CS2020 Data Structures and Algorithms

Welcome!

Coding Quiz

Coding Under Pressure

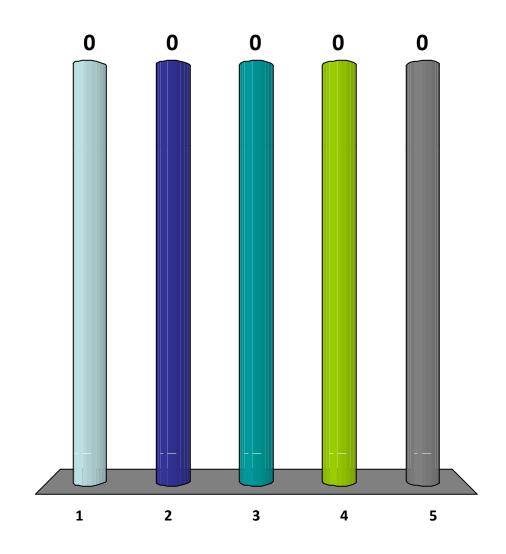
- Hard!
- Stressful!

Goal:

- Questions were not, individually, hard.
- Lots of coding required.
- Lots of places for small mistakes

The Coding Quiz was:

- 1. Very hard
- 2. Hard
- 3. Ok
- 4. Easy
- 5. Very easy.



Today

- DNA Analysis
 - Finish the analysis of the Longest-Common-Substring.
- Resolving Collisions
 - Open Addressing
- Advanced Hashing
 - Universal Hashing
 - Perfect Hashing

DNA Analysis

How similar is chimp DNA to human DNA?

- Problem:
 - Given human DNA string: ACAAGCGGTAA
 - Given chimp DNA string: CCAAGGGGTAA
 - How similar are they?

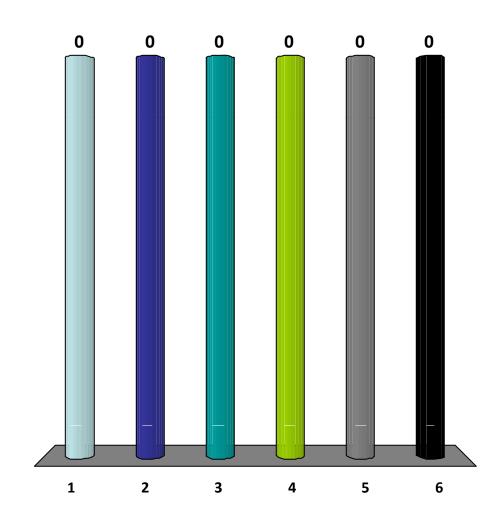
- Similarity = longest common substring
 - Implies a gene that is shared by both.
 - Count genes that are shared by both.

```
exists-substring(X1, X2, L)
  1. for (i = 0 \text{ to } n - L - 1) do:
          hash = h(X1[i:i+L])
          T.hash-insert(hash, i))
  4. for (i = 0 \text{ to } n - L - 1) do:
  5.
          hash = h(X2[i:i+L])
  6.
          if (T.hash-lookup(hash, s)) then
  7.
                 return true.
```

8. return false

The performance of exists-substring(X1, X2, L) on strings of length n is:

- 1. O(1)
- 2. $O(\log n)$
- 3. O(n)
- 4. $O(n^2)$
- 5. $O(n^2 \log(n))$
- 6. $O(n^3)$



```
exists-substring(X1, X2, L)
```

- 1. for $(i = 0 \text{ to } n L 1) \text{ do:} \leftarrow \text{Loop } n L \text{ times.}$
- 2. hash = h(X1[i:i+L]) Calculate hash: O(L).
- 3. T.hash-insert(hash, i))
- 4. ... Insert: O(1)

Assume:

- Simple uniform hashing
- m >= n

Total cost:
$$O(L(n-L)) = O(n^2)$$

DNA Analysis

In order to speed up exists-substring:

- 1. Reduce false positives
 - If the hash is in the table, then it is very likely that the string is in the hash table.

2. Compute hash faster

It is too slow to re-compute the hash function (n − L) times.

Reduce false positives:

- Use two different hash functions.
 - $h_1: U \to \{1..m\}, m < 4n$.
 - $h_2: U \to \{1..n^2\}.$

- Using a hash function as a signature.
 - A hash of a large data structure gives a small signature.
 - Example:
 - Are two databases identical?
 - Compare hash!
 - Think of a hash as a fingerprint.

Reduce false positives:

- Use two different hash functions.
 - $h_1: U \to \{1..m\}, m < 4n$.
 - $h_2: U \to \{1..n^2\}.$

hash-insert(s):

Table[$h_1(s)$].LLinsert($h_2(s)$, s)

Reduce false positives:

- Use two different hash functions.
 - $h_1: U \to \{1..m\}, m < 4n$.
 - $h_2: U \to \{1..n^2\}.$

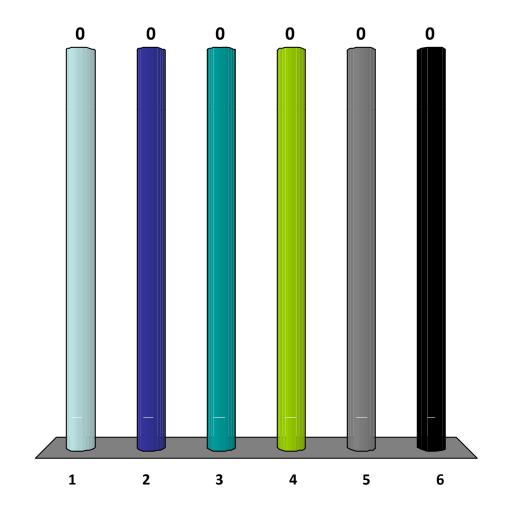
hash-lookup(s):

```
if (Table[h_1(s)] != null) then  (sig, t) = Table[h_1(s)]  if (h_2(s) == sig) then  if (s == t) \text{ then return true;}
```

```
Analysis: hash-lookup(s)
  - Case 1: string s is in table: O(L)
  - Case 2: Table [h_1(s)] = null: O(1)
  - Case 3: Table [h_1(s)]!= null: ??
  hash-lookup(s):
     if (Table[h_1(s)] != null) then
            (sig, t) = Table[h_1(s)]
            if (h_2(s) == sig) then
                   if (s == t) then return true;
```

Let $h_2: U \rightarrow \{1..n^2\}$ be a hash function. For strings s and t, what is the probability that $h_2(s) == h_2(t)$?

- 1. 1/n
- $2. \ 2/n$
- 3. $1/n^2$
- 4. $1/\sqrt{n}$
- 5. 1/2
- 6. None of the above.

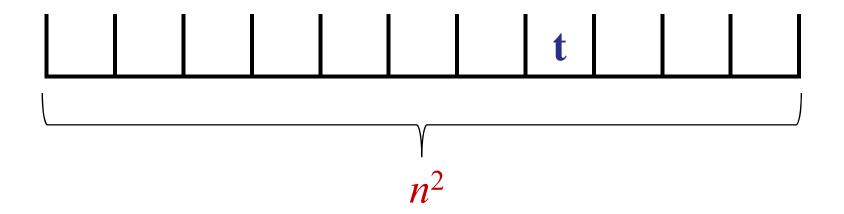


Analysis: hash-lookup(s)

(Assume SUHA.)

