CHAPTER 2

Greedy algorithms and Local search

Introduction

 A greedy algorithm <u>builds a solution</u> step by step: Each time going for the option that gives the most profit or smallest cost at that step. It stops when a feasible solution is found.

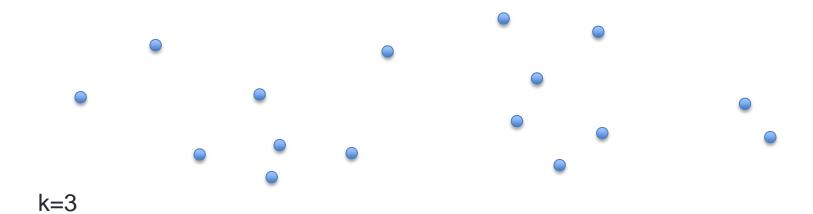
 A local search algorithm starts with a feasible solution and changes the solution step by step: Each time selecting an improved solution in the neighborhood of the current solution. It stops when no local improvement is possible.

Instance: Set V of n points in a metric space. Integer k.

Solution: $S \subseteq V$ with |S|=k

Cost: $\max_{j \in V} dist(j,S)$ ($dist(j,S):= \min_{s \in S} dist(j,s)$)

Goal: Find a solution of minimum cost.

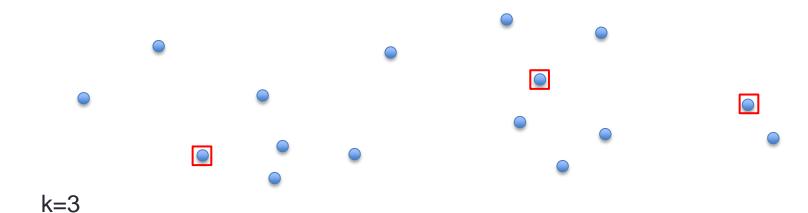


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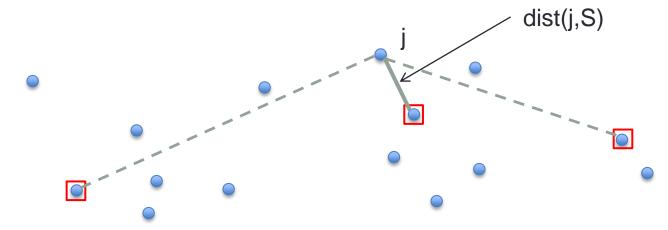


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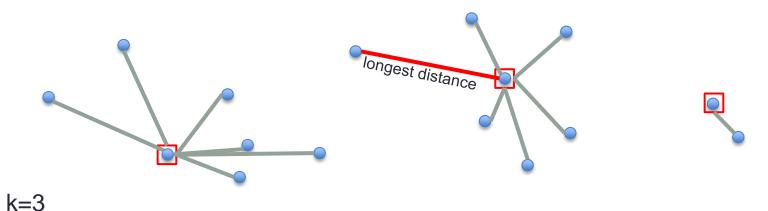
k=3

Instance: Set V of n points in a metric space. Integer k.

Solution: $S \subseteq V$ with |S|=k

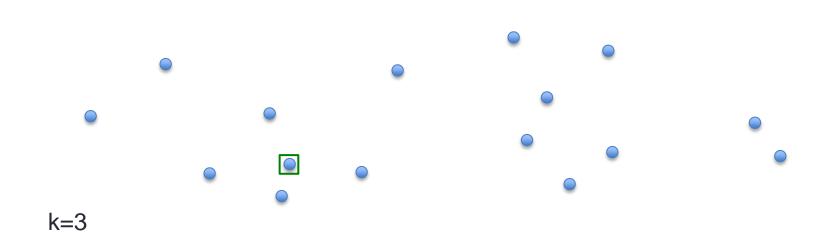
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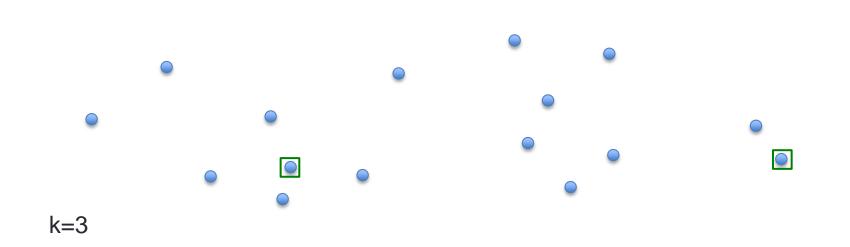


Connect each to its nearest center

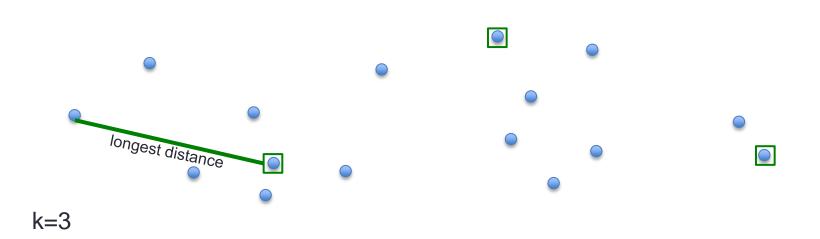
Greedy: Pick the first center arbitrarily. Next, always choose the point that is furthest away from the set of centers already chosen.



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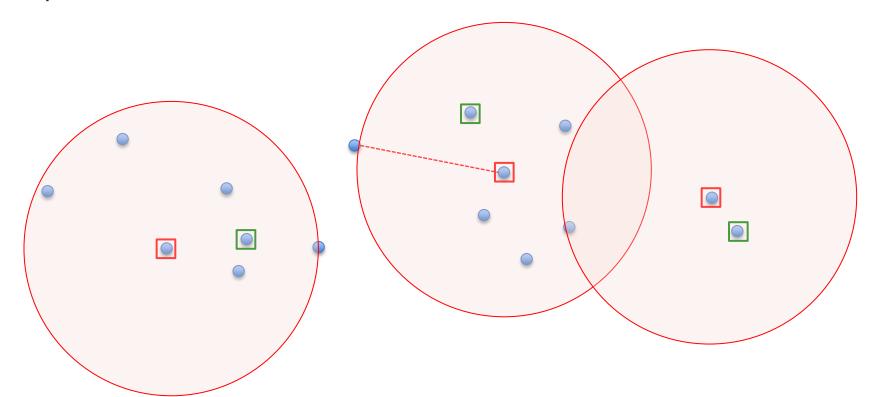
Greedy: Pick the first center arbitrarily. Next, always choose the point that is furthest away from the set of centers already chosen.



Theorem: Greedy is a 2-approximation algorithm.

