

# CS5314

## Randomized Algorithms

### Lecture 11: Chernoff Bounds (Application)

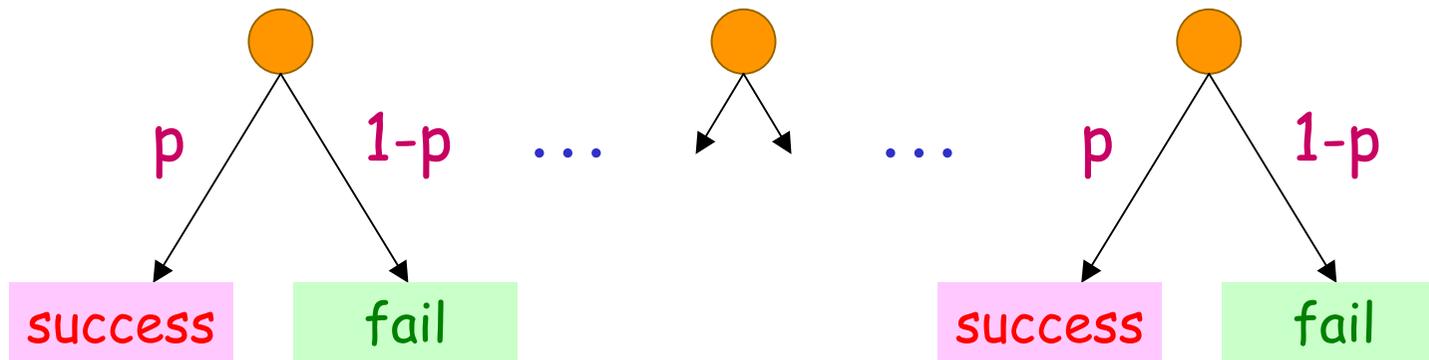
# Objectives

- Apply **Chernoff bounds** to bound the tail and the head distributions of **sum of Poisson trials**
  - General case of Binomial random variable
- Revisit the Coin Flip example

# Sum of Bernoulli Trials

Recall that:  $X = \text{Bin}(n, p)$  is a random variable for the sum of  $n$  independent indicators, each with success probability  $p$

→ Each indicator is called a **Bernoulli trial**

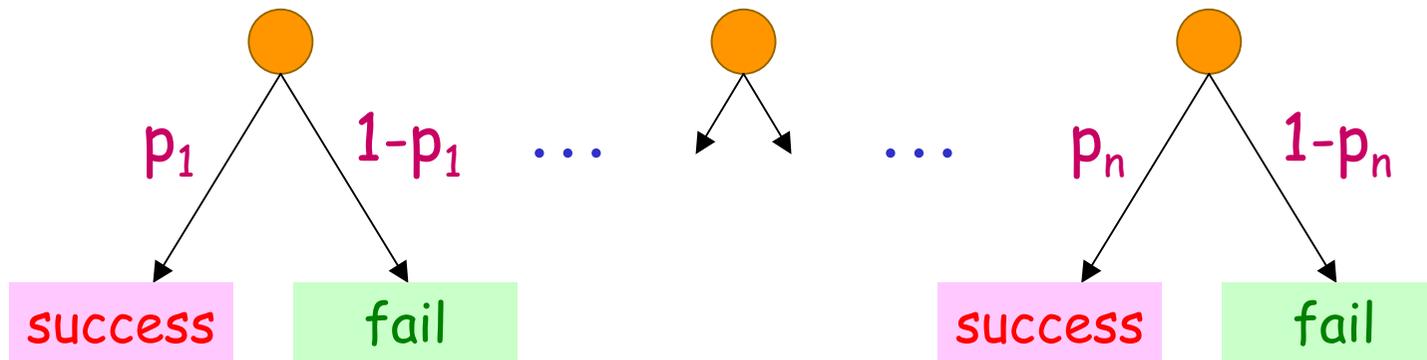


$n = \#$  trials       $X =$  total  $\#$  success

# Sum of Poisson Trials

Suppose that we allow each of these indicators to choose its own success probability (instead of a fixed  $p$ )

