CC5212-1
Procesamiento Masivo de Datos
Otoño 2016

Lecture 1: Introduction

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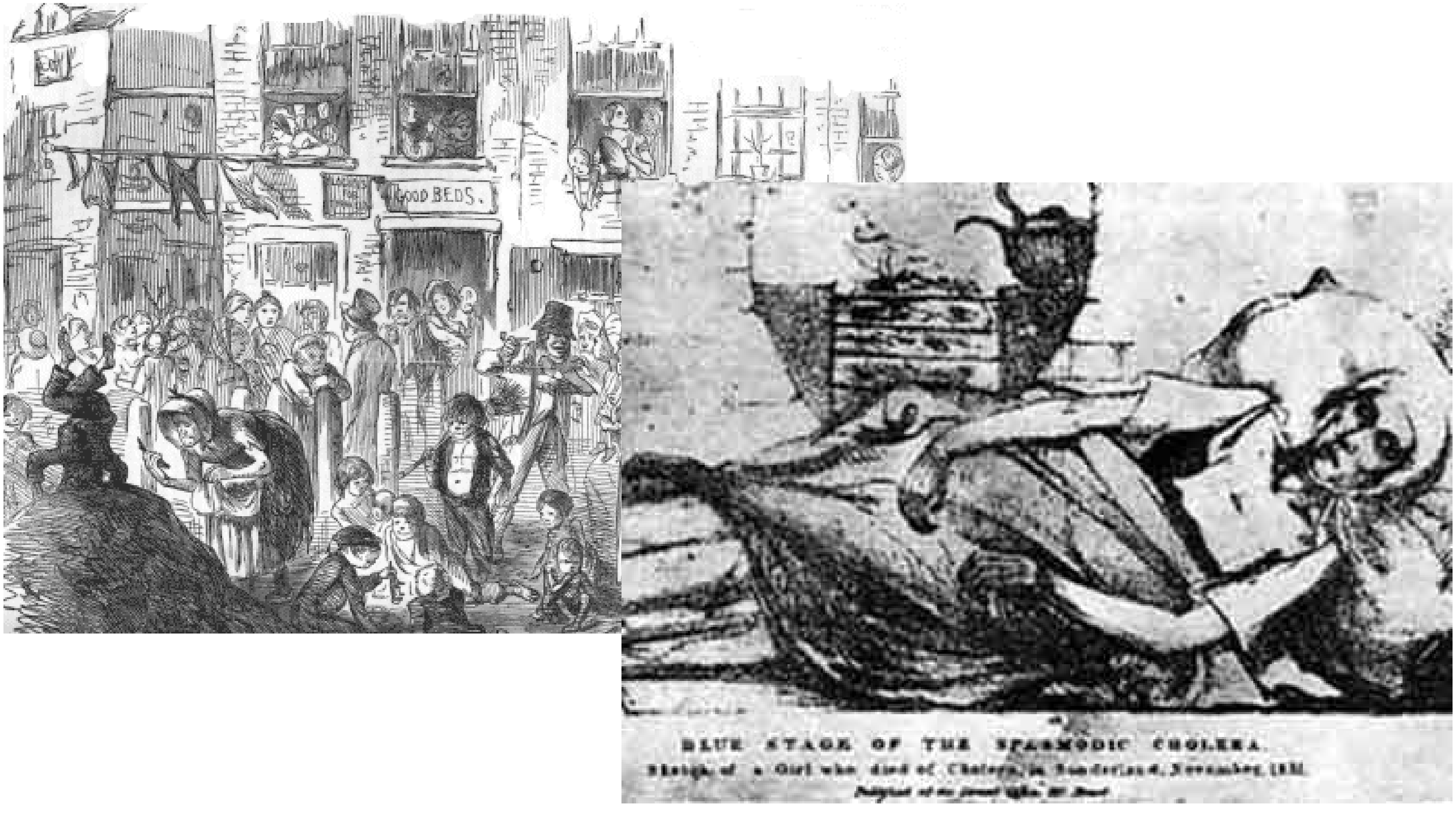
THE VALUE OF DATA

Soho, London, 1854



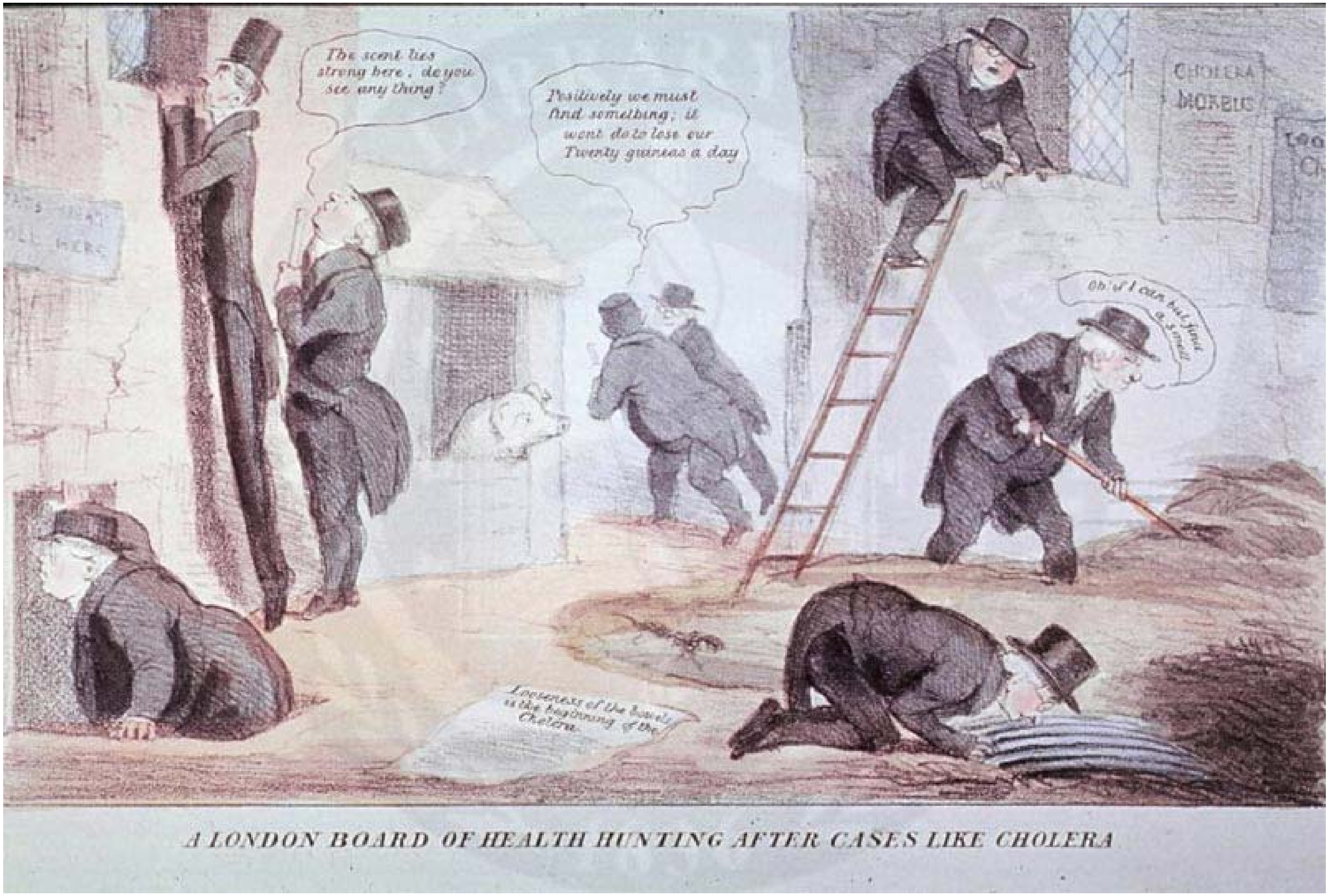
BLUE STAGE OF THE SPASMODIC CHOLERA.

Sketch of a Girl who died of Cholera, in Sunderland, November 1831.

Published at the [illegible]

The mystery of cholera

The hunt for the invisible cholera


The scent lies strong here, do you see any thing?
Positively we must find something; it wont do to lose our Twenty guineas a day
CHOLERA MORBUS
Oh! if I can but find a smell
Looseness of the bowels is the beginning of the Cholera
A LONDON BOARD OF HEALTH HUNTING AFTER CASES LIKE CHOLERA

Cholera: Galen’s miasma theory

John Snow: 1813–1858

The Survey of Soho

Data collection

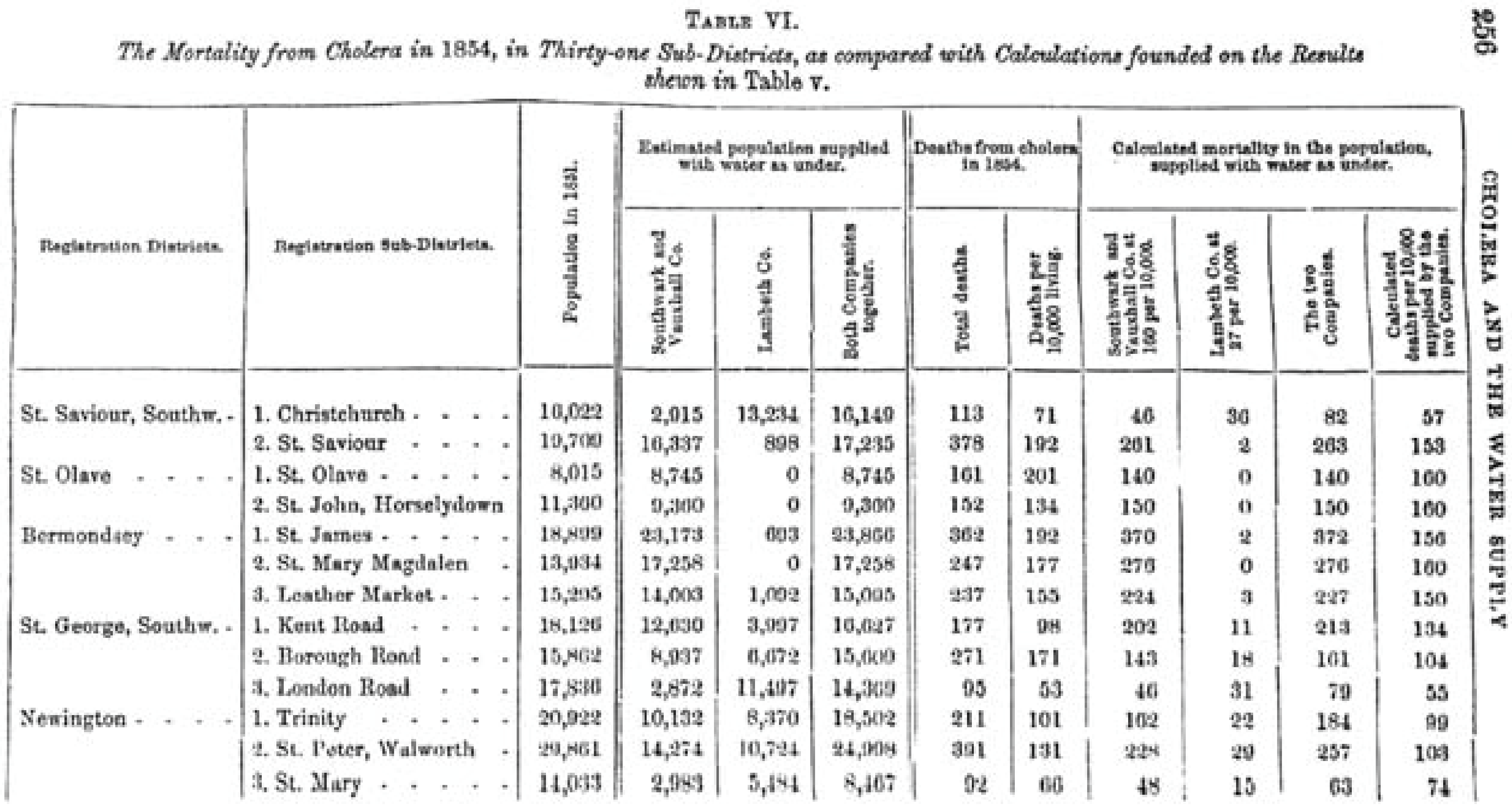
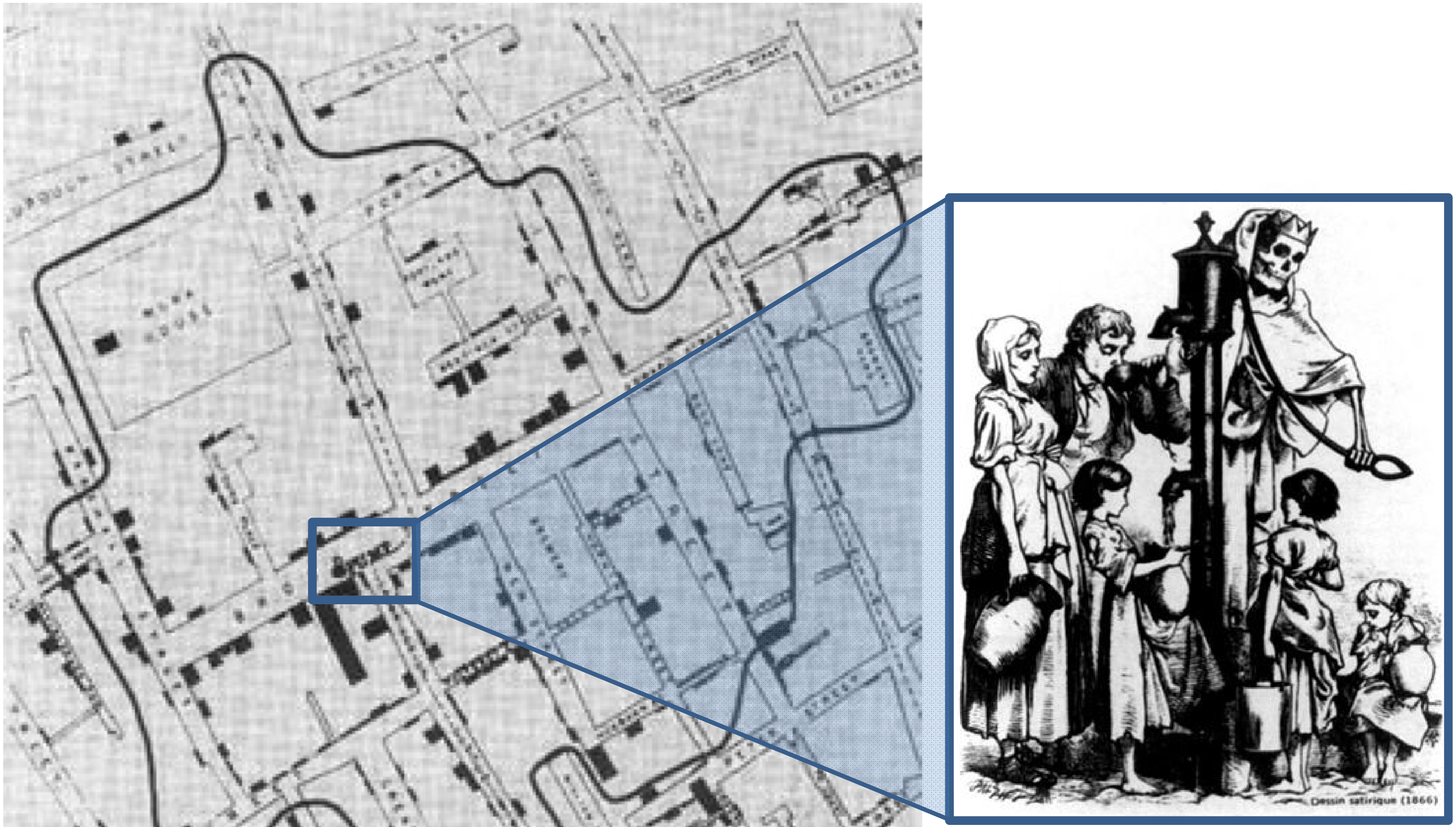


