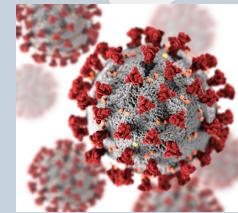
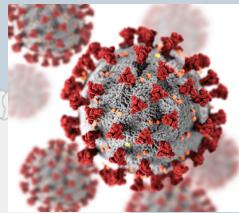


Overview of Data Science

Promises and Pitfalls, Tools and Techniques

Professor Widom's Instructional Odyssey
www.professorwidom.org

COVID Edition



 Stanford University

Google



Association for
Computing Machinery

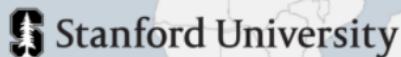


Very Large Data Bases
Endowment Inc.



The “Instructional Odyssey”

STANFORD COMPUTER SCIENCE
PROFESSOR OFFERS FREE IN-PERSON
SHORT-COURSES AND WORKSHOPS,
WORLDWIDE



Jennifer Widom, Stanford computer science professor, school of engineering dean, and MOOC pioneer, has traveled the globe offering free short-courses in data science, workshops in design thinking & collaborative problem-solving, and roundtables with women in technology. She began the odyssey full-time during her 2016-17 sabbatical year and has continued since then on an occasional basis. Navigate the website to learn more about Professor Widom and her motivation for the endeavor, to see details about the courses and workshops offered, to locate course materials, social media, and participant feedback, and to find out how to be an institutional host.



Stanford University

Locations (2016-2020)



The Second “COVID Edition”



Overview of Data Science

Promises and Pitfalls, Tools and Techniques



Here we go!



Association for
Computing Machinery



Very Large Data Bases
Endowment Inc.



Data is Everywhere

- Explosion in data-driven scientific discovery, business practices, medicine, education, politics, societal interventions, ...
- And it's just the beginning
 - Ability to collect data across many domains will continue to accelerate
 - Data analysis techniques will continue to improve

“Data is the oil of the 21st century”



Data is Everywhere

- Explosion in data-driven scientific discovery, business practices, medicine, education, politics, societal interventions, ...
- And it's just the beginning
 - Ability to collect data across many domains will continue to accelerate
 - Data analysis techniques will continue to improve

“Data is the oil fuel of the 21st century”



The Two Steps of Working with Data

(1) Collect data

Via computers, sensors, people, events ...

(2) Do something with it

Make decisions, confirm hypotheses,
gain insights, predict future ...

“Data Science” = Going from (1) to (2)



This Session

- Promises of data science
 - Applications and services
- Data tools and techniques
 - Data analysis
 - Data mining and machine learning
 - Data visualization
- Pitfalls in data science
 - Correlation and causation
 - Underfitting and overfitting
 - Privacy and a few others
- Data systems and platforms



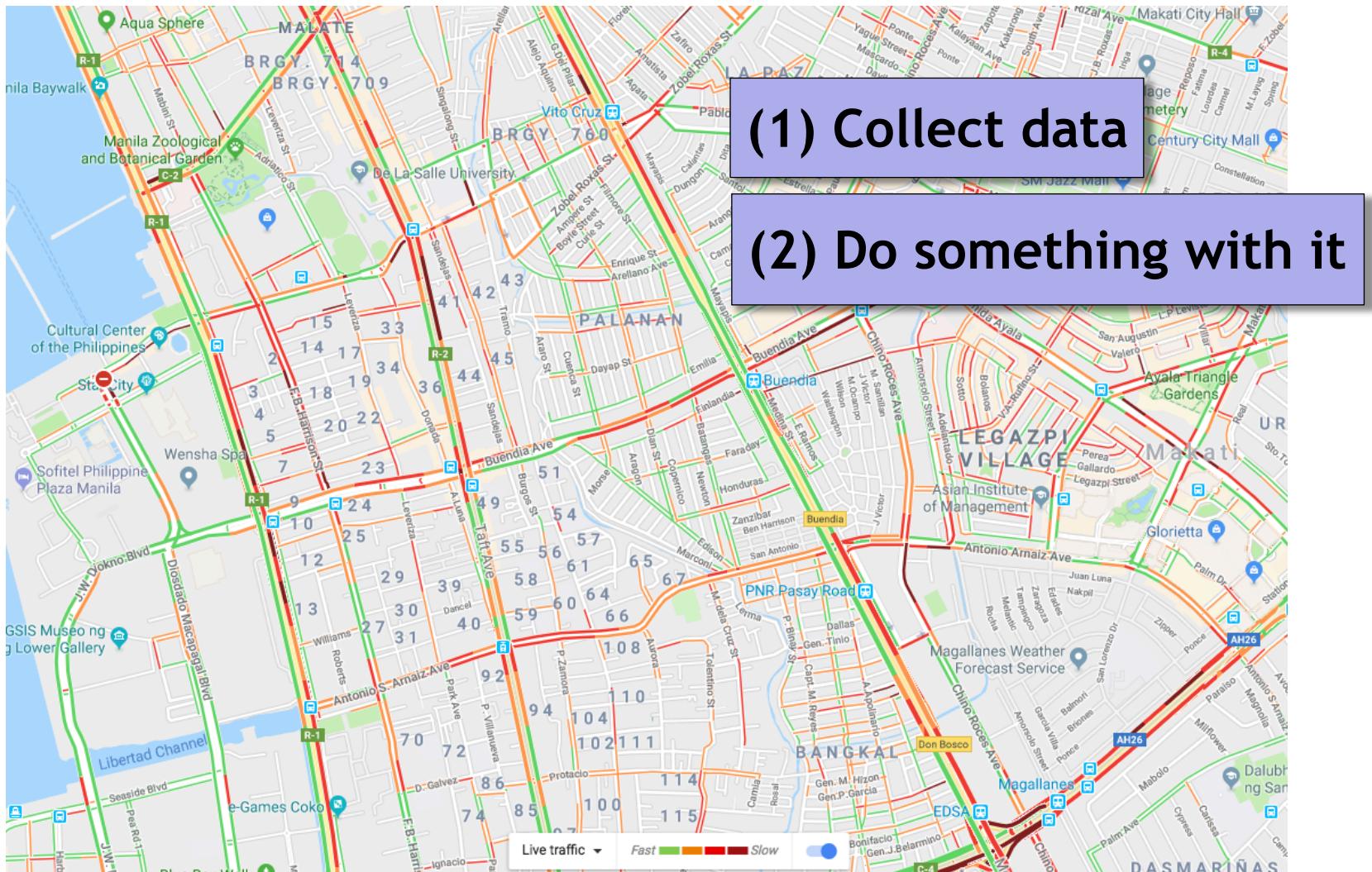
Promises of Data Science

- (1) Collect data
- (2) Do something with it

beneficial



Traffic



Recommender Systems

The screenshot shows a portion of an Amazon search results page. At the top, there's a navigation bar with the Amazon logo, a search bar containing 'All', a magnifying glass icon, and a 'Valentine's Day Gift Shop' button. Below the search bar, it says 'Deliver to Jennifer Stanford 94305'. The main content area has a heading 'Recommended for you, Jennifer' followed by several movie posters. A purple callout box labeled '(1) Collect data' points to the 'Recommended for you' text. Another purple callout box labeled '(2) Do something with it' points to the movie posters.

