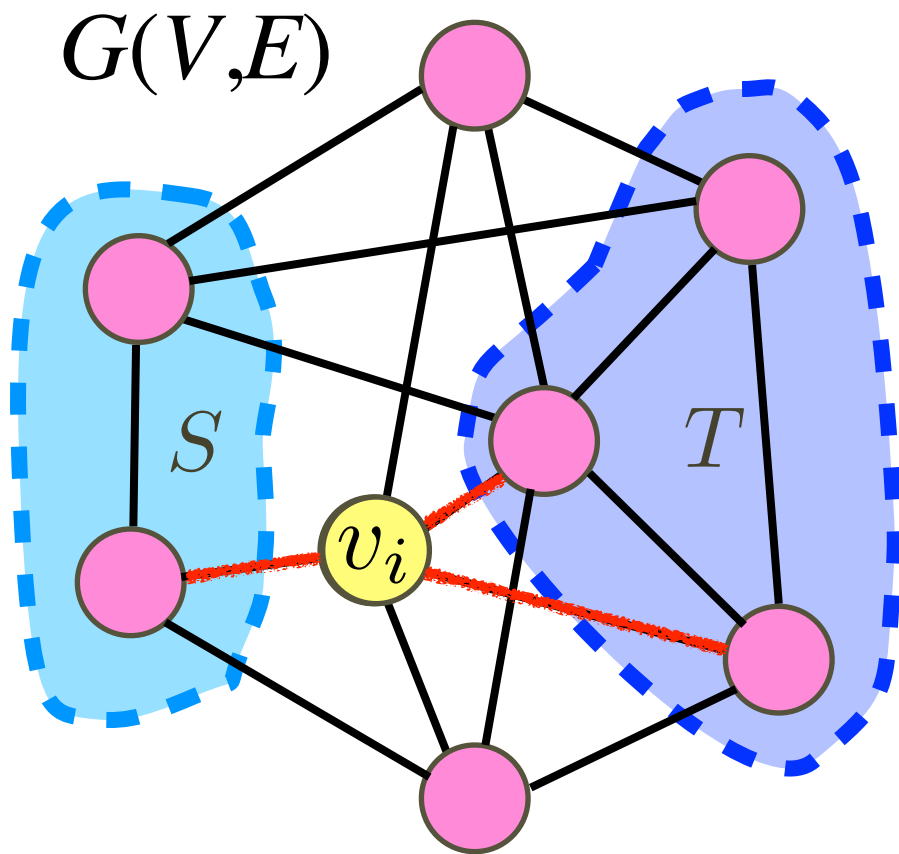
$$\frac{\text{SOL}_G}{\text{OPT}_G} \geq \frac{\text{SOL}_G}{|E|} \geq \frac{1}{2}$$

$\forall v_i, \geq 1/2$ of $|E(S_i, v_i)| + |E(T_i, v_i)|$
contributes to SOL_G

$$|E| = \sum_{i=1}^n (|E(S_i, v_i)| + |E(T_i, v_i)|)$$

Approximation Algorithm

initially, $S=T=\emptyset$
for $i = 1, 2, \dots, n$
 v_i joins one of S, T
 to maximize **current** $E(S, T)$



$$\frac{\text{SOL}_G}{\text{OPT}_G} \geq \frac{\text{SOL}_G}{|E|} \geq \frac{1}{2}$$

