

Computational Physics

① What problems in physics can we solve with a computer?



Computational problems : scaling of computing time

"Size of the problem" : N # of degrees of freedom
(D dimensions of the problem)

$1/\epsilon$: accuracy of the solution

$$T(N, \epsilon) ?$$

time to solution

$\alpha < \infty$

Efficient algorithm

$$T(N, \epsilon) \sim \begin{cases} \text{poly}_n(N) \\ \text{poly}_n(\frac{1}{\epsilon}) \end{cases} \quad \left(\begin{array}{l} \text{ex. } \sim N^n \\ \sim \left(\frac{1}{\epsilon}\right)^n \end{array} \right)$$

Inefficient algorithm / hard computational problem

$$T(N, \epsilon) \sim \begin{cases} B \exp(A N^\alpha) \\ B \exp(A \frac{1}{\epsilon} \alpha) \end{cases}$$

Eigenvalue problems

A Hermitian $N \times N$ matrix

$$A^\dagger = A$$

$$A_{ij} = A_{ji}^* \in \mathbb{C}$$

$$A \vec{x}_n = \lambda_n \vec{x}_n$$

$$n = 1, \dots, N$$

↑

$$\Rightarrow (A |x_n\rangle = \lambda_n |x_n\rangle)$$

$$\lambda_n \in \mathbb{R}$$

1) Quantum mechanics

$$\hat{O} |\psi_n\rangle = \underbrace{O_n}_{\text{eigenvalue}} |\psi_n\rangle$$

basis of Hilbert space $\mathcal{H}$

$$\{|\phi_n\rangle\}$$

$$\sum_{n=1}^D |\phi_n\rangle \langle \phi_n| = \mathbb{1}_D$$

$$\left(\sum_n \vec{\phi}_n \vec{\phi}_n^T = \mathbb{1} \right)$$

$$\langle \phi_m | \hat{O} |\phi_n\rangle \langle \phi_n | \psi_n\rangle = \langle \phi_m | \psi_n\rangle O_n$$

$$|\psi\rangle \in \mathcal{H}$$

$$\left(\begin{array}{l} O_n \in \mathbb{R} \\ \hat{O} = \hat{O}^\dagger \end{array} \right)$$

$$n = 1, \dots, D$$

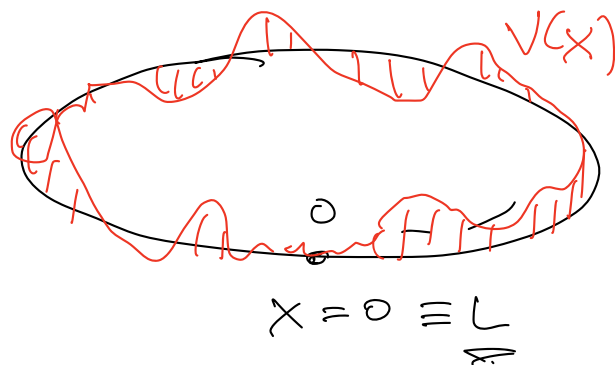
↑

$$\left\{ \sum_n \mathcal{O}_{mn} \psi_n^{(k)} = \mathcal{O}_k \psi_m^{(k)} \right\}$$

$$\langle \phi_m | \hat{O} | \phi_n \rangle = \mathcal{O}_{mn}$$

$$\langle \phi_m | \psi_n^{(k)} \rangle = \psi_m^{(k)}$$

Example : 1d particle in a potential
(with periodic boundary conditions)



L = length
of the ring

$$\hat{H} = \frac{\hat{p}^2}{2m} + V(\hat{x})$$

a) momentum basis

$$|q_n\rangle : \quad \hat{p} |q_n\rangle = \hbar q_n |q_n\rangle$$

$$\langle x | q_n \rangle = \frac{1}{\sqrt{L}} e^{i q_n x}$$

$$q_n \equiv \frac{2\pi}{L} n$$

$$n \in \mathbb{Z}$$

truncate the dimensions of H from ∞ to $\mathbb{D}$

$$n : -\frac{\mathbb{D}}{2} + 1, \dots, \frac{\mathbb{D}}{2}$$

↑

$$\langle q_n | \hat{H} | q_m \rangle = \frac{\hbar^2 q_n^2}{2M} \delta_{nm} \leftarrow$$

