

An Introduction to Geometric Multigrid

Nicholas Moore

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1 Introduction

We follow the analysis from “A Multigrid Tutorial” by William Briggs. This explanation will focus on the use of the Multigrid Method as a solver for the 1D Poisson problem, though the concepts and ideas can be applied to problems of higher dimension, or as a preconditioner instead of a solver.

```
[1]: from prettytable import PrettyTable
from IPython.display import HTML
import time
import numpy as np
from numpy.linalg import norm, solve
import scipy.sparse as sp
import scipy.sparse.linalg as splu
import matplotlib.pyplot as plt
from numpy.random import MT19937, RandomState, SeedSequence
rs = RandomState(MT19937(SeedSequence(123456789)))

# We will be profiling code later, this extension allows line-by-line profiling
%load_ext line_profiler

# Unified mmult user interface for both scipy.sparse and numpy matrices.
# In scipy.sparse, mmult is done using the overloaded * operator, e.g., A*x.
# In numpy, mmult is done using the dot() function, e.g., dot(A,x).
# This function chooses which to use based on whether A is stored as
# a sparse matrix.
def mvmult(A, x):
    if sp.issparse(A):
        return A*x
    else:
        return np.dot(A,x)
```

2 Analyzing the Jacobi Method

2.1 Problem Set Up

First, we create the A matrix. For simplicity and easy of understanding, we will choose the 1D poisson problem with Dirichlet Boundary Conditions.

The matrix for this problem is given by

$$A = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & & & \\ -1 & 2 & -1 & & & \\ & -1 & 2 & -1 & & \\ & & \ddots & \ddots & \ddots & \\ & & & -1 & 2 & -1 \\ & & & & -1 & 2 \end{bmatrix}$$

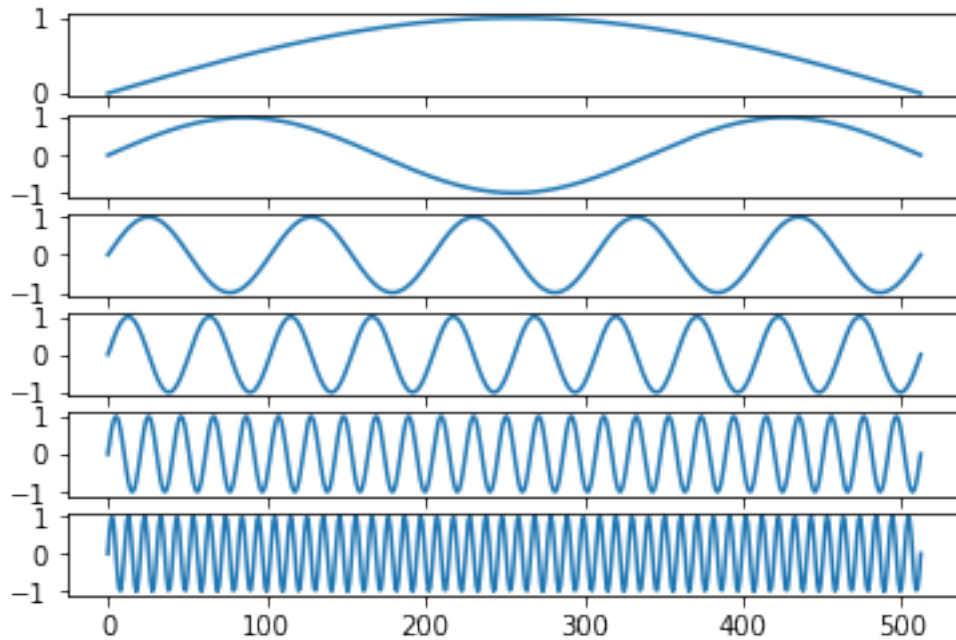
so the problem can be written as $Ax = b$. If N is the number of subintervals we divide the domain into, then this matrix is $N - 1 \times N - 1$.

For the sake of demonstration, we let the right-hand side vector b correspond to the case of Dirichlet boundary conditions where both ends are held at 0. We choose this because the true solution is therefore the zero vector so the error corresponds exactly with the current iterate.

```
[21]: def GeneratePoisson(N):  
    # Generate A matrix for poisson problem with N subintervals (N-1 unknowns)  
    # Result will be a N-1 x N-1 matrix  
    row = N*N*np.array([-1, 2, -1], dtype=np.double)  
    A = sp.diags(row, [-1, 0, 1], shape=(N-1, N-1), dtype=np.double,   
    ↪format="csr")  
    return A  
  
N = 512  
A = GeneratePoisson(N)  
b = np.zeros((N-1,1), dtype=np.double)
```

We also generate some initial guesses (which are also initial errors) which are sine waves with varying frequencies.

```
[22]: x = np.linspace(0,1,N+1)  
waveNumbers = [1, 3, 10, 20, 50, 100]  
#waveNumbers = [1, 10, 50, 100]  
xinitial = [np.sin(w*np.pi*x) for w in waveNumbers]  
fig, axs = plt.subplots(len(waveNumbers),1)  
for (i,p) in enumerate(xinitial):  
    axs[i].plot(p)
```



2.2 Create a Jacobi Function

```
[23]: def Jacobi(x, A, b, numiters=1):
    for i in range(numiters):
        # Need a copy of x since we'll be updating x in place
        xold = x.copy()

        # Loop through the rows
        for i in range(len(xold)):
            # Calculate the indices of the CSR data array that hold the row
            rowindices = range(A.indptr[i], A.indptr[i+1])

            r = 0.
            for j in rowindices:
                col = A.indices[j]
                if col != i:
                    r += A.data[j]*xold[col]
                else:
                    d = A.data[j]

            # Update x
            x[i] = (b[i] - r)/d
    return x
```

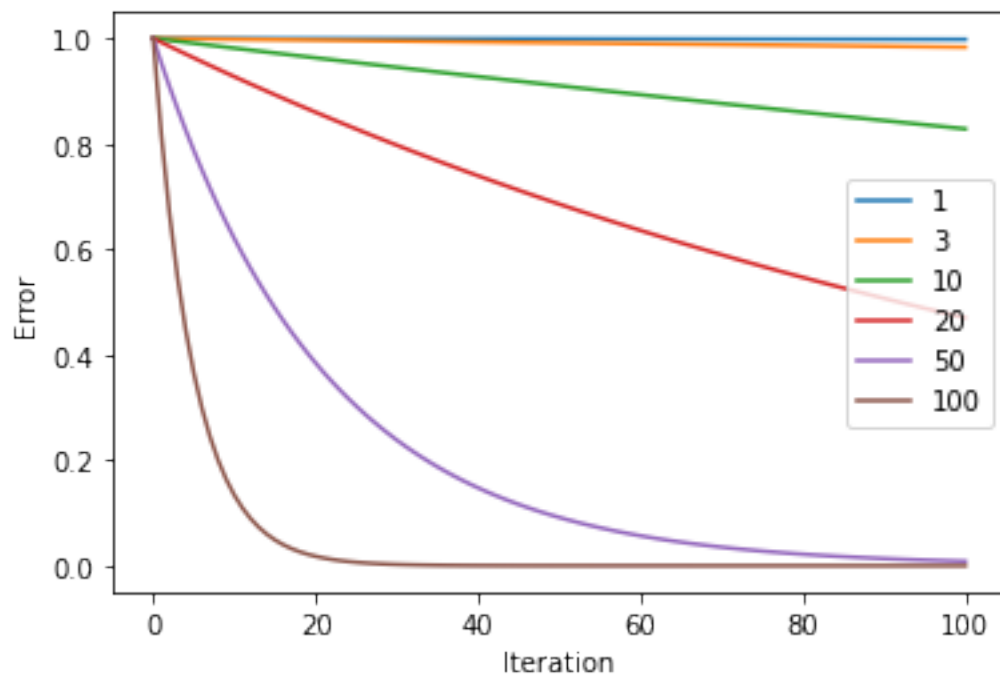
2.3 Running Jacobi

Now let's run 100 Jacobi iterations on each of the initial conditions, tracking the error at each iteration.

```
[24]: numJacobiIters = 100

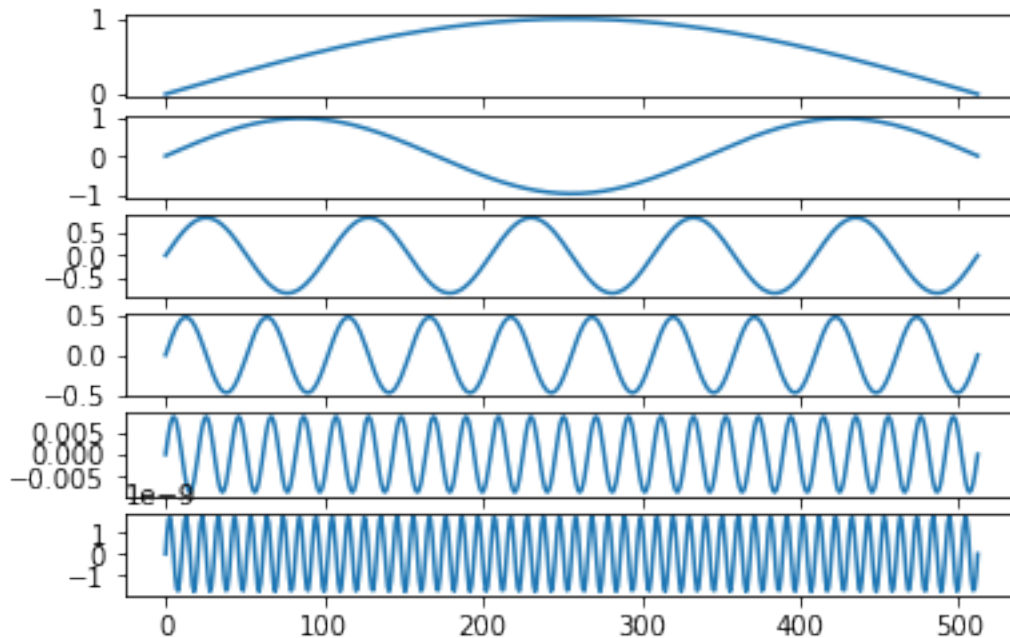
errors = [np.zeros((numJacobiIters+1,1), dtype=np.double) for i in
    range(len(waveNumbers))]
initialErrorNorms = [np.linalg.norm(w) for w in xinitial]
x_working = xinitial.copy()
for j in range(numJacobiIters+1):
    for (i, w) in enumerate(x_working):
        if j == 0:
            errors[i][j] = np.linalg.norm(w[1:-1])/initialErrorNorms[i]
        else:
            errors[i][j] = np.linalg.norm(Jacobi(w[1:-1], A, b, 1))/
    initialErrorNorms[i]
```

```
[25]: for (i,w) in enumerate(errors):
        plt.plot(w, label = waveNumbers[i])
plt.legend(loc="right")
plt.xlabel("Iteration")
plt.ylabel("Error")
plt.show()
```



We can also look at our iterates now:

```
[26]: fig, axs = plt.subplots(len(waveNumbers),1)
      for (i,p) in enumerate(x_working):
          axs[i].plot(p)
```



2.4 Why Multigrid Works

Here we see the key to understanding the effectiveness of multigrid: The Jacobi iteration scheme is much better at eliminating high frequency error than low frequency error.

2.5 Other Iteration Methods

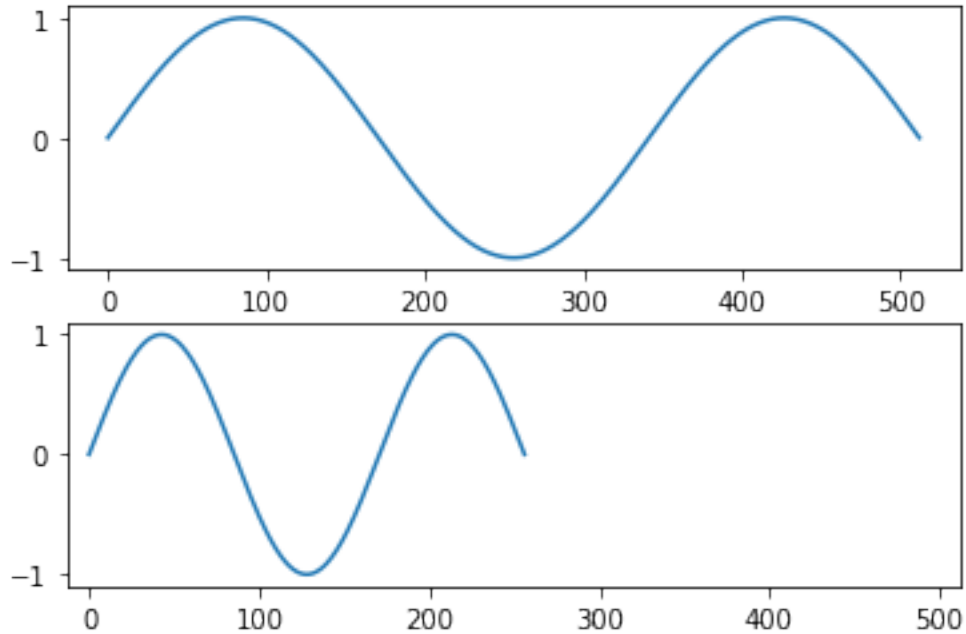
While the preceeding discussion uses Jacobi iteration, all relaxation-type iterations methods like Gauss-Seidel and variations of Jacobi and Gauss-Seidel also present this property. In multigrid terminology, these are all generally referred to as relaxations.

2.6 How Do We Use This?

The matrix system does not have any explicit information about the physical structure of the problem. Hence, if we take a longer vector with low frequency error, and remove half of the points:

```
[27]: y_fine = np.sin(3*np.pi*x)
      x_coarse = np.array([x[i] for i in range(len(x)) if i % 2 == 0])
      y_coarse = np.sin(3*np.pi*x_coarse)
```

```
fig, axs = plt.subplots(2, 1)
axs[0].plot(y_fine)
axs[1].plot(y_coarse)
plt.xlim(right=N)
plt.show()
```



we can see that we have the same number of oscillations, but in half the number of nodes. For Jacobi, which has no information about what the entries represent, the shorter vector has higher frequency error than the longer vector so it would be more effective on this new shorter vector.

3 In Practice

Consider a discretized PDE problem on a grid (which we'll denote Ω^h) where h represents the spacing between nodes. As the name suggests, for the multigrid method we'll be using multiple grids, each with a different spacing of nodes. From here on, we'll be using superscript to denote which grid a quantity is on.

Our discretized problem is written as $A^h x^h = b^h$. We'll start with k Jacobi iterations. Since we don't expect our current iteration x^h to be the exact solution, let's assume the exact solution is of the form $x^* = x^h + e^h$. This gives us an equation of the form:

$$A^h(x^h + e^h) = b^h$$

Rearranging this equation gives

$$A^h e^h = b^h - A^h x^h = r^h$$

So if we calculate r^h and solve $A^h e^h = r^h$ for e^h , then we could find the exact solution as $x^* = x^h + e^h$.

So how do we find or (more accurately) approximate e^h ? Running more Jacobi iterations at this level has already shown to be less effective since the high frequency error has already been removed. Only the lower frequency error remains. Instead, we will move the problem down to a coarser grid, Ω^{2h} . In the coarser grid, the low frequency error changes to higher frequency error and Jacobi can be more effective.

That is, we want to solve $A^{2h}e^{2h} = r^{2h}$, where A^{2h} , e^{2h} , and r^{2h} are the "coarse grid versions" of A^h , e^h , and r^h . We will discuss how to find these later.

This coarser grid problem is smaller (by a factor of 4) so it will take less computational effort. We can either solve the system exactly or use another method to approximate the solution to the coarse grid system. We then "transfer" this e^{2h} solution back into the Ω^h grid and it becomes an approximation to e^h . We then calculate $x^h + e^h$ to get a better approximation for x^h . In doing so, the transfer may have introduced more high frequency error, so we typically complete more Jacobi iterations at the fine level to smooth them out. This process leverages the change of grids to use Jacobi iteration more effectively.

4 Moving Between Grids

We need a way to transform the problem, and all the quantities involved, between the various grids in order to leverage such a scheme. We will examine the simplest case for geometric multi-grid in 1D. Assume that the coarse grid has grid spacing which is twice as large as the finer grid (that is, the coarse grid is the fine grid with every other node removed). This is almost universal practice since evidence does not seem to indicate there is any advantage to choosing a different ratio.

4.1 Restriction Operator

First, let's talk about an operator for transforming from the fine grid to the coarse grid. This is typically referred to as the **restriction** operator. We will denote it as I_h^{2h} and there are a few reasonable options for how to build this operator. One option is to simply remove half of the grid points. This option could work, but tends to remove too much information. The more recommended option is **full weighting**. With this operator, we produce coarse grid vectors according to the rule $I_h^{2h}x^h = x^{2h}$ where

$$x_j^{2h} = \frac{1}{4} \left(x_{2j-1}^h + 2x_{2j}^h + x_{2j+1}^h \right)$$

For example, if we have 8 subintervals in our fine grid (that is 7 interior nodes), and 4 subintervals in our coarse grid (with 3 interior nodes), then we have the following:

$$I_h^{2h}x^h = \frac{1}{4} \begin{bmatrix} 1 & 2 & 1 & & & & \\ & & 1 & 2 & 1 & & \\ & & & & 1 & 2 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix}_h = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}_{2h} = x^{2h}$$

We can also represent this operator with a “stencil” (a common representation for weighted averages of geometric nodes) given by

$$\frac{1}{4} \begin{bmatrix} 1 & 2 & 1 \end{bmatrix}$$

This operator also has another advantage that we’ll mention later.

```
[8]: # Let's build a function to generate the Full Weighting operator for transforming
# a vector of length 2^n-1 to a vector of length 2^(n-1) - 1
def BuildFullWeighting(N):
    # We assume N = 2^n-1 is the number of unknown in the fine mesh

    # We calculate the number of unknowns in the coarse mesh
    # Note: this is doing a cast to integer which discards any decimal components
    Nc = int(N/2)

    # We will build it in coordinate format, though it with a little more effort,
    # it could be efficiently built in CSR format as well.
    #
    # There are 3*Nc non-zeros in the matrix
    row_indicies = np.zeros(3*Nc, dtype="int")
    col_indicies = np.zeros(3*Nc, dtype="int")
    data = np.zeros(3*Nc)
    for i in range(Nc):
        row_indicies[3*i:3*i+3] = [i, i, i]
        col_indicies[3*i:3*i+3] = [2*i, 2*i + 1, 2*i + 2]
        data[3*i:3*i+3] = [0.25, 0.5, 0.25]

    # Build the matrix
    I_FW = sp.coo_matrix((data, (row_indicies,col_indicies))).tocsr()
    return I_FW
```

Let’s look at how this operator acts on a short vector:

```
[9]: # Set up the fine grid first
x_fine = np.linspace(0,1,9)
y_fine = np.sin(3*np.pi*x_fine)

# Now the coarse grid
x_coarse = np.linspace(0,1,5)
y_coarse = np.zeros((5,1))

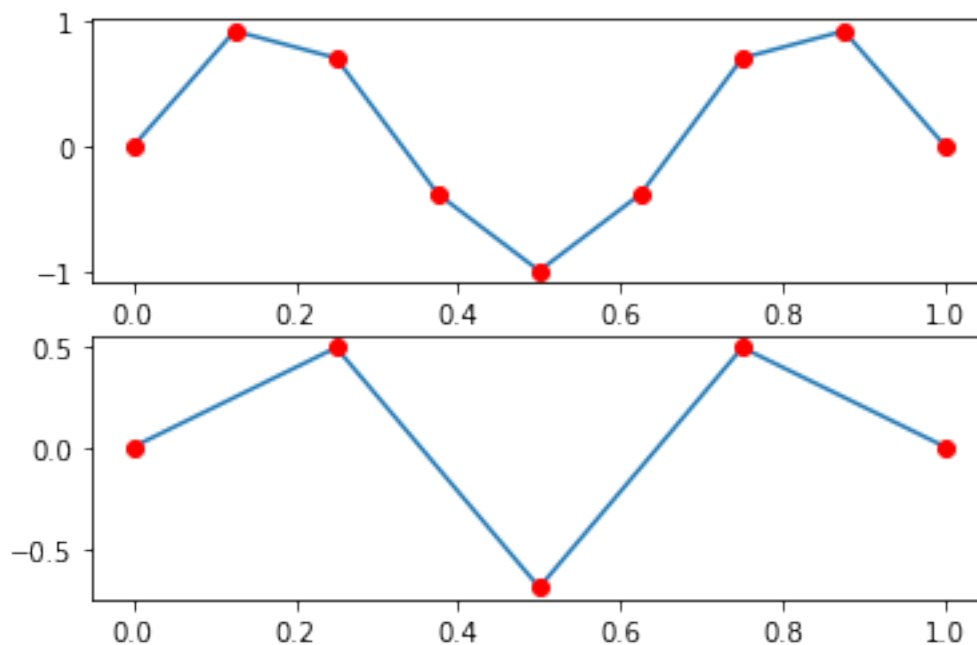
# Create the restriction matrix using full weighting
I_restrict = BuildFullWeighting(7)

# Interpolate from the coarse y values into the finer y-values
y_coarse[1:4,0] = mvmult(I_restrict,y_fine[1:8])
```



```
# Plot the coarse grid quantities as a blue line and the fine grid as red circles
fig, axs = plt.subplots(2,1)
axs[0].plot(x_fine, y_fine, '-', x_coarse, y_coarse, 'ro')
axs[1].plot(x_coarse, y_coarse, '-', x_coarse, y_coarse, 'ro')
```

[9]: [<matplotlib.lines.Line2D at 0x7f39ea8e9dc0>,
<matplotlib.lines.Line2D at 0x7f39ea8e9df0>]



While, for simplicity in presentation, we will not be presenting a 2D problem, the stencil for the full weighting operator in this case is given:

$$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

4.2 Interpolation Operator

Now, let's discuss what's typically referred to as the **interpolation** or **prolongation** operator. It takes vectors in a coarse grid and interpolates them into a finer grid. We will denote it as I_{2h}^h and it produces fine grid vectors according to the rule $I_{2h}^h x^{2h} = x^h$ where

$$x_{2j}^h = x_j^{2h}$$

$$x_{2j+1}^h = \frac{1}{2} (x_j^{2h} + x_{j+1}^{2h})$$

In other words, for the shared grid points, we simply let the values coincide and for the additional fine grid points, we use the average of the surrounding coarse grid points. We can describe this

transformation with a matrix operator. For example, if we have 8 subintervals in our fine grid (that is 7 interior nodes), and 4 subintervals in our coarse grid (with 3 interior nodes), then we have the following:

$$I_{2h}^h x^{2h} = \frac{1}{2} \begin{bmatrix} 1 & & & \\ 2 & & & \\ 1 & 1 & & \\ & 2 & & \\ & 1 & 1 & \\ & & 2 & \\ & & 1 & \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}_{2h} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix}_h = x^h$$

Another advantage of using the full weighting operator for the restriction operator is that $I_{2h}^h = c(I_h^{2h})^T$. This is an important property for a lot of the theory of multigrid. We can also depict this graphically.

```
[10]: # Set up the coarse grid first
x_coarse = np.linspace(0,1,5)
y_coarse = np.sin(3*np.pi*x_coarse)

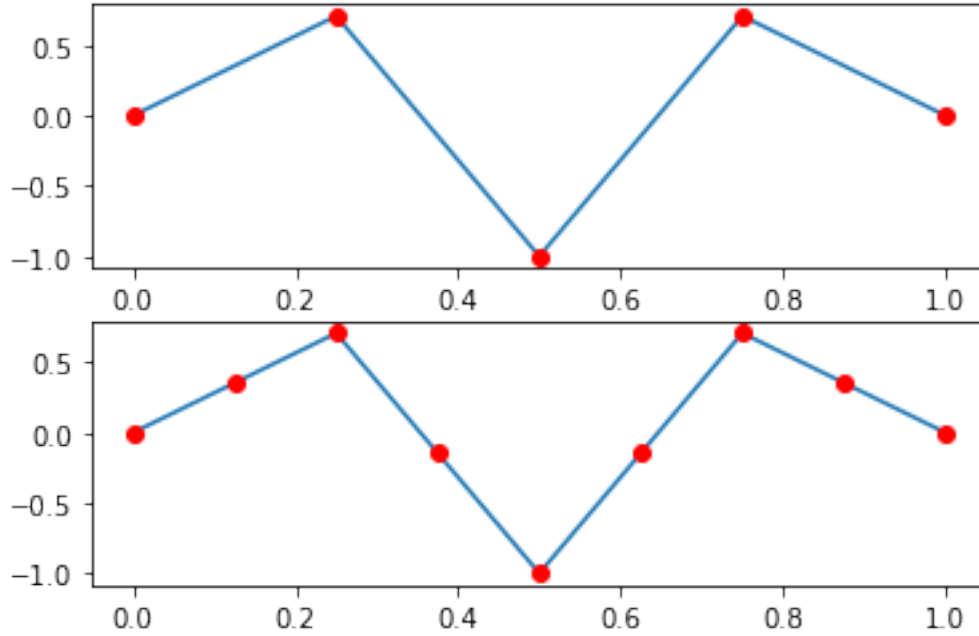
# Now the fine grid
x_fine = np.linspace(0,1,9)
y_fine = np.zeros((9,1))

# Create the prolongation matrix - it's the transpose of the restriction
# → operator created earlier
I_prolong = 2*I_restrict.T

# Interpolate from the coarse y values into the finer y-values
y_fine[1:8,0] = mvmult(I_prolong, y_coarse[1:4])

# Plot the coarse grid quantities as a blue line and the fine grid as red circles
fig, axs = plt.subplots(2,1)
axs[0].plot(x_coarse,y_coarse,'-',x_coarse, y_coarse, 'ro')
axs[1].plot(x_fine, y_fine, '-', x_fine, y_fine,'ro')
```

```
[10]: [<matplotlib.lines.Line2D at 0x7f39ea88dc70>,
      <matplotlib.lines.Line2D at 0x7f39ea88dca0>]
```



4.3 Galerkin Projection

The last piece we need to discuss is the creation of the coarse grid version of the A^{2h} matrix. One option is to generate a discretization for the coarse grid as well as the fine grid. This technique can be cumbersome, and adds to the effort involved in utilizing the multigrid method. Another option is to use the **Galerkin Projection**:

$$A^{2h} = I_h^{2h} A^h I_{2h}^h$$

As it turns out, if we use full weighting on the 1D problem, this projection will be the same as the projection created by a discretization of the coarse grid. Let's demonstrate this, step-by-step.

First, let e_j^{2h} denote the vector on the coarse grid with a 1 in the j th entry, and zeros elsewhere. Then $A^{2h} e_j^{2h}$ will be the j th column of A^{2h} . We will calculate this column in steps:

$$I_{2h}^h e_j^{2h} = \frac{1}{2} \begin{bmatrix} 1 & & & & \\ 2 & & & & \\ 1 & 1 & & & \\ & 2 & & & \\ & 1 & 1 & & \\ & & 2 & & \\ & & 1 & 2 & \\ & & & 1 & \ddots \\ & & & & \ddots \\ & & & & & \ddots \\ & & & & & & \ddots \\ & & & & & & & \ddots \\ & & & & & & & & \ddots \end{bmatrix} \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \frac{1}{2} \\ 1 \\ \frac{1}{2} \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Notice, this vector now lies in the fine grid so we can now apply the fine grid operator A^h to this vector:

$$A^h I_{2h}^h e_j^{2h} = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & \ddots & \ddots & \ddots \end{bmatrix} \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \frac{1}{2} \\ 1 \\ \frac{1}{2} \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \frac{-1}{2h^2} \\ \frac{1}{h^2} - \frac{1}{h^2} \\ \frac{-1}{2h^2} + \frac{2}{h^2} - \frac{1}{h^2} \\ \frac{-1}{h^2} + \frac{1}{h^2} \\ \frac{-1}{2h^2} \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \frac{-1}{2h^2} \\ 0 \\ \frac{1}{h^2} \\ 0 \\ \frac{-1}{2h^2} \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Finally, we apply the restriction operator to this vector to obtain a vector in the coarse grid space:

$$I_h^{2h} A^h I_{2h}^h e_j^{2h} = \begin{bmatrix} \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & & & \\ & \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & & \\ & & \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & \\ & & & \frac{1}{2} & \frac{1}{4} & \\ & & & & \ddots & \ddots & \ddots \end{bmatrix} \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \frac{-1}{2h^2} \\ 0 \\ \frac{1}{h^2} \\ 0 \\ \frac{-1}{2h^2} \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \frac{-1}{4h^2} \\ \frac{1}{2h^2} \\ \frac{-1}{4h^2} \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \frac{-1}{(2h)^2} \\ \frac{2}{(2h)^2} \\ \frac{-1}{(2h)^2} \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Notice that this is exactly the same column we obtain from creating discretization on the coarse grid. This projection will not be the same as the coarse grid discretization in a 2D problem or if full weighting is not used. Nevertheless, it is a common practice and has been shown to produce good results. It also has the advantage that it requires no extra effort on the part of the user, it can simply be another step in the algorithm.

5 A Formal Two-Grid Cycle

(in Briggs, this is called a Coarse Grid Correction Scheme)

1. Relax ν_1 times on $A^h x^h = b^h$ on Ω^h with initial guess x^h
2. Compute $r^{2h} = I_{2h}^{2h}(b^h - A^h x^h)$.
3. Solve $A^{2h} e^{2h} = r^{2h}$ on Ω^{2h}
4. Correct fine grid approximation: $x^h \leftarrow x^h + I_{2h}^h e^{2h}$
5. Relax ν_2 times on $A^h x^h = b^h$ on Ω^h with initial guess x^h

```
[11]: # Import CG code
import os
import sys
```

```

module_path = os.path.abspath(os.path.join('../CGProgrammingProblem'))
if module_path not in sys.path:
    sys.path.append(module_path)
from PCG import PCG

def TwoGridScheme(A_fine, b, numPreRelax, numPostRelax, numiters=1):
    # For simplicity, we assume A_fine is (2^n-1) by (2^n-1) for some n

    # We will also assume that A is SPD so that we can use CG to solve the
    →coarse system

    # Build the restriction and prolongation operators
    # They can be re-used if we run more than 1 iteration
    I_Restrict = BuildFullWeighting(A_fine.shape[0])
    I_Prolong = 2*I_Restrict.T

    # Use an initial guess of zero
    x = np.zeros_like(b)

    # The coarse A only needs to be calculated once, using Galerkin Projection
    A_coarse = I_Restrict.dot(A_fine.dot(I_Prolong))

    # We could run this scheme more than once if more accuracy is required
    for i in range(numiters):
        # First we relax on the fine grid:
        x = Jacobi(x, A_fine, b, numiters=numPreRelax)

        # Now compute the restricted residual
        r_coarse = mvmult(I_Restrict, b - mvmult(A_fine, x))

        # Now we solve the coarse problem Ae = r, which is
        # cheaper than solving the fine grid problem due to the decrease in size
        # We use the initial guess of zero
        (conv, _, e_coarse, _, _) = PCG(A_coarse, r_coarse, maxiter=100000)
        if not conv:
            raise RuntimeError("PCG did not converge on the coarse_grid")

        # Correct the fine-grid x with the prolonged residual
        x += mvmult(I_Prolong, e_coarse)

        # The above Prolongation could be introducing additional high frequency
    →errors

    # So we relax again to get rid of them
    x = Jacobi(x, A_fine, b, numiters=numPostRelax)

    return x

```

Let's test it out. We will generate A_{fine} to be $(2^{16} - 1) \times (2^{16} - 1)$. We use the method of manufactured solutions to generate b from a random true solution x^* and start with $x_0 = 0$ for an initial guess. We will run 5 iterations of Jacobi before and after the transfer to the coarse grid.

```
[12]: N = 2**16

A_fine = GeneratePoisson(N)
xTrue = rs.rand(N-1)
b = mvmult(A_fine, xTrue)
x = np.zeros_like(b)

results = PrettyTable()
results.field_names = ["Algorithm", "Num. Iterations", "Rel. Error", "Time_
    ↪(sec)"]
results.align = "l"

# Run Jacobi - 1000 iterations
startT = time.time()
x_Jac = Jacobi(np.zeros_like(b), A_fine, b, 100)
endT = time.time()
relError_Jac = norm(x_Jac - xTrue)/norm(xTrue)
results.add_row(["Jacobi", 100, relError_Jac, endT-startT ])

# Run TwoGrid - 1 pre and 1 post relax, 1 iteration
startT = time.time()
x_TG = TwoGridScheme(A_fine, b, 1, 1, 1)
endT = time.time()
relError = norm(x_TG - xTrue)/norm(xTrue)
results.add_row(["Two Grid (1 pre, 1 post)", 1, relError, endT-startT])

# Run TwoGrid - 1 pre and 1 post relax, 3 iteration
startT = time.time()
x_TG = TwoGridScheme(A_fine, b, 1, 1, 3)
endT = time.time()
relError = norm(x_TG - xTrue)/norm(xTrue)
results.add_row(["Two Grid (1 pre, 1 post)", 3, relError, endT-startT])

# Run TwoGrid - 3 pre and 3 post relax, 1 iteration
startT = time.time()
x_TG = TwoGridScheme(A_fine, b, 3, 3, 1)
endT = time.time()
relError = norm(x_TG - xTrue)/norm(xTrue)
results.add_row(["Two Grid (3 pre, 3 post)", 1, relError, endT-startT])

display(HTML(results.get_html_string()))
```

Algorithm	Iter	Rel Error	Time (sec)
Jacobi	100	0.87381	37.455
Two Grid (1 pre, 1 post)	1	0.29484	8.900
Two Grid (1 pre, 1 post)	3	0.23544	32.962
Two Grid (3 pre, 3 post)	1	0.23544	11.599

While these numbers look impressive, you can't read too much into it since we are actually cheating a little bit by using Conjugate Gradient on the coarse level. There is some hope, however, looking at the last two rows. The run that completes more relaxation and few CG solves achieves the same error in half the time. Let's see how long it takes CG to solve the fine grid problem to the same relative residual and try using more relaxations for the Two Grid method.

```
[13]: # Run TwoGrid - 5 pre and 5 post relax, 1 iteration
startT = time.time()
x_TG = TwoGridScheme(A_fine, b, 5, 5, 1)
endT = time.time()
relError = norm(x_TG - xTrue)/norm(xTrue)
results.add_row(["Two Grid (5 pre, 5 post)", 1, relError, endT-startT])

# Run CG to the similar relative error
startT = time.time()
(conv, iters_CG, x_CG, _, _) = PCG(A_fine, b, maxiter=100000, tau=1.8e-9)
endT = time.time()
relError = norm(x_CG - xTrue)
results.add_row(["CG", iters_CG, relError, endT-startT])

display(HTML(results.get_html_string()))
```

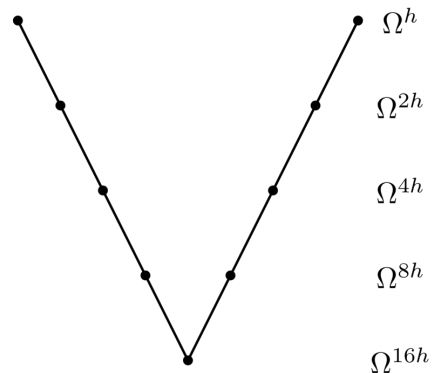
Algorithm	Iter	Rel Error	Time (sec)
Jacobi	100	0.87381	37.455
Two Grid (1 pre, 1 post)	1	0.29484	8.900
Two Grid (1 pre, 1 post)	3	0.23544	32.962
Two Grid (3 pre, 3 post)	1	0.23544	11.599
Two Grid (5 pre, 5 post)	1	0.20961	14.517
CG	46078	0.21183	28.235

Looking at these results, we see that we get the same error, but about a 2x speedup if we use CG on the coarse grid then just use Jacobi on the fine grid to refine that solution. Still, there's more we can do to make this better. If you look at step 3 in the algorithm above, you'll notice we do a linear system solve on the coarse grid, but this solve is also of the form $Ax = b$. That means we could apply this process **recursively** which is where the real power of Multigrid appears.

6 Typical Multigrid Cycles

There are several ways to create a recursive multigrid pattern. The most common by far is known as the V-Cycle. In the V-Cycle, we run the above Two-Grid Cycle, but replace the solve on the coarse grid with a recursive call another Two-Grid Cycle, where we move to yet another coarser

mesh. This is called a V-Cycle because if you trace the work done on the various grid levels, you get a picture in the shape of a V:



We can get this cycle by modifying the TwoGridScheme function above:

```
[14]: def VCycle(A_fine, b, numPreRelax, numPostRelax, coarsest_N, numiters=1, x=None):
    # For simplicity, we assume A_fine is (2^n-1) by (2^n-1)
    #                                     and A_coarse is (2^(n-1)-1) by (2^(n-1)-1) for some n
    #
    # We will also assume that A is SPD so that we can use CG to solve the
    →coarse system
    #
    # It should be noted that this implementation is not best to use if numiters
    →is not 1
    # since we are not caching the calculated A, I_restrict, I_prolong matrices
    # here we re-calculate them during each V, doing much extra computation

    # Build the restriction and prolongation operators
    # They can be re-used if we run more than 1 iteration
    N = A_fine.shape[0]
    I_Restrict = BuildFullWeighting(N)
    I_Prolong = 2*I_Restrict.T

    # start with the initial guess of zero if one isn't given
    if x is None:
        x = np.zeros_like(b)

    # Calculate the coarse mesh
    A_coarse = I_Restrict.dot(A_fine.dot(I_Prolong))
    N_coarse = A_coarse.shape[0]

    # We could run more than once if more accuracy is required
    for i in range(numiters):
        # First we relax on the fine grid:
        x = Jacobi(x, A_fine, b, numiters=numPreRelax)
```



```

    # Now compute the restricted residual
    r_coarse = mvmult(I_Restrict, b - mvmult(A_fine, x))

    # If not on the "bottom of the V", we call recursively
    if N_coarse > coarsest_N:
        # We start with an initial guess of zero, only 1 iteration to get
        →the V-Cycle
        e_coarse = VCycle(A_coarse, r_coarse, numPreRelax, numPostRelax,
        →coarsest_N, 1)
    else: # If on the bottom of the V, we solve the coarsest matrix exactly
        (conv, _, e_coarse, _, _) = PCG(A_coarse, r_coarse, maxiter=100000)
        if not conv:
            raise RuntimeError("PCG did not converge on the coarse_grid")

    # Correct the fine-grid x with the prolonged residual
    x += mvmult(I_Prolong, e_coarse)

    # The above Prolongation could be introducing additional high frequency
    →errors
    # So we relax again to get rid of them
    x = Jacobi(x, A_fine, b, numiters=numPostRelax)

    return x

```

```

[15]: # Run VCycle
startT = time.time()
x_VCyc = VCycle(A_fine, b, 3, 3, 128, numiters=1)
endT = time.time()
relError = norm(x_VCyc - xTrue)/norm(xTrue)
results.add_row(["V-Cycle (3 pre, 3 post, 127x127 coarse)", 1, relError,
→endT-startT])

# Run VCycle
startT = time.time()
x_VCyc = VCycle(A_fine, b, 3, 3, 128, numiters=3)
endT = time.time()
relError = norm(x_VCyc - xTrue)/norm(xTrue)
results.add_row(["V-Cycle (3 pre, 3 post, 127x127 coarse)", 3, relError,
→endT-startT])

# Run VCycle
startT = time.time()
x_VCyc = VCycle(A_fine, b, 5, 5, 128, numiters=1)
endT = time.time()
relError = norm(x_VCyc - xTrue)/norm(xTrue)

```

```

results.add_row(["V-Cycle (5 pre, 5 post, 127x127 coarse)", 1, relError,
    →endT-startT])

display(HTML(results.get_html_string()))

```

Algorithm	Iter	Rel Error	Time (sec)
Jacobi	100	0.87381	37.455
Two Grid (1 pre, 1 post)	1	0.29484	8.900
Two Grid (1 pre, 1 post)	3	0.23544	32.962
Two Grid (3 pre, 3 post)	1	0.23544	11.599
Two Grid (5 pre, 5 post)	1	0.20961	14.517
CG	46078	0.21183	28.235
V-Cycle (3 pre, 3 post, 127x127 coarse)	1	0.23201	4.7490
V-Cycle (3 pre, 3 post, 127x127 coarse)	3	0.18222	13.906
V-Cycle (5 pre, 5 post, 127x127 coarse)	1	0.20767	7.6766

This looks like a good improvement, they are the fastest single run so far and achieve about the same error as the other runs. During these runs, I observed that the CPU usage in my multi-core CPU is higher for the some of the computation and gets lower for the coarser meshes. This makes sense, those matrices are smaller and hence, take less computation. This however means that the size of the coarsest grid might make a difference. If the course grid is too small, the CPU is under-utilized, and if the coarse grid is too large, CG will take longer than moving to a coarser grid. Let's see if we can find a more optimal coarse-grid size.

We run trials of 1 V-Cycle with 5 pre and 5 post relaxations for differing coarse matrix sizes:

```

[16]: coarseGridSize_results = PrettyTable()
coarseGridSize_results.field_names = ["Coarse Matrix Size", "Rel Error", "Time",
    →(sec)]
coarseGridSize_results.align = "l"

relErrors = np.ones(14)
timings = np.zeros(14)

for exp in range(2,16):
    startT = time.time()
    x_VCyc = VCycle(A_fine, b, 5, 5, 2**exp, numiters=1)
    endT = time.time()
    relErrors[exp-2] = norm(x_VCyc - xTrue)/norm(xTrue)
    timings[exp-2] = endT-startT
    coarseGridSize_results.add_row([f'{2**exp - 1}x{2**exp-1}',
    →relErrors[exp-2], timings[exp-2]])

display(HTML(coarseGridSize_results.get_html_string()))

