

Bio-Inspired Algorithms

Local Search

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Bio-inspired algorithms:

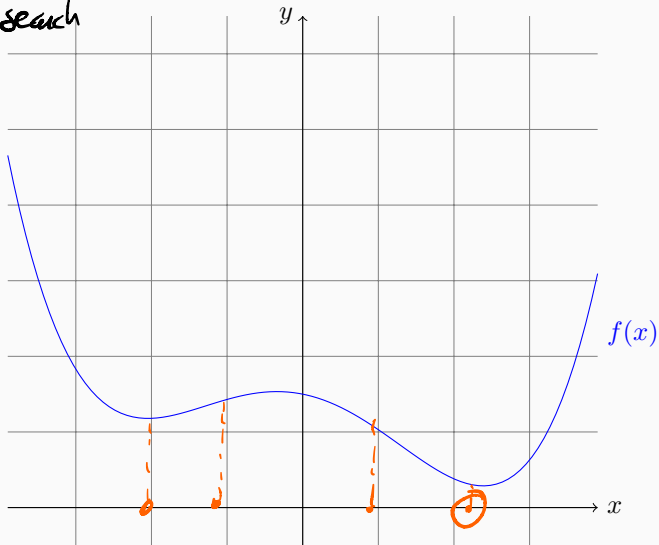
- Inspired in nature
- Mostly for **optimization problems**
 - Find the solution with the best fitness
- **NP-hard** problems: as hard as any in NP
- We will use **heuristic** approaches
 - which use practical knowledge

Some simple heuristics:

- **Random search**: tests random sampled solutions
- **Hill climbing**: moves to better neighbors
- **A***: uses heuristic to center shortest path search

