



Chapter 2

Greedy Algorithms

Algorithm Theory
WS 2015/16

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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)

Traveling Salesperson Problem (TSP)



Input:

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

Solution:

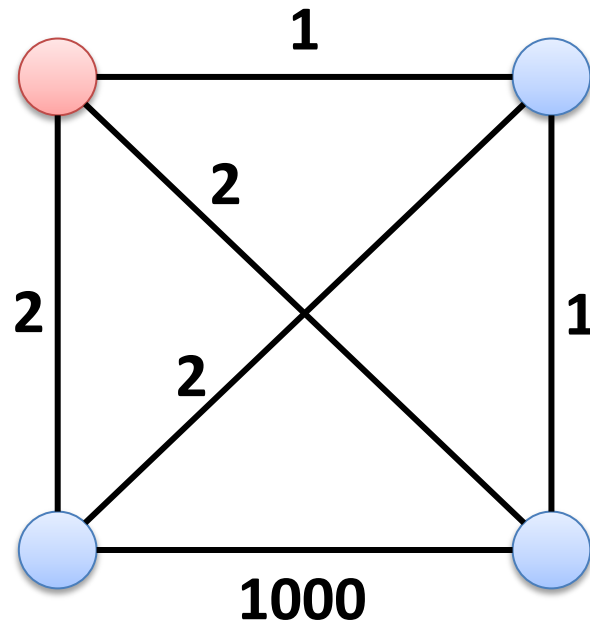
- Ordering/permutation v_1, v_2, \dots, v_n of nodes
- Length of TSP path: $\sum_{i=1}^{n-1} d(v_i, v_{i+1})$
- Length of TSP tour: $d(v_n, v_1) + \sum_{i=1}^{n-1} d(v_i, v_{i+1})$

Goal:

- Minimize length of TSP path or TSP tour

Nearest Neighbor (Greedy)

