



香港中文大學 (深圳)
The Chinese University of Hong Kong

CSC3100 Data Structures

Lecture 18: Hashing

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Search problem

- ▶ Find items with **keys** matching a given **search key**
 - Given an array A , containing n keys, and a search key x , find the index i such as $x = A[i]$
- ▶ A record is often represented by a key-value pair
 - Example of key-value pair:
 - Key: student ID
 - Value: other information like name, major, age, sex...

example of a record

Key	other data
-----	------------



Applications

- ▶ Keeping track of customer account information at a bank
 - Query customer account by name, ID, account number, etc.
- ▶ Keep track of reservations on flights
 - Cancel/modify reservations
- ▶ Search engine
 - Looks for all documents containing a given word
- ▶ Applications need a lot of queries
 - Once the data are inserted, deletion operations are not very often



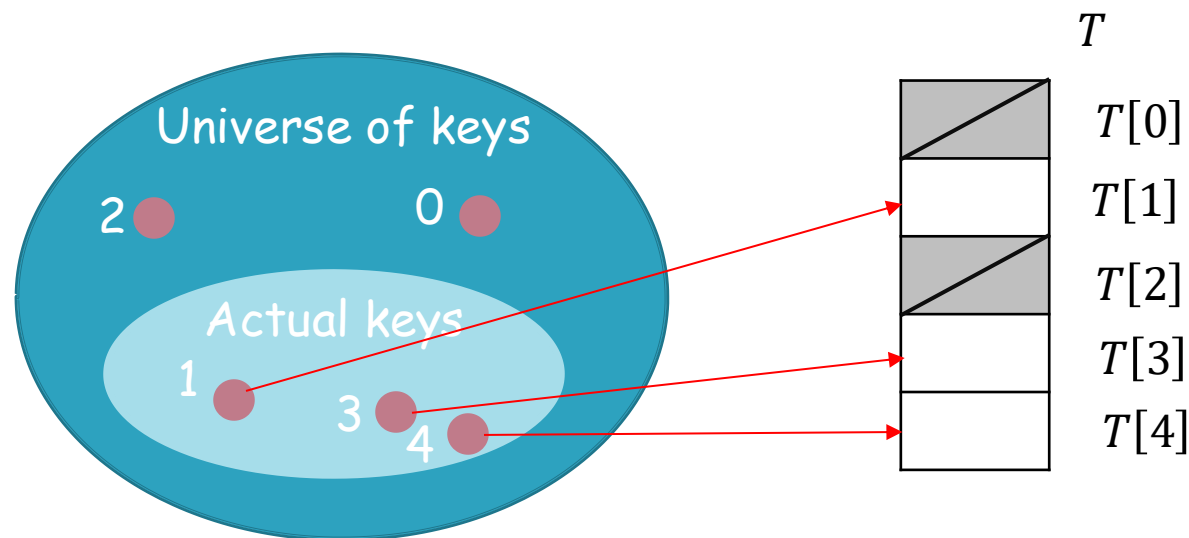
First solution: direct addressing

- ▶ Assumptions:
 - Key values are distinct
 - Each key is drawn from a universe $U = \{0, 1, \dots, m - 1\}$
- ▶ Idea:
 - Store the items in an array, indexed by keys
- ▶ Direct-address table representation:
 - An array $T[0 \dots m - 1]$
 - Each corresponds to a key in U
 - $T[k]$ stores a pointer to x (or x itself) with key k
 - $T[k]$ may be empty



Direct-address tables

- ▶ If the keys of the records are integers from $[U] = \{0, 1, 2, \dots, U - 1\}$
 - We maintain an array T of size U
 - To insert a record r : $T[r.\text{key}] = r$
 - To delete a record r : $T[r.\text{key}] = \text{NULL}$
 - To search the record with key k : return $T[k]$





Limitation of direct-address table

- ▶ The universe of the keys are usually very large
 - All the integers in the range $[0, 2^{31} - 1]$, i.e., $U = 2^{31}$
 - But the number of records may be far less than U
- ▶ Example
 - Let $U = 2^{31} - 1 \approx 2.1 \text{ billion}$
 - Let the number of distinct keys be only 1 million
 - We need to create a direct-address table of size 2.1 billion when there are only 1 million records, so **99% of the space is wasted!**



