

Topics in Algorithmic Game Theory and Economics

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Lecture 10
Matroid Secretary Problems

Matroids (recap)

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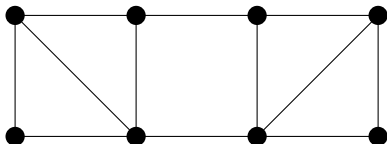
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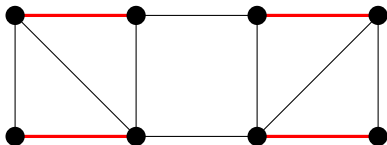


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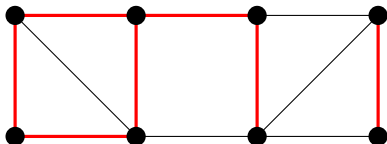


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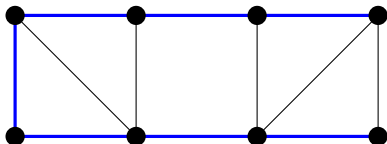


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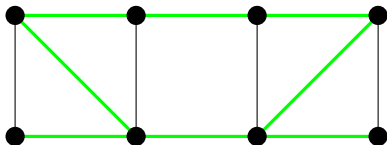


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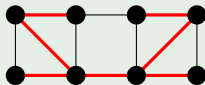
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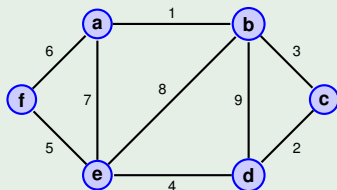
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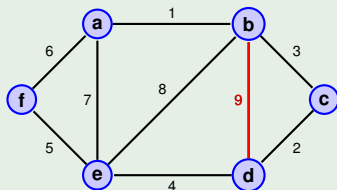
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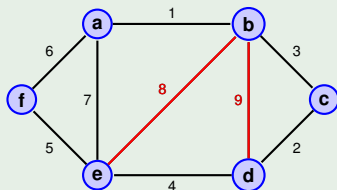
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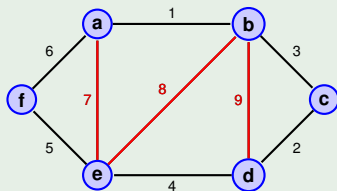
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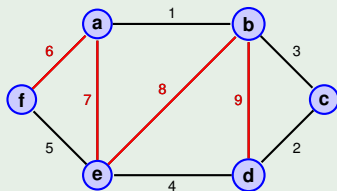
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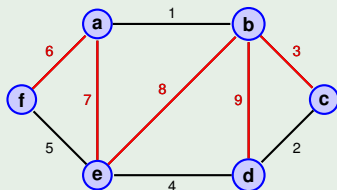
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- Would yield (another) generalization of secretary problem.

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$\Omega\left(\frac{1}{\log(r)}\right)$ -approximation

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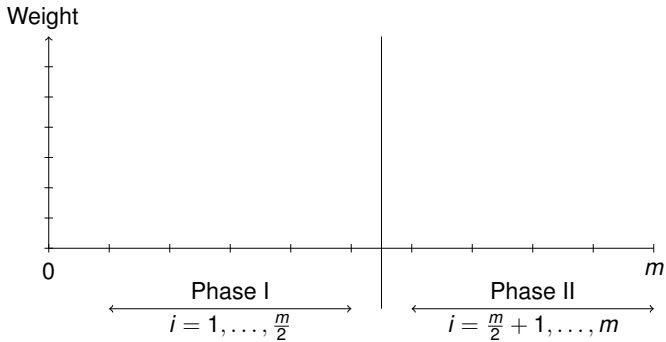
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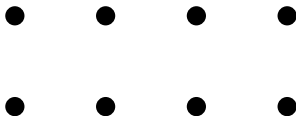
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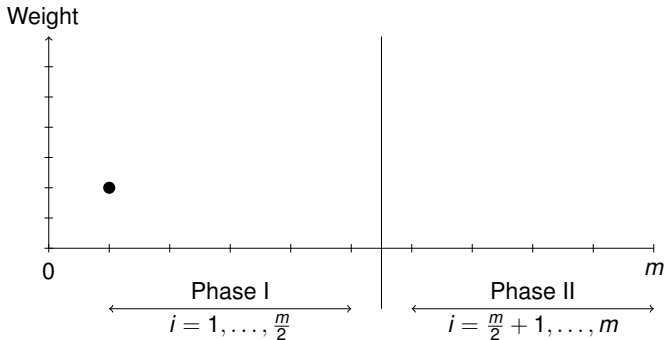
$$t = \frac{w}{2^j}.$$

- For $i = \frac{m}{2} + 1, \dots, m$: Select $\sigma(i)$ if $w_{\sigma(i)} \geq t$ and $X + \sigma(i) \in \mathcal{I}$.

