

# Exponentially Small Probabilities

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November 30, 2025



# 1 Chernoff Bound

# Begin at Markov's Inequality

**A common feature:** With large probability,  $X \approx \mathbb{E}X$

We will estimate  $\mathbb{P}(X \geq \mathbb{E}X + t)$  that decrease exponentially as  $t \rightarrow \infty$ .

## Theorem 1 (Markov's inequality)

Let  $X \geq 0$  be a random variable, for any  $a \geq 0$ , we have

$$\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}X}{a}. \quad (1)$$

# Bernstein's Method (1924)

For any  $u \geq 0$ , we have

$$\mathbb{P}(X \geq \mathbb{E}X + t) = \mathbb{P}(e^{ux} \geq e^{u(\mathbb{E}X+t)}) \leq \frac{\mathbb{E}e^{uX}}{e^{u(\mathbb{E}X+t)}}. \quad (2)$$

If we consider  $X = X_1 + X_2 + \cdots + X_n$  where  $X_i \sim \text{Be}(p_i)$ , we have

$$\mathbb{P}(X \geq \mathbb{E}X + t) \leq \exp\left\{-u\left(\sum_{i=1}^n p_i + t\right)\right\} \cdot \prod_{i=1}^n (1 - p_i + e^u \cdot p_i). \quad (3)$$

Moreover, if  $X \sim \text{Bi}(n, p)$ , i.e.  $p_i = p(i \in \{1, 2, \dots, n\})$ , we have

$$\mathbb{P}(X \geq \mathbb{E}X + t) \leq \exp\{-u(np + t)\} \cdot (1 - p + e^u \cdot p)^n. \quad (4)$$

If  $t > (1 - p)n = n - np$ , i.e.  $np + t > n$ , the probability is 0 as  $n \rightarrow \infty$ .

# Chernoff Bound

If  $t \leq (1 - p)n$ , choose  $u$  such that

$$e^u = \frac{(1 - p)(np + t)}{(n - np - t)p}. \quad (5)$$

Therefore, we have the Chernoff Bound(1952).

## Lemma 2 (Chernoff Bound, initial version)

Let  $X \sim \text{Bi}(n, p)$ , for any  $t \geq 0$ , we have

$$\mathbb{P}(X \geq \mathbb{E}X + t) \leq \begin{cases} \left(\frac{np}{np+t}\right)^{np+t} \cdot \left(\frac{n-np}{n-np-t}\right)^{n-np-t}, & 0 \leq t \leq n - np \\ 0, & t > n - np \end{cases}. \quad (6)$$

A large but simpler bound?

$$\varphi(x) = (1+x)\log x - x, \text{ for } x \geq -1$$

Let  $\varphi(x) = (1+x)\log x - x$ , for  $x \geq -1$ , we have

- $\varphi(x) \geq 0$  for any  $x$ ;  $\varphi(0) = 0$ .
- $\varphi'(x) = \log(1+x)$ , thus

$$\varphi(x) \geq \frac{x^2}{2}, \quad \forall -1 \leq x \leq 0. \tag{7}$$

- Since  $\varphi(0) = \varphi'(0) = 0$  and

$$\varphi''(x) = \frac{1}{1+x} \geq \frac{1}{(1+x/3)^3} = \left( \frac{x^2}{2(1+x/3)} \right)^{''}. \tag{8}$$

thus

$$\varphi(x) \geq \frac{x^2}{2(1+x/3)}. \tag{9}$$

# A Large But Simpler Bound

Let  $\lambda = np$ , so we can rewrite

$$\mathbb{P}(X \geq \mathbb{E}X + t) \leq \left(\frac{\lambda}{\lambda+t}\right)^{\lambda+t} \cdot \left(\frac{n-\lambda}{n-\lambda-t}\right)^{n-\lambda-t}, \quad 0 \leq t \leq n-\lambda \quad (10)$$

as

$$\mathbb{P}(X \geq \mathbb{E}X + t) \leq \exp\left\{-\lambda\varphi\left(\frac{t}{\lambda}\right) - (n-\lambda)\varphi\left(\frac{-t}{n-\lambda}\right)\right\}, \quad 0 \leq t \leq n-\lambda. \quad (11)$$

Replacing  $X$  by  $n - X$  and we obtain also

$$\mathbb{P}(X \leq \mathbb{E}X - t) \leq \exp\left\{-\lambda\varphi\left(\frac{-t}{\lambda}\right) - (n-\lambda)\varphi\left(\frac{t}{n-\lambda}\right)\right\}, \quad 0 \leq t \leq \lambda. \quad (12)$$

Thus we have

$$\mathbb{P}(X \geq \mathbb{E}X + t) \leq \exp\left\{-\lambda\varphi\left(\frac{t}{\lambda}\right)\right\}, \quad \mathbb{P}(X \leq \mathbb{E}X - t) \leq \exp\left\{-\lambda\varphi\left(\frac{-t}{\lambda}\right)\right\}, t \geq 0. \quad (13)$$

# Chernoff Bound

Using  $\varphi(x) \geq x^2/(2(1 + x/3))$ , we have

$$\exp\left\{-\lambda\varphi\left(\frac{t}{\lambda}\right)\right\} \leq \exp\left\{-\frac{t^2}{2(\lambda + t/3)}\right\}, \exp\left\{-\lambda\varphi\left(\frac{-t}{\lambda}\right)\right\} \leq \exp\left\{-\frac{t^2}{2\lambda}\right\}. \quad (14)$$

Therefore, we have the Chernoff Bound.

