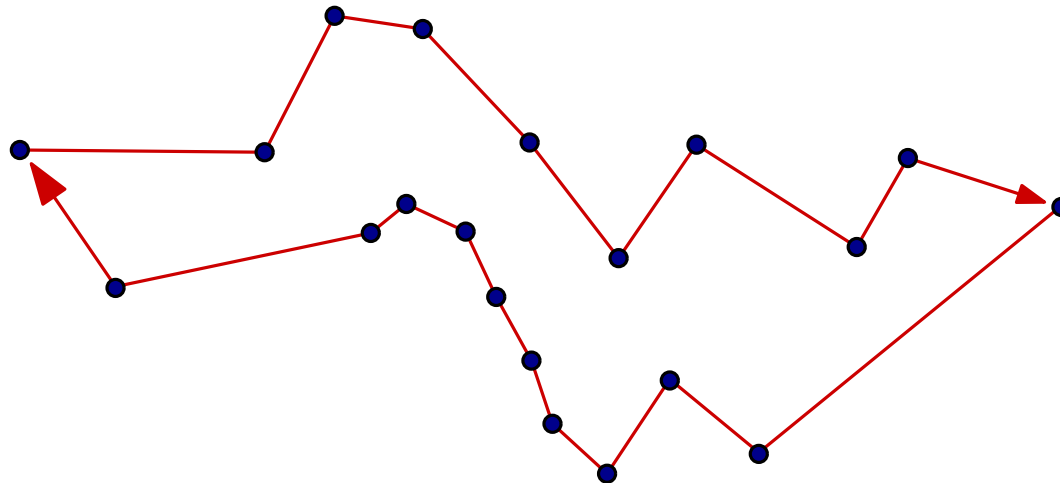


# Fine-Grained Complexity Analysis of Two Classic TSP Variants



Mark de Berg   Kevin Buchin   Bart Jansen   Gerhard Woeginger

TU Eindhoven

# Traveling Salesman Problem (TSP)



Compute min-length tour  
visiting all cities

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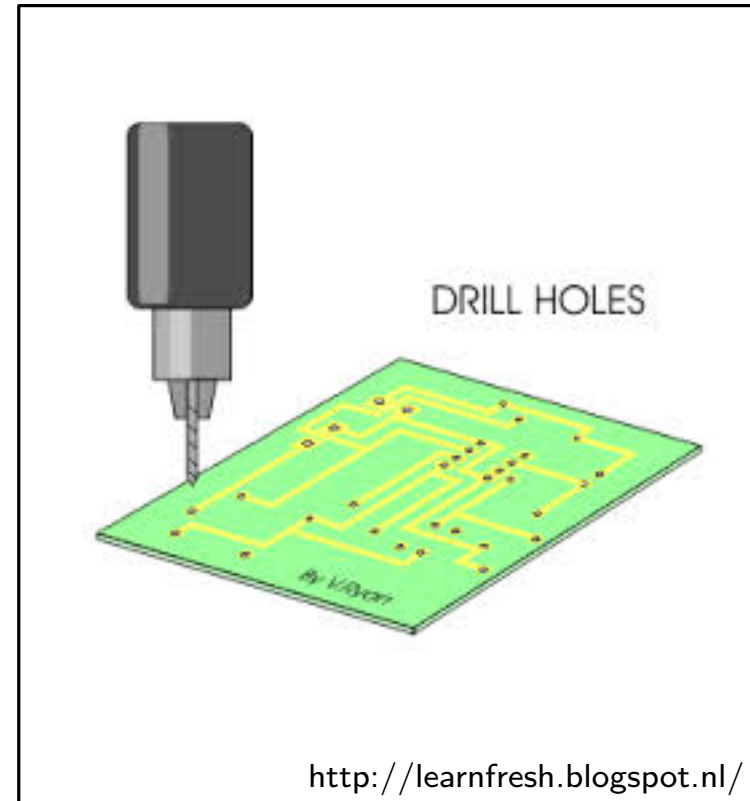


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# Traveling Salesman Problem (TSP)



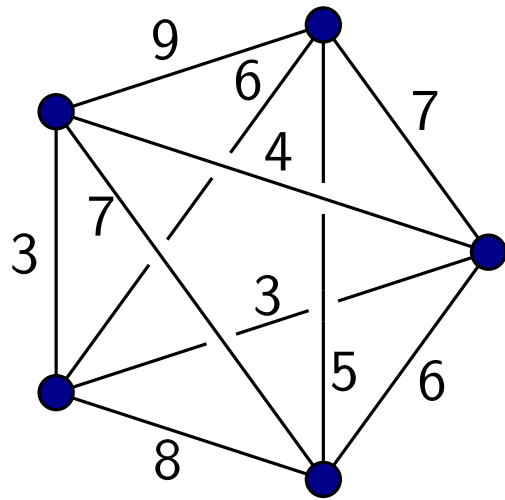
Compute min-length tour  
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Compute min-length tour  
visiting all holes to be drilled

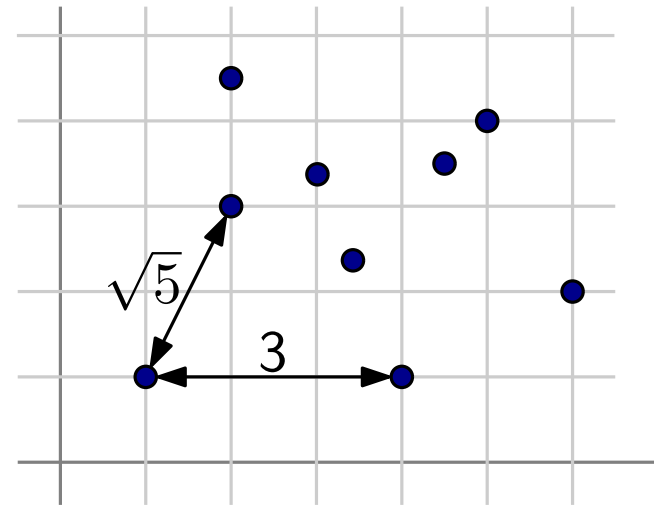
# TSP: general setting vs Euclidean setting

General setting



- cities = nodes in a graph
- arbitrary edge lengths  
(satisfying triangle inequality)

Euclidean setting

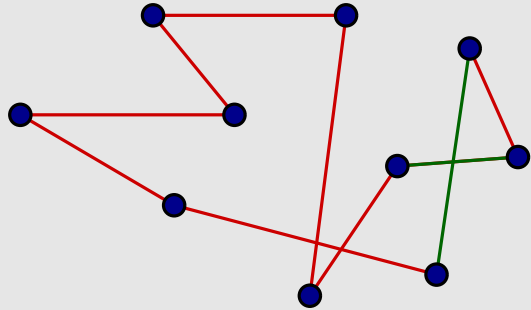


- cities = points in the plane
- edge length = Euclidean distance

TSP is NP-hard, even in Euclidean setting

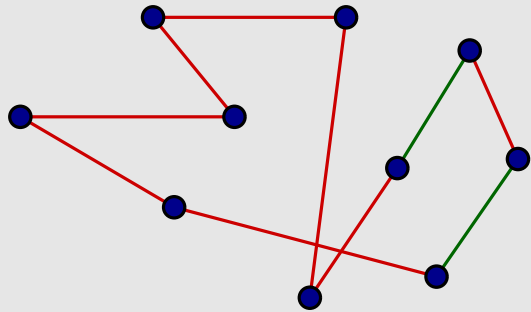
→ fast algorithm impossible (unless  $P = NP$ )

# $k$ -OPT: a classic heuristic for TSP



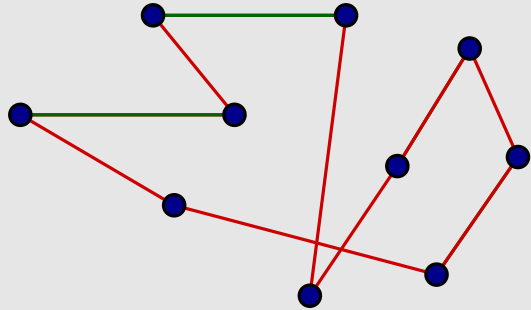
2-OPT: apply 2-swaps as long as they reduce tour length

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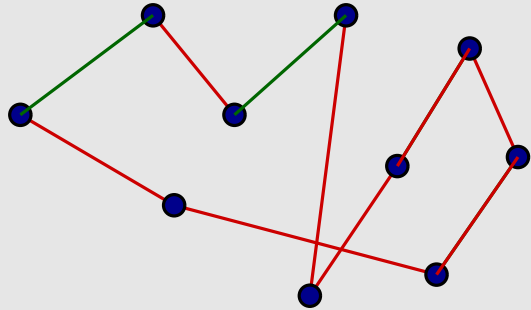
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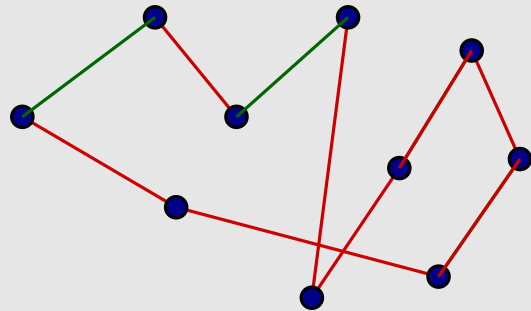


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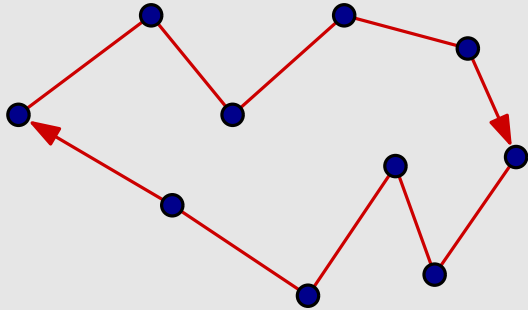
## Quality of $k$ -OPT solution

- $k = 2$ : within few percent of optimum
- $k > 2$ : even slightly better

## How fast can we find $k$ -swaps?

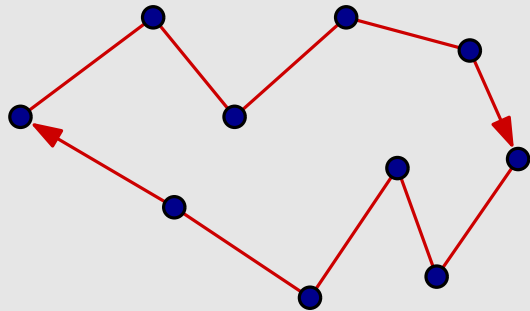
- $O(n^k)$  is trivial
- for  $k = 2$  this is optimal
- what about  $k \geq 3$ ?

# Bitonic TSP: a classic geometric variant



bitonic TSP (Euclidean variant):  
only allow tours that go  
left-to-right and then right-to-left

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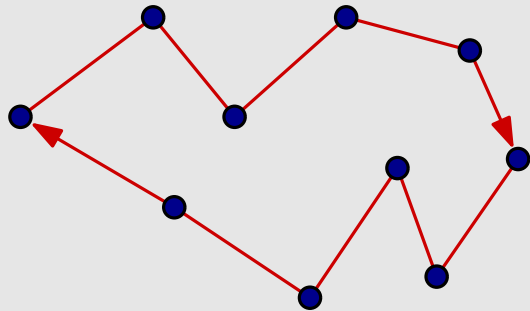


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Classic exercise:  
 $O(n^2)$  algorithm using dynamic  
programming  
no faster algorithms known

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Classic exercise:  
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programming  
no faster algorithms known

pyramidal TSP:

- cities are numbered  $1, \dots, n$
- only allow unimodal permutations:  
1, 3, 6, 9, 10, 8, 7, 5, 4, 2, 1

# FINE-GRAINED COMPLEXITY ANALYSIS

## Fine-grained complexity

**Traditional complexity analysis:** Distinguish tractable (polynomial-time solvable) problems from intractable problems.

- Problem X can be solved in polynomial time
- Problem Y cannot be solved in polynomial time, unless  $P=NP$   
(in other words: under  $P \neq NP$  Hypothesis)

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(in other words: under  $P \neq NP$  Hypothesis)

**Fine-grained analysis:** prove more precise bounds

- Problem X can be solved in  $O(n^3)$  time
- Problem X cannot be solved in  $O(n^{3-\varepsilon})$ , unless ...
- Problem Y can be solved in  $2^{O(n)}$  time
- Problem Y cannot be solved in  $2^{O(n/\log n)}$  time, unless ...



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Problem  $X$  cannot be solved in  $O(\dots)$  time, under ...

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- Strong Exponential-Time Hypothesis (SETH)

CNF-SAT:  $(x_1 \vee \bar{x}_2) \wedge (x_1 \vee x_3 \vee x_4 \vee \bar{x}_5) \wedge (\bar{x}_1 \vee \bar{x}_3 \vee x_5)$  satisfiable?