```

Coarse Matrix Size	Rel Error	Time (sec)
3x3	0.20863	7.64522
7x7	0.20801	7.70789
15x15	0.20784	7.62153
31x31	0.20774	7.64096
63x63	0.20768	7.68061
127x127	0.20767	7.65519
255x255	0.20766	7.82747
511x511	0.20767	7.94081
1023x1023	0.20770	8.07504
2047x2047	0.20777	7.64995
4095x4095	0.20790	7.38173
8191x8191	0.20816	7.14767
16383x16383	0.20868	8.89681
32767x32767	0.20961	14.0686

It appears that a 8191×8191 matrix is the most efficient coarse grid size for this computer. Any larger and the CG method takes too long, either due to cache size, number of cache misses, or simply the number of iterations CG needs to converge for the coarse problem (due to the increased condition number). Let's add this run to our table to see all the results together:

```
[17]: results.add_row(["V-Cycle (5 pre, 5 post, 8191x8191 coarse)", 1, relErrors[11],
    →timings[11]])

display(HTML(results.get_html_string()))
```

Algorithm	Iter	Rel Error	Time (sec)
Jacobi	100	0.87381	37.455
Two Grid (1 pre, 1 post)	1	0.29484	8.900
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V-Cycle (5 pre, 5 post, 127x127 coarse)	1	0.20767	7.6766
V-Cycle (5 pre, 5 post, 8191x8191 coarse)	1	0.20816	7.1476

Finally, let's run some extra iterations to see what the convergence looks like. Since the code below interrupts the V-Cycle function after every V-Cycle, we are doing extra work and so the timings are not representative, hence we won't calculate them.

```
[18]: maxIters = 30
coarseGridSize = 2**13
numRelax = 5

# container to hold the errors
relError = np.ones(maxIters+1)
```

```

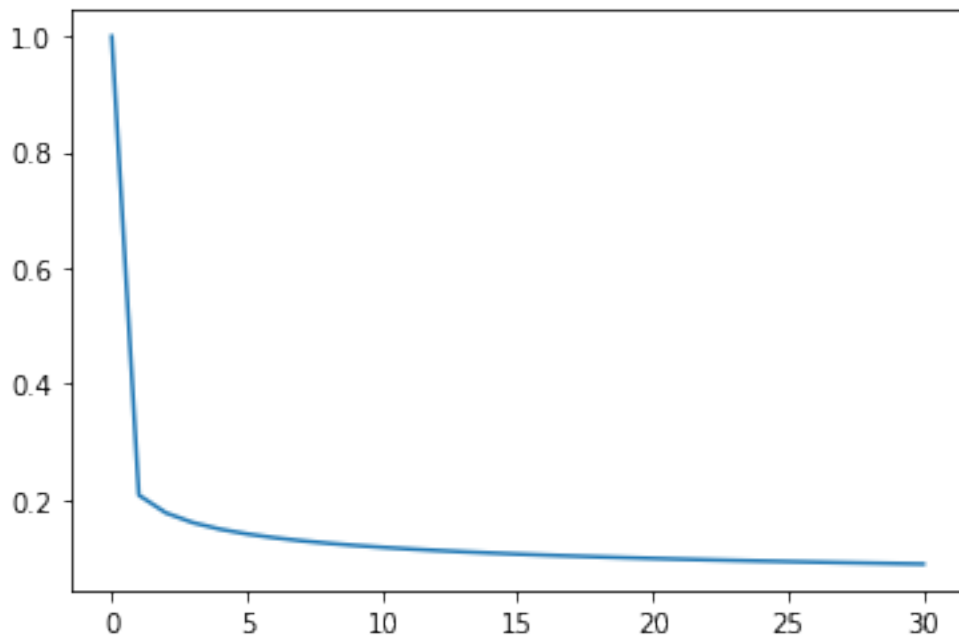
# Provide an initial guess
x_VCyc = np.zeros_like(b)

for i in range(1,maxIters+1):
    x_VCyc = VCycle(A_fine, b, numRelax, numRelax, coarseGridSize, numiters=1,
    →x=x_VCyc)
    relError[i] = norm(x_VCyc - xTrue)/norm(xTrue)

plt.plot(relError)

```

[18]: [<matplotlib.lines.Line2D at 0x7f39eaaf60a0>]



Notice the large decrease in error from the first iteration (80% reduction). This is one of the primary reasons why one iteration of multigrid is widely used as a preconditioner.

7 Other Multigrid Cycles

While the V-Cycle is the most popular, there are other proposed cycles as well. One possible extension is to recursively run two consecutive V-Cycles:

once. The cost here is mitigated, however, since the dimensions of the coarse matrices decreases exponentially.

Another negative aspect of multigrid is the fact that it is not as effective on smaller matrices. For example, straight CG is often faster than multigrid for smaller matrix sizes, where CG does not have to complete as many iterations.

10 Algebraic Multigrid

While geometric multigrid is useful for gaining intuition into multigrid methods, it's not often used in practice. It's tougher to design the restriction and prolongation operators for non-uniform meshes where the number of bordering nodes is variable. It's also less useful for systems with more than one state variable, since only the physical dimensions can be made coarser. Instead, we will use the same idea to develop a multigrid method that doesn't explicitly depend on the mesh, but instead depends on the coefficient matrix.

If we look at our matrix

$$A = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & \ddots & \ddots & \ddots \\ & & & -1 & 2 & -1 \\ & & & & -1 & 2 \end{bmatrix}$$

we can interpret it in the following way: an entry's magnitude in the matrix corresponds to its level of contribution in calculating the element on the diagonal. For example, row 2 has $-1/h^2$, $2/h^2$, and $-1/h^2$ in the first three columns. This signifies that only x_1, x_2, x_3 directly contribute to the node x_2 , with the value x_2 contributing more than x_1 and x_3 . In algebraic multigrid, we use this idea of "significance" to determine which unknowns can be "merged" to obtain a coarse matrix. This process will also create prolongation and restriction operators which only depend on the coefficient matrix and not on the geometric structure of the physical problem. Algebraic multigrid can therefore be programmed in a more general way and can more easily be extended to more problems. This property also contributes to its usefulness as a preconditioner since it takes less setup and quickly gives modest accuracy.