Evolutionary Computation - Assignment 9 Report

- Kajetan Sulwiński 151954
- Mikołaj Marmurowicz 151956

Problem description

Problem

We were to find a cycle that consisted of exactly 50% of the available nodes, where each node had its own cost along with x and y coordinates. The objective function was a sum of node costs and distances (Euclidean) between each traveled node.

Solution implementation

We have added a new method - Hybrid evolutionary algorithm with two different recombination operators.

- **Hybrid evolutionary algorithm**
  - **Input:**
    - `costDistanceInfo` : A symmetric matrix of distances and costs between nodes
    - `popSize` : The size of a population
    - `maxRuntime` : The maximum runtime of the algorithm
    - `recombinationFunction` : A function that combines two parents
    - `useLocalSearchAfterRecombination` : A boolean value determining whether to use local search on children
  - **Output:**
    - An array of new `cycle` node IDs
  - **Function:**

```
FUNCTION generateCycle()
    population = []
    while size(population) < popSize:
    candidate = generateRandomSolution()
    candidate = localSearch(candidate)
    if population does not contain candidate:
        population.add(candidate)
```

```
    population = sortByObjectiveFunction(population)
    timeStart = timeNow()
    currTime = timeNow()
    while currTime - timeStart < maxRuntime:
        parentA, parentB = selectParents(population)
        Child = recombinationFunction(parentA, parentB)
        if useLocalSearchAfterRecombination:
            child = localSearch(child)
        childIndexToInsert = popSize
        addChild = true
        for i from popSize - 1 to 0:
            if objectiveFunction(child) >
objectiveFunction(population[i]):
                Break
            else if objectiveFunction(child) ==
objectiveFunction(population[i]):
                addChild = false # If child has the same evaluation
as a solution in population, skip the child as it is most likely a
duplicate
                Break
            childIndexToInsert = i
        if addChild and childIndexToInsert < popSize:
            population = insertElementAtPosition(population, child,
childIndexToInsert)
            population = removeLastElement(population)
        currTime = timeNow()
    return population[0]
END FUNCTION

FUNCTION recombination1(parentA, parentB)
    commonSubcomponents = findCommonComponentsInCycles(parentA,
parentB)
    commonElements = flatten(commonSubcomponents)
    unusedNodes = []
    for i from 0 to costDIstanceInfo.numberOfNodes():
        If i not in commonElements:
            unusedNodes.add(i)
    shuffle(commonSubcomponents)
    shuffle(unusedNodes)
    gapsSizeTotal = size(parentA) - size(commonElements):
    gapSizes = []
    gapCount = size(commonSubcomponents):
    for i from 0 to gapCount:
        gap = generateRandomIntInRange(0, gapsSizeTotal)
        gapsSizeTotal -= gap
        gapSizes.add(gap)
    gapSizes.add(gapSizeTotal)
    shuffle(gapSizes)
    child = []
    while size(commonSubcomponents) > 0:
        gap = gapSizes.pop()
For i from 0 to gap:
```

```
    nodeIdToAdd = unusedNodes.pop()
    child.add(nodeIdToAdd)
commonComponent = commonSubcomponents.pop()
For nodeId in commonComponent:
    child.add(nodeId)
    gap = gapSizes.pop()
for i from 0 to gap:
nodeIdToAdd = unusedNodes.pop()
    child.add(nodeIdToAdd)
return child
END FUNCTION

FUNCTION recombination2(parentA, parentB)
    commonSubcomponents =  findCommonComponentsInCycles(parentA,
parentB)
    shuffle(commonSubcomponents)
    childPartial = flatten(commonSubcomponents)
    child = generate2RegretGreedyCycle(childPartial)
    return child
END FUNCTION
```

Presenting the results

Results presented as minimum, average and maximum of objective function

Presented in a table below, each method and each problem instance is shown.

Out[25]:

Method	TSPA	TSPB
Evolutionary - Complex Recomb. - LS	70044.63 (69829 - 70257)	44466.32 (44015 - 44784)
Evolutionary - Complex Recomb. - No LS	71707.53 (71654 - 71807)	47066.53 (46314 - 47530)
Evolutionary - Simple Recomb. - LS	70891.79 (70534 - 71264)	45118.74 (44676 - 45466)
Greedy LS (Edges) on 2-Regret Weighted 200 runs	71509.42 (70571 - 72485)	50033.92 (45855 - 54814)
Iterated LS 20 runs	69256.11 (69095 - 69614)	43634.53 (43448 - 44215)
LNS No LS 20 runs	70097.05 (69336 - 71100)	44849.16 (43961 - 47055)
LNS With LS 20 runs	70020.58 (69373 - 71128)	44481.84 (43845 - 45540)
Multiple start LS 20 runs	71250.74 (70684 - 71957)	45795.84 (45108 - 46295)
Steepest LS (Edges) on 2-Regret Weighted 200 runs	71470.14 (70510 - 72614)	49895.7 (45867 - 54814)

Information regarding running time and iterations of main loop of different methods.

