

# 1 Extra material

## 1.1 Jensens inequality

Finite case: For a real convex function  $\phi$

$$\phi\left(\sum_{i=1}^N \theta_i x_i\right) \leq \sum_{i=1}^N \theta_i \phi(x_i)$$

*Proof.* By induction:  $n = 2$  follows from convexity and for  $N + 1$ :

$$\phi\left(\sum_{i=1}^{N+1} \theta_i x_i\right) = \phi\left(\theta_1 x_1 + (1 - \theta_1) \sum_{i=2}^{N+1} \frac{\theta_i}{1 - \theta_1} x_i\right)$$

By convexity of the case  $n = 2$  the result follows.  $\square$

Probability formulation: Let  $X$  be some random variable, and let  $f(x)$  be a convex function (defined at least on a segment containing the range of  $X$ ). Then:

$$\mathbb{E}[f(x)] \geq f(\mathbb{E}[X])$$

*Proof.* Let  $c = \mathbb{E}[X]$ . Since  $f(x)$  is convex there exists a supporting line for  $f(x)$  at  $c$ :

$$\phi(x) = \alpha(x - c) + f(c)$$

for some  $\alpha$ , and  $\phi(x) \leq f(x)$ . Then

$$\mathbb{E}[f(X)] \geq \mathbb{E}[\phi(X)] = \mathbb{E}[\alpha(X - c) + f(c)] = f(c)$$

$\square$

## 1.2 Youngs Inequality

Let  $a, b, p, q \in \mathbb{R}_{++}$  such that

$$\frac{1}{p} + \frac{1}{q} = 1$$

then:

$$ab \leq \frac{a^p}{p} + \frac{b^q}{q}$$

*Proof.*

$$ab = \exp\left(\frac{1}{p} \ln(a^p) + \frac{1}{q} \ln(b^q)\right) \leq \frac{1}{p} \exp(\ln(a^p)) + \frac{1}{q} \exp(\ln(b^q)) = \frac{a^p}{p} + \frac{b^q}{q}$$

where the inequality follows from the convexity of the exponential function.  $\square$

### 1.2.1 Standard version

Let  $f : [0, c] \rightarrow R$  be a continuous and strictly increasing function, where  $f(0) = 0$ .

$$ab \leq \int_0^a f(x)dx + \int_0^b f^{-1}(x)dx$$

*Proof.* By visual inspection. □

## 1.3 Hölders inequality

### 1.3.1 Standard version

Let  $(S, \sum, \mu)$  be a measure space and let  $q \leq p, q \leq \infty$  with  $\frac{1}{p} + \frac{1}{q} = 1$  then for all measurable real- or complex-valued functions  $f$  and  $g$  on  $S$

$$\|fg\|_1 \leq \|f\|_p \|g\|_q,$$

in the case  $p = 2$  this becomes the Cauchy inequality.

*Proof.* If  $\|f\|_t = 0$  for  $t = p$  or  $t = q$  the left side is zero almost everywhere, so we can assume that  $\|f\|_t > 0$ . For  $\|f\|_t = \infty$  the right hand side could be infinite large. If  $t = \infty$  then  $|fg| \leq \|f\|_\infty |g|$  almost everywhere and Hölders inequality follows from the monotonicity of the Lebesgue integral (?). Normalizing the equation we can expect

$$\|f\|_p = \|g\|_q = 1.$$

Using Youngs inequality

$$|f(s)g(s)| \leq \frac{|f(s)|^p}{p} + \frac{|g(s)|^q}{q} \quad s \in S$$

Integrating both sides:

$$\|fg\|_1 = \int_S |f(s)g(s)|ds \leq \int_S \left( \frac{|f(s)|^p}{p} + \frac{|g(s)|^q}{q} \right) ds = \frac{\|f\|_p^p}{p} + \frac{\|g\|_q^q}{q} = 1 = \|f\|_p \|g\|_q$$

□

### 1.3.2 With sums

Using summation to define the norm :

$$\|x\|_p = \left( \sum_k |x_k|^p \right)^{\frac{1}{p}}$$

*Proof.* Then (without normalization)

$$\frac{|\sum_k x_k y_k|}{\|x\|_p \|y\|_q} \leq \sum_k \frac{|x_k| |y_k|}{\|x\|_p \|y\|_q} \leq \frac{1}{p} \sum_k \frac{|x_k|^p}{\|x\|_p^p} + \frac{1}{q} \sum_k \frac{|y_k|^q}{\|y\|_q^q} = \frac{1}{p} + \frac{1}{q} = 1$$

hence

$$|(x, y)| = \left| \sum_k x_k y_k \right| \leq \|x\|_p \|y\|_q$$

□

The equality holds (proof) iff  $\arg x_j y_j$  and  $|x_j|^p |y_j|^q$  are independent of  $j$ . For any  $x \in \ell^p$  we can choose  $y \in \ell^q$  so we get equality (proof?). Hence we get

$$\|x\|_p = \max_{\|y\|_q=1} \|(x, y)\|_1$$

## 1.4 Minkowski

For the  $\ell^p$  spaces (same holds for  $L^p$ )

$$\|x + y\|_p \leq \|x\|_p + \|y\|_p$$

*Proof.* (?) Using the second formulation of Hölders inequality and noting that  $\|xy\|_1$  could be written as a scalar product and that scalar products are bilinear

$$\|x + y\|_p = \max_{\|u\|_q=1} |(x + y, u)| \leq \max_{\|u\|_q=1} |(x, u)| + |(y, u)| \leq \|x\|_p + \|y\|_q.$$

Where we in the last inequality split the max and use Hölder inequality together with fact that  $\|u\|_q = 1$ . □

## 1.5 Cauchy inequality

A scalar product in a linear space  $X$  over  $\mathbb{C}$  is a real valued function that fulfils

- sesquilinearity:  $(ax, y) = a(x, y)$ ,  $(x, ay) = \bar{a}(x, y)$
- Skew symmetry:  $(y, x) = \overline{(x, y)}$
- positivity:  $(x, x) > 0$ ,  $x \neq 0$

This also lets us define the norm

$$\|x\| = (x, x)^{\frac{1}{2}}$$

### 1.5.1 Schwarz Inequality in $\mathbb{C}$

$$|(x, y)| \leq \|x\| \|y\|$$

(This is just a special case of Hölders inequality with  $p = 2$ )

*Proof.* For any  $t \in \mathbb{R}$  and  $y \neq 0$

$$0 \leq \|x + ty\|^2 = \|x\|^2 + 2t \operatorname{Re}(x, y) + t^2 \|y\|^2 \quad (1)$$

By choosing  $t = -\operatorname{Re}(x, y)/\|y\|^2$  and multiplying with  $\|y\|^2$

$$(\operatorname{Re}(x, y))^2 \leq \|x\|^2 \|y\|^2 \quad (2)$$

Let  $x = ax$ ,  $a \in \mathbb{C}$  such that  $|a| = 1$  and  $\operatorname{Im}(a(x, y)) = 0$  results in

$$|(x, y)| \leq \|x\| \|y\| \quad (3)$$

This also gives as a corollary that every vector in a scalar product space can be written as

$$\|x\| = \max_{\|y\|=1} \|(x, y)\|_1$$

□

### 1.6 Parallelogram Identity

Set  $t \pm 1$  in (1) and we end up with the parallelogram identity, which is true for all scalar product induced norms.

$$\|x + y\|^2 + \|x - y\|^2 = 2(\|x\|^2 + \|y\|^2) \quad (4)$$

Actually every norm that comes from an scalar product must have this equality (von Neumann)

### 1.7 Polarization Identity

For a real vector space, if the norm fullfills the Parallelogram Identity then it induces a scalar product

$$(x, y) = \frac{1}{4} (\|x + y\|^2 - \|x - y\|^2) \quad (5)$$

And for the complex vector space

$$(x, y) = \frac{1}{4} (\|x + y\|^2 - \|x - y\|^2 + i\|x + iy\|^2 - i\|x - iy\|^2) \quad (6)$$

## 2 Finite

### 2.0.1 Lemma x

Let  $Y$  be a subset of the metric space  $X$ , then  $x \in X$  is adherent to  $Y$  iff there is a sequence in  $Y$  that converges to  $x$ .

*Proof.* ( $\Rightarrow$ ) For each  $n \geq 1$  there exists some point  $x_n \in B(x; 1/n) \cap Y$  the sequence  $(x_n)$  then converges to  $x$ .

( $\Leftarrow$ ) If there is a sequence  $(x_n)$  converging to  $x$  then all balls centered at  $x$  contains points from the sequence.  $\square$

### 2.0.2 Every subspace of a normed space of finite dimension is closed

Let  $(V, |\cdot|)$  be a normed vector space of finite dimension, and  $S \subset V$  a finite dimensional subspace. Then  $S$  is closed.

*Proof.* Let  $a \in \overline{S}$  and choose a sequence  $(a_n)$ , with  $a_n \in S$  converging to  $a$  ???. Then  $(a_n)$  is a cauchy sequence in  $V$  and also a cauchy sequence in  $S$ . Since  $V$  is finite dimensional,  $V$  is a Banach space,  $S$  is complete, so  $(a_n)$  converges to an element in  $S$ . Since limits in a normed space are unique, that limits must be  $a$ , so  $a \in S$ .  $\square$

### 2.0.3 Every finite dimensional subspace of a normed space is closed

*Proof.* Let  $(V, |\cdot|)$  be a normed vector space, and  $S \subset V$  a finite dimensional subspace. Then  $S$  is closed. Let  $x \in V$  and let  $(a_n)$  be a sequence in  $S$  with converges to  $x$ . Because  $S$  is of finite dimension, we have a basis  $\{x_1 \dots x_k$  of  $S$ . Also  $x \in \text{span}(x_1 \dots x_k, x)$ . But as proved in the case when  $V$  is finite dimensional, we have that  $S$  is closed in  $\text{span}(x_1 \dots x_k, x)$  (taken with the normed induced by  $(V, |\cdot|)$ ) with  $a_n \rightarrow x$ , and  $x \in S$ .  $\square$