# CS 473: Algorithms 

Ruta Mehta

University of Illinois, Urbana-Champaign
Spring 2018

## CS 473: Algorithms, Spring 2018

## High Probability Analysis \& Universal Hashing <br> Lecture 09

Feb 13, 2018

Most slides are courtesy Prof. Chekuri

## Outline

## Randomized QuickSort w.h.p. (any questions?)

What is the probability that the algorithm will terminate in $O(n \log n)$ time?

## Balls \& Bins

- Expected bin size.
- Expected max bin size $\rightarrow$ max size w.h.p.
- Analogy to hashing

Hashing

## Randomized QuickSort (Contd.)

## Randomized QuickSort: Recall

Input: Array $\boldsymbol{A}$ of $\boldsymbol{n}$ distinct numbers. Output: Numbers in sorted order.

## Randomized QuickSort

(1) Pick a pivot element uniformly at random from $\boldsymbol{A}$.
(2) Split array into 2 subarrays: those smaller than pivot (L), and those larger than pivot (R).
(3) Recursively sort the subarrays, and concatenate them.

## Randomized QuickSort: Recall

Input: Array $\boldsymbol{A}$ of $\boldsymbol{n}$ distinct numbers. Output: Numbers in sorted order.

## Randomized QuickSort

(1) Pick a pivot element uniformly at random from $\boldsymbol{A}$.
(2) Split array into 2 subarrays: those smaller than pivot (L), and those larger than pivot (R).
(3) Recursively sort the subarrays, and concatenate them.

Note: On every input randomized QuickSort takes $O(n \log n)$ time in expectation. On every input it may take $\Omega\left(n^{2}\right)$ time with some small probability.

## Randomized QuickSort: Recall

Input: Array $\boldsymbol{A}$ of $\boldsymbol{n}$ distinct numbers. Output: Numbers in sorted order.

## Randomized QuickSort

(1) Pick a pivot element uniformly at random from $\boldsymbol{A}$.
(2) Split array into 2 subarrays: those smaller than pivot (L), and those larger than pivot (R).
(3) Recursively sort the subarrays, and concatenate them.

Note: On every input randomized QuickSort takes $O(n \log n)$ time in expectation. On every input it may take $\Omega\left(n^{2}\right)$ time with some small probability.
Question: With what probability it takes $O(n \log n)$ time?

## Randomized QuickSort: High Probability Analysis

## Informal Statement

Random variable $Q(A)=\#$ comparisons done by the algorithm. We will show that $\operatorname{Pr}[Q(A) \leq 32 n \ln n] \geq 1-1 / n^{3}$.

## Randomized QuickSort: High Probability Analysis

## Informal Statement

Random variable $Q(A)=\#$ comparisons done by the algorithm. We will show that $\operatorname{Pr}[Q(A) \leq 32 n \ln n] \geq 1-1 / n^{3}$.

If $n=100$ then this gives $\operatorname{Pr}[Q(A) \leq 32 n \ln n] \geq 0.99999$.

## Randomized QuickSort: High Probability Analysis

## Informal Statement

We will show that $\operatorname{Pr}[Q(A) \leq 32 n \ln n] \geq 1-1 / n^{3}$.

## Outline of the proof

- If depth of recursion is $k$ then $Q(A) \leq k n$.
- Prove that depth of recursion $\leq 32 \ln \boldsymbol{n}$ with high probability (w.h.p.) . This will imply the result.


## Randomized QuickSort: High Probability Analysis

## Informal Statement

We will show that $\operatorname{Pr}[Q(A) \leq 32 n \ln n] \geq 1-1 / n^{3}$.

## Outline of the proof

- If depth of recursion is $k$ then $Q(A) \leq k n$.
- Prove that depth of recursion $\leq 32 \ln \boldsymbol{n}$ with high probability (w.h.p.) . This will imply the result.
(1) Focus on a single element. Prove that it "participates" in
$>32 \ln \boldsymbol{n}$ levels with probability (w.p.) at most $\mathbf{1} / \boldsymbol{n}^{4}$.
(2) By union bound, any of the $\boldsymbol{n}$ elements participates in $>32 \boldsymbol{l n} \boldsymbol{n}$ levels w.p. at most


## Randomized QuickSort: High Probability Analysis

## Informal Statement

We will show that $\operatorname{Pr}[Q(A) \leq 32 n \ln n] \geq 1-1 / n^{3}$.

## Outline of the proof

- If depth of recursion is $k$ then $Q(A) \leq k n$.
- Prove that depth of recursion $\leq 32 \ln \boldsymbol{n}$ with high probability (w.h.p.) . This will imply the result.
(1) Focus on a single element. Prove that it "participates" in
$>32 \ln \boldsymbol{n}$ levels with probability (w.p.) at most $\mathbf{1} / \boldsymbol{n}^{4}$.
(2) By union bound, any of the $\boldsymbol{n}$ elements participates in $>32 \ln \boldsymbol{n}$ levels w.p. at most $\mathbf{1} / \boldsymbol{n}^{3}$.


## Randomized QuickSort: High Probability Analysis

## Informal Statement

We will show that $\operatorname{Pr}[Q(A) \leq 32 n \ln n] \geq 1-1 / n^{3}$.

## Outline of the proof

- If depth of recursion is $k$ then $Q(A) \leq k n$.
- Prove that depth of recursion $\leq 32 \ln \boldsymbol{n}$ with high probability (w.h.p.) . This will imply the result.
(1) Focus on a single element. Prove that it "participates" in
$>32 \ln n$ levels with probability (w.p.) at most $1 / \boldsymbol{n}^{4}$.
(2) By union bound, any of the $\boldsymbol{n}$ elements participates in $>32 \ln \boldsymbol{n}$ levels w.p. at most $\mathbf{1} \boldsymbol{n}^{\mathbf{3}}$.
(3) Therefore, all elements participate in $\leq 32 \ln n$ w.p. $\left(1-1 / n^{3}\right)$.


## Randomized QuickSort: High Probability Analysis

## Informal Statement

An element participates in $>32 \ln n$ w.p. $\leq 1 / n^{4}$.

## Intuition

(1) When we pick a pivot from an array of size $n$ uniformly at random, what is the probability that its rank is between $n / 4$ and $3 n / 4$ ?

## Randomized QuickSort: High Probability Analysis

## Informal Statement

An element participates in $>32 \ln n$ w.p. $\leq 1 / n^{4}$.

## Intuition

(1) When we pick a pivot from an array of size $n$ uniformly at random, what is the probability that its rank is between $n / 4$ and $3 n / 4$ ? 1/2.

## Randomized QuickSort: High Probability Analysis

## Informal Statement

An element participates in $>32 \ln n$ w.p. $\leq 1 / n^{4}$.

## Intuition

(1) When we pick a pivot from an array of size $n$ uniformly at random, what is the probability that its rank is between $n / 4$ and $3 n / 4$ ? $1 / 2$.
(2) If we pick such a pivot then the size of $L$ and $R$ is at most?

## Randomized QuickSort: High Probability Analysis

## Informal Statement

An element participates in $>32 \ln n$ w.p. $\leq 1 / n^{4}$.

## Intuition

(1) When we pick a pivot from an array of size $n$ uniformly at random, what is the probability that its rank is between $n / 4$ and $3 n / 4$ ? $1 / 2$.
(2) If we pick such a pivot then the size of $L$ and $R$ is at most? $3 n / 4$. (Balanced split)

## Randomized QuickSort: High Probability Analysis

## Informal Statement

An element participates in $>32 \ln n$ w.p. $\leq 1 / n^{4}$.

## Intuition

(1) When we pick a pivot from an array of size $n$ uniformly at random, what is the probability that its rank is between $n / 4$ and $3 n / 4$ ? $1 / 2$.
(2) If we pick such a pivot then the size of $L$ and $R$ is at most? $3 n / 4$. (Balanced split)
(3) If an array is reduced to at least its 3/4th size every time, then after how many rounds only one element remains?

## Randomized QuickSort: High Probability Analysis

## Informal Statement

An element participates in $>32 \ln n$ w.p. $\leq 1 / n^{4}$.

## Intuition

(1) When we pick a pivot from an array of size $n$ uniformly at random, what is the probability that its rank is between $n / 4$ and $3 n / 4$ ? $1 / 2$.
(2) If we pick such a pivot then the size of $L$ and $R$ is at most? $3 n / 4$. (Balanced split)
(3) If an array is reduced to at least its $3 / 4$ th size every time, then after how many rounds only one element remains? $\leq 4 \ln n$.

## Randomized QuickSort: High Probability Analysis

## Informal Statement

An element participates in $>\mathbf{3 2} \ln \boldsymbol{n}$ w.p. $\leq \mathbf{1} / \boldsymbol{n}^{4}$.

## Intuition

(1) When we pick a pivot from an array of size $n$ uniformly at random, what is the probability that its rank is between $n / 4$ and $3 n / 4$ ? $1 / 2$.
(2) If we pick such a pivot then the size of $L$ and $R$ is at most? $3 n / 4$. (Balanced split)
(3) If an array is reduced to at least its $3 / 4$ th size every time, then after how many rounds only one element remains? $\leq 4 \ln n$.
(4) If $32 \ln \boldsymbol{n}$ splits, then $\mathbf{E}[$ Balanced-split] $=16 \ln n$. Out of these there are $<4 \ln \boldsymbol{n}$ balanced split w.p. $\leq 1 / \boldsymbol{n}^{4}$.

## Randomized QuickSort: High Probability Analysis

- If $\boldsymbol{k}$ levels of recursion then $\boldsymbol{k} \boldsymbol{n}$ comparisons.


## Randomized QuickSort: High Probability Analysis

- If $\boldsymbol{k}$ levels of recursion then $\boldsymbol{k} \boldsymbol{n}$ comparisons.
- Fix an element $s \in \boldsymbol{A}$. We will track it at each level.
- Let $S_{i}$ be the partition containing $s$ at $\boldsymbol{i}^{\text {th }}$ level.
- $S_{1}=A$ and $S_{k}=\{s\}$.


## Randomized QuickSort: High Probability Analysis

- If $k$ levels of recursion then $k n$ comparisons.
- Fix an element $s \in \boldsymbol{A}$. We will track it at each level.
- Let $S_{i}$ be the partition containing $s$ at $i^{\text {th }}$ level.
- $S_{1}=A$ and $S_{k}=\{s\}$.
- We call $s$ lucky in $i^{\text {th }}$ iteration, if balanced split:

$$
\left|S_{i+1}\right| \leq(3 / 4)\left|S_{i}\right| \text { and }\left|S_{i} \backslash S_{i+1}\right| \leq(3 / 4)\left|S_{i}\right| .
$$

## Randomized QuickSort: High Probability Analysis

- If $k$ levels of recursion then $k n$ comparisons.
- Fix an element $s \in \boldsymbol{A}$. We will track it at each level.
- Let $S_{i}$ be the partition containing $s$ at $i^{\text {th }}$ level.
- $S_{1}=A$ and $S_{k}=\{s\}$.
- We call $s$ lucky in $i^{\text {th }}$ iteration, if balanced split:

$$
\left|S_{i+1}\right| \leq(3 / 4)\left|S_{i}\right| \text { and }\left|S_{i} \backslash S_{i+1}\right| \leq(3 / 4)\left|S_{i}\right| .
$$

- If $\rho=\#$ lucky rounds in first $k$ rounds, then $\left|S_{k}\right| \leq(3 / 4)^{\rho} n$.


## Randomized QuickSort: High Probability Analysis

- If $k$ levels of recursion then $k n$ comparisons.
- Fix an element $s \in \boldsymbol{A}$. We will track it at each level.
- Let $S_{i}$ be the partition containing $s$ at $i^{\text {th }}$ level.
- $S_{1}=A$ and $S_{k}=\{s\}$.
- We call $s$ lucky in $i^{\text {th }}$ iteration, if balanced split:

$$
\left|S_{i+1}\right| \leq(3 / 4)\left|S_{i}\right| \text { and }\left|S_{i} \backslash S_{i+1}\right| \leq(3 / 4)\left|S_{i}\right| .
$$

- If $\rho=\#$ lucky rounds in first $k$ rounds, then $\left|S_{k}\right| \leq(3 / 4)^{\rho} n$.
- For $\left|S_{k}\right|=1, \rho=4 \ln n \geq \log _{4 / 3} n$ suffices.


## How may rounds before $4 \ln n$ lucky rounds?

- $X_{i}=1$ if $s$ is lucky in $i^{\text {th }}$ iteration.


## How may rounds before $4 \ln n$ lucky rounds?

- $X_{i}=1$ if $s$ is lucky in $i^{\text {th }}$ iteration.
- Observation: $X_{1}, \ldots, X_{k}$ are independent variables.
- $\operatorname{Pr}\left[X_{i}=1\right]=\frac{1}{2} \quad$ Why?


## How may rounds before $4 \ln n$ lucky rounds?

- $X_{i}=1$ if $s$ is lucky in $i^{\text {th }}$ iteration.
- Observation: $X_{1}, \ldots, X_{k}$ are independent variables.
- $\operatorname{Pr}\left[X_{i}=1\right]=\frac{1}{2} \quad$ Why?
- Clearly, $\rho=\sum_{i=1}^{k} X_{i}$. Let $\mu=\mathrm{E}[\rho]=\frac{k}{2}$.


## How may rounds before $4 \ln n$ lucky rounds?

- $X_{i}=1$ if $s$ is lucky in $i^{\text {th }}$ iteration.
- Observation: $X_{1}, \ldots, X_{k}$ are independent variables.
- $\operatorname{Pr}\left[X_{i}=1\right]=\frac{1}{2} \quad$ Why?
- Clearly, $\rho=\sum_{i=1}^{k} X_{i}$. Let $\mu=\mathrm{E}[\rho]=\frac{k}{2}$.
- Set $k=32 \ln n$ and $\delta=\frac{3}{4}$. $(1-\delta)=\frac{1}{4}$.


## How may rounds before $4 \ln n$ lucky rounds?

- $X_{i}=1$ if $s$ is lucky in $i^{\text {th }}$ iteration.
- Observation: $X_{1}, \ldots, X_{k}$ are independent variables.
- $\operatorname{Pr}\left[X_{i}=1\right]=\frac{1}{2} \quad$ Why?
- Clearly, $\rho=\sum_{i=1}^{k} X_{i}$. Let $\mu=\mathrm{E}[\rho]=\frac{k}{2}$.
- Set $k=32 \ln n$ and $\delta=\frac{3}{4} .(1-\delta)=\frac{1}{4}$.

Probability of $\leq \mathbf{4} \ln \boldsymbol{n}$ lucky rounds out of $\mathbf{3 2} \boldsymbol{\operatorname { l n }} \boldsymbol{n}$ rounds is,

## How may rounds before $4 \ln n$ lucky rounds?

- $X_{i}=1$ if $s$ is lucky in $i^{\text {th }}$ iteration.
- Observation: $X_{1}, \ldots, X_{k}$ are independent variables.
- $\operatorname{Pr}\left[X_{i}=1\right]=\frac{1}{2} \quad$ Why?
- Clearly, $\rho=\sum_{i=1}^{k} X_{i}$. Let $\mu=\mathrm{E}[\rho]=\frac{k}{2}$.
- Set $k=32 \ln n$ and $\delta=\frac{3}{4}$. $(1-\delta)=\frac{1}{4}$.

Probability of $\leq 4 \ln \boldsymbol{n}$ lucky rounds out of $\mathbf{3 2} \ln \boldsymbol{n}$ rounds is,

$$
\begin{aligned}
\operatorname{Pr}[\rho \leq 4 \ln n] & =\operatorname{Pr}[\rho \leq k / 8] \\
& =\operatorname{Pr}[\rho \leq(1-\delta) \mu]
\end{aligned}
$$

## How may rounds before $4 \ln n$ lucky rounds?

- $X_{i}=1$ if $s$ is lucky in $i^{\text {th }}$ iteration.
- Observation: $X_{1}, \ldots, X_{k}$ are independent variables.
- $\operatorname{Pr}\left[X_{i}=1\right]=\frac{1}{2} \quad$ Why?
- Clearly, $\rho=\sum_{i=1}^{k} X_{i}$. Let $\mu=\mathrm{E}[\rho]=\frac{k}{2}$.
- Set $k=32 \ln n$ and $\delta=\frac{3}{4} .(1-\delta)=\frac{1}{4}$.

Probability of $\leq 4 \ln \boldsymbol{n}$ lucky rounds out of $\mathbf{3 2} \ln \boldsymbol{n}$ rounds is,

$$
\begin{aligned}
\operatorname{Pr}[\rho \leq 4 \ln n] & =\operatorname{Pr}[\rho \leq k / 8] \\
& =\operatorname{Pr}[\rho \leq(1-\delta) \mu] \\
\text { (Chernoff) } & \leq 2 e^{-\frac{\delta^{2} \mu}{2}} \\
& =2 e^{-\frac{9 k}{64}} \\
& =2 e^{-4.5 \ln n} \leq \frac{1}{n^{4}}
\end{aligned}
$$

## Randomized QuickSort w.h.p. Analysis

- n input elements. Probability that depth of recursion in QuickSort $>32 \ln n$ is at most $\frac{1}{n^{4}} * n=\frac{1}{n^{3}}$.


## Randomized QuickSort w.h.p. Analysis

- n input elements. Probability that depth of recursion in QuickSort $>32 \ln n$ is at most $\frac{1}{n^{4}} * n=\frac{1}{n^{3}}$.


## Theorem

With high probability (i.e., $1-\frac{1}{n^{3}}$ ) the depth of the recursion of QuickSort is $\leq \mathbf{3 2} \ln \boldsymbol{n}$. Due to $\boldsymbol{n}$ comparisons in each level, with high probability, the running time of QuickSort is $O(n \ln n)$.

## Randomized QuickSort w.h.p. Analysis

- n input elements. Probability that depth of recursion in QuickSort $>32 \ln n$ is at most $\frac{1}{n^{4}} * n=\frac{1}{n^{3}}$.


## Theorem

With high probability (i.e., $1-\frac{1}{n^{3}}$ ) the depth of the recursion of QuickSort is $\leq \mathbf{3 2} \ln \boldsymbol{n}$. Due to $\boldsymbol{n}$ comparisons in each level, with high probability, the running time of QuickSort is $O(n \ln n)$.

Q: How to increase the probability?

## Part II

## Balls and Bins

## Expected Bin Size

## Problem

If $n$ balls are thrown independently and uniformly into $n$ bins, how many balls lend in a bin in expectation (expected size of a bin)?

## Expected Bin Size

## Problem

If $n$ balls are thrown independently and uniformly into $n$ bins, how many balls lend in a bin in expectation (expected size of a bin)?

## Solution

- Fix a bin, say $j$.


## Expected Bin Size

## Problem

If $\boldsymbol{n}$ balls are thrown independently and uniformly into $\boldsymbol{n}$ bins, how many balls lend in a bin in expectation (expected size of a bin)?

## Solution

- Fix a bin, say $j$.
- Random variable $\boldsymbol{X}_{i j}$ is $\mathbf{1}$ if $\boldsymbol{i}$ th balls falls in $\boldsymbol{j}$ th bin, otherwise $\mathbf{0}$.


## Expected Bin Size

## Problem

If $\boldsymbol{n}$ balls are thrown independently and uniformly into $\boldsymbol{n}$ bins, how many balls lend in a bin in expectation (expected size of a bin)?

## Solution

- Fix a bin, say $\boldsymbol{j}$.
- Random variable $X_{i j}$ is $\mathbf{1}$ if $\boldsymbol{i}$ th balls falls in $\boldsymbol{j}$ th bin, otherwise $\mathbf{0}$.
- $\mathrm{E}\left[X_{i j}\right]=\operatorname{Pr}\left[X_{i j}=1\right]=$


## Expected Bin Size

## Problem

If $\boldsymbol{n}$ balls are thrown independently and uniformly into $\boldsymbol{n}$ bins, how many balls lend in a bin in expectation (expected size of a bin)?

## Solution

- Fix a bin, say $\boldsymbol{j}$.
- Random variable $X_{i j}$ is $\mathbf{1}$ if $\boldsymbol{i}$ th balls falls in $\boldsymbol{j}$ th bin, otherwise $\mathbf{0}$.
- $\mathrm{E}\left[X_{i j}\right]=\operatorname{Pr}\left[X_{i j}=1\right]=1 / n$.


## Expected Bin Size

## Problem

If $\boldsymbol{n}$ balls are thrown independently and uniformly into $\boldsymbol{n}$ bins, how many balls lend in a bin in expectation (expected size of a bin)?

## Solution

- Fix a bin, say $\boldsymbol{j}$.
- Random variable $X_{i j}$ is $\mathbf{1}$ if $i$ th balls falls in $j$ th bin, otherwise $\mathbf{0}$.
- $E\left[X_{i j}\right]=\operatorname{Pr}\left[X_{i j}=1\right]=1 / n$.
- R.V. $Y_{j}=\#$ balls in $j$ th bin $=\sum_{i=1}^{n} X_{i j}$.


## Expected Bin Size

## Problem

If $\boldsymbol{n}$ balls are thrown independently and uniformly into $\boldsymbol{n}$ bins, how many balls lend in a bin in expectation (expected size of a bin)?

## Solution

- Fix a bin, say $\boldsymbol{j}$.
- Random variable $X_{i j}$ is $\mathbf{1}$ if $i$ th balls falls in $j$ th bin, otherwise $\mathbf{0}$.
- $E\left[X_{i j}\right]=\operatorname{Pr}\left[X_{i j}=1\right]=1 / n$.
- R.V. $Y_{j}=\#$ balls in $j$ th bin $=\sum_{i=1}^{n} X_{i j}$.
- $\mathrm{E}\left[Y_{j}\right]=\sum_{i=1}^{n} \mathrm{E}\left[X_{i j}\right]=n \cdot 1 / n=1$.


## Expected Max Bin Size

## Problem

If $\boldsymbol{n}$ balls are thrown independently and uniformly into $\boldsymbol{n}$ bins, what is the expected "maximum" bin size?

## Expected Max Bin Size

## Problem

If $\boldsymbol{n}$ balls are thrown independently and uniformly into $\boldsymbol{n}$ bins, what is the expected "maximum" bin size?

$$
E\left[\max _{j=1}^{n} Y_{j}\right] ?
$$

## Expected Max Bin Size

## Problem

If $\boldsymbol{n}$ balls are thrown independently and uniformly into $\boldsymbol{n}$ bins, what is the expected "maximum" bin size?

$$
E\left[\max _{j=1}^{n} Y_{j}\right] ?
$$

## Possible Solution

- R.V. $Z=\max _{j=1}^{n} Y_{j} . \mathrm{E}[Z]=\sum_{k=1}^{n} \operatorname{Pr}[Z=k] k$.


## Expected Max Bin Size

## Problem

If $\boldsymbol{n}$ balls are thrown independently and uniformly into $\boldsymbol{n}$ bins, what is the expected "maximum" bin size?

$$
E\left[\max _{j=1}^{n} Y_{j}\right] ?
$$

## Possible Solution

- R.V. $Z=\max _{j=1}^{n} Y_{j} . \mathrm{E}[Z]=\sum_{k=1}^{n} \operatorname{Pr}[Z=k] k$.
- How to compute $\operatorname{Pr}[Z=k]$, i.e., count configurations where no bin has more than $k$ balls and at least one has $k$ balls.


## Expected Max Bin Size

## Problem

If $\boldsymbol{n}$ balls are thrown independently and uniformly into $\boldsymbol{n}$ bins, what is the expected "maximum" bin size?

$$
E\left[\max _{j=1}^{n} Y_{j}\right] ?
$$

## Possible Solution

- R.V. $Z=\max _{j=1}^{n} Y_{j} . \mathrm{E}[Z]=\sum_{k=1}^{n} \operatorname{Pr}[Z=k] k$.
- How to compute $\operatorname{Pr}[Z=k]$, i.e., count configurations where no bin has more than $k$ balls and at least one has $k$ balls.
- Too many to count!!


## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size?

$$
\text { R.V. } Z=\max _{j=1}^{n} Y_{j} \text {. Show } \mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right) \text { ? }
$$

## Possible Solution

- If $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$, then: define $A=\frac{8 \ln n}{\ln \ln n}$.


## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size?

$$
\text { R.V. } Z=\max _{j=1}^{n} Y_{j} \text {. Show } \mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right) \text { ? }
$$

## Possible Solution

- If $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$, then: define $A=\frac{8 \ln n}{\ln \ln n}$.

$$
\begin{aligned}
\mathrm{E}[Z] & =\sum_{k=1}^{n} \operatorname{Pr}[Z=k] k \\
& \leq \sum_{k=1}^{A} \operatorname{Pr}[Z=k] A+\sum_{k=A+1}^{n} \operatorname{Pr}[Z=k] n
\end{aligned}
$$

## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size?

$$
\text { R.V. } Z=\max _{j=1}^{n} Y_{j} \text {. Show } \mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right) \text { ? }
$$

## Possible Solution

- If $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$, then: define $A=\frac{8 \ln n}{\ln \ln n}$.

$$
\begin{aligned}
\mathrm{E}[Z] & =\sum_{k=1}^{n} \operatorname{Pr}[Z=k] k \\
& \leq \sum_{k=1}^{A} \operatorname{Pr}[Z=k] A+\sum_{k=A+1}^{n} \operatorname{Pr}[Z=k] n \\
& \leq A \cdot \operatorname{Pr}[Z \leq A]+n \cdot \operatorname{Pr}[Z>A] \\
& \leq A \cdot(1)+n \cdot\left(1 / n^{2}\right)=O(A)=O\left(\frac{\ln n}{\ln \ln n}\right)
\end{aligned}
$$

## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size?

$$
\text { R.V. } Z=\max _{j=1}^{n} Y_{j} \text {. Show } \mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right) \text { ? }
$$

## Possible Solution

- If $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$, then: define $A=\frac{8 \ln n}{\ln \ln n}$.

$$
\begin{aligned}
\mathrm{E}[Z] & =\sum_{k=1}^{n} \operatorname{Pr}[Z=k] k \\
& \leq \sum_{k=1}^{A} \operatorname{Pr}[Z=k] A+\sum_{k=A+1}^{n} \operatorname{Pr}[Z=k] n \\
& \leq A \cdot \operatorname{Pr}[Z \leq A]+n \cdot \operatorname{Pr}[Z>A] \\
& \leq A \cdot(1)+n \cdot\left(1 / n^{2}\right)=O(A)=O\left(\frac{\ln n}{\ln \ln n}\right)
\end{aligned}
$$

$$
\text { Bound } \operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \text {. }
$$

## Expected Max Bin Size (Contd.)

Bound $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right]$ using Chernoff inequality.

## Chernoff Ineq. We Saw

$X_{1}, \ldots, X_{k}$ independent binary R.V., and $X=\sum_{i=1}^{k} X_{i}$, $\mu=\mathrm{E}[X]$, then for $\mathbf{0}<\delta<\mathbf{1}$

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

## Expected Max Bin Size (Contd.)

Bound $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right]$ using Chernoff inequality.

## Chernoff Ineq. We Saw

$X_{1}, \ldots, X_{k}$ independent binary R.V., and $X=\sum_{i=1}^{k} X_{i}$, $\mu=\mathrm{E}[X]$, then for $\mathbf{0}<\delta<\mathbf{1}$

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

## Stronger Versions

- For $\delta>0, \operatorname{Pr}[X>(1+\delta) \mu]<\left(\frac{e^{\delta}}{(1+\delta)^{(1+\delta)}}\right)^{\mu}$.
- For $0<\delta<1 \operatorname{Pr}[X<(1-\delta) \mu]<\left(\frac{e^{-\delta}}{(1-\delta)^{(1-\delta)}}\right)^{\mu}$


## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size? Let $Z=\max _{j=1}^{\boldsymbol{j}} Y_{j}$. Show $\mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right)$. $\rightarrow$ Show $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$.

## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size? Let $Z=\max _{j=1}^{\boldsymbol{n}} Y_{j}$. Show $\mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right)$. $\rightarrow$ Show $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$.

## Solution

- Recall: $Y_{j}=\#$ balls in bin $j, \mathrm{E}\left[Y_{j}\right]=1$, and $A=\frac{8 \ln n}{\ln \ln n}$

$$
\operatorname{Pr}\left[Y_{j}>A\right]=\operatorname{Pr}\left[Y_{j} \geq A E[Y]\right]<\left(\frac{e^{A-1}}{A^{A}}\right)<\left(\frac{n^{6 / \ln \ln n}}{A^{A}}\right)
$$

## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size? Let $Z=\max _{j=1}^{\boldsymbol{n}} Y_{j}$. Show $\mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right)$. $\rightarrow$ Show $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$.

## Solution

- Recall: $Y_{j}=\#$ balls in bin $j, \mathrm{E}\left[Y_{j}\right]=1$, and $A=\frac{8 \ln n}{\ln \ln n}$

$$
\begin{aligned}
& \operatorname{Pr}\left[Y_{j}>A\right]=\operatorname{Pr}\left[Y_{j} \geq A E[Y]\right]<\left(\frac{e^{A-1}}{A^{A}}\right)<\left(\frac{n^{6 / \ln \ln n}}{A^{A}}\right) \\
& A^{A}=\left(\frac{8 \ln n}{\ln \ln n}\right)^{\frac{8 \ln n}{\ln \ln n}} \geq(\sqrt{\ln n})^{\frac{8 \ln n}{\ln n} n}=(\ln n)^{\frac{4 \ln n}{\ln n} n}=e^{4 \lg n}=n^{4}
\end{aligned}
$$

## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size? Let $Z=\max _{j=1}^{\boldsymbol{n}} Y_{j}$. Show $\mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right)$. $\rightarrow$ Show $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$.

