

Knapsack experiment Full Report: Team Sleepless

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Introduction

In this set of experiments, we explore the performance of a simple genetic algorithm and compare it to the performance of the basic hill-climber algorithm. Our algorithm is essentially an expanded version of hill-climber that works on an entire population instead of on individuals. The hill-climber starts with a randomly generated answer, and then repeatedly mutates the best answer found so far, keeping the better of the original and the tweaked answer at each step. Our method was to create a population of random instances, creating our first generation, and then mutate that generation to create our second generation. We then combined the two generations, sorted them, and took the better half of the individuals. We repeat this process on each successive population until we find the ideal solution or until we reach the maximum number of tries. Our algorithm is much slower than the hill-climber algorithm in running time because it's running on populations instead of on individuals.

For both algorithms, we used the lexi-score method to score our instances. Lexi-score is a method Nic McPhee created *MORE INFO HERE ABOUT HOW LEXI SCORE WORKS!*

We used McPhee's mutation method as well *WE CAN EITHER TAKE HIS DESCRIPTION AND CREDIT HIM OR REFERENCE HIS PAPER SOMEHOW*

Experimental setup

We initially started with a `max-tries` value of 1000 for the 3 different types of knapsack problems:

- `knapPI_11_20_1000_4`
- `knapPI_13_20_1000_4`
- `knapPI_16_20_1000_4`
- `knapPI_11_200_1000_4`
- `knapPI_13_200_1000_4`
- `knapPI_16_200_1000_4`

Half of these are 20 item problems, and half are 200 item problems. We did 5 independent runs of each treatment on each problem.

As we progressed, we switched to focusing on instances of the type `knapsackPI_16` variety. We utilized five of the twenty item instances:

- `knapPI_16_20_1000_1`
- `knapPI_16_20_1000_2`
- `knapPI_16_20_1000_3`
- `knapPI_16_20_1000_4`
- `knapPI_16_20_1000_5`

and later we used five of the thousand item instances:

- `knapPI_16_1000_1000_1`

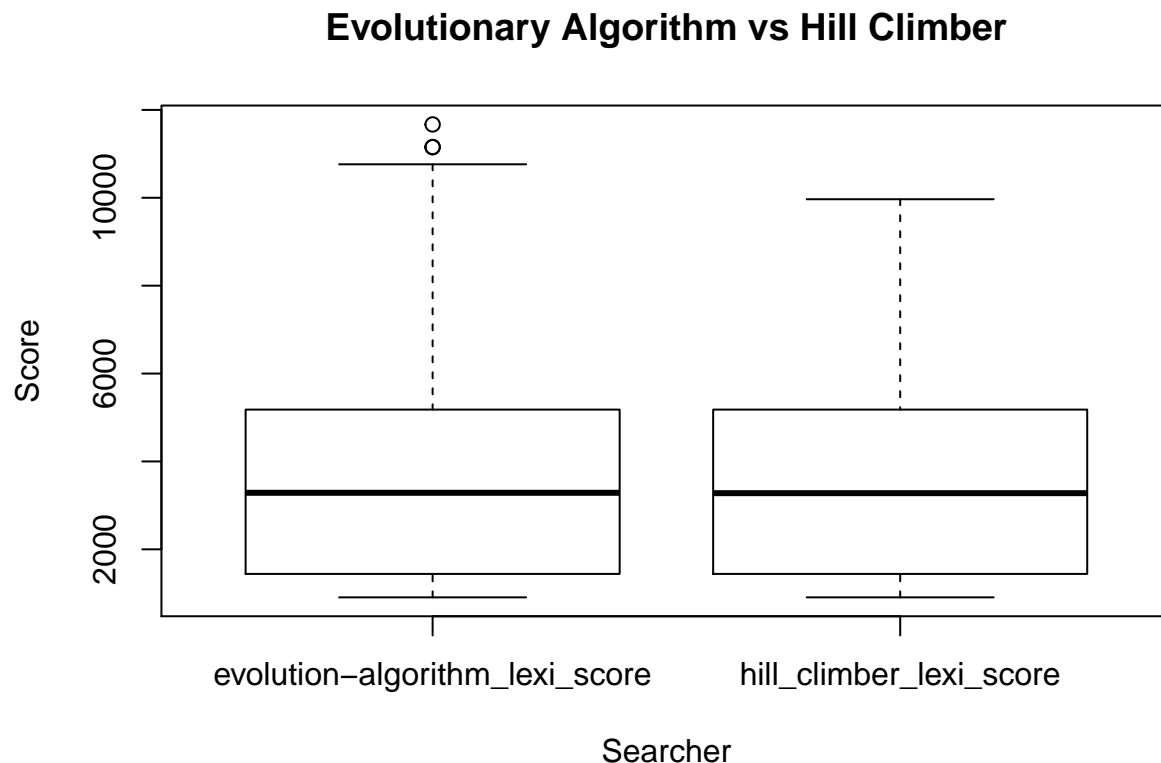
- knapPI_16_1000_1000_2
- knapPI_16_1000_1000_3
- knapPI_16_1000_1000_4
- knapPI_16_1000_1000_5