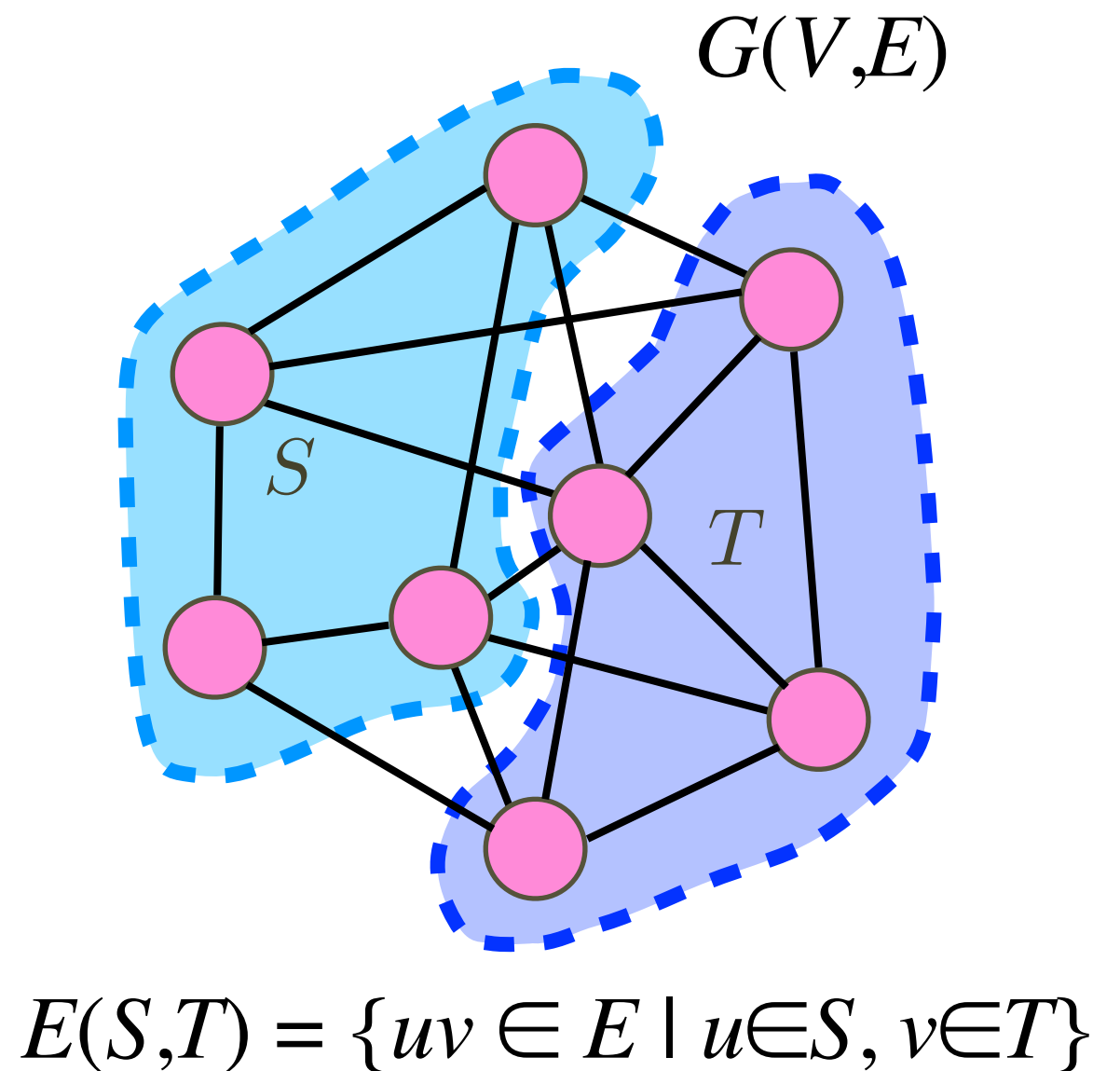
approximation ratio: $1/2$

running time: $O(m)$

$$E(S, T) = \{uv \in E \mid u \in S, v \in T\}$$

Max-Cut

- **Partition** V into two parts:
 S and T
- **Maximize** the **cut** $E(S,T)$
- **NP-hard**
 - one of Karp's 21 NP-complete problems
- greedy algorithm:
0.5-approximation



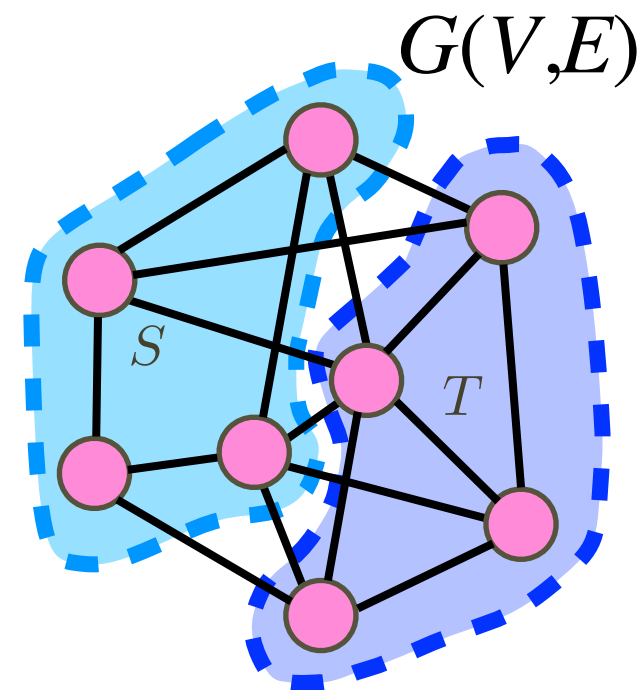
Random Cut

for each vertex $v \in V$

uniform & independent $Y_v \in \{0, 1\}$

$Y_v = 1 \Rightarrow v \in S$

$Y_v = 0 \Rightarrow v \in T$



for each edge $uv \in E$

$$Y_{uv} = \begin{cases} 1 & Y_u \neq Y_v \\ 0 & Y_u = Y_v \end{cases} \quad |E(S, T)| = \sum_{uv \in E} Y_{uv}$$

$$\mathbf{E}[|E(S, T)|] = \sum_{uv \in E} \Pr[Y_u \neq Y_v] = \frac{|E|}{2} \geq \frac{OPT}{2}$$

