

Section 1: Vector spaces

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Algebraic structures

Definition

A **group** is a set G and associative binary operation $*$ with:

- **closure**: $a, b \in G$ implies $a * b \in G$;
- **identity**: there exists $e \in G$ such that $a * e = e * a = a$ for all $a \in G$;
- **inverses**: for all $a \in G$, there is $b \in G$ such that $a * b = e$.

A group is **abelian** if $a * b = b * a$ for all $a, b \in G$.

Definition

A **field** is a set $\mathbb{F}$ (or K) containing $1 \neq 0$ with two binary operations: $+$ (addition) and $\cdot$ (multiplication) such that:

- (i) $\mathbb{F}$ is an abelian group under addition;
- (ii) $\mathbb{F} \setminus \{0\}$ is an abelian group under multiplication;
- (iii) The distributive law holds: $a(b + c) = ab + ac$ for all $a, b, c \in \mathbb{F}$.

Remarks

- $\mathbb{Q}, \mathbb{R}, \mathbb{C}, \mathbb{Z}_p$ (prime p), $\mathbb{Q}(\sqrt{2}) := \{a + b\sqrt{2} : a, b \in \mathbb{Q}\}$ are all fields.
- $\mathbb{Z}$ is not a field. Nor is $\mathbb{Z}_n$ (composite n).
- the *additive identity* is 0, and the inverse of a is $-a$.
- the *multiplicative identity* is 1, and the inverse of a is a^{-1} , or $\frac{1}{a}$.

Vector spaces

Definition

A **vector space** is a set X (“vectors”) over a field $\mathbb{F}$ (“scalars”) such that:

- (i) X is an **abelian group** under addition;
- (ii) $+$ and $\cdot$ are “compatible” via natural **associative** and **distributive** laws relating the two:
 - $a(bv) = (ab)v$, for all $a, b \in \mathbb{F}$, $v \in X$;
 - $a(v + w) = av + aw$, for all $a \in \mathbb{F}$, $v, w \in X$;
 - $(a + b)v = av + bv$, for all $a \in \mathbb{F}$, $v, w \in X$;
 - $1v = v$, for all $v \in X$.

Intuition

Think of a vector space as a **set of vectors** that is:

- (i) Closed under addition and subtraction;
- (ii) Closed under scalar multiplication;
- (iii) Equipped with the “natural” associative and distributive laws.

Proposition (exercise)

In any vector space X ,

- (i) The zero vector 0 is unique;
- (ii) $0x = 0$ for all $x \in X$;
- (iii) $(-1)x = -x$ for all $x \in X$.

□

Linear maps

Definition

A **linear map** between vector spaces X and Y over $\mathbb{F}$ is a function $\varphi: X \rightarrow Y$ satisfying:

- $\varphi(v + w) = \varphi(v) + \varphi(w)$, for all $v, w \in X$;
- $\varphi(av) = a\varphi(v)$, for all $a \in \mathbb{F}$, $v \in X$.

An **isomorphism** is a linear map that is bijective (1–1 and onto).

Proposition

The two conditions for linearity above can be replaced by the single condition:

$$\varphi(av + bw) = a\varphi(v) + b\varphi(w), \quad \text{for all } v, w \in X \text{ and } a, b \in \mathbb{F}.$$

Examples of vector spaces

- (i) $K^n = \{(a_1, \dots, a_n) : a_i \in K\}$. Addition and multiplication are defined componentwise.
- (ii) Set of functions $\mathbb{R} \rightarrow \mathbb{R}$ (with $K = \mathbb{R}$).
- (iii) Set of functions $S \rightarrow K$ for an arbitrary set S .
- (iv) Set of polynomials of degree $< n$, with coefficients from K .

Exercise

In the list of vector spaces above, (i) is isomorphic to (iv), and to (iii) if $|S| = n$. □

Subspaces

Definition

A subset Y of a vector space X is a **subspace** if it too is a vector space. We'll write $Y \leq X$.

Examples

- (i) $Y = \{(0, a_2, \dots, a_{n-1}, 0) : a_i \in K\} \subseteq K^n$.
- (ii) $Y = \{\text{functions with period } T \mid \pi\} \subseteq \{\text{functions } \mathbb{R} \rightarrow \mathbb{R}\}$.
- (iii) $Y = \{\text{constant functions } S \rightarrow K\} \subseteq \{\text{functions } S \rightarrow K\}$.
- (iv) $Y = \{a_0 + a_2x^2 + a_4x^4 + \dots + a_{n-1}x^{n-1} : a_i \in K\} \subseteq \{\text{polynomials of degree } < n\}$.