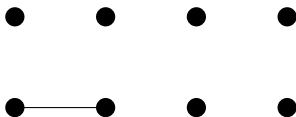


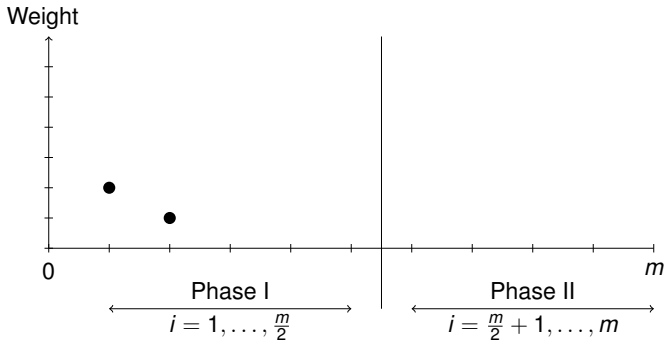
Consider graphic matroid as example:



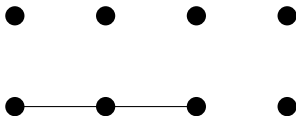


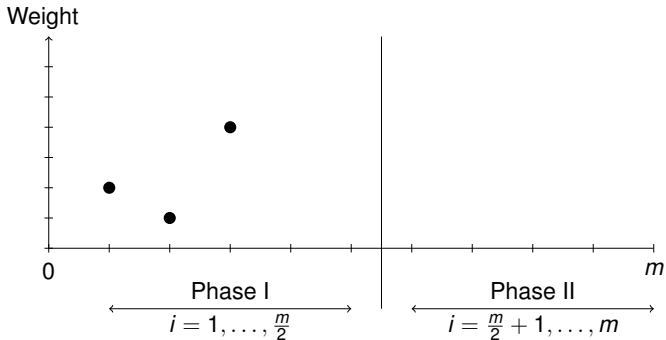
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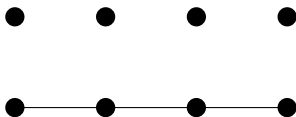


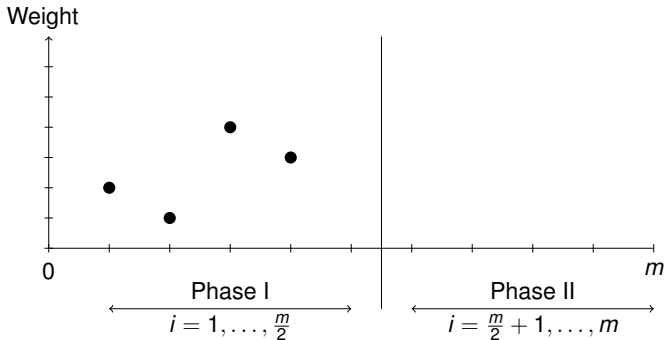
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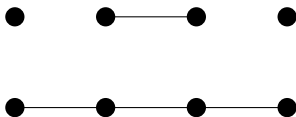


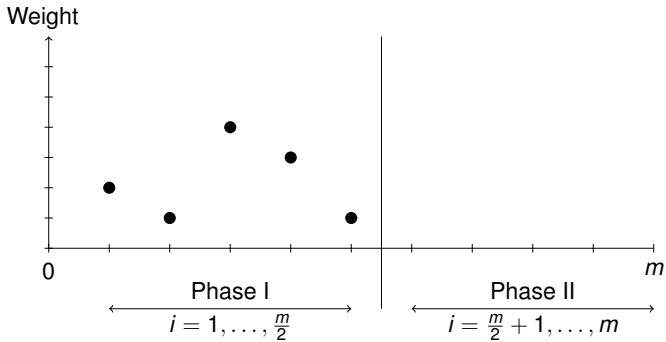
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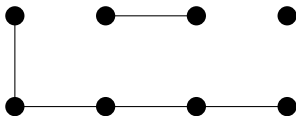


