Part III

Approximation Algorithms

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- Exploit special structure of instances occurring in practise.
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- We need algorithms for hard problems.
- It gives a rigorous mathematical base for studying heuristics.
- It provides a metric to compare the difficulty of various optimization problems.
- Proving theorems may give a deeper theoretical understanding which in turn leads to new algorithmic approaches.

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Definition 3
An optimization problem $P = (\mathcal{I}, \mathrm{sol}, m, \mathrm{goal})$ is in **NPO** if

- $x \in \mathcal{I}$ can be decided in polynomial time
- $y \in \mathrm{sol}(\mathcal{I})$ can be verified in polynomial time
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In other words: the decision problem is there a solution y with $m(x, y)$ at most/at least z is in NP.

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- y is candidate solution
- $m^*(x)$ cost/profit of an optimal solution

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$$R(x,y) := \max\left\{\frac{m(x,y)}{m^*(x)}, \frac{m^*(x)}{m(x,y)}\right\}$$

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An algorithm A is an r-approximation algorithm iff

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A PTAS for a problem P from NPO is an algorithm that takes as input $x \in \mathcal{I}$ and $\epsilon > 0$ and produces a solution y for x with

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- Set Cover
- Minimum Multicut
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Class APX not important in practise.

Instead of saying problem P is in APX one says problem P admits a 4-approximation.

One only says that a problem is APX-hard.

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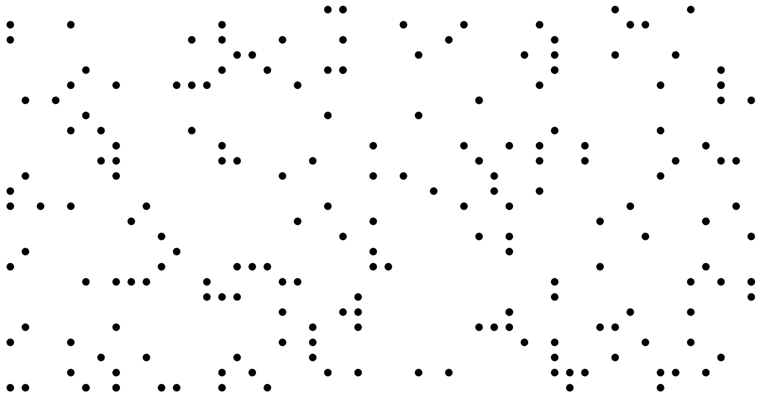

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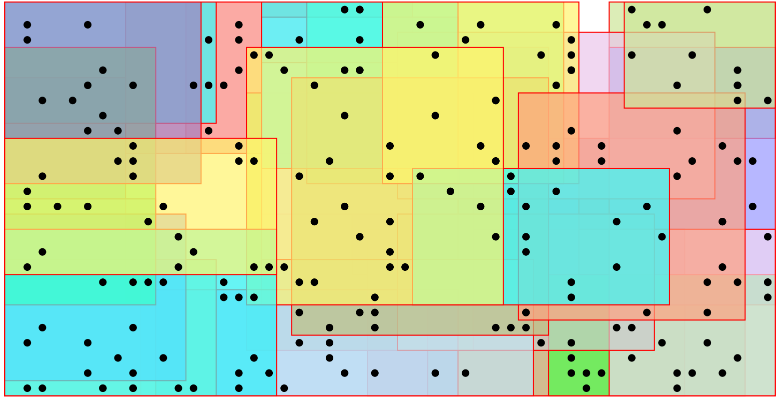

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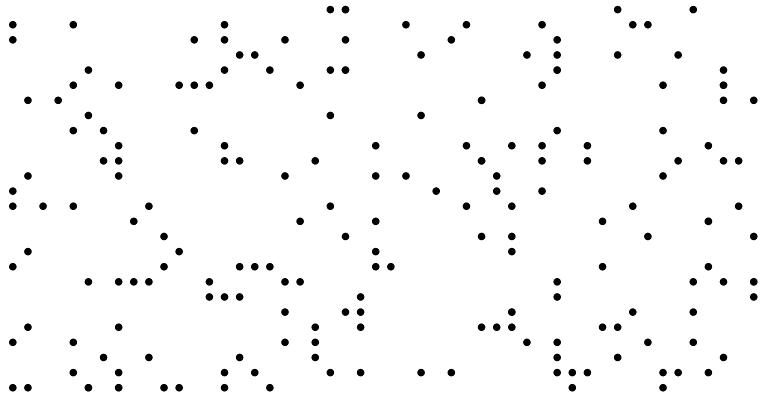

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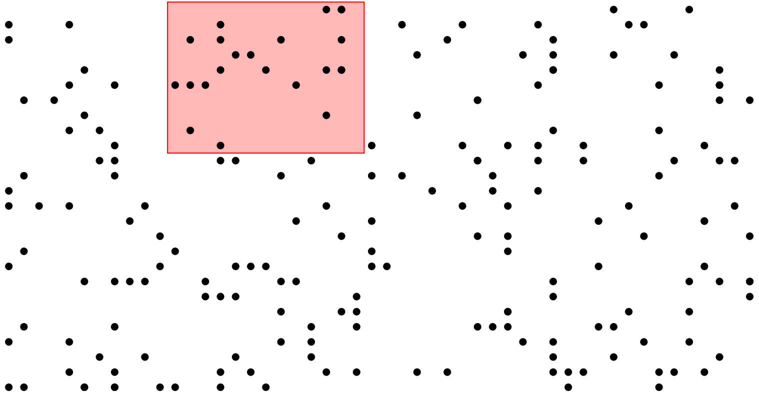

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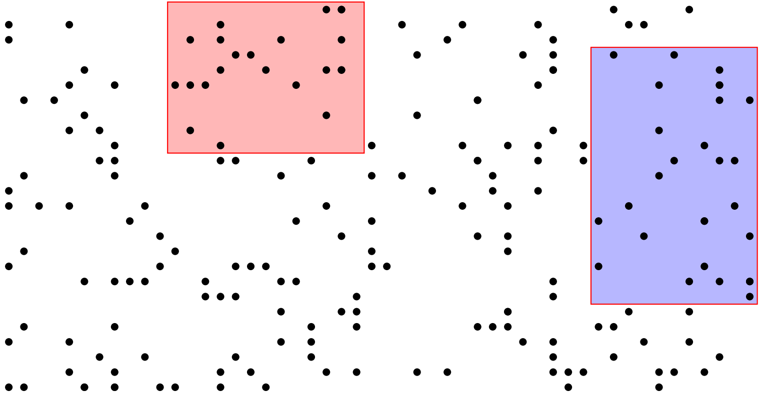

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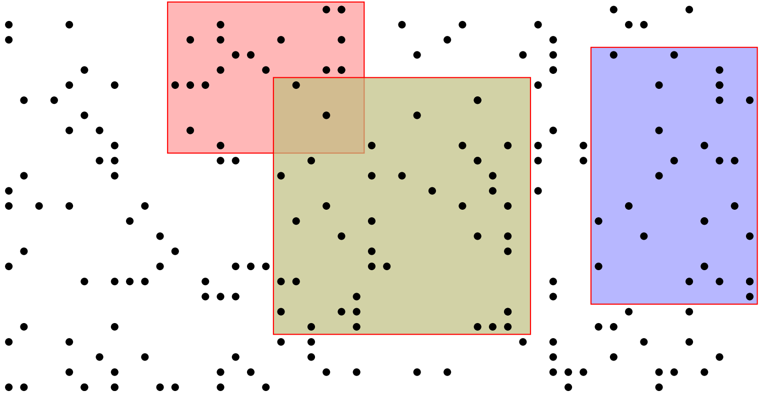

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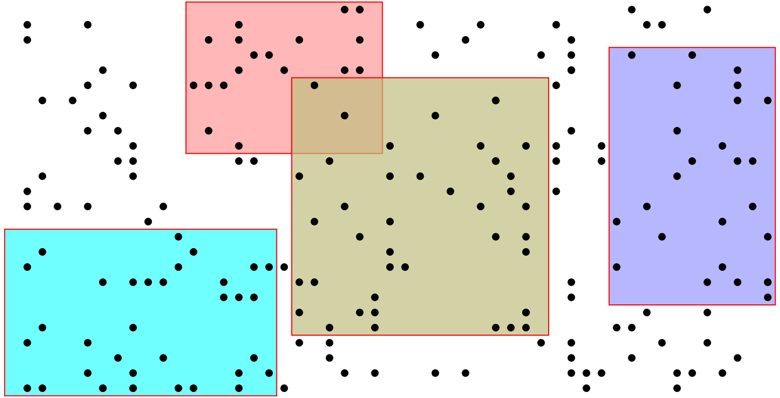

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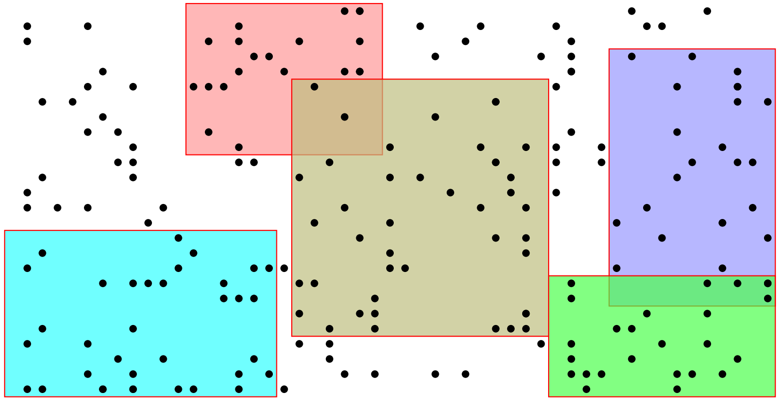

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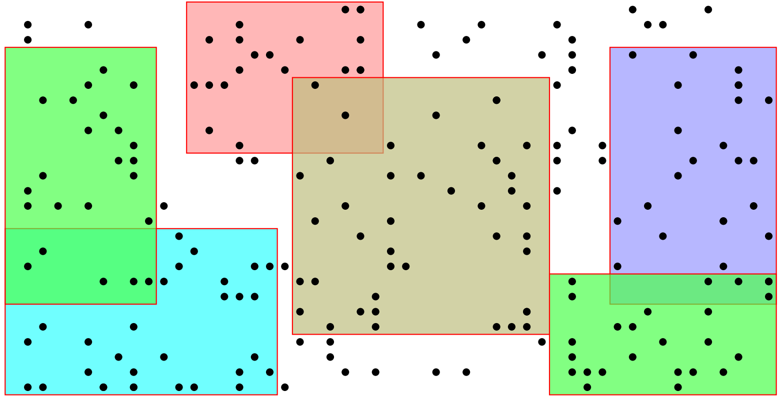

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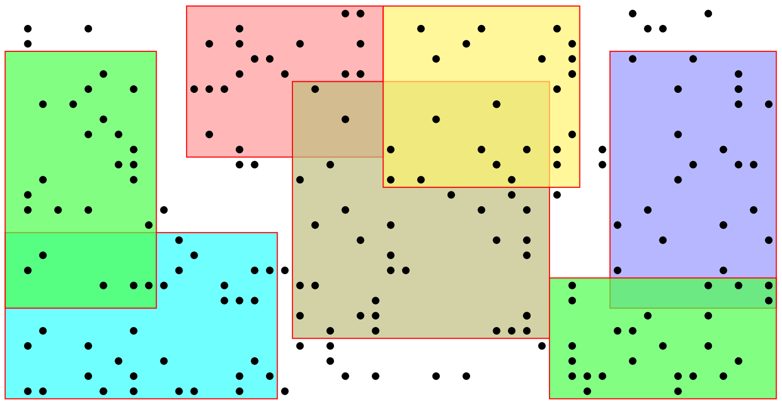

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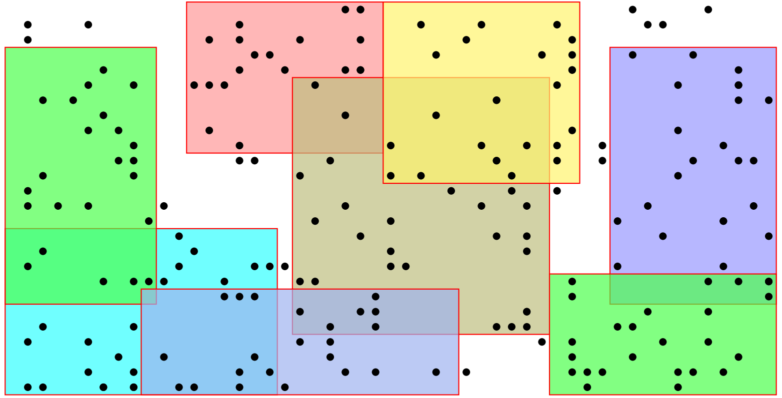

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EADS II
Harald Räcke
12 Integer Programs

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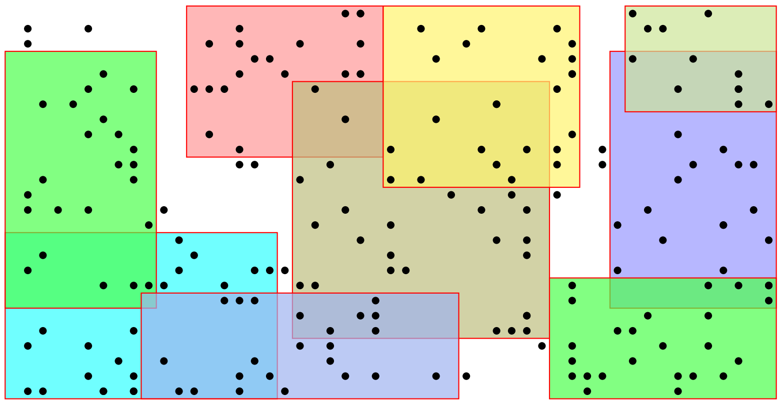

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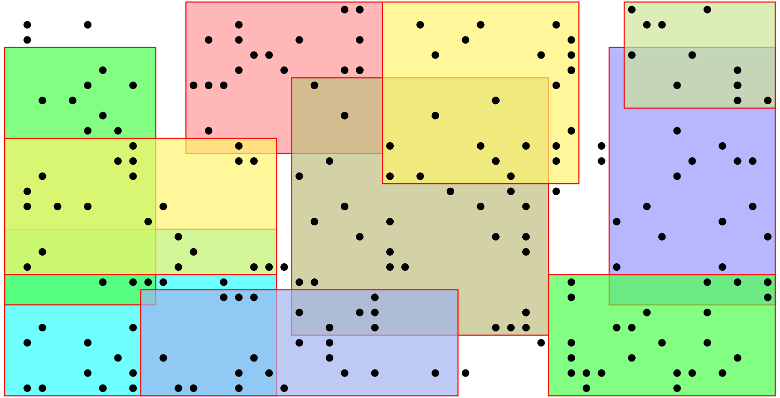

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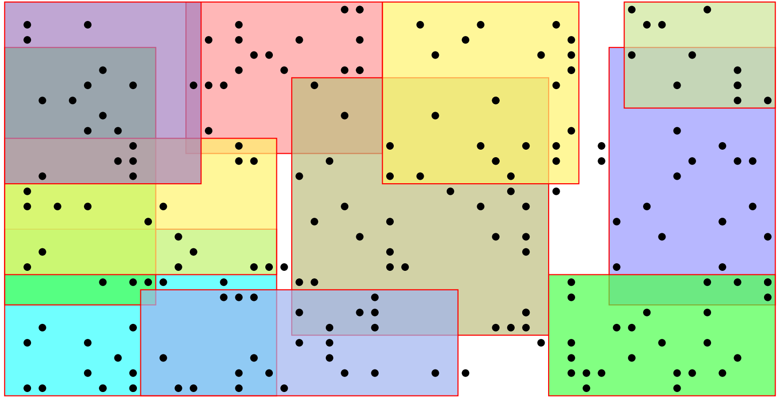

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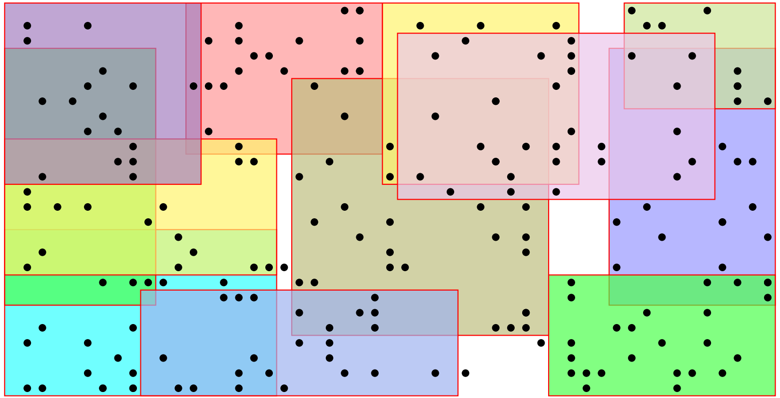

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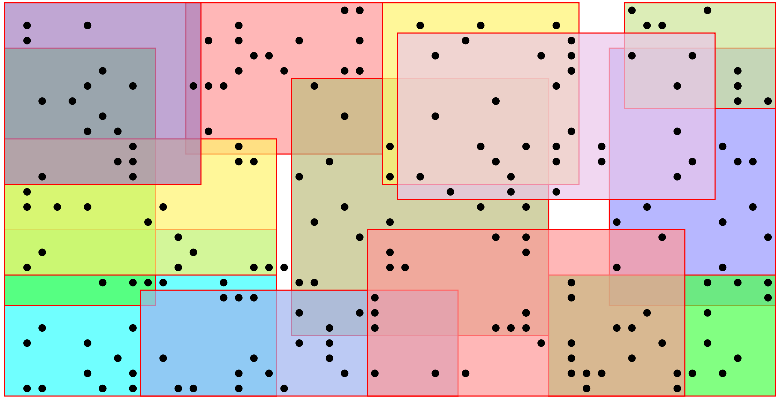

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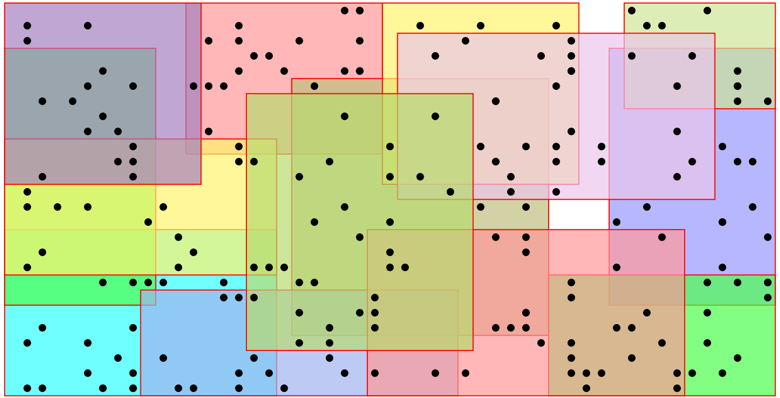
Set Cover



Set Cover

Given a ground set U, a collection of subsets $S_1, \dots, S_k \subseteq U$, where the i-th subset S_i has weight/cost w_i. Find a collection $I \subseteq \{1, \dots, k\}$ such that

$$\forall u \in U \exists i \in I: \; u \in S_i \quad \text{(every element is covered)}$$

and

$$\sum_{i \in I} w_i \quad \text{is minimized.}$$

IP-Formulation of Set Cover

$$
\begin{array}{lrcrr}
\min & & \sum_i w_i x_i & & \\
\text{s.t.} & \forall u \in U & \sum_{i:u\in S_i} x_i & \geq & 1 \\
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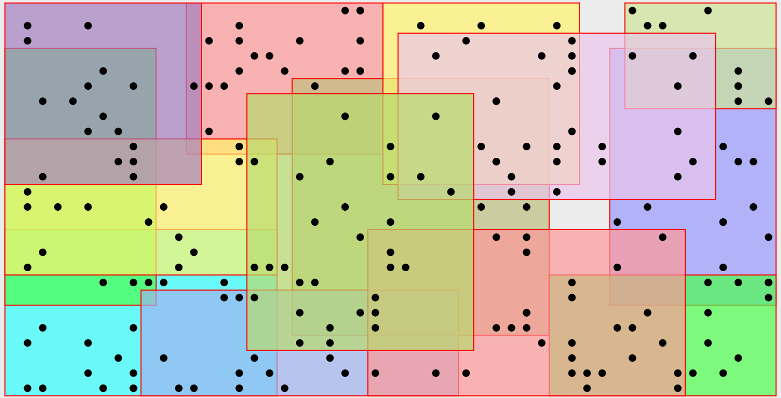

Vertex Cover

Given a graph $G = (V, E)$ and a weight w_v for every node. Find a vertex subset $S \subseteq V$ of minimum weight such that every edge is incident to at least one vertex in S.

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Maximum Weighted Matching

Given a graph $G = (V, E)$, and a weight w_e for every edge $e \in E$. Find a subset of edges of maximum weight such that no vertex is incident to more than one edge.

$$\begin{array}{llrcl} \max & & \sum_{e\in E} w_e x_e & & \\ \text{s.t.} & \forall v \in V & \sum_{e:v\in e} x_e & \leq & 1 \\ & \forall e \in E & x_e & \in & \{0,1\} \end{array}$$

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Knapsack

Given a set of items $\{1,\dots,n\}$, where the i-th item has weight w_i and profit p_i, and given a threshold K. Find a subset $I \subseteq \{1,\dots,n\}$ of items of total weight at most K such that the profit is maximized.

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Relaxations

Definition 12
A linear program LP is a relaxation of an integer program IP if any feasible solution for IP is also feasible for LP and if the objective values of these solutions are identical in both programs.

We obtain a relaxation for all examples by writing $x_i \in [0,1]$ instead of $x_i \in \{0,1\}$.

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By solving a relaxation we obtain an upper bound for a maximization problem and a lower bound for a minimization problem.

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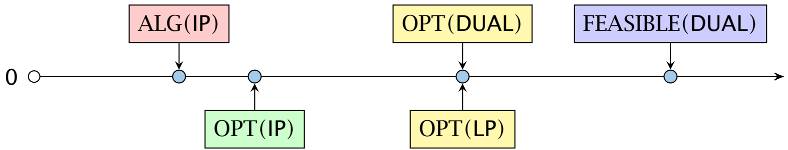
Relations

Maximization Problems:



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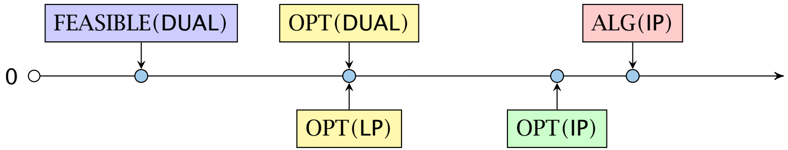

By solving a relaxation we obtain an upper bound for a maximization problem and a lower bound for a minimization problem.

Technique 1: Round the LP solution.

We first solve the LP-relaxation and then we round the fractional values so that we obtain an integral solution.

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Let f_u be the number of sets that the element u is contained in (the frequency of u). Let $f = \max_u \{f_u\}$ be the maximum frequency.

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Set all x_i-values with $x_i \geq \frac{1}{f}$ to 1. Set all other x_i-values to 0.

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Lemma 13
The rounding algorithm gives an f-approximation.

Proof: Every $u \in U$ is covered.

- We know that $\sum_{i: u \in S_i} x_i \ge 1$.
- The sum contains at most $f_u \le f$ elements.
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Dual:

$$\begin{array}{lrl} \max & \sum_{u\in U} y_u & \\ \text{s.t. } \forall i & \sum_{u:u\in S_i} y_u & \leq w_i \\ & y_u & \geq 0 \end{array}$$

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The resulting index set is an f-approximation.

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Technique 2: Rounding the Dual Solution.

Lemma 14
The resulting index set is an f-approximation.

Proof:
Every $u \in U$ is covered.

- Suppose there is a u that is not covered.
- This means $\sum_{u:u\in S_i} y_u < w_i$ for all sets S_i that contain u.
- But then y_u could be increased in the dual solution without violating any constraint. This is a contradiction to the fact that the dual solution is optimal.

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This means I' is never better than I.

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Technique 3: The Primal Dual Method

The previous two rounding algorithms have the disadvantage that it is necessary to solve the LP. The following method also gives an f-approximation without solving the LP.

For estimating the cost of the solution we only required two properties.

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Algorithm 1 PrimalDual

1: $y \leftarrow 0$
2: $I \leftarrow \emptyset$
3: **while** exists $u \notin \bigcup_{i\in I} S_i$ **do**
4: increase dual variable y_u until constraint for some new set S_ℓ becomes tight
5: $I \leftarrow I \cup \{\ell\}$

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Algorithm 1 Greedy

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2: $\hat{S}_j \leftarrow S_j \quad$ for all j
3: **while** I not a set cover **do**
4: $\quad \ell \leftarrow \arg\min_{j:\hat{S}_j \neq 0} \frac{w_j}{|\hat{S}_j|}$
5: $\quad I \leftarrow I \cup \{\ell\}$
6: $\quad \hat{S}_j \leftarrow \hat{S}_j - S_\ell \quad$ for all j

In every round the Greedy algorithm takes the set that covers remaining elements in the most cost-effective way.

We choose a set such that the ratio between cost and still uncovered elements in the set is minimized.

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Lemma 15
Given positive numbers $a_1, \dots, a_k$ *and* $b_1, \dots, b_k$*, and* $S \subseteq \{1, \dots, k\}$ *then*

$$\min_i \frac{a_i}{b_i} \leq \frac{\sum_{i \in S} a_i}{\sum_{i \in S} b_i} \leq \max_i \frac{a_i}{b_i}$$

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Let n_ℓ denote the number of elements that remain at the beginning of iteration ℓ. $n_1 = n = |U|$ and $n_{s+1} = 0$ if we need s iterations.

In the ℓ-th iteration

$$\min_j \frac{w_j}{|\tilde{S}_j|} \le \frac{\sum_{j\in\mathrm{OPT}} w_j}{\sum_{j\in\mathrm{OPT}} |\tilde{S}_j|} = \frac{\mathrm{OPT}}{\sum_{j\in\mathrm{OPT}} |\tilde{S}_j|} \le \frac{\mathrm{OPT}}{n_\ell}$$

since an optimal algorithm can cover the remaining n_ℓ elements with cost OPT.

Let $\hat{S}_j$ be a subset that minimizes this ratio. Hence, $w_j/|\hat{S}_j| \le \frac{\mathrm{OPT}}{n_\ell}$.

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Adding this set to our solution means $n_{\ell+1} = n_\ell - |\hat{S}_j|$.

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$$\sum_{j\in I} w_j \le \sum_{\ell=1}^{s} \frac{n_\ell - n_{\ell+1}}{n_\ell} \cdot \mathrm{OPT}$$
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$$\begin{aligned}\sum_{j\in I} w_j &\le \sum_{\ell=1}^{s} \frac{n_\ell - n_{\ell+1}}{n_\ell}\cdot \mathrm{OPT}\\ &\le \mathrm{OPT}\sum_{\ell=1}^{s}\left(\frac{1}{n_\ell}+\frac{1}{n_\ell - 1}+\cdots+\frac{1}{n_{\ell+1}+1}\right)\\ &= \mathrm{OPT}\sum_{i=1}^{k}\frac{1}{i}\\ &= H_n\cdot \mathrm{OPT} \le \mathrm{OPT}(\ln n + 1)\ .\end{aligned}$$

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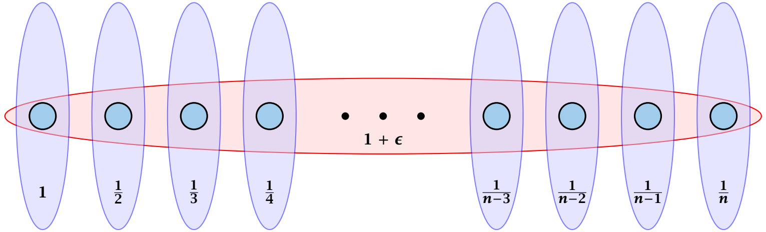
A tight example:



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Technique 5: Randomized Rounding

One round of randomized rounding:
Pick set S_j uniformly at random with probability $1 - x_j$ (for all j).

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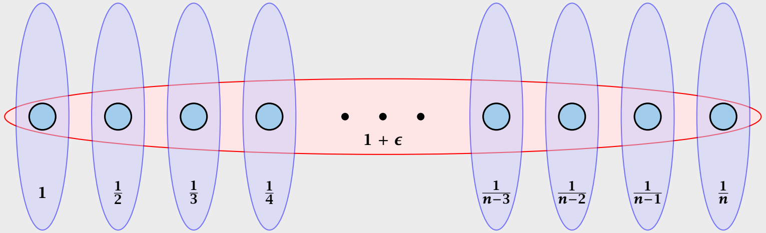

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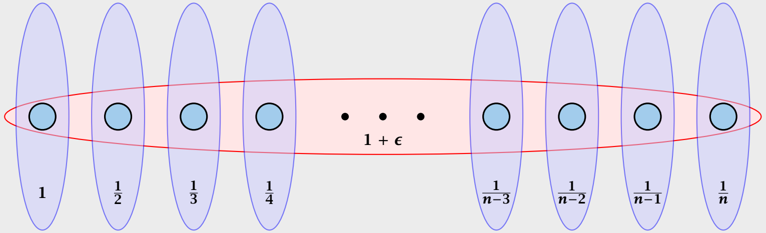

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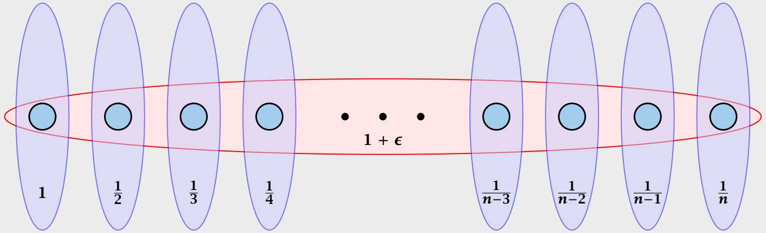

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Lemma 16
With high probability $\mathcal{O}(\log n)$ rounds suffice.

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With high probability $\mathcal{O}(\log n)$ *rounds suffice.*

With high probability:

For any constant α the number of rounds is at most $\mathcal{O}(\log n)$ with probability at least $1 - n^{-\alpha}$.

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Probability that $u \in U$ is not covered (after ℓ rounds):

$$\Pr[u \text{ not covered after } \ell \text{ round}] \leq \frac{1}{e^\ell} .$$

Proof: We have

$$\Pr[\#\text{rounds} \geq (\alpha+1)\ln n] \leq ne^{-(\alpha+1)\ln n} = n^{-\alpha} .$$

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  Repeat for $s = (\alpha + 1)\ln n$ rounds. If you don't have a cover simply take for each element u the cheapest set that contains u.

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  $$E[\text{cost}] \le (\alpha+1)\ln n \cdot \text{cost}(LP) + (n \cdot \text{OPT}) n^{-\alpha}$$

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$$E[\text{cost}] =$$

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E[\text{cost}] &= \Pr[\text{success}] \cdot E[\text{cost} \mid \text{success}] \\
&\quad + \Pr[\text{no success}] \cdot E[\text{cost} \mid \text{no success}]
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for $n \ge 2$ and $\alpha \ge 1$.

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Randomized rounding gives an $\mathcal{O}(\log n)$ approximation. The running time is polynomial with high probability.

Theorem 17 (without proof)

There is no approximation algorithm for set cover with approximation guarantee better than $\frac{1}{2}\log n$ unless NP has quasi-polynomial time algorithms (algorithms with running time $2^{\mathrm{poly}(\log n)}$).

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Integrality Gap

The integrality gap of the SetCover LP is $\Omega(\log n)$.

- $n = 2^k - 1$
- Elements are all vectors $\vec{x}$ over $GF[2]$ of length k (excluding zero vector).
- Every vector $\vec{y}$ defines a set as follows

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- each set contains 2^{k-1} vectors; each vector is contained in 2^{k-1} sets
- $x_i = \frac{1}{2^{k-1}} = \frac{2}{n+1}$ is fractional solution.

Randomized rounding gives an $\mathcal{O}(\log n)$ approximation. The running time is polynomial with high probability.

Theorem 17 (without proof)

There is no approximation algorithm for set cover with approximation guarantee better than $\frac{1}{2}\log n$ unless NP has quasi-polynomial time algorithms (algorithms with running time $2^{\text{poly}(\log n)}$).

Integrality Gap

Every collection of $p < k$ sets does not cover all elements.

Hence, we get a gap of $\Omega(\log n)$.

Integrality Gap

The integrality gap of the SetCover LP is $\Omega(\log n)$.

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Techniques:

- Deterministic Rounding
- Rounding of the Dual
- Primal Dual
- Greedy
- Randomized Rounding
- Local Search
- Rounding Data + Dynamic Programming

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Scheduling Jobs on Identical Parallel Machines

Given n jobs, where job $j \in \{1, \ldots, n\}$ has processing time p_j. Schedule the jobs on m identical parallel machines such that the Makespan (finishing time of the last job) is minimized.

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\begin{array}{llrcl}
\min & & & L & \\
\text{s.t.} & \forall \text{machines } i & \sum_j p_j \cdot x_{j,i} & \le & L \\
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Here the variable $x_{j,i}$ is the decision variable that describes whether job j is assigned to machine i.

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Lower Bounds on the Solution

Let for a given schedule C_j denote the finishing time of machine j, and let $C_{\max}$ be the makespan.

Let $C^*_{\max}$ denote the makespan of an optimal solution.

Clearly

$$C^*_{\max} \geq \max_j p_j$$

as the longest job needs to be scheduled somewhere.

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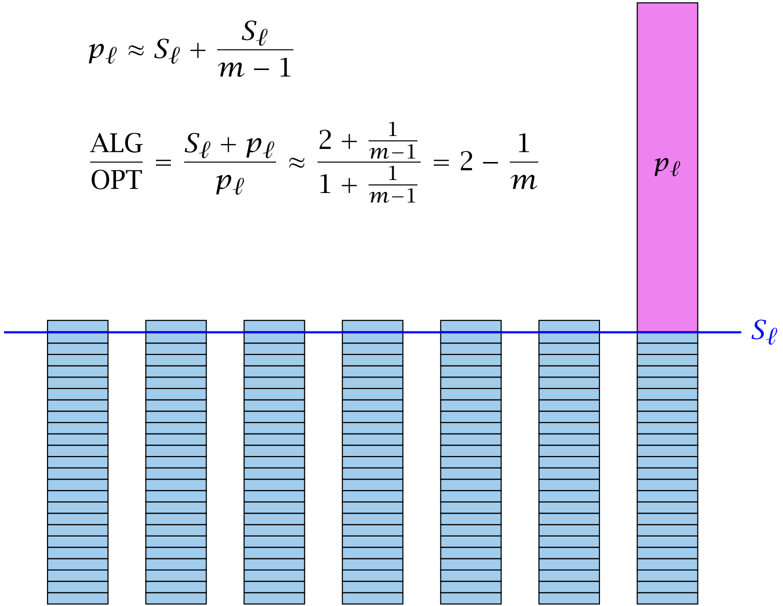
$$p_\ell \approx S_\ell + \frac{S_\ell}{m-1}$$

$$\frac{\mathrm{ALG}}{\mathrm{OPT}} = \frac{S_\ell + p_\ell}{p_\ell} \approx \frac{2+\frac{1}{m-1}}{1+\frac{1}{m-1}} = 2 - \frac{1}{m}$$



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A Greedy Strategy

List Scheduling:
Order all processes in a list. When a machine runs empty assign the next yet unprocessed job to it.