→ Each indicator is called a **Poisson trial**



$n = \#$  trials       $X =$  total  $\#$  success

# Bounding Sum of Poisson Trials

Let  $X_1, X_2, \dots, X_n$  be a sequence of independent Poisson trials, such that

$$\Pr(X_i = 1) = p_i$$

Let  $X = X_1 + X_2 + \dots + X_n$

Then,

$$\begin{aligned}\mu &= E[X] = E[X_1 + X_2 + \dots + X_n] \\ &= p_1 + p_2 + \dots + p_n\end{aligned}$$

# Bounding Sum of Poisson Trials

We shall use **Chernoff** bound to bound the tail distribution  $\Pr(X \geq (1+\delta)\mu)$  :

Let  $M_X$  be the MGF of  $X$ , and

$M_{X_i}$  be the MGF of  $X_i$

Since  $X_i$ 's are independent, we have

$$M_X(t) = \prod_i M_{X_i}(t) \quad \dots \text{(why?)}$$

# Bounding Sum of Poisson Trials

Question: What is  $M_{X_i}(t)$ ?

By definition,

$$\begin{aligned}M_{X_i}(t) &= E[e^{tX_i}] \\&= p_i e^{t(1)} + (1-p_i) e^{t(0)} \\&= p_i e^t + (1-p_i) \\&= 1 + p_i (e^t - 1) \\&\leq e^{p_i (e^t - 1)} \quad \dots \text{(why?)}\end{aligned}$$

# Bounding Sum of Poisson Trials

So,

$$\begin{aligned}M_X(t) &= \prod_i M_{X_i}(t) \\ &\leq \prod_i e^{p_i(e^t-1)} \quad \dots \text{(why?)} \\ &= \exp \left\{ \sum_i p_i(e^t-1) \right\} \\ &= e^{\mu(e^t-1)}\end{aligned}$$

# Bounding Sum of Poisson Trials

Theorem: Let  $X_1, X_2, \dots, X_n$  be independent Poisson trials such that  $\Pr(X_i = 1) = p_i$ .

Let  $X = X_1 + X_2 + \dots + X_n$  and  $\mu = E[X]$ .

Then, for all  $\delta > 0$ ,

$$\Pr(X \geq (1+\delta)\mu) \leq (e^\delta / (1+\delta)^{(1+\delta)})^\mu$$

How to prove?

Proof: For any  $t > 0$ , we have

$$\begin{aligned} & \Pr(X \geq (1+\delta)\mu) \\ &= \Pr(e^{tX} \geq e^{t(1+\delta)\mu}) \\ &\leq E[e^{tX}] / e^{t(1+\delta)\mu} \\ &= M_X(t) / e^{t(1+\delta)\mu} \\ &\leq e^{\mu(e^t-1)} / e^{t(1+\delta)\mu} \end{aligned}$$

... (by which inequality?)

To get the best bound for  $\Pr(X \geq (1+\delta)\mu)$ , we now choose  $t$  so as to minimize the term

$$e^{\mu(e^t-1)} / e^{t(1+\delta)\mu}$$

# Proof (cont)

Question: Which  $\dagger$  should we choose?

Observation:

$$\begin{aligned} & \text{To minimize } e^{\mu(e^\dagger-1)} / e^{\dagger(1+\delta)\mu} \\ \Leftrightarrow & \text{ to minimize } \log_e (e^{\mu(e^\dagger-1)} / e^{\dagger(1+\delta)\mu}) \end{aligned}$$

So, we want to choose  $\dagger$  so as to minimize the term  $\log_e (e^{\mu(e^\dagger-1)} / e^{\dagger(1+\delta)\mu})$ , which is

$$\mu(e^\dagger-1) - \dagger(1+\delta)\mu$$

By calculus, the best  $\dagger$  will be  $\log_e (1+\delta)$

# Proof (cont)

So, by substituting  $t = \log_e (1+\delta)$  in the previous inequality:

$$\Pr(X \geq (1+\delta)\mu) \leq e^{\mu(e^t-1)} / e^{t(1+\delta)\mu}$$

we get:

$$\begin{aligned} \Pr(X \geq (1+\delta)\mu) &\leq e^{\mu(\delta)} / (1+\delta)^{(1+\delta)\mu} \\ &= (e^\delta / (1+\delta)^{(1+\delta)})^\mu \end{aligned}$$

# Two Weaker but Easier Bounds

Theorem: Let  $X_1, X_2, \dots, X_n$  be independent Poisson trials such that  $\Pr(X_i = 1) = p_i$ .

