## Basic Inequalities in Probability ${ }^{1}$

Standard Notations: $\mu_{x}=\mathbb{E} X$ (expected value), $\sigma_{x}^{2}=\mathbb{E}\left(X-\mu_{x}\right)^{2}$ (variance).

## Fundamental inequalities.

(1) Re-ARRANGEMENT: for every ream numbers $a_{1} \leq a_{2} \leq \cdots \leq a_{n}$ and $b_{1} \leq b_{2} \leq \cdots \leq b_{n}$, and every permutation $\tau$ of the set $\{1,2, \ldots, n\}$,

$$
a_{1} b_{n}+a_{2} b_{n-1}+\ldots+a_{n} b_{1} \leq a_{1} b_{\tau(1)}+a_{2} b_{\tau(2)}+\ldots+a_{n} b_{\tau(n)} \leq a_{1} b_{1}+a_{2} b_{2}+\ldots+a_{n} b_{n} .
$$

Proof: induction can work.
Example: if $x, y, z>0$, then $\frac{x}{y+z}+\frac{y}{x+z}+\frac{z}{x+y} \geq \frac{3}{2}$. Indeed, with no loss of generality, assume that $x \leq y \leq z$, so that $y+z \geq x+z \geq x+y$ and $1 /(y+z) \leq 1 /(x+z) \leq 1 /(x+y)$. Now take $a_{1}=1 /(y+z), a_{2}=1 /(x+z), a_{3}=1 /(x+y), b_{1}=x, b_{2}=y, b_{3}=z$, and note that $3=a_{1}\left(b_{2}+b_{3}\right)+a_{2}\left(b_{1}+b_{3}\right)+a_{3}\left(b_{1}+b_{2}\right) \leq 2\left(a_{1} b_{1}+a_{2} b_{2}+a_{3} b_{3}\right)$.
(2) Power mean: If $a_{1}>0, a_{2}>0, \ldots, a_{n}>0$, and

$$
M_{p}= \begin{cases}\left(\frac{1}{n} \sum_{k=1}^{n} a_{k}^{p}\right)^{1 / p}, & p \neq 0, \pm \infty, \\ M_{0}=\left(a_{1} a_{2} \cdots a_{n}\right)^{1 / n}, & p=0, \\ M_{+\infty}=\max \left(a_{1}, \ldots, a_{n}\right), & p=+\infty, \\ M_{-\infty}=\min \left(a_{1}, \ldots, a_{n}\right), & p=-\infty,\end{cases}
$$

then

$$
\lim _{p \rightarrow 0} M_{p}=M_{0}, \lim _{p \rightarrow-\infty} M_{p}=M_{-\infty}, \lim _{p \rightarrow+\infty} M_{p}=M_{+\infty},
$$

and the function $p \rightarrow M_{p}$ is strictly increasing unless $a_{1}=a_{2}=\ldots=a_{n}$.
Proof: induction can work.
Special names: $M_{1}$ is arithmetic mean (AG), $M_{0}$ is geometric mean (GM), $M_{-1}$ is harmonic mean (HM). The (famous) AG/GM/HM inequality, $M_{1} \geq M_{0} \geq M_{-1}$, is a particular case of the power mean inequality.
Concentration inequalities.
(1) Markov [1880]: if $Y>0$, then

$$
\mathbb{P}(Y \geq a) \leq \frac{\mathbb{E} Y}{a}
$$

Proof. $\mathbb{E} Y \geq \mathbb{E} Y I_{Y \geq a} \geq a \mathbb{E} I_{Y \geq 0}=a \mathbb{P}(Y \geq a)$.
(2) Chebyshev [1865]: with $\mu_{X}=\mathbb{E} X, \sigma_{X}^{2}=\mathbb{E}\left(X-\mu_{X}\right)^{2}$,

$$
\mathbb{P}\left(\left|X-\mu_{X}\right| \geq a\right) \leq \frac{\sigma_{X}^{2}}{a^{2}}
$$

Proof. Apply Markov with $Y=\left(X-\mu_{X}\right)^{2}$. Variations.