Alternatively:
Consider processes in some order. Assign the i-th process to the least loaded machine.

It is easy to see that the result of these greedy strategies fulfill the local optimally condition of our local search algorithm. Hence, these also give 2-approximations.

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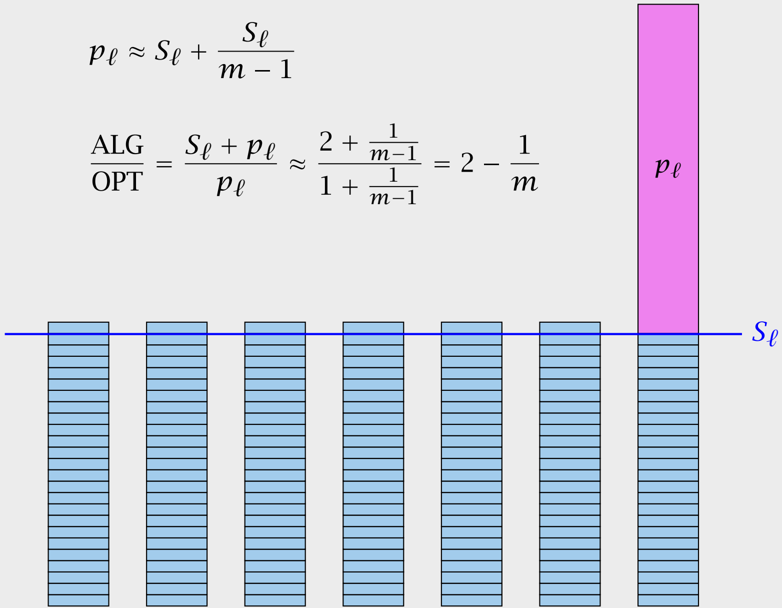

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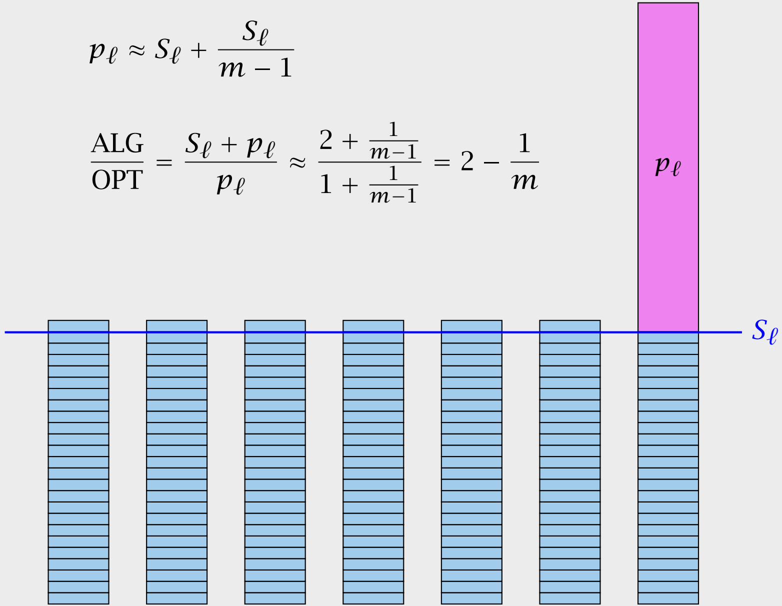

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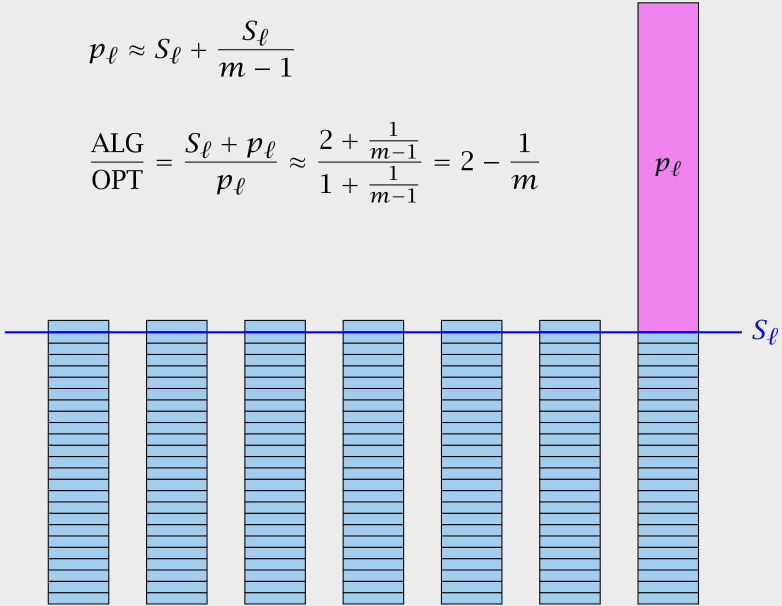

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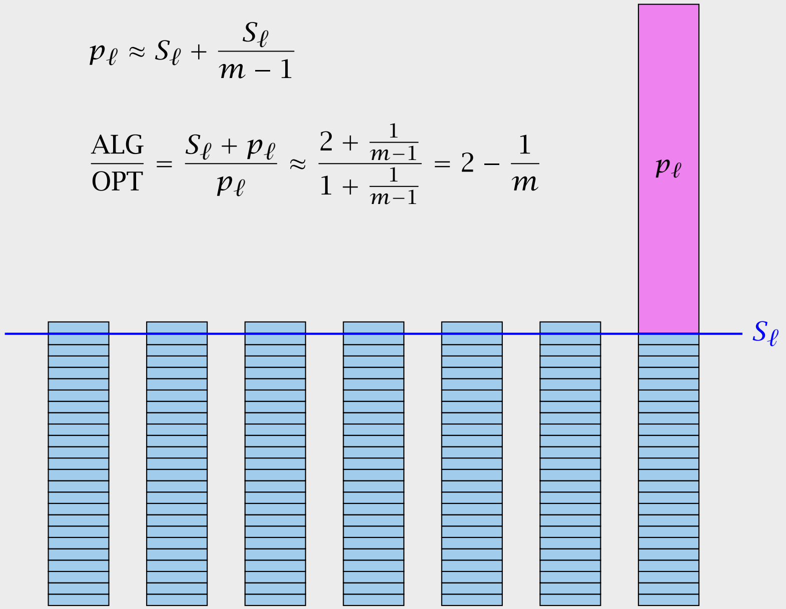

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If we order the list according to non-increasing processing times the approximation guarantee of the list scheduling strategy improves to $4/3$.

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Proof:

- Let $p_1 \geq \cdots \geq p_n$ denote the processing times of a set of jobs that form a counter-example.
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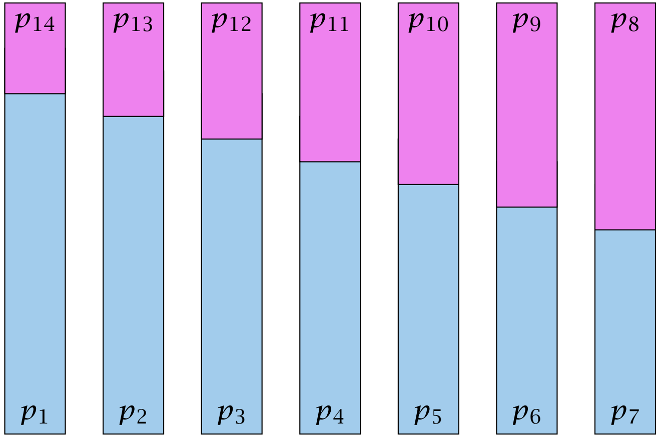
When in an optimal solution a machine can have at most 2 jobs the optimal solution looks as follows.



Proof:

- Let $p_1 \geq \cdots \geq p_n$ denote the processing times of a set of jobs that form a counter-example.
- Wlog. the last job to finish is n (otw. deleting this job gives another counter-example with fewer jobs).
- If $p_n \leq C^*_{\max}/3$ the previous analysis gives us a schedule length of at most

$$C^*_{\max} + p_n \leq \frac{4}{3} C^*_{\max} \ .$$

  Hence, $p_n > C^*_{\max}/3$.
- This means that all jobs must have a processing time $> C^*_{\max}/3$.
- But then any machine in the optimum schedule can handle at most two jobs.
- For such instances Longest-Processing-Time-First is optimal.

- We can assume that one machine schedules p_1 and p_n (the largest and smallest job).
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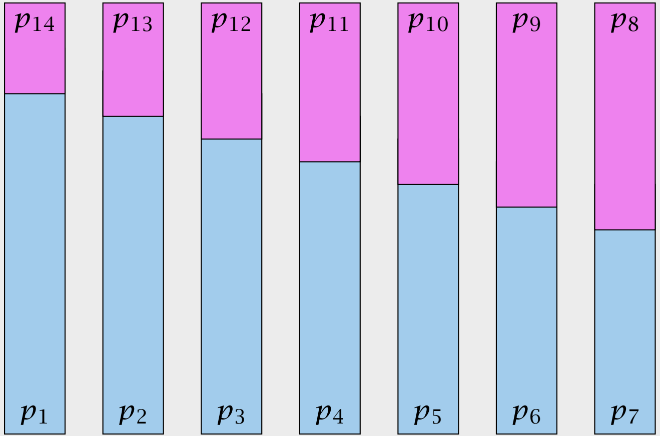

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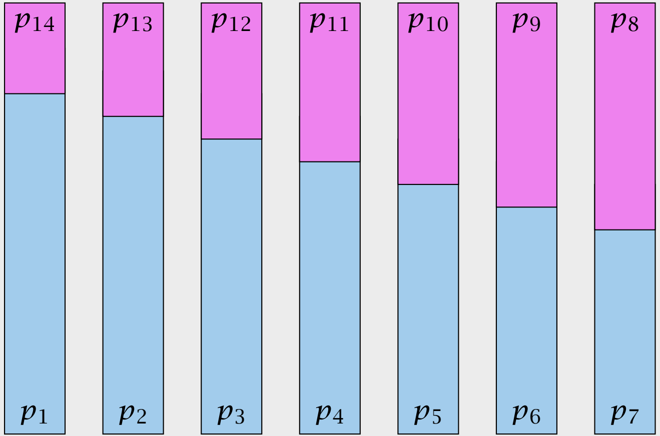

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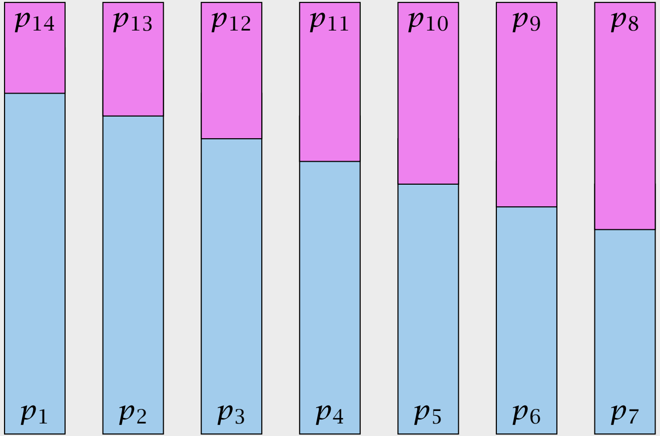

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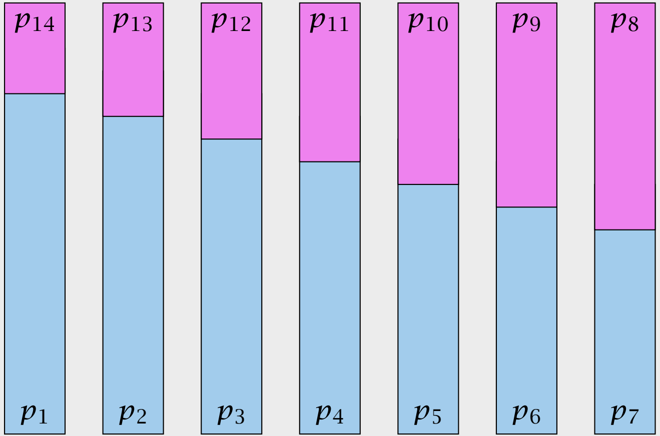

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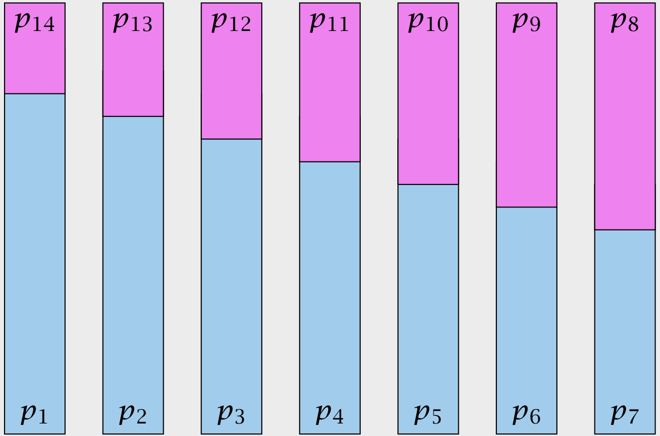

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- $2m + 1$ jobs

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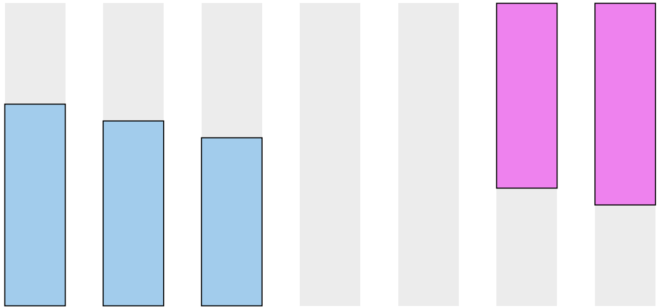

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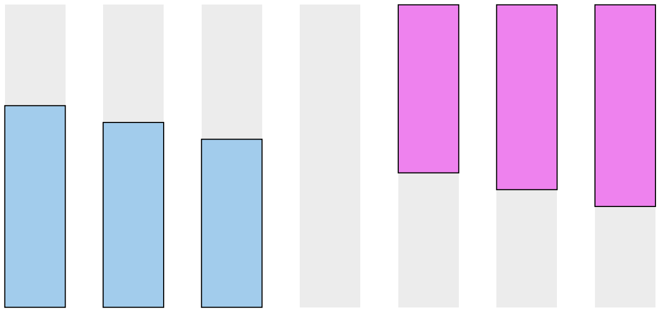

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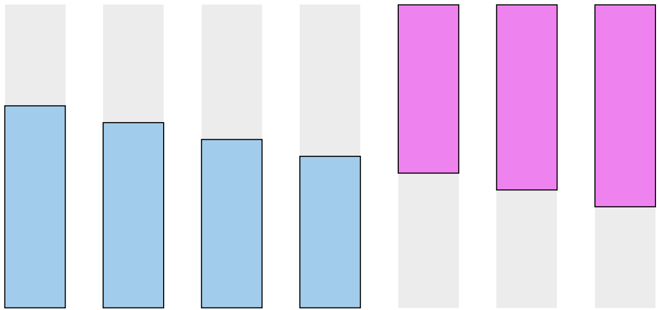

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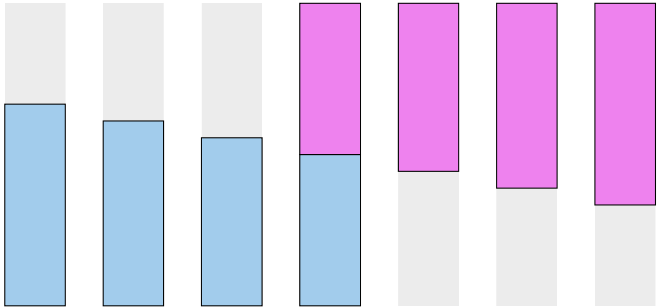

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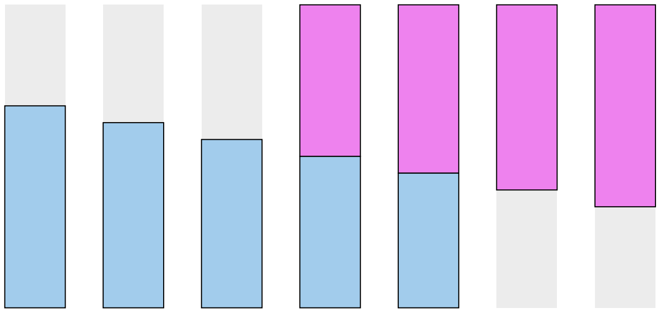

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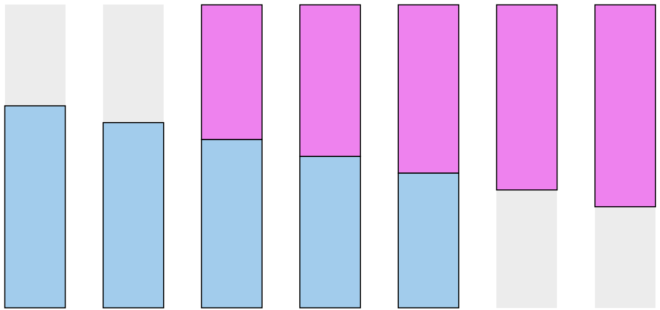

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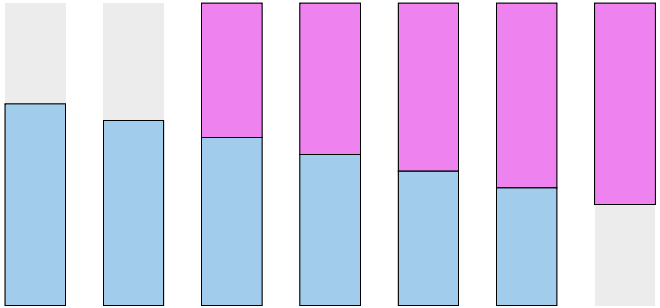

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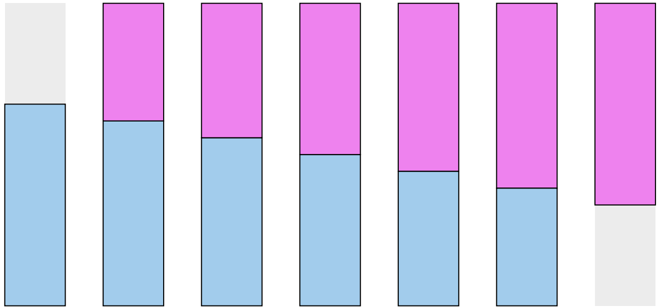

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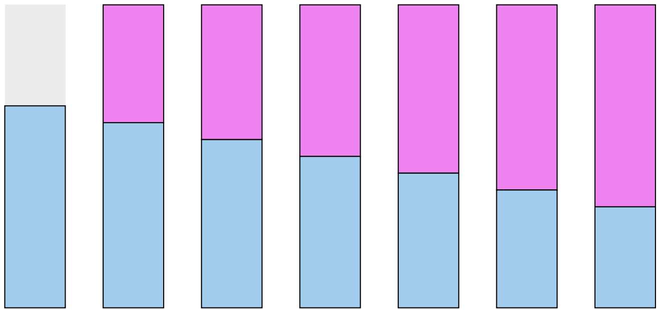

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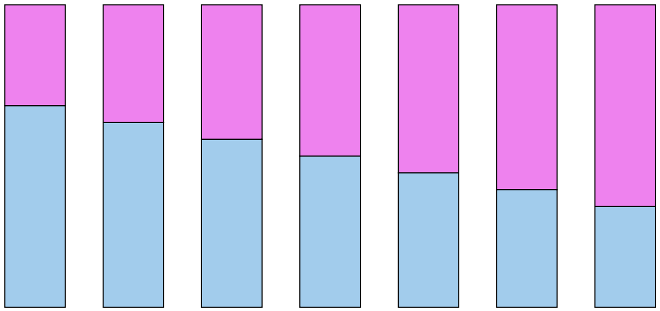

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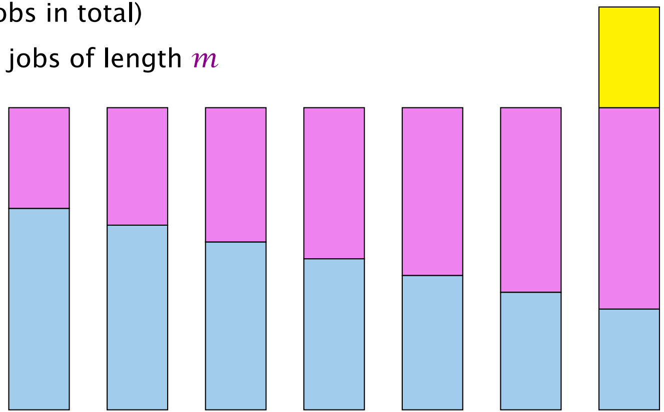

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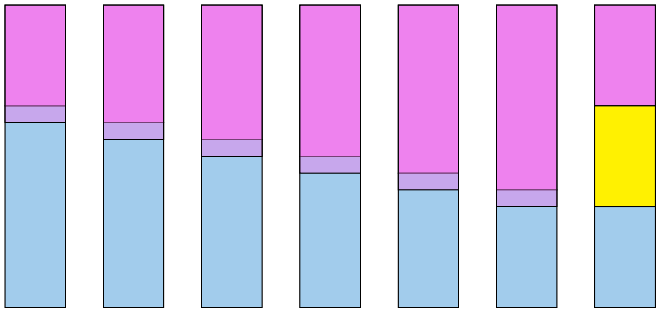

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EADS II
Harald Räcke
14.2 Greedy

Traveling Salesman

Given a set of cities ($\{1, \dots, n\}$) and a symmetric matrix $C = (c_{ij})$, $c_{ij} \geq 0$ that specifies for every pair $(i, j) \in [n] \times [n]$ the cost for travelling from city i to city j. Find a permutation π of the cities such that the round-trip cost

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There does not exist an $O(2^n)$-approximation algorithm for TSP.

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Given a set of cities ($\{1, \dots, n\}$) and a symmetric matrix $C = (c_{ij})$, $c_{ij} \geq 0$ that specifies for every pair $(i, j) \in [n] \times [n]$ the cost for travelling from city i to city j. Find a permutation π of the cities such that the round-trip cost

$$c_{\pi(1)\pi(n)} + \sum_{i=1}^{n-1} c_{\pi(i)\pi(i+1)}$$

is minimized.

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Theorem 19

There does not exist an $O(2^n)$-approximation algorithm for TSP.

Hamiltonian Cycle:
For a given undirected graph $G = (V, E)$ decide whether there exists a simple cycle that contains all nodes in G.

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Lemma 20
The cost $\mathrm{OPT}_{TSP}(G)$ *of an optimum traveling salesman tour is at least as large as the weight* $\mathrm{OPT}_{MST}(G)$ *of a minimum spanning tree in* G.

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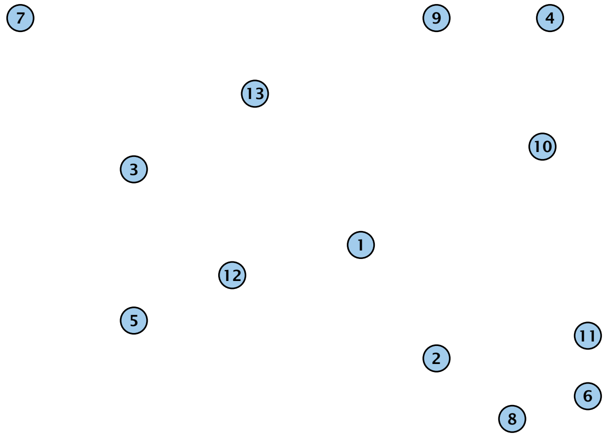

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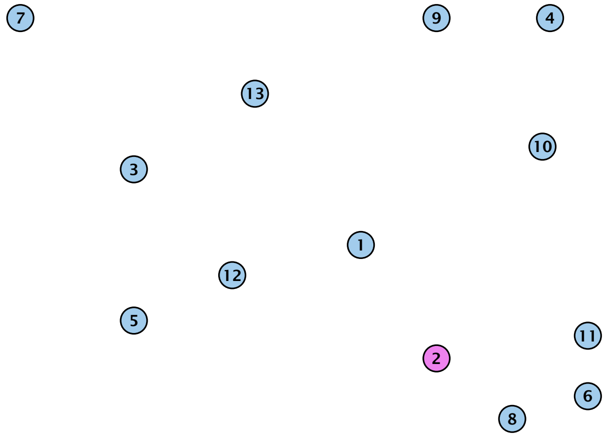

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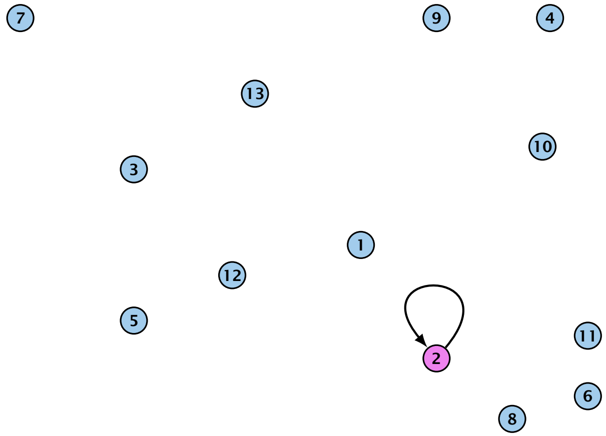

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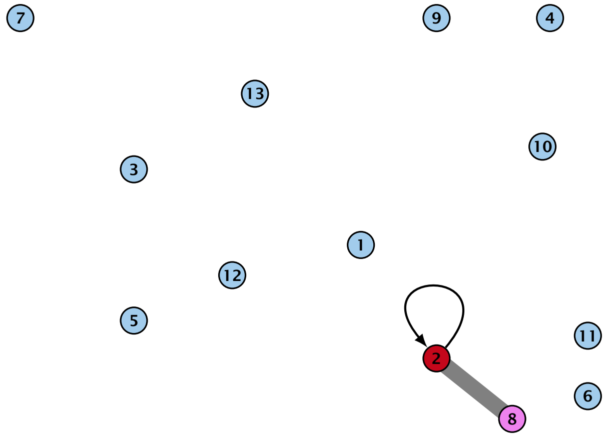

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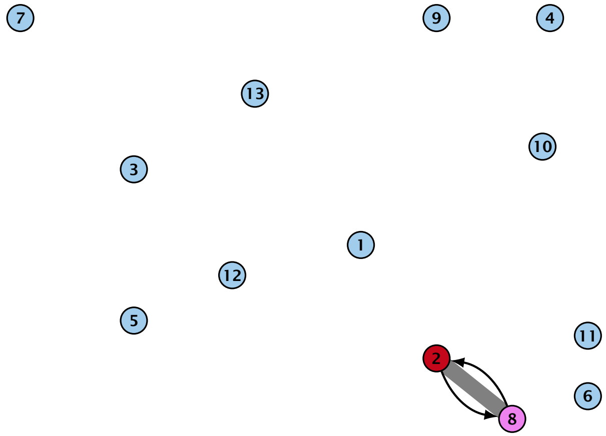

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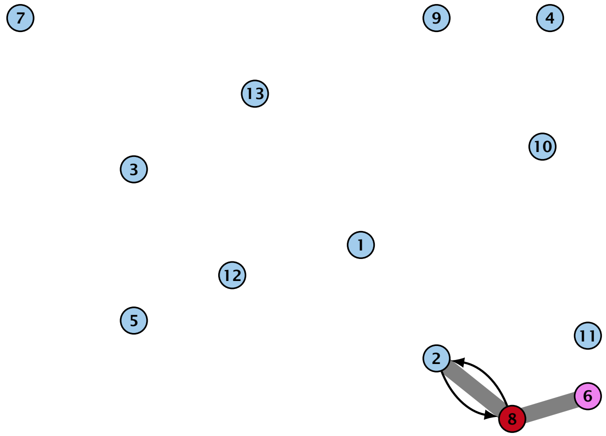

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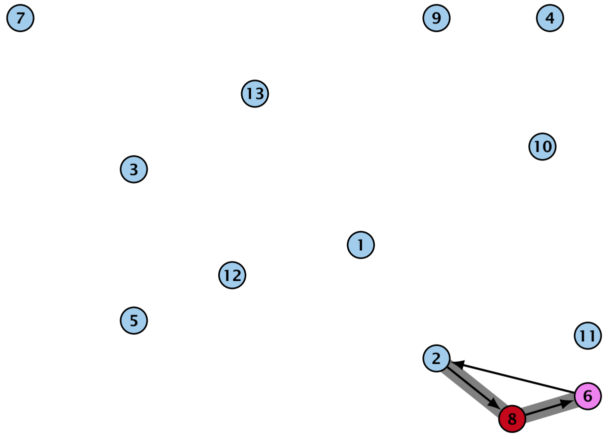

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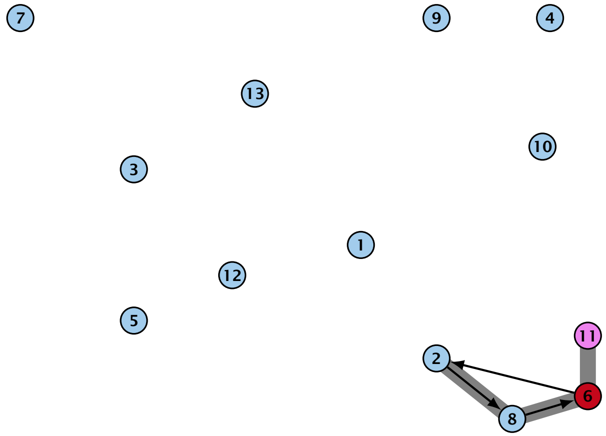

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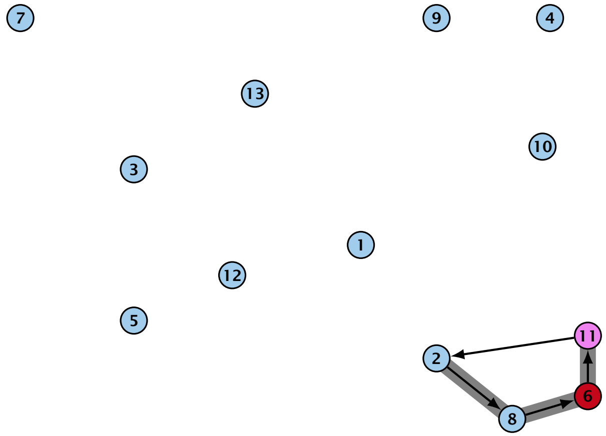

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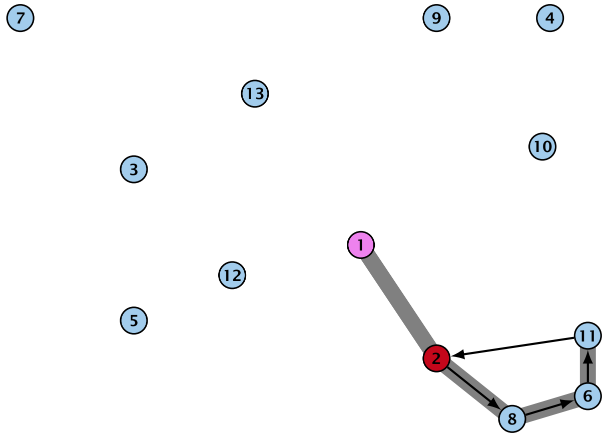

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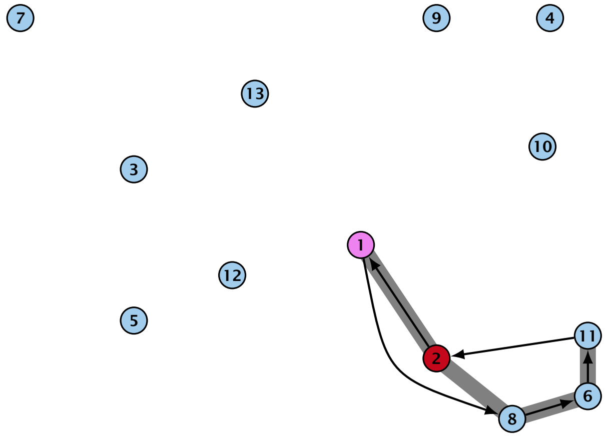

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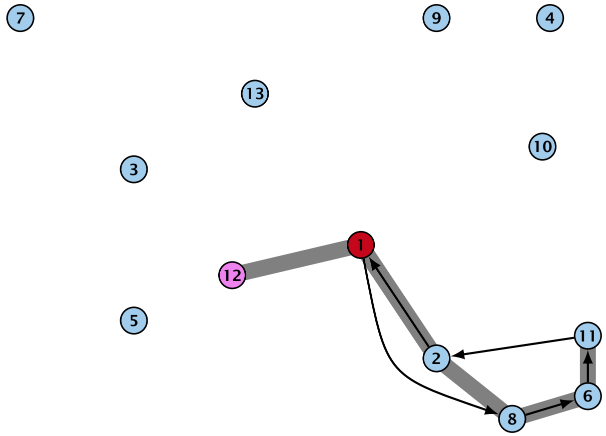

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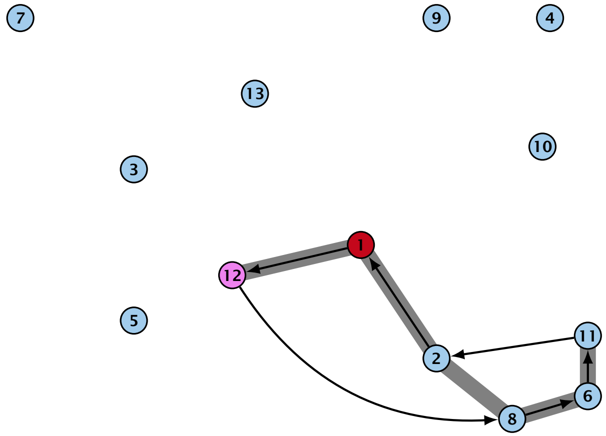

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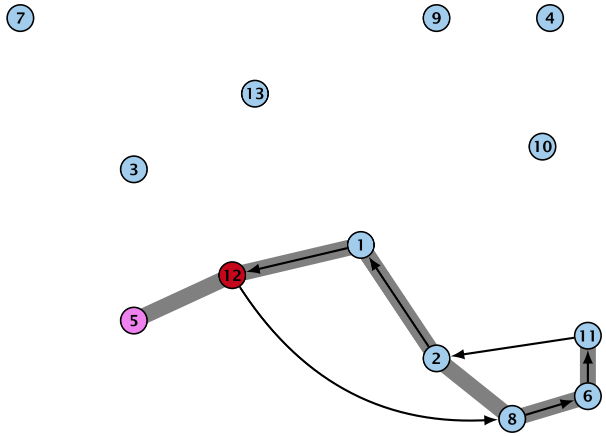

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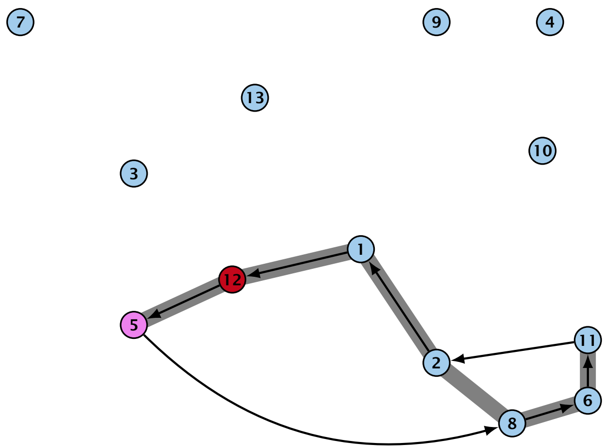

