

Algorithms and Datastructures

Hash Map, Universal Hashing

Albert-Ludwigs-Universität Freiburg



**UNI
FREIBURG**

Prof. Dr. Rolf Backofen

Bioinformatics Group / Department of Computer Science
Algorithms and Datastructures, November 2017

Associative Arrays

- Introduction

- Hash Map

Universal Hashing

- Introduction

- Probability Calculation

- Proof

- Examples

Associative Arrays

Introduction

Hash Map

Universal Hashing

Introduction

Probability Calculation

Proof

Examples

Reminder:

- An associative array is like a normal array, only that the indices are not 0, 1, 2, ..., but different, e.g. telephone numbers

Reminder:

- An associative array is like a normal array, only that the indices are not 0, 1, 2, ..., but different, e.g. telephone numbers

Problem:

- Quickly find a element with a specific key

Reminder:

- An associative array is like a normal array, only that the indices are not 0, 1, 2, ..., but different, e.g. telephone numbers

Problem:

- Quickly find a element with a specific key
- Naive solution: Store pairs of key and value in a normal field

Reminder:

- An associative array is like a normal array, only that the indices are not $0, 1, 2, \dots$, but different, e.g. telephone numbers

Problem:

- Quickly find a element with a specific key
- Naive solution: Store pairs of key and value in a normal field
- For n keys searching requires $\Theta(n)$ time

Reminder:

- An associative array is like a normal array, only that the indices are not $0, 1, 2, \dots$, but different, e.g. telephone numbers

Problem:

- Quickly find a element with a specific key
- Naive solution: Store pairs of key and value in a normal field
- For n keys searching requires $\Theta(n)$ time
- With a **hash map** this just requires $\Theta(1)$ in the best case, ... regardless how many elements are in the map!

Associative Arrays

Introduction

Hash Map

Universal Hashing

Introduction

Probability Calculation

Proof

Examples

Idea:

- Mapping the keys onto indices with a [hash function](#)
- Store the values at the calculated indices in a normal array

Example:

- Key set: $x = \{3904433, 312692, 5148949\}$

Idea:

- Mapping the keys onto indices with a **hash function**
- Store the values at the calculated indices in a normal array

Example:

- Key set: $x = \{3904433, 312692, 5148949\}$
- Hash function: $h(x) = x \bmod 5$, in the range $[0, \dots, 4]$

Idea:

- Mapping the keys onto indices with a **hash function**
- Store the values at the calculated indices in a normal array

Example:

- Key set: $x = \{3904433, 312692, 5148949\}$
- Hash function: $h(x) = x \bmod 5$, in the range $[0, \dots, 4]$
- We need an array **T** with **5** elements.
A “hashtable” with 5 “buckets”

Idea:

- Mapping the keys onto indices with a **hash function**
- Store the values at the calculated indices in a normal array

Example:

- Key set: $x = \{3904433, 312692, 5148949\}$
- Hash function: $h(x) = x \bmod 5$, in the range $[0, \dots, 4]$
- We need an array **T** with **5** elements.
A “hashtable” with 5 “buckets”
- The element with the key **x** is stored in $T[h(x)]$

Storage:

Figure: Hashtable T



Storage:

■ `insert(3904433, "A")`: $h(3904433) = 3 \Rightarrow T[3] = (3904433, "A")$

Figure: Hashtable T



Storage:

- `insert(3904433, "A")`: $h(3904433) = 3 \Rightarrow T[3] = (3904433, "A")$
- `insert(312692, "B")`: $h(312692) = 2 \Rightarrow T[2] = (312692, "B")$

Figure: Hashtable T



Storage:

- `insert(3904433, "A")`: $h(3904433) = 3 \Rightarrow T[3] = (3904433, "A")$
- `insert(312692, "B")`: $h(312692) = 2 \Rightarrow T[2] = (312692, "B")$
- `insert(5148949, "C")`: $h(5148949) = 4 \Rightarrow T[4] = (5148949, "C")$

Figure: Hashtable T



Searching:

■ `search(3904433): $h(3904433) = 3 \Rightarrow T[3] \rightarrow (3904433, "A")$`

Figure: Hashtable T



Searching:

- $\text{search}(3904433): h(3904433) = 3 \Rightarrow T[3] \rightarrow (3904433, "A")$
- $\text{search}(123459): h(123459) = 4 \Rightarrow T[4]$
 \Rightarrow Value with key 123459 does not exist

Figure: Hashtable T

0	
1	
2	← 312692 B
3	← 3904433 A
4	← 5148949 C

Searching:

- $\text{search}(3904433): h(3904433) = 3 \Rightarrow T[3] \rightarrow (3904433, "A")$
- $\text{search}(123459): h(123459) = 4 \Rightarrow T[4]$
 \Rightarrow Value with key 123459 does not exist
- Search time for this example: $\mathcal{O}(1)$

Figure: Hashtable T

0	
1	
2	← 312692 B
3	← 3904433 A
4	← 5148949 C

Further inserting:

- `insert(876543, "D")`: $h(876543) = 3$

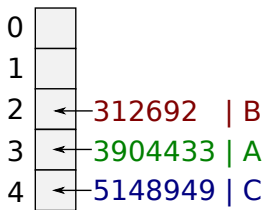
Figure: Hashtable T



Further inserting:

- `insert(876543, "D")`: $h(876543) = 3$
 $\Rightarrow T[3] = (876543, "D") \Rightarrow$ Collision

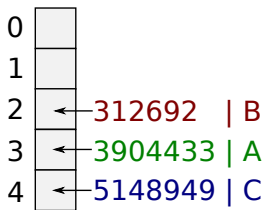
Figure: Hashtable T



Further inserting:

- `insert(876543, "D")`: $h(876543) = 3$
 $\Rightarrow T[3] = (876543, "D") \Rightarrow$ Collision
- This happens more often than expected
 - **Birthday problem:** With 23 people we have the probability of 50 % that 2 of them have birthday at the same day

Figure: Hashtable T



Problem:

- Two keys are equal $h(x) = h(y)$ but not the values $x \neq y$



Problem:

- Two keys are equal $h(x) = h(y)$ but not the values $x \neq y$

Easiest Solution:

Problem:

- Two keys are equal $h(x) = h(y)$ but not the values $x \neq y$

Easiest Solution:

- Represent each bucket as list of key value pairs

Figure: Hashtable T



Problem:

- Two keys are equal $h(x) = h(y)$ but not the values $x \neq y$

Easiest Solution:

- Represent each bucket as list of key value pairs
- Append new values to the end of the list

Figure: Hashtable T



Best case:

- We have n keys which are equally distributed over m buckets
- We have $\approx \frac{n}{m}$ pairs per bucket
- The runtime for searching is nearly $\mathcal{O}(1)$ when **not** $n \gg m$

Best case
($m = 5, n = 10$)



Worst case:

- All n keys are mapped onto the same bucket
- The runtime is $\Theta(n)$ for searching

Worst case
($m = 5, n = 10$)



Associative Arrays

Introduction

Hash Map

Universal Hashing

Introduction

Probability Calculation

Proof

Examples

Thought Experiment:

- A **hash function** is defined for a given **key set**

Thought Experiment:

- A **hash function** is defined for a given **key set**
- Find a **set of keys** resulting in a degenerated **hash table**

Thought Experiment:

- A **hash function** is defined for a given **key set**
- Find a **set of keys** resulting in a degenerated **hash table**
 - *The **hash function** stays fixed*

Thought Experiment:

- A **hash function** is defined for a given **key set**
- Find a **set of keys** resulting in a degenerated **hash table**
 - *The **hash function** stays fixed*
 - *For table size of 100: Try $100 \times (99 + 1)$ different numbers*

Thought Experiment:

- A **hash function** is defined for a given **key set**
- Find a **set of keys** resulting in a degenerated **hash table**
 - *The **hash function** stays fixed*
 - *For table size of 100: Try $100 \times (99 + 1)$ different numbers*
 - *Worst case: All 100 **key sets** map to one bucket*
- **Now:** Find a solution to avoid that problem

Solution: universal hashing

- Out of a set of hash functions we randomly choose one



Figure: Hash func. 1



Figure: Hash func. 2



Figure: Hash func.
coll.

Solution: universal hashing

- Out of a set of hash functions we randomly choose one
- The **expected result** of the hash function is an equal distribution over the buckets



Figure: Hash func. 1



Figure: Hash func. 2



Figure: Hash func.
coll.

Solution: universal hashing

- Out of a set of hash functions we randomly choose one
 - The **expected result** of the hash function is an equal distribution over the buckets
 - This hash function stays fixed for the lifetime of table
- Optional: copy table with new hash when degenerated



Figure: Hash func. 1



Figure: Hash func. 2



Figure: Hash func.
coll.

Definition:

- We call \mathcal{U} the set (universum) of possible keys

Key universe \mathcal{U}



Definition:

- We call \mathcal{U} the set (universum) of possible keys
- The size m of the hash table T

Key universe \mathcal{U}



T (Hashtable)



Definition:

- We call \mathbb{U} the set (universum) of possible keys
- The size m of the hash table T
- Set of hash functions $\mathbb{H} = \{h_1, h_2, \dots, h_n\}$ with $h_i : \mathbb{U} \rightarrow \{0, \dots, m-1\}$

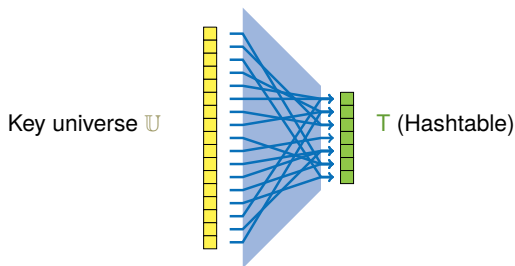


Figure: Hash function h_1

Definition:

- We call \mathbb{U} the set (universum) of possible keys
- The size m of the hash table T
- Set of hash functions $\mathbb{H} = \{h_1, h_2, \dots, h_n\}$ with $h_i : \mathbb{U} \rightarrow \{0, \dots, m-1\}$



Figure: Hash function h_1

Definition:

- We call \mathbb{U} the set (universum) of possible keys
- The size m of the hash table T
- Set of hash functions $\mathbb{H} = \{h_1, h_2, \dots, h_n\}$ with $h_i : \mathbb{U} \rightarrow \{0, \dots, m-1\}$
- Idea: runtime should be $O(1 + \frac{|\mathbb{S}|}{m})$, where $\frac{|\mathbb{S}|}{m}$ is the table load



Figure: Hash function h_1

- We choose two random keys $x, y \in \mathbb{U} \mid x \neq y$



Figure: Set of hash functions \mathbb{H}

- We choose two random keys $x, y \in \mathbb{U} \mid x \neq y$
- An average of 3 out of 15 functions produce collisions



Figure: Set of hash functions \mathbb{H}

Definition: \mathbb{H} is c -universal if $\forall x, y \in \mathbb{U} \mid x \neq y :$

Number of hash functions that create collisions

$$\frac{|\{h \in \mathbb{H} : h(x) = h(y)\}|}{|\mathbb{H}|} \leq c \cdot \frac{1}{m}, \quad c \in \mathbb{R}$$

Number of hash functions

Definition: \mathbb{H} is c -universal if $\forall x, y \in \mathbb{U} \mid x \neq y :$

Number of hash functions that create collisions

$$\frac{|\{h \in \mathbb{H} : h(x) = h(y)\}|}{|\mathbb{H}|} \leq c \cdot \frac{1}{m}, \quad c \in \mathbb{R}$$

Number of hash functions

- With other words, given a arbitrary but fixed pair x, y .
If $h \in \mathbb{H}$ is chosen randomly then

Definition: \mathbb{H} is c -universal if $\forall x, y \in \mathbb{U} \mid x \neq y :$

Number of hash functions that create collisions

$$\frac{|\{h \in \mathbb{H} : h(x) = h(y)\}|}{|\mathbb{H}|} \leq c \cdot \frac{1}{m}, \quad c \in \mathbb{R}$$

Number of hash functions

- With other words, given a arbitrary but fixed pair x, y .
If $h \in \mathbb{H}$ is chosen randomly then

$$\text{Prob}(h(x) = h(y)) \leq c \cdot \frac{1}{m}$$

Definition: \mathbb{H} is c -universal if $\forall x, y \in \mathbb{U} \mid x \neq y :$

Number of hash functions that create collisions

$$\frac{|\{h \in \mathbb{H} : h(x) = h(y)\}|}{|\mathbb{H}|} \leq c \cdot \frac{1}{m}, \quad c \in \mathbb{R}$$

Number of hash functions

- With other words, given a arbitrary but fixed pair x, y .
If $h \in \mathbb{H}$ is chosen randomly then

$$\text{Prob}(h(x) = h(y)) \leq c \cdot \frac{1}{m}$$

Note: If the hash function assigns each key x and y randomly to buckets then:

Definition: \mathbb{H} is c -universal if $\forall x, y \in \mathbb{U} \mid x \neq y :$

Number of hash functions that create collisions

$$\frac{|\{h \in \mathbb{H} : h(x) = h(y)\}|}{|\mathbb{H}|} \leq c \cdot \frac{1}{m}, \quad c \in \mathbb{R}$$

Number of hash functions

- With other words, given a arbitrary but fixed pair x, y .
If $h \in \mathbb{H}$ is chosen randomly then

$$\text{Prob}(h(x) = h(y)) \leq c \cdot \frac{1}{m}$$

Note: If the hash function assigns each key x and y randomly to buckets then:

$$\text{Prob}(\text{Collision}) = \frac{1}{m} \Leftrightarrow c = 1$$

- \mathbb{U} : Key universe
- \mathbb{S} : Used Keys
- $\mathbb{S}_i \subseteq \mathbb{S}$: Keys mapping to Bucket i (“synonyms”)
- Ideal would be $|\mathbb{S}_i| = \frac{|\mathbb{S}|}{m}$



Figure: Hash function $h \in \mathbb{H}$

- Let \mathcal{H} be a c -universal class of hash functions



- Let \mathcal{H} be a c -universal class of hash functions
- Let \mathcal{S} be a set of keys and $h \in \mathcal{H}$ selected randomly

- Let \mathbb{H} be a c -universal class of hash functions
- Let \mathbb{S} be a set of keys and $h \in \mathbb{H}$ selected randomly
- Let \mathbb{S}_i be the key x for which $h(x) = i$

- Let \mathbb{H} be a c -universal class of hash functions
- Let \mathbb{S} be a set of keys and $h \in \mathbb{H}$ selected randomly
- Let \mathbb{S}_i be the key x for which $h(x) = i$
- The expected average number of elements to search through per bucket is

$$\mathbb{E}[|\mathbb{S}_i|] \leq 1 + c \cdot \frac{|\mathbb{S}|}{m}$$

- Let \mathbb{H} be a c -universal class of hash functions
- Let \mathbb{S} be a set of keys and $h \in \mathbb{H}$ selected randomly
- Let \mathbb{S}_i be the key x for which $h(x) = i$
- The expected average number of elements to search through per bucket is

$$\mathbb{E}[|\mathbb{S}_i|] \leq 1 + c \cdot \frac{|\mathbb{S}|}{m}$$

- Particularity: If $(m = \Omega(|\mathbb{S}|))$ then $\mathbb{E}[|\mathbb{S}_i|] = \mathcal{O}(n)$

Associative Arrays

Introduction

Hash Map

Universal Hashing

Introduction

Probability Calculation

Proof

Examples

Universal Hashing

Probability Calculation



**UNI
FREIBURG**

- We just discuss the discrete case

- We just discuss the discrete case
- Probability space Ω with elementary (simple) events



- We just discuss the discrete case
- Probability space Ω with elementary (simple) events
- Events e have probabilities ...

$$\sum_{e \in \Omega} P(e) = 1$$

- We just discuss the discrete case
- Probability space Ω with elementary (simple) events
- Events e have probabilities ...

$$\sum_{e \in \Omega} P(e) = 1$$

- The probability for a subset of events $E \subseteq \Omega$ is

$$P(E) = \sum_{e \in E} P(e) \mid e \in E$$

- We just discuss the discrete case
- Probability space Ω with elementary (simple) events
- Events e have probabilities ...

$$\sum_{e \in \Omega} P(e) = 1$$

- The probability for a subset of events $E \subseteq \Omega$ is

$$P(E) = \sum_{e \in E} P(e) \mid e \in E$$

Table: Throwing a dice

e	$P(e)$
1	$1/6$
2	$1/6$
3	$1/6$
4	$1/6$
5	$1/6$
6	$1/6$

Example:

Example:

- Rolling a dice twice ($\Omega = \{1, \dots, 6\}^2$)

Example:

- Rolling a dice twice ($\Omega = \{1, \dots, 6\}^2$)
- Each event $e \in \Omega$ has the probability $P(e) = 1/36$

Table: Throwing a dice twice

e	$P(e)$
(1, 1)	$1/36$
(1, 2)	$1/36$
(1, 3)	$1/36$
...	...
(6, 5)	$1/36$
(6, 6)	$1/36$

Example:

- Rolling a dice twice ($\Omega = \{1, \dots, 6\}^2$)
- Each event $e \in \Omega$ has the probability $P(e) = 1/36$
- $E =$ if both results are even, then $P(E) =$

Table: Throwing a dice twice

e	$P(e)$
(1, 1)	$1/36$
(1, 2)	$1/36$
(1, 3)	$1/36$
...	...
(6, 5)	$1/36$
(6, 6)	$1/36$

Example:

- Random variable

Example:

- Random variable
 - Assigns a number to the result of an experiment

Example:

- Random variable
 - Assigns a number to the result of an experiment
 - For example: X = Sum of results for rolling twice

Example:

- Random variable
 - Assigns a number to the result of an experiment
 - For example: X = Sum of results for rolling twice
 - $X = 12$ and $X \geq 7$ are regarded as events

Table: Throwing a dice twice

e	$P(e)$	X
(1, 1)	$1/36$	2
(1, 2)	$1/36$	3
(1, 3)	$1/36$	4
...
(6, 5)	$1/36$	11
(6, 6)	$1/36$	12

Example:

- Random variable
 - Assigns a number to the result of an experiment
 - For example: X = Sum of results for rolling twice
 - $X = 12$ and $X \geq 7$ are regarded as events
 - Example 1: $P(X = 2) =$

Table: Throwing a dice twice

e	$P(e)$	X
(1, 1)	$1/36$	2
(1, 2)	$1/36$	3
(1, 3)	$1/36$	4
...
(6, 5)	$1/36$	11
(6, 6)	$1/36$	12

Example:

- Random variable
 - Assigns a number to the result of an experiment
 - For example: X = Sum of results for rolling twice
 - $X = 12$ and $X \geq 7$ are regarded as events
 - Example 1: $P(X = 2) =$
 - Example 2: $P(X = 4) =$

Table: Throwing a dice twice

e	$P(e)$	X
(1, 1)	$1/36$	2
(1, 2)	$1/36$	3
(1, 3)	$1/36$	4
...
(6, 5)	$1/36$	11
(6, 6)	$1/36$	12

Expected value is defined as $\mathbb{E}(X) = \sum (k \cdot P(X = k))$

Expected value is defined as $\mathbb{E}(X) = \sum (k \cdot P(X = k))$

- Intuitive: The weighted average of possible values of X , where the weights are the probabilities of the values

Expected value is defined as $\mathbb{E}(X) = \sum (k \cdot P(X = k))$

- Intuitive: The weighted average of possible values of X , where the weights are the probabilities of the values

Table: Throwing a dice once

X	$P(X)$
1	$1/6$
2	$1/6$
3	$1/6$
4	$1/6$
5	$1/6$
6	$1/6$

Table: Throwing a dice twice

X	$P(X)$
2	$1/36$
3	$2/36$
4	$3/36$
...	...
11	$2/36$
12	$1/36$

Expected value is defined as $\mathbb{E}(X) = \sum (k \cdot P(X = k))$

- Intuitive: The weighted average of possible values of X , where the weights are the probabilities of the values

Table: Throwing a dice once

X	$P(X)$
1	$1/6$
2	$1/6$
3	$1/6$
4	$1/6$
5	$1/6$
6	$1/6$

Table: Throwing a dice twice

X	$P(X)$
2	$1/36$
3	$2/36$
4	$3/36$
...	...
11	$2/36$
12	$1/36$

- Example rolling once:

Expected value is defined as $\mathbb{E}(X) = \sum (k \cdot P(X = k))$

- Intuitive: The weighted average of possible values of X , where the weights are the probabilities of the values

Table: Throwing a dice once

X	$P(X)$
1	$1/6$
2	$1/6$
3	$1/6$
4	$1/6$
5	$1/6$
6	$1/6$

Table: Throwing a dice twice

X	$P(X)$
2	$1/36$
3	$2/36$
4	$3/36$
...	...
11	$2/36$
12	$1/36$

- Example rolling once: $\mathbb{E}(X) = 1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + \dots + 6 \cdot \frac{1}{6} = 3.5$

Expected value is defined as $\mathbb{E}(X) = \sum (k \cdot P(X = k))$

- Intuitive: The weighted average of possible values of X , where the weights are the probabilities of the values

Table: Throwing a dice once

X	$P(X)$
1	$1/6$
2	$1/6$
3	$1/6$
4	$1/6$
5	$1/6$
6	$1/6$

Table: Throwing a dice twice

X	$P(X)$
2	$1/36$
3	$2/36$
4	$3/36$
...	...
11	$2/36$
12	$1/36$

- Example rolling once: $\mathbb{E}(X) = 1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + \dots + 6 \cdot \frac{1}{6} = 3.5$
- Example rolling twice:

Expected value is defined as $\mathbb{E}(X) = \sum (k \cdot P(X = k))$

- Intuitive: The weighted average of possible values of X , where the weights are the probabilities of the values

Table: Throwing a dice once

X	$P(X)$
1	$1/6$
2	$1/6$
3	$1/6$
4	$1/6$
5	$1/6$
6	$1/6$

Table: Throwing a dice twice

X	$P(X)$
2	$1/36$
3	$2/36$
4	$3/36$
...	...
11	$2/36$
12	$1/36$

- Example rolling once: $\mathbb{E}(X) = 1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + \dots + 6 \cdot \frac{1}{6} = 3.5$
- Example rolling twice: $\mathbb{E}(X) = 2 \cdot \frac{1}{36} + 3 \cdot \frac{2}{36} + \dots + 12 \cdot \frac{1}{36} = 7$

Sum of expected values: For arbitrary discrete random variables X_1, \dots, X_n we can write:

$$\mathbb{E}(X_1 + \dots + X_n) = \mathbb{E}(X_1) + \dots + \mathbb{E}(X_n)$$

Sum of expected values: For arbitrary discrete random variables X_1, \dots, X_n we can write:

$$\mathbb{E}(X_1 + \dots + X_n) = \mathbb{E}(X_1) + \dots + \mathbb{E}(X_n)$$

Example: Throwing two dice

Sum of expected values: For arbitrary discrete random variables X_1, \dots, X_n we can write:

$$\mathbb{E}(X_1 + \dots + X_n) = \mathbb{E}(X_1) + \dots + \mathbb{E}(X_n)$$

Example: Throwing two dice

- X_1 : Expected result of dice 1: $\mathbb{E}(X_1) = 3.5$

Sum of expected values: For arbitrary discrete random variables X_1, \dots, X_n we can write:

$$\mathbb{E}(X_1 + \dots + X_n) = \mathbb{E}(X_1) + \dots + \mathbb{E}(X_n)$$

Example: Throwing two dice

- X_1 : Expected result of dice 1: $\mathbb{E}(X_1) = 3.5$
- X_2 : Expected result of dice 2: $\mathbb{E}(X_2) = 3.5$

Sum of expected values: For arbitrary discrete random variables X_1, \dots, X_n we can write:

$$\mathbb{E}(X_1 + \dots + X_n) = \mathbb{E}(X_1) + \dots + \mathbb{E}(X_n)$$

Example: Throwing two dice

- X_1 : Expected result of dice 1: $\mathbb{E}(X_1) = 3.5$
- X_2 : Expected result of dice 2: $\mathbb{E}(X_2) = 3.5$
- $X = X_1 + X_2$: Expected total number:

$$\mathbb{E}(X) = \mathbb{E}(X_1 + X_2) = \mathbb{E}(X_1) + \mathbb{E}(X_2) = 3.5 + 3.5 = 7$$



Corollary:

The probability of the event E is $p = P(E)$. Let X be the occurrences of the event E and n be the number of executions of the experiment. Then $\mathbb{E}(X) = n \cdot P(E) = n \cdot p$

Corollary:

The probability of the event E is $p = P(E)$. Let X be the occurrences of the event E and n be the number of executions of the experiment. Then $\mathbb{E}(X) = n \cdot P(E) = n \cdot p$

Example (Rolling the dice 60 times:)

$$\mathbb{E}(\text{occurrences of } 6) = \frac{1}{6} \cdot 60 = 10$$



Proof Corollary:

Indicator variable: X_i



Proof Corollary:

Indicator variable: X_i

$$X_i = \begin{cases} 1, & \text{if event occurs} \\ 0, & \text{else} \end{cases}$$

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

Proof Corollary:

Indicator variable: X_i

$$X_i = \begin{cases} 1, & \text{if event occurs} \\ 0, & \text{else} \end{cases}$$

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

$$\mathbb{E}(X) = \mathbb{E}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \mathbb{E}(X_i) \stackrel{\text{def. } \mathbb{E}\text{-value}}{=} \sum_{i=1}^n p = n \cdot p$$



Proof Corollary:

Indicator variable: X_i

$$X_i = \begin{cases} 1, & \text{if event occurs} \\ 0, & \text{else} \end{cases}$$

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

$$\mathbb{E}(X) = \mathbb{E}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \mathbb{E}(X_i) \stackrel{\text{def. } \mathbb{E}\text{-value}}{=} \sum_{i=1}^n p = n \cdot p$$



Def. \mathbb{E} -value: $\mathbb{E}(X_i) = 0 \cdot P(X_i = 0) + 1 \cdot P(X_i = 1) = P(X_i = 1)$

Associative Arrays

Introduction

Hash Map

Universal Hashing

Introduction

Probability Calculation

Proof

Examples

Given:

- We pick two random keys $x, y \in \mathbb{S} \mid x \neq y$ and a random hash function $h \in \mathbb{H}$

Given:

- We pick two random keys $x, y \in \mathbb{S} \mid x \neq y$ and a random hash function $h \in \mathbb{H}$
- We know the probability of a collision:

$$P(h(x) = h(y)) \leq c \cdot \frac{1}{m}$$

Given:

- We pick two random keys $x, y \in \mathbb{S} \mid x \neq y$ and a random hash function $h \in \mathbb{H}$
- We know the probability of a collision:

$$P(h(x) = h(y)) \leq c \cdot \frac{1}{m}$$

To proof:

$$\mathbb{E}[|S_i|] \leq 1 + c \cdot \frac{|\mathbb{S}|}{m} \quad \forall i$$



We know:

$$\mathbb{S}_i = \{x \in \mathbb{S} : h(x) = i\}$$



We know:

$$\mathbb{S}_i = \{x \in \mathbb{S} : h(x) = i\}$$

If $\mathbb{S}_i = \emptyset \Rightarrow |\mathbb{S}_i| = 0$

We know:

$$\mathbb{S}_i = \{x \in \mathbb{S} : h(x) = i\}$$

If $\mathbb{S}_i = \emptyset \Rightarrow |\mathbb{S}_i| = 0$ otherwise, let $x \in \mathbb{S}_i$ be any key

We know:

$$\mathbb{S}_i = \{x \in \mathbb{S} : h(x) = i\}$$

If $\mathbb{S}_i = \emptyset \Rightarrow |\mathbb{S}_i| = 0$ otherwise, let $x \in \mathbb{S}_i$ be any key

We define an indicator variable:

$$I_y = \begin{cases} 1, & \text{if } h(y) = i \\ 0, & \text{else} \end{cases} \quad y \in \mathbb{S} \setminus \{x\}$$

We know:

$$\mathbb{S}_i = \{x \in \mathbb{S} : h(x) = i\}$$

If $\mathbb{S}_i = \emptyset \Rightarrow |\mathbb{S}_i| = 0$ otherwise, let $x \in \mathbb{S}_i$ be any key

We define an indicator variable:

$$I_y = \begin{cases} 1, & \text{if } h(y) = i \\ 0, & \text{else} \end{cases} \quad y \in \mathbb{S} \setminus \{x\}$$

$$\Rightarrow |\mathbb{S}_i| = 1 + \sum_{y \in \mathbb{S} \setminus x} I_y$$

We know:

$$\mathbb{S}_i = \{x \in \mathbb{S} : h(x) = i\}$$

If $\mathbb{S}_i = \emptyset \Rightarrow |\mathbb{S}_i| = 0$ otherwise, let $x \in \mathbb{S}_i$ be any key

We define an indicator variable:

$$I_y = \begin{cases} 1, & \text{if } h(y) = i \\ 0, & \text{else} \end{cases} \quad y \in \mathbb{S} \setminus \{x\}$$

$$\Rightarrow |\mathbb{S}_i| = 1 + \sum_{y \in \mathbb{S} \setminus x} I_y$$

$$\Rightarrow \mathbb{E}(|\mathbb{S}_i|) = \mathbb{E}\left(1 + \sum_{y \in \mathbb{S} \setminus x} I_y\right) = 1 + \sum_{y \in \mathbb{S} \setminus x} \mathbb{E}(I_y)$$



Auxiliary calculation:

$$\begin{aligned}\mathbb{E}[I_y] &= P(I_y = 1) \\ &= P(h(y) = i) \\ &= P(h(y) = h(x)) \\ &\leq c \cdot \frac{1}{m}\end{aligned}$$



Auxiliary calculation:

$$\begin{aligned}\mathbb{E}[I_y] &= P(I_y = 1) \\ &= P(h(y) = i) \\ &= P(h(y) = h(x)) \\ &\leq c \cdot \frac{1}{m}\end{aligned}$$

Auxiliary calculation:

$$\begin{aligned}\mathbb{E}[I_y] &= P(I_y = 1) \\ &= P(h(y) = i) \\ &= P(h(y) = h(x)) \\ &\leq c \cdot \frac{1}{m}\end{aligned}$$

Hence:

$$\begin{aligned}\mathbb{E}[|S_i|] &= 1 + \sum_{y \in S \setminus x} \mathbb{E}[I_y] \leq 1 + \sum_{y \in S \setminus x} c \cdot \frac{1}{m} \\ &= 1 + (|S| - 1) \cdot c \cdot \frac{1}{m} \\ &\leq 1 + |S| \cdot c \cdot \frac{1}{m} \\ &= 1 + c \cdot \frac{|S|}{m}\end{aligned}$$

□

Auxiliary calculation:

$$\begin{aligned}\mathbb{E}[I_y] &= P(I_y = 1) \\ &= P(h(y) = i) \\ &= P(h(y) = h(x)) \\ &\leq c \cdot \frac{1}{m}\end{aligned}$$

Hence:

$$\mathbb{E}[|S_i|] = 1 + \sum_{y \in S \setminus x} \mathbb{E}[I_y] \leq 1 + \sum_{y \in S \setminus x} c \cdot \frac{1}{m}$$

$$\begin{aligned}&\leq 1 + |S| \cdot c \cdot \frac{1}{m} \\ &= 1 + c \cdot \frac{|S|}{m}\end{aligned}$$



Auxiliary calculation:

$$\begin{aligned}\mathbb{E}[I_y] &= P(I_y = 1) \\ &= P(h(y) = i) \\ &= P(h(y) = h(x)) \\ &\leq c \cdot \frac{1}{m}\end{aligned}$$

Hence:

$$\begin{aligned}\mathbb{E}[|S_i|] &= 1 + \sum_{y \in S \setminus x} \mathbb{E}[I_y] \leq 1 + \sum_{y \in S \setminus x} c \cdot \frac{1}{m} \\ &= 1 + (|S| - 1) \cdot c \cdot \frac{1}{m} \\ &\leq 1 + |S| \cdot c \cdot \frac{1}{m} \\ &= 1 + c \cdot \frac{|S|}{m}\end{aligned}$$

□

Associative Arrays

Introduction

Hash Map

Universal Hashing

Introduction

Probability Calculation

Proof

Examples



Negative example:

Negative example:

- The set of all h for which $h_a(x) = (a \cdot x) \bmod m$, for a $a \in \mathbb{U}$

Negative example:

- The set of all h for which $h_a(x) = (a \cdot x) \bmod m$, for a $a \in \mathbb{U}$
- Is not c -universal. Why?

Negative example:

- The set of all h for which $h_a(x) = (a \cdot x) \bmod m$, for a $a \in \mathbb{U}$
- Is not c -universal. Why?
- If universal:

$$\forall x, y \quad x \neq y: \frac{|\{h \in \mathbb{H} : h(x) = h(y)\}|}{|\mathbb{H}|} \leq c \cdot \frac{1}{m}$$

Negative example:

- The set of all h for which $h_a(x) = (a \cdot x) \bmod m$, for a $a \in \mathbb{U}$
- Is not c -universal. Why?
- If universal:

$$\forall x, y \quad x \neq y: \frac{|\{h \in \mathbb{H} : h(x) = h(y)\}|}{|\mathbb{H}|} \leq c \cdot \frac{1}{m}$$

- Which x, y lead to a relative collision count bigger than $\frac{c}{m}$?



Positive example:

- Let p be a big prime number, $p > m$ and $p \geq |\mathcal{U}|$

Positive example:

- Let p be a big prime number, $p > m$ and $p \geq |\mathcal{U}|$
- Let \mathcal{H} be the set of all h for which:

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

where $1 \leq a < p$, $0 \leq b < p$

Positive example:

- Let p be a big prime number, $p > m$ and $p \geq |\mathcal{U}|$
- Let \mathcal{H} be the set of all h for which:

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

where $1 \leq a < p$, $0 \leq b < p$

- This is ≈ 1 -universal, see [Exercise 4.11](#) in Mehlhorn/Sanders

Positive example:

- Let p be a big prime number, $p > m$ and $p \geq |\mathbb{U}|$
- Let \mathbb{H} be the set of all h for which:

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

where $1 \leq a < p$, $0 \leq b < p$

- This is \approx 1-universal, see Exercise 4.11 in Mehlhorn/Sanders
- E.g.: $U = \{0, \dots, 99\}$, $p = 101$, $a = 47$, $b = 5$

Positive example:

- Let p be a big prime number, $p > m$ and $p \geq |\mathbb{U}|$
- Let \mathbb{H} be the set of all h for which:

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

where $1 \leq a < p$, $0 \leq b < p$

- This is \approx 1-universal, see Exercise 4.11 in Mehlhorn/Sanders
- E.g.: $U = \{0, \dots, 99\}$, $p = 101$, $a = 47$, $b = 5$
- Then $h(x) = ((47 \cdot x + 5) \bmod 101) \bmod m$

Positive example:

- Let p be a big prime number, $p > m$ and $p \geq |\mathbb{U}|$
- Let \mathbb{H} be the set of all h for which:

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

where $1 \leq a < p$, $0 \leq b < p$

- This is \approx 1-universal, see Exercise 4.11 in Mehlhorn/Sanders
- E.g.: $U = \{0, \dots, 99\}$, $p = 101$, $a = 47$, $b = 5$
- Then $h(x) = ((47 \cdot x + 5) \bmod 101) \bmod m$
- Easy to implement but hard to proof

Positive example:

- Let p be a big prime number, $p > m$ and $p \geq |\mathbb{U}|$
- Let \mathbb{H} be the set of all h for which:

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

where $1 \leq a < p$, $0 \leq b < p$

- This is ≈ 1 -universal, see [Exercise 4.11](#) in Mehlhorn/Sanders
- E.g.: $U = \{0, \dots, 99\}$, $p = 101$, $a = 47$, $b = 5$
- Then $h(x) = ((47 \cdot x + 5) \bmod 101) \bmod m$
- Easy to implement but hard to proof
- Exercise: show empirically that it is 2-universal



Positive example:

- The set of hash functions is c -universal:

$$h_a(x) = a \bullet x \mod m, \quad a \in \mathbb{U}$$

Positive example:

- The set of hash functions is \mathcal{C} -universal:

$$h_a(x) = a \bullet x \mod m, \quad a \in \mathbb{U}$$

- We define:

$$a = \sum_{0, \dots, k-1} a_i \cdot m^i, \quad k = \text{ceil}(\log_m |\mathbb{U}|)$$

$$x = \sum_{0, \dots, k-1} x_i \cdot m^i$$

Positive example:

- The set of hash functions is c -universal:

$$h_a(x) = a \bullet x \mod m, \quad a \in \mathbb{U}$$

- We define:

$$a = \sum_{0, \dots, k-1} a_i \cdot m^i, \quad k = \text{ceil}(\log_m |\mathbb{U}|)$$

$$x = \sum_{0, \dots, k-1} x_i \cdot m^i$$

- **Intuitive:** Scalar product with base m

$$a \bullet x = \sum_{0, \dots, k-1} a_i \cdot x_i$$

Example ($\mathbb{U} = \{0, \dots, 999\}$, $m = 10$, $a = 348$)

With $a = 348$: $a_2 = 3$, $a_1 = 4$, $a_0 = 8$

$$\begin{aligned} h_{348}(x) &= (a_2 \cdot x_2 + a_1 \cdot x_1 + a_0 \cdot x_0) \mod m \\ &= (3x_2 + 4x_1 + 8x_0) \mod 10 \end{aligned}$$

With $x = 127$: $x_2 = 1$, $x_1 = 2$, $x_0 = 7$

$$\begin{aligned} h_{348}(127) &= (3 \cdot x_2 + 4 \cdot x_1 + 8 \cdot x_0) \mod 10 \\ &= (3 \cdot 1 + 4 \cdot 2 + 8 \cdot 7) \mod 10 \\ &= 7 \end{aligned}$$

■ General for this Lecture

[CRL01] Thomas H. Cormen, Ronald L. Rivest, and Charles E. Leiserson.

Introduction to Algorithms.

MIT Press, Cambridge, Mass, 2001.

[MS08] Kurt Mehlhorn and Peter Sanders.

Algorithms and data structures, 2008.

<https://people.mpi-inf.mpg.de/~mehlhorn/ftp/Mehlhorn-Sanders-Toolbox.pdf>.

■ Hash Map - Theory

[Wik] [Hash table](#)

https://en.wikipedia.org/wiki/Hash_table

■ Hash Map - Implementations / API

[Cpp] [C++ - hash_map](#)

http://www.sgi.com/tech/stl/hash_map.html

[Jav] [Java - HashMap](#)

<https://docs.oracle.com/javase/7/docs/api/java/util/HashMap.html>

[Pyt] [Python - Dictionaries \(Hash table\)](#)

https://en.wikipedia.org/wiki/Hash_table