

Lecture 11: Linear Algebra

Sets of simultaneous equations

Eigenvalue problem

Revisiting the Schrodinger equation without the shooting method

Simultaneous Sets of Linear Equations

Linear algebra (`scipy.linalg`)

Linear algebra functions.

$$\begin{aligned}a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + a_{14}x_4 &= b_1 \\a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + a_{24}x_4 &= b_2 \\a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + a_{34}x_4 &= b_3 \\a_{41}x_1 + a_{42}x_2 + a_{43}x_3 + a_{44}x_4 &= b_4\end{aligned}$$

N linear equations, N unknowns
(solvable for linearly independent equations)

A diagram showing the equation $Ax = b$ in a large serif font. Below the A is an upward-pointing arrow labeled "known". Below the x is an upward-pointing arrow labeled "unknown". To the right of the $=$ is another upward-pointing arrow labeled "known" pointing to the b .

Many solvers depending on properties of matrix **A**.

`solve(a, b[, sym_pos, lower, overwrite_a, ...])`

Solves the linear equation set $a * x = b$ for the unknown x for square a matrix.

`solve_banded(l_and_u, ab, b[, overwrite_ab, ...])`

Solve the equation $a x = b$ for x , assuming a is banded matrix.

`solveh_banded(ab, b[, overwrite_ab, ...])`

Solve equation $a x = b$.

`solve_circulant(c, b[, singular, tol, ...])`

Solve $C x = b$ for x , where C is a circulant matrix.

`solve_triangular(a, b[, trans, lower, ...])`

Solve the equation $a x = b$ for x , assuming a is a triangular matrix.

$$\begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{pmatrix}$$

You want to pick the solver which is the **least** general for your matrix.

If Matrix has symmetry, can be taken advantage of to speed up solution.

Eigenvalue Problem

Linear algebra (**scipy.linalg**)

Linear algebra functions.

$$Ax = \lambda x$$

Diagram illustrating the eigenvalue problem equation $Ax = \lambda x$. The matrix A is labeled "known". The vector x is labeled "unknown". The scalar λ is labeled "unknown".

$$\begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \lambda \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix}$$

- Input

- matrix

- Output

- Eigenvalues
- Eigenvectors

`eig(a[, b, left, right, overwrite_a, ...])`

Solve an ordinary or generalized eigenvalue problem of a square matrix.

`eigvals(a[, b, overwrite_a, check_finite, ...])`

Compute eigenvalues from an ordinary or generalized eigenvalue problem.

`eigh(a[, b, lower, eigvals_only, ...])`

Solve a standard or generalized eigenvalue problem for a complex Hermitian or real symmetric matrix.

`eigvalsh(a[, b, lower, overwrite_a, ...])`

Solves a standard or generalized eigenvalue problem for a complex Hermitian or real symmetric matrix.

`eig_banded(a_band[, lower, eigvals_only, ...])`

Solve real symmetric or complex Hermitian band matrix eigenvalue problem.

`eigvals_banded(a_band[, lower, ...])`

Solve real symmetric or complex Hermitian band matrix eigenvalue problem.

`eigh_tridiagonal(d, e[, eigvals_only, ...])`

Solve eigenvalue problem for a real symmetric tridiagonal matrix.

`eigvalsh_tridiagonal(d, e[, select, ...])`

Solve eigenvalue problem for a real symmetric tridiagonal matrix.

Tridiagonal matrix

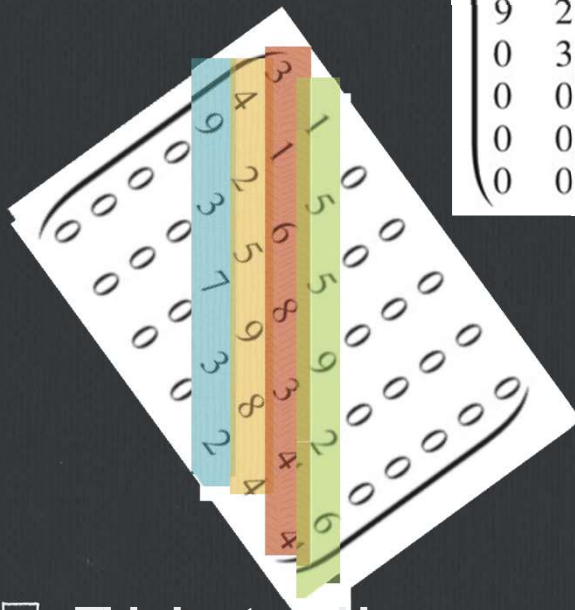
`tridag.h` `void tridag(VecDoub_I &a, VecDoub_I &b, VecDoub_I &c, VecDoub_I &r, VecDoub_O &u)`
Solves for a vector `u[0..n-1]` the tridiagonal linear set given by equation (2.4.1). `a[0..n-1]`, `b[0..n-1]`, `c[0..n-1]`, and `r[0..n-1]` are input vectors and are not modified.

$$\begin{bmatrix} b_0 & c_0 & 0 & \cdots \\ a_1 & b_1 & c_1 & \cdots \\ & & \cdots & \\ & & \cdots & a_{N-2} & b_{N-2} & c_{N-2} \\ & & \cdots & 0 & a_{N-1} & b_{N-1} \end{bmatrix} \cdot \begin{bmatrix} u_0 \\ u_1 \\ \cdots \\ u_{N-2} \\ u_{N-1} \end{bmatrix} = \begin{bmatrix} r_0 \\ r_1 \\ \cdots \\ r_{N-2} \\ r_{N-1} \end{bmatrix}$$

Need only store vectors `a`, `b`, `c`, and `r`.

- ❑ The tridiagonal matrix algorithm scales as $O(N)$, instead of $O(N^3)$.

Band-diagonal



$$\begin{pmatrix} 3 & 1 & 0 & 0 & 0 & 0 & 0 \\ 4 & 1 & 5 & 0 & 0 & 0 & 0 \\ 9 & 2 & 6 & 5 & 0 & 0 & 0 \\ 0 & 3 & 5 & 8 & 9 & 0 & 0 \\ 0 & 0 & 7 & 9 & 3 & 2 & 0 \\ 0 & 0 & 0 & 3 & 8 & 4 & 6 \\ 0 & 0 & 0 & 0 & 2 & 4 & 4 \end{pmatrix}$$

$$\begin{pmatrix} x & x & 3 & 1 \\ x & 4 & 1 & 5 \\ 9 & 2 & 6 & 5 \\ 3 & 5 & 8 & 9 \\ 7 & 9 & 3 & 2 \\ 3 & 8 & 4 & 6 \\ 2 & 4 & 4 & x \end{pmatrix}$$



This is stored in a compact form

Example from SciPy

Examples

Solve the banded system $a x = b$, where:

$$a = \begin{bmatrix} 5 & 2 & -1 & 0 & 0 \\ 1 & 4 & 2 & -1 & 0 \\ 0 & 1 & 3 & 2 & -1 \\ 0 & 0 & 1 & 2 & 2 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} \quad b = \begin{bmatrix} 0 \\ 1 \\ 2 \\ 2 \\ 3 \end{bmatrix}$$

There is one nonzero diagonal below the main diagonal ($l = 1$), and two above ($u = 2$). The diagonal banded form of the matrix is:

$$ab = \begin{bmatrix} * & * & -1 & -1 & -1 \\ * & 2 & 2 & 2 & 2 \\ 5 & 4 & 3 & 2 & 1 \\ 1 & 1 & 1 & 1 & * \end{bmatrix}$$

```
>>> from scipy.linalg import solve_banded
>>> ab = np.array([[0, 0, -1, -1, -1],
...               [0, 2, 2, 2, 2],
...               [5, 4, 3, 2, 1],
...               [1, 1, 1, 1, 0]])
>>> b = np.array([0, 1, 2, 2, 3])
>>> x = solve_banded((1, 2), ab, b)
>>> x
array([-2.37288136,  3.93220339, -4.          ,  4.3559322 , -1.3559322 ])
```

scipy.linalg.solve_banded

`scipy.linalg.solve_banded(l_and_u, ab, b, overwrite_ab=False, overwrite_b=False, debug=None, check_finite=True)`

[\[source\]](#)

Solve the equation $a x = b$ for x , assuming a is banded matrix.

The matrix a is stored in ab using the matrix diagonal ordered form:

```
ab[u + i - j, j] == a[i,j]
```

Linear Algebra and HPC



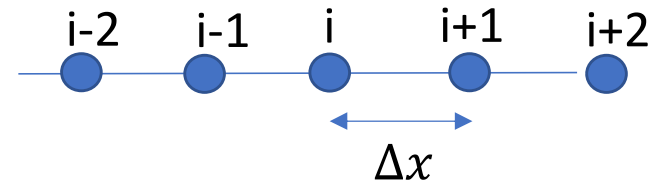
Rank	System	Cores	Rmax (TFlop/s)	Rpeak (TFlop/s)	Power (kW)
1	Supercomputer Fugaku - Supercomputer Fugaku, A64FX 48C 2.2GHz, Tofu interconnect D, Fujitsu RIKEN Center for Computational Science Japan	7,630,848	442,010.0	537,212.0	29,899
2	Summit - IBM Power System AC922, IBM POWER9 22C 3.07GHz, NVIDIA Volta GV100, Dual-rail Mellanox EDR Infiniband, IBM DOE/SC/Oak Ridge National Laboratory United States	2,414,592	148,600.0	200,794.9	10,096
3	Sierra - IBM Power System AC922, IBM POWER9 22C 3.1GHz, NVIDIA Volta GV100, Dual-rail Mellanox EDR Infiniband, IBM / NVIDIA / Mellanox DOE/NNSA/LLNL United States	1,572,480	94,640.0	125,712.0	7,438
4	Sunway TaihuLight - Sunway MPP, Sunway SW26010 260C 1.45GHz, Sunway, NRCPC National Supercomputing Center in Wuxi China	10,649,600	93,014.6	125,435.9	15,371
5	Perlmutter - HPE Cray EX235n, AMD EPYC 7763 64C 2.45GHz, NVIDIA A100 SXM4 40 GB, Slingshot-10, HPE DOE/SC/LBNL/NERSC United States	706,304	64,590.0	89,794.5	2,528

Lapack (linear algebra package)
BLAS (basic linear algebra
subprograms)

Highly optimized linear algebra
Routines for C/Fortran

From mathematics to computer: finite differences

real space grid: $f(x) \rightarrow f_i$



Forward Formula:

$$\frac{\partial f(x)}{\partial x} = \frac{f(x+h) - f(x)}{h} + o(h) \quad \Rightarrow \quad \frac{\partial f(x)}{\partial x} = \frac{f_{i+1} - f_i}{\Delta x}$$

Centered Formulas:

$$\frac{\partial f(x)}{\partial x} = \frac{f\left(x + \frac{h}{2}\right) - f\left(x - \frac{h}{2}\right)}{h} + o(h^2) \quad \Rightarrow \quad \frac{\partial f(x)}{\partial x} = \frac{\partial f_i}{\partial x} = \frac{f_{i+1} - f_{i-1}}{2\Delta x}$$

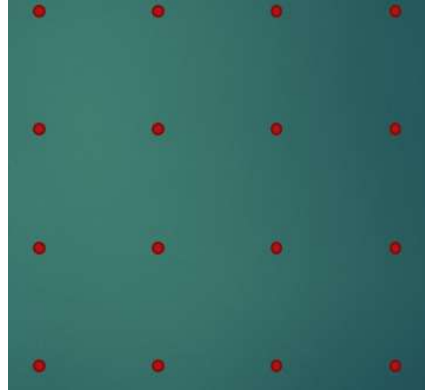
$$\frac{\partial^2 f(x)}{\partial x^2} = \frac{f(x+h) + f(x-h) - 2f(x)}{h^2} + o(h^2) \quad \Rightarrow \quad \frac{\partial^2 f(x)}{\partial x^2} = \frac{f_{i+1} + f_{i-1} - 2f_i}{\Delta x^2}$$

Application to PDEs

$$\frac{\partial f(x)}{\partial x} = \frac{f_{i+1} - f_i}{\Delta x} \quad (\text{FD})$$

$$\frac{\partial f(x)}{\partial x} = \frac{f_{i+1} - f_{i-1}}{2\Delta x} \quad (\text{CD})$$

$$\frac{\partial^2 f(x)}{\partial x^2} = \frac{f_{i+1} + f_{i-1} - 2f_i}{\Delta x^2}$$



Wave Equation

$$\nabla^2 U(x, t) = \frac{1}{c^2} \frac{\partial^2 U}{\partial t^2}$$

$$\frac{\partial^2 U(x, t)}{\partial x^2} = \frac{1}{c^2} \frac{\partial^2 U}{\partial t^2}$$

$$\frac{U_{i+1,j} + U_{i-1,j} - 2U_{i,j}}{\Delta x^2} = \frac{1}{c^2} \frac{U_{i,j+1} + U_{i,j-1} - 2U_{i,j}}{\Delta t^2}$$

Poisson Equation: $U(x, y) \rightarrow U_{i,j}$

$$\nabla^2 U(x, y) = -4\pi\rho(x, y)$$

$$\frac{\partial^2 U(x, y)}{\partial x^2} + \frac{\partial^2 U(x, y)}{\partial y^2} = -4\pi\rho(x, y)$$

$$\frac{U_{i+1,j} + U_{i-1,j} - 2U_{i,j}}{\Delta x^2} + \frac{U_{i,j+1} + U_{i,j-1} - 2U_{i,j}}{\Delta y^2} = -4\pi\rho_{i,j}$$

Heat Equation

$$\nabla^2 U(x, t) = \frac{a \partial U}{\partial t}$$

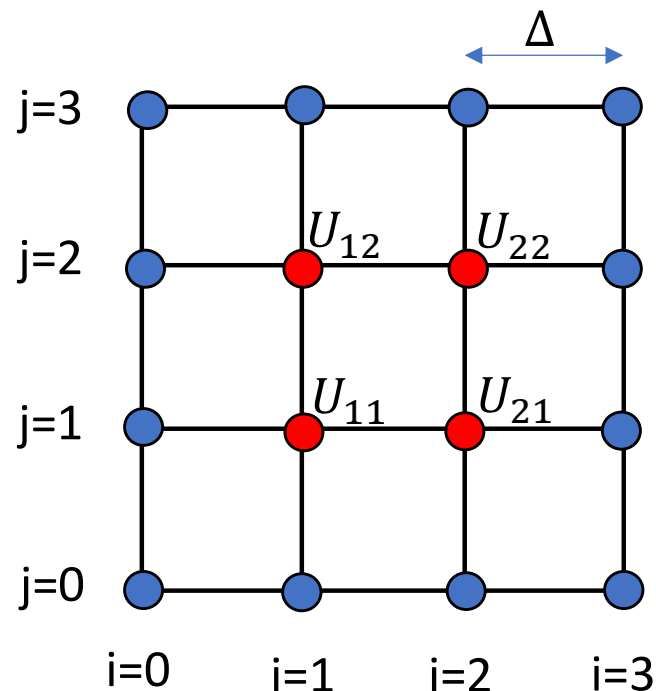
$$\frac{\partial^2 U(x, t)}{\partial x^2} = \frac{a \partial U}{\partial t}$$

$$\frac{f_{i+1,j} + f_{i-1,j} - 2f_{i,j}}{\Delta x^2} = a \frac{f_{i,j+1} - f_{i,j}}{\Delta t}$$

Poisson Equation:

$$\frac{U_{i+1,j} + U_{i-1,j} - 2U_{i,j}}{\Delta x^2} + \frac{U_{i,j+1} + U_{i,j-1} - 2U_{i,j}}{\Delta y^2} = -4\pi\rho_{i,j} \quad (\Delta x = \Delta y = \Delta)$$

$$\frac{1}{4}(U_{i+1,j} + U_{i-1,j} + U_{i,j+1} + U_{i,j-1}) - U_{i,j} = -4\pi\Delta^2\rho_{i,j} \quad (\rho = 0 \rightarrow \text{Laplace equation})$$



boundary conditions: blue points
unknown potential: red points

$$\begin{aligned} U_{11} &= 1/4(U_{10} + U_{12} + U_{01} + U_{21}) \\ U_{21} &= 1/4(U_{20} + U_{22} + U_{31} + U_{11}) \\ U_{12} &= 1/4(U_{11} + U_{13} + U_{02} + U_{22}) \\ U_{22} &= 1/4(U_{21} + U_{23} + U_{12} + U_{32}) \end{aligned}$$

Use matrix solver to simultaneously solve for the potential at each grid point.

$$\mathbf{A} \mathbf{x} = \mathbf{b}$$

$$\begin{pmatrix} 4 & -1 & -1 & 0 \\ -1 & 4 & 0 & -1 \\ -1 & 0 & 4 & -1 \\ 0 & -1 & -1 & 4 \end{pmatrix} \begin{pmatrix} U_{11} \\ U_{21} \\ U_{12} \\ U_{22} \end{pmatrix} = \begin{pmatrix} U_{10} + U_{01} \\ U_{20} + U_{31} \\ U_{13} + U_{02} \\ U_{23} + U_{32} \end{pmatrix}$$

Schrodinger equation (1D)

$$-\frac{1}{2} \frac{\partial^2 \Psi(x)}{\partial x^2} + V(x)\Psi(x) = E\Psi(x)$$

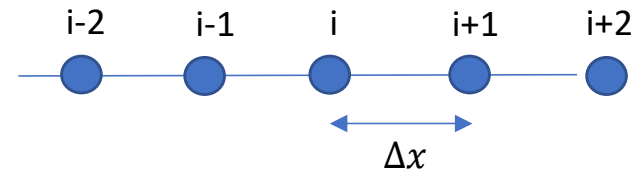


$$-\frac{1}{2} \frac{(\Psi_{i+1} + \Psi_{i-1} - 2\Psi_i)}{\Delta x^2} + V_i \Psi_i = E\Psi_i$$

(equation for each grid point \rightarrow N equations)

$$f(x) \rightarrow f_i$$

$$\frac{\partial^2 f(x)}{\partial x^2} = \frac{f_{i+1} + f_{i-1} - 2f_i}{\Delta x^2}$$



$$i = 0: \quad -\frac{1}{2} \frac{(\Psi_1 + \Psi_{-1} - 2\Psi_0)}{\Delta x^2} + V_0 \Psi_0 = E\Psi_0$$

$$i = 1: \quad -\frac{1}{2} \frac{(\Psi_2 + \Psi_0 - 2\Psi_1)}{\Delta x^2} + V_1 \Psi_1 = E\Psi_1$$

$$i = 2: \quad -\frac{1}{2} \frac{(\Psi_3 + \Psi_1 - 2\Psi_2)}{\Delta x^2} + V_2 \Psi_2 = E\Psi_2$$

$$i = 3: \quad -\frac{1}{2} \frac{(\Psi_4 + \Psi_2 - 2\Psi_3)}{\Delta x^2} + V_3 \Psi_3 = E\Psi_3$$

...

What is the matrix form of this set of equations??

Kinetic Energy

Potential Energy

$$-\frac{1}{2\Delta x^2} \begin{pmatrix} -2 & 1 & 0 & 0 & 0 \\ 1 & -2 & 1 & 0 & 0 \\ 0 & 1 & -2 & 1 & 0 \\ 0 & 0 & 1 & -2 & 1 \\ 0 & 0 & 0 & 1 & -2 \end{pmatrix} \begin{pmatrix} \Psi_0 \\ \Psi_1 \\ \Psi_2 \\ \Psi_3 \\ \Psi_4 \end{pmatrix} + \begin{pmatrix} V_0 & 0 & 0 & 0 & 0 \\ 0 & V_1 & 0 & 0 & 0 \\ 0 & 0 & V_2 & 0 & 0 \\ 0 & 0 & 0 & V_3 & 0 \\ 0 & 0 & 0 & 0 & V_4 \end{pmatrix} \begin{pmatrix} \Psi_0 \\ \Psi_1 \\ \Psi_2 \\ \Psi_3 \\ \Psi_4 \end{pmatrix} = E \begin{pmatrix} \Psi_0 \\ \Psi_1 \\ \Psi_2 \\ \Psi_3 \\ \Psi_4 \end{pmatrix}$$

Eigenvalue problem:

$$\hat{H}\Psi = E\Psi$$

Hamiltonian matrix is tridiagonal and Hermitian.

$$i = 0: -\frac{1}{2} \frac{(\Psi_1 + \Psi_{-1} - 2\Psi_0)}{\Delta x^2} + V_0\Psi_0 = E\Psi_0$$

$$i = 1: -\frac{1}{2} \frac{(\Psi_2 + \Psi_0 - 2\Psi_1)}{\Delta x^2} + V_1\Psi_1 = E\Psi_1$$

$$i = 2: -\frac{1}{2} \frac{(\Psi_3 + \Psi_1 - 2\Psi_2)}{\Delta x^2} + V_2\Psi_2 = E\Psi_2$$

$$i = 3: -\frac{1}{2} \frac{(\Psi_4 + \Psi_2 - 2\Psi_3)}{\Delta x^2} + V_3\Psi_3 = E\Psi_3$$

...

In 1-D, with a real space basis, the Laplacian ∇^2 can be represented as:

$$\frac{1}{\Delta x^2} \begin{pmatrix} -2 & 1 & 0 & 0 & 0 \\ 1 & -2 & 1 & 0 & 0 \\ 0 & 1 & -2 & 1 & 0 \\ 0 & 0 & 1 & -2 & 1 \\ 0 & 0 & 0 & 1 & -2 \end{pmatrix}$$

Setting up matrix

for N=5

$$-\frac{1}{2\Delta x^2} \begin{pmatrix} -2 & 1 & 0 & 0 & 0 \\ 1 & -2 & 1 & 0 & 0 \\ 0 & 1 & -2 & 1 & 0 \\ 0 & 0 & 1 & -2 & 1 \\ 0 & 0 & 0 & 1 & -2 \end{pmatrix}$$

```
np.diag(np.ones(N-1),k=-1)
```

```
array([[0., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.]])
```

```
np.diag(np.ones(N-1),k=0)
```

```
array([[1., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 1.]])
```

```
np.diag(np.ones(N-1),k=1)
```

```
array([[0., 1., 0., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 1.],
       [0., 0., 0., 0., 0.]])
```

```
np.diag(np.ones(N-1),k=-1)+np.diag(-2*np.ones(N),k=0)+np.diag(np.ones(N-1),k=1)
```

```
array([[ -2.,  1.,  0.,  0.,  0.],
       [  1., -2.,  1.,  0.,  0.],
       [  0.,  1., -2.,  1.,  0.],
       [  0.,  0.,  1., -2.,  1.],
       [  0.,  0.,  0.,  1., -2.]])
```

```
L=1 #actual length of x domain
N=10 #number of x grid points
dx= L/(N-1) # space between grid points
```

```
KE=(np.diag(-2*np.ones(N))+np.diag(np.ones(N-1),k=1)+np.diag(np.ones(N-1),k=-1))
KE=-0.5*KE/(dx**2)
print(KE)
```

```
[[ 81. -40.5 -0.  -0.  -0.  -0.  -0.  -0.  -0.  -0.]
 [-40.5 81. -40.5 -0.  -0.  -0.  -0.  -0.  -0.  -0.]
 [-0. -40.5 81. -40.5 -0.  -0.  -0.  -0.  -0.  -0.]
 [-0. -0. -40.5 81. -40.5 -0.  -0.  -0.  -0.  -0.]
 [-0. -0. -0. -40.5 81. -40.5 -0.  -0.  -0.  -0.]
 [-0. -0. -0. -0. -40.5 81. -40.5 -0.  -0.  -0.]
 [-0. -0. -0. -0. -0. -40.5 81. -40.5 -0.  -0.]
 [-0. -0. -0. -0. -0. -0. -40.5 81. -40.5 -0.]
 [-0. -0. -0. -0. -0. -0. -0. -40.5 81. -40.5]
 [-0. -0. -0. -0. -0. -0. -0. -0. -40.5 81. ]]
```

No potential → infinite square well

Solving

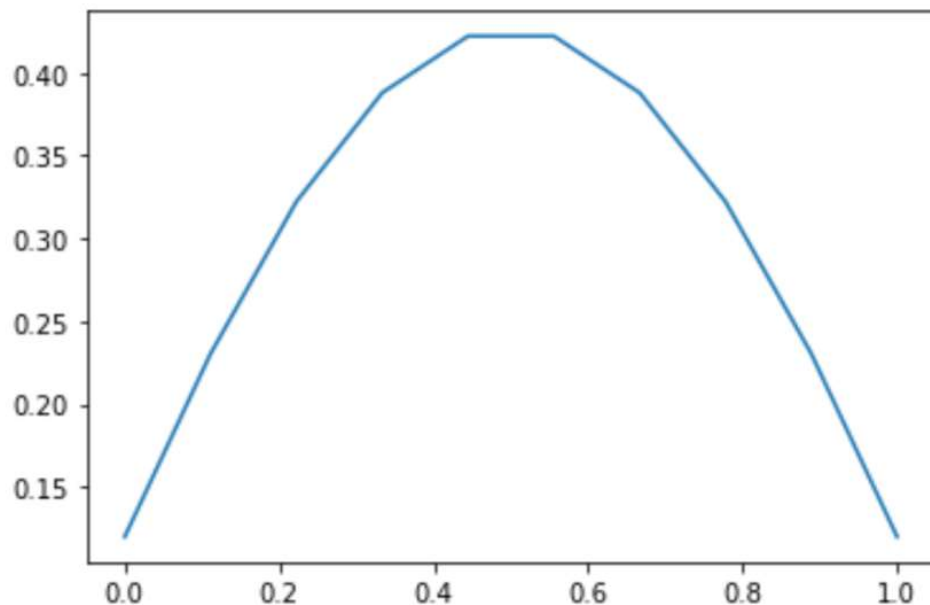
(N=10)

```
from scipy import linalg  
  
xs=delta*np.arange(N)  
w,v=linalg.eigh(KEmatrix) # w=eigenvalues, v = eigenvectors
```

w

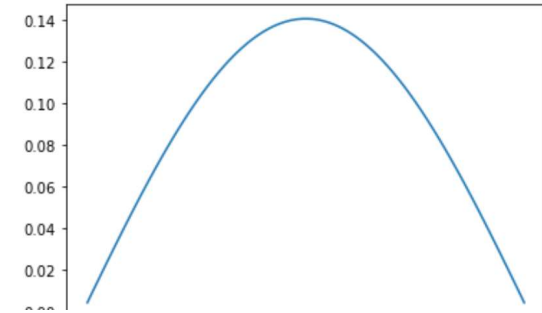
```
array([  3.28106914,  12.85846384,  27.95628055,  47.35138395,  
        69.4724981 ,  92.5275019 , 114.64861605, 134.04371945,  
       149.14153616, 158.71893086])
```

```
plt.plot(xs,v[:,0])  
plt.show()
```



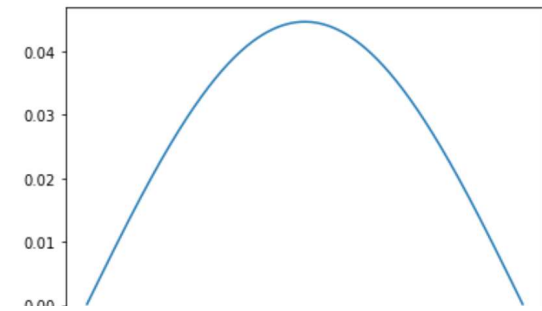
```
print(N)  
print(w[0])  
plt.plot(xs,v[:,0])  
plt.show()
```

```
100  
4.7409172562290305
```



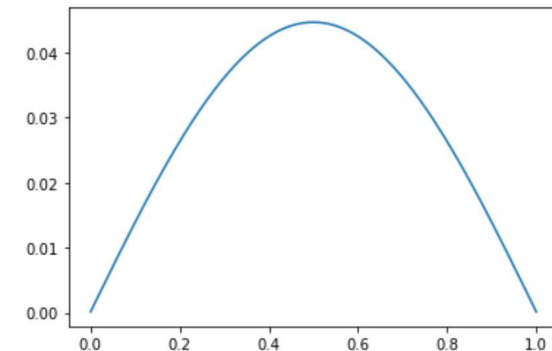
```
print(N)  
print(w[0])  
plt.plot(xs,v[:,0])  
plt.show()
```

```
1000  
4.915098376750613
```



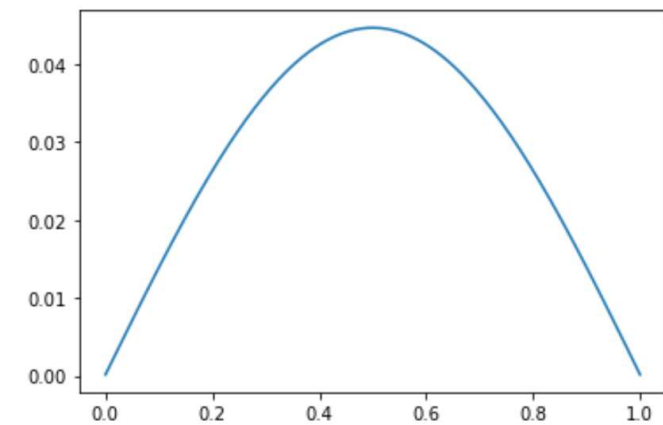
```
print(N)  
print(w[0])  
plt.plot(xs,v[:,0])  
plt.show()
```

```
10000  
4.915098376750613
```



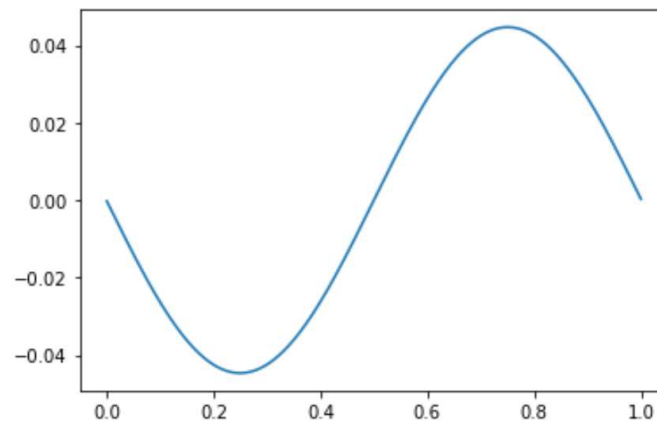
```
print(N)
print(w[0])
plt.plot(xs,v[:,0])
plt.show()
```

1000
4.915098376750613



```
print(N)
print(w[1])
plt.plot(xs,v[:,1])
plt.show()
```

1000
19.66034509328222



```
print(N)
print(w[2])
plt.plot(xs,v[:,2])
plt.show()
```

1000
44.235594911021856

