UNIVERSITY OF MARYLAND

MSML610: Advanced Machine Learning

Introduction

::: columns :::: {.column width=75%}

Instructor: Dr. GP Saggese - `gsaggese@umd.edu`

References:

Data Science

- **Promises of data science** (DS)
- Give a competitive advantages
- Make better strategic and tactical business decisions
- Optimize business processes
- **Data science is not new**, it was called:
- Operation research (~1970-80s)
- Decision support, Business intelligence (~1990s)
- Predictive analytics (Early 2010s)
- ...
- **What has changed**
- Now learning and applying DS is easy**
  - No need for hiring a consulting company
- Tools are open-source
  - E.g., Python + pydata stack (numpy, scipy, Pandas, sklearn)
- Large data sets available
- Cheap computing (e.g., AWS, Google Cloud)

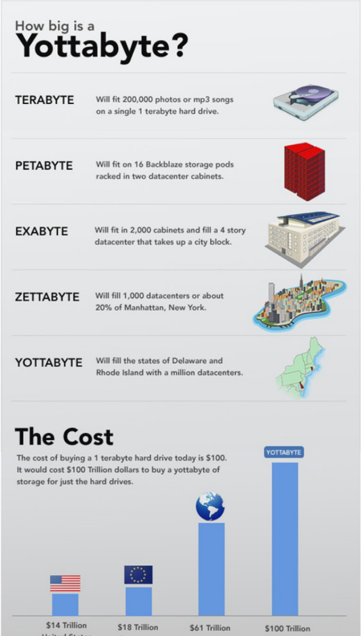
Motivation: Data Overload

- **"Data science is the number one catalyst for economic growth**"
  - McKinsey, 2013
- **Explosion of data in every domain**
  - Sensing devices/networks monitor processes 24/7
    - E.g., temperature of your room, your vital signs, pollution in the air
  - Sophisticated smart-phones (80% of the world population)
  - Internet and social networks make it easy to publish data
  - Internet of Things (IoT): everything is connected to the internet
    - E.g., power supply, toasters
  - Datafication: turn all aspects of life into data
    - E.g., what you like/enjoy turned into a stream of your "likes"
- **Challenges**
  - How to handle the increasing amount data?
  - How to extract actionable insights and scientific knowledge from data?

Scale of Data Size

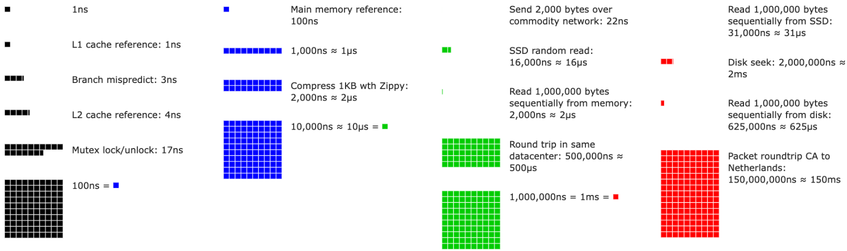
- **Megabyte** = 210 approx 106 bytes
  - Typical English book
- **Gigabyte** = 109 bytes = 1000 MB
  - 1/2 hour of video
  - Wikipedia (compressed, without media) is 22GB
- **Terabyte** = 1M MB
  - Human genome: ~1TB
  - 100,000 photos
  - LHC generates 100TB of data per day
  - 50 to buy 1TB HDD, 23/mo on AWS S3
- **Petabyte** = 1000 TB
  - 13 years of HD video
  - 250k (USD) /year on AWS S3
- **Exabyte** = 1M TB
  - Global yearly Internet traffic in 2004
- **Zetabyte** = 1B TB = 1021 bytes
  - Global yearly Internet traffic in 2016
- **Yottabytes** = 1024 bytes
  - Yottabyte costs (USD) 100T
- **Brontobytes** = 1027 bytes

Scale of Data Size



Constants Everybody Should Know

From Latency Numbers Every Programmer Should Know (by year) - A CPU running at 3GHz executes an instruction every 0.3ns - L1 cache reference/register: 1ns - L2 cache reference: 4ns - Main memory reference: 100ns - Send 1KB over network: 10ns - Read 1MB from memory: 2us - SSD random read: 16us - Disk seek: 2ms - Packet round-trip from CA to Netherland: 150ms