$$+ \underbrace{\langle q_n | V(\hat{x}) | q_m \rangle}$$

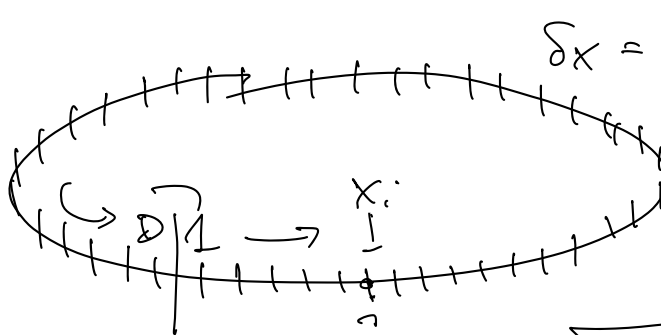
(ex.) $\frac{1}{L} \int dx V(x) e^{-i(q_n - q_m)x}$

$$\begin{pmatrix} \frac{\hbar^2 q_1^2}{2M} + \langle q_1 | V | q_1 \rangle & \langle q_1 | V | q_2 \rangle & \dots \\ \langle q_2 | V | q_1 \rangle & \frac{\hbar^2 q_2^2}{2M} + \langle q_2 | V | q_2 \rangle & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$$

$$|q_n| < \frac{2\pi}{L} D$$

$$\delta x > \frac{L}{D} = (\delta x)_{\min}$$

b) discretized position basis $|x\rangle$

$$\delta x = \frac{L}{D} \quad x \in [0, L]$$


$$\langle x | \hat{H} | \psi \rangle = \langle x | E | \psi \rangle$$

$$\Rightarrow \left(-\frac{\hbar^2}{2M} \frac{d^2}{dx^2} + V(x) \right) \psi(x) = E \psi(x)$$

$$\frac{d}{dx} \psi(x) \Big|_{x=x_i} = \frac{\psi(x_{i+1}) - \psi(x_i)}{\delta x} + o(\delta x)$$

$$\frac{d^2}{dx^2} \psi(x) \Big|_{x_i} \approx \frac{\psi(x_{i+1}) + \psi(x_{i-1}) - 2\psi(x_i)}{(\delta x)^2} + o(\delta x)$$

$$V(X_i) = V_c$$

$$\psi(x_i) \Rightarrow \psi_i$$

$$-\frac{\hbar^2}{2m(\delta x)^2} (\psi_{i+1} + \psi_{i-1} - 2\psi_i) + V_i \psi_i = E \psi_i$$

$$\textcircled{H} \begin{matrix} \rightarrow \\ \downarrow \\ 1 \end{matrix} \psi = \sum \begin{matrix} \rightarrow \\ \downarrow \\ 2 \end{matrix} \psi$$

$(H) \psi = E \psi$

$H = \begin{pmatrix} V_1 + 2\epsilon_0 & -\epsilon_0 & & \\ -\epsilon_0 & V_2 + 2\epsilon_0 & & \\ & & \ddots & \\ -\epsilon_0 & & & V_N + 2\epsilon_0 \end{pmatrix}$

