Chapter 2
Greedy Algorithms

Algorithm Theory
WS 2017/18

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Greedy Algorithms

- No clear definition, but essentially:

In each step make the choice that looks best at the moment!

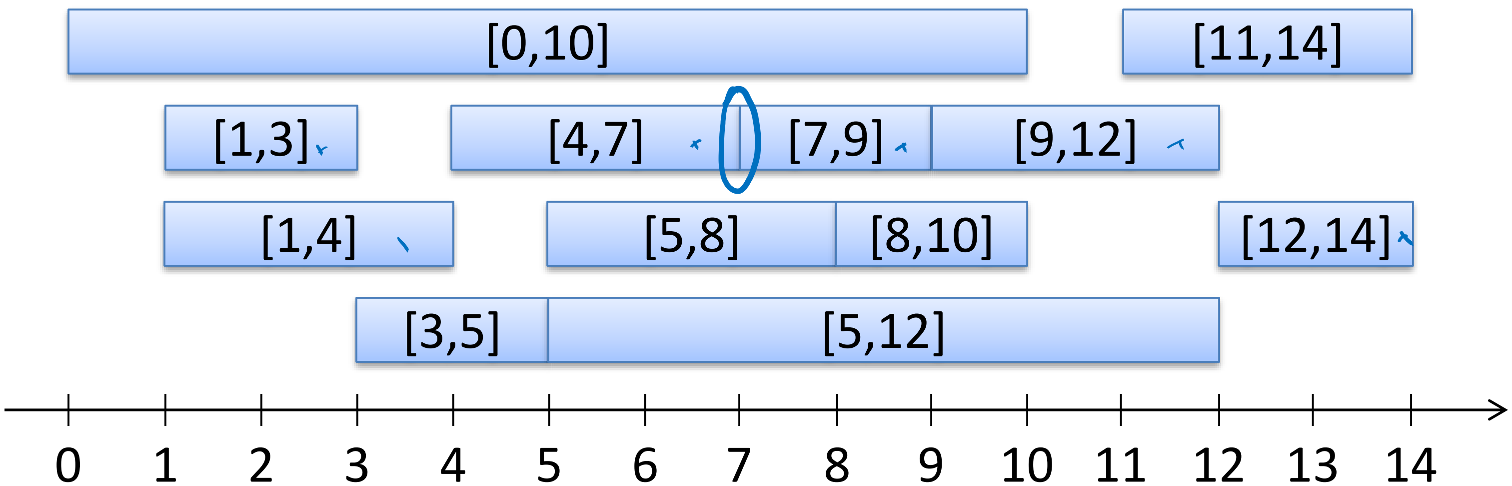
no backtracking

- Depending on problem, greedy algorithms can give
  - Optimal solutions
  - Close to optimal solutions
  - No (reasonable) solutions at all
- If it works, very interesting approach!
  - And we might even learn something about the structure of the problem

Goal: Improve understanding where it works (mostly by examples)

Interval Scheduling

- **Given:** Set of intervals, e.g.
[0,10],[1,3],[1,4],[3,5],[4,7],[5,8],[5,12],[7,9],[9,12],[8,10],[11,14],[12,14]



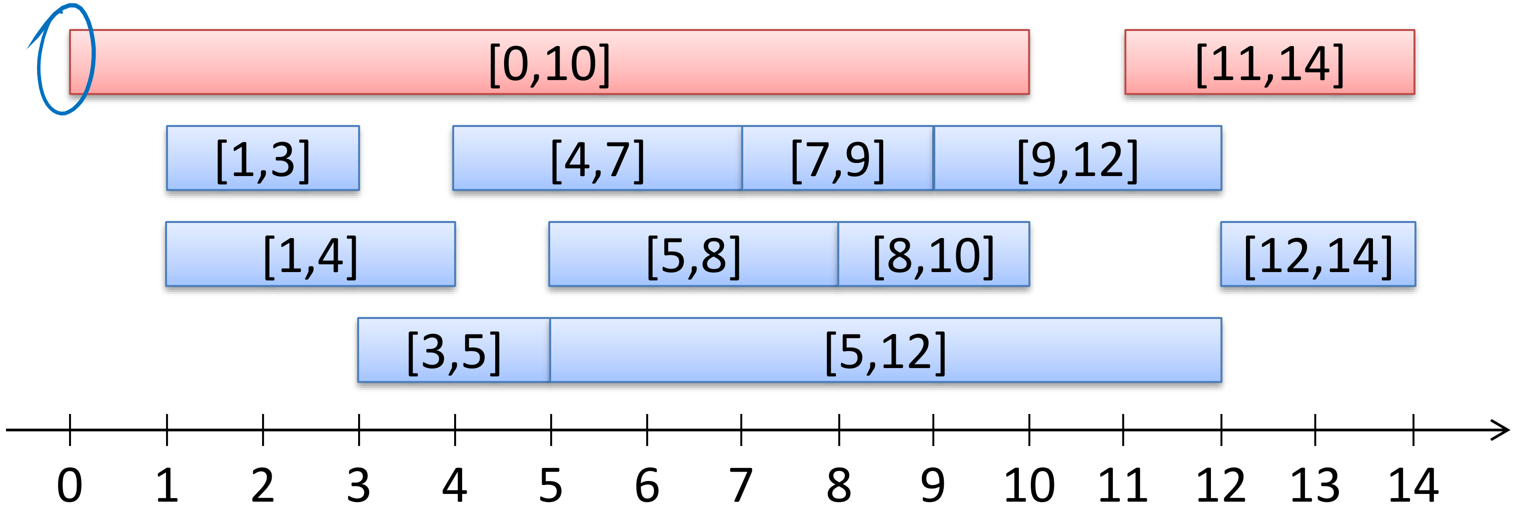
- **Goal:** Select largest possible non-overlapping set of intervals
  - For simplicity: overlap at boundary ok
    (i.e., [4,7] and [7,9] are non-overlapping)

- **Example:** Intervals are room requests; satisfy as many as possible

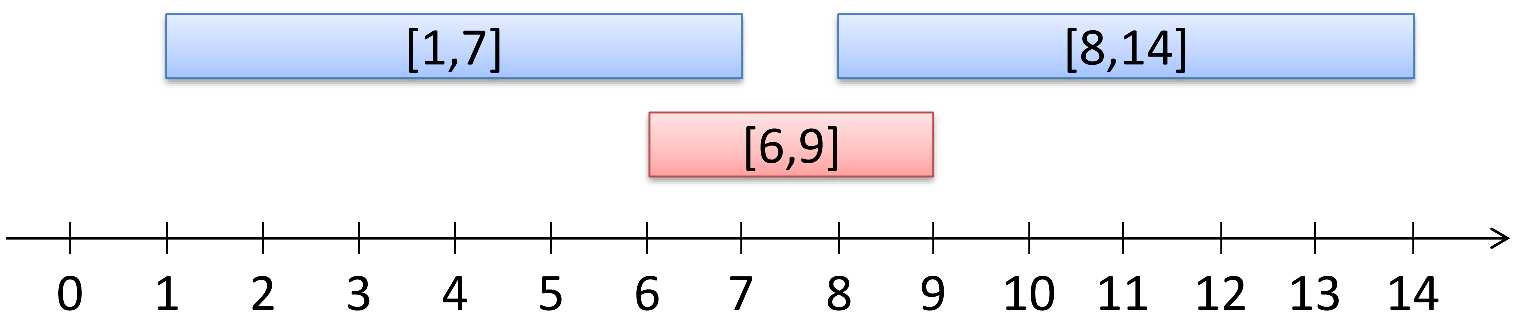
Greedy Algorithms

- Several possibilities…

Choose first available interval:

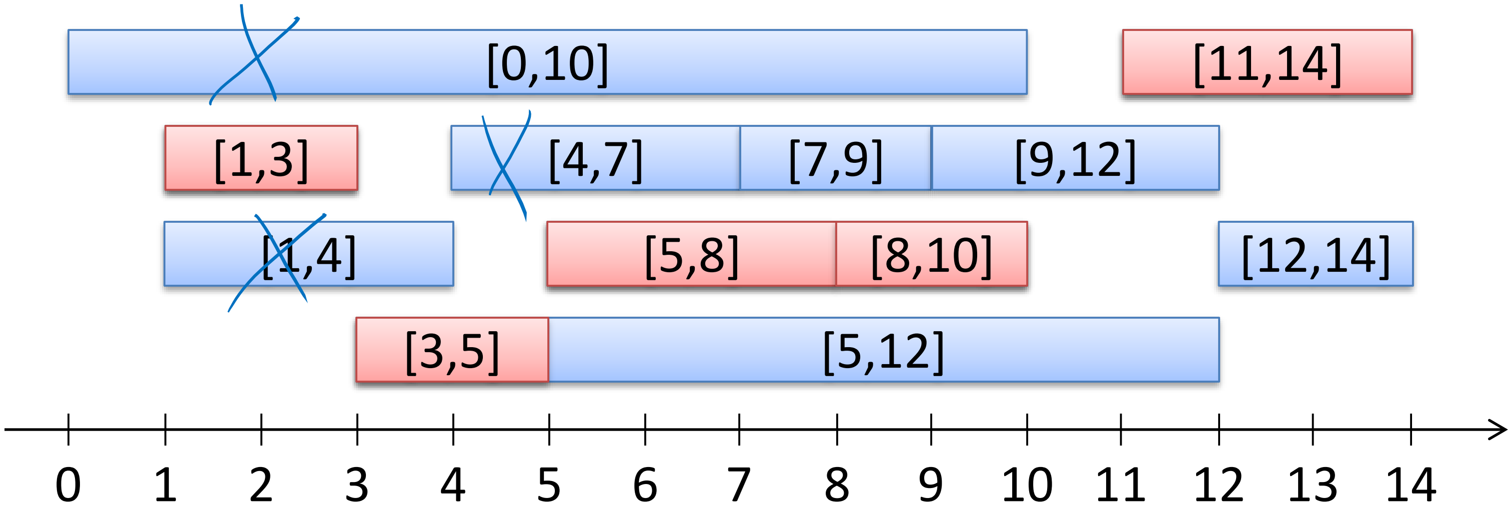


Choose shortest available interval:



Greedy Algorithms

Choose available request with earliest finishing time:

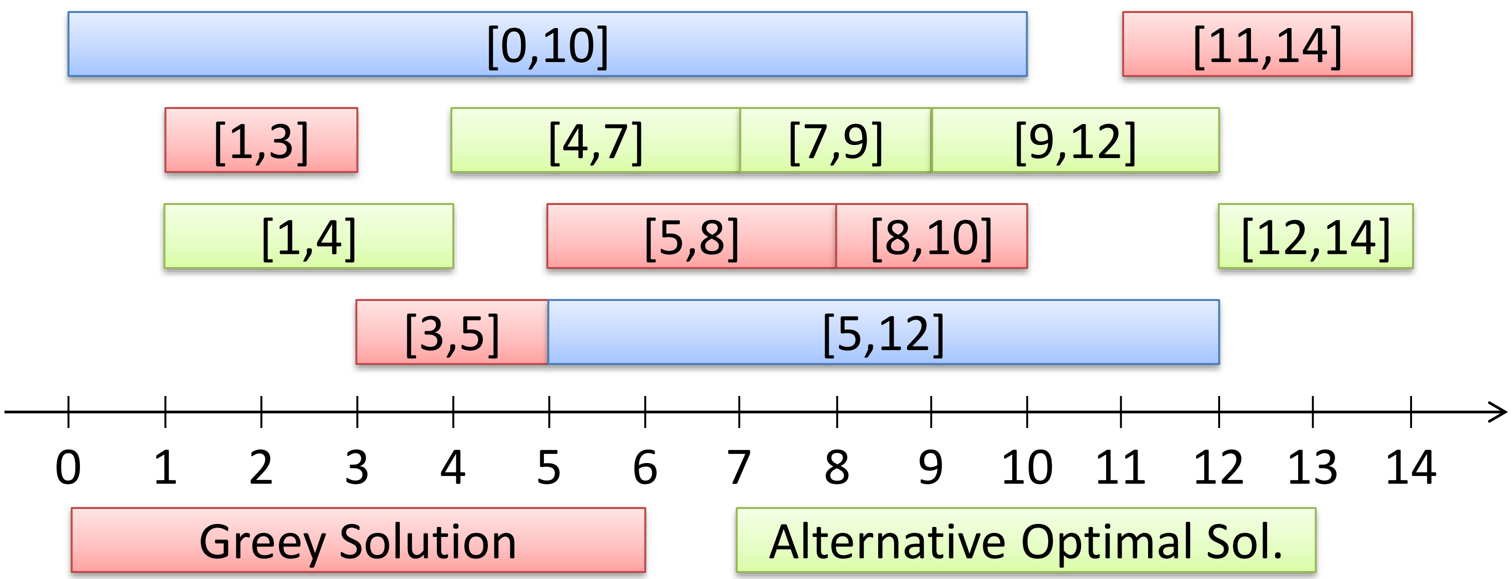


R := set of all requests; S := empty set;
while R is not empty **do**
    choose $r \in R$ with smallest finishing time
    add r to S
    delete all requests from R that are not compatible with r
end   // S is the solution

Earliest Finishing Time is Optimal

- Let O be the set of intervals of an optimal solution

- Can we show that $S = O$?
  - No…



- Show that $|S| = |O|$.

Greedy Stays Ahead

$|S| \geq |O|$

- Greedy solution S: $a_1 \leq b_1 \leq a_2 \leq b_2 \leq \dots$

  $$[a_1, b_1], [a_2, b_2], \dots, [a_{|S|}, b_{|S|}], \qquad \text{where } b_i \leq a_{i+1}$$

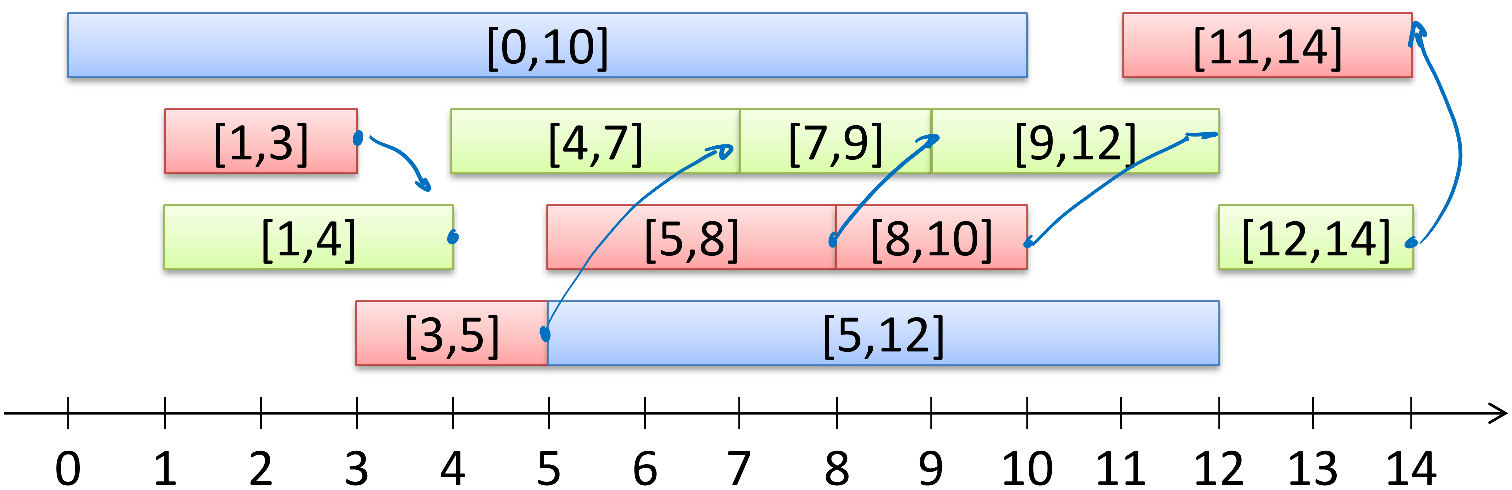
  $b_1 \leq a_2$

- Some optimal solution O:

  $$[a_1^*, b_1^*], [a_2^*, b_2^*], \dots, [a_{|O|}^*, b_{|O|}^*], \qquad \text{where } b_i^* \leq a_{i+1}^*$$

- Definde $b_i := \infty$ for $i > |S|$ and $b_i^* := \infty$ for $i > |O|$

Claim: For all $i \geq 1$, $b_i \leq b_i^*$ $\implies |S| \geq |O|$



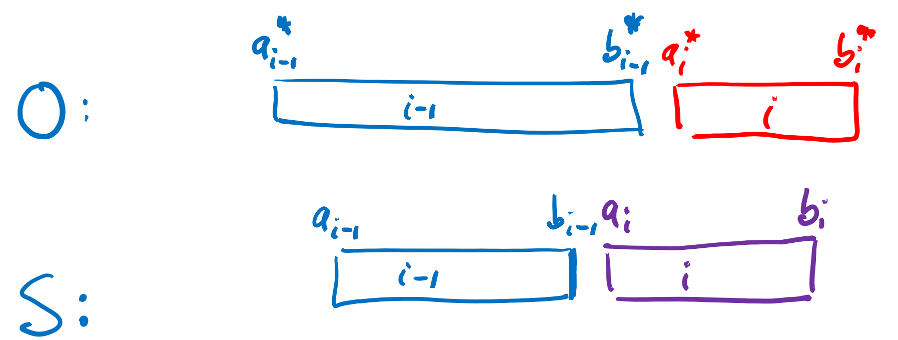
Greedy Stays Ahead

Claim: For all $i \geq 1$, $b_i \leq b_i^*$

Proof (by induction on i):

base: $i=1$ $\quad b_1 \leq b_1^*$

step: $i-1 \rightarrow i$ $\quad$ I.H.: $b_{i-1} \leq b_{i-1}^*$



need to show that

$b_i \leq b_i^*$ ✓

red interval available to greedy because

$b_{i-1} \leq b_{i-1}^* \leq a_i^*$

□

Corollary: Earliest finishing time algorithm is optimal.

Weighted Interval Scheduling

Weighted version of the problem:

- Each interval has a weight
- Goal: Non-overlapping set with maximum total weight

Earliest finishing time greedy algorithm fails:

- Algorithm needs to look at weights
- Else, the selected sets could be the ones with smallest weight…

No simple greedy algorithm:

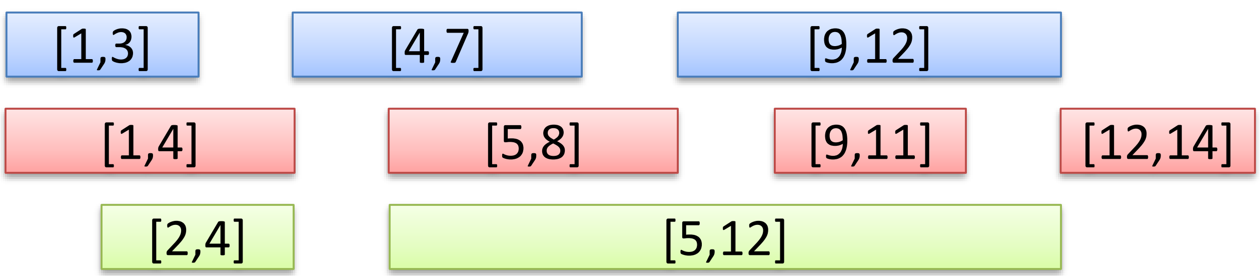
- We will see an algorithm using another design technique later.

Interval Partitioning

- **Schedule all intervals**: Partition intervals into as few as possible non-overlapping sets of intervals
  - Assign intervals to different resources, where each resource needs to get a non-overlapping set

- Example:
  - Intervals are requests to use some room during this time
  - Assign all requests to some room such that there are no conflicts
  - Use as few rooms as possible

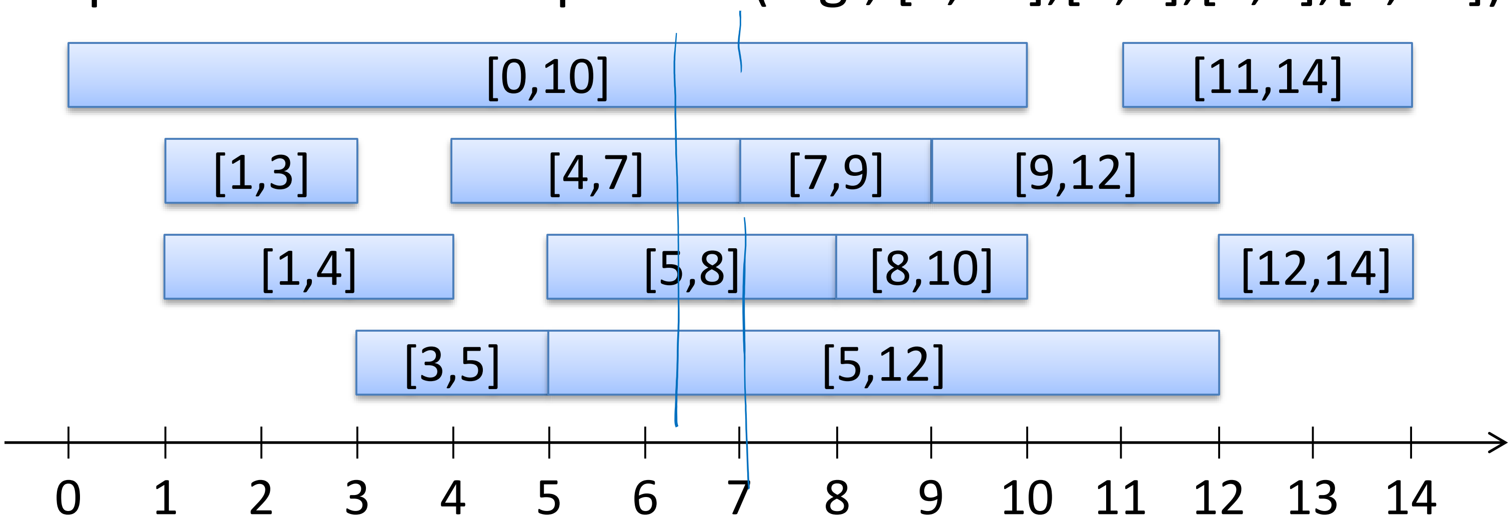
- Assignment to 3 resources:



Depth

Depth of a set of intervals:

- Maximum number passing over a single point in time
- Depth of initial example is 4 (e.g., [0,10],[4,7],[5,8],[5,12]):



Lemma: Number of resources needed $\geq$ depth

Greedy Algorithm

Can we achieve a partition into "depth" non-overlapping sets?

- Would mean that the only obstacles to partitioning are local…

Algorithm:

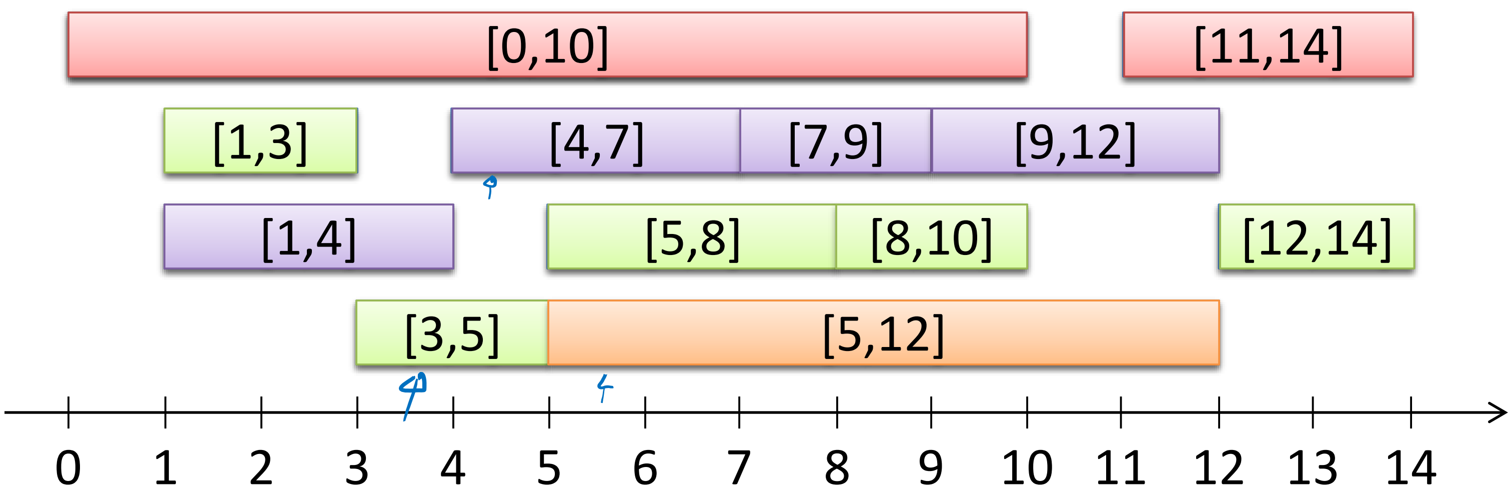
- Assign labels 1, … to the intervals; same label → non-overlapping

