CS 561, Randomized Data Structures: Hash Tables, Skip Lists, Bloom Filters, Count-Min sketch

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Outline

- Hash Tables
- Skip Lists
- Count-Min Sketch
A dictionary ADT implements the following operations

- \textit{Insert}(x): puts the item $x$ into the dictionary
- \textit{Delete}(x): deletes the item $x$ from the dictionary
- \textit{IsIn}(x): returns true iff the item $x$ is in the dictionary
Dictionary ADT

- Frequently, we think of the items being stored in the dictionary as *keys*
- The keys typically have *records* associated with them which are carried around with the key but not used by the ADT implementation
- Thus we can implement functions like:
  - $\text{Insert}(k, r)$: puts the item $(k, r)$ into the dictionary if the key $k$ is not already there, otherwise returns an error
  - $\text{Delete}(k)$: deletes the item with key $k$ from the dictionary
  - $\text{Lookup}(k)$: returns the item $(k, r)$ if $k$ is in the dictionary, otherwise returns null
Implementing Dictionaries

- The simplest way to implement a dictionary ADT is with a linked list
- Let \( l \) be a linked list data structure, assume we have the following operations defined for \( l \)
  - head(l): returns a pointer to the head of the list
  - next(p): given a pointer \( p \) into the list, returns a pointer to the next element in the list if such exists, null otherwise
  - previous(p): given a pointer \( p \) into the list, returns a pointer to the previous element in the list if such exists, null otherwise
  - key(p): given a pointer into the list, returns the key value of that item
  - record(p): given a pointer into the list, returns the record value of that item
At-Home Exercise

Implement a dictionary with a linked list

• Q1: Write the operationLookup(k) which returns a pointer to the item with key k if it is in the dictionary or null otherwise
• Q2: Write the operation Insert(k,r)
• Q3: Write the operation Delete(k)
• Q4: For a dictionary with $n$ elements, what is the runtime of all of these operations for the linked list data structure?
• Q5: Describe how you would use this dictionary ADT to count the number of occurrences of each word in an online book.
Dictionaries

- This linked list implementation of dictionaries is very slow
- Q: Can we do better?
- A: Yes, with hash tables, AVL trees, etc
Hash Tables

Hash Tables implement the Dictionary ADT, namely:

- Insert(x) - $O(1)$ expected time, $\Theta(n)$ worst case
- Lookup(x) - $O(1)$ expected time, $\Theta(n)$ worst case
- Delete(x) - $O(1)$ expected time, $\Theta(n)$ worst case
Direct Addressing

- Suppose universe of keys is $U = \{0, 1, \ldots, m - 1\}$, where $m$ is not too large
- Assume no two elements have the same key
- We use an array $T[0..m-1]$ to store the keys
- Slot $k$ contains the elem with key $k$
Direct Address Functions

DA-Search(T,k){ return T[k];}
DA-Insert(T,x){ T[key(x)] = x;}
DA-Delete(T,x){ T[key(x)] = NIL;}

Each of these operations takes $O(1)$ time
Direct Addressing Problem

- If universe $U$ is large, storing the array $T$ may be impractical
- Also much space can be wasted in $T$ if number of objects stored is small
- Q: Can we do better?
- A: Yes we can trade time for space
Hash Tables

• “Key” Idea: An element with key *k* is stored in slot *h*(*k*), where *h* is a hash function mapping *U* into the set \{0, ..., *m* − 1\}
• Main problem: Two keys can now hash to the same slot
• Q: How do we resolve this problem?
• A1: Try to prevent it by hashing keys to “random” slots and making the table large enough
• A2: Chaining
• A3: Open Addressing
Chained Hash

In chaining, all elements that hash to the same slot are put in a linked list.

