

WLLN

 $(X_n)_{n \in \mathbb{N}}$ 

iid r.v.

s.t.

$$\mu = \mathbb{E}[X_1] < +\infty$$

$$\sigma^2 = \text{Var}[X_1] < +\infty$$



$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$$

$$\approx \frac{\mu}{n}$$

 $\forall \varepsilon > 0$ 

$$\boxed{\mathbb{P}[|\bar{X}_n - \mu| \geq \varepsilon] \leq \frac{\sigma^2}{n \varepsilon^2}}$$

$\forall n$   
 $\forall \varepsilon > 0$

Chernoff's bounds

Let  $X_1, \dots, X_n$  be iid r.v's and set

$$\underline{\mu}(t) := \mathbb{E}[e^{t \cdot X_1}] \quad \text{mgf of } X_1 (X_1, \dots)$$

We assume that  $\underline{\mu}(t) < +\infty$  for  $t \in (-\varepsilon, \varepsilon)$ for a suitable  $\varepsilon > 0$ .

$$P[\underbrace{|\bar{X}_n - \mu|}_{\leq \varepsilon} \geq \varepsilon] = P[\underbrace{\bar{X}_n - \mu \geq \varepsilon}_{\text{1}}] +$$

$$+ P[\underbrace{\bar{X}_n - \mu \leq -\varepsilon}_{\text{2}}]$$

$$P[\bar{X}_n - \mu \geq \varepsilon] = \frac{1}{\mu + \varepsilon} \int_{\mu + \varepsilon}^{\infty} \dots$$

$$= P[\bar{X}_n \geq \mu + \varepsilon]$$

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$$

$$= P[\underbrace{X_1 + X_2 + \dots + X_n}_{\text{1}} \geq n(\mu + \varepsilon)]$$

$$\boxed{t > 0}$$

$$= P[e^{t(X_1 + \dots + X_n)} \geq e^{tn(\mu + \varepsilon)}] \quad t \geq s \Leftrightarrow e^t \geq e^s$$

$t$  positive r.v.

Markov  
Folgerung

$$\leq \frac{E[e^{t(X_1 + \dots + X_n)}]}{e^{tn(\mu + \varepsilon)}}$$

$X_i$  sind  
iid

$$m(t) = E[e^{tX_1}] \cdot E[e^{tX_2}] \cdots \stackrel{\text{IND}}{=} \frac{E[e^{tX_1} \cdot e^{tX_2} \cdots e^{tX_n}]}{e^{tn(\mu + \varepsilon)}}$$

$$P[\bar{X}_n \geq \mu + \varepsilon] \leq \exp(-nt(\mu + \varepsilon) + n \log(m(t)))$$

$$\frac{(m(t))^n}{e^{nt(\mu + \varepsilon)}} = \exp($$

$$(m(t))^n = e^{\log((m(t))^n)} = e^{n \log(m(t))}$$

$$\frac{1}{e^{nt(\mu + \varepsilon)}} = e^{-nt(\mu + \varepsilon)}$$

$$= \exp(-n \cdot g(t))$$

$t \geq 0$

where  $\boxed{g(t) = t(\mu + \varepsilon) - \log(m(t))}$

$$P[\bar{X}_n \geq \mu + \varepsilon] \leq \exp(-n g(t))$$

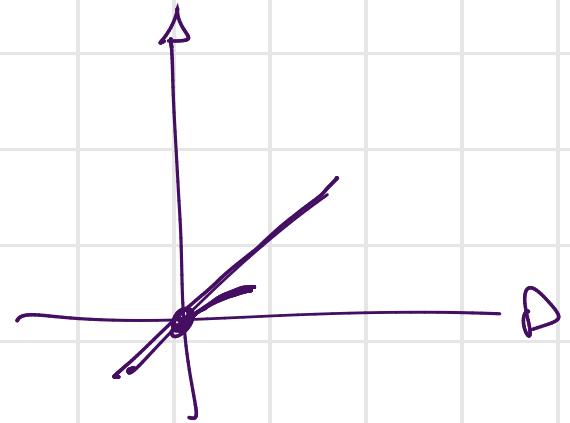
$$\boxed{\begin{array}{l} g(t) > 0 \\ t > 0 \end{array}}$$

