

# CS 758/858: Algorithms

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<http://www.cs.unh.edu/~ruml/cs758>

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## Searching

■ Dictionaries

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# Searching

# Dictionaries

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'associative array', 'map', 'look-up table', 'set'

# Dictionaries

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'associative array', 'map', 'look-up table', 'set'  
 $n$  items, key length  $k$

Structure	Find	Insert	Delete
List (unsorted)			
List (sorted)			
Array (unsorted)			
Array (sorted)			
Heap			
Hash table			
Binary tree (unbalanced)			
Binary tree (balanced)			

Searching

**Hash Tables**

- Hash Tables
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# Hash Tables

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applications:

1. dictionaries
2. object method tables
3. string matching
4. set operations:  $\cup, \cap, -$

first methods:

1. direct-address tables: small key range. eg, bit vectors.
2. chaining: deletion?

# Time Complexity

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$n$  items in  $m$  buckets

time complexity of search =

# Time Complexity

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$n$  items in  $m$  buckets

time complexity of search = number of items per bucket

assume nice hash:  $P(h(i) = x) = 1/m$

# Time Complexity

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$n$  items in  $m$  buckets

time complexity of search = number of items per bucket

assume nice hash:  $P(h(i) = x) = 1/m$

let  $X_i$  be 1 iff  $h(i) = x$ , 0 otherwise

$$\begin{aligned} E\left[\sum_{i=1}^n X_i\right] &= \sum_{i=1}^n E[X_i] \\ &= \sum_{i=1}^n 1/m \\ &= n/m \end{aligned}$$

let  $\alpha = \frac{n}{m}$  'load factor'

expected number of items per bucket is  $\alpha$

expected time is  $\Theta(1 + \alpha)$

# More Collisions

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probability that  $k$  of  $n$  elements land in same of  $m$  bins:

let  $\alpha = \frac{n}{m}$  'load factor'

$$\binom{n}{k} \left(\frac{1}{m}\right)^k \left(1 - \frac{1}{m}\right)^{n-k} \approx \frac{\alpha^k}{e^\alpha k!}$$

if  $n = m$ ,  $\approx \frac{1}{ek!}$ :

$k$	probability
0	0.37
1	0.37
2	0.18
3	0.06
4	0.015
5	0.003
> 5	0.002 total

# Open Addressing

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1. linear probing:  $h(k, i) = (h_1(k) + i) \bmod m$  for increasing  $i$ 
  - the runs
2. double hashing:  $h(k, i) = (h_1(k) + ih_2(k)) \bmod m$  for increasing  $i$ 
  - requires:  $h_2 \neq 0$ ,  $h_2(k)$  and  $m$  relatively prime
  - eg,  $m$  prime and  $h_2(k) < m$
  - or,  $m = 2^x$  and  $h_2(k)$  odd
3. cuckoo hashing: lookups  $O(1)$ , insertions amortized expected  $O(1)$

moral: low load factor

deletion?

# Break

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# Hash Functions

# Hash Functions

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$$h : key \rightarrow 0..m - 1$$

1. mediocre is easy, good takes effort
2. want time (at most) linear in key size
3. perfect hashing is possible (and efficient) if keys known
  - linear time to construct, linear space to store
4. minimal perfect hashing is possible!

# Hash Functions

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$$h : key \rightarrow 0..m - 1$$

1. mediocre is easy, good takes effort
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  - linear time to construct, linear space to store
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bad news:

- if  $|keys| \geq m$ , there must be collisions
- if  $|keys| \geq n \cdot m$ , then  $\exists$  set of  $n$  that map to same bin

# Hash Functions

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Desiderata:

- make collisions unlikely
  - ◆ spread keys across all hashes
  - ◆ for each key, each hash equally likely
- similar keys get different hashes
  - ◆ all bits of key affect the hash
  - ◆ every bit of key affects every bit of hash
- no input always gives worst-case behavior
- fast to compute
- low memory requirement
- easy to implement

# Basic Multiplicative Hashing

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1.  $hash \leftarrow 0$
2. for each *byte* of key
3.  $hash \leftarrow (hash \times multiplier) + byte$
5. return  $hash \bmod m$

want *multiplier* to smear bits, not shift them (to avoid interaction with table size)

$multiplier = 31$  or  $127$

# Tabulation Hashing

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assume we have an array of 256 random integers

1.  $hash \leftarrow 0$
2. for each *byte* of key
3. rotate the bits in *hash* by 1
4.  $hash \leftarrow hash \text{ xor } array[byte]$
5. return  $hash \bmod m$

each byte affects all bits  
rotate makes order matter

**universal** class of hash functions : for randomly chosen keys,  
randomly chosen function from class has  $P(\text{collision}) = 1/m$

good on average case (over inputs)  $\neq$  good average case on any  
input

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**Related**

- Bloom Filters
- Merkle Trees
- Blockchain
- EOLQs

# Related Data Structures

# Bloom Filters

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set of  $n$  items using  $m$  bits with false positives  
set addition: hash element to bit index, set to true  
do this with  $k$  hash functions

no removal

for false positive rate  $\epsilon$ :

$$m/n = -\frac{\lg \epsilon}{\ln 2} \approx -1.44 \lg \epsilon \text{ and}$$

$$k = -\lg \epsilon$$

independent of  $n$  or  $m$ !

for 1% false positive rate:

= 9.6 bits per elt

= 7 hash functions

# Merkle Trees

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■ Bloom Filters

■ Merkle Trees

■ Blockchain

■ EOLQs

a leaf node represents a data block, contains its hash  
internal nodes contain hash of hashes of children  
to verify that node's data is part of  $n$  block tree,  $\lg n$  hashes are required

# Blockchain

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■ Bloom Filters

■ Merkle Trees

■ **Blockchain**

■ EOLQs

block contains hash of previous block, timestamp, transaction data

linked list version of Merkle tree

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■ Bloom Filters

■ Merkle Trees

■ Blockchain

■ **EOLQs**

- What's still confusing?
- What question didn't you get to ask today?
- What would you like to hear more about?

Please write down your most pressing question about algorithms and put it in the box on your way out.

*Thanks!*