CH-Insert(T,x){Insert x at the head of list T[h(key(x))];}
CH-Search(T,k){search for elem with key k in list T[h(k)];}
CH-Delete(T,x){delete x from the list T[h(key(x))];}
Analysis

- CH-Insert takes $O(1)$ time if the list is doubly linked and there are no duplicate keys.
- Q: How long does CH-Search and CH-Delete take?
- A: It depends. In particular, depends on the load factor, $\alpha = n/m$ (i.e. average number of elems in a list).
CH-Search Analysis

- Worst case analysis: everyone hashes to one slot so $\Theta(n)$
- For average case, make the *simple uniform hashing* assumption: any given elem is equally likely to hash into any of the $m$ slots, indep. of the other elems
- Let $n_i$ be a random variable giving the length of the list at the $i$-th slot
- Then time to do a search for key $k$ is $1 + n_{h(k)}$
CH-Search Analysis

- Q: What is $E(n_{h(k)})$?
- A: We know that $h(k)$ is uniformly distributed among $\{0, \ldots, m-1\}$
- Thus, $E(n_{h(k)}) = \sum_{i=0}^{m-1} (1/m)n_i = n/m = \alpha$
Hash Functions

- Want each key to be equally likely to hash to any of the $m$ slots, independently of the other keys
- Key idea is to use the hash function to “break up” any patterns that might exist in the data
- We will always assume a key is a natural number (can e.g. easily convert strings to naturaly numbers)
Division Method

- \( h(k) = k \mod m \)
- Want \( m \) to be a *prime number*, which is not too close to a power of 2
- Why? Reduces collisions in the case where there is periodicity in the keys inserted
Hash Tables implement the Dictionary ADT. Assuming $n = O(m)$ we have:

- Insert(x) - $O(1)$ expected time, $\Theta(n)$ worst case
- Lookup(x) - $O(1)$ expected time, $\Theta(n)$ worst case
- Delete(x) - $O(1)$ expected time, $\Theta(n)$ worst case
Skip List

- Enables insertions and searches for ordered keys in $O(\log n)$ expected time
- Very elegant randomized data structure, simple to code but analysis is subtle
- They guarantee that, with high probability, all the major operations take $O(\log n)$ time (e.g. Find-Max, Predecessor/Successor)
- Can even enable ”find-i-th value” if store with each edge the number of elements that edge skips
Skip List

• A skip list is basically a collection of doubly-linked lists, $L_1, L_2, \ldots, L_x$, for some integer $x$
• Each list has a special head and tail node, the keys of these nodes are assumed to be $-\text{MAXNUM}$ and $+\text{MAXNUM}$ respectively
• The keys in each list are in sorted order (non-decreasing)
Skip List

- Every node is stored in the bottom list
- For each node in the bottom list, we flip a coin over and over until we get tails. For each heads, we make a duplicate of the node.
- The duplicates are stacked up in levels and the nodes on each level are strung together in sorted linked lists
- Each node $v$ stores a search key ($\text{key}(v)$), a pointer to its next lower copy ($\text{down}(v)$), and a pointer to the next node in its level ($\text{right}(v)$).
Example
Search

- To do a search for a key, $x$, we start at the leftmost node $L$ in the highest level
- We then scan through each level as far as we can without passing the target value $x$ and then proceed down to the next level
- The search ends either when we find the key $x$ or fail to find $x$ on the lowest level
SkipListFind(x, L){
    v = L;
    while (v != NULL) and (Key(v) != x){
        if (Key(Right(v)) > x)
            v = Down(v);
        else
            v = Right(v);
    }
    return v;
}
Search Example
coin() returns "heads" with probability 1/2

Insert(k){
First call Search(k), let pLeft be the leftmost elem <= k in L_1
Insert k in List 0, to the right of pLeft
i = 1;
while (coin() = "heads"){
    insert k in List i;
    i++;
}
• Deletion is very simple
• First do a search for the key to be deleted
• Then delete that key from all the lists it appears in from the bottom up, making sure to “zip up” the lists after the deletion
Analysis

