

INTRACTABILITY III

- ▶ *special cases: trees*
- ▶ *special cases: planarity*
- ▶ *approximation algorithms: vertex cover*
- ▶ *approximation algorithms: knapsack*
- ▶ *exponential algorithms: 3-SAT*
- ▶ *exponential algorithms: TSP*

Lecture slides by Kevin Wayne

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<http://www.cs.princeton.edu/~wayne/kleinberg-tardos>

Abdur Rashid Tushar
Lecturer, CSE, BUET

Coping with NP-completeness

Q. Suppose I need to solve an **NP**-hard problem. What should I do?

A. Sacrifice one of three desired features.

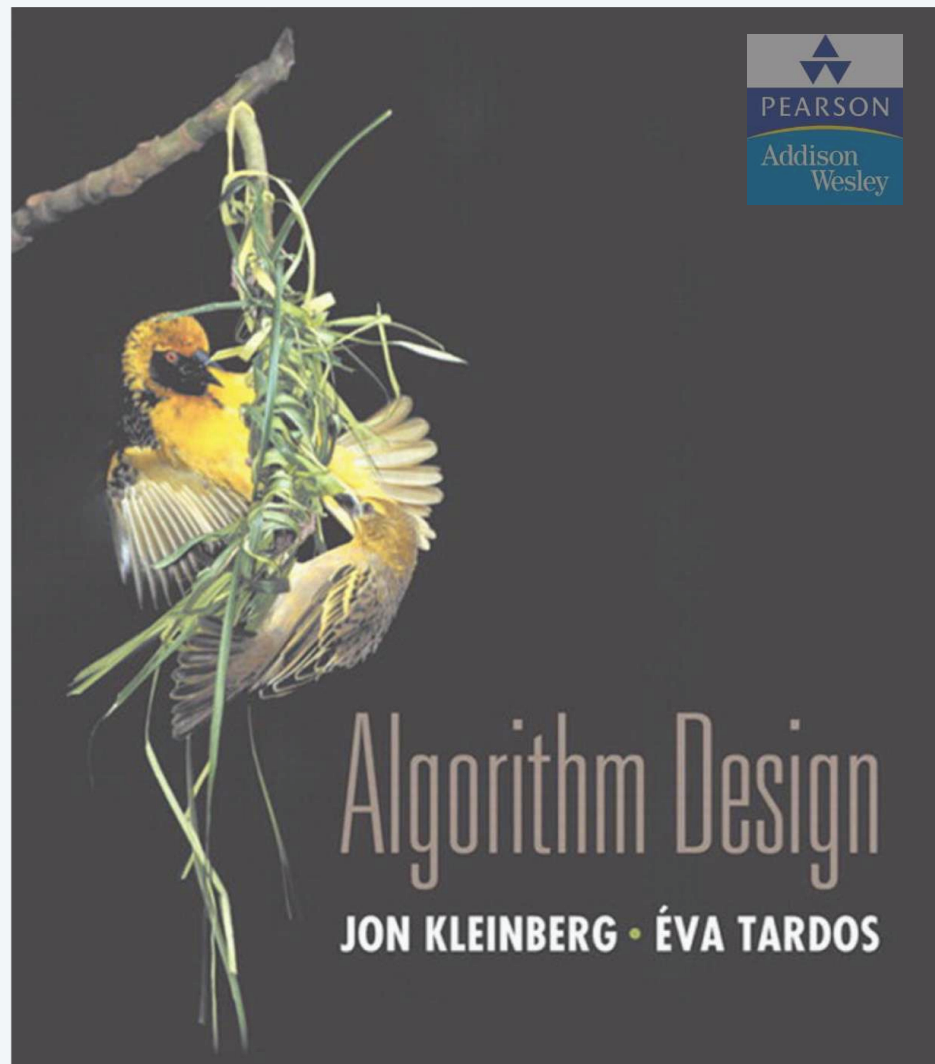
- i. Solve **arbitrary instances** of the problem.
- ii. Solve problem to **optimality**.
- iii. Solve problem in **polynomial time**.

Coping strategies.

- i. Design algorithms **for special cases** of the problem.
- ii. Design **approximation algorithms** or **heuristics**.
- iii. Design algorithms that may take **exponential time**.

↑
using greedy,
dynamic programming,
divide-and-conquer, and
network flow algorithms!
↓





SECTION 10.2

INTRACTABILITY III

- ▶ *special cases: trees*
- ▶ *special cases: planarity*
- ▶ *approximation algorithms: vertex cover*
- ▶ *approximation algorithms: knapsack*
- ▶ *exponential algorithms: 3-SAT*
- ▶ *exponential algorithms: TSP*

Independent set on trees

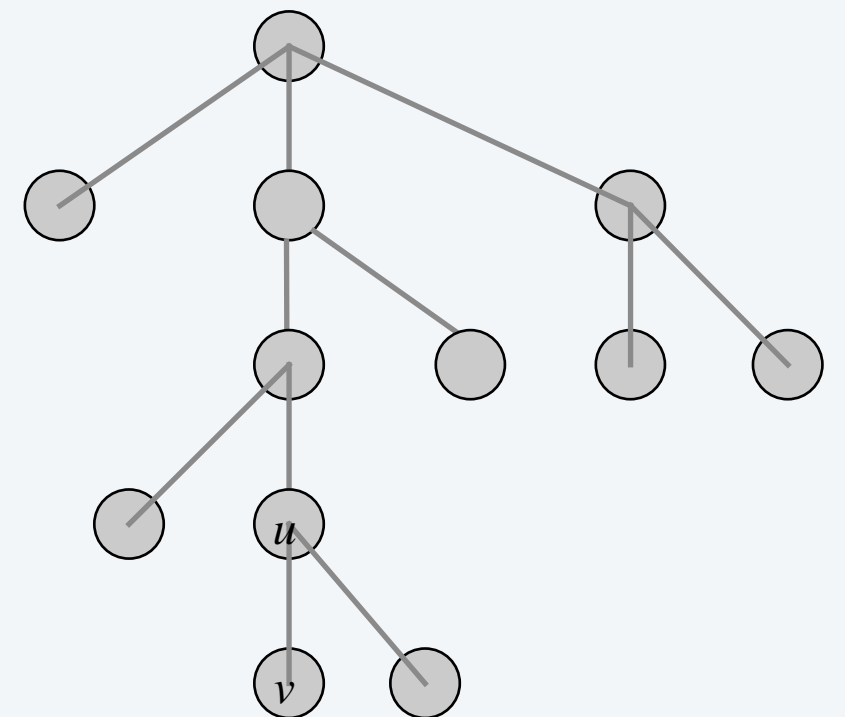
Independent set on trees. Given a **tree**, find a max-cardinality subset of nodes such that no two are adjacent.

Fact. A tree has at least one node that is a leaf (degree = 1).

Key observation. If node v is a leaf, there exists a max-cardinality independent set containing v .

Pf. [exchange argument]

- Consider a max-cardinality independent set S .
- If $v \in S$, we're done.
- Otherwise, let (u, v) denote the lone edge incident to v .
 - if $u \notin S$ and $v \notin S$, then $S \cup \{v\}$ is independent $\Rightarrow S$ not maximum
 - if $u \in S$ and $v \notin S$, then $S \cup \{v\} - \{u\}$ is independent ▪



Independent set on trees: greedy algorithm

Theorem. The greedy algorithm finds a max-cardinality independent set in forests (and hence trees).



Pf. Correctness follows from the previous key observation. ▀

INDEPENDENT-SET-IN-A-FOREST(F)

$S \leftarrow \emptyset$.

WHILE (F has at least 1 edge)

Let v be a leaf node and let (u, v) be the lone edge incident to v .

$S \leftarrow S \cup \{ v \}$.

$F \leftarrow F - \{ u, v \}$. ← delete both u and v (including all incident edges)

RETURN $S \cup \{ \text{nodes remaining in } F \}$.

Remark. Can implement in $O(n)$ time by maintaining nodes of degree 1.



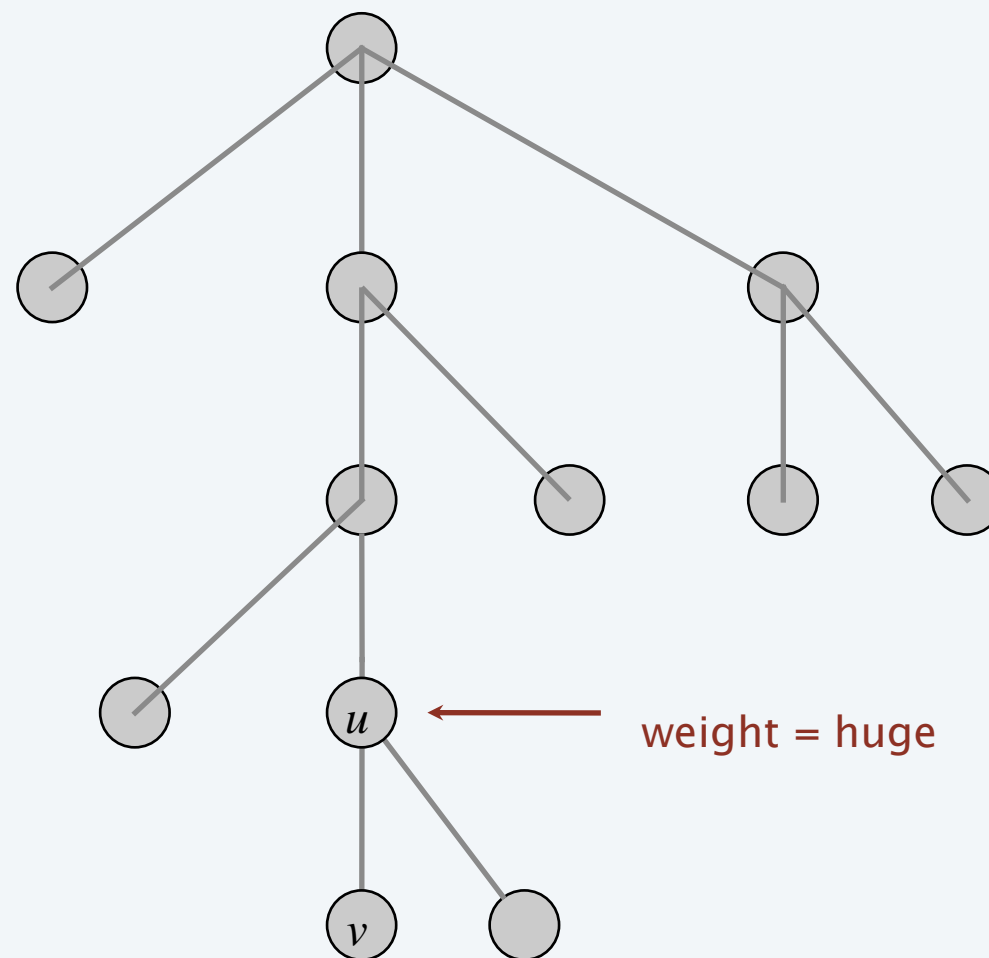
How might the greedy algorithm fail if the graph is not a tree/forest?

- A. Might get stuck.
- B. Might take exponential time.
- C. Might produce a suboptimal independent set.
- D. Any of the above.

Weighted independent set on trees

Weighted independent set on trees. Given a tree and node weights $w_v \geq 0$, find an independent set S that maximizes $\sum_{v \in S} w_v$.

Greedy algorithm can fail spectacularly.



Weighted independent set on trees

Weighted independent set on trees. Given a tree and node weights $w_v \geq 0$, find an independent set S that maximizes $\sum_{v \in S} w_v$.

Dynamic-programming solution. Root tree at some node, say r .

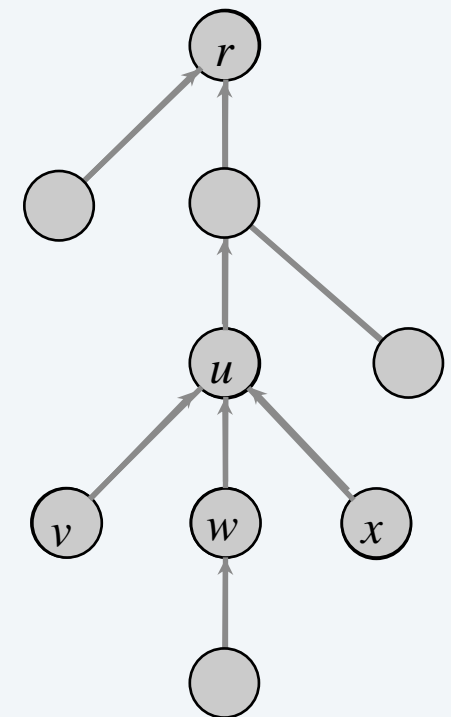
- $OPT_{in}(u)$ = max-weight IS in subtree rooted at u , containing u .
- $OPT_{out}(u)$ = max-weight IS in subtree rooted at u , not containing u .
- Goal: $\max \{ OPT_{in}(r), OPT_{out}(r) \}$.

Bellman equation.

$$OPT_{in}(u) = w_u + \sum_{v \in \text{children}(u)} OPT_{out}(v)$$

$$OPT_{out}(u) = \sum_{v \in \text{children}(u)} \max \{ OPT_{in}(v), OPT_{out}(v) \}$$

overlapping
subproblems



children(u) = { v, w, x }



In which order to solve the subproblems?

- A. Preorder.
- B. Postorder.
- C. Level order.
- D. Any of the above.

Weighted independent set on trees: dynamic-programming algorithm

Theorem. The DP algorithm computes max weight of an independent set in a tree in $O(n)$ time.

can also find independent set itself
(not just value)

WEIGHTED-INDEPENDENT-SET-IN-A-TREE (T)

Root the tree T at any node r .

$S \leftarrow \emptyset$.

FOREACH (node u of T in postorder/topological order)

IF (u is a leaf node)

$$M_{in}[u] = w_u.$$

$$M_{out}[u] = 0.$$

ELSE

$$M_{in}[u] = w_u + \sum_{v \in \text{children}(u)} M_{out}[v].$$

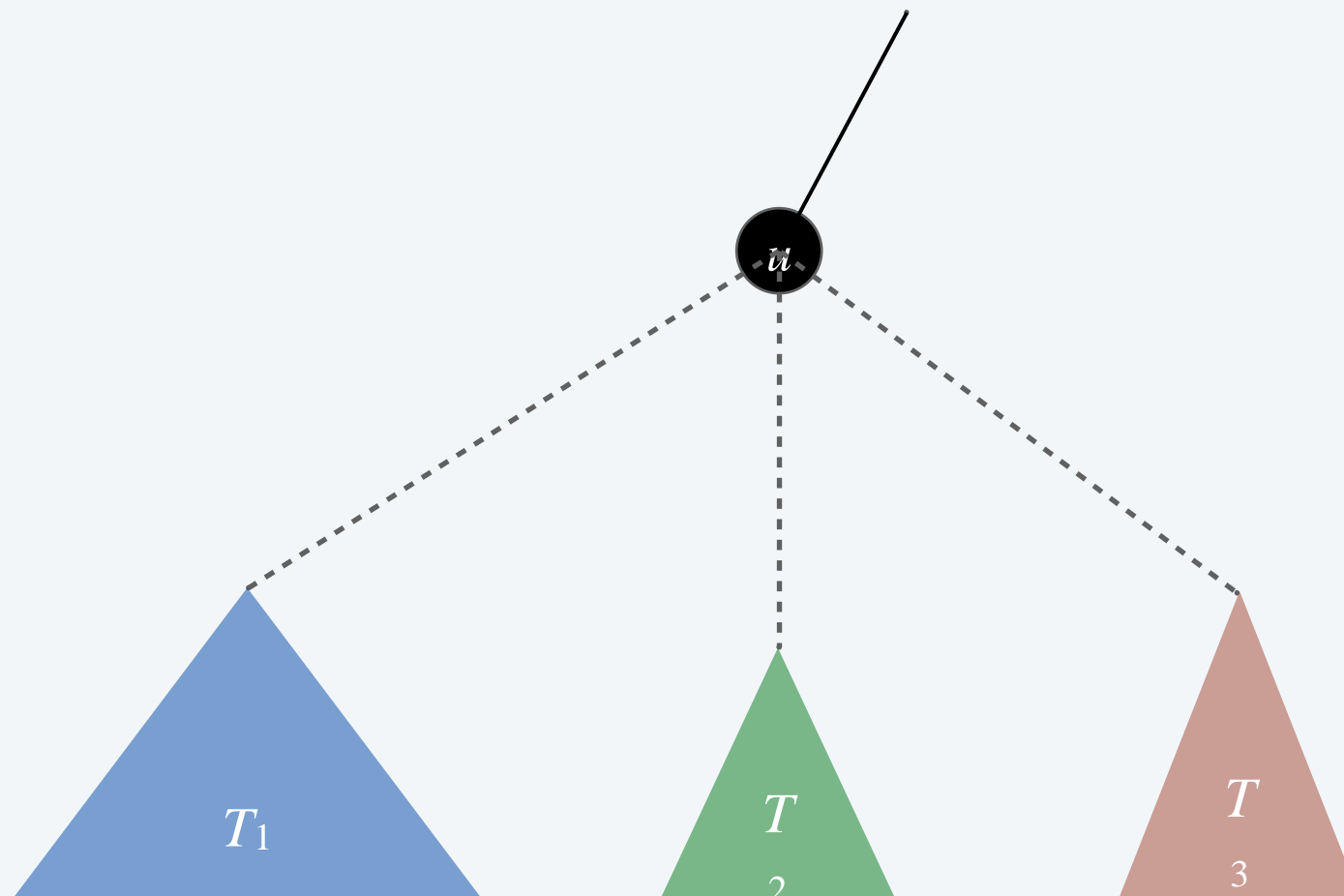
$$M_{out}[u] = \sum_{v \in \text{children}(u)} \max \{ M_{in}[v], M_{out}[v] \}.$$

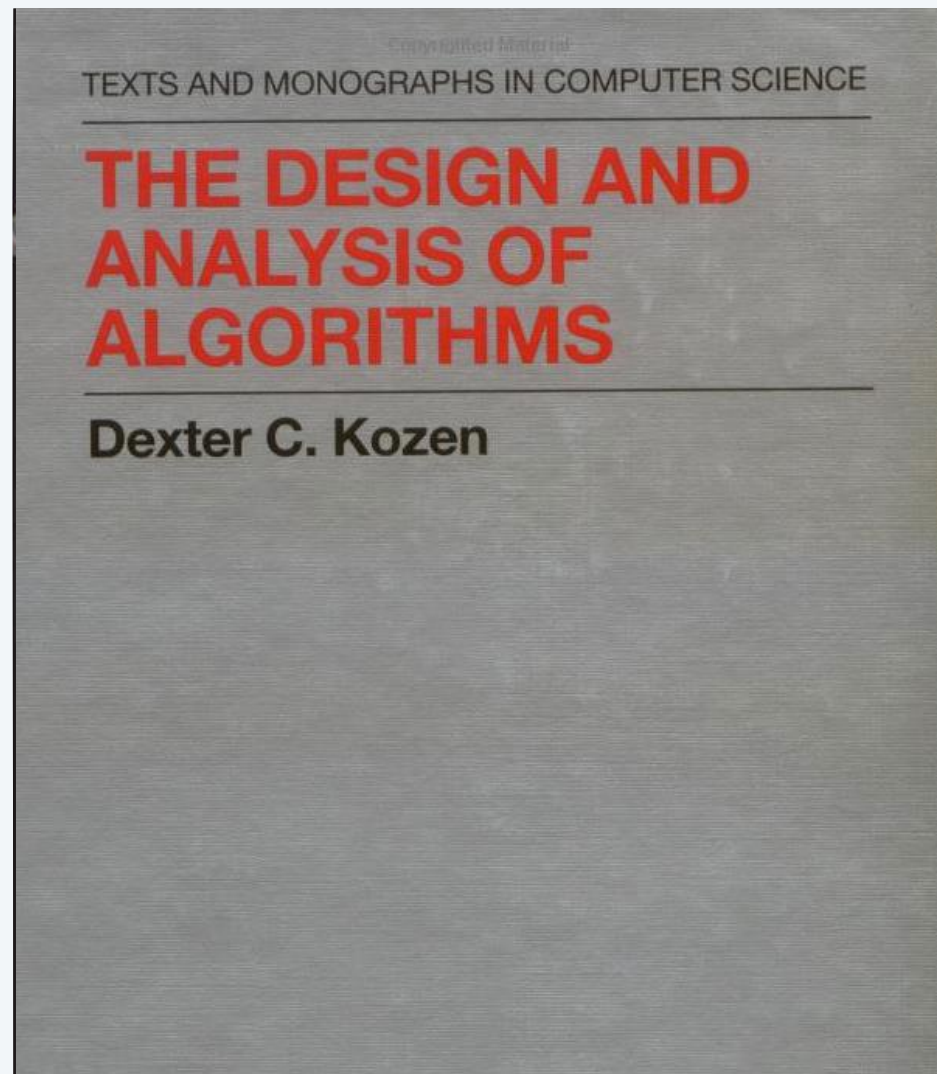
RETURN $\max \{ M_{in}[r], M_{out}[r] \}$.

ensures a node is processed
after all of its descendants

NP-hard problems on trees: context

Independent set on trees. Tractable because we can find a node that breaks the communication among the subproblems in different subtrees.





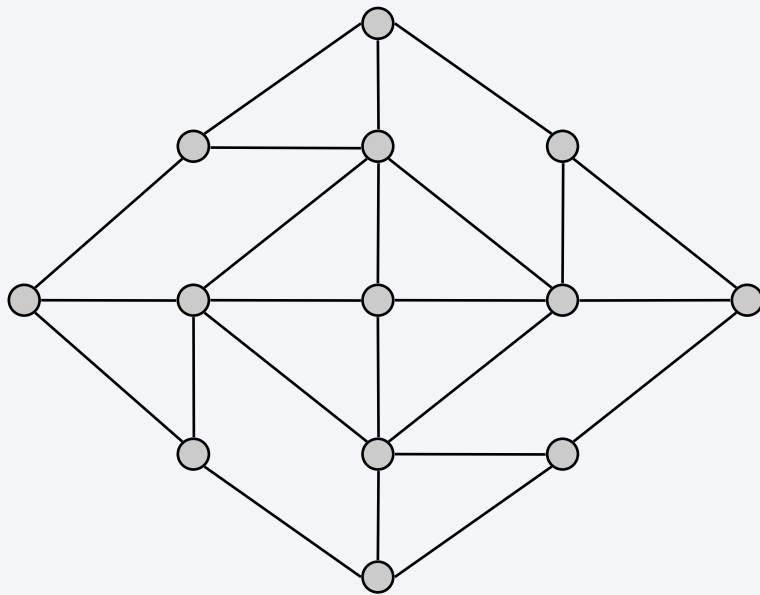
SECTION 23.1

INTRACTABILITY III

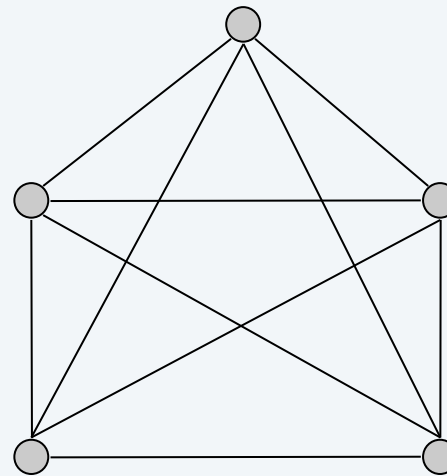
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Planarity

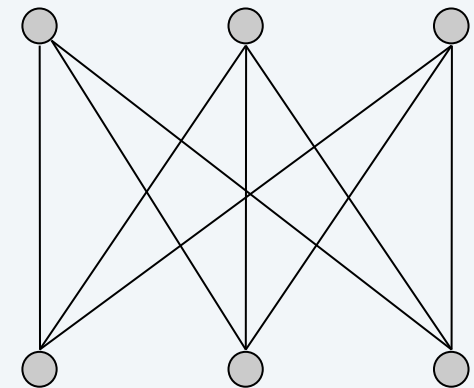
Def. A graph is **planar** if it can be embedded in the plane in such a way that no two edges cross.



planar



K_5 is nonplanar



$K_{3,3}$ is nonplanar

Applications. VLSI circuit design, computer graphics, ...

Planarity testing

Theorem. [Hopcroft–Tarjan 1974] There exists an $O(n)$ time algorithm to determine whether a graph is planar.

↖
simple planar graph
has at $\leq 3n$ edges

Efficient Planarity Testing

JOHN HOPCROFT AND ROBERT TARJAN

Cornell University, Ithaca, New York

ABSTRACT. This paper describes an efficient algorithm to determine whether an arbitrary graph G can be embedded in the plane. The algorithm may be viewed as an iterative version of a method originally proposed by Auslander and Parter and correctly formulated by Goldstein. The algorithm uses depth-first search and has $O(V)$ time and space bounds, where V is the number of vertices in G . An ALGOL implementation of the algorithm successfully tested graphs with as many as 900 vertices in less than 12 seconds.

Problems on planar graphs

Fact 0. Many graph problems can be solved faster in planar graphs.

Ex. Shortest paths, max flow, MST, matchings, ...

Fact 1. Some **NP**-complete problems become tractable in planar graphs.

Ex. MAX-CUT, ISING, CLIQUE, GRAPH-ISOMORPHISM, 4-COLOR, ...

Fact 2. Other **NP**-complete problems become easier in planar graphs.

Ex. INDEPENDENT-SET, VERTEX-COVER, TSP, STEINER-TREE, ...

An $O(n \log n)$ Algorithm for Maximum st -Flow in a Directed Planar Graph

GLENCORA BORRADAILE AND PHILIP KLEIN

Brown University, Providence, Rhode Island

Abstract. We give the first correct $O(n \log n)$ algorithm for finding a maximum st -flow in a directed planar graph. After a preprocessing step that consists in finding single-source shortest-path distances in the dual, the algorithm consists of repeatedly saturating the leftmost residual s -to- t path.

SIAM J. COMPUT.
Vol. 9, No. 3, August 1980

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0097-5397/80/0903-0013 \$01.00/0

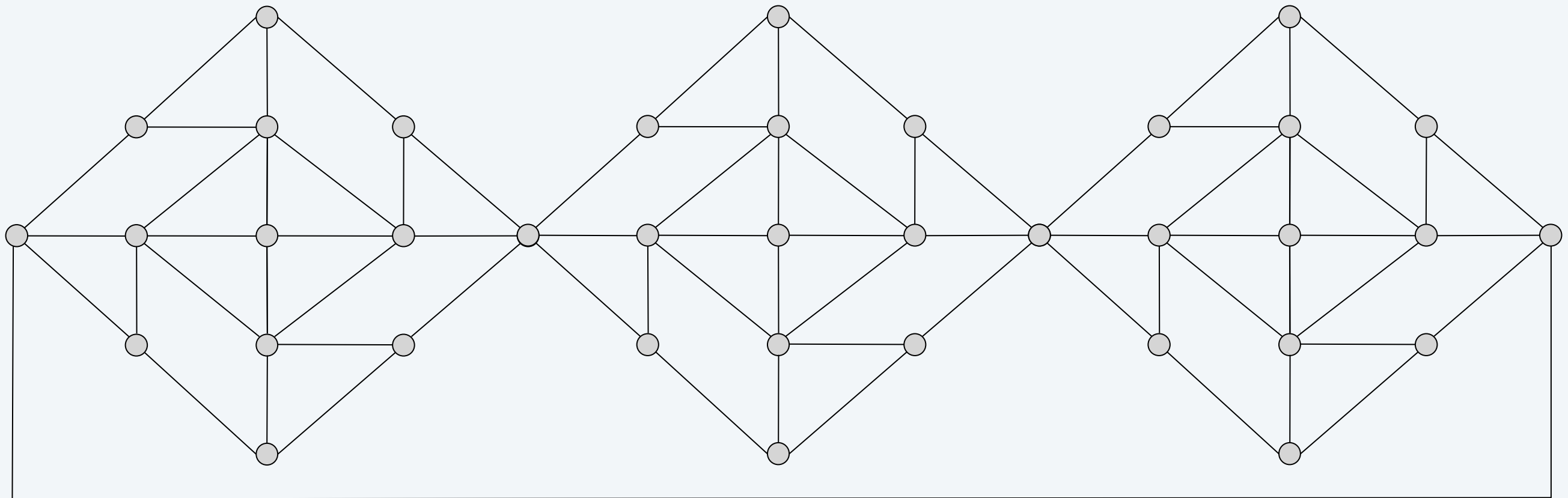
APPLICATIONS OF A PLANAR SEPARATOR THEOREM*

RICHARD J. LIPTON† AND ROBERT ENDRE TARJAN‡

Abstract. Any n -vertex planar graph has the property that it can be divided into components of roughly equal size by removing only $O(\sqrt{n})$ vertices. This separator theorem, in combination with a divide-and-conquer strategy, leads to many new complexity results for planar graph problems. This paper describes some of these results.

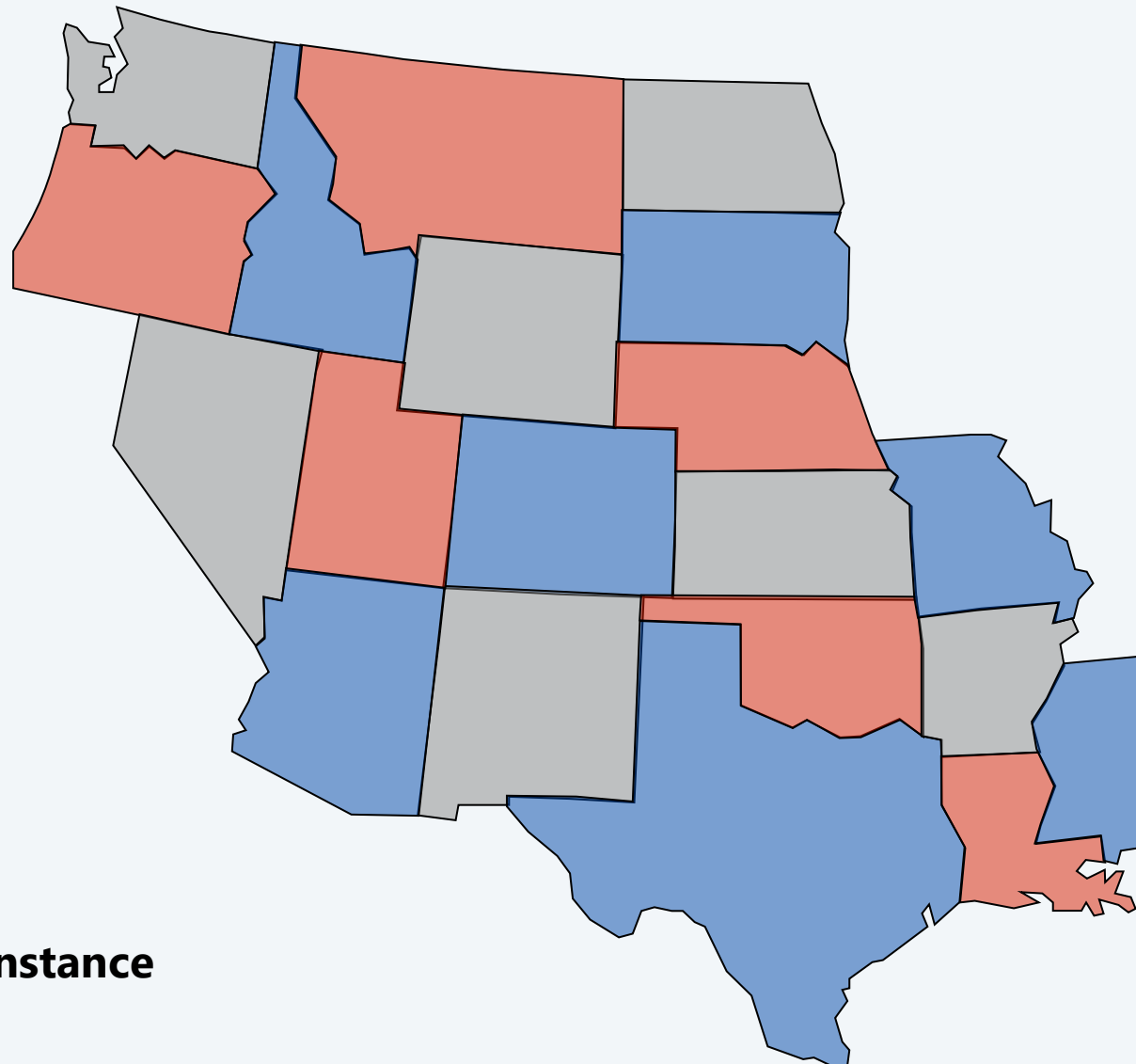
Planar graph 3-colorability

PLANAR-3-COLOR. Given a planar graph, can it be colored using 3 colors so that no two adjacent nodes have the same color?



Planar map 3-colorability

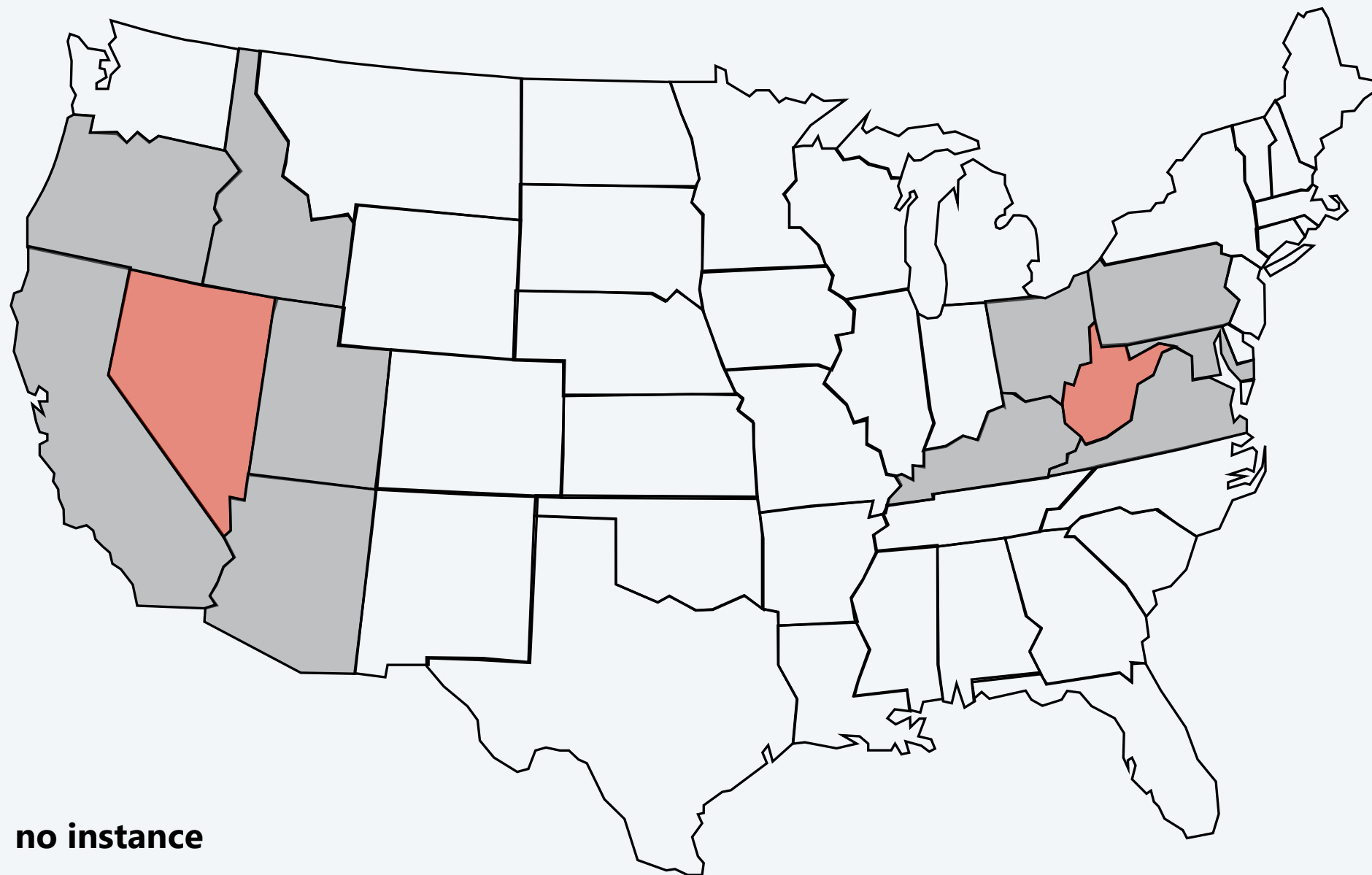
PLANAR-MAP-3-COLOR. Given a planar map, can it be colored using 3 colors so that no two adjacent regions have the same color?



yes instance

Planar map 3-colorability

PLANAR-MAP-3-COLOR. Given a planar map, can it be colored using 3 colors so that no two adjacent regions have the same color?



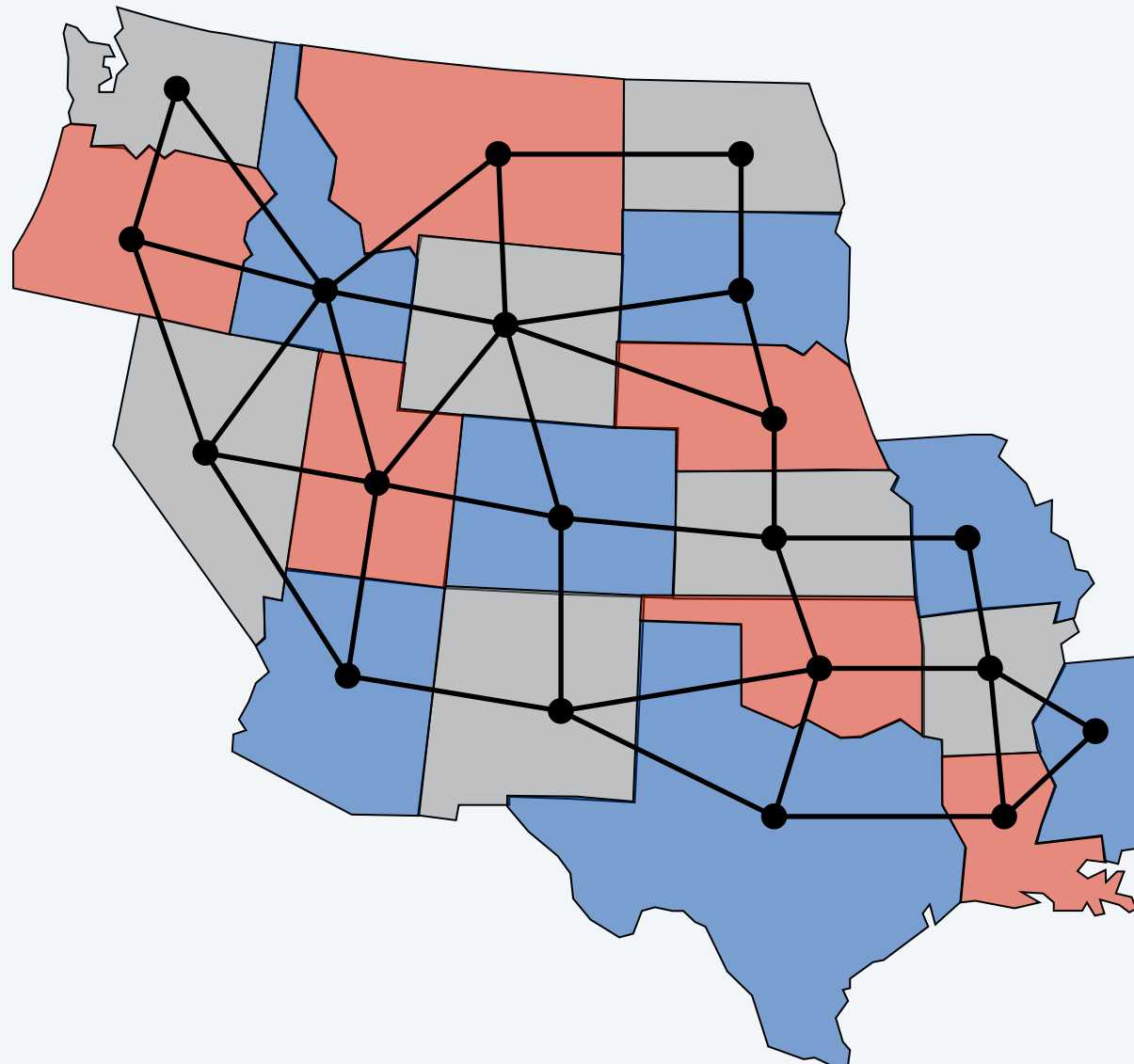
no instance

Planar graph and map 3-colorability reduce to one another

Theorem. $\text{PLANAR-3-COLOR} \equiv_P \text{PLANAR-MAP-3-COLOR}$.

Pf sketch.

- Nodes correspond to regions.
- Two nodes are adjacent iff they share a nontrivial border.



↖
e.g., not Arizona
and Colorado

Planar 3-colorability is NP-complete

Theorem. PLANAR-3-COLOR \in **NP**-complete.

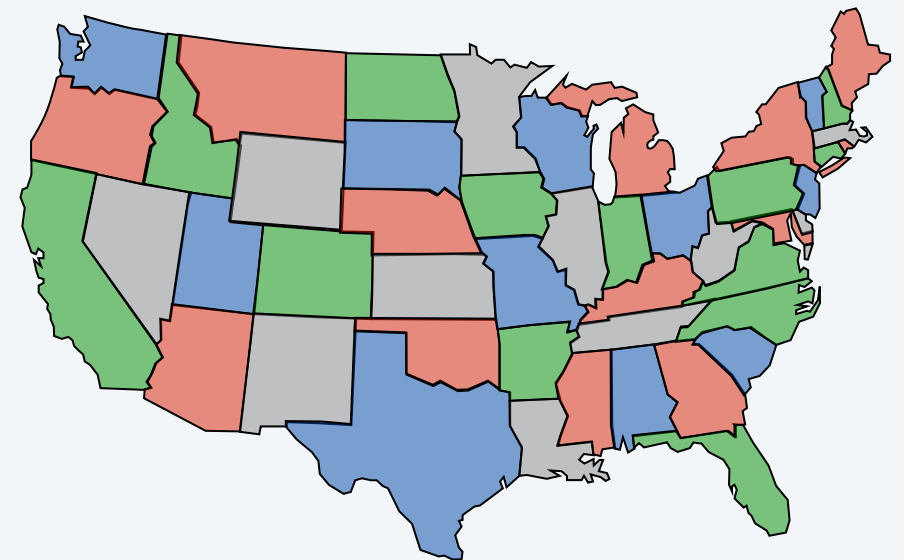
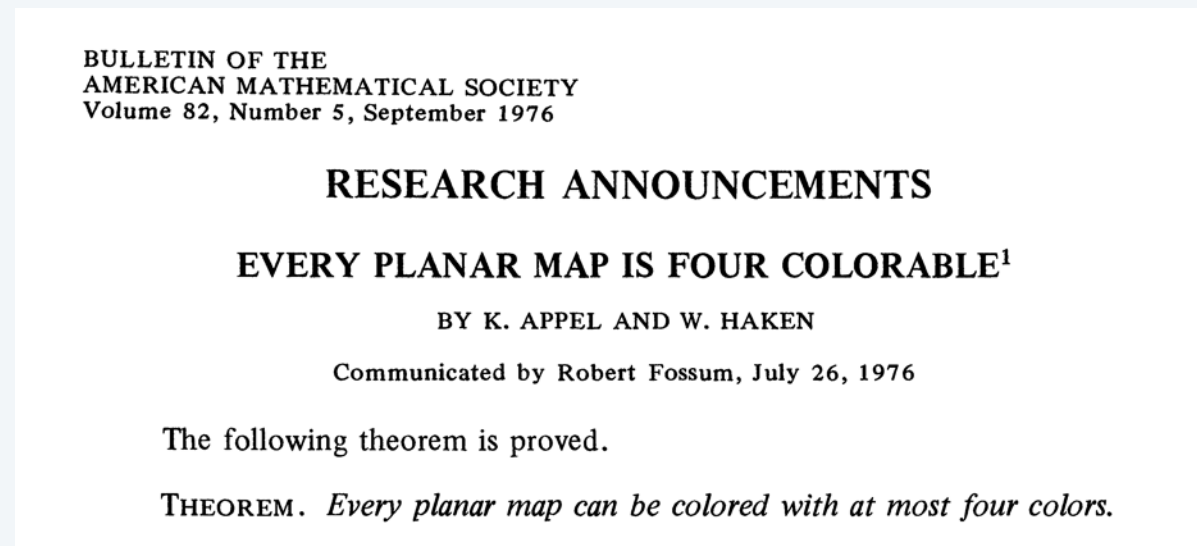
Pf.

- Easy to see that PLANAR-3-COLOR \in **NP**.
- We show $3\text{-COLOR} \leq_P \text{PLANAR-3-COLOR}$.
- Given 3-COLOR instance G , we construct an instance of PLANAR-3-COLOR that is 3-colorable iff G is 3-colorable.

Planar map k-colorability

Theorem. [Appel–Haken 1976] Every planar map is 4-colorable.

- Resolved century-old open problem.
- Used 50 days of computer time to deal with many special cases.
- First major theorem to be proved using computer.



Remarks.

- Appel–Haken yields $O(n^4)$ algorithm to 4-color of a planar map.
- Best known: $O(n^2)$ to 4-color; $O(n)$ to 5-color.
- Determining whether 3 colors suffice is **NP**-complete.

Poly-time special cases of NP-hard problems

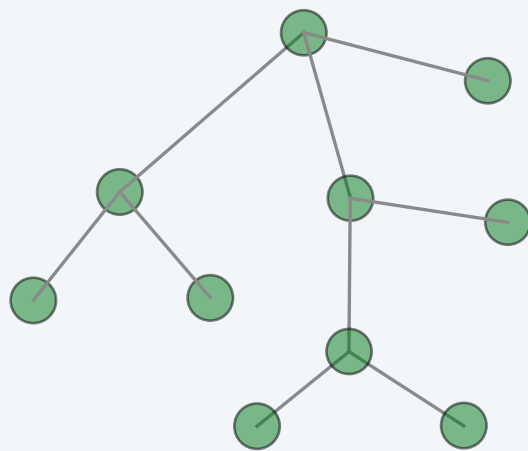
Trees. VERTEX-COVER, INDEPENDENT-SET, LONGEST-PATH, GRAPH-ISOMORPHISM, ...

Bipartite graphs. VERTEX-COVER, INDEPENDENT-SET, 3-COLOR, EDGE-COLOR, ...

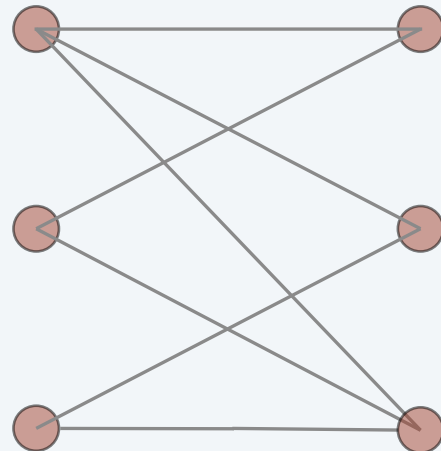
Planar graphs. MAX-CUT, ISING, CLIQUE, GRAPH-ISOMORPHISM, 4-COLOR, ...

Bounded treewidth. HAM-CYCLE, INDEPENDENT-SET, GRAPH-ISOMORPHISM, ...

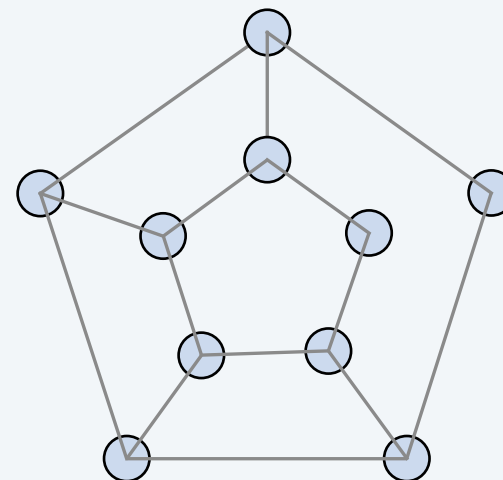
Small integers. SUBSET-SUM, KNAPSACK, PARTITION, ...



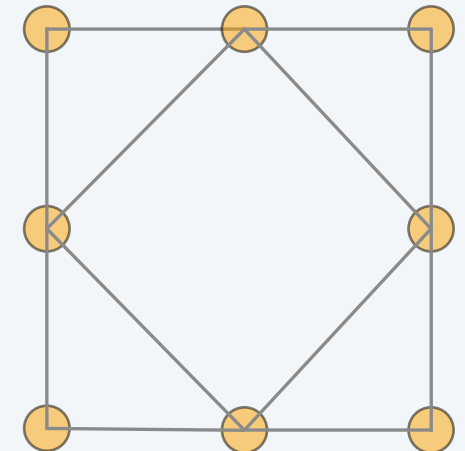
tree



bipartite



planar



bounded treewidth

10. EXTENDING TRACTABILITY

- ▶ *special cases: trees*
- ▶ *special cases: planarity*
- ▶ *approximation algorithms*
- ▶ ***register allocation***
- ▶ *exponential algorithms*

Register allocation

Register. One of k of high-speed memory locations in computer's CPU.

say 32

Register allocator. Part of an optimizing compiler that controls which variables are saved in the registers as compiled program executes.

variables or temporaries

Interference graph. Nodes are “live ranges.” Edge (u, v) if there exists an operation where both u and v are “live” at the same time.

Observation. [Chaitin 1982] Can solve register allocation problem iff interference graph is k -colorable.


Spilling. If graph is not k -colorable (or we can't find a k -coloring), we “spill” certain variables to main memory and swap back as needed.

typically infrequently used
variables that are not in inner loops

A useful property

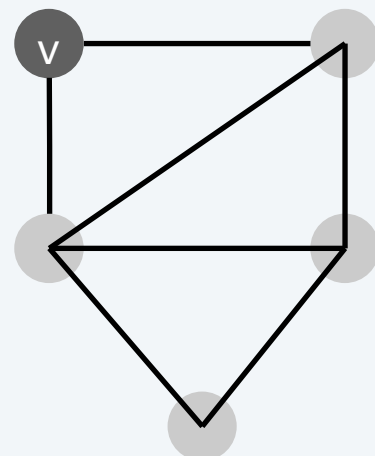
Remark. Register allocation problem is NP-hard.

Key fact. If a node v in graph G has fewer than k neighbors, G is k -colorable iff $G - \{v\}$ is k -colorable.

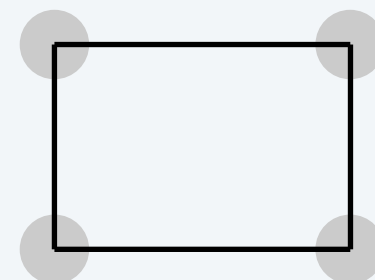
 delete v and all incident edges

Pf. Delete node v from G and color $G - \{v\}$.

- If $G - \{v\}$ is not k -colorable, then neither is G .
- If $G - \{v\}$ is k -colorable, then ≥ 1 remaining color left for v . ▪



$k = 3$




$k = 2$

**G is 2-colorable even though
all nodes have degree 2**

Chaitin's algorithm

```
Vertex-Color(G, k) {  
  while (G is not empty) {  
    Pick a node v with fewer than k neighbors  
    Push v on stack  
    Delete v and all its incident edges  
  }  
  while (stack is not empty) {  
    Pop next node v from the stack  
    Assign v a color different from its neighboring  
    nodes which have already been colored  
  }  
}
```

say, node with fewest neighbors




Chaitin's algorithm

Theorem. [Kempe 1879, Chaitin 1982] Chaitin's algorithm produces a k -coloring of any graph with max degree $k - 1$.

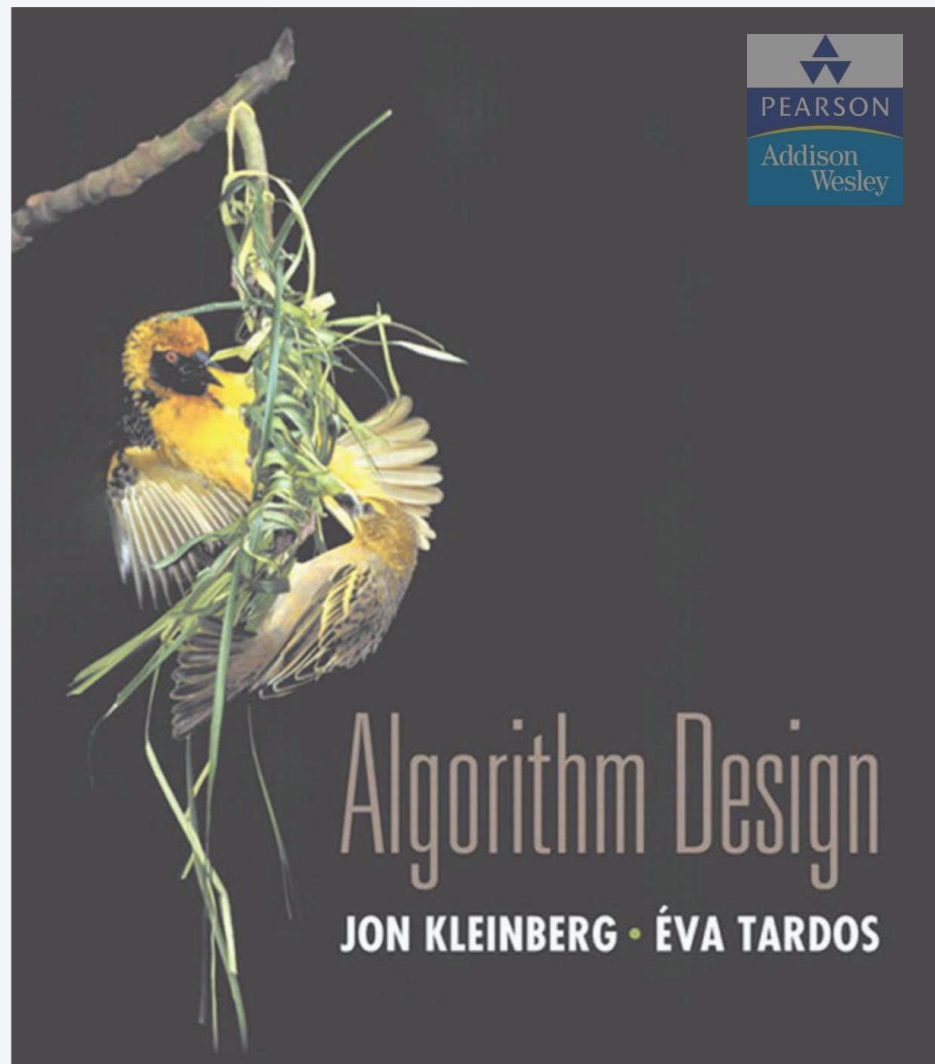
Pf. Follows from key fact since each node has fewer than k neighbors.

algorithm succeeds in k -coloring
many graphs with max degree $\geq k$



Remark. If algorithm never encounters a graph where all nodes have degree $\geq k$, then it produces a k -coloring.

Practice. Chaitin's algorithm (and variants) are extremely effective and widely used in real compilers for register allocation.



SECTION 11.8

INTRACTABILITY III

- ▶ *special cases: trees*
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- ▶ *exponential algorithms: TSP*

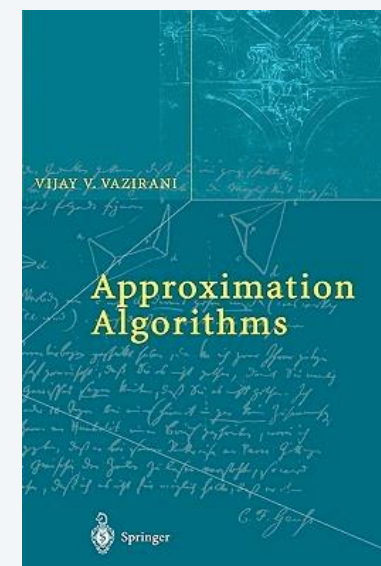
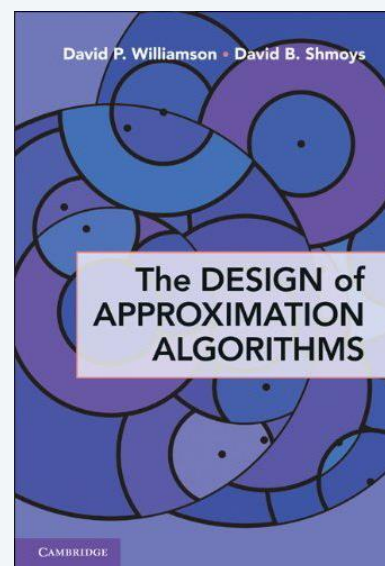
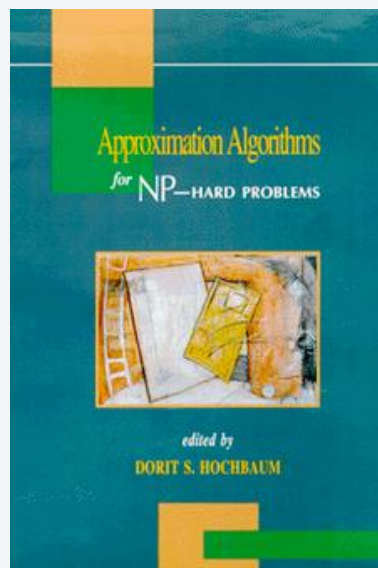
Approximation algorithms

ρ -approximation algorithm.

- Runs in polynomial time.
- Applies to arbitrary instances of the problem.
- Guaranteed to find a solution within ratio ρ of true optimum.

Ex. Given a graph G , can find a vertex cover that uses $\leq 2 \text{OPT}(G)$ vertices in $O(m + n)$ time.

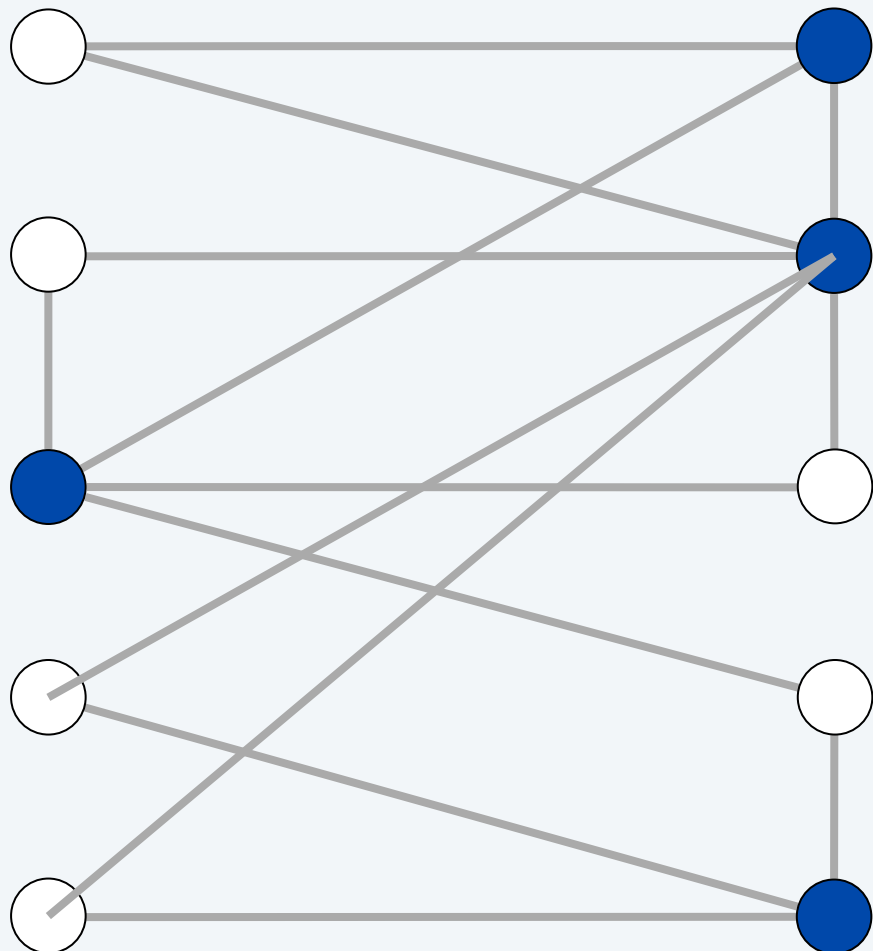
Challenge. Need to prove a solution's value is close to optimum value, without even knowing what optimum value is!



Vertex cover

VERTEX-COVER. Given a graph $G = (V, E)$, find a min-size vertex cover.

↑
for each edge $(u, v) \in E$:
either $u \in S$, $v \in S$, or both



● vertex cover of size 4

Vertex cover: greedy algorithm

VERTEX-COVER. Given a graph $G = (V, E)$, find a min-size vertex cover.



GREEDY-VERTEX-COVER(G)

$S \leftarrow \emptyset$.

$E' \leftarrow E$.

WHILE ($E' \neq \emptyset$)

Let $(u, v) \in E'$ be an arbitrary edge.

$M \leftarrow M \cup \{(u, v)\}$.

$S \leftarrow S \cup \{u\} \cup \{v\}$.

Delete from E' all edges incident to either u or v .

RETURN S .

every vertex cover must take
at least one of these; we take both

← M is a matching

Running time. Can be implemented in $O(m + n)$ time.



Given a graph G , let M be any matching and let S be any vertex cover. Which of the following must be true?

- A. $|M| \leq |S|$
- B. $|S| \leq |M|$
- C. $|S| = |M|$
- D. None of the above.

Vertex cover: greedy algorithm is a 2-approximation algorithm

Theorem. Let S^* be a minimum vertex cover. Then, greedy algorithm computes a vertex cover S with $|S| \leq 2|S^*|$. ← 2-approximation algorithm

Pf.

- S is a vertex cover. ← delete edge only after it's already covered
- M is a matching. ← when (u, v) added to M , all edges incident to either u or v are deleted
- $|S| = 2|M| \leq 2|S^*|$. ▪
 - ↑
design
 - ↑
weak duality

Corollary. Let M^* be a maximum matching. Then, greedy algorithm computes a matching M with $|M| \geq \frac{1}{2}|M^*|$.

Pf. $|M| = \frac{1}{2}|S| \geq \frac{1}{2}|M^*|$. ▪

↑
weak duality

Vertex cover inapproximability

Theorem. [Dinur–Safra 2004] If $\mathbf{P} \neq \mathbf{NP}$, then no ρ -approximation for VERTEX-COVER for any $\rho < 1.3606$.

On the Hardness of Approximating Minimum Vertex Cover

Irit Dinur*

Samuel Safra[†]

May 26, 2004

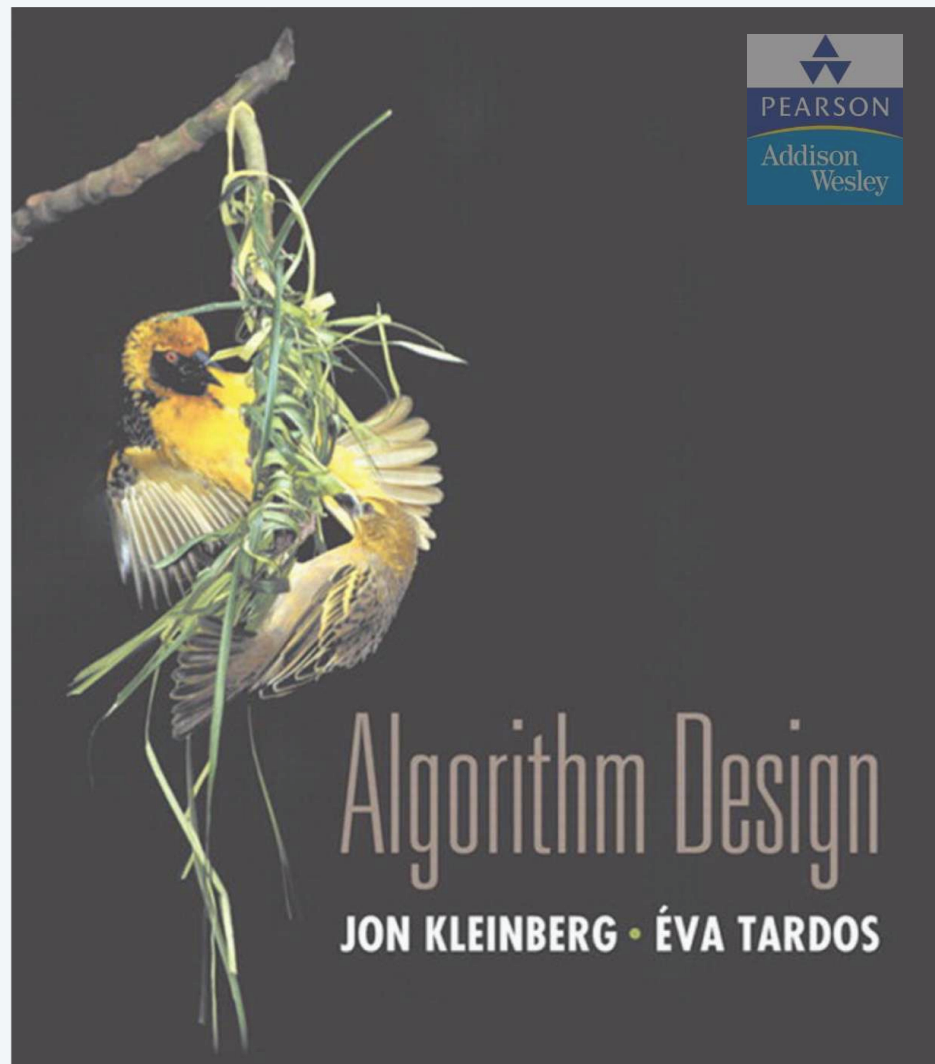
Abstract

We prove the Minimum Vertex Cover problem to be NP-hard to approximate to within a factor of 1.3606, extending on previous PCP and hardness of approximation technique. To that end, one needs to develop a new proof framework, and borrow and extend ideas from several fields.



Open research problem. Close the gap.

Conjecture. no ρ -approximation for VERTEX-COVER for any $\rho < 2$.



SECTION 11.8

INTRACTABILITY III

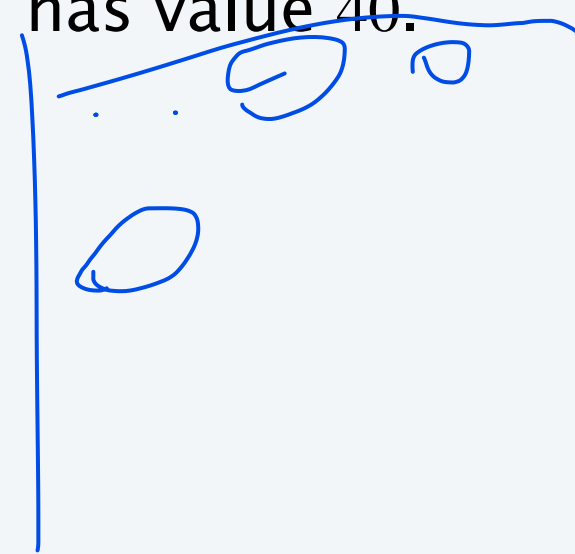
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Knapsack problem

Knapsack problem.

- Given n objects and a knapsack.
- Item i has value $v_i > 0$ and weighs $w_i > 0$. ← we assume $w_i \leq W$ for each i
- Knapsack has weight limit W .
- Goal: fill knapsack so as to maximize total value.

Ex: { 3, 4 } has value 40.



item	value	weight
1	1	1
2	6	2
3	18	5
4	22	6
5	28	7

original instance ($W = 11$)

Knapsack is NP-complete

SUBSET-SUM. Given a set X , values $u_i \geq 0$, and an integer U , is there a subset $S \subseteq X$ whose elements sum to exactly U ?

KNAPSACK. Given a set X , weights $w_i \geq 0$, values $v_i \geq 0$, a weight limit W , and a target value V , is there a subset $S \subseteq X$ such that:



$$\sum_{i \in S} w_i \leq W$$

$$\sum_{i \in S} v_i \leq V$$

Theorem. $\text{SUBSET-SUM} \leq_P \text{KNAPSACK}$.

Pf. Given instance (u_1, \dots, u_n, U) of SUBSET-SUM, create KNAPSACK instance:

$$v_i = w_i = u_i \quad \sum_{i \in S} u_i \leq U$$

$$V = W = U \quad \sum_{i \in S} u_i \geq U$$

Knapsack problem: dynamic programming I

Def. $OPT(i, w)$ = max value subset of items $1, \dots, i$ with **weight** limit w .

Case 1. OPT does not select item i .

- OPT selects best of $1, \dots, i-1$ using up to weight limit w .

Case 2. OPT selects item i .

- New weight limit = $w - w_i$.
- OPT selects best of $1, \dots, i-1$ using up to weight limit $w - w_i$.

$$OPT(i, w) = \begin{cases} 0 & \text{if } i = 0 \\ OPT(i-1, w) & \text{if } w_i > w \\ \max\{OPT(i-1, w), v_i + OPT(i-1, w - w_i)\} & \text{otherwise} \end{cases}$$

Theorem. Computes the optimal value in $O(n W)$ time.

- Not polynomial in input size.
- Polynomial in input size if weights are small integers.

Knapsack problem: dynamic programming II

Def. $OPT(i, v)$ = min weight of a knapsack for which we can obtain a solution of value $\geq v$ using a subset of items $1, \dots, i$.

Note. Optimal value is the largest value v such that $OPT(n, v) \leq W$.

Case 1. OPT does not select item i .

- OPT selects best of $1, \dots, i-1$ that achieves value $\geq v$.

Case 2. OPT selects item i .

- Consumes weight w_i , need to achieve value $\geq v - v_i$.
- OPT selects best of $1, \dots, i-1$ that achieves value $\geq v - v_i$.

$$OPT(i, v) = \begin{cases} 0 & \text{if } v \leq 0 \\ \infty & \text{if } i = 0 \text{ and } v > 0 \\ \min \{OPT(i-1, v), w_i + OPT(i-1, v - v_i)\} & \text{otherwise} \end{cases}$$

Knapsack problem: dynamic programming II

Theorem. Dynamic programming algorithm II computes the optimal value in $O(n^2 v_{\max})$ time, where v_{\max} is the maximum of any value.

Pf.

- The optimal value $V^* \leq n v_{\max}$.
- There is one subproblem for each item and for each value $v \leq V^*$.
- It takes $O(1)$ time per subproblem. ▪

Remark 1. Not polynomial in input size!

Remark 2. Polynomial time if values are small integers.

Knapsack problem: poly-time approximation scheme

Intuition for approximation algorithm.

- Round all values up to lie in smaller range.
- Run dynamic programming algorithm II on rounded/scaled instance.
- Return optimal items in rounded instance.

item	value	weight
1	934221	1
2	5956342	2
3	1781001 3	5
4	2121780 0	6
5	2734319 9	7

item	value	weight
1	1	1
2	6	2
3	18	5
4	22	6
5	28	7

rounded instance ($W = 11$)

Knapsack problem: poly-time approximation scheme

Round up all values:

- $0 < \varepsilon \leq 1$ = precision parameter.
- v_{\max} = largest value in original instance.
- θ = scaling factor = $\varepsilon v_{\max} / 2n$.

$$\bar{v}_i = \left\lceil \frac{v_i}{\theta} \right\rceil \theta, \quad \hat{v}_i = \left\lceil \frac{v_i}{\theta} \right\rceil$$

Observation. Optimal solutions to problem with \bar{v} are equivalent to optimal solutions to problem with \hat{v} .

Intuition. \bar{v} close to v so optimal solution using \bar{v} is nearly optimal;
 \hat{v} small and integral so dynamic programming algorithm II is fast.

Knapsack problem: poly-time approximation scheme

Theorem. If S is solution found by rounding algorithm and S^* is any other feasible solution, then $(1 + \epsilon) \sum_{i \in S} v_i \geq \sum_{i \in S^*} v_i$

Pf. Let S^* be any feasible solution satisfying weight constraint.

$$\begin{aligned} \sum_{i \in S^*} v_i &\leq \sum_{i \in S^*} \bar{v}_i && \text{always round up} \\ &\leq \sum_{i \in S} \bar{v}_i && \text{solve rounded instance optimally} \\ &\leq \sum_{i \in S} (v_i + \theta) && \text{never round up by more than } \theta \\ &\leq \sum_{i \in S} v_i + n\theta && |S| \leq n \\ &= \sum_{i \in S} v_i + \frac{1}{2} \epsilon v_{\max} && \theta = \epsilon v_{\max} / 2n \\ &\leq (1 + \epsilon) \sum_{i \in S} v_i && v_{\max} \leq 2 \sum_{i \in S} v_i \end{aligned}$$

subset containing
only the item
of largest value

choosing $S^* = \{ \max \}$

$$v_{\max} \leq \sum_{i \in S} v_i + \frac{1}{2} \epsilon v_{\max}$$

$$\leq \sum_{i \in S} v_i + \frac{1}{2} v_{\max}$$

thus

$$v_{\max} \leq 2 \sum_{i \in S} v_i$$

Knapsack problem: poly-time approximation scheme

Theorem. For any $\varepsilon > 0$, the rounding algorithm computes a feasible solution whose value is within a $(1 + \varepsilon)$ factor of the optimum in $O(n^3 / \varepsilon)$ time.

Pf.

- We have already proved the accuracy bound.
- Dynamic program II running time is $O(n^2 \hat{v}_{\max})$, where

$$\hat{v}_{\max} = \left\lceil \frac{v_{\max}}{\theta} \right\rceil = \left\lceil \frac{2n}{\varepsilon} \right\rceil$$

INTRACTABILITY III

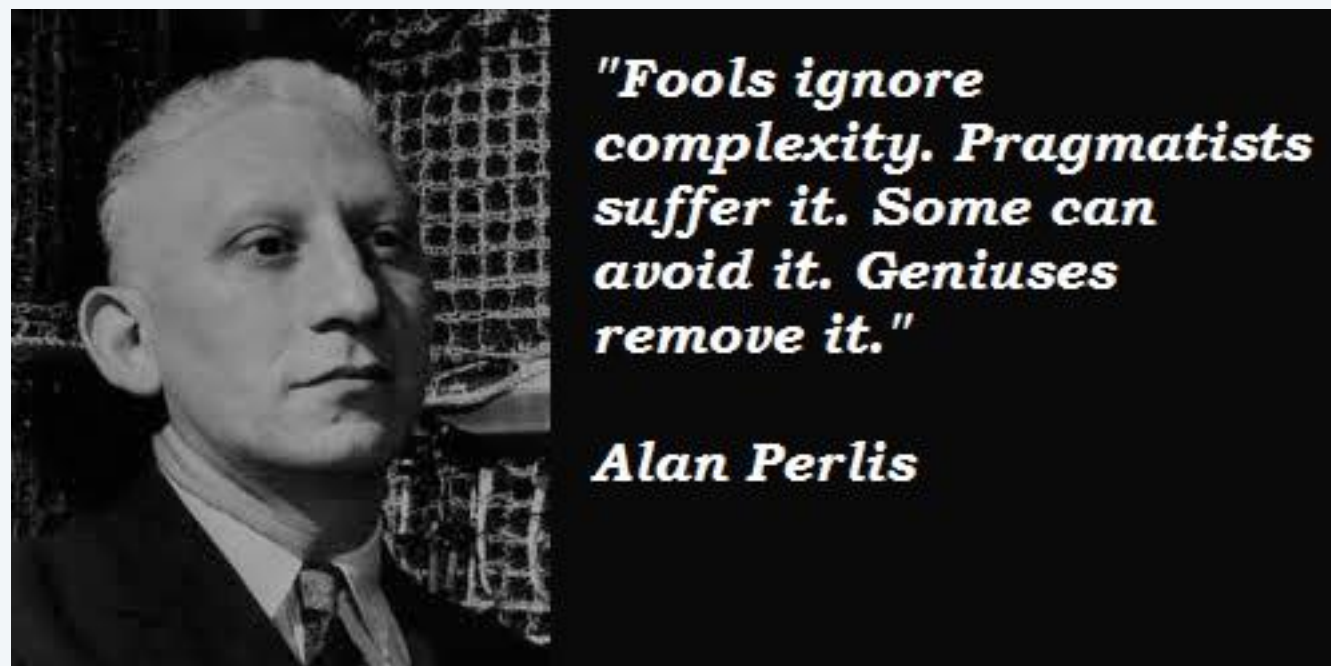
- ▶ *special cases: trees*
- ▶ *special cases: planarity*
- ▶ *approximation algorithms: vertex cover*
- ▶ *approximation algorithms: knapsack*
- ▶ ***exponential algorithms: 3-SAT***
- ▶ *exponential algorithms: TSP*

Exact exponential algorithms

Complexity theory deals with worst-case behavior.

- Instances you want to solve may be “easy.”

“For every polynomial-time algorithm you have, there is an exponential algorithm that I would rather run.” — Alan Perlis



INTRACTABILITY III

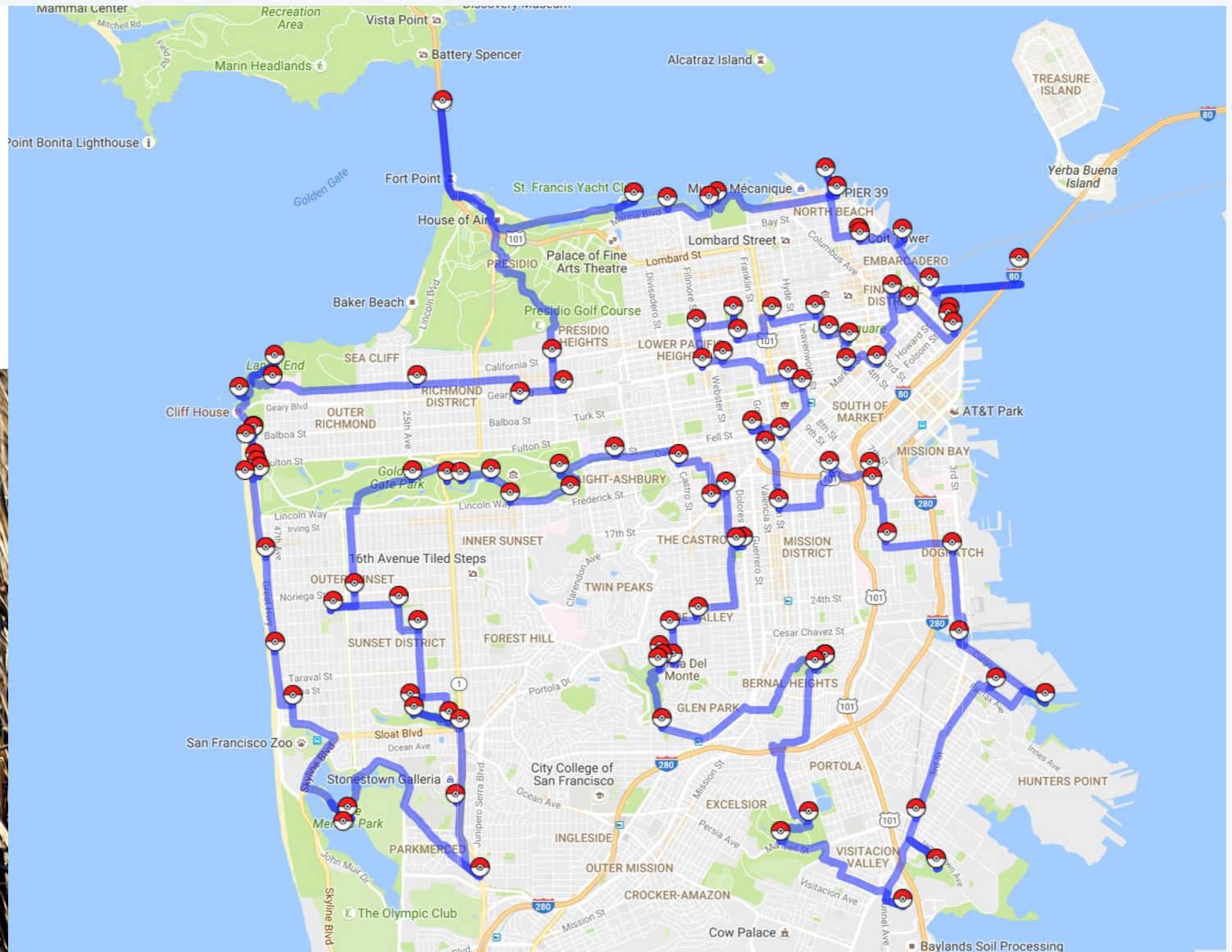
- ▶ *special cases: trees*
- ▶ *special cases: planarity*
- ▶ *approximation algorithms: vertex cover*
- ▶ *approximation algorithms: knapsack*
- ▶ *exponential algorithms: 3-SAT*
- ▶ ***exponential algorithms: TSP***

Pokemon Go

Given the locations of n Pokémon, find shortest tour to collect them all.

Map: Where to catch 123 Pokémon in San Francisco

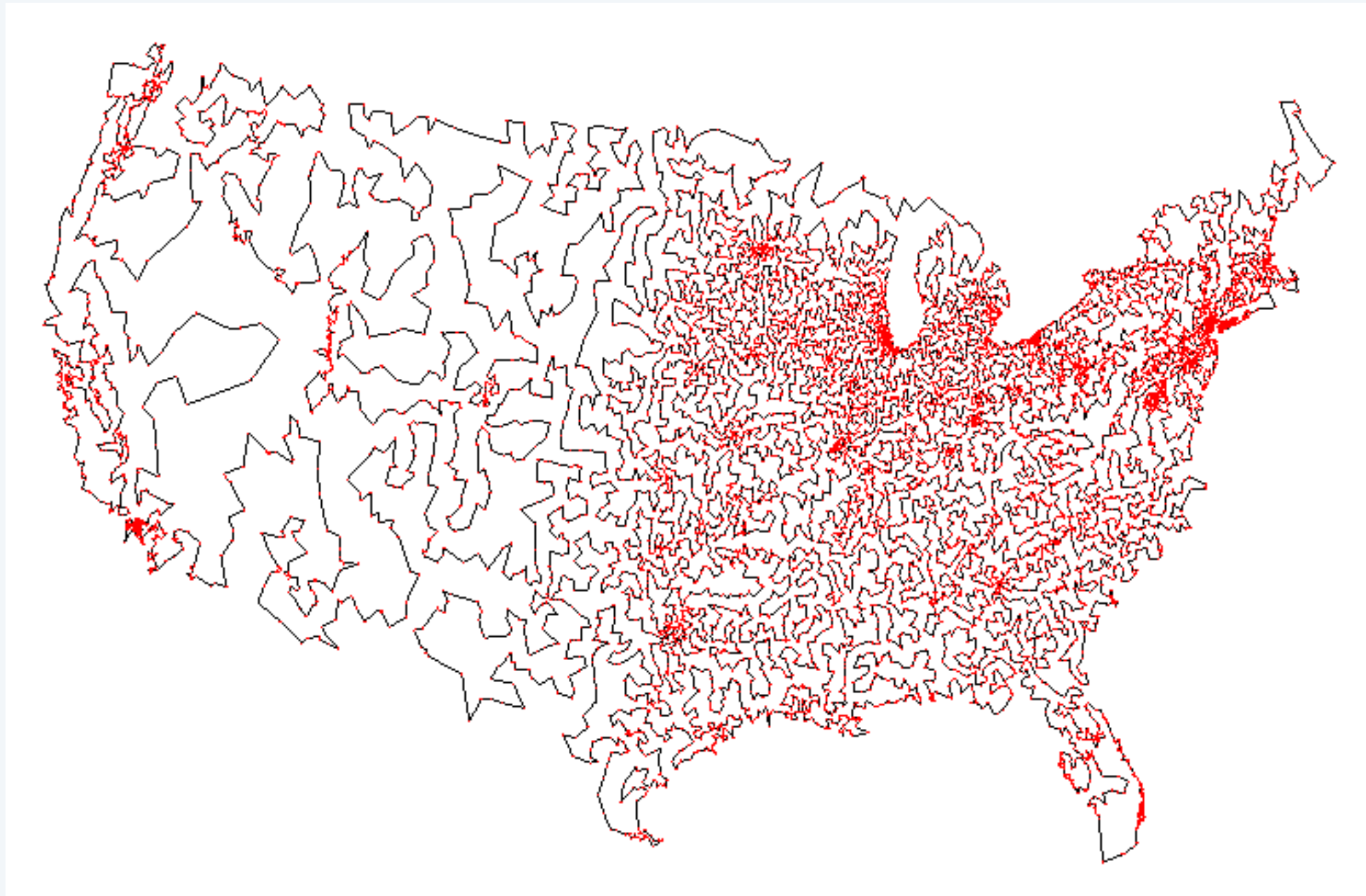
BY ADAM BRINKLOW | OCT 4, 2016, 6:33AM PDT



Traveling salesperson problem

TSP. Given a set of n cities and a pairwise distance function $d(u, v)$,
is there a tour of length $\leq D$?

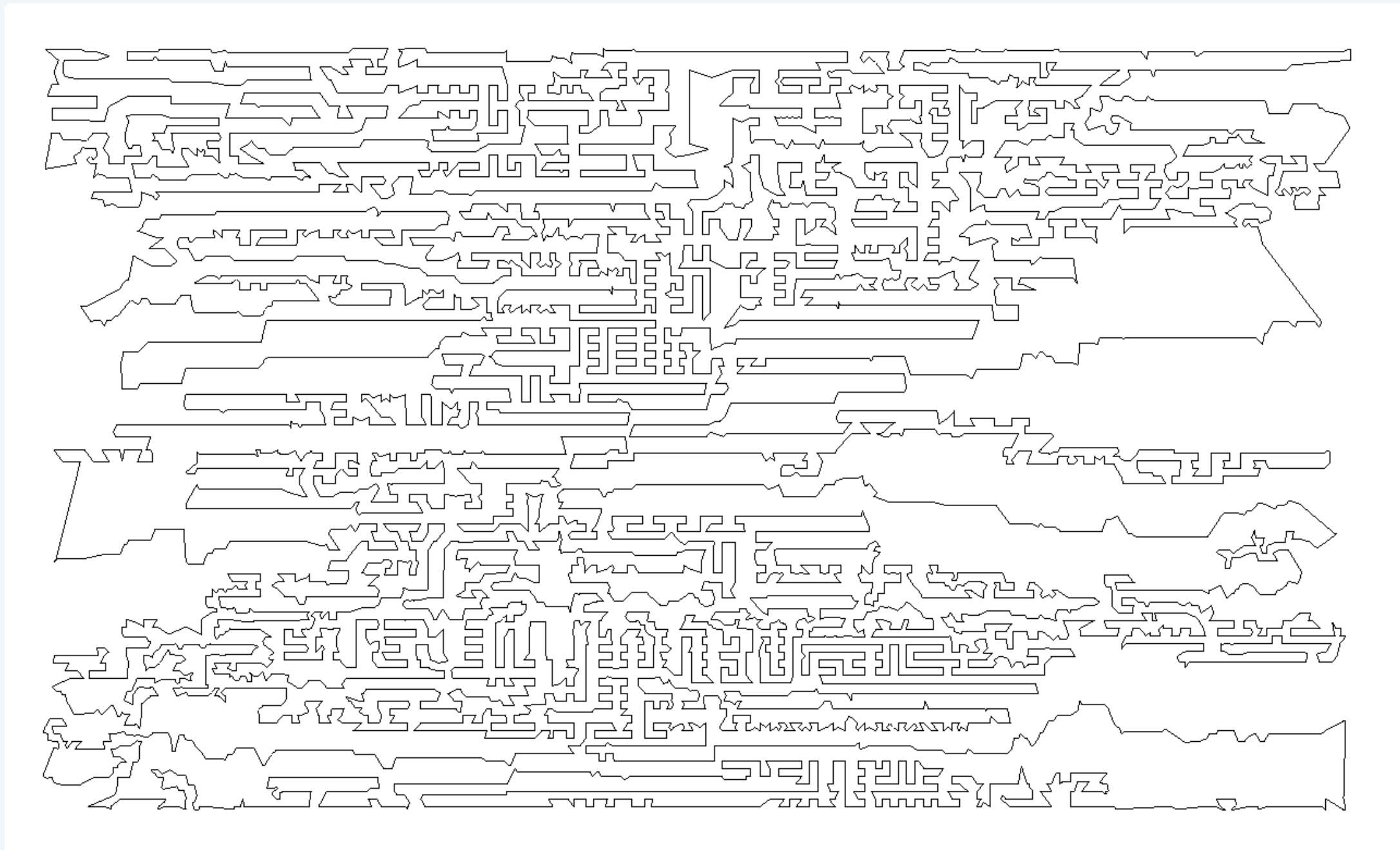
can view as a complete graph



13,509 cities in the United States
<http://www.math.uwaterloo.ca/tsp>

Traveling salesperson problem

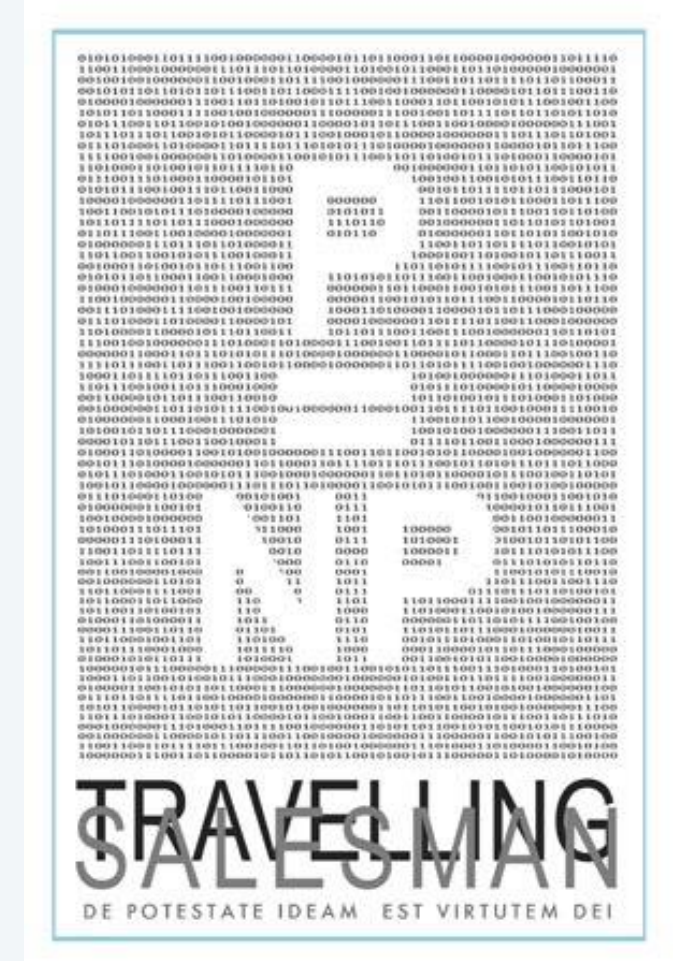
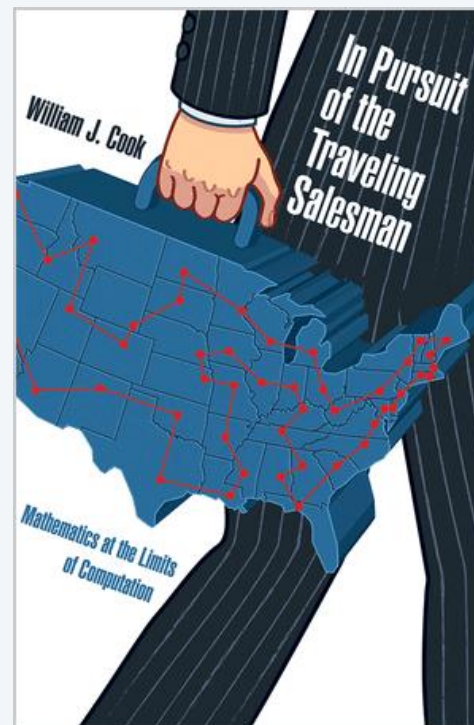
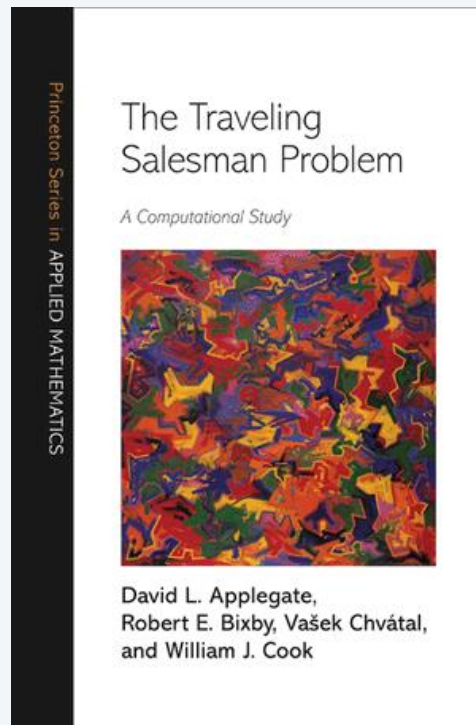
TSP. Given a set of n cities and a pairwise distance function $d(u, v)$,
is there a tour of length $\leq D$?



11,849 holes to drill in a programmed logic array

<http://www.math.uwaterloo.ca/tsp>

TSP books, apps, and movies



Hamilton cycle reduces to traveling salesperson problem

TSP. Given a set of n cities and a pairwise distance function $d(u, v)$, is there a tour of length $\leq D$?

HAMILTON-CYCLE. Given an undirected graph $G = (V, E)$, does there exist a cycle that visits every node exactly once?

Theorem. $\text{HAMILTON-CYCLE} \leq_p \text{TSP}$.

Pf.

- Given an instance $G = (V, E)$ of HAMILTON-CYCLE, create $n = |V|$ cities with distance function

$$d(u, v) = \begin{cases} 1 & \text{if } (u, v) \in E \\ 2 & \text{if } (u, v) \notin E \end{cases}$$

- TSP instance has tour of length $\leq n$ iff G has a Hamilton cycle. ▪



What is complexity of TSP? Choose the best answer.

A. $O(n^2)$

B. $O^*(1.657^n)$

C. $O^*(2^n)$

D. $O^*(n!)$



O^* hides $\text{poly}(n)$ terms

Exponential algorithm for TSP: dynamic programming

Theorem. [Held–Karp, Bellman 1962] TSP can be solved in $O(n^2 2^n)$ time.

