Randomized Algorithms Part Four

Announcements

- Problem Set Three due right now.
 - Due Wednesday using a late day.
- Problem Set Four out, due next Monday, July 29.
 - Play around with randomized algorithms!
 - Approximate **NP**-hard problems!
 - Explore a recent algorithm and why hashing matters!
- Handout: "Guide to Randomized Algorithms" also released.

Outline for Today

- Chained Hash Tables
 - How can you compactly store a small subset of a large set of elements?
- Universal Hash Functions
 - Groups of functions that distribute elements nicely.

Associative Structures

- The data structures we've seen so far are linear:
 - Stacks, queues, priority queues, lists, etc.
- In many cases, we want to store data in an unordered fashion.
- Queries like
 - Add element *x*.
 - Remove element *x*.
 - Is element *x* contained?

- A bitvector is a data structure for storing a set of integers in the range {0, 1, 2, 3, ..., Z - 1}.
- Store as an array of Z bits.
- If bit at position *x* is 0, *x* does not appear in the set.
- If bit at position *x* is 1, *x* appears in the set.

Analyzing Bitvectors

- What is the runtime for
 - Inserting an element?
 - Removing an element?
 - Checking if an element is present?
- How much space is used if the bitvector contains all ${\cal Z}$ possible elements?
- How much space is used if the bitvector contains *n* of the *Z* possible elements?

Another Idea

- Store elements in an unsorted array.
- To determine whether *x* is contained, scan over the array elements and return whether *x* is found.
- To add *x*, check to see *x* is contained and, if not, append *x*.
- To remove *x*, check to see if *x* is contained and, if so, remove *x*.

Analyzing this Approach

- How much space is used if the array contains all Z possible elements?
- How much space is used if the array contains *n* of the *Z* possible elements?
- What is the runtime for
 - Inserting an element?
 - Removing an element?
 - Checking if an element is present?

The Tradeoff

- Bitvectors are fast because we know where to look to find each element.
- Bitvectors are space-inefficient because we store one bit per possible element.
- Unsorted arrays are slow because we have to scan every element.
- Unsorted arrays are space-efficient because we only store the elements we use.
- This is a **time-space tradeoff**: we can improve performance by using more space.

Combining the Approaches

- Bitvectors always use a fixed amount of space and support fast lookups.
 - Good when number of possible elements is low, bad when number of possible elements is large.
- Unsorted arrays use variable space and don't support fast lookups.
 - Good when number of *used* elements is low, bad when number of *used* elements is large.

Chained Hash Tables

- Suppose we have a **universe** *U* consisting of all possible elements that we could want to store.
- Create *m* buckets, numbered {0, 1, 2, ..., *m* 1} as an array of length *m*. Each bucket is an unsorted array of elements.
- Find a rule associating each element in *U* with some bucket.
- To see if x is contained, look in the bucket x is associated with and see if x is there.
- To add *x*, see if *x* is contained and add it to the appropriate bucket if it's not.
- To remove *x*, see if *x* is contained and remove it from its bucket if it is.



Association rule: (*length of first name*) mod 4



Analyzing Runtime

- The three basic operations on a hash table (insert, remove, lookup) all run in time O(1 + X), where X is the total number of elements in the bucket visited.
 - (Why is there a 1 here?)
- Runtime depends on how well the elements are distributed.
- If *n* elements are distributed evenly across all the buckets, runtime is O(1 + n / m).
- If there are n elements distributed all into the same bucket, runtime is O(n).

Hash Functions

- Chained hash tables only work if we have a mechanism for associating elements of the universe with buckets.
- A hash function is a function

 $h: U \to \{0, 1, 2, ..., m - 1\}$

- In other words, for any $x \in U$, the value of h(x) is the bucket that x belongs to.
- Since *h* is a mathematical function, it's defined for all inputs in *U* and always produces the same output given the same input.
- For simplicity, we'll assume hash functions can be computed in O(1) time.

Choosing Good Hash Functions

- The efficiency of a hash table depends on the choice of hash function.
- In the upcoming analysis, we will assume $|U| \gg m$ (that is, there are vastly more elements in the universe than there are buckets in the hash table.)
 - Assume at least |U| > mn, but probably more.

A Problem

- **Theorem:** For any hash function *h*, there is a series of *n* values that, if stored in the table, all hash to the same bucket.
- **Proof:** Because there are *m* buckets, under the assumption that |U| > mn, by the pigeonhole principle there must be at least n + 1 elements that hash to the same bucket. Inserting any *n* of those elements into the hash table places all those elements into the same bucket.

A Problem

- No matter how clever we are with our choice of hash function, there will always be an input that will degenerate operations to worst-case $\Omega(n)$ time.
- Theoretically, limits the worst-case effectiveness of chained hashing.
- Practically, leads to denial-of-service attacks.

Randomness to the Rescue

- For any *fixed* hash function, there is a degenerate series of inputs.
- The hash function itself cannot involve randomness.
 - (Why?)
- However, what if we choose which hash function to use at random?

A (Very Strong) Assumption

- Let's suppose that when we create our hash table, we choose a *totally random* function $h: U \rightarrow \{0, 1, 2, ..., m 1\}$ as our hash function.
 - This has some issues; more on that later.
- Under this assumption, what would the expected cost of the three major hash table operations be?

