

# Content



## 0. Introduction

## 1. Differential equations

1.1 Classical equation of motion (classical mechanics, pendulum)

1.2 Partial differential equation relaxation methods (electromagnetism, diffusion)

1.3 Partial differential equation in space-time (traffic flow, tsunami)

## 2. Eigenvalue problem

2.1 Schrödinger equation and Hamiltonian (Harmonic oscillator, wave package)

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2.3 Exact diagonalization of spin chain (Spin wave, Haldane conjecture, topology)

2.4 Matrix product state and density matrix renormalization group (DMRG)

# Content



## **3. Statistical and many-body physics**

**3.1 Classical Monte Carlo and phase transitions (Ising model and critical phenomena)**

**3.2 Quantum Monte Carlo methods (Path-integral and cluster update)**

## **4. Machine learning in physics and High performance computation**

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**4.2 HPC and parallelism**

**4.3 ...**

# Partial differential equations

1st, 2nd derivatives of spatial and time coordinates

📌 Poisson equation

$$\Delta\phi(\vec{r}) = -\frac{1}{\epsilon_0}\rho(\vec{r})$$

Laplacian  $\Delta = \sum_{i=1}^d \frac{\partial^2}{\partial x_i^2}$

$\rho(\vec{r})$  charge density inside domain  $V$

$\phi(\vec{r})$  electrostatic potential

elliptic PDE

Dirichlet boundary condition  $\phi(\vec{r}), \vec{r} \in \partial V$

Neumann boundary condition  $(\vec{n} \cdot \vec{\nabla})\phi(\vec{r}), \vec{r} \in \partial V$

📌 Diffusion equation

$$\frac{\partial u(\vec{r}, t)}{\partial t} - D\Delta u(\vec{r}, t) = S(\vec{r}, t)$$

$u(\vec{r}, t)$  concentration of a substance at position  $\vec{r}$  and time  $t$

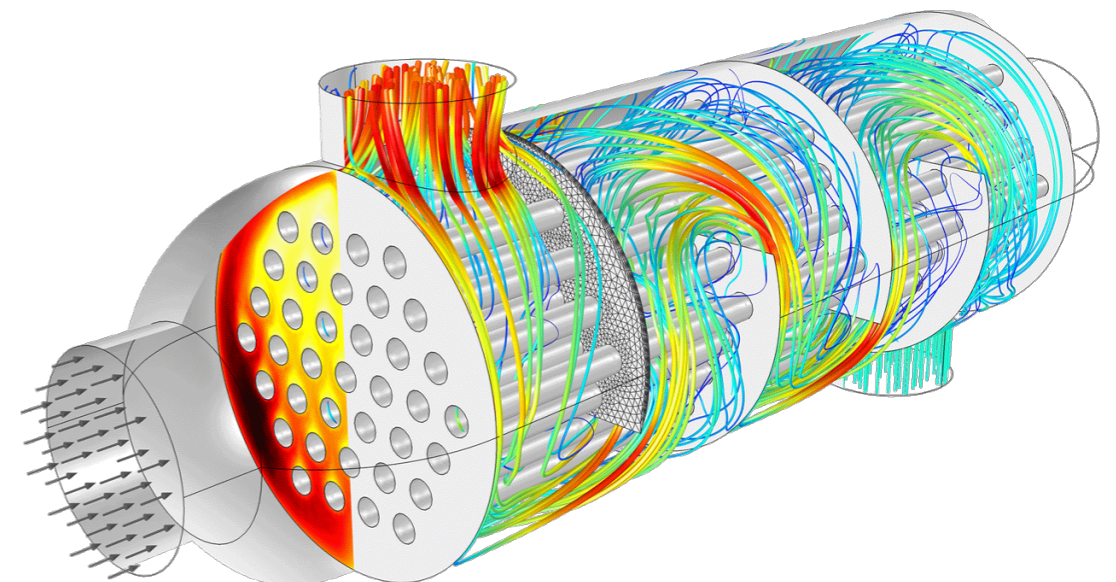
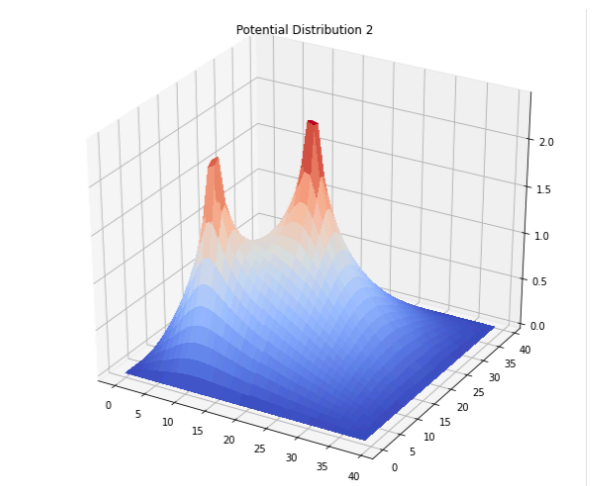
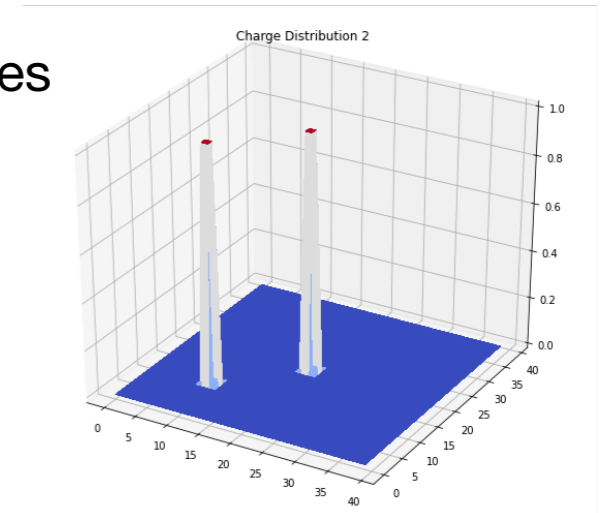
$S(\vec{r}, t)$  source/drain  $D$  diffusion coefficient

parabolic PDE asymmetrical under time-reversal  $t \rightarrow -t$

Cauchy initial value problem  $u(\vec{r}, t = 0)$  on domain  $V$

Neumann boundary condition  $(\vec{n} \cdot \vec{\nabla})u(\vec{r}) = 0, \vec{r} \in \partial V$

Initial configuration must be consistent with the boundary condition



📌 Wave equation  $\frac{1}{c^2} \frac{\partial^2 u(\vec{r}, t)}{\partial t^2} - \Delta u(\vec{r}, t) = S(\vec{r}, t)$

$c$  wave velocity

Hyperbolic PDE symmetrical under time-reversal, oscillations  $t \rightarrow -t$

initial value problem  $u(\vec{r}, t = 0), \frac{\partial u(\vec{r}, t)}{\partial t} \Big|_{t=0}$

