### Maps and hash tables

nal Linguistics III (ISCL-BA-07)

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## Maps and sets

- \* Two common data structures that use hashing is sets and maps (Python dict) set abstract data type is based on the sets in mathematics: unordered collection without duplicates
  - msp abstract data type is a collection that allows indexing with almost any data type (Python dicts require immutable data types) Basic operations include

### Maps . Check whether an object is in the set Retrieve the value of a key (d[key])

- Add an element to a set (s.add(x))
- · Remove an element from a set
- (s.remove(x))

A trivial array implementation



+ All operations are O(1) - Cannot handle non-integer,

Associate a key with value
(d[key] = val)

Remove key-value pair

(del d[key])

non-negative keys - Wastes a lot of memory if key value

- . A hash function is a one-way function that takes a variable-length object, and turns it into a fixed-length bit string ons is the map (or associative array, or
  - Most common applications of hash funct dictionary, or symbol table) data structure
- · Maps are array-like data structures (O(1) access/update) but can be indexed
- using arbitrary objects (e.g., strings) Hashing has many other application
- sasruing has many other appaications

   Database indicking

   Cache management

   Efficient duplicate detection

   File signatures: verification against corrupt/tempered file

   Password storage

Hashing and hash-based data structure

- Electronic signatures
   As part of many other cryptographic algorithms/application

### Implementing sets and maps

	Check/retrieve	Add	Remove
Sorted array:	O(log n)	O(n)	O(n)
Unsorted array:	O(n)	O(1)	O(n)
Skip list:	O(log n)	O(log n)	O(log n)
Balanced search trees:	O(log n)	O(log n)	O(log n)
Hash tables:	O(1)	O(1)	O(1)

Hash functions

- \* A hash function h() maps a key to an integer index between 0 and m (size of the array)
- $\bullet$  We use h(k) as an index to an array (of size  $\mathfrak{m})$ \* If we map two different key values to the same integer, a collision occurs
- $\star\,$  The main challenge with implementing hash maps is to avoid and handle the
- We can think of a hash function in two parts:
  - map any object (variable bit string) to an integer (e.g., 32 or 64 bit)
     compress the range of integers to map size (m)

list)

# Compressing the hash codes



- range [0, m] is to use modulo m + Good hash functions minimize collisions, but collisions occur
- Collisions has to be handled by a map data structure. Two commo approaches:

  - Separate chain

  - Open addressi

Separate chaining

Separate chaining wed add 0 10

· Each array element keeps a poi to a secondary container (typically a When a collision occurs, add the item to the list,

Separate chaining



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## Separate chaining



- · Each array element keeps a pointer to a secondary container (typically a list)
- . When a collision occurs, add the item to the list,
- . Why not just add to the head of the

Complexity of separate chaining Load factor for separate chaining 0 10 - 30 - 40 1 11 2 3 - 3 · All operations require locating the ele-. Load factor of a hash map is first · Cost of locating an element include hashing load factor - number of entries (constant) + search in secondary data structure · Low load factor means better run time (fewer collisi 15 → 25 This means worst-case complexity is O(n) · With a good hash function, the probability of - more memory usage a collisions is n/m: average bucket size is O(n/m) = O(1) (if m > n) When load factor is over a threshold, the map is extended (needs rehash) Recommendation vary, but a load factor around 0.75 is considered optimal Expected complexity for all operations is O(1) Rehashing Open addressing (linear probing) 0 1 2 3 4 5 6 7 8 9 10 1 3 97 8 add(8) add(97) a44(11) During insertion, if there is a collision, look for the next empty slot, and insert 16=9/13 During lookup, probe until there is an empty slot Open addressing (linear probing) Open addressing (linear probing) 10 1 40 3 22 add (8) add (97) add(11) add(10) add(40) add(11) on, if there is a collision, look for the next ertion, if there is a collision, look for the next add (22) empty slot, and insert empty slot, and insert During lookup, probe until there is an empty slot During lookup, probe until there is an empty slot Open addressing (linear probing) Open addressing (linear probing) 10 1 40 3 22 97 8 · We can locate an element as usual, and delete ii nt as usual, and delete i Open addressing (linear probing) Open addressing (linear probing) ement as usual, and delete it · However, this breaks probing: now h(22) will point to an . However, this breaks probing: now h(22) will point to ar empty slot empty slot · Rearranging the remaining items is complex & costly . Rearranging the remaining items is complex & costly We insert a special value,
 During lookup, treat it as full - During insertion, treat it as empty Quadratic probing Double hashing · Linear probing tends to create clusters of items, especially if load factor is high (> 0.5) · Similar to quadratic probing, probe non-linearly . Quadratic probing provides some improvements Instead of probing next item, probe  $(h(k) + i \times h'(k)) \mod m$  for i = 0, 1, ... where h'(k) another hash function • Probe  $(h(k) + t^2) \mod m$  for t = 0, 1, ... until an empty slot is found • If m is prime, and load factor is less than 0.5, quadratic probing is guaranteed to find an empty slot \* A common choice is  $h'(k) = q - (k \!\!\mod q)$  for a prime number q < mAlthough better than linear porobing, quadratic probing creates its own kind of clustering

