CSE 332: Data Abstractions

Lecture 8: Memory Hierarchy & B Trees

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Announcements

- **Homework 2** – due NOW!
- **Homework 3** – coming soon!
- **Project 2** – posted!
  Partner selection due by 11pm Wed 10/16 *at the latest*.

Today

- Dictionaries
  - AVL Trees (finish up)

- The Memory Hierarchy and you

- Dictionaries
  - B-Trees

Now what?

- We have a data structure for the dictionary ADT (AVL tree) that has worst-case $O(\texttt{log}\ n)$ behavior
  - One of several interesting/fantastic balanced-tree approaches

- We are about to learn another balanced-tree approach: B Trees

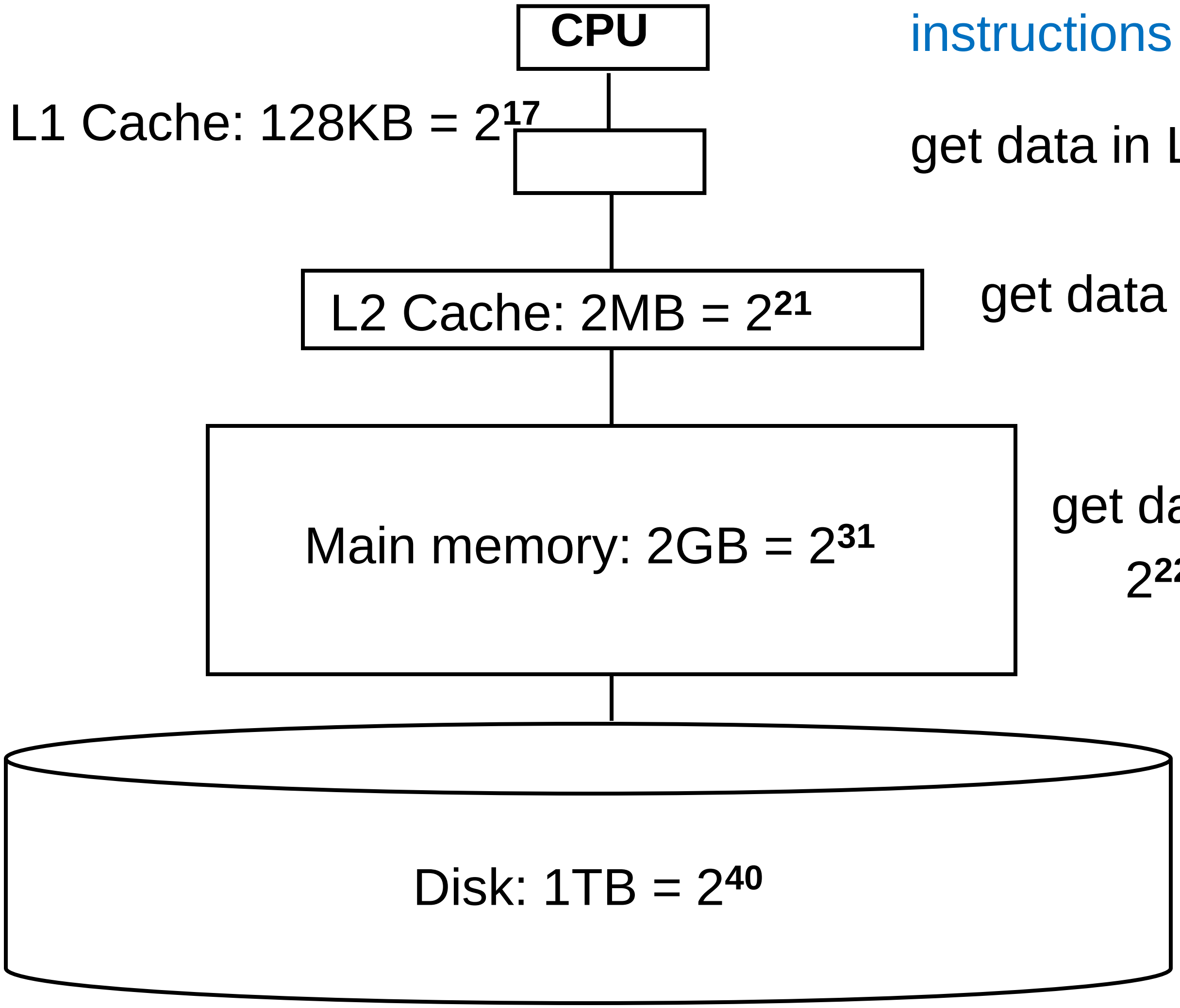
- First, to motivate why B trees are better for really large dictionaries (say, over 1GB = 2^{30} bytes), need to understand some ***memory-hierarchy basics***
  - Don't always assume "every memory access has an unimportant *O(1)* cost"
  - Learn more in CSE351/333/471, focus here on relevance to data structures and efficiency

Why do we need to know about the memory hierarchy?