(1) Collect data

(2) Do something with it

Top Picks for Matthew

Popular on Netflix

GRIMM

STAR TREK THE NEXT GENERATION

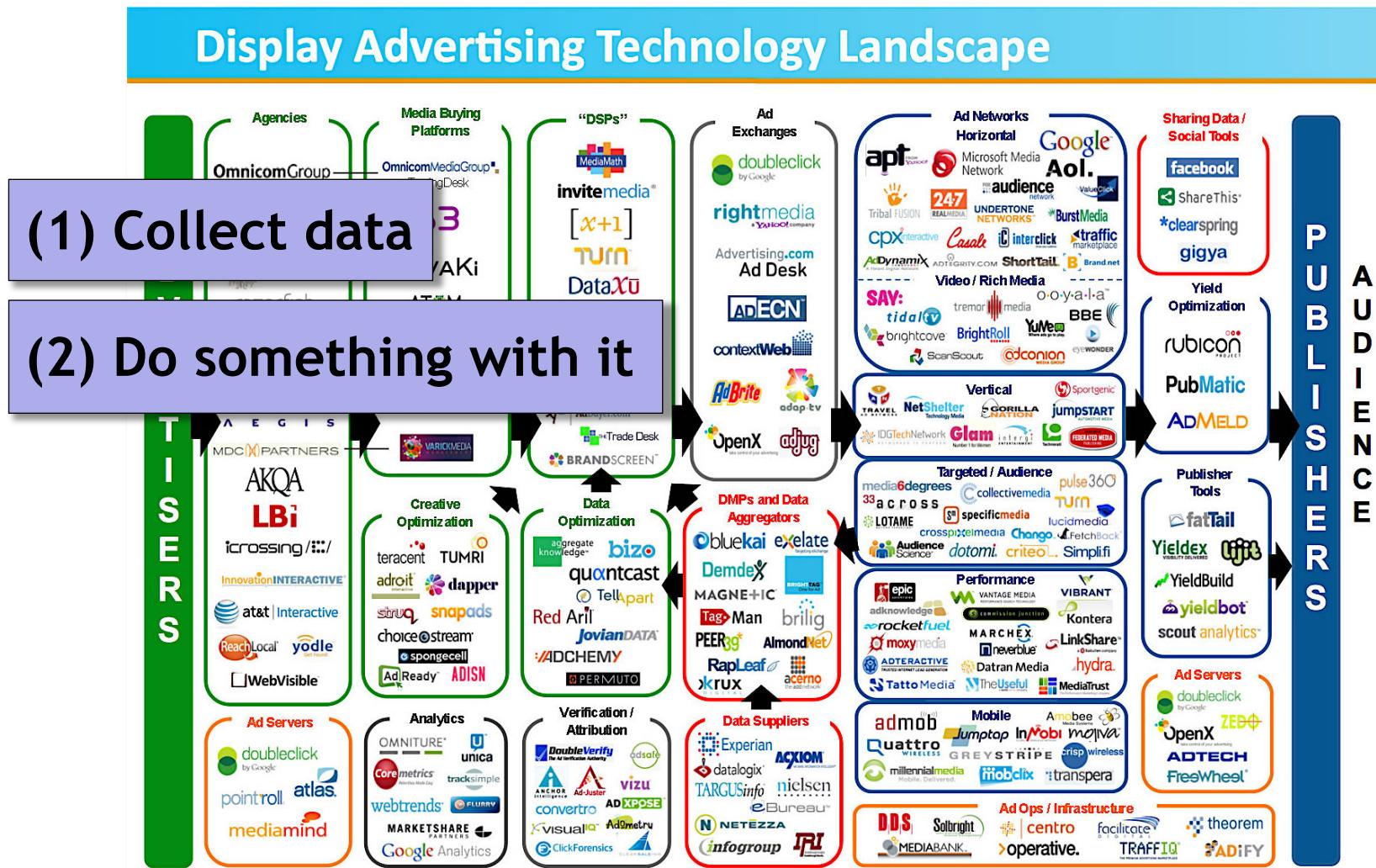
CASTLE

REMEMBER MY

TOY STORY 3

+ music, news, friends, romantic partners, and many more!

Online Advertising



Sports



(1) Collect data



(2) Do something with it

"Remember, the other team is counting on Big Data insights based on previous games. So, kick the ball with your other foot."



How Big Data is Changing the World of Football

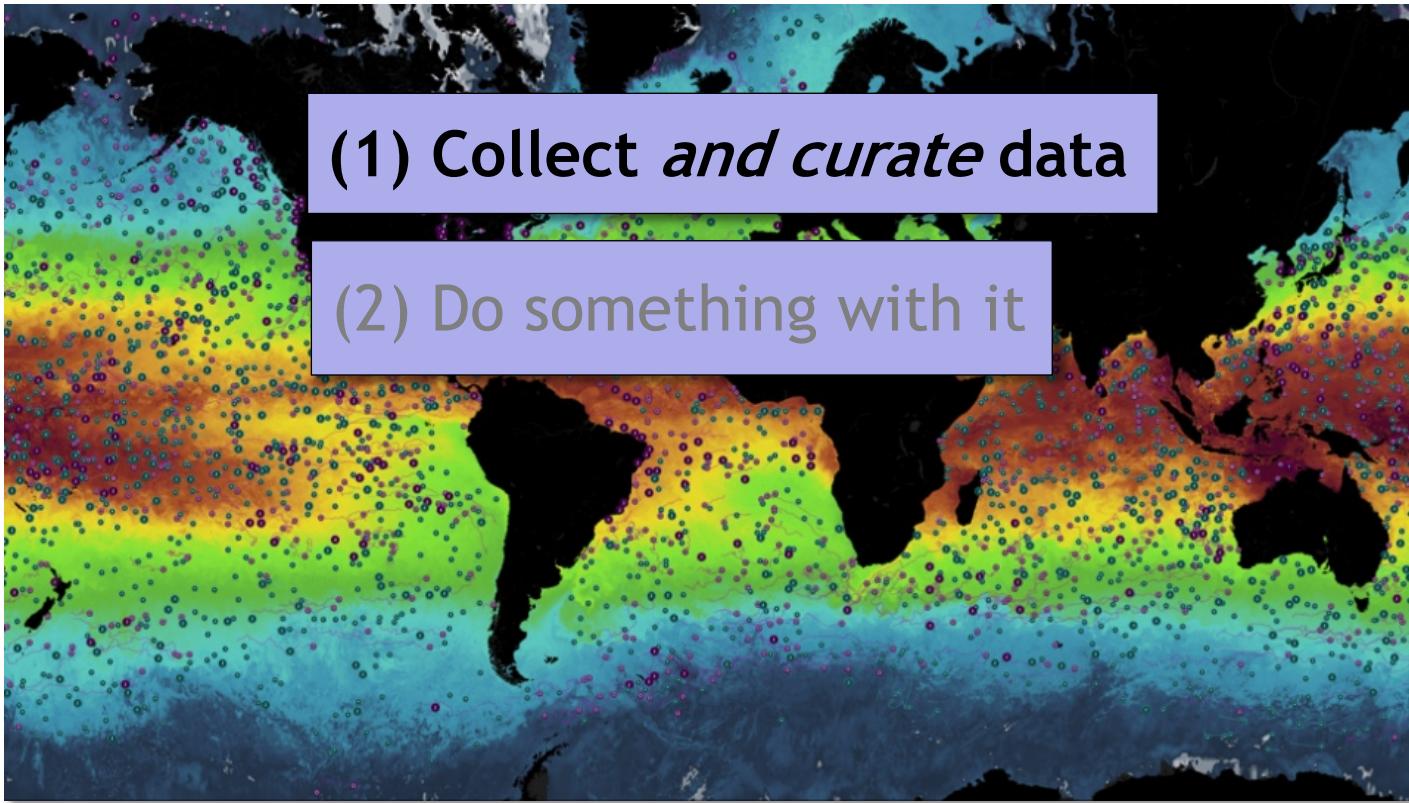
Athletes to analysts: How big data gave the German football team a leg up

