Hashing

December 6th #CS136#Datastructures#AdvancedProgramming #Bills

Administrative Details

- No lab today
- Practice exam, study guide will be posted online
 - Don't panic: much longer than our exam will be!
- TAs available this weekend (see calendar)
- Bill² Review: Tuesday @ 1:30-2:30pm in Physics 205

Today's Outline

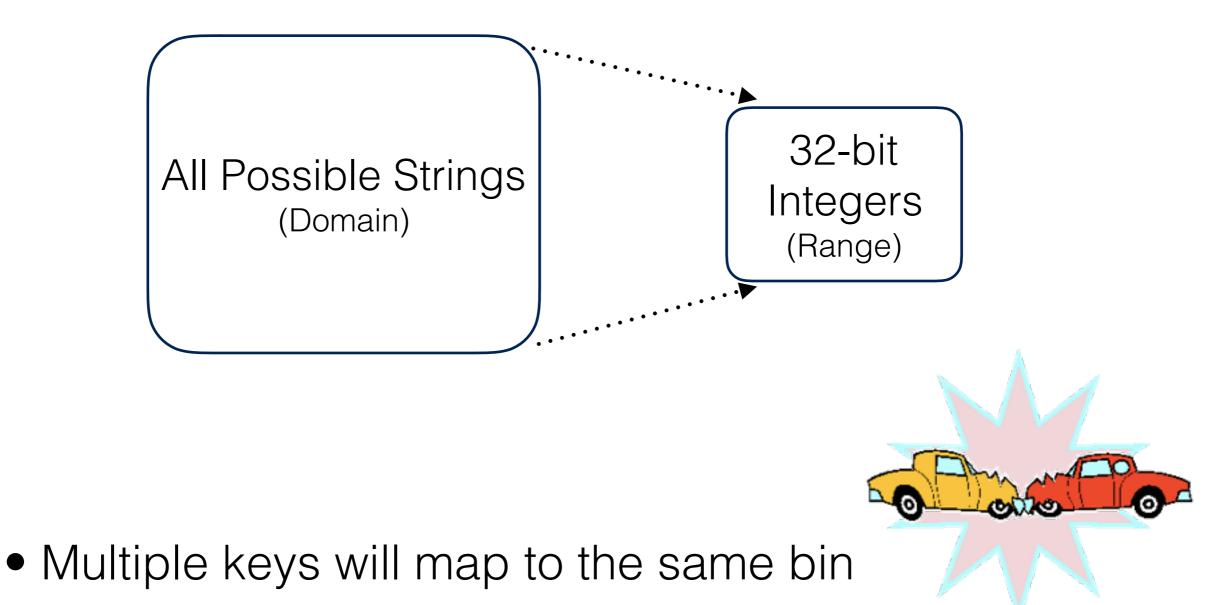
- More applications of Hashing!
 - Cuckoo hashing
 - Sets/Membership Queries
 - Checksums/Integrity
 - Duplicate Detection
- (new material not on CS136 exam)

Quick Hash Table Review

- •A hash function maps a **key** to an **index**
- •The **index** specifies a hash table **bin** where the **keyvalue pair** should be stored.
- •Assuming:
 - •Computing the hash function is O(1)
 - •Our hash function evenly distributes objects
 - •We have a reasonable **load factor**
 - •Bins have O(1) random access (e.g., an array)
- We can get/put key-value pairs in O(1) time!!!

Problems?

• Typically, the domain (set of possible keys) is larger than the range (possible of hash function outputs)



Managing Collisions

- Collision: two keys map to the same bin
- We can minimize cost of collisions in a few ways:
 - Use a hash function that uniformly distributes keys across the range
 - Keep the load factor low
 - Use an array with a (relatively) prime-number-length
 - ► Why?
 - •Consider this String hash function:

 $h(s) = s[0] + k^1 * s[1] + k^2 * s[2] + ... k^{n-1} * s[n]$ Strings with the same s[0] hash the same modulo k.

Techniques to Resolve Collisions

• Linear Probing

- When something else is in our bin, scan and insert into the first bin without an element
- When we delete a key-value pair, drop a placeholder to note that other elements may have been shifted past the newly "emptied" bin

External Chaining

- Instead of key-value pairs, each bin holds a list
- To insert: place a key-value pair at end of its bin's list
- Downside: extra space required to store lists

New Technique: Cuckoo Hashing



img: https://en.wikipedia.org/wiki/File:Eastern_Phoebe-nest-Brown-headed-Cowbird-egg.jpg

Techniques to Resolve Collisions

Cuckoo Hashing

- Select 2 independent hash functions
 - A key can now land in 1 of 2 places
- Resolve collisions by "pushing" others out of our bin and placing them in the bin associated with their other hash
- The process may need to repeat
- What happens when we:
 - put(X) where $hash_1(X) = 0$?
 - put(Y) where $hash_1(Y) = 7?$

We must avoid

cycles!

