



# Assignment 5 - Python

The following code represents my solution for a) b)

```
"""
Let  $f: \mathbb{R} \rightarrow \mathbb{R}$  be differentiable. To minimize  $f$ , consider the gradient descent method
 $x_{n+1} = x_n - \eta f'(x_n)$ ,
where  $x_1 \in \mathbb{R}$  and  $\eta > 0$  (learning rate).
(a) Take a convex  $f$  and show that for small  $\eta$  the method converges to the minimum of  $f$ .
(b) Show that by increasing  $\eta$  the method can converge faster (in fewer steps).

Let  $f: \mathbb{R} \rightarrow \mathbb{R}$ ,  $f(x) = x^2$  be the convex function
"""
import math

import numpy as np
import matplotlib.pyplot as plt

def f1_prime(x):
    return 2*x # 2x

def find_new_element(x, learning_rate):
    return x - learning_rate * f1_prime(x)

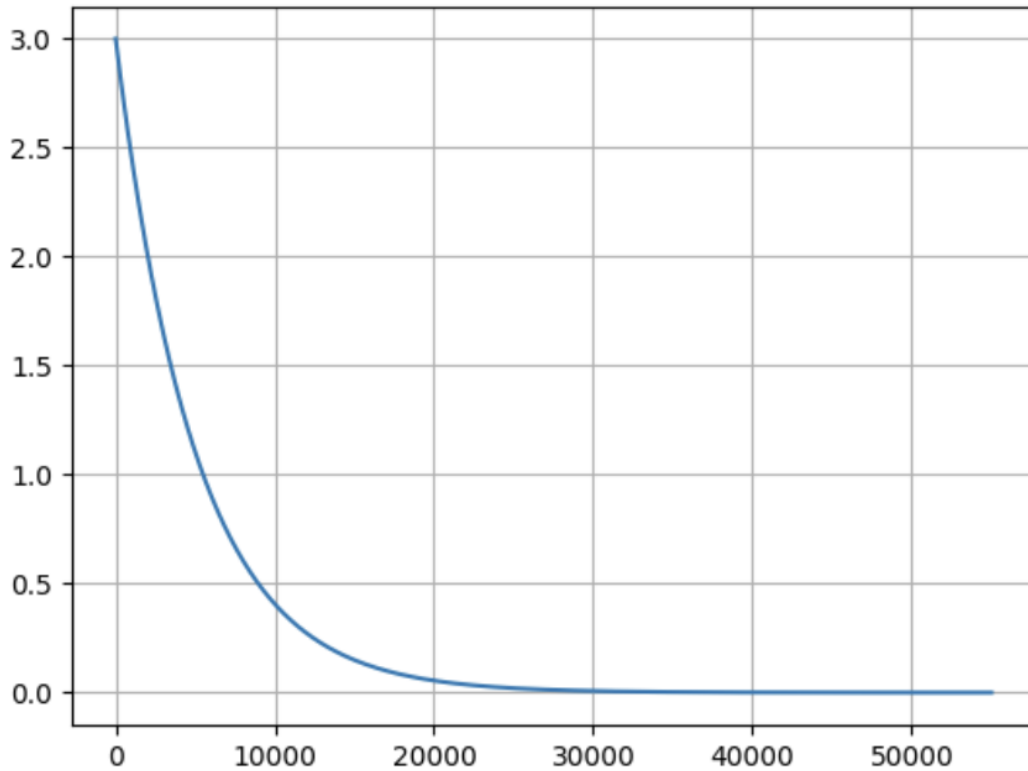
series = []
max_number_of_iterations = 10000
precision = 0.000001
x_1 = 3
series.append(x_1)
learning_rate = 0.0001
previous_precision = 1
iteration_counter = 0
while previous_precision > precision and iteration_counter < max_number_of_iterations:
    iteration_counter += 1
    previous_precision = abs(x_1 - find_new_element(x_1, learning_rate))
    x_1 = find_new_element(x_1, learning_rate)
    series.append(x_1)

print("The local minimum occurs at", x_1)

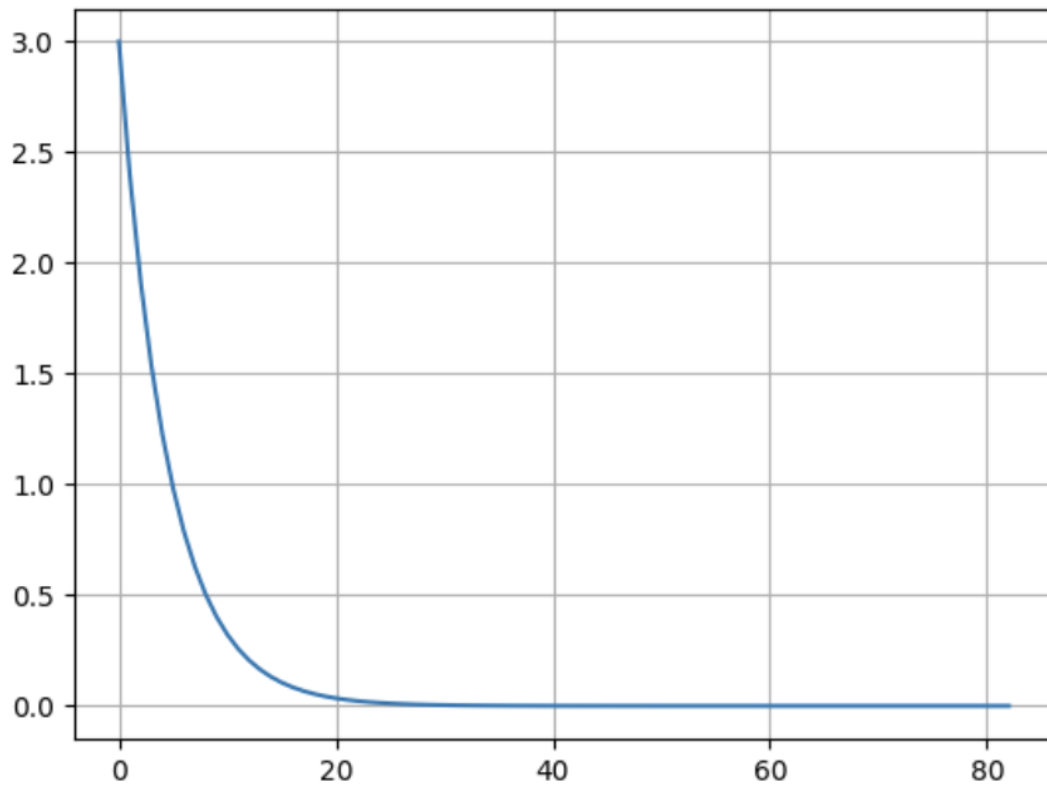
plt.plot(series)
plt.grid()
plt.show()
```

