

Mathematics Bootcamp Lecture Notes

Department of Statistical Sciences, University of Toronto

Emma Kroell

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Preface

These lecture notes were prepared for the Mathematics course at the inaugural Department of Statistical Sciences Graduate Student Bootcamp at the University of Toronto. The course taught an overview of necessary mathematics prerequisites to incoming statistics graduate students, with an emphasis on proofs.

These lectures are based on the following books or lecture notes:

1. *An Introduction to Mathematical Structures and Proofs* by Larry J. Gerstein
2. *A Taste of Topology* by Volker Runde
3. *Linear Algebra Done Right* by Sheldon Axler
4. *Linear Algebra Done Wrong* by Sergei Treil
5. *Introduction to Real Analysis* by William F. Trench
6. *Understanding Analysis* by Stephen Abbott
7. *Real Mathematical Analysis* by Charles C. Pugh
8. *Lecture notes in Mathematics for Economics and Statistics* by Piotr Zwiernik
9. *Real Analysis Lecture Notes* by Laurent Marcoux

The material in these notes belongs to these texts. All of these texts are available online to University of Toronto users (some to everyone).

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Contents

1	Review of proof techniques	5
1.1	Propositional logic	5
1.1.1	Truth values	5
1.1.2	Logical equivalence	5
1.2	Types of proof	6
1.2.1	Direct Proof	6
1.2.2	Proof by contrapositive	6
1.2.3	Proof by contradiction	6
1.2.4	Summary	7
1.2.5	Induction	7
1.3	Exercises	7
1.4	References	8
2	Set theory	8
2.1	Basics	8
2.2	Ordered sets	9
2.3	Functions	10
2.4	Cardinality	10
2.5	Exercises	13
2.6	References	13
3	Metric spaces and sequences	13
3.1	Metric spaces	13
3.2	Sequences	15
3.3	Continuity	16
3.4	Equivalence of metrics	16
3.5	Extra properties of \mathbb{R}^n	17
3.6	Exercises	17
3.7	References	18
4	Topology	18
4.1	Basic definitions	18
4.2	Compactness	18
4.3	Continuity	18
4.4	Exercises	18
4.5	References	18
5	Linear Algebra	18
5.1	Vector spaces	18
5.1.1	Axioms of a vector space	18
5.1.2	Subspaces	19
5.1.3	Exercises	19
5.2	Linear (in)dependence and bases	19
5.2.1	Exercises	20
5.3	Linear transformations	21
5.3.1	Exercises	22
5.4	Linear maps and matrices	22
5.5	Determinants	22
5.6	Inner product spaces	22
5.7	Spectral theory	23
5.7.1	Exercises	24
5.8	Matrix decomposition	24
5.9	References	24

6	Calculus	24
6.1	Differentiation	24
6.2	Integration	25
6.3	Exercises	25
6.4	References	25
7	Multivariable calculus	25
7.1	Differentiation	25
7.2	Implicit Function Theorem	25
7.3	Integration	25
7.4	Exercises	25
7.5	References	25

1 Review of proof techniques

1.1 Propositional logic

Propositions are statements that could be true or false. They have a corresponding **truth value**. We will use capital letters to denote propositions.

ex. “ n is odd” and “ n is divisible by 2” are propositions .

Let’s call them P and Q . Whether they are true or not (i.e. their truth value) depends on what n is.

We can negate statements: $\neg P$ is the statement “ n is not odd”

We can combine statements:

- $P \wedge Q$ is the statement “ n is odd and n is divisible by 2”.
- $P \vee Q$ is the statement “ n is odd or n is divisible by 2”. We always assume the inclusive or unless specifically stated otherwise.

Examples:

- If it’s not raining, I won’t bring my umbrella.
- I’m a banana or Toronto is in Canada.
- If I pass this exam, I’ll be both happy and surprised.

1.1.1 Truth values

Example 1.1. Write the following using propositional logic *If it is snowing, then it is cold out. It is snowing. Therefore, it is cold out.*

Solution. $P \implies Q$

P

Conclusion: Q

■

To examine if statement is true or not, we use a truth table

P	Q	$P \implies Q$
T	T	T
T	F	F
F	T	T
F	F	T

1.1.2 Logical equivalence

P	Q	$P \implies Q$
T	T	T
T	F	F
F	T	T
F	F	T

P	Q	$\neg P$	$\neg P \vee Q$
T	T	F	T
T	F	F	F
F	T	T	T
F	F	T	T

What is $\neg(P \implies Q)$?

1.2 Types of proof

- Direct
- Contradiction
- Contrapositive
- Induction

1.2.1 Direct Proof

Approach: Use the definition and known results.

Example 1.2. *The product of an even number with another integer is even.*

Approach: use the definition of even.

Definition 1.3. *We say that an integer n is **even** if there exists another integer j such that $n = 2j$. We say that an integer n is **odd** if there exists another integer j such that $n = 2j + 1$.*

Proof. Let $n, m \in \mathbb{Z}$, with n even. By definition, there $\exists j \in \mathbb{Z}$ such that $n = 2j$. Then

$$nm = (2j)m = 2(jm)$$

Therefore nm is even by definition. □

Definition 1.4. *Let $a, b \in \mathbb{Z}$. We say that “ a divides b ”, written $a|b$, if the remainder is zero when b is divided by a , i.e. $\exists j \in \mathbb{Z}$ such that $b = aj$.*

Example 1.5. *Let $a, b, c \in \mathbb{Z}$ with $a \neq 0$. Prove that if $a|b$ and $b|c$, then $a|c$.*

Proof. Suppose $a|b$ and $b|c$. Then by definition, there exists $j, k \in \mathbb{Z}$ such that $b = aj$ and $c = kb$. Combining these two equations gives $c = k(aj) = a(kj)$. Thus $a|c$ by definition. □

1.2.2 Proof by contrapositive

Example 1.6. *If an integer squared is even, then the integer is itself even.*

How would you approach this proof?

$$P \implies Q \qquad \neg P \implies \neg Q$$

P	Q	$P \implies Q$
T	T	T
T	F	F
F	T	T
F	F	T

P	Q	$\neg P$	$\neg Q$	$\neg Q \implies \neg P$
T	T	F	F	T
T	F	F	T	T
F	T	T	F	F
F	F	T	T	T

Proof. We prove the contrapositive. Let n be odd. Then there exists $k \in \mathbb{Z}$ such that $n = 2k + 1$. We compute

$$n^2 = (2k + 1)^2 = 4k^2 + 4k + 1 = 2(2k^2 + 2k) + 1.$$

Thus n^2 is odd. □

1.2.3 Proof by contradiction

Example 1.7. *The sum of a rational number and an irrational number is irrational.*

Proof. Let $q \in \mathbb{Q}$ and $r \in \mathbb{R} \setminus \mathbb{Q}$. Suppose in order to derive a contradiction that their sum is rational, i.e. $r + q = s$ where $s \in \mathbb{Q}$. But then $r = s - q \in \mathbb{Q}$. Contradiction. □

1.2.4 Summary

In sum, to prove $P \implies Q$:

- Direct proof: assume P , prove Q
- Proof by contrapositive: assume $\neg Q$, prove $\neg P$
- Proof by contradiction: assume $P \wedge \neg Q$ and derive something that is impossible

[EK: add section explaining \forall and \exists and how to do proofs with them?]

1.2.5 Induction

Theorem 1.8 (Well-ordering principle for \mathbb{N}). *Every nonempty set of natural numbers has a least element.*

Theorem 1.9 (Principle of mathematical induction). *Let n_0 be a non-negative integer. Suppose P is a property such that*

1. (base case) $P(n_0)$ is true
2. (induction step) For every integer $k \geq n_0$, if $P(k)$ is true, then $P(k+1)$ is true.

Then $P(n)$ is true for every integer $n \geq n_0$

Note: Principle of strong mathematical induction: For every integer $k \geq n_0$, if $P(n)$ is true for every $n = n_0, \dots, k$, then $P(k+1)$ is true.

Example 1.10. $n! > 2^n$ if $n \geq 4$.

Proof. We prove this by induction on n .

Base case: Let $n = 4$. Then $n! = 4! = 24 > 16 = 2^4$.

Inductive hypothesis: Suppose for some $k \geq 4$, $k! > 2^k$.

Then

$$(k+1)! = (k+1)k! > (k+1)2^k > 2(2^k) = 2^{k+1}.$$

□

Example 1.11. *Every integer $n \geq 2$ can be written as the product of primes.*

Proof. We prove this by induction on n .

Base case: $n = 2$ is prime.

Inductive hypothesis: Suppose for some $k \geq 2$ that one can write every integer n such that $2 \leq n \leq k$ as a product of primes.

We must show that we can write $k+1$ as a product of primes.

First, if $k+1$ is prime then we are done.