Saheli Roy Choudhury | @sahelirc
Thursday, 7 Jul 2016 | 12:39 AM ET

CNBC



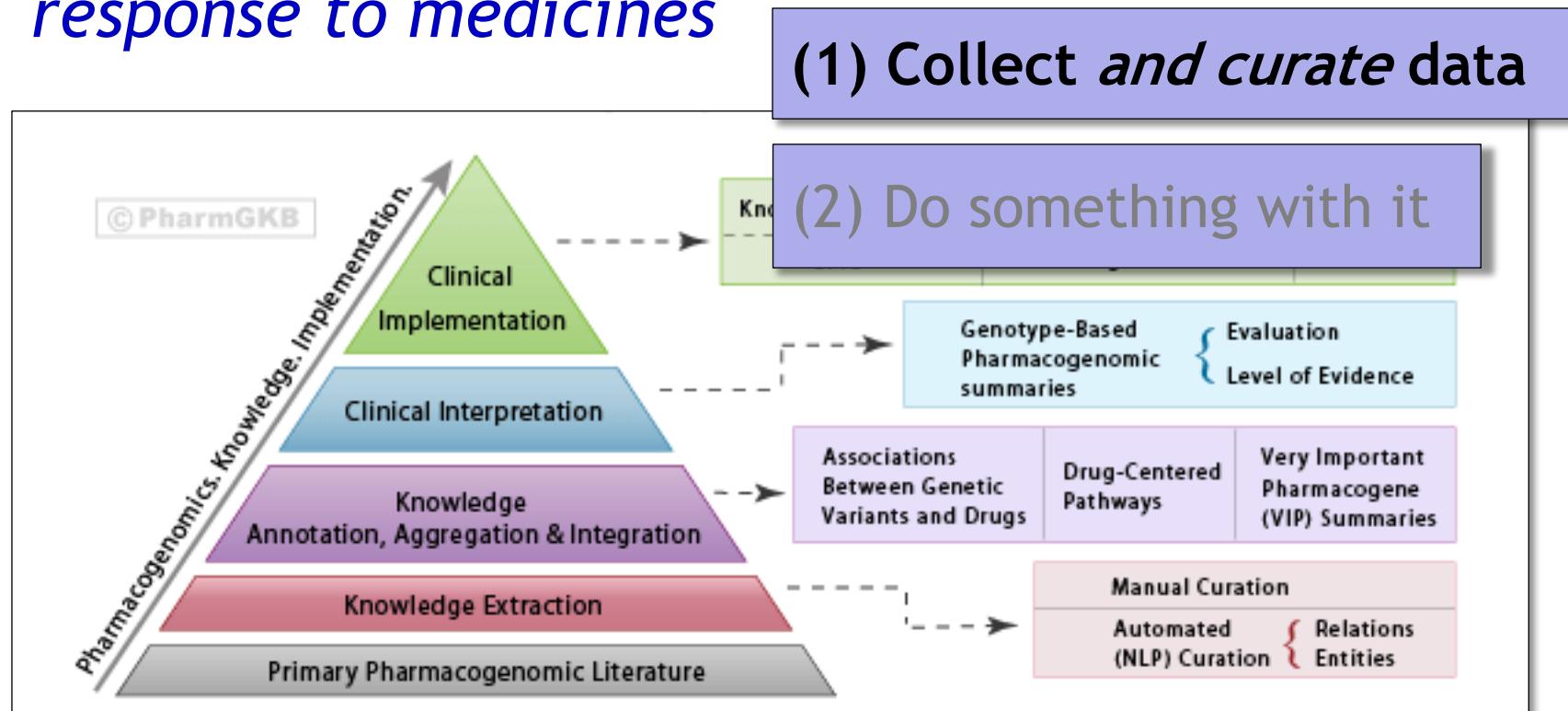
Ocean Health



44,000 sensors, over 2 billion measurements
Physical, chemical, biological ...

Genetics-Medicine Relationships

PharmGKB collects, curates, and disseminates knowledge about how human genetics affects response to medicines



And Many More

- Weather prediction
- Medical diagnosis
- Financial markets
- Resource management
- Computational social science
- Smart buildings and cities
-

The list goes on and on,
and it's still early days



Data Tools and Techniques

- Basic Data Manipulation and Analysis
Performing well-defined computations or asking well-defined questions (“queries”)
- Data Mining
Looking for patterns in data
- Machine Learning
Using data to build models and make predictions
- Data Visualization
Graphical depiction of data
- Data Collection and Preparation



Basic Data Manipulation and Analysis

Performing well-defined computations or asking well-defined questions (“queries”)

- Average January low temperature for each country over last 20 years
- Number of items over \$100 bought by females between ages 20 and 30
- Frequency of specific medicine relieving specific symptoms
- The ten stocks whose price varied the most over the past year



Basic Data Manipulation and Analysis

Performing well-defined computations or asking well-defined questions (“queries”)

- Average rainfall per month
 - Spreadsheets
 - Relational (SQL) database systems
- Number of distinct users per month
 - “NoSQL” / scalable systems
 - Programming languages with data support (e.g., Python, R)
- Frequent words in news articles
 - Specific symptoms
- The ten stocks whose price varied the most over the past year



Data Mining

Looking for patterns in data

- Items X,Y,Z are bought together frequently
- People who like movie X also like movie Y
- Patients who respond well to medicines X and Y also respond well to medicine Z
- Students going to the same university are frequently online friends
- Wealthier people are moving from cities to suburbs



Data Mining

Looking for patterns in data

- Items X,Y,Z are bought together frequently
- People X, Y, Z like movie Y
- Patients X, Y, Z have diseases X, Y, Z
- Students X, Y, Z study together
- Students X, Y, Z are frequently online friends
- Wealthier people are moving from cities to suburbs

- Frequent item-sets
- Association rules
- Specialized techniques for graphs, text, multimedia

Machine Learning

Using data to build models and make predictions

- Customers who are women over age 20 are likely to respond to an advertisement
- Students with good grades are predicted to do well on entrance exams
- The temperature of a city can be estimated as the average of its nearby cities, unless some of the cities are on the coast or in the mountains



Machine Learning

Using data to build models and make predictions

- Customers who are over age 20 are likely to respond to an advertisement
 - Students who are predicted to do well on entrance exams are predicted to do well on entrance exams
 - Roughly: Basic data analysis and data mining give answers from the available data, while machine learning uses the available data to make predictions about missing or future data
- Regression
 - Classification
 - Clustering

Data Visualization

“A picture is worth a thousand words”



Data Visualization

“A picture is worth a ~~thousand words~~
trillion data points”



Early Data Visualization

Napoleon's Army

Carte Figurative des pertes successives en hommes de l'Armée Française dans la campagne de Russie 1812-1813.

Dessiné par M. Minard, Inspecteur Général des Ponts et Chaussées en retraite — Paris, le 20 Novembre 1869.