## Solution

- Recall: $Y_{j}=\#$ balls in bin $j, \mathrm{E}\left[Y_{j}\right]=1$, and $A=\frac{8 \ln n}{\ln \ln n}$

$$
\operatorname{Pr}\left[Y_{j}>A\right]=\operatorname{Pr}\left[Y_{j} \geq A E[Y]\right]<\left(\frac{e^{A-1}}{A^{A}}\right)<\left(\frac{n^{6 / \ln \ln n}}{A^{A}}\right)
$$

$$
A^{A}=\left(\frac{8 \ln n}{\ln \ln n}\right)^{\frac{8 \ln n}{\ln n}} \geq(\sqrt{\ln n})^{\frac{8 \ln n}{\ln n} n}=(\ln n)^{\frac{4 \ln n}{\ln \ln n}}=e^{4 / \lg n}=n^{4}
$$

$$
\operatorname{Pr}\left[Y_{j}>\frac{8 \ln n}{\ln \ln n}\right]<1 / n^{3}
$$

## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size? Let $Z=\max _{j=1}^{n} Y_{j}$. Show $\mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right) \rightarrow$ Show $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$.

## Solution

- Recall: $Y_{j}=\#$ balls in bin $j . \mathrm{E}\left[Y_{j}\right]=1$.

$$
\operatorname{Pr}\left[Y_{j}>8 \ln n / \ln \ln n\right] \leq 1 / n^{3}
$$

(Using Chernoff)

## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size? Let $Z=\max _{j=1}^{\boldsymbol{i}} Y_{j}$. Show $\mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right) \rightarrow$ Show $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$.

## Solution

- Recall: $Y_{j}=\#$ balls in bin $j . \mathrm{E}\left[Y_{j}\right]=1$.

$$
\operatorname{Pr}\left[Y_{j}>8 \ln n / \ln \ln n\right] \leq 1 / n^{3} \quad \text { (Using Chernoff) }
$$

- (Union bound)

$$
\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq \sum_{j=1}^{n} \operatorname{Pr}\left[Y_{j}>\frac{8 \ln n}{\ln \ln n}\right] \leq n \cdot 1 / n^{3}=1 / n^{2} .
$$

## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size? Let $Z=\max _{j=1}^{\boldsymbol{i}} Y_{j}$. Show $\mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right) \rightarrow$ Show $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$.

## Solution

- Recall: $Y_{j}=\#$ balls in bin $j . \mathrm{E}\left[Y_{j}\right]=1$.

$$
\operatorname{Pr}\left[Y_{j}>8 \ln n / \ln \ln n\right] \leq 1 / n^{3} \quad \text { (Using Chernoff) }
$$

- (Union bound)

$$
\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq \sum_{j=1}^{n} \operatorname{Pr}\left[Y_{j}>\frac{8 \ln n}{\ln \ln n}\right] \leq n \cdot 1 / n^{3}=1 / n^{2} .
$$

- Max bin size is at most $O\left(\frac{\ln n}{\ln \ln n}\right)$ with probability $1-1 / n^{2}$.


## Expected Max Bin Size (Contd.)

## Problem

What is the expected maximum bin size? Let $Z=\max _{j=1}^{\boldsymbol{i}} Y_{j}$. Show $\mathrm{E}[Z] \leq O\left(\frac{\ln n}{\ln \ln n}\right) \rightarrow$ Show $\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq 1 / n^{2}$.

## Solution

- Recall: $Y_{j}=\#$ balls in bin $j . \mathrm{E}\left[Y_{j}\right]=1$.

$$
\operatorname{Pr}\left[Y_{j}>8 \ln n / \ln \ln n\right] \leq 1 / n^{3} \quad \text { (Using Chernoff) }
$$

- (Union bound)

$$
\operatorname{Pr}\left[Z>\frac{8 \ln n}{\ln \ln n}\right] \leq \sum_{j=1}^{n} \operatorname{Pr}\left[Y_{j}>\frac{8 \ln n}{\ln \ln n}\right] \leq n \cdot 1 / n^{3}=1 / n^{2} .
$$

- Max bin size is at most $O\left(\frac{\ln n}{\ln \ln n}\right)$ with probability $1-1 / n^{2}$.

$$
\Omega\left(\frac{\ln n}{\ln \ln n}\right) \text { is a lower bound as well! }
$$

## Balls $n$ Bins $\rightarrow$ Hashing

## Hashing

Storing elements in a table such that look up is $O(1)$-time.

## Balls $n$ Bins $\rightarrow$ Hashing

## Hashing

Storing elements in a table such that look up is $O(1)$-time.

## Throwing numbered balls

Imagine that $\boldsymbol{n}$ balls have numbers coming from a universe $\mathcal{U}$. $|\mathcal{U}| \gg n$.

## Balls $n$ Bins $\rightarrow$ Hashing

## Hashing

Storing elements in a table such that look up is $O(1)$-time.

## Throwing numbered balls

Imagine that $\boldsymbol{n}$ balls have numbers coming from a universe $\mathcal{U}$. $|\mathcal{U}| \gg n$.

Hashing: throw balls (elements) randomly into $\boldsymbol{n}$ bins such that bin sizes are small

## Balls n Bins $\rightarrow$ Hashing

## Hashing

Storing elements in a table such that look up is $O(1)$-time.

## Throwing numbered balls

Imagine that $\boldsymbol{n}$ balls have numbers coming from a universe $\mathcal{U}$. $|\mathcal{U}| \gg n$.

Hashing: throw balls (elements) randomly into $\boldsymbol{n}$ bins such that bin sizes are small and also lookup is easy!.

## Part III

## Hash Tables

## Dictionary Data Structure

(1) $\mathcal{U}$ : universe of keys with total order: numbers, strings, etc.
(2) Data structure to store a subset $S \subseteq \mathcal{U}$
(3) Operations:
(1) Search/lookup: given $x \in \mathcal{U}$ is $x \in S$ ?
(2) Insert: given $x \notin S$ add $x$ to $S$.
(3) Delete: given $x \in S$ delete $x$ from $S$

## Dictionary Data Structure

(1) $\mathcal{U}$ : universe of keys with total order: numbers, strings, etc.
(2) Data structure to store a subset $S \subseteq \mathcal{U}$
(3) Operations:
(1) Search/lookup: given $x \in \mathcal{U}$ is $x \in S$ ?
(2) Insert: given $x \notin S$ add $x$ to $S$.
(3) Delete: given $\boldsymbol{x} \in \boldsymbol{S}$ delete $\boldsymbol{x}$ from $\boldsymbol{S}$
(9) Static structure: $S$ given in advance or changes very infrequently, main operations are lookups.

## Dictionary Data Structure

(1) $\mathcal{U}$ : universe of keys with total order: numbers, strings, etc.
(2) Data structure to store a subset $S \subseteq \mathcal{U}$
(3) Operations:
(1) Search/lookup: given $x \in \mathcal{U}$ is $x \in S$ ?
(2) Insert: given $x \notin S$ add $x$ to $S$.
(3) Delete: given $x \in S$ delete $x$ from $S$
(9) Static structure: $S$ given in advance or changes very infrequently, main operations are lookups.
(5) Dynamic structure: $S$ changes rapidly so inserts and deletes as important as lookups.

## Dictionary Data Structures

Common solutions:
(1) Static:
(1) Store $S$ as a sorted array
(2) Lookup: Binary search in $\boldsymbol{O}(\log |S|)$ time (comparisons)
(2) Dynamic:
(1) Store $\boldsymbol{S}$ in a balanced binary search tree
(2) Lookup, Insert, Delete in $\boldsymbol{O}(\log |\boldsymbol{S}|)$ time (comparisons)

## Dictionary Data Structures

Question: "Should Tables be Sorted?"
(also title of famous paper by Turing award winner Andy Yao)

## Dictionary Data Structures

Question: "Should Tables be Sorted?"
(also title of famous paper by Turing award winner Andy Yao)
Hashing is a widely used \& powerful technique for dictionaries.

## Motivation:

(1) Universe $\mathcal{U}$ may not be (naturally) totally ordered.
© Keys correspond to large objects (images, graphs etc) for which comparisons are very expensive.
(0 Want to improve "average" performance of lookups to $O(\mathbf{1})$ even at cost of extra space or errors with small probability: many applications for fast lookups in networking, security, etc.

## Hashing and Hash Tables

Hash Table data structure:
(1) A (hash) table/array $\boldsymbol{T}$ of size $\boldsymbol{m}$ (the table size).
(2) A hash function $h: \mathcal{U} \rightarrow\{0, \ldots, m-1\}$.
(3) Item $x \in \mathcal{U}$ hashes to slot $h(x)$ in $T$.

## Hashing and Hash Tables

Hash Table data structure:
(1) A (hash) table/array $\boldsymbol{T}$ of size $\boldsymbol{m}$ (the table size).
(2) A hash function $h: \mathcal{U} \rightarrow\{0, \ldots, m-1\}$.
(3) Item $x \in \mathcal{U}$ hashes to slot $h(x)$ in $T$.

Given $S \subseteq \mathcal{U}$. How do we store $S$ and how do we do lookups?

## Hashing and Hash Tables

Hash Table data structure:
(1) A (hash) table/array $\boldsymbol{T}$ of size $\boldsymbol{m}$ (the table size).
(2) A hash function $h: \mathcal{U} \rightarrow\{0, \ldots, m-1\}$.
(3) Item $x \in \mathcal{U}$ hashes to slot $h(x)$ in $T$.

Given $S \subseteq \mathcal{U}$. How do we store $S$ and how do we do lookups?

## Ideal situation:

(1) Each element $x \in S$ hashes to a distinct slot in $T$. Store $x$ in slot $h(x)$
(2) Lookup: Given $y \in \mathcal{U}$ check if $T[h(y)]=y . O(1)$ time!

## Hashing and Hash Tables

Hash Table data structure:
(1) A (hash) table/array $\boldsymbol{T}$ of size $\boldsymbol{m}$ (the table size).
(2) A hash function $h: \mathcal{U} \rightarrow\{0, \ldots, m-1\}$.
(3) Item $x \in \mathcal{U}$ hashes to slot $\boldsymbol{h ( x )}$ in $T$.

Given $S \subseteq \mathcal{U}$. How do we store $S$ and how do we do lookups?

## Ideal situation:

(1) Each element $x \in S$ hashes to a distinct slot in $T$. Store $x$ in slot $h(x)$
(2) Lookup: Given $y \in \mathcal{U}$ check if $T[h(y)]=y . O(1)$ time!

Collisions unavoidable if $|\boldsymbol{T}|<|\mathcal{U}|$. Several techniques to handle them.

## Handling Collisions: Chaining

Collision: $h(x)=h(y)$ for some $x \neq y$.
Chaining to handle collisions:
(1) For each slot $i$ store all items hashed to slot $i$ in a linked list. $T[i]$ points to the linked list
(2) Lookup: to find if $y \in \mathcal{U}$ is in $T$, check the linked list at $T[h(y)]$. Time proportion to size of linked list.


This is also known as Open hashing.

## Handling Collisions

Several other techniques:
(1) Cuckoo hashing.

Every value has two possible locations. When inserting, insert in one of the locations, otherwise, kick stored value to its other location. Repeat till stable. if no stability then rebuild table.
(2) ...
© Others.

## Understanding Hashing

Does hashing give $O(1)$ time per operation for dictionaries?

## Understanding Hashing

Does hashing give $O(1)$ time per operation for dictionaries?

## Questions:

(1) Complexity of evaluating $h$ on a given element?
(2) Relative sizes of the universe $\mathcal{U}$ and the set to be stored $S$.
(0) Size of table relative to size of $S$.

- Worst-case vs average-case vs randomized (expected) time?
(0. How do we choose $\boldsymbol{h}$ ?


## Understanding Hashing

(1) Complexity of evaluating $\boldsymbol{h}$ on a given element? Should be small.
(2) Relative sizes of the universe $\mathcal{U}$ and the set to be stored $S$ : typically $|\mathcal{U}| \gg|S|$.

## Understanding Hashing

(1) Complexity of evaluating $\boldsymbol{h}$ on a given element? Should be small.
(2) Relative sizes of the universe $\mathcal{U}$ and the set to be stored $S$ : typically $|\mathcal{U}| \gg|S|$.
© Size of table relative to size of $S$. The load factor of $T$ is the ratio $n / m$ where $n=|S|$ and $m=|T|$.

## Understanding Hashing

(1) Complexity of evaluating $\boldsymbol{h}$ on a given element? Should be small.
(2) Relative sizes of the universe $\mathcal{U}$ and the set to be stored $S$ : typically $|\mathcal{U}| \gg|S|$.
© Size of table relative to size of $S$. The load factor of $T$ is the ratio $n / m$ where $n=|S|$ and $m=|T|$. Typically $n / m$ is a small constant smaller than 1.

Also known as the fill factor.

## Understanding Hashing

(1) Complexity of evaluating $\boldsymbol{h}$ on a given element? Should be small.
(2) Relative sizes of the universe $\mathcal{U}$ and the set to be stored $S$ : typically $|\mathcal{U}| \gg|S|$.
© Size of table relative to size of $S$. The load factor of $T$ is the ratio $n / m$ where $n=|S|$ and $m=|T|$. Typically $n / m$ is a small constant smaller than 1.

Also known as the fill factor.

Main and interrelated questions:
(1) Worst-case vs average-case vs randomized (expected) time?
(2) How do we choose $\boldsymbol{h}$ ?

## Single hash function

(1) $\mathcal{U}$ : universe (very large).
(2) Assume $N=|\mathcal{U}| \gg m$ where $\boldsymbol{m}$ is size of table $T$. In particular assume $N \geq m^{2}$ (very conservative).

## Single hash function

(1) $\mathcal{U}$ : universe (very large).
(2) Assume $N=|\mathcal{U}| \gg m$ where $m$ is size of table $T$. In particular assume $\boldsymbol{N} \geq \boldsymbol{m}^{2}$ (very conservative).
(3) Fix hash function $h: \mathcal{U} \rightarrow\{0, \ldots, m-1\}$.

## Single hash function

(1) $\mathcal{U}$ : universe (very large).
(2) Assume $N=|\mathcal{U}| \gg m$ where $m$ is size of table $T$. In particular assume $N \geq m^{2}$ (very conservative).
( Fix hash function $h: \mathcal{U} \rightarrow\{0, \ldots, \boldsymbol{m}-\mathbf{1}\}$.

- $N$ items hashed to $m$ slots. Minimize the max load. Howmuch is it?


## Single hash function

(1) $\mathcal{U}$ : universe (very large).
(2) Assume $N=|\mathcal{U}| \gg m$ where $m$ is size of table $T$. In particular assume $N \geq \boldsymbol{m}^{2}$ (very conservative).
( Fix hash function $h: \mathcal{U} \rightarrow\{0, \ldots, \boldsymbol{m}-\mathbf{1}\}$.
(0) $N$ items hashed to $m$ slots. Minimize the max load. Howmuch is it? By pigeon hole principle, $N / m \geq m$ !.

## Single hash function

(1) $\mathcal{U}$ : universe (very large).
(2) Assume $N=|\mathcal{U}| \gg m$ where $\boldsymbol{m}$ is size of table $T$. In particular assume $N \geq \boldsymbol{m}^{2}$ (very conservative).
( Fix hash function $h: \mathcal{U} \rightarrow\{0, \ldots, m-1\}$.
(0) $N$ items hashed to $m$ slots. Minimize the max load. Howmuch is it? By pigeon hole principle, $N / m \geq m$ !.
(0. Implies that there is a set $S \subseteq \mathcal{U}$ where $|S|=m$ such that all of $S$ hashes to same slot. Ooops.

## Single hash function

(1) $\mathcal{U}$ : universe (very large).
(2) Assume $N=|\mathcal{U}| \gg m$ where $\boldsymbol{m}$ is size of table $T$. In particular assume $N \geq m^{2}$ (very conservative).
(3) Fix hash function $h: \mathcal{U} \rightarrow\{0, \ldots, m-1\}$.
(4) $N$ items hashed to $m$ slots. Minimize the max load. Howmuch is it? By pigeon hole principle, $N / m \geq m!$.
(5) Implies that there is a set $S \subseteq \mathcal{U}$ where $|S|=m$ such that all of $S$ hashes to same slot. Ooops.

Lesson: For every hash function there is a very bad set. Bad set. Bad.

## How many hash functions are there, anyway?

Let $\mathcal{H}$ be the set of all functions from $\mathcal{U}=\{\mathbf{1}, \ldots, \boldsymbol{U}\}$ to $\{1, \ldots, m\}$. The number of functions in $\mathcal{H}$ is
(A) $U+m$.
(B) Um.
(C) $U^{m}$.
(D) $m^{U}$.
(E) $\binom{U+m}{m}$.
(F) The answer is blowing in the wind.

## How many bits one need?

Let $\mathcal{H}$ be a set of functions from $\mathcal{U}=\{\mathbf{1}, \ldots, \boldsymbol{U}\}$ to $\{\mathbf{1}, \ldots, m\}$. Specifying a function in $\mathcal{H}$ requires:
(A) $O(U+m)$ bits.
(B) $O(U m)$ bits.
(C) $O\left(U^{m}\right)$ bits.
(D) $O\left(m^{U}\right)$ bits.
(E) $O(\log |\mathcal{H}|)$ bits.
(F) Many many bits. At least two.

## Picking a hash function

(1) Hash function are often chosen in an ad hoc fashion. Implicit assumption is that input behaves well.
(2) May work well for aircraft control. Susceptible to denial of service attack in routing.

## Picking a hash function

(1) Hash function are often chosen in an ad hoc fashion. Implicit assumption is that input behaves well.
(2) May work well for aircraft control. Susceptible to denial of service attack in routing.

Parameters: $N=|\mathcal{U}|, m=|T|, n=|S|$
(1) $\mathcal{H}$ is a family of hash functions: each function $\boldsymbol{h} \in \mathcal{H}$ should be efficient to evaluate (that is, to compute $\boldsymbol{h}(\boldsymbol{x})$ ).

## Picking a hash function

(1) Hash function are often chosen in an ad hoc fashion. Implicit assumption is that input behaves well.
(2) May work well for aircraft control. Susceptible to denial of service attack in routing.

Parameters: $N=|\mathcal{U}|, m=|T|, n=|S|$
(1) $\mathcal{H}$ is a family of hash functions: each function $\boldsymbol{h} \in \mathcal{H}$ should be efficient to evaluate (that is, to compute $\boldsymbol{h}(\boldsymbol{x})$ ).
(2) $\boldsymbol{h}$ is chosen randomly from $\mathcal{H}$ (typically uniformly at random). Implicitly assumes that $\mathcal{H}$ allows an efficient sampling.

## Picking a hash function

(1) Hash function are often chosen in an ad hoc fashion. Implicit assumption is that input behaves well.
(2) May work well for aircraft control. Susceptible to denial of service attack in routing.

Parameters: $N=|\mathcal{U}|, m=|T|, n=|S|$
(1) $\mathcal{H}$ is a family of hash functions: each function $\boldsymbol{h} \in \mathcal{H}$ should be efficient to evaluate (that is, to compute $\boldsymbol{h}(\mathrm{x})$ ).
(2) $h$ is chosen randomly from $\mathcal{H}$ (typically uniformly at random). Implicitly assumes that $\mathcal{H}$ allows an efficient sampling.
(3) Randomized guarantee: should have the property that for any fixed set $\boldsymbol{S} \subseteq \mathcal{U}$ of size $\boldsymbol{m}$ the expected number of collisions for a function chosen from $\mathcal{H}$ should be "small". Here the expectation is over the randomness in choice of $\boldsymbol{h}$.

## Picking a hash function

Question: Why not let $\mathcal{H}$ be the set of all functions from $\mathcal{U}$ to $\{0,1, \ldots, m-1\}$ ?

## Picking a hash function

Question: Why not let $\mathcal{H}$ be the set of all functions from $\mathcal{U}$ to $\{0,1, \ldots, m-1\}$ ?
(1) Too many functions! A random function has high complexity! \# of functions: $M=m^{|\mathcal{U}|}$.
Bits to encode such a function $\approx \log M=|\mathcal{U}| \log m$.

## Picking a hash function

Question: Why not let $\mathcal{H}$ be the set of all functions from $\mathcal{U}$ to $\{0,1, \ldots, m-1\}$ ?
(1) Too many functions! A random function has high complexity! \# of functions: $M=m^{|\mathcal{U}|}$.
Bits to encode such a function $\approx \log M=|\mathcal{U}| \log m$.

Question: Are there good and compact families $\mathcal{H}$ ?

## Picking a hash function

Question: Why not let $\mathcal{H}$ be the set of all functions from $\mathcal{U}$ to $\{0,1, \ldots, m-1\}$ ?
(1) Too many functions! A random function has high complexity! \# of functions: $M=m^{|\mathcal{U}|}$.
Bits to encode such a function $\approx \log M=|\mathcal{U}| \log m$.

Question: Are there good and compact families $\mathcal{H}$ ?
(1) Yes... But what it means for $\mathcal{H}$ to be good and compact.

## Uniform hashing

Question: What are good properties of $\mathcal{H}$ in distributing data?

## Uniform hashing

Question: What are good properties of $\mathcal{H}$ in distributing data?
(1) Consider any element $x \in \mathcal{U}$. If $\boldsymbol{h} \in \mathcal{H}$ is picked randomly then $x$ should go into a random slot in $T$. In other words $\operatorname{Pr}[h(x)=i]=1 / m$ for every $0 \leq i<m$. (Uniform)

## Uniform hashing

Question: What are good properties of $\mathcal{H}$ in distributing data?
(1) Consider any element $x \in \mathcal{U}$. If $\boldsymbol{h} \in \mathcal{H}$ is picked randomly then $x$ should go into a random slot in $T$. In other words $\operatorname{Pr}[h(x)=i]=1 / m$ for every $0 \leq i<m$. (Uniform)
(2) Consider any two distinct elements $x, y \in \mathcal{U}$. Then if $\boldsymbol{h} \in \mathcal{H}$ is picked randomly then the probability of a collision between $x$ and $y$ should be at most $\mathbf{1 / m}$. In other words $\operatorname{Pr}[h(x)=h(y)]=1 / m$ (cannot be smaller).

## Uniform hashing

Question: What are good properties of $\mathcal{H}$ in distributing data?
(1) Consider any element $x \in \mathcal{U}$. If $\boldsymbol{h} \in \mathcal{H}$ is picked randomly then $x$ should go into a random slot in $T$. In other words $\operatorname{Pr}[h(x)=i]=1 / m$ for every $0 \leq i<m$. (Uniform)
(2) Consider any two distinct elements $x, y \in \mathcal{U}$. Then if $\boldsymbol{h} \in \mathcal{H}$ is picked randomly then the probability of a collision between $x$ and $y$ should be at most $\mathbf{1 / m}$. In other words $\operatorname{Pr}[h(x)=h(y)]=1 / m$ (cannot be smaller).
(0. Second property is stronger than the first and the crucial issue.

## Definition

A family of hash function $\mathcal{H}$ is (2-)universal if for all distinct $x, y \in \mathcal{U}, \operatorname{Pr}_{h}[h(x)=h(y)]=1 / m$ where $m$ is the table size.

## Uniform hashing

Question: What are good properties of $\mathcal{H}$ in distributing data?
(1) Consider any element $x \in \mathcal{U}$. If $\boldsymbol{h} \in \mathcal{H}$ is picked randomly then $x$ should go into a random slot in $T$. In other words $\operatorname{Pr}[h(x)=i]=1 / m$ for every $0 \leq i<m$. (Uniform)
(2) Consider any two distinct elements $x, y \in \mathcal{U}$. Then if $\boldsymbol{h} \in \mathcal{H}$ is picked randomly then the probability of a collision between $x$ and $y$ should be at most $\mathbf{1 / m}$. In other words $\operatorname{Pr}[h(x)=h(y)]=1 / m$ (cannot be smaller).

- Second property is stronger than the first and the crucial issue.


## Definition

A family of hash function $\mathcal{H}$ is (2-)universal if for all distinct $x, y \in \mathcal{U}, \operatorname{Pr}_{h}[h(x)=h(y)]=1 / m$ where $m$ is the table size.

Note: The set of all hash functions satisfies stronger properties!

## Analyzing Universal Hashing

(1) $\boldsymbol{T}$ is hash table of size $\boldsymbol{m}$.
(2) $S \subseteq \mathcal{U}$ is a fixed set of size $\leq \boldsymbol{m}$.
(3) $\boldsymbol{h}$ is chosen randomly from a universal hash family $\mathcal{H}$.
(4) $\boldsymbol{x}$ is a fixed element of $\mathcal{U}$.

Question: What is the expected time to look up $x$ in $T$ using $h$ assuming chaining used to resolve collisions?

## Analyzing Universal Hashing

Question: What is the expected time to look up $x$ in $\boldsymbol{T}$ using $\boldsymbol{h}$ assuming chaining used to resolve collisions?
(1) The time to look up $x$ is the size of the list at $T[h(x)]$ : same as the number of elements in $S$ that collide with $x$ under $\boldsymbol{h}$.

## Analyzing Universal Hashing

Question: What is the expected time to look up $x$ in $\boldsymbol{T}$ using $\boldsymbol{h}$ assuming chaining used to resolve collisions?
(1) The time to look up $x$ is the size of the list at $T[h(x)]$ : same as the number of elements in $S$ that collide with $x$ under $h$.
(2) Let $\ell(x)$ be this number. We want $\mathrm{E}[\ell(x)]$

## Analyzing Universal Hashing

Question: What is the expected time to look up $x$ in $T$ using $h$ assuming chaining used to resolve collisions?
(1) The time to look up $x$ is the size of the list at $T[h(x)]$ : same as the number of elements in $S$ that collide with $x$ under $h$.
(2) Let $\ell(x)$ be this number. We want $\mathrm{E}[\ell(x)]$
( For $y \in S$ let $A_{y}$ be the event that $x, y$ collide and $D_{y}$ be the corresponding indicator variable.

## Analyzing Universal Hashing

## Continued...

Number of elements colliding with $x: \ell(x)=\sum_{y \in S} D_{y}$.

## Analyzing Universal Hashing

## Continued...

Number of elements colliding with $x: \ell(x)=\sum_{y \in S} D_{y}$.

$$
\begin{array}{rlr}
\Rightarrow \mathrm{E}[\ell(x)] & =\sum_{y \in S} \mathrm{E}\left[D_{y}\right] \quad \text { linearity of expectation } \\
& =\sum_{y \in S} \operatorname{Pr}[h(x)=h(y)] \\
& =\sum_{y \in S} \frac{1}{m} \quad \text { (since } \mathcal{H} \text { is a universal hash family) } \\
& =|S| / m & \\
& =\frac{n}{m} & \\
& \leq 1 & (\text { if }|S| \leq m)
\end{array}
$$

## Analyzing Universal Hashing

Question: What is the expected time to look up $x$ in $T$ using $h$ assuming chaining used to resolve collisions?

Answer: $O(n / m)$.

## Analyzing Universal Hashing

Question: What is the expected time to look up $x$ in $\boldsymbol{T}$ using $\boldsymbol{h}$ assuming chaining used to resolve collisions?

Answer: $O(n / m)$.
Comments:
(1) $O(1)$ expected time also holds for insertion.

## Analyzing Universal Hashing

Question: What is the expected time to look up $x$ in $T$ using $h$ assuming chaining used to resolve collisions?

Answer: $O(n / m)$.
Comments:
(1) $O(1)$ expected time also holds for insertion.
(2) Analysis assumes static set $S$ but holds as long as $S$ is a set formed with at most $O(m)$ insertions and deletions.
(0) Worst-case: look up time can be large! How large?

## Analyzing Universal Hashing

Question: What is the expected time to look up $x$ in $T$ using $h$ assuming chaining used to resolve collisions?

Answer: $O(n / m)$.
Comments:
(1) $O(1)$ expected time also holds for insertion.
(2) Analysis assumes static set $S$ but holds as long as $S$ is a set formed with at most $O(m)$ insertions and deletions.
(0) Worst-case: look up time can be large! How large? $\Omega(\log n / \log \log n)$
[Lower bound holds even under stronger assumptions.]

## Universal Hash Family

Universal: $\mathcal{H}$ such that $\operatorname{Pr}[h(x)=h(y)]=1 / m$.

## Universal Hash Family

Universal: $\mathcal{H}$ such that $\operatorname{Pr}[h(x)=h(y)]=1 / m$.

## All functions

$\mathcal{H}$ : Set of all possible functions $\boldsymbol{h}: \mathcal{U} \rightarrow\{0, \ldots, m-1\}$.

- Universal.


## Universal Hash Family

Universal: $\mathcal{H}$ such that $\operatorname{Pr}[h(x)=h(y)]=1 / m$.

## All functions

$\mathcal{H}$ : Set of all possible functions $\boldsymbol{h}: \mathcal{U} \rightarrow\{\mathbf{0}, \ldots, \boldsymbol{m}-\mathbf{1}\}$.

- Universal.
- $|\mathcal{H}|=m^{|\mathcal{U}|}$
- representing $h$ requires $|\mathcal{U}| \log m-\operatorname{Not} O(1)$ !


## Universal Hash Family

Universal: $\mathcal{H}$ such that $\operatorname{Pr}[h(x)=h(y)]=1 / m$.

## All functions

$\mathcal{H}$ : Set of all possible functions $\boldsymbol{h}: \mathcal{U} \rightarrow\{0, \ldots, m-1\}$.

- Universal.
- $|\mathcal{H}|=m^{|\mathcal{U}|}$
- representing $h$ requires $|\mathcal{U}| \log m-\operatorname{Not} O(1)$ !

We need compactly representable universal family.

## Compact Universal Hash Family

Parameters: $N=|\mathcal{U}|, m=|T|, n=|S|$
(1) Choose a prime number $p>N$. Define function $h_{a, b}(x)=((a x+b) \bmod p) \bmod m$.

## Compact Universal Hash Family

Parameters: $N=|\mathcal{U}|, m=|T|, n=|S|$
(1) Choose a prime number $p>N$. Define function $h_{a, b}(x)=((a x+b) \bmod p) \bmod m$.
(2) Let $\mathcal{H}=\left\{h_{a, b} \mid a, b \in \mathbb{Z}_{p}, a \neq 0\right\}\left(\mathbb{Z}_{p}=\{0,1, \ldots, p-1\}\right)$.

## Compact Universal Hash Family

Parameters: $N=|\mathcal{U}|, m=|T|, n=|S|$
(1) Choose a prime number $p>N$. Define function $h_{a, b}(x)=((a x+b) \bmod p) \bmod m$.
(2) Let $\mathcal{H}=\left\{h_{a, b} \mid a, b \in \mathbb{Z}_{p}, a \neq 0\right\}\left(\mathbb{Z}_{p}=\{0,1, \ldots, p-1\}\right)$. Note that $|\mathcal{H}|=p(p-1)$.

## Compact Universal Hash Family

Parameters: $N=|\mathcal{U}|, m=|T|, n=|S|$
(1) Choose a prime number $p>N$. Define function $h_{a, b}(x)=((a x+b) \bmod p) \bmod m$.
(2) Let $\mathcal{H}=\left\{h_{a, b} \mid a, b \in \mathbb{Z}_{p}, a \neq 0\right\}\left(\mathbb{Z}_{p}=\{0,1, \ldots, p-1\}\right)$. Note that $|\mathcal{H}|=p(p-1)$.

## Theorem

$\mathcal{H}$ is a universal hash family.

## Compact Universal Hash Family

Parameters: $N=|\mathcal{U}|, m=|T|, n=|S|$
(1) Choose a prime number $p>N$. Define function $h_{a, b}(x)=((a x+b) \bmod p) \bmod m$.
(2) Let $\mathcal{H}=\left\{h_{a, b} \mid a, b \in \mathbb{Z}_{p}, a \neq 0\right\}\left(\mathbb{Z}_{p}=\{0,1, \ldots, p-1\}\right)$. Note that $|\mathcal{H}|=p(p-1)$.

## Theorem

## $\mathcal{H}$ is a universal hash family.

Comments:
(1) $\boldsymbol{h}_{\mathrm{a}, \mathrm{b}}$ can be evaluated in $O(\mathbf{1})$ time.
(2) Easy to store, i.e., just store a, b. Easy to sample.

## Some math required...

## Lemma (LemmaUnique)

Let $\boldsymbol{p}$ be a prime number, and $\mathbb{Z}_{\boldsymbol{p}}=\{\mathbf{0}, \mathbf{1}, \ldots, p-1\}$.
$\boldsymbol{x}$ : an integer number in $\mathbb{Z}_{\boldsymbol{p}}, \boldsymbol{x} \neq \mathbf{0}$
$\Longrightarrow$ There exists a unique $y \in \mathbb{Z}_{p}$ s.t. $x y=1 \bmod p$.

In other words: For every element there is a unique inverse.
$\Longrightarrow$ set $\mathbb{Z}_{\boldsymbol{p}}=\{0,1, \ldots, \boldsymbol{p}-1\}$ when working modulo $p$ is a field.

## Proof of LemmaUnique

## Claim

Let $p$ be a prime number. For any $x, y, z \in\{1, \ldots, p-1\}$ s.t. $y \neq z$, we have that $x y \bmod p \neq x z \bmod p$.

## Proof of LemmaUnique

## Claim

Let $p$ be a prime number. For any $x, y, z \in\{1, \ldots, p-1\}$ s.t. $y \neq z$, we have that $x y \bmod p \neq x z \bmod p$.

## Proof.

Assume for the sake of contradiction $x y \bmod p=x z \bmod p$. Then

$$
\begin{aligned}
& x(y-z)=0 \quad \bmod p \\
& \Longrightarrow \quad p \text { divides } x(y-z) \\
& \Longrightarrow \quad p \text { divides } y-z \\
& \Longrightarrow \quad y-z=0 \Longrightarrow y=z
\end{aligned}
$$

And that is a contradiction.

## Proof of LemmaUnique

## Lemma (LemmaUnique)

Let $p$ be a prime number, $x$ : an integer number in $\{\mathbf{1}, \ldots, p-1\}$.
$\Longrightarrow$ There exists a unique $y$ s.t. $x y=1 \bmod p$.

## Proof.

By the above claim if $x y=1 \bmod p$ and $x z=1 \bmod p$ then $y=z$. Hence uniqueness follows.

## Proof of LemmaUnique

## Lemma (LemmaUnique)

Let $p$ be a prime number,
$x$ : an integer number in $\{\mathbf{1}, \ldots, p-1\}$.
$\Longrightarrow$ There exists a unique $y$ s.t. $x y=1 \bmod p$.

## Proof.

By the above claim if $x y=1 \bmod p$ and $x z=1 \bmod p$ then $y=z$. Hence uniqueness follows.

Existence. For any $x \in\{1, \ldots, p-1\}$ we have that $\{x * 1 \bmod p, x * 2 \bmod p, \ldots, x *(p-1) \bmod p\}=$

## Proof of LemmaUnique

## Lemma (LemmaUnique)

Let $\boldsymbol{p}$ be a prime number,
$x$ : an integer number in $\{\mathbf{1}, \ldots, p-1\}$.
$\Longrightarrow$ There exists a unique $y$ s.t. $x y=1 \bmod p$.

## Proof.

By the above claim if $x y=1 \bmod p$ and $x z=1 \bmod p$ then $y=z$. Hence uniqueness follows.

Existence. For any $x \in\{1, \ldots, p-1\}$ we have that $\{x * 1 \bmod p, x * 2 \bmod p, \ldots, x *(p-1) \bmod p\}=$ $\{1,2, \ldots, p-1\}$.
$\Longrightarrow$ There exists a number $y \in\{1, \ldots, p-1\}$ such that $x y=1 \bmod p$.

## Proof of the Theorem: Outline

$$
\left.h_{a, b}(x)=((a x+b) \bmod p) \bmod m\right) .
$$

## Theorem

$\mathcal{H}=\left\{h_{a, b} \mid a, b \in \mathbb{Z}_{\boldsymbol{p}}, a \neq 0\right\}$ is universal.

## Proof.

Fix $x, y \in \mathcal{U}$. We need to show that
$\operatorname{Pr}_{h_{a, b} \sim \mathcal{H}}\left[h_{a, b}(x)=h_{a, b}(y)\right] \leq 1 / m$. Note that $|\mathcal{H}|=p(p-1)$.

## Proof of the Theorem: Outline

$$
\left.h_{a, b}(x)=((a x+b) \bmod p) \bmod m\right) .
$$

## Theorem

$\mathcal{H}=\left\{h_{a, b} \mid a, b \in \mathbb{Z}_{\boldsymbol{p}}, a \neq 0\right\}$ is universal.

## Proof.

Fix $x, y \in \mathcal{U}$. We need to show that
$\operatorname{Pr}_{h_{a, b} \sim \mathcal{H}}\left[h_{a, b}(x)=h_{a, b}(y)\right] \leq 1 / m$. Note that $|\mathcal{H}|=p(p-1)$.
(1) Let $(\boldsymbol{a}, \boldsymbol{b})$ (equivalently $\boldsymbol{h}_{\boldsymbol{a}, \boldsymbol{b}}$ ) be bad for $\boldsymbol{x}, \boldsymbol{y}$ if $h_{a, b}(x)=h_{a, b}(y)$.
(2) Claim: Number of bad $(a, b)$ is at most $p(p-1) / m$.
(3) Total number of hash functions is $p(p-1)$ and hence probability of a collision is $\leq 1 / m$.

## Intuition for the Claim

$$
g_{a, b}(x)=(a x+b) \bmod p, h_{a, b}(x)=\left(g_{a, b}(x)\right) \bmod m
$$

$$
\text { First } \operatorname{map} x \neq y \text { to } r=g_{a, b}(x) \text { and } s=g_{a, b}(y)
$$

LemmaUnique $\Longrightarrow r \neq s$


## Intuition for the Claim

$g_{a, b}(x)=(a x+b) \bmod p, h_{a, b}(x)=\left(g_{a, b}(x)\right) \bmod m$
First map $x \neq y$ to $r=g_{a, b}(x)$ and $s=g_{a, b}(y)$.
LemmaUnique $\Longrightarrow r \neq s$


As $(a, b)$ varies, $(r, s)$ takes all possible $p(p-1)$ values. Since $(a, b)$ is picked u.a.r., every value of $(r, s)$ has equal probability.

## Intuition for the Claim

$$
g_{a, b}(x)=(a x+b) \bmod p, h_{a, b}(x)=\left(g_{a, b}(x)\right) \bmod m
$$




## Intuition for the Claim

$$
g_{a, b}(x)=(a x+b) \bmod p, \quad h_{a, b}(x)=\left(g_{a, b}(x)\right) \bmod m
$$




## Intuition for the Claim

$g_{a, b}(x)=(a x+b) \bmod p, h_{a, b}(x)=\left(g_{a, b}(x)\right) \bmod m$
(1) First part of mapping maps $(x, y)$ to a random location $\left(g_{a, b}(x), g_{a, b}(y)\right)$ in the "matrix".
(2) $\left(g_{a, b}(x), g_{a, b}(y)\right)$ is not on main diagonal.
(3) All blue locations are "bad" map by $\bmod \boldsymbol{m}$ to a location of collision.
(4) But... at most $\mathbf{1} / \boldsymbol{m}$ fraction of allowable locations in the matrix are bad.


## We need

to show at most $1 / \mathrm{m}$ fraction of bad $\boldsymbol{h}_{a, b}$

$$
h_{a, b}(x)=(((a x+b) \bmod p) \operatorname{modm})
$$

2 lemmas ...
Fix $x \neq y \in \mathbb{Z}_{p}$, and let $r=(a x+b) \bmod p$ and $s=(a y+b) \bmod p$.

## We need

to show at most $1 / \mathrm{m}$ fraction of bad $\boldsymbol{h}_{a, b}$

$$
h_{a, b}(x)=(((a x+b) \bmod p) \operatorname{modm})
$$

2 lemmas ...
Fix $x \neq y \in \mathbb{Z}_{\boldsymbol{p}}$, and let $r=(a x+b) \bmod p$ and $s=(a y+b) \bmod p$.
(1) 1-to-1 correspondence between $p(p-1)$ pairs of $(a, b)$ (equivalently $h_{a, b}$ ) and $p(p-1)$ pairs of $(r, s)$.

## We need

to show at most $1 / \mathrm{m}$ fraction of bad $\boldsymbol{h}_{a, b}$

$$
h_{a, b}(x)=(((a x+b) \bmod p) \operatorname{modm})
$$

2 lemmas ...
Fix $x \neq y \in \mathbb{Z}_{\boldsymbol{p}}$, and let $r=(a x+b) \bmod p$ and $s=(a y+b) \bmod p$.
(1) 1-to-1 correspondence between $p(p-1)$ pairs of $(a, b)$ (equivalently $h_{a, b}$ ) and $p(p-1)$ pairs of $(r, s)$.
(2) Out of all possible $p(p-1)$ pairs of $(r, s)$, at most $p(p-1) / m$ fraction satisfies $r \bmod m=s \bmod m$.

## Some Lemmas

## Lemma

If $x \neq y$ then for any $a, b \in \mathbb{Z}_{\boldsymbol{p}}$ such that $\boldsymbol{a} \neq \mathbf{0}$, we have $a x+b \bmod p \neq a y+b \bmod p$.

## Some Lemmas

## Lemma

If $x \neq y$ then for any $a, b \in \mathbb{Z}_{\boldsymbol{p}}$ such that $\boldsymbol{a} \neq \mathbf{0}$, we have $a x+b \bmod p \neq a y+b \bmod p$.

## Proof.

Suppose not
$a x+b \bmod p=a y+b \bmod p \Rightarrow a(x-y) \quad \bmod p=0$

## Some Lemmas

## Lemma

If $x \neq y$ then for any $a, b \in \mathbb{Z}_{\boldsymbol{p}}$ such that $\boldsymbol{a} \neq \mathbf{0}$, we have $a x+b \bmod p \neq a y+b \bmod p$.

## Proof.

Suppose not
$a x+b \bmod p=a y+b \bmod p \Rightarrow a(x-y) \bmod p=0$
But, $a \neq 0$ and $(x-y) \neq 0$.

## Some Lemmas

## Lemma

If $x \neq y$ then for any $a, b \in \mathbb{Z}_{\boldsymbol{p}}$ such that $\boldsymbol{a} \neq \mathbf{0}$, we have $a x+b \bmod p \neq a y+b \bmod p$.

## Proof.

Suppose not
$a x+b \bmod p=a y+b \bmod p \Rightarrow a(x-y) \bmod p=0$
But, $a \neq 0$ and $(x-y) \neq 0$. And $a$ and $(x-y)$ cannot divide $p$ since $p$ is prime and $a<p$ and $(x-y)<p$. Contradiction!

## Some Lemmas

## Lemma

If $x \neq y$ then for each $(r, s)$ such that $r \neq s$ and $0 \leq r, s \leq p-1$ there is exactly one $a, b$ such that $a x+b \bmod p=r$ and $a y+b \bmod p=s$

## Proof.

Solve the two equations:

$$
a x+b=r \quad \bmod p \quad \text { and } \quad a y+b=s \quad \bmod p
$$

## Some Lemmas

## Lemma

If $x \neq y$ then for each $(r, s)$ such that $r \neq s$ and
$0 \leq r, s \leq p-1$ there is exactly one $a, b$ such that $a x+b \bmod p=r$ and $a y+b \bmod p=s$

## Proof.

Solve the two equations:

$$
a x+b=r \quad \bmod p \quad \text { and } \quad a y+b=s \quad \bmod p
$$

We get $a=\frac{r-s}{x-y} \bmod p$ and $b=r-a x \bmod p$.
One-to-one correspondence between $(a, b)$ and $(r, s)$

## Understanding the hashing

Once we fix $\boldsymbol{a}$ and $\boldsymbol{b}$, and we are given a value $\boldsymbol{x}$, we compute the hash value of $x$ in two stages:
(1) Compute: $r \leftarrow(a x+b) \bmod p$.
(2) Fold: $r^{\prime} \leftarrow r \bmod m$

## Collision...

Given two distinct values $x$ and $y$ they might collide only because of folding.

## Lemma

\# not equal pairs $(r, s)$ of $\mathbb{Z}_{\boldsymbol{p}} \times \mathbb{Z}_{\boldsymbol{p}}$ that are folded to the same number is $p(p-1) / m$.

## Folding numbers

## Lemma

$\#$ pairs $(r, s) \in \mathbb{Z}_{\boldsymbol{p}} \times \mathbb{Z}_{\boldsymbol{p}}$ such that $r \neq s$ and $r \bmod m=s$ $\bmod m$ (folded to the same number) is $p(p-1) / m$.

## Proof.

Consider a pair $(r, s) \in\{0,1, \ldots, p-1\}^{2}$ s.t. $r \neq s$. Fix $r$ :
(1) $a=r \bmod m$.

## Folding numbers

## Lemma

$\#$ pairs $(r, s) \in \mathbb{Z}_{\boldsymbol{p}} \times \mathbb{Z}_{\boldsymbol{p}}$ such that $r \neq s$ and $r \bmod m=s$ $\bmod m($ folded to the same number) is $p(p-1) / m$.

## Proof.

Consider a pair $(r, s) \in\{0,1, \ldots, p-1\}^{2}$ s.t. $r \neq s$. Fix $r$ :
(1) $a=r \bmod m$.
(2) There are $\lceil p / m\rceil$ values of $s$ that fold into $a$. That is $r \bmod m=s \quad \bmod m$.
(3) One of them is when $r=s$.

- $\Longrightarrow$ \# of colliding pairs


## Folding numbers

## Lemma

$\#$ pairs $(r, s) \in \mathbb{Z}_{\boldsymbol{p}} \times \mathbb{Z}_{\boldsymbol{p}}$ such that $r \neq s$ and $r \bmod m=s$ $\bmod m($ folded to the same number) is $p(p-1) / m$.

## Proof.

Consider a pair $(r, s) \in\{0,1, \ldots, p-1\}^{2}$ s.t. $r \neq s$. Fix $r$ :
(1) $a=r \bmod m$.
(2) There are $\lceil p / m\rceil$ values of $s$ that fold into $a$. That is

$$
r \quad \bmod m=s \quad \bmod m
$$

(3) One of them is when $r=s$.
(4) $\Longrightarrow \#$ of colliding pairs $(\lceil p / m\rceil-1) p \leq(p-1) p / m$

## Proof of Claim

 \# of bad pairs is $\mathrm{p}(\mathrm{p}-1) / \mathrm{m}$
## Proof.

Let $a, b \in \mathbb{Z}_{\boldsymbol{p}}$ such that $\boldsymbol{a} \neq 0$ and $\boldsymbol{h}_{a, b}(x)=h_{a, b}(y)$.
(1) Let $r=a x+b \bmod p$ and $s=a y+b \bmod p$.
(2) Collision if and only if $r \bmod \boldsymbol{m}=\boldsymbol{s} \bmod \boldsymbol{m}$.
(3) (Folding error): Number of pairs $(r, s)$ such that $r \neq s$ and $0 \leq r, s \leq p-1$ and $r \bmod m=s \bmod m$ is $p(p-1) / m$.
(4) From previous lemma there is one-to-one correspondence between $(\boldsymbol{a}, \boldsymbol{b})$ and $(\boldsymbol{r}, \boldsymbol{s})$. Hence total number of bad $(\boldsymbol{a}, \boldsymbol{b})$ pairs is $p(p-1) / m$.

## Proof of Claim

 \# of bad pairs is $p(p-1) / m$
## Proof.

Let $a, b \in \mathbb{Z}_{\boldsymbol{p}}$ such that $\boldsymbol{a} \neq 0$ and $\boldsymbol{h}_{a, b}(x)=h_{a, b}(y)$.
(1) Let $r=a x+b \bmod p$ and $s=a y+b \bmod p$.
(2) Collision if and only if $r \bmod m=s \bmod m$.
(3) (Folding error): Number of pairs $(r, s)$ such that $r \neq s$ and $0 \leq r, s \leq p-1$ and $r \bmod m=s \bmod m$ is $p(p-1) / m$.
(4) From previous lemma there is one-to-one correspondence between $(\boldsymbol{a}, \boldsymbol{b})$ and $(\boldsymbol{r}, \boldsymbol{s})$. Hence total number of bad $(\boldsymbol{a}, \boldsymbol{b})$ pairs is $p(p-1) / m$.

Prob of $x$ and $y$ to collide: $\frac{\# \text { bad }(a, b) \text { pairs }}{\#(a, b) \text { pairs }}=\frac{\boldsymbol{p}(\boldsymbol{p}-1) / \boldsymbol{m}}{\boldsymbol{p}(\boldsymbol{p}-1)}=\frac{\mathbf{1}}{\boldsymbol{m}}$.

## Rehashing, amortization and...

making the hash table dynamic
So far we assumed fixed $S$ of size $\simeq \boldsymbol{m}$.
Question: What happens as items are inserted and deleted?
(1) If $|S|$ grows to more than $\mathbf{c m}$ for some constant $c$ then hash table performance clearly degrades.
(2) If $|S|$ stays around $\simeq \boldsymbol{m}$ but incurs many insertions and deletions then the initial random hash function is no longer random enough!

## Rehashing, amortization and...

making the hash table dynamic
So far we assumed fixed $S$ of size $\simeq \boldsymbol{m}$.
Question: What happens as items are inserted and deleted?
(1) If $|S|$ grows to more than $\mathbf{c m}$ for some constant $c$ then hash table performance clearly degrades.
(2) If $|\boldsymbol{S}|$ stays around $\simeq \boldsymbol{m}$ but incurs many insertions and deletions then the initial random hash function is no longer random enough!
Solution: Rebuild hash table periodically!
(1) Choose a new table size based on current number of elements in table.
(2) Choose a new random hash function and rehash the elements.
(3) Discard old table and hash function.

Question: When to rebuild? How expensive?

## Rebuilding the hash table

(1) Start with table size $\boldsymbol{m}$ where $\boldsymbol{m}$ is some estimate of $|\boldsymbol{S}|$ (can be some large constant).
(2) If $|S|$ grows to more than twice current table size, build new hash table (choose a new random hash function) with double the current number of elements. Can also use similar trick if table size falls below quarter the size.
(3) If $|S|$ stays roughly the same but more than $c|S|$ operations on table for some chosen constant $c$ (say 10), rebuild.

The amortize cost of rebuilding to previously performed operations. Rebuilding ensures $O(\mathbf{1})$ expected analysis holds even when $S$ changes. Hence $O(\mathbf{1})$ expected look up/insert/delete time dynamic data dictionary data structure!