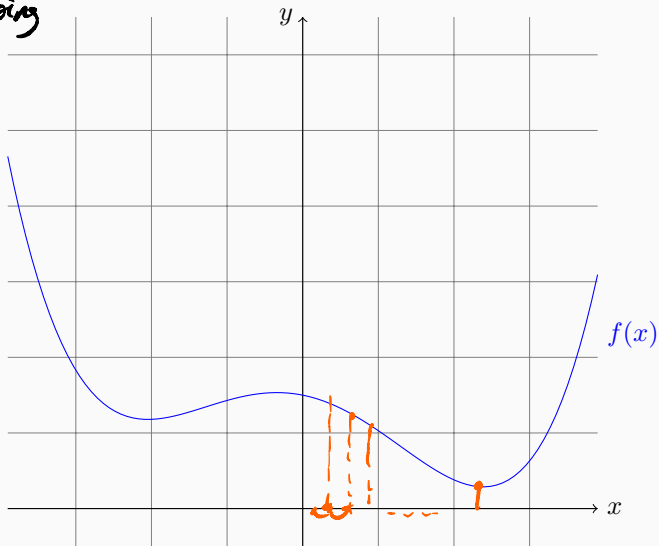
Example

Random search

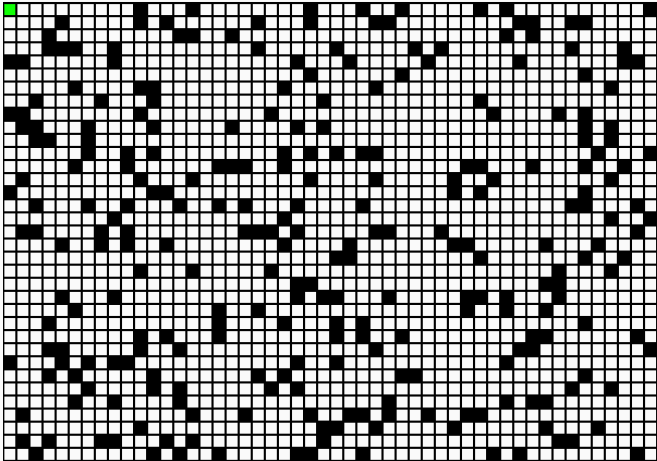


Example

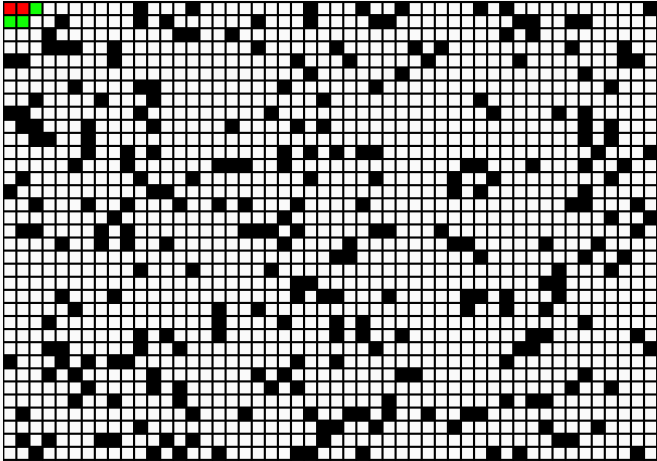
Hill Climbing



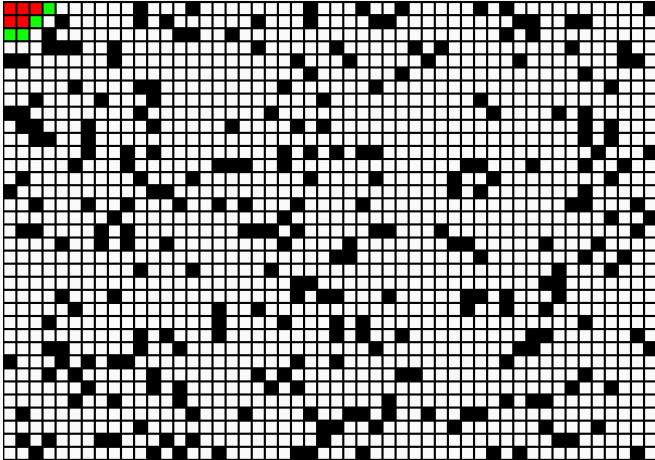
A* Algorithm



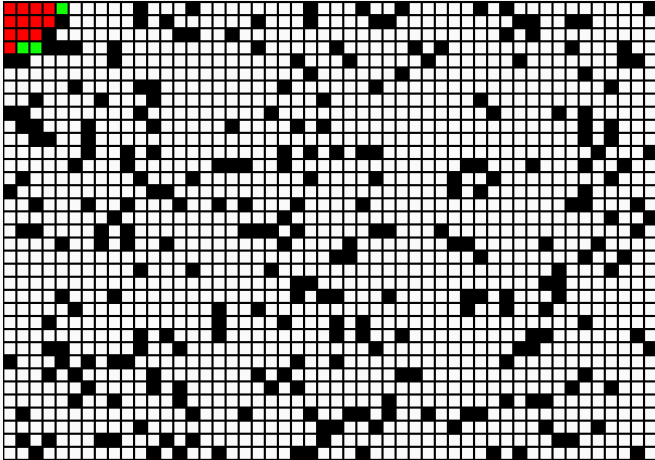
A* Algorithm



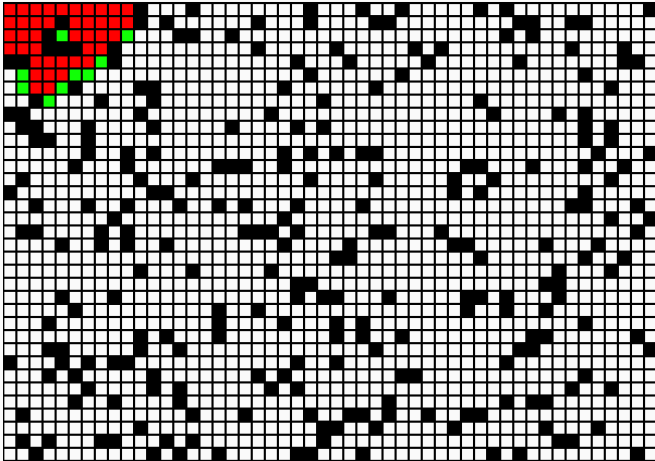
A* Algorithm



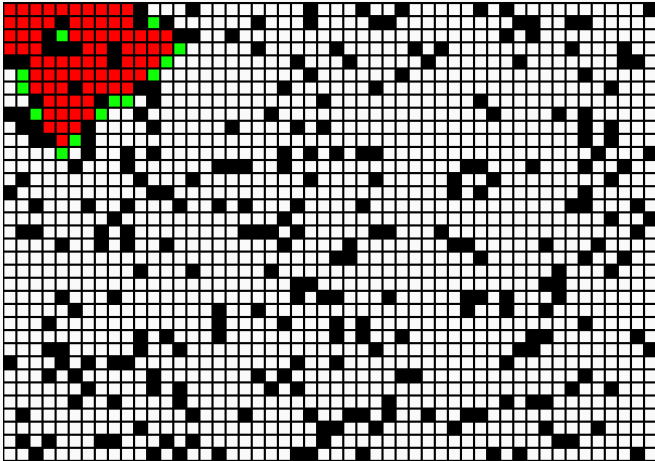
A* Algorithm



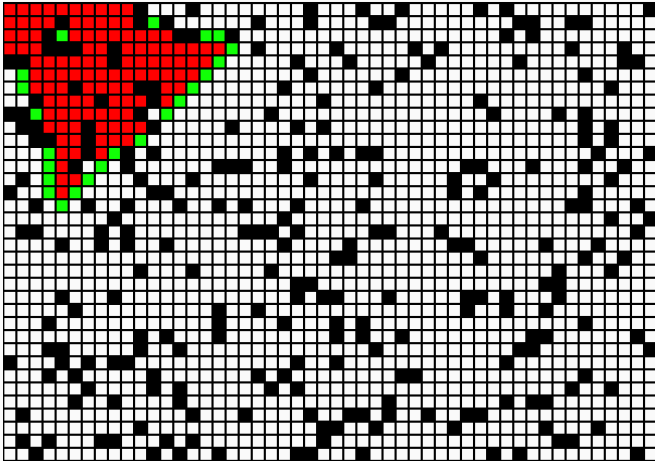
A* Algorithm



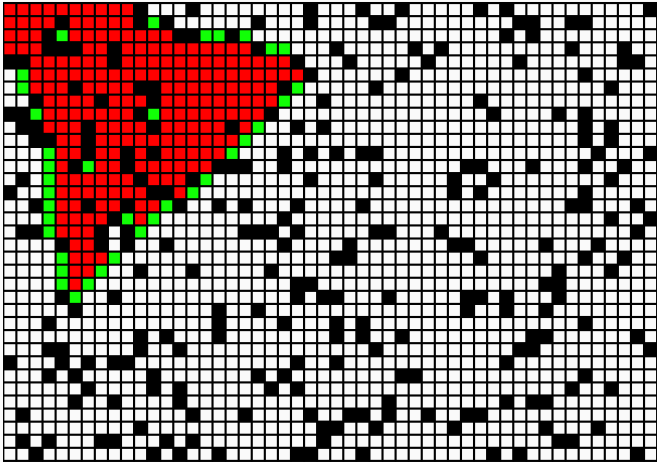
A* Algorithm



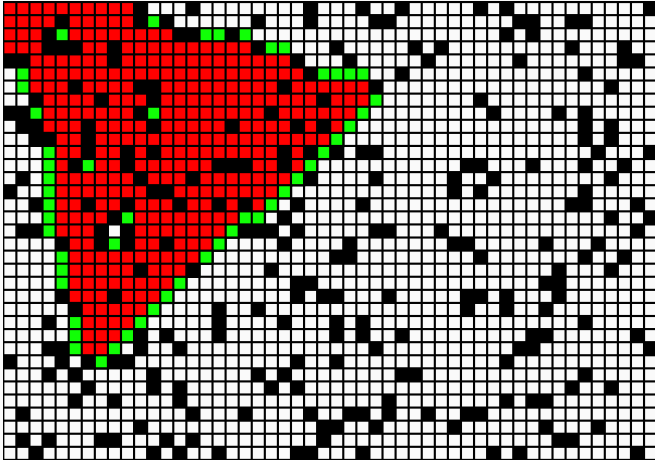
A* Algorithm



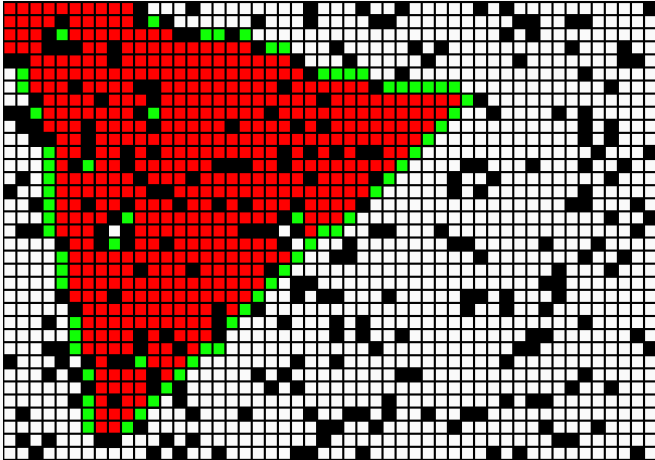
A* Algorithm



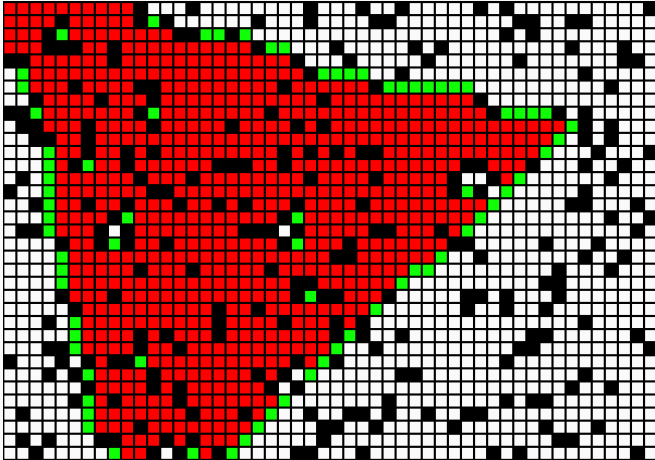
A* Algorithm



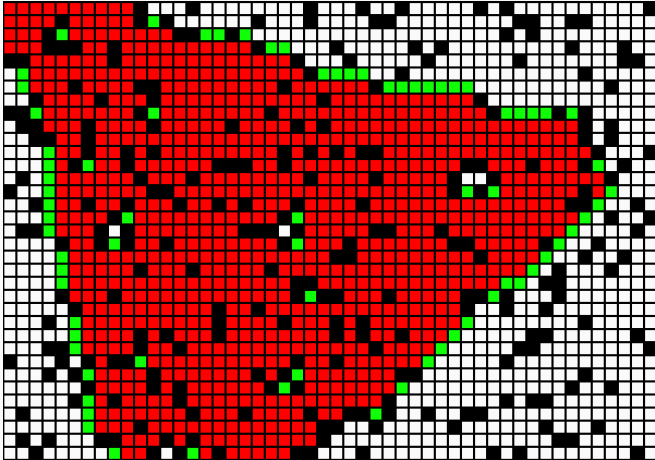
A* Algorithm



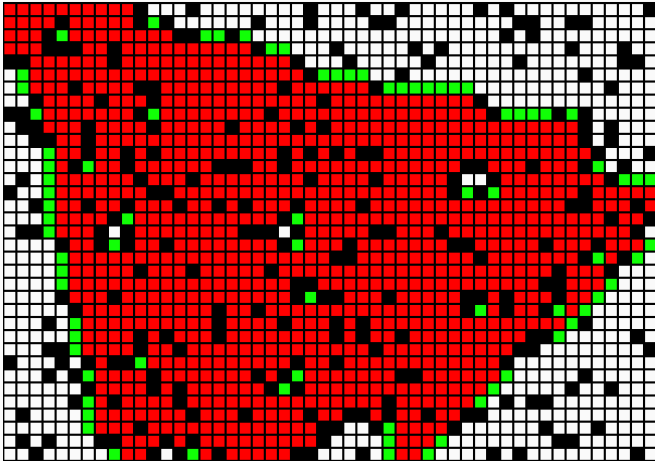
A* Algorithm



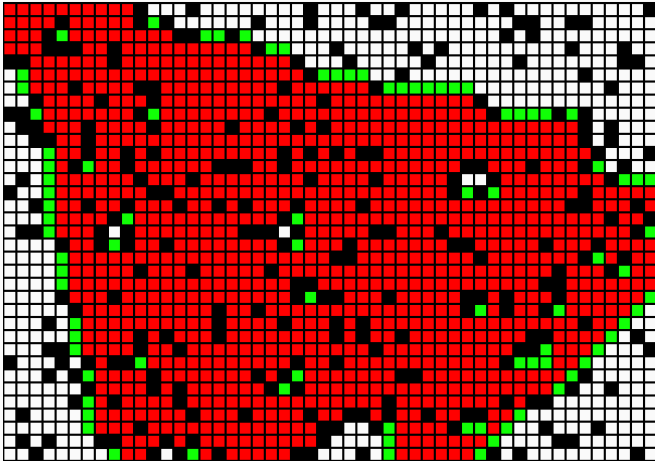
A* Algorithm



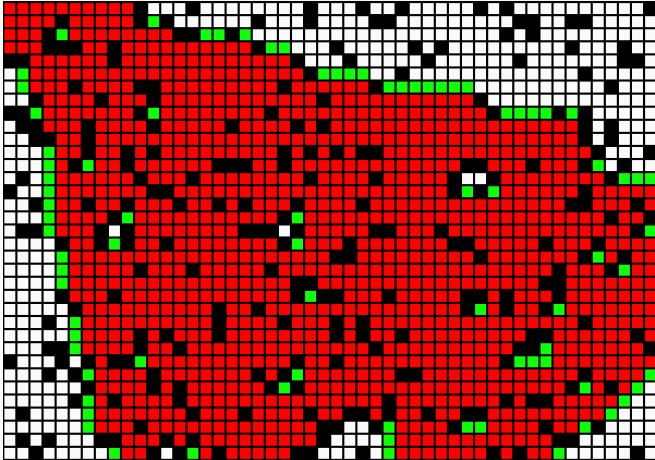
A* Algorithm



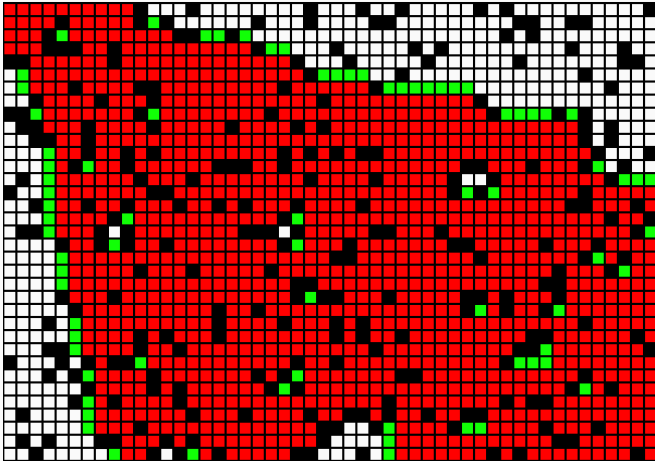
A* Algorithm



A* Algorithm



A* Algorithm



Local Search

Base principle

- We have a single solution
- We improve it step by step

Inspiration

- Very natural behaviour
- Given a solution, try to move in the right direction

What we need to know:

- How to **represent a solution**
- What is a **move**

Characterization:

- **Exploitation**: Using local information to make small steps
- **Exploration**: Moving blindly to find better solutions globally

Representing a solution

How to represent a solution?

- Very problem-dependent

Some main approaches:

- Values: binary, integers, reals, strings
- Represent different dimensions as elements of a vector

Examples:

- Real function optimization: vector of reals
 - (3.5, 2.4)
- Secret binary vector: vector of 0s and 1s
 - (0, 1, 1, 0, 0)
- Shortest path: sequence of vertices

What is a move

What is a move?

Defined by the concept of **neighbor**:

- Move: replacing a solution by one of its neighbors
