Welcome to CSC 276
Data Science

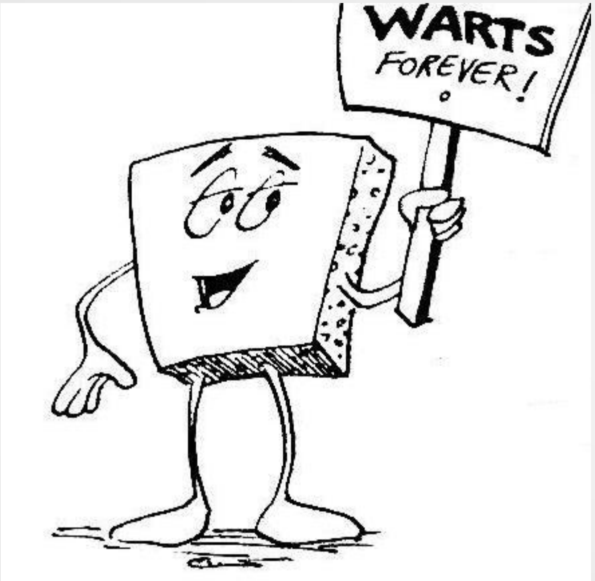
CSC 276: Data Science
Lecture #2
Introduction

Dr.Fatema Nafa

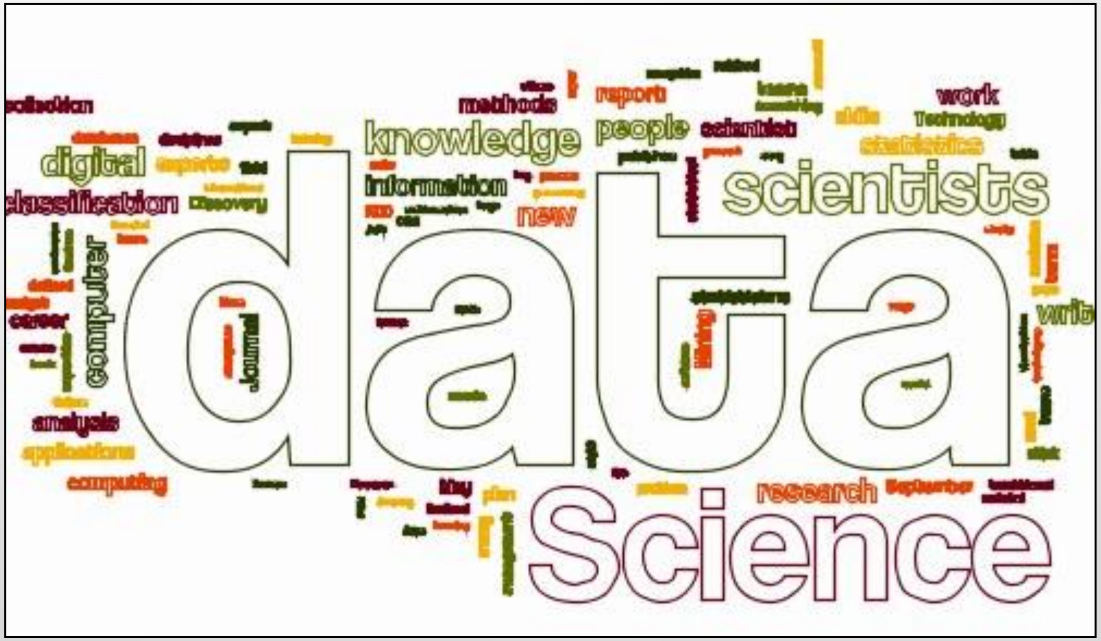
Fall 2022

9/8/2022

Welcome to CSC 276!



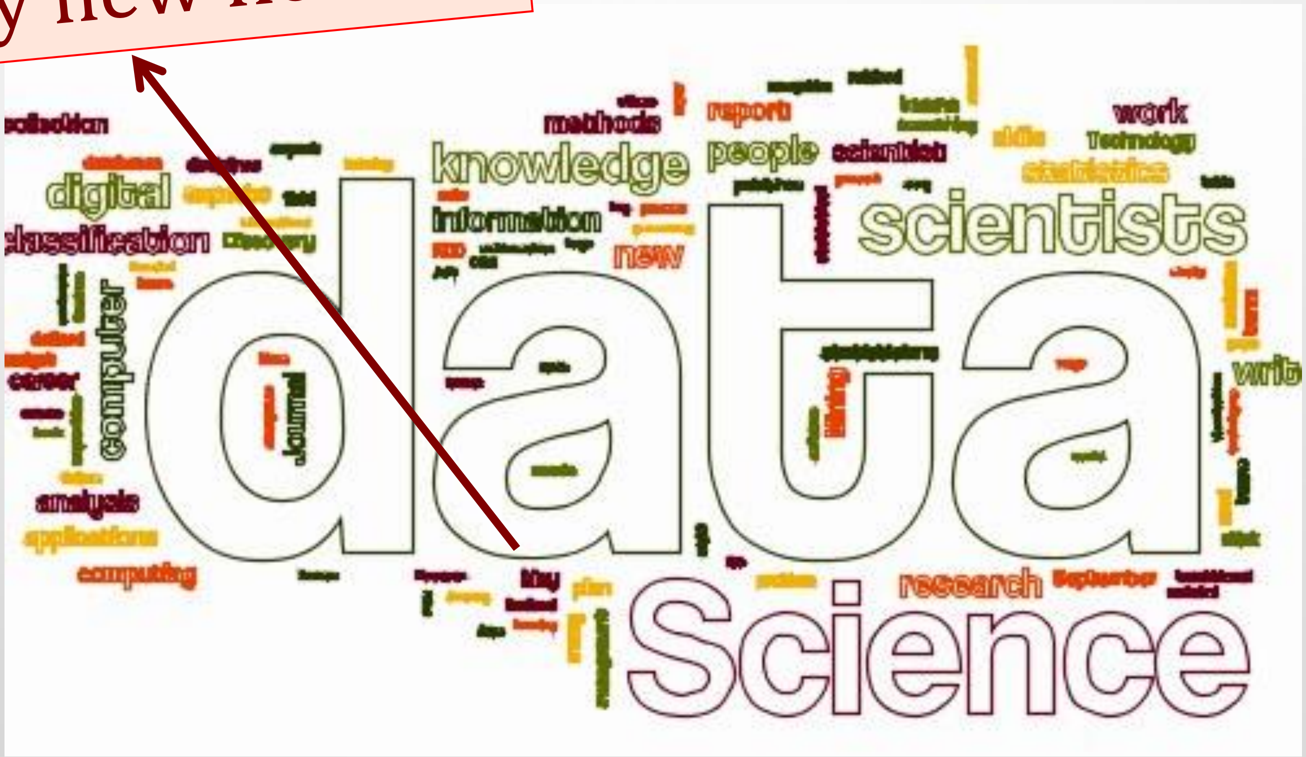
Data Science



Welcome to CSC 276!

This class is truly seminar-style: I'm here, as you are, in order to gain insights into this very new field… .

Data Science



Lecture Outline

- **The Art of Data Science**
- Volume, Velocity, Variety
- The Logic of Data Science
- How to Be Agile
- Treating Data as Evidence
- Python
    - Fundamentals of Data Manipulation
    - Basic Data Processing with Pandas
    - Answering Questions with Messy Data

Any
Questions

Data Science – A Definition

a data scientist is someone who asks unique, interesting questions of data based on formal or informal theory, to generate rigorous and useful insights.

It is likely to be an individual with multi-disciplinary training in computer science, business, economics, statistics, and armed with the **necessary quantity of domain knowledge relevant to the question at hand**.

The potential of the field is enormous for just a few well-trained data scientists armed with big data have the potential to transform organizations and societies.

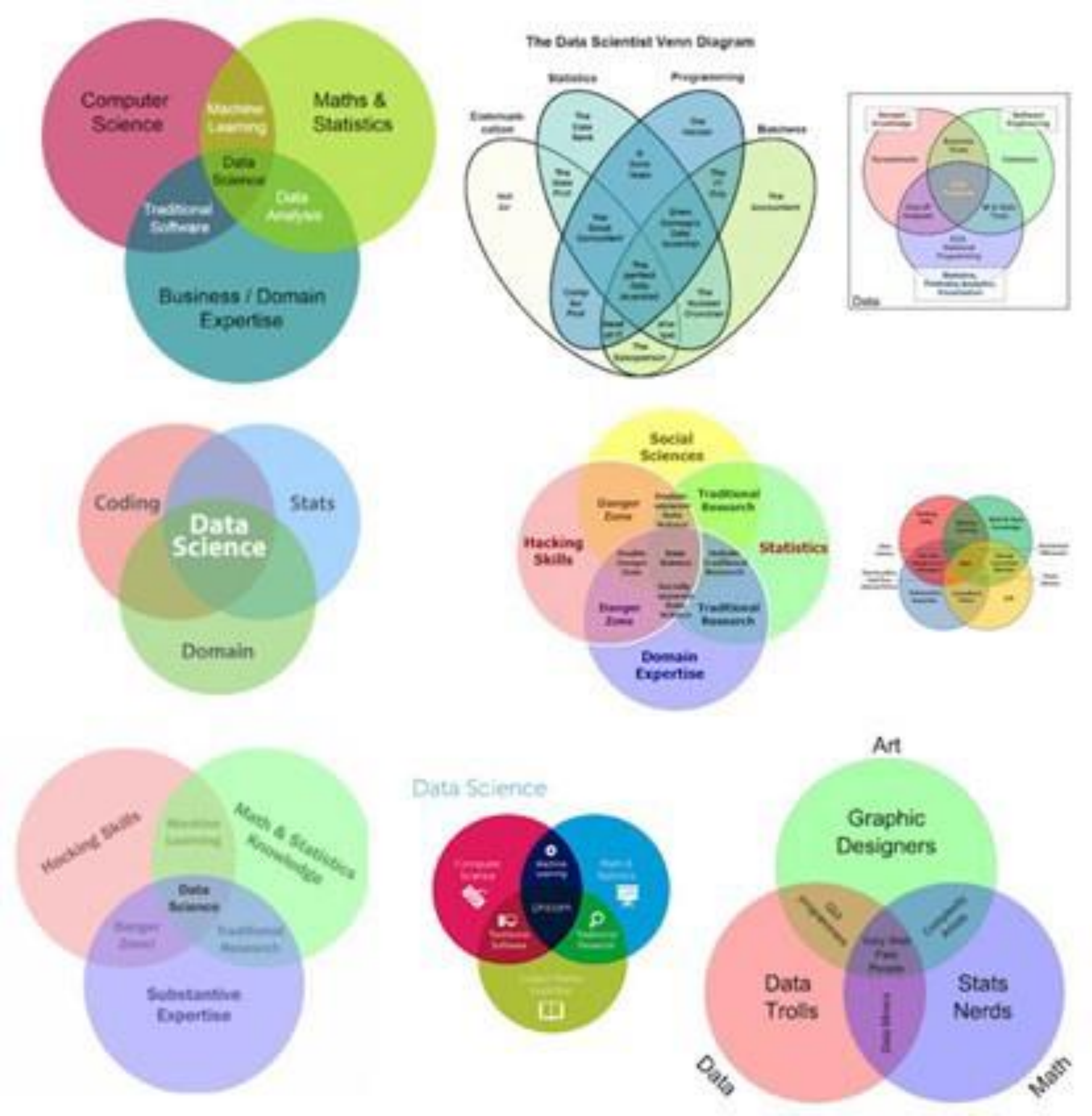
In the narrower domain of business life, the role of the data scientist is to generate applicable business intelligence.

