Lecture 4: Balls & Bins

Rafael Oliveira

University of Waterloo Cheriton School of Computer Science

rafael.oliveira.teaching@gmail.com

May 18, 2023

Overview

Introduction

- Probability basic notions
- Balls and Bins
- Analyses

• Coupon Collector and Power of Two Choices

- Coupon Collector
- Power of Two Choices

• Acknowledgements

Event Spaces and Inclusion-Exclusion

< □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □

Union Bound and Inclusion-Exclusion

◆□ ▶ < □ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ > < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ < ■ ▶ <

Union Bound and Inclusion-Exclusion

<ロト<回ト<巨ト<Eト 目 のQの 5/73

• The *conditional probability* of E_1 given E_2 is

$$\Pr[E_1 \mid E_2] := \frac{\Pr[E_1 \cap E_2]}{\Pr[E_2]}$$

• The *conditional probability* of E_1 given E_2 is

$$\Pr[E_1 \mid E_2] := \frac{\Pr[E_1 \cap E_2]}{\Pr[E_2]}$$

• If E_1, \ldots, E_k partition our sample space, then for any event E

$$\Pr[E] = \sum_{i=1}^{k} \Pr[E \mid E_i] \cdot \Pr[E_i]$$

• The *conditional probability* of E_1 given E_2 is

$$\Pr[E_1 \mid E_2] := \frac{\Pr[E_1 \cap E_2]}{\Pr[E_2]}$$

• If E_1, \ldots, E_k partition our sample space, then for any event E

$$\Pr[E] = \sum_{i=1}^{k} \Pr[E \mid E_i] \cdot \Pr[E_i]$$

• Simple Bayes' rule:

$$\Pr[E_1 \mid E_2] = \frac{\Pr[E_2 \mid E_1] \cdot \Pr[E_1]}{\Pr[E_2]}$$

イロン 不得 とうほう イロン 二日

8/73

• The *conditional probability* of E_1 given E_2 is

$$\Pr[E_1 \mid E_2] := \frac{\Pr[E_1 \cap E_2]}{\Pr[E_2]}$$

• If E_1, \ldots, E_k partition our sample space, then for any event E

$$\Pr[E] = \sum_{i=1}^{k} \Pr[E \mid E_i] \cdot \Pr[E_i]$$

• Simple Bayes' rule:

$$\Pr[E_1 \mid E_2] = \frac{\Pr[E_2 \mid E_1] \cdot \Pr[E_1]}{\Pr[E_2]}$$

• **Bayes' rule**: E_1, \ldots, E_k partition our sample space then for event E

$$\Pr[E_i \mid E] = \frac{\Pr[E \cap E_i]}{\Pr[E]} = \frac{\Pr[E \mid E_i] \cdot \Pr[E_i]}{\sum_{j=1}^k \Pr[E \mid E_j] \cdot \Pr[E_j]}$$

Setup: we have m balls and we want to put them in n bins.

We will do this by throwing each ball into a *uniformly random* bin *independently*.

Setup: we have m balls and we want to put them in n bins.

We will do this by throwing each ball into a *uniformly random* bin *independently*.

Setup: we have m balls and we want to put them in n bins.

We will do this by throwing each ball into a *uniformly random* bin *independently*.

We are interested in the following questions:

• What is the *expected* number of balls in a bin?

Setup: we have m balls and we want to put them in n bins.

We will do this by throwing each ball into a *uniformly random* bin *independently*.

- What is the *expected* number of balls in a bin?
- What is the *expected* number of empty bins?

Setup: we have m balls and we want to put them in n bins.

We will do this by throwing each ball into a *uniformly random* bin *independently*.

- What is the *expected* number of balls in a bin?
- What is the *expected* number of empty bins?
- What is "typically" the maximum number of balls in any bin?

Setup: we have m balls and we want to put them in n bins.

We will do this by throwing each ball into a *uniformly random* bin *independently*.

- What is the *expected* number of balls in a bin?
- What is the *expected* number of empty bins?
- What is "typically" the maximum number of balls in any bin?
- What is the *expected* number of bins with k balls in them?

Setup: we have m balls and we want to put them in n bins.

We will do this by throwing each ball into a *uniformly random* bin *independently*.

- What is the *expected* number of balls in a bin?
- What is the *expected* number of empty bins?
- What is "typically" the maximum number of balls in any bin?
- What is the *expected* number of bins with k balls in them?
- For what values of *m* do we expect to have *no empty bins*? (coupon collector)

Why Learn About Balls and Bins?

