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Question: toss a fair coin $n = 10000$ times. How many heads?

$X = \sum_{i=1}^{n}$, $X_i \sim \text{Bern}(1/2)$. $\mathbb{E}[X] = 5000$. But $\mathbb{P}(X = 5000) = \binom{10^4}{5000} \cdot 2^{-10^4} \approx 0.008$.

By WLLN, $\mathbb{P}(X \in [5000 - n\varepsilon, 5000 + n\varepsilon]) \approx 1$.

Theorem 0.1 (Central Limit Theorem) Let $X_1, ..., X_n$ be IID RVs with mean $\mathbb{E}[X_1] = \mu$. Let $\text{Var}(X_1) = \sigma^2 < \infty$. Then $\frac{1}{\sigma\sqrt{n}} \sum_{i=1}^{n}(X_i - \mu) \underset{D}{\to} N(0, 1)$, i.e.

$$\mathbb{P}\left(\frac{1}{\sigma\sqrt{n}} \sum_{i=1}^{n}(X_i - \mu) \in A\right) \to \int_A \frac{1}{\sqrt{2n}} e^{-x^2/2} \,\mathrm{d}x$$

for all A.

So $\mathbb{P}\Big(X \in \Big[\frac{n}{2} - \frac{\sqrt{n}}{2}Q^{-1}(\delta), \frac{n}{2} + \frac{\sqrt{n}}{2}Q^{-1}(\delta)\Big]\Big) \geq 1 - \delta$, for n large enough, where $Q(\delta) = \int_\delta^\infty \frac{1}{\sqrt{2n}} e^{-x^2/2d} \,\mathrm{d}x$. We have $Q^{-1}(x) \propto \sqrt{\log \frac{1}{x}}$. So interval has length $\propto \sqrt{n}\sqrt{\log \frac{1}{\delta}}$.

Theorem 0.2 (Chebyshev's Inequality) $\mathbb{P}(|X - \mu| \geq \varepsilon) \leq \frac{\text{Var}(X)}{\varepsilon^2}$ for all $\varepsilon > 0$.

Corollary 0.3 $\mathbb{P}\Big(\Big|\sum_{i=1}^{n}(X_i) - \frac{n}{2}\Big| \geq t\Big) \leq \frac{\text{Var}\left(\sum_{i=1}^{n} X_i\right)}{t^2} = n\frac{\sigma^2}{t^2} \leq \delta$ where $t = \sqrt{n}\sigma/\sqrt{\delta}$.

So $\mathbb{P}(X \in [\frac{n}{2} -, \frac{n}{2}]) \geq 1 - \delta$.

Question 2: we have N coupons. Each day receive one uniformly at random independent of the past. How many days until all coupons received?

We have $X = \sum_{i=1}^{n} X_i$, $X_i \sim \text{Geom}\left(\frac{i}{n}\right)$. $\mathbb{E}[X] = \sum_i \mathbb{E}[X_i] \approx n \log n$ (verify this).

Question 3: Let $(X_1, ..., X_n), (Y_1, ..., Y_n)$ be IID. What is the longest common subsequence, i.e. $f(X_1, ..., X_n, Y_1, ..., Y_n) = \max\Big\{k : \exists i_1, ..., i_k, j_1, ..., j_k \text{ s.t. } X_{i_j} = Y_{i_j}\ \forall j \in [k]\Big\}$. Computing f is NP-hard. f is smooth.

Principle: a smooth function of many independent random variables concentrates around its mean.

Tower property of conditional expectation: $\mathbb{E}(\mathbb{E}(Z \mid X, Y) \mid Y) = \mathbb{E}(Z \mid Y)$.