Proof: Let S*, r* be, respectively, optimal solution and its value.

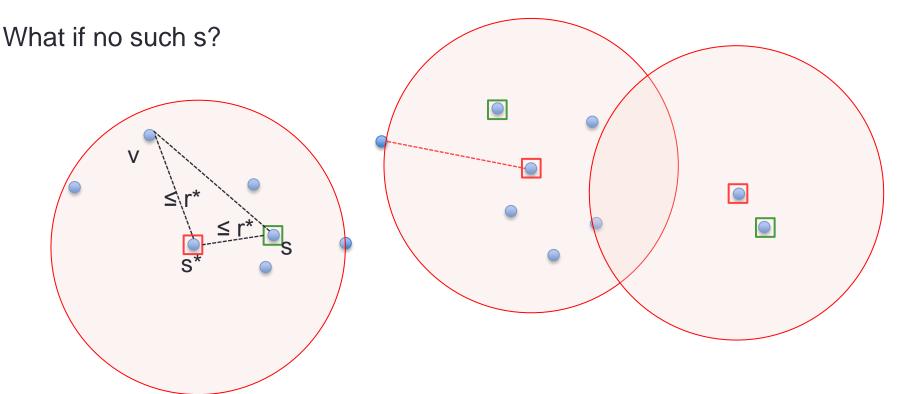
→ All points are within distance r* from S*



Proof (cont.):

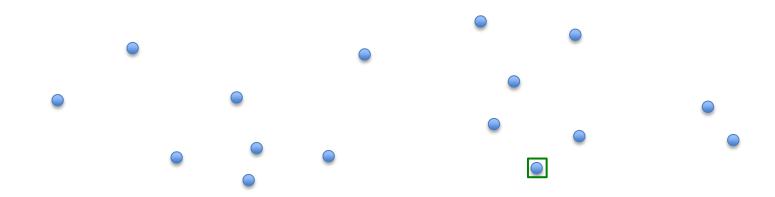
Take any $v \in V$. There must be an $s^* \in S^*$ with $dist(v,s^*) \le r^*$.

<u>If</u> there is an s∈ S with dist(s,s*) ≤ r*. Then OK by triangle inequality.



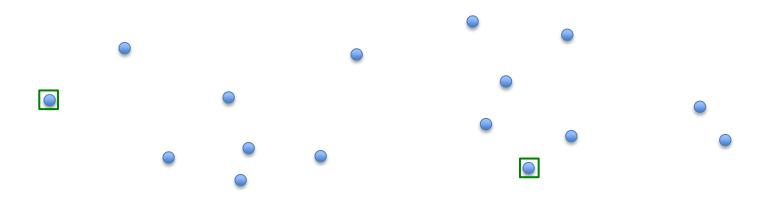
Proof (cont.):

Another Greedy solution:



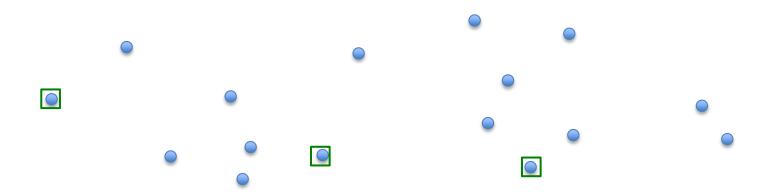
Proof (cont.):

Another Greedy solution:



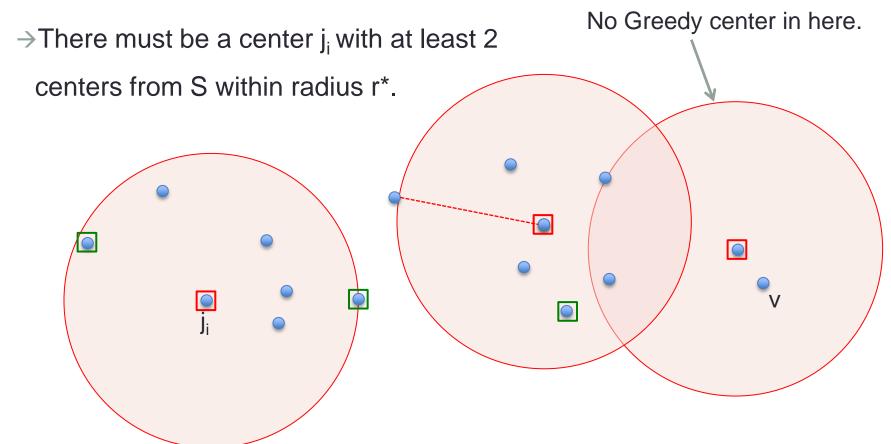
Proof (cont.):

Another Greedy solution:



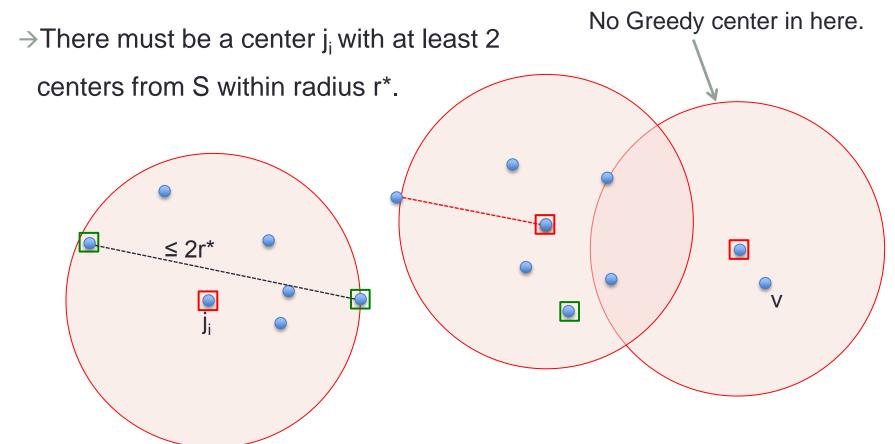
Proof (cont.):

Can not use the same argument here.



