Chapter 2
Greedy Algorithms

Algorithm Theory
WS 2018/19

Fabian Kuhn

Greedy Algorithms

- No clear definition, but essentially:

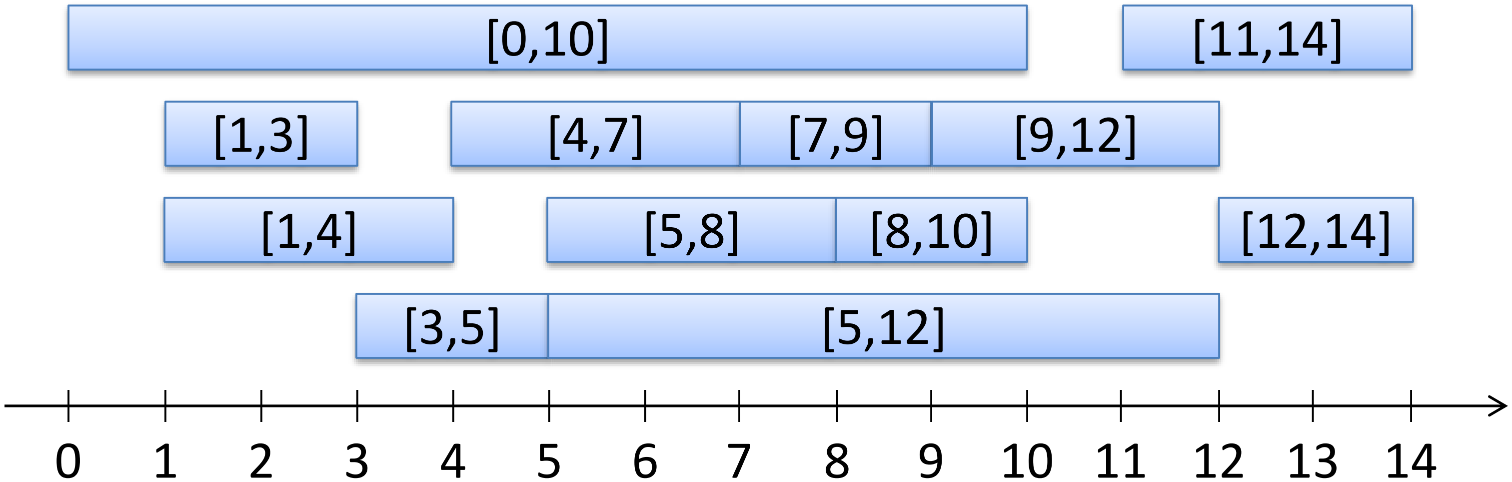
In each step make the choice that looks best at the moment!

- 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)

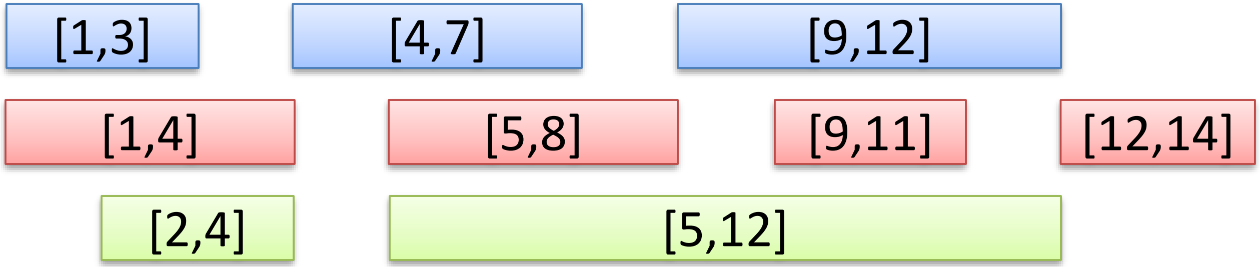
- **Example:** Intervals are room requests; satisfy as many as possible

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

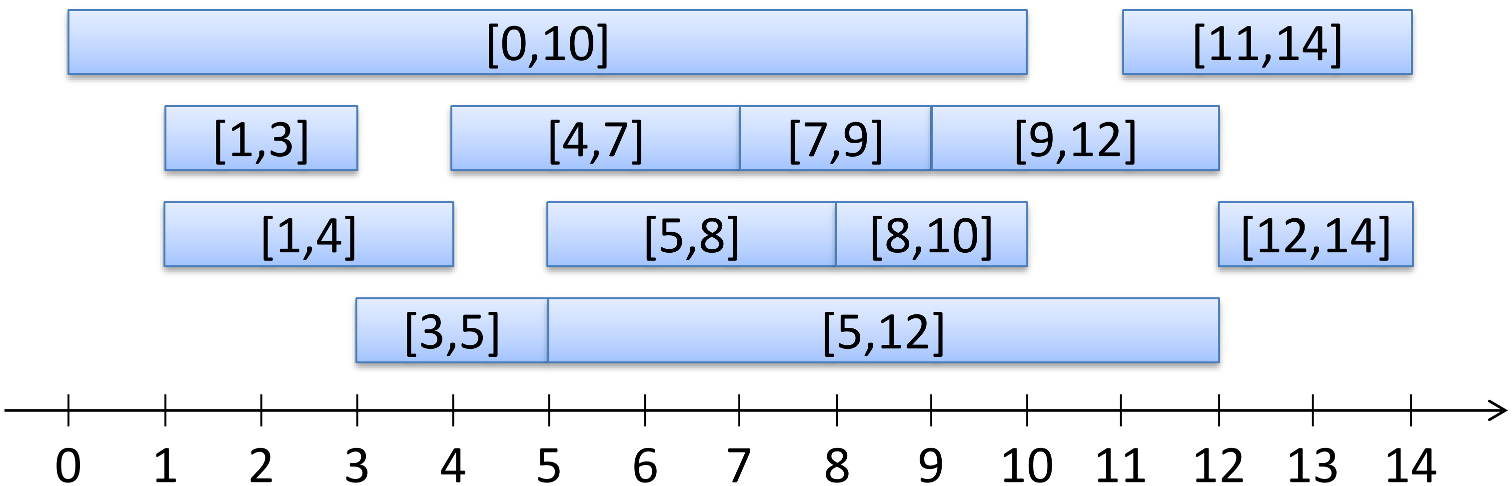
- Assignment to 3 resources:



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:

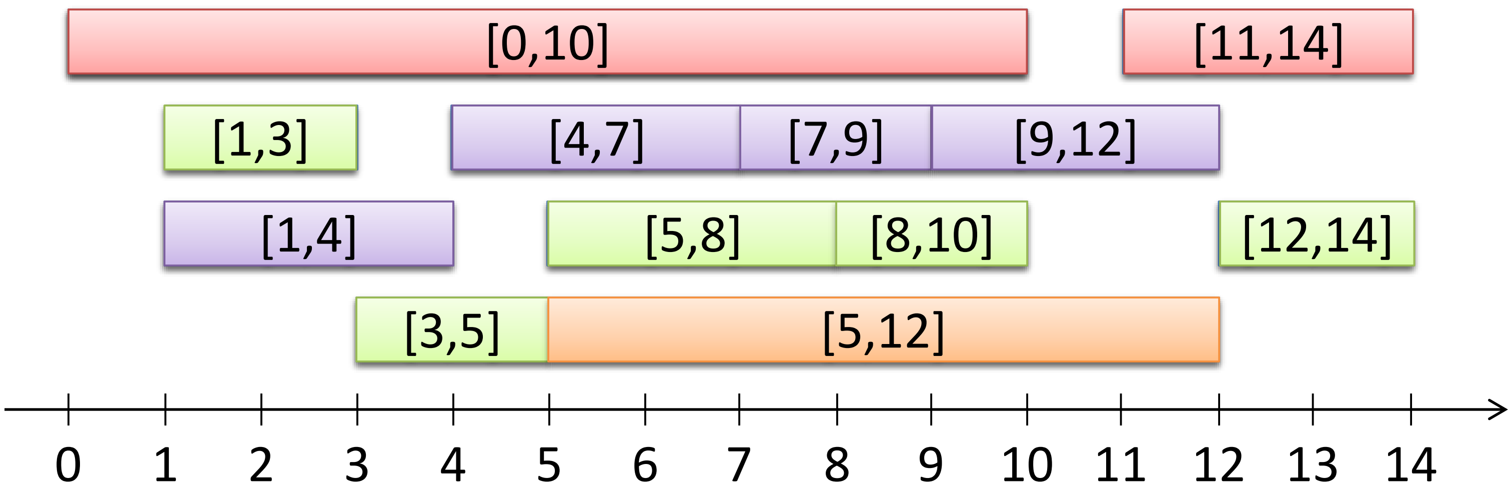
- Assign labels 1, … to the intervals; same label → non-overlapping

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

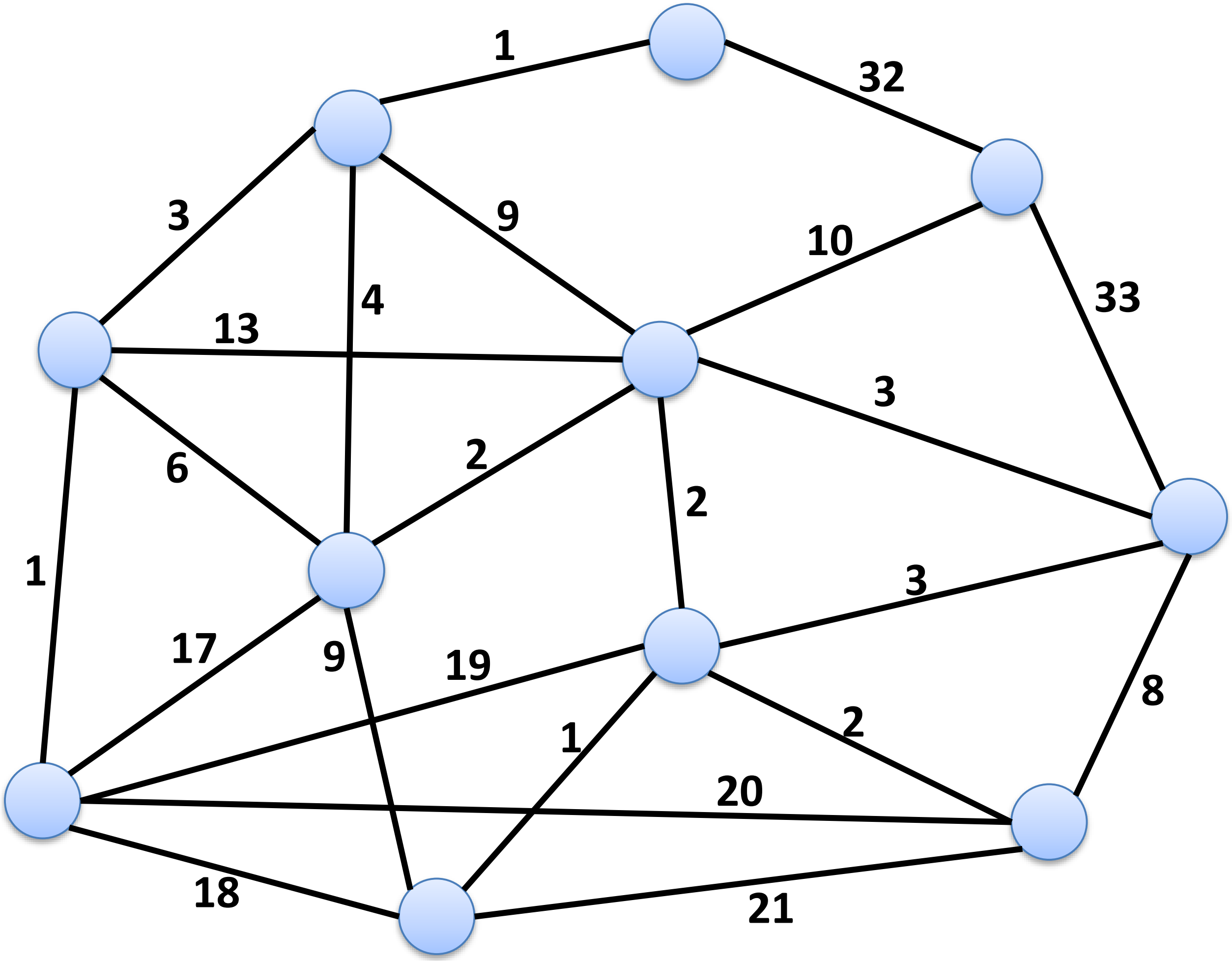
Solution:

- 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:

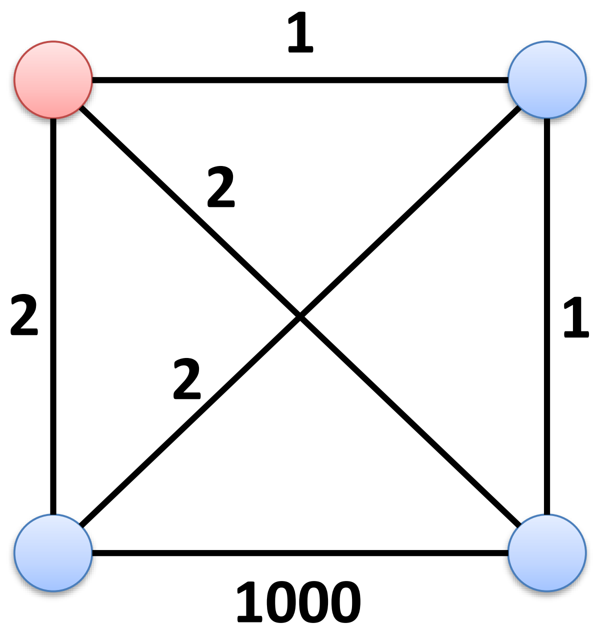
Length: 86

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

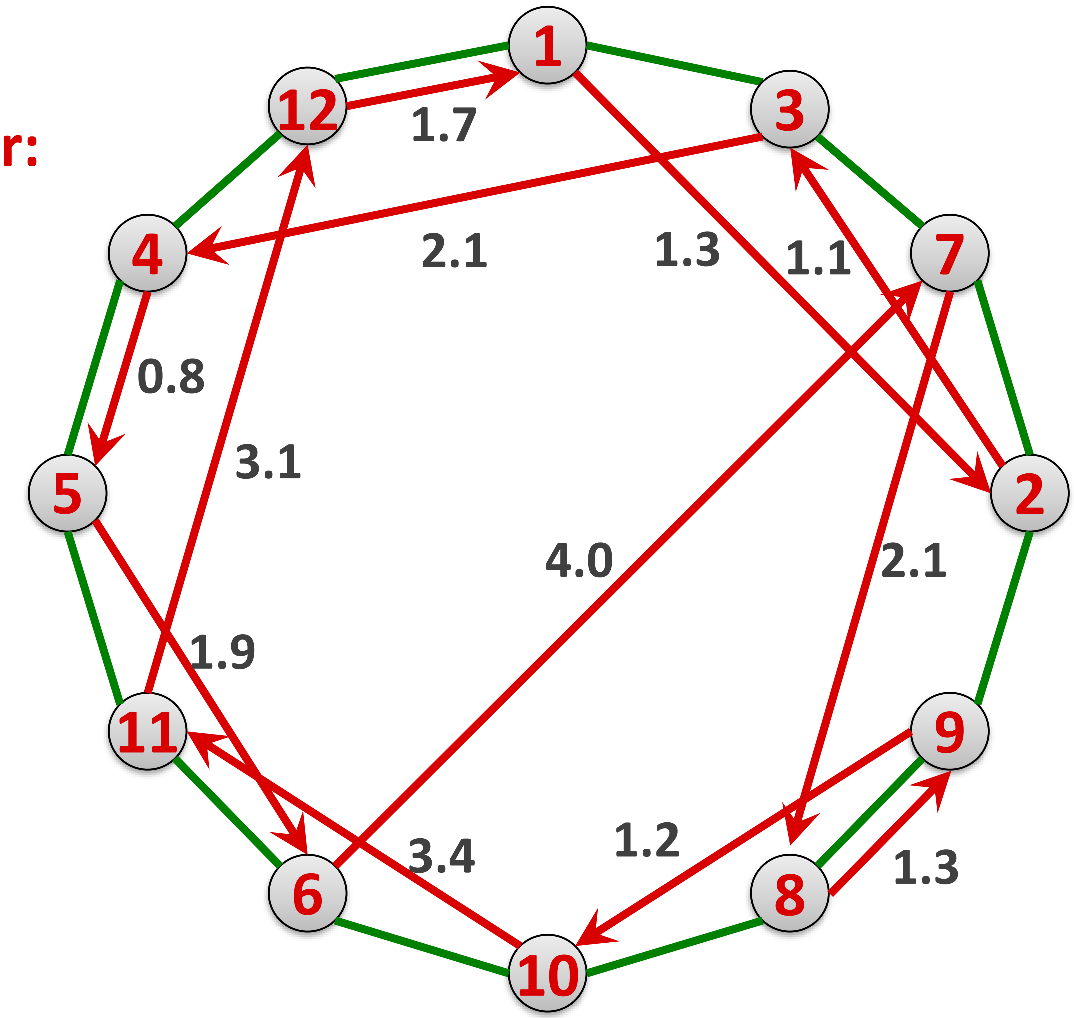
- Symmetric TSP
  - arbitrary non-negative distance/cost function
  - nearest neighbor arbitrarily bad
  - NP-hard to get within any bound of optimum

