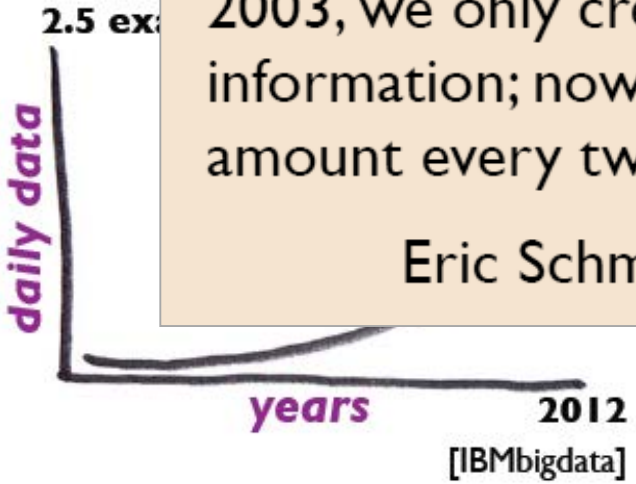
Data Science

Lecture 1: Overview / Data Munging

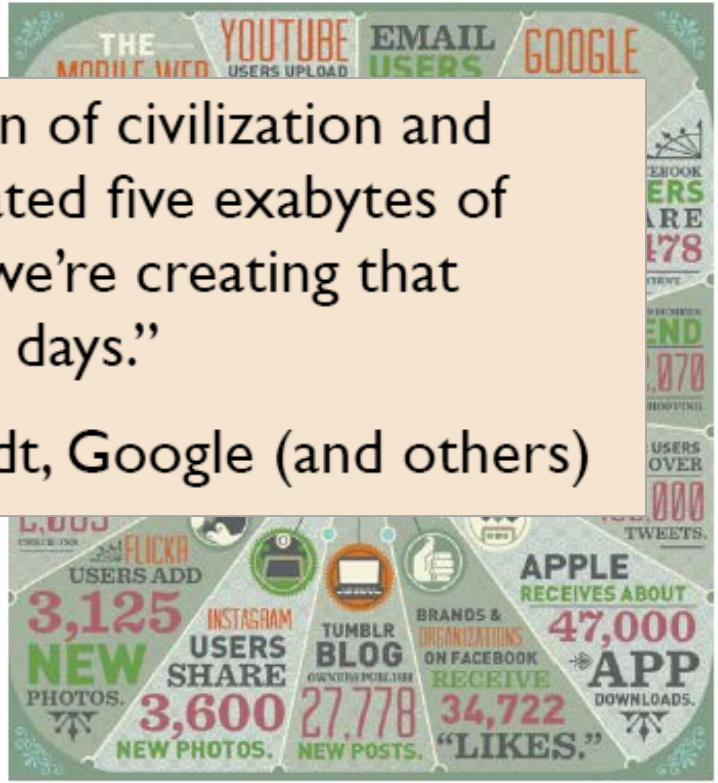
Big Data

"Between the dawn of civilization and 2003, we only created five exabytes of information; now we're creating that amount every two days."

Eric Schmidt, Google (and others)



[IBMbigdata]



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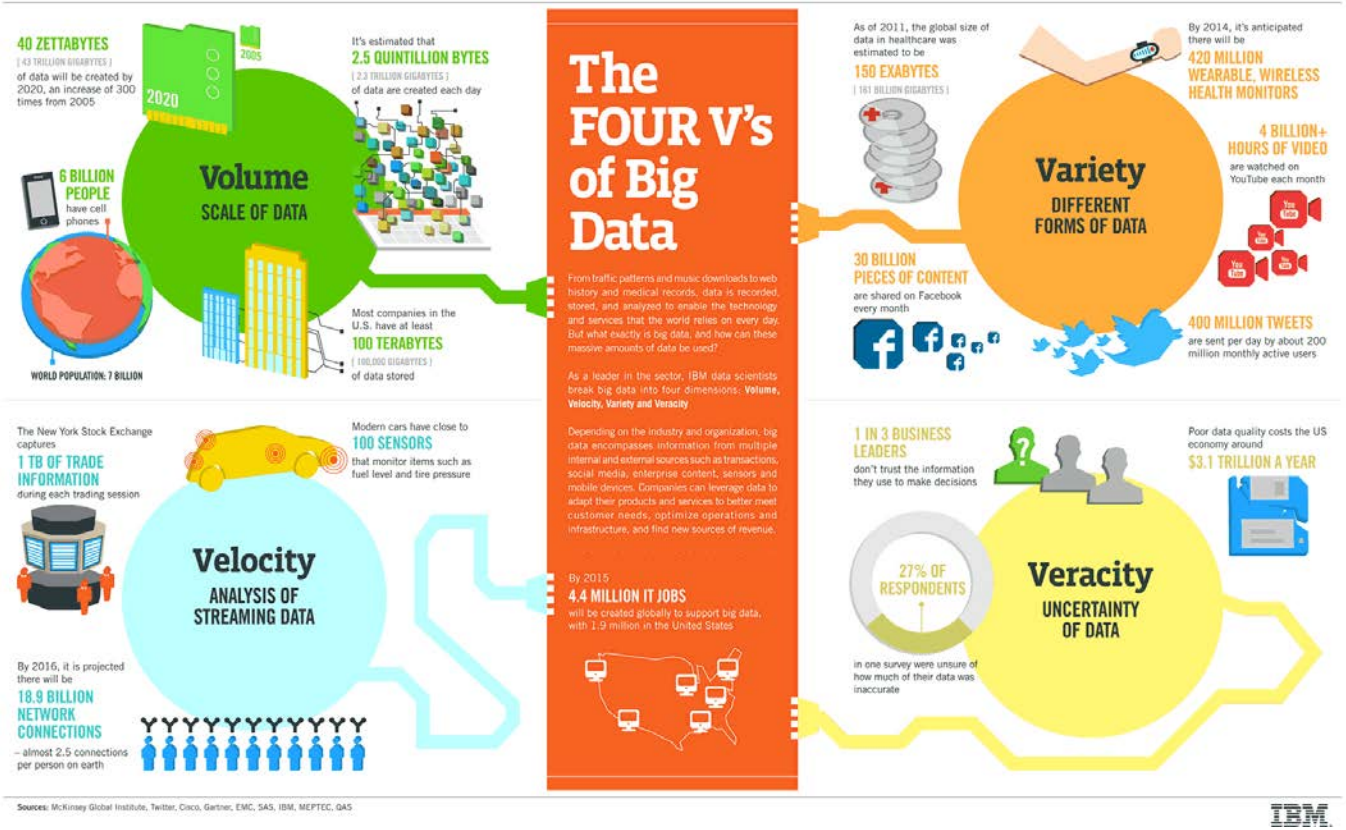
Big Data Explosion



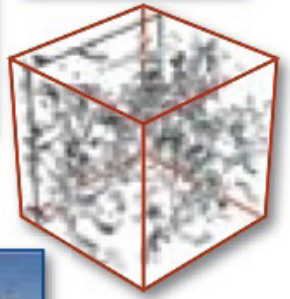
Big Data Challenges

- Big Data
  - Large and complex data
  - E.g., social data, web data, financial transaction data, academic articles, genomic data etc.
- Two challenges:
  - Efficient storage and access
  - Data analytics to mine valuable information

Science Paradigms

- Thousand years ago:
  science was **empirical**
  describing natural phenomena
- Last few hundred years:
  theoretical branch
  using models, generalizations
- Last few decades:
  a **computational** branch
  simulating complex phenomena
- Today: **data exploration** (eScience)
  unify theory, experiment, and simulation
  - Data captured by instruments or generated by simulator
  - Processed by software
  - Information/knowledge stored in computer
  - Scientist analyzes database/files using data management and statistics

$$\left(\frac{\dot{a}}{a}\right)^2 = \frac{4\pi G p}{3} - \mathrm{K}\frac{c^2}{a^2}$$



Jim Gray, Microsoft

Science Paradigms

- Thousand years ago:
  science was **empirical**
  describing natural phenomena
- Last few hundred years:
  theoretical branch
  using models, generalizations
- **Future: Data-driven Science**
  - Data-driven Hypothesis Generation
- Today: **data exploration** (eScience)
  unify theory, experiment, and simulation
  - Data captured by instruments or generated by simulator
  - Processed by software
  - Information/knowledge stored in computer
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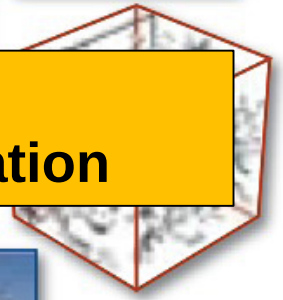


Jim Gray, Microsoft

Market demands for Big Data Scientists

(*Harvard Business Review*, 2012)

Data Scientist:

The Sexiest Job of the 21st Century

Meet the people who can coax treasure out of messy, unstructured data.