Big Data Applications

- **Personalized marketing**
- Target each consumer instead of the consumers at large
  - E.g., Amazon personalizes suggestions using signals from:
    - Your shopping history
    - What you have searched for (or clicked, browsed)
    - Other consumers and trends
    - Reviews (through NLP and sentiment analysis)
- Brands want to understand how customers relate to products
  - Use sentiment analysis from:
    - Social media, on-line reviews, blogs, surveys
  - Positive, negative, neutral feeling
- E.g.,
  - In 2022, (USD)600B spent on digital marketing
  - 50 Stats Showing The Power Of Personalization

Big Data Applications

- **Mobile advertisement**
- Mobile phones are ubiquitous
  - 80% of world population has one
  - 6.5b smart phones
- Integration of on-line and off-line databases, e.g.,
  - GPS location
  - Search history
  - Credit card transactions
- E.g.,
  - You've bought a new house
  - You google questions about house renovations
  - You watch shows about renovations
  - Your phone tracks where you are
  - Google sends you coupons for the closest Home Depot
  - "I feel like Google is following me", "it's like Facebook is reading my mind"

Big Data Applications

Big Data Applications

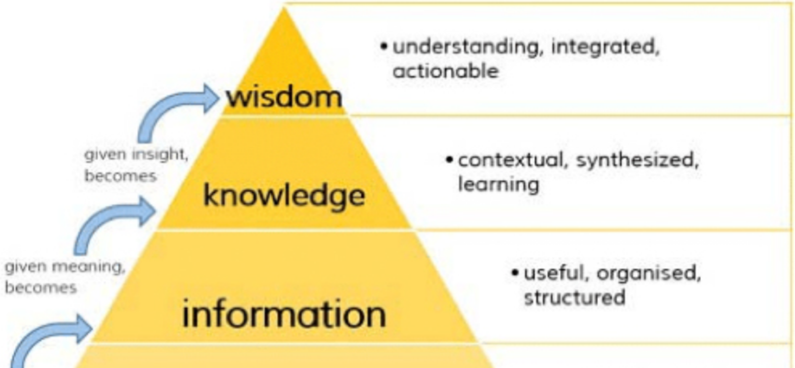
- **Biomedical data**
- Personalized medicine
  - Patients can receive treatment tailored to them to maximize efficacy
  - Genetics
  - Daily activities
  - Environment
  - Habits
- Genome sequencing
- Health tech
  - Personal health trackers (e.g., smart rings, phones)

Big Data Applications

- **Smart cities**
- Interconnected mesh of sensors
  - E.g., traffic sensors, camera networks, satellites
- Goals:
  - Monitor air pollution
  - Minimize traffic congestion
  - Optimal urban services
  - Maximize energy savings

Goal of Data Science

- **Goal**: from data to wisdom
  - Data (raw bytes)
  - Information (organized, structured)
  - Knowledge (learning)
  - Wisdom (understanding)
- Insights enable decisions and actions
- Combine streams of big data to generate new data
  - New data can be "big data" itself



Four V's of Big Data

- Characteristics of big data
- **Volume**
  - Vast amount of data is generated
- **Variety**
  - Different forms
- **Velocity**
  - Speed at which data is generated
- **Veracity**
  - Biases, noise, abnormality in data
  - Uncertainty, trustworthiness
- (**Valence**)
  - Connectedness of big data in the form of graphs
- (**Value**)
  - Data needs to be valuable
  - Big data needs to benefit an organization

