## <span id="page-0-0"></span>Using SVD to "see" a Linear Transformation

Linear Algebra MATH 2076



## The Four Fundamental Vector SubSpaces Assoc'd with A

The four canonical vector subspaces associated with an  $m \times n$  matrix A are:

- the null space  $\mathcal{NS}(A)$  of  $A$  (a vector subspace of  $\mathbb{R}^n)$ ,
- the column space  $\mathcal{CS}(A)$  of  $A$  (a vector subspace of  $\mathbb{R}^m$ ),
- the orthogonal complement  $\mathcal{CS}(A)^\perp=\mathcal{NS}(A^\mathcal{T})$  (a VSS of  $\mathbb{R}^m)$ ,
- the orthogonal complement  $\mathcal{N}\mathcal{S}(A)^{\perp}=\mathcal{CS}(A^{\mathcal{T}})$  (a VSS of  $\mathbb{R}^n).$ Suppose  $A=\begin{bmatrix}\vec{u}_1\;\vec{u}_2\ldots\vec{u}_m\end{bmatrix}\Sigma\begin{bmatrix}\vec{v}_1\;\vec{v}_2\ldots\vec{v}_n\end{bmatrix}^T$  is an SVD for  $A$ . Then:  $\bullet \{\vec{u_1}, \ldots, \vec{u_r}\}$  is an orthonormal basis for  $CS(A)$ ,
	- $\{\vec{u}_{r+1},\ldots,\vec{u}_m\}$  is an *orthonormal basis* for  $\mathcal{CS}(A)^{\perp}=\mathcal{NS}(A^{\mathcal{T}})$ ,
	- $\bullet \ \{\vec{v}_{r+1}, \ldots, \vec{v}_n\}$  is an orthonormal basis for  $NS(A)$ , and
	- $\{\vec{\mathsf{v}}_1,\ldots,\vec{\mathsf{v}}_r\}$  is an *orthonormal basis* for  $\mathcal{N}\mathcal{S}(A)^{\perp}=\mathcal{CS}(A^{\mathsf{T}}).$



$$
A = \begin{bmatrix} \vec{a}_1 & \vec{a}_2 & \dots & \vec{a}_n \end{bmatrix} m \times n \text{ and } \mathbb{R}^n \xrightarrow{T} \mathbb{R}^m \text{ given by } T(\vec{x}) = A\vec{x}
$$

 $\vec{x}=\vec{\rho}+\vec{z},\vec{\rho}=\mathsf{Proj}_{\mathcal{NS}(A)^\perp}(\vec{x}), \vec{z}=\mathsf{Proj}_{\mathcal{NS}(A)}(\vec{x}) \implies A\vec{x}=A\vec{\rho}+A\vec{z}=A\vec{\rho}.$ Recall:  $\mathcal{NS}(A)^\perp=\mathcal{CS}(A^{\mathcal{T}})$  and  $\mathcal{CS}(A)^\perp=\mathcal{NS}(A^{\mathcal{T}})$ . When have an <code>SVD</code>  $\mathcal{A}=\left[\right.\vec{u}_1 \left.\vec{u}_2 \ldots \vec{u}_m\right] \Sigma\left[\right.\vec{v}_1 \left.\vec{v}_2 \ldots \vec{v}_n\right] ^\mathsf{T}, \text{ get orthon bases }\mathcal{V}=\left\{\vec{v}_1, \vec{v}_2 \ldots, \vec{v}_n\right\}$  (for  $\mathbb{R}^n$ ),  $\mathcal{U}=\left\{\vec{\mathit{u}}_1,\vec{\mathit{u}}_2\dots,\vec{\mathit{u}}_m\right\}$  (for  $\mathbb{R}^m$ ), and  $\left[\left.{\mathsf{T}}\right]_{\mathcal{U}\mathcal{V}}=\Sigma.$  Also, these give....