In **this lecture**, we will analyse random processes (*balls & bins*) which underlie several randomized algorithms!

Applications ranging from:

- data structures
- I routing in parallel computers
- 3 many more!

Let us label the *m* balls $1, \ldots, m$, and the *n* bins $1, 2, \ldots, n$. Let B_{ij} be the indicator variable that ball *i* was thrown into bin *j*.

Let us label the *m* balls $1, \ldots, m$, and the *n* bins $1, 2, \ldots, n$. Let B_{ij} be the indicator variable that ball *i* was thrown into bin *j*.

$$\mathbb{E}[\# \text{ balls in bin } j] = \mathbb{E}\left[\sum_{i=1}^{m} B_{ij}\right]$$

Let us label the *m* balls $1, \ldots, m$, and the *n* bins $1, 2, \ldots, n$. Let B_{ij} be the indicator variable that ball *i* was thrown into bin *j*.

$$\mathbb{E}[\# \text{ balls in bin } j] = \mathbb{E}\left[\sum_{i=1}^{m} B_{ij}\right]$$
$$= \sum_{i=1}^{m} \mathbb{E}\left[B_{ij}\right]$$

(linearity of expectation)

Let us label the *m* balls $1, \ldots, m$, and the *n* bins $1, 2, \ldots, n$. Let B_{ij} be the indicator variable that ball *i* was thrown into bin *j*.

$$\mathbb{E}[\# \text{ balls in bin } j] = \mathbb{E}\left[\sum_{i=1}^{m} B_{ij}\right]$$
$$= \sum_{i=1}^{m} \mathbb{E}[B_{ij}] \qquad (\text{linearity of expectation})$$
$$= \sum_{i=1}^{m} \Pr[\text{ball } i \text{ in bin } j]$$

Let us label the *m* balls $1, \ldots, m$, and the *n* bins $1, 2, \ldots, n$. Let B_{ij} be the indicator variable that ball *i* was thrown into bin *j*.

$$\mathbb{E}[\# \text{ balls in bin } j] = \mathbb{E}\left[\sum_{i=1}^{m} B_{ij}\right]$$

$$= \sum_{i=1}^{m} \mathbb{E}[B_{ij}] \qquad (\text{linearity of expectation})$$

$$= \sum_{i=1}^{m} \Pr[\text{ball } i \text{ in bin } j]$$

$$= \sum_{i=1}^{m} \frac{1}{n} = \frac{m}{n} \qquad (\text{uniformly at random})$$

Let us label the *m* balls $1, \ldots, m$, and the *n* bins $1, 2, \ldots, n$. Let B_{ij} be the indicator variable that ball *i* was thrown into bin *j*.

$$\mathbb{E}[\# \text{ balls in bin } j] = \mathbb{E}\left[\sum_{i=1}^{m} B_{ij}\right]$$

$$= \sum_{i=1}^{m} \mathbb{E}[B_{ij}] \qquad (\text{linearity of expectation})$$

$$= \sum_{i=1}^{m} \Pr[\text{ball } i \text{ in bin } j]$$

$$= \sum_{i=1}^{m} \frac{1}{n} = \frac{m}{n} \qquad (\text{uniformly at random})$$

When m = n, expectation of one ball per bin. How often will this actually happen?

Let N_i be the indicator variable that bin *i* is empty.

Let N_i be the indicator variable that bin *i* is empty.

$$\mathbb{E}[\# \text{ empty bins}] = \mathbb{E}\left[\sum_{i=1}^{n} N_i\right]$$

Let N_i be the indicator variable that bin *i* is empty.

$$\mathbb{E}[\# \text{ empty bins}] = \mathbb{E}\left[\sum_{i=1}^{n} N_i\right]$$
$$= \sum_{i=1}^{n} \mathbb{E}[N_i]$$

(linearity of expectation)

Let N_i be the indicator variable that bin *i* is empty.

$$\mathbb{E}[\# \text{ empty bins}] = \mathbb{E}\left[\sum_{i=1}^{n} N_i\right]$$
$$= \sum_{i=1}^{n} \mathbb{E}[N_i] \qquad \text{(linearity of expectation)}$$
$$= \sum_{i=1}^{n} \Pr[\text{bin } i \text{ is empty}]$$

Let N_i be the indicator variable that bin *i* is empty.

$$\mathbb{E}[\# \text{ empty bins}] = \mathbb{E}\left[\sum_{i=1}^{n} N_i\right]$$

$$= \sum_{i=1}^{n} \mathbb{E}[N_i] \qquad \text{(linearity of expectation)}$$

$$= \sum_{i=1}^{n} \Pr[\text{bin } i \text{ is empty}]$$

$$= \sum_{i=1}^{n} (1 - 1/n)^m$$

$$= n \cdot (1 - 1/n)^m \approx n \cdot e^{-m/n}$$

Let N_i be the indicator variable that bin *i* is empty.

$$\mathbb{E}[\# \text{ empty bins}] = \mathbb{E}\left[\sum_{i=1}^{n} N_i\right]$$

$$= \sum_{i=1}^{n} \mathbb{E}[N_i] \quad \text{(linearity of expectation)}$$

$$= \sum_{i=1}^{n} \Pr[\text{bin } i \text{ is empty}]$$

$$= \sum_{i=1}^{n} (1 - 1/n)^m$$

$$= n \cdot (1 - 1/n)^m \approx n \cdot e^{-m/n}$$

When m = n, expected fraction of empty bins is $\frac{1}{e}$.

(日)

When m = n, first calculation had expectation of *one ball per bin*.

When m = n, first calculation had expectation of *one ball per bin*.

When m = n, second calculation had expectation of 1/e fraction of empty bins.

When m = n, first calculation had expectation of *one ball per bin*.

When m = n, second calculation had expectation of 1/e fraction of empty bins.

Which expectation should I actually "expect"?

When m = n, first calculation had expectation of one ball per bin.

When m = n, second calculation had expectation of 1/e fraction of empty bins.

Which expectation should I actually "expect"?

As we mentioned earlier, this is where *concentration of probability measure* tries to address. It turns out that the *second random variable* (and thus second calculation) is concentrated around the mean (i.e., expectation).

So we "expect" (or it is "typical") to see around 1/e-fraction of empty bins when m = n

What is the "typical" maximum number of balls in a bin?

As we saw in the previous slide, "typical" is related to concentration of probability measure.

What is the "typical" maximum number of balls in a bin? As we saw in the previous slide, "typical" is related to concentration of probability measure.

Let us first see a simpler problem, which is known as the *birthday paradox*: for what value of m do we expect to see two balls in one bin?

Birthday Paradox

The probability that there are no collisions after we have thrown m balls is:

$$1 \cdot \left(1 - \frac{1}{n}\right) \cdot \left(1 - \frac{2}{n}\right) \cdots \cdot \left(1 - \frac{m-1}{n}\right) \le e^{-1/n} \cdots e^{-\frac{m-1}{n}} \approx e^{\frac{-m^2}{2n}}$$

Birthday Paradox

The probability that there are no collisions after we have thrown m balls is:

$$1 \cdot \left(1 - \frac{1}{n}\right) \cdot \left(1 - \frac{2}{n}\right) \cdots \cdot \left(1 - \frac{m-1}{n}\right) \leq e^{-1/n} \cdots e^{-\frac{m-1}{n}} \approx e^{\frac{-m^2}{2n}}$$

This is $\leq 1/2$ when $m = \sqrt{2n \ln(2)}$. For n = 365, this is $m \approx 22.4$ for the probability that two people *(balls)* have birthday on the same date *(bins)* to become $\geq 1/2$.

Birthday Paradox

The probability that there are no collisions after we have thrown m balls is:

$$1 \cdot \left(1 - \frac{1}{n}\right) \cdot \left(1 - \frac{2}{n}\right) \cdots \cdot \left(1 - \frac{m-1}{n}\right) \leq e^{-1/n} \cdots e^{-\frac{m-1}{n}} \approx e^{\frac{-m^2}{2n}}$$

This is $\leq 1/2$ when $m = \sqrt{2n \ln(2)}$. For n = 365, this is $m \approx 22.4$ for the probability that two people *(balls)* have birthday on the same date *(bins)* to become $\geq 1/2$.

Thus, expect to see collision (two balls in the same bin) when $m = \Theta(\sqrt{n})$. This appears in several places:

- hashing
- factoring
- many more

$$\mathsf{Pr}[\mathsf{bin} \ 1 \ \mathsf{has} \ \geq k \ \mathsf{balls}] \leq \sum_{\substack{\mathsf{S} \ \mathsf{subset}[n] \ |\mathcal{S}| = k}} \prod_{i \in \mathcal{S}} \mathsf{Pr}[\mathsf{ball} \ i \ \mathsf{in} \ \mathsf{bin} \ 1]$$

$$\begin{aligned} \Pr[\text{bin 1 has } \geq k \text{ balls}] &\leq \sum_{\substack{S \text{ subset}[n] \\ |S|=k}} \prod_{i \in S} \Pr[\text{ball } i \text{ in bin 1}] \\ &= \sum_{\substack{S \text{ subset}[n] \\ |S|=k}} \prod_{i \in S} \frac{1}{n} \end{aligned}$$

$$\Pr[\text{bin 1 has } \ge k \text{ balls}] \le \sum_{\substack{S \text{ subset}[n] \\ |S|=k}} \prod_{i \in S} \Pr[\text{ball } i \text{ in bin 1}]}$$
$$= \sum_{\substack{S \text{ subset}[n] \\ |S|=k}} \prod_{i \in S} \frac{1}{n}$$
$$= \binom{n}{k} \cdot \frac{1}{n^k} \le \left(\frac{ne}{k}\right)^k \cdot \frac{1}{n^k} = \frac{e^k}{k^k}$$

What is the probability that a particular bin (say bin 1) has $\geq k$ balls in it?

$$\Pr[\text{bin 1 has } \ge k \text{ balls}] \le \sum_{\substack{S \text{ subset}[n] \\ |S|=k}} \prod_{i \in S} \Pr[\text{ball } i \text{ in bin 1}]$$
$$= \sum_{\substack{S \text{ subset}[n] \\ |S|=k}} \prod_{i \in S} \frac{1}{n}$$
$$= \binom{n}{k} \cdot \frac{1}{n^k} \le \left(\frac{ne}{k}\right)^k \cdot \frac{1}{n^k} = \frac{e^k}{k^k}$$

By union bound

$$\Pr[\text{some bin has } \ge k \text{ balls}] \le \sum_{i=1}^{n} \Pr[\text{bin i has } \ge k \text{ balls}] \le n \cdot \frac{e^{k}}{k^{k}}$$

<ロ><回><一><一><一><一><一><一</td>43/73

$$\Pr[\text{some bin has } \geq k \text{ balls}] \leq n \cdot \frac{e^k}{k^k} = e^{\ln n + k - k \ln k}$$

$$\Pr[\text{some bin has } \geq k \text{ balls}] \leq n \cdot rac{e^k}{k^k} = e^{\ln n + k - k \ln k}$$

 $\Pr[\max \text{ load is } \leq k] = 1 - \Pr[\text{some bin has } > k \text{ balls}] \geq 1 - e^{\ln n + k - k \ln k}$

$$\Pr[\text{some bin has } \geq k \text{ balls}] \leq n \cdot \frac{e^k}{k^k} = e^{\ln n + k - k \ln k}$$

 $\Pr[\max \text{ load is } \leq k] = 1 - \Pr[\text{some bin has } > k \text{ balls}] \geq 1 - e^{\ln n + k - k \ln k}$

When will the above probability be large (say >> 1/2)?

$$\Pr[\text{some bin has } \geq k \text{ balls}] \leq n \cdot rac{e^k}{k^k} = e^{\ln n + k - k \ln k}$$

 $\Pr[\max \text{ load is } \leq k] = 1 - \Pr[\text{some bin has } > k \text{ balls}] \geq 1 - e^{\ln n + k - k \ln k}$

When will the above probability be large (say >> 1/2)?

When
$$k \ln k > \ln n$$
. Setting $k = 3 \frac{\ln n}{\ln \ln n}$ does it.

$$\Pr[\text{some bin has } \geq k \text{ balls}] \leq n \cdot rac{e^k}{k^k} = e^{\ln n + k - k \ln k}$$

 $\Pr[\max \text{ load is } \leq k] = 1 - \Pr[\text{some bin has } > k \text{ balls}] \geq 1 - e^{\ln n + k - k \ln k}$

When will the above probability be large (say >> 1/2)?

When
$$k \ln k > \ln n$$
. Setting $k = 3 \frac{\ln n}{\ln \ln n}$ does it.

With high probability, max load is $O\left(\frac{\ln n}{\ln \ln n}\right)$.

$$\Pr[\text{some bin has } \geq k \text{ balls}] \leq n \cdot rac{e^k}{k^k} = e^{\ln n + k - k \ln k}$$

 $\Pr[\max \text{ load is } \leq k] = 1 - \Pr[\text{some bin has } > k \text{ balls}] \geq 1 - e^{\ln n + k - k \ln k}$

When will the above probability be large (say >> 1/2)?

When
$$k \ln k > \ln n$$
. Setting $k = 3 \frac{\ln n}{\ln \ln n}$ does it.

With high probability, max load is $O\left(\frac{\ln n}{\ln \ln n}\right)$.

This comes up in hashing and in analysis of approximation algorithms (for instance, best known approximation ratio for congestion minimization).

Introduction

- Probability basic notions
- Balls and Bins
- Analyses
- Coupon Collector and Power of Two Choices
 - Coupon Collector
 - Power of Two Choices
- Acknowledgements

For what value of m do we expect to have no empty bins?

For what value of *m* do we expect to have no empty bins?

Why is this problem called the coupon collector problem?

Because we can formulate it in the following way:

- suppose each bin is a different coupon
- we buy one coupon at random (like kinder eggs/pack action cards)
- what is the number of coupons that we need to buy to collect all of them?

For what value of *m* do we expect to have no empty bins?

Why is this problem called the coupon collector problem?

Because we can formulate it in the following way:

- suppose each bin is a different coupon
- we buy one coupon at random (like kinder eggs/pack action cards)
- what is the number of coupons that we need to buy to collect all of them?

Let X_i be the number of balls thrown to get from *i* empty bins to i - 1 empty bins. Let X be the number of balls thrown until we have no empty bins.

$$X = \sum_{i=1}^{n} X_i$$

イロト 不得 トイヨト イヨト ヨー うらつ

- $X_i \leftarrow \#$ balls thrown to get from *i* empty bins to i-1 empty bins
- $X \leftarrow \#$ balls thrown until we have no empty bins

- $X_i \leftarrow \#$ balls thrown to get from i empty bins to i-1 empty bins
- $X \leftarrow \#$ balls thrown until we have no empty bins

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} \mathbb{E}[X_i]$$

- $X_i \leftarrow \#$ balls thrown to get from *i* empty bins to i-1 empty bins
- $X \leftarrow \#$ balls thrown until we have no empty bins

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} \mathbb{E}\left[X_i\right]$$

What is $\mathbb{E}[X_i]$?

- $X_i \leftarrow \#$ balls thrown to get from *i* empty bins to i-1 empty bins
- $X \leftarrow \#$ balls thrown until we have no empty bins

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} \mathbb{E}[X_i]$$

What is $\mathbb{E}[X_i]$?

 X_i geometric random variable with parameter $p = \frac{i}{n}$.

Number of trials until the first success, where success probability p.

$$\Pr[X_i = k] = (1 - p)^{k-1} \cdot p$$

Coupon Collector - Computing $\mathbb{E}[X]$

<ロト < 回 ト < 巨 ト < 巨 ト 三 の < © 58 / 73

Coupon Collector - Computing $\mathbb{E}[X]$

This *n* ln *n* bound shows up in:

- cover time of random walks in complete graph
- number of edges needed in graph sparsification
- many more places

We now know that when *n* balls are thrown into *n* bins, the maximum load is $\Theta(\ln n / \ln \ln n)$ with constant probability.¹

¹we'll maybe see lower bound later

We now know that when *n* balls are thrown into *n* bins, the maximum load is $\Theta(\ln n / \ln \ln n)$ with constant probability.¹

Consider following variant: what if when throwing a ball in a bin, *before* we throw the ball we choose *two* bins *uniformly at random* and put the ball in the *bin with fewer balls*?

¹we'll maybe see lower bound later

We now know that when *n* balls are thrown into *n* bins, the maximum load is $\Theta(\ln n / \ln \ln n)$ with constant probability.¹

Consider following variant: what if when throwing a ball in a bin, *before* we throw the ball we choose *two* bins *uniformly at random* and put the ball in the *bin with fewer balls*?

This simple modification reduces maximum load to $O(\ln \ln n)!$

¹we'll maybe see lower bound later

We now know that when *n* balls are thrown into *n* bins, the maximum load is $\Theta(\ln n / \ln \ln n)$ with constant probability.¹

Consider following variant: what if when throwing a ball in a bin, *before* we throw the ball we choose *two* bins *uniformly at random* and put the ball in the *bin with fewer balls*?