by Thomas H. Davenport and D.J. Patil

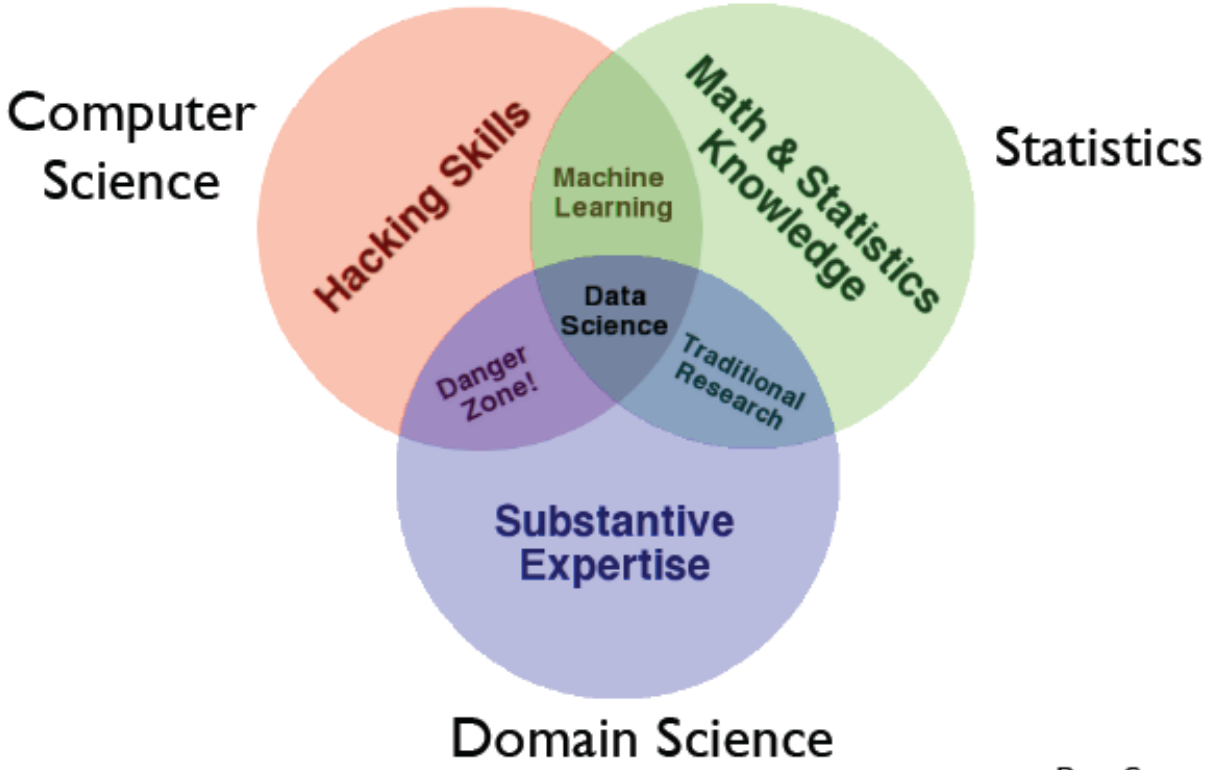
When Jonathan Goldman arrived for work in June 2006 at LinkedIn, the business networking site, the place still felt like a start-up. The company had just under 8 million accounts, and the number was growing quickly as existing members invited their friends and colleagues to join. But users weren't seeking out connections with the people who were already on the site at the rate executives had expected. Something was apparently missing in the social experience. As one LinkedIn manager put it, "It was like arriving at a conference reception and realizing you don't know anyone. So you just stand in the corner sipping your drink—and you probably leave early."

What is Data Science?

Like any emerging field, it isn’t yet well defined, but incorporates elements of:

- Exploratory Data Analysis and Visualization
- Machine Learning and Statistics
- High-Performance Computing technologies for dealing with scale.

Data Science



Drew Conway

A Data Scientist Is...

"A data scientist is someone who knows more statistics than a computer scientist and more computer science than a statistician."

- Josh Blumenstock

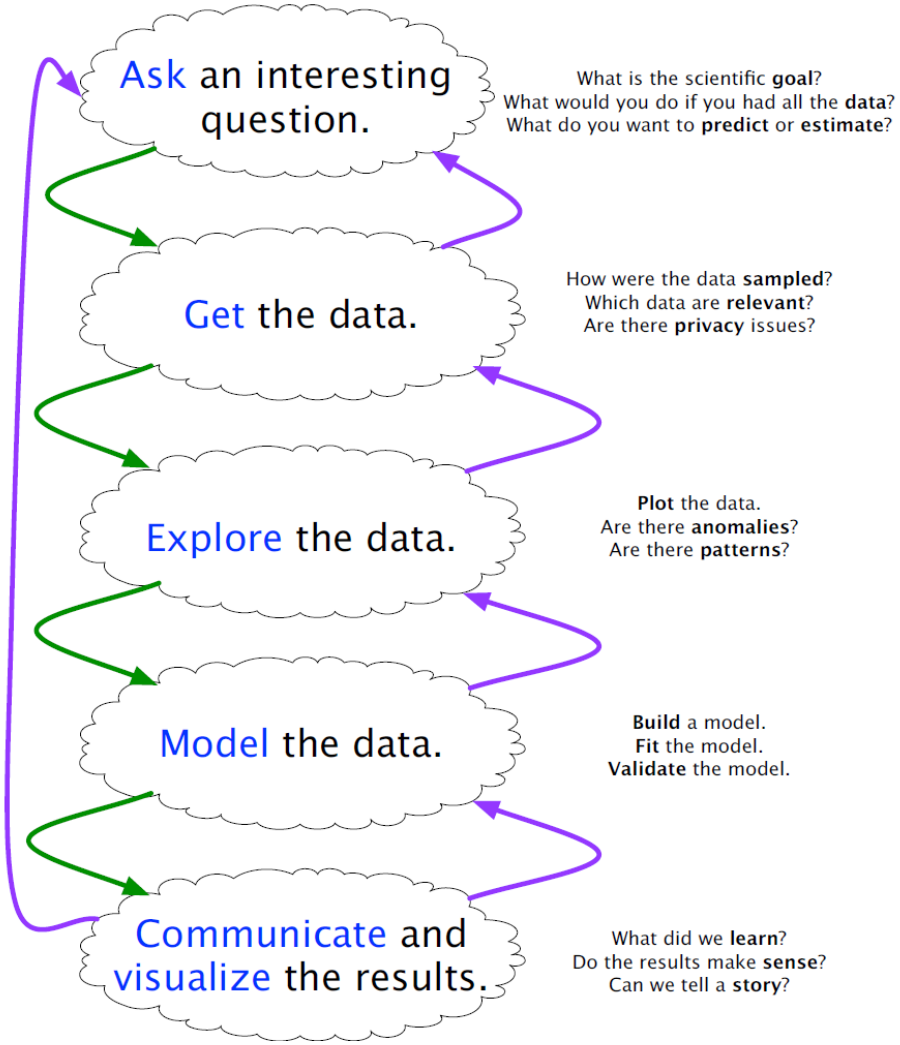
"Data Scientist = statistician + programmer + coach + storyteller + artist"

- Shlomo Aragmon

Hal Varian Explains...

The ability to take **data** – to be able to **understand** it, to **process** it, to **extract value** from it, to **visualize** it, to **communicate** it's going to be a hugely important skill in the next decades, not only at the professional level but even at the educational level for elementary school kids, for high school kids, for college kids. Because now we really do have essentially free and **ubiquitous data**." – Hal Varian

Typical Data Science Pipeline



What do data scientists do?

Enterprise Data Analysis and Visualization: An Interview Study

Sean Kandel, Andreas Paepcke, Joseph M. Hellerstein, and Jeffrey Heer

Abstract—Organizations rely on data analysts to model customer engagement, streamline operations, improve production, inform business decisions, and combat fraud. Though numerous analysis and visualization tools have been built to improve the scale and efficiency at which analysts can work, there has been little research on how analysis takes place within the social and organizational context of companies. To better understand the enterprise analysts' ecosystem, we conducted semi-structured interviews with 35 data analysts from 25 organizations across a variety of sectors, including healthcare, retail, marketing and finance. Based on our interview data, we characterize the process of industrial data analysis and document how organizational features of an enterprise impact it. We describe recurring pain points, outstanding challenges, and barriers to adoption for visual analytic tools. Finally, we discuss design implications and opportunities for visual analysis research.

Index Terms—Data, analysis, visualization, enterprise.

1 Introduction

Organizations gather increasingly large and complex data sets each year. These organizations rely on data analysis to model customer engagement, streamline operations, improve production, inform sales and business decisions, and combat fraud. Within organizations, an increasing number of individuals — with varied titles such as "business analyst", "data analyst" and "data scientist" — perform such analyses. These analysts constitute an important and rapidly growing user population for analysis and visualization tools.

Enterprise analysts perform their work within the context of a larger organization. Analysts often work as a part of an analysis team or business unit. Little research has observed how existing infrastructure, available data and tools, and administrative and social conventions within an organization impact the analysis process within the enterprise. Understanding how these issues shape analytic workflows can inform the design of future tools.

To better understand the day-to-day practices of enterprise analysts ery and wrangling, often the most tedious and time-consuming aspects of an analysis, are underserved by existing visualization and analysis tools. We discuss recurring pain points within each task as well as difficulties in managing workflows across these tasks. Example pain points include integrating data from distributed data sources, visualizing data at scale and operationalizing workflows. These challenges are typically more acute within large organizations with a diverse and distributed set of data sources.

We conclude with a discussion of future trends and the implications of our interviews for future visualization and analysis tools. We argue that future visual analysis tools should leverage existing infrastructures for data processing to enable scale and limit data migration. One avenue for achieving better interoperability is through systems that specify analysis or data processing operations in a high-level language, enabling retargeting across tools or platforms. We also note that the current lack of reusable workflows could be improved via less

What do data scientists do?

