

FEDERAL STATE AUTONOMOUS EDUCATIONAL INSTITUTION  
OF HIGHER EDUCATION  
ITMO UNIVERSITY

Report

on the practical task No. 3

“Algorithms for unconstrained nonlinear optimization. First- and second- order methods”

Performed by

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### Task# 3

Language : python

**Goal :** The use of first- and second-order methods (Gradient Descent, Non-linear Conjugate Gradient Descent, Newton's method and Levenberg-Marquardt algorithm) in the tasks of unconstrained nonlinear optimization

**Problem :** Generate random numbers  $\alpha \in (0,1)$  and  $\beta \in (0,1)$ . Furthermore, generate the noisy data  $\{x_+, y_+\}$ , where  $k = 0, \dots, 100$ , according to the following rule:

$$Y = AX + B + \text{noise}$$

$$X = k / 1000$$

where  $\delta_+ \sim N(0,1)$  are values of a random variable with standard normal distribution. Approximate the data by the following linear and rational functions:

1.  $F(x,a,b)=ax+b$  (linear approximant), 2.  $F(x, a, b) =$  (rational approximant),  
by means of least squares through the numerical minimization (with precision  $\varepsilon = 0.001$ ) of the following function:

$$D(a,b) = \sum (F(x_+,a,b) - y_+)^2$$

**Theory:**

**Gradient descent :**

Step 1 : Initialize  $x = 3$ . Then, find the gradient of the function,  $dy/dx = 2*(x+5)$ .

Step 2 : Move in the direction of the negative of the gradient (Why?). But wait, how much to move? For that, we require a learning rate. Let us assume the learning rate  $\rightarrow 0.01$

Step 3 : Let's perform 2 iterations of gradient descent

Step 4 : We can observe that the  $X$  value is slowly decreasing and should converge to -5 (the local minima). However, how many iterations should we perform?

**Conjugate gradient descent :**

1. Initialize  $x_0$
2. Calculate  $r_0 = Ax_0 - b$
3. Assign  $p_0 = -r_0$
4. For  $k = 0, 1, 2, \dots$ :
  - \* calculate  $\alpha_k = -r_k'p_k / p_k'Ap_k$
  - \* update  $x_{k+1} = x_k + \alpha_k p_k$
  - \* calculate  $r_{k+1} = Ax_{k+1} - b$

- \* calculate  $\beta_{k+1} = r_{k+1}' A p_k / p_k' A p_k$
- \* update  $p_{k+1} = -r_{k+1} + \beta_{k+1} p_k$

### Newton method :

Hessian matrix =  $H(x_k)$

Gradient matrix =  $f'(x_k)$

$$x_{k+1} = x_k - H(x_k)^{-1} \times f'(x_k)$$

### Levenberg-Marquardt algorithm :

This is one algorithm which combine Newton method and gradient descent .