Theorem 0.4 (Holder's Inequality) Let $p \geq 1$ and $1/p + 1/q = 1$. Then

$$\mathbb{E}[XY] \leq \mathbb{E}[|X|^p]^{1/p} \cdot \mathbb{E}[|X|^q]^{1/q}.$$

1. The Chernoff-Cramer method

1.1. The Chernoff bound and Cramer transform

Theorem 1.1 (Weak Law of Large Numbers) Let $X_1, ..., X_n$ be IID RVs with mean $\mathbb{E}[X_1] = \mu$. Then, for all $\varepsilon > 0$,

$$\mathbb{P}\left(\left|\frac{1}{n}\sum_{i=1}^{n} X_i - \mu\right| > \varepsilon\right) \to 0 \quad \text{as } n \to \infty.$$

Theorem 1.2 (Markov's Inequality) Let Y be a non-negative RV. For any $t \geq 0$,

$$\mathbb{P}(Y \geq t) \leq \frac{\mathbb{E}[Y]}{t}.$$

Proof (Hints). Split Y using indicator variables. $\square$

Proof. We have $Y = Y \cdot \mathbb{I}_{\{Y \geq t\}} + Y \cdot \mathbb{I}_{\{Y < t\}} \geq t \cdot \mathbb{I}_{\{Y \geq t\}}$. Taking expectations gives the result. $\square$

Corollary 1.3 Let $\varphi : \mathbb{R} \to \mathbb{R}_+$ be non-decreasing, then

$$\mathbb{P}(Y \geq t) \leq \mathbb{P}(\varphi(Y) \geq \varphi(t)) \leq \frac{\mathbb{E}[\varphi(Y)]}{\varphi(t)}.$$

For $\varphi(t) = t^2$, we can use $\operatorname{Var}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \operatorname{Var}(X_i)$.

Corollary 1.4 (Chebyshev's Inequality) For any RV Y and $t > 0$,

$$\mathbb{P}(|Y - \mathbb{E}[Y]| \geq t) \leq \frac{\operatorname{Var}(Y)}{t^2}.$$

Proof (Hints). Straightforward. $\square$

Proof. Take $Z = |Y - \mathbb{E}[Y]|$ and use Corollary 1.3 with $\varphi(t) = t^2$. $\square$

Exercise 1.5 Prove WLLN, assuming that $\operatorname{Var}(X_1) < \infty$, using Chebyshev's inequality.

Remark 1.6 If higher moments exist, we can use them in a similar way: let $\varphi(t) = t^q$ for $q > 0$, then for all $t > 0$,

$$\mathbb{P}(|Z - \mathbb{E}[Z]| \geq t) \leq \frac{\mathbb{E}[|Z - \mathbb{E}[Z]|^q]}{t^q}.$$

We can then optimise over q to pick the lowest bound on $\mathbb{P}(|Z - \mathbb{E}[Z]| \geq t)$. Note that Chebyshev's Inequality is the most popular form of this bound due to the additivity of variance.

Definition 1.7 The **moment generating function (MGF)** of F is

$$F(\lambda) := \mathbb{E}[e^{\lambda Z}] = \sum_{k=0}^{\infty} \frac{\lambda^k \mathbb{E}[Z^k]}{k!}.$$

Definition 1.8 The **log-MGF** of Z is $\psi_Z(\lambda) = \log F(\lambda)$.

Note that $\psi_Z(\lambda)$ is additive: if $Z = \sum_{i=1}^n Z_i$, with $Z_1, \ldots, Z_n$ independent, then

$$\psi_Z(\lambda) = \log\left(\mathbb{E}[e^{\lambda Z}]\right) = \sum_{i=1}^n \log \mathbb{E}[e^{\lambda Z_i}] = \sum_{i=1}^n \psi_{Z_i}(\lambda).$$

Definition 1.9 The **Cramer transform** of Z is

$$\psi_Z^*(t) = \sup\{\lambda t - \psi_Z(\lambda) : \lambda > 0\}.$$

Proposition 1.10 (Chernoff Bound) Let Z be an RV. For all $t > 0$,

$$\mathbb{P}(Z \geq t) \leq e^{-\psi_Z^*(t)}.$$

Proof. By Corollary 1.3, we have

$$\mathbb{P}(Z \geq t) \leq \frac{\mathbb{E}[e^{\lambda Z}]}{e^{\lambda t}} = e^{-(\lambda t - \psi_Z(\lambda))}.$$

