Linear Algebra Notes

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I — Vector Spaces

Definition 1.1: Let k be a field. A **vector space** over k is a set V equipped with two binary operations $+$ and $\cdot$ such that for all $u, v, w \in V$ and $c, d \in k$,

1. $u + v \in V$ and $cv \in V$.
2. $u + v = v + u$.
3. $u + (v + w) = (u + v) + w$ and $c(dv) = (cd)v$.
4. $c(u + v) = cu + cv$ and $(c + d)v = cv + dv$.
5. There is a vector $0 \in V$ that satisfies $v + 0 = v$ for all $v \in V$.
6. There is a vector $1 \in V$ that satisfies $1v = v$ for all $v \in V$.
7. For all $v \in V$, there is a vector $-v \in V$ such that $v + (-v) = 0$.

Proposition 1.2: The element 0 is unique.

Proof: Suppose there were two elements $0, 0'$ satisfying $v + 0 = v + 0' = v$ for all $v \in V$. Then $0 + 0' = 0$, but $0 + 0' = 0' + 0 = 0'$, so $0 = 0'$.

Proposition 1.3: For each $v \in V$, $-v$ is unique.

Proof: Suppose there were two elements $-v, (-v)'$ satisfying $v + (-v) = v + (-v)' = 0$. Then $-v = -v + (v + (-v)')$, so $-v = (-v)'$.

Proposition 1.4: For all $v \in V$, $0v = 0$ and $(-1)v = -v$.

Proof: We have

$$\begin{aligned} 0 &= 0v + (-0v) \\ &= (0+0)v + (-0v) \\ &= 0v + (0 + (-0))v \\ &= 0v \end{aligned}$$

and

$$\begin{aligned} (-1)v &= (-1)v + 0 \\ &= (-1)v + v + (-v) \\ &= (-1+1)v + (-v) \\ &= -v. \end{aligned}$$

Definition 1.5: Let V be a vector space. A **subspace** of V is a nonempty set $U \subseteq V$ such that

1. $u + v \in U$ for all $u, v \in U$.
2. $cu \in U$ for all $u \in U$ and $c \in k$.

Definition 1.6: Let V be a vector space and U and V subspaces of V. The sum of U and V is $U + W = \{u + w \mid u \in U, w \in W\}$. If each element of V can be expressed uniquely as an element of $U + W$, we say that $U + W$ is a **direct sum**, and we write $U \oplus W$.

Proposition 1.7: $U + W$ is a direct sum if and only if the only expression of 0 in $U + W$ is $0 + 0$.

Proof: ($\Rightarrow$) If $U + W$ is direct, then since $0 = 0 + 0$ is one expression of 0, it must be the only one.

($\Leftarrow$) Let $v \in U + W$ and suppose $v = u + w = u' + w'$ for some $u, u' \in U$ and $w, w' \in W$. Then $0 = v - v = (u + w) + (u' + w') = (u - u') + (w - w')$. Thus $u - u' = w - w' = 0$, so $u = u'$ and $w = w'$.

Proposition 1.8: $U + W$ is a direct sum if and only if $U \cap W = \{0\}$.

Proof: ($\Rightarrow$) Suppose $U + W$ is direct and let $v \in U \cap W$. Then $0 = v + (-v)$, so by the previous result, $v = -v = 0$.

($\Leftarrow$) Assume $U \cap W = \{0\}$ and suppose $u + w = 0$. Then $u = -w \in W$, so $u \in U \cap W$ and is therefore 0. Thus $u = w = 0$, so the previous proposition gives that $U + W$ is direct.

II — Bases and Dimension

Definition 2.1: Vectors $v_1, ..., v_n \in V$ are **linearly independent** if $c_1 v_1 + \cdots + c_n v_n = 0$ for $c_i \in k$ implies $c_1 = \cdots = c_n = 0$, and **linearly dependent** if not (i.e. $c_1 v_1 + \cdots + c_n v_n = 0$ for some $c_i \in k$ not all zero).

Definition 2.2: The **span** of $v_1, ..., v_n \in V$ is the set $\operatorname{span}\{v_1, ..., v_n\} = \{c_1 v_1 + \cdots + c_n v_n \mid c_i \in k\}$. A set of vectors $\{v_1, ..., v_n\} \subseteq V$ **spans** V if $\operatorname{span}\{v_1, ..., v_n\} = V$.

Proposition 2.3: Let $v_1, ..., v_n \in V$. Then $\operatorname{span}\{v_1, ..., v_n\}$ is a subspace of V.

Proof: First, $0 \in \operatorname{span}\{v_1, ..., v_n\}$, so the set is nonempty. Next, $(c_1 v_1 + \cdots + c_n v_n) + (d_1 v_1 + \cdots + d_n v_n) = (c_1 + d_1) v_1 + \cdots + (c_n + d_n) v_n \in \operatorname{span}\{v_1, ..., v_n\}$, so the set is closed under addition, and finally, $c(c_1 v_1 + \cdots + c_n v_n) = (cc_1) v_1 + \cdots + (cc_n) v_n \in \operatorname{span}\{v_1, ..., v_n\}$, so it is closed under scalar multiplication. Thus $\operatorname{span}\{v_1, ..., v_n\}$ is a subspace of V.

Definition 2.4: A **basis** for a vector space V is a set of vectors $\{v_1, ..., v_n\} \subseteq V$ that are linearly independent and span V.

Definition 2.5: A vector space is **finite-dimensional** if it has a finite basis.

Theorem 2.6: Let V be a finite-dimensional vector space. If $v_1, ..., v_k \in V$ are linearly independent, then they can be extended to form a basis for V.

Proof: Suppose $\operatorname{span}\{w_1, ..., w_n\} = V$. Then $\operatorname{span}\{v_1, ..., v_k, w_1, ..., w_n\} = V$, so if $v_1, ..., v_k, w_1, ..., w_n$ are linearly independent, $\{v_1, ..., v_k, w_1, ..., w_n\}$ is a basis. Otherwise, $c_1 v_1 + \cdots + c_k v_k + d_1 w_1 + \cdots + d_n w_n = 0$ for some $c_i, d_i \in k$. Not all the d_i can be zero, since then $v_1, ..., v_k$ would be linearly dependent, so there is a $d_j \neq 0$. Then $\operatorname{span}\{v_1, ..., v_k, w_1, ..., w_{j-1}, w_{j+1}, ..., w_n\} = \operatorname{span}\{v_1, ..., v_k, w_1, ..., w_n\}$, since we can create w_j from the other vectors. Continue removing w_i until the set is linearly independent (this will terminate, since at most we will have $v_1, ..., v_k$ once again).

Theorem 2.7: Every basis for a finite-dimensional vector space has the same number of elements.

Proof: Let $\{v_1, ..., v_n\}$ and $\{w_1, ..., w_m\}$ be bases for V. Then by definition, $v_1 = c_1 w_1 + \cdots + c_m w_m$ for some $c_i \in k$ not all zero. Without loss of generality, assume $c_1 \neq 0$. Then $w_1 = (-c_1)^{-1}(-v_1 + c_2 w_2 + \cdots + c_m w_m) \in \operatorname{span}\{v_1, w_2, ..., w_m\}$, so $\operatorname{span}\{v_1, w_2, ..., w_m\} = \operatorname{span}\{w_1, ..., w_m\} = V$. Repeat this process until we have $V = \operatorname{span}\{v_1, ..., v_n, w_{n+1}, ..., w_m\}$. If $n > m$, then $V = \operatorname{span}\{v_1, ..., v_m\}$, but then $v_1, ..., v_n$ are not linearly independent. Thus $n \leq m$, and repeating the proof by eliminating the v_i gives that $m \leq n$, so $n = m$.

