

# **COMP 446 / 546**

# **ALGORITHM DESIGN**

# **AND ANALYSIS**

**LECTURE 15 APPROXIMATION ALGORITHMS**

**ALPTEKİN KÜPÇÜ**

Based on slides of Shafi Goldwasser, Michael Goodrich, and Roberto Tamassia

# DEALING WITH NP-COMPLETE PROBLEMS

- **Conjecture:  $P \neq NP$**

- A widely believed conjecture is that no NP-complete problem has a polynomial time algorithm.

- **Alternatives:**

- Run an **exponential-time** algorithm which **always** outputs the **correct** solution. (Useful if input is small.)
- Run a **polynomial-time** algorithm which produces **potentially incorrect** solutions for some (or all) inputs.
  - **Heuristic:** a strategy for producing solutions with no guarantee for their correctness.
- Run an **approximation algorithm** which always runs in **polynomial time** and produces a solution which is **provably** within a guaranteed **approximation factor** from the **optimal** solution.

# OPTIMIZATION PROBLEMS

- **Optimization Problems**

- We have some problem instance  $x$  that has many feasible solutions.
- We are trying to minimize (or maximize) some cost function  $c(S)$  for a solution  $S$  to  $x$ .

- **Examples**

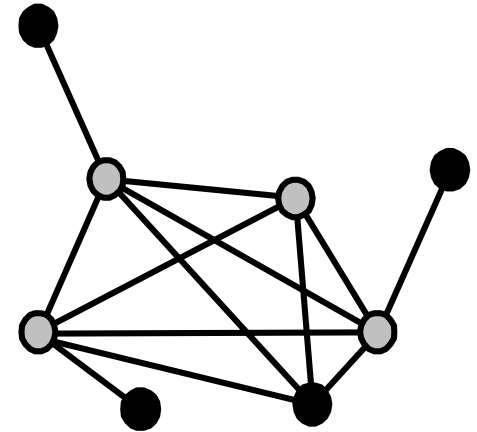
- Find a minimum spanning tree of a graph
- Find a smallest vertex cover of a graph
- Find a shortest traveling salesperson tour in a graph

# APPROXIMATION

- An approximation produces a solution **T**
  - **T** is a **k-approximation** to the optimal solution **OPT** if  $c(T)/c(OPT) \leq k$ 
    - For maximization problems, use  $c(OPT)/c(T)$
    - $k=1$  exactly when  $c(OPT)=c(T)$
    - For example if  $k=2$  and  $c(OPT)=5$ , then  $5 \leq c(T) \leq 10$ .
  - The approximation is **provable**.
- A problem has a **polynomial-time approximation scheme (PTAS)** if it has a polynomial-time  **$(1+\epsilon)$ -approximation** algorithm, for any **constant  $\epsilon > 0$**  ( $\epsilon$  may affect the running time).
  - Some NP-complete problems have PTAS for small **constant k**.
  - For some other NP-complete problems, computing **any approximation with constant k** is still **NP-complete**.

# MIN VERTEX COVER

- **Input:** An undirected graph  $G=(V,E)$
- **Problem:** Find a subset  $S$  of  $V$  that is a **vertex cover** of **minimum size** (every edge in  $E$  has **at least one** end point in  $S$ , and all other vertex covers contain **at least  $|S|$**  vertices)



- **Theorem:** MIN-VERTEX-COVER is NP-Hard
- **Proof:** Enough to show that the decision version is NP-Complete

# MIN VERTEX COVER

## 2-APPROXIMATION

MIN-VERTEX-COVER-2 ( $G \langle V, E \rangle$ )

$C \leftarrow \emptyset$

$E' \leftarrow E$

while  $E' \neq \emptyset$  do //some edges are not covered yet

    pick any edge  $e \in E'$  where  $e = (u, v)$

$C \leftarrow C \cup \{u, v\}$  //add both  $u$  &  $v$  to  $C$

    forall  $e \in \text{incidentEdges}(u)$  do

$E'.\text{remove}(e)$

    forall  $e \in \text{incidentEdges}(v)$  do

$E'.\text{remove}(e)$

return  $C$

**Polynomial-Time**

# MIN VERTEX COVER

## 2-APPROXIMATION

- **Theorem:** The **MIN-VERTEX-COVER-2** algorithm is a  $k = 2$  approximation algorithm for minimum vertex cover problem. Namely, for every graph  $G$ , if  $OPT$  is the optimal (minimal) vertex cover and  $T$  is the vertex cover computed by the algorithm, then we have  $|T| \leq 2 |OPT|$
- **Proof:**
  - First, the algorithm returns a vertex cover. *Why?*
    - Since we iterate until every edge is covered.
  - A minimal vertex cover must include **at least one** vertex incident to each edge
  - The algorithm includes **two**.
    - At most twice the size.

# MIN VERTEX COVER

## 2-APPROXIMATION (LP)

- **For each vertex:**
  - Create a variable  $x_i$
  - Add constraint  $0 \leq x_i \leq 1$  (think of  $x_i = 1$  as picking the vertex)
- **For each edge (i,j)**
  - Add constraint  $1 \leq x_i + x_j$
- **Objective function:** minimize  $\sum_i x_i$
- The resulting **linear program**:

**minimize**  $\sum_i x_i$

**s.t.**  $0 \leq x_i \leq 1$

$1 \leq x_i + x_j$



# MIN VERTEX COVER 2-APPROXIMATION (LP)

- **MIN-VERTEX-COVER-LP (G)**

- Solve the linear program:

$$\text{minimize } \sum_i x_i$$

$$\text{s.t. } 0 \leq x_i \leq 1$$

$$1 \leq x_i + x_j$$

- LP solution (call **OPT-frac**) may have fractional  $x_i$  values. Add each vertex  $i$  to the vertex cover iff  $\frac{1}{2} \leq x_i$ .

- **Theorem:** The **MIN-VERTEX-COVER-LP** algorithm is a  **$k = 2$**  approximation algorithm for minimum vertex cover problem.

- Observe that  $|\text{OPT-frac}| \leq |\text{OPT}|$  **WHY??**
- The algorithm's solution **T** is a vertex cover. **WHY??**
- We have  $|\text{T}| \leq 2 |\text{OPT-frac}|$ . Thus  $|\text{T}| \leq 2 |\text{OPT}|$ . **WHY??**

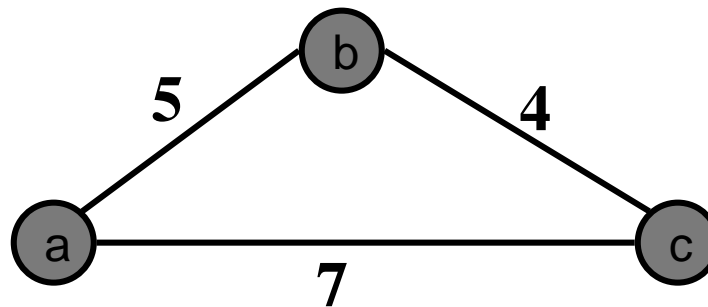
# LP-BASED APPROXIMATION

- **General LP-based Method:** Formulate a linear program that includes all solutions to an NP-hard problem, including fractional solutions (remember LP-relaxation). Then round up/down.
- **Interestingly, for Vertex Cover:**
  - No algorithm is known that achieves better than  $2 - O(1 / \sqrt{\log n})$ 
    - Not even 1.9
  - **Theorem (Hastad):** It is NP-hard to achieve an approximation algorithm with ratio better than  $7/6$ .
    - Even an approximation is NP-hard.

# SPECIAL CASE OF TSP

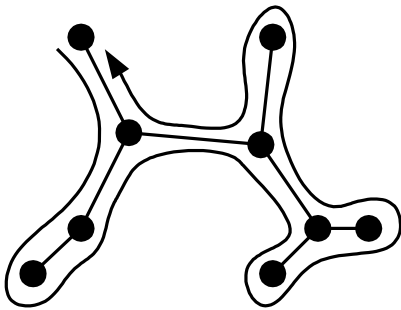


- **OPT-TSP:** Given a complete, weighted graph, find a simple cycle of minimum cost that visits each vertex.
  - OPT-TSP is NP-hard
- **Special case:** Edge weights satisfy the triangle inequality
  - $w(a,b) + w(b,c) \geq w(a,c)$
  - Common in many applications

