

Search Algorithms: Object-Oriented Implementation (Part B)

구현 시작 !

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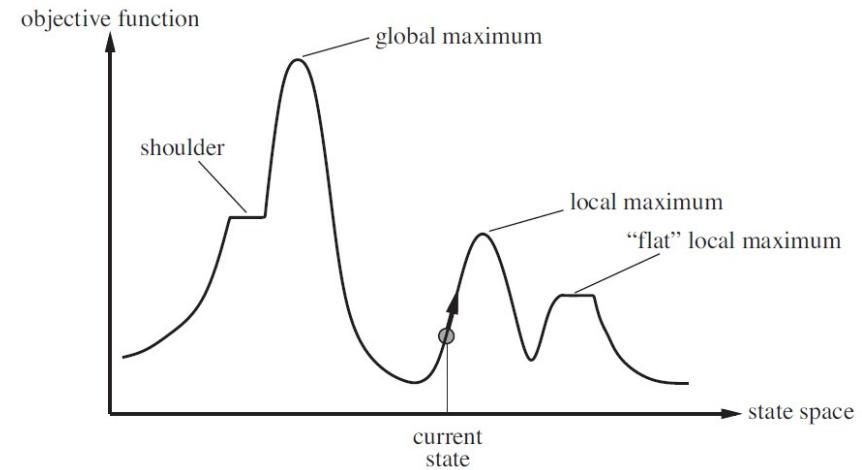
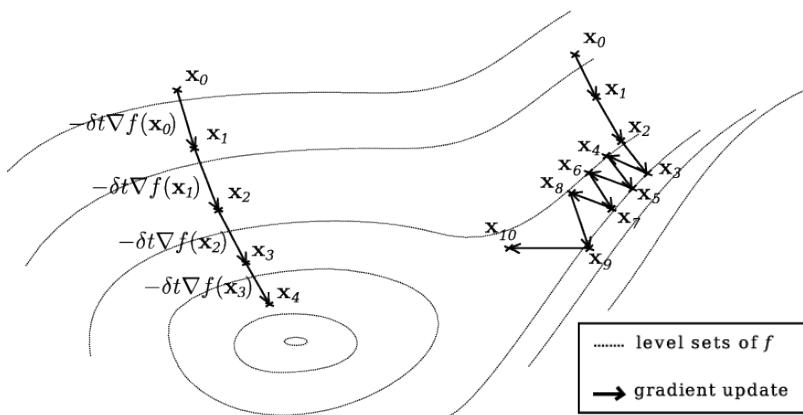
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앞으로는, **Search Algo** 을 구현하는 과제가
진행되고, 과제에서 구현해야 하는 코드의
일부를 수업시간에 살펴보는 방식으로
진행합니다.



Implementation Reference Notes

- Search Algorithm
 - The techniques/algorithms covered in the class are methods for **iteratively finding the optimal solution**, and are called **Search Algorithms**.
 - However, the optimal solution found by the algorithm can be **global optimal** or **local optimal**.



Implementation Reference Notes

- Search Tool
 - In order to **execute a Search Algo.** (Algorithm), tasks such as **problem generation/loading and parameter setting** must be performed. // **Preprocessing** (or 'pre-work')
 - Additionally, a function to **display the Search Algo. execution results** is also necessary. // **Post-processing** (or 'post-work')
 - A program that performs the above steps: 1) Preprocessing, 2) Algorithm execution, and 3) Post-processing is called a **Search Tool**.

Implementation Reference Notes

- Search Tool Version
 - The Search Tool is implemented in various versions (iteratively expanded & improved).
 - v0 (강의 . Search Algo. B) : A version where **all the code to implement one algorithm is contained in a single file**
 - v1 (강의 . Search Algo. B) : A version implemented by **modularizing the logic common to different pieces of code into a separate file**, then importing and using that module/file (code refactoring & reuse)
 - v2 (강의 . Search Algo. C) : A version implemented using **classes** (v2.1, v2.2)
 - v3~v5 : Versions implemented using classes, with some algorithms added, leading to **iterative improvements in the code structure**
 - v3 : 강의 . Search Algo. D
 - v4 : 강의 . Search Algo. E
 - v5 : 강의 . Search Algo. F

