



APSTA-GE 2352

Statistical Computing: Lecture 12

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Announcements

- PS6 is posted
 - I think there is one tricky coding part
 - The rest is really interpretation—use historical and geographical resources to help you!
- Lab next week is still cancelled
- After today:
 - 2 more lectures
 - 2 more labs
 - 1 final exam

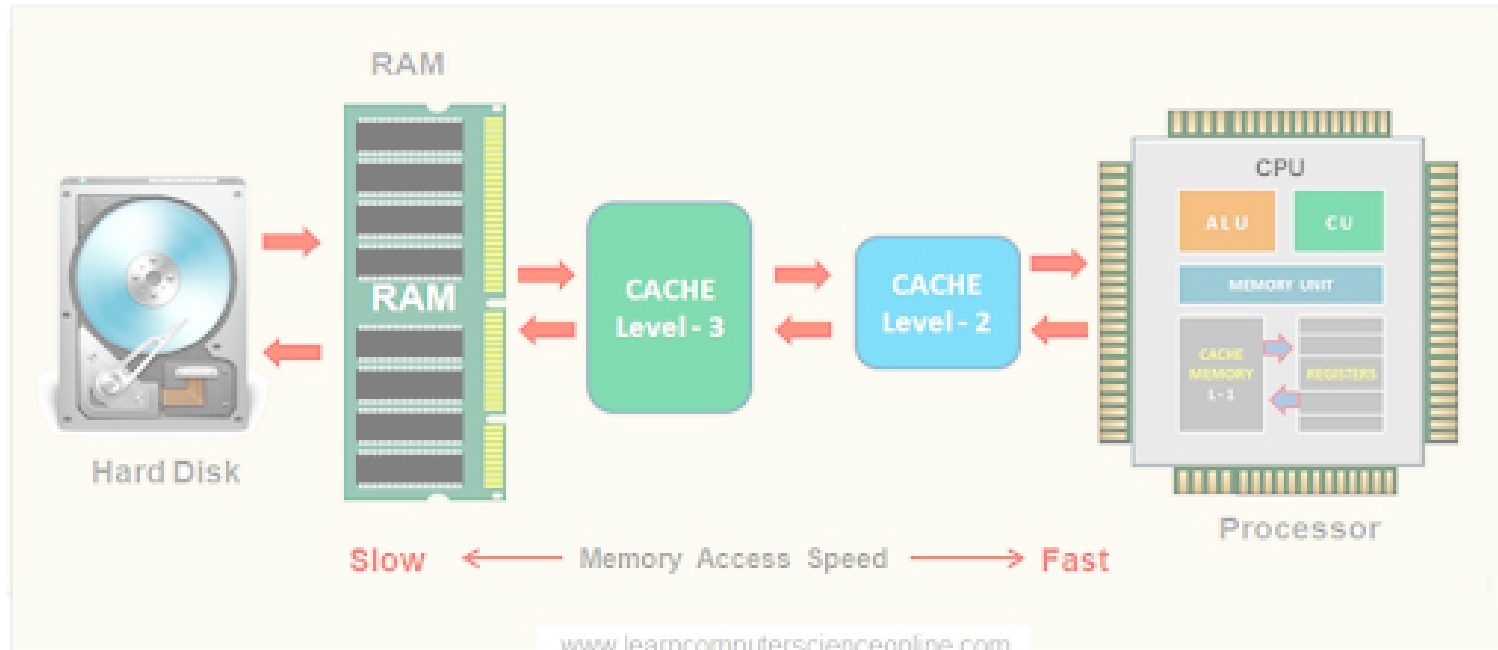
Course-related Announcements

- You should be registered for my Generalized Linear Models and Extensions course (GLMs)
 - You will learn a lot about GLMs
 - Treatment is practical and mathematical
 - Course has a lot less programming (but it's still me, so you know)
 - What are the extensions?
 - Multilevel Models (MLMs)
 - Generalized Additive Models (GAMs)
- You might be interested in Modern Approaches in Measurement
 - Unsupervised machine learning approaches to latent variable measurement
 - We deal with continuous and categorical latent variables
 - Real data: item response/survey data, behavioral data, and text
 - People generally like it!
 - It's also generally a pre-req for summer research opportunities with me

