CS 6240: Parallel Data Processing in MapReduce

Mirek Riedewald

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Course Information

- Homepage: http://www.ccs.neu.edu/home/mirek/classes/2012-F-CS6240/
  - Announcements
  - Lecture handouts
  - Office hours
- Homework management through Blackboard
- Prerequisites: CS 5800/CS 7800, or consent of instructor

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Grading

- Homework/project: 60%
- Midterm 30%
- Participation 10%
  - Ask/answer in class; answer questions on Piazza
- No copying or sharing of homework solutions!
  - But you can discuss general challenges and ideas
- Material allowed for exams
  - Any handwritten notes (originals, no photocopies)
  - Printouts of lecture summaries distributed by instructor

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Instructor Information

- Instructor: Mirek Riedewald (332 WVH)
  - Office hours: Tue 4:00-5:30pm
  - Post questions on Piazza
  - Email for appointment if you cannot make it during office hours (or stop by for 1-minute questions)
- TA: Alper Okcan (472 WVH)

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Course Materials

- Hadoop: The Definitive Guide by Tom White
- Hadoop in Action by Chuck Lam
  - Both available from Safari Books Online at http://0-proquest.safaribooksonline.com.ilsprod.lib.neu.edu/
  - Use your myNEU credentials
- Other resources mentioned in syllabus and class homepage

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Course Content and Objectives

- How to process Big Data
  - Different from traditional approaches to parallel computation for smaller data
- Learn important fundamentals of selected approaches
  - Current trends and architectures
  - Parallel programming in (raw) MapReduce
    - Programming model and Hadoop open source implementation
  - Creating data processing workflows with Pig Latin
  - HBase for storing and managing big data
  - MapReduce versus SQL and other related approaches
- Various problem types and design patterns

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Course Content and Objectives

- Gain an intuition for how to deal with big-data problems
- Hands-on MapReduce practice
  - Writing MapReduce programs and running them on the Amazon Cloud
  - Understanding the system architecture and functionality below MapReduce
  - Learning about limitations of MapReduce
- Might produce publishable research

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Words of Caution 1

- We can only cover a small part of the parallel computation universe
  - Do not expect all possible architectures, programming models, theoretical results, or vendors to be covered
  - Explore complementary courses in CCIS and ECE
- This really is an algorithms course, not a basic programming course
  - But you will need to do a lot of non-trivial programming

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Words of Caution 2

- This is still a fairly a new course, so expect rough edges like too slow/fast pace, uncertainty in homework load estimation
- There are few certain answers, as people in research and leading tech companies are trying to understand how to deal with big data
- We are working with cutting edge technology
  - Bugs, lack of documentation, new Hadoop API
- In short: you have to be able to deal with inevitable frustrations and plan your work accordingly…
- …but if you can do that and are willing to invest the time, it will be a rewarding experience

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Running Your Code

- You need to set up an account with Amazon Web Services (AWS)
- Requires a credit card
- We give you $100 in credit for this course
- Should be sufficient for all assignments
  - Develop and test on your laptop
  - Deploy once you are confident things work
  - Monitor your job and make sure it terminates as expected

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How to Succeed

- Attend the lectures and take your own notes
  - Helps remembering (compared to just listening)
  - Capture lecture content more individually than our handouts
  - Free preparation for exams
- Go over notes, handouts, book soon after lecture
  - Try to explain material to yourself or friend
- Look at content from previous lecture right before the next lecture to “page-in the context”

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How to Succeed

- Ask questions during the lecture
  - Even seemingly simple questions show that you are thinking about the material and are genuinely interested
- Work on the HW assignment as soon as it comes out
  - Can do most of the work on your own laptop
  - Time to ask questions and deal with unforeseen problems
  - We might not be able to answer all last-minute questions right before the deadline

- Students with disabilities: contact me by September 18

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What Else to Expect?

- Need strong Java programming skills
  - Code for Hadoop system is in Java
  - Hadoop supports other languages, but use at your own risk (we cannot help you and have not tested it)
- Need strong algorithms background
  - Analyze problems and solve them using an unfamiliar framework
- Basic understanding of important system concepts
  - File system, processes, network basics, computer architecture

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Why Focus on MapReduce?

- MapReduce is viewed as one of the biggest breakthroughs for processing massive amounts of data.
- It is widely used at technology leaders like Google, Yahoo, Facebook.
- It has huge support by the open source community.
- Amazon provides special support for setting up Hadoop MapReduce clusters on its cloud infrastructure.
- It plays a major role in current database research conferences (and many other research communities)

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Let us first look at some recent trends and developments that motivated MapReduce and other approaches to parallel data processing.

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Why Parallel Processing?

- Answer 1: big data

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How Much Information?

- Source: http://www2.sims.berkeley.edu/research/projects/how-much-info-2003/execsum.htm
- 5 exabytes (10^{18}) of new information from print, film, optical storage in 2002
  - 37,000 times Library of Congress book collections (17M books)
- New information on paper, film, magnetic and optical media doubled between 2000 and 2003
- Information that flows through electronic channels—telephone, radio, TV, Internet—contained 18 exabytes of new information in 2002

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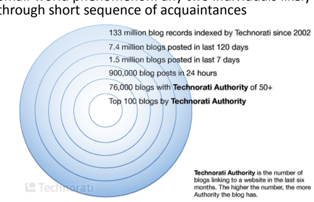
Web 2.0

- Billions of Web pages, social networks with millions of users, millions of blogs
  - How do friends affect my reviews, purchases, choice of friends
  - How does information spread?
  - What are "friendship patterns"
    - Small-world phenomenon: any two individuals likely to be connected through short sequence of acquaintances



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Facebook Statistics

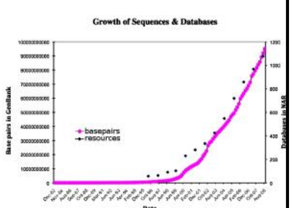
- 955M active users (June ‘12), 81% outside US/Canada
- More than 100 petabytes of photos and videos
- August 2011: 30 billion pieces of content (web links, news stories, blog posts, notes, photo albums, etc.) shared each month
  – Avg. user created 90 pieces of content per month

Business World

- Fraudulent/criminal transactions in bank accounts, credit cards, phone calls
  – Billions of transactions, real-time detection
- Retail stores
  – What products are people buying together?
  – What promotions will be most effective?
- Marketing
  – Which ads should be placed for which keyword query?
  – What are the key groups of customers and what defines each group?
- Spam filtering

eScience Examples

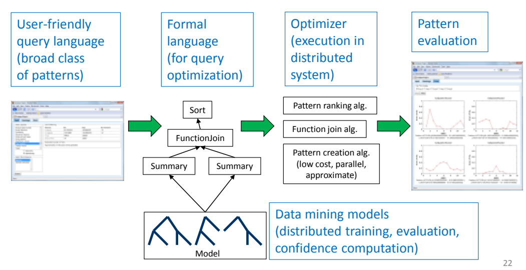
- Genome data
- Large Hadron Collider
  – Petabytes of raw data per year
- SkyServer
  – 818 GB, 3.4 billion rows
- DataONE
  – “Universal access to data about life on earth and the environment”
- Cornell Lab of Ornithology
  – 107M observations, 100s of attributes



Source: Nature

Our Scolopax Project

- Search for patterns in prediction models based on user preferences
  Make this as easy and fast as Web search

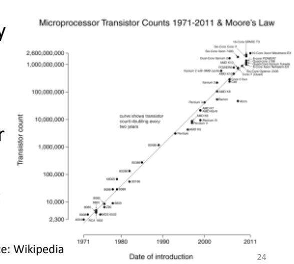


Why Parallel Processing?