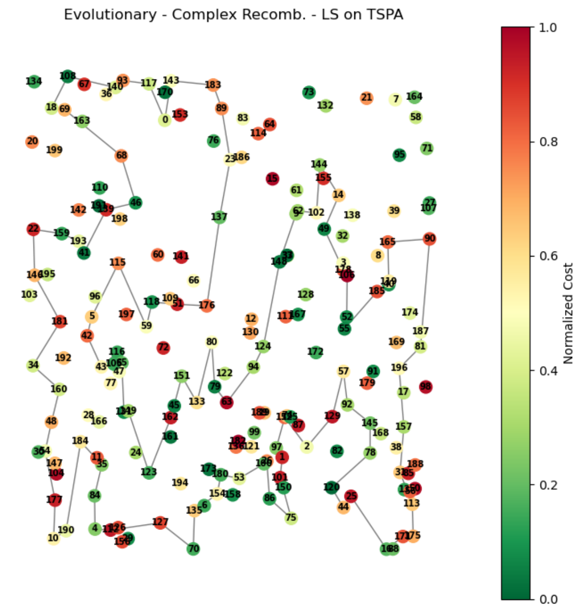
Out[26]:

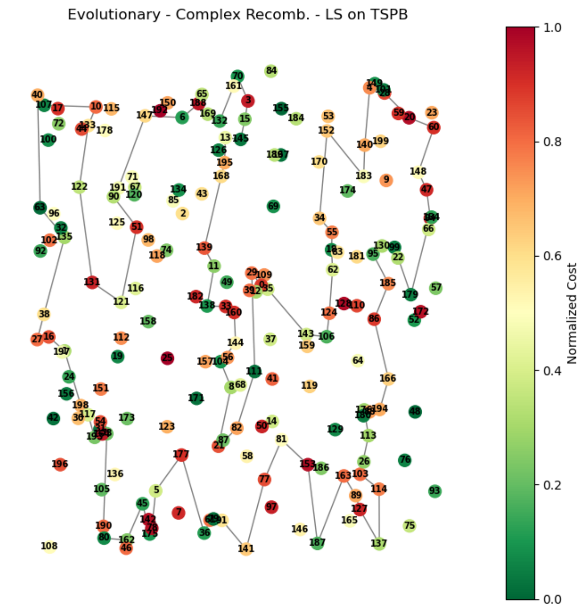
Method	TSPA	TSPB
Evolutionary - Complex Recomb. - LS	173.1 (164 - 188) runs	266.7 (256 - 279) runs
Evolutionary - Complex Recomb. - No LS	2397.2 (2284 - 2536) runs	3043.95 (2898 - 3163) runs
Evolutionary - Simple Recomb. - LS	133.7 (124 - 197) runs	204.35 (201 - 207) runs
Iterated LS	2602.95 (2358 - 2823) runs	2611.65 (2416 - 2886) runs
LNS No LS	4271.3 (4105 - 4412) runs	3747.8 (2524 - 4215) runs
LNS With LS	3460.75 (2903 - 3698) runs	2837.95 (1847 - 3562) runs
Multiple start LS	36404.82 (33524.3 - 38601.8) ms	34441.575 (33030.7 - 38215.2) ms

Visualization of the best path for each method

Additionally, a list of node indices is presented.