TABLE VI.

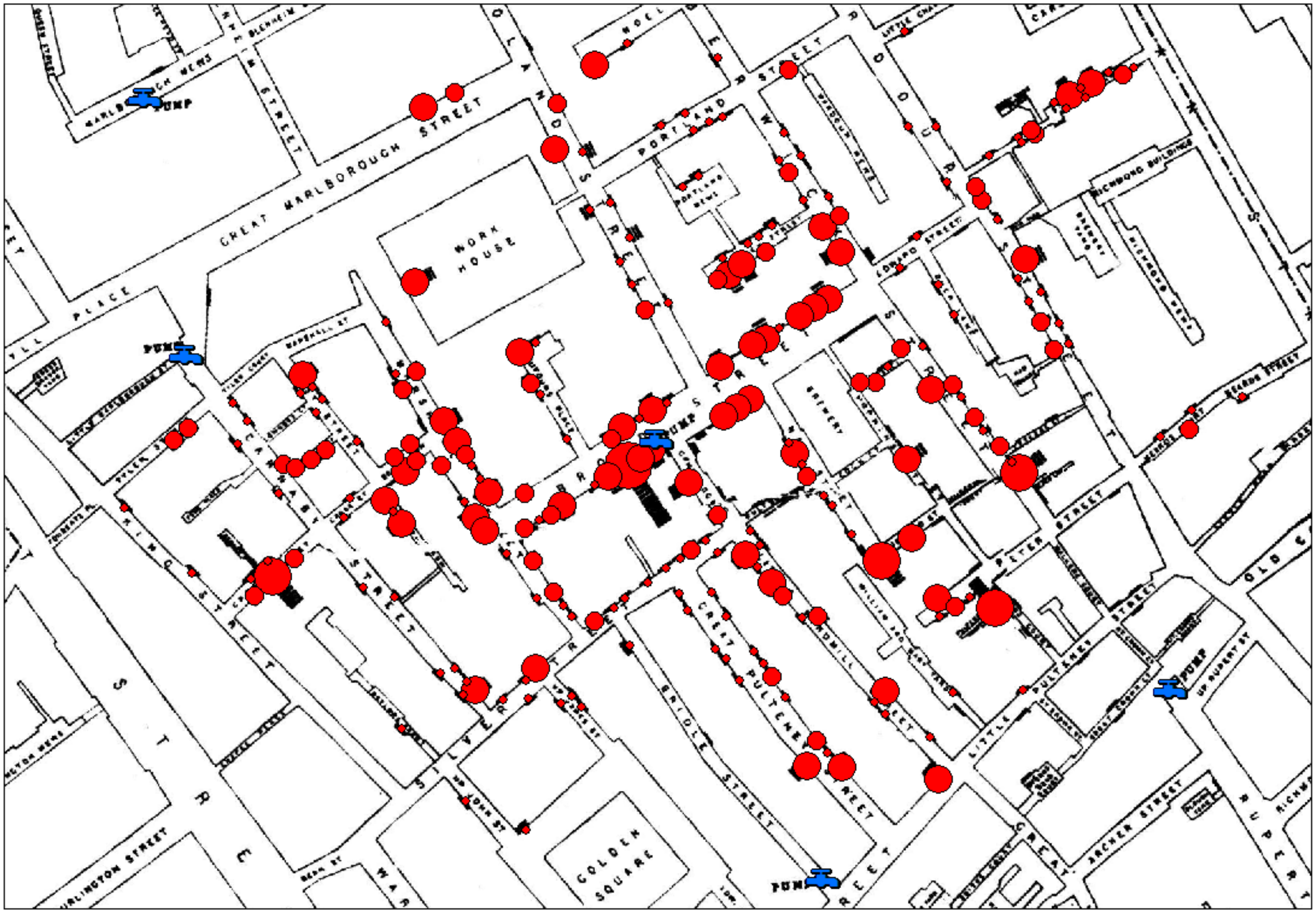
The Mortality from Cholera in 1854, *in Thirty-one Sub-Districts, as compared with Calculations founded on the Results shewn in* Table v.

Registration Districts.	Registration Sub-Districts.	Population in 1851.	Estimated population supplied with water as under.			Deaths from cholera in 1854.		Calculated mortality in the population, supplied with water as under.			
			Southwark and Vauxhall Co.	Lambeth Co.	Both Companies together.	Total deaths.	Deaths per 10,000 living.	Southwark and Vauxhall Co. at 150 per 10,000.	Lambeth Co. at 37 per 10,000.	The two Companies.	Calculated deaths per 10,000 supplied by the two Companies.
St. Saviour, Southw. -	1. Christchurch - - - -	10,022	2,015	13,234	16,149	113	71	46	30	82	57
	2. St. Saviour - - - -	19,709	16,337	898	17,235	378	192	261	2	263	153
St. Olave - - - -	1. St. Olave - - - - - -	8,015	8,745	0	8,745	161	201	140	0	140	160
	2. St. John, Horselydown	11,360	9,360	0	9,360	152	134	150	0	150	160
Bermondsey - - -	1. St. James - - - - - -	18,899	23,173	693	23,866	362	192	370	2	372	156
	2. St. Mary Magdalen -	13,934	17,258	0	17,258	247	177	276	0	276	160
	3. Leather Market - - -	15,295	14,003	1,092	15,095	237	155	224	3	227	150
St. George, Southw. -	1. Kent Road - - - -	18,126	12,630	3,997	16,627	177	98	202	11	213	134
	2. Borough Road - - -	15,862	8,937	6,072	15,009	271	171	143	18	161	104
	3. London Road - - -	17,836	2,872	11,497	14,369	93	53	46	31	79	55
Newington - - - -	1. Trinity - - - - -	20,922	10,132	8,370	18,502	211	101	162	22	184	99
	2. St. Peter, Walworth -	29,861	14,274	10,724	24,998	391	131	228	29	257	103
	3. St. Mary - - - - -	14,033	2,983	5,484	8,467	92	66	48	15	63	74

What the data showed …



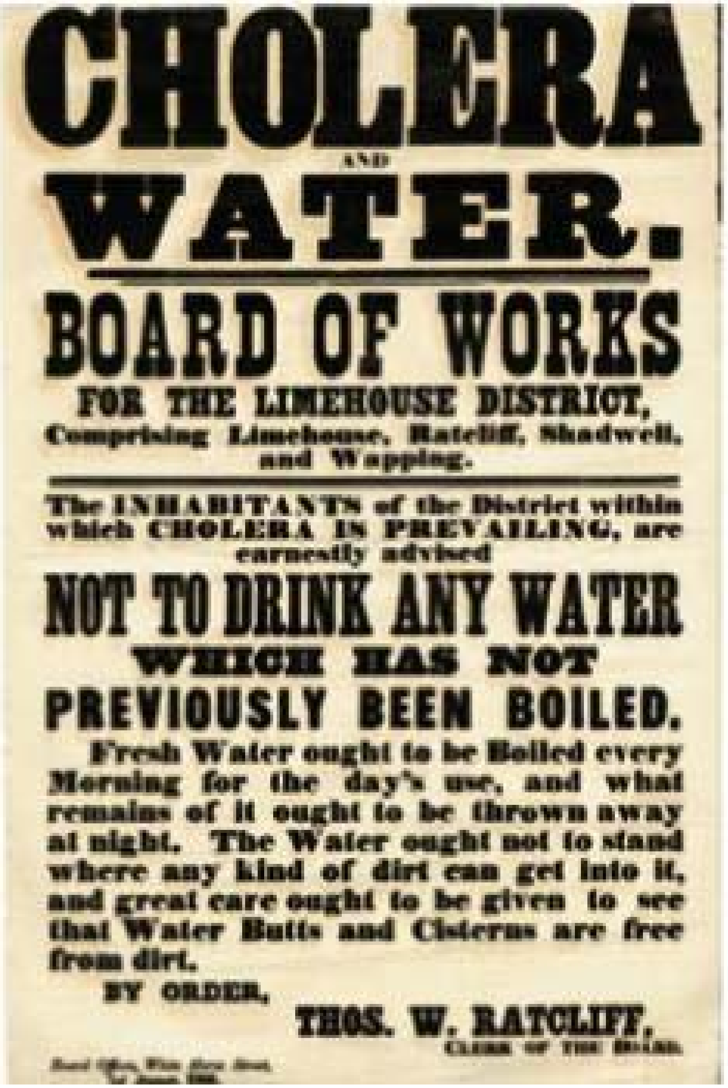
What the data showed …



616 deaths, 8 days later …

The Red Granite kerbstone
marks the site of the historic
BROAD STREET PUM
associated with Dr. John Snow'
discovery in 1854
that Cholera is conveyed by wate

Cholera notice ca. 1866



CHOLERA

AND

WATER.

BOARD OF WORKS

FOR THE LIMEHOUSE DISTRICT,
Comprising Limehouse, Ratcliff, Shadwell, and Wapping.