Definition

If Y and Z are **subsets** of a vector space X , then their:

- **sum** is $Y + Z = \{y + z \mid y \in Y, z \in Z\}$;
- **intersection** is $Y \cap Z = \{x \mid x \in Y, x \in Z\}$.

Exercise

If Y and Z are subspaces of X , then $Y + Z$ and $Y \cap Z$ are also subspaces. □

Spanning and Independence

Definition

A **linear combination** of vectors $x_1, \dots, x_k$ is a vector of the form $a_1x_1 + \dots + a_kx_k$, where each $a_i \in K$.

Definition

Given a subset $S \subseteq X$, the subspace **spanned** by S is the set of all linear combinations of vectors in S , and denoted $\text{Span}(S)$.

Exercise

For any subset $S \subseteq X$,

$$\text{Span}(S) = \bigcap_{S \subseteq Y_\alpha \leq X} Y_\alpha,$$

where the intersection is taken over all subspaces of X that contain S . □

Definition

The vectors $x_1, \dots, x_k$ are **linearly dependent** if we can write $a_1x_1 + \dots + a_kx_k = 0$, where not all $a_i = 0$. Otherwise, the vectors are **linearly independent**.

Spanning and linear independence

Lemma 1.1

If $X = \text{Span}(x_1, \dots, x_n)$, and the vectors $y_1, \dots, y_k \in X$ are linearly independent, then $k \leq n$.

Proof outline (details to be done on the board)

Write $y_1 = a_1x_1 + \dots + a_nx_n$, and assume WLOG that $a_1 \neq 0$.

Now, “solve” for x_1 and eliminate it, and conclude that

$$\text{Span}(x_1, x_2, \dots, x_n) = \text{Span}(y_1, x_2, \dots, x_n) = X$$

Repeat this process: eliminating each $x_2, x_3, \dots$.

Note that $k > n$ is impossible. (Why?)



Basis of a vector space

Definition

A set $B \subseteq X$ is a **basis** for X if:

- B **spans** X . (is “big enough”);
- B is **linearly independent**. (isn’t “too big”).

Exercise

The following are equivalent for a subset $B \subseteq X$:

- (i) B is a basis of X ;
- (ii) B is a minimal spanning set;
- (iii) B is a maximal linearly independent set.

Examples

Let’s find bases for some familiar vector spaces.

1. $K^n = \{(a_1, \dots, a_n) : a_i \in K\}$. Addition and multiplication are defined componentwise.
2. Set of functions $S \rightarrow K$ from a finite set S .
3. Set of polynomials of degree $< n$, with coefficients from K .

Bases

Lemma 1.2

If $\text{Span}(x_1, \dots, x_n) = X$, then some subset of $\{x_1, \dots, x_n\}$ is a basis for X .

Proof

If $x_1, \dots, x_n$ are linearly dependent, then we can write (WLOG; renumber if necessary)

$$x_n = a_1 x_1 + \dots + a_{n-1} x_{n-1}.$$

Now, $\text{Span}(x_1, \dots, x_{n-1}) = X$, and we can repeat this process until the remaining set is linearly independent. □

Definition

A vector space X is **finite dimensional** (f.d.) if it has a finite basis.

Examples

- (i) In $\mathbb{R}^n$, any two vectors that don't lie on the same line (i.e., aren't scalar multiples) are linearly independent.
- (ii) In $\mathbb{R}^3$, any three vectors are linearly independent iff they do not lie on the same plane.
- (iii) Any two vectors in $\mathbb{R}^2$ that aren't scalar multiples form a basis.

Dimension

Theorem / Definition 1.3

All bases for a f.d. vector space have the same cardinality, called the **dimension** of X .

Proof

Let $x_1, \dots, x_n$ and $y_1, \dots, y_m$ be two bases for X . By Lemma 1.1, $m \leq n$ and $n \leq m$. $\square$

Theorem 1.4

Every linear independent set of vectors $y_1, \dots, y_j$ in a finite-dimensional vector space X can be **extended** to a basis of X .

