

Asymptotic Properties of a Probabilistic Tabu Search Algorithm

Siyeong Lee

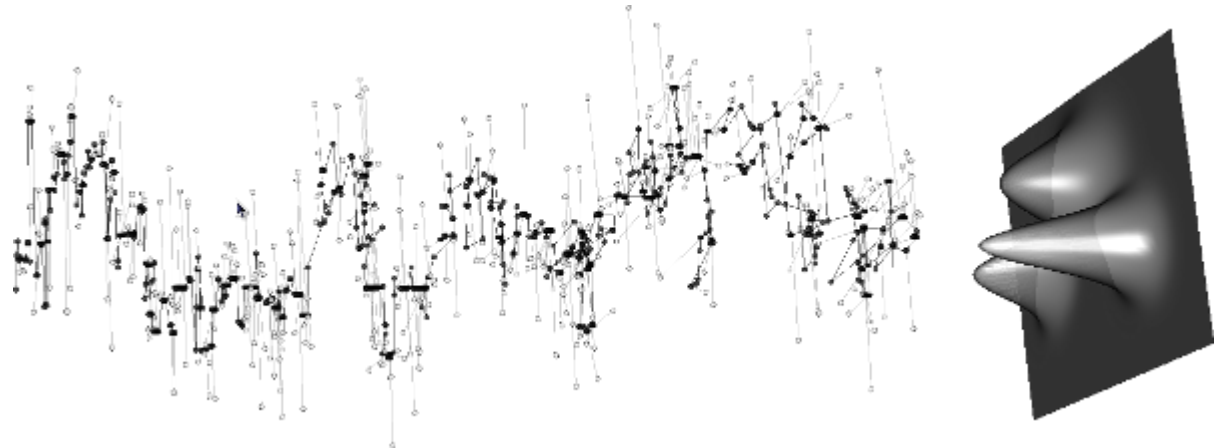
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Introduction

- Unfortunately, we still know little about the behavior of the method, its asymptotic properties, and probability of finding an optimal solution, even for classical combinatorial problems.



Introduction

■ Strategy

- Memorize the feature of local optima → “Tabu list(queue)”
 - prevent repetition of the same state
- Efficient search space exploration
 - search for an optimum solution without stagnation

■ Good

- This method can be **easy adapted** to complicated models and is simple to code

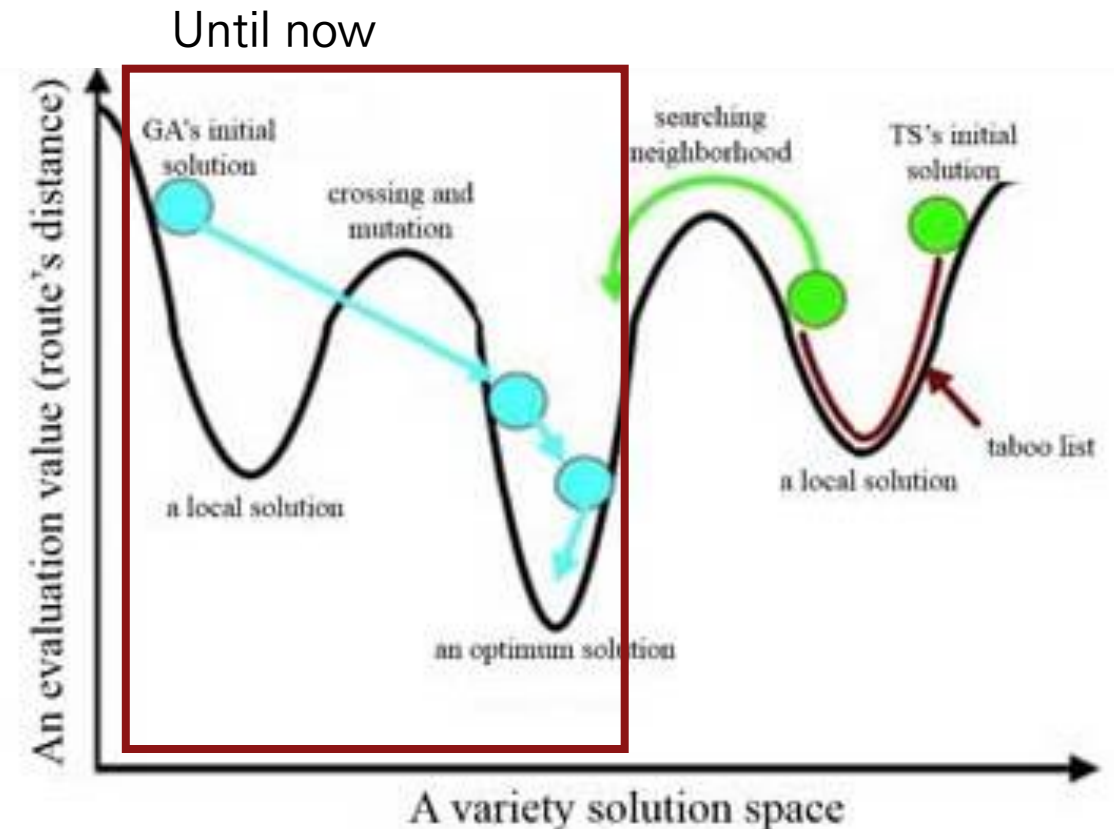


Figure 1: Difference between GA and TS

Problem setting – Optimization problem

Definition 1. Combinatory Optimization problem

\mathbf{B} : the boolean cube

Minimize $f_0(x)$

Subject to $f_i(x) \leq b_i, i = 1, \dots, m$

$f_0 : \mathbf{B}^n \rightarrow \mathbf{R}$; Objective function

$x = (x_1, \dots, x_n) \in \mathbf{B}^n$: Optimization variables

To find the global optimum $f_{opt} = f(x_{opt})$

Representation

■ Terminology

- A neighborhood of the point x : $N(x)$
 - Assume that it contains all neighboring points $y \in B^n$ with Hamming distance $d(x, y) \leq 2$.
 - * At most, differ from 2 bit.
- A randomized neighborhood $N_p(x)$ with probabilistic threshold p , $0 \leq p \leq 1$,
 - Subset of $N(x)$
 - For each $y \in N(x)$, $y \in N_p(x)$ randomly with prob. p
 - Independently from other points.

Representation

- Consider a finite sequence $\{x_t\}$, $1 \leq t \leq k$ with property $x_{t+1} \in N(x_t)$.
- Tabu list (or tabu queue)
 - An ordered set $\varphi = \{(i_k, j_k), (i_{k-1}, j_{k-1}), \dots, (i_{k-l+1}, j_{k-l+1})\}$
 - if vectors x_t and x_{t+1} differ by coordinates (i_t, j_t) .
 - The constant l is called the length of the tabu list.

1. i_t and j_t may be equal

* the vectors x_t and x_{t+1} are differed by exactly one coordinate.

2. $i_t = j_t = 0$ if $x_{t+1} = x_t$.

- $N_p(x_t, \varphi)$: a set of points $y \in N_p(x_t)$ not forbidden by the tabu list φ .

$N_p(x_t, \varphi)$ may be empty for nonempty set $N_p(x_t)$.