Look for  $t^*$  s.t.  $g(t^*) \geq g(t) \quad \forall t \geq 0$

$$\Rightarrow e^{-n g(t^*)} \leq e^{-n g(t)} \quad \Downarrow$$

$$-n g(t^*) \leq -n g(t) \quad \forall t \geq 0$$

$\exists \bar{t} > 0$  s.t.  $f(\bar{t}) > 0$



$t \mapsto g(t)$

$t \geq 0$

$$g(t) = t(\mu + \varepsilon) - \underbrace{\log(m(t))}_{\text{concave down}}$$

$$\begin{aligned} g(0) &= 0 \cdot (\mu + \varepsilon) - \log(m(0)) \\ &= 0 - \log(1) = 0 \end{aligned}$$

$$\begin{aligned} m(0) &= \mathbb{E}[e^{0 \cdot X}] \\ &= \mathbb{E}[1] \\ &= 1 \end{aligned}$$

if we are able to prove that  $g'(0) > 0$

$$\Rightarrow \boxed{\exists \bar{t} > 0 \text{ s.t. } g(\bar{t}) > 0}$$

$$g'(t) = \mu + \varepsilon - \frac{1}{m(t)} \cdot m'(t)$$

$$\left. \frac{m'(t)}{t=0} \right| = \mathbb{E}[X]$$

$$g'(t)|_{t=0} = \mu + \varepsilon - \frac{1}{1} \cdot \mu = \varepsilon > 0$$

Upper tail estimate

$$\mathbb{P}[\bar{X}_n \geq \mu + \varepsilon] \leq e^{-n g(\bar{t})} \quad \text{Theorem}$$

$$\textcircled{2} \quad P[\bar{X}_n \leq \mu - \varepsilon]$$

$$= P[X_1 + X_2 + \dots + X_n \leq n(\mu - \varepsilon)]$$

$$= P[e^{-t(X_1 + \dots + X_n)} \geq e^{-tn(\mu - \varepsilon)}] \quad t \geq 0$$

H.I

$$\leq \frac{\mathbb{E}[e^{-t(X_1 + \dots + X_n)}]}{e^{-tn(\mu - \varepsilon)}} =$$

$$= \exp \left( \underbrace{-n}_{=} (-t(\mu - \varepsilon) - \log(n(-t))) \right)$$

$$= \exp(-n h(t))$$

$$h(t) = \underbrace{-t(\mu - \varepsilon)}_{=} - \underbrace{\log(n(-t))}_{}$$

$$h(0) = 0 - \log(n(0)) = 0$$

$$h'(t) = -(\mu - \varepsilon) \rightarrow \frac{1}{n(-t)} \cdot \underbrace{n'(-t)}_{(-t)}$$

$$= \varepsilon - \mu + \underbrace{\frac{n'(-t)}{n(-t)}}_{t > 0} \quad h'(0) = \varepsilon - \mu + \mu = \varepsilon > 0$$

$$\exists \bar{t} > 0 \quad \text{s.t.} \quad h(\bar{t}) > 0$$

Lower tail estimate

$$P[\bar{X}_n \leq \mu - \varepsilon] \leq e^{-n h(\bar{t})}$$

$$\boxed{\bar{t} > 0}$$

$$\boxed{\varepsilon}$$

$$\boxed{\bar{t}(\varepsilon)}$$

Example 1 : Normal r.v.'s

$X_1, \dots, X_n \sim N(0, 1)$  independent

$$\boxed{\mu = 0}$$

$$m(t) = e^{t^2/2} \quad t \in \mathbb{R}$$

Upper tail estimate

$$P[\bar{X}_n \geq \mu + \varepsilon] \leq e^{-n g(\bar{t})}, \quad \bar{t} > 0$$

