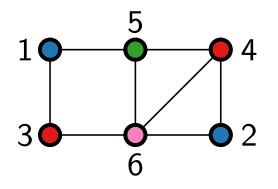


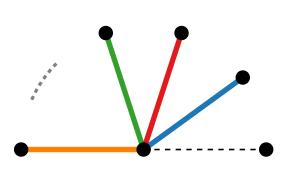
Advanced Algorithms

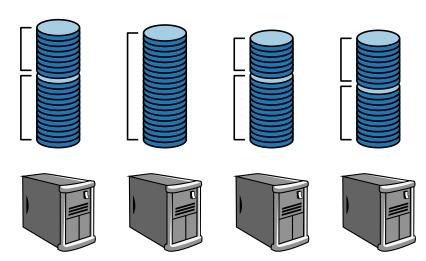
Approximation Algorithms

Coloring and Scheduling Problems

Alexander Wolff · WS22



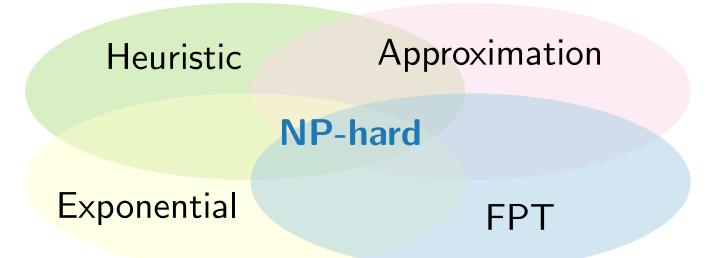




Dealing with NP-Hard Optimization Problems

What should we do?

- Sacrifice optimality for speed
 - Heuristics
 - Approximation algorithms
- Optimal solutions
 - Exact exponential-time algorithms
 - Fine-grained analysis parameterized algorithms



this lecture

Approximation Algorithms

Problem.

- For NP-hard optimization problems, we cannot compute the optimal solution of every instance efficiently (unless P = NP).
- Heuristics offer no guarantee on the quality of their solutions.

Goal.

- Design approximation algorithms:
 - run in polynomial time and
 - compute solutions of guaranteed quality.
- Study techniques for the design and analysis of approximation algorithms.

Overview.

- Approximation algorithms that compute solutions with/that are
 - additive guarantee, relative guarantee, "arbitrarily good".

PTAS (polynomial-time approximation

scheme)

Approximation with Additive Guarantee

Definition.

Let Π be an optimization problem, let \mathcal{A} be a polynomial-time algorithm for Π , let I be an instance of Π , and let $\mathsf{ALG}(I)$ be the value of the objective function of the solution that \mathcal{A} computes given I.

Then \mathcal{A} is called an approximation algorithm with additive guarantee δ (which can depend on I) if

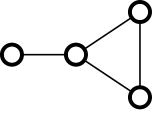
$$|\mathsf{OPT}(I) - \mathsf{ALG}(I)| \le \delta$$

for every instance I of Π .

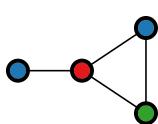
Most problems that we know do not admit an approximation algorithm with additive guarantee.

Minimum Vertex Coloring

Input. A graph G = (V, E). Let Δ be the maximum degree of G.



Output. A minimum vertex coloring, that is, an assignment of the vertices of G to colors such that no two adjacent vertices get the same color and the number of colors is minimum.



- Minimum Vertex Coloring is NP-hard.
- Even Vertex 3-Coloring is NP-complete.

GreedyVertexColoring(connected graph G)
Color vertices in some order with the lowest feasible color.

5 1 3 4 2

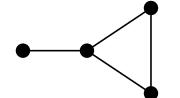
Theorem 1.

The algorithm GreedyVertexColoring computes a vertex coloring with at most $\Delta+1$ colors in $\mathcal{O}(V+E)$ time. Hence, it has an additive approximation gurantee of $\Delta-1$.

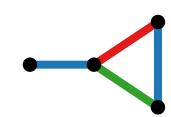
We can get $\Delta - 2$ if we return a 2-coloring whenever G is bipartite.

Minimum Edge Coloring

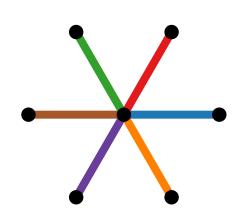
Input. A graph G = (V, E). Let Δ be the maximum degree of G.



