Introduction to Artificial Intelligence – Laboratory 1

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1 Source code

1.1 Task generator

```python
def generate_task(n, w, s, output_file):
    max_wi = floor(10 * w / n)
    max_si = floor(10 * s / n)
    w_sum = 0
    s_sum = 0

    while w_sum <= 2 * w or s_sum <= 2 * s:
        w_arr = []
        s_arr = []
        c_arr = []
        w_sum = 0
        s_sum = 0
        for i in range(n):
            wi = randint(1, max_wi)
            w_sum += wi
            w_arr.append(wi)

            si = randint(1, max_si)
            s_sum += si
            s_arr.append(si)

            c_arr.append(randint(1, n - 1))
    with open(output_file, 'w') as f:
        f.write(f'{n},{w},{s}\n')
        for i in range(n):
            f.write(f'{w_arr[i]},{s_arr[i]},{c_arr[i]}\n')
```

In the beginning, the function calculates the maximum weight and size for a single item. After that, it randomly chooses parameters for each item. The while loop repeats that process until the given criteria are met. My observations show that in almost all cases the requirements are satisfied after the first iteration. Finally, results are being written to the given file in the desired format.

1.2 Item class

```python
class Item:
    def __init__(self, w, s, c):
        self.w = w
        self.s = s
        self.c = c
```

Item class consists of a simple constructor, that saves informations about items weight, size and cost.

1.3 Task class

```python
class Task:
    def __init__(self, n, w, s):
        self.n = n
        self.w = w
        self.s = s
        self.items = []

    def push_item(self, item):
        self.items.append(item)
```

Task class consists of a simple constructor, that saves informations about the number if items, maximum weight and size. In addition, it initializes an empty list designed for storing items. The class has a *push_item* method, that simplifies the insertion of items.

1.4 Task loading

```python
def read_task(input_file):
    with open(input_file, 'r') as f:
        n, w, s = f.readline().split(',')
        task = Task(int(n), int(w), int(s))
        for line in f:
            w, s, c = line.split(',')
            item = Item(int(w), int(s), int(c))
            task.push_item(item)
    return task
```

The task is loaded from a csv file. The first line contains informations about the number of items, the maximum weight and size. There are saved in an object of the Task class. The rest of the lines represents items and theirs parameters. The data are stored as the objects of the Item class and pushed to the task object. All the numbers are converted to integers.

1.5 Population class

1.5.1 Constructor

```
class Population:
    def __init__(self, indivs=None):
        if not indivs:
            self.population = None
            self.pop_size = 0
        else:
            self.population = np.array(indivs)
            self.pop_size = self.population.shape[0]
```

The constructor uses a parameter *indivs* to pass a list of individuals. That list is converted into NumPy array (NumPy is a powerful package for scientific computing with Python). If no individuals are provided, an empty population is created.

1.5.2 Get individual by id method

```
def get_by_idx(self, index):
    return self.population[index]
```

This method simplifies the process of obtaining the desired individual

1.5.3 Generate random population method

```
def generate_rand_pop(self, pop_size, genes_num):
    self.pop_size = pop_size
    pop_temp = []
    for i in range(pop_size):
        pop_temp.append([randint(0, 4) // 4 for _ in range(genes_num)])
    self.population = np.array(pop_temp)
```

This method generates a *pop_size* number of individuals, each having *genes_num* genes. Genes informs which items are present in the knapsack. A gene can be either 0 (item absent) or 1 (item present). There is 80% chance to get 0 and 20% to get 1.

1.5.4 Fitness method

```
def calc_fitness(self, task):
    fitness_temp = []

    values = np.array([t.c for t in task.items])
    weights = np.array([t.w for t in task.items])
    sizes = np.array([t.s for t in task.items])

    sum_weights = self.population @ np.transpose(weights)
    sum_sizes = self.population @ np.transpose(sizes)
    sum_values = self.population @ np.transpose(values)

    for i in range(self.pop_size):
        if sum_sizes[i] > task.s or sum_weights[i] > task.w:
            fitness_temp.append([0])
        else:
            fitness_temp.append([sum_values[i]])

    self.fitness_arr = np.array(fitness_temp)
```

At the beginning I split the items stored in the task object into three arrays representing values, weights and sizes. Then I do matrix multiplication, as a result of which I get three vectors informing about the total value, weight and size of items in the knapsack for each individual. Thanks to NumPy package, such calculations are carried out faster than other methods using loops. The fitness values for individuals meeting the task conditions are equal to the sum of the values of the items in their knapsacks. Individuals that exceed the maximum values have zeroed values. Results are assigned to the population objects, so that the tournament function will not be forced to repeat the calculations during each invocation.

