

Computational Physics Homework II

[Link to GitHub repository](#)

10/10

1 Overrelaxation

We aim to numerically find a solution to the equation

$$x' = f(x) \quad (1)$$

using the method of overrelaxation. I start by deriving an estimate for the error. In the case of overrelaxation, the current estimate of the solution x and next estimate x' are related by

$$x' = (1 + \omega)f(x) - \omega x, \quad (2)$$

where the parameter ω is some value, generally greater than zero, that is found heuristically. If we define the true solution of our equation to be x^* , we can write the error of our current estimate as

$$\epsilon = x^* - x, \quad (3)$$

and that of the next step as

$$\epsilon' = x^* - x'. \quad (4)$$

Taylor-expansion of Equation 2 close to the real solution x^* gives

$$x' \approx (1 + \omega)f(x^*) - \omega x^* + (x - x')((1 + \omega)f'(x^*) - \omega), \quad (5)$$

and identifying $f(x^*) = x^*$ per definition, we arrive at

$$\epsilon' = \epsilon((1 + \omega)f'(x^*) - \omega), \quad (6)$$

and thus,

$$x^* = x + \epsilon = x + \frac{\epsilon'}{(1 + \omega)f'(x^*) - \omega} = x' + \epsilon'. \quad (7)$$

Solving for the error ϵ' we arrive at the estimate

$$\epsilon' = \frac{x - x'}{1 - 1/(1 + \omega)f'(x^*) - \omega} \approx \frac{x - x'}{1 - 1/(1 + \omega)f'(x) - \omega}. \quad (8)$$

I implement both the relaxation and the overrelaxation method in my code and use them to iteratively solve the equation

$$x = 1 - e^{2x}. \quad (9)$$

With a starting point of $x_0 = 0.5$ it takes 16 iterations to solve the equation to a precision of 10^{-6} using relaxation. With overrelaxation, I only need 3 iterations to reach the same precision, with the same starting point and a parameter $\omega = 0.7$ (found by trial and error). In some cases, a negative ω might be beneficial, if ...

2 Wien's displacement constant

We start out with Planck's radiation law for the intensity of radiation per unit area per unit wavelength λ for a black body at temperature T :

$$I(\lambda) = \frac{2\pi hc^2 \lambda^{-5}}{e^{hc/\lambda k_B T}} \quad (10)$$

We want to find the wavelength of maximal radiation, so we differentiate:

$$\frac{dI}{d\lambda} = -5 \frac{2\pi hc^2 \lambda^{-6}}{e^{hc/\lambda k_B T}} - \frac{2\pi hc^2 \lambda^{-5}}{(e^{hc/\lambda k_B T})^2} (hc/\lambda^2 k_B T) \stackrel{!}{=} 0 \quad (11)$$

and with some basic manipulations we arrive at the equation

$$\frac{hc}{\lambda k_B T} + 5e^{-hc/\lambda k_B T} - 5 = 0. \quad (12)$$

With the substitution $x = \frac{hc}{\lambda k_B T}$, this is equivalent to

$$x + 5e^{-x} - 5 = 0, \quad (13)$$

and we can write the wavelength of maximal radiation as

$$\lambda = \frac{hc}{k_B T x} \equiv \frac{b}{T}, \quad (14)$$

where we have defined Wien's displacement constant $b = \frac{hc}{k_B x}$. I implement a binary search method to find the solution of Equation 13. I obtain $x = 4.96511$ m within 22 iterations. This corresponds to a displacement constant of $b = 2.8982 \times 10^{-3}$ mK (meters times Kelvin).

For a centre wavelength of $\lambda = 502$ nm of the sun's radiation spectrum, we obtain a temperature of the sun of

$$T_{\text{sun}} = \frac{b}{\lambda} \approx \underline{5770 \text{ K}} \quad (15)$$

from Equation 14.

3 Multi-dimensional gradient descent

I start out by implementing a gradient descent algorithm and testing it on the simple function

$$f(x, y) = (x - 2)^2 + (y - 2)^2. \quad (16)$$

Figure 1 shows the x value versus the numbers of iteration for different starting values. The y starting values are chosen to be the same as the x -values.

