Slido: #ADA2022

CSIE 2136 Algorithm Design and Analysis, Fall 2022





Approximation Algorithms

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Announcement

- P HW4 deadlines
 - Problem 1-2: 2022/12/20 14:20
 - Problem 3-5: 2022/12/30 23:59
 - Problem 6: 2023/01/07 23:59
- Final exam: 2022/12/22
 - Closed book
 - Scope: all topics taught in ADA, focusing on those after the midterm
 - Details will be released on COOL later
- If you need to know your grade early, please notify us by email.
- No TA hours on and after 2022/12/22
- 優良助教問卷、期末教學意見調查

Agenda

- What is approximation? (same as last week's slides)
- Vertex cover
 - Approximate vertex cover (same as last week's slides)
 - Approximate weighted vertex cover
- P Traveling salesman problem
 - Proving NP-completeness
 - Approximation for metric TSP & inapproximability
- Randomized approximation algorithms

 - A MAX-CUT

What is approximation?

What is approximation?



- "A value or quantity that is nearly but not exactly correct"
- Approximation algorithms
 - applied to optimization problem, not decision problems
 - should guaranteed to find solutions close to optimality, returning near-optimal answers
 - Cf. heuristics search: no guarantee
 - P How "near" is near-optimal?

Approximation algorithms

- $\rho(n)$ -approximation algorithm
 - Efficient: guaranteed to run in polynomial time
 - General: guaranteed to solve every instance of the problem
 - Near-optimal: guaranteed to find solution within a factor of $\rho(n)$ of the cost of an optimal solution
- Approximation ratio $\rho(n)$
 - n: input size
 - C*: cost of an optimal solution
 - C: cost of the solution produced by the approximation algorithm

$$\max\left(\frac{C}{C^*}, \frac{C^*}{C}\right) \leq \rho(n)$$
 Maximization problem: $\frac{c^*}{c} \leq \rho(n)$ Minimization problem: $\frac{c}{c^*} \leq \rho(n)$

Approximate ratio p(n)

$$\max\left(\frac{C}{C^*}, \frac{C^*}{C}\right) \le \rho(n)$$

n: input size

C*: cost of optimal solution

C: cost of approximate solution

- $\rho \quad \rho(n) \ge 1$
- ρ $\rho(n)$ 越小越好!
- An exact algorithm has $\rho(n) = 1$
- \circ Challenge: prove that C is close to C^* without knowing C^* !

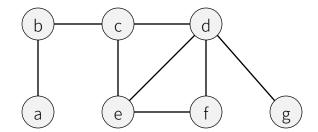
Approximate Vertex-Cover

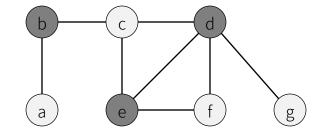
Vertex Cover

A vertex cover of G = (V, E) is a subset $V' \subseteq V$ such that if $(w, v) \in E$, then $w \in V'$ or $v \in V'$ or both

The Vertex-Cover Problem (Optimization)

Find a vertex cover of minimum size in G

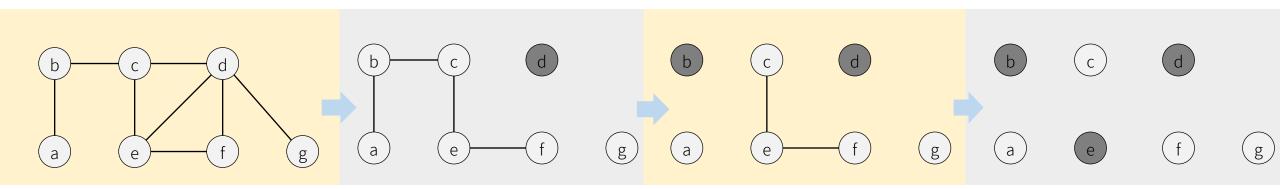




b, d, e is a minimum vertex cover (size = 3)

Q: Consider a greedy heuristic: In each iteration, cover as many edges as possible (vertex with the maximum degree) and then delete the covered edges. Does it always find an optimal solution?

▶ No. Otherwise, we would have proven P=NP.



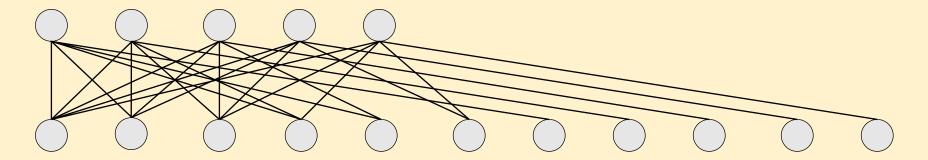
b, d, e is a vertex cover of size 3 found by the greedy algorithm (and it happens to be optimal!)

Q: Construct a graph on which the above greedy heuristic does not yield an optimal solution

Select d, c, a, e sequentially on the previous slide

Exercise 35.1-3 Construct a graph on which the above greedy heuristic does not have an approximation ratio of 2.

Hint: Try a bipartite graph with vertices of uniform degree on the left and vertices of varying degree on the right.



An approximation algorithm to VERTEX-COVER

- APPROX-VERTEX-COVER
 - Randomly select one edge at a time
 - Add both vertices to the cover
 - Remove all incident edges
- Running time = O(V + E)
- ho Claim: Approximation ratio $\rho(n) = 2$

```
APPROX-VERTEX-COVER (G)

1 C = \emptyset

2 E' = G.E

3 while E' \neq \emptyset

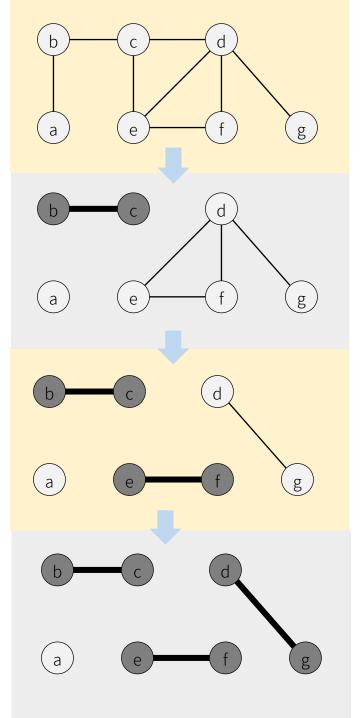
4 let (u, v) be an arbitrary edge of E'

5 C = C \cup \{u, v\}

6 remove from E' every edge incident on either u or v

7 return C
```

An approximation algorithm to VERTEX-COVER: example



b, c, d, e, f, g is a vertex cover of size 6 found by the approximation algorithm (not optimal!)

APPROX-VERTEX-COVER is 2-approximation

Let A denote the set of edges picked in line 4. \Rightarrow size of the vertex cover |S| = 2|A|

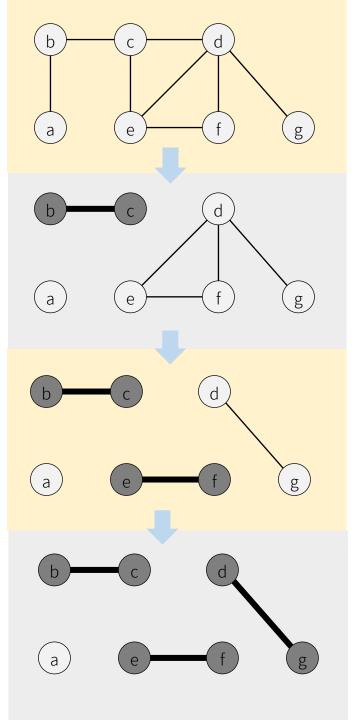
In any vertex cover S' (including S^*), every vertex v in S' covers at most one edge in A because no two edges in A share a vertex.

$$\Rightarrow |A| \leq |S^*|$$

Combing the two equations, we have $\frac{1}{2}|S| = |A| \le |S^*|$

$$\Rightarrow \rho(n) = 2$$

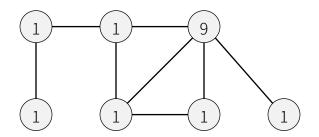
Note: the proof doesn't require knowing the actual value of |S*|

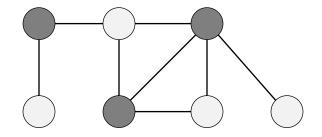


Approximate Weighted-Vertex-Cover

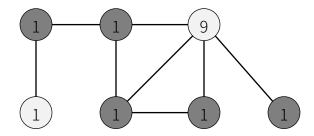
The Weighted-Vertex-Cover Problem (Optimization)

Given an undirected graph G = (V, E), and a weight function w(v) for all $v \in V$. Find a vertex cover whose total weight is minimized.





minimum vertex cover (size = 3)



minimum weighted vertex cover (weight = 5)

Q: Is the decision problem of weighted vertex cover a NPC problem? Q: Is APPROX-VERTEX-COVER also a 2-approximation algorithm for finding minimum weighted vertex cover?

Modeling weighted vertex cover via integer programming

- Recall the Integer programming formulation for vertex cover
- Weighted vertex cover can be modeled similarly:
 - \circ Variables: $x_i \in \{0,1\}$ represents whether vertex v_i is covered
 - $\text{Minimize: } z^* = \sum_{i=1}^{|V|} w(v_i) x_i$
 - Subject to
 - $x_i + x_j \ge 1, \forall e = (v_i, v_j) \in E$
 - $P \quad x_i \in \{0,1\}, \forall i = 1,2,..., |V|$

Approximating weighted vertex cover via linear programming

- Now we relax the integer programming formulation to linear programming, i.e., allowing non-integer variables
- Linear programming to approximate weighted vertex cover
 - \circ Variables: $0 \le x_i \le 1$
 - $\text{Minimize: } \hat{z}^* = \sum_{i=1}^{|V|} w(v_i) x_i$
 - Subject to
 - $P \quad x_i + x_j \ge 1, \forall e = (v_i, v_j) \in E$
 - $0 \le x_i \le 1, \forall i = 1, 2, ..., |V|$

Q: Argue that $\hat{z}^* \leq z^*$. That is, the LP solution is a lower bound of the IP solution.

An approximation algorithm to WEIGHTED-VERTEX-COVER

```
APPROX-WEIGHTED-VERTEX-

COVER(G, w)

C = \emptyset

X = \text{LinearProgram}(G, w)

for each v \in V

if x_v \ge 1/2

C = C \cup \{v\}

return C
```

```
LinearProgram(G, w)

Variables: 0 \le x_i \le 1

Minimize: \sum_{i=1}^{|V|} w(v_i) x_i

Subject to x_i + x_j \ge 1, \forall e = (v_i, v_j) \in E

0 \le x_i \le 1, \forall i = 1, 2, ..., |V|
```

Q: Show that APPROX-WEIGHTED-VERTEX-COVER outputs a vertex cover.

To satisfy the constraint $x_i + x_j \ge 1$, $\forall e = (v_i, v_j) \in E$, either x_i or x_j must be $\ge 1/2$. Thus, by choosing v_i whose $x_i \ge 1/2$, we ensure all edges are covered.

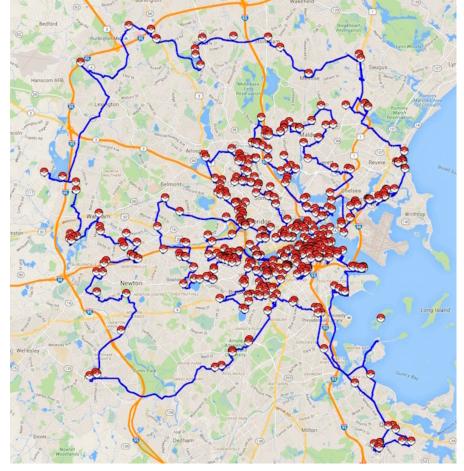
Q: show that APPROX-WEIGHTED-VERTEX-COVER is a 2-approximation algorithm for weighted vertex cover.

Hint: what's the relationship among \hat{z}^* , z^* , and w(C)?

Traveling Salesman Problem: Proving NP-Completeness

Traveling Salesman Problem (TSP)

- Optimization problem: Given an undirected complete graph G = (V, E) and a nonnegative edge cost function w, find a tour of lowest cost
- Pecision problem: Given an undirected complete graph G = (V, E) and a nonnegative edge cost function w, find a tour of cost at most k
- Properties Tour = visit each vertex exactly once and return to the beginning



A tour to catch every (518) Pokémon in Boston https://www.math.uwaterloo.ca/tsp/poke/index.html

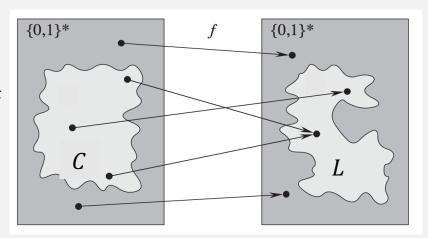
The TSP Problem

TSP = $\{(G, w, k): G = (V, E) \text{ is a complete graph, } w \text{ is a non-negative cost function for edges, } G \text{ has a traveling-salesman tour with cost at most } k\}$

- Prove that TSP ∈ NP-COMPLETE
- Polynomial-time reduction: HAM-CYCLE \leq_p TSP

Step-by-step approach for proving *L* in NPC:

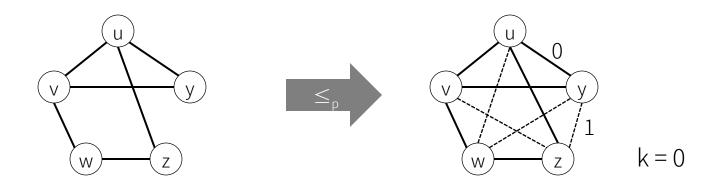
- 1. Prove $L \subseteq NP$
- 2. Prove $L \subseteq NP$ -hard $(C \leq_p L)$
 - Select a known NPC problem C
 - Construct a reduction f transforming every instance of C to an instance of L
 - 3 Prove that x in C if and only if f(x) in L for all x in $\{0,1\}^*$
 - 4 Prove that f is a polynomial time transformation



The TSP Problem

TSP = $\{(G, w, k): G = (V, E) \text{ is a complete graph, } w \text{ is a non-negative cost function for edges, } G \text{ has a traveling-salesman tour with cost at most } k\}$

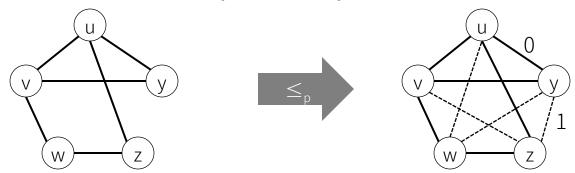
- ② Construct a reduction f transforming every HAM-CYCLE's instance $G_H = (V_H, E_H)$ to a TSP instance with cost at most k
 - We construct a TSP instance in which G is a complete graph with $V = V_H$, and w(i,j) = 0 if $(i,j) \in E_H$; w(i,j) = 1, otherwise.
 - ho With this reduction function, we set k=0



$\mathsf{HAM}\text{-}\mathsf{CYCLE} \leq_p \mathsf{TSP}$

- ③ Prove that $x \in \text{HAM_CYCLE} \Leftrightarrow f(x) \in \text{TSP}$ Correctness proof: $x \in \text{HAM-CYCLE} \Leftrightarrow f(x) \in \text{TSP}$
- More specifically, we want to prove that G contains a Hamiltonian cycle $h = \langle v_1, v_2, ..., v_n, v_1 \rangle$ if and only if $\langle v_1, v_2, ..., v_n, v_1 \rangle$ is a traveling-salesman tour with cost at most 0

u, y, v, w, z, u is a Hamiltonian cycle ⇔ u, y, v, w, z, u is a traveling-salesman tour with cost 0

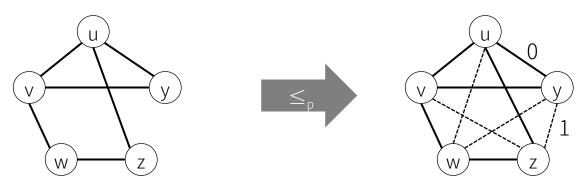


$\mathsf{HAM}\text{-}\mathsf{CYCLE} \leq_p \mathsf{TSP}$

③ Prove that $x \in \mathsf{HAM}_\mathsf{CYCLE} \Leftrightarrow f(x) \in \mathsf{TSP}$

Correctness proof: $x \in HAM$ -CYCLE $\Rightarrow f(x) \in TSP$

- Suppose the Hamiltonian cycle is $h = \langle v_1, v_2, ..., v_n, v_1 \rangle$
- $\Rightarrow h$ is also a tour in the transformed TSP instance
- \Rightarrow The cost of the tour h is 0 since there are n consecutive edges in E, and so has cost 0 in f(x)
- $\Rightarrow f(x) \in \mathsf{TSP}(f(x) \text{ has a TSP tour with cost} \le 0)$



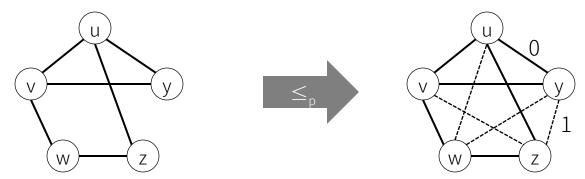
u, y, v, w, z, u is a Hamiltonian cycle

u, y, v, w, z, u is a traveling-salesman tour with cost 0

$\mathsf{HAM}\text{-}\mathsf{CYCLE} \leq_p \mathsf{TSP}$

③ Prove that $x \in \mathsf{HAM}_\mathsf{CYCLE} \Leftrightarrow f(x) \in \mathsf{TSP}$ Correctness proof: $f(x) \in \mathsf{TSP} \Rightarrow x \in \mathsf{HAM}-\mathsf{CYCLE}$

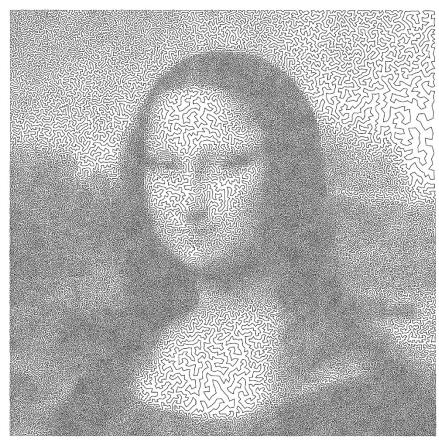
- Suppose after reduction, there is a TSP tour with cost ≤ 0 . Let it be $\langle v_1, v_2, ..., v_n, v_1 \rangle$
- $ho \Rightarrow$ The TSP tour contains only edges in E_H
- \triangleright \Rightarrow Thus, $\langle v_1, v_2, ..., v_n, v_1 \rangle$ is a Hamiltonian cycle ($x \in HAM\text{-CYCLE}$).



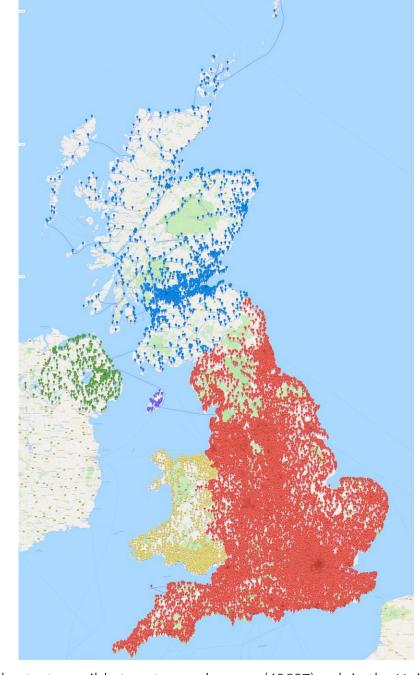
u, y, v, w, z, u is a Hamiltonian cycle

u, y, v, w, z, u is a traveling-salesman tour with cost 0

TSP arts and challenges



Mona Lisa TSP: \$1,000 Prize for a 100,000-city challenge problem http://www.math.uwaterloo.ca/tsp/



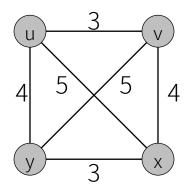
Shortest possible tour to nearly every (49687) pub in the United Kingdom https://www.math.uwaterloo.ca/tsp/uk/

Traveling Salesman Problem: Approximation for Metric TSP

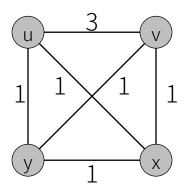
Metric TSP

- Optimization problem: Given a set of cities and their pairwise distances, find a tour of lowest cost that visits each city exactly once, and the pairwise distances satisfy triangle inequality.
 - Priangle inequality: $\forall u, v, w \in V, d(u, w) ≤ d(u, v) + d(v, w).$

Satisfy triangle inequality



Do not satisfy triangle inequality



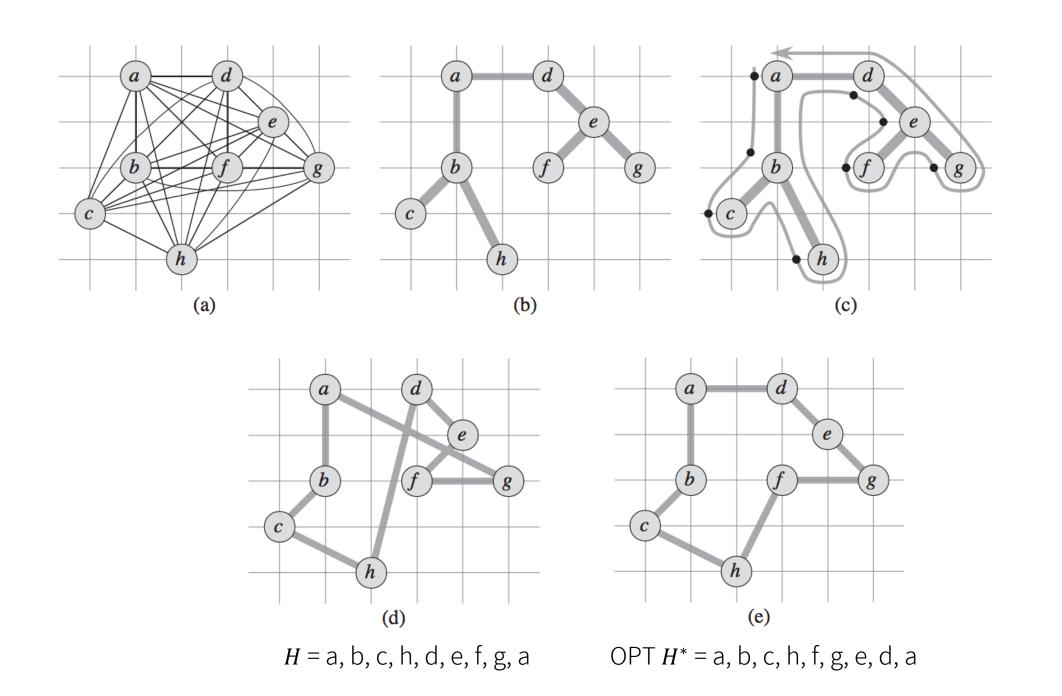
Show that Metric TSP is also in NPC

<u>Hint</u>: reduce from either HAM-CYCLE or general TSP; make sure the metric TSP instance satisfies the triangle inequality

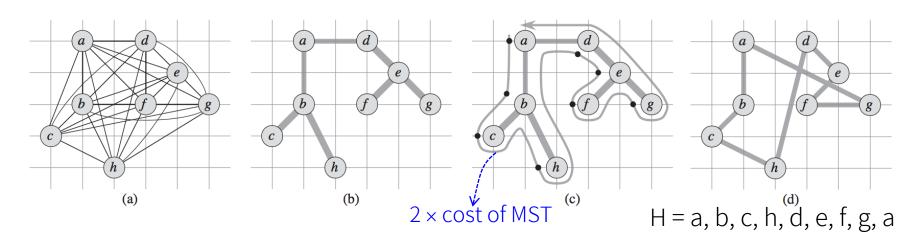
2-approximation algorithm for Metric TSP

APPROX-TSP-TOUR(G) 1. select a vertex $r \in G.V$ to be a "root" vertex 2. grow a minimum spanning tree T for G3. let H be the list of vertices visited in a preorder tree walk of T4. **return** H

- Running time is dominated by finding a MST
 - \circ MST is in P: $O(V^2)$ when using adjacency matrix
- P Claim: Approximation ratio $\rho(n) = 2$



2-approximation algorithm for Metric TSP



- Let H^* denote an optimal tour, H the TSP tour found by the algorithm, T^* a MST
- \circ With triangle inequality, immediately we have $w(H) \leq 2w(T^*)$
- Also, H^* is formed by some tree T plus some edge e, i.e., $w(H^*) = w(T) + w(e)$
- \circ Combining $w(H) \le 2w(T^*)$ and $w(T^*) \le w(H^*)$, we have $w(H) \le 2w(T^*) \le 2w(H^*)$
- $\rho \Rightarrow \rho(n) = 2$

Traveling Salesman Problem: Inapproximability of General TSP

Theorem 35.3 General TSP (when triangle inequality may not hold)

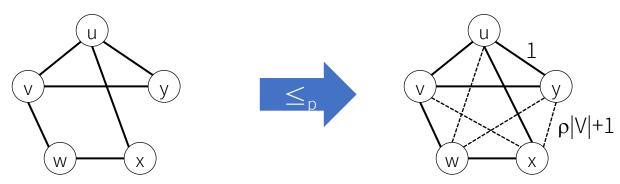
If P \neq NP, there is no polynomial-time approximation algorithm with a constant ratio bound ρ for the general TSP.

Proof by contradiction

- Suppose there is such an algorithm Alg_{AT} to approximate TSP with a constant ρ . We will use Alg_{AT} to construct Alg_{HC} to solve HAM-CYCLE in polynomial time.
- P Consider the following reduction algorithm f converting an instance of HAM-CYCLE α into an instance of TSP f(α)
 - $\alpha = \{G = (V, E)\}; f(\alpha) = \{G' = (V, E'), w, k = \rho |V|\}$
 - Part is, we construct a TSP instance with a complete graph G' = (V, E'), where w(u, v) = 1 if $(i, j) \in E$; $w(u, v) = \rho |V| + 1$, otherwise.
 - Run Alg_{AT} on $f(\alpha)$
 - ρ If $Alg_{AT}(f(\alpha))$ returns a tour whose cost ≤ $\rho|V|$, then $Alg_{HC}(\alpha) = 1$ (i.e., G contains a Hamiltonian cycle); otherwise, $Alg_{HC}(\alpha) = 0$.

Proof by contradiction (cont'd)

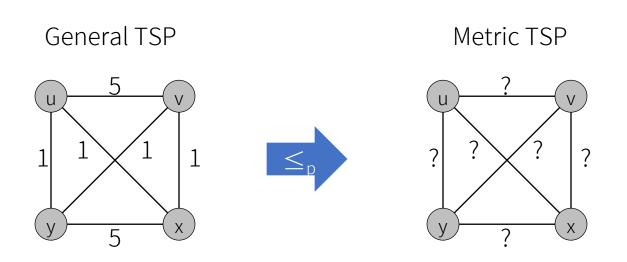
- Correctness of reduction
 - ρ If G has an HC: G' contains a tour of cost |V| by picking edges in E, each with cost of 1. Then, Alg_{AT} guarantees to return a tour whose cost ≤ ρ|V|.
 - Point of the proof of the
- $\Rightarrow Alg_{HC}$ can solve HAM-CYCLE in polynomial time, contradiction!



u, y, v, w, x, u is a Hamiltonian Cycle

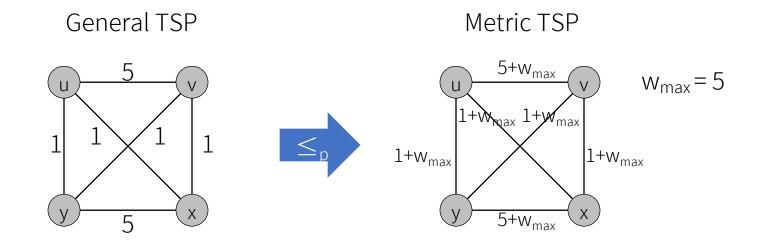
u, y, v, w, x, u is a traveling-salesman tour with cost |V|

Exercise 35.2-2 Show how in polynomial time we can transform one instance of the traveling-salesman problem into another instance whose cost function satisfies the triangle inequality. The two instances must have the same set of optimal tours. Explain why such a polynomial-time transformation does not contradict Theorem 35.3, assuming that P≠NP.

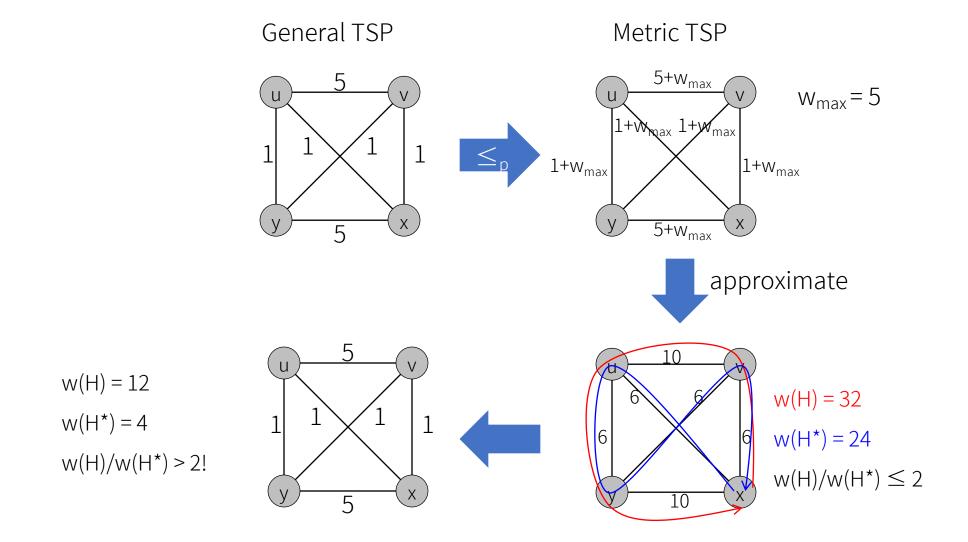


Exercise 35.2-2

- Por example, we can add w_{max} (the largest cost) to each edge
- P G contains a tour of minimum cost $k \Leftrightarrow G'$ contains a tour of minimum cost $k + w_{max} * |V|$
- G' satisfies triangle inequality because $\forall t, u, v \in V$, $w'(u, v) = w(u, v) + w_{max} \le 2 * w_{max} \le w'(t, u) + w'(t, v)$



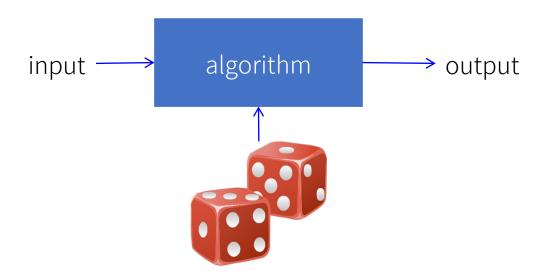
Exercise 35.2-2



Randomized Approximation Algorithms

Randomness

- A randomized algorithm is an algorithm that employs a degree of randomness as part of its logic
- A randomized data structure is a data structure that employs a degree of randomness as part of its logic
- A randomized algorithm's behavior is determined not only by its input but also by values produced by a random-number generator



Randomized approximation algorithm

	Exact	Approximate
Deterministic	Prim's (MST)	APPROX-TSP-TOUR
Randomized	Quick Sort	MAX-3-CNF-SAT MAX-CUT

MAX-3-CNF Satisfiability

- 3-CNF-SAT: Satisfiability of Boolean formulas in 3-conjunctive normal form (3-CNF)
 - 3-CNF = AND of clauses, each is the OR of exactly 3 distinct literals
 - ho A literal is an occurrence of a variable or its negation, e.g., x_1 or $\neg x_1$
- 2-CNF-SAT is a decision problem. What should be an optimization version of 3-CNF-SAT?