Taking the infimum over all $\lambda > 0$ gives $\mathbb{P}(Z \geq t) \leq \inf\{e^{-(\lambda t - \psi_Z(\lambda))} : \lambda > 0\}$, which gives the result. ☐

Remark 1.11 Our goal is to obtain an upper bound on $\psi_Z(\lambda)$, as this will give exponential concentration. The function $\psi_{Z-\mathbb{E}[Z]}(\lambda)$ gives upper bounds on $\mathbb{P}(Z - \mathbb{E}[Z] \geq t)$, the function $\psi_{-Z+\mathbb{E}[Z]}(\lambda)$ gives upper bounds on $\mathbb{P}(Z - \mathbb{E}[Z] \leq -t)$.

Proposition 1.12

1. $\psi_Z(\lambda)$ is convex and infinitely differentiable on $(0, b)$, where $b = \sup_{\lambda > 0}\{\mathbb{E}[e^{\lambda Z}] < \infty\}$.
2. $\psi_Z^*(t)$ is non-negative and convex.
3. If $t > \mathbb{E}[Z]$, then $\psi_Z^*(t) = \sup_{\lambda \in \mathbb{R}}\{\lambda t - \psi_Z(\lambda)\}$, the **Fenchel-Legendre** dual.

Proof (Hints).

1. Differentiability proof omitted. For convexity, use Holder's Inequality.
2. Straightforward (note that each $t \mapsto \lambda t - \psi_Z(\lambda)$ is linear).
3. Straightforward.

☐

Proof.

1. $\psi_Z(\alpha\lambda_1 + (1-\alpha)\lambda_2) = \log \mathbb{E}\left[e^{\alpha\lambda_1 Z} \cdot e^{(1-\alpha)\lambda_2 Z}\right] \leq \alpha \log \mathbb{E}\left[e^{\lambda_1 Z}\right] + (1 - \alpha) \log \mathbb{E}\left[e^{\lambda_2 Z}\right]$ by Holder's inequality. The differentiability proof is omitted.
2. $\lambda t - \psi_Z(\lambda)|_{\lambda=0} = 0$, so $\psi_Z^*(t) \geq 0$ by definition. Convexity follows since it is a supremum of linear functions.
3. By convexity and Jensen's inequality, $\mathbb{E}[e^{\lambda Z}] \geq e^{\lambda \mathbb{E}[Z]}$. So for $\lambda < 0$, $\lambda t - \psi_Z(\lambda) \leq \lambda(t - \mathbb{E}[Z]) < 0 = \lambda t - \psi_Z(\lambda)|_{\lambda=0}$.

☐

Example 1.13 Let $Z \sim N(0, \sigma^2)$. Then the MGF of Z is

$$\begin{aligned}
\mathbb{E}[e^{\lambda Z}] &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-x^2/2\sigma^2} e^{\lambda x} \, \mathrm{d}x \\
&= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x^2 - 2\lambda\sigma^2 x + \lambda^2\sigma^4)/2\sigma^2} e^{\lambda^2 \frac{\sigma^2}{2}} \, \mathrm{d}x \\
&= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x - \lambda\sigma^2)^2/2\sigma^2} e^{\lambda^2 \frac{\sigma^2}{2}} \, \mathrm{d}x \\
&= e^{\lambda^2\sigma^2/2}.
\end{aligned}$$

By Proposition 1.12, for $t > 0 = \mathbb{E}[Z]$, the Cramer transform is

$$\psi_Z^*(t) = \sup_{\lambda \in \mathbb{R}} \{\lambda t - \lambda^2 \sigma^2 / 2\} =: \sup_{\lambda \in \mathbb{R}} g(\lambda).$$

