# Lecture 8: Hashing

### Lecture Overview

- Dictionaries and Python
- Motivation
- Prehashing
- Hashing
- Chaining to resolve collisons
- Simple uniform hashing
- "Good" hash functions

## **Dictionary Problem**

Abstract Data Type (ADT) — maintain a set of items, each with a key, subject to

- insert(item): add item to set
- delete(item): remove item from set
- search(key): return item with key if it exists

We assume items have distinct keys (or that inserting a new item with the same key overwrites the old item).

We could add another operation "create()" to create an empty dictionary.

Balanced BSTs solve in  $O(\lg n)$  time per op. (in addition to inexact searches like next-largest). Goal: O(1) time per operation.

#### Python Dictionaries:

```
Items are (key, value) pairs e.g. d = \{\text{`algorithms': 5, `cool': 42}\}
```

```
\begin{array}{lll} \text{d.items()} & \rightarrow & \text{[('algorithms', 5),('cool',5)]} \\ \text{d['cool']} & \rightarrow & 42 \\ \text{d[42]} & \rightarrow & \text{KeyError} \\ \text{'cool' in d} & \rightarrow & \text{True} \\ \text{5 in d} & \rightarrow & \text{False} \end{array}
```

Python set is really dict where items are keys (no values)

### Motivation

Dictionaries are perhaps the most popular data structure in CS

- built into most modern programming languages (Python, Perl, Ruby, JavaScript, Java, C++, C#, ...)
- e.g. best docdist code: word counts & inner product
- implement databases: (DB\_HASH in Berkeley DB)
  - English word  $\rightarrow$  definition (literal dict.)
  - English words: for spelling correction
  - word  $\rightarrow$  all webpages containing that word
  - username  $\rightarrow$  account object
- compilers & interpreters: names  $\rightarrow$  variables
- network routers: IP address  $\rightarrow$  wire
- network server: port number  $\rightarrow$  socket/app.
- virtual memory: virtual address  $\rightarrow$  physical

Less obvious, using hashing techniques:

- substring search (grep, Google)
- string commonalities (DNA
- file or directory synchronization (rsync)
- cryptography: file transfer & identification

## How do we solve the dictionary problem?

So we know what we want to do, and why, but how can we manage it?

Using what we know till now, we could try using a balanced BST like AVL, would give us  $O(\lg n)$  access time. Advantage: "Nearby" values are correlated, or we know how to find them (we can find the next largest key, etc.). But we don't need this. Can we sacrifice this and somehow get better access time? Yes! In fact, the less "correlated" the better.

#### Simple Approach: Direct Access Table

This means items would need to be stored in an array, indexed by key (<u>random access</u>)

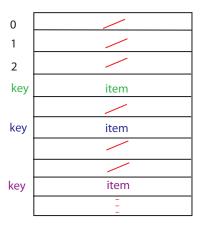


Figure 1: Direct-access table

#### **Problems:**

- 1. keys must be nonnegative integers (or using two arrays, integers)
- 2. large key range  $\implies$  large space e.g. one key of  $2^{256}$  is bad news.

#### 2 Solutions:

Solution to 1: "prehash" keys to integers.

- In theory, possible because keys are finite  $\implies$  set of keys is countable
- In Python: <u>hash(object)</u> (actually hash is misnomer should be "prehash") where object is a number, string, tuple, etc. or object implementing \_hash\_\_ (default = id = memory address)
- In theory,  $x = y \Leftrightarrow hash(x) = hash(y)$
- Python applies some heuristics for practicality: for example, hash('\0B') = 64 = hash('\0\0C')
- Object's key should not change while in table (else cannot find it anymore)
- No mutable objects like lists

Solution to 2: hashing (verb from French 'hache' = hatchet, & Old High German 'happja' = scythe)

- Reduce universe  $\mathcal{U}$  of all keys (say, integers) down to reasonable size m for table
- idea:  $m \approx n = \#$  keys stored in dictionary
- hash function h:  $\mathcal{U} \to \{0, 1, \dots, m-1\}$

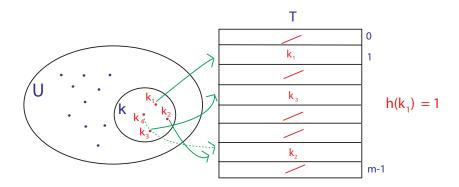


Figure 2: Mapping keys to a table

• two keys  $k_i, k_j \in K$  <u>collide</u> if  $h(k_i) = h(k_j)$ 

#### <u>How</u> do we deal with collisions?

## Chaining

Linked list of colliding elements in each slot of table

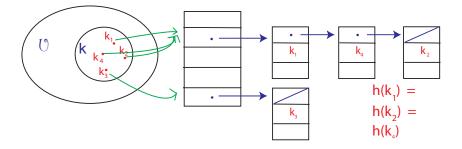


Figure 3: Chaining in a Hash Table

- Search must go through whole list T[h(key)]
- Worst case: all n keys hash to same slot  $\implies \Theta(n)$  per operation

# Simple Uniform Hashing:

An assumption (cheating): Each key is equally likely to be hashed to any slot of table, independent of where other keys are hashed.

let n = # keys stored in table

m = # slots in table

 $\underline{\text{load factor}}\,\alpha \ = \ n/m = \text{ expected } \# \text{ keys per slot} = \text{expected length of a chain}$ 

#### Performance

This implies that expected running time for search is  $\Theta(1+\alpha)$  — the 1 comes from applying the hash function and random access to the slot whereas the  $\alpha$  comes from searching the list. This is equal to O(1) if  $\alpha = O(1)$ , i.e.,  $m = \Omega(n)$ .

### Hash Functions

So what makes a good hash function? A hash function must be deterministic – the same input must always map to the same output. On the other hand, we also want it to be "random" in the sense of randomly or evenly distributing our items across our array, so as to minimize  $\alpha$ . We cover three methods to achieve the above performance:

#### **Division Method:**

$$h(k) = k \mod m$$

This is practical when m is prime but not too close to power of 2 or 10 (then just depending on low bits/digits).

But it is inconvenient to find a prime number, and division is slow.

### **Multiplication Method:**

$$h(k) = [(a \cdot k) \mod 2^w] \gg (w - r)$$

where a is random, k is w bits, and  $m = 2^r$ .

This is practical when a is odd &  $2^{w-1} < a < 2^w$  & a not too close to  $2^{w-1}$  or  $2^w$ .

Multiplication and bit extraction are faster than division.

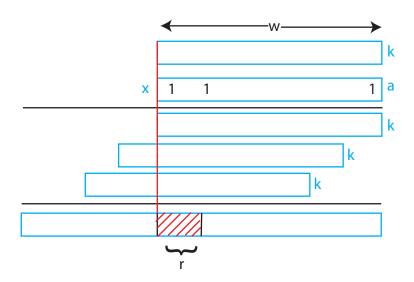


Figure 4: Multiplication Method

### Universal Hashing

[6.046; CLRS 11.3.3]

For example:  $h(k) = [(ak+b) \mod p] \mod m$  where a and b are random  $\in \{0, 1, \dots p-1\}$ , and p is a large prime  $(> |\mathcal{U}|)$ .

This implies that for worst case keys  $k_1 \neq k_2$ , (and for a, b choice of h):

$$Pr_{a,b}\{\text{event } X_{k_1k_2}\} = Pr_{a,b}\{h(k_1) = h(k_2)\} = \frac{1}{m}$$

This lemma not proved here

This implies that:

$$E_{a,b}[\# \text{ collisions with } k_1] = E[\sum_{k_2} X_{k_1 k_2}]$$

$$= \sum_{k_2} E[X_{k_1 k_2}]$$

$$= \sum_{k_2} \underbrace{Pr\{X_{k_1 k_2} = 1\}}_{\frac{1}{m}}$$

$$= \frac{n}{m} = \alpha$$

This is just as good as above!