

# CS5314

## Randomized Algorithms

Lecture 14: Balls, Bins, Random Graphs  
(Poisson Approximation)

# Objectives

- **Poisson Approximation** for Balls-and-Bins :  
to approximate # balls in each bin as independent Poisson RV with  $\mu = m/n$
- Revisit Coupon Collector

# Poisson Approximation

- Suppose we throw  $m$  balls into  $n$  bins independently and uniformly at random
- From previous lecture, we observe that:
  - # balls in a particular bin
  - $\sim$  Poisson RV with  $\mu = m/n$
- How about distribution of balls in all  $n$  bins ?

# Poisson Approximation

Question: Will distribution of  $n$  balls be the same as  $n$  independent Poisson RVs with mean  $m/n$ ?

Ans. No !

For instance, total # of balls is always exactly  $m$ , but sum of  $n$  independent Poisson RVs can be any value

The difference is because of dependency !

# Poisson Approximation

- Though  
    "n independent Poisson RVs"  
do not have the same distribution as  
    "m balls into n bins"  
we can show that they are related, so  
that we can use the "Poisson Case" to  
approximate the "Exact Case"

Hopefully, the approximation will be useful ...

# Poisson Approximation

Formally, we define

$$X_1^{(m)}, X_2^{(m)}, \dots, X_n^{(m)}$$

where  $X_j^{(m)} = \#$  balls in Bin  $j$  (in Exact Case)

$$Y_1^{(m)}, Y_2^{(m)}, \dots, Y_n^{(m)}$$

which are  $n$  independent Poisson RVs with parameter  $m/n$  (in Poisson Case)

# When Two Distributions Meet

Theorem: Suppose  $\sum_{j=1 \text{ to } n} y_j^{(m)} = k$ . Under this condition, the distribution of

$$(y_1^{(m)}, y_2^{(m)}, \dots, y_n^{(m)})$$

is **exactly** the **same** as the distribution of

$$(x_1^{(k)}, x_2^{(k)}, \dots, x_n^{(k)})$$

regardless of the value of  $m$  or  $k$

How to prove?

Throwing  $k$   
balls in total

# Proof

- Let  $k_1, k_2, \dots, k_n$  be non-negative integers whose sum is  $k$
- When throwing  $k$  balls into  $n$  bins,

$$\Pr( (X_1^{(k)}, \dots, X_n^{(k)}) = (k_1, \dots, k_n) )$$

$$= \frac{k!}{k_1! k_2! \cdots k_n! n^k}$$



# Proof

Next,

$$\begin{aligned} & \Pr((Y_1^{(m)}, \dots, Y_n^{(m)}) = (k_1, \dots, k_n) \mid \sum_j Y_j^{(m)} = k) \\ &= \frac{\Pr((Y_1^{(m)} = k_1) \cap \dots \cap (Y_n^{(m)} = k_n))}{\Pr(\sum_j Y_j^{(m)} = k)} \quad \dots \text{(why?)} \end{aligned}$$

Question: What is this probability??

# Proof

First,

$$\Pr(Y_j^{(m)} = k_j) = e^{-m/n} (m/n)^{k_j} / k_j!$$

Since  $Y_1^{(m)}, \dots, Y_n^{(m)}$  are independent, so

$$\begin{aligned} & \Pr((Y_1^{(m)} = k_1) \cap \dots \cap (Y_n^{(m)} = k_n)) \\ &= \prod_j e^{-m/n} (m/n)^{k_j} / k_j! \\ &= \frac{e^{-m} m^k}{k_1! k_2! \dots k_n! n^k} \end{aligned}$$

# Proof

On the other hand,

$$\Pr(\sum_j Y_j^{(m)} = k) = e^{-m} m^k / k! \quad \dots \text{ [why??]}$$

So combining the previous results,

$$\begin{aligned} & \Pr((Y_1^{(m)}, \dots, Y_n^{(m)}) = (k_1, \dots, k_n) \mid \sum_j Y_j^{(m)} = k) \\ &= \Pr((X_1^{(k)}, \dots, X_n^{(k)}) = (k_1, \dots, k_n)) \end{aligned}$$