HAMILTON-CYCLE is a special case

J. SOC. INDUST. APPL. MATH.
Vol. 10, No. 1, March, 1962
Printed in U.S.A.

A DYNAMIC PROGRAMMING APPROACH TO SEQUENCING PROBLEMS*

MICHAEL HELD† AND RICHARD M. KARP†

INTRODUCTION

Many interesting and important optimization problems require the determination of a best order of performing a given set of operations. This paper is concerned with the solution of three such *sequencing problems*: a scheduling problem involving arbitrary cost functions, the traveling-salesman problem, and an assembly-line balancing problem. Each of these problems has a structure permitting solution by means of recursion schemes of the type associated with dynamic programming. In essence, these recursion schemes permit the problems to be treated in terms of *combinations*, rather than *permutations*, of the operations to be performed. The dynamic programming formulations are given in §1, together with a discussion of various extensions such as the inclusion of precedence constraints. In each case the proposed method of solution is computationally effective for problems in a certain limited range. Approximate solutions to larger problems may be obtained by solving sequences of small derived problems, each having the same structure as the original one. This procedure of successive approximations is developed in detail in §2 with specific reference to the traveling-salesman problem, and §3 summarizes computational experience with an IBM 7090 program using the procedure.

Dynamic Programming Treatment of the Travelling Salesman Problem*

RICHARD BELLMAN

RAND Corporation, Santa Monica, California

Introduction

The well-known travelling salesman problem is the following: “A salesman is required to visit once and only once each of n different cities starting from a base city, and returning to this city. What path minimizes the total distance travelled by the salesman?”

The problem has been treated by a number of different people using a variety of techniques; cf. Dantzig, Fulkerson, Johnson [1], where a combination of ingenuity and linear programming is used, and Miller, Tucker and Zemlin [2], whose experiments using an all-integer program of Gomory did not produce results in cases with ten cities although some success was achieved in cases of simply four cities. The purpose of this note is to show that this problem can easily be formulated in dynamic programming terms [3], and resolved computationally for up to 17 cities. For larger numbers, the method presented below, combined with various simple manipulations, may be used to obtain quick approximate solutions. Results of this nature were independently obtained by M. Held and R. M. Karp, who are in the process of publishing some extensions and computational results.

Exponential algorithm for TSP: dynamic programming

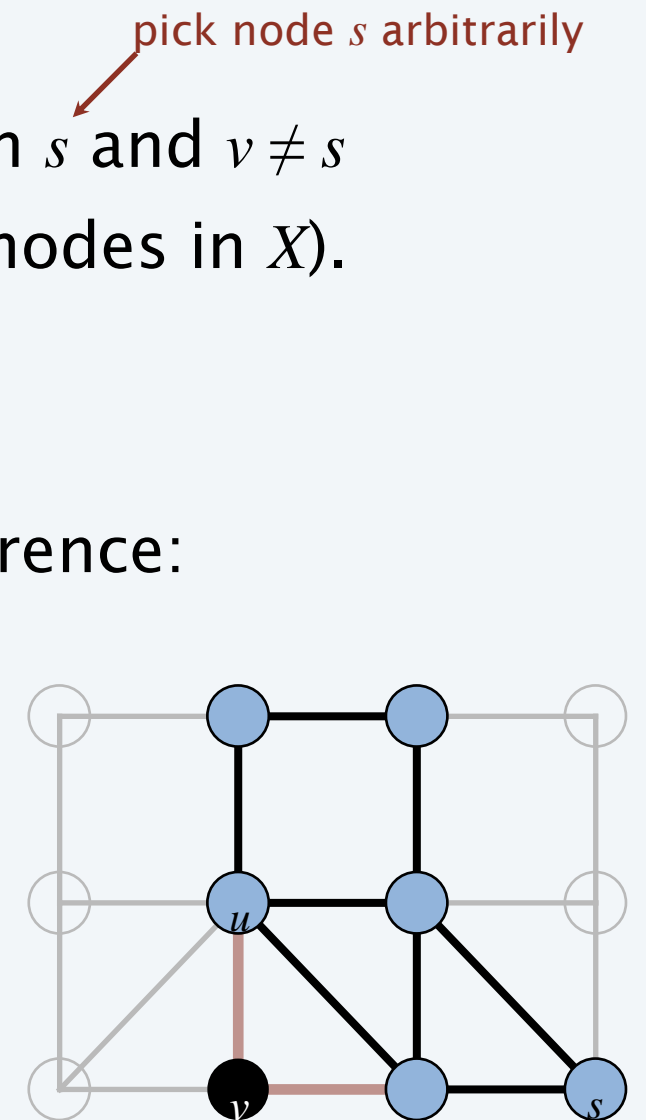
Theorem. [Held–Karp, Bellman 1962] TSP can be solved in $O(n^2 2^n)$ time.

Pf. [dynamic programming]

- Subproblems: $c(s, v, X)$ = cost of cheapest path between s and $v \neq s$ that visits every node in X exactly once (and uses only nodes in X).
- Goal: $\min_{v \in V} c(s, v, V) + c(v, s)$
- There are $\leq n 2^n$ subproblems and they satisfy the recurrence:

$$c(s, v, X) = \begin{cases} c(s, v) & \text{if } |X| = 2 \\ \min_{u \in X \setminus \{s, v\}} c(s, u, X \setminus \{v\}) + c(u, v) & \text{if } |X| > 2. \end{cases}$$

- The values $c(s, v, X)$ can be computed in increasing order of the cardinality of X . ▪



22-city TSP instance takes 1,000 years

The Washington Post

Quantum computers are straight out of science fiction. Take the “traveling salesman problem,” where a salesperson has to visit a specific set of cities, each only once, and return to the first city by the most efficient route possible. As the number of cities increases, the problem becomes exponentially complex. It would take a laptop computer 1,000 years to compute the most efficient route between 22 cities, for example. A quantum computer could do this within minutes, possibly seconds.

$$2^{22} = 4,194,304$$


$$22! = 1,124,000,727,777,607,680,000 \sim 10^{21}$$

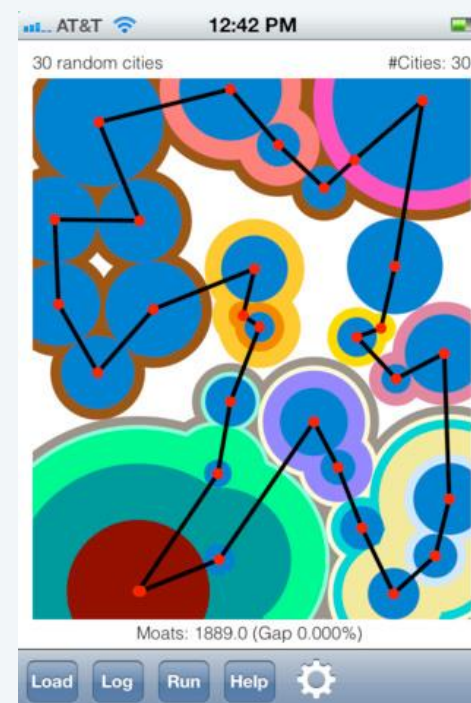
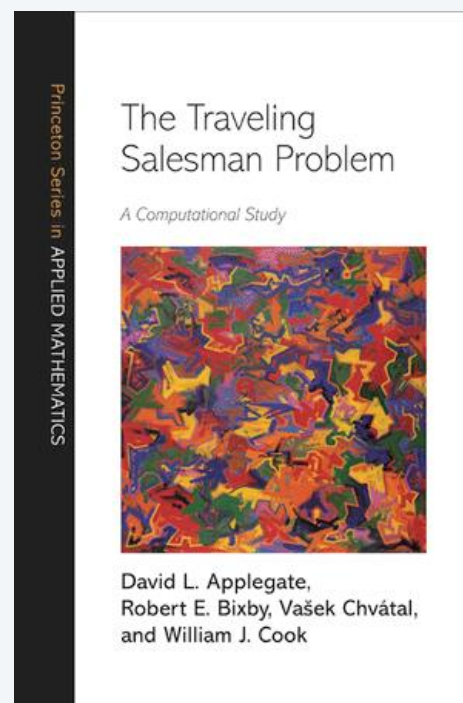

Concorde TSP solver

Concorde TSP solver. [Applegate–Bixby–Chvátal–Cook]

- Linear programming + branch-and-bound + polyhedral combinatorics.
- Greedy heuristics, including Lin–Kernighan.
- MST, Delaunay triangulations, fractional b -matchings, ...

Remarkable fact. Concorde has solved all 110 TSPLIB instances.

largest instance has 85,900 cities!



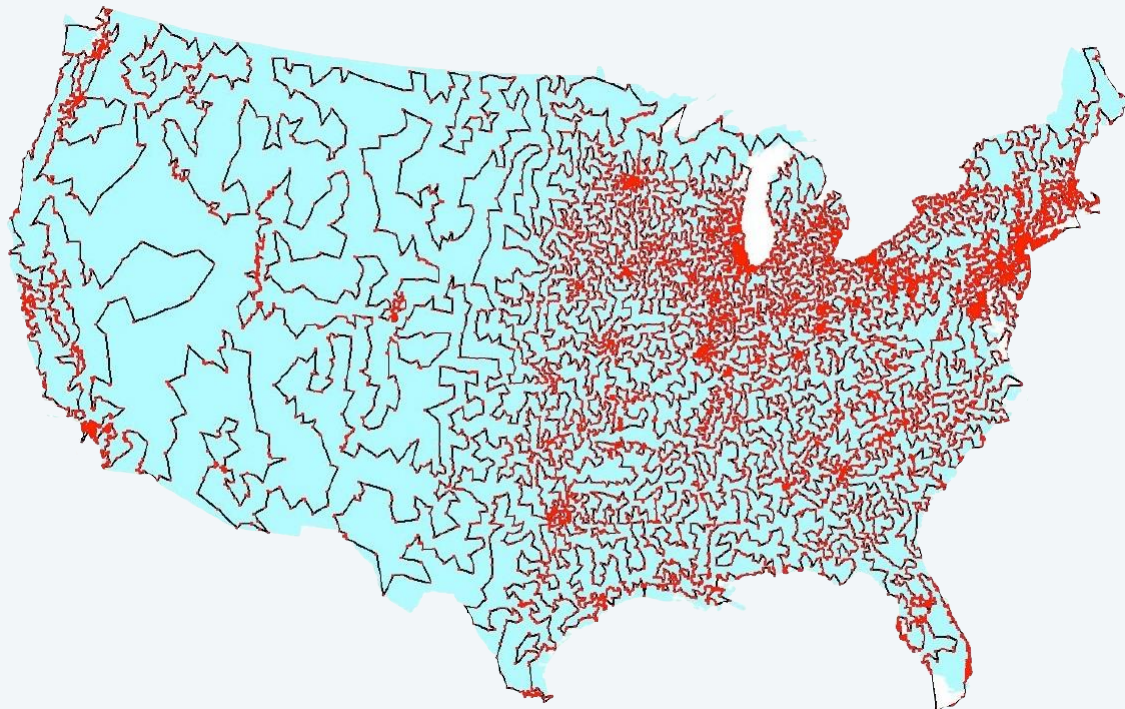
Euclidean traveling salesperson problem

Euclidean TSP. Given n points in the plane and a real number L , is there a tour that visit every city exactly once that has distance $\leq L$?

Fact. $3\text{-SAT} \leq_P \text{EUCLIDEAN-TSP}$.

Remark. Not known to be in **NP**.

$$\sqrt{5} + \sqrt{6} + \sqrt{18} < \sqrt{4} + \sqrt{12} + \sqrt{12}$$
$$8.928198407 < 8.928203230$$



13509 cities in the USA and an optimal tour

THE EUCLIDEAN TRAVELING SALESMAN PROBLEM IS NP-COMPLETE*

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Communicated by Richard Karp

Received August 1975

Revised July 1976

Abstract. The Traveling Salesman Problem is shown to be NP-Complete even if its instances are restricted to be realizable by sets of points on the Euclidean plane.

← using rounded weights

Euclidean traveling salesperson problem

Theorem. [Arora 1998, Mitchell 1999] Given n points in the plane, for any constant $\varepsilon > 0$: there exists a poly-time algorithm to find a tour whose length is at most $(1 + \varepsilon)$ times that of the optimal tour.

Pf recipe. Structure theorem + divide-and-conquer + dynamic programming.

Polynomial Time Approximation Schemes for Euclidean Traveling Salesman and other Geometric Problems

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We present a polynomial time approximation scheme for Euclidean TSP in fixed dimensions. For every fixed $c > 1$ and given any n nodes in \mathbb{R}^2 , a randomized version of the scheme finds a $(1 + 1/c)$ -approximation to the optimum traveling salesman tour in $O(n(\log n)^{O(c)})$ time. When the nodes are in \mathbb{R}^d , the running time increases to $O(n(\log n)^{O(\sqrt{d}c)^{d-1}})$. For every fixed c, d the running time is $n \cdot \text{poly}(\log n)$, i.e., *nearly linear* in n . The algorithm can be derandomized, but this increases the running time by a factor $O(n^d)$. The previous best approximation algorithm for the problem (due to Christofides) achieves a $3/2$ -approximation in polynomial time.

GUILLOTINE SUBDIVISIONS APPROXIMATE POLYGONAL SUBDIVISIONS: A SIMPLE POLYNOMIAL-TIME APPROXIMATION SCHEME FOR GEOMETRIC TSP, K -MST, AND RELATED PROBLEMS

JOSEPH S. B. MITCHELL*

Abstract. We show that any polygonal subdivision in the plane can be converted into an “ m -guillotine” subdivision whose length is at most $(1 + \frac{c}{m})$ times that of the original subdivision, for a small constant c . “ m -Guillotine” subdivisions have a simple recursive structure that allows one to search for shortest such subdivisions in polynomial time, using dynamic programming. In particular, a consequence of our main theorem is a simple polynomial-time approximation scheme for geometric instances of several network optimization problems, including the Steiner minimum spanning tree, the traveling salesperson problem (TSP), and the k -MST problem.