6.S079 SOFTWARE SYSTEMS FOR DATA SCIENCE

ADMINISTRIVIA

Lecturers:

Tim Kraska

Sam Madden

TAs:

Markos Markakis

Amadou Ngom

Website: http://dsg.csail.mit.edu/6.5079/

Piazza: http://piazza.com/mit/fall2022/6s079









The Economist

Obama the warrior

Misgoverning Argentina

The economic shift from West to East

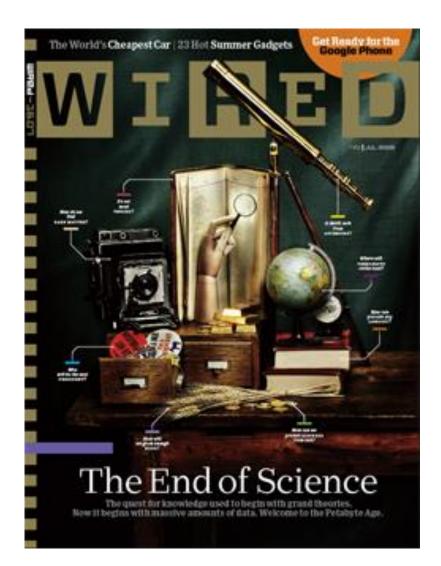
Genetically modified crops blossom

The right to eat cats and dogs

The data deluge

AND HOW TO HANDLE IT: A 14-PAGE SPECIAL REPORT





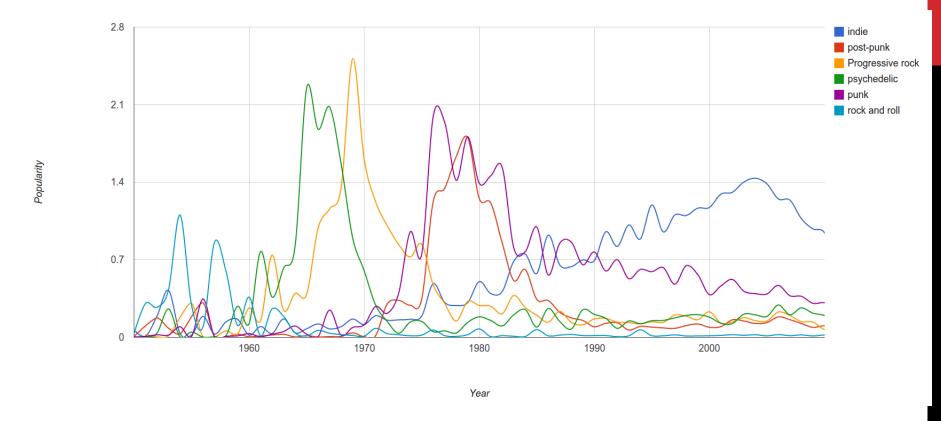
The Unreasonable Effectiveness of Data

NETFLIX





LAST.FM



"Since we have a massive amount of user tag data available we can easily correlate tags and years and measure "popularity" of a genre by counting the number of artists formed in a specific year."

HOW WOULD YOU ESTIMATE THE EXPRESSION OF EMOTIONS OVER THE 20TH CENTURY?

(read: before Twitter)

EXPRESSION OF EMOTIONS OVER THE 20TH CENTURY

1) Convert all the digitized books in the 20th century into n-grams (Thanks, Google!)

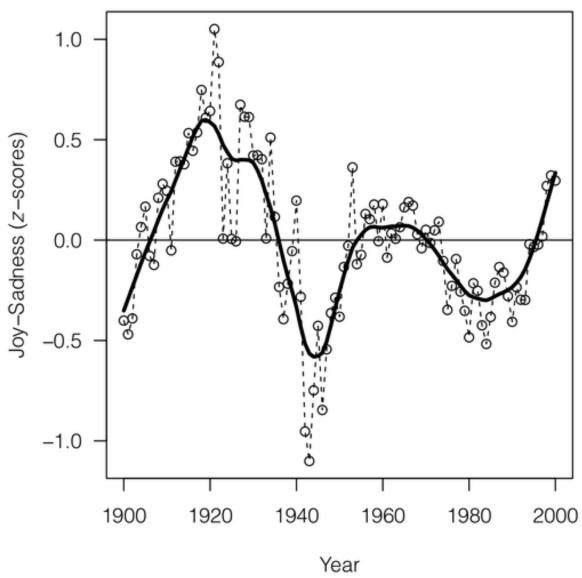
(http://books.google.com/ngrams/)

