## Exercises 07: Optimization

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## 1 Exercise 1

The scikit-optimize python extension implements bayesian optimization using gaussian processes with  $gp\_minimize()$ . Some of the used parameters can be seen in table 2.

| Parameter    | Description                          | Value            |  |
|--------------|--------------------------------------|------------------|--|
| func         | Function to minimize                 | polynomial       |  |
| dimensions   | The search space                     | [(x_min, x_max)] |  |
| n_calls      | Number of calls to func              | 4                |  |
| acq_func     | Aquisition function                  | "EI"             |  |
| random_state | Set for reproducible results         | 1234             |  |
| noise        | Adds noise to the objective function | 1e-10            |  |
|              | (minimum: 1e-10)                     |                  |  |

Table 1: Parameters used in gp\_minimize() function

The number of loops done is determined by the  $n\_calls$  parameter. To compare this implementation with the implementation of exercise 6 both optimization algorithms are run 4 times with  $x\_min = 1$  and  $x\_max = 20$ . The comparison can be seen in figure 1. Noticeable is the switch to a discrete X dimension. The MSE value is hold until the next integer is reached. This is done automatically by the  $gp\_minimize$  function when the dimensions parameters are integers. The two implementations also chose completely different Observations witch each iteration. The best degree found was 11 with MSE = 0.0062 for  $gp\_minimize()$  and 10 with MSE = 0.0128 in exercise 6. However, given the randomness of the  $gp\_minimize()$  function, the result will likely change with a different  $random\_state$  value.

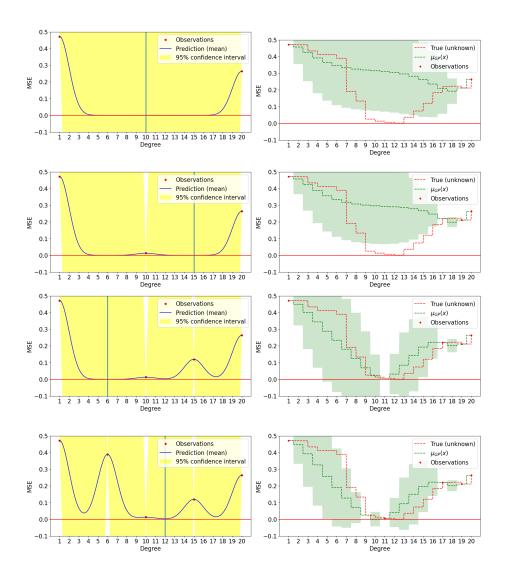


Figure 1: Left: Implementation Ex. 6, Right: Implementation Ex. 7

## 2 Exercise 2

The aim of this exercise is to benchmark Knapsack Problem with different items with their values and objects for multiple iterations.

The knapsack problem is a problem in combinatorial optimization: Given a set of items, each with a weight and a value, determine the number of each item included in a collection so that the total weight is less than or equal to a given limit and the total value is as large as possible. This exercise is using Pyomo, a Python-based open-source software package that supports a diverse set of optimization capabilities for formulating, solving, and analyzing optimization models. A core capability of Pyomo is modelling structured optimization applications.

The most common problem being solved is the 0-1 knapsack problem, which restricts the number  $x_i$  of copies of each kind of item to zero or one. Given a set of k items numbered from 1 up to k, each with a weight  $w_i$  and a value  $v_i$ , along with a maximum weight capacity limit,

maximize 
$$\sum_{i=1}^{k} v_i x_i$$
 subject to  $\sum_{i=1}^{k} w_i x_i \leq limit$  where  $x_i \in \{0,1\}$ 

v-Item value, w- Item weight, k-No. of items, limit-Weight limit  $x_i$ - the number of instances of item i to include in the knapsack.

## Steps:

- 1. Items generator: This function generates a given number of items with a random name of string less than 10 as well as a random value between 1 to 20 and weight between 1 to 10.
- 2. Recording execution time for n (i.e. n = 5) number of iterations.
- 3. Calculating the mean of a recorded set of time (i.e. Set of n).
- 4. Calculating variance of a recorded set of time (i.e. Set of n).
- 5. Visual representation of time vs iteration.

The following table represents the benchmarking results:

Number of items = 10Number of iterations n = 5

| Iteration $(n)$ | Execution Time (sec) | Value | Weight |
|-----------------|----------------------|-------|--------|
| 1               | 0.054                | 37    | 10     |
| 2               | 0.038                | 37    | 10     |
| 3               | 0.043                | 37    | 10     |
| 4               | 0.030                | 37    | 10     |
| 5               | 0.030                | 37    | 10     |

Table 2: Benchmarking results for n iterations

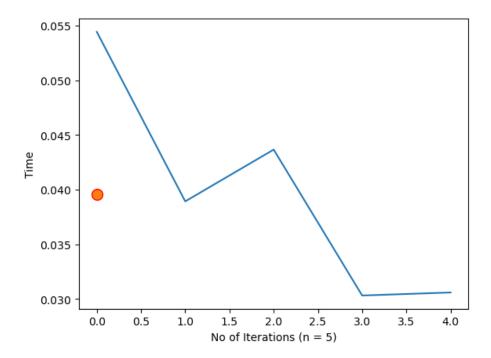


Figure 2: Execution time plot for n iterations

The mean execution time for above n iterations is **0.04 sec** (0.039 sec).

The variance of execution time for above n iterations is **8.07 Sec**.