Today's

Implementing Hill-Climbing Algorithms

- Our eventual goal is to implement an **optimization tool** that can run various search algorithms
- We begin to implement **two hill climbing algorithms** each **for two different types of problems**: (we implement a total of **four** hill climbing algorithms)
 - Steepest-ascent hill climbing **for numerical optimization** (**SAHC-N**)
 - First-choice hill climbing **for numerical optimization** (**FCHC-N**)
 - Steepest-ascent hill climbing **for TSP** (**SAHC-T**)
 - First-choice hill climbing **for TSP** (**FCHC-T**)

Ref:

- numerical optimization : The task of finding the variables that **maximize or minimize** the objective function/value given a mathematical expression/objective function. // **continuous**
- TSP : The problem of calculating the shortest distance to visit all given cities and return to the starting city. // **discrete**

복습 : Hill Climbing Algo. (왼쪽) vs first-choice hill climbing (오른쪽)

[Steepest ascent version]

```
1: function HILL-CLIMBING(problem) returns a state that is a local maximum  
2:  
3: current  $\leftarrow$  MAKE-NODE(problem.INITIAL-STATE)  
4: loop do  
5:   neighbor  $\leftarrow$  a highest-valued successor of current  
6:   if neighbor.VALUE  $\leq$  current.VALUE then return current.STATE  
7:   else current  $\leftarrow$  neighbor
```

– First-choice (simple) hill climbing:

- Generates successors randomly until one is found that is better than the current state
- 후보 state를 무작위로 선택하고, current state 보다 좋다면 선택(계산이 간단)

- If the goal is to maximize (\$\maximize\$) the objective function, and there is no better solution (neighbor):
- XXX.VALUE: Refers to the **calculated value of the objective function** for the solution XXX.
- Example: If objective function(x) = x^2 , current($x = 4$), then current.VALUE = $(4)^2$.

Today, we'll only looked at how to implement the two problems of the **Numerical Optimization** type.



Implementation by including all necessary logic in a single source code file

SEARCH TOOL V0

Numerical Optimization

- The problem of **finding the variable values to minimize or maximize a given mathematical expression.**
- Assume the problem is input via a **text file**, as shown below.
 - The problem is to find the variable values that **minimize the mathematical expression** entered on the first line
 - Each variable has a minimum and maximum value range.
 - For example, the variables $x_1 \sim x_5$ below can only select values in the range of -30 to +30.

```
Convex.txt
1 (x1 - 2) ** 2 + 5 * (x2 - 5) ** 2 + 8 * (x3 + 8) ** 2
2 x1,-30,30
3 x2,-30,30
4 x3,-30,30
5 x4,-30,30
6 x5,-30,30
```

Numerical Optimization

- Execution Results (Example using the **Steepest-Ascent Algorithm**)

```
Enter the file name of a function: problem/Convex.txt
```

Input the name and path of the .txt file defining the problem (User Input).

Objective function:

$$(x_1 - 2)^2 + 5(x_2 - 5)^2 + 8(x_3 + 8)^2 + 3(x_4 + 1)^2 + 6(x_5 - 7)^2$$

Search space:

$x_1: (-30.0, 30.0)$
 $x_2: (-30.0, 30.0)$
 $x_3: (-30.0, 30.0)$
 $x_4: (-30.0, 30.0)$
 $x_5: (-30.0, 30.0)$

- * **Variable and Range:** The value of each variable can be changed within its specified range.
- * **Problem Goal:** Find the x_1, \dots, x_5 values that make the **value of the objective function the smallest.**

Search algorithm: **Steepest-Ascent** Hill Climbing

Mutation step size: 0.01

The calculated optimal solution

Solution found: (1.006, 5.002, 7.007, 1.005, 7.002)

Minimum value: 0.000

The result when the optimal solution is substituted into the objective function.