- $h_2 : U \rightarrow \{1..n^2\}$
- For two strings s and t:

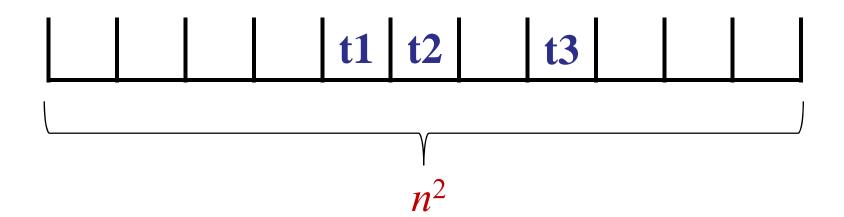
Probability($h_2(s) == h_2(t)$): $1/n^2$



```
Analysis: hash-lookup(s) (Assume SUHA.)
- h_2: U \rightarrow \{1..n^2\}
```

– For string s:

Probability($h_2(s) == h_2(t)$ for any string t): $n/n^2 \le 1/n$



```
Analysis: hash-lookup(s)
  - Case 1: string s is in table: O(L)
  - Case 2: Table [h_1(s)] = null: O(1)
  - Case 3: Table [h_1(s)] != null : O(1 + L/n)
  hash-lookup(s):
     if (Table[h_1(s)] != null) then
             (sig, t) = Table[h_1(s)]
                                            with probability ≤ 1/n
            if (h_2(s) == sig) then

    Cost: O(L).

                   if (s == t) then return true;
```

Analysis:

- Size of signature.
 - $h_2: U \to \{1..n^2\}.$
 - $\log(n^2) = 2\log(n)$

- Assume that we can read/write/compare log(n) bits in time O(1).
 - Why? A machine word is $> \log(n)$.
- Cost of comparing two signatures = O(1).

exists-substring(X1, X2, L)

```
1. ...

2. for (i = 0 \text{ to } n - L - 1) \text{ do}:

Calculate hash: O(L).

3. hash = h(X2[i : i + L])

4. if (T.hash-lookup(hash, s)) then

5. return true.

Lookup: E[cost] = 1 + L/n
```

Total cost:
$$O((n - L)(L + 1 + L/n)) = O(n^2)$$

DNA Analysis

In order to speed up exists-substring:

- 1. Reduce false positives
 - Use second hash function as a signature.
 - Reduce cost of collisions.

- 2. Compute hash faster
 - It is too slow to re-compute the hash function (n − L) times.

Abstract data type:

- insert(s): sets string equal to string s
- delete-first-letter()
- append-letter(c)
- hash(): returns hash of current string

Example:

```
- insert("arith")
          string == "arith"
- hash() \rightarrow 17
delete-first-letter()
          string == "rith"
- hash() \rightarrow 47
append-letter('m')
          string == "rithm"
- hash() \rightarrow 4
```

Costs:

- insert(s) : O(|S|)
- delete-first-letter() : O(1)
- append-letter(c) : O(1)
- hash() : O(1)

Example:

- insert("arith") : 5c
- delete-first-letter(), append-letter(m) : O(1) = c
 string == "rithm"
- delete-first-letter(), append-letter(e) : O(1) = c
 string == "ithme"
- delete-first-letter(), append-letter(t) : O(1) = c
 string == "thmet"
- delete-first-letter(), append-letter(i) : O(1) = c
 string == "hmeti"
- delete-first-letter(), append-letter(c) : O(1) = c
 string == "metic"

Conclusion: n - L = 6 hashes for cost 10c = O(n).

```
exists-substring(X1, X2, L)
  1. rollhash.insert(X1[i:i+L])
  2. for (i = 0 \text{ to } n - L - 1) do:
          T.hash-insert(rollhash.hash(), i))
  3.
          rollhash.delete-first-letter()
  4.
  5.
          rollhash.append-letter(X1[i + L])
```

```
exists-substring(X1, X2, L)

1. rollhash.insert(X1[i:i+L])

2. for(i=0 to n-L-1) do:

1. loop n-L times.

2. loop n-L times.

2. loop n-L times.

3. loop n-L times.
```

rollhash.delete-first-letter() <

5. rollhash.append-letter(
$$X1[i+L]$$
)
6. ... Update hash: O(1).

Total cost:
$$O(n - L + L) = O(n)$$

```
exists-substring(X1, X2, L)
  1. ...
  2. rollhash.insert(X2[i:i+L])
  3. for (i = 0 \text{ to } n - L - 1) do:
          if (T.hash-lookup(rollhash.hash(), s)) then
  5.
                 return true.
  6.
          rollhash.delete-first-letter()
          rollhash.append-letter(X1[i + L])
  7.
```

```
exists-substring(X1, X2, L)
```

```
2. rollhash.insert(X2[i:i+L]) ___Loop n-L times.
3. for (i = 0 \text{ to } n - L - 1) do: Lookup: E[\cos t] = 1 + L/n
        if (T.hash-lookup(rollhash.hash(), s)) then
5.
               return true.
                                        Update hash: O(1).
        rollhash.delete-first-letter()
6.
        rollhash.append-letter(X1[i + L])
7.
```

Total cost:
$$O((n - L)(1 + L/n) + L) = O(n)$$

Abstract data type:

- insert(s): sets string equal to string s
- delete-first-letter()
- append-letter(c)
- hash(): returns hash of current string

Basic idea:

- Initially (on "insert"), calculate hash of string.
- Whenever the string is updated, update the hash.
- When a hash() is requested, output the pre-computed hash.

Step 1: Represent a string as a number

- Assume all letters in a string are 8-bit chars.
- Given a sequence of letters:

$$c_{L-1} c_{L-2} \dots c_1 c_0$$

Define: 8L bit integer

$$s = 00101001$$
, 10110111 , ... 10010000 , 10010000 , c_{L-1} c_{L-2} c_{1} c_{0}

Step 1: Represent a string as a number

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- Given a sequence of letters:

$$c_{L-1} c_{L-2} \dots c_1 c_0$$

Define: 8L bit integer

$$s = \underbrace{00101001}_{c_{L-1}} \underbrace{10110111}_{c_{L-2}} \dots \underbrace{10010000}_{c_{0}} \underbrace{10010000}_{c_{0}}$$

$$s = \sum_{i=0}^{L-1} c_{i} \cdot 2^{8i}$$

Step 1: Represent a string as a number

- Assume all letters in a string are 8-bit chars.
- Given a sequence of letters:

$$\mathbf{c}_{\mathrm{L-1}} \, \mathbf{c}_{\mathrm{L-2}} \dots \, \mathbf{c}_1 \, \mathbf{c}_0$$