→ this completes the proof

# A Stronger Result

- With the previous result between **exact case** and **Poisson case**, we can show a stronger result ...
- Before we proceed, let us obtain a useful upper bound for  **$n!$**

# Upper Bound for $n!$

Lemma:  $n! \leq en^{1/2} (n/e)^n$

Proof: Since  $\ln x$  is a concave function,

$$\int_{j-1}^j \ln x \, dx \geq (\ln(j-1) + \ln j) / 2 \quad \dots \text{(why?)}$$

$$\rightarrow \int_1^n \ln x \, dx \geq \ln(n!) - (\ln n)/2 \quad \dots \text{(why?)}$$

$$\rightarrow n \ln n - n + 1 \geq \ln(n!) - (\ln n)/2$$

$\rightarrow$  Lemma follows by exponentiation

# Expectation of Loads

- We now show a relationship between the expectation of **any** non-negative function of the loads in the two cases :

Theorem:

Let  $f(x_1, \dots, x_n)$  be a non-negative function.

Then,

$$E[f(X_1^{(m)}, \dots, X_n^{(m)})] \leq e^{\sqrt{m}} E[f(Y_1^{(m)}, \dots, Y_n^{(m)})]$$

How to prove?

# Proof

$$E[f(Y_1^{(m)}, \dots, Y_n^{(m)})]$$

$$= \sum_k E[f(Y_1^{(m)}, \dots, Y_n^{(m)}) \mid \sum_j Y_j^{(m)} = k] \Pr(\sum_j Y_j^{(m)} = k)$$

$$\geq E[f(Y_1^{(m)}, \dots, Y_n^{(m)}) \mid \sum_j Y_j^{(m)} = m] \Pr(\sum_j Y_j^{(m)} = m)$$

$$= E[f(X_1^{(m)}, \dots, X_n^{(m)})] \Pr(\sum_j Y_j^{(m)} = m) \quad \dots \text{(why?)}$$

# Proof

Next, using upper bound of  $m!$  ,

$$\begin{aligned} \Pr(\sum_j Y_j^{(m)} = m) &= e^{-m} m^m / m! && \dots \text{ (why?)} \\ &\geq 1 / (em^{1/2}) \end{aligned}$$

Thus,

$$\begin{aligned} &E[f(Y_1^{(m)}, \dots, Y_n^{(m)})] \\ &\geq E[f(X_1^{(m)}, \dots, X_n^{(m)})] / (em^{1/2}) \end{aligned}$$

→ This completes the proof



# Remark

- The previous theorem holds for **any** non-negative function **f**
- E.g., if **f** = **MAX**, then we can relate the expected maximum load in the two cases
- E.g., if **f** = an indicator for an event **Z**, then the theorem gives the relationship of **Pr(Z occurs)** in the two cases

This latter gives the following corollary:

# Bounding Exact Case

Corollary: Referring to the scenario of throwing  $m$  balls into  $n$  bins.

Any event  $Z$  that takes place with probability  $p$  in the Poisson case implies:

$Z$  takes place with probability at most  $em^{1/2}p$  in the exact case

How to prove?

# Bounding Exact Case

Proof: Let  $f$  be the indicator for event  $Z$

Then,

$$\begin{aligned} & \Pr(Z \text{ occurs in exact case}) \\ &= E[f(X_1^{(m)}, \dots, X_n^{(m)})] \\ &\leq em^{1/2} E[f(Y_1^{(m)}, \dots, Y_n^{(m)})] \\ &= em^{1/2} \Pr(Z \text{ occurs in Poisson case}) \\ &= em^{1/2} p \end{aligned}$$

# An Even Stronger Result

If we know more about  $f$ , we can obtain an even stronger bound:

Theorem: Let  $f(x_1, \dots, x_n)$  be a non-negative function such that  $E[f(X_1^{(m)}, \dots, X_n^{(m)})]$  is monotonically increasing in  $m$ .

Then,

$$E[f(X_1^{(m)}, \dots, X_n^{(m)})] \leq 2 E[f(Y_1^{(m)}, \dots, Y_n^{(m)})]$$

How to prove? (Ex. 5.13, 5.14)

# Bounding Exact Case (2)

Corollary:

Let  $Z$  be an event whose probability is monotonically increasing in # balls.