Output. A minimum edge coloring, that is, an assignment of colors to the edges of G such that now two adjacent edges get the same color and the number of colors is minimum.



- Minimum Edge Coloring is NP-hard.
- Even Edge 3-Coloring is NP-complete.
- The minimum number of colors needed for an edge coloring of G is called the **chromatic index** $\chi'(G)$.
- $\chi'(G)$ is lowerbounded by Δ .
- We show that $\chi'(G) \leq \Delta + 1$.



Minimum Edge Coloring - Upper Bound

Vizing's Theorem.

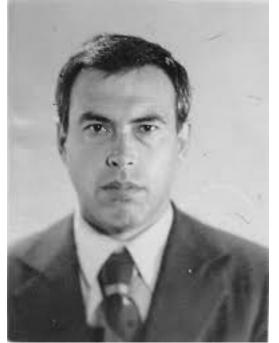
For every graph G=(V,E) with maximum degree Δ , it holds that $\Delta \leq \chi'(G) \leq \Delta + 1$.

Proof by induction on m = |E|.

Base case m=1 is trivial.

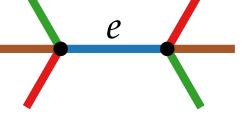
Let G be a graph on m edges, and let e = uv be an edge of G.

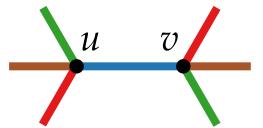
- By induction, G e has a $(\Delta(G e) + 1)$ -edge coloring.
- If $\Delta(G) > \Delta(G e)$, color e with color $\Delta(G) + 1$.
- If $\Delta(G) = \Delta(G e)$, change the coloring such that u and v miss the same color α .
- Then color e with α .



Vadim G. Vizing (Kiew 1937 – 2017 Odessa)





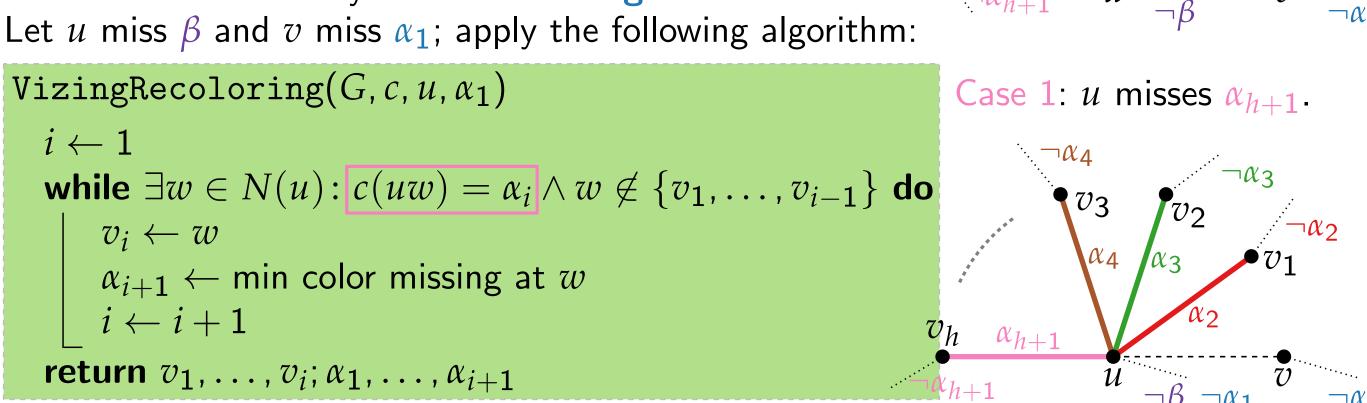


Minimum Edge Coloring – Recoloring

Lemma 2.

Let G be a graph with a $(\Delta + 1)$ -edge coloring c, let u, v be non-adjacent vertices with deg(u), $deg(v) < \Delta$. Then c can be changed s.t. u and v miss the same color.

Proof. Note that every vertex is missing a color.