Define: 8L bit integer

$$s = \underbrace{00101001}_{\mathbf{c}_{L-1}} \underbrace{10110111}_{\mathbf{c}_{L-2}} \dots \underbrace{10010000}_{\mathbf{c}_{0}} \underbrace{10010000}_{\mathbf{c}_{0}}$$

$$s = \sum_{i=0}^{L-1} c_{i} \cdot 2^{8i} = \sum_{i=0}^{L-1} c_{i} \ll 8i$$

Step 2: Updating the string

Deleting character c_{L-1} :

```
s = 00101001 \ 10110111 \ \dots \ 10010000 \ 10010000
-00101001 \ 00000000 \ \dots \ 00000000 \ 00000000
10110111 \ \dots \ 10010000 \ 10010000
```

Step 2: Updating the string

Deleting character c_{L-1} :

$$s = 00101001 \ 10110111 \ \dots \ 10010000 \ 10010000$$
 $-00101001 \ 00000000 \ \dots \ 00000000 \ 00000000$
 $10110111 \ \dots \ 10010000 \ 10010000$

Step 2: Updating the string

Appending character c:

```
s = 00000000 \ 10110111 \ \dots \ 10010000 \ 10010000
```

10110111 ... 10010000 10010000 00000000

Step 2: Updating the string

Appending character c:

```
s = 000000000 \ 101101111 \dots 100100000 \ 1001000000
* \qquad \qqquad \qqqq \qqq \qqqq \qq
```

Step 2: Updating the string

Appending character c:

$$s = 00000000 \ 10110111 \ \dots \ 10010000 \ 10010000$$
 $* \ 10110111 \ \dots \ 10010000 \ 10010000 \ 00000000$
 $+ \ 10101101$

10110111 ... 10010000 10010000 10101101

$$s = s * 2^{8} + c$$

$$= (s \ll 8) + c \qquad \text{Shift, addition: O(1)}$$

Step 3: The Hash Function

The Division Method

$$h(s) = s \mod p$$

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$$h(s) = s \mod p$$

Appending a character:

$$h(s \ll 8 + c)$$

Step 3: The Hash Function

The Division Method

$$h(s) = s \mod p$$

Appending a character: O(1)

$$h(s \ll 8 + c)$$

- $= [(s \ll 8) + c] \mod p$
- $= [(s \mod p) \ll 8) \mod p + c] \mod p$
- $= [h(s) \ll 8 + c] \mod p$

Step 3: The Hash Function

The Division Method

$$h(s) = s \mod p$$

Deleting the first character:

$$h\left(s-\left(c_{L-1}\ll 8(L-1)\right)\right)$$

Step 3: The Hash Function

The Division Method

$$h(s) = s \mod p$$

Deleting the first character: O(1)

$$h\left(s-\left(c_{L-1}\ll 8(L-1)\right)\right)$$

$$= [h(s) - (c_{L-1} \ll 8(L-1) \bmod p)] \bmod p$$

Rolling Hash Function

Costs:

- insert(s) : O(|S|)
- delete-first-letter() : O(1)
- append-letter(c) : O(1)
- hash() : O(1)

DNA Analysis

Longest Common Substring

For any length L:

exists-substring(X1, X2, L)

has cost O(n).

Using binary search to find maximum value of L, we find the longest common substring in time:

 $O(n \log n)$

DNA Analysis

Longest Common Substring

For any length L:

exists-substring(X1, X2, L)

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Using binary search to find maximum value of L, we find the longest common substring in time:

 $O(n \log n)$

The story continues... suffix-trees... O(n)....

DNA Analysis Summary

Using Hash Tables

- To get efficient algorithms, you have to be careful!
- Signatures...
 - Hash functions are useful as a "summary" of a longer / bigger document.
- Rolling hashes...
 - Fast way to calculate hashes in an incremental fashion.

Today

- DNA Analysis
 - Finish the analysis of the Longest-Common-Substring.
- Resolving Collisions
 - Open Addressing
- Advanced Hashing
 - Universal Hashing
 - Perfect Hashing

Resolving Collisions

- Basic problem:
 - What to do when two items hash to the same bucket?

- Solution 1: Chaining
 - Insert item into a linked list.

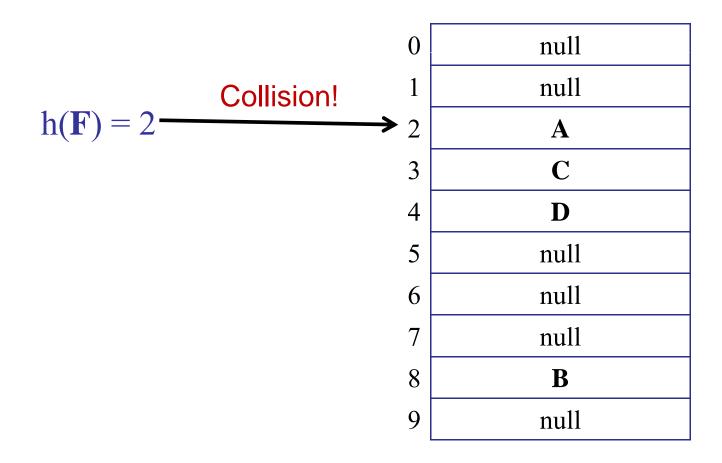
- Solution 2: Open Addressing
 - Find another free bucket.

Advantages:

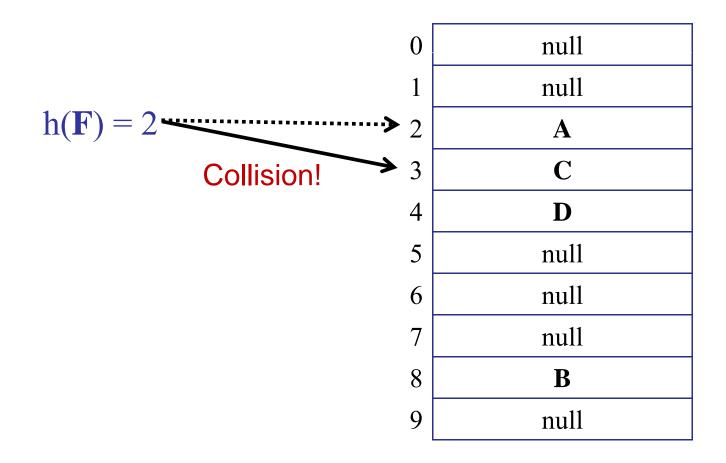
- No linked lists!
- All data directly stored in the table.
- One item per slot.