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



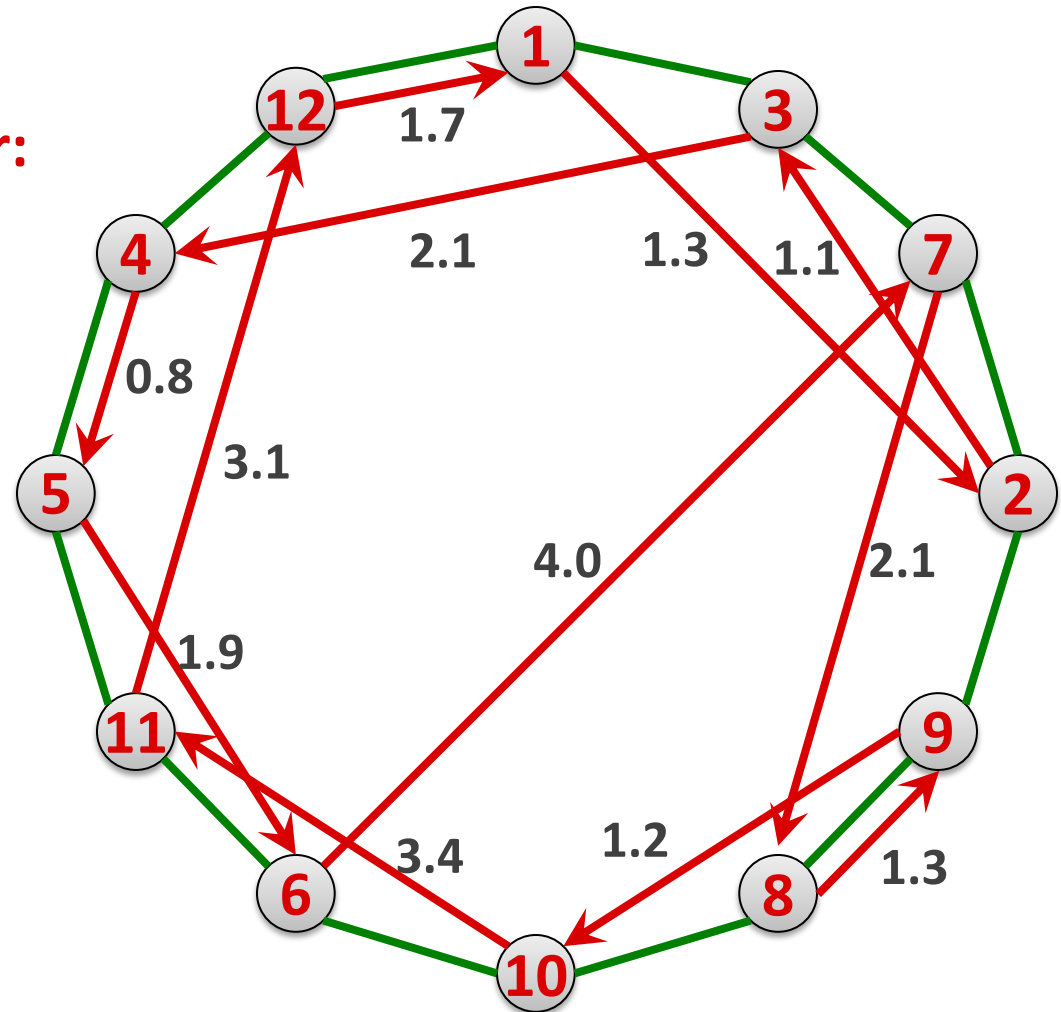
TSP Variants

- Symmetric / 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:

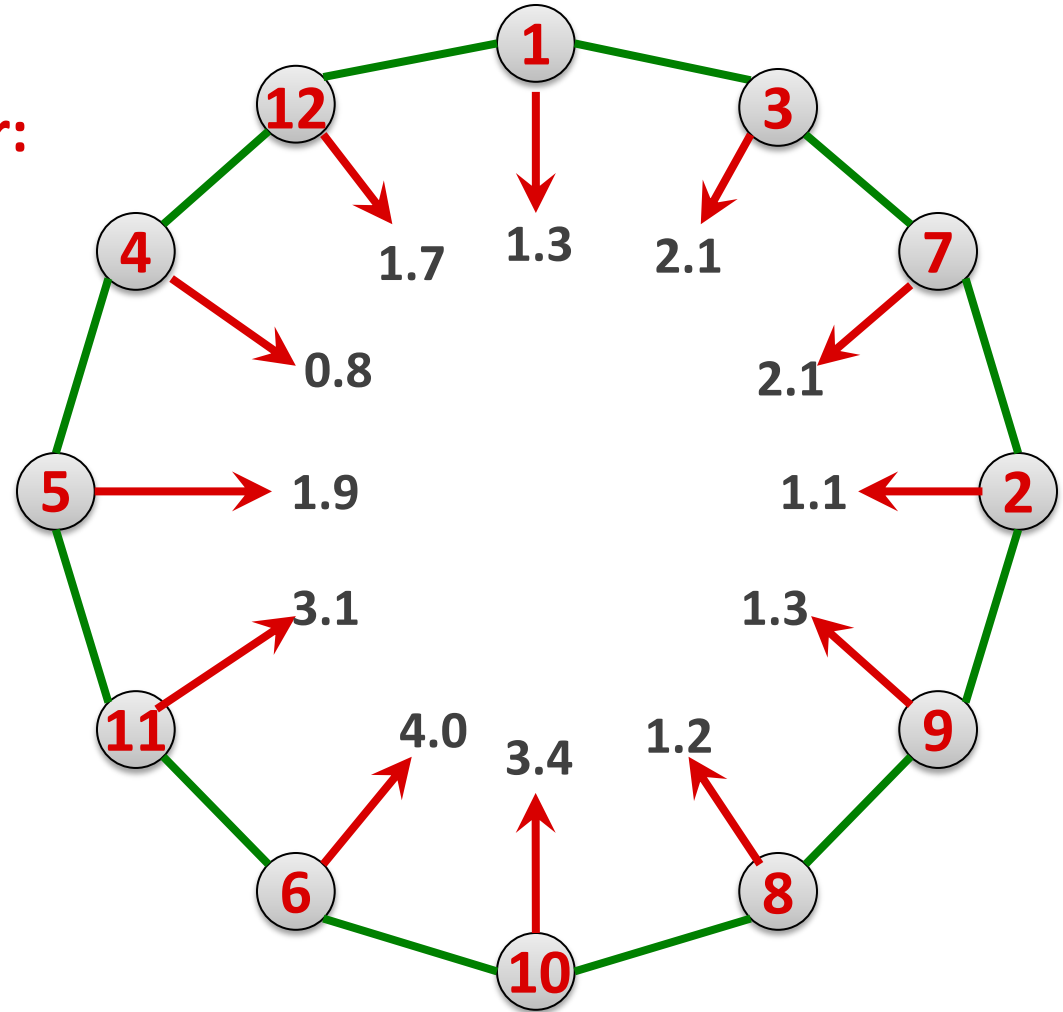


Metric TSP, Nearest Neighbor

Optimal TSP tour:

Nearest-Neighbor TSP tour:

cost = 24



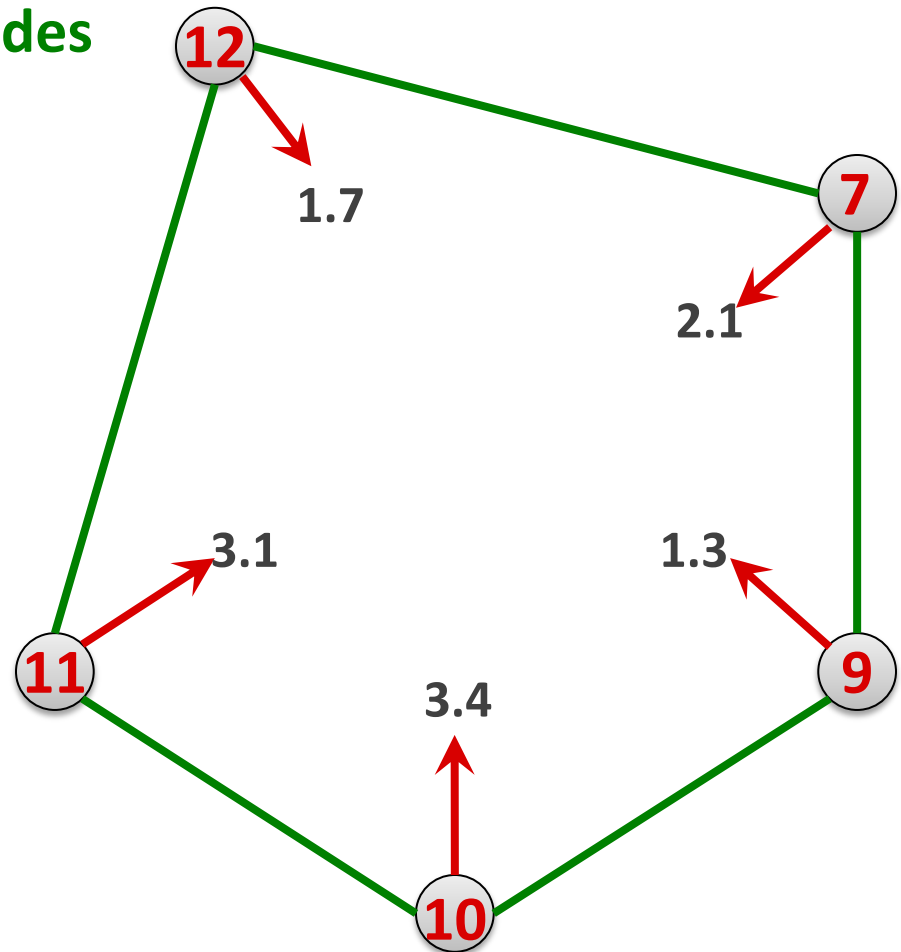
Metric TSP, Nearest Neighbor

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

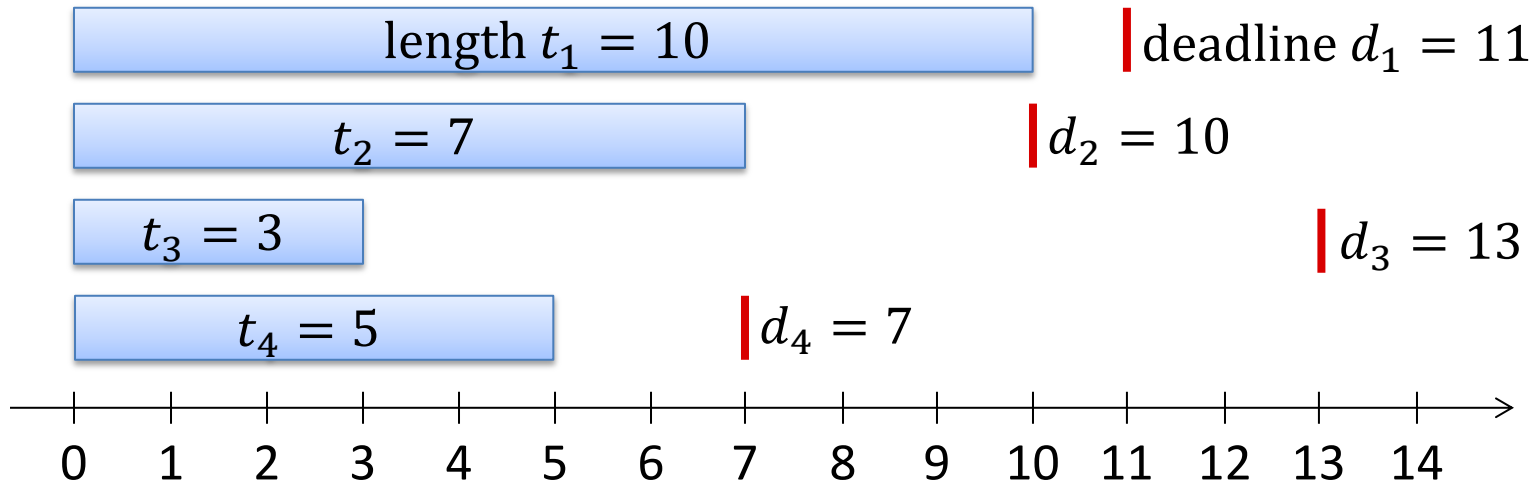
- We have shown:

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

- 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:

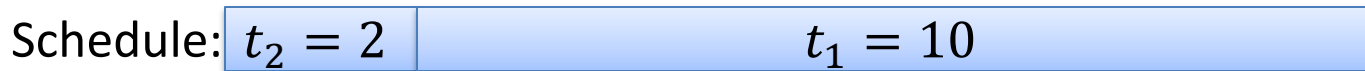
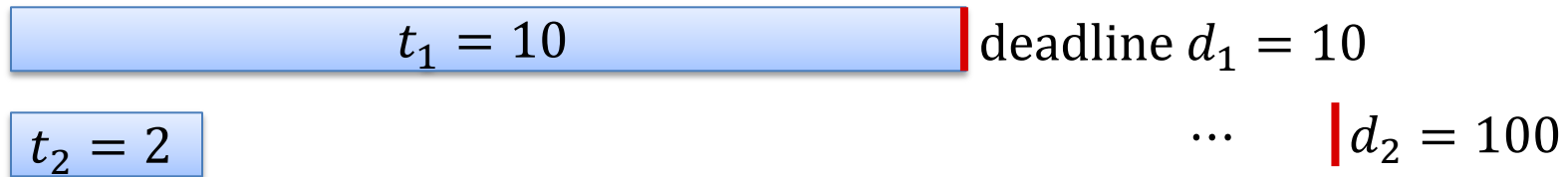