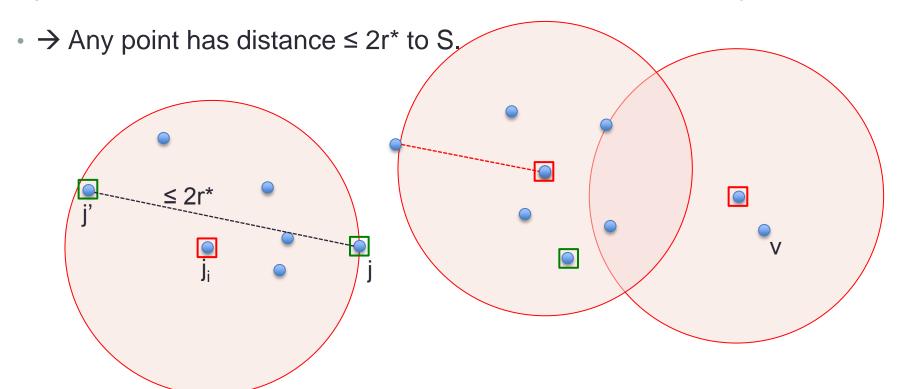
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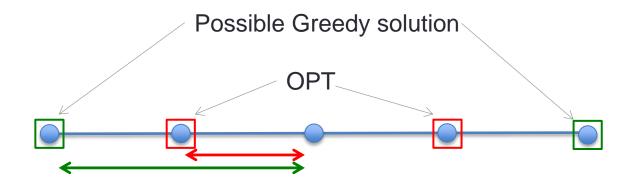
Proof (cont.):

- j was picked after j'.
- j had maximum distance to the chosen centers when it was picked.



Theorem Greedy is not better than a 2-approximation.

Proof See example.



Theorem There is no α -approximation algorithm for any α < 2, unless P=NP.

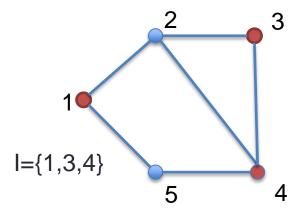
Proof By a reduction from the Dominating Set problem. (Next slides)

Dominating Set

Similar to Vertex Cover.

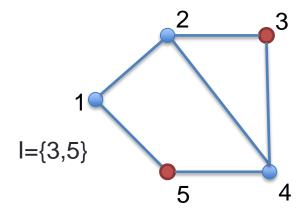
Vertex Cover:

Any edge has an endpoint in I



Dominating Set:

Any vertex is in I or has a neighbour in I.

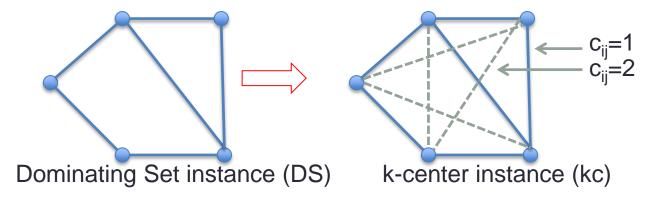


Dominating Set

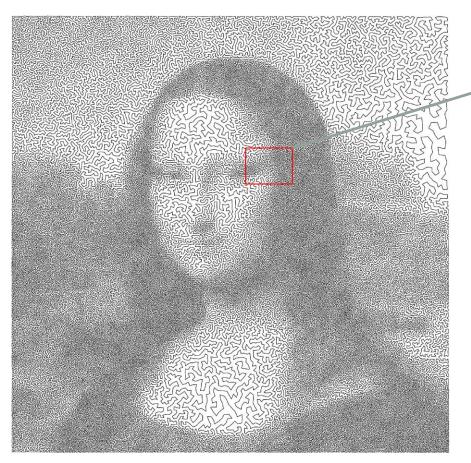
Fact: Dominating Set is NP-complete (Somebody once proved this).

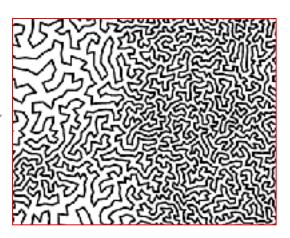
Corollary: There is no α -approximation algorithm for any α < 2, unless P=NP.

Proof: Let G=(V,E) be an instance of DS. Is $OPT \le k$? This can be answered if we would have an α -approximation algorithm ALG for k-center with $\alpha < 2$.



$$OPT^{DS} \le k$$
 \longrightarrow $OPT^{kc} = 1$ \longrightarrow $ALG \le \alpha OPT^{kc} < 2$ \longrightarrow $ALG = 1$ $OPT^{DS} > k$ \longrightarrow $OPT^{kc} = 2$ \longrightarrow $ALG = 2$



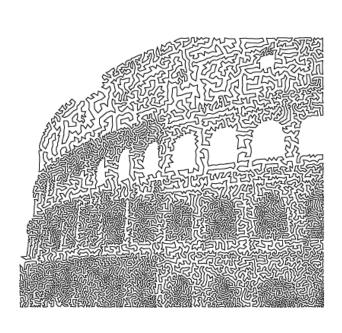


The current best known results for the Mona Lisa TSP are:

Tour: 5,757,191 Lower Bound: 5,757,084 Gap: 107 (0.0019%)

\$1,000 prize to the first person to find a tour shorter than 5,757,191.

Source: http://www.math.uwaterloo.ca/tsp/data/ml/monalisa.html





TSP	Metric (Δ-inequality)		Non-metric	
Symmetric				
	2 3		2 1	
	4	1.5-approx. Section 2.4	4	No α-approx. Section 2.4
Asymmetric				
	2 1 1 2 3 2	O(log n) -approx. Exercise 1.3	2 1 1 2 3 7	No α-approx. Section 2.4

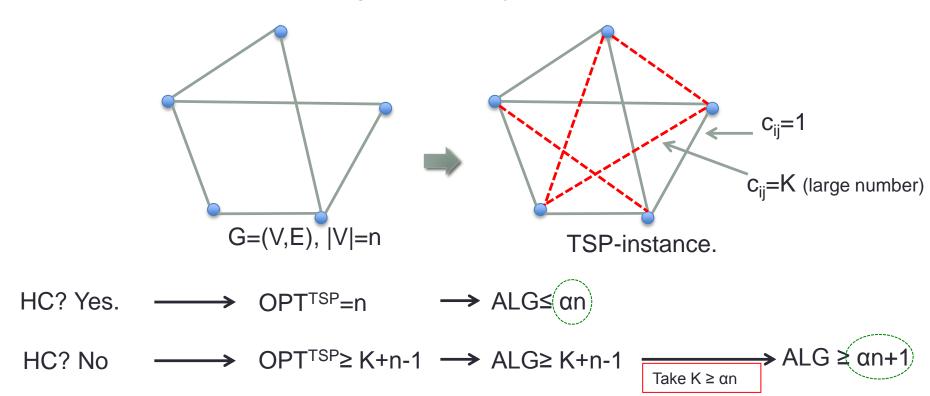
A special case of Symmetric metric TSP is *Euclidean TSP* (Pictures on previous slides)

Theorem For TSP without the triangle inequality assumption, there does not exist an α -approximation algorithm for any $\alpha \ge 1$, provided P \ne NP.

Proof (next slide) Follows from a reduction from Hamiltonian Cycle (HC). We show that, if there exists an α -approximation algorithm ALG with $\alpha \ge 1$, then the HC problem can be solved in polynomial time.