Les nombres d'hommes présents sont représentés par les largeurs des zones colorées à raison d'un millimètre pour dix mille hommes; ils sont de plus écrits en travers des zones. Le rouge désigne les hommes qui entrent en Russie, le noir ceux qui en sortent. — Les renseignements qui ont servi à dresser la carte ont été puisés dans les ouvrages de M. M. Chiers, de Ségur, de Fezensac, de Chambray et le journal médical de Jacob, pharmacien de l'Armée depuis le 28 Octobre.

Pour mieux faire juger à l'œil la diminution de l'armée, j'ai supposé que les corps du Prince Jérôme et du Maréchal Davout, qui avaient été détachés sur Minsk et Mohilow et qui rejoignirent vers Orsha et Witebsk, avaient tous deux marché avec l'armée.

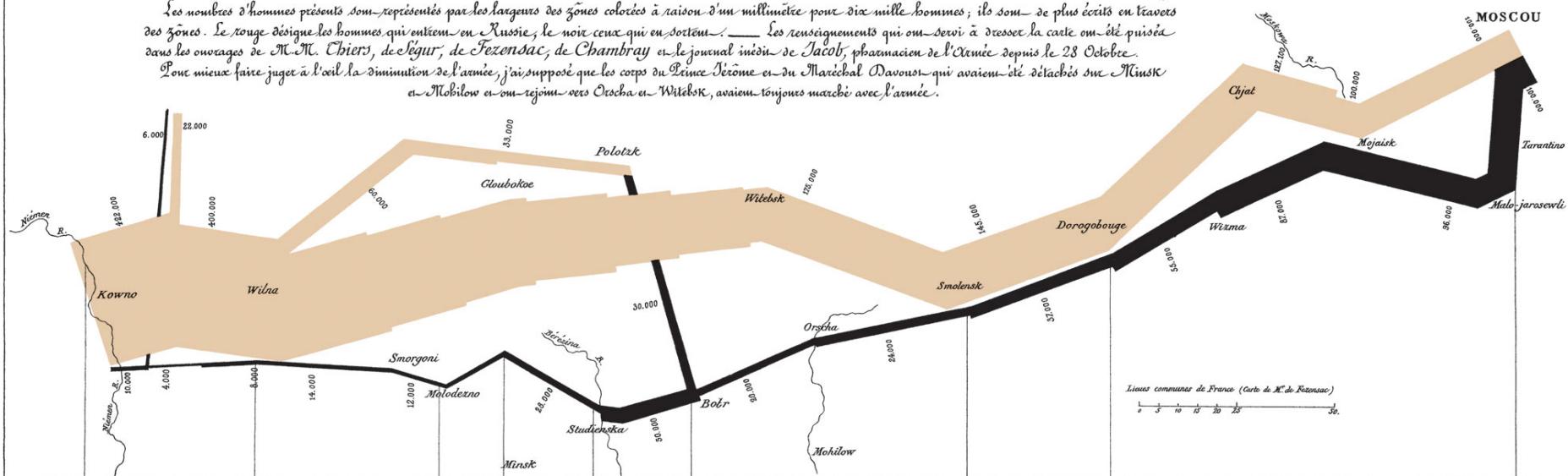
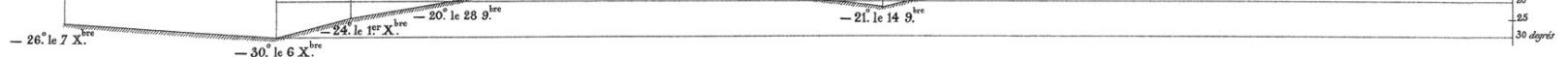


TABLEAU GRAPHIQUE de la température en degrés du thermomètre de Réaumur au dessous de zéro.

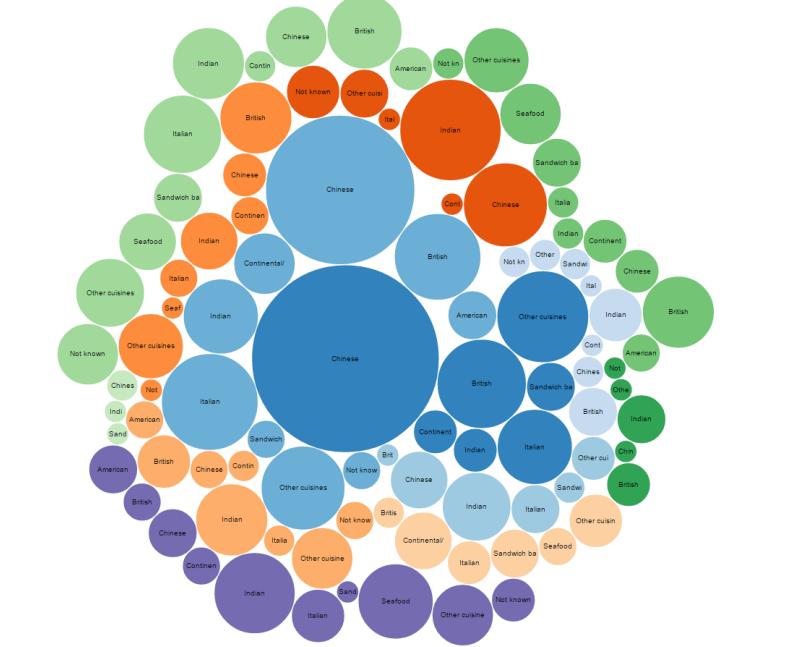
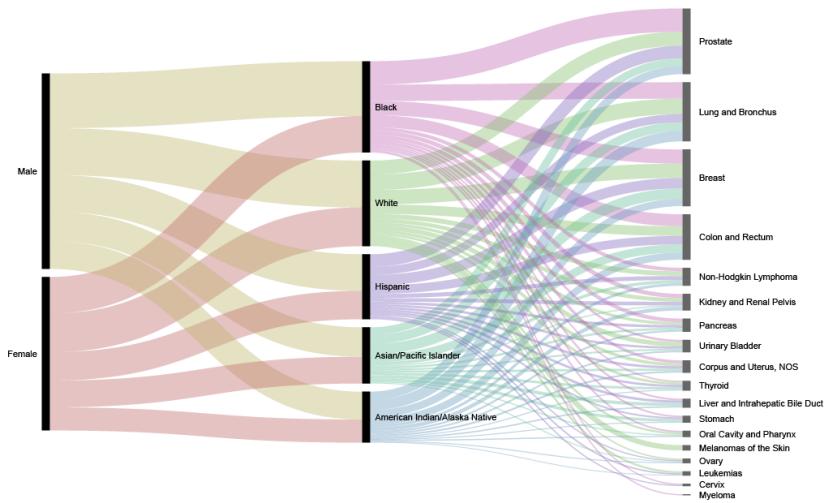
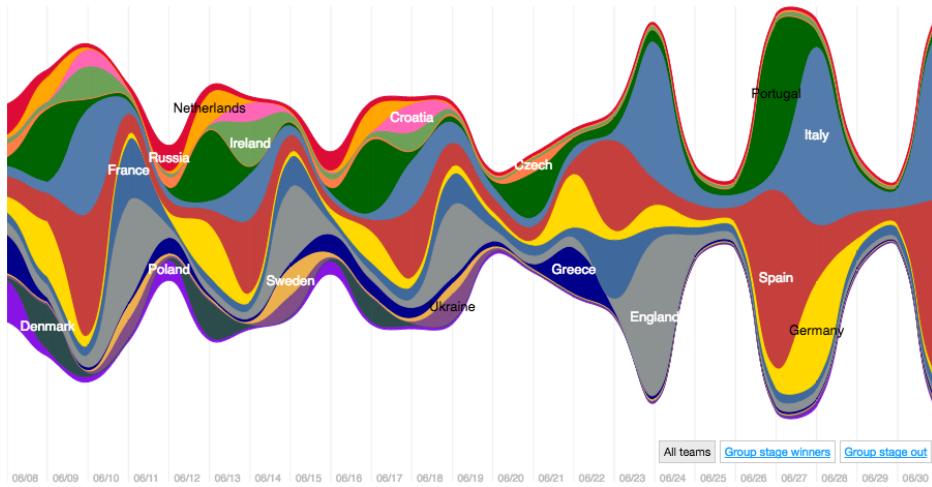
Les cosaques passent au galop
le Niémen gelé.