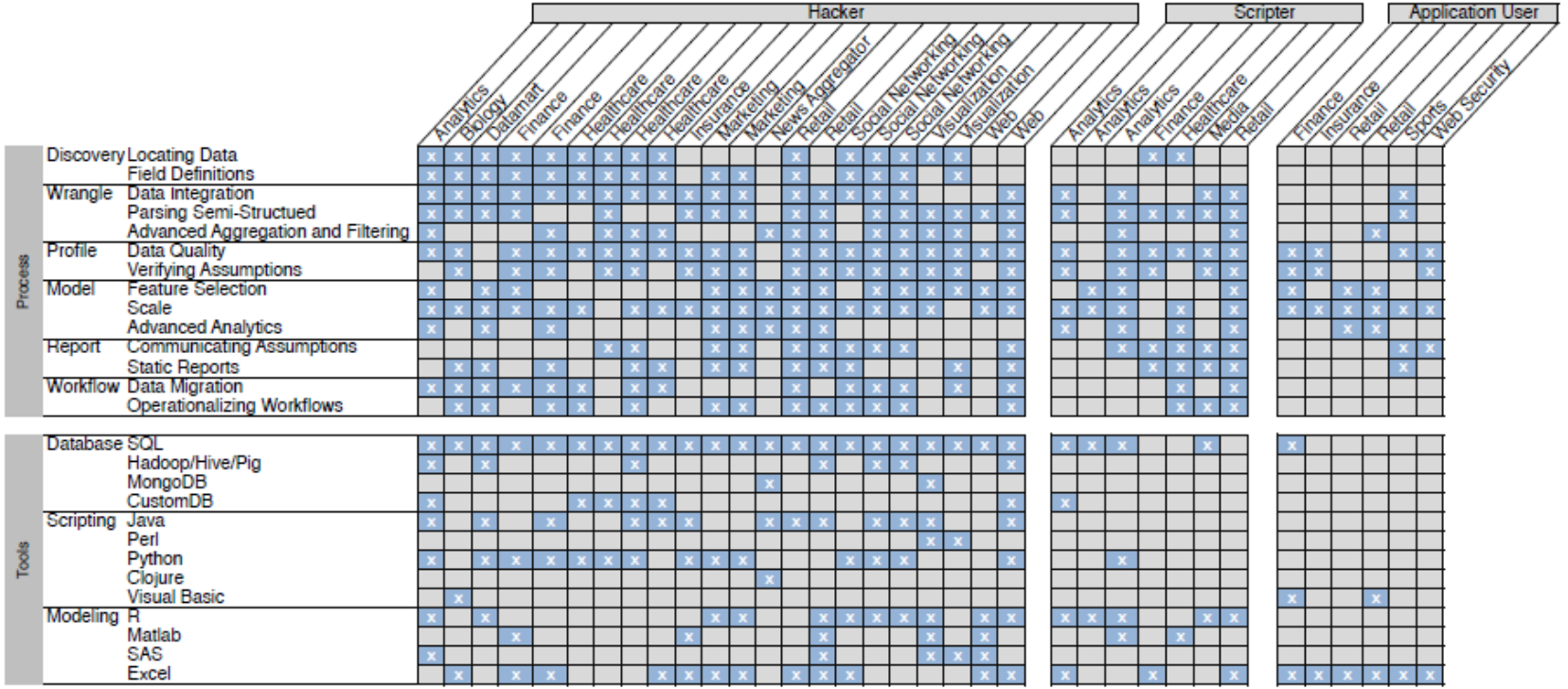


Fig. 1. Respondents, Challenges and Tools. The matrix displays interviewees (grouped by archetype and sector) and their corresponding challenges and tools. *Hackers* faced the most diverse set of challenges, corresponding to the diversity of their workflows and toolset. *Application users* and *scripters* typically relied on the IT team to perform certain tasks and therefore did not perceive them as challenges.

Data Cleaning

"In our experience, the tasks of exploratory data mining and data cleaning constitute 80% of the effort that determines 80% of the value of the ultimate data."

T. Dasu and T. Johnson
Authors of *Exploratory Data Mining and Data Cleaning*

Distinguishing Data Science from...

- *Business Intelligence / Statistics / Database Management / Visualization / Machine Learning*

- If you’re a DBA, you need to learn to deal with unstructured data.
- If you’re a statistician, you need to learn to deal with data that does not fit in memory.
- If you’re a software engineer, you need to learn statistical modeling and how to communicate results.
- If you’re a business analyst, you need to learn about algorithms and tradeoffs at scale.

Industry to be transformed by ML, BD

SEP 27, 2016 @ 01:30 AM 108,681 VIEWS The Little Black Book of Bill

3 Industries That Will Be Transformed By AI, Machine Learning And Big Data In The Next Decade

Bernard Marr, CONTRIBUTOR
I write about big data, analytics and enterprise performance FULL BIO
Opinions expressed by Forbes Contributors are their own.

Historically, when new technologies become easier to use, they transform industries.

That's what's happening with artificial intelligence and big data; as the barriers to implementation disappear (cost, computing power, etc.), more and more industries will put the technologies into use, and more and more startups will appear with new ideas of how to disrupt the status quo with these technologies.

By my predictions, the AI revolution isn't coming, it's already here, and we'll see it first in a few key sectors.

Healthcare

Most people agree that healthcare is broken, and many startups believe that the biggest answer is putting the power back in the hands of the patient.

We're all carrying the equivalent of Star Trek's tricorder around in our

3 Industries to be transformed by ML, BD

1. Healthcare
2. Finance
3. Insurance

Forbes, 2016.09.27

MAY 13, 2017 @ 09:21 PM 72,363

IBM Predicts Demand For Data Scientists Will Soar 28% By 2020

Louis Columbus, CONTRIBUTOR
FULL BIO
Opinions expressed by Forbes Contributors are their own.

- Jobs requiring machine learning skills are paying an average of $114,000. Advertised data scientist jobs pay an average of $105,000 and advertised data engineering jobs pay an average of $117,000.
- 59% of all Data Science and Analytics (DSA) job demand is in Finance and Insurance, Professional Services, and IT.
- Annual demand for the fast-growing new roles of data scientist, data developers, and data engineers will reach nearly 700,000 openings by 2020

IBM Predicts Demand For Data Scientists Will Soar 28% By 2020 (*Forbes, May 13, 2017*)

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https://www.forbes.com/sites/louiscolumbus/2017/05/13/ibm-predicts-demand-for-data-scientists-will-soar-28-by-2020/#375c130f7e3b

Big Data Revolution!

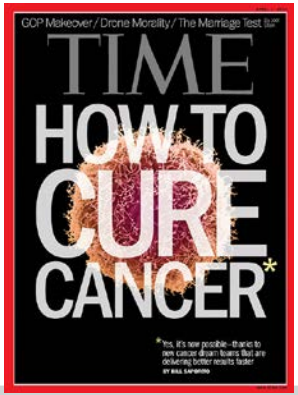
Google

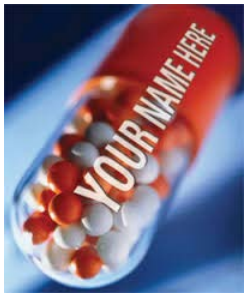
amazon

Walmart

Renaissance

facebook





Topics

- Lec 1: Introduction / Data Munging
- Lec 2: Statistical Analysis / Visualizing Data
- Lec 3: Linear and Logistic Regression / Machine Learning

Cultural Differences between Computer Science and Real Science (1)

Scientists

- Data driven
- Try to understand messy natural world
- Focus on results (findings)
- Discover things
- Data is 1st class citizen

Computer Scientists

- Algorithm driven
- Build their own clean virtual world
- Focus on methods
- Invent things
- Random data ok for prove correctness

Cultural Differences between Computer Science and Real Science (2)

Scientists

- 8/13 ≈ 0.62
- Care what it means
- Nothing is completely true
- Meaning

Computer Scientists

- 8/13 = 0.61538461538
- Care what number is
- Either correct or wrong
- Accuracy

Data Scientists

- Data scientists must learn to think like real scientists.
- Software developers are hired to produce code, while data scientists are hired to produce “ “.

Asking Good Questions

Software developers are not encouraged to ask questions, but data scientists are:

- What exciting things might you be able to learn from a given data set?
- What things do you/your people really want to know?
- What data sets might get you there?

Let’s Practice Asking Questions!

Who, What, Where, When, and Why on the following datasets:

- International Movie Database (IMBb)
- NYC taxi cab records
- Google Trends

IMDb: Movie Data (https://www.imdb.com/)

IMDb: Actor Data (https://www.imdb.com/)

James Stewart (I) (1908–1997)

Top 5000

Actor | Soundtrack | Director

James Maitland Stewart was born on 20 May 1908 in Indiana, Pennsylvania, where his father owned a hardware store. He was educated at a local prep school, Mercersburg Academy, where he was a keen athlete (football and track), musician (singing and accordion playing), and sometime actor. In 1929 he won a place at Princeton, where he studied ... See full bio »

Born: James Maitland Stewart
May 20, 1908 in Indiana, Pennsylvania, USA

Died: July 2, 1997 (age 89) in Los Angeles, California, USA

230 photos | 42 videos | 1180 news articles »

Won 1 Oscar. Another 25 wins & 19 nominations. See more awards »

Cast

Edit

Cast overview, first billed only:

James Stewart	...	George Bailey
Donna Reed	...	Mary Hatch
Lionel Barrymore	...	Mr. Potter
Thomas Mitchell	...	Uncle Billy
Henry Travers	...	Clarence
Beulah Bondi	...	Mrs. Bailey
Frank Faylen	...	Ernie
Ward Bond	...	Bert
Gloria Grahame	...	Violet
H.B. Warner	...	Mr. Gower

Movie Questions

- Predict movie ratings?
- What does the social network of actors look like? (Six degrees of Kevin Bacon, https://oracleofbacon.org/)

NYC Taxi Cab Data

- Gives driver/owner, pickup/dropoff location, and fare data for every taxi trip taken.
- Data obtained from NYC via Freedom of Information Act Request (FOA)

4													
5	Trip data, 2013 ->												
6													
7	medallion	hack_license	vendor_id	rate_code	pickup_datetime	dropoff_datetim	passenger_c	trip_time_	trip_distance	pickup_longitud	pickup_latitude	dropoff_longitude	dropoff_latitude
8	89D227B655E5C82AEC	BA96DE419E7116	CMT	1	1/1/13 15:11	1/1/13 15:18	4	382	1	-73.978165	40.757977	-73.989838	40.751171
9	0BD7C8F5BA12B88E0B	9FD8F69F0804BD	CMT	1	1/6/13 0:18	1/6/13 0:22	1	259	1.5	-74.006683	40.731781	-73.994499	40.75066
10	0BD7C8F5BA12B88E0B	9FD8F69F0804BD	CMT	1	1/5/13 18:49	1/5/13 18:54	1	282	1.1	-74.004707	40.73777	-74.009834	40.726002
11	...												
12													
13													
14	Fare data, 2013 ->												
15													
16	medallion	hack_license	vendor_id	pickup_datetime	fare_amount	surcharge	mta_tax	tip_amou	tolls_amount	total_amount			
17	89D227B655E5C82AEC	BA96DE419E7116	CMT	1/1/13 15:11	6.5	0	0.5	0	0	7			
18	0BD7C8F5BA12B88E0B	9FD8F69F0804BD	CMT	1/6/13 0:18	6	0.5	0.5	0	0	7			
19	0BD7C8F5BA12B88E0B	9FD8F69F0804BD	CMT	1/5/13 18:49	5.5	1	0.5	0	0	7			