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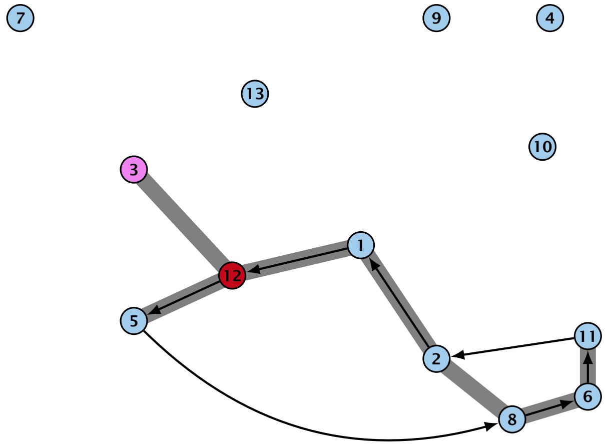

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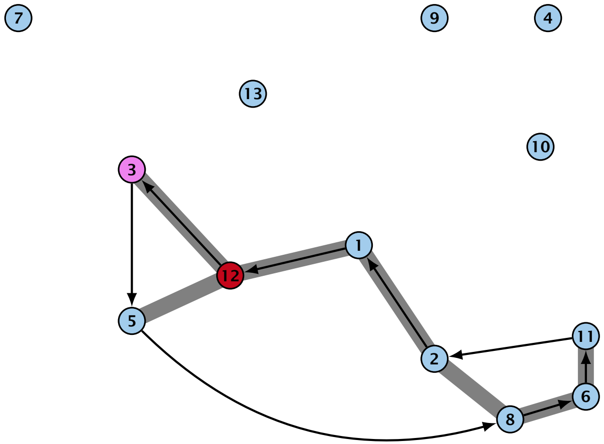

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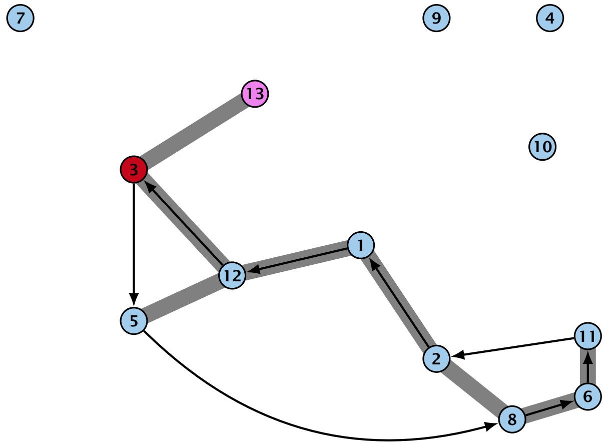

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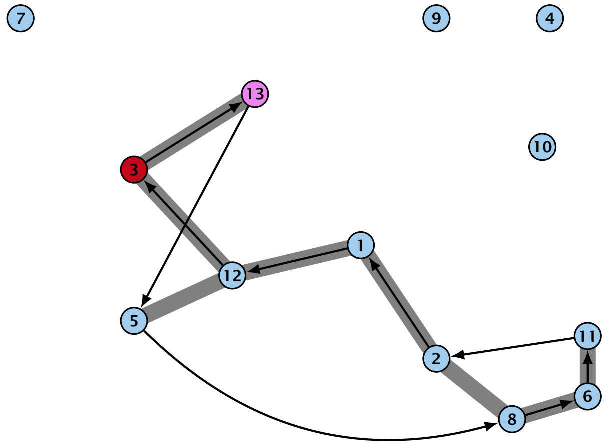

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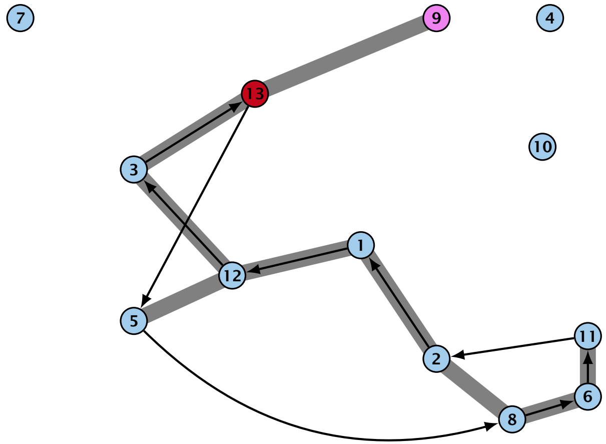

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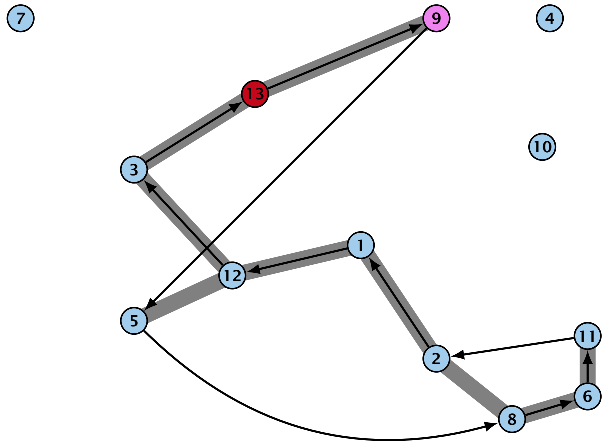

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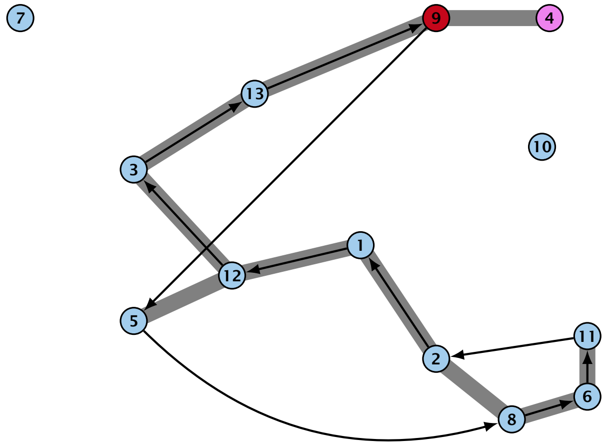

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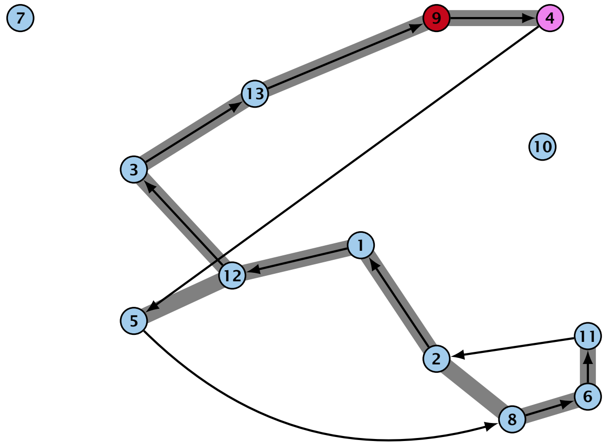

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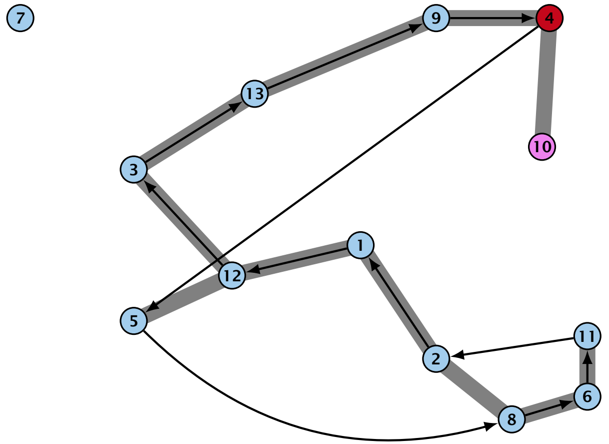

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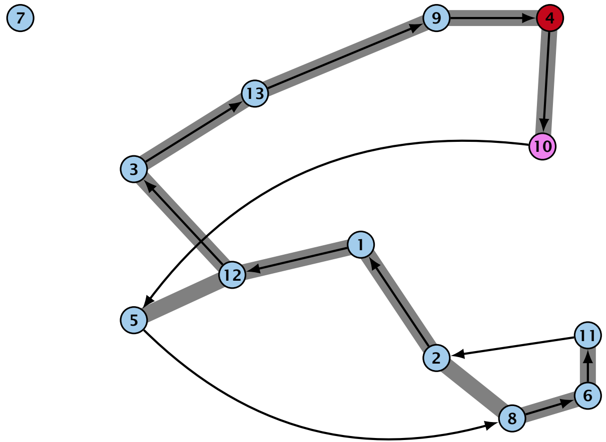

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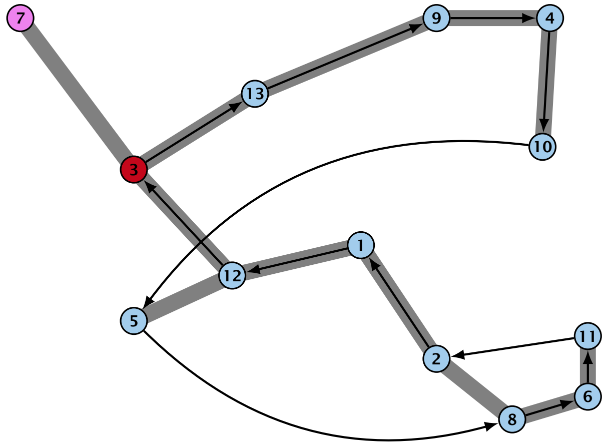

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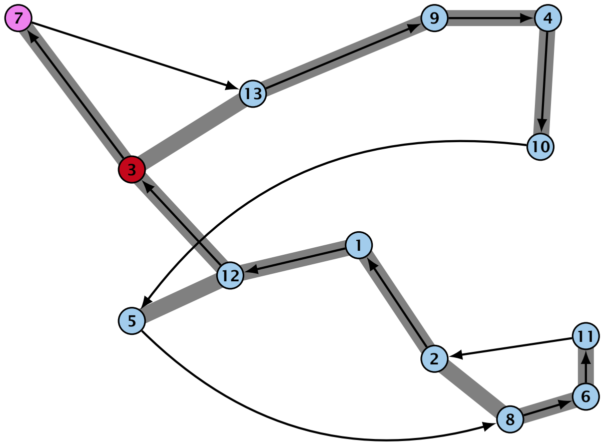

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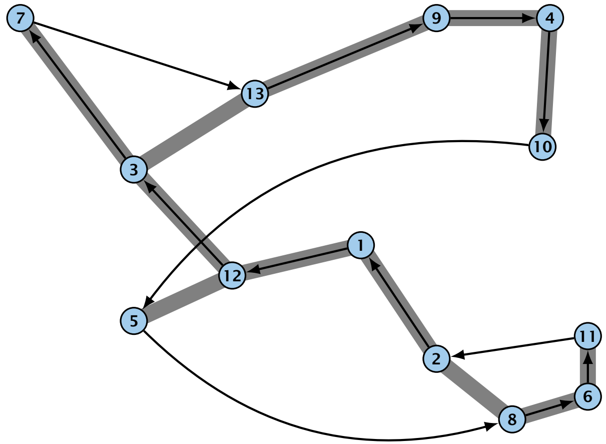

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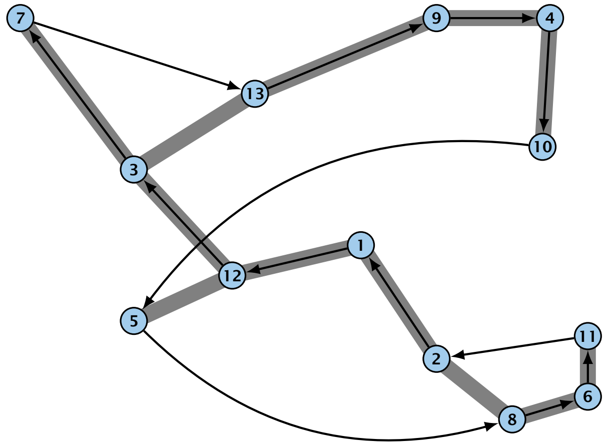

The gray edges form an MST, because exactly these edges are taken in Prims algorithm.

TSP: Greedy Algorithm

- Start with a tour on a subset S containing a single node.
- Take the node v closest to S. Add it S and expand the existing tour on S to include v.
- Repeat until all nodes have been processed.

TSP: Greedy Algorithm

Lemma 21

The Greedy algorithm is a 2-approximation algorithm.

Let S_i be the set at the start of the i-th iteration, and let v_i denote the node added during the iteration.

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Let r_i denote the successor of s_i in the tour before inserting v_i.

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This increases the cost by

$$c_{s_i,v_i} + c_{v_i,r_i} - c_{s_i,r_i} \le 2c_{s_i,v_i}$$

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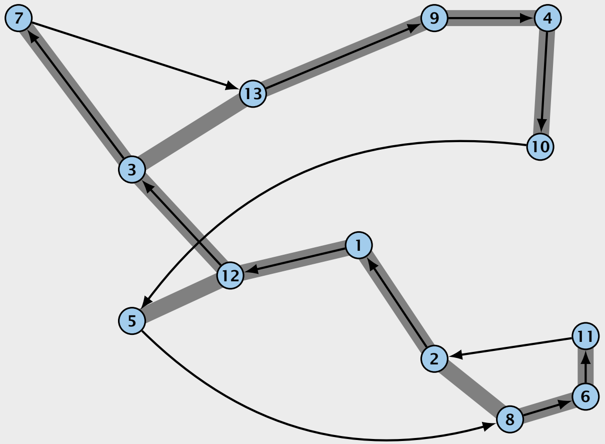

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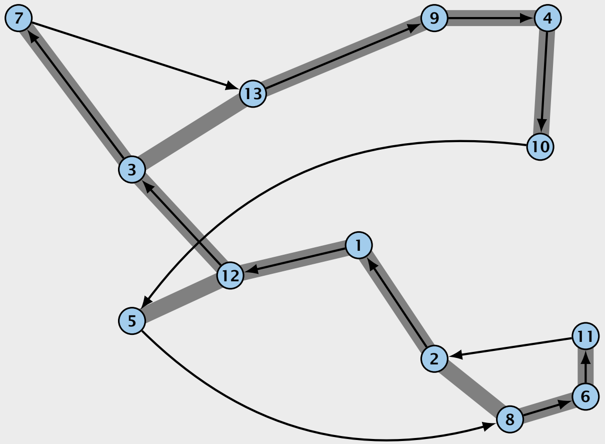

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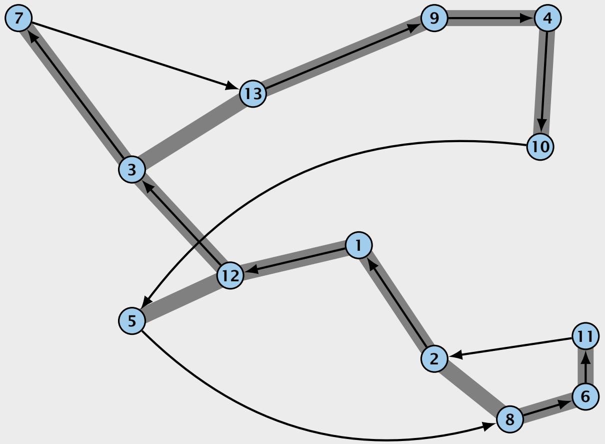

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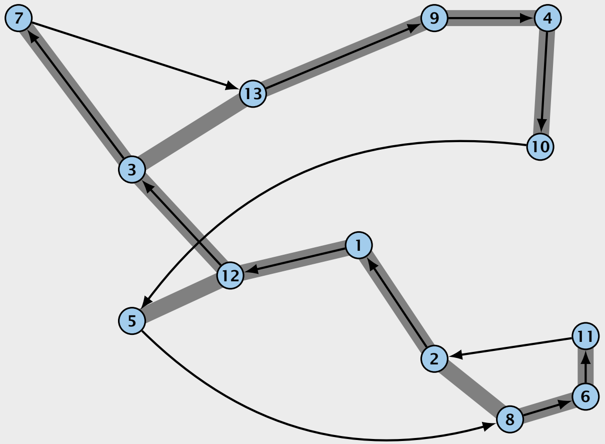

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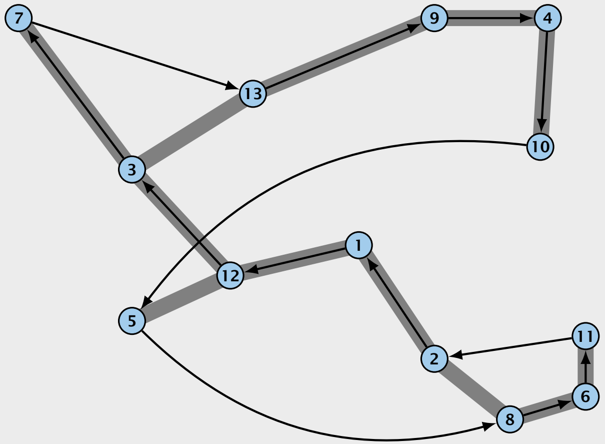

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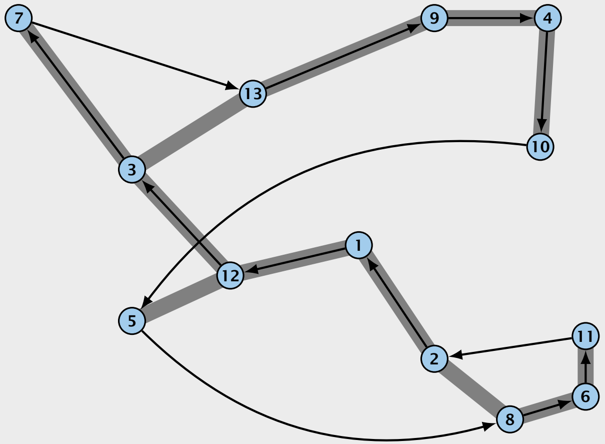

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Then we can find a TSP-tour of cost at most

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This technique is known as short cutting the Euler tour.

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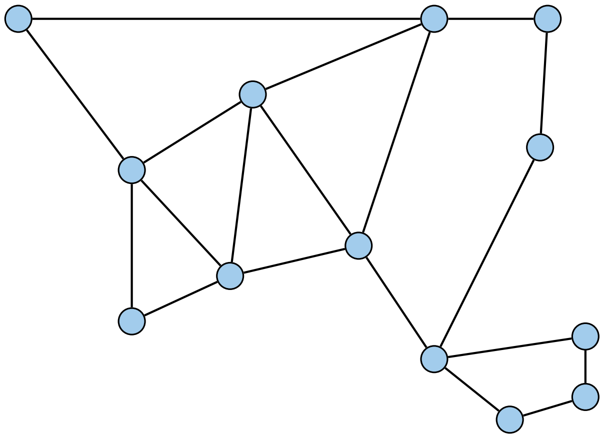

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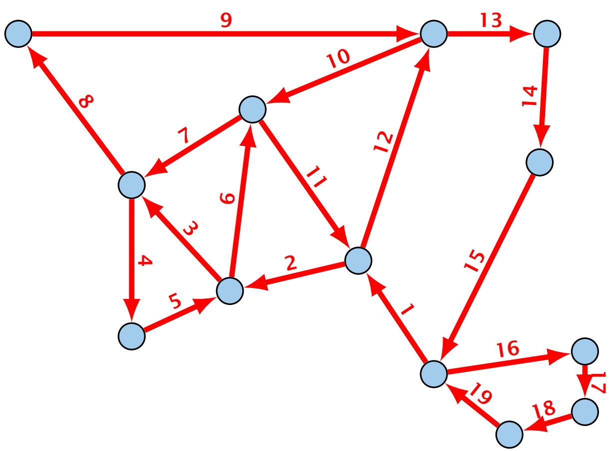

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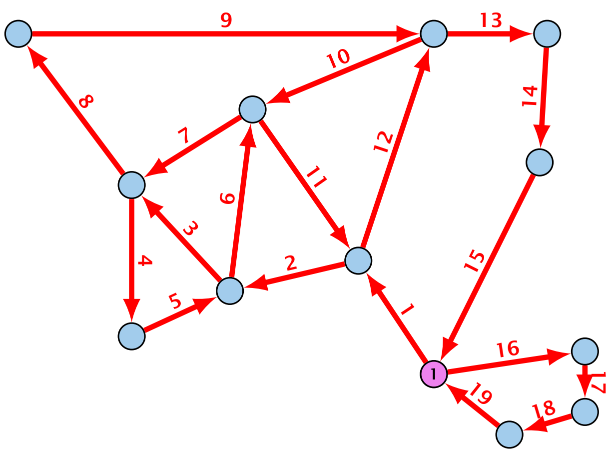

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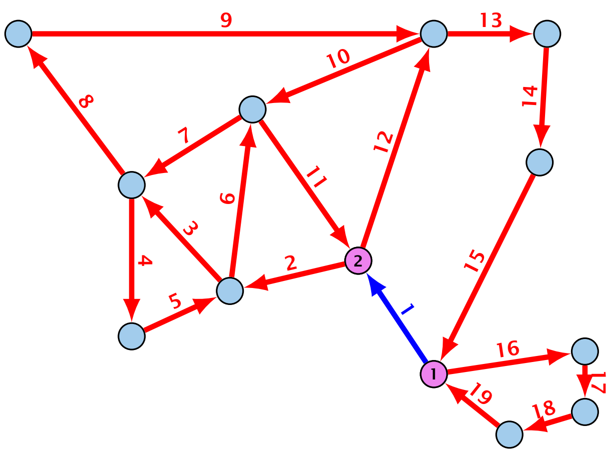

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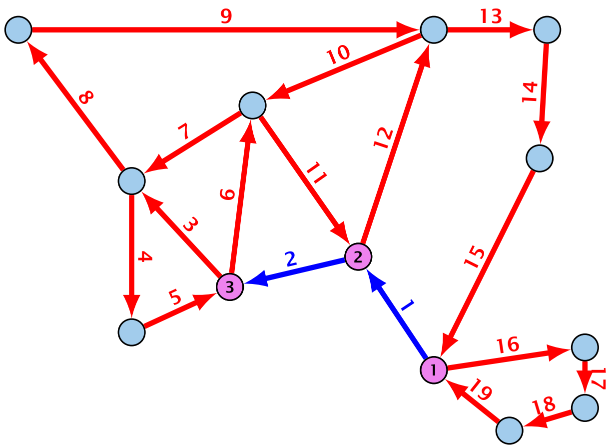

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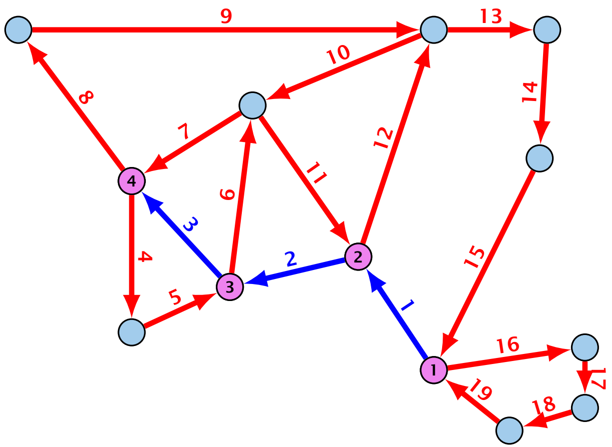

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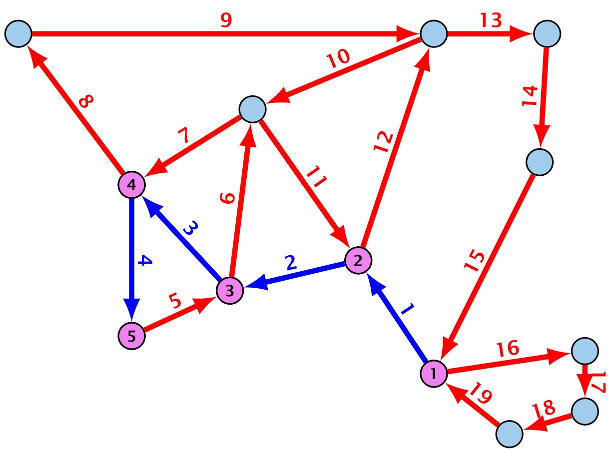

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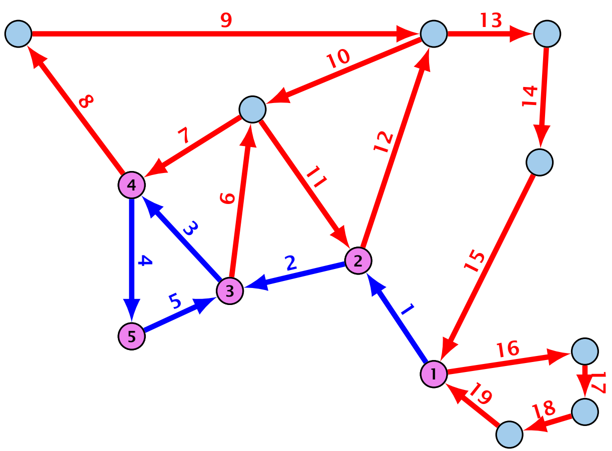

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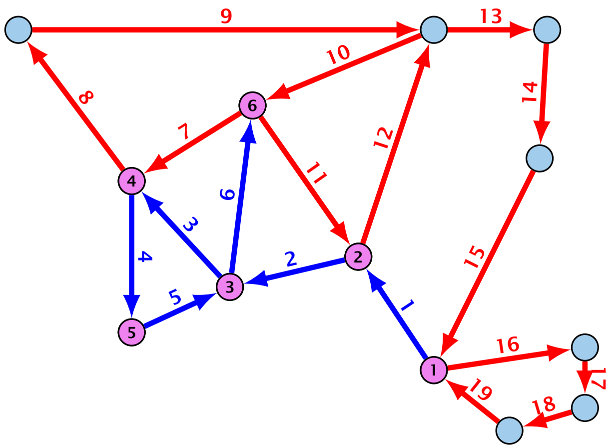

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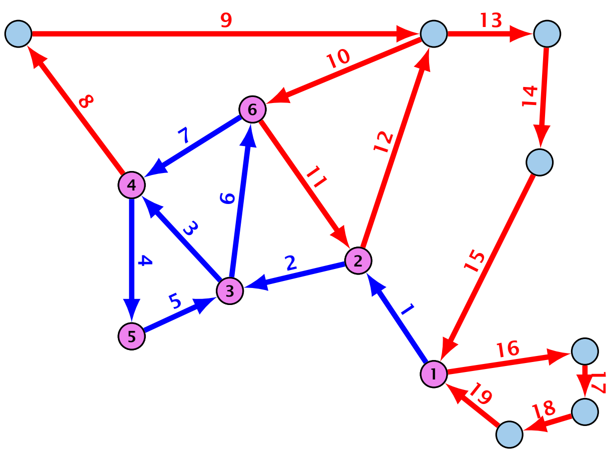

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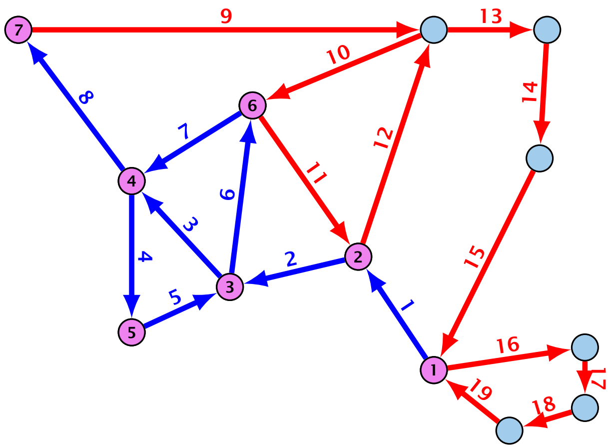

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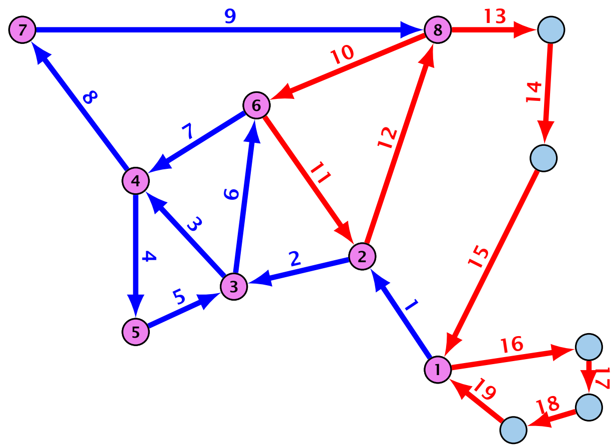

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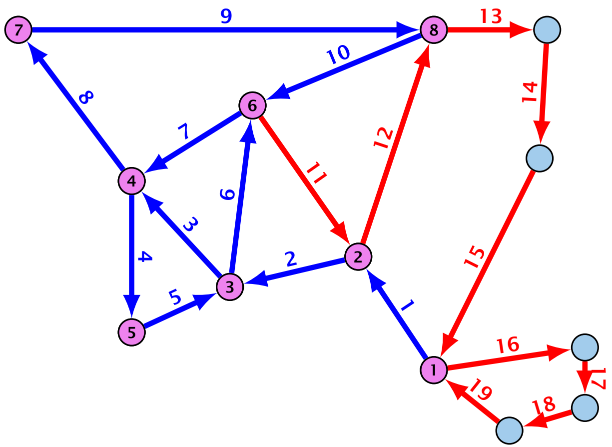

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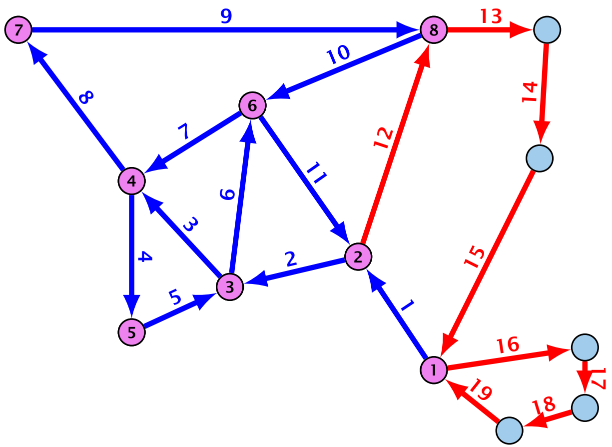

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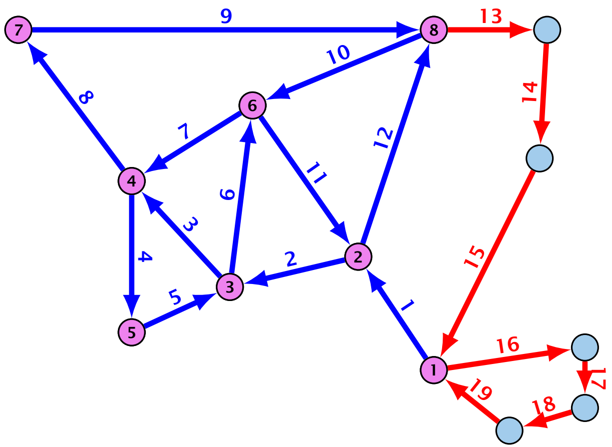

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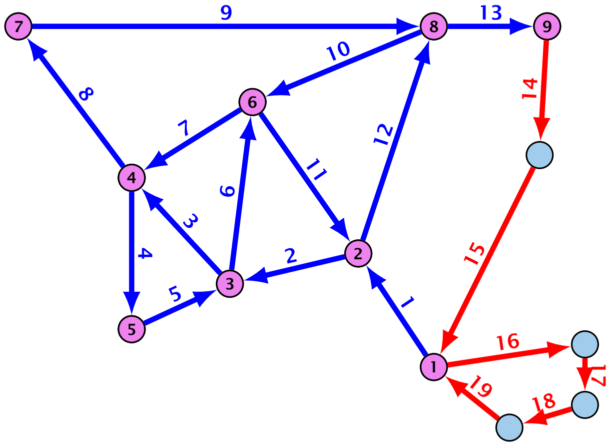

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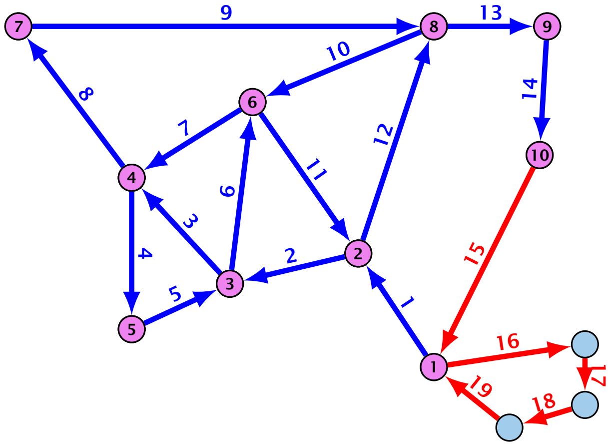

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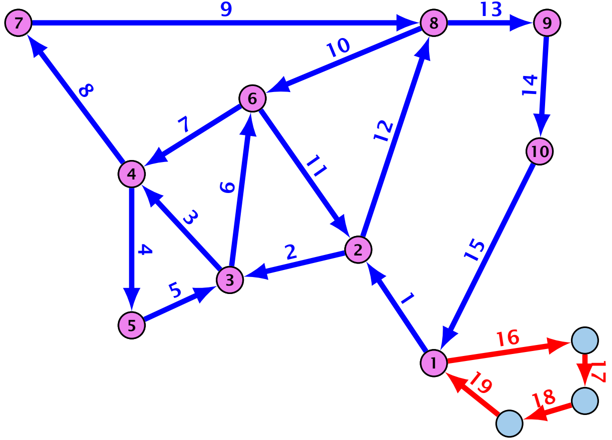

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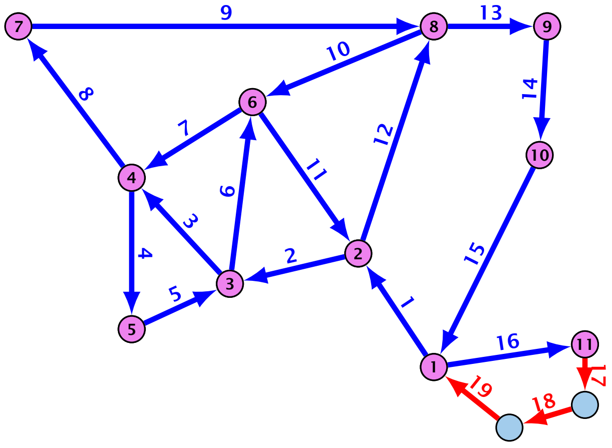

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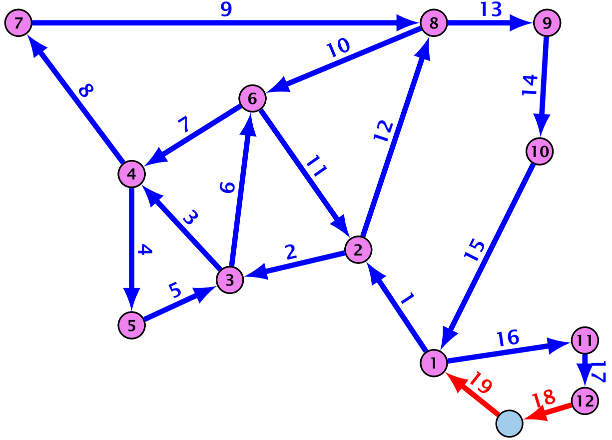