Since I need to (different) values in the gradient descent step of the loop, in order to not divide by zero, I give a second initial value produced by adding my estimate of the inverse second derivative, γ to the first one (where *gamma* just serves as a small number that is larger than the convergence limit). I then cycle through the values in each loop, and stop when the maximum of the current distances between values is below a preset threshold or when a maximum number of steps is reached.

I then apply the code to fitting a function of the given form

$$n(M_{\text{gal}}) = \Phi^* \left(\frac{M_{\text{gal}}}{M_*} \right)^{\alpha+1} \exp \left(-\frac{M_{\text{gal}}}{M_*} \right) \ln(10) \quad (17)$$

to the provided data. Here the function that is minimised is the χ^2 of the fit. I guessed parameters of $\Phi = 0.002$, $M_* = 10^{10.8}$, and $\alpha = -1$ from plotting the data, but for my best fit I used the results of previous fits as starting parameters.

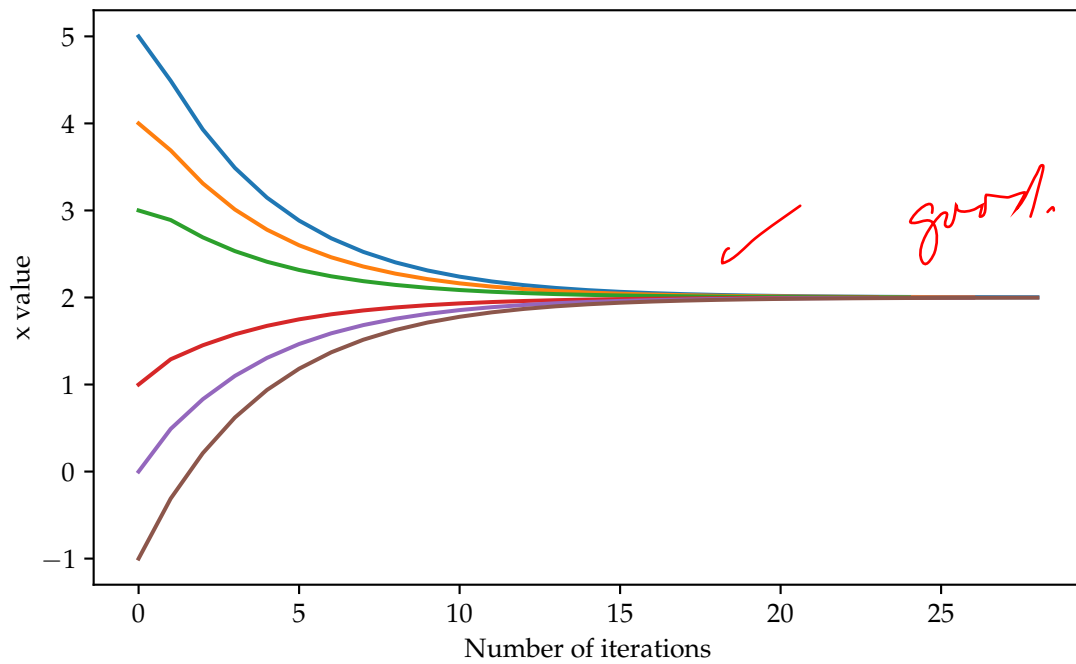


Figure 1: Convergence of gradient descent algorithm when finding the minimum of Equation 2 for different starting values.

I had some problems with the convergence of M_* , since the numbers are so large. Consequently I fitted $\log(M_*)$ instead.

With $\gamma = 10^{-4}$ and sufficient number of steps, I can get the results to converge for different starting values, however the fit does not always look great for large values of M_{gal} .