Total number of evaluations: 95,321

Numerical Optimization

- Execution Results (Example using the **First-Choice Algorithm**)

```
Enter the file name of a function: problem/Convex.txt  
Input the name and path of the .txt file defining the problem (User Input).  
  
Objective function: Value goal  

$$(x_1 - 2)^2 + 5(x_2 - 5)^2 + 8(x_3 + 8)^2 + 3(x_4 + 1)^2 + 6(x_5 - 7)^2$$
  
  
Search space:  
x1: (-30.0, 30.0)  
x2: (-30.0, 30.0)  
x3: (-30.0, 30.0)  
x4: (-30.0, 30.0)  
x5: (-30.0, 30.0)  
  
• * Variable and Range: The value of each variable can be changed within its specified range.  
• * Problem Goal: Find the  $x_1, \dots, x_5$  values that make the value of the objective function the smallest.  
  
Search algorithm: First-Choice Hill Climbing  
  
Mutation step size: 0.01  
Max evaluations with no improvement: 100 iterations  
  
Solution found: (2.00, 5.00, -8.00, -1.00, 7.00) Main changes  
Minimum value: 0.000 The calculated optimal solution  
  
Total number of evaluations: 37,336
```

TSP Problem

- The problem of planning the **route (= order of visits)** to visit all cities with the **shortest total distance**.
- Assume the problem is input via a **text file**, as shown below.
 - The **number of cities** is on the first line.
 - The subsequent lines contain the **coordinates of each city**.

tsp30.txt	
1	30
2	(8, 31)
3	(54, 97)
4	(50, 50)
5	(65, 16)
6	(70, 47)
7	(25, 100)
8	(55, 74)
9	(77, 87)
10	(6, 46)

TSP Problem

- Execution Results (Example using the **First-Choice Algorithm**)

```
Enter the file name of a TSP: problem/tsp30.txt
```

Input the name and path of the .txt file defining the problem (User Input).

Number of cities: 30

City locations:

(8, 31)	(54, 97)	(50, 50)	(65, 16)	(70, 44)
(25, 100)	(55, 74)	(77, 87)	(6, 46)	(70, 78)
(13, 38)	(100, 32)	(26, 35)	(55, 16)	(26, 77)
(17, 67)	(40, 36)	(38, 27)	(33, 2)	(48, 9)
(62, 20)	(17, 92)	(30, 2)	(80, 75)	(32, 26)
(43, 79)	(57, 49)	(18, 24)	(96, 76)	(81, 1)

City starts from index 0...

The last city is City 29

Search algorithm: **First-Choice** Hill Climbing

Max evaluations with no improvement: 100 iterations

Best order of visits:

4	26	2	24	16	27	0	8	10	12
17	18	22	19	3	13	20	29	11	28
23	7	9	6	25	1	14	15	21	5

The Optimal Order of Visits

Minimum tour cost: 491

Total number of evaluations: 677

The Total Distance traveled when following the optimal route.

TSP Problem

- Execution Results (Example using the **Steepest-Ascent Algorithm**)

Enter the file name of a TSP: problem/tsp30.txt

Input the name and path of the .txt file defining the problem (User Input).

Number of cities: 30

City locations:

(8, 31)	(54, 97)	(50, 50)	(65, 16)	(70, 47)
(25, 100)	(55, 74)	(77, 87)	(6, 46)	(70, 78)
(13, 38)	(100, 32)	(26, 35)	(55, 16)	(26, 77)
(17, 67)	(40, 36)	(38, 27)	(33, 2)	(48, 9)
(62, 20)	(17, 92)	(30, 2)	(80, 75)	(32, 36)
(43, 79)	(57, 49)	(18, 24)	(96, 76)	(81, 39)

Search algorithm: Steepest-Ascent Hill Climbing

Best order of visits:

11	29	20	13	3	4	28	23	9	1
7	6	2	16	26	25	21	5	8	12
14	10	0	12	27	24	17	19	18	22

The Optimal Order of Visits

Minimum tour cost: 620

Total number of evaluations: 807

The **Total Distance** traveled when following the optimal route.

Steepest-Ascent Hill Climbing for Numerical Optimization

- **main()**:
 - Creates a problem instance by reading a function expression and its domain information from the file given by the user (`createProblem`)
 - Returns : $p = (\text{expr}, \text{domain})$
 - `expr` : Objective Function
 - `domain` : minimization/maximization
 - Calls the search algorithm (`steepestAscent`) and obtains the results
 - Shows the specifics of the problem just solved (`describeProblem`)
 - Shows the settings of the search algorithm (`displaySettings`)
 - Reports the results (`displayResults`)