## Example: using an SVD  $A = U \Sigma V^T$

Let's try to "see" the linear transformation  $\mathbb{R}^2 \overset{\mathcal{T}}{\rightarrow} \mathbb{R}^3$  defined by  $T(\vec{x}) = A\vec{x}$  where  $A = U \Sigma V^{T}$  is given below.

Here 
$$
A = \begin{bmatrix} 1 & 2 \\ 2 & 0 \\ 0 & 2 \end{bmatrix}
$$
 and we will find  $U, \Sigma, V$  so that  $A = U \Sigma V^{T}$ .

Recall that  $A$  is the standard matrix for  $\mathcal{T}$ ; i.e.,  $A = \big[\mathcal{T}\big]_{\mathcal{E}}.$  It turns out that  $\mathsf{\Sigma} = \big[\, \mathsf{\mathcal{T}} \big]_{\mathcal{U}\mathcal{V}}$  where

$$
\mathcal{V} = \{\vec{v}_1, \vec{v}_2\} \quad \text{and} \quad \mathcal{U} = \{\vec{u}_1, \vec{u}_2, \vec{u}_3\}
$$

are the orthonormal bases for  $\mathbb{R}^2$  and  $\mathbb{R}^3$  (respectively) with

$$
V = \begin{bmatrix} \vec{v}_1 & \vec{v}_2 \end{bmatrix} \quad \text{and} \quad U = \begin{bmatrix} \vec{u}_1 & \vec{u}_2 & \vec{u}_3 \end{bmatrix}.
$$

In fact, it even gets better, but lets just work this simple example.

<span id="page-4-0"></span>For 
$$
A = \begin{bmatrix} 1 & 2 \\ 2 & 0 \\ 0 & 2 \end{bmatrix}
$$
,  $A^T A = \begin{bmatrix} 5 & 2 \\ 2 & 8 \end{bmatrix}$  which has evs  $\lambda_1 = 9, \lambda_2 = 4$ .  
\nThus  $\sigma_1 = 3, \sigma_2 = 2$  and  $\Sigma = \begin{bmatrix} 3 & 0 \\ 0 & 2 \\ 0 & 0 \end{bmatrix}$ . Get associd e $\vec{v}$ s  $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$ ,  $\begin{bmatrix} -2 \\ 1 \end{bmatrix}$  so  
\ntake  $\vec{v}_1 = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ ,  $\vec{v}_2 = \frac{1}{\sqrt{5}} \begin{bmatrix} -2 \\ 1 \end{bmatrix}$  and then  $V = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & -2 \\ 2 & 1 \end{bmatrix}$ .  
\nGet  $A \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 5 \\ 2 \\ 4 \end{bmatrix}$ ,  $A \begin{bmatrix} -2 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ -4 \\ 2 \end{bmatrix}$  so  $\vec{u}_1 = \frac{1}{3\sqrt{5}} \begin{bmatrix} 5 \\ 2 \\ 4 \end{bmatrix}$ ,  $\vec{u}_2 = \frac{1}{\sqrt{5}} \begin{bmatrix} 0 \\ -2 \\ 1 \end{bmatrix}$ .  
\nNow  $\{\vec{u}_3\}$  is a basis for  $\mathcal{NS}(A^T)$ , so we can take  $\vec{u}_3 = \frac{1}{3} \begin{bmatrix} -2 \\ 1 \\ 2 \end{bmatrix}$ . Then  
\n $U = \frac{1}{3\sqrt{5}} \begin{bmatrix} 5 & 0 & -2\sqrt{5} \\ 2 & -6 & \sqrt{5} \\ 4 & 3 & 2\sqrt{5} \end{bmatrix}$ .  $\frac{1}{15} \begin{bmatrix} 5 & 0 & -2\sqrt{5} \\ 2 & -6 & \sqrt{5} \\ 4 & 3 & 2\sqrt{5} \end{bmatrix} \begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ -2 & 1 \end{bmatrix} =$