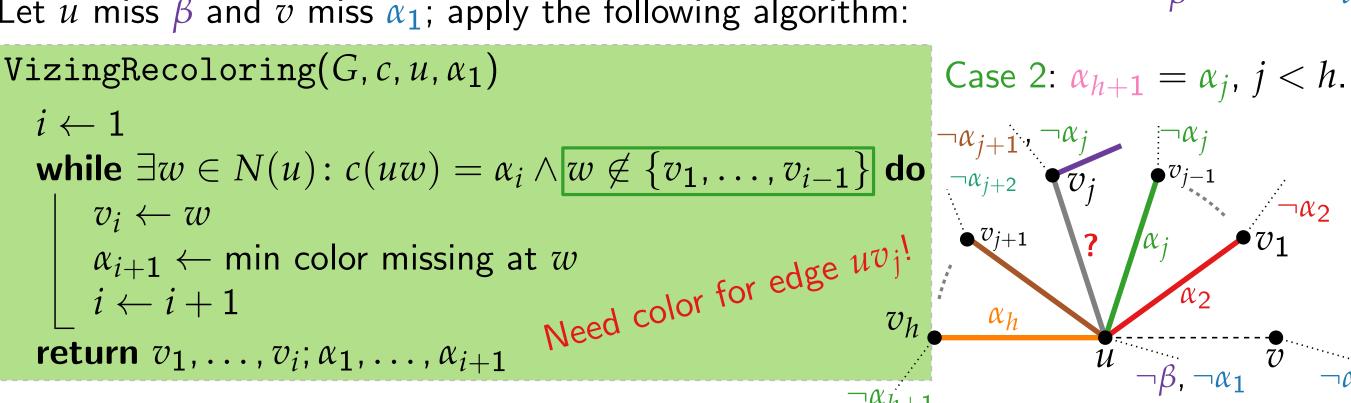


Minimum Edge Coloring – Recoloring

Lemma 2.

Let G be a graph with a $(\Delta + 1)$ -edge coloring c, let u, v be non-adjacent vertices with $\deg(u)$, $\deg(v) < \Delta$. Then c can be changed s.t. u and v miss the same color.

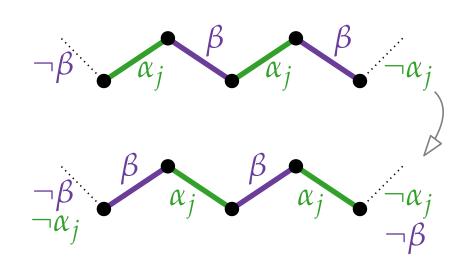
Proof. Note that every vertex is **missing** a color. Let u miss β and v miss α_1 ; apply the following algorithm:

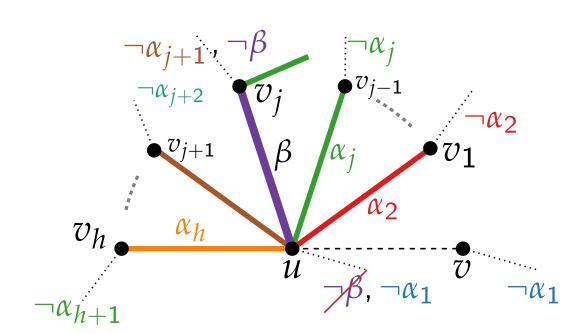


Minimum Edge Coloring – Recoloring

Proof continued for Case 2: $\alpha_{h+1} = \alpha_j$, j < h, and we need to find a color for edge uv_j .

- Consider subgraph G' of G induced by the edges of colors β and α_i .
- Since $\Delta(G') \leq 2$, we can recolor components.
- Nodes u, v_j , v_h are all leaves in G'. \Rightarrow They are not all in the same component of G'.
- If u and v_j are not in the same component:
 - lacktriangleright recolor component ending at v_i ,
 - \mathbf{v}_j now misses β ;
 - lacksquare color uv_i with β .
- What if u and v_i are in the same component?





Minimum Edge Coloring – Algorithm

VizingEdgeColoring(graph G, coloring $c \equiv 0$)

if $E(G) \neq \emptyset$ then

Let e = uv be an arbitrary edge of G.

$$G_e \leftarrow G - e$$

VizingEdgeColoring (G_e, c)

if
$$\Delta(G_e) < \Delta(G)$$
 then

Color *e* with lowest free color.

else

Recolor G_e as in Lemma 2.

Color e with color now missing at u and v.

Theorem 4.

VIZINGEDGECOLORING is an approximation algorithm with additive approximation guarantee $ALG(G) - OPT(G) \leq 1$.

Approximation with Relative Factor

An additive approximation guarantee can rarely be achieved; but sometimes, there is a multiplicative approximation!

