Exercise 1 Delivery: Constructive Analysis

Fellipe Pessanha

September 5, 2025

1 Exercise Description

The task in hand was to implement solution constructors for the specified software dependency problem, in specific a *random constructor*, *randomized greedy constructor*, and a *greedy constructor*, then perform a statistical analysis of their performance.

2 Implementation Details

The implementation was carried out using **Julia**. The implementation steps involved

1. Parsing the input data to extract problem context
2. Implement a prototype evaluator in order to assess solution quality
3. Write tests that make sure each step is working as expected

The best way to understand the code structure is to check the repository's test suite at `./test/runtest.jl`

2.1 Constructive implementation

The randomized greedy constructive was implemented using a combination of a max heap H – keeping track of all the available packages sorted by their *benefit* – and a vector V – used to store all the n best evaluated packages by the same criterion, guaranteeing optimal $O(N \cdot log(\#H))$, where N is the number of packages selected packages, and $\#H$ is the mean number of packages available in the unused heap throughout the execution.

The size of the vector is determined by the parameter $\alpha \in [0, 1]$, and the random constructive was simply implemented by setting $\alpha = 1$, and the greedy constructive by setting $\alpha = 0$.

3 Analysis Methodology

The analysis was performed for 30 equidistant values of $\alpha \in [0, 1]$.

In each step, 30 independent runs were performed for each constructor, and captured the average solution quality, standard deviation, and execution time, evaluated with Julia's BenchmarkTools package, which accounts for garbage collection, precompilation time, and other Julia specific nuances.

4 Results

The results of the analysis, normalized in % values, can be seen in Figure 1.

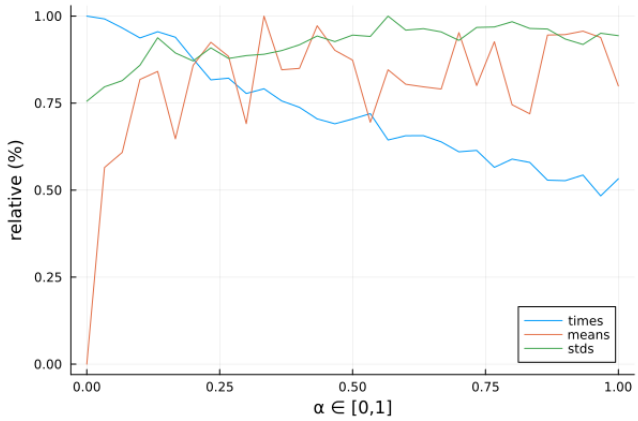

Figure 1: mean solution quality, standar deviation, and time elapsed by α

In it, we can see the impact of the parameter α on the solution quality – which is higher but less diverse – in the lower¡0.05 ranges. As α increases, solution quality and standard deviation plateaus, and the time elapsed decreases in a manner that can be interpreted as linear logarithmic, as the algorithm complexity suggested previously.

5 Conclusion

With the results in hand, we can conclude that very low values of α have the benefit of providing extremely consistent, high value solutions, which can be useful in certain scenarios but, whenever solution diversity is required, values of $\alpha \in [0.75, 1]$ should be prefereed, as they will be slightly more performant, while still maintaining a similar mean solution quality and standard deviation.