A 1-gram: "yesterday"

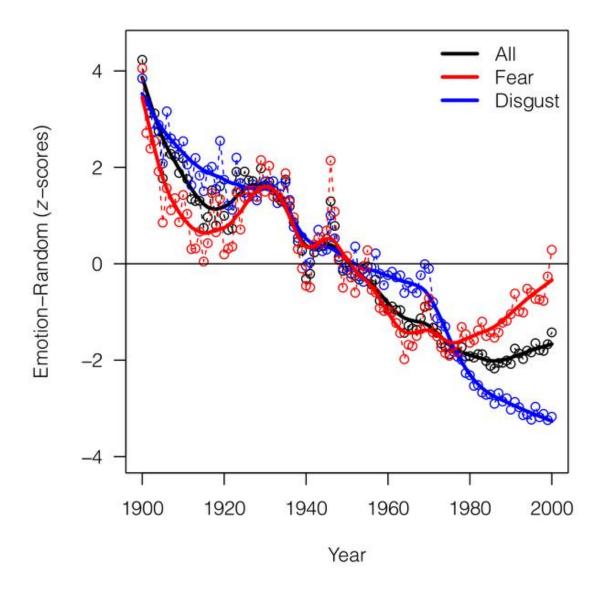
A 5-gram: "analysis is often described as"

- 2) Label each 1-gram (word) with a mood score. (Thanks, WordNet Affect)
- 3) Count the occurrences of each mood word

$$\mathcal{M}_{Y} = \frac{1}{n} \sum_{i=1}^{n} \frac{c_{i}}{C_{\text{the}}}, \qquad \mathcal{M}_{ZY} = \frac{\mathcal{M}_{Y} - \mu_{\mathcal{M}}}{\sigma_{\mathcal{M}}},$$



Acerbi A, Lampos V, Garnett P, Bentley RA (2013) **The Expression of Emotions in 20th Century Books**. PLoS ONE 8(3): e59030. doi:10.1371/journal.pone.0059030



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PAPERS CITED BY THEM

. . .

2. Michel J-P, Shen YK, Aiden AP, Veres A, Gray MK, et al. (2011) *Quantitative* analysis of culture using millions of digitized books. Science 331: 176–182. doi: 10.1126/science.1199644. Find this article online

3. Lieberman E, Michel J-P, Jackson J, Tang T, Nowak MA (2007) *Quantifying the* evolutionary dynamics of language. Nature 449: 713–716. doi:

10.1038/nature06137. Find this article online

4. Pagel M, Atkinson QD, Meade A (2007) Frequency of word-use predicts rates of lexical evolution throughout Indo-European history. Nature 449: 717–720. doi: 10.1038/nature06176. Find this article online

. . .

6. DeWall CN, Pond RS Jr, Campbell WK, Twenge JM (2011) *Tuning in to Psychological Change: Linguistic Markers of Psychological Traits and Emotions Over Time in Popular U.S. Song Lyrics*. Psychology of Aesthetics, Creativity and the Arts 5: 200–207. doi: 10.1037/a0023195. Find this article online

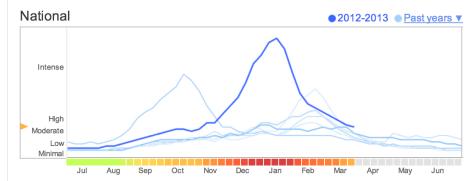
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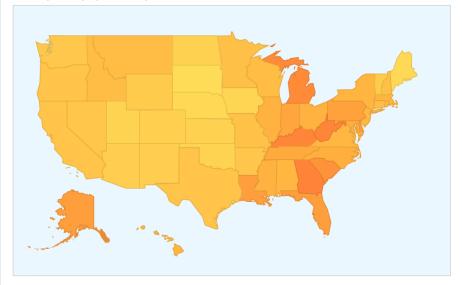
HOW WOULD YOU BUILD A FLU PREDICTION MODEL?

