

Evolutionary Computation

Software Implementation of Metaheuristics:

Genetic Algorithms
Simulated Annealing
Particle Swarm Optimization



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Knapsack Problem

Knapsack is a combinatorial search space problem defined as follows:

- Given a list of items each containing a '*value*' & a '*weight*'
- We can only take a certain amount of items, limited by the total *weight* of the items selected; thus we have a maximum *Capacity* that cannot be exceeded (the maximum what of fulling a knapsack).
- We wish to take a combination of items that *Maximizes* the *Total Value* of the selected items (items in the knapsack).

Whilst seemingly simplistic, the knapsack problem becomes very difficult as the number of items balloons: as the number of combinations grows exponentially as a function of the number of items.

The given Knapsack contains 150 items. Each item can either be

- Selected: 1
- Not Selected: 0

Resulting in:

$$2^{150} = 1.4272477e + 45$$

Permutations.

Consequently randomly search (trying all possibly combinations) is infeasible & would take millions of years to compute. We thus rely on intelligent search algorithms to attempt many possible combinations in a sophisticated way to find an elegant solution.

Though Knapsack is a toy problem, one can easily imagine how this algorithm could be applied to ANY combinatoric search space (& in fact is generalizable to any complex search domain).

Specifications

The given knapsack:

Combinatorial space: $2^{150} = 1427247692705960000000000000000000000000000000000$

Maximum capacity: 822

Maximum iterations: 10'000

Best known optimum: 997

The same problem is solved by 3 algorithms: Genetic Algorithms (GA), Simulated Annealing (SA) & Particle Swarm Optimization (PSO). Full algorithm descriptions are available on the [GitHub repository](#).

Genetic Algorithm (GA)

This GA implementation includes: one-point crossover (1PX); two-point crossover (2PX); roulette-wheel selection (RWS); tournament selection (TS); bit-flip mutation (BFM); exchange mutation (EXM); inverse mutation (IVM); insertion mutation (ISM); displacement mutation (DPM).

Algorithm sudo code (full description available on the [git repository](#)):

Algorithm 3.2.1: Pseudocode for the Genetic Algorithm.

Input: $Population_{size}$, $Problem_{size}$, $P_{crossover}$, $P_{mutation}$

Output: S_{best}

```

1 Population  $\leftarrow$  InitializePopulation( $Population_{size}$ ,
  Problem $_{size}$ );

```

```
2 EvaluatePopulation(Population);
```

3 $S_{best} \leftarrow \text{GetBestSolution}(\text{Population});$

```
4 while  $\neg$ StopCondition() do
```

```
5 | Parents ← SelectParents(Population,  $Population_{size}$ );
```

6	Children $\leftarrow \emptyset$;
---	-----------------------------------

7 **foreach** $Parent_1, Parent_2 \in \text{Parents}$ **do**8 $Child_1, Child_2 \leftarrow \text{Crossover}(Parent_1, Parent_2, P_{crossover});$ 9 Children \leftarrow Mutate($Child_1$, $P_{mutation}$);

10	Children \leftarrow Mutate($Child_2$, $P_{mutation}$);
----	---

11	end
----	-----

12	EvaluatePopulation(Children);
----	-------------------------------

```

13  $S_{best} \leftarrow \text{GetBestSolution}(\text{Children});$ 

```

14 Population \leftarrow Replace(Population, Children);

15 end

16 return S_{best} ;

Simulated Annealing (SA)

Algorithm sudo code (full description available on the [git repository](#)):

Algorithm 4.2.1: Pseudocode for Simulated Annealing.

Input: ProblemSize, $iterations_{max}$, $temp_{max}$
Output: S_{best}

```
1  $S_{current} \leftarrow \text{CreateInitialSolution}(\text{ProblemSize});$ 
2  $S_{best} \leftarrow S_{current};$ 
3 for  $i = 1$  to  $iterations_{max}$  do
4    $S_i \leftarrow \text{CreateNeighborSolution}(S_{current});$ 
5    $temp_{curr} \leftarrow \text{CalculateTemperature}(i, temp_{max});$ 
6   if  $\text{Cost}(S_i) \leq \text{Cost}(S_{current})$  then
7      $S_{current} \leftarrow S_i;$ 
8     if  $\text{Cost}(S_i) \leq \text{Cost}(S_{best})$  then
9        $S_{best} \leftarrow S_i;$ 
10    end
11  else if  $\text{Exp}(\frac{\text{Cost}(S_{current}) - \text{Cost}(S_i)}{temp_{curr}}) > \text{Rand}()$  then
12     $S_{current} \leftarrow S_i;$ 
13  end
14 end
15 return  $S_{best};$ 
```

Particle Swarm Optimization (PSO)

Algorithm sudo code (full description available on the [git repository](#)):

Algorithm 6.2.1: Pseudocode for PSO.