Initial configuration must be consistent with the boundary condition

📌 Schrödinger equation  $i\hbar \frac{\partial \Psi(\vec{r}, t)}{\partial t} = H\Psi(\vec{r}, t)$

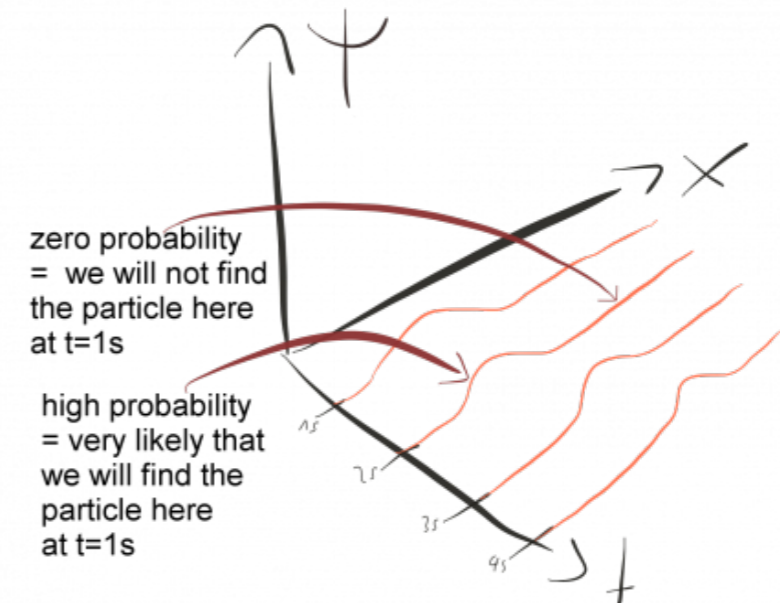
For free particle  $H = -\frac{\hbar^2}{2m} \Delta$

diffusion equation in imaginary time

📌 Fluid Dynamics, Navier-Stokes equation



浮世绘, 葛饰北斋, 神奈川冲浪里



Animating Schrödinger's Equation

<https://www.youtube.com/watch?v=Xj9PdeY64rA>

# Discretization

boundary  $\partial V$

$\vec{e}_i, i = 1, \dots, d$  unit vectors of a d-dimensional hyper cubic lattice

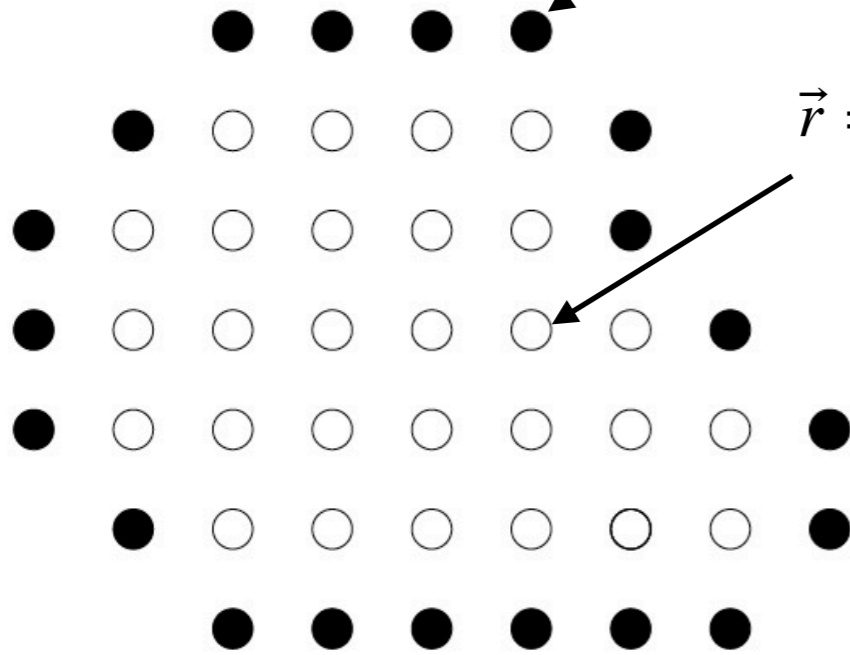
$$\vec{r} = \sum_{i=1}^{d=2} h_i r_i \vec{e}_i = \sum_{i=1}^{d=2} r_i \vec{e}_i$$

$h_i = h = 1$  lattice spacing

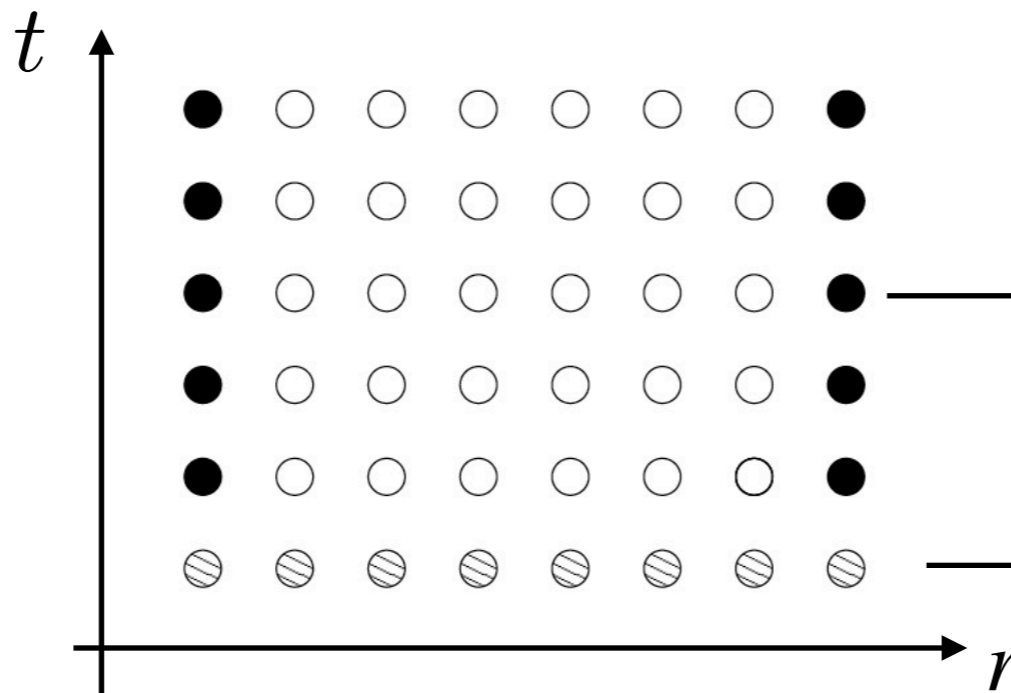
$r_i$  defines the domain  $V$

$$t_n = n\tau, n = 0, 1, 2, \dots$$

$$u(\vec{r}, t) \rightarrow u(\vec{r}_i, t_n)$$



Discretisation of space-time domain



Compatible boundary conditions

Initial values

$$u(\vec{r}, t = 0), \frac{\partial u(\vec{r}, t)}{\partial t} \Big|_{t=0}$$

Forward time (FT) discretisation

$$\frac{\partial u(\vec{r}, t_n)}{\partial t} \rightarrow \frac{u(\vec{r}, t_{n+1}) - u(\vec{r}, t_n)}{\tau} + O(\tau)$$