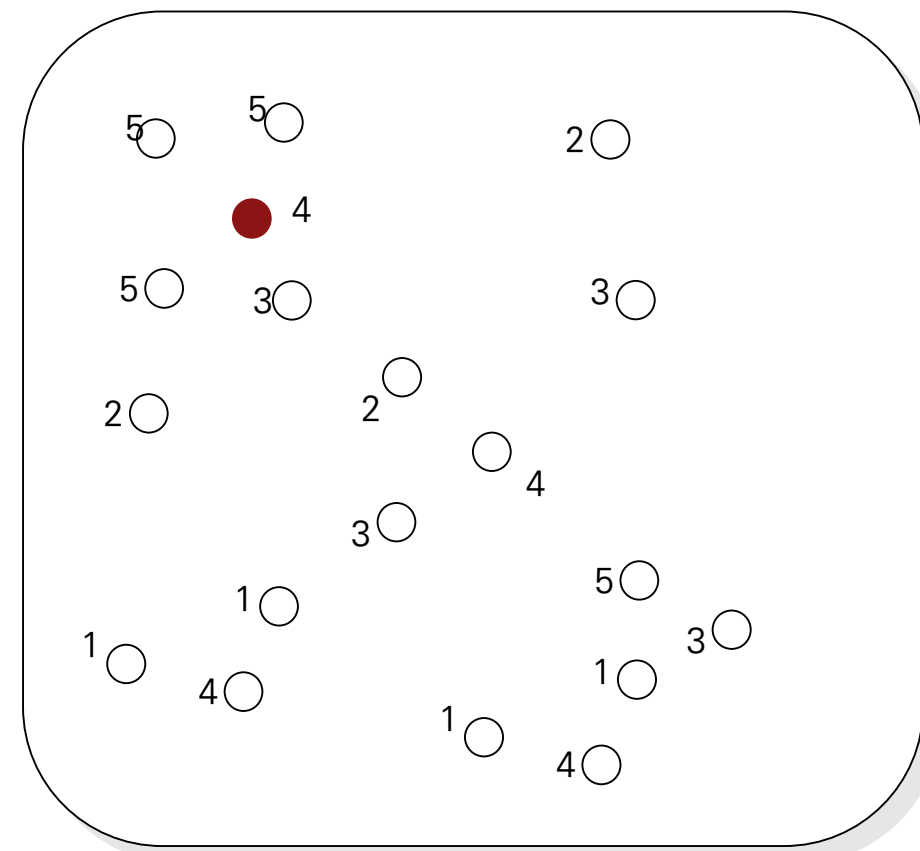
Pseudo Code

Algorithm PTS

1. Initialize $x_0 \in B^n$, $f^* := f(x_0)$, $\varphi := \emptyset$, $t := 0$.
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 - 2.1. Generate neighborhood $N_p(x_t, \varphi)$.
 - 2.2. If $N_p(x_t, \varphi) = \emptyset$ then $x_{t+1} := x_t$,
 else find x_{t+1} such that $f(x_{t+1}) = \min\{f(y), y \in N_p(x_t, \varphi)\}$.
 - 2.3. If $f(x_{t+1}) < f^*$ then $f^* := f(x_{t+1})$.
 - 2.4. Update the tabu list φ and the counter $t := t + 1$.

$$\varphi = \emptyset$$

(Current Point) ●



Search space S

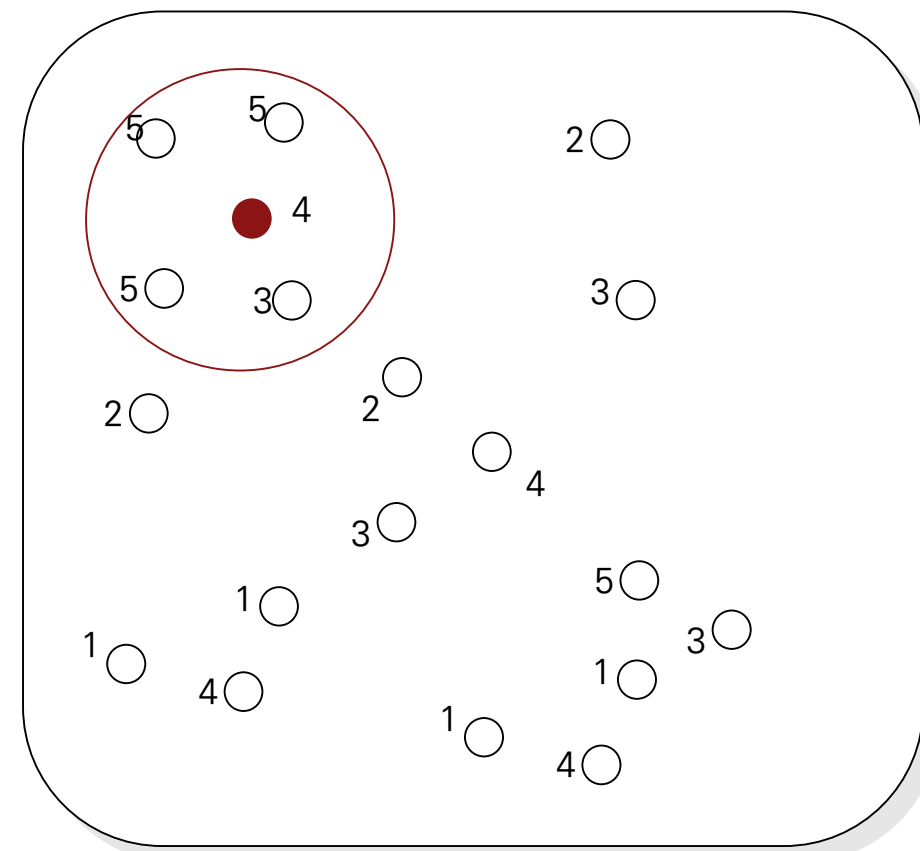
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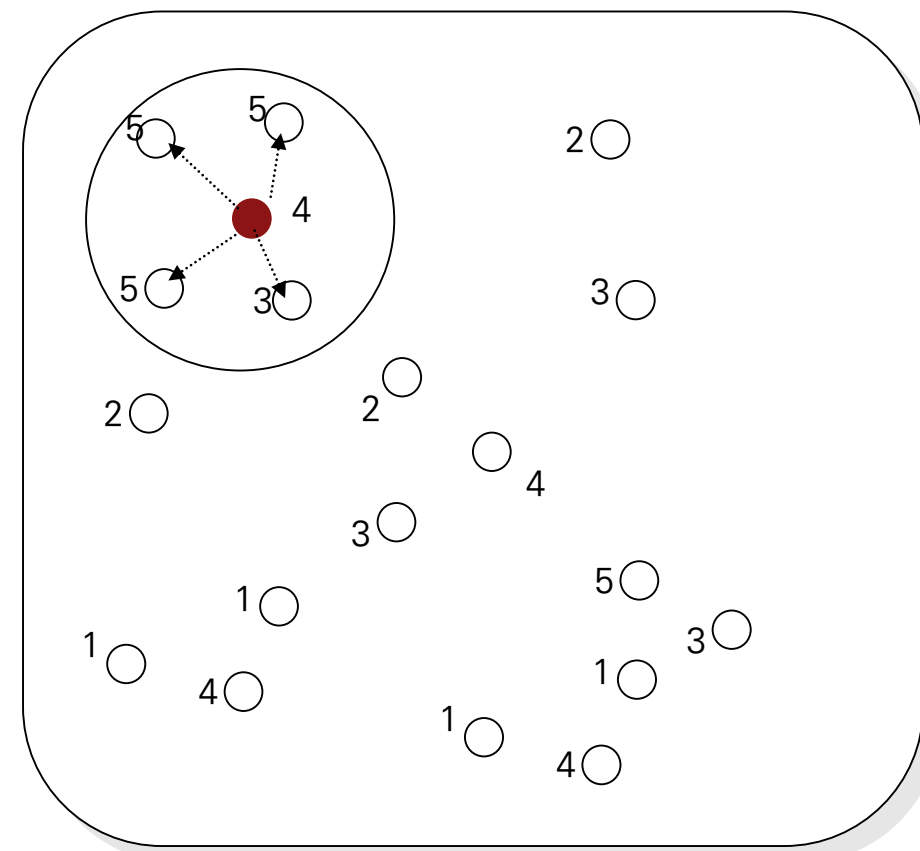
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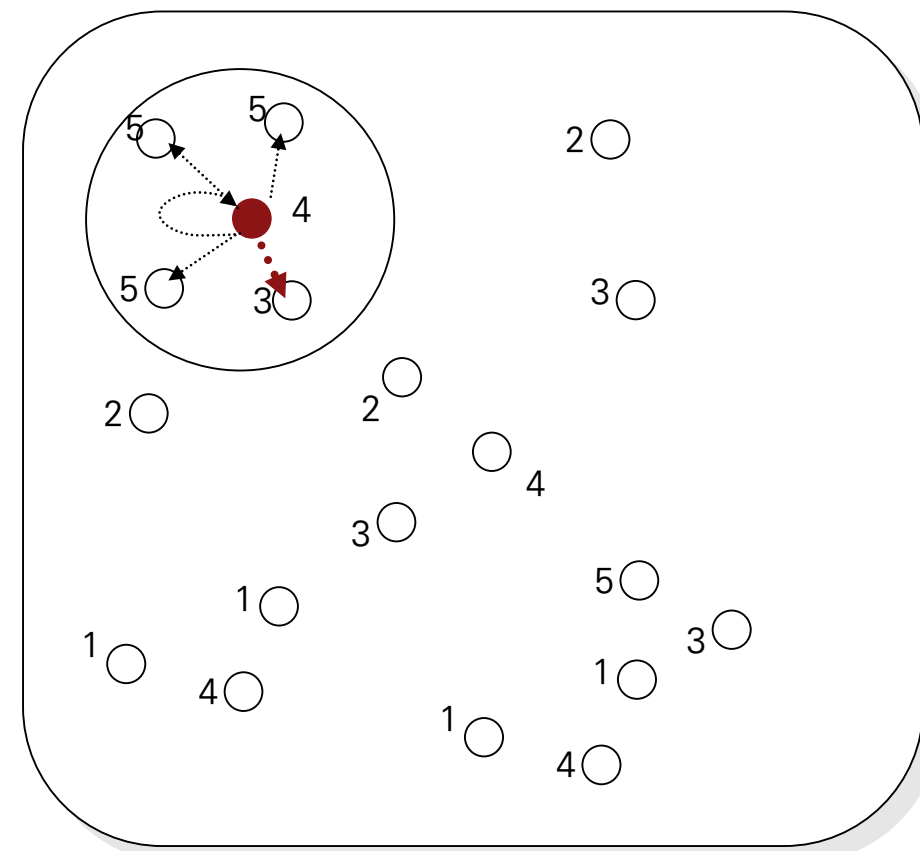
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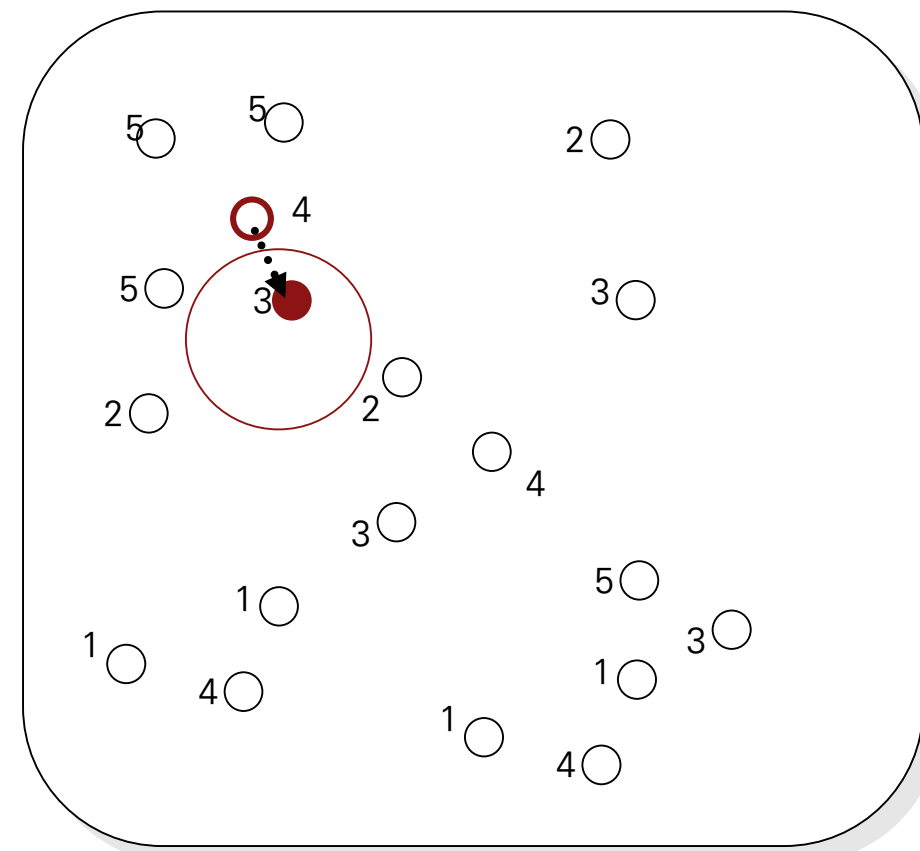
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$$\varphi = \{(1,1)\}$$

