Data Management in Large-Scale Distributed Systems

Introduction

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Teaching staff

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Organization of the course

18 hours

- 12 hours of lectures
- 6 hours of practical sessions

Grading

- Graded Lab (30% of the final grade)
- Written exam (70% of the final grade)

Covered topics

- The challenges of Big Data and distributed data processing
- The Map/Reduce programming model
- Batch and stream processing systems
- Distributed databases
- Performance of distributed data processing

Overview of this lecture

- Introduction to the Big Data challenges
- Challenges of distributed computing
- Introduction to Cloud Computing
- Scalability techniques

Agenda

The challenges of Big Data

Distributed and Parallel Systems

Cloud Computing

Running at scale

References

- Coursera Big Data, University of California San Diego
- The lecture notes of V. Leroy
- The lecture notes of R. Lachaize
- Designing Data-Intensive Applications by Martin Kleppmann

The data deluge

Many sources of data

The data deluge

Many sources of data

- Sensors
- Social media
- Scientific experiments
- Industry activity
- Etc.

Some numbers

- Every 2 days, we create as much information as we did since 2013¹
- 40K search queries on Google every second²
- 30M messages posted on Facebook every minute
- 6.1 Billions of smartphone users by 2020 (and 50 Billions connected devices)
- 570 new web sites every minute
- Largest database: 3.2 Trillions rows (AT&T)
- 40 TB of data every second during an experiment at the Large Hadron Collider

https://www.slideshare.net/BernardMarr/big-data-25-facts

²https://www.newgenapps.com/blog/

 $[\]verb|big-data-statistics-predictions-on-the-future-of-big-data|\\$

Hardware capacity

Storage

- All the music of the world stored for 500\$
- Large Amazon EC2 instance: 768GB of RAM, 3.6TB of SSD

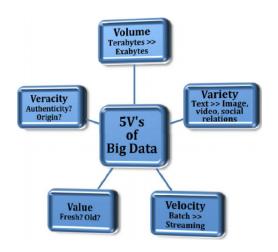
Computing resources

- Google data-centers: more than 2.5M servers (2016)
- Amazon capacity increase each day = size of Amazon in 2005

Huge opportunities for storing and processing data

source: Big Data for Modern Industry: Challenges and Trends

source: Big Data for Modern Industry: Challenges and Trends



- Volume: Amount of data generated
- Variety: all kinds of data are generated (text, image, voice, time series, etc.)
- Velocity: Rate at which data are produced and should be processed
- Veracity: Noise/anomalies in data, truthfulness
- Value: How do we extract/learn valuable knowledge from the data

In this course we are going to deal with:

- Volume
- Velocity

Variety

Questions to be answered:

- How to build a system and algorithms that can process huge amount of data?
- How to build a system and algorithms that can process data in a timely manner?
- (Bonus questions) How to build software that can deal with the variety of data?

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Motivation

The solution to process large amount of data:

Using large amount of resources

Note that:

- Different strategies can be used to leverage these resources
- Using large amount of resources presents new challenges

Increasing the processing power and the storage capacity

Goals

- Increasing the amount of data that can be processed (weak scaling)
- Decreasing the time needed to process a given amount of data (strong scaling)

Two solutions

- Scaling up
- Scaling out

Vertical scaling (scaling up)

Idea

Increase the processing power by adding resources to existing nodes:

- Upgrade the processor (more cores, higher frequency)
- Increase memory volume
- Increase storage volume

Vertical scaling (scaling up)

Idea

Increase the processing power by adding resources to existing nodes:

- Upgrade the processor (more cores, higher frequency)
- Increase memory volume
- Increase storage volume

- © Performance improvement without modifying the application
- Limited scalability (capabilities of the hardware, cf The end of Moore's law)
- Expensive (non linear costs)

Horizontal scaling (scaling out)

Idea

Increase the processing power by adding more nodes to the system

Cluster of commodity servers

Horizontal scaling (scaling out)

Idea

Increase the processing power by adding more nodes to the system

Cluster of commodity servers

- Often requires modifying applications
- Less expensive (nodes can be turned off when not needed)
- Infinite scalability

Horizontal scaling (scaling out)

Idea

Increase the processing power by adding more nodes to the system

• Cluster of commodity servers

Pros and Cons

- Often requires modifying applications
- Less expensive (nodes can be turned off when not needed)
- Infinite scalability

The solution studied in this course

Large scale infrastructures



Figure: Google Data-center



Figure: Amazon Data-center



Figure: Barcelona Supercomputing Center

Distributed computing: Definition

A distributed computing system is a system including several computational entities where:

- Each entity has its own local memory
- All entities communicate by message passing over a network

Each entity of the system is called a node.