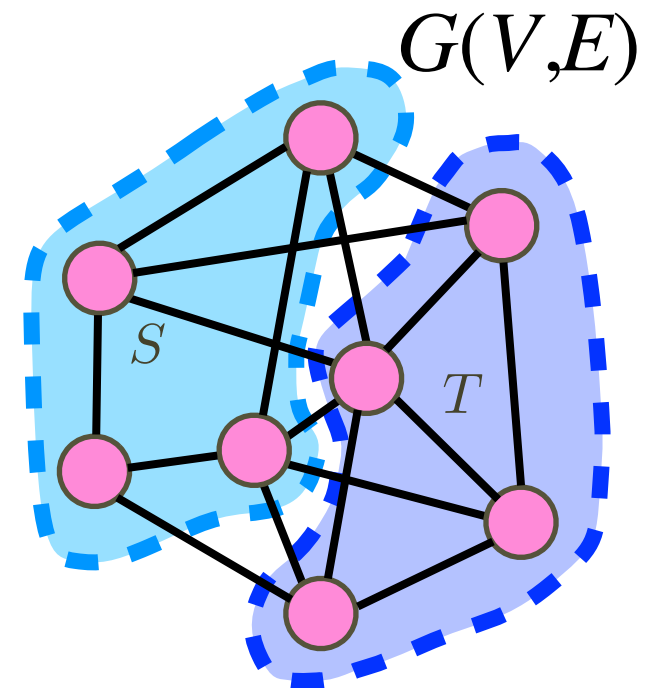
Random Cut

for each vertex $v \in V$

uniform & **2-wise** independent $Y_v \in \{0, 1\}$

$$Y_v = 1 \Rightarrow v \in S$$

$$Y_v = 0 \Rightarrow v \in T$$



for each edge $uv \in E$

$$Y_{uv} = \begin{cases} 1 & Y_u \neq Y_v \\ 0 & Y_u = Y_v \end{cases} \quad |E(S, T)| = \sum_{uv \in E} Y_{uv}$$

$$\mathbf{E}[|E(S, T)|] = \sum_{uv \in E} \Pr[Y_u \neq Y_v] = \frac{|E|}{2} \geq \frac{OPT}{2}$$

Definition:

Events $\mathcal{E}_1, \mathcal{E}_2, \dots, \mathcal{E}_n$ are **mutually independent** if for any subset $I \subseteq \{1, 2, \dots, n\}$,

$$\Pr [\bigwedge_{i \in I} \mathcal{E}_i] = \prod_{i \in I} \Pr[\mathcal{E}_i].$$

Definition:

Random variables X_1, X_2, \dots, X_n are **mutually independent** if for any subset $I \subset [n]$ and any values x_i , where $i \in I$,

$$\Pr [\bigwedge_{i \in I} (X_i = x_i)] = \prod_{i \in I} \Pr[X_i = x_i].$$

k -wise Independence

Definition:

Events $\mathcal{E}_1, \mathcal{E}_2, \dots, \mathcal{E}_n$ are k -wise independent if for any subset $I \subseteq \{1, 2, \dots, n\}$, with $|I| \leq k$

$$\Pr [\bigwedge_{i \in I} \mathcal{E}_i] = \prod_{i \in I} \Pr[\mathcal{E}_i].$$

Definition:

Random variables X_1, X_2, \dots, X_n are k -wise independent if for any subset $I \subset [n]$ and any values x_i , where $i \in I$, with $|I| \leq k$

$$\Pr [\bigwedge_{i \in I} (X_i = x_i)] = \prod_{i \in I} \Pr[X_i = x_i].$$

pairwise: 2-wise

2-wise Independent Bits

uniform & independent bits: (random source)

$$X_1, X_2, \dots, X_m \in \{0, 1\}$$

Goal: 2-wise independent uniform bits:

$$Y_1, Y_2, \dots, Y_n \in \{0, 1\} \quad n \gg m$$

a	b	$a \oplus b$
0	0	0
0	1	1
1	0	1
1	1	0

nonempty subsets:

$$\emptyset \neq S_1, S_2, \dots, S_{2^m-1} \subseteq \{1, 2, \dots, m\}$$

$$Y_j = \bigoplus_{i \in S_j} X_i$$

uniform & independent bits: $X_1, X_2, \dots, X_m \in \{0, 1\}$

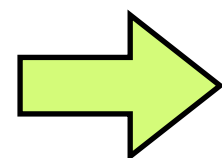
nonempty subsets: $S_1, S_2, \dots, S_{2^m-1} \subseteq \{1, 2, \dots, m\}$