- 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:

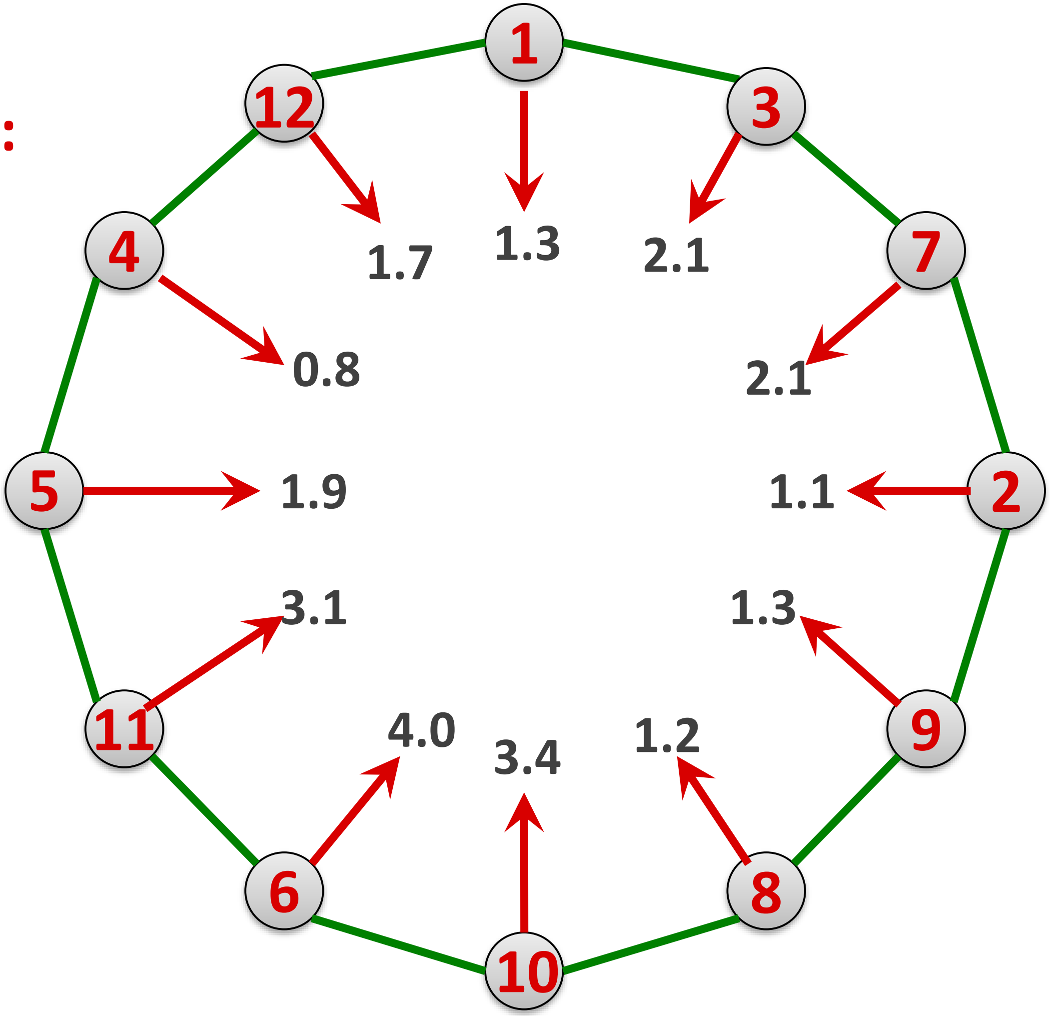


Metric TSP, Nearest Neighbor

Optimal TSP tour:

Nearest-Neighbor TSP tour:

cost = 24



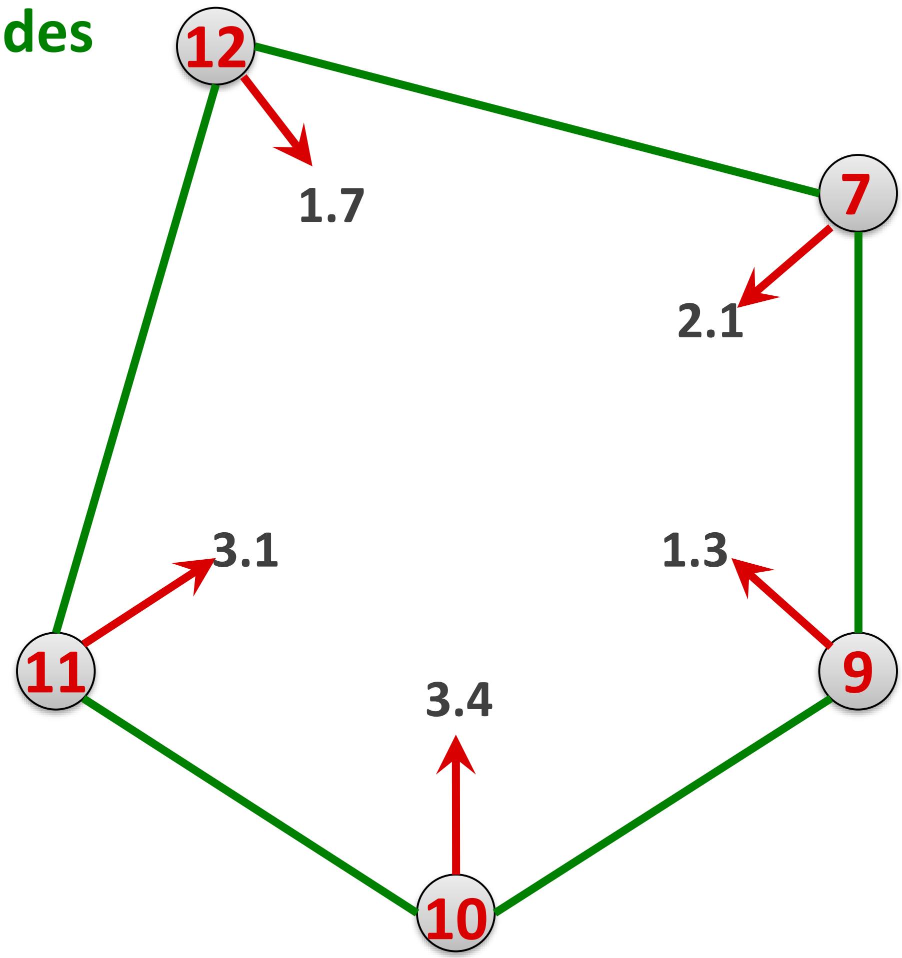
Metric TSP, Nearest Neighbor

Triangle Inequality:

optimal tour on remaining nodes

$\leq$

overall optimal tour



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:

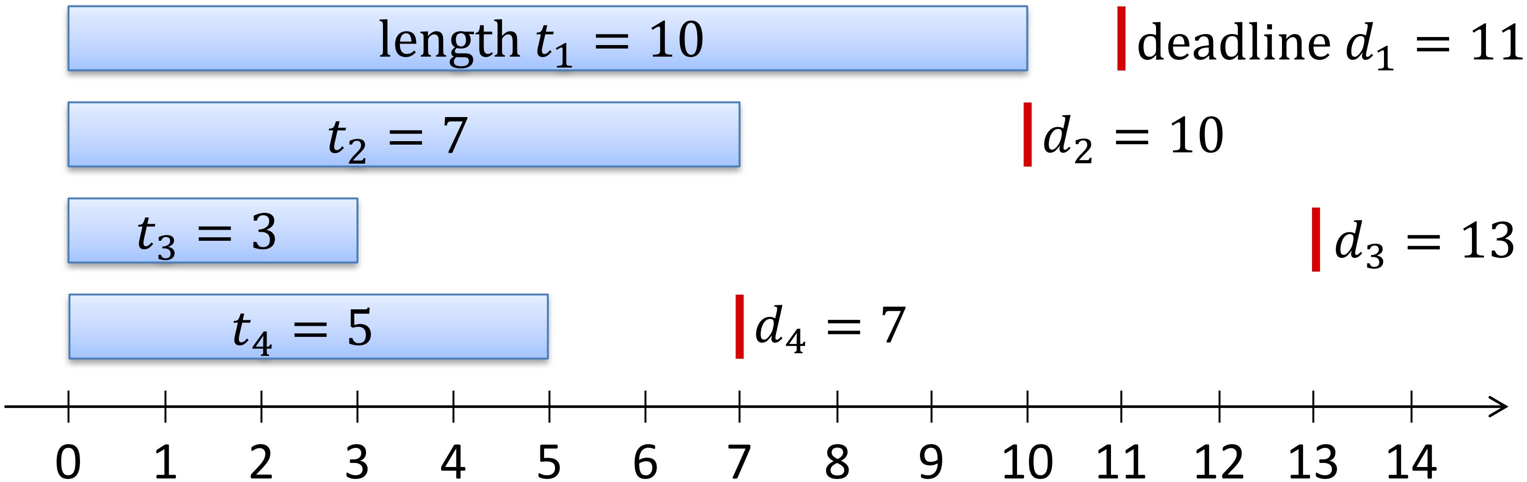
$$\frac{\text{NN}}{\text{OPT}} \leq 1 + \log_2 n$$