Otherwise, if $k+1$ is not prime, by definition it can be written as a product of some integers a, b such that $1 < a, b < k+1$. By the induction hypothesis, a and b can both be written as products of primes, so we are done. □

1.3 Exercises

1. Prove De Morgan's Laws for propositions: $\neg(P \wedge Q) = \neg P \vee \neg Q$ and $\neg(P \vee Q) = \neg P \wedge \neg Q$ (Hint: use truth tables).
2. If $a|b$ and $a, n \in \mathbb{Z}_{>0}$ (positive integers), then $a \leq b$.

3. If $a|b$ and $a|c$, then $a|(xb + yc)$, where $x, y \in \mathbb{Z}$.
4. Let $a, b, n \in \mathbb{Z}$. If n does not divide the product ab , then n does not divide a and n does not divide b .
5. Prove that for all integers $n \geq 1$, $3|(2^{2n} - 1)$.
6. Prove the Fundamental Theorem of Arithmetic, that every integer $n \geq 2$ has a unique prime factorization (i.e. prove that the prime factorization from the last proof is unique).

1.4 References

A good resource for this is Gerstein [1]. Lakins [2] is also a great resource, but sadly it is not freely available online or at U of T.

2 Set theory

2.1 Basics

For our purposes, we define a *set* to be a collection of mathematical objects. If S is a set and x is one of the objects in the set, we say x is an element of S and denote it by $x \in S$. The set of no elements is called empty set and is denoted by \emptyset .

Definition 2.1 (Subsets, Union, Intersection). *Let S, T be sets.*

- We say that S is a subset of T , denoted $S \subseteq T$, if $s \in S$ implies $s \in T$.
- We say that $S = T$ if $S \subseteq T$ and $T \subseteq S$.
- We define the union of S and T , denoted $S \cup T$, as all the elements that are in either S and T .
- We define the intersection of S and T , denoted $S \cap T$, as all the elements that are in both S and T .
- We say that S and T are disjoint if $S \cap T = \emptyset$.

Example 2.2. $\mathbb{N} \subset \mathbb{N}_0 \subset \mathbb{Z} \subset \mathbb{Q} \subset \mathbb{R} \subset \mathbb{C}$

Example 2.3. Let $a < b \cup \{-\infty, \infty\}$.

Open interval: $(a, b) := \{x \in \mathbb{R} : a < x < b\}$

Closed interval: $[a, b] := \{x \in \mathbb{R} : a \leq x \leq b\}$

We can also define half-open intervals.

Example 2.4. Let $A = \{x \in \mathbb{N} : 3|x\}$ and $B = \{x \in \mathbb{N} : 6|x\}$ Show that $B \subseteq A$.

Proof. Let $x \in B$. Then $6|x$, i.e. $\exists j \in \mathbb{Z}$ such that $x = 6j$. Therefore $x = 3(2j)$, so $3|x$. Thus $x \in A$. \square

Definition 2.5. Let $A, B \subseteq X$. We define the set-theoretic difference of A and B , denoted $A \setminus B$ (sometimes $A - B$) as the elements of X that are in A but not in B .

The complement of a set $A \subseteq X$ is the set $A^c := X \setminus A$.

We extend the definition of union and intersection to an arbitrary family of sets as follows:

Definition 2.6. Let S_α , $\alpha \in A$, be a family of sets. A is called the index set. We define

$$\bigcup_{\alpha \in A} S_\alpha := \{x : \exists \alpha \text{ such that } x \in S_\alpha\}$$

$$\bigcap_{\alpha \in A} S_\alpha := \{x : x \in S_\alpha \forall \alpha \in A\}$$

Example 2.7.

$$\bigcup_{n=1}^{\infty} [-n, n] = \mathbb{R}$$

$$\bigcap_{n=1}^{\infty} \left(-\frac{1}{n}, \frac{1}{n}\right) = \{0\}$$

Theorem 2.8 (De Morgan's Laws). *Let $\{S_\alpha\}_{\alpha \in A}$ be an arbitrary collection of sets. Then*

$$\left(\bigcup_{\alpha \in A} S_\alpha\right)^c = \bigcap_{\alpha \in A} S_\alpha^c \quad \text{and} \quad \left(\bigcap_{\alpha \in A} S_\alpha\right)^c = \bigcup_{\alpha \in A} S_\alpha^c$$

Proof. For the first part: Let $x \in \left(\bigcup_{\alpha \in A} S_\alpha\right)^c$. This is true if and only if $x \notin \left(\bigcup_{\alpha \in A} S_\alpha\right)$, or in other words $x \in S_\alpha^c \forall \alpha \in A$. This is true if and only if $x \in \bigcap_{\alpha \in A} S_\alpha^c$, which gives the result. The second part is similar and is left as an exercise. \square

Since a set is itself a mathematical object, a set can itself contain sets.

Definition 2.9. *The power set $\mathcal{P}(S)$ of a set S is the set of all subsets of S .*

Example 2.10. *Let $S = \{a, b, c\}$. Then $\mathcal{P}(S) = \{\emptyset, \{a\}, \{b\}, \{c\}, \{a, b\}, \{b, c\}, \{a, c\}, S\}$.*

Another way of building a new set from two old ones is the Cartesian product of two sets.

Definition 2.11. *Let S, T be sets. The Cartesian product $S \times T$ is defined as the set of tuples with elements from S, T , i.e*

$$S \times T = \{(s, t) : s \in S \text{ and } t \in T\}.$$

This can also be extended inductively.

2.2 Ordered sets

Definition 2.12. *A relation R on a set X is a subset of $X \times X$. A relation \leq is called a partial order on X if it satisfies*

1. *reflexivity: $x \leq x$ for all $x \in X$*
2. *transitivity: for $x, y, z \in X$, $x \leq y$ and $y \leq z$ implies $x \leq z$*
3. *anti-symmetry: for $x, y \in X$, $x \leq y$ and $y \leq x$ implies $x = y$*

The pair (X, \leq) is called a partially ordered set.

A chain or totally ordered set $C \subseteq X$ is a subset with the property $x \leq y$ or $y \leq x$ for any $x, y \in C$.

Example 2.13. *The real numbers with the usual ordering, (\mathbb{R}, \leq) are totally ordered.*

Example 2.14. *The power set of a set X with the ordering given by subsets, $(\mathcal{P}(X), \subseteq)$ is partially ordered set.*

Example 2.15. *Let $X = \{a, b, c, d\}$. What is $\mathcal{P}(X)$? Find a chain in $\mathcal{P}(X)$.*

$\mathcal{P}(X) = \{\emptyset, \{a\}, \{b\}, \{c\}, \{d\}, \{a, b\}, \{b, c\}, \{c, d\}, \{b, d\}, \{a, c\}, \{a, d\}, \{a, b, c\}, \{b, c, d\}, \{a, b, d\}, \{a, c, d\}, X\}$
An example of a chain $C \subseteq \mathcal{P}(X)$ is $C = \{\emptyset, \{b\}, \{b, c\}, \{a, b, c\}, X\}$

Example 2.16. *Consider the set $C([0, 1], \mathbb{R}) := \{f : [0, 1] \rightarrow \mathbb{R} : f \text{ is continuous}\}$.*

For two function $f, g \in C([0, 1], \mathbb{R})$, we define the ordering as $f \leq g$ if $f(x) \leq g(x)$ for $x \in [0, 1]$. Then $(C([0, 1], \mathbb{R}), \leq)$ is a partially ordered set. Can you think of a chain that is a subset of $(C([0, 1], \mathbb{R}))$?

Definition 2.17. *A non-empty partially ordered set (X, \leq) is well-ordered if every non-empty subset $A \subseteq X$ has a minimum element.*

Recall that we already saw that \mathbb{N} is well-ordered, as we used it to prove the principle of mathematical induction. \mathbb{R} does not have this property.

2.3 Functions

One way to define a function is as follows [3, Definition 1.1.14]:

Definition 2.18. A function f from a set X to a set Y is a subset of $X \times Y$ with the properties:

1. For every $x \in X$, there exists a $y \in Y$ such that $(x, y) \in f$
2. If $(x, y) \in f$ and $(x, z) \in f$, then $y = z$.

X is called the domain of f .

How does this connect to other descriptions of functions you may have seen?

Example 2.19. For a set X , the identity function is:

$$1_X : X \rightarrow X, \quad x \mapsto x$$

Definition 2.20 (Image and pre-image). Let $f : X \rightarrow Y$ and $A \subseteq X$ and $B \subseteq Y$. The image of f is the set $f(A) := \{f(x) : x \in A\}$ and the pre-image of f is the set $f^{-1}(B) := \{x : f(x) \in B\}$

Helpful way to think about it for proofs:

If $y \in f(A)$, then $y \in Y$, and there exists an $x \in A$ such that $y = f(x)$.