 - usually with better fitness

Depending on the representation:

- Defined by **distance**: $N(s) = \{s' : d(s, s') \leq x\}$
- Defined by **operations** $\{f_i\}$: $N(s) = \{f_i(s) : \forall i\}$

Local Search

Algorithm LocalSearch

Input: domain D , fitness f

Output: solution $x \in D$

1: $x_0 := \text{INITIALSOLUTION}(D)$

2: $i := 1$

3: **while** not FINISHED **do**

4: $N := \text{NEIGHBORS}(x_i, D)$

5: $x_{i+1} := \text{SELECTION}(N, x_i)$ *// May keep the same solution*

6: $i := i + 1$

7: **end while**

8: **return** x_{i-1}

Local Search

Hill Climbing

Hill Climbing

Algorithm HillClimbingFunc

Input: n , domain D , function $f: D \rightarrow \mathbb{R}$

Output: solution $x \in D$

```
1:  $x := \text{RANDOM\_SOLUTION}(D)$ 
2: for  $i = 1$  to  $n - 1$  do
3:    $c := \text{RANDOM\_NEIGHBOR}(x)$ 
4:   if  $f(c) < f(x)$  then
5:      $x := c$ 
6:   end if
7: end for
8: return  $x$ 
```

Algorithm LocalSearch

Input: domain D , fitness f

Output: solution $x \in D$

```
1:  $x_0 := \text{INITIALSOLUTION}(D)$ 
2:  $i := 1$ 
3: while not FINISHED do
4:    $N := \text{NEIGHBORS}(x, D)$ 
5:    $x_i := \text{SELECTION}(N, x)$            // May keep the same solution
6:    $i := i + 1$ 
7: end while
8: return  $x_{i-1}$ 
```

Local Search

Greedy Local Search

Greedy Local Search

Idea:

- Choose the neighbor **minimizing the fitness**
- Stop once there is no improvement

Properties:

- Pure exploitation, no exploration
- Can be **inefficient** (depending on the neighborhood)
- Very **general**
- Can get trapped in **local minima**

Algorithm GreedyLocalSearch

Input: domain D , fitness f

Output: solution $x \in D$

```
1:  $x_0 := \text{RANDOM\_SOLUTION}(D)$ 
2:  $i := 1$ 
3: while true do
4:    $N := \text{NEIGHBORS}(x, D)$ 
5:    $x_i := \text{argmin}\{f(c) : c \in N\}$ 
6:   if  $f(x_i) \geq f(x_{i-1})$  then
7:     break
8:   end if
9:    $i := i + 1$ 
10: end while
11: return  $x_i$ 
```