- 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: $f(i) = s(i) + t_i$

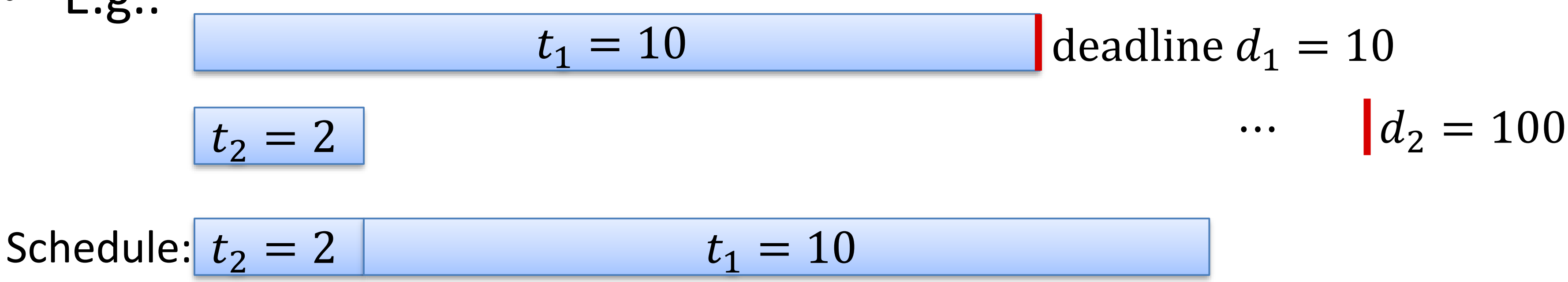
- Lateness $L := \max\left\{0, \max_i \{f(i) - d_i\}\right\}$
  - largest amount of time by which some job finishes late

- Many other natural objective functions possible…

Greedy Algorithm?

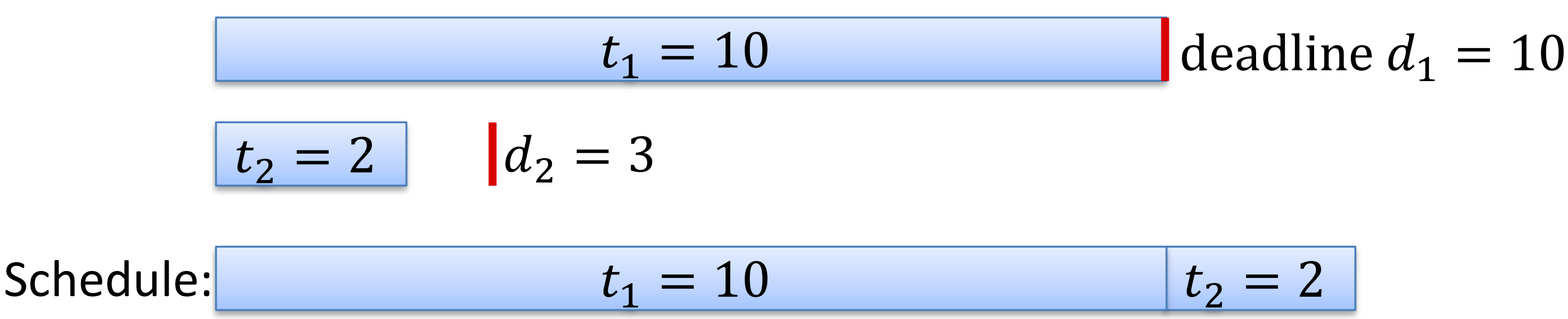
Schedule jobs in order of increasing length?

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



Schedule by increasing slack time?

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



Greedy Algorithm

Schedule by earliest deadline?

- Schedule in increasing order of d_i
- Ignores lengths of jobs: too simplistic?
- Earliest deadline is optimal!

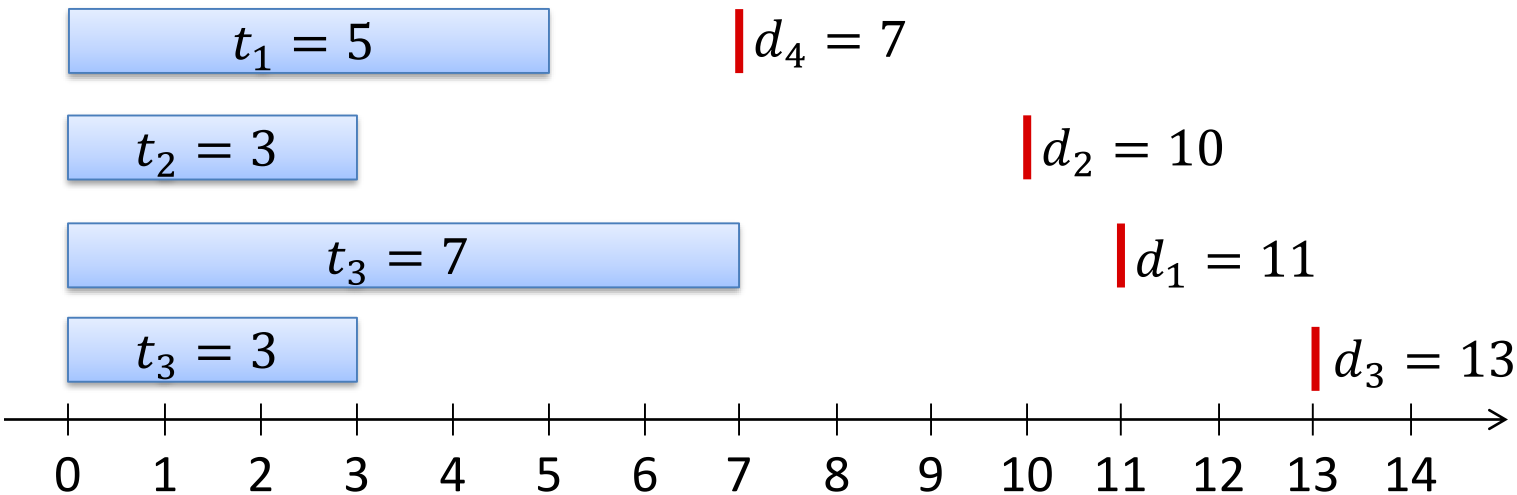
Algorithm:

- 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: $s(i+1) = f(i)$

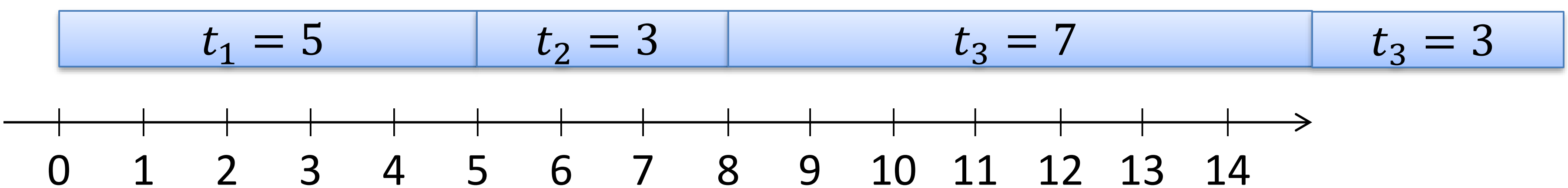
  (idle time: gaps in a schedule → alg. gives schedule with no idle time)

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, ∃ pair (i, j), s.t. i is scheduled immediately before j and $d_j < d_i$

- 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

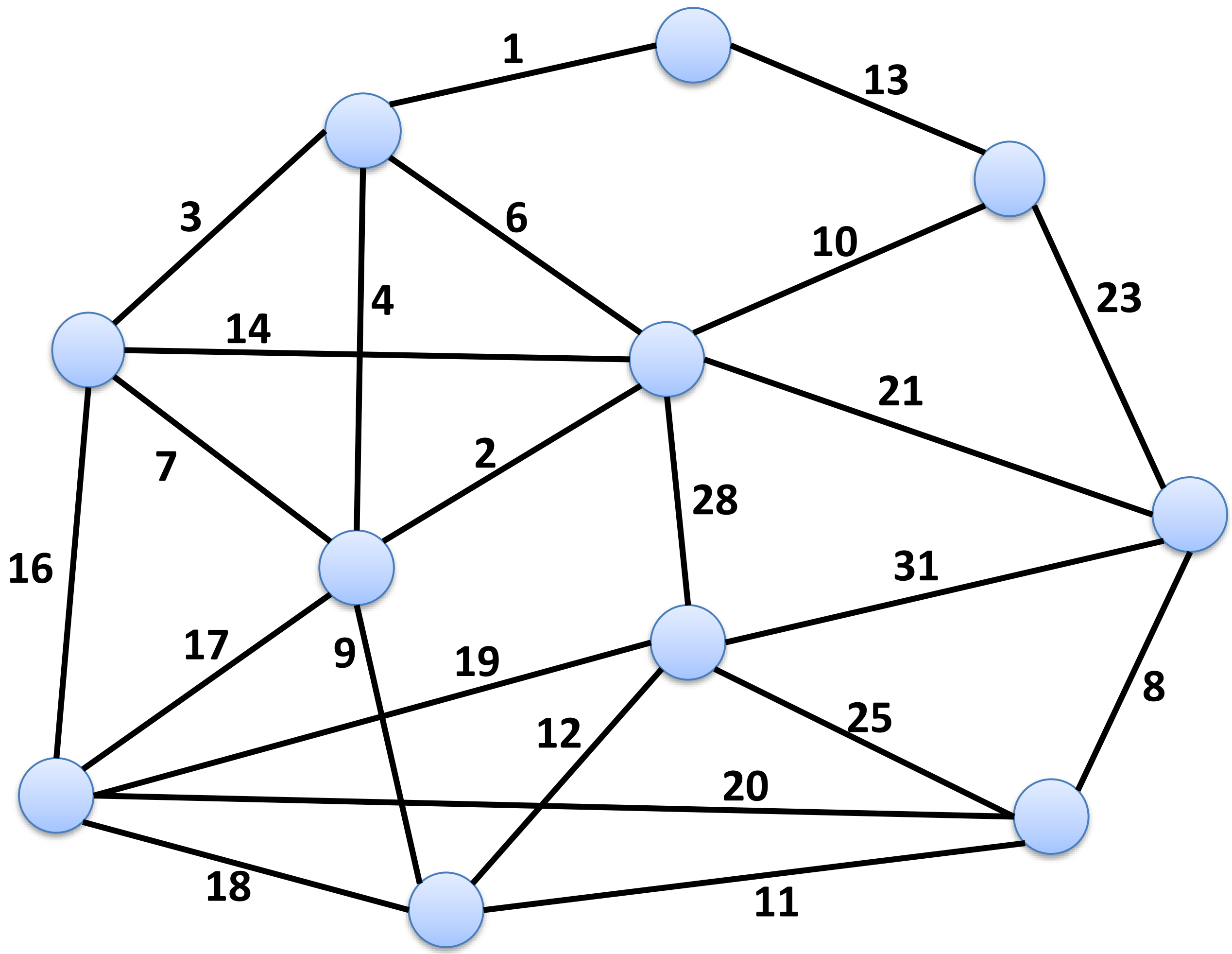
- **Minimum spanning tree (MST)** problem
  - Classic graph-theoretic optimization problem

