

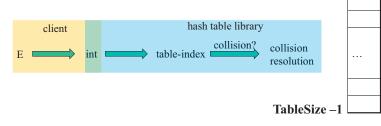


CSE332: Data Abstractions Lecture 11: Hash Tables

Dan Grossman Spring 2012

Hash Tables: Review

- Aim for constant-time (i.e., O(1)) find, insert, and delete
 - "On average" under some reasonable assumptions
- A hash table is an array of some fixed size
 - But growable as we'll see



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Collision resolution

Collision:

When two keys map to the same location in the hash table

We try to avoid it, but number-of-keys exceeds table size

So hash tables should support collision resolution

– Ideas?

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Separate Chaining

/ /

3 /

2

4 / 5 /

6 /

7 /

8 / 9 /

Chaining:

All keys that map to the same table location are kept in a list (a.k.a. a "chain" or "bucket")

hash table

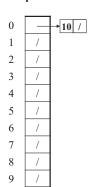
As easy as it sounds

Example:

insert 10, 22, 107, 12, 42 with mod hashing and TableSize = 10

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Separate Chaining



Chaining:

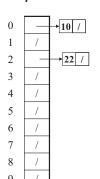
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Separate Chaining



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All keys that map to the same table location are kept in a list (a.k.a. a "chain" or "bucket")

As easy as it sounds

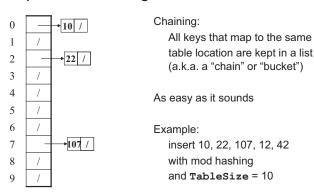
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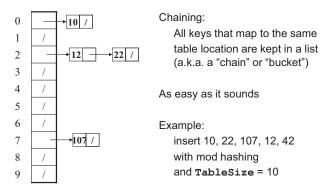
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Separate Chaining



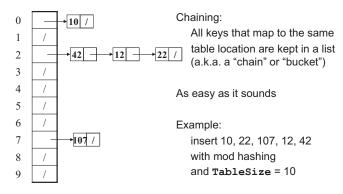
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Separate Chaining



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Separate Chaining



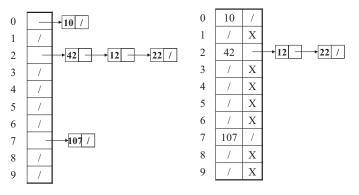
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Thoughts on chaining

- Worst-case time for find?
 - Linear
 - But only with really bad luck or bad hash function
 - So not worth avoiding (e.g., with balanced trees at each bucket)
- Beyond asymptotic complexity, some "data-structure engineering" may be warranted
 - Linked list vs. array vs. chunked list (lists should be short!)
 - Move-to-front (cf. Project 2)
 - Better idea: Leave room for 1 element (or 2?) in the table itself, to optimize constant factors for the common case
 - A time-space trade-off...

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Time vs. space (constant factors only here)



More Rigorous Chaining Analysis

Definition: The load factor, λ , of a hash table is

$$\lambda = \frac{N}{TableSize} \quad \leftarrow \text{number of elements}$$

Under chaining, the average number of elements per bucket is ____

So if some inserts are followed by *random* finds, then on average:

- Each unsuccessful find compares against items
- Each successful **find** compares against _____ items

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More rigorous chaining analysis

Definition: The load factor, λ , of a hash table is

$$\lambda = \frac{N}{\text{TableSize}} \leftarrow \text{number of elements}$$

Under chaining, the average number of elements per bucket is λ

So if some inserts are followed by random finds, then on average:

- Each unsuccessful find compares against *λ* items
- Each successful find compares against λ/2 items

So we like to keep λ fairly low (e.g., 1 or 1.5 or 2) for chaining

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Alternative: Use empty space in the table

· Another simple idea: If h (key) is already full, - try (h(key) + 1) % TableSize. If full,

- try (h(key) + 2) % TableSize. If full,

- try (h(key) + 3) % TableSize. If full...