- $f(x^2)$  is the convex function  $\Rightarrow$  the minimum of the function is 0. When we take a small leaning rate (for instance leaning\_rate = 0.0001) the method will converge to the minimum of

the function, which is 0. This can be observed in the following graph:



- By increasing the leaning rate (leaning\_rate = 0.1) the method will converge faster. In this example, il only takes around 80 iterations to reach the precision 0.00000001



To solve c) “Show that taking eta too large might lead to the divergence of the method”, I wrote another plotting algorithm that can print the graph in a more pleasant way

```

"""
Let  $f: \mathbb{R} \rightarrow \mathbb{R}$  be differentiable. To minimize  $f$ , consider the gradient descent method  $x_{n+1} = x_n - \eta f'(x_n)$ ,
where  $x_1 \in \mathbb{R}$  and  $\eta > 0$  (learning rate).
(c) Show that taking eta too large might lead to the divergence of the method.
"""

import matplotlib.pyplot as plt
def f1_prime(x):
    return 2*x # 2x

def find_new_element(x, learning_rate):
    return x - learning_rate * f1_prime(x)

x=[]
y=[]

max_number_of_iterations = 1000
precision = 0.00000001
x_1 = 3
x.append(x_1)

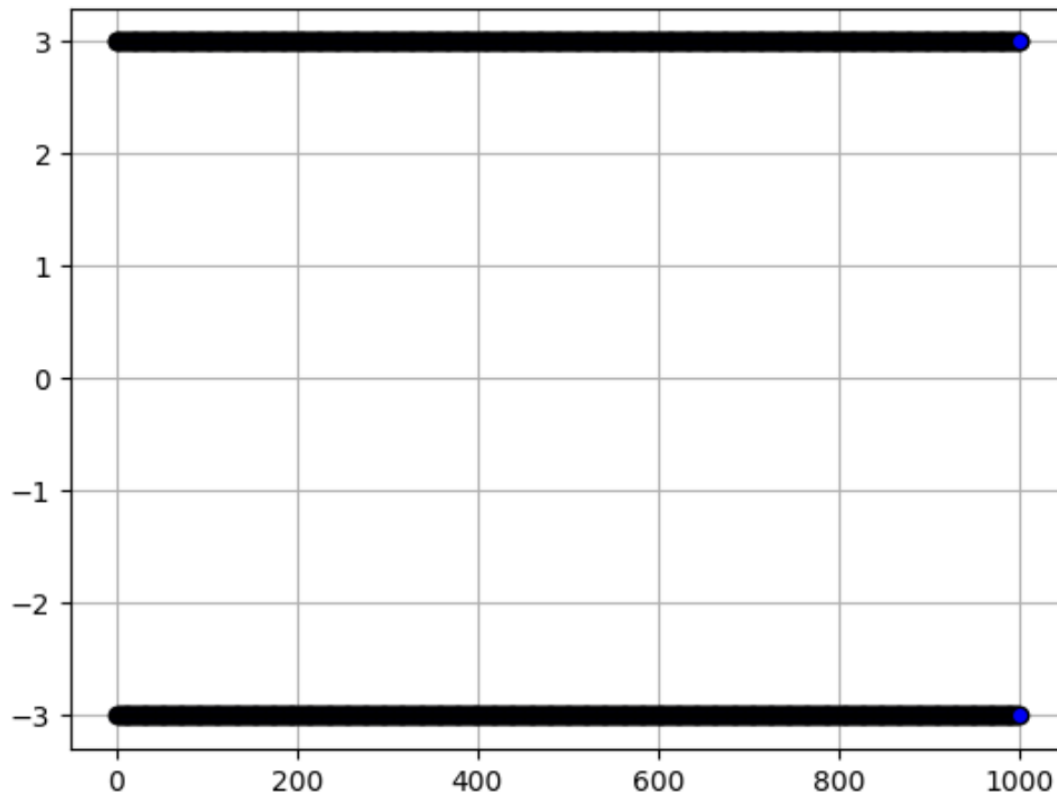
```

```

learning_rate = 1
previous_precision = 1
iteration_counter = 0
y.append(iteration_counter)
while previous_precision > precision and iteration_counter < max_number_of_iterations:
    iteration_counter += 1
    previous_precision = abs(x_1 - find_new_element(x_1, learning_rate))
    x_1 = find_new_element(x_1, learning_rate)
    x.append(x_1)
    y.append(iteration_counter)
plt.plot(y,x, color='none', linestyle='dashed', linewidth = 3,marker='o', markerfacecolor='blue')
plt.grid()
plt.show()

