Lecture 23

Question:

In $AV_k = V_{k+1} T_{k+1}$ with $V_k^T V_k = I$.

Are there any degrees of freedom?

$V_k e_1 = b / \|b\|$

1. Are there cases when $[b, Ab, \ldots, A^k b]$ doesn't have dimension $k+1$ ✓

- For CG do we need to run Arnoldi to completion or do we get a good answer part way through? [2 variations]
- Can we apply Lanczos to non-sym matrices? Yes – but Bi-Lanczos, and it doesn't work well.
- Why does projection onto the Krylov subspace help solve $Ax = b$ / Eigenvalues ✓
  - → Why is this a good subspace
  - → Why faster than stationary!

How do rounding errors impact orthogonality of Lanczos.
↳ Can we mitigate? ✓

Lanczos → Lanczos-tri.

How does Arnoldi build an orthogonal basis for $K_k(A, b)$? ✓

- Why does Arnoldi rely on a Hessenberg matrix? ✓

- Can we say projection to V_k reveals the Tridiag structure? That's why it works?

Krylov makes a new polynomial @ each step. Does this impact convergence?

It chooses the "best" poly at each iteration!

$$A[v_1 \; v_2 \; v_3] = [v_1 \; v_2 \; v_3 \; v_4] \begin{bmatrix} \alpha_1 & \beta_2 & \gamma_3 \\ \beta_2 & \alpha_2 & \beta_3 \\ & \beta_3 & \alpha_3 \\ & & \beta_4 \end{bmatrix}$$

(γ_2?)

$v_1 \to$ input / fixed.

$A v_1 = \alpha_1 v_1 + \beta_2 v_2 \qquad v_2^T v_1 = 0.$

$\alpha_1 = v_1^T A v_1 \to$ fixed!

$\beta_2 v_2 = A v_1 - \alpha_1 v_1$ also $\|v_2\| = 1.$

β_2, v_2 are "fixed" up to sign.

v_1 - fixed
α_1 - fixed
β_2 - fixed up to sign
v_2 - fixed up to sign.

$A v_2 = \beta_2 v_1 + \alpha_2 v_2 + \beta_3 v_3$

$y = A v_2 = \gamma_2 v_1 + \alpha_2 v_2 + \beta_3 v_3$

$v_1^T y = \gamma_2 v_1^T v_1 = \gamma_2$

$v_1^T A v_2 = v_2^T A v_1$ by symmetry

$v_2^T A v_2 = \alpha_2 \to$ fixed?

$\beta_3 = \|y - \gamma_2 v_1 - \alpha_2 y\|$. up to sign.

What happens if you relax orthogonality?

$A V_k = V_{k+1} T_{k+1}$ but we don't assume orthogonality?

Suppose V_k wasn't orthogonal! (But $\|v_i\| = 1$)

Then we choose α_k s.t.:

$\|\underbrace{A v_k - \beta_k v_{k-1}}_{\text{"b"}} - \underbrace{\alpha}_{\text{"x"}} \underbrace{v_k}_{\text{"A"}}\| = \beta_{k+1}$

is as small as possible.

Then we will get orthog V_k and β_k will be as small as poss.

