

## Atividade Prática 2 - Algoritmos de Busca

- Fazer um comparativo entre os algoritmos Simulated Annealing e Hill Climbing para as bases P01 a P07;
- Desenvolver a função de aptidão knapsack no Mlrose;
- Apresentar a melhor solução encontrada por cada algoritmo e comparar com a melhor solução global disponível para a base de dados;
- Enviar os arquivos \*.ipynb e uma versão pdf do código fonte.

Responsável: Marcos Angelo Cemim

```

1 from urllib.request import urlopen
2 import numpy as np
3 import six
4 import sys
5 sys.modules['sklearn.externals.six'] = six
6 import mlrose
7 import time
8 import warnings
9 warnings.filterwarnings("ignore")

1 #Iterates over 7 bases
2 for _ in range(1,8):
3
4     base = f'p0{__}'
5     # Assign values of current base to variables
6     c = int(urlopen(f'https://people.sc.fsu.edu/~jburkardt/datasets/knapsack_01/{base}_c.txt').read().decode('utf-8').split())
7     w = [int(x) for x in urlopen(f'https://people.sc.fsu.edu/~jburkardt/datasets/knapsack_01/{base}_w.txt').read().decode('utf-8').split()]
8     p = [int(x) for x in urlopen(f'https://people.sc.fsu.edu/~jburkardt/datasets/knapsack_01/{base}_p.txt').read().decode('utf-8').split()]
9     s = [int(x) for x in urlopen(f'https://people.sc.fsu.edu/~jburkardt/datasets/knapsack_01/{base}_s.txt').read().decode('utf-8').split()]
10
11     # Print to check mistakes
12     # print(f'{"*" * 15} Base: {base} {"*" * 15}')
13     # print(f'Capacity: {c}')
14     # print(f'Weight: {w}')
15     # print(f'Profit: {p}')
16     # print(f'Optimal Selection: {s}')
17
18     # Define fitness function (total profit = solution_array * profit_array) . If total weight > capacity, penalizes returnin
19     def fn_fitness(solution):
20         if sum(np.multiply(solution, w).tolist()) <= c:
21             return sum(np.multiply(solution, p).tolist())
22         else:
23             return 1
24
25     # Assign fitness function to mlrose format
26     fitness = mlrose.CustomFitness(fn_fitness)
27
28     # Define problem
29     problema = mlrose.DiscreteOpt(length = len(s), fitness_fn = fitness,
30                                 maximize = True, max_val = 2)
31
32     # Run "Hill Climb" algorithm
33     start_time_hc = time.time()
34     best_fit_hc = 0
35     len_curve_hc = 0
36     while best_fit_hc < sum(np.multiply(s, p).tolist()):
37         solution_hc, best_fit_hc, curve_hc = mlrose.hill_climb(problema, restarts=10, curve=True)
38         len_curve_hc += len(curve_hc)
39     end_time_hc = time.time()
40
41     # Run "Simulated Annealing" algorithm
42     start_time_sa = time.time()
43     best_fit_sa = 0
44     len_curve_sa = 0
45     while best_fit_sa < sum(np.multiply(s, p).tolist()):
46         solution_sa, best_fit_sa, curve_sa = mlrose.simulated_annealing(problema, max_attempts=10, curve=True)
47         len_curve_sa += len(curve_sa)
48     end_time_sa = time.time()
49
50     # Results
51     print(f' Base P0{__} '.center(98, '*'))
52     print(f'{"Algorithm":20s | {"Solutions Tried":15s} | {"Fitness Value":13s} | {"Optimal Fitness":15s} | {"Time (ms)":9s}'
53           f'{"-" * 20} | {"-" * 15} | {"-" * 13} | {"-" * 15} | {"-" * 9} | {"-" * 10}')
54     print(f'{"Hill Climb":20s} | {len_curve_hc:15d} | {best_fit_hc:13.0f} | {sum(np.multiply(s, p).tolist()):15.0f} | {1000 *
55           f'{"Simulated Annealing":20s} | {len_curve_sa:15d} | {best_fit_sa:13.0f} | {sum(np.multiply(s, p).tolist()):15.0f}

```

```
56 print()
57
58
59
```

***** Base P01 *****					
Algorithm	Solutions Tried	Fitness Value	Optimal Fitness	Time (ms)	Array Size
-----	-----	-----	-----	-----	-----
Hill Climb	11	309	309	1.9975	10
Simulated Annealing	275	309	309	4.1316	10
***** Base P02 *****					
Algorithm	Solutions Tried	Fitness Value	Optimal Fitness	Time (ms)	Array Size
-----	-----	-----	-----	-----	-----
Hill Climb	6	51	51	0.0000	5
Simulated Annealing	52	51	51	0.9990	5
***** Base P03 *****					
Algorithm	Solutions Tried	Fitness Value	Optimal Fitness	Time (ms)	Array Size
-----	-----	-----	-----	-----	-----
Hill Climb	7	150	150	1.0014	6
Simulated Annealing	84	150	150	0.9973	6
***** Base P04 *****					
Algorithm	Solutions Tried	Fitness Value	Optimal Fitness	Time (ms)	Array Size
-----	-----	-----	-----	-----	-----
Hill Climb	17	107	107	1.9982	7
Simulated Annealing	649	107	107	8.5533	7
***** Base P05 *****					
Algorithm	Solutions Tried	Fitness Value	Optimal Fitness	Time (ms)	Array Size
-----	-----	-----	-----	-----	-----
Hill Climb	60	900	900	5.0151	8
Simulated Annealing	273	900	900	4.0448	8
***** Base P06 *****					
Algorithm	Solutions Tried	Fitness Value	Optimal Fitness	Time (ms)	Array Size
-----	-----	-----	-----	-----	-----
Hill Climb	20	1735	1735	3.1841	7
Simulated Annealing	205	1735	1735	2.5451	7
***** Base P07 *****					
Algorithm	Solutions Tried	Fitness Value	Optimal Fitness	Time (ms)	Array Size
-----	-----	-----	-----	-----	-----
Hill Climb	1761	1458	1458	561.2063	15
Simulated Annealing	14519	1458	1458	196.5473	15

Conclusion:

De forma geral, o algoritmo Hill Climb leva vantagem com relação ao número de iterações até encontrar a solução ótima, porém perde quando medimos o tempo necessário para atingir tal ponto. Em arrays maiores, essa diferença fica ainda maior. Esse tempo pode (e deve) ser ajustado em função dos parâmetros dos modelos (restarts / max\_attempts) para cada aplicação.