

## Part III

# Approximation Algorithms

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Heuristics

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## Definition 2

An  $\alpha$ -approximation for an optimization problem is a polynomial-time algorithm that for all instances of the problem produces a solution whose value is within a factor of  $\alpha$  of the value of an optimal solution.

## Why approximation algorithms?

- ▶ They are also interesting in their own right
- ▶ They give a rigorous mathematical base for studying algorithms
- ▶ They provide a means to compare the difficulty of various optimization problems
- ▶ Proving theorems may give a deeper theoretical understanding which in turn leads to new algorithmic approaches

## Why not?

- ▶ Sometimes the results are very pessimistic due to the fact that an algorithm has to provide a close-to-optimum solution on every instance.



## Why approximation algorithms?

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### Definition 3

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

- ▶  $x \in \mathcal{I}$  can be **decided** in polynomial time
- ▶  $y \in \text{sol}(\mathcal{I})$  can be **verified** in polynomial time
- ▶  $m$  can be computed in polynomial time
- ▶  $\text{goal} \in \{\text{min}, \text{max}\}$

In other words: the decision problem **is there a solution  $y$  with  $m(x, y)$  at most/at least  $z$**  is in NP.

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

#### Definition 4 (Performance Ratio)

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



## Definition 5 ( $r$ -approximation)

An algorithm  $A$  is an  $r$ -approximation algorithm iff

$$\forall x \in \mathcal{I} : R(x, A(x)) \leq r ,$$

and  $A$  runs in polynomial time.

## Definition 6 (PTAS)

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

$$R(x, y) \leq 1 + \epsilon .$$

The running time is polynomial in  $|x|$ .

approximation with arbitrary good factor... fast?

## Problems that have a PTAS

**Scheduling.** Given  $m$  jobs with known processing times; schedule the jobs on  $n$  machines such that the MAKESPAN is minimized.

## Definition 7 (FPTAS)

An FPTAS 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

$$R(x, y) \leq 1 + \epsilon .$$

The running time is polynomial in  $|x|$  and  $1/\epsilon$ .

approximation with arbitrary good factor... fast!

## Problems that have an FPTAS

**KNAPSACK.** Given a set of items with profits and weights choose a subset of total weight at most  $W$  s.t. the profit is maximized.

### Definition 8 (APX – approximable)

A problem  $P$  from NPO is in APX if there exist a constant  $r \geq 1$  and an  $r$ -approximation algorithm for  $P$ .

constant factor approximation...

## Problems that are in APX

**MAXCUT.** Given a graph  $G = (V, E)$ ; partition  $V$  into two disjoint pieces  $A$  and  $B$  s. t. the number of edges between both pieces is maximized.

**MAX-3SAT.** Given a 3CNF-formula. Find an assignment to the variables that satisfies the maximum number of clauses.

## Problems with polylogarithmic approximation guarantees

- ▶ Set Cover
- ▶ Minimum Multicut
- ▶ Sparsest Cut
- ▶ Minimum Bisection

There is an  $r$ -approximation with  $r \leq \mathcal{O}(\log^c(|x|))$  for some constant  $c$ .

Note that only for some of the above problem a matching lower bound is known.



## There are really difficult problems!

### Theorem 9

*For any constant  $\epsilon > 0$  there does not exist an  $\Omega(n^{1-\epsilon})$ -approximation algorithm for the maximum clique problem on a given graph  $G$  with  $n$  nodes unless  $P = NP$ .*

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## There are weird problems!

Asymmetric  $k$ -Center admits an  $\mathcal{O}(\log^* n)$ -approximation.

There is no  $o(\log^* n)$ -approximation to Asymmetric  $k$ -Center unless  $NP \subseteq DTIME(n^{\log \log \log n})$ .

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.**

A crucial ingredient for the design and analysis of approximation algorithms is a technique to obtain an upper bound (for maximization problems) or a lower bound (for minimization problems).

Therefore **Linear Programs** or **Integer Linear Programs** play a vital role in the design of many approximation algorithms.

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Therefore **Linear Programs** or **Integer Linear Programs** play a vital role in the design of many approximation algorithms.

## Definition 10

An **Integer Linear Program** or **Integer Program** is a Linear Program in which all variables are required to be integral.

## Definition 11

A **Mixed Integer Program** is a Linear Program in which a subset of the variables are required to be integral.



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Many important combinatorial optimization problems can be formulated in the form of an Integer Program.

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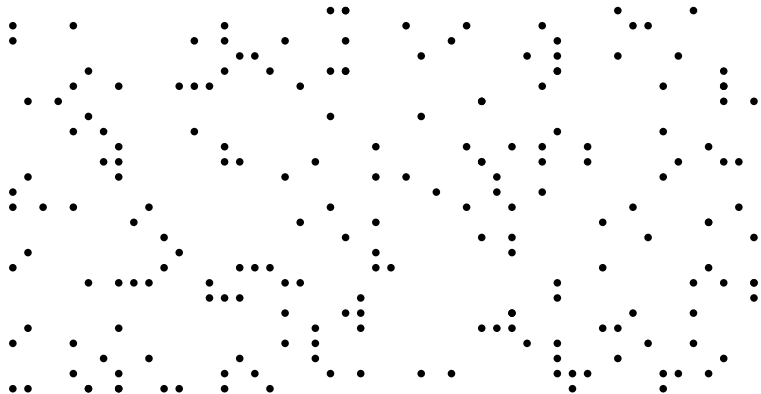
Given a ground set  $U$ , a collection of subsets  $S_1, \dots, S_k \subseteq U$ , where the  $i$ -th subset  $S_i$  has weight/cost  $w_i$ . Find a collection  $I \subseteq \{1, \dots, k\}$  such that

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

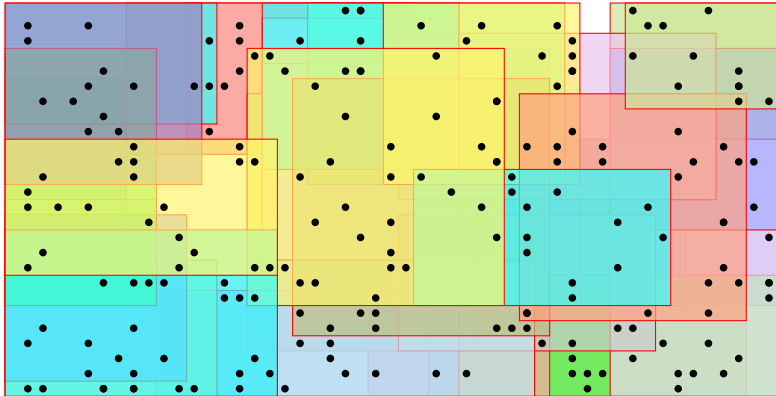
and

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

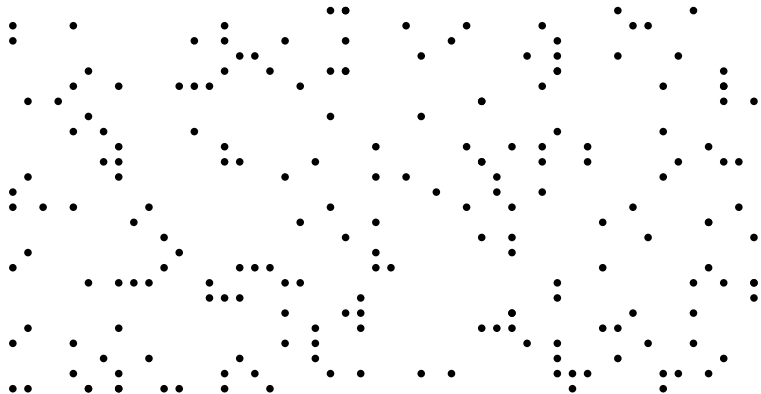
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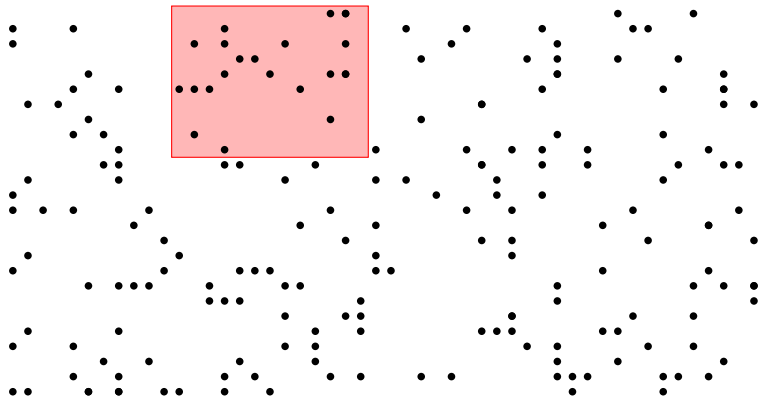
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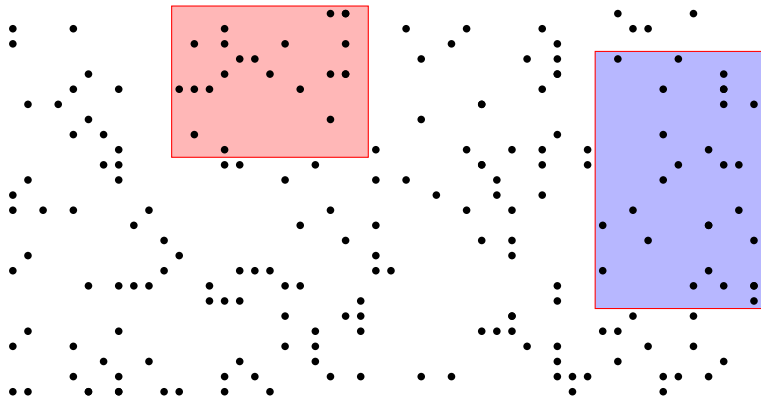


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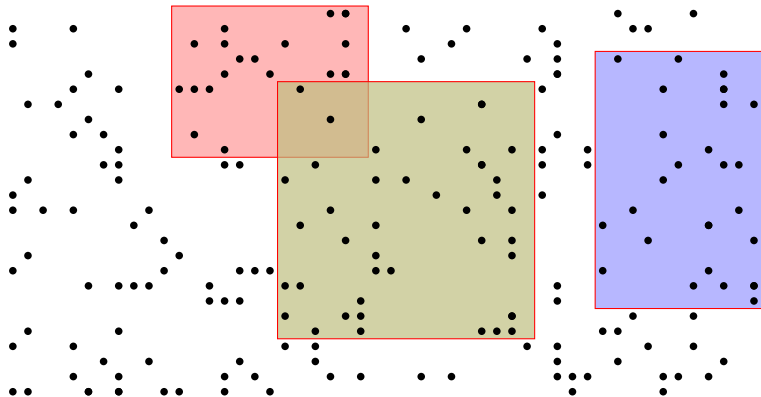




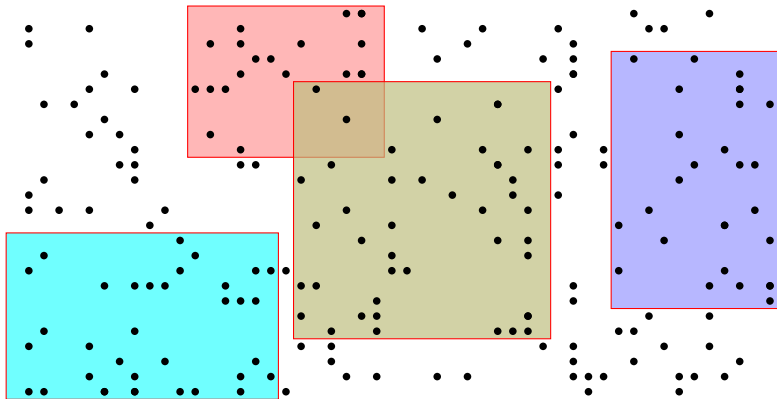
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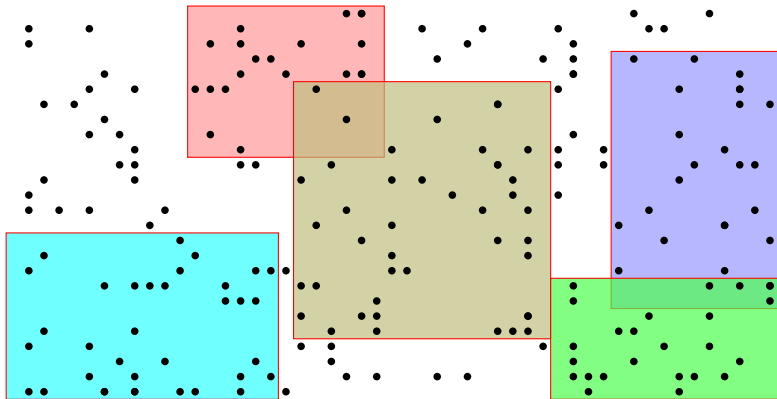
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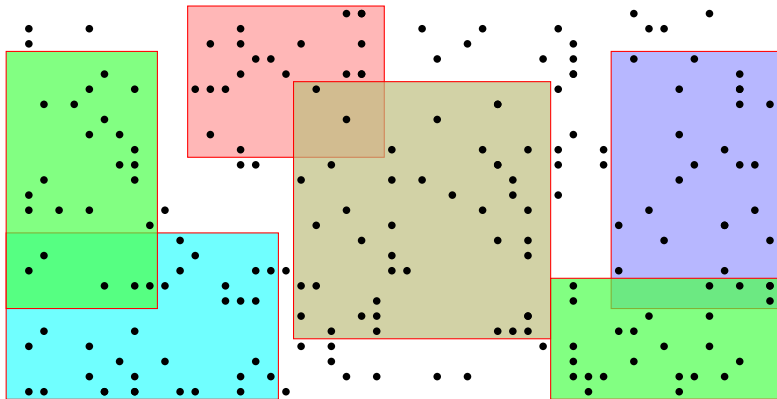
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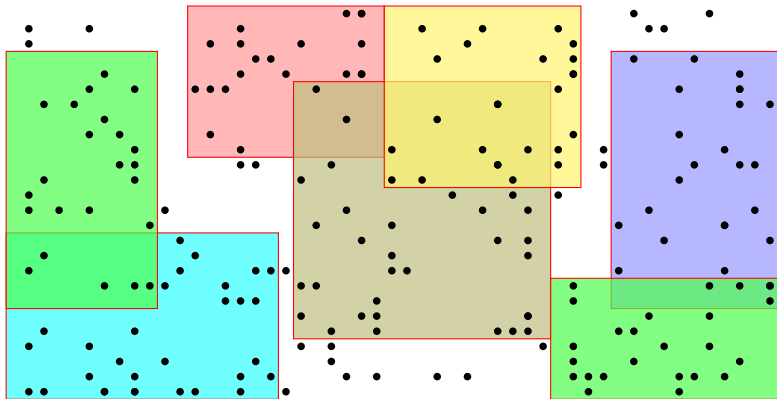
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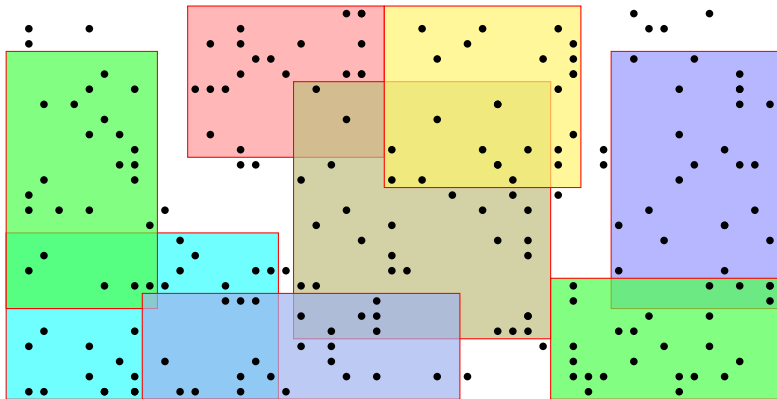
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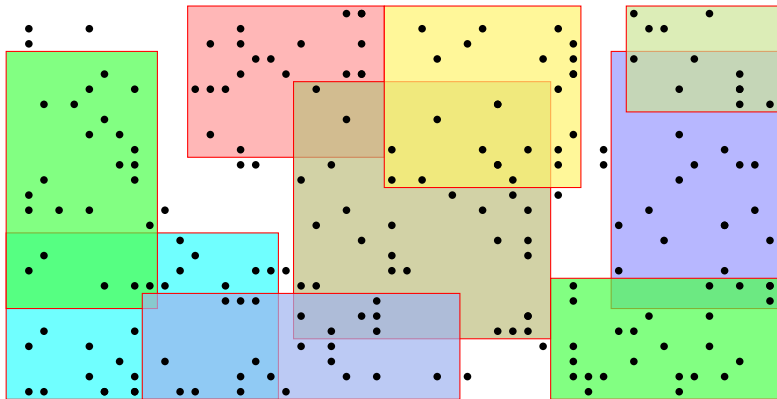
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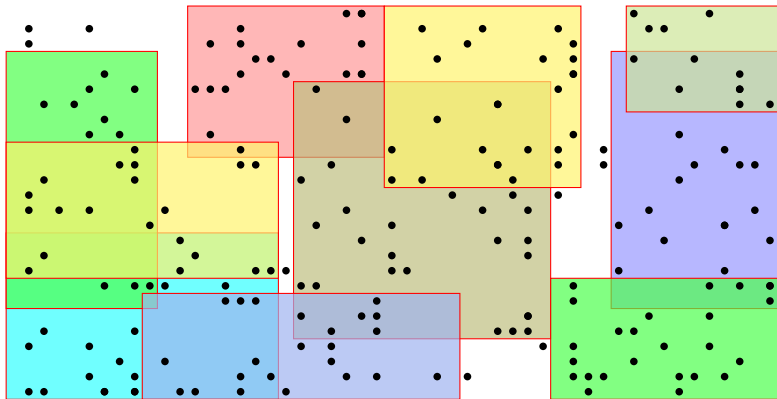