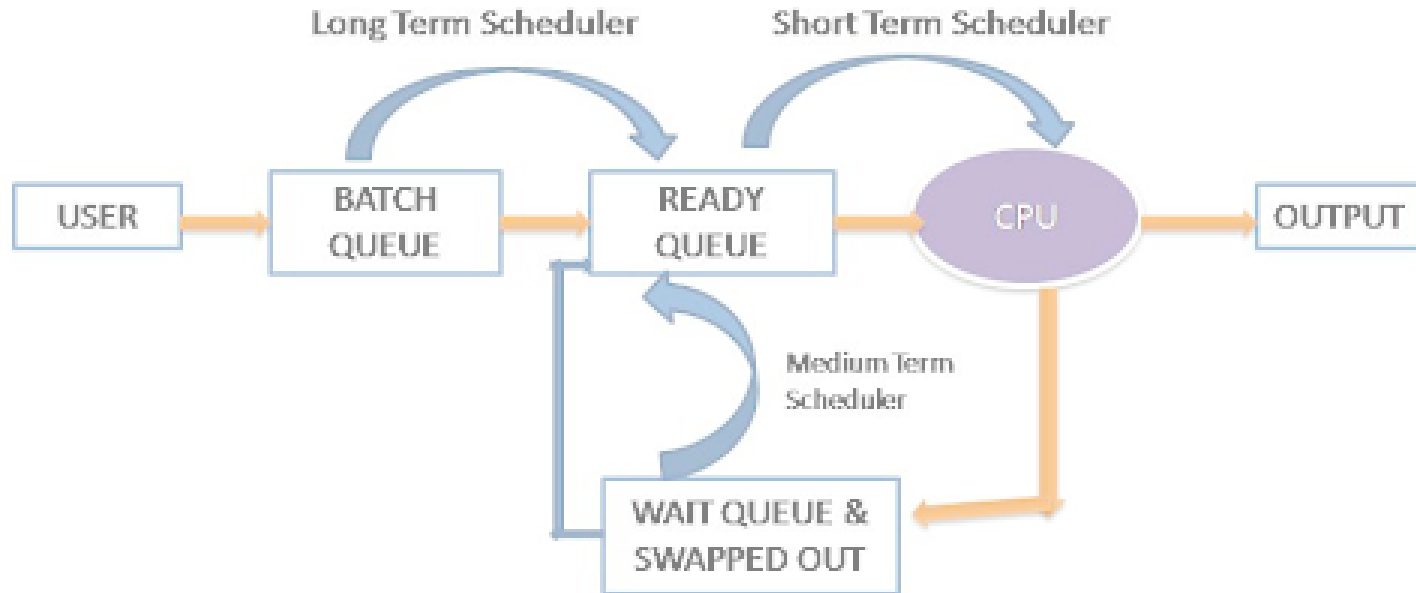
Computer Architecture

Memory

Computer System Memory Hierarchy

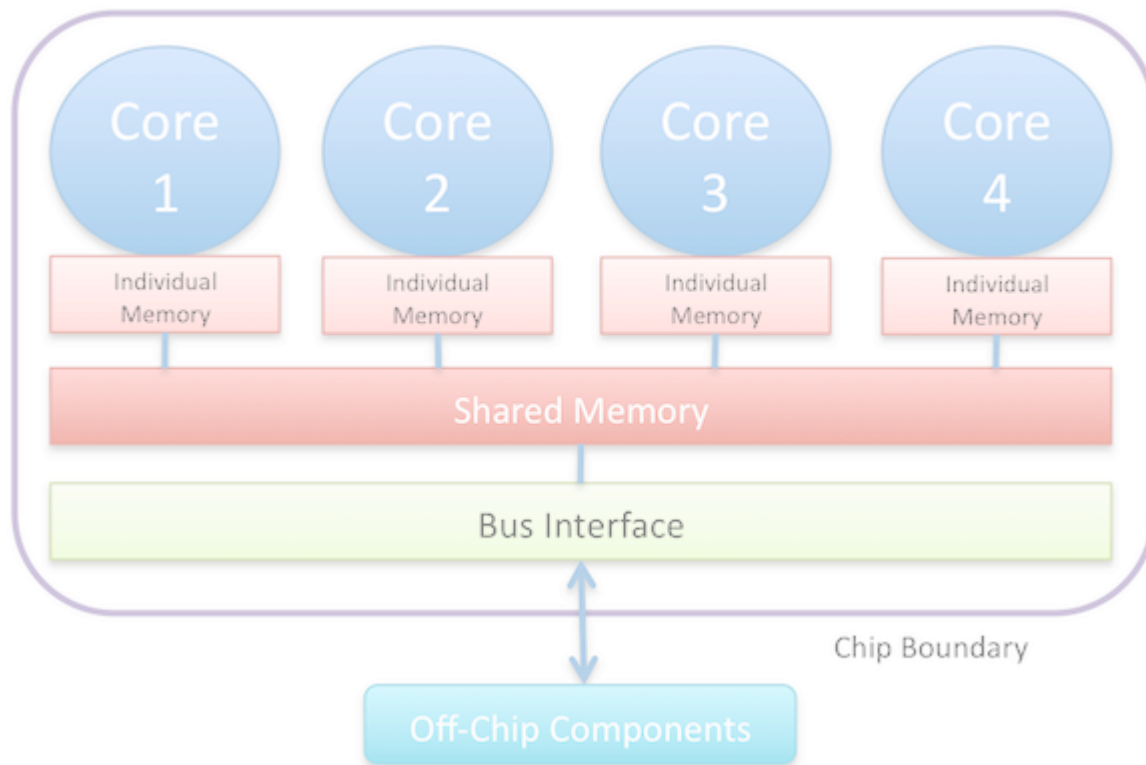


Scheduling



Multi-core Processing

Multi-core Processor



CPUs vs GPUs

Parallel Computing

Parallelization

- Some computations and tasks depend on previous results
 - We call these sequential computations
 - MCMC is a great example of this!
- Some computations don't!
 - Bootstrap replications are a great example of this!
 - If they're really easy to separate, we call them *embarrassingly parallel*
- Some computations can be parallelized (or partially parallelized) with some work
 - Map-Reduce is a great example of this!

What is Parallel Computing?

- Parallel computing refers to engaging multiple compute cores in a task simultaneously
- Computers with multiple cores and multiple processors can do multiple things at once
- Modern computers often have high core counts (my Macbook Air has eight, my desktop at home has 24!)
- Graphical processing units (GPUs) are purpose built for parallel matrix multiplication operations
- Parallel computing engages more resources in a task, so computation happens simultaneously
- Parallel computing also allocates memory resources to tasks, so there are fewer costs with moving things around and accessing slower memory

What about Vectorization?

- Vectorized code takes advantage of *implicit parallelization*
- An example of single instruction, multiple data (SIMD) computation
- At the compiler level, the computer knows how to interact with the scheduler to divide up this work across multiple cores and/or threads
- This is why vectorized computation is so much faster: It's parallel by default!

Implementation in R

- We'll use the `parallel` package
