## Learning Objectives:

- Understand how to construct a singular value decomposition of a matrix

The Singular Values of an $m \times n$ Matrix

Definition: If $A$ is an $m \times n$ matrix, the singular values of $A$ are the $\qquad$ of the eigenvalues of $\qquad$ , denoted by $\sigma_{1}, \ldots, \sigma_{n}$, and they are arranged in decreasing order.

That is, $\sigma_{i}=$ $\qquad$ for $1 \leq i \leq n$, where $\lambda_{1} \geq \lambda_{2} \geq \cdots \geq \lambda_{n} \geq 0$.

Note: The singular values of $A$ are the $\qquad$ of the vectors $\qquad$ -

Theorem 7.9. Suppose $\left\{\mathbf{v}_{1}, \ldots, \mathbf{v}_{n}\right\}$ is an orthonormal basis of $\mathbb{R}^{n}$ consisting of eigenvectors of $A^{T} A$, arranged so that the corresponding eigenvalues of $A^{T} A$ satisfy $\qquad$ and suppose $A$ has $\qquad$ nonzero singular values.

Then $\left\{A \mathbf{v}_{1}, \ldots, A \mathbf{v}_{r}\right\}$ is an $\qquad$ for $\operatorname{Col} A$, and $\operatorname{rank} A=r$.

Remark: In practice, the most reliable way to estimate the rank of a large matrix $A$ is to count the number of nonzero singular values.

## The Singular Value Decomposition

The decomposition of $A$ involves an $m \times n$ "diagonal" matrix $\Sigma$ of the form

$$
\Sigma=
$$

where $D$ is an $\qquad$ diagonal matrix for some $r$ not exceeding the smaller of $m$ and $n$.

## Theorem 7.10 (The Singular Value Decomposition).

Let $A$ be an $m \times n$ matrix with rank $r$. Then there exists an $m \times n$ matrix $\Sigma$ (as shown above) for which the diagonal entries in $D$ are the first $\qquad$ of $A$, $\sigma_{1} \geq \sigma_{2} \geq \cdots \geq \sigma_{r}>0$, and there exists an $m \times m$ $\qquad$ matrix $U$ and an
$n \times n$ $\qquad$ matrix $V$ such that

$$
A=
$$

## How to find a singular value decomposition If $A$ is an $m \times n$ matrix...

Step 1: Find an orthogonal diagonalization of $A^{T} A$. This means to find all the eigenvalues $\lambda_{1} \geq \lambda_{2} \geq \cdots \geq \lambda_{n}$ (each listed as many times as its multiplicity) and an orthonormal basis $\mathbf{v}_{\mathbf{1}}, \ldots, \mathbf{v}_{\mathbf{n}}$ of $\mathbb{R}^{n}$ consisting of eigenvectors of $A^{T} A$ (that match up with the eigenvalues, so $\mathbf{v}_{\mathbf{i}}$ has eigenvalue $\lambda_{i}$ ).

Step 2: Fill in $\Sigma$ and $V$. We compute the singular values $\sigma_{i}=\sqrt{\lambda_{i}}$, and fill them into $\Sigma$, and fill in the columns of $V$ with the corresponding orthonormal basis of eigenvectors for $A^{T} A$.

Step 3: Construct $U$. The first $r(=\operatorname{rank}(A))$ columns of $U$ are the normalized (unit length) vectors obtained from $A \mathbf{v}_{\mathbf{1}}, \ldots, A \mathbf{v}_{\mathbf{r}}$. If $r<m$, then use Gram-Schmidt to complete an orthonormal basis for $\mathbb{R}^{m}$.