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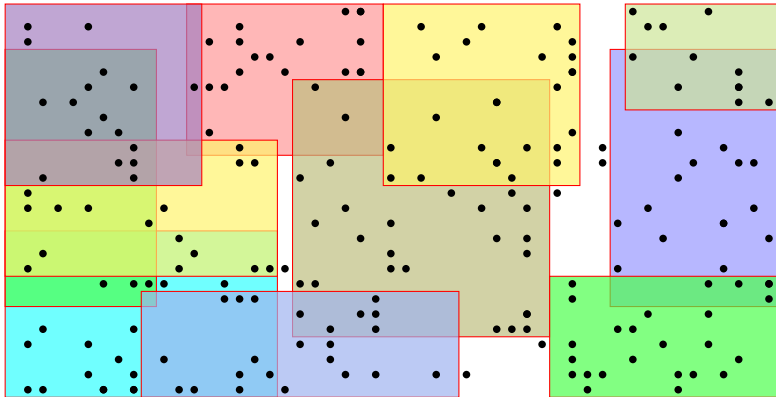




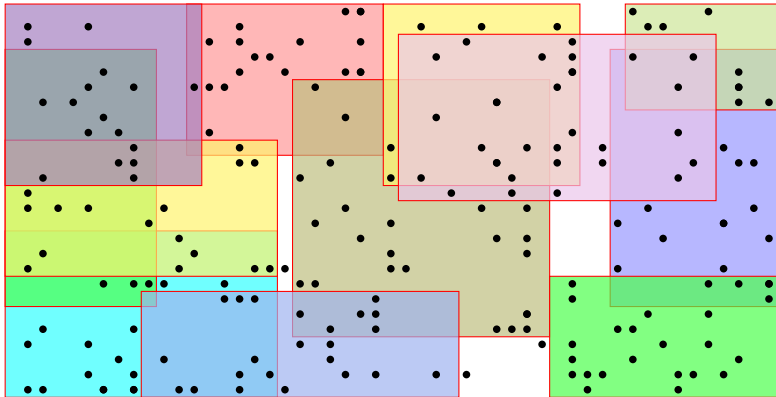
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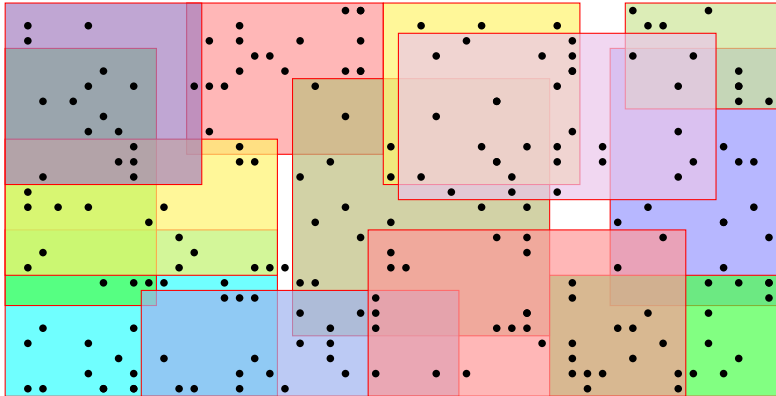
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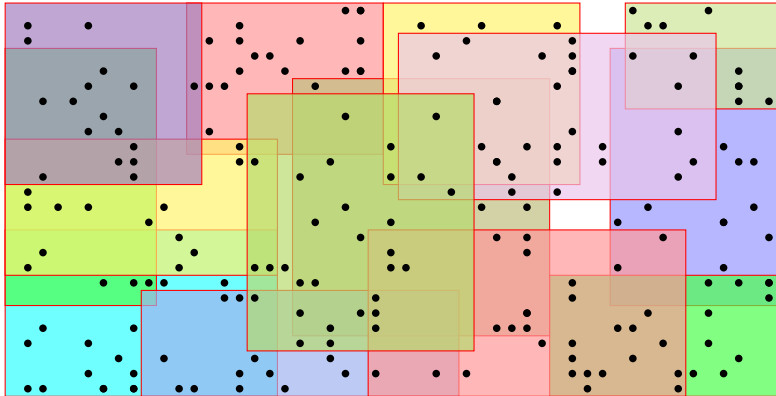
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# IP-Formulation of Set Cover

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

# 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  $S$ .

# IP-Formulation of Vertex Cover

$$\begin{array}{ll} \min & \sum_{v \in V} w_v x_v \\ \text{s.t.} & \forall e = (i, j) \in E \quad x_i + x_j \geq 1 \\ & \forall v \in V \quad x_v \in \{0, 1\} \end{array}$$



# 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.

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

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# Maximum Independent Set

Given a graph  $G = (V, E)$ , and a weight  $w_v$  for every node  $v \in V$ . Find a subset  $S \subseteq V$  of nodes of maximum weight such that no two vertices in  $S$  are adjacent.

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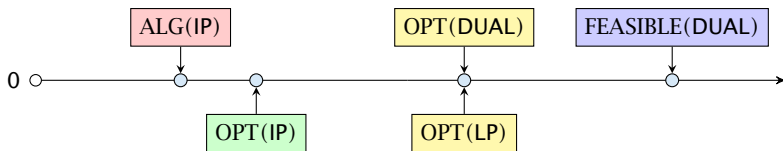
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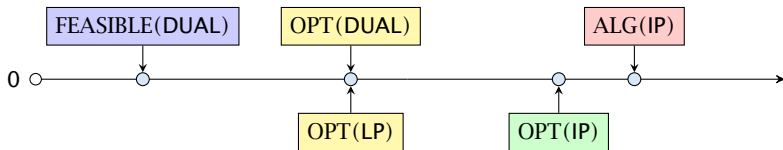
By solving a relaxation we obtain an upper bound for a maximization problem and a lower bound for a minimization problem.

# Relations

## Maximization Problems:



## Minimization Problems:



## 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.

Set Cover relaxation:

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

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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## Technique 1: Round the LP solution.

### Rounding Algorithm:

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

# Technique 1: Round the LP solution.

## Lemma 13

*The rounding algorithm gives an  $f$ -approximation.*

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

We know that

The sum of the  $x_i$  is at least  $f$ .

The sum of the  $x_i$  is at most  $f$ .

Therefore, the sum of the  $x_i$  is exactly  $f$ .

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## Technique 2: Rounding the Dual Solution.

### Relaxation for Set Cover

Primal:

$$\begin{array}{ll} \min & \sum_{i \in I} w_i x_i \\ \text{s.t. } \forall u & \sum_{i: u \in S_i} x_i \geq 1 \\ & x_i \geq 0 \end{array}$$

Dual:

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

## Technique 2: Rounding the Dual Solution.

### Relaxation for Set Cover

**Primal:**

$$\begin{array}{ll} \min & \sum_{i \in I} w_i x_i \\ \text{s.t. } \forall u & \sum_{i: u \in S_i} x_i \geq 1 \\ & x_i \geq 0 \end{array}$$

**Dual:**

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

## Technique 2: Rounding the Dual Solution.

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## Technique 2: Rounding the Dual Solution.

### Rounding Algorithm:

Let  $I$  denote the index set of sets for which the dual constraint is tight. This means for all  $i \in I$

$$\sum_{u:u \in S_i} y_u = w_i$$

## 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  $u \in U$  not covered.

This means that the dual constraint for  $u$  is not satisfied.

But that can't be because the dual solution is optimal.

Therefore, every  $u \in U$  is covered. This is a contradiction to the fact

that the dual solution is optimal.

## Technique 2: Rounding the Dual Solution.

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- ▶ 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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**Proof:**

$$\begin{aligned}\sum_{i \in I} w_i &= \sum_{i \in I} \sum_{u: u \in S_i} \gamma_u \\ &= \sum_u |\{i \in I : u \in S_i\}| \cdot \gamma_u \\ &\leq \sum_u f_u \gamma_u \\ &\leq f \sum_u \gamma_u \\ &\leq f \text{cost}(x^*) \\ &\leq f \cdot \text{OPT}\end{aligned}$$

Let  $I$  denote the solution obtained by the first rounding algorithm and  $I'$  be the solution returned by the second algorithm. Then

$$I \subseteq I' .$$

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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.

The solution is dual feasible.

The solution is primal feasible.

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## Technique 3: The Primal Dual Method

### 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  $S_\ell$  becomes tight
- 5:      $I \leftarrow I \cup \{\ell\}$

## Technique 4: The Greedy Algorithm

### Algorithm 1 Greedy

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

## Technique 4: The Greedy Algorithm

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

In the  $\ell$ -th iteration

since an optimal algorithm can cover the remaining  $n_\ell$  elements with cost  $\text{OPT}$ .

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

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

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$$\begin{aligned}\sum_{j \in I} w_j &\leq \sum_{\ell=1}^s \frac{n_\ell - n_{\ell+1}}{n_\ell} \cdot \text{OPT} \\ &\leq \text{OPT} \sum_{\ell=1}^s \left( \frac{1}{n_\ell} + \frac{1}{n_\ell - 1} + \dots + \frac{1}{n_{\ell+1} + 1} \right)\end{aligned}$$

## Technique 4: The Greedy Algorithm

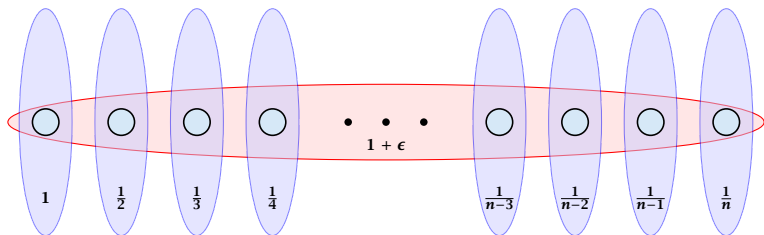
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# Technique 4: The Greedy Algorithm

A tight example:



## Technique 5: Randomized Rounding

One round of randomized rounding:

Pick set  $S_j$  uniformly at random with probability  $1 - x_j$  (for all  $j$ ).

Version A: Repeat rounds until you nearly have a cover. Cover remaining elements by some simple heuristic.

Version B: Repeat for  $s$  rounds. If you have a cover STOP. Otherwise, repeat the whole algorithm.

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

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





$\Pr[\exists u \in U \text{ not covered after } \ell \text{ round}]$

$$\begin{aligned} & \Pr[\exists u \in U \text{ not covered after } \ell \text{ round}] \\ &= \Pr[u_1 \text{ not covered} \vee u_2 \text{ not covered} \vee \dots \vee u_n \text{ not covered}] \end{aligned}$$

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## Lemma 16

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

$$\begin{aligned} & \Pr[\exists u \in U \text{ not covered after } \ell \text{ round}] \\ &= \Pr[u_1 \text{ not covered} \vee u_2 \text{ not covered} \vee \dots \vee u_n \text{ not covered}] \\ &\leq \sum_i \Pr[u_i \text{ not covered after } \ell \text{ rounds}] \leq ne^{-\ell} . \end{aligned}$$

## Lemma 16

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

**With high probability:**

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

**Proof:** We have

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

# Expected Cost

- ▶ Version A.

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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Repeat for  $s = (\alpha + 1) \ln n$  rounds. If you don't have a cover simply repeat the whole process.

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for  $n \geq 2$  and  $\alpha \geq 1$ .

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  $2^{\text{poly}(\log n)}$ ).*

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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

$$S_{\vec{y}} := \{\vec{x} \mid \vec{x}^T \vec{y} = 1\}$$

- ▶ 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.

# Integrality Gap

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

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

## Techniques:

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

# Scheduling Jobs on Identical Parallel Machines

Given  $n$  jobs, where job  $j \in \{1, \dots, n\}$  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.

$$\begin{array}{ll} \min & L \\ \text{s.t.} & \forall \text{machines } i \quad \sum_j p_j \cdot x_{j,i} \leq L \\ & \forall \text{jobs } j \quad \sum_i x_{j,i} \geq 1 \\ & \forall i, j \quad x_{j,i} \in \{0, 1\} \end{array}$$

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

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# Local Search

A local search algorithm successively makes certain small (cost/profit improving) changes to a solution until it does not find such changes anymore.

It is conceptionally very different from a Greedy algorithm as a feasible solution is always maintained.

Sometimes the running time is difficult to prove.

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**Local Search Strategy:** Take the job that finishes last and try to move it to another machine. If there is such a move that reduces the makespan, perform the switch.

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# Local Search Analysis

Let  $\ell$  be the job that finishes last in the produced schedule.

Let  $S_\ell$  be its start time, and let  $C_\ell$  be its completion time.

Note that every machine is busy before time  $S_\ell$ , because otherwise we could move the job  $\ell$  and hence our schedule would not be locally optimal.

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We can split the total processing time into two intervals one from 0 to  $S_\ell$  the other from  $S_\ell$  to  $C_\ell$ .

The interval  $[S_\ell, C_\ell]$  is of length  $p_\ell \leq C_{\max}^*$ .

During the first interval  $[0, S_\ell]$  all processors are busy, and, hence, the total work performed in this interval is

$$m \cdot S_\ell \leq \sum_{j \neq \ell} p_j .$$

Hence, the length of the schedule is at most

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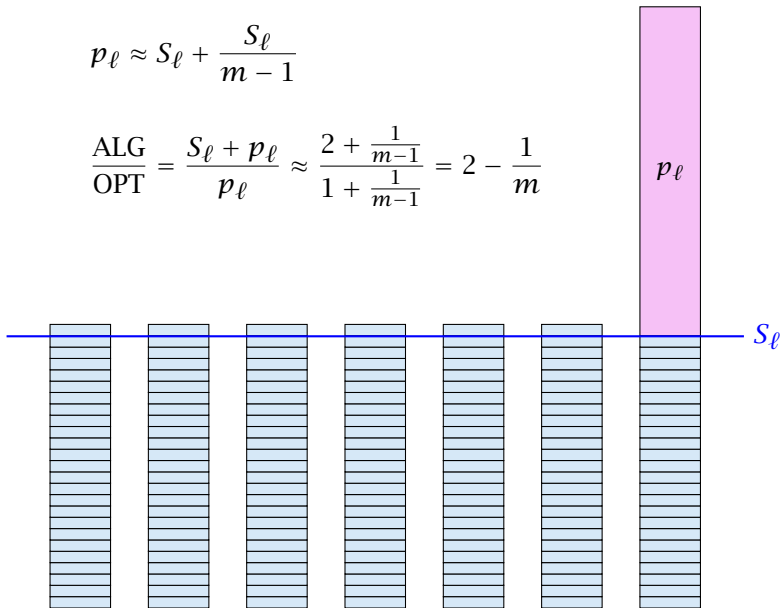
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## A Tight Example

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

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



# 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 optimality condition of our local search algorithm. Hence, these also give 2-approximations.

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# A Greedy Strategy

## Lemma 18

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

## Proof:

- ▶ Let  $p_1 \geq \dots \geq p_n$  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

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

This means that all jobs must have a processing time

greater than one third of any machine in the optimum schedule and hence

the  $\frac{4}{3} C_{\max}^*$  instance cannot be a counter-example.  $\square$

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Therefore, the number of jobs is at most 3.



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- ▶ 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.

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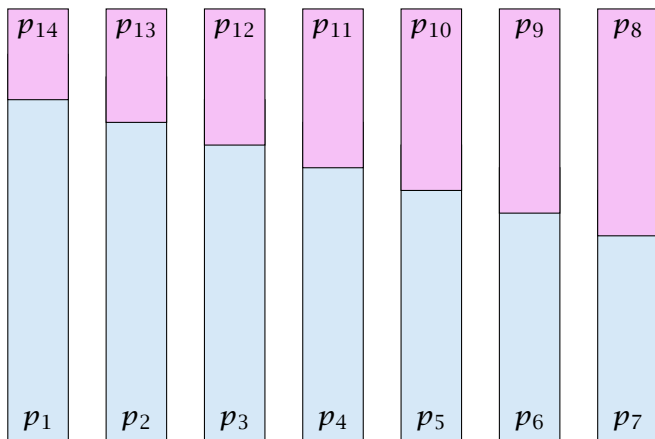
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When in an optimal solution a machine can have at most 2 jobs the optimal solution looks as follows.



- ▶ We can assume that one machine schedules  $p_1$  and  $p_n$  (the largest and smallest job).
- ▶ If not assume wlog. that  $p_1$  is scheduled on machine  $A$  and  $p_n$  on machine  $B$ .
- ▶ Let  $p_A$  and  $p_B$  be the other job scheduled on  $A$  and  $B$ , respectively.
- ▶  $p_1 + p_n \leq p_1 + p_A$  and  $p_A + p_B \leq p_1 + p_A$ , hence scheduling  $p_1$  and  $p_n$  on one machine and  $p_A$  and  $p_B$  on the other, cannot increase the Makespan.
- ▶ Repeat the above argument for the remaining machines.

