

# Simple iteration procedure

Solve  $Ax = b$

Preconditioning:  $\left\{ \begin{array}{l} M^{-1}Ax = M^{-1}b \\ M = D \longrightarrow \text{Jacobi} \\ M = L \longrightarrow \text{Gauss-Seidel} \end{array} \right.$

Known approximate solution

Lower triangle

$r_0 = b - Ax_0 \longrightarrow$  residue

$Mz_0 = r_0 \longrightarrow$  use of pre-conditionner

$x_k = x_{k-1} + z_{k-1} \longrightarrow$  correction

$r_k = b - Ax_k \longrightarrow$  residue

$Mz_k = r_k \longrightarrow$  use of pre-conditionner

## Convergence

$$e_k = A^{-1} b - x_k$$

$$e_k = (I - M^{-1} A) e_{k-1} = \dots = (I - M^{-1} A)^k e_0$$

$$\lim_{k \rightarrow \infty} \|(I - M^{-1} A)^k\| = 0$$

$$\begin{array}{ccc} \longleftrightarrow & \rho(I - M^{-1} A) < 1 & \\ \uparrow & \longleftarrow & \text{Spectral radius (magnitude} \\ & & \text{of largest eigenvalue)} \\ Z^k v = \lambda^k v \longrightarrow 0 & & \end{array}$$

Convergence rate (from now on, we replace  $M^{-1}A$  by  $A$  and  $M^{-1}b$  by  $y$ ):

$$\|r_{k+1}\| \leq \sqrt{1 - d^2 / \|A\|^2} \|r_k\| \quad (0 \notin \mathcal{F}(A^H))$$

$$\left| \frac{y^H A^H y}{y^H y} \right| \geq d$$

Field of values:

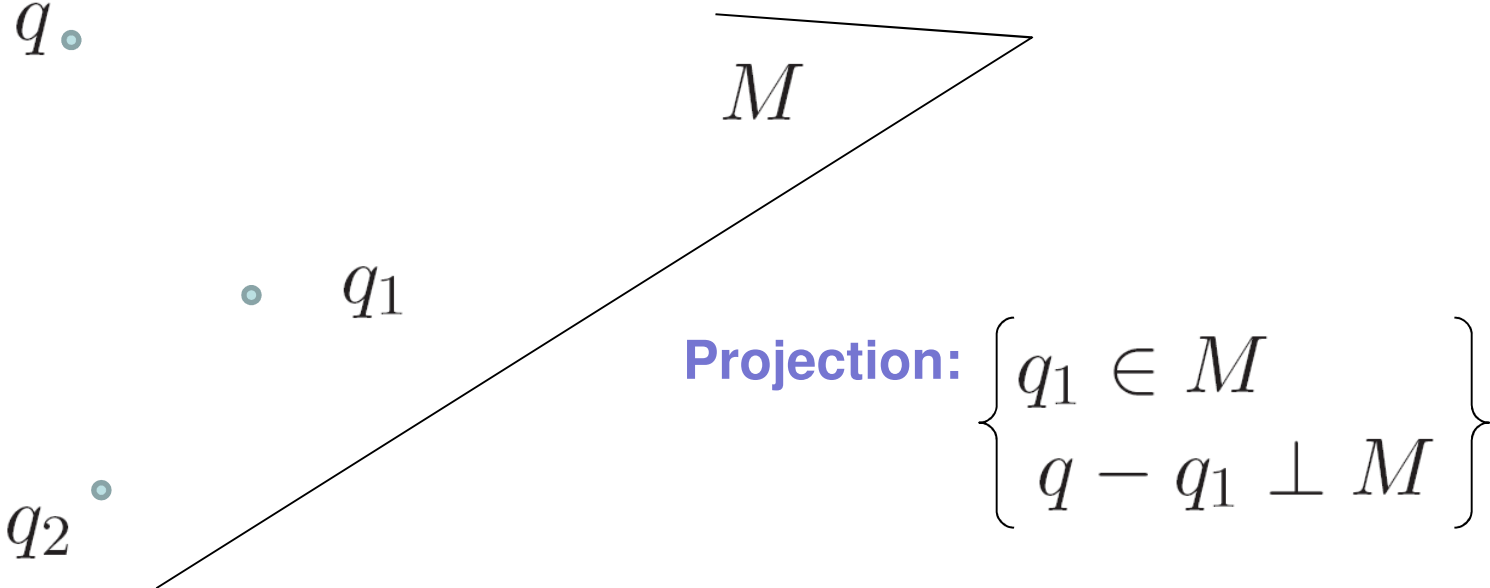
$$\mathcal{F}(A) = \{y^H A y : y \in \mathbf{C}^n, y^H y = 1\}$$