If $x \in f^{-1}(B)$, then $x \in X$ and $f(x) \in B$.

Definition 2.21 (Surjective, injective and bijective). Let $f : X \rightarrow Y$, where X and Y are sets. Then

- f is injective if $x_1 \neq x_2$ implies $f(x_1) \neq f(x_2)$
- f is surjective if for every $y \in Y$, there exists an $x \in X$ such that $y = f(x)$
- f is bijective if it is both injective and surjective

Example 2.22. Let $f : X \rightarrow Y$, $x \mapsto x^2$.

If $X = \mathbb{R}$ and $Y = [0, \infty)$: f is surjective.

If $X = [0, \infty)$ and $Y = \mathbb{R}$: f is injective.

If $X = Y = [0, \infty)$: f is bijective.

If $X = Y = \mathbb{R}$, then f is neither surjective nor injective.

Proposition 2.23. Let $f : X \rightarrow Y$ and $A \subseteq X$. Prove that $A \subseteq f^{-1}(f(A))$, with equality iff f is injective.

Proof. First we show $A \subseteq f^{-1}(f(A))$.

Let $x \in A$. Let $B = f(A)$, $B \subseteq Y$. By definition, $f(x) \in B$. So then again by definition, $x \in f^{-1}(B)$. Thus $x \in f^{-1}(f(A))$.

Next, suppose f is injective. We have already shown that $A \subseteq f^{-1}(f(A))$, so it remains to show that $f^{-1}(f(A)) \subseteq A$. Let $x \in f^{-1}(f(A))$. Then $f(x) \in f(A)$ by the definition of the pre-image. This means that there exists a $\tilde{x} \in A$ such that $f(x) = f(\tilde{x})$. Since f is injective, we have $x = \tilde{x}$, and hence $x \in A$. \square

2.4 Cardinality

Definition 2.24. The cardinality of a set A , denoted $|A|$, is the number of elements in the set.

We say that the empty set has cardinality 0 and is finite.

Proposition 2.25. If X is finite set of cardinality n , then the cardinality of $\mathcal{P}(X)$ is 2^n .

Proof. We proceed by induction. First, suppose $n = 0$. Then $X = \emptyset$, and $\mathcal{P}(X) = \{\emptyset\}$ which has cardinality $1 = 2^0$.

Next, suppose that the claim holds for some $n \in \mathbb{N}_0$. Let X have $n + 1$ elements. Let's call them $\{x_1, \dots, x_n, x_{n+1}\}$. Then we can split X up into subsets $A = \{x_1, \dots, x_n\}$ and $B = \{x_{n+1}\}$. By the inductive hypothesis, $\mathcal{P}(A)$ has cardinality 2^n . Any subset of X must either be a subset of A or contain x_{n+1} .

How many subsets are there for the latter form? Let's count them out. Each subset will be formed by taking elements from A and combining them with x_{n+1} . We start with no elements from A and count up to all of them:

$$\begin{aligned} & 1 + \binom{n}{1} + \binom{n}{2} + \dots + \binom{n}{n-1} + \binom{n}{n} \\ &= \sum_{k=0}^n \binom{n}{k} \\ &= 2^n \end{aligned}$$

Therefore the total number of elements in $\mathcal{P}(X)$ is the number of subsets of A (2^n) plus the number of mixed subsets (2^n), i.e. the cardinality of $\mathcal{P}(X)$ is $2^n + 2^n = 2^{n+1}$.

Thus the claim holds by induction. \square

Definition 2.26. Two sets A and B have same cardinality, $|A| = |B|$, if there exists bijection $f : A \rightarrow B$.

Example 2.27. Which is bigger, \mathbb{N} or \mathbb{N}_0 ?

Intuitively (at least to me), it seems that \mathbb{N}_0 should be bigger, since it includes exactly one more element than \mathbb{N} , namely 0. However, clearly the function $f : \mathbb{N}_0 \rightarrow \mathbb{N}$ defined by $n \mapsto n + 1$ is a bijection. Therefore \mathbb{N}_0 and \mathbb{N} have the same cardinality! One way to think about this is that \mathbb{N}_0 and \mathbb{N} are the “same size” of infinity.

It may sometimes be difficult to find such a bijection. However you can also use the following definition and theorem to instead show that two sets have the same cardinality by finding two injective functions between them.

Definition 2.28. We say that the cardinality of a set A is less than the cardinality of a set B , denoted $|A| \leq |B|$ if there exists an injection $f : A \rightarrow B$.

Theorem 2.29 (Cantor-Schröder-Bernstein). Let A, B , be sets. If $|A| \leq |B|$ and $|B| \leq |A|$, then $|A| = |B|$.

Proof is omitted. See [3, Theorem 1.2.7]

Example 2.30. $|\mathbb{N}| = |\mathbb{N} \times \mathbb{N}|$

Proof. First, we show $|\mathbb{N}| \leq |\mathbb{N} \times \mathbb{N}|$. The function $f : \mathbb{N} \rightarrow \mathbb{N} \times \mathbb{N}$ defined by $n \mapsto (n, 1)$ is a injection, thus $|\mathbb{N}| \leq |\mathbb{N} \times \mathbb{N}|$.

Next, we show $|\mathbb{N} \times \mathbb{N}| \leq |\mathbb{N}|$. We define the function $g : \mathbb{N} \times \mathbb{N} \rightarrow \mathbb{N}$ by $(n, m) \mapsto 2^n 3^m$. Why is this an injection? Assume we have n_1, n_2, m_1, m_2 such that $2^{n_1} 3^{m_1} = 2^{n_2} 3^{m_2}$. We need to show $n_1 = n_2$ and $m_1 = m_2$. By the Fundamental Theorem of Arithmetic, every natural number greater than 1 has a unique prime factorization, so therefore the result must hold. \square

Definition 2.31. Let A be a set.

1. A is finite if there exists an $n \in \mathbb{N}$ and a bijection $f : \{1, \dots, n\} \rightarrow A$
2. A is countably infinite if there exists a bijection $f : \mathbb{N} \rightarrow A$
3. A is countable if it is finite or countably infinite
4. A is uncountable otherwise

Example 2.32. The rational numbers are countable, and in fact $|\mathbb{Q}| = |\mathbb{N}|$.

Let's look at $\mathbb{Q}^+ := \{x \in \mathbb{Q} : x > 0\}$. The fact that the rationals are countable relies on this famous way of

listing the rational numbers:

$$\begin{array}{cccccc}
 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \dots \\
 2 & \frac{2}{2} & \frac{2}{3} & \frac{2}{4} & \frac{2}{5} & \dots \\
 3 & \frac{3}{2} & \frac{3}{3} & \frac{3}{4} & \frac{3}{5} & \dots \\
 4 & \frac{4}{2} & \frac{4}{3} & \frac{4}{4} & \frac{4}{5} & \dots \\
 \vdots & \vdots & \vdots & \vdots & \vdots & \ddots
 \end{array}$$

This is a map from \mathbb{N} to \mathbb{Q}^+ . As long as we skip any fraction that is already in our list as we go along, it is injective. Since we can find an injection from \mathbb{Q}^+ to $\mathbb{N} \times \mathbb{N}$ (exercise), we have that $|\mathbb{Q}^+| = |\mathbb{N}|$. We can extend this to \mathbb{Q} . To do so, let $f: \mathbb{N} \rightarrow \mathbb{Q}^+$ be a bijection (which exists by the previous part). Then we can define another bijection $g: \mathbb{N} \rightarrow \mathbb{Q}$ by setting $g(1) = 0$ and

$$g(n) = \begin{cases} f(n) & \text{if } n \text{ is even,} \\ -f(n) & \text{if } n \text{ is odd,} \end{cases}$$

for $n > 1$.

Next we show that \mathbb{N} is “smaller” than $(0, 1)$.

Theorem 2.33. *The cardinality of \mathbb{N} is smaller than that of $(0, 1)$.*

Proof. First, we show that there is an injective map from \mathbb{N} to $(0, 1)$. The map $n \rightarrow \frac{1}{n}$ fulfils this.

Next, we show that there is no surjective map from \mathbb{N} to $(0, 1)$. We use the fact that every number $r \in (0, 1)$ has a binary expansion of the form $r = 0.\sigma_1\sigma_2\sigma_3\dots$ where $\sigma_i \in \{0, 1\}$, $i \in \mathbb{N}$.