(Current Point) ●



Search space S

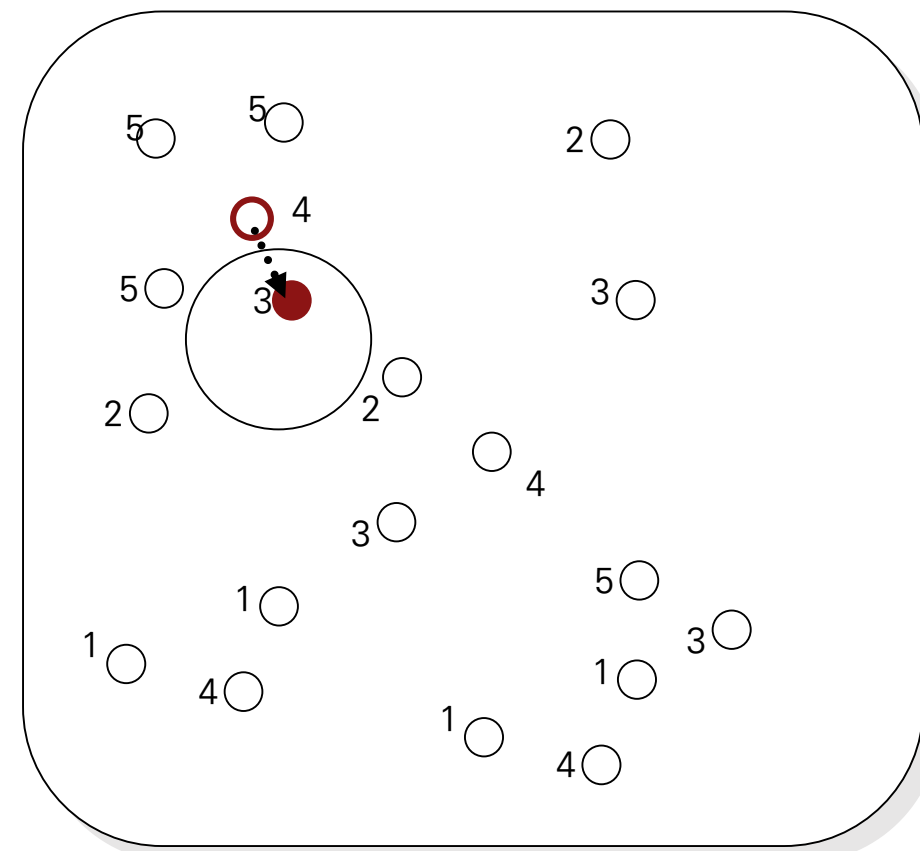
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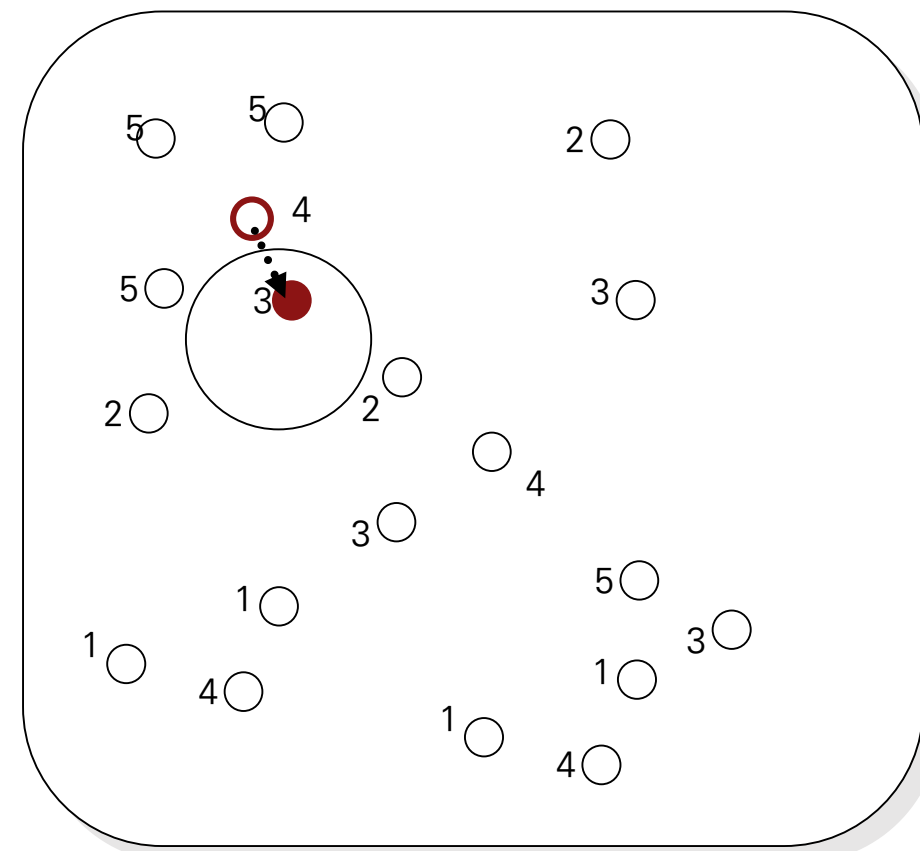
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Search space S

