

1. Probability (Technical note 11.9 v0.6)

1A. Concentration inequalities and tail bounds

Unless otherwise specified, all variables are real \mathbb{R} . Inequalities come as one-sided $\Pr(\cdots \leq \cdots)$ and two-sided $\Pr(|\cdots| \leq \cdots)$. Notation: X is a random variable, $\mu := \mathbb{E}[X]$, $\sigma^2 := \text{Var}[X]$, $S_n := X_1 + \cdots + X_n$.

Inequality	Conditions		Common form	Notes / Alternate form
Single random variable				
Markov ¹	Non-negative	$X \geq 0$	$\Pr[X \geq a] \leq \frac{\mathbb{E}[X]}{a}$	$\forall a > 0$ $\Pr[X \geq kE[X]] \leq \frac{1}{k} \quad k > 1$ [3, Sec. 5.1] [6, Thm 1.13]
extension	+ non-negative, strictly increasing func Φ	$X \geq 0$ $\Phi(X) \geq 0$ increasing	$\Pr[X \geq a] = \Pr[\Phi(X) \geq \Phi(a)] \leq \frac{\mathbb{E}(\Phi(X))}{\Phi(a)}$	$\forall a > 0$ Wiki
Reverse Markov	upper-bounded by U (can be positive)	$\max X = U$	$\Pr[X \leq a] \leq \frac{U - \mathbb{E}[X]}{U - a}$	$\forall a > 0$ [1, Sec. 3.1]
Chebyshev ²	Finite mean and variance	$\mathbb{E}[X], \text{Var}[X]$ finite	$\Pr[X - \mathbb{E}[X] \geq a] \leq \frac{\sigma^2}{a^2}$	$\Pr[X - \mathbb{E}[X] \geq a \cdot \sigma] \leq \frac{1}{a^2}$ [1, Sec. 3.2] $\forall a > 0, \sigma^2 = \text{Var}[X]$ [3, Sec. 5.1] [2, Thm 18.11]
Cantelli	Improved Chebyshev	(same; but one-sided)	$\Pr[X - \mathbb{E}[X] \geq a] \leq \frac{\sigma^2}{\sigma^2 + a^2}$	$\forall a > 0, \sigma^2 = \text{Var}[X]$ Wiki
Chernoff ³	Generic		$\Pr[X \geq a] = \Pr[e^{tX} \geq e^{ta}]$	$\forall t > 0, \quad a \in \mathbb{R}$ [1, Sec. 3.3]
Jensen		$f : \mathbb{R} \rightarrow \mathbb{R}; f$ convex	$f(\mathbb{E}[X]) \leq \mathbb{E}[f(X)]$	[3, Prob. 5.3] [6, Thm 1.14]
Hoeffding's lemma		$\mathbb{E}[X] = \mu$ $a \leq X \leq b$	$\mathbb{E}[e^{\lambda X}] \leq e^{\lambda \mu} e^{\frac{\lambda^2 (b-a)^2}{8}}$	$\lambda \in \mathbb{R}$ [1, Sec. 3.4]
Sum of random variables				
Chernoff-Hoeffding (one-sided)	n independent random vars	X_1, \dots, X_n indep $S_n = X_1 + \dots + X_n$ $X_i \in [a_i, b_i] \quad \forall i$	$\Pr[S_n - \mathbb{E}[S_n] \geq t] \leq \exp\left(\frac{-2t^2 n^2}{\sum_{i=1}^n (b_i - a_i)^2}\right)$	[1, Sec. 3.5]
(two-sided) ⁴	(same as above)		$\Pr[S_n - \mathbb{E}[S_n] > t] \leq 2 \exp\left(\frac{-2t^2}{\sum_{i=1}^n (b_i - a_i)^2}\right)$	$\forall t \in (0, \frac{1}{2})$ [5, Thm.1.1]
(two-sided iid)	same plus iid, range, mean μ for each	$X_1, \dots, X_n \in [0, 1]$ $\mathbb{E}[X_i] = \mu$ iid	$\Pr\left[\left \frac{S_n}{n} - \mu\right \geq \epsilon\right] \leq 2 \exp(-2n\epsilon^2)$	$\forall \epsilon > 0$ [6, Thm 1.16]
Thm 1.3	n independent random vars	X_1, \dots, X_n indep $S_n = X_1 + \dots + X_n$	$\Pr[S_n - \mathbb{E}[S_n] > \epsilon] \leq 2 \exp\left(\frac{-\epsilon^2}{4 \sum_{i=1}^n \text{Var}[X_i]}\right)$	$\epsilon \in (0, 2 \text{Var}[S_n] / (\max_i X_i - \mathbb{E}[X_i]))$ [5, Thm. 1.3]
Azuma				
Weak law of large numbers	n independent iid random vars	X_1, \dots, X_n indep $\mathbb{E}[X_i] = \mu$ iid	$\lim_{n \rightarrow \infty} \Pr\left[\left \frac{1}{n} S_n - \mu\right \geq \epsilon\right] = 0$	$\forall \epsilon > 0$ [3, Sec. 5.2] [6, Thm 1.15]
Strong law of large numbers	(same)	(same)	$\Pr\left[\lim_{n \rightarrow \infty} \frac{1}{n} S_n = \mu\right] = 1$	[3, Sec. 5.5]
Advanced				
Bennett	n independent zero-mean	X_1, \dots, X_n indep $\mathbb{E}[X_i] = 0$ iid	$\Pr[S_n > \epsilon] \leq \exp\left(-n\sigma^2 h\left(\frac{\epsilon}{n\sigma^2}\right)\right)$	$\sigma^2 := \frac{1}{n} \sum_{i=1}^n \text{Var}[X_i], \forall \epsilon > 0,$ $h(a) := (1+a) \log(1+a) - a$ for $a \geq 0$ [1, 4.1]
Bernstein	(same)	(same)	$\Pr[S_n > \epsilon] \leq \exp\left(\frac{-n\epsilon^2}{2(\sigma^2 + \epsilon/3)}\right)$	(same) [1, 4.2]
Efron-Stein	scalar func of vars $f : \chi^n \rightarrow \mathbb{R}$	X_1, \dots, X_n indep w/ values in set χ	$\text{Var}[Z] \leq \sum_{i=1}^n \mathbb{E}\left[(Z - \mathbb{E}_i[Z])^2\right]$	$Z := g(X_1, \dots, X_n)$ $\mathbb{E}_i[Z] := \mathbb{E}[Z X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n]$ [1, 4.3]
McDiarmid's	scalar func of vars $f : \chi^n \rightarrow \mathbb{R}$	X_1, \dots, X_n indep w/ values in set χ	$\Pr[f(X_1, \dots, X_n) - \mathbb{E}[f(X_1, \dots, X_n)] \geq \epsilon] \leq \exp\left(\frac{-2\epsilon^2}{\sum_{i=1}^n c_i^2}\right)$	condition: c -bounded difference property $\forall \epsilon > 0$ [1, 4.4] $ f(X_1, \dots, X_i, \dots, X_n) - f(X_1, \dots, X'_i, \dots, X_n) \leq c_i$

¹Markov's inequality bounds the first moment of random variable. Use it when a constant probability bound is sufficient [1, Sec. 3.3].
²Chebyshev is derived from Markov. It bounds the second moment. It is the appropriate one when the variance σ is known. If σ is unknown, we can use the bounds of $X \in [a, b]$.
³Chernoff bound is used to bound the tails of the distribution for a sum of independent random variables. By far the most useful tool in randomized algorithms [1, Sec. 3.3].
⁴This probability can be interpreted as the level of significance ϵ (probability of making an error) for a confidence interval around the mean of size 2ϵ . Therefore, we require at least $\log(2\alpha)/2t^2$ samples to acquire $1 - \alpha$ confidence interval $\mathbb{E}[\bar{X}] \pm t$.

1 of 2

1. Probability (Technical note 11.9 v0.6)

Zlatko Minev

Other expressions

- Union bound [5, Thm. (4.1)]
- Schwarz inequality $(\mathbb{E}[XY])^2 \leq \mathbb{E}[X]^2 \mathbb{E}[Y]^2$ [3, Ch. 5]
- Exponential inequalities. $\frac{1}{2}(e^x + e^{-x}) \leq e^{x^2/2}$ [5, Eq. (4.1)]
- Core references: [3, Ch. 5] (core classical theory), [6, Ch. 1] (quantum info essentials, formal), [4, App A], [5], [1], [2, Ch. 18]; see summary on [wiki](#).

Acknowledgments: Many thanks to [John Watrous](#), who was kind to provide me with some useful references on the subject. I have included these in the bibliography.

Bibliography

- [1] Kumar Abhishek, Sneha Maheshwari, and Sujit Gujar. Introduction to Concentration Inequalities. oct 2019.
- [2] Boaz Barak. Introduction to Theoretical Computer Science.
- [3] D Bertsekas and J N Tsitsiklis. *Introduction to Probability*. Athena Scientific optimization and computation series. Athena Scientific, 2008.

- [4] P Kaye, P.K.R.L.M. Mosca, I.Q.C.P. Kaye, R Laflamme, and M Mosca. *An Introduction to Quantum Computing*. OUP Oxford, 2007.
- [5] Jeff M. Phillips. Chernoff-Hoeffding Inequality and Applications. sep 2012.
- [6] John Watrous. *The Theory of Quantum Information*. Cambridge University Press, apr 2018.

Copyright ©2021–2022 Zlatko K. Minev ([zlatko-minev.com](#)). This note is a

mix of a cheatsheet, a technical note, and a cookbook and borrows liberally from sources.

Caveat emptor These pages are a work in progress, inevitably imperfect, incomplete, and surely enriched with typos and unannounced inaccuracies. Sources credited in Bibliography to the best of my ability, though certain omissions certainly remain.