Explore flu trends - United States

We've found that certain search terms are good indicators of flu activity. Google Flu Trends uses aggregated Google search data to estimate flu activity. Learn more »



States | Cities (Experimental)



Estimates were made using a model that proved accurate when compared to historic official flu activity data. Data current through March 30, 2013.

flu risk

"Scientific hindsight shows that Google Flu Trends far overstated this year's flu season..."

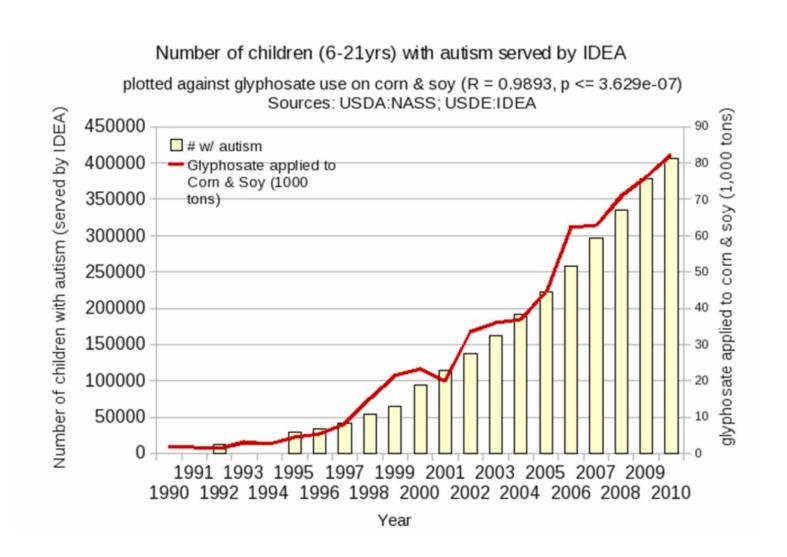
"Lots of media attention to this year's flu season skewed Google's search engine traffic."

David Wagner, Atlantic Wire, Feb 13 2013

source:

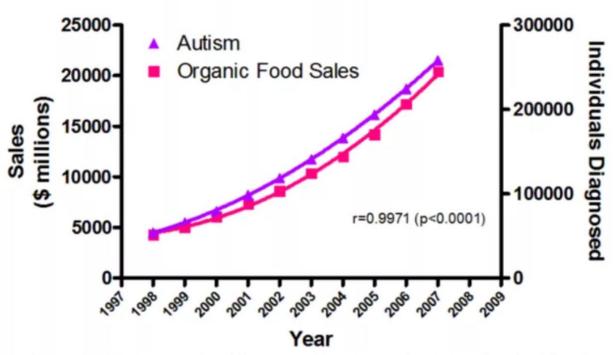
http://www.google.org/flutrends/us/#US

BUT DATA CAN BE MISLEADING, AND ANALYSIS IS HARD



BUT DATA CAN BE MISLEADING, AND ANALYSIS IS HARD (SOURCE)

The real cause of increasing autism prevalence?



Sources: Organic Trade Association, 2011 Organic Industry Survey; U.S. Department of Education, Office of Special Education Programs, Data Analysis System (DANS), OMB# 1820-0043: "Children with Disabilities Receiving Special Education Under Part B of the Individuals with Disabilities Education Act

BUT DATA IS EASY TO ABUSE OR MISINTERPRET

Table 4. Vaccination status for individuals ≥12 years infected with Omicron compared to other variants, data included in the table are from 22 November to 16 December 2021

Tabel 4. Vaccinationsstatus for personer ≥12 år med omikron-infektion sammenlignet med andre varianter i perioden fra og med 22. november 2021 til og med 16. december 2021

	011	011		
Vaccination status	Other variants	Other variants	Omicron (No.	Omicron
(12+ year olds)	(No. of cases)	(%)	of cases)	(%)
Booster vaccinated	8,866	8.6	1,851	10.8
Fully vaccinated	67,034	65.3	13,546	79.0
Not vaccinated	23,492	22.9	1,454	8.5
Received first dose	3,216	3.1	304	1.8
Total	102,608	99.9	17,155	100.0

Individuals aged 5-11 years have recently been invited for COVID-19 vaccination, hence the vaccination coverage is relatively low in this age group and not included in Table 4.