1. sort intervals by starting time: $I_1, I_2, \dots, I_n$
2. **for** $i = 1$ **to** n **do**
3. assign smallest possible label to I_i
   (possible label: different from conflicting intervals $I_j, j < i$)
4. **end**

Interval Partitioning Algorithm

Example:

- Labels:



- Number of labels = depth = 4

Interval Partitioning: Analysis

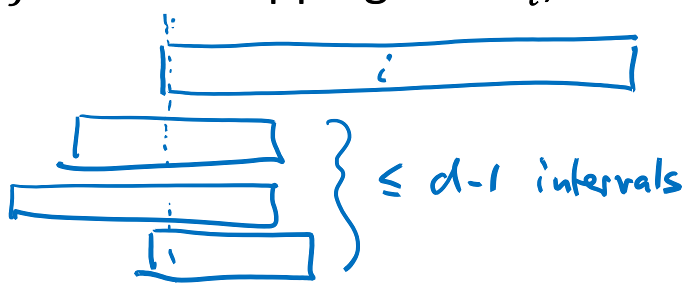
Theorem:

a) Let d be the depth of the given set of intervals. The algorithm assigns a label from $1, \dots, d$ to each interval.

b) Sets with the same label are non-overlapping

Proof:

- b) holds by construction
- For a):
  - All intervals $I_j, j < i$ overlapping with I_i, overlap at the beginning of I_i

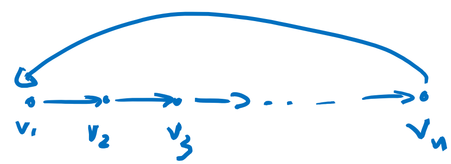


  - At most $d - 1$ such intervals → some label in $\{1, \dots, d\}$ is available.

Traveling Salesperson Problem (TSP)

Input:

- Set V of n nodes (points, cities, locations, sites)
- Distance function $d: V \times V \to \mathbb{R}^{+}$, i.e., $d(u,v)$: dist. from u to v
- Distances usually symmetric, asymm. distances → asymm. TSP



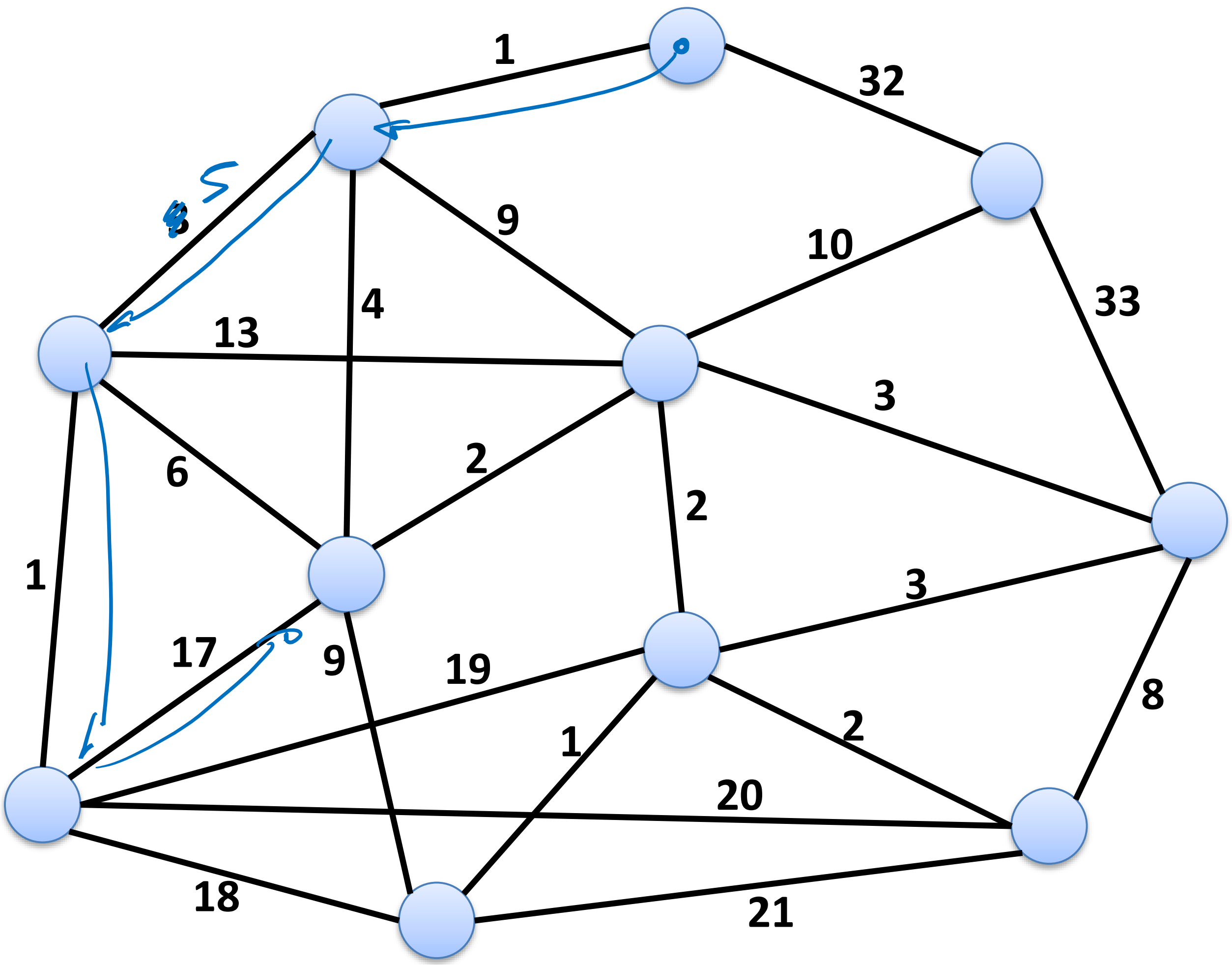
Solution:

- Ordering/permutation $v_1, v_2, \dots, v_n$ of nodes
- Length of TSP path: $\sum_{i=1}^{n-1} d(v_i, v_{i+1})$
- Length of TSP tour: $d(v_n, v_1) + \sum_{i=1}^{n-1} d(v_i, v_{i+1})$

Goal:

- Minimize length of TSP path or TSP tour

Example



Optimal Tour:

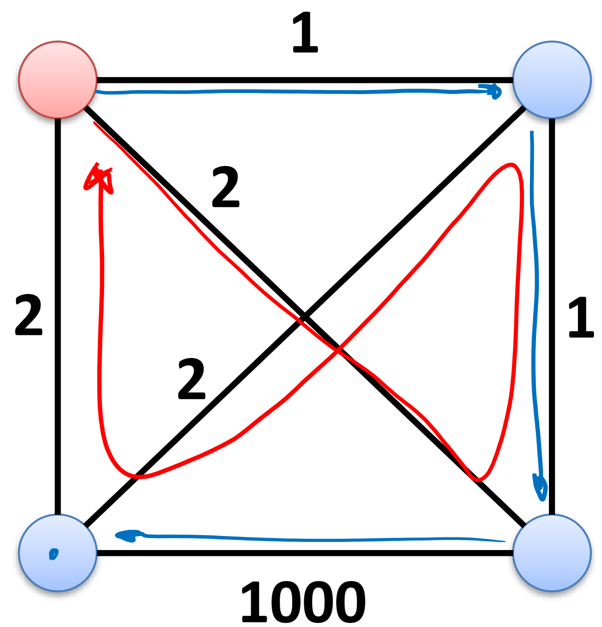
Length: 86

Greedy Algorithm?