Definition 2.8: Let V be a vector space. The **dimension** of V, denoted $\dim V$, is the number of elements in a basis for it.

Proposition 2.9: If $v_1, ..., v_n \in V$ are linearly independent and $\dim V = n$, then $\{v_1, ..., v_n\}$ is a basis for V.

Proof: Suppose not. Extend $\{v_1, ..., v_n\}$ to form a basis for V. But then that basis would have more than n elements. $\lightning$

Proposition 2.10: If $v_1, ..., v_n \in V$ span V and $\dim V = n$, then $\{v_1, ..., v_n\}$ is a basis for V.

III — Linear Maps

Definition 3.1: Let V and W be vector spaces. A **linear map** from V to W is a function $T : V \longrightarrow W$ such that

1. For all $u, v \in V$, $T(u + v) = Tu + Tv$.
2. For all $u \in V$ and $c \in k$, $T(cu) = cTu$.

We write Tu to mean $T(u)$. The set of all linear maps from V to W is denoted $\mathcal{L}(V, W)$.

Proposition 3.2: $\mathcal{L}(V, W)$ is a vector space under function addition and composition.

Proposition 3.3: Let $\{v_1, ..., v_n\}$ be a basis for V and let $w_1, ..., w_n \in W$. Then there is a unique linear map $T \in \mathcal{L}(V, W)$ such that $Tv_i = w_i$ for each i.

Proof: Such a T exists, since we can define it by $T(c_1v_1 + \cdots + c_nv_n) = c_1w_1 + \cdots + c_nw_n$, and it follows that every linear map S with $Sv_i = w_i$ is equal to T by the properties of linear maps.

Definition 3.4: Let $T \in \mathcal{L}(V, W)$. The **null space** of T is the set null $T = \{x \in V \mid Tx = 0\}$, and the **range** of T is the set range $T = \{Tv \mid v \in V\}$.

Proposition 3.5: Let $T \in \mathcal{L}(V, W)$. Then null T is a subspace of V and range T is a subspace of W.

Theorem 3.6: (The Fundamental Theorem of Linear Maps) Let $T \in \mathcal{L}(V, W)$. Then $\dim V = \dim \operatorname{null} T + \dim \operatorname{range} T$.

Proof: Let $\{v_1, ..., v_k\}$ be a basis for null T and extend it to $\{v_1, ..., v_n\}$ to form a basis for V. We claim that $\{Tv_{k+1}, ..., Tv_n\}$ is a basis for range T.

Suppose $c_{k+1}Tv_{k+1} + \cdots + c_nTv_n = 0$. Then $T(c_{k+1}v_{k+1} + \cdots + c_nv_n) = 0$, so $c_{k+1}v_{k+1} + \cdots + c_nv_n \in \operatorname{null} T$. Since $\{v_1, ..., v_k\}$ is a basis for null T, $c_{k+1}v_{k+1} + \cdots + c_nv_n = c_1v_1 + \cdots + c_kv_k$ for some $c_1, ..., c_k \in k$. Since $v_1, ..., v_n$ are linearly independent, $c_1 = \cdots = c_n = 0$, so in particular, $c_{k+1} = \cdots + c_n = 0$. Thus $Tv_{k+1}, ..., Tv_n$ are linearly independent.

Let $w \in \operatorname{range} T$. Then $T(c_1v_1 + \cdots + c_nv_n) = w$ for some $c_1, ..., c_n \in k$, and since $c_1v_1 + \cdots + c_kv_k \in \operatorname{null} T$, $T(c_1v_1 + \cdots + c_kv_k) = 0$, so $T(c_{k+1}v_{k+1} + \cdots + c_nv_n) = w$. Then $w = c_{k+1}Tv_{k+1} + \cdots + c_nTv_n$, so $w \in \operatorname{span}\{Tv_{k+1}, ..., Tv_n\}$. Thus $Tv_{k+1}, ..., Tv_n$ span range T.

Thus $\{Tv_{k+1}, ..., Tv_n\}$ is a basis for range T, so in particular, $\dim \operatorname{range} T = n - k$ and $\dim V = n = \dim \operatorname{null} T + \dim \operatorname{range} T = k + (n - k)$.

Proposition 3.7: A linear map $T \in \mathcal{L}(V, W)$ is injective if and only if null $T = \{0\}$.

Proof: ($\Rightarrow$) Let $x \in \operatorname{null} T$. Then $Tx = T0 = 0$, so $x = 0$, since T is injective.

($\Leftarrow$) Suppose $Tu = Tv$ for $u, v \in V$. Then $T(u - v) = 0$, so $u - v = 0$, since null $T = \{0\}$. Thus T is injective.

Proposition 3.8: Let $T \in \mathcal{L}(V, W)$. If $\dim V > \dim W$, then null $T \neq 0$.

Proof: $\dim \operatorname{null} T = \dim V - \dim \operatorname{range} T \geq \dim V - \dim W > 0$.

Definition 3.9: Let $T \in \mathcal{L}(V, W)$. An **inverse linear map** to T is a $T^{-1} \in \mathcal{L}(V, W)$ such that $T^{-1}T = I_V$ and $TT^{-1} = I_W$. If such a T^{-1} exists, we call T **invertible**.

Proposition 3.10: Let $T \in \mathcal{L}(V, W)$. Then T^{-1} is unique.

Proof: Suppose T_1^{-1} and T_2^{-1} are both inverses to T. Then $T_1^{-1} = T_1^{-1}TT_2^{-1} = T_2^{-1}$.

Definition 3.11: An **isomorphism** from V to W is an invertible linear map $T \in \mathcal{L}(V, W)$. V and W are **isomorphic**, denoted $V \simeq W$, if there is an isomorphism from V to W.

Proposition 3.12: If $\dim V = \dim W$, then $V \simeq W$.

Proof: Let $\{v_1, ..., v_n\}$ and $\{w_1, ..., w_n\}$ be bases for V and W and define $T \in \mathcal{L}(V, W)$ by $Tv_i = w_i$. Then T is injective and surjective, so it is an isomorphism.

Definition 3.13: Let $\{v_1, ..., v_n\}$ and $\{w_1, ..., w_m\}$ be bases for V and W and let $T \in \mathcal{L}(V, W)$. The **matrix** of T with respect to the chosen bases is the $m \times n$ rectangle of numbers

$$M(T) = \begin{bmatrix} | & & | \\ Tv_1 & \cdots & Tv_n \\ | & & | \end{bmatrix} = \begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mn} \end{bmatrix}$$

where $Tv_i = c_{1i}w_1 + \cdots + c_{mi}w_m$. Notice that if $v = c_1v_1 + \cdots + c_nv_n$, then

$$M(T)\begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} = \begin{bmatrix} | & & | \\ Tv_1 & \cdots & Tv_n \\ | & & | \end{bmatrix}\begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} = c_1Tv_1 + \cdots + c_nTv_n = Tv.$$

Definition 3.14: Let $A \in M_{m,n}(k)$ and $v_1, ..., v_k \in k^n$. We define **matrix multiplication** by

$$A\begin{bmatrix} | & & | \\ v_1 & \cdots & v_k \\ | & & | \end{bmatrix} = \begin{bmatrix} | & & | \\ Av_1 & \cdots & Av_n \\ | & & | \end{bmatrix}.$$

Notice that if $T \in \mathcal{L}(V, W)$ and $S \in \mathcal{L}(W, U)$, then $M(S)M(T) = M(ST)$.