Now we suppose in order to derive a contradiction that there does exist a surjective map f from \mathbb{N} to $(0, 1)$, i.e. for $n \in \mathbb{N}$ we have $f(n) = 0.\sigma_1(n)\sigma_2(n)\sigma_3(n)\dots$. This means we can list out the binary expansions, for example like

$$\begin{aligned}
 f(1) &= 0.00000000\dots \\
 f(2) &= 0.11111111\dots \\
 f(3) &= 0.01010101\dots \\
 f(4) &= 0.10101010\dots
 \end{aligned}$$

We will construct a number $\tilde{r} \in (0, 1)$ that is not in the image of f . Define $\tilde{r} = 0.\tilde{\sigma}_1\tilde{\sigma}_2\dots$, where we define the n th entry of \tilde{r} to be the the opposite of the n th entry of the n th item in our list:

$$\tilde{\sigma}_n = \begin{cases} 1 & \text{if } \sigma_n(n) = 0, \\ 0 & \text{if } \sigma_n(n) = 1. \end{cases}$$

Then \tilde{r} differs from $f(n)$ at least in the n th digit of its binary expansion for all $n \in \mathbb{N}$. Hence, $\tilde{r} \notin f(\mathbb{N})$, which is a contradiction to f being surjective. This technique is often referred to as Cantor’s diagonal argument. \square

Proposition 2.34. *$(0, 1)$ and \mathbb{R} have the same cardinality.*

Proof. The map $f: \mathbb{R} \rightarrow (0, 1)$ defined by $x \mapsto \frac{1}{\pi} \left(\arctan(x) + \frac{\pi}{2} \right)$ is a bijection. \square

We have shown that there are different sizes of infinity, as the cardinality of \mathbb{N} is infinite but still smaller than that of \mathbb{R} or $(0, 1)$. In fact, we have

$$|\mathbb{N}| = |\mathbb{N}_0| = |\mathbb{Z}| = |\mathbb{Q}| < |\mathbb{R}|.$$

Because of this, there are special symbols for these two cardinalities: The cardinality of \mathbb{N} is denoted \aleph_0 , while the cardinality of \mathbb{R} is denoted \mathfrak{c} . There is even a relationship between them:

Proposition 2.35. $\mathfrak{c} = 2^{\aleph_0}$, i.e. the cardinality of \mathbb{R} is the same as the cardinality of $\mathcal{P}(\mathbb{N})$.

This proof is omitted; see [3, Proposition 1.2.9].

2.5 Exercises

1. Is $\mathbb{R} \times \mathbb{R}$ with the ordering $(x_1, y_1) \preceq (x_2, y_2)$ if $x_1 \leq y_1$ a partially ordered set?
2. [3, Exercise 1.3.1] Let S be a non-empty set. A relation R on S is called an equivalence relation if it is
 - (i) Reflexive: $(x, x) \in R$ for all $x \in S$
 - (ii) Symmetric: if $(x, y) \in R$ then $(y, x) \in R$ for all $x, y \in S$
 - (iii) Transitive: if $(x, y), (y, z) \in R$ then $(x, z) \in R$ for all $x, y, z \in S$

Given $x \in S$ the equivalence class of x (with respect to a given equivalence relation R) is defined to consist of those $y \in S$ for which $(x, y) \in R$. Show that two equivalence classes are either disjoint or identical.

3. Let $f : X \rightarrow Y$ be defined by the map $x \mapsto \sin(x)$. For what choices of X and Y is f injective, surjective, bijective, or neither?
4. Show that for sets $A, B \subseteq X$ and $f : X \rightarrow Y$, $f(A \cap B) \subseteq f(A) \cap f(B)$.
5. Let $f : X \rightarrow Y$ and $B \subseteq Y$. Prove that $f(f^{-1}(B)) \subseteq B$, with equality iff f is surjective.
6. Prove that $f(\cup_{i \in I} A_i) = \cup_{i \in I} f(A_i)$.
7. Show that \mathbb{N} and \mathbb{Z} have the same cardinality.
8. Show that $|(0, 1)| = |(1, \infty)|$.

2.6 References

The content in this section comes following texts:

A Taste of Topology [3]

The first chapter in Laurent Marcoux's Real Analysis notes (University of Waterloo) [4]

The first chapter of Piotr Zwiernik's *Lecture notes in Mathematics for Economics and Statistics* [5]

3 Metric spaces and sequences

3.1 Metric spaces

Definition 3.1. A metric on a set X is a function $d : X \times X \rightarrow \mathbb{R}$ that satisfies:

- (a) Positive definiteness: $d(x, y) \geq 0$ for $x, y \in X$ and $d(x, y) = 0 \Leftrightarrow x = y$
- (b) Symmetry: for $x, y \in X$, $d(x, y) = d(y, x)$
- (c) Triangle inequality: for $x, y, z \in X$, $d(x, z) \leq d(x, y) + d(y, z)$

A set together with a metric is called a metric space.

Example 3.2. \mathbb{R}^n with the Euclidean distance

$$d(x, y) = \sqrt{\sum_{j=1}^n (x_j - y_j)^2}$$

is a metric space

Definition 3.3. A norm on a linear space E is a function $\|\cdot\| : E \rightarrow \mathbb{R}$ that satisfies:

- (a) *Positive definiteness:* $\|x\| \geq 0$ for $x \in E$ and $\|x\| = 0 \Leftrightarrow x = 0$
- (b) *Homogeneity:* for $x \in E$ and $\alpha \in \mathbb{F}$, $\|\alpha x\| = |\alpha| \|x\|$
- (c) *Triangle inequality:* for $x, y \in E$, $\|x + y\| \leq \|x\| + \|y\|$

A linear space with a norm is called a normed space. A normed space can be turned into a metric space using the metric $d(x, y) = \|x - y\|$.

Example 3.4. The p -norm is defined for $p \geq 1$ for a vector $x = (x_1, \dots, x_n)$ as

$$\|x\|_p = \left(\sum_{i=1}^n |x_i|^p \right)^{1/p}.$$

The infinity norm is the limit of the p -norm as $p \rightarrow \infty$, defined as

$$\|x\|_\infty = \max_{i=1, \dots, n} |x_i|.$$

If we look at the space of continuous functions $C([0, 1]; \mathbb{R})$, the p -norm is

$$\|f\|_p = \left(\int_0^1 |f(x)|^p dx \right)^{1/p}$$

and the ∞ -norm is

$$\|f\|_\infty = \max_{x \in [0, 1]} |f(x)|.$$

Definition 3.5. Let (X, d) be a metric space. We define the open ball centred at a point $x_0 \in X$ of radius $r > 0$ as

$$B_r(x_0) := \{x \in X : d(x, x_0) < r\}.$$

Example 3.6. Consider \mathbb{R}^2 with the taxicab or Manhattan metric (1-norm) $d(x, y) = \sum_{i=1}^2 |x_i - y_i|$, the usual Euclidean distance (2-norm) $d(x, y) = \sqrt{\sum_{j=1}^2 (x_j - y_j)^2}$, and the ∞ -norm $d(x, y) = \max_{j=1, 2} |x_j - y_j|$. The open ball $B_r(0)$ in these three metric spaces is shown in Fig. 1.

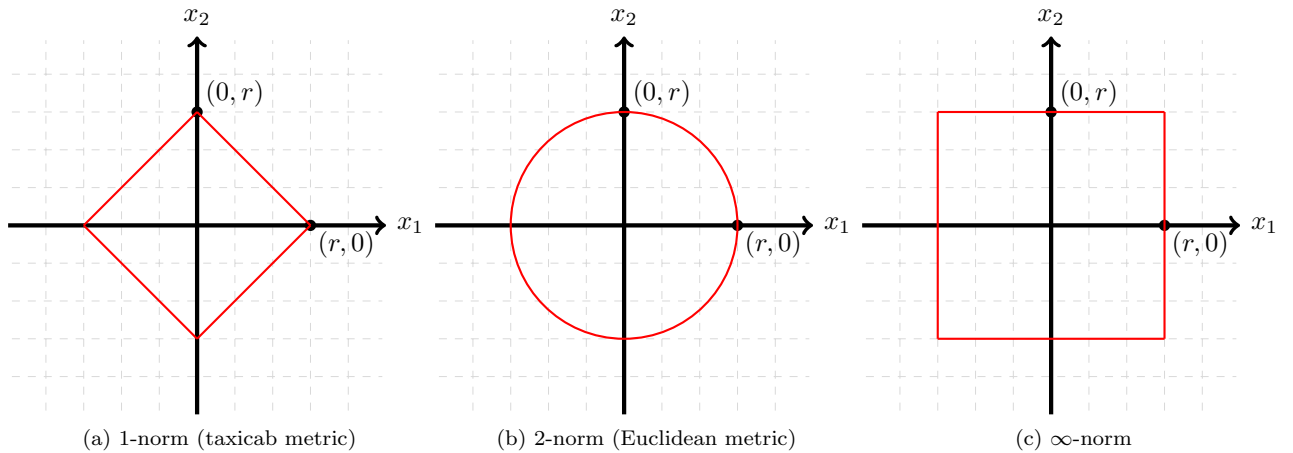


Figure 1: $B_r(0)$ for different metrics

Definition 3.7 (Open and closed sets). Let (X, d) be a metric space.