```

- For the learning\_rate = 1, the graph is:



it is obvious that this method diverges

The following code plots the graph for a nonconvex function  $f=x^3$

```

"""
Let  $f: \mathbb{R} \rightarrow \mathbb{R}$  be differentiable. To minimize  $f$ , consider the gradient descent method  $x_{n+1} = x_n - \eta f'(x_n)$ ,
where  $x_1 \in \mathbb{R}$  and  $\eta > 0$  (learning rate).
(d) Take a nonconvex  $f$  and show that the method can get stuck in a local minimum.

Let  $f: \mathbb{R} \rightarrow \mathbb{R}$ ,  $f(x) = x^3$ 
"""

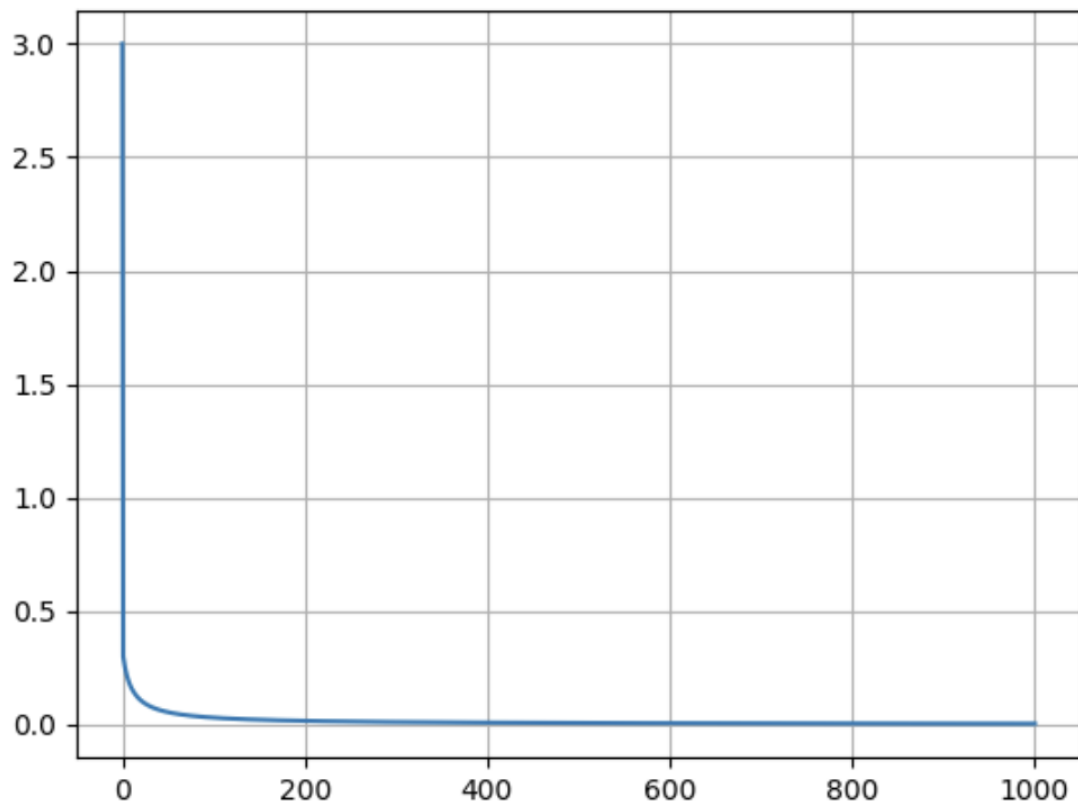
import math
import numpy as np
import matplotlib.pyplot as plt

def f2_nonconvex_prime(x):
    return 3*x**2 #  $3x^2$ 
def find_new_element(x, learning_rate):
    return x - learning_rate * f2_nonconvex_prime(x)

series = []
series.append(3)
max_number_of_iterations = 1000
precision = 0.00000001
x_1 = 3
learning_rate = 0.1
previous_precision = 1
iteration_counter = 0
while previous_precision > precision and iteration_counter < max_number_of_iterations:
    iteration_counter += 1
    previous_precision = abs(x_1 - find_new_element(x_1, learning_rate))
    x_1 = find_new_element(x_1, learning_rate)
    series.append(x_1)
    print(x_1)

print("The local minimum occurs at", x_1)
plt.plot(series)
plt.grid()
plt.show()

```



- We observe that for a learning\_rate = 0.1 and a maximum of 1000 iterations, the method gets stuck at a local minimum equal to 0.0032851306356031645