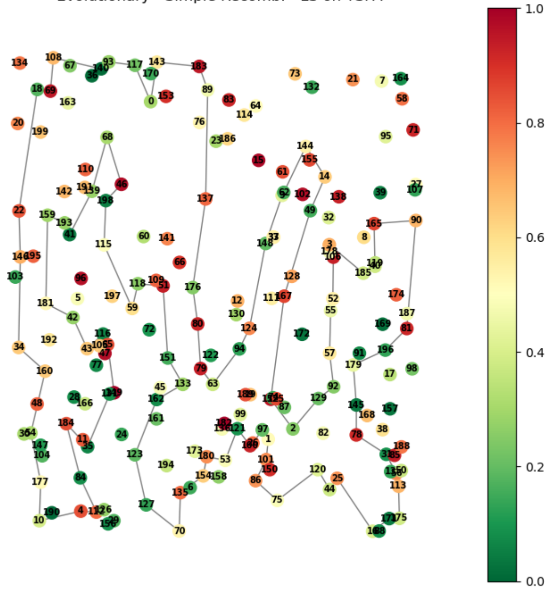
Evolutionary - Complex Recomb. - LS
TSPA
[4, 84, 35, 184, 190, 10, 177, 54, 48, 160, 34, 181, 146, 22, 159, 193, 41, 139, 46,
68, 69, 18, 108, 140, 93, 117, 0, 143, 183, 89, 23, 137, 176, 51, 118, 59, 115, 5, 4
2, 43, 116, 65, 131, 149, 123, 162, 151, 133, 80, 79, 63, 94, 124, 148, 9, 62, 102,
144, 14, 49, 178, 106, 52, 55, 185, 40, 165, 90, 81, 196, 157, 31, 113, 175, 171, 16
, 25, 44, 120, 78, 145, 92, 57, 129, 2, 152, 97, 1, 101, 75, 86, 26, 100, 53, 180, 1
54, 135, 70, 127, 112]
TSPB
[145, 15, 3, 70, 161, 132, 169, 188, 6, 147, 191, 90, 51, 121, 131, 122, 133, 10, 10
7, 40, 63, 135, 38, 27, 16, 1, 198, 117, 193, 31, 54, 73, 190, 80, 162, 45, 175, 78,
5, 177, 36, 61, 91, 141, 77, 81, 153, 187, 163, 89, 127, 137, 114, 103, 113, 176, 19
4, 166, 86, 185, 95, 130, 99, 179, 94, 47, 148, 60, 20, 28, 149, 4, 140, 183, 152, 3
4, 55, 18, 62, 124, 106, 143, 35, 109, 0, 29, 111, 82, 21, 8, 104, 144, 160, 33, 138
, 11, 139, 168, 195, 13]



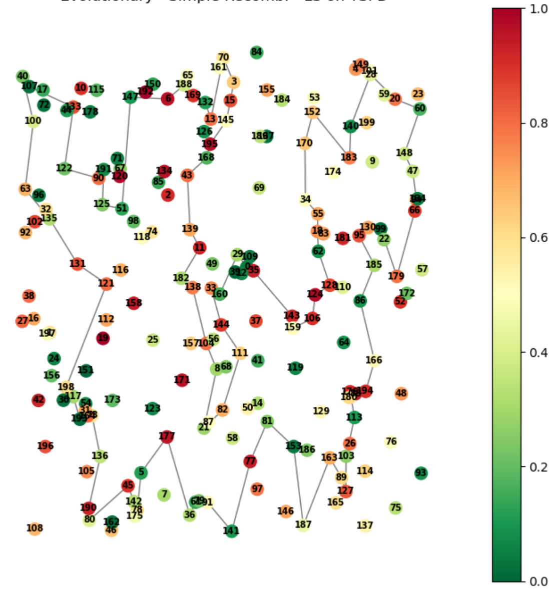


Evolutionary - Simple Recomb. - LS
TSPA
[2, 129, 92, 57, 55, 52, 106, 178, 3, 185, 40, 165, 90, 81, 196, 179, 145, 78, 31, 5
6, 113, 175, 171, 16, 25, 44, 120, 75, 86, 101, 1, 97, 26, 100, 121, 53, 180, 154, 1
35, 70, 127, 123, 162, 133, 151, 51, 118, 59, 115, 198, 46, 68, 139, 41, 193, 159, 1
81, 42, 43, 116, 65, 149, 131, 35, 184, 84, 112, 4, 10, 177, 54, 160, 34, 146, 22, 1
8, 69, 108, 140, 93, 117, 0, 143, 183, 89, 137, 176, 80, 79, 63, 94, 124, 148, 9, 62
, 144, 14, 49, 167, 152]
TSPB
[153, 81, 77, 141, 91, 61, 36, 177, 5, 78, 175, 142, 45, 80, 190, 136, 73, 164, 54,
31, 193, 117, 198, 121, 131, 135, 63, 100, 40, 107, 133, 122, 90, 191, 125, 51, 147,
6, 188, 169, 132, 13, 70, 3, 15, 145, 195, 168, 43, 139, 11, 182, 138, 104, 8, 21, 8
2, 111, 144, 33, 160, 29, 0, 109, 35, 143, 159, 106, 124, 128, 62, 18, 55, 34, 170,
152, 183, 140, 28, 20, 60, 148, 47, 94, 66, 179, 99, 130, 95, 185, 86, 166, 194, 176
, 113, 103, 127, 89, 163, 187]

