

(Arnold, 1951) Implicitly Restarted Arnoldi method. (SORENSEN 1992) Implicit application of polynomial filters in a k-step Arnoldi method.

Let initial vector $q = c_1 v_1 + \dots + c_k v_k$

where v_1, v_2, \dots, v_k are eigenvectors

and $k \ll n$.

Then Arnoldi iteration terminates in k steps or fewer.

and $\text{Span}\{q_1, \dots, q_k\} = \text{Span}\{v_1, \dots, v_k\}$

Thus ~~if~~ ^{we would like to} we get hold of a vector v that is linear combination of a few eigenvectors.

Let A be semi-simple.

$$\text{and } |\lambda_1| \geq |\lambda_2| \geq \dots \geq |\lambda_n|$$

$$\text{and } |\lambda_k| > |\lambda_{k+1}|$$

~~Suppose~~ we would like to compute $\lambda_1, \dots, \lambda_k$.

For arbitrary $q \in \mathbb{R}^n$

$$q = c_1 v_1 + \dots + c_n v_n.$$

(Components along all directions)

Our goal is to come up with
a vector $\hat{q} = \hat{c}_1 v_1 + \dots + \hat{c}_n v_n$

$$\text{s.t. } \hat{c}_{k+1} \approx \hat{c}_{k+2} \approx \dots \approx \hat{c}_n = 0$$

Such a choice can be got hold off by

taking
$$\hat{q} = p(A) a$$

where p is some polynomial,

$$\hat{q} = c_1 p(\lambda_1) v_1 + \dots + c_n p(\lambda_n) v_n$$

if p is selected s.t. $p(\lambda_1) \dots p(\lambda_k)$
are large compared to $p(\lambda_{k+1}) \dots p(\lambda_n)$
then it is good.

IRA - Part I

We want k eigenvalues of A .

~~Do m iterations of~~

perform m Arnoldi iterations.

where $m = k + j$, k and j are comparable.

Start with q . After m steps we

Get

$$A Q_m = Q_m H_m + \alpha_{m+1} e_m^T$$

Compute eigenvalues of H_m . (Ritz values of A)
associated to $\text{Colspan}\{q_1, \dots, q_m\}$
 μ_1, \dots, μ_m
in order $|\mu_1| \geq |\mu_2| \geq \dots \geq |\mu_m|$.

~~that~~ μ_1, \dots, μ_k are estimates of k dominant eigenvalues of A .

whereas μ_{k+1}, \dots, μ_m approximate remain ones we are not interested in.

part II.

Perform QR algorithm on H_m with shifts ν_1, \dots, ν_j . Using $\nu_1 = \mu_{k+1}, \dots, \nu_j = \mu_m$ as shifts.

QR with shifts.

$$(i) \quad H_m - \nu_1 I_m = V_1 R_1$$

$$R_1 V_1 + \nu_1 I_m = H_m$$

$$H_m - \nu_2 I_m = V_2 R_2$$

$$R_2 V_2 + \nu_2 I_m = H_m$$

⋮

$$H_m - \nu_j I_m = V_j R_j$$

$$R_j V_j + \nu_j I_m = H_m$$

Repeat until convergence.

~~End~~
$$V_m = V_1 V_2 \dots V_j$$

$$R_m = R_1 R_2 \dots R_j$$

~~$$H_m = V_m^T H_m V_m$$~~

(Ex-6.2.36)

Effectively, $\hat{H}_m = H_m = V_m^T H_m V_m$

$$(H_m - \nu_1 I) (H_m - \nu_2 I) \dots (H_m - \nu_j I) = V_m R_m$$

$$p(H_m) = V_m R_m$$

where $p(z) = (z - \nu_1)(z - \nu_2) \dots (z - \nu_j)$

Update let $\hat{Q}_m = Q_m V_m$

$$\hat{q}_1 = \hat{Q}_m \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

Next IRA iteration starts with

\hat{q}_1 for m steps. But we don't

need to recompute \hat{Q}_m, \hat{H}_m .

start Arnoldi iteration from scratch.

~~We can use \hat{Q}_m~~

$$A \hat{Q}_m = \hat{Q}_m \hat{H}_m + \alpha_{m+1} h_{m+1,m} e_m^T$$

$$A \hat{Q}_m V_m = \hat{Q}_m \hat{H}_m V_m + \alpha_{m+1} h_{m+1,m} e_m^T V_m$$

$$A \hat{Q}_m = \hat{Q}_m \hat{H}_m + \alpha_{m+1} h_{m+1,m} e_m^T V_m.$$

(solve ^{from Watkins.} 6.4.21) ^{to show.} $e_m^T V_m$ has ^{just} $m-j-1$ as zeroes.

and $m-j$ th entry is non-zero.

$$\begin{bmatrix} 0 & 0 & \dots & 0 & \beta & * & \dots & * \\ 1 & 2 & & m-j-1 & m-j & \underbrace{\quad \quad \quad}_{\text{last } j \text{ entries}} \end{bmatrix}$$

If we drop $*$ then we get a vector of the form βe_k^T where $k = m-j$

Drop last j columns. from

$$A \hat{Q}_m^p = \hat{Q}_m \hat{H}_m + \alpha_{m+1} h_{m+1,m} e_m^T V_m.$$

We get

$$A \hat{Q}_k = \hat{Q}_k \hat{H}_{k+1,k} + \underbrace{\alpha_{k+1} h_{k+1,k} e_k^T + \alpha_{m+1} h_{m+1,m} e_m^T}_{\beta e_k^T}$$

$$\text{let } \hat{v}_{k+1} = \sqrt{\left(\alpha_{k+1} h_{k+1,k} + \alpha_{m+1} h_{m+1,m} \beta \right)}$$

\hat{v} is s.t. $\|\hat{v}_{k+1}\|_2 = 1$.

Then

$$A \hat{Q}_k = \hat{Q}_k \hat{H}_k + \hat{q}_{k+1} \hat{h}_{k+1,k} e_k^T$$

where $\hat{h}_{k+1,k} = \frac{1}{r}$.

\hat{Q}_k is the columns are exactly those vectors which ^{we} would ~~would~~ get if we started Arnoldi method from \hat{q}_1 .

Implicitly restarting,
perform remaining ~~steps~~ j steps and
build \hat{Q}_m^{new} again.

For symmetric A

Lanczos iteration.

Implicitly restarted Lanczos method.