• Example: insert 38, 19, 8, 109, 10

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Alternative: Use empty space in the table

- Another simple idea: If h (key) is already full,
 - try (h(key) + 1) % TableSize. If full,
 - try (h(key) + 2) % TableSize. If full,
 - try (h(key) + 3) % TableSize. If full...
- Example: insert 38, 19, 8, 109, 10
- 2 3 4

13

- 5 6
- 38 19

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Alternative: Use empty space in the table

- · Another simple idea: If h (key) is already full,
 - try (h(key) + 1) % TableSize. If full,
 - try (h(key) + 2) % TableSize. If full,
 - try (h(key) + 3) % TableSize. If full...
- Example: insert 38, 19, 8, 109, 10

1	/
2	/
3	/
4	/
5	/
6	/
7	/
8	38
9	19

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Alternative: Use empty space in the table

- · Another simple idea: If h (key) is already full,
 - try (h(key) + 1) % TableSize. If full,
 - try (h(key) + 2) % TableSize. If full,
 - try (h(key) + 3) % TableSize. If full...
- Example: insert 38, 19, 8, 109, 10
- 0 1 109 2 3 4
- 5 / 6 7
- 8 38
- 19

Alternative: Use empty space in the table

- · Another simple idea: If h (key) is already full,
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- Example: insert 38, 19, 8, 109, 10
- 0 8 1 109 2 10 3 / 4 / 5 6 / 7 8 38 9 19

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Open addressing

This is one example of open addressing

In general, open addressing means resolving collisions by trying a sequence of other positions in the table.

Trying the next spot is called probing

- We just did linear probing
 - ith probe was (h(key) + i) % TableSize
- In general have some probe function f and use h(key) + f(i) % TableSize

Open addressing does poorly with high load factor λ

- So want larger tables
- Too many probes means no more O(1)

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Terminology

We and the book use the terms

- "chaining" or "separate chaining"
- "open addressing"

Very confusingly,

- "open hashing" is a synonym for "chaining"
- "closed hashing" is a synonym for "open addressing"

(If it makes you feel any better, most trees in CS grow upside-down (2)





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Other operations

insert finds an open table position using a probe function

What about find?

- Must use same probe function to "retrace the trail" for the data
- Unsuccessful search when reach empty position

What about delete?

- Must use "lazy" deletion. Why?
 - Marker indicates "no data here, but don't stop probing"
- Note: delete with chaining is plain-old list-remove

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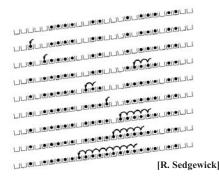
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(Primary) Clustering

It turns out linear probing is a bad idea, even though the probe function is quick to compute (which is a good thing)

Tends to produce clusters, which lead to long probing sequences

- Called primary clustering
- Saw this starting in our example



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Analysis of Linear Probing

- Trivial fact: For any $\lambda < 1$, linear probing will find an empty slot
 - It is "safe" in this sense: no infinite loop unless table is full
- Non-trivial facts we won't prove:

Average # of probes given λ (in the limit as TableSize $\rightarrow \infty$)

Average # of probes given
$$\lambda$$
 (in the limit a – Unsuccessful search:
$$\frac{1}{2} \left(1 + \frac{1}{(1-\lambda)^2} \right)$$

$$\frac{1}{2}\left(1+\frac{1}{(1-\lambda)^2}\right)$$

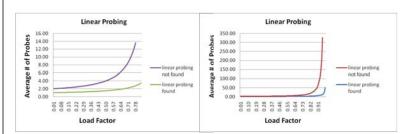
- Successful search:

$$\frac{1}{2} \left(1 + \frac{1}{\left(1 - \lambda \right)} \right)$$

This is pretty bad: need to leave sufficient empty space in the table to get decent performance (see chart)

In a chart

- · Linear-probing performance degrades rapidly as table gets full
 - (Formula assumes "large table" but point remains)



By comparison, chaining performance is linear in λ and has no trouble with $\lambda > 1$

Quadratic probing

- · We can avoid primary clustering by changing the probe function (h(key) + f(i)) % TableSize
- · A common technique is quadratic probing:

$$f(i) = i^2$$

- So probe sequence is:
 - 0th probe: h(key) % TableSize
 - 1st probe: (h(key) + 1) % TableSize
 - 2nd probe: (h(key) + 4) % TableSize
 - 3rd probe: (h(key) + 9) % TableSize

 - ith probe: (h(key) + i²) % TableSize
- · Intuition: Probes quickly "leave the neighborhood"

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Quadratic Probing Example

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Quadratic Probing Example

0	
1	
2	
3	
4	
5	
6	
7	
8	
9	89

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Quadratic Probing Example

0	
1	
2	
3	
4	
5	
6	
7	
8	18
9	89

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Quadratic Probing Example

0	49
1	
2	
3	
4	
5	
6	
7	
8	18
9	89

Quadratic Probing Example

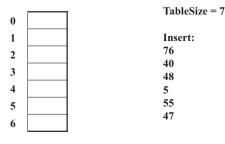
0	49
1	
2	58
3	
4	
5	
6	
7	
8	18
9	89

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Quadratic Probing Example

0	49
1	
2	58
2	79
4	
5	
6	
7	
8	18
9	89

Another Quadratic Probing Example



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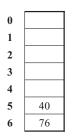
Another Quadratic Probing Example