The INHABITANTS of the District within which CHOLERA IS PREVAILING, are earnestly advised

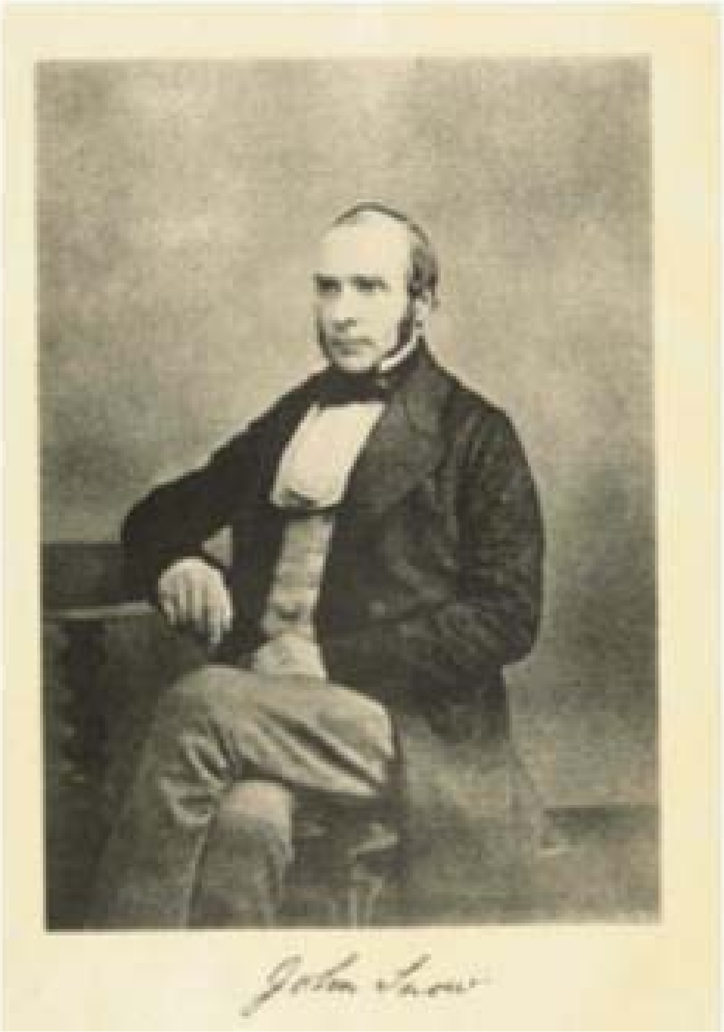
NOT TO DRINK ANY WATER WHICH HAS NOT PREVIOUSLY BEEN BOILED.

Fresh Water ought to be Boiled every Morning for the day's use, and what remains of it ought to be thrown away at night. The Water ought not to stand where any kind of dirt can get into it, and great care ought to be given to see that Water Butts and Cisterns are free from dirt.

BY ORDER,

THOS. W. RATCLIFF,
CLERK OF THE BOARD.

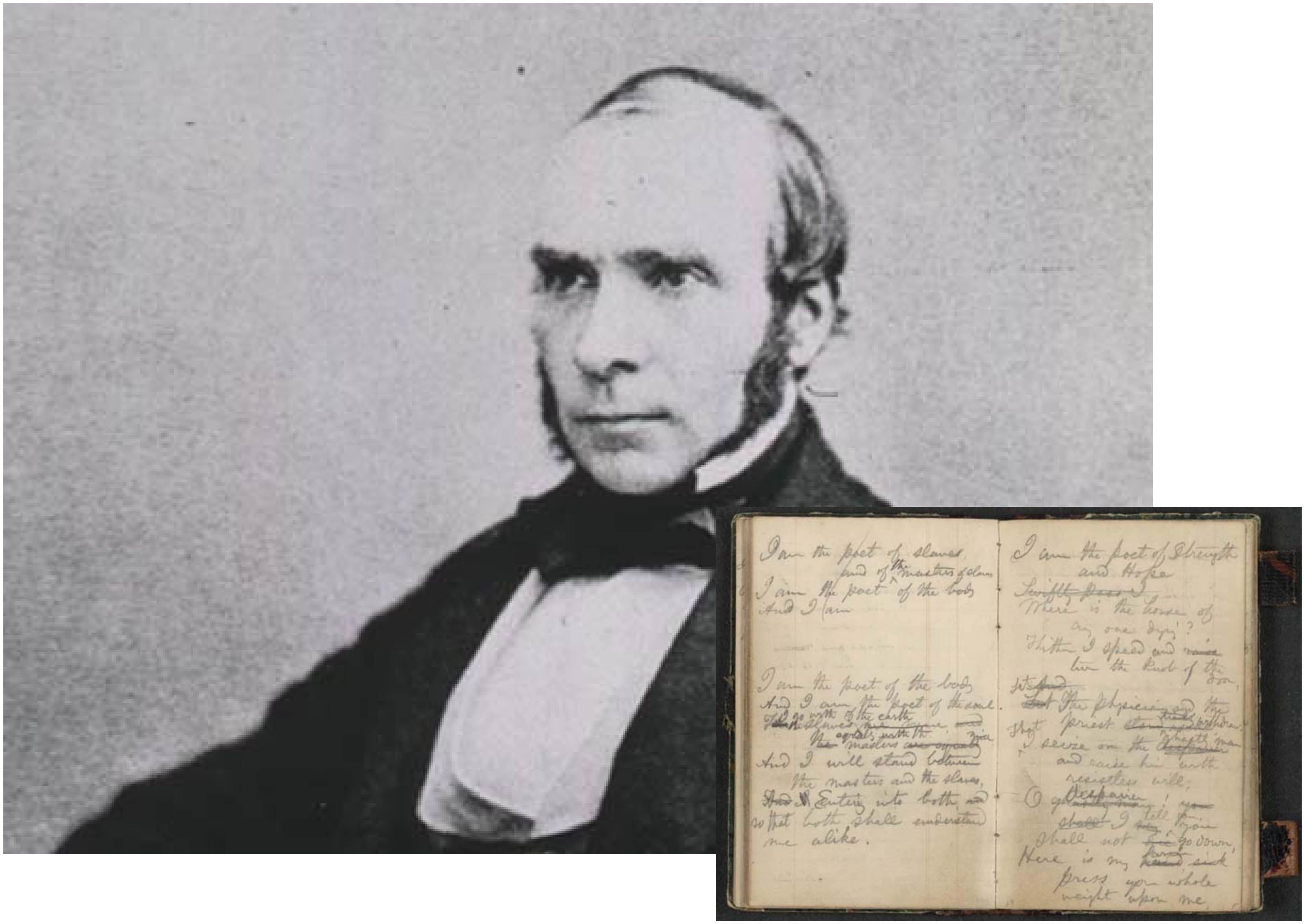
Board Office, White Horse Street,
[illegible]



John Snow

Thirty years before discovery of *V. cholerae*

John Snow: Father of Epidemiology



I am the poet of slaves,
and of the masters of slaves
I am the poet of the body
And I am

I am the poet of the body
And I am the poet of the soul.
~~The~~ I go with ~~the slaves~~ of the earth ~~are mine, and~~
~~the~~ equals with the masters ~~are equally~~ mine
And I will stand between
the masters and the slaves,
~~And~~ Entering into both, ~~and~~
so that both shall understand
me alike.

I am the poet of Strength
and Hope
~~Swiftly pass I~~
Where is the house of
any one dying?
Thither I speed and ~~raise~~
turn the knob of the
door,
~~And~~ Let
~~Let~~ The physician and the
That priest ~~stand~~ timidly withdraw,
I seize on the ~~despairer~~ ghastly man
and raise him with
resistless will,
O ~~ghastly man~~ despairer! ~~you~~
~~shall~~ I ~~say~~ tell you
Shall not ~~be~~ go down,
Here is my ~~hand~~ arm, sick
press your whole
weight upon me.

Epidemiology's Success Stories

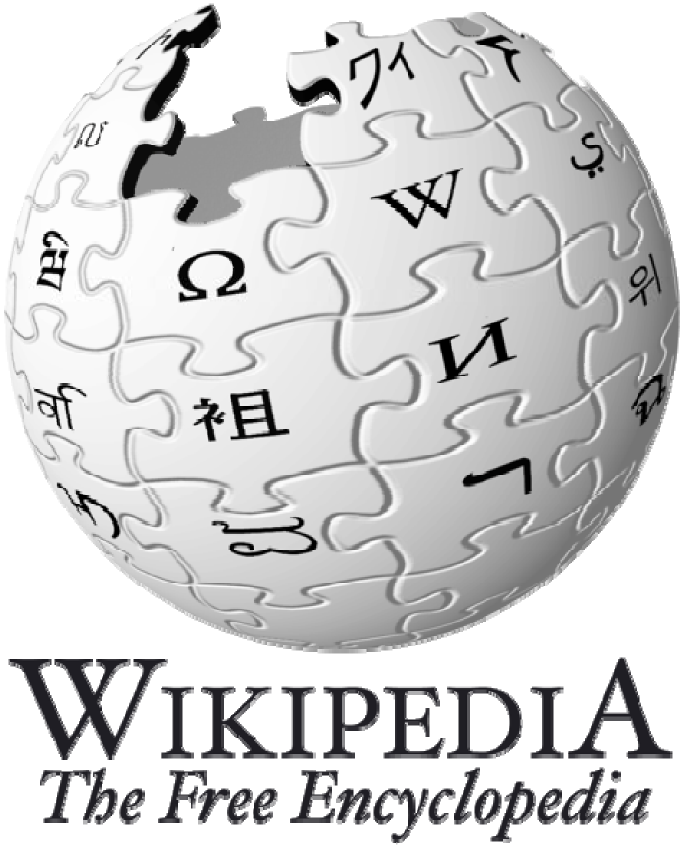
WORLD HEAL
THE MAGAZINE OF THE WORLD HEALTH ORGANIZATION
mallpox is dead
1988
2014*
Countri
Countri

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

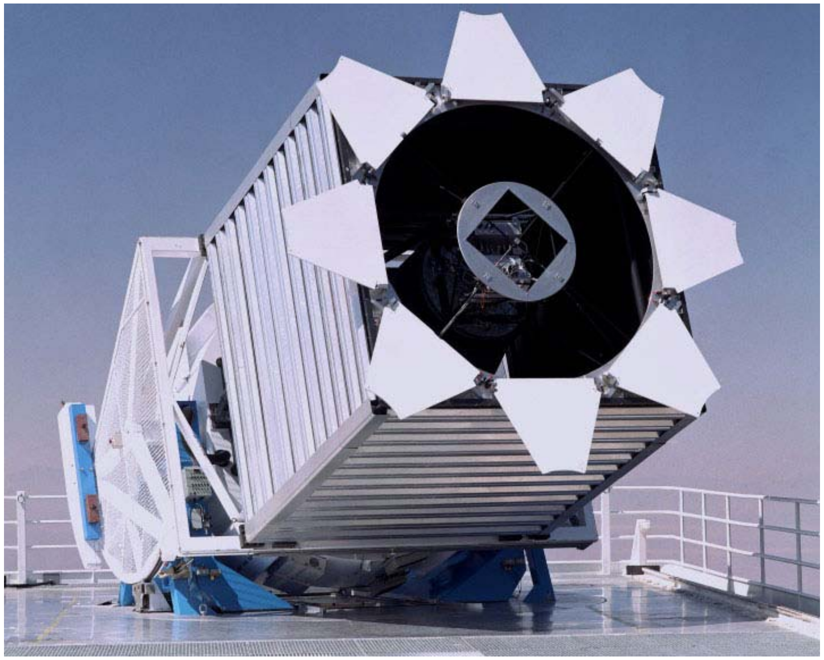
“Big Data”

US Library of Congress

≈ 235 TB archived

≈ 40 Wiki

“Big Data”



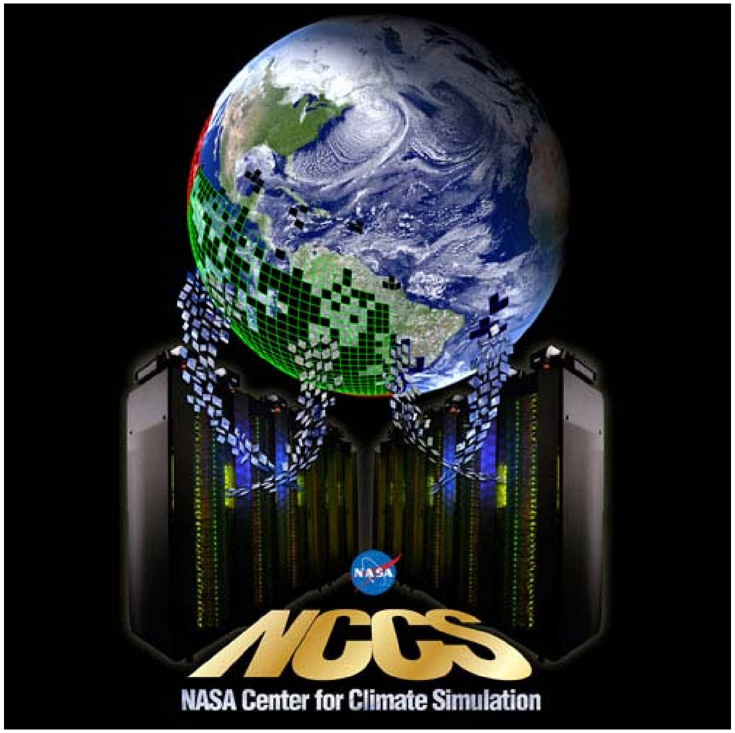
Sloan Digital Sky Survey

≈ 200 GB/day

≈ 73 TB/year

≈ 12 Wiki/year

“Big Data”

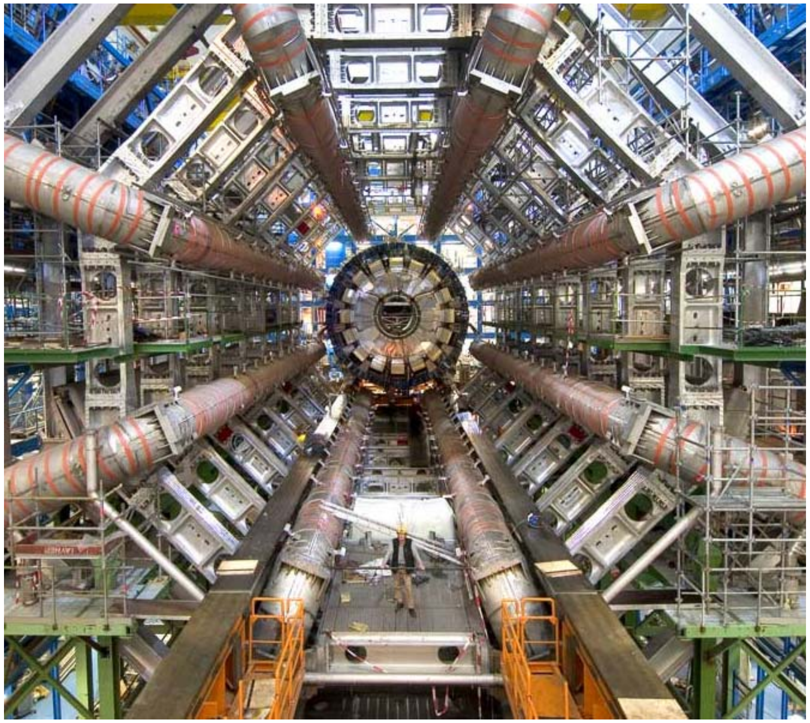


NASA Center for Climate Simulation
≈ 32 PB archived
≈ 5,614 Wiki

“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

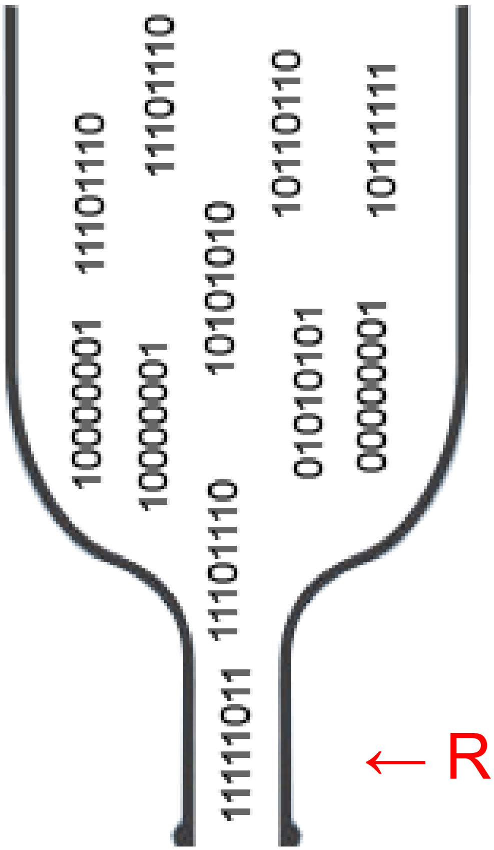
"Big Data"

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.)

Data: A Modern-day Bottleneck?



← Rate at which data are produced

← Rate at which data can be understood

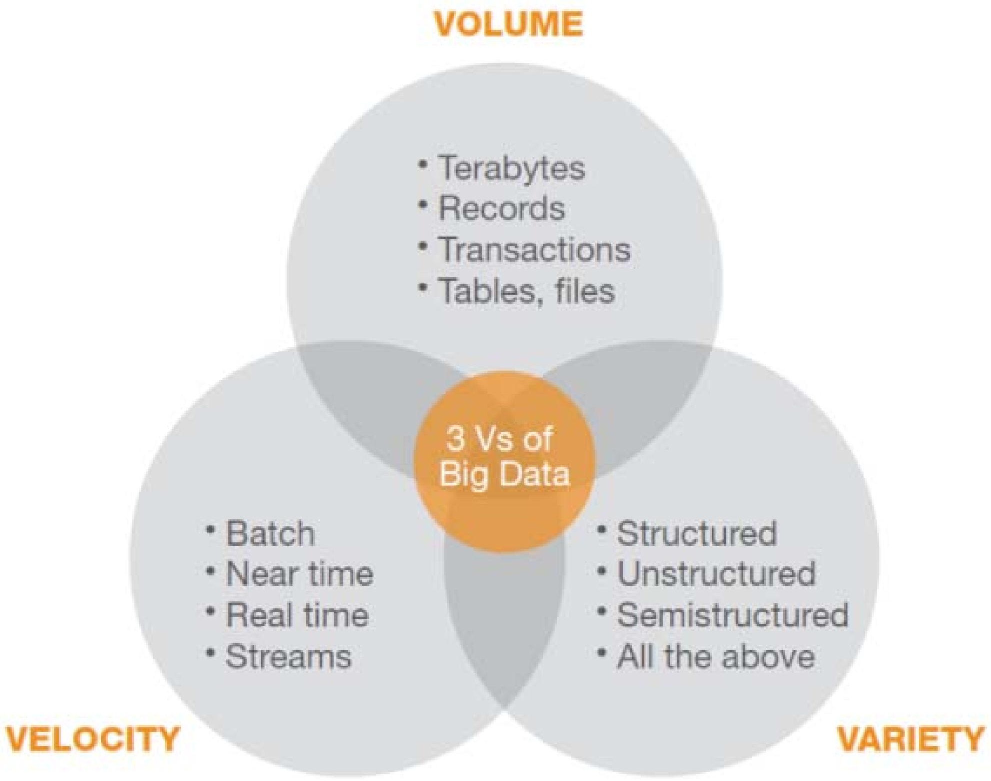
BIG DATA

“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)

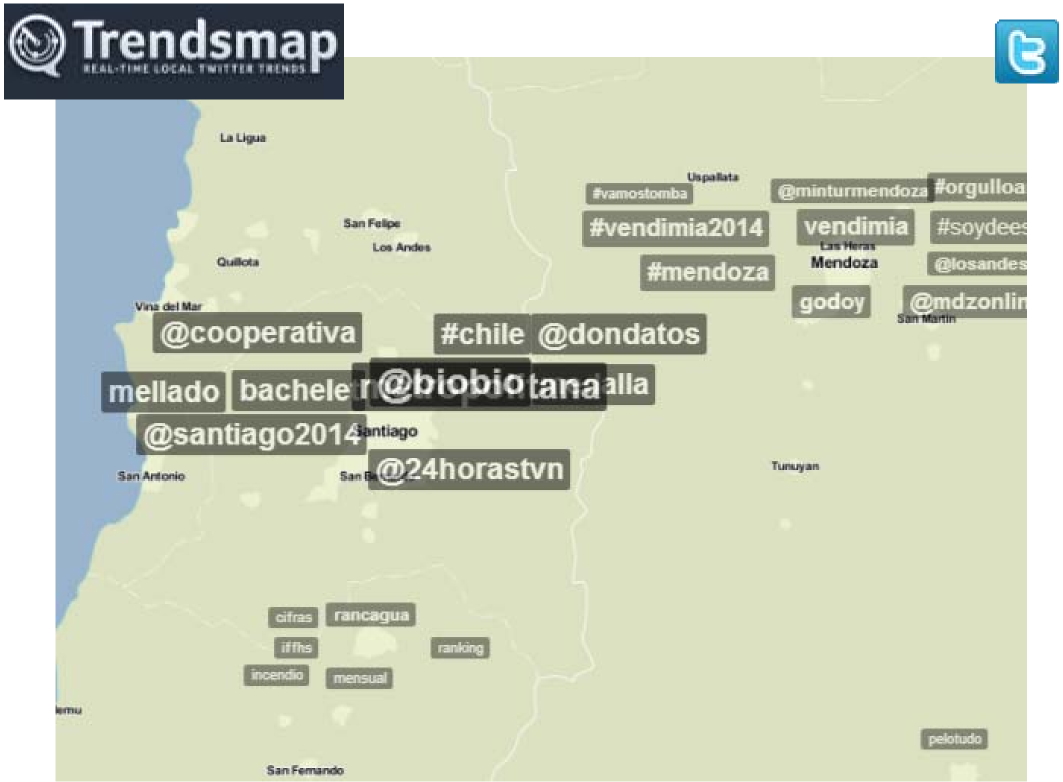
“BIG DATA” IN ACTION …

Social Media

What’s happening here? (Trendsmap)

“What are the hot topics of discussion in an area”

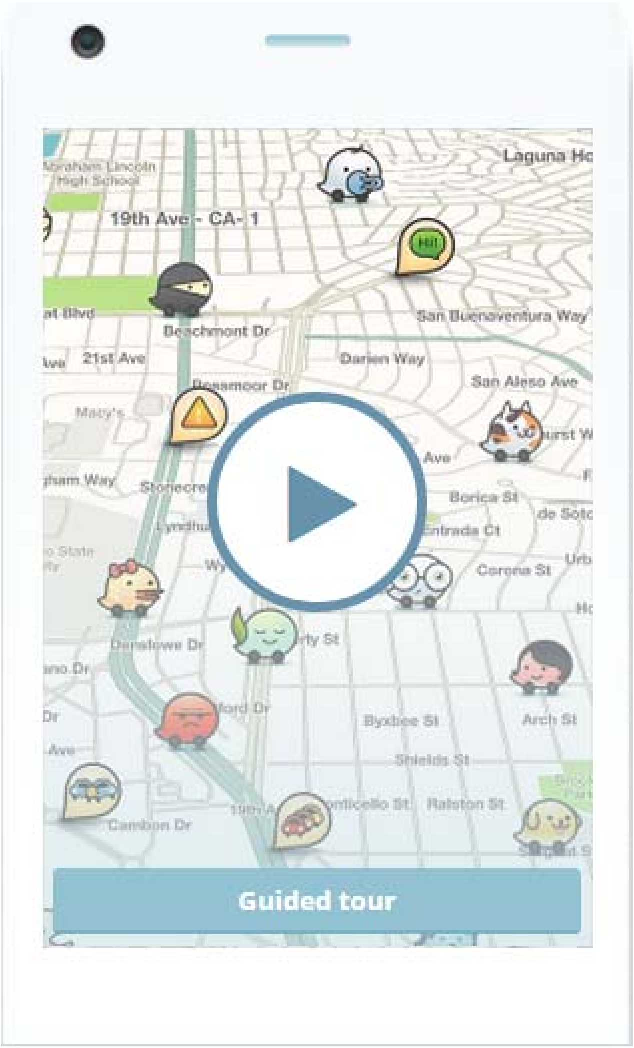
- Analyse tags of geographical tweets



What’s the fastest route? (Waze)

“What’s the fastest route to get home right now?”

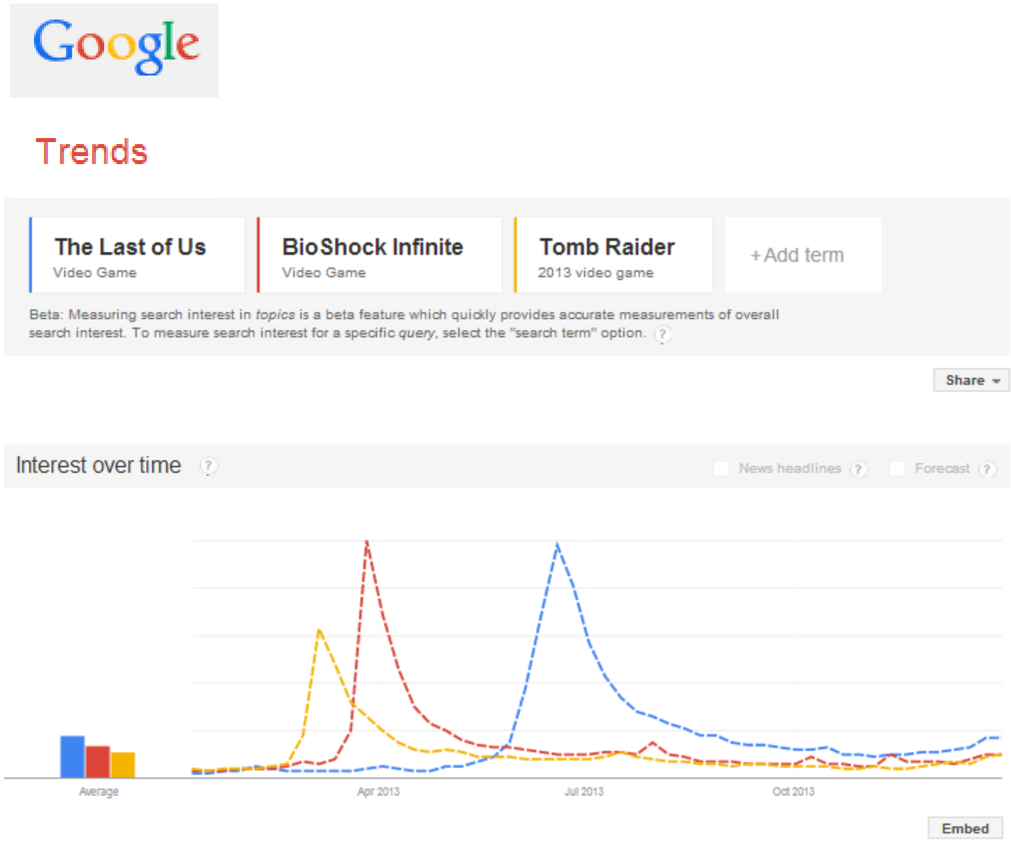
- Processes real journeys to build background knowledge
- “Participatory Sensing”



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



The Last of Us
Video Game

BioShock Infinite
Video Game

Tomb Raider
2013 video game

Beta: Measuring search interest in *topics* is a beta feature which quickly provides accurate measurements of overall search interest. To measure search interest for a specific *query*, select the "search term" option.

Get Elected President (Narwhal)

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

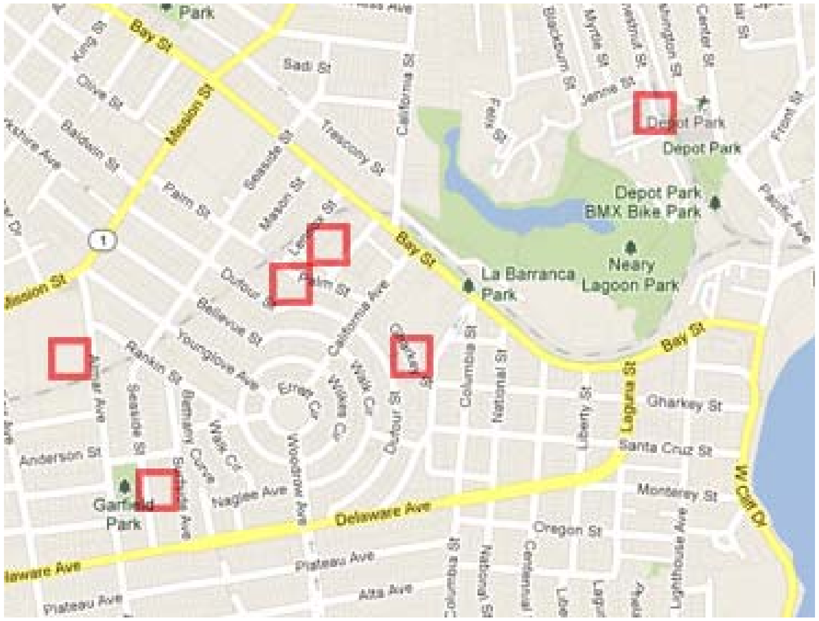
- User profiles built and integrated from online sources
- Targeted emails sent to voters based on profile

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!

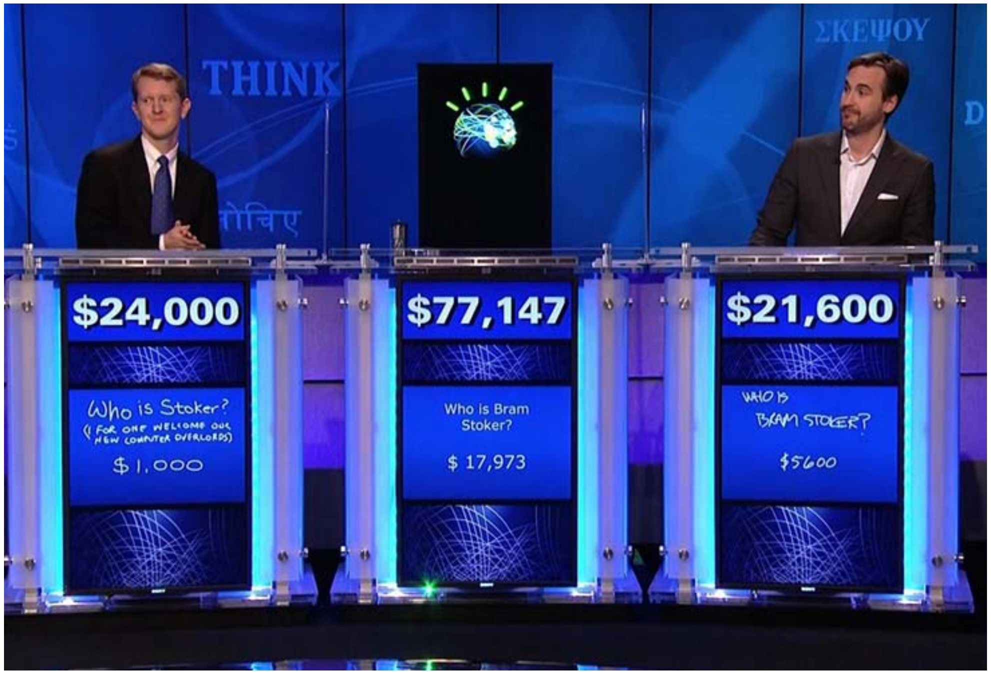
PredPol®
Predict Crime in Real Time.
PredPol provides targeted, real-time crime prediction designed for and successfully tested by officers in the field.
Pendagast Ave
Wilkes Cir



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 …

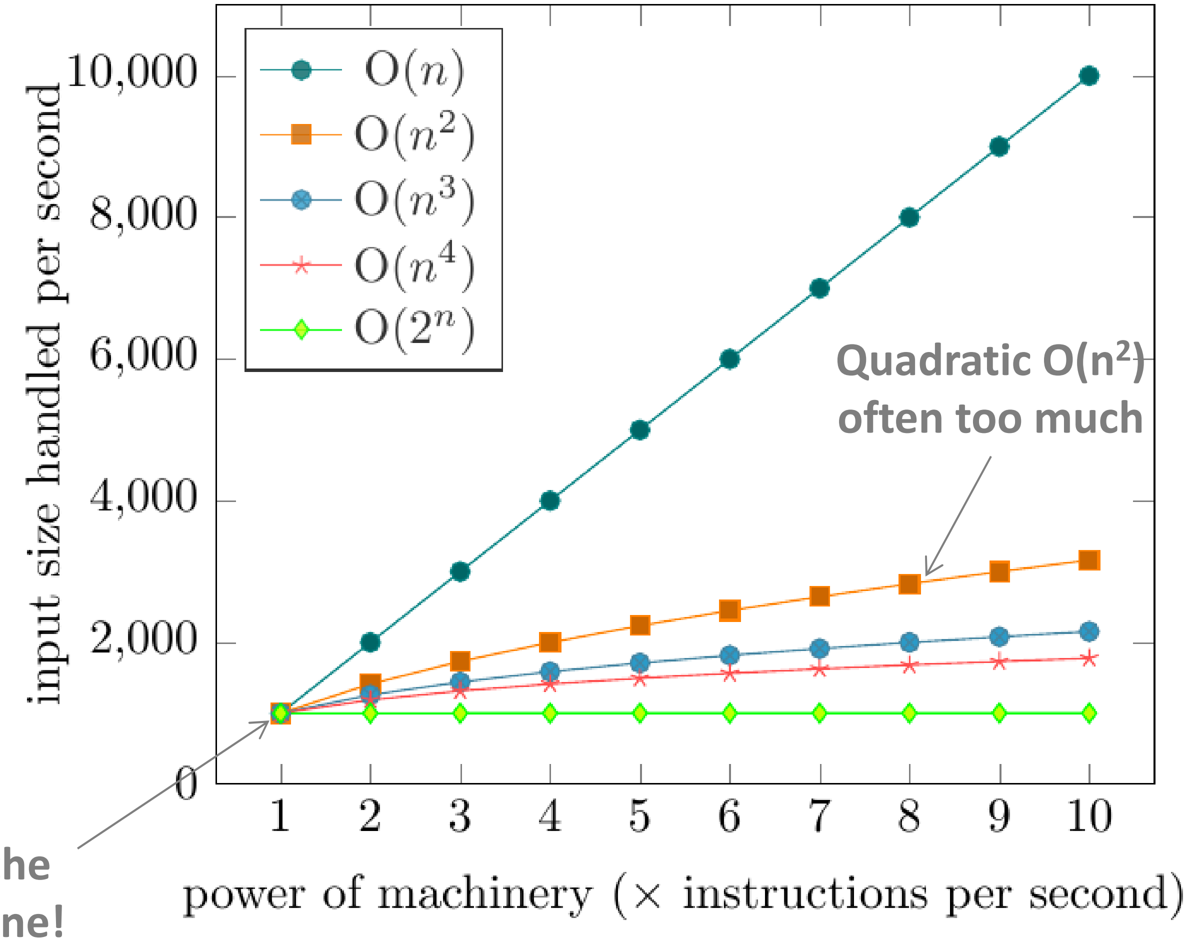
- Cannot run expensive algorithms

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 <u>n</u> times as powerful, how many input items can I process in an hour?

Depends on algorithm complexity of course!



Quadratic O(n^2) often too much

Note: Not the same machine!

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 …

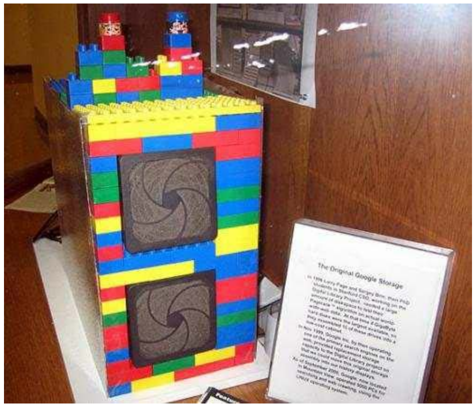
- Data-intensive (our focus!)
  - Inexpensive algorithms / Large inputs
  - e.g., Google, Facebook, Twitter
- Compute-intensive (not our focus!)
  - More expensive algorithms / Smaller inputs
  - e.g., climate simulations, chess games, combinatorials
- No black and white!

“MASSIVE DATA PROCESSING” NEEDS “DISTRIBUTED COMPUTING” …

Distributed Computing

- Need more than one machine!

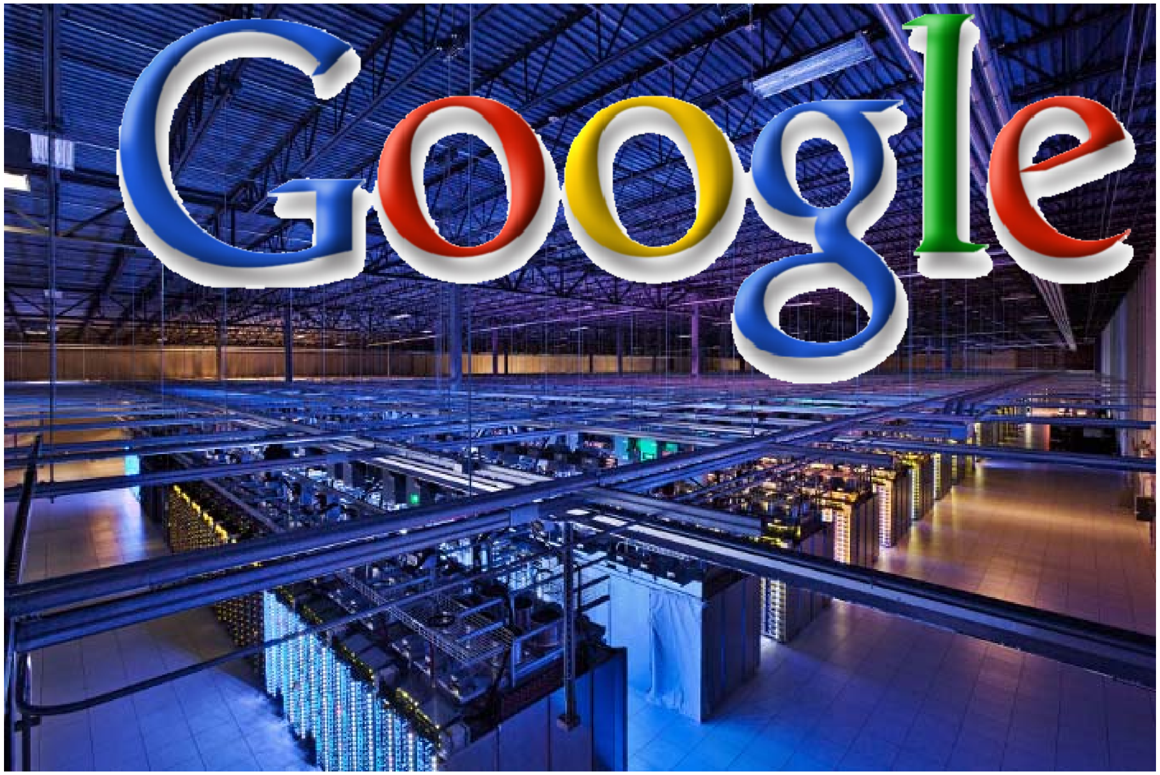
- Google ca. 1998:



Distributed Computing

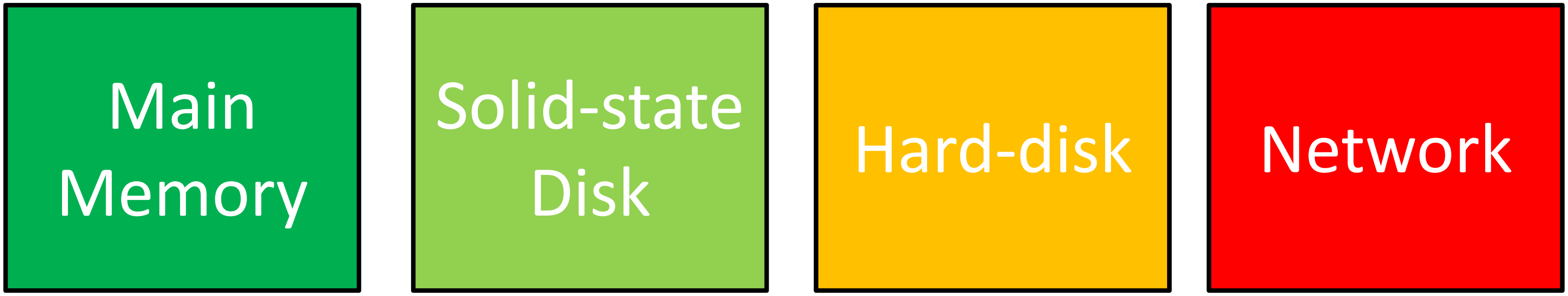
- Need more than one machine!

