Implementation exercises for the course Heuristic Optimization

Dr. Manuel López-Ibáñez manuel.lopez-ibanez@ulb.ac.be

IRIDIA, CoDE, ULB

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Implement iterative local search algorithms for the SMTWTP

- The Single Machine Total Weighted Tardiness Problem
- First-improvement and Best-Improvement Iterative Local Search
- Transpose, exchange and insert neighborhoods
- Random initialization vs. Earliest due date heuristic
- Statistical Empirical Analysis

The Single Machine Total Weighted Tardiness Problem

Given

- Single machine, continuously available
- n jobs, for each job j is given its processing time p_j, its due date d_j and its importance w_j

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The Single Machine Total Weighted Tardiness Problem (SMTWTP)

- Completion time of job j: C_j (when it finished)
- Tardiness: $T_j = \max\{C_j d_j, 0\}$ (how late after it should)
- Find a permutation π of the jobs that minimizes the sum of the weighted tardiness:

$$\min_{\pi \in \Phi^n} F(\pi) = \sum_{i=1}^n w_{\pi_i} \cdot T_{\pi_i}$$

Implement 12 iterative improvements algorithms for the SMTWTP

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 - first-improvement
 - best-improvement
- Neighborhood:
 - Transpose
 - Exchange
 - Insert
- Initial solution:
 - Random permutation
 - Earliest due date heuristic

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- Pivoting rule:
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- 2 pivoting rules \times 3 neighborhoods \times 2 initialization methods = **12 combinations**

Implement 12 iterative improvements algorithms for the SMTWTP

Don't implement 12 programs!

Reuse code and use command-line parameters

```
smptwtp-ii --first --transpose --earliest-due-date
smptwtp-ii --best --exchange --random-init
...
```

Iterative Improvement

```
\pi := \text{GenerateInitialSolution} \ ()
while \pi is not a local optimum do
choose a neighbour \pi' \in \mathcal{N}(\pi) such that F(\pi') < F(\pi)
\pi := \pi'
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Which neighbour to choose? Pivoting rule

Best Improvement: choose best from all neighbours of s

 First improvement: evaluate neighbours in fixed order and choose first improving neighbour.

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 - Better quality
 - Requires evaluation of all neighbours in each step
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Which neighbour to choose? Pivoting rule

- Best Improvement: choose best from all neighbours of s
 - Better quality
 - Requires evaluation of all neighbours in each step
- First improvement: evaluate neighbours in fixed order and choose first improving neighbour.
 - More efficient
 - Order of evaluation may impact quality / performance

Iterative Improvement

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Initial solution

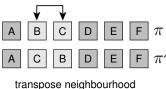
- Random permutation
- Earliest due date heuristic (sort jobs by increasing due date)

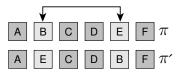
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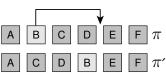
Which neighborhood $\mathcal{N}(\pi)$?

- Transpose
- Exchange
- Insertion

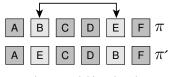




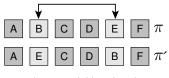
exchange neighbourhood



insert neighbourhood



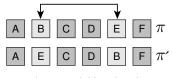
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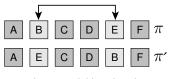
Example: Exchange π_i and π_j (i < j), $\pi' = \text{Exchange}(\pi, i, j)$

• k < i: Same C_{π_k} , same T_{π_k}



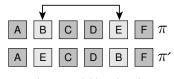
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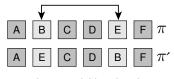
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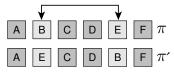


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Only jobs between i and j are affected! Equivalent speed-ups with Transpose and Insertion

Instances

- 125 SMTWTP instances in a single file: wt100.txt
- More info: http://iridia.ulb.ac.be/~stuetzle/Teaching/HO/

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Experiments

Apply each algorithm k once to each instance i and compute:

- Relative percentage deviation $\Delta_{ki} = 100 \cdot \frac{\text{cost}_{ki} \text{best-known}_i}{\text{best-known}_i}$
- 2 Computation time (t_{ki})

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Report for each algorithm *k*

- Average relative percentage deviation
- Sum of computation time

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Statistical test

- Paired t-test
- Wilcoxon signed-rank test

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Background: Statistical hypothesis tests (1)

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 - *Example:* For the Wilcoxon signed-rank test, the null hypothesis is that 'the median of the differences is zero'.

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- The *significance level* (α) determines the maximum allowable probability of incorrectly rejecting the null hypothesis. Typical values of α are 0.05 or 0.01.

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Background: Statistical hypothesis tests (2)

 The application of a test to a given data set results in a p-value, which represents the probability that the null hypothesis is incorrectly rejected.

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- The application of a test to a given data set results in a p-value, which represents the probability that the null hypothesis is incorrectly rejected.
- The null hypothesis is rejected iff this p-value is smaller than the previously chosen significance level.
- Most common statistical hypothesis tests are already implemented in statistical software such as the R software environment (http://www.r-project.org/).

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t.test (a.cost, b.cost, paired=T)$p.value
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t.test (a.cost, b.cost, paired=T)$p.value
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wilcox.test (a.cost, b.cost, paired=T)$p.value
[1] 0.0019212</pre>
```

Implement 8 VND algorithms for the SMTWTP

- Type:
 - standard VND
 - piped VND
- Pivoting rule: first-improvement
- Neighborhood order:
 - \bullet transpose \rightarrow exchange \rightarrow insert
 - 2 transpose \rightarrow insert \rightarrow exchange
- Initial solution:
 - Random permutation
 - Earliest due date heuristic

Variable Neighbourhood Descent (VND)

```
k neighborhoods \mathcal{N}_1, \ldots, \mathcal{N}_k
\pi := GenerateInitialSolution()
i := 1
repeat
   choose the first improving neighbor \pi' \in \mathcal{N}_i(\pi)
   if \nexists \pi' then
      i := i + 1
   else
      \pi := \pi'
      i := 1
until i > k
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```

Piped VND

- Simply chain different II algorithms one after the other
- Use final solution of one II as initial solution of the next

Implement 8 VND algorithms for the SMTWTP

- Instances: Same as 1.1
- Experiments: one run of each algorithm per instance
- Report: Same as 1.1
- Statistical tests: Same as 1.1