

# Lecture 15: Approximation Algorithms for Travelling Salesman Problem

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# Overview

- Equivalent Versions of Traveling Salesman Problem
- Approximation Algorithms for Traveling Salesman Problem
- Conclusion
- Acknowledgements

# Traveling Salesman Problem

- **Input:** set of points  $X$  and a symmetric distance function

$$d : X \times X \rightarrow \mathbb{R}_{\geq 0}$$

$$d(x, y) = d(y, x) \geq 0$$

# Traveling Salesman Problem

- **Input:** set of points  $X$  and a symmetric distance function

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- For any path  $p_0 \rightarrow p_1 \rightarrow \dots \rightarrow p_t$  in  $X$ , *length* of the path is sum of distances traveled

$$\sum_{i=0}^{t-1} d(p_i, p_{i+1})$$

$$d(p_0, p_1) + d(p_1, p_2) + \dots + d(p_{t-1}, p_t)$$

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- Comes in many flavours...



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$$d(x, y) \leq d(x, z) + d(z, y)$$

$$\forall x, y, z \in X.$$

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$$r(n) = 2^n$$

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### Lemma

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# Metric TSP-NR equivalent to Metric TSP-R

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- 1 If  $(X, d)$  is an input to Metric TSP, the cost of the optimum is the same whether or not we allow repetitions.*
- 2 Every  $c$ -approximation algorithm for Metric TSP-NR is also a  $c$ -approximation algorithm for Metric TSP-R.*

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- 3 Every  $c$ -approximation algorithm for Metric TSP-R can be turned into a  $c$ -approximate algorithm for Metric TSP-NR, after adding a linear time post-processing.*

*$OPT_R(X, d)$  be cost of optimal solution for  $(X, d)$  in Metric TSP-R*

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  - 3 Every  $c$ -approximation algorithm for Metric TSP-R can be turned into a  $c$ -approximate algorithm for Metric TSP-NR, after adding a linear time post-processing.*
- $OPT_R(X, d)$  be cost of optimal solution for  $(X, d)$  in Metric TSP-R
  - $OPT_{NR}(X, d)$  be the cost of optimal solution for  $(X, d)$  in Metric TSP-NR.

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- ① *If  $(X, d)$  is an input to Metric TSP, the cost of the optimum is the same whether or not we allow repetitions.*

- Solution space of Metric TSP-R is larger than solution space of Metric TSP-NR. Thus  $OPT_R(X, d) \leq OPT_{NR}(X, d)$  *and includes solutions to Metric TSP-NR*

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- 1 If  $(X, d)$  is an input to Metric TSP, the cost of the optimum is the same whether or not we allow repetitions.

Example:  $a \rightarrow b \rightarrow c \rightarrow b \rightarrow d \rightarrow a \mapsto a \rightarrow b \rightarrow c \rightarrow d \rightarrow a$

$$\text{cost}(C) - \text{cost}(C') = d(c, b) + d(b, d) - d(c, d) \geq 0 \text{ (METRIC)}$$

- Let  $C = p_0 \rightarrow p_1 \rightarrow p_2 \rightarrow \dots \rightarrow p_m = p_0$  be a solution to  $\text{OPT}_R(X, d)$ . Now, create a cycle  $C'$  from  $C$  simply by removing the repetitions

$a \rightarrow b \rightarrow \dots c \rightarrow \overset{\text{middle}}{\cancel{a}} \rightarrow d \rightarrow \dots$

becomes

$a \rightarrow b \rightarrow \dots \boxed{c \rightarrow d} \rightarrow \dots$

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- (2) Every  $c$ -approximation algorithm for Metric TSP-NR is also a  $c$ -approximation algorithm for Metric TSP-R.*



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*For every  $c \geq 1$  there is a polynomial time  $c$ -approximation for Metric TSP-NR if, and only if, there is a polynomial time  $c$ -approximation for Metric TSP-R. In particular:*

(2) *Every  $c$ -approximation algorithm for Metric TSP-NR is also a  $c$ -approximation algorithm for Metric TSP-R.*