Evolutionary - Simple Recomb. - LS on TSPA

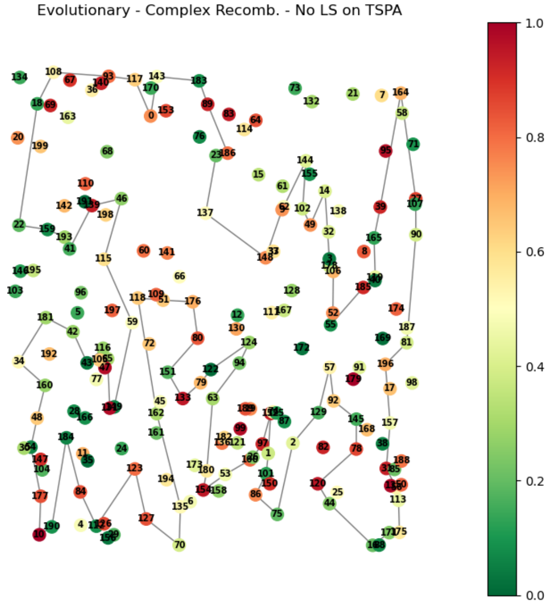


Evolutionary - Simple Recomb. - LS on TSPB

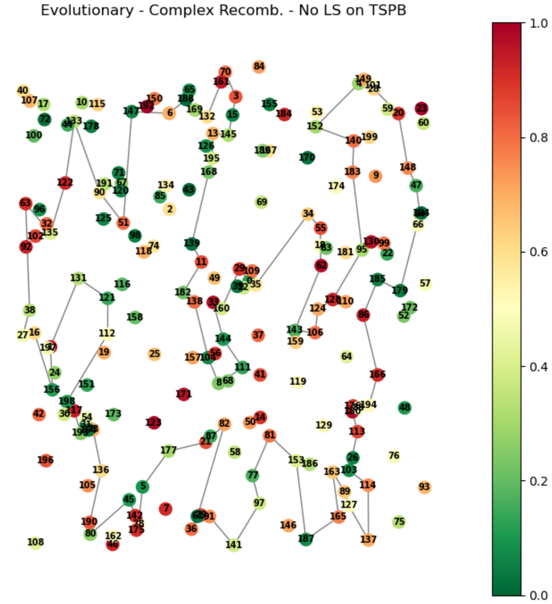



```
Evolutionary - Complex Recomb. - No LS
TSPA
[44, 16, 171, 175, 113, 56, 31, 157, 196, 81, 90, 27, 164, 39, 165, 119, 40, 185, 55
, 52, 106, 178, 3, 14, 49, 102, 144, 62, 9, 148, 137, 23, 186, 89, 183, 143, 0, 117,
93, 108, 18, 22, 159, 193, 41, 139, 46, 115, 59, 149, 131, 65, 116, 43, 42, 181, 34,
160, 48, 54, 177, 10, 190, 184, 84, 112, 123, 127, 70, 135, 162, 118, 51, 176, 80, 1
51, 133, 79, 122, 124, 94, 63, 180, 154, 53, 100, 26, 97, 152, 1, 101, 86, 75, 2, 12
9, 57, 92, 145, 78, 120]
TSPB
[31, 193, 117, 198, 112, 121, 131, 1, 156, 16, 27, 38, 63, 135, 122, 133, 90, 51, 14
7, 6, 188, 169, 132, 70, 3, 145, 13, 195, 168, 139, 11, 182, 138, 104, 8, 111, 144,
33, 160, 29, 0, 109, 35, 34, 55, 18, 62, 143, 106, 124, 128, 95, 183, 140, 152, 4, 1
49, 28, 20, 148, 47, 94, 179, 185, 86, 166, 194, 176, 180, 113, 103, 114, 137, 127,
89, 163, 165, 187, 153, 81, 77, 97, 141, 91, 79, 36, 61, 82, 21, 177, 5, 78, 175, 14
2, 45, 80, 190, 136, 73, 54]
```

Evolutionary - Complex Recomb. - No LS on TSPA



Evolutionary - Complex Recomb. - No LS on TSPB



Additional Information

Solution checker

We have checked all of the best solutions via the solution checker provided.

Source code link

The source code is available in a repository here under the Lab9 folder.

Conclusions

The results of the evolutionary methods highlight the significant impact of both recombination complexity and the use of local search (LS). Complex Recombination with LS outperforms every other evolutionary configuration in terms of the objective function value. Additionally, it is able to outperform the number of iterations of Simple Recombinations with LS. That is because of the LS's ability to refine solutions after initial recombination, effectively exploiting local optima. In contrast, Complex Recombination without LS shows drastically higher number of iterations and broader ranges of objective value function, as not using LS leaves the method reliant solely on recombination, which is slower and less precise. Simple Recombination with LS objective function value results ten to be slightly worse to Complex Recombination with LS, as the recombination operator lack the depth to explore solution space thouroughly. When compared to methods like Iterated LS or LNS, evolutionary methods excel in smaller problem instances due to their efficient population-based exploration, though they face more runtime challenges in larger instances, highlighting that recombination complexity and LS integration are critical to their performance.

Authors

- Kajetan Sulwiński 151954
- Mikołaj Marmurowicz 151956