#Hashing

CS136
May 10
Bill Jannen

Administrative Details

- No lab this week
- Sample exam, study guide online
- Review next Monday, 7-9pm, Physics 203
- Questions about the Final?

Applications of Hashing

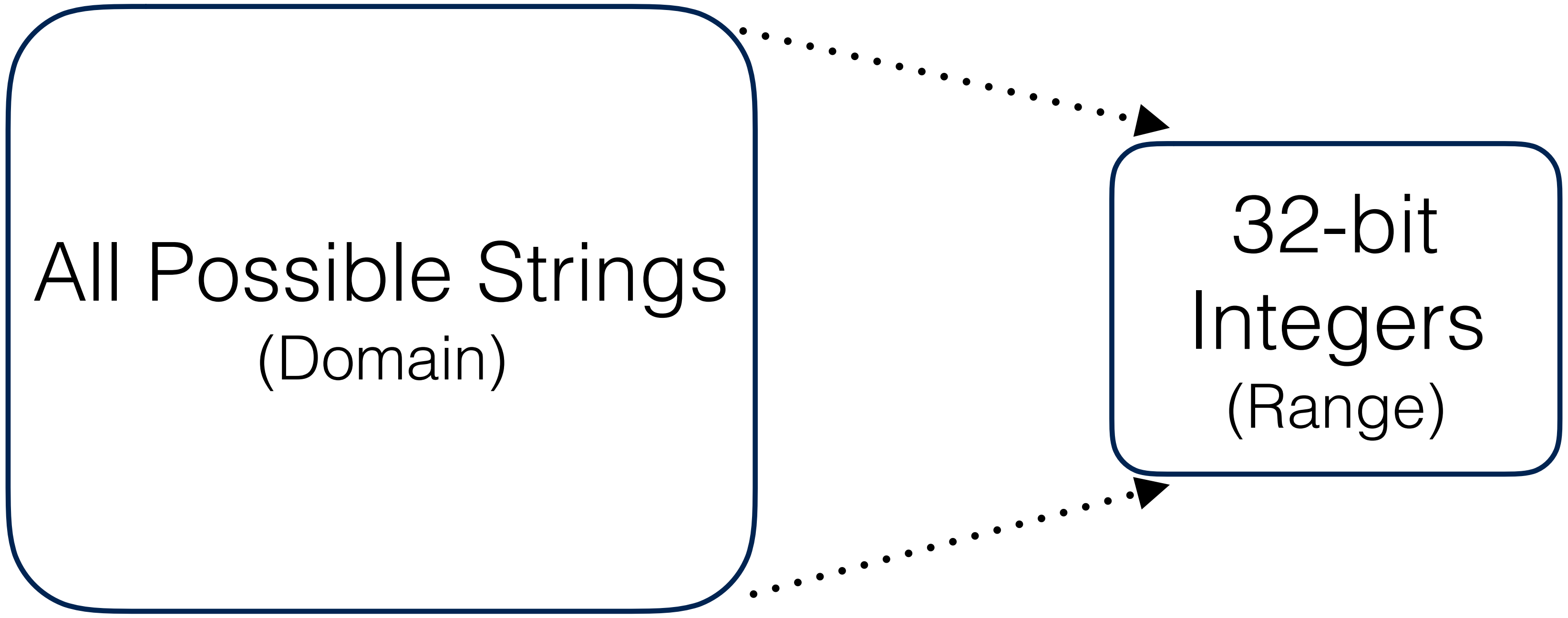
- Hash tables
- Sets/Membership Queries
- Checksums/Integrity
- Duplicate Detection

Quick Hash Table Review

- A hash function maps a **key** to an **index**
- The **index** specifies a hash table **bin** where the **key-value pair** should be stored.
- Assuming:
  - Computing the hash function is O(1)
  - 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)



- Multiple keys will map to the same bin

Managing Collisions

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

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 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