## Key elements of iterative solvers

- Good pre-conditioner (often based on nearest interactions)
- Fast matrix-vector multiplication (e.g. based on Fast Multipoles)  
(get far below  $N^2$  complexity, e.g.  $N \log_2 N$ )
- Iterative technique with good convergence/stability properties  
(get far below  $N$  iterations)

→ Get far below  $O(N^3)$  complexity ( $D N \log_2 N$ )  
↑  
Number of iterations

# Minimization by projection



Distance:

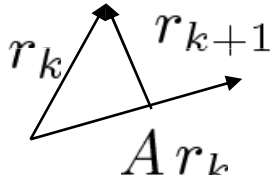
$$|q - q_2|^2 = |q_2 - q_1|^2 + |q_1 - q|^2$$

## Orthomin(1) and orthomin(2)

$x_k \in \text{span} \{b, A b, \dots, A^{k-1} b\} \longrightarrow$  Krylov subspace

$$p_k = r_k \begin{cases} x_{k+1} = x_k + a_k (b - A x_k) \\ r_{k+1} = r_k - a_k A p_k \end{cases}$$

Residue orthogonal to subspace  $\parallel A r_k$



$$a_k = \frac{\langle r_k, A r_k \rangle}{\langle A r_k, A r_k \rangle} \longrightarrow \text{Projection on } A r_k$$

**Orthomin(2):**

$$\tilde{p}_k = r_k - \frac{\langle A r_k, A p_{k-1} \rangle}{\langle A p_{k-1}, A p_{k-1} \rangle} p_{k-1} \longrightarrow \text{Project on larger subspace}$$

$$0 \notin \mathcal{F}(A^H)$$

Beyond that, project on all previous values of  $A r_i$

Orthodir(n)

GMRES

## Modified Gram-Schmidt (MGS) algorithm

$$r_{11} = \|v_1\|$$

$$q_1 = v_1 / r_{11}$$

$$k = 1, \dots, n$$

$$\tilde{q}_k = v_k$$

$$i = 1, \dots, k - 1$$

$$\tilde{q}_k \leftarrow \tilde{q}_k - \underbrace{\langle \tilde{q}_k, q_i \rangle}_{r_{ik}} q_i$$

$$r_{kk} = \|\tilde{q}_k\|$$

$$q_k = \tilde{q}_k / r_{kk}$$

## MGS defines a QR decomposition

$$v_k - \sum_{i=1}^{k-1} r_{ik} q_i = r_{kk} q_k$$

$$A = QR$$

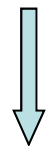


$$\left\{ \begin{array}{l} Ax = b \\ QRx = b \\ Rx = Q^H b \end{array} \right.$$

For overdetermined problems,

QR solution = least-squares solution

Normal equations:  $A^H A x = A^H b$



$$Rx = Q^H b$$

## Arnoldi algorithm: MGS on Krylov subspace

$$\begin{array}{c} \text{span} \{ r_0, A r_0, \dots, A^k r_0 \} \\ \downarrow \\ \|q_1\| = 1 \\ \uparrow \text{normalize} \\ j = 1, 2, \dots, \end{array}$$

$$\tilde{q}_{j+1} = A q_j$$

$$i = 1, \dots, j$$

$$h_{ij} = \langle \tilde{q}_{j+1}, q_i \rangle$$

$$\tilde{q}_{j+1} \leftarrow \tilde{q}_{j+1} - h_{ij} q_i$$

$$h_{j+1,j} = \|\tilde{q}_{j+1}\|$$

$$q_{j+1} = \tilde{q}_{j+1} / h_{j+1,j}$$

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## Formation of Krylov subspace

$$x'_k = x_k - x_o$$

If A already preconditionned:

$$x'_k = x'_{k-1} + (b - A x_{k-1})$$

$$x'_k = x'_{k-1} + (b - A x_o - A x'_{k-1})$$

$$x'_k = r_o + (I - A x'_{k-1})$$

$$x'_1 = r_o$$

$$x'_k \in \text{span} \{r_o, A r_o, \dots, A^k r_o\}$$

## Primitive GMRES (Generalized Minimum Residual)

**Principle:** the solution belongs to the (orthogonalized) Krylov subspace...

$$x_k = x_0 + Q_k y_k$$

...with coefficients  $y_k$  obtained in the least-square sense

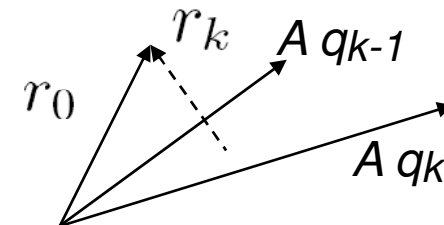
...for instance with the help of a QR solution !

