



- 1 a)  $A$  is a lower triangular matrix with non-zero diagonal  $\implies$  non-singular. A direct computation shows that  $x_i^* = (-1)^{i+1}$ .
- b)  $r_0 = e_1$ . An inductive argument utilizing the equality  $Ae_i = e_i + e_{i+1}$ ,  $i < n$ , shows that  $K_m(A, r_0) = \text{span}\langle e_1, \dots, e_m \rangle$ ,  $1 \leq m \leq n$ .
- c) By construction  $x_m \in 0 + K_m(A, r_0)$ , in particular  $(x_m)_{m+1} = \dots = (x_m)_n = 0$ . This and the formula for  $x^*$  imply immediately that  $\|x_m - x^*\|_2^2 \geq \sum_{i=m+1}^n (-1)^{2(i+1)} = n - m$ . As  $\| -A^{-1}r_m \|_2 = \|x_m - x^*\|_2$  and therefore  $\|r_m\|_2 \geq \|A^{-1}\|_2^{-1} \|x_m - x^*\|_2$ , from which the required bound follows.
- d) Perhaps the easiest way in the present situation when the matrix is small is to find the basis vectors  $r_0, Ar_0, \dots, A^{m-1}r_0$  directly and then solve a few small least squares problems producing the polynomial coefficients of  $p_{m-1}$ .

For example, when  $m = 1$  we solve  $\|r_0 - y_1 Ar_0\|_2 \rightarrow \min$ , or in Matlab notation

```
r_0 = [1 0 0 0 0]';
A = spdiags(ones(5,2), -1:0,5,5)
y_1 = (A*r_0)\r_0
```

from which  $y_1 = 0.5$ ,  $\tilde{p}_1(t) = 1 - 0.5t$ .

For  $m = 2$  we have  $\|r_0 - y_1 Ar_0 - y_2 A^2 r_0\|_2 \rightarrow \min$ , or in Matlab notation

```
y_2 = [A*r_0, A^2*r_0]\r_0
```

which yields  $y = [1, -1/3]'$  and  $\tilde{p}_2(t) = 1 - t + 1/3t^2$ .

Proceeding in this way we find that  $\tilde{p}_3(t) = 1 - 3/2t + t^2 - 1/4t^3$ ,  $\tilde{p}_4(t) = 1 - 2t + 2t^2 - 1t^3 + 1/5t^4$ ,  $\tilde{p}_5(t) = 1 - 5t + 10t^2 - 10t^3 + 5t^4 - t^5 = (1 - t)^5 = \det(I - tA)$ , see Fig. 1 (left).

Finally

| $i$ | $\ \tilde{p}_i(A)\ _2$ | $\ \tilde{p}_i(A)r_0\ _2$ | $\ \tilde{p}_i((A + A^T)/2)\ _2$ | $\ \tilde{p}_i((A + A^T)/2)r_0\ _2$ |
|-----|------------------------|---------------------------|----------------------------------|-------------------------------------|
| 1   | 0.9595                 | 0.7071                    | 0.8928                           | 0.4472                              |
| 2   | 0.8921                 | 0.5774                    | 0.7474                           | 0.2673                              |
| 3   | 0.8036                 | 0.5000                    | 0.5797                           | 0.1826                              |
| 4   | 0.7027                 | 0.4472                    | 0.4071                           | 0.1348                              |
| 5   | 0                      | 0                         | 0                                | 0                                   |

- e) The eigenvalues of a lower triangular matrix appear on its diagonal, thus  $\sigma(A) = \{1\}$ . The eigenvalue-based error bounds rely critically on the diagonalizability of  $A$ , say  $A = X^{-1}\Lambda X$ , when the estimate