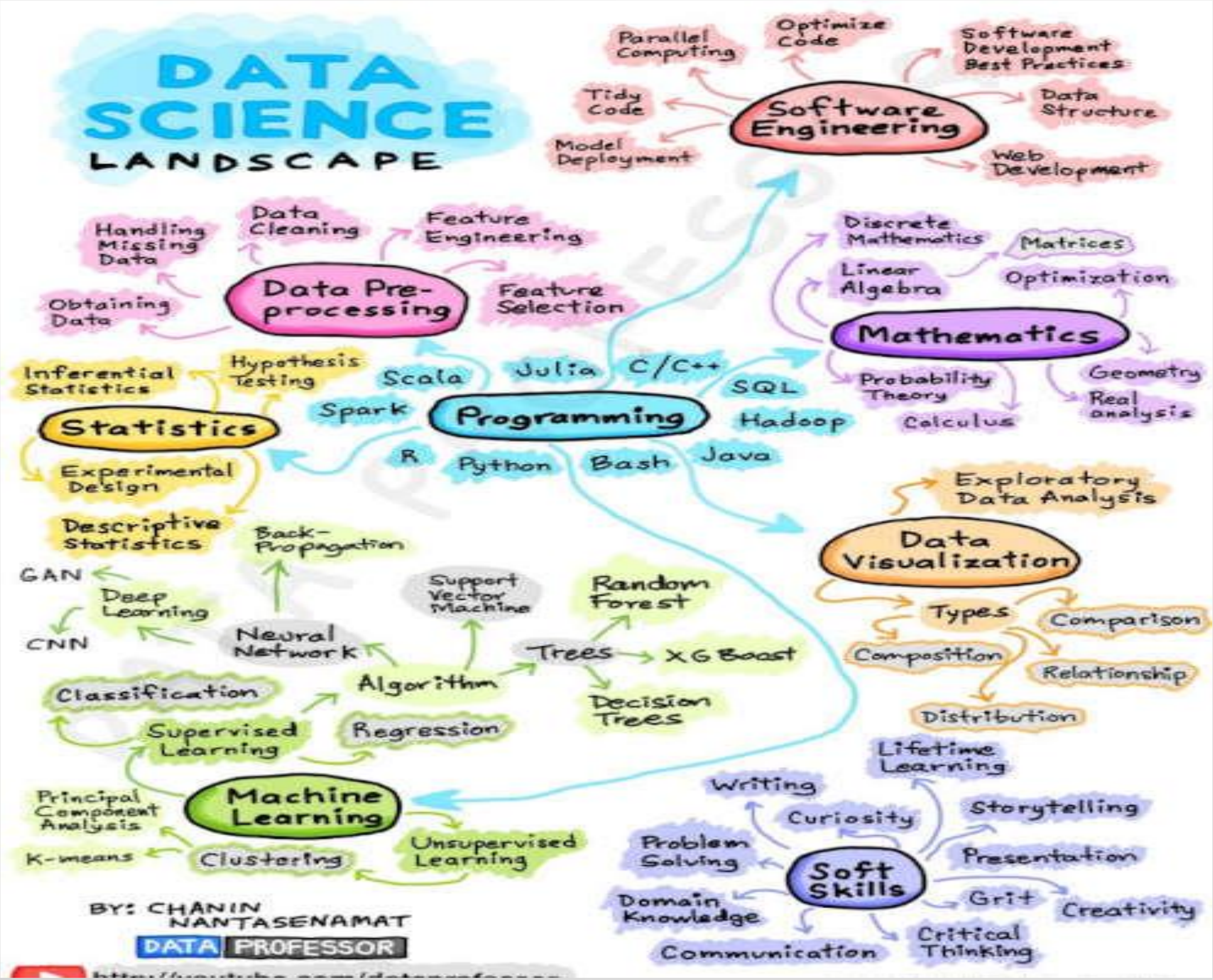
Among all the new buzzwords in business – and there are many –

Data Science – A Definition

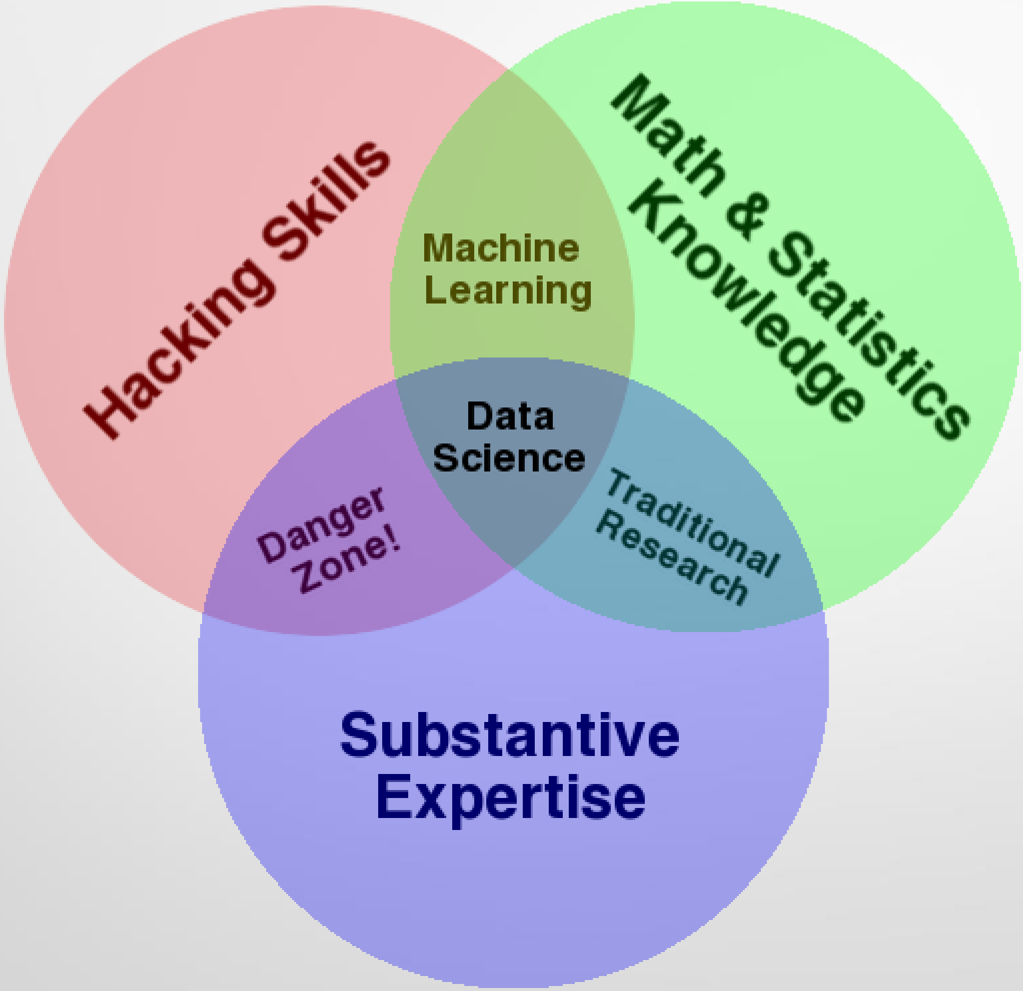
Being a data scientist is inherently interdisciplinary.

Good questions come from many disciplines, and the best answers are likely to come from people who are interested in multiple fields, or at least from teams that co-mingle varied skill sets.

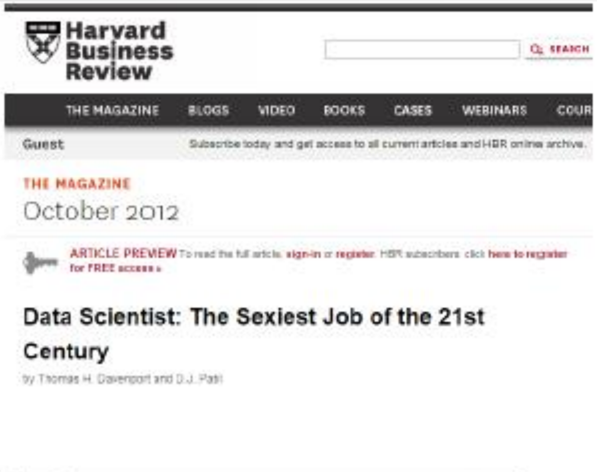

Computer Science
Maths & Statistics
Machine Learning
Data Science
Traditional Software
Data Analytics
Business / Domain Expertise
The Data Scientist Venn Diagram
Statistics
Programming
Communication
Business
Data
Coding
Stats
Data Science
Domain
Social Sciences
Danger Zone
Traditional Research
Hacking Skills
Statistics
Danger Zone
Traditional Research
Domain Expertise
Hacking Skills
Machine Learning
Math & Statistics Knowledge
Data Science
Danger Zone!
Traditional Research
Substantive Expertise
Data Science
Computer Science
Math & Statistics
Unicorn
Art
Graphic Designers
Data Trolls
Stats Nerds
Data
Math