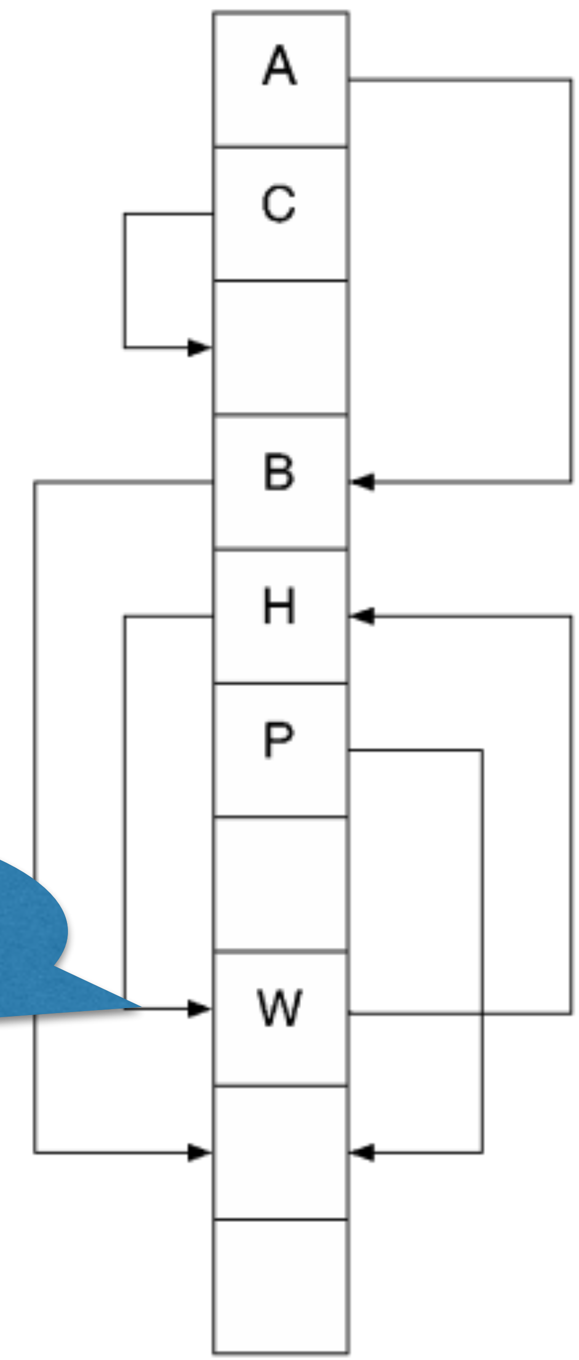
New Technique: Cuckoo Hashing

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!