- Standartized:

$$
\mathbb{P}\left(\left|X-\mu_{X}\right| \geq k \sigma_{X}\right) \leq \frac{1}{k^{2}}
$$

- Cantelli [1928]:

$$
\mathbb{P}\left(X-\mu_{X} \geq a\right) \leq \frac{\sigma_{X}^{2}}{\sigma_{X}^{2}+a^{2}}
$$

Proof. For $t>0$, by Markov, $\mathbb{P}\left(X-\mu_{X}+t>a+t\right)=\mathbb{P}\left(\left(X-\mu_{X}+t\right)^{2}>(a+t)^{2}\right) \leq\left(\sigma_{X}^{2}+t^{2}\right) /(a+t)^{2}$. Direct computations show that the right hand side is minimized by taking $t=\sigma_{X}^{2} / a$.

- Vysochanskij-Petunin [1980]: if $X$ is unimodal, then

$$
\mathbb{P}\left(\left|X-\mu_{X}\right|>k \sigma_{X}\right) \leq \frac{4}{9 k^{2}} .
$$

[^0](3) Chernoff [1955]: If $M_{X}(t)=\mathbb{E} e^{t X}$ exists for all $t>0$, and $a>0$, then
$$
\mathbb{P}(X \geq a) \leq e^{\ln M_{X}(t)-a t}
$$
with subsequent minimization of the right-hand side with respect to $t>0$.
Proof. Use Markov with $Y=e^{t X}$.
Example. If $X$ is standard normal, then $M_{X}(t)=e^{t^{2} / 2}$, so that $\left(t^{2} / 2\right)-a t \geq-a^{2} / 2$, with the lower bound achieved for $t=a / 2$, and therefore $\mathbb{P}(X \geq a) \leq e^{-a^{2} / 2}$.
(4) Paley-Zygmund [1932]: if $Y>0$ and $0<\theta<1$, then
$$
\mathbb{P}\left(Y>\theta \mu_{Y}\right) \geq(1-\theta)^{2} \frac{\mu_{Y}^{2}}{\sigma_{Y}^{2}+\mu_{Y}^{2}}
$$

Proof. Keeping in mind that $\mathbb{E} Y^{2}=\sigma_{Y}^{2}+\mu_{Y}^{2}, \mu_{Y}=\mathbb{E} Y I_{Y \leq \theta \mu_{Y}}+\mathbb{E} Y I_{Y>\theta \mu_{Y}}$. Then $\mathbb{E} Y I_{Y<\theta \mu_{Y}} \leq \theta \mu_{Y}$ (obviously), and $\mathbb{E} Y I_{Y>\theta \mu_{Y}} \leq \sqrt{\mathbb{E} Y^{2}} \sqrt{\mathbb{P}\left(Y>\theta \mu_{Y}\right)}$ (Cauchy-Schwarz; see below).

## Moment inequalities.

(1) Jensen [1905]: If $g=g(x), x \in \mathbb{R}$, is convex, then

$$
\mathbb{E} g(X) \geq g(\mathbb{E} X) \quad\left(\text { e.g. } \mathbb{E} e^{X} \geq e^{\mu_{X}} .\right)
$$

If $f=f(x)$ is concave, then

$$
\mathbb{E} f(X) \leq f(\mathbb{E} X) \quad\left(\text { e.g. } X>0 \Rightarrow \mathbb{E} \ln X \leq \ln \mu_{X} .\right)
$$

Proof: $g$ convex $\Leftrightarrow$ for every $x_{0} \in \mathbb{R}$ there is a number $C \in \mathbb{R}$ such that $g(x) \geq g\left(x_{0}\right)+C\left(x-x_{0}\right)$; if $g^{\prime}$ exists, then $C=g^{\prime}\left(x_{0}\right)$ [the graph of $g$ is above the tangent line at $\left.x_{0}\right]$. Now put $x=X, x_{0}=\mu_{X}$, and take expected value on both sides.
(2) Lyapunov [1900]: if $0<p<r$, then

$$
\left(\mathbb{E}|X|^{p}\right)^{1 / p} \leq\left(\mathbb{E}|X|^{r}\right)^{1 / r}
$$