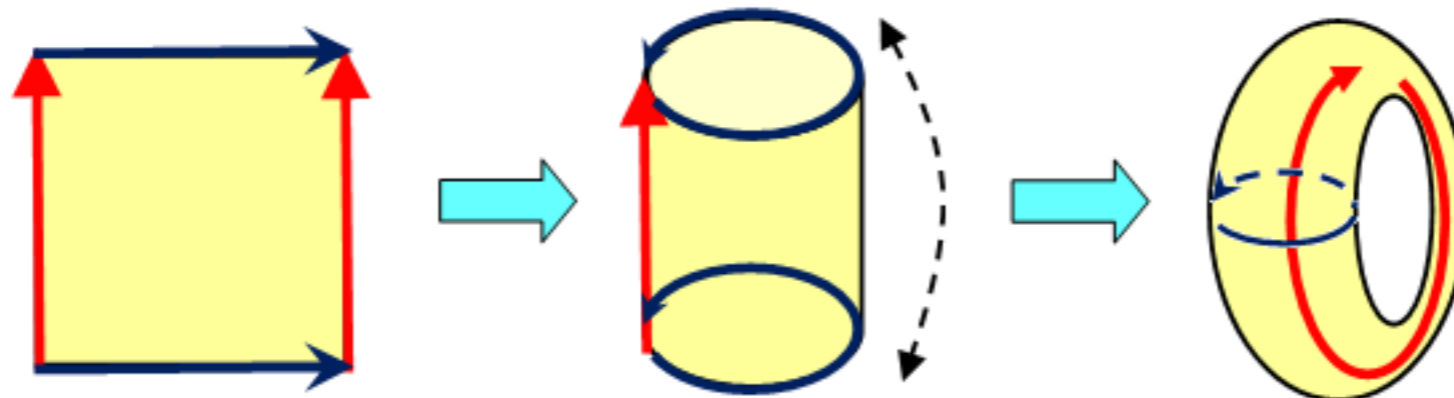
Centered space (CS) discretisation

$$\frac{\partial u(\vec{r}, t_n)}{\partial x_i} \rightarrow \frac{u(\vec{r} + h_i \vec{e}_i, t_n) - u(\vec{r} - h_i \vec{e}_i, t_n)}{2h_i} + O(h^2)$$

$$\frac{\partial^2 u(\vec{r}, t_n)}{\partial x_i^2} \rightarrow \frac{u(\vec{r} + h_i \vec{e}_i, t_n) + u(\vec{r} - h_i \vec{e}_i, t_n) - 2u(\vec{r}, t_n)}{h_i^2} + O(h^2)$$

Boundary conditions

Periodic boundary conditions (PBC)  $u(\vec{r} + N_i h_i \vec{e}_i) = u(\vec{r})$



1d ring  
2d torus (donut)  
higher-d tori

## Poisson equation (Potential Problems)

$$\Delta\phi(\vec{r}) = -\frac{1}{\epsilon_0}\rho(\vec{r}) \quad \vec{E} = -\nabla\phi \quad \Delta\phi(\vec{r}) = 4\pi G\rho(\vec{r}) \quad \vec{g} = -\nabla\phi$$

$$\phi(\vec{r}) = \frac{Q}{4\pi\epsilon_0|\vec{r}|} \quad \phi(\vec{r}) = -\frac{Gm}{|\vec{r}|}$$



1781-1842  
French mathematician,  
physicist

Centered three-point formula in each direction

$$\Delta\phi(\vec{r}) \rightarrow \frac{1}{h^2}(-2d\phi(\vec{r}) + \sum_{i=1}^d (\phi(\vec{r} + h\vec{e}_i) + \phi(\vec{r} - h\vec{e}_i))) + O(h^2)$$

$$\phi(\vec{r}) = \frac{1}{2d} \sum_{i=1}^d (\phi(\vec{r} + h\vec{e}_i) + \phi(\vec{r} - h\vec{e}_i)) + \frac{h^2}{2d\epsilon_0}\rho(\vec{r})$$

### Jacobi Relaxation

1. Initial configuration for  $\phi(\vec{r})$  (an educated guess) with boundary conditions

2. Calculation a new configuration  $\phi^{new}(\vec{r}) = \frac{1}{2d} \sum_{i=1}^d [\phi(\vec{r} + h\vec{e}_i) + \phi(\vec{r} - h\vec{e}_i)] + \frac{h^2}{2d\epsilon_0}\rho(\vec{r})$

Use the boundary condition to determine  $\phi^{new}(\vec{r}), \vec{r} \in \partial V$

3. Calculate the deviation  $\delta\phi = \max_{\vec{r}} |\phi^{new}(\vec{r}) - \phi(\vec{r})|$

4. Replace  $\phi$  by  $\phi^{new}$ . If  $\delta\phi$  smaller than the bound, stop; otherwise, repeat from step 2.

Relax towards the actual solution from boundary to the interior of  $V$

Computational complexity    # iterations  $\approx \frac{1}{2}pN_s^{2/d}$  to improve the error by  $10^{-p}$

for  $d = 2, \sim N_s$

 Gauss-Seidel Relaxation    no need to work with two arrays  $\phi$  and  $\phi^{new}$

Change the 2nd step in Jacobi    
$$\phi(\vec{r}) = \frac{1}{2d} \sum_{i=1}^d (\phi(\vec{r} + h\vec{e}_i) + \phi(\vec{r} - h\vec{e}_i)) + \frac{h^2}{2d\epsilon_0} \rho(\vec{r})$$

As one systematically carry out the relaxation

$\phi(\vec{r})$  contains both old and new values during the iteration through the lattice

Save the memory

Speed-up    # iterations  $\approx \frac{1}{4}pN_s^{2/d}$



📌 Successive Overrelaxation (SOR)

$$\phi(\vec{r}) \rightarrow (1 - \omega)\phi(\vec{r}) + \omega\left(\frac{1}{2d} \sum_{i=1}^d (\phi(\vec{r} + h\vec{e}_i) + \phi(\vec{r} - h\vec{e}_i)) + \frac{h^2}{2d\epsilon_0}\rho(\vec{r})\right)$$

relaxation parameter  $\omega$

Gauss-Seidel  $\omega = 1$

Underrelaxation  $0 < \omega < 1$

overrelaxation  $1 < \omega < 2$

Put more weight to the new value than in Gauss-Seidel

- Stable for  $\omega < 2$
- Converges faster than Gauss-Seidel
- Optimal value of the  $\omega_{opt}$  close to 2
- # iterations  $\approx \frac{1}{3}pN_s^{1/d}$

$$\omega_{opt} = \frac{2}{1 + \sqrt{1 - \frac{1}{4}(\cos(\frac{\pi}{N_x}) + \cos(\frac{\pi}{N_y}))^2}} \approx 1.939$$

with N=100

$N_x \times N_y$  square lattice with Dirichlet boundary condition

$$d = 2, \quad N_s^{2/d} \sim N_s$$

$$d = 2, \quad N_s^{1/d} \sim \sqrt{N_s}$$

Our bible



Chap. 20.5.

