## Numerical methods for matrix functions <br> SF2524 - Matrix Computations for Large-scale Systems

Lecture 15: Krylov methods for matrix functions

## Problem

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Note: $(\star)$ is a shifted linear system of equations:

$$
(A-z l) x=b
$$

We will solve the shifted linear system using an Arnoldi method.

The rest of this lecture

1. Arnoldi's method for shifted systems
2. GMRES-variant (FOM) for shifted systems
3. Use Cauchy definition $\Rightarrow$ Krylov method for matrix functions
4. Application to exponential integrators

Shift invariance of Krylov subspaces

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$\left[b, A b, A^{2} n, \ldots, A^{n-1} b\right] R=\left[b,(A-\sigma l) b,(A-\sigma l)^{2} b, \ldots,(A-\sigma l)^{n-1} b\right]$

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Recall: $W=V R$ and $R$ non-singular and $w_{1}, \ldots, w_{m}$ linear independent $\Rightarrow \operatorname{span}\left(w_{1}, \ldots, w_{m}\right)=\operatorname{span}\left(v_{1}, \ldots, v_{m}\right)$

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## Lemma

Suppose $Q_{m} \in \mathbb{C}^{n \times m}, \underline{H}_{m} \in \mathbb{C}^{(m+1) \times m}$ is an Arnoldi factorization ( $\star$ ) associated with $\mathcal{K}_{m}(A, b)$. Then, for any $\sigma \in \mathbb{C}, Q_{m} \in \mathbb{C}^{n \times m}$ and $\underline{H}_{m}-\sigma I_{m+1, m}$ is an Arnoldi factorization associated with $\mathcal{K}_{m}(A-\sigma I, b)$,

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where

$$
I_{m+1, m}=\left[\begin{array}{ccc}
1 & & \\
& \ddots & \\
& & 1 \\
0 & \cdots & 0
\end{array}\right] \in \mathbb{R}^{(m+1) \times m}
$$

## FOM - almost GMRES for linear system

We now wish to solve linear systems:

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C x=b
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(where we later set $C=A-\sigma l$.)

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- Compute an Arnoldi factorization $A Q_{n}=Q_{n+1} \underline{H}_{n}$
- Compute $z=H(1: n, 1: n) \backslash e 1 \Leftrightarrow z=H_{n}^{-1} e_{1}$
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## Relationship with GMRES

- GMRES corresponds to $\left(A Q_{n}\right)^{T}(A \tilde{x}-b)=0$ (lecture 8)
- FOM corresponds to $Q_{n}^{T}(A \tilde{x}-b)=0$

Now consider shifted system:

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FOM for shifted systems

1. Compute an Arnoldi factorization $A Q_{n}=Q_{n+1} \underline{H}_{n} \quad$ from $(A, b)$
2. Compute $\mathrm{zs}=(\mathrm{H}(1: \mathrm{n}, 1: \mathrm{n})-\sigma \mathrm{I}) \backslash \mathrm{e} 1 \Leftrightarrow z_{\sigma}=\left(H_{n}-\sigma /\right)^{-1} e_{1}$
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Note: Step 1 is independent of $\sigma$ and the Step 2-3 can be done for many $\sigma$ without carrying out Arnoldi method:

$$
x_{\sigma} \approx \tilde{x}_{\sigma}=Q_{n}\left(H_{n}-\sigma I\right)^{-1} e_{1}\|b\| .
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## Error analysis of Krylov approximation

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## Theorem

Suppose $A \in \mathbb{C}^{n \times n}$ is a normal matrix and suppose $\Omega \subset \mathbb{C}$ is a convex compact set such that $\lambda(A) \subset \Omega$. Let $f_{m}$ be the Krylov approximation of $f(A) b$. Then,

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\left\|f(A) b-f_{m}\right\| \leq 2\|b\| \min _{p \in P_{m-1}} \max _{z \in \Omega}|f(z)-p(z)|
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Application to exponential integrators PDF lecture notes 4.4.3

We already know that the initial value problem

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has the solution

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y(t)=\exp (t A) y_{0} .
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We wish to numerically solve the initial value problem using matrix functions:

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- Look at linear inhomogeneous ODE
- Use to approximate nonlinear ODE


## Lemma (Explicit solution linear inhomogeneous ODE)

In the special case of a linear inhomogeneous ODE with right-hand side $g(y)=g_{1}(y):=A y+b$, and

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The matrix function $\varphi$ is called a $\varphi$-function

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Let $0=t_{0}<t_{1}<\cdots<t_{N}$. The forward Euler exponential integrator generate the approximations $y_{k} \approx y\left(t_{k}\right), k=, \ldots, N$ defined as

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\begin{equation*}
y_{k+1}=y_{k}+h_{k} \varphi\left(h_{k} A_{k}\right) g\left(y_{k}\right) \tag{3}
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where $h_{k}=t_{k+1}-t_{k}$ and $A_{k}:=g^{\prime}\left(y_{k}\right)$.

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- Exact for the linear inhomogeneous case (1), and one step can be proven to be second order in $h$ in the general case.
- Requires the computation of $\varphi\left(h_{k} A_{k}\right) g\left(y_{k}\right)$ in every step. Suitable to be used with matrix functions.


## Step-length trade-off

## We want

Trade-off of time-step $h$

- small $h \Rightarrow$ small Krylov error; $\quad\left\|\varphi(h A) b-f_{m}\right\|=\mathcal{O}\left(h^{m}\right)$


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More elaborate example in Lecture notes PDF.

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SF2526 "Numerics for data science" [link]

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Exam preparation information

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$\Rightarrow$ Solve many problems as preparation:
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Good luck on the exam
Please fill out the course evaluation (later)