ϵ_0

$N + (N-1)2$

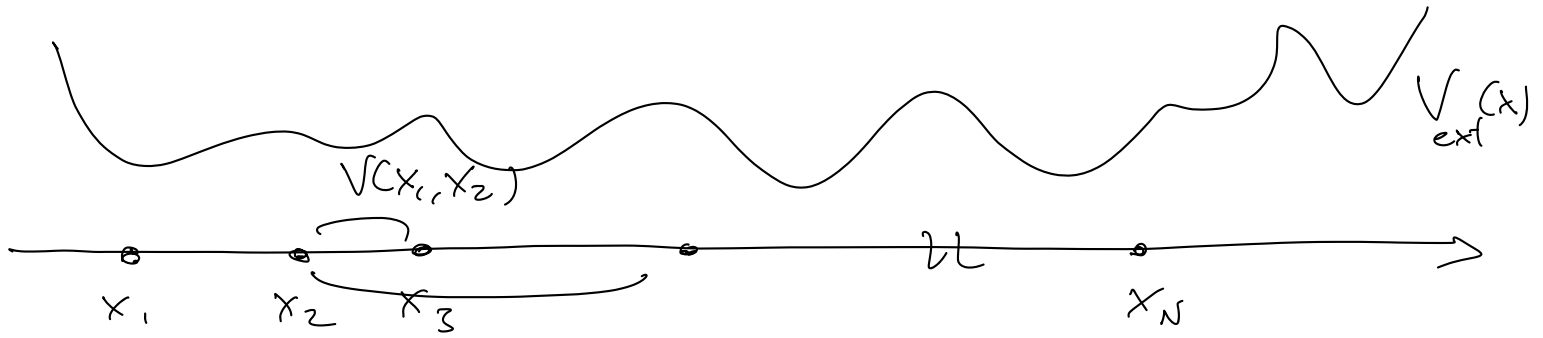
$$N + (N-1)2$$

+ 2

$$= 2\sqrt{}$$

Sparse matrix

2) Normal-mode analysis



$$H = \sum_{i=1}^N \frac{p_i^2}{2M} + \underbrace{\sum_i V_{\text{ext}}(x_i) + \frac{1}{2} \sum_{i \neq j} V(x_i, x_j)}_{U(\{x_i\})}$$

$$M \ddot{x}_k = - \frac{\partial U}{\partial x_k}$$

$$\min U(\{x_i\})$$

$$\rightarrow x_i = x_i^{(0)}$$

$$U(\{x_i\}) = U(\{x_i^{(0)}\}) + \sum_{i=1}^N \left(\frac{\partial U}{\partial x_i} \right)_{\{x_i^{(0)}\}} (x_i - x_i^{(0)})$$

$$+ \frac{1}{2} \sum_{i,j} \left(\frac{\partial^2 U}{\partial x_i \partial x_j} \right)_{\{x_i^{(0)}\}} (x_i - x_i^{(0)}) (x_j - x_j^{(0)}) + \dots$$

Hessian

$$M \ddot{x}_k = - \sum_j H_{kj} (x_j - x_j^{(0)})$$

$$\rightarrow y_k = x_k - x_k^{(0)}$$

$$\ddot{y}_k = - \sum_j \left(\frac{H_{kj}}{M} \right) y_j$$

$$\ddot{\vec{y}} = - \tilde{H} \vec{y}$$

$$k = 1, \dots, N$$

$$\vec{y}(t) = \vec{y}(0) e^{i(\omega t + \phi)}$$

$$\hookrightarrow \cos(\omega t + \phi)$$

$$\omega_n^2 \vec{y}_n(0) = \tilde{H} \vec{y}_n(0)$$

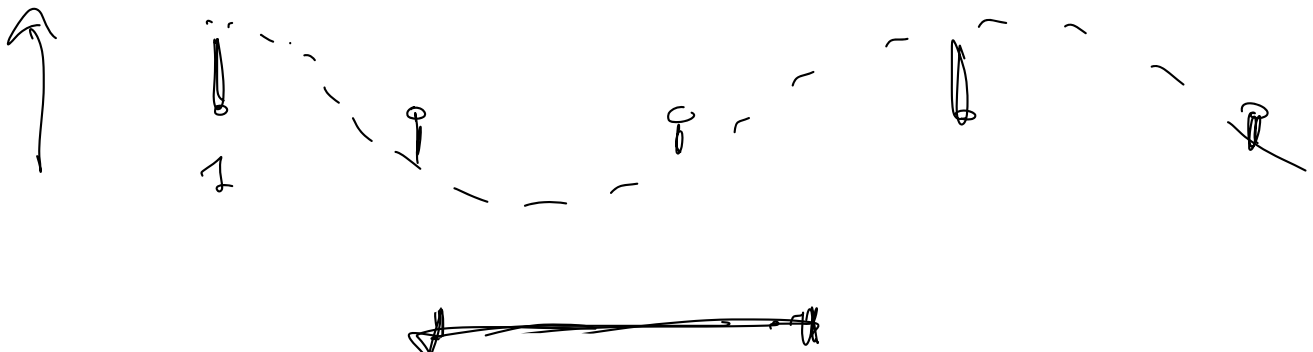
Diagonalize the Hessian matrix

$$\tilde{H} : \text{semi-positive definite}$$

$$\omega^2 \geq 0$$

$$\underline{U_{\text{ext}} = 0}$$

$$\vec{y}_n = \{ \cos(q_n x_n) \}$$



Full diagonalization of a matrix

LA Rack

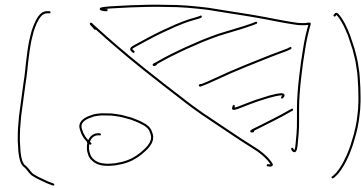
QR algorithm

$$A = QR$$

Hermitian $\downarrow$ $\rightarrow$ upper triangular matrix
 $N \times N$ unitary

$$Q^+ Q = \underline{1}$$

$$\mathcal{O}(N^3)$$



$$A_1 = RQ = Q^+ A Q = Q_1 R_1$$

$$A_2 = R_1 Q_1 = Q_1^+ A_1 Q_1 = Q_2 R_2$$

...

