Lecture 29

Q: What is the difference between SVD and EVD on $A = A^T, A \succeq 0$.

Find:

· Why $\begin{bmatrix} 0 & A \\ A^T & 0 \end{bmatrix}$ in the first place? ✓✓

What, in practice, are λ-vals of $\begin{bmatrix} 0 & A \\ A^T & 0 \end{bmatrix}$ ✓

✓ $\begin{bmatrix} 0 & A \\ A^T & 0 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} = \sigma \begin{bmatrix} x \\ y \end{bmatrix}$

Do we know $x = y$?

No! $x \neq y$ (may not even have same dims)

· Golub-Kahan Bidiag... vs. Lanczos, Householder.

· How to use Golub-Kahan? ✓

Why this matrix?

$\begin{bmatrix} 0 & A \\ A^T & 0 \end{bmatrix}$

A^TA, AA^T

$\begin{bmatrix} 0 & A \\ A^T & 0 \end{bmatrix}\begin{bmatrix} 0 & A \\ A^T & 0 \end{bmatrix} = \begin{bmatrix} AA^T & 0 \\ 0 & A^TA \end{bmatrix}$

Weird Cool matrix.

Gene Golub was famous for figuring out how to get QR on

$\begin{bmatrix} 0 & B \\ B^T & 0 \end{bmatrix} = C$

w/o forming C.

$U^TAV \to B$ a bidiag. matrix?

Use Double implicit shifted QR...

$\begin{bmatrix} 0 & A \\ A^T & 0 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} = \sigma \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} Ay \\ A^Tx \end{bmatrix}$

$\begin{bmatrix} 0 & A \\ A^T & 0 \end{bmatrix}\begin{bmatrix} x \\ -y \end{bmatrix} = \begin{bmatrix} -Ay \\ A^Tx \end{bmatrix} = \begin{bmatrix} -\sigma x \\ \sigma y \end{bmatrix} = -\sigma \begin{bmatrix} x \\ -y \end{bmatrix}$

$Ay = \sigma x$

$A = U \Sigma V^T \Rightarrow AV = U\Sigma$, $Av_i = \sigma_i u_i$

What if $A = A^T, A \succeq 0$.

$A = Q \Lambda Q^T$ is EVD

$A = U \Sigma V^T$ is SVD.

But if $A = A^T$ ~ $U \neq V$ but if $A = A^T, A \succeq 0$, then

Uniqueness of SVD.

If $\sigma_i \neq \sigma_j$ for all $i \neq j$, then $\underline{u}_i, \underline{v}_i$ are unique! (up to scaling).

If $\sigma_i = \sigma_j$ for some pair, we are unique in subspace.....

So if $A = A^T, A \succeq 0$, and $\sigma_i \neq \sigma_j$ $i \neq j$, the EVD = SVD always.

Golub-Kahan $\iff$ Lanczos for $\begin{bmatrix} 0 & A \\ A^T & 0 \end{bmatrix}$

Golub-Kahan gives

$AX_k = Y_{k+1} B_{k+1,k} = \begin{bmatrix} \alpha_1 & & \\ \beta_2 & \ddots & \alpha_k \\ & & \beta_{k+1} \end{bmatrix}$

$X_k^T X_k = I$

$Y_k^T Y_k = I$.

σ-vals of $A \approx \sigma$-vals of B_k.

$B_{k+1} = \tilde{U}_k \tilde{\Sigma}_k \tilde{V}_k^T$, $\therefore A X_k = Y_{k+1} U_k \Sigma_k V^T$

$A \underbrace{X_k \tilde{V}_k}_{V_k} = \underbrace{Y_k \tilde{U}_k}_{U_k} \Sigma_k$

$A \approx U_k \Sigma_k V_k^T$

$U_k^T A V_k = \Sigma_k$.