Proof

If $\text{Span}(y_1, \dots, y_j) \neq X$, then find $y_{j+1} \in X$ not in $\text{Span}(y_1, \dots, y_j)$, add it to the set and repeat the process.

This will terminate in less than $n = \dim X$ steps because otherwise, X would contain more than n linearly independent vectors. $\square$

An example from ODEs

Let X be the set of all smooth functions $x(t)$ that satisfy the second order differential equation $\frac{d^2}{dt^2}x + x = 0$.

If $x_1(t)$, $x_2(t)$ are solutions, then so are $x_1(t) + x_2(t)$ and $cx_1(t)$. Thus X is a vector space.

Solutions describe the motion of a mass-spring system (**simple harmonic motion**). A particular solution is determined completely by specifying:

$$x(0) = x_0 \quad (\text{initial position}) \qquad x'(0) = v_0 \quad (\text{initial velocity}).$$

Thus, we can describe an element $x(t) \in X$ by a pair (x_0, v_0) , where $x_0, v_0 \in \mathbb{R}$ (or in $\mathbb{C}$).

This defines an **isomorphism** $X \longrightarrow \mathbb{C}^2$, by $x(t) \longmapsto (x(0), x'(0))$.

Note that $\cos x$ and $\sin x$ are two **linearly independent** solutions, so the **general solution** to this ODE is $a \cos x + b \sin x$; $a, b \in \mathbb{C}$.

Said differently, $\{\cos x, \sin x\}$ is a **basis for the solution space of $x'' + x = 0$** .

Note that $\cos x + i \sin x = e^{ix}$ and $\cos x - i \sin x = e^{-ix}$ are linearly independent, and so $\{e^{ix}, e^{-ix}\}$ is another basis! Thus, the general solution can be written as $C_1 e^{ix} + C_2 e^{-ix}$ instead!

Complements and direct sums

Theorem 1.5

- (a) Every subspace Y of a finite-dimensional vector space X is finite-dimensional.
- (b) Every subspace Y has a **complement** in X : another subspace Z such that every vector $x \in X$ can be written uniquely as

$$x = y + z, \quad y \in Y, z \in Z, \quad \dim X = \dim Y + \dim Z.$$

Proof

Pick $y_1 \in Y$ and extend this to a basis $y_1, \dots, y_j$ of Y . By Lemma 1.1, $j \leq \dim X < \infty$.

Extend this to a basis $y_1, \dots, y_j, z_{j+1}, \dots, z_n$ of X [and define $Z := \text{Span}(z_{j+1}, \dots, z_n)$].

Clearly, Y and Z are complements, and $\dim X = n = j + (n - j) = \dim Y + \dim Z$. $\square$

Definition

X is the **direct sum** of subspaces Y and Z that are complements of each other.

More generally, X is the direct sum of subspaces $Y_1, \dots, Y_m$ if every $x \in X$ can be expressed uniquely as

$$x = y_1 + \cdots + y_m, \quad y_i \in Y_i.$$

We denote this as $X = Y_1 \oplus \cdots \oplus Y_m$.

Direct products

Definition

The **direct product** of X_1 and X_2 is the vector space

$$X_1 \times X_2 := \{(x_1, x_2) : x_1 \in X_1, x_2 \in X_2\},$$

with addition and multiplication defined componentwise.

Proposition

$$\blacksquare \dim(Y_1 \oplus \cdots \oplus Y_m) = \sum_{i=1}^m \dim Y_i;$$

$$\blacksquare \dim(X_1 \times \cdots \times X_m) = \sum_{i=1}^m \dim X_i.$$

Example

Let $X = \mathbb{R}^4$, $Y_1 = \{(a, b, 0, 0) : a, b \in \mathbb{R}\}$, $Y_2 = \{(0, 0, c, d) : c, d \in \mathbb{R}\}$, $X_1 = X_2 = \mathbb{R}^2$.

Clearly, $X = Y_1 \oplus Y_2$, since $(a, b, c, d) = (a, b, 0, 0) + (0, 0, c, d)$ [uniquely].

$$X_1 \times X_2 = \{((a, b), (c, d)) : (a, b) \in \mathbb{R}^2, (c, d) \in \mathbb{R}^2\} \cong \{(a, b, c, d) : a, b, c, d \in \mathbb{R}\} = X.$$

Direct sums vs. direct products

In the finite-dimensional cases, there is no difference (up to isomorphism) of direct sums vs. direct products.

