

# Optimization\_professor

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## 1 Optimización

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Versión: 0.1 (2019/09/13)  
0.2 (2019/10/02): Solutions added

### 1.1 Exercise: compute the minimum of a real-valued function

The goal of this exercise is to implement and test optimization algorithms for the minimization of a given function. Gradient descent and Newton's method will be explored.

Our goal it so find the minimizer of the real-valued function

$$f(w) = -w \exp(-w)$$

but the whole code will be easily modified to try with other alternative functions.

You will need to import some libraries (at least, numpy and matplotlib). Insert below all the imports needed along the whole notebook. Remind that numpy is usually abbreviated as np and matplotlib.pyplot is usually abbreviated as plt.

```
In [28]: # <SOL>
import numpy as np
import matplotlib.pyplot as plt
# </SOL>
```

#### 1.1.1 Part 1: The function and its derivatives.

**Question 1.1:** Implement the following three methods:

- Method **f**: given  $w$ , it returns the value of function  $f(w)$ .
- Method **df**: given  $w$ , it returns the derivative of  $f$  at  $w$
- Method **d2f**: given  $w$ , it returns the second derivative of  $f$  at  $w$

```
In [29]: # Function f
# <SOL>
def f(w):
    y = - w * np.exp(-w)
```

```

        return y
# </SOL>

# First derivative
# <SOL>
def df(w):
    y = (w - 1) * np.exp(-w)
    return y
# </SOL>

# Second derivative
# <SOL>
def d2f(w):
    y = (2 - w) * np.exp(-w)
    return y
# </SOL>

```

### 1.1.2 Part 2: Gradient descent.

**Question 2.1:** Implement a method `gd` that, given  $w$  and a learning rate parameter  $\rho$  applies a single iteration of the gradient descent algorithm

```

In [30]: # <SOL>
def gd(w0, rho):
    y = w0 - rho * df(w)
    return y
# </SOL>

```

**Question 2.2:** Apply the gradient descent to optimize the given function. To do so, start with an initial value  $w = 0$  and iterate 20 times. Save two lists:

- A list of successive values of  $w_n$
- A list of successive values of the function  $f(w_n)$ .

```

In [31]: # <SOL>
wn = []
fwn = []
niter = 20
rho = 0.2
w = 0
wn.append(w)
fwn.append(f(w))

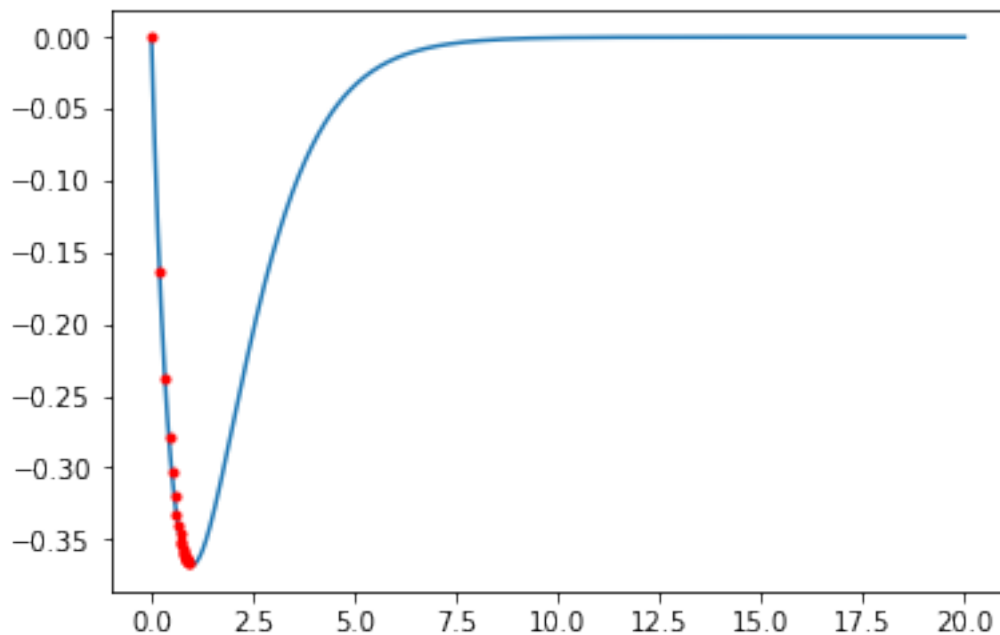
for k in range(niter):
    w = gd(w, rho)
    wn.append(w)
    fwn.append(f(w))
# </SOL>