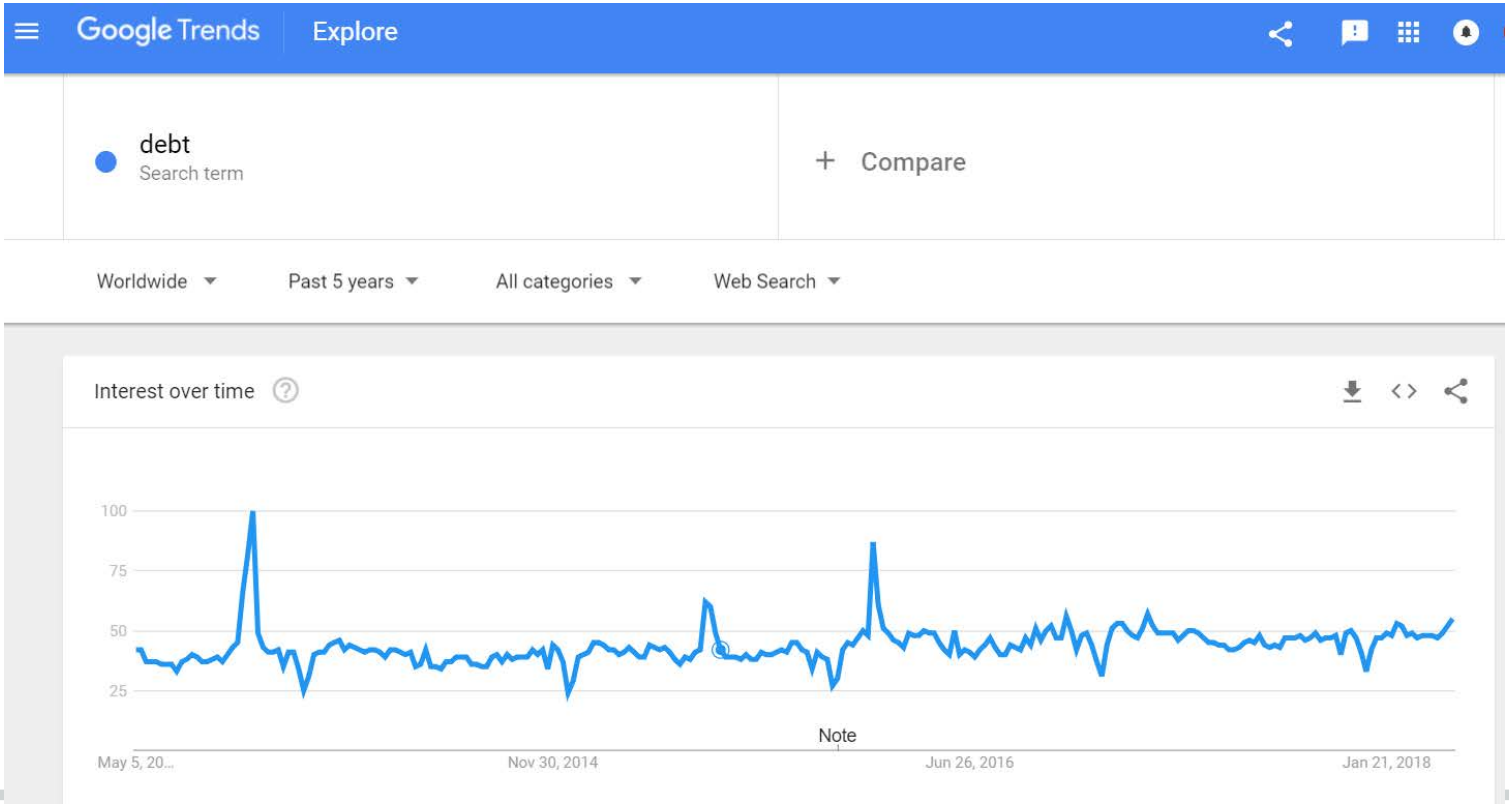
Taxicab Questions

- How much do drivers make each night?
- How far do they travel?

Google Trends

- Shows how often a particular search-term is entered relative to the total search-volume across various regions of the world, and in various languages.
- Allows users to compare the relative search volume of searches between two or more terms.

Google Trends (https://trends.google.com/trends/)



An Example…

OPEN

SUBJECT AREAS:

STATISTICAL PHYSICS, THERMODYNAMICS AND NONLINEAR DYNAMICS

APPLIED PHYSICS

COMPUTATIONAL SCIENCE

INFORMATION THEORY AND COMPUTATION

Received
25 February 2013

Accepted
3 April 2013

Quantifying Trading Behavior in Financial Markets Using *Google Trends*

Tobias Preis[1]*, Helen Susannah Moat[2,3]* & H. Eugene Stanley[2]*

[1]Warwick Business School, University of Warwick, Scarman Road, Coventry, CV4 7AL, UK, [2]Department of Physics, Boston University, 590 Commonwealth Avenue, Boston, Massachusetts 02215, USA, [3]Department of Civil, Environmental and Geomatic Engineering, UCL, Gower Street, London, WC1E 6BT, UK.

Crises in financial markets affect humans worldwide. Detailed market data on trading decisions reflect some of the complex human behavior that has led to these crises. We suggest that massive new data sources resulting from human interaction with the Internet may offer a new perspective on the behavior of market participants in periods of large market movements. By analyzing changes in *Google* query volumes for search terms related to finance, we find patterns that may be interpreted as "early warning signs" of stock market moves. Our results illustrate the potential that combining extensive behavioral data sets offers for a better understanding of collective human behavior.

An Example…Cont'd

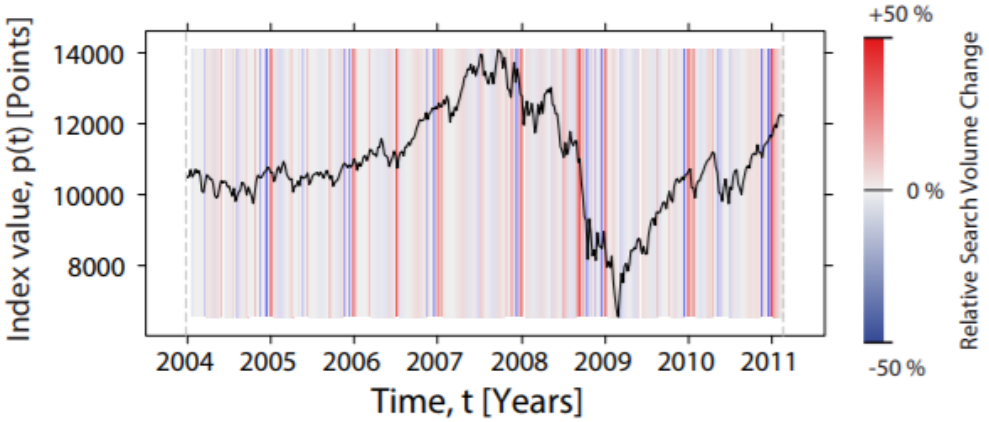


Figure 1 | Search volume data and stock market moves. Time series of closing prices $p(t)$ of the *Dow Jones Industrial Average* (DJIA) on the first day of trading in each week t covering the period from 5 January 2004 until 22 February 2011. The color code corresponds to the relative search volume changes for the search term *debt*, with $\Delta t = 3$ weeks. Search volume data are restricted to requests of users localized in the United States of America.

An Example…Cont'd

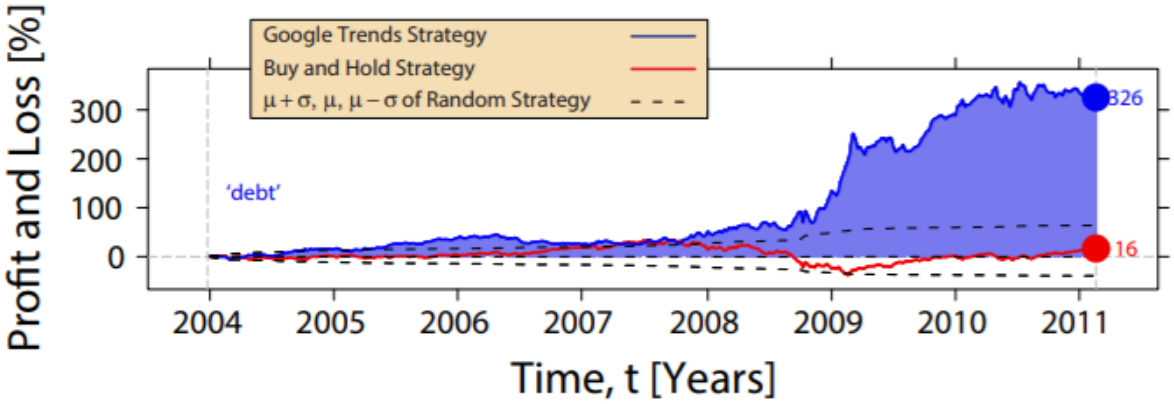
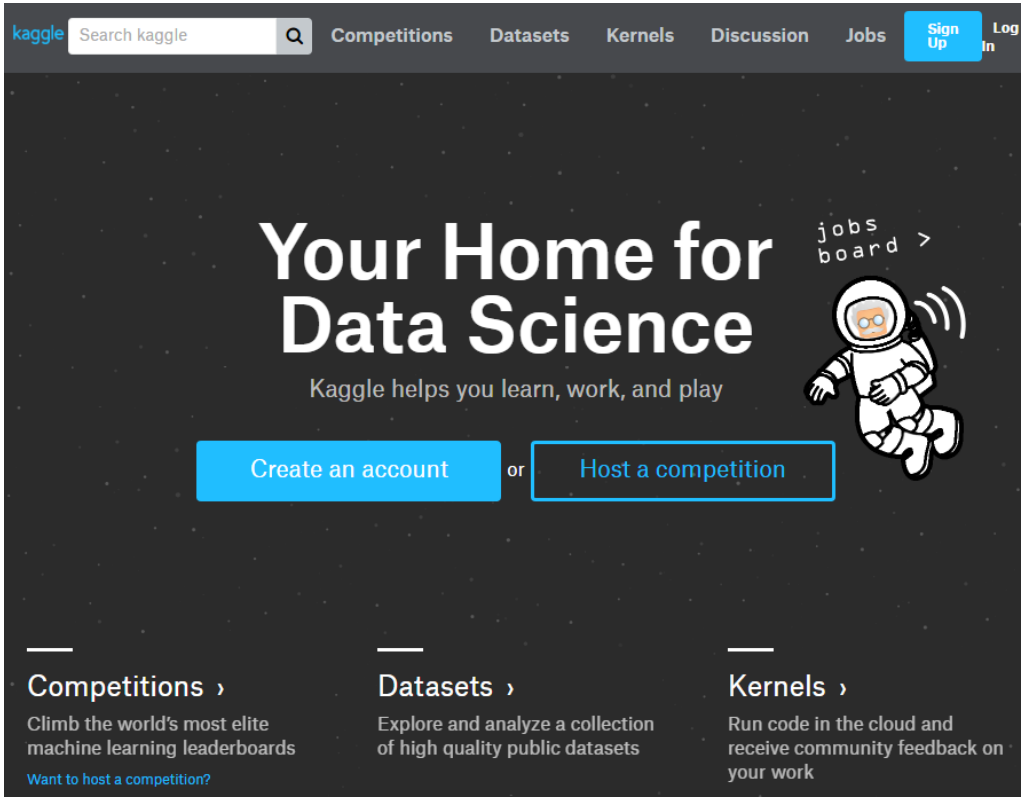