SETH: CNF-SAT cannot be solved in  $O(2^{(1-\varepsilon)n})$  time

# Fine-grained complexity: conditional lower bounds

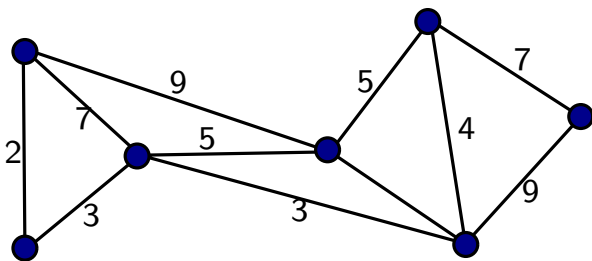
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- or Exponential-Time Hypothesis (ETH), or 3-SUM Conjecture
- All-Pairs Shortest Paths (APSP) Conjecture

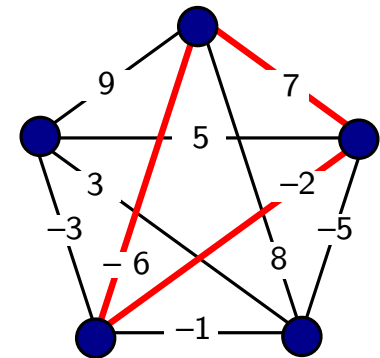


APSP Conjecture: Computing all pairwise distances in weighted graph cannot be done in  $O(n^{3-\varepsilon})$  time.

# Fine-grained complexity: conditional lower bounds

## Examples:

- **Longest Common Subsequence (LCS)** cannot be solved in  $O(n^{2-\varepsilon})$  time, under SETH [Bringmann, Künnemann 2015]
- **Fréchet Distance** cannot be solved in  $O(n^{2-\varepsilon})$  time, under SETH [Bringmann 2014]
- **Negative-Weight Triangle** cannot be solved in  $O(n^{3-\varepsilon})$  time, under APSP Conjecture [Vassilevska-Williams, Williams 2010]  
(in fact, Negative-Weight Triangle and APSP are “equivalent”)



# Our Results

## $k$ -OPT in general setting

- $k = 3$ : lower bound of  $\Omega(n^{3-\varepsilon})$  under APSP Conjecture
- $k > 3$ : algorithm with  $O(n^{\lfloor 2k/3 \rfloor + 1})$  running time
- iterated  $k$ -OPT:  $O(n^2)$  preprocessing,  $O(n \log n)$  per iteration ( $k = 2$ )  
[  $O(n^3)$  preprocessing,  $O(n^2 \log n)$  per iteration ( $k = 3$ ) ]
- Euclidean setting: algorithm with  $O(n^{8/5+\varepsilon})$  running time ( $k = 2$ )  
algorithm with  $O(n^{80/31+\varepsilon})$  running time ( $k = 3$ )

## Bitonic (more generally: pyramidal) Euclidean TSP in the plane

- algorithm with  $O(n \log^2 n)$  running time
- bottleneck variant:  $O(n \log^3 n)$

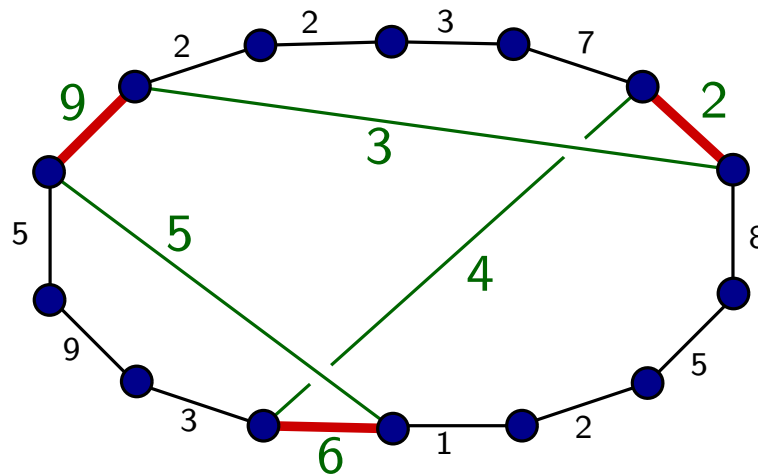
## RESULTS ON $k$ -OPT

# Conditional Lower Bound for 3-OPT DETECTION

## 3-OPT DETECTION

Given: Tour  $T$  in undirected complete graph  $G$  on  $n$  vertices  
with positive edge weights satisfying triangle inequality

Question: Is there a 3-swap that reduces tour length?

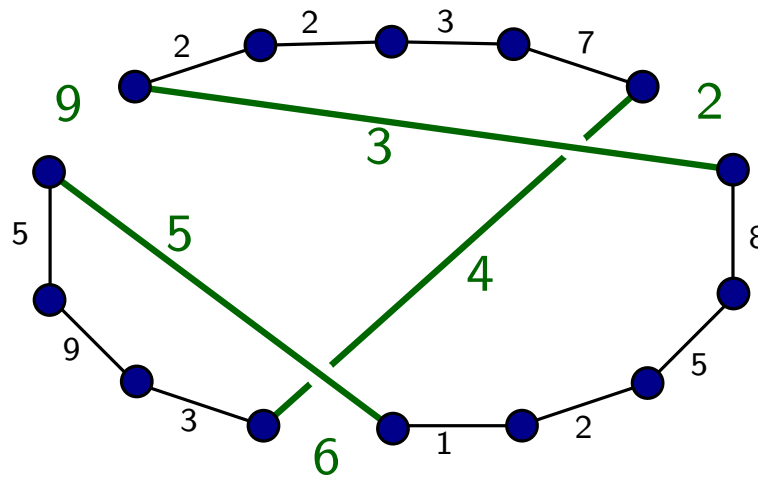


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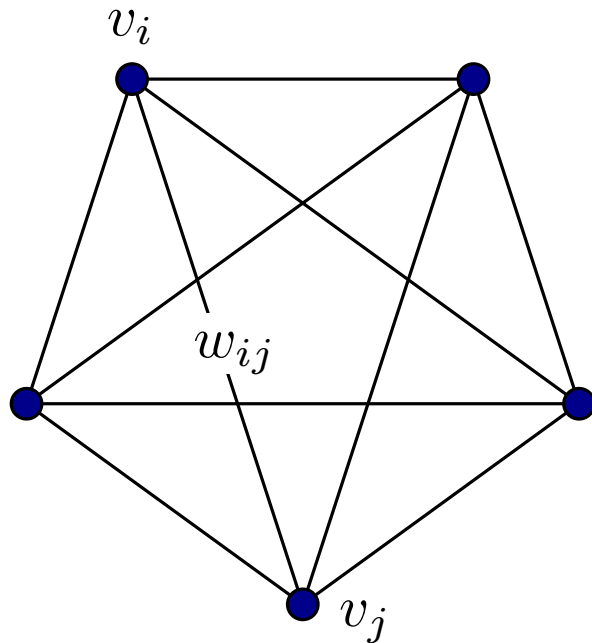




# Conditional Lower Bound for 3-OPT DETECTION

**Theorem.** 3-OPT DETECTION cannot be solved in  $O(n^{3-\varepsilon})$  time under the APSP Conjecture.

**Proof.** Reduction from NEGATIVE-WEIGHT TRIANGLE



transform input graph  $G$  into graph  $G'$  with  $O(n)$  vertices and tour  $T$  in  $G'$  such that

