## Matrix Canonical Forms

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## A variant of the QR factorization

- $A \in M_{n, m}$ with $n \geq m \Rightarrow A=Q R$ with $Q$ unitary, $R=\left[\begin{array}{c}R_{1} \\ 0\end{array}\right] \in M_{n}$, and $R_{1}$ upper triangular (zero entries below the main diagonal).
- $K_{m}=\left[\begin{array}{ll} & 1 \\ 1\end{array} \quad l \in M_{m}\right.$ is the reversal matrix. It is unitary and $K_{m}^{2}=l$.
- $A K=Q R \Rightarrow A=Q\left(R K_{m}\right), Q$ unitary, $R K_{m}=\left[\begin{array}{c}R_{1} K_{m} \\ 0\end{array}\right]$, and $R_{1} K_{m}$ has zero entries below the anti-diagonal.
- What do we get if we write $A=Q\left(R K_{m}\right)=\left(Q K_{n}\right)\left(K_{n} R K_{m}\right)$ ? or $A=Q R=\left(Q K_{n}\right)\left(K_{n} R\right)$ ?


## Schur triangularization: Some consequences

- (2.4.6) Every square matrix is block diagonalizable by similarity.
- Let $\lambda_{1}, \ldots, \lambda_{d}$ be the distinct eigenvalues of $A$ and let $A$ be unitarily similar to an upper triangular matrix $T=\left[T_{i j}\right]_{i, j=1}^{d}$ in which all the diagonal entries of $T_{i i}$ are $\lambda_{i}$.
- Partition $T=\left[\begin{array}{cc}T_{11} & Y \\ 0 & S_{2}\end{array}\right]$. Let $M=\left[\begin{array}{cc}1 & X \\ 0 & 1\end{array}\right]$, so
$M^{-1}=\left[\begin{array}{cc}1 & -X \\ 0 & 1\end{array}\right]$. Compute

$$
M^{-1} T M=\left[\begin{array}{cc}
T_{11} & T_{11} X-X S_{2}+Y \\
0 & S_{2}
\end{array}\right]=\left[\begin{array}{cc}
T_{11} & 0 \\
0 & S_{2}
\end{array}\right]
$$

if we choose $X$ so that $T_{11} X-X S_{2}=-Y$.

- Repeat the reduction on $S_{2}$.
- $A$ is similar to $T_{11} \oplus \cdots \oplus T_{d d}$.


## Canonical form for normal matrices under unitary similarity

- $A \in M_{n}$ is normal if $A A^{*}=A^{*} A$
- Example: $A=A^{*}$ (Hermitian) or $A=-A^{*}$ (skew Hermitian)
- Example: $U U^{*}=I$, that is, $U^{*}=U^{-1}$ (unitary)
- (2.5.2) A (block) upper triangular normal matrix is (block) diagonal
- Example: $A=\left[\begin{array}{cc}\lambda_{1} & a_{12} \\ 0 & \lambda_{2}\end{array}\right]$
- $A A^{*}=\left[\begin{array}{cc}\lambda_{1} & a_{12} \\ 0 & \lambda_{2}\end{array}\right]\left[\begin{array}{cc}\overline{\lambda_{1}} & 0 \\ \overline{a_{12}} & \overline{\lambda_{2}}\end{array}\right]=\left[\begin{array}{cc}\left|\lambda_{1}\right|^{2}+\left|a_{12}\right|^{2} & \star \\ \star & \star\end{array}\right]$
- $A^{*} A=\left[\begin{array}{cc}\overline{\lambda_{1}} & \frac{0}{a_{12}}\end{array}\right]\left[\begin{array}{cc}\lambda_{1} & a_{12} \\ 0 & \lambda_{2}\end{array}\right]=\left[\begin{array}{cc}\left|\lambda_{1}\right|^{2} & \star \\ \star & \star\end{array}\right]$
- Let $U$ be unitary. Then $A$ is normal if and only if $\mathcal{A}=U^{*} A U$ is normal.
- $\mathcal{A A ^ { * }}=\left(U^{*} A U\right)\left(U^{*} A U\right)^{*}=U^{*} A U U^{*} A^{*} U=U^{*} A A^{*} U=U^{*} A^{*} A U=$ $U^{*} A^{*} U U^{*} A U=\mathcal{A}^{*} \mathcal{A}$
- (2.5.3) $A$ is normal if and only if it is unitarily diagonalizable, that is, $A=U \Lambda U^{*}$ with a unitary $U$ and $\Lambda=\operatorname{diag}\left(\lambda_{1}, \ldots, \lambda_{n}\right)$.