Not the case when $\dim X = \infty$. Consider the vector space:

$$X = \mathbb{R}^\infty := \{(a_1, a_2, a_3, \dots) : a_i \in \mathbb{R}\} \cong \mathbb{R} \times \mathbb{R} \times \mathbb{R} \times \dots$$

and the following subspaces:

$$X_1 = \{(a_1, 0, 0, 0, \dots) : a_1 \in \mathbb{R}\}, \quad X_2 = \{(0, a_2, 0, 0, \dots) : a_2 \in \mathbb{R}\}, \quad \text{and so on.}$$

Elements in the subspace $X_1 \oplus X_2 \oplus X_3 \oplus \dots$ of X are finite sums

$$x = x_{i_1} + x_{i_2} + \dots + x_{i_k}, \quad x_{i_j} \in X_{i_j}.$$

Thus, we can write the direct sum as follows:

$$X_1 \oplus X_2 \oplus X_3 \oplus \dots = \{(a_1, \dots, a_k, 0, 0, \dots) : a_i \in \mathbb{R}, k \in \mathbb{Z}\} \subsetneq \mathbb{R} \times \mathbb{R} \times \mathbb{R} \times \dots$$

- Elements in the direct product are sequences, e.g., $x = (1, 1, 1, \dots)$.
- Elements in the direct sum are finite sums, e.g., $x = 3e_1 - 5.25e_4 + 78e_{11}$.

Congruence of subspaces

Sums and products “multiply” vector spaces. We can also “divide” by a subspace.

Definition

If Y is a subspace of X , then two vectors $x_1, x_2 \in X$ are **congruent modulo Y** , denoted $x_1 \equiv x_2 \pmod{Y}$, if $x_1 - x_2 \in Y$.

Proposition (exercise)

Congruence modulo Y is an **equivalence relation**, i.e., it is:

- (i) **symmetric**: $x \equiv y$ implies $y \equiv x$;
- (ii) **reflexive**: $x \equiv x$ for all $x \in X$;
- (iii) **transitive**: $x \equiv y$ and $y \equiv z$ implies $x \equiv z$. □

The equivalence classes are called **congruence classes mod Y** , or **cosets**. Denote the class containing x by $\{x\}$. [Sometimes written $\bar{x}$ or $x + Y := \{x + y : y \in Y\}$.]

Example

Let $X = \mathbb{R}^3$, $Y = \{(x, y, 0) : x, y \in \mathbb{R}\} = \text{xy-plane}$, $Z = \{(0, 0, z) : z \in \mathbb{R}\} = \text{z-axis}$.

- $v \equiv w \pmod{Y}$ if they lie on the same horizontal plane.
- $v \equiv w \pmod{Z}$ if they lie on the same vertical line.

Quotient spaces

Let X/Y denote the set of equivalence classes in X , modulo Y .

This can be made into a vector space by defining addition and scalar multiplication as

$$\{x\} + \{z\} := \{x + z\}, \quad a\{x\} := \{ax\}.$$

Need to check that this is **well-defined**, i.e., that it is *independent of the choice of representative* from the classes.

This means showing (HW exercise) that if $x_1 \equiv x_2 \pmod{Y}$ and $z_1 \equiv z_2 \pmod{Y}$, then

$$\{x_1\} + \{z_1\} = \{x_2\} + \{z_2\}, \quad a\{x_1\} = a\{x_2\}.$$

Definition

The vector space X/Y is called the **quotient space** of X modulo Y .

Alternate notations

Since $\{x\}$ is sometimes written $\bar{x}$, or $x + Y := \{x + y : y \in Y\}$, then addition and multiplication becomes:

- $\bar{x} + \bar{z} = \overline{x + z}$, and $a\bar{x} = \overline{ax}$;
- $(x + Y) + (z + Y) = x + z + Y$, and $a(x + Y) = ax + Y$.

Dimension of quotient spaces

Theorem 1.6

If Y is a subspace of a finite-dimensional vector space X , then $\dim Y + \dim X/Y = \dim X$.

Proof

Let $y_1, \dots, y_k$ be a basis for Y . Extend this to a basis $y_1, \dots, y_k, x_{k+1}, \dots, x_n$ of X .

Claim: $\{x_{k+1}\}, \dots, \{x_n\}$ is a basis of X/Y .