DATA SCIENCE LANDSCAPE
Software Engineering
Parallel Computing
Optimize Code
Software Development Best Practices
Tidy Code
Data Structure
Model Deployment
Web Development
Data Pre-processing
Handling Missing Data
Data Cleaning
Feature Engineering
Obtaining Data
Feature Selection
Mathematics
Discrete Mathematics
Matrices
Linear Algebra
Optimization
Probability Theory
Geometry
Real analysis
Calculus
Statistics
Inferential Statistics
Hypothesis Testing
Experimental Design
Descriptive Statistics
Programming
Scala
Julia
C/C++
SQL
Spark
Hadoop
R
Python
Bash
Java
Data Visualization
Exploratory Data Analysis
Types
Comparison
Composition
Relationship
Distribution
Machine Learning
Back-Propagation
GAN
Deep Learning
CNN
Neural Network
Support Vector Machine
Random Forest
Trees
XGBoost
Algorithm
Decision Trees
Classification
Supervised Learning
Regression
Principal Component Analysis
K-means
Clustering
Unsupervised Learning
Soft Skills
Lifetime Learning
Writing
Curiosity
Storytelling
Problem Solving
Presentation
Domain Knowledge
Grit
Creativity
Critical Thinking
Communication
BY: CHANIN NANTASENAMAT
DATA PROFESSOR
http://youtube.com/dataprofessor

Data Science – One Definition



Data Scientists are in high demand



Harvard Business Review

SEARCH

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Guest

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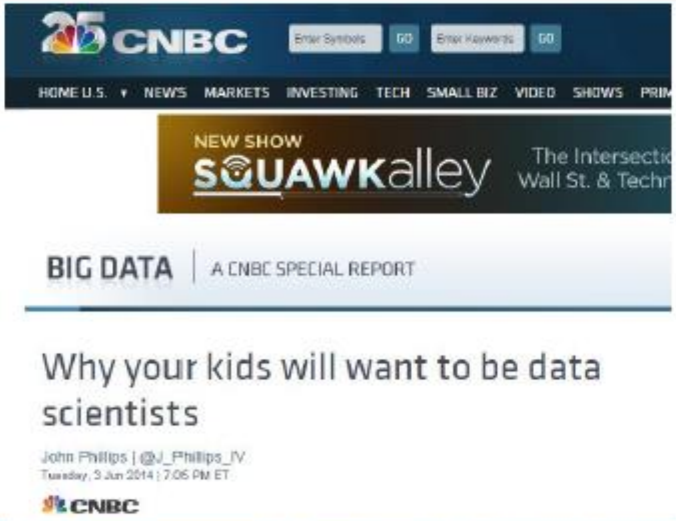
October 2012

ARTICLE PREVIEW To read the full article, sign-in or register. HBR subscribers click here to register for FREE access »

Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil



CNBC

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HOME U.S. ▾ NEWS MARKETS INVESTING TECH SMALL BIZ VIDEO SHOWS PRIM

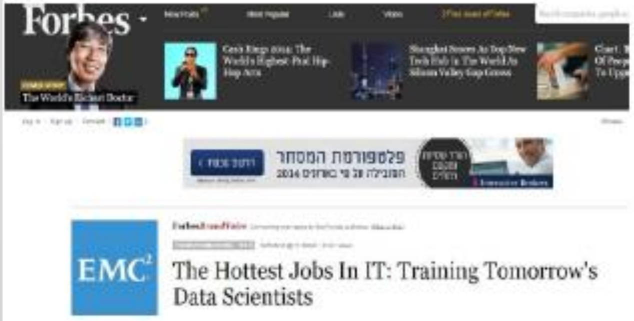
NEW SHOW SQUAWKalley The Intersecti Wall St. & Techn

BIG DATA | A CNBC SPECIAL REPORT

Why your kids will want to be data scientists

John Phillips | @J_Phillips_IV
Tuesday, 3 Jun 2014 | 7:06 PM ET

CNBC



Forbes

New Posts Most Popular Lists Video

The World's Richest Doctor

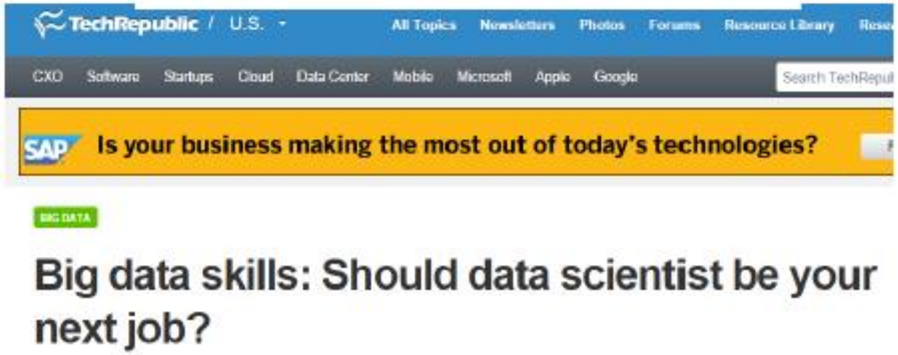
Cash Kings 2014: The World's Highest-Paid Hip-Hop Acts

Shanghai Soars As Top New Tech Hub In The World As Silicon Valley Gap Grows

פלטפורמת המסחר

EMC²

The Hottest Jobs In IT: Training Tomorrow's Data Scientists



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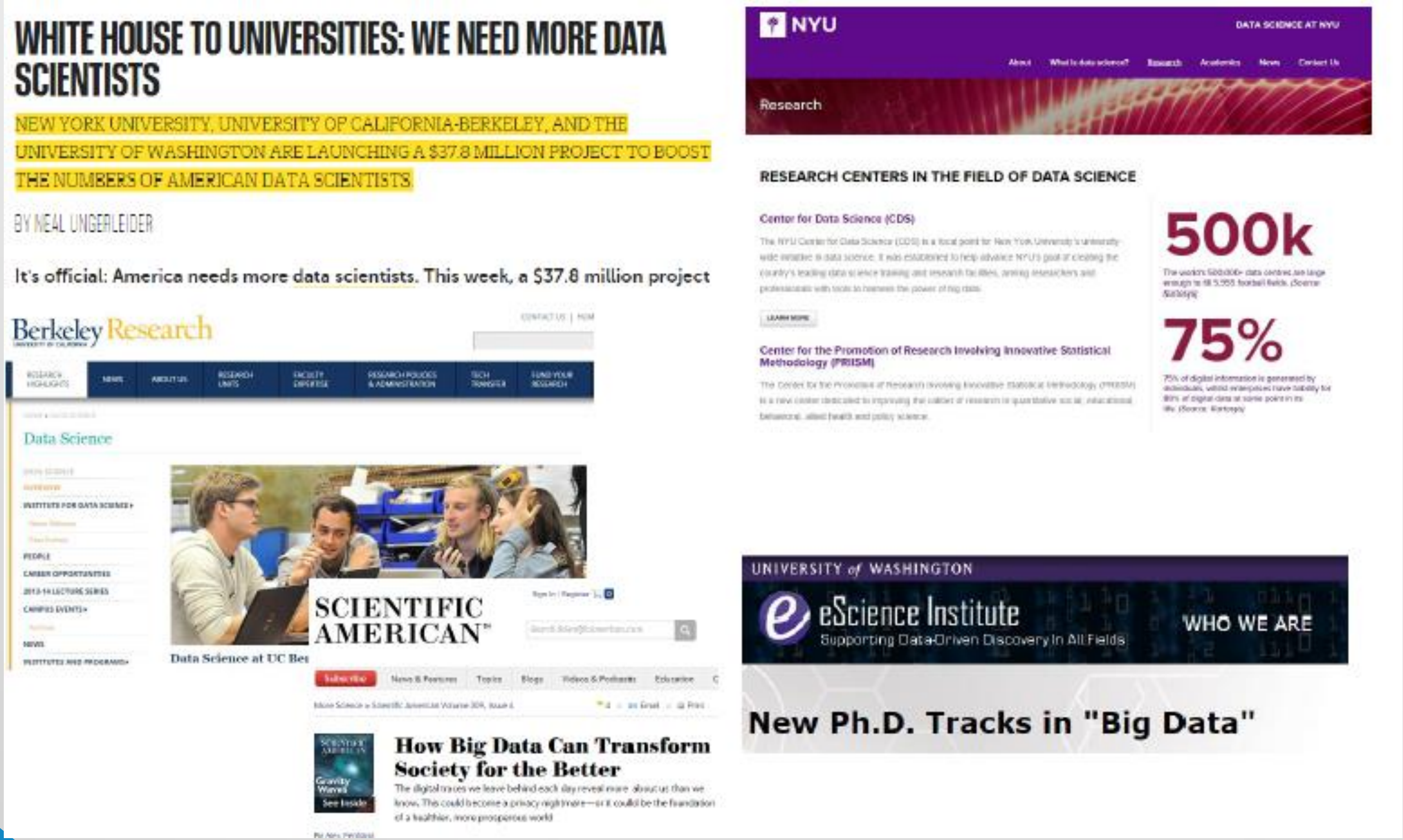
CXO Software Startups Cloud Data Center Mobile Microsoft Apple Google Search TechRepubl

SAP Is your business making the most out of today's technologies?

BIG DATA

Big data skills: Should data scientist be your next job?

Also, in academia



WHITE HOUSE TO UNIVERSITIES: WE NEED MORE DATA SCIENTISTS

NEW YORK UNIVERSITY, UNIVERSITY OF CALIFORNIA-BERKELEY, AND THE UNIVERSITY OF WASHINGTON ARE LAUNCHING A $37.8 MILLION PROJECT TO BOOST THE NUMBERS OF AMERICAN DATA SCIENTISTS.

BY NEAL UNGERLEIDER

It's official: America needs more data scientists. This week, a $37.8 million project

Berkeley Research

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Data Science

Data Science at UC Ber

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How Big Data Can Transform Society for the Better

The digital traces we leave behind each day reveal more about us than we know. This could become a privacy nightmare—or it could be the foundation of a healthier, more prosperous world

NYU

DATA SCIENCE AT NYU

About | What is data science? | Research | Academics | News | Contact Us

Research

RESEARCH CENTERS IN THE FIELD OF DATA SCIENCE

Center for Data Science (CDS)

The NYU Center for Data Science (CDS) is a focal point for New York University's university-wide initiative in data science. It was established to help advance NYU's goal of creating the country's leading data science training and research facilities, arming researchers and professionals with tools to harness the power of big data.

LEARN MORE

Center for the Promotion of Research Involving Innovative Statistical Methodology (PRIISM)

The Center for the Promotion of Research Involving Innovative Statistical Methodology (PRIISM) is a new center dedicated to improving the caliber of research in quantitative social, educational, behavioral, allied health and policy science.

500k

The world's 500,000+ data centres are large enough to fill 5,955 football fields. (Source: Kartoops)

75%

75% of digital information is generated by individuals, whilst enterprises have liability for 80% of digital data at some point in its life. (Source: Kartoops)

UNIVERSITY of WASHINGTON

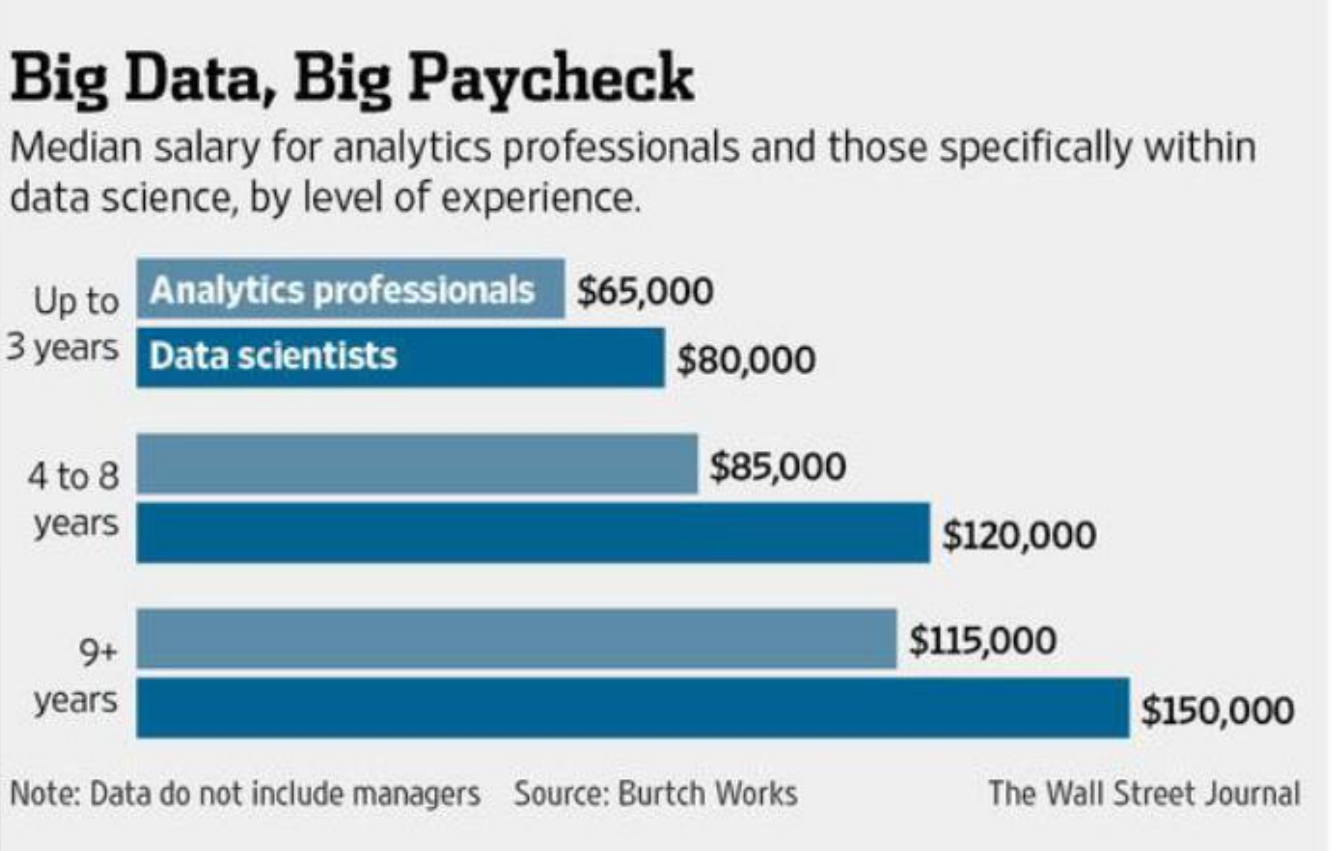
eScience Institute

Supporting Data-Driven Discovery In All Fields

WHO WE ARE

New Ph.D. Tracks in "Big Data"

Pays Well



Big Data, Big Paycheck

Median salary for analytics professionals and those specifically within data science, by level of experience.

Note: Data do not include managers Source: Burtch Works The Wall Street Journal

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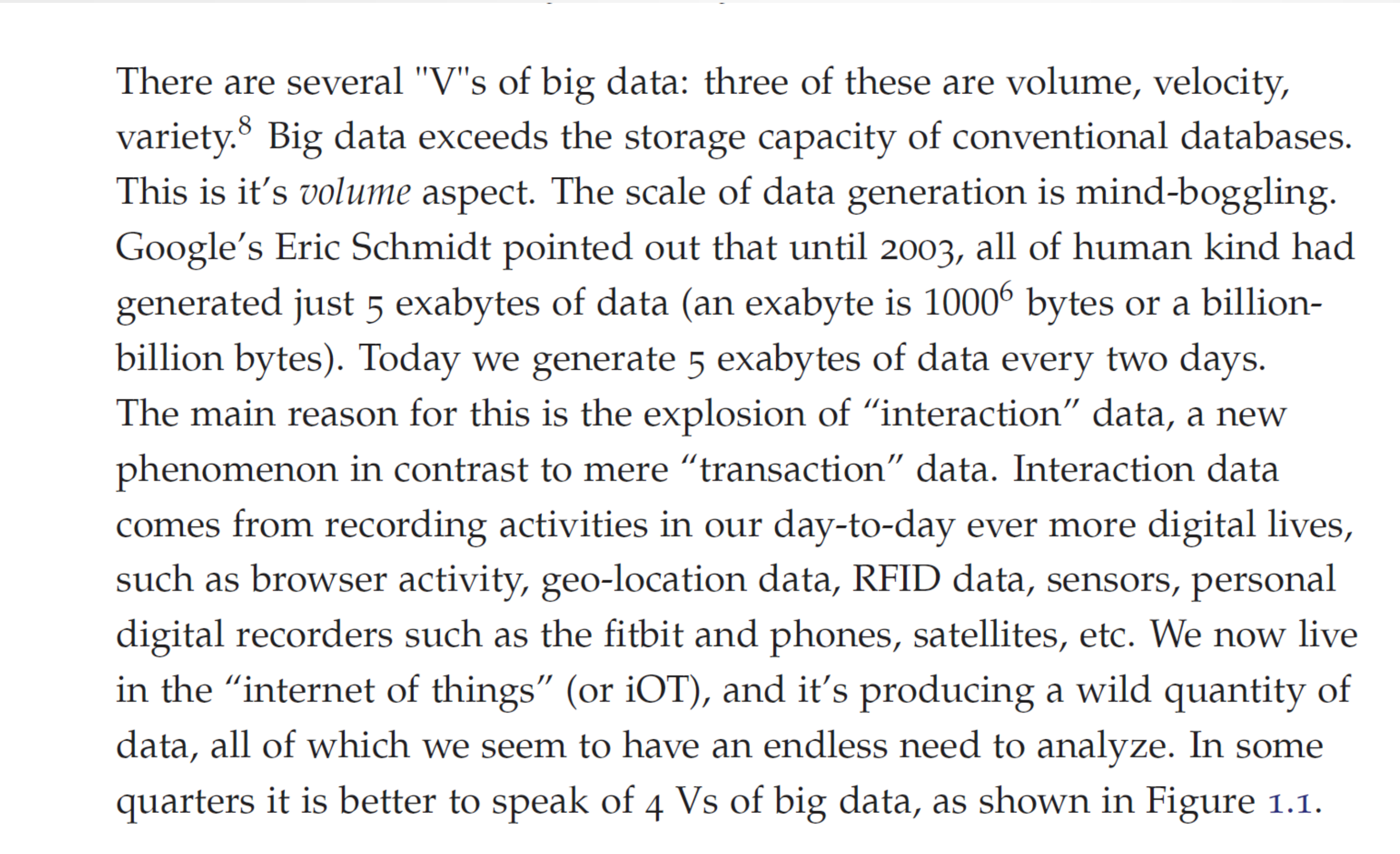
Introduction



There are several "V"s of big data: three of these are volume, velocity, variety.[8] Big data exceeds the storage capacity of conventional databases. This is it's *volume* aspect. The scale of data generation is mind-boggling. Google's Eric Schmidt pointed out that until 2003, all of human kind had generated just 5 exabytes of data (an exabyte is 1000^6 bytes or a billion-billion bytes). Today we generate 5 exabytes of data every two days. The main reason for this is the explosion of "interaction" data, a new phenomenon in contrast to mere "transaction" data. Interaction data comes from recording activities in our day-to-day ever more digital lives, such as browser activity, geo-location data, RFID data, sensors, personal digital recorders such as the fitbit and phones, satellites, etc. We now live in the "internet of things" (or iOT), and it's producing a wild quantity of data, all of which we seem to have an endless need to analyze. In some quarters it is better to speak of 4 Vs of big data, as shown in Figure 1.1.

Goal of Data Science

Turn data into data products.

Analysis

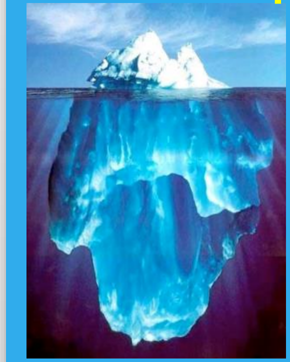
What kinds of data will you use?

- Almost anything is OK, except other predictions.
- **History**: individual or pair-wise?
- Team or players?
- Numerical or text?
- What kind of model will you build?
- What assumptions are safe to make?

Where does data come from?

“Big Data” Sources

It’s All Happening On-line



Every:
Click
Ad impression
Billing event
Fast Forward, pause,…
Server request
Transaction
Network message
Fault
…

User Generated (Web & Mobile)

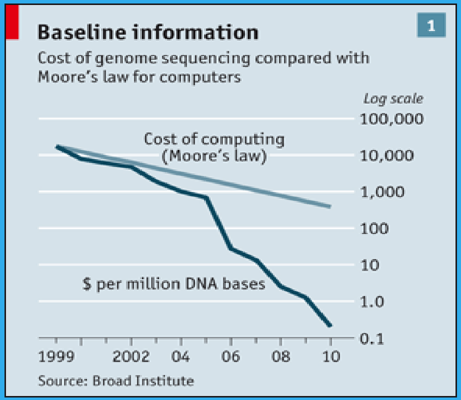
…

..