Figure 2 | Cumulative performance of an investment strategy based on *Google Trends* data. Profit and loss for an investment strategy based on the volume of the search term *debt*, the best performing keyword in our analysis, with $\Delta t = 3$ weeks, plotted as a function of time (*blue line*). This is compared to the "buy and hold" strategy (*red line*) and the standard deviation of 10,000 simulations using a purely random investment strategy (*dashed lines*). The *Google Trends* strategy using the search volume of the term *debt* would have yielded a profit of 326%.

Data Science Challenges

- Kaggle (https://www.kaggle.com/)
  - a platform for predictive modelling and analytics competitions.
- DreamChallenge (http://dreamchallenges.org/)
  - poses fundamental questions about systems biology and translational medicine.

Kaggle - data science projects



9 active competitions

Sort By Prize

Active All Entered

All Categories

Data Science Bowl 2017

Can you improve lung cancer detection?

Featured · A month to go · 688 kernels

$1,000,000

1,339 teams

The Nature Conservancy Fisheries Monitoring

Can you detect and classify species of fish?

Featured · A month to go · 326 kernels

$150,000

1,730 teams

Google Cloud & YouTube-8M Video Understanding Challenge

Can you produce the best video tag predictions?

Featured · 3 months to go · 63 kernels

$100,000

220 teams

Dstl Satellite Imagery Feature Detection

Can you train an eye in the sky?

Featured · A day to go · 174 kernels

$100,000

409 teams

Two Sigma Connect: Rental Listing Inquiries

How much interest will a new rental listing on RentHop receive?

Recruitment · 2 months to go · 348 kernels

Jobs

927 teams

Data Science Bowl 2017

Can you improve lung cancer detection?

$1,000,000 · 1,339 teams · a month to go (25 days to go until merger deadline)

- **March 31, 2017** - Entry deadline. You must accept the competition rules before this date in order to compete.
- **March 31, 2017** - Team merger deadline. This is the last day participants may join or merge teams.
- **April 7, 2017** - Stage one deadline and stage two data release. Your model must be finalized and uploaded to Kaggle by this deadline. After this deadline, the test set is released, the answers to the validation set are released, and participants make predictions on the test set. ***PLEASE NOTE: If you do not make a submission during the second stage of the competition, you will not appear on the final competition leaderboard and you will not receive competition ranking points.***
- **April 12, 2017** - Final submission deadline.

All deadlines are at 11:59 PM UTC on the corresponding day unless otherwise noted. The competition organizers reserve the right to update the contest timeline if they deem it necessary.

Data Science Bowl 2017

Can you improve lung cancer detection?

$1,000,000 · 1,339 teams · a month to go (25 days to go until merger deadline)

- 1st place - $500,000
- 2nd place - $200,000
- 3rd place - $100,000
- 4th place - $25,000
- 5th place - $25,000
- 6th place - $25,000
- 7th place - $25,000
- 8th place - $25,000
- 9th place - $25,000
- 10th place - $25,000
- $5,000 each to the top three most highly voted Kernels (Total of $15,000)

Data Science Bowl 2017

Can you improve lung cancer detection?

$1,000,000 · 1,339 teams · a month to go (25 days to go until merger deadline)

Overview | Data | Kernels | Discussion | **Leaderboard** | More | **Submit Predictions**

Public Leaderboard | Private Leaderboard

This leaderboard is calculated with all of the test data. Raw leaderboard data | Refresh

#	△1w	Team Name * in the money	Kernel	Team Members	Score	Entries	Last
1	—	* Oleg Trott			0.00000	16	2mo
2	▲ 11...	* myunggi			0.00000	5	5d
3	▲ 12...	* ccc12345			0.00000	18	4d
4	new	* Vijay			0.00000	7	3d
5	new	* jiwupeng			0.00000	4	3d
6	▲ 12...	* dtw_2017			0.34888	29	5d
7	▲ 43	* yarn			0.35344	17	8h

Jobs • 175 teams

Yelp Restaurant Photo Classification

Mon 21 Dec 2015 — Tue 12 Apr 2016 (35 days to go)

Dashboard

Home
- Data
- Make a submission

Information
- Description
- Evaluation
- Rules
- Jobs at Yelp
- Timeline

Forum

Scripts
- New Script
- New Notebook

Leaderboard

My Submissions

Public Leaderboard

1. u1234x1234
2. John Armstrong
3. Plankton
4. Pavel Gonchar
5. Zimovnov Andrey

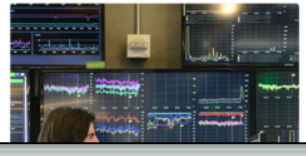
Competition Details » Get the Data » Make a submission

Predict attribute labels for restaurants using user-submitted photos

Does your favorite Ethiopian restaurant take reservations? Will a first date at that authentic looking bistro break your wallet? Is the diner down the street a good call for breakfast? Restaurant labels help Yelp users quickly answer questions like these, narrowing down their results to only restaurants that fit their nuanced needs.

In this competition, Yelp is challenging Kagglers to build a model that automatically tags restaurants with multiple labels using a dataset of user-submitted photos. Currently, restaurant labels are manually selected by Yelp users when they submit a review. Selecting the labels is optional, leaving some restaurants un- or only partially-categorized.

In an age of food selfies and photo-centric social storytelling, it may be no surprise to hear that Yelp's users upload an enormous amount of photos every day alongside their written reviews. Can you turn their pictures into (less than a thousand) words?



5. Zimovnov Andrey
6. y
7. Jesse Hull
8. Alexander Bauer
9. vgng
10. course project 2

76 Scripts

Expensive restaurants look like this
17 Votes / 33 days ago / Python

util for data exploration
6 Votes / 33 days ago / Python

load_data with get_dummies
1 Vote / 8 days ago / Python

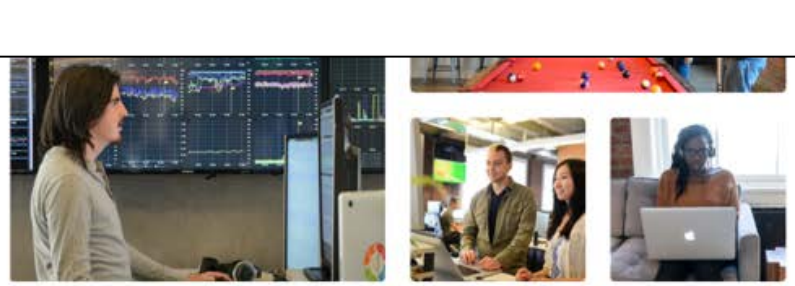
Naive Benchmark (0.61)
2 Votes / 27 days ago / Python

deneme1
0 Votes / 3 days ago / R

Random guess
1 Vote / 29 days ago / Python

Forum (24 topics)

Deep learning starter code



Yelp isn't only looking for your best model; we're looking for data mining engineers that can help us use our data in novel ways while pushing code to production. The prize for this competition is a fast track through the recruiting process and an opportunity to show our data mining teams just what you've got! For more information about exciting opportunities at Yelp, check out the Jobs at Yelp competition page and Yelp's own careers page.

Started: 6:37 pm, Monday 21 December 2015 UTC
Ends: 11:59 pm, Tuesday 12 April 2016 UTC (113 total days)
Points: this competition awards standard ranking points
Tiers: this competition counts towards tiers

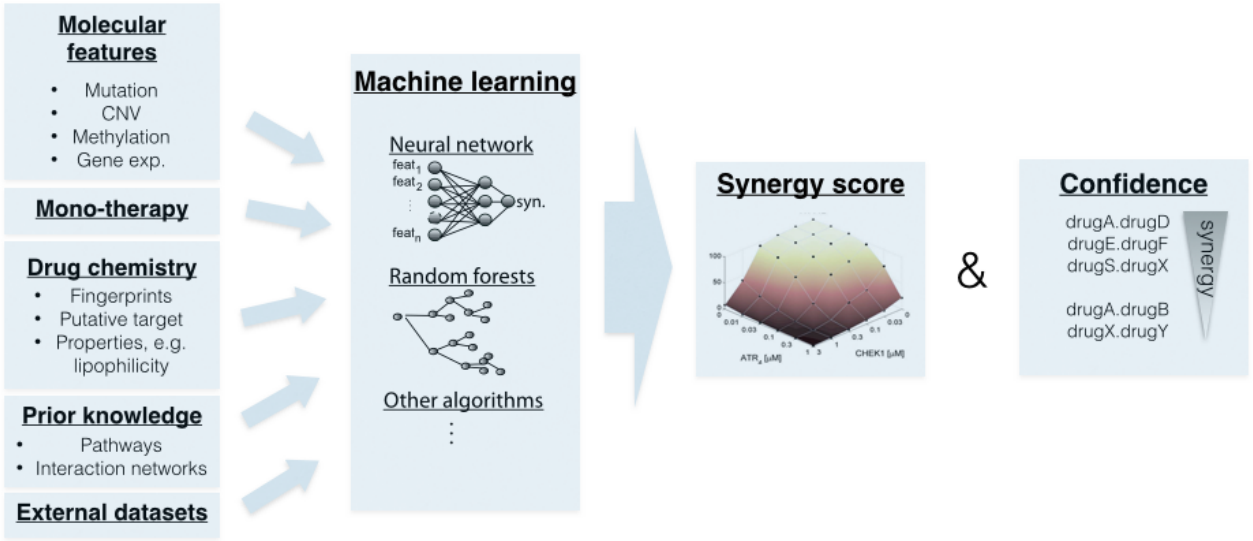
DreamChallenges – Kaggle of Bio-medicine

Drug Combination Prediction DREAM Challenge

- Community challenge to explore fundamental traits that underlie effective combinational treatments and synergistic drug behavior, using baseline genetic data in a large panel of cell lines.