If  $Z$  has probability  $p$  in the Poisson case,  
→  $Z$  has probability at most  $2p$  in the exact case

# Maximum Load (Revisited)

- Some time ago, we have shown that for sufficiently large  $n$ , if we throw  $n$  balls into  $n$  bins, then w.h.p. :  
Maximum load  $\leq 3 \ln n / \ln \ln n$
- The proof is simply based on counting and union bound
- Let's see how the latest result can help in giving a **lower** bound...

# Maximum Load (Revisited)

Lemma:

Suppose  $n$  balls are thrown to  $n$  bins, independently and uniformly at random.

Then w.h.p. (at least  $1-1/n$ ):

$$\text{Maximum load} \geq \ln n / \ln \ln n$$

How to prove?

Let's bound the probability for the Poisson case, and then...

# Proof

Let  $M = \ln n / \ln \ln n$

In the Poisson case,

$$\begin{aligned} & \Pr(\# \text{ of balls in Bin } 1 \geq M) \\ & \geq \Pr(\# \text{ of balls in Bin } 1 = M) \\ & = e^{-1}(1)^M / M! = 1/(eM!) \end{aligned}$$

→ In the Poisson case,

$$\begin{aligned} \Pr(\text{Max-Load} < M) & \leq (1 - 1/(eM!))^n \\ & \leq \exp\{-n/(eM!)\} \end{aligned}$$



# Proof

Next, we simplify the bound by showing:

$$-n / (eM!) \leq -c \ln n \quad \text{for some } c$$

Recall that

$$\begin{aligned} M! &\leq eM^{1/2} (M/e)^M \\ &\leq M (M/e)^M \quad \text{[for large } n] \end{aligned}$$

$$\begin{aligned} \rightarrow \ln M! &\leq \ln M + M \ln M - M \\ &\leq \ln \ln n + \ln n - M \\ &\leq \ln n - \ln \ln n - \ln(2e) \quad \text{[for large } n] \end{aligned}$$

# Proof

Thus,

$$M! \leq n / (2e \ln n) \quad [\text{for large } n]$$

$$\rightarrow \exp\{-n / (eM!)\} \leq \exp\{-2 \ln n\} = 1/n^2$$

So, in the Poisson case

$$\Pr(\text{Max-Load} < M) \leq 1/n^2$$

$\rightarrow$  In the Exact case

$$\Pr(\text{Max-Load} < M) \leq e n^{1/2} (1/n^2) \leq 1/n$$

# Coupon Collector (Revisited)

- Previously we have shown that if we want to collect a set of  $n$  coupons, the expected number of coupons we buy is

$$n H(n) \approx n \ln n$$

- Suppose we have bought  $n \ln n + cn$  coupons already. What is the probability that we have obtained a full collection?

# Coupon Collector (Revisited)

- After buying  $n \ln n + cn$  coupons:

$\Pr(\text{not having } i^{\text{th}} \text{ coupon})$

$$= (1 - 1/n)^{n \ln n + cn}$$

$$\leq e^{-(1/n)(n \ln n + cn)} = e^{-c} / n$$

- After buying  $n \ln n + cn$  coupons:

$\Pr(\text{not having a full collection}) \leq e^{-c}$

→  $\Pr(\text{having a full collection}) \geq 1 - e^{-c}$

# Coupon Collector (Revisited)

- Recently, we have seen that **Chernoff bound** usually gives a much tighter result

Question:

Can we apply **Chernoff bound** to get an even better result ?

# Coupon Collector (Revisited)

Theorem: Let  $X$  be the number of coupons we buy before getting one card of each  $n$  types of coupons. Then, for any  $c$ ,

$$\lim_{n \rightarrow \infty} \Pr(X > n \ln n + cn) = 1 - e^{-e^{-c}}$$

Remark: When  $c = -4$ ,  $1 - e^{-e^{-c}} \approx 1$

When  $c = 4$ ,  $1 - e^{-e^{-c}} \approx 0.02$

→ For large  $n$ , #coupons is between  $n \ln n \pm 4n$  is  $\sim 98\%$  !!!

→ This is an example of **sharp threshold**, where the random variable's distribution is concentrated around its mean

# Proof

- We can consider the coupon collector's problem as a balls-and-bins problem (What are the balls? How many bins?)
- We shall use Poisson approximation so that intermediate steps will be easier
- Suppose # balls in each bin is a Poisson RV with mean  $\ln n + c$ , so that the expected total # balls is  $m = n \ln n + cn$

# Proof

Then, in the Poisson case,

$$\Pr(\text{Bin 1 is empty}) = e^{-(\ln n + c)} = e^{-c/n}$$

Let **NE** be the event that no bin is empty  
in Poisson case

$$\begin{aligned} \text{So, } \Pr(\text{NE}) &= (1 - e^{-c/n})^n \\ &= e^{-e^{-c}} \end{aligned} \quad \dots \text{ [when } n \rightarrow \infty \text{]}$$



# Two Facts

Let  $Y$  be # balls thrown in the Poisson case

Let  $r = \sqrt{2m \ln m}$

We claim that as  $n \rightarrow \infty$ ,

1.  $\Pr(|Y-m| > r) = 0$  (i.e.,  $Y$  is very close to mean)
2.  $\Pr(\text{NE} \mid |Y-m| \leq r) = \Pr(\text{NE} \mid Y=m)$

In case  $Y$  is very close to mean, we can just assume  $Y = m$  when computing  $\Pr(\text{NE})$

Suppose our claim is true ...

# Consequence of Two Facts

As  $n \rightarrow \infty$ ,

$$e^{-e^{-c}} = \Pr(\text{NE})$$

$$= \Pr(\text{NE} \mid |Y-m| > r) \Pr(|Y-m| > r) + \\ \Pr(\text{NE} \mid |Y-m| \leq r) \Pr(|Y-m| \leq r)$$

$$= \Pr(\text{NE} \mid |Y-m| > r) 0 + \Pr(\text{NE} \mid Y=m) 1$$

$$= \Pr(\text{NE} \mid Y=m)$$

$$= \Pr(\text{no bin is empty in Exact Case} \\ \text{when } m \text{ balls are thrown})$$

# Consequence of Two Facts

→ Pr(some bin is still empty in Exact Case  
when  $m$  balls are thrown)  
 $= 1 - e^{-e^{-c}}$

Recall:  $X$  = # balls thrown in the exact case  
until every bin is non-empty

So  $X > m$  occurs if and only if some bin is  
still empty when  $m$  balls are thrown

Thus,

$$\Pr(X > m) = 1 - e^{-e^{-c}}$$

Fact 1:  $Y$  is very close to mean

Recall:

$n$  = number of bins

$Y$  = # balls thrown in Poisson case

$m = n \ln n + cn = E[Y]$

$r = (2m \ln m)^{1/2}$

Fact 1: In the Poisson case, as  $n \rightarrow \infty$ ,

$$\Pr(|Y - m| > r) = 0$$

# Proof of Fact 1

First,  $Y$  is a Poisson RV with mean  $m$

To obtain the bound for

$$\Pr(|Y-m| > r),$$

recall the Chernoff bounds: (Lecture 13, page 21)

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

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

# Proof of Fact 1

So,  $\Pr(|Y-m| > r) = \Pr(Y > m+r) + \Pr(Y < m-r)$

For the first term,

$$\begin{aligned}\Pr(Y > m+r) &\leq e^{-m} (em)^{m+r} / (m+r)^{m+r} \\ &= e^r (m)^{m+r} / (m+r)^{m+r} \\ &= \exp\{ r - (m+r) \ln((m+r)/m) \} \\ &= \exp\{ r - (m+r) \ln(1 + (r/m)) \}\end{aligned}$$

Next, we use the inequality that (for  $|z| < 1$ )

$$\ln(1+z) \geq z - z^2/2$$

# Proof of Fact 1

So, (with  $r = (2m \ln m)^{1/2}$  )

$$\Pr(Y > m+r)$$

$$\leq \exp\{ r - (m+r)\left(\frac{r}{m} - \frac{r^2}{2m^2}\right) \}$$

$$= \exp\{ r - (m+r)\left(\frac{r}{m} - \frac{\ln m}{m}\right) \}$$

$$= \exp\{ r - (r - \ln m) - \left(\frac{r^2}{m} - r \ln m/m\right) \}$$

$$= \exp\{ \ln m - (2 \ln m - (r \ln m/m)) \}$$

$$= \exp\{ - \ln m + o(\ln m) \}$$

$$= 0$$

... as  $n \rightarrow \infty$ , so that  $m \rightarrow \infty$

# Proof of Fact 1

On the other hand, (with  $r = (2m \ln m)^{1/2}$  )

$$\begin{aligned} \Pr(Y < m-r) &\leq e^{-m} (em)^{m-r} / (m-r)^{m-r} \\ &= e^{-r} (m)^{m-r} / (m-r)^{m-r} \\ &= \exp\{ -r - (m-r) \ln((m-r)/m) \} \\ &\leq \exp\{ -r - (m-r)((-r/m) - (r^2/2m^2)) \} \\ &= \exp\{ -r + r - r^2/(2m) - (r \ln m/m) \} \\ &= \exp\{ -\ln m - o(\ln m) \} \\ &= 0 \quad \dots \text{ as } n \rightarrow \infty, \text{ so that } m \rightarrow \infty \end{aligned}$$



# Proof of Fact 1

Thus, in the Poisson case,

$$\begin{aligned} 0 &\leq \Pr(|Y-m| > r) \\ &= \Pr(Y > m+r) + \Pr(Y < m-r) \\ &\leq 0 + 0 \quad \dots \text{as } n \rightarrow \infty, \text{ so that } m \rightarrow \infty \\ &= 0 \end{aligned}$$

$$\Rightarrow \Pr(|Y-m| > r) = 0 \quad \dots \text{as } n \rightarrow \infty, \text{ so that } m \rightarrow \infty$$

# Fact 2

Recall:

$n$  = number of bins

$Y$  = # balls thrown in the Poisson case

$$m = n \ln n + cn = E[Y]$$

$$r = (2m \ln m)^{1/2}$$

$NE$  = the event that no bin is empty

Fact 2: In Poisson case, as  $n \rightarrow \infty$ ,

$$\Pr(NE \mid |Y-m| \leq r) = \Pr(NE \mid Y=m)$$

# Proof of Fact 2

Firstly, we observe that

$\Pr(\text{NE} \mid Y=k)$  is increasing in  $k$  ... (why?)

$$\rightarrow \Pr(\text{NE} \cap Y=k) / \Pr(Y=k)$$

$$\leq \Pr(\text{NE} \mid Y=k+1) \leq \Pr(\text{NE} \mid Y=k+2) \leq \dots$$

In other words,

$$\Pr(\text{NE} \cap Y=k) \leq \Pr(Y=k) \Pr(\text{NE} \mid Y=k+1)$$

$$\leq \Pr(Y=k) \Pr(\text{NE} \mid Y=k+2) \leq \dots$$

## Proof of Fact 2

$$\begin{aligned} \text{So, } & \Pr(\text{NE} \mid |Y-m| \leq r) \\ &= \sum_{k=m-r}^{m+r} \Pr(\text{NE} \cap Y=k) / \sum_{k=m-r}^{m+r} \Pr(Y=k) \\ &\leq \frac{\sum_{k=m-r}^{m+r} \Pr(Y=k) \Pr(\text{NE} \mid Y=m+r)}{\sum_{k=m-r}^{m+r} \Pr(Y=k)} \\ &= \Pr(\text{NE} \mid Y=m+r) \end{aligned}$$

Similarly,  $\Pr(\text{NE} \mid Y=m-r) \leq \Pr(\text{NE} \mid |Y-m| \leq r)$

## Proof of Fact 2

Next, we want to upper bound this term:

$$\left| \Pr(\text{NE} \mid |Y-m| \leq r) - \Pr(\text{NE} \mid Y=m) \right|$$

Hopefully, we can show this to be 0

However, we don't know if  $\Pr(\text{NE} \mid Y=m)$  is larger, or  $\Pr(\text{NE} \mid |Y-m| \leq r)$  is larger...