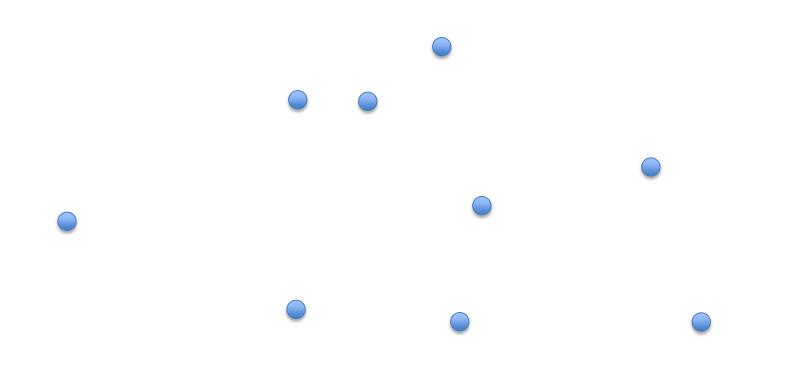
Fact The Hamiltonian Cycle problem is NP-complete (Somebody once proved this)

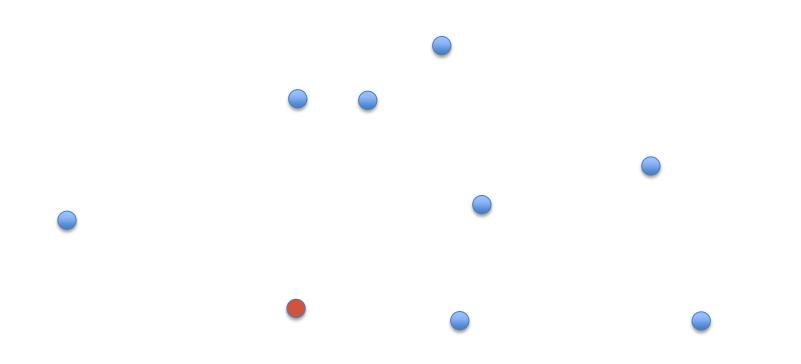
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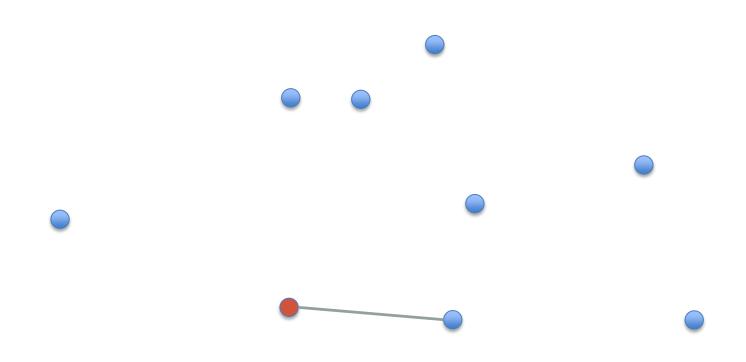


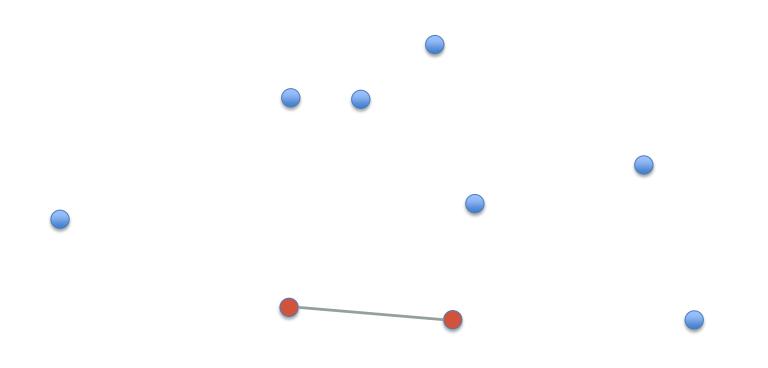
Three algorithms for metric symmetric TSP:

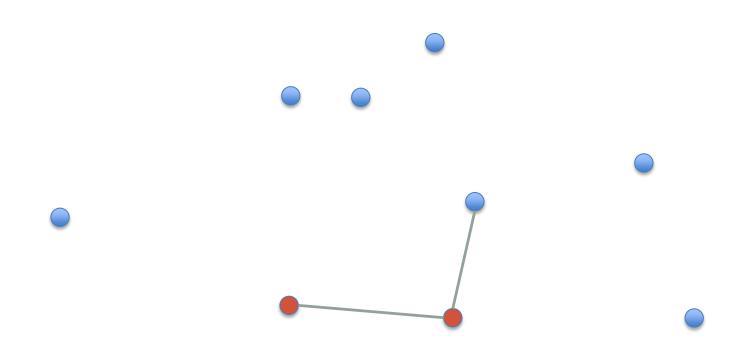
- Double tree
- Nearest addition
- Christofides' algorithm

