

# Lecture 1: *Computational Complexity 101*

## **Advanced Algorithms**

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# 《《Computational Complexity 101》》



# Algorithms vs. Heuristics

## Definition (Algorithms)

- Based on good understanding of performance and optimality with rigorous analysis
- Supported by theoretical evidence and universal results
- E.g., approximation algorithms with proven approximation ratios

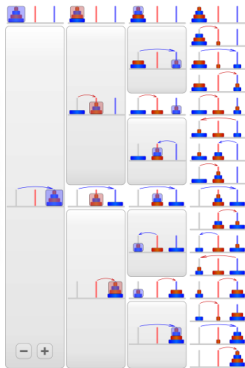
## Definition (Heuristics)

- Based on mostly guess work
- Empirically driven, but with no universal result and not backed by rigorous analysis
- E.g., meta-heuristics (e.g. genetic algorithms)

# How to solve Towers of Hanoi? Is it Hard?



Towers of Hanoi  
by divide-and-conquer



- Let  $\text{Hanoi}[n, r]$  be the algorithm that moves the smallest  $n$  disks from the left rod to rod  $r \in \{\text{middle}, \text{right}\}$

## Algorithm $\text{Hanoi}[n, r]$

- If  $n > 1$  then
  - ▶  $\text{Hanoi}[n - 1, \{\text{middle}, \text{right}\} \setminus \{r\}]$
  - ▶ Move the remaining  $n$ -th disk to rod  $r$
  - ▶  $\text{Hanoi}[n - 1, r]$
- Else
  - ▶ Move the smallest disk to rod  $r$

- Running time of  $\text{Hanoi}[n, r]$  is  $\Omega(2^n)$
- Is Towers of Hanoi a hard problem to solve?

# How to solve Sudoku? Is it Hard?

1				4				
4				8			3	6
				7		9		
2	7			8			6	
					4		8	
		1			5		2	4
	6	3	1					
7								

$3^2 \times 3^2$  Sudoku

	E	C	D	7		9	2								
	4	D	1	0			C		9		8				
1						9	3	6	D		E	7			
9				A	E			4			0	D			
	7		4	0						3	B				
B	C			1		0	5		7	E	4				
	A	2	4			E	B			F	8				
E	8	5	B	3	6		4	C			9				
	A				9	4		3	5		D				
3	C	8	B				E	1			9	F	5		
5			E				2			D	A				
	7	9			3			A	B		1	2			
		B	D	2		0	6	7	F		1	9			
7	4	3			1	F	2			D					
D	8	0	9		5	B		C	3		4				
A	F	1		E		7	D		0	6	C	5			

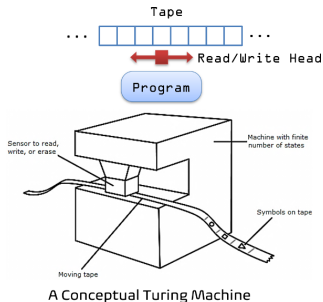
$4^2 \times 4^2$  Sudoku

J	A	N						C	B	2	M	P		E	H	O
H	D	O	6					8		1	A	B	G	C	E	L
8	1		A	K	O	3	B		L	F	5	1	H	7		C
B		A			G	L	N	I	H	6	8				D	M
	L	1	5	M	4	2	N		F		D	J	6	9	B	8
F	H	N	O	4	5			D		M	J	1		6	9	C
5		M		6	F			D		K	9	A	C		1	L
	1			1	2	J	K		7	A	B			N	H	O
6	A	E	G	9			C	L		O	2	5	7	1	3	F
1	J		K	D	1					E	G	3	H			B
M	5	3	L	7	N	A	C	1		F	B	G		K	E	
	F		B	G	O		1	8		E	7	1	5	K	D	6
K						1		5	O	H	6		9		N	
D	G			J	5	H	3		K	P	B		N	1	C	8
1	C	B	7	F	6	K	D	2		M	N		4	J		5
L	I		5			A	E	B	1	7	F	N	J			C
8	6	A	H				C	O			1			F	5	7
3	C	B	1			L	F	9		A	4			7	5	2
		5	O	7	1	3		C	L	4	2			H		K
		F		O			H	I	4	C	1			D	3	E
N	6	F	H				M	E	K	3			9	P		
G	O	5	3	C	P	E	8		F	6				4	B	J
	9	I	D	8	L	B	6		G		4	H	5	J		C
	J	1	G		F	7			5	9	N	L	2	A	6	
B			C		9				A		G	8			K	D

$5^2 \times 5^2$  Sudoku


- Can you solve a  $3^2 \times 3^2$  Sudoku? How about solving a  $n^2 \times n^2$  Sudoku?
- Can you check a given  $3^2 \times 3^2$  Sudoku solution? How about checking a  $n^2 \times n^2$  Sudoku solution?

# Mathematical Formalization of Algorithms



A Conceptual Turing Machine




Figure: Watch a real-life Turing machine:  <https://youtu.be/E3keLeMwfHY>

- Algorithms are represented by mechanical operations (i.e. program) of a universal problem solver (i.e. Turing machine)
  - An algorithm is a mapping from a tape of input sequence of symbols (i.e. problem instance) to an output sequence of symbols (i.e. answer)
  - Universal Turing Machine - Can simulate any programs and the tape is also consisted of an input program

# Abstract Representation of Problems

## Definition (Problems, Instances, Languages)

- We fix a certain encoding scheme  $\text{Enc}(\cdot)$  that maps a linguistic representation of a sentence to a binary representation (e.g. ASCII)
- A problem is represented by a subset of all (finite or infinite) binary strings  $\subseteq \{0, 1\}^*$ 
  - ▶ An instance of a problem is translated to a binary string by  $\text{Enc}(\cdot)$ , denoted by  $\mathcal{I} \in \{0, 1\}^*$
  - ▶ Multiple instances may have the same answer
  - ▶ The simplest of answer is binary (yes/no) for a decision problem
  - ▶ A decision problem can be represented by all the “yes” instances, denoted by a subset  $\mathcal{L} \subseteq \{0, 1\}^*$
  - ▶  $\mathcal{L}$  is also called a “language”
-  **Caveat:** Don't need to pay attention to a particular encoding scheme
  - ▶ We focus on an abstract representation of a problem

# Example: Decision Problem

## Example (Problem: isPrime(X))


- $\text{Enc}(\text{"isPrime(23)"}) \mapsto 101000100100$
  - $\text{Enc}(\text{"isPrime(25)"}) \mapsto 000010110011$
  - $\text{Enc}(\text{"isPrime(27)"}) \mapsto 1100010110011$
  - $\text{Enc}(\text{"isPrime(29)"}) \mapsto 0000000100010$
  - .....
  - Problem isPrime is represented by  $\mathcal{L}_{\text{isPrime}} = \{101000100100, 0000000100010, \dots\}$
  - Let  $\overline{\mathcal{L}}_{\text{isPrime}} \triangleq \{0, 1\}^* \setminus \mathcal{L}_{\text{isPrime}} = \{000010110011, 1100010110011, \dots\}$
- Why do we need an abstract representation of a problem?
    - ▶ Need a universal formalism, independent of any linguistic/programming languages



# Abstract Representation of Problems

- We can classify problems by their abstract representation
  - ▶ **Which problems are easy or hard?**
  - ▶ Which problems need a lot of memory space?
  - ▶ Which problems can be solved by a quantum computer?

## Definition

- Denote a realization of Turing Machine by  $\mathcal{M}$ , which implements an algorithm for problem  $\mathcal{L}$ 
  - ▶ Running time of  $\mathcal{M}$  should be polynomial in the input size ( $|\mathcal{I}|$ , or the #bits to represent  $\mathcal{I}$ )
- If you claim that you know an answer of a decision problem (yes/no), then you should be able to present a proof
  - ▶ Denote an instance of  $\mathcal{L}$  by  $\mathcal{I}$ , a witness (a proof of yes) by  $w$
  - ▶  **Caveat:** A witness does not need to be a solution for  $\mathcal{I}$
  - ▶  $\mathcal{M}(\mathcal{I}, w)$  should return TRUE, if  $w$  is a witness for  $\mathcal{I}$
  - ▶ Example:  $\mathcal{M}(\text{isComposite}(21), 3 \times 7)$  returns TRUE

# What are Hard Problems?

## Definition (Class NP)

- Let  $|\mathcal{I}| = \# \text{bits to represent } \mathcal{I}$  and  $|w| = \# \text{bits to represent } w$
- Define a class of problems called NP: For all  $\mathcal{L} \in \text{NP}$ , there exist a polynomial-time bound  $\mathcal{M}$  and a polynomial function  $p(\cdot)$ , such that
  - ▶ If  $\mathcal{I} \in \mathcal{L}$ , then there exists a witness  $w$  where  $|w| \leq p(|\mathcal{I}|)$ , such that  $\mathcal{M}(\mathcal{I}, w)$  returns TRUE, and
  - ▶ If  $\mathcal{I} \notin \mathcal{L}$ , then for any witness  $w$  where  $|w| \leq p(|\mathcal{I}|)$ ,  $\mathcal{M}(\mathcal{I}, w)$  returns FALSE
- NP stands for Non-deterministic Polynomial-time
- NP are the problems that can be verified efficiently when given a proof
- Question: Is  $\mathcal{L}_{\text{isPrime}} \in \text{NP}$ ? Is  $\mathcal{L}_{\text{isComposite}} \in \text{NP}$ ?

# What are Hard Problems?

## Definition (Class co-NP)

- Define a class of problems called co-NP: For all  $\mathcal{L} \in \text{co-NP}$ , there exist a polynomial-time bound  $\mathcal{M}$  and a polynomial function  $p(\cdot)$ , such that
  - ▶ If  $\mathcal{I} \notin \mathcal{L}$ , then there exists a witness  $w$  where  $|w| \leq p(|\mathcal{I}|)$ , such that  $\mathcal{M}(\mathcal{I}, w)$  returns TRUE, and
  - ▶ If  $\mathcal{I} \in \mathcal{L}$ , then for any witness  $w$  where  $|w| \leq p(|\mathcal{I}|)$ ,  $\mathcal{M}(\mathcal{I}, w)$  returns FALSE
- co-NP are problems that can be verified efficiently when given a counter-example
- $\mathcal{L} \in \text{co-NP} \iff \overline{\mathcal{L}} \in \text{NP}$
- Question: Is  $\mathcal{L}_{\text{isPrime}} \in \text{co-NP}$ ? Is  $\mathcal{L}_{\text{isComposite}} \in \text{co-NP}$ ?

# What are Hard Problems?

## Definition (Class P)

- Define a class of problems called P: For all  $\mathcal{L} \in P$ , there exists a polynomial-time bound  $\mathcal{M}$ , such that
  - ▶ If  $\mathcal{I} \notin \mathcal{L}$ , then without any witness,  $\mathcal{M}(\mathcal{I}, ?)$  returns TRUE, and
  - ▶ If  $\mathcal{I} \in \mathcal{L}$ , then without any witness,  $\mathcal{M}(\mathcal{I}, ?)$  returns FALSE
- P are problems that can generate a proof or a counter-example efficiently
- $P \subseteq \text{co-NP} \cap \text{NP}$
- Question: Is  $\mathcal{L}_{\text{isPrime}} \in P$ ?
- What are Hard Problems?
  - ▶ Conventional wisdom of computer scientists is that any problems that are not in P are hard
  - ▶ Otherwise, it is not time efficient to solve the problem (i.e. generating a proof or a counter-example)
  - ▶ Is that true? Million-dollar question that makes you immortal:  $P \stackrel{?}{=} \text{NP}$

# Solve New Problems from Known Problems

## Definition (Reduction)

- Consider two decision problems  $\mathcal{L}_1, \mathcal{L}_2 \in \text{NP}$ 
    - ▶ There may exist a polynomial-time bound  $\mathcal{M}$  such that it maps an instance  $\mathcal{I}_1 \in \mathcal{L}_1$  to an instance  $\mathcal{I}_2 \in \mathcal{L}_2$
  - A *polynomial-time reduction* from  $\mathcal{L}_1$  to  $\mathcal{L}_2$  if there exists a polynomial-time bound  $\mathcal{M}$ , such that
    - ▶ If  $\mathcal{I}_1 \in \mathcal{L}_1$ , then  $\mathcal{M}(\mathcal{I}_1) \in \mathcal{L}_2$
  - If  $\mathcal{L}_1$  can be polynomial-time reduced to  $\mathcal{L}_2$ , we write  $\mathcal{L}_1 \preceq \mathcal{L}_2$
- 
- Intuitively, if we can solve every  $\mathcal{I}_2 \in \mathcal{L}_2$ , then we can also solve every  $\mathcal{I}_1 \in \mathcal{L}_1$  (but not necessarily vice versa). Namely,  $\mathcal{L}_2$  is harder than  $\mathcal{L}_1$

# Example: Reduction from HamCyc to TSP

## Definition

- $\text{TSP}(C)$  (Travel Salesman Problem):
  - ▶ Given complete graph  $\mathcal{G}$  of  $n$  vertices & non-negative edge costs
  - ▶ Decide if the minimum cost cycle that visits every vertex exactly once has a cost  $\leq C$
- HamCyc (Hamiltonian Cycle Problem):
  - ▶ Given a graph  $\mathcal{G}'$  (may be not complete) of  $n$  vertices,
  - ▶ Decide if there is a cycle that visits every vertex exactly once
- We can show  $\text{HamCyc} \preceq \text{TSP}(c \cdot n)$  for any constant  $c > 1$ 
  - ▶ Given  $\mathcal{G}'$ , we construct  $\mathcal{G}$  with the same set of vertices in  $\mathcal{G}'$ 
    - ★ If  $e \in \mathcal{G}'$ , then  $c_{\mathcal{G}}(e) = 1$ , otherwise,  $c_{\mathcal{G}}(e) = c \cdot n$
  - ▶ This is a reduction, because that
    - ★ If  $\mathcal{G}'$  has a Hamiltonian cycle, then there exists a Hamiltonian cycle in  $\mathcal{G}$  with a cost  $\leq c \cdot n$
    - ★ If  $\mathcal{G}'$  has no Hamiltonian cycle, then any Hamiltonian cycle in  $\mathcal{G}$  will have a cost  $> c \cdot n$

# Are all Hard Problems equally Hard?

## Definition (NP-hard and NP-complete )

- Define a class of problems called NP-hard:
  - ▶ If  $\mathcal{L}' \preceq \mathcal{L}$  for any problem  $\mathcal{L}' \in \text{NP}$ , then  $\mathcal{L} \in \text{NP-hard}$
- Define a class of problems called NP-complete :
  - ▶ If  $\mathcal{L} \in \text{NP-hard}$  and  $\mathcal{L} \in \text{NP}$ , then  $\mathcal{L} \in \text{NP-complete}$
- $\text{NP-complete} = \text{NP} \cap \text{NP-hard}$
- NP-hard refers to the problems that are at least as hard as any problem in NP
- NP-complete refers to the hardest problem in NP
- Which is the hardest problem in NP?

