# Exercises V

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# Exercise 2

### 1. Gaussian Elimination

Gaussian elimination means putting the matrix into row echelon form, i.e. getting rid of the coefficients  $a_i$ , where the set of equations reads  $a_i x_{i-1} + b_i x_i + c_i x_{i+1}$  with i = 1...N and  $a_1 = c_N = 0$ . In the following we do not bother making the diagonal components  $b_i$  equal to 1, the usual first step in Gaussian elimination. Doing so would simply result in dividing by a  $b_i$ .

Before reduction, an arbitrary two rows will have the form

$$a_i x_{i-1} + b_i x_i + c_i x_{i+1} = y_i$$
  
$$a_{i+1} x_i + b_{i+1} x_{i+1} + c_{i+1} x_{i+2} = y_{i+1}$$

After reducing the first row (row i) and hence removing  $a_i$ , the coefficients read

$$\tilde{b}_i x_i + \tilde{c}_i x_{i+1} = \tilde{y}_i \tag{1}$$

$$a_{i+1}x_i + b_{i+1}x_{i+1} + c_{i+1}x_{i+2} = y_{i+1}$$
 (2)

We see that for the first row,  $\tilde{b}_1 = b_1$ ,  $\tilde{c}_i = c_i$  since this row is the starting point of the algorithm. For the other rows, we now eliminate  $a_{i+1}$  by multiplying row i+1 by  $\tilde{b}_i$  and subtracting row i multiplied by  $a_{i+1}$ , leading to:

$$(\tilde{b}_{i}a_{i+1} - a_{i+1}\tilde{b}_{i})x_{i} + (\tilde{b}_{i}b_{i+1} - a_{i+1}\tilde{c}_{i})x_{i+1} + \tilde{b}_{i}c_{i+1}x_{i+2} = \tilde{b}_{i}y_{i+1} - a_{i+1}\tilde{y}_{i}$$

$$\Rightarrow \tilde{a}_{i+1}x_{i+1} + \tilde{b}_{i+1}x_{i+1} + \tilde{c}_{i+1}x_{i+2} = \tilde{y}_{i+1}$$

where

$$\tilde{a}_{i+1} = 0$$
  $\tilde{b}_{i+1} = \tilde{b}_i b_{i+1} - a_{i+1} \tilde{c}_i$   $\tilde{c}_{i+1} = \tilde{b}_i c_{i+1}$   $\tilde{y}_{i+1} = \tilde{b}_i y_{i+1} - a_{i+1} \tilde{y}_i$ 

Looping through the rows (i = 2...N) yields an echelon form matrix ready for backwards substitution. We call this subroutine gaussian\_elimination:

```
def gaussian_elimination(a, b, c, y):
    """Given coefficients in an NxN tridiagonal matrix,
    reduce to echelon form.
    a, b, c, y: Nx1 arrays such that
    a_i x_{i-1} + b_i x_i + c_i x_{i+1} = y_i
    Note that a_1 and c_N should be 0.
    """

N = a.size

for i in range(1, N):
    y[i] = b[i - 1] * y[i] - a[i] * y[i - 1]
    b[i] = b[i - 1] * b[i] - a[i] * c[i - 1]
    c[i] = c[i] * b[i - 1]
    a[i] = 0
    return b, c, y
```

## 2. Backwards Elimination

Once the matrix is in echelon form, the last row has only one entry:  $b_N x_N = y_N$ . We can solve this immediately for  $x_N = y_N/b_N$  and use it in the rest of the equations. For the second-to-last row, we have

$$b_{N-1}x_{N-1} + c_{N-1}x_N = y_{N-1}$$

$$\Rightarrow x_{N-1} = \frac{1}{b_{N-1}}(y_{N-1} - c_{N-1}x_N)$$

where the tildes have been dropped. Generalizing to a row i and looping through the rows backwards (i = N, N - 1, ...2),

$$x_i = \frac{1}{b_i}(y_i - c_i x_{i+1})$$

where again  $c_N = 0$ . We name this subroutine backwards\_substitution:

```
def backwards_substitution(b, c, y):
    """Given coefficients in an NxN echelon form matrix,
    use backwards substitution to solve for x.
    All inputs are Nx1 arrays such that
    b_i x_i + c_i x_{i+1} = y_i.
    Note that c_N should be 0. """
```

```
N = b.size
x = np.zeros(N + 1)  # For last row
for i in range(N - 1, -1, -1):
    x[i] = (y[i] - c[i] * x[i + 1]) / b[i]
return x[:-1]
```

#### 3. Gaussian Solve

With our two subroutines in hand, the solving itself goes fairly easily:

```
def gaussian_solve(a, b, c, y):
    """Given coefficients in an NxN tridiagonal matrix,
        use gaussian elimination and backwards substitution
        to solve for x.
        All inputs are Nx1 arrays such that
        a_i x_{i-1} + b_i x_i + c_i x_{i+1} = y_i.
        Note that a_0, c_N should be 0.
        """

b, c, y = gaussian_elimination(a, b, c, y)
    x = backwards_substitution(b, c, y)
    return x
```

# 4. Example Solve

```
With a_i = -1, b_i = 2, c_i = -1, and y_i = 0.1, we find \vec{x} = (0.5, 0.9, 1.2, 1.4, 1.5, 1.5, 1.4, 1.2, 0.9, 0.5)
```

# 5. Solver Check

Multiplying the tridiagonal matrix by the solution found above, we achieve relative errors on the order of  $10^{-15}$  and  $10^{-16}$ , which is pretty good.