Lecture 8: Hashing I

Lecture Overview

- Dictionaries and Python
- Motivation
- Prehashing
- Hashing
- Chaining
- Simple uniform hashing

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 new one clobbers old).

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

Goal: O(1) time per operation.

We saw in the last lecture a lower-bound of $\Omega(\lg n)$ for searching and $\Omega(n \lg n)$ for sorting in the comparison model. We also saw that by moving out of the comparison model and using the fact that items are (bounded-size) integers, we can sort faster, in linear time. In this and the next two lectures, we will see how hashing lets us do O(1) search, overcoming the $\Omega(\lg n)$ lower bound.

A caveat: The time for search is O(1) not in the worst-case, but is an average-case, high probability statement.

Python Dictionaries:

```
Items are (key, value) pairs e.g. d = \{\text{`algorithms'}: 5, \text{`cool'}: 42\}
\begin{array}{rcl} \text{d.items()} & \rightarrow & [(\text{`algorithms'}, 5),(\text{`cool'},5)] \\ \text{d[`cool']} & \rightarrow & 42 \\ \text{d[42]} & \rightarrow & \text{KeyError} \\ \text{`cool' in d} & \rightarrow & \text{True} \\ 42 \text{ 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) [L9]
- file or directory synchronization (rsync)
- cryptography: file transfer & identification [L10]

How do we solve the dictionary problem?

Simple Approach: Direct Access Table

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

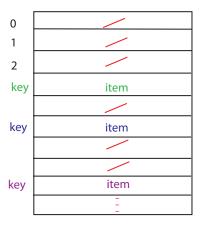


Figure 1: Direct-access table

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)

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

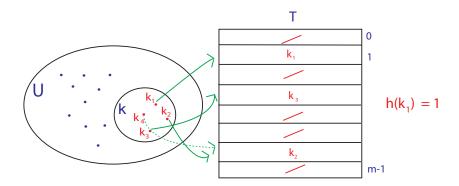


Figure 2: Mapping keys to a table

- <u>hash function</u> h: $\mathcal{U} \to \{0, 1, \dots, m-1\}$
- two keys $k_i, k_j \in K$ <u>collide</u> if $h(k_i) = h(k_j)$

How do we deal with collisions?

We will see two ways

1. Chaining: TODAY

2. Open addressing: L10

Chaining

Linked list of colliding elements in each slot of table

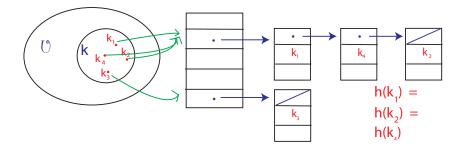


Figure 3: Chaining in a Hash Table

- 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 \frac{\log d \operatorname{factor} \alpha}{\log n}=n/m=\operatorname{expected} \# \operatorname{keys} \operatorname{per} \operatorname{slot}=\operatorname{expected} \operatorname{length} \operatorname{of} \operatorname{a} \operatorname{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 α comes from searching the list. This is equal to O(1) if $\alpha = O(1)$, i.e., $m = \Omega(n)$.

We will see three examples of hash functions, two in the recitations and one in [L9].