# Hardness: Are all hard problems equally hard?

## Definition (SAT (Boolean Satisfiability Problem))

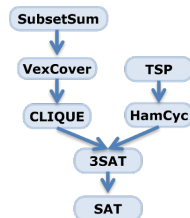
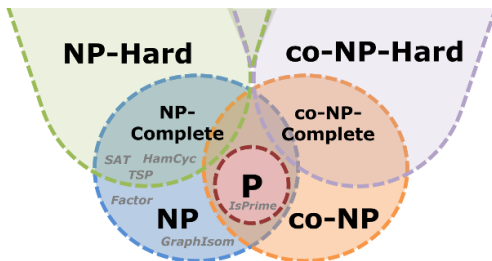
- A SAT is to decide if a given Boolean expression (that combines Boolean variables with Boolean operators) is satisfiable (i.e. there exists an assignment of truth values to the variables to make entire expression true)
- E.g., decide if  $\neg x_1 \vee (x_2 \wedge x_4) \vee (x_1 \wedge \neg x_3 \wedge x_4 \wedge x_5)$  is satisfiable

## Theorem (Cook's Theorem)

- SAT is NP-complete
- Cook's theorem implies that all NP-hard problems in NP are as hard as SAT



# Hierarchy of Hardness

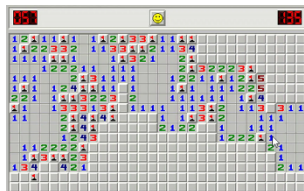


- ⚠ Unknown:  $P \subsetneq \text{co-NP} \cap \text{NP}$ ?  $P \neq \text{co-NP-complete} \neq \text{NP-complete}$ ?  $P = \text{co-NP} = \text{NP}$ ?
- Chains of reductions for NP-complete problems
  - ▶ E.g.,  $\text{HamCyc} \preceq \text{TSP}$  and  $\text{SAT} \preceq \text{HamCyc}$
  - ▶ Hence, HamCyc and TSP are also NP-complete

# NP-Complete Problems

- 3SAT:
  - ▶ 3-literal satisfiability problem, where each clause is limited to at most three literals
  - ▶ E.g.,  $(\neg x_1 \vee x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee \neg x_4) \wedge (x_1 \vee \neg x_2 \vee x_4)$
- CLIQUE:
  - ▶ Decide if there exists a clique (a complete sub-graph) of a certain size in a given graph
- VexCover:
  - ▶ Decide if there exists a subset of vertices of a certain size that include at least one endpoint of every edge of a given graph
- SubsetSum:
  - ▶ Decide if there exists a subset of numbers that sum to a certain value in a given set of numbers
- and many real-life NP-complete problems ...

# Hard Recreational Games 🎮



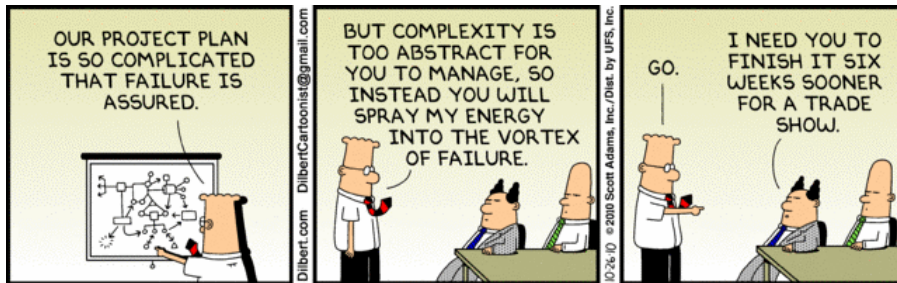
Minesweeper



Super Mario

- Sudoku is NP-complete
- Minesweeper is NP-complete
  - ▶ Decide if there exist consistent mine locations for the uncovered cells given a number of covered cells in a Minesweeper game
- SuperMario is NP-complete
  - ▶ Decide if there exists a game play to win a Super Mario game
  - ▶ Watch a proof for the NP-Hardness of SuperMario: 🎬 <https://youtu.be/oS8m9fSk-Wk>

# Hard Problems: So What? 🙄



# Optimization Problems

- Often, we don't need to solve the hard problems **exactly**

## Definition (NP-optimization)

- An optimization problem  $\mathcal{X}$  has an objective function  $f(\cdot)$ , which maps every instance  $\mathcal{I}$  and solution (or witness)  $\mathcal{S}$  to a numerical value  $f(\mathcal{I}, \mathcal{S})$ 
    - ▶ E.g., In TSP,  $\mathcal{I}$  is a graph  $\mathcal{G}$ ,  $\mathcal{S}$  is a cycle in  $\mathcal{G}$ ,  $f(\cdot)$  measures the total cost of  $\mathcal{S}$
  - A minimization (or maximization) problem  $\mathcal{X}$  is optimization problem  $\mathcal{X}$  to find  $\mathcal{S}$  such that  $f(\mathcal{S}, \mathcal{I})$  is minimized (or maximized) for a given instance  $\mathcal{I}$
  - A minimization (or maximization) problem  $\mathcal{X}$  is NP-optimization, if deciding there exists  $\mathcal{S}$  such that  $f(\mathcal{S}, \mathcal{I}) \leq C$  (or  $f(\mathcal{S}, \mathcal{I}) \geq C$ ) is NP-hard
- 
- We also call a NP-optimization problem NP-hard
    - ▶ Finding an optimal solution is harder than deciding if a solution of a certain value exists

# Approximation Algorithms

- Finding an optimal solution to a NP-hard problem is difficult. How about approximation?

## Definition (Approximation Ratio for Minimization Problem)

- Consider an NP-hard minimization problem  $\mathcal{X}$  with an instance denoted by  $\mathcal{I}$ 
  - ▶ Let  $\text{Opt}(\mathcal{I})$  be an optimal solution, and objective function be  $f(\text{Opt}(\mathcal{I}))$
  - ▶ Consider a polynomial-time algorithm  $\mathcal{A}$  that produces a solution  $\mathcal{A}(\mathcal{I})$
- Define minimization approximation ratio:  $\alpha_n(\mathcal{A}) = \max_{\mathcal{I}: |\mathcal{I}| \leq n} \frac{f(\mathcal{A}(\mathcal{I}))}{f(\text{Opt}(\mathcal{I}))}$

## Definition (Approximation Ratio for Maximization Problem)

- Consider an NP-hard maximization problem  $\mathcal{X}$  with an instance denoted by  $\mathcal{I}$ 
  - ▶ Consider a polynomial-time algorithm  $\mathcal{A}$  that produces a solution  $\mathcal{A}(\mathcal{I})$
- Define maximization approximation ratio:  $\alpha_n(\mathcal{A}) = \min_{\mathcal{I}: |\mathcal{I}| \leq n} \frac{f(\mathcal{A}(\mathcal{I}))}{f(\text{Opt}(\mathcal{I}))}$

# Approximation Algorithms

- We aim to find a polynomial-time **approximation algorithm**  $\mathcal{A}$  with a good approximation ratio  $\alpha_n(\mathcal{A})$  to bound the gap from an optimal solution
  - ▶ Minimization Problem:  $f(\mathcal{A}(\mathcal{I})) \leq \alpha_n(\mathcal{A}) \cdot f(\text{Opt}(\mathcal{I}))$
  - ▶ Maximization Problem:  $f(\mathcal{A}(\mathcal{I})) \geq \alpha_n(\mathcal{A}) \cdot f(\text{Opt}(\mathcal{I}))$
- $\alpha_n(\mathcal{A})$  depends on the input size  $|\mathcal{I}|$ 
  - ▶  $\alpha_n(\mathcal{A})$  is the worst-case ratio considering all instances that are bounded by size  $n$
- For a NP-hard problem,  $\alpha_n(\mathcal{A}) = 1$  is impossible, unless  $P = NP$
- However, can we come up with a polynomial-time algorithm  $\mathcal{A}$ , such that  $\alpha_n(\mathcal{A})$  is sufficiently good? What is the best  $\alpha_n(\mathcal{A})$  that we can achieve?

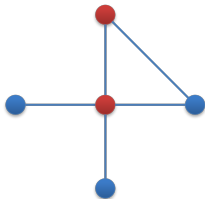
# Approximation Algorithm: Vertex Cover

## Example (VexCover)

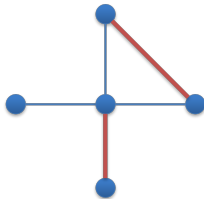
- VexCover (Minimum Vertex Cover Problem):
  - ▶ Given a graph  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ , find a minimum subset of vertices  $\tilde{\mathcal{V}} \subseteq \mathcal{V}$ , such that every  $e \in \mathcal{E}$  has one end-vertex in  $\tilde{\mathcal{V}}$
- MaximalMatch (Maximal Matching Problem):
  - ▶ Given a graph  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ , find a maximal subset of edges  $\tilde{\mathcal{E}} \subseteq \mathcal{E}$ , such that no  $e \in \tilde{\mathcal{E}}$  share the same vertex
- VexCover is NP-complete
- But MaximalMatch is easy
  - ▶ Is MaximalMatch in P?



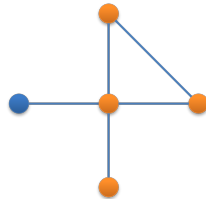
# Approximation Algorithm: Vertex Cover



Min Vex Cover



Max Matching



End-vertices of  
Max Matching

# Approximation Algorithm: Vertex Cover

## Algorithm $\mathcal{A}_{\text{vxc}}$

- Solve MaximalMatch on  $\mathcal{G}$ , and the solution is denoted by  $\tilde{\mathcal{E}}$
- Output the set of end-vertices in every  $e \in \tilde{\mathcal{E}}$

## Theorem (2-Approximability of VexCover)

$\mathcal{A}_{\text{vxc}}$  always outputs a vertex cover. The approximation ratio of  $\mathcal{A}_{\text{vxc}}$  is  $\alpha_n(\mathcal{A}_{\text{vxc}}) \leq 2$

Proof:

- Let Opt be a minimum set of vertex cover
- Consider an edge  $(u, v)$  in a maximal matching  $\tilde{\mathcal{E}}$
- One of  $u, v$  must be in Opt, otherwise,  $(u, v)$  is not covered. Hence,  $|\tilde{\mathcal{E}}| \leq |\text{Opt}|$
- The number of vertices output from  $\mathcal{A}_{\text{vxc}}$  is  $f(\mathcal{A}_{\text{vxc}}) \leq 2|\tilde{\mathcal{E}}|$ . Hence,  $f(\mathcal{A}_{\text{vxc}}) \leq 2|\text{Opt}|$

# Approximation Algorithm: TSP

## Example (TSP)

- Recall that  $\text{HamCyc} \preceq \text{TSP}(c \cdot n)$  for any constant  $c > 1$

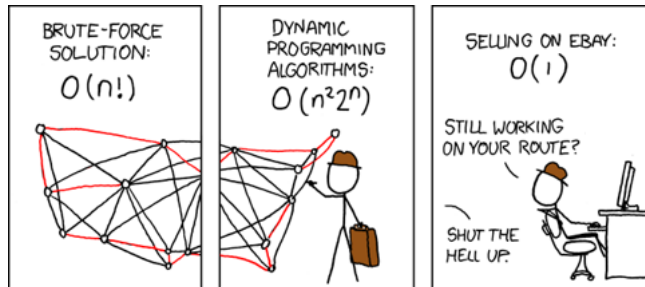
## Theorem (Inapproximability of TSP)

*There exists no polynomial-time  $\mathcal{A}$  for TSP such that  $\alpha_n(\mathcal{A})$  is a constant  $c$ , unless  $P = NP$*

Proof:

- Let  $\text{Opt}$  be a minimum cycle in TSP
- Use contradiction – suppose  $\alpha_n(\mathcal{A}) = c$ , and use reduction  $\text{HamCyc} \preceq \text{TSP}(c \cdot n)$
- Then there exists a polynomial-time algorithm  $\mathcal{A}$  that produces a cycle in TSP with  $f(\mathcal{A}) \leq c \cdot f(\text{Opt})$
- By reduction  $\text{HamCyc} \preceq \text{TSP}(c \cdot n)$ , if there exists a Hamiltonian cycle,  $f(\text{Opt}) = n$
- Hence,  $f(\mathcal{A}) \leq c \cdot n \iff$  there exists a Hamiltonian cycle
- This gives a polynomial-time algorithm to solve HamCyc and hence,  $P = NP$

# TSP is Really Hard 🤔



- TSP is not only NP-hard, but also inapproximable within any constant approximation ratio
  - ▶ In fact, it is inapproximable within any polynomial approximation ratio
- Is it inapproximable in practice?
  - ▶ Not in specific settings, e.g. in an Euclidean space

## Follow-up Questions 🖐️

- Is NP-hardness an accurate description of computational hardness?
  - ▶ No, but it is close. Turing Machine, with no memory access bottleneck, is not a realistic computer model
  - ▶ A more realistic model is von Neumann model, which has a memory hierarchy with different access speeds and capacities
- Why do we expect  $P \neq NP$ , even though we may not be able to prove it?
  - ▶ “If  $P = NP$ , then the world would be a profoundly different place than we usually assume it to be. There would be no special value in “creative leaps,” no fundamental gap between solving a problem and recognizing the solution once it’s found. Everyone who could appreciate a symphony would be Mozart; everyone who could follow a step-by-step argument would be Gauss; everyone who could recognize a good investment strategy would be Warren Buffett.” - **Scott Aaronson**
  - ▶ Cryptography critically relies on efficiently verifiable but intractable problems. If  $P = NP$ , then there will be no asymmetric cryptography, or one-way hash function

## Follow-up Questions 🖐️

- Why do we bother NP-hard problems, if powerful quantum computers are coming soon?
  - ▶ Only two useful quantum algorithms can solve classical (non-quantum) problems: Shor algorithm and Grover algorithm – both are insufficient to solve NP-hard problems in general
  - ▶ Quantum heuristics are applied to solve classical problems. But they are not proven to be better than classical approximation algorithms - in fact, there are a lot of skepticisms
  - ▶ Quantum computers are better for solving quantum problems
- Why do we bother approximation algorithms, if machine learning can solve many hard problems?
  - ▶ Machine learning is mostly heuristics – do not have universal results on approximation ratios
  - ▶ Many empirical results are not replicable, or are specific to particular experimental data
  - ▶ Machine learning can not be extended to a problem of arbitrary size – it needs a lot of training data, which is impractical for large problems
  - ▶ But there are provable machine learning algorithms for limited applications




## References

### Reference Materials

- Introduction to Algorithms (Cormen, Leiserson, Rivest, Stein), 4th ed, MIT Press
  - ▶ Chapters 34-35
- Approximation Algorithms (V. Vazirani), Springer
  - ▶ Chapter 1, Appendix A

### Recommended Materials

- Survey of  $P \stackrel{?}{=} NP$  (Scott Aaronson),  
<https://www.scottaaronson.com/papers/pnp-kindle.pdf>
-  Watch online tutorial videos:  
[https://youtube.com/playlist?list=PLlwsleWT767dnN25K\\_QgvdKkovK\\_t4K6-](https://youtube.com/playlist?list=PLlwsleWT767dnN25K_QgvdKkovK_t4K6-)

### Related Courses in Other Universities

- Harvard (CS 224) Advanced Algorithms:  
<https://people.seas.harvard.edu/~cs224/fall14/lec.html>
- CMU (15-850) Advanced Algorithms:  
<http://www.cs.cmu.edu/~15850/>
- Princeton (COS 521) Advanced Algorithm Design:  
<https://www.cs.princeton.edu/courses/archive/fall18/cos521/>
- MIT (6.854J) Advanced Algorithms:  
<https://ocw.mit.edu/courses/6-854j-advanced-algorithms-fall-2005/>
- Stanford (CS 361B) Advanced Algorithms:  
<https://web.stanford.edu/class/cs361b/>