Cuckoo Hashing

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

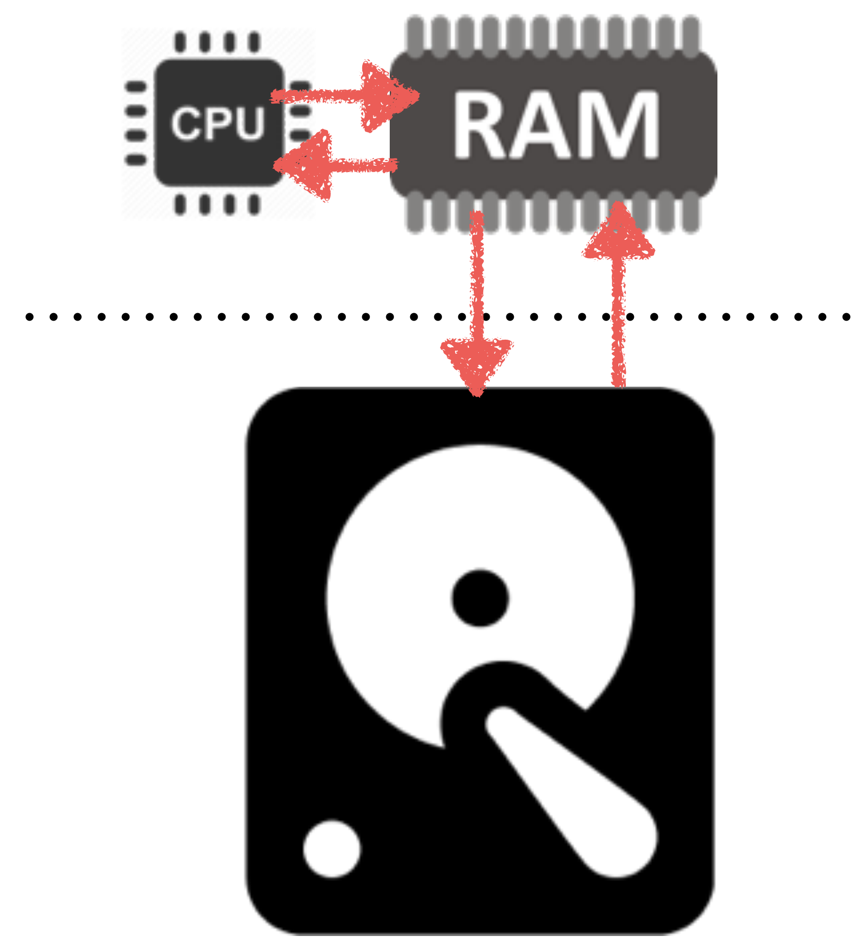
Membership Queries

Memory Hierarchy

- **Problem 1:** Sometimes (almost always) we have more data than fits in memory

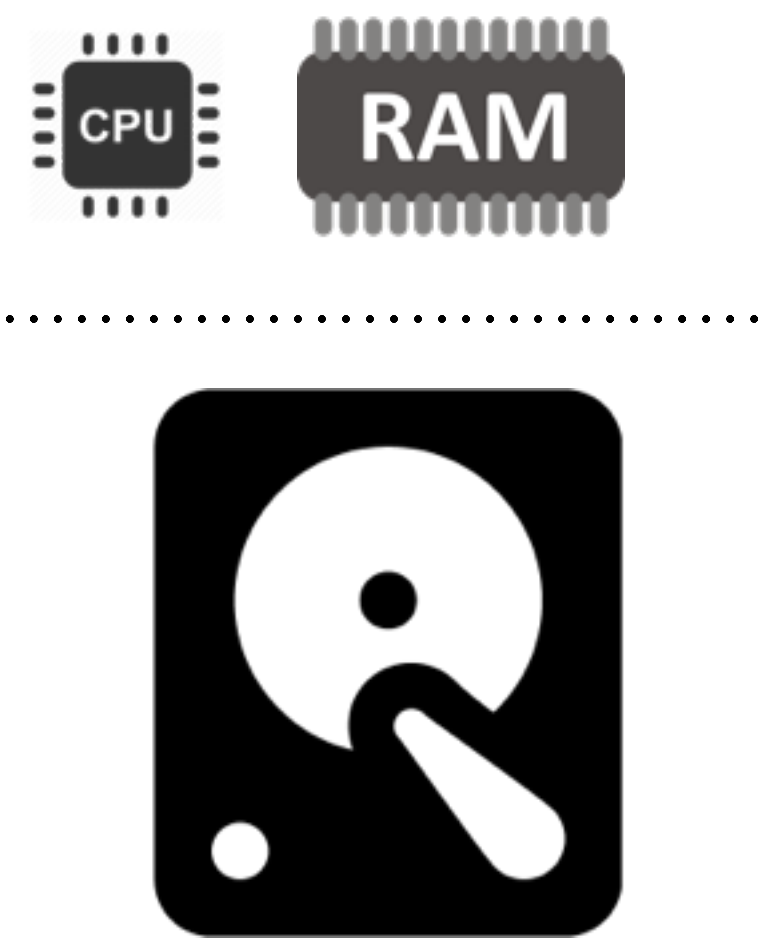
- **Solution:** Store a subset of our data in a cache

    - When we need something that isn't in cache, we kick out the least valuable to make room for the thing we need