- A set $U \subseteq X$ is open if for every $x \in U$ there exists $\epsilon > 0$ such that $B_\epsilon(x) \subseteq U$.
- A set $K \subseteq X$ is closed if $K^c := X \setminus K$ is open.

We note that \emptyset and X are both open and closed!

Proposition 3.8. *Let (X, d) be a metric space.*

- (i) *Let $A_1, A_2 \subseteq X$. If A_1 and A_2 are open, then $A_1 \cap A_2$ is open.*
- (ii) *If $A_i \subseteq X$, $i \in I$ are open, then $\cup_{i \in I} A_i$ is open.*

Proof. (i) Since A_1 is open, for each $x \in A_1$, there exists an $\epsilon_1 > 0$ such that $B_{\epsilon_1}(x) \subseteq A_1$. Since A_2 is open, for each $x \in A_2$, there exists an $\epsilon_2 > 0$ such that $B_{\epsilon_2}(x) \subseteq A_2$. Let $x \in A_1 \cap A_2$. Choose $\epsilon = \min\{\epsilon_1, \epsilon_2\}$. Then $B_\epsilon(x) \subseteq A_1 \cap A_2$ as required.

(ii) Let $x \in \cup_{i \in I} A_i$. Then there exists $i \in I$ such that $x \in A_i$, and since A_i is open there exists $\epsilon > 0$ such that $B_\epsilon(x) \subseteq A_i$. Since $A_i \subseteq \cup_{i \in I} A_i$, we are done. □

We immediately have the following corollary:

Corollary 3.9. *Let (X, d) be a metric space.*

- (i) *Let $A_1, A_2 \subseteq X$. If A_1 and A_2 are closed, then $A_1 \cup A_2$ is closed.*
- 1. *If $A_i \subseteq X$, $i \in I$ are closed, then $\cap_{i \in I} A_i$ is closed.*

Definition 3.10 (Interior and closure). *Let $A \subseteq X$ where (X, d) is a metric space.*

- The closure of A is $\bar{A} := \{x \in X : \forall \epsilon > 0, B_\epsilon(x) \cap A \neq \emptyset\}$
- The interior of A is $\dot{A} := \{x \in A : \exists \epsilon > 0 \text{ s.t. } B_\epsilon(x) \subseteq A\}$
- The boundary of A is $\partial A := \{x \in X : \forall \epsilon > 0, B_\epsilon(x) \cap A \neq \emptyset \text{ and } B_\epsilon(x) \cap A^c \neq \emptyset\}$

The closure of a set is the smallest closed set that contains it while the interior of a set is the largest open set contained by it.

Proposition 3.11. *Let $A \subseteq X$ where (X, d) is a metric space. Then $\dot{A} = A \setminus \partial A$.*

Proof. First, we show $\dot{A} \subseteq A \setminus \partial A$. Let $x \in \dot{A}$. Then by definition $\exists \epsilon > 0$ s.t. $B_\epsilon(x) \subseteq A$. Clearly $x \in A$ and also by definition, $x \notin \partial A$.

Next, we show $A \setminus \partial A \subseteq \dot{A}$. Let $x \in A \setminus \partial A$. Then $x \in A$ and $x \notin \partial A$. The latter means that $\exists \epsilon > 0$ such that $B_\epsilon(x) \cap A \neq \emptyset$ or $B_\epsilon(x) \cap A^c \neq \emptyset$. Since $x \in B_\epsilon(x) \cap A$ for any ϵ , the former cannot be true for any ϵ . Therefore $\exists \epsilon > 0$ such that $B_\epsilon(x) \cap A^c \neq \emptyset$, i.e. $B_\epsilon(x) \subseteq A$. Thus $x \in \dot{A}$. □

Definition 3.12. *A subset A of a metric space (X, d) is bounded if there exists $M > 0$ such that $d(x, y) < M$ for all $x, y \in A$.*

3.2 Sequences

Definition 3.13. *Let (X, d) be a metric space. A sequence is a list of points x_n , $n \in \mathbb{N}$, in X , denoted $(x_n)_{n \in \mathbb{N}}$. We say that a sequence $(x_n)_{n \in \mathbb{N}}$ converges to a point $x \in X$ if*

$$\forall \epsilon > 0 \exists n_\epsilon \in \mathbb{N} \text{ s.t. } d(x_n, x) < \epsilon \text{ for all } n \geq n_\epsilon.$$

Proposition 3.14. *Let (X, d) be a metric space, and let $A \subseteq X$. Then \bar{A} is equal to the set of points in X which are limits of a sequence in A .*

Proof. Let $x \in \bar{A}$. Then by definition, for every $\epsilon > 0$, $B_\epsilon(x) \cap A \neq \emptyset$. In particular this is true for $\epsilon = 1/n$. Thus, for any $n \in \mathbb{N}$, we can choose an $x_n \in A$ such that $x_n \in B_{1/n}(x)$, which means $d(x, x_n) < \frac{1}{n}$ by the definition of an open ball. Since $1/n$ decreases monotonically to zero, we must have $x_n \rightarrow x$. Let $x \in X$ be the limit of a sequence $(x_n)_{n \in \mathbb{N}} \in A$. Then for $\epsilon > 0$, $\exists n_\epsilon \in \mathbb{N}$ such that $d(x_n, x) < \epsilon$ for all $n \geq n_\epsilon$. This means there $x_n \in B_\epsilon(x)$, and since $x_n \in A$, $B_\epsilon(x) \cap A \neq \emptyset$. Thus $x \in \bar{A}$. \square

Corollary 3.15. *A set $K \subseteq X$, where (X, d) is a metric space, is closed if and only if every sequence in K which converges in X converges to a point in K .*

Definition 3.16 (Cauchy sequence). *Let (X, d) be a metric space. A sequence denoted $(x_n)_{n \in \mathbb{N}} \in X$ is called a Cauchy sequence if*

$$\forall \epsilon \exists n_\epsilon \in \mathbb{N} \text{ s.t. } d(x_n, x_m) < \epsilon \text{ for all } n, m \geq n_\epsilon.$$

Proposition 3.17. *Let (X, d) be a metric space, and let $(x_n)_{n \in \mathbb{N}}$ be a convergent sequence in X . The $(x_n)_{n \in \mathbb{N}}$ is Cauchy.*

Proof. Let $\epsilon > 0$ be arbitrary. Let $(x_n)_{n \in \mathbb{N}}$ be a convergent sequence in a metric space (X, d) . Then there exists $n_\epsilon \in \mathbb{N}$ such that $d(x_n, x) < \frac{\epsilon}{2}$ for all $n \geq n_\epsilon$. Then for $n, m \geq n_\epsilon$, using the triangle inequality we have

$$d(x_n, x_m) \leq d(x_n, x) + d(x, x_m) < \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon.$$

Thus $(x_n)_{n \in \mathbb{N}}$ is Cauchy. \square

Definition 3.18. *A metric space where every Cauchy sequence converges is called complete.*

In addition, a normed space that is complete with respect to the metric induced by the norm is called a *Banach space*. \mathbb{R}^n with the Euclidean distance is complete (and is in fact a Banach space).

[EK: add subsequences, accumulation point of a set]

3.3 Continuity

[EK: Topics:

- Continuous functions on metric spaces
- Equivalent definitions of continuity ($\epsilon - \delta$, sequential continuity, left- and right-continuity, topological definition)
- Other notions of continuity (Uniform continuity, Lipschitz continuity, Holder continuity)
- contractions and fixed points; Banach contraction mapping theorem

]

3.4 Equivalence of metrics

Definition 3.19 (Equivalent metrics). *Two metrics d_1 and d_2 on a set X are equivalent if the identity maps from (X, d_1) to (X, d_2) and from (X, d_2) to (X, d_1) are continuous.*

Proposition 3.20. *Two metrics d_1, d_2 on a set X are equivalent iff they have the same open sets or the same closed sets.*

Definition 3.21. *Two metrics d_1 and d_2 on a set X are strongly equivalent if for every $x, y \in X$, there exists constants $\alpha > 0$ and $\beta > 0$ such*

$$\alpha d_1(x, y) \leq d_2(x, y) \leq \beta d_1(x, y).$$

If two metrics are strongly equivalent then they are equivalent. The proof of this is one of the exercises.

Example 3.22. We show that the Euclidean distance (induced by 2-norm) and the metric induced by the ∞ -norm are equivalent on \mathbb{R}^n .