- 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.

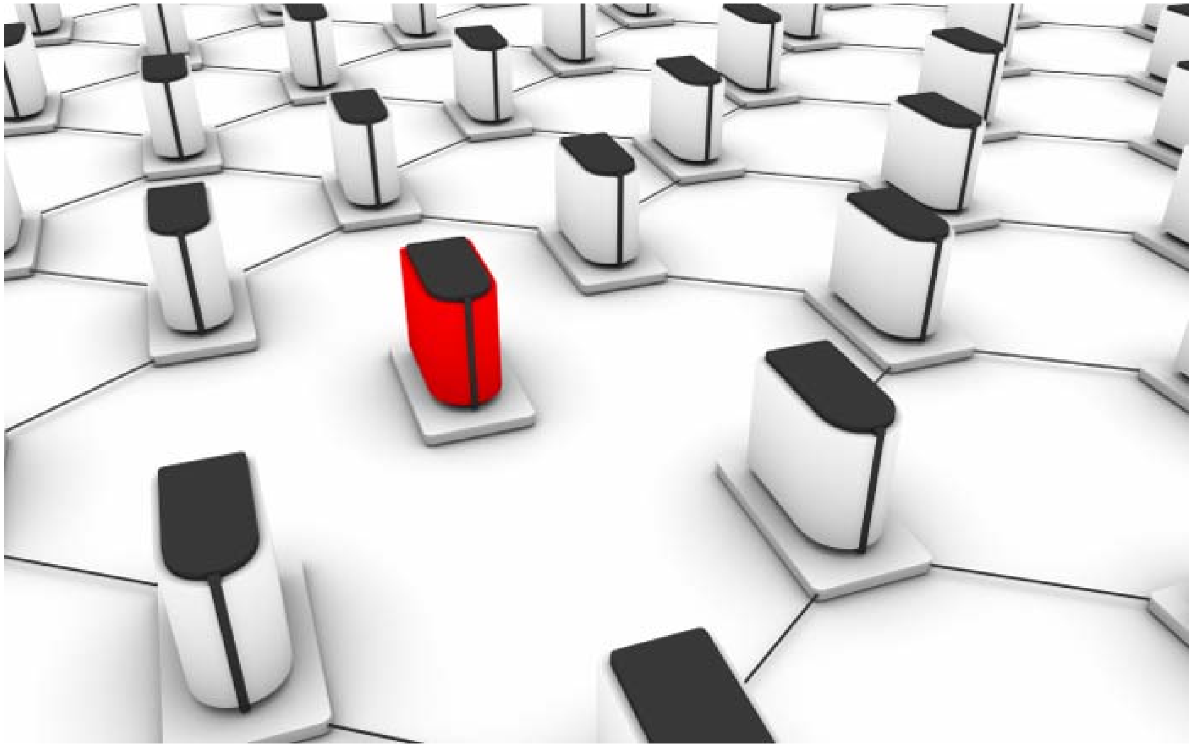
How should I split the data up over the machines?

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!

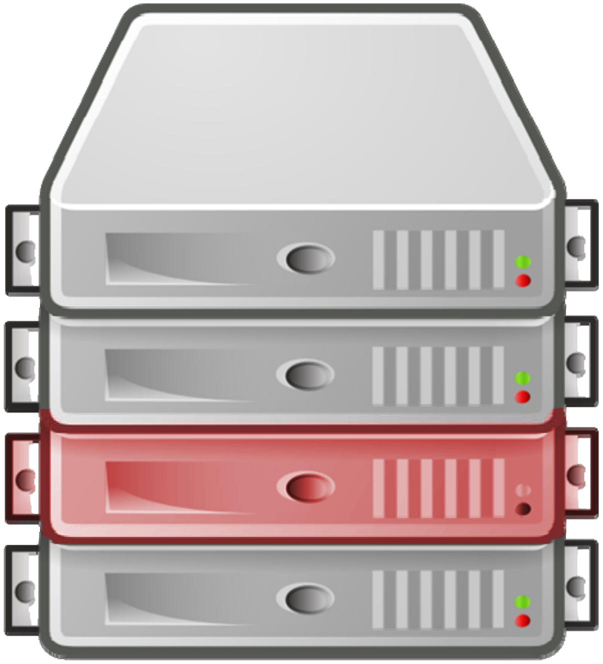
I have four machines to run my website. I have 10 million users.

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

How should I split the data up over the machines?

Depends on application of course!

(But good design principles apply universally!)

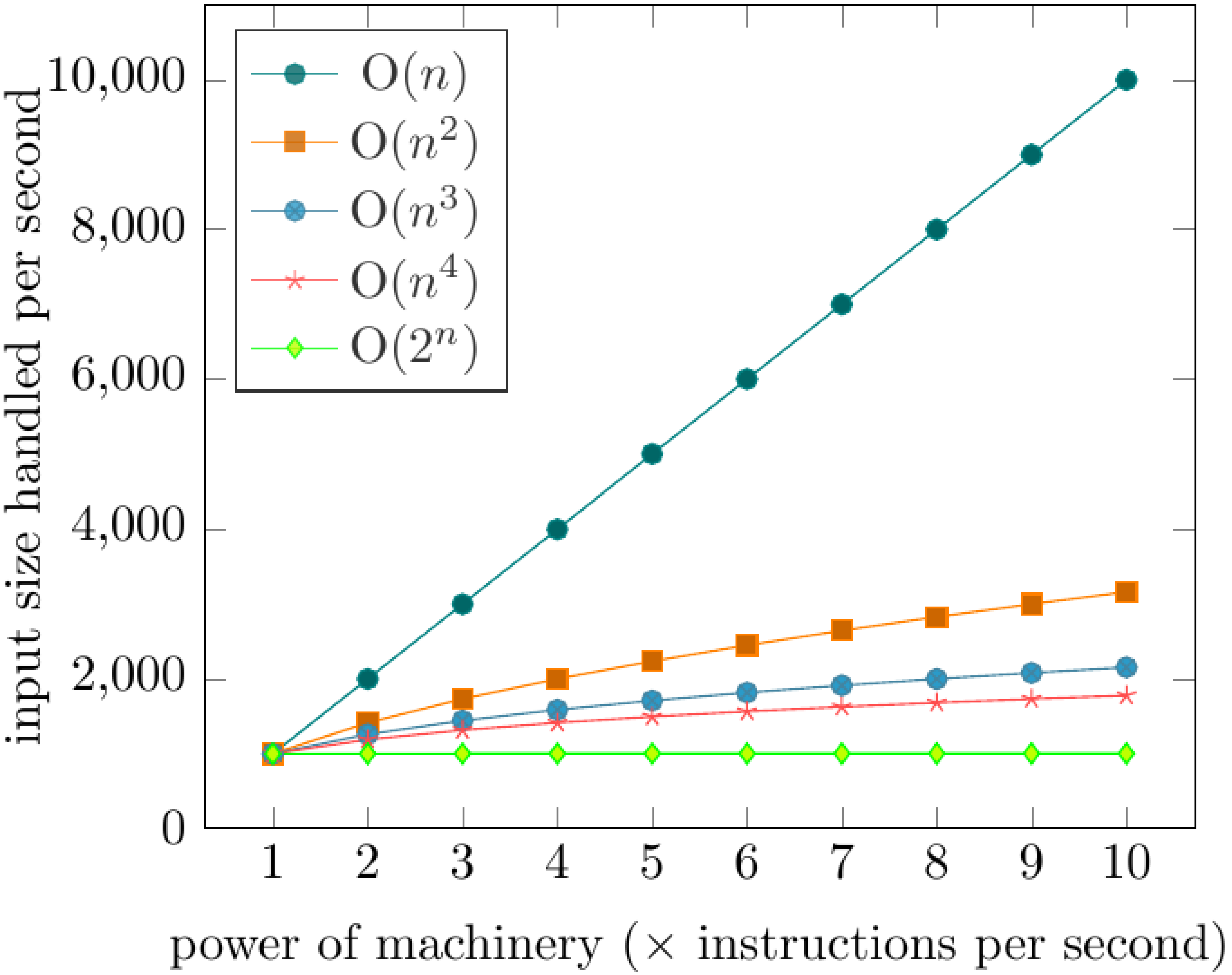


Human Distributed Computation

Similar Principles!

“DISTRIBUTED COMPUTING” LIMITS & CHALLENGES …

Distribution Not Always Applicable!

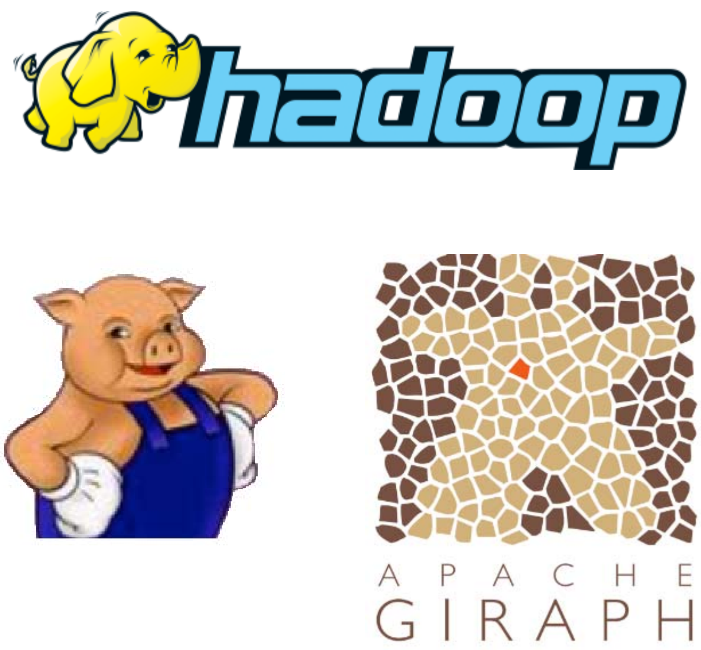


Distributed Development Difficult

- 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

HBASE
cassandra
Apache
CouchDB
Apache
Solr
mongoDB
accumulo

HOW DOES TWITTER WORK?

Based on 2013 slides by Twitter lead architect: Raffi Krikorian

Twitter
@twitter

Madonna's performance during the Super Bowl's halftime show saw an average of 8,000 Tweets per second for five minutes.