Distributed computing: Challenges¹

¹Read Chapter 1 of *Designing Data-Intensive Applications* for further details

Distributed computing: Challenges¹

Scalability

 How to take advantage of a large number of distributed resources?

Performance

- How to take full advantage of the available resources?
- Moving data is costly
 - How to maximize the ratio between computation and communication?
- How to ensure that the latency of requests processing remains below some upper bound?

¹Read Chapter 1 of *Designing Data-Intensive Applications* for further details

Distributed computing: Challenges

Fault tolerance

- The more resources, the higher the probability of failure
- MTBF (Mean Time Between Failures)
 - MTBF of one server = 3 years
 - MTBF of 1000 servers \simeq 19 hours (beware: over-simplified computation)
- How to ensure computation completion?
- How to ensure that results are correct?

Programmability

- How to provide programming models that hide the complexity of distributed computing? (while remaining efficient)
- What high level services should be made available to ease life of programmers?

A warning about distributed computing

You can have a second computer once you've shown you know how to use the first one. (P. Braham)

Horizontal scaling is very popular.

But not always the most efficient solution (both in time and cost)

Examples

- Processing a few 10s of GB of data is often more efficient on a single machine that on a cluster of machines
- Sometimes a single threaded program outperforms a cluster of machines (F. McSherry et al. "Scalability? But at what COST!". 2015.)

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Cloud Computing

Running at scale

Where to find computing resources?

Cloud computing

• A service provider gives access to computing resources through an internet connection.

Where to find computing resources?

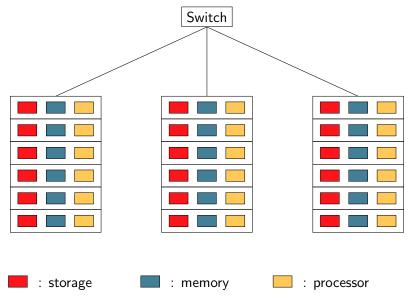
Cloud computing

 A service provider gives access to computing resources through an internet connection.

- Pay only for the resources you use
- © Get access to large amount of resources
 - Amazon Web Services features millions of servers
- Volatility
 - Low control on the resources
 - Example: Access to resources based on bidding
 - See "The Netflix Simian Army"
- Performance variability
 - Physical resources shared with other users

Architecture of a data center

Simplified



Architecture of a data center

A shared-nothing architecture

- Horizontal scaling
- No specific hardware

A hierarchical infrastructure

- Resources clustered in racks
- Communication inside a rack is more efficient than between racks
- Resources can even be geographically distributed over several datacenters

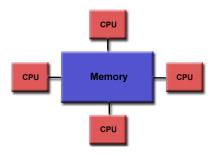
A hybrid system

Two paradigms for communicating between computing entities:

- Shared memory
- Message passing

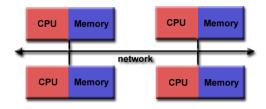
Shared memory

- Entities share a global memory
- Communication by reading and writing to the globally shared memory
- Communication between threads inside one node



Message passing

- Entities have their own private memory
- Communication by sending/receiving messages over a network
- Communication between nodes



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Cloud Computing

Running at scale

Running at scale

How to distribute data?

Partitioning

Running at scale

How to distribute data?

Partitioning

Replication

Replication

- Several nodes host a copy of the data
- Main goal: Fault tolerance
 - No data lost if one node crashes

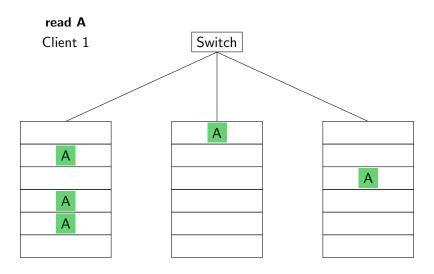
- Splitting the data into partitions
- Partitions are assigned to different nodes
- Main goal: Performance
 - Partitions can be processed in parallel

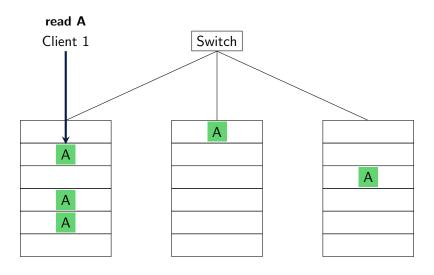
Purposes

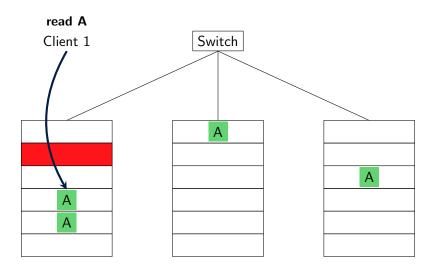
- Continuing to serve requests when parts of the system fail
- Keep data close to the users
- Having multiple servers able to answer read requests