<http://numerical.recipes/book.html>

## Matrix-Formulation

$$\Delta\phi(\vec{r}) = -\frac{1}{\epsilon_0}\rho(\vec{r})$$

$$\phi(\vec{r}) = \frac{1}{2d} \sum_{i=1}^d (\phi(\vec{r} + h\vec{e}_i) + \phi(\vec{r} - h\vec{e}_i)) + \frac{h^2}{2d\epsilon_0}\rho(\vec{r})$$

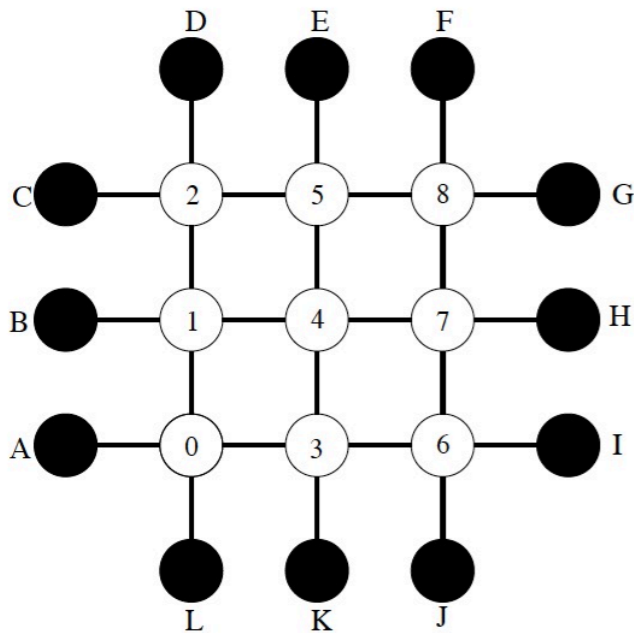
A set of linear equations

$$A\vec{\phi} = \vec{b}$$

$$\vec{\phi} = \begin{pmatrix} \phi(\vec{x}_0) \\ \phi(\vec{x}_{\vec{r}_1}) \\ \vdots \\ \phi(\vec{x}_{\vec{r}_{N-1}}) \end{pmatrix}$$

$\vec{b}$  boundary condition

$A$  Laplace operator  $-\Delta$



$$\text{on site 0 : } -\phi_3 - \phi_A - \phi_1 - \phi_L + 4\phi_0 = \frac{h^2}{\epsilon_0}\rho_0$$

$$\text{on site 1 : } -\phi_4 - \phi_B - \phi_2 - \phi_0 + 4\phi_1 = \frac{h^2}{\epsilon_0}\rho_1$$

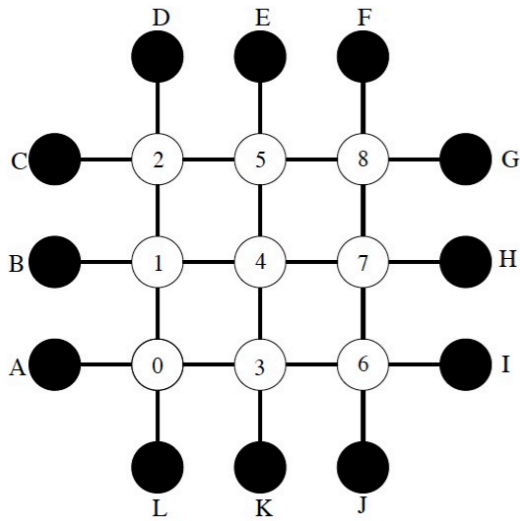
$\vdots$

$$\text{on site 4 : } -\phi_7 - \phi_1 - \phi_5 - \phi_3 + 4\phi_4 = \frac{h^2}{\epsilon_0}\rho_4$$

$\vdots$

$$\text{on site 8 : } -\phi_G - \phi_5 - \phi_F - \phi_7 + 4\phi_8 = \frac{h^2}{\epsilon_0}\rho_8$$

# Matrix-Formulation



$$A\vec{\phi} = \vec{b}$$

$$\begin{aligned} -\phi_3 - \phi_1 + 4\phi_0 &= \frac{h^2}{\epsilon_0} \rho_0 + \phi_A + \phi_L =: b_0 \\ -\phi_4 - \phi_2 - \phi_0 + 4\phi_1 &= \frac{h^2}{\epsilon_0} \rho_1 + \phi_B =: b_1 \\ &\vdots \\ -\phi_7 - \phi_1 - \phi_5 - \phi_3 + 4\phi_4 &= \frac{h^2}{\epsilon_0} \rho_4 =: b_4 \\ &\vdots \\ -\phi_5 - \phi_7 + 4\phi_8 &= \frac{h^2}{\epsilon_0} \rho_8 + \phi_G + \phi_F =: b_8 \end{aligned}$$

$$\begin{pmatrix} 4 & -1 & 0 & -1 & 0 & 0 & 0 & 0 & 0 \\ -1 & 4 & -1 & 0 & -1 & 0 & 0 & 0 & 0 \\ 0 & -1 & 4 & 0 & 0 & -1 & 0 & 0 & 0 \\ -1 & 0 & 0 & 4 & -1 & 0 & -1 & 0 & 0 \\ 0 & -1 & 0 & -1 & 4 & -1 & 0 & -1 & 0 \\ 0 & 0 & -1 & 0 & -1 & 4 & 0 & 0 & -1 \\ 0 & 0 & 0 & -1 & 0 & 0 & 4 & -1 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & -1 & 4 & -1 \\ 0 & 0 & 0 & 0 & 0 & -1 & 0 & -1 & 4 \end{pmatrix} \begin{pmatrix} \phi_0 \\ \phi_1 \\ \phi_2 \\ \phi_3 \\ \phi_4 \\ \phi_5 \\ \phi_6 \\ \phi_7 \\ \phi_8 \end{pmatrix} = \begin{pmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \\ b_6 \\ b_7 \\ b_8 \end{pmatrix}$$

A is symmetric  $A^T = A$

A is sparse  $A_{ii} = 2d, A_{ij} = -1$  only if  $\langle i, j \rangle$

A is positive definite  $\vec{x}^T A \vec{x} > 0$ , for  $\vec{x} \neq 0$

$$\int d^d x f^*(\vec{x})(-\Delta)f(\vec{x}) = \int d^d x |\nabla f(\vec{x})|^2 > 0,$$

