Approximation algorithms 1 Set cover, vertex cover, scheduling

CS240

Spring 2023

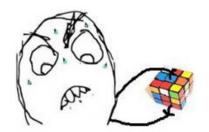
Rui Fan

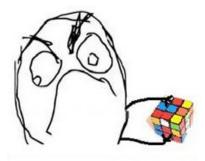


Approximation algorithms

- Up to now, most of our algorithms have been exact. I.e. they find an optimal solution.
- But there are many problems for which we don't know how to find an optimal solution.
 - A key example is NP-complete problems.
 We don't know efficient algorithms for any NPC problem.
- Many such problems are important in practice. What do we do?
- If we can't get find the best answer, let's try for good enough.
- Approximation algorithms find an approximately optimal answer.

*le me struggling with rubic cube











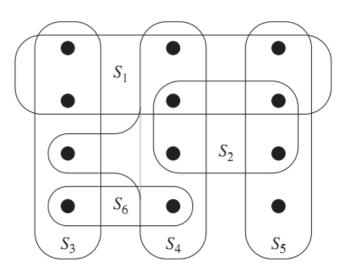
Approximation ratio

- Let X be a maximization problem. Let A be an algorithm for X.
- Let $\alpha > 1$ be a constant.
- A is an α -approximation algorithm for X if A always returns an answer that's at least $1/\alpha$ times the optimal.
 - □ Ex If X is max-flow, A is a 2-approx algorithm if it always returns a flow that's at least ½ the optimal.
 - \square The closer α is to 1, the better the approximation.
- If X is a minimization problem, A is an α-approximation algorithm for X if it always returns an answer that's at most α times larger than the optimal.
 - □ Ex If X is min-cut, A is a 2-approx algorithm if it always returns a cut that's at most 2 times the size of the optimal.
 - \square Again, the closer α is to 1, the better the approximation.



Coverings

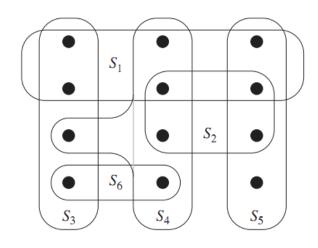
- Suppose there's a set of teachers, and each can teach a certain set of classes.
 - □ Let S_i be the set of classes teach i can teach.
- The entire set of classes is X.
- We want to pick the minimum set of teachers to teach all the classes.
 - □ Let T be set of teachers we pick.
 - \square We want $U_{i \in T} S_i = X$, and T to be the smallest possible.





Set covering

- Input A collection F of sets. Each set has a cost. The union of all the sets is X.
- Output A subset G of F, whose union is X.
- Goal Minimize the total cost of the sets in G.



If all sets have same cost, S_3 , S_4 and S_5 is a min cost set cover of X.

- Minimum cost set cover is NP-complete.
- We'll see a ln(n)-approximation algorithm, where n=|X|.



A greedy approximation alg

- A natural greedy heuristic is to choose sets which cover points most cheaply.
 - □ For each set, let c be its cost, and m be the number of points it covers.
 - We want to use the set with the smallest c/m value, because this is the cheapest way to cover some new points.
- After we pick this set, remove all the points it covers. Then we consider the per unit cost of the remaining sets and again choose the cheapest.

A greedy approximation alg

- \Box F is the entire collection of sets. The union of these sets is X.
- □Each set S in F has a cost cost(S).
- □U is the set of elements of X we haven't covered yet.
- □C is the set cover we eventually output.

- while U≠∅

 - \square choose $S \in F-C$ with min $|cost(S)|/|S \cap U|$

$$\Box C = C \cup \{S\}$$

$$\Box U = U - S$$

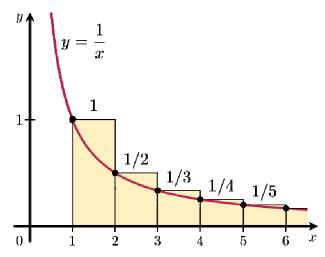
output C

Per unit cost to cover new elements.



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- We always output a set cover, because the while loop continues till X is covered.
- We'll prove the approximation ratio is at most $1+1/2+1/3+...+1/n \approx ln(n)$.
 - □ If the min cost of a set cover is V, our set cover costs at most ln(n)*V.
- The basic plan is to bound the cost of the set cover the algorithm outputs using the "average cost" per element.