Four V's of Big Data

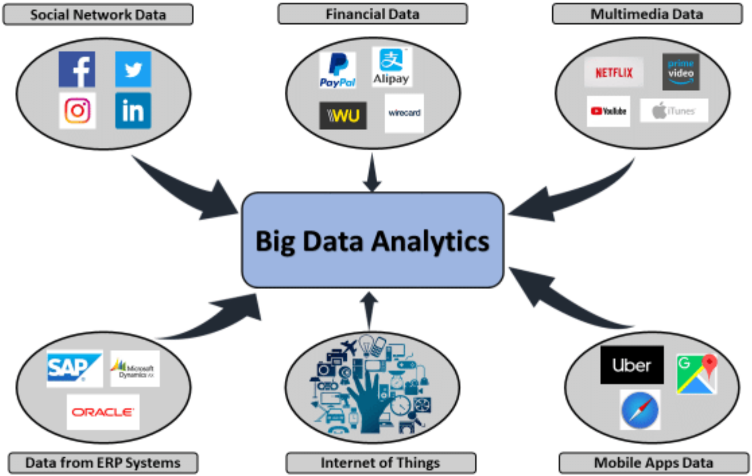
- **Volume**
- Exponentially increasing amount of data
- Every day 2.5 exabytes (1m of TB) of data is generated
  - 90% of all the data in the world was generated in the last 2 years
  - Total amount of stored data doubles every 1.2 years
- Twitter / X: 500M tweets/day (2022)
- Google processes 8.5B queries/day (2022)
- Meta generates 4PB of data/day (2022)
- Walmart: 2.5PB of unstructured data/hour (2022)
- **Variety**
- Data has different forms
  - Structured data (e.g., spreadsheets, relational data)
  - Semi-structured data (e.g., text, sales receipts, your class notes)
  - Unstructured data (e.g., photos, videos)
- Data comes in different formats (e.g., binary, CSV, XML, JSON)

Four V's of Big Data

- **Velocity**
- Relates to the speed at which data is generated
  - E.g., sensors generate data streams
- Sometimes data can be processed off-line
- Real-time analytics: consume data as fast as it is generated
- **Veracity**
- Relates to data quality
- How to remove noise and bad data?
- How to fill in missing values?
- What is an outlier?
- How do you decide what data to trust?

Sources of Big Data

- We can distinguish Big Data in terms of its source
  - Machines
  - People
  - Organizations



Sources of Big Data: Machines

- **Machines** generate data
  - Real-time sensors (e.g., sensors on Boeing 787)
  - Cars
  - Website tracking
  - Personal health trackers
  - Scientific experiments
- **Pros**
  - Highly structured
- **Cons**
  - Can't be easily moved, but need to be computed in-place or in centralized fashion
  - Streaming, not batch

Sources of Big Data: People

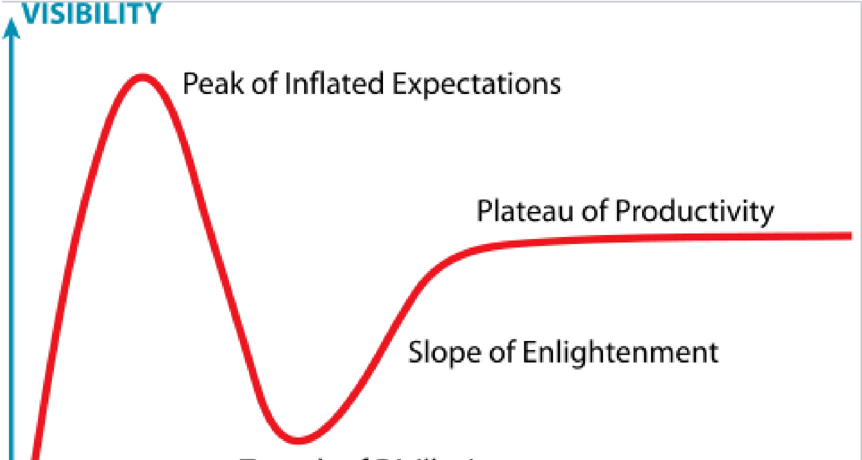
- **People** and their activities generate data
  - Social media (e.g., Instagram, Twitter, LinkedIn)
  - Video sharing (e.g., YouTube, TikTok)
  - Blogging and commenting on a website
  - Internet searches
  - Text messages (e.g., SMS, Whatsapp, Signal, Telegram)
  - Personal documents (e.g., Google Docs, emails)
- **Pros**
  - Allow personalization
  - Highly valuable for business intelligence
- **Cons**
  - Typically semi-structured or unstructured data
    - Text, data605/lectures_source/images, movies
  - It takes an investment before you can reap the value
    - Acquire → Store → Clean → Retrieve → Process → Insights
  - Surveillance capitalism

Sources of Big Data: Orgs

- **Organizations** generate data
  - Commercial transactions
  - Credit cards
  - E-commerce
  - Banking
  - Medical records
  - Clicks on a website
- **Pros**
  - Highly structured
- **Cons**
  - Need to store every event in the past to predict the future
    - Missing opportunities
  - Stored in “data silos” with different data models
    - Each department has its own data system
    - Additional complexity
    - Data is outdated/not visible
    - Cloud computing helps (e.g., data lakes, data warehouses)

Is Data Science Just Hype?