- Show this spans X/Y :

Pick $\{x\}$ in X/Y and write $x = \sum_{i=1}^k a_i y_i + \sum_{j=k+1}^n b_j x_j$. By definition,

$$\{x\} = \left\{ \sum a_i y_i + \sum b_j x_j \right\} = \sum a_i \{y_i\} + \sum b_j \{x_j\} = \sum b_j \{x_j\}.$$

- Show this is linearly independent:

Suppose $\sum_{j=k+1}^n c_j \{x_j\} = \{0\}$, which means $\sum c_j x_j = y$ for some $y \in Y$.

Write $y = \sum_{i=1}^k d_i y_i$, and so $\sum c_k x_k - \sum d_i y_i = 0$, and hence all $c_k, d_i = 0$ (Why?). □

Corollary

If a subspace Y of a finite-dimensional space X has $\dim Y = \dim X$, then $Y = X$. □

Dimension of sums

Theorem 1.7

Let U, V be subspaces of a finite-dimensional space X with $U + V = X$. Then

$$\dim X = \dim U + \dim V - \dim(U \cap V).$$

Proof

Let $W = U \cap V$. The result trivially holds when $W = \{0\}$ (Theorem 1.5).

Define $\overline{U} = U/W$, $\overline{V} = V/W$ and $\overline{X} = X/W$.

Note that $\overline{U} \cap \overline{V} = \{0\}$ (why?), and $\overline{X} = \overline{U} + \overline{V}$, so $\dim \overline{X} = \dim \overline{U} + \dim \overline{V}$ (Theorem 1.5).

By Theorem 1.6: $\dim \overline{X} = \dim X - \dim W$

$$\dim \overline{U} = \dim U - \dim W$$

$$\dim \overline{V} = \dim V - \dim W$$

Therefore, $(\dim X - \dim W) = (\dim U - \dim W) + (\dim V - \dim W)$.

From which it easily follows that $\dim X = \dim U + \dim V - \dim W$. □

Scalar functions

Let X be a vector space over a field K . A **scalar function** is any function from X to K .

A scalar function $\ell: X \rightarrow K$ is **linear** if

- $\ell(x + y) = \ell(x) + \ell(y)$, for all $x, y \in X$;
- $\ell(cx) = c\ell(x)$, for all $x \in X$, $c \in K$.

Or equivalently, if

$$\ell(c_1x_1 + \cdots + c_nx_n) = c_1\ell(x_1) + \cdots + c_n\ell(x_n), \quad \text{for all } c_i \in K, x_i \in X.$$

Definition

The set of linear scalar functions $\ell: X \rightarrow K$ is a vector space called the **dual** of X , and denoted X' .

Addition and scalar multiplication is defined naturally:

- Addition: $(\ell + m)(x) := \ell(x) + m(x)$,
- Scalar multiplication: $(c\ell)(x) := c\ell(x)$.

Examples of scalar functions

Example 1

Let $X = \mathcal{C}([0, 1], \mathbb{R})$, the continuous functions $[0, 1] \rightarrow \mathbb{R}$, and fix $t_1, \dots, t_n \in [0, 1]$. The following are linear scalar functions:

- $\ell(f) = f(t_1)$;
- $\ell(f) = \sum_{i=1}^n a_i f(t_i), \quad a_i \in \mathbb{R}$;
- $\ell(f) = \int_0^1 f(t) dt$.

Example 2

Let $X = \mathcal{C}^\infty(\mathbb{R})$ be the set of smooth functions $\mathbb{R} \rightarrow \mathbb{R}$. For a fixed $t_0 \in \mathbb{R}$,

$$\ell := \sum_{i=1}^n a_i \left. \frac{d^i}{dt^i} \right|_{t=t_0}, \quad \ell: f \mapsto \sum_{i=1}^n a_i \left. \frac{d^i f}{dt^i} \right|_{t=t_0}$$

is a linear scalar function (i.e., an element of X').

The dual space

If $\dim X = n$, then $X \cong K^n$. Thus, we can associate a vector $x \in X$ with an n -tuple $x = (c_1, \dots, c_n)$ of scalars.

For any fixed $a_1, \dots, a_n \in K$, the function

$$\ell: X \longrightarrow K, \quad \ell(x) = a_1 c_1 + \dots + a_n c_n \quad (1)$$

is linear, i.e., $\ell \in X'$.

Theorem 1.8

If $\dim X = n < \infty$, then every $\ell \in X'$ can be written as in Eq. (1).