Internet of Things / M2M

retail
ambient assisted living
health care
productive Business environment
smart energy
smart transports
logistics
smart cities
smart houses

Health/Scientific Computing



Baseline information

Cost of genome sequencing compared with Moore’s law for computers

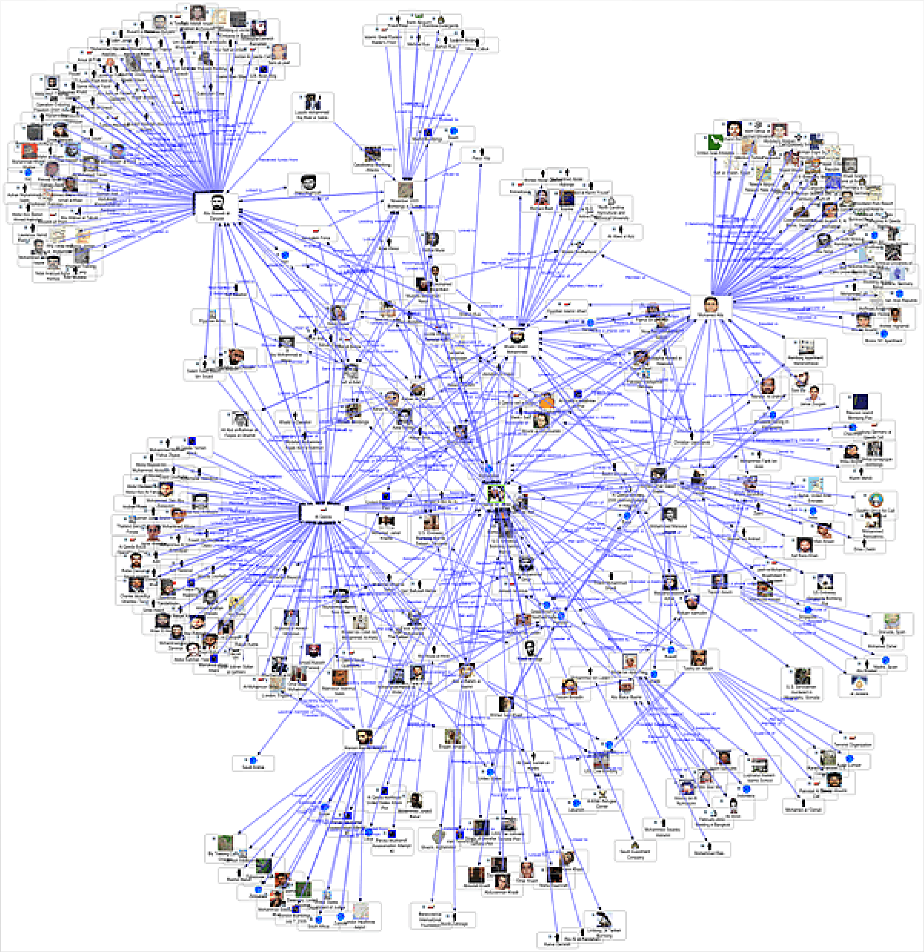
Source: Broad Institute

Graph Data

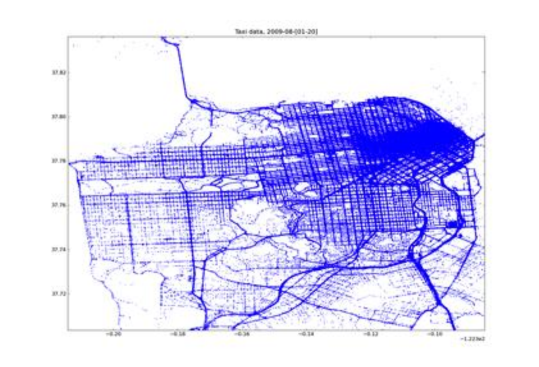
Lots of interesting data
has a graph structure:

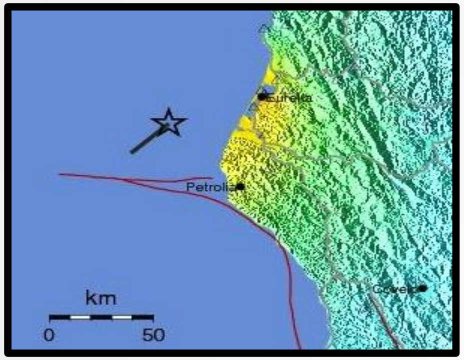
- Social networks
- Communication networks
- Computer Networks
- Road networks
- Citations
- Collaborations/Relationships
- …

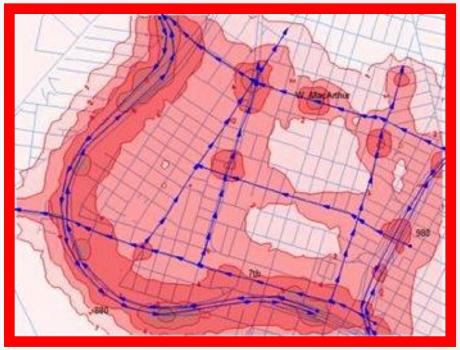
Some of these graphs can get quite large (e.g., Facebook* user graph)



What can you do with the data?







Crowdsourcing + physical modeling + sensing + data assimilation

to produce:

cingular
9:41 AM
Earthquake
Strong Shaking
in 5 seconds
Get under desk

From Alex Bayen, UCB

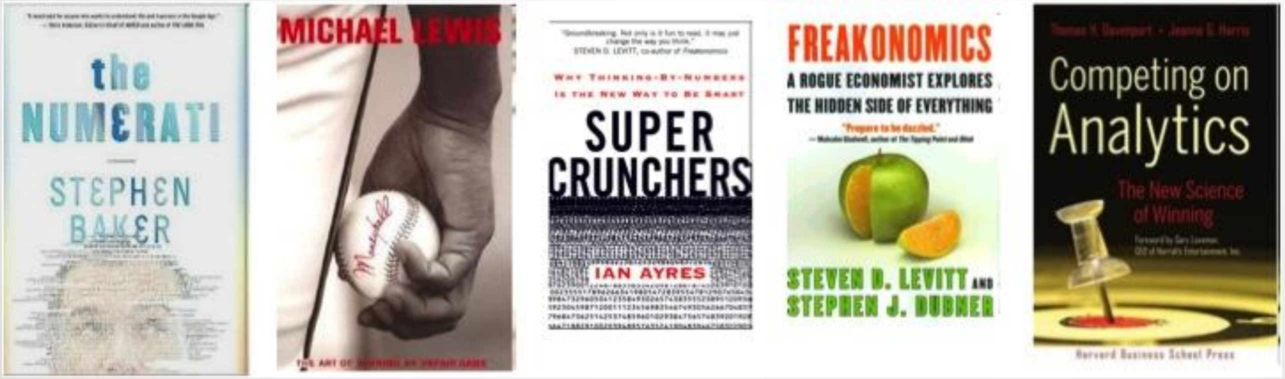
Any
Questions

Contrast: Databases

	Databases	Data Science
Data Value	"Precious"	"Cheap"
Data Volume	Modest	Massive
Examples	Bank records, Personnel records, Census, Medical records	Online clicks, GPS logs, Tweets, Building sensor readings
Priorities	Consistency, Error recovery, Auditability	Speed, Availability, Query richness
Structured	Strongly (Schema)	Weakly or none (Text)
Realizations	SQL	NoSQL: Riak, Memcached, Apache River, MongoDB, CouchDB, Hbase, Cassandra,…

Contrast: Databases

Databases	Data Science
Querying the past	Querying the future


the NUMERATI
STEPHEN BAKER
MICHAEL LEWIS
WHY THINKING-BY-NUMBERS IS THE NEW WAY TO BE SMART
SUPER CRUNCHERS
IAN AYRES
FREAKONOMICS
A ROGUE ECONOMIST EXPLORES THE HIDDEN SIDE OF EVERYTHING
STEVEN D. LEVITT AND STEPHEN J. DUBNER
Thomas H. Davenport · Jeanne G. Harris
Competing on Analytics
The New Science of Winning
Harvard Business School Press

Business intelligence (**BI**) is the transformation of raw data into meaningful and useful information for business analysis purposes. BI can handle enormous amounts of unstructured data to help identify, develop and otherwise create new strategic business opportunities - Wikipedia

Contrast: Scientific Computing

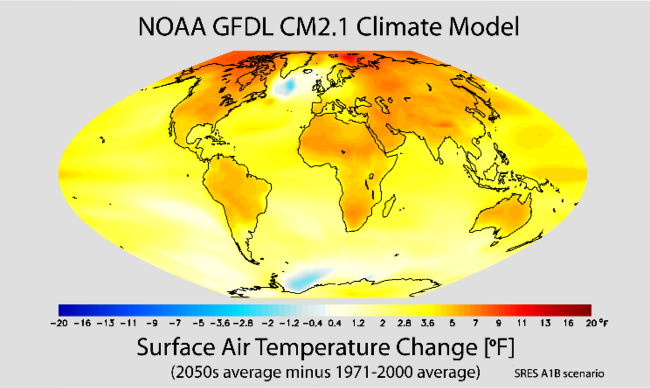
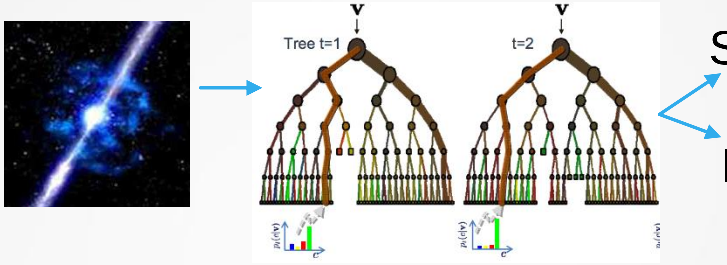

NOAA GFDL CM2.1 Climate Model
−20 −16 −13 −11 −9 −7 −5 −3.6 −2.8 −2 −1.2 −0.4 0.4 1.2 2 2.8 3.6 5 7 9 11 13 16 20 °F
Surface Air Temperature Change [°F]
(2050s average minus 1971-2000 average)
SRES A1B scenario