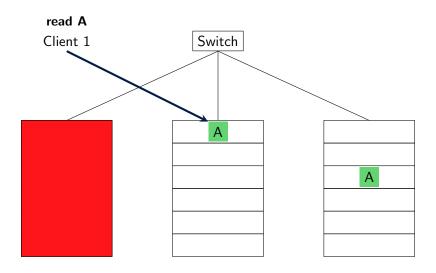
Challenges

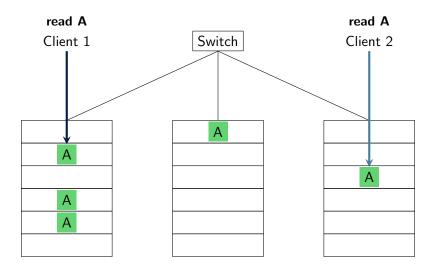
- How to handle operations that modify data? (write operations)
 - Consistency (Consensus in a distributed system is a very difficult problem)
 - Performance

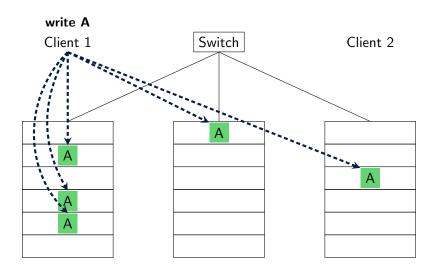


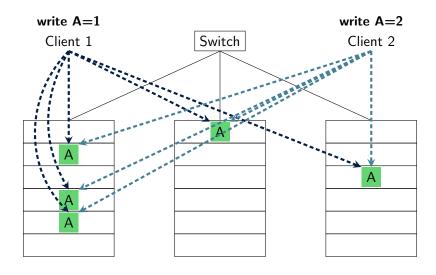


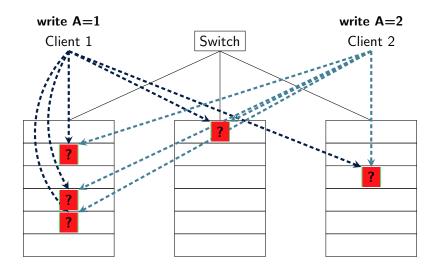












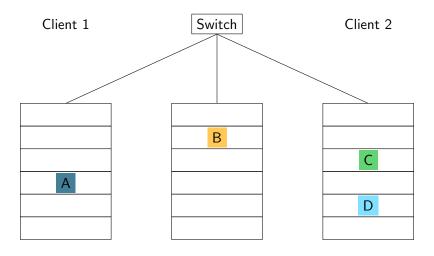
Sharding

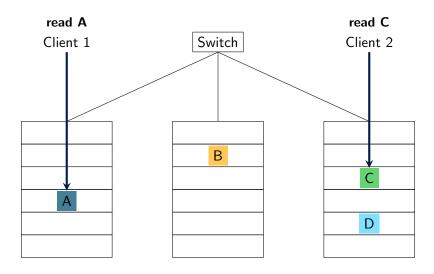
Purposes

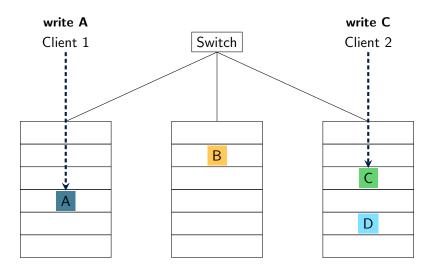
- Performance
 - Distributing the load over several nodes

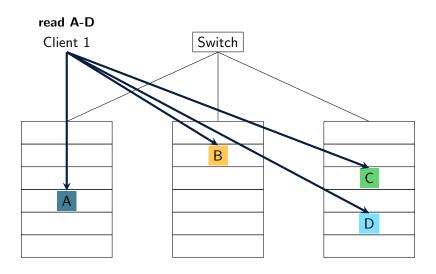
Challenges

- How to partition the data?
 - Evenly distributed load (even for skewed workloads)
 - Range queries

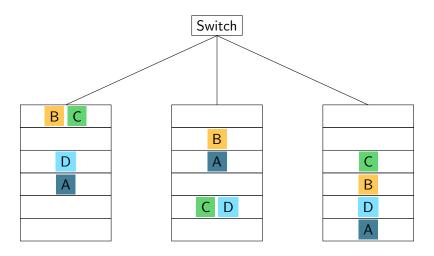








Partitioning + Replication



More references

Mandatory reading

 Big data and its technical challenges, by Jagadish et al, CACM 2014.

Suggested reading

- Chapter 1 of Designing Data-Intensive Applications by Martin Kleppmann
- The Netflix Simian Army¹

 $^{^{1}} https://medium.com/netflix-techblog/the-netflix-simian-army-16e57fbab116$