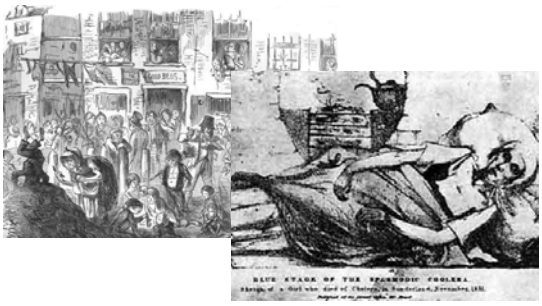
CC5212-1
PROCESAMIENTO MASIVO DE DATOS
OTOÑO 2015

Lecture 1: Introduction

Aidan Hogan
aidhog@gmail.com

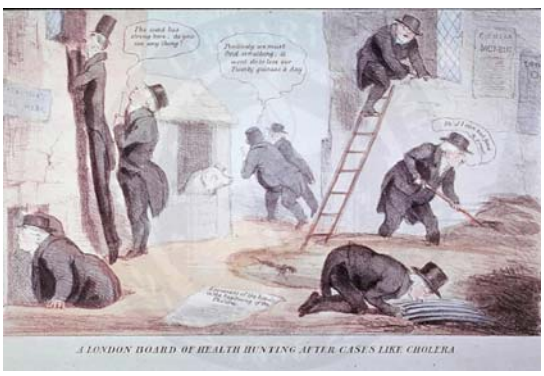
THE VALUE OF DATA

Soho, London, 1854



The mystery of cholera

The Hunt for the invisible cholera



Cholera: Galen's miasma theory

John Snow: 1813–1858

The Survey of Soho

Data collection

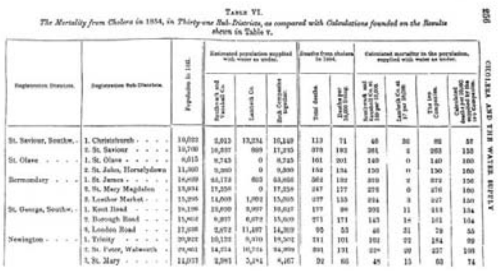


TABLE VI.

The Mortality from Cholera in 1854, in Thirty-one Sub-Districts, as compared with Calculations founded on the Results shown in Table v.

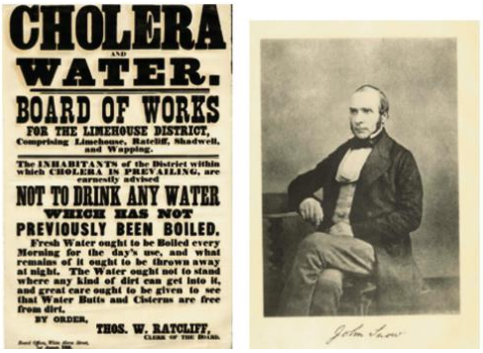
Registration Districts.	Registration Sub-Districts.	Population in 1851.	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
St. Saviour, Southw.	1. Christchurch	[illegible]	[illegible]	[illegible]	[illegible]	113	71	[illegible]	[illegible]	[illegible]	[illegible]
	2. St. Saviour	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
St. Olave	1. St. Olave	[illegible]	[illegible]	0	[illegible]	161	[illegible]	[illegible]	0	140	[illegible]
	2. St. John, Horselydown	[illegible]	[illegible]	0	[illegible]	[illegible]	134	130	[illegible]	130	[illegible]
Bermondsey	1. St. James	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	2. St. Mary Magdalen	[illegible]	[illegible]	0	[illegible]	[illegible]	177	[illegible]	0	[illegible]	[illegible]
	3. Leather Market	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
St. George, Southw.	1. Kent Road	[illegible]	[illegible]	[illegible]	[illegible]	177	[illegible]	[illegible]	11	[illegible]	[illegible]
	2. Borough Road	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	171	[illegible]	[illegible]	[illegible]	[illegible]
	3. London Road	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	21	[illegible]	[illegible]
Newington	1. Trinity	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	101	[illegible]	[illegible]	[illegible]	[illegible]
	2. St. Peter, Walworth	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	131	[illegible]	[illegible]	[illegible]	[illegible]
	3. St. Mary	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	15	[illegible]	74