Stunning numbers from Denmark:

56% double vaccinated are catching 65% of "other variants" & 79% of Omicron

Most vulnerable group to Omicron BY FAR

25% boosted still catch 10% of Omicron cases, while unvaccinated catch 8.5%

This is worse than vaccine failure. This is damage.

1:08 AM · Dec 20, 2021 · Twitter Web App

805 Retweets 136 Quote Tweets

1.146 Likes

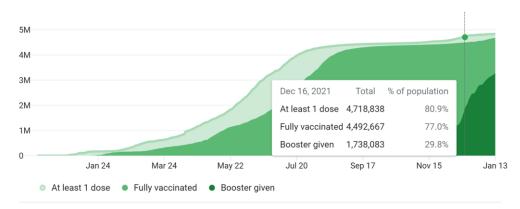
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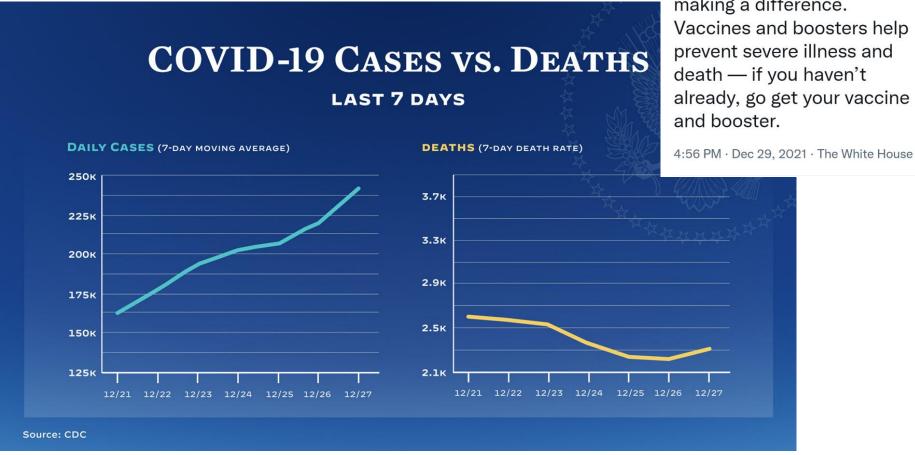
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BUT DATA IS EASY TO ABUSE OR **MISINTERPRET**



Omicron cases are on the rise, but it's clear that vaccines and boosters are making a difference. Vaccines and boosters help prevent severe illness and death — if you haven't already, go get your vaccine



Any thoughts on what is wrong with this?







SIMPLE TRUTHS

"Power of data"

- the more data the merrier (GB -> TB)
- data comes from everywhere in all shapes
- value of data often discovered later

Services turn data into \$

- the more services the merrier
- need to adapt quickly

E.g.: Google, Amadeus, Disney, Walmart, BMW, ...

Tools: Oracle/Vertica/PostgreSQL, Tableau, Python, Spark, SciKitLearn,....

BIG DATA QUESTION: YES OR NO?

Cure for cancer?

Find a spouse?

How to treat a cough?

Should I give Tim a loan?

Premium for fire insurance?

Which book should I read next?

Translate from English to German.

SOME RECURRING THEMES

simple methods
repurposing data
communication matters

Other themes

- "Data products" not just answers
- "Speed of thought" analysis

WHAT IS DATA SCIENCE?

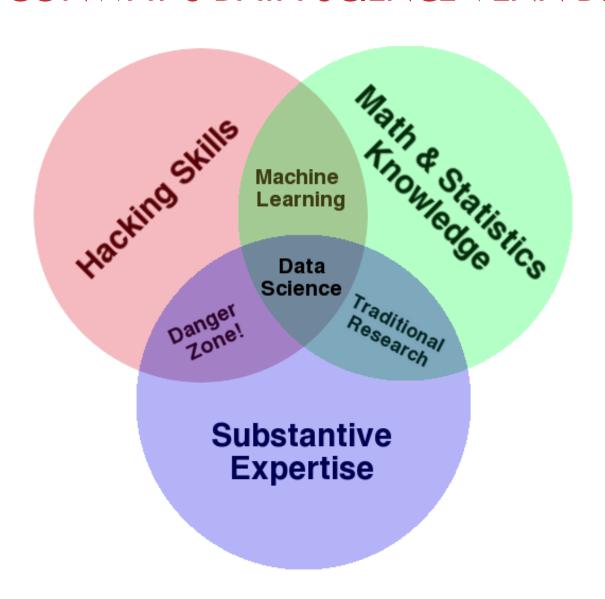
"Data Scientists: The Definition of Sexy"