$$g(t) = t(\mu + \varepsilon) - \log(m(t))$$

$$g(t) = t \cdot \varepsilon - t^2/2$$

$$\boxed{t \geq 0}$$

$$g(t) = t \cdot \varepsilon - \frac{t^2}{2}$$

$$g(t) = 0$$

$$t=0$$

$$t_{1/2} - \varepsilon = 0$$

$$t = 2 \cdot \varepsilon$$

$$g'(t) = \varepsilon - t$$

$$g'(t) = 0 \Leftrightarrow t = \varepsilon$$

$$t^* : g(t^*) \geq g(t) \quad \forall t \geq 0$$

$$\boxed{t^* = \varepsilon}$$

$$g(t^*) = g(\varepsilon) = \frac{\varepsilon^2}{2}$$

$$X_1 \sim N(0,1)$$

$$P[\bar{X}_n \geq \varepsilon] \leq C^{-n} \varepsilon^2$$

Standard Normal

$$X \sim N(0,1)$$

$$P[X > x] \leq \left(\frac{1}{x}\right) \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}, \quad x \geq 0$$

Example 2:  $Z_1, \dots, Z_n$  indep.  $N(0,1)$ ,  $\forall i=1, \dots, n$

$X_i = Z_i^2 \sim \text{Chi-square distribution with 1 degree of freedom}$

$X_i \sim P(\chi_2, 1)$  (Gamma)

$$E[X_i] = E[Z_i^2] = 1 \quad g(z) = e^{t \cdot z^2}$$

$$m(t) = E[e^{t \cdot X_1}] = E[e^{t \cdot Z_1^2}] =$$

$$= \int_{-\infty}^{+\infty} g(z) f_{Z_1}(z) dz$$

$$= \int_{-\infty}^{+\infty} e^{t \cdot z^2} \cdot \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{z^2}{2}} dz$$

$$= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} \cdot e^{t \frac{z^2}{2} - \frac{z^2}{2}} dz$$

$$1-2t \geq 0$$

$$S = \sqrt{1-2t} \cdot z$$

$$S^2 = (1-2t)z^2$$

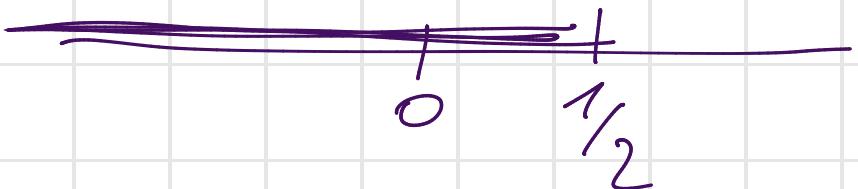
$$dz = \frac{1}{\sqrt{1-2t}} \cdot dS$$

$$\begin{aligned} 1-2t &= 0 \\ 1-2t &< 0 \end{aligned}$$

$$= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{S^2}{2}} \cdot \left( \frac{1}{\sqrt{1-2t}} \right) dS$$

$$m(t) = \begin{cases} +\infty & t-2t \leq 0 \\ \frac{1}{\sqrt{1-2t}} & t > \frac{1}{2} \end{cases}$$

$$\begin{cases} 1-2t > 0 \\ t < \frac{1}{2} \end{cases}$$



$$P[\bar{X}_n \geq \mu + \varepsilon] \leq e^{-n g(t)}$$

$$(-\varepsilon, \varepsilon)$$

$$\boxed{g(t) = t(\mu + \varepsilon) - \log(m(t))}$$

$\mu = E[X]$   
 $= 1$

$$= t(1 + \varepsilon) - \log\left(\frac{1}{\sqrt{1-2t}}\right)$$

$\boxed{t < \frac{1}{2}}$

$$= t(1 + \varepsilon) - \overbrace{\log((1-2t)^{-\frac{1}{2}})}$$

$$= t(1 + \varepsilon) + \frac{1}{2} \log(1-2t)$$

$\hat{t}^*$

$$\boxed{g'(t) = 0} \Leftrightarrow \boxed{(1+\varepsilon) + \frac{1}{2} \cdot \frac{1}{1-2t} \cdot (-2)} = 0$$

$$1+\varepsilon - \frac{t}{1-2t} = 0 \quad (\Rightarrow) \quad 1+\varepsilon = \frac{1}{1-2t}$$