What the data showed …

What the data showed …

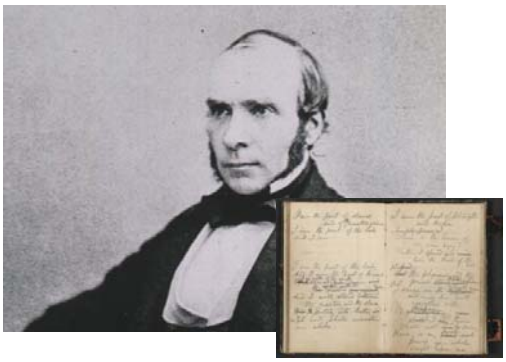
616 deaths, 8 days later …

Cholera notice ca. 1866



Thirty years before discovery of *V. cholerae*

John Snow: Father of Epidemiology



Epidemiology's Success Stories

Value of data: Not just epidemiology

(Paper) notebooks no longer good enough

THE GROWTH OF DATA

"Big Data"

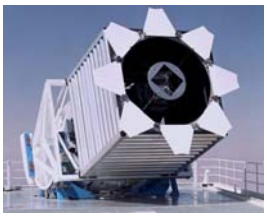
Wikipedia
≈ 5.9 TB of data
(*Jan. 2010 Dump*)

1 Wiki = 1 Wikipedia

"Big Data"

US Library of Congress
≈ 235 TB archived
≈ 40 Wiki

"Big Data"



Sloan Digital Sky Survey
≈ 200 GB/day
≈ 73 TB/year
≈ 12 Wiki/year

"Big Data"

NASA Center for Climate Simulation
≈ 32 PB archived
≈ 5,614 Wiki

"Big Data"

Facebook
≈ 100 TB/day added
≈ 17 Wiki/day
≈ 6,186 Wiki/year
(*as of Mar. 2010*)

"Big Data"

Large Hadron Collider
≈ 15 PB/year
≈ 2,542 Wikipedias/year

"Big Data"

Google
≈ 20 PB/day processed
≈ 3,389 Wiki/day
≈ 7,300,000 Wiki/year
(Jan. 2010)

"Big Data"

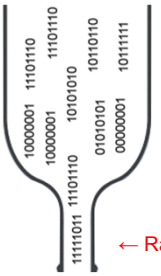
Internet (2016)
≈ 1.3 ZB/year
≈ 220,338,983 Wiki/year
(2016 IP traffic; Cisco est.)

Bigger and Bigger Data

"There were 5 exabytes of data online in 2002, which had risen to 281 exabytes in 2009. That's a growth rate of 56 times over seven years."

-- Google VP Marissa Mayer

Data: A Modern-day Bottleneck?



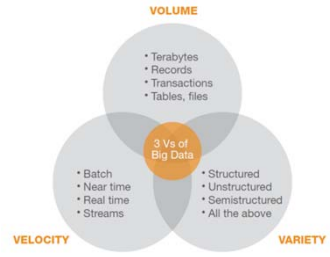
← Rate at which data are produced

← Rate at which data can be understood

"Big Data"

- A buzz-word: no *precise* definition?
- Data that are too big to process by "conventional means"
- A call for Computer Scientists to produce new techniques to crunch even more data
- Storage, processing, querying, analytics, data mining, applications, visualisations …

How many V's in "Big Data"?



- Three 'V's:
  - Volume (large amounts of data)
  - Velocity (rapidly changing data)
  - Variety (different data sources and formats)
- Maybe more (Value, Veracity)

"BIG DATA" IN ACTION …

Social Media

twitter Google+ StumbleUpon delicious YouTube facebook digg flickr Linked in Technorati

What's happening here? (Trendsmap)

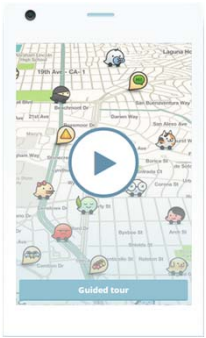
"What are the hot topics of discussion in an area"

- Analyse tags of geographical tweets

What's the fastest route? (Waze)

"What's the fastest route to get home right now?"

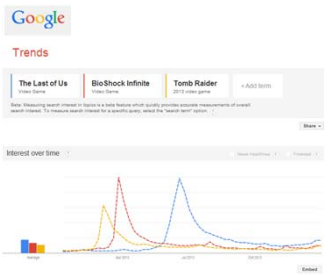
- Processes real journeys to build background knowledge
- "Participatory Sensing"



Christmas Predictions for Stores

"What will be the hot items to stock up on this Christmas? We don't want to sell out!"

- Analyse product hype on Twitter, Search Engines and Social Networks
- Analyse transaction histories



Get Elected President (Narwhal)

"Who are the undecided voters and how can I convince them to vote for me?"

- User profiles built and integrated from online sources
- Targeted emails sent to voters based on profile

Predicting Pre-crime (PredPol)

"What areas of the city are most need of police patrol at 13:55 on Mondays?"