Proof

The dual space

Corollary 1.9

If $\dim X < \infty$, then $X \cong X'$.

One way to think of this is to:

1. associate a vector $x \in X$ with a column vector,
2. associate a scalar function $\ell \in X'$ with a row vector.

Notation

A linear function $\ell \in X'$ applied to a vector $x \in X$ depends on the n -tuples $(c_1, \dots, c_n)$ for x and $(a_1, \dots, a_n)$ for ℓ . We can use **scalar product notation**

$$(\ell, x) := \ell(x).$$

Sometimes, elements $\ell \in X'$ are called **co-vectors**, or **dual vectors**.

Definition

Let $x_1, \dots, x_n$ be a basis for X . The **dual basis** in X' is $\ell_1, \dots, \ell_n$, where

$$(\ell_i, x_j) = \begin{cases} 1 & i = j \\ 0 & i \neq j. \end{cases}$$

Think of ℓ_i as the function that “picks off” the coefficient of x_i .

Duality in infinite dimensional spaces

Consider the vector space

$$X = \ell^1(\mathbb{R}) := \left\{ (x_1, x_2, \dots) \mid x_i \in \mathbb{R}, \sum_{i=1}^{\infty} |x_i| < \infty \right\}.$$

Given vectors $y = (a_1, a_2, \dots)$ and $x = (c_1, c_2, \dots)$,

$$(y, x) = \sum_{i=1}^{\infty} a_i c_i < \infty,$$

so every $y \in X$ defines a co-vector in X' .

But there are others! If $z = (1, 1, 1, \dots)$,

$$(z, x) = \sum_{i=1}^{\infty} c_i < \infty,$$

but $z \notin X$.

The double dual

The scalar product (ℓ, x) is a **bilinear** function of ℓ and x . That is, if we fix one argument, it is linear in the other. Equivalently,

$$\underbrace{(a\ell, x)}_{=a\ell(x)} = a(\ell, x) = \underbrace{(\ell, ax)}_{\ell(ax)} \quad \text{for all } x \in X, \ell \in X', a \in K.$$

If $\dim X = n < \infty$, then every linear scalar function $X \rightarrow K$ is of the form

$$(\ell, x), \quad \text{for some fixed } \ell = (a_1, \dots, a_n) \in K^n.$$

Since X' is a vector space, it has a dual, called the **double dual** of X , and denoted $X'' := (X')'$. Every linear scalar function $X' \rightarrow K$ is of the form

$$(\ell, x), \quad \text{for some fixed } x = (c_1, \dots, c_n) \in K^n.$$

Key points

Let $x_1, \dots, x_n$ be a basis of X

- Think of the dual basis $\ell_1, \dots, \ell_n$ as “*pick-off functions*”
- Think of elements in the double dual as “*evaluation functions*”

The bilinear function (ℓ, x) naturally identifies X'' with X .

Annihilators

Definition

Let $Y \leq X$. The set of linear functions that vanish on Y is its **annihilator**, denoted

$$Y^\perp = \{\ell \in X' \mid \ell(y) = 0, \forall y \in Y\}.$$

Theorem 1.10

Let $Y \leq X$ with $\dim X < \infty$. Then

$$\dim Y + \dim Y^\perp = \dim X.$$

Proof

The annihilator of the annihilator

Definition

The dimension of $Y^\perp$ is called the **codimension** of Y in X , denoted $\text{codim } Y$.

By Theorem 1.10,

$$\dim Y + \text{codim } Y = \dim X.$$

Since $Y^\perp$ is a subspace of X' , its annihilator $Y^{\perp\perp}$ is a subspace of X'' .

Theorem 1.11

Assume $\dim X < \infty$ and identify X'' with X . Then $Y^{\perp\perp} = Y$.

Proof

The annihilator of a subset

We can define the annihilator of an arbitrary subset $S \subseteq X$, as

$$S^\perp := \{\ell \in X' \mid \ell(s) = 0, \forall s \in S\}.$$

Recall that the smallest subspace containing S is

$$\text{Span}(S) = \bigcap_{S \subseteq Y_\alpha \leq X} Y_\alpha.$$

Exercises

Let $S, T \subseteq X$.

- If $S \subseteq T$, then $T^\perp \subseteq S^\perp$,
- $S^\perp = \text{Span}(S)^\perp$.