A is diagonal

$$u \gg 1$$

Storage

:

N^2 matrix elements

8 bytes for each number

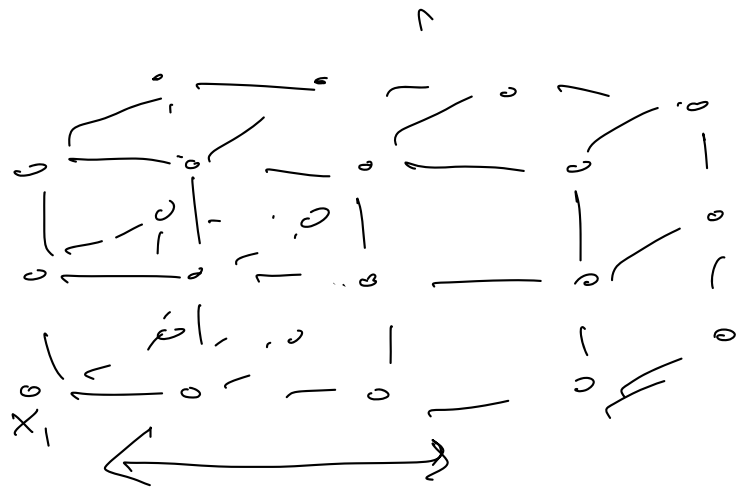
RAM

$u \times 10^3$ bytes

$$u \approx 10$$

$$N^2 = \frac{u \times 10^3}{8} = 10^5$$

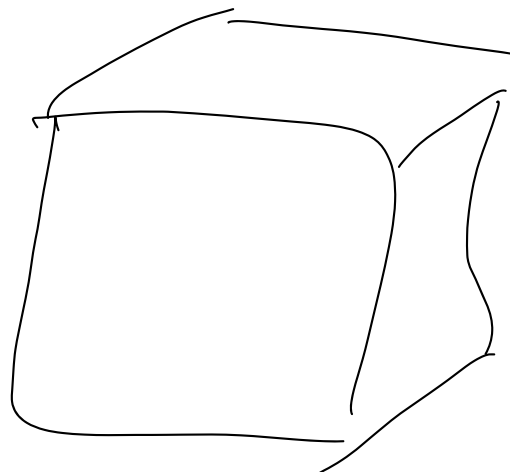
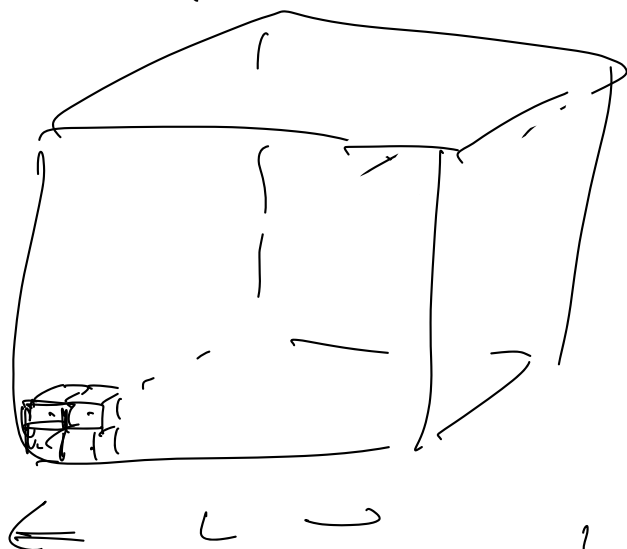
$$N \approx 10^{5/2} \approx 32000$$