- PredPol system used by Santa Cruz (US) police to target patrols
- Predictions based on analysis of 8 years of historical crime data
- Minority Report!

IBM Watson: Jeopardy Winner

"William Wilkinson's "An Account of the Principalities of Wallachia and Moldavia" inspired this author's most famous novel."

- Indexed 200 million pages of structured and unstructured content
- An ensemble of 100 techniques simulating AI-like behaviour

Check it out on YouTube!

"BIG DATA" NEEDS "MASSIVE DATA PROCESSING" …

Every Application is Different …

- **Data** can be
  - Structured data (JSON, XML, CSV, Relational Databases, HTML form data)
  - Unstructured data (text document, comments, tweets)
  - And everything in-between!
  - **Often a mix!**

Every Application is Different …

- **Processing** can involve:
  - Natural Language Processing (sentiment analysis, topic extraction, entity recognition, etc.)
  - Machine Learning and Statistics (pattern recognition, classification, event detection, regression analysis, etc.)
  - Even inference! (Datalog, constraint checking, etc.)
  - And everything in-between!
  - **Often a mix!**

Scale is a Common Factor …

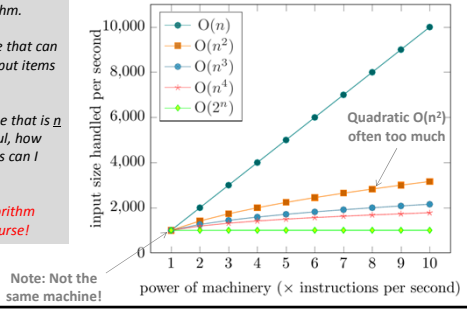
- Cannot run expensive algorithms

I have an algorithm.

I have a machine that can process 1,000 input items in an hour.

If I buy a machine that is n times as powerful, how many input items can I process then?

Depends on algorithm complexity of course!



Scale is a Common Factor …

- One machine that's *n* times as powerful?

vs.

- *n* machines that are equally as powerful?

Scale is a Common Factor …

- Data-intensive (our focus!)
  - Inexpensive algorithms / Large inputs
  - e.g., Google, Facebook, Twitter
- Compute-intensive (not our focus!)
  - More expensive algorithms / Smaller inputs
  - e.g., climate simulations, chess games, combinatorials
- No black and white!

"MASSIVE DATA PROCESSING" NEEDS "DISTRIBUTED COMPUTING" …

Distributed Computing

- Need more than one machine!
- Google ca. 1998:

Distributed Computing

- Need more than one machine!
- Google ca. 2014:

Data Transport Costs

- Need to divide tasks over many machines
  - Machines need to communicate
    - … but not too much!
  - Data transport costs (*simplified*):

Main Memory	Solid-state Disk	Hard-disk	Network

Need to minimise network costs!

Data Placement

- Need to think carefully about where to put what data!

I have four machines to run my website. I have 10 million users.

Each user has personal profile data, photos, friends and games.

How should I split the data up over the machines?

Depends on application of course!

(But good design principles apply universally!)

Network/Node Failures

- Need to think about failures!

Lot of machines: likely one will break!

Network/Node Failures

- Need to think (even more!) carefully about where to put what data!

I have four machines to run my website. I have 10 million users.

Each user has a personal profile, photos, friends and apps.

How should I split the data up over the machines?

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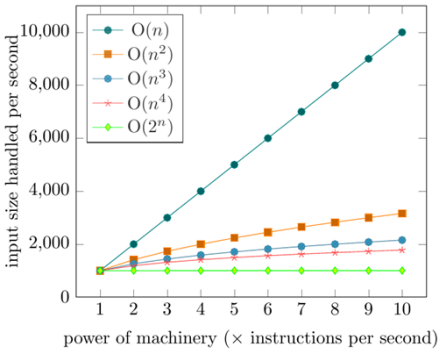
Human Distributed Computation

"DISTRIBUTED COMPUTING" LIMITS & CHALLENGES …

Distribution Not Always Applicable!



Distributed Development Difficult

- Distributed systems can be complex
- Tasks take a long time!
  - Bugs may not become apparent for hours
  - Lots of data = lots of counter-examples
  - **Need to balance load!**
- Multiple machines to take care of
  - Data in different locations
  - Logs and messages in different places
  - **Need to handle failures!**

Frameworks/Abstractions can Help

- For Distrib. Processing
- For Distrib. Storage

HOW DOES TWITTER WORK?