## Canonical form for normal matrices under unitary similarity

- (2.5.4) Uniqueness of unitary diagonalization of a normal matrix.
- Suppose that $A$ is normal and has distinct eigenvalues $\lambda_{1}, \ldots, \lambda_{d}$. Let $\Lambda=\lambda_{1} I_{n_{1}} \oplus \cdots \oplus \lambda_{d} I_{n_{d}}$. Then $A=U \Lambda U^{*}=V \Lambda V^{*}$ with unitary $U, V$ if and only if $U=V W$ in which $W=W_{1} \oplus \cdots \oplus W_{d}$ is unitary and conformal to $\Lambda$.
- Two normal matrices of the same size are unitarily similar if and only if they have the same eigenvalues.
- $A=U \Lambda U^{*} \Rightarrow \Lambda=U^{*} A U$
- $B=V \Lambda V^{*}=V\left(U^{*} A U\right) V^{*}=\left(V U^{*}\right) A\left(V U^{*}\right)^{*}$
- A normal matrix is Hermitian (skew Hermitian) if and only if its eigenvalues are real (pure imaginary)

$$
\text { - } A= \pm A^{*} \Leftrightarrow \Lambda= \pm \Lambda^{*}= \pm \bar{\Lambda} \Leftrightarrow \lambda= \pm \bar{\lambda}
$$

- A normal matrix is unitary if and only its eigenvalues have unit modulus
- $U^{*}=U^{-1} \Leftrightarrow \bar{\Lambda}=\Lambda^{-1} \Leftrightarrow \bar{\lambda}=\lambda^{-1} \Leftrightarrow \lambda \bar{\lambda}=|\lambda|^{2}=1$


## Unitary equivalence and simultaneous triangularization

- $A, B \in M_{n, m}$ are unitarily equivalent if there are unitary $V \in M_{n}$ and $W \in M_{m}$ such that $A=V B W^{*}$
- Given matrices $A, B \in M_{n}$ need not be simultaneously upper triangularizable.
- (2.3.3) Commutativity is a sufficient but not necessary condition.
- (2.4.8.7) McCoy's Theorem gives a necessary and sufficient condition.
- However any $A, B \in M_{n}$ can be simultaneously upper triangularized by unitary equivalence (2.6.1)
- First suppose $B$ is nonsingular.
- Use Schur to write $B^{-1} A=U T U^{*}$, then use the $Q R$ decomposition to write $B U=Q R$.
- $A=B U T U^{*}=(Q R)\left(T U^{*}\right)=Q(R T) U^{*} \Rightarrow Q^{*} A U$ is upper triangular
- $B=(B U) U^{*}=(Q R) U^{*}=Q R U^{*} \Rightarrow Q^{*} B U$ is upper triangular


## Unitary equivalence and simultaneous triangularization

- If both $A$ and $B$ are singular, let $B_{\varepsilon}=B+\varepsilon l$ (all sufficiently small $\varepsilon$ so that $B_{\varepsilon}$ is nonsingular. Why is this possible?) and let $Q_{\varepsilon}$ and $U_{\varepsilon}$ be unitary and such that $Q_{\varepsilon}^{*} A U_{\varepsilon}$ and $Q_{\varepsilon}^{*} B_{\varepsilon} U_{\varepsilon}$ are upper triangular. Let $\varepsilon_{k} \rightarrow 0$ in such a way that $Q_{\varepsilon_{k}} \rightarrow Q$, and $U_{\varepsilon_{k}} \rightarrow U$ (the unitary group is compact). Of course, $B_{\varepsilon_{k}}=B+\varepsilon_{k} I \rightarrow B$. Then
- $Q_{\varepsilon_{k}}^{*} A U_{\varepsilon_{k}} \rightarrow Q^{*} A U$ is upper triangular
- $Q_{\varepsilon_{k}}^{*} B_{\varepsilon_{k}} U_{\varepsilon_{k}} \rightarrow Q^{*} B U$ is upper triangular


## Unitary equivalence and the singular value decomposition

- Only normal matrices can be diagonalized by unitary similarity, but any matrix can be diagonalized by unitary equivalence.
- First suppose that $A$ is square: $A \in M_{n}$
- $A A^{*}$ and $A^{*} A$ are Hermitian matrices with the same eigenvalues, so they are unitarily similar: $A^{*} A=U\left(A A^{*}\right) U^{*}$
- $(U A)(U A)^{*}=U A A^{*} U^{*}=A^{*} A$
- $(U A)^{*}(U A)=A^{*}\left(U^{*} U\right) A=A^{*} A$
- Thus, $U A$ is normal so $U A=V \Lambda V^{*}$ in which $\Lambda=\operatorname{diag}\left(\lambda_{1}, \ldots, \lambda_{n}\right)$, $\left|\lambda_{1}\right| \geq \cdots \geq\left|\lambda_{n}\right|$, and each $\lambda_{j}=\left|\lambda_{j}\right| e^{i \theta_{j}}$
- Let $\Sigma=\operatorname{diag}\left(\left|\lambda_{1}\right|, \ldots,\left|\lambda_{n}\right|\right)$
- Let $E=\operatorname{diag}\left(e^{i \theta_{1}}, \ldots, e^{i \theta_{n}}\right)$, which is unitary; $\Lambda=\Sigma E$
- Then $A=U^{*} V \Lambda V^{*}=U^{*} V(\Sigma E) V^{*}=\left(U^{*} V\right) \Sigma\left(E V^{*}\right)$
- (2.6.3) This is the SVD for square matrices: $A=V \Sigma W^{*}$ in which $V$ and $W$ are unitary and $\Sigma=\operatorname{diag}\left(\sigma_{1} \ldots, \sigma_{n}\right)$ is a nonnegative diagonal matrix whose diagonal entries are the decreasingly ordered square roots of the eigenvalues of $A^{*} A$, which are also the eigenvalues of $A A^{*}$.


## Unitary equivalence and the singular value decomposition

- Now suppose $A \in M_{n, m}$ with $n<m$. Then $\operatorname{rank} A \leq n$ so the dimension of the null space of $A$ is at least $m-n$.
- Choose any set of $m-n$ orthonormal vectors in the null space of $A$ and let them be the columns of $X_{2} \in M_{m, m-n}$. Let $X=\left[\begin{array}{ll}X_{1} & X_{2}\end{array}\right] \in M_{m}$ be unitary, so $X_{1} \in M_{m, n}$.
- $A X=A\left[\begin{array}{ll}X_{1} & X_{2}\end{array}\right]=\left[\begin{array}{ll}A X_{1} & A X_{2}\end{array}\right]=\left[\begin{array}{ll}A X_{1} & 0\end{array}\right]$ and $A X_{1} \in M_{n}$ so the preceding case ensures that $A X_{1}=V \Sigma W^{*}$ with unitary $V, W \in M_{n}$ and $\Sigma=\operatorname{diag}\left(\sigma_{1} \ldots, \sigma_{n}\right)$ with $\sigma_{1} \geq \cdots \geq \sigma_{n} \geq 0$. Then

$$
A=\left[V \Sigma W^{*} 0\right] X^{*}=V[\Sigma 0]\left(X\left[\begin{array}{cc}
W & 0 \\
0 & I_{m-n}
\end{array}\right]\right)^{*}=V\left[\begin{array}{ll}
\Sigma & 0
\end{array} Z^{*}\right.
$$

- If $n>m$, apply the preceding case to $A^{*}$ to get

$$
A=V\left[\begin{array}{l}
\Sigma \\
0
\end{array}\right] W^{*}, \quad \Sigma \in M_{m}
$$

## Some consequences of the SVD

- $A=V \Sigma W^{*}$ and both $V$ and $W$ have full rank, so $\operatorname{rank} A=\operatorname{rank} \Sigma=$ the number of positive singular values
- The $\sigma_{i}^{2}$ are (all of) the eigenvalues of the smaller of $A A^{*}$ or $A^{*} A$; the larger one has additional (trivial) zero eigenvalues.
- If $A \rightarrow V A W^{*}$, then $A A^{*} \rightarrow V\left(A A^{*}\right) V^{*}$ and $A^{*} A \rightarrow W\left(A^{*} A\right) W^{*}$, so the eigenvalues are preserved in either case. So...unitarily equivalent matrices have the same singular values.
- If $A=V \Sigma W^{*}$ and $B=U \Sigma Z^{*}$ then $\Sigma=U^{*} B Z$ and $A=\left(V U^{*}\right) B\left(Z W^{*}\right)$, so $A$ and $B$ are unitarily equivalent.
- What is a canonical form for unitary equivalence?
- $\{\Sigma\}$
- The factor $\Sigma$ is uniquely determined, but the unitary factors are never uniquely determined: $V \rightarrow-V$ and $W \rightarrow-W$ leaves the SVD unchanged.


