Université libre de Bruxelles École Polytechnique de Bruxelles M-IRIFS



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Linear ordering problem

IMPLEMENTATION EXERCISE 1

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Abstract

In this study, we report the results of using iterative improvement algorithms and variable neighbourhood descent algorithms in C++ to solve the linear ordering problem (LOP) for various instances. We used iterative improvement algorithms with various pivoting rules (first and best improvement), neighbourhoods (transpose, exchange, and insert) and initial solutions (random permutation and the Chenery-Watanabe heuristic). We also employed a two-variable neighbourhood descent method, with a first improvement and two neighborhood orders (transpose, exchange, then insert and transpose, insert, then exchange). To evaluate the performance of each algorithm combination across all instances, statistical analysis is performed using metrics such as average percentage deviation from the best-known solutions and total computation time. Statistical tests such as the Student t-test and Wilcoxon test are also employed to assess wheter there is statistically significant difference between the solutions generated by each algorithm combination.

Keywords: linear ordering problem, iterative improvement, variable neighbourhood descent, Chenery-Watanabe heuristic, Student t-test, Wilcoxon test, C++.

1 Introduction

The goal of this first implementation exercise was to implement iterative improvement algorithms (Exercise 1.1) and variable neighborhood descent algorithms (Exercise 1.2) with different rules (initial solutions, neighbourhood and pivoting) to solve the linear ordering problem. A set of instances with sizes 150 and 250, accompanied by corresponding best-known solutions were given for this exercise and served as test cases for the implemented algorithms. To evaluate the performance of each algorithm, we computed statistics such as average percentage deviation and computation time for all instances and employed statistical analysis using Student-t test and Wilcoxon test to determine if there were significant differences between the solutions.

The paper is organized as follows: Section 2 describe the linear ordering problem, Section 3 explain the data used the algorithms, Section 4 interpret the results obtained and Section 5 is the conclusion.

1.1 Structure

The file tree below contains a short description of the implementation directories:

```
linear-ordering-problem
   best_known - best-known scores for each instance
   doc - report
   instances - instances of size 150 and 250
   references - articles
   src
     rules - rules like inital solutions, neighbourhood and pivoting
     configuration.cpp
     instance.cpp
     main.cpp
   statistics
     experiments - relative deviations for each algorithm for each instance
     reports - average deviation for each algorithm for all instances
     statistical_tests - Student-t test and Wilcoxon test
   Makefile
   statistical_tests.r
  statistics.sh
```

2 Problem description

2.1 Linear ordering problem (LOP)

The Linear Ordering Problem (LOP) is a combinatorial optimization challenge focused on arranging a set of items in a specific linear order to optimize a given objective function. In this problem, the task is to find a permutation of elements from a given set such that certain criteria are optimized.

Mathematically, the LOP can be defined as follows: Given an $n \times n$ matrix C, the objective is to find a permutation π of indices from 1 to n that maximizes the sum of elements in the upper triangle of C. This objective function is represented as:

$$f(\pi) = \sum_{i=1}^{n} \sum_{j=i+1}^{n} c_{\pi_i \pi_j} \tag{1}$$

where $c_{\pi_i\pi_j}$ denotes the element of the matrix C located at row π_i and column π_j after the permutation π has been applied. [1]

The Linear Ordering Problem has significant applications across various disciplines. In economics, it assists in the triangularization of input-output matrices, facilitating efficient resource allocation. In sociology, it aids in understanding social hierarchies and preferences. Moreover, in graph theory, linear orderings are crucial for representing partial orders and scheduling tasks. Additionally, in archaeology, the problem finds utility in establishing chronological sequences, as evidenced by the application of the Harris Matrix. [2]

3 Material and methods

3.1 Data

The data used in this study consists of instances provided by the teacher. These instances vary in size between 150 and 250. These can be found in the folder ./instances/.

3.2 Algorithms

For the implementation of algorithms, various combinations were considered:

- Iterative Improvement (II) algorithms:
 - Initial solutions: random permutation and Chenery-Watanabe heuristic
 - Neighborhoods: transpose, exchange, and insert
 - First improvement and best improvement pivoting rules
- Variable Neighborhood Descent (VND) algorithms:
 - Chenery-Watanabe heuristic
 - Neighborhood orderings: transpose-exchange-insert and transpose-insert-exchange
 - Applied only to first improvement iterative algorithms

This results in 12 algorithms for iterative improvement and 2 for variable neighbourhood descent algorithms so 14 in total. The implementations of each rule can be found in ./src/rules/ and each algorithm in ./src/algorithm.cpp.