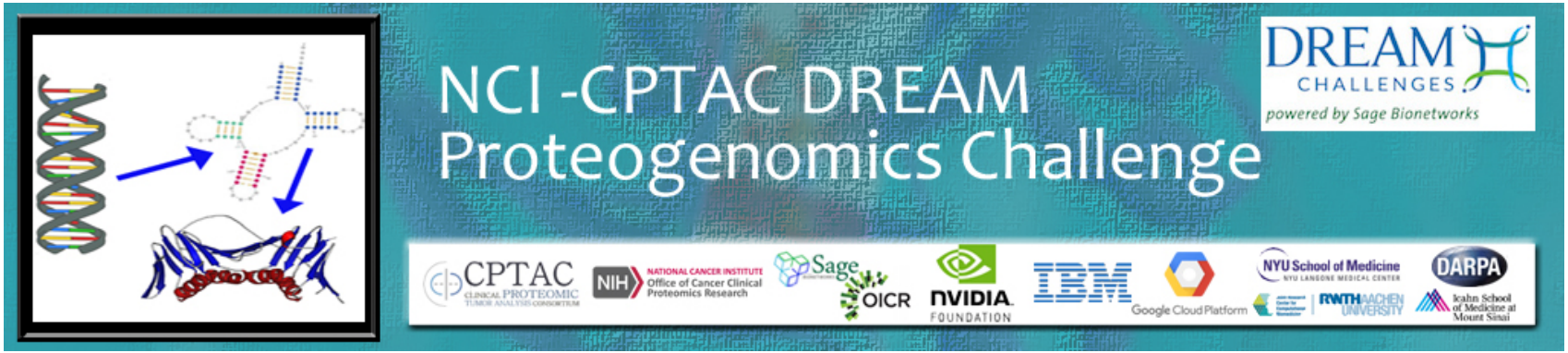
- 85 cell lines from 8 tissues and combination of 118 unique drugs were provided.

Subchallenge 1-A



- Predict drug synergy of 167 combinations in the panel of 85 cell lines
  - -Training set size : 2749
  - -Test set size : 1090
- Predict drug synergy from all available data using Machine learning model

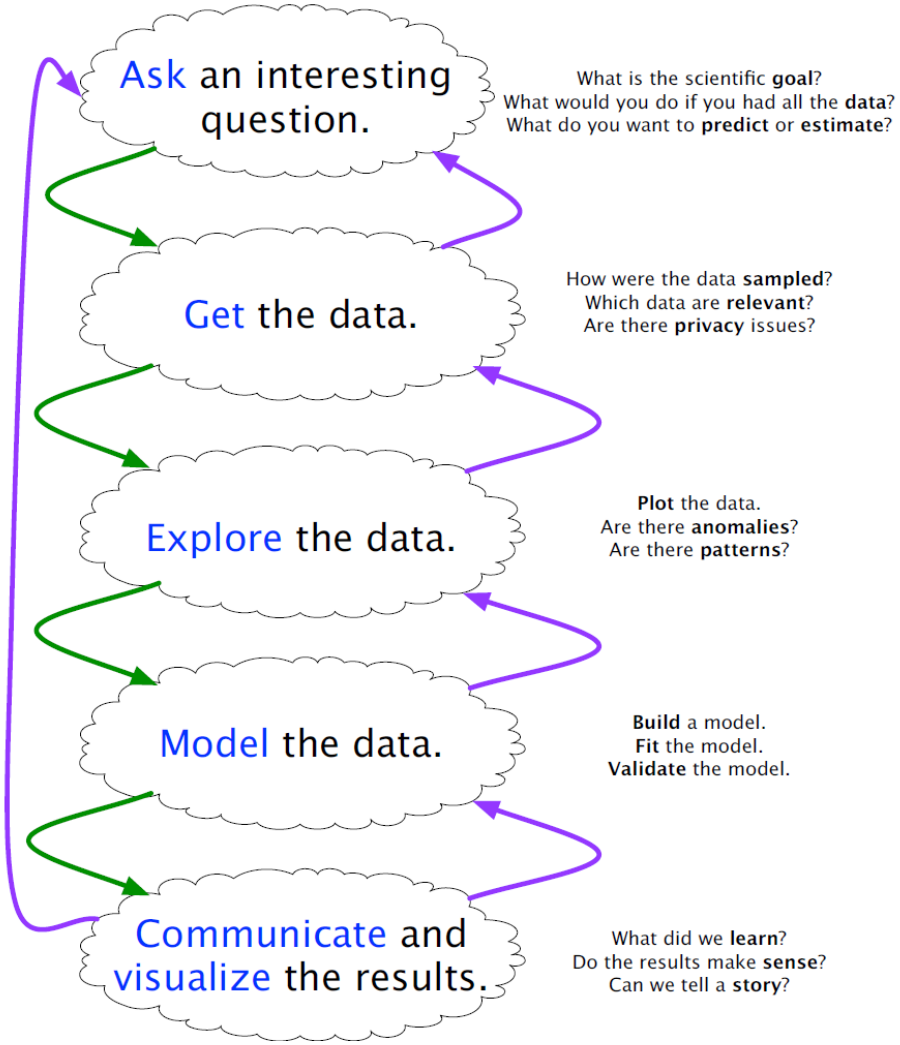
NCI-CPTAC DREAM Proteogenomics Challenge



- Community challenge to understand the association between genome, trascriptome and proteome in tumors.
- Participants are challenged to predict protein abundances based on public and novel proteogenomics dataset.

Data Munging

Typical Data Science Pipeline



Data Munging

Good data scientists spend most of their time cleaning and formatting data.

The rest spend most of their time complaining there is no data available.

Data munging or *data wrangling* is the art of acquiring data and preparing (cleaning) it for analysis.

Languages for Data Science

- *Python*: contains libraries and features (e.g regular expressions) for easier munging.

- *R*: programming language of statisticians.

- *Matlab*: fast and efficient matrix operations.
- *Java/C++*: language for Big Data systems.

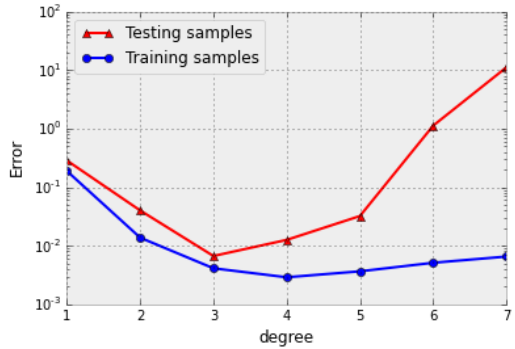
- *Excel*: bread and butter tool for exploration.

Notebook Environments

Result of data science project should be a computable notebook tying together the code, data, computational results, and written analysis.

- reproducible
- tweakable
- documented

In [40]:
```
degrees = range(1, 8)
errors = np.array([regressor3(d) for d in degrees])
plt.plot(degrees, errors[:, 0], marker='^', c='r', label='Testing samples
plt.plot(degrees, errors[:, 1], marker='o', c='b', label='Training sample
plt.yscale('log')
plt.xlabel("degree"); plt.ylabel("Error")
  = plt.legend(loc='best')
```



By sweeping the degree we discover two regions of model performance:

- **Underfitting** (degree < 3): Characterized by the fact that the testing error will get lower if we increase the model capacity.
- **Overfitting** (degree > 3): Characterized by the fact the testing will get higher if we increase the model capacity. Note, that the training error is getting lower or just staying the same!.

Acquiring Data

- Mostly mean “find stuff on the internet!”
- A lot of data stored in text files and on government websites
- Files (CSV, XML, JSON)
- Databases (SQL server)
- API (Application Programming Interface)
- Web Scraping (HTML)

Common Data Formats

- CSV (Comma-Separated Values)

```
StudentID, Name, Dept, Birthdate, Gender, AdvisorID, GPA
3219875, Lee Sedol, CS, 2000/1/1, M, 111212, 3.7
3219774, Alpha Go, CS, 2007/2/7,, 223123, 4.5
3219875, Hong Gildong, CS, 9999/9/9, M, 111212, -0.5
                                                    :
```

StudentID	Name	Dept	Birthdate	Gender	AdvisorID	GPA
3219875	Lee Sedol	CS	2000/1/1	M	111212	3.7
3219774	Alpha Go	CS	2007/2/7		223123	4.5
3219875	Hong Gildong	CS	9999/9/9	M	111212	-0.5

- XML (eXtensible Markup Language)

```
<Document Element>
        <Student Table>
                <Student>
                        <StudentID> 3219875 </StudentID>
                        <Name> Lee Sedol </Name>
                        <Dept> CS </Dept>
                        <Birthdate> 2000/1/1 </Birthdate>
                        <Gender> M </Gender>
                        <AdvisorID> 111212 </AdvisorID>
                        <GPA> 3.7 </GPA>
                </Student>
                <Student>
                        <StudentID> 3219774 </StudentID>
                        <Name> Alpha Go </Name>
                        <Dept> CS </Dept>
                                :
```