- One of the assumptions that Big-Oh makes is that all operations take the same amount of time.
- Is that really true?

A typical hierarchy

"Every desktop/laptop/server is different" but here is a plausible configuration these days



instructions (e.g., addition): 2^{30}/sec

get data in L1: 2^{29}/sec = 2 instructions

get data in L2: 2^{25}/sec = 30 instructions

get data in main memory: 2^{22}/sec = 250 instructions

get data from "new place" on disk: 2^{7}/sec =8,000,000 instructions

Morals

It is much faster to do:	Than:
5 million arithmetic ops	1 disk access
2500 L2 cache accesses	1 disk access
400 main memory accesses	1 disk access

Why are computers built this way?

- Physical realities (speed of light, closeness to CPU)
- Cost (price per byte of different technologies)
- Disks get much bigger not much faster
  - Spinning at 7200 RPM accounts for much of the slowness and unlikely to spin faster in the future
- Speedup at higher levels (e.g. a faster processor) makes lower levels *relatively slower*
- Later in the course: more than 1 CPU!

“Fuggedaboutit”, usually

The hardware automatically moves data into the caches from main memory for you

- Replacing items already there
- So algorithms much faster if “data fits in cache” (often does)

Disk accesses are done by software (e.g., ask operating system to open a file or database to access some data)

So most code “just runs” but sometimes it’s worth designing algorithms / data structures with knowledge of memory hierarchy

- And when you do, you often need to know one more thing…

How does data move up the hierarchy?

- Moving data up the memory hierarchy is slow because of *latency* (think distance-to-travel)
  - Since we're making the trip anyway, may as well carpool
    - Get a block of data in the same time it would take to get a byte
  - Sends *nearby memory* because:
    - It's easy
    - And likely to be asked for soon (think fields/arrays)

Spatial Locality

- Side note: Once a value is in cache, may as well keep it around for awhile; accessed once, *a particular value* is more likely to be accessed again in the near future (more likely than some random other value)

Temporal locality

Locality

Temporal Locality (locality in time) – If an address is referenced, ***it*** will tend to be referenced again soon.

Spatial Locality (locality in space) – If an address is referenced, ***addresses that are close by*** will tend to be referenced soon.

Block/line size

- The amount of data moved from disk into memory is called the "**block**" size or the "**page**" size
  - Not under program control
- The amount of data moved from memory into cache is called the cache "**line**" size
  - Not under program control

Connection to data structures

- An array benefits more than a linked list from block moves
  - Language (e.g., Java) implementation can put the list nodes anywhere, whereas array is typically contiguous memory
- Suppose you have a queue to process with 2^{23} items of 2^7 bytes each on disk and the block size is 2^{10} bytes
  - An **array** implementation needs 2^{20} disk accesses
    - If “perfectly streamed”, > 4 seconds
    - If “random places on disk”, 8000 seconds (> 2 hours)
  - A **list** implementation in the worst case needs 2^{23} “random” disk accesses (> 16 hours) – probably not that bad
- Note: “array” doesn’t necessarily mean “good”
  - Binary heaps “make big jumps” to percolate (different block)

BSTs?

- Looking things up in balanced binary search trees is $O(\log n)$, so even for $n = 2^{39}$ (512GB) we need not worry about minutes or hours

- Still, number of disk accesses matters:
  - Pretend for a minute we had an AVL tree of height 55
  - The total number of nodes could be?__________
  - Most of the nodes will be on disk: the tree is shallow, but it is still many gigabytes big so the entire *tree* cannot fit in memory
    - Even if memory holds the first 25 nodes on our path, we still potentially need 30 disk accesses if we are traversing the entire height of the tree.

Note about numbers; moral

- **Note:** All the numbers in this lecture are “ballpark” “back of the envelope” figures

- **Moral**: Even if they are off by, say, a factor of 5, the moral is the same:

  If your data structure is mostly on disk,
  you want to minimize disk accesses

- A better data structure in this setting would exploit the block size and relatively fast memory access to ***avoid disk accesses***…

Trees as Dictionaries

(N= 10 million) [Example from Weiss]

In worst case, each node access is a disk access, number of accesses:

<u># Disk accesses</u>

- BST
- AVL
- B Tree

Our goal

- **Problem**: A dictionary with so much data *most of it is on disk*
- **Desire**: A balanced tree (logarithmic height) that is even shallower than AVL trees so that we can minimize disk accesses and exploit disk-block size
- **A key idea**: Increase the branching factor of our tree