- Order the sets in C by when they're added to C, earliest set first.
 - \square Let the order be S₁, S₂,...,S_m.
- Cost of the set cover is $L=\Sigma_i \cos(S_i)$.
- Order the elements in X by when they're added, earliest element first.
 - \square Let the order be $e_1, e_2,...,e_n$.
 - \square So, the first few e's are added by S₁, the next few added by S₂, etc.
 - Every element in X is in the list, because C covers X.

b/A

- Let n_i be the number of new elements S_i covers.
 - \square So, n_i is the number of elements in S_i , but not in $S_1,...,S_{i-1}$.
- Divide the cost of S_i evenly among the new elements it covers.
 - \square If e is newly covered by S_i , then $cost(e) = cost(S_i)/n_i$.
- - □ Every element is covered by some S_i, and S_i covers n_i new elements.
- We'll prove $cost(e_k) \le OPT/(n-k+1)$, for any k.
- Suppose this is true, then

$$L = \sum_{k} cost(e_k) \le \sum_{k} OPT/(n-k+1) \approx In(n)*OPT$$

The per element cost

- Let's focus on some element e_k, and let S_j be the set which covers e_k for the first time.
- Let $C_1,...,C_r$ be the sets in an optimal cover, each of which covers some elements of $U=\{e_k,e_{k+1},e_{k+2},...,e_n\}$.
 - □ Let n'₁,...,n'_r be the number of elements of U which C₁,...,C_r cover.
- Obs 1 Σ_i n'_i \geq n-k+1.
 - \square Because $C_1,...,C_r$ cover U.
- Obs 2 Σ_i cost(C_i) \leq OPT.
 - □ Because C₁,...,C_r are a subset of an optimal cover, which has cost OPT.

b/A

The per element cost

- Obs 3 None of $C_1,...,C_r$ are among $S_1,...,S_{i-1}$.
 - □ If some C_i is among $S_1,...,S_{j-1}$, then since C_i covers some e in U, e would be covered by $\{S_1,...,S_{j-1}\}$. So, e would be among the first k-1 elements covered. Contradiction.
- Obs 4 There exists some C_i among $C_1,...,C_r$ with $cost(C_i)/n'_i \le OPT/(n-k+1)$.
 - □ If every C_i in C₁,...,C_r has cost(C_i)/n'_i>OPT/(n-k+1), then

$$\begin{aligned} &\mathsf{OPT} \geq \Sigma_i \, \mathsf{cost}(C_i) = \Sigma_i \, n'_i ^* \mathsf{cost}(C_i) / n'_i > \\ &\Sigma_i \, n'_i ^* \mathsf{OPT} / (n \text{-} k \text{+} 1) \geq \mathsf{OPT} / (n \text{-} k \text{+} 1) \, \Sigma_i \, n'_i \geq \\ &\mathsf{OPT} / (n \text{-} k \text{+} 1) ^* (n \text{-} k \text{+} 1) = \mathsf{OPT}. \\ &\mathsf{Contradiction.} \end{aligned}$$

Proof of approximation ratio

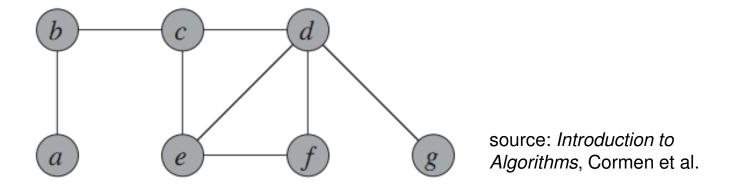
- Lemma cost(S_i)/ $n_i \le OPT/(n-k+1)$.
- Proof When choosing S_j, the only sets the algorithm is not allowed to choose are S₁,...,S_{i-1}.
 - \square By obs 3, C₁,...,C_r aren't in S₁,...,S_{i-1}.
 - □ By obs 4, there's some C_i in $C_1,...,C_r$, with cost(C_i)/ n'_i ≤ OPT/(n-k+1).
 - \square S_j was chosen so that cost(S_j)/n_j is min among all sets not in S₁,...,S_{i-1}.
 - \square So $cost(S_i)/n_i \le cost(C_i)/n_i \le OPT/(n-k+1)$.
- Since $cost(S_j)/n_j = cost(e_k)$, we have $cost(e_k) \le OPT/(n-k+1)$.
- The approx ratio follows because

$$L = \sum_{k} cost(e_k) = \sum_{k} OPT/(n-k+1) \approx In(n)*OPT$$



Vertex cover

- Input A graph with vertices V and edges E.
- Output A subset V' of the vertices, so that every edge in E touches some vertex in V'.
- Goal Make |V'| as small as possible.