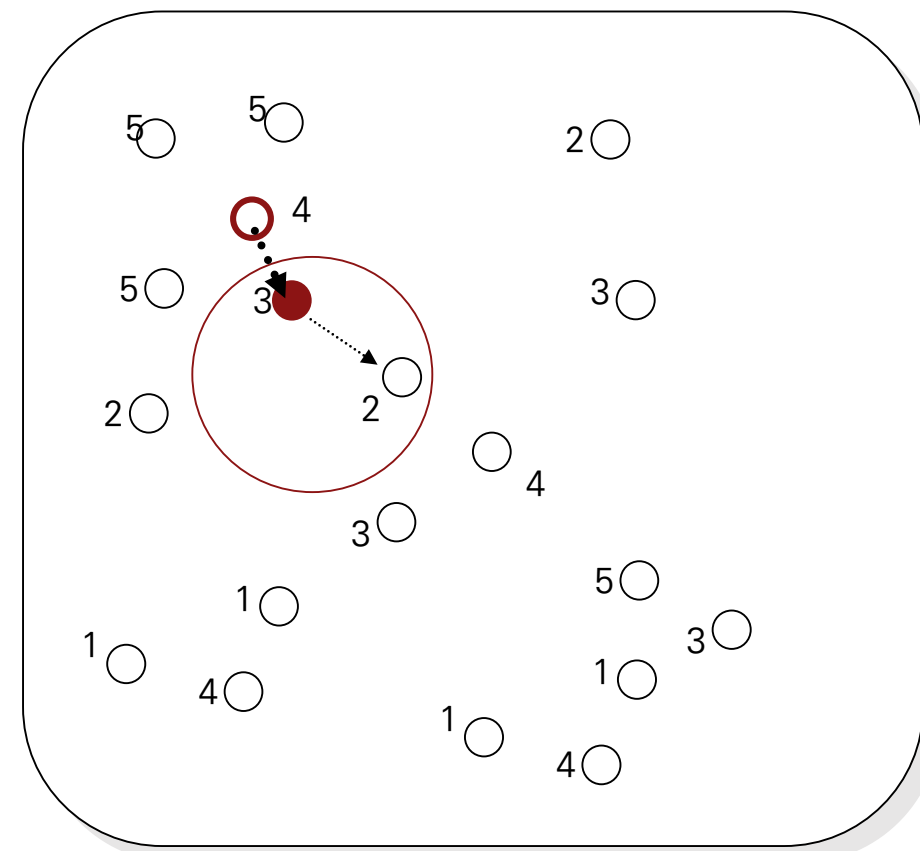
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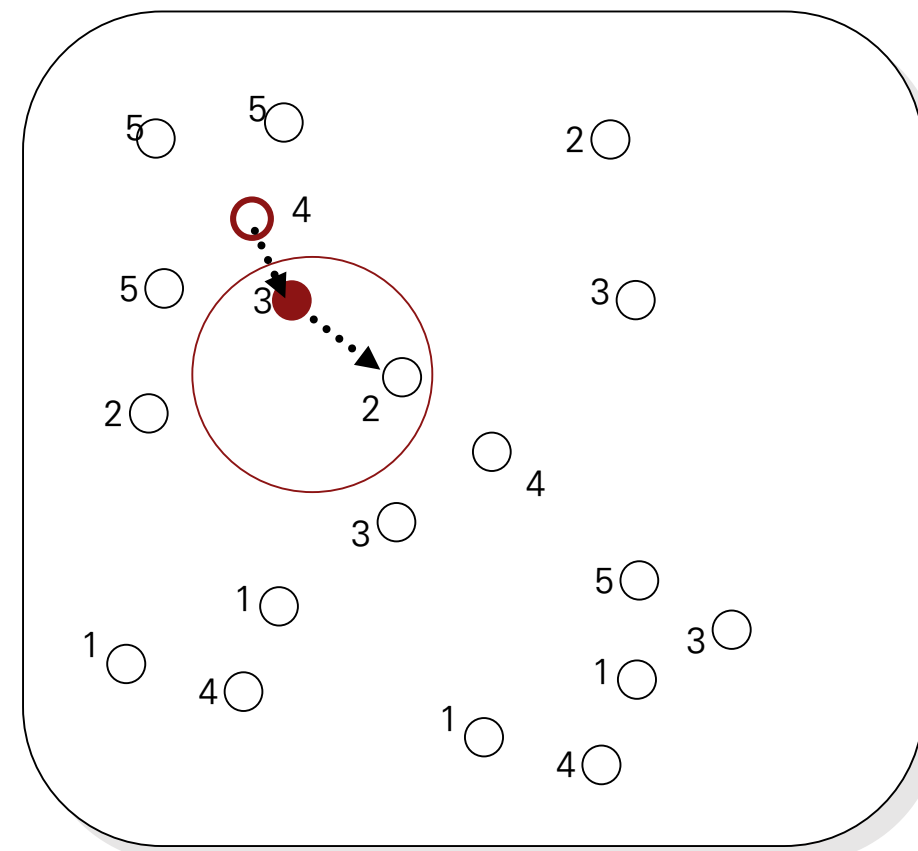
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Search space S

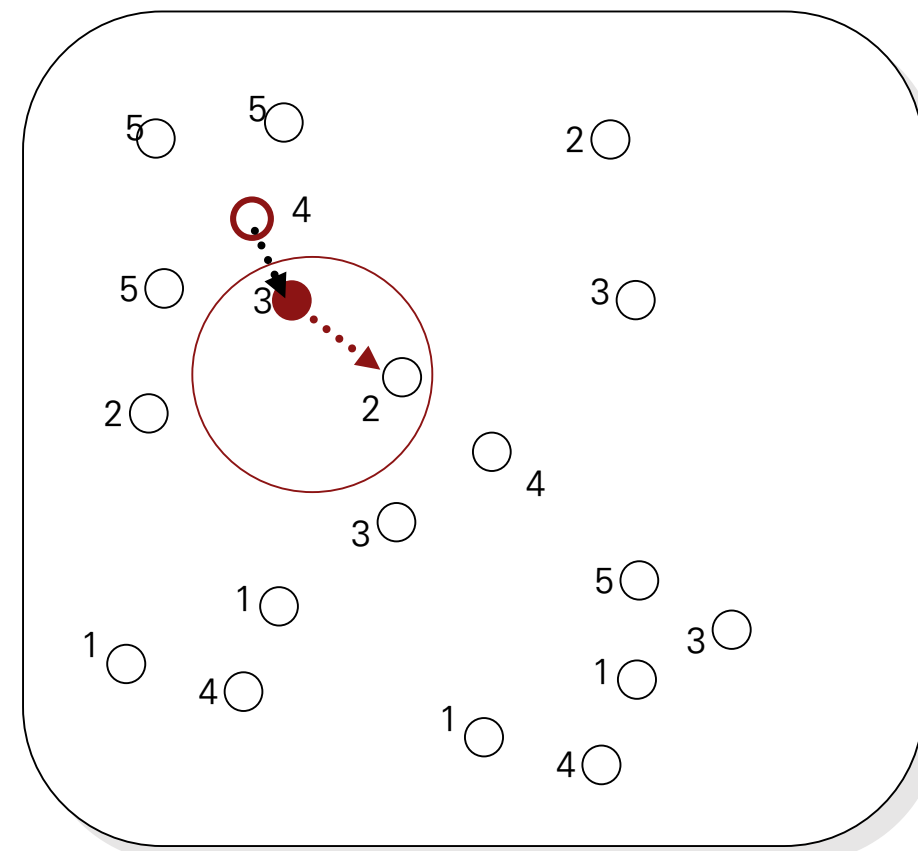
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(Current Point) ●