Memory Hierarchy

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



Memory Hierarchy

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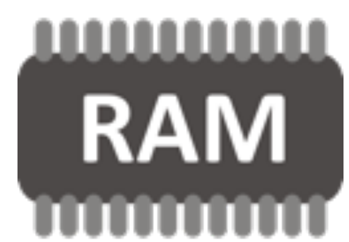
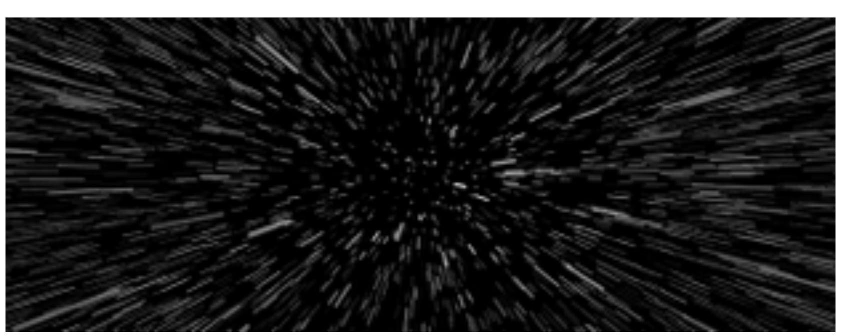