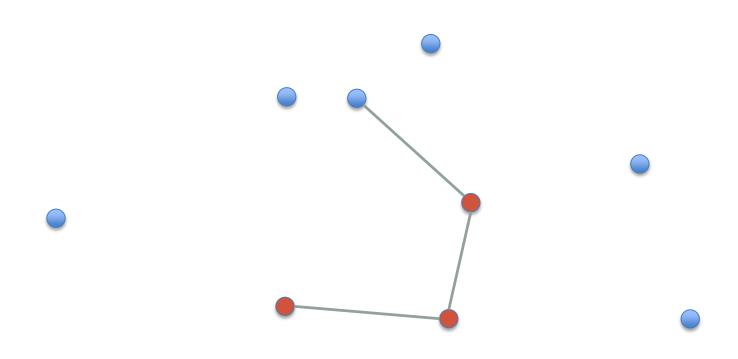


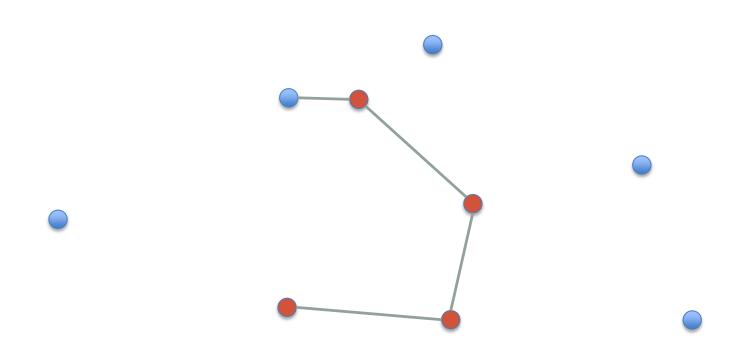


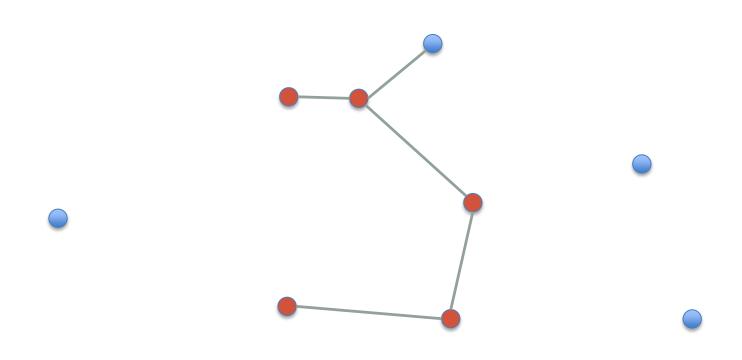


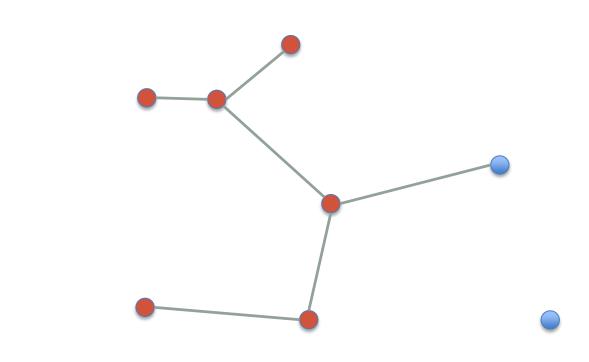






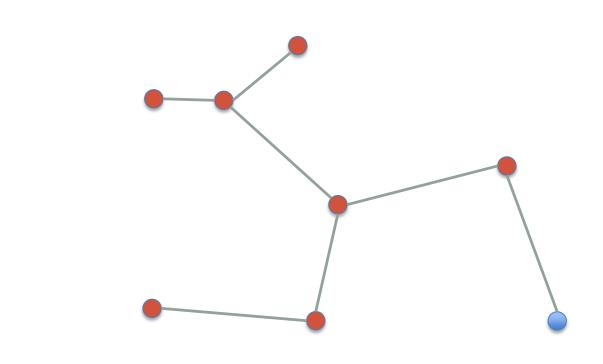






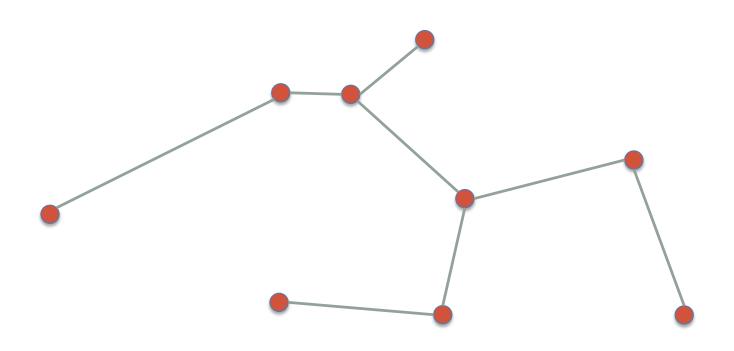
Prim's Minimum Spanning Tree (MST) algorithm:

Start with any point. Keep adding the point that is nearest to the already chosen points.



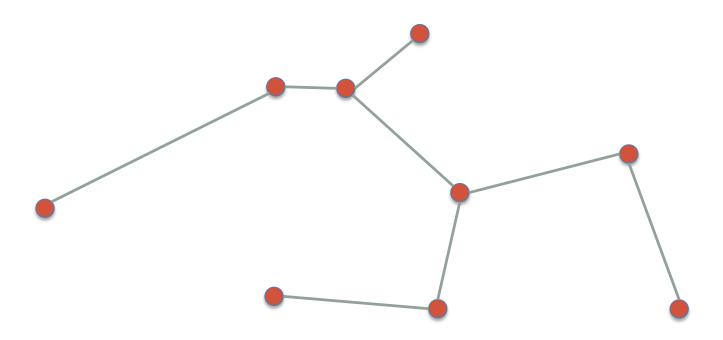
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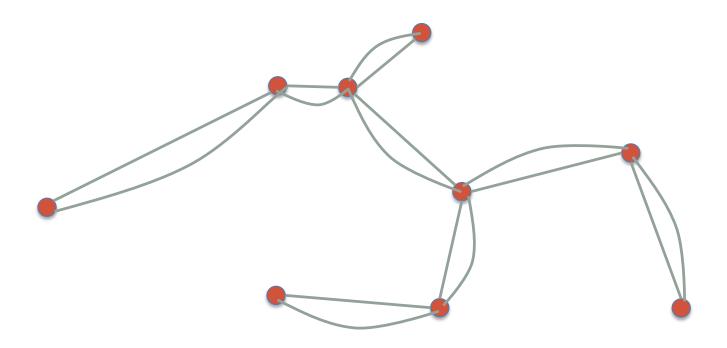


- 1. Find an MST
- 2. Double the edges
- 3. Find an Euler tour
- 4. Cut short

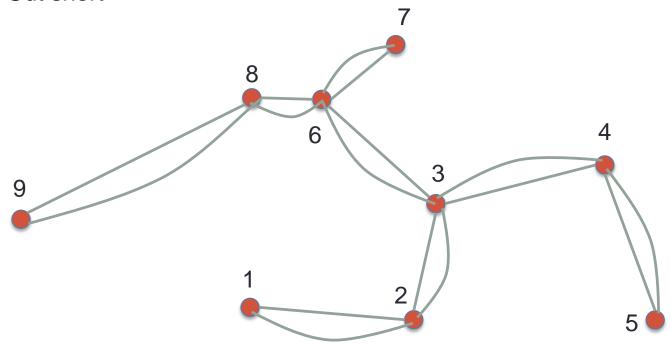
- 1. Find an MST
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- 1. Find an MST
- 2. <u>Double the edges</u>
- 3. Find an Euler tour
- 4. Cut short

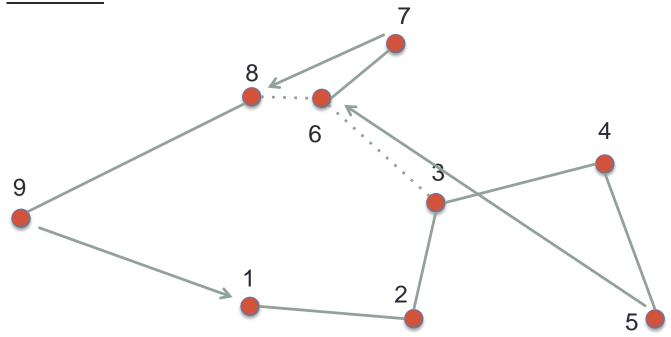


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Euler tour: 1,2,3,4,5,4,3,6,7,6,8,9,8,6,3,2,1

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TSP tour: 1,2,3,4,5, 4,3,6,7,6,8,9,8,6,3,2,1

Theorem Double Tree is a 2-approximation algorithm

Proof [1] running time. OK

[2] Feasible OK

[3] Ratio:?

