

Linear Algebra Cheat Sheet for OR

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Abstract

This document contains a list of all linear algebra results that I needed for my Operations Research coursework at UIUC. The target audience of this document is Operations Research students. It can be helpful to [page](#) these results into your brain before a linear-algebra-heavy exam/project, and proving these results yourself (except those marked DWAP) is a good exercise.

Notation:

- DWAP abbreviates “Don’t Worry About the Proof”.
- For any integer $n \geq 0$, define $[n] := \{1, 2, \dots, n\}$.

Contents

| | | |
|----------|---|----------|
| 1 | Vector Spaces | 1 |
| 1.1 | Field | 1 |
| 1.2 | Vector Space | 2 |
| 1.3 | Linear Independence and Basis | 2 |
| 1.4 | Affine Independence | 3 |
| 2 | Matrices | 3 |
| 3 | Miscellaneous | 4 |

1 Vector Spaces

1.1 Field

Definition 1 (Field). *A field is a set F equipped with two operations $+$ and \times that satisfy some special properties. (you don’t need to know the properties, unless you want to be a pure mathematician, in which case you can find them [here](#)). Every field has two special elements, called the additive identity (usually denoted by 0), and the multiplicative identity (usually denoted by 1).*

Theorem 1 (DWAP). *The following are fields: \mathbb{Q} (the set of rational numbers), \mathbb{R} (the set of real numbers), \mathbb{C} (the set of complex numbers).*

Theorem 2 (DWAP). *$\mathbb{Z}_p := \{0, 1, \dots, p-1\}$ is a field when p is prime, where $+$ and \times are addition and multiplication modulo p .*

1.2 Vector Space

Definition 2. *A vector space V over a field F is a set with a vector addition operation ($V \times V \mapsto V$) and a scalar multiplication operation ($F \times V \mapsto V$) which satisfies some special properties. (you don't need to know the properties, unless you want to be a pure mathematician, in which case you can find them [here](#)).*

Every vector space has a special vector, called the additive identity, denoted by $\mathbf{0}$. The elements of V are called vectors. The elements of F are called scalars.

Definition 3 (Subspace). *Let V be a vector space. U is called a subspace of V if $U \subseteq V$ and U is also a vector space.*

Theorem 3 (DWAP). *The set of all polynomials over field F forms a vector space.*

Theorem 4 (DWAP). *For a field F , F^d is a vector space.*

Definition 4 (Linear and affine combinations). *Let V be a vector space over field F . Let $X := \{x^{(i)} : i \in [k]\}$, where $x^{(i)} \in V$. Let $y = \sum_{i=1}^k \alpha_i x^{(i)}$, where $\alpha_i \in F$.*

- *y is called a linear combination of X .*
- *If $\sum_{i=1}^k \alpha_i = 1$, then y is called an affine combination of X .*

Definition 5 (Span). *$\text{span}(X)$ is defined as the set of all linear combinations of X . For sets X and Y of vectors, X is called a spanning set of Y if $Y \subseteq \text{span}(X)$.*

Lemma 5. *If X spans S , then X also spans $\text{span}(S)$.*

Theorem 6 (DWAP). *Let X be a finite subset of F^d , where F is a field. Then $\text{span}(X)$ is a vector space.*

1.3 Linear Independence and Basis

Definition 6 (Linear independence). *A set $\{x_1, x_2, \dots, x_n\}$ of vectors over field F is called linearly independent iff*

$$\forall (\alpha_1, \dots, \alpha_n) \in F^n, \left(\sum_{i=1}^n \alpha_i x_i = 0 \implies (\alpha_i = 0 \ \forall i \in [n]) \right).$$

Lemma 7 (Incrementing a linearly independent set). *Let X be a linearly independent set of vectors and y be a vector. If $y \notin \text{span}(X)$, then $X \cup \{y\}$ is linearly independent.*

Lemma 8 (Decrementing a linearly dependent set). *Let X be a linearly dependent set of vectors. Then $\exists x \in X$ such that $\text{span}(X) = \text{span}(X - \{x\})$.*

Theorem 9 (DWAP). *Let X be a spanning set of vector space V . If $Y \subseteq V$ and $|Y| > |X|$, then Y is linearly dependent.*

Definition 7 (Basis). *Let S be a subset of vector space V . Then $X \subseteq S$ is a basis of S iff (the following definitions are equivalent):*

- X is linearly independent and spans S .
- X is the largest linearly independent subset of S .
- X is a maximal linearly independent subset of S .
- X is the smallest spanning subset of S .
- X is a minimal spanning subset of S .

Equivalence of these definitions can be proven using Theorem 9 and Lemmas 7 and 8.

Lemma 10. *If X is a basis of S , then X is also a basis of $\text{span}(S)$.*

Lemma 11. *Let F be a field. Let $e^{(i)} \in F^d$ be a vector whose i^{th} coordinate is 1 and other coordinates are 0. Then $E := \{e^{(i)} : i \in [d]\}$ is a basis of F^d . (E is called the standard basis of F^d .)*

Theorem 12. *All bases of S have the same size. This size is called the rank of S (denoted as $\text{rank}(S)$). If S is a vector space, it's called the dimension of S (denoted as $\dim(S)$).*

Theorem 13. *Let X be a set of $\text{rank}(S)$ vectors. Then*

$$X \text{ is a basis of } S \iff X \text{ is linearly independent} \iff X \text{ spans } S.$$

Theorem 14 (Coordinatization). *Let $B := \{b^{(1)}, b^{(2)}, \dots, b^{(k)}\}$ be a basis of vector space V . Then $\forall x \in V$ there is a unique tuple $(\alpha_1, \alpha_2, \dots, \alpha_k)$ such that $x = \sum_{i=1}^k \alpha_i b^{(i)}$.*

1.4 Affine Independence

Definition 8. *A set $\{x_1, x_2, \dots, x_n\}$ of vectors over field F is called linearly independent iff*

$$\forall (\alpha_1, \dots, \alpha_n) \in F^n, \left(\left(\sum_{i=1}^n \alpha_i = 0 \text{ and } \sum_{i=1}^n \alpha_i x_i = 0 \right) \implies (\alpha_i = 0 \forall i \in [n]) \right).$$

Theorem 15. *The set $\{x^{(i)} : i \in [n]\}$ of vectors is affinely independent iff $\{x^{(i)} - x^{(n)} : i \in [n-1]\}$ is linearly independent.*

Theorem 16. *The set $\{x^{(i)} : i \in [n]\}$ of vectors from F^d is affinely independent iff $\{(x^{(i)}, 1) : i \in [n]\}$ is linearly independent.*

2 Matrices

Definition 9 (row space, column space). *Let F be a field and $A \in F^{m \times n}$ be a matrix, Let $\text{rows}(A)$ be the set of all row vectors of A , and $\text{cols}(A)$ be the set of all column vectors of A . Then*

- $\text{rowSpace}(A) := \text{span}(\text{rows}(A))$,
- $\text{colSpace}(A) := \text{span}(\text{cols}(A))$,
- $\text{rank}(A) := \text{rowRank}(A) := \text{rank}(\text{rows}(A))$,
- $\text{colRank}(A) := \text{rank}(\text{cols}(A))$.

Theorem 17 (DWP). *For any matrix A , $\text{rowRank}(A) = \text{colRank}(A)$.*

Definition 10 (Nullspace and nullity). *For a matrix $A \in F^{m \times n}$, $\text{nullSpace}(A) := \{x \in F^n : Ax = 0\}$ and $\text{nullity}(A) := \dim(\text{nullSpace}(A))$.*

Theorem 18 (Rank-nullity theorem, DWP). $\text{rank}(A) + \text{nullity}(A) = |\text{cols}(A)|$.

Proof sketch. We can show that row space and nullspace are not affected by elementary row operations on A . Hence, we can assume that A is in Reduced-Row Echelon Form. There are $\text{rank}(A)$ pivot columns in A . Given any value of non-pivot variables, we can compute the value of pivot variables such that $Ax = 0$. Hence, $\text{nullity}(A) = |\text{cols}(A)| - \text{rank}(A)$. \square

Theorem 19 (DWP). *If V is a subspace of F^d , then $\exists A$ such that $V = \text{nullSpace}(A)$.*

Theorem 20 (DWP). *Basic results on matrix multiplication:*

- *Matrix multiplication is associative, i.e., $(AB)C = A(BC)$.*
- $(AB)^T = B^T A^T$.
- $|AB| = |A||B|$ if A and B are square ($|A|$ is the determinant of A).
- $(AB)^{-1} = B^{-1}A^{-1}$ if A and B are invertible.

Theorem 21 (Matrix singularity, DWP). *Let $A \in F^{n \times n}$. The following are equivalent:*

- $\text{rank}(A) = n$.
- 0 is the unique solution to $Ax = 0$.
- $|A| \neq 0$ ($|A|$ is the determinant of A).
- A is invertible, i.e., $\exists B \in F^{n \times n}$ such that $AB = BA = I$.

3 Miscellaneous

Definition 11 (p -norms). *For $x \in \mathbb{R}^d$,*

$$\|x\|_p := \left(\sum_{i=1}^d |x_i|^p \right)^{1/p} \quad \|x\|_\infty := \max_{i=1}^d |x_i| \quad \|x\| := \|x\|_2$$

Definition 12 (Linear combinations). *Let V be a vector space over field \mathbb{R} . Let $X := \{x^{(i)} : i \in [k]\}$, where $x^{(i)} \in V$. Let $y = \sum_{i=1}^k \alpha_i x^{(i)}$, where $\alpha_i \in F$.*

- y is called a linear combination of X .
- If $\alpha_i \geq 0$ for all $i \in [k]$, then y is called a non-negative linear combination of X .
- If $\sum_{i=1}^k \alpha_i = 1$, then y is called an affine combination of X .
- A non-negative affine combination is called a convex combination.

Theorem 22 (Cauchy-Schwarz inequality). $\forall x, y \in \mathbb{R}^d$, $|x^T y| \leq \|x\| \|y\|$.