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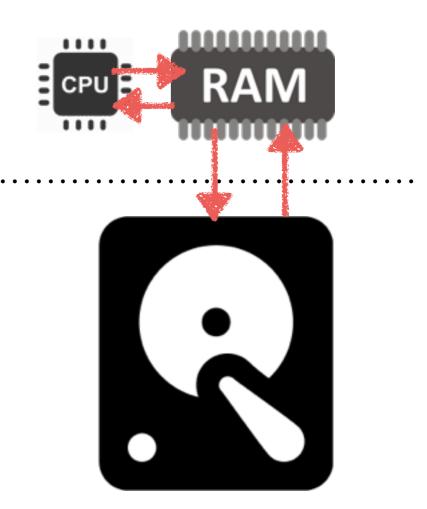
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Cuckoo Hashing

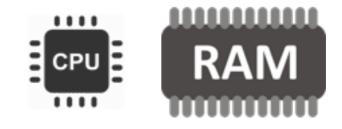
- For independent hash functions and low load factor, O(1)
- •No runs like we have with linear probing
 - No shifting "down the line" on inserts
 - At most 2 checks per lookup

Membership Queries

- **Problem 1:** Sometimes (almost always?) we have more data than fits in memory
- Solution: Store a subset of our data in a cache
 - When we need something that isn't in cache, we kick out the least valuable things to make room for the thing we need



• **Problem 2:** Not all levels in our cache have the same cost





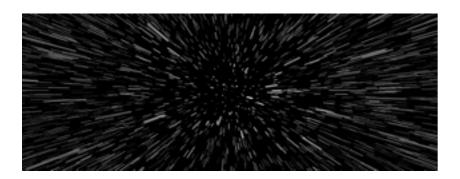
• **Problem 2:** Not all levels in our cache have the same cost



https://www.istockphoto.com/photo/pile-of-money-gm172637949-581154 http://www.freephotosbank.com/photographers/photos1/45/med_53ff4957d796d0ff0a7d3151ec4e4a20.jpg

• **Problem 3:** Not all levels in our cache have the same speed





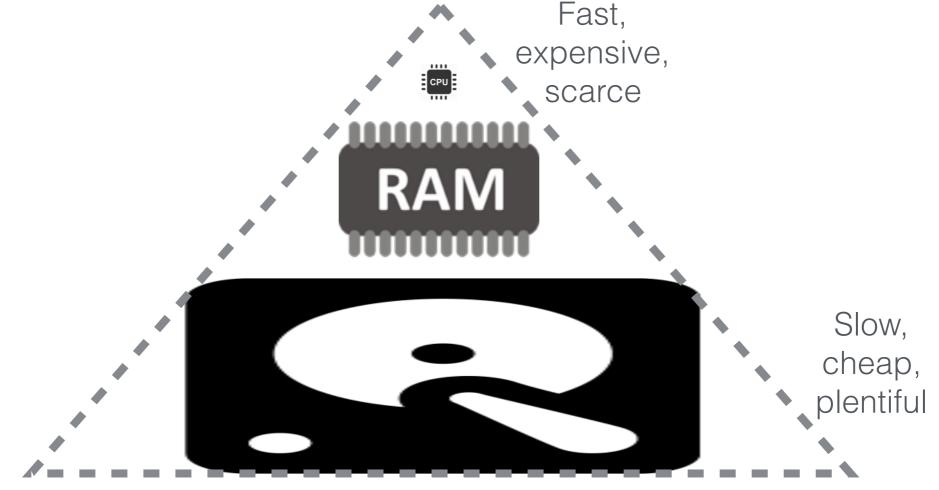








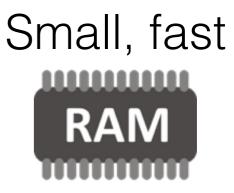
- Result: we have a lot of slow, cheap storage, less RAM, and very little CPU cache.
 - We will focus on the interaction between RAM and disk



Scenario: Photo Storage

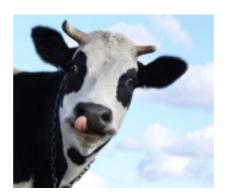
Suppose:

- We have a small RAM cache that holds 2 photos
- Our cache is initially empty
- We read from disk into cache, and evict the least recently used photo when we need space





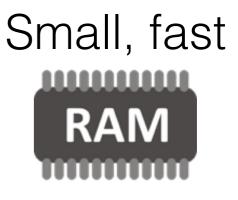






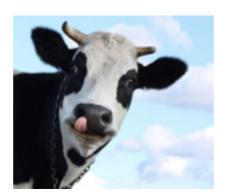


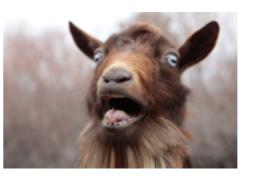
get(cat)







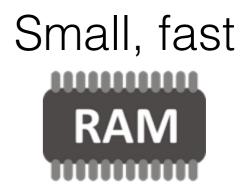




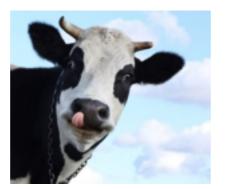


get(cat)







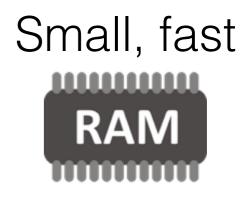




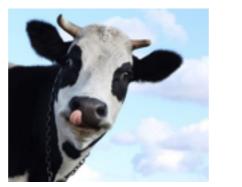


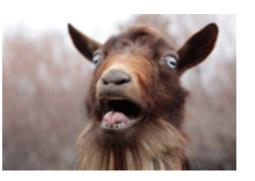
get(cat)
get(cow)







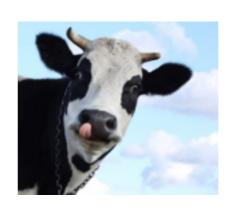






get(cat)
get(cow)





Small, fast RAM



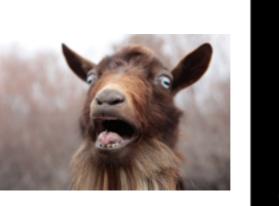


get(cat)
get(cow)
get(dog)





Small, fast RAM





get(cat)
get(cow)
get(dog)





Small, fast RAM





get(cat)
get(cow)
get(dog)
get(goat)





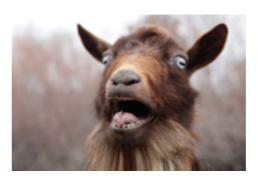
Small, fast





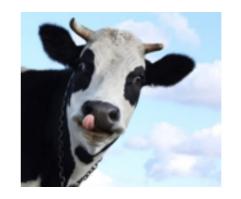
get(cat)
get(cow)
get(dog)
get(goat)





Small, fast RAM

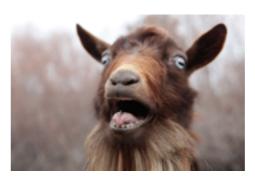






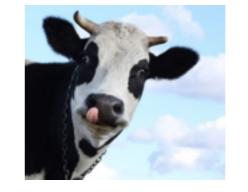
get(cat)
get(cow)
get(dog)
get(goat)
get(cat)





Small, fast RAM

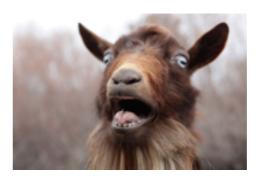






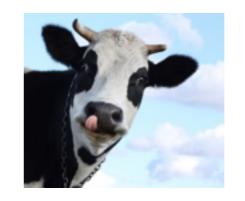
get(cat)
get(cow)
get(dog)
get(goat)
get(cat)





Small, fast RAM

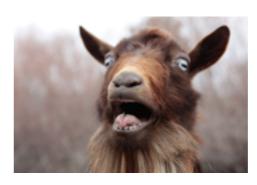






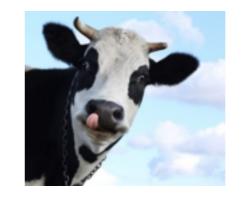
get(cat)
get(cow)
get(dog)
get(goat)
get(cat)
get(liger)





Small, fast

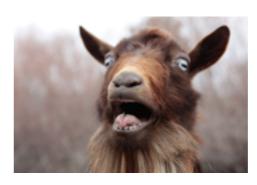






get(cat)
get(cow)
get(dog)
get(goat)
get(cat)
get(liger)





Small, fast







- **Problem:** We paid an expensive cost just to find out the thing we were looking for didn't exist!!
- Idea: Cache a set of all the keys (names of all photos on disk)
 - 1. Check the names set first *before* checking disk
 - 2. Don't go to disk if we know the thing isn't there