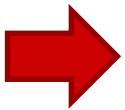
- JSON (JavaScript Object Notation)

```
{
    “sedol”: {
                    “StudentID”: 3219875,
                    “Name”: “Lee Sedol”,
                    “Dept”: “CS”,
                    “Birthdate”: 2000/1/1,
                    “Gender”: “M”,
                    “AdvisorID”: 111212,
                    “GPA”: 3.7
                    }
    “alpha”: {
                    “StudentID”: 3219774
                    “Name”: “Alpha Go”
                    “Dept”: “CS”
                                :
```

Loading data from files (CSV example)

```
import pandas
student_data = pandas.read_csv("student_table.csv")
```

StudentID, Name, Dept, Birthdate, Gender, AdvisorID, GPA
3219875, Lee Sedol, CS, 2000/1/1, M, 111212, 3.7
3219774, Alpha Go, CS, 2007/2/7,, 223123, 4.5
3219875, Hong Gildong, CS, 9999/9/9, M, 111212, -0.5
:



Pandas dataframe

- Loading data from XML and JSON files is similar

Getting data from Relational DB

```
import pandas
student_data = pandas.read_sql_query(sql_string, db_uri)
```

StudentID	Name	Dept	Birthdate	Gender	AdvisorID	GPA
3219875	Lee Sedol	CS	2000/1/1	M	111212	3.7
3219774	Alpha Go	CS	2007/2/7		223123	4.5
3219875	Hong Gildong	CS	9999/9/9	M	111212	-0.5

- SELECT * FROM student_table
- SELECT studentid, name FROM student_table WHERE gpa > 3.5
- SELECT S.name, A.name
  FROM student_table S, advisor_table A
  WHERE S.advisorid = A.id

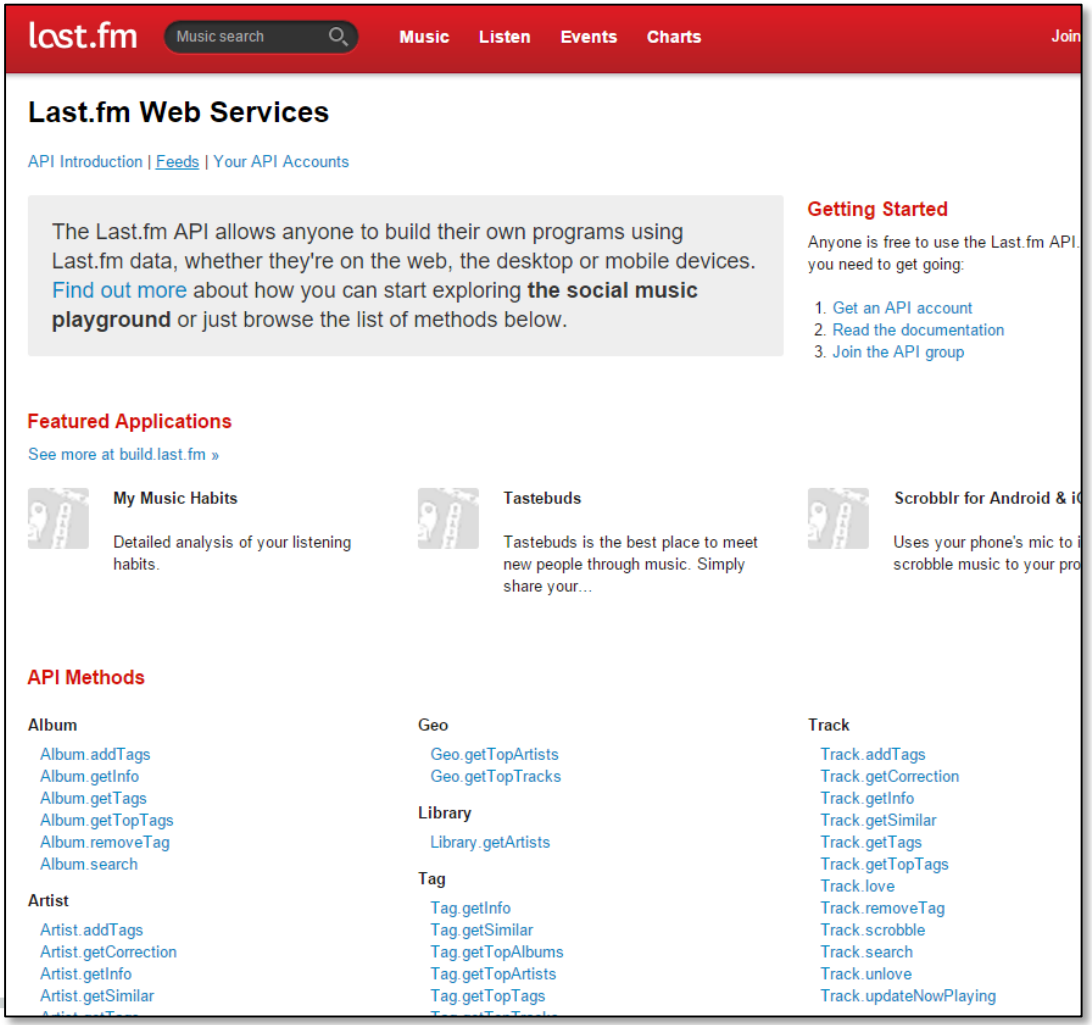
StudentID	Name	Dept	Birthdate	Gender	AdvisorID	GPA
3219875	Lee Sedol	CS	2000/1/1	M	111212	3.7
3219774	Alpha Go	CS	2007/2/7		223123	4.5
3219875	Hong Gildong	CS	9999/9/9	M	111212	-0.5

- SELECT S.advisorid, avg(S.gpa)
  FROM student_table S
  GROUP BY S.advisorid

- SELECT S.advisorid, sum(S.gpa)
  FROM student_table S
  WHERE S.birthdate >= 2000/1/1 AND S.birthdate < 2010/1/1
  GROUP BY S.advisorid

Getting data using API

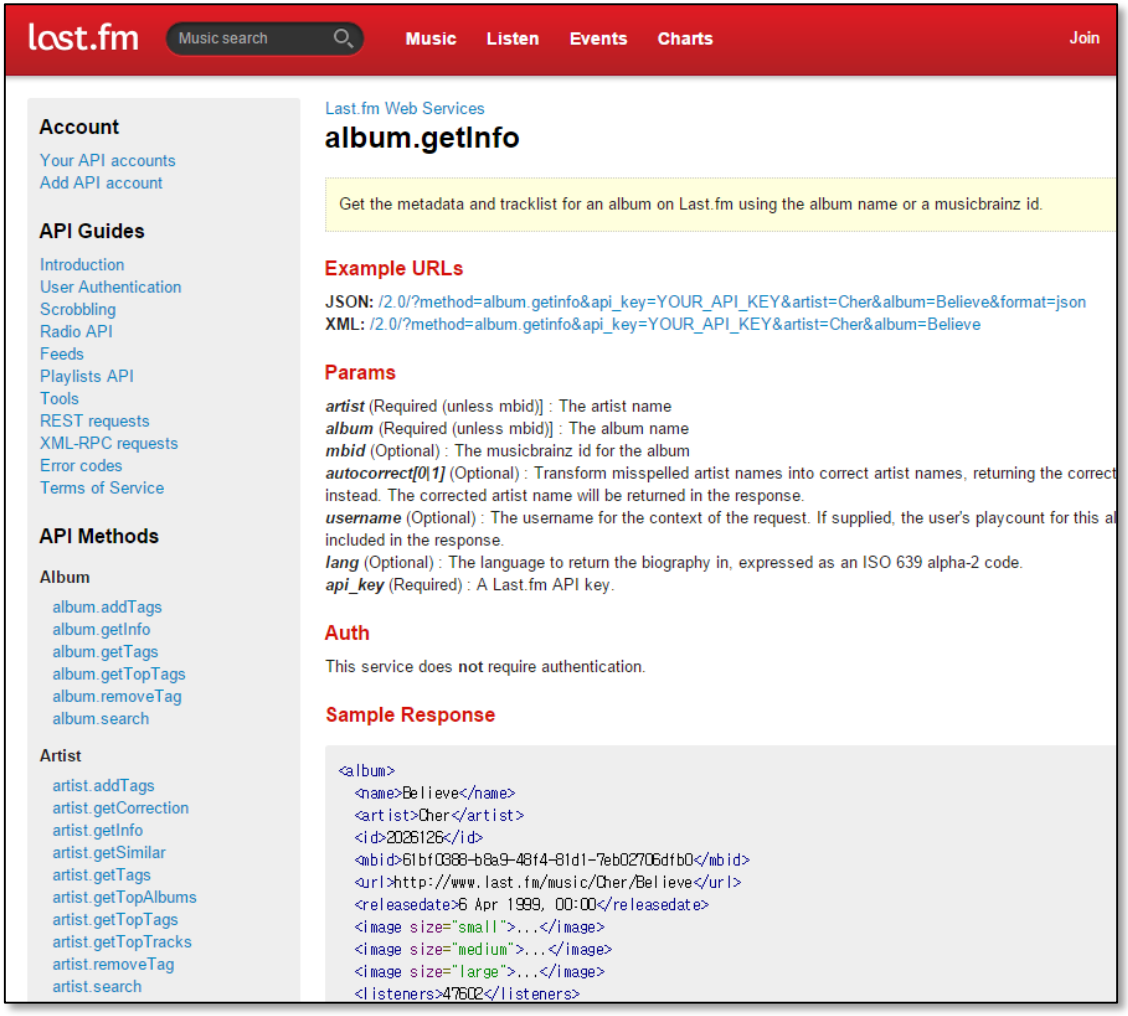
- REST (Representational State Transfer) API



REST (Last.fm): album info

/2.0/?method=album.getinfo&api_key=KEY&artist=Cher&album=Believe

```
<album>
  <name>Believe</name>
  <artist>Cher</artist>
  <id>2026126</id>
  <mbid>61bf0388-b8a9-48f4-81d1-7eb02706dfb0<
  <url>http://www.last.fm/music/Cher/Believe<
  <releasedate>6 Apr 1999, 00:00</releasedate
  <image size="small">...</image>
  <image size="medium">...</image>
  <image size="large">...</image>
  <listeners>47602</listeners>
  <playcount>212991</playcount>
  <toptags>
    <tag>
      <name>pop</name>
      <url>http://www.last.fm/tag/pop</url>
    </tag>
```



Getting data using API

```
import json
import requests
url =
‘http://ws.audioscrobbler.com/2.0/?method=album
.getinfo&api_key=KEY&artist=Cher&album=Believe&
format=json’
data = requests.get(url).text
parsed_data = json.loads(data)
```

Web Scraping (HTML DOM)

Document Object Model: the hierarchical structure of HTML

```
<html>
	<head>
		<title> Data Science </title>
	</head>

	<body>
		<h1>Hello World!</h1>
		<p> Welcome to COSE 471 Data Science </p>
	</body>
</html>
```

Sources of Data

- Proprietary data sources
- Government data sets
- Academic data sets
- Web search /Scraping
- Sensor data
- Crowdsourcing
- Sweat equity

Proprietary Data Sources

Facebook, Google, Amazon, Blue Cross, etc. have exciting user/transaction/log data sets.