Theorem 3.15: Let V and W be vector spaces. Then $\dim \mathcal{L}(V, W) = (\dim V)(\dim W)$.

Proof: Let $\{v_1, ..., v_n\}$ and $\{w_1, ..., w_m\}$ be bases for V and W. We claim that $\mathcal{L}(V, W) \simeq M_{n,m}(k)$. Define $M : \mathcal{L}(V, W) \longrightarrow M_{n,m}(k)$ by sending a linear map to its matrix.

($\hookrightarrow$) Suppose $M(T) = M(S)$. Then the columns of each are equal, so $Tv_i = Sv_i$ for all i. Thus $T = S$, so M is injective.

($\twoheadrightarrow$) Let $A \in M_{n,m}(k)$ and define $T \in \mathcal{L}(V, W)$ by $Tv_i = c_1w_1 + \cdots + c_mw_m$, where the c_j form the ith column of A. Then $M(T) = A$, so M is surjective.

Definition 3.16: Let V be a vector space. The **dual space** to V is the vector space $V' = \mathcal{L}(V, k)$. By the previous theorem, $\dim V' = \dim V$.

Definition 3.17: Let $\{v_1, ..., v_n\}$ be a basis for V. The dual basis to $\{v_1, ..., v_n\}$ is $\{\varphi_{v_1}, ..., \varphi_{v_n}\}$, where

$$\varphi_{v_i}(v_j) = \begin{cases} 1, & j = i \\ 0, & j \neq i \end{cases}.$$

Proposition 3.18: Let $\{v_1, ..., v_n\}$ be a basis for V. Then $\{\varphi_{v_1}, ..., \varphi_{v_n}\}$ is a basis for V'.

Definition 3.19: Let $T \in \mathcal{L}(V, W)$. The dual map $T' \in \mathcal{L}(W', V')$ is defined by $T'\varphi = \varphi T$.

Theorem 3.20: Let $T \in \mathcal{L}(V, W)$. Then $M(T') = M(T)^{\mathrm{T}}$.

Proof: $M(T')_{ij}$ is the coefficient of φ_{v_i} in $T'\varphi_{w_j} = \varphi_{w_j}T$. If $\varphi_{w_j}T = c_1\varphi_{v_1} + \cdots + c_n\varphi_{v_n}$, then $M(T')_{ij} = c_i$. But by the definition of φ_{w_j}, $\varphi_{w_j}Tv_i$ is the coefficient of w_j in the expression of Tv_i, which is the definition of $M(T)_{ji}$. Thus $M(T)_{ji} = M(T')_{ij}$, so $M(T') = M(T)^{\mathrm{T}}$.

Definition 3.21: Let $U \subseteq V$ (not necessarily a subspace). The **annihilator** of U is the set $U^0 = \{\varphi \in V' \mid \varphi u = 0 \text{ for all } u \in U\}$.

Proposition 3.22: Let U be a subspace of V. Then $\dim V = \dim U + \dim U^0$.

Proof: Let $\{v_1, ..., v_k\}$ be a basis for U and extend it to $\{v_1, ..., v_n\}$ to form a basis for V. Then $\{\varphi_{v_1}, ..., \varphi_{v_n}\}$ is a basis for V', so $\varphi_{v_{k+1}}, ..., \varphi_{v_n}$ are linearly independent. Since $\operatorname{span}\{\varphi_{v_{k+1}}, ..., \varphi_{v_n}\} = U^0$, $\dim U^0 = n - k$, so $\dim V = n = \dim U + \dim U^0 = k + (n - k)$.

Proposition 3.23: Let $T \in \mathcal{L}(V, W)$. Then $\operatorname{null} T' = (\operatorname{range} T)^0$.

Proof: We have $\varphi \in \operatorname{null} T'$ if and only if $T'\varphi = 0$, if and only if $\varphi T = 0$, if and only if $\varphi T v = 0$ for all $v \in V$, if and only if $\varphi w = 0$ for all $w \in \operatorname{range} T$, if and only if $\varphi \in (\operatorname{range} T)^0$.

Proposition 3.24: Let $T \in \mathcal{L}(V, W)$. Then $\operatorname{range} T' = (\operatorname{null} T)^0$.

Proposition 3.25: Let $T \in \mathcal{L}(V, W)$. Then T' is injective if and only if T is surjective.

Proof: T' is injective if and only if null $T' = \{0\}$, if and only if $(\text{range } T)^0 = \{0\}$, if and only if $\dim\,(\text{range } T)^0 = 0$, if and only if $\dim \text{range } T = \dim W$, if and only if range $T = W$.

Corollary 3.25.1: Let $T \in \mathcal{L}(V, W)$. Then $\dim \text{range } T' = \dim \text{range } T$.

IV — Eigenvalues and Eigenvectors

Definition 4.1: An **eigenvalue** of a linear map $T \in \mathcal{L}(V) = \mathcal{L}(V, V)$ is an element $\lambda \in k$ such that $Tv = \lambda v$ for some nonzero $v \in V$. This v is called the **eigenvector** corresponding to λ.

Proposition 4.2: Let $T \in \mathcal{L}(V)$ and $\lambda \in k$. Then λ is an eigenvalue of T if and only if $T - \lambda I$ is not invertible.

Proof: We have that λ is an eigenvalue of T if and only if $Tv = \lambda v$ for some $v \neq 0$, if and only if $(T - \lambda I)v = 0$ for some $v \neq 0$, if and only if null $(T - \lambda I) \neq \{0\}$, if and only if $T - \lambda I$ is not invertible.

Theorem 4.3: If $\lambda_1, ..., \lambda_k$ are distinct eigenvalues of T, then the corresponding eigenvectors $v_1, ..., v_k$ are linearly independent.

Proof: Suppose not. Then there is a minimum j for which $v_1, ..., v_j$ are linearly dependent, so $v_j = c_1 v_1 + \cdots + c_{j-1} v_{j-1}$ for some $c_1, ..., c_{j-1} \in k$. Then

$$\lambda_j v_j = \lambda_j (c_1 v_1 + \cdots + c_{j-1} v_{j-1}) = c_1 \lambda_j v_1 + \cdots + c_{j-1} \lambda_j v_{j-1}.$$

But we also have

$$\lambda_j v_j = T v_j = T(c_1 v_1 + \cdots + c_{j-1} v_{j-1}) = c_1 \lambda_1 v_1 + \cdots + c_{j-1} \lambda_{j-1} v_{j-1},$$

so

$$c_1(\lambda_1 - \lambda_j) v_1 + \cdots + c_1(\lambda_{j-1} - \lambda_j) v_{j-1} = 0.$$

Since j was minimal, $v_1, ..., v_{j_1}$ are linearly independent, so $c_i(\lambda_i - \lambda_j) = 0$ for all $i \in \{1, ..., j-1\}$. Not every $c_i = 0$, since then $v_j = 0$, so some $c_i \neq 0$, and therefore $\lambda_i = \lambda_j$. But then the eigenvalues are not distinct. $\lightning$

Definition 4.4: A linear map $T \in \mathcal{L}(V)$ is **diagonalizable** if there is a basis of eigenvectors of T for V — that is, a basis such that

$$M(T) = \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_n \end{bmatrix}.$$

Proposition 4.5: If $\dim V = n$ and $T \in \mathcal{L}(V)$ has n distinct eigenvalues, then T is diagonalizable.