negative weight triangle in  $G$

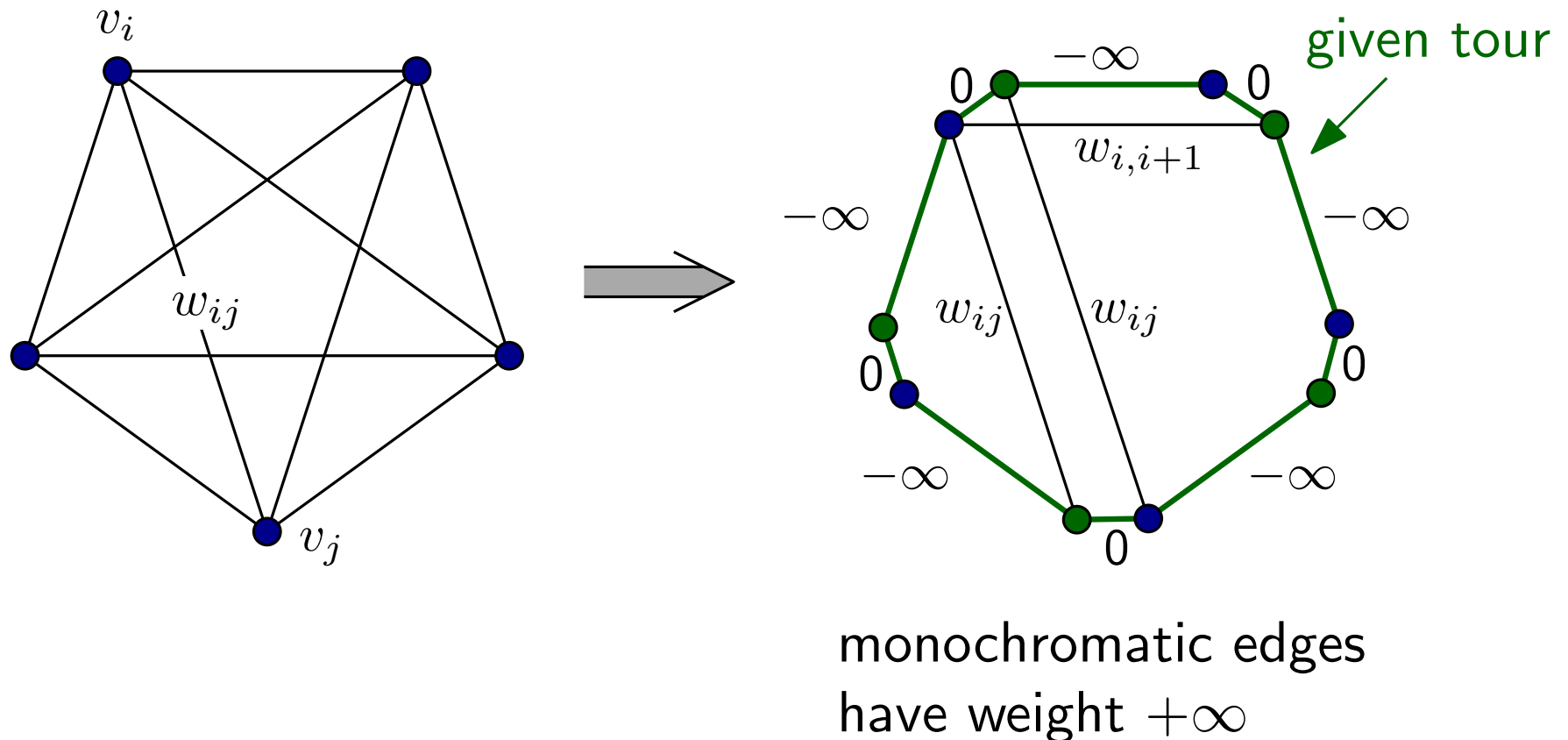
$\equiv$

improving 3-swap in  $T$

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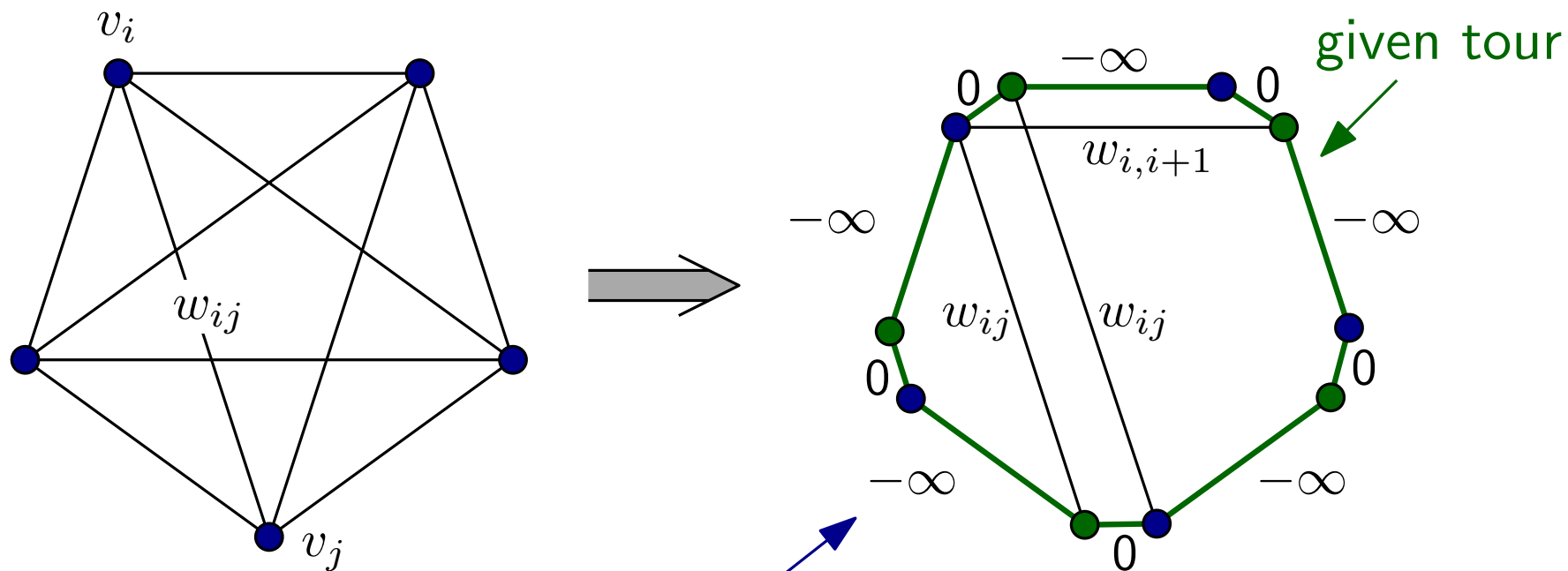
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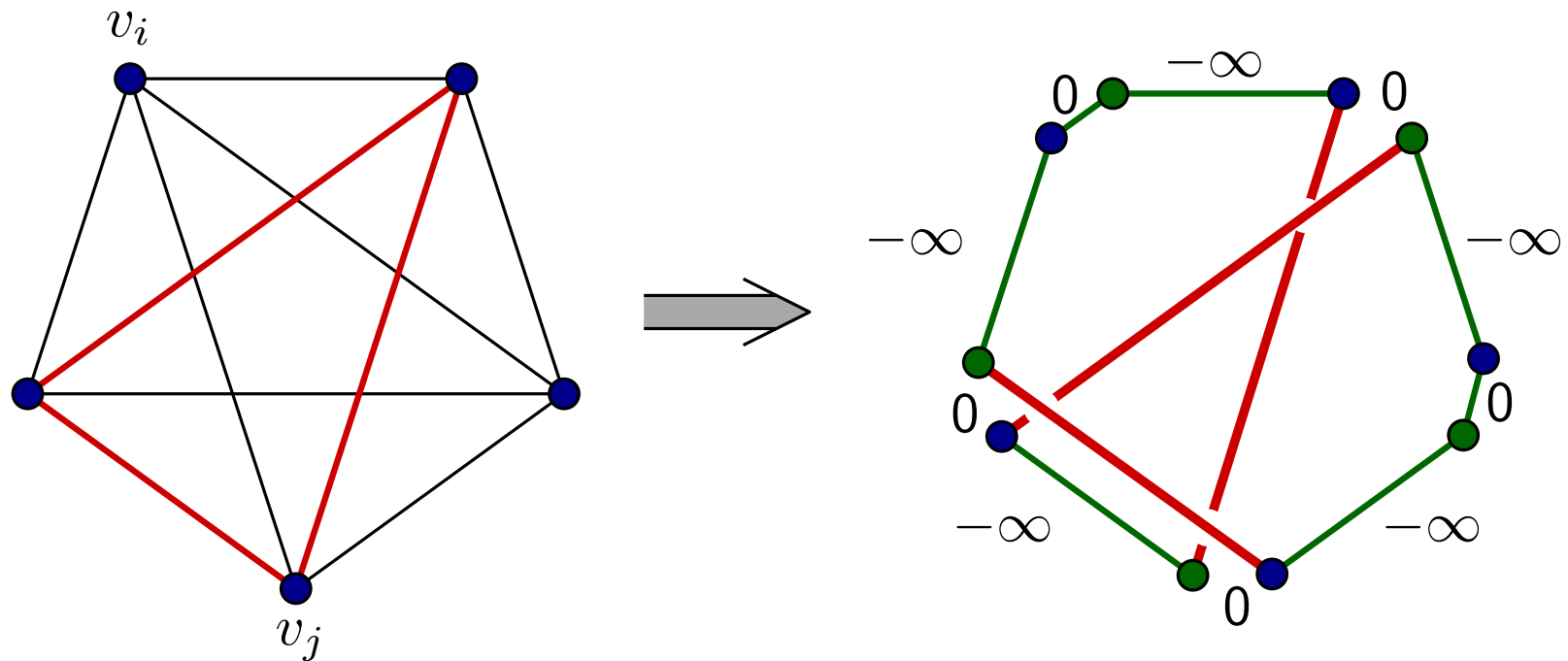
(negative weights can be avoided)

monochromatic edges  
have weight  $+\infty$

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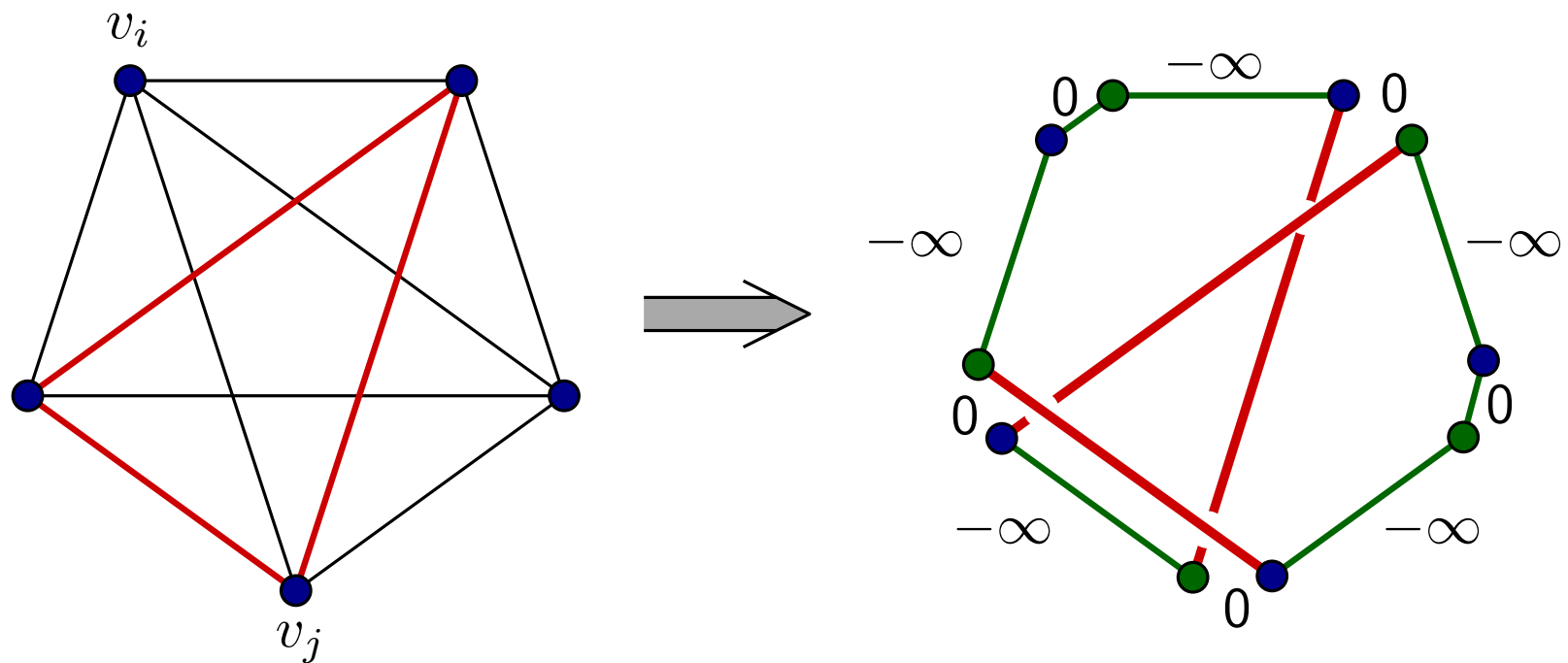


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monochromatic edges  
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# Complexity of $k$ -OPT

## complexity bounds for $k$ -OPT

- trivial upper bound:  $O(n^k)$
- lower bounds
  - $k = 2$ :  $\Omega(n^2)$  (must look at every edge)
  - $k = 3$ :  $O(n^{3-\varepsilon})$  time impossible under the APSP Conjecture

What about  $k > 3$ ? Do we basically need  $\Omega(n^k)$  time?

## A faster algorithm for $k$ -OPT for $k \geq 4$

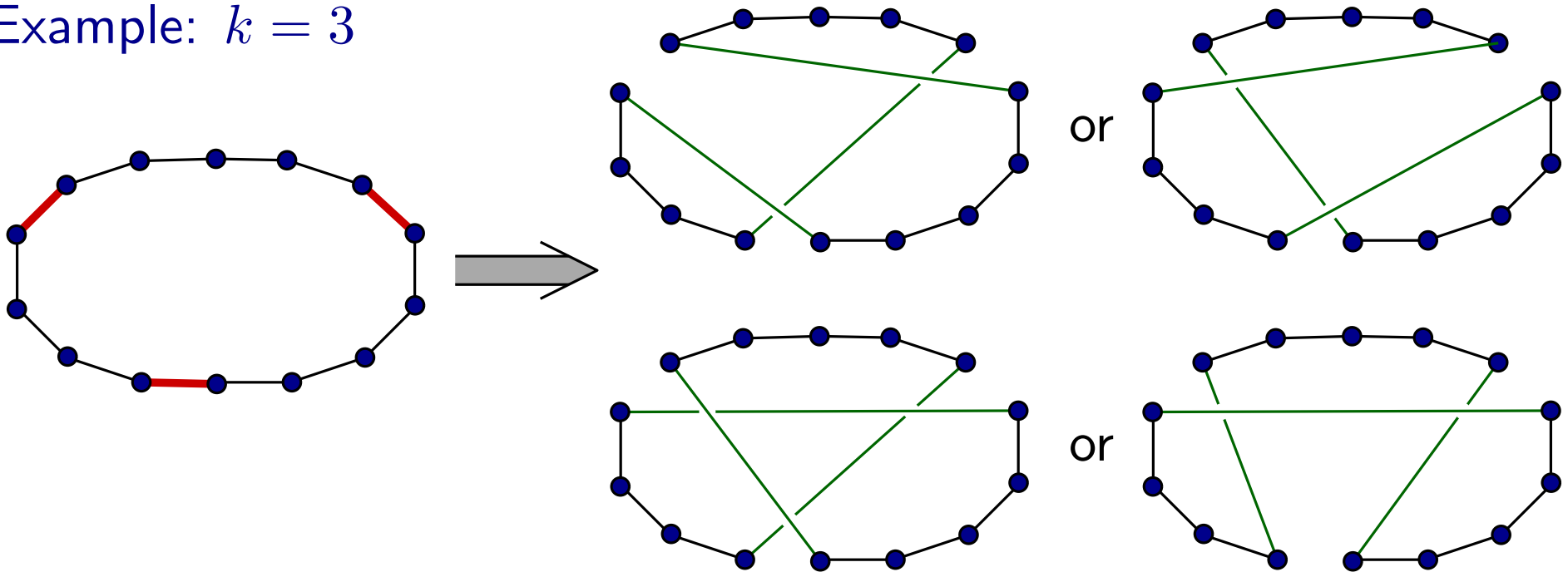
**Theorem.** For any fixed  $k \geq 4$  we can find the best  $k$ -swap in  $O(n^{\lfloor 2k/3 \rfloor + 1})$  time.

Proof. ....

# A faster algorithm for $k$ -OPT for $k \geq 4$

For  $k > 2$  there are several combinations of edges that can replace  $k$  given edges.