Steepest-Ascent Hill Climbing for Numerical Optimization

- **main()**:
 - Creates a problem instance (`createProblem`)
 - Calls the search algorithm (`steepestAscent`) and obtains the results
 - Shows the specifics of the problem just solved (`describeProblem`)
 - Shows the settings of the search algorithm (`displaySettings`)
 - Reports the results (`displayResults`)

```
def main():
    # Create an instance of numerical optimization problem
    p = createProblem()    # 'p': (expr, domain)
    # Call the search algorithm
    solution, minimum = steepestAscent(p)
    # Show the problem and algorithm settings
    describeProblem(p)
    displaySetting()
    # Report results
    displayResult(solution, minimum)
```

Steepest-Ascent Hill Climbing for Numerical Optimization

- **createProblem()**:

- Gets a file name from the user and reads information from the file
 - Function expression – saved as a string **# problem instance**
 - Variable names – saved as a list of strings
 - Lower bounds of the variables – saved as a list of floats
 - Upper bounds of the variables – saved as a list of floats
 - Returns the problem instance as a list of expression and domain, where the domain is a list of the followings :

- Variable names
 - Lower bounds
 - Upper bounds

the problem to be solved

domain

Prints createProblem return value
(=problem instance)

```
# Create an instance of numerical optimization problem
p = createProblem()    # 'p': (expr, domain)
print(p[0], end="")
print(p[1][0])
print(p[1][1])
print(p[1][2])
```

```
Enter the file name of a function: problem/Convex.txt
(x1 - 2) ** 2 + 5 * (x2 - 5) ** 2 + 8 * (x3 + 8) ** 2 + 3 * (x4 + 1) ** 2 + 6 * (x5 -
7) ** 2
['x1', 'x2', 'x3', 'x4', 'x5'] # var
[-30.0, -30.0, -30.0, -30.0, -30.0] # lower
[ 30.0, 30.0, 30.0, 30.0, 30.0] # upper
```

Steepest-Ascent Hill Climbing for Numerical Optimization

- **steepestAscent (p) :**
 - Given a problem `p`, takes a random initial point (`randomInit`) as a current point and evaluates it (`evaluate`)
 - Repeats updating the current point:
 - Generate multiple neighbors (`mutants`)
 - Finds the best one (`bestOf`) among them
 - If it is better than current, update and continue
Otherwise, stop
 - Returns the final current point and its evaluation value

- “neighbor” = Solution adjacent to `current`
- Adjacent solution = Solution obtained by slightly changing current solution

Steepest-Ascent Hill Climbing for Numerical Optimization

- **steepestAscent(p):**

```
def steepestAscent(p):
    current = randomInit(p) # 'current' is a list of values
    valueC = evaluate(current, p)
    while True:
        neighbors = mutants(current, p)
        successor, valueS = bestOf(neighbors, p)
        if valueS >= valueC:
            break
        else:
            current = successor
            valueC = valueS
    return current, valueC
```

Steepest-Ascent Hill Climbing for Numerical Optimization

- **randomInit (p):**
 - Given a problem **p**, returns a point randomly chosen within **p**'s domain

Generates a solution (point) randomly within the range that satisfies the specified minimum and maximum (upper bound) conditions.
- **mutants (current, p):** One of the methods for generating the adjacent (neighboring) successors of **current**
 - Returns $2n$ neighbors of **current** (n : # of variables)
 - i -th variable value **plus DELTA** n number of times
 - i -th variable value **minus DELTA** n number of times
 - Each neighbor is made by copying **current**, choosing an i -th variable of **p**, and then altering its value (**mutate**) by both adding and subtracting DELTA (d)
 - **DELTA** is a named constant representing the step size of axis-parallel mutation

Steepest-Ascent Hill Climbing for Numerical Optimization

- ~ **mutate(current, i, d, p):**
 - Makes a copy of `current`, alter the value of i -th variable by adding `d` as long as the new value remains within the domain of `p`, and returns the resulting mutant

```
def mutate(current, i, d, p): ## Mutate i-th of 'current' if legal
    curCopy = current[:]
    domain = p[1]          # [VarNames, low, up]
    l = domain[1][i]        # Lower bound of i-th
    u = domain[2][i]        # Upper bound of i-th
    if l <= (curCopy[i] + d) <= u:
        curCopy[i] += d
    return curCopy
```