4 Results

The results from exercise 1.1 and exercise 1.2 are merged for convenience. A bash script (./statistics.sh) was used to save the differents results in the folder ./statistics/.

4.1 Statistics

For each combination algorithm, the average deviation (in %) and total computation time (in second) is calculated on all instances. The Table 1 summarise all the 12 combinations of II algorithms for exercise 1.1 and also all the 2 combinations VND algorithms for exercise 1.2.

4.1.1 Average percentage deviations and total computation time

The transpose neighbourhood has the best computation times, but the worst solutions (highest average percentage deviation). The exchange neighbourhood provides the best solutions but with high computation time.

Configuration	Average deviation	Total computation time				
ii_cw_exchange_best	4.394455	3247.509990				
ii_cw_exchange_first	30.963442	1.370133				
ii_cw_insert_best	13.742654	260.923158				
ii_cw_insert_first	30.985910	1.294789				
ii_cw_transpose_best	30.109363	15.094090				
ii_cw_transpose_first	30.977256	1.273179				
ii_random_exchange_best	3.624083	3852.671460				
ii_random_exchange_first	35.407036	0.053327				
ii_random_insert_best	14.067337	257.784736				
ii_random_insert_first	35.416426	0.074736				
ii_random_transpose_best	34.225995	19.884247				
ii_random_transpose_first	35.417441	0.051101				
vnd_cw_transpose-exchange-insert_first	30.924140	1.414506				
vnd_cw_transpose-insert-exchange_first	30.892497	1.418386				

Table 1: Average deviation (in %) and total computation time (in second) for each configuration

4.2 Statistical tests

These statistical tests use a statement called the null hypothesis which in this case is: "the median of the differences between results in two experiments is zero". We fix the significance level α to 0.05. If the computed p-value is below α , the null hypothesis is rejected which in this case means that there is a significant difference between experiments. An R script (./statistical_tests.r) was written in order to apply these tests to all possible pairs of experiments. The output was saved in the ./statistics/statistical_tests/.

Since there is no space to display the tables, here is the mapping for rows and columns

- \bullet V1 \rightarrow ii_cw_exchange_best
- $V2 \rightarrow ii_cw_exchange_first$
- $V3 \rightarrow ii_cw_insert_best$
- $V4 \rightarrow \text{ii_cw_insert_first}$
- $V5 \rightarrow \text{ii_cw_transpose_best}$

- $\bullet~V6
 ightarrow { iny ii_cw_transpose_first}$
- $V7 \rightarrow ii_random_exchange_best$
- $V8 \rightarrow \text{ii_random_exchange_first}$
- $V9 \rightarrow ii_random_insert_best$
- $V10 \rightarrow ii_random_insert_first$
- ullet V11 ightarrow ii_random_transpose_best
- $V12 \rightarrow ii_random_transpose_first$
- $V13 \rightarrow vnd_cw_transpose-exchange-insert_first$
- $V14 \rightarrow vnd_cw_transpose_insert_exchange_first$

4.2.1 Student-t test and Wilcoxon test

The random and Chenery-Watanabe initial solutions have statically different qualities for all combinations. The random initial solution is preferable because it gives a lesser deviation compared to Chenery-Watanabe (V3-V9).

All neighborhoods have statically different qualities. The table 1 shows that the exchange neighborhood give the better solutions. It is weird because insert neighborhood should give better solutions since it has a larger neighbourhood. Last is transpose giving the less good results.

The first and best pivoting rules have statically different qualities. Best is giving always better results except for transpose.