Let  $X = X_1 + X_2 + \dots + X_n$  and  $\mu = E[X]$ . Then,

(1) for all  $0 < \delta \leq 1$ ,

$$\Pr(X \geq (1+\delta)\mu) \leq e^{-\mu\delta^2/3}$$

(2) For  $R \geq 6\mu$ ,

$$\Pr(X \geq R) \leq 2^{-R}$$

How to prove?

# Proof of (1)

To prove (1), it is sufficient to show  
whenever  $0 < \delta \leq 1$ ,

$$e^\delta / (1+\delta)^{(1+\delta)} \leq e^{-\delta^2/3}$$

Equivalently, we want to show

$$\delta - (1+\delta) \log_e (1+\delta) \leq -\delta^2/3$$

(this is obtained by taking log on both sides)

Let  $f(\delta) = \delta - (1+\delta) \log_e (1+\delta) + \delta^2/3$

Target: to show  $f(\delta) \leq 0$

# Proof of (1)

$$\begin{aligned}\text{Then, } f'(\delta) &= 1 - (1+\delta)/(1+\delta) - \log_e(1+\delta) + 2\delta/3 \\ &= -\log_e(1+\delta) + 2\delta/3\end{aligned}$$

and

$$f''(\delta) = -1/(1+\delta) + 2/3$$

So, we see that

$$f''(\delta) < 0 \quad \text{for } 0 \leq \delta < 1/2$$

$$f''(\delta) \geq 0 \quad \text{for } 1/2 \leq \delta \leq 1$$

# Proof of (1)

This implies that

$f'(\delta)$  is decreasing for  $0 \leq \delta < 1/2$

$f'(\delta)$  is increasing for  $1/2 \leq \delta \leq 1$

Next, from  $f'(\delta) = -\log_e(1+\delta) + 2\delta/3$ ,

we see that  $f'(0) = 0$  and  $f'(1) < 0$

Together with the above, we conclude that

$f'(\delta) \leq 0$  in the interval  $[0,1]$

# Proof of (1)

Since  $f'(\delta) \leq 0$  in the interval  $[0,1]$ ,  
 $f$  is decreasing in the interval  $[0,1]$   
 $\rightarrow f(0)$  is the maximum point of  $f$  in the  
interval  $[0,1]$

Thus, for  $0 < \delta \leq 1$ ,

$$\begin{aligned} f(\delta) &= \delta - (1+\delta) \log_e (1+\delta) + \delta^2/3 \\ &\leq f(0) = 0 \end{aligned}$$

This completes the proof of (1)

# Proof of (2)

For (2), we want to show for  $R \geq 6\mu$ ,

$$\Pr(X \geq R) \leq 2^{-R}$$

Let  $R = (1+\delta)\mu$ , so that  $\delta \geq 5 > 0$

Then, we have

$$\begin{aligned} \Pr(X \geq (1+\delta)\mu) &\leq (e^\delta / (1+\delta)^{(1+\delta)})^\mu \\ &\leq (e^{(1+\delta)} / (1+\delta)^{(1+\delta)})^\mu \\ &= (e / (1+\delta))^{\mu(1+\delta)} \\ &\leq (e/6)^R \leq 2^{-R} \end{aligned}$$

# Bounding the Head Distribution

Theorem: Let  $X_1, X_2, \dots, X_n$  be independent Poisson trials such that  $\Pr(X_i = 1) = p_i$ .

Let  $X = X_1 + X_2 + \dots + X_n$  and  $\mu = E[X]$ .

Then, for  $0 < \delta < 1$ ,

$$(1) \quad \Pr(X \leq (1-\delta)\mu) \leq (e^{-\delta}/(1-\delta)^{(1-\delta)})^\mu$$

$$(2) \quad \Pr(X \leq (1-\delta)\mu) \leq e^{-\mu\delta^2/2}$$

How to prove?