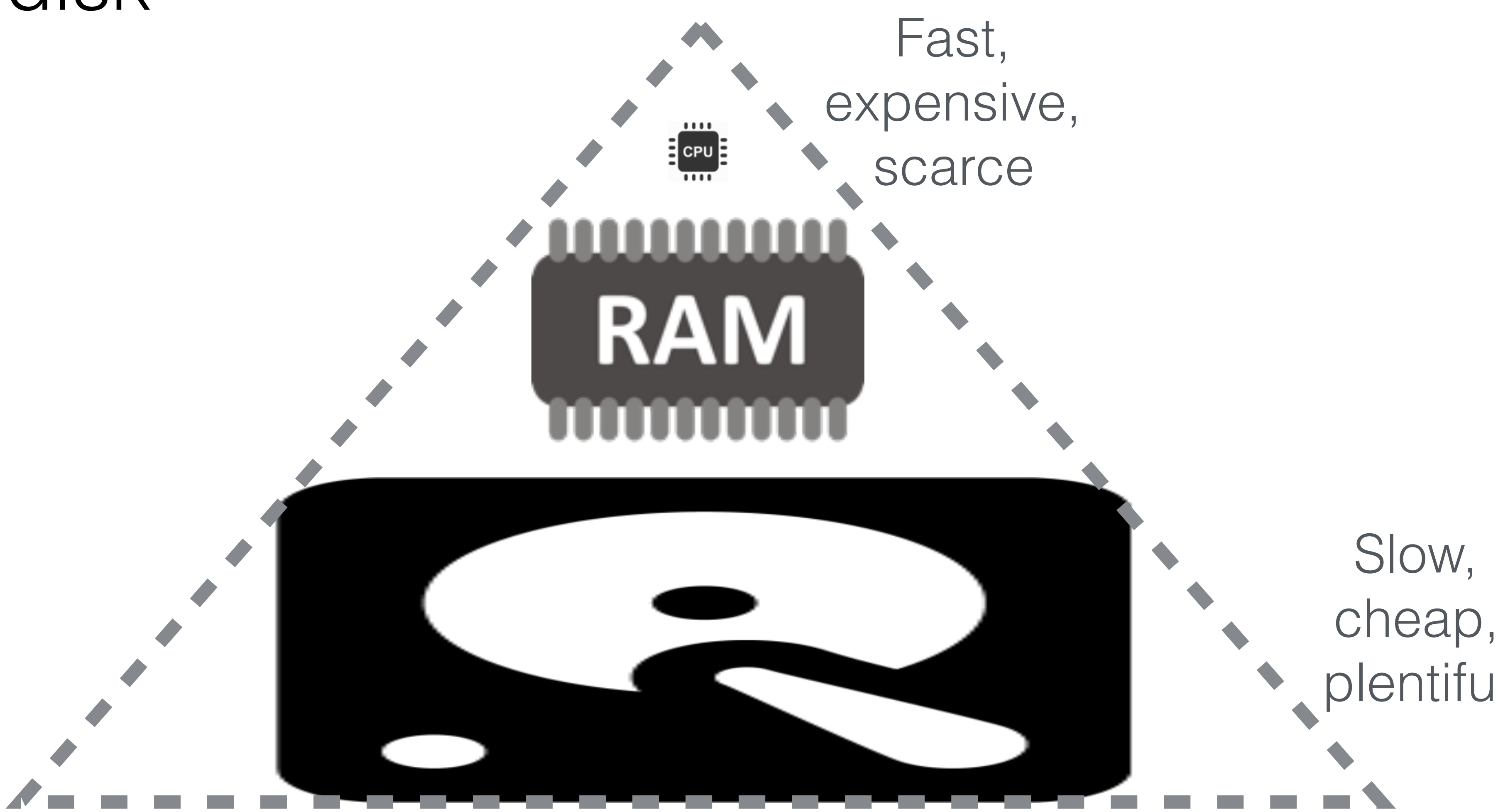
Memory Hierarchy

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



Memory Hierarchy

- 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

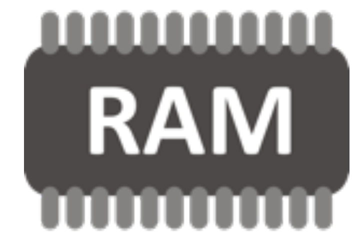


Scenario: Photo Storage

- 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

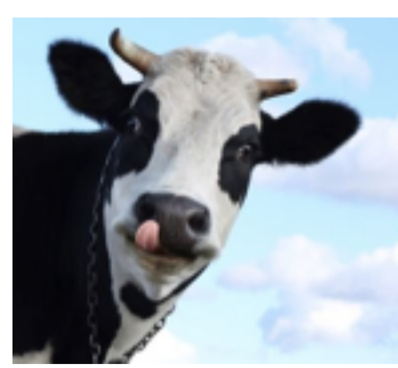
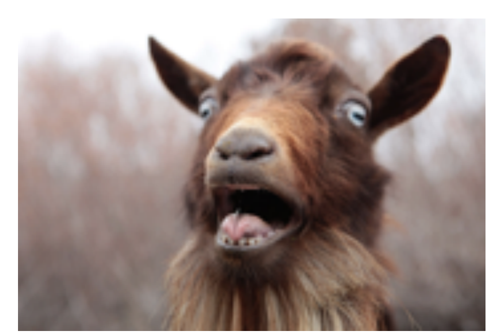
Memory Hierarchy

Small, fast



Big, slow

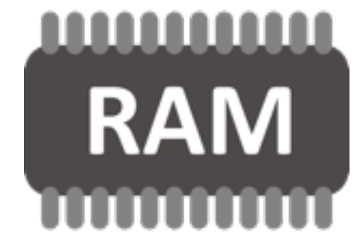



Memory Hierarchy

`get(cat)`

Small, fast



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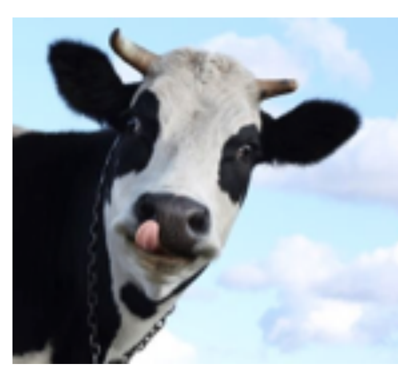

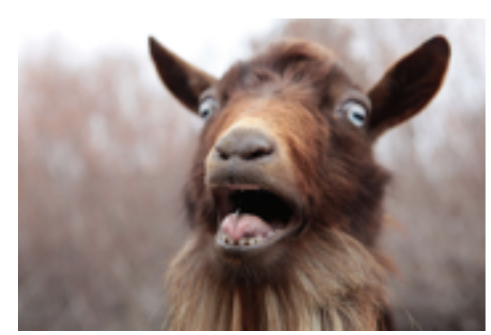

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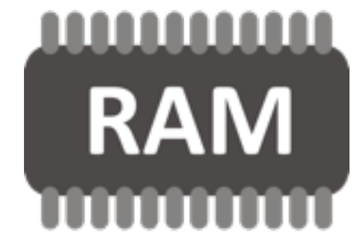

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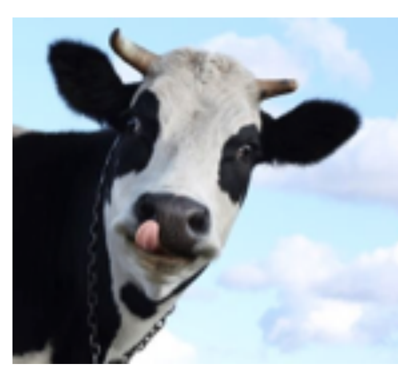
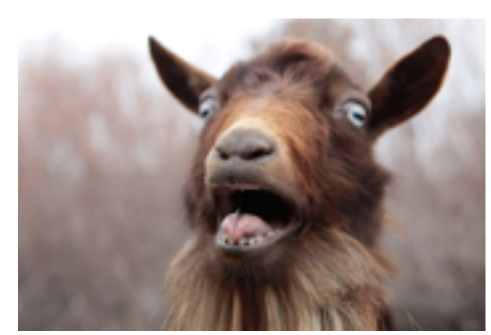
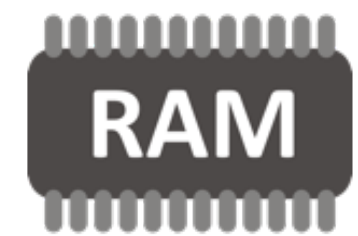




Memory Hierarchy

```
get(cat)
get(cow)
```

Small, fast



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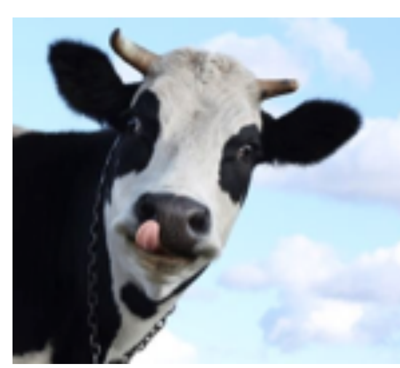

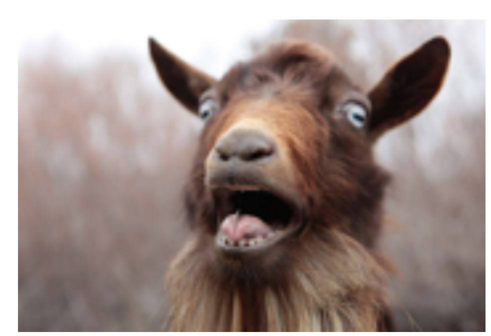

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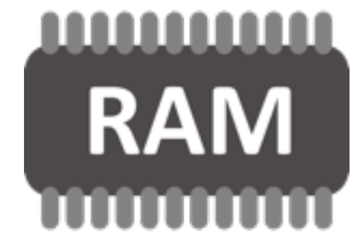

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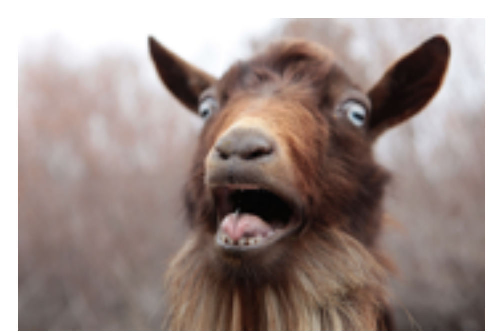
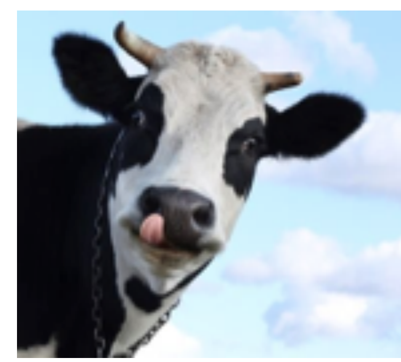


