

# ECUACIONES DIFERENCIALES PARCIALES DE SEGUNDO ORDEN

---

Manuel Carlevaro

Departamento de Ingeniería Mecánica

Grupo de Materiales Granulares - UTN FRLP

manuel.carlevaro@gmail.com

Cálculo Avanzado • 2023

 ·  $\text{\LaTeX}$  · 

**Ecuación diferencial parcial (EDP) lineal de segundo orden:**

$$A \frac{\partial^2 \phi}{\partial x^2} + B \frac{\partial^2 \phi}{\partial x \partial y} + C \frac{\partial^2 \phi}{\partial y^2} + D \frac{\partial \phi}{\partial x} + E \frac{\partial \phi}{\partial y} + F \phi = S$$

donde  $A, B, C, D, E, F$  y  $S$  son funciones de  $x$  y  $y$  en  $D \in \mathbf{R}^2$ .

## Ecuación diferencial parcial (EDP) lineal de segundo orden:

$$A \frac{\partial^2 \phi}{\partial x^2} + B \frac{\partial^2 \phi}{\partial x \partial y} + C \frac{\partial^2 \phi}{\partial y^2} + D \frac{\partial \phi}{\partial x} + E \frac{\partial \phi}{\partial y} + F \phi = S$$

donde  $A, B, C, D, E, F$  y  $S$  son funciones de  $x$  y  $y$  en  $D \in \mathbf{R}^2$ .

### Tipos:

- ▶ Parabólica:  $B^2 - 4AC = 0$
- ▶ Elíptica:  $B^2 - 4AC < 0$
- ▶ Hiperbólica:  $B^2 - 4AC > 0$

para todo  $(x, y) \in D$ .

### Casos:

- ▶ Conducción de calor en sólidos, flujo de fluidos
- ▶ Ejemplos:
  - › Conducción de calor:

$$\rho c \frac{\partial T}{\partial t} = k \frac{\partial^2 T(x, t)}{\partial x^2} + Q(x)$$

- › Transporte convectivo:

$$\frac{\partial \phi}{\partial t} = - \frac{\partial}{\partial x} u(x) \phi + D \frac{\partial^2 \phi}{\partial x^2}$$

## Ecuación diferencial parcial (EDP) lineal de segundo orden:

$$A \frac{\partial^2 \phi}{\partial x^2} + B \frac{\partial^2 \phi}{\partial x \partial y} + C \frac{\partial^2 \phi}{\partial y^2} + D \frac{\partial \phi}{\partial x} + E \frac{\partial \phi}{\partial y} + F \phi = S$$

donde  $A, B, C, D, E, F$  y  $S$  son funciones de  $x$  y  $y$  en  $D \in \mathbf{R}^2$ .

### Tipos:

- ▶ Parabólica:  $B^2 - 4AC = 0$
- ▶ Elíptica:  $B^2 - 4AC < 0$
- ▶ Hiperbólica:  $B^2 - 4AC > 0$

para todo  $(x, y) \in D$ .

### Casos:

- ▶ Problemas estacionarios de 2 y 3 dimensiones
- ▶ Conducción de calor en sólidos, vibración de membranas
- ▶ Ejemplos:

› Ecuación de Poisson:

$$-\nabla^2 \phi(x, y) = S(x, y)$$

› Ecuación de Laplace:

$$-\nabla^2 \phi(x, y) = 0$$

## Ecuación diferencial parcial (EDP) lineal de segundo orden:

$$A \frac{\partial^2 \phi}{\partial x^2} + B \frac{\partial^2 \phi}{\partial x \partial y} + C \frac{\partial^2 \phi}{\partial y^2} + D \frac{\partial \phi}{\partial x} + E \frac{\partial \phi}{\partial y} + F \phi = S$$

donde  $A, B, C, D, E, F$  y  $S$  son funciones de  $x$  y  $y$  en  $D \in \mathbf{R}^2$ .

### Tipos:

- ▶ Parabólica:  $B^2 - 4AC = 0$
- ▶ Elíptica:  $B^2 - 4AC < 0$
- ▶ Hiperbólica:  $B^2 - 4AC > 0$

para todo  $(x, y) \in D$ .

### Casos:

- ▶ Problemas oscilatorios, propagación de ondas, fluidos
- ▶ Ejemplos:
  - › Ecuación de onda:

$$\frac{\partial^2 u(x, y, z, t)}{\partial t^2} = c^2 \nabla^2 u(x, y, z, t)$$

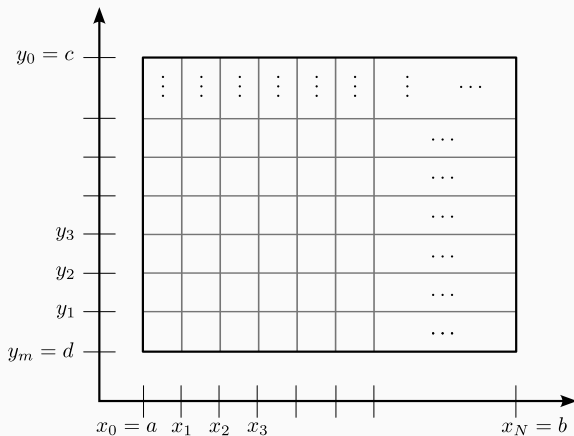
- › Navier-Stokes (incompresible):

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla) \mathbf{u} - \nu \nabla^2 \mathbf{u} = -\nabla \left( \frac{p}{\rho_0} \right) + \mathbf{g}$$

## Ecuación de Poisson (elíptica):

$$\nabla^2 u(x, y) = \frac{\partial^2 u}{\partial x^2}(x, y) + \frac{\partial^2 u}{\partial y^2}(x, y) = f(x, y)$$

en  $R = \{(x, y) | a < x < b, c < y < d\}$ , con  $u(x, y) = g(x, y)$  para  $(x, y) \in S$ , siendo  $S$  la frontera de  $R$ .



### Malla:

- ▶ División  $[a, b]$  y  $[c, d]$  en  $n$  y  $m$  partes iguales
- ▶  $h = (b - a)/n$ ,  $k = (d - c)/m$
- ▶  $x_i = a + ih$ ,  $i = 0, 1, \dots, n$
- ▶  $y_j = c + jk$ ,  $j = 0, 1, \dots, m$

### Aproximación en diferencias finitas (serie de Taylor):

$$\frac{\partial^2 u}{\partial x^2} = \frac{u(x_{i+1}, y_j) - 2u(x_i, y_j) + u(x_{i-1}, y_j))}{h^2} + \mathcal{O}(h^2)$$

$$\frac{\partial^2 u}{\partial y^2} = \frac{u(x_i, y_{j+1}) - 2u(x_i, y_j) + u(x_i, y_{j-1}))}{k^2} + \mathcal{O}(k^2)$$

Con  $u(x_i, y_j) \mapsto u_{i,j}$ :

$$\frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} + \frac{u_{i,j+1} - 2u_{i,j} + u_{i,j-1}}{k^2} = f_{i,j} + \frac{h^2}{12} \frac{\partial^4 u}{\partial x^4}(\xi_i, y_j) + \frac{k^2}{12} \frac{\partial^4 u}{\partial y^4}(x_i, \eta_j)$$

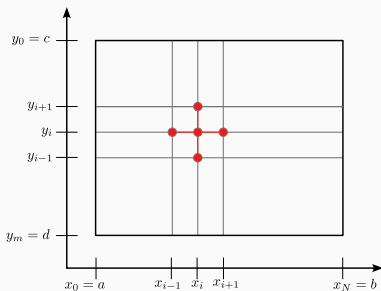
para  $i = 1, 2, \dots, n-1, j = 1, 2, \dots, m-1$  y condiciones de contorno:

$$u_{0,j} = g_{0,j} \quad \text{y} \quad u_{n,j} = g_{n,j}, \quad j = 0, 1, \dots, m;$$

$$u_{i,0} = g_{i,0} \quad \text{y} \quad u_{i,m} = g_{i,m}, \quad i = 0, 1, \dots, n$$

Resulta:

$$2 \left[ \left( \frac{h}{k} \right)^2 + 1 \right] u_{i,j} - (u_{i+1,j} + u_{i-1,j}) - \left( \frac{h}{k} \right)^2 (u_{i,j+1} + u_{i,j-1}) = -h^2 f_{i,j}, \quad i \in [1, n-1], \quad j \in [1, m-1]$$



Con  $u(x_i, y_j) \mapsto u_{i,j}$ :

$$\frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} + \frac{u_{i,j+1} - 2u_{i,j} + u_{i,j-1}}{k^2} = f_{i,j} + \frac{h^2}{12} \frac{\partial^4 u}{\partial x^4}(\xi_i, y_j) + \frac{k^2}{12} \frac{\partial^4 u}{\partial y^4}(x_i, \eta_j)$$

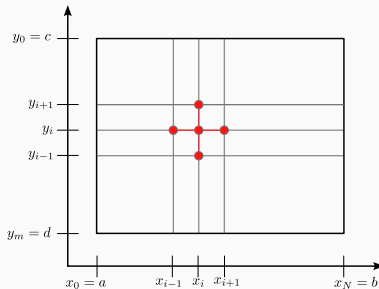
para  $i = 1, 2, \dots, n-1, j = 1, 2, \dots, m-1$  y condiciones de contorno:

$$u_{0,j} = g_{0,j} \quad \text{y} \quad u_{n,j} = g_{n,j}, \quad j = 0, 1, \dots, m;$$

$$u_{i,0} = g_{i,0} \quad \text{y} \quad u_{i,m} = g_{i,m}, \quad i = 0, 1, \dots, n$$

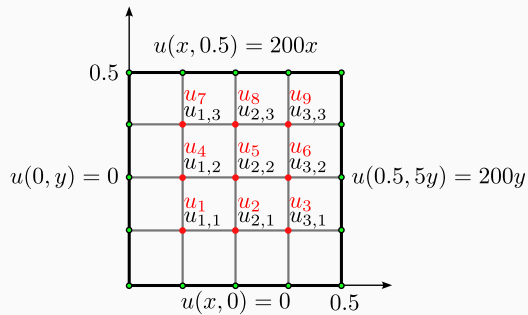
Resulta:

$$2 \left[ \left( \frac{h}{k} \right)^2 + 1 \right] u_{i,j} - (u_{i+1,j} + u_{i-1,j}) - \left( \frac{h}{k} \right)^2 (u_{i,j+1} + u_{i,j-1}) = -h^2 f_{i,j}, \quad i \in [1, n-1], \quad j \in [1, m-1]$$



**Ejemplo:** Determinar la distribución estacionaria de temperaturas en una placa de  $0.5 \times 0.5$  m usando  $n = m = 4$ . Dos bordes adyacentes se mantienen a  $0^\circ\text{C}$  y la temperatura se incrementa linealmente en los otros bordes hasta llegar a  $100^\circ\text{C}$  en la esquina de unión.





$$\frac{\partial^2 u}{\partial x^2}(x, y) + \frac{\partial^2 u}{\partial y^2}(x, y) = 0; \quad (x, y) \in [0, 0.5]^2$$

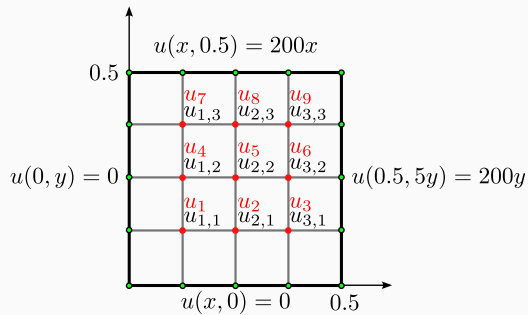
$$h = k = 1/8$$

$$u_{i,j} \mapsto u_l, \quad l = i + m(j - 1)$$

$$u_{1,1} = u_1, \quad u_{2,1} = u_2, \quad u_{3,1} = u_3$$

$$u_{1,2} = u_4, \quad u_{2,2} = u_5, \quad u_{3,2} = u_6$$

$$u_{1,3} = u_7, \quad u_{2,3} = u_8, \quad u_{3,3} = u_9$$



$$\frac{\partial^2 u}{\partial x^2}(x, y) + \frac{\partial^2 u}{\partial y^2}(x, y) = 0; (x, y) \in [0, 0.5]^2$$

$$h = k = 1/8$$

Ecuaciones:

$$4u_{i,j} - u_{i+1,j} - u_{i-1,j} - u_{i,j-1} - u_{i,j+1} = 0$$

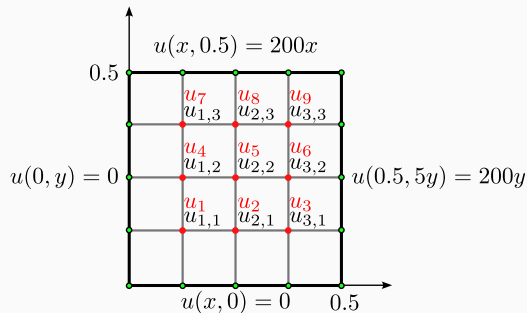
para  $i = 1, 2, 3; j = 1, 2, 3$ .

$$u_{i,j} \mapsto u_l, l = i + m(j - 1)$$

$$u_{1,1} = u_1, u_{2,1} = u_2, u_{3,1} = u_3$$

$$u_{1,2} = u_4, u_{2,2} = u_5, u_{3,2} = u_6$$

$$u_{1,3} = u_7, u_{2,3} = u_8, u_{3,3} = u_9$$



$$u_{i,j} \mapsto u_l, \quad l = i + m(j - 1)$$

$$u_{1,1} = u_1, \quad u_{2,1} = u_2, \quad u_{3,1} = u_3$$

$$u_{1,2} = u_4, \quad u_{2,2} = u_5, \quad u_{3,2} = u_6$$

$$u_{1,3} = u_7, \quad u_{2,3} = u_8, \quad u_{3,3} = u_9$$

$$\frac{\partial^2 u}{\partial x^2}(x, y) + \frac{\partial^2 u}{\partial y^2}(x, y) = 0; \quad (x, y) \in [0, 0.5]^2$$

$$h = k = 1/8$$

Ecuaciones:

$$4u_{i,j} - u_{i+1,j} - u_{i-1,j} - u_{i,j-1} - u_{i,j+1} = 0$$

para  $i = 1, 2, 3; j = 1, 2, 3$ .

Condiciones de borde:

$$u_{0,0} = u_{0,1} = u_{0,2} = u_{0,3} = u_{0,4} = 0$$

$$u_{1,0} = u_{2,0} = u_{3,0} = u_{4,0} = 0$$

$$u_{1,4} = u_{4,1} = 25; u_{2,4} = u_{4,2} = 50$$

$$u_{3,4} = u_{4,3} = 75; u_{4,4} = 100$$

$$\begin{bmatrix}
4 & -1 & 0 & -1 & 0 & 0 & 0 & 0 & 0 \\
-1 & 4 & -1 & 0 & -1 & 0 & 0 & 0 & 0 \\
0 & -1 & 4 & 0 & 0 & -1 & 0 & 0 & 0 \\
-1 & 0 & 0 & 4 & -1 & 0 & -1 & 0 & 0 \\
0 & -1 & 0 & -1 & 4 & -1 & 0 & -1 & 0 \\
0 & 0 & -1 & 0 & -1 & 4 & 0 & 0 & -1 \\
0 & 0 & 0 & -1 & 0 & 0 & 4 & -1 & 0 \\
0 & 0 & 0 & 0 & -1 & 0 & -1 & 4 & -1 \\
0 & 0 & 0 & 0 & 0 & -1 & 0 & -1 & 4
\end{bmatrix}
\begin{bmatrix}
u_1 \\
u_2 \\
u_3 \\
u_4 \\
u_5 \\
u_6 \\
u_7 \\
u_8 \\
u_9
\end{bmatrix}
=
\begin{bmatrix}
u_{0,1} + u_{1,0} \\
u_{0,2} \\
u_{0,3} + u_{4,1} \\
u_{0,2} \\
0 \\
u_{4,2} \\
u_{0,3} + u_{1,4} \\
u_{2,4} \\
u_{3,4} + u_{3,4}
\end{bmatrix}
\rightarrow
\begin{bmatrix}
u_1 \\
u_2 \\
u_3 \\
u_4 \\
u_5 \\
u_6 \\
u_7 \\
u_8 \\
u_9
\end{bmatrix}
=
\begin{bmatrix}
6.25 \\
12.5 \\
18.75 \\
12.5 \\
25 \\
37.5 \\
18.75 \\
37.5 \\
56.25
\end{bmatrix}$$

$$\begin{bmatrix}
4 & -1 & 0 & -1 & 0 & 0 & 0 & 0 & 0 \\
-1 & 4 & -1 & 0 & -1 & 0 & 0 & 0 & 0 \\
0 & -1 & 4 & 0 & 0 & -1 & 0 & 0 & 0 \\
-1 & 0 & 0 & 4 & -1 & 0 & -1 & 0 & 0 \\
0 & -1 & 0 & -1 & 4 & -1 & 0 & -1 & 0 \\
0 & 0 & -1 & 0 & -1 & 4 & 0 & 0 & -1 \\
0 & 0 & 0 & -1 & 0 & 0 & 4 & -1 & 0 \\
0 & 0 & 0 & 0 & -1 & 0 & -1 & 4 & -1 \\
0 & 0 & 0 & 0 & 0 & -1 & 0 & -1 & 4
\end{bmatrix}
\begin{bmatrix}
u_1 \\
u_2 \\
u_3 \\
u_4 \\
u_5 \\
u_6 \\
u_7 \\
u_8 \\
u_9
\end{bmatrix}
=
\begin{bmatrix}
u_{0,1} + u_{1,0} \\
u_{0,2} \\
u_{0,3} + u_{4,1} \\
u_{0,2} \\
0 \\
u_{4,2} \\
u_{0,3} + u_{1,4} \\
u_{2,4} \\
u_{3,4} + u_{3,4}
\end{bmatrix}
\rightarrow
\begin{bmatrix}
u_1 \\
u_2 \\
u_3 \\
u_4 \\
u_5 \\
u_6 \\
u_7 \\
u_8 \\
u_9
\end{bmatrix}
=
\begin{bmatrix}
6.25 \\
12.5 \\
18.75 \\
12.5 \\
25 \\
37.5 \\
18.75 \\
37.5 \\
56.25
\end{bmatrix}$$

Solución exacta:  $u(x, y) = 400xy$  por lo que la aproximación en diferencias finitas no tiene error:

$$\frac{\partial^4 u}{\partial x^4} = \frac{\partial^4 u}{\partial y^4} = 0$$

**Ecuación de calor (parabólica):**

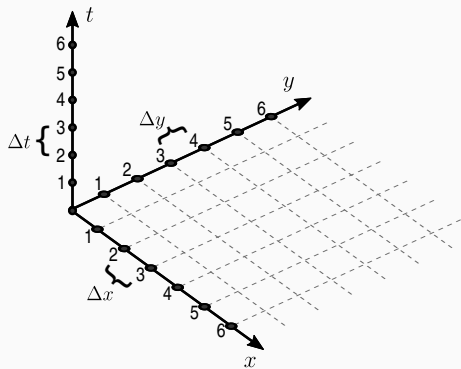
$$\frac{\partial u}{\partial t} = \alpha \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right)$$

Ecuación de calor (parabólica):

$$\frac{\partial u}{\partial t} = \alpha \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right)$$

Grilla:

$$x_i = i\Delta x, \quad y_j = j\Delta y, \quad t_k = k\Delta t, \quad u(x, y, t) = u_{i,j}^k$$



Ecuación de calor (parabólica):

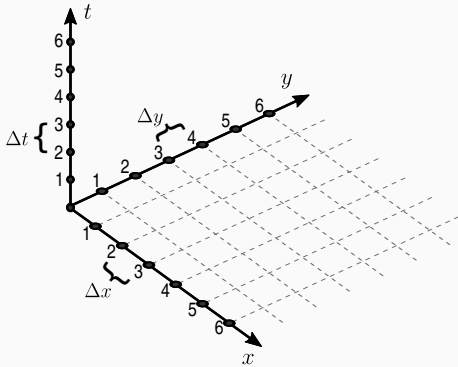
$$\frac{\partial u}{\partial t} = \alpha \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right)$$

Grilla:

$$x_i = i\Delta x, \quad y_j = j\Delta y, \quad t_k = k\Delta t, \quad u(x, y, t) = u_{i,j}^k$$

Diferencias finitas (hacia adelante - explícito):

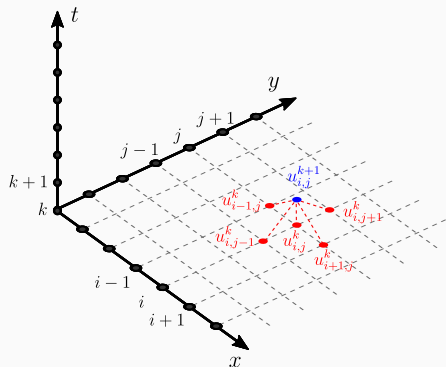
$$\frac{u_{i,j}^{k+1} - u_{i,j}^k}{\Delta t} = \alpha \left( \frac{u_{i+1,j}^k - 2u_{i,j}^k + u_{i-1,j}^k}{\Delta x^2} \right) + \left( \frac{u_{i,j+1}^k - 2u_{i,j}^k + u_{i,j-1}^k}{\Delta y^2} \right)$$





## Ecuación de calor (parabólica):

$$\frac{\partial u}{\partial t} = \alpha \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right)$$



Grilla:

$$x_i = i\Delta x, \quad y_j = j\Delta y, \quad t_k = k\Delta t, \quad u(x, y, t) = u_{i,j}^k$$

Diferencias finitas (hacia adelante - explícito):

$$\frac{u_{i,j}^{k+1} - u_{i,j}^k}{\Delta t} = \alpha \left( \frac{u_{i+1,j}^k - 2u_{i,j}^k + u_{i-1,j}^k}{\Delta x^2} \right) + \left( \frac{u_{i,j+1}^k - 2u_{i,j}^k + u_{i,j-1}^k}{\Delta y^2} \right)$$

Hacemos  $\Delta x = \Delta y$ ,  $\gamma = \alpha \frac{\Delta t}{\Delta x^2}$ :

$$u_{i,j}^{k+1} = \gamma \left( u_{i+1,j}^k + u_{i-1,j}^k + u_{i,j+1}^k + u_{i,j-1}^k - 4u_{i,j}^k \right) + u_{i,j}^k$$

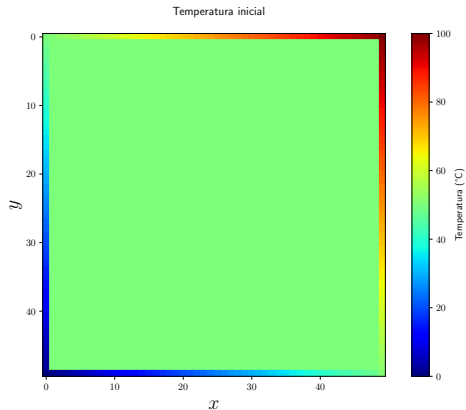
Método explícito:  $\Delta t \leq \frac{\Delta x^2}{4\alpha} \leftrightarrow$  estabilidad numérica.

Stencil:

$$u_{i,j}^{k+1} = \gamma \left( u_{i+1,j}^k + u_{i-1,j}^k + u_{i,j+1}^k + u_{i,j-1}^k - 4u_{i,j}^k \right) + u_{i,j}^k$$

$$\frac{\partial u}{\partial t} - \alpha \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right) = 0$$

$$0 \leq x \leq L_x, 0 \leq y \leq L_y$$



Condiciones de borde:

$$u(x, 0) = 50 + \frac{x(100 - 50)}{L_x}$$

$$u(0, y) = 50 - y \frac{50}{L_y}$$

$$u(x, L_y) = 50 \frac{x}{L_x}$$

$$u(L_x, y) = 100 - y \frac{50}{L_y}$$

Condición inicial:

$$u(x, y)_{t=0} = 50$$

---

```

1  #!/usr/bin/env python3
2
3  import numpy as np
4
5  Lx, Ly = 50, 50
6  max_iter_tiempo = 750
7  alpha = 5
8  delta_x = 1
9  delta_t = (delta_x ** 2)/(4 * alpha)
10 gamma = (alpha * delta_t) / (delta_x ** 2)
11
12 # Condiciones de borde
13 u_S0 = 0.0
14 u_N0, u_SE = 50.0, 50.0
15 u_NE = 100.0
16
17 # Condición inicial interior
18 u_inicial = 50

```

---



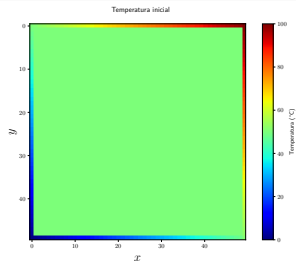
---

```

20 def inicializar_u(max_iter_tiempo, ni=Lx, nj=Ly):
21     # Inicializar la solución: u(k, i, j)
22     u = np.full((max_iter_tiempo, ni, nj), u_inicial)
23     # Establecer condiciones de borde
24     u[:, 0, :] = u_N0 + np.arange(ni) * delta_x
25                 * (u_NE - u_N0) / Lx
26     u[:, :, 0] = u_N0 - np.arange(nj) * delta_x
27                 * u_N0 / Ly
28     u[:, -1, :] = np.arange(ni) * delta_x * u_SE / Lx
29     u[:, :, -1] = u_NE - np.arange(nj) * delta_x
30                 * u_SE / Ly
31     return u
32
33 u = inicializar_u(max_iter_tiempo)

```

---



---

```

35 import matplotlib
36 import matplotlib.pyplot as plt
37 matplotlib.rcParams.update({"text.usetex": True})
38 fig, ax = plt.subplots(figsize=(8,6))
39 mappable = ax.imshow(u[0], interpolation=None,
40                      cmap=plt.cm.jet)
41 fig.colorbar(mappable, label="Temperatura (°C)", ax=ax)
42 ax.set_xlabel(r"$x$", fontsize=20)
43 ax.set_ylabel(r"$y$", fontsize=20)
44 fig.suptitle("Temperatura inicial")
45 fig.tight_layout()
46 fig.savefig("temp-inicial.pdf")
47 plt.close()

```

---



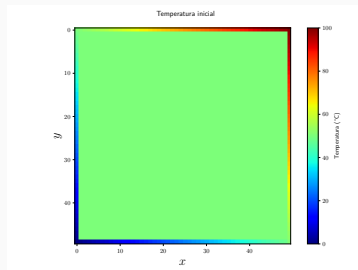
---

```

49 # Código que aplica el stencil en la grilla (i, j) y en cada t.
50 def calcular(u):
51     nk, ni, nj = u.shape
52     for k in range(0, nk-1):
53         for i in range(1, ni-1):
54             for j in range(1, nj-1):
55                 u[k + 1, i, j] = gamma * (u[k][i+1][j] + u[k][i-1][j]
56                                           + u[k][i][j+1] + u[k][i][j-1]
57                                           - 4*u[k][i][j]) + u[k][i][j]
58     return u
59
60 u = calcular(u)

```

---



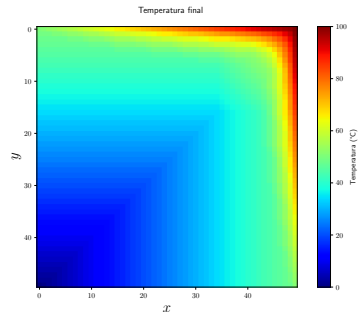
---

```

49 # Código que aplica el stencil en la grilla (i, j) y en cada tiempo k
50 def calcular(u):
51     nk, ni, nj = u.shape
52     for k in range(0, nk-1):
53         for i in range(1, ni-1):
54             for j in range(1, nj-1):
55                 u[k + 1, i, j] = gamma * (u[k][i+1][j] + u[k][i-1][j]
56                                           + u[k][i][j+1] + u[k][i][j-1]
57                                           - 4*u[k][i][j] + u[k][i][j])
58     return u
59
60 u = calcular(u)
61 fig, ax = plt.subplots(figsize=(8,6))
62 mappable = ax.imshow(u[-1], interpolation=None,
63                      cmap=plt.cm.jet)
64 fig.colorbar(mappable, label="Temperatura (°C)", ax=ax)
65 ax.set_xlabel(r"$x$", fontsize=20)
66 ax.set_ylabel(r"$y$", fontsize=20)
67 fig.suptitle("Temperatura final")
68 fig.tight_layout()
69 fig.savefig("temp-final.pdf")
70 plt.close()

```

---



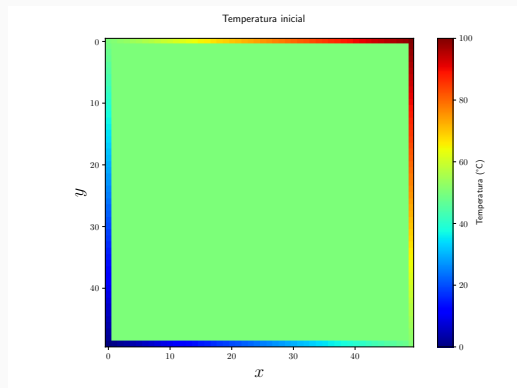
---

```

72 def plotheatmap(u_k, k):
73     # Limpiamos la figura
74     plt.clf()
75
76     plt.title(f"Temperatura en t = {k*delta_t:.2f} u.t.")
77     plt.xlabel(r"$x$", fontsize=20)
78     plt.ylabel(r"$y$", fontsize=20)
79
80     # Ploteamos u_k (u_{i,j} en `paso de tiempo k)
81     plt.imshow(u_k, cmap=plt.cm.jet,
82               interpolation="bicubic", vmin=0, vmax=100)
83     plt.colorbar()
84
85     return plt
86
87 import matplotlib.animation as animation
88 from matplotlib.animation import FuncAnimation
89
90 def animate(k):
91     plotheatmap(u[k], k)
92
93 anim = animation.FuncAnimation(plt.figure(),
94                               animate, interval=50, frames=max_iter_tiempo,
95                               repeat=False)
96 anim.save("solucion_ecuacion_calor_t.mp4")

```

---



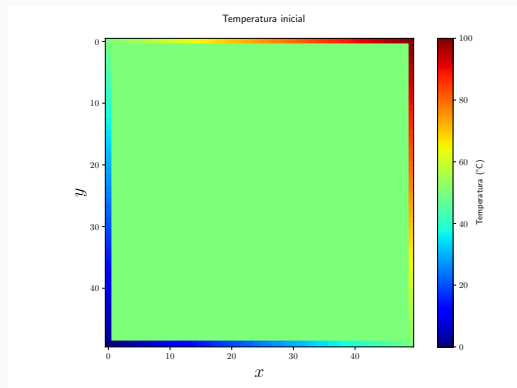
---

```

72 def plotheatmap(u_k, k):
73     # Limpiamos la figura
74     plt.clf()
75
76     plt.title(f"Temperatura en t = {k*delta_t:.2f} u.t.")
77     plt.xlabel(r"$x$", fontsize=20)
78     plt.ylabel(r"$y$", fontsize=20)
79
80     # Ploteamos u_k (u_{i,j} en `paso de tiempo k)
81     plt.imshow(u_k, cmap=plt.cm.jet,
82               interpolation="bicubic", vmin=0, vmax=100)
83     plt.colorbar()
84
85     return plt
86
87 import matplotlib.animation as animation
88 from matplotlib.animation import FuncAnimation
89
90 def animate(k):
91     plotheatmap(u[k], k)
92
93 anim = animation.FuncAnimation(plt.figure(),
94                               animate, interval=50, frames=max_iter_tiempo,
95                               repeat=False)
96 anim.save("solucion_ecuacion_calor_t.mp4")

```

---





### Análisis de estabilidad:

$$\frac{\partial u}{\partial t}(x, t) = \alpha^2 \frac{\partial^2 u}{\partial x^2}(x, t), \quad 0 < x < l, \quad 0 < t$$

Condiciones de frontera:

$$u(0, t) = u(l, t) = 0, t > 0;$$

$$u(x, 0) = f(x), 0 \leq x \leq l$$

Diferencia hacia adelante (o progresiva):

$$\begin{aligned}\frac{\partial u}{\partial t}(x_i, t_j) &= \frac{u(x_i, t_j + k) - u(x_i, t_j)}{k} - \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_j) \\ \frac{\partial^2 u}{\partial x^2}(x_i, t_j) &= \frac{u(x_i + h, t_j) - 2u(x_i, t_j) + u(x_i - h, t_j)}{h^2} \\ &\quad - \frac{h^2}{12} \frac{\partial^4 u}{\partial x^4}(\xi_i, t_j)\end{aligned}$$

con  $t_j \in (t_j, t_{j+1}), \xi_i \in (x_i, x_{i+1})$

Resulta:

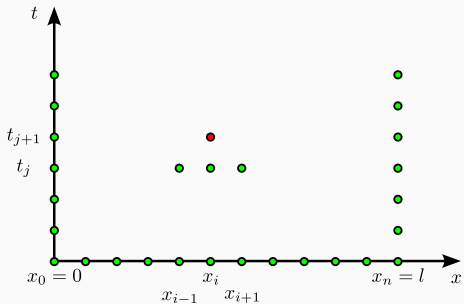
$$\frac{u_{i,j+1} - u_{i,j}}{k} - \alpha^2 \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} = 0$$

con un error local de truncación:

$$\epsilon_{i,j} = \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_j) - \alpha^2 \frac{h^2}{12} \frac{\partial^4 u}{\partial x^4}(\xi_i, t_j)$$

Solución explícita:

$$u_{i,j+1} = \left(1 - \frac{2\alpha k}{h^2}\right) u_{i,j} + \alpha^2 \frac{k}{h^2} (u_{i+1,j} + u_{i-1,j})$$



Matriz  $(n-1) \times (n-1)$ :

$$\mathbf{A} = \begin{bmatrix} (1-2\lambda) & \lambda & 0 & \cdots & 0 \\ \lambda & (1-2\lambda) & \lambda & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & \lambda \\ 0 & \cdots & 0 & \lambda & (1-2\lambda) \end{bmatrix}$$

con  $\lambda = \alpha^2 k / h^2$

Si  $\mathbf{u}^{(0)} = (f(x_1), f(x_2), \dots, f(x_{n-1}))^T$ , la solución aproximada es:

$$\mathbf{u}^{(j)} = \mathbf{A} \mathbf{u}^{(j-1)}$$

Supongamos un error  $\mathbf{e}^{(0)} = (e_1^{(0)}, e_2^{(0)}, \dots, e_{n-1}^{(0)})^T$ :

$$\mathbf{u}^{(1)} = \mathbf{A}(\mathbf{u}^{(0)} + \mathbf{e}^{(0)}) = \mathbf{A} \mathbf{u}^{(0)} + \mathbf{A} \mathbf{e}^{(0)}$$

Para el paso  $k$ , el error en  $\mathbf{u}^{(k)} = \mathbf{A}^k \mathbf{e}^{(0)}$ . El método es **estable** si  $\|\mathbf{A}^k \mathbf{e}^{(0)}\| \leq \|\mathbf{e}^{(0)}\|$

$$\|\mathbf{A}^k\| \leq 1 \implies \rho(\mathbf{A}^k) = (\rho(\mathbf{A}))^k \leq 1$$

Matriz  $(n-1) \times (n-1)$ :

$$\mathbf{A} = \begin{bmatrix} (1-2\lambda) & \lambda & 0 & \cdots & 0 \\ \lambda & (1-2\lambda) & \lambda & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & \lambda \\ 0 & \cdots & 0 & \lambda & (1-2\lambda) \end{bmatrix}$$

con  $\lambda = \alpha^2 k / h^2$

Si  $\mathbf{u}^{(0)} = (f(x_1), f(x_2), \dots, f(x_{n-1}))^T$ , la solución aproximada es:

$$\mathbf{u}^{(j)} = \mathbf{A} \mathbf{u}^{(j-1)}$$

Supongamos un error  $\mathbf{e}^{(0)} = (e_1^{(0)}, e_2^{(0)}, \dots, e_{n-1}^{(0)})^T$ :

$$\mathbf{u}^{(1)} = \mathbf{A}(\mathbf{u}^{(0)} + \mathbf{e}^{(0)}) = \mathbf{A} \mathbf{u}^{(0)} + \mathbf{A} \mathbf{e}^{(0)}$$

Para el paso  $k$ , el error en  $\mathbf{u}^{(k)} = \mathbf{A}^k \mathbf{e}^{(0)}$ . El método es **estable** si  $\|\mathbf{A}^k \mathbf{e}^{(0)}\| \leq \|\mathbf{e}^{(0)}\|$

$$\|\mathbf{A}^k\| \leq 1 \implies \rho(\mathbf{A}^k) = (\rho(\mathbf{A}))^k \leq 1$$

Autovalores de  $\mathbf{A}$ :

$$\mu_i = 1 - 4\lambda \left( \sin \left( \frac{i\pi}{2n} \right) \right)^2$$

Norma  $L_\infty$ :

$$\rho(\mathbf{A}) = \max_{1 \leq i \leq n} \left| 1 - 4\lambda \left( \sin \left( \frac{i\pi}{2n} \right) \right)^2 \right|$$

que se simplifica a

$$0 \leq \lambda \left( \sin \left( \frac{i\pi}{2n} \right) \right)^2 \leq \frac{1}{2}, \quad i = 1, 2, \dots, n-1$$

Esta desigualdad debe valer cuando  $h \rightarrow 0, n \rightarrow \infty$ :

$$\lim_{n \rightarrow \infty} \left[ \sin \left( \frac{(n-1)\pi}{2n} \right)^2 \right] = 1$$

Por lo tanto habrá estabilidad si  $0 \leq \lambda \leq 1/2$ :

$$\alpha^2 \frac{k}{h^2} \leq \frac{1}{2} \quad \leftarrow \text{condicionalmente estable.}$$

## Ejemplo:

Solución: `parabolica-progresiva.py`

$$\frac{\partial u}{\partial t}(x, t) = \alpha \frac{\partial^2 u}{\partial x^2}(x, t), \quad 0 < x < l, \quad 0 < t$$

$$u(0, t) = u(l, t) = 0, \quad t > 0;$$

$$u(x, 0) = \sin(\pi x), \quad 0 \leq x \leq 1$$

► con  $h = 0.1$  y  $k = 0.0005$ . (1000 pasos)

► con  $h = 0.1$  y  $k = 0.01$ . (50 pasos)

Solución exacta:

$$u(x, t) = e^{-\pi^2 t} \sin(\pi x)$$

$i$	$x_i$	$u_{i,50}$	$u(x_i, 50)$	$ u_{i,50} - u(x_i, 50) $
0	0.0	0.00000	0.00000	0.000e+00
1	0.1	0.00229	0.00222	6.411e-05
2	0.2	0.00435	0.00423	1.219e-04
3	0.3	0.00599	0.00582	1.678e-04
4	0.4	0.00704	0.00684	1.973e-04
5	0.5	0.00740	0.00719	2.075e-04
6	0.6	0.00704	0.00684	1.973e-04
7	0.7	0.00599	0.00582	1.678e-04
8	0.8	0.00435	0.00423	1.219e-04
9	0.9	0.00229	0.00222	6.411e-05
10	1.0	0.00000	0.00000	8.808e-19

### Ejemplo:

$$\frac{\partial u}{\partial t}(x, t) = \alpha \frac{\partial^2 u}{\partial x^2}(x, t), \quad 0 < x < l, \quad 0 < t$$

$$u(0, t) = u(l, t) = 0, \quad t > 0;$$

$$u(x, 0) = \sin(\pi x), \quad 0 \leq x \leq 1$$

► con  $h = 0.1$  y  $k = 0.0005$ . (1000 pasos)

► con  $h = 0.1$  y  $k = 0.01$ . (50 pasos)

Solución exacta:

$$u(x, t) = e^{-\pi^2 t} \sin(\pi x)$$

Solución: `parabolica-progresiva.py`

$i$	$x_i$	$u_{i,50}$	$u(x_i, 50)$	$ u_{i,50} - u(x_i, 50) $
0	0.0	0.000e+00	0.00000	0.000e+00
1	0.1	2.637e+05	0.00222	2.637e+05
2	0.2	-5.026e+05	0.00423	5.026e+05
3	0.3	6.938e+05	0.00582	6.938e+05
4	0.4	-8.186e+05	0.00684	8.186e+05
5	0.5	8.643e+05	0.00719	8.643e+05
6	0.6	-8.254e+05	0.00684	8.254e+05
7	0.7	7.047e+05	0.00582	7.047e+05
8	0.8	-5.135e+05	0.00423	5.135e+05
9	0.9	2.704e+05	0.00222	2.704e+05
10	1.0	0.000e+00	0.00000	8.808e-19

**Incondicionalmente estable:** diferencias regresivas  
(implícito).

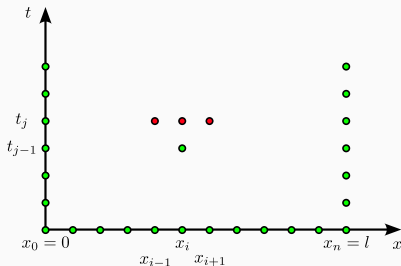
$$\frac{\partial u}{\partial t}(x_i, t_j) = \frac{u(x_i, t_j) - u(x_i, t_{j-1})}{k} - \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_j)$$

con  $\mu_j \in (t_{j-1}, t_j)$ .

Reemplazando en la ecuación en derivadas parciales:

$$\frac{u_{i,j} - u_{i,j-1}}{k} - \alpha^2 \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} = 0$$

para  $i = 1, 2, \dots, n-1$  y  $j = 1, 2, \dots$



**Incondicionalmente estable:** diferencias regresivas (implícito).

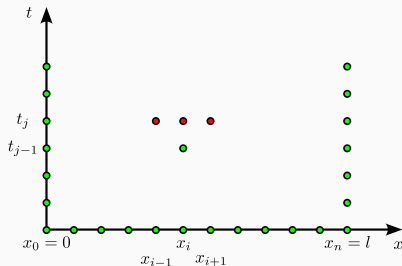
$$\frac{\partial u}{\partial t}(x_i, t_j) = \frac{u(x_i, t_j) - u(x_i, t_{j-1})}{k} - \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_j)$$

con  $\mu_j \in (t_{j-1}, t_j)$ .

Reemplazando en la ecuación en derivadas parciales:

$$\frac{u_{i,j} - u_{i,j-1}}{k} - \alpha^2 \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} = 0$$

para  $i = 1, 2, \dots, n-1$  y  $j = 1, 2, \dots$



Hacemos  $\lambda = \alpha^2 k / h^2$ :

$$(1 + 2\lambda)u_{i,j} - \lambda u_{i+1,j} - \lambda u_{i-1,j} = u_{i,j-1}$$

Con las condiciones de frontera:

$$u_{i,0} = f(x_i), \quad i = 1, 2, \dots, n-1$$

$$u_{0,j} = u_{n,j} = 0, \quad j = 1, 2, \dots$$

Matriz  $(n-1) \times (n-1)$ :

$$A = \begin{bmatrix} (1+2\lambda) & -\lambda & 0 & \cdots & 0 \\ -\lambda & (1+2\lambda) & -\lambda & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & -\lambda \\ 0 & \cdots & 0 & -\lambda & (1+2\lambda) \end{bmatrix}$$

$$\mathbf{u}^{(j)} = (u_{1,j}, u_{2,j}, \dots, u_{n-1,j})^T,$$

$$\mathbf{u}^{(j-1)} = (u_{1,j-1}, u_{2,j-1}, \dots, u_{n-1,j-1})^T$$

$$\mapsto A\mathbf{u}^{(j)} = \mathbf{u}^{(j-1)}, \quad j = 1, 2, \dots$$

### Ejemplo:

$$\frac{\partial u}{\partial t}(x, t) = \alpha \frac{\partial^2 u}{\partial x^2}(x, t), \quad 0 < x < 1, \quad 0 < t$$

$$u(0, t) = u(1, t) = 0, \quad t > 0;$$

$$u(x, 0) = \text{sen}(\pi x), \quad 0 \leq x \leq 1$$

con  $h = 0.1$  y  $k = 0.01$ .

Solución exacta:

$$u(x, t) = e^{-\pi^2 t} \text{sen}(\pi x)$$

Solución: `parabolica-regresiva.py`

$i$	$x_i$	$u_{i,50}$	$u(x_i, 50)$	$ u_{i,50} - u(x_i, 50) $
0	0.0	0.00000	0.00000	0.000e+00
1	0.1	0.00780	0.00222	5.576e-03
2	0.2	0.01236	0.00423	8.133e-03
3	0.3	0.01591	0.00582	1.010e-02
4	0.4	0.01817	0.00684	1.133e-02
5	0.5	0.01894	0.00719	1.175e-02
6	0.6	0.01817	0.00684	1.133e-02
7	0.7	0.01591	0.00582	1.010e-02
8	0.8	0.01236	0.00423	8.133e-03
9	0.9	0.00780	0.00222	5.576e-03
10	1.0	0.00000	0.00000	8.808e-19



### Ejemplo:

$$\frac{\partial u}{\partial t}(x, t) = \alpha \frac{\partial^2 u}{\partial x^2}(x, t), \quad 0 < x < 1, \quad 0 < t$$

$$u(0, t) = u(1, t) = 0, \quad t > 0;$$

$$u(x, 0) = \text{sen}(\pi x), \quad 0 \leq x \leq 1$$

con  $h = 0.1$  y  $k = 0.01$ .

Solución exacta:

$$u(x, t) = e^{-\pi^2 t} \text{sen}(\pi x)$$

Solución: `parabolica-regresiva.py`

Autovalores de  $\mathbf{A}$ :

$$\mu_i = 1 + 4\lambda \left[ \text{sen} \left( \frac{i\pi}{2n} \right) \right]^2$$

para  $i = 1, 2, \dots, n-1$ . Como  $\lambda > 0$ ,  $\mu_i > 0$ .

$i$	$x_i$	$u_{i,50}$	$u(x_i, 50)$	$ u_{i,50} - u(x_i, 50) $
0	0.0	0.00000	0.00000	0.000e+00
1	0.1	0.00780	0.00222	5.576e-03
2	0.2	0.01236	0.00423	8.133e-03
3	0.3	0.01591	0.00582	1.010e-02
4	0.4	0.01817	0.00684	1.133e-02
5	0.5	0.01894	0.00719	1.175e-02
6	0.6	0.01817	0.00684	1.133e-02
7	0.7	0.01591	0.00582	1.010e-02
8	0.8	0.01236	0.00423	8.133e-03
9	0.9	0.00780	0.00222	5.576e-03
10	1.0	0.00000	0.00000	8.808e-19

Entonces  $\rho(\mathbf{A}^{-1}) < 1 \mapsto \mathbf{A}$  es una matriz convergente:

$$\lim_{j \rightarrow \infty} (\mathbf{A}^{-1})^j \mathbf{e}^{(0)} = \mathbf{0} \quad \leftarrow \text{incondicionalmente estable.}$$

### Ejemplo:

$$\frac{\partial u}{\partial t}(x, t) = \alpha \frac{\partial^2 u}{\partial x^2}(x, t), \quad 0 < x < 1, \quad 0 < t$$

$$u(0, t) = u(1, t) = 0, \quad t > 0;$$

$$u(x, 0) = \text{sen}(\pi x), \quad 0 \leq x \leq 1$$

con  $h = 0.1$  y  $k = 0.01$ .

Solución exacta:

$$u(x, t) = e^{-\pi^2 t} \text{sen}(\pi x)$$

Solución: `parabolica-regresiva.py`

Autovalores de  $\mathbf{A}$ :

$$\mu_i = 1 + 4\lambda \left[ \text{sen} \left( \frac{i\pi}{2n} \right) \right]^2$$

para  $i = 1, 2, \dots, n-1$ . Como  $\lambda > 0$ ,  $\mu_i > 0$ .

$i$	$x_i$	$u_{i,50}$	$u(x_i, 50)$	$ u_{i,50} - u(x_i, 50) $
0	0.0	0.00000	0.00000	0.000e+00
1	0.1	0.00780	0.00222	5.576e-03
2	0.2	0.01236	0.00423	8.133e-03
3	0.3	0.01591	0.00582	1.010e-02
4	0.4	0.01817	0.00684	1.133e-02
5	0.5	0.01894	0.00719	1.175e-02
6	0.6	0.01817	0.00684	1.133e-02
7	0.7	0.01591	0.00582	1.010e-02
8	0.8	0.01236	0.00423	8.133e-03
9	0.9	0.00780	0.00222	5.576e-03
10	1.0	0.00000	0.00000	8.808e-19

Entonces  $\rho(\mathbf{A}^{-1}) < 1 \mapsto \mathbf{A}$  es una matriz convergente:

$$\lim_{j \rightarrow \infty} (\mathbf{A}^{-1})^j \mathbf{e}^{(0)} = \mathbf{0} \quad \leftarrow \text{incondicionalmente estable.}$$

Precisión:  $\mathcal{O}(k + h^2) \leftarrow \text{👉}$

el método de la diferencia promediado:

$$\frac{u_{i,j+1} - u_{i,j}}{k} - \alpha^2 \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} = 0$$

con error de truncamiento:

$$\epsilon_p = \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_j) + \mathcal{O}(h^2)$$

Diferencias regresivas:

$$\frac{u_{i,j+1} - u_{i,j}}{k} - \alpha^2 \frac{u_{i+1,j+1} - 2u_{i,j+1} + u_{i-1,j+1}}{h^2} = 0$$

con error de truncamiento:

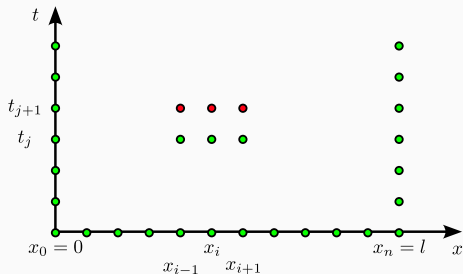
$$\epsilon_r = -\frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \hat{\mu}_j) + \mathcal{O}(h^2)$$

Suponiendo que:

$$\frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_j) \approx \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \hat{\mu}_j)$$

$$\frac{u_{i,j+1} - u_{i,j}}{k} - \frac{\alpha^2}{2} \left[ \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} + \frac{u_{i+1,j+1} - 2u_{i,j+1} + u_{i-1,j+1}}{h^2} \right] = 0$$

tiene un error de truncamiento  $\mathcal{O}(k^2 + h^2) \leftarrow \text{👍}$



En forma matricial:

$$\mathbf{A}\mathbf{u}^{(j+1)} = \mathbf{B}\mathbf{u}^{(j)}, \quad \text{para cada } j = 0, 1, \dots, \quad \text{donde } \lambda = \alpha^2 \frac{k}{h^2}, \quad \mathbf{u}^{(j)} = (u_{1,j}, u_{2,j}, \dots, u_{n-1,j})^T$$

y

$$\mathbf{A} = \begin{bmatrix} (1 + \lambda) & -\lambda/2 & 0 & \cdots & 0 \\ -\lambda/2 & (1 + \lambda) & -\lambda/2 & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & -\lambda/2 \\ 0 & \cdots & 0 & -\lambda/2 & (1 + \lambda) \end{bmatrix} \quad \text{y} \quad \mathbf{B} = \begin{bmatrix} (1 - \lambda) & \lambda/2 & 0 & \cdots & 0 \\ \lambda/2 & (1 - \lambda) & \lambda/2 & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & \lambda/2 \\ 0 & \cdots & 0 & \lambda/2 & (1 - \lambda) \end{bmatrix}$$

### Ejemplo:

$$\frac{\partial u}{\partial t}(x, t) = \alpha^2 \frac{\partial^2 u}{\partial x^2}(x, t), \quad 0 < x < 1, \quad 0 < t$$

$$u(0, t) = u(1, t) = 0, \quad t > 0;$$

$$u(x, 0) = \sin(\pi x), \quad 0 \leq x \leq 1$$

con  $h = 0.1$  y  $k = 0.01$ .

Solución exacta:

$$u(x, t) = e^{-\pi^2 t} \sin(\pi x)$$

Solución: `crank-nicolson.py`

$i$	$x_i$	$u_{i,50}$	$u(x_i, 50)$	$ u_{i,50} - u(x_i, 50) $
0	0.0	0.00000	0.00000	0.000e+00
1	0.1	0.00488	0.00222	2.660e-03
2	0.2	0.00812	0.00423	3.895e-03
3	0.3	0.01066	0.00582	4.842e-03
4	0.4	0.01228	0.00684	5.436e-03
5	0.5	0.01283	0.00719	5.639e-03
6	0.6	0.01228	0.00684	5.436e-03
7	0.7	0.01066	0.00582	4.842e-03
8	0.8	0.00812	0.00423	3.895e-03
9	0.9	0.00488	0.00222	2.660e-03
10	1.0	0.00000	0.00000	8.808e-19

## Ecuación de onda (hiperbólica)

$$\frac{\partial^2 u}{\partial t^2}(x, t) - \alpha^2 \frac{\partial^2 u}{\partial x^2}(x, t) = 0, \quad 0 < x < l, \quad 0 < t$$

Con las ecuaciones de frontera:

$$u(0, t) = u(l, t) = 0, \quad t > 0;$$

$$u(x, 0) = f(x), \quad \frac{\partial u}{\partial t}(x, 0) = g(x); \quad 0 \leq x \leq l$$

Malla:

$$x_i = ih, \quad t_j = jk$$

para  $i = 0, 1, \dots, n$  y  $j = 0, 1, \dots$

En todos los puntos de la malla interior:

$$\frac{\partial^2 u}{\partial t^2}(x_i, t_j) - \alpha^2 \frac{\partial^2 u}{\partial x^2}(x_i, t_j) = 0$$

Diferencias centrales para las derivadas segundas:

$$\begin{aligned} \frac{\partial^2 u}{\partial t^2}(x_i, t_j) &= \frac{u(x_i, t_{j+1}) - 2u(x_i, t_j) + u(x_i, t_{j-1}))}{k^2} \\ &\quad - \frac{k^2}{12} \frac{\partial^4 u}{\partial t^4}(x_i, \mu_j) \end{aligned}$$

$$\begin{aligned} \frac{\partial^2 u}{\partial x^2}(x_i, t_j) &= \frac{u(x_{i+1}, t_j) - 2u(x_i, t_j) + u(x_{i-1}, t_j))}{h^2} \\ &\quad - \frac{h^2}{12} \frac{\partial^4 u}{\partial x^4}(\xi_i, t_j) \end{aligned}$$

donde  $\xi_i \in (x_{i-1}, x_{i+1})$ ,  $\mu_i \in (t_{j-1}, t_{j+1})$ . Resulta:

$$\begin{aligned} \frac{u_{i,j+1} - 2u_{i,j} + u_{i,j-1}}{k^2} \\ - \alpha^2 \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} = \epsilon_{i,j} \end{aligned}$$

con

$$\epsilon_{i,j} = \frac{1}{12} \left[ k^2 \frac{\partial^4 u}{\partial t^4}(x_i, t_j) - \alpha^2 h^2 \frac{\partial^4 u}{\partial x^4}(x_i, t_j) \right]$$

Ignorando  $\epsilon_{i,j}$  y haciendo  $\lambda = \alpha k/h$  (número de Courant):

$$u_{i,j+1} - 2u_{i,j} + u_{i,j-1} - \lambda^2 u_{i+1,j} + 2\lambda^2 u_{i,j} - \lambda^2 u_{i-1,j} = 0$$

Resolviendo para el paso temporal:

$$u_{i,j+1} = 2(1 - \lambda^2)u_{i,j} + \lambda^2(u_{i+1,j} + u_{i-1,j}) - u_{i,j-1}$$

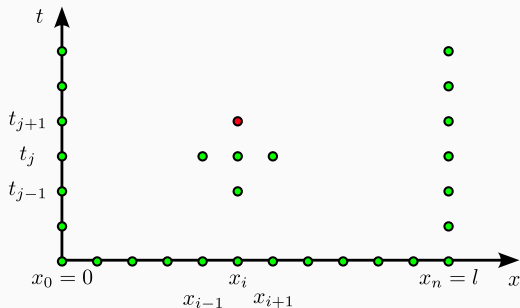
para  $i = 1, 2, \dots, n-1$  y  $j = 1, 2, \dots$

Las condiciones de frontera resultan:

$$u_{0,j} = u_{n,j} = 0, \quad j = 1, 2, \dots$$

y la condición inicial:

$$u_{i,0} = f(x_i), \quad i = 1, 2, \dots, n-1$$



Enfoque matricial:

$$\mathbf{u}^{(j+1)} = \mathbf{A}\mathbf{u}^{(j)} - \mathbf{u}^{(j-1)}$$

$$\begin{bmatrix} u_{1,j+1} \\ u_{2,j+1} \\ u_{3,j+1} \\ \vdots \\ u_{n-1,j+1} \end{bmatrix} = \begin{bmatrix} 2(1-\lambda^2) & \lambda^2 & 0 & \dots & 0 \\ \lambda^2 & 2(1-\lambda^2) & \lambda^2 & \dots & 0 \\ 0 & \dots & \dots & \dots & 0 \\ 0 & \dots & \dots & \dots & \lambda^2 \\ 0 & \dots & 0 & \lambda^2 & 2(1+\lambda^2) \end{bmatrix} \begin{bmatrix} u_{1,j} \\ u_{2,j} \\ u_{3,j} \\ \vdots \\ u_{n-1,j} \end{bmatrix} - \begin{bmatrix} u_{1,j-1} \\ u_{2,j-1} \\ u_{3,j-1} \\ \vdots \\ u_{n-1,j-1} \end{bmatrix}$$



$$\begin{bmatrix} u_{1,j+1} \\ u_{2,j+1} \\ u_{3,j+1} \\ \vdots \\ u_{n-1,j+1} \end{bmatrix} = \begin{bmatrix} 2(1-\lambda^2) & \lambda^2 & 0 & \dots & 0 \\ \lambda^2 & 2(1-\lambda^2) & \lambda^2 & \dots & 0 \\ 0 & \dots & \dots & \dots & 0 \\ 0 & \dots & \dots & \dots & \lambda^2 \\ 0 & \dots & 0 & \lambda^2 & 2(1+\lambda^2) \end{bmatrix} \begin{bmatrix} u_{1,j} \\ u_{2,j} \\ u_{3,j} \\ \vdots \\ u_{n-1,j} \end{bmatrix} - \begin{bmatrix} u_{1,j-1} \\ u_{2,j-1} \\ u_{3,j-1} \\ \vdots \\ u_{n-1,j-1} \end{bmatrix}$$

Problema: ¿ $u_{i,1}$ ?

Condición de velocidad inicial:

$$\frac{\partial u}{\partial t}(x, 0) = g(x), \quad 0 \leq x \leq l$$

Aproximación por diferencias progresivas:

$$\frac{\partial u}{\partial t}(x, 0) = \frac{u(x_i, t_1) - u(x_i, 0)}{k} - \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_i)$$

Resolviendo:

$$u(x_i, t_1) = u(x_i, 0) + kg(x_i) + \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_i)$$

Error de truncamiento:  $\mathcal{O}(k) \leftarrow \text{🗨️}$

$$\begin{bmatrix} u_{1,j+1} \\ u_{2,j+1} \\ u_{3,j+1} \\ \vdots \\ u_{n-1,j+1} \end{bmatrix} = \begin{bmatrix} 2(1-\lambda^2) & \lambda^2 & 0 & \dots & 0 \\ \lambda^2 & 2(1-\lambda^2) & \lambda^2 & \dots & 0 \\ 0 & \dots & \dots & \dots & 0 \\ 0 & \dots & \dots & \dots & \lambda^2 \\ 0 & \dots & 0 & \lambda^2 & 2(1+\lambda^2) \end{bmatrix} \begin{bmatrix} u_{1,j} \\ u_{2,j} \\ u_{3,j} \\ \vdots \\ u_{n-1,j} \end{bmatrix} - \begin{bmatrix} u_{1,j-1} \\ u_{2,j-1} \\ u_{3,j-1} \\ \vdots \\ u_{n-1,j-1} \end{bmatrix}$$

**Problema:** ¿ $u_{i,1}$ ?

Condición de velocidad inicial:

$$\frac{\partial u}{\partial t}(x, 0) = g(x), \quad 0 \leq x \leq l$$

Aproximación por diferencias progresivas:

$$\frac{\partial u}{\partial t}(x, 0) = \frac{u(x_i, t_1) - u(x_i, 0)}{k} - \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_i)$$

Resolviendo:

$$u(x_i, t_1) = u(x_i, 0) + kg(x_i) + \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_i)$$

Error de truncamiento:  $\mathcal{O}(k) \leftarrow \text{👎}$

Mejora: expansión de McLaurin ( $\sim$  Taylor):

$$u(x_i, t_1) = u(x_i, 0) + k \frac{\partial u}{\partial t}(x_i, 0) + \frac{k^2}{2} \frac{\partial^2 u}{\partial t^2}(x_i, 0) + \frac{k^3}{6} \frac{\partial^3 u}{\partial t^3}(x_i, \hat{\mu}_i)$$

Si  $f''$  existe:

$$\frac{\partial^2 u}{\partial t^2}(x_i, 0) = \alpha^2 \frac{\partial^2 u}{\partial x^2}(x_i, 0) = \alpha^2 f''(x_i)$$

entonces:

$$u(x_i, t_1) = u(x_i, 0) + kg(x_i) + \frac{\alpha^2 k^2}{2} f''(x_i)$$

con error  $\mathcal{O}(k^3) \leftarrow \text{👍}$ .

$$\begin{bmatrix} u_{1,j+1} \\ u_{2,j+1} \\ u_{3,j+1} \\ \vdots \\ u_{n-1,j+1} \end{bmatrix} = \begin{bmatrix} 2(1-\lambda^2) & \lambda^2 & 0 & \dots & 0 \\ \lambda^2 & 2(1-\lambda^2) & \lambda^2 & \dots & 0 \\ 0 & \dots & \dots & \dots & 0 \\ 0 & \dots & \dots & \dots & \lambda^2 \\ 0 & \dots & 0 & \lambda^2 & 2(1+\lambda^2) \end{bmatrix} \begin{bmatrix} u_{1,j} \\ u_{2,j} \\ u_{3,j} \\ \vdots \\ u_{n-1,j} \end{bmatrix} - \begin{bmatrix} u_{1,j-1} \\ u_{2,j-1} \\ u_{3,j-1} \\ \vdots \\ u_{n-1,j-1} \end{bmatrix}$$

**Problema:** ¿ $u_{i,1}$ ?

Condición de velocidad inicial:

$$\frac{\partial u}{\partial t}(x, 0) = g(x), \quad 0 \leq x \leq l$$

Aproximación por diferencias progresivas:

$$\frac{\partial u}{\partial t}(x, 0) = \frac{u(x_i, t_1) - u(x_i, 0)}{k} - \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_i)$$

Resolviendo:

$$u(x_i, t_1) = u(x_i, 0) + kg(x_i) + \frac{k}{2} \frac{\partial^2 u}{\partial t^2}(x_i, \mu_i)$$

Error de truncamiento:  $\mathcal{O}(k) \leftarrow \blacksquare$

Mejora: expansión de McLaurin ( $\sim$  Taylor):

$$u(x_i, t_1) = u(x_i, 0) + k \frac{\partial u}{\partial t}(x_i, 0) + \frac{k^2}{2} \frac{\partial^2 u}{\partial t^2}(x_i, 0) + \frac{k^3}{6} \frac{\partial^3 u}{\partial t^3}(x_i, \hat{\mu}_i)$$

Si  $f''$  existe:

$$\frac{\partial^2 u}{\partial t^2}(x_i, 0) = \alpha^2 \frac{\partial^2 u}{\partial x^2}(x_i, 0) = \alpha^2 f''(x_i)$$

entonces:

$$u(x_i, t_1) = u(x_i, 0) + kg(x_i) + \frac{\alpha^2 k^2}{2} f''(x_i)$$

con error  $\mathcal{O}(k^3) \leftarrow \blacksquare$ . ¿Y si no tenemos  $f''(x_i)$ ?

Ecuación en diferencias:

$$f''(x_i) = \frac{f(x_{i+1}) - 2f(x_i) + f(x_{i-1}))}{h^2} - \frac{h^2}{12} f^{(4)}(\xi_i)$$

Usando  $\lambda = \alpha k/h$ :

$$u(x_i, 1) = (1 - \lambda^2)f(x_i) + \frac{\lambda^2}{2}f(x_{i+1}) + \frac{\lambda^2}{2}f(x_{i-1}) + kg(x_i) + \mathcal{O}(k^3 + h^2k^2)$$

Entonces, para  $i = 1, 2, \dots, n-1$  usamos:

$$u_{i,1} = (1 - \lambda^2)f(x_i) + \frac{\lambda^2}{2}f(x_{i+1}) + \frac{\lambda^2}{2}f(x_{i-1}) + kg(x_i)$$

y la ecuación matricial para  $j = 2, 3, \dots$

```
6 # Parámetros
7 L, T = 1.0, 1.0      # Dominio
8 Nx, Nt = 100, 1000   # Grilla
9 c = 1.0              # Velocidad
10 # Discretización
11 h, k = L / (Nx - 1), T / (Nt - 1)
12 l2 = (c * k / h)**2  # lambda**2
13 x = np.linspace(0, L, Nx)
14 t = np.linspace(0, T, Nt)
15
16 # Inicialización
17 u = np.zeros((Nt, Nx))
18 u[0, :] = np.sin(np.pi * x) # Condición inicial
19 u[1, 1:Nx-1] = u[0, 1:Nx-1] + 0.5 * l2 * (u[0, 2:Nx] \
20     - 2 * u[0, 1:Nx-1] + u[0, 0:Nx-2])
21
22 # Iteración en el tiempo
23 for n in range(1, Nt - 1):
24     for i in range(1, Nx - 1):
25         u[n + 1, i] = 2 * (1 - l2) * u[n, i] \
26             - u[n - 1, i] + l2 * (u[n, i + 1] \
27                 + u[n, i - 1])
```

---

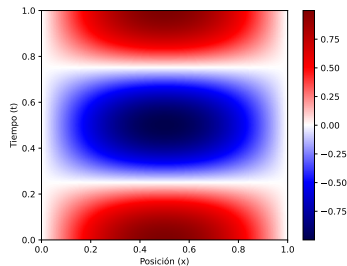
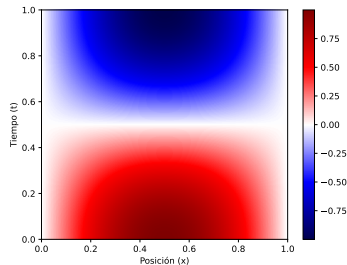
---

```

6 # Parámetros
7 L, T = 1.0, 1.0 # Dominio
8 Nx, Nt = 100, 1000 # Grilla
9 c = 1.0 # Velocidad
10 # Discretización
11 h, k = L / (Nx - 1), T / (Nt - 1)
12 l2 = (c * k / h)**2 # lambda**2
13 x = np.linspace(0, L, Nx)
14 t = np.linspace(0, T, Nt)
15
16 # Inicialización
17 u = np.zeros((Nt, Nx))
18 u[0, :] = np.sin(np.pi * x) # Condición inicial
19 u[1, 1:Nx-1] = u[0, 1:Nx-1] + 0.5 * l2 * (u[0, 2:Nx] \
20     - 2 * u[0, 1:Nx-1] + u[0, 0:Nx-2])
21
22 # Iteración en el tiempo
23 for n in range(1, Nt - 1):
24     for i in range(1, Nx - 1):
25         u[n + 1, i] = 2 * (1 - l2) * u[n, i] \
26             - u[n - 1, i] + l2 * (u[n, i + 1] \
27                 + u[n, i - 1])

```

---



- ▶ R.L. Burden, D.J. Faires y A.M. Burden. ***Análisis numérico***. 10.<sup>a</sup> ed. Mexico: Cengage Learning, 2017. Capítulo 12.
- ▶ E. Kreyszig, H. Kreyszig y E.J. Norminton. ***Advanced Engineering Mathematics***. Hoboken, USA: John Wiley & Sons, Inc, 2011. Capítulo 21.
- ▶ H.P. Langtangen y S. Linge. ***Finite Difference Computing with PDEs - A Modern Software Approach***. <https://hplgit.github.io/fdm-book/doc/web/index.html>. 2016. Capítulo 3.