

# Tutorial\_2 Notebook

March 19, 2019

## 0.1 Optimisation and Minimization

*Notebook for Tutorial 2, Phys3112 S1 2019*

Try running the cells in this notebook and understanding them.

```
In [1]: import scipy.optimize
import numpy as np
import random
from matplotlib import pyplot as plt
```

## 1 1-D Brute force solver

This is a simple brute force solver! We are going to find the minimum of a function by randomly guessing until we have found an acceptable point. Our function takes only one input (x) so this is a One Dimensional input problem. We also will only have one output.

```
In [2]: # Define a function that we are going to try and minimize
# Feel free to change this function around!
def func_1(x):
    return np.abs(-x**4 + 5*x**3 - 2*x**2 + 17*x - 10)
```

```
In [3]: # We will stop our search after finding this output or lower!
threshold = 0.001
# Our range of input values
input_min = 0
input_max = 10
searching = True
# Number of iterations we have tried (just so we can count them!)
n_iter = 0
# Number of iterations before we give up (important, so we don't have an infinite loop
max_iter = 10000000

# Our searching loop
while searching:
    n_iter += 1
    # Get a random x to guess, within our range
    x = random.uniform(input_min, input_max)
    # Check if our guess gives us a 'good enough' value
```

```

    if func_1(x) < threshold:
        # Yay! We have an acceptable input.
        searching = False
        success = True
    if n_iter >= max_iter:
        searching = False
        success = False

if success:
    print('Acceptable solution found after ' + str(n_iter) + ' iterations.')
    print('Input of ' + str(x) + ' gives output of ' + str(func_1(x)))
else:
    print('We were unable to find a suitable input!')

```

Acceptable solution found after 106580 iterations.

Input of 0.5773795637732904 gives output of 1.847198885052137e-05

### Homework:

Modify the above code to return the best guess for  $x$  it had tried, if it didn't manage to find one that met the threshold!

## 1.1 2-D Gradient Descent

This code is a SUPER BASIC gradient descent. It 'looks around' it's current position, and steps to the best looking option. The purpose of this code is to show you the basic structure of a descent method - it is a pretty terrible implementation.

The quality of implementation you can use depends on whether or not your function is differentiable, and how smooth the output regime is.

```

In [12]: # Define a new function that we will minimize. This one takes two inputs.
def func_2(x):
    # x is a variable with two values; x[0] is the first, and x[1] is the second.
    return(x[0]**2 + 4*x[1]**2 - x[0]*x[1] - 4*x[0] + 3)

In [16]: init_guess = [5, 100]
        jump_size = 0.001
        max_iter = 1000000
        n_iter = 0

        search = True

        x = init_guess
        while search:
            n_iter += 1

            # Generate our new guesses
            left_x = np.asarray((x[0] - jump_size, x[1]))
            right_x = np.asarray((x[0] + jump_size, x[1]))

```

```

up_x = np.asarray((x[0], x[1] + jump_size))
down_x = np.asarray((x[0], x[1] - jump_size))

# Jump to the best guess.
guesses = np.asarray((x, left_x, right_x, up_x, down_x))
results = np.asarray((func_2(x), func_2(left_x), func_2(right_x), func_2(up_x), func_2(down_x)))
if np.argmin(results) == 0:
    # The current guess is our best position!
    search = False
    success = True
else:
    x = guesses[np.argmin(results)]
if n_iter >= max_iter:
    search = False
    success = False

if success:
    print('Local minimum found after ' + str(n_iter) + ' iterations.')
    print('Input of ' + str(x) + ' gives output of ' + str(func_2(x)))
else:
    print('We were unable to find the local minimum!')
    print('Best guess: an input of ' + str(x) + ' gives output of ' + str(func_2(x)))

```

Local minimum found after 102601 iterations.

Input of [2.133 0.267] gives output of -1.266666000000034

### Homework:

Have a look at the [wikipedia implementation](#) of a gradient descent - it uses the actual function derivative and 'jumps' in proportion to the size of the gradient. Write your own func\_2 (and derivative) and implement the wikipedia descent!