Partial integration over an infinite domain

Positive semi-definite  $v^T Q v = v^T X^T X v = (Xv)^T (Xv) = u^T u \geq 0$

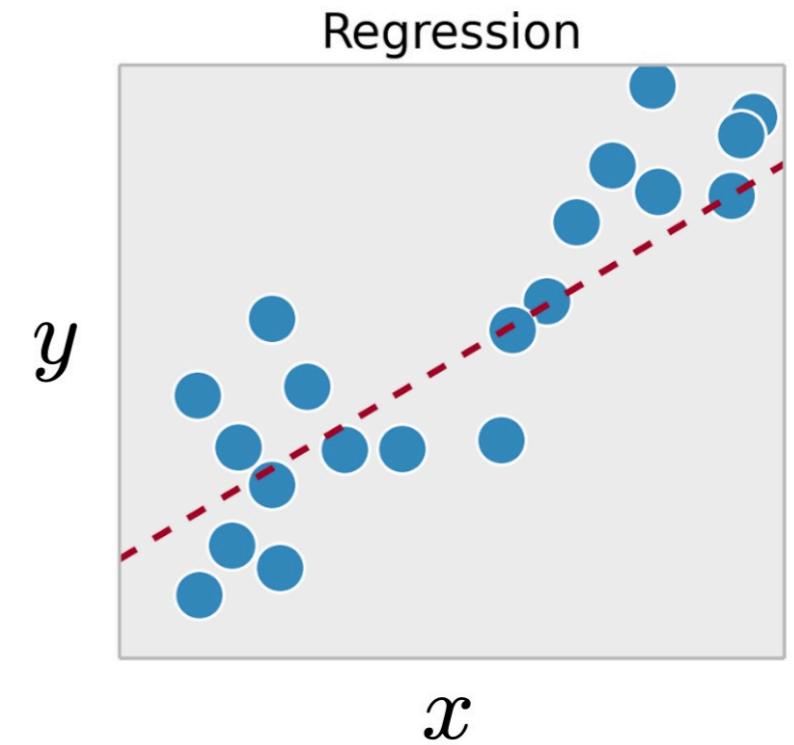
# Remember what we learnt in the machine learning lecture ?

[https://quantummc.xyz/wp-content/uploads/2023/03/lecture1\\_1.pdf](https://quantummc.xyz/wp-content/uploads/2023/03/lecture1_1.pdf)

$$\{(x_j^{(i)}, y^{(i)}), \theta_j\}; j = 1, 2, \dots, N; i = 1, 2, \dots, M; N < M$$

$$y^{(i)} = \theta_0 + \theta_1 x_1^{(i)} + \theta_2 x_2^{(i)} + \dots + \theta_N x_N^{(i)}$$

$$\mathbb{R}^{M \times (N+1)} \begin{bmatrix} 1 & x_1^{(1)} & x_2^{(1)} & \dots & x_N^{(1)} \\ 1 & x_1^{(2)} & x_2^{(2)} & \dots & x_N^{(2)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_1^{(M)} & x_2^{(M)} & \dots & x_N^{(M)} \end{bmatrix} \cdot \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_N \end{bmatrix} = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(M)} \end{bmatrix}$$



$$\underline{X} \cdot \underline{\Theta} = \underline{Y}$$

## Paraboloid and positive-definite

$$f(x) = \frac{1}{2} x^T A x - b^T x + c \quad \nabla_x f(x) = A x - b = 0 \quad A x = b$$

$$A = \frac{1}{M} X^T X \quad \mathbb{R}^{(N+1) \times (N+1)}$$

$$b = X^T Y \quad \mathbb{R}^{(N+1) \times 1}$$

$$A = \underbrace{\begin{bmatrix} \langle 1 \rangle & \langle x_1 \rangle & \langle x_2 \rangle & \dots & \langle x_N \rangle \\ \langle x_1 \rangle & \langle (x_1)^2 \rangle & \langle x_1 x_2 \rangle & \dots & \langle x_1 x_N \rangle \\ \langle x_2 \rangle & \langle x_2 x_1 \rangle & \langle (x_2)^2 \rangle & \dots & \langle x_2 x_N \rangle \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \langle x_N \rangle & \langle x_N x_1 \rangle & \langle x_N x_2 \rangle & \dots & \langle (x_N)^2 \rangle \end{bmatrix}}_{\mathbb{R}^{(N+1) \times (N+1)}}$$

# Gauss Elimination

$$\begin{array}{rclcl} x_0 & + & x_1 & + & x_2 & = & 6 \\ -x_0 & + & 2x_1 & & & = & 3 \\ 2x_0 & & & + & x_2 & = & 5 \end{array}$$

$$A = \begin{pmatrix} 1 & 1 & 1 \\ -1 & 2 & 0 \\ 2 & 0 & 1 \end{pmatrix}, \quad \vec{b} = \begin{pmatrix} 6 \\ 3 \\ 5 \end{pmatrix}, \quad \text{and } \vec{x} = \begin{pmatrix} x_0 \\ x_1 \\ x_2 \end{pmatrix}$$

Eliminate  $x_0$  from 2nd and 3rd equation

$$\begin{array}{rclcl} x_0 & + & x_1 & + & x_2 & = & 6 \\ & & 3x_1 & + & x_2 & = & 9 \\ & & -2x_1 & - & x_2 & = & -7 \end{array}$$

Forward elimination  $O(n^3)$

For  $j = 0, \dots, n - 2$  do:

Test with  $3 \times 3$  matrix

For  $i = j + 1, \dots, n - 1$  do:

Eliminate  $x_1$  from 3rd equation

$$\begin{array}{rclcl} x_0 & + & x_1 & + & x_2 & = & 6 \\ & & 3x_1 & + & x_2 & = & 9 \\ & & & - & \frac{1}{3}x_2 & = & -1 \end{array}$$

$$f := -A_{ij}/A_{jj}$$

$$A_{ik} \rightarrow A_{ik} + fA_{jk}, \quad k = j, \dots, n - 1$$

$$b_i \rightarrow b_i + fb_j.$$

Trigonal system  $(\tilde{A}, \tilde{b})$

$$\tilde{A} = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 3 & 1 \\ 0 & 0 & -\frac{1}{3} \end{pmatrix}, \quad \tilde{b} = \begin{pmatrix} 6 \\ 9 \\ -1 \end{pmatrix}$$

backsubstitution  $O(n^2)$

$$x_{n-1} = \frac{\tilde{b}_{n-1}}{\tilde{A}_{n-1,n-1}}, \quad x_i = \frac{1}{\tilde{A}_{ii}} \left[ \tilde{b}_i - \sum_{j=i+1}^{n-1} \tilde{A}_{ij}x_j \right], \quad i = n - 2, \dots, 0.$$

Problem: after a few iterations,  $A_{ii}$  (almost) zero      Divide very small numbers, leads to breakdown