```

**Question 2.3:** Plot, in a single figure:

- The given function, for values ranging from 0 to 20.
- The sequence of points  $(w_n, f(w_n))$ .

```
In [32]: # <SOL>
npoints = 1000
w_grid = np.linspace(0,20,npoints)
plt.plot(w_grid, f(w_grid))
plt.plot(w_n,fwn,'r. ')
plt.show()
# </SOL>
```



You can check the effect of modifying the value of the learning rate.

### 1.1.3 Part 2: Newton's method.

**Question 3.1:** Implement a method `newton` that, given `w` and a learning rate parameter `rho` applies a single iteration of the Newton's method

```
In [33]: # <SOL>
def newton(w0, rho):
    y = w0 - rho * df(w) / d2f(w)
    return y
# </SOL>
```

**Question 3:** Apply the Newton's method to optimize the given function. To do so, start with an initial value  $w = 0$  and iterate 20 times. Save two lists:

- A list of successive values of  $w_n$
- A list of successive values of the function  $f(w_n)$ .

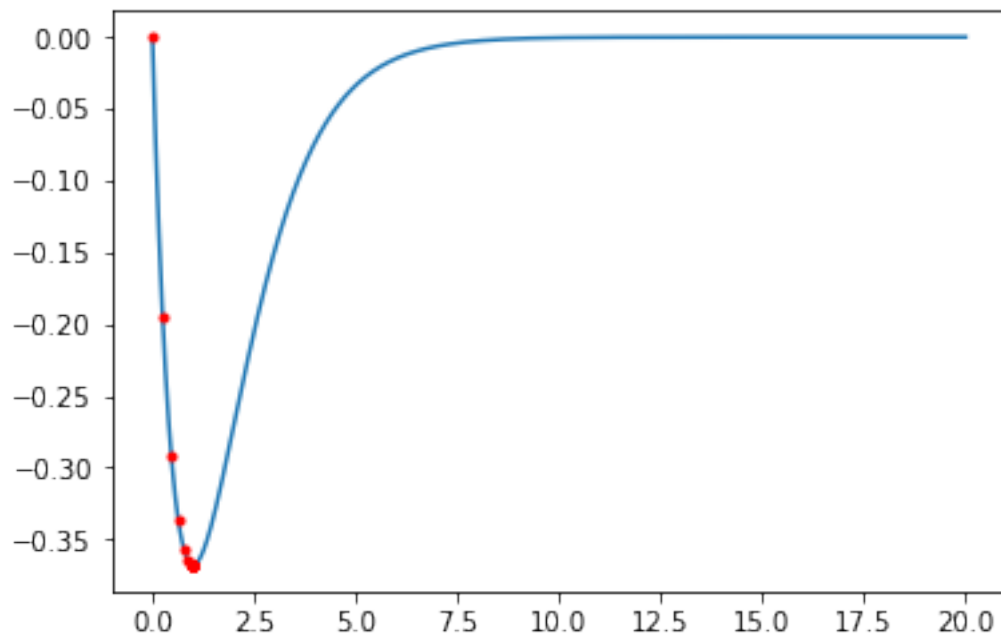
```
In [34]: # <SOL>
wn = []
fwn = []
niter = 20
rho = 0.5
w = 0
wn.append(w)
fwn.append(f(w))

for k in range(niter):
    w = newton(w,rho)
    wn.append(w)
    fwn.append(f(w))
# </SOL>
```

**Question 4:** Plot, in a single figure:

- The given function, for values ranging from 0 to 20.
- The sequence of points  $(w_n, f(w_n))$ .

```
In [35]: # <SOL>
npoints = 1000
w_grid = np.linspace(0,20,npoints)
plt.plot(w_grid, f(w_grid))
plt.plot(wn,fwn,'r. ')
plt.show()
# </SOL>
```



You can check the effect of modifying the value of the learning rate.

#### **1.1.4 Part 3: Optimize other cost functions**

Now you are ready to explore these optimization algorithms with other more sophisticated functions. Try with them.

In [ ]: