EE 441: General vector spaces over a field

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I. Axioms for a Vector Space $\mathcal V$ over a Field $\mathbb F$

Let \mathbb{F} be a general field. Let \mathcal{V} be a set of objects called "vectors." We say that \mathcal{V} is a *vector space over the field* \mathbb{F} if there are rules for vector addition and scalar multiplication such that \mathcal{V} is closed with respect to these operations, that is:

- $v_1 + v_2 \in \mathcal{V}$ for any two vectors $v_1, v_2 \in \mathcal{V}$.
- $\alpha v \in \mathcal{V}$ for any vector $v \in \mathcal{V}$ and any scalar $\alpha \in \mathbb{F}$. and such that the following additional six properties hold:
 - 1) (Commutativity)

$$v_1 + v_2 = v_2 + v_1$$
 (for all $v_1, v_2 \in \mathcal{V}$)

2) (Associativity)

$$(\boldsymbol{v}_1 + \boldsymbol{v}_2) + \boldsymbol{v}_3 = \boldsymbol{v}_1 + (\boldsymbol{v}_2 + \boldsymbol{v}_3)$$
 (for all $\boldsymbol{v}_1, \boldsymbol{v}_2, \boldsymbol{v}_3 \in \mathcal{V}$)
 $(\alpha \beta) \boldsymbol{v} = \alpha(\beta \boldsymbol{v})$ (for all $\alpha, \beta, \in \mathbb{F}$ and $\boldsymbol{v} \in \mathcal{V}$)

3) (Distributive Properties)

$$\alpha(\boldsymbol{v}_1 + \boldsymbol{v}_2) = \alpha \boldsymbol{v}_1 + \alpha \boldsymbol{v}_2$$
 (for all $\boldsymbol{v}_1, \boldsymbol{v}_2 \in \mathcal{V}$, and $\alpha \in \mathbb{F}$)
$$(\alpha + \beta)\boldsymbol{v} = \alpha \boldsymbol{v} + \beta \boldsymbol{v}$$
 (for all $\boldsymbol{v} \in \mathcal{V}$, and $\alpha, \beta \in \mathbb{F}$)

4) (Additive Identity) There exists a vector $\mathbf{0} \in \mathcal{V}$ such that:

$$v + 0 = v$$
 for all $v \in \mathcal{V}$

5) (Additive Inverse) For every $v \in \mathcal{V}$, there exists a vector $-v \in \mathcal{V}$ such that:

$$v + -v = 0$$

6) (Multiplicative Identity) 1v = v for every vector $v \in \mathcal{V}$.

Note that the vector space \mathbb{R}^n over the field \mathbb{R} satisfies all these properties. Similarly, the set \mathbb{F}^n is a vector space over \mathbb{F} , where vector addition and scalar multiplication are defined entrywise via the arithmetic of \mathbb{F} . Other examples of vector spaces:

- The vector space \mathcal{V} over the field \mathbb{F} (where \mathbb{F} is any general field), consisting of all countably infinite tuples (x_1, x_2, x_3, \ldots) , where $x_i \in \mathbb{F}$ for all entries $i \in \{1, 2, \ldots, \}$, and where arithmetic is defined entrywise using arithmetic in \mathbb{F} .
- The vector space \mathcal{V} over the field \mathbb{R} , where \mathcal{V} is the set of all continuous functions of time t for $t \in (-\infty, \infty)$.
- The vector space $\mathcal V$ over the field $\mathbb R$, where $\mathcal V$ is the set of all polynomial functions f(t) of degree less than or equal to n. That is, $\mathcal V=\{f(t)\mid f(t)=\alpha_0+\alpha_1t+\alpha_2t^2+\ldots+\alpha_nt^n,\alpha_i\in\mathbb R\}.$

II. SIMPLE LEMMAS FOR VECTOR SPACES

Let \mathcal{V} be a vector space over a field \mathbb{F} .

Lemma 1: (Uniqueness of 0) The vector $0 \in \mathcal{V}$ is the unique additive identity.

Proof: Suppose that w satisfies v + w = v for any $v \in \mathcal{V}$. Then adding -v to both sides of the equation v + w = v yields:

$$-\boldsymbol{v} + \boldsymbol{v} + \boldsymbol{w} = -\boldsymbol{v} + \boldsymbol{v}$$

and hence: 0 + w = 0. Therefore, w = 0.