Autog. par Regnier, 8. Pas. S^e Marie S^e G^e à Paris.

Imp. Lith. Regnier et Dourdet.

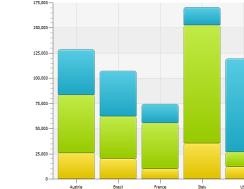
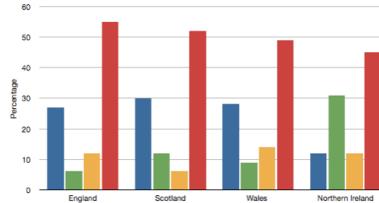
Modern Data Visualization



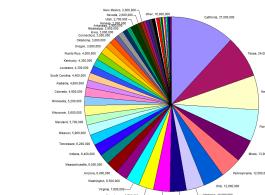
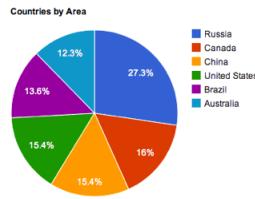
Basic Data Visualization

Don't underestimate the power of basic visualizations

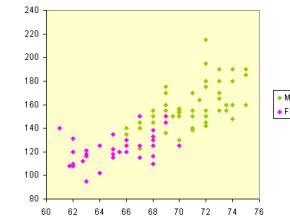
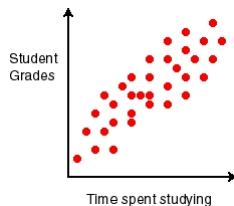
- Bar charts



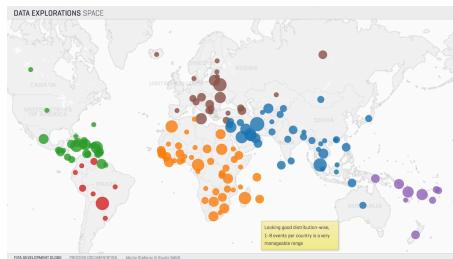
- Pie charts



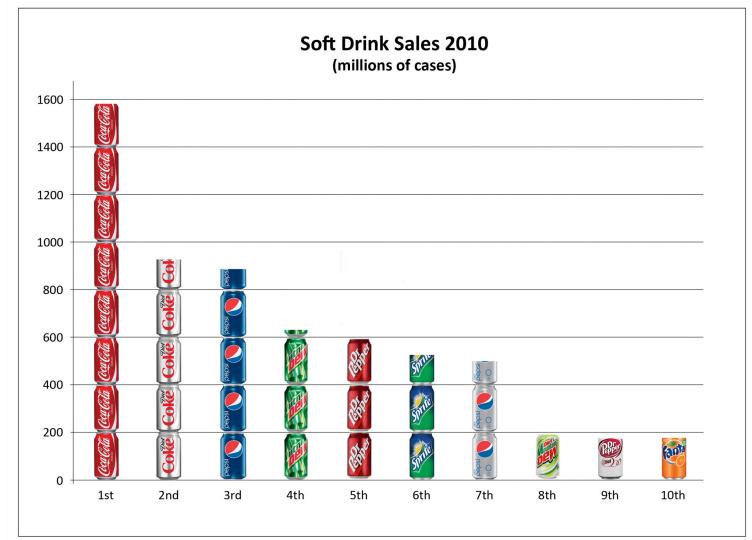
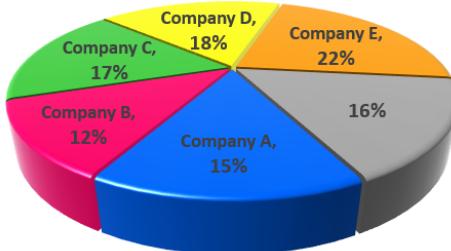
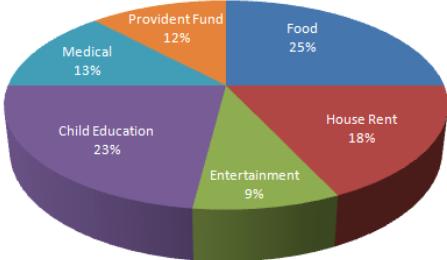
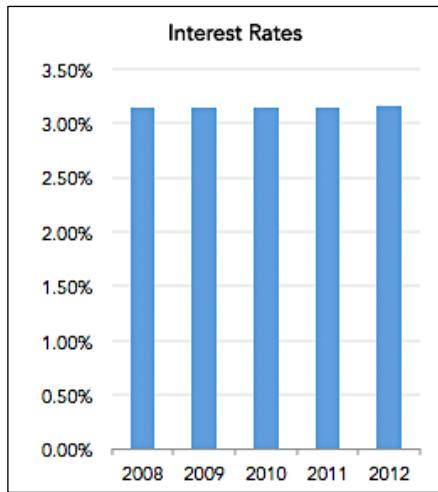
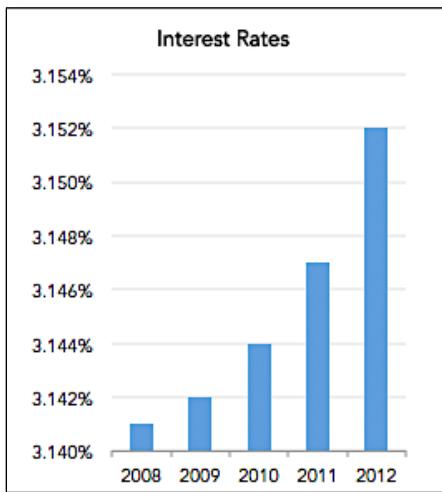
- Scatterplots



- Maps



Misleading Data Visualization



Data Collection and Preparation

The “dirty” secret of working with data

- Extracting data from difficult sources
- Filling in missing values
- Removing suspicious data
- Making formats, encoding, and units consistent
- De-duplicating and matching

Data preparation often
consumes 80% or more of the
effort in a data-driven project



Pitfalls of Data Science

- (1) Collect data
- (2) Do something with it

correct



Correlation and Causation

Data analysis, data mining, and machine learning can reveal relationships between data values

Correlation - Values track each other

- Height and Shoe Size
- Grades and Entrance Exam Scores

Causation - One value directly influences another

- Education Level → Starting Salary
- Temperature → Cold Drink Sales



Correlation and Causation

“Correlation does not imply causation”

Correlation - Values track each other

- Height and Shoe Size
- Grades and Entrance Exam Scores

Causation - One value directly influences another

- Education Level → Starting Salary
- Temperature → Cold Drink Sales



Correlation and Causation

“Correlation does not imply causation”

- Correlation can be result of causation from a hidden “confounding variable”
- A and B are correlated because there's a hidden C such that $C \rightarrow A$ and $C \rightarrow B$
 - ❖ Homeless population and crime rate
Confounding variable: unemployment
 - ❖ Forgetfulness and poor eyesight
Confounding variable: age
 - ❖ Height and shoe size
 - ❖ Grades and entrance exam scores



Correlation and Causation

“Correlation does not imply causation”

- Correlation can be result of causation from a hidden “confounding variable”
- A and B are correlated because there’s a hidden C such that $C \rightarrow A$ and $C \rightarrow B$

- Correlation is usually “easy” to test
- Causation is typically impossible to test



Correlation and Causation



"I wish they didn't turn on that seatbelt sign so much! Every time they do, it gets bumpy."