Forbes, 2012

"Data Scientist: The Sexiest Job of the 21st Century"

Harvard Business Review, 2012

DREW CONWAY'S DATA SCIENCE VENN DIAGRAM



MIKE DRISCOLL'S THREE SEXY SKILLS OF DATA GEEKS

"data wrangling"

"data jujitsu"

"data munging"

Data Wrangling

parsing, scraping, and formatting data

Statistics

traditional analysis

Visualization

• graphs, tools, etc.

DOING DATA SCIENCE

PETER HUBER:

- 1. Inspection
- 2. Error checking
- 3. Modification
- 4. Comparison
- 5. Modeling and model fitting
- 6. Simulation
- 7. What-if analyses
- 8. Interpretation
- 9. Presentation of conclusions

DOING DATA SCIENCE

BEN FRY:

- 1. Acquire
- 2. Parse
- 3. Filter
- 4. Mine
- 5. Represent
- 6. Refine
- 7. Interact

COLIN MALLOWS:

- Identify data to collect and its relevance to your problem
- 2. Statistical specification of the problem
- 3. Method selection
- 4. Analysis of method
- 5. Interpret results for non-statisticians

A PRACTICAL DEFINITION

Data Science is about the whole processing pipeline to extract information out of data

Data Scientist understand and care about the whole data pipeline and produce data products

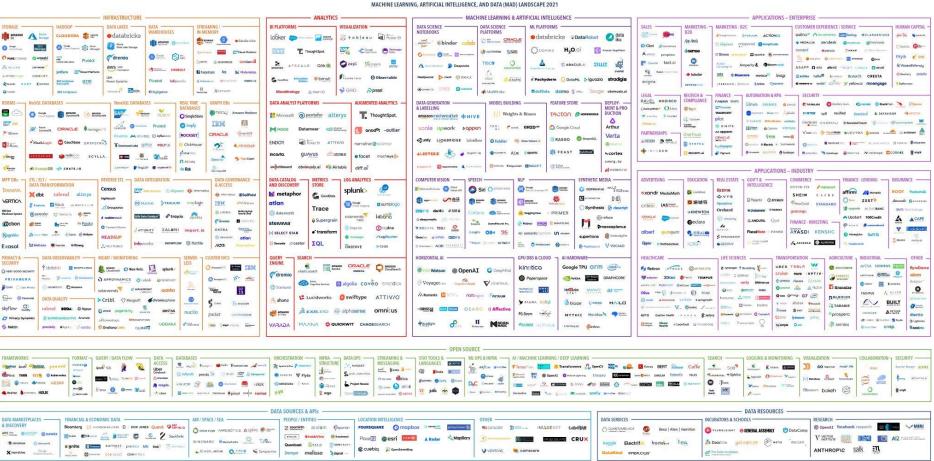
A data pipeline consists of 3 steps:

1) Preparing to run a model

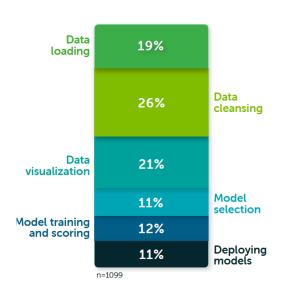
Gathering, cleaning, integrating, restructuring, transforming, loading, filtering, deleting, combining, merging, verifying, extracting, shaping

- 2) Running the model
- 3) Communicating the results / Create data products

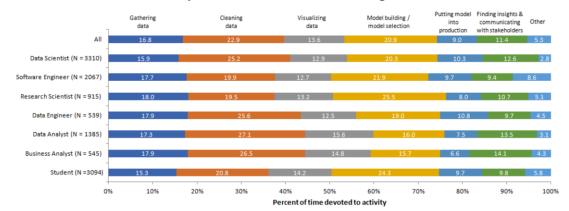
WHAT TOOLS ARE INVOLVED



WHERE DO DATA SCIENTIST SPEND THEIR TIME?



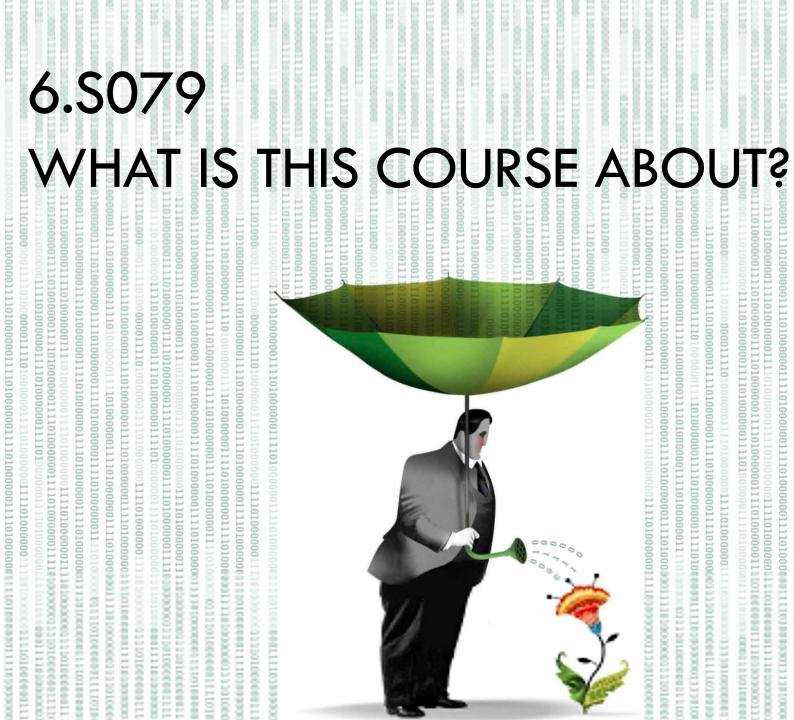
During a typical data science project at work or school, approximately what proportion of your time is devoted to the following?



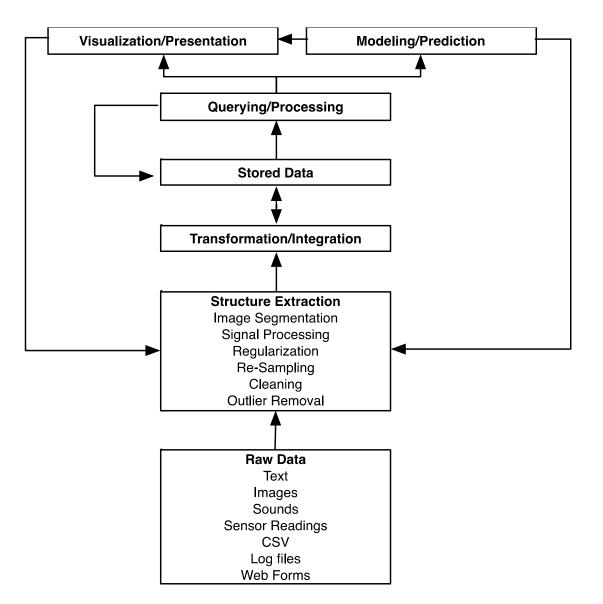
Note: Data are from the 2018 Kaggle ML and Data Science Survey. You can learn more about the study here: http://www.kaggle.com/kaggle/survey-2018.

Atotal of 23859 respondents completed the survey; the percentages in the graph are based on a total of 15937 respondents who provided an answer to this question. Only selected job titles are presented.

Anaconda's annual survey. https://www.datanami.com/2020/07/06/data-prep-still-dominates-data-scientists-time-survey-finds/



DATA PROCESSING PIPELINE



Course will investigate all of these topics

Structured data
SQL Databases / Pandas

Data Cleaning & Wrangling

Entity Resolution

ML & Embeddings
Not a deep treatment

Visualization

Scaling & Performance

Cloud Data

COURSE STRUCTURE

2 lectures per weekWeekly readings2 Quizzes (but no final exam)

Grading Rubric:

Final Project: 35%

• Proposal: 2.5%

• Check-in 1: 2.5%

• Check-in 2: 5%

Poster & presentation: 10%

• Report: 15%

Labs: 35% (weighted equally)

Quizzes: 25%

• Quiz 1: 12.5%

• Quiz 2: 12.5%

Participation: 5% (Piazza, class, ...)