- Big data (or data science)
  - "Any process where interesting information is inferred from data"
- Data scientist called the "sexiest job" of the 21st century
  - The term has becoming very muddled at this point
- **Is it all hype?**

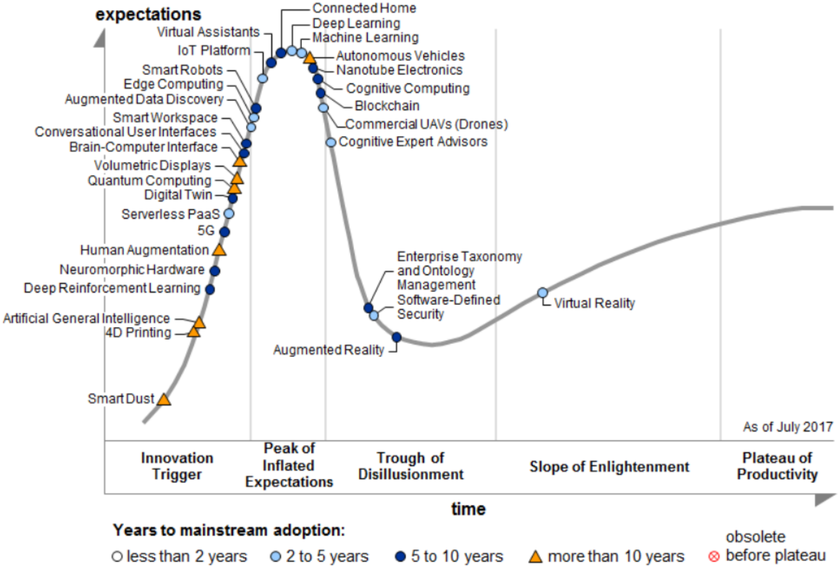


Is Data Science Just Hype?

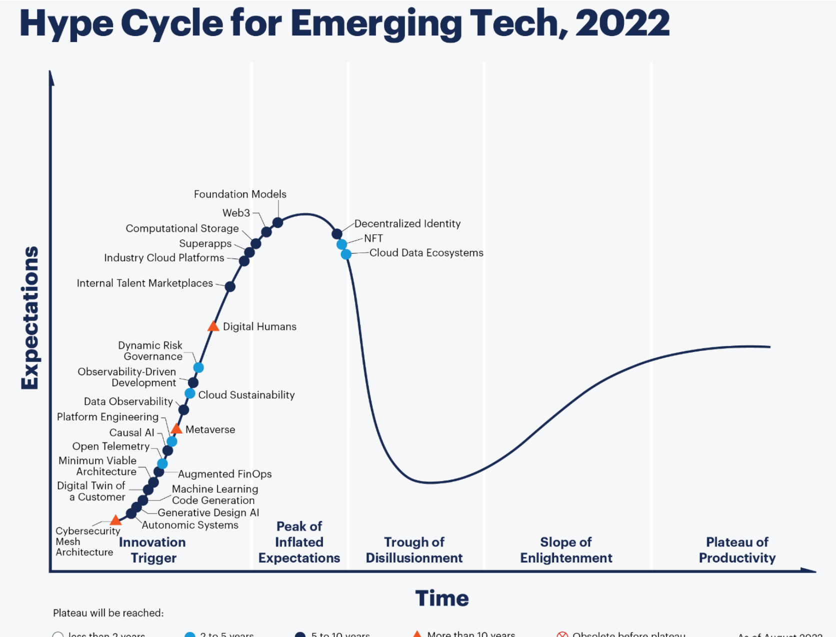
- **No**
  - Extracting insights and knowledge from data Is very important and will continue to increase in importance
  - Big data techniques are revolutionizing the world in many domains
    - E.g., education, food supply, disease epidemics, ...
- **But**
  - Not much different from what statisticians have been doing for many years
- **What is different?**
  - Much more data is digitally available than ever before
  - Easy-to-use programming frameworks (e.g., Hadoop) = much easier to analyze it
  - Cloud computing (e.g., AWS) = much cheaper to analyze it
  - Often large-scale data + simple algorithms » small data + complex algorithms

What was Cool in 2012?