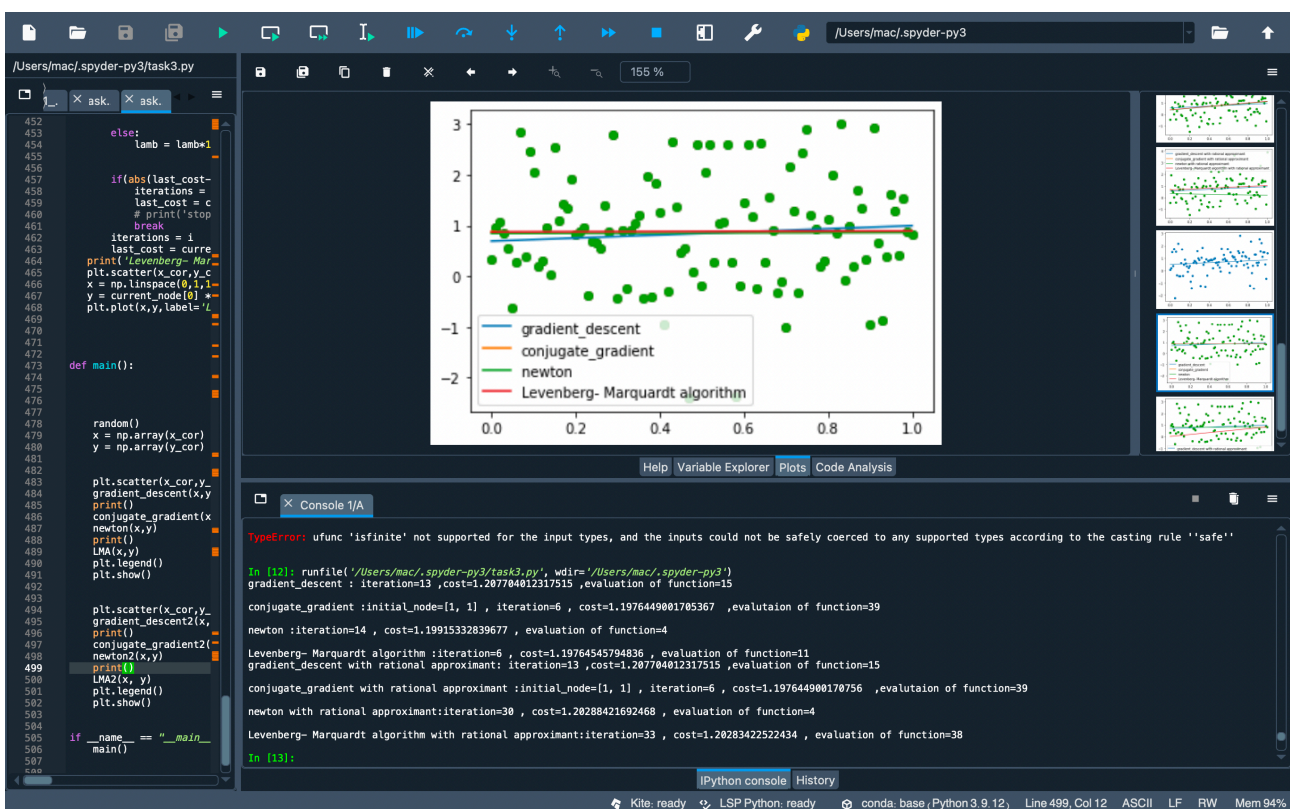
It applicate two method depends on situation , and alter lambda , a learning rate which can adjust proportion of two methods , depending on the steepness of slope