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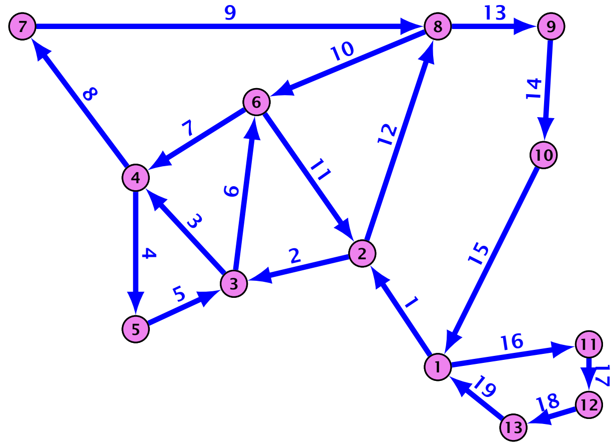

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EADS II
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15 TSP

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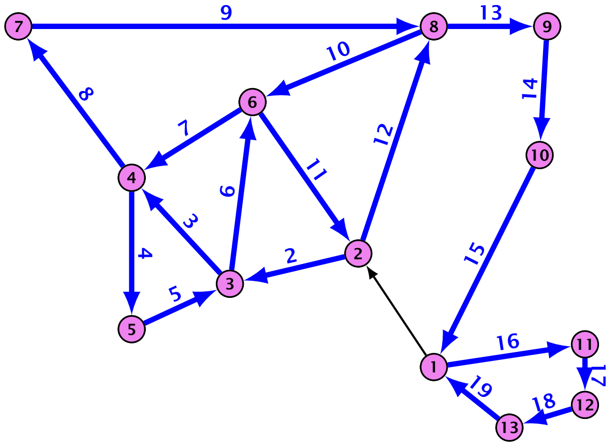

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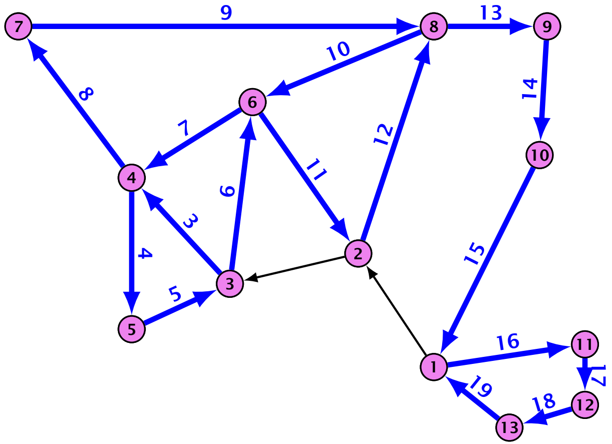

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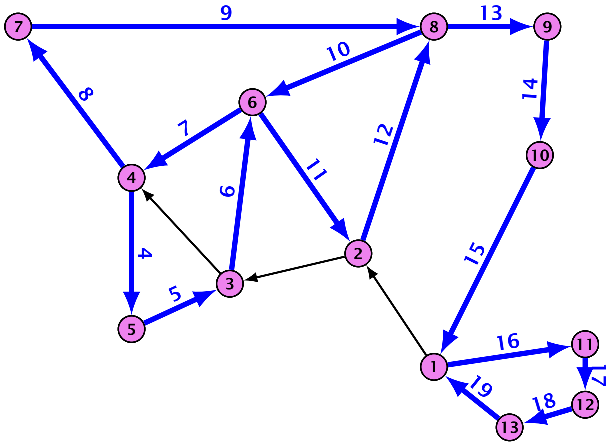

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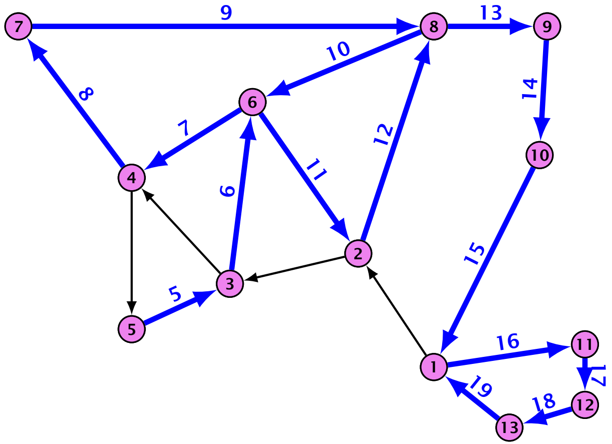

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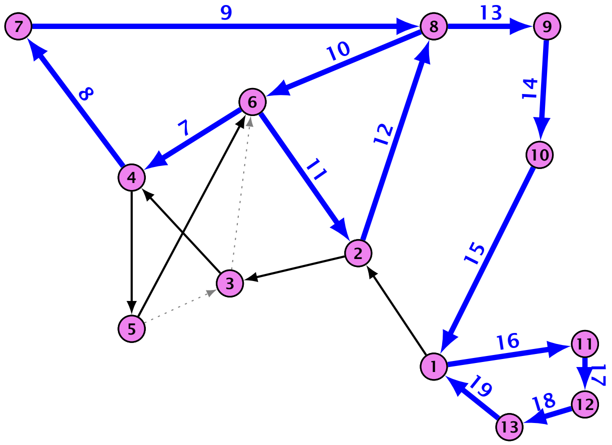

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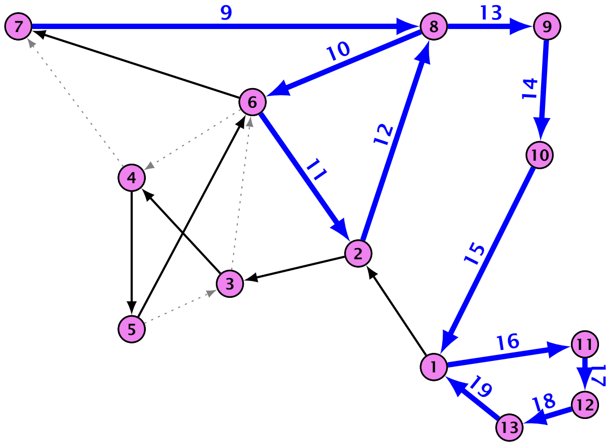

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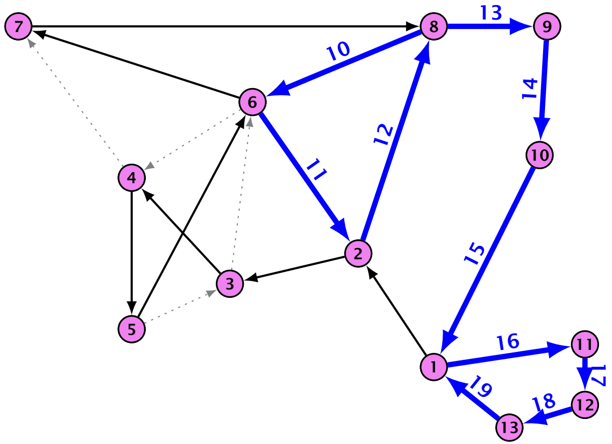

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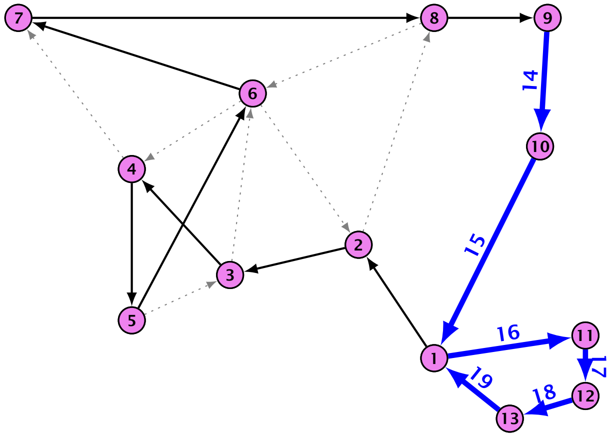

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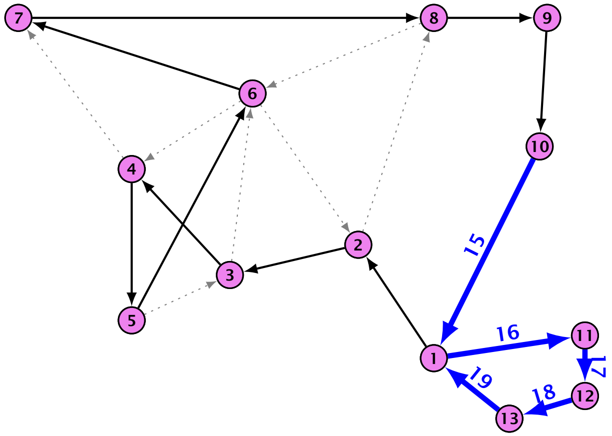

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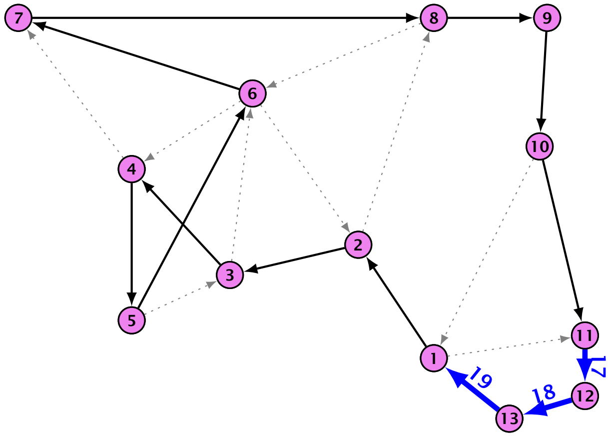

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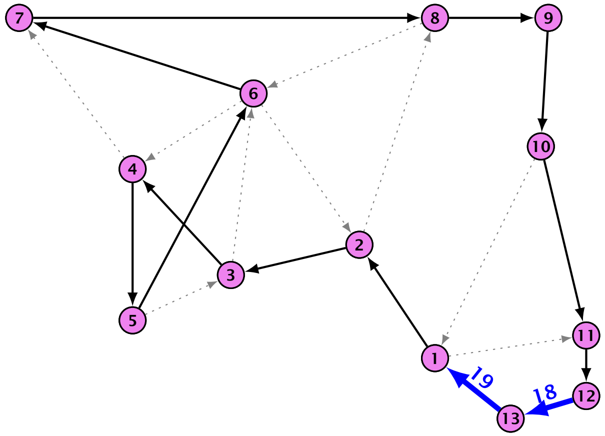

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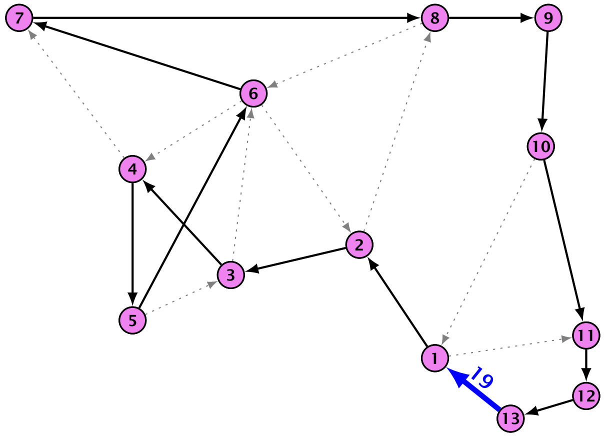

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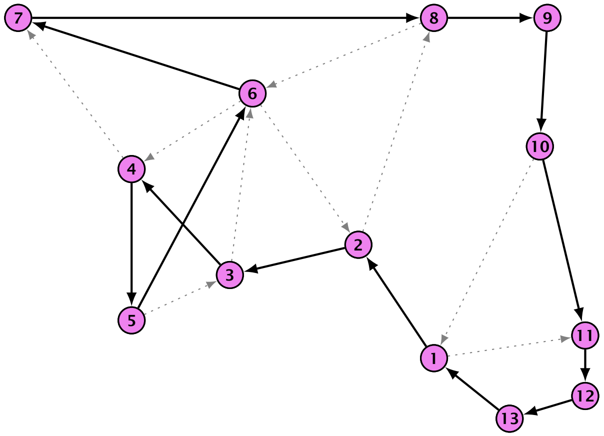

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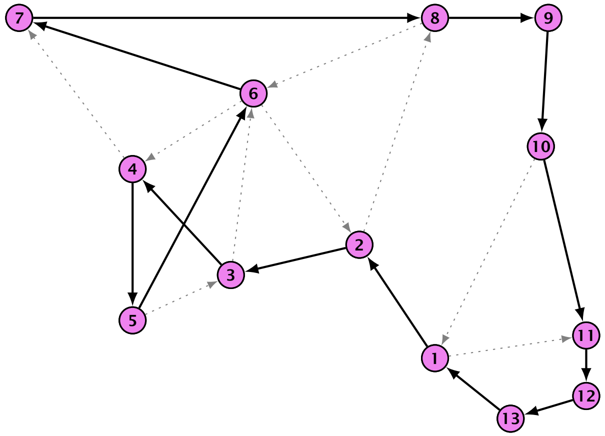

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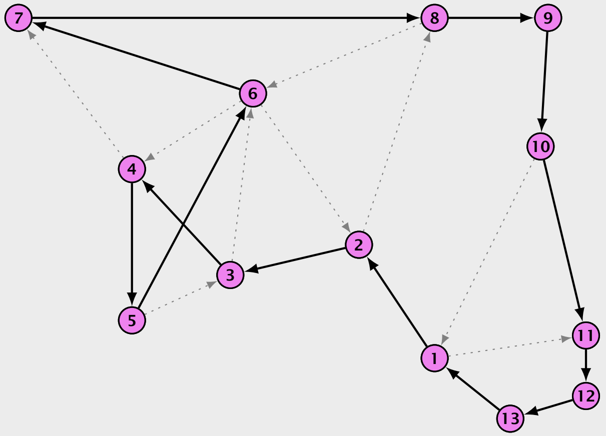

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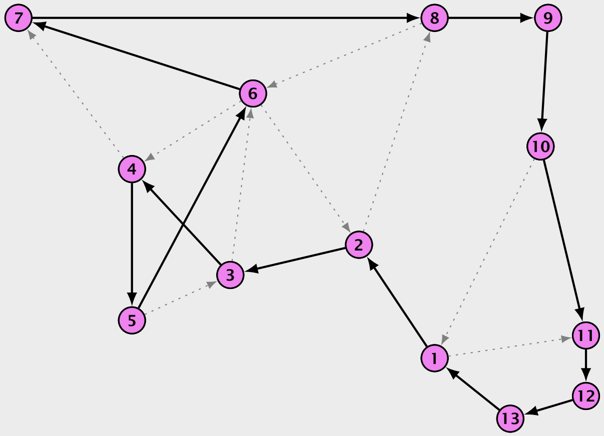

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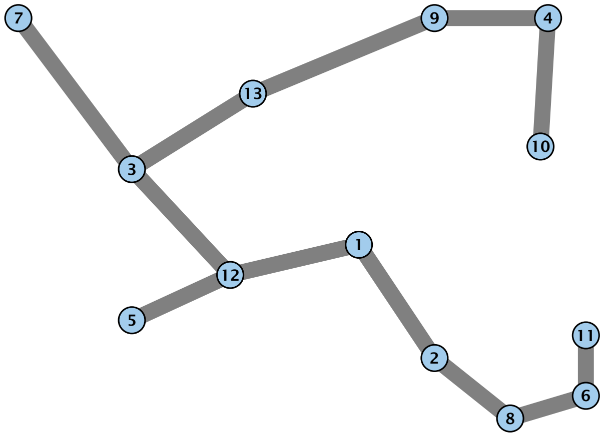

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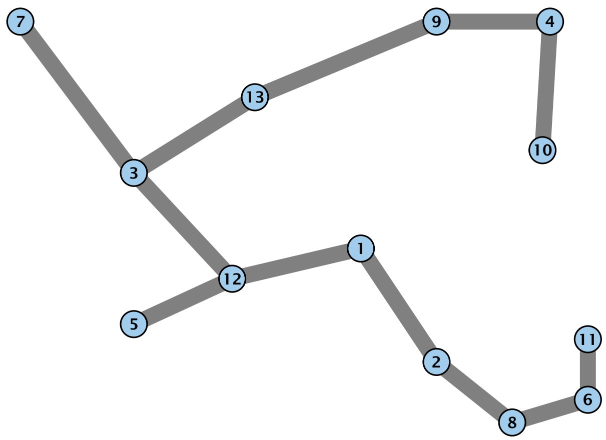

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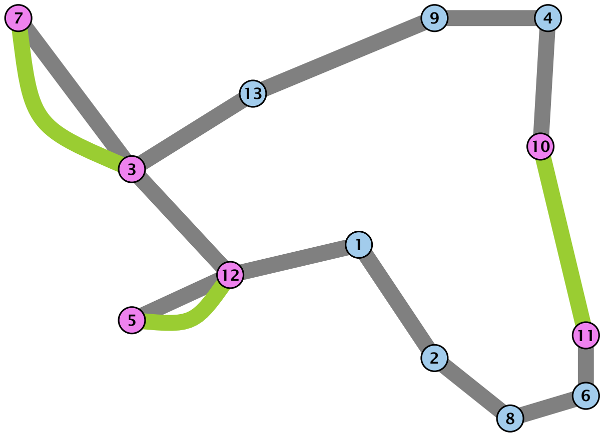

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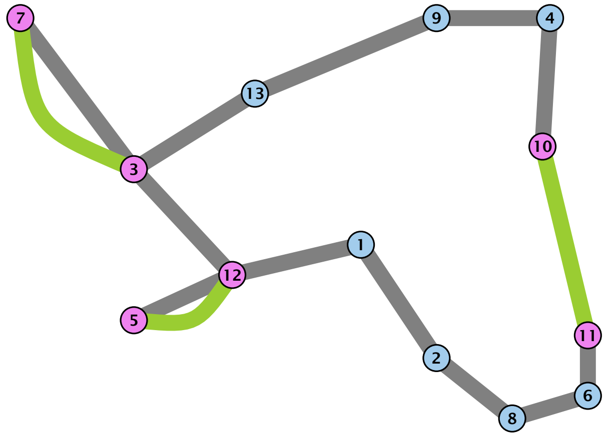

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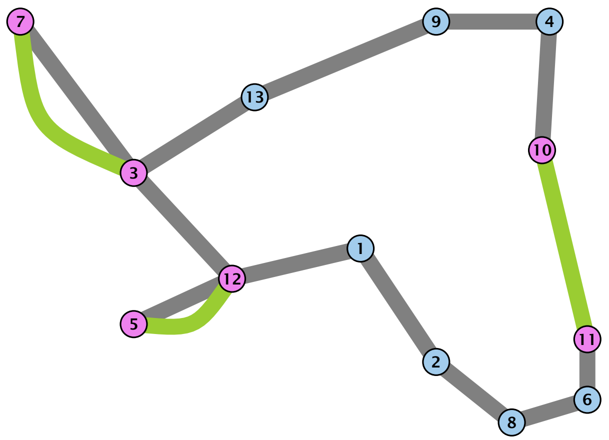

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This graph is Eulerian, and the total cost of all edges is at most $2 \cdot \mathrm{OPT}_{\mathrm{MST}}(G)$.

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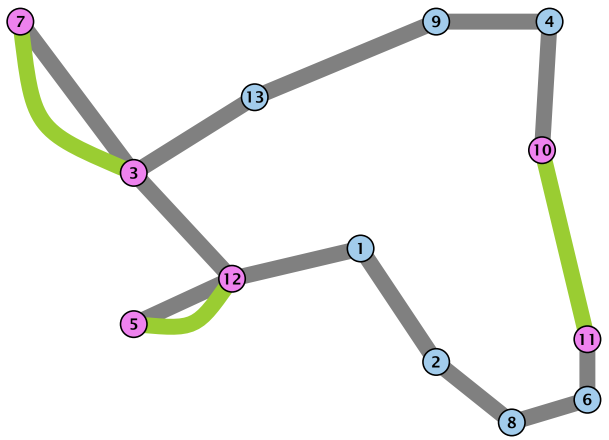

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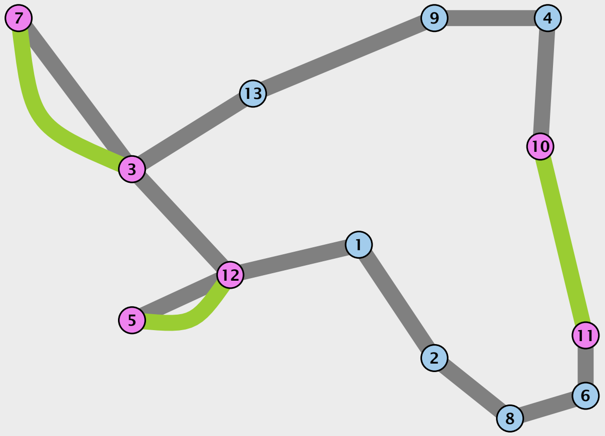

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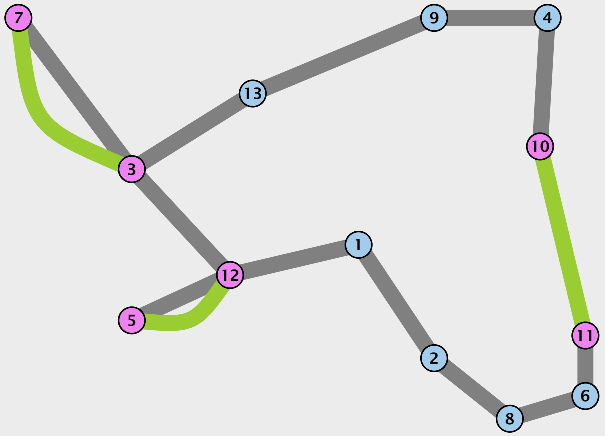

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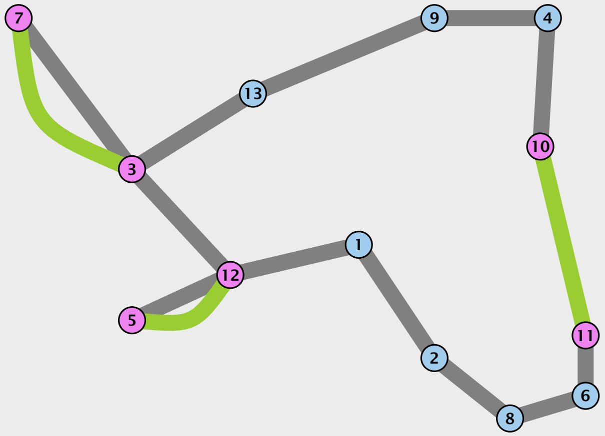

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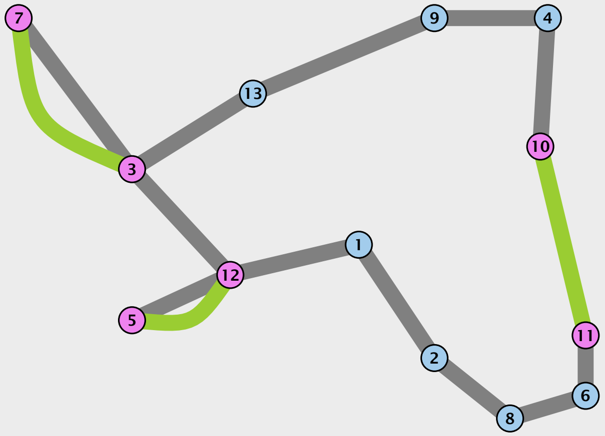

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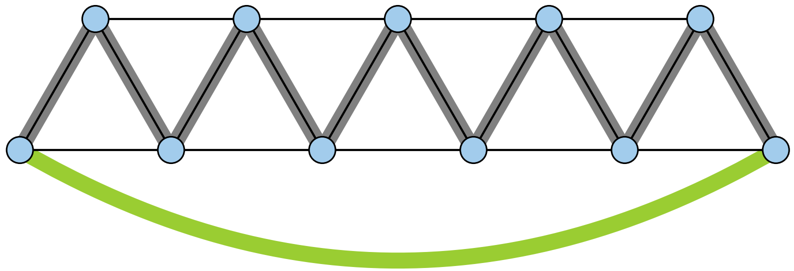

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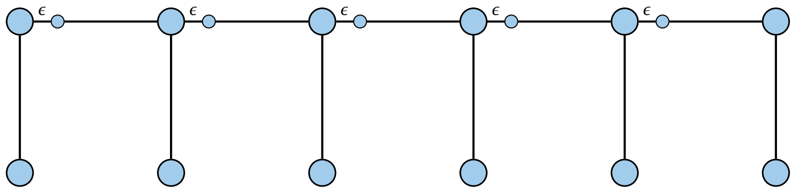

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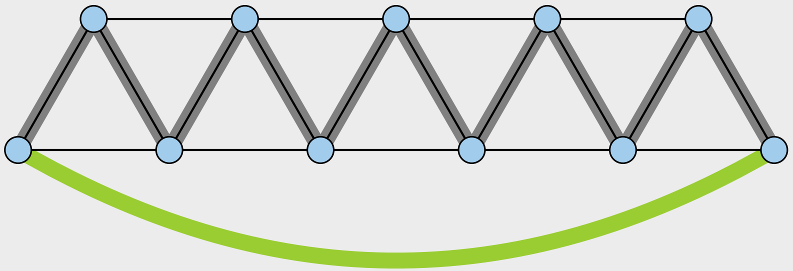

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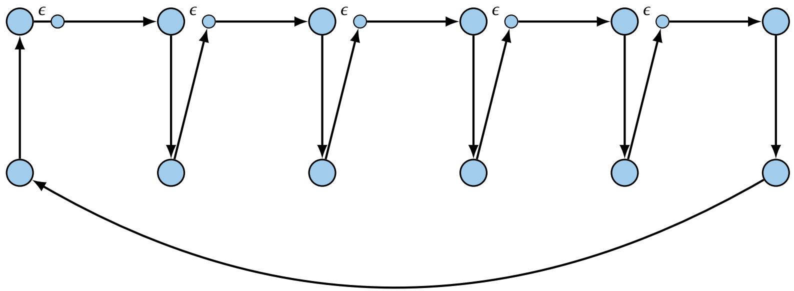

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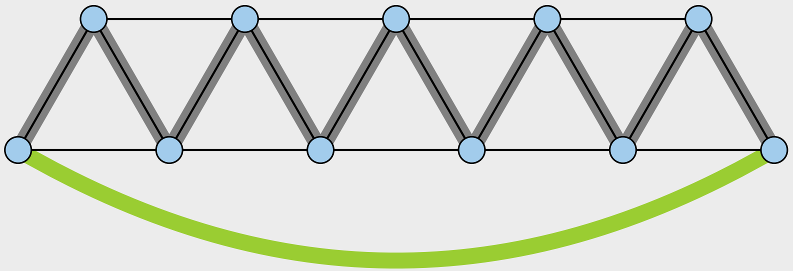

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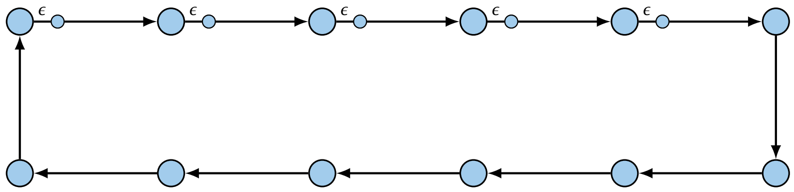

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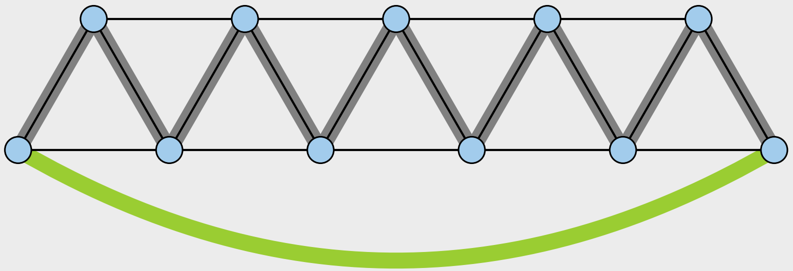

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Knapsack:
Given a set of items $\{1,\ldots,n\}$, where the i-th item has weight $w_i \in \mathbb{N}$ and profit $p_i \in \mathbb{N}$, and given a threshold W. Find a subset $I \subseteq \{1,\ldots,n\}$ of items of total weight at most W such that the profit is maximized (we can assume each $w_i \le W$).

$$
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Scheduling Revisited

The previous analysis of the scheduling algorithm gave a makespan of

$$\frac{1}{m}\sum_{j\neq\ell} p_j + p_\ell$$

where ℓ is the last job to complete.

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The previous analysis of the scheduling algorithm gave a makespan of

$$\frac{1}{m}\sum_{j\neq\ell} p_j + p_\ell$$

where ℓ is the last job to complete.

Together with the obervation that if each $p_i \geq \frac{1}{3}C^*_{\max}$ then LPT is optimal this gave a $4/3$-approximation.

16 Rounding Data + Dynamic Programming

Let S be the set of items returned by the algorithm, and let O be an optimum set of items.

$$\begin{aligned}\sum_{i\in S} p_i &\geq \mu\sum_{i\in S} p_i' \\ &\geq \mu\sum_{i\in O} p_i' \\ &\geq \sum_{i\in O} p_i - |O|\mu \\ &\geq \sum_{i\in O} p_i - n\mu \\ &= \sum_{i\in O} p_i - \epsilon M \\ &\geq (1-\epsilon)\mathrm{OPT}\ .\end{aligned}$$

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Partition the input into long jobs and short jobs.

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Hence we get a schedule of length at most

$$\Big(1 + \frac{1}{k}\Big) C^*_{\max}$$

There are at most km long jobs. Hence, the number of possibilities of scheduling these jobs on m machines is at most m^{km}, which is constant if m is constant. Hence, it is easy to implement the algorithm in polynomial time.

Theorem 23
The above algorithm gives a polynomial time approximation scheme (PTAS) for the problem of scheduling n jobs on m identical machines if m is constant.

We choose $k = \lceil \frac{1}{\epsilon} \rceil$.

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We choose $k = \lceil\frac{1}{\epsilon}\rceil$.

- We round all long jobs down to multiples of T/k^2.
- For these rounded sizes we first find an optimal schedule.
- If this schedule does not have length at most T we conclude that also the original sizes don't allow such a schedule.
- If we have a good schedule we extend it by adding the short jobs according to the LPT rule.

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After the first phase the rounded sizes of the long jobs assigned to a machine add up to at most T.

There can be at most k (long) jobs assigned to a machine as otw. their rounded sizes would add up to more than T (note that the rounded size of a long job is at least T/k).

Since, jobs had been rounded to multiples of T/k^2 going from rounded sizes to original sizes gives that the Makespan is at most

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During the second phase there always must exist a machine with load at most T, since T is larger than the average load.
Assigning the current (short) job to such a machine gives that the new load is at most

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Running Time for scheduling large jobs: There should not be a job with rounded size more than T as otw. the problem becomes trivial.

Hence, any large job has rounded size of $\frac{i}{k^2}T$ for $i \in \{k, \dots, k^2\}$. Therefore the number of different inputs is at most n^{k^2} (described by a vector of length k^2 where, the i-th entry describes the number of jobs of size $\frac{i}{k^2}T$). This is polynomial.

The schedule/configuration of a particular machine x can be described by a vector of length k^2 where the i-th entry describes the number of jobs of rounded size $\frac{i}{k^2}T$ assigned to x. There are only $(k+1)^{k^2}$ different vectors.

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Let $\mathrm{OPT}(n_1, \ldots, n_{k^2})$ be the number of machines that are required to schedule input vector $(n_1, \ldots, n_{k^2})$ with Makespan at most T.

If $\mathrm{OPT}(n_1, \ldots, n_{k^2}) \leq m$ we can schedule the input.

We have

$$\mathrm{OPT}(n_1, \ldots, n_{k^2}) = \begin{cases} 0 & (n_1, \ldots, n_{k^2}) = 0 \\ 1 + \min\limits_{(s_1, \ldots, s_{k^2}) \in C} \mathrm{OPT}(n_1 - s_1, \ldots, n_{k^2} - s_{k^2}) & (n_1, \ldots, n_{k^2}) \geq 0 \\ \infty & \text{otw.} \end{cases}$$

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Hence, the running time is roughly $(k+1)^{k^2} n^{k^2} \approx (nk)^{k^2}$.

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Running Time for scheduling large jobs: There should not be a job with rounded size more than T as otw. the problem becomes trivial.

Hence, any large job has rounded size of $\frac{i}{k^2}T$ for $i \in \{k, \dots, k^2\}$. Therefore the number of different inputs is at most n^{k^2} (described by a vector of length k^2 where, the i-th entry describes the number of jobs of size $\frac{i}{k^2}T$). This is polynomial.

The schedule/configuration of a particular machine x can be described by a vector of length k^2 where the i-th entry describes the number of jobs of rounded size $\frac{i}{k^2}T$ assigned to x. There are only $(k+1)^{k^2}$ different vectors.

This means there are a constant number of different machine configurations.

We can turn this into a PTAS by choosing $k = \lceil 1/\epsilon \rceil$ and using binary search. This gives a running time that is exponential in $1/\epsilon$.

Can we do better?
Scheduling on identical machines with the goal of minimizing Makespan is a strongly NP-complete problem.

Theorem 24
There is no FPTAS for problems that are strongly NP-hard.

Let $\mathrm{OPT}(n_1,\dots,n_{k^2})$ be the number of machines that are required to schedule input vector $(n_1,\dots,n_{k^2})$ with Makespan at most T.

If $\mathrm{OPT}(n_1,\dots,n_{k^2}) \le m$ we can schedule the input.

We have

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More General

Let $\mathrm{OPT}(n_1, \dots, n_A)$ be the number of machines that are required to schedule input vector $(n_1, \dots, n_A)$ with Makespan at most T (A: number of different sizes).

If $\mathrm{OPT}(n_1, \dots, n_A) \leq m$ we can schedule the input.

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where C is the set of all configurations.

$|C| \leq (B+1)^A$, where B is the number of jobs that possibly can fit on the same machine.

The running time is then $O((B+1)^A n^A)$ because the dynamic programming table has just n^A entries.

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Bin Packing

Given n items with sizes $s_1, \ldots, s_n$ where

$$1 > s_1 \geq \cdots \geq s_n > 0 \ .$$

Pack items into a minimum number of bins where each bin can hold items of total size at most 1.

Theorem 25

There is no ρ-approximation for Bin Packing with $\rho < 3/2$ unless $\mathrm{P} = \mathrm{NP}$.

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Proof

- In the partition problem we are given positive integers $b_1, \dots, b_n$ with $B = \sum_i b_i$ even. Can we partition the integers into two sets S and T s.t.

$$\sum_{i \in S} b_i = \sum_{i \in T} b_i \quad ?$$

- We can solve this problem by setting $s_i := 2b_i/B$ and asking whether we can pack the resulting items into 2 bins or not.
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Definition 26
An asymptotic polynomial-time approximation scheme (APTAS) is a family of algorithms $\{A_\epsilon\}$ along with a constant c such that A_ϵ returns a solution of value at most $(1+\epsilon)\mathrm{OPT}+c$ for minimization problems.

- Note that for Set Cover or for Knapsack it makes no sense to differentiate between the notion of a PTAS or an APTAS because of scaling.
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Again we can differentiate between small and large items.

Lemma 27

Any packing of items into ℓ bins can be extended with items of size at most γ s.t. we use only $\max\{\ell, \frac{1}{1-\gamma}\mathrm{SIZE}(I) + 1\}$ bins, where $\mathrm{SIZE}(I) = \sum_i s_i$ is the sum of all item sizes.