- If we have a  $c$ -approximation algorithm for Metric TSP-NR, then we know that our solution (cycle  $C$ ) satisfies:

$$\begin{aligned} \underline{\text{cost}(C)} &\leq c \cdot \underline{\text{OPT}_{NR}(X, d)} \\ &= c \cdot \text{OPT}_R(X, d) \end{aligned}$$

# Metric TSP-NR equivalent to Metric TSP-R

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*For every  $c \geq 1$  there is a polynomial time  $c$ -approximation for Metric TSP-NR if, and only if, there is a polynomial time  $c$ -approximation for Metric TSP-R. In particular:*

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- If we have a  $c$ -approximation algorithm for Metric TSP-NR, then we know that our solution (cycle  $\mathcal{C}$ ) satisfies:

$$\text{cost}(\mathcal{C}) \leq c \cdot \text{OPT}_{NR}(X, d)$$

- Since  $\text{OPT}_{NR}(X, d) = \text{OPT}_R(X, d)$  and  $\mathcal{C}$  is also a solution to Metric TSP-R, we are done.

# Metric TSP-NR equivalent to Metric TSP-R

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*For every  $c \geq 1$  there is a polynomial time  $c$ -approximation for Metric TSP-NR if, and only if, there is a polynomial time  $c$ -approximation for Metric TSP-R. In particular:*

- (3) Every  $c$ -approximation algorithm for Metric TSP-R can be turned into a  $c$ -approximate algorithm for Metric TSP-NR, after adding a linear time post-processing.*

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For every  $c \geq 1$  there is a polynomial time  $c$ -approximation for Metric TSP-NR if, and only if, there is a polynomial time  $c$ -approximation for Metric TSP-R. In particular:

(3) Every  $c$ -approximation algorithm for Metric TSP-R can be turned into a  $c$ -approximate algorithm for Metric TSP-NR, after adding a linear time post-processing.

- Given any solution to Metric TSP-R, simply run the procedure that removes repeated visits to a vertex. This only decreases cost by metric property.

and again, we know that

$$\text{OPT}_{NR}(X, d) = \text{OPT}_R(X, d)$$

# Metric TSP-R equivalent to General TSP-R

## Lemma

*For every  $c \geq 1$  there is a polynomial time  $c$ -approximation for Metric TSP-R if, and only if, there is a polynomial time  $c$ -approximation for General TSP-R. In particular:*

- 1 Every  $c$ -approximation algorithm for General TSP-R is also a  $c$ -approximation algorithm for Metric TSP-R.*
- 2 Every  $c$ -approximation algorithm for Metric TSP-R can be turned into a  $c$ -approximate algorithm for General TSP-R, after adding a polynomial time pre and post-processing.*

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- ① *Every  $c$ -approximation algorithm for General TSP-R is also a  $c$ -approximation algorithm for Metric TSP-R. ✓*
- ② *Every  $c$ -approximation algorithm for Metric TSP-R can be turned into a  $c$ -approximate algorithm for General TSP-R, after adding a polynomial time pre and post-processing.*

- First item follows by the fact that Metric TSP-R is a special case of General TSP-R, when the distance function satisfies the triangle inequality.

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- On input  $(X, d)$  to General TSP-R, let  $G(X, E, w)$  be the complete weighted graph such that  $w(x, y) = \underline{d(x, y)}$ . Now compute new distance  $\delta : X \rightarrow \mathbb{R}_{\geq 0}$  such that

$\delta(x, y) \leftarrow$  length of shortest path from  $x$  to  $y$  in  $G$

$$E = K_X \quad (X, k_x, d)$$

$$\delta(x, y) \leq \underline{d(x, y)}$$



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$(X, \delta)$  Metric TSP problem

$$\delta(x, y) \leftarrow \text{length of shortest path from } x \text{ to } y \text{ in } G$$

- Note that  $\delta$  satisfies triangle inequality!