Image General purpose classifier



Supernova

Not

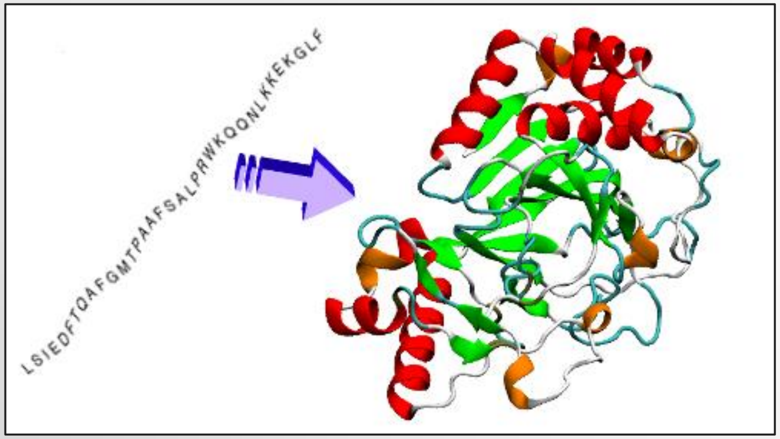
Nugent group / C3 LBL

Scientific Modeling
Physics-based models
Problem-Structured
Mostly deterministic, precise
Run on Supercomputer or High-end Computing Cluster

Data-Driven Approach
General inference engine replaces model
Structure not related to problem
Statistical models handle true randomness, and **unmodeled complexity**.
Run on cheaper computer Clusters (EC2)

Contrast: Computational Science

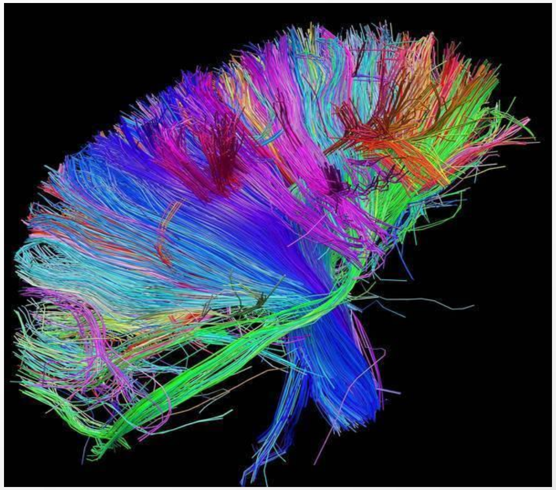
CASP: A Worldwide, Biannual Protein Folding Contest



Quark
Rich, Complex Energy Models
Faithful, Physical Simulation

Raptor-X
Data-intensive, general ML models
Feature-based inference
Conditional Neural Fields

Brain Mapping: Allen Institute, White House, Berkeley



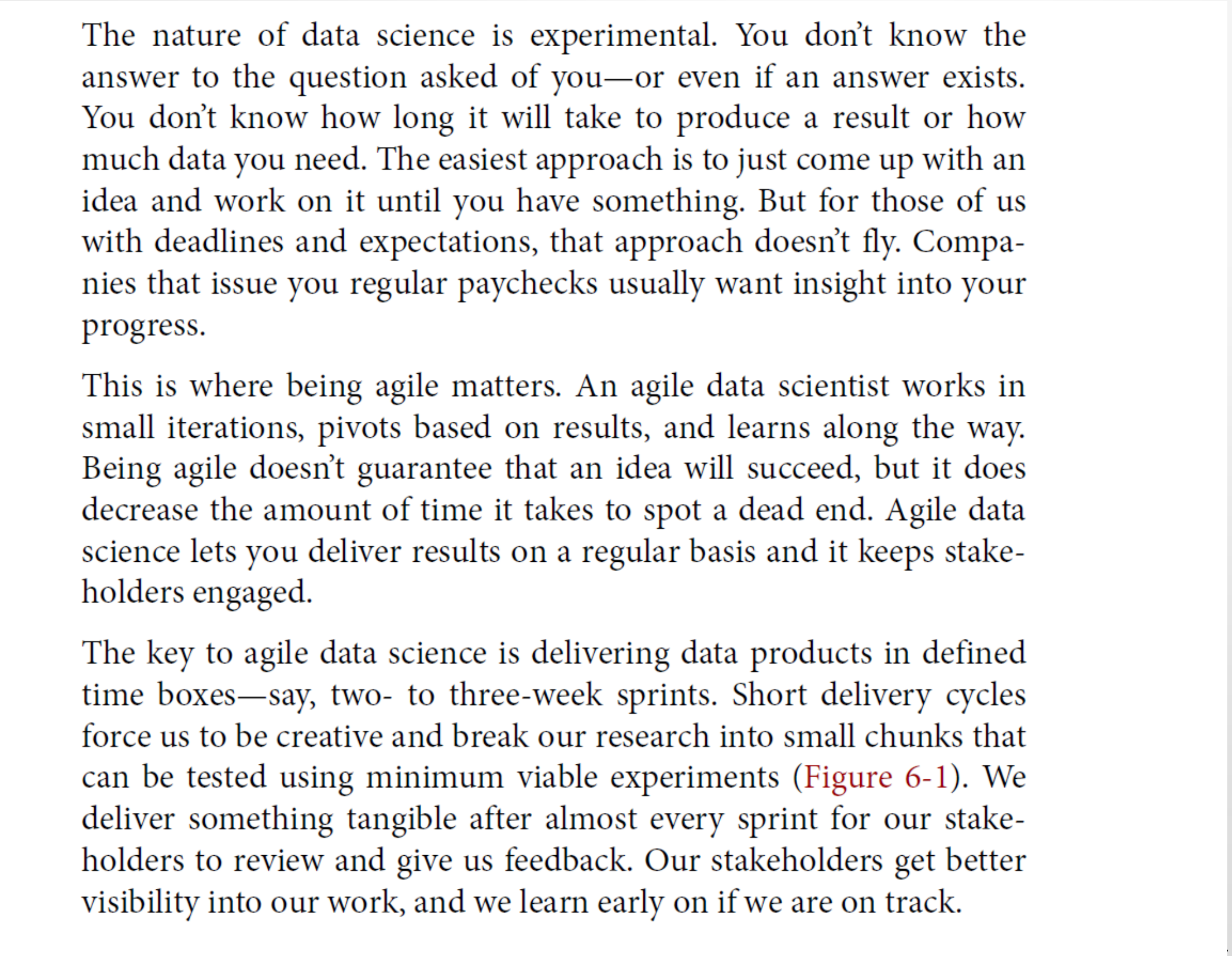
Techniques (Massive ML)
Principal Component Analysis
Independent Component Analysis
Sparse Coding
Spatial (Image) Filtering

Contrast: Machine Learning

Machine Learning
Develop new (individual) models
Prove mathematical properties of models
Improve/validate on a few, relatively clean, small datasets
Publish a paper

Data Science
Explore many models, build and tune hybrids
Understand empirical properties of models
Develop/use tools that can handle massive datasets
Take action!

How to Be Agile

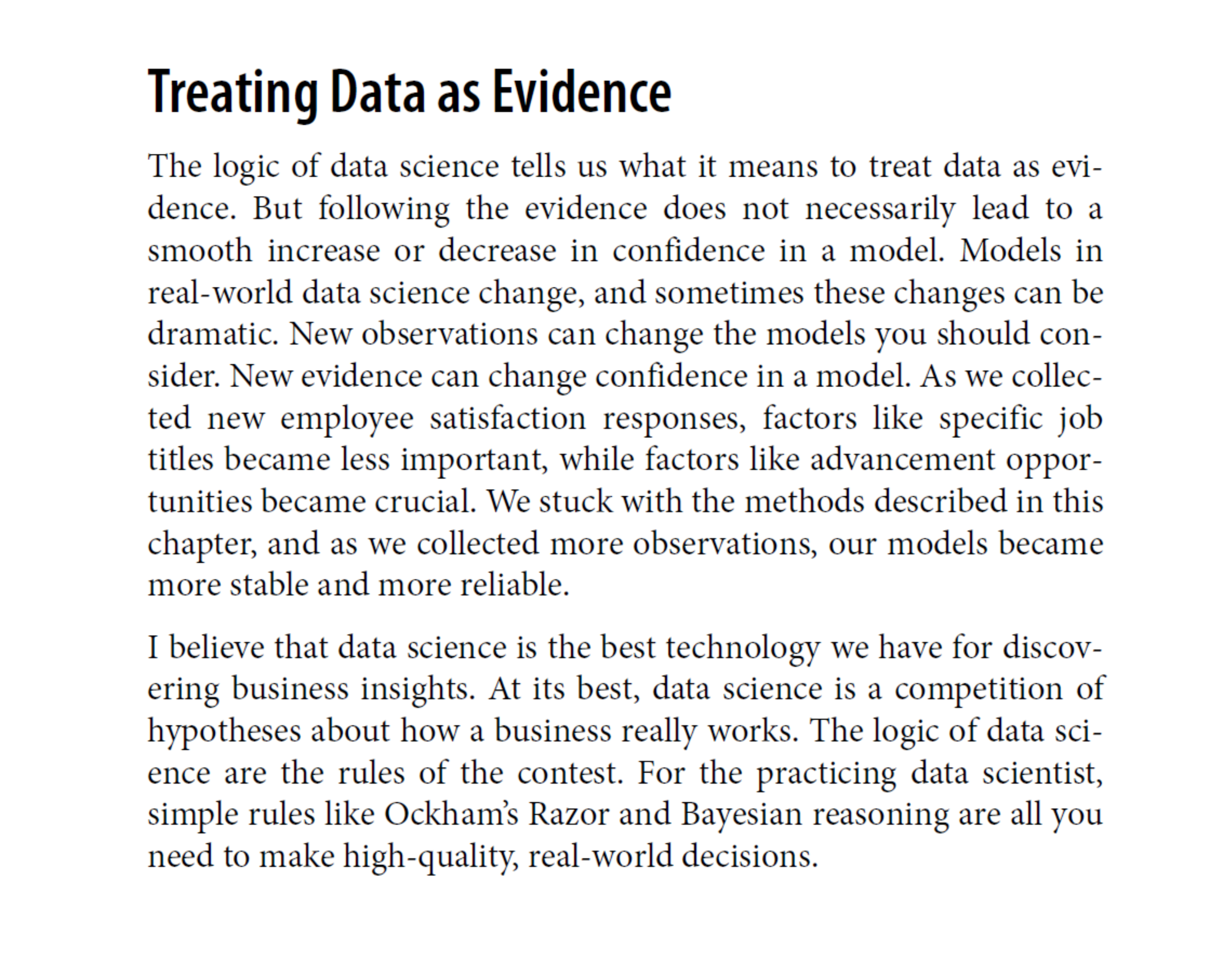


The nature of data science is experimental. You don't know the answer to the question asked of you—or even if an answer exists. You don't know how long it will take to produce a result or how much data you need. The easiest approach is to just come up with an idea and work on it until you have something. But for those of us with deadlines and expectations, that approach doesn't fly. Companies that issue you regular paychecks usually want insight into your progress.