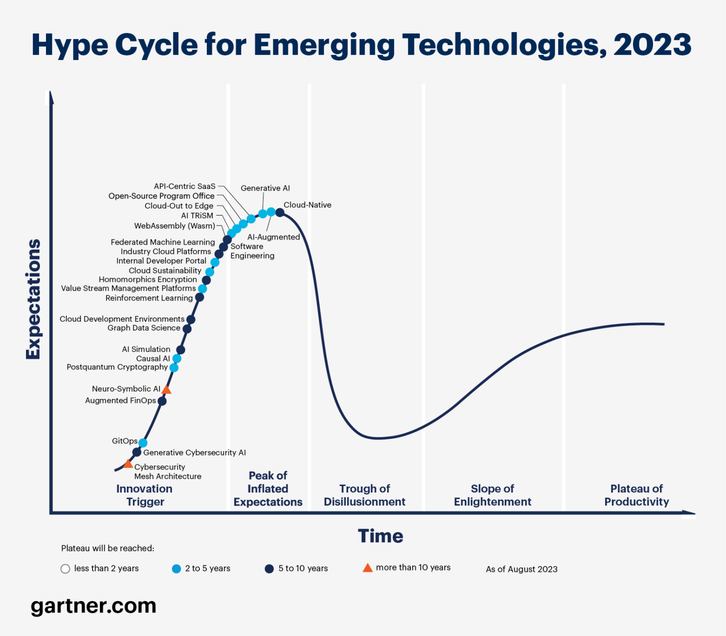
What was Cool in 2017?



What was Cool in 2022?



What is Cool in 2023?

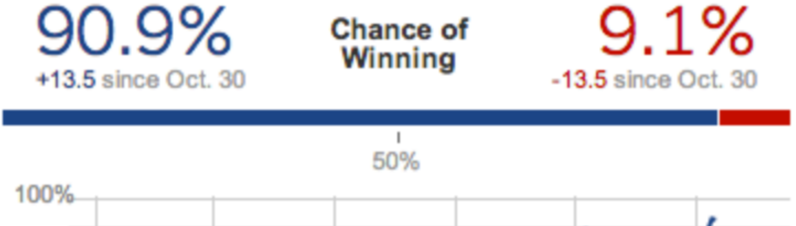


Key Shifts Before/After Big-Data

- **Datasets: small, curated, clean → large, uncurated, messy**
  - Before:
    - Statistics based on small, carefully collected random samples
    - Costly and careful planning for experiments
    - Hard to do fine-grained analysis
  - Today:
    - Easily collect huge volume of data
    - Feed it into algorithms
    - Usually the signal is strong enough to overcome the noise
- **Causation → Correlation**
  - Goal: figure out what caused what
  - Causation very hard to figure out → give up causation for correlation
    - Finding out if two things are correlated is good enough
    - E.g., people buying diapers and beer together at the supermarket
- **"Data-fication"**
  - = process of converting abstract things into concrete data
  - E.g., "sitting posture" is data-fied by 100's of sensors placed in your seat
  - Your preference is data-fied into a stream of likes
- From: Rise of Big Data, 2013

Examples: Election Prediction

- Nate Silver and the 2012 Elections
  - 49 out of 50 in calling each state in 2008 US elections
  - 50 out of 50 in 2012 US elections
  - Didn't work that well in 2016, did it?
- Some reasons why he got things right
  - Many sources of data, irrespective of quality
  - Incorporation of historical accuracy
  - Use of statistical models
  - Understanding correlations
  - Monte-Carlo simulations to compute the probabilities of electoral college
  - Focus on probabilities instead of predictions
  - Great communication and presentation skills