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- If after Greedy we use more than ℓ bins, all bins (apart from the last) must be full to at least $1 - \gamma$.
- Hence, $r(1-\gamma) \le \mathrm{SIZE}(I)$ where r is the number of nearly-full bins.
- This gives the lemma.

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- Note that for Set Cover or for Knapsack it makes no sense to differentiate between the notion of a PTAS or an APTAS because of scaling.
- However, we will develop an APTAS for Bin Packing.

Bin Packing

Again we can differentiate between small and large items.

Lemma 27

Any packing of items into ℓ bins can be extended with items of size at most γ s.t. we use only $\max\{\ell, \frac{1}{1-\gamma}\text{SIZE}(I) + 1\}$ bins, where $\text{SIZE}(I) = \sum_i s_i$ is the sum of all item sizes.

- If after Greedy we use more than ℓ bins, all bins (apart from the last) must be full to at least $1 - \gamma$.
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Linear Grouping:

Generate an instance I' (for large items) as follows.

- Order large items according to size.
- Let the first k items belong to group 1; the following k items belong to group 2; etc.
- Delete items in the first group;
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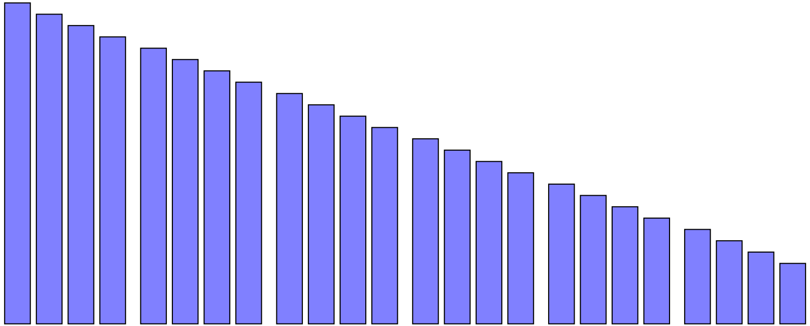

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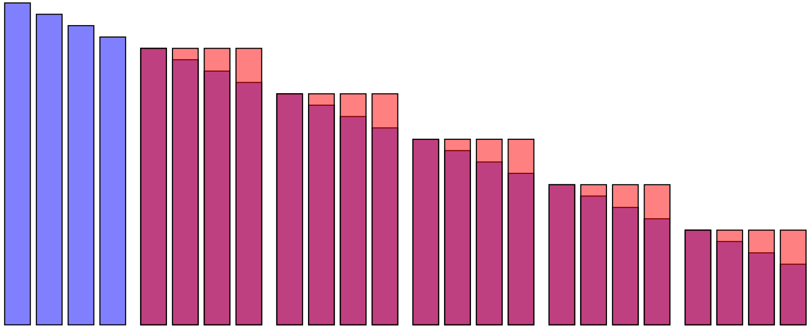

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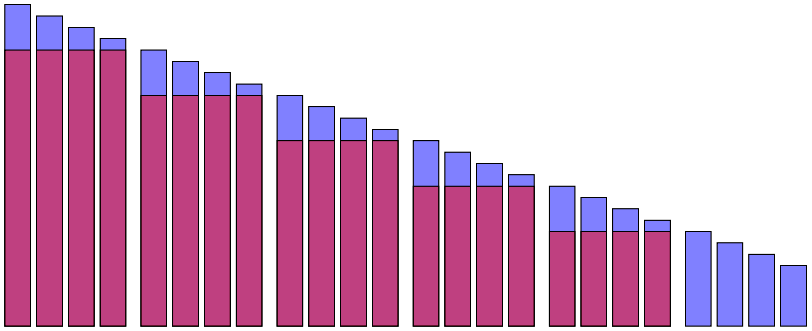

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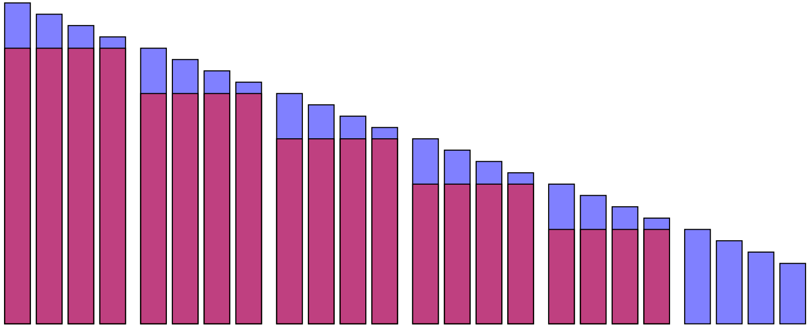

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Lemma 28

$\mathrm{OPT}(I') \le \mathrm{OPT}(I) \le \mathrm{OPT}(I') + k$

Proof 1:

- Any bin packing for I gives a bin packing for I' as follows.
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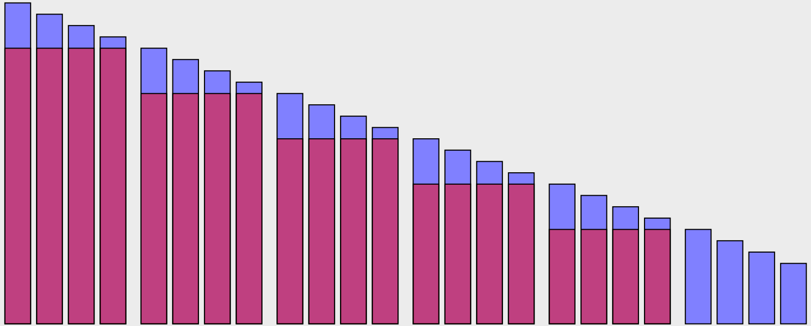

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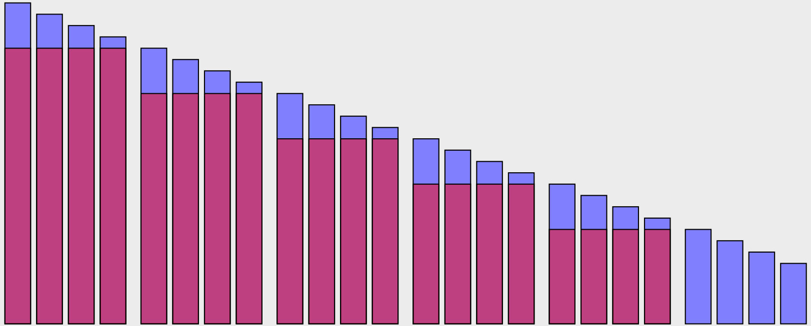

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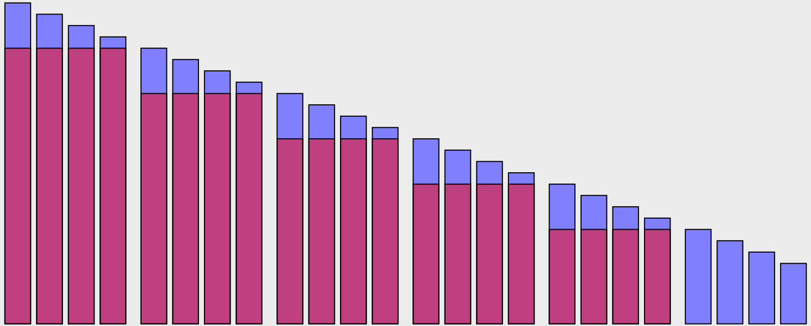

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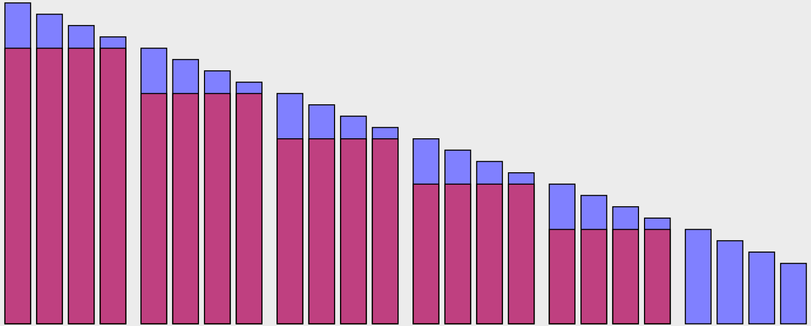

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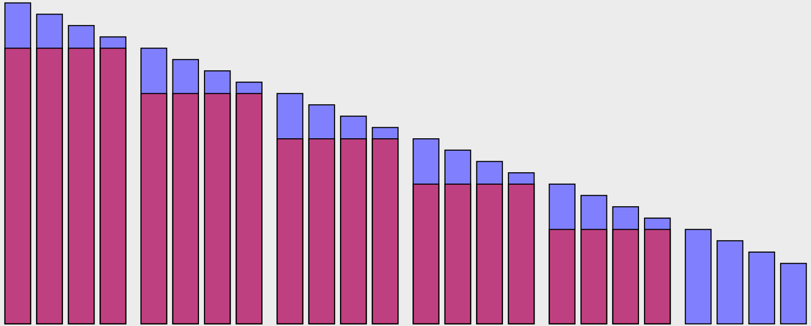

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Change of Notation:

- Group pieces of identical size.
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- s_2 is second largest size and b_2 number of pieces of size s_2;
- $\dots$
- s_m smallest size and b_m number of pieces of size s_m.

Can we do better?

In the following we show how to obtain a solution where the number of bins is only

$$\mathrm{OPT}(I) + \mathcal{O}(\log^2(\mathrm{SIZE}(I))) \ .$$

Note that this is usually better than a guarantee of

$$(1+\epsilon)\mathrm{OPT}(I) + 1 \ .$$

Configuration LP

A possible packing of a bin can be described by an m-tuple $(t_1, \ldots, t_m)$, where t_i describes the number of pieces of size s_i. Clearly,

$$\sum_i t_i \cdot s_i \leq 1 \ .$$

We call a vector that fulfills the above constraint a configuration.

Configuration LP

Change of Notation:

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Let N be the number of configurations (exponential).

Let $T_1,\dots,T_N$ be the sequence of all possible configurations (a configuration T_j has T_{ji} pieces of size s_i).

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\begin{array}{llrcl}
\min & & \sum_{j=1}^{N} x_j & & \\
\text{s.t.} & \forall i \in \{1 \dots m\} & \sum_{j=1}^{N} T_{ji} x_j & \geq & b_i \\
 & \forall j \in \{1,\dots,N\} & x_j & \geq & 0 \\
 & \forall j \in \{1,\dots,N\} & x_j & & \text{integral}
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How to solve this LP?

later...

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We can assume that each item has size at least $1/\mathrm{SIZE}(I)$.

How to solve this LP?

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Harmonic Grouping

- Sort items according to size (monotonically decreasing).
- Process items in this order; close the current group if size of items in the group is at least 2 (or larger). Then open new group.
- I.e., G_1 is the smallest cardinality set of largest items s.t. total size sums up to at least 2. Similarly, for $G_2, \ldots, G_{r-1}$.
- Only the size of items in the last group G_r may sum up to less than 2.

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From the grouping we obtain instance I' as follows:

- Round all items in a group to the size of the largest group member.
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Lemma 30

The number of different sizes in I' is at most $\mathrm{SIZE}(I)/2$.

- Each group that survives (recall that G_1 and G_r are deleted) has total size at least 2.
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The total size of deleted items is at most $\mathcal{O}(\log(\mathrm{SIZE}(I)))$.

- The total size of items in G_1 and G_r is at most 6 as a group has total size at most 3.
- Consider a group G_i that has strictly more items than G_{i-1}.
- It discards $n_i - n_{i-1}$ pieces of total size at most

$$3\frac{n_i - n_{i-1}}{n_i} \leq \sum_{j=n_{i-1}+1}^{n_i} \frac{3}{j}$$

since the smallest piece has size at most $3/n_i$.
- Summing over all i that have $n_i > n_{i-1}$ gives a bound of at most

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Algorithm 1 BinPack

1: **if** $\text{SIZE}(I) < 10$ **then**
2: pack remaining items greedily
3: Apply harmonic grouping to create instance I'; pack discarded items in at most $\mathcal{O}(\log(\text{SIZE}(I)))$ bins.
4: Let x be optimal solution to configuration LP
5: Pack $\lfloor x_j \rfloor$ bins in configuration T_j for all j; call the packed instance I_1.
6: Let I_2 be remaining pieces from I'
7: Pack I_2 via BinPack(I_2)

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$$\mathrm{OPT}_{\mathrm{LP}}(I_1) + \mathrm{OPT}_{\mathrm{LP}}(I_2) \le \mathrm{OPT}_{\mathrm{LP}}(I') \le \mathrm{OPT}_{\mathrm{LP}}(I)$$

Proof:

- Each piece surviving in I' can be mapped to a piece in I of no lesser size. Hence, $\mathrm{OPT}_{\mathrm{LP}}(I') \le \mathrm{OPT}_{\mathrm{LP}}(I)$
- $\lfloor x_j \rfloor$ is feasible solution for I_1 (even integral).
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Analysis

Each level of the recursion partitions pieces into three types

1. Pieces discarded at this level.
2. Pieces scheduled because they are in I_1.
3. Pieces in I_2 are handed down to the next level.

Pieces of type 2 summed over all recursion levels are packed into at most $\mathrm{OPT}_{\mathrm{LP}}$ many bins.

Pieces of type 1 are packed into at most

$$\mathcal{O}(\log(\mathrm{SIZE}(I))) \cdot L$$

many bins where L is the number of recursion levels.

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$$\mathrm{OPT}_{\mathrm{LP}}(I_1) + \mathrm{OPT}_{\mathrm{LP}}(I_2) \le \mathrm{OPT}_{\mathrm{LP}}(I') \le \mathrm{OPT}_{\mathrm{LP}}(I)$$

Proof:

- Each piece surviving in I' can be mapped to a piece in I of no lesser size. Hence, $\mathrm{OPT}_{\mathrm{LP}}(I') \le \mathrm{OPT}_{\mathrm{LP}}(I)$
- $\lfloor x_j \rfloor$ is feasible solution for I_1 (even integral).
- $x_j - \lfloor x_j \rfloor$ is feasible solution for I_2.

Analysis

Each level of the recursion partitions pieces into three types

1. Pieces discarded at this level.
2. Pieces scheduled because they are in I_1.
3. Pieces in I_2 are handed down to the next level.

Pieces of type 2 summed over all recursion levels are packed into at most $\mathrm{OPT}_{\mathrm{LP}}$ many bins.

Pieces of type 1 are packed into at most

$$\mathcal{O}(\log(\mathrm{SIZE}(I))) \cdot L$$

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Analysis

We can show that $\mathrm{SIZE}(I_2) \leq \mathrm{SIZE}(I)/2$. Hence, the number of recursion levels is only $\mathcal{O}(\log(\mathrm{SIZE}(I_{\text{original}})))$ in total.

- The number of non-zero entries in the solution to the configuration LP for I' is at most the number of constraints, which is the number of different sizes ($\leq \mathrm{SIZE}(I)/2$).
- The total size of items in I_1 can be at most $\sum_{j=1}^{N} x_j - \lfloor x_j \rfloor$ which is at most the number of non-zero entries in the solution to the configuration LP.

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Primal

$$\begin{array}{llrcl} \min & & \sum_{j=1}^{N} x_j & & \\ \text{s.t.} & \forall i \in \{1 \dots m\} & \sum_{j=1}^{N} T_{ji} x_j & \geq & b_i \\ & \forall j \in \{1, \dots, N\} & x_j & \geq & 0 \end{array}$$

Dual

$$\begin{array}{llrcl} \max & & \sum_{i=1}^{m} y_i b_i & & \\ \text{s.t.} & \forall j \in \{1, \dots, N\} & \sum_{i=1}^{m} T_{ji} y_i & \leq & 1 \\ & \forall i \in \{1, \dots, m\} & y_i & \geq & 0 \end{array}$$

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Separation Oracle

Suppose that I am given variable assignment y for the dual.

How do I find a violated constraint?

I have to find a configuration $T_j = (T_{j1}, \ldots, T_{jm})$ that

is feasible, i.e.,

and has a large profit

But this is the Knapsack problem.

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We have FPTAS for Knapsack. This means if a constraint is violated with $1+\epsilon' = 1+\frac{\epsilon}{1-\epsilon}$ we find it, since we can obtain at least $(1-\epsilon)$ of the optimal profit.

The solution we get is feasible for:

Dual′

$$\begin{array}{llrcl} \max & & \sum_{i=1}^m y_i b_i & & \\ \text{s.t.} & \forall j \in \{1,\dots,N\} & \sum_{i=1}^m T_{ji} y_i & \le & 1+\epsilon' \\ & \forall i \in \{1,\dots,m\} & y_i & \ge & 0 \end{array}$$

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If the value of the computed dual solution (which may be infeasible) is z then

$$\mathrm{OPT} \leq z \leq (1+\epsilon')\mathrm{OPT}$$

How do we get good primal solution (not just the value)?

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- Suppose that we drop all unused constraints in DUAL. We will compute the same solution feasible for DUAL'.
- Let DUAL'' be DUAL without unused constraints.
- The dual to DUAL'' is PRIMAL where we ignore variables for which the corresponding dual constraint has not been used.
- The optimum value for PRIMAL'' is at most $(1+\epsilon')\mathrm{OPT}$.
- We can compute the corresponding solution in polytime.

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We have FPTAS for Knapsack. This means if a constraint is violated with $1+\epsilon' = 1+\frac{\epsilon}{1-\epsilon}$ we find it, since we can obtain at least $(1-\epsilon)$ of the optimal profit.

The solution we get is feasible for:

Dual′

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\text{s.t.} & \forall j \in \{1,\dots,N\} & \sum_{i=1}^m T_{ji} y_i & \le & 1+\epsilon' \\
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This gives that overall we need at most

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bins.

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Lemma 32 (Chernoff Bounds)

Let $X_1, \dots, X_n$ *be* n *independent 0-1 random variables, not necessarily identically distributed. Then for* $X = \sum_{i=1}^{n} X_i$ *and* $\mu = E[X]$, $L \leq \mu \leq U$, *and* $\delta > 0$

$$\Pr[X \geq (1+\delta)U] < \left(\frac{e^{\delta}}{(1+\delta)^{1+\delta}}\right)^{U} ,$$

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Lemma 33

For $0 \le \delta \le 1$ *we have that*

$$\left(\frac{e^{\delta}}{(1+\delta)^{1+\delta}}\right)^{U} \le e^{-U\delta^2/3}$$

and

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Markovs Inequality:
Let X be random variable taking non-negative values.
Then
$$\Pr[X \geq a] \leq \mathrm{E}[X]/a$$

Trivial!

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That's awfully weak :(

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$$\mathrm{E}\left[e^{tX}\right] = \mathrm{E}\left[e^{t\sum_i X_i}\right] = \mathrm{E}\left[\prod_i e^{tX_i}\right] = \prod_i \mathrm{E}\left[e^{tX_i}\right]$$

$$\mathrm{E}\left[e^{tX_i}\right] = (1-p_i) + p_i e^t = 1 + p_i(e^t - 1) \leq e^{p_i(e^t-1)}$$

$$\prod_i \mathrm{E}\left[e^{tX_i}\right] \leq \prod_i e^{p_i(e^t-1)} = e^{\sum p_i(e^t-1)} = e^{(e^t-1)U}$$

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Lemma 34

For $0 \le \delta \le 1$ *we have that*

$$\left(\frac{e^{\delta}}{(1+\delta)^{1+\delta}}\right)^U \le e^{-U\delta^2/3}$$

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$f(0) = 0$ and $f(1) = -\ln(2) + 2/3 < 0$

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Integer Multicommodity Flows

- Given s_i-t_i pairs in a graph.
- Connect each pair by a path such that not too many path use any given edge.

$$\begin{array}{llrcl}
\min & & & & W \\
\text{s.t.} & \forall i & \sum_{p\in\mathcal{P}_i} x_p & = & 1 \\
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Integer Multicommodity Flows

Randomized Rounding:
For each i choose one path from the set $\mathcal{P}_i$ at random according to the probability distribution given by the Linear Programming solution.

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Theorem 35
If $W^* \geq c \ln n$ for some constant c, then with probability at least $n^{-c/3}$ the total number of paths using any edge is at most $W^* + \sqrt{cW^* \ln n}$.

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Let X_e^i be a random variable that indicates whether the path for s_i-t_i uses edge e.

Then the number of paths using edge e is $Y_e = \sum_i X_e^i$.

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Choose $\delta = \sqrt{(c \ln n)/W^*}$.

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17.3 MAXSAT

Problem definition:

- n Boolean variables
- m clauses $C_1, \dots, C_m$. For example

$$C_7 = x_3 \vee \bar{x}_5 \vee \bar{x}_9$$

- Non-negative weight w_j for each clause C_j.
- Find an assignment of true/false to the variables sucht that the total weight of clauses that are satisfied is maximum.

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$$\Pr[Y_e \geq (1+\delta)W^*] < e^{-W^*\delta^2/3} = \frac{1}{n^{c/3}}$$

17.3 MAXSAT

Terminology:

- A variable x_i and its negation $\bar{x}_i$ are called literals.
- Hence, each clause consists of a set of literals (i.e., no duplications: $x_i \vee x_i \vee \bar{x}_j$ is **not** a clause).
- We assume a clause does not contain x_i and $\bar{x}_i$ for any i.
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- Clauses of length one are called unit clauses.

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Problem definition:

- n Boolean variables
- m clauses $C_1, \dots, C_m$. For example

$$C_7 = x_3 \vee \bar{x}_5 \vee \bar{x}_9$$

- Non-negative weight w_j for each clause C_j.
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MAXSAT: Flipping Coins

Set each x_i independently to true with probability $\frac{1}{2}$ (and, hence, to false with probability $\frac{1}{2}$, as well).

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Define random variable X_j with

$$X_j = \begin{cases} 1 & \text{if } C_j \text{ satisfied} \\ 0 & \text{otw.} \end{cases}$$

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- Let for a clause C_j, P_j be the set of positive literals and N_j the set of negative literals.

$$C_j = \bigvee_{j \in P_j} x_i \vee \bigvee_{j \in N_j} \bar{x}_i$$

$$\begin{array}{llrcl} \max & & \sum_j w_j z_j & & \\ \text{s.t.} & \forall j & \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) & \ge & z_j \\ & \forall i & y_i & \in & \{0,1\} \\ & \forall j & z_j & \le & 1 \end{array}$$

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Set each x_i independently to true with probability y_i (and, hence, to false with probability $(1 - y_i)$).

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Lemma 37 (Geometric Mean $\leq$ Arithmetic Mean)

For any nonnegative $a_1, \ldots, a_k$

$$\left(\prod_{i=1}^{k} a_i\right)^{1/k} \leq \frac{1}{k}\sum_{i=1}^{k} a_i$$

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Definition 38

A function f on an interval I is concave if for any two points s and r from I and any $\lambda \in [0,1]$ we have

$$f(\lambda s + (1-\lambda)r) \geq \lambda f(s) + (1-\lambda)f(r)$$

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The function $f(z) = 1 - (1 - \frac{z}{\ell})^{\ell}$ is concave. Hence,

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$f''(z) = -\frac{\ell-1}{\ell}\left[1 - \frac{z}{\ell}\right]^{\ell-2} \leq 0$ for $z \in [0,1]$. Therefore, f is concave.

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$$\Pr[C_j \text{ satisfied}] \geq 1 - \left(1 - \frac{z_j}{\ell_j}\right)^{\ell_j}$$
$$\geq \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] \cdot z_j \ .$$

$f''(z) = -\frac{\ell-1}{\ell}\left[1 - \frac{z}{\ell}\right]^{\ell-2} \leq 0$ for $z \in [0,1]$. Therefore, f is concave.

$$\begin{aligned} E[W] &= \sum_j w_j \Pr[C_j \text{ is satisfied}] \\ &\ge \sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] \\ &\ge \left(1 - \frac{1}{e}\right) \mathrm{OPT} \ . \end{aligned}$$

The function $f(z) = 1 - (1 - \frac{z}{\ell})^\ell$ is concave. Hence,

$$\begin{aligned} \Pr[C_j \text{ satisfied}] &\ge 1 - \left(1 - \frac{z_j}{\ell_j}\right)^{\ell_j} \\ &\ge \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] \cdot z_j \ . \end{aligned}$$

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MAXSAT: The better of two

Theorem 40
Choosing the better of the two solutions given by randomized rounding and coin flipping yields a $\frac{3}{4}$-approximation.

$$
\begin{aligned}
E[W] &= \sum_j w_j \Pr[C_j \text{ is satisfied}] \\
&\geq \sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] \\
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\end{aligned}
$$

Let W_1 be the value of randomized rounding and W_2 the value obtained by coin flipping.

$$E[\max\{W_1, W_2\}]$$

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\begin{aligned}
& E[\max\{W_1, W_2\}] \\
& \qquad \geq E[\tfrac{1}{2}W_1 + \tfrac{1}{2}W_2]
\end{aligned}
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$$E[\max\{W_1, W_2\}]$$
$$\geq E[\tfrac{1}{2}W_1 + \tfrac{1}{2}W_2]$$
$$\geq \frac{1}{2}\sum_j w_j z_j \left[1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right] + \frac{1}{2}\sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right)$$

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&\quad \geq \sum_j w_j z_j \Bigg[\underbrace{\frac{1}{2}\left(1 - \left(1 - \frac{1}{\ell_j}\right)^{\ell_j}\right) + \frac{1}{2}\left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right)}_{\geq \frac{3}{4} \text{for all integers}}\Bigg]
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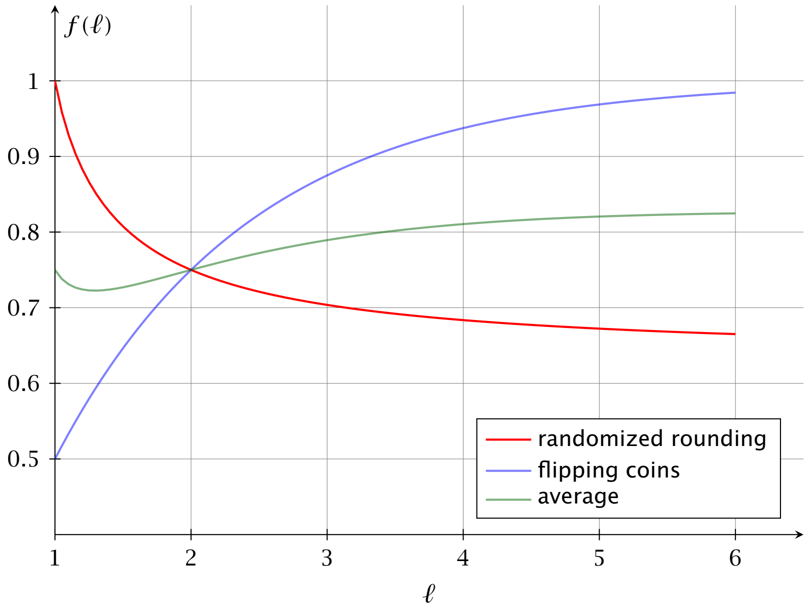

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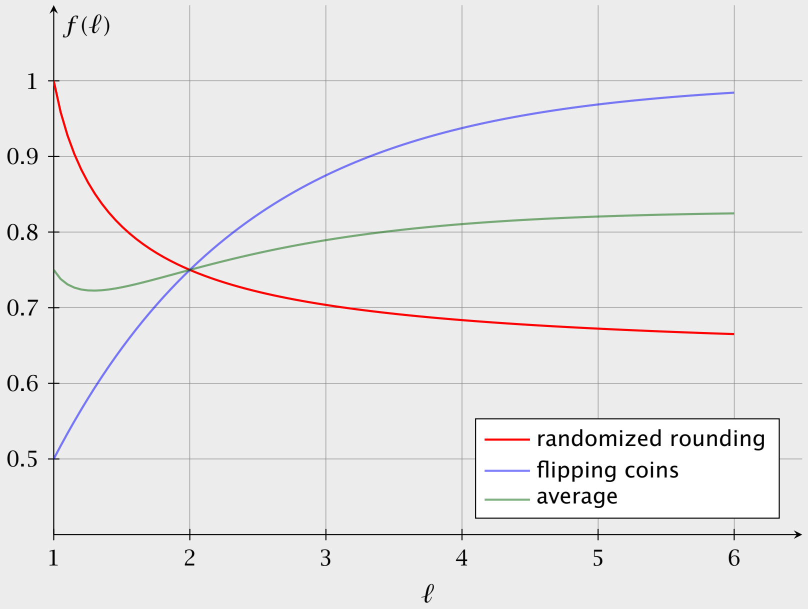
MAXSAT: Nonlinear Randomized Rounding

So far we used linear randomized rounding, i.e., the probability that a variable is set to 1/true was exactly the value of the corresponding variable in the linear program.

We could define a function $f : [0,1] \to [0,1]$ and set x_i to true with probability $f(y_i)$.



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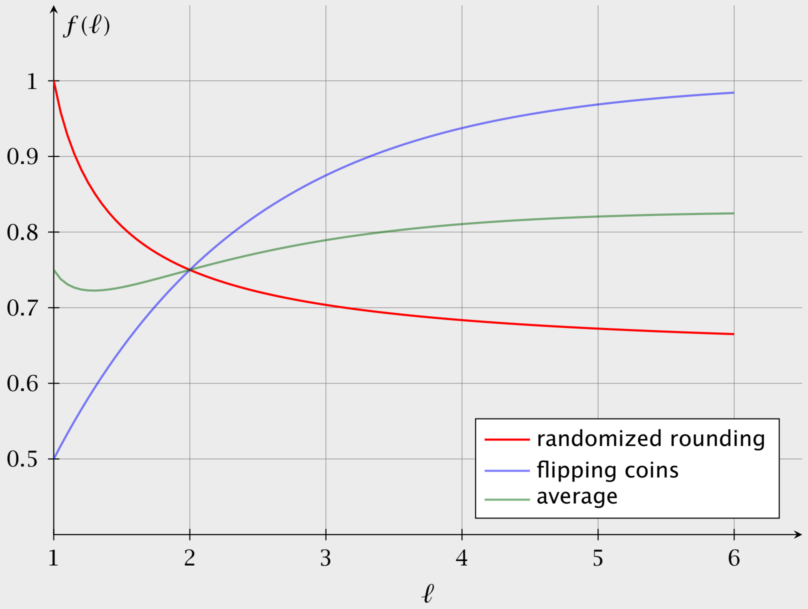

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17.3 MAXSAT

MAXSAT: Nonlinear Randomized Rounding

Let $f : [0,1] \to [0,1]$ be a function with

$$1 - 4^{-x} \le f(x) \le 4^{x-1}$$

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Rounding the LP-solution with a function f of the above form gives a $\frac{3}{4}$-approximation.

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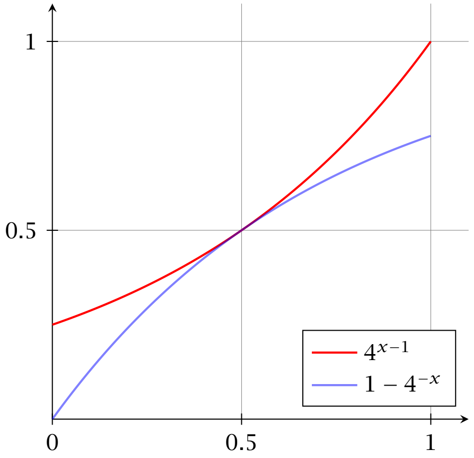

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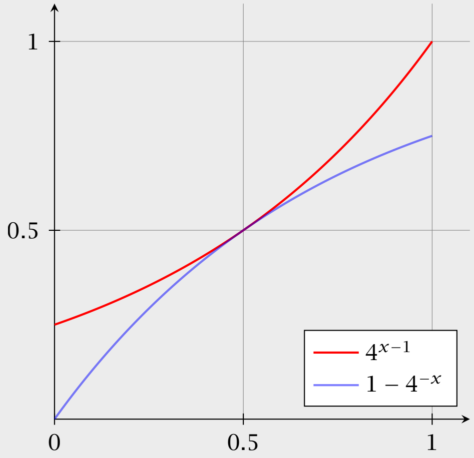
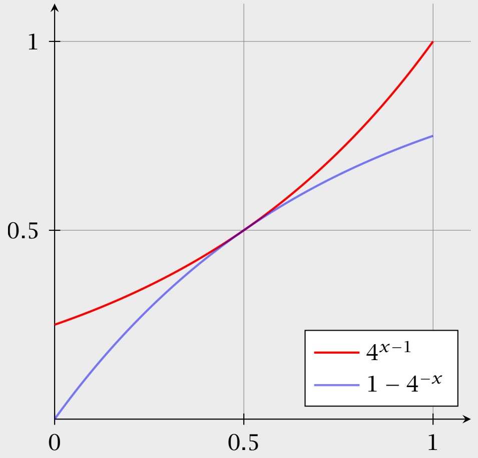
$\Pr[C_j \text{ not satisfied}]$



$$\Pr[C_j \text{ not satisfied}] = \prod_{i \in P_j} (1 - f(y_i)) \prod_{i \in N_j} f(y_i)$$



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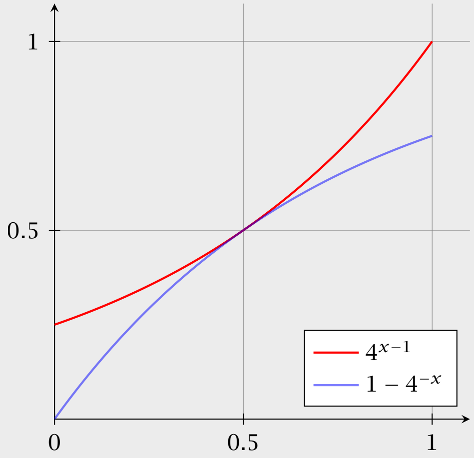
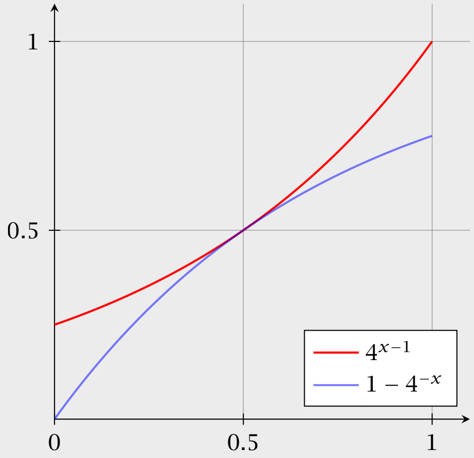
Harald Räcke
17.3 MAXSAT

$$\Pr[C_j \text{ not satisfied}] = \prod_{i\in P_j}(1-f(y_i))\prod_{i\in N_j} f(y_i)$$
$$\le \prod_{i\in P_j} 4^{-y_i}\prod_{i\in N_j} 4^{y_i-1}$$



$$\begin{aligned}\Pr[C_j \text{ not satisfied}] &= \prod_{i\in P_j}(1-f(y_i))\prod_{i\in N_j} f(y_i)\\ &\le \prod_{i\in P_j} 4^{-y_i}\prod_{i\in N_j} 4^{y_i-1}\\ &= 4^{-(\sum_{i\in P_j} y_i+\sum_{i\in N_j}(1-y_i))}\end{aligned}$$



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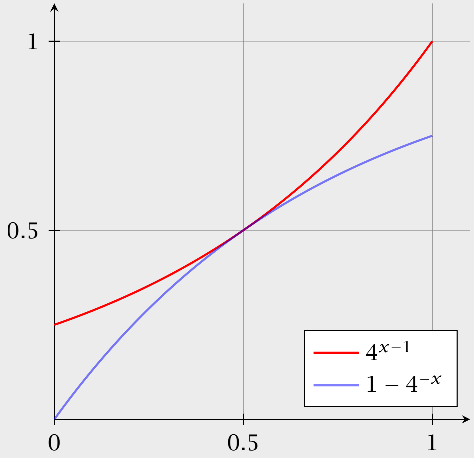
&\le 4^{-z_j}
\end{aligned}
$$



The function $g(z) = 1 - 4^{-z}$ is concave on $[0,1]$. Hence,

$$
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\Pr[C_j \text{ not satisfied}] &= \prod_{i\in P_j}(1-f(y_i))\prod_{i\in N_j} f(y_i) \\
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The function $g(z) = 1 - 4^{-z}$ is concave on $[0,1]$. Hence,

$$\Pr[C_j \text{ satisfied}] \geq 1 - 4^{-z_j}$$

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Therefore,

$$E[W]$$

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&\leq 4^{-z_j}
\end{aligned}$$

Can we do better?