Steepest-Ascent Hill Climbing for Numerical Optimization

- **evaluate(current, p):**
 - Evaluates the expression of problem p after assigning the values of `current` to its variables, and returns the result
 - Global variable `NumEval` is used to count the number of evaluations

```
def evaluate(current, p):  
    ## Evaluate the expression of 'p' after assigning  
    ## the values of 'current' to the variables  
    global NumEval  
  
    NumEval += 1  
    expr = p[0]          # p[0] is function expression  
    varNames = p[1][0]   # p[1] is domain  
    for i in range(len(varNames)):  
        assignment = varNames[i] + '=' + str(current[i])  
        exec(assignment)  
    return eval(expr)
```

Steepest-Ascent Hill Climbing for Numerical Optimization

- **bestOf(neighbors, p):**
 - Evaluates each candidate solution in `neighbors` (`evaluate`), identifies the best one, and returns it with its evaluation value
- **describeProblem(p):**
 - Shows the expression and the domain of problem `p`

```
def describeProblem(p):  
    print()  
    print("Objective function:")  
    print(p[0])    # Expression  
    print("Search space:")  
    varNames = p[1][0] # p[1] is domain: [VarNames, low, up]  
    low = p[1][1]  
    up = p[1][2]  
    for i in range(len(low)):  
        print(" " + varNames[i] + ":", (low[i], up[i]))
```

Steepest-Ascent Hill Climbing for Numerical Optimization

- **displaySetting()**:
 - Shows that the steepest-ascent hill climbing has been used as the search algorithm
 - Displays the step size (**DELTA**) of the axis-parallel mutation

```
def displaySetting():
    print()
    print("Search algorithm: Steepest-Ascent Hill Climbing")
    print()
    print("Mutation step size:", DELTA)
```

```
DELTA = 0.01    # Mutation step size
```

Steepest-Ascent Hill Climbing for Numerical Optimization

- **displayResult(solution, minimum):**
 - Reports the result of optimization, which consists of
 - **solution** (the best solution found),
 - **minimum** (its evaluation value), and
 - the total number of evaluations
 - **solution** is transformed to a tuple (**coordinate**) before printing
- **coordinate(solution):**
 - Rounds up **solution** and returns it (to the third decimal place)

Steepest-Ascent Hill Climbing for Numerical Optimization

- **displayResult(solution, minimum):**
- **coordinate(solution):**

```
def displayResult(solution, minimum):  
    print()  
    print("Solution found:")  
    print(coordinate(solution)) # Convert list to tuple  
    print("Minimum value: {:.3f}".format(minimum))  
    print()  
    print("Total number of evaluations: {}".format(NumEval))  
  
def coordinate(solution):  
    c = [round(value, 3) for value in solution]  
    return tuple(c) # Convert the list to a tuple
```

Steepest-Ascent Hill Climbing for Numerical Optimization

- The program is required to import ‘random.py’ and ‘math.py’

```
import random  
import math
```

First-Choice Hill Climbing for Numerical Optimization

- **main()**:
 - The only difference is that it calls **firstChoice** instead of **steepestAscent**

```
def main():
    # Create an instance of numerical optimization problem
    p = createProblem()    # 'p': (expr, domain)
    # Call the search algorithm
    solution, minimum = firstChoice(p)
    # Show the problem and algorithm settings
    describeProblem(p)
    displaySetting()
    # Report results
    displayResult(solution, minimum)
```

First-Choice Hill Climbing for Numerical Optimization

- **firstChoice (p) :**
 - Only one random successor is generated (**randomMutant**) to update the current solution
 - The algorithm stops if no improvement is observed for a certain consecutive number (**LIMIT_STUCK**) of iterations assuming that the search is stuck at a local minimum
 - **LIMIT_STUCK** is a named constant in this implementation
 - Unlike the method of generating multiple **neighbor soln** and selecting the best among them, only one random neighbor soln is selected.
 - If a worse solution appears consecutively for the number of **LIMIT_STUCK** iterations, the program stops.
 - We assume **LIMIT_STUCK** = 100

