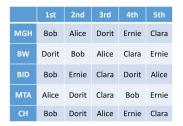
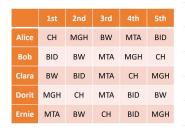
Introduction

- Topics and pre-requisites
- · Course Policies
- Grading Scheme
 - 5 Assignments (60% for ugrad; 50% for grad)
 - o Final exam 40%
 - Scribe notes 10% (for grad)
- References

Stable Matching (or marriage)

- n doctors and n hospitals
- each doctor has an ordered preference list of hospitals
- each hospital has an ordered preference list of doctors
- Goal: Find a perfect matching (each doctor matched to one hospital)





Credit: tables/figures from KW slides

Definition A matching of doctors and hospitals is unstable if there is an "unstable pair"

Suppose (H',D) and (H,D') are two matched pairs; then (H,D) is unstable if H prefers D to D' and D' prefers H to H' (so both H and D prefer to break their current pairing)

so both prefer to break the tie.

Def. A stable matching is a perfect matching with no unstable pairs.

Stable matching problem. Given the preference lists of n hospitals and n doctors, find a stable matching (if one exists)



Question: Do stable matchings always exist? Not obvious immediately.

We develop an algorithm that always finds one (hence proof of existence too)

Gale-shapely deferred acceptance Algorithm

Input: preference list for hospitals & doctors

Goal: Find a stable matching M

let $M = \Phi$

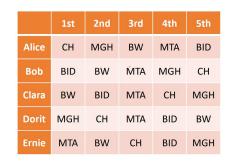
while there is an unmatched hospital h do:

 h offers to the next doctor on its list it has not made an offer before

- o if d has no job then add (h,d) to M
- o if d has job with h' and h'>h do nothing
- if d has job with h' and h>h' then:
 remove (h',d) from M & add (h,d) to M
 return M

2nd MGH Bob Alice Dorit Ernie Clara Dorit Bob Alice Clara Bob Ernie Clara Dorit Alice Alice Dorit Clara Bob Frnie

Dorit Alice Ernie Clara



Observation: once a doctor gets a job then s/he never becomes jobless

Things to consider:

- The algorithm terminates and outputs a matching
- Hospitals go down" their list; doctors go-up"

Why a matching at the end?

- No hospital is matched to more than 1 doctor.
- No doctor is matched to more than 1 hospital.
- If a hospital h is not matched at the end --> there is an unmatched doctor d;
- h must have proposed to d; so either it is matched or d was matched.

1 1 1 1 1

Why M is stable?

Why M is stable?

- suppose there is an unstable pair:
 (d,h) and (d',h')
- d_h d:h'>h

 d'=h' h':d>d'
- case 2: h' made an offer to d:
 - od accepted but later switched to h
 - od rejected, so it was matched to h">h'>h

This matching is in favor of hospitals; can do it based on preference lists of doctors

National resident matching program (NRMP).

Centralized to match med-school students to hospitals.

Began in 1952 to fix unraveling of offer dates.

Originally used the "Boston Pool" algorithm.

Algorithm overhauled in 1998.

- med-school student optimal
- deals with various side constraints

(e.g., allow couples to match together)

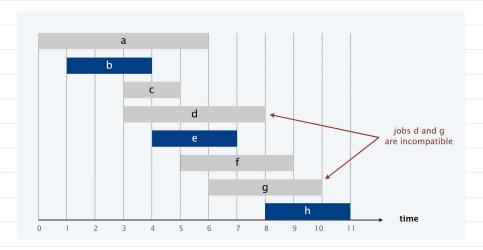
Greedy Algorithms

- used for optimization problems (e-g. coin change, shortest paths in weighted graphs, scheduling)
- Decisions made are locally the best and often never changed.

- Algorithms developed are typically efficient.
- Proof often is based on induction and uses an exchange argument.

Example 1: Interval scheduling

- Given a set of n jobs J
- ullet each job j has a start time s_j and finish f_j
 - Two jobs are compatible if their intervals don't overlap.
- Goal: Find a largest set of compatible jobs.



Several ways to design by greedy:

1- sort by
$$s_j$$

2 - Sort by interval length $f_j - s_j$

3 - Sort by f_i : this might work!

