

Error control in scientific modelling (MATH 500, Herbst)

# Sheet 2: Morse oscillator (10 P)

To be handed in via moodle by 05.10.2023

1 using PlutoTeachingTools

## Introduction

In this exercise we want to explore the different error contributions based on the Morse oscillator. The Morse oscillator is a simple quantum-mechanical model for a chemical bond. Even though nowadays more accurate models exist, it is still used due to its simplicity. One remarkable feature of the model is that it is able to produce a realistic description of chemical bonding. At the same time the associated Schrödinger equation still has an analytic solution — even though we will not attempt this computation here: See wikipedia if you are curious.

In this exercise we will consider the model in one dimension, i.e. our computational domain is simply the real line  $\mathbb{R}$ . The Hamiltonian of the Morse potential has the usual form of

$$H^M = -\frac{1}{2}\Delta + V^M,$$

where  $V^M$  is the Morse potential energy function, which for all  $x \in \mathbb{R}$  is defined as

$$V^M(x) = D \left( 1 - \exp \left( -\frac{\omega}{\sqrt{2D}} (x - x_0) \right) \right)^2$$

with  $D$  is the dissociation energy and  $\omega^2$  the force constant and  $x_0$  the equilibrium bond length. For our computations we consider the parameters

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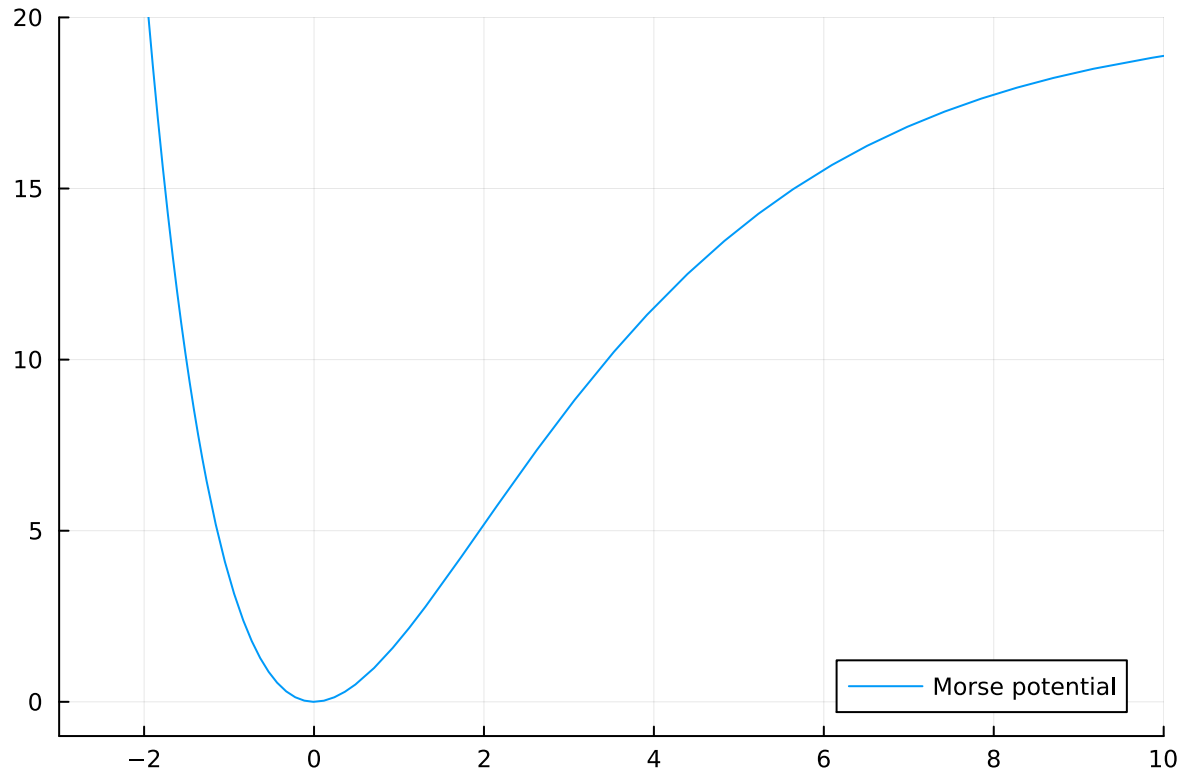
```
1 begin
2     D = 20.0
3     ω = 2.25
4     x0 = 0.0
5 end;
```

for which the potential looks as such

1 using Plots

Vm (generic function with 1 method)

```
1 Vm(x) = D * (1 - exp( -ω / sqrt(2D) * (x - x0) )) ^2
```



```
1 plot(Vm, xlims=(-3, 10), ylims=(-1, 20), label="Morse potential")
```

Following our discussion about the Schrödinger equation in the lectures, we are interested in the eigenvalues and eigenfunctions of this Hamiltonian, i.e. the  $(E_n^M, \varphi_n^M) \in \mathbb{R} \times L^2(\mathbb{R})$  pairs satisfying

$$H^M \varphi_n^M = E_n^M \varphi_n^M.$$

As mentioned above, this system can actually be solved *analytically* with its eigenvalues given by

$$E_n^M = \omega \left( n + \frac{1}{2} \right) - \omega \chi \left( n + \frac{1}{2} \right)^2 \quad n = 0, 1, 2, \dots, \lfloor \frac{2D}{\omega} - \frac{1}{2} \rfloor$$

where

$$\chi = \frac{\omega}{4D}$$

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is the so-called anharmonicity constant.

## Exercise 1 (1 + 1 P)

While the Morse oscillator provides already a relatively simple model for a chemical bond, a yet even simpler model is often sufficient: The Harmonic oscillator. Its potential simply takes the form

$$V^H(x) = \frac{1}{2}\omega^2(x - x_0)^2.$$

Again we are able to find analytical eigenpairs  $(E_n^H, \varphi_n^H)$  of the Harmonic oscillator Hamiltonian

$$H^H = -\frac{1}{2}\Delta + V^H = -\frac{1}{2}\Delta + \frac{1}{2}\omega^2(x - x_0)^2,$$

where in particular

$$E_n^H = \omega \left( n + \frac{1}{2} \right) \quad \text{for } n = 0, 1, 2, \dots$$

(a) Show that  $V^H(x)$  is the leading-order (in  $x - x_0$ ) term of  $V^M(x)$ , i.e. that the Harmonic oscillator is indeed a simplified version of the Morse oscillator.

**(a) Solution:**

We have

$$V^H(x) = \frac{1}{2}\omega^2(x - x_0)^2$$

and

$$V^M(x) = D \left( 1 - \exp \left( -\frac{\omega}{\sqrt{2D}} (x - x_0) \right) \right)^2$$

One can take the Taylor expansion of  $e^{-\frac{\omega}{\sqrt{2D}}(x-x_0)}$  around  $x_0$ :

$$\begin{aligned} V^M &\approx \left( 1 - 1 + \frac{\omega}{\sqrt{2D}}(x - x_0) + O((x - x_0)^2) \right)^2 \\ &= \frac{\omega^2}{2D}(x - x_0)^2 + O((x - x_0)^4). \end{aligned}$$

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Therefore,

$$V^M(x) \approx V^H(x) + O((x - x_0)^4).$$

**(b)** Show that the ground state (lowest-eigenvalue eigenfunction) is given by

$$\tilde{\varphi}_0^H(x) = \exp\left(-\frac{1}{2}\omega(x - x_0)^2\right)$$

and normalise this function with respect to the standard  $L^2(\mathbb{R})$  norm

$$\|f\| = \sqrt{\int_{\mathbb{R}} |f(x)|^2 dx}.$$

For the normalised function we will use the symbol  $\varphi_0^H$  in the following.

**(b) Solution:**

One need to test that the function  $\tilde{\varphi}_0^H(x)$  satisfies the following condition:  $H^H \tilde{\varphi}_0^H(x) = E_0^H \tilde{\varphi}_0^H(x)$

$$H^H \tilde{\varphi}_0^H(x) = -\frac{1}{2}\Delta + V^H = -\frac{1}{2}\Delta \tilde{\varphi}_0^H(x) + \frac{1}{2}\omega^2(x - x_0)^2 \tilde{\varphi}_0^H(x)$$

with

$$\Delta \tilde{\varphi}_0^H(x) = \frac{d^2}{dx^2}(\exp(-\frac{1}{2}\omega(x - x_0)^2)) = e^{-\frac{1}{2}\omega(x - x_0)^2}(\omega^2(x - x_0)^2 - \omega)$$

Therefore,

$$-\frac{1}{2}e^{-\frac{1}{2}\omega(x - x_0)^2}(\omega^2(x - x_0)^2 - \omega) + \frac{1}{2}\omega^2(x - x_0)^2 e^{-\frac{1}{2}\omega(x - x_0)^2} = \frac{1}{2}\omega e^{-\frac{1}{2}\omega(x - x_0)^2}$$

after simplifications:

$$-\omega^2(x - x_0)^2 + \omega + \omega^2(x - x_0)^2 = \omega$$

$$\omega = \omega$$

Which is true.

Then, we compute the norm of the function:

$$\|\tilde{\varphi}_0^H(x)\| = \sqrt{\int_{\mathbb{R}} |\tilde{\varphi}_0^H(x)|^2 dx} = \sqrt{\int_{\mathbb{R}} |e^{-\frac{1}{2}\omega(x - x_0)^2}|^2 dx},$$

where

$$\int_{\mathbb{R}} e^{-\omega(x - x_0)^2} dx = \frac{\sqrt{\pi}}{\omega}.$$

From which the normalizing constant can be deduced, giving:

$$\varphi_0^H(x) = \sqrt{\frac{\omega}{\sqrt{\pi}}} \tilde{\varphi}_0^H(x)$$

## Exercise 2 (1 + 1 + 1 + 1 P)

We now want to solve the Harmonic oscillator problem numerically using finite differences. To avoid the infinite computational domain, which cannot be treated within a finite differences approach, we will solve the problem only within  $\Omega = [-a, a]$  for  $a > 0$ .

We perform an  $N$ -point finite-difference approximation within  $\Omega$ , i.e. we split the domain into  $N$  intervals of length  $h = \frac{2a}{N-1}$ . Recall that for this setup the finite-difference Laplacian is given by

```
1 using LinearAlgebra
```

fd\_laplacian (generic function with 1 method)

```
1 function fd_laplacian(N, a; T=Float64)
2     h = 2a / (T(N-1))
3     diagonal = -2ones(T, N) ./ h^2
4     side_diagonal = ones(T, N-1) ./ h^2
5     SymTridiagonal(diagonal, side_diagonal)
6 end
```

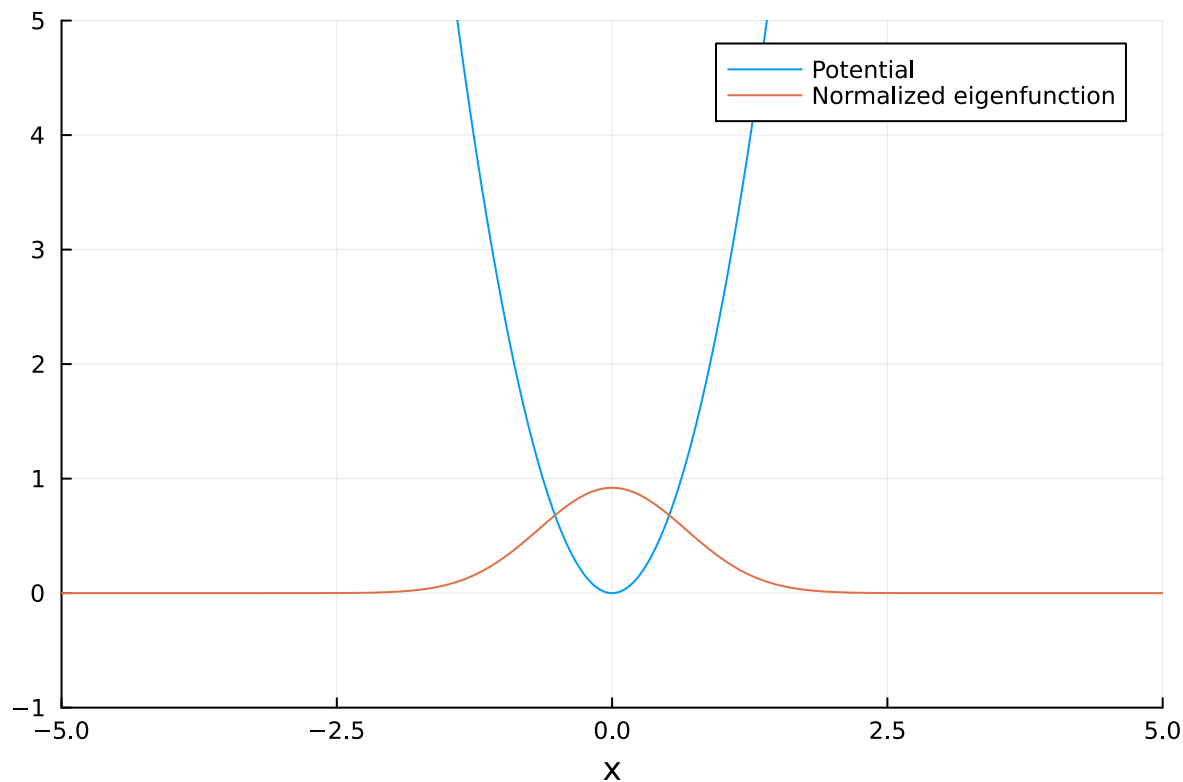
(a) Compute the function values of the potential  $V^H(x)$  and the normalised first eigenfunction  $\varphi_0^H(x)$  on the grid points of a finite differences approximation with  $a = 5$  and  $N = 1000$  and use this to plot  $V^H(x)$  and  $\varphi_0^H(x)$  within our computational domain.

### Hint

(a) Solution:

```
1 begin
2     N = 1000
3     a = 5
4     Vh(x) = 0.5 * ω ^2 * (x-x0)^2
5 end;
```

```
1 begin
2     norm_cte = (ω / π)^(0.25)
3     phi_0(x) = norm_cte * exp(-0.5 * ω * (x - x0)^2)
4
5     grid_points = range(-a, stop=a, length=N)
6     potential_values = [Vh(x) for x in grid_points]
7     eigenfunction_values = [phi_0(x) for x in grid_points]
8 end;
```



(b) Within the finite-differences approximation the potential is just a diagonal term (see the `Diagonal` Julia object). Use Julia's `eigen` function to compute an approximation to the ground state eigenvalue and eigenfunction for  $a = 5$  and  $N = 1000$ .

### Hint

Remember that the first column of the matrix is the ground state.

```
1 begin
2     fd_Hh = - 0.5 * fd_laplacian(N, a) + 0.5 * ω^2 * Diagonal(grid_points.^2)
3     evalues_H, evectors_H = eigen(fd_Hh)
4 end;
```

```
[1.13097e-14, 2.27604e-14, 3.44933e-14, 4.66524e-14, 5.93856e-14, 7.28465e-14, 8.71963e-14,
```

```
1 begin
2     # Eigenvalues are sorted in increasing order
3     low_idx = 1
4     # Get the lowest eigenvalue
5     energy_approx_H = evalues_H[low_idx]
6     # Get the corresponding eigenfunction
7     efunction_approx_H = evectors_H[:, low_idx]
8 end
```

(c) Use the expressions for the exact ground state energy and ground state eigenfunction  $\varphi_0$  from Exercise 1 to verify that the eigenvalue is converged to  $10^{-4}$  and the  $L^2(\mathbb{R})$ -error of the eigenvector is also around  $10^{-4}$ .

*Hint:* Note, that `eigen` does indeed return the finite difference approximation  $(f(x_1), \dots, f(x_n))^T$  to the eigenfunction  $f$ , where  $\{x_i\}_{i=1}^N$  are the points of your finite differences grid. However, since it normalises the vectors in  $\mathbb{R}^N$  using the Euclidean norm, the resulting approximate function  $f$  is *not* appropriately  $L^2(\mathbb{R})$ -normalised. To see this, consider the finite differences approximation to the integral

$$\int_{\Omega} f(x) dx,$$

which itself is an approximation to  $\int_{\mathbb{R}} f(x) dx$ .

### Hint

Example: Approximate the integral of a function  $f$  over the interval  $[a, b]$ .

1. Discretize the interval  $[a, b]$  into  $N$  points,  $x_1, \dots, x_N$ , to approximate the integral  $\int_a^b f(x) dx$  by the Riemann sum  $\sum_{i=1}^N f(x_i) \Delta x$ , where  $\Delta x = (b-a)/(N-1)$ .
2. Approximate the function  $f$  at the points  $x_i$  by the values  $f(x_i)$  returned by the function `f`.

discretized\_l2\_norm (generic function with 1 method)

```
1 function discretized_l2_norm(f, a)
2     dx = 2a / (length(f) - 1)
3     l2_norm = sqrt(sum(abs.(f) .^ 2) * dx)
4     return l2_norm
5 end
```

discretized\_l2\_error (generic function with 1 method)

```
1 function discretized_l2_error(f1, f2, a)
2     l2_error = discretized_l2_norm(f1 - f2, a)
3     return l2_error
4 end
```



```

1
2 begin
3     # The ground state eigenvalue
4     μ_exact_H = ω * 0.5
5
6     # Normalizing the eigenfunction
7     efunc_norm = discretized_l2_norm(efunction_approx_H, a)
8     efunc_approx_normalized = efunction_approx_H/efunc_norm
9
10    # Computing the errors
11    efunc_error = discretized_l2_error(efunc_approx_normalized, eigenfunction_values,
12    a)
13    evalue_error = abs(energy_approx_H - μ_exact_H)
14
15    println("Eigenvalue error: $evalue_error")
16    println("Eigenfunction error: $efunc_error")
17 end

```

```

Eigenvalue error: 1.5852219709344695e-5
Eigenfunction error: 1.0370831859818148e-5

```



We can see that indeed the eigenvalue is converged to  $10^{-4}$  and the  $L^2(\mathbb{R})$ -error of the eigenvector is also around  $10^{-4}$ .

(d) Use the same computational setup to determine an approximation for the first eigenpair of the Morse oscillator Hamiltonian  $H^M$ . What is the deviation in the numerically obtained ground state eigenvalue between the Morse and Harmonic oscillator model and how does it compare to the expected deviation considering the analytical eigenvalues? Plot the numerical ground state eigenfunctions of  $H^M$  and  $H^H$ . Where do these functions differ?

(d) Solution:

```

1 begin
2     fd_Hm = - 0.5 * fd_laplacian(N, a) + Diagonal(Vm.(grid_points) )
3     evalues_M, evectors_M = eigen(fd_Hm)
4 end;

```

```

1 begin
2     energy_approx_M = evalues_M[low_idx]
3     efunction_approx_M = evectors_M[:, low_idx]
4
5     # Deviation in the numerically obtained ground state eigenvalue
6     energy_deviation_numerical = abs(energy_approx_M - energy_approx_H)
7
8 end;

```

```

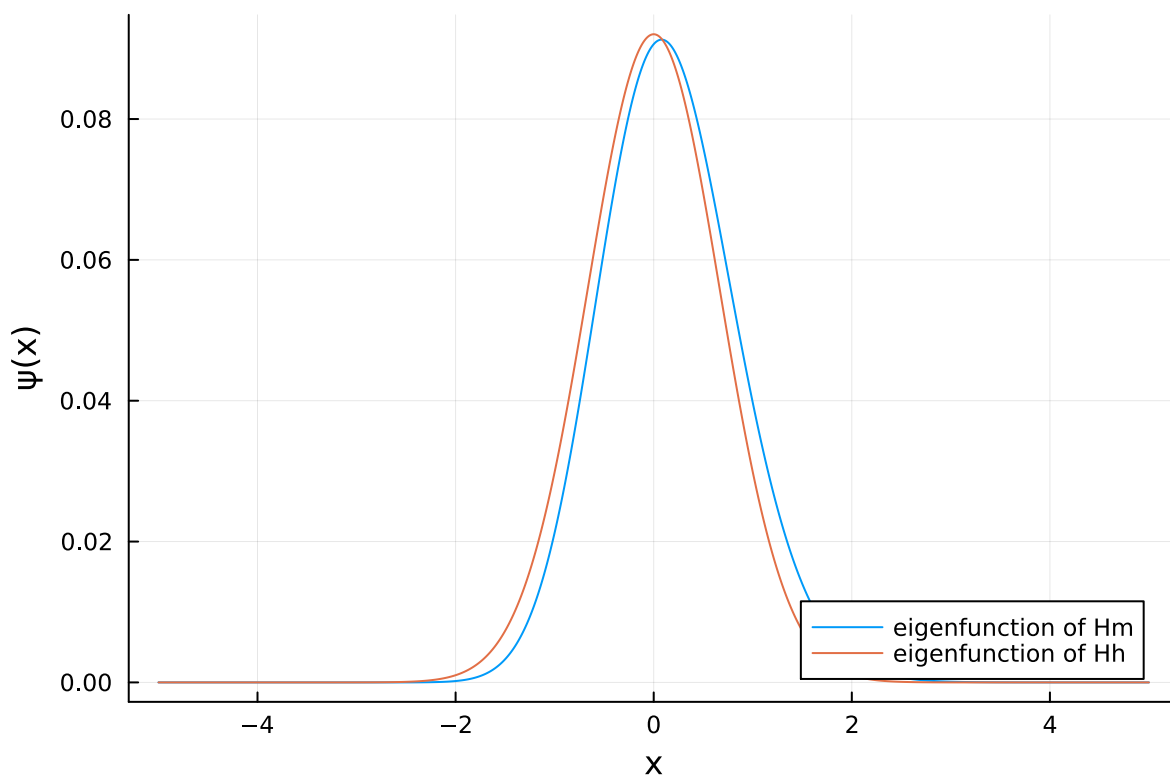
1 begin
2      $\mu\_exact\_M = 0.5 * \omega - 0.25 * \omega^2 / (4 * D)$ 
3     energy_deviation_expected = abs( $\mu\_exact\_M$  -  $\mu\_exact\_H$ )
4     println("Expected deviation in ground state eigenvalue:
5         $energy_deviation_expected")
6     println("Numerical deviation in ground state eigenvalue:
7         $energy_deviation_numerical")
8     difference = abs(energy_deviation_expected - energy_deviation_numerical)
9     println("Difference: $difference")
10 end

```

```

Expected deviation in ground state eigenvalue: 0.015820312500000044
Numerical deviation in ground state eigenvalue: 0.01581972223205197
Difference: 5.902679480751516e-7

```



```

1 begin
2     plot(grid_points, efunction_approx_M, label="eigenfunction of Hm", xlabel="x",
3         ylabel="ψ(x)")
4     plot!(grid_points, efunction_approx_H, label="eigenfunction of Hh",
5         legend=:bottomright)
6 end

```

By analyzing the plots we can notice that the peak of the Morse oscillator ground state eigenfunction is **shifted** in comparison with the Harmonic oscillator ground state eigenfunction. The heights of the two curves also look slightly different.

## Exercise 3 (1 + 2 + 1 P)

We return to the problem of finding numerically an approximate eigenfunction of the Harmonic oscillator  $H^H$  and replace the diagonalisation using `eigen` in *Exercise 2(b)* by the inverse power method discussed in the lecture:

`inverse_power_method` (generic function with 1 method)

```
1 function inverse_power_method(A; u=randn(eltype(A), size(A, 2)),
2                               tol=1e-6, maxiter=500)
3     norm_Δu = NaN
4     Afac = factorize(A) # Factorise A to make A \ x more economical
5     for i in 1:maxiter
6         u_prev = u
7         u = Afac \ u
8         normalize!(u)
9         norm_Δu = min(norm(u - u_prev), norm(-u - u_prev))
10        norm_Δu < tol && break
11    end
12    μ = dot(u, A, u)
13    norm_Δu ≥ tol && @warn "Inverse power not converged $norm_Δu"
14    (; μ, u)
15 end
```

(a) For the numerical setup of *Exercise 2(b)* tune the tolerance `tol` such that we obtain an  $L^2$ -error in the eigenvector and an error in the eigenvalue below  $10^{-4}$ . Run your computation in both double and single precision. Is single precision sufficiently accurate to not impact the quality of the result?

(a) Solution:

```
1 begin
2     fd_Hh_64 = - 0.5 * fd_laplacian(N, a; T=Float64) + 0.5 * ω^2 *
3     Diagonal(grid_points.^2)
4     fd_Hh_32 = - 0.5 * fd_laplacian(N, a; T=Float32) + 0.5 * ω^2 *
5     Diagonal(grid_points.^2)
6
7     tol=1e-4
8
9     μ_64, u_64=inverse_power_method(fd_Hh_64,tol=tol)
10    μ_32, u_32=inverse_power_method(fd_Hh_32,tol=tol)
11
12    efunc_approx_64 = u_64/discretized_l2_norm(u_64, a)
13    efunc_approx_32 = u_32/discretized_l2_norm(u_32, a)
14 end;
```

```

1 begin
2     # Computing the errors
3     efunc_error_64 = discretized_l2_error(efunc_approx_64, eigenfunction_values, a)
4     evalue_error_64 = abs(μ_64 - μ_exact_H)
5
6     efunc_error_32 = discretized_l2_error(efunc_approx_32, eigenfunction_values, a)
7     evalue_error_32 = abs(μ_32 - μ_exact_H)
8
9     println("\nComparing the algorithm error for both types\n")
10
11    println("\nSingle Precision:")
12    println("    Eigenvalue Error: $evalue_error_64")
13    println("    Eigenfunction Error: $efunc_error_64")
14
15
16    println("\nDouble Precision:")
17    println("    Eigenvalue Error: $evalue_error_32")
18    println("    Eigenfunction Error: $evalue_error_32")
19 end

```

Comparing the algorithm error for both types

Single Precision:

Eigenvalue Error: 1.585150748062425e-5

Eigenfunction Error: 2.0660544323363654e-5

Double Precision:

Eigenvalue Error: 1.5809366900043642e-5

Eigenfunction Error: 1.5809366900043642e-5

We can conclude that single precision is sufficiently accurate for the problem not to impact the quality of the computed solution.

**(b)** Assume our goal is to approximate the ground state eigenvalue of the Morse oscillator using the single-precision procedure in (a), i.e. the computation of the ground state eigenvalue of the harmonic oscillator using the inverse power method in single precision. Compute the total error against the analytical ground state eigenvalue  $E_0^M$ . Split this total error into error contributions (model error, discretisation error, algorithm error, arithmetic error) as discussed in the lecture and indicate their respective sizes in each case. Use `BigFloat` as a proxy for estimating the result for "exact" floating-point arithmetic.

**(b) Solution:**

Let's start by doing a recap of all the error types:

- the arithmetic error due to the storage of the data:  $|\mu_1^{(\text{fp32})} - \mu_1^{(\text{big})}|$ ;
- the algorithm error due to the non-null tolerance:  $|\mu_1^{(\text{big})} - \mu_1|$ ;
- the discretization error due to the finite number of mesh points:  $|\mu_1 - \lambda_1|$ ;
- the model error due to the simplifying assumptions of our model:  $|\lambda_1 - \lambda_*|$ .

The total error is  $|\mu_1^{(\text{fp32})} - \lambda_*|$ .

In our case, without knowing the analytical formula of eigenvalue  $\mu_1$  for the discretized problem we can calculate the difference between numerical and analytical solutions,  $\mu_1^{(\text{big})}$  and  $\lambda_1$ :

$$|\mu_1^{(\text{big})} - \lambda_1| \leq e_{\text{algorithm}} + e_{\text{discretization}}$$

```
1 begin
2     fd_Hh_big = - 0.5 * fd_laplacian(N, a; T=BigFloat) + 0.5 * ω^2 *
        Diagonal(grid_points.^2)
3
4     μ_big, u_big=inverse_power_method(fd_Hh_big,tol=tol)
5 end;
```

```
e_arithmetic =
4.150802751155198715889828711290971550666891679732478382434248128321495248191626e-08
```

```
1 # Arithmetic error
2 e_arithmetic = abs(μ_big - μ_32)
```

```
e_discrit_plus_algorithm =
1.585087492755519407732674854307909623894416891679732478382434248128321495248192e-05
```

```
1 # Computing the discretization and algorithm errors together
2 e_discrit_plus_algorithm = abs(μ_big - μ_exact_H)
```

```
e_model = 0.0158203125000000044
```

```
1 # Model error
2 e_model = abs(μ_exact_M - μ_exact_H)
```

```
e_total = 0.0158045031331
```

```
1 # The total error against the analytical ground state eigenvalue
2 e_total = abs(μ_32 - μ_exact_M)
```

**(c)** Use the numerical parameters of your setup to balance all error contributions with the model error, i.e. tune  $N$ ,  $\text{tol}$  and decide between `Float32` and `Float64`, such that each of the error contributions you computed in (b) are roughly on the order of the model error.

```

1 begin
2     tolerance = 0.26
3     N_points = 100
4     points = range(-a, stop=a, length=N_points)
5
6     Hh = - 0.5 * fd_laplacian(N, a; T=Float32) + 0.5 * ω^2 * Diagonal(grid_points.^2)
7     μ, _=inverse_power_method(Hh,tol=tolerance)
8
9     Hh_big = - 0.5 * fd_laplacian(N, a; T=BigFloat) + 0.5 * ω^2 *
10    Diagonal(grid_points.^2)
11    μbig, _=inverse_power_method(Hh_big,tol=tolerance)
12 end;

```

```
0.01542595763817480231300915387249932205068840811597412089225813928026713523026179
```

```
1 abs(μbig - μ) # arithmetic error
```

```
0.01784907439935958711946905590151817118513359854566162089225813928026713523026179
```

```
1 abs(μbig - μ_exact_H) # discretization and algorithm errors together
```

```
0.0158203125000000044
```

```
1 abs(μ_exact_M - μ_exact_H) # model error
```

```
0.01824342926118483
```

```
1 abs(μ - μ_exact_M) # total error
```

After tuning the number of points in the grid and the tolerance we can see that each of the error contributions is roughly on the order of the model error.