Insert: 76 (76 % 7 = 6)40 (40 % 7 = 5)48 (48 % 7 = 6)5 (5%7=5)55 (55 % 7 = 6)47 (47 % 7 = 5)

TableSize = 7

Another Quadratic Probing Example



0

2

3

4

5

TableSize = 7**Insert:** 76 (76 % 7 = 6)(40 % 7 = 5)48 (48 % 7 = 6)5 (5%7=5)55 (55 % 7 = 6)47 (47 % 7 = 5)

(76 % 7 = 6)

(40 % 7 = 5)

(48 % 7 = 6)

(5%7=5)

(55 % 7 = 6)

(47 % 7 = 5)

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Another Quadratic Probing Example



Insert: 76 (76 % 7 = 6)40 (40 % 7 = 5)48 (48 % 7 = 6)5 (5 % 7 = 5)55 (55 % 7 = 6)(47 % 7 = 5)

TableSize = 7

Another Quadratic Probing Example

48	TableSize	TableSize = 7	
	Insert:		
5	76	(76 % 7 = 6)	
	40	(40 % 7 = 5)	
	48	(48 % 7 = 6)	
	5	(5%7=5)	
40	55	(55 % 7 = 6)	
76	47	(47 % 7 = 5)	

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Another Quadratic Probing Example

0 48 1 2 5 3 55 4 5 40 6 76

TableSize = 7

Insert:	
76	(76 % 7 = 6)
40	(40 % 7 = 5)
48	(48 % 7 = 6)
5	(5%7=5)
55	(55 % 7 = 6)
47	(47 % 7 = 5)

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Another Quadratic Probing Example

0	48	TableSize	TableSize = 7	
1	70	Insert:		
2	5	76	(76% 7 = 6)	
3	55	40 48	(40 % 7 = 5) (48 % 7 = 6)	
4		5	(5%7=5)	
5	40	55	(55 % 7 = 6)	
6	76	47	(47 % 7 = 5)	

Doh!: For all n, ((n*n) +5) % 7 is 0, 2, 5, or 6

- Excel shows takes "at least" 50 probes and a pattern
- Proof uses induction and (n^2+5) % 7 = $((n-7)^2+5)$ % 7
 - In fact, for all c and k, (n^2+c) % $k = ((n-k)^2+c)$ % k

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From Bad News to Good News

- Bad news:
 - Quadratic probing can cycle through the same full indices, never terminating despite table not being full
- · Good news:
 - If TableSize is prime and λ < ½, then quadratic probing will find an empty slot in at most TableSize/2 probes
 - So: If you keep λ < ½ and TableSize is prime, no need to detect cycles
 - Proof is posted in lecture11.txt
 - · Also, slightly less detailed proof in textbook
 - Key fact: For prime \mathbf{T} and $0 < \mathbf{i}, \mathbf{j} < \mathbf{T}/2$ where $\mathbf{i} \neq \mathbf{j}$, $(\mathbf{k} + \mathbf{i}^2) % \mathbf{T} \neq (\mathbf{k} + \mathbf{j}^2) % \mathbf{T}$ (i.e., no index repeat)

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Clustering reconsidered

- Quadratic probing does not suffer from primary clustering: no problem with keys initially hashing to the same neighborhood
- · But it's no help if keys initially hash to the same index
 - Called secondary clustering
- Can avoid secondary clustering with a probe function that depends on the key: double hashing...

