

# CS5314

## Randomized Algorithms

Lecture 13: Balls, Bins, Random Graphs  
(Balls-and-Bins Model)

# Objectives

- **Balls-and-Bins Model**
  - throwing  $m$  balls into  $n$  bins
  - can be applied in many practical situations, e.g., assigning jobs to servers
- **Bounds on various scenario**
  - E.g., maximum load, number of empty bins
- **Poisson Distribution**

# Balls-and-Bins Model

- Suppose we throw  $m$  balls to  $n$  bins, independently and uniformly at random

Some interesting questions:

1. What will be the distribution of balls?
2. How many bins are empty?
3. How many balls in the fullest bin?  
(We call this number the **maximum load**)

# Maximum Load

Theorem: Suppose we throw  $n$  balls into  $n$  bins independently and uniformly at random.

Let  $L$  = maximum load

Then, for sufficiently large  $n$ ,

$$\Pr(L \geq (3 \ln n) / (\ln \ln n)) \leq 1/n$$

(Throughout the notes, we use  $\ln x$  to denote  $\log_e x$ )

How to prove?

# Maximum Load (Proof)

Let  $p = \Pr(\text{Bin 1 receives at least } M \text{ balls})$

$\rightarrow p = \Pr(\text{some set of } M \text{ balls is in Bin 1})$

$$\leq C_M^n (1/n)^M \quad \dots \text{ (why?)}$$

Then, since

$$C_M^n (1/n)^M \leq 1/(M!) \quad \dots \text{ (why?)}$$

$$M^M/(M!) \leq \sum_j (M^j)/j! = e^M \quad \dots \text{ (why?)}$$

we have:

$$p \leq (e/M)^M$$

# Maximum Load (Proof)

Let  $P = \Pr(L \geq M) = \Pr(\text{some bin has } M \text{ balls})$

$$\rightarrow P \leq np \leq n(e/M)^M \quad \dots \text{ (why?)}$$

By setting  $M = (3 \ln n) / (\ln \ln n)$ ,

$$\Pr(L \geq (3 \ln n) / (\ln \ln n))$$

$$\leq n(e/M)^M$$

$$\leq n \left( (\ln \ln n) / (\ln n) \right)^M \quad \dots \text{ (why?)}$$

$$= e^{\ln n} \left( e^{\ln \ln \ln n - \ln \ln n} \right)^{3 \ln n / \ln \ln n}$$

$$= e^{-2 \ln n + o(\ln n)} \leq 1/n \quad \text{(for large enough } n)$$

# Bucket Sort

Suppose we have  $n=2^m$  integers to be sorted

We can sort these integers by Bucket Sort:

1. Create  $n$  buckets,  $B_0, B_1, \dots, B_{n-1}$
2. Put the integer into  $B_j$ , if its first  $m$  bits = binary representation of  $j$
3. Sort each bucket using Bubble-Sort
4. Output the sorted integers in  $B_0$ , then those in  $B_1$ , then those in  $B_2$ , and so on

Remark: Buckets = Bins, Integers = Balls

# Bucket Sort

Suppose each integer is drawn independently and uniformly from  $[0, 2^k)$  for some  $k \geq m$

Question:

What is the *expected time* for the previous Bucket Sort (assume Steps 1 and 2 are done in  $O(n)$  time)?

[Note: the expectation is over the random input]



# Bucket Sort

Let  $X_j$  be the number of integers in  $B_j$

So,  $X_j = \text{Bin}(n, 1/n)$

- Suppose the time to bubble-sort the bucket  $B_j$  is  $cX_j^2$  for some constant  $c$

Then, expected time

$$= E[\sum cX_j^2] + O(n) = \sum E[cX_j^2] + O(n)$$

$$= cn E[X_j^2] + O(n)$$

# Bucket Sort

Since for  $X = \text{Bin}(n, p)$ , its second moment is

$$\begin{aligned} E[X^2] &= (E[X])^2 + \text{Var}[X] \\ &= (np)^2 + np(1-p) \end{aligned}$$

So,  $E[X_j^2] = (n(1/n))^2 + n(1/n)(1-1/n) < 2$

and we have:

$$\text{expected time} < 2cn + O(n) = O(n)$$

# Fraction of Empty Bins

- Next, we consider the fraction of empty bins, when we throw  $m$  balls into  $n$  bins uniformly and independently
- Since each ball hits Bin 1 with probability  $1/n$ , we have

$$\begin{aligned}\Pr(\text{Bin 1 is empty}) &= (1 - (1/n))^m \\ &\approx e^{-m/n}\end{aligned}$$

# Fraction of Empty Bins

Let  $X_j = 1$  if Bin  $j$  is empty  
 $X_j = 0$  otherwise

Let  $X =$  total number of empty bins  
 $= X_1 + X_2 + \dots + X_n$

Then,  $E[X] = E[X_1 + X_2 + \dots + X_n]$   
 $\approx n e^{-m/n}$

→ expected fraction of empty bins  $\approx e^{-m/n}$

# Fraction of Bins with $r$ Balls

How about the expected fraction of bins with **exactly**  $r$  balls (for constant  $r$ )?

- Using similar approach, we compute  $\Pr(\text{Bin 1 has exactly } r \text{ balls})$ , which is

$$C_r^m (1/n)^r (1 - (1/n))^{m-r}$$

$$\approx (m^r/r!) (1/n)^r e^{-m/n} \quad \text{when } m, n \gg r$$

$$= e^{-m/n} (m/n)^r / r! = \text{desired fraction}$$

# Poisson Distribution

This leads to the following definition:

Definition:

A discrete **Poisson random variable**  $X$  with parameter  $\mu$  is given by the following probability distribution for  $r = 0, 1, 2, \dots$ :

$$\Pr(X = r) = e^{-\mu} \mu^r / r!$$

Remark: Poisson RV  $\neq$  Poisson trial !!!