We increased the `max-tries` value to 10000 for these in order to see if there was a definite difference in the two algorithms. We ran this data 1000 times to make sure we had consistent data. *NOT SURE WHAT WE SHOULD SAY ABOUT THIS, BUT WE SHOULD MENTION HOW MANY RUNS WE DID AND WHAT IT CHANGED/HOW IT HELPED*

Results

A comparison of our searcher to basic hill-climber

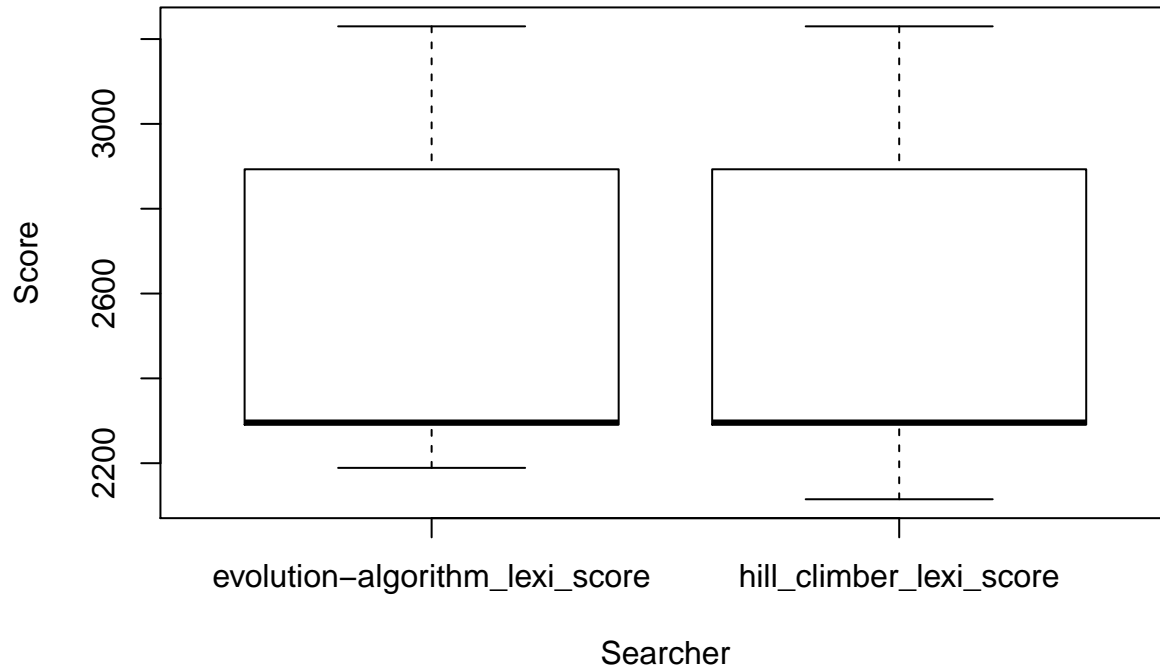
In our first graph, we show the comparison of our evolutionary algorithm to the basic hill-climber algorithm on the 3 different types of knapsack problem instances:



Here we can see that the algorithms mostly performed the same, but our evolutionary algorithm had a few outliers that were better than the hill-climber. Looking into this further, we discovered that our data performed the same on the knapsack problems 11 and 13, but our algorithm outperformed hill-climber on problem 16. This is where our few outliers came from on our graph.