Greedy Interval Scheduling

Sort the jobs based on finish time so $f_1 \leq f_2 \leq \cdots \leq f_n$

let $S = \phi$

For i=1 to n do

if [si, fi] does not conflict with anything in S

add i to S

Return S

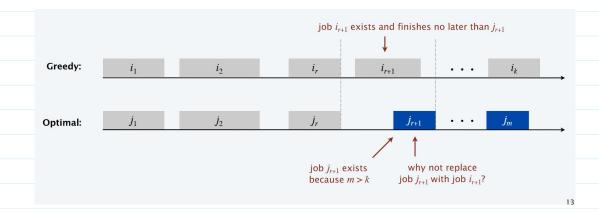
Proposition. Can implement in O(n log n) time.

- · Keep track of job j* that was added last to S.
- · Job j is compatible with S iff $s_j \geq f_{j^*}$.
- · Sorting by finish times takes O(n log n) time.

Theorem: This algorithm finds an optimum schedule.

Proof: Assume greedy is not optimal

- Let $i_1, i_2, ..., i_k$ denote set of jobs selected by greedy.
- Let $j_1, j_2, ..., j_m$ denote set of jobs in an optimal solution with $i_1 = j_1, i_2 = j_2, ..., i_r = j_r$ for the largest possible value of r.
- · Clearly m>k



- we can replace j_{r+1} in opt with i_{r+1}
- We can use this fact to prove the following by induction on m:

Lemma: For any m>=1, after our algorithm completes m intervals, an optimum has completed <=m intervals.

Example 2: What if we have to schedule all the jobs but on minimum number of machines?

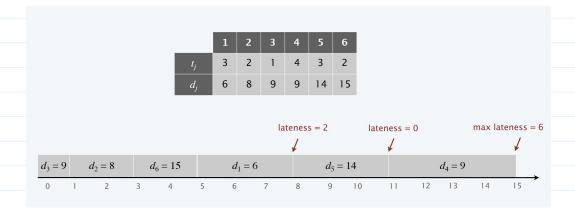
Exercie: Think of another Greedy Algorithm for this problem.

Example 3: Minimum Lateness schedule

Input: n jobs, each has a length trand deadline of

- if job i starts at time 5; will finish at time 5i+ti
- and will have lateness $\max\{0, f_i d_i\} = l_i$

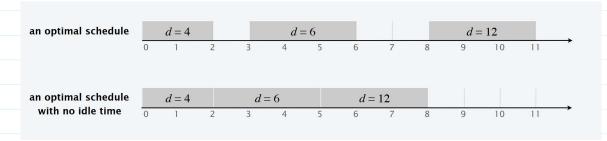
Goal: Find an ordering of the jobs (to run on a machine) that minimizes the max $\{l_i\}$



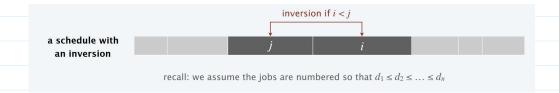
Greedy: What order?

sort by deadline s.t. $d_1 \leq d_2 \leq \cdots \leq d_n$

Observation 1: There is an optimum solution with no idle time.



Definition: Given a schedule S, an inversion is a pair of jobs i and j such that: i < j but j is scheduled before i.

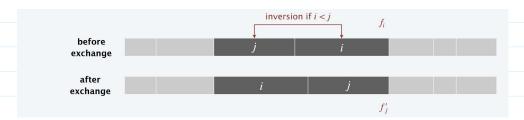


Observation 2. The earliest-deadline-first schedule is the unique idle-free schedule with no inversions.

Observation 3. If an idle-free schedule has an inversion, then it has an adjacent inversion

(think of sorting, if it's not sorted two adjacent items are wrong order)

Key Observation: Exchanging two adjacent, inverted jobs i and j reduces the number of inversions by 1 and does not increase the max lateness.



suppose we swap i,j. let l_i , l_j be the new lateness of these jobs. Note: lateness of other jobs don't change and l_i $\leq l_i$

Theorem: Earliest deadline-first schedule S is optimum.