# Poisson Distribution

Before we proceed, let us verify that for the previous probability distribution,

$$\Pr(X = 0) + \Pr(X = 1) + \Pr(X = 2) + \dots = 1$$

By definition:

$$\sum_{r=0 \text{ to } \infty} \Pr(X = r)$$

$$= \sum_{r=0 \text{ to } \infty} e^{-\mu} \mu^r / r!$$

$$= e^{-\mu} \sum_{r=0 \text{ to } \infty} \mu^r / r! = e^{-\mu} e^{\mu} = 1$$

# Expectation of Poisson RV

Theorem: Let  $X$  be a Poisson random variable with parameter  $\mu$ . Then,

$$E[X] = \mu$$

Proof:  $E[X] = \sum_{r=0 \text{ to } \infty} r \Pr(X = r)$

$$= \sum_{r=1 \text{ to } \infty} r \Pr(X = r)$$

$$= \sum_{r=1 \text{ to } \infty} r e^{-\mu} \mu^r / r!$$

$$= \mu \sum_{r=1 \text{ to } \infty} e^{-\mu} \mu^{r-1} / (r-1)! = \mu \quad \dots(\text{why?})$$



# Sum of Independent Poisson RV

Theorem: Let  $X_1, X_2, \dots, X_n$  be independent Poisson random variables with parameters  $\mu_1, \mu_2, \dots, \mu_n$ .

$$\text{Let } X = X_1 + X_2 + \dots + X_n$$

Then,  $X$  is a Poisson random variable with parameter  $\mu = \mu_1 + \mu_2 + \dots + \mu_n$ .

How to prove? First prove two RVs. Then general case follows by induction

# Sum of Independent Poisson RV

Proof: Consider  $X = X_1 + X_2$

Then,  $\Pr(X = r) = \Pr(X_1 + X_2 = r)$

$$= \sum_{k=0 \text{ to } r} \Pr((X_1 = k) \cap (X_2 = r-k))$$

$$= \sum_{k=0 \text{ to } r} (e^{-\mu_1} \mu_1^k / k!) (e^{-\mu_2} \mu_2^{r-k} / (r-k)!) \dots (\text{why?})$$

$$= (e^{-(\mu_1 + \mu_2)} / r!) \sum_{k=0 \text{ to } r} C_k^r \mu_1^k \mu_2^{r-k} \dots (\text{why?})$$

$$= (e^{-(\mu_1 + \mu_2)} / r!) (\mu_1 + \mu_2)^r$$

$$= e^{-(\mu_1 + \mu_2)} (\mu_1 + \mu_2)^r / r!$$

# MGF of Poisson RV

Theorem: Let  $X$  be a Poisson random variables with parameter  $\mu$

Then, the MGF for  $X$  is

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

How to prove?

# Proof

For any  $t$ ,

$$\begin{aligned}M_X(t) &= E[e^{tX}] \\&= \sum_{r=0}^{\infty} e^{tr} \Pr(X = r) \\&= \sum_{r=0}^{\infty} e^{tr} (e^{-\mu} \mu^r / r!) \\&= e^{-\mu} \sum_{r=0}^{\infty} (e^t \mu)^r / r! \\&= e^{-\mu} e^{e^t \mu} \\&= e^{\mu(e^t - 1)}\end{aligned}$$

# Chernoff Bound for Poisson RV

Theorem: Let  $Y$  be a Poisson random variables with parameter  $\mu$

Then,

$$(1) \text{ If } x > \mu, \quad \Pr(Y \geq x) \leq e^{-\mu} (e\mu)^x / x^x$$

$$(2) \text{ If } x < \mu, \quad \Pr(Y \leq x) \leq e^{-\mu} (e\mu)^x / x^x$$

How to prove?

# Poisson RV vs Binomial RV

- When throwing  $m$  balls to  $n$  bins, the number of balls in a certain bin is a Binomial RV  $\text{Bin}(m, 1/n)$
- However, we see that  $\text{Bin}(m, 1/n)$  is close to a Poisson RV, with parameter  $m/n$
- In fact, there is a very strong relation between the Poisson and the Binomial distribution ...

# Limit of Binomial Distribution

Theorem: Let  $X_n$  be a Binomial random variable with parameters  $n$  and  $p$ , where  $p$  is a function of  $n$  with  $\lim_{n \rightarrow \infty} np = \lambda$  for some constant  $\lambda$

Then, for any fixed  $r$

$$\lim_{n \rightarrow \infty} \Pr(X_n = r) = e^{-\lambda} \lambda^r / r!$$

How to prove?

# Proof

- We will assume the following inequality:

$$\text{For } |x| \leq 1, \quad e^x(1-x^2) \leq 1+x \leq e^x$$

(The proof is left as an exercise)

Firstly,

$$\begin{aligned} \Pr(X_n = r) &= C_r^n p^r (1-p)^{n-r} \\ &\leq (n^r/r!) p^r (1-p)^n (1-p)^{-r} \\ &\leq \left( (np)^r/r! \right) e^{-np} (1-p)^{-r} \end{aligned}$$



# Proof

Also,

$$\begin{aligned}\Pr(X_n = r) &\geq ((n-r+1)^r / r!) p^r (1-p)^{n-r} \\ &\geq ((n-r+1)p)^r / r! (1-p)^n \\ &\geq ((n-r+1)p)^r / r! e^{-np} (1-p^2)^n \\ &\geq ((n-r+1)p)^r / r! e^{-np} (1-np^2)\end{aligned}$$

Now, by taking limits on the two inequalities,  
we get the desired bound