Greedy Local Search (Python)

```
1 def greedy_local_search(D, f):
2     x = D.sample()
3     while True:
4         N = D.neighbors(x)
5         fc, c = min( (f(c), c) for c in N )
6         if f(c) < f(x):
7             x = c
8         else:
9             break
10    return x
11
12 D = DomainBinVec(n) # n=10
13 f = lambda x: sum(secret[i] != x[i] for i in range(n) )
14 x = greedy_local_search(D, f)
15 print(f"f({x}) = {f(x)}")
16 # f((0, 0, 0, 0, 1, 1, 1, 1, 1, 0)) = 0
```

Greedy Local Search (Python)

```
1 @dataclass
2 class DomainBinVec:
3     n: int
4     def sample(self):
5         return tuple(randrange(2) for i in range(self.n))
6     def neighbor(self, x):
7         i = randrange(self.n)
8         return x[:i] + (1-x[i],) + x[i+1:]
9     def neighbors(self, x):
```

L = []

for i in range(n):

L.append(x[:i] + (1-x[i],) + x[i+1:])

return L

Local Search

Examples

Examples

- Minimizing a function
- TSP
- Group work scheduling
- Maze solving

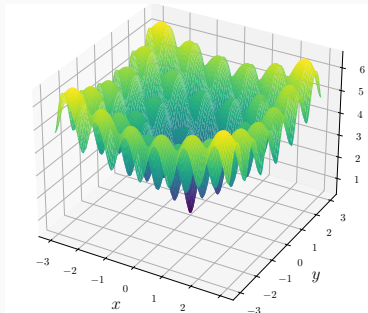
What we need:

- Representation
- Neighborhood

Example 1: Minimizing a Function

Input:

- Function to minimize (or maximize)
- Domain $D \subseteq \mathbb{R}^d$



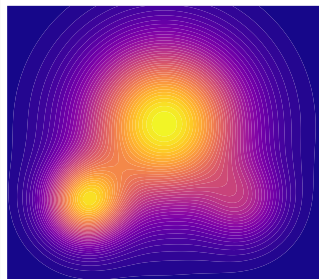
Example 1: Minimizing a Function

Input:

- Function to minimize (or maximize)
- Domain $D \subseteq \mathbb{R}^d$

Example:

- Sum of Gaussians
- $f(x) = \sum_i e^{-(x-x_i)^2-(y-y_i)^2}$



Example 1: Minimizing a Function

Solution:

- Vector in $\mathbb{R}^d$
- Precision?

Neighborhood:

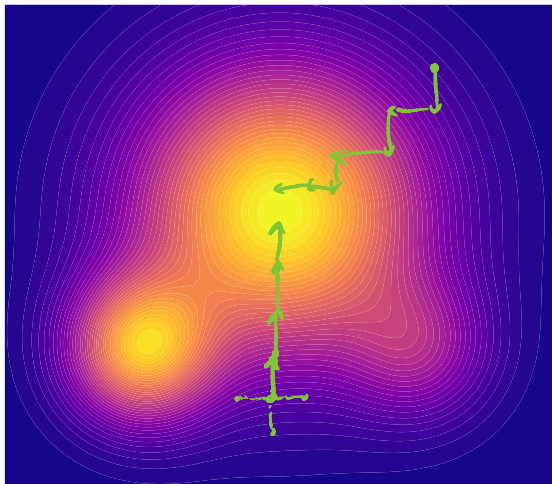
1. Single change at i : $x'_i = x_i \pm \lambda, \quad x'_j = x_j, j \neq i;$
2. Multiple change: $x'_j = x_j + \{-\lambda, 0, \lambda\}$
3. Gradient descent: $x' = x - \lambda \nabla f(x)$

(not local search)

number
2d
3d

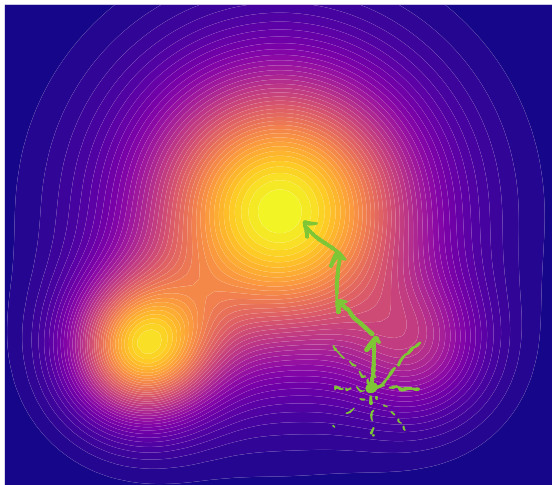
Example 1: Minimizing a Function

Operator 1

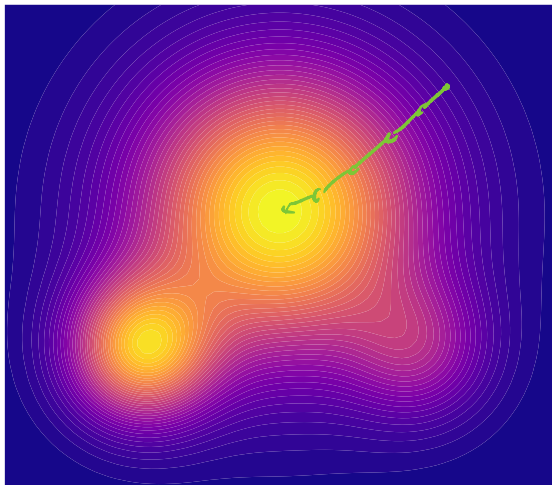


Example 1: Minimizing a Function

Operator 2



Example 1: Minimizing a Function



Example 2: Traveling Salesperson Problem

Input:

- Complete graph G
- Edge lengths w
(with Δ -inequality)

Goal: Find a cycle

- through each vertex
- with minimum length



Example 2: Traveling Salesperson Problem

Solution:

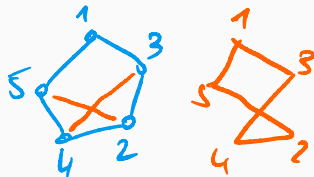
- Sequence of vertices (permutation)

Neighborhood operators: many possibilities

1. Switch two vertices
2. Exchange two edges (2-opt)
3. Exchange k edges (k -opt)
4. Lin-Kernighan (alternating trails)

$(1, \underline{3}, 2, \underline{4}, 5) \rightarrow (1, 4, 2, 3, 5)$

$(1, \underline{3}, 2, \underline{4}, 5) \rightarrow (1, 3, 4, 2, 5)$



Example 2: Traveling Salesperson Problem

Solution:

- Sequence of vertices (permutation)

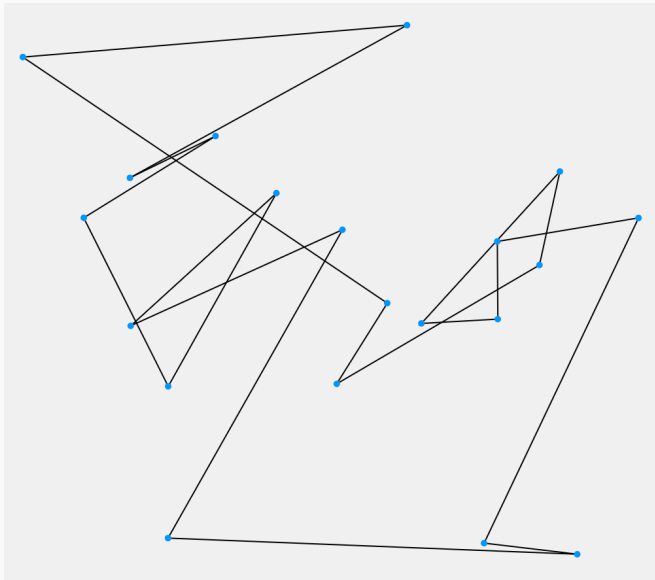
Neighborhood operators:

- E.g. switch two vertices
- Implies a neighborhood

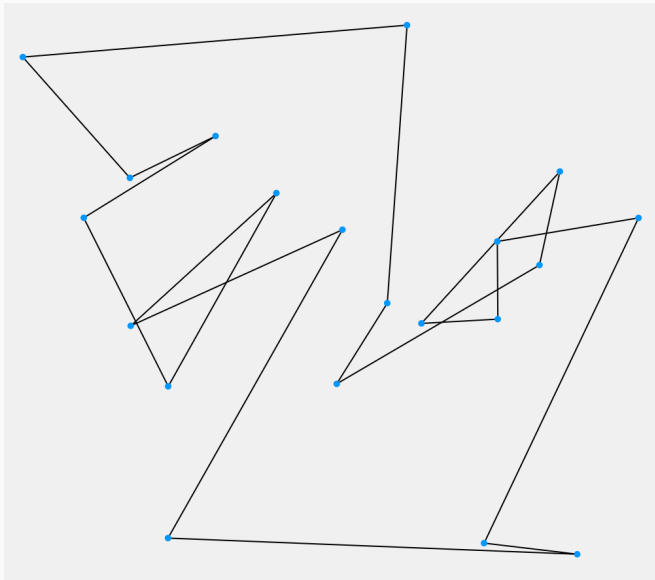
Complexity:

- Each iteration, look at all possible switches
- How many? $O(n^2)$
- What about 2-opt and k -opt?
 $O(n^2)$ $O(n^k)$

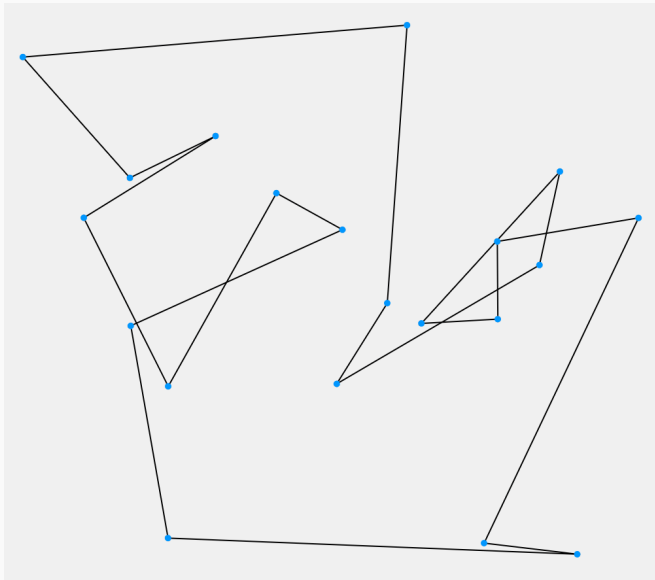
Example 2: Traveling Salesperson Problem



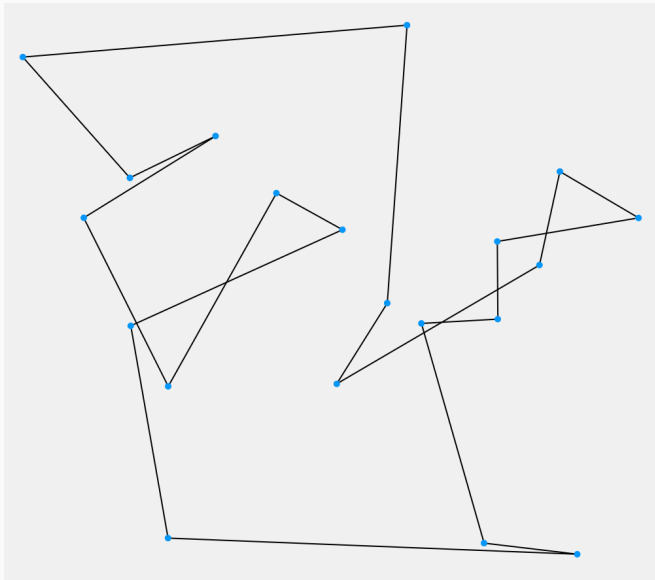
Example 2: Traveling Salesperson Problem



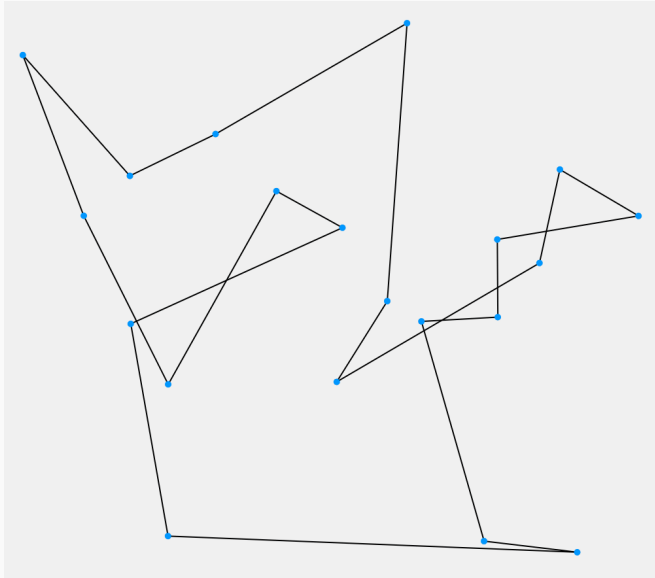
Example 2: Traveling Salesperson Problem



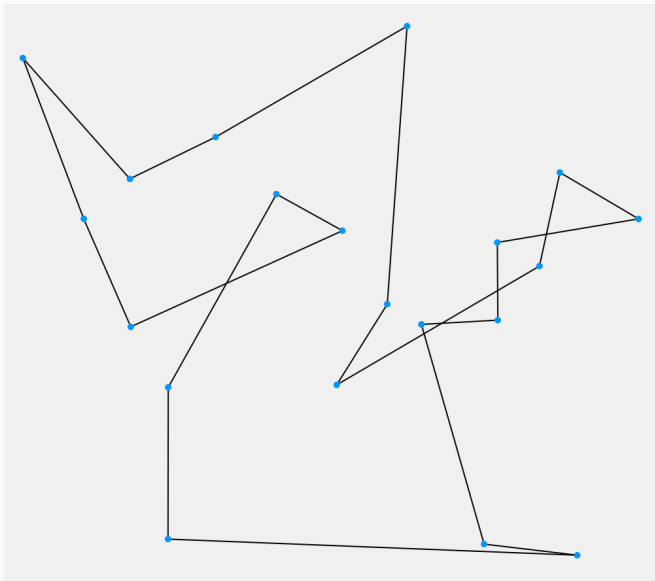
Example 2: Traveling Salesperson Problem