Proof: Define S* to be an optimal schedule with the fewest inversions.

- Can assume S* has no idle time.
- Case 1. [S* has no inversions] Then S = S*.
- · Case 2. [S* has an inversion]: let i-j be an adjacent inversion
- exchanging jobs i and j decreases the number of inversions by 1
- without increasing the max lateness
- contradicts "fewest inversions" part of the definition of S*.

Example 3: Minimum Lateness schedule

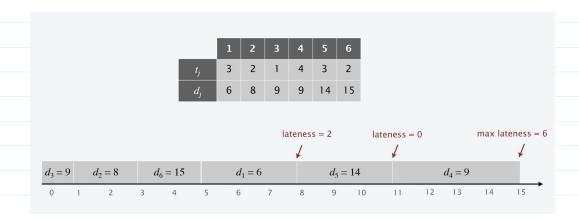
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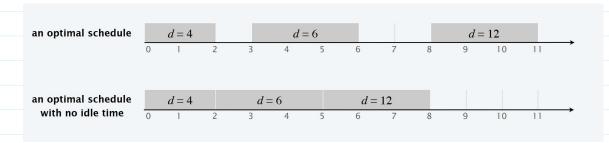
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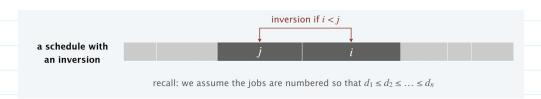
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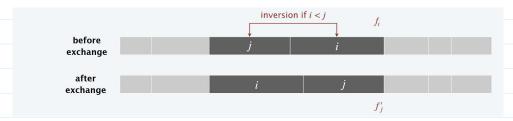
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Dynamic Programming

- One of the most powerful technique in designing

efficient algorithms; often asked about in job interview

- It can be quite involved and solve intricate problems

- The basic principle is simple but coming up with

the right approach that works can be quite challenging.

Main idea:

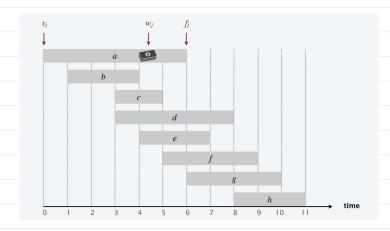
- break the problem to smaller subproblems
- Solve the subproblems and Store the partial solutions into a table
- Use partial solutions recursively to solve the bigger Subproblems.

Most important step (of missed by students)

Define the proper subproblem & a table to store the solution (what is it you are storing?)

Example 1: weighted interval scheduling

Given a set J of n jobs: Si Start time
fi finish time
wi Value/weight
Goal: find a subset of compatible jobs (no two overlap)
with maximum total value.



How does greedy do?

We saw greedy works well when all $\omega_i=1$.

Earliest finish time first:

W=1 W 7100

Decide based on largest wi to smaller: 1918

what is a good subproblem?

- lets consider the jobs in increasing order of finish time; so $f_1 \le f_2 \le --- \le f_n$

- For each job j let p(j) be the largest index i < j s.t. job i does not ovelap with j. (p(j) = 0) if no such job exists)

- Let Opt[j] denote the max weight of a.

Schedule that uses only jobs (a subset) of jobs in $\{1,2,--,j\}$ clearly our goal is computing Opt[n] and opt[I] is trivial $(=\omega_1)$.

- When considering job j:

(case 1: optimum of the first j jobs does NOT include j; so opt [j] = opt[j-1]

(ase 2: j belongs to the best schedule of the first j, so it must be the last in that schedule and we have to find the best schedule of jobs 1---P(j)

 $\begin{array}{c|c}
i & j \\
\hline
Sj & f_j & time \\
OP+ [j] = \omega_j + OP+[P(j)]
\end{array}$

we don't know which of the two cases 50 opt [j-1] opt [j] = max $\begin{cases} opt [j-1] \\ opt [p(j)] + \omega_j \end{cases}$

opt[o]=o

opt 1 2 3 4 5 6
2 4 6
4 244
2003 W.3

Index

Weighted-Interval-DP

$$-0[0] = 0$$

- This computes the value of optimum in O(nlogn)

- To find the actual schedule: trace back

the Selection