Definition 4.6: A matrix $A \in M_n(k)$ is **upper triangular** if it has the form

$$A = \begin{bmatrix} * & * & \cdots & * & * \\ 0 & * & \cdots & * & * \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & * & * \\ 0 & 0 & \cdots & 0 & * \end{bmatrix},$$

where the $*$ are elements of k.

Definition 4.7: Let $T \in \mathcal{L}(V)$. A subspace U of V is **T-invariant** if $Tu \in U$ for all $u \in U$.

Theorem 4.8: Let V be a vector space over an algebraically closed field k with $\dim V = n$ and let $T \in \mathcal{L}(V)$. Then there is a basis for V such that $M(T)$ is upper triangular.

Proof: We will proceed by induction. The base case is trivial, since every 1×1 matrix is upper triangular.

Assume that every linear map in $\mathcal{L}(V)$ has such a basis if $\dim V < n$. Let $T \in \mathcal{L}(V)$ and let λ be an eigenvalue of T (This exists, since we can choose any basis for V and perform elementary row operations on $M(T)$ to eliminate every element of a non-leading-zero column below the top one). Let U = range $(T - \lambda I)$. Then U is T-invariant, since $T(Tv - \lambda v) = T(Tv) - \lambda(Tv) \in U$, so $T|_U \in \mathcal{L}(U)$. Since the eigenvector corresponding to λ is an element of null $(T - \lambda I)$, $U \neq V$. Thus $\dim U < \dim V$, so by assumption, there is a basis $\{u_1, ..., u_k\}$ for U such that $M(T|_U)$ is upper triangular. Extend this to $\{u_1, ..., u_k, v_1, ..., v_j\}$ to form a basis for V. Then $Tv_i = Tv_i - \lambda v_i + \lambda v_i = c_1 u_1 + \cdots + c_k u_k + \lambda v_i$ for some $c_1, ..., c_k \in k$, and so

$$M(T) = \begin{bmatrix} T & * \\ 0 & \lambda I \end{bmatrix},$$

where T is a $k \times k$ upper triangular matrix, $*$ is unspecified, 0 is the zero matrix, and λI is a $j \times j$ diagonal matrix. Thus $M(T)$ is upper triangular.

Theorem 4.9: If $M(T)$ is upper triangular with respect to the basis $v_1, ..., v_n$ and has diagonal entries $\lambda_1, ..., \lambda_n$, then T is invertible if and only if no $\lambda_i = 0$.

Proof: (⇒) Assume T^{-1} exists and suppose some $\lambda_i = 0$. Let $U = \text{span}\{v_1, ..., v_i\}$. Then U is T-invariant, but $T|_U$ is not surjective, so it is not invertible, and therefore neither is T. ↯

(⇐) It is enough to show that null $T = \{0\}$, so suppose $T(c_1v_1 + \cdots + c_nv_n) = 0$. Then $c_1Tv_1 + \cdots + c_nTv_n = 0$. Since $Tv_i \in \text{span}\{v_1, ..., v_i\}$, $c_n = 0$, since $v_n appears only in Tv_n$ and $\lambda_n \neq 0$. Similarly, $c_1 = \cdots = c_{n-1} = 0$. Thus null $T = \{0\}$.

Theorem 4.10: If $M(T)$ is upper triangular with diagonal entries $\lambda_1, ..., \lambda_n$, then T has eigenvalues $\lambda_1, ..., \lambda_n$.

Proof: If λ is an eigenvalue of T, then $T - \lambda I$ is not invertible. Then $\lambda_i - \lambda = 0$ for some i, since

$$M(T - \lambda I) = \begin{bmatrix} \lambda_1 - \lambda & * & \cdots & * \\ 0 & \lambda_2 - \lambda & \cdots & * \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n - \lambda \end{bmatrix}.$$

Repeat for all i.

V — Inner Product Spaces

Definition 5.1: Let V be a vector space over $k = \mathbb{R}$ or $\mathbb{C}$. An **inner product** on V is a function $\langle \cdot, \cdot \rangle : V \times V \longrightarrow \mathbb{C}$ such that

1. $\langle v, v \rangle \in \mathbb{R}^+$ for all nonzero $v \in V$ and $\langle v, v \rangle = 0$ if and only if $v = 0$.
2. $\langle cu + v, w \rangle = c\langle u, w \rangle + \langle v, w \rangle$ for all $u, v, w \in V$ and $c \in k$.
3. $\langle u, v \rangle = \overline{\langle v, u \rangle}$ for all $u, v \in V$.

An **inner product space** is a vector space equipped with an inner product.

Definition 5.2: The **norm** of an element $v \in V$ is $||v|| = \sqrt{\langle v, v \rangle}$.

Definition 5.3: The **distance** between two vectors $u, v \in V$ is $||u - v||$.

Proposition 5.4: For all $v \in V$ and $c \in k$, $||cv|| = |c| \cdot ||v||$.

Proof: Since $||cv||^2 = \langle cv, cv\rangle = c\overline{c}\langle v, v\rangle = |c|^2||v||^2$, $||cv|| = |c| \cdot ||v||$.

Definition 5.5: Two vectors $u, v \in V$ are **orthogonal** if $\langle u, v\rangle = 0$.

Proposition 5.6: (The Pythagorean Theorem) Let $u, v \in V$ be orthogonal. Then $||u + v||^2 = ||u||^2 + ||v||^2$.

Proof: We have $||u+v||^2 = \langle u+v, u+v\rangle = \langle u, u\rangle + \langle u, v\rangle + \langle v, u\rangle + \langle v, v\rangle = \langle u, u\rangle + \langle v, v\rangle = ||u||^2 + ||v||^2$.

Proposition 5.7: (The Cauchy-Schwarz Inequality) For all $u, v \in V$, $||u|| \cdot ||v|| \geq |\langle u, v\rangle|$.

Proof: Let $c = \frac{\langle u,v\rangle}{\langle v,v\rangle}$. Then $||u||^2||v||^2 = ||u - cv + cv||^2||v||^2$, and since $u - cv$ is orthogonal to cv, $||u||^2||v||^2 = \left(||u - cv||^2 + ||cv||^2\right)||v||^2 \geq ||cv||^2||v||^2 = |c|^2||v||^4 = |\langle u, v\rangle|^2$.

Proposition 5.8: For all $u, v \in V$, $||u|| + ||v|| \geq ||u + v||$.

Lemma 5.8.1: For all $z \in \mathbb{C}$, $2|z| \geq z + \overline{z}$.