$$\|p(A)\|_2 \leq \kappa_2(X) \max_i |p(\lambda_i)|$$

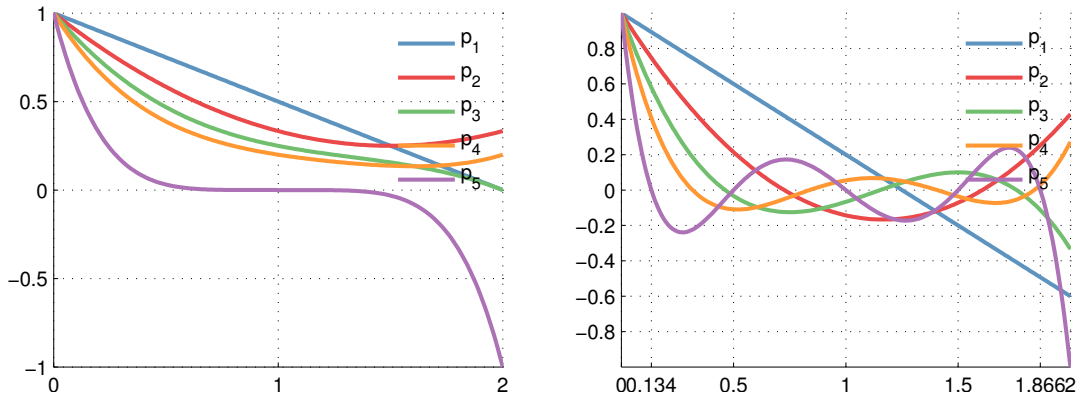


Figure 1: Optimal polynomials  $\tilde{p}_i$  for  $A$  (left) and  $(A + A^T)/2$  (right). Eigenvalues are marked with vertical dotted lines.

is used. Without diagonalizability this argument cannot be applied; one may only claim that

$$\|p(A)\|_2 \leq \kappa_2(X) \|p(J)\|_2,$$

where  $A = X^{-1}JX$  is the Jordan canonical form of  $A$ . The behaviour of powers of Jordan blocks is relatively complicated: see Section 4.2.1 in [Saad].

2 Proceeding as in Proposition 6.32 in [Saad] we obtain the estimate

$$\begin{aligned} \frac{\|r_m\|_2}{\|r_0\|_2} &\leq \kappa_2(X) \min_{\tilde{p}_m \in \mathbb{P}_m: \tilde{p}_m(0)=1} \max_i |\tilde{p}_m(\lambda_i)| \\ &\leq \kappa_2(X) \min_{\tilde{p}_m \in \mathbb{P}_m: \tilde{p}_m(0)=1} \max\{|\tilde{p}_m(\bar{\lambda})|, \max_{\lambda_{\min} \leq \lambda \leq \lambda_{\max}} |\tilde{p}_m(\lambda)|\} \end{aligned}$$

We now replace the minimum polynomial  $\tilde{p}_m$  with

$$\tilde{p}_m(\lambda) = \frac{C_{m-1}(t(\lambda)) \bar{\lambda} - \lambda}{C_{m-1}(t(0)) \bar{\lambda}},$$

which is  $m$ th degree polynomial renormalized so that  $\tilde{p}_m(0) = 1$ . By estimating the first factor as in Theorem 6.29 in [Saad] we obtain the following:

$$\frac{\|r_m\|_2}{\|r_0\|_2} \leq 2\kappa_2(X) \left[ \frac{\sqrt{\lambda_{\max}} - \sqrt{\lambda_{\min}}}{\sqrt{\lambda_{\max}} + \sqrt{\lambda_{\min}}} \right]^{m-1} \frac{\max\{|\bar{\lambda} - \lambda_{\min}|, |\bar{\lambda} - \lambda_{\max}|\}}{|\bar{\lambda}|}.$$

If  $A$  is normal and  $|\bar{\lambda}| \gg \max\{\lambda_{\min}, \lambda_{\max}\}$  then  $\kappa_2(X) = 1$  and  $\max\{|\bar{\lambda} - \lambda_{\min}|, |\bar{\lambda} - \lambda_{\max}|\}/|\bar{\lambda}| \approx 1$ .

3 The short story is: all residuals need to be scaled by  $\delta$ , but the search space and the constraint space remain the same. Indeed,  $\text{span}\langle r_0, Ar_0, \dots, A^{m-1}r_0 \rangle = \text{span}\langle \delta r_0, \delta^2 Ar_0, \dots, \delta^m A^{m-1}r_0 \rangle$ . Furthermore,  $r_m \perp \mathcal{L}$  if and only if  $\delta r_m \perp \mathcal{L}$ , since  $\mathcal{L}$  is a linear space.