

Singular Value Decomposition

We here give a complete description and proof for the Singular Value Decomposition (SVD) Theorem. First, recall that the inner product defined on \mathbb{C}^n is $\langle x, y \rangle = x^*y, \forall x, y \in \mathbb{C}^n$. We now introduce the following important lemma:

Lemma 1 *Let $A \in \mathbb{C}^{m \times n}$ and A^* be its conjugate transpose. We then always have:*

$$\text{Nu}(AA^*) = \text{Nu}(A^*), \quad \text{Ra}(AA^*) = \text{Ra}(A).$$

Proof: To prove $\text{Nu}(AA^*) = \text{Nu}(A^*)$, we have:

- (a) $AA^*x = \theta \Rightarrow \langle x, AA^*x \rangle = \|A^*x\|^2 = 0 \Rightarrow A^*x = \theta$, hence $\text{Nu}(AA^*) \subseteq \text{Nu}(A^*)$.
- (b) $A^*x = \theta \Rightarrow AA^*x = \theta$, hence $\text{Nu}(AA^*) \supseteq \text{Nu}(A^*)$.

To prove $\text{Ra}(AA^*) = \text{Ra}(A)$, we first need to prove that \mathbb{C}^n is a direct sum of $\text{Ra}(A^*)$ and $\text{Nu}(A)$. We prove this by showing that a vector x is in $\text{Nu}(A)$ if and only if it is orthogonal to $\text{Ra}(A^*)$: $x \in \text{Nu}(A) \Leftrightarrow \langle A^*x, y \rangle = 0, \forall y \in \text{Ra}(A^*) \Leftrightarrow \langle x, Ay \rangle = 0, \forall y$. Hence $\text{Nu}(A)$ is exactly the subspace which is orthogonal supplementary to $\text{Ra}(A^*)$ (sometimes denoted as $\text{Ra}(A^*)^\perp$). Therefore \mathbb{C}^n is a direct sum of $\text{Ra}(A^*)$ and $\text{Nu}(A)$. Let $\text{Img}_A(S)$ denote the image of a subspace S under the map A . Then we have: $\text{Ra}(A) = \text{Img}_A(\mathbb{C}^n) = \text{Img}_A(\text{Ra}(A^*)) = \text{Ra}(AA^*)$ (in the second equality we used the fact that \mathbb{C}^n is a direct sum of $\text{Ra}(A^*)$ and $\text{Nu}(A)$.) ■

In the above A can be regarded as a linear map from \mathbb{C}^n to \mathbb{C}^m . In fact the same result still holds even if the domain of the linear map A is replaced by an infinite dimensional linear space with an inner product (*i.e.*, \mathbb{C}^n is replaced by a Hilbert space). In that case, this lemma is also known as the *Finite Rank Operator Fundamental Lemma*, which will be useful for obtaining conditions of controllability and observability for LTI systems.

We are now ready to give a complete proof for the Singular Value Decomposition Theorem is:

Theorem 1 (Singular Value Decomposition) *Let $F = \mathbb{R}$ or \mathbb{C} . Let $A \in F^{m \times n}$ be a matrix of rank r . Then there exist matrices $U \in F^{m \times m}$ and $V \in F^{n \times n}$, and $\Sigma_1 \in \mathbb{R}^{r \times r}$ such that:*

1. $V = [V_1 : V_2], V_1 \in F^{n \times r}$, satisfies:
 V is unitary, *i.e.*, $V^*V = I_{n \times n}$,
 $\text{Ra}(V_1) = \text{Ra}(A^*)$; the columns of V_1 form an orthonormal basis of $\text{Ra}(A^*)$
 $\text{Ra}(V_2) = \text{Nu}(A)$; the columns of V_2 form an orthonormal basis of $\text{Nu}(A)$
The columns of V form a complete orthonormal basis of eigenvectors of A^*A .
2. $U = [U_1 : U_2], U_1 \in F^{m \times r}$, satisfies:
 U is unitary, *i.e.*, $U^*U = I_{m \times m}$,
 $\text{Ra}(U_1) = \text{Ra}(A)$; the columns of U_1 form an orthonormal basis of $\text{Ra}(A)$
 $\text{Ra}(U_2) = \text{Nu}(A^*)$; the columns of U_2 form an orthonormal basis of $\text{Nu}(A^*)$
The columns of U form a complete orthonormal basis of eigenvectors of AA^* .