MAX-3-CNF Satisfiability

- MAX-3-CNF-SAT: find an assignment of the variables that satisfies as many clauses as possible
 - Closeness to optimum is measured by the fraction of satisfied clauses
- Can you design a randomized 8/7-approximation algorithm?

$$(x_1 \lor \neg x_1 \lor \neg x_2) \land (x_3 \lor x_2 \lor x_4) \land (\neg x_1 \lor \neg x_3 \lor \neg x_4)$$

 $<\mathsf{x}_1, \mathsf{x}_2, \mathsf{x}_3, \mathsf{x}_4> = <0, 0, 1, 1> \text{ satisfies 3 clauses}$
 $<\mathsf{x}_1, \mathsf{x}_2, \mathsf{x}_3, \mathsf{x}_4> = <1, 0, 1, 1> \text{ satisfies 2 clauses}$

Randomized 8/7-approximation algorithm for MAX-3-CNF-SAT

- A randomized 8/7-approximation algorithm:
 - · 丟硬幣決定變數要設成 0 或是 1
 - Part it.

Theorem 35.6

Given an instance of MAX-3-CNF-SAT with n variables $x_1, x_2, ..., x_n$ and m clauses, the randomized algorithm that independently sets each variable to 1 with probability 1/2 and to 0 with probability 1/2 is a randomized 8/7-approximation algorithm.

^{*} Satisfying 7/8 of the clauses in expectation

Theorem 35.6

Given an instance of MAX-3-CNF-SAT with n variables $x_1, x_2, ..., x_n$ and m clauses, the randomized algorithm that independently sets each variable to 1 with probability 1/2 and to 0 with probability 1/2 is a randomized 8/7-approximation algorithm.

<u>Proof</u>

- A clause that contains both a variable and its negation is always evaluated to 1
- P The rest of the clauses is the OR of exactly 3 distinct literals, and no variable and its negation appear at the same time
 - $Pr[x_i = 0] = Pr[x_i = 1] = 1/2$
 - \Rightarrow for all $x_1 \neq x_2 \neq x_3$, $\Pr[(x_1 \lor x_2 \lor \neg x_3) = 0] = 1/8$
- ⇒ E[# of satisfied clauses] = m * E[clause j is satisfied]≥ $m * (1 - \frac{1}{8}) = \frac{7}{8}m$
- $\rho \Rightarrow \rho(n) = \max \# \text{ of satisfied clauses } / E[\# \text{ of satisfied clauses}] \le 8/7$

MAX-CUT

- Poptimization problem: Given an unweighted undirected graph G = (V, E), find a cut whose size is maximized
 - A cut partitions V into V_0 and V_1 ; a cut consists of the edges across the partition
- Parallel Decision problem: Given an unweighted undirected graph G = (V, E), there exists a cut whose size is k
- MAX-CUT problem is NP-complete
 - C.f. MIN-CUT is in P
- Can you design a randomized 2-approximation algorithm?

Randomized 2-approximation algorithm for MAX-CUT

- \triangleright Randomly assign each vertex to either V_1 and V_2 with equal probablity
- Done!

<u>Proof</u>

- Let C be the cut found by the algorithm; C*is the maximum cut
- Property For any edge e = (u, v) on G, the probability that e ∈ C is ½
- Let x_e be an indicator variable for event $e \in C$; that is, $x_e = 1$ if $e \in C$, otherwise, 0.

$$> E[|C|] = E[\Sigma_{e \in E} x_e] = \Sigma_{e \in E} E[x_e]$$

$$= \Sigma_{e \in E} (Pr[e \in C] * 1 + Pr[e \notin C] * 0) = \frac{|E|}{2} \ge \frac{|C^*|}{2}$$

Suppose vertices are numbered from 1 to n, show that the following greedy algorithm achieves 2-approximation max cut:

- 1. Initially $V_0^1 = \{1\}, V_1^1 = \{\}$
- 2. Adding the *i*th vertex to the subset that results in a better cut, say $V_x, V_x^i = V_x^{i-1} \cup \{i\}, V_{1-x}^i = V_{1-x}^{i-1}$
- 3. Output V_0^n , V_1^n

Hint: consider the edges introduced by adding the ith vertex