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# Tight Example

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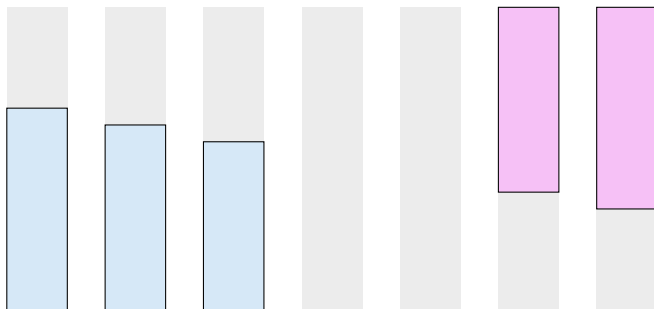
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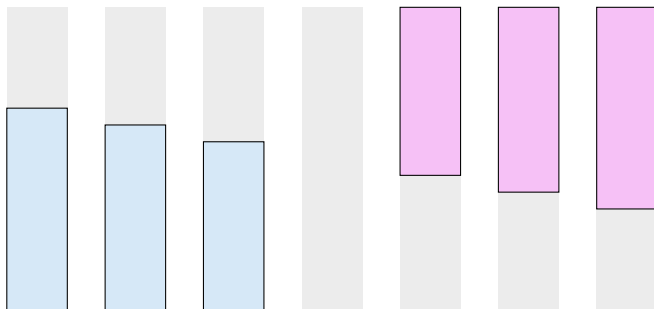
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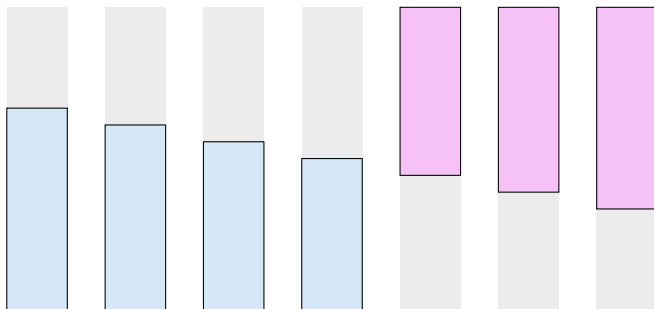
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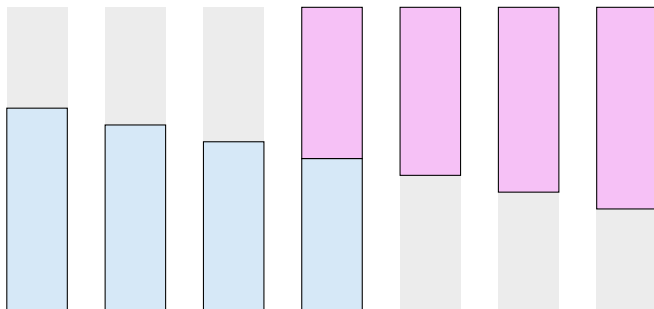
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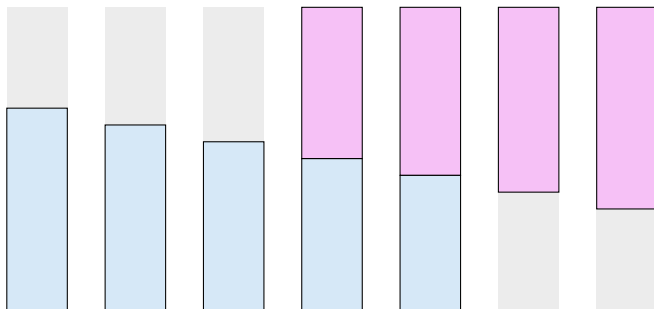
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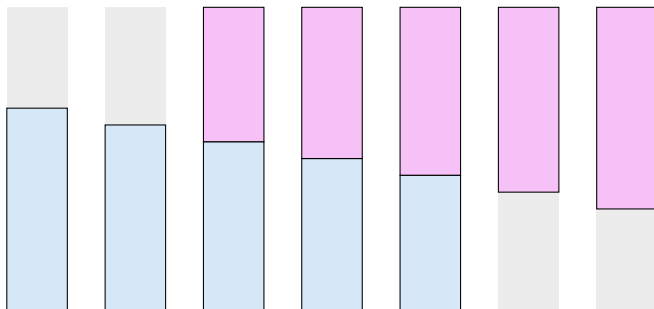
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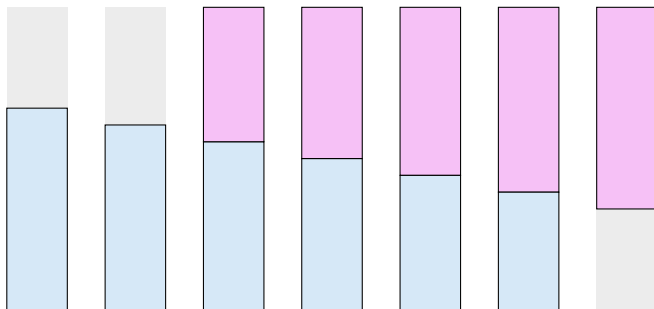
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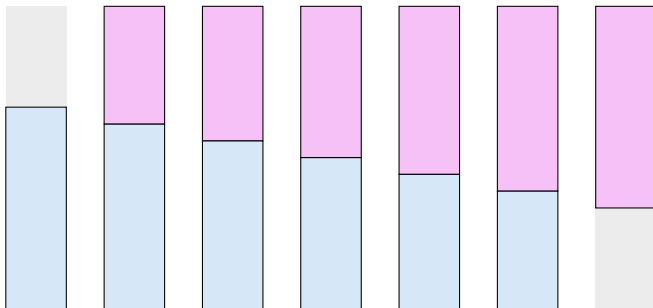
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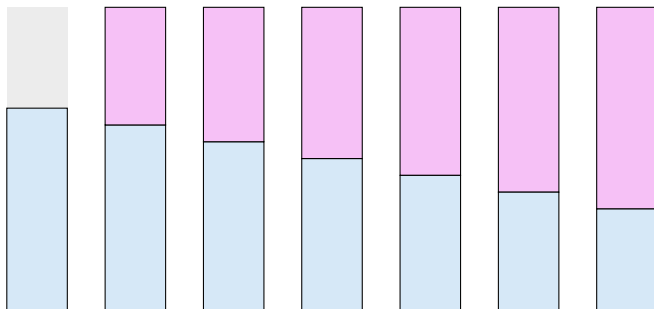
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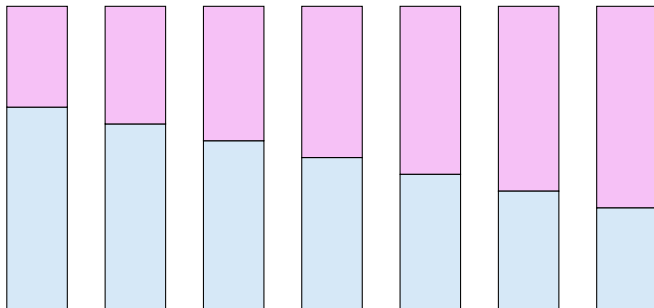
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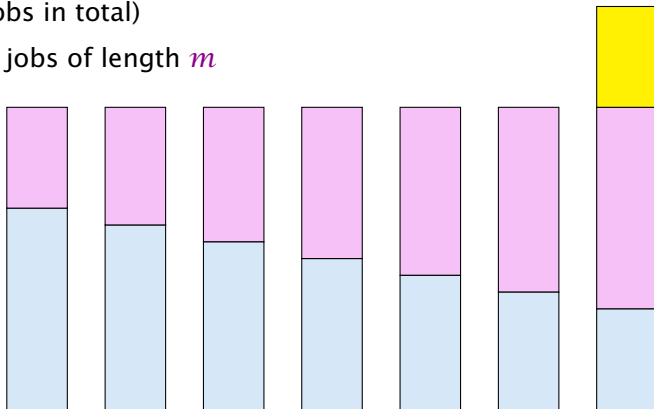
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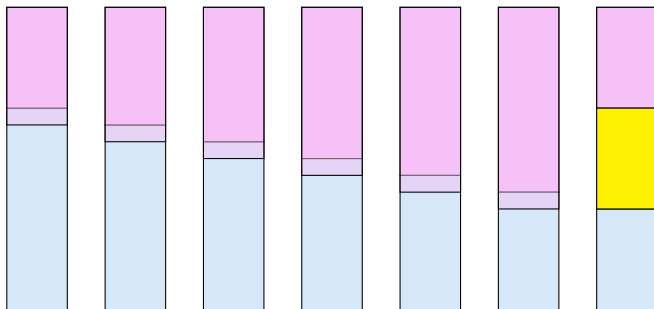
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# 15 Rounding Data + Dynamic Programming

## Knapsack:

Given a set of items  $\{1, \dots, n\}$ , 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  $I \subseteq \{1, \dots, n\}$  of items of total weight at most  $W$  such that the profit is maximized (we can assume each  $w_i \leq W$ ).

$$\begin{array}{ll} \max & \sum_{i=1}^n p_i x_i \\ \text{s.t.} & \sum_{i=1}^n w_i x_i \leq W \\ & \forall i \in \{1, \dots, n\} \quad x_i \in \{0, 1\} \end{array}$$

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## 15 Rounding Data + Dynamic Programming

### Algorithm 1 Knapsack

```
1:  $A(1) \leftarrow [(0, 0), (p_1, w_1)]$ 
2: for  $j \leftarrow 2$  to  $n$  do
3:    $A(j) \leftarrow A(j - 1)$ 
4:   for each  $(p, w) \in A(j - 1)$  do
5:     if  $w + w_j \leq W$  then
6:       add  $(p + p_j, w + w_j)$  to  $A(j)$ 
7:       remove dominated pairs from  $A(j)$ 
8: return  $\max_{(p, w) \in A(n)} p$ 
```

The running time is  $\mathcal{O}(n \cdot \min\{W, P\})$ , where  $P = \sum_i p_i$  is the total profit of all items. This is only **pseudo-polynomial**.



# 15 Rounding Data + Dynamic Programming

## Definition 19

An algorithm is said to have pseudo-polynomial running time if the running time is polynomial when the numerical part of the input is encoded in unary.

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# Scheduling Revisited

The previous analysis of the scheduling algorithm gave a makespan of

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

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**Idea:**

1. Find the optimum Makespan for the long jobs by brute force.
2. Then use the list scheduling algorithm for the short jobs, always assigning the next job to the least loaded machine.

We still have a cost of

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If  $\ell$  is a short job its length is at most

$$p_\ell \leq \sum_j p_j / (mk)$$

which is at most  $C_{\max}^* / k$ .

Hence we get a schedule of length at most

$$\left(1 + \frac{1}{k}\right) C_{\max}^*$$

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 20

*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.*

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## How to get rid of the requirement that $m$ is constant?

We first design an algorithm that works as follows:

On input of  $T$  it either finds a schedule of length  $(1 + \frac{1}{k})T$  or certifies that no schedule of length at most  $T$  exists (assume  $T \geq \frac{1}{m} \sum_j p_j$ ).

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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 otherwise their rounded sizes would add up to more than  $T$  (note that the rounded size of a long job is at least  $T/k$ ).

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

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

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

We have

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

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Can we do better?

Scheduling on identical machines with the goal of minimizing Makespan is a **strongly NP-complete** problem.

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- ▶ Suppose we have an instance with polynomially bounded processing times  $p_i \leq q(n)$

- ▶ We set  $k := \lceil 2nq(n) \rceil \geq 2 \text{OPT}$

- ▶ Then

$$\text{ALG} \leq \left(1 + \frac{1}{k}\right) \text{OPT} \leq \text{OPT} + \frac{1}{2}$$

- ▶ But this means that the algorithm computes the optimal solution as the optimum is integral.
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## More General

Let  $\text{OPT}(n_1, \dots, n_A)$  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).

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

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# Bin Packing

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

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

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

## Theorem 22

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



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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.
- ▶ A  $\rho$ -approximation algorithm with  $\rho < 3/2$  cannot output 3 or more bins when 2 are optimal.
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An asymptotic polynomial-time approximation scheme (APTAS) is a family of algorithms  $\{A_\epsilon\}$  along with a constant  $c$  such that  $A_\epsilon$  returns a solution of value at most  $(1 + \epsilon)\text{OPT} + c$  for minimization problems.

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# Bin Packing

Again we can differentiate between small and large items.

## Lemma 24

*Any packing of items into  $\ell$  bins can be extended with items of size at most  $\gamma$  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.*

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- ▶ If after Greedy we use more than  $\ell$  bins, all bins (apart from the last) must be full to at least  $1 - \gamma$ .
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Choose  $\gamma = \epsilon/2$ . Then we either use  $\ell$  bins or at most

$$\frac{1}{1 - \epsilon/2} \cdot \text{OPT} + 1 \leq (1 + \epsilon) \cdot \text{OPT} + 1$$

bins.

It remains to find an algorithm for the large items.

## 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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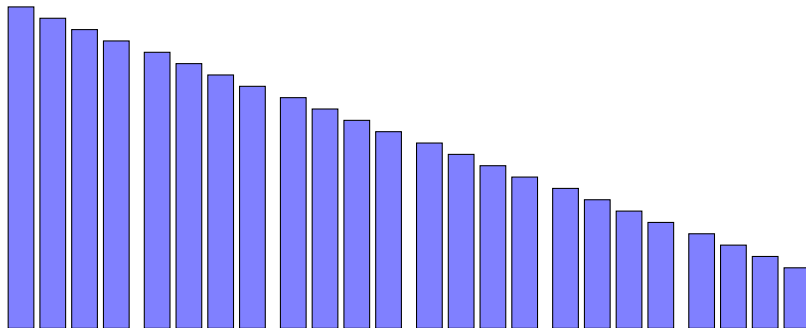


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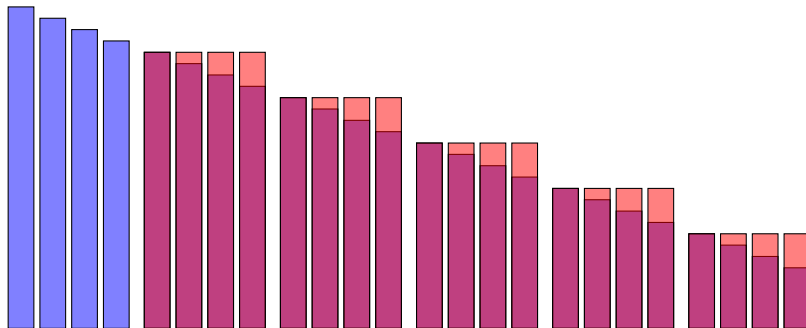
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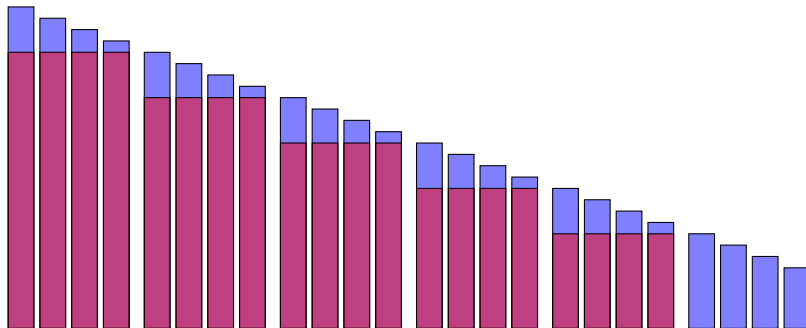
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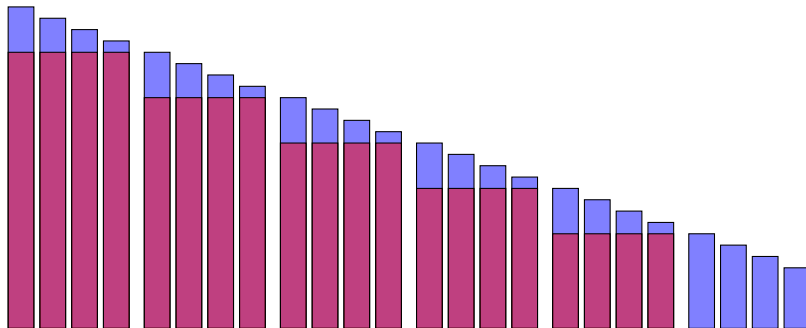
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## Lemma 25

$$\text{OPT}(I') \leq \text{OPT}(I) \leq \text{OPT}(I') + k$$

Proof 1:

Any bin packing for  $I'$  gives a bin packing for  $I$  as follows:

• pack the items of subset  $S$  into the packing for  $I'$ .  
• for each group  $g$ , have  $|g|$  bins packed.

• pack the items of groups  $g$  where in the packing for  $I'$  the items for group  $g$  have been packed.

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Assume that our instance does not contain pieces smaller than  $\epsilon/2$ . Then  $\text{SIZE}(I) \geq \epsilon n/2$ .

We set  $k = \lfloor \epsilon \text{SIZE}(I) \rfloor$ .

Then  $n/k \leq n/\lfloor \epsilon^2 n/2 \rfloor \leq 4/\epsilon^2$  (note that  $\lfloor \alpha \rfloor \geq \alpha/2$  for  $\alpha \geq 1$ ).

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We can find an optimal packing for such instances by the previous Dynamic Programming approach.

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

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# Configuration LP

## Change of Notation:

- ▶ Group pieces of identical size.
- ▶ Let  $s_1$  denote the largest size, and let  $b_1$  denote the number of pieces of size  $s_1$ .
- ▶  $s_2$  is second largest size and  $b_2$  number of pieces of size  $s_2$ ;
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A possible packing of a bin can be described by an  $m$ -tuple  $(t_1, \dots, t_m)$ , 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**.

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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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**How to solve this LP?**

later...

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

# 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  $G_2, \dots, G_{r-1}$ .
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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 27

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

Let  $I'$  be the set of items that are not packed in the first bin. Let  $S$  be the set of sizes of items in  $I'$ . Let  $n_s$  be the number of items of size  $s$  in  $I'$ . Let  $n$  be the number of items in  $I'$ . Let  $k$  be the number of items in  $I'$  that have the same size as the largest item in  $I'$ .

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

- ▶ 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 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 average piece size is only  $3/n_i$ .

- ▶ 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  $\text{BinPack}(I_2)$

$$\text{OPT}_{\text{LP}}(I_1) + \text{OPT}_{\text{LP}}(I_2) \leq \text{OPT}_{\text{LP}}(I') \leq \text{OPT}_{\text{LP}}(I)$$

Proof:

- Each LP feasible solution for  $I'$  can be mapped to a feasible solution for  $I$  (no larger size, hence,  $\text{OPT}_{\text{LP}}(I) \geq \text{OPT}_{\text{LP}}(I')$ )
- The LP solution for  $I'$  is given by  $x_1, \dots, x_n$ .
- The LP solution for  $I$  is given by  $y_1, \dots, y_n$ .



$$\text{OPT}_{\text{LP}}(I_1) + \text{OPT}_{\text{LP}}(I_2) \leq \text{OPT}_{\text{LP}}(I') \leq \text{OPT}_{\text{LP}}(I)$$

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- ▶ Each piece surviving in  $I'$  can be mapped to a piece in  $I$  of no lesser size. Hence,  $\text{OPT}_{\text{LP}}(I') \leq \text{OPT}_{\text{LP}}(I)$
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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  $\text{OPT}_{1P}$  many bins.

Pieces of type 1 are packed into at most

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

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# Analysis

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

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# How to solve the LP?

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

In total we have  $b_i$  pieces of size  $s_i$ .

## Primal

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

## Dual

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

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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  $T_j = (T_{j1}, \dots, T_{jm})$  that

is feasible for  $P_j$ .

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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'

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

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

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

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

The constraints used when computing  $z$  imply that the solution is feasible for

the LP where we drop all unused constraints. We will assume the remaining constraints are all satisfied by the optimal solution. We will call these used constraints.

The dual to this LP is feasible and we can compute  $z$ . The corresponding dual constraint was not even used.

The primal value is at least  $(1 - \epsilon')\text{OPT}$ .

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- ▶ The constraints used when computing  $z$  **certify** that the solution is feasible for **DUAL'**.
- ▶ 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.
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This gives that overall we need at most

$$(1 + \epsilon') \text{OPT}_{\text{LP}}(I) + \mathcal{O}(\log^2(\text{SIZE}(I)))$$

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## Lemma 29 (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  $\delta > 0$

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

and

$$\Pr[X \leq (1 - \delta)L] < \left( \frac{e^{-\delta}}{(1 - \delta)^{1-\delta}} \right)^L,$$



## Lemma 30

For  $0 \leq \delta \leq 1$  we have that

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

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# Proof of Chernoff Bounds

## Markov's Inequality:

Let  $X$  be random variable taking non-negative values.

