Vandermonde with Arnoldi

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- 1. VANDERMONDE
- 2. MONOMIALS
- 3. ARNOLDI
- 4. EIGHT EXAMPLES

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1. VANDERMONDE

$$p(x) = \sum_{k=0}^{n} c_k x^k$$

Interpolation or least-squares: $Ac \approx f$

$$\begin{pmatrix} 1 & x_1 & \cdots & x_1^n \\ 1 & x_2 & \cdots & x_2^n \\ \vdots & \vdots & & \vdots \\ 1 & x_m & \cdots & x_m^n \end{pmatrix} \begin{pmatrix} c_0 \\ \vdots \\ c_n \end{pmatrix} \approx \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_m \end{pmatrix}$$

function c = polyfit(x,f,n)
A = x.^(0:n);
c = A\f;

Evaluation: y = Bc

 $\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{pmatrix} = \begin{pmatrix} 1 & s_1 & \cdots & s_1^n \\ 1 & s_2 & \cdots & s_2^n \\ \vdots & \vdots & & \vdots \\ \vdots & \vdots & & \vdots \\ 1 & s_M & \cdots & s_M^n \end{pmatrix} \begin{pmatrix} c_0 \\ \vdots \\ c_n \end{pmatrix} \qquad \begin{array}{c} \text{function } y = \text{polyval}(c,s) \\ & \text{function } y = \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{function } y = \text{function } y \\ & \text{func$

These days the rectangular case is particularly interesting. Redundant bases, frames,...

2. MONOMIALS

1, x, ..., x^n is exponentially ill-conditioned on [-1,1] (on any domain except a disk)

x = chebfun('x'); cond(x.^(0:10)) ... 20,40 plot(x.^(0:40)) xx = chebpts(1000); cond(xx.^(0:10)) ... 20,40

 $\kappa \approx \left(1 + \sqrt{2}\right)^n$ (Gautschi 1975)

Computational consequence: $n \gg 30$ never works.

```
x^n has numerical degree O(\sqrt{n}) on [-1,1]
```

Newman & Rivlin 1976

length(x^10) ... 20, 40, 80, 1000, 4000, 16000
length(chebpoly(16000))

Müntz-Szász theorem

3. ARNOLDI

Problem: $\{1, x, x^2, ...\}$ is ill-conditioned, so computations fail.

Solution: $\{1, x, x^2, ...\} = \{q_0, Aq_0, A^2q_0, ...\}$ where A = diag(x). So do Arnoldi!

Idea of Arnoldi: instead of forming A^n then orthogonalizing, orthogonalize at each step.

Applied to $\{1, x, x^2, ...\}$, this is Stieltjes orthogonalization. A very old idea.

Austin et al., Betcke, Björck & Pereyra, Forsythe, Gautschi, Gragg, Hochman, Reichel, Saad, Stylianopoulos, undoubtedly many others.

This is a technique we should use routinely. Not just "when we want to construct orthogonal polynomials."

3. ARNOLDI, cont.

Arnoldi/Stieltjes applied to $\{1, x, x^2, ...\}$ constructs discrete orthogonal polynomials related to the monomials by a Hessenberg matrix *H*.

We now pass around H as well as a coefficient vector.

```
[d,H] = polyfitA(x,f,n)  y = polyvalA(d,H,s)
function [d,H] = polyfitA(x,f,n)
                                               function y = polyvalA(d,H,s)
m = length(x);
                                               M = length(s);
Q = ones(m, 1);
                                               W = ones(M, 1);
H = zeros(n+1,n);
                                               n = size(H,2);
for k = 1:n
                                               for k = 1:n
    q = x.*Q(:,k);
                                                   w = s.*W(:,k);
    for j = 1:k
                                                  for j = 1:k
       H(j,k) = Q(:,j)'*q/m;
                                                       w = w - H(j,k) * W(:,j);
        q = q - H(j,k) * Q(:,j);
                                                   end
    end
                                                   W = [W w/H(k+1,k)];
    H(k+1,k) = norm(q)/sqrt(m);
                                               end
    Q = [Q q/H(k+1,k)];
                                               y = W*d;
end
d = Q \setminus f;
```

```
O(mn^2) flops, same as polyfit. O(Mn^2) flops; polyval is O(Mn).

n =  degree, m =  no. of sample pts, M =  no. of evaluation points
```

 $(O(mn) \text{ and } O(Mn) \text{ possible when } x \text{ is real via Arnoldi} \rightarrow \text{Lanczos, though we don't do this.})$