- Goal: schedule all jobs with minimum lateness L
 - Schedule: $s(i), f(i)$: start and finishing times of request i
Note: $f(i) = s(i) + t_i$
- Lateness $L := \max\{0, \max_i\{f(i) - d_i\}\}$
 - largest amount of time by which some job finishes late
- Many other natural objective functions possible...

Greedy Algorithm?

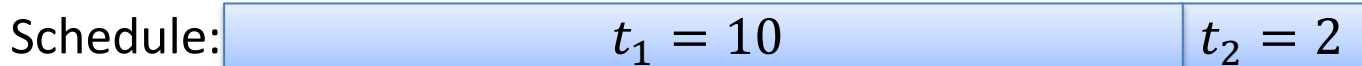
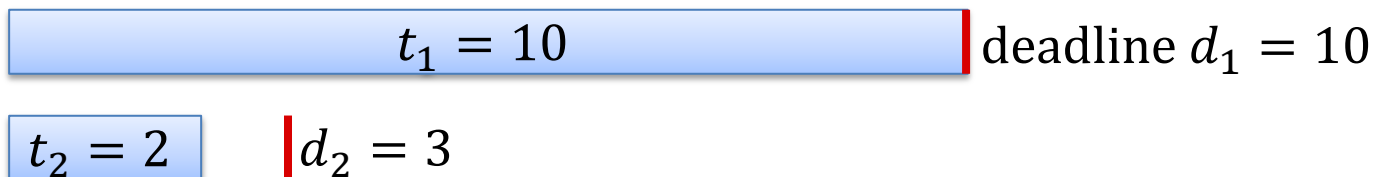
Schedule jobs in order of increasing length?

- 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!

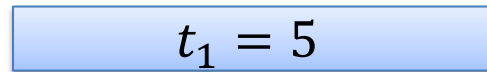
Algorithm:

- Assume jobs are reordered such that $d_1 \leq d_2 \leq \dots \leq d_n$
- 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: $s(i + 1) = f(i)$

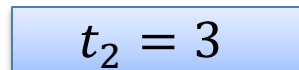
(idle time: gaps in a schedule \rightarrow alg. gives schedule with no idle time)

Example

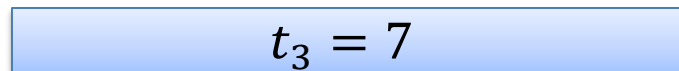
Jobs ordered by deadline:



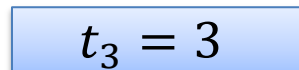
$d_4 = 7$



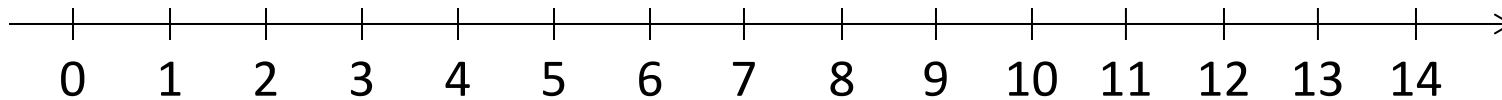
$d_2 = 10$



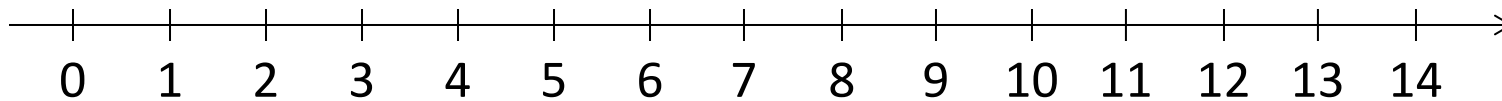
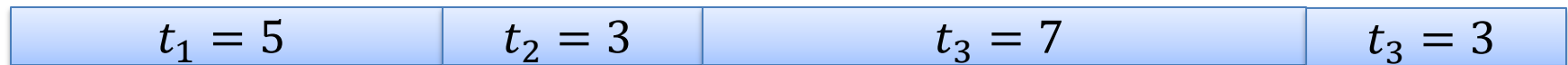
$d_1 = 11$