This is where being agile matters. An agile data scientist works in small iterations, pivots based on results, and learns along the way. Being agile doesn't guarantee that an idea will succeed, but it does decrease the amount of time it takes to spot a dead end. Agile data science lets you deliver results on a regular basis and it keeps stakeholders engaged.

The key to agile data science is delivering data products in defined time boxes—say, two- to three-week sprints. Short delivery cycles force us to be creative and break our research into small chunks that can be tested using minimum viable experiments (Figure 6-1). We deliver something tangible after almost every sprint for our stakeholders to review and give us feedback. Our stakeholders get better visibility into our work, and we learn early on if we are on track.

Introduction



Treating Data as Evidence

The logic of data science tells us what it means to treat data as evidence. But following the evidence does not necessarily lead to a smooth increase or decrease in confidence in a model. Models in real-world data science change, and sometimes these changes can be dramatic. New observations can change the models you should consider. New evidence can change confidence in a model. As we collected new employee satisfaction responses, factors like specific job titles became less important, while factors like advancement opportunities became crucial. We stuck with the methods described in this chapter, and as we collected more observations, our models became more stable and more reliable.

I believe that data science is the best technology we have for discovering business insights. At its best, data science is a competition of hypotheses about how a business really works. The logic of data science are the rules of the contest. For the practicing data scientist, simple rules like Ockham's Razor and Bayesian reasoning are all you need to make high-quality, real-world decisions.

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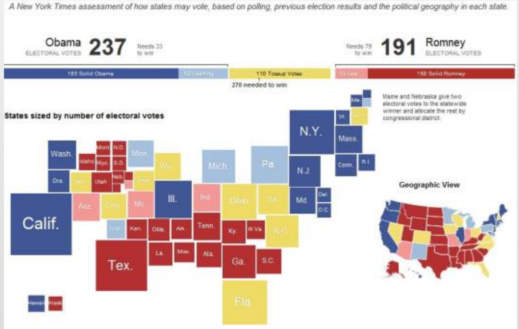
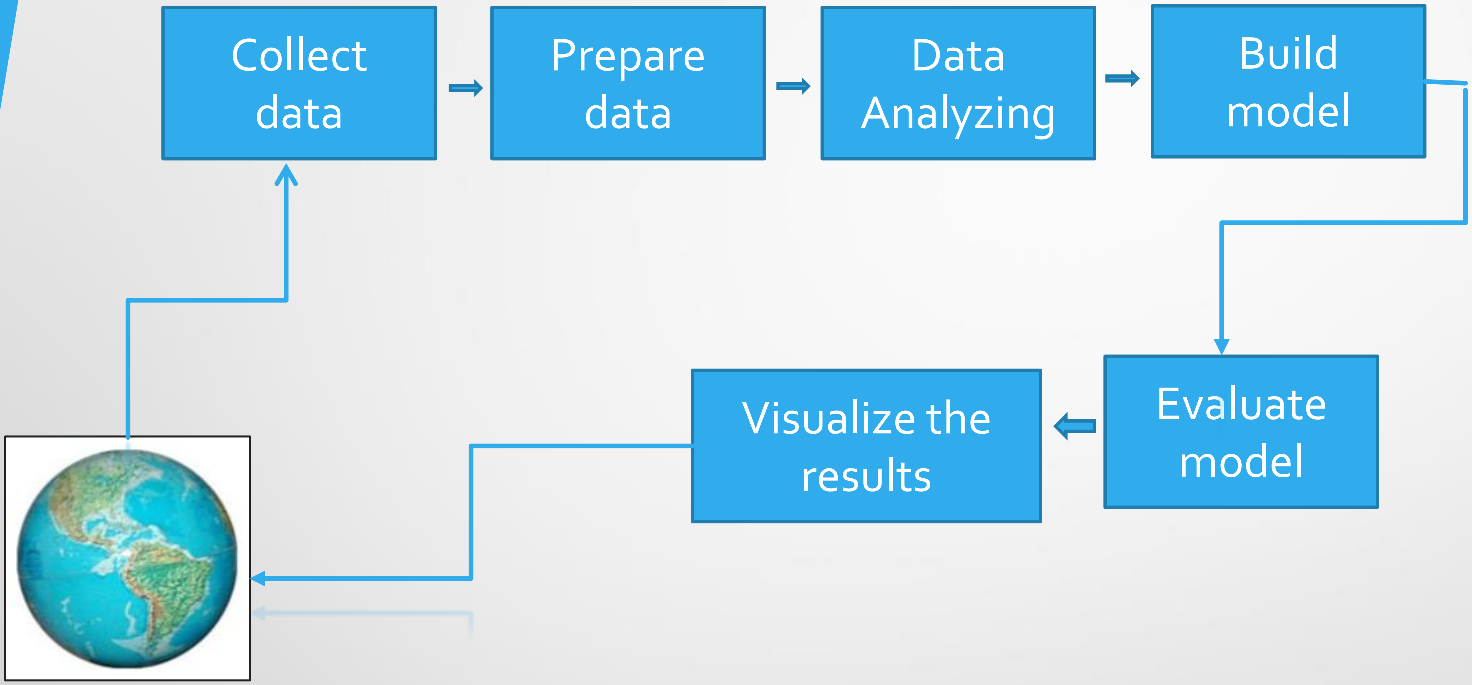
1. Data sources
2. Collect data(**download**)
3. Prepare data (integrate, transform, clean, filter, aggregate)
4. Build model
5. Evaluate model
6. Visualize the results