- Finding the minimum vertex cover is NP-complete.
- Vertex cover is a special case of (unweighted) set cover, where each element (edge) can be covered by at most two sets (vertices).
- We'll see a simple 2 approximation for this problem.

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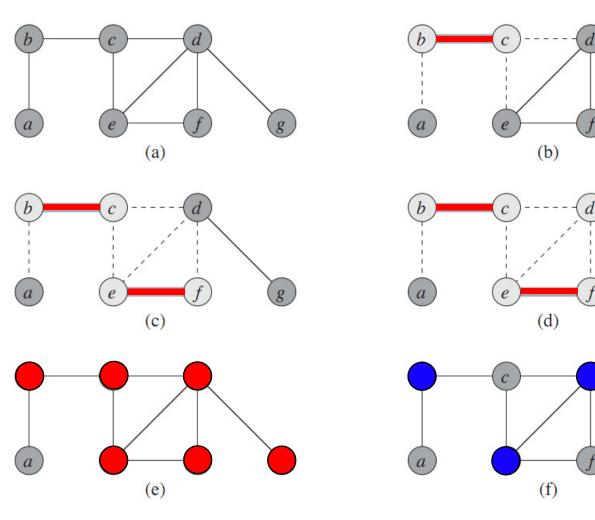
A vertex cover algorithm

- Initially, let D be all the edges in the graph, and C be the empty set.
 - C is our eventual vertex cover.
- Repeat as long as there are edge left in D.
 - □ Take any edge (u,v) in D.
 - \square Add $\{u,v\}$ to C.
 - Remove all the edges adjacent to u or v from D.
- Output C as the vertex cover.



Example

source: CLRS



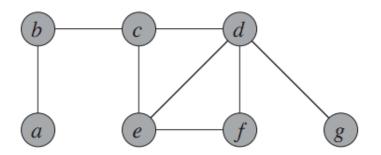
Algorithm's vertex cover

Optimal vertex cover



- The output is certainly a vertex cover.
 - □ In each iteration, we only take out edges that get covered.
 - We keep adding vertices till all edges are covered.
- Now, we show it's a 2 approximation.
- Let C* be an optimal vertex cover.
- Let A be the set of edges the algorithm picked.

- None of the edges in A touch each other.
 - □ Each time we pick an edge, we remove all adjacent edges.
- So each vertex in C* covers at most one edge in A.
 - ☐ The edges covered by a vertex all touch each other.
- Every edge in A is covered by a vertex in C*.
 - □ Because C* is a vertex cover.
- So $|C^*| \ge |A|$.
- The number of vertices the algorithm uses is 2|A|.
 - \square If alg picks edge (u,v), it uses {u,v} in the cover.
- So (# vertices alg uses) / (# vertices in opt cover) = $2|A| / |C^*| \le 2|A| / |A| = 2$.





Parallel computing and scheduling

- Computers today are parallel.
 - Multiple processors in a system.
 - Multiple tasks for the processors to run.
- Multiprocessor scheduling is the problem of deciding which tasks to run on which processors at what time.
- Many possible objectives.
 - □ Throughput, fairness, energy usage.
 - Latency, i.e. finishing all jobs as fast as possible.



