Large-Scale Data Management and Distributed Systems

Introduction

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Teaching staff

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Organization of the course

2 complementary topics

- Distributed systems (V. Quema) – 18 hours
- Data management (T. Ropars) – 18 hours

Data Management

- 12 hours of lectures
- 6 hours of practical sessions

Grading

- Graded Lab (25% of the final grade)
- Written exam (75% 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 (NoSQL) databases
• About the design of these systems:
  ▶ Their underlying design principles
  ▶ The impact of Cloud characteristics
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 2013\(^1\)
  - 90% of all data has been created in the last two years
- 40K search queries on Google every second\(^2\)
- 45M messages on WhatsApp every minute
- 40 Billions of IoT devices by 2025.
- 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

\(^1\)https://www.slideshare.net/BernardMarr/big-data-25-facts
\(^2\)https://www.newgenapps.com/blog/
big-data-statistics-predictions-on-the-future-of-big-data
Hardware capacity

Storage

- All the music of the world stored for $\sim 500$
- Large Amazon EC2 instance: 3.9TB of RAM, 8x7.5TB 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
Big data challenges: The V’s

source: Big Data for Modern Industry: Challenges and Trends
Big data challenges: The V’s
source: Big Data for Modern Industry: Challenges and Trends
Big data challenges: The V’s

• **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
Big data challenges: The V’s

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

Pros and Cons
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

Pros and Cons

😊 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

Pros and Cons
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
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: Barcelona Supercomputing Center

Figure: Amazon Data-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: Challenges\(^1\)

\(^1\)Read Chapter 1 of *Designing Data-Intensive Applications* for further details
Distributed computing: Challenges\(^1\)

**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?

\(^1\)Read 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 ≃ 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.)
Agenda

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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.

Pros and Cons
Where to find computing resources?

Cloud computing

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

Pros and Cons

😊 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

Switch

- : storage
- : memory
- : processor
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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The challenges of Big Data

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Cloud Computing

Running at scale
Running at scale

How to distribute data?

- Partitioning
- Replication

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

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

How to distribute data?

- Partitioning
- Replication

Replication

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Partitioning

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

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
Replication

Client 1 reads A

Switch

Client 2 writes A to 1 and 2
Replication

Client 1 reads A and writes A.

Switch

Client 1 reads A.


Client 2 reads A.

Client 2 reads A.

Client 2 reads A.

Client 2 reads A.
Replication

Client 1 reads A and writes A=1.

Client 2 reads A and writes A=2.

The switch forwards the writes to all replica nodes.
Replication

Client 1

Switch

read A

write A=1

write A=2
Replication

Client 1

Client 2

read A

write A

Switch
Replication

Client 1

write A

Client 2
Replication

**write A=1**

Client 1

write A=1

Switch

write A=2

Client 2

write A=2
Replication

write $A=1$
Client 1

Switch

write $A=2$
Client 2

Client 2
write $A=2$

Client 1
write $A=1$
Partitioning
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

Client 1  Switch  Client 2

Client 1 reads A and C, writes A and C.
Client 2 reads A and D.
Partitioning

Client 1

Client 2

A

B

C

D

read A

write A

read C

write C

read A-D
Partitioning

write A
Client 1

write C
Client 2

A

Switch

B

C

D

read A
read C
write A
write C
read A-D
Partitioning

Client 1

read A-D

Switch

A

B

C

D
Partitioning + Replication

Switch

- B
- C

D
A

- B
- A

C
D

- C
- B

D
A
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 Army

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¹https://medium.com/netflix-techblog/the-netflix-simian-army-16e57fbab116