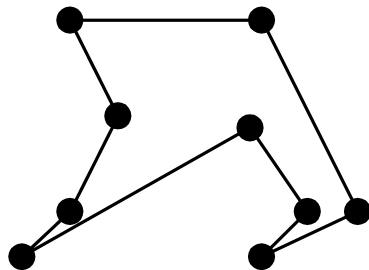


# TSP SPECIAL CASE

## 2-APPROXIMATION



Euler tour  $P$  of MST  $M$



Output tour  $T$

### TSPApprox( $G$ )

**Input:** weighted complete graph  $G$ , satisfying the triangle inequality

**Output:** a TSP tour  $T$  for  $G$

$M \leftarrow$  a minimum spanning tree for  $G$

$P \leftarrow$  an Euler tour traversal of  $M$ , starting at some vertex  $s$

$T \leftarrow$  empty list

for each vertex  $v$  in  $P$  //in traversal order

    if this is  $v$ 's first appearance in  $P$  then

$T.insertLast(v)$

$T.insertLast(s)$

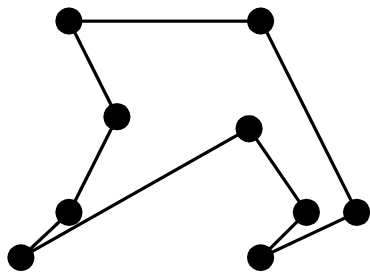
return  $T$

# TSP SPECIAL CASE

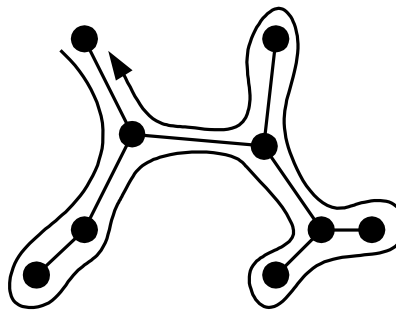
## 2-APPROXIMATION

- **Proof of 2-approximation:**

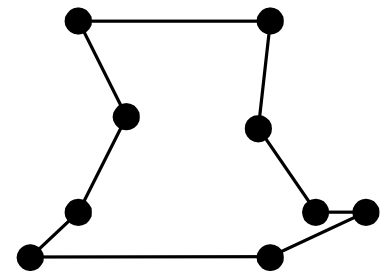
- Optimal tour is a spanning tour (must visit each vertex)  $\rightarrow |M| \leq |OPT|$
- The Euler tour  $P$  visits each edge of  $M$  twice  $\rightarrow |P| = 2|M|$
- Each time we shortcut a vertex in the Euler Tour, we will not increase the total length  $\rightarrow |T| \leq |P|$ .
  - Remember the triangle inequality  $w(a,b) + w(b,c) \geq w(a,c)$
- Therefore,  $|T| \leq |P| = 2|M| \leq 2|OPT|$



Output tour  $T$   
(at most the cost of  $P$ )



Euler tour  $P$  of MST  $M$   
(twice the cost of  $M$ )



Optimal tour  $OPT$   
(at least the cost of MST  $M$ )

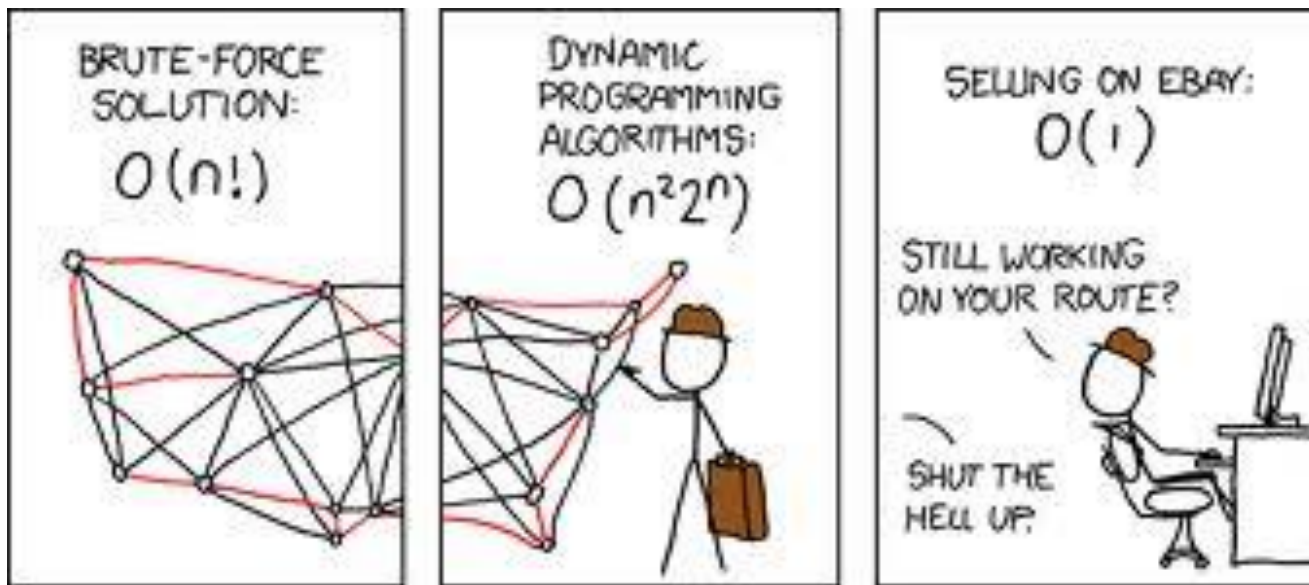
# CONCLUSIONS

- We can sometimes find efficient approximation algorithms for NP-hard problems.
  - for CLIQUE  $k = n / \log n$
  - for VERTEX-COVER  $k = 2$
  - for SET-COVER  $k = \log n$
  - for TSP special case  $k = 2$
- **Conclusion:** The fact that decision versions are computationally equivalent does not mean that problems can be approximated within the same factor!

# I WANT MORE !!!

- **To understand the underlying theory**
  - Take **Computation and Complexity** course
  - Join the reading/discussion group (email **complexity@ku**)
- **To understand how to make use of hard problems**
  - Take **Modern Cryptography** course
  - Join the reading/discussion group (email **crypto@ku**)
  - Check the website: <https://crypto.ku.edu.tr>
- **To work on similar topics**
  - Come talk with me
  - Join our group at any level (undergrad, master's, phd, post-doc)
- **Please make use of the skills you gained in this course...**

# TSP OPTIMAL SOLUTION



credit: xkcd