LABS

- Lab 0 Setting up the environment
- Lab 1 Working with Data (SQL, Dataframes)
- Lab 2 Data Cleaning and Wrangling
- Lab 3 Using Machine Learning
- Lab 4 Embeddings
- Lab 5 Visualization
- Lab 6 Parallelism

PROJECT

Two options:

1. Build a system for working with data

2. Choose a data set and do some end to end modeling on it

EXAMPLE "SYSTEMS"

Given a twitter keyword, analyze the distribution of sentiment in tweets about it

Build a tool to extract structured data from a particular type of document, i.e., go from scanned PDF → tabular data

Build a high performance visualization system for some data set

MAPO (MASSIVELY PARALLEL DATABASE)

MAPO (MASSIVELY PARALLEL DATABASE)

OF BISTON OF B

Interactive Large-Scale Visualization using a GPU Database

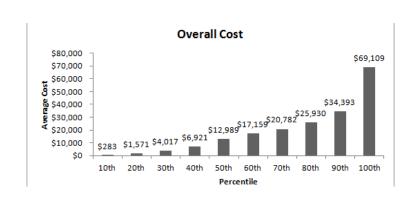
Todd Mostak

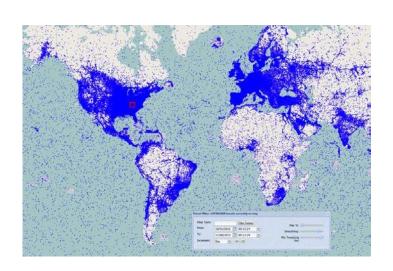
The Need for Interactive Analytics

Idea: often need to browse massive data sets

Browsing is best supported through visualization

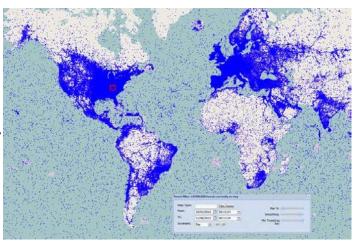
→ ad-hoc analytics, with millisecond response times





MapD: GPU Accelerated SQL Database

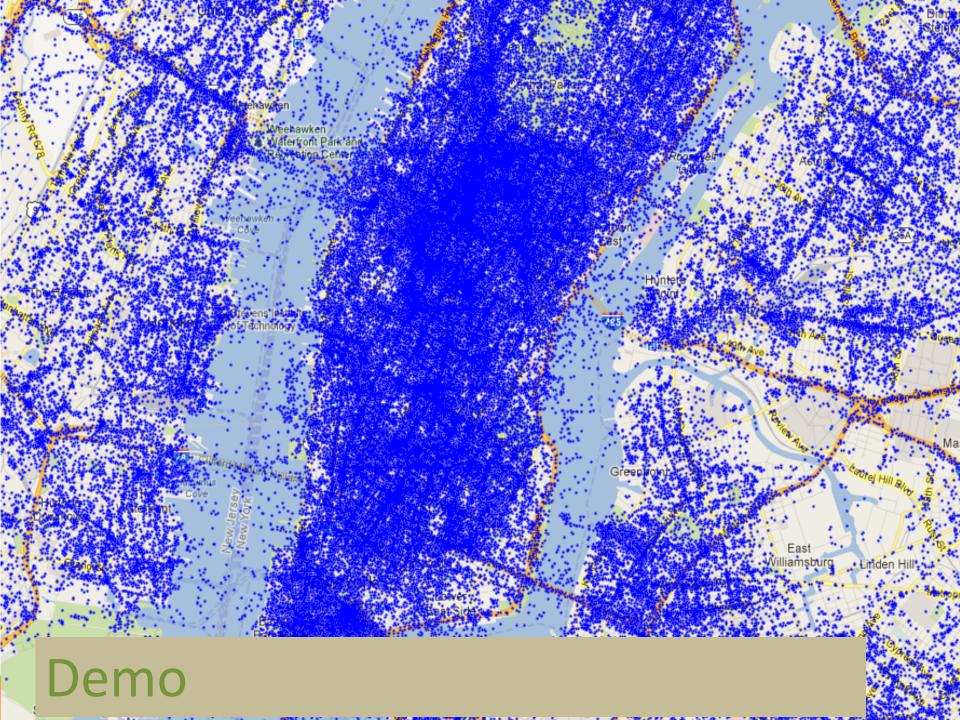
- Key insight: GPUs have enough memory that a cluster of them can store substantial amounts of data
- Not an accelerator, but a full blown query processor!
- Massive parallelism enables interactive browsing interfaces
 - 4x GPUs can provide > 1 TB/sec of bandwidth
 - 12 Tflops compute
 - Order of magnitude speedups over CPUs, when data is on GPU
- "Shared nothing" arrangement