- Answer 1: big data
- Answer 2: hardware trends

The Good Old Days

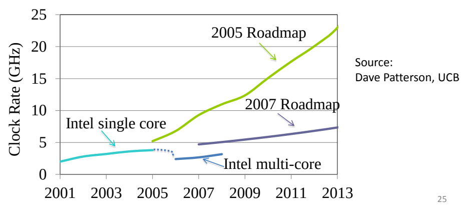
- Moore’s Law: number of transistors that can be placed inexpensively on an integrated circuit doubles about every 2 years
- Computational capability improved at similar rate
  – Sequential programs became automatically faster
- Parallel computing never became mainstream
  – Reserved for high-performance computing niches



Source: Wikipedia

“New” Realities

- “Party” ended around 2004
- Heat issues prevent higher clock speeds
- Clock speed remains below 4 GHz

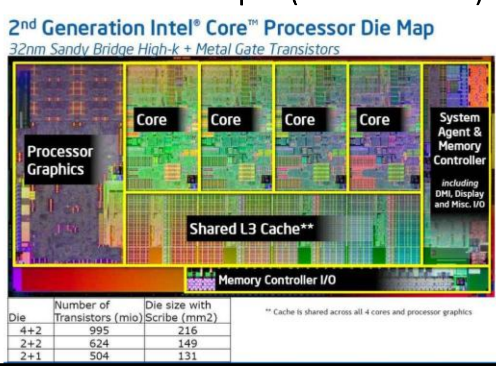


Source:
Dave Patterson, UCB

Multi-Core CPUs

- Clock speed stagnates, but number of cores increases
  - Core is like a processor, but shares chip with other cores
  - Cores typically share some cache, memory bus, access to same main memory
- Need to keep multiple cores busy to exploit additional transistors on chip
  - Multi-threaded applications

Processor Example (Source: Intel)



Typical Multi-Core Properties

- Each core has some local cache (e.g., L1, L2)
- The cores share some cache (e.g., L3)
- All cores access same memory through bus
- Misses become much more expensive from L1 to L3, even more when accessing memory

Important Numbers (Source: Google’s Jeff Dean @LADIS’09)

L1 cache reference	0.5
Branch mispredict	5
L2 cache reference	7
Mutex lock/unlock	25
Main memory reference	100
Compress 1 KB with Zippy	3,000
Send 2 KB over 1 Gbps network	20,000
Read 1 MB sequentially from memory	250,000
Round trip within same data center	500,000
Disk seek	10,000,000
Read 1 MB sequentially from disk	20,000,000
Send packet CA -> Holland -> CA	150,000,000

All times in ns.

Other Trends

- Datacenter as a computer
  - Hundreds to tens of thousands of commodity machines for large-scale data processing
- Cloud computing
  - Often powered by data center(s)
- GPU computing
  - Initially developed for fast parallel graphics computations, now also used for general computations
- Parallel data processing is becoming mainstream

Parallel Architectures

- Multi-core chips
- Datacenter as a computer

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Warehouse-Scale Computer (WSC)

- Hundreds or thousands of commodity PCs
  - Better cost per unit of computational capability than specialized hardware due to economies of scale of commodity hardware
  - Easy to "scale out" by adding more machines
- Organized in racks in data centers
- Relatively homogenous hardware and system software platform with common system management layer
  - Often run smaller number of very large applications like Internet services

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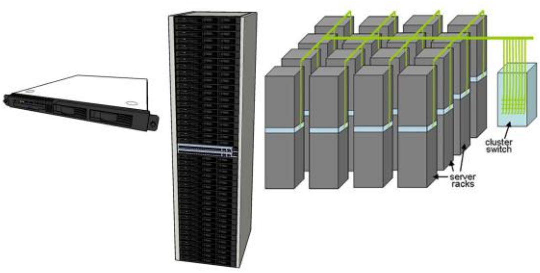
Basic Architecture



Source: Barroso, Holzle (2009)