Then

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Trivial!

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Hence:

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**Hence:**

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Hence:

$$\Pr[X \geq (1 + \delta)U] \leq \frac{E[X]}{(1 + \delta)U} \approx \frac{1}{1 + \delta}$$

That's awfully weak :(

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Set  $p_i = \Pr[X_i = 1]$ . Assume  $p_i > 0$  for all  $i$ .

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$$\Pr[X \geq (1 + \delta)U] = \Pr[e^{tX} \geq e^{t(1+\delta)U}]$$



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Now, we apply Markov:

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**This may be a lot better (!?)**

# Proof of Chernoff Bounds

$$\mathbb{E}[e^{tX}]$$

# Proof of Chernoff Bounds

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

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

Now, we apply Markov:

$$\begin{aligned}\Pr[X \geq (1 + \delta)U] &= \Pr[e^{tX} \geq e^{t(1+\delta)U}] \\ &\leq \frac{E[e^{tX}]}{e^{t(1+\delta)U}}\end{aligned}$$

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## Lemma 31

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Take logarithms:

$$U(\delta - (1+\delta)\ln(1+\delta)) \leq -U\delta^2/3$$

Show:

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

Take logarithms:

$$U(\delta - (1+\delta)\ln(1+\delta)) \leq -U\delta^2/3$$

True for  $\delta = 0$ .

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True for  $\delta = 0$ . Divide by  $U$  and take derivatives:

$$-\ln(1+\delta) \leq -2\delta/3$$

**Reason:**

As long as derivative of left side is smaller than derivative of right side the inequality holds.

$$f(\delta) := -\ln(1 + \delta) + 2\delta/3 \leq 0$$



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A convex function ( $f''(\delta) \geq 0$ ) on an interval takes maximum at the boundaries.

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$$f'(\delta) = -\frac{1}{1 + \delta} + 2/3 \quad f''(\delta) = \frac{1}{(1 + \delta)^2}$$

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

For  $\delta \geq 1$  we show

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Take logarithms:

$$U(\delta - (1+\delta)\ln(1+\delta)) \leq -U\delta/3$$

True for  $\delta = 0$ . Divide by  $U$  and take derivatives:

$$-\ln(1+\delta) \leq -1/3 \iff \ln(1+\delta) \geq 1/3 \quad (\text{true})$$

**Reason:**

As long as derivative of left side is smaller than derivative of right side the inequality holds.



Show:

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

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Take logarithms:

$$L(-\delta - (1-\delta)\ln(1-\delta)) \leq -L\delta^2/2$$

Show:

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

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Show:

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

Take logarithms:

$$L(-\delta - (1-\delta)\ln(1-\delta)) \leq -L\delta^2/2$$

True for  $\delta = 0$ . Divide by  $L$  and take derivatives:

$$\ln(1-\delta) \leq -\delta$$

**Reason:**

As long as derivative of left side is smaller than derivative of right side the inequality holds.

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This holds for  $0 \leq \delta < 1$ .



# Integer Multicommodity Flows

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

$$\begin{array}{ll} \min & W \\ \text{s.t.} & \forall i \quad \sum_{p \in \mathcal{P}_i} x_p = 1 \\ & \sum_{p: e \in p} x_p \leq W \\ & x_p \in \{0, 1\} \end{array}$$

# 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.

### Theorem 32

If  $W^* \geq c \ln n$  for some constant  $c$ , then with probability at least  $1 - n^{-c/3}$  the total number of paths using any edge is at most  $W^* + \sqrt{cW^* \ln n} = \mathcal{O}(W^*)$ .

### Theorem 33

With probability at least  $1 - n^{-c/3}$  the total number of paths using any edge is at most  $\mathcal{O}(W^* + c \ln n)$ .

# Integer Multicommodity Flows

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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# Integer Multicommodity Flows

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

Then

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

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## 16.3 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 such that the total weight of clauses that are **satisfied** is maximum.

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## 16.3 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  $i$ .
- ▶  $x_i$  is called a **positive literal** while the negation  $\bar{x}_i$  is called a **negative literal**.
- ▶ For a given clause  $C_j$  the number of its literals is called its **length** or **size** and denoted with  $\ell_j$ .
- ▶ Clauses of length one are called **unit clauses**.



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- ▶ Clauses of length one are called **unit clauses**.

# 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).

Define random variable  $X_j$  with

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

Then the total weight  $W$  of satisfied clauses is given by

$$W = \sum_j w_j X_j$$

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$E[W]$

$$E[W] = \sum_j w_j E[X_j]$$

$$\begin{aligned} E[W] &= \sum_j w_j E[X_j] \\ &= \sum_j w_j \Pr[C_j \text{ is satisfied}] \end{aligned}$$

$$\begin{aligned} E[W] &= \sum_j w_j E[X_j] \\ &= \sum_j w_j \Pr[C_j \text{ is satisfied}] \\ &= \sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right) \end{aligned}$$

$$\begin{aligned} E[W] &= \sum_j w_j E[X_j] \\ &= \sum_j w_j \Pr[C_j \text{ is satisfied}] \\ &= \sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right) \\ &\geq \frac{1}{2} \sum_j w_j \end{aligned}$$

$$\begin{aligned} E[W] &= \sum_j w_j E[X_j] \\ &= \sum_j w_j \Pr[C_j \text{ is satisfied}] \\ &= \sum_j w_j \left(1 - \left(\frac{1}{2}\right)^{\ell_j}\right) \\ &\geq \frac{1}{2} \sum_j w_j \\ &\geq \frac{1}{2} \text{OPT} \end{aligned}$$

# MAXSAT: LP formulation

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

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

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

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# MAXSAT: Randomized Rounding

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

## Lemma 34 (Geometric Mean $\leq$ Arithmetic Mean)

For any nonnegative  $a_1, \dots, a_k$

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

### Definition 35

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

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

### Lemma 36

Let  $f$  be a concave function on the interval  $[0, 1]$ , with  $f(0) = a$  and  $f(1) = a + b$ . Then

$$f(\lambda)$$

for  $\lambda \in [0, 1]$ .

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### Lemma 36

Let  $f$  be a concave function on the interval  $[0, 1]$ , with  $f(0) = a$  and  $f(1) = a + b$ . Then

$$\begin{aligned} f(\lambda) &= f((1 - \lambda)0 + \lambda 1) \\ &\geq (1 - \lambda)f(0) + \lambda f(1) \\ &= a + \lambda b \end{aligned}$$

for  $\lambda \in [0, 1]$ .

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for  $\lambda \in [0, 1]$ .

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

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



$$\begin{aligned}\Pr[C_j \text{ not satisfied}] &= \prod_{i \in P_j} (1 - y_i) \prod_{i \in N_j} y_i \\ &\leq \left[ \frac{1}{\ell_j} \left( \sum_{i \in P_j} (1 - y_i) + \sum_{i \in N_j} y_i \right) \right]^{\ell_j}\end{aligned}$$

$$\begin{aligned}\Pr[C_j \text{ not satisfied}] &= \prod_{i \in P_j} (1 - y_i) \prod_{i \in N_j} y_i \\ &\leq \left[ \frac{1}{\ell_j} \left( \sum_{i \in P_j} (1 - y_i) + \sum_{i \in N_j} y_i \right) \right]^{\ell_j} \\ &= \left[ 1 - \frac{1}{\ell_j} \left( \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) \right) \right]^{\ell_j}\end{aligned}$$

$$\begin{aligned}
\Pr[C_j \text{ not satisfied}] &= \prod_{i \in P_j} (1 - y_i) \prod_{i \in N_j} y_i \\
&\leq \left[ \frac{1}{\ell_j} \left( \sum_{i \in P_j} (1 - y_i) + \sum_{i \in N_j} y_i \right) \right]^{\ell_j} \\
&= \left[ 1 - \frac{1}{\ell_j} \left( \sum_{i \in P_j} y_i + \sum_{i \in N_j} (1 - y_i) \right) \right]^{\ell_j} \\
&\leq \left( 1 - \frac{z_j}{\ell_j} \right)^{\ell_j} .
\end{aligned}$$

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

$\Pr[C_j \text{ satisfied}]$

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

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

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

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

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

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

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

$E[W]$



$$E[W] = \sum_j w_j \Pr[C_j \text{ is satisfied}]$$

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

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

# MAXSAT: The better of two

## Theorem 37

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

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

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

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

$$\begin{aligned} E[\max\{W_1, W_2\}] \\ \geq E[\frac{1}{2}W_1 + \frac{1}{2}W_2] \end{aligned}$$

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

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

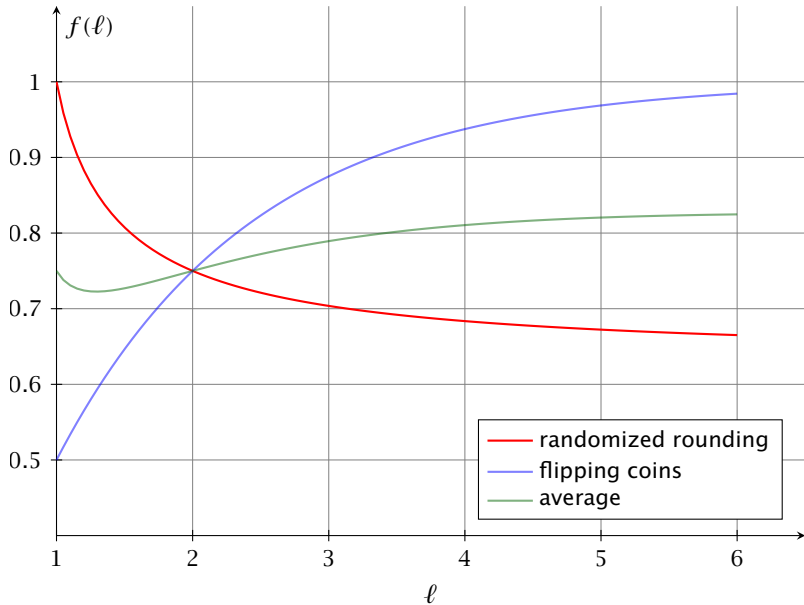
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# MAXSAT: Nonlinear Randomized Rounding

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  $f : [0, 1] \rightarrow [0, 1]$  and set  $x_i$  to true with probability  $f(y_i)$ .

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

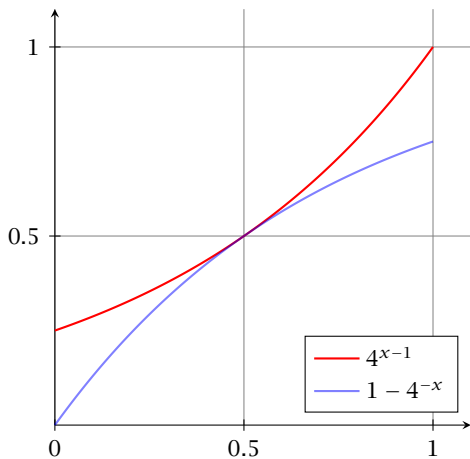
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Not if we compare ourselves to the value of an optimum LP-solution.

### Definition 39 (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.

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## Lemma 40

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

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

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
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## 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

# Semidefinite Programming

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

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

Note that wlog. we can assume that all variables appear in this matrix. Suppose we have a non-negative scalar  $z$  and want to express something like

$$\sum_{i,j} a_{ijk} x_{ij} + z = b_k$$

where  $x_{ij}$  are variables of the positive semidefinite matrix. We can add  $z$  as a diagonal entry  $x_{\ell\ell}$ , and additionally introduce constraints  $x_{\ell r} = 0$  and  $x_{r\ell} = 0$ .

# Vector Programming

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

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

This is equivalent!

## **Fact [without proof]**

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



# Quadratic Programs

**Quadratic Program for MaxCut:**

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

This is exactly MaxCut!

# Semidefinite Relaxation

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

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

# 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  $y_i = -1$

## 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

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

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.

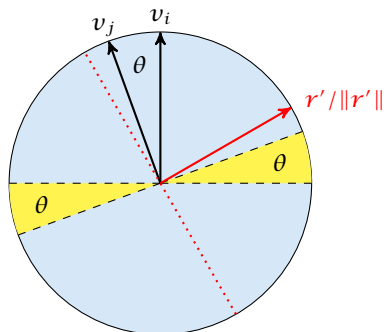
Note that this is clear if  $e_1$  and  $e_2$  are standard basis vectors.

# Rounding the SDP-Solution

## Corollary

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

# Rounding the SDP-Solution



- ▶ if the normalized projection falls into the shaded region,  $v_i$  and  $v_j$  are rounded to different values
- ▶ this happens with probability  $\theta/\pi$



# Rounding the SDP-Solution

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

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

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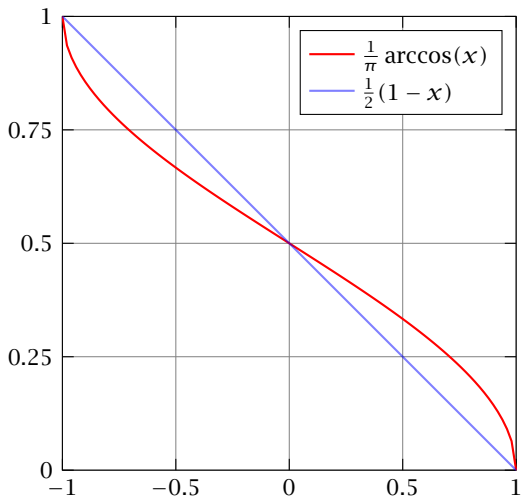
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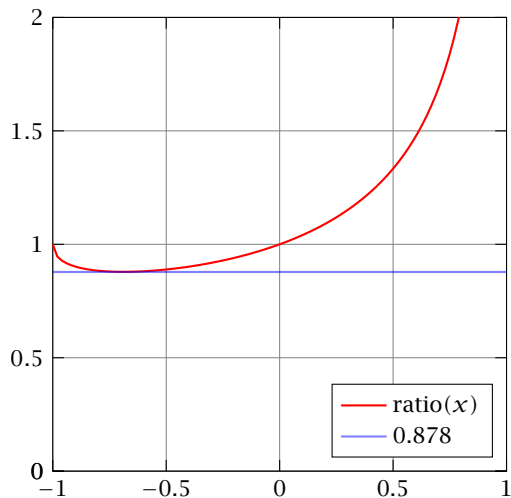
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## Theorem 41

*Given the unique games conjecture, there is no  $\alpha$ -approximation for the maximum cut problem with constant*

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

*unless  $P = NP$ .*

# Repetition: Primal Dual for Set Cover

## Primal Relaxation:

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

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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!!!!**

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This is sufficient to show that the solution is an  $f$ -approximation.

Suppose we have a primal/dual pair

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

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and solutions that fulfill approximate slackness conditions:

$$x_j > 0 \Rightarrow \sum_i a_{ij} y_i \geq \frac{1}{\alpha} c_j$$

$$y_i > 0 \Rightarrow \sum_j a_{ij} x_j \leq \beta b_i$$

Then

$$\sum_j c_j x_j$$

Then

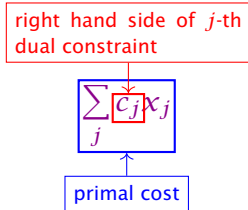
$$\sum_j c_j x_j$$

↑

primal cost

A diagram consisting of a blue-bordered box containing the mathematical expression  $\sum_j c_j x_j$  in purple. Below this box is a blue-bordered box containing the text "primal cost" in blue. A blue arrow points upwards from the "primal cost" box to the mathematical expression box.

Then



Then

$$\boxed{\sum_j c_j x_j} \leq \alpha \sum_j \left( \sum_i a_{ij} y_i \right) x_j$$

↑  
primal cost



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$$\boxed{\sum_j c_j x_j} \leq \alpha \sum_j \left( \sum_i a_{ij} y_i \right) x_j$$

↑

$$\boxed{\text{primal cost}} = \alpha \sum_i \left( \sum_j a_{ij} x_j \right) y_i$$

Then

$$\begin{aligned} \boxed{\sum_j c_j x_j} &\leq \alpha \sum_j \left( \sum_i a_{ij} y_i \right) x_j \\ \uparrow \\ \boxed{\text{primal cost}} &= \alpha \sum_i \left( \sum_j a_{ij} x_j \right) y_i \\ &\leq \alpha \beta \cdot \sum_i b_i y_i \end{aligned}$$

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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  $v \in V$ .

# Feedback Vertex Set for Undirected Graphs

- ▶ Given a graph  $G = (V, E)$  and non-negative weights  $w_v \geq 0$  for vertex  $v \in V$ .
- ▶ Choose a minimum cost subset of vertices s.t. every cycle contains at least one vertex.

We can encode this as an instance of Set Cover

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- ▶ However, this encoding gives a Set Cover instance of non-polynomial size.
- ▶ The  $O(\log n)$ -approximation for Set Cover does not help us to get a good solution.



Let  $\mathcal{C}$  denote the set of all cycles (where a cycle is identified by its set of vertices)

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### Primal Relaxation:

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

### Dual Formulation:

$$\begin{array}{ll} \max & \sum_{C \in \mathcal{C}} y_C \\ \text{s.t.} & \forall v \in V \quad \sum_{C: v \in C} y_C \leq w_v \\ & \forall C \quad y_C \geq 0 \end{array}$$

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  - ▶ Increase  $y_C$  until dual constraint for some vertex  $v$  becomes tight.
  - ▶ set  $x_v = 1$ .

Then

$$\sum_v w_v x_v$$

Then

$$\sum_v w_v x_v = \sum_v \sum_{C:v \in C} y_C x_v$$



Then

$$\begin{aligned}\sum_v w_v x_v &= \sum_v \sum_{C:v \in C} y_C x_v \\ &= \sum_{v \in S} \sum_{C:v \in C} y_C\end{aligned}$$

where  $S$  is the set of vertices we choose.

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where  $S$  is the set of vertices we choose.

If every cycle is short we get a good approximation ratio, but this is unrealistic.