$$L = \left(\frac{N}{3}\right)^{1/3}$$

$$L = \left(\frac{10^{5/2}}{3}\right)^{1/3} \approx 22$$

1 quantum particle in 3d



$$L \approx N^{1/3} \approx 10^{3/2} \approx 32$$

$$L = \sqrt[3]{N} \approx 8$$

Tricks



① $A : N \times N$

Sparse matrix

of non-zero elements being
of $O(N^\alpha)$, $\alpha < 2$

② Use symmetries

$$[A, V] = 0 \quad \Rightarrow \quad AV - VA$$

A, V admit a common basis of eigenvectors

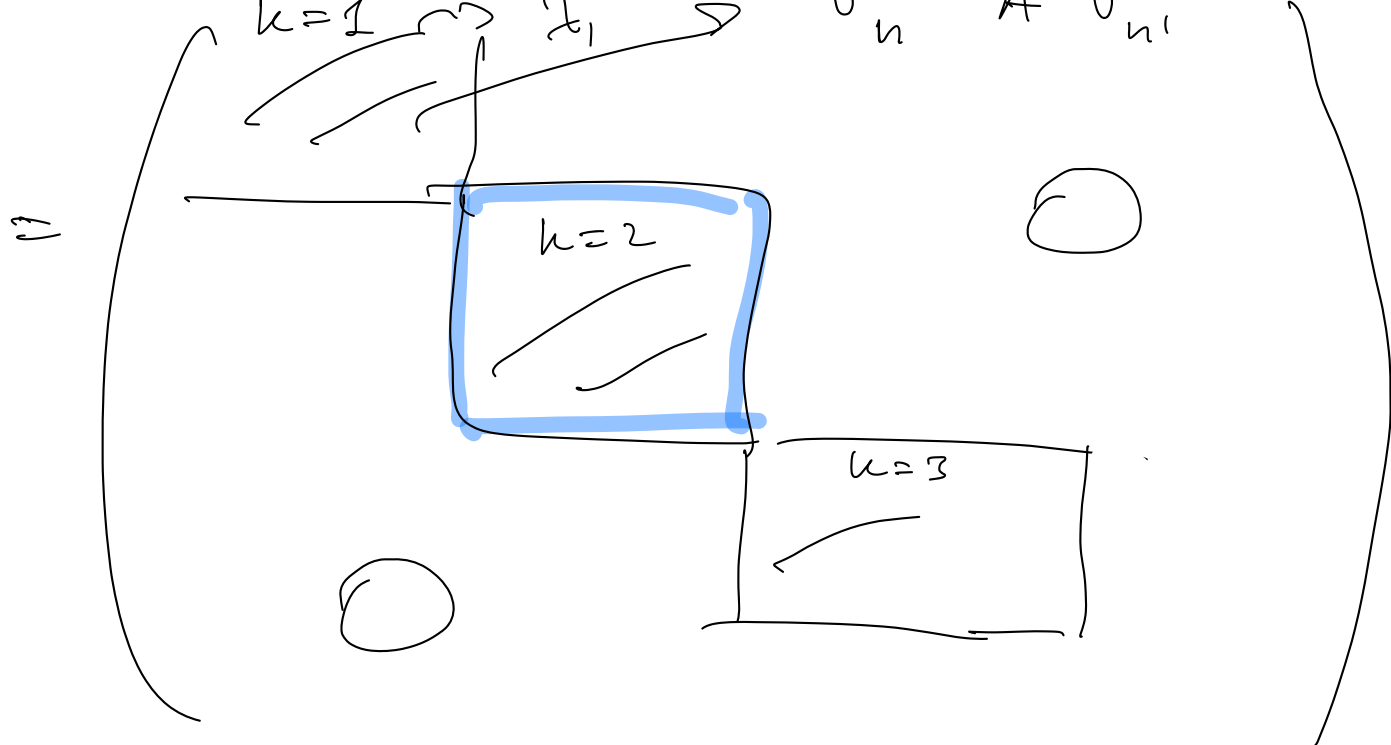
V is easy to diagonalize

$$\Rightarrow V \cdot \vec{v}_n^{(u)} = \lambda_n \vec{v}_n^{(u)}$$

d_u degeneracy of
the u -th
eigenvalue
 $u = 1, \dots, d_u$

Within the
degenerate eigenspace $\{\vec{v}_n^{(u)}\}$ $u = 1, \dots, d_u$
I can find an eigenvector of A

$$\underbrace{\left(\vec{v}_n^{(u)} \right)^T A \vec{v}_{n'}^{(u)}}_{\sim \delta_{nn'}} \sim \delta_{nn'}$$



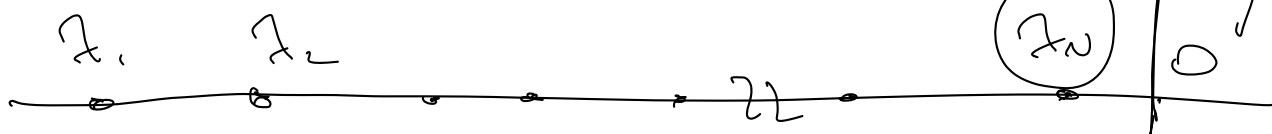
{ Ex. $A = \hat{H}$ which is translationally invariant
 $V = \hat{P}$ momentum operator }