## 1.2 Writing a SCIPY Wrapper

Writing a scipy wrapper for a curve fitting function. Here we will implement the `scipy.optimize.leastsquares` method to find the curve parameters that best fit our data. Although we could use `curve_fit`, doing things this way allows us to specify the equation of our curve arbitrarily - we don't have to fit to one of the common functions (eg exponential, log, lorentzian) available in the `curve_fit` library.

We will be making use of the `**kwargs` variable, which allows us to pass variables through nested functions without needing to explicitly pack and unpack them at every level.

BEFORE going through this section, be sure to read the [least\\_squares](#) man page

```

In [21]: ## Defining our curve equation (can be as janky as you like, as long as it will NEVER
def curve(x, b):
    y = x*b - b**2*x + np.exp(x-b)
    return (y)

```

```

In [18]: ## Definining our SCIPY wrapper for the curve function
def curve_wrapper(b_guess, **kwargs):
    # kwargs should contain our x and y DATA, which we would use to evaluate how good
    x = kwargs.get('x')
    y = kwargs.get('y')

    # Calculate the residuals; difference between our guess-curve's output and the ac
    residuals = curve(x, b_guess) - y
    return residuals

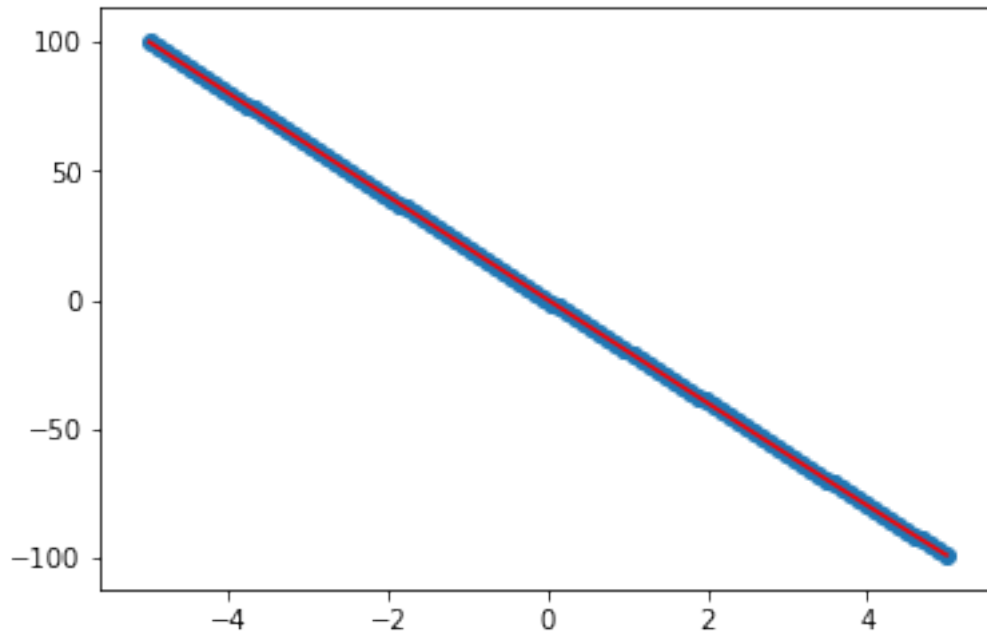
In [23]: ## Implementing a SCIPY fitting routine
# Generate some x and y data first
b_true = 2
x = np.linspace(-5,5,100)
y = curve(x, b_true)
# Get scipy to guess what our value of 'b' was, given only the x and y data
# Generate the kwargs dictionary to be passed through the optimisation function.
kwargs = {
    "x":x,
    "y":y
}
b_guess = scipy.optimize.least_squares(curve_wrapper, x0=1, bounds=(-100,100), kwargs=
print('Guess for b is ' + str(b_guess))

# Plot the output
plt.figure()
plt.plot(x, curve(x, b_guess), 'r')
plt.scatter(x,y)

```

Guess for b is [5.]

Out[23]: <matplotlib.collections.PathCollection at 0x1ef86183ef0>



**Homework:**

Add some random noise to the initial data and see how the curve fit performs!