We have $g'(\lambda) = t - \lambda \sigma^2 = 0$ iff $\lambda = t/\sigma^2$. So $\psi_Z^*(t) = t^2/\sigma^2 - \sigma^2 t^2 / 2\sigma^4 = t^2/2\sigma^2$. So Chernoff Bound gives

$$\mathbb{P}(Z \geq t) \leq e^{-t^2/2\sigma^2}.$$

Definition 1.14 Let X be an RV with $\mathbb{E}[X] = 0$. X is **sub-Gaussian** with variance parameter ν if

$$\psi_X(\lambda) \leq \frac{\lambda^2 \nu}{2} \quad \forall \lambda \in \mathbb{R}.$$

The set of all such variables is denoted $\mathcal{G}(\nu)$.

Proposition 1.15 For any sub-Gaussian RV X,
1. If $X \in \mathcal{G}(\nu)$, then $\mathbb{P}(X \geq t), \mathbb{P}(X \leq -t) \leq e^{-t^2/2\nu}$ for all $t > 0$.
2. If $X_1, ..., X_n$ are independent with each $X_i \in \mathcal{G}(\nu_i)$ then $\sum_{i=1}^n X_i \in \mathcal{G}\left(\sum_{i=1}^n \nu_i\right)$.
3. If $X \in \mathcal{G}(\nu)$, then $\mathrm{Var}(X) \leq \nu$.

Proof. Exercise. □

Definition 1.16 The **Gamma function** is defined as

$$\Gamma(z) := \int_0^\infty t^{z-1} e^{-t} \, \mathrm{d}t.$$

Theorem 1.17 Let $\mathbb{E}[X] = 0$. TFAE for suitable choices of ν, b, c, d:
1. $X \in \mathcal{G}(\nu)$.
2. $\mathbb{P}(X \geq t), \mathbb{P}(X \leq -t) \leq e^{-t^2/2b}$ for all $t > 0$.
3. $\mathbb{E}[X^{2q}] \leq q! c^q$ for all $q \geq \mathbb{N}$.
4. $\mathbb{E}\left[e^{dX^2}\right] \leq 2$.

Proof (Hints).
- $(1 \Rightarrow 2)$: straightforward.
- $(2 \Rightarrow 3)$: Explain why we can assume $b = 1$. Use that $\mathbb{E}[Y] = \int_0^\infty \mathbb{P}(Y > t) \, \mathrm{d}t$ for $Y \geq 0$, and the Γ function.
- $(3 \Rightarrow 1)$: show that $\mathbb{E}[e^{\lambda X}] \leq \mathbb{E}\left[e^{\lambda(X - X')}\right]$ where X' is an IID copy of X. Show that $\mathbb{E}[(X - X')^{2q}] \leq \mathbb{E}[X^{2q}]$. Expand $\mathbb{E}\left[e^{\lambda(X - X')}\right]$ as a series. Conclude that $X \in \mathcal{G}(4c)$.
- $(3 \Leftrightarrow 4)$: exercise.

□

Proof. $(1 \Rightarrow 2)$ instantly follows (with $b = \nu$) by Proposition 1.15.

$(2 \Rightarrow 3)$: WLOG, $b = 1$. Otherwise consider $\widetilde{X} = X/\sqrt{b}$. Recall that for $Y \geq 0$, $\mathbb{E}[Y] = \int_0^\infty \mathbb{P}(Y > t) \, \mathrm{d}t$. Now

$$\begin{aligned}
\mathbb{E}\left[X^{2q}\right] &= \int_0^\infty \mathbb{P}\left(X^{2q} > t\right) \mathrm{d}t = \int_0^\infty \mathbb{P}\left(|X| > t^{1/2q}\right) \mathrm{d}t \\
&\leq 2 \int_0^\infty e^{-t^{1/q}/2} \, \mathrm{d}t \\
&= 2 \cdot 2^q \cdot q \int_0^\infty u^{q-1} e^{-u} \, \mathrm{d}u \\
&= 2 \cdot 2^q \cdot q \cdot \Gamma(q) \\
&= 2^{q+1} \cdot q! \leq c^q q!
\end{aligned}$$

for some constant c, where we use the substitution $t^{1/q}/2 = u$, so $t = (2u)^q$, so $\mathrm{d}t = 2^q q u^{q-1} \, \mathrm{d}u$.