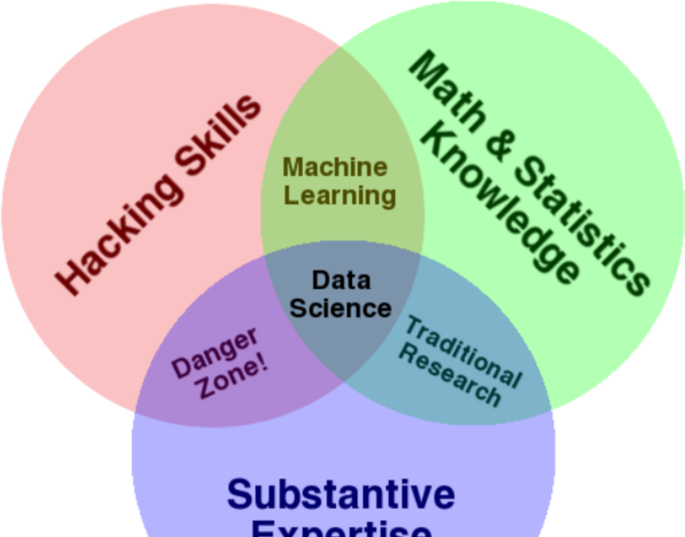


Examples: Google Flu Trends

- 5% to 20% of US population contracts flu every year and 40k deaths
- Earlier warnings allow prevention and control
- Google Flu Trends
  - Early warning of flu outbreaks by analyzing search queries
    - What terms people searched for (45 search terms)
    - IP to determine location
  - Predict regional outbreaks of flu up to 1 or 2 weeks ahead of CDC
  - Service in activity from 2008 to 2015
- Caveat: accuracy not as good any more
  - Google claimed 97% accuracy
  - Out of sample accuracy lower (overshot CDC data by 30%)
  - People search about flu without knowing how to diagnose flu
    - E.g., people searching for "fever" and "cough"
  - Google Flu Trends: The Limits of Big Data

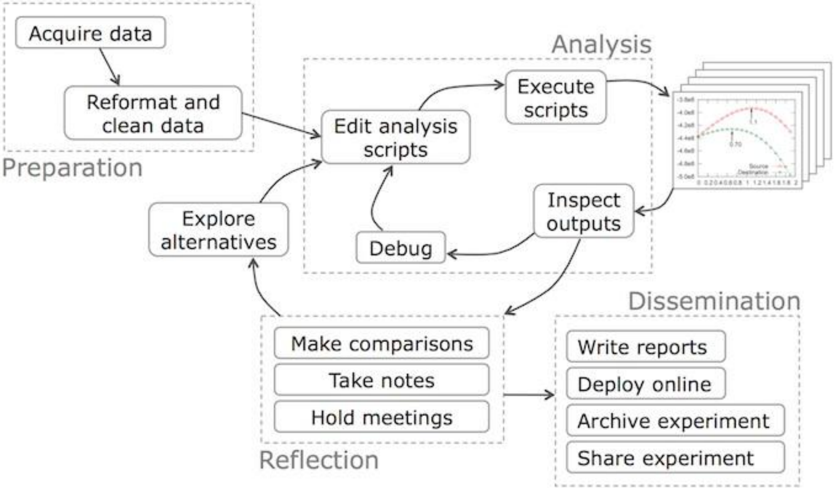
Data Scientist

- Very ambiguous and ill-defined term
- From Drew Conway's Venn Diagram



Typical Data Scientist Workflow

- From Data Science Workflow



Where Data Scientist Spends Most Time

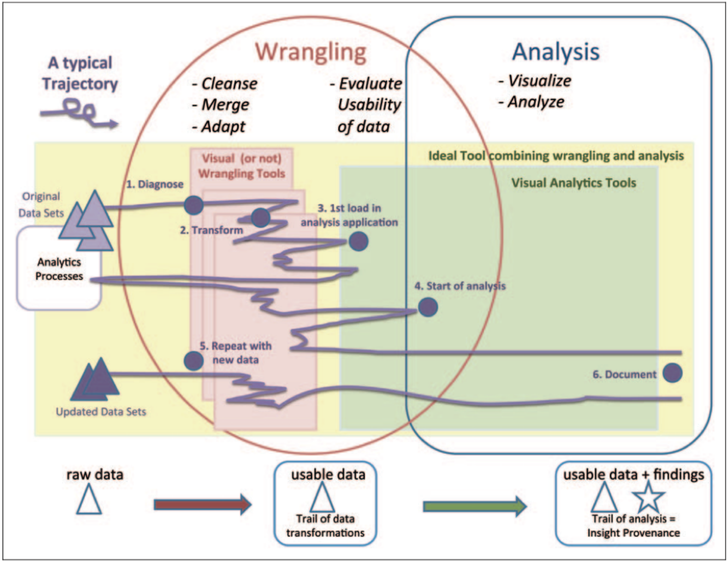


Figure 1. The iterative process of wrangling and analysis. One or more initial data sets may be used and new versions may come later. The wrangling and analysis phases overlap. While wrangling tools tend to be separated from the visual analysis tools, the ideal system would provide integrated tools (light yellow). The purple line illustrates a typical iterative process with multiple back and forth steps. Much wrangling may need to take place before the data can be loaded within