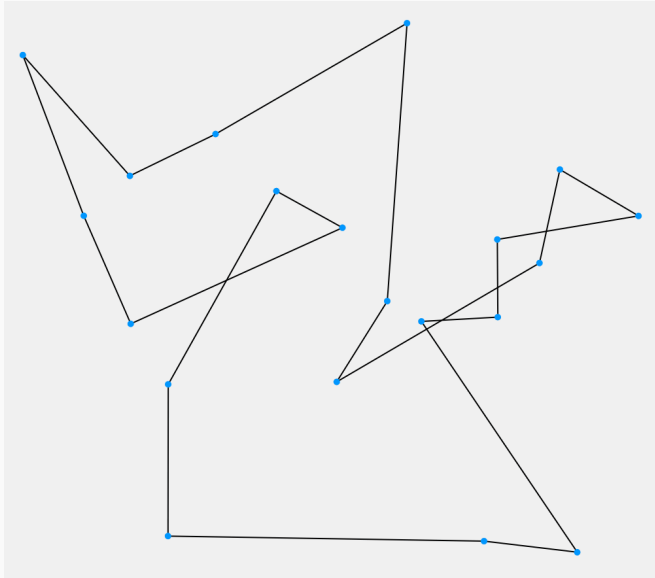
Example 2: Traveling Salesperson Problem



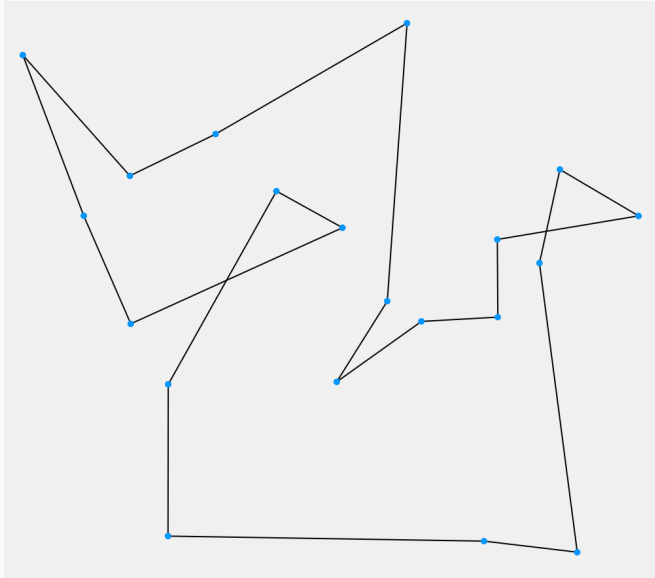
Example 2: Traveling Salesperson Problem



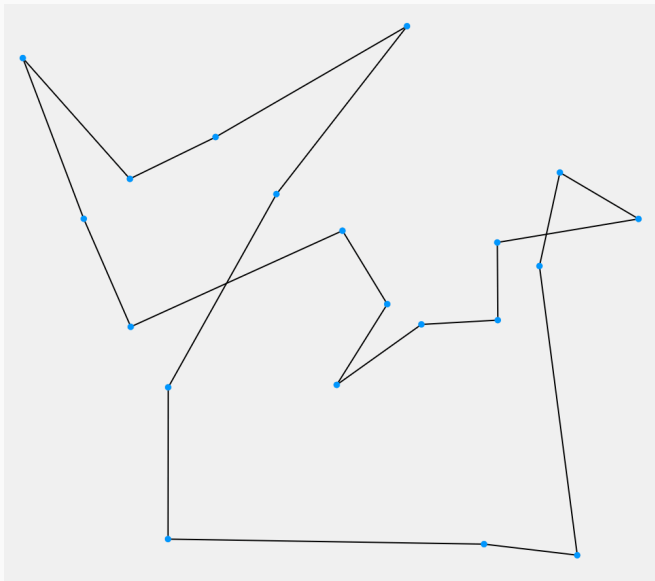
Example 2: Traveling Salesperson Problem



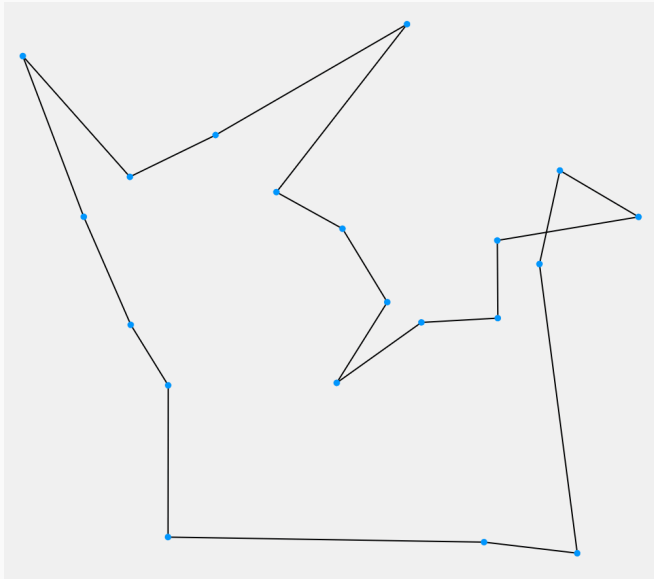
Example 2: Traveling Salesperson Problem



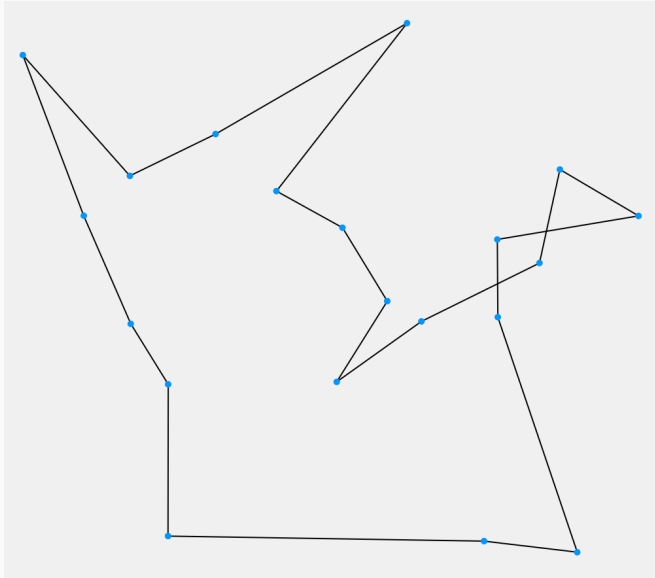
Example 2: Traveling Salesperson Problem



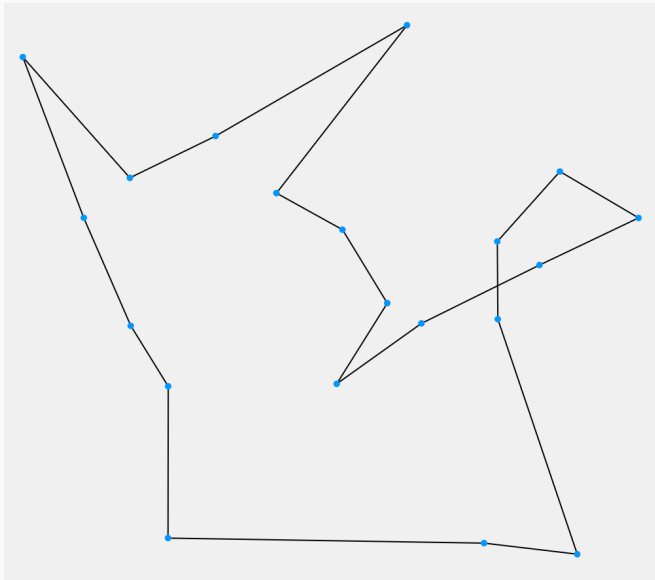
Example 2: Traveling Salesperson Problem



