# COMPSCI 514: ALGORITHMS FOR DATA SCIENCE

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University of Massachusetts Amherst. Fall 2020.

Lecture 3

## **LOGISTICS**

# By Thursday:

- · Sign up for Piazza.
- Sign up for Gradescope (code on class website) and fill out the Gradescope consent poll on Piazza. Contact me via email if you don't consent to use Gradescope.

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**First Problem Set:** released Saturday, due 9/11 at 8pm in Gradescope.

• Remember you can complete in a group of up to 3 students, who all turn in one submission with three names on it.

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91 students completed the quizzes – make sure that if you are enrolled you are doing the quiz each week.

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**Question 1:** The expected number of inches of rain on Saturday is 2 and the expected number of inches on Sunday is 6. There is a 50% chance of rain on Saturday. If it rains on Saturday, there is a 75% chance of rain on Sunday. If it does not rain on Saturday, there is only a 25% chance of rain on Sunday. What is the expected number of inches of rainfall total over the weekend?

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**Concerns:** Probability/linear algebra background, proofs/derivations.

## Last Class We Covered:

- Markov's inequality: the most fundamental concentration bound.
- Algorithmic applications of Markov's inequality, linearity of expectation, and indicator random variables:
  - · Counting collisions to estimate CAPTCHA database size.
  - Counting collisions to understand the runtime of hash tables with random hash functions.

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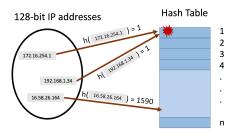
- Markov's inequality: the most fundamental concentration bound.
- Algorithmic applications of Markov's inequality, linearity of expectation, and indicator random variables:
  - · Counting collisions to estimate CAPTCHA database size.
  - Counting collisions to understand the runtime of hash tables with random hash functions.
- · Collision counting is closely related to the birthday paradox.

# Today:

- · Finish up random hash functions and hash tables.
- See an applications of random hashing to load balancing in distributed systems.
- · Through these applications learn about:
  - · Chebyshev's inequality, which strengthens Markov's inequality.
  - The union bound, for understanding the probabilities of correlated random events.

#### HASH TABLES

We store m items from a large universe in a hash table with n positions.



- · Want to show that when  $\mathbf{h}: U \to [n]$  is a random hash function, query time is O(1) with good probability.
- Equivalently: want to show that there are few collisions between hashed items.

## **COLLISION FREE HASHING**

When storing m items in a table of size n, the expected number of pairwise collisions (two items stored in the same slots) is:

$$\mathbb{E}[\mathbf{C}] = \frac{m(m-1)}{2n}$$

m: total number of stored items, n: hash table size, C: total pairwise collisions in table.

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- By Markov's inequality there no collisions with probability at least  $\frac{7}{8}$ .

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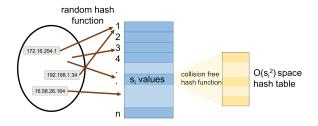
O(1) query time, but we are using  $O(m^2)$  space to store m items...

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Want to preserve O(1) query time while using O(m) space.

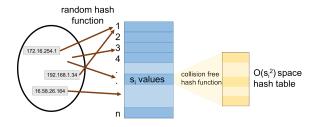
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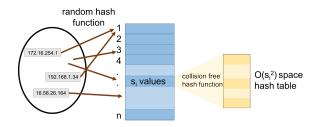
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• For each bucket with  $s_i$  values, pick a collision free hash function mapping  $[s_i] \rightarrow [s_i^2]$ .

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# Two-Level Hashing:



- For each bucket with  $s_i$  values, pick a collision free hash function mapping  $[s_i] \rightarrow [s_i^2]$ .
- Just Showed: A random function is collision free with probability  $\geq \frac{7}{8}$  so can just generate a random hash function and check if it is collision free.

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Collisions again!

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,  $\mathbb{E}\left[\mathbb{I}_{\mathbf{h}(x_j)=i} \cdot \mathbb{I}_{\mathbf{h}(x_k)=i}\right] = \frac{1}{n^2}$ .

**Total Expected Space Usage:** (if we set n = m)

$$\mathbb{E}[S] = n + \sum_{i=1}^{n} \mathbb{E}[\mathbf{s}_{i}^{2}] \le n + n \cdot 2 = 3n = 3m.$$

# Near optimal space with O(1) query time!

 $x_j, x_k$ : stored items, m: # stored items, n: hash table size, h: random hash function, S: space usage of two level hashing,  $s_i$ : # items stored at pos i.

So Far: we have assumed a fully random hash function h(x) with  $Pr[h(x) = i] = \frac{1}{n}$  for  $i \in 1, ..., n$  and h(x), h(y) independent for  $x \neq y$ .

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 To compute a random hash function we have to store a table of x values and their hash values. Would take at least O(m) space and O(m) query time if we hash m values. Making our whole quest for O(1) query time pointless!

| X                     | h(x) |
|-----------------------|------|
| X <sub>1</sub>        | 45   |
| <b>X</b> <sub>2</sub> | 1004 |
| <b>X</b> <sub>3</sub> | 10   |
| :                     | ::   |
| X <sub>m</sub>        | 12   |

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**Efficient Alternative:** Let p be a prime with  $p \ge |U|$ . Choose random  $a, b \in [p]$  with  $a \ne 0$ . Let:

$$h(x) = (ax + b \mod p) \mod n.$$

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**Remember:** A fully random hash function is both 2-universal and pairwise independent. But it is not efficiently implementable.

### **NEXT STEP**

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- 1. We'll consider an application where our toolkit of linearity of expectation + Markov's inequality doesn't give much.
- 2. Then we'll show how a simple twist on Markov's can give a much stronger result.

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# Randomized Load Balancing:



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· Often assignment is done via a random hash function. Why?

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$$\mathbb{E}[\mathsf{R}_i] = \sum_{j=1}^n \mathbb{E}[\mathbb{I}_{\text{request } j \text{ assigned to } i}] = \sum_{j=1}^n \Pr[j \text{ assigned to } i] = \frac{n}{k}.$$

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Not great...half the servers may be overloaded.

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