

Fourmlas Sheet.

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Probability.

Multiplicative Chernoff bound. Suppose X_1, \dots, X_n are independence random variables taking values in $\{0, 1\}$. Let X denote their sum and let $\mu = \mathbf{E}[\sum_i^n X_i]$ denote the sum's expected value. Then for any $\delta > 0$:

$$\begin{aligned}\Pr[X \geq (1 + \delta)\mu] &\leq e^{-2\frac{\delta^2\mu^2}{n}} \\ \Pr[|X - \mu| \geq \delta\mu] &\leq 2e^{-\delta^2\mu/3}, \quad 0 \leq \delta \leq 1\end{aligned}$$

Jensen's inequality. If X is a random variable and ϕ is a convex function, then:

$$\begin{aligned}\phi(\mathbf{E}[X]) &\leq \mathbf{E}[\phi(X)] \Rightarrow \mathbf{E}[X] \leq \phi^{-1}(\mathbf{E}[\phi(X)]) \\ \mathbf{E}[X] &\leq \ln(\mathbf{E}[e^X]) \\ \mathbf{E}[X] &\geq e^{\mathbf{E}[\ln(X)]}\end{aligned}$$

Paley–Zygmund inequality. bounds the probability that a positive random variable is small, in terms of its first two moments. Could be thought as the lower bound Markov version. If a r.v X is always positive and has a finite variance, then for $0 \leq \tau \leq 1$:

$$\begin{aligned}\Pr[X > \tau\mathbf{E}[X]] &\geq (1 - \tau)^2 \frac{\mathbf{E}[X]^2}{\mathbf{E}[X^2]} \\ \Pr[X > \mathbf{E}[X] - \tau\sigma] &\geq \frac{\tau^2}{1 + \tau^2}\end{aligned}$$