Some Notation

- As before, let *n* be the number of elements in a hash table.
- Let those elements be $x_1, x_2, ..., x_n$.
- Suppose that the element that we're looking up is the element z.
 - Perhaps z is in the list; perhaps it's not.

Analyzing Efficiency

- Suppose we perform an operation (insert, lookup, delete) on element *z*.
- The runtime is proportional to the number of elements in the same bucket as z.
- For any x_k , let C_k be an indicator variable that is 1 if x_k and z hash to the same bucket (i.e. $h(x_k) = h(z)$) and is 0 otherwise.
- Let random variable X be equal to the number of elements in the same bucket as z. Then

$$X = \sum_{x_i \neq z} C_i$$

Analyzing Efficiency $E[X] = E[\sum_{x_i \neq z} C_i]$

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So the expected cost of an operation is O(1 + E[X]) = O(1 + n / m)

Analyzing Efficiency

- Assuming we choose a function uniformly at random from all functions, the expected cost of a hash table operation is O(1 + n / m).
- What's the space usage?
 - O(*m*) space for buckets.
 - O(*n*) space for elements.
 - Some unknown amount of space to store the hash function.

Analyzing Efficiency

Assuming we choose a function uniformly at random from all functions, the expected cost of a hash table operation is O(1 + n / m).

What's the space usage?

O(*m*) space for buckets.

O(n) space for elements.

• Some unknown amount of space to store the hash function.

A Problem

- We assume h is chosen uniformly at random from all functions from U to $\{0, 1, ..., m 1\}$.
- There are $m^{|U|}$ possible functions from U to $\{0, 1, ..., m 1\}$. (Why?)
- How much memory does it take to store *h*?
- If we assign k bits to store h, there are 2^k possible combinations of those bits.
- We need at least $|U| \log_2 m$ bits to store h.
- **Question:** How can we get this performance without the huge space penalty?



So the expected cost of an operation is O(1 + E[X]) = O(1 + n / m)

Universal Hash Functions

 A set *H* of hash functions from U to {0, 1, ..., m – 1} is called a universal family of hash functions iff

For any $x, y \in U$ where $x \neq y$, if h is drawn uniformly at random from \mathcal{H} , then $P(h(x) = h(y)) \leq 1 / m$

• In other words, the probability of a collision between two elements is at most 1 / m as long as we choose h from \mathscr{H} uniformly at random.

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So the expected cost of an operation is O(1 + E[X]) = O(1 + n / m)

Universal Hash Functions

- The set of all possible functions from U to $\{0, 1, ..., m 1\}$ is a universal family of hash functions.
 - However, requires $\Omega(|U| \log m)$ space.
- For certain types of elements, can find families of universal hash functions we can evaluate in O(1) time and store in O(1) space.
- **The Good News:** The intuitions behind these functions are quite nice.
- **The Bad News:** Formally proving that they're universal requires number theory and/or field theory, which is beyond the scope of this class.

Simple Universal Hash Functions

- We'll start with a simplifying assumption and generalize from there.
- Assume $U = \{0, 1, 2, ..., m 1\}$ and that m is prime. (We'll relax this later.)
- Let ${\mathscr H}$ be the set of all functions of the form

$h(x) = ax + b \pmod{m}$

- Where $a, b \in \{0, 1, 2, ..., m 1\}$
- **Claim:** \mathscr{H} is universal.

Showing Universality

We'll show *H* is universal by showing it obeys a stronger property called 2-independence:

For any $x_1, x_2 \in U$ where $x_1 \neq x_2$, if *h* is chosen uniformly at random from \mathscr{H} , then for any y_1 and y_2 we have

$P(h(x_1) = y_1 \land h(x_2) = y_2) = 1 / m^2.$

- (The probability that you can guess where any two distinct elements will be hashed is $1 / m^2$).
- **Claim:** Any 2-independent family of hash functions is universal.

h(x) = ax + b



Showing Universality

- If $h(x) = ax + b \pmod{m}$, knowing two points on the line determines the entire line.
- Can only guess the output at two points by guessing the coefficients: probability is 1 / m^2 !
- Need to use some more advanced math to formalize why this works; revolves around the fact that \mathbb{F}_m is a finite field.

Generalizing the Result

- This hash function only works if m is prime and |U| = m.
- Suppose we can break apart any $x \in U$ into k integer "blocks" $x_1, x_2, ..., x_k$, where each block is between 0 and m 1.
- Then the set \mathscr{H} of all hash functions of the form $h(x) = a_1x_1 + a_2x_2 + ... + a_kx_k + b \pmod{m}$

is universal.

 Intuitively, after evaluating k – 1 of the products, you're left with a linear function in one remaining block and the same argument applies.

A Quick Aside

- Most programming languages associate "a" hash code with each object:
 - Java: Object.hashCode
 - Python: <u>hash</u>
 - C++: std::hash
- Unless special care is taken, there always exists the possibility of extensive hash collisions!

Looking Forward

- This is not the only type of hash table; others exist as well:
 - **Dynamic perfect hash tables** have *worst-case* O(1) lookup times and O(*n*) total storage space, but use a bit more memory.
 - Open addressing hash tables avoid chaining and have better locality, but require stronger guarantees on the hash function.
- Hash functions have *lots* of applications beyond hash tables; you'll see one in the problem set.

Next Time

- Greedy Algorithms
- Interval Scheduling