Example:  $k = 3$

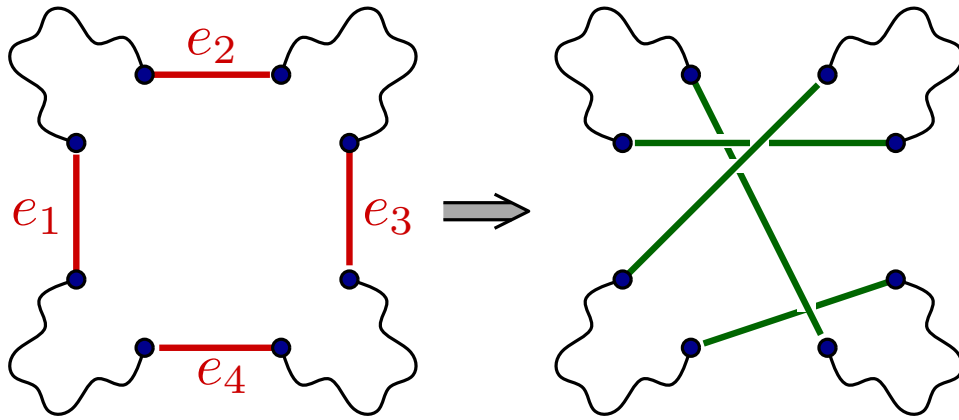


Let's handle them separately



# A faster algorithm for $k$ -OPT for $k \geq 4$

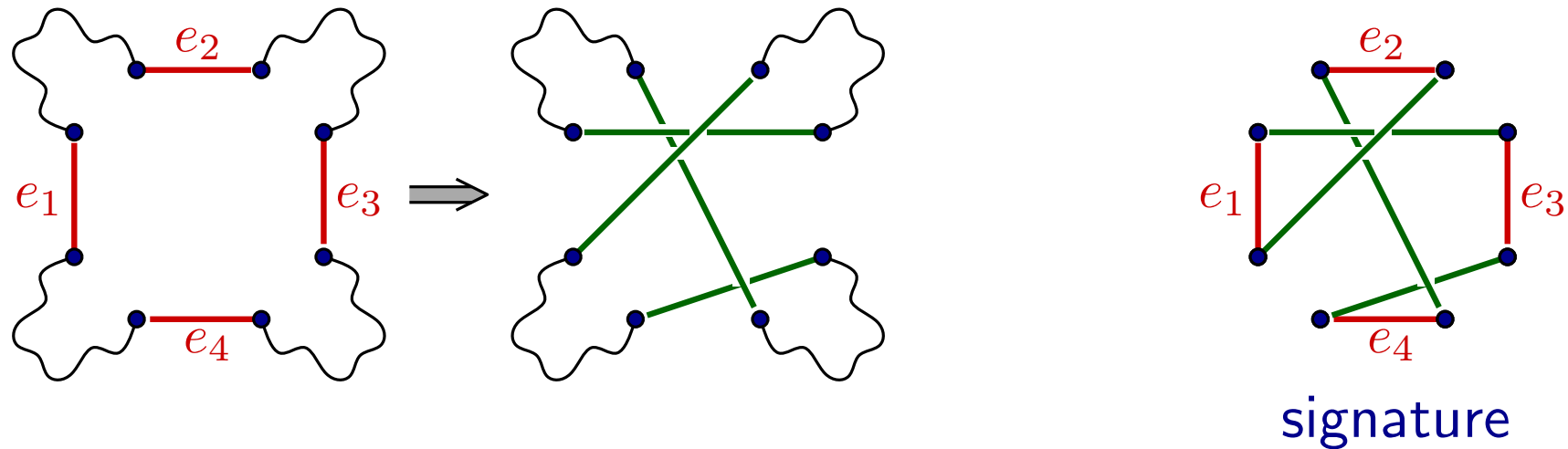
signature of a  $k$ -swap  $E = \{e_1, e_2, \dots, e_k\} \rightarrow F = \{f_1, f_2, \dots, f_k\}$



signature

# A faster algorithm for $k$ -OPT for $k \geq 4$

signature of a  $k$ -swap  $E = \{e_1, e_2, \dots, e_k\} \rightarrow F = \{f_1, f_2, \dots, f_k\}$



find best  $k$ -swap for each signature separately

## A faster algorithm for $k$ -OPT for $k \geq 4$

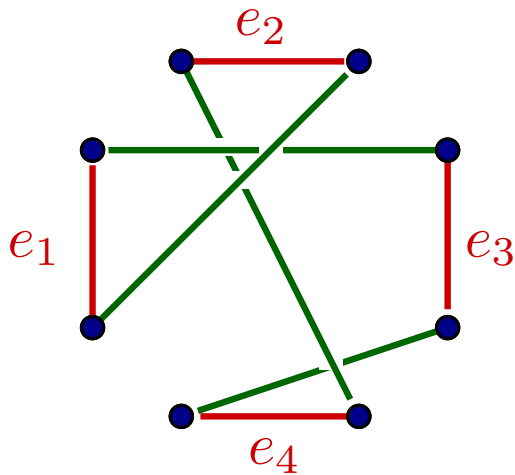
finding best  $k$ -swap  $E = \{e_1, \dots, e_k\} \rightarrow F$  for given signature  
 $\equiv$  finding best locations for edges in  $E$

How to do this without checking all  $O(n^k)$  possibilities for  $E$ ?

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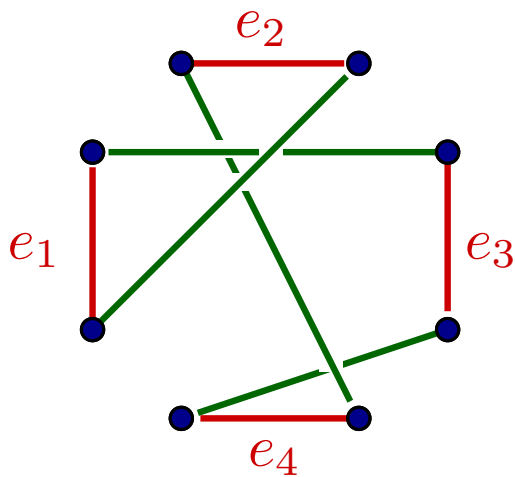
$e_i$  and  $e_j$  interfere for given signature:

there is an edge in  $F$  connecting  $e_i$  to  $e_j$

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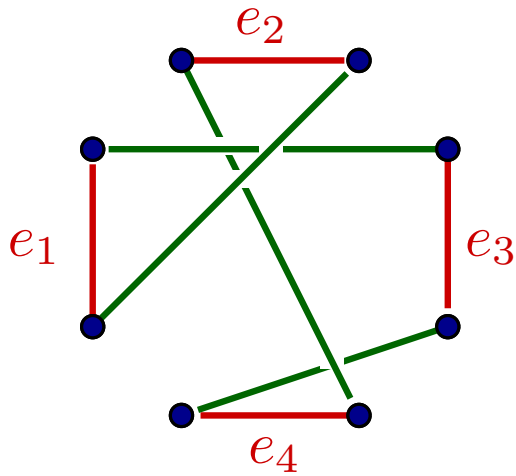
$e_2$  interferes with  $e_1$  and  $e_4$ , but not with  $e_3$

## A faster algorithm for $k$ -OPT for $k \geq 4$

**Lemma.** For any signature, there is a subset of at least  $\lceil k/3 \rceil$  pairwise non-interfering edges.

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- $E \cup F$  consists of one or more cycles
- along each cycle the edges from  $E$  and  $F$  alternate

per cycle at least  $1/3$  of edges from  $E$  are pairwise non-interfering



## A faster algorithm for $k$ -OPT for $k \geq 4$

finding best  $k$ -swap  $E = \{e_1, \dots, e_k\} \rightarrow F$  for given signature  
 $\equiv$  finding best locations to “embed” edges in  $E$  into tour

How to do this without checking all  $O(n^k)$  possibilities for  $E$ ?



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How to do this without checking all  $O(n^k)$  possibilities for  $E$ ?

1. determine set  $E^* \subset E$  of  $\lceil k/3 \rceil$  pairwise non-interfering edges for given signature

2. try all possible choices for the  $\lfloor 2k/3 \rfloor$  edges in  $E \setminus E^*$

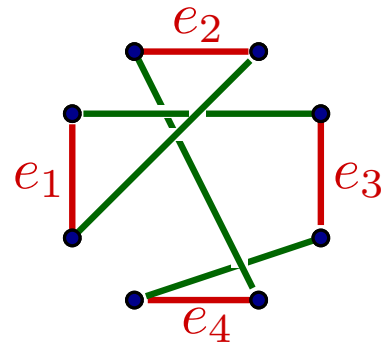
for each of these  $O(n^{\lfloor 2k/3 \rfloor})$  choices, compute the best way to embed remaining  $\lfloor k/3 \rfloor$  edges

can be done in  $O(n)$  time

# A faster algorithm for $k$ -OPT for $k \geq 4$

How to add pairwise non-interfering edges in  $O(n)$  time

Example:  $k=4$  and signature

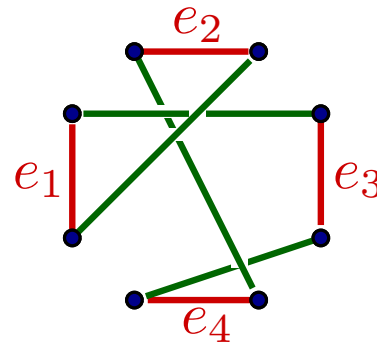


and  $e_2, e_3$  non-interfering

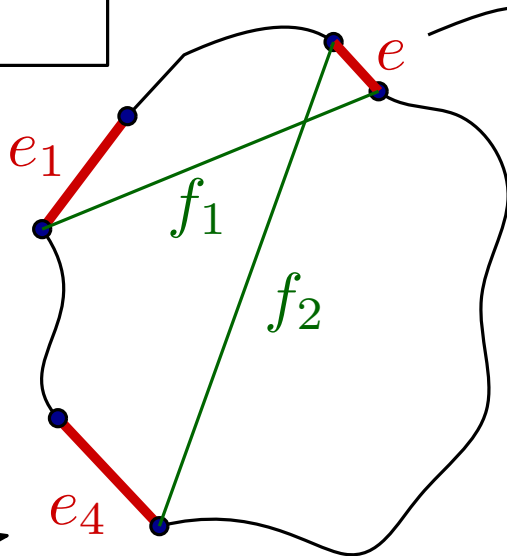
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How to add pairwise non-interfering edges in  $O(n)$  time

Example:  $k=4$  and signature  $e_1, e_2, e_3, e_4$  and  $e_2, e_3$  non-interfering

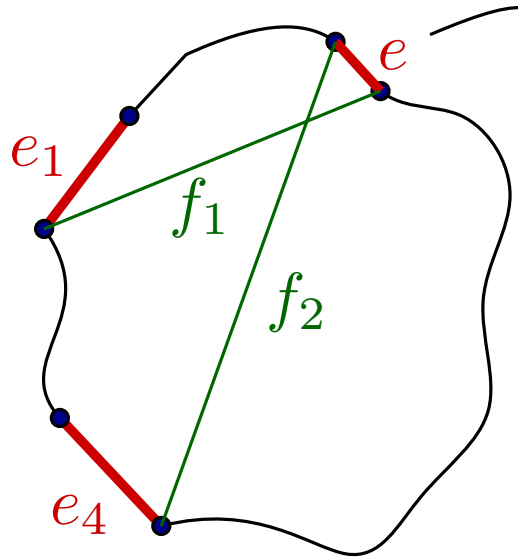


fixed choice  
for embedding  
 $e_1$  and  $e_4$



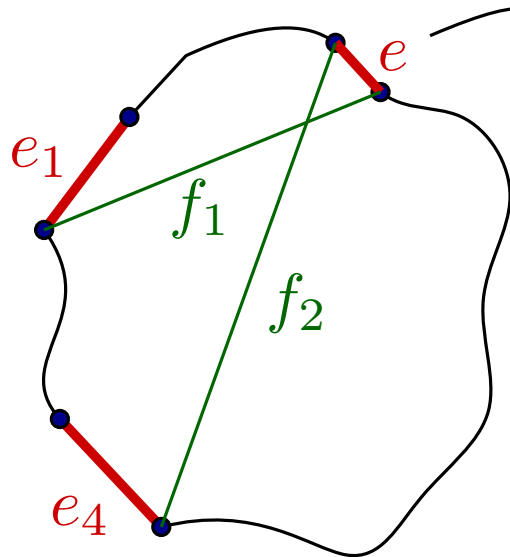
- cost of embedding  $e_2$  into  $e$ :  
 $\text{cost}(e_2 \rightarrow e) = |f_1| + |f_2| - |e|$
- independent of where we embed  $e_3$

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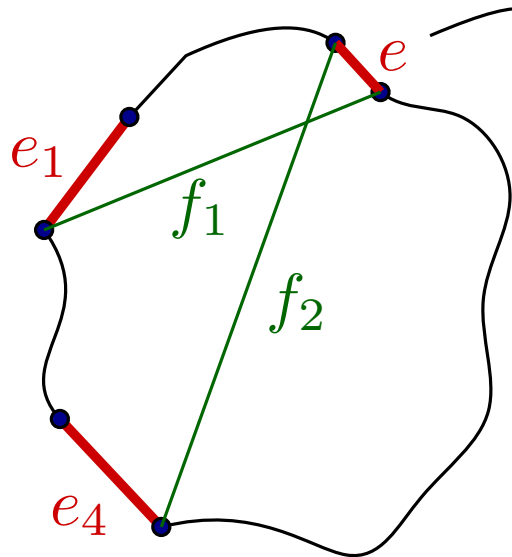


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- $e_1^*, \dots, e_{k/3}^*$  = edges we still need to embed
- $e'_1, \dots, e'_n$  = tour edges
- $\text{Cost}[\ell, r] := \min$  cost of embedding  $e_1^*, \dots, e_\ell^*$  into  $e'_1, \dots, e'_r$

$$\text{Cost}[\ell, r] = \min (\text{Cost}[\ell, r - 1], \text{Cost}[\ell - 1, r - 1] + \text{cost}(e_\ell^* \rightarrow e'_r))$$