Lemma

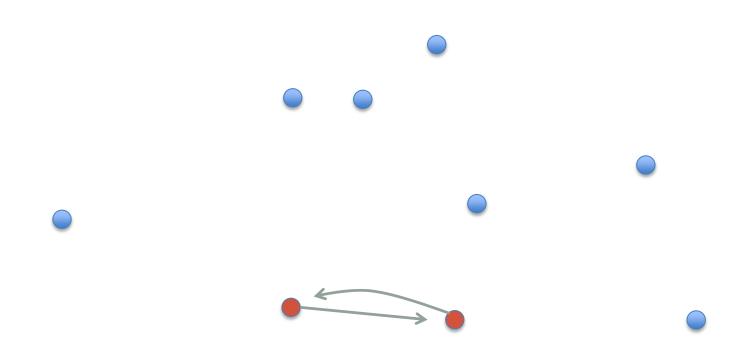
Let T be an MST and OPT the value of the smallest TSP tour. Then cost(T) < OPT.

Proof Take an optimal TSP tour and remove one edge. This gives a spanning tree. The cost of this tree is no more than cost(T).

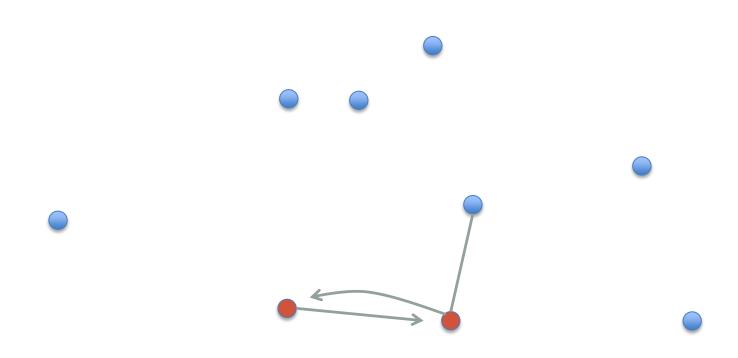
Cost of the Eulertour is 2cost(T) < 2OPT. Shortcutting does not increase the length since triangle inequality holds.

- 1. Start with a tour on 2 points
- 2. Keep adding the nearest point.