What a Data Scientist Should Know

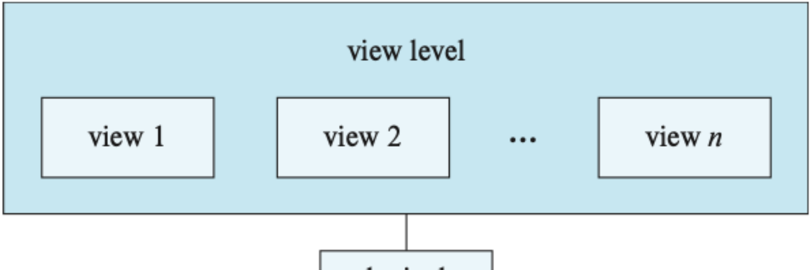
- From: How to hire a data scientist
- **Data grappling skills**
  - How to move data around and manipulate it with some programming language
  - Scripting languages (e.g., Python)
  - Data storage tools like relational databases, key-value stores
  - Programming frameworks like SQL, Hadoop, Spark, etc.
- **Data visualization experience**
  - How to draw informative pictures of data
  - Many tools (e.g., D3.js, plotting libraries)
  - Harder question is knowing what to draw
- **Knowledge of statistics**
  - E.g., error-bars, confidence intervals
  - Python libraries; Matlab; R
- **Experience with forecasting and prediction**
  - Basic machine learning techniques
- **Communication skills**
  - Tell the story, communicate the findings

Data Models

- **Data modeling**
  - $=$ process of representing and capturing the structure and properties of real-world entities
  - Process of abstraction: real-world $\rightarrow$ representation**
- **Data model**
  - $=$ description of how data is *represented* (e.g., relational, key-value) and *accessed* (e.g., insert operations, how to query)
  - E.g., schema in a DB describes a specific collection of data, using a given data model
- **Why do we need data model?**
  - Need to know the structure of the data (to some extent) to be able to write general purpose code
  - Allow to share data across programs, organizations, systems
  - Need to integrate information from multiple sources
  - Preprocess data to make access efficient (e.g., building an index on a data field)

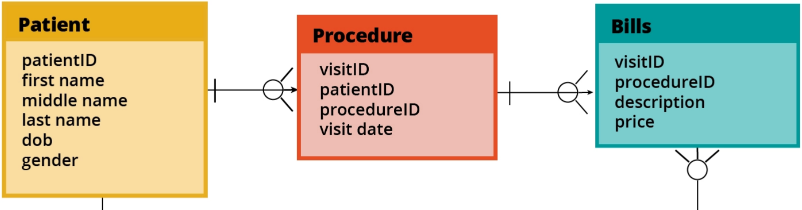
Multiple Layers of Data Modeling

- **Physical layer**
  - How is the data physically stored
  - How to represent complex data structures (e.g., B-trees for indexing)
- **Logical layer**
  - Entities
  - Attributes
  - Type of information stored
  - Relationships among the above
- **Views**
  - Restrict information flow
  - Security and/or ease-of-use



Data Models: Logical Layer

- **Modeling constructs**
  - A collection of concepts used to represent the structure in the data
  - E.g.,
    - Types of entities
    - Entity attributes
    - Types of relationships between entities
    - Types of relationships between attributes
- **Integrity constraints**
  - Ensure data integrity
    - Goal: avoid errors and data inconsistencies
    - E.g., a field can't be empty, is an integer
- **Manipulation constructs**
  - E.g., insert, update, delete data



Examples of Data Models

- We will cover:
  - Relational model (SQL)
  - Entity-relationship (ER) model
  - XML
  - Object-oriented (OO)
  - Object-relational
  - RDF
  - Property graph
- Serialization formats are also data models
  - CSV
  - Parquet
  - JSON
  - Protocol Buffer
  - Avro/Thrift
  - Python Pickle

Good Data Models

- We would like a data model to be:
  - Expressive
    - Capture real-world data well
  - Easy to use
  - Good performance
- Tension between the above characteristics
  - More powerful models
    - Can represent more datasets
    - Harder to use/to query
    - Less efficient (e.g., more memory, more time)
- The evolution of data modeling tools is an attempt to capture the structure in the data
  - Structured data $\rightarrow$ Relational DBs
  - Semi-structured web data $\rightarrow$ XML, JSON
  - Unstructured data $\rightarrow$ NoSQL DBs