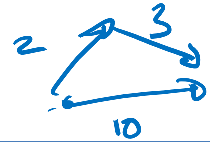
Length: 121

Nearest Neighbor (Greedy)

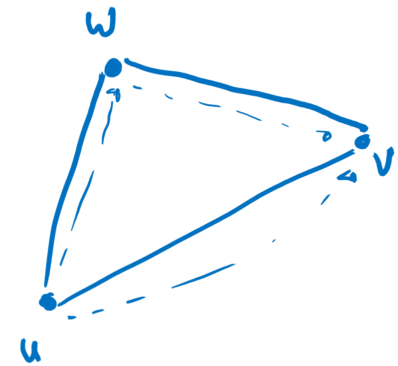
- Nearest neighbor can be arbitrarily bad, even for TSP paths



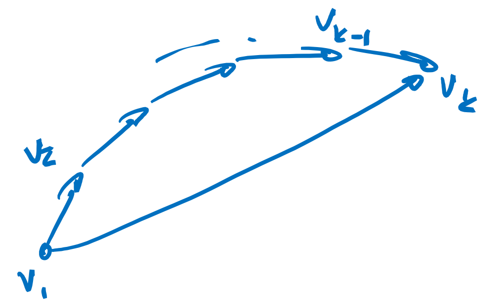
TSP Variants



- Asymmetric TSP
  - arbitrary non-negative distance/cost function
  - most general, nearest neighbor arbitrarily bad
  - NP-hard to get within any bound of optimum



- Symmetric TSP
  - arbitrary non-negative distance/cost function
  - nearest neighbor arbitrarily bad
  - NP-hard to get within any bound of optimum

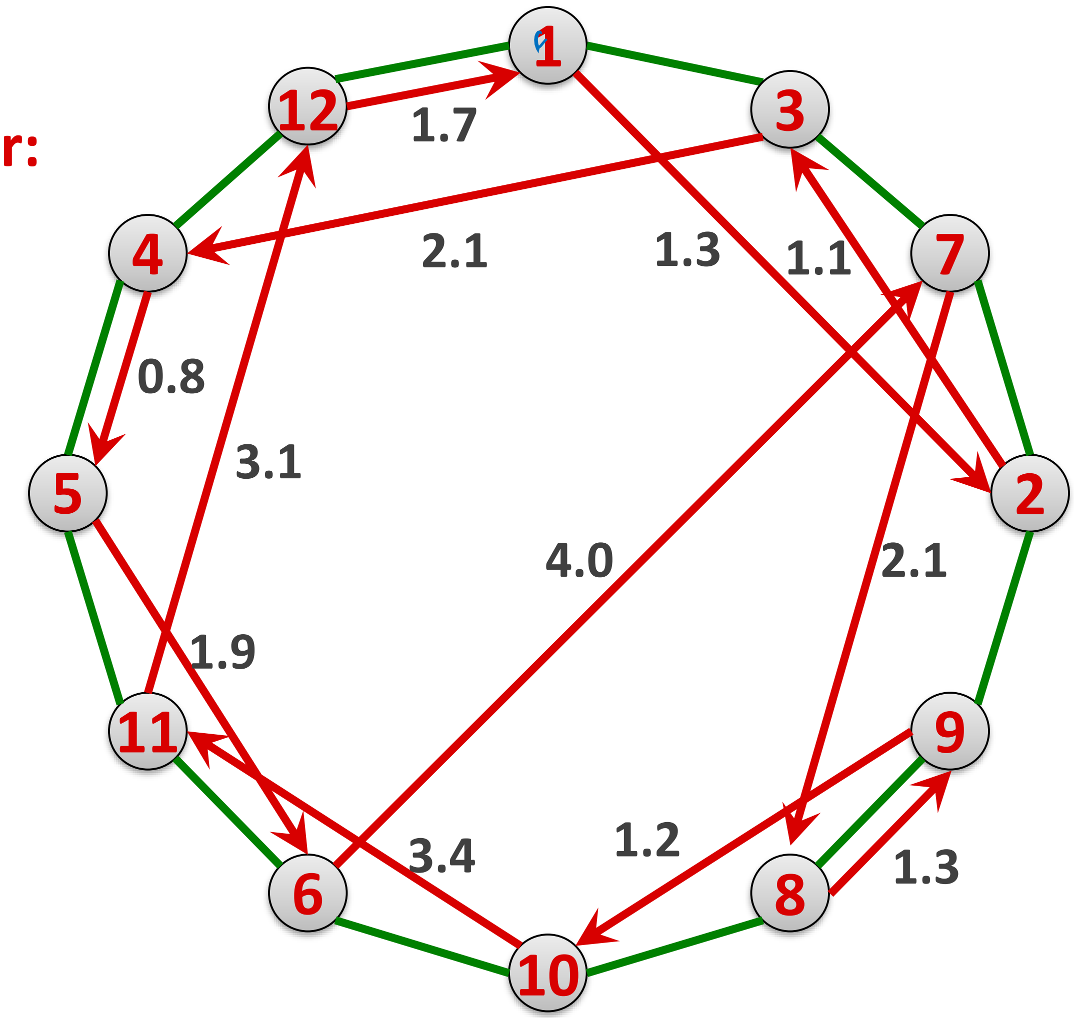


- Metric TSP
  - distance function defines metric space: symmetric, non-negative, triangle inequality: $d(u,v) \leq d(u,w) + d(w,v)$
  - possible to get close to optimum (we will later see factor $^3/_2$)
  - what about the nearest neighbor algorithm?

Metric TSP, Nearest Neighbor

Optimal TSP tour:

Nearest-Neighbor TSP tour:



Metric TSP, Nearest Neighbor

Optimal TSP tour:

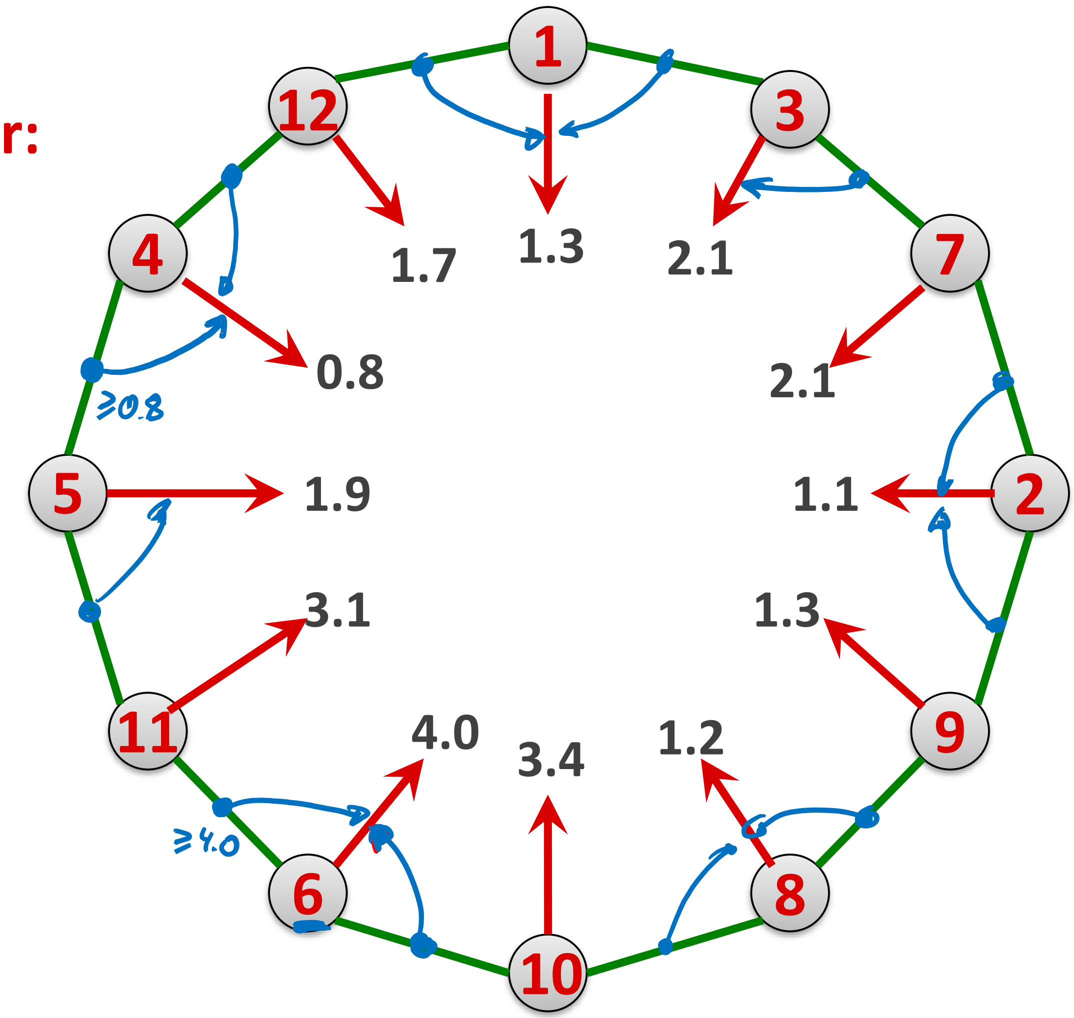
Nearest-Neighbor TSP tour:

cost = 24

marked red edge: arrow to it

green edges ≥ marked red edges

marked red edges: at least half



Metric TSP, Nearest Neighbor

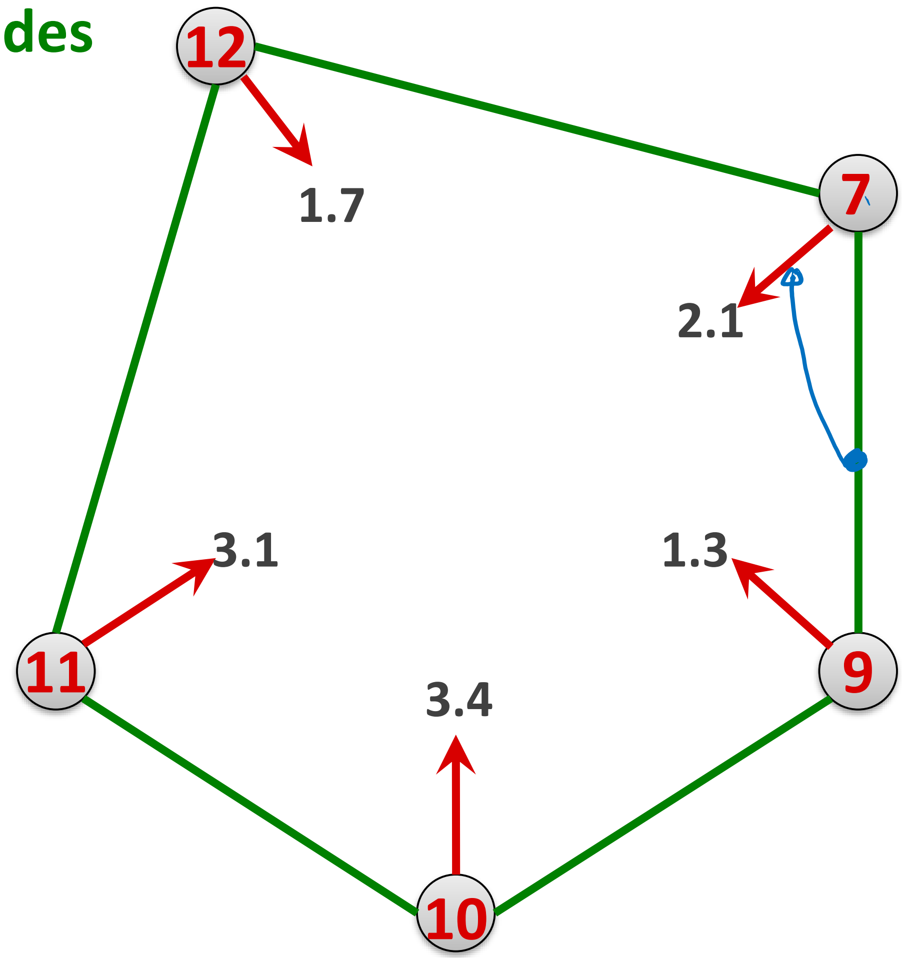
Triangle Inequality:

optimal tour on remaining nodes

$\leq$

overall optimal tour

green ≥ marked red



Metric TSP, Nearest Neighbor

Analysis works in phases:

- In each phase, assign each optimal edge to some greedy edge
  - Cost of greedy edge $\leq$ cost of optimal edge
- Each greedy edge gets assigned ≤ 2 optimal edges
  - At least half of the greedy edges get assigned
- At end of phase:
  Remove points for which greedy edge is assigned
  Consider optimal solution for remaining points
- **Triangle inequality:** remaining opt. solution $\leq$ overall opt. sol.

- Cost of greedy edges assigned in **each phase $\leq$ opt. cost**
- **Number of phases $\leq \log_2 n$**
  - +1 for last greedy edge in tour

Metric TSP, Nearest Neighbor

- Assume:

  NN: cost of greedy tour, OPT: cost of optimal tour

- We have shown:

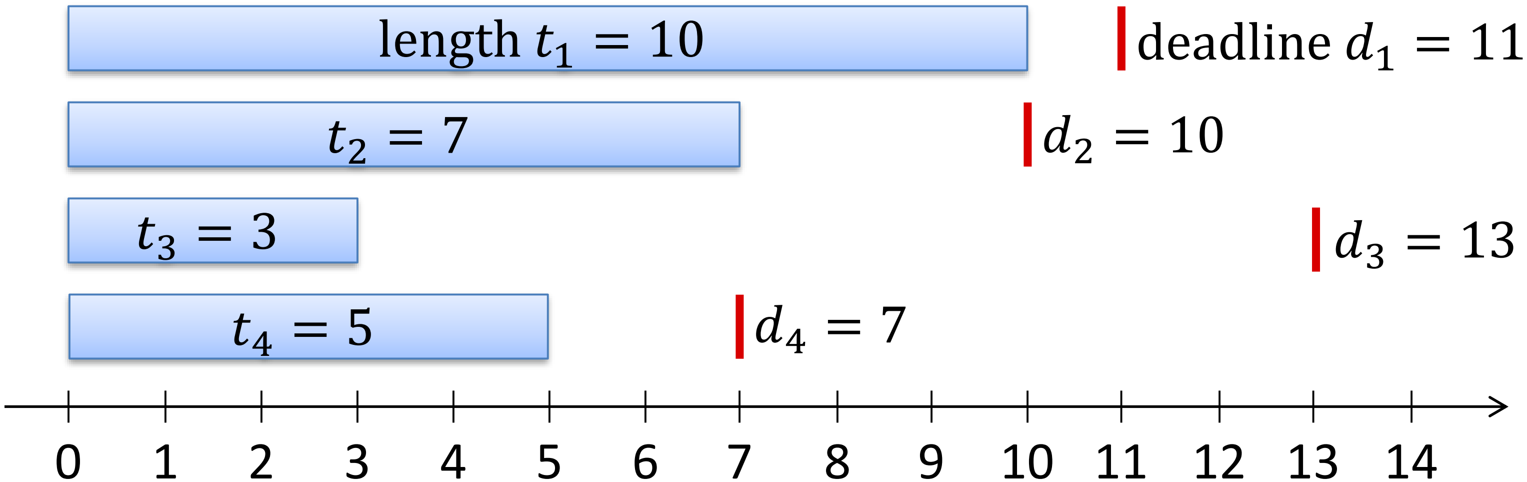
$$\frac{\mathrm{NN}}{\mathrm{OPT}} \leq \underbrace{1 + \log_2 n}_{\text{approximation ratio}}$$

- Example of an **approximation algorithm**

- We will later see a $^3/_2$-approximation algorithm for metric TSP

Back to Scheduling

- Given: n requests / jobs with deadlines:



- Goal: schedule all jobs with minimum lateness L
  - Schedule: $s(i), f(i)$: start and finishing times of request i
    Note: $f(i) = s(i) + t_i$ lateness of job i : $\max\{f(i) - d_i, 0\}$

- Lateness $L := \max\left\{0, \max_i\{f(i) - d_i\}\right\}$
  - largest amount of time by which some job finishes late

- Many other natural objective functions possible…

Greedy Algorithm?

Schedule jobs in order of increasing length?