Introduction



Collect data

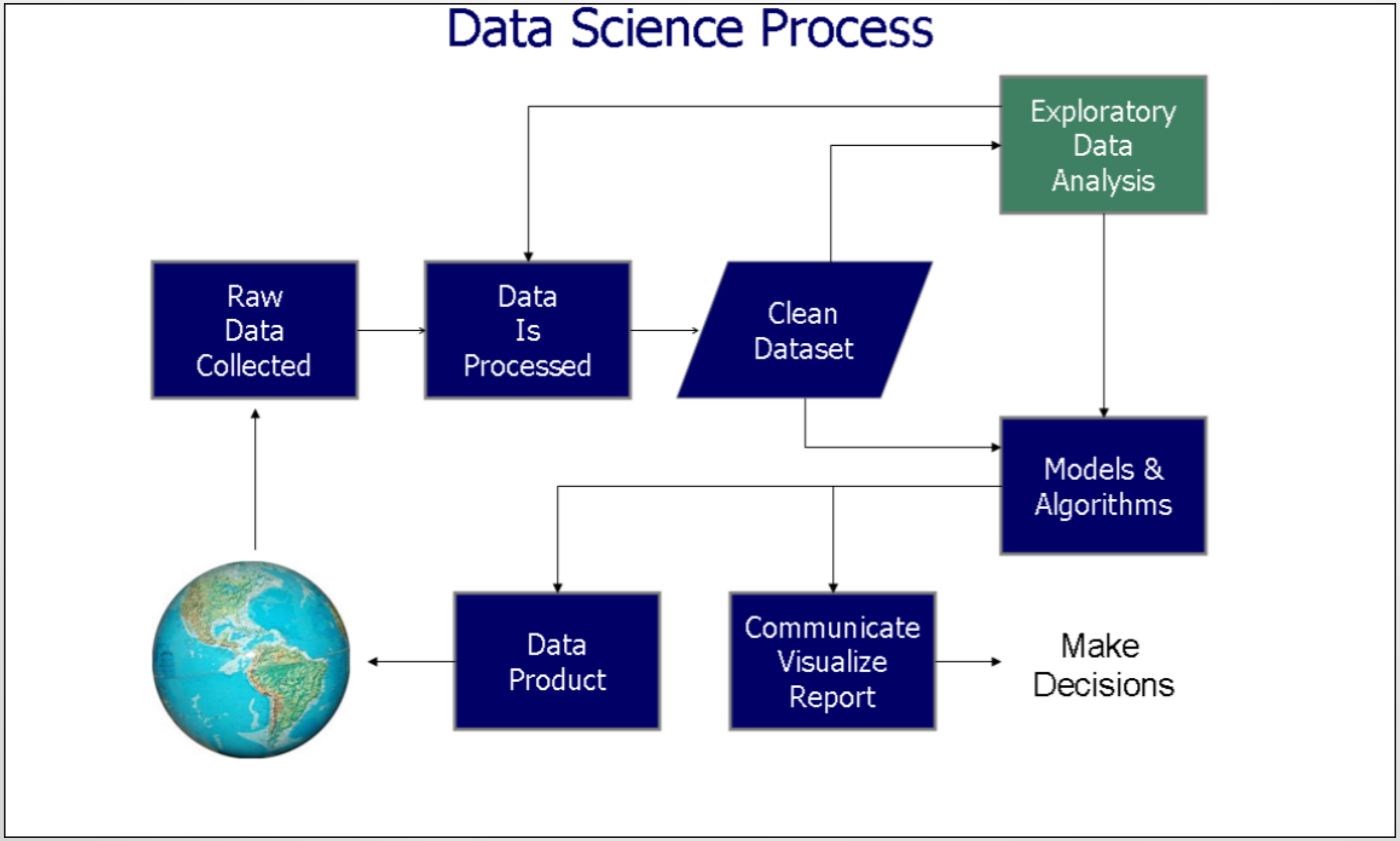
Prepare data

Data Analyzing

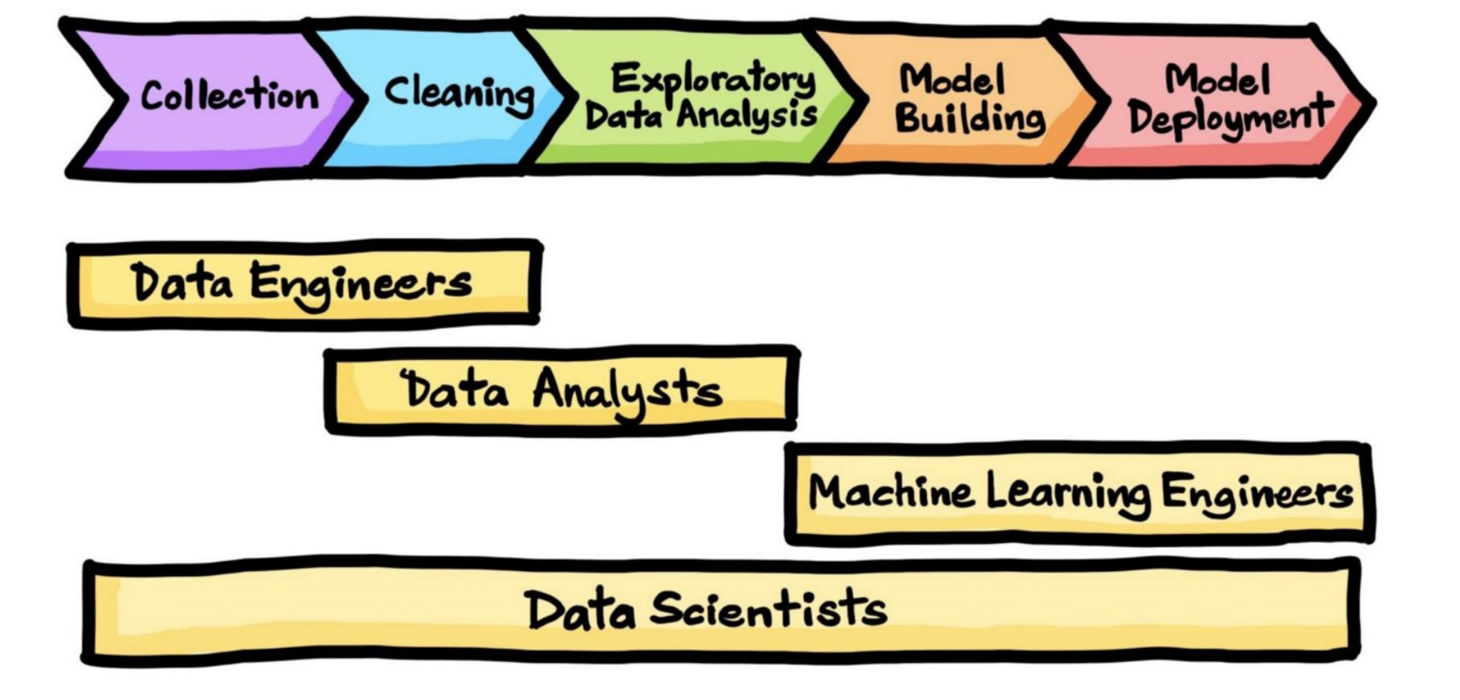
Build model

Evaluate model

Visualize the results

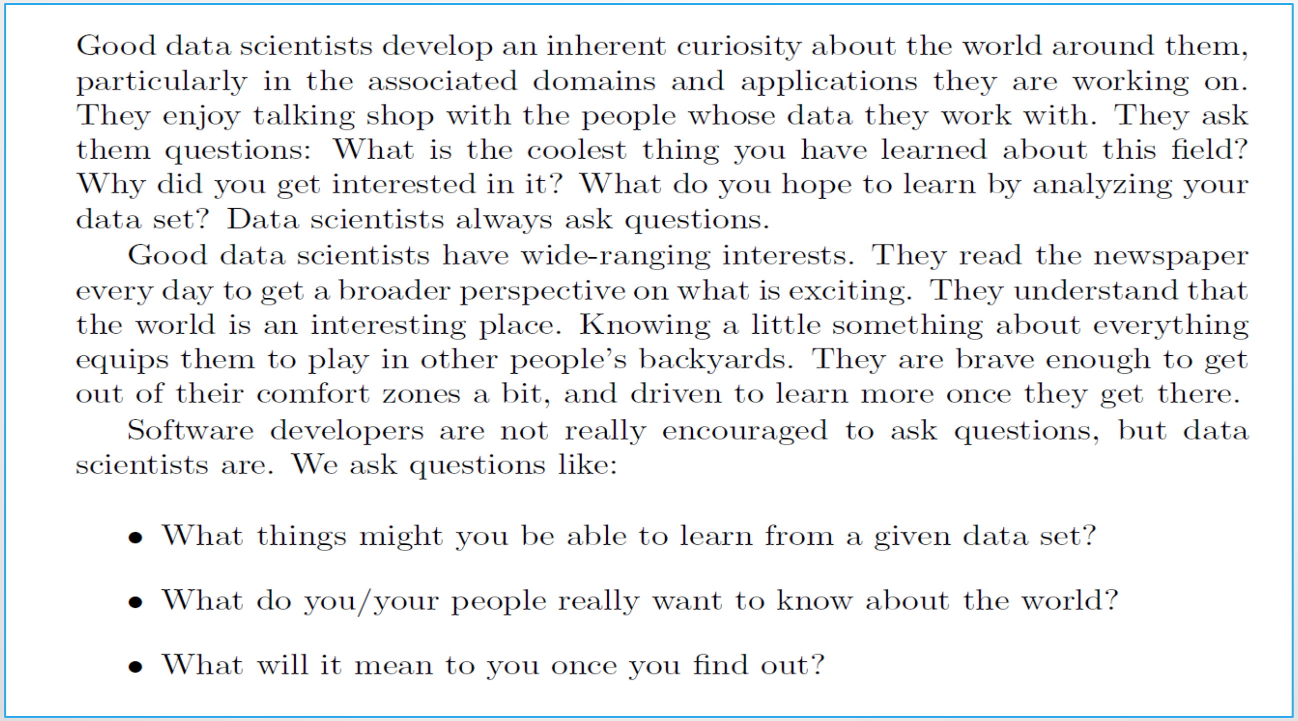


Data Science Process


Collection
Cleaning
Exploratory Data Analysis
Model Building
Model Deployment
Data Engineers
Data Analysts
Machine Learning Engineers
Data Scientists

Asking Interesting Questions from Data

Introduction



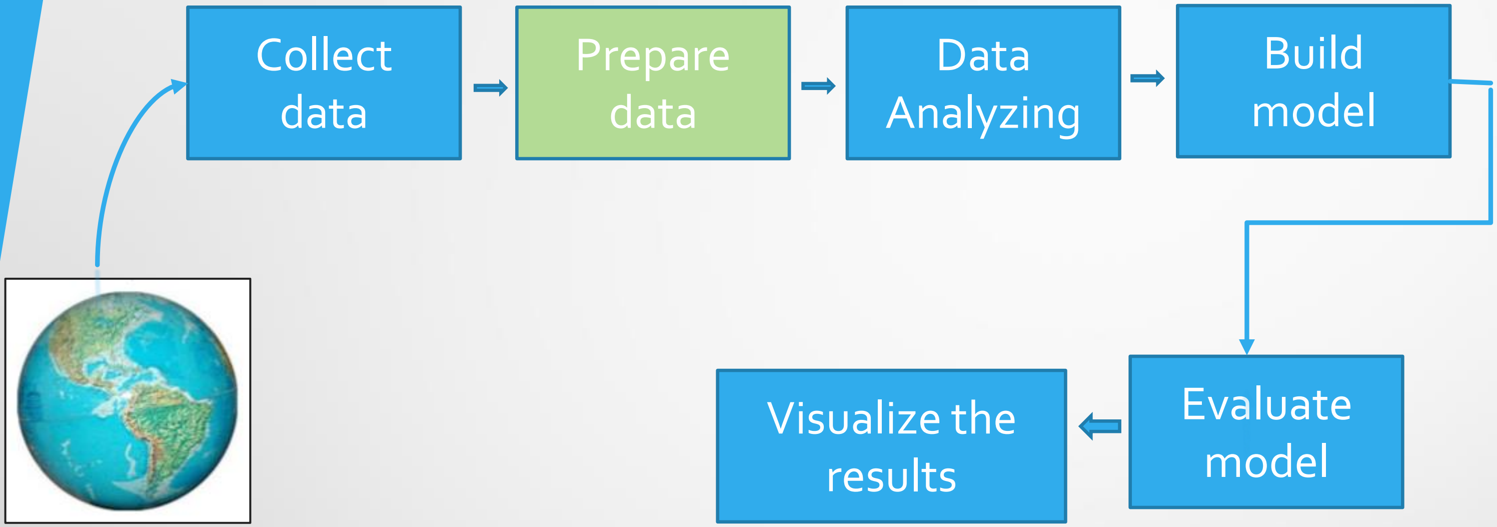
Good data scientists develop an inherent curiosity about the world around them, particularly in the associated domains and applications they are working on. They enjoy talking shop with the people whose data they work with. They ask them questions: What is the coolest thing you have learned about this field? Why did you get interested in it? What do you hope to learn by analyzing your data set? Data scientists always ask questions.

Good data scientists have wide-ranging interests. They read the newspaper every day to get a broader perspective on what is exciting. They understand that the world is an interesting place. Knowing a little something about everything equips them to play in other people's backyards. They are brave enough to get out of their comfort zones a bit, and driven to learn more once they get there.

Software developers are not really encouraged to ask questions, but data scientists are. We ask questions like:

- What things might you be able to learn from a given data set?
- What do you/your people really want to know about the world?
- What will it mean to you once you find out?

- After you understand what kind of information is available, try to come up with, say,
- 10 interesting questions you might explore/answer with access to the data set.



Collect data

Prepare data

Data Analyzing

Build model

Evaluate model

Visualize the results

My DATA

Statistical information about my data

What’s Hard about Data Science

- Overcoming assumptions
- Making ad-hoc explanations of data patterns
- Overgeneralizing
- Communication
- Not checking enough (validate models, data pipeline integrity, etc.)
- Using statistical tests correctly
- Prototype → Production transitions
- Data pipeline complexity (who do you ask?)

Readings

Read next week readings and complete it before next class.

- Chapter Two: Python Language Basics, IPython, and Jupyter Notebooks
- Chapter Three: Built-In Data Structures, Functions, and Files

python for data analysis 2nd edition pdf

Any
Questions