

Prof: Yaniv Plan  
("Yuh-neev. Plan")

Class website:

[www.yanivplan.com/math-608d](http://www.yanivplan.com/math-608d)

Theory: Understanding

"probabilistic objects" in high dimensions, e.g., random variables, random matrices, functions with random input, shapes as seen through "prob. lens".

Applications: Compressed sensing, statistical estimation, dimension reduction, etc.

# Concentration of measure

## 1. Deviation inequalities for sums of indep r.v.'s

### 1.1 CLT: asymptotic and non asymptotic

Normal r.v.:  $g \sim N(0, 1)$

$$\text{density } f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2}$$

Ubiquitous in science. Why?

Thm: (CLT, Lindeberg-Levy)

Let  $X_1, X_2, \dots$  be iid r.v.'s with  $\mathbb{E} X_i = 0$ ,  $\text{Var}(X_i) = 1$ . Then

$$\lim_{n \rightarrow \infty} \frac{1}{\sqrt{n}} \sum_{i=1}^n X_i \rightarrow N(0, 1)$$

uniformly in distribution.

Remarks:

① Role of  $\frac{1}{\sqrt{n}}$ :  $\text{Var}\left(\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i\right) = \text{Var}(g) = 1.$

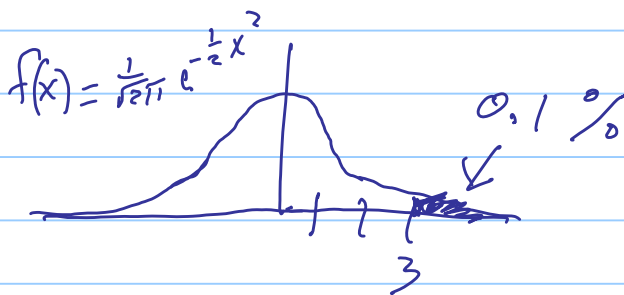
(2) "Uniformly in distribution"

$$\lim_{n \rightarrow \infty} \sup_{t \in \mathbb{R}} \left| P\left(\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i < t\right) - P(g < t) \right| \rightarrow 0$$

$\uparrow$  c.d.f. of  $\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i$        $\uparrow$  normal c.d.f.

Why is  $N(0,1)$  so useful?

• Fast tail decay



Roughly:  $P(g > t) \approx \frac{1}{t} \frac{e^{-\frac{1}{2}t^2}}{\sqrt{2\pi}} = \frac{1}{t} f(t)$

See: [Durrett, Probability: Theory & Examples  
Thm 1.4]

Precisely:  $\left(\frac{1}{t} - \frac{1}{t^3}\right) f(t) \leq P(g > t) \leq \frac{1}{t} f(t)$

$P(g > t) \leq \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}t^2}, t \geq 1$

$\uparrow$

super-exponential tail decay

Question Does  $\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i$  have the same fast tail decay?

CLT suggests "yes", but this does not follow from CLT. Depends on convergence rate of CLT.

Thm (CLT: Berry-Esseen)

$$\sup_{t \in \mathbb{R}} \left| P\left(\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i < t\right) - P(g < t) \right| \leq \frac{C\rho}{\sqrt{n}}$$

where  $\rho := \mathbb{E}|X_1|^3$ ,  $C = \text{abs. const}$

HW

Show by example that the rate  $\sim \frac{\rho}{\sqrt{n}}$  cannot be improved, i.e., find a distribution for  $X_i$  and an abs. const  $c$ , so that

$$\sup_t \left| P\left(\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i < t\right) - P(g < t) \right| \geq \frac{c\rho}{\sqrt{n}} \quad \text{for all } n \geq 1.$$

Remark: Non-asymptotic version of CLT.

This gives a non-asymptotic tail bound:

$$P\left(\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i > t\right) \leq P(g > t) + \frac{C\rho}{\sqrt{n}} \leq e^{-t^2} + \frac{\rho}{\sqrt{n}}$$

↑  
hides abs. const.