Using a pseudo random number generator Aside: hash DoS attacks . A denial-of-service (DoS) attack aims to break or slow down an Internet \* This method probes  $(h(k) + i \times r_i) \mod m$  for i = 0, 1, ... where  $r_i$  is the inumber generated by a pseudo random number genera · A particular attack (in 2003, but also 2011) made use of hash table Pseudo random number generators generate numbers that are close to uniform. However given the same seed, the sequence is deterministic implementation of popular programming languages . Input to a web-based program is passed as key-value pairs, wh typically stored in a dictionary This approach is the most common choice for modern programming . If one intentionally posts an input with a large number of colliding keys languages/environments the hash table implementation needs to chain long sequences (separa chaining) or probe a large number of times (open addressing)
 and eventually re-hash · This also avoids problems with inputs that intentionally generate hash \* This increases expected to O(1) time to  $\nu$ Hash functions Hash codes · Earlier we suggested dividing the hash function into two A has code that maps a variable-size object to an integer
 A compression method that squeezes the integer value to hash table size . A hash function must be consistent: if a == b, h(a) == h(b) . A hash function should minimize collisions: values for h should be uniformly · A hash code avoid collisions: colliding hash codes are unavoidably mapped distributed the same table address . A hash function should be fast to compute (...or maybe not - if you are using . A naive approach is to truncate (e.g., take the most or least significant bits), or

it for passwords)

Hash codes

nor or add · A simple approach is based on

- Bitwise add each k-bit seemer
- ignoring the overflow:  $h(x) = \sum_i x_i$  Similarly, one can use XOR instead of addition
- These methods meet the hash code requirement:
- b, then h(a) However, in practice, they create many collisions because of their associativity
- abc, bca and cba all get the same hash code

Cyclic-shift hash codes

1010011001110100 · Instead of multiplying with powers of a constant, cyclic-shift hashing shifts 1010111000110100 c shift(s): some bits from one end of the other at each step in running sum

def cyclic\_shift(s):
 mask = 0xffff
h = 0
for ch in s:
 h = (h << 5 & mask) | (h >> 11)
h += ord(ch) simple, this is a fast way of obtaining a non-associative valid has code

Summary

· Hash functions are useful for implementing map ADT efficiently

- · Hash functions have a wide range of other applications
- The main issue in implementing a hash function is avoiding collisions, and handling them efficiently when they occur
- Reading: Goodrich, Tamassia, and Goldwasser (2013, chapter 10) Next:
- Algorithms on strings: pattern matching, edit distance, tries
- Reading: Goodrich, Tamassia, and Goldwasser (2013, chapter 13), Jurafsky and Martin (2009, section 3.11, or 2.5 in online draft)

pad with an arbitrary pattern (if object is shorter than the hash code) . This approach creates many collisions in real-world usage

Polynomial hash codes

· Polynomial hash codes are calculated using

- $h(x) = \sum_{i=1}^{n} x_i a^{n-i-1} = x_0 a^{n-1} + x_1 a^{n-2} + ... + x_{n-1}$ . The important aspect is that now the function will produce different val
- ith the same ite in a different
- . The exact form is motivated by quick computation if rewritten as
  - $x_{n-1} + a(x_{n-2} + a(x_{n-3} + ...))$

A short divergence: cryptographic hash functions

- Hash functions has an important role in cryptography
   In cryptography, it is important to have hash functions for which it is difficult
- to find two keys with the same hash value

  There are a wide range of well-known hash functions (which are also available in most programming environments)
  - MD5
- SHA-1 RIPEMD-160 Whirlpool SHA-2 SHA-3 - BLAKE2
- BLAKET These functions are designed for applications like digital fingerprinting
- password storage Computationally inefficient for use in data structures

Acknowledgments, credits, references

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