Proof: If $z = a + bi$, then $2|z| = 2|a + bi| = 2\sqrt{a^2 + b^2} \geq 2\sqrt{a^2} = 2a = z + \overline{z}$.

Proof: We have $(||u|| + ||v||)^2 = ||u||^2 + 2||u|| \cdot ||v|| + ||v||^2 \geq ||u||^2 + 2|\langle u, v\rangle| + ||v||^2 \geq ||u||^2 + \langle u, v\rangle + \overline{\langle u, v\rangle} + ||v||^2 = \langle u, u\rangle + \langle u, v\rangle + \langle v, u\rangle + \langle v, v\rangle = \langle u + v, u + v\rangle = ||u + v||^2$.

Definition 5.9: Vectors $e_1, ..., e_k \in V$ are **orthonormal** if $||e_i|| = 1$ for all i and $\langle e_i, e_j\rangle = 0$ for all $i \neq j$.

Proposition 5.10: If $e_1, ..., e_k \in V$ are orthonormal, then $||c_1e_1 + \cdots + c_ke_k||^2 = |c_1|^2 + \cdots + |c_k|^2$.

Proof: We will induct upon k. The base case is obvious, since $||c_1e_1||^2 = |c_1|^2||e_1||^2 = |c_1|^2$. For the induction step, assume $||c_1e_1 + \cdots |c_ke_k||^2 = |c_1|^2 + \cdots + |c_k|^2$. Since $c_1e_1 + \cdots + c_ke_k$ and $c_{k+1}e_{k+1}$ are orthogonal, $||c_1e_1 + \cdots + c_{k+1}e_{k+1}||^2 = ||c_1e_1 + \cdots + c_ke_k||^2 + ||c_{k+1}e_{k+1}||^2 = |c_1|^2 + \cdots + |c_k|^2 + |c_{k+1}|^2$.

Proposition 5.11: Orthonormal vectors are linearly independent.

Proof: Suppose $e_1, ..., e_k \in V$ are orthonormal and $c_1e_1 + \cdots + c_ke_k = 0$. Then $||c_1e_1 + \cdots + c_ke_k||^2 = |c_1|^2 + \cdots + |c_k|^2 = 0$, so $c_1 = \cdots = c_k = 0$.

Proposition 5.12: Let $\{e_1, ..., e_n\}$ be an orthonormal basis for V and let $v \in V$. Then $v = \langle v, e_1\rangle e_1 + \cdots + \langle v, e_n\rangle e_n$.

Proof: If $v = c_1e_1 + \cdots + c_ne_n$, then $\langle v, e_i\rangle = \langle c_1e_1 + \cdots + c_ne_n, e_i\rangle = \langle c_ie_i, e_i\rangle = c_i$.

Theorem 5.13: (The Gram-Schmidt Process) Every finite-dimensional inner product space has an orthonormal basis.

Proof: Let $\{v_1, ..., v_n\}$ be a basis for V. Let $e_1' = v_1$ and $e_1 = \frac{e_1'}{||e_1'||}$. Then for each $i \in \{2, ..., n\}$, let

$$e_i' = v_i - (\langle v_1, e_1\rangle e_1 + \cdots + \langle v_{i-1}, e_{i-1}\rangle e_{i-1})$$

and $e_i = \frac{e_i'}{||e_i'||}$. Then $\{e_1, ..., e_n\}$ is an orthonormal basis for V.

Theorem 5.14: (Riesz Representation) Let $\varphi_u \in V'$ be defined by $\varphi_u v = \langle v, u\rangle$. Then for each $T \in V'$, there is a unique $u \in V$ such that $T = \varphi_u$.

Proof: Let $\{e_1, ..., e_n\}$ be an orthonormal basis for V and let $u = \overline{Te_1}e_1 + \cdots + \overline{Te_n}e_n$. Then if $v = c_1e_1 + \cdots + c_ne_n$,

$$\begin{aligned}
\varphi_u v &= \langle v, u\rangle \\
&= \langle c_1e_1 + \cdots + c_ne_n, \overline{Te_1}e_1 + \cdots + \overline{Te_n}e_n\rangle \\
&= c_1Te_1 + \cdots + c_nTe_n \\
&= T(c_1e_1 + \cdots + c_ne_n) \\
&= Tv.
\end{aligned}$$

Definition 5.15: Let $U \subseteq V$. The **orthogonal complement** to U is the set $U^\perp = \{v \in V \mid \langle u, v\rangle = 0 \text{ for all } u \in U\}$.

Proposition 5.16: If U is a subspace of V, then so is $U^\perp$.

Theorem 5.17: If U is a finite-dimensional subspace of V, then $V = U \oplus U^\perp$.

Proof: Let $\{e_1, ..., e_n\}$ be an orthonormal basis for U, let $v \in V$, and let $u = c_1e_1 + \cdots + c_ne_n \in U$. Then $v = u + (v-u)$. If $v - u \in U^\perp$, this will be an expression of v in $U + U^\perp$. For $v - u$ to be in $U^\perp$, $\langle v-u, e_i\rangle = 0$ for all i, so $c_i = \langle u, e_i\rangle = \langle v, e_i\rangle$ for all i. Thus u is completely determined by v, so the expression of v as $u + (v-u)$ is unique. Thus $V = U \oplus U^\perp$.

Corollary 5.17.1: If U is a finite-dimensional subspace of V, then $\dim V = \dim U + \dim U^\perp$.

Proposition 5.18: Let $U \subseteq V$. Then $(U^\perp)^\perp = U$.

Proof: Let $u \in U$ and $v \in U^\perp$. Then $\langle u, v\rangle = 0$ by definition, so $u \in (U^\perp)^\perp$. Thus $U \subseteq (U^\perp)^\perp$. Also, $\dim U + \dim U^\perp = \dim V = \dim U^\perp + \dim(U^\perp)^\perp$, so $\dim U = \dim(U^\perp)^\perp$. Thus $U = (U^\perp)^\perp$.

Definition 5.19: The **projection** of V onto a subspace U is the linear map $P_U \in \mathcal{L}(V, U)$ given by $P_U v = u$, where $v = u + u' \in U \oplus U^\perp$.

Proposition 5.20: Let U be a subspace of a vector space V with $\dim U = k$ and $\dim V = n$, and let $\{u_1, ..., u_k, u'_{k+1}, ..., u'_n\}$ be a basis for V composed of bases for U and $U^\perp$. Then

$$M(P_U) = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 \end{bmatrix}.$$

Theorem 5.21: Let V be a vector space and U a subspace. Then for all $v \in V$ and $u \in U$, $\|v - P_U v\| \leq \|v - u\|$; that is, the closest vector to v in U is $P_U v$.

Proof: Since $v - P_U v \notin U$, $v - P_U v \in U^\perp$, so $v - P_U v$ and $P_U v - u$ are orthogonal. Then $\|v-u\|^2 = \|v - P_U v + P_U v - u\|^2 = \|v - P_U v\|^2 + \|P_U v - u\|^2 \geq \|v - P_U v\|^2$.

VI — Linear Maps and Inner Products

Definition 6.1: Let $T \in \mathcal{L}(V, W)$. The **adjoint** of T is the linear map $T^* \in \mathcal{L}(W, V)$ such that $\langle Tv, w\rangle_W = \langle v, T^*w\rangle_V$ for all $v \in V$ and $w \in W$.