1.5.5 Get the best individual method

```
def best(self):
    return self.population[self.fitness_arr.argmax()], self.fitness_arr.max(initial=0)
```

This method returns the best individual and his fitness value.

1.6 Tournament Function

```
def tournament(population, tourn_size):
    indexes = np.random.randint(population.pop_size, size=tourn_size)
    fitness_arr = list(map(lambda idx: population.fitness_arr[idx], indexes))
    best_idx = indexes[np.argmax(fitness_arr)]
    return population.get_by_idx(best_idx)
```

This function selects a random slice from the population, retrieves fitness values for that subset and returns the best individual.

1.7 Crossover Function

```
def crossover(parent1, parent2, probab):
    if randint(0, 1) / 100 > probab:
        return parent1
    cutting_point = len(parent1) // 3
    return list(parent1[:cutting_point]) + list(parent2[cutting_point:])
```

In the beginning a real number from the range [0, 1] is drawn. If that number is bigger than the given probability, no crossover occurs and the first parent is returned. Otherwise, a child is formed from clippings from both parents.

1.8 Mutation Function

```
def mutate(genes, rate):
    genes_num = len(genes)
    to_mutate_num = floor(genes_num * rate)
    to_mutate = np.random.randint(genes_num, size=to_mutate_num)
    for gene_idx in to_mutate:
        genes[gene_idx] = int(not genes[gene_idx])
```

The function selects random genes from an individual and converts their values to the opposite. Modification is done in place, so there is not need to return anything.

1.9 Knapsack Function

```python
def knapsack(task, POP_SIZE=1000, TOURN_SIZE=200, CROSS_RATE=0.5, MUT_RATE=0.001, ITERATIONS=250):
    scores_per_gen = []

    pop = Population()
    pop.generate_rand_pop(POP_SIZE, task.n)
    i = 1
    while i < ITERATIONS:
        pop.calc_fitness(task)
        _, best_fit = pop.best()
        scores_per_gen.append(best_fit)
        print('Generation:', i, ', fitness:', best_fit)

        new_pop = []
        j = 0
        while j < POP_SIZE:
            parent1 = tournament(pop, TOURN_SIZE)
            parent2 = tournament(pop, TOURN_SIZE)
            child = crossover(parent1, parent2, CROSS_RATE)
            mutate(child, MUT_RATE)
            new_pop.append(child)
            j += 1
        pop = Population(new_pop)
        i += 1

    pop.calc_fitness(task)
    best, best_fit = pop.best()
    scores_per_gen.append(best_fit)
    print('Generation:', i, ', fitness:', best_fit)
    return best, np.array(scores_per_gen)
```