Memory Hierarchy

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



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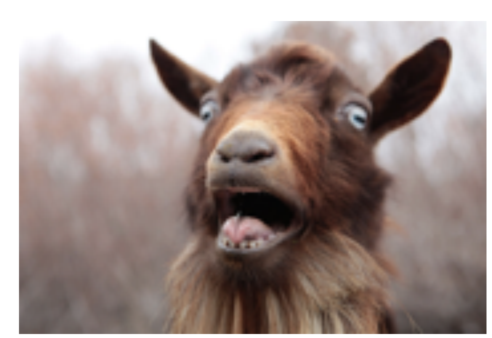

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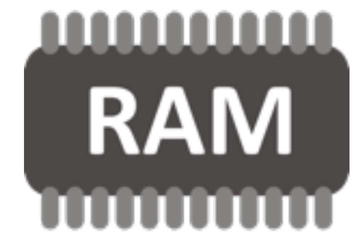

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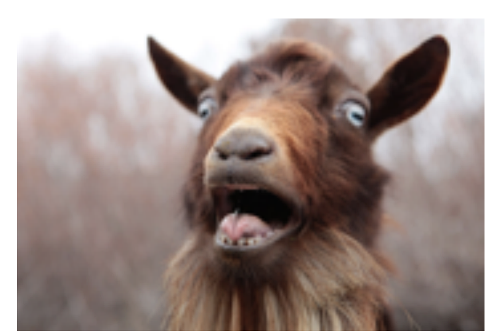
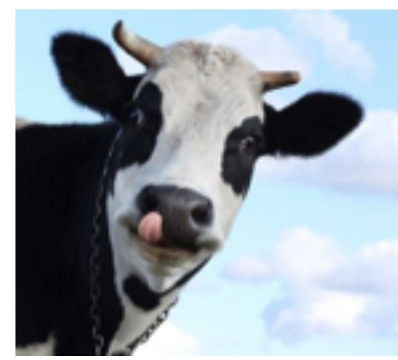


Memory Hierarchy

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



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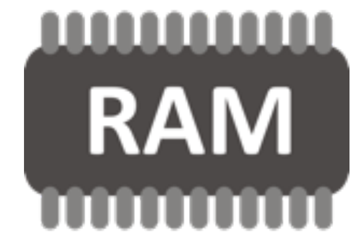

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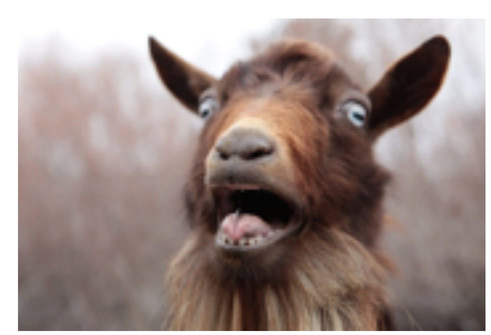

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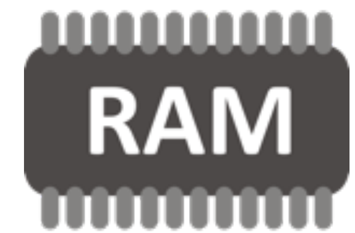

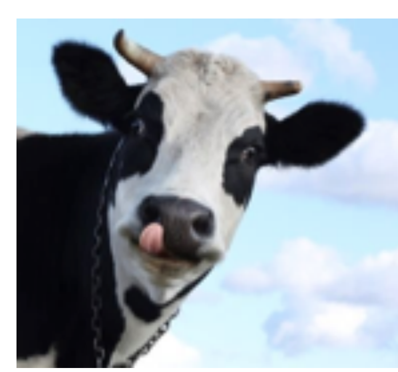

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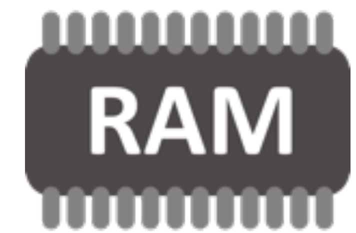