Membership Queries

- How to implement our name set?
 If we want to look things up quickly, use a hash set
- If we want to avoid collisions:
 - Make it big
 - Use a large hash so to uniquely fingerprint each file (P(collision) == small)
- New problem: keys can be long, fingerprints are large. Now our set takes up a large portion of our cache

Membership Queries

- **Insight**: we don't need to be perfect.
- If we go to disk an extra time, no worse off
 - False positives are not ideal, but they are OK
- If we don't go to disk when something exists, BAD (or sick)
 - False negatives are correctness bugs, not OK
- We will build a structure that does **approximate membership queries** and is more efficient than a set.

Bloom Filter

- Answers with "possibly in set" or "definitely not in set"
- We save space by not explicitly storing hashes or keys
- How it works:
 - Create a bit array of *m* bits
 - Select k hash functions
 - Hash each element k times and set all k bits
 - An element is missing if **any** of its *k* bits is unset
 - An element may be present if **all** of its *k* bits are set

Bloom Filters

Insert(key):

for hashFunction_i in hashFuncions_{i...k}:
 bitmap[hashFunction_i(key) % m] = 1

Query(key):

for hashFunction_i in hashFuncions_{i...k}:
 if (bitmap[hashFunction_i(key) % m] != 1):
 return "not in set"
 return "maybe in set"

Bloom Filters

- Deleting keys?
 - A key maps to k bits, and although setting any one of those k bits to zero would remove that key from the set, it will also remove every key that maps to one of those bits.
 - Deleting would introduce false negatives!
- Resizing Bitmap?
 - No way to grow array using just the bit values
 - Although keys are not stored, they are often available
 - When the false positive rate gets too high (overloaded, too many "deletes" still in bitmap), read keys from slower media and resize+rehash

Related DS: Quotient Filters

- A nifty idea with an even nifty-er paper name (Don't Thrash: How to Cache your Hash in Flash)
- Uses linear probing to support efficient deletes and merges
- "Write-optimized" data structure (my research area)
- Based on an end-of-chapter problem in an undergraduate data structures textbook
 - You can publish a paper with the skills you already have!
 - (and if you were like Bloom, you could name it after yourself)

Integrity/Tamper Evidence

- Sometimes we can't trust the integrity of our stuff
 - Our laptop is from 2006, and our HDD is dying...
 - We store our data in "the cloud" and we don't trust "the man"
 - We live in a place with government censorship and we want to ensure no one has modified a document
 - We download something from the internet and we are afraid a "man-in-the-middle" has given us a decoy or a virus
 - We are a multi-national company that wants to verify that people pay for official software/media (DRM)

- **Observation:** cryptographic hash functions have the following properties
 - Deterministic
 - Non-invertible (given hash(x) impractical to find x)
 - Large Range (many bits in hash)
 - Evenly distributed
 - Insight: If we pick a good enough hash function, we can trust it to uniquely identify the contents
 - (related ideas: checksumming/fingerprinting)

- Calculate a fingerprint (cryptographic hash) of objects that we store, and we keep the fingerprint safe
- If we later retrieve the thing we stored, recompute the fingerprint
 - If they match, we are (almost) guaranteed to be safe
 - If they differ by even one bit, there is a problem

- Download verification (ubuntu .iso example)
- Scanning files for errors
- Git

Detecting Duplicates

Deduplication

- Imagine you are a cloud storage provider, and someone uploads the hit song Shoot_Pass_Slam.mp3
 - Millions of other people will as well (Shaq Diesel went platinum after all)
 - Do we really need to store millions of copies of the same file?
 - NO! Hash tables/sets can map duplicate keys to the same value
 - Map every file called "Shoot_Pass_Slam.mp3" to the same file contents
 - What if the file names different?

Deduplication

Instead of mapping:

file_name -> file_contents

map:

file_name -> hash_of_contents

Then have a separate key-value store mapping: hash_of_contents -> file_contents

Insight: many problems in computer science can be solved with a layer of indirection!

Deduplication

- What if we aren't storing music, but file that are actively modified?
 - We may not want to deduplicate at the coarse granularity of whole files
- Instead, break a file into chunks, and deduplicate chunks
 - Now we map:

file_name -> recipe*

*A recipe contains (file offset, chunk length, fingerprint) triples

• We only store one copy of unchanged chunks!

Summary

- Hashing is a powerful technique with many uses
- We can build interesting new data structures
- We can add new twists to existing data structures
- We must be careful to use the right hash function for the task