### Algorithm 1 FeedbackVertexSet

- 1:  $y \leftarrow 0$
- 2:  $x \leftarrow 0$
- 3: **while** exists cycle  $C$  in  $G$  **do**
- 4:     increase  $y_C$  until there is  $v \in C$  s.t.  $\sum_{C:v \in C} y_C = w_v$
- 5:      $x_v = 1$
- 6:     remove  $v$  from  $G$
- 7:     repeatedly remove vertices of degree 1 from  $G$

**Idea:**

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

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**Observation:**

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

## Observation:

If we always choose a cycle for which the number of vertices of degree at least 3 is at most  $\alpha$  we get a  $2\alpha$ -approximation.

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## Theorem 42

*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.*

This means we have

$$y_C > 0 \Rightarrow |S \cap C| \leq \mathcal{O}(\log n) .$$



# Primal Dual for Shortest Path

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

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

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:**

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

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# Primal Dual for Shortest Path

We can interpret the value  $\gamma_S$  as the width of a moat surrounding the set  $S$ .

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

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### Algorithm 1 PrimalDualShortestPath

- 1:  $\gamma \leftarrow 0$
- 2:  $F \leftarrow \emptyset$
- 3: **while** there is no  $s$ - $t$  path in  $(V, F)$  **do**
- 4:     Let  $C$  be the connected component of  $(V, F)$  containing  $s$
- 5:     Increase  $\gamma_C$  until there is an edge  $e' \in \delta(C)$  such that  $\sum_{S:e' \in \delta(S)} \gamma_S = c(e')$ .
- 6:      $F \leftarrow F \cup \{e'\}$
- 7: **Let  $P$  be an  $s$ - $t$  path in  $(V, F)$**
- 8: **return  $P$**

## Lemma 43

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

Proof:

Assume that  $F$  contains a cycle. Then the cycle is contained in  $F$  and  $F$  is not a tree. This contradicts the fact that  $F$  is a forest. Therefore,  $F$  is a tree.

## Lemma 43

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

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

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

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by weak duality.

Hence, we find a shortest path.

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  $\gamma_S$ ,  $S$  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.

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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  $c : E \rightarrow \mathbb{R}^+$  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  $F$ .

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

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

$$\begin{array}{ll}
 \max & \sum_{S: \exists i \text{ s.t. } S \in S_i} \gamma_S \\
 \text{s.t.} & \forall e \in E \quad \sum_{S: e \in \delta(S)} \gamma_S \leq c(e) \\
 & \gamma_S \geq 0
 \end{array}$$

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).

### Algorithm 1 FirstTry

- 1:  $\gamma \leftarrow 0$
- 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  $\gamma_C$  until there is an edge  $e' \in \delta(C)$  s.t.  
       $\sum_{S \in S_i: e' \in \delta(S)} \gamma_S = c_{e'}$
- 6:      $F \leftarrow F \cup \{e'\}$
- 7: **return**  $\bigcup_i P_i$

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If we show that  $y_S > 0$  implies that  $|\delta(S) \cap F| \leq \alpha$  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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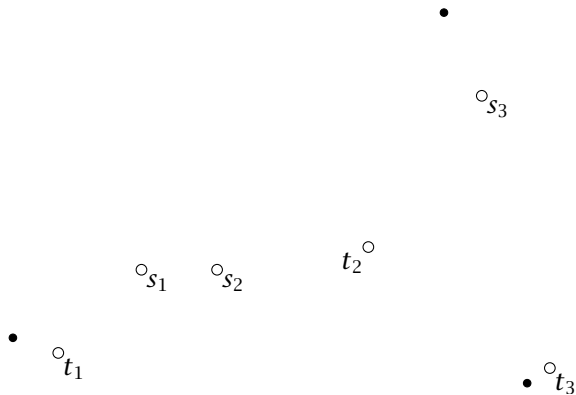
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- ▶ The final set  $F$  contains all edges  $\{v_0, v_i\}$ ,  $i = 1, \dots, k$ .
- ▶  $y_{\{v_0\}} > 0$  but  $|\delta(\{v_0\}) \cap F| = k$ .

### Algorithm 1 SecondTry

```
1:  $\gamma \leftarrow 0; F \leftarrow \emptyset; \ell \leftarrow 0$ 
2: while not all  $s_i-t_i$  pairs connected in  $F$  do
3:    $\ell \leftarrow \ell + 1$ 
4:   Let  $\mathfrak{C}$  be set of all connected components  $C$  of  $(V, F)$ 
      such that  $|C \cap \{s_i, t_i\}| = 1$  for some  $i$ .
5:   Increase  $\gamma_C$  for all  $C \in \mathfrak{C}$  uniformly until for some edge
       $e_\ell \in \delta(C')$ ,  $C' \in \mathfrak{C}$  s.t.  $\sum_{S: e_\ell \in \delta(S)} \gamma_S = c_{e_\ell}$ 
6:    $F \leftarrow F \cup \{e_\ell\}$ 
7:  $F' \leftarrow F$ 
8: for  $k \leftarrow \ell$  downto 1 do // reverse deletion
9:   if  $F' - e_k$  is feasible solution then
10:     remove  $e_k$  from  $F'$ 
11: return  $F'$ 
```

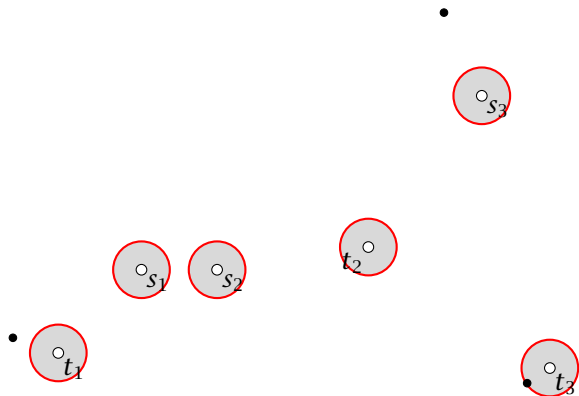
The reverse deletion step is not strictly necessary this way. It would also be sufficient to simply delete all unnecessary edges in any order.

# Example

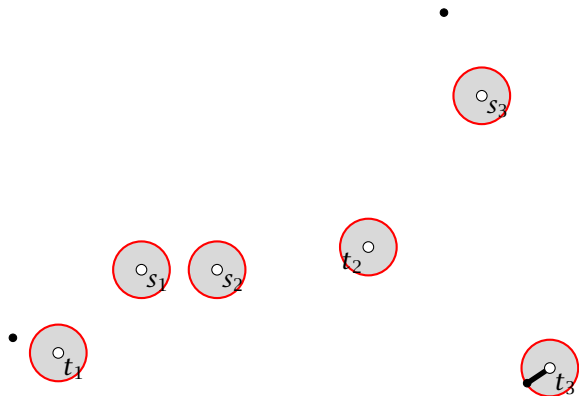




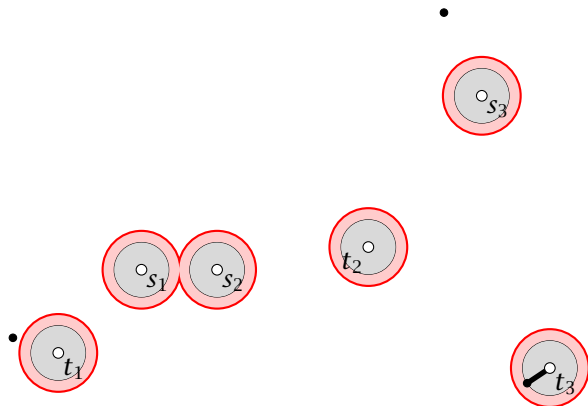
# Example



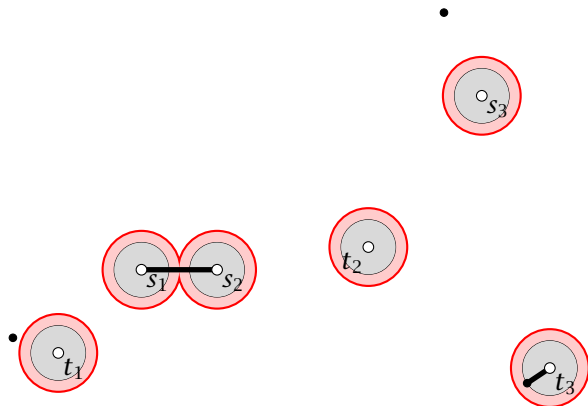
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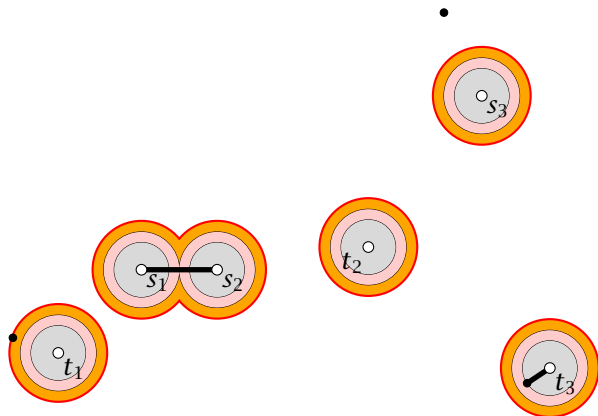
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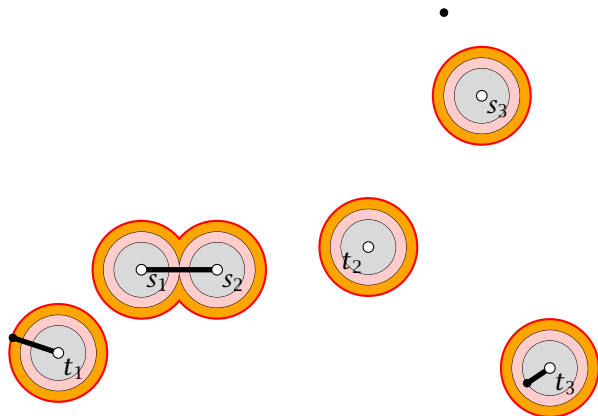
# Example



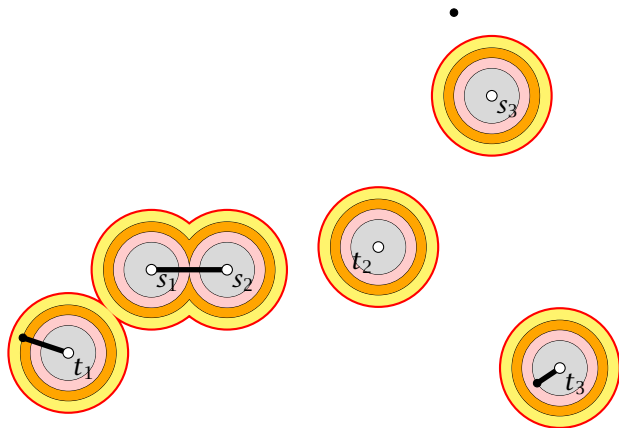
# Example



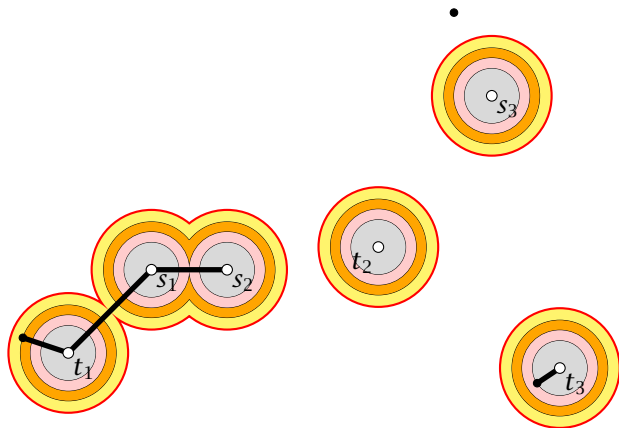
# Example



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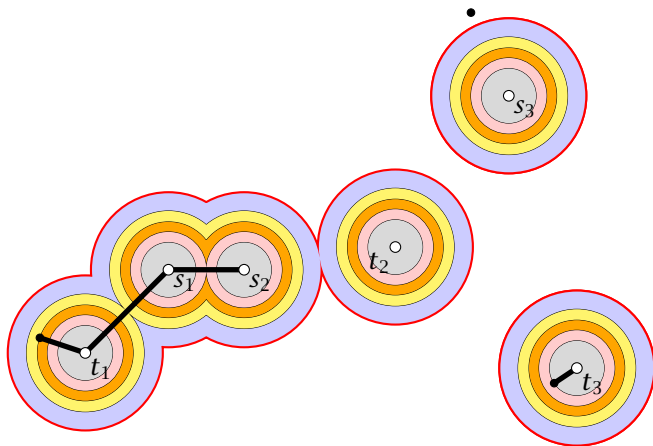


# Example

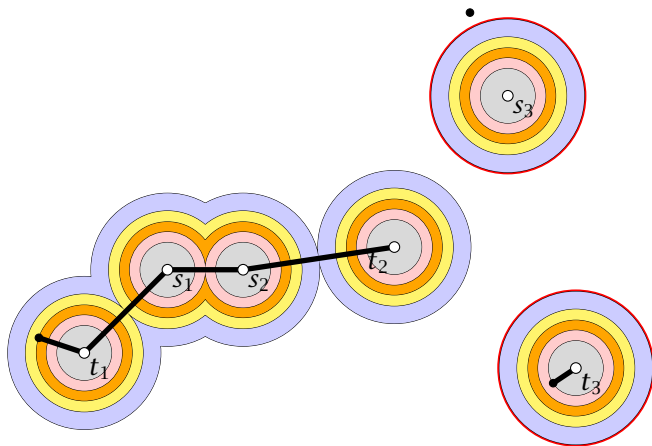




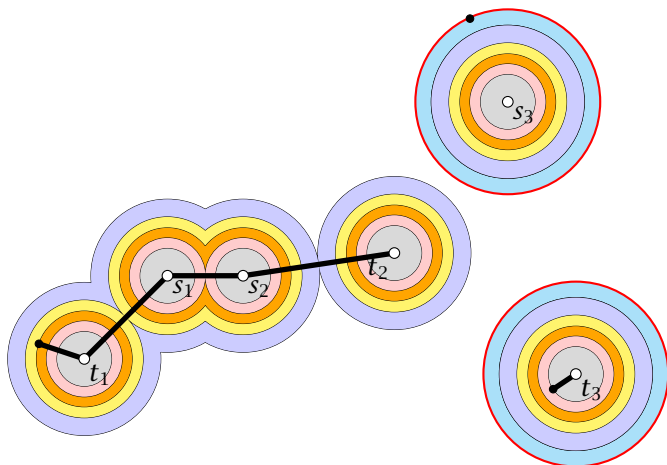
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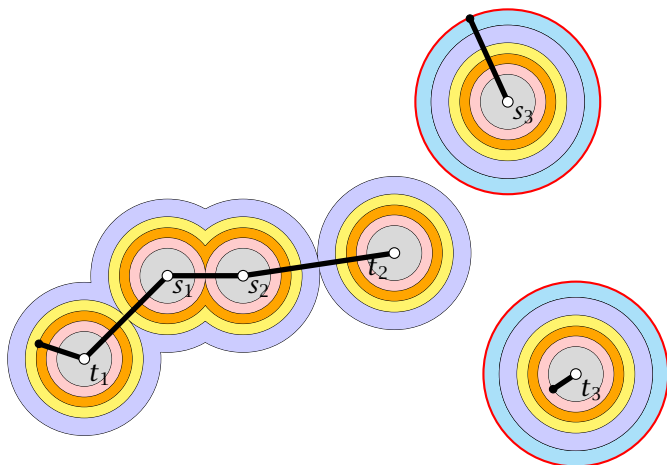
# Example