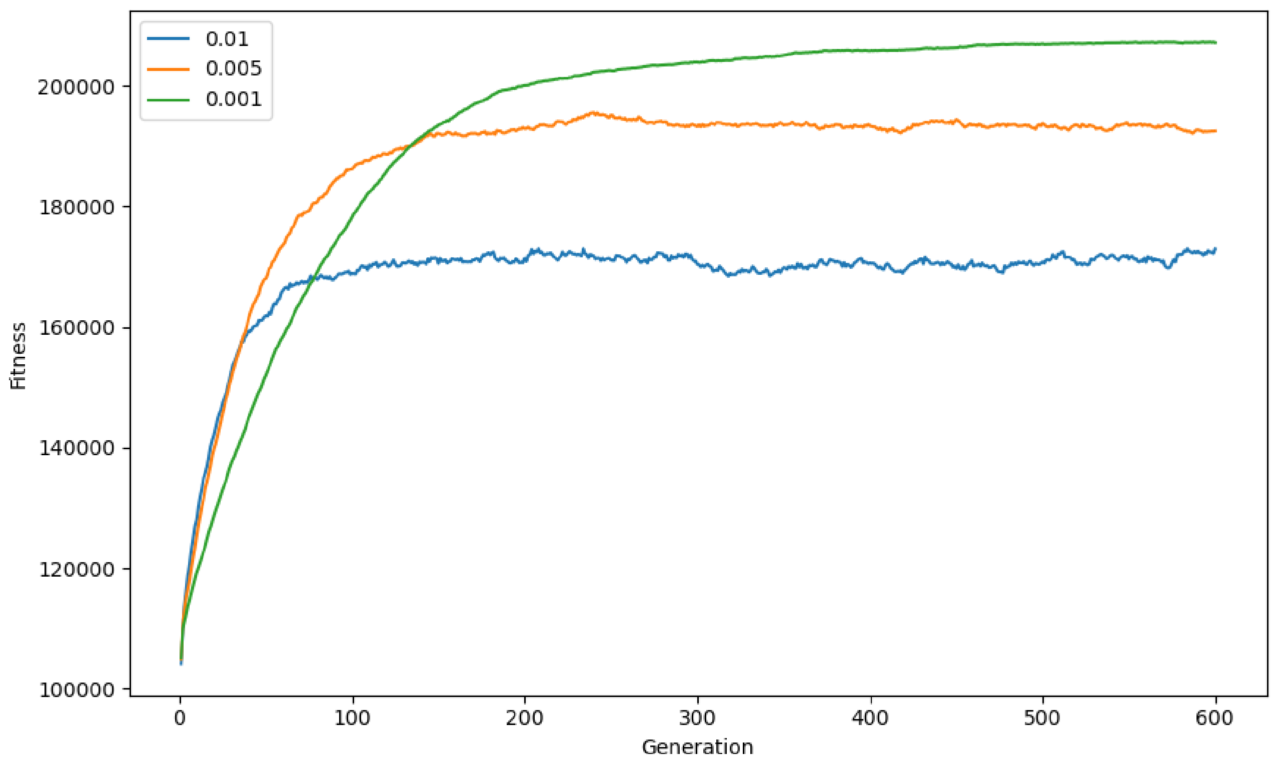
This function combines the others to find the best solution for the given knapsack problem. First, a random population is initiated. The creation of new generations will be carried out until the final condition is met. In this case the goal is to reach the given number of iterations. Two parents are selected using the tournament function. They are combined using the crossover function. A newly created child is mutated and stored in a new population. The best fitness value for each iteration is stored in the *scored_per_gen* list. The function returns the best individual from the last generation and the array *scored_per_gen*.

2 Analysis of the impact of the parameters

The following default parameters were used:

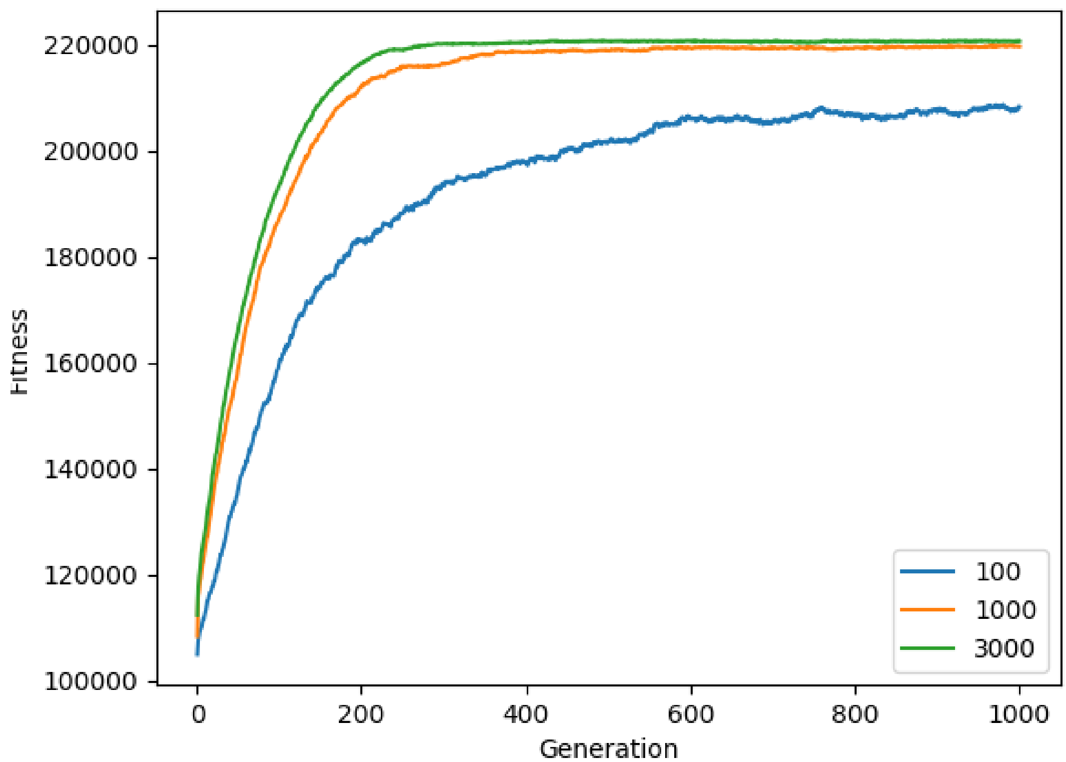
- Population size = 1000
- Tournament size = 200
- Crossover probability = 0.5
- Mutation rate = 0.001
- Iterations = 600