Let $\|x - y\|_2 = \sqrt{\sum_{j=1}^n (x_j - y_j)^2}$ be the Euclidean metric and $\|x - y\|_\infty = \max_{j=1, \dots, n} |x_j - y_j|$ be the ∞ -norm metric. We have

$$\|x - y\|_2 = \sqrt{\sum_{j=1}^n (x_j - y_j)^2} \leq \sqrt{n \max_{j=1, \dots, n} (x_j - y_j)^2} = \sqrt{n} \max_{j=1, \dots, n} |x_j - y_j| = \sqrt{n} \|x - y\|_\infty$$

and

$$\|x - y\|_\infty = \max_{j=1, \dots, n} |x_j - y_j| = \sqrt{\max_{j=1, \dots, n} (x_j - y_j)^2} \leq \sqrt{\sum_{j=1}^n (x_j - y_j)^2} = \|x - y\|_2.$$

Thus the two metrics are strongly equivalent.

3.5 Extra properties of \mathbb{R}^n

[EK: series, Conditional and absolute convergence, Convergence tests
sup, inf lim sup, lim inf]

3.6 Exercises

1. Show that the infinity norm $\|x\|_\infty$, $x \in \mathbb{R}^n$, defined in Example 3.4 is a norm.
2. Let (X, d) be any metric space, and define $\tilde{d} : X \times X \rightarrow \mathbb{R}$ by

$$\tilde{d}(x, y) = \frac{d(x, y)}{1 + d(x, y)}, \quad x, y \in X.$$

Show that \tilde{d} is a metric on X .

3. Let X be a set and define $d : X \times X \rightarrow \mathbb{R}$ by $d(x, x) = 0$ and $d(x, y) = 1$ for $x \neq y \in X$. Prove that d is a metric on X . What do open balls look like for different radii $r > 0$? What does an arbitrary open set look like?
4. Following up on Proposition 3.8 and Corollary 3.9: Show that the infinite intersection of open sets may not be open and that the infinite union of closed sets may not be closed.
5. Find the closure, interior, and boundary of the following sets using Euclidean distance:
 - (i) $\{(x, y) \in \mathbb{R}^2 : y < x^2\} \subseteq \mathbb{R}^2$
 - (ii) $[0, 1) \times [0, 1) \subseteq \mathbb{R}^2$
 - (iii) $\{0\} \cup \{1/n : n \in \mathbb{N}\} \subseteq \mathbb{R}$
6. Prove the following: Let $(x_n)_{n \in \mathbb{N}}$ be a sequence in a metric space (X, d) that converges to a point $x \in X$. Then x is unique.
7. Prove the following: Let $(x_n)_{n \in \mathbb{N}}$ and $(y_n)_{n \in \mathbb{N}}$ be sequences in \mathbb{R} such that $x_n \rightarrow x$ and $y_n \rightarrow y$, with $\alpha, x, y, \in \mathbb{R}$.
 - (i) Show that $\alpha x_n \rightarrow \alpha x$.
 - (i) Show that $x_n + y_n \rightarrow x + y$.
8. Show that discrete metric spaces are complete.
9. Prove the following: If two metrics are strongly equivalent then they are equivalent.

3.7 References

The content in this section comes following texts:

A Taste of Topology [3]

The first chapter of Piotr Zwiernik's *Lecture notes in Mathematics for Economics and Statistics* [5]

4 Topology

4.1 Basic definitions

4.2 Compactness

4.3 Continuity

4.4 Exercises

4.5 References

5 Linear Algebra

5.1 Vector spaces

5.1.1 Axioms of a vector space

Let V be a set and let \mathbb{F} be a field.

Definition 5.1. We call V a **vector space** if the following hold:

Addition:

- (A) *Commutativity in addition:* $\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u}$ for all $\mathbf{u}, \mathbf{v} \in V$
- (B) *Associativity in addition:* $\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w}$ for all $\mathbf{u}, \mathbf{v}, \mathbf{w} \in V$
- (C) *Existence of a neutral element, addition:* There exists a vector $\mathbf{0}$ such that for any $\mathbf{v} \in V$, $\mathbf{0} + \mathbf{v} = \mathbf{v}$
- (D) *Additive inverse:* For every $\mathbf{v} \in V$, there exists another vector, which we denote $-\mathbf{v}$, such that $\mathbf{v} + (-\mathbf{v}) = \mathbf{0}$.

Multiplication by a scalar:

- (E) *Existence of a neutral element, multiplication:* For any $\mathbf{v} \in V$, $1 \times \mathbf{v} = \mathbf{v}$
- (F) *Associativity in multiplication:* Let $\alpha, \beta \in \mathbb{F}$. For any $\mathbf{v} \in V$, $(\alpha\beta)\mathbf{v} = \alpha(\beta\mathbf{v})$

Associativity:

- (G) Let $\alpha \in \mathbb{F}, \mathbf{u}, \mathbf{v} \in V$. $\alpha(\mathbf{u} + \mathbf{v}) = \alpha\mathbf{u} + \alpha\mathbf{v}$.
- (H) Let $\alpha, \beta \in \mathbb{F}, \mathbf{v} \in V$. $(\alpha + \beta)\mathbf{v} = \alpha\mathbf{v} + \beta\mathbf{v}$.

Elements of the vector space are called vectors.

Most often we will assume $\mathbb{F} = \mathbb{C}$ or \mathbb{R} .

Examples of vector spaces: \mathbb{R}^n , \mathbb{C}^n , $M_{m \times n}$ (matrices of size $m \times n$), \mathbb{P}_n (polynomials of degree n , $p(x) = a_0 + a_1x + \dots + a_nx^n$).

Lemma 5.2. For every $\mathbf{v} \in V$, we have $-\mathbf{v} = (-1) \times \mathbf{v}$.

Proof. Our goal is to show that $(-1) \times \mathbf{v}$ is the additive inverse of \mathbf{v} . We show this as follows:

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

The last step uses Exercise 5.8. **[EK: Do by hand in class]**

□

5.1.2 Subspaces

Definition 5.3. A subset U of V is called a **subspace** of V if U is also a vector space (using the same addition and scalar multiplication as on V).

Proposition 5.4. A subset U of V is a subspace of V if and only if U satisfies the following three conditions:

1. $\mathbf{0} \in U$
2. Closed under addition: $u, w \in U$ implies $\mathbf{u} + \mathbf{v} \in U$
3. Closed under scalar multiplication: $\alpha \in \mathbb{F}$ and $u \in U$ implies $\alpha \mathbf{u} \in U$

Proof. \Rightarrow If U is a subspace of V , then U satisfies these 3 properties by Definition 5.1.

\Leftarrow Suppose U satisfies the given 3 conditions. Then for any $\mathbf{v} \in U$, there must exist $-\mathbf{v} \in U$ by property 3, since $-\mathbf{v} = (-1) \times \mathbf{v}$ by Lemma 5.2 (property D). Property 1 assures property C. Properties 2 and 3, and the fact that $U \subset V$, assure the remaining properties hold. □

This characterisation allows us to easily show that the intersection of subspaces is again a subspace.

Proposition 5.5. Let V be a vector space and let $U_1, U_2 \subseteq V$ be subspaces. Then $U_1 \cap U_2$ is also a subspace of V .

Proof. We use the characterization in Proposition 5.4. First, since $\mathbf{0} \in U_1$ and $\mathbf{0} \in U_2$, we have $\mathbf{0} \in U_1 \cap U_2$. Second, for $\mathbf{u}, \mathbf{v} \in U_1 \cap U_2$, since in particular $\mathbf{u}, \mathbf{v} \in U_1$ and $\mathbf{u}, \mathbf{v} \in U_2$ and U_1, U_2 are subspaces, $\mathbf{u} + \mathbf{v} \in U_1$ and $\mathbf{u} + \mathbf{v} \in U_2$. Thus, $\mathbf{u} + \mathbf{v} \in U_1 \cap U_2$. Similarly, one shows $\alpha \mathbf{u} \in U_1 \cap U_2$ for $\alpha \in \mathbb{F}$. □

On the contrary the union of two subspaces is not a subspace in general (see Exercise 5.12). However, the next definition introduces the smallest subspace containing the union.

Definition 5.6. Suppose U_1, \dots, U_m are subsets of V . The sum of U_1, \dots, U_m , denoted $U_1 + \dots + U_m$, is the set of all possible sums of elements of U_1, \dots, U_m . More precisely,

$$U_1 + \dots + U_m = \{\mathbf{u}_1 + \dots + \mathbf{u}_m : \mathbf{u}_1 \in U_1, \dots, \mathbf{u}_m \in U_m\}$$

Proposition 5.7. Suppose U_1, \dots, U_m are subspaces of V . Then $U_1 + \dots + U_m$ is the smallest subspace of V containing U_1, \dots, U_m .

5.1.3 Exercises

Exercise 5.8 (1.1.7 in [6]). Show that $0\mathbf{v} = \mathbf{0}$ for $\mathbf{v} \in V$.