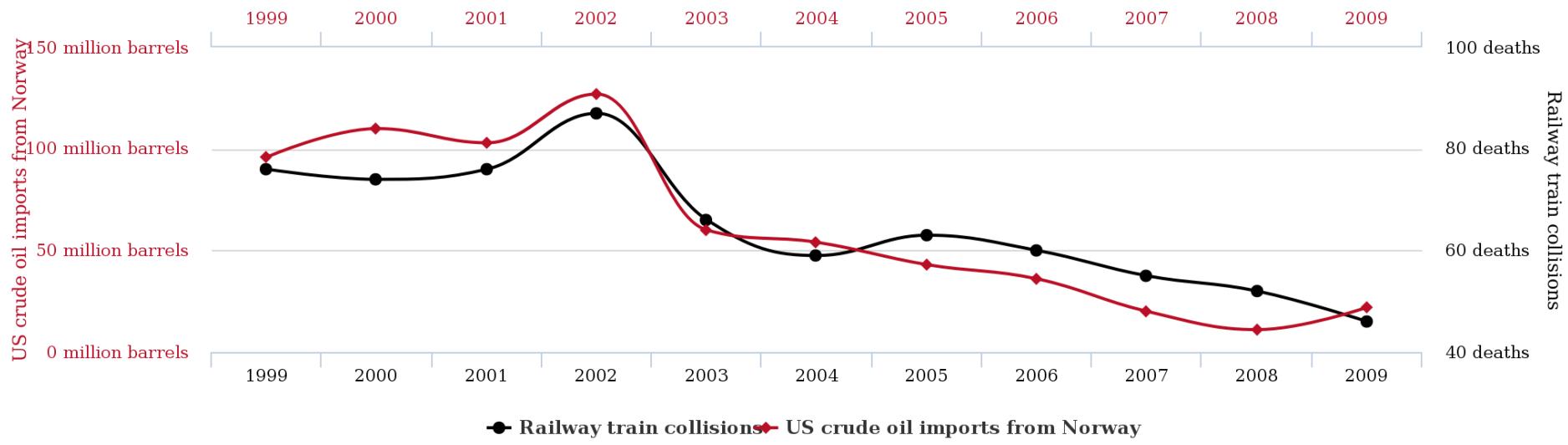
Excellent health statistics - smokers are less likely to die of age related illnesses.'

Surprising Correlation #1

US crude oil imports from Norway

correlates with

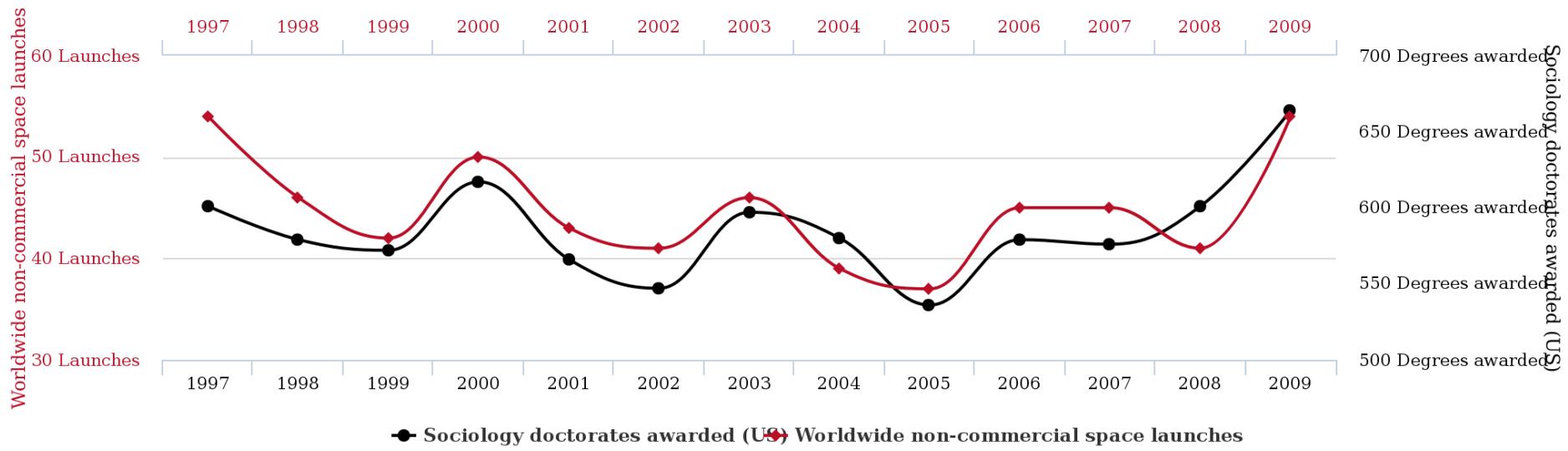
Drivers killed in collision with railway train



tylervigen.com

Surprising Correlation #2

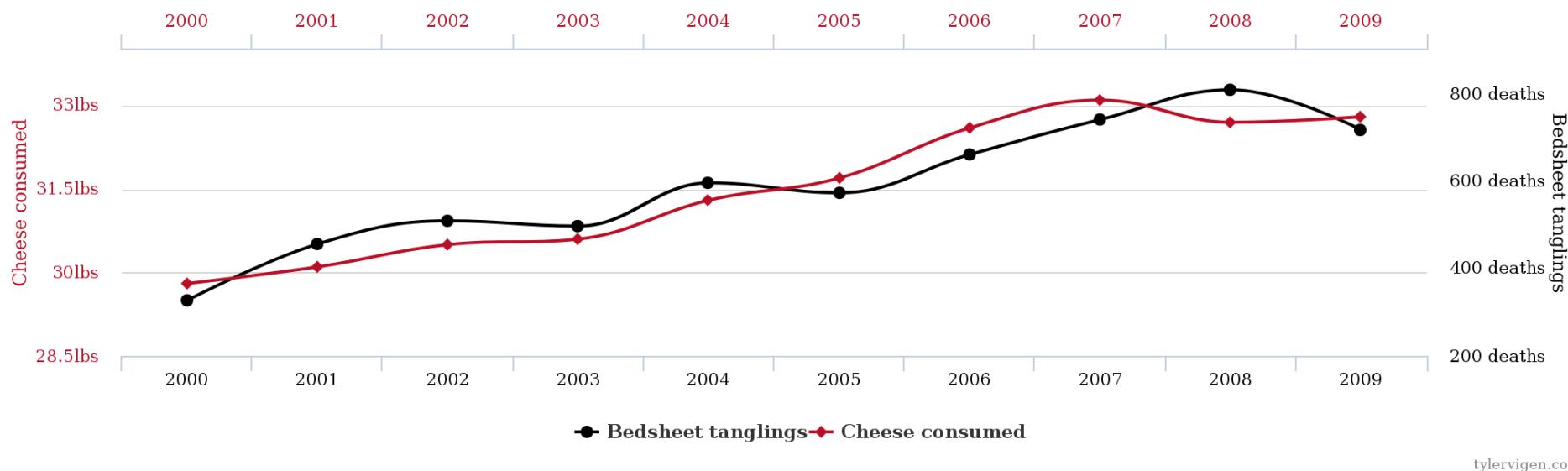
Worldwide non-commercial space launches
correlates with
Sociology doctorates awarded (US)



tylervigen.com

Surprising Correlation #3

Per capita cheese consumption
correlates with
Number of people who died by becoming tangled in their bedsheets



tylervigen.com

“Spurious Correlations” Website

<http://www.tylervigen.com/>



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Underfitting and Overfitting