50+ RETWEETS 50+ FAVORITES

7:43 PM - 5 Feb 12 via Twitter for iPhone · Embed this Tweet

“Twitter Timelines at Scale”

Big Data at Twitter

- 150 million active worldwide users
- 400 million tweets per day
  - mean: 4,600 tweets per second
  - max: 143,199 tweets per second

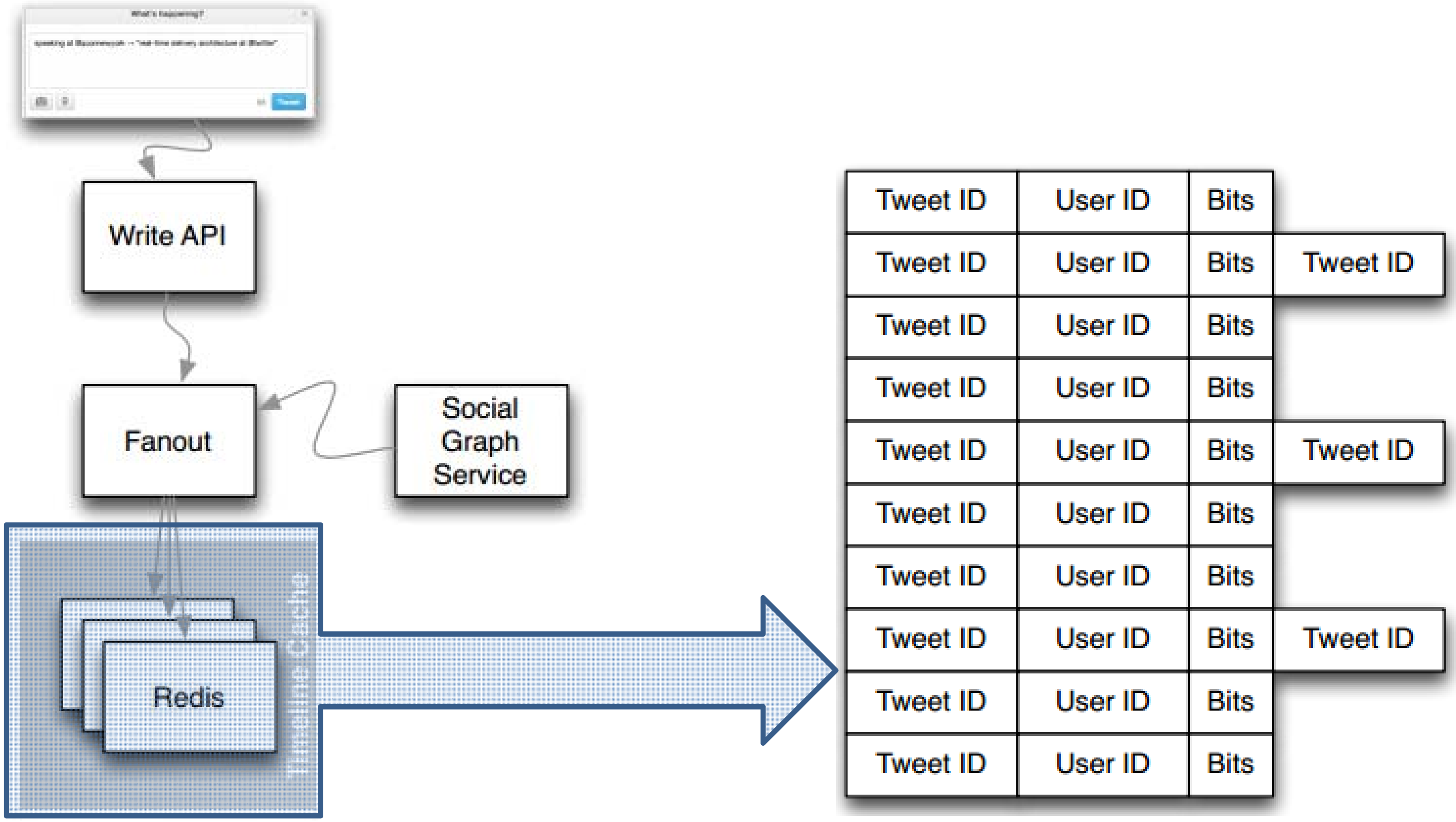
- 300 thousand queries/sec for user timelines

- 6 thousand queries/sec for custom search

What should be the priority for optimisation?

Supporting timelines:write

- 300 thousand queries per second



Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	Tweet ID
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	Tweet ID
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	Tweet ID
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	

High-fanout

@ladygaga ✓
31 million followers

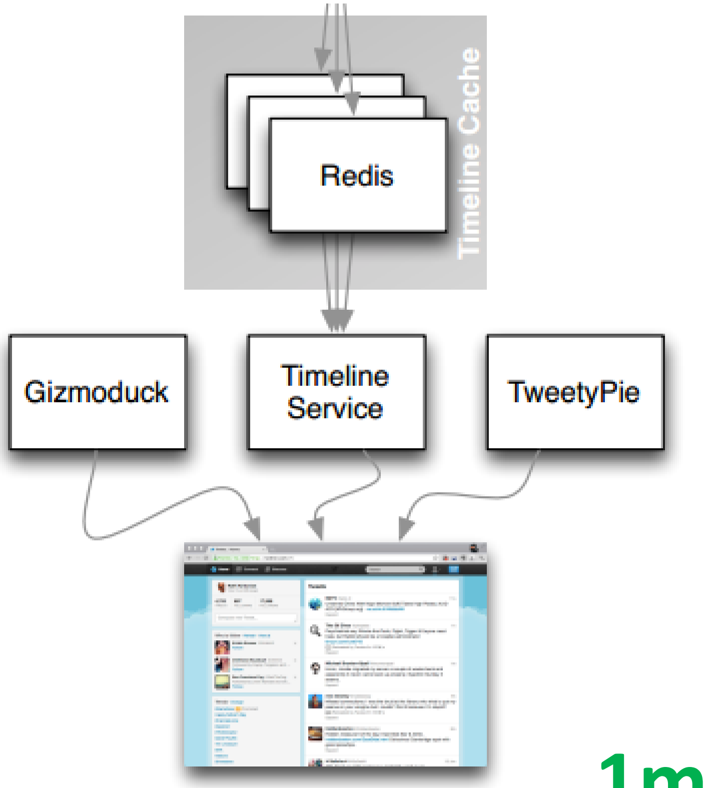
@katyperry ✓
28 million followers

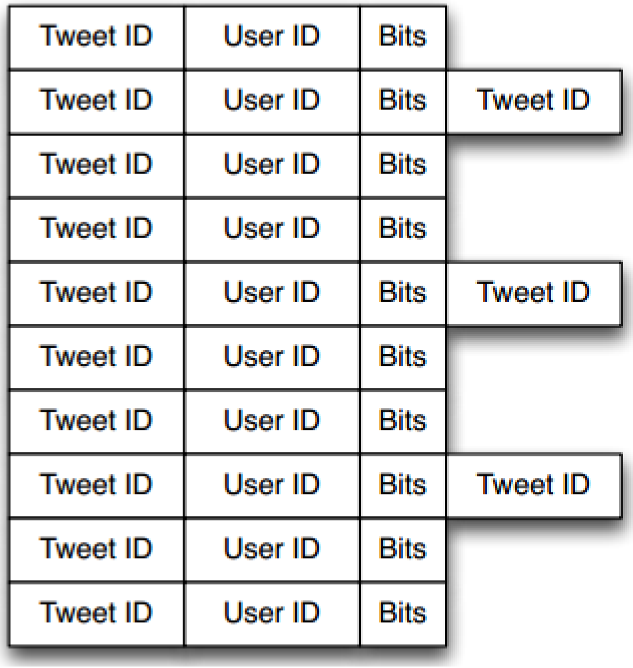
@justinbieber ✓
28 million followers

@barackobama ✓
23 million followers

Supporting timelines: read

- 300 thousand queries per second





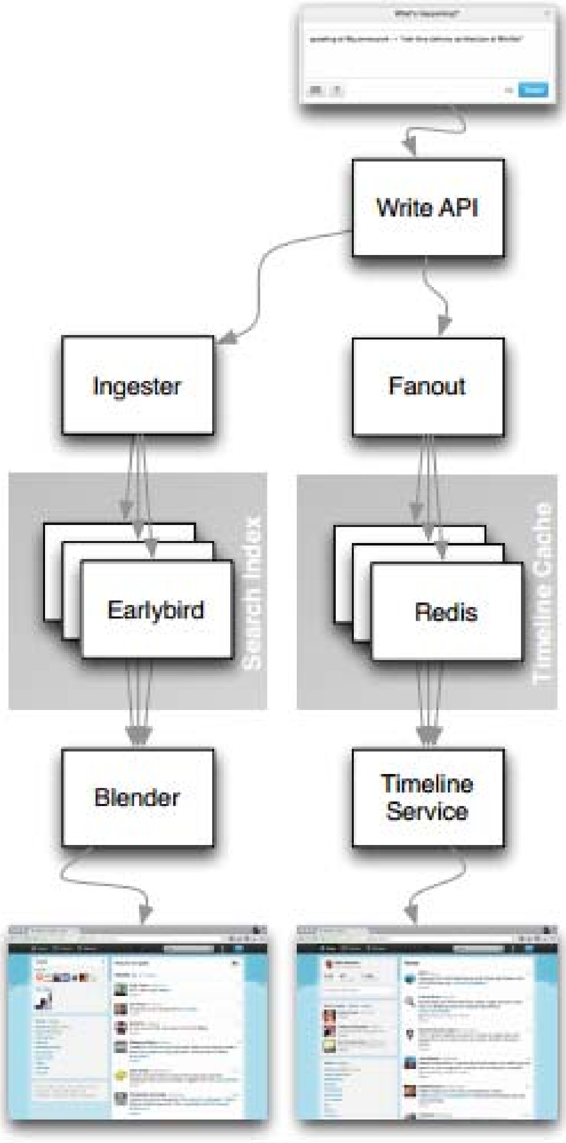
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	Tweet ID
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	Tweet ID
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	Tweet ID
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	