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Typical Specs

- Low-end servers in 1U enclosure in 7' rack
- Rack-level switch with 1- or 10-Gbps links
- Connected by one or more cluster switches
  - Can include >10,000 servers
- Local (cheap) disks on each server
  - Managed by global distributed file system
- Might have Network Attached Storage (NAS) devices for more centralized storage solution

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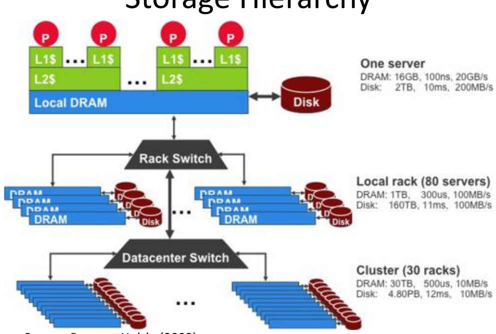
Storage Hierarchy



Source: Barroso, Holzle (2009)

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Programming WSCs

- Build cluster infrastructure and services that hide architecture complexity from developers
  - Program it like a single big computer, but avoid inefficient code
- Need easy way to keep hundreds or thousands of CPUs busy
- Handle failures transparently
  - With 1000 commodity machines, failures are the norm, not the exception
  - Developers want to focus on their application, not how to deal with failures of hardware and low-level services
- This is where MapReduce comes into the picture!

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Parallel Architectures

- Multi-core chips
- Datacenter as a computer
- Cloud computing

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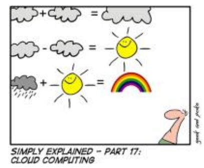
The Cloud

- Many different versions of Clouds
- Common idea: customers use virtual resources without knowing details about underlying hardware
  – Could run on cluster, multiple data centers, or large parallel machine
- Typical use 1: reserve virtual machines to create virtual cluster
- Typical use 2: connect through Web browser and run favorite application
- Typical use 3: build own app on top of services offered by Cloud provider
  – Database, document management, Web design, workflow, analytics



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Cloud Computing

- Goal: Move data and programs from desktop PCs and corporate server rooms to "compute cloud"
- Related buzzwords: on-demand computing, software as a service (SaaS), Internet as platform
- Starts to replace shrink-wrap software
  – MSFT Word on desktop PC vs. Google Docs

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Back to the Future…

- 1960s: service bureaus, time-sharing systems
  – Hub-and-spoke configuration: terminal access through phone lines, central site for computation
- 1980s: PCs "liberate" programs and data from central computing center
  – Customization of computing environment
  – Client-server model

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…or not?

- Cloud is not the same as 1960's hub
  – Client can communicate with many servers at the same time
  – Servers can communicate with each other
- Still, functions migrate to distant data centers
  – "Core" and "fringe"
    - Storage, computing, high bandwidth, and careful resource management in core
    - End users initiate requests from fringe

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Why Clouds?

- High price of total control
  – Software installation, configuration, and maintenance
  – Maintenance of computing infrastructure
  – Difficult to grow and shrink capacity on demand
- Easier software development
  – Replaces huge variety of operating environments by computing platform of vendor's choosing
  – But: server interaction with variety of clients
- Easier to deploy updates and bug fixes
- Easier to leverage multi-core, parallel systems
  – Single instance of Word cannot utilize 100 cores, but 100 instances of Word can

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Example Cloud Offerings

- Document processing
  - Google Docs: word processor, spreadsheet, presentations
  - Adobe: Acrobat.com, Photoshop Express
  - Microsoft Office 365
- Enterprise applications
  - Salesforce.com: customer relationship management, sales marketing apps
  - Microsoft Dynamics CRM, IBM Tivoli Live
- Cloud infrastructure
  - Amazon Web Services: storage, computing as needed (pay as you go)
  - IBM Smart Cloud, Google App Engine, Force.com, Microsoft Azure
- Cloud OS
  - User interface in Web browser
  - New browser wars: browser as new Cloud OS

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Challenges

- Scalability
  - More users, complex interactions between applications
- Many-to-many communication
  - Client invokes programs on multiple servers, server talks to multiple clients
- Browser is limited compared to traditional OS
  - Limited functionality
  - Fewer development tools