$(3 \Rightarrow 1)$: $\mathbb{E}\left[e^{-\lambda X}\right] \cdot \mathbb{E}\left[e^{\lambda X}\right] = \mathbb{E}\left[e^{\lambda(X - X')}\right]$, where X' is an IID copy of X. By Jensen's inequality, $\mathbb{E}\left[e^{-\lambda X}\right] \geq e^{-\lambda \mathbb{E}[X]} = 1$. So

$$\mathbb{E}\left[e^{\lambda X}\right] \leq \mathbb{E}\left[e^{\lambda(X - X')}\right] = \sum_{q=0}^\infty \frac{\lambda^{2q} \mathbb{E}\left[(X - X')^{2q}\right]}{(2q)!}$$

(we can ignore odd powers since $X - X'$ is a symmetric RV: $X - X'$ has the same distribution as $X' - X$). Now

$$\mathbb{E}\left[(X - X')^{2q}\right] = \sum_{k=0}^{2q} \binom{2q}{k} \mathbb{E}\left[X^k\right] \mathbb{E}\left[(X')^{2q-k}\right] \leq \sum_{k=0}^{2q} \binom{2q}{k} \mathbb{E}\left[X^{2q}\right] = 2^{2q} \cdot \mathbb{E}\left[X^{2q}\right],$$

by Holder's inequality with $p = 2q/k$ and $q = 2q/(2q - k)$ for each k. Thus,

$$\begin{aligned}
\mathbb{E}\left[e^{\lambda X}\right] &\leq \sum_{q=0}^\infty \frac{\lambda^{2q} \mathbb{E}\left[X^{2q}\right] \cdot 2^{2q}}{(2q)!} \\
&\leq \sum_{q=0}^\infty \frac{\lambda^{2q} c^q q! 2^{2q}}{(2q)!} \\
&\leq \sum_{q=0}^\infty \frac{\lambda^{2q} \cdot c^q 2^q}{q!} = \sum_{q=0}^\infty \frac{\left(\lambda^2 \cdot 2c\right)^q}{q!} = e^{2\lambda^2 c},
\end{aligned}$$

where we used that $(2q)!/q! = \prod_{j=1}^q (q+1)! \geq 2^q \cdot q!$. Hence $\psi_X(\lambda) = 2\lambda^2 c = \frac{\lambda^2 \cdot 4c}{2}$, hence $X \in \mathcal{G}(4c)$.

$(3 \Leftrightarrow 4)$: exercise. □

1.2. Hoeffding's and related inequalities

Lemma 1.18 (Hoeffding's Lemma) Let Y be a RV with $\mathbb{E}[Y] = 0$ and $Y \in [a, b]$ almost surely (with probability 1). $\psi_Y''(\lambda) \leq (b - a)^2/4$ and $Y \in \mathcal{G}((b - a)^2/4)$.

Proof (Hints).

- Define a new distribution based on λ, which should be obvious after expanding $\psi_Y'(\lambda)$.

- To conclude the result, use a Taylor expansion at 0 of $\psi_Y(\lambda)$.