Comparing different solutions

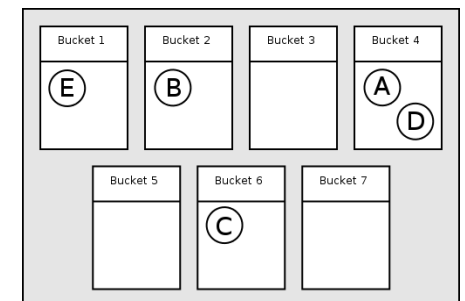
- ▶ Solving search using:
 - Direct addressing
 - Ordered/unordered arrays
 - Ordered/unordered linked lists
 - Binary search tree

	Insert	Search
direct addressing (keys are the indexes)	$O(1)$	$O(1)$
ordered array (keys are not indexes)	$O(N)$	$O(\log N)$
ordered linked list	$O(N)$	$O(N)$
unordered array (keys are not indexes)	$O(N)$	$O(N)$
unordered linked list	$O(1)$	$O(N)$
binary search tree	$O(\log N)$	$O(\log N)$



Hashing: the main idea

- ▶ In direct-addressing, the record with key k is stored in slot k of the array T , i.e., $T[k]$
- ▶ In hashing, the element is stored in slot $h(k)$, i.e., $T[h(k)]$, where h is a **hash function**
 - Assume keys are integers in the range of $[0, U - 1]$
 - Denote by $[x]$ the set of integers from 0 to $x - 1$
 - A **hash function** h is a function from $[U]$ to $[m]$
 - For any integer k , $h(k)$ returns an integer in $[m]$
 - The value $h(k)$ is called the **hash value** of k
 - $U > m$





Simple hash functions

- ▶ For numeric keys, one simple hash function is
 $\text{Key} \bmod \text{TableSize}$,
where *TableSize* is a prime number

E.g., select *TableSize* to be 4999, a prime number close to 5000

<u>Key Value</u>	<u>Address</u>		<u>Key Value</u>	<u>Address</u>	
123456789	1485		987654118	1688	**
123456790	1486		555555555	1688	**
000000504	0504	*	101129183	4412	
200120472	0504	*	200120473	0505	
118920912	4700		010600010	2130	
200120000	0032		027001191	1592	

* and ** indicate collisions



Example of hash functions

- ▶ If we have a set S of keys $\{1,2,3,5,7,8\}$, and the hash function is $h(x) = x \% 3$ (module)
 - What are the hash values of the integers in S ?
 - $h(1) = 1 \% 3 = 1$
 - $h(2) = 2 \% 3 = 2$
 - $h(3) = 3 \% 3 = 0$
 - $h(5) = 5 \% 3 = 2$
 - $h(7) = 7 \% 3 = 1$
 - $h(8) = 8 \% 3 = 2$
 - What are U and m ?
- Diagram illustrating a collision: Arrows from $h(2) = 2$, $h(5) = 2$, and $h(8) = 2$ point to the word "Collision".



Hash table ADT

► Operations:

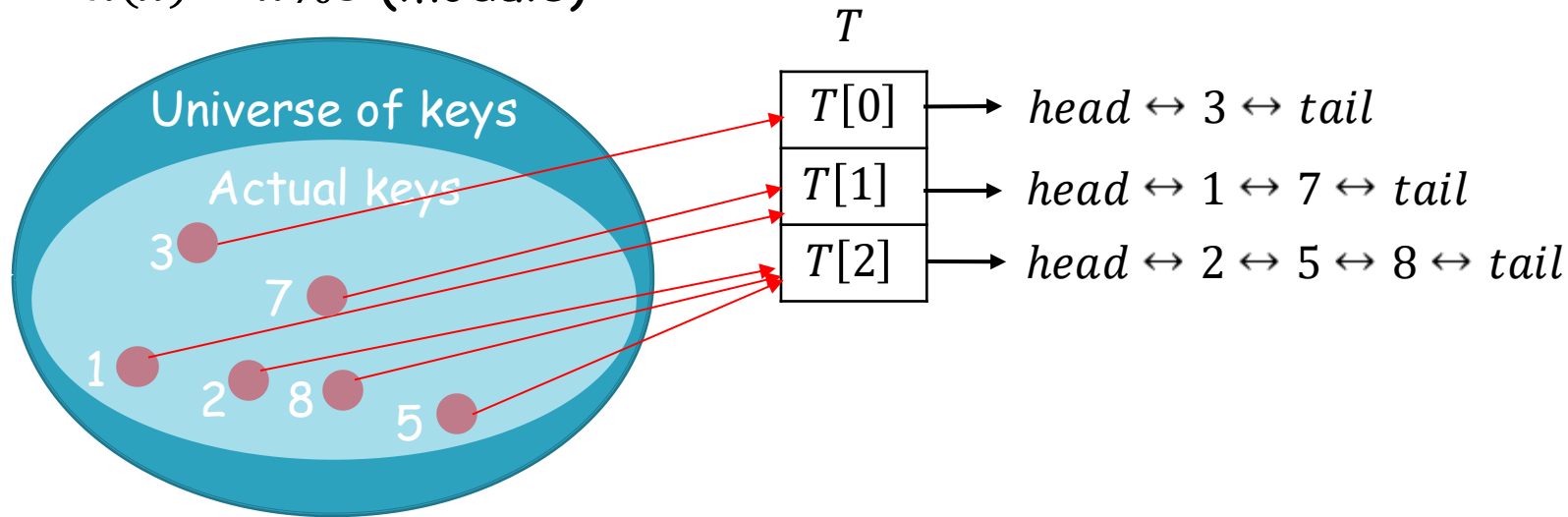
- `createTable(size)`: create a hash table of size `size`
- `search(hashtable, key)`: return the value if the hashtable contains the key, otherwise return NULL
- `insert(hashtable, key, value)`: insert the key value pair to the hashtable
- `delete(hashtable, key)`: remove the key and values stored on the hashtable
- `isFull(hashtable)`: return true if no element can be inserted to `hashtable`, otherwise return false



Collision resolution 1: chaining

- ▶ **Collision**: two keys hash to the same slot
- ▶ **Chaining**: we place all elements that hash to the same slot into the same **linked list**

$$h(x) = x \% 3 \text{ (module)}$$





Hash table initialization with chaining

- ▶ Assume $h(x)$ hashes keys to the range $[0, m - 1]$
 - Create an array of size m with each entry storing a linked list

Algorithm: createTable(sizem)

```
1 hashtable ← allocate an array of size sizem
2 for i from 0 to sizem-1
3     hashtable[i] ← allocate an empty linkedlist
4 return hashtable
```

- ▶ search(hashtable, key): search record with key key :
 - Retrieve linked list $L_{h(key)}$ and search from $L_{h(key)}$

Algorithm: search(hashtable, key)

```
hashid = h(key)
node = hashtable[hashid].head.next
while node != hashtable[hashid].tail
    if node.data.key == key
        return node.data.value
    node = node.next
return NULL
```



Collision resolution 1: chaining

- ▶ `insert(hashtable, key, record)`: insert record r with key key :
 - L_i : the linked list containing elements hashes to i
 - Find the linked list $L_{h(key)}$
 - Insert r to the end of $L_{h(key)}$

Algorithm: `insert(hashtable, key, record)`

1	<code>hashid = h(key)</code>	Or simply: <code>Insert_linklist(hashtable[hashid], key, record)</code>
2	<code>keyValuePair ← (key, record)</code>	
3	<code>Insert_linklist(hashtable[hashid], keyvaluepair)</code>	



Collision resolution 1: chaining

- ▶ `delete(hashtable, key)`: delete record with key *key*
 - Retrieve linked list $L_{h(key)}$
 - Search from $L_{h(key)}$ and get the node containing key *key*, and delete this node

Algorithm: `delete(hashtable, key)`

```
1 hashid = h(key)
2 node=hashtable[hashid].head.next
3 while node != hashtable[hashid].tail
4     if node.data.key == key
5         break
6     node = node.next
7 if node != hashtable[hashid].tail
8     delete_linkedlist(hashtable[hashid], node)
```

- ▶ `isFull(hashtable)`: always return false



Practice

- ▶ Given a hash function $h(k) = k \% 7$, show the hash table after inserting 1, 3, 9, 20, 30, 51, 25, 23, 36
 - T[0]:
 - T[1]: 1, 36
 - T[2]: 9, 30, 51, 23
 - T[3]: 3
 - T[4]: 25
 - T[5]:
 - T[6]: 20



Analysis of hashing with chaining

► Load factor α : the average number of elements stored in a chain

- If the hash table has size m and stores n elements in it, then $\alpha = \frac{n}{m}$
- Assumption: uniform hashing of $h(k)$
 - Elements are equally likely to hash into any of the m slots
 - L_i : the linked list containing the elements hashes to i

Theorem 1: In a hash table with collision resolved by chaining, the search/insertion/deletion takes $O(1 + \alpha)$ time in expectation if $h(k)$ is uniform hashing.