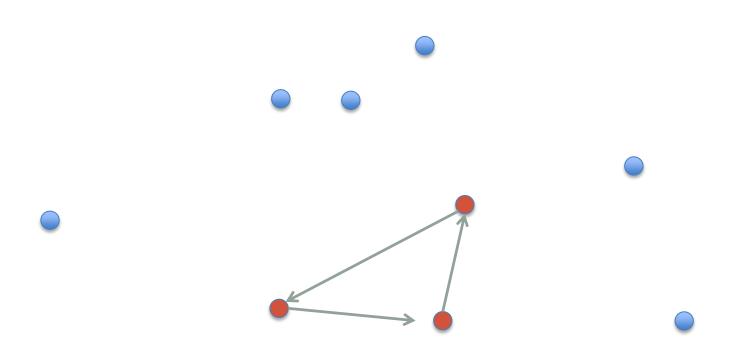
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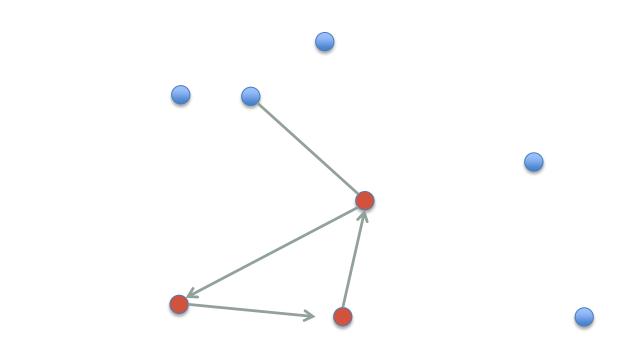
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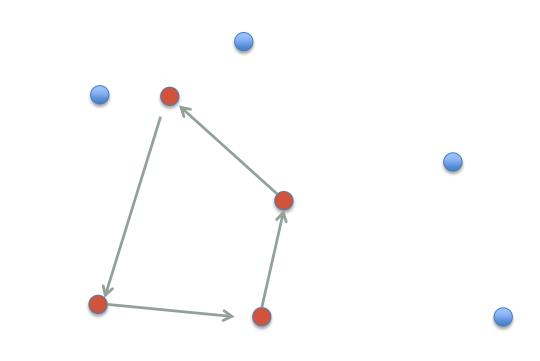
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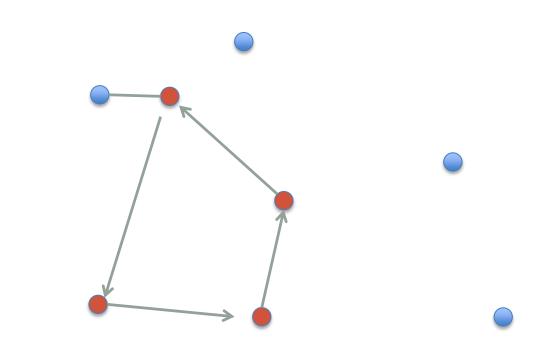
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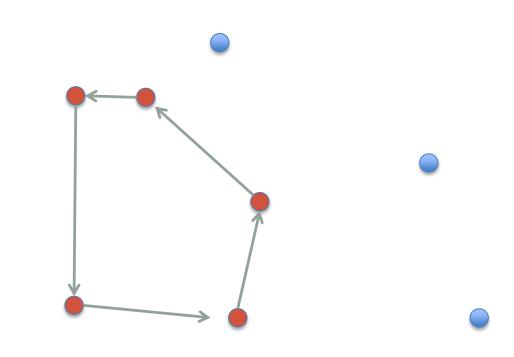
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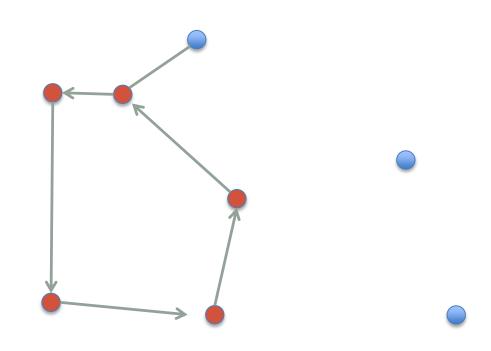
- 1. Start with a tour on 2 points
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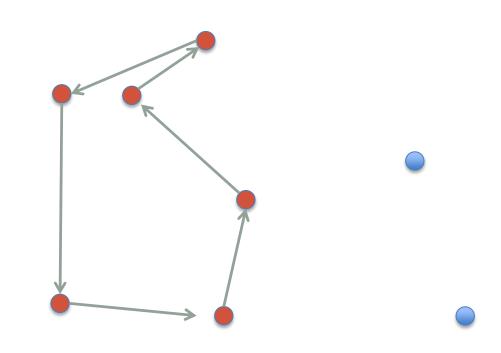
- 1. Start with a tour on 2 points
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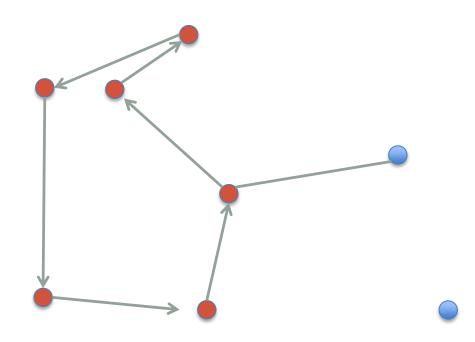
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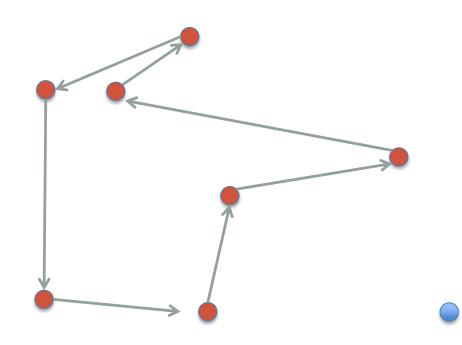
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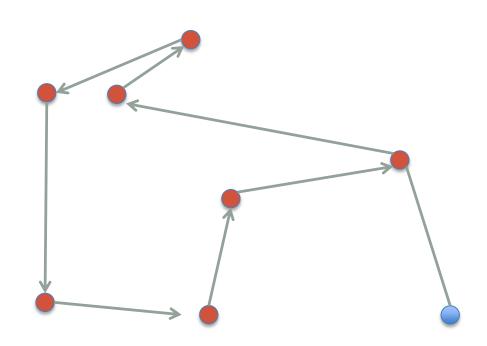
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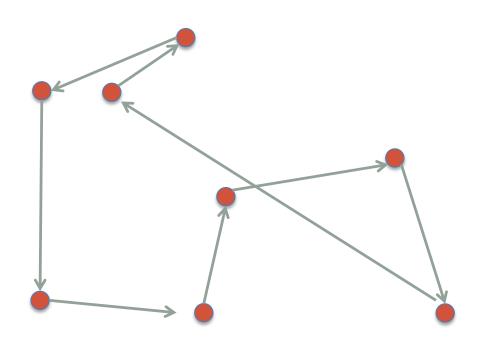
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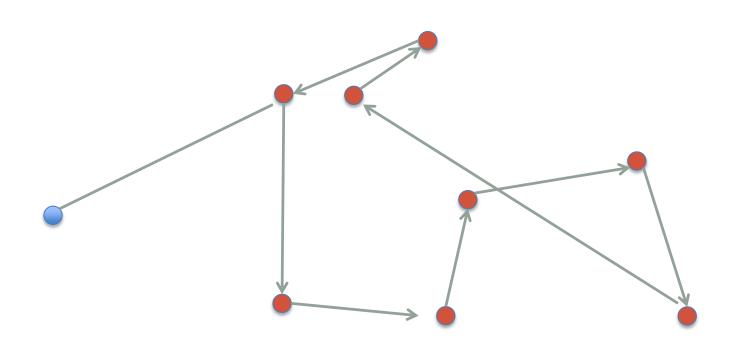
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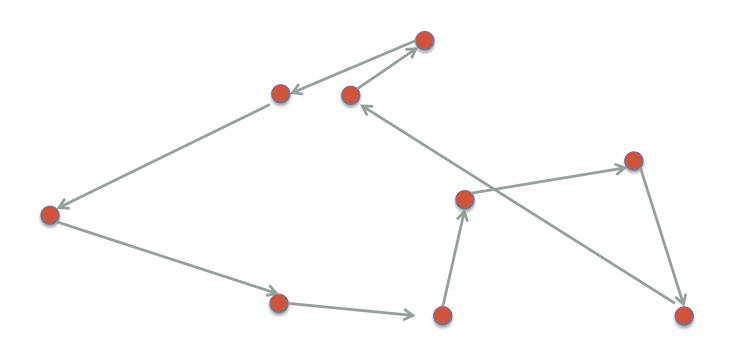
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Theorem Nearest Addition is a 2-approximation algorithm

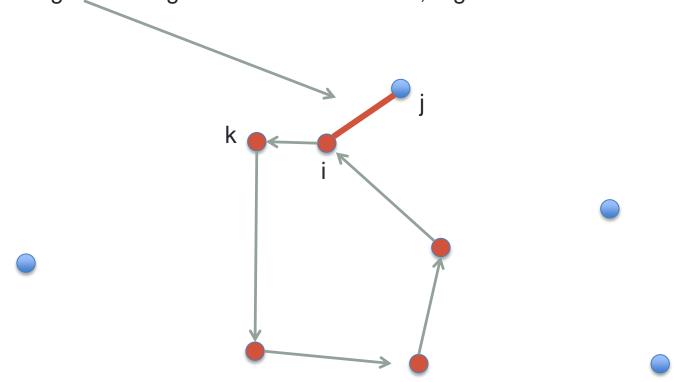
Proof [1] running time. OK

[2] Feasible OK

[3] Ratio:

The algorithm behaves exactly like Prim's MST algorithm:

The edges defining the minimum distance, together form an MST.