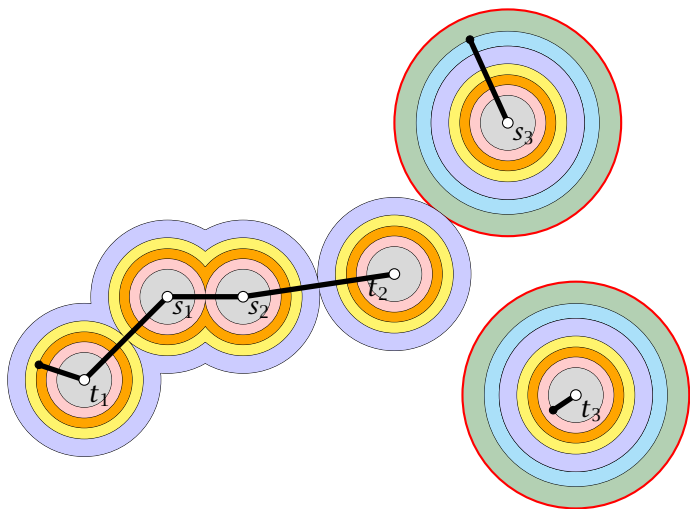
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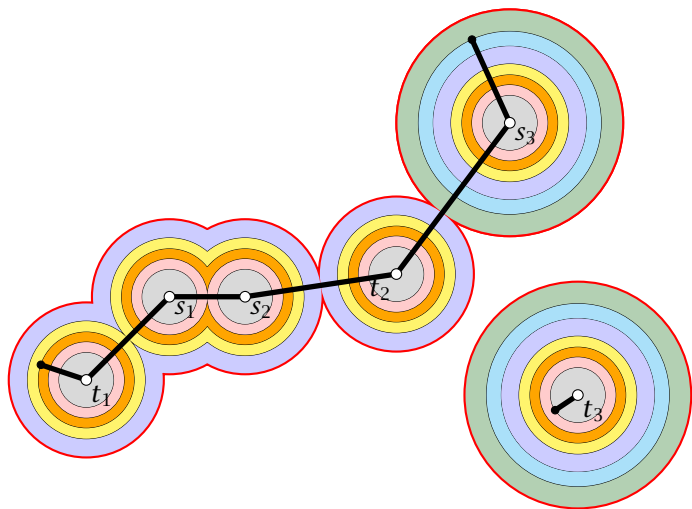
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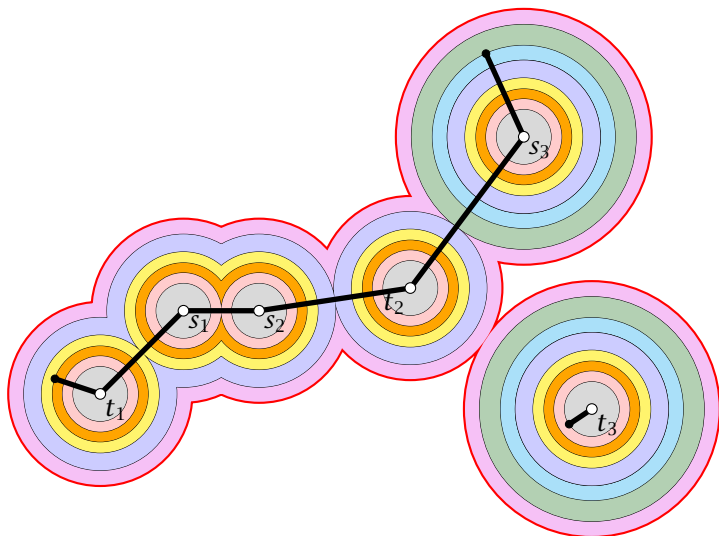
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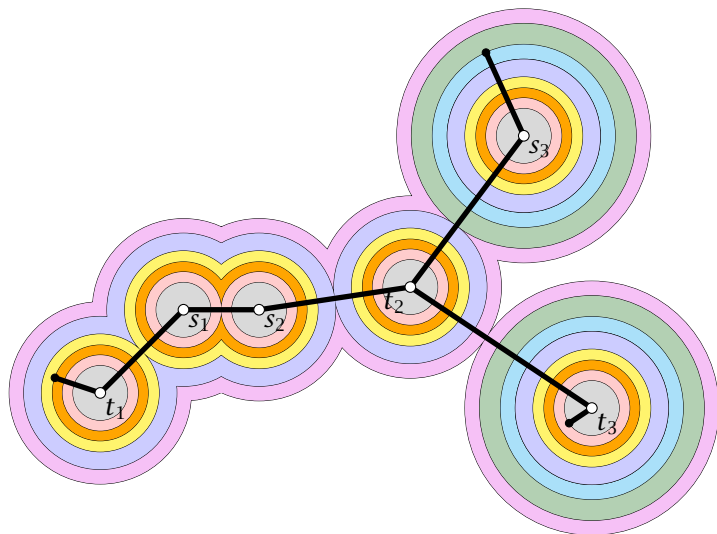
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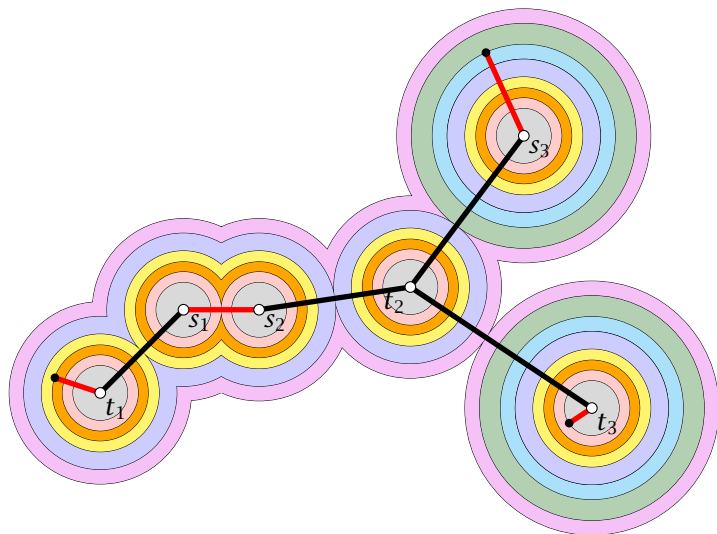


# Example





# Example



## Lemma 44

For any  $\mathcal{C}$  in any iteration of the algorithm

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

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

**Proof:** later...

$$\sum_{e \in F'} c_e = \sum_{e \in F'} \sum_{S: e \in \delta(S)} \gamma_S = \sum_S |F' \cap \delta(S)| \cdot \gamma_S.$$

We want to show that

$$\sum_S |F' \cap \delta(S)| \cdot \gamma_S \leq 2 \sum_S \gamma_S$$

At each iteration the increase of the left-hand side is

at most  $\gamma_S$  (because  $|F' \cap \delta(S)|$  increases by at most 1).

At the same time the increase of the right-hand side is  $2\gamma_S$ .

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

$$\sum_{e \in F'} c_e = \sum_{e \in F'} \sum_{S: e \in \delta(S)} \gamma_S = \sum_S |F' \cap \delta(S)| \cdot \gamma_S.$$

We want to show that

$$\sum_S |F' \cap \delta(S)| \cdot \gamma_S \leq 2 \sum_S \gamma_S$$

by induction over the increase of the left-hand side. In

the base case, the inequality holds since  $|F' \cap \delta(S)| \leq 2$ .

Assume that the inequality holds for all  $F'$  with  $|F'| \leq k$ .

Consider the increase of the right hand side to  $k+1$ .

By the previous lemma, the inequality holds after the addition if it holds in the beginning of the induction.

$$\sum_{e \in F'} c_e = \sum_{e \in F'} \sum_{S: e \in \delta(S)} \gamma_S = \sum_S |F' \cap \delta(S)| \cdot \gamma_S .$$

We want to show that

$$\sum_S |F' \cap \delta(S)| \cdot \gamma_S \leq 2 \sum_S \gamma_S$$

Let us consider the increase of the left-hand side if we

add an edge  $e$  to  $F'$ . The increase is  $\sum_{S: e \in \delta(S)} \gamma_S$ .

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Since by the previous lemma the inequality holds after the addition of  $e$ , it holds in the beginning of the algorithm.

$$\sum_{e \in F'} c_e = \sum_{e \in F'} \sum_{S: e \in \delta(S)} y_S = \sum_S |F' \cap \delta(S)| \cdot y_S .$$

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We want to show that

$$\sum_S |F' \cap \delta(S)| \cdot y_S \leq 2 \sum_S y_S$$

- ▶ In the  $i$ -th iteration the increase of the left-hand side is

$$\epsilon \sum_{C \in \mathcal{C}} |F' \cap \delta(C)|$$

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

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

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## Lemma 45

For any set of connected components  $\mathcal{C}$  in any iteration of the algorithm

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

Proof:

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### 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.

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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  $\mathbb{C}$  (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)
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  - ▶ But then it must be a red node.

# 18 Cuts & Metrics

## Shortest Path

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

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

The Dual:

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

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

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# 18 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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- ▶ We have  $d(u, v) = l_e$  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.

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Suppose that  $\ell_e$ -values are solution to Minimum Cut LP.

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- ▶ 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  $\ell_e$ .
- ▶ We have  $d(u, v) = \ell_e$  for every edge  $e = (u, v)$ , as otw. we could reduce  $\ell_e$  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?

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

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

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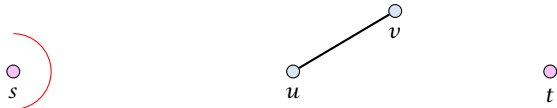
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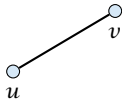
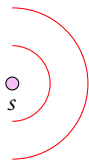
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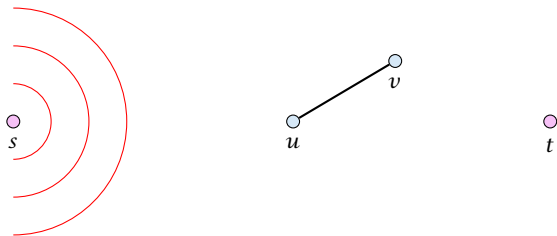
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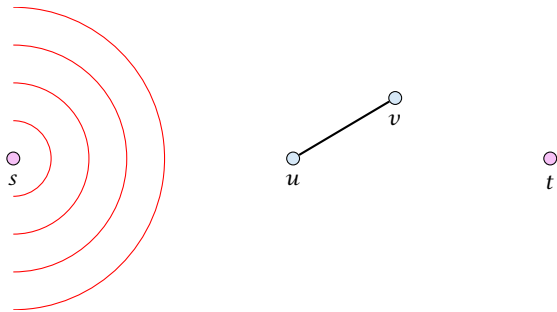
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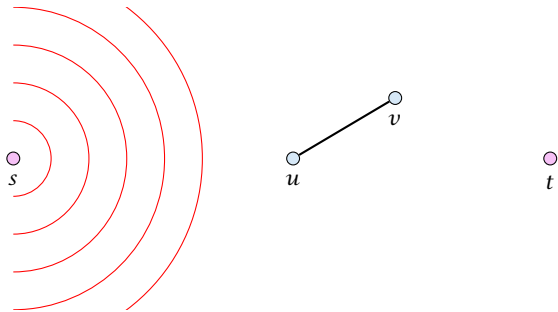
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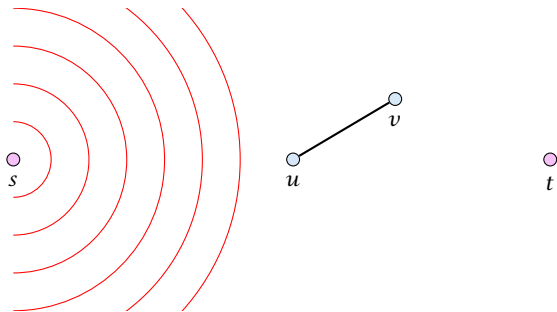


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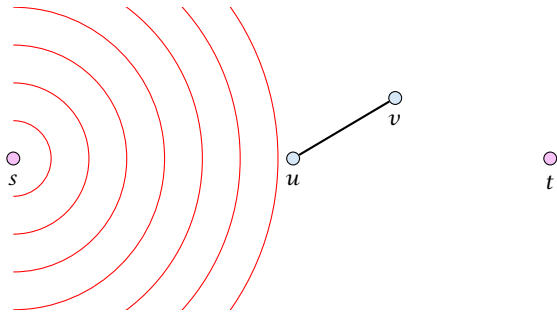




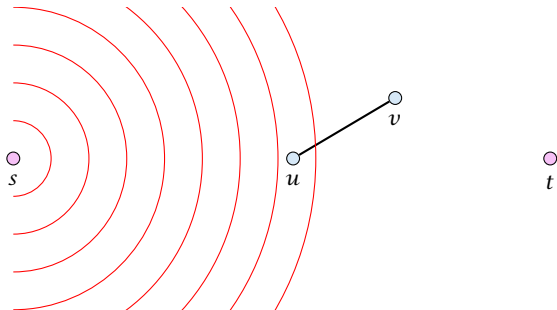
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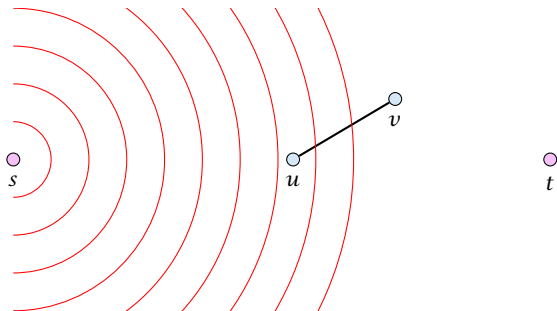
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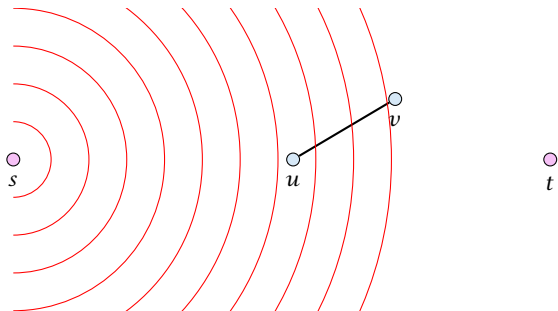
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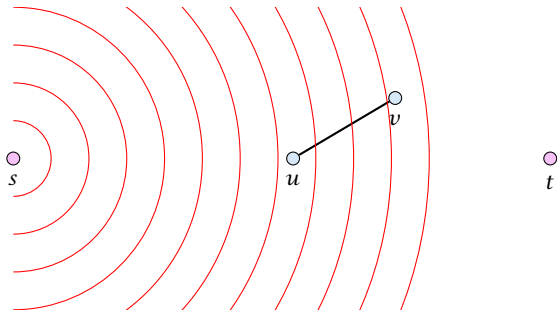
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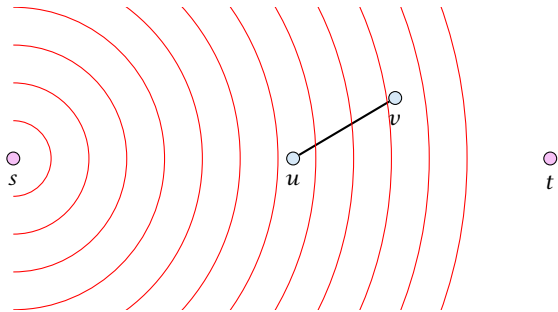
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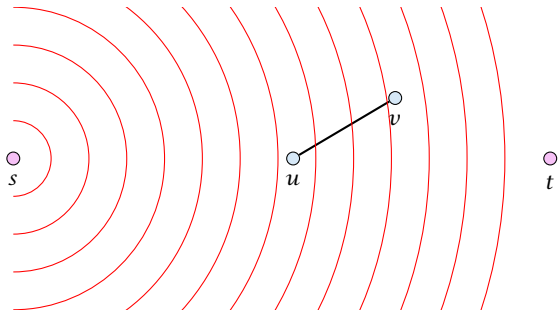
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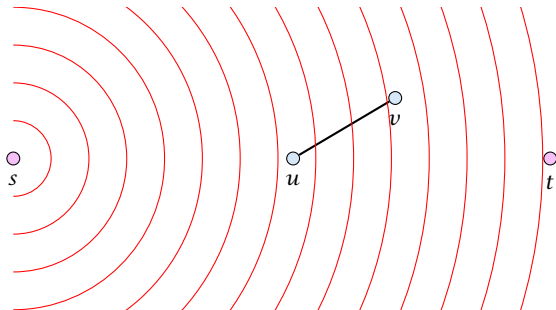


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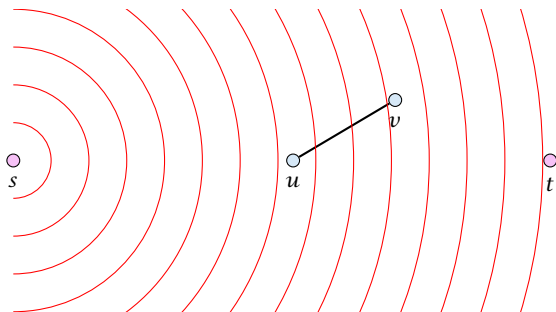




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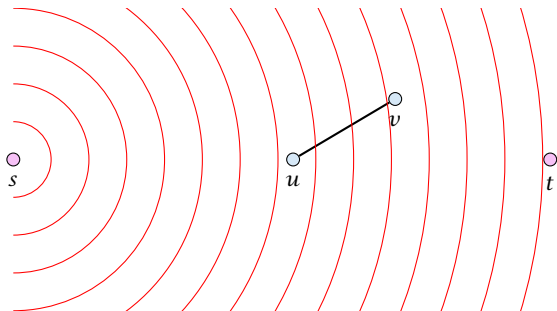
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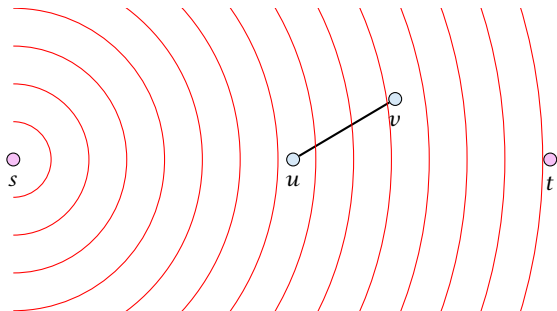
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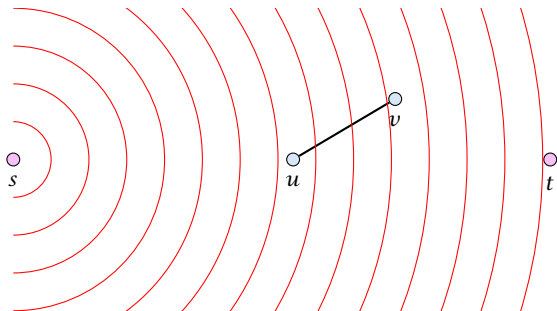
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On the other hand:

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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  $c : E \rightarrow \mathbb{R}^+$  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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$$E[\text{cutsize}] = \Pr[\text{success}] \cdot E[\text{cutsize} \mid \text{success}] \\ + \Pr[\text{no success}] \cdot E[\text{cutsize} \mid \text{no success}]$$

$$E[\text{cutsize} \mid \text{succ.}] = \frac{E[\text{cutsize}] - \Pr[\text{no succ.}] \cdot E[\text{cutsize} \mid \text{no succ.}]}{\Pr[\text{success}]} \\ \leq \frac{E[\text{cutsize}]}{\Pr[\text{success}]} \leq \frac{1}{1 - \frac{1}{k^2}} 6 \ln k \cdot \text{OPT} \leq 8 \ln k \cdot \text{OPT}$$

Note: success means all source-target pairs separated

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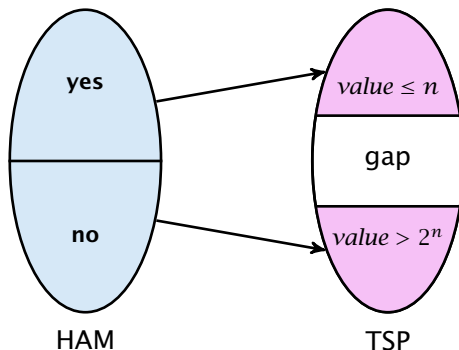
We assume  $k \geq 2$ .

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

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

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

## Gap Introducing Reduction



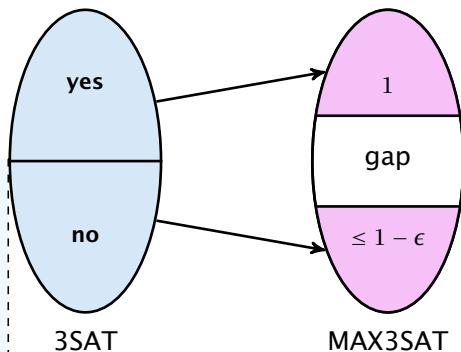
### Reduction from Hamiltonian cycle to TSP

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

# PCP theorem: Approximation View

## Theorem 46 (PCP Theorem A)

*There exists  $\epsilon > 0$  for which there is gap introducing reduction between 3SAT and MAX3SAT.*



The standard formulation of the PCP theorem looks very different but the above theorem is equivalent. Originally, the PCP theorem is a result about interactive proof systems and its importance to hardness of approximation is somewhat a side effect.