First-Choice Hill Climbing for Numerical Optimization

- **firstChoice(p):**

```
def firstChoice(p):  
    current = randomInit(p)    # 'current' is a list of values  
    valueC = evaluate(current, p)  
    i = 0  
    while i < LIMIT_STUCK:  
        successor = randomMutant(current, p)  
        valueS = evaluate(successor, p)  
        if valueS < valueC:  
            current = successor  
            valueC = valueS  
            i = 0                 # Reset stuck counter  
        else:  
            i += 1  
    return current, valueC
```

First-Choice Hill Climbing for Numerical Optimization

- **randomMutant(current, p):**
 - Returns a mutant of `current`, which is made by randomly choosing a variable of `p` and then altering its value (`mutate`) by either adding or subtracting DELTA
 - The **randomMutant** function is implemented by calling the **mutate** function. When doing so, it must decide **which index's stored value to modify** ($d = \text{DELTA} = 0.01$).

```
def mutate(current, i, d, p): ## Mutate i-th of 'current' if legal
    curCopy = current[:]
    domain = p[1]          # [VarNames, low, up]
    l = domain[1][i]        # Lower bound of i-th
    u = domain[2][i]        # Upper bound of i-th
    if l <= (curCopy[i] + d) <= u:
        curCopy[i] += d
    return curCopy
```

First-Choice Hill Climbing for Numerical Optimization

- **displaySetting():**
 - Shows that the search algorithm used is first-choice hill climbing

```
def displaySetting():
    print()
    print("Search algorithm: First-Choice Hill Climbing")
    print()
    print("Mutation step size:", DELTA)
```

- The functions `createProblem`, `randomInit`, `evaluate`, `mutate`, `describeProblem`, `displayResult`, and `coordinate` are all reused without change

Hill Climbing for TSP (외판원 문제)

- For TSP, the structure of the problem and its implementation are **nearly identical** to the **NumericalOptimization** problem
 - However, the logic for generating mutant are different
 - TSP generate the mutant (adjacent solution) using mutate by inversion (refer to the previous lecture)
- inversion : Generating one adjacent solution
 - Reverse the items from index i to index j

```
def inversion(current, i, j): # Perform inversion
    curCopy = current[:]
    while i < j:
        curCopy[i], curCopy[j] = curCopy[j], curCopy[i]
        i += 1
        j -= 1
    return curCopy
```

The **TSP implementation** will be examined in detail in the next lecture.



Hill Climbing for TSP (외판원 문제)

- **First-Choice (TSP)** : generating a single **mutant**

```
def randomMutant(current, p): # Apply inversion
    while True:
        i, j = sorted([random.randrange(p[0])
                      for _ in range(2)])
        if i < j:
            curCopy = inversion(current, i, j)
            break
    return curCopy
```

- Variable **p[0]**: **number of cities, N** (Read from the first line of the defined problem file).
- **random.randrange(N)**: Returns a random integer from $0 \sim N - 1$.
 - When the number of cities is N , each city is identified by a number from **0, 1, ..., N – 1**.
- The process:
 - **Two random numbers are generated and stored in a list, then the list is sorted.** (This ensures that the two values are in order, i.e., $i \leq j$).
 - **If i and j are different ($i < j$), they are treated as valid indices**, and the function calls **inversion(current, i, j)** to generate a single mutant. (The while True: loop continues until two different indices are selected such that $i < j$).

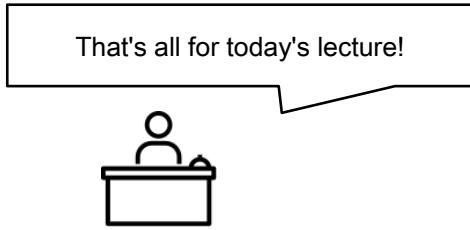
Hill Climbing for TSP (외판원 문제)

- **Steepest-Ascent (TSP)** : Create a number of **mutants**

```
def mutants(current, p): # Apply inversion
    n = p[0]
    neighbors = []
    count = 0
    triedPairs = []
    while count <= n: # Pick two random loci for inversion
        i, j = sorted([random.randrange(n) for _ in range(2)])
        if i < j and [i, j] not in triedPairs:
            triedPairs.append([i, j])
            curCopy = inversion(current, i, j)
            count += 1
            neighbors.append(curCopy)
    return neighbors
```

Code

- Ref :
 - The **code omitted from the lecture materials must be implemented in the homework.**



That's all for today's lecture!