Exercise 5.9 (1.B.1 in [7]). Show that $-(-v) = v$ for $\mathbf{v} \in V$.

Exercise 5.10 (1.B.2 in [7]). Suppose that $\alpha \in \mathbb{F}, \mathbf{v} \in V$, and $\alpha \mathbf{v} = \mathbf{0}$. Prove that $\alpha = 0$ or $\mathbf{v} = \mathbf{0}$.

Exercise 5.11 (1.B.4 in [7]). Why is the empty space not a vector space?

Exercise 5.12 (7.4.1 in [6]). Let U_1 and U_2 be subspaces of a vector space V . Prove that $U_1 \cup U_2$ is a subspace of V if and only if $U_1 \subseteq U_2$ or $U_2 \subseteq U_1$.

5.2 Linear (in)dependence and bases

Definition 5.13. A linear combination of vectors $\mathbf{v}_1, \dots, \mathbf{v}_n$ in V is a vector of the form

$$\alpha_1 \mathbf{v}_1 + \dots + \alpha_n \mathbf{v}_n = \sum_{k=1}^n \alpha_k \mathbf{v}_k$$

where $\alpha_1, \dots, \alpha_m \in \mathbb{F}$.

Definition 5.14. The set of all linear combinations of a list of vectors v_1, \dots, v_m in V is called the **span** of v_1, \dots, v_m , denoted $\text{span}\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$. In other words,

$$\text{span}\{\mathbf{v}_1, \dots, \mathbf{v}_n\} = \{\alpha_1 \mathbf{v}_1 + \dots + \alpha_n \mathbf{v}_n : \alpha_1, \dots, \alpha_n \in \mathbb{F}\}$$

The span of the empty list is defined to be $\{\mathbf{0}\}$.

Definition 5.15. A system of vectors $\mathbf{v}_1, \dots, \mathbf{v}_n$ is called a **basis** (for the vector space V) if any vector $\mathbf{v} \in V$ admits a unique representation as a linear combination

$$\mathbf{v} = \alpha_1 \mathbf{v}_1 + \dots + \alpha_n \mathbf{v}_n = \sum_{k=1}^n \alpha_k \mathbf{v}_k$$

In undergrad, you likely thought about this as: the equation $\mathbf{v} = \alpha_1 \mathbf{v}_1 + \dots + \alpha_n \mathbf{v}_n$, where the x_i are unknown, has a unique solution.

Example of bases:

For \mathbb{R}^n : $e_1 = (1, 0, \dots, 0)$, $e_2 = (0, 1, 0, \dots, 0)$, \dots , $e_n = (0, \dots, 0, 1)$

For \mathbb{P}^n : $1, x, x^2, \dots, x^n$

Definition 5.16. The linear combination $\alpha_1 \mathbf{v}_1 + \dots + \alpha_n \mathbf{v}_n$ is called **trivial** if $\alpha_k = 0$ for every k .

Proposition 5.17. A system of vectors $\mathbf{v}_1, \dots, \mathbf{v}_n \in V$ is a basis if and only if it is linearly independent and complete (generating).

[EK: Proof done by hand]

5.2.1 Exercises

From Harvard: Exercise: Suppose v_1, v_2, v_3, v_4 (a) spans V and (b) is linearly independent. Prove that the list

$$v_1 - v_2, v_2 - v_3, v_3 - v_4, v_4$$

also (a) spans V and (b) is linearly independent.

Exercise: Suppose v_1, \dots, v_m is linearly independent in V and $w \in V$. Prove that if $v_1 + w, \dots, v_m + w$ is linearly dependent, then $w \in \text{span}(v_1, \dots, v_m)$.

Exercise: Suppose that v_1, \dots, v_m is linearly independent in V and $w \in V$. Show that v_1, \dots, v_m, w is linearly independent if and only if

$$w \notin \text{span}(v_1, \dots, v_m)$$

onExercises Exercise: Suppose v_1, v_2, v_3, v_4 (a) spans V and (b) is linearly independent. Prove that the list

$$v_1 - v_2, v_2 - v_3, v_3 - v_4, v_4$$

also (a) spans V and (b) is linearly independent.

Exercise: Suppose v_1, \dots, v_m is linearly independent in V and $w \in V$. Prove that if $v_1 + w, \dots, v_m + w$ is linearly dependent, then $w \in \text{span}(v_1, \dots, v_m)$.

Exercise: Suppose that v_1, \dots, v_m is linearly independent in V and $w \in V$. Show that v_1, \dots, v_m, w is linearly independent if and only if

$$w \notin \text{span}(v_1, \dots, v_m)$$

[EK: Add a few from books]

5.3 Linear transformations

Definition 5.18. A **map** T from domain X to codomain Y is a rule that assigns an output $y = T(x) \in Y$ to each input $x \in X$

Definition 5.19. A map from a vector space U to a vector space V is **linear** if

$$T(\alpha \mathbf{u} + \beta \mathbf{v}) = \alpha T(\mathbf{u}) + \beta T(\mathbf{v}) \quad \text{for any } \mathbf{u}, \mathbf{v} \in V, \alpha, \beta \in \mathbb{F}$$

Let's denote the set of all linear maps from vector space U to vector space V by $\mathcal{L}(U, V)$.

Example 5.20 (Differentiation is a linear map). Let $D \in \mathcal{L}(\mathcal{P}(\mathbb{R}), \mathcal{P}(\mathbb{R}))$, (i.e. D is a linear map from the polynomials on \mathbb{R} to the polynomials on \mathbb{R}), defined as $Dp = p'$. The fact that such a map is linear follows from basic facts about derivatives, i.e. $\frac{d}{dx}(\alpha f(x) + \beta g(x)) = \alpha f'(x) + \beta g'(x)$.

Other examples: integration, rotation of vectors, reflection of vectors

Lemma 5.21. Let $T \in \mathcal{L}(U, V)$. Then $T(0) = 0$.

Proof. By linearity, $T(0) = T(0 + 0) = T(0) + T(0)$. Add $-T(0)$ to both sides to obtain the result. \square

Theorem 5.22. Let $S, T \in \mathcal{L}(U, V)$ and $\alpha \in \mathbb{F}$. $\mathcal{L}(U, V)$ is a vector space with addition defined as the sum $S + T$ and multiplication as the product αT .

Definition 5.23 (Product of linear maps). Let $S \in \mathcal{L}(U, V)$ and $T \in \mathcal{L}(V, W)$. We define the product $ST \in \mathcal{L}(U, W)$ for $\mathbf{u} \in U$ as $ST(\mathbf{u}) = S(T(\mathbf{u}))$.

Definition 5.24. Let $T : U \rightarrow V$ be a linear transformation. We define the following important subspaces:

- Kernel or null space: $\ker T = \{\mathbf{u} \in U : T\mathbf{u} = 0\}$
- Range $\text{range } T = \{\mathbf{v} \in V : \exists \mathbf{u} \in U \text{ such that } \mathbf{v} = T\mathbf{u}\}$

The dimensions of these spaces are often called the following:

- Nullity $\text{nullity}(T) = \dim(\ker(T))$
- Rank $\text{rank}(T) = \dim(\text{range}(T))$

Example 5.25. The null space of the differentiation map (see Example 5.20) is the set of constant functions.

Definition 5.26 (Injective and surjective). Let $T : U \rightarrow V$. T is injective if $T\mathbf{u} = T\mathbf{v}$ implies $\mathbf{u} = \mathbf{v}$ and T is surjective if $\forall \mathbf{u} \in U, \exists \mathbf{v} \in V$ such that $\mathbf{v} = T\mathbf{u}$, i.e. if $\text{range } T = V$.

Theorem 5.27. $T \in \mathcal{L}(U, v)$ is injective $\iff \ker T = 0$.

Proof. \Rightarrow Suppose T is injective. By Lemma 5.21, we know that 0 is in the null space of T , i.e. $T(0) = 0$. Suppose $\exists \mathbf{v} \in \ker T$. Then $T(\mathbf{v}) = 0 = T(0)$, and by injectivity, $\mathbf{v} = 0$.

\Leftarrow Suppose $\ker T = 0$. Let $T\mathbf{u} = T\mathbf{v}$; we want to show $\mathbf{u} = \mathbf{v}$.

$T\mathbf{u} = T\mathbf{v} \implies T(\mathbf{u} - \mathbf{v}) = 0$, which implies $\mathbf{u} - \mathbf{v} \in \ker T$. But $\ker T = 0$, so then $\mathbf{u} - \mathbf{v} = 0 \implies \mathbf{u} = \mathbf{v}$. \square

Theorem 5.28 (Rank Theorem). For a matrix A or equivalently a linear transformation $A : \mathbb{F}^n \rightarrow \mathbb{F}^m$:

$$\text{rank } A = \text{rank } A^T$$

Theorem 5.29. Rank Nullity Theorem Let $T : U \rightarrow V$ be a linear transformation, where U and V are finite-dimensional vector spaces. Then

$$\text{rank } T + \text{nullity } T = \dim U.$$

5.3.1 Exercises

Exercise 5.30. Let $T \in \mathcal{L}(\mathbb{P}(\mathbb{R}), \mathbb{P}(\mathbb{R}))$ be the map $T(p(x)) = x^2 p(x)$ (multiplication by x^2).