Theorem Nearest Addition is a 2-approximation algorithm

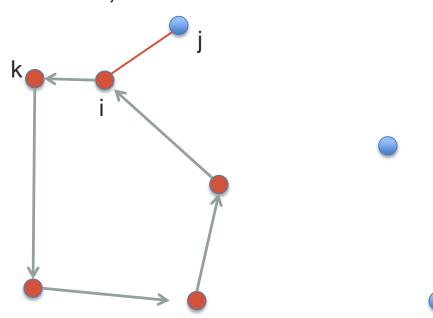
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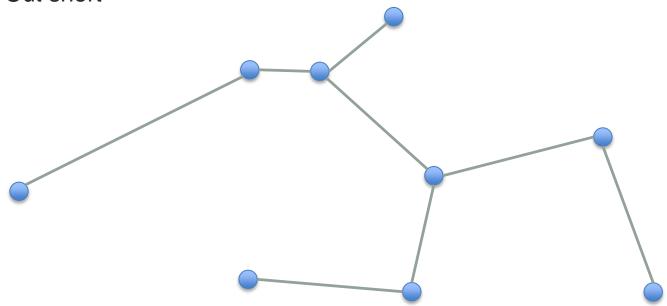
By triangle inequality: $c_{jk} \le c_{ji} + c_{ik} \rightarrow c_{jk} - c_{ik} \le c_{ji}$

Cost in this step: $c_{ij} + c_{jk} - c_{ik} \le 2c_{ij}$. \rightarrow Total cost $\le 2cost(MST) \le 2OPT$.

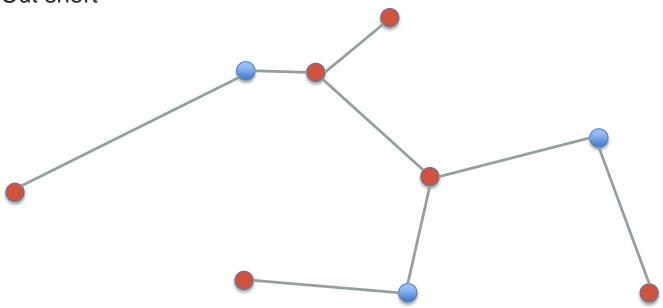


- 1. Find a minimum spanning tree T
- 2. Find a minimum matching M for the odd-degree vertices in T
- 3. Add M to T
- 4. Find an Euler tour
- 5. Cut short

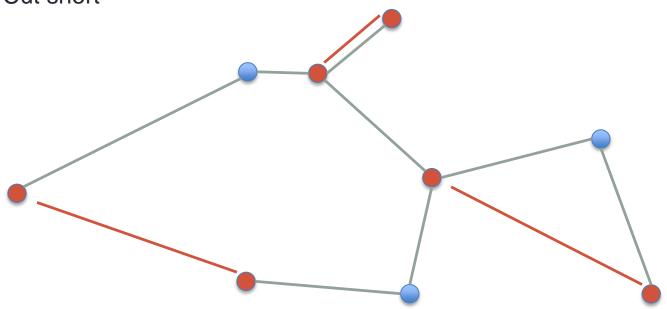
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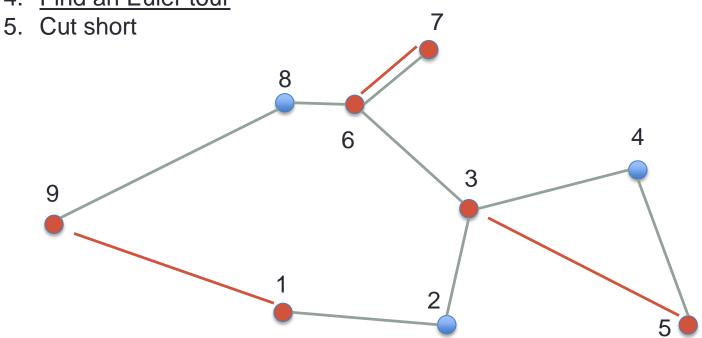
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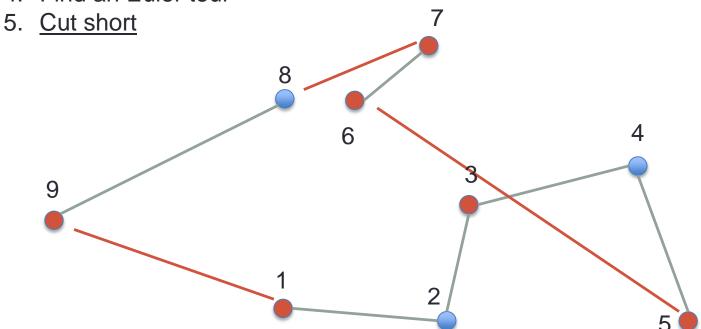


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Euler tour: 1,2,3,4,5,3,6,7,6,8,9,1

- 1. Find a minimum spanning tree T
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Short cut: 1,2,3,4,5,3,6,7,6,8,9,1

Christofides' Algorithm is a 1.5-approximation algorithm

Proof

[1] Time? MST and Matching can be found in polynomial time.

[2] Feasible. OK

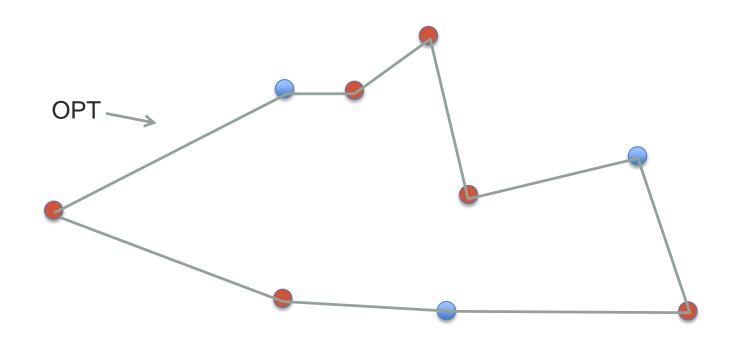
[3] Cost of TSP is at most the cost of the Euler tour.

Cost of Euler tour is cost(T)+cost(M)

Know: cost(T) < OPT.

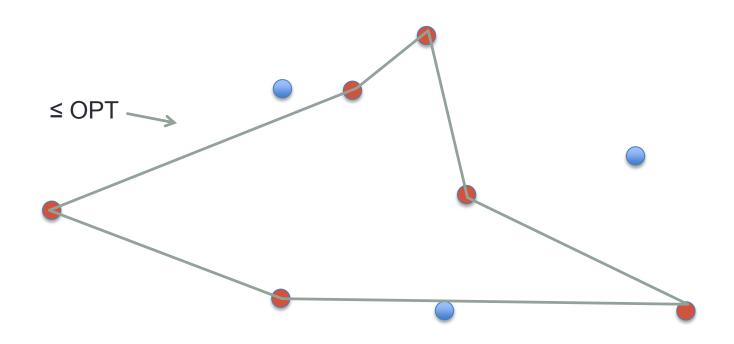
Christofides' Algorithm is a 1.5-approximation algorithm

Proof



Christofides' Algorithm is a 1.5-approximation algorithm

Proof



Christofides' Algorithm is a 1.5-approximation algorithm

Proof