$$\underbrace{\text{shortest path } x \rightarrow y}_{\delta(x, y)} \leq \underbrace{\text{shortest path } x \rightarrow y \text{ passing through } z}_{\text{shortest } x \rightarrow z + \text{shortest } z \rightarrow y}$$

$\delta(x, z) + \delta(z, y)$

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- Note that  $\delta$  satisfies triangle inequality!
- Give input  $(X, \delta)$  to our algorithm for Metric TSP-R. Let  $\mathcal{C}$  be the cycle it outputs. Thus

$$\text{cost}(\mathcal{C}) \leq c \cdot \text{OPT}_R(X, \delta)$$

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$$\text{cost}(\mathcal{C}) \leq c \cdot \text{opt}_R(X, \delta)$$

- For every pair  $(x, y) \in X^2$ , note that  $\delta(x, y) \leq d(x, y)$ , so

$$\text{OPT}_R(X, \delta) \leq \text{OPT}_{GR}(X, d)$$

$$\Gamma = p_0 \rightarrow p_1 \rightarrow \dots \rightarrow p_{m-1} \rightarrow p_0$$
$$\text{cost}_{GR}(\Gamma) = \sum_{i=0}^{m-1} d(p_i, p_{i+1})$$

$$\text{cost}_R(\Gamma) = \sum_{i=0}^{m-1} \delta(p_i, p_{i+1}) \leq \text{cost}_{GR}(\Gamma)$$

## Metric TSP-R equivalent to General TSP-R

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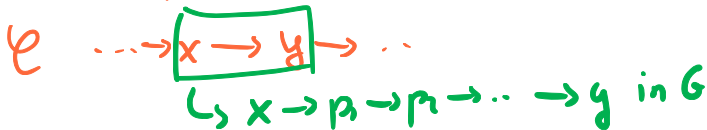
$$\text{cost}_R(\mathcal{C}) \leq c \cdot \text{opt}_R(X, \delta) \leftarrow c \cdot \text{OPT}_{GR}(X, d)$$

- For every pair  $(x, y) \in X^2$ , note that  $\delta(x, y) \leq d(x, y)$ , so

$$\text{OPT}_R(X, \delta) \leq \text{OPT}_{GR}(X, d)$$

- Let  $\Gamma$  be the cycle obtained from  $\mathcal{C}$  by simply replacing every  $x \rightarrow y$  by the shortest path  $x \rightarrow p_1 \rightarrow \dots \rightarrow p_t \rightarrow y$  in  $G$ .

$$\text{cost}_R(\mathcal{C}) \leq \text{cost}_{GR}(\mathcal{C}) \text{ wrong way}$$



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- For every pair  $(x, y) \in X^2$ , note that  $\delta(x, y) \leq d(x, y)$ , so

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- Let  $\Gamma$  be the cycle obtained from  $\mathcal{C}$  by simply replacing every  $x \rightarrow y$  by the shortest path  $x \rightarrow p_1 \rightarrow \dots \rightarrow p_t \rightarrow y$  in  $G$ .

- 1 Note that

$$\text{cost}(\mathcal{C}, \delta) = \text{cost}(\Gamma, d)$$

General  
TSP w/  
repetition

$\delta(x, y) =$  length (under  $d$ ) of shortest path from  $x$  to  $y$  in  $X$ .

## Metric TSP-R equivalent to General TSP-R

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- Combining the inequalities so far, we get:

$$\text{cost}(\Gamma, d) = \text{cost}(\mathcal{C}, \delta) \leq c \cdot \text{opt}_R(X, \delta) \leq c \cdot \text{opt}_{GR}(X, d)$$

*metric R*                      *general R*

- Equivalent Versions of Traveling Salesman Problem
- **Approximation Algorithms for Traveling Salesman Problem**
- Conclusion
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The following lemma gives us a way to get a 2-approximation algorithm:

### Lemma

Let  $T(X, E, d)$  be a weighted tree with vertices  $X$  and weights given by the distance function  $d : X \times X \rightarrow \mathbb{R}_{\geq 0}$ . There is a cycle  $\mathcal{C}$  that reaches each vertex at least once, and such that

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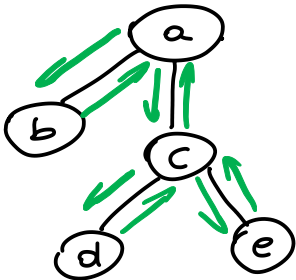
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There is a polynomial-time 2-approximation algorithm for General TSP-R.

**Idea:** find a minimum spanning tree on the complete weighted graph  $G(\underline{X}, \underline{K_X}, \underline{d})$ .

# Example

Tree



DFS goes!

$a \rightarrow b \rightarrow a \rightarrow c \rightarrow d \rightarrow c$   
 $\rightarrow e \rightarrow c \rightarrow a$

Edges:

$\{a, b\}$ ,  $\{a, b\}$ ,  $\{a, c\}$ ,  
 $\{c, d\}$ ,  $\{c, d\}$ ,  $\{c, e\}$ ,  
 $\{c, e\}$ ,  $\{a, c\}$

# Proof of Theorem

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Cost of minimum spanning tree easy to get  
is lower bound on optimum solution  
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  - Note that the weighted graph  $H(\underline{X}, \underline{F}, d)$  is connected. Let  $T'$  be a spanning tree of this graph.

$$\underbrace{\text{cost}(T', d)}_{T' \subset F} \leq \underbrace{\text{cost}(\mathcal{C}, d)}_{\text{has all edges in } F} = \text{OPT}_{GR}(X, d)$$

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  - Note that the weighted graph  $H(X, F, d)$  is connected. Let  $T'$  be a spanning tree of this graph.

$$\text{cost}(T', d) \leq \text{cost}(\mathcal{C}, d) = OPT_{GR}(X, d)$$

- Since  $T'$  is a spanning tree of  $X$ , we have that

$$\boxed{\text{cost}(T, d)} \leq \boxed{\text{cost}(T', d)} \leq OPT_{GR}(X, d)$$

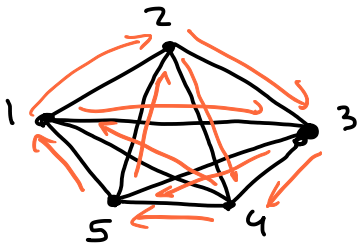
and we are done.

# Eulerian Tours

## Definition (Eulerian Cycle)

An Eulerian cycle in a multigraph  $G(V, E)$  is a cycle  $p_0 \rightarrow p_1 \rightarrow \dots \rightarrow p_m = p_0$  such that the number of edges  $\{u, v\} \in E$  is equal to the number of times  $\{u, v\}$  is used in the cycle.

In other words, each edge is used *exactly once*.



$1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 5 \rightarrow 1 \rightarrow 3$   
 $\rightarrow 5 \rightarrow 2 \rightarrow 4 \rightarrow 1$



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## Theorem (Eulerian Cycle Existence and Algorithm)

A multi-graph  $G(V, E)$  has an Eulerian cycle if, and only if, every vertex has *even degree* and the vertices of positive degree are *connected*.

Moreover, there is a polynomial time algorithm that, on input a connected graph  $G(V, E)$  in which every vertex has even degree, outputs an Eulerian cycle.



## Proof of Theorem 1

$(\Rightarrow)$   $G(V, E)$  has Eulerian cycle,  $u \in V$

$\Rightarrow$  for each "incoming edge" of the cycle  $(w, u)$ , by following cycle we can pair it with the subsequent "outgoing edge"  $(u, w')$ .  $\Rightarrow \deg(u)$  even, as all edges are distinct.

## Proof of Theorem II

( $\Leftarrow$ ) Induction on # edges in graph.

If  $G(V, E)$  connected and all vertices have even degree, then  $G$  has a cycle.

If every vertex has degree 2, then  $G$  must be a cycle (since it's connected). This case we are done.