## Gauss Elimination with pivoting

- Rescale each row of  $(A, \vec{b})$  so that the maximum element in each row of  $A$  equals 1.
- Initialize the index vector,  $v(i) = i, i = 0, \dots, n - 1$ . for bookkeeping
- For  $j = 0, \dots, n - 2$  do:
  - Search for the pivot element:  $|A_{v(p),j}| = \max\{|A_{v(i),j}|, i = j, \dots, n - 1\}$   
If  $j \neq p$ , exchange the  $j$ -th and  $p$ -th entries of  $v$ :  $v(j) \leftrightarrow v(p)$   
This corresponds to exchanging the  $j$ -th and  $p$ -th row.
  - For  $i = j + 1, \dots, n - 1$  do:

$$\begin{aligned} f &:= -A_{v(i)j} / A_{v(j)j} \\ A_{v(i)k} &\rightarrow A_{v(i)k} + f A_{v(j)k}, \quad k = j, \dots, n - 1 \\ b_{v(i)} &\rightarrow b_{v(i)} + f b_{v(j)}. \end{aligned}$$

Backsubstitution with trigonal system  $(\tilde{A}, \vec{\tilde{b}})$

$$x_{n-1} = \frac{\tilde{b}_{v(n-1)}}{\tilde{A}_{v(n-1),n-1}}, \quad x_i = \frac{1}{\tilde{A}_{v(i)i}} \left[ \tilde{b}_{v(i)} - \sum_{j=i+1}^{n-1} \tilde{A}_{v(i)j} x_j \right], \quad i = n-2, \dots, 0.$$

# LU Decomposition

$$\tilde{A} = MA \text{ where } M = M^{(n-2)} M^{(n-1)} \dots M^{(1)} M^{(0)}$$

$\tilde{A}$  is upper triangular matrix

$M^{(j)}$  are lower triangular matrices

$$A = \underbrace{M^{-1}}_L \cdot \underbrace{\tilde{A}}_U = L \cdot U$$

$$M_{ii}^{(j)} = 1$$

$$M_{ij}^{(j)} = -\frac{A_{ij}}{A_{jj}}, i > j$$

Complexity still scales  $O(N^3)$

$$M_{ij}^{(j)} = 0 \text{ otherwise}$$

$O(N^2)$  once the LU decomposition is known.

$$A\vec{x} = LU\vec{x} = L(U\vec{x}) = \vec{b}$$

Forward substitution  $L\vec{y} = \vec{b}$

$$y_0 = \frac{b_0}{L_{00}}, \quad y_i = \frac{1}{L_{ii}} \left[ b_i - \sum_{j=0}^{i-1} L_{ij} y_j \right], \quad i = 1, \dots, n-1$$

**Our bible**



Backsubstitution  $U\vec{x} = \vec{y}$

$$x_{n-1} = \frac{y_{n-1}}{U_{n-1,n-1}}, \quad x_i = \frac{1}{U_{ii}} \left[ y_i - \sum_{j=i+1}^{n-1} U_{ij} x_j \right], \quad i = n-2, \dots, 0$$

Chap.2.3.

<http://numerical.recipes/book/book.html>

# Steepest descent and Conjugate Gradient methods

$$f(x) = \frac{1}{2}x^T Ax - b^T x + c \quad \nabla_x f(x) = Ax - b = 0 \quad Ax = b \quad A = \frac{1}{M}X^T X \quad \mathbb{R}^{(N+1) \times (N+1)}$$

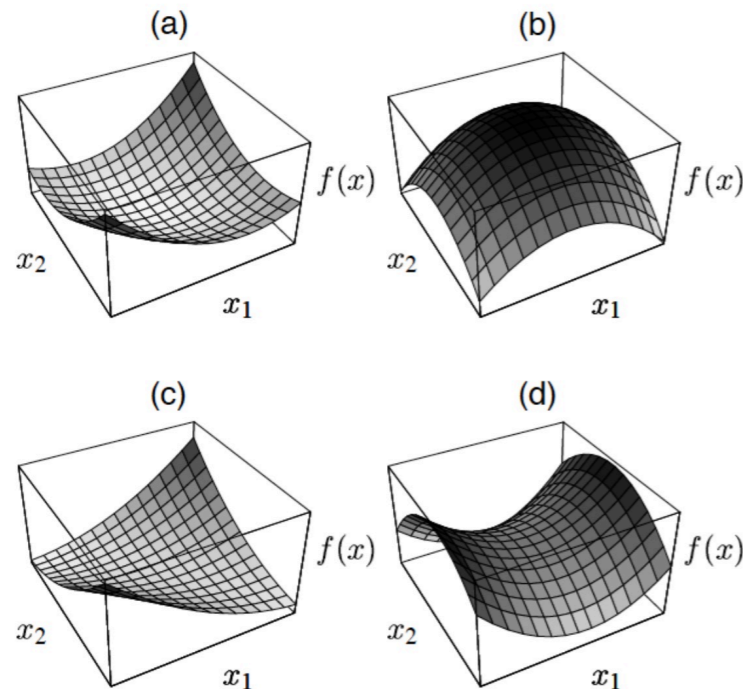
$$b = X^T Y \quad \mathbb{R}^{(N+1) \times 1}$$

$$A = \begin{bmatrix} 3 & 2 \\ 2 & 6 \end{bmatrix} \quad b = \begin{bmatrix} 2 \\ -8 \end{bmatrix} \quad c = 0$$

**Remember what we learnt in the machine learning lecture ?**

[https://quantummc.xyz/wp-content/uploads/2023/03/lecture1\\_1.pdf](https://quantummc.xyz/wp-content/uploads/2023/03/lecture1_1.pdf)

Iteration times  $O(N)$

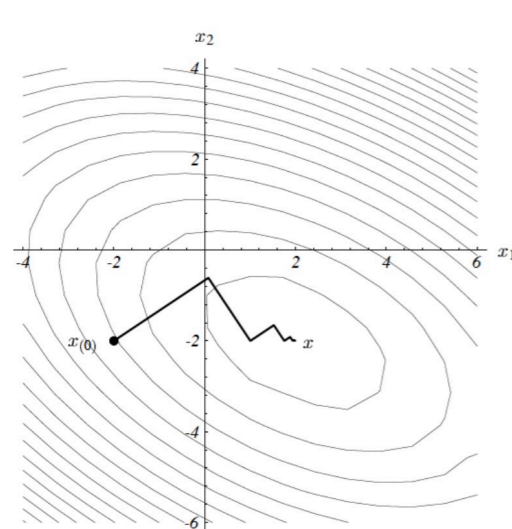
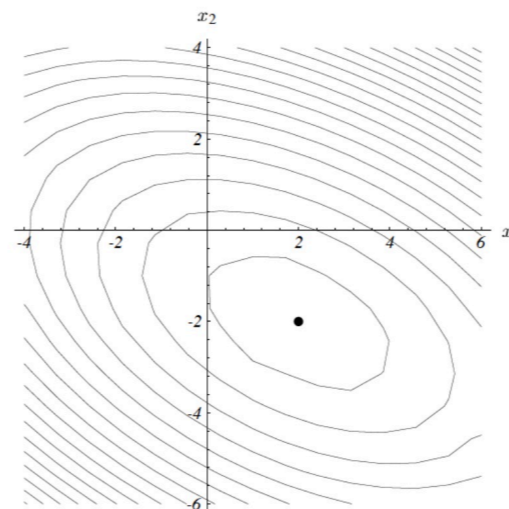