• Intuitively, each level of the skip list has about half the number of nodes of the previous level, so we expect the total number of levels to be about $O(\log n)$
• Similarly, each time we add another level, we cut the search time in half except for a constant overhead
• So after $O(\log n)$ levels, we would expect a search time of $O(\log n)$
• We will now formalize these two intuitive observations
• For some key, $k$, let $X_k$ be the maximum height of $k$ in the skip list.
• Q: What is the probability that $X_k \geq 2 \log n$?
• A: If $p = 1/2$, we have:

\[
P(X_k \geq 2 \log n) = \left(\frac{1}{2}\right)^{2\log n}
= \frac{1}{(2^{\log n})^2}
= \frac{1}{n^2}
\]

• Thus the probability that a particular key $k$ achieves height $2 \log n$ is $\frac{1}{n^2}$
Height of Skip List

• Q: What is the probability that any key achieves height \(2 \log n\)?
• A: We want

\[ P(X_1 \geq 2 \log n \text{ or } X_2 \geq 2 \log n \text{ or } \ldots \text{ or } X_n \geq 2 \log n) \]

• By a Union Bound, this probability is no more than

\[ P(X_1 \geq 2 \log n) + P(X_2 \geq 2 \log n) + \cdots + P(X_n \geq 2 \log n) \]

• Which equals:

\[ \sum_{i=1}^{n} \frac{1}{n^2} = \frac{n}{n^2} = \frac{1}{n} \]
Height of Skip List

- This probability gets small as $n$ gets large
- In particular, the probability of having a skip list of size exceeding $2 \log n$ is $o(1)$
- If an event occurs with probability $1 - o(1)$, we say that it occurs with high probability
- **Key Point:** The height of a skip list is $O(\log n)$ with high probability.
A trick for computing expectations of discrete positive random variables:

- Let $X$ be a discrete r.v., that takes on values from 1 to $n$

$$E(X) = \sum_{i=1}^{n} P(X \geq i)$$
\[ \sum_{i=1}^{n} P(X \geq i) = P(X = 1) + P(X = 2) + P(X = 3) + \ldots \]
\[ + \quad P(X = 2) + P(X = 3) + P(X = 4) + \ldots \]
\[ + \quad P(X = 3) + P(X = 4) + P(X = 5) + \ldots \]
\[ + \quad \ldots \]
\[ = \quad 1 \cdot P(X = 1) + 2 \cdot P(X = 2) + 3 \cdot P(X = 3) + \ldots \]
\[ = \quad E(X) \]
Q: How much memory do we expect a skip list to use up?

- Let $X_k$ be the number of lists that key $k$ is inserted in.
- Q: What is $P(X_k \geq 1)$, $P(X_k \geq 2)$, $P(X_k \geq 3)$?
- Q: What is $P(X_k \geq i)$ for $i \geq 1$?
- Q: What is $E(X_k)$?
- Q: Let $X = \sum_{k=1}^{n} X_k$. What is $E(X)$?
Search Time

- It's easier to analyze the search time if we imagine running the search backwards.
- Imagine that we start at the found node $v$ in the bottommost list and we trace the path backwards to the top leftmost sentinel, $L$.
- This will give us the length of the search path from $L$ to $v$ which is the time required to do the search.
Backwards Search

SLFback(v) {
    while (v != L) {
        if (Up(v) != NIL)
            v = Up(v);
        else
            v = Left(v);
    }
}
Backward Search

• For every node \( v \) in the skip list \( \text{Up}(v) \) exists with probability \( 1/2 \). So for purposes of analysis, SLFBack is the same as the following algorithm:

\[
\text{FlipWalk}(v)\{
  \text{while (} v \neq \text{L})\{
    \text{if (} \text{COINFLIP} == \text{HEADS}) \quad v = \text{Up}(v); \\
    \text{else} \quad v = \text{Left}(v); \\
  \}\}
\]
• For this algorithm, the expected number of heads is exactly the same as the expected number of tails
• Thus the expected run time of the algorithm is twice the expected number of upward jumps
• Since we already know that the number of upward jumps is $O(\log n)$ with high probability, we can conclude that the expected search time is $O(\log n)$
Bloom Filters