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Double hashing

Idea:

- Given two good hash functions h and g, it is very unlikely that for some key, h (key) == g (key)
- So make the probe function f(i) = i*g(key)

Probe sequence:

- 0th probe: h(key) % TableSize
- 1st probe: (h(key) + g(key)) % TableSize
- 2nd probe: (h(key) + 2*g(key)) % TableSize
- 3rd probe: (h(key) + 3*g(key)) % TableSize
- ...
- i^{th} probe: (h(key) + i*g(key)) % TableSize

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Detail: Make sure g (key) cannot be 0

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Double-hashing analysis

- Intuition: Because each probe is "jumping" by g (key) each time, we "leave the neighborhood" and "go different places from other initial collisions"
- But we could still have a problem like in quadratic probing where we are not "safe" (infinite loop despite room in table)
 - It is known that this cannot happen in at least one case:
 - h(key) = key % p
 - g(key) = q (key % q)
 - 2 < q < p
 - p and q are prime

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More double-hashing facts

- · Assume "uniform hashing"
 - Means probability of g(key1) % p == g(key2) % p is 1/p
- Non-trivial facts we won't prove:

Average # of probes given λ (in the limit as **TableSize** $\rightarrow \infty$)

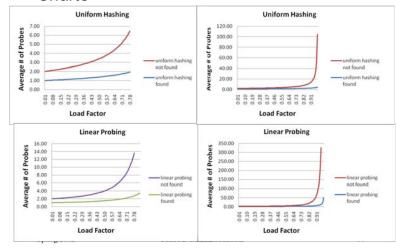
Unsuccessful search (intuitive):

- Successful search (less intuitive): $\frac{1}{\lambda} \log_{e} \left(\frac{1}{1-\lambda} \right)$

 Bottom line: unsuccessful bad (but not as bad as linear probing), but successful is not nearly as bad

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Charts



Where are we?

- · Chaining is easy
 - find, delete proportional to load factor on average
 - insert can be constant if just push on front of list
- · Open addressing uses probing, has clustering issues as table fills
 - Why use it:
 - · Less memory allocation?
 - · Easier data representation?
- Now:
 - Growing the table when it gets too full ("rehashing")
 - Relation between hashing/comparing and connection to Java

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Rehashing

- As with array-based stacks/queues/lists, if table gets too full, create a bigger table and copy everything
- · With chaining, we get to decide what "too full" means
 - Keep load factor reasonable (e.g., < 1)?
 - Consider average or max size of non-empty chains?
- · For open addressing, half-full is a good rule of thumb
- New table size
 - Twice-as-big is a good idea, except, uhm, that won't be prime!
 - So go about twice-as-big
 - Can have a list of prime numbers in your code since you won't grow more than 20-30 times

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More on rehashing

- · What if we copy all data to the same indices in the new table?
 - Will not work; we calculated the index based on TableSize
- Go through table, do standard insert for each into new table
 - Run-time?
 - O(n): Iterate through old table
- Resize is an O(n) operation, involving n calls to the hash function
 - Is there some way to avoid all those hash function calls?
 - Space/time tradeoff: Could store h (key) with each data item
 - Growing the table is still O(n); only helps by a constant factor

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Hashing and comparing

- Need to emphasize a critical detail:

 - While chaining or probing we compare to E
 - · Just need equality testing (i.e., "is it what I want")
- · So a hash table needs a hash function and a comparator
 - In Project 2, you will use two function objects
 - The Java library uses a more object-oriented approach:
 each object has an equals method and a hashCode method

```
class Object {
  boolean equals(Object o) {...}
  int hashCode() {...}
  ...
}
```

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Equal Objects Must Hash the Same

- The Java library (and your project hash table) make a very important assumption that clients must satisfy...
- · Object-oriented way of saying it:

```
If a.equals (b), then we must require
a.hashCode() == b.hashCode()
```

· Function-object way of saying it:

```
If c.compare(a,b) == 0, then we must require
h.hash(a) == h.hash(b)
```

· Why is this essential?

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Java bottom line

- Lots of Java libraries use hash tables, perhaps without your knowledge
- So: If you ever override equals, you need to override hashCode also in a consistent way
 - See CoreJava book, Chapter 5 for other "gotchas" with equals

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Bad Example

· Think about using a hash table holding points

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By the way: comparison has rules too

We have not empahsized important "rules" about comparison for:

- All our dictionaries
- Sorting (next major topic)

Comparison must impose a consistent, total ordering:

For all a, b, and c,

- If compare (a,b) < 0, then compare (b,a) > 0
- If compare (a,b) == 0, then compare (b,a) == 0
- If compare(a,b) < 0 and compare(b,c) < 0,
 then compare(a,c) < 0</pre>

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Final word on hashing

- The hash table is one of the most important data structures
 - Supports only find, insert, and delete efficiently
- Important to use a good hash function
- · Important to keep hash table at a good size
- What we skipped: Perfect hashing, universal hash functions, hopscotch hashing, cuckoo hashing
- Side-comment: hash functions have uses beyond hash tables
 - Examples: Cryptography, check-sums

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