- **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:

Matroids

- Same, but more abstract…

Matroid: **pair (E, I)**

- $\boldsymbol{E}$: set, called the **ground set**
- $\boldsymbol{I}$: finite family of finite subsets of E (i.e., $I \subseteq 2^E$), called **independent sets**

(E, I) needs to satisfy 3 properties:

1. Empty set is independent, i.e., $\emptyset \in \boldsymbol{I}$ (implies that $I \neq \emptyset$)
2. **Hereditary property**: For all $A \subseteq E$ and all $A' \subseteq A$,

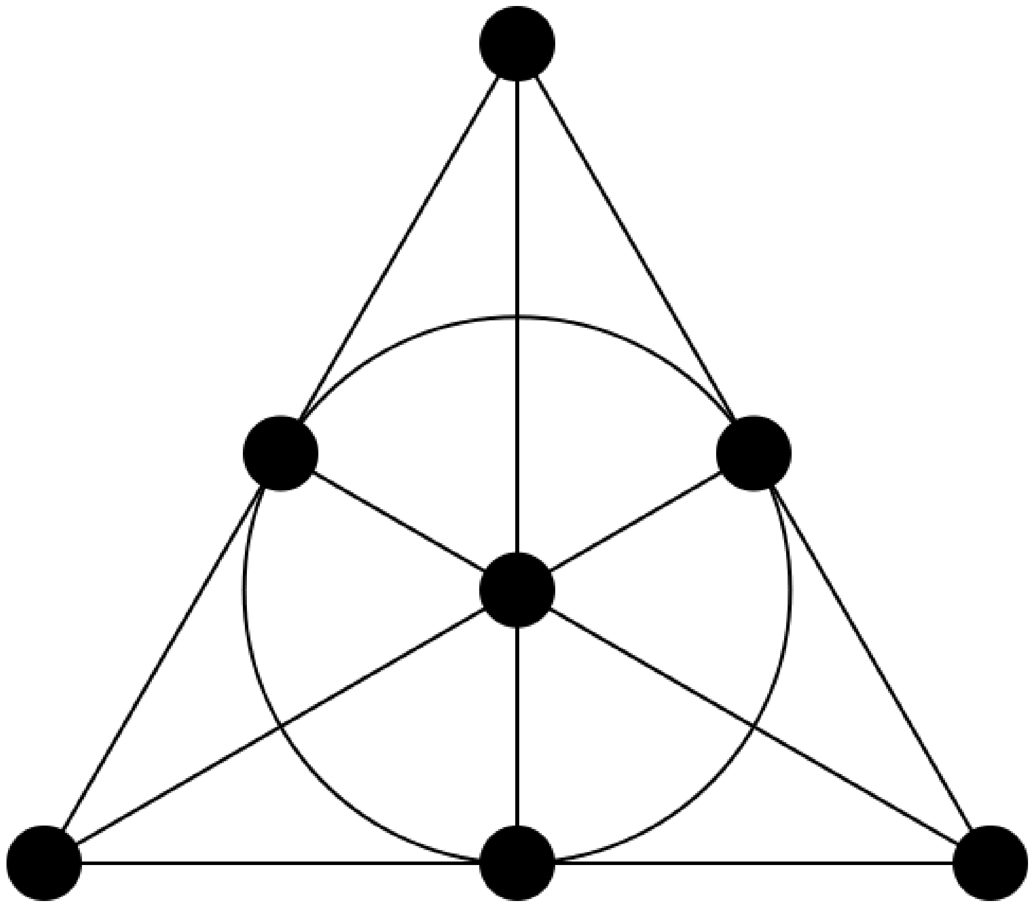
   if $A \in I$, then also $A' \in I$

3. **Augmentation / Independent set exchange property:**
   If $A, B \in I$ and $|A| > |B|$, there exists $x \in A \setminus B$ such that

   $$\mathbf{B}' := B \cup \{x\} \in I$$

Example

- Fano matroid:
  - Smallest finite projective plane of order 2…



Matroids and Greedy Algorithms

Weighted matroid: each $e \in E$ has a weight $w(e) > 0$

Goal: find maximum weight independent set

Greedy algorithm:

1. Start with $S = \emptyset$
2. Add max. weight $e \in E \setminus S$ to S such that $S \cup \{e\} \in I$

Claim: greedy algorithm computes optimal solution

Greedy is Optimal

- S: greedy solution $\qquad$ A: any other solution

Matroids: Examples

Forests of a graph $\boldsymbol{G = (V, E)}$:

- forest F: subgraph with no cycles (i.e., $F \subseteq E$)
- $\mathcal{F}$: set of all forests → $(E, \mathcal{F})$ is a matroid
- Greedy algorithm gives maximum weight forest (equivalent to MST problem)

Bicircular matroid of a graph $\boldsymbol{G = (V, E)}$:

- $\mathcal{B}$: set of edges such that every connected subset has ≤ 1 cycle
- $(E, \mathcal{B})$ is a matroid → greedy gives max. weight such subgraph

Linearly independent vectors:

- Vector space V, E: finite set of vectors, I: sets of lin. indep. vect.
- Fano matroid can be defined like that