Investigating this further, we generated data solely for instances of problem 16. Here, we plot the results of 1000 runs with 10000 `max-tries` on five of the 20 item problems:

Knapsack 16: Twenty-Item Problems



It is difficult to see any difference between the two, as they have similar performance. Here is a summary:

Hill Climber

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2115	2291	2296	2576	2893	3230

Evolutionary Algorithm

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2189	2291	2296	2580	2893	3230

Pairwise comparisons using Wilcoxon rank sum test

data: twenty_item\$Score and twenty_item\$Search_method

```

          evolution-algorithm_lexi_score
hill_climber_lexi_score 0.2

```

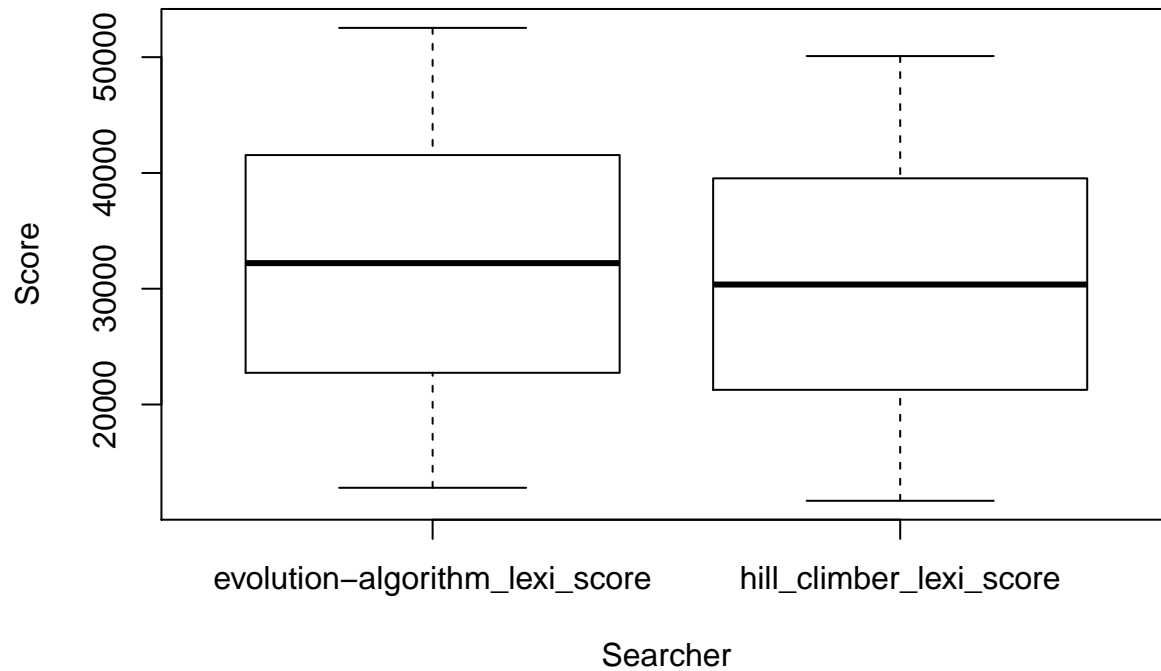
P value adjustment method: holm

In this case, our algorithm is *not* statistically significantly different. We received a p value of 0.2. We think that we received such a high p-value because of our number of max-tries; we must have found the absolute max (or close to it) with both algorithms, meaning neither algorithm could outperform the other because they both found the best possible result.

We decided to investigate this a little further by running the search-methods on some of the problem 16 instances with 1000 items. This meant we would most likely not reach the absolute max because we had more complex problems which would mean we could see if our algorithm was reaching higher than hill-climber consistently or if they truly were about the same and not statistically significant.