Search space S

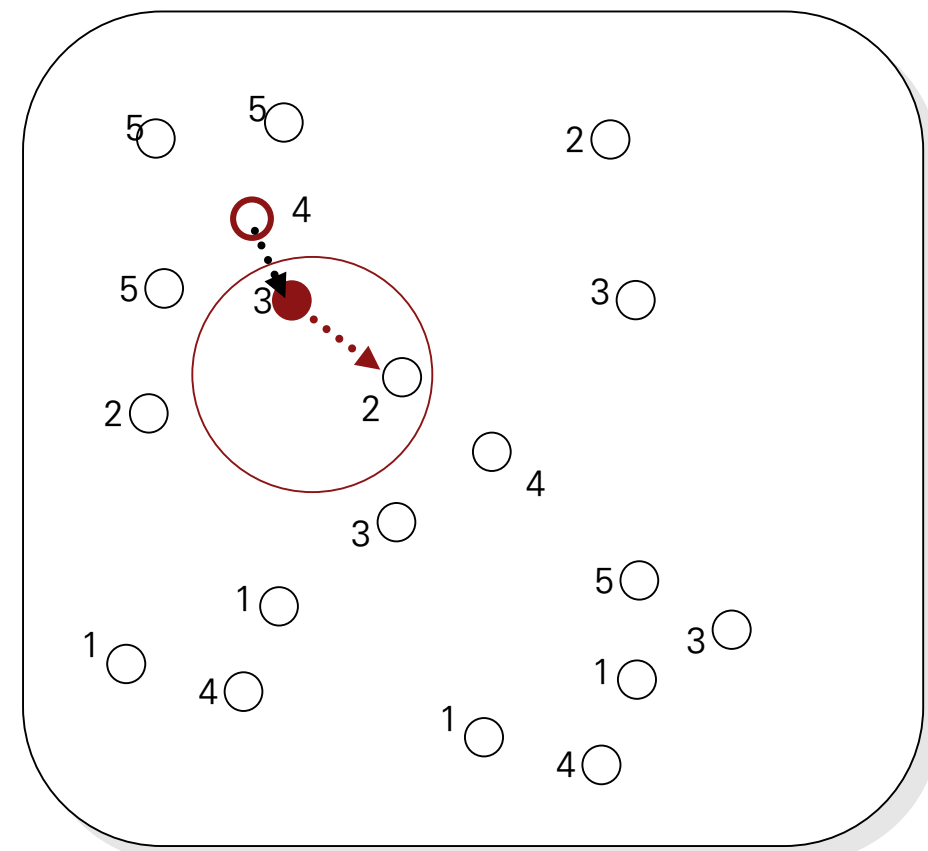
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 - 2.3. If $f(x_{t+1}) < f^*$ then $f^* := f(x_{t+1})$.
 - 2.4. Update the tabu list φ and the counter $t := t + 1$.

$$\varphi = \{(1,4), (0,0), (1,1)\}$$

(Current Point) ●



Search space S

Toy Problem

Search space S

■ Representation of Solutions

x_1	x_2	x_3	x_4	x_5
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$$x_i = \begin{cases} 1 & \text{if project } i \rightarrow O \\ 0 & \text{if project } i \rightarrow \times \end{cases}$$

■ Neighbor of current solution x

- $N(x) = \{y \in S \mid \text{hamming distance } d(x, y) \leq 2\}$
- $N_p(x, \varphi) \subset N(x)$; *For each $y \in N(x)$, $y \in N_p(x)$ randomly with prob. p*

■ Tabu condition

- If Project j added (removed) in this step,
will not be removed (added) for the next k steps.

Toy Problem

• Current Solution

1	1	0	0	0	Cost: 60
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Solutions					Cost
0	1	0	0	0	40
1	0	0	0	0	20
1	1	1	0	0	10
1	1	0	1	0	75
1	1	0	0	1	80
0	1	1	0	1	60 <i>N(x)</i>
0	1	1	1	1	55
⋮					

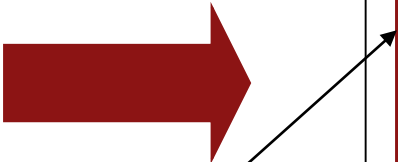
✓ Tabu list: add Project 3 : 0 → 1
 $\varphi = \{(3,3)\}$

• Current Solution

1	1	1	0	0	Cost: 10
---	---	---	---	---	----------

Solutions					Cost
0	1	0	0	0	40
1	1	0	0	1	20
1	1	0	0	0	0
1	1	0	1	0	75
1	0	1	0	0	80
0	0	0	0	1	75 <i>N(x)</i>
0	1	1	1	1	90
⋮					

✓ Tabu list: $\varphi = \{(3,3)\}$



Preliminary

■ Properties of Markov chain

- *finite*
 - if the set of outcomes is finite.
- *homogeneous*
 - if the transition probabilities do not depend on the step number.
 - e.g. For $l = 0$, PTS algorithm generates a finite homogeneous Markov chain on the Boolean cube B^n .
- *irreducible*
 - if for each pair of outcomes x, y , there is a positive probability of reaching y from x in a finite number of steps.

Convergence behavior to an optimal solution

Theorem 1.

*For arbitrary $l > 0$ and $0 < p < 1$,
the PTS algorithm generates an irreducible Markov chain on Ω .*

proof. Suppose $l = 0$

- Therefore, the selection of x_{t+1} depends on the current point x_t .
and does not depend on the previous points $x_s, s < t$

✓ a finite homogeneous Markov chain on the boolean cube B^n

Convergence behavior to an optimal solution

- From the definition of $N_p(x)$, it follows that the Markov chain is irreducible
 - So, we can obtain

$$f^* = \min_{t \leq k} f(x_t) = f_{opt} \text{ for large } k.$$

irreducible

if for each pair of outcomes x, y , there is a positive probability of reaching y from x in a finite number of steps.

- Without any restrictions for the length of tabu list l ?
 - If $l > |N(x)|$, then all points may be forbidden and $N_p(x, \varphi) = \emptyset$
 - For this case, we get $x_{t+1} = x_t$ on the *step 2.2* and $(i_t, j_t) = (0, 0)$
- The algorithm regulates the tabu list by itself.

Convergence behavior to an optimal solution

- From the definition of $N_p(x)$, it follows that the Markov chain is irreducible
 - So, we can obtain

$$f^* = \min_{t \leq k} f(x_t) = \dots$$

This element of self learning allows us to prove the theorem and get asymptotic properties of the algorithm

For any pair of outcomes x, y , there is a positive probability of reaching y from x in a finite number of steps.

- Restrictions for the length of tabu list l ?
 - If $l \geq |N(x)|$, then all points may be forbidden and $N_p(x, \varphi) = \emptyset$
 - For this case, we get $x_{t+1} = x_t$ on the *step 2.2* and $(i_t, j_t) = (0, 0)$
- The algorithm regulates the tabu list by itself.

Convergence behavior to an optimal solution



This element of self learning allows us
to prove the theorem and get asymptotic properties of the algorithm

- Denote a randomized neighborhood of x by $N_r(x, \varphi)$ which contains exactly $r > 1$ unforbidden points from $N(x)$
 - The algorithm PTS with $N_r(x, \varphi)$ neighborhood generates a Markov chain
 - But we can not prove the irreducibility for this case

In $r = |N_x - l|$, Deterministic Tabu Search algorithm DTS

- If the l is too small algorithm, DTS finds a local optimum and has no opportunity to escape from it
- If not, DTS can not find the optimal solution.