4. EIGHT EXAMPLES

- 1. Degree *n* interpolation of $1/(1 + 25x^2)$ in Chebyshev pts
- 2. Degree *n* least-squares fit to sign(*x*) on $\left[-1, -\frac{1}{3}\right] \cup \left[\frac{1}{3}, 1\right]$
- 3. Degree 30 Chebyshev polynomial on a triangle in ${\mathbb C}$
- 4. Degree *n* Fourier extension fit of 1/(10 9x) on [-1,1]
- 5. Bivariate polynomial fit on a starfish domain
- 6. Conformal mapping via polynomial approximation of Green's function
- 7. Lightning Laplace solver
- 8. Stokes flow

Example 1: Degree *n* interpolation of $1/(1 + 25x^2)$ in Chebyshev points



FIG. 2.1. On the left, the degree n Chebyshev interpolant to $f(x) = 1/(1 + 25x^2)$ computed unstably by direct application of (1.2) and (1.3) via the codes polyfit and polyval for n = 80(above) and its error for even values of n from 2 to 200 (below). (The results computed by the MATLAB versions of polyval and polyfit would be worse.) On the right, the same computations with the Arnoldi-based codes polyfitA and polyvalA.

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Example 2: Degree *n* least-squares fit to sign(*x*) on $\left[-1, -\frac{1}{3}\right] \cup \left[\frac{1}{3}, 1\right]$



FIG. 3.1. Images as in Fig. 2.1 but now for a least-squares problem: polynomial fitting to sign(x) on 500 equispaced points each in the two intervals [-1, -1/3] and [1/3, 1]. The unstable algorithm stagnates at 5 digits of accuracy, which is enough that to the eye, the computation appears successful.

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Example 3: Degree 30 Chebyshev polynomial on a triangle in ${\mathbb C}$



Minimal monic polynomial with p(0) = 1.

We use the Lawson algorithm (iteratively reweighted least-squares).

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Example 4: Degree *n* Fourier extension fit of 1/(10 - 9x) on [-1,1]



FIG. 5.1. A Fourier extension example from [1], with f(x) = 1/(10 - 9x) approximated over [-1,1] by Fourier series scaled to the larger interval [-2,2]. This is equivalent to approximation by powers z^k over just half of the unit circle, leading to exponential ill-conditioning of the Vandermonde matrix.

Example 4: Degree *n* Fourier extension fit of 1/(10 - 9x) on [-1,1]

Vandermonde Vandermonde + Arnoldi Example from n = 40n = 40Adcock + Huybrechs, $(x)_{d}^{0.5}$ $(x)_{d}^{0.5}$ SIAM Review 2019 -2 -1 0 1 2 -2 -1 0 1 2 Key observation: xx10⁰ 10⁰ Fourier series on subinterval of [-2,2]10⁻⁵ 10⁻⁵ $\|d \|d -$ [⊷] 10⁻¹⁰ [€] 10⁻¹⁰ Laurent polynomial on subarc of unit circle 10⁻¹⁵ 10⁻¹⁵ 50 150 200 50 100 0 100 0 150 200 nn

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Example 5: Bivariate polynomial fit on a starfish domain

Hokanson, Nakatsukasa, T. + Webb, work in progress See also Austin et al., arXiv, 2019.

It would be interesting to try Lawson iteration here too.







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Example 6: Conformal mapping via polynomial approx of Green's function



FIG. 6.1. Conformal mapping of a blob onto the unit disk by the polynomial expansion method of (6.1)-(6.4). The two upper-right images correspond to n = 200.

T., Computational Methods and Function Theory, to appear

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FIG. 6.1. Conformal mapping of a blob onto the unit disk by the polynomial expansion method of (6.1)-(6.4). The two upper-right images correspond to n = 200.

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Example 7: Lightning Laplace solver

Gopal + T., SINUM 2019

Solution is approximated by real part of polynomial + rational function with exponentially clustered poles via least-squares on boundary.





P = [-3 3 3+2i 1i -3+2i]; laplace(P, 'tol', 1e-12, 'noarnoldi');

> Demonstration of laplace.m and confmap.m Codes available at Trefethen home page



Example 7: Lightning Laplace solver

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Example 8: Stokes flow

Brubeck + T., in preparation

Biharmonic equation is reduced to Laplace problem using Goursat representation.





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DISCUSSION

Numerical analysts tend to be expert at linear algebra

but relatively uninquisitive when it comes to basic issues of approximation.

For example we've seen this unfortunate message for decades:

```
>> x = 1:50;
>> y = -0.3*x + 2*randn(1,50);
>> p = polyfit(x,y,6);
Warning: Polynomial is badly conditioned. Add points with
distinct X values, reduce the degree of the polynomial, or try
centering and scaling as described in HELP POLYFIT.
> In polyfit (line 79)
```

In fact, this polynomial is not badly conditioned — only the basis $\{1, x, x^2, ..., x^6\}$.

A sociological and historical accident:

LINEAR ALGEBRAAPPROXIMATIONDominated by numerical peopleDominated by theoretical people

Yet they are equally fundamental for numerical computation.