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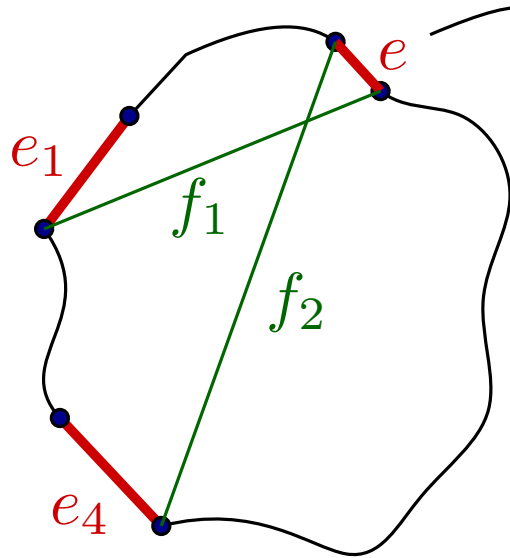
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↓

if we are allowed to embed  $e_\ell^*$  into  $e'_r$

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- final answer:  $\text{Cost}[k/3, n]$
- time:  $O(nk) = O(n)$

if we are allowed to embed  $e_\ell^*$  into  $e'_r$

## Complexity of $k$ -OPT

**Theorem.** For any fixed  $k \geq 4$  we can find the best  $k$ -swap in  $O(n^{\lfloor 2k/3 \rfloor + 1})$  time.



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## complexity bounds for $k$ -OPT

- $k = 2$ :  $\Theta(n^2)$
- $k = 3$ :  $O(n^3)$ ,  $O(n^{3-\varepsilon})$  impossible under the APSP Conjecture
- $k \geq 4$ :  $O(n^{\lfloor 2k/3 \rfloor + 1})$   
 $n^{o(k/\log k)}$  impossible under ETH [Guo et al.]

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## complexity bounds for $k$ -OPT

- $k = 2$ :  $\Theta(n^2)$
- $k = 3$ :  $O(n^3)$ ,  $O(n^{3-\varepsilon})$  impossible under the APSP Conjecture
- $k \geq 4$ :  $O(n^{\lfloor 2k/3 \rfloor + 1})$   
 $n^{o(k/\log k)}$  impossible under ETH [Guo et al.]

**other results:** bounds for  $k = 2, 3$  can be improved for

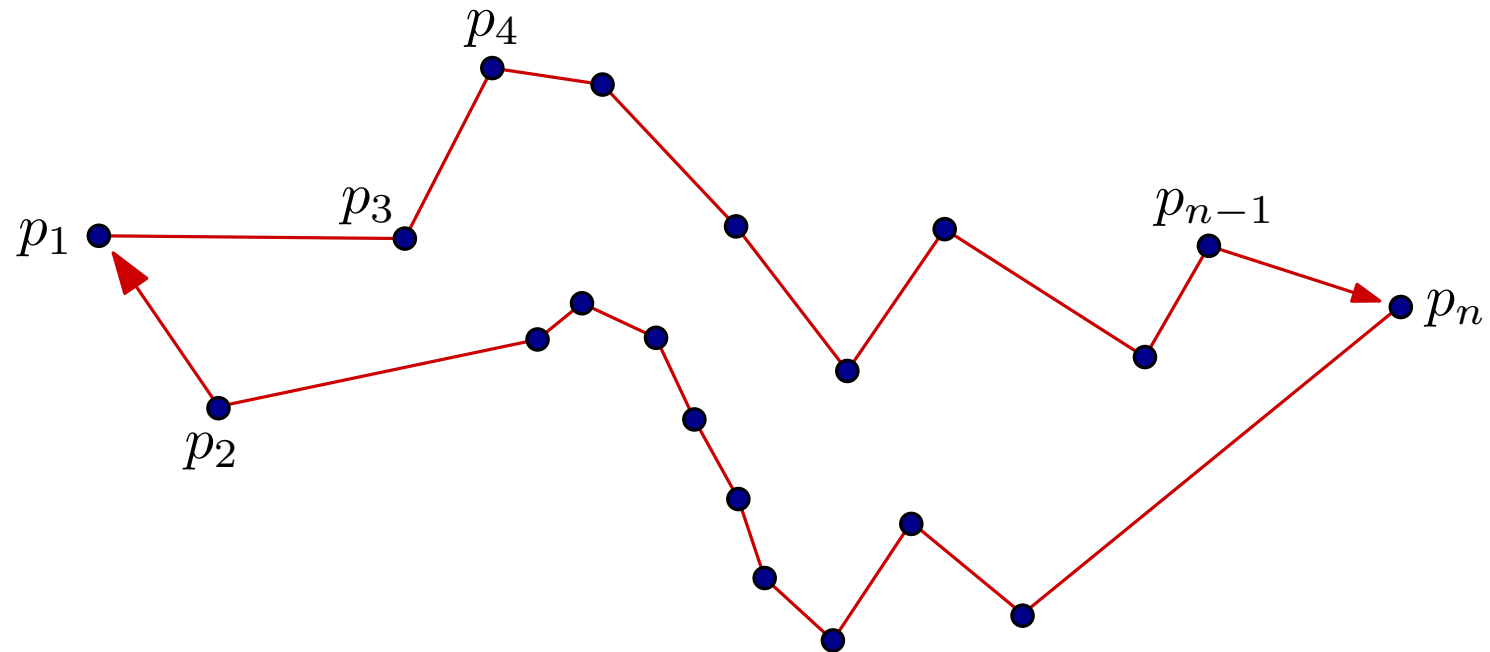
- iterated 2-OPT  $O(n \log n)$  [ iterated 3-OPT  $O(n^2 \log n)$  ]
- Euclidean  $k$ -OPT:  $O(n^{8/5+\varepsilon})$  resp.  $O(n^{80/31+\varepsilon})$

## RESULTS ON BITONIC TSP

# Bitonic TSP in the plane

## Bitonic TSP

- find min-length tour on points in the plane, Euclidean distances
- only allow tours that go left-to-right and then right-to-left



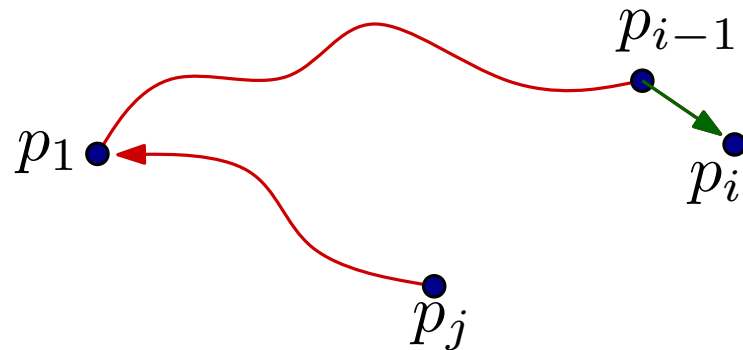
$p_1, p_2, \dots, p_n$ : points numbered from left to right



# Bitonic TSP in the plane: textbook solution

Recursive formula for  $A[i, j]$

case (i):  $j < i - 1$



must connect  $p_{i-1}$  to  $p_i$

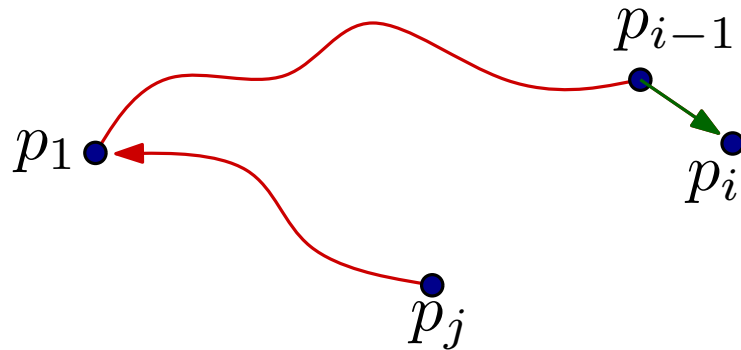
$$A[i, j] = \begin{cases} A[i - 1, j] + |p_{i-1}p_i| & \text{if } 1 \leq j < i - 1 \\ \min_{1 \leq k < i-1} (A[i - 1, k] + |p_k p_i|) & \text{if } j = i - 1 \end{cases}$$

where  $A[2, 1] = |p_1 p_2|$ .

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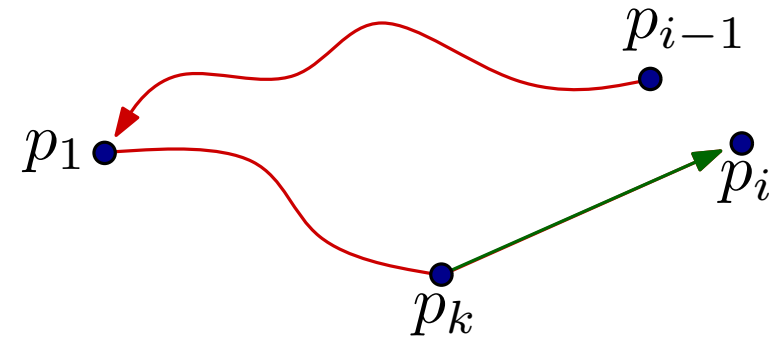
Recursive formula for  $A[i, j]$

case (i):  $j < i - 1$



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case (ii):  $j = i - 1$



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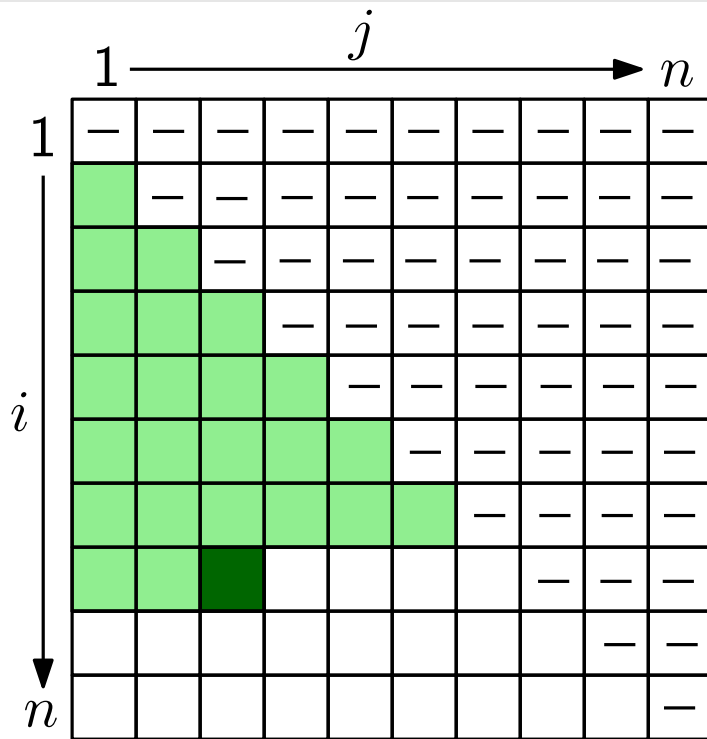
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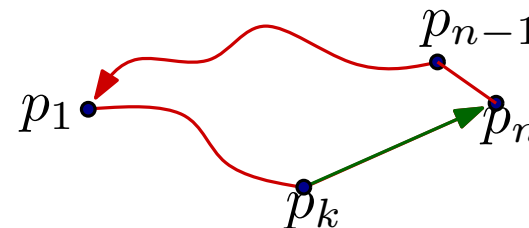


## Algorithm

1. Fill in table row by row, using recursive formula.

2. Compute final solution:

$$\min_{1 \leq k < n} (A[n, k] + |p_k p_n|)$$

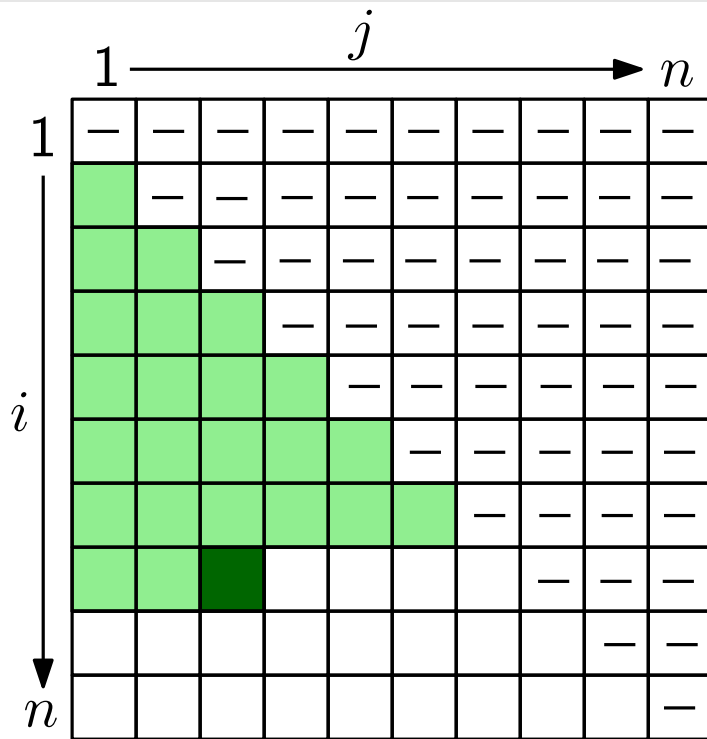




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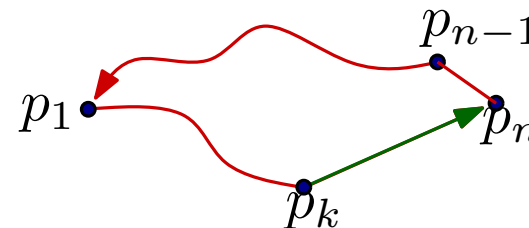
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**Algorithm** runs in  $O(n^2)$  time