## Lemma 3 (Chernoff Bound)

If  $X \in \text{Bi}(n, p)$  and  $\lambda = np$ , we have

$$\begin{aligned} \mathbb{P}(X \geq \mathbb{E}X + t) &\leq \exp\left\{-\frac{t^2}{2(\lambda + t/3)}\right\}, t \geq 0 \\ \mathbb{P}(X \leq \mathbb{E}X - t) &\leq \exp\left\{-\frac{t^2}{2\lambda}\right\}, t \geq 0 \end{aligned} \quad . \quad (15)$$

# The exponents in the Estimates

$$\mathbb{P}(X \geq \mathbb{E}X + t) \leq \exp \left\{ -\frac{t^2}{2(\lambda + t/3)} \right\}, t \geq 0. \quad (16)$$

When  $t$  is small, i.e.  $(t \leq \lambda)$ , the exponent is  $\Theta(t^2)$ .

When  $t$  is large,

In particular, let  $t = \varepsilon \mathbb{E}X$ , we have

$$\mathbb{P}(X - \mathbb{E}X \geq \varepsilon \mathbb{E}X) \leq \exp \left\{ -\mathbb{E}X \cdot \varphi \left( \frac{\varepsilon \mathbb{E}X}{\mathbb{E}X} \right) \right\} = \exp \{-\varphi(\varepsilon)\} \leq \exp \left\{ -\frac{\varepsilon^2}{3} \mathbb{E}X \right\}. \quad (17)$$

since  $\varphi(-\varepsilon) > \varphi(\varepsilon) \geq \varepsilon^2/3$  when  $\varepsilon \leq 2/3$ . Therefore, we have the Chernoff Bound.

## Theorem 4 (Chernoff Bound)

If  $X \sim \text{Bi}(n, p)$  and for any  $0 < \varepsilon < 3/2$ , we have

$$\mathbb{P}(|X - \mathbb{E}X| \geq \varepsilon \mathbb{E}X) \leq 2 \exp \left\{ -\frac{\varepsilon^2 \mathbb{E}X}{3} \right\}. \quad (18)$$

For  $X \sim \text{Be}(p_i)$  and  $X \sim H(n, M, N)$ , Chernoff Bound still works.

Single variable  $\rightarrow$  More variables ?

# McDiarmid's Inequality for $n$ Independent Trials

## Definition 5 ( $C$ -Lipschitz)

$X$  is called  $C$ -Lipschitz if  $|X(\omega) - X(\omega')| \leq C$  whenever  $\omega$  and  $\omega'$  differ in at most 1-coordinate.

## Theorem 6 (McDiarmid's inequality)

Let  $X$  be  $C$ -Lipschitz random variable on a product probability space with  $n$  coordinates. Then, for any  $t > 0$ ,

$$\mathbb{P}(|X - \mathbb{E}X| > \gamma \mathbb{E}X) \leq 2 \exp \left\{ -\frac{\gamma^2 \mathbb{E}X^2}{nC^2} \right\}. \quad (19)$$

If  $\mathbb{E}X = o(\sqrt{n})$ , McDiarmid's inequality doesn't work. **The dependency on  $n$ !**

# Talagrand's Inequality

## Theorem 7 (Talagrand's Inequality)

Let  $X$  be a non-negative r.v. determined by  $n$  independent trials, and satisfying the following for some  $r, c > 0$ .

1.  $X$  is  $C$ -Lipschitz.
2. For any  $s$ , and sample  $\omega$  with  $X(\omega) > s$ , there are  $\leq rs$  indices of  $\omega$ , so that for all other samples  $\omega'$  that agree with  $\omega$  on those  $\leq rs$  indices,  $X(\omega' > s)$  also.

Then, for all  $t > \sqrt{\mathbb{E}X}$ , if  $\mathbb{E}X$  is sufficiently large and  $\beta < 1/8c^2r$ , we have:

$$\mathbb{P}(|X - \mathbb{E}X| \geq t) \leq 2 \exp \left\{ -\frac{\beta t^2}{\mathbb{E}X} \right\}. \quad (20)$$

When  $t = \varepsilon \mathbb{E}X$ , RHS is  $2 \exp\{-\beta \varepsilon^2 \mathbb{E}X\}$ , not depend on  $n$ . **How about dependent trials?**

# Azuma's Inequality

## Lemma 8 (Azuma's Inequality)

Let  $X$  be a r.v. determined by not necessarily independent outcomes of  $n$  trials,  $T_1, T_2, \dots, T_n$ , such that for any  $i \in [n]$ , and any two possible sequences of outcomes  $t_1, \dots, t_{i-1}, t_i$  and  $t_1, \dots, t_{i-1}, t'_i$ , we have

$$\left| \mathbb{E} \left( X \mid \bigcap_{j=1}^i T_j = t_j \right) - \mathbb{E} \left( X \mid \bigcap_{j=1}^{i-1} T_j = t_j, T_i = t_i \right) \right| \leq c_i. \quad (21)$$

then

$$\mathbb{P}(|X - \mathbb{E}X| > t) \leq 2 \exp \left\{ - \frac{t^2}{\sum_{i=1}^n c_i^2} \right\}. \quad (22)$$