Here the goal of the MAX3SAT-problem is to maximize the **fraction** of satisfied clauses. The above theorem implies that we cannot approximate MAX3SAT with a ratio better than  $1 - \epsilon$ .



# PCP theorem: Proof System View

## Definition 47 (NP)

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

### $[x \in L]$ completeness

There exists a proof string  $y$ ,  $|y| = \text{poly}(|x|)$ , s.t.  $V(x, y) = \text{"accept"}$ .

### $[x \notin L]$ soundness

For any proof string  $y$ ,  $V(x, y) = \text{"reject"}$ .

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

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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  $\pi_{TSP}$  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  $y$ ,  $\pi_y$  is an oracle that upon given an index  $i$  returns the  $i$ -th character  $y_i$  of  $y$ .

# Probabilistic Checkable Proofs

**Non-adaptive** means that e.g. the second proof-bit read by the verifier may not depend on the value of the first bit.

## Definition 48 (PCP)

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

$[x \in L]$  There exists a proof string  $y$ , s.t.  $V^{\pi y}(x) = \text{“accept”}$  with probability  $\geq c(n)$ .

$[x \notin L]$  For any proof string  $y$ ,  $V^{\pi y}(x) = \text{“accept”}$  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.

Note that the proof itself does not count towards the input of the verifier. The verifier has to write the number of a bit-position it wants to read onto a special tape, and then the corresponding bit from the proof is returned to the verifier. The proof may only be exponentially long, as a polynomial time verifier cannot address longer proofs.

# Probabilistic Checkable Proofs

$c(n)$  is called the **completeness**. If not specified otw.  $c(n) = 1$ .  
Probability of accepting a correct proof.

$s(n) < c(n)$  is called the **soundness**. If not specified otw.  
 $s(n) = 1/2$ . Probability of accepting a wrong proof.

$r(n)$  is called the **randomness complexity**, i.e., how many  
random bits the (randomized) verifier uses.

$q(n)$  is the **query complexity** of the verifier.

# Probabilistic Checkable Proofs

RP = coRP = P is a commonly believed conjecture. RP stands for randomized polynomial time (with a non-zero probability of rejecting a YES-instance).

- ▶  $P = \text{PCP}(0, 0)$

verifier without randomness and proof access is deterministic algorithm

- ▶  $\text{PCP}(\log n, 0) \subseteq P$

we can simulate  $\log n$  random bits in deterministic polynomial time

- ▶  $\text{PCP}(0, \log n) \subseteq P$

we can simulate short proofs in polynomial time

- ▶  $\text{PCP}(\text{poly}(n), 0) = \text{coRP} \stackrel{?!}{=} P$

(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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- ▶  $\text{PCP}(\text{poly}(n), 0) = \text{coRP} \stackrel{?!}{=} P$

(The equality in the last statement is randomized polynomial time with a small but positive probability of accepting NO-instances.)

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- ▶  $PCP(0, \text{poly}(n)) = NP$   
by definition; NP-verifier does not use randomness and asks polynomially many queries
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NP-verifier can simulate  $\mathcal{O}(\log n)$  random bits
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- ▶  $NP \subseteq PCP(\log n, 1)$   
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# PCP theorem: Proof System View

## Theorem 49 (PCP Theorem B)

$$\text{NP} = \text{PCP}(\log n, 1)$$

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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

$$G_0 \equiv H \implies P[H] = 0$$

$$G_1 \equiv H \implies P[H] = 1$$

$$G_0, G_1 \not\equiv H \implies P[H] = \text{arbitrary}$$

# Probabilistic Proof for Graph NonIsomorphism

## Verifier:

- ▶ choose  $b \in \{0, 1\}$  at random
- ▶ take graph  $G_b$  and apply a random permutation to obtain a labeled graph  $H$
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If  $G_0 \not\cong G_1$  then by using the obvious proof the verifier will always accept.



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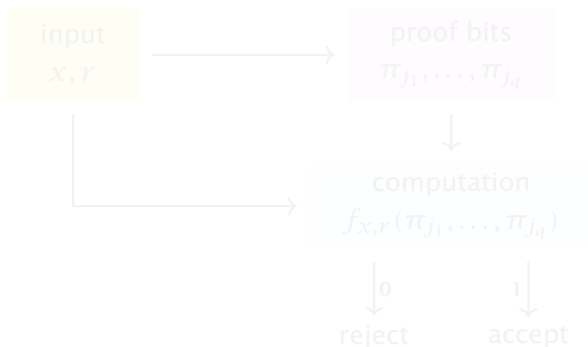
If  $G_0 \not\equiv G_1$  then by using the obvious proof the verifier will always accept.

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  $\pi_{\text{rand}}$  we reject for  $b = 0$  and permutation  $\pi_{\text{rand}} \circ \pi$

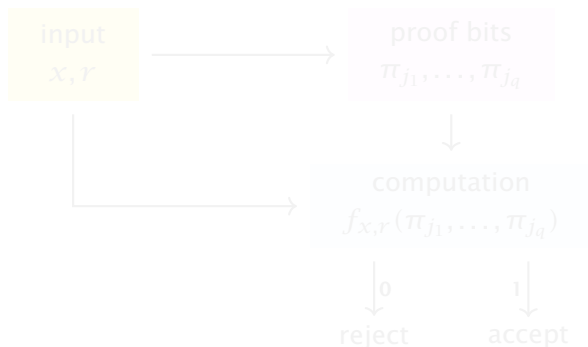
## Version B $\Rightarrow$ Version A

- ▶ 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  $r$ :



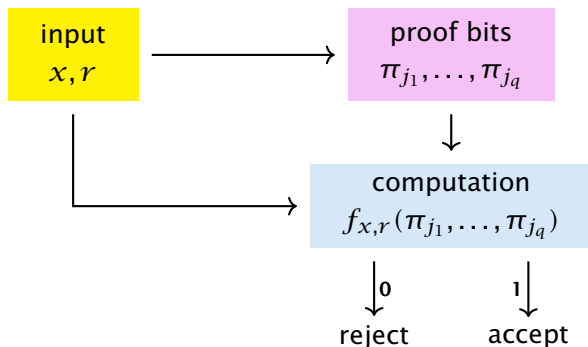
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## Version B $\Rightarrow$ Version A

- ▶ transform Boolean formula  $f_{x,r}$  into 3SAT formula  $C_{x,r}$  (constant size, variables are proof bits)
- ▶ consider 3SAT formula  $C_x = \bigwedge_r C_{x,r}$

$[x \in L]$  There exists proof string  $y$ , s.t. all formulas  $C_{x,r}$  evaluate to 1. Hence, all clauses in  $C_x$  satisfied.

$[x \notin L]$  For any proof string  $y$ , at most 50% of formulas  $C_{x,r}$  evaluate to 1. Since each contains only a constant number of clauses, a constant fraction of clauses in  $C_x$  are not satisfied.

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## Version A $\Rightarrow$ Version B

We show: **Version A**  $\Rightarrow$   $\text{NP} \subseteq \text{PCP}_{1,1-\epsilon}(\log n, 1)$ .

given  $L \in \text{NP}$  we build a PCP-verifier for  $L$

**Verifier:**

1. SAT is NP-complete; map instance  $\varphi$  for  $L$  into SAT

2.  $\varphi$  satisfiable  $\Leftrightarrow$  SAT satisfiable  $\text{iff}$

3.  $\varphi$  has a satisfying assignment  $\alpha$

4. interpret  $\alpha$  as assignment to variables in  $\Sigma$

5. choose random clause  $C \in \Sigma$

6. query variable assignment  $\alpha$  for  $C$

7. accept  $\text{iff } C$  is satisfied

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Verifier:

1. On input  $x$ , compute map instance  $(\{u_i, v_i\}_{i=1}^n)$ .

2. Choose  $i, j$  uniformly at random.

3. Accept iff  $u_i$  and  $v_j$  agree.

4. Repeat for  $\frac{1}{\epsilon}$  trials and accept iff all trials accept.

5. If all trials accept, then  $x \in L$ .

6. If any trial rejects, then  $x \notin L$ .

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### Verifier:

- ▶ 3SAT is NP-complete; map instance  $x$  for  $L$  into 3SAT instance  $I_x$ , s.t.  $I_x$  satisfiable iff  $x \in L$
- ▶ map  $I_x$  to MAX3SAT instance  $C_x$  (PCP Thm. Version A)
- ▶ interpret proof as assignment to variables in  $C_x$
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- ▶ query variable assignment  $\sigma$  for  $X$ ;
- ▶ accept if  $X(\sigma) = \text{true}$  otw. reject

## Version A $\Rightarrow$ Version B

We show: **Version A**  $\Rightarrow$   $\text{NP} \subseteq \text{PCP}_{1,1-\epsilon}(\log n, 1)$ .

given  $L \in \text{NP}$  we build a PCP-verifier for  $L$

### Verifier:

- ▶ 3SAT is NP-complete; map instance  $x$  for  $L$  into 3SAT instance  $I_x$ , s.t.  $I_x$  satisfiable iff  $x \in L$
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## Version A $\Rightarrow$ Version B

- $[x \in L]$  There exists proof string  $y$ , s.t. all clauses in  $C_x$  evaluate to 1. In this case the verifier returns 1.
- $[x \notin L]$  For any proof string  $y$ , at most a  $(1 - \epsilon)$ -fraction of clauses in  $C_x$  evaluate to 1. The verifier will reject with probability at least  $\epsilon$ .

To show Theorem B we only need to run this verifier a constant number of times to push rejection probability above  $1/2$ .

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

Note that this approach has strong connections to error correction codes.

$\text{PCP}(\text{poly}(n), 1)$  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

- ▶ a code-word whose pre-image does not correspond to a satisfying assignment
- ▶ or, a sequence of bits that does not correspond to a code-word

We can detect both cases by querying a few positions.

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# The Code

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

**Walsh-Hadamard Code:**

$\text{WH}_u : \{0, 1\}^n \rightarrow \{0, 1\}, x \mapsto x^T u$  (over  $\text{GF}(2)$ )

The code-word for  $u$  is  $\text{WH}_u$ . We identify this function by a bit-vector of length  $2^n$ .

# The Code

## Lemma 50

If  $u \neq u'$  then  $WH_u$  and  $WH_{u'}$  differ in at least  $2^{n-1}$  bits.

Proof:

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

$$WH_u(x) \neq WH_{u'}(x) \iff (u - u')^T x \neq 0$$

This holds for  $2^{n-1}$  different vectors  $x$ .

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Suppose we are given access to a function  $f : \{0, 1\}^n \rightarrow \{0, 1\}$  and want to check whether it is a codeword.

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

Can we just check a constant number of positions?

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

Observe that for two codewords  
 $\Pr_{x \in \{0,1\}^n} [f(x) = g(x)] = 1/2.$

## Definition 51

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

$$\Pr_{x \in \{0,1\}^n} [f(x) = g(x)] \geq \rho .$$

## Theorem 52 (proof deferred)

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

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

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

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

We need  $\mathcal{O}(1/\delta)$  trials to be sure that  $f$  is  $(1 - \delta)$ -close to a linear function with (arbitrary) constant probability.

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

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

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?

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

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

## QUADEQ

Given a system of quadratic equations over  $GF(2)$ . Is there a solution?

# QUADEQ is NP-complete

- ▶ given 3SAT instance  $C$  represent it as Boolean circuit  
e.g.  $C = (x_1 \vee x_2 \vee x_3) \wedge (x_3 \vee x_4 \vee \bar{x}_5) \wedge (x_6 \vee x_7 \vee x_8)$

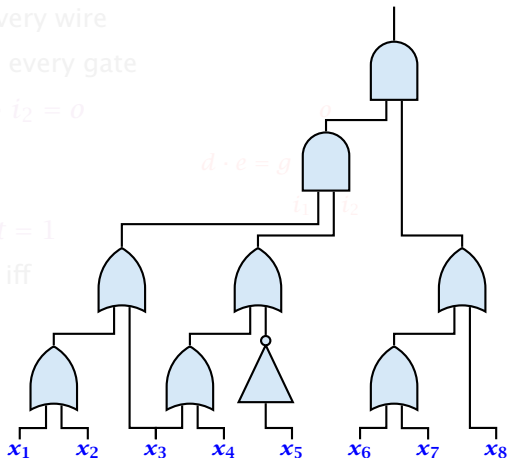
- ▶ add variable for every wire
- ▶ add constraint for every gate

OR:  $i_1 + i_2 + i_1 \cdot i_2 = 0$

AND:  $i_1 \cdot i_2 = 0$

NEG:  $i = 1 - o$

- ▶ add constraint  $out = 1$
- ▶ system is feasible iff  $C$  is satisfiable



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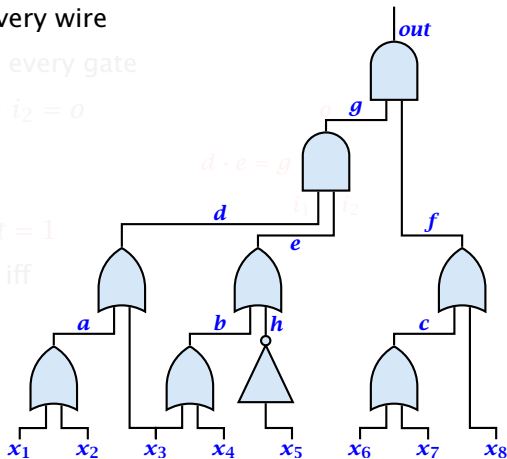
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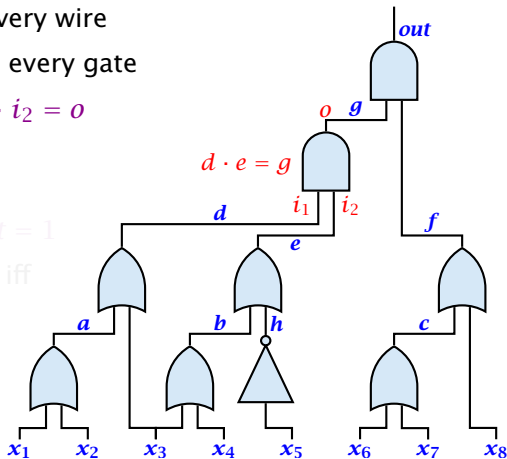
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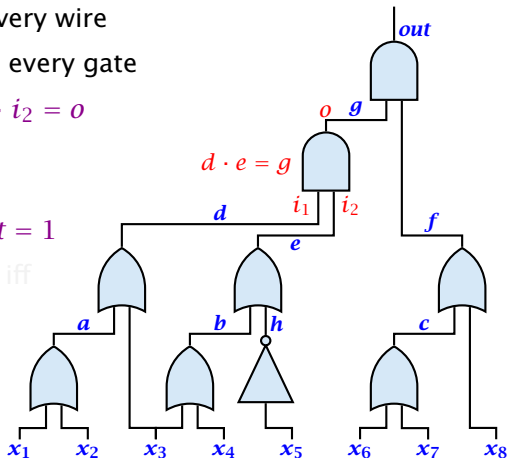
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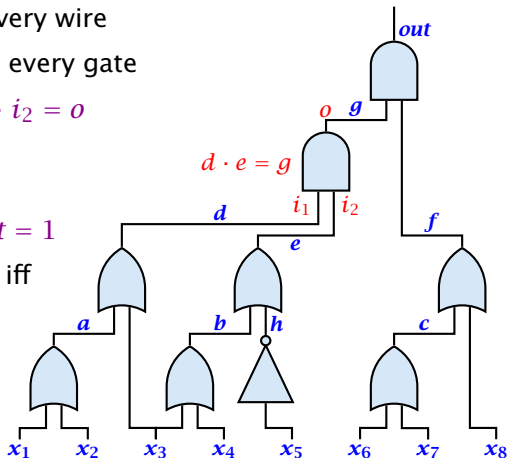
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## $\text{NP} \subseteq \text{PCP}(\text{poly}(n), 1)$

Note that over  $\text{GF}(2)$   $x = x^2$ . Therefore, we can assume that there are no terms of degree 1.

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

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

has a solution.

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

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  $u \otimes u$ .

We also have to reject proofs that correspond to codewords for vectors of the form  $z$ , and  $z \otimes z$ , where  $z$  is not a satisfying assignment.

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

Recall that for a correct proof there is no difference between  $f$  and  $\tilde{f}$ .

## Step 1. Linearity Test.

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

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

We need to show that the probability of accepting a wrong proof is small.

This first step means that in order to fool us with reasonable probability a wrong proof needs to be very close to a linear function. The probability that we accept a proof when the functions are not close to linear is just a small constant.

Similarly, if the functions are close to linear then the probability that the Walsh Hadamard decoding fails (for *any* of the remaining accesses) is just a small constant. If we ignore this small constant error then a malicious prover could also provide a linear function (as a near linear function  $f$  is “rounded” by us to the corresponding linear function  $\tilde{f}$ ). If this rounding is successful it doesn’t make sense for the prover to provide a function that is not linear.

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

**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

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

A correct proof survives the test

$$f(r) \cdot f(r')$$

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

A correct proof survives the test

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



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

Suppose that the proof is not correct and  $w \neq u \otimes u$ .

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$$f(r) f(r')$$

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$$f(r)f(r') = u^T r \cdot u^T r' = r^T U r'$$

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

For a non-zero vector  $x$  and a random vector  $r$  (both with elements from GF(2)), we have  $\Pr[x^T r \neq 0] = \frac{1}{2}$ . This holds because the product is zero iff the number of ones in  $r$  that “hit” ones in  $x$  in the product is even.

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

**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.

In this case  $r^T A(u \otimes u) \neq r^T b_k$ . The left hand side is equal to  $g(A^T r)$ .

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

We used the following theorem for the linearity test:

## Theorem 52

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

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

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

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

## Fourier Transform over 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  $f : \{-1, 1\}^n \rightarrow \mathbb{R}$  form a  $2^n$ -dimensional **Hilbert space**.



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

## 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

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

for some vector  $L$ .

