

# Lecture 6

## Last time

- ▷ Johnson-Lindenstrauss Lemma.
- ▷ Orlicz norms

## Today

- ▷ Orlicz norms cont.
- ▷ Mc Diarmid's Ineq.

## Orlicz norms

We finished with:

Proposition: Let  $X$  be a r.v. the following are equivalent (modulo const. factors):

- 1)  $\exists K_1 > 0$  s.t.  $P(|X| > t) \leq 2e^{-t/K_1} \quad \forall t \geq 0$ .
- 2)  $\exists K_2 > 0$  s.t.  $\|X\|_{2_p} := (\mathbb{E}|X|^p)^{1/p} \leq K_2 \quad \forall p \geq 1$ .
- 3)  $\exists K_3 > 0$  s.t.  $\mathbb{E} \exp(|X|/K_3) \leq 2$ .

Moreover, if  $\mathbb{E}X = 0$  then, these are equivalent to

- 4)  $\exists K_4 > 0$  s.t.  $\mathbb{E} \exp(\lambda X) \leq \exp(K_4^2 \lambda^2) \quad \forall |\lambda| \leq \frac{1}{K_4}$ .

This motivates the following. †

Def: The subexponential norm of a r.v. is

$$\|X\|_{Y_1} := \inf \{K > 0 : \mathbb{E} \exp(|X|/K) \leq 2\}. \quad \text{†}$$

Just as before  $\| \cdot \|_{\psi_1}$  is a norm over the set of subexponentials. Moreover

$$\| X - \mathbb{E}X \|_{\psi_1} \leq C \| X \|_{\psi_1}.$$

We motivated subexponential via  $\chi^2$  distributions, in turn products of sub-Gaussians are always subexponential.

Lemma: Suppose  $X, Y$  are sub-Gaussian, then

$$\| XY \|_{\psi_1} \leq \| X \|_{\psi_2} \| Y \|_{\psi_2}. \quad \dagger$$

Proof: WLOG  $\| X \|_{\psi_2} = \| Y \|_{\psi_2} = 1$ . Then

$$\mathbb{E} \exp(|XY|) \leq \mathbb{E} \exp(X^2/2 + Y^2/2)$$

Young's ineq.  $|ab| \leq a^2/2 + b^2/2$

$$= \mathbb{E} \exp(X^2/2) \exp(Y^2/2)$$

$$\leq \frac{1}{2} (\mathbb{E} \exp(X^2) + \mathbb{E} \exp(Y^2))$$

$$\leq \frac{1}{2}(2+2) = 2. \quad \ddagger$$

It is natural to wonder whether other functions besides exponentials define other norms capturing different growth / tails. Indeed, this is the case

Def: Given a convex, nondecreasing function  $\Psi: \mathbb{R}_+ \rightarrow \mathbb{R}_+$  s.t.  $\Psi(0) = 0$  with  $\Psi(t) \xrightarrow{t \rightarrow \infty} \infty$ , define the Orlicz norm of a r.v.  $X$  as

$$\|X\|_\Psi = \inf \{K > 0 \mid \mathbb{E} \Psi(|X|/K) \leq 1\}.$$

One can show that this defines a norm on  $\{X \mid \|X\|_\Psi < \infty\}$ .

Example: For  $\Psi(t) = t^p$  with  $p \geq 1$  defines  $L_p$ . While  $\Psi_2(t) = e^{t^2} - 1$  and  $\Psi_1(t) = e^t - 1$  define sub-Gaussians and sub-exponentials, respectively.

## Concentration of functions of iid r.v.

So far we have studied concentration of sums. However, this is a more general phenomenon. The following principle it's good to have in mind

If  $X_1, \dots, X_n$  are independent r.v. then  $f(X_1, \dots, X_n)$  concen-

brates near  $\mathbb{E} f(x_1, \dots, x_n)$  provided  $f$  is not too sensitive to any coordinate.

We will instantiate this principles for two notions of "sensitivity."

Our goal is to prove the following.

**Theorem (McDiarmid):** Let  $x_1, \dots, x_n$  be ind. r.v.s and  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  be a function s.t.  $\forall j \in [n] \exists c_j > 0$  with

$$|f(z_1, \dots, z_j, \dots, z_n) - f(z_1, \dots, \tilde{z}_j, \dots, z_n)| \leq c_j$$

$\forall z_1, z_2, \dots, z_n, \tilde{z}_j \in \mathbb{R}$ . Then,

$$\mathbb{P}(|f(x) - \mathbb{E} f(x)| > t) \leq 2e^{-2t^2/\|c\|_2^2}.$$

To prove this result we will use the so-called Martingale method, which is useful beyond this proof.

**Def (Martingale):** We say that a sequence of r.v.  $Y_0, Y_1, \dots$  is a r.v. with respect to another sequence of r.v.

$X_0, X_1, \dots$  if  $Y_n$  we have

- $E|Y_n| < \infty$   $\downarrow Y_n = f(X_0, \dots, X_n)$
- $Y_n$  is measurable w.r.t.  $X_0, \dots, X_n$
- $E(Y_{n+1} | X_0, \dots, X_n) = Y_n$

+

Martingales model fair games. They are helpful to derive results when full independence fails (CLTs, concentration).

They are covered in Prob. Theory II.  
We will need to remember a few facts.

Fact (Tower law): If  $j < k$

$$E[E[Y | X_1, \dots, X_k] | X_1, \dots, X_j] = E[Y | X_1, \dots, X_j].$$

Fact: If  $Y$  is measurable w.r.t.  $X_1, \dots, X_k$ ,

$$E[Y | X_1, \dots, X_k] = Y.$$

The idea for the proof is to consider  $Y_0 = E f(x)$  and  $Y_j = E[f(x)(X_1, \dots, X_j)]$ . Then,

Then, we can decompose

$$f(x) - E f(x) = Y_n - Y_0 = \sum_{j=0}^{n-1} (Y_{j+1} - Y_j). \quad (\star)$$

It is not hard to see that  $2Y_n Y_0$

is a Martingale with respect to  $\{X_k\}$ :

$$\mathbb{E}[Y_{j+1} | X_1, \dots, X_j] = \mathbb{E}[\mathbb{E}[f(X) | X_1, \dots, X_{j+1}] | X_1, \dots, X_j]$$

$$\begin{aligned}\text{Tower law} \rightarrow &= \mathbb{E}[f(X) | X_1, \dots, X_j] \\ &= Y_j.\end{aligned}\quad (\heartsuit)$$

Thus, in order to control the difference  $|f(X) - \mathbb{E} f(X)|$  it suffices to control sums of Martingale differences.

Lemma (Azuma): Suppose that  $\{Y_k\}$  is a Martingale w.r.t.  $\{X_k\}$  and set

$$\Delta_k = Y_k - Y_{k-1}. \text{ Further, assume } \forall k$$

$$\mathbb{E}[e^{\lambda \Delta_{k+1}} | X_1, \dots, X_k] \leq e^{\lambda^2 \sigma_k^2 / 2} \text{ a.s. (ö)}$$

Then, the sum  $\sum_{k=1}^n \Delta_k$  is  $\|\sigma\|_2^2$ -sub-Gaussian. +

We will come back to the proof of this result next time.