$\square$

Proof. Let Y have distribution P. We have

$$\psi_Y'(\lambda) = \frac{\mathbb{E}_{Y\sim P}[Ye^{\lambda Y}]}{\mathbb{E}_{Y\sim P}[e^{\lambda Y}]} = \mathbb{E}_{Y\sim P}\left[Y \cdot \frac{e^{\lambda Y}}{\mathbb{E}[e^{\lambda Y}]}\right] = \mathbb{E}_{Y\sim P_\lambda}[Y],$$

where if P is discrete, then P_λ is the discrete distribution with PMF

$$P_\lambda(y) = \frac{e^{\lambda y}P(y)}{\sum_z P(z)e^{\lambda z}},$$

and if P is continuous with PDF f, then P_λ is the continuous distribution with PDF

$$f_\lambda(y) = \frac{e^{\lambda y}f(y)}{\int_{-\infty}^{\infty} f(z)e^{\lambda z}\,\mathrm{d}z}.$$

Now

$$\begin{aligned}\psi_Y''(\lambda) &= \frac{\mathbb{E}_{Y\sim P}[Y^2e^{\lambda Y}]\cdot\mathbb{E}_{Y\sim P}[e^{\lambda Y}] - \mathbb{E}_{Y\sim P}[Ye^{\lambda Y}]^2}{\mathbb{E}_{Y\sim P}[e^{\lambda Y}]^2} \\ &= \mathbb{E}_{Y\sim P}\left[Y^2\frac{e^{\lambda Y}}{\mathbb{E}_{Y\sim P}[e^{\lambda Y}]}\right] - \mathbb{E}\left[Y\frac{e^{\lambda Y}}{\mathbb{E}_{Y\sim P}[e^{\lambda Y}]}\right]^2 \\ &= \mathbb{E}_{Y\sim P_\lambda}[Y^2] - \mathbb{E}_{Y\sim P_\lambda}[Y]^2 = \mathrm{Var}_{Y\sim P_\lambda}(Y).\end{aligned}$$

Note that if $Y \in [a,b]$, then $\left|Y - \frac{b-a}{2}\right|^2 \le (b-a)^2/4$. So we have

$$\mathrm{Var}_{Y\sim P_\lambda}(Y) = \mathrm{Var}_{Y\sim P_\lambda}(Y-(b-a)/2) \le \mathbb{E}_{Y\sim P_\lambda}\left[\left(Y - \frac{b-a}{2}\right)^2\right] \le \frac{(b-a)^2}{4}.$$

Finally, using a Taylor expansion at 0, we obtain

$$\psi_Y(\lambda) = \psi_Y(0) + \lambda_Y'(0)\lambda + \psi_Y''(\xi)\frac{\lambda^2}{2} = \psi_Y''(\xi)\frac{\lambda^2}{2} \le \lambda^2\frac{(b-a)^2}{8},$$

for some $\xi \in [0,\lambda]$, since $\mathbb{E}_{Y\sim P}[Y] = \mathbb{E}_{Y\sim P_0}[Y] = 0$. $\square$

Remark 1.19 The distribution P_λ in the above proof is called the **exponentially tilted** distribution.

Theorem 1.20 (Hoeffding's Inequality) Let $X_1, ..., X_n$ be independent RVs where each X_i takes values in $[a_i, b_i]$. Then for all $t \ge 0$,

$$\mathbb{P}\left(\sum_{i=1}^n (X_i - \mathbb{E}[X_i]) \ge t\right) \le \exp\left(-\frac{2t^2}{\sum_{i=1}^n (b_i - a_i)^2}\right).$$

Proof. Apply Hoeffding's Lemma to $X_i - \mathbb{E}[X_i]$ and use the additivity of $\psi_{\sum_{i=1}^n X_i}(\lambda)$.
$\square$

Remark 1.21 A drawback of Hoeffding's Inequality is that the bound does not involve $\mathrm{Var}(X_i)$. This is addressed by Bennett's inequality:

Theorem 1.22 (Bennett's Inequality) Let $X_1, ..., X_n$ be independent RVs with $\mathbb{E}[X_i] = 0$ and $|X_i| \leq c$ for all i. Let $\nu = \mathrm{Var}(X_1) + \cdots + \mathrm{Var}(X_n)$. Then for all $t \geq 0$,

$$\mathbb{P}\left(\sum_{i=1}^n X_i \geq t\right) \leq \exp\left(-\frac{\nu}{c^2} h_1\left(\frac{ct}{\nu}\right)\right),$$

where $h_1(x) = (1+x)\log(1+x) - x$ for $x > 0$.