Most organizations have/should have internal data sets of interest to their business.

Companies sometimes release rate-limited APIs, including Twitter and Google.

Proprietary Data Sources

However, getting outside access to proprietary corporate data is usually difficult for two reasons:

- Business issues: fear of helping competitors
- Privacy issues: fear of offending customers

Case Study: 2006 AOL search log release

- What business and privacy issues were there?

Government Data Sources

- City, State, and Federal governments are increasingly committed to open data.
- Data.gov has over 100,000 open data sets!
- The Freedom of Information Act (FOI) enables you to ask if something is not open.
- Preserving privacy is often the big issue in whether a data set can be released.

Academic Data Sets

- Making data available is now a requirement for publication in many fields.
- Expect to be able to find economic, medical, demographic, and meteorological data if you look hard enough.
- Track down from relevant papers.
  - Find links to data, if none, ask authors.

Web Search/Scraping

Scraping is the fine art of stripping text/data from a webpage.

Libraries exist in Python to help parse/scrape the web, but first search:

- Are APIs available from the source?
- Did someone previously write a scraper?

Terms of service limit what you can legally do.

Available Data Sources

- Bulk Downloads: e.g. Wikipedia, IMDB, Million Song Database.
- API access: e.g. New York Times, Twitter, Facebook, Google.

Be aware of limits and terms of use.

Crowdsourcing

Many amazing open data resources have been built up by teams of contributors:

- Wikipedia/Freebase
- IMDB

Crowdsourcing platforms like Amazon Turk and CrowdFlower enable you to pay for armies of people to help you gather data, like human annotation.

Cleaning Data: Garbage In, Garbage Out

Many issues can arise in cleaning data for analysis:

- Distinguishing errors from artifacts.
- Data compatibility / unification.
- Imputation of missing values.
- Estimating unobserved (zero) counts.
- Outlier detection.

Errors vs. Artifacts

- Data errors represent information that is fundamentally lost in acquisition.
- Artifacts are systematic problems arising from data processing.

The key to detecting artifacts is the sniff test, examining the product closely enough to get a whiff of something bad.

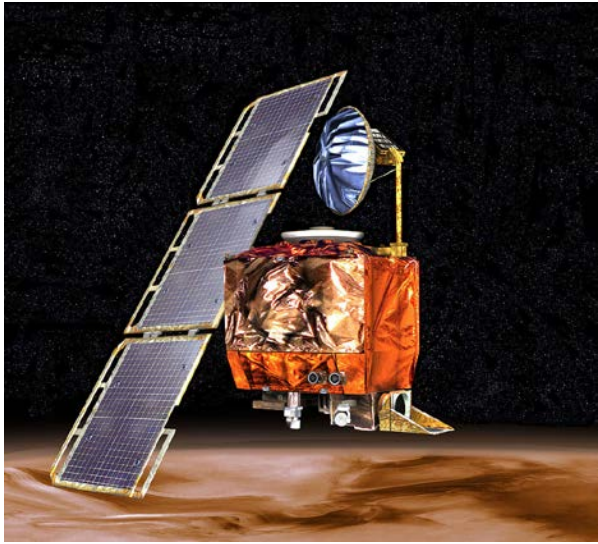
Data Compatibility

Data needs to be carefully massaged to make ``apple to apple'' comparisons:

- Unit conversions
- Number / character code representations
- Name unification
- Time/date unification
- Financial unification

Unit Conversions

NASA’s Mars Climate Orbiter lost in 1999 due to a unit conversion issue between metric unit (kg, m) and US customary unit (lb, ft).



- Even sticking to the metric system has potential inconsistencies: cm, m, km?
- Bimodal distributions can indicate trouble
- Z-scores are dimensionless quantities.

Vigilance in data integration is essential.

Number / Character Representations

The Ariane 5 rocket exploded in 1996 due to a bad 64-bit float to 16-bit integer conversion.

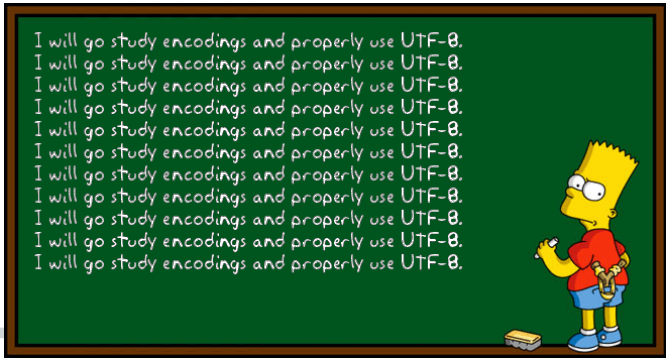
- Avoid integer approximation of real numbers
- Measurements should generally be decimal numbers
- Counts should be integers.
- Fractional quantities should be decimal, not (q,r) like (pounds,ounce) or (feet,inches).

Character Representations

A particularly nasty cleaning issue in textual data is unifying character code representations:

- ISO 8859-1 is a single byte code for ASCII
- UTF-8 is a multibyte encoding for all Unicode characters.

Unicode font, UTF8 format	Unicode font, XXX... format
搜索简体中文网页	????????
Recherche avancée	Recherche avancée
網路畫廊，含中、港、澳參展作品	????????????????
โทรด ดง่ายกว่า	????????????????
ウエブ全体から	???????
kehren Sie zur Suche zurück	kehren Sie zur Suche zurück
Сделайте Google стартово	???????? Google ????????
إخدوقت بحث أقل ووقت مطالعة أطول	?????? ??? ??? ???? ?????? ????



Name Unification

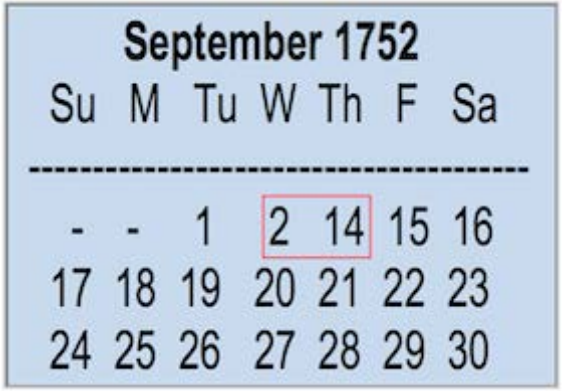
Same person appears on the web as:

(Steve|Steven|S.) (S.|Sol|_) (Skiena|Skeina|Skienna)

- Use simple transformations to unify names, like lower case, removing middle names or use initials instead, etc.

Tradeoff between false positives and negatives.

Time / Date Unification



Aligning temporal events from different datasets/systems can be problematic.

- Use Coordinated Universal Time (UTC), a modern standard subsuming GMT.
- Financial time series are tricky because of weekends and holidays: how do you correlate stock prices and temperatures?

Financial Unification

- Currency conversion uses exchange rates.
- Use returns / percentage change instead of absolute price changes.
- Correct stock prices for splits and dividends.
- The time value of money needs correction for inflation for fair long-term comparisons.

Dealing with Missing Data

An important aspect of data cleaning is properly representing missing data:

- What is the year of death of a living person?
- What about a field left blank or filled with an obviously outlandish value?
- The frequency of events too rare to see?

Setting such values to zero is generally wrong

Imputing Missing Values

With enough training data, one might drop all records with missing values, but we may want to use the model on records with missing fields.

Often it is better to estimate or impute missing values instead of leaving them blank.

Imputation Methods

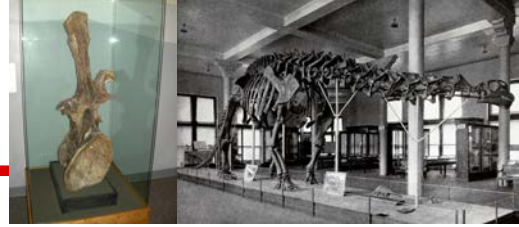
- *Heuristic-based imputation* – a good guess for your death year is birth year+80.
- *Mean value imputation* - leaves mean same.
- *Random value imputation* - repeatedly selecting random values permits statistical evaluation of the impact of imputation.

Imputation Methods

- *Imputation by nearest neighbor* – identify closest record and use it to infer the missing values.

- *Imputation by interpolation* - using linear regression to predict missing values works well if few fields are missing per record.

Outlier Detection



The largest reported dinosaur vertebra is 50% larger than all others: presumably a data error.

- Look critically at the maximum and minimum values for all variables.
- Normally distributed data should not have large outliers, *k sigma* from the mean.

Fix why you have an outlier. Don’t just delete.

Detecting Outliers

- Visually, it is easy to detect outliers, but only in low dimensional spaces.
- It can be thought of as an unsupervised learning problem, like clustering.
- Points which are far from their cluster center are good candidates for outliers

Normalization and Z-scores

It is critical to normalize different variables to make their range/distribution comparable.

Z-scores are computed:

$$Z_i = (X_i - \bar{X})/\sigma$$

Z-scores of height measured in inches is the same as height measured in miles.

Z-scores have mean 0 and sigma=1.

Z-score Examples

The sign identifies if it is above/below the mean.

Thus Z-scores of different variables are of comparable magnitude.