# CS 357: Numerical Methods 

# Lecture 14: <br> Orthogonal Iteration <br> Singular Value Decomposition 

Eric Shaffer

## Finding Eigenvectors

- Can we simultaneously (sort of) find all the eigenvectors of A?
- What about this algorithm

$$
\begin{aligned}
& X_{0}=\text { arbitrary } n \times p \text { matrix of rank } p \\
& \text { for } k=1,2, \ldots \\
& X_{k}=A X_{k-1}
\end{aligned}
$$

## Orthogonal Iteration

- How about this?
$\mathrm{X}_{0}=\mathrm{n} \times \mathrm{p}$ matrix of rank p
for $k=1,2, \ldots$.
\#compute reduced QR factorization

$$
\begin{aligned}
& Q_{k+1} R_{k+1}=X_{k} \\
& X_{k+1}=A Q_{k}
\end{aligned}
$$

## Orthogonal Iteration

$$
\begin{aligned}
& X_{0}=n \times p \text { matrix of rank } p \\
& \text { for } k=1,2, \ldots \\
& \quad \# \text { compute reduced } Q R \text { factorization } \\
& Q_{k+1} R_{k+1}=X_{k} \\
& X_{k+1}=A Q_{k}
\end{aligned}
$$

The Schur Form: Finding Eigenvalues

The Schur Form: Finding Eigenvectors

## Singular Value Decomposition (SVD)

$$
A=U \Sigma V^{T}
$$

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$$
A=U \Sigma V^{T}
$$

## Inversion using SVD

$$
A=U \Sigma V^{T}
$$

Assume $A$ is an $n \times n$ matrix

## The Pseudo Inverse

When A is not square we can compute the pseudo-inverse

Pseudo Inverse and Least Squares

Notes on Computing the SVD