0	null
1	null
2	\mathbf{A}
3	null
4	null
5	null
6	null
7	null
8	В
9	null

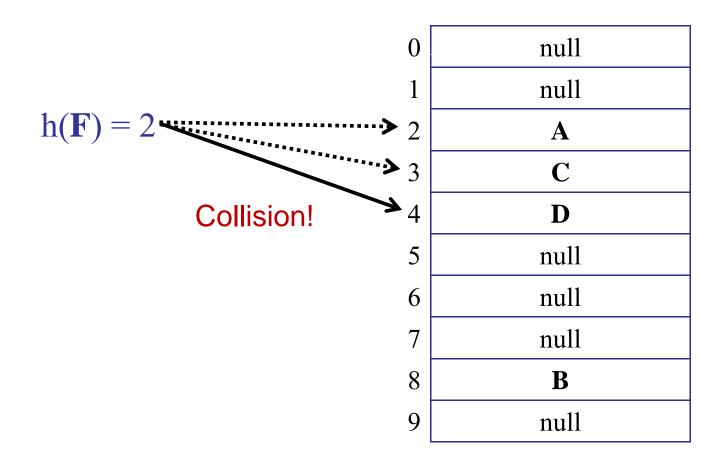
On collision:



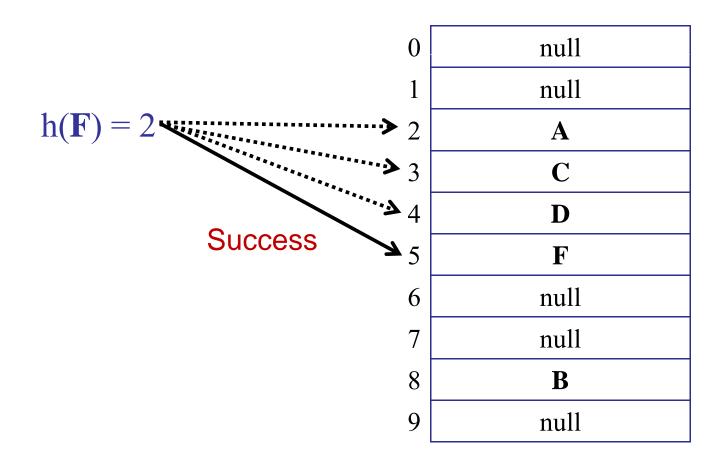
On collision:



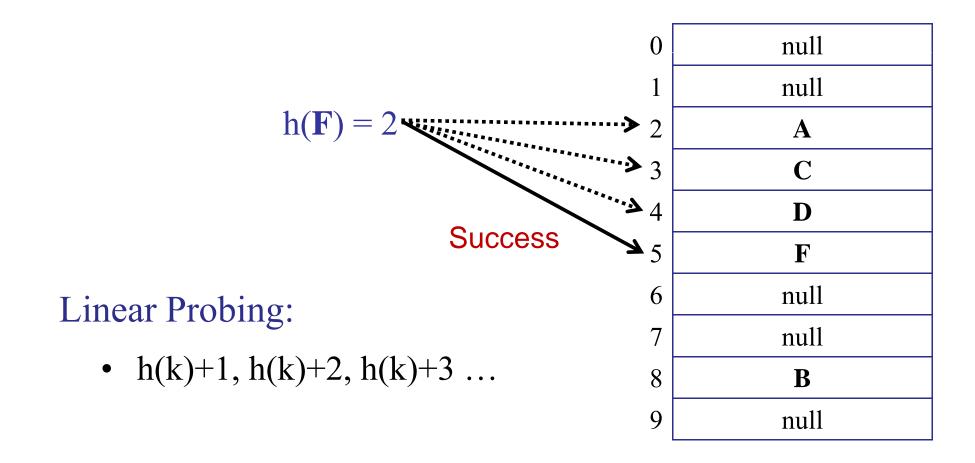
On collision:



On collision:



On collision:



Hash Function re-defined:

```
h(\text{key, i}): U \rightarrow \{1..m\}
```

Two parameters:

- key : the thing to map
- i : number of collisions

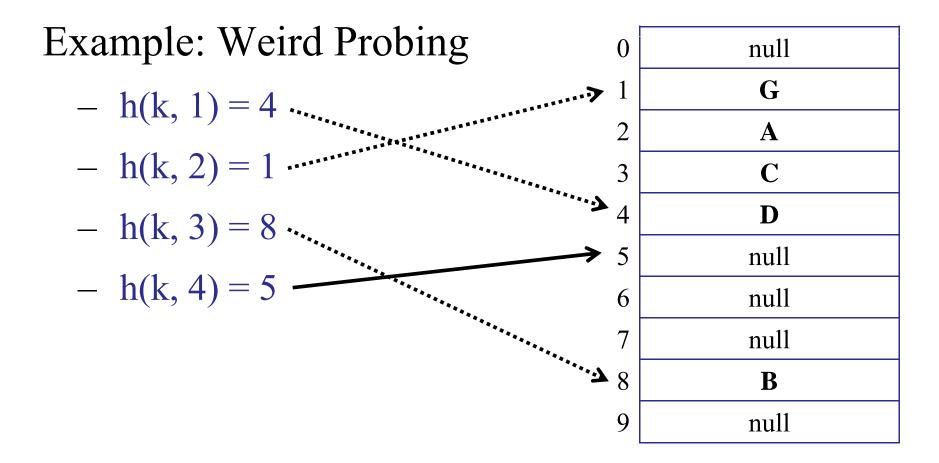
Hash Function re-defined:

$$h(\text{key, i}): U \rightarrow \{1..m\}$$

Example: Linear Probing	0	null
- h(k, 1) = hash of key k	1	null
	2	\mathbf{A}
- h(k, 2) = h(k, 1) + 1	3	\mathbf{C}
- h(k, 3) = h(k, 1) + 2	4	D
	5	${f F}$
- h(k, 4) = h(k, 1) + 4	6	null
-	7	null
1 /1 0 1 /1 1 1	8	В
$- h(k, i) = h(k, 1) + i \mod m$	9	null

Hash Function re-defined:

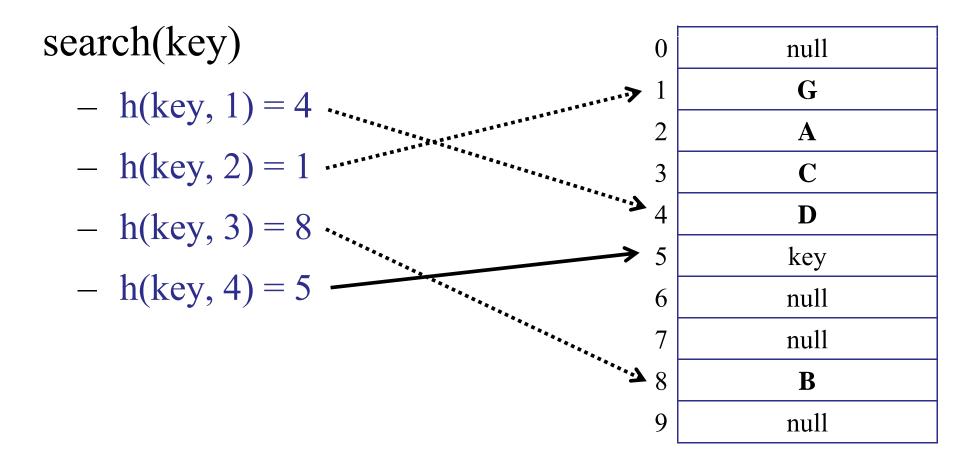
$$h(\text{key, i}): U \rightarrow \{1..m\}$$



```
hash-insert(key, data)
1. int i = 1;
2. while (i \le m) {
                                           // Try every bucket
        int bucket = h(key, i);
3.
        if (T[bucket] == null){ // Found an empty bucket
4.
5.
              T[bucket] = {key, data}; // Insert key/data
                                           // Return
6.
              return success;
7.
      i++;
8.
9. }
                                            // Table full!
10.return table-full;
```

Hash Function re-defined:

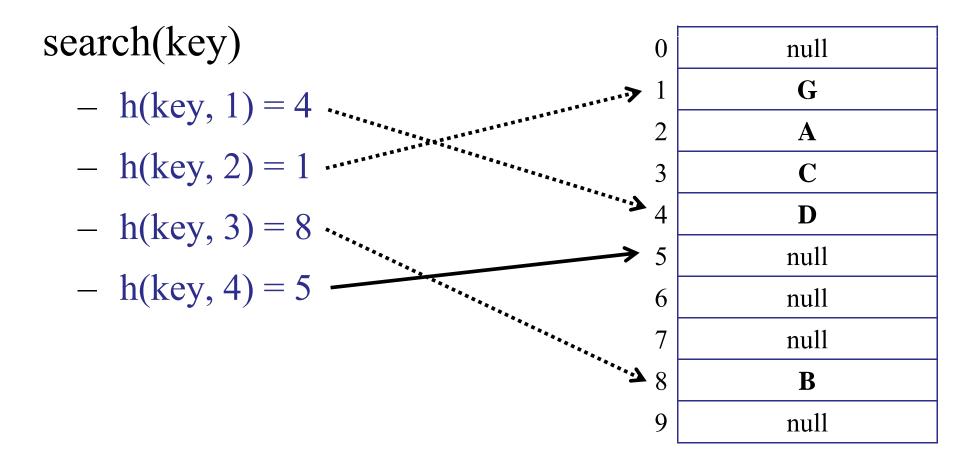
$$h(\text{key, i}): U \rightarrow \{1..m\}$$



```
hash-search(key)
1. int i = 1;
2. while (i <= m) {
3.
       int bucket = h(key, i);
       if (T[bucket] == null) // Empty bucket!
4.
5.
             return key-not-found;
6.
       if (T[bucket].key == key) // Full bucket.
7.
                  return T[bucket].data;
8.
     i++;
9.
10.return key-not-found; // Exhausted entire table.
```

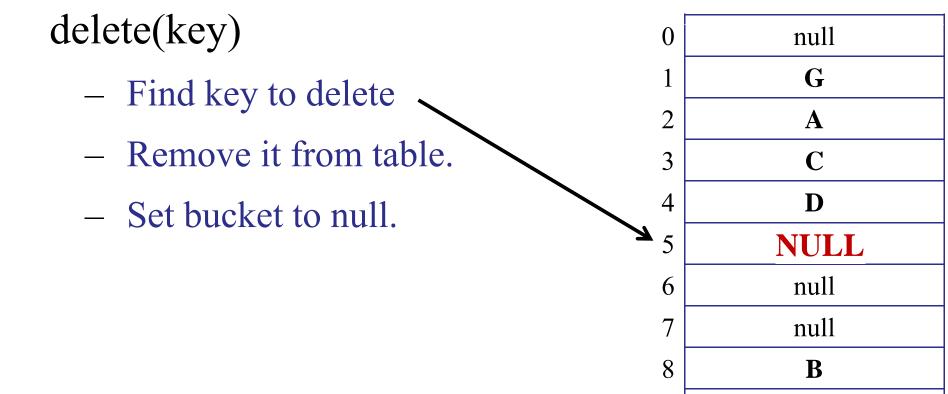
Hash Function re-defined:

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Hash Function re-defined:

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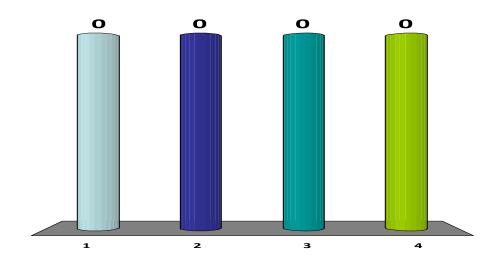


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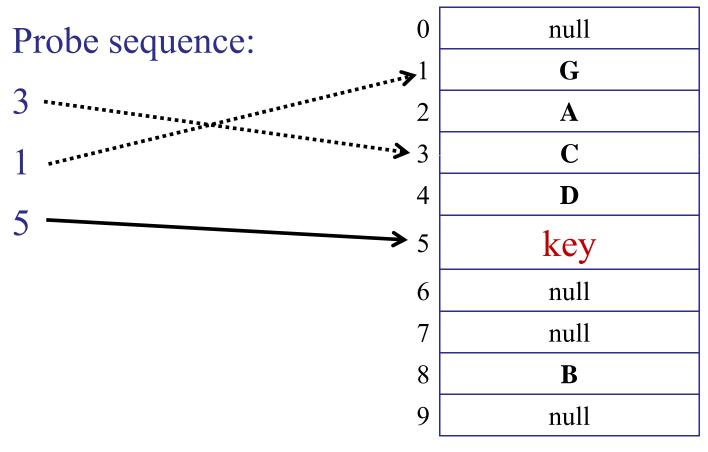
null

What is wrong with delete?

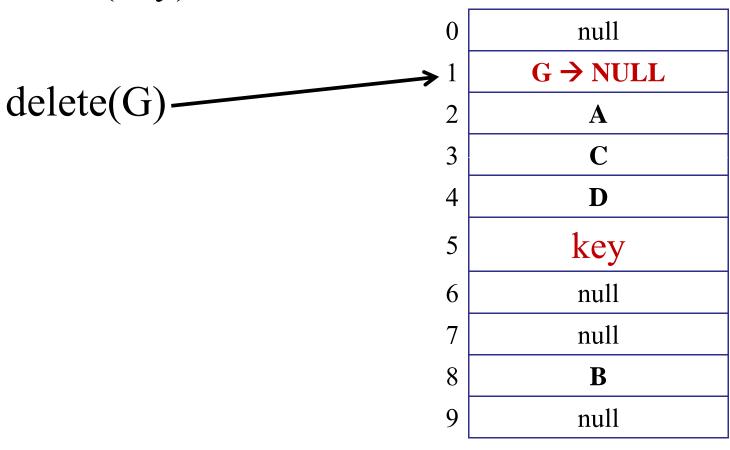
- 1. Search may fail to find an element.
- 2. The table will have gaps in it.
- 3. Space is used inefficiently.
- 4. If the key is inserted again, it may end up in a different bucket.



insert(key)



insert(key)



insert(key)

delete(G)

search(key)

0	null
1	NULL
2	${f A}$
234	C
4	D
5	key
6	null
7	null
8	В
9	null

insert(key)

delete(G)

search(key)

Probe sequence.