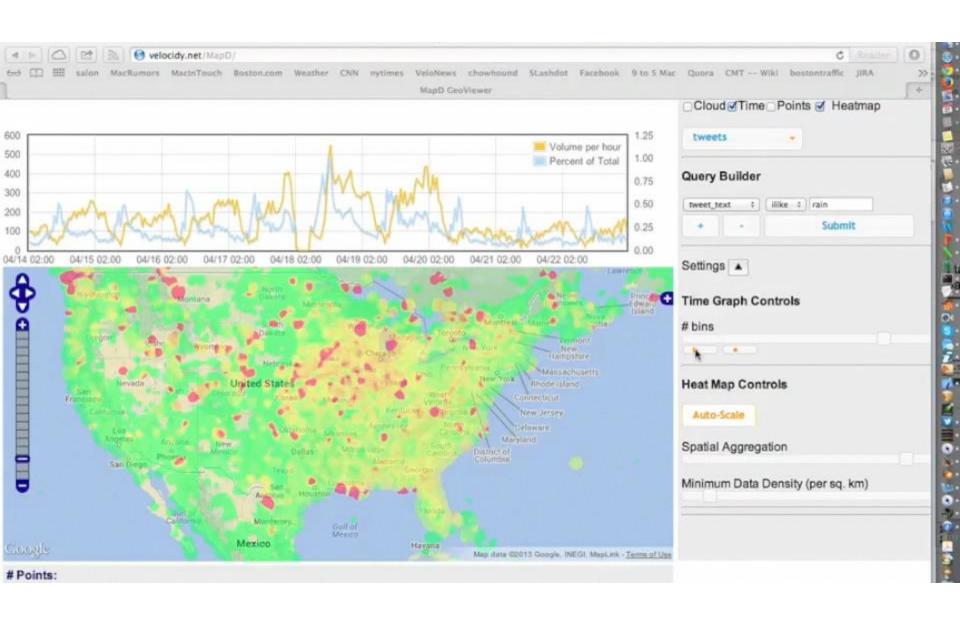


147,201,658 tweets from Oct 1, 2012 to Nov 6, 2012

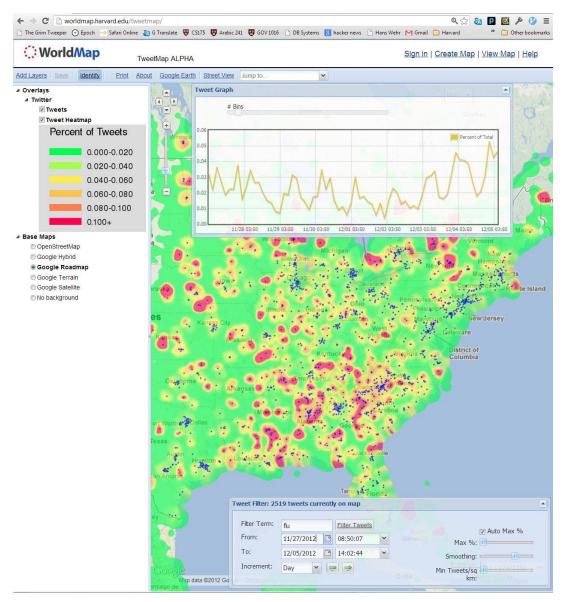


Relative intensity of "tornado" on Twitter (with point overlay) from Febuary 29, 2012 to March 1, 2012









Search for "flu" showing outbreak over Southeastern U.S.

EXAMPLE DATA SETS

- Election data (donations, fundrasing)
- Sports data, at fine granularity (e.g., individual shots / passes)
- Education data (admissions, jobs, costs, loans)
- Medical data (medicare, billing, etc.)
- Federal funding (defense, nsf, etc)
- Real estate (transactions, property prices, restaurants, etc)