$$(\Rightarrow) \quad 1-2t = \frac{1}{1+\varepsilon}$$

$$(\Rightarrow) \quad 2t = 1 - \frac{1}{1+\varepsilon} = \frac{1+\varepsilon-1}{1+\varepsilon} = \frac{\varepsilon}{1+\varepsilon}$$

$$t^* = \frac{\varepsilon}{2(1+\varepsilon)}$$

? YES

$$\mathbb{P}[\bar{X}_n \geq 1+\varepsilon] \leq e^{-n g(t^*)}$$

$$g(t^*)$$

$$g(t) = t(1+\varepsilon) + \frac{1}{2} \log(1-2t)$$

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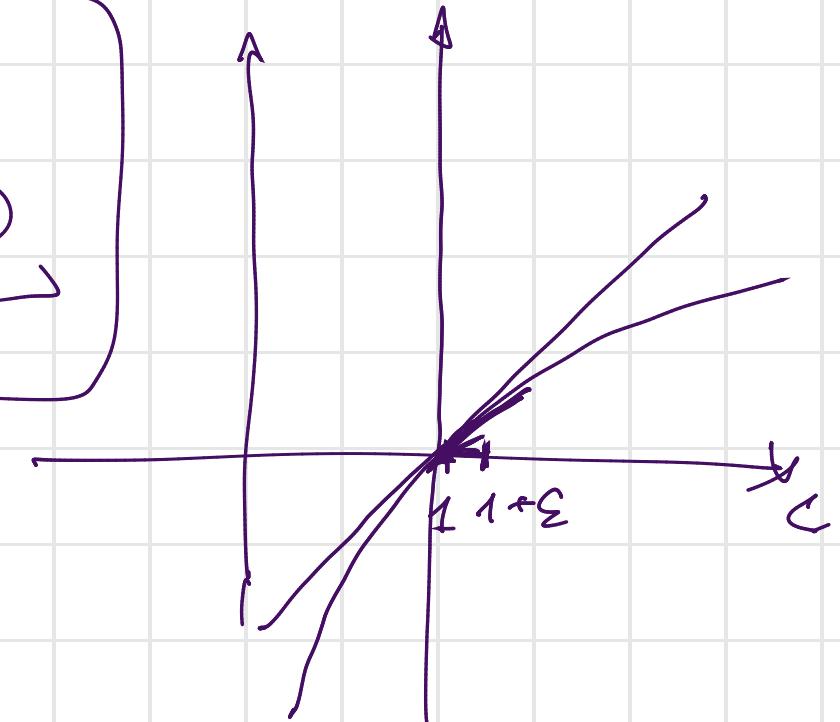
$$\frac{\varepsilon}{2(1+\varepsilon)} \cdot (1+\varepsilon) + \frac{1}{2} \log\left(\frac{1}{1+\varepsilon}\right) = \\ = \frac{\varepsilon}{2} - \frac{1}{2} \log(1+\varepsilon)$$

$$1-2t^* = 1 - \cancel{2} \cdot \frac{\varepsilon}{\cancel{2}(1+\varepsilon)} = \frac{1+\varepsilon-\varepsilon}{1+\varepsilon} = \\ = \frac{1}{1+\varepsilon}$$

$$\mathbb{P}[\bar{X}_n \geq 1+\varepsilon] \leq C^{-n} g\left(\frac{\varepsilon}{2(1+\varepsilon)}\right)$$

$$g\left(\frac{\varepsilon}{2(1+\varepsilon)}\right) = \frac{1}{2} \cdot \left(\varepsilon - \underbrace{\log(1+\varepsilon)}_{\text{approximation}}\right)$$

$$\log(1+\varepsilon) \leq \varepsilon - \frac{\varepsilon^2}{2(1+\varepsilon)}$$



$$a(\varepsilon) = \log(1+\varepsilon)$$

$$b(\varepsilon) = \varepsilon - \frac{\varepsilon^2}{2(1+\varepsilon)}$$

$$[a(\varepsilon) \leq b(\varepsilon)]$$

sufficiently small  $\varepsilon$

$$\varepsilon = 0 \quad a', b'$$