Proof of (1): For any  $t < 0$ , we have

$$\Pr(X \leq (1-\delta)\mu)$$

$$= \Pr(e^{tX} \geq e^{t(1-\delta)\mu})$$

$$\leq E[e^{tX}] / e^{t(1-\delta)\mu} \quad \dots \text{(by which inequality?)}$$

$$= M_X(t) / e^{t(1-\delta)\mu}$$

$$\leq e^{\mu(e^t-1)} / e^{t(1-\delta)\mu}$$

To get the best bound for  $\Pr(X \leq (1-\delta)\mu)$ , we now choose  $t$  so as to minimize the term

$$e^{\mu(e^t-1)} / e^{t(1-\delta)\mu}$$

# Proof of (1)

By calculus, the best  $\dagger$  is equal to  $\log_e (1-\delta)$

So, by substituting  $\dagger = \log_e (1-\delta)$  in the previous inequality, we get

$$\begin{aligned}\Pr(X \leq (1-\delta)\mu) &\leq e^{\mu(-\delta)} / (1-\delta)^{(1-\delta)\mu} \\ &= (e^{-\delta} / (1-\delta)^{(1-\delta)})^{\mu}\end{aligned}$$

# Proof of (2)

To prove (2), it is sufficient to show  
whenever  $0 < \delta < 1$ ,

$$e^{-\delta}/(1-\delta)^{(1-\delta)} \leq e^{-\delta^2/2}$$

Equivalently, we want to show

$$-\delta - (1-\delta) \log_e (1-\delta) \leq -\delta^2/2$$

(this is obtained by taking log on both sides)

Let  $g(\delta) = -\delta - (1-\delta) \log_e (1-\delta) + \delta^2/2$

Target: to show  $g(\delta) \leq 0$

# Proof of (2)

Then,

$$\begin{aligned}g'(\delta) &= -1 + (1-\delta)/(1-\delta) + \log_e(1-\delta) + 2\delta/2 \\ &= \log_e(1-\delta) + \delta\end{aligned}$$

and

$$g''(\delta) = -1/(1-\delta) + 1$$

So, we see that

$$g''(\delta) < 0 \quad \text{for } 0 \leq \delta < 1$$

# Proof of (2)

This implies that

$g'(\delta)$  is decreasing for  $0 \leq \delta < 1$

Next, from  $g'(\delta) = -\log_e(1+\delta) + 2\delta/3$ ,

we see that  $g'(0) = 0$

Together with the above, we conclude that

$g'(\delta) \leq 0$  in the interval  $[0,1)$

## Proof of (2)

Since  $g'(\delta) \leq 0$  in the interval  $[0,1)$ ,  
 $g$  is decreasing in the interval  $[0,1)$   
 $\rightarrow g(0)$  is the maximum point of  $g$  in the  
interval  $[0,1)$

Thus, for  $0 < \delta < 1$ ,

$$\begin{aligned} g(\delta) &= -\delta - (1-\delta) \log_e (1-\delta) + \delta^2/2 \\ &\leq g(0) = 0 \end{aligned}$$

This completes the proof of (2)

# Useful Corollary

Corollary: Let  $X_1, X_2, \dots, X_n$  be independent Poisson trials such that  $\Pr(X_i = 1) = p_i$ .

Let  $X = X_1 + X_2 + \dots + X_n$  and  $\mu = E[X]$ . Then, for all  $0 < \delta < 1$ ,

$$\Pr(|X - \mu| \geq \delta\mu) \leq 2e^{-\mu\delta^2/3}$$

How to prove?

# Example: Coin Flip

Let  $X$  = # heads in  $n$  fair coin flips

By Markov:  $\Pr(X \geq 3n/4) \leq 2/3$

By Chebyshev:  $\Pr(X \geq 3n/4) \leq 4/n$

By Chernoff:

$$\begin{aligned}\Pr(X \geq 3n/4) &= \Pr(X \geq (1.5)\mu) \\ &\leq e^{-\mu(0.5)^2/3} = e^{-n/24}\end{aligned}$$

In fact, **w.h.p.**, #heads is around the mean:

$$\begin{aligned} & \Pr(|X - n/2| \geq (6n \log_e n)^{0.5}/2) \\ &= \Pr(|X - n/2| \geq ((6n \log_e n)^{0.5}/n)(n/2)) \\ &\leq 2 \exp \left\{ -(1/3)(n/2)((6n \log_e n)/n^2) \right\} \\ &= 2 \exp \{-\log_e n\} = 2/n \end{aligned}$$