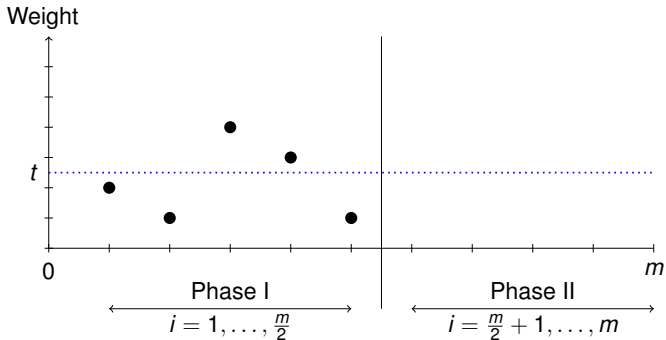
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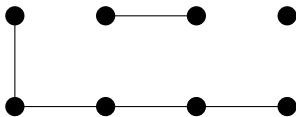


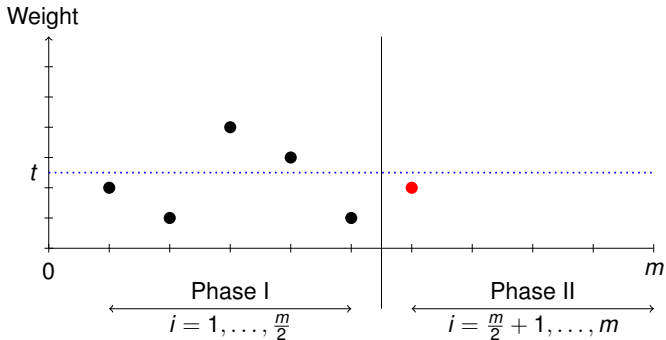
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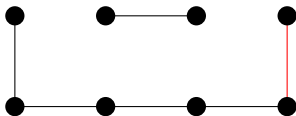


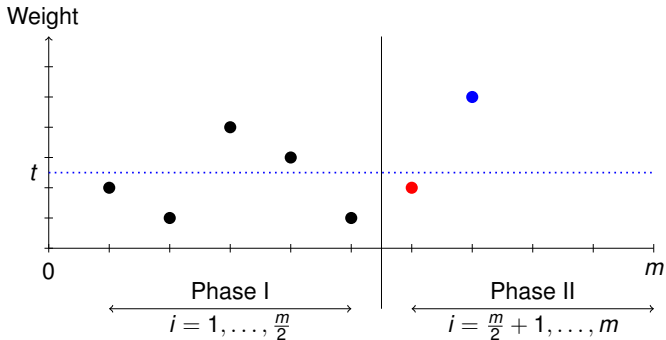
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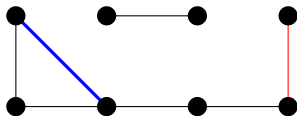


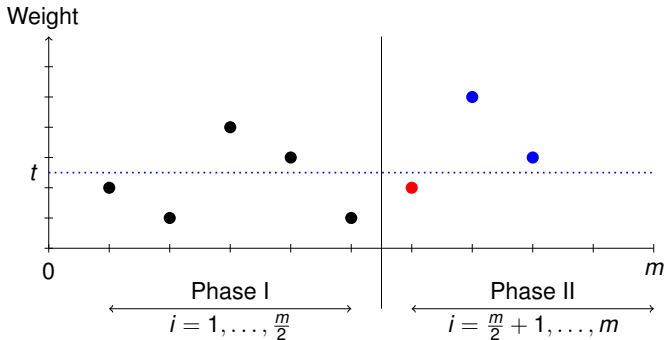
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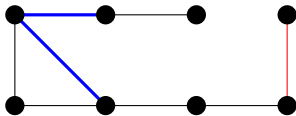


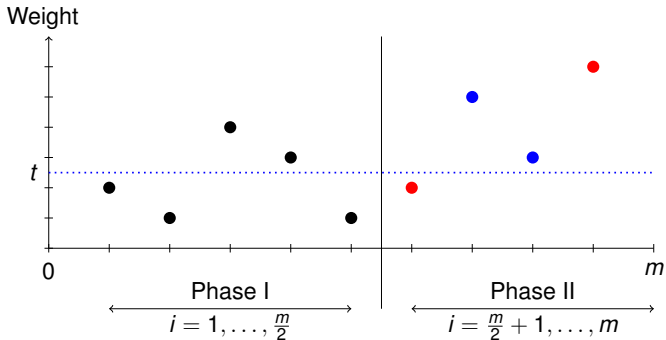
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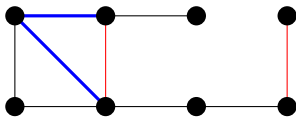