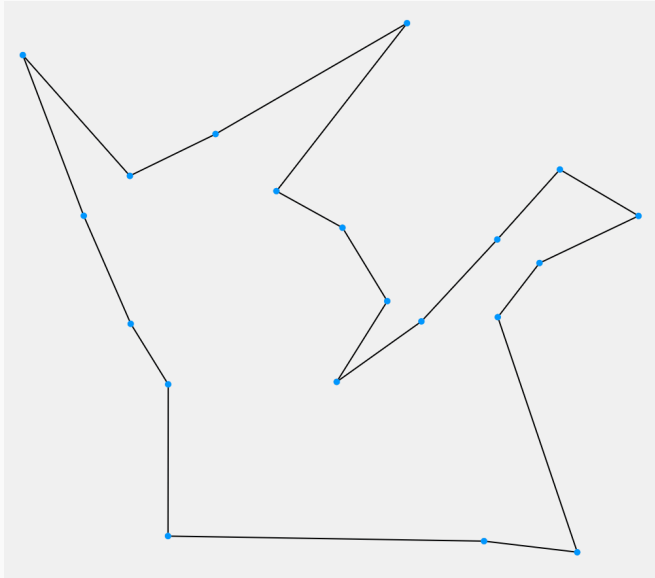
Example 2: Traveling Salesperson Problem



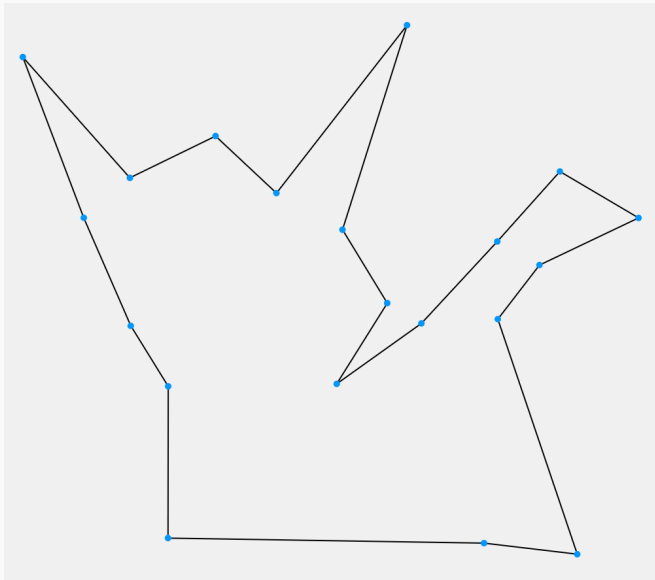
Example 2: Traveling Salesperson Problem



Example 2: Traveling Salesperson Problem



Example 2: Traveling Salesperson Problem



Example 3: Group work scheduling

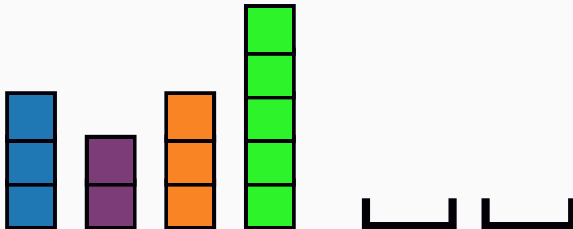
Input:

- n tasks
- k students
- task i takes t_i hours

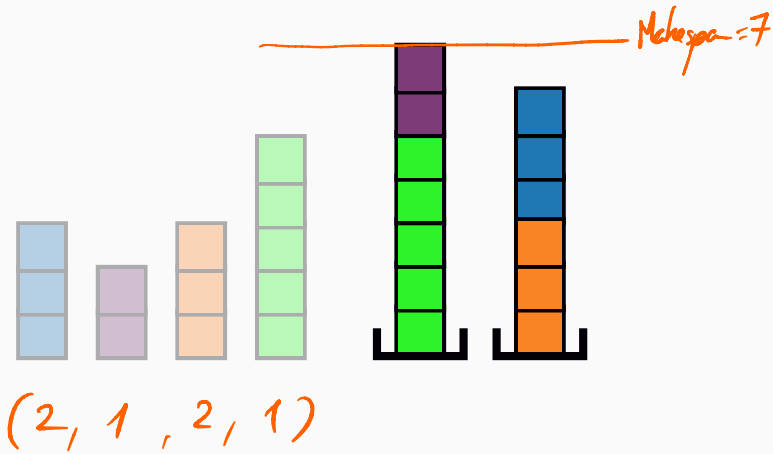
Goal: Find an assignment of tasks to students

- That completes as soon as possible
- Without splitting tasks
- **Makespan:** Maximum work of any student

Example 3: Group work scheduling



Example 3: Group work scheduling



Example 3: Group work scheduling

Solution:

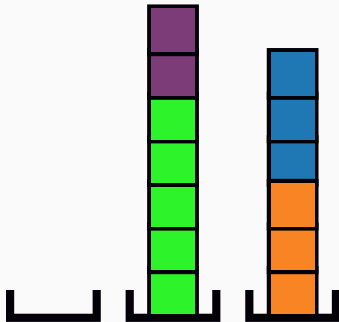
- Assignment of tasks to students
- Vector v where student v_i does task i

Neighborhood operators:

1. Move a task
2. Exchange two tasks

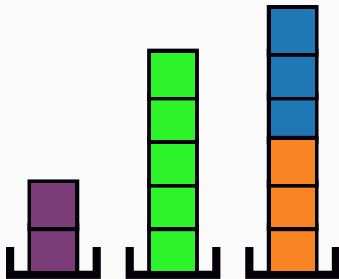
Example 3: Group work scheduling

Operator: move a task



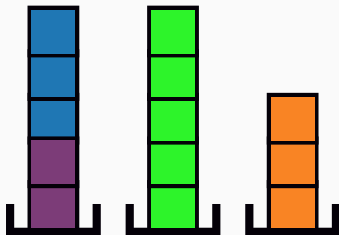
Example 3: Group work scheduling

Operator: move a task



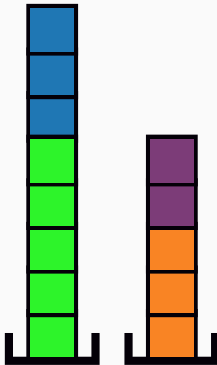
Example 3: Group work scheduling

Operator: move a task



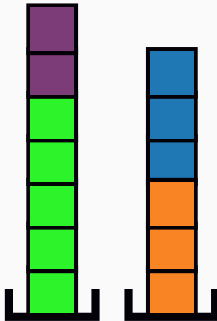
Example 3: Group work scheduling

Operator: exchange two tasks



Example 3: Group work scheduling

Operator: exchange two tasks



Example 3: Group work scheduling

Problem:

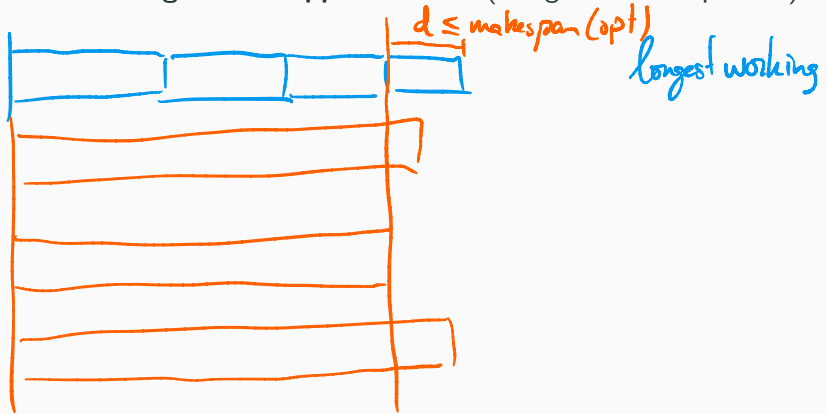
- Simplest version of a scheduling problem
- Scheduling problems are an important class

Local Search:

- Always at most $2\times$ the optimum makespan
- It is a 2-approximation algorithm