- Randomized data structure for representing a set. Implements:
  - Insert(x):
  - IsMember(x):
- Allow false positives but require very little space
- Used frequently in: Databases, networking problems, p2p networks, packet routing
Bloom Filters

- Have \( m \) slots, \( k \) hash functions, \( n \) elements; assume hash functions are all independent
- Each slot stores 1 bit, initially all bits are 0
- Insert(\( x \)) : Set the bit in slots \( h_1(x), h_2(x), ..., h_k(x) \) to 1
- IsMember(\( x \)) : Return yes iff the bits in \( h_1(x), h_2(x), ..., h_k(x) \) are all 1
Analysis Sketch

- $m$ slots, $k$ hash functions, $n$ elements; assume hash functions are all independent
- Then $P(\text{fixed slot is still 0}) = (1 - 1/m)^{kn}$
- Useful fact from Taylor expansion of $e^{-x}$:
  $$e^{-x} - x^2/2 \leq 1 - x \leq e^{-x} \text{ for } x < 1$$
- Then if $x \leq 1$
  $$e^{-x}(1 - x^2) \leq 1 - x \leq e^{-x}$$
• Thus we have the following to good approximation.

\[ Pr(\text{fixed slot is still 0}) = (1 - 1/m)^{kn} \]
\[ \approx e^{-kn/m} \]

• Let \( p = e^{-kn/m} \) and let \( \rho \) be the fraction of 0 bits after \( n \) elements inserted then

\[ Pr(\text{false positive}) = (1 - \rho)^k \approx (1 - p)^k \]

• Where this last approximation holds because \( \rho \) is very close to \( p \) (by a Martingale argument beyond the scope of this class)
Analysis

- Want to minimize \((1 - p)^k\), which is equivalent to minimizing 
  \[ g = k \ln(1 - p) \]
- Trick: Note that 
  \[ g = -(m/n) \ln(p) \ln(1 - p) \]
- By symmetry, this is minimized when \( p = 1/2 \) or equivalently 
  \[ k = (m/n) \ln 2 \]
- False positive rate is then 
  \[ (1/2)^k \approx (.6185)^{m/n} \]
Tricks

- Can get the union of two sets by just taking the bitwise-or of the bit-vectors for the corresponding Bloom filters
- Can easily half the size of a bloom filter - assume size is power of 2 then just bitwise-or the first and second halves together
- Can approximate the size of the intersection of two sets - inner product of the bit vectors associated with the Bloom filters is a good approximation to this.
Extensions

- Bloomier Filters: Also allow for data to be inserted in the filter - similar functionality to hash tables but less space, and the possibility of false positives.
Data Streams

• A router forwards packets through a network
• A natural question for an administrator to ask is: what is the list of substrings of a fixed length that have passed through the router more than a predetermined threshold number of times
• This would be a natural way to try to, for example, identify worms and spam
• Problem: the number of packets passing through the router is *much* too high to be able to store counts for every substring that is seen!
Data Streams

- This problem motivates the data stream model
- Informally: there is a stream of data given as input to the algorithm
- The algorithm can take at most one pass over this data and must process it sequentially
- The memory available to the algorithm is much less than the size of the stream
- In general, we won’t be able to solve problems exactly in this model, only approximate
Our Problem

- We are presented with a stream of items \( i \)
- We want to get a good approximation to the value \( \text{Count}(i, T) \), which is the number of times we have seen item \( i \) up to time \( T \)
Count-Min Sketch

- Our solution will be to use a data structure called a Count-Min Sketch
- This is a randomized data structure that will keep approximate values of Count(i, T)
- It is implemented using $k$ hash functions and $m$ counters
Count-Min Sketch

• Think of our $m$ counters as being in a 2-dimensional array, with $m/k$ counters per row and $k$ rows
• Let $C_{a,b}$ be the counter in row $a$ and column $b$
• Our hash functions map items from the universe into counters
• In particular, hash function $h_a$ maps item $i$ to counter $C_{a,h_a(i)}$
Updates