Let Π be a minimization problem, and let $\alpha \in \mathbb{Q}^+$. A factor- α approximation algorithm for Π is a polynomial-time algorithm \mathcal{A} that computes, for every instance I of Π , a solution of value ALG(I) such that

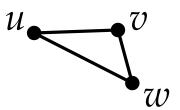
$$\frac{\mathsf{ALG}(I)}{\mathsf{OPT}(I)} \stackrel{\geq}{\leq} \alpha.$$

We call α the approximation factor of \mathcal{A} .

2-Approximation for Metric TSP (from AGT)

Input.

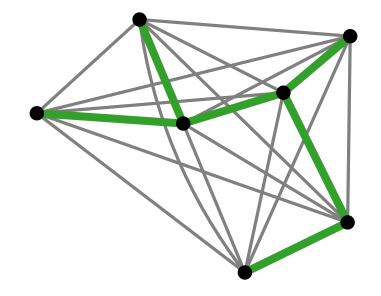
Complete graph G = (V, E) and a distance function $d: E \to \mathbb{R}_{\geq 0}$ that satisfies the triangle inequality, i.e., $\forall u, v, w \in V: d(u, w) \leq d(u, v) + d(v, w)$.



Output. A shortest Hamiltonian cycle in G.

Algorithm.

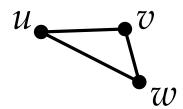
Compute MST.



2-Approximation for Metric TSP (from AGT)

Input.

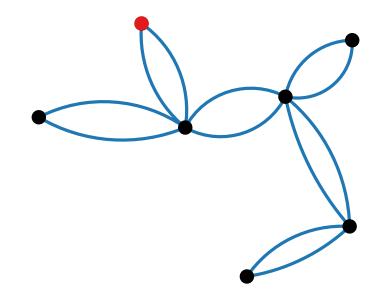
Complete graph G = (V, E) and a distance function $d: E \to \mathbb{R}_{\geq 0}$ that satisfies the triangle inequality, i.e., $\forall u, v, w \in V: d(u, w) \leq d(u, v) + d(v, w)$.



Output. A shortest Hamiltonian cycle in G.

Algorithm.

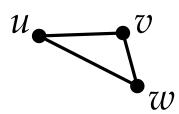
- Compute MST.
- Double edges.
- Walk along tree,



2-Approximation for Metric TSP (from AGT)

Input. Complete graph G=(V,E) and a distance function $d\colon E\to\mathbb{R}_{\geq 0}$ that satisfies the triangle inequality,

i.e.,
$$\forall u, v, w \in V : d(u, w) \leq d(u, v) + d(v, w)$$
.



Output. A shortest Hamiltonian cycle in G.

Algorithm.

- Compute MST.
- Double edges.
- Walk along tree,
- skipping visited vertices
- and adding shortcuts.

Theorem 5.

The MST edge doubling algorithm is a 2-approximation algorithm for metric TSP.

Proof.

$$ALG \le d(cycle) = 2d(MST) \le 2OPT.$$

Nearest Addition Algorithm for Metric TSP

NearestAdditionAlgorithm(G = (V, E), d)

Find closest pair, say i and k.

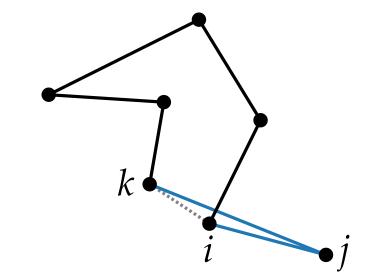
Set tour T to go from i to k to i (clockwise).

while $T \subseteq V$ do

Find pair $(i, j) \in T \times (V \setminus T)$ minimizing d(i, j).

Let k be vertex after i in T.

Add j between i and k.



Theorem 6.

NearestAdditionAlgorithm is a 2-approximation algorithm for metric TSP.

Proof.

- Exercise.
- Hints: MST and Prim's algorithm.

Approximation Schemes

In some cases, we can get arbitrarily good approximations.

maximization

Let Π be a minimization problem. An algorithm \mathcal{A} is called a polynomial-time approximation scheme (PTAS) if \mathcal{A} computes, for every input (I, ε) (consisting of an instance Iof Π and a real $\varepsilon > 0$), a value ALG(I) such that:

$$\geq (1-\varepsilon)$$

- $\geq (1 \varepsilon)$ ALG $(I) \leq (1 + \varepsilon) \cdot \mathsf{OPT}(I)$, and
- \blacksquare the runtime of \mathcal{A} is polynomial in |I| for every $\varepsilon > 0$.

 \mathcal{A} is called a fully polynomial-time approximation scheme **(FPTAS)** if it runs in time polynomial in |I| and $1/\varepsilon$.

Examples.

$$\bigcirc \mathcal{O}\left(n^2 + n^{\frac{1}{\varepsilon}}\right) \Rightarrow \mathsf{PTAS} \; \mathsf{but} \; \mathsf{not} \; \mathsf{FPTAS}$$

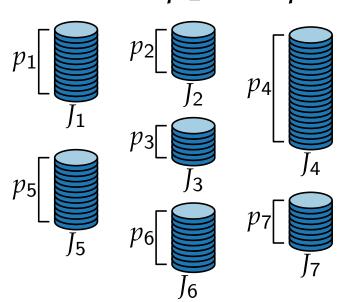
$$\bigcirc \mathcal{O}\left(n^2 \cdot 3^{\frac{1}{\varepsilon}}\right) \Rightarrow \mathsf{PTAS} \mathsf{\ but\ not\ FPTAS}$$

$$\bigcirc \mathcal{O}\left(n^4 \cdot \left(\frac{1}{\varepsilon}\right)^2\right) \Rightarrow \mathsf{FPTAS}$$

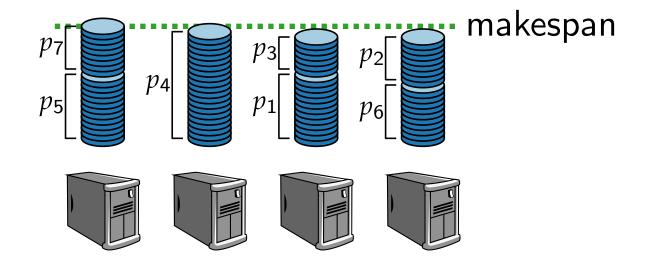
Multiprocessor Scheduling

Input.

n jobs J_1, \ldots, J_n with durations p_1, \ldots, p_n .



 \blacksquare m identical machines (m < n)



Output. Assignment of jobs to machines such that the time when all jobs have been processed is minimum.

This is called the makespan of the assignment.

Multiprocessor scheduling is NP-hard.

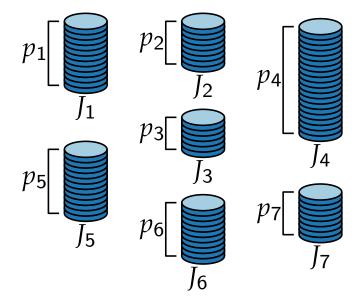
Multiprocessor Scheduling – List Scheduling

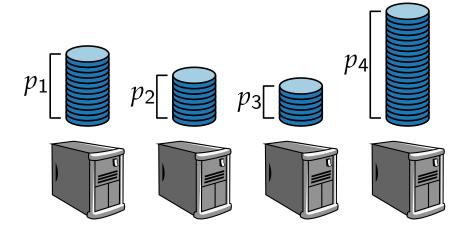
LISTSCHEDULING (J_1, \ldots, J_n, m)

Put the first m jobs on the m machines.

Put the next job on the first free machine.

Example.



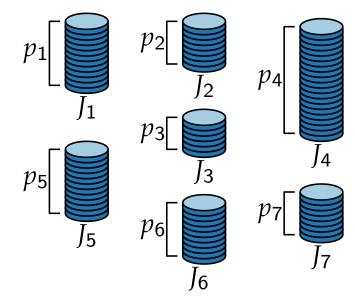


Multiprocessor Scheduling – List Scheduling

LISTSCHEDULING (J_1, \ldots, J_n, m)

Put the first m jobs on the m machines. Put the next job on the first free machine.

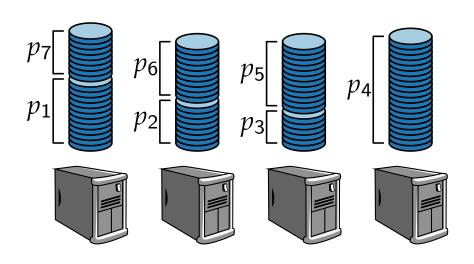
Example.



LISTSCHEDULING runs in $\mathcal{O}(n)$ time.

Theorem 7.

LISTSCHEDULING is a factor- $\left(2-\frac{1}{m}\right)$ approximation algorithm.



Multiprocessor Scheduling – List Scheduling (Proof)

LISTSCHEDULING(J_1, \ldots, J_n, m)

Put the first m jobs on the m machines. Put the next job on the first free machine.

Theorem 7.

LISTSCHEDULING is a $(2-\frac{1}{m})$ -approximation alg.

Proof. Let $J_k = (S_k, T_k)$ be the last job, that is, T_k determines the makespan.

No machine idles at time S_k .

$$S_k \le \frac{1}{m} \sum_{i \ne k} p_i$$
 weight of all jobs but J_k evenly distributed on m machines

For the optimal makespan T_{OPT} , we have:

$$T_{\mathsf{OPT}} \geq p_k$$

■
$$T_{\text{OPT}} \ge p_k$$

■ $T_{\text{OPT}} \ge \frac{1}{m} \sum_{i=1}^n p_i$ weight of all jobs evenly distributed

$$M_4$$
 M_3 M_2 M_1 M_2 M_3 M_4 M_5 M_6 M_6 M_6 M_6 M_7 M_8 M_8 M_8 M_9 M_9

Hence:

$$T_{k} = S_{k} + p_{k}$$

$$\leq \frac{1}{m} \cdot \sum_{i \neq k} p_{i} + p_{k}$$

$$= \frac{1}{m} \cdot \sum_{i=1}^{n} p_{i} + \left(1 - \frac{1}{m}\right) \cdot p_{k}$$

$$\leq T_{\mathsf{OPT}} + \left(1 - \frac{1}{m}\right) \cdot T_{\mathsf{OPT}}$$

$$= \left(2 - \frac{1}{m}\right) \cdot T_{\mathsf{OPT}}$$

Multiprocessor Scheduling – PTAS

For a constant ℓ ($1 \le \ell \le n$) define the algorithm \mathcal{A}_{ℓ} as follows.

$$\mathcal{A}_{\ell}(J_1,\ldots,J_n, m)$$

Sort jobs in descending order of runtime.

Schedule the ℓ longest jobs J_1, \ldots, J_{ℓ} optimally.

Use LISTSCHEDULING for the remaining jobs $J_{\ell+1}, \ldots, J_n$.

Example.

$$\ell = 6$$

sorted jobs

<i>J</i> <u>1</u>
J_2
J ₃
J ₄
J ₅
J ₅

M_{4}	J_1		
M_3	J ₂	J_5	
M_2	J ₃		
M_1	J ₄	J ₆	

Multiprocessor Scheduling – PTAS

For a constant ℓ $(1 \le \ell \le n)$ define the algorithm \mathcal{A}_{ℓ} as follows.

$$\mathcal{A}_{\ell}(J_1,\ldots,J_n,m)$$
Sort jobs in descending order of runtime.

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Use ListScheduling for the remaining jobs $J_{\ell+1},\ldots,J_n$.

 $\mathcal{O}(n\log n)$

$$\mathcal{O}(n\log n)$$
 $\mathcal{O}(m^{\ell})$
 $\mathcal{O}(n\log m)$

Polynomial time for constant ℓ : $\mathcal{O}(m^{\ell})$ $\mathcal{O}(m^{\ell} + n \log n)$

Theorem 8.

For constant $1 \leq \ell \leq n$, the algorithm \mathcal{A}_{ℓ} is a $1 + \frac{1 - \frac{1}{m}}{1 + |\frac{\ell}{m}|}$ -approximation algorithm.

- For $\varepsilon > 0$, choose ℓ such that $\mathcal{A}_{\varepsilon} = \mathcal{A}_{\ell(\varepsilon)}$ is a $(1+\varepsilon)$ -approximation algorithm.
- \blacksquare $\{A_{\varepsilon} \mid \varepsilon > 0\}$ is not an FPTAS since the running time is not polynomial in $\frac{1}{\varepsilon}$.

Corollary 9.

For a constant number of machines, $\{A_{\varepsilon} \mid \varepsilon > 0\}$ is a PTAS.

Multiprocessor Scheduling – PTAS (Proof)

Theorem 8.

For constant $1 \le \ell \le n$, the algorithm \mathcal{A}_{ℓ} is a $1 + \frac{1 - \frac{1}{m}}{1 + \left|\frac{\ell}{m}\right|}$ -approximation algorithm.

$$\mathcal{A}_{\ell}(J_1,\ldots,J_n,\ m)$$

Sort jobs in descending order of runtime.
Schedule the ℓ longest jobs J_1,\ldots,J_{ℓ} optimally.

Use LISTSCHEDULING for the remaining jobs $J_{\ell+1}, \ldots, J_n$.

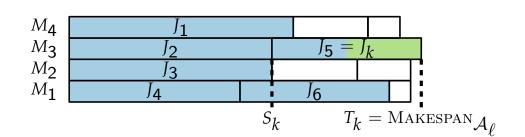
Proof. Let $J_k = (S_k, T_k)$ be the last job, that is, T_k determines the makespan.

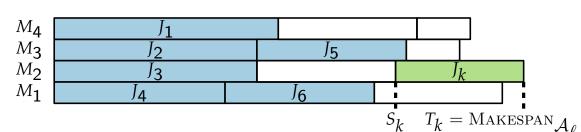
Case 1. J_k is one of the longest ℓ jobs J_1, \ldots, J_{ℓ} .

- Solution is optimal for J_1, \ldots, J_k
- \blacksquare Hence, solution is optimal for J_1, \ldots, J_n

Case 2. J_k is not one of the longest ℓ jobs J_1, \ldots, J_{ℓ} .

- Similar analysis to ListScheduling
- Use that there are $\ell+1$ jobs that are at least as long as J_k (including J_k).





Multiprocessor Scheduling – PTAS (Proof)

Theorem 8.

For constant $1 \leq \ell \leq n$, the algorithm \mathcal{A}_{ℓ} is a $1+rac{1-rac{1}{m}}{1+\left|rac{\ell}{m}\right|}$ -approximation algorithm.

$$\mathcal{A}_{\ell}(J_1,\ldots,J_n, m)$$

Sort jobs in descending order of runtime.

Schedule the ℓ longest jobs J_1, \ldots, J_{ℓ} optimally.

Use ListScheduling for the remaining jobs $J_{\ell+1}, \ldots, J_n$.

Proof of Case 2.

$$S_k \leq \frac{1}{m} \sum_{i \neq k} p_i$$

Consider only J_1, \ldots, J_ℓ, J_k :

$$T_{\mathrm{OPT}} \geq p_k \cdot \left(1 + \left\lfloor \frac{\ell}{m} \right
floor
ight)$$
 one machine has this many jobs* each has length $\geq p_k$

- lacksquare on average, each machine has more than $rac{\ell}{m}$ of the $\ell+1$ jobs
- at least one machine achieves the average

$$M_4$$
 J_1 M_3 J_2 J_5 M_2 J_3 J_4 J_6 S_k $T_k = \text{Makespan}_{\mathcal{A}_{\ell}}$

$$T_{k} = S_{k} + p_{k}$$

$$\leq \frac{1}{m} \cdot \sum_{i \neq k} p_{i} + p_{k}$$

$$= \frac{1}{m} \cdot \sum_{i=1}^{m} p_{i} + \left(1 - \frac{1}{m}\right) \cdot p_{k}$$

$$\leq T_{\text{OPT}} + \frac{1 - \frac{1}{m}}{1 + \left|\frac{\ell}{m}\right|} \cdot T_{\text{OPT}}$$

Discussion

- Only "easy" NP-hard problems admit FPTAS (PTAS).
- Some problems cannot be approximated very well (e.g., Maximum Clique).
- Study of approximability of NP-hard problems yields a more fine-grained classification of the difficulty.
- Approximation algorithms exist also for non-NP-hard problems
- Approximation algorithms can be of various types: greedy, local search, geometric, DP, ...
- One important technique is LP-relaxation (next lecture).
- Minimum Vertex Coloring on planar graphs can be approximated with an additive approximation guarantee of 2.
- Christofides' approximation algorithm for Metric TSP has approximation factor 1.5.

Approximation

Literature

Main references

- [Jansen & Margraf, 2008: Ch3] "Approximative Algorithmen und Nichtapproximierbarkeit"
- [Williamson & Shmoys, 2011: Ch3] "The Design of Approximation Algorithms"

Another book recommendation:

■ [Vazirani, 2013] "Approximation Algorithms"