Determination of the extreme eigenvalues

→ power method $(A^n \vec{u})$

$A : \begin{cases} \lambda_1 < \lambda_2 < \dots < \lambda_N \\ |\lambda_1| > |\lambda_2| > |\lambda_3| > \dots > |\lambda_N| \end{cases}$

$A \rightarrow A - \sigma \mathbb{1}$



↓
von degenerierte

$$A \vec{v}_1 = \lambda_1 \vec{v}_1$$

$$A \vec{v}_n = \lambda_n \vec{v}_n$$

$\vec{u}$ random vector

$$C_1 = \boxed{\vec{v}_1 \cdot \vec{u} \neq 0}$$

$$A^n \vec{u} = A^n \left(\sum_{k=1}^N C_k \vec{v}_k \right)$$

$$= A^n \left(C_1 \vec{v}_1 + \sum_{k=2}^N C_k \vec{v}_k \right)$$

$$= C_1 \lambda_1^n \vec{v}_1 + \sum_{k=2}^N C_k \lambda_k^n \vec{v}_k$$

$$= \lambda_1^n \left(C_1 \vec{v}_1 + \sum_{k=2}^N C_k \left(\frac{\lambda_k}{\lambda_1} \right)^n \vec{v}_k \right)$$

$n \rightarrow \infty$

$$\left| \frac{\lambda_k}{\lambda_1} \right| < 1$$

$$\exp \left[- \left(\log \left| \frac{\lambda_k}{\lambda_1} \right| \right) n \right]$$

↑

$$\text{sign} \left(\frac{\lambda_k}{\lambda_1} \right)$$

→

$$\lambda_1^n C_1 \vec{v}_1$$

$n \rightarrow \infty$



$$\boxed{\frac{A^n \vec{u}}{\|A^n \vec{u}\|} \xrightarrow{n \rightarrow \infty} \vec{v}_1}$$

convergence is exponential with a rate

$$\Rightarrow \left| \log \left| \frac{\lambda_2}{\lambda_1} \right| \right|$$

$$\vec{u}, A\vec{u}, \underbrace{A^2\vec{u}}_{A(A\vec{u})}, A^3\vec{u}, \dots, \underbrace{A^{M-1}\vec{u}}_{\underline{\underline{A^{M-1}\vec{u}}}}$$

$\underbrace{\hspace{10em}}_{M \text{ vectors}}$

$$\text{span} \left(\underbrace{\vec{u}}_1, \underbrace{A\vec{u}}_2, \underbrace{A^2\vec{u}}_3, \dots, A^{M-1}\vec{u} \right) = K_M$$

Krylov space

if $\vec{u}$ is not an eigenvector of A

$$\underline{\dim(K_M) = M}$$

Gram-Schmidt orthogonalization

$\vec{u}$ is normalized

$$\|\vec{u}\| = 1$$

$$\vec{u}_0 = \vec{u}$$

$$\|\vec{u}_k\| = 1$$

$$\begin{aligned} \beta_1 \vec{u}_1 &= A \vec{u}_0 - (\underbrace{\vec{u}_0^+ A \vec{u}_0}_{\alpha_0}) \vec{u}_0 \\ \beta_2 \vec{u}_2 &= A \vec{u}_1 - (\underbrace{\vec{u}_1^+ A \vec{u}_1}_{\alpha_1}) \vec{u}_1 - (\vec{u}_0^+ A \vec{u}_1) \vec{u}_0 \\ \beta_3 \vec{u}_3 &= A \vec{u}_2 - (\underbrace{\vec{u}_2^+ A \vec{u}_2}_{\alpha_2}) \vec{u}_2 - (\vec{u}_1^+ A \vec{u}_2) \vec{u}_1 \\ &\quad - (\vec{u}_0^+ A \vec{u}_2) \vec{u}_0 \end{aligned}$$

$$\begin{aligned} \vec{u}_0^+ A \vec{u}_2 &= (A \vec{u}_0)^+ \cdot \vec{u}_2 \\ &= (\beta_1 \vec{u}_1 + (\vec{u}_0^+ A \vec{u}_0) \vec{u}_0)^+ \cdot \vec{u}_2 = 0 \end{aligned}$$

$$\beta_k \vec{u}_k = A \vec{u}_{k-1} - (\vec{u}_{k-1}^+ A \vec{u}_{k-1}) \vec{u}_{k-1} - (\vec{u}_{k-2}^+ A \vec{u}_{k-1}) \vec{u}_{k-2}$$

Lanczos basis

M vectors

$$k = M-1$$

