Today: Review

- Hoeffdring's lemma
- Horoffding's magnality
- · Sub-Gaussian RV
- · Bennett's inequality

Review: • Horffding's lemma: for a random vanishble X with E[X] = 0 and $a \le X \le b$, $E[e^{SX}] \le e^{S^2 \cdot (b-a)^2}$

Ruall L(h) = -hp + log [(1-p) + p.eh] where $h = 8.(b-a), p = -\frac{a}{(b-a)}$

L"(h) & I for any h.

• Holfding's inequality! If $S_n = \sum_{i=1}^n x_i$ where x_i 's are independent Rv_s with $a_i \le x_i \le b_i$ then $P \le S_n - ES_n \ge t$ $3 \le exp \left[\frac{-2t^2}{5(b_i - a_i)^2} \right]$,

$$P\{S_n-ES_n\geq t\} \leq e^{\frac{-2t}{2}} \frac{1}{2} \frac{1}{(b_i-a_i)^2}$$

· Taybor's theorem: If f(a) is a combinious function in the bounded interval [a, b) and has f'(a), and f'(a) defined in this cinterval thm $f(h) = f(0) \cdot h^0 + f'(0) \cdot \frac{h'}{1!} + f''(v) \frac{h^2}{2!}$ where $v \in (0, h)$.

- · Snb- Gaussian RV: A real valued RV x is sovid to be 02- snb. Gamman if there exists a or such that Elexx] < exp (xerl) for any & e 18.
- o observation about the boeffding's enequality: the bound does not involve the variance of the RV.
- · Question: Can we find a tighter bound when the KV has low variance? Yes, via the Bennett's enequality.

Bunnell's inequality! Let X, ... Xn be independent RVs with finite variance and $X_i \le b$ for b > 0 reliminate sharely for $i \le n$. Let $v = \sum_{i=1}^{N} E[x_i^2]$. If $S = \sum_{i=1}^{N} (x_i - E[x_i])$, thus

log [Ee 2] < n. log [1+ w \$ \$ (7)] < 2 \$ (76),

where $\beta(u) = e^{u} - u - 1$ $u \in \mathbb{N}$.

Proof: Let no assume b = 1.

· Show that u-2. Ø(u) is a non decreasing function.

 $g(n) = \varphi(n) \Rightarrow g'(n) = \underbrace{e^{n}(n-2) + (n-2)}_{N^{3}} \Rightarrow 0$ $(\lambda x_{i})^{2} \varphi(\lambda x_{i}) \leqslant \lambda^{2} \varphi(\lambda) \text{ (due } X_{i} \leqslant 1, \lambda > 0$ $\text{to } g(n) \text{ being non-degree}_{N^{3}}$ $\Rightarrow \varphi(\lambda x_{i}) \leqslant X_{i}^{2} \varphi(\lambda)$

$$\Rightarrow \phi(\lambda \times i) \leq \chi i^2 \phi(\lambda)$$

r.e. $e^{\lambda \kappa c} - \lambda \kappa c - 1 \leqslant \kappa^2 (e^{\lambda} - \lambda - 1)$.

Apply the expectation reprotor. $E[e^{\lambda x_i} - \lambda x_i - 1] \leq \emptyset(\lambda) \cdot E[x_i^2]$ $E[e^{\lambda x_i}] \leq (E[\lambda x_i] + 1 + E[x_i^2] \cdot \emptyset(\lambda))$ $\lim_{n \to \infty} E[e^{\lambda x_i}] \leq \lim_{n \to \infty} (E[\lambda x_i] + 1 + E[x_i^2] \cdot \beta(\lambda))$ $\lim_{n \to \infty} E[e^{\lambda x_i}] \leq \lim_{n \to \infty} (E[\lambda x_i] + 1 + E[x_i^2] \cdot \beta(x))$ $\lim_{n \to \infty} E[e^{\lambda x_i}] \leq \lim_{n \to \infty} (E[\lambda x_i] + 1 + E[x_i^2] \cdot \beta(x))$ $\lim_{i \to 1} \left[\lim_{i \to 1} \frac{\lambda \cdot x_i - \varepsilon(x_i)}{1 + \sum_{i \to 1} \sum_{j \to 1} \frac{x_j}{1 + \sum_{i \to 1} \sum_{j \to 1} \frac{x_j}{1 + \sum_{j \sum_{j \to 1}$ (45 (x) where 45 (x) = log [E[exs]]. $=) \quad \forall y(\lambda) \leq \sum_{i=1}^{n} \log \left[E(\lambda X_i) + 1 + E(X_i^2) \beta(\lambda) \right].$ $- \sum_{i=1}^{N} \lambda_i \cdot E[x_i].$ $\leq n \sum_{i=1}^{N} \frac{\log_2 L}{\log_2 L}$] - \(\frac{n.}{2} \rangle E(\ki)