2.1 The impact of the mutation rate



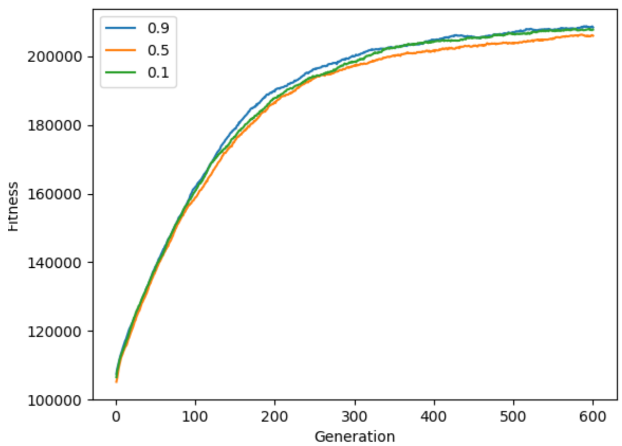
Despite the weak beginning (due to the small number of genes to mutate), the best fitness values were obtained for the mutation coefficient equal 0.001. It should also be noted here the smoothness of the lines on the graph, which indicates the stability provided by this parameter. The worst option turned out to be the coefficient equal 0.01, which due to a large number of genes to change led to a large number of overshoots, which resulted not only in oscillating far below the values obtained by the other parameters, but also could not stabilize to the form of a line.