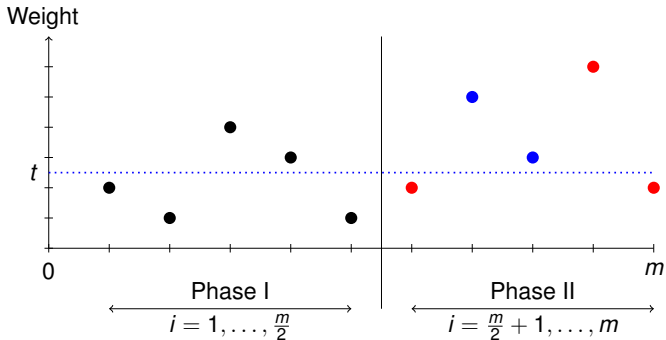
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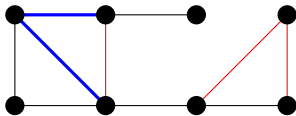


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Analysis (sketch)

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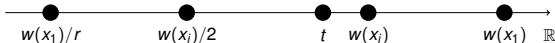
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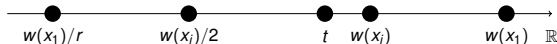
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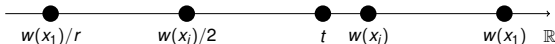
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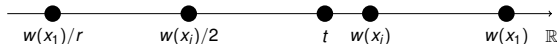
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Beyond matroids

Online selection problems

Consider

- Finite set of **elements** $E = \{e_1, \dots, e_m\}$.
- **Weight function** $w : E \rightarrow \mathbb{R}_{\geq 0}$.
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In general, for arbitrary downward-closed set systems, no constant-factor approximation exists.

Online selection for general systems

Theorem (Babai et al. (2007))

There is no randomized algorithm that, for every downward-closed set system $\mathcal{F} = (E, \mathcal{I})$ with m elements and (random) weights in $\{0, 1\}$, obtains an approximation guarantee better than $O(\ln \ln(n) / \ln(n))$.

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There is no randomized algorithm that, for every downward-closed set system $\mathcal{F} = (E, \mathcal{I})$ with m elements and (random) weights in $\{0, 1\}$, obtains an approximation guarantee better than $O(\ln \ln(n) / \ln(n))$.

Proof (very informal): Let $n \geq 0$ be an integer and set $r = \ln(n)$.

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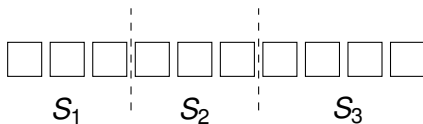
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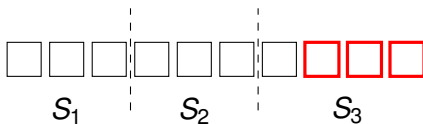
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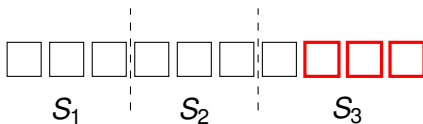
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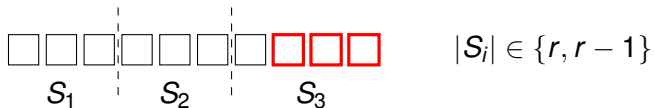


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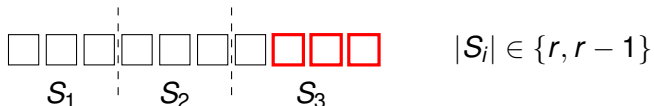
This set system is (structurally) very “far away” from a matroid.

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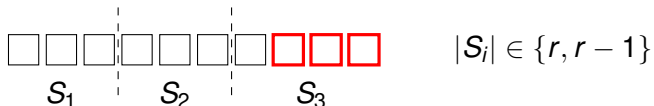


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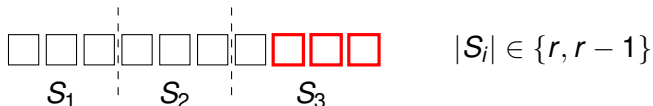
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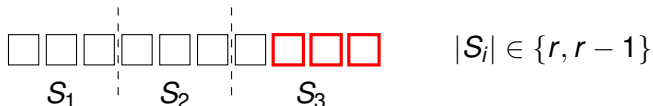


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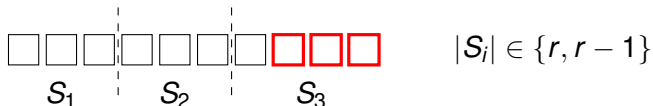
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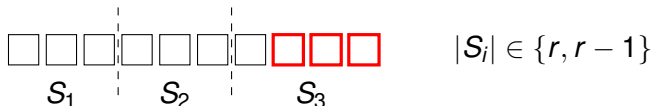
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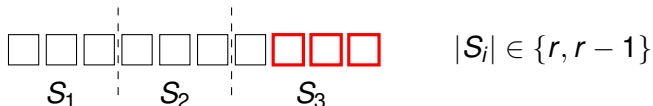
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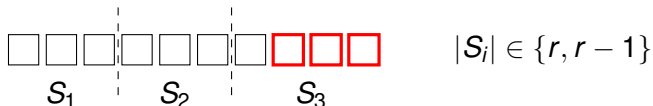
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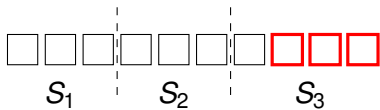
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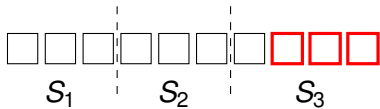
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- Therefore, set selected by \mathcal{A} has weight at most 2 in expectation.

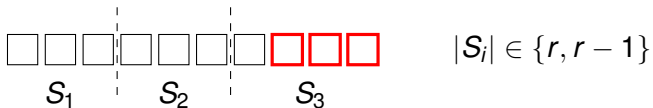


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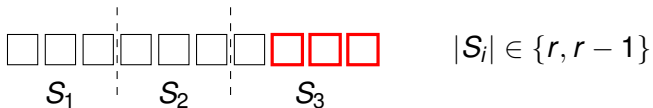
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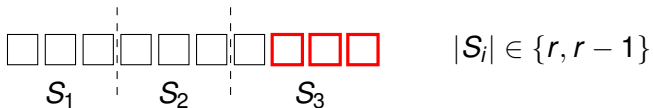
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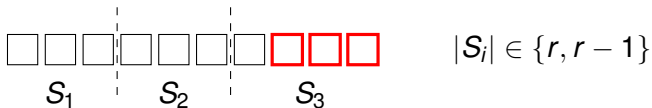


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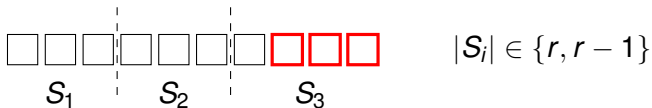
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- This is then tight up to a factor $\log \log(n)$.

Graphic matroid

Korula-Pál algorithm

Graphic matroid secretary problem

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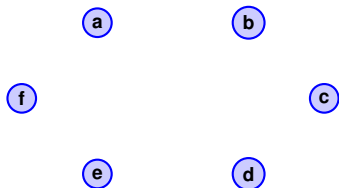
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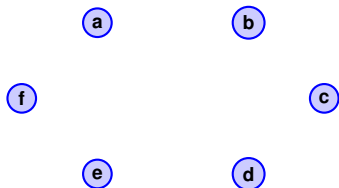


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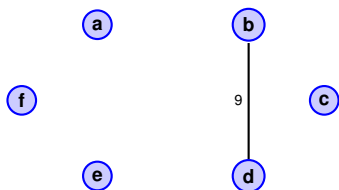


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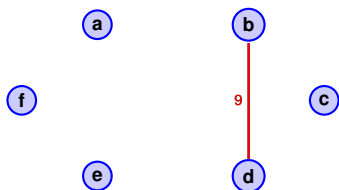


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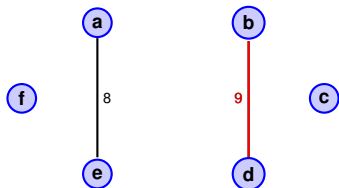


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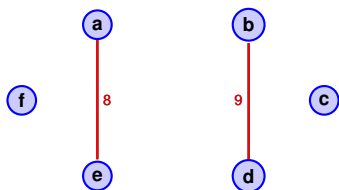