Proposition 6.2: Let $T \in \mathcal{L}(U, V)$, $S \in \mathcal{L}(V, W)$, and $c \in k$. Then

1. $(cT + S)^* = \overline{c}T^* + S^*$.
2. $(T^*)^* = T$.
3. $I^* = I$.
4. $(ST)^* = T^*S^*$.

Theorem 6.3: Let $\{e_1, ..., e_n\}$ and $\{f_1, ..., f_m\}$ be orthonormal bases for V and W and let $T \in \mathcal{L}(V, W)$. Then $M(T^*) = \overline{M(T)}^{\mathrm{T}}$.

Proof: The jth column of $M(T^*)$ is T^*f_j expressed in the basis $\{e_1, ..., e_n\}$. Since this is orthonormal, $T^*f_j = \langle T^*f_j, e_1\rangle e_1 + \cdots + \langle T^*f_j, e_n\rangle e_n$, so $M(T^*)_{ij} = \langle T^*f_j, e_i$. But $M(T)_{ji} = \langle Te_i, f_j\rangle = \langle e_i, T^*f_j\rangle = \overline{\langle T^*f_j, e_i\rangle} = \overline{M(T^*)_{ij}}$, so $M(T^*) = \overline{M(T)}^{\mathrm{T}}$.

Definition 6.4: A linear map $T \in \mathcal{L}(V)$ is **self-adjoint** if $T^* = T$.

Proposition 6.5: Let $T \in \mathcal{L}(V)$ be self-adjoint. Then if $\langle Tv, v\rangle = 0$ for all $v \in V$, $T = 0$.

Definition 6.6: A linear map $T \in \mathcal{L}(V)$ is **normal** if $T^*T = TT^*$.

Proposition 6.7: A linear map $T \in \mathcal{L}(V)$ is **normal** if and only for all $v \in V$, $\|Tv\| = \|T^*v\|$.

Proof: ($\Rightarrow$) If T is normal, then $\langle Tv, Tv\rangle = \langle v, T^*Tv\rangle = \langle v, TT^*v\rangle = \langle T^*v, T^*v\rangle$.

($\Leftarrow$) Suppose $\langle Tv, Tv\rangle = \langle T^*v, T^*v\rangle$ for all $v \in V$. Then $\langle TT^*v - T^*Tv, v\rangle = 0$ for all $v \in V$, so $TT^* - T^*T = 0$.

Proposition 6.8: If T is normal and $Tv = \lambda v$ for some $v \neq 0$, then $T^*v = \overline{\lambda}v$.

Proof: $(T-\lambda I)^*(T-\lambda I)$ is normal, since $(T-\lambda I)^*(T-\lambda I) = T^*T - \overline{\lambda}IT - \lambda IT + \lambda\overline{\lambda}I = (T-\lambda I)(T-\lambda I)^*$. Then $0 = \|(T-\lambda I)v\| = \|(T-\lambda I)^*v\| = \|(T^*-\overline{\lambda})v\|$, so $T^*v = \overline{\lambda}v$.

Proposition 6.9: Let $T \in \mathcal{L}(V)$ be normal. If v and w are eigenvectors of T with distinct eigenvalues λ_1 and λ_2, then v and w are orthogonal.

Proof: Since $\lambda_1 \neq \lambda_2$, $\lambda_1 - \lambda_2 \neq 0$. Then $(\lambda_1-\lambda_2)\langle v,w\rangle = \langle \lambda_1 v - \lambda_2 v, w\rangle = \langle Tv,w\rangle - \langle v, \overline{\lambda_2}w\rangle = \langle Tv,w\rangle - \langle v, T^*w\rangle = \langle Tv,w\rangle - \langle Tv,w\rangle = 0$, so $\langle v,w\rangle = 0$.

Theorem 6.10: (Complex Spectral) Let V be a finite-dimensional vector space over $\mathbb{C}$ and let $T \in \mathcal{L}(V)$. Then T is normal if and only if there is an orthonormal basis of eigenvectors of T for V.

Proof: ($\Rightarrow$) We will induct on $n = \dim V$. The base case is trivial, since if $\dim V = 1$ and $T \in \mathcal{L}(V)$, then any nonzero unit vector in V constitutes an orthonormal basis of eigenvectors of T.

Suppose the theorem holds for $n-1$-dimensional vector spaces and let $T \in \mathcal{L}(V)$ be normal with $\dim V = n$. Let $\{e_1, \ldots, e_n\}$ be an orthonormal basis for V such that $M(T)$ is upper triangular (this is possible, since the Gram-Schmidt process preserves upper triangularity). Then we have

$$M(T) = \begin{bmatrix} \lambda_1 & *_{1,2} & \cdots & *_{1,n} \\ 0 & \lambda_2 & \cdots & *_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix},$$

where $*_i$ is the vector of the first $i-1$ entries in column i of $M(T)$. Consider the first column of $M(T)$ and $M(T^*) = \overline{M(T)}^{\mathrm{T}}$. We have $Te_1 = \lambda_1 e_1$ and $T^*e_1 = \overline{\lambda_1}e_1 + \overline{*_{1,2}}e_2 + \cdots + \overline{*_{1,n}}e_n$, but T is normal, so $\|Te_1\| = \|T^*e_1\|$. Thus $|\lambda_1|^2 = |\overline{\lambda_1}|^2 + |*_{1,2}|^2 + \cdots + |*_{1,n}|^2$, so $|*_{1,2}|^2 + \cdots + |*_{1,n}|^2 = 0$, and therefore $*_{1,2} = \cdots + *_{1,n} = 0$. Thus the first row and column of $M(T)$ are zero, except for λ_1, and similarly for $M(T^*)$. By restricting T to $\operatorname{span}\{e_2, \ldots, e_n\}$, which has dimension $n-1$, we are done by induction.

($\Leftarrow$) If $\{e_1, \ldots, e_n\}$is an orthonormal basis of eigenvectors of T, then

$$M(T)M(T^*) = \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_n \end{bmatrix}\begin{bmatrix} \overline{\lambda_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \overline{\lambda_n} \end{bmatrix} = \begin{bmatrix} \overline{\lambda_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \overline{\lambda_n} \end{bmatrix}\begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_n \end{bmatrix} = M(T^*)M(T),$$

so T is normal.

Theorem 6.11: (Real Spectral) Let V be a finite-dimensional vector space over $\mathbb{R}$ and let $T \in \mathcal{L}(V)$. Then T is self-adjoint if and only if there is an orthonormal basis of eigenvectors of T with real eigenvalues.

Proof: By the Complex Spectral Theorem, there is an orthonormal basis for V of eigenvectors of T. Since T is self-adjoint, $M(T) = M(T^*) = \overline{M(T)}^{\mathrm{T}} = \overline{M(T)}$. Thus each $\lambda_i = \overline{\lambda_i}$, so all of T's eigenvalues are real.

Definition 6.12: A linear map $T \in \mathcal{L}(V)$ is **positive** if T is self-adjoint and $\langle Tv, v\rangle \geq 0$ for all $v \in V$.