(a) positive-definite, symmetric

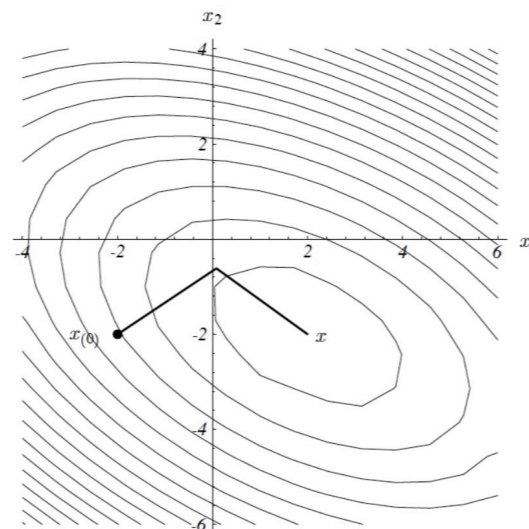
(b) negative-definite

(c) singular, a set of solution

(d) saddle point



Many steps to find the solution



Only takes N-steps to find the solution

**Our bible**



Chap.10.8.

<http://numerical.recipes/book/book.html>



## Parabolic PDEs

Time-dependent PDEs: diffusion equation

$$\frac{\partial u(t, \vec{r})}{\partial t} - D\Delta u(t, \vec{r}) = S(t, \vec{r})$$

$$\frac{\partial u}{\partial t} = D \frac{\partial^2 u}{\partial x^2}$$

$$t_n = n \cdot \tau, \quad n = 0, 1, \dots$$

$$\vec{r} = r \cdot h, \quad r = 0, 1, \dots, N-1$$

**FTCS:** Forward time (FT) Centered space (CS) scheme

$$\frac{u(n+1, r) - u(n, r)}{\tau} = D \frac{u(n, r+1) - 2u(n, r) + u(n, r-1)}{h^2}$$

Also called Explicit Euler method

$$u(n+1, r) = u(n, r) + \frac{D\tau}{h^2} (u(n, r+1) - 2u(n, r) + u(n, r-1))$$

Gaussian wave package as a solution

(can you see this ?)

$$u(t, r) = \frac{1}{\sqrt{2\pi\sigma(t)}} \exp\left[-\frac{r^2}{2\sigma(t)^2}\right] \quad \sigma(t) = \sqrt{2Dt}$$

Characteristic diffusion-time

$$t_h = \frac{h^2}{2D}$$

Width  $\sigma$  Increase from 0 to  $h$

Stability

$$\tau \ll t_h$$

## Von Neumann Stability Analysis

Plane wave ansatz  $u(n, r) = A^n e^{ikrh}$   $u(n + 1, r) = u(n, r) + \frac{D\tau}{h^2}(u(n, r + 1) - 2u(n, r) + u(n, r - 1))$

$$AA^n e^{ikrh} = A^n e^{ikrh} + \frac{D\tau}{h^2}(A^n e^{ikrh} e^{ikh} - 2A^n e^{ikrh} + A^n e^{ikrh} e^{-ikh})$$

$$A = 1 + \frac{D\tau}{h^2}(e^{ikh} + e^{-ikh} - 2)$$

$$= 1 - 2\frac{D\tau}{h^2}(1 - \cos(kh))$$

$$= 1 - \frac{4D\tau}{h^2} \sin^2\left(\frac{kh}{2}\right)$$

**decrease h to h/2**  
**decrease tau to tau/4**

$d = 1$   $|A| \leq 1 \longrightarrow \frac{4D\tau}{h^2} \leq 2 \longrightarrow \tau \leq \frac{h^2}{2D}$  Higher dimension d  $\tau \leq \frac{h^2}{2dD}$

With maximum  $\tau = \frac{h^2}{2D}$  FTCS becomes  $u(n + 1, r) = \frac{1}{2}(u(n, r + 1) + u(n, r - 1))$

Similar with the Jacobi relaxation for Poisson equation when  $d = 1$  and  $\rho = 0$

[https://en.wikipedia.org/wiki/Von\\_Neumann\\_stability\\_analysis](https://en.wikipedia.org/wiki/Von_Neumann_stability_analysis)

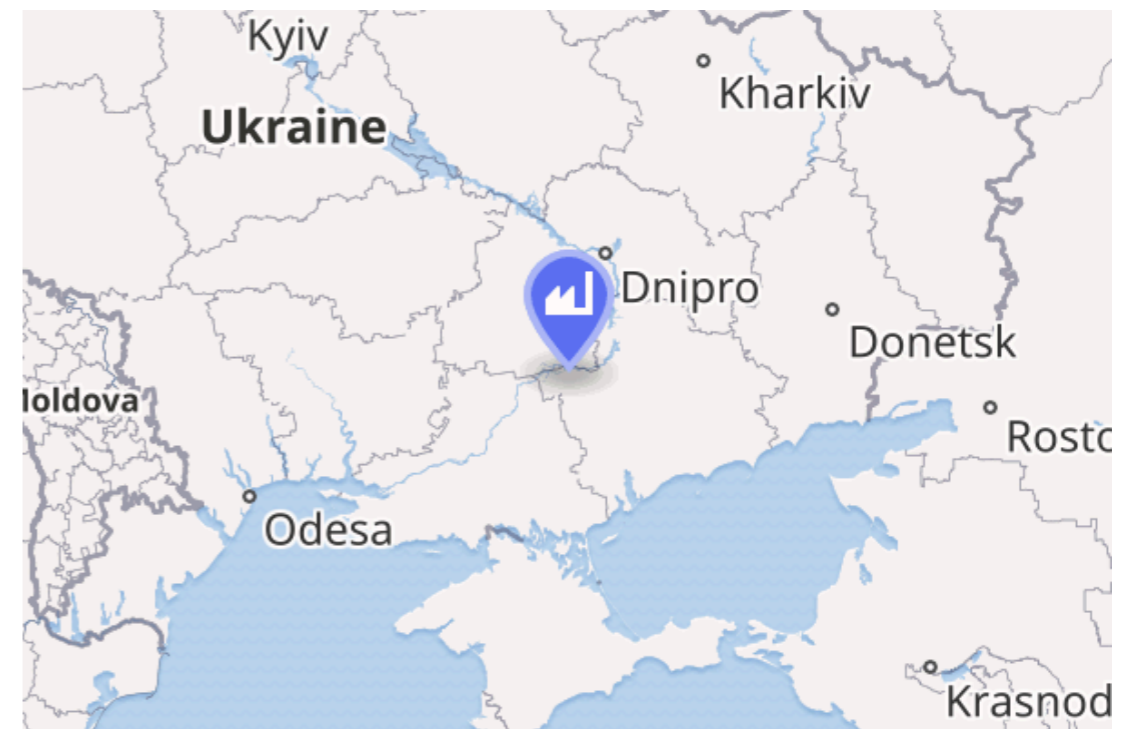
## Ukraine: Zaporizhzhya nuclear plant initiates reactor shutdown following water leak, reports IAEA