Convergence behavior to an optimal solution

Corollary 2.

For an arbitrary initial point $x_0 \in B^n$

- 1. $\lim_{t \rightarrow \infty} \Pr\{f^* = f_{opt}\} = 1$*
- 2. there exist constants $b > 0$ and $1 > c > 0$ such that $\Pr\{\min_{\tau \leq t} f(x_\tau) \neq f_{opt}\} \leq bc^t$*
- 3. the Markov chain $\{x_t, \varphi_t\}$ has a unique stationary distribution $\pi > 0$.*

Proof. The first and the second properties immediately follow from the property of irreducibility. In order to prove the last statement, it suffice to note that the Markov chain is aperiodic

Convergence behavior to an optimal solution

■ Property 1

- obtains an optimal solution with probability 1 for sufficiently large number of steps.
- Don't say that
 - $\lim_{t \rightarrow \infty} \Pr\{x_t \in X_{opt}\} = 1$, where X_{opt} is the set of all optimal solutions.

■ Property 2

- guarantees a geometrical rate of convergence with the constant $c < 1$.

■ Property 3

- generates an ergodic Markov chain with a positive limiting distribution $\pi(x,)$
- we can find a global optimum from an arbitrary initial point.

?

Stopping Rules

- Many stopping rules for Markov chains
 - Stopping after a prescribed number of steps
 - Stopping if the best solution f^* so far does not change during a prescribed number of steps

Denote by $H(x, y)$ the expected number of steps to reach y from x . Suppose that at the t -th step, we are at the points x_t

Corollary 3.

For each $x \in B^n$, we have $\pi(x) = \sum_{\varphi} \pi(x, \varphi) = 1/H(x, x)$

The value of $\pi(x)$: the probability to be in the point x on the t for large t

Stopping Rules

- Obviously, x depends on the parameters p and l of algorithm PTS.

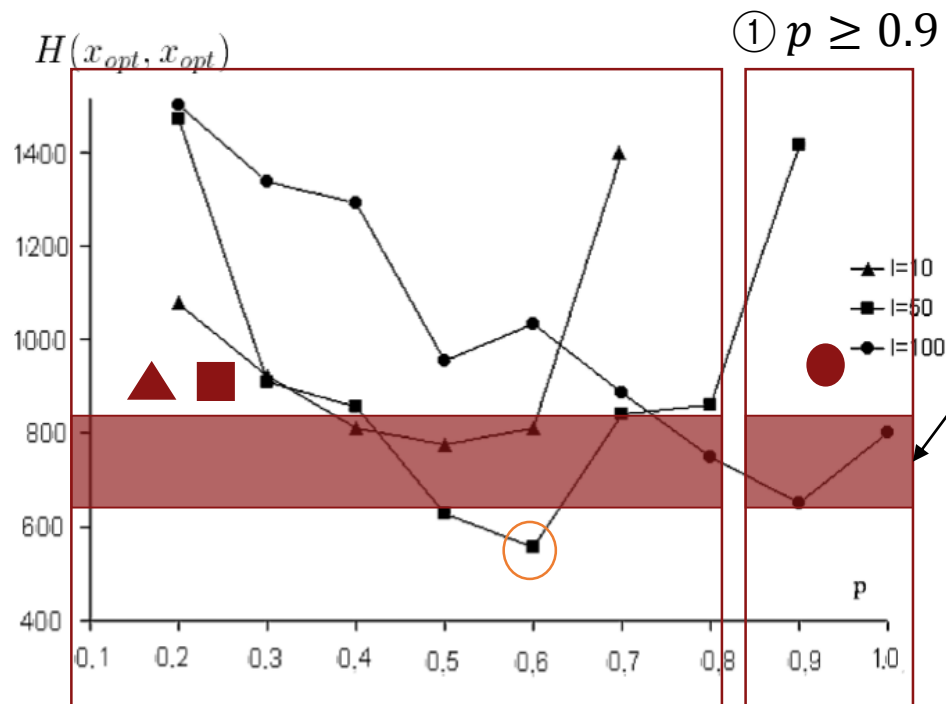


Figure 2: $H(x_{opt}, x_{opt})$ as a function of the threshold p

- ✓ About p
 - For large values of the threshold $p > 0.9$, the least value of H is achieved on the large tabu list $l = 100$
 - For small p , best results are obtained with small tabu lists $l = 10, 50$

- ✓ About the minima
 - The pair $p = 0.6, l = 50$ seems to be best values of the parameters H

The best values of the parameters $H(x_{opt}, x_{opt}) \approx 500$



If PTS returns to x very often then the algorithm is stopped and restarted with a new initial point.

Application of the algorithm for an NP-C/NP-hard example

■ Traveling Salesman Problem

- Finding a shortest closed tour
 - Visiting each node of a given graph with given edge length exactly once.

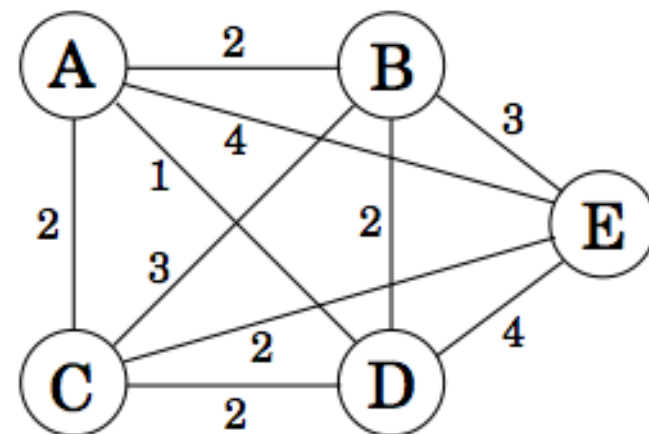
Figure 3: Traveling Salesman Problem.

Let $G = (X, E, W)$ be a complete weight graph,

$$X = (x_1, x_2, \dots, x_n) \ (n \geq 3)$$

$$E = \{e_{ij} | x_i, x_j \in X\}$$

$$W = \{w_{ij} | w_{ij} \geq 0 \text{ and } w_{ii} = 0, \quad \text{for all } i, j \in \{1, 2, \dots, n\}\}$$



Application of the algorithm for an NP-C/NP-hard example

■ Solution Representation

- represented as a sequence of nodes
 - each node appearing only once and in the order it is visited.

3	5	2	4	7	6	8	1
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Figure 4: Solution Representation

■ Initial solution

- Each time find the nearest unvisited node from the current node until all the nodes are visited

Application of the algorithm for an NP-C/NP-hard example

■ Neighborhood

- given solution, any other solution that is obtained by a pair wise exchange of any two nodes in the solution.