## Some consequences of the SVD

- (2.6.5) Nevertheless, all the possible unitary factors for a given $A \in M_{n, m}$ are related in a simple way. If $A=V \Sigma W^{*}=\hat{V} \Sigma \hat{W}^{*}$, then
- There are unitary matrices $U_{1}, \ldots, U_{d}, \tilde{V}, \tilde{W}$ such that
- $\hat{V}=V\left(U_{1} \oplus \cdots \oplus U_{d} \oplus \tilde{V}\right)$
- $\hat{W}=W\left(U_{1} \oplus \cdots \oplus U_{d} \oplus \tilde{W}\right)$
- $d=$ the number of distinct positive singular values
- the size of each $U_{i}$ is the multiplicity of $\sigma_{i}$
- Using the preceding uniqueness theorem, one can prove a variety of special SVDs for matrices with special properties. For example:
- Suppose $A$ is symmetric: $A=A^{T}$. Then

$$
A=V \Sigma W^{*} \Rightarrow A=A^{T}=\bar{W} \Sigma V^{T}
$$

- $\hat{V}=\bar{W}=V\left(U_{1} \oplus \cdots \oplus U_{d} \oplus \tilde{V}\right)$
- $\hat{W}=V^{T}=W\left(U_{1} \oplus \cdots \oplus U_{d} \oplus \tilde{W}\right)$
- With a little work one discovers that each $U_{i}$ must be symmetric and that there is a single unitary $Z$ such that $A=Z \Sigma Z^{T}$. (L. Autonne, ~ 1915) (2.6.6)


## Some consequences of the SVD

- If $A$ is normal, $A=U \Lambda U^{*}$, so $A A^{*}=U \Lambda U^{*} U \bar{\Lambda} U^{*}=U|\Lambda|^{2} U^{*}$ and the singular values of $A$ are $\left|\lambda_{i}\right|$
- For what normal matrices are all $\lambda_{i}=\sigma_{i}$ ?
- Singular values are really more like norms than eigenvalues. For example, the spectral norm is

$$
\begin{aligned}
\|A\|^{2} & =\max _{\|x\|_{2}=1}\|A x\|^{2}=\max _{\|x\|_{2}=1}(A x)^{*}(A x)=\max _{\|x\|_{2}=1} x^{*} A^{*} A x \\
& =\max _{\|x\|_{2}=1} x^{*} W \Sigma^{2} W^{*} x=\max _{\|x\|_{2}=1}\left(W^{*} x\right)^{*} \Sigma^{2}\left(W^{*} x\right) \\
& =\max _{\|\xi\|_{2}=1} \xi^{*} \Sigma^{2} \xi=\max _{\|\xi\|_{2}=1}\left(\sigma_{1}^{2}|\xi|^{2}+\cdots+\sigma_{n}^{2}\left|\xi_{n}\right|^{2}\right)=\sigma_{1}^{2}
\end{aligned}
$$

- Thus, $\sigma_{1}(A)=\|A\|$ (unitarily invariant)
- Individually, $\sigma_{2}, \ldots, \sigma_{n}$ are not norms (they can be zero for a nonzero matrix), but the sums $\sigma_{1}+\sigma_{2}, \sigma_{1}+\sigma_{2}+\sigma_{3}, \ldots, \sigma_{1}+\cdots+\sigma_{n}$ are unitarily invariant norms (very important!).


## Some consequences of the SVD

- $A=V \Sigma W^{*}$ has rank $r \Rightarrow A=\sum_{i=1}^{r} \sigma_{i} v_{i} w_{i}^{*}$. For any $k=1, \ldots, k$, $\sum_{i=1}^{k} \sigma_{i} v_{i} w_{i}^{*}$ is the best rank $k$ approximation to $A$ (in the Frobenius norm (least squares)) (E. Schmidt, ~ 1905)
- Every decent numerical software package today has an SVD routine that is fast and very accurate. It is at the heart of a great many modern numerical algorithms.
- SIAM News article: "SVD is the Swiss Army knife of matrix computation."