Example 3: Group work scheduling

Local Search gives a 2-approximation (using the move operator)



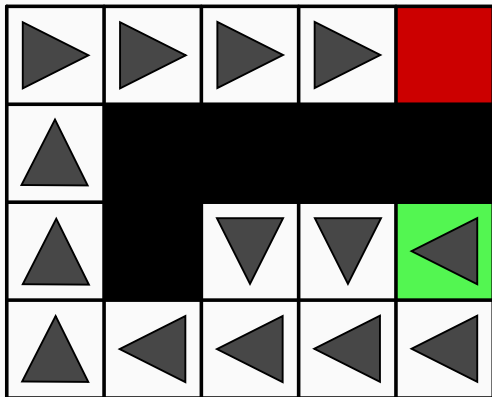
students finish at
 $d + t \leq 2 \cdot \text{opt.}$

$t \leq \text{makespan}(\text{opt})$

Example 4: Maze Solving

Problem:

- Given a labyrinth, place directions on each tile
- A robot should reach the exit following the arrows



Example 4: Maze Solving

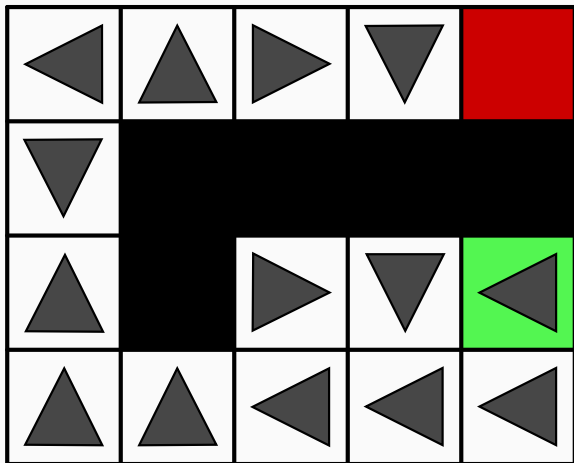
Local Search:

- Solution: One of $\{\uparrow, \rightarrow, \downarrow, \leftarrow\}$ on each cell
- Operator: Change one arrow
- Fitness: Number of steps

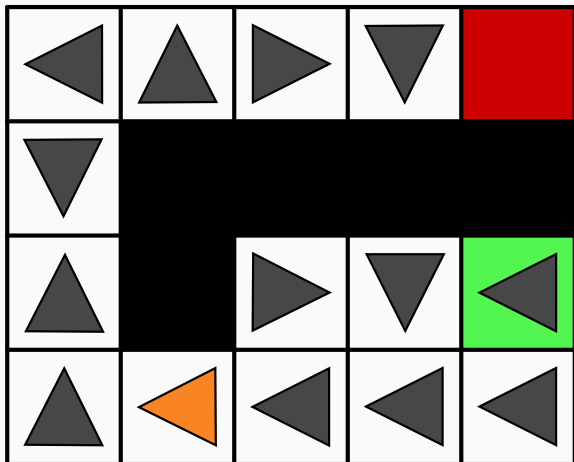
Problems:

- What if the solution is infeasible?
- And if multiple neighbors have similar fitness?

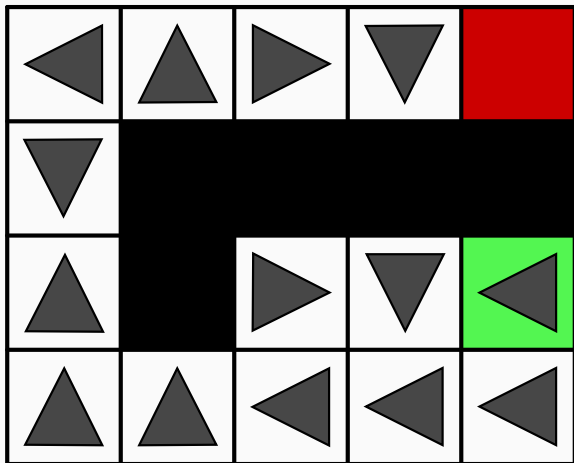
Example 4: Maze Solving



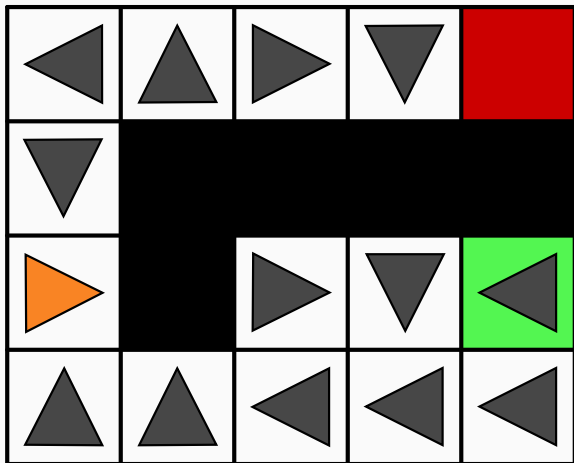
Example 4: Maze Solving



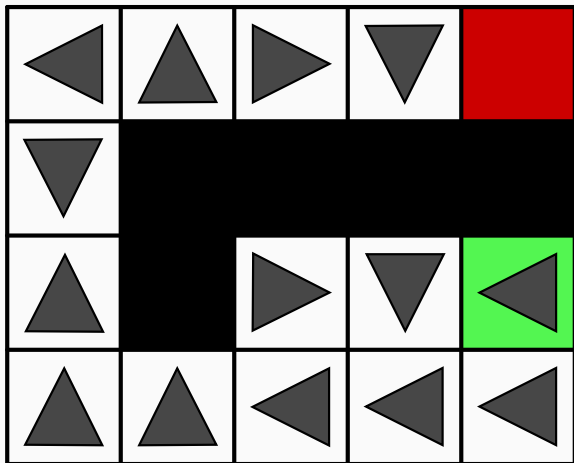
Example 4: Maze Solving



Example 4: Maze Solving



Example 4: Maze Solving



Example 4: Maze Solving

Guided search:

- Incorporate infeasibility into fitness
 - If infeasible, give higher fitness
- Specialize the operators
 - Only allow changes on tiles visited by the robot

Another option: allow fitness to increase

- Topic for later

Local Search

Improving Local Search

Choice of neighbor:

- Best possible
 - Very inefficient
- A random improving neighbor
 - Random behavior not always desired
 - Multiple tries?
 - When to stop?
- First improving move
 - Biased towards first neighbors
 - Inefficient in the worst case
 - Threshold?

Running time optimization

Can we improve the running time?

Fitness evaluation

- Repeated many times
 - Even small improvements count
- Idea: Compute **difference between solutions**
 - TSP: length of changed edges
 - Often $O(1)$ instead of $O(n)$

Neighbor set

- Running time is proportional to its size
- If possible, discard bad neighbors
 - If sure that there is no improvement

- Example: TSP in $\mathbb{R}^2$
 - Always uncross edges first

$$d(u,v) = \sqrt{(u_1-v_1)^2 + (u_2-v_2)^2}$$



Local minima: big problem for local search

- Change the fitness
- Change the neighborhood
- Change the strategy

Strategies: increase exploration

- Random restart: once stuck, generate new random solution
- Simulated annealing: accept bad moves “sometimes”
- Tabu search: change the neighborhood dynamically

Local search:

- Repeated **local improvement**
- Need **solution representation** and **neighborhood**
- Focused on **exploitation**, little or no **exploration**

Greedy local search:

- Choose neighbor that **minimizes fitness**
- **Inefficient**, but very **general**
- Gets trapped in **local minima**
- Examples: minimization, TSP, scheduling, maze solving
- Variations, optimization, and improvements