- Ignores deadlines: seems too simplistic…
- E.g.:

$t_1 = 10$ deadline $d_1 = 10$

$t_2 = 2$ … $d_2 = 100$

L

Schedule: $t_2 = 2$ $t_1 = 10$

Schedule by increasing slack time?

- Should be concerned about slack time: $d_i - t_i$

$t_1 = 10$ deadline $d_1 = 10$

$t_2 = 2$ $d_2 = 3$

$L = 9$

Schedule: $t_1 = 10$ $t_2 = 2$

Greedy Algorithm

Schedule by earliest deadline?

- Schedule in increasing order of d_i
- Ignores lengths of jobs: too simplistic?

- Earliest deadline is optimal!

Algorithm:

- Assume jobs are reordered such that $d_1 \leq d_2 \leq \cdots \leq d_n$
- Start/finishing times:
  - First job starts at time $s(1) = 0$
  - Duration of job i is t_i: $f(i) = s(i) + t_i$
  - No gaps between jobs: $s(i+1) = f(i)$

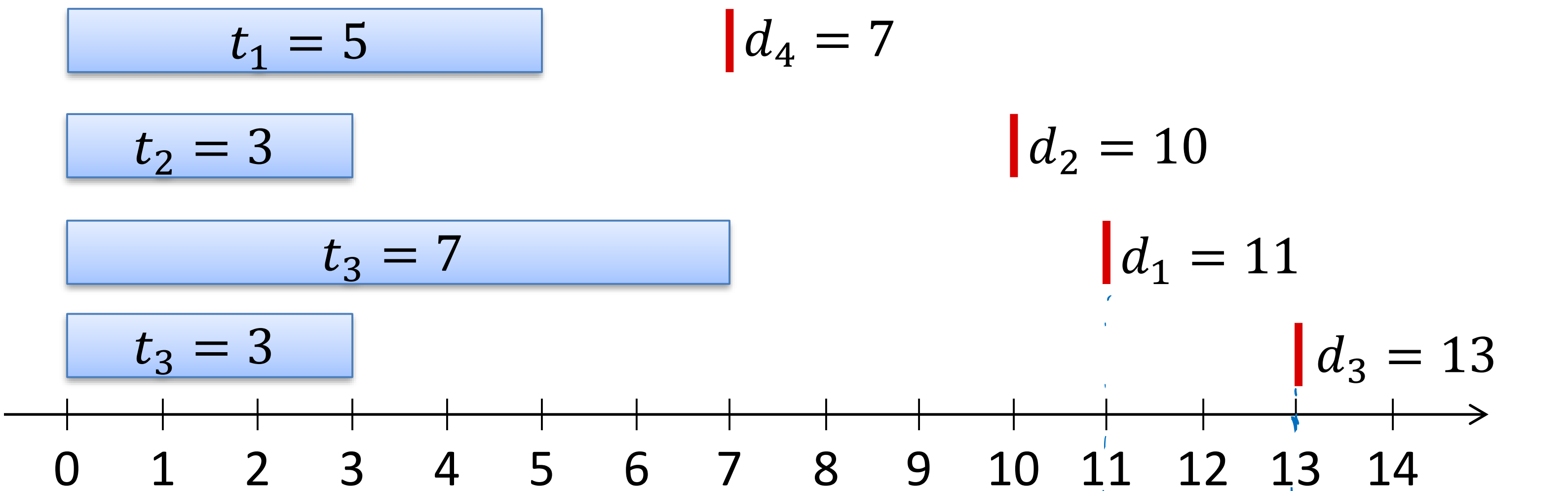
$f(1) = s(1) + t_1 = t_1$

$s(2) = f(1)$

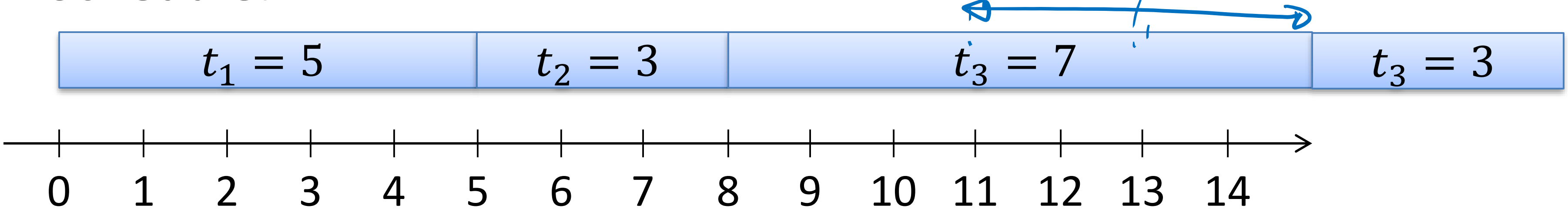
(idle time: gaps in a schedule → alg. gives schedule with no idle time)

Example

Jobs ordered by deadline:



Schedule:

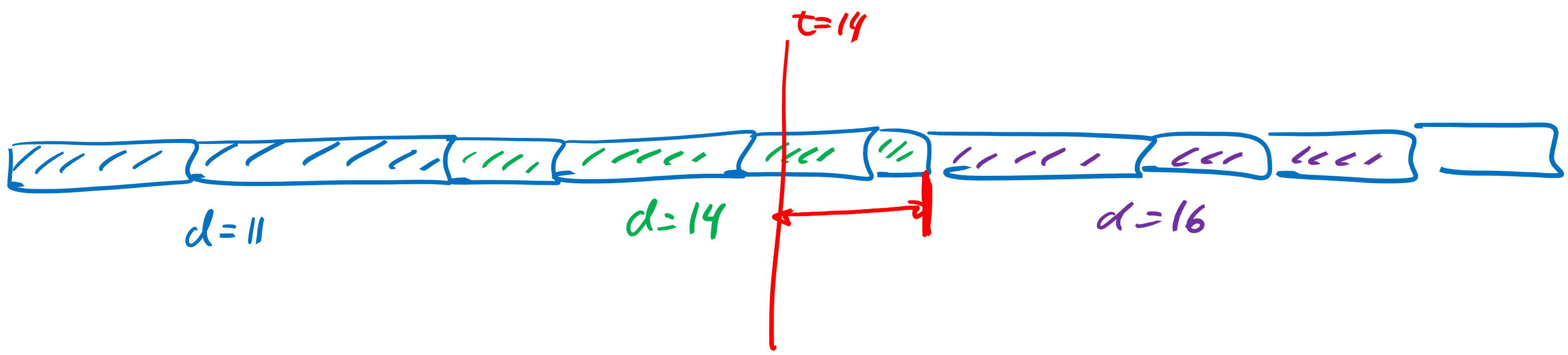


Lateness: job 1: 0, job 2: 0, job 3: 4, job 4: 5

Basic Facts

1. There is an optimal schedule with no idle time
   – Can just schedule jobs earlier…

2. Inversion: Job i scheduled before job j if $d_i > d_j$
   Schedules with no inversions have the same maximum lateness



Earliest Deadline is Optimal

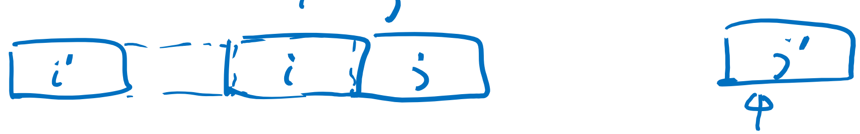
Theorem:
There is an optimal schedule $\mathcal{O}$ with no inversions and no idle time.