1. Fill in table row by row, using recursive formula.
2. Compute final solution:  
 $\min_{1 \leq k < n} (A[n, k] + |p_k p_n|)$



# Bitonic TSP in the plane: our solution

$$A[i, j] = \begin{cases} A[i-1, j] + |p_{i-1}p_i| & \text{if } 1 \leq j < i-1 \\ \min_{1 \leq k < i-1} (A[i-1, k] + |p_k p_i|) & \text{if } j = i-1 \end{cases}$$

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|          |   |   |   |   |   |   |   |   |   |
|----------|---|---|---|---|---|---|---|---|---|
| 1        | - | - | - | - | - | - | - | - | - |
|          |   | - | - | - | - | - | - | - | - |
|          |   |   | - | - | - | - | - | - | - |
|          |   |   |   | - | - | - | - | - | - |
| <i>i</i> |   |   |   |   | - | - | - | - | - |
|          |   |   |   |   |   | - | - | - | - |
|          |   |   |   |   |   |   | - | - | - |
| <i>n</i> |   |   |   |   |   |   |   | - | - |

Construct **implicit representation** of rows, in  $O(\log^2 n)$  time per row

- need to find best  $k$  quickly
- entries change in same way



# Bitonic TSP in the plane: our solution

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|          |   | - | - | - | - | - | - | - | - |
|          |   |   | - | - | - | - | - | - | - |
|          |   |   |   | - | - | - | - | - | - |
| <i>i</i> |   |   |   |   | - | - | - | - | - |
|          |   |   |   |   |   | - | - | - | - |
|          |   |   |   |   |   |   | - | - | - |
| <i>n</i> |   |   |   |   |   |   |   | - | - |

Construct implicit representation of rows, in  $O(\log^2 n)$  time per row

- need to find best  $k$  quickly

- entries change in same way

Need data structure supporting queries, insertions and bulk updates

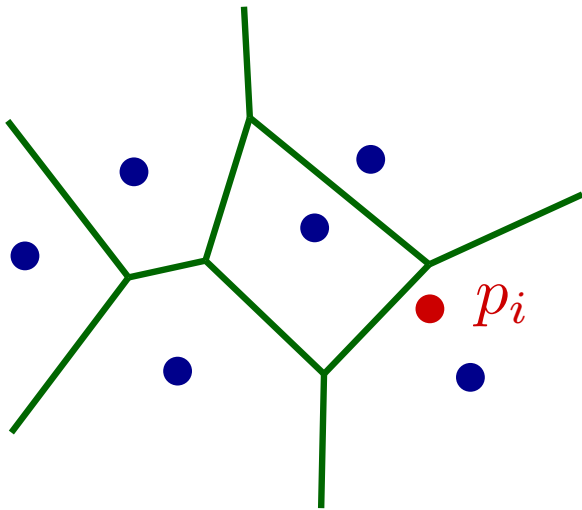
## The data structure

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without term  $A[k - 1]$  we would be looking for nearest neighbor

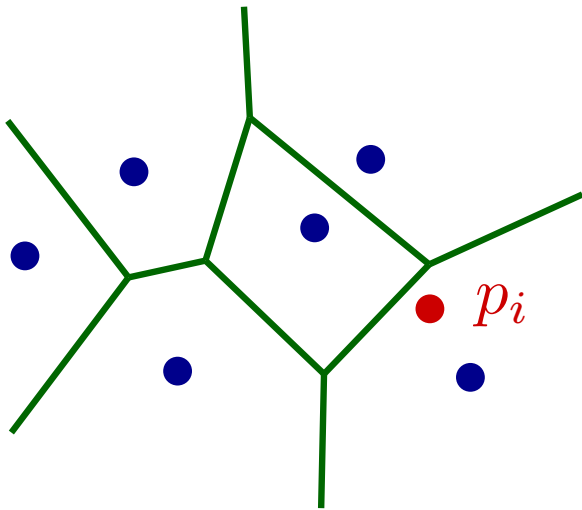


- point location with  $p_i$  in **Voronoi diagram** of  $\{p_1, \dots, p_{i-1}\}$
- $O(i \log i)$  preprocessing,  $O(\log i)$  query

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- point location with  $p_i$  in **Voronoi diagram** of  $\{p_1, \dots, p_{i-1}\}$
- $O(i \log i)$  preprocessing,  $O(\log i)$  query

- view  $w_k := A[i - 1, k]$  as weight of  $p_k$
- work with **additively weighted distance function**

## The data structure

- $P$  = set of point sites
- $w_k$  = weight of point  $p_k \in P$
- distance of  $p_k \in P$  to any point  $q \in \mathbb{R}^2$ :  $\text{dist}(p_k, q) = w_k + |p_k q|$

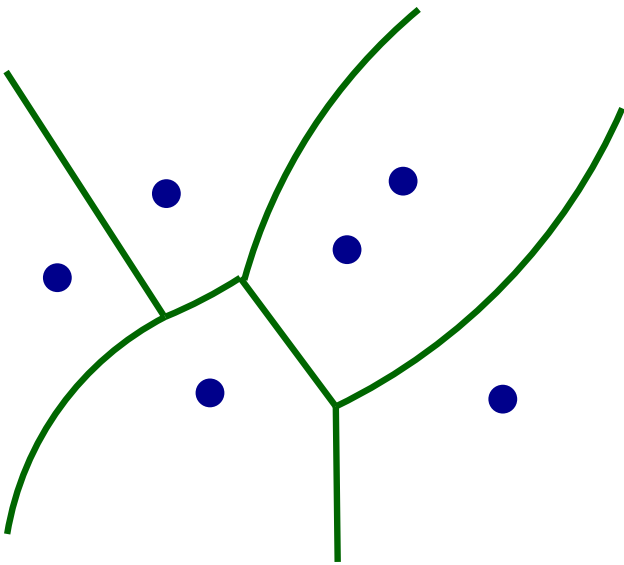
additively weighted Voronoi diagram = subdivision of  $\mathbb{R}^2$  into cells such that  $\text{Cell}(p_k)$  contains points  $q \in \mathbb{R}^2$  for which  $p_k$  is closest site



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- cell boundaries are line segments or hyperbolic arcs
- some points may not have a corresponding cell
- complexity still  $O(i)$  for  $i$  points
- can be computed (with point location structure) in  $O(i \log i)$  time

# The data structure

$$A[i, j] = \begin{cases} A[i-1, j] + |p_{i-1}p_i| & \text{if } 1 \leq j < i-1 \\ \min_{1 \leq k < i-1} (A[i-1, k] + |p_k p_i|) & \text{if } j = i-1 \end{cases}$$

|   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|
| - | - | - | - | - | - | - | - | - | - |
|   | - | - | - | - | - | - | - | - | - |
|   |   | - | - | - | - | - | - | - | - |
|   |   |   | - | - | - | - | - | - | - |
|   |   |   |   | - | - | - | - | - | - |
|   |   |   |   |   | - | - | - | - | - |
|   |   |   |   |   |   | - | - | - | - |
|   |   |   |   |   |   |   | - | - | - |
|   |   |   |   |   |   |   |   | - | - |
|   |   |   |   |   |   |   |   |   | - |

Computing the next row

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|   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|
| - | - | - | - | - | - | - | - | - | - |
|   | - | - | - | - | - | - | - | - | - |
|   |   | - | - | - | - | - | - | - | - |
|   |   |   | - | - | - | - | - | - | - |
|   |   |   |   | - | - | - | - | - | - |
|   |   |   |   |   | - | - | - | - | - |
|   |   |   |   |   |   | - | - | - | - |
|   |   |   |   |   |   |   | - | - | - |
|   |   |   |   |   |   |   |   | - | - |
|   |   |   |   |   |   |   |   |   | - |

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|---|---|---|---|---|---|---|---|---|---|
| - | - | - | - | - | - | - | - | - | - |
|   | - | - | - | - | - | - | - | - | - |
|   |   | - | - | - | - | - | - | - | - |
|   |   |   | - | - | - | - | - | - | - |
|   |   |   |   | - | - | - | - | - | - |
|   |   |   |   |   | - | - | - | - | - |
|   |   |   |   |   |   | - | - | - | - |
|   |   |   |   |   |   |   | - | - | - |
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How can we do this quickly?

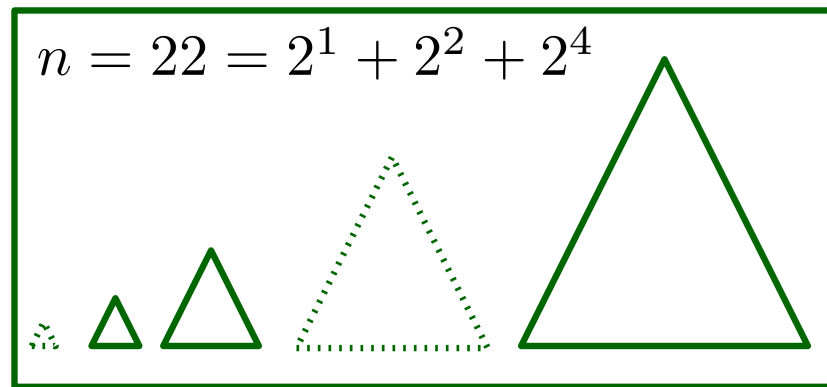
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insertions and bulk updates in additively weighted Voronoi diagrams

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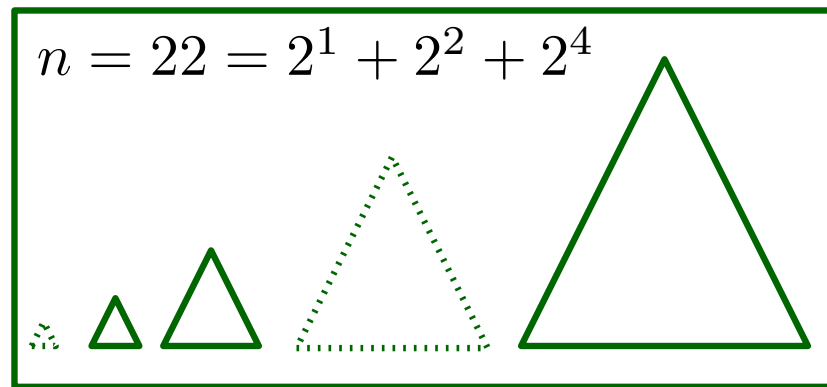
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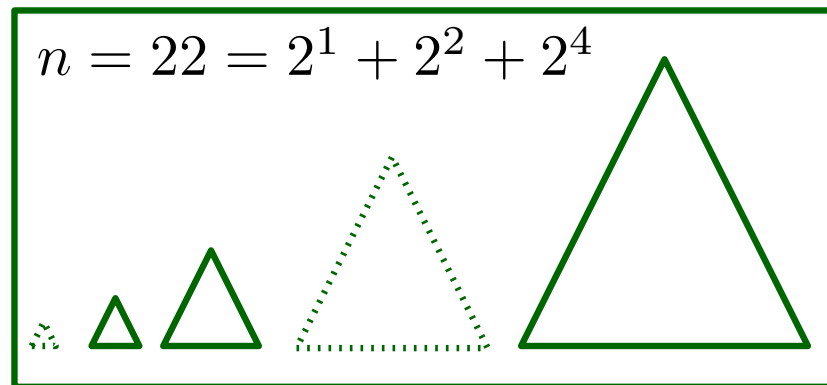