2.2 The impact of the population size



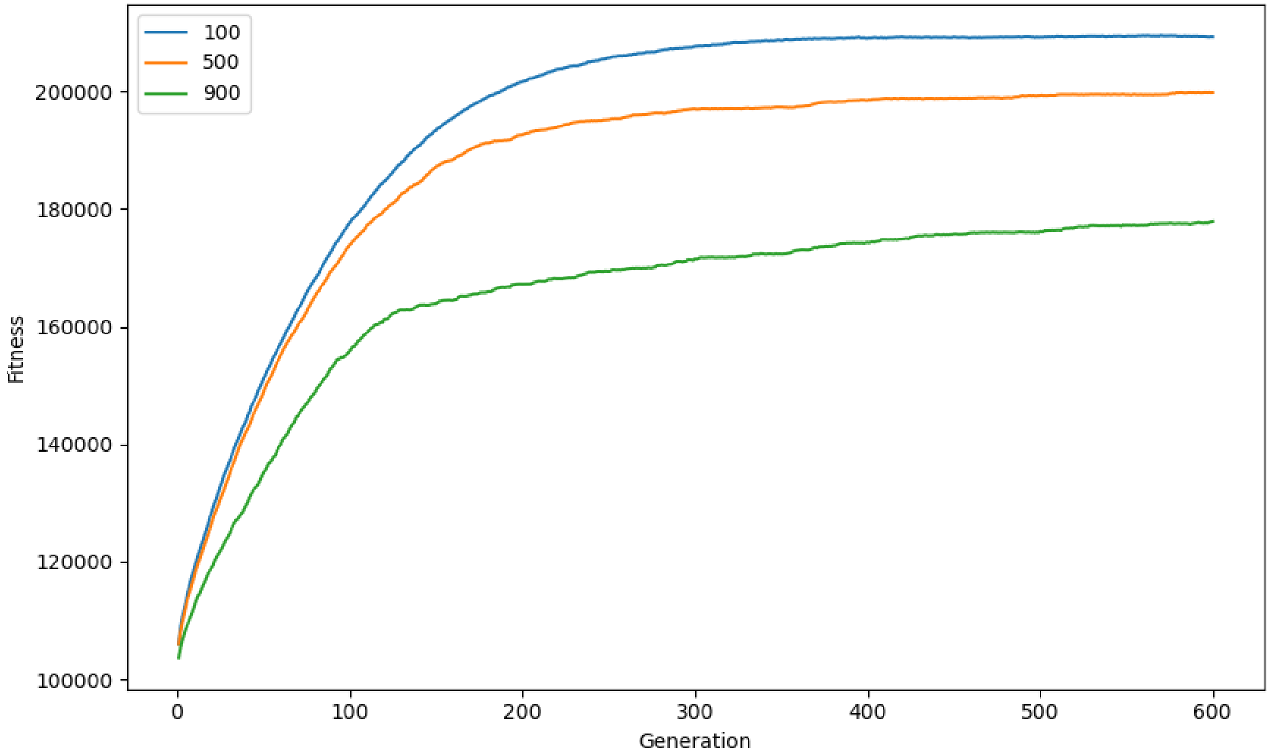
The difference in values obtained for parameters 1000 and 3000 is so small that we can conclude that a further increase in the population size is not justified. The graph shows that the larger the population size, the more combinations can be checked, which is why the increase in value at the beginning is faster, but at the end of the test the parameter 1000 almost equaled the winner. Its shorter execution time should also be taken into account. The test for parameter 100 was the shortest, but its poor result rejects it on the spot. Since the goal was to find the best arrangement of items that can be put in a knapsack, the best option is a population size of 3000.

2.3 The impact of the crossover probability



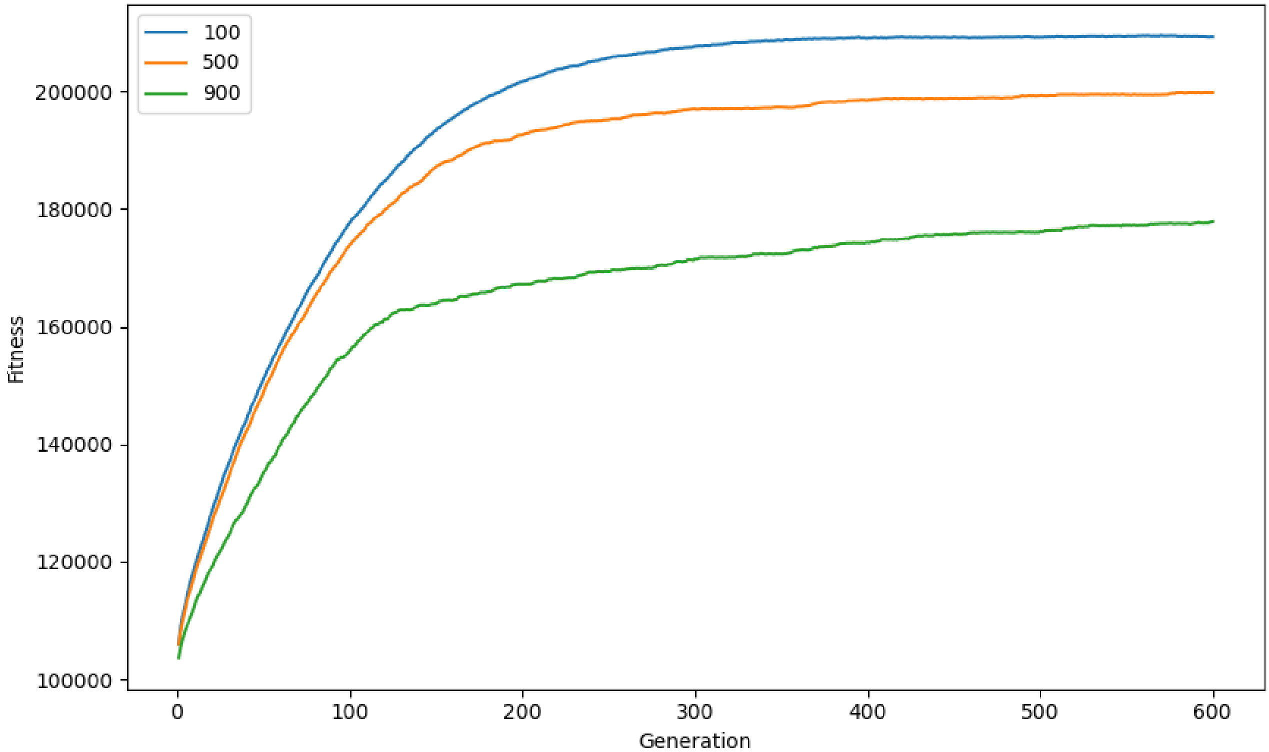
The best value of the parameter turned out to be 0.9, however, the impact of this parameter does not seem to have a key impact on the algorithm's efficiency.