Input: ProblemSize, $Population_{size}$
Output: P_{g_best}

```
1  $\text{Population} \leftarrow \emptyset;$ 
2  $P_{g\_best} \leftarrow \emptyset;$ 
3 for  $i = 1$  to  $Population_{size}$  do
4    $P_{velocity} \leftarrow \text{RandomVelocity}();$ 
5    $P_{position} \leftarrow \text{RandomPosition}(Population_{size});$ 
6    $P_{cost} \leftarrow \text{Cost}(P_{position});$ 
7    $P_{p\_best} \leftarrow P_{position};$ 
8   if  $P_{cost} \leq P_{g\_best}$  then
9      $P_{g\_best} \leftarrow P_{p\_best};$ 
10  end
11 end
12 while  $\neg \text{StopCondition}()$  do
13   foreach  $P \in \text{Population}$  do
14      $P_{velocity} \leftarrow \text{UpdateVelocity}(P_{velocity}, P_{g\_best}, P_{p\_best});$ 
15      $P_{position} \leftarrow \text{UpdatePosition}(P_{position}, P_{velocity});$ 
16      $P_{cost} \leftarrow \text{Cost}(P_{position});$ 
17     if  $P_{cost} \leq P_{p\_best}$  then
18        $P_{p\_best} \leftarrow P_{position};$ 
19       if  $P_{cost} \leq P_{g\_best}$  then
20          $P_{g\_best} \leftarrow P_{p\_best};$ 
21       end
22     end
23   end
24 end
25 return  $P_{g\_best};$ 
```

Results

The full implementation & results are available at [GitHub](#)

Each algorithm was run for a varied spectrum of hyper parameters (defining changes in basic behaviour like the cooling rate of SA or the number of particles in a swarm in PSO).

Performance of each specification was measured by ‘*squality*’ or ‘*Solution Quality*’ P which compares the best learnt solution for a given algorithm (maximum value of the knapsack) with best known solution of 997 - computed by random search on a super-computer. Squality gives the best performance as percentage of 997.

Given the limited computational power, an $squality \geq 0.8$ would be considered successful, however all algorithms exceeded this benchmark, with GA & PSO maxing out at $squality > 1$ (meaning better than the best known solution).

Summary reports of highest performing configurations of each algorithm are below:

```
Evaluation | 2020-04-22 13:37
Configuration: ga_default_25.json
GA | #10000 | TS | 2PX (0.003) | EXM (0.7)

=====
weight value squality genotype
0 881 670 0.672016 [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, ...
1 881 670 0.672016 [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, ...
2 881 670 0.672016 [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, ...
3 884 714 0.716148 [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
4 884 714 0.716148 [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
...
9995 820 1046 1.049147 [0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, ...
9996 820 1046 1.049147 [0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, ...
9997 820 1046 1.049147 [0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, ...
9998 820 1046 1.049147 [0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, ...
9999 820 1046 1.049147 [0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, ...

[10000 rows x 4 columns]

[Statistics]
Runtime 890840.5028 ms
Convergence
weight value squality
2500 799 972 0.974925
5000 822 NaN NaN
7500 819 1041 1.044132
10000 820 1046 1.049147
Plateau
Longest sequence, 30-9999 with improvement less average 3%
Best Run
index: 9395
weight: 820
value: 1046
squality: 1.0491474423269809
genotype: 0000000101...
```

```
Evaluation | 2020-04-24 17:11
Configuration: pso_def[mut_15].json
PSO | #1000 | inertia=0.85 | n particles=100 | c1=0.6 | c2=0.5

=====
weight value squality genotype
0 816 625 0.639713 [0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, ...
1 817 429 0.439699 [0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, ...
2 888 686 0.702149 [0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, ...
3 787 457 0.477994 [0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, ...
4 790 421 0.438911 [0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, ...
...
995 818 1067 1.092119 [0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, ...
996 799 554 0.557042 [0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, ...
997 822 1063 1.088025 [0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, ...
998 111 163 0.165837 [0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, ...
999 798 559 0.572160 [0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, ...

[1000 rows x 4 columns]

[Statistics]
Runtime 1953839.2534 ms
Convergence
weight value squality
250 819 985 1.008108
500 813 507 0.518936
750 798 608 0.622313
1000 798 559 0.572160
Plateau
Longest sequence, 566-995 with improvement less average 3%
Best Run
index: 995
weight: 818
value: 1067
squality: 1.0921107308085978
genotype: 0000000101...
```

```
Evaluation | 2020-04-23 14:00
Configuration: sa_default_01.json
SA | #39609 | Initial Temp:10000 | Cooling Rate:0.5

=====
weight value squality genotype
0 802 555 0.568066 [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
1 818 536 0.548618 [0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, ...
2 791 543 0.553703 [0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, ...
3 820 483 0.494371 [0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, ...
4 809 519 0.531218 [0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
...
39604 804 545 0.557830 [0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, ...
39605 806 491 0.502550 [1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, ...
39606 811 522 0.534209 [0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, ...
39607 803 559 0.572160 [1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, ...
39608 790 552 0.564995 [0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, ...

[39609 rows x 4 columns]

[Statistics]
Runtime 914755.7757 ms
Convergence
weight value squality
9902 798 531 0.543501
10804 795 452 0.462641
29706 807 490 0.501535
39609 790 552 0.564995
Plateau
Longest sequence, 8857-39608 with improvement less average 3%
Best Run
index: 8857
weight: 810
value: 826
squality: 0.8454452405322416
genotype: 0000001001...
```

These truly remarkable algorithms are capable of effective search in inconceivably sparse high dimensional spaces. Note, whilst these applications are applied to discrete problem the same techniques are readily applied to continuous search spaces with minor re-specifications (simple genotype encoding, phenotype encoding & fitness evaluation updates). Thus applications may be extended to any domain that can be mapped to a theoretical mathematical function.

Fin.