Machine learning uses data to create a “model” and uses model to make predictions

- Customers who are women over age 20 are likely to respond to an advertisement
- Students with good grades are predicted to do well on entrance exams
- The temperature of a city can be estimated as the average of its nearby cities, unless some of the cities are on the coast or in the mountains



Underfitting

Model used for predictions is too simplistic

- 60% of men and 70% of women responded to an advertisement, therefore all future ads should go to women
- If a furniture item has four legs and a flat top it is a dining room table
- The temperature of a city can be estimated as the average of its nearby cities, unless some of the cities are on the coast or in the mountains



Overfitting

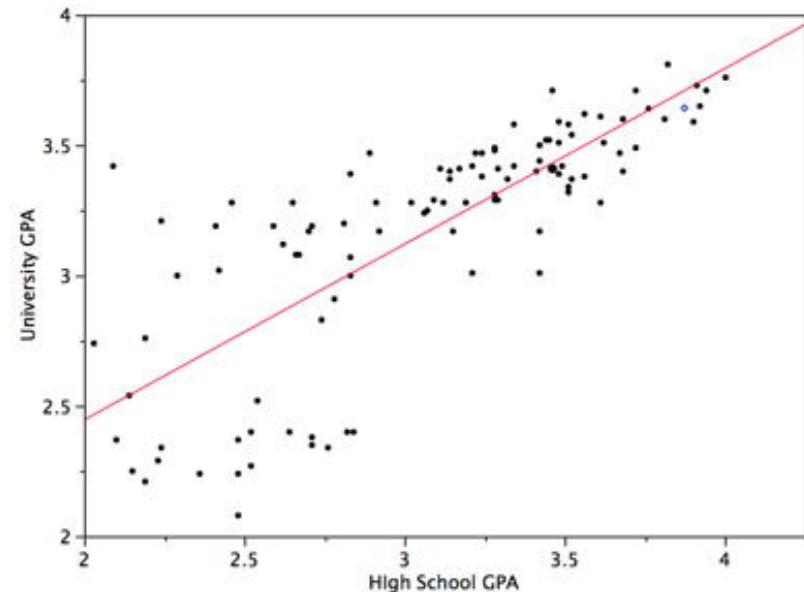
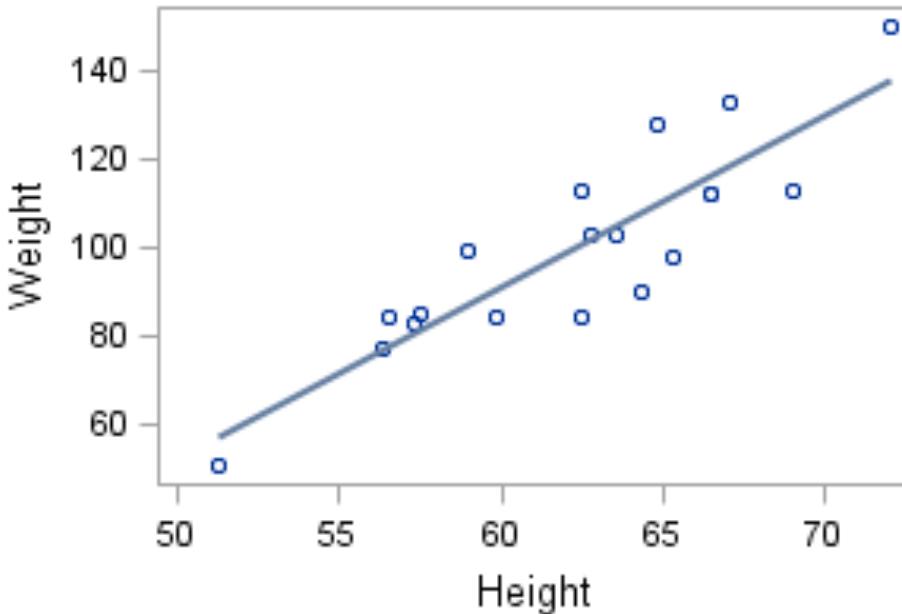
Model used for predictions is too specific

- The best targets for an advertisement are married women between 25 and 27 years with short black hair, one child, and one pet dog
- If a furniture item has four 100 cm legs with decoration and a flat polished wooden top with rounded edges then it is a dining room table



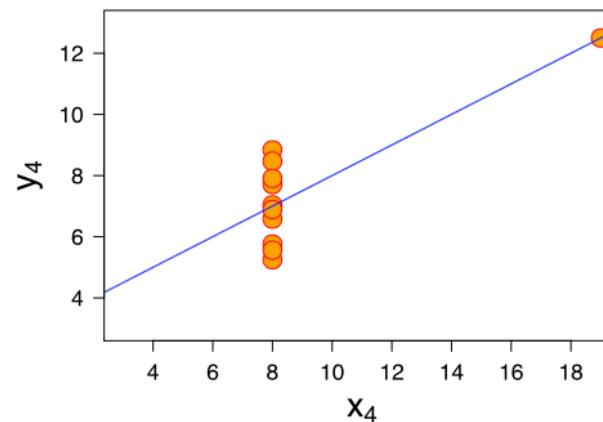
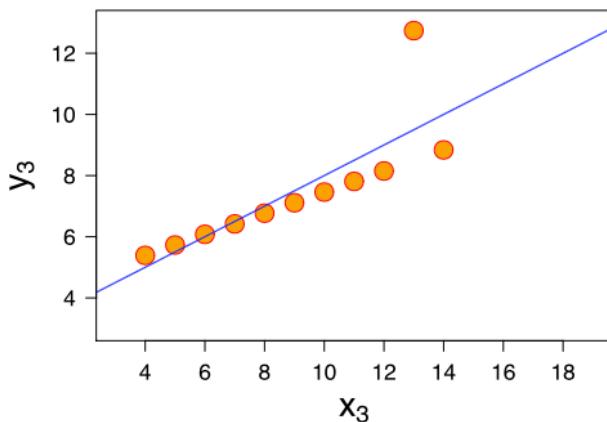
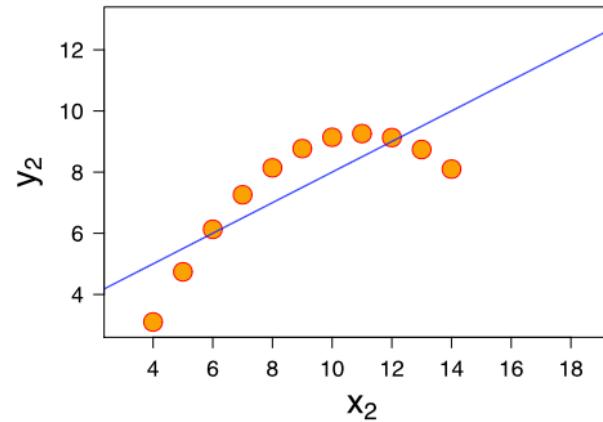
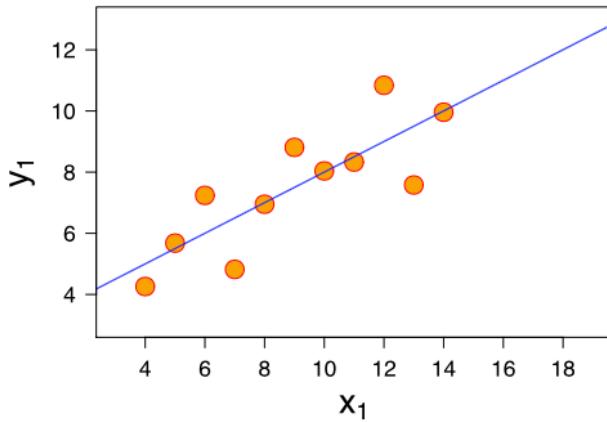
Regression