Lemma 2: (Uniqueness of -v) For any vector $v \in \mathcal{V}$, if there is a vector $w \in \mathcal{V}$ such that v + w = 0, then w = -v.

Proof: Suppose that v + w = 0. Adding -v to both sides yields 0 + w = -v, and hence w = -v.

Lemma 3: 0v = 0 for any $v \in V$.

Proof: Take any vector $v \in \mathcal{V}$. Then:

$$v = 1v = (1+0)v = 1v + 0v$$

and hence v = v + 0v. Adding -v to both sides yields 0 = 0v, proving the result.

Lemma 4: $\alpha \mathbf{0} = \mathbf{0}$ for any $\alpha \in \mathbb{F}$.

Proof: Take any $\alpha \in \mathbb{F}$ and any vector $\mathbf{v} \in \mathcal{V}$. Then:

$$\alpha \mathbf{v} = \alpha (\mathbf{v} + \mathbf{0})$$
$$= \alpha \mathbf{v} + \alpha \mathbf{0}$$

Thus, we have $\alpha v = \alpha v + \alpha 0$. Adding $-(\alpha v)$ to both sides yields $0 = \alpha 0$, proving the result.

Lemma 5: $-\mathbf{v} = (-1)\mathbf{v}$ for any $\mathbf{v} \in \mathcal{V}$.

Proof: Take any vector $v \in \mathcal{V}$. Then:

$$\mathbf{0} = 0\mathbf{v} = (1+-1)\mathbf{v} = 1\mathbf{v} + (-1)\mathbf{v} = \mathbf{v} + (-1)\mathbf{v}$$

Thus, $\mathbf{0} = \mathbf{v} + (-1)\mathbf{v}$. Adding $-\mathbf{v}$ to both sides yields $-\mathbf{v} = (-1)\mathbf{v}$, proving the result.

III. SUBSPACES

Definition 1: Let \mathcal{V} be a vector space over a field \mathbb{F} . Let $\mathcal{S} \subset \mathcal{V}$ be a subset of \mathcal{V} . We say that \mathcal{S} is a subspace if:

$$egin{aligned} oldsymbol{v}_1 + oldsymbol{v}_2 \in \mathcal{S} & ext{ for all } oldsymbol{v}_1, oldsymbol{v}_2 \in \mathcal{S} \ & ext{ aligned} oldsymbol{v} \in \mathcal{V}, \ lpha \in \mathbb{F} \end{aligned}$$

where addition and scalar multiplication are the same in S as they are in V.

It is easy to prove that if S is a subspace of vector space V over field \mathbb{F} , then S is *itself* a vector space over field \mathbb{F} . (It is important to note that $-\mathbf{v} = (-1)\mathbf{v}$ in proving this...why?).

IV. LINEAR COMBINATIONS AND LINEAR INDEPENDENCE

Definition 2: Let $\{x_1, \ldots, x_k\}$ be a collection of vectors in a vector space \mathcal{V} over a field \mathbb{F} . We say that a vector $\mathbf{v} \in \mathcal{V}$ is a linear combination of $\{x_1, \ldots, x_k\}$ if it can be written: $\mathbf{v} = \alpha_1 \mathbf{x}_1 + \ldots + \alpha_k \mathbf{x}_k$ for some scalars $\alpha_i \in \mathbb{F}$ for $i \in \{1, \ldots, k\}$.

Definition 3: Let $\{x_1, \ldots, x_k\}$ be a collection of vectors in a vector space \mathcal{V} over a field \mathbb{F} . We define $Span\{x_1, \ldots, x_k\}$ as the set of all linear combinations of $\{x_1, \ldots, x_k\}$. Note that $Span\{x_1, \ldots, x_k\} \subset \mathcal{V}$.

Definition 4: Let S be a subspace of a vector space V over a field \mathbb{F} . We say that a collection of vectors $\{x_1, \dots, x_k\}$ span S if $Span\{x_1, \dots, x_k\} = S$.

Definition 5: We say that a collection of vectors $\{x_1, \ldots, x_k\}$ in a vector space \mathcal{V} (over a field \mathbb{F}) are linearly independent if the equation $\alpha_1 v_1 + \alpha_2 v_2 + \ldots + \alpha_k v_k = \mathbf{0}$ can only be true if $\alpha_i = 0$ for all $i \in \{1, \ldots, k\}$.

Definition 6: A collection of vectors $\{x_1, \ldots, x_k\}$ is a basis for a subspace S if the collection $\{x_1, \ldots, x_k\}$ is linearly independent in S and spans S.

