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proof of Bennett inequality

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By <http://planetmath.org/ChernoffCramerBound> Chernoff-Cramèr inequality, we have:

$$\Pr \left\{ \sum_{i=1}^n (X_i - E[X_i]) > \varepsilon \right\} \leq \exp \left[- \sup_{t \geq 0} (t\varepsilon - \psi(t)) \right]$$

where

$$\psi(t) = \sum_{i=1}^n (\ln E[e^{tX_i}] - tE[X_i]) .$$

Keeping in mind that the condition

$$\Pr \{|X_i| \leq M\} = 1 \quad \forall i$$

implies that, for all i ,

$$E[|X_i|^k] \leq M^k \quad \forall k \geq 0$$

(see <http://planetmath.org/RelationBetweenAlmostSurelyAbsolutelyBoundedRandomVariables> for a proof) and since $\ln x \leq x - 1 \quad \forall x > 0$, and

$$E[|X|^k] \leq M^k \implies E[|X|^k] \leq E[X^2] M^{k-2} \quad \forall k \geq 2, k \in \mathbb{N}$$

(see <http://planetmath.org/AbsoluteMomentsBoundingNecessaryAndSufficientConditions>)

for a proof), one has:

$$\begin{aligned}
\psi(t) &= \sum_{i=1}^n (\ln E[e^{tX_i}] - tE[X_i]) \\
&\leq \sum_{i=1}^n E[e^{tX_i}] - tE[X_i] - 1 \\
&= \sum_{i=1}^n E \left[\sum_{k=0}^{\infty} \frac{(tX_i)^k}{k!} \right] - tE[X_i] - 1 \\
&= \sum_{i=1}^n \left(\sum_{k=0}^{\infty} \frac{t^k E[X_i^k]}{k!} \right) - tE[X_i] - 1 \\
&= \sum_{i=1}^n \left(\sum_{k=2}^{\infty} \frac{t^k E[X_i^k]}{k!} \right) \\
&\leq \sum_{i=1}^n \left(\sum_{k=2}^{\infty} \frac{t^k E[|X_i|^k]}{k!} \right) \\
&\leq \sum_{i=1}^n \left(\sum_{k=2}^{\infty} \frac{t^k E[X_i^2] M^{k-2}}{k!} \right) \\
&= \sum_{k=2}^{\infty} \frac{t^k M^{k-2} \sum_{i=1}^n E[X_i^2]}{k!} \\
&= \frac{v^2}{M^2} \sum_{k=2}^{\infty} \frac{(tM)^k}{k!} \\
&= \frac{v^2}{M^2} [\exp(tM) - tM - 1]
\end{aligned}$$

One can now write

$$\sup_{t \geq 0} (t\varepsilon - \psi(t)) \geq \sup_{t \geq 0} \left(t\varepsilon - \frac{v^2}{M^2} (e^{tM} - tM - 1) \right) = \sup_{t > 0} \left[\frac{v^2}{M^2} \left(\frac{M^2 \varepsilon}{v^2} t - (e^{tM} - tM - 1) \right) \right].$$

By elementary calculus, we obtain the value of t that maximizes the expression in round brackets:

$$t_{opt} = \frac{1}{M} \ln \left(1 + \frac{M\varepsilon}{v^2} \right)$$

which, once plugged into the bound, yields

$$\Pr \left\{ \sum_{i=1}^n (X_i - E[X_i]) > \varepsilon \right\} \leq \exp \left[-\frac{v^2}{M^2} \left(\left(1 + \frac{M\varepsilon}{v^2} \right) \ln \left(1 + \frac{M\varepsilon}{v^2} \right) - \frac{M\varepsilon}{v^2} \right) \right].$$

Observing that $(1+x) \ln(1+x) - x \geq \frac{x}{2} \ln(1+x) \forall x \geq 0$ (see <http://planetmath.org/ASimpleInequality>) one gets the sub-optimal yet more easily manageable formula:

$$\Pr \left\{ \sum_{i=1}^n (X_i - E[X_i]) > \varepsilon \right\} \leq \exp \left[-\frac{\varepsilon}{2M} \ln \left(1 + \frac{\varepsilon M}{v^2} \right) \right].$$