$d_3 = 13$



Schedule:



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

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 optimal 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 $d_j < d_i$

- Claim: Swapping i and j gives schedule with
 1. Less 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}'

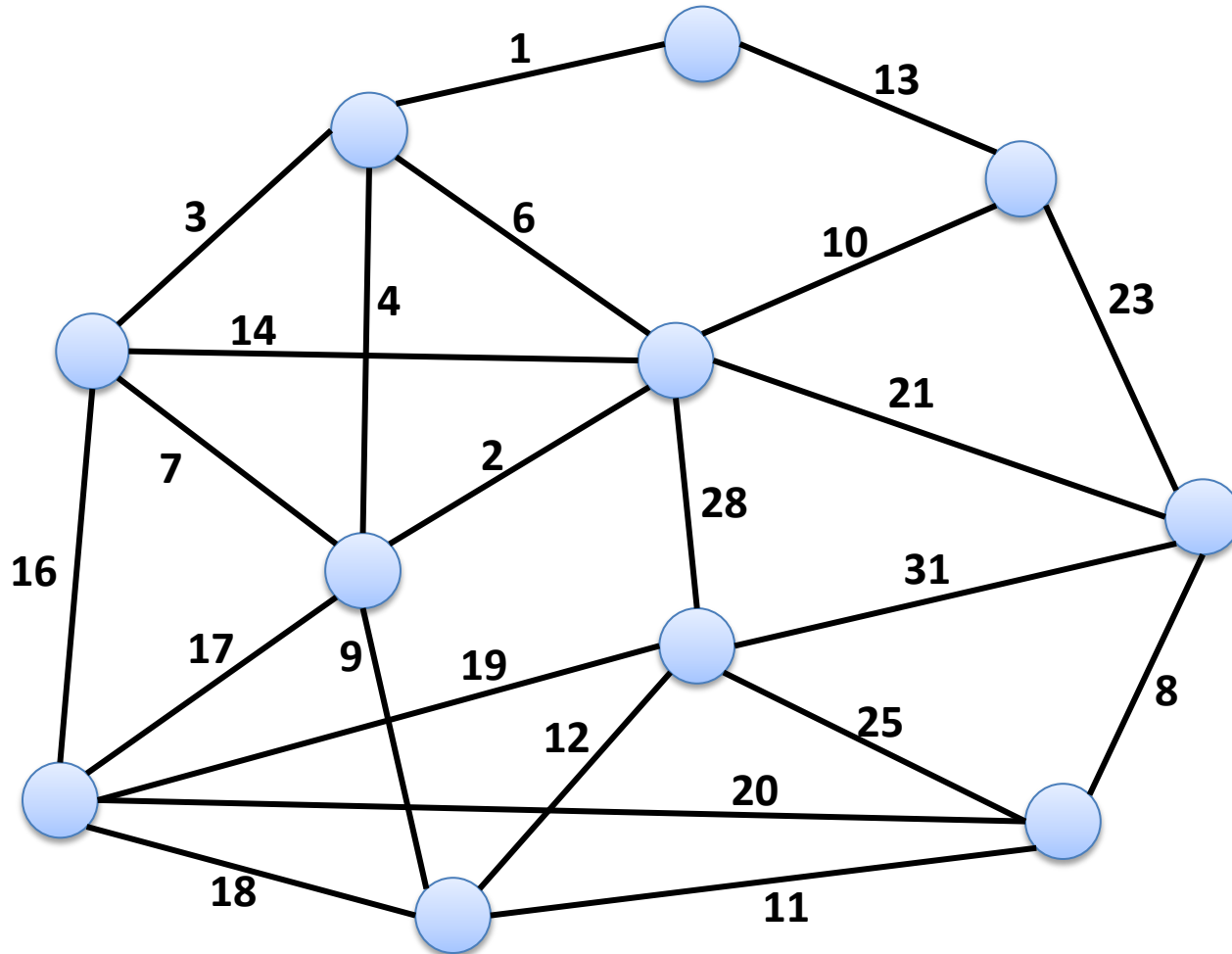