Not if we compare ourselves to the value of an optimum LP-solution.

Definition 42 (Integrality Gap)

The integrality gap for an ILP is the worst-case ratio over all instances of the problem of the value of an optimal IP-solution to the value of an optimal solution to its linear programming relaxation.

Note that the integrality is less than one for maximization problems and larger than one for minimization problems (of course, equality is possible).

Note that an integrality gap only holds for one specific ILP formulation.

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Lemma 43

Our ILP-formulation for the MAXSAT problem has integrality gap at most $\frac{3}{4}$.

$$\begin{array}{llrcl}
\max & & \sum_j w_j z_j & & \\
\text{s.t.} & \forall j & \sum_{i\in P_j} y_i + \sum_{i\in N_j}(1-y_i) & \geq & z_j \\
 & \forall i & y_i & \in & \{0,1\} \\
 & \forall j & z_j & \leq & 1
\end{array}$$

Consider: $(x_1 \vee x_2) \wedge (\bar{x}_1 \vee x_2) \wedge (x_1 \vee \bar{x}_2) \wedge (\bar{x}_1 \vee \bar{x}_2)$

- any solution can satisfy at most 3 clauses
- we can set $y_1 = y_2 = 1/2$ in the LP; this allows to set $z_1 = z_2 = z_3 = z_4 = 1$
- hence, the LP has value 4.

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Consider: $(x_1 \vee x_2) \wedge (\bar{x}_1 \vee x_2) \wedge (x_1 \vee \bar{x}_2) \wedge (\bar{x}_1 \vee \bar{x}_2)$

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MaxCut

MaxCut
Given a weighted graph $G = (V, E, w)$, $w(v) \geq 0$, partition the vertices into two parts. Maximize the weight of edges between the parts.

Trivial 2-approximation

Lemma 43
Our ILP-formulation for the MAXSAT problem has integrality gap at most $\frac{3}{4}$.

$$\begin{array}{llrcl} \max & & \sum_j w_j z_j & & \\ \text{s.t.} & \forall j & \sum_{i\in P_j} y_i + \sum_{i\in N_j}(1-y_i) & \geq & z_j \\ & \forall i & y_i & \in & \{0,1\} \\ & \forall j & z_j & \leq & 1 \end{array}$$

Consider: $(x_1 \vee x_2) \wedge (\bar{x}_1 \vee x_2) \wedge (x_1 \vee \bar{x}_2) \wedge (\bar{x}_1 \vee \bar{x}_2)$

- any solution can satisfy at most 3 clauses
- we can set $y_1 = y_2 = 1/2$ in the LP; this allows to set $z_1 = z_2 = z_3 = z_4 = 1$
- hence, the LP has value 4.

Semidefinite Programming

$$
\begin{array}{llrcl}
\text{max / min} & & \sum_{i,j} c_{ij} x_{ij} & & \\
\text{s.t.} & \forall k & \sum_{i,j,k} a_{ijk} x_{ij} & = & b_k \\
 & \forall i,j & x_{ij} & = & x_{ji} \\
 & & \multicolumn{3}{c}{X = (x_{ij}) \text{ is psd.}}
\end{array}
$$

- linear objective, linear contraints
- we can constrain a square matrix of variables to be symmetric positive definite

MaxCut

MaxCut
Given a weighted graph $G = (V, E, w)$, $w(v) \geq 0$, partition the vertices into two parts. Maximize the weight of edges between the parts.

Trivial 2-approximation

Vector Programming

$$\begin{array}{llrcl} \max / \min & & \sum_{i,j} c_{ij}(v_i^t v_j) & & \\ \text{s.t.} & \forall k & \sum_{i,j,k} a_{ijk}(v_i^t v_j) & = & b_k \\ & \forall i,j & x_{ij} & = & x_{ji} \\ & & v_i \in \mathbb{R}^n & & \end{array}$$

- variables are vectors in n-dimensional space
- objective functions and contraints are linear in inner products of the vectors

This is equivalent!

Semidefinite Programming

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Fact [without proof]

We (essentially) can solve Semidefinite Programs in polynomial time...

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Quadratic Programs

Quadratic Program for MaxCut:

$$\boxed{\begin{array}{lrcl} \max & \frac{1}{2}\sum_{i,j} w_{ij}(1-y_iy_j) & & \\ \forall i & y_i & \in & \{-1,1\} \end{array}}$$

This is exactly MaxCut!

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Semidefinite Relaxation

$$\begin{array}{llrcl} \max & & \frac{1}{2}\sum_{i,j} w_{ij}(1-v_i^t v_j) & & \\ & \forall i & v_i^t v_i & = & 1 \\ & \forall i & v_i & \in & \mathbb{R}^n \end{array}$$

- this is clearly a relaxation
- the solution will be vectors on the unit sphere

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Rounding the SDP-Solution

- Choose a random vector r such that $r/\|r\|$ is uniformly distributed on the unit sphere.
- If $r^t v_i > 0$ set $y_i = 1$ else set $y_i = -1$

Semidefinite Relaxation

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Rounding the SDP-Solution

Choose the i-th coordinate r_i as a Gaussian with mean 0 and variance 1, i.e., $r_i \sim \mathcal{N}(0,1)$.

Density function:

$$\varphi(x) = \frac{1}{\sqrt{2\pi}} e^{x^2/2}$$

Then

$$\begin{aligned}\Pr[r = (x_1, \dots, x_n)] &\\ &= \frac{1}{(\sqrt{2\pi})^n} e^{x_1^2/2} \cdot e^{x_2^2/2} \cdot \ldots \cdot e^{x_n^2/2} \, dx_1 \cdot \ldots \cdot dx_n \\ &= \frac{1}{(\sqrt{2\pi})^n} e^{\frac{1}{2}(x_1^2 + \ldots + x_n^2)} \, dx_1 \cdot \ldots \cdot dx_n\end{aligned}$$

Hence the probability for a point only depends on its distance to the origin.

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Rounding the SDP-Solution

Fact
The projection of r onto two unit vectors e_1 and e_2 are independent and are normally distributed with mean 0 and variance 1 iff e_1 and e_2 are orthogonal.

Note that this is clear if e_1 and e_2 are standard basis vectors.

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Corollary
If we project r onto a hyperplane its normalized projection ($r'/\|r'\|$) is uniformly distributed on the unit circle within the hyperplane.

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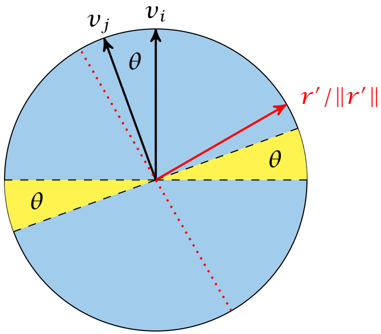

- if the normalized projection falls into the shaded region, v_i and v_j are rounded to different values
- this happens with probability θ/π

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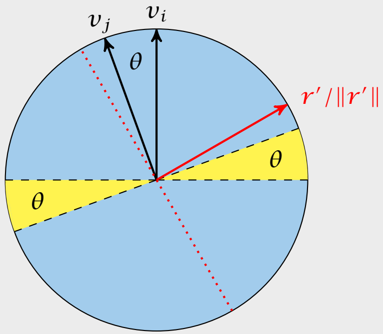
- contribution of edge (i,j) to the SDP-relaxation:

$$\frac{1}{2}w_{ij}\left(1 - v_i^t v_j\right)$$

- (expected) contribution of edge (i,j) to the rounded instance $w_{ij}\arccos(v_i^t v_j)/\pi$
- ratio is at most

$$\min_{x\in[-1,1]} \frac{2\arccos(x)}{\pi(1-x)} \geq 0.878$$

Rounding the SDP-Solution



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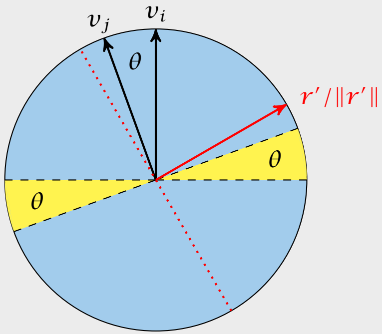

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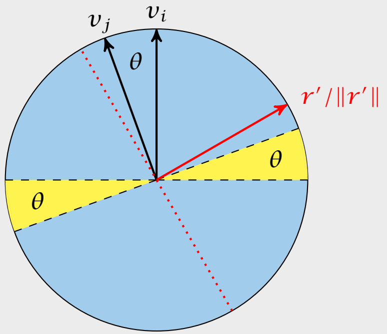

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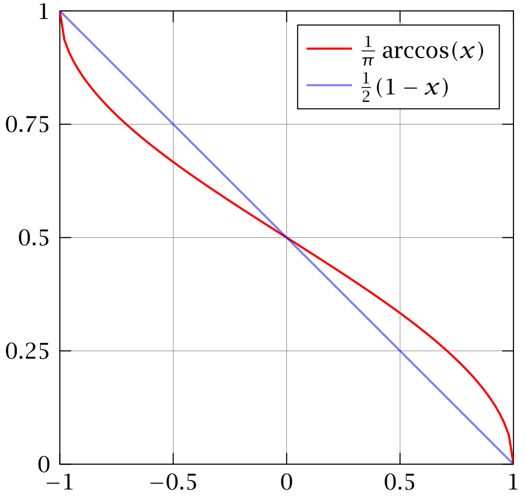

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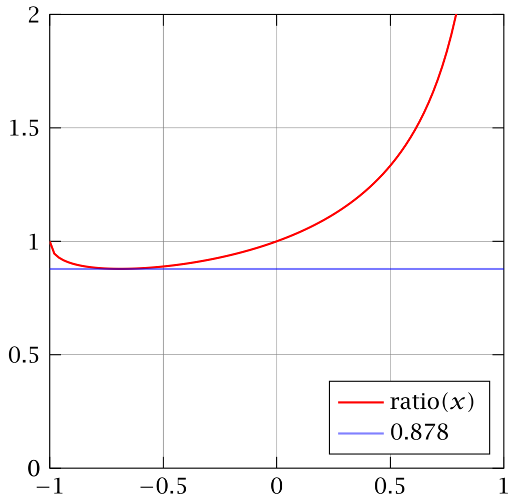

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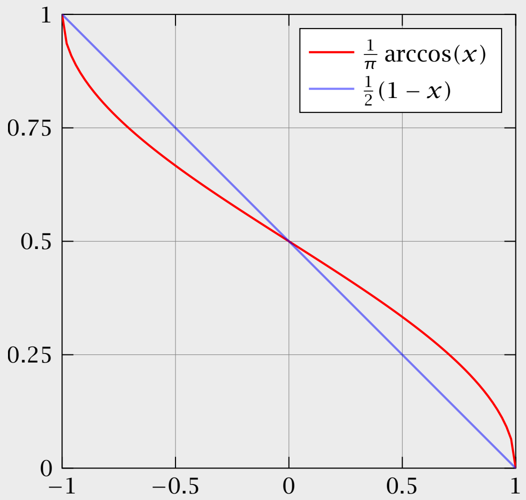


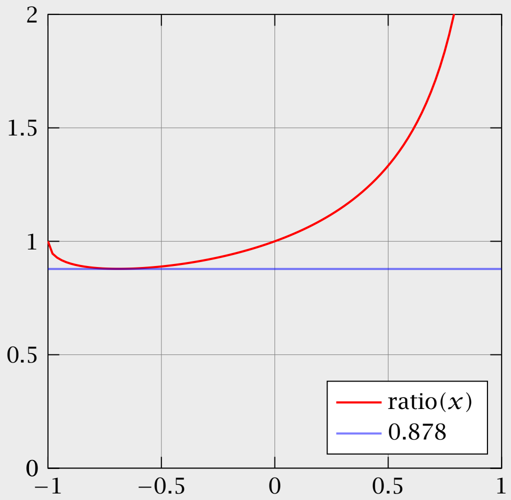
Rounding the SDP-Solution

Theorem 44
Given the unique games conjecture, there is no α*-approximation for the maximum cut problem with constant*

$$\alpha > \min_{x\in[-1,1]} \frac{2\arccos(x)}{\pi(1-x)}$$

unless $\mathrm{P} = \mathrm{NP}$.

Rounding the SDP-Solution



Repetition: Primal Dual for Set Cover

Primal Relaxation:

$$
\begin{array}{llrcl}
\min & & \sum_{i=1}^{k} w_i x_i & & \\
\text{s.t.} & \forall u \in U & \sum_{i:u\in S_i} x_i & \geq & 1 \\
& \forall i \in \{1,\dots,k\} & x_i & \geq & 0
\end{array}
$$

Dual Formulation:

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This means

$$x_j > 0 \Rightarrow \sum_{e \in S_j} y_e = w_j$$

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$$\sum_j w_j x_j = \sum_j \sum_{e \in S_j} y_e = \sum_e |\{j : e \in S_j\}| \cdot y_e$$
$$\le f \cdot \sum_e y_e \le f \cdot \mathrm{OPT}$$

Note that the constructed pair of primal and dual solution fulfills primal slackness conditions.

This means

$$x_j > 0 \Rightarrow \sum_{e \in S_j} y_e = w_j$$

If we would also fulfill dual slackness conditions

$$y_e > 0 \Rightarrow \sum_{j : e \in S_j} x_j = 1$$

then the solution would be optimal!!!

Repetition: Primal Dual for Set Cover

Analysis:

- For every set S_j with $x_j = 1$ we have

$$\sum_{e \in S_j} y_e = w_j$$

- Hence our cost is

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Suppose we have a primal/dual pair

$$\begin{array}{lllll} \min & & \sum_j c_j x_j & & \\ \text{s.t.} & \forall i & \sum_{j:} a_{ij} x_j & \geq & b_i \\ & \forall j & x_j & \geq & 0 \end{array}$$

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Feedback Vertex Set for Undirected Graphs

- Given a graph $G = (V, E)$ and non-negative weights $w_v \geq 0$ for vertex $v \in V$.

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$$
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We can encode this as an instance of Set Cover

- Each vertex can be viewed as a set that contains some cycles.

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Primal Relaxation:

$$\begin{array}{llrcl} \min & & \sum_v w_v x_v & & \\ \text{s.t.} & \forall C \in \mathbb{C} & \sum_{v \in C} x_v & \geq & 1 \\ & \forall v & x_v & \geq & 0 \end{array}$$

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where S is the set of vertices we choose.

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Algorithm 1 FeedbackVertexSet

```
y ← 0
x ← 0
while exists cycle C in G do
    increase y_C until there is v ∈ C s.t. ∑_{C:v∈C} y_C = w_v
    x_v = 1
    remove v from G
    repeatedly remove vertices of degree 1 from G
```


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Always choose a short cycle that is not covered. If we always find a cycle of length at most α we get an α-approximation.

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For any path P of vertices of degree 2 in G the algorithm chooses at most one vertex from P.

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Theorem 45
In any graph with no vertices of degree 1, there always exists a cycle that has at most $\mathcal{O}(\log n)$ vertices of degree 3 or more. We can find such a cycle in linear time.

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Primal Dual for Shortest Path

Given a graph $G = (V, E)$ with two nodes $s, t \in V$ and edge-weights $c : E \to \mathbb{R}^+$ find a shortest path between s and t w.r.t. edge-weights c.

$$\begin{array}{llrcl} \min & & \sum_e c(e)x_e & & \\ \text{s.t.} & \forall S \in \mathcal{S} & \sum_{e:\delta(S)} x_e & \geq & 1 \\ & \forall e \in E & x_e & \in & \{0,1\} \end{array}$$

Here $\delta(S)$ denotes the set of edges with exactly one end-point in S, and $\mathcal{S} = \{S \subseteq V : s \in S, t \notin S\}$.

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Primal Dual for Shortest Path

The Dual:

$$
\begin{array}{|llrcl|}
\hline
\max & & \sum_S y_S & & \\
\text{s.t.} & \forall e \in E & \sum_{S: e \in \delta(S)} y_S & \le & c(e) \\
& \forall S \in \mathcal{S} & y_S & \ge & 0 \\
\hline
\end{array}
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\hline
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Here $\delta(S)$ denotes the set of edges with exactly one end-point in S, and $\mathcal{S} = \{S \subseteq V : s \in S, t \notin S\}$.

Primal Dual for Shortest Path

The Dual:

$$\begin{array}{llrcl} \max & & \sum_S y_S & & \\ \text{s.t.} & \forall e \in E & \sum_{S: e\in\delta(S)} y_S & \le & c(e) \\ & \forall S \in \mathcal{S} & y_S & \ge & 0 \end{array}$$

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Primal Dual for Shortest Path

Given a graph $G = (V, E)$ with two nodes $s, t \in V$ and edge-weights $c : E \to \mathbb{R}^+$ find a shortest path between s and t w.r.t. edge-weights c.

$$\begin{array}{llrcl} \min & & \sum_e c(e) x_e & & \\ \text{s.t.} & \forall S \in \mathcal{S} & \sum_{e:\delta(S)} x_e & \ge & 1 \\ & \forall e \in E & x_e & \in & \{0,1\} \end{array}$$

Here $\delta(S)$ denotes the set of edges with exactly one end-point in S, and $\mathcal{S} = \{S \subseteq V : s \in S, t \notin S\}$.

Primal Dual for Shortest Path

We can interpret the value y_S as the width of a moat surounding the set S.

Each set can have its own moat but all moats must be disjoint.

An edge cannot be shorter than all the moats that it has to cross.