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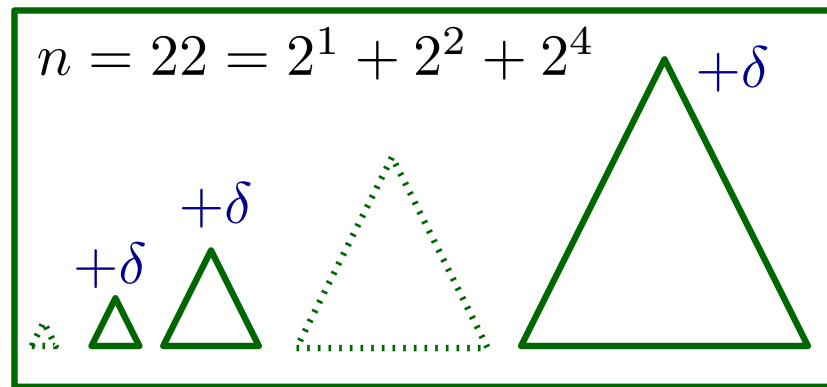
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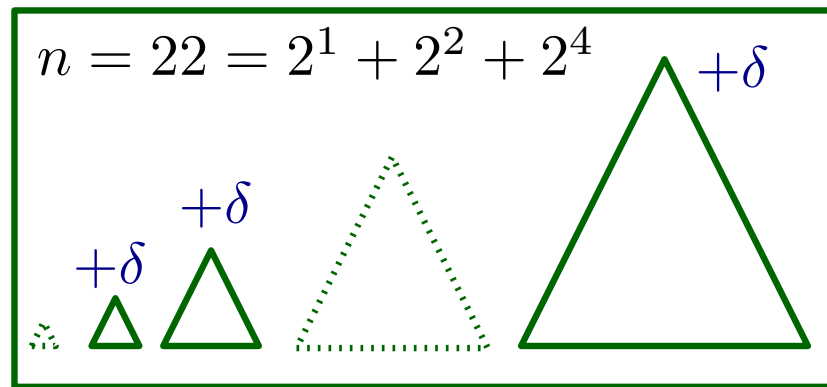


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# The data structure

insertions and bulk updates in additively weighted Voronoi diagrams

use logarithmic method  $\implies$  maintain  $O(\log n)$  data structures on subsets of exponentially increasing sizes



- query: do on all structures and take best answer  $O(\log n \cdot Q(n))$
- insertion: find first empty structure, destroy all smaller structures, build new one from scratch  $O(\log n \cdot B(n)/n)$  amortized
- bulk update: add correction term to each structure  $O(\log n)$

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|   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|
| - | - | - | - | - | - | - | - | - | - |
|   | - | - | - | - | - | - | - | - | - |
|   |   | - | - | - | - | - | - | - | - |
|   |   |   | - | - | - | - | - | - | - |
|   |   |   |   | - | - | - | - | - | - |
|   |   |   |   |   | - | - | - | - | - |
|   |   |   |   |   |   | - | - | - | - |
|   |   |   |   |   |   |   | - | - | - |
|   |   |   |   |   |   |   |   | - | - |
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$O(\log n)$

$O(\log^2 n)$

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**Theorem.** Finding the shortest bitonic tour (or: pyramidal tour) on a set of  $n$  points in the plane can be done in  $O(n \log^2 n)$  time.

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results on bottleneck bitonic TSP

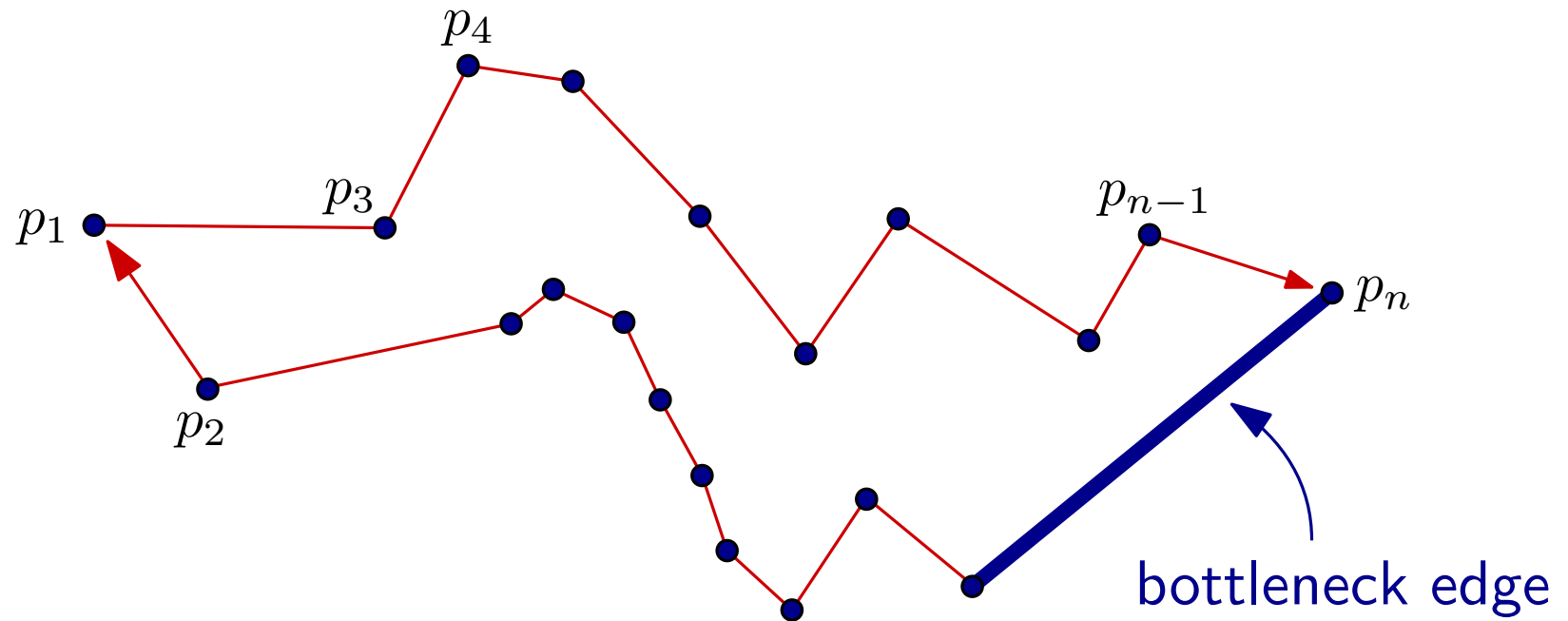
→ minimize max (instead of sum) of edge lengths

- decision problem:  $O(n \log n)$
- optimization problem:  $O(n \log^3 n)$

# Bitonic Bottleneck TSP in the plane

## Bitonic Bottleneck TSP — decision variant

- is there a tour whose bottleneck edge has length  $\leq B$ ?
- only allow tours that go left-to-right and then right-to-left



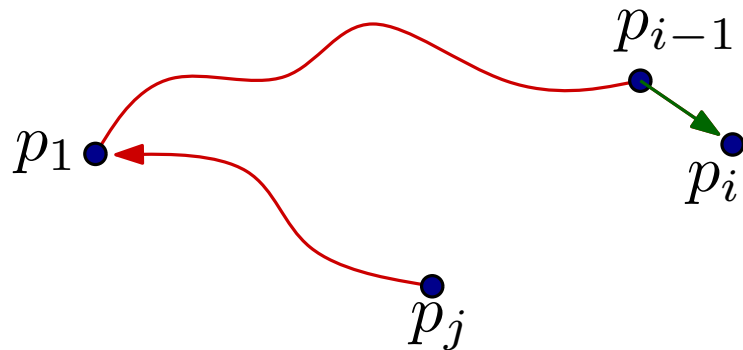
$p_1, p_2, \dots, p_n$ : points numbered from left to right



# Bitonic TSP in the plane: standard DP solution

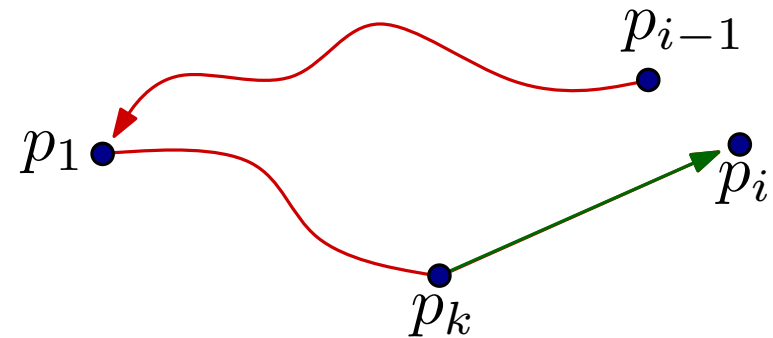
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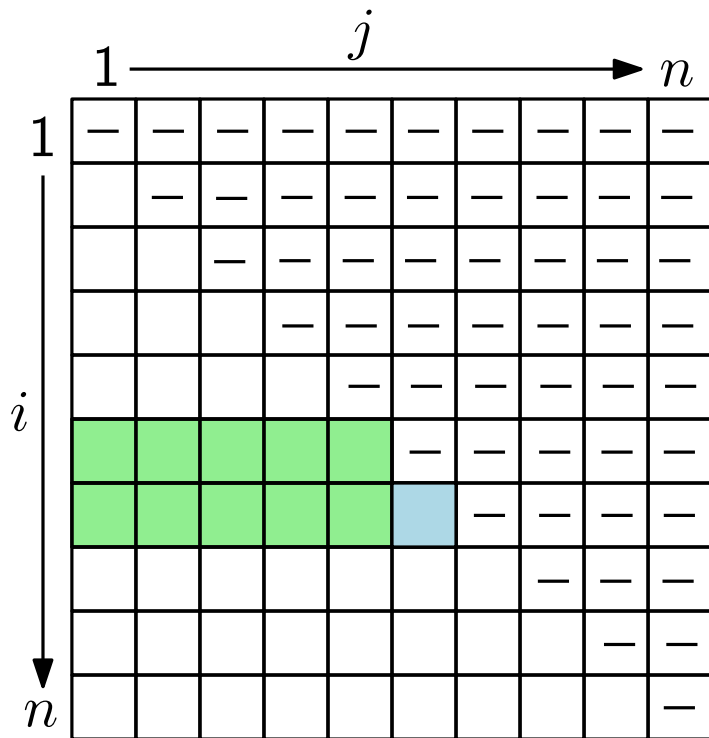
$$A[i, j] = \begin{cases} A[i - 1, j] \wedge (|p_{i-1}p_i| \leq B) & \text{if } 1 \leq j < i - 1 \\ \bigvee_{1 \leq k < i-1} (A[i - 1, k] \wedge (|p_k p_i| \leq B)) & \text{if } j = i - 1 \end{cases}$$

where  $A[2, 1] = \text{TRUE}$  if  $|p_1 p_2| \leq B$ .



# Bitonic TSP in the plane: our solution

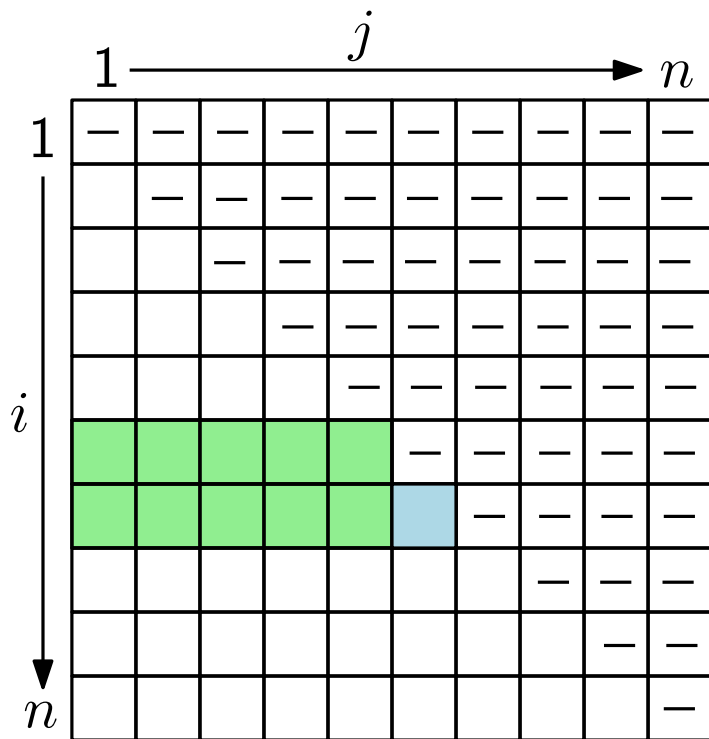
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Implicit representation of  $i$ -th row:  
set  $S$  containing those points  $p_j$   
with  $j < i$  such that  $A[i, j] = \text{TRUE}$

