

# Partial Differential Equations

## Part 1

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# The Heat equation in 1D

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- ▶ The PDE

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In what follows we will solve the simpler case  $q(x, t) = 0$

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- ▶ We also need approximations for higher derivatives, e.g

$$u_{xx}(x_i, t_n) \approx \frac{u_{i+1}^n - 2u_i^n + u_{i-1}^n}{(\Delta x)^2}$$

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- can be written in a matrix form  $\mathbf{u}^{(n+1)} = A\mathbf{u}^{(n)}$  where  $\mathbf{u}^{(n)} = (u_1^n, u_2^n, \dots, u_{N-1}^n)^T$

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