The residue:  $b - Ax_k = b - Ax_0 - A Q_k y_k$

$$r_k = r_0 - A Q_k y_k$$

is minimized if orthogonal to the subspace

formed by  $A Q_k$



## Primitive FOM (Full orthogonalization method)

**Principle:** the solution belongs to the (orthogonalized) Krylov subspace...

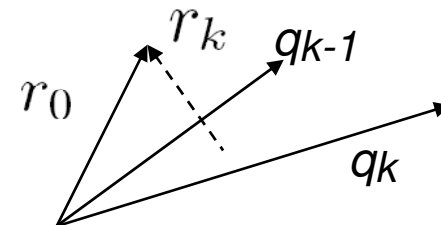
$$x_k = x_0 + Q_k y_k$$

...with coefficients  $y_k$  obtained such that (**for SDP A matrices**) the A-norm of the error gets minimized:

$$\epsilon = (\tilde{x} - x)^H A (\tilde{x} - x)$$

$$\tilde{x} \rightarrow \tilde{x} + \delta_v \quad \delta_v \in \text{span} \{r_0, A r_0, \dots, A^k r_0\}$$

$$\delta_v^H (A (\tilde{x} - x)) + \delta_v^H A \delta_v > 0$$



## « Brutal » algorithm for FOM and GMRES

```
q1=ro;q=q1; % hyp: xo=0, q = Krylov
stop=0; k=0;
```

```
while (stop==0)
k=k+1;
```

```
p1=A*q1; % matrix-vector product
q=[q,p1]; % A*Krylov subspace
```

```
qa=q(:,1:k); % Krylov subspace K
qb=q(:,2:k+1); % A*Krylov subspace
[qa,rr]=qr(qa,0); % Orthogonalize K
qb=(rr\qb)'; % same transformation to A*K
```



*We should not orthogonalize  
at each step !*

```
if (gmres)
[qq,rr]=qr(qb,0); % GMRES
% has been simplified w.r.t. course
y=rr\ (qq'*ro);
elseif (fom)
[qq,rr]=qr(qa'*qb,0); % FOM
y=rr\ (qq'*qa'*ro);
end

x=qa*y;
res=norm(qb*y-ro)/norm(ro) % residue
if ((res<1e-12)|| (k>20)) stop=1;
end

end
```

## Arnoldi algorithm: Upper Hessenberg Matrix

$$\|q_1\| = 1$$

$$j = 1, 2, \dots,$$

$$\tilde{q}_{j+1} = A q_j$$

$$i = 1, \dots, j$$

$$h_{ij} = \langle \tilde{q}_{j+1}, q_i \rangle$$

$$\tilde{q}_{j+1} \leftarrow \tilde{q}_{j+1} - h_{ij} q_i$$

$$h_{j+1,j} = \|\tilde{q}_{j+1}\|$$

$$q_{j+1} = \tilde{q}_{j+1} / h_{j+1,j}$$

$h_{11}$	$h_{12}$	$h_{13}$
$h_{21}$	$h_{22}$	$h_{23}$
0	$h_{32}$	$h_{33}$
0	0	$h_{43}$

$H_{33}$

$H_{43}$

## Arnoldi recursion

From orthogonalization algorithm:

$$A q_j - \sum_{i=1}^j h_{ij} q_i = h_{j+1,j} q_{j+1}$$

Recursion formula:

$$\underbrace{A}_{n \times n} \underbrace{Q_k}_{n \times k} = \underbrace{Q_k}_{n \times k} \underbrace{H_k}_{k \times k} + \underbrace{\left[ 0_{n \times k-1} \quad h_{k+1,k} \quad q_{k+1} \right]}_{h_{k+1,k} q_{k+1} e_k^T} = \underbrace{Q_{k+1}}_{n \times (k+1)} \underbrace{H_{k+1,k}}_{(k+1) \times k}$$