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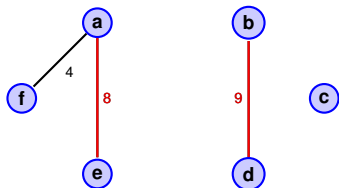


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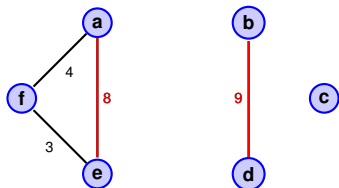


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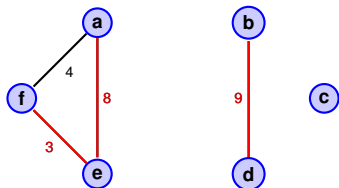


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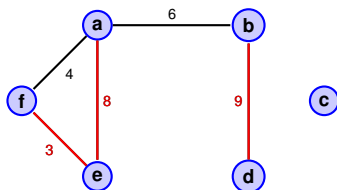


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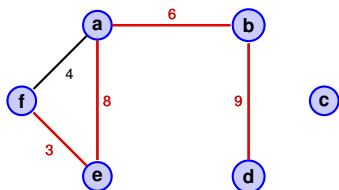


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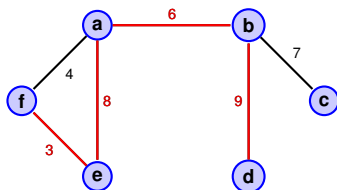


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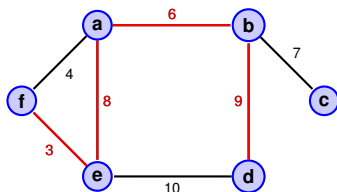


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- Decide irrevocably whether to accept or reject it.
 - Acceptance is only allowed if $X + e$ is forest of G .
 - That is, $X + e$ does not contain a cycle.

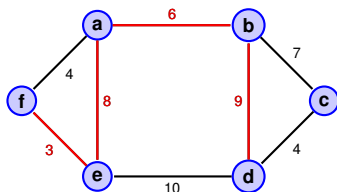


Graphic matroid secretary problem

For many special matroids, there exists a constant-factor approximation (often based on a reduction to secretary problems).

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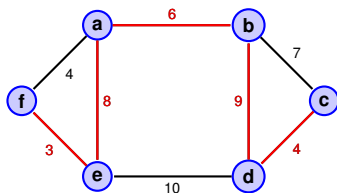


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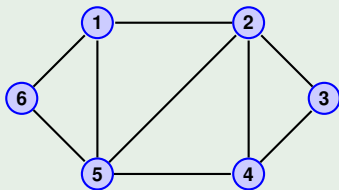
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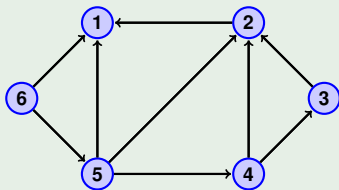
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- For every $z \in V$ at most one arc from every A_z is selected.

Example (Every edge oriented to lowest index node)



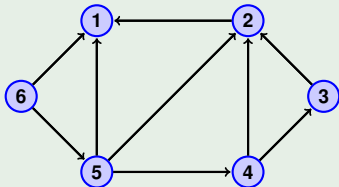
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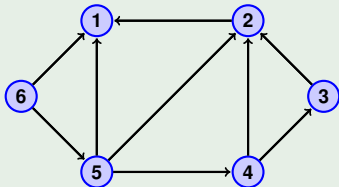
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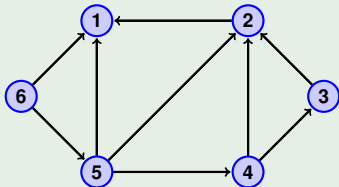
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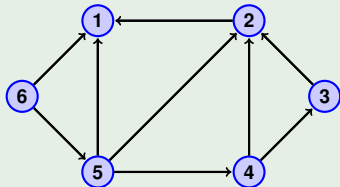
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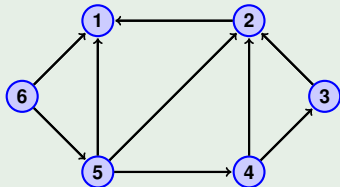
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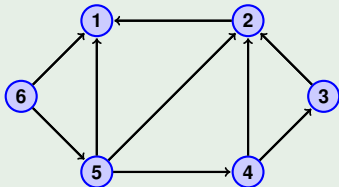
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Is there $\frac{1}{e}$ -approximation for graphic matroid secretary problem?