Proof:

- Consider some schedule $\mathcal{O}'$ with no idle time
- If $\mathcal{O}'$ has inversions, $\exists$ pair (i, j), s.t. i is scheduled immediately before j and $d_j < d_i$

$d_{i'} > d_{j'}$

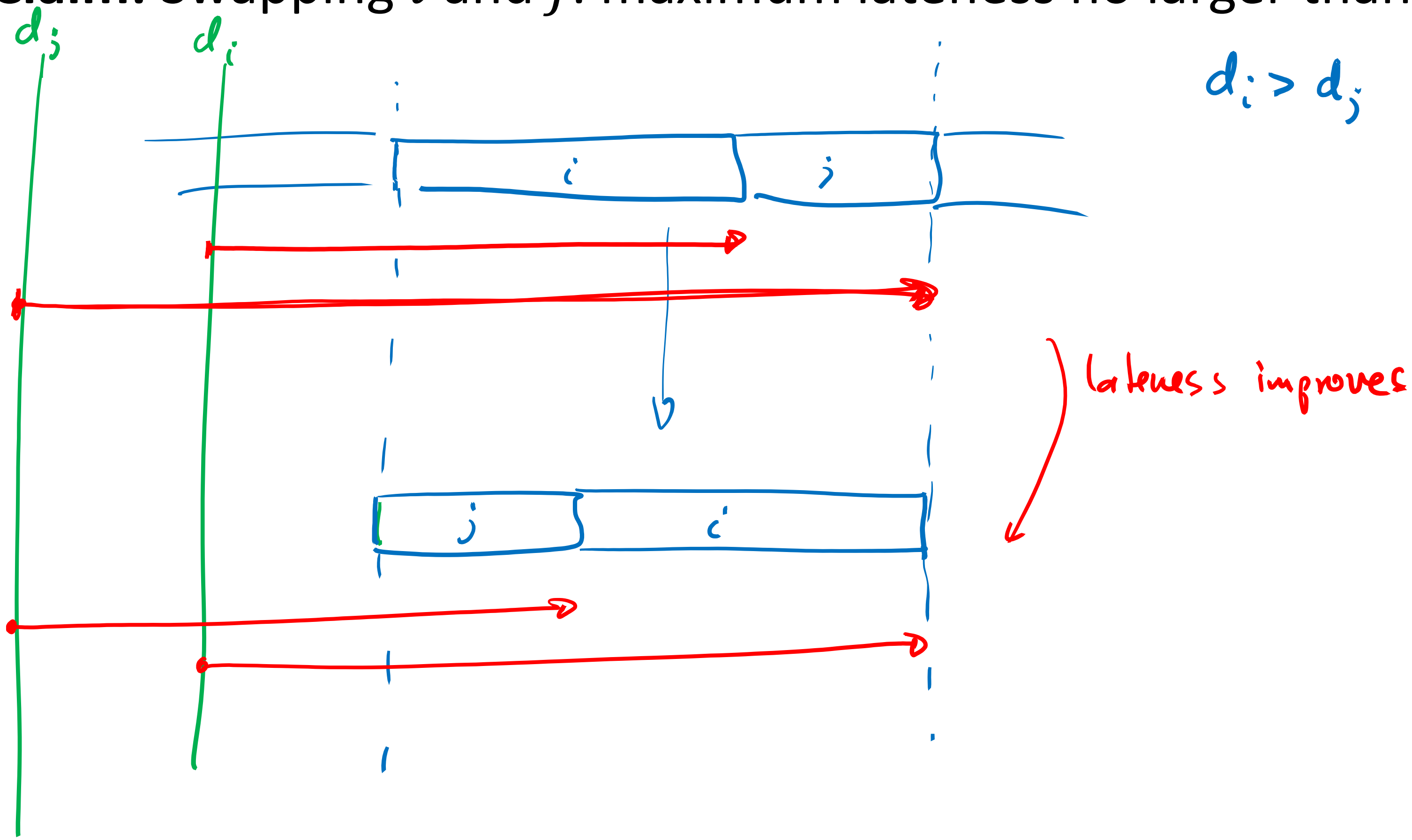
$d_i > d_j$



- Claim: Swapping i and j gives a schedule with
  1. Fewer inversions
  2. Maximum lateness no larger than in $\mathcal{O}'$

Earliest Deadline is Optimal

Claim: Swapping i and j: maximum lateness no larger than in $\mathcal{O}'$



Exchange Argument

- General approach that often works to analyze greedy algorithms

- Start with any solution
- Define basic exchange step that allows to transform solution into a new solution that is not worse
- Show that exchange step move solution closer to the solution produced by the greedy algorithm
- Number of exchange steps to reach greedy solution should be finite…

Another Exchange Argument Example

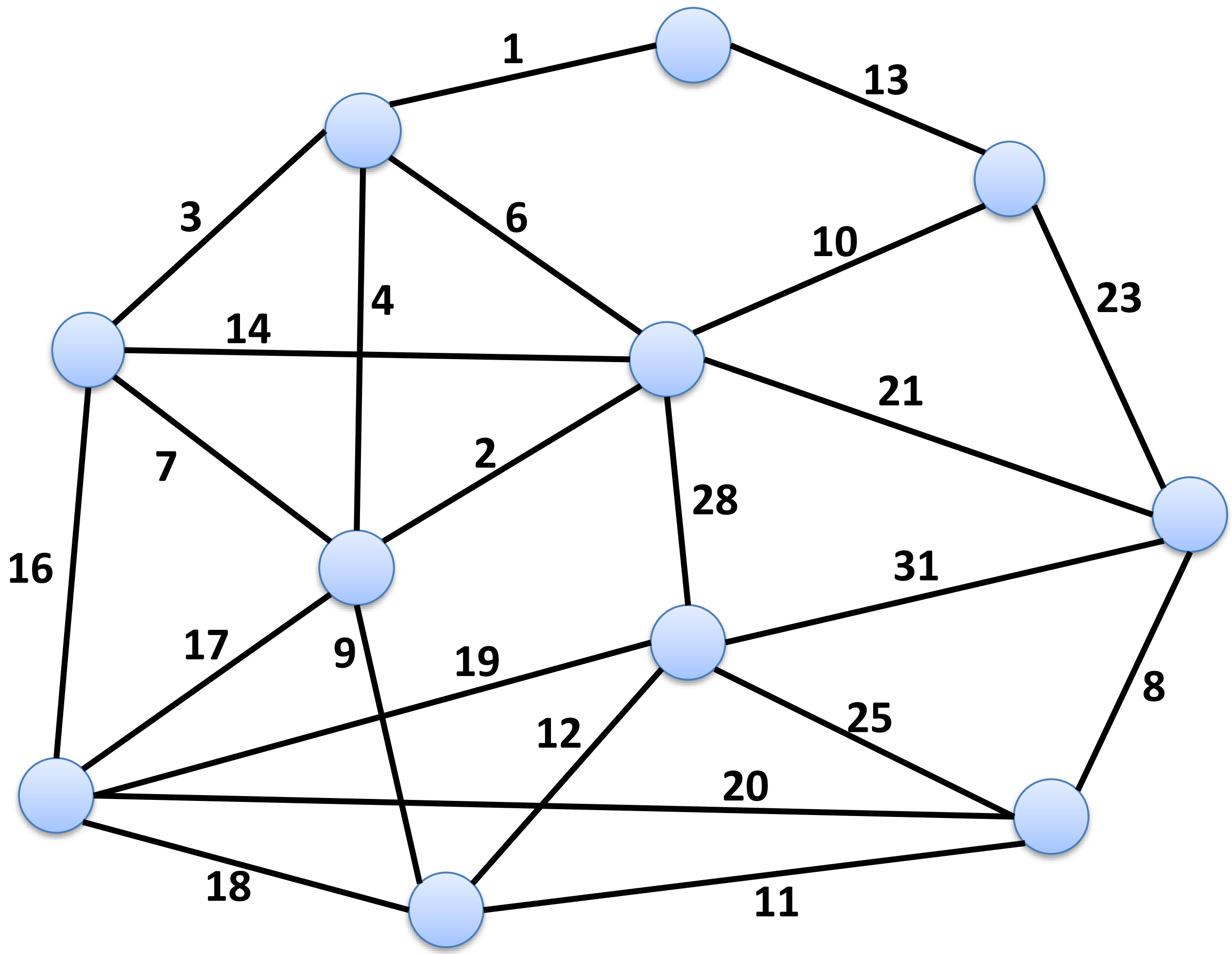
- **Minimum spanning tree (MST)** problem
  - Classic graph-theoretic optimization problem

- **Given**: weighted graph
- **Goal**: spanning tree with min. total weight

- Several greedy algorithms work

- Kruskal's algorithm:
  - Start with empty edge set
  - As long as we do not have a spanning tree:
    add minimum weight edge that doesn't close a cycle

Kruskal Algorithm: Example



Kruskal is Optimal

- Basic exchange step: swap to edges to get from tree T to tree T'
  - Swap out edge not in Kruskal tree, swap in edge in Kruskal tree
  - Swapping does not increase total weight
- For simplicity, assume, weights are unique: