

CH08-320201

# Algorithms and Data Structures

ADS

## Lecture 17

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# Choosing a Hash Function (1)

- ▶ What makes a good hash function?
  - ▶ The goal for creating a hash function is to distribute the keys as uniformly as possible to the slots.
- ▶ Division method
  - ▶ Define hashing function  $h(k) = k \bmod m$ .
  - ▶ **Deficiency**: Do not pick an  $m$  that has a small divisor  $d$ , as a prevalence of keys with the same modulo  $d$  can negatively effect uniformity.
  - ▶ **Example**: if  $m$  is a power of 2, the hash function only depends on a few bits: If  $k = 1011000111011010$  and  $m = 2^6$ , then  $h(k) = 011010$ .

## Choosing a Hash Function (2)

- ▶ **Division method** (continue)
  - ▶ **Common choice:** Pick  $m$  to be a prime not too close to a power of 2 or 10 and not otherwise prominently used in computing environments.
  - ▶ **Example:**  $n = 2000$ ; we are ok with average 3 elements in our collision chain  $\Rightarrow m = 701$  (a prime number close to  $2000/3$ ),  $h(k) = k \bmod 701$ .

## Choosing a Hash Function (3)

### ► Multiplication method

- On advantage of the multiplication method is that the value of  $m$  is not critical
- Knuth suggests that  $A \approx (\sqrt{5} - 1)/2$  works well
- Assume all keys are integers,  $m = 2^r$ , and the computer uses  $w$ -bit words.
- Define hash function  $h(k) = (A \cdot k \bmod 2^w) \gg (w - r)$ , where " $\gg$ " is the right bit-shift operator and  $A$  is an odd integer with  $2^{w-1} < A < 2^w$ .
- **Example:**  $m = 2^3 = 8$  and  $w = 7$ .

$$\begin{array}{r}
 \phantom{\times} \phantom{10010100} 1011001 = A \\
 \times \phantom{10010100} 1101011 = k \\
 \hline
 10010100 \phantom{110011} \\
 \phantom{10010100} \underbrace{\phantom{110011}}_{h(k)}
 \end{array}$$

## Resolving Collisions by Open Addressing

- ▶ No additional storage is used.
- ▶ Only store one element per slot.
- ▶ Insertion probes the table systematically until an empty slot is found.
- ▶ The hash function depends on the key and the probe number, i.e.,  $h : U \times \{0, 1, \dots, m - 1\} \rightarrow \{0, 1, \dots, m - 1\}$ .
- ▶ The probe sequence  $\langle h(k, 0), h(k, 1), \dots, h(k, m - 1) \rangle$  should be a permutation of  $\{0, 1, \dots, m - 1\}$ .

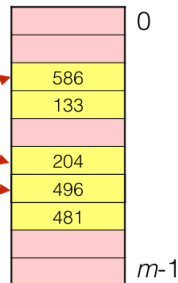
# Insert Example

- Insert key  $k = 496$ :

**0.** Probe  $h(496, 0)$

**1.** Probe  $h(496, 1)$

**2.** Probe  $h(496, 2)$



**HASH-INSERT**( $T, k$ )

```
1   $i = 0$ 
2  repeat
3       $j = h(k, i)$ 
4      if  $T[j] == \text{NIL}$ 
5           $T[j] = k$ 
6          return  $j$ 
7      else  $i = i + 1$ 
8  until  $i == m$ 
9  error "hash table overflow"
```

# Search Example

`HASH-SEARCH( $T, k$ )`

```

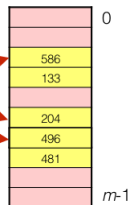
1   $i = 0$ 
2  repeat
3       $j = h(k, i)$ 
4      if  $T[j] == k$ 
5          return  $j$ 
6       $i = i + 1$ 
7  until  $T[j] == \text{NIL}$  or  $i == m$ 
8  return NIL

```

0. Probe  $h(496, 0)$

1. Probe  $h(496, 1)$

2. Probe  $h(496, 2)$



## ► Search key $k = 496$

- Search uses the same probe sequence, terminating successfully if it finds the key and unsuccessfully if it encounters an empty slot (or made it all the way through the list)
- Search times no longer depend on load factor  $\alpha$

## ► What about delete?

- Have a special node type: DELETED
- Chaining more commonly used when keys must also be deleted

# Probing Strategies (1)

## Linear probing:

- ▶ Given an ordinary hash function  $h'(k)$ , linear probing uses the hash function  $h(k, i) = (h'(k) + i) \bmod m$ .
- ▶ This is a simple computation.
- ▶ However, it may suffer from **primary clustering**, where long runs of occupied slots build up and tend to get longer.
  - ▶ empty slot preceded by  $i$  full slots gets filled next with probability  $(i + 1)/m$



## Probing Strategies (2)

### Quadratic probing:

- ▶ Quadratic probing uses the hash function
$$h(k, i) = (h'(k) + c_1 \cdot i + c_2 \cdot i^2) \bmod m.$$
- ▶ Offset by amount that depends on quadratic manner, works much better than linear probing
- ▶ But, it may still suffer from **secondary clustering**: If two keys have initially the same value, then they also have the same probe sequence
- ▶ In addition  $c_1$ ,  $c_2$ , and  $m$  need to be constrained to make full use of the hash table

## Probing Strategies (3)

### Double hashing:

- ▶ Given two ordinary hash functions  $h_1(k)$  and  $h_2(k)$ , double hashing uses the hash function  $h(k, i) = (h_1(k) + i \cdot h_2(k)) \bmod m$ .
- ▶ The initial probe goes to position  $T[h_1(k)]$ ; successive probe positions are offset by  $h_2(k) \rightarrow$  the initial probe position, the offset, or both, may vary
- ▶ This method generates excellent results, if  $h_2(k)$  is relatively prime to the hash-table size  $m$ ,

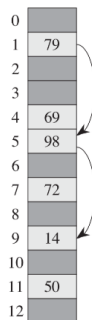
## Probing Strategies (4)

### Double hashing (continue):

- ▶ e.g., by making  $m$  a power of 2 and design  $h_2(k)$  to only produce odd numbers.
- ▶ or let  $m$  be prime and design  $h_2$  such that it always returns a positive integer less than  $m$ , e.g. let  $m'$  be slightly less than  $m$ :

$$h_1(k) = k \bmod m$$

$$h_2(k) = 1 + (k \bmod m')$$



$$h_1(k) = k \bmod 13$$

$$h_2(k) = 1 + (k \bmod 11)$$

$$\rightarrow k=14; h_1(k)=1, h_2(k)=4$$

$$\rightarrow k=27; h_1(k)=1, h_2(k)=6$$

## Analysis of Open Addressing (1)

### Theorem:

- ▶ Assume uniform hashing, i.e., each key is likely to have any one of the  $m!$  permutations as its probe sequence.
- ▶ Given an open-addressed hash table with load factor  $\alpha = n/m < 1$ .
- ▶ The expected number of probes in an unsuccessful search is, at most  $\frac{1}{1 - \alpha}$ .

## Analysis of Open Addressing (2)

### Proof:

- ▶ At least, one probe is always necessary.
- ▶ With probability  $n/m$ , the first probe hits an occupied slot, i.e., a second probe is necessary.
- ▶ With probability  $(n-1)/(m-1)$ , the second probe hits an occupied slot, i.e., a third probe is necessary.
- ▶ With probability  $(n-2)/(m-2)$ , the third probe hits an occupied slot, i.e., a fourth probe is necessary.
- ▶ ...

## Analysis of Open Addressing (3)

Given that  $\frac{n-i}{m-i} < \frac{n}{m} = \alpha$  for  $i = 1, 2, \dots, n$ .

$$\begin{aligned} & 1 + \frac{n}{m} \left( 1 + \frac{n-1}{m-1} \left( 1 + \frac{n-2}{m-2} \left( \dots \left( 1 + \frac{1}{m-n+1} \right) \dots \right) \right) \right) \\ & \leq 1 + \alpha (1 + \alpha (1 + \alpha (\dots (1 + \alpha) \dots))) \\ & \leq 1 + \alpha + \alpha^2 + \alpha^3 + \dots \\ & = \sum_{i=0}^{\infty} \alpha^i \\ & = \frac{1}{1-\alpha}. \end{aligned}$$

## Analysis of Open Addressing (4)

- ▶ The successful search takes less number of probes  
[expected number is at most  $\frac{1}{\alpha} \ln \frac{1}{1-\alpha}$ ].
- ▶ We conclude that if  $\alpha$  is constant, then accessing an open-addressed hash table takes constant time.
- ▶ For example, if the table is half full, the expected number of probes is  $1/(1 - 0.5) = 2$ .
- ▶ Or, if the table is 90% full, the expected number of probes is  $1/(1 - 0.9) = 10$ .

## Summary

- ▶ Dynamic sets with queries and modifying operations.
- ▶ Array: Random access, search in  $O(\lg n)$ , but modifying operations  $O(n)$ .
- ▶ Stack: LIFO only. Operations in  $O(1)$ .
- ▶ Queue: FIFO only. Operations in  $O(1)$ .
- ▶ Linked list: Modifying operations in  $O(1)$ , but search  $O(n)$ .
- ▶ BST: All operations in  $O(h)$ .
- ▶ Red-black trees: All operations in  $O(\lg n)$ .
- ▶ Heap: All operations in  $O(\lg n)$ .
- ▶ Hash tables: Operations in  $O(1)$ , but additional storage space.



# Design Concepts

- ▶ We have been looking into different algorithms and, in particular, emphasized one design concept, namely, the Divide & Conquer strategy, which was based on recursions and whose analysis was given by recurrences.
- ▶ Now, we are going to look into further design concepts.