V14	5.3e-72	0.000148	6.94e-59	4.59e-06	1.07e-27	6.34e-07	8.26e-73	5.51e-15	3.75e-59	5.02e-15	3.23e-10	4.98e-15	0.05	0
V13	5.21e-72	0.000122	7.82e-59	0.000144	1.86e-31	5.56e-06	7.97e-73	5.17e-15	3.1e-59	4.7e-15	3.31e-10	4.67e-15	0	0
V12	1.73e-67	7.59e-15	6.84e-54	1.04e-14	1.47e-18	9.05e-15	3.77e-68	0.00898	1.2e-53	0.123	5.88e-32	0	0	0
V11		5.29e-10	1.71e-52	7.21e-10	7.31e-14	6.24e-10	4.36e-67	5.16e-32	4.6e-52	6.7e-32	0	0	0	0
V10	1.74e-67	7.65e-15	6.9e-54	1.05e-14	1.48e-18	9.12e-15	3.81e-68	0.0128	1.21e-53	0	0	0	0	0
6/	7.4e-68	3.38e-59	0.0186	3.58e-59	2.22e-57	3.13e-59	6.64e-72	1.25e-53	0	0	0	0	0	0
8/	1.8e-67	8.4e-15	7.08e-54	1.15e-14	1.62e-18	1e-14	3.93e-68	0	0	0	0	0	0	0
77	8.63e-11	8.52e-73	1.57e-74	1.01e-72	1.24e-71	7.73e-73	0	0	0	0	0	0	0	0
9/	4.94e-72	0.0464	7.53e-59	0.46	8.44e-33	0	0	0	0	0	0	0	0	0
V5	8.75e-71	9.33e-32	4.65e-57	9.15e-31	0	0	0	0	0	0	0	0	0	0
V4	6.8e-72	0.0246	1.05e-58	0	0	0	0	0	0	0	0	0	0	0
V3	1.3e-73	8.79e-59	0	0	0	0	0	0	0	0	0	0	0	0
V2	5.69e-72	0	0	0	0	0	0	0	0	0	0	0	0	0
V1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		2	က	4	ಬ	9	7	∞	6	10	11	12	13	14

Table 2: Student-t statistical test

V14	1.72e-14	1.08e-09	1.72e-14	1.71e-14	2e-14	1.71e-14	1.72e-14	3.57e-14	1.72e-14	3.57e-14	2.1e-12	3.57e-14	0.000594	0
V13	1.72e-14	9.6e-14	1.72e-14	1.85e-14	1.72e-14	1.72e-14	1.72e-14	3.86e-14	1.72e-14	3.86e-14	2.42e-12	3.86e-14	0	0
V12	1.72e-14	4.16e-14	1.72e-14	4.33e-14	1.78e-14	4.49e-14	1.72e-14	0.409	1.72e-14	0.00334	1.72e-14	0	0	0
V11	1.72e-14	3.7e-12	1.72e-14	5.08e-12	6.58e-14	4.26e-12	1.72e-14	1.72e-14	1.72e-14	1.72e-14	0	0	0	0
V10	1.72e-14	4.16e-14	1.72e-14	4.33e-14	1.78e-14	4.49e-14	1.72e-14	0.0638	1.72e-14	0	0	0	0	0
6/	1.72e-14	1.72e-14	0.0571	1.72e-14	1.72e-14	1.72e-14	1.72e-14	1.72e-14	0	0	0	0	0	0
8/	1.72e-14	4.16e-14	1.72e-14	4.33e-14	1.78e-14	4.49e-14	1.72e-14	0	0	0	0	0	0	0
77	2.14e-09	1.72e-14	1.72e-14	1.72e-14	1.72e-14	1.72e-14	0	0	0	0	0	0	0	0
9/	1.72e-14	0.248	1.72e-14	0.117	1.72e-14	0	0	0	0	0	0	0	0	0
	l			1.72e-14		0	0	0	0	0	0	0	0	0
V4	1.72e-14	0.0389	1.72e-14	0	0	0	0	0	0	0	0	0	0	0
V3	1.72e-14	1.72e-14	0	0	0	0	0	0	0	0	0	0	0	0
V2	, ,	0	0	0	0	0	0	0	0	0	0	0	0	0
V1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		2	က	4	ഹ	9	7	∞	6	10	11	12	13	14

Table 3: Wilcoxon statistical test

5 Conclusion

For each combinaison of algorithm, we implementede successfully and obtained results for each algorithm.

References

- [1] The Linear Ordering Problem: Instances, Search Space Analysis and Algorithms, Tommaso Schiavinotto & Thomas Stützle
- [2] Stochastic Local Search Foundations and Applications, Elsevier, 2004, Holger H. Hoos & Thomas Stützle