3. $\Sigma_1 = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_r) \in \mathbb{R}^{r \times r}$ such that $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$. $A \in F^{m \times n}$ has a dyadic expansion:

$$A = U_1 \Sigma_1 V_1^*, \quad \text{or equivalently,} \quad A = \sum_{i=1}^r \sigma_i u_i v_i^*$$

where u_i, v_i are the columns of U_1 and V_1 respectively.

4. $A \in F^{m \times n}$ has a singular value decomposition (SVD):

$$A = U \Sigma V^*, \quad \text{with} \quad \Sigma = \begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix}_{n \times n}.$$

Proof: 1. $A \in F^{m \times n}$ has rank r , hence the nonnegative (or, equivalently, positive semidefinite) Hermitian matrix A^*A has rank r according to the Lemma. It has n nonnegative eigenvalues σ_i^2 ordered as:

$$\sigma_1^2 \geq \sigma_2^2 \geq \dots \geq \sigma_r^2 > 0 = \sigma_{r+1}^2 = \dots = \sigma_n^2$$

to which corresponds a complete orthonormal eigenvector basis $(v_i)_{i=1}^n$ of A^*A . This family of vectors (in F^n) form the columns of a unitary $n \times n$ matrix, say, V . From the lemma, $\text{Ra}(A^*A) = \text{Ra}(A^*)$ and $\text{Nu}(A^*A) = \text{Nu}(A)$, the properties listed in 1 follow.

2. Define a diagonal matrix $\Sigma_1 = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_r) \in \mathbb{R}^{r \times r}$. We then have $A^*AV_1 = V_1\Sigma_1^2$, hence $(AV_1\Sigma_1^{-1})^*(AV_1\Sigma_1^{-1}) = I_{r \times r}$. This defines a $m \times r$ matrix:

$$U_1 = AV_1\Sigma_1^{-1}. \tag{1}$$

Then $U_1^*U_1 = I_{r \times r}$. Since A^*A and AA^* both have exactly r nonzero eigenvalues, it follows that the columns of U_1 form an orthonormal basis for $\text{Ra}(AA^*)$ and $\text{Ra}(A)$. Thus the properties of U_1 listed in 2 hold. Now define an $m \times (m - r)$ matrix U_2 with orthonormal columns which are orthogonal to columns of U_1 . Then $U = [U_1 : U_2]$ is clearly a unitary matrix. From the proof of the lemma, columns of U_2 form an orthonormal basis of $\text{Nu}(A^*)$ or $\text{Nu}(AA^*)$. Therefore, columns of U_2 are all the eigenvectors corresponding to the zero eigenvalue. Hence columns of U form a complete orthonormal basis of eigenvectors of AA^* . List 2 is then fully proven.

3. From the definition of U_1 in (1), we have:

$$A = U_1 \Sigma_1 V_1^*.$$

The dyadic expansion directly follows.

4. The singular value decomposition follows because:

$$A[V_1 : V_2] = [U_1 \Sigma_1 : 0] = [U_1 : U_2] \Sigma \Rightarrow A = U \Sigma V^*.$$

■

After we have gone through all the trouble proving this theorem, you must know that SVD has become a numerical routine available in many computational softwares such as MATLAB. Within MATLAB, to compute the SVD of a given $m \times n$ matrix A , simply use the command “[U, S, V] = $SVD(A)$ ” which returns matrices U, S, V satisfying $A = USV^*$ (where S represents Σ as defined above).