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More Challenges

- Heterogeneous environment
  - Database backend with SQL
  - JavaScript, HTML at client
  - Server app written in PHP, Java, Python
  - Information exchanged as XML
- New role for open source movement?
  - Open source word processor vs. running a service

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Biggest Problems

- Privacy, security, reliability
  - What if the service is not accessible?
  - Who owns the data?
  - Lose access to data if bill not paid?
  - Guarantee that deleted documents are really gone?
  - How aggressive about protecting data, e.g., against government access?
  - How to know if data is leaked to third party?

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Parallel Architectures

- Multi-core chips
- Datacenter as a computer
- Cloud computing
- GPU computing

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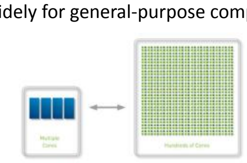
GPU vs. CPU

- Optimized for massively parallel processing
  - Graphics processing
- Challenge: how to create applications for 100s of cores?
  - Example: NVIDIA developed CUDA
  - Used widely for general-purpose computations



Source: NVIDIA

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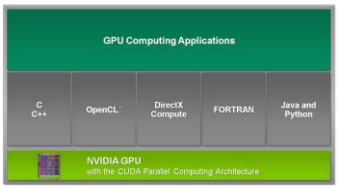
CUDA (Source: NVIDIA)

- CUDA programming model provides abstractions for data and task parallelism
  - Programmer can express parallelism in high-level languages such as C, C++, Fortran or driver APIs such as OpenCL™ and DirectX™-11 Compute
  - Programming model guides programmers to partition the problem into coarse sub-problems that can be solved independently in parallel
  - Fine grain parallelism in the sub-problems is then expressed such that each sub-problem can be solved cooperatively in parallel.



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Course Content in a Nutshell

- In big-data processing, usually the same computation needs to be applied to a lot of data
  - Possibly many such steps (think “workflow”)
- Divide the work between multiple processors
  - Make sure you can handle data transfer efficiently
- Combine intermediate results from multiple processors

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Why This Is Not So Easy

- How can the work be partitioned?
- What if too much intermediate data is produced?
- How do we start up and manage 1000s of jobs?
- How do we get large data sets to processors or move processing to the data?
- How do we deal with slow responses and failures?

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More Problems

- Shared resources limit scalability
  - Cost of managing concurrent access
- Shared-nothing architectures still need communication for processes to share data
- Easy to get into problems like deadlocks and race conditions
- It is generally difficult to reason about the behavior and correctness of concurrent processes
  - Especially when failures are part of the model
- Inherent tradeoff between consistency, availability, and partition tolerance (Brewer’s Conjecture)

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What Can We Do?

- Work at the right level of abstraction
  - Too low-level: difficult to write programs, e.g., to deal with locks; need to customize code for different systems
  - Too high-level: poor performance if control for crucial bottleneck is “abstracted away”
- Use more declarative style of programming
  - Define WHAT needs to be computed, not HOW this is done at the low level
  - Well-known success story: SQL and databases

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Recipes for Success

- Use hardware that can scale out, not just up
  - Doubling the number of commodity servers is easy, but buying a double-sized SMP machine is not.
- Have data located near the processors
  - Sending petabytes around is not a good idea
- Avoid centralized resources that are likely bottlenecks, e.g., single shared memory bus for many cores
- Read and write data sequentially
  - Assume random I/O takes 20 msec, disk streams data sequentially at 100 MB/sec, and record size is 1 KB
  - During 1 random I/O, can read 2000 records sequentially
- MapReduce does all this, and its level of abstraction seems to have hit a sweet spot

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Algorithms First

- No matter which parallel programming model we use, we first need to understand what part of a computation can be performed in parallel
- More precisely…