## Arnoldi recursion applied to FOM

**Preliminary:**  $Q_m^T A Q_m = H_m$

**Orthogonality w.r.t. Q:**  $Q_m^T r_m = Q_m^T (b - A(x_o + Q_m y_m)) = 0$

$$Q_m^T r_o = Q_m^T A Q_m y_m$$

$$\begin{aligned} \beta e_1 &= H_m y_m \\ \left\| r_o \right\| \leftarrow y_m &= H_m^{-1} (\beta e_1) \end{aligned}$$

**Residue:**

$$\beta q_1 - A Q_m y_m = \cancel{\beta q_1} - \cancel{Q_m H_m y_m} - h_{m+1,m} q_{m+1} e_m^T y_m$$

## GMRES: residue minimization

$$\begin{aligned} \min_y \|r_0 - A Q_k y\| &= \min_y \|r_0 - Q_{k+1} H_{k+1,k} y\| = \\ \min_y \|Q_{k+1} (\beta e_1 - H_{k+1,k} y)\| &= \min_y \|\beta e_1 - H_{k+1,k} y\| \end{aligned}$$

$\|r_0\| \downarrow$   
 All 0's, except entry 1

as proven earlier

$$\|b - A x_k\| = \|\beta e_1 - \underbrace{F^H R}_{\text{QR decomposition of } H_{k+1,k}} y^k\| = \|\beta F e_1 - R y_k\|$$

QR decomposition of  $H_{k+1,k}$

Succession of orthonormal transformations:

$$FF^H = I$$

k+1 comp. of  $\beta \|F \zeta_1\|$

# Recursive orthogonal transformations for H

Orthogonalisation realised  
at previous iteration:

$$(F_k \dots F_1) H_{k+1,k} = \begin{bmatrix} x & x & \dots & x \\ 0 & x & \dots & x \\ \dots & \dots & \dots & x \\ 0 & \dots & 0 & x \\ 0 & \dots & \dots & 0 \end{bmatrix}$$

Same operations on new  
Hessenberg matrix:

$$(F_k \dots F_1) H_{k+2,k+1} = \begin{bmatrix} x & x & \dots & x & x \\ 0 & x & \dots & x & x \\ \dots & \dots & \dots & x & x \\ 0 & \dots & 0 & x & x \\ 0 & \dots & \dots & 0 & d \\ 0 & \dots & \dots & 0 & h \end{bmatrix}$$

Find new operation to null that entry

from same operations applied to new column of H

## Givens rotations

$$F_i = \begin{bmatrix} I & & & \\ & c_i & s_i & \\ & -s_i^* & c_i & \\ & & & I \end{bmatrix}$$

$$c = |d|/\sqrt{|d|^2 + |h|^2} \quad s^* = ch/d \quad \text{if } d \neq 0$$

$$c = 0 \quad s = 1 \quad \text{if } d = 0$$

## Expression of residual

$$\begin{aligned} \|b - Ax_k\|^2 &= \|\beta \zeta_1 - F^H R y^k\|^2 = \|\beta F \zeta_1 - R y_k\|^2 \\ &= \text{Norm}^2 \text{ of } k+1 \text{ comp. of } F \zeta_1 \end{aligned}$$

## Conjugate Gradients for symmetric DP matrices

$$H_m = Q_m^T A Q_m \text{ must be symmetric} \quad H_m = T_m$$

**Tri-diagonal !!!**

$$j = 1, 2, \dots,$$

$$\beta_j = h_{j-1,j} = \langle q_{j-1}, A q_j \rangle$$

$$\tilde{q}_j \leftarrow A q_j - \beta_j q_{j-1}$$

$$\alpha_j = \langle \tilde{q}_j, q_j \rangle$$

$$\tilde{q}_j \leftarrow \tilde{q}_j - \alpha_j q_j$$

$$\beta_{j+1} = \|\tilde{q}_j\|$$

$$q_{j+1} = \tilde{q}_j / \beta_{j+1}$$

General Arnoldi:

---

$$j = 1, 2, \dots,$$

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## Conjugate Gradients for symmetric DP matrices

$$H_m = Q_m^T A Q_m \text{ must be symmetric} \quad H_m = T_m$$

**Tri-diagonal**

**Solution:**  $y_m = T_m^{-1}(\beta e_1)$

**Arnoldi's 3-terms recurrence:**

$$\beta_{j+1} q_{j+1} = A q_j - \alpha_j q_j - \beta_{j-1} q_{j-1}$$