Exchange Argument

- 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)

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

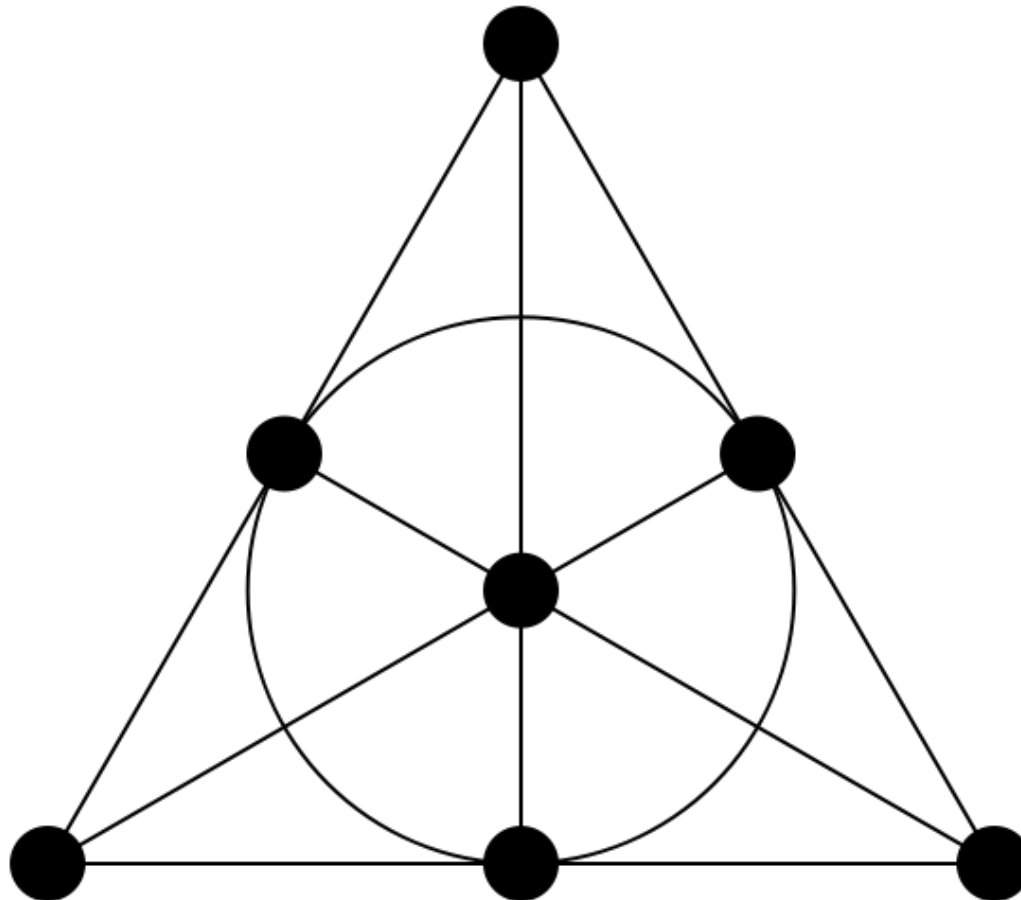
(E, I) needs to satisfy 3 properties:

1. Empty set is independent, i.e., $\emptyset \in I$ (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

A : any other solution