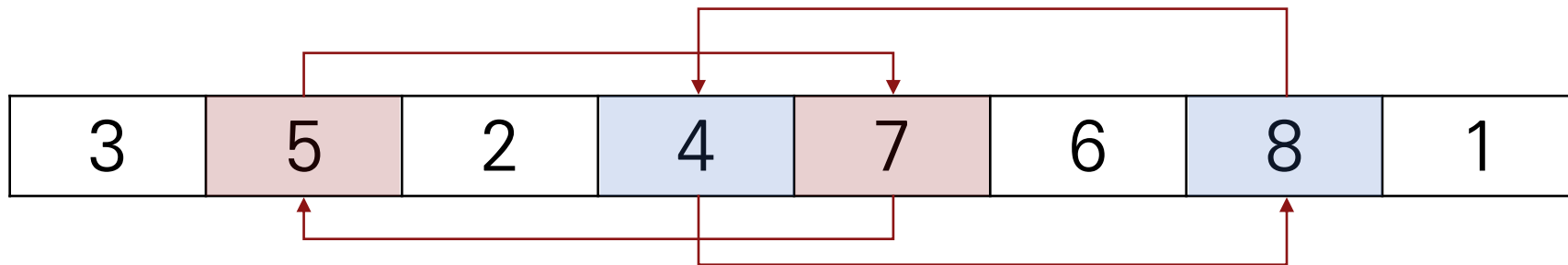


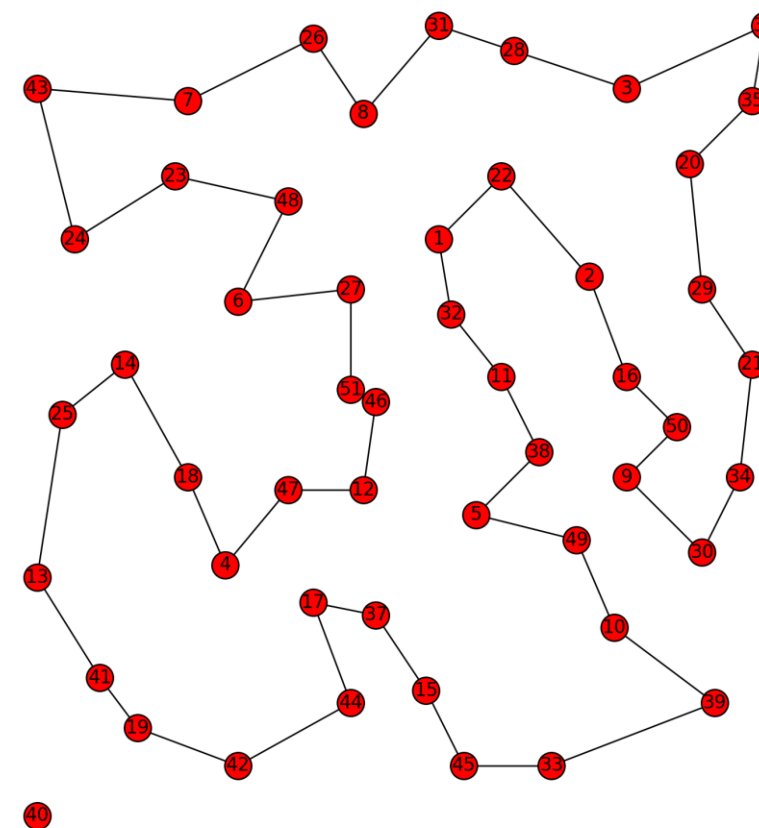
Figure 5: example of Neighborhood solution

■ Tabu list

- the attribute used is a pair of nodes that have been exchanged recently.

Application of the algorithm for an NP-C/NP-hard example

- Best Objective Value: 704.73
- Number of Customers Visited: 49
- Sequence of Customers Visited
 - [1, 32, 11, 38, 5, 49, 10, 39, 33, 45, 15, 37, 17, 44, 42, 19, 41, 13, 25, 14, 18, 4, 47, 12, 46, 51, 27, 6, 48, 23, 24, 43, 7, 26, 8, 31, 28, 3, 36, 35, 20, 29, 21, 34, 30, 9, 50, 16, 2, 22, 1]
- CPU Time (s): 39.19

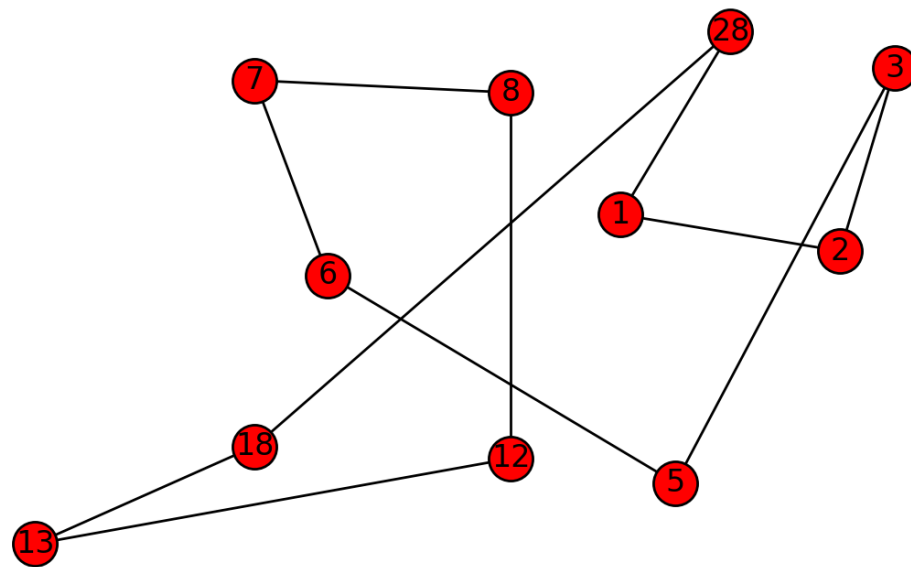


Application of the algorithm for an NP-C/NP-hard example

- Initial solution

- path = [1,2,3,5,6,7,8,12,13,18,28,1]
- greedy solution

	x	y	prof
0			
1	37	52	0
2	49	49	27
3	52	64	31
4	20	26	26
5	40	30	17
6	21	47	18
7	17	63	32
8	31	62	29
9	52	33	20
10	51	21	18

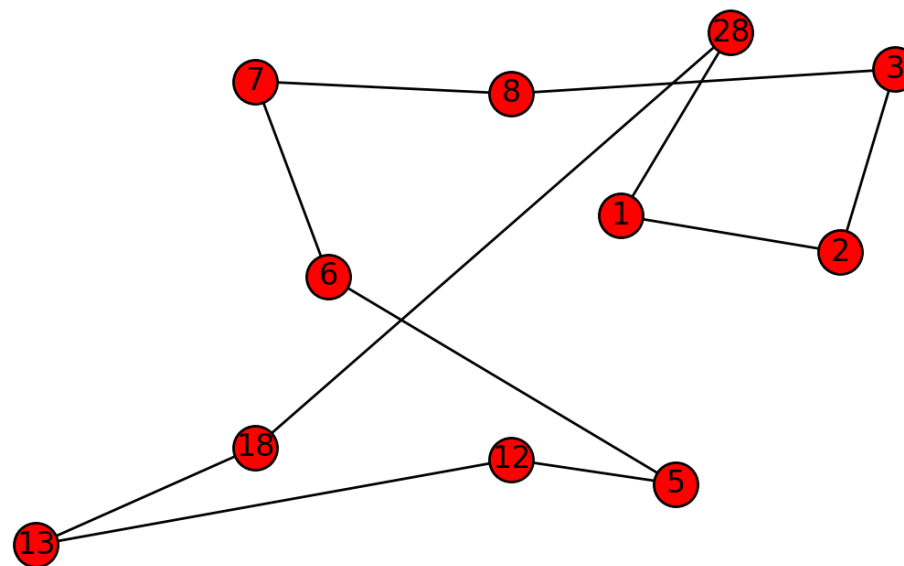


Application of the algorithm for an NP-C/NP-hard example

■ Current solution

- path = [1,2,3,8,7,6,5,12,13,18,28,1]
- Change \rightarrow [3,5 – 8,12]

	x	y	prof
0			
1	37	52	0
2	49	49	27
3	52	64	31
4	20	26	26
5	40	30	17
6	21	47	18
7	17	63	32
8	31	62	29
9	52	33	20
10	51	21	18