The following lemmas have proofs that are identical (or nearly identical) to the corresponding lemmas proven in class for the vector space \mathbb{R}^n . The proofs are left as an exercise.

Lemma 6: A collection of vectors $\{x_1, \dots, x_k\}$ are linearly independent if and only if none of the vectors can be written as a linear combination of the others.

Lemma 7: If $\{x_1, \ldots, x_k\}$ are linearly independent in a vector space \mathcal{V} , and if $\mathbf{w} \in \mathcal{V}$ and $\mathbf{w} \notin Span\{x_1, \ldots, x_k\}$, then $\{x_1, x_2, \ldots, x_k, \mathbf{w}\}$ are linearly independent.

Lemma 8: $(k \leq m)$ Let $\{x_1, \ldots, x_k\}$ be a collection of vectors that are linearly independent in a subspace S. Let $\{y_1, \ldots, y_m\}$ be a collection of vectors that span S. Then $k \leq m$.

Lemma 9: Any two bases of a subspace S have the same size, defined as the dimension of the subspace.

Lemma 10: The dimension of \mathbb{F}^n is n.

Lemma 11: Let S be a subspace of a vector space V, where V has dimension n. Then S has a finite basis, and the dimension of S is less than or equal to n.

Note that the *standard basis* for \mathbb{F}^n is given by $\{e_1, \dots, e_n\}$, where e_i is a *n*-tuple with all entries equal to 0 except for entry i, which is equal to 1.

Note that the collection $\{1, t, t^2, \dots, t^n\}$ is a basis for the vector space \mathcal{V} over the field \mathbb{R} , where \mathcal{V} is the space of all polynomial functions of degree less than or equal to n (why is this true?). Thus, this vector space has dimension n+1. Note also that, for any n, this vector space is a *subspace* of the vector space over \mathbb{R} defined by all continuous functions. Thus, the dimension of the vector space of all continuous functions is infinite (as it contains subspaces of dimension n for arbitrarily large n).

V. MATRICES

Let A be a $m \times n$ matrix with elements in \mathbb{F} . Note that the equation Ax = 0 (where $0 \in \mathbb{F}^m$ and $x \in \mathbb{F}^n$) has only the trivial solution $x = 0 \in \mathbb{F}^n$ if and only if the columns of A are linearly independent.

Lemma 12: A square $n \times n$ matrix A (with elements in \mathbb{F}) is non-singular if and only if its columns are linearly independent, if and only if Ax = 0 has only the trivial solution.

The above lemma follows from the fact that if A is non-singular, it has a single unique solution to Ax = b for all $b \in \mathbb{F}^n$ (which is true by Gaussian Elimination), and if it is singular it does not have a solution for some vectors $b \in \mathbb{F}^n$ and it has multiple solutions for the remaining $b \in \mathbb{F}^n$.

Lemma 13: Let A, B be square $n \times n$ matrices. If AB = I, then both A and B are invertible, and $A^{-1} = B$ and $B^{-1} = A$. The above lemma follows from the fact that AB = I implies A is non-singular (why?) and hence invertible.

Lemma 14: A square $n \times n$ matrix A (with elements in \mathbb{F}) has linearly independent columns (and hence is invertible) if and only if its transpose A^T has linearly independent columns (and hence is invertible). Thus, a square invertible matrix A has both linearly independent rows and linearly independent columns.

The above lemma follows from the fact that $AA^{-1} = I$, and hence $(A^{-1})^T A^T = I$.

VI. BASIC PROBABILITY

The next several lectures on erasure coding will use the following simple but important probability facts:

- If a probability experiment has K equally likely outcomes, then the probability of each individual outcome is 1/K.
- Let E_1, E_2, \dots, E_m be a set of independent events (say, from m independent probability experiments). Then:

$$Pr[E_1 \cap E_2 \cap \cdots \cap E_m] = Pr[E_1]Pr[E_2] \cdots Pr[E_m]$$

That is, the probability that all independent events occur is equal to the product of the individual event probabilities.

• (Union Bound) Let E_1, E_2, \dots, E_m be a collection of m events (possibly not independent). Then:

$$Pr[E_1 \cup E_2 \cup \dots \cup E_m] \le \sum_{i=1}^m Pr[E_i]$$

That is, the probability that at least one of the events occurs is less than or equal to the sum of the individual event probabilities.