2.4 The impact of the tournament size



Experience has shown a large impact of the tournament size on the final result. Too large sizes blocked the population at the local maximums, which is why the results obtained are far from satisfactory. Meanwhile, the smallest parameter, by giving the chance to worse individuals, could find a global maximum. The advantage of a tournament size of 100 is visible across the entire chart width.

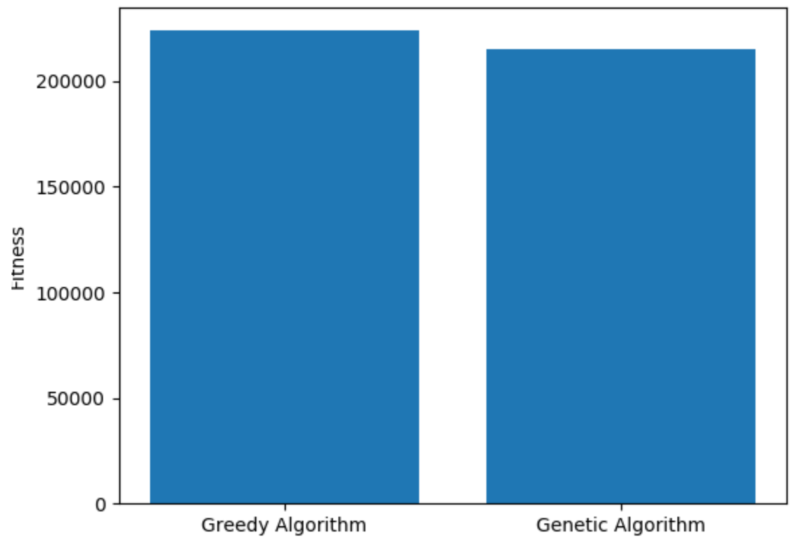
2.5 Comparison of the best parameters with the worst



3 Comparison with non-evolutionary method

```
def greedySearch(task):
    items = [(item.c / (item.w + item.s), item.c, item.w, item.s) for item in task.items]
    values_sorted = sorted(items, key=lambda x: x[0], reverse=True)
    w_sum = c_sum = s_sum = 0
    for item in values_sorted:
        print(item)
        if w_sum > task.w or s_sum > task.s:
            break
        c_sum += item[1]
        w_sum += item[2]
        s_sum += item[3]
    return c_sum
```

An example of a non-evolutionary solution to a knapsack problem can be a greedy algorithm that selects items with the highest ratio of value to the sum of weight and size, until the total weight and size of the items do not exceed the maximum values.



The greedy algorithm turned out to be better than the genetic one. This may be due to the low level of complexity of the knapsack problem. The greedy algorithm also has an advantage in terms of execution time, because it is executed almost immediately. The genetic algorithm performs a huge number of calculations that take time. It seems that this task is not the best place to apply genetic algorithms.