## Activity-Selection Problem (1)

- ▶ Suppose we have a set  $S = \{a_1, a_2, \dots, a_n\}$  of  $n$  activities.
- ▶ The activities wish to use a resource, which can only be used by one activity at a time.
- ▶ Each activity  $a_i$  has a start time  $s_i$  and a finish time  $f_i$ , where  $0 \leq s_i < f_i < \infty$ .
- ▶ Two activities  $a_i$  and  $a_j$  are compatible, if  $[s_i, f_i)$  and  $[s_j, f_j)$  are disjoint.
- ▶ The activity-selection problem is to select a maximum-size subset of mutually compatible activities.

# Activity-Selection Problem (2)

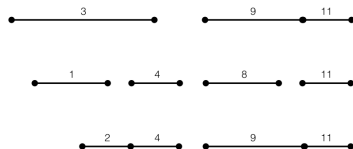
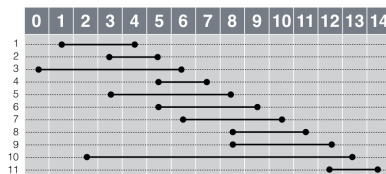
## ► Example:

$i$  1 2 3 4 5 6 7 8 9 10 11

$s_i$  1 3 0 5 3 5 6 8 8 2 12

$f_i$  4 5 6 7 8 9 10 11 12 13 14

- $\{a_3, a_9, a_{11}\}$  is a subset of mutually compatible activities.
- $\{a_1, a_4, a_8, a_{11}\}$  is a largest subset of mutually compatible activities.
- $\{a_2, a_4, a_9, a_{11}\}$  is another largest subset of mutually compatible activities.



# Sorting

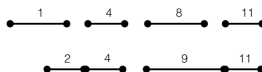
- ▶ We can apply a sorting algorithm to the finish times, which operates in  $O(n \lg n)$  time.
- ▶ Then, we can assume that the activities are sorted, i.e.,  
 $f_1 \leq f_2 \leq \dots \leq f_n$ .

# Greedy Algorithm

- ▶ A greedy algorithm always makes the choice that looks best at the moment.
- ▶ I.e., it makes a locally optimal choice in the hope that it will lead to a globally optimal solution.

## Greedy Approach (1)

- ▶ After sorting,  $a_1$  has the earliest finish time  $f_1$ .
- ▶ A greedy approach starts with taking  $a_1$  as a locally optimal choice.
- ▶ **Lemma:**  
The greedy choice of picking  $a_1$  as first choice is optimal.
- ▶ **Proof:**
  - ▶ Suppose  $A$  is a globally optimal solution for set  $S$ .
  - ▶ Let  $a_k \in A$  be the activity with earliest finish time  $f_k$  in  $A$ .
  - ▶ If  $k = 1$ , then  $a_1 \in A$  and we are done.
  - ▶ If  $k > 1$ , then we can replace  $A$  by  $(A \setminus \{a_k\}) \cup \{a_1\}$ .
  - ▶ Since  $f_1 \leq f_k$ , this is still an optimal solution.
  - ▶ Hence, we can always start with  $a_1$ .



## Greedy Approach (2)

- ▶ After the first step, we consider the subproblem  $S' = \{a_i \in S : s_i \geq f_1\}$ .
- ▶ We apply the same greedy strategy.
- ▶ **Lemma:**  
 $A \setminus \{a_1\}$  is the optimal solution for  $S'$ .
- ▶ **Proof:**
  - ▶ Let  $B$  be a solution for  $S'$  that is larger than  $A \setminus \{a_1\}$ .
  - ▶ Then,  $B \cup \{a_1\}$  would be solution for  $S$  that is larger than  $A$ .
  - ▶ Contradiction.

## Greedy Approach (3)

Using the two lemmata we can prove by induction that the greedy approach delivers the globally optimal solution.



# Greedy Algorithm

```
1 Greedy-Selector(S)
2   // Assume S = {a[1], ..., a[n]}
3   // with activities sorted by f[i].
4   A := {a[1]}
5   j := 1
6   for i := 2 to n do
7       if s[i] >= f[j]
8           then A := A union {a[i]}
9           j := i
10  return A
```

# Greedy Algorithm (Recursive)

RECURSIVE-ACTIVITY-SELECTOR( $s, f, k, n$ )

```
1   $m = k + 1$ 
2  while  $m \leq n$  and  $s[m] < f[k]$       // find the first activity in  $S_k$  to finish
3       $m = m + 1$ 
4  if  $m \leq n$ 
5      return  $\{a_m\} \cup \text{RECURSIVE-ACTIVITY-SELECTOR}(s, f, m, n)$ 
6  else return  $\emptyset$ 
```

RECURSIVE-ACTIVITY-SELECTOR( $s, f, 0, n$ ).