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

## 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.

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

## fourier basis

For  $\alpha \subseteq [n]$  define

$$\chi_\alpha(x) = \prod_{i \in \alpha} x_i$$

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

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Note that

$$\langle \chi_\alpha, \chi_\beta \rangle$$

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## fourier basis

For  $\alpha \subseteq [n]$  define

$$\chi_\alpha(x) = \prod_{i \in \alpha} x_i$$

Note that

$$\langle \chi_\alpha, \chi_\beta \rangle = E_x [\chi_\alpha(x) \chi_\beta(x)]$$

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

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For  $\alpha \subseteq [n]$  define

$$\chi_\alpha(x) = \prod_{i \in \alpha} x_i$$

Note that

$$\langle \chi_\alpha, \chi_\beta \rangle = E_x[\chi_\alpha(x)\chi_\beta(x)] = E_x[\chi_{\alpha \Delta \beta}(x)]$$

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This means the  $\chi_\alpha$ 's also define an orthonormal basis. (since we have  $2^n$  orthonormal vectors...)



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

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

This means the function  $\chi_\alpha$  correspond to linear functions in the GF(2) world.

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

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

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

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

## Lemma 53

1.  $\langle f, g \rangle = \sum_{\alpha} \hat{f}_{\alpha} \hat{g}_{\alpha}$
2.  $\langle f, f \rangle = \sum_{\alpha} \hat{f}_{\alpha}^2$

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

$$\langle f, f \rangle = E_{\mathbf{x}}[f(\mathbf{x})^2] = 1$$

# 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.

# 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  $f : \{\pm 1\}^n \rightarrow \{-1, 1\}$  fulfills

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

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

Here  $x \circ y$  denotes the  $n$ -dimensional vector with entry  $x_i y_i$  in position  $i$  (**Hadamard product**).  
Observe that we have  $\chi_\alpha(x \circ y) = \chi_\alpha(x)\chi_\alpha(y)$ .

# Linearity Test

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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$$2\epsilon \leq \hat{f}_\alpha = \langle f, \chi_\alpha \rangle$$

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

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

# 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

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

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

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

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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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&= 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] \\
&= \sum_{\alpha,\beta,\gamma} \hat{f}_{\alpha} \hat{f}_{\beta} \hat{f}_{\gamma} \cdot E_x \left[ \chi_{\alpha}(x) \chi_{\beta}(x) \right] E_y \left[ \chi_{\alpha}(y) \chi_{\gamma}(y) \right]
\end{aligned}$$

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



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

# Approximation Preserving Reductions

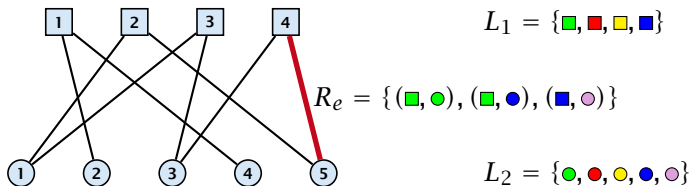
## AP-reduction

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

# 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



The label cover problem also has its origin in proof systems. It encodes a 2PR1 (2 prover 1 round system). Each side of the graph corresponds to a prover. An edge is a query consisting of a question for prover 1 and prover 2. If the answers are consistent the verifier accepts otherwise it rejects.

# 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)

# 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:



The verifier accepts if the labelling (assignment to variables in clauses at the top + assignment to variables at the bottom) causes the clause to evaluate to true and is consistent, i.e., the assignment of e.g.  $x_4$  at the bottom is the same as the assignment given to  $x_4$  in the labelling of the clause.

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  $C$

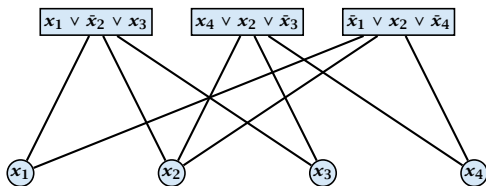
$$R = \{((F, F, F), F), ((F, T, F), F), ((F, F, T), T), ((F, T, T), T), ((T, T, T), T), ((T, T, F), F), ((T, F, F), F)\}$$

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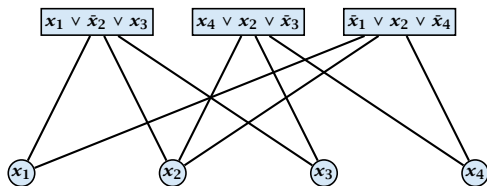
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# MAX E3SAT via Label Cover

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:



The verifier accepts if the labelling (assignment to variables in clauses at the top + assignment to variables at the bottom) causes the clause to evaluate to true and is consistent, i.e., the assignment of e.g.  $x_4$  at the bottom is the same as the assignment given to  $x_4$  in the labelling of the clause.

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

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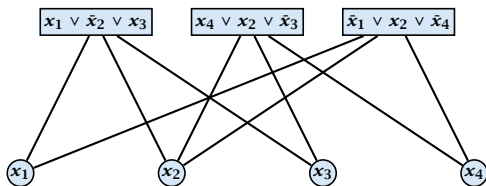
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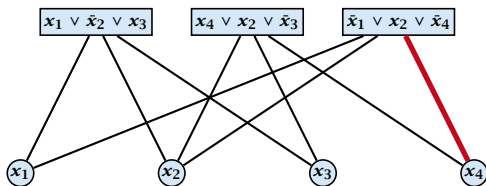


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# MAX E3SAT via Label Cover

## Lemma 54

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

Proof:

# MAX E3SAT via Label Cover

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### 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)
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# MAX E3SAT via Label Cover

## Lemma 55

*If we can satisfy at most  $k$  clauses in  $\Phi$  we can make at most  $3k + 2(m - k) = 2m + k$  edges happy.*

Proof:

# MAX E3SAT via Label Cover

## Lemma 55

*If we can satisfy at most  $k$  clauses in  $\Phi$  we can make at most  $3k + 2(m - k) = 2m + k$  edges happy.*

### Proof:

- ▶ the labeling of nodes in  $V_2$  gives an assignment
- ▶ every unsatisfied clause in this assignment cannot be assigned a label that satisfies all 3 incident edges
- ▶ hence at most  $3m - (m - k) = 2m + k$  edges are happy

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# Hardness for Label Cover

Here  $\epsilon > 0$  is the constant from PCP Theorem A.

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 56

*There is a constant  $\rho$  s.t. MAXE3SAT is hard to approximate with a factor of  $\rho$  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
- ▶ it is hard to approximate for a constant  $\alpha < 1$
- ▶ given a label  $\ell_1$  for  $x$  there is at most one label  $\ell_2$  for  $y$  that makes edge  $(x, y)$  happy (uniqueness property)

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## (3, 5)-regular instances

The previous theorem can be obtained with a series of **gap-preserving reductions**:

- ▶  $\text{MAX3SAT} \leq \text{MAX3SAT}(\leq 29)$
- ▶  $\text{MAX3SAT}(\leq 29) \leq \text{MAX3SAT}(\leq 5)$
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- ▶  $\text{MAX3SAT}(= 5) \leq \text{MAXE3SAT}(= 5)$

Here  $\text{MAX3SAT}(\leq 29)$  is the variant of  $\text{MAX3SAT}$  in which a variable appears in at most 29 clauses. Similar for the other problems.

# Regular instances

We take the  $(3, 5)$ -regular instance. We make 3 copies of every clause vertex and 5 copies of every variable vertex. Then we add edges between clause vertex and variable vertex iff the clause contains the variable. This increases the size by a constant factor. The gap instance can still either only satisfy a constant fraction of the edges or all edges. The uniqueness property still holds for the new instance.

## Theorem 57

*There is a constant  $\alpha < 1$  such if there is an  $\alpha$ -approximation algorithm for Label Cover on  $15$ -regular instances then  $P=NP$ .*

Given a label  $\ell_1$  for  $x \in V_1$  there is at most one label  $\ell_2$  for  $y$  that makes  $(x, y)$  happy. (**uniqueness property**)

# Parallel Repetition

We would like to increase the inapproximability for Label Cover.

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.

Unfortunately, we have a 2P1R-system, i.e., we are stuck with a single round and cannot simply repeat.

The idea is to use **parallel repetition**, i.e., we simply play several rounds in parallel and hope that the acceptance probability of wrong proofs goes down.



# Parallel Repetition

Given Label Cover instance  $I$  with  $G = (V_1, V_2, E)$ , label sets  $L_1$  and  $L_2$  we construct a new instance  $I'$ :

- ▶  $V'_1 = V_1^k = V_1 \times \dots \times V_1$
- ▶  $V'_2 = V_2^k = V_2 \times \dots \times V_2$
- ▶  $L'_1 = L_1^k = L_1 \times \dots \times L_1$
- ▶  $L'_2 = L_2^k = L_2 \times \dots \times L_2$
- ▶  $E' = E^k = E \times \dots \times E$

An edge  $((x_1, \dots, x_k), (y_1, \dots, y_k))$  whose end-points are labelled by  $(\ell_1^x, \dots, \ell_k^x)$  and  $(\ell_1^y, \dots, \ell_k^y)$  is happy if  $(\ell_i^x, \ell_i^y) \in R_{x_i, y_i}$  for all  $i$ .

# 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  $\sigma$  that satisfies just an  $\epsilon$ -fraction of edges in  $I$ .

We transfer this labelling to instance  $I'$ .

Each edge in  $I'$  gets label  $\sigma$ .

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What fraction of edges is satisfied?

How does this fraction compare to  $\epsilon$ ?

# 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  $\alpha$ -fraction of edges in  $I$ .
- ▶ We transfer this labelling to instance  $I'$ :  
vertex  $(x_1, \dots, x_k)$  gets label  $(l_1(x_1), \dots, l_1(x_k))$ ,  
vertex  $(y_1, \dots, y_k)$  gets label  $(l_2(y_1), \dots, l_2(y_k))$ .
- ▶ How many edges are happy?  
only  $\alpha$  fraction of edges are happy (just  $\alpha$  fraction)

Does this always work?

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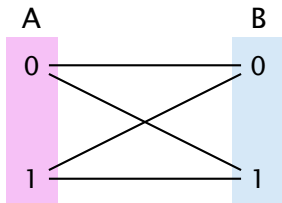
# Counter Example

## 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.
- ▶ The provers win if they give **the same answer** and if the **answer is correct**.

# Counter Example

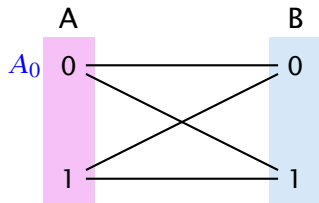
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Regardless what we do 50% of edges are unhappy!

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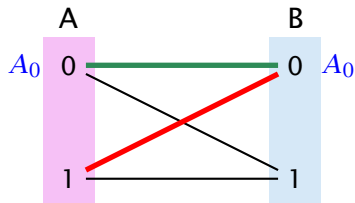
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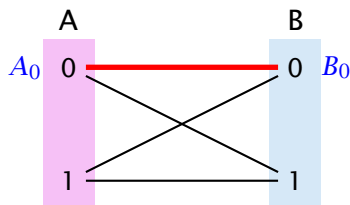
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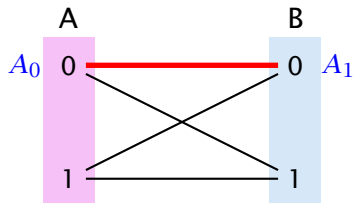
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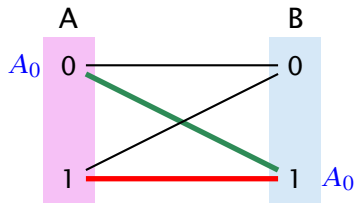
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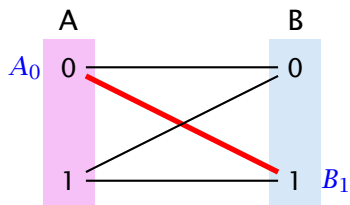
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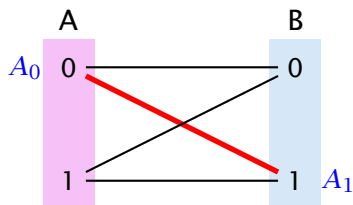


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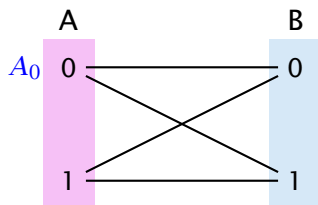
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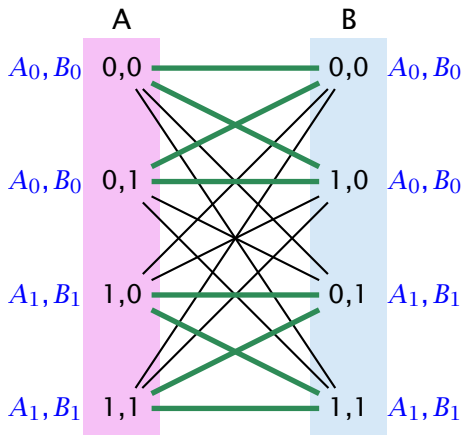
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Regardless what we do 50% of edges are unhappy!

## Counter Example

In the repeated game the provers can also win with probability  $1/2$ :



For the first game/coordinate the provers give an answer of the form "A has received..." ( $A_0$  or  $A_1$ ) and for the second an answer of the form "B has received..." ( $B_0$  or  $B_1$ ).

If the answer a prover has to give is about himself a prover can answer correctly. If the answer to be given is about the other prover the same bit is returned. This means e.g. Prover B answers  $A_1$  for the first game iff in the second game he receives a 1-bit.

By this method the provers always win if Prover A gets the same bit in the first game as Prover B in the second game. This happens with probability  $1/2$ .

This strategy is not possible for the provers if the game is repeated sequentially. How should prover B know (for her answer in the first game) which bit she is going to receive in the second game?

## Theorem 58

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

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# Hardness of Label Cover

## Theorem 59

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

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

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

## Corollary 60

There is no  $\alpha$ -approximation for Label Cover for *any* constant  $\alpha$ .

# Hardness of Set Cover

## Theorem 61

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

- ▶ *all edges are satisfiable, or*
- ▶ *at most a  $1/\log^2(|L_1||E|)$ -fraction is satisfiable*

*unless NP-problems have algorithms with running time  $\mathcal{O}(n^{\mathcal{O}(\log \log n)})$ .*

choose  $k \geq \frac{2}{c} \log_{1/(1-\delta)}(\log(|L_1||E|)) = \mathcal{O}(\log \log n)$ .

# Hardness of Set Cover

## Partition System $(s, t, h)$

- ▶ universe  $U$  of size  $s$
- ▶  $t$  pairs of sets  $(A_1, \bar{A}_1), \dots, (A_t, \bar{A}_t)$ ;  
 $A_i \subseteq U, \bar{A}_i = U \setminus A_i$
- ▶ choosing from any  $h$  pairs only one of  $A_i, \bar{A}_i$  we do not cover the whole set  $U$

**we will show later:**

for any  $h, t$  with  $h \leq t$  there exist systems with  $s = |U| \leq 4t^2 2^h$



# Hardness of Set Cover

Given a Label Cover instance we construct a Set Cover instance;

The universe is  $E \times U$ , where  $U$  is the universe of some partition system; ( $t = |L_1|$ ,  $h = \log(|E||L_1|)$ )

for all  $u \in V_1, \ell_1 \in L_1$

$$S_{u, \ell_1} = \{(u, v), a \mid (u, v) \in E, a \in A_{\ell_1}\}$$

for all  $v \in V_2, \ell_2 \in L_2$

$$S_{v, \ell_2} = \{(u, v), a \mid (u, v) \in E, a \in \bar{A}_{\ell_1}, \text{ where } (\ell_1, \ell_2) \in R_{(u, v)}\}$$

note that  $S_{v, \ell_2}$  is well defined because of uniqueness property

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Given a Label Cover instance we construct a Set Cover instance;

The universe is  $E \times U$ , where  $U$  is the universe of some partition system; ( $t = |L_1|$ ,  $h = \log(|E||L_1|)$ )

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Suppose that we can make all edges happy.

Choose sets  $S_{u,\ell_1}$ 's and  $S_{v,\ell_2}$ 's, where  $\ell_1$  is the label we assigned to  $u$ , and  $\ell_2$  the label for  $v$ . ( $|V_1|+|V_2|$  sets)

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# Hardness of Set Cover

## Lemma 62

*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.*

If the Label Cover instance cannot satisfy a  $2/h^2$ -fraction we cannot cover with  $\frac{h}{8}(|V_1| + |V_2|)$  sets.

Since differentiating between both cases for the Label Cover instance is hard, we have an  $\mathcal{O}(h)$ -hardness for Set Cover.

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- ▶  $n_u$ : number of  $S_{u,i}$ 's in cover
- ▶  $n_v$ : number of  $S_{v,j}$ 's in cover
- ▶ at most  $1/4$  of the vertices can have  $n_u, n_v \geq h/2$ ; mark these vertices
- ▶ at least half of the edges have both end-points unmarked, as the graph is regular
- ▶ for such an edge  $(u, v)$  we must have chosen  $S_{u,i}$  and a corresponding  $S_{v,j}$ , s.t.  $(i, j) \in R_{u,v}$  (making  $(u, v)$  happy)
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## Theorem 63

*There is no  $\frac{1}{32} \log n$ -approximation for the unweighted Set Cover problem unless problems in NP can be solved in time  $\mathcal{O}(n^{\mathcal{O}(\log \log n)})$ .*



Given label cover instance  $(V_1, V_2, E)$ , label sets  $L_1$  and  $L_2$ ;

Set  $h = \log(|E||L_1|)$  and  $t = |L_1|$ ; Size of partition system is

$$s = |U| = 4t^2 2^h = 4|L_1|^2 (|E||L_1|)^2 = 4|E|^2 |L_1|^4$$

The size of the ground set is then

$$n = |E||U| = 4|E|^3 |L_1|^4 \leq (|E||L_2|)^4$$

for sufficiently large  $|E|$ . Then  $h \geq \frac{1}{4} \log n$ .

If we get an instance where all edges are satisfiable there **exists** a cover of size only  $|V_1| + |V_2|$ .

If we find a cover of size at most  $\frac{h}{8} (|V_1| + |V_2|)$  we can use this to satisfy at least a fraction of  $2/h^2 \geq 1/\log^2(|E||L_1|)$  of the edges. **this is not possible...**

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# Partition Systems

## Lemma 64

Given  $h$  and  $t$  with  $h \leq t$ , there is a partition system of size  $s = \ln(4t)h2^h \leq 4t2^h$ .

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.

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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  $1 - \frac{1}{2^h}$ .

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

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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!

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

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

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

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

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## Theorem 65

For any positive constant  $\epsilon > 0$ , it is the case that  $\text{NP} \subseteq \text{PCP}_{1-\epsilon, 1/2+\epsilon}(\log n, 3)$ . 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  $\delta$ .

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