Data Independence

- **Logical data independence**
  - Can change the representation of data without changing programs that operate on it
  - E.g., an API abstracting the backend
- **Physical data independence**
  - Can change the layout of data on disk and programs won't change
    - Index the data
    - Partition/distribute/replicate the data
    - Compress the data
    - Sort the data

Databases: A Brief History

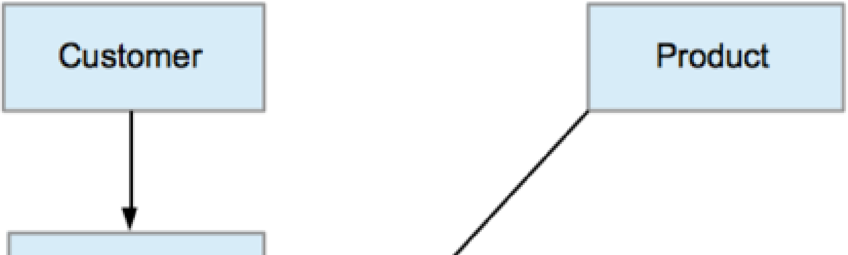
- **1960s: Early beginning**
  - Computers finally become attractive technology
  - Enterprises start adopting computers
  - Most applications initially used their own data stores
    - Each application had its own format
    - Data was basically unavailable to other programs
  - **Database**: term coined in military information systems to denote "shared data banks" by multiple applications
    - Define a data format
    - Store it as a "data dictionary" (schema)
    - Implement general-purpose "database management" software to access data
  - Issues:
    - How to write data dictionaries?
    - How to access data?
    - Who controls the data?
    - E.g., integrity, security, privacy concerns

Databases: A Brief History

- **1960s, Hierarchical and network model (before relational model)**
  - Both allowed connecting records of different types
  - E.g., connect accounts with customers
  - Network model attempted to be very general and flexible
- IBM designed IMS hierarchical database in 1966 for the Apollo space program
  - Predates *hard disks*
  - Still around today!
  - *.. more than 95 percent of the top Fortune 1000 companies use IMS to process 50 billion transactions a day and manage 15 million gigabytes of critical business data* (from IBM Website on IMS)
- Cons:
  - Hierarchical/network models exposed too much of the internal data (e.g., structures/pointers to the users)
  - Leaky abstraction

Relational, Hierarchical, Network model

- **Relational model**
  - Data is represented as tuples grouped in relations
  - Omnipresent SQL
- **Hierarchical model**
  - Data is organized into a tree-like structure
    - Each record has one parent record and many children
    - Records connected through links
  - Resurgence in 1990s with XML DBs
- **Network model**
  - Data is organized in a graph
    - Each record can have multiple parent and child records
  - Resurgence in 2010s with graph DBs

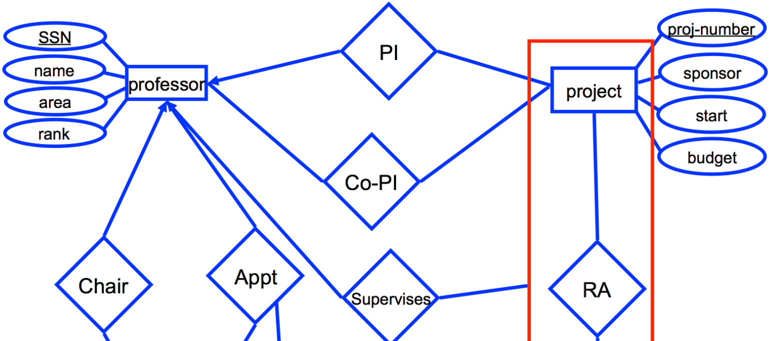


Databases: A Brief History

- **1970s: Relational model**
  - Set theory, first-order predicate logic
    - Ted Codd developed the Relational Model
  - Elegant, formal model
    - Provided almost complete *data independence*
    - Users didn't need to worry about how the data was stored, processed
  - High-level query language
    - SQL based on relational algebra
  - Notion of *normal forms*
    - Allowed one to reason about data and its relations
    - Remove