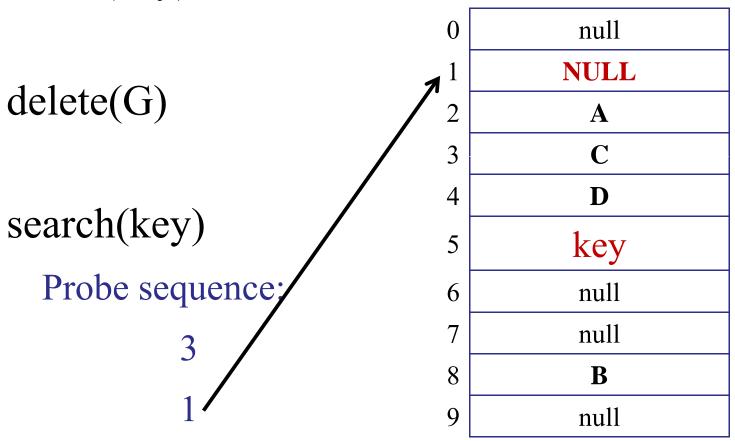
3

1

5

0	null
•	
1	NULL
2	A
234	\mathbf{C}
4	D
5	key
6	null
7	null
8	В
9	null

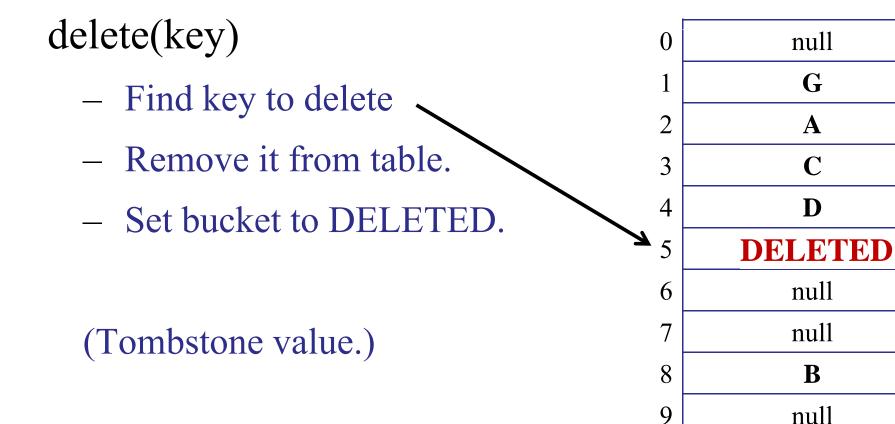
insert(key)



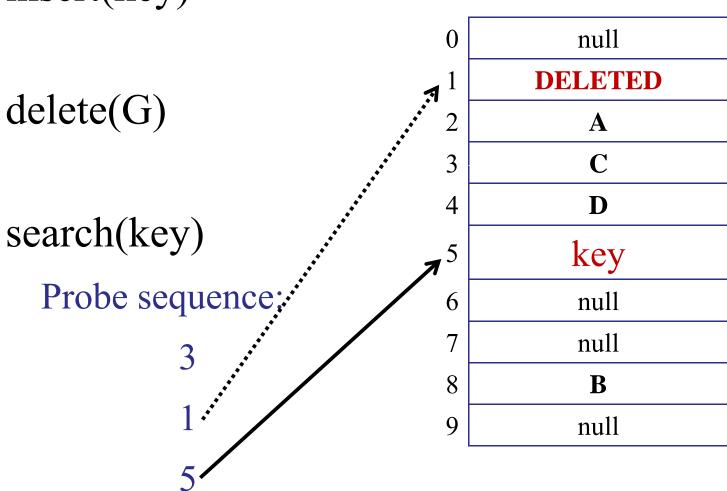
Not found!

Hash Function re-defined:

$$h(\text{key, i}): U \rightarrow \{1..m\}$$



insert(key)



Properties of a good hash function:

1. h(key, i) enumerates all possible buckets.

For every bucket *j*, there is some *i* such that:

$$h(key, i) = j$$

The hash function is permutation of $\{1..m\}$.

For linear probing: true!

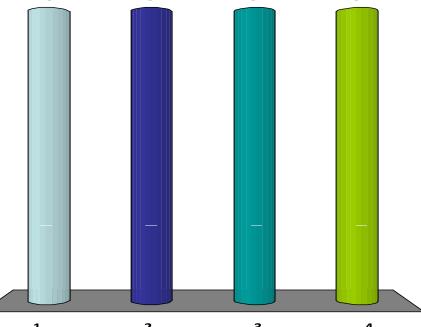
Enter question text...

- 1. Search incorrectly returns key-not-found.
- 2. Delete fails.

0 of 60

3. Insert puts a key in the wrong place

4. Returns table-full even when there is still space left.



Properties of a good hash function:

2. Simple Uniform Hashing Assumption

Every key is equally likely to be mapped to every bucket, independently of every other key.

For h(*key*, 1)?

For every h(key, i)?

Properties of a good hash function:

2. Uniform Hashing Assumption

Every key is equally likely to be mapped to every *permutation*, independent of every other key.

n! permutations for probe sequence: e.g.,

- 1234
- 1243
- 1423
- 1432

•

Properties of a good hash function:

2. Uniform Hashing Assumption

Every key is equally likely to be mapped to every *permutation*, independent of every other key.

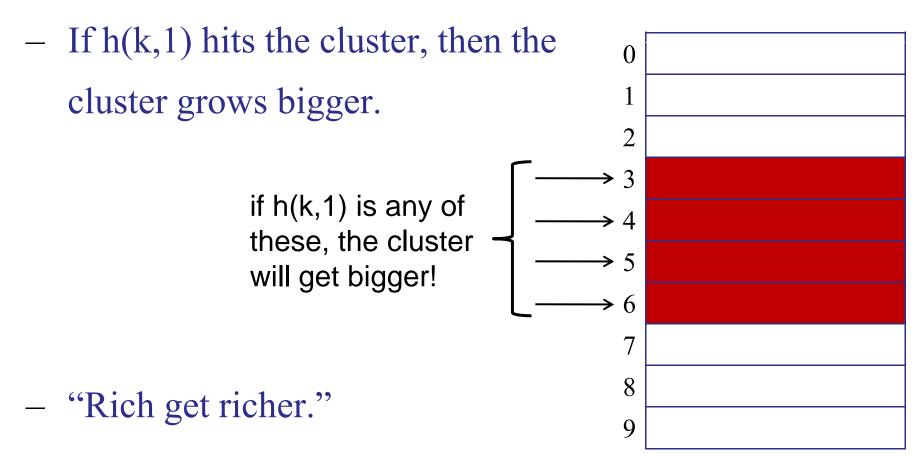
n! permutations for probe sequence: e.g.,

- 1 2 3 4 Pr(1/m)
- 1 2 4 3 Pr(0) NOT Linear Probing
- 1 4 2 3 Pr(0)
- 1 4 3 2 Pr(0)

•

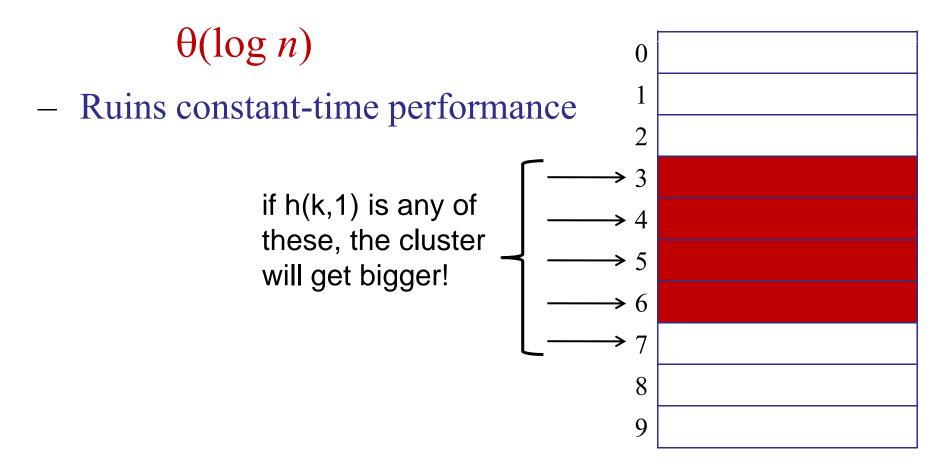
Problem with linear probing: clusters

 If there is a cluster, then there is a higher probability that the next h(k) will hit the cluster.



Problem with linear probing: clusters

If the table is 1/4 full, then there will be clusters of size:



Properties of a good hash function:

2. Uniform Hashing Assumption

Every key is equally likely to be mapped to every *permutation*, independent of every other key.

n! permutations for probe sequence: e.g.,

- 1234
- 1243
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•

Double Hashing

• Start with two ordinary hash functions:

• Define new hash function:

$$h(k, i) = f(k) + i \cdot g(k) \mod m$$

- Note:
 - Since f(k) is good, f(k, 1) is "almost" random.
 - Since g(k) is good, the probe sequence is "almost" random.

Double Hashing

Hash function

$$h(k, i) = f(k) + i \cdot g(k) \mod m$$

Claim: if g(k) is relatively prime to m, then h(k, i) hits all buckets.

- Assume not: then for some distinct i, j < m:

$$f(k) + i \cdot g(k) = f(k) + j \cdot g(k) \mod m$$

- $\rightarrow i \cdot g(k) = j \cdot g(k) \mod m$
- \rightarrow $(i-j)\cdot g(k) = 0 \mod m$
- \rightarrow g(k) not relatively prime to m. since $(i,j \le m)$

Double Hashing

Hash function

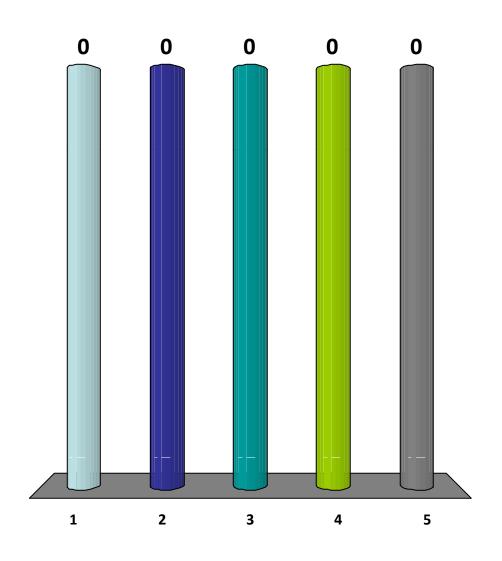
$$h(k, i) = f(k) + i \cdot g(k) \mod m$$

Claim: if g(k) is relatively prime to m, then h(k, i) hits all buckets.

Example: if $(m = 2^r)$, then choose g(k) odd.

If (m==n), what is the expected insert time, under uniform hashing assumption?

- 1. O(1)
- 2. O(log n)
- 3. O(n)
- 4. $O(n^2)$
- 5. None of the above.



• Chaining:

- When (m==n), we can still add new items to the hash table.
- We can still search efficiently.

Open addressing:

- When (m==n), the table is full.
- We cannot insert any more items.
- We cannot search efficiently.

Define:

- Load $\alpha = n / m$ Average # items / bucket
- Assume α < 1.

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Average # items / bucket

Claim:

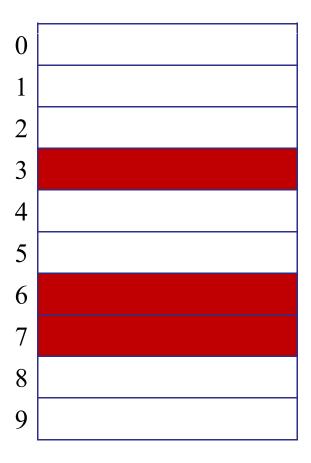
For *n* items, in a table of size *m*, assuming *uniform hashing*, the expected cost of an operation is:

$$\leq \frac{1}{1-\alpha}$$

Example: if (α =90%), then E[# probes] = 10

Proof of Claim:

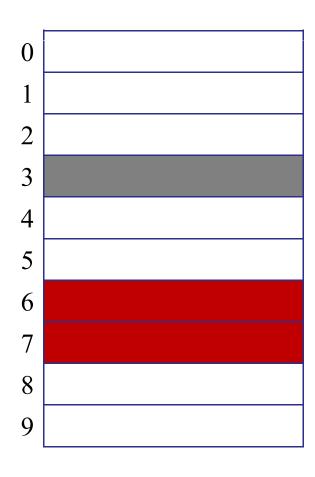
First probe: probability that
 first bucket is full is: n/m



Proof of Claim:

First probe: probability that
 first bucket is full is: n/m

- Second probe: if first bucket is full, then the probability that the second bucket is also full: (n-1)/(m-1)

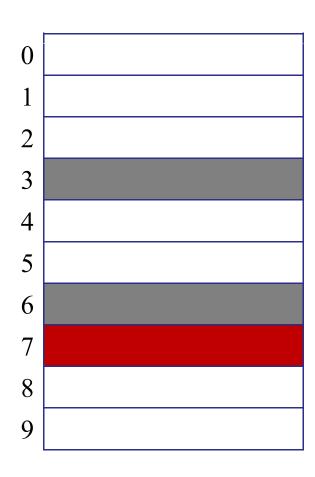


Proof of Claim:

First probe: probability that
 first bucket is full is: n/m

- Second probe: if first bucket is full, then the probability that the second bucket is also full: (n-1)/(m-1)

- Third probe: probability is full: (n-2)/(m-2)



Proof of Claim:

$$1 + \frac{n}{m} \left(1 + \frac{n-1}{m-1} \left(1 + \frac{n-2}{m-1} \left(\dots \right) \right) \right)$$
First probe Second probe Third probe

Proof of Claim:

– Expected cost:

$$1 + \frac{n}{m} \left(1 + \frac{n-1}{m-1} \left(1 + \frac{n-2}{m-1} \left(\dots \right) \right) \right)$$

– Note:

$$\frac{n-i}{m-i} \le \frac{n}{m} \le \alpha$$

Proof of Claim:

$$1 + \frac{n}{m} \left(1 + \frac{n-1}{m-1} \left(1 + \frac{n-2}{m-1} \left(\dots \right) \right) \right)$$

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$$\leq \frac{1}{1-\alpha}$$

Define:

- Load $\alpha = n / m$
- Assume α < 1.

Average # items / bucket

Claim:

For *n* items, in a table of size *m*, assuming *uniform hashing*, the expected cost of an operation is:

$$\leq \frac{1}{1-\alpha}$$

Example: if (α =90%), then E[# probes] = 10

Advantages...

Open addressing:

- Saves space (no linked lists)
- Rarely allocate memory
- Better cache performance
 - Table all in one place in memory
 - Fewer accesses to bring table into cache.
 - Linked lists can wander all over the memory.

Disadvantages...

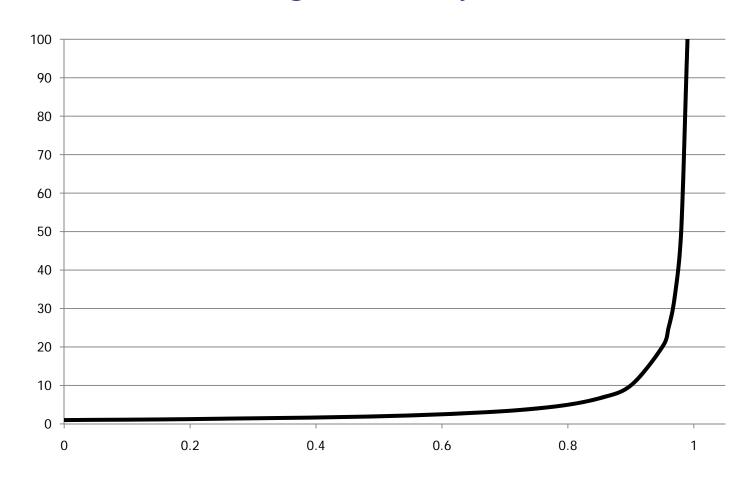
Open addressing:

- More sensitive to choice of hash functions.
 - Clustering is a common problem.
 - See issues with linear probing.
- More sensitive to load.
 - Performance degrades badly as $\alpha \rightarrow 1$.

Disadvantages...

Open addressing:

- Performance degrades badly as $\alpha \rightarrow 1$.



Universal Hashing

- Any one hash function might be bad.
- Imagine:
 - I choose hash function h today.
 - I ship my application.
 - Bad luck! Function h is not a good hash function.

Universal Hashing

Choose a "universal family" of hash functions:

$$h_1, h_2, h_3, h_4, ..., h_k$$

 Select a hash function at random every time you build a hash table.

Example: Multiplication Method parameterized by A.
 Choose A at random.

$$h(k) = (Ak) \bmod 2^w \gg (w - r)$$

Universal Hashing

Choose a "universal family" of hash functions:

$$h_1, h_2, h_3, h_4, ..., h_k$$

- Select a hash function at random every time you build a hash table.
- Prove that for every x, y,: $Pr(h(x)==h(y)) \le 1/m$
- No simple uniform hashing assumption!
- O(1) expected cost per operations.

Universal Hashing

Fun exercise: prove that the following is a universal family of hash functions:

Let *m* be a prime number.

Define
$$h_{ab}(k) = a \cdot k + b \pmod{m}$$

Even Better: Perfect Hashing

- Hash table with zero collision.
- No linked lists, no probe sequences.
- Guarantee O(1) worst-case search.

Only for a static set of keys:

Given a fixed set of elements to store in a hash table.

Idea 1: Use a very big table

- If $(m = n^2)$, then an element collides with probability: $n/n^2 < 1/n$

The probability that no two elements collide:

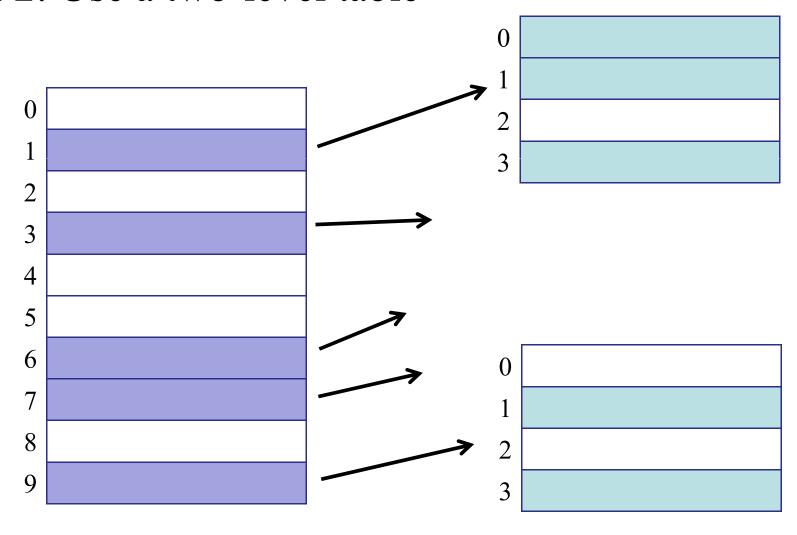
$$\leq \left(1 - \frac{1}{n}\right)^n \leq \frac{1}{2}$$

Repeatedly choose new hash function until no collision.

Expected number of re-tries: O(1)

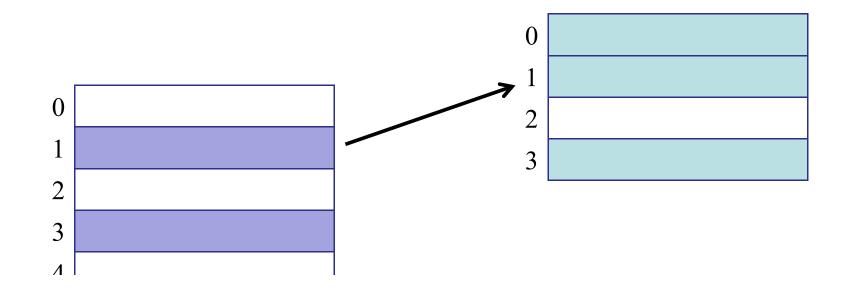
Perfect Hashing: Hierarchical Approach

Idea 2: Use a two-level table



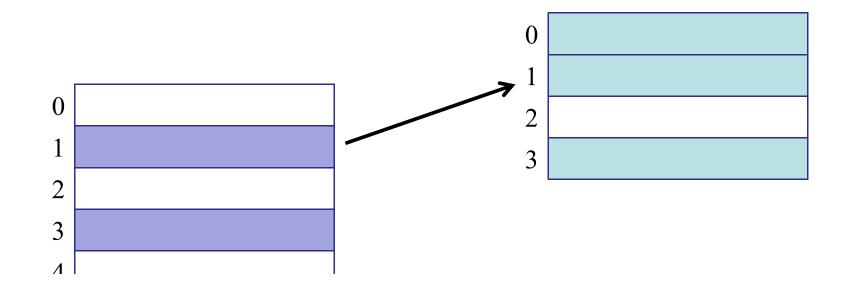
Idea 2: Use a two-level table

- Table 1: size = $\Theta(n)$
- Expected number of items / bucket: $\Theta(1)$



Idea 2: Use a two-level table

- Assume table contains k elements.
- Table 2: size = $\Theta(k^2)$
- On average: constant # of items in Table 2.
- On average: constant size...



Idea 2: Use a two-level table

Prove: expected space is O(n)

- What happens when new items are inserted?
 - Collision in table 1, with constant probability.
 - Collision in table 2, with constant probability.
 - Every so often, rebuild all tables.
 - Amortized analysis??

Summary

Open Addressing

- Efficient technique for keeping items in the table.
- Many different techniques for probing.
 - Quadratic Probing
 - Cuckoo hashing

Advanced Hashing

- Universal Hashing
- Perfect Hashing