$Ax = b$

⇓

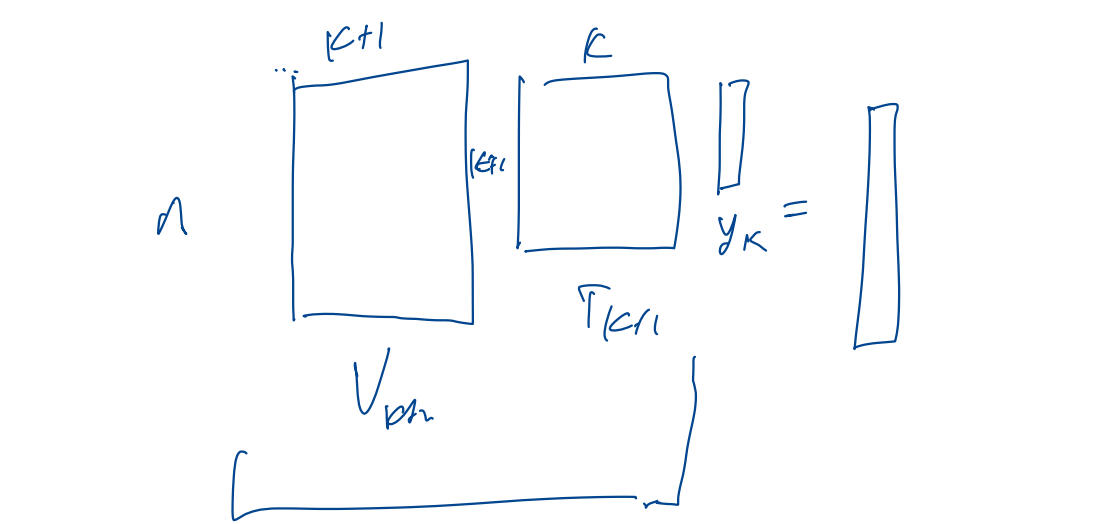
If $x_k \in K_k(A, b)$

Then $x_k = V_k y_k$ for some y_k.

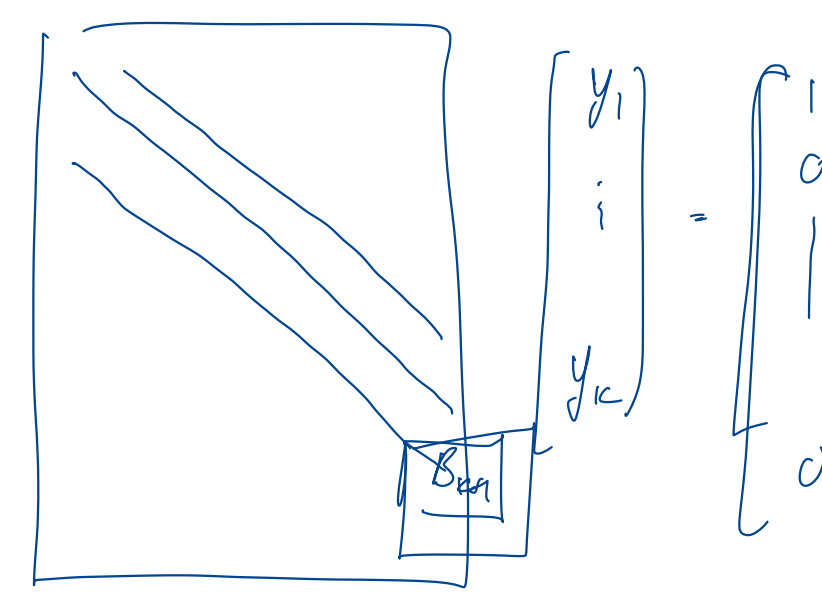
$A V_k y_k = b$

$V_{k+1} T_{k+1} y_k = V_{k+1} e_1 \cdot \|b\|$

To



If $T_{k+1} y_k = e_1$, I'm done!?



CG:

min $\frac{1}{2} x^T A x - x^T b$

s.t. $x_k \in K_k(A, b)$

MinRes

min $\|Ax - b\|_2$

s.t. $x_k \in K_k(A, b)$

if you stop iteration when $\frac{\|Ax - b\|_2}{\|b\|_2} \le tol.$

Then MinRes must use no more iterations than CG.

- Why faster than stationary!

SD computes

$x_k \in K_k(A, b)$.

A

$[b, Ab, \ldots, A^k b] = QR = M_k$

I want to update to

$[b, Ab, \ldots, A^k b, A^{k+1} b] = M_{k+1}$

$M_{k+1} = [QR \;\; v]$

$Q^T M_{k+1} = [R \;\; Q^T v] = [\nabla |]$

$A Q_k = Q_{k+1} H_{k+1}$

Assume Q_k spans $[b, Ab, \ldots, A^{k-1} b]$

Then $A Q_k$ has vectors in

$[Ab, \ldots, A^k b]$.