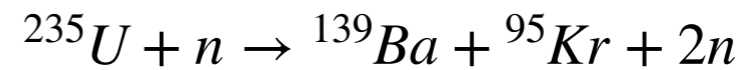
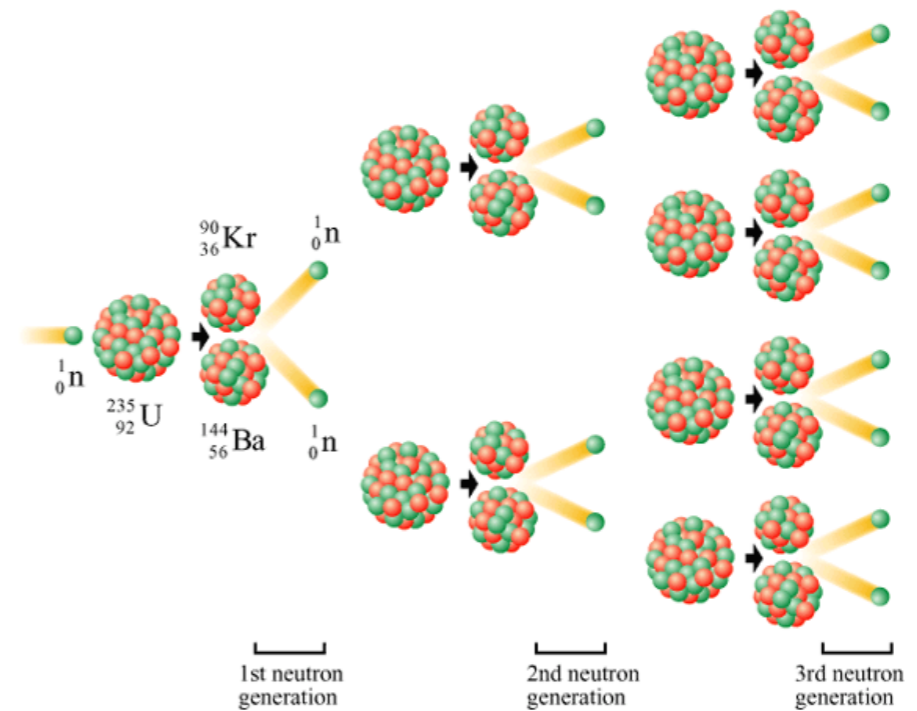
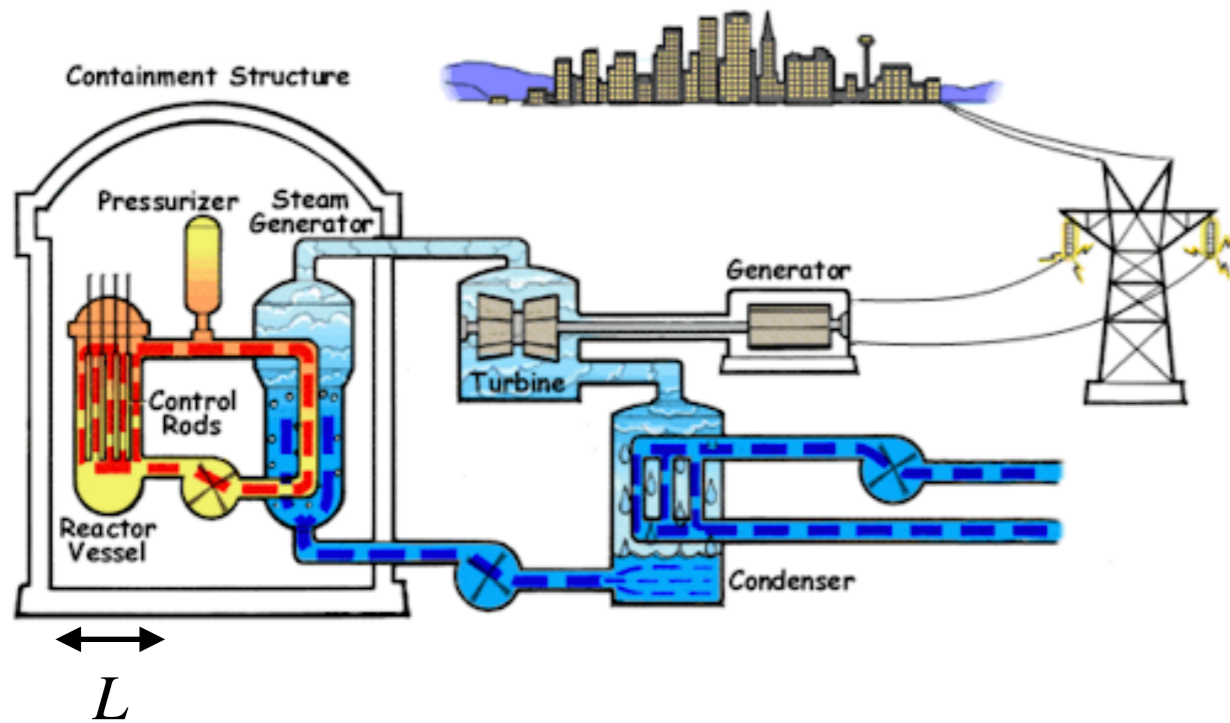
© IAEA/Fredrik Dahl | An IAEA expert mission team walks around the Zaporizhzhya Nuclear Power Plant and its surrounding area. (file)

10 August 2023 | [Peace and Security](#)

The **Zaporizhzhia Nuclear Power Station** ([Ukrainian](#): Запорізька атомна електростанція, [romanized](#): *Zaporiz'ka atomna elektrostantsiia*) in southeastern [Ukraine](#) is the largest [nuclear power plant](#) in Europe and [among the 10 largest in the world](#).



# Diffusion of neutrons from the chain reaction of Uranium



For  ${}^{235}\text{U}$  Diffusion constant  $D \approx 10^5 \text{m}^2/\text{s}$  Creation rate  $C \approx 10^8 \text{s}^{-1}$

$$\frac{\partial}{\partial t} n(t, \vec{r}) = D \Delta n(t, \vec{r}) + C n(t, \vec{r})$$

**FTCS**  $n(n+1, r) = (1 + C\tau)n(n, r)$

Dirichlet BC  $n(\partial V) = 0$   $V = L^d$

$$+ \frac{D\tau}{h^2} (u(n, r+1) - 2u(n, r) + u(n, r-1))$$

Critical length  $L_c = \pi \sqrt{\frac{dD}{C}}$

Stability  $\tau \leq \frac{h^2}{2dD} = \frac{h^2}{4D}$   $d = 2$

$$D = C = 1, L_c = \sqrt{2}\pi$$