Here we plot the results of 50 runs with 10000 max-tries on five of the 1000 item problems:

Knapsack problem 16: Thousand-Item Problems



The graph shows that, overall, we are performing slightly better than hill-climber. A summary of our results:

Hill Climber

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
11680	21270	30360	30370	39530	50090

Evolutionary Algorithm

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
12810	22740	32210	32250	41540	52530

We are clearly performing better, *but are we finding a difference that is statistical significant?* Below we run a wilcoxon-test to see if our p value has improved:

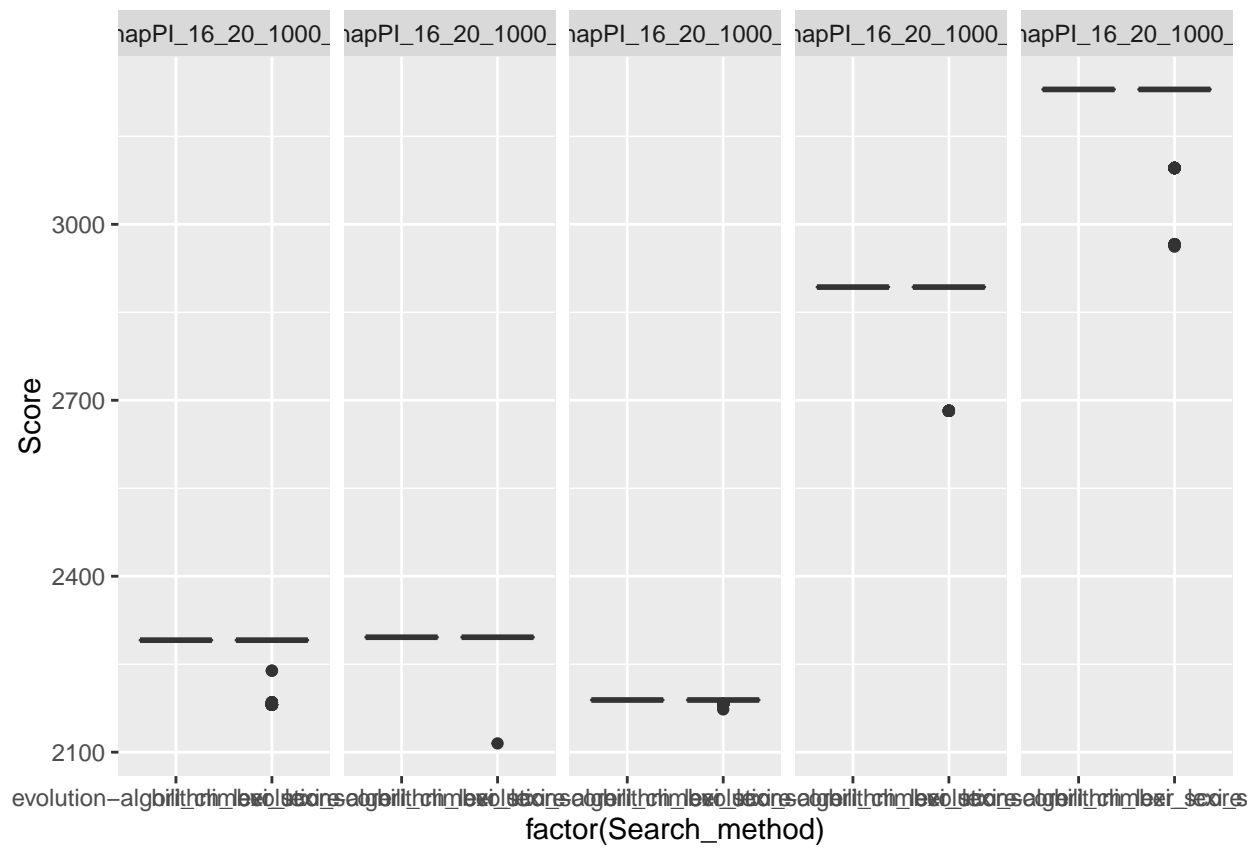
Pairwise comparisons using Wilcoxon rank sum test

```
data: thousand_item$Score and thousand_item$Search_method
```