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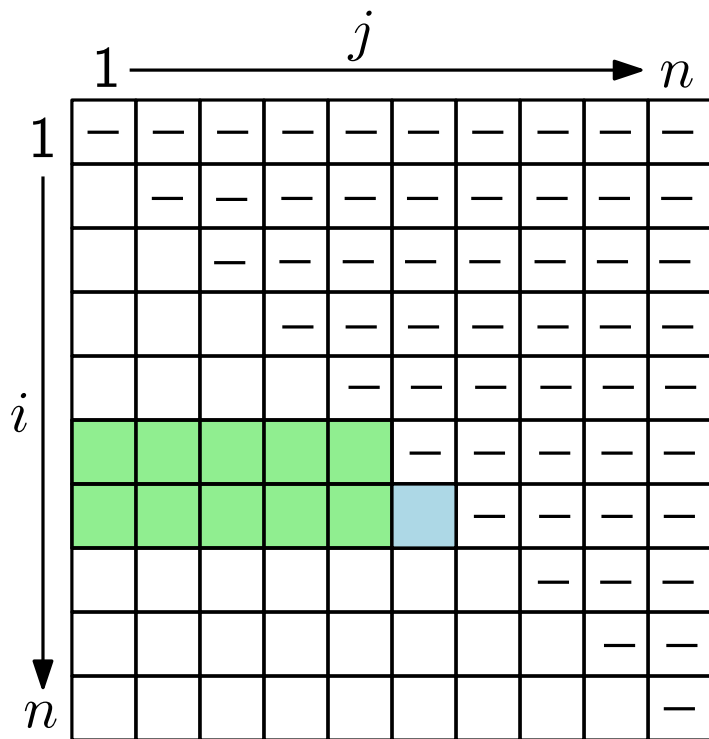
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To handle  $p_i$  we check if

- (i)  $|p_{i-1}p_i| \leq B$
  - (ii) there is a  $p_k \in S$  with  $|p_k p_i| \leq B$
- answer to (i) is yes  $\implies$  keep  $S$   
 answer to (i) is no  $\implies$  empty  $S$   
 answer to (ii) is yes  $\implies$  add  $p_i$  to  $S$

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data structure  
needed

Implicit representation of  $i$ -th row:  
set  $S$  containing those points  $p_j$   
with  $j < i$  such that  $A[i, j] = \text{TRUE}$

To handle  $p_i$  we check if

- (i)  $|p_{i-1}p_i| \leq B$
  - (ii) there is a  $p_k \in S$  with  $|p_k p_i| \leq B$
- answer to (i) is yes  $\implies$  keep  $S$   
 answer to (i) is no  $\implies$  empty  $S$   
 answer to (ii) is yes  $\implies$  add  $p_i$  to  $S$

## The data structure

- $S$  = set of point sites
- $B$  = threshold distance

queries: given point  $q$ , is there a point  $p_k \in S$  with  $|p_k q| \leq B$ ?

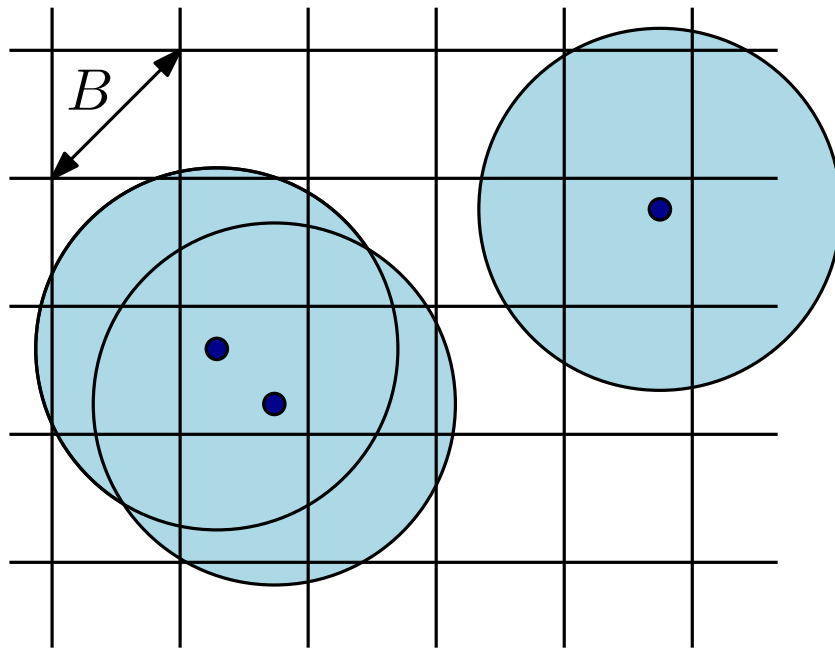
insertions must also be supported

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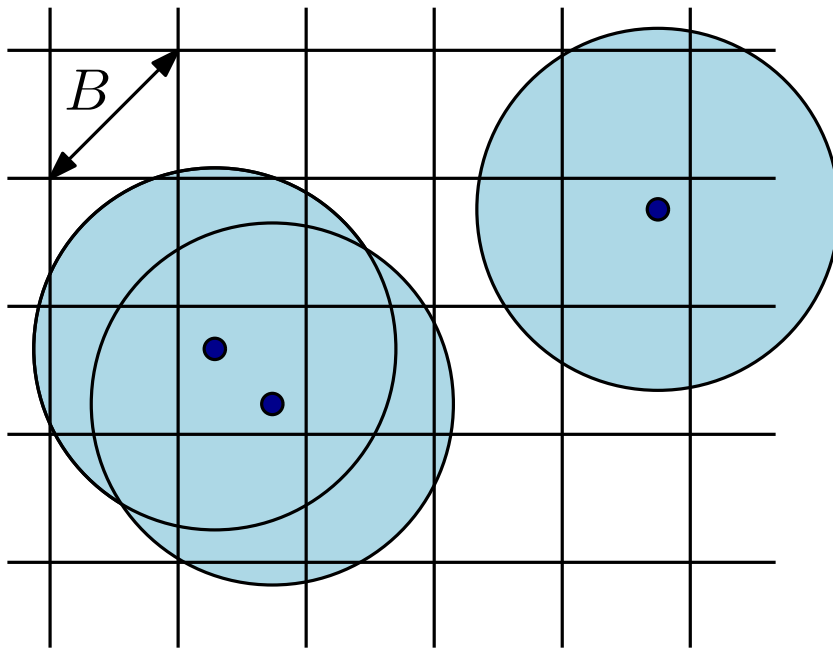
for each cell  $C$ : maintain point location structure on union of radius- $B$  disks centered at points in  $S \cap C$

# The data structure

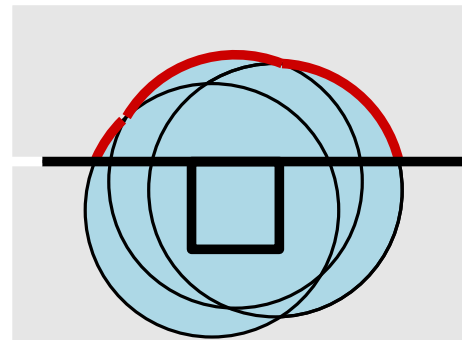
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order of pieces on boundary  $\equiv$  left-to-right order of centers

# The data structure

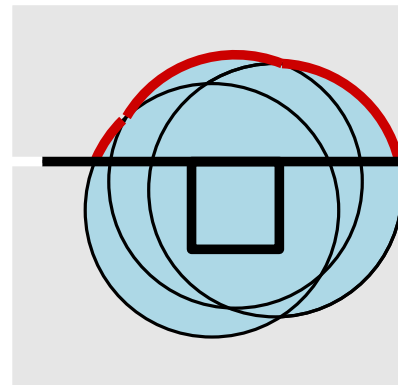
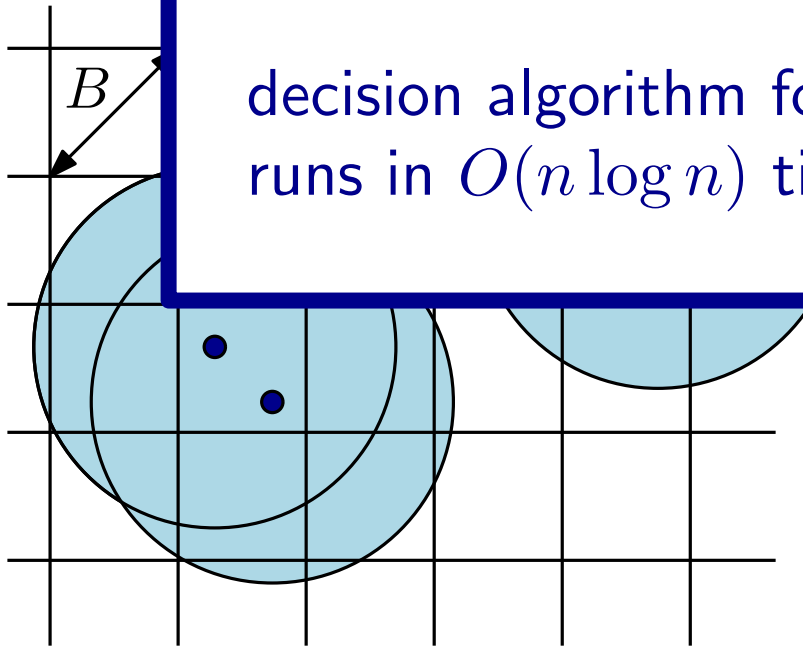
- $S$  = set of point sites
- $B$  = threshold distance

queries:  $g$

insertions

- queries:  $O(\log n)$  time
- insertions:  $O(\log n)$  time amortized

decision algorithm for Bitonic Bottleneck TSP  
runs in  $O(n \log n)$  time



order of pieces on  
boundary  $\equiv$   
left-to-right order  
of centers

# Our Results

## $k$ -OPT in general setting

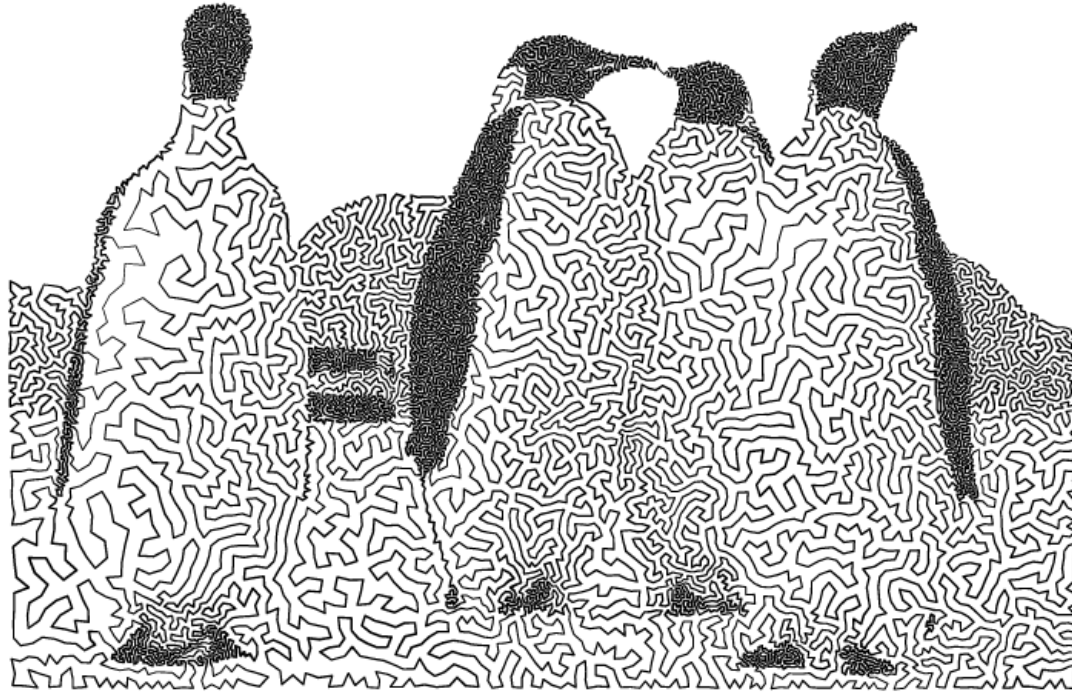
- $k = 3$ : lower bound of  $\Omega(n^{3-\varepsilon})$  under APSP Conjecture
- $k > 3$ : algorithm with  $O(n^{\lfloor 2k/3 \rfloor + 1})$  running time
- iterated  $k$ -OPT:  $O(n^2)$  preprocessing,  $O(n \log n)$  per iteration ( $k = 2$ )  
[  $O(n^3)$  preprocessing,  $O(n^2 \log n)$  per iteration ( $k = 3$ ) ]
- Euclidean setting: algorithm with  $O(n^{8/5+\varepsilon})$  running time ( $k = 2$ )  
algorithm with  $O(n^{80/31+\varepsilon})$  running time ( $k = 3$ )

## Bitonic (more generally: pyramidal) Euclidean TSP in the plane

- algorithm with  $O(n \log^2 n)$  running time
- bottleneck variant:  $O(n \log^3 n)$



Thanks for your attention!



TSP Art by Carig Kaplan and Robert Bosch