1ms @p50

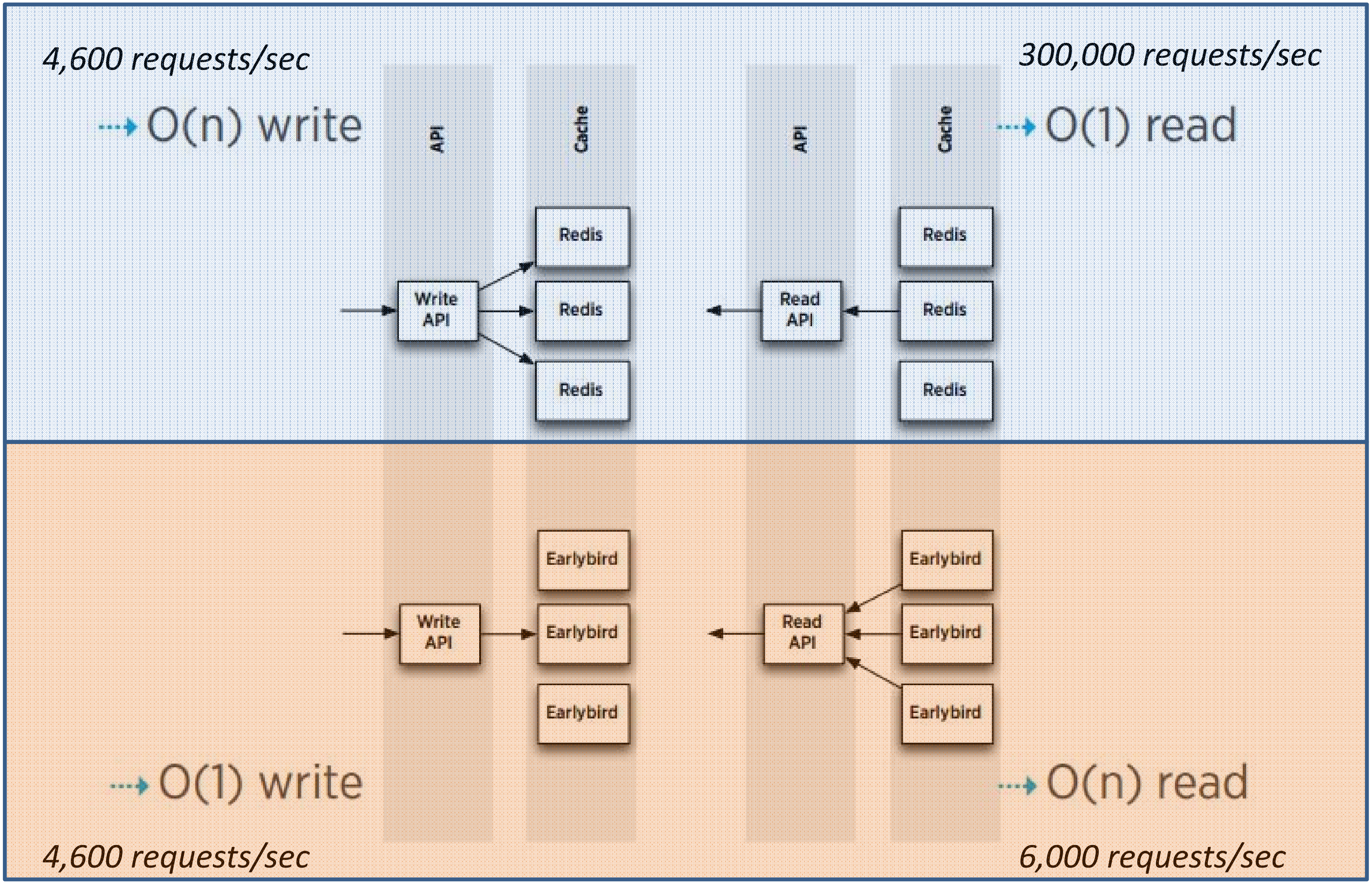
4ms @p99

Supporting text search

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



Timeline vs. Search



4,600 requests/sec

O(n) write

300,000 requests/sec

O(1) read

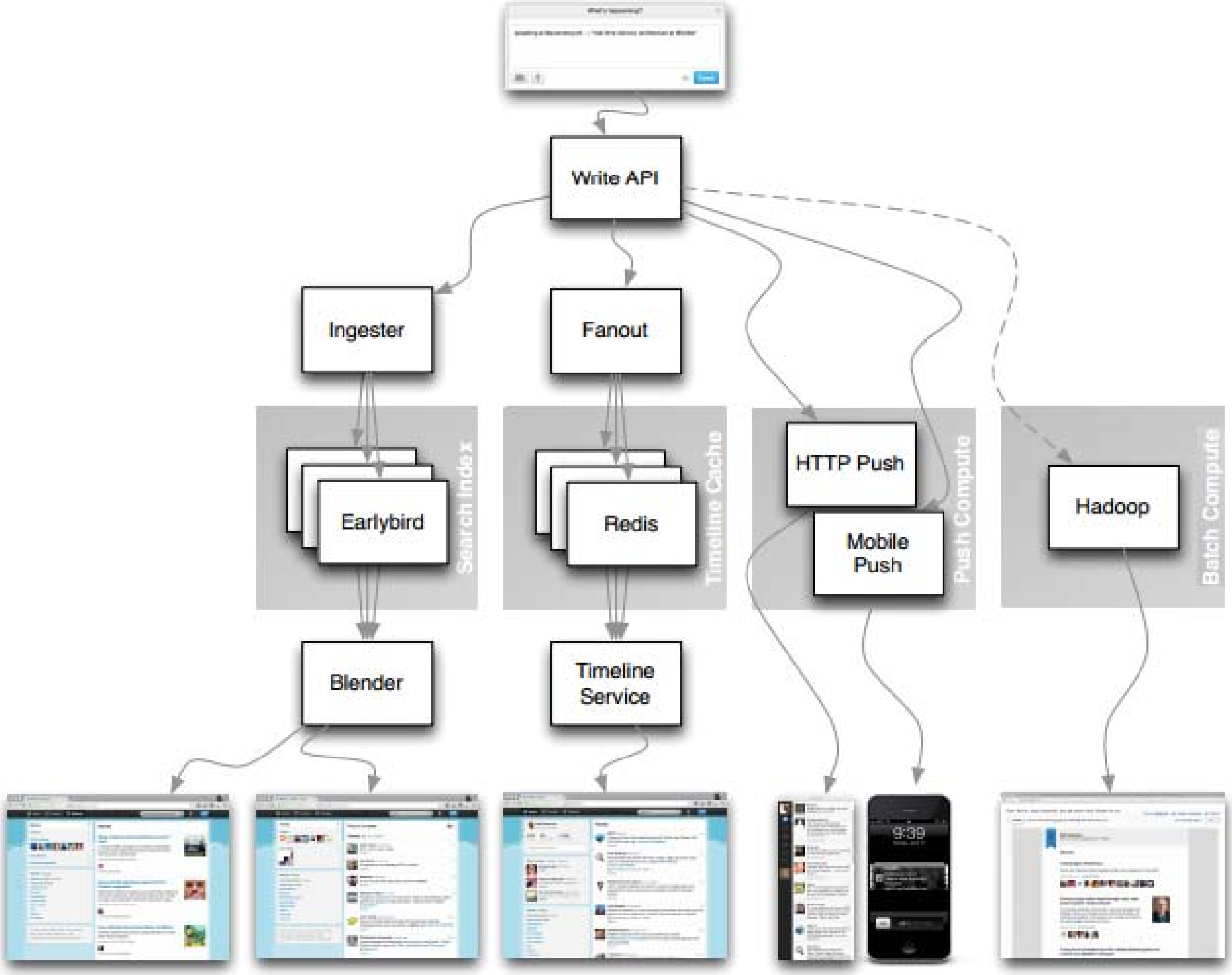
O(1) write

4,600 requests/sec

O(n) read

6,000 requests/sec

Twitter: Full Architecture



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

“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 [2 weeks]
- Distributed Processing Frameworks [3 weeks]
- Information Retrieval [3 weeks]
- Principles of Distributed Databases [3 weeks]
- Projects [2 weeks]

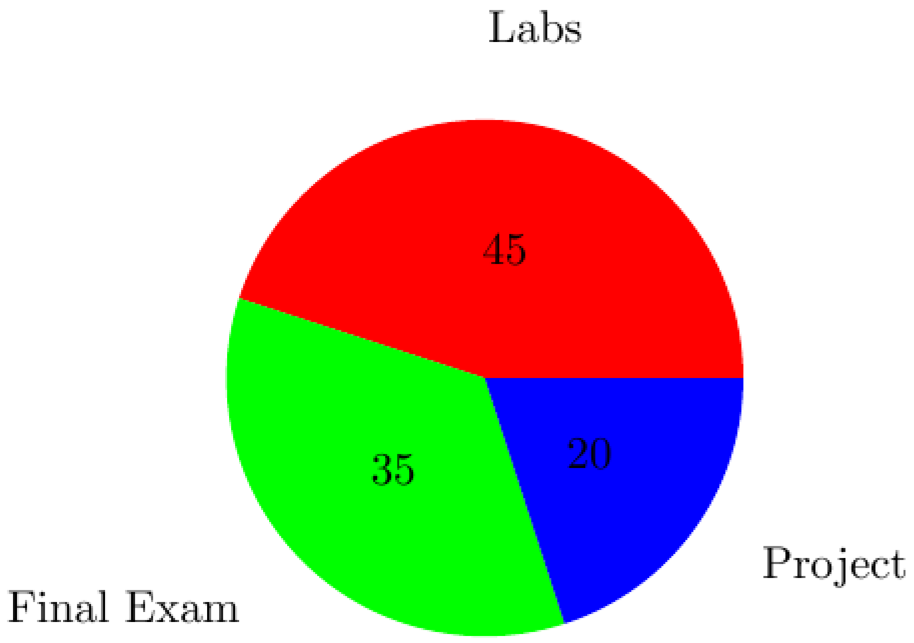
Course Structure

- ~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 Lab on 3rd floor, edificio norte

http://aidanhogan.com/teaching/cc5212-1-2016/

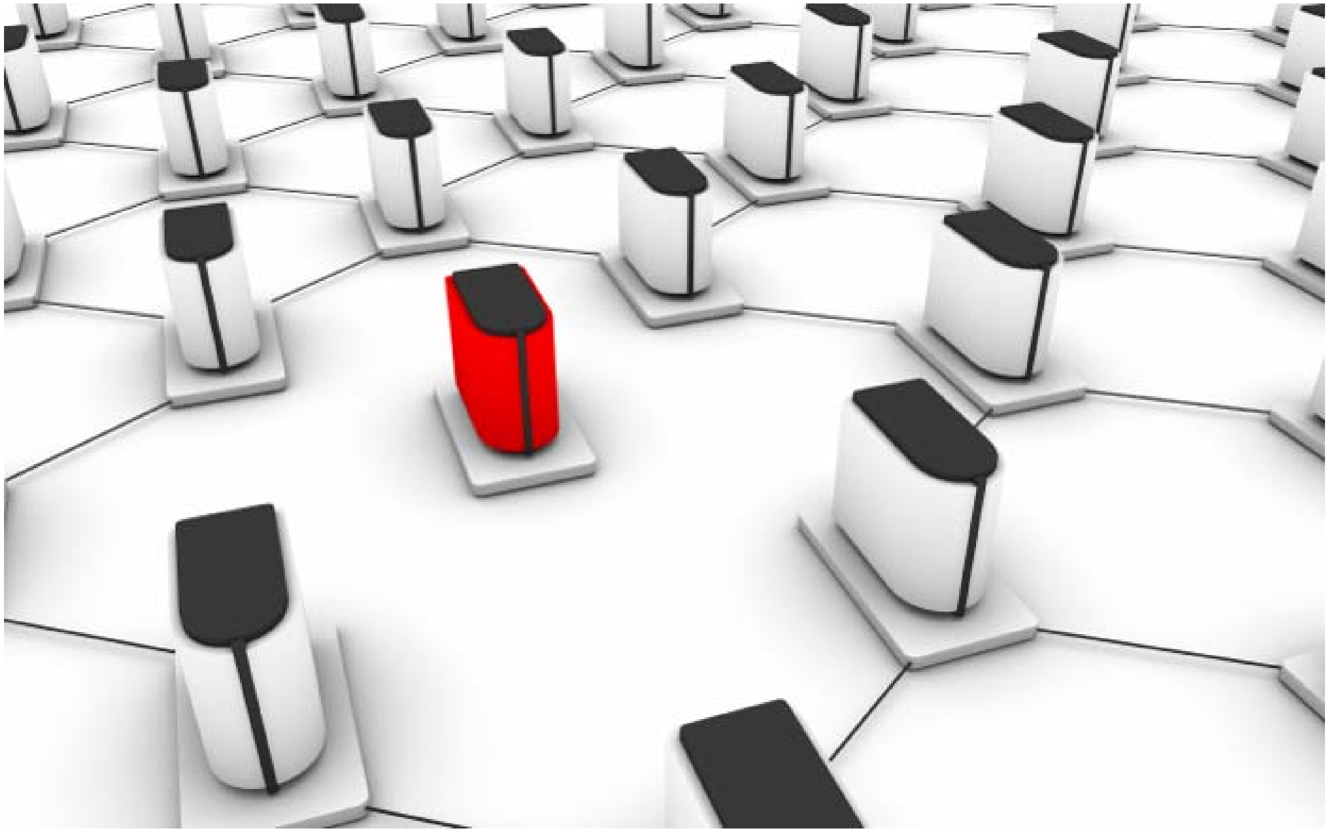
Course Marking

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



Outcomes!

Outcomes!



Outcomes!

hadoop
HBASE
Apache CouchDB
cassandra
Apache Solr
mongoDB
APACHE GIRAPH
accumulo

Outcomes!

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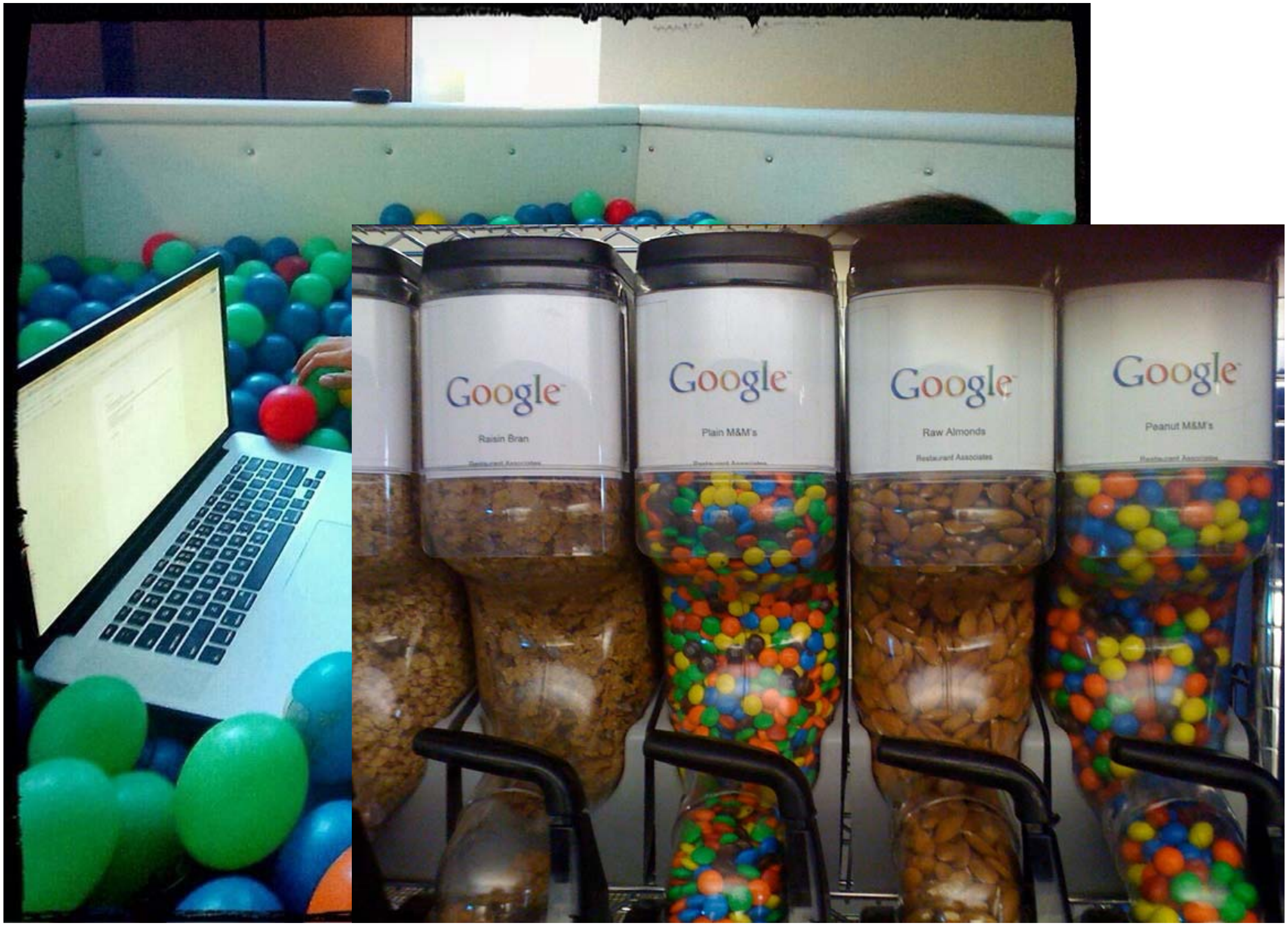
Outcomes!


Google
Raisin Bran
Google
Plain M&M's
Google
Raw Almonds
Restaurant Associates
Google
Peanut M&M's
Restaurant Associates

Outcomes!

Questions?