- Proof: check appendix in the slides
- By choosing m so that $\frac{n}{m} = \alpha = O(1)$, the query time is $O(1)$

All theorems and proofs of hashing will not be tested in the exam



Collision resolution 2: open addressing

- ▶ All elements are stored in the hash table
 - Unlike chaining, no elements are stored outside the table
 - The hash table may “fill up” such no insertion can be made
 - Load factor α is always smaller than 1
- ▶ For insertion, we examine, or **probe**, the hash table until an empty slot is found to put the key
 - How to probe the hash table?
 - Linear probing, double Hashing
 - Quadratic probing (not discussed in the lecture)
- ▶ Deletion: not efficiently supported (why?)



Linear probing

- ▶ For **insertion**, we probe $h(k), h(k) + 1, h(k) + 2, \dots, h(k) + (m - 1)$ one by one until we find an empty slot, and insert the record to this slot
 - Formally we probe $h(k, i) = (h(k) + i) \% m$ from $i = 0$ to $i = m - 1$ until we find an empty slot to insert
- ▶ When **searching** for a record with a certain key,
 - Compute $h(k)$
 - Examine the hash table buckets in order $T[h(k, i)]$ for $0 \leq i \leq m - 1$ until one of the following happens:
 - $T[h(k, i)]$ has the record with key equal to k
 - $T[h(k, i)]$ is empty, then no record contains key k in the hash table



A running example: linear probing

- ▶ If we have a hash table with size $m = 17$ and the hash function $h(k) = k \% 17$
 - Consider inserting the following records: 6, 12, 34, 29, 28, 11, 23, 7, 0, 33, 30, 45
 - $h(6,0) = 6\%17 = 6 \rightarrow$ empty, insert here
 - $h(12,0) = 12\%17 = 12 \rightarrow$ empty, insert here
 - $h(34,0) = 34\%17 = 0 \rightarrow$ empty, insert here
 - $h(29,0) = 29\%17 = 12 \rightarrow$ not empty
Try inserting at $h(29,1)$, empty, insert here
 - ...

0			4			8			12			16				
34	0	45				6	23	7			28	12	29	11	30	33



Practice

- ▶ If we have a hash table with size $m = 17$ and the hash function $h(k) = k \% 17$
 - Assume that we use linear probing to address collisions
 - Given the following hash table, show the hash table after inserting 21 and 13
 - Given the following hash table, show the records examined when searching for 14

0				4				8				12				16
34	0	45				6	23	7			28	12	29	11	30	33



Double hashing

- ▶ Deficiency of linear probing
 - Long sequence of occupied slots, which degrades the query efficiency
- ▶ Double hashing
 - We have an additional hash function $h' > 0$
 - **Insertion**: we probe $h(k, i) = (h(k) + i \cdot h'(k)) \% m$ one by one for i from 0 to $m - 1$ until an empty slot is found
 - **Search**: we search $h(k, i)$ for i from 0 to $m - 1$ until one of the following happens:
 - $T[h(k, i)]$ has the record with key equal to k
 - $T[h(k, i)]$ is empty, then no record contains key k in the hash table



A running example: double hashing

- ▶ If we have a hash table with size $m = 17$ and the hash function $h(k) = k \% 17$ and $h'(k) = 1 + k \% 5$
- ▶ Insert the following records: 6, 12, 34, 29, 28 using double hashing to resolve collisions
 - $h(6,0) = 6 \% 17 = 6 \rightarrow$ empty, insert here
 - $h(12,0) = 12 \% 17 = 12 \rightarrow$ empty, insert here
 - $h(34,0) = 34 \% 17 = 0 \rightarrow$ empty, insert here
 - $h(29,0) = 29 \% 17 = 12 \rightarrow$ not empty,
try $h(29,1) = (12 + 1 + 29 \% 5) \% 17 = 0$, not empty,
try $h(29,2) = (12 + 2 \cdot (1 + 29 \% 5)) \% 17 = 5$, empty, insert here
 - $h(28,0) = 28 \% 17 = 11 \rightarrow$ empty, insert here

0		4				8				12				16		
34					29	6					28	12				



Practice

- ▶ Consider a hash table with size $m = 17$ and the hash function $h(k) = k \% 17$ and $h'(k) = 1 + k \% 5$
 - Assume that we use double hashing,
 - Given the following hash table, show the hash table after inserting 11 and 27
 - After inserting 11 and 27, show the records examined when searching for 23

0				4				8				12				16
34					29	6				27	28	12	11			



Analysis of open addressing

- ▶ **Load factor α** : If the hash table T has size m and we store n elements in the hash table
 - $\alpha = \frac{n}{m}$

- ▶ **Assumption: uniform hashing of $h(k, i)$**
 - The probing sequence $\langle h(k, 0), h(k, 1), h(k, 2), \dots, h(k, m - 1) \rangle$ used to insert or search for each key k is equally likely to be any permutation of $\langle 0, 1, 2, \dots, m - 1 \rangle$

Theorem 2: In a hash table with collision resolved by open addressing, the search takes $O(\frac{1}{1-\alpha})$ time in expectation if $h(k, i)$ is uniform hashing.

- Proof: check appendix at the end of the slides
- If $\alpha = O(1)$, then the query time is $O(1)$

All theorems and proofs of hashing will not be tested in the exam



Chaining vs open addressing

► Pros of chaining

- Less sensitive to hash functions and load factors (α can be larger than 1), while open addressing requires to avoid long probes, and its load factor $\alpha < 1$
- Support deletion, while open addressing is difficult to support deletion

► Pros of open addressing

- Usually much faster than chaining



What makes a good hash function?

- ▶ A good hash function satisfies the **uniform hashing** property:
 - Each key is equally likely to hash to any of the m slots, independent of where other keys will hash to
- ▶ We learn two hashing functions: **division** and **universal hashing**
 - Division is effective in practice **without** any theoretical guarantee on $O(1)$ query time
 - Universal hashing provides theoretical guarantees on $O(1)$ query time



Hash function: division

- ▶ $h(k) = k \bmod m = k \% m$
 - If $m = 10^p$, then $h(k)$ only uses the lowest-order p digits of the key value k
 - We cannot use all digits to generate hash keys, and we should not choose such an m
 - In a similar way, we should not choose $m = 2^p$
 - Option of m : choose a prime number not close to the power of 2 or 10
 - Example: $U = 2000$, we choose $m = 701$



Universal hashing

- ▶ Let \mathcal{H} be a family of hash functions from $[U]$ to $[m]$
- ▶ \mathcal{H} is called universal if the following condition holds:

Let k_1, k_2 be two distinct integers from $[U]$. By picking a function $h \in \mathcal{H}$ uniformly at random, we guarantee that

$$\Pr[h(k_1) = h(k_2)] \leq \frac{1}{m}$$

- Then, we choose one from \mathcal{H} uniformly at random and use it as the hash function h for all operations
- ▶ Theoretical guarantee with universal hashing
 - With a universal hash function h
 - Query time of chaining: $O(1 + \alpha)$ (Proof: check appendix)
 - Query time of open addressing: more complicated (Omit), see [1]



Designing a family of universal functions

- ▶ We construct a universal family \mathcal{H} of hash function from $[U]$ to $[m]$
 - Pick a prime number p such that $p > U$
 - For every $a \in \{1, 2, \dots, p-1\}$, and every $b \in \{0, 1, 2, \dots, p-1\}$
 - $h_{a,b}(k) = ((a \cdot k + b) \bmod p) \bmod m$
 - This defines $p \cdot (p-1)$ functions, which constitutes \mathcal{H}
 - Proof of universal: Omitted. Interested readers may refer to textbook, Chapter 11.3.3, pages 265-268
 - We then randomly select one function from these $p \cdot (p-1)$ functions



Example of universal function

- ▶ If $U = 10$ and $m = 5$
 - First select a prime number $p = 11$ ($p > U$)
 - We then have $11 \cdot 10 = 110$ functions in this universal family \mathcal{H}
 - For $a \in \{1, 2, \dots, 10\}$, and $b \in \{0, 1, 2, \dots, 10\}$, we have
 - $h_{a,b}(k) = ((a \cdot k + b) \bmod 11) \bmod 5$
- ▶ Does such p always exists? ($p > U$)
 - We can always find a prime number between $[U, 2U]$ according to number theorem (the proof is out of the scope, you may refer to [2] if you are interested)



Recommended reading

- ▶ Reading this week
 - Textbook Chapters 11.1-11.4
- ▶ Next week
 - Graphs, Textbook Chapters 22.1-22.3



Appendix: Proof of Theorem 1

What we have: the uniform hashing assumption.

For any two keys k_i and k_j , $\Pr[h(k_i) = h(k_j)] = \frac{1}{m}$.

If we have query key q , the query cost is: $1 + |L_{h(q)}|$.

Recap: $L_{h(q)}$ is the linked list containing elements hashes to $h(q)$.

Define a random variable X_i to be 1 if the i -th element of the stored n elements has the same hash value as $h(q)$.

$$|L_{h(q)}| = \sum_{i=1}^n X_i$$
$$E[|L_{h(q)}|] = E[\sum_{i=1}^n X_i] = \sum_{i=1}^n E[X_i] \text{ (By linearity of expectation)}$$

$$E[X_i] = 1 \cdot \Pr[h(q) = h(k_i)] + 0 \cdot \Pr[h(q) \neq h(k_i)] = \frac{1}{m}$$

$\Rightarrow E[|L_{h(q)}|] = \sum_{i=1}^n \frac{1}{m} = \frac{n}{m} = \alpha$. We prove search can be finished in $O(1 + \alpha)$ time. We can similarly prove for insertion and deletion.



Appendix: Proof of Theorem 2

Given a query q , denote X_q be the number of probes, i.e., $h(q, 0)$, $h(q, 1), \dots, h(q, X_q - 1)$, are occupied while $h(q, X_q)$ is not occupied.

The expected search cost is then:

$$\begin{aligned} E[X_q] &= 1 \cdot \Pr[X_q = 1] + 2 \cdot \Pr[X_q = 2] + \dots + m \cdot \Pr[X_q = m] \\ &= \sum_{i=1}^m i \cdot \Pr[X_q = i] = \sum_{i=1}^m i \cdot (\Pr[X_q \geq i] - \Pr[X_q \geq i + 1]) \\ &= \sum_{i=1}^m \Pr[X_q \geq i] \end{aligned}$$

The probability that $\Pr[X_q \geq i]$?

The 1st one is occupied by one of the n elements. Probability: $\frac{n}{m}$

The 2nd one is occupied by one of the remaining $n-1$ elements.

Probability: $\frac{n-1}{m-1}$,

...

The $(i-1)$ -th one is occupied by one of the remaining $n-i+2$ elements: $\frac{n-i+2}{m-i+2}$.



Proof of Theorem 2

$$\text{Therefore: } \Pr[X_q \geq i] = \frac{n}{m} \cdot \frac{n-1}{m-1} \cdot \frac{n-2}{m-2} \cdots \frac{n-i+2}{m-i+2} \leq \left(\frac{n}{m}\right)^{i-1} = \alpha^{i-1}$$

$$E[X_q] = \sum_{i=1}^m \Pr[X_q \geq i] \leq 1 + \alpha + \alpha^2 + \cdots \alpha^{m-1} \leq \frac{1}{1-\alpha}$$

Hence, the expected search cost can be bounded by $O(\frac{1}{1-\alpha})$.



Appendix: Query time with universal hashing

What we have: the universal hashing assumption.

For any two keys k_i and k_j , $\Pr[h(k_i) = h(k_j)] \leq \frac{1}{m}$.

If we have query key q , the query cost is: $1 + |L_{h(q)}|$.

Recap: $L_{h(q)}$ is the linked list containing elements hashes to $h(q)$.

Define a random variable X_i to be 1 if the i -th element of the stored n elements has the same hash value as $h(q)$.

$$|L_{h(q)}| = \sum_{i=1}^n X_i$$
$$E[|L_{h(q)}|] = E[\sum_{i=1}^n X_i] = \sum_{i=1}^n E[X_i] \text{ (By linearity of expectation)}$$

$$E[X_i] = 1 \cdot \Pr[h(q) = h(k_i)] + 0 \cdot \Pr[h(q) \neq h(k_i)] \leq \frac{1}{m}$$

Therefore, $E[|L_{h(q)}|] \leq \sum_{i=1}^n \frac{1}{m} = \frac{n}{m} = \alpha$. Proof done.