- Initially all counters are set to 0
- When we see item $i$ in the data stream we do the following
- For each $1 \leq a \leq k$, increment $C_{a,h_a(i)}$
Count Approximations

- Let $C_{a,b}(T)$ be the value of the counter $C_{a,b}$ after processing $T$ tuples
- We approximate Count($i, T$) by returning the value of the smallest counter associated with $i$
- Let $m(i, T)$ be this value
Main Theorem:

- For any item \( i \), \( m(i, T) \geq \text{Count}(i, T) \)
- With probability at least \( 1 - e^{-m\epsilon/e} \) the following holds: \( m(i, T) \leq \text{Count}(i, T) + \epsilon T \)
Proof

- Easy to see that \( m(i, T) \geq \text{Count}(i, T) \), since each counter \( C_{a,h_a(i)} \) incremented by \( c_t \) every time pair \((i, c_t)\) is seen
- Hard Part: Showing \( m(i, T) \leq \text{Count}(i, T) + \epsilon T \).
- To see this, we will first consider the specific counter \( C_{1,h_1(i)} \) and then use symmetry.
Proof

• Let $Z_1$ be a random variable giving the amount the counter is incremented by items other than $i$
• Let $X_t$ be an indicator r.v. that is 1 if $j$ is the $t$-th item, and $j \neq i$ and $h_1(i) = h_1(j)$
• Then $Z_1 = \sum_{t=1}^{T} X_t$
• But if the hash functions are “good”, then if $i \neq j$, $Pr(h_1(i) = h_1(j)) \leq k/m$ (specifically, we need the hash functions to come from a 2-universal family, but we won’t get into that in this class)
• Hence, $E(X_t) \leq k/m$
Proof

- Thus, by linearity of expectation, we have that:

\[ E(Z_1) = \sum_{t=1}^{T} (k/m) \]  \hspace{1cm} (1)
\[ \leq Tk/m \]  \hspace{1cm} (2)

- We now need to make use of a very important inequality: Markov’s inequality
Markov’s Inequality

- Let $X$ be a random variable that only takes on non-negative values
- Then for any $\lambda > 0$:
  \[ \Pr(X \geq \lambda) \leq \frac{E(X)}{\lambda} \]
- Proof of Markov’s: Assume instead that there exists a $\lambda$ such that $\Pr(X \geq \lambda)$ was actually larger than $E(X)/\lambda$
- But then the expected value of $X$ would be at least $\lambda \cdot \Pr(X \geq \lambda) > E(X)$, which is a contradiction!!!
Proof

- Now, by Markov’s inequality,

\[ Pr(Z_1 \geq \epsilon T) \leq (Tk/m)/(\epsilon T) = k/(m\epsilon) \]

- This is the event where \( Z_1 \) is “bad” for item \( i \).
Proof (Cont’d)

• Now again assume our $k$ hash functions are “good” in the sense that they are independent
• Then we have that

$$\prod_{i=1}^{k} \Pr(Z_j \geq \epsilon T) \leq \left( \frac{k}{m \epsilon} \right)^k$$
Proof

- Finally, we want to choose a $k$ that minimizes $f(k) = \left(\frac{k}{m\epsilon}\right)^k$
- Note that $\frac{\partial f}{\partial k} = \left(\frac{k}{m\epsilon}\right)^k \left(\ln \frac{k}{m\epsilon} + 1\right)$
- From this, we can see that the probability is minimized when $k = m\epsilon/e$, in which case
  \[
  \left(\frac{k}{m\epsilon}\right)^k = e^{-m\epsilon/e}
  \]
- This completes the proof!
Recap

- Our Count-Min Sketch is very good at giving estimating counts of items with very little external space.
- Tradeoff is that it only provides approximate counts, but we can bound the approximation!
- Note: Can use the Count-Min Sketch to keep track of all the items in the stream that occur more than a given threshold ("heavy hitters")
- Basic idea is to store an item in a list of "heavy hitters" if its count estimate ever exceeds some given threshold.