Proposition 6.13: Let $T \in \mathcal{L}(V)$ be self-adjoint. Then T is positive if and only if every eigenvalue of T is nonnegative.

Proof: Let $\{e_1, ..., e_n\}$ be an orthonormal basis for V of eigenvectors of T with eigenvectors $\lambda_1, ..., \lambda_n$. Then T is positive if and only if $\langle T(c_1e_1 + \cdots + c_ne_n), c_1e_1 + \cdots + c_ne_n\rangle \geq 0$ for all $c_1, ..., c_n \in k$, if and only if $\langle c_1\lambda_1e_1 + \cdots + c_n\lambda_ne_n, c_1e_1 + \cdots + c_ne_n\rangle \geq 0$ for all $c_1, ..., c_n \in k$, if and only if $|c_1|^2\lambda_1 + \cdots |c_n|^2\lambda_n \geq 0$ for all $c_1, ..., c_n \in k$, if and only if each $\lambda_i \geq 0$ (for each i, choose $c_i = 1$ and $c_j = 0$ for $j \neq i$).

Definition 6.14: Let $T \in \mathcal{L}(V)$. A **square root** of T is a linear map $R \in \mathcal{L}(V)$ such that $R^2 = T$.

Theorem 6.15: Let $T \in \mathcal{L}(V)$ be positive. Then there is a unique positive square root of T.

Proof: We will only show existence — the proof of uniqueness is difficult, tedious, and unenlightening. Let $\{e_1, ..., e_n\}$ be an orthonormal basis for V of eigenvectors of T with eigenvectors $\lambda_1, ..., \lambda_n$. Then each $\lambda_i \geq 0$, so the map $R \in \mathcal{L}(V)$ defined by $Re_i = \sqrt{\lambda_i}e_i$ is positive, and clearly $R^2 = T$. Thus T has a positive square root.

Definition 6.16: Let $T \in \mathcal{L}(V)$ be positive. The unique positive square root of T is denoted $\sqrt{T}$.

Definition 6.17: A linear map $T \in \mathcal{L}(V)$ is an **isometry** if $||Tv|| = ||v||$ for all $v \in V$.

Proposition 6.18: A linear map $T \in \mathcal{L}(V)$ is an isometry if and only if $T^*T = I$.

Proof: T is an isometry if and only if $\langle Tv, Tv\rangle = \langle v, v\rangle$ for all $v \in V$, if and only if $\langle T^*Tv, v\rangle - \langle Iv, v\rangle = 0$ for all $v \in V$, if and only if $T^*T - I = 0$, since $T^*T - I$ is self-adjoint.

Theorem 6.19: A linear map $T \in \mathcal{L}(V)$ is an isometry if and only if there is an orthonormal basis of eigenvectors of T with eigenvalues $\lambda_1, ..., \lambda_n$ such that $|\lambda_i| = 1$.

Proof: ($\Rightarrow$) If T is an isometry, then it is normal, so there is an orthonormal basis of eigenvectors $\{e_1, ..., e_n\}$ with eigenvalues $\lambda_1, ..., \lambda_n$ by the Complex Spectral Theorem. Then $|\lambda_i| = \|\lambda_i e_i\| = \|Te_i\| = \|e_i\| = 1$.

($\Leftarrow$) Let $v = c_1e_1 + \cdots + c_ne_n \in V$. Then $\|Tv\| = \|c_1\lambda_1e_1 + \cdots + c_n\lambda_ne_n\| = \|c_1e_1 + \cdots + c_ne_n\| = \|v\|$, so T is an isometry.

Theorem 6.20: (Polar Decomposition) Let $T \in \mathcal{L}(V)$. Then there is an isometry $S \in \mathcal{L}(V)$ such that $T = S\sqrt{T^*T}$.

Proof: Let $\{e_1, ..., e_n\}$ be an orthonormal basis of eigenvectors of $T * T$ with eigenvalues $\lambda_1, ..., \lambda_n$ and suppose without loss of generality that $\lambda_1 = \cdots = \lambda_k = 0$. Let $\{f_1, ..., f_k\}$ be an orthonormal basis for $(\text{range } T)^\perp$ (the dimension is k since $\dim \text{range } T = \dim \text{null } T^*$). Then define S by

$$Se_i = \begin{cases} f_i, & i \leq k \\ \frac{1}{\sqrt{\lambda_i}}Te_i, & i > k \end{cases}.$$

It follows that S is an isometry and $T = S\sqrt{T^*T}$.

Definition 6.21: The **singular values** of a linear map $T \in \mathcal{L}(V, W)$ are $\sigma_1, ..., \sigma_k$, where $\sigma_i = \sqrt{\lambda_i}$ and $\lambda_1, ..., \lambda_k$ are the nonzero eigenvalues of T^*T.

Theorem 6.22: (Singular Value Decomposition) Let V and W be vector spaces with $\dim V = n$ and $\dim W = m$. Let $\{e_1, ..., e_n\}$ be an orthonormal basis of eigenvectors of T^*T with eigenvalues $\lambda_1 \geq \cdots \geq \lambda_k > 0 = \lambda_{k+1} = \cdots = \lambda_n$. Then there is an orthonormal basis $\{f_1, ..., f_m\}$ for W such that

$$Tv = \sigma_1\langle v, e_1\rangle f_1 + \cdots + \sigma_k\langle v, e_k\rangle f_k,$$

or equivalently,

$$M(T) = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_k & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \end{bmatrix}.$$

Proof: Let $f_i = \frac{1}{\sigma_i}Te_i$ for all $i \leq k$ and extend and orthonormalize to form a basis for W.

Theorem 6.23: Let $A \in M_{m\times n}(k)$. Then there are isometries $U \in M_m(k)$ and $V \in M_n(k)$ such that $A = U\Sigma V^*$, where $\Sigma \in M_{m,n}$ contains the singular values of A.

Proof:

$$\text{Let } U = \begin{bmatrix} | & & | \\ f_1 & \cdots & f_m \\ | & & | \end{bmatrix},\ \Sigma = \begin{bmatrix} \sigma_1 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_k & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \end{bmatrix},\ \text{and } V = \begin{bmatrix} | & & | \\ e_1 & \cdots & e_n \\ | & & | \end{bmatrix}.$$

Definition 6.24:

$$\text{Let } \Sigma = \begin{bmatrix} \sigma_1 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_k & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \end{bmatrix}. \text{ The } \textbf{pseudoinverse} \text{ to } \Sigma \text{ is } \Sigma^+ = \begin{bmatrix} \sigma_1^{-1} & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_k^{-1} & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \end{bmatrix}^{\mathrm{T}}.$$

Definition 6.25: Let $A = U\Sigma V^*$. The **pseudoinverse** to A is $A^+ = V\Sigma^+U^*$.

Proposition 6.26: Let $A \in M_n(k)$ be invertible. Then $A^+ = A^{-1}$.

Proof: Since A is invertible, no entry along the diagonal of Σ is zero, so $\Sigma^+ = \Sigma^{-1}$. Since U and V are isometries, $V^*V = UU^* = I$, so $AA^+ = U\Sigma V^*V\Sigma^+U^* = U\Sigma\Sigma^+U^* = UU^* = I$. Thus $A^+ = A^{-1}$.