- Fit a line or curve to a set of points (model)
- Use model to predict values for new points



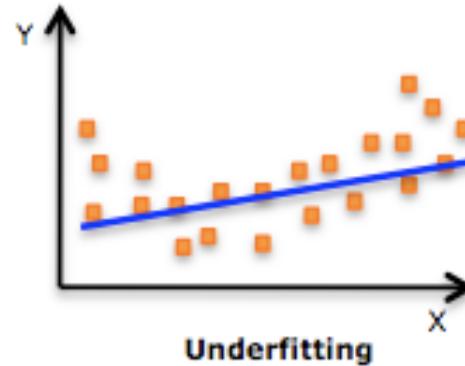
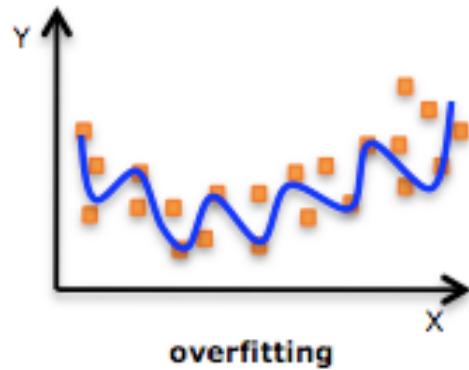
Underfitting

Model is too simplistic



Overfitting

Model is too specific



Soccer Match Prediction Scam

- Friday: receive email from “Psychic Sally” predicting which teams will be the winners in the weekend’s five soccer matches. She’s right about all of them!
- Same thing the following weekend: five games, all winners predicted correctly
- And the following one: five more correct
- Fourth Friday: Sally offers to give you her predictions for the coming weekend’s games, for a fee

Should you do it?



Soccer Match Prediction Scam

How many contacts must Sally start with on week one to ensure she has 100 potential buyers by week four, i.e., 100 people who received 15 correct predicted winners?
(Assume no draws)



Data Privacy

Of significant concern in some sectors

- Individual data collected covertly
 - Edward Snowden, “metadata” argument
- Individual data collected legally but used questionably
 - Individual “information trails” are enormous
 - Target stores pregnancy mailing
- Individual data deduced from “anonymous” public data
 - Governor of Massachusetts health record



Languages, Systems, Platforms

- Spreadsheets

Surprisingly versatile and powerful for data analysis tasks, provided data is not *too* large

- Programming languages with data support

- R Language - powerful statistical features
- Python - general-purpose language with R-like add-ons (Pandas, SciPy, scikit-learn)



Languages, Systems, Platforms

- Relational Database Management Systems
 - Also called RDBMS, SQL Systems
 - Long-standing solution for reliability, efficiency, powerful query processing
 - Works for all but truly extreme data sizes, or highly unstructured data
- “NoSQL” Systems
 - Distributed/scalable processing
 - Some specifically target unstructured data (documents, graphs)



Languages, Systems, Platforms

- Specialized languages on scalable systems
 - MapReduce / Hadoop
 - Spark generalized data flow
- Systems for data preparation
- Systems for data visualization



Languages, Systems, Platforms

- Data processing in the cloud
 - Amazon Web Services, Google Cloud, Microsoft Azure
 - Data storage
 - Data processing: SQL, Hadoop, Spark
 - Machine learning libraries
 - Integration with visualization systems



How Much Data is There?

Complete works of William Shakespeare
5 megabytes

Average individual
50 gigabytes (10,000 Shakespeares)

USA Library of Congress
10 terabytes (2 million Shakespeares)

Uploaded to Facebook daily
1 petabyte (200 million Shakespeares)

Produced by humanity daily
2.5 exabytes (500 trillion Shakespeares)



“Big Data”

Some domains produce vast quantities of data, and some analyses require “big data” to be effective

- Most tools and techniques apply to data of all sizes
- Big insights can come from small/medium data

Sometimes twenty Spark servers
in the cloud are required.

More often a laptop with SQL, Python,
or simple spreadsheets does the job.

Rest of the Short-Course

- Data Analysis Using Spreadsheets
- Data Visualization Using Spreadsheets
- Advanced Data Visualization Using Tableau
- Relational Databases and Basic SQL
- Using Python for Data Analysis

If extra time (last day) decide among...

- Machine Learning - Regression and Classification
- Network Analysis
- Advanced SQL
- The R Language



Getting Started with Google Sheets

professorwidom.org > Courses > Course Materials

Step 1: Create a Google account: accounts.google.com

Step 2: Copy data files

- a) Follow link for module in “Getting Started” document
- b) Select all files (control/command-a), control/right-click, “Make a copy”
- c) Go to “My Drive”, rename/reorganize files if desired

Step 3: Open files using Google Sheets: double-click

Step 4 (optional): Enable working offline; see “Getting Started” document for details



Stanford University

Prof. Widom

Getting Started with Tableau Public

professorwidom.org > Courses > Course Materials

Step 1: Install Tableau Public: public.tableau.com

Step 2: Copy data files

- a) Follow link in “Getting Started” document
- b) Download each file: double-click to open, select File > Download as > Comma-separated values
- c) Rename/relocate files if desired

Step 3: Open Tableau Public, click “Text File”, select downloaded file. (If the data loads but looks strange, try clicking “Excel” instead of “Text File”.)



Stanford University

Prof. Widom

Getting Started with Instabase

professorwidom.org > Courses > Course Materials

Step 1: Get an Instabase account: follow link in “Getting Started” document, use provided token

Step 2: Manage workspaces and repositories

Step 3: Copy notebooks and data files

- a) Follow link for module in “Getting Started” document
- b) Select all files, Actions menu > Copy
- c) Select repository, click Instabase Drive, Copy

Step 4: Open notebook: right-click, Open With > Jupyter



Stanford University

Prof. Widom

Overview of Data Science

Promises and Pitfalls, Tools and Techniques



Questions?



Association for
Computing Machinery



Very Large Data Bases
Endowment Inc.