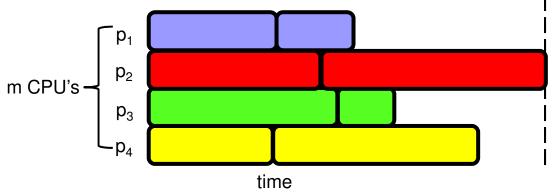






Makespan scheduling

- n independent jobs.
 - Jobs have different sizes, i.e. time needed to perform job.
 - □ Jobs can be done in any order.
 - □ Any job can be done on any machine.
- m processors.
 - □ All have the same speed.
 - □ Each processors can do one job at a time.
- Assign the jobs to the processors.
- Makespan is when the last processor finishes all its jobs.
- Minimize the makespan.
 - □ I.e., finish all the jobs as fast as possible. makespan





Graham's list scheduling

- Since scheduling is NPC, it's unlikely we can find the min makespan in polytime.
- List scheduling is a simple greedy algorithm.
 - ☐ Finds a schedule with makespan at most twice the minimum.
 - □ A 2-approximation.
- If there are n tasks and m processors, list scheduling only takes O(n log m) time.
 - □ Compare this to n! C(n+m-1, m-1) time to try all possible schedules and pick the best.

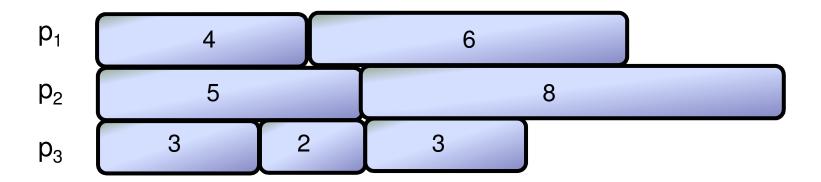


Graham's list scheduling

- List the jobs in any order.
- As long as there are unfinished jobs.
 - □ If any processor doesn't have a job now, give it the next job in the list.

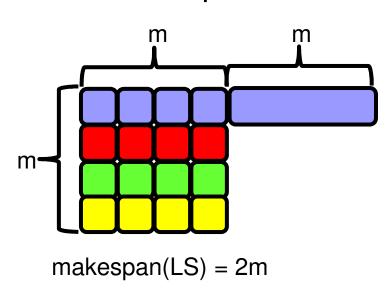
Example

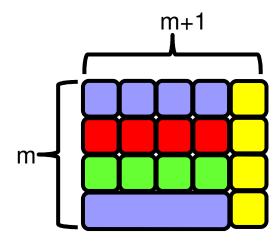
- 3 processors. The jobs have length 2, 3, 3, 4, 5, 6, 8.
- List them in any order. Say 4, 5, 3, 2, 6, 8, 3.
- Initially, no proc has a job. Give first 3 jobs to the 3 procs.
- At time 3, proc 3 is done. Give it next job in list, 2.
- At time 4, proc 2 is done. Give it next job in list, 6.
- At time 5, both 1, 3 are done. Give them next jobs in list, 8,3.
- Everybody finishes by time 13.
 - □ The makespan of this schedule is 13.



The worst case for LS

- How badly can list scheduling do compared to optimal?
- Say there are m² jobs with length 1, and one job with length m.
 - □ Suppose they're listed in the order 1,1,1,...,1,m.
 - □ LS has makespan 2m. Optimal makespan is m+1.
 - □ makespan(LS) / makespan(opt) = $2m/(m+1) \approx 2$.
- This is worst possible case for list scheduling.



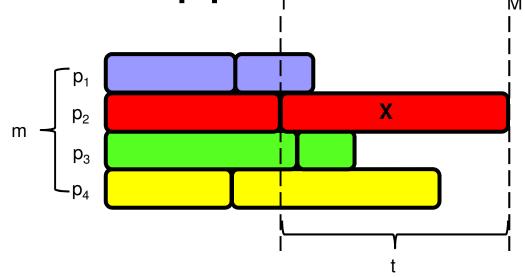


makespan(opt) = m+1

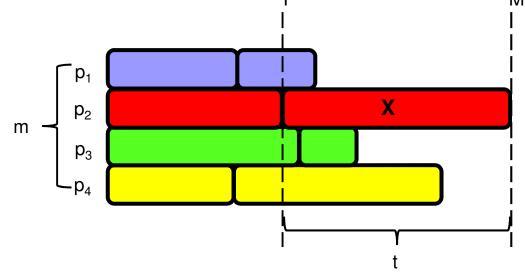
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- Next, we prove LS always gives a schedule at most twice the optimal.
- Suppose LS gives makespan of M.
- Let the optimal schedule have makespan M*.
- We prove that $M \le 2M^*$.