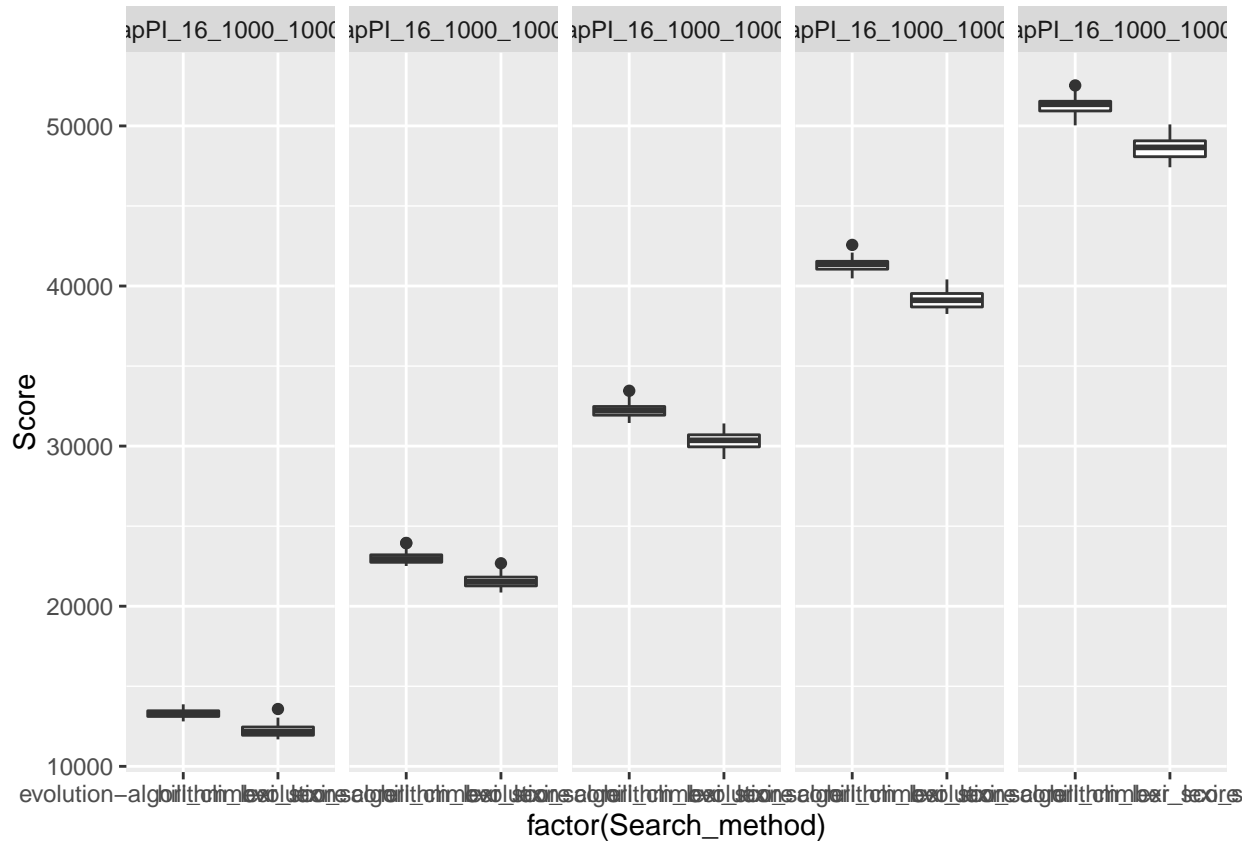
```
evolution-algorithm_lexi_score
hill_climber_lexi_score 0.00013
```

P value adjustment method: holm

Our p-value is 1.3^{-4} which is less than the desired 0.05 p-value. We can conclude there is a mildly significant difference between the two algorithms. Here is a comparison of score for each search method for the 1000 runs of the twenty item instances:



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How do things change by max evals?

When we do not reach the absolute max of a problem, we can see a significant difference in data between our evolutionary algorithm and the hill-climber algorithm. This means that if we cut down on max evals, we will likely see an increase in the statistical significance between the search-methods. This is because the evolutionary algorithm reaches a better score slightly faster because it explores more optima than hill-climber. Sometimes hill-climber can also get stuck, and our algorithm is better here because having a population of individuals allows us to explore more local optima in the hopes of finding the absolute maximum.

Conclusions

Our algorithm runs much slower than the hill-climber algorithm. This is because we are essentially running hill-climber on an entire population instead of on a single individual. However, our evolutionary algorithm is slightly better than hill-climber in that it can achieve higher scores with the same inputs. If both algorithms reach the absolute maximum of a problem, we will not see a statistically significant difference in our data because we are only checking the highest score at the end of the runs. Despite this, our algorithm will outperform hill-climber in all cases and this is easiest to see in the complex problems where finding the absolute maximum is much more difficult. For improvements to our experiment, we should run everything again with fewer max evals to see if we can find when our algorithm reaches the absolute maximum compared to when hill-climber reaches the absolute maximum.