- (i) Show that T is linear.
- (ii) Find $\ker T$.

5.4 Linear maps and matrices

We can use matrices to represent linear maps.

Definition 5.31. Let $T \in \mathcal{L}(U, V)$ where U and V are vector spaces. Let u_1, \dots, u_n and v_1, \dots, v_m be bases for U and V respectively. The matrix of T with respect to these bases is the $m \times n$ matrix $\mathcal{M}(T)$ with entries $A_{i,j}$, $i = 1, \dots, m$, $j = 1, \dots, n$ defined by

$$Tu_k = A_{1,k}v_1 + \dots + A_{m,k}v_m$$

i.e. the k th column of A is the scalars needed to write Tu_k as a linear combination of the basis of V :

$$Tu_k = \sum_{i=1}^m A_{i,k}v_i$$

Example 5.32. Let $D \in \mathcal{L}(\mathcal{P}_5(\mathbb{R}), \mathcal{P}_4(\mathbb{R}))$ be the differentiation map, $Dp = p'$. Find the matrix of D with respect to the standard bases of $\mathcal{P}_4(\mathbb{R})$ and $\mathcal{P}_5(\mathbb{R})$.

Standard basis: $1, x, x^2, x^3, x^4, (x^5)$

$$T(u_1) = (1)' = 0$$

$$T(u_2) = (x)' = 1$$

$$T(u_3) = (x^2)' = 2x$$

$$T(u_4) = (x^3)' = 3x^2$$

$$T(u_5) = (x^4)' = 4x^3$$

$$\mathcal{M}(D) = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 4 \end{pmatrix}$$

This way of looking at matrices gives us an intuitive explanation for why we do matrix multiplication the way we do! Let $T : U \rightarrow V$ and $S : V \rightarrow W$, where T, S are linear maps and U, V, W are vector spaces with bases u_1, \dots, u_n , v_1, \dots, v_m , and w_1, \dots, w_p . If we want to have

$$\mathcal{M}(ST) := \mathcal{M}(S)\mathcal{M}(T),$$

how would we need to define matrix multiplication?

Let $A = \mathcal{M}(S)$ and $B = \mathcal{M}(T)$. Then

$$(ST)u_k = S(T(u_k)) = S(Bu_k) = S(b_k) = Ab_k,$$

where b_k is the k th column of B .

We also have $\mathcal{M}(S + T) = \mathcal{M}(S) + \mathcal{M}(T)$ when $S, T \in \mathcal{L}(U, V)$.

5.5 Determinants

5.6 Inner product spaces

[EK:

- transpose, adjoint

- inner products and norms
- Orthogonal matrices and unitary matrices
- Orthonormalization and Gram-Schmidt
- Orthogonal projections and decompositions

]

5.7 Spectral theory

Note: here we will assume $\mathbb{F} = \mathbb{C}$, so that we are working on an algebraically closed field.

Let $T: V \rightarrow V$ be a linear map, where V is a vector space. We would like to describe the action of this linear map in a particularly “nice” way. For example, if there exists a basis $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ of V such that $T\mathbf{v}_i = \alpha_i \mathbf{v}_i$ where $\alpha_i \in \mathbb{F}$ for $i = 1, \dots, n$, then T acts on this basis merely by scaling the basis vectors. If we look at the matrix of T with respect to this basis, T is a diagonal matrix with α_i in the diagonal.

Definition 5.33. Let V be a vector space. Given a linear map $T: V \rightarrow V$ and $\alpha \in \mathbb{F}$, α is called an **eigenvalue** of T if there exists a non-zero vector $\mathbf{v} \in V \setminus \{\mathbf{0}\}$ such that $T\mathbf{v} = \alpha\mathbf{v}$. We call such \mathbf{v} an **eigenvector** of T with eigenvalue α . We call the set of all eigenvalues of T **spectrum** of T and denote it by $\sigma(T)$.

[EK: Define just for matrices?]

Note that $T\mathbf{v} = \alpha\mathbf{v}$ can be rewritten as $(T - \alpha I)\mathbf{v} = \mathbf{0}$. Thus, if α is an eigenvalue, the map $T - \alpha I$ is not invertible, since it must have non-trivial kernel. Using the known characterizations of invertability, this gives the following characterization for eigenvalues.

Theorem 5.34. Let V be a vector space and $T: V \rightarrow V$ be a linear map and let A_T be a matrix representation of T . The following are equivalent

1. $\alpha \in \mathbb{F}$ is an eigenvalue of T ,
2. $(A_T - \alpha I)\mathbf{x} = \mathbf{0}$ has a non-trivial solution,
3. $\det(A_T - \alpha I) = 0$.

Theorem 5.35. Suppose A is a square matrix with distinct eigenvalues $\alpha_1, \dots, \alpha_k$. Let $\mathbf{v}_1, \dots, \mathbf{v}_k$ be eigenvectors corresponding to these eigenvalues. Then $\mathbf{v}_1, \dots, \mathbf{v}_k$ are linearly independent.

Proof. Induction on k . □

Hence, if all the eigenvalues are distinct, there exists a basis of eigenvectors. This gives the next result.

Corollary 5.36. If a $A \in M_n(\mathbb{C})$ has n distinct eigenvalues, then A is diagonalizable. That is there exists an invertible matrix $U \in M_n(\mathbb{C})$ such that $A = UDU^{-1}$, where D is a diagonal matrix with the eigenvalues of A in the diagonal.

[EK: mention problem of eigenspaces not having high enough dimension when eigenvalues are repeated, possibly mention geometric and algebraic multiplicity]

Theorem 5.37. Let $A \in M_n(\mathbb{C})$ be a Hermitian matrix. Then, there exists a unitary matrix $U \in M_n(\mathbb{C})$ such that $A = UDU^*$, where D is a diagonal matrix with the eigenvalues of A in the diagonal. Furthermore, all eigenvalues of A are real.

Proof. It suffices to show that there exists an orthogonal basis of eigenvectors and that the eigenvalues are real. We will prove the former by induction. □

Note that in the previous theorem, the orthogonality of the eigenvectors is special. In general, even if a matrix is diagonalizable, there might not exist a orthogonal eigenbasis. The next theorem states a characterization of matrices that exhibit an orthogonal eigenbasis.

Theorem 5.38. *A matrix A is diagonalizable by a unitary matrix if and only if $AA^* = A^*A$. We call such a matrix **normal**.*

Proof omitted.

[EK:

- *Characteristic and minimal polynomials*
- *Cayley-Hamilton theorem*
- *Jordan Canonical Form (and block matrices)*
- *Matrix norms?*

]

5.7.1 Exercises

Exercise 5.39. Let $A, U \in M_n(\mathbb{F})$ be matrices, where U is invertible. Show that $\sigma(A) = \sigma(UAU^{-1})$.

Exercise 5.40. Let $A \in M_n(\mathbb{C})$ be an invertible matrix with $\sigma(A) = \{\alpha_1, \dots, \alpha_n\}$ counted with multiplicities. Determine $\sigma(A^{-1})$, $\sigma(A^T)$ and $\sigma(A^*)$.

5.8 Matrix decomposition

[EK:

- *singular value decomposition*
- *LU & QR decompositions*
- *PCA*

]

5.9 References

The following texts:

Linear Algebra Done Right [7]

Linear Algebra Done Wrong [6]

6 Calculus

6.1 Differentiation

[EK: *Topics:*

- *k -th order differentiability and smoothness*
- *Local extrema and derivative tests*
- *L'Hopital's rule*
- *Mean value theorem*
- *Ordinary differential equations*

]

6.2 Integration

[EK: *Topics:*

- *The Riemann integral*
- *Construction via Riemann sums*
- *Fundamental theorem of Calculus*
- *Riemann-Stieltjes integrals*

]

6.3 Exercises

6.4 References

7 Multivariable calculus

7.1 Differentiation

[EK: *Topics:*

- *Gradients, directional derivatives, Lagrange multipliers*
- *Partial derivatives, Hessians, Jacobians*
- *Taylor's theorem*
- *Inverse function theorem*
- *Multivariate chain rule*

]

7.2 Implicit Function Theorem

7.3 Integration

[EK: *Topics:*

- *Change-of-variables*
- *Exchange of integrals*

]

7.4 Exercises

7.5 References

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