## Statistics 240 Lecture Notes

P.B. Stark www.stat.berkeley.edu/~stark/index.html

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ROUGH DRAFT!
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## 1 Part 1: Mathematical preliminaries.

References:

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### 1.1 Sets

A set is a collection of objects, called members or elements of the set, without regard for their order. $a \in A$, pronounced " $a$ is an element of $A$," " $a$ is in $A$," or " $a$ is a member of $A$ " means that $a$ is an element of the set $A$. This is the same as writing $A \ni a$, which is pronounced " $A$ contains $a$." If $a$ is not an element of $A$, we write $a \notin A$. Sets may be described explicitly by listing their contents, or implicitly by specifying a property that all elements of the set share, or a condition that they satisfy. The contents of sets are enclosed in curly braces: $\}$. Examples:

- $A=\{a, b, c, d\}$ : the set containing the four elements $a, b, c$, and $d$.
- $\emptyset=\{ \}$ : the empty set, the set that contains no elements.
- $\mathbf{Z} \equiv\{\ldots,-2,-1,0,1,2, \ldots\}$ : the integers.
- $\mathbb{N} \equiv\{1,2,3, \ldots\}$ : the natural (counting) numbers.
- $\mathbb{R} \equiv(-\infty, \infty)$ : the real numbers.
- $\mathbb{R}^{+} \equiv[-\infty, \infty]$ : the extended real numbers.
- $\mathbf{C} \equiv\{a+b i: a, b \in \mathbb{R}\}$, where $i=\sqrt{-1}$ : the complex numbers.
- $\mathbf{Q} \equiv\{a / b: a, b \in \mathbf{Z}\}$ : the rational numbers.
$B$ is a subset of $A$, written $B \subset A$ or $A \supset B$, if every element of the set $B$ is also an element of the set $A$. Thus $\mathbb{N} \subset \mathbf{Z} \subset \mathbf{Q} \subset \mathbb{R} \subset \mathbf{C}$. The empty set $\emptyset$ is a subset of every set. If $A \subset B$ and $B \subset A, A$ and $B$ are the same set, and we write $A=B$. If $B$ is not a subset of $A$, we write $B \not \subset A$ or $A \not \supset B . B$ is a proper subset of $A$ if $B \subset A$ but $A \not \subset B$.

The complement of $A$ (with respect to the universe $\mathcal{X}$ ), written $A^{c}$ or $A^{\prime}$, is the set of all objects under consideration $(\mathcal{X})$ that are not elements of $A$. That is, $A^{c} \equiv\{a \in \mathcal{X}: a \notin A\}$.

The intersection of $A$ and $B$, written $A \cap B$ or $A B$, is the set of all objects that are elements of both $A$ and $B$ :

$$
\begin{equation*}
A \cap B \equiv\{a: a \in A \text { and } a \in B\} . \tag{1}
\end{equation*}
$$

If $A \cap B=\emptyset$, we say $A$ and $B$ are disjoint or mutually exclusive.

The union of $A$ and $B$, written $A \cup B$, is the set of all objects that are elements of $A$ or of $B$ (or both):

$$
\begin{equation*}
A \cup B \equiv\{a: a \in A \text { or } a \in B \text { or both }\} \tag{2}
\end{equation*}
$$

The difference of $A$ and $B, A \backslash B$, pronounced " $A$ minus $B$," is the set of all elements of $A$ that are not elements of $B$ :

$$
\begin{equation*}
A \backslash B \equiv\{a \in A: a \notin B\}=A \cap B^{c} \tag{3}
\end{equation*}
$$

Intervals are special subsets of $\mathbb{R}$ :

$$
\begin{aligned}
{[a, b] } & \equiv\{x \in \mathbb{R}: a \leq x \leq b\} \\
(a, b] & \equiv\{x \in \mathbb{R}: a<x \leq b\} \\
{[a, b) } & \equiv\{x \in \mathbb{R}: a \leq x<b\} \\
(a, b) & \equiv\{x \in \mathbb{R}: a<x<b\}
\end{aligned}
$$

Sometimes we have a collection of sets, indexed by elements of another set: $\left\{A_{\beta}: \beta \in B\right\}$. Then $B$ is called an index set. If $B$ is a subset of the integers $\mathbf{Z}$, usually we write $A_{i}$ or $A_{j}$, etc., rather than $A_{\beta}$. If $B=\mathbb{N}$, we usually write $\left\{A_{j}\right\}_{j=1}^{\infty}$ rather than $\left\{A_{\beta}: \beta \in \mathbb{N}\right\}$.

$$
\begin{equation*}
\bigcap_{\beta \in B} A_{\beta} \equiv\left\{a: a \in A_{\beta} \forall \beta \in B\right\} \tag{4}
\end{equation*}
$$

( $\forall$ means "for all.") If $B=\{1,2, \ldots, n\}$, we usually write $\bigcap_{j=1}^{n} A_{j}$ rather than $\bigcap_{j \in\{1,2, \ldots, n\}} A_{j}$. The notation $\bigcup_{\beta \in B} A_{\beta}$ and $\bigcup_{j=1}^{n} A_{j}$ are defined analogously.

A collection of sets $\left\{A_{\beta}: \beta \in B\right\}$ is pairwise disjoint if $A_{\beta} \cap A_{\beta^{\prime}}=\emptyset$ whenever $\beta \neq \beta^{\prime}$. The collection $\left\{A_{\beta}: \beta \in B\right\}$ exhausts or covers the set $A$ if $A \subset \bigcup_{\beta \in B} A_{\beta}$. The collection $\left\{A_{\beta}: \beta \in B\right\}$ is a partition of the set $A$ if $A=\cup_{\beta \in B} A_{\beta}$ and the sets $\left\{A_{\beta}: \beta \in B\right\}$ are pairwise disjoint. If $\left\{A_{\beta}: \beta \in B\right\}$ are pairwise disjoint and exhaust $A$, then $\left\{A_{\beta} \cap A: \beta \in B\right\}$ is a partition of $A$.

A set is countable if its elements can be put in one-to-one correspondence with a subset of $\mathbb{N}$. A set is finite if its elements can be put in one-to-one correspondence with $\{1,2, \ldots, n\}$ for some $n \in \mathbb{N}$. If a set is not finite, it is infinite. $\mathbb{N}, \mathbf{Z}$, and $\mathbf{Q}$ are infinite but countable; $\mathbb{R}$ is infinite and uncountable.

The notation $\# A$, pronounced "the cardinality of $A$ " is the size of the set $A$. If $A$ is finite, $\# A$ is the number of elements in $A$. If $A$ is not finite but $A$ is countable (if its elements can be put in one-to-one correspondence with the elements of $\mathbb{N}$ ), then $\# A=\aleph_{0}$ (aleph-null).

The power set of a set $A$ is the set of all subsets of the set $A$. For example, the power set of $\{a, b, c\}$ is

$$
\begin{equation*}
\{\emptyset,\{a\},\{b\},\{c\},\{a, b\},\{a, c\},\{b, c\},\{a, b, c\}\} . \tag{5}
\end{equation*}
$$

If $A$ is a finite set, the cardinality of the power set of $A$ is $2^{\# A}$. This can be seen as follows: suppose $\# A=n$ is finite. Consider the elements of $A$ to be written in some canonical order. We can specify an element of the power set by an $n$-digit binary number. The first digit is 1 if the first element of $A$ is in the subset, and 0 otherwise. The second digit is 1 if the second element of $A$ is in the subset, and 0 otherwise, etc. There are $2^{n} n$-digit binary numbers, so there are $2^{n}$ subsets. The cardinality of the power set of $\mathbb{N}$ is not $\aleph_{0}$.

If $A$ is a finite set, $B$ is a countable set and $\left\{A_{j}: \beta \in B\right\}$ is a partition of $A$, then

$$
\begin{equation*}
\# A=\sum_{\beta \in B} \# A_{\beta} . \tag{6}
\end{equation*}
$$

### 1.2 Cartesian Products

The notation $\left(s_{1}, s_{2}, \ldots, s_{n}\right) \equiv\left(s_{j}\right)_{j=1}^{n}$ denotes an ordered $n$-tuple consisting of $s_{1}$ in the first position, $s_{2}$ in the second position, etc. The parentheses are used instead of curly braces to distinguish $n$-tuples from sets: $\left(s_{j}\right)_{j=1}^{n} \neq\left\{s_{j}\right\}_{j=1}^{n}$. The $k$ th component of the $n$-tuple $s=\left(s_{j}\right)_{j=1}^{n}$, is $s_{k}$, $k=1,2, \ldots, n$. Two $n$-tuples are equal if their components are equal. That is, $\left(s_{j}\right)_{j=1}^{n}=\left(t_{j}\right)_{j=1}^{n}$ means that $s_{j}=t_{j}$ for $j=1, \ldots, n$. In particular, $(s, t) \neq(t, s)$ unless $s=t$. In contrast, $\{s, t\}=\{t, s\}$ always.

The Cartesian product of $S$ and $T$ is $S \otimes T \equiv\{(s, t): s \in S$ and $t \in T\}$. Unless $S=T$, $S \otimes T \neq T \otimes S . \mathbb{R}^{n}$ is the Cartesian product of $\mathbb{R}$ with itself, $n$ times; its elements are $n$-tuples of real numbers. If $s$ is the $n$-tuple $\left(s_{1}, s_{2}, \ldots, s_{n}\right)=\left(s_{j}\right)_{j=1}^{n}$,

Let $A$ be a finite set with $\# A=n$. A permutation of (the elements of) $A$ is an element $s$ of $\bigotimes_{j=1}^{n} A=A^{n}$ whose components are distinct elements of $A$. That is, $s=\left(s_{j}\right)_{j=1}^{n} \in A^{n}$ is a permutation of $A$ if $\#\left\{s_{j}\right\}_{j=1}^{n}=n$. There are $n!=n(n-1) \cdots 1$ permutations of a set with $n$ elements: there are $n$ choices for the first component of the permutation, $n-1$ choices for the second (whatever the first might be), $n-2$ for the third (whatever the first two might be), etc. This is an illustration of the fundamental rule of counting: in a sequence of $n$ choices, if there are $m_{1}$ possibilites for the first choice, $m_{2}$ possibilities for the second choice (no matter which was chosen
in the first place), $m_{3}$ possibilities for the third choice (no matter which were chosen in the first two places), and so on, then there are $m_{1} m_{2} \cdots m_{n}=\prod_{j=1}^{n} m_{j}$ possible sequences of choices in all.

The number of permutations of $n$ things taken $k$ at a time, ${ }_{n} P_{k}$, is the number of ways there are of selecting $k$ of $n$ things, then permuting those $k$ things. There are $n$ choices for the object that will be in the first place in the permutation, $n-1$ for the second place (regardless of which is first), etc., and $n-k+1$ choices for the item that will be in the $k$ th place. By the fundamental rule of counting, it follows that ${ }_{n} P_{k}=n(n-1) \cdots(n-k+1)=n!/(n-k)$ !.

The number of subsets of size $k$ that can be formed from $n$ objects is

$$
\begin{equation*}
{ }_{n} C_{k}=\binom{n}{k}={ }_{n} P_{k} / k!=n(n-1) \cdots(n-k+1) / k!=\frac{n!}{k!(n-k)!} . \tag{7}
\end{equation*}
$$

Because the power set of a set with $n$ elements can be partitioned as

$$
\begin{equation*}
\cup_{k=0}^{n}\{\text { all subsets of size } k\}, \tag{8}
\end{equation*}
$$

it follows that

$$
\begin{equation*}
\sum_{j=0}^{n}{ }_{n} C_{k}=2^{n} \tag{9}
\end{equation*}
$$

### 1.3 Mappings and Functions

Functions are subsets of Cartesian products. We write $f: \mathcal{X} \rightarrow \mathcal{Y}$, pronounced " $f$ maps $\mathcal{X}$ into $\mathcal{Y}$ " or " $f$ is a function with domain $\mathcal{X}$ and co-domain $\mathcal{Y}$ " if $f \subset \mathcal{X} \otimes \mathcal{Y}$ such that for each $x \in \mathcal{X}$, $\exists 1 y \in \mathcal{Y}$ such that $(x, y) \in f$. (The notation $\exists 1 y$ means that there exists exactly one value of y.) The set $\mathcal{X}$ is called the domain of $f$ and $\mathcal{Y}$ is called the co-domain of $f$. If the $\mathcal{X}$-component of an element of $f$ is $x$, we denote the $\mathcal{Y}$-component of that element of $f$ by $f x$ or $f(x)$, so that $(x, f x) \in f$; we write $f: x \mapsto y=f(x)$. The functions $f$ and $g$ are equal if they are the same subset of $\mathcal{X} \otimes \mathcal{Y}$, which means that they have the same domain $\mathcal{X}$, and $f x=g x \forall x \in \mathcal{X}$.

Let $A \subset \mathcal{X}$. The image of $A$ under $f$ is

$$
f A=f(A) \equiv\{y \in \mathcal{Y}:(x, y) \in f \text { for some } x \in A\}
$$

More colloquially, we would write this as

$$
f A=\{y \in \mathcal{Y}: f(x)=y \text { for some } x \in A\} .
$$

If $f \mathcal{X}$ is a proper subset of $\mathcal{Y}, f$ is into. If $f \mathcal{X}=\mathcal{Y}, f$ is onto. For $B \subset \mathcal{Y}$, the inverse image of $B$ under $f$ or pre-image of $B$ under $f$ is

$$
f^{-1} B \equiv\{x \in \mathcal{X}: f x \in B\}
$$

Similarly, $f^{-1} y \equiv\{x \in \mathcal{X}: f x=y\}$ If $\forall y \in \mathcal{Y}, \#\left\{f^{-1} y\right\} \leq 1, f$ is one-to-one (1:1). If $f$ is one-to-one and onto, i.e., if $\forall y \in \mathcal{Y}, \#\left\{f^{-1} y\right\}=1, f$ is a bijection.

## Exercise 1 1. Does $f^{-1}(f A)=A$ ?

2. Does $f\left(f^{-1} B\right)=B$ ?
3. Does $f^{-1}(C \cap D)=f^{-1} C \cap f^{-1} D$ ?
4. Does $f(C \cap D)=f C \cap f D$ ?
5. Does $f(C \cup D)=f C \cup f D$ ?

### 1.4 Groups

Definition $1 A$ group is an ordered pair $(\mathcal{G}, \times)$, where $\mathcal{G}$ is a collection of objects (the elements of the group) and $\times$ is a mapping from $\mathcal{G} \otimes \mathcal{G}$ onto $\mathcal{G}$,

$$
\begin{aligned}
\times: \mathcal{G} \otimes \mathcal{G} & \rightarrow \mathcal{G} \\
(a, b) & \mapsto a \times b,
\end{aligned}
$$

satisfying the following axioms:

1. $\exists e \in \mathcal{G}$ s.t. $\forall a \in \mathcal{G}, e \times a=a$. The element $e$ is called the identity.
2. For each $a \in \mathcal{G}, \exists a^{-1} \in \mathcal{G}$ s.t. $a^{-1} \times a=e$. (Every element has an inverse.)
3. If $a, b, c \in \mathcal{G}$, then $a \times(b \times c)=(a \times b) \times c$. (The group operation is associative.)

If, in addition, for every $a, b \in \mathcal{G}, a \times b=b \times a$ (if the group operation commutes), we say that $(\mathcal{G}, \times)$ is an Abelian group or commutative group.

Examples of groups include the real numbers together with ordinary addition, $(\mathbb{R},+)$; the real numbers other than zero together with ordinary multiplication, $(\mathbb{R} \backslash\{0\}, *)$; the rational numbers together with ordinary addition, $(\mathbf{Q},+)$; and the integers 0 to $p-1, p$ prime, together with addition modulo $p,(\{0,1, \ldots, p-1\},+)$.

Exercise 2 1. Show that $\forall a \in \mathcal{G}, a \times a^{-1}=e$. (The inverse from the left is also the inverse from the right; equivalently, $\left.\left(a^{-1}\right)^{-1}=a.\right)$
2. Show that $\forall a \in \mathcal{G}, a e=a$. (The identity from the left is also the identity from the right.)

### 1.5 Fields

Definition 2 An ordered triple $(\mathcal{F}, \times,+)$ is a field if $\mathcal{F}$ is a collection of objects and $\times$ and + are operations on $\mathcal{F} \times \mathcal{F}$ such that

1. $\mathcal{F}$ is an Abelian group under the operation + , with identity 0.
2. $\mathcal{F} \backslash\{0\}$ is an Abelian group under the operation $\times$, with identity 1 .
3. $\times$ is distributive over + . I.e., for any $a, b, c \in \mathcal{F} a \times(b+c)=a \times b+a \times c$ and $(a+b) \times c=$ $a \times c+b \times c$.

The additive inverse of $a$ is denoted $-a$; the multiplicative inverse of $a$ is $a^{-1}=1 / a$.
Examples: $(\mathbb{R}, \times,+)$, where $\times$ is ordinary (real) multiplication and + is ordinary (real) addition. The complex numbers $\mathbf{C}$, with complex multiplication and addition.

These (and the extended reals) are the only fields we will use.

### 1.6 Arithmetic with $\infty$

We shall use the following conventions:

- $0 \cdot \infty=\infty \cdot 0=0$
- $x+\infty=\infty+x=\infty, x \in \mathbb{R}$
- $x \cdot \infty=\infty \cdot x=\infty, x>0$

With these conventions, $([-\infty, \infty], \times,+)$ is a field.

### 1.7 Linear Vector Spaces

Definition 3 A linear vector space is an ordered quadruple $\left(\left(\mathcal{F}, \times,+_{1}\right), \mathcal{X}, \cdot,+_{2}\right)$ where $\left(\mathcal{F}, \times,+_{1}\right)$ is a field, $\mathcal{X}$ is a set of objects (the vectors), and $\cdot$ is an operation on $\mathcal{F} \otimes \mathcal{X}$ and $+_{2}$ is an operation on $\mathcal{X} \otimes \mathcal{X}$ such that:

1. $\left(\mathcal{X},+_{2}\right)$ is an Abelian group with identity 0 (the zero vector)
2. $\cdot: \mathcal{F} \times \mathcal{X} \rightarrow \mathcal{X} ;(\alpha, x) \mapsto \alpha \cdot x$ such that:
(a) If 1 is the multiplicative identity on $\mathcal{F}, 1 \cdot x=x \forall x \in \mathcal{X}$.
(b) $\alpha \cdot\left(x+{ }_{2} y\right)=\alpha \cdot x+{ }_{2} \alpha \cdot y \forall \alpha \in \mathcal{F}, x, y \in \mathcal{X}$. (distribution)
(c) $\alpha \cdot(\beta \cdot x)=(\alpha \times \beta) \cdot x \forall \alpha, \beta \in \mathcal{F}, x \in \mathcal{X}$. (association)
(d) $\left(\alpha+{ }_{1} \beta\right) \cdot x=\alpha \cdot x+{ }_{2} \beta \cdot x, \forall \alpha, \beta \in \mathcal{F}, x \in \mathcal{X}$. (distribution)

We rarely distinguish notationally between $+_{1}$ and $+_{2}$, between $\times$ and $\cdot$, or between the additive identity 0 of the field $\mathcal{F}$ and the identity 0 of the Abelian group $\mathcal{X}$. Sometimes, the multiplication symbols are omitted; e.g., $\alpha \cdot x=\alpha x$. Usually, one just calls $\mathcal{X}$ a linear vector space (LVS), omitting mention of the other elements of the quadruple. For our purposes, $\mathcal{F}$ is almost always $\mathbb{R}$. In that case, $\mathcal{X}$ is called a real linear vector space (RLVS).

Definition $4 A$ functional on a linear vector space is a mapping from the vectors $\mathcal{X}$ to the field $\mathcal{F}$ of the linear vector space.

Definition $5 A$ linear combination of $\left\{x_{j}\right\}_{j=1}^{n} \subset \mathcal{X}, \mathcal{X}$ a linear vector space, is a vector $x=$ $\sum_{j=1}^{n} \alpha_{j} x_{j}$, where $\left\{\alpha_{j}\right\}_{j=1}^{n} \subset \mathcal{F} A$ set $\left\{x_{\alpha}: \alpha \in A\right\} \subset \mathcal{X}$ is linearly dependent if there exist constants $\left\{\beta_{\alpha}: \alpha \in A\right\} \subset \mathcal{F}$, not all equal to zero, such that $\sum_{\alpha \in A} \beta_{\alpha} x_{\alpha}=0$. A set is linearly independent if it is not linearly dependent.

Definition $6 A$ subspace of a linear vector space $\mathcal{X}$ is a subset of $\mathcal{X}$ that is a linear vector space with the same field $\mathcal{F}$ and operations $+_{1}, \cdot,+{ }_{2}, \times$ as $\mathcal{X}$.

Definition 7 Let $\mathcal{X}$ be a linear vector space, $A, B \subset \mathcal{X}, x \in x, \alpha \in \mathcal{F}$.

- $\alpha A \equiv\{\alpha a: a \in A\}$
- $-A \equiv\{-1 \cdot a: a \in A\}$
- $x+A \equiv\{x+a: a \in A\}=A+x$
- $x-A \equiv\{x-a: a \in A\}$
- $A+B \equiv\{a+b: a \in A, b \in B\}$


## Exercise 3 1. Does $x-A=-(A-x)$ ?

2. Does $A+A=2 A$ ?
3. When does $A-A=2 A$ ?

If you cannot find necessary conditions, give sufficient ones.

Definition 8 A mapping $M$ from a linear vector space $\mathcal{X}$ into a linear vector space $\mathcal{Y}$ with the same field $\mathcal{F}$ is linear iff

$$
M(\alpha x+\beta y)=\alpha M x+\beta M y, \quad \forall \alpha, \beta \in \mathcal{F}, \quad x, y \in \mathcal{X}
$$

Definition 9 Let $\mathcal{X}$ be a real linear vector space. $A$ set $C \subset \mathcal{X}$ is convex iff $\alpha C+(1-\alpha) C \subset C$ $\forall \alpha \in[0,1]$. $A$ set $B \subset \mathcal{X}$ is balanced iff $\alpha B \subset B \forall \alpha$ with $|\alpha| \leq 1$.

Note that this requires us to define $|\cdot|$ on the field $\mathcal{F}$. For $\mathcal{F}=\mathbb{R}$, let $|\cdot|$ be absolute value; for $\mathcal{F}=\mathbf{C}$, let $|\cdot|$ be the modulus.

Exercise 4 Show that if $C, D \subset \mathcal{X}$ are convex, then

1. $\alpha C$ is convex, $\alpha \in \mathbb{R}$
2. $C \cap D$ is convex.

Definition 10 A linear combination $\sum_{j} \beta_{j} x_{j}$ of elements $\left\{x_{j}\right\}$ of a linear vector space is a convex combination if

1. $\left\{\beta_{j}\right\} \subset \mathbb{R}$,
2. $\beta_{j} \geq 0, \forall j$, and
3. $\sum_{j} \beta_{j}=1$.

Definition 11 The convex hull of a set $A \subset \mathcal{X}$ is the intersection of all convex sets that contain A. Equivalently, it is the set of all convex combinations of elements of $A$. If $C$ is convex, a point $x \in C$ is an extreme point of $C$ if $x$ cannot be written as a convex combination of a subset of $C$ unless that subset contains $x$. A polytope is the convex hull of a finite collection of points.

Definition $12 A$ set $\left\{x_{\alpha}: \alpha \in A\right\}$ is a basis for a linear vector space $\mathcal{X}$ if every $x \in \mathcal{X}$ has a unique representation $x=\sum_{\alpha \in A} \beta_{\alpha} x_{\alpha}$ with $\left\{\beta_{\alpha}: \alpha \in A\right\} \subset \mathcal{F}$. If $\mathcal{X}$ has a basis with n elements, $n \in \mathbb{I N}$, $\mathcal{X}$ is finite-dimensional and the dimension of $\mathcal{X}, \operatorname{dim}(\mathcal{X})$, is $n$. If $\mathcal{X}$ is not finite-dimensional, it is infinite-dimensional.

Exercise 5 Show that if $\mathcal{Y}$ is a subspace of $\mathcal{X}$ and $\operatorname{dim}(\mathcal{X})=n$, then $\operatorname{dim}(\mathcal{Y}) \leq n$.

Definition 13 A Hamel basis for a linear vector space $\mathcal{X}$ is a maximal linearly independent subset of $\mathcal{X}$.

### 1.8 Normed linear vector spaces

Norms, completeness.

### 1.9 Metric spaces

### 1.10 Topological spaces

Neighborhoods, completeness. Topologies induced by metrics. Cauchy sequences.

### 1.11 Duals of linear vector spaces

Linear functionals, duality, norms of linear functionals.

### 1.12 Banach Spaces

Normed linear vector spaces that are complete w.r.t. topology induced by norm.

### 1.13 Hilbert Spaces

Complete inner product spaces. Self-dual. Riesz Hilbert space representation theorem. Isometric isomorphism between $\mathcal{H}^{*}$, normed dual of $\mathcal{H}$, and $\mathcal{H}$ itself. That is, every bounded linear functional on $\mathcal{H}$ can be written as the inner product with an element of $\mathcal{H}$; every element of $\mathcal{H}$ defines a bounded linear functional on $\mathcal{H}$; norm of the linear functional and norm of the element are equal.

### 1.14 Reproducing Kernel Hilbert Spaces

Hilbert space $\mathcal{H}$ of functions on some domain $\mathcal{D}$. Point evaluator (the linear functional that evaluates an element of $\mathcal{H}$ at an arbitrary point $x \in \mathcal{D}$ ) is a bounded linear functional. By Riesz representation theorem, point evaluator is the inner product with an element of $\mathcal{H}$. Elements of $\mathcal{H}$ are functions on $\mathcal{D}$. Denote by $K_{x}(y)$ the element of $\mathcal{H}$ corresponding to evaluation at the point $x \in \mathcal{D}$. Kernel is $K_{x}(y)$, viewed as a function of $(x, y) \in \mathcal{D} \times \mathcal{D}$.

Examples: finite-dimensional spaces of functions are reproducing Kernel Hilbert spaces. Suppose $\mathcal{H}$ is an $n$-dimensional set of functions. Let $\left\{f_{j}(y)\right\}_{j=1}^{n}$ be an orthonormal basis for $\mathcal{H}$, so that any element $f$ of $\mathcal{H}$ can be written $f=\sum_{j=1}^{n} \alpha_{j} f_{j}(y)$ for some set of real numbers $\left\{\alpha_{j}\right\}_{j=1}^{n}$. Since $\left\{f_{j}(y)\right\}_{j=1}^{n}$ are orthonormal, $\alpha_{j}=\left\langle f, f_{j}\right\rangle$. Hence

$$
\begin{align*}
f(x) & =\sum_{j=1}^{n}\left\langle f, f_{j}\right\rangle f_{j}(x) \\
& =\left\langle f, \sum_{j=1}^{n} f_{j}(x) f_{j}\right\rangle \tag{10}
\end{align*}
$$

Thus $K_{x}(y)=\sum_{j=1}^{n} f_{j}(x) f_{j}(y)$.

### 1.15 Partial order and convexity

Definition $14 A$ relation $\leq$ is a partial order on a set $\mathcal{X}$ if for all $x, y, z \in \mathcal{X}$,

1. $x \leq x, \forall x \in \mathcal{X}$
2. if $x \leq y$ and $y \leq x$, then $x=y$
3. if $x \leq y$ and $y \leq z$ then $x \leq z$

If, in addition, for any $x, y \in \mathcal{X}$, either $x \leq y$ or $y \leq x$ (or both), then $\leq i s$ an order.

The usual $\leq$ is an order on $\mathbb{R}$. Set inclusion gives an order among the power set (set of all subsets) of a given set: $x \leq y$ if $x \subset y$. One can think of orders as subsets of $\mathcal{X} \otimes \mathcal{X}$ or as mappings from $\mathcal{X} \otimes \mathcal{X} \rightarrow\{0,1\}$. Henceforth, we take $\mathbb{R}$ to be ordered by $\leq$.

Definition $15 A$ set $C \subset \mathcal{X}, \mathcal{X}$ a linear vector space, is a cone with vertex 0 iff $\alpha C \subset C \forall \alpha \geq 0$. $A$ set $C \subset \mathcal{X}, \mathcal{X}$ a linear vector space, is a cone with vertex $p$ if $C=p+C_{0}$, where $C_{0}$ is a cone with vertex 0 .

Definition 16 Let $\mathcal{X}$ be a LVS and let $P \subset \mathcal{X}$ be a convex cone with vertex 0 . For any $x, y \in \mathcal{X}$, we write $x \leq y$ (w.r.t. $P$ ) if $y-x \in P$. The cone $P$ is called the positive cone in $\mathcal{X} . N \equiv-P$ is the negative cone. We write $x \geq y$ if $y-x \in N$ (equivalently, if $x-y \in P$ ).

Examples. In $\mathbb{R},[0, \infty)$ is the usual positive cone. In $\mathbb{R}^{n}$, the positive orthant ( $n$-tuples whose components are all non-negative) is the usual positive cone. The set of non-negative functions and the set of monotone functions can form the positive cones in some function spaces.

Note: the relation $\leq$ defined above is almost-but not quite-a partial order on the linear vector space $\mathcal{X}$ : it does not satisfy the second axiom. If $P$ satisfies $(x \in P$ and $-x \in P)$ implies $x=0$, then the relation $\leq$ is a partial order.

Exercise 6 For $x, y \in \mathbb{R}^{n}$, define

$$
R(x, y)= \begin{cases}\text { true }, & \max _{j=1}^{n}\left(y_{j}-x_{j}\right) \geq 0  \tag{11}\\ \text { false, }, & \text { otherwise }\end{cases}
$$

Does $R(\cdot, \cdot)$ define a partial order on $\mathbb{R}^{n}$ ? Why or why not?
Definition 17 Let $\mathcal{X}$ and $\mathcal{Y}$ be linear vector spaces, let $P$ be the positive cone on $\mathcal{Y}$, and let $T: \mathcal{X} \rightarrow \mathcal{Y}$ have domain $D . T$ is convex if

1. $D$ is a convex subset of $\mathcal{X}$
2. $T\left(\alpha x_{1}+(1-\alpha) x_{2}\right) \leq \alpha T x_{1}+(1-\alpha) T x_{2}, \forall x_{1}, x_{2} \in D$, and all $\alpha \in[0,1]$.

Note that convexity depends on the definition of the positive cone $P$ in $\mathcal{Y}$ ! Convexity and related (such as pseudoconvexity and quasiconvexity), play a crucial role in optimization theory. (A mapping $T$ is quasiconvex if its domain is convex and $T\left(\alpha x_{1}+(1-\alpha) x_{2}\right) \leq \max \left(T x_{1}, T x_{2}\right)$, $\forall x_{1}, x_{2} \in D$, and all $\left.\alpha \in[0,1].\right)$

Definition 18 Let $T$ be a subset of a linear vector space $\mathcal{X}$. The cone generated by $T$ or star of $T$ is the set

$$
\begin{equation*}
C(T) \equiv\{\alpha t: \alpha \in[0, \infty), t \in T\} \subset \mathcal{X} \tag{12}
\end{equation*}
$$

### 1.16 General-purpose Inequalities

1.16.1 The Arithmetic-Geometric Mean Inequality

### 1.16.2 Rearrangement Inequalities

Two functions, three functions.

### 1.16.3 The Triangle Inequality and Generalizations

### 1.16.4 The Cauchy-Schwartz Inequality

If $\mathcal{H}$ is a Hilbert space and $x, y \in \mathcal{H}$, then

$$
\begin{equation*}
|(x, y)| \leq\|x\|\|y\| . \tag{13}
\end{equation*}
$$

### 1.16.5 Parseval's Theorem

### 1.16.6 The Projection Theorem

### 1.17 Probability Inequalities

This follows [?] rather closely.

### 1.17.1 A Helpful Identity

If $X$ is a nonnegative real-valued random variable,

$$
\begin{equation*}
\mathbb{E} X=\int_{0}^{\infty} \operatorname{Pr}\{X \geq x\} d x \tag{14}
\end{equation*}
$$

### 1.17.2 Jensen's Inequality

If $\phi$ is a convex function from $\mathcal{X}$ to $\Re$, then $\phi(\mathbb{E} X) \leq \mathbb{E} \phi(X)$.

### 1.17.3 Markov's, Chebychev's, and related inequalities

From 13,

$$
\begin{equation*}
\mathbb{E} X \geq \int_{0}^{t} \operatorname{Pr}\{X \geq x\} d x \geq t \operatorname{Pr}\{X \geq t\} \tag{15}
\end{equation*}
$$

so

$$
\begin{equation*}
\operatorname{Pr}\{X \geq t\} \leq \frac{\mathbb{E} X}{t} \tag{16}
\end{equation*}
$$

Moreover, for any strictly monotonic function $f$ and nonnegative $X$,

$$
\begin{equation*}
\operatorname{Pr}\{X \geq t\}=\operatorname{Pr}\{f(X) \geq f(t)\} \leq \frac{\mathbb{E} f(X)}{f(t)} \tag{17}
\end{equation*}
$$

In particular, for any real-valued $X$ and real $q>0,|X-\mathbb{E} X|$ is a nonnegative random variable and $f(x)=x^{q}$ is strictly monotonic, so

$$
\begin{equation*}
\operatorname{Pr}\{|X-\mathbb{E} X| \geq t\}=\operatorname{Pr}\left\{|X-\mathbb{E} X|^{q} \geq t^{q}\right\} \leq \frac{\mathbb{E}|X-\mathbb{E} X|^{q}}{t^{q}} \tag{18}
\end{equation*}
$$

Chebychev's inequality is a special case:

$$
\begin{equation*}
\operatorname{Pr}\left\{|X-\mathbb{E} X|^{2} \geq t^{2}\right\} \leq \frac{\mathbb{E}|X-\mathbb{E} X|^{2}}{t^{2}}=\frac{\operatorname{Var} X}{t^{2}} \tag{19}
\end{equation*}
$$

### 1.17.4 Chernoff bounds

Apply 16 with $f(x)=e^{s x}$ for positive $s$ :

$$
\begin{equation*}
\operatorname{Pr}\{X \geq t\}=\operatorname{Pr}\left\{e^{s X} \geq e^{s t}\right\} \leq \frac{\mathbb{E} e^{s X}}{e^{s t}} \tag{20}
\end{equation*}
$$

for all $s$. For particular $X$, can optimize over $s$.

### 1.17.5 Hoeffding's Inequality

Let $\left\{X_{j}\right\}_{j=1}^{n}$ be independent, and define $S_{n} \equiv \sum_{j=1}^{n} X_{j}$. Then, applying 19 gives

$$
\begin{equation*}
\operatorname{Pr}\left\{S_{n}-\mathbb{E} S_{n} \geq t\right\} \leq e^{-s t} \mathbb{E} e^{s S_{n}}=e^{-s t} \prod_{j=1}^{n} e^{s\left(X_{j}-E X_{j}\right)} \tag{21}
\end{equation*}
$$

Hoeffding bounds the moment generating function for a bounded random variable $X$ : If $a \leq X \leq b$ with probability 1 , then

$$
\begin{equation*}
\mathbb{E} e^{s X} \leq e^{s^{2}(b-a)^{2} / 8} \tag{22}
\end{equation*}
$$

from which follows Hoeffding's tail bound.
If $\left\{X_{j}\right\}_{j=1}^{n}$ are independent and $\operatorname{Pr}\left\{a_{j} \leq X_{j} \leq b_{j}\right\}=1$, then

$$
\begin{equation*}
\operatorname{Pr}\left\{S_{n}-\mathbb{E} S_{n} \geq t\right\} \leq e^{-2 t^{2} / \sum_{j=1}^{n}\left(b_{j}-a_{j}\right)^{2}} \tag{23}
\end{equation*}
$$

and

$$
\begin{equation*}
\operatorname{Pr}\left\{S_{n}-\mathbb{E} S_{n} \leq-t\right\} \leq e^{-2 t^{2} / \sum_{j=1}^{n}\left(b_{j}-a_{j}\right)^{2}} \tag{24}
\end{equation*}
$$

### 1.17.6 Hoeffding's Other Inequality

Suppose $f$ is a convex, real function and $\mathcal{X}$ is a finite set. Let $\left\{X_{j}\right\}_{j=1}^{n}$ be a simple random sample from $\mathcal{X}$ and let $\left\{Y_{j}\right\}_{j=1}^{n}$ be an iid uniform random sample (with replacement) from $\mathcal{X}$. Then

$$
\begin{equation*}
\mathbb{E} f\left(\sum_{j=1}^{n} X_{j}\right) \leq \mathbb{E} f\left(\sum_{j=1}^{n} Y_{j}\right) \tag{25}
\end{equation*}
$$

### 1.17.7 Bernstein's Inequality

Suppose $\left\{X_{j}\right\}_{j=1}^{n}$ are independent with $\mathbb{E} X_{j}=0$ for all $j, \operatorname{Pr}\left\{\left|X_{j}\right| \leq c\right\}=1, \sigma_{j}^{2}=\mathbb{E} X_{j}^{2}$ and $\sigma=\frac{1}{n} \sum_{j=1}^{n} \sigma_{j}^{2}$. Then for any $\epsilon>0$,

$$
\begin{equation*}
\operatorname{Pr}\left\{S_{n} / n>\epsilon\right\} \leq e^{-n \epsilon^{2} / 2\left(\sigma^{2}+c \epsilon / 3\right)} \tag{26}
\end{equation*}
$$

1.17.8 The Probability Transform
1.17.9 The Massart-Dvoretsky-Kiefer-Wolfowitz Inequality
1.17.10 Transformed order statistics
1.17.11 Martingales; the Optional Stopping Theorem
1.17.12 The Neyman-Pearson Lemma
1.17.13 Vapnik-Cervonenkis Classes
1.17.14 Convergence of Empirical Processes

### 1.18 Optimization

1.18.1 Convex optimization
1.18.2 Nonsmooth optimization
1.18.3 Numerical Programming: Linear, Quadratic, and Integer
1.18.4 Combinatorial Problems
1.18.5 The Knapsack Problem