Theorem 6.27: Let $A \in M_{m,n}(k)$. Then the map given by AA^+ is the projection onto range A, so the vector $\mathbf{x}$ closest to a solution to $A\mathbf{x} = \mathbf{b}$ is $\mathbf{x} = A^+\mathbf{b}$.

Proof: Let $\{e_1, ..., e_n\}$ be an orthonormal basis of eigenvectors of A^*A, let $\sigma_1, ..., \sigma_k$ be the singular values of A, and let $\{f_1, ..., f_m\}$ be the orthonormal basis given by the Singular Value Decomposition of A. Then

$$\begin{aligned} AA^+v &= A(\frac{1}{\sigma_1}\langle v, f_1\rangle e_1 + \cdots + \frac{1}{\sigma_k}\langle v, f_k\rangle e_k) \\ &= \sigma_1\langle \frac{1}{\sigma_1}\langle v, f_1\rangle e_1, e_1\rangle f_1 + \cdots + \sigma_k\langle \frac{1}{\sigma_k}\langle v, f_k\rangle e_k, e_k\rangle f_k \\ &= \langle v, f_1\rangle f_1 + \cdots + \langle v, f_k\rangle f_k, \end{aligned}$$

so if $v = c_1f_1 + \cdots + c_mf_m$, then $AA^+v = c_1f_1 + \cdots + c_kf_k$. Since range $A = \operatorname{span}\{f_1, ..., f_k\}$, $AA^+ = P_{\text{range } A}$.

Definition 6.28:

$$\text{Let } \Sigma = \begin{bmatrix} \sigma_1 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_k & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \end{bmatrix}. \text{ The } \textbf{rank } \boldsymbol{r} \textbf{ approximation} \text{ to } \Sigma \text{ is } \Sigma_r = \begin{bmatrix} \sigma_1 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_r & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \end{bmatrix}$$

Definition 6.29: Let $A = U\Sigma V^*$. The **rank r approximation** to A is $A_r = U\Sigma_r V^*$.

Theorem 6.30: Let $A \in M_{m,n}(k)$. Then A_r is the rank r matrix closest to A — that is, it minimizes $||A - X||$, where $\langle A, X\rangle = \text{trace } (X^* A)$.

VII — Determinants

Definition 7.1: The **symmetric group** S_n is the group $\{\sigma : \{1, ..., n\} \hookrightarrow \{1, ..., n\}\}$, with composition given by composition of functions. The elements of S_n are called **permutations** and are written as $\sigma = \sigma_1 \cdots \sigma_n$, where $\sigma(i) = \sigma_i$.

Definition 7.2: Let σ be a permutation. The **inversion** of σ, denoted inv σ, is the number of pairs (i, j) with $i < j$ and $\sigma_i > \sigma_j$.

Definition 7.3: The **sign** of a permutation σ is sign $\sigma = (-1)^{\text{inv } \sigma}$.

Proposition 7.4: Let σ be a permutation and $\hat{\sigma}$ be a permutation identical to σ, except with σ_i and σ_j interchanged. Then sign $\hat{\sigma} = -$sign σ.

Proof: Suppose $\sigma = — i — j —$. Then $\hat{\sigma} = — j — i —$. Since any inversion that does not involve either i or j is unchanged from σ to $\hat{\sigma}$, we need only consider those do. Any inversion of the form (x, i) or (j, x) is unchanged, since if $x < i$, then $x < j$, and if $x > j$, then $x > i$. Thus we only need to consider the x that lie between i and j. Each one causes two inversions in $\hat{\sigma}$ — (j, x) and (x, i) — and therefore does not affect sign $\hat{\sigma}$. But we have not accounted for the inversion (j, i). Thus sign $\hat{\sigma} = -$sign σ.

Definition 7.5: Let A = $[a_{ij}] \in M_{m,n}(k)$. The **determinant** of A is given by

$$\det A = \sum_{\sigma \in S_n} (\text{sign } \sigma)(a_{\sigma_1,1}) \cdots (a_{\sigma_n,n}).$$

Theorem 7.6: The set

$$\mathcal{A} = \{f : (\mathbb{R}^n)^n \longrightarrow \mathbb{R} \mid f(a_1, ..., a_i, ..., a_j, ..., a_n) = -f(a_1, ..., a_j, ..., a_i, ..., a_n),\ f \text{ is coordinate-wise linear}\}$$

has dimension 1 (and therefore, one basis is $\{\det\}$).

Lemma 7.6.1: Let $\{v_1, ..., v_n\}$ be a basis for $\mathbb{R}^n$ and let $f \in \mathcal{A}$. Then if $f(v_1, ..., v_n) = 0$, $f(w_1, ..., w_n) = 0$ for all $w_1, ..., w_n \in \mathbb{R}^n$.

Proof: Expand each w_i as $w_i = c_{i1}v_1 + \cdots + c_{in}v_n$. Since f is linear in each coordinate, we have

$$f(w_1, ..., w_n) = f(c_{11}v_1 + \cdots + c_{1n}v_n, ..., c_{n1}v_1 + \cdots + c_{nn}v_n) = \sum c_i f(v_{i_1}, ..., v_{i_n}).$$

Now any term of this sum with some $v_{i_j} = v_{i_k}$ will have $f(v_{i_1}, ..., v_{i_n}) = -f(v_{i_1}, ..., v_{i_n}) = 0$ by the previous result, and for the rest, we can rearrange the terms to get $f(v_{i_1}, ..., v_{i_n}) = \pm(v_1, ..., v_n) = 0$. Thus $f(w_1, ..., w_n) = 0$.

Proof: Let $f, g \in \mathcal{A}$ with $g \neq 0$, let $\{v_1, ..., v_n\}$ be a basis for $\mathbb{R}^n$, and let $c = \frac{f(v_1,...,v_n)}{g(v_1,...,v_n)}$ ($g(v_1, ..., v_n) \neq 0$, since otherwise $g = 0$ by the lemma). Then $(f - cg)(v_1, ..., v_n = 0)$, so by the lemma, $f - cg = 0$. Thus $f = cg$, so every function in $\mathcal{A}$ is a multiple of another.

Theorem 7.7: Let $A, B \in M_n(k)$. Then $\det AB = (\det A)(\det B)$.

Proof: Define $f \in \mathcal{A}$ by $f(C) = \det AC$. By the previous result, there is a c such that $f = c \cdot \det$. Since $f(I) = \det A$ and $f(I) = c \cdot \det I = c$, $c = \det A$. Then $f(B) = \det AB = c \cdot \det B = (\det A)(\det B)$.

Theorem 7.8: Let $A \in M_n(k)$ with eigenvalues $\lambda_1, ..., \lambda_n$. Then $\det A = \lambda_1 \cdots \lambda_n$.

Proof: Let $\{v_1, ..., v_n\}$ be a basis for $\mathbb{R}^n$ such that A is upper triangular. Then $A = SUS^{-1}$, where

$$S = \begin{bmatrix} | & & | \\ v_1 & \cdots & v_n \\ | & & | \end{bmatrix} \text{ and } U = \begin{bmatrix} \lambda_1 & \cdots & * \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_n \end{bmatrix}.$$

Then $\det A = \det SUS^{-1} = (\det S)(\det U)(\det S^{-1}) = \det U = \lambda_1 \cdots \lambda_n$.