Otherwise take cycle without repetition starting from vertex of degree  $\geq 4$ . (such cycle must exist as  $G$  connected). Removing this cycle (and vertices of degree 0) we get smaller connected graph with even degrees.  $\square$

Procedure above gives poly-time algorithm!

How to find small cycle? (DFS!) 

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$$\underbrace{\sum_{v \in T} \deg(v)}_{\text{odd}} = \underbrace{2 \cdot |E|}_{\text{even}}$$
$$\sum_{v \in O} \deg(v) + \sum_{u \in E} \deg(u) = 2 \cdot |E|$$
$$\sum_{v \in O} \deg(v) = \sum_{u \in E} \deg(u)$$

Handwritten notes: The first equation shows the sum of degrees in a tree is even. The second equation shows the sum of degrees in the double tree is also even. The third equation shows that the sum of degrees of odd-degree vertices in the tree must be even, equal to the sum of degrees of even-degree vertices.



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*complete*

$(O, K_O, d)$

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  - Thus we get a 3/2-approximation!

## Putting Everything Together

use this form for simplicity  
as they are equivalent!

- 1 **Input:**  $(X, d)$  instance of *Metric TSP-R*
- 2 **Output:** Cycle  $\mathcal{C}$  over  $X$  covering every vertex at least once, with

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- 6 Let  $E$  be the set of edges of  $T$  together with the set of edges of  $\mathcal{M}$
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- 8 Output  $\mathcal{C}$

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$$\text{cost}(\mathcal{C}, d) = \text{cost}(T, d) + \text{cost}(\mathcal{M}, d)$$

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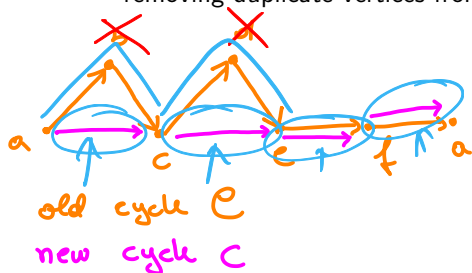
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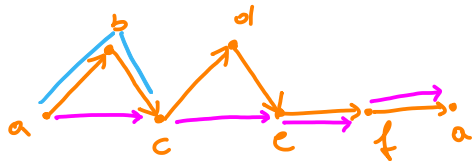
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old cycle  $\mathcal{C}$

new cycle  $\mathcal{C}$



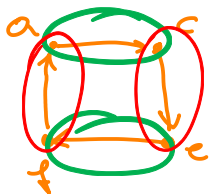
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  - Thus:

$$\underbrace{\text{cost}(\mathcal{M}, d)} \leq \underbrace{\frac{1}{2} \cdot \text{cost}(C, d)} \stackrel{\text{metric}}{\downarrow} \underbrace{\frac{1}{2} \cdot \text{cost}(\Gamma, d)} \stackrel{\text{optimality}}{\downarrow} \underbrace{\frac{1}{2} \cdot \text{OPT}_R(X, d)}$$

## Conclusion

- Traveling Salesman Problem - important, but NP-hard
- Equivalent variants of TSP

(The first variant is **NOT** equivalent to other 3 because the last 3 have c-approx. algorithm and first hard to approximate)

# Conclusion

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# Conclusion

- Traveling Salesman Problem - important, but NP-hard
- Equivalent variants of TSP
- Combinatorial Approximation Algorithms for TSP
- Achieve approximation algorithm by looking at an object (minimum spanning tree) which is a *lower bound* on the cost of the optimum
- This object (minimum spanning tree) is also easy to find, so exploit that to our advantage to get approximation algorithm.

# Acknowledgement

- Lecture based largely on:
  - Lectures 2-4 of Luca's Optimization class
- See Luca's Lecture 3 notes at <https://lucatrevisan.github.io/teaching/cs261-11/lecture03.pdf>
- See Luca's Lecture 4 notes at <https://lucatrevisan.github.io/teaching/cs261-11/lecture04.pdf>