This simple modification reduces maximum load to $O(\ln \ln n)!$

Intuition/idea: let the height of a bin be the # balls in that bin. This process tells us that to get one bin with height h + 1 we must have at least two bins of height h.

We can bound # bins with height at least h (because this will tell us how likely it is to get to height h + 1).

¹we'll maybe see lower bound later

$$\Pr[\text{at least one bin of height } h+1] \leq \left(\frac{N_h}{n}\right)^2$$

 $N_h :=$ number of bins with height at least h

$$\Pr[\text{at least one bin of height } h+1] \leq \left(\frac{N_h}{n}\right)^2$$

• Say we have only n/4 bins with 4 items (i.e. height 4)

$$\mathsf{Pr}[\mathsf{at} \ \mathsf{least} \ \mathsf{one} \ \mathsf{bin} \ \mathsf{of} \ \mathsf{height} \ h+1] \leq \left(rac{N_h}{n}
ight)^2$$

- Say we have only n/4 bins with 4 items (i.e. height 4)
- $\bullet\,$ Probability of selecting two such bins is 1/16

$$\mathsf{Pr}[\mathsf{at} \ \mathsf{least} \ \mathsf{one} \ \mathsf{bin} \ \mathsf{of} \ \mathsf{height} \ h+1] \leq \left(rac{\mathsf{N}_h}{\mathsf{n}}
ight)^2$$

- Say we have only n/4 bins with 4 items (i.e. height 4)
- Probability of selecting two such bins is 1/16
- So we should expect only n/16 bins with height 5
- And only $n/256 = n/16^2 = n/2^{2^3}$ bins with height 6

$$\mathsf{Pr}[\mathsf{at} \ \mathsf{least} \ \mathsf{one} \ \mathsf{bin} \ \mathsf{of} \ \mathsf{height} \ h+1] \leq \left(rac{N_h}{n}
ight)^2$$

- Say we have only n/4 bins with 4 items (i.e. height 4)
- Probability of selecting two such bins is 1/16
- So we should expect only n/16 bins with height 5
- And only $n/256 = n/16^2 = n/2^{2^3}$ bins with height 6
- Repeating this, we should expect $\frac{n}{2^{2^{h-3}}}$ bins of height h

$$\mathsf{Pr}[\mathsf{at} \ \mathsf{least} \ \mathsf{one} \ \mathsf{bin} \ \mathsf{of} \ \mathsf{height} \ h+1] \leq \left(rac{N_h}{n}
ight)^2$$

- Say we have only n/4 bins with 4 items (i.e. height 4)
- Probability of selecting two such bins is 1/16
- So we should expect only n/16 bins with height 5
- And only $n/256 = n/16^2 = n/2^{2^3}$ bins with height 6
- Repeating this, we should expect $\frac{n}{2^{2^{h-3}}}$ bins of height h
- So expect log log *n* maximum height after throwing *n* balls.

 $N_h :=$ number of bins with height at least h

$$\mathsf{Pr}[\mathsf{at} \ \mathsf{least} \ \mathsf{one} \ \mathsf{bin} \ \mathsf{of} \ \mathsf{height} \ h+1] \leq \left(rac{\mathsf{N}_h}{\mathsf{n}}
ight)^2$$

- Say we have only n/4 bins with 4 items (i.e. height 4)
- Probability of selecting two such bins is 1/16
- So we should expect only n/16 bins with height 5
- And only $n/256 = n/16^2 = n/2^{2^3}$ bins with height 6
- Repeating this, we should expect $\frac{n}{2^{2^{h-3}}}$ bins of height h

• So expect log log *n* maximum height after throwing *n* balls. How do we turn this into a proof? See [Mitzenmacher & Upfal, Chapter 14] and Lap Chi's notes.

Acknowledgement

- Lecture based largely on Lap Chi's notes and on [Motwani & Raghavan 2007, Chapter 3].
- See Lap Chi's notes at https://cs.uwaterloo.ca/~lapchi/cs466/notes/L04.pdf

References I



Motwani, Rajeev and Raghavan, Prabhakar (2007) Randomized Algorithms

Mitzenmacher, Michael, and Eli Upfal (2017)

Probability and computing: Randomization and probabilistic techniques in algorithms and data analysis.

Cambridge university press, 2017.