- Unfortunately,  $\frac{\rho}{\sqrt{n}}$  does not depend on  $t$ , and can ruin exponential decay.

• Further, one cannot hope for exponential decay with only the condition  $|X| \leq \infty$ . (why?)

Soln: Deviation inequalities: Bound tail of  $\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i$  directly, without comparing to  $N(0,1)$ .

1.2: Hoeffding's inequality for Rademacher r.v.'s

Def:  $X \sim \text{Rademacher}$  iff

$$P(X=1) = P(X=-1) = 0.5$$

Consider  $\sum_{i=1}^n a_i X_i$ ,  $X_i \stackrel{iid}{\sim} \text{Rademacher}$

Normalization: Require  $\text{var}(X_i) = 1$ .

$$\text{Var}(\sum a_i X_i) = \sum a_i^2 \text{Var}(X_i) = \sum a_i^2$$

Req:  $\sum_{i=1}^n a_i^2 = 1$

First attempt: Bound tail with moment bound.

$$P(\sum a_i X_i > t) = P((\sum a_i X_i)^2 > t^2)$$

$$\stackrel{\text{Chebychev}}{\leq} \frac{\mathbb{E}(\sum a_i X_i)^2}{t^2} = \frac{1}{t^2}$$

$\frac{1}{t^2}$  is not exponential!

2<sup>nd</sup> attempt:

$$P\left(\sum_i a_i X_i > t\right) = P\left(\exp\left(\lambda \sum_i a_i X_i\right) > e^{\lambda t}\right)$$

$\lambda$  will be optimized later

1<sup>st</sup> expon.

(Chebychev  $\neq$ )

$$\rightarrow \leq e^{-\lambda t} \mathbb{E} \exp\left(\lambda \sum_i a_i X_i\right)$$

$$= e^{-\lambda t} \prod_{i=1}^n \mathbb{E} e^{\lambda a_i X_i} \quad (\text{by indep.})$$
$$= (*)$$

$$\mathbb{E} e^{\lambda a_i X_i} = \frac{1}{2} e^{\lambda a_i} + \frac{1}{2} e^{-\lambda a_i} = \cosh(\lambda a_i)$$

Note:  $\cosh(x) = 1 + \frac{x^2}{2!} + \frac{x^4}{4!} + \dots$

$$\exp\left(\frac{x^2}{2}\right) = 1 + \frac{x^2}{2} + \frac{x^4}{4 \cdot 2!} + \dots$$

Exercise:  $\cosh(x) \leq \exp\left(\frac{x^2}{2}\right)$

$$\Rightarrow (*) \leq e^{-\lambda t} \prod e^{\frac{(\lambda a_i)^2}{2}} = \exp\left(-\lambda t + \frac{\lambda^2}{2} \sum a_i^2\right)$$
$$= \exp\left(-\lambda t + \frac{\lambda^2}{2}\right)$$

Optimize  $\lambda$ :  $\lambda = t$

$$\Rightarrow (*) \leq \exp\left(\frac{-t^2}{2}\right)$$

We have proven:

Thm Hoeffding  $\neq$

Let  $X_i$  be indep. Rademacher.

$$\sum_{i=1}^n a_i^2 = 1. \quad \text{Then}$$

$$P\left(\sum_{i=1}^n a_i X_i > t\right) \leq \exp\left(-\frac{t^2}{2}\right), \quad t > 0.$$

Remarks:

① ~ matches normal tail  $P(Z > t) \sim e^{-\frac{t^2}{2}}$

② Non-asymptotic

③ Method is very flexible.

(Due to S. Bernstein.)

Generalizes to other distributions.

(Even to random matrices.)

Literature: [G. Lugosi, concentration of measure inequalities]

Next lecture: Largest class of r.v.'s s.t. result of above flavor occurs.