Hessian matrix =  $H(x_k)$

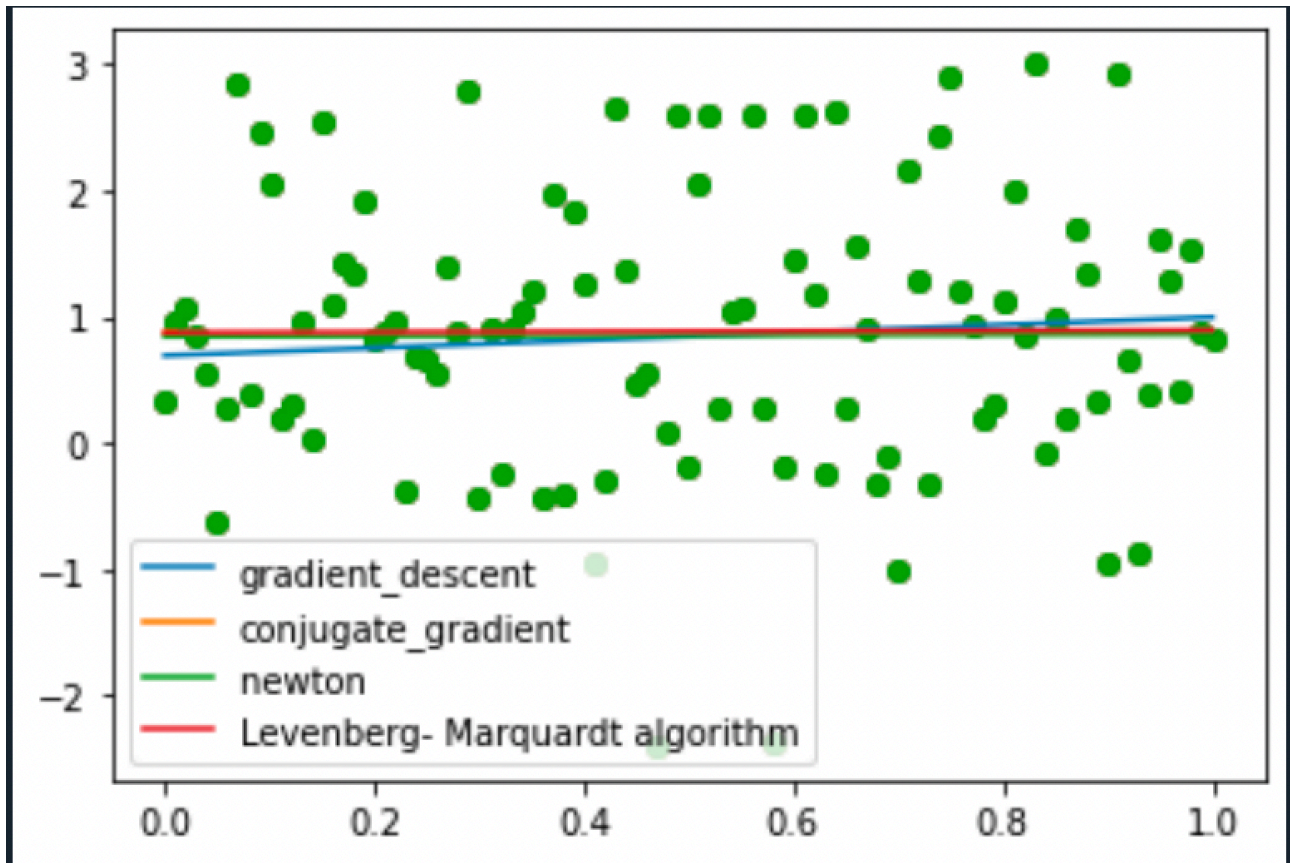
Gradient matrix =  $f'(x_k)$

$$x_{k+1} = x_k - (H(x_k) + \lambda \text{Identity matrix})^{-1} \times f'(x_k)$$

### Results



*This is result for linear approximation*



```
gradient_descent : iteration=13 ,cost=1.207704012317515 ,evaluation of function=15
conjugate_gradient :initial_node=[1, 1] , iteration=6 , cost=1.1976449001705367 ,evalutaion of function=39
newton :iteration=14 , cost=1.19915332839677 , evaluation of function=4
Levenberg- Marquardt algorithm :iteration=6 , cost=1.19764545794836 , evaluation of function=11
```