Let's get a bound that works for **both** cases

# Proof of Fact 2

Case 1: Suppose  $\Pr(\text{NE} \mid Y=m)$  is larger

Then, we know that

$$\begin{aligned} & \left| \Pr(\text{NE} \mid |Y-m| \leq r) - \Pr(\text{NE} \mid Y=m) \right| \\ &= \Pr(\text{NE} \mid Y=m) - \Pr(\text{NE} \mid |Y-m| \leq r) \\ &\leq \Pr(\text{NE} \mid Y=m) - \Pr(\text{NE} \mid Y=m-r) \\ &\leq \Pr(\text{NE} \mid Y=m+r) - \Pr(\text{NE} \mid Y=m-r) \end{aligned}$$

# Proof of Fact 2

Case 2: Suppose  $\Pr(\text{NE} \mid Y=m)$  is smaller

Then, we know that

$$\begin{aligned} & \left| \Pr(\text{NE} \mid |Y-m| \leq r) - \Pr(\text{NE} \mid Y=m) \right| \\ &= \Pr(\text{NE} \mid |Y-m| \leq r) - \Pr(\text{NE} \mid Y=m) \\ &\leq \Pr(\text{NE} \mid Y=m+r) - \Pr(\text{NE} \mid Y=m) \\ &\leq \Pr(\text{NE} \mid Y=m+r) - \Pr(\text{NE} \mid Y=m-r) \end{aligned}$$

# Proof of Fact 2

Conclusion:

It is always true that:

$$\begin{aligned} & \left| \Pr(\text{NE} \mid |Y-m| \leq r) - \Pr(\text{NE} \mid Y=m) \right| \\ & \leq \Pr(\text{NE} \mid Y=m+r) - \Pr(\text{NE} \mid Y=m-r) \end{aligned}$$

Question: What is the physical meaning of

$$\Pr(\text{NE} \mid Y=m+r) - \Pr(\text{NE} \mid Y=m-r)?$$



# Proof of Fact 2

By Theorem on Page 7, it is the difference of the probability, in the exact case, that all bins have at least one balls when  $m+r$  balls and when  $m-r$  balls are thrown ...

Also equals to  $\Pr(\text{success})$  in the following:

Step 1. Throw  $m-r$  balls

Step 2. If all bins non-empty, failure

Step 3. Else, throw  $2r$  more balls

Step 4. If all bins non-empty, **success**.  
Else, failure

Will  $\Pr(\text{success})$  be large? Or small?

## Proof of Fact 2

Then, (with  $m = n \ln n + cn$ ,  $r = (2m \ln m)^{1/2}$  )

$\Pr(\text{success})$

$= \Pr(\text{some bins empty after } m-r \text{ balls and}$   
 $\text{all bins nonempty after } 2r \text{ extra balls})$

$\leq \Pr(\text{some bins empty after } m-r \text{ balls and}$   
 $\text{a specific empty bin becomes nonempty}$   
 $\text{after } 2r \text{ extra balls})$

$\leq \Pr(\text{a specific empty bin becomes nonempty}$   
 $\text{after } 2r \text{ extra balls})$

$\leq 2r/n$  [union bound]  $= 0$  as  $n \rightarrow \infty$

# Proof of Fact 2

Thus,

$$\begin{aligned} 0 &\leq \left| \Pr(\text{NE} \mid |Y-m| \leq r) - \Pr(\text{NE} \mid Y=m) \right| \\ &\leq \Pr(\text{NE} \mid Y=m+r) - \Pr(\text{NE} \mid Y=m-r) \\ &= \Pr(\text{success}) \leq 0 \quad \dots \text{ as } n \rightarrow \infty \end{aligned}$$

→ As  $n \rightarrow \infty$ ,

$$\left| \Pr(\text{NE} \mid |Y-m| \leq r) - \Pr(\text{NE} \mid Y=m) \right| = 0$$

or,  $\Pr(\text{NE} \mid |Y-m| \leq r) = \Pr(\text{NE} \mid Y=m)$