$$Y_j = \bigoplus_{i \in S_j} X_i$$

2-wise independent **uniform** bits:

$$Y_1, Y_2, \dots, Y_{2^m-1} \in \{0, 1\}$$

$\log_2 n$ total random bits



$n-1$ pairwise independent bits

Derandomization

for each vertex $v \in V$

uniform & **2-wise** independent $Y_v \in \{0, 1\}$

$$Y_v = 1 \Rightarrow v \in S$$

$$Y_v = 0 \Rightarrow v \in T$$

for each edge $uv \in E$

$$\mathbf{E}[|E(S, T)|] = \sum_{uv \in E} \Pr[Y_u \neq Y_v] = \frac{|E|}{2} \geq \frac{OPT}{2}$$

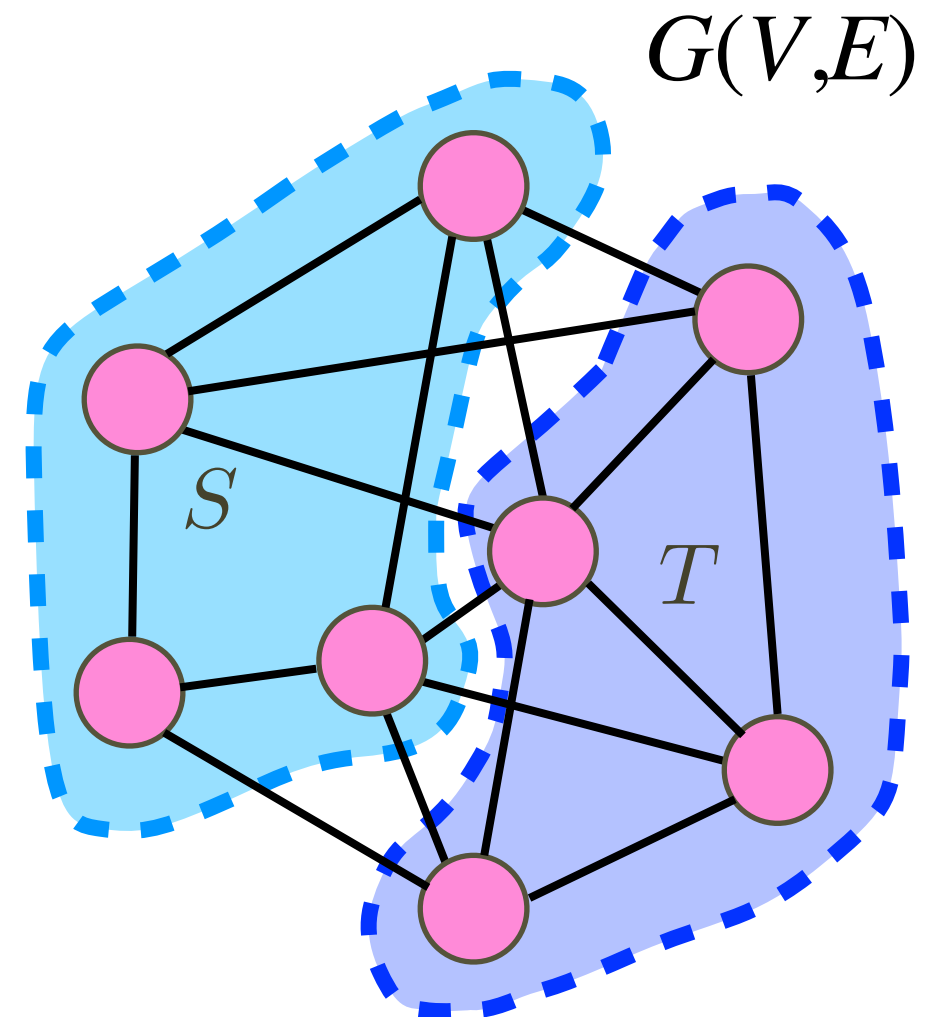
$$V = \{v_1, v_2, \dots, v_n\}$$

$Y_{v_1}, Y_{v_2}, \dots, Y_{v_n}$ constructed from $\lceil \log_2(n+1) \rceil$ bits

try all $2^{\lceil \log_2(n+1) \rceil} = O(n^2)$ possibilities!

Max-Cut

- **Partition** V into two parts:
 S and T
- **Maximize** the **cut** $E(S,T)$
- **NP-hard**
- greedy algorithm: **0.5-approx.**
- best known approx. ratio for poly-time algorithms: **0.878~**
- **unique game conjecture:**
no poly-time algorithm with approx. ratio $>0.878~$



$$E(S, T) = \{uv \in E \mid u \in S, v \in T\}$$