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Writing Parallel Programs

- Analyze problem and identify what can be done in parallel
  - Dependencies: if I need data D as input for a task, then I cannot run this task and the creation of D in parallel.
  - Coordination requirements: when do parallel tasks have to communicate and how much data is sent?
  - Best sequential algorithm might not be easy to parallelize—find alternative solutions
- Create an efficient implementation
  - Make sure solution is a good fit for the given architecture and programming model

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Examples

- Let us look at some examples to get a feeling for the challenges

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Sum Of Integers

- Compute sum of a large set of integers
- Sequential: simple for-loop (scan)
- Parallel: assign chunk of data to each processor to compute local sum, then add them together
- Algorithmically easy, but…
  - Where do the chunks come from? Partitioning data file into multiple chunks might take as long as sequential computation.
  - What if data transfer is the bottleneck? Then pushing k chunks from disk to k cores might not be a good idea.
  - Who computes final sum and how do the local sums get there?

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Word Count

- Count the number of occurrences of each word in a large document
- Sequential: read document sequentially, update counters for each word
  - Need data structure, e.g., hash map, to keep track of counts
- Parallel: each processor does this for a chunk using local data structure, then counts are aggregated
- Improvement (?): use shared data structure for counts
  - Good: no "replication", no need for final summation step
  - Bad: need to coordinate access to shared data structure, not a good fit for shared-nothing architecture
- What if some documents are much larger than others?
  - Need to deal with data skew, e.g., break up large documents

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Median

- Find the median of a set of integers
- Holistic aggregate function
  - Chunk assigned to a processor might contain mostly smaller or mostly larger values, and the processor does not know this without communicating extensively with the others
- Parallel implementation might not do much better than sequential one
- Efficient approximation algorithms exist

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Parallel Office Tools

- Parallelize Word, Excel, email client?
- Need to rewrite them as multi-threaded applications
  - Seem to naturally have low degree of parallelism
- Leverage economies of scale: *n* processors (or cores) support *n* desktop users by hosting the service in the Cloud
  - E.g., Google docs

Before exploring parallel algorithms in more depth, how do we know if our parallel algorithm or implementation actually does well or not?

Measures Of Success

- If sequential version takes time t, then parallel version on n processors should take time t/n
  - Speedup = sequentialTime / parallelTime
  - Note: job, i.e., work to be done, is fixed
- Response time should stay constant if number of processors increases at same rate as "amount of work"
  - Scaleup = workDoneParallel / workDoneSequential
  - Note: time to work on job is fixed

Things to Consider: Amdahl's Law

- Consider job taking sequential time 1 and consisting of two sequential tasks taking time t_1 and $1-t_1$, respectively
- Assume we can perfectly parallelize the first task on n processors
  - Parallel time: $t_1/n + (1 - t_1)$
- Speedup = $1 / (1 - t_1(n-1)/n)$
  - $t_1=0.9$, n=2: speedup = 1.81
  - $t_1=0.9$, n=10: speedup = 5.3
  - $t_1=0.9$, n=100: speedup = 9.2
  - Max. possible speedup for $t_1=0.9$ is 1/(1-0.9) = 10

Implications of Amdahl's Law

- Parallelize the tasks that take the longest
- Sequential steps limit maximum possible speedup
  - Communication between tasks, e.g., to transmit intermediate results, can inherently limit speedup, no matter how well the tasks themselves can be parallelized
- If fraction x of the job is inherently sequential, speedup can never exceed 1/x
  - No point running this on too many processors

Performance Metrics

- Total execution time
  - Part of both speedup and scaleup
- Total resources consumed
- Total amount of money paid
- Total energy consumed
- Optimize some combination of the above
  - E.g., minimize total execution time, subject to a money budget constraint

Popular Solution: Load Balancing

- Avoid overloading one processor while other is idle
  - Careful: if better balancing increases total load, it might not be worth it
  - Careful: optimizes for response time, but not necessarily other metrics like $ paid
- Static load balancing
  - Need cost analyzer like in DBMS
- Dynamic load balancing
  - Easy: Web search
  - Hard: join

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