Based on 2013 slides by Twitter lead architect: Raffi Krikorian

"Twitter Timelines at Scale"

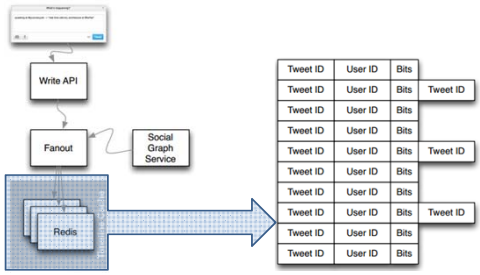
Big Data at Twitter

- 150 million active worldwide users
- 400 million tweets per day
  - 4,600 tweets per second
  - max: 143,199 tweets per second
- 300 thousand queries/sec for user timelines
- 6 thousand queries/sec for custom search

What should be the priority for optimisation?

Supporting timelines:write

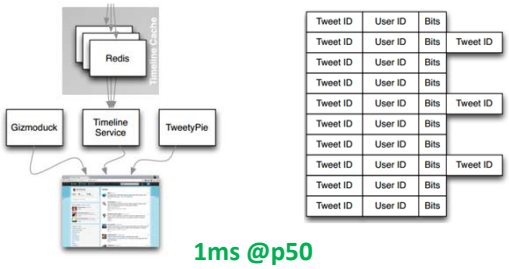
- 300 thousand queries per second



High-fanout

Supporting timelines: read

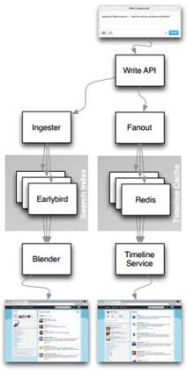
- 300 thousand queries per second



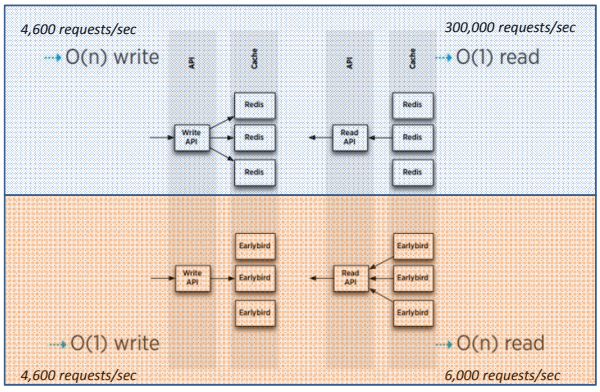
1ms @p50
4ms @p99

Supporting text search

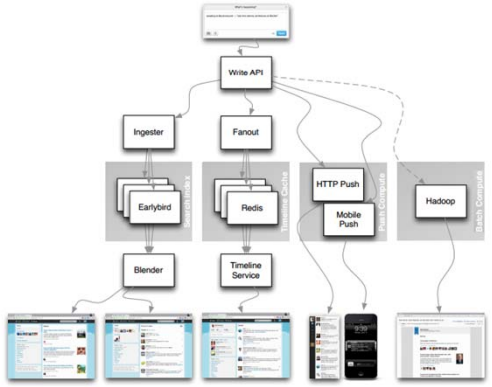
- Information retrieval
  - Earlybird: Lucene clone
  - Write once
  - Query many



Timeline vs. Search



Twitter: Full Architecture



Big Data at Twitter

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"Procesamiento Masivo de Datos" ABOUT THE COURSE …

What the Course Is/Is Not

- Data-intensive not Compute-intensive
- Distributed tasks not networking
- Commodity hardware not big supercomputers
- General methods not specific algorithms
- Practical methods with a little theory

What the Course *Is*!

- Principles of Distributed Computing [3 weeks]
- Distributed Processing Frameworks [4 weeks]
- Principles of Distributed Databases [3 weeks]
- Information Retrieval [3 weeks]

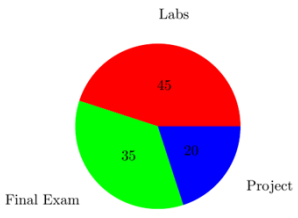
Course Structure

- ~1.5 hours of lectures per week [Monday]
- 1.5 hours of labs per week [Wednesday]
  - To be turned in by Friday evening
  - Mostly Java
  - In **Laboratorio 1 (Cuarto Piso, DCC)**

http://aidanhogan.com/teaching/cc5212-1/

Course Marking

- 45% for Weekly Labs (~3% a lab!)
- 35% for Final Exam
- 20% for Small Class Project



Outcomes!

Outcomes!

Outcomes!

Outcomes!

Outcomes!

Outcomes!

Questions?