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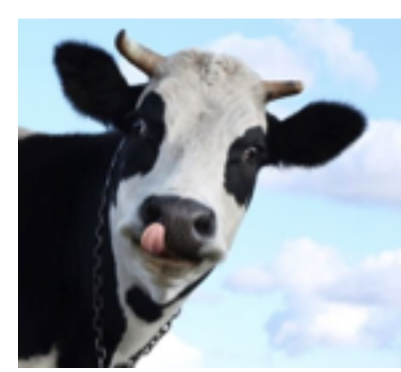
Big, slow



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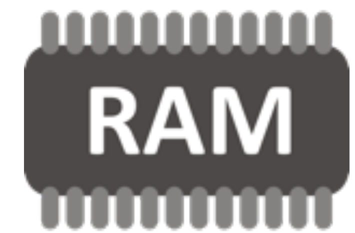

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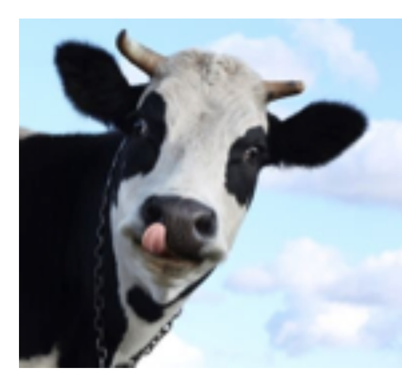
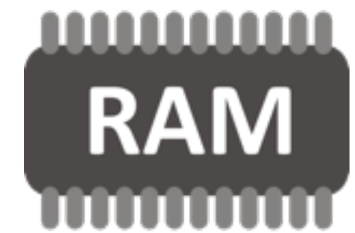


Memory Hierarchy

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

Small, fast



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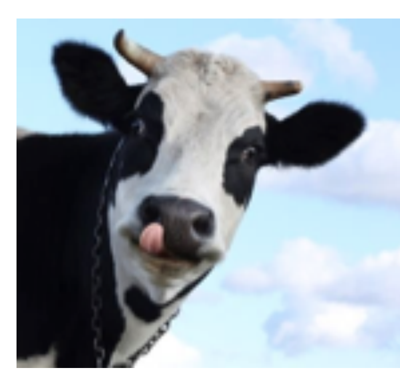

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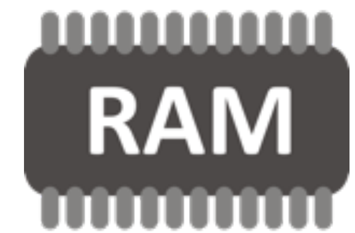

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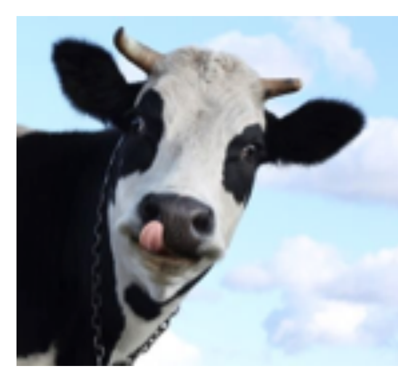

Memory Hierarchy

- **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)
    - Check the set first *before* checking disk
    - Don't go to disk if we know the thing isn't there

Membership Queries

- How to implement?
  - If we want to look things up quickly, use a hash table

- 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, fingerprint is 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 hashFunctioni in hashFuncionsi…k:
    bitmap[hashFunctioni(key) % m] = 1
```

Query(key):

```
for hashFunctioni in hashFuncionsi…k:
    if (bitmap[hashFunctioni(key) % m] != 1):
        return “not in set”
return “maybe in set”
```

Bloom Filters

- Deleting keys?
  - An key maps to *k* bits, and although setting any one of those *k* bits to zero would remove that key from the set, it may also remove any 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

Integrity/Tamper Evidence

Detecting Changes

- Sometimes we can't trust the integrity of our stuff
  - Our laptop is from 2006, and our HDD is ready to go…
  - 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

Detecting Changes

- **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)

Detecting Changes

- 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

Detecting Changes

- Download verification (MD5 example)
- Scanning files for errors
- Git
- …

Detecting Duplicates

Deduplication

- Imagine you are a cloud storage provider, and someone uploads 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:

```
file_name -> recipe*
```

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

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