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Algorithm 1 PrimalDualShortestPath

```
y ← 0
F ← ∅
while there is no s-t path in (V, F) do
    Let C be the connected component of (V, F) containing s
    Increase y_C until there is an edge e' ∈ δ(C) such that ∑_{S:e'∈δ(S)} y_S = c(e').
    F ← F ∪ {e'}
Let P be an s-t path in (V, F)
return P
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Lemma 46

At each point in time the set F forms a tree.

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EADS II
Harald Räcke
18.3 Primal Dual for Shortest Path

Lemma 46

At each point in time the set F forms a tree.

Proof:

- In each iteration we take the current connected component from (V, F) that contains s (call this component C) and add some edge from $\delta(C)$ to F.
- Since, at most one end-point of the new edge is in C the edge cannot close a cycle.

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1: $y \leftarrow 0$
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6: $F \leftarrow F \cup \{e'\}$
7: Let P be an s-t path in (V,F)
8: **return** P

$$\sum_{e \in P} c(e)$$

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$$\sum_{e\in P} c(e) = \sum_{e\in P} \sum_{S:e\in\delta(S)} y_S$$

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If we can show that $y_S > 0$ implies $|P\cap\delta(S)| = 1$ gives

$$\sum_{e\in P} c(e) = \sum_S y_S \le \mathrm{OPT}$$

by weak duality.

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If S contains two edges from P then there must exist a subpath P' of P that starts and ends with a vertex from S (and all interior vertices are not in S).

When we increased y_S, S was a connected component of the set of edges F' that we had chosen till this point.

$F' \cup P'$ contains a cycle. Hence, also the final set of edges contains a cycle.

This is a contradiction.

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Steiner Forest Problem:
Given a graph $G = (V, E)$, together with source-target pairs s_i, t_i, $i = 1, \dots, k$, and a cost function $c : E \to \mathbb{R}^+$ on the edges. Find a subset $F \subseteq E$ of the edges such that for every $i \in \{1, \dots, k\}$ there is a path between s_i and t_i only using edges in F.

$$\begin{array}{llrcl} \min & & \sum_e c(e) x_e & & \\ \text{s.t.} & \forall S \subseteq V : S \in S_i \text{ for some } i & \sum_{e \in \delta(S)} x_e & \geq & 1 \\ & \forall e \in E & x_e & \in & \{0,1\} \end{array}$$

Here S_i contains all sets S such that $s_i \in S$ and $t_i \notin S$.

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The difference to the dual of the shortest path problem is that we have many more variables (sets for which we can generate a moat of non-zero width).

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Algorithm 1 FirstTry

$y \leftarrow 0$
$F \leftarrow \emptyset$
while not all s_i-t_i pairs connected in F **do**
    Let C be some connected component of (V, F) such that $|C \cap \{s_i, t_i\}| = 1$ for some i.
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$$\sum_{e\in F} c(e) = \sum_{e\in F}\sum_{S:e\in\delta(S)} y_S = \sum_S |\delta(S)\cap F|\cdot y_S\ .$$

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If we show that $y_S > 0$ implies that $|\delta(S)\cap F| \le \alpha$ we are in good shape.

However, this is not true:

- Take a complete graph on $k+1$ vertices $v_0, v_1, \dots, v_k$.

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- Take a complete graph on $k+1$ vertices $v_0, v_1, \dots, v_k$.
- The i-th pair is v_0-v_i.
- The first component C could be $\{v_0\}$.
- We only set $y_{\{v_0\}} = 1$. All other dual variables stay 0.

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- Take a complete graph on $k+1$ vertices $v_0, v_1, \dots, v_k$.
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- The first component C could be $\{v_0\}$.
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1: $y \leftarrow 0$
2: $F \leftarrow \emptyset$
3: **while** not all s_i-t_i pairs connected in F **do**
4: Let C be some connected component of (V,F) such that $|C \cap \{s_i, t_i\}| = 1$ for some i.
5: Increase y_C until there is an edge $e' \in \delta(C)$ s.t. $\sum_{S\in S_i:e'\in\delta(S)} y_S = c_{e'}$
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y ← 0; F ← ∅; ℓ ← 0
while not all s_i-t_i pairs connected in F do
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    Increase y_C for all C ∈ ℭ uniformly until for some edge
    e_ℓ ∈ δ(C'), C' ∈ ℭ s.t. ∑_{S: e_ℓ ∈ δ(S)} y_S = c_{e_ℓ}
    F ← F ∪ {e_ℓ}
F' ← F
for k ← ℓ downto 1 do // reverse deletion
    if F' − e_k is feasible solution then
        remove e_k from F'
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The reverse deletion step is not strictly necessary this way. It would also be sufficient to simply delete all unnecessary edges in any order.

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Example

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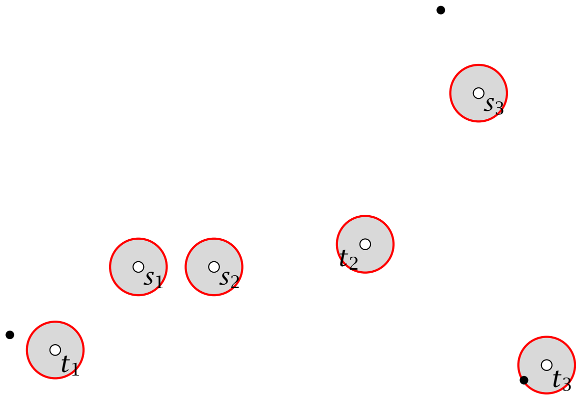

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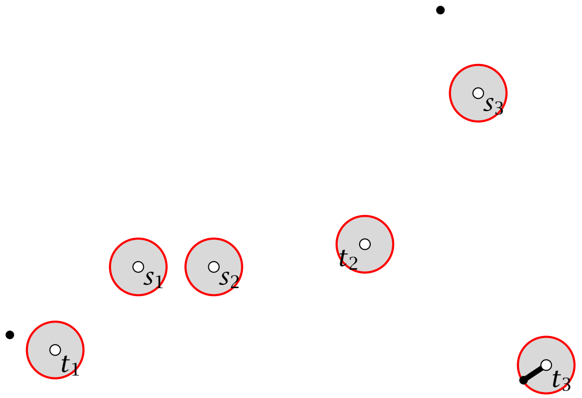

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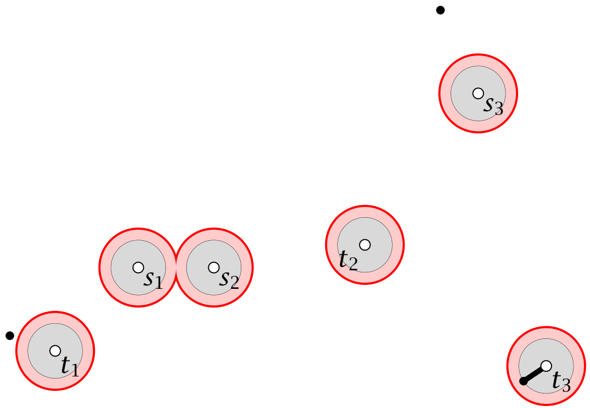

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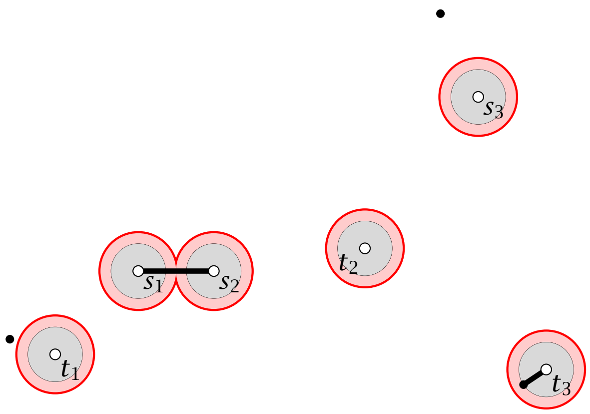

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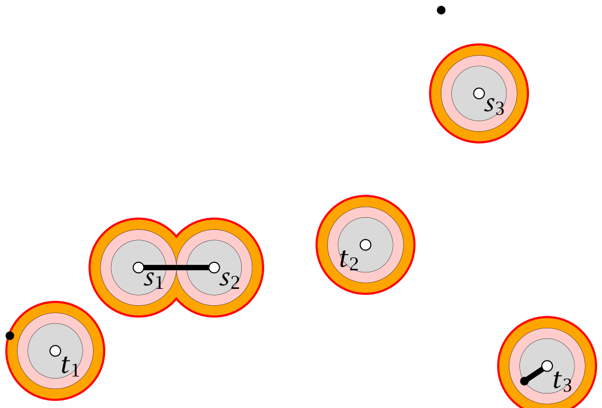

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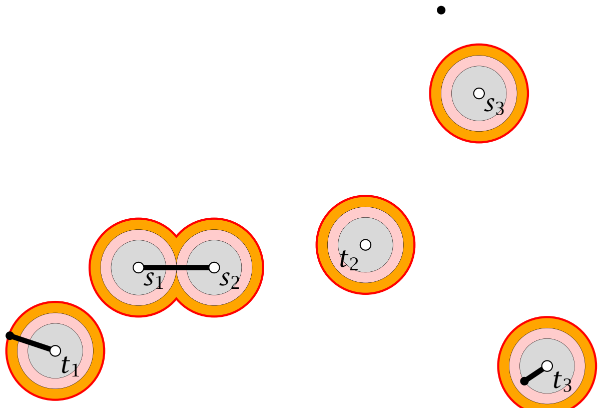

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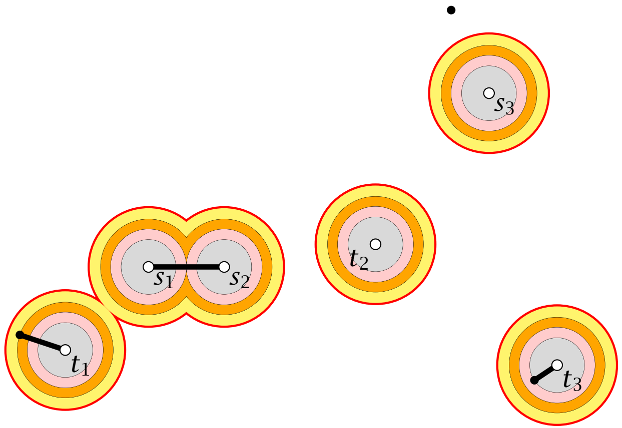

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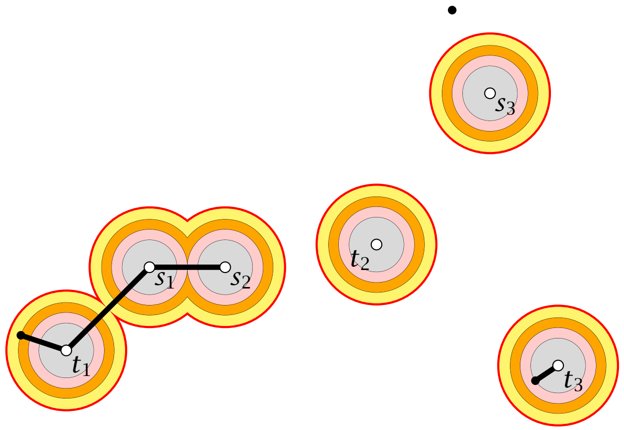

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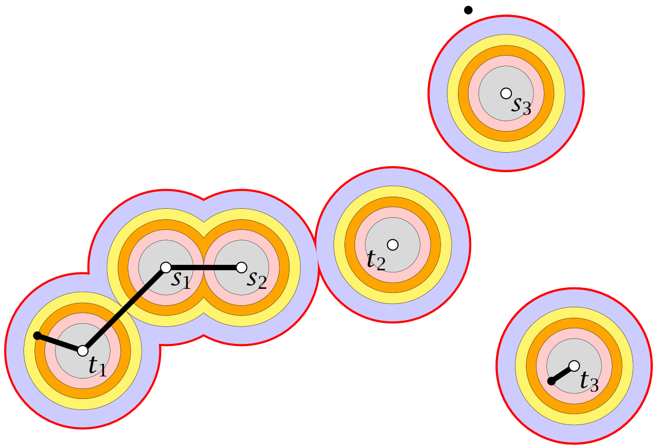

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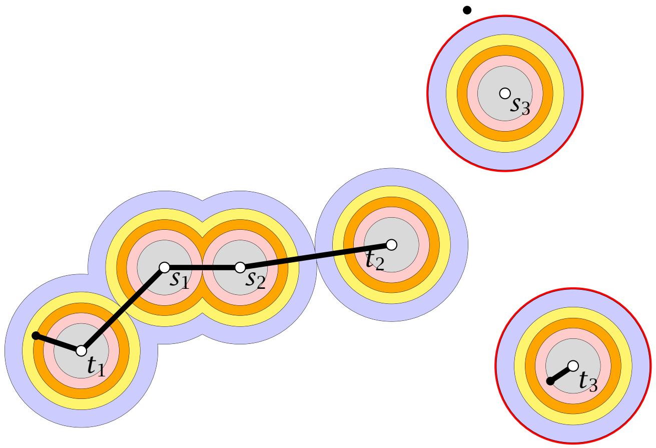

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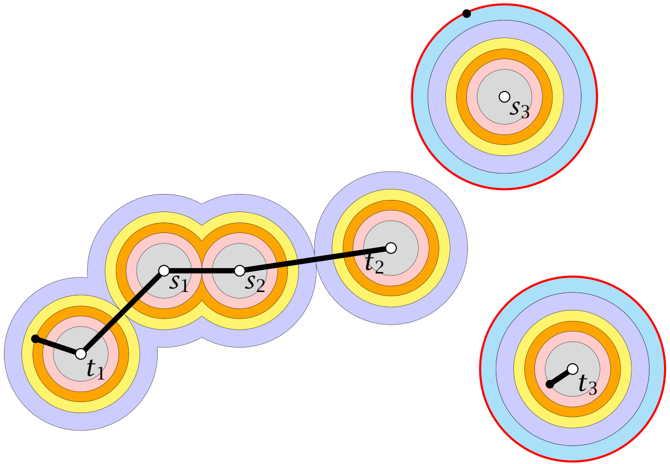

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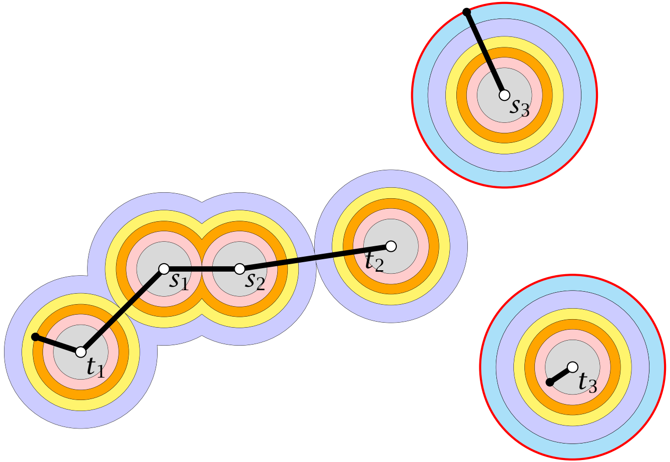

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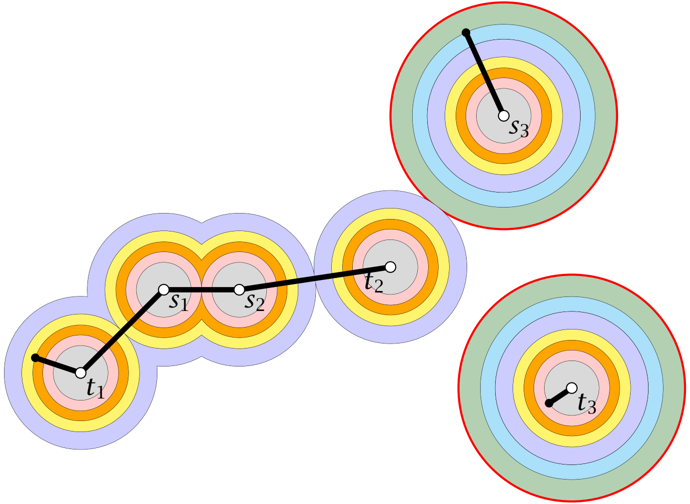

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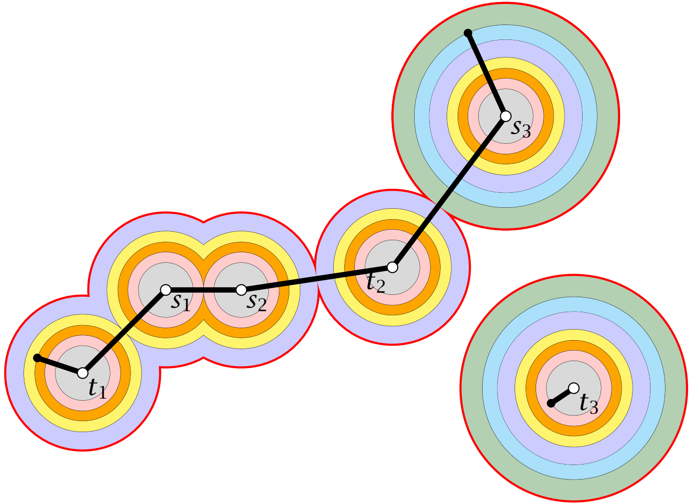

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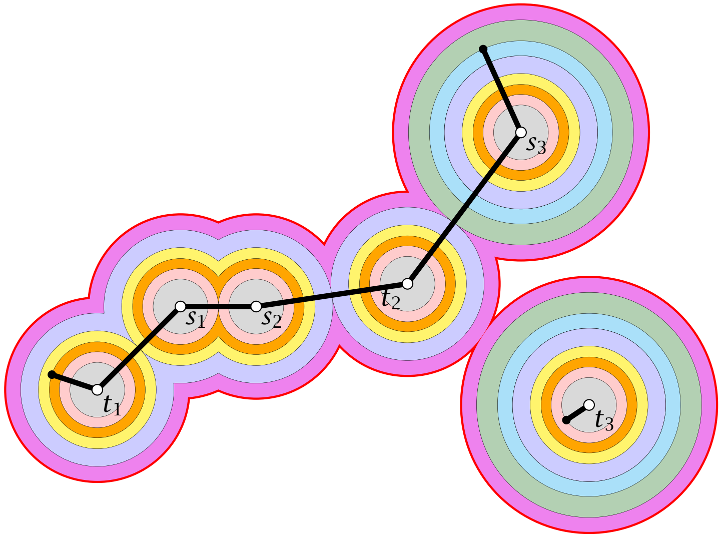

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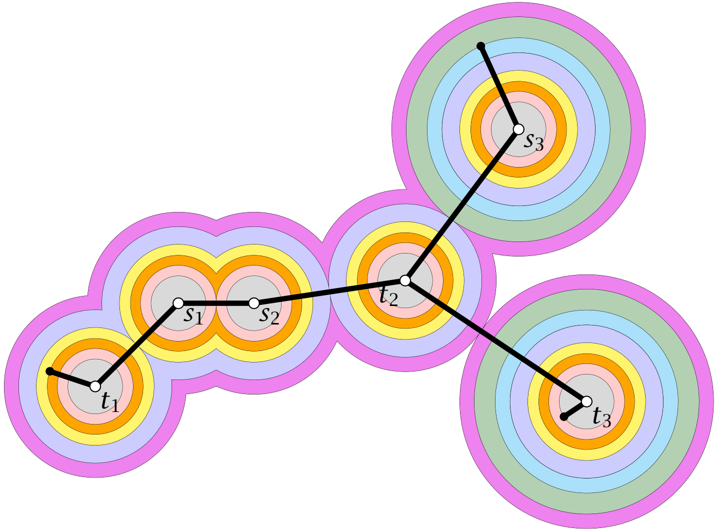

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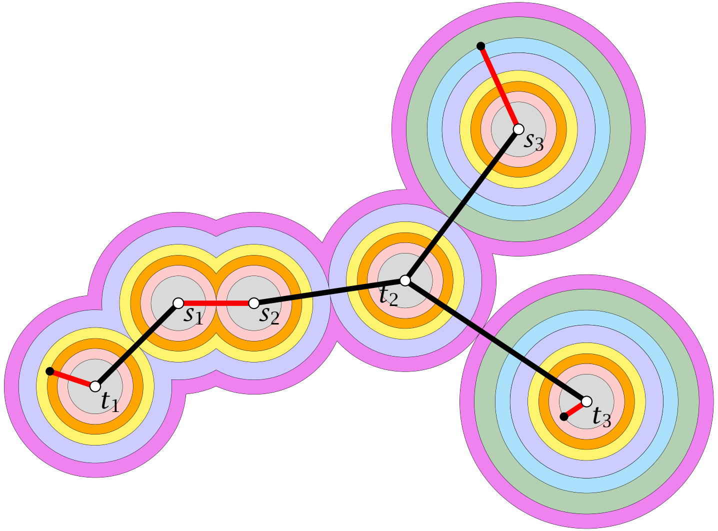

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EADS II
Harald Räcke
18.4 Steiner Forest

Lemma 47
For any $\mathfrak{C}$ in any iteration of the algorithm

$$\sum_{C\in\mathfrak{C}} |\delta(C)\cap F'| \le 2|\mathfrak{C}|$$

This means that the number of times a moat from $\mathfrak{C}$ is crossed in the final solution is at most twice the number of moats.

Proof: later...

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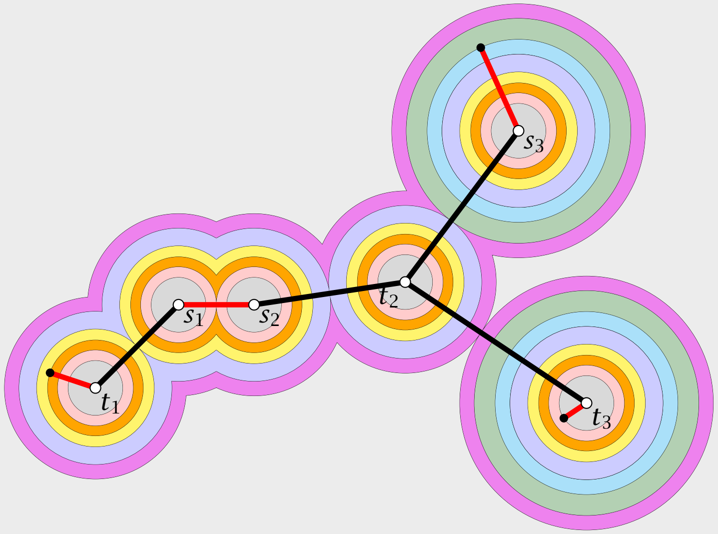

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  and the increase of the right hand side is $2\epsilon|\mathfrak{C}|$.

- Hence, by the previous lemma the inequality holds after the iteration if it holds in the beginning of the iteration.

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- Contract all edges in F_i into single vertices V'.
- We can consider the forest H on the set of vertices V'.
- Let $\deg(v)$ be the degree of a vertex $v \in V'$ within this forest.
- Color a vertex $v \in V'$ red if it corresponds to a component from $\mathfrak{C}$ (an active component). Otw. color it blue. (Let B the set of blue vertices (with non-zero degree) and R the set of red vertices)
- We have

$$\sum_{v\in R} \deg(v) \geq \sum_{C\in\mathfrak{C}} |\delta(C)\cap F'| \overset{?}{\leq} 2|\mathfrak{C}| = 2|R|$$

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$$\sum_{v \in R} \deg(v) \geq \sum_{C \in \mathfrak{C}} |\delta(C) \cap F'| \overset{?}{\leq} 2|\mathfrak{C}| = 2|R|$$

Lemma 48
For any set of connected components $\mathfrak{C}$ in any iteration of the algorithm

$$\sum_{C \in \mathfrak{C}} |\delta(C) \cap F'| \leq 2|\mathfrak{C}|$$

Proof:

- At any point during the algorithm the set of edges forms a forest (why?).
- Fix iteration i. Let F_i be the set of edges in F at the beginning of the iteration.
- Let $H = F' - F_i$.
- All edges in H are necessary for the solution.

- Suppose that no node in B has degree one.

- Contract all edges in F_i into single vertices V'.
- We can consider the forest H on the set of vertices V'.
- Let $\deg(v)$ be the degree of a vertex $v \in V'$ within this forest.
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$$\begin{aligned}\sum_{v\in R}\deg(v) &= \sum_{v\in R\cup B}\deg(v) - \sum_{v\in B}\deg(v)\\ &\le 2(|R|+|B|) - 2|B|\end{aligned}$$

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19 Cuts & Metrics

Shortest Path

$$\begin{array}{llrcl} \min & & \sum_e c(e)x_e & & \\ \text{s.t.} & \forall S \in \mathcal{S} & \sum_{e\in\delta(S)} x_e & \geq & 1 \\ & \forall e \in E & x_e & \in & \{0,1\} \end{array}$$

$\mathcal{S}$ is the set of subsets that separate s from t.

The Dual:

$$\begin{array}{llrcl} \max & & \sum_S y_S & & \\ \text{s.t.} & \forall e \in E & \sum_{S:e\in\delta(S)} y_S & \leq & c(e) \\ & \forall S \in \mathcal{S} & y_S & \geq & 0 \end{array}$$

The Separation Problem for the Shortest Path LP is the Minimum Cut Problem.

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19 Cuts & Metrics

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19 Cuts & Metrics

Observations:

Suppose that ℓ_e-values are solution to Minimum Cut LP.

- We can view ℓ_e as defining the length of an edge.
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Remark for bean-counters:
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How do we round the LP?

- Let $B(s,r)$ be the ball of radius r around s (w.r.t. metric d). Formally:

$$B = \{v \in V \mid d(s,v) \le r\}$$

- For $0 \le r < 1$, $B(s,r)$ is an s-t-cut.

Which value of r should we choose? choose randomly!!!

Formally:
choose r u.a.r. (uniformly at random) from interval $[0,1)$

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Suppose that ℓ_e-values are solution to Minimum Cut LP.

- We can view ℓ_e as defining the length of an edge.
- Define $d(u,v) = \min_{\text{path } P \text{ btw. } u \text{ and } v} \sum_{e \in P} \ell_e$ as the Shortest Path Metric induced by ℓ_e.
- We have $d(u,v) = \ell_e$ for every edge $e = (u,v)$, as otw. we could reduce ℓ_e without affecting the distance between s and t.

Remark for bean-counters:
d is not a metric on V but a semimetric as two nodes u and v could have distance zero.

How do we round the LP?

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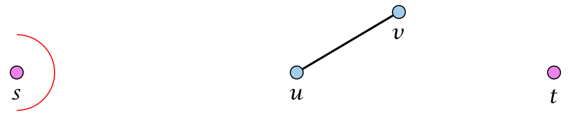

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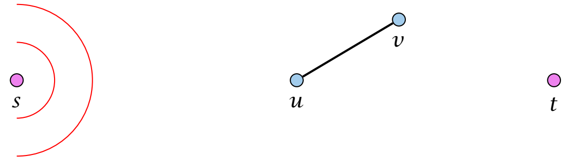

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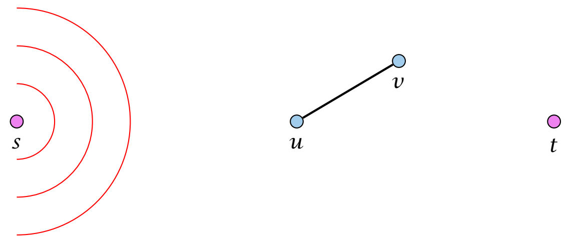

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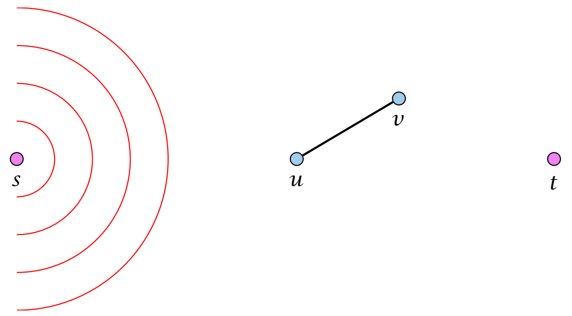

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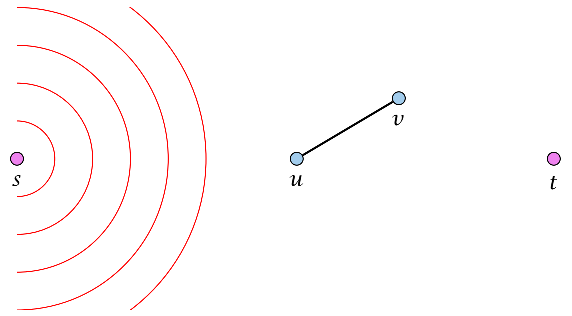

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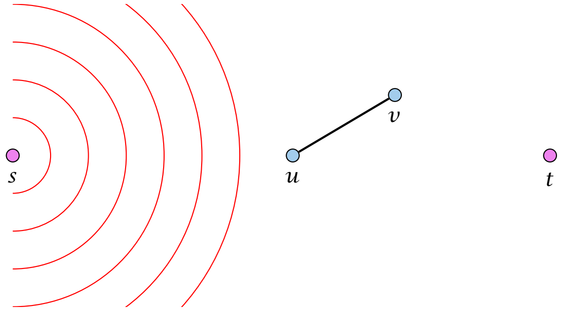

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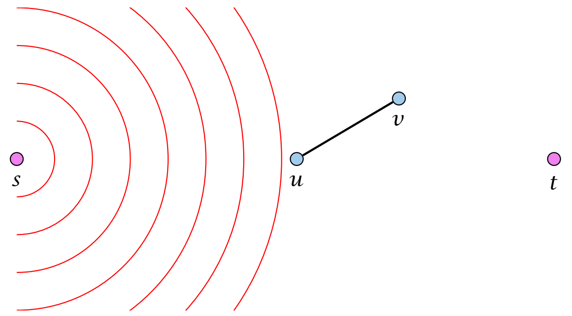

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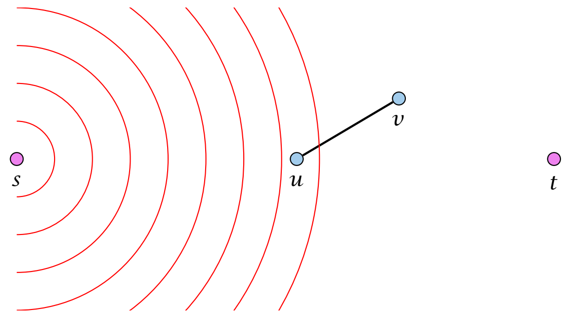

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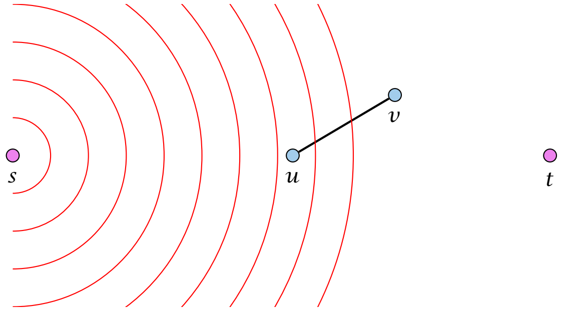

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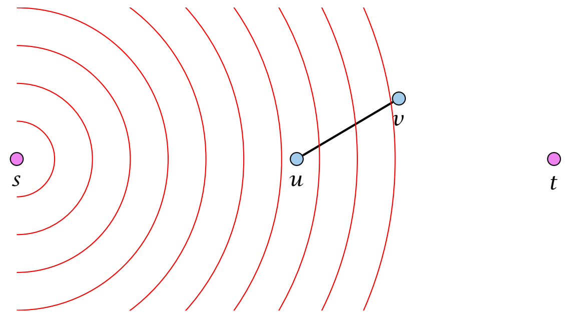

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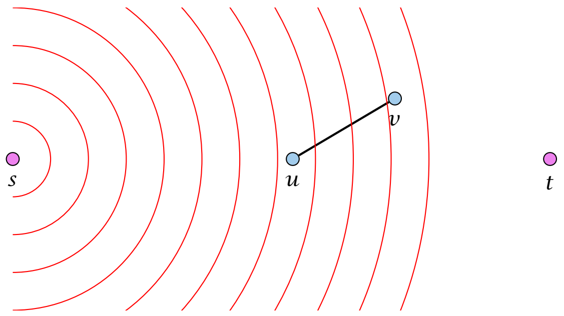

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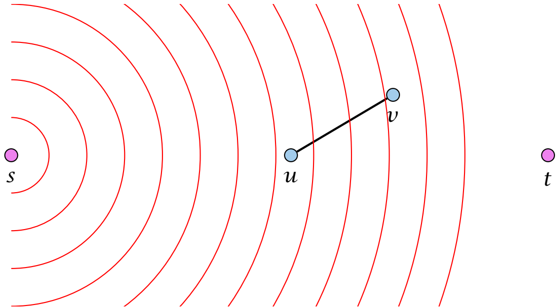

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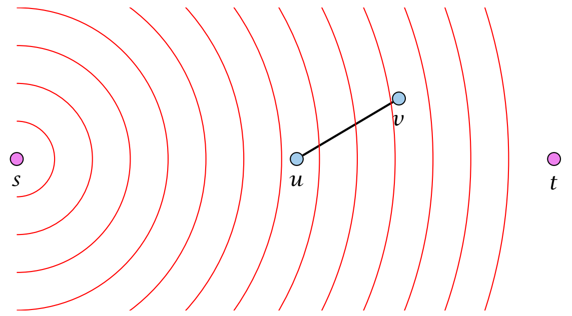

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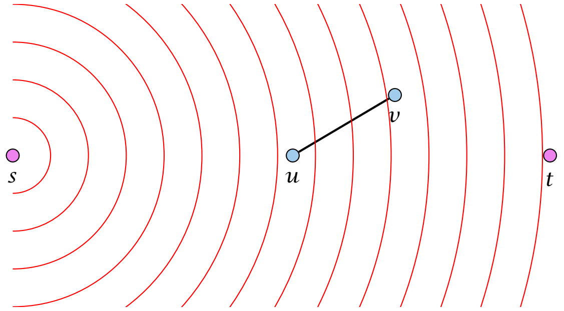

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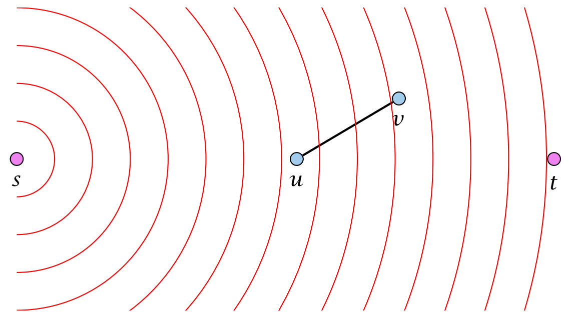

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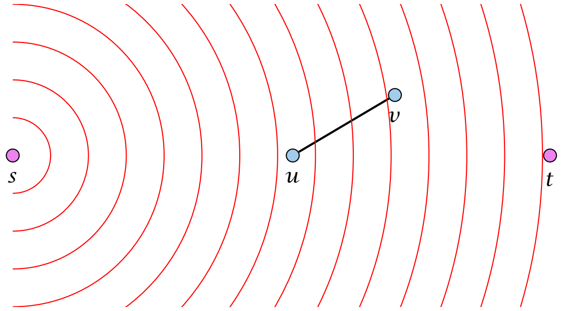

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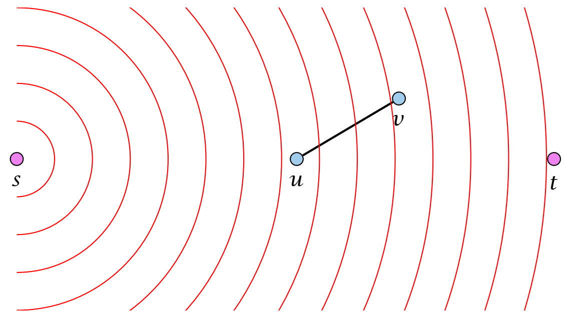

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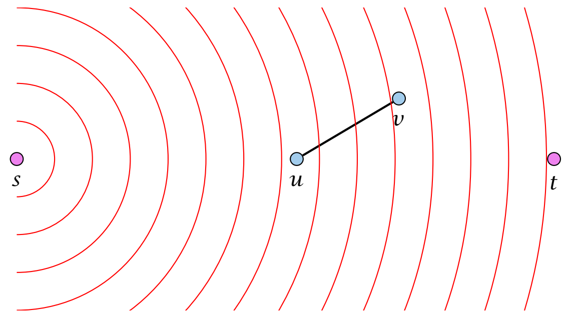

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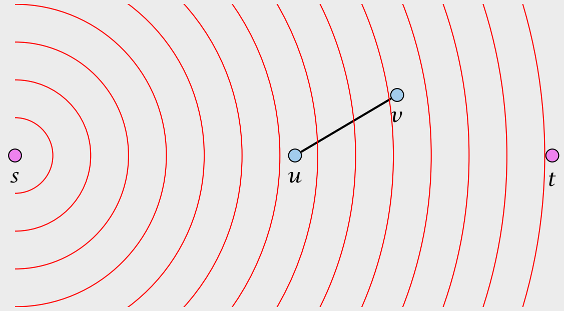

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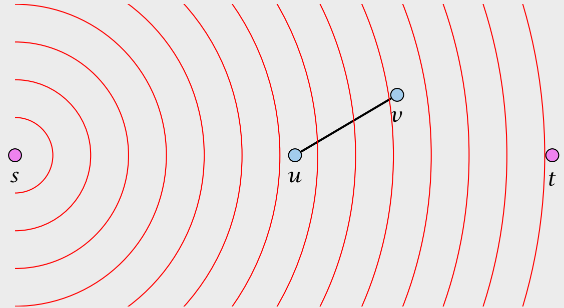

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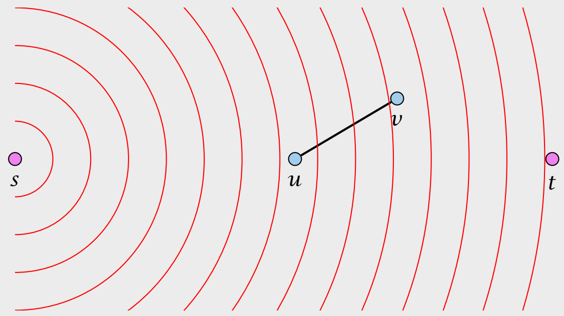

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Given a graph $G = (V, E)$, together with source-target pairs s_i, t_i, $i = 1, \dots, k$, and a capacity function $c : E \to \mathbb{R}^+$ on the edges. Find a subset $F \subseteq E$ of the edges such that all s_i-t_i pairs lie in different components in $G = (V, E \setminus F)$.

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Re-using the analysis for the single-commodity case is difficult.

$$\Pr[e \text{ is cut}] \leq ?$$

- If for some R the balls $B(s_i, R)$ are disjoint between different sources, we get a $1/R$ approximation.
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$$\Pr[e \text{ is cut}] \le \mathbf{?}$$

- If for some R the balls $B(s_i, R)$ are disjoint between different sources, we get a $1/R$ approximation.
- However, this cannot be guaranteed.

Minimum Multicut:

Given a graph $G = (V, E)$, together with source-target pairs s_i, t_i, $i = 1, \dots, k$, and a capacity function $c : E \to \mathbb{R}^+$ on the edges. Find a subset $F \subseteq E$ of the edges such that all s_i-t_i pairs lie in different components in $G = (V, E \setminus F)$.

$$\begin{array}{llrcl}
\min & & \sum_e c(e)\ell_e & & \\
\text{s.t.} & \forall P \in \mathcal{P}_i \text{ for some } i & \sum_{e \in P} \ell_e & \ge & 1 \\
 & \forall e \in E & \ell_e & \in & \{0, 1\}
\end{array}$$

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Algorithm 1 RegionGrowing(s_i, p)

```
1: z ← 0
2: repeat
3:     flip a coin (Pr[heads] = p)
4:     z ← z + 1
5: until heads
6: return B(s_i, z)
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Problem:

We may not cut all source-target pairs.

A component that we remove may contain an s_i-t_i pair.

If we ensure that we cut before reaching radius $1/2$ we are in good shape.

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- choose $p = 6\ln k \cdot \delta$
- we make $\frac{1}{2\delta}$ trials before reaching radius $1/2$.
- we say a Region Growing is not successful if it does not terminate before reaching radius $1/2$.

$$\Pr[\text{not successful}] \le (1-p)^{\frac{1}{2\delta}} = \left((1-p)^{1/p}\right)^{\frac{p}{2\delta}} \le e^{-\frac{p}{2\delta}} \le \frac{1}{k^3}$$

- Hence,

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If we are not successful we simply perform a trivial k-approximation.

This only increases the expected cost by at most $\frac{1}{k^2} \cdot k\mathrm{OPT} \le \mathrm{OPT}/k$.

Hence, our final cost is $\mathcal{O}(\ln k) \cdot \mathrm{OPT}$ in expectation.

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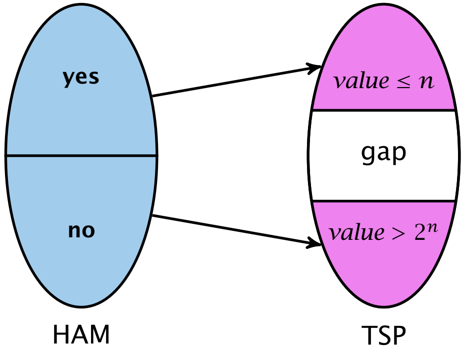
Gap Introducing Reduction

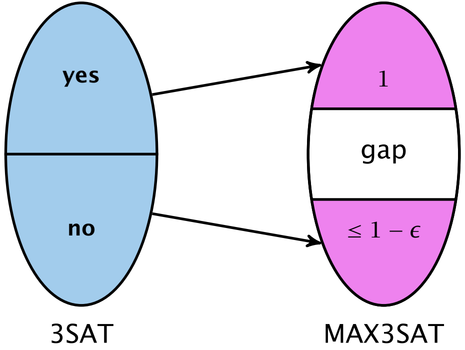


Reduction from Hamiltonian cycle to TSP

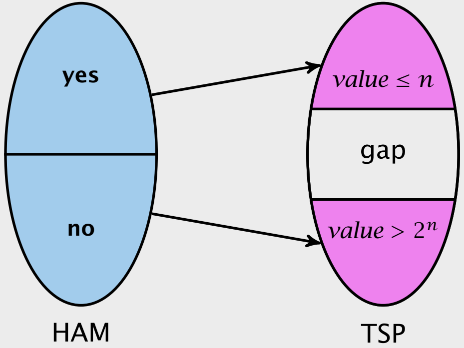
- instance that has Hamiltonian cycle is mapped to TSP instance with small cost
- otherwise it is mapped to instance with large cost
- $\Longrightarrow$ there is no $2^n/n$-approximation for TSP

PCP theorem: Approximation View

Theorem 49 (PCP Theorem A)
There exists $\epsilon > 0$ for which there is gap introducing reduction between 3SAT and MAX3SAT.



Gap Introducing Reduction



Reduction from Hamiltonian cycle to TSP

- instance that has Hamiltonian cycle is mapped to TSP instance with small cost
- otherwise it is mapped to instance with large cost
- $\Longrightarrow$ there is no $2^n/n$-approximation for TSP

PCP theorem: Proof System View

Definition 50 (NP)

A language $L \in \mathrm{NP}$ if there exists a polynomial time, deterministic verifier V (a Turing machine), s.t.

$[x \in L]$ completeness
There exists a proof string y, $|y| = \mathrm{poly}(|x|)$, s.t. $V(x, y) =$ “accept”.

$[x \notin L]$ soundness
For any proof string y, $V(x, y) =$ “reject”.

Note that requiring $|y| = \mathrm{poly}(|x|)$ for $x \notin L$ does not make a difference (**why?**).

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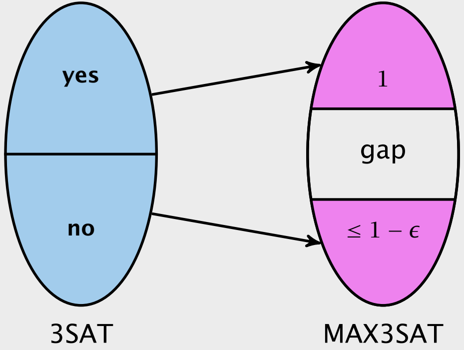

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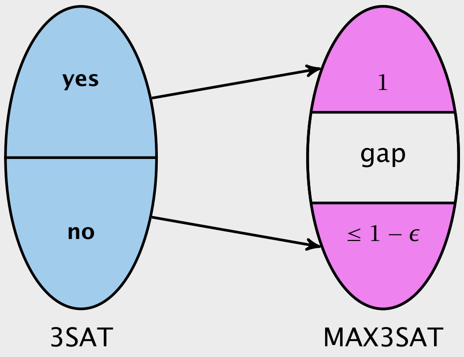

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Probabilistic Checkable Proofs

An Oracle Turing Machine M is a Turing machine that has access to an oracle.

Such an oracle allows M to solve some problem in a single step.

For example having access to a TSP-oracle π_{TSP} would allow M to write a TSP-instance x on a special oracle tape and obtain the answer (yes or no) in a single step.

For such TMs one looks in addition to running time also at query complexity, i.e., how often the machine queries the oracle.

For a proof string y, π_y is an oracle that upon given an index i returns the i-th character y_i of y.

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Probabilistic Checkable Proofs

Definition 52 (PCP)

A language $L \in \mathrm{PCP}_{c(n),s(n)}(r(n), q(n))$ if there exists a polynomial time, non-adaptive, randomized verifier V, s.t.

[$x \in L$] There exists a proof string y, s.t. $V^{\pi_y}(x) =$ "accept" with proability $\geq c(n)$.

[$x \notin L$] For any proof string y, $V^{\pi_y}(x) =$ "accept" with probability $\leq s(n)$.

The verifier uses at most $\mathcal{O}(r(n))$ random bits and makes at most $\mathcal{O}(q(n))$ oracle queries.

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  by definition; coRP is randomized polytime with one sided error (positive probability of accepting NO-instance)

Note that the first three statements also hold with equality

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Probabilistic Proof for Graph NonIsomorphism

GNI is the language of pairs of non-isomorphic graphs

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Verifier gets input (G_0, G_1) (two graphs with n-nodes)

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Probabilistic Proof for Graph NonIsomorphism

GNI is the language of pairs of non-isomorphic graphs

Verifier gets input (G_0, G_1) (two graphs with n-nodes)

It expects a proof of the following form:

- For any labeled n-node graph H the H's bit $P[H]$ of the proof fulfills

$$\begin{aligned} G_0 \equiv H &\implies P[H] = 0 \\ G_1 \equiv H &\implies P[H] = 1 \\ G_0, G_1 \not\equiv H &\implies P[H] = \text{arbitrary} \end{aligned}$$

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Verifier:

- choose $b \in \{0, 1\}$ at random
- take graph G_b and apply a random permutation to obtain a labeled graph H
- check whether $P[H] = b$

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If $G_0 \equiv G_1$ a proof only accepts with probability $1/2$.

- suppose $\pi(G_0) = G_1$
- if we accept for $b = 1$ and permutation π_{rand} we reject for $b = 0$ and permutation $\pi_{\text{rand}} \circ \pi$

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Version B $\Longrightarrow$ Version A

- For 3SAT there exists a verifier that uses $c \log n$ random bits, reads $q = \mathcal{O}(1)$ bits from the proof, has completeness 1 and soundness $1/2$.
- fix x and r:

Probabilistic Proof for Graph NonIsomorphism

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- if we accept for $b = 1$ and permutation π_{rand} we reject for $b = 0$ and permutation $\pi_{\text{rand}} \circ \pi$

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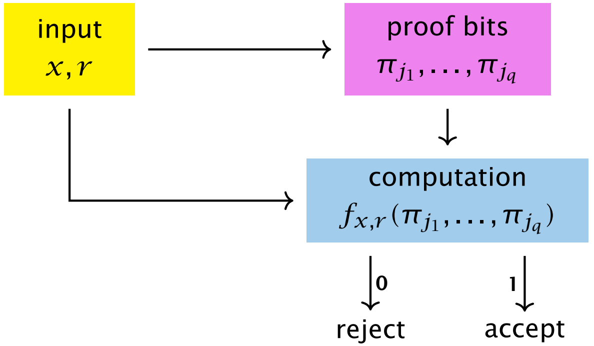

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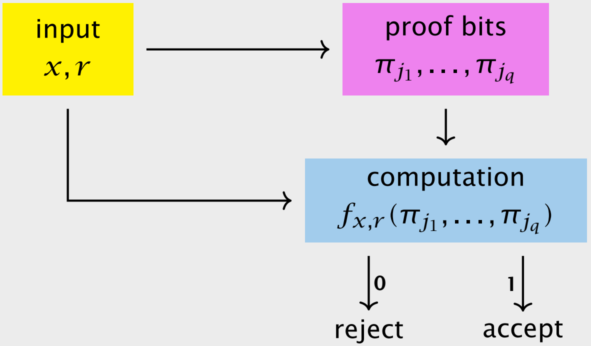

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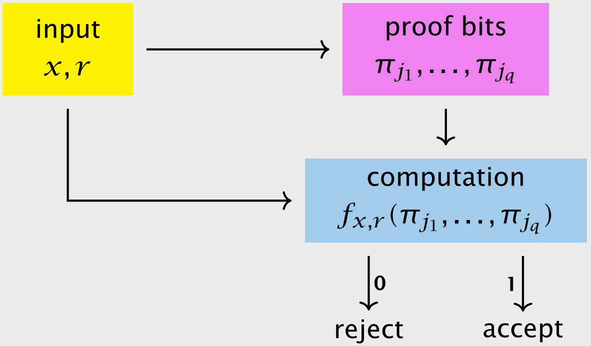

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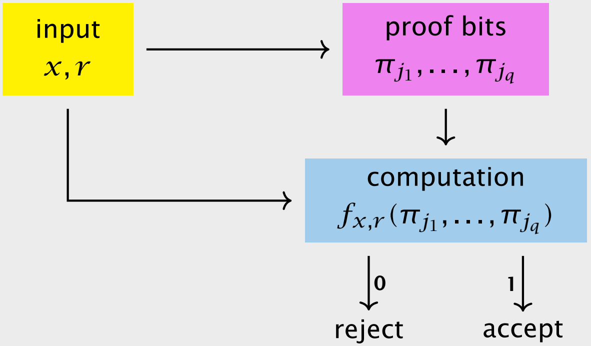

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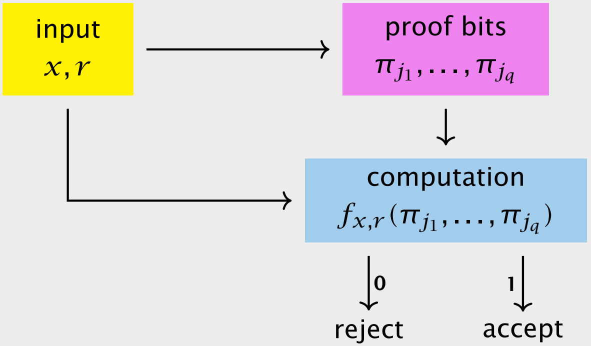

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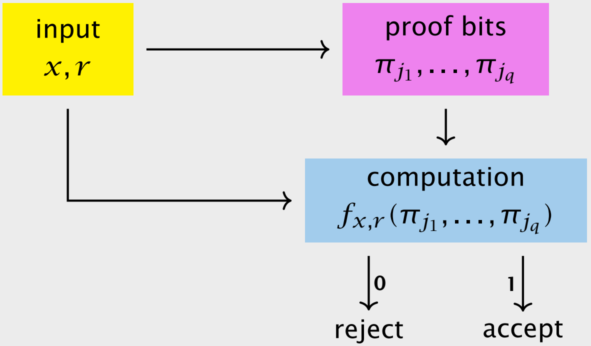

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$\mathrm{PCP}(\mathrm{poly}(n), 1)$ means we have a potentially exponentially long proof but we only read a constant number of bits from it.

The idea is to encode an NP-witness (e.g. a satisfying assignment (say n bits)) by a code whose code-words have 2^n bits.

A wrong proof is either

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$u \in \{0,1\}^n$ (satisfying assignment)

Walsh-Hadamard Code:
$\mathrm{WH}_u : \{0,1\}^n \to \{0,1\}, x \mapsto x^T u$ (over $\mathrm{GF}(2)$)

The code-word for u is WH_u. We identify this function by a bit-vector of length 2^n.

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Lemma 54
If $u \neq u'$ then WH_u and $\mathrm{WH}_{u'}$ differ in at least 2^{n-1} bits.