Proof. Denote $\sigma_i^2 = \mathrm{Var}(X_I)$. We have

$$\begin{aligned}
\mathbb{E}[e^{\lambda X_i}] &= \sum_{k=0}^\infty \frac{\lambda^k \mathbb{E}[X_i^k]}{k!} \\
&= 1 + \sum_{k=1}^\infty \frac{\lambda^k \mathbb{E}[X_i^{k-2} X_i^2]}{k!} \\
&\leq 1 + \frac{\sigma_i^2}{c^2} \sum_{k=2}^\infty \frac{\lambda^k c^k}{k!} \\
&= 1 + \frac{\sigma_i^2}{c^2} \left(\sum_{k=0}^\infty \frac{\lambda^k c^k}{k!} - \lambda c - 1\right) \\
&= 1 + \frac{\sigma_i^2}{c^2} (e^{\lambda c} - \lambda c - 1).
\end{aligned}$$

So $\psi_{X_i}(\lambda) = \log\left(1 + \frac{\sigma_i^2}{c^2}(e^{\lambda c} - \lambda c - 1)\right) \leq \frac{\sigma_i^2}{c^2}(e^{\lambda c} - \lambda c - 1)$. So by additivity of ψ, we have

$$\psi_{\sum_{i=1}^n X_i}(\lambda) \leq \frac{\nu}{c^2} e^{\lambda c} - \frac{\nu}{c^2}\lambda c - \frac{\nu}{c^2}.$$

So for $t \geq 0$,

$$\psi^*_{\sum X_i}(t) \geq \sup_{\lambda \in \mathbb{R}} \left\{\lambda t - \frac{\nu}{c^2} e^{\lambda c} + \frac{\nu}{c}\lambda + \frac{\nu}{c^2}\right\} =: \sup_{\lambda \in \mathbb{R}} \{g(\lambda)\}$$

We have $g'(\lambda) = t - \frac{\nu}{c} e^{\lambda c} + \frac{\nu}{c}$ which is 0 iff $t + \frac{\nu}{c} = \frac{\nu}{c} e^{\lambda c}$, i.e. iff $\lambda = \frac{1}{c}\log(1 + t\frac{c}{v}) =: \lambda^*$. So

$$\begin{aligned}
\psi^*_{\sum X_i}(t) &\geq \frac{1}{c} t \log\left(1 + \frac{tc}{\nu}\right) - \frac{\nu}{c^2}\left(1 + \frac{tc}{\nu}\right) + \frac{\nu}{c^2}\log\left(1 + \frac{tc}{\nu}\right) + \frac{\nu}{c^2} \\
&= \frac{\nu}{c^2}\left(\left(1 + \frac{tc}{\nu}\right)\log\left(1 + \frac{tc}{\nu}\right) - \frac{tc}{\nu}\right) \\
&= \frac{\nu}{c^2} h_1\left(\frac{tc}{\nu}\right).
\end{aligned}$$

So we are done by the Chernoff Bound. $\square$

Remark 1.23 We can show that $h_1(x) \geq \frac{x^2}{2(\frac{x}{3}+1)}$ for $x \geq 0$. So by Bennett's Inequality, we obtain

$$\mathbb{P}\left(\sum_{i=1}^{n} X_i \geq t\right) \leq \exp\left(-\frac{t^2}{2\left(\frac{tc}{3}+\nu\right)}\right),$$

which is **Bernstein's inequality**. If $\nu \gg ct$, then this yields a sub-Gaussian tail bound, and if $\nu \ll tc$, then this yields an exponential bound. So Bernstein misses a log factor.

Remark 1.24 If $Z \sim \mathrm{Pois}(\lambda)$, then $\psi_Z(\lambda) = \nu\left(e^{\lambda} - \lambda - 1\right)$

2. The variance method

2.1. The Efron-Stein inequality