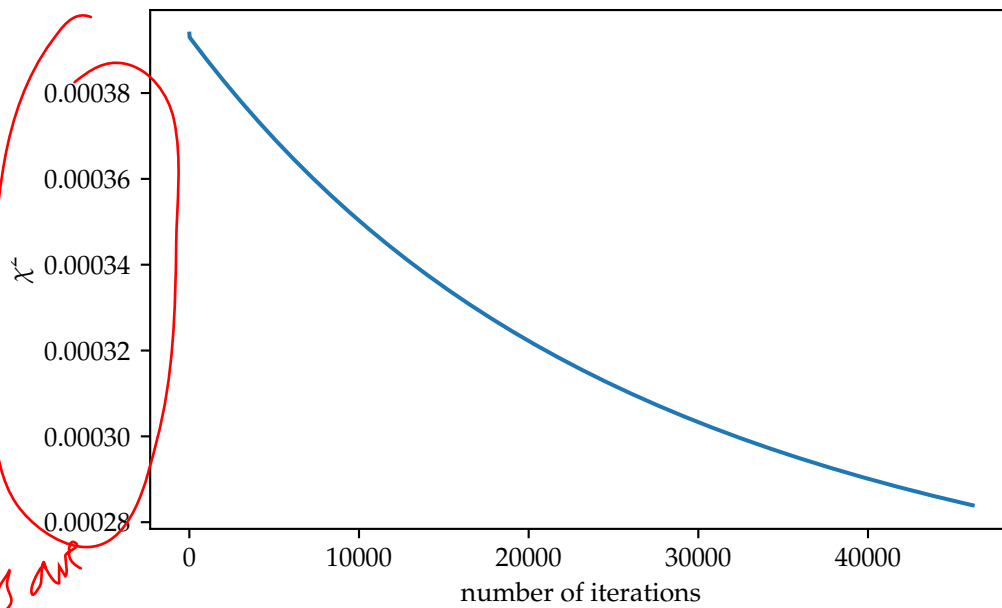


Figure 2: Convergence of χ^2 when minimising using the gradient decent algorithm.

these
numbers are
weird.
did you use
the χ^2 defn from
class?

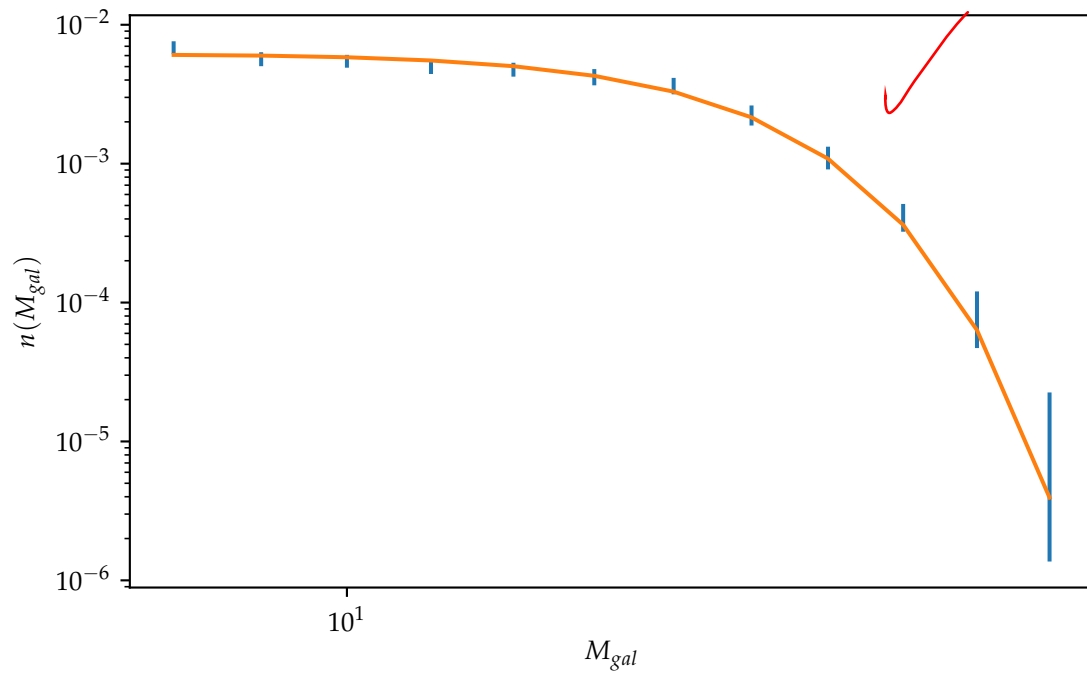


Figure 3: Given initial data and best fit produced by my code, with a convergence to 3×10^{-7} in 46174 iterations. The resulting parameters are $\Phi = 0.0030859$, $M_* = 10^{10.9208646}$, and $\alpha = -0.9637289$.