Poisson's equation

Suppose that we want to describe the distribution of heat throughout a region Ω . Let h(x) represent the temperature on the boundary of Ω ($\partial\Omega$), and let g(x) represent the initial heat distribution at time t = 0. If we let f(x, t) represent any heat sources/sinks in Ω , then the flow of heat can be described by the boundary value problem (BVP)

$$u_t = \Delta u + f(x,t), \quad x \in \Omega, \quad t > 0,$$

$$u(x,t) = h(x), \quad x \in \partial\Omega,$$

$$u(x,0) = g(x).$$

(1.1)

When the source term f does not depend on time, there is often a steady-state heat distribution u_{∞} that is approached as $t \to \infty$. This steady state u_{∞} is a solution of the BVP

$$\Delta u + f(x) = 0, \quad x \in \Omega,$$

$$u(x,t) = h(x), \quad x \in \partial\Omega.$$
(1.2)

This last partial differential equation, $\Delta u = -f$, is called Poisson's equation. This equation is satisfied by the steady-state solutions of many other evolutionary processes. Poisson's equation is often used in electrostatics, image processing, surface reconstruction, computational fluid dynamics, and other areas.

Poisson's equation in two dimensions

Consider Poisson's equation together with Dirichlet boundary conditions on a square domain $R = [a, b] \times [c, d]$:

$$u_{xx} + u_{yy} = f, \quad x \text{ in } R \subset \mathbb{R}^2,$$

$$u = g, \quad x \text{ on } \partial R.$$
 (1.3)

Let $a = x_{-1}, x_0, \ldots, x_{N-1} = b$ be a partition of [a, b], and let $c = y_{-1}, y_0, \ldots, y_{N-1} = d$ be a partition of [c, d]. Suppose that there are N + 1 evenly spaced points, so that

N is the number of subintervals in each dimension, and x_i, y_j are given by

$$x_i = a + (i+1)h,$$

 $y_j = c + (j+1)h,$

for i, j = 0, ..., N-2, where $h = x_i - x_{i-1} = y_i - y_{i-1}$. We look for an approximation $U_{i,j}$ on the grid $\{(x_i, y_j)\}_{i,j=-1}^{N-1}$.

Recall that

$$\Delta u = u_{xx}(x, y) + u_{yy}(x, y)$$

$$= \frac{u(x+h, y) - 2u(x, y) + u(x-h, y)}{h^2}$$

$$+ \frac{u(x, y+h) - 2u(x, y) + u(x, y-h)}{h^2} + \mathcal{O}(h^2).$$

We replace \triangle with the finite difference operator \triangle_h , defined by

$$\Delta_h U_{ij} = \frac{U_{i+1,j} - 2U_{i,j} + U_{i-1,j}}{h^2} + \frac{U_{i,j+1} - 2U_{i,j} + U_{i,j-1}}{h^2},$$
$$= \frac{1}{h^2} (U_{i-1,j} + U_{i+1,j} + U_{i,j-1} + U_{i,j+1} - 4U_{i,j}).$$

Then the set of equations

$$\Delta_h U_{ij} = f_{ij}, \quad i, j = 0, \dots, N-2,$$

can be written in matrix form as

$$AU + p + q = f.$$

A is a block tridiagonal matrix, given by

$$\frac{1}{h^2} \begin{bmatrix} T & I & & & \\ I & T & I & & \\ & \ddots & \ddots & \ddots & \\ & & I & T & I \\ & & & I & T \end{bmatrix}$$
(1.4)

where I is the $N - 1 \times N - 1$ identity matrix, and T is the tridiagonal matrix

$$\begin{bmatrix} -4 & 1 & & & \\ 1 & -4 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & 1 & -4 & 1 \\ & & & 1 & -4 \end{bmatrix}$$

The vector U is given by

$$U = \begin{bmatrix} U^0 \\ U^1 \\ U^{N-2} \end{bmatrix} \text{ where } U^j = \begin{bmatrix} U_{0,j} \\ U_{1,j} \\ U_{N-2,j} \end{bmatrix} \text{ for each } j, \ 0 \le j \le N-2.$$

$$p = \begin{bmatrix} p^0 \\ \cdots \\ p^{N-2} \end{bmatrix}, \quad q = \begin{bmatrix} q^0 \\ \cdots \\ q^{N-2} \end{bmatrix},$$

where

$$p^{j} = \frac{1}{h^{2}} \begin{bmatrix} g_{-1, j} \\ 0 \\ \vdots \\ 0 \\ g_{N-1, j} \end{bmatrix}, \quad 0 \le j \le N-2,$$

and

$$q^{0} = \frac{1}{h^{2}} \begin{bmatrix} g_{0,-1} \\ g_{1,-1} \\ \vdots \\ g_{N-3,-1} \\ g_{N-2,-1} \end{bmatrix}, \quad q^{N-2} = \frac{1}{h^{2}} \begin{bmatrix} g_{0,N-1} \\ g_{1,N-1} \\ \vdots \\ g_{N-3,N-1} \\ g_{N-2,N-1} \end{bmatrix}, \quad q^{j} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}, \quad 1 \le j \le N-3.$$

The following code implements the greater portion of the finite difference method; it leaves the construction of the matrix A in (1.4) to problem 1.5.

```
from __future__ import division
from scipy.sparse import spdiags
from scipy.sparse.linalg import spsolve
def poisson_square(a1,b1,c1,d1,n,bcs, source):
    # n = number of subintervals
    # We discretize in the x dimension by
    # a1 = x_0 < x_1 < \ldots < x_n=b1, and
    # We discretize in the y dimension by
    # c1 = y_0 < y_1 < \ldots < y_n = d1.
    # This means that we have interior points
    # {x_1, ..., x_{n-1}}\times {y_1, ..., y_{n-1}}
    # or \{x_1, \ldots, x_m\}\times \{y_1, \ldots, y_m\} where m = n-1.
    # In Python, this is indexed as
    # {x_0, ..., x_{m-1}}\times {y_0, ..., y_{m-1}}
    # We will have m**2 pairs of interior points, and
    # m**2 corresponding equations.
    # We will organize these equations by their
    # y coordinates: all equations centered
    # at (x_i, y_0) will be listed first,
    # then (x_i, y_1), and so on till (x_i, y_{m-1})
    delta_x, delta_y, h, m = (b1-a1)/n, (d1-c1)/n, (b1-a1)/n, n-1
    ####
            Construct the matrix A
                                       ####
    ####
            Here we construct the vector b
                                               ####
   b, Array = np.zeros(m**2), np.linspace(0.,1.,m+2)[1:-1]
    # In the next line, source represents
    # the inhomogenous part of Poisson's equation
    for j in xrange(m):
```

```
b[j*m:(j+1)*m] = source(a1+(b1-a1)*Array, c1+(j+1)*h*np.ones(m) )
# In the next four lines, bcs represents the
# Dirichlet conditions on the boundary
\# v = c1+h, d1-h
b[0:m] -= h**(-2.)*bcs(a1+(b1-a1)*Array,c1*np.ones(m))
b[(m-1)*m:m**2] -= h**(-2.)*bcs(a1+(b1-a1)*Array,d1*np.ones(m))
# x = a1+h, b1-h
b[0::m] -= h**(-2.)*bcs(a1*np.ones(m),c1+(d1-c1)*Array)
b[(m-1)::m] -= h**(-2.)*bcs(b1*np.ones(m),c1+(d1-c1)*Array)
####
       Here we solve the system A*soln = b
                                               ####
soln = spsolve(A,b)
# We return the solution, and the boundary values,
# in the array z.
z = np.zeros((m+2,m+2))
for j in xrange(m):
   z[1:-1,j+1] = soln[j*m:(j+1)*m]
x, y = np.linspace(a1,b1,m+2), np.linspace(c1,d1,m+2)
z[:,0], z[:,m+1] = bcs(x,c1*np.ones(len(x)) ), bcs(x,d1*np.ones(len(x)) )
z[0,:], z[m+1,:] = bcs(a1*np.ones(len(x)),y), bcs(b1*np.ones(len(x)),y)
return z
```

Problem 1. Construct the matrix A in (1.4). Make sure your matrix is sparse. Then use the code above to solve the boundary value problem

$$\Delta u = 0, \quad x \in [0, 1] \times [0, 1], \iota(x, y) = x^3, \quad (x, y) \in \partial([0, 1] \times [0, 1]).$$
(1.5)

Plot the 3D solution with n = 100.

Poisson's equation and conservative forces

In physics Poisson's equation is used to describe the scalar potential of a conservative force. In general

$$\Delta V = -f$$

where V is the scalar potential of the force, or the potential energy a particle would have at that point, and f is a source term. Examples of conservative forces include Newton's Law of Gravity (where matter become the source term) and Coulomb's Law, which gives the force between two charge particles (where charge is the source term).

In electrostatics the electric potential is also known as the voltage, and is denoted by V. From Maxwell's equations it can be shown that that the voltage obeys Poisson's equation with the electric charge density (like a continuous cloud of electrons) being the source term:

$$\Delta V = -\frac{\rho}{\epsilon_0},$$

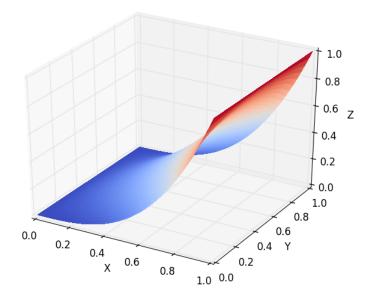


Figure 1.1: The solution of (1.5).

where ρ is the charge density and ϵ_0 is the permissivity of free space, which is a constant that we'll leave as 1.

Usually a non zero V at a point will cause a charged particle to move to a lower potential, changing ρ and the solution to V. However, in this analysis we'll assume that the charges are fixed in place.

Suppose we have 3 nested pipes. The outer pipe is attached to "ground," which usually we define to be V = 0, and the inner two have opposite relative charges. Physically the two inner pipes would function like a capacitor.

The following code will plot the charge distribution of this setup.

<pre>import matplotlib.colors as mcolors</pre>
<pre>def source(X,Y): """</pre>
Takes arbitrary arrays of coordinates X and Y and returns an array of the \leftrightarrow same shape
representing the charge density of nested charged squares
<pre>src = np.zeros(X.shape) src[np.logical_or(</pre>
<pre>np.logical_and(np.logical_or(abs(X-1.5) < .1,abs(X+1.5) < .1) ,abs(Y) < ↔ 1.6),</pre>
np.logical_and(np.logical_or(abs(Y-1.5) < .1,abs(Y+1.5) < .1) ,abs(X) < ↔ 1.6))] = 1
<pre>src[np.logical_or(np.logical_and(np.logical_or(abs(X-0.9) < .1,abs(X+0.9) < .1) ,abs(Y) < ↔</pre>

```
1.0).
       np.logical_and( np.logical_or(abs(Y-0.9) < .1, abs(Y+0.9) < .1) , abs(X) < \leftarrow
            1.0))] = -1
   return src
#Generate a color dictionary for use with LinearSegmentedColormap
#that places red and blue at the min and max values of data
#and white when data is zero
def genDict(data):
   zero = 1/(1 - np.max(data)/np.min(data))
   cdict = {'red': [(0.0, 1.0, 1.0),
                 (zero, 1.0, 1.0),
(1.0, 0.0, 0.0)],
        'green': [(0.0, 0.0, 0.0),
                  (zero, 1.0, 1.0),
                  (1.0, 0.0, 0.0)],
        'blue': [(0.0, 0.0, 0.0),
                 (zero, 1.0, 1.0),
                  (1.0, 1.0, 1.0)]
   return cdict
a1 = -2.
b1 = 2.
c1 = −2.
d1 = 2.
n =100
X = np.linspace(a1,b1,n)
Y = np.linspace(c1,d1,n)
X,Y = np.meshgrid(X,Y)
source(X,Y))))
plt.colorbar(label="Relative Charge")
plt.show()
```

The function genDict scales the color values to be white when the charge density is zero. This is mostly to help visualize where there are neutrally charged zones by forcing them to be white. You may find it useful to also apply it when you solve for the electric potential.

With this definition of the charge density, we can solve Poisson's equation for the potential field.

Problem 2. Solve

$$\Delta V = -\rho(x, y), \quad x \in [-2, 2] \times [-2, 2], u(x, y) = 0, \quad (x, y) \in \partial([-2, 2] \times [-2, 2]).$$
(1.6)

for the electric potential V. Use the source function $(-\rho)$ defined above. Plot the 2D solution using n = 100.

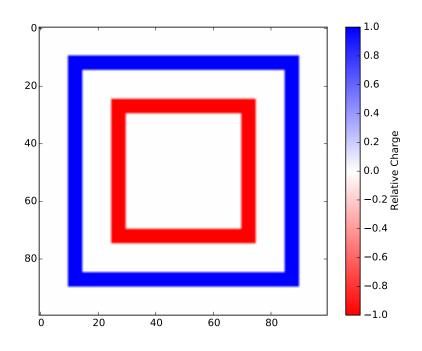


Figure 1.2: The charge density of the 3 nested pipes.

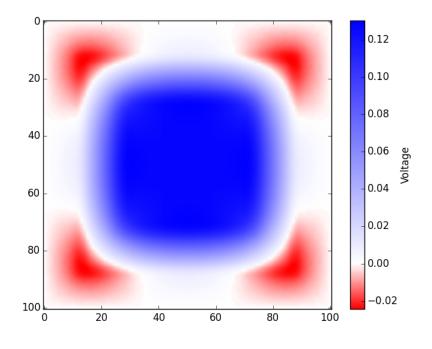


Figure 1.3: The electric potential of the 3 nested pipes.