Proof: Use Jensen with $g(x)=|x|^{r / p}$ and $|X|^{p}$ instead of $X$.
(3) Hölder [1885]: if $p>1, q>1$, and $(1 / p)+(1 / q)=1$, then

$$
\mathbb{E}|X Y| \leq\left(\mathbb{E}|X|^{p}\right)^{1 / p}\left(\mathbb{E}|Y|^{q}\right)^{1 / q}
$$

The inequality is strict unless $X=c Y$ for some non-random number $c$.
Proof. Using concavity of the log function, argue that $a b \leq\left(a^{p} / p\right)+\left(b^{q} / q\right), a, b>0$. Then set $a=$ $|X| /\left(\mathbb{E}|X|^{p}\right)^{1 / p}, b=|Y| /\left(\mathbb{E}|Y|^{q}\right)^{1 / q}$, and take expectation on both sides. Note that the Hölder inequality is trivial if $\mathbb{E}|X|^{p}=0$ and/or $\mathbb{E}|Y|^{q}=0$.
(4) Cauchy-Bunyakovsky-Schwarz [1820 $\rightarrow 1855 \rightarrow 1885]$ :

$$
\mathbb{E}|X Y| \leq \sqrt{\mathbb{E} X^{2}} \sqrt{\mathbb{E} Y^{2}}
$$

Proof: take $p=q=2$.
(5) Minkowski [1900]: if $p \geq 1$, then

$$
\left(\mathbb{E}|X+Y|^{p}\right)^{1 / p} \leq\left(\mathbb{E}|X|^{p}\right)^{1 / p}+\left(\mathbb{E}|Y|^{p}\right)^{1 / p}
$$

(that is, the functional $X \mapsto\left(\mathbb{E}|X|^{p}\right)^{1 / p}$ satisfies the triangle inequality and thus defines a norm on the space of random variables with finite $p$-th moment.)
Proof. $p=1$ is obvious. For $p>1$, take $q=p /(p-1)$ [so that $(1 / p)+(1 / q)=1$ ], note that $|X+Y|^{p}=$ $|X+Y| \cdot|X+Y|^{p-1} \leq|X| \cdot|X+Y|^{p-1}+|Y| \cdot|X+Y|^{p-1}$, and then, by Hölder, $\mathbb{E}\left(|X| \cdot|X+Y|^{p-1}\right) \leq$ $\left(\mathbb{E}|X|^{p}\right)^{1 / p}\left(\mathbb{E}|X+Y|^{p}\right)^{1 / q}, \mathbb{E}\left(|Y| \cdot|X+Y|^{p-1}\right) \leq\left(\mathbb{E}|Y|^{p}\right)^{1 / p}\left(\mathbb{E}|X+Y|^{p}\right)^{1 / q}$. It remains to combine the inequalities: $\mathbb{E}|X+Y|^{p} \leq\left(\left(\mathbb{E}|X|^{p}\right)^{1 / p}+\left(\mathbb{E}|Y|^{p}\right)^{1 / p}\right)\left(\mathbb{E}|X+Y|^{p}\right)^{1 / q}$ and then simplify, keeping in mind that $1-(1 / q)=1 / p$.

## The people.

A.-L. Cauchy (1789-1857), French. V. Ya. Bunyakovsky (1804-1889), Russian.<br>P. L. Chebyshev (1821-1894), Russian. K. H. A. Schwarz (1843-1921), German.<br>A. A. Markov (1856-1922), Russian.<br>A. M. Lyapunov (1857-1918), Russian.<br>J. L. W. V. Jensen (1859-1925), Danish.<br>H. Minkowski (1864-1909), German.<br>F. P. Cantelli (1875-1966), Italian.<br>A. Zygmund (1900-1992), Polish-American.<br>R. E. A. C. Paley (1907-1933), English.<br>H. Chernoff (b. 1923), American.<br>Y. I. Petunin (1937-2011), Soviet.


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