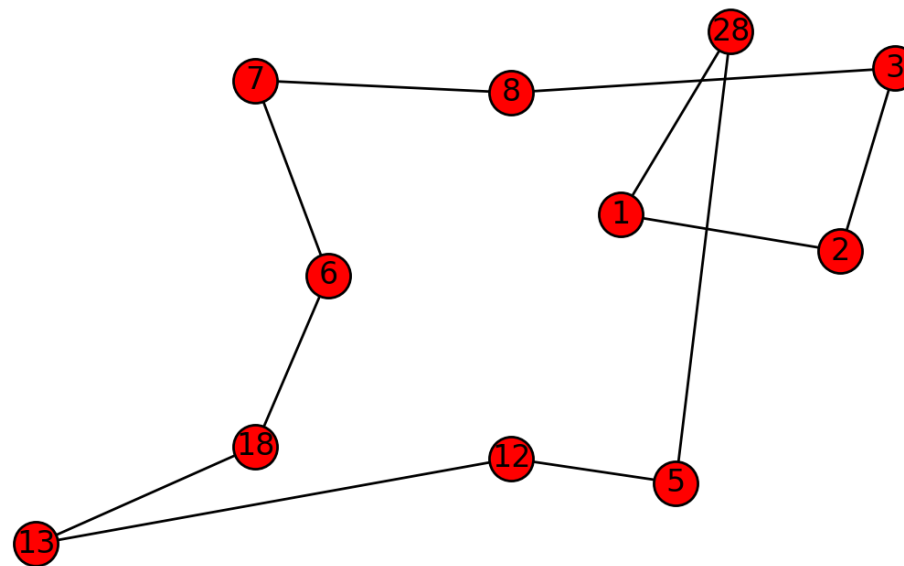


Application of the algorithm for an NP-C/NP-hard example

- Current solution

- path = [1,2,3,8,7,6,18,13,12,5,28,1]
- Change \rightarrow [6,5 - 18,28]

	x	y	prof
0			
1	37	52	0
2	49	49	27
3	52	64	31
4	20	26	26
5	40	30	17
6	21	47	18
7	17	63	32
8	31	62	29
9	52	33	20
10	51	21	18

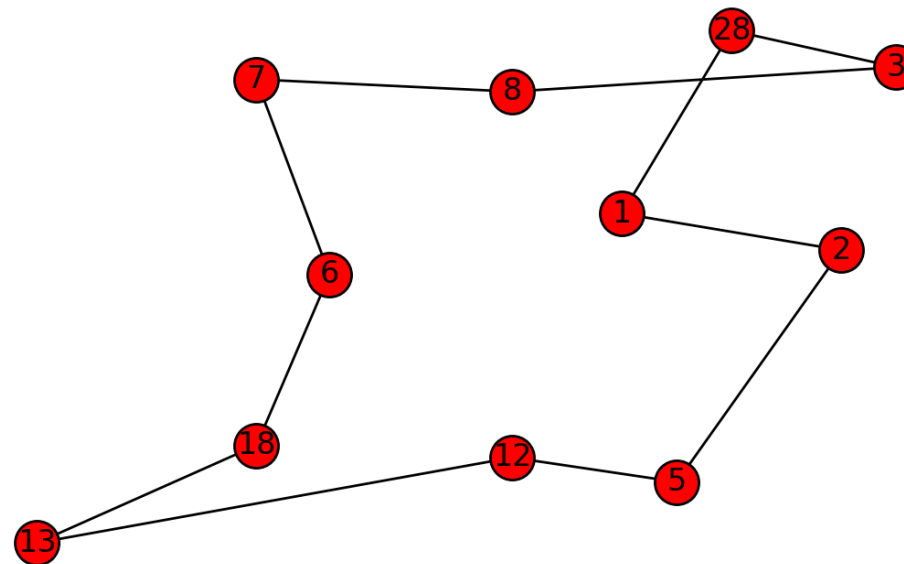


Application of the algorithm for an NP-C/NP-hard example

■ Current solution

- path = [1,2,5,12,13,18,6,7,8,3,28,1]
- Change \rightarrow [2,3 - 5,28]

	x	y	prof
0			
1	37	52	0
2	49	49	27
3	52	64	31
4	20	26	26
5	40	30	17
6	21	47	18
7	17	63	32
8	31	62	29
9	52	33	20
10	51	21	18

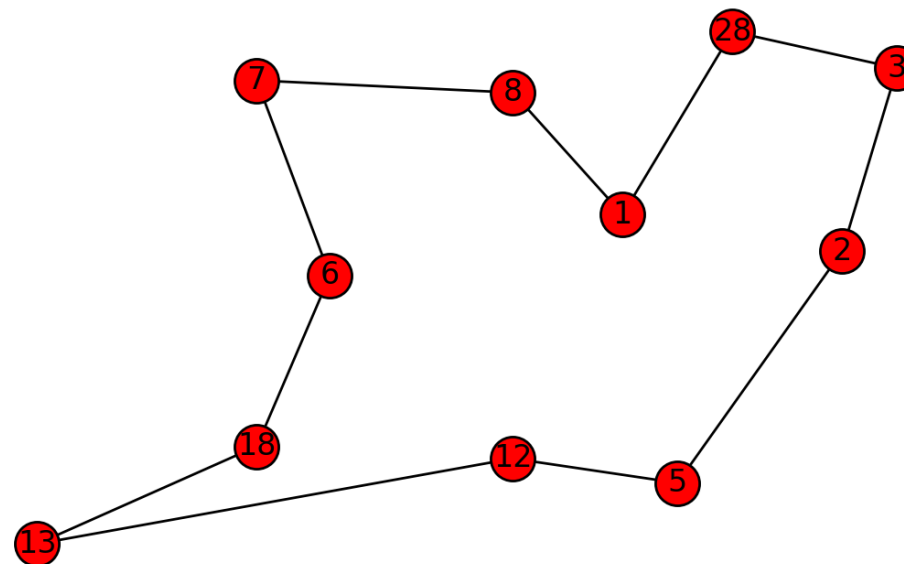


Application of the algorithm for an NP-C/NP-hard example

■ Current solution

- path = [1,28,3,2,5,12,13,18,6,7, 8,1]
- Change \rightarrow [1,2 - 8,3]

	x	y	prof
0			
1	37	52	0
2	49	49	27
3	52	64	31
4	20	26	26
5	40	30	17
6	21	47	18
7	17	63	32
8	31	62	29
9	52	33	20
10	51	21	18

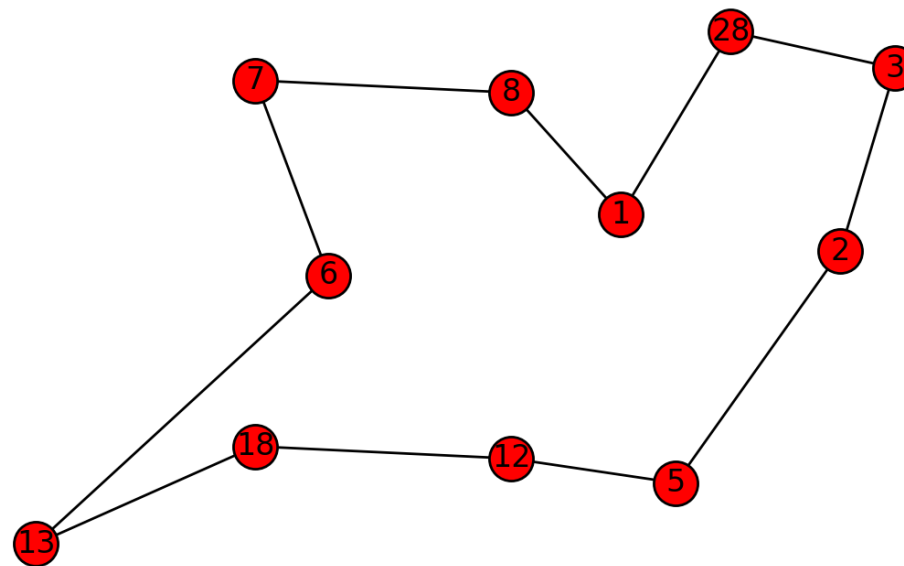


Application of the algorithm for an NP-C/NP-hard example

■ Current solution

- path = [1,28,3,2,5,12,18,13,6,7, 8,1]
- Change \rightarrow [6,18 - 13,12]

	x	y	prof
0			
1	37	52	0
2	49	49	27
3	52	64	31
4	20	26	26
5	40	30	17
6	21	47	18
7	17	63	32
8	31	62	29
9	52	33	20
10	51	21	18



References

- [1] Kochetov, Yuri A., and Eugene N. Goncharov. "BEHAVIOR OF A PROBABILISTIC TABU SEARCH ALGORITHM FOR THE MULTI STAGE UNCAPACITATED FACILITY LOCATION PROBLEM."
- [2] Kochetov, Yuri A., and Eugene N. Goncharov. "Probabilistic tabu search algorithm for the multi-stage uncapacitated facility location problem ." *Operations research proceedings*. Springer Berlin Heidelberg, 2001.