Proof:
Suppose that $u - u' \neq 0$. Then

$$\mathrm{WH}_u(x) \neq \mathrm{WH}_{u'}(x) \iff (u - u')^T x \neq 0$$

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Since the set of codewords is the set of all linear functions $\{0,1\}^n$ to $\{0,1\}$ we can check

$$f(x+y) = f(x) + f(y)$$

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Let $\rho \in [0,1]$. We say that $f, g : \{0,1\}^n \to \{0,1\}$ are ρ-close if

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Theorem 56 (proof deferred)

Let $f : \{0,1\}^n \to \{0,1\}$ with

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Theorem 56 (proof deferred)

Let $f : \{0,1\}^n \to \{0,1\}$ with

$$\Pr_{x,y\in\{0,1\}^n}\Big[f(x) + f(y) = f(x+y)\Big] \geq \rho > \frac{1}{2} \ .$$

Then there is a linear function $\tilde{f}$ such that f and $\tilde{f}$ are ρ-close.

$\mathrm{NP} \subseteq \mathrm{PCP}(\mathrm{poly}(n), 1)$

Suppose for $\delta < 1/4$ f is $(1-\delta)$-close to some linear function $\tilde{f}$.

$\tilde{f}$ is uniquely defined by f, since linear functions differ on at least half their inputs.

Suppose we are given $x \in \{0,1\}^n$ and access to f. Can we compute $\tilde{f}(x)$ using only constant number of queries?

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1. Choose $x' \in \{0,1\}^n$ u.a.r.
2. Set $x'' := x + x'$.
3. Let $y' = f(x')$ and $y'' = f(x'')$.
4. Output $y' + y''$.

x' and x'' are uniformly distributed (albeit dependent). With probability at least $1 - 2\delta$ we have $f(x') = \tilde{f}(x')$ and $f(x'') = \tilde{f}(x'')$.

Then the above routine returns $\tilde{f}(x)$.

This technique is known as local decoding of the Walsh-Hadamard code.

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We show that $\mathrm{QUADEQ} \in \mathrm{PCP}(\mathrm{poly}(n), 1)$. The theorem follows since any PCP-class is closed under polynomial time reductions.

QUADEQ
Given a system of quadratic equations over $\mathrm{GF}(2)$. Is there a solution?

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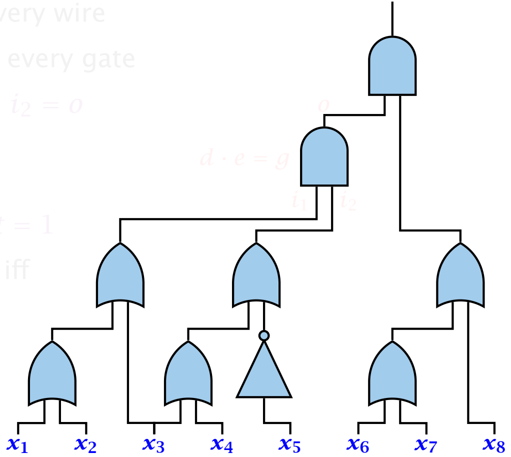
QUADEQ is NP-complete

- given 3SAT instance C represent it as Boolean circuit
  e.g. $C = (x_1 \vee x_2 \vee x_3) \wedge (x_3 \vee x_4 \vee \bar{x}_5) \wedge (x_6 \vee x_7 \vee x_8)$
- add variable for every wire
- add constraint for every gate
  OR: $i_1 + i_2 + i_1 \cdot i_2 = o$
  AND: $i_1 \cdot i_2 = o$
  NEG: $i = 1 - o$
- add constraint $out = 1$
- system is feasible iff
  C is satisfiable



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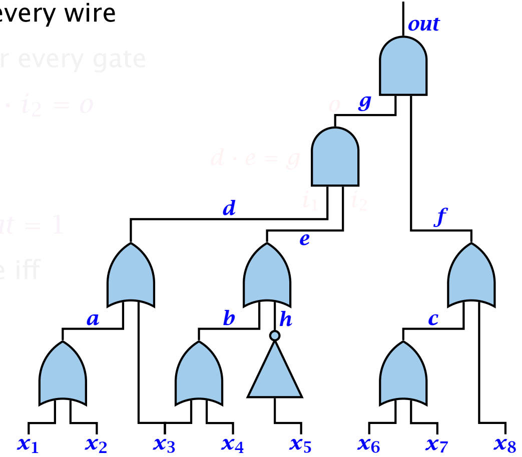

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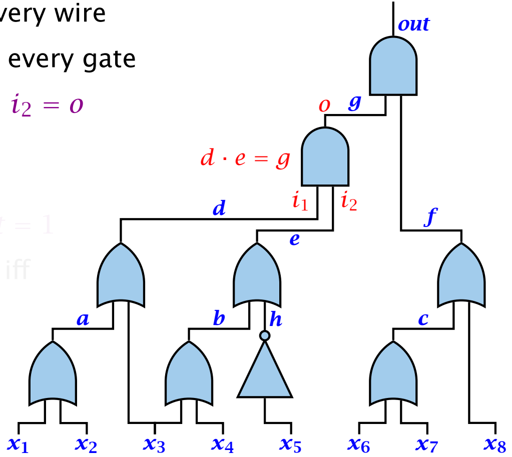

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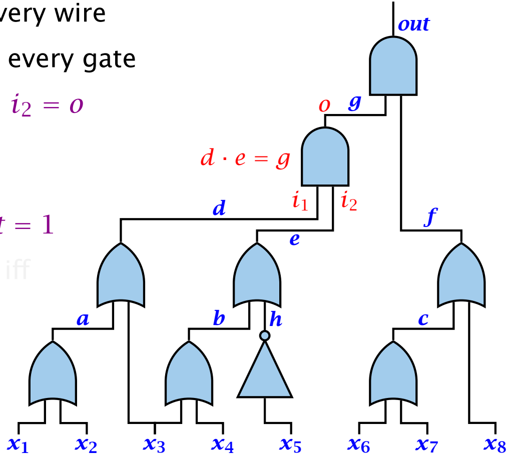

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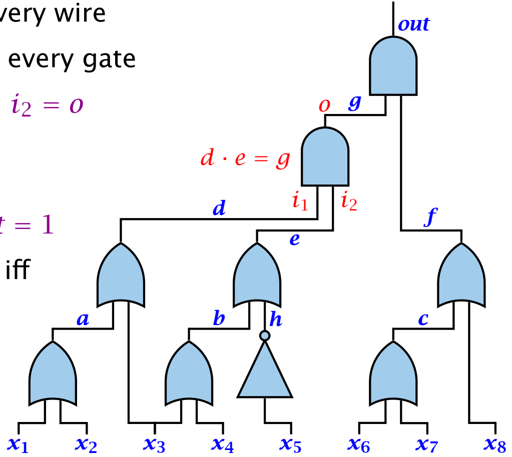

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We encode an instance of QUADEQ by a matrix A that has n^2 columns; one for every pair i, j; and a right hand side vector b.

For an n-dimensional vector x we use $x \otimes x$ to denote the n^2-dimensional vector whose i, j-th entry is $x_i x_j$.

Then we are asked whether

$$A(x \otimes x) = b$$

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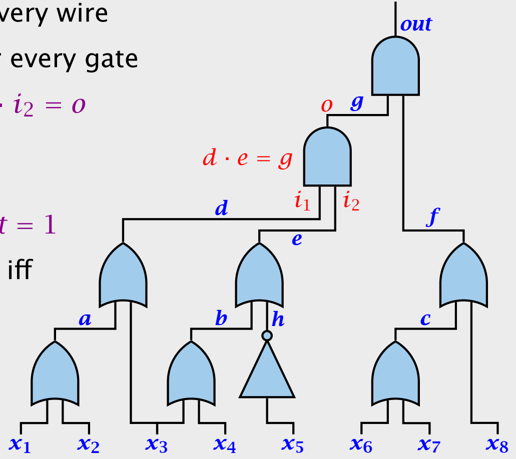

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Let A, b be an instance of QUADEQ. Let u be a satisfying assignment.

The correct PCP-proof will be the Walsh-Hadamard encodings of u and $u \otimes u$. The verifier will accept such a proof with probability 1.

We have to make sure that we reject proofs that do not correspond to codewords for vectors of the form u, and $u \otimes u$.

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Step 1. Linearity Test.
The proof contains $2^n + 2^{n^2}$ bits. This is interpreted as a pair of functions $f : \{0,1\}^n \to \{0,1\}$ and $g : \{0,1\}^{n^2} \to \{0,1\}$.

We do a 0.999-linearity test for both functions (requires a constant number of queries).

We also assume that for the remaining constant number of accesses WH-decoding succeeds and we recover $\tilde{f}(x)$.

Hence, our proof will only ever see $\tilde{f}$. To simplify notation we use f for $\tilde{f}$, in the following (similar for g, $\tilde{g}$).

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Step 2. Verify that g encodes $u \otimes u$ where u is string encoded by f.

$f(r) = u^T r$ and $g(z) = w^T z$ since f, g are linear.

- choose r, r' independently, u.a.r. from $\{0,1\}^n$
- if $f(r)f(r') \neq g(r \otimes r')$ reject
- repeat 3 times

NP $\subseteq$ PCP(poly(n), 1)

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A correct proof survives the test

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NP $\subseteq$ PCP(poly(n), 1)

A correct proof survives the test

$$\begin{aligned} f(r) \cdot f(r') &= u^T r \cdot u^T r' \\ &= \Big(\sum_i u_i r_i\Big) \cdot \Big(\sum_j u_j r'_j\Big) \\ &= \sum_{ij} u_i u_j r_i r'_j \\ &= (u \otimes u)^T (r \otimes r') \\ &= g(r \otimes r') \end{aligned}$$

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If $U \neq W$ then $Wr' \neq Ur'$ with probability at least 1/2. Then $r^T W r' \neq r^T U r'$ with probability at least 1/4.

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Step 3. Verify that f encodes satisfying assignment.

We need to check

$$A_k(u \otimes u) = b_k$$

where A_k is the k-th row of the constraint matrix. But the left hand side is just $g(A_k^T)$.

We can handle this by a single query but checking all constraints would take $\mathcal{O}(m)$ steps.

We compute $r^T A$, where $r \in_R \{0,1\}^m$. If u is not a satisfying assignment then with probability 1/2 the vector r will hit an odd number of violated constraints.

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We used the following theorem for the linearity test:

Theorem 56
Let $f : \{0,1\}^n \to \{0,1\}$ *with*

$$\Pr_{x,y\in\{0,1\}^n}\Big[f(x) + f(y) = f(x+y)\Big] \geq \rho > \frac{1}{2}\ .$$

Then there is a linear function $\tilde{f}$ *such that* f *and* $\tilde{f}$ *are* ρ*-close.*

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Fourier Transform over $\mathrm{GF}(2)$

In the following we use $\{-1, 1\}$ instead of $\{0, 1\}$. We map $b \in \{0, 1\}$ to $(-1)^b$.

This turns summation into multiplication.

The set of function $f : \{-1, 1\}^n \to \mathbb{R}$ form a 2^n-dimensional Hilbert space.

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Hilbert space

- addition $(f+g)(x) = f(x) + g(x)$
- scalar multiplication $(\alpha f)(x) = \alpha f(x)$
- inner product $\langle f, g\rangle = E_{x\in\{-1,1\}^n}[f(x)g(x)]$
  (bilinear, $\langle f, f\rangle \geq 0$, and $\langle f, f\rangle = 0 \Rightarrow f = 0$)
- completeness: any sequence x_k of vectors for which

$$\sum_{k=1}^{\infty} \|x_k\| < \infty \text{ fulfills } \left\| L - \sum_{k=1}^{N} x_k \right\| \to 0$$

for some vector L.

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standard basis

$$e_x(y) = \begin{cases} 1 & x = y \\ 0 & \text{otw.} \end{cases}$$

Then, $f(x) = \sum_i \alpha_i e_i(x)$ where $\alpha_x = f(x)$, this means the functions e_i form a basis. This basis is orthonormal.

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For $\alpha \subseteq [n]$ define

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A function χ_α multiplies a set of x_i's. Back in the $\mathrm{GF}(2)$-world this means summing a set of z_i's where $x_i = (-1)^{z_i}$.

This means the function χ_α correspond to linear functions in the $\mathrm{GF}(2)$ world.

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We can write any function $f : \{-1,1\}^n \to \mathbb{R}$ as

$$f = \sum_\alpha \hat{f}_\alpha \chi_\alpha$$

We call $\hat{f}_\alpha$ the α^{th} Fourier coefficient.

Lemma 57

1. $\langle f, g\rangle = \sum_\alpha f_\alpha g_\alpha$
2. $\langle f, f\rangle = \sum_\alpha f_\alpha^2$

Note that for Boolean functions $f : \{-1,1\}^n \to \{-1,1\}$, $\langle f, f\rangle = 1$.

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Linearity Test

in GF(2):
We want to show that if $\Pr_{x,y}[f(x) + f(y) = f(x + y)]$ is large than f has a large agreement with a linear function.

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For Boolean functions $\langle f, g\rangle$ is the fraction of inputs on which f, g agree **minus** the fraction of inputs on which they disagree.

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For Boolean functions $\langle f, g \rangle$ is the fraction of inputs on which f, g agree **minus** the fraction of inputs on which they disagree.

$$2\epsilon \le \hat{f}_\alpha = \langle f, \chi_\alpha \rangle = \text{agree} - \text{disagree} = 2\text{agree} - 1$$

This gives that the agreement between f and χ_α is at least $\frac{1}{2} + \epsilon$.

Linearity Test

in GF(2):
We want to show that if $\Pr_{x,y}[f(x) + f(y) = f(x + y)]$ is large than f has a large agreement with a linear function.

in Hilbert space: (we will prove)
Suppose $f : \{\pm 1\}^n \to \{-1, 1\}$ fulfills

$$\Pr_{x,y}[f(x)f(y) = f(x \circ y)] \ge \frac{1}{2} + \epsilon \ .$$

Then there is some $\alpha \subseteq [n]$, s.t. $\hat{f}_\alpha \ge 2\epsilon$.

Linearity Test

$$\Pr_{x,y}[f(x \circ y) = f(x)f(y)] \geq \frac{1}{2} + \epsilon$$

means that the fraction of inputs x, y on which $f(x \circ y)$ and $f(x)f(y)$ agree is at least $1/2 + \epsilon$.

This gives

$$\begin{aligned} E_{x,y}[f(x \circ y)f(x)f(y)] &= \text{agreement} - \text{disagreement} \\ &= 2\text{agreement} - 1 \\ &\geq 2\epsilon \end{aligned}$$

Linearity Test

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This gives that the agreement between f and χ_α is at least $\frac{1}{2} + \epsilon$.

$$2\epsilon \leq E_{x,y}\left[f(x \circ y)f(x)f(y)\right]$$

Linearity Test

$$\Pr_{x,y}[f(x \circ y) = f(x)f(y)] \geq \frac{1}{2} + \epsilon$$

means that the fraction of inputs x, y on which $f(x \circ y)$ and $f(x)f(y)$ agree is at least $1/2 + \epsilon$.

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$$2\epsilon \le E_{x,y}\Big[f(x\circ y)f(x)f(y)\Big]$$

$$= E_{x,y}\Big[\big(\textstyle\sum_\alpha \hat{f}_\alpha\chi_\alpha(x\circ y)\big)\cdot\big(\sum_\beta \hat{f}_\beta\chi_\beta(x)\big)\cdot\big(\sum_\gamma \hat{f}_\gamma\chi_\gamma(y)\big)\Big]$$

Linearity Test

$$\Pr_{x,y}[f(x\circ y)=f(x)f(y)] \ge \frac{1}{2}+\epsilon$$

means that the fraction of inputs x,y on which $f(x\circ y)$ and $f(x)f(y)$ agree is at least $1/2+\epsilon$.

This gives

$$\begin{aligned} E_{x,y}[f(x\circ y)f(x)f(y)] &= \text{agreement} - \text{disagreement} \\ &= 2\text{agreement} - 1 \\ &\ge 2\epsilon \end{aligned}$$

$$
\begin{aligned}
2\epsilon \leq E_{x,y}&\left[f(x\circ y)f(x)f(y) \right]\\
&= E_{x,y}\left[\left(\sum_\alpha \hat{f}_\alpha \chi_\alpha(x\circ y)\right)\cdot\left(\sum_\beta \hat{f}_\beta \chi_\beta(x)\right)\cdot\left(\sum_\gamma \hat{f}_\gamma \chi_\gamma(y)\right)\right]\\
&= E_{x,y}\left[\sum_{\alpha,\beta,\gamma} \hat{f}_\alpha \hat{f}_\beta \hat{f}_\gamma \chi_\alpha(x)\chi_\alpha(y)\chi_\beta(x)\chi_\gamma(y)\right]
\end{aligned}
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Linearity Test

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&= \sum_\alpha \hat{f}_\alpha^3
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Approximation Preserving Reductions

AP-reduction

- $x \in I_1 \Rightarrow f(x,r) \in I_2$
- $\mathrm{SOL}_1(x) \neq \emptyset \Rightarrow \mathrm{SOL}_1(f(x,r)) \neq \emptyset$
- $y \in \mathrm{SOL}_2(f(x,r)) \Rightarrow g(x,y,r) \in \mathrm{SOL}_1(x)$
- f, g are polynomial time computable
- $R_2(f(x,r),y) \leq r \Rightarrow R_1(x,g(x,y,r)) \leq 1 + \alpha(r-1)$

$$
\begin{aligned}
2\epsilon &\leq E_{x,y}\Big[f(x\circ y)f(x)f(y)\Big]\\
&= E_{x,y}\Big[\Big(\textstyle\sum_\alpha \hat{f}_\alpha\chi_\alpha(x\circ y)\Big)\cdot\Big(\sum_\beta \hat{f}_\beta\chi_\beta(x)\Big)\cdot\Big(\sum_\gamma \hat{f}_\gamma\chi_\gamma(y)\Big)\Big]\\
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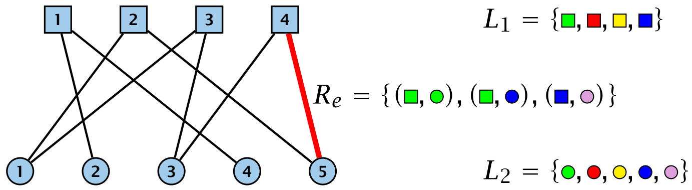
&= \textstyle\sum_{\alpha,\beta,\gamma}\hat{f}_\alpha\hat{f}_\beta\hat{f}_\gamma\cdot E_x\Big[\chi_\alpha(x)\chi_\beta(x)\Big]E_y\Big[\chi_\alpha(y)\chi_\gamma(y)\Big]\\
&= \sum_\alpha \hat{f}_\alpha^3\\
&\leq \max_\alpha \hat{f}_\alpha\cdot\sum_\alpha \hat{f}_\alpha^2 = \max_\alpha \hat{f}_\alpha
\end{aligned}
$$

Label Cover

Input:

- bipartite graph $G = (V_1, V_2, E)$
- label sets L_1, L_2
- for every edge $(u, v) \in E$ a relation $R_{u,v} \subseteq L_1 \times L_2$ that describe assignments that make the edge happy.
- maximize number of happy edges



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Label Cover

- an instance of label cover is (d_1, d_2)-regular if every vertex in L_1 has degree d_1 and every vertex in L_2 has degree d_2.
- if every vertex has the same degree d the instance is called d-regular

Minimization version:

- assign a set $L_x \subseteq L_1$ of labels to every node $x \in L_1$ and a set $L_y \subseteq L_2$ to every node $y \in L_2$
- make sure that for every edge (x, y) there is $\ell_x \in L_x$ and $\ell_y \in L_y$ s.t. $(\ell_x, \ell_y) \in R_{x,y}$
- minimize $\sum_{x \in L_1} |L_x| + \sum_{y \in L_2} |L_y|$ (total labels used)

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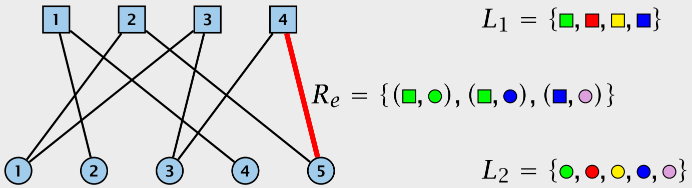

MAX E3SAT via Label Cover

instance:

$\Phi(x) = (x_1 \vee \bar{x}_2 \vee x_3) \wedge (x_4 \vee x_2 \vee \bar{x}_3) \wedge (\bar{x}_1 \vee x_2 \vee \bar{x}_4)$

corresponding graph:

label sets: $L_1 = \{T, F\}^3, L_2 = \{T, F\}$ (T=true, F=false)

relation: $R_{C,x_i} = \{((u_i, u_j, u_k), u_i)\}$, where the clause C is over variables x_i, x_j, x_k and assignment (u_i, u_j, u_k) satisfies C

$R = \{((F,F,F),F), ((F,T,F),F), ((F,F,T),T), ((F,T,T),T),$
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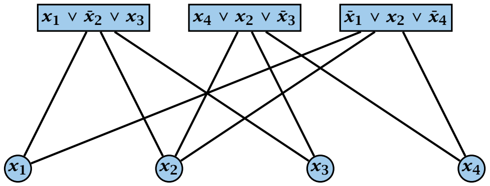

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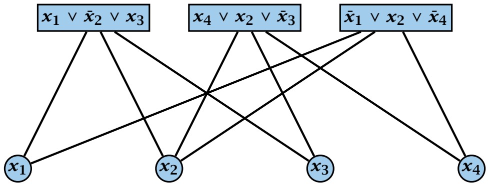

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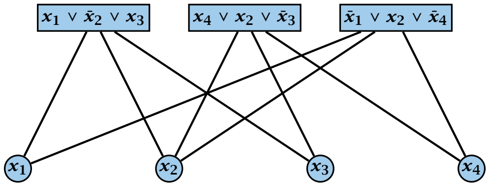

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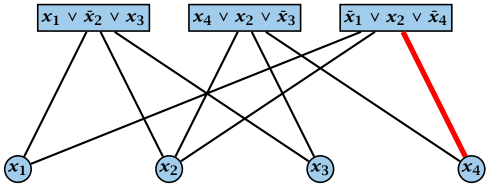

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MAX E3SAT via Label Cover

Lemma 58

If we can satisfy k *out of* m *clauses in* ϕ *we can make at least* $3k + 2(m - k)$ *edges happy.*

Proof:

MAX E3SAT via Label Cover

instance:

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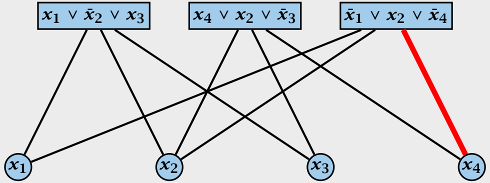

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MAX E3SAT via Label Cover

Lemma 58
If we can satisfy k out of m clauses in ϕ we can make at least $3k + 2(m - k)$ edges happy.

Proof:

- for V_2 use the setting of the assignment that satisfies k clauses
- for satisfied clauses in V_1 use the corresponding assignment to the clause-variables (gives $3k$ happy edges)
- for unsatisfied clauses flip assignment of one of the variables; this makes one incident edge unhappy (gives $2(m - k)$ happy edges)

MAX E3SAT via Label Cover

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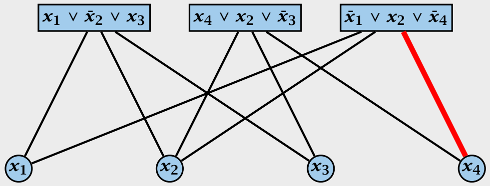

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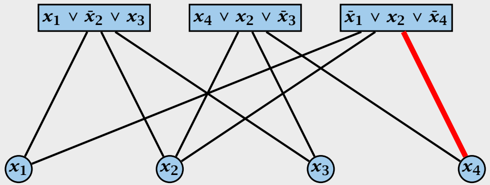

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relation: $R_{C,x_i} = \{((u_i, u_j, u_k), u_i)\}$, where the clause C is over variables x_i, x_j, x_k and assignment (u_i, u_j, u_k) satisfies C

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MAX E3SAT via Label Cover

Lemma 58
If we can satisfy k out of m clauses in ϕ we can make at least $3k + 2(m - k)$ edges happy.

Proof:

- for V_2 use the setting of the assignment that satisfies k clauses
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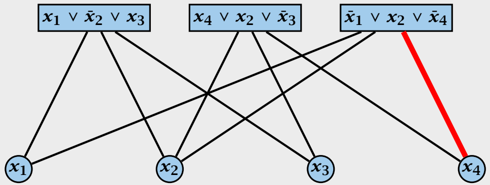
MAX E3SAT via Label Cover

instance:
$\Phi(x) = (x_1 \vee \bar{x}_2 \vee x_3) \wedge (x_4 \vee x_2 \vee \bar{x}_3) \wedge (\bar{x}_1 \vee x_2 \vee \bar{x}_4)$

corresponding graph:



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Hardness for Label Cover

We cannot distinguish between the following two cases

- all $3m$ edges can be made happy
- at most $2m + (1-\epsilon)m = (3-\epsilon)m$ out of the $3m$ edges can be made happy

Hence, we cannot obtain an approximation constant $\alpha > \frac{3-\epsilon}{3}$.

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$(3,5)$-regular instances

Theorem 60
There is a constant ρ s.t. MAXE3SAT is hard to approximate with a factor of ρ even if restricted to instances where a variable appears in exactly 5 clauses.

Then our reduction has the following properties:

- the resulting Label Cover instance is $(3,5)$-regular
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- MAX3SAT $\leq$ MAX3SAT(≤ 29)
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Here MAX3SAT(≤ 29) is the variant of MAX3SAT in which a variable appears in at most 29 clauses. Similar for the other problems.

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In the verifier view, in order to decrease the acceptance probability of a wrong proof (or as here: a pair of wrong proofs) one could repeat the verification several times.

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Parallel Repetition

If I is regular than also I'.

If I has the uniqueness property than also I'.

Did the gap increase?

- Suppose we have labelling ℓ_1, ℓ_2 that satisfies just an α-fraction of edges in I.
- We transfer this labelling to instance I':
  vertex $(x_1, \dots, x_k)$ gets label $(\ell_1(x_1), \dots, \ell_1(x_k))$,
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- How many edges are happy?

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Non interactive agreement:

- Two provers A and B
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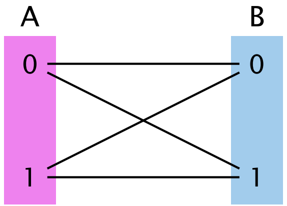

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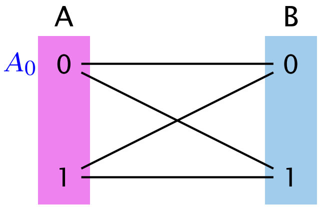

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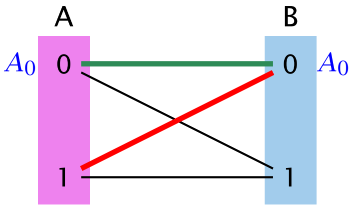

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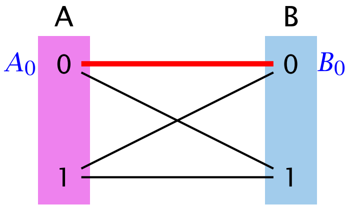

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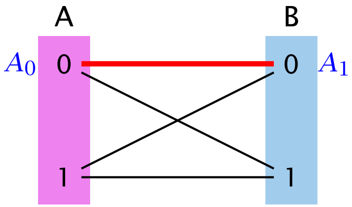

Regardless what we do 50% of edges are unhappy!

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Non interactive agreement:

- Two provers A and B
- The verifier generates two random bits b_A, and b_B, and sends one to A and one to B.
- Each prover has to answer one of A_0, A_1, B_0, B_1 with the meaning $A_0 :=$ prover A has been given a bit with value 0.
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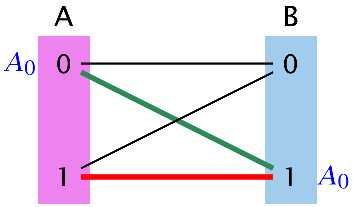

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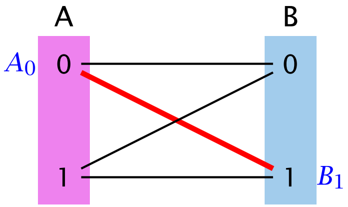

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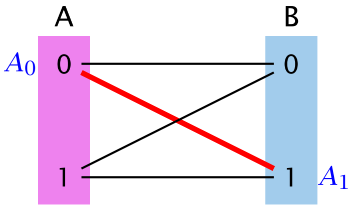

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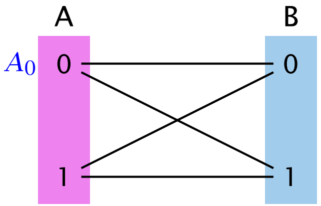

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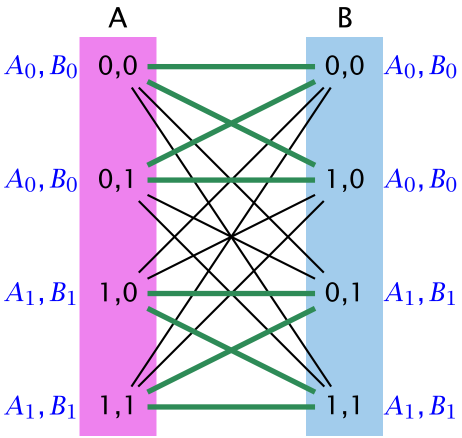

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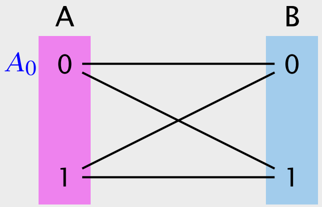

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Boosting

Theorem 62
There is a constant $c > 0$ such if $\mathrm{OPT}(I) = |E|(1-\delta)$ then $\mathrm{OPT}(I') \le |E'|(1-\delta)^{\frac{ck}{\log L}}$, where $L = |L_1| + |L_2|$ denotes total number of labels in I.

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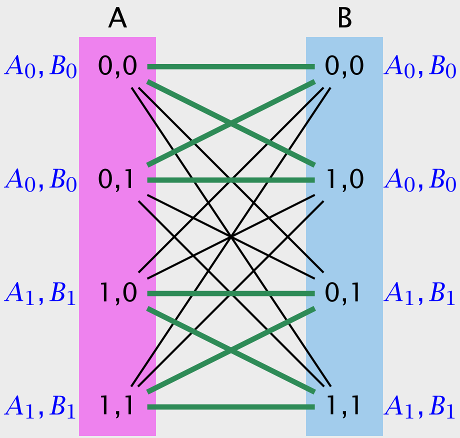

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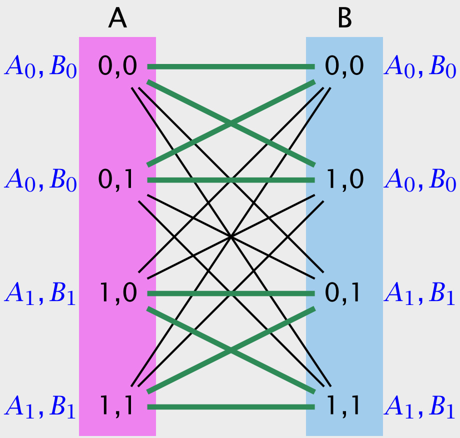

Hardness of Label Cover

Theorem 63
There are constants $c > 0$, $\delta < 1$ s.t. for any k we cannot distinguish regular instances for Label Cover in which either

- $\mathrm{OPT}(I) = |E|$, *or*
- $\mathrm{OPT}(I) = |E|(1-\delta)^{ck}$

unless each problem in NP has an algorithm running in time $\mathcal{O}(n^{\mathcal{O}(k)})$.

Corollary 64
There is no α-approximation for Label Cover for any constant α.

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There exist regular Label Cover instances s.t. we cannot distinguish whether

- *all edges are satisfiable, or*
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unless NP-problems have algorithms with running time $\mathcal{O}(n^{\mathcal{O}(\log\log n)})$.

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Partition System (s, t, h)

- universe U of size s
- t pairs of sets $(A_1, \bar{A}_1), \dots, (A_t, \bar{A}_t)$; $A_i \subseteq U, \bar{A}_i = U \setminus A_i$
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for any h, t with $h \leq t$ there exist systems with $s = |U| \leq 4t^2 2^h$

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Suppose that we can make all edges happy.

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Lemma 66
Given a solution to the set cover instance using at most $\frac{h}{8}(|V_1| + |V_2|)$ sets we can find a solution to the Label Cover instance satisfying at least $\frac{2}{h^2}|E|$ edges.

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Choose sets S_{u,ℓ_1}'s and S_{v,ℓ_2}'s, where ℓ_1 is the label we assigned to u, and ℓ_2 the label for v. ($|V_1|+|V_2|$ sets)

For an edge (u,v), S_{v,ℓ_2} contains $\{(u,v)\} \times A_{\ell_2}$. For a happy edge S_{u,ℓ_1} contains $\{(u,v)\} \times \bar{A}_{\ell_2}$.

Since all edges are happy we have covered the whole universe.

If the Label Cover instance is completely satisfiable we can cover with $|V_1| + |V_2|$ sets.

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Lemma 66
Given a solution to the set cover instance using at most $\frac{h}{8}(|V_1| + |V_2|)$ sets we can find a solution to the Label Cover instance satisfying at least $\frac{2}{h^2}|E|$ edges.

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- at least half of the edges have both end-points unmarked, as the graph is regular
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Theorem 67
There is no $\frac{1}{32}\log n$*-approximation for the unweighted Set Cover problem unless problems in NP can be solved in time* $\mathcal{O}(n^{\mathcal{O}(\log\log n)})$.

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The probability that all u are covered is $(1 - \frac{1}{2^h})^s$

The probability that there exists a choice such that all u are covered is at most

$$\binom{t}{h}2^h\left(1-\frac{1}{2^h}\right)^s \le (2t)^h e^{-s/2^h} = (2t)^h \cdot e^{-h\ln(4t)} < \frac{1}{2} \ .$$

The random process outputs a partition system with constant probability!

Partition Systems

Lemma 68
Given h and t with $h \le t$, there is a partition system of size $s = \ln(4t)h2^h \le 4t^2 2^h$.

We pick t sets at random from the possible $2^{|U|}$ subsets of U.

Fix a choice of h of these sets, and a choice of h bits (whether we choose A_i or $\bar{A}_i$). There are $2^h \cdot \binom{t}{h}$ such choices.

What is the probability that a given choice covers U?

The probability that an element $u \in A_i$ is $1/2$ (same for $\bar{A}_i$).

The probability that u is covered is $1 - \frac{1}{2^h}$.

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Advanced PCP Theorem

Theorem 69
For any positive constant $\epsilon > 0$, it is the case that $\mathrm{NP} \subseteq \mathrm{PCP}_{1-\epsilon,1/2+\epsilon}(\log n, 3)$. Moreover, the verifier just reads three bits from the proof, and bases its decision only on the parity of these bits.

It is NP-hard to approximate a MAXE3LIN problem by a factor better than $1/2 + \delta$, for any constant δ.

It is NP-hard to approximate MAX3SAT better than $7/8 + \delta$, for any constant δ.

What is the probability that a given choice covers U?

The probability that an element $u \in A_i$ is $1/2$ (same for $\bar{A}_i$).

The probability that u is covered is $1 - \frac{1}{2^h}$.

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$$\binom{t}{h} 2^h \left(1 - \frac{1}{2^h}\right)^s \leq (2t)^h e^{-s/2^h} = (2t)^h \cdot e^{-h\ln(4t)} < \frac{1}{2} .$$

The random process outputs a partition system with constant probability!