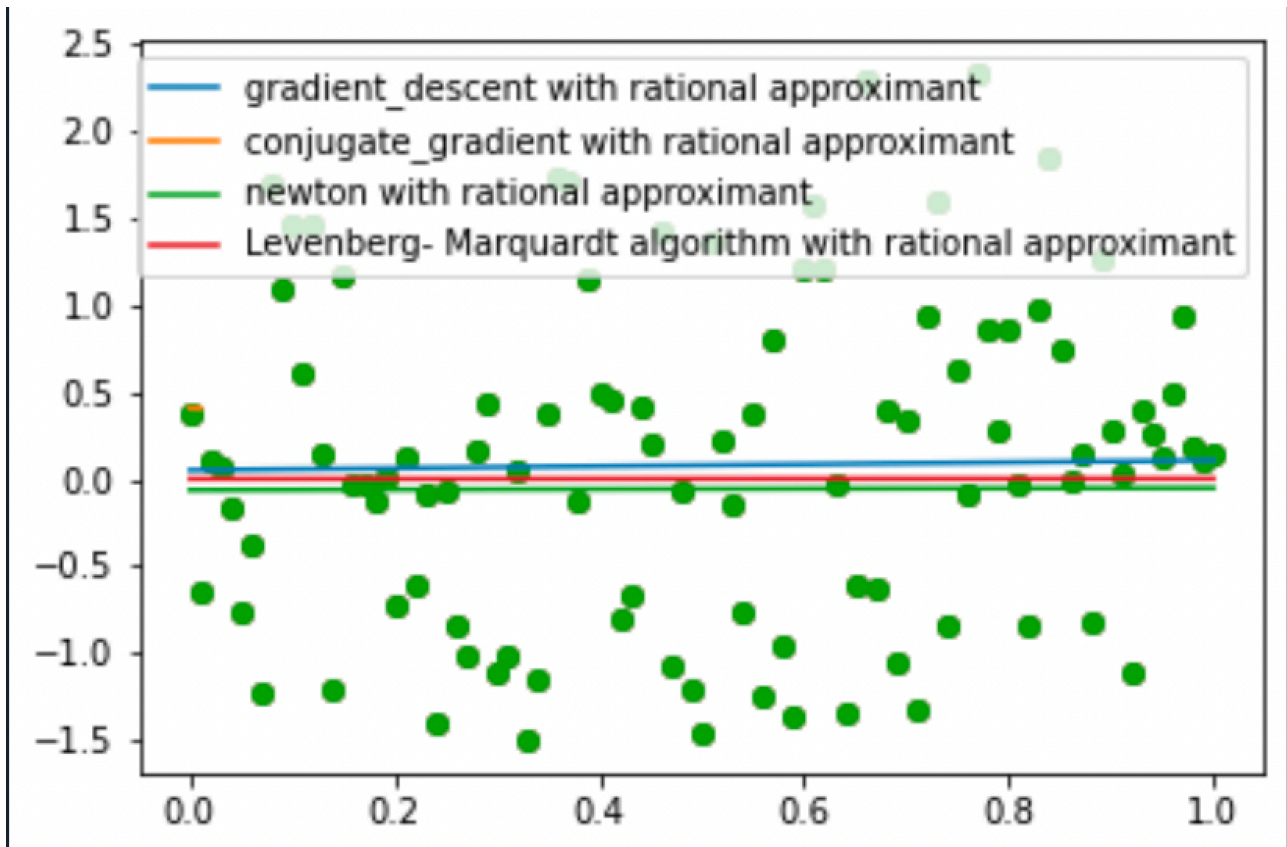
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newton :iteration=14 , cost=1.19915332839677 , evaluation of function=4

Levenberg- Marquardt algorithm :iteration=6 , cost=1.19764545794836 , evaluation of function=11

*This is result for non-linear approximation*



```
gradient_descent with rational approximant: iteration=13 ,cost=1.207704012317515 ,evaluation of function=15
conjugate_gradient with rational approximant :initial_node=[1, 1] , iteration=6 , cost=1.197644900170756 ,evalutaion of function=39
newton with rational approximant:iteration=30 , cost=1.20288421692468 , evaluation of function=4
Levenberg- Marquardt algorithm with rational approximant:iteration=33 , cost=1.20283422522434 , evaluation of function=38
```

gradient\_descent with rational approximant : iteration=13 ,cost=1.207704012317515 ,evaluation of function=15

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## *Conclusion*

*As we can see , using linear approximation , best line can almost converge to same line with all methods which we have used in analysis .*

*In non-linear approximation graph , all method converged to very very close line , but we can see that there is still little deviation , but as result , it is acceptable .*

*As I know , newton method has many shortcomings . Closer initial point to most optimized point , it is more likely to get to most optimized result . And also if its hessian matrix is not positive definite , its direction will not point in descent direction , and if it is singular matrix, it will not move at all . Also calculation of hessian matrix is very time-consuming when its size is large .*

*Comparing with methods in task 2 , we can see that method using derivative is highly efficient , usually can be done with few iteration .*

<https://github.com/MaChengYuan/task3/blob/de41cd3dc95d698533193a62abecd8fe6ebd3827/task3.py>