 - Built into `R` and a combination of two old packages: `snow` and `multicore`
 - The core idea is this: if you can modify your code to use an `apply()` function to solve your problem, you can parallelize for almost no additional cost
- Other options for parallelization in `R` exist
 - The `doParallel` and `foreach` package work together in ways I find to be really silly
 - The `future` package is another option for parallelization

Workflow

- Create a local cluster using `makeCluster()`
- Export data and functions to the cluster using `clusterExport()`
- Replace your `apply()` function with a parallelized version
 - `parApply()` , `parLapply()` , `parSapply()` are drop-in replacements
 - I usually use `clusterMap()` , which is like `mapply()` or `Map()`
- Stop the cluster with `stopCluster()` (This is important!)
- There are also load-balanced versions like `parLapplyLB()` and `clusterMap()` has a dynamic scheduling option
 - Normal versions use *static* scheduling, where work is divided among cores before starting
 - Load-balanced versions use *dynamic* scheduling, assigning tasks to cores as other tasks finish
 - In most small to medium sized tasks, normal versions are more efficient
 - Load-balancing is most effective when individual jobs have wildly different runtimes

Wrap Up

Recap

- Debugging is challenging, but we have four (five?) main tools:
 - Googling error messages
 - `print()` statements
 - `traceback()`
 - `browser()`
 - Maybe ChatGPT if you like it?
- The `apply()` family of functions allows you to hide loops
 - Not more efficient, but *safer* than loops
 - Encourages functionalization of code
 - Makes code easier to read

Final Thoughts

- [PollEv.com/klintkanopka](https://pollev.com/klintkanopka)