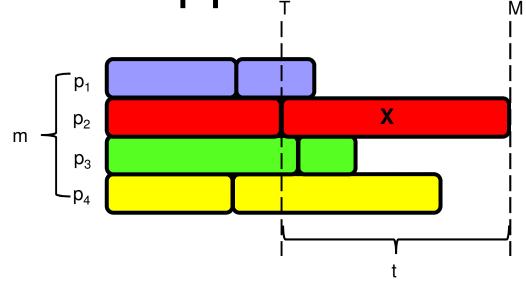
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- The picture above is the schedule produced by list scheduling.
- Consider task X that finishes last.
 - □ Say X starts at time T, and has length t.
- Claim 1 M* ≥ t.
 - □ In any schedule, X has to run on some process.
 - □ Since X takes t time, every schedule, including the opt, takes ≥ t time.



- Claim 2 M* ≥ T.
 - □ Up to time T, no processor is ever idle.
 - Up to T, there's always some unfinished job.
 - As soon as a processor finishes one job, it's assigned another one.
 - □ So at time T, each processor completed T units of work.
 - \square So total amount of work in all the jobs is \ge mT.
 - □ In the opt schedule, m processors complete at most m units of work per time unit.
 - □ So length of opt schedule is \geq (total work)/m \geq mT/m = T.



- From Claims 1 and 2, we have M* ≥ t and M* ≥ T.
- So $M^* \ge max(T,t)$.
- M = T + t, because X is last job to finish.
- So $M/M^* \le (T+t)/max(T,t) \le 2$.

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LPT scheduling

- Worst case for LS occurred when longest job was scheduled last.
 - □ Large jobs are "dangerous" at end.
- Let's try to schedule longest jobs first.
- Longest processing time (LPT) schedule is just like list scheduling, except it first sorts tasks by nonincreasing order of size.
- Ex For three processors and tasks with sizes 2, 3, 3, 4, 5, 6, 8, LPT first sorts the jobs as 8,6,5,4,3,3,2. Then it assigns p₁ tasks 8,3, p₂ tasks 6,3, p₃ tasks 5,4,2, for a makespan of 11.
- LPT has an approximation ratio of 4/3.

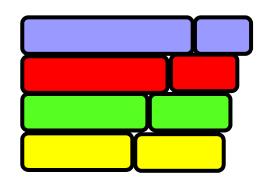


LPT is a 4/3-approximation

- Thm Suppose the optimal makespan is M*, and LPT produces a schedule with makespan M. Then M ≤ 4/3 M*.
- Let X be the last job to finish. Assume it starts at time T and has size t.
- Assume WLOG that X is the last job to start.
 - ☐ If not, then say Y starts after T.
 - ☐ Y finishes before T+t. So we can remove Y without increasing the makespan.
- Cor 1 X is the smallest job.
 - X is the last job to start, so due to LPT scheduling it's the smallest.

LPT is a 4/3-approximation

- Claim 1 LPT's makespan = T+t ≤ M*+t.
 - \square As in LS, no processor is idle up to time T, so M* \ge T.
- Case 1 t ≤ M*/3.
 - □ Then LPT's makespan \leq M* + t \leq M* + M*/3 = 4/3 M*.
- Case 2 t > $M^*/3$.
 - □ Since X is the smallest task, all tasks have size > M*/3.
 - So the optimal schedule has at most 2 tasks per processor. So n ≤ 2m.
 - □ If $1 \le n \le m$, then LPT and optimal schedule both put one task per processor.
 - □ If $m < n \le 2m$, then optimal schedule is to put tasks in nonincreasing order on processors 1,...,m, then on m,...,1.
 - LPT also schedules tasks this way, so it's optimal.





LS vs LPT

- LPT gives better approx ratio, has same running time. Why bother with LS?
- LS is online.
 - □ Imagine the jobs are coming one by one.
 - LS just puts them on any idle computer.
- LPT is offline
 - □ It needs to know all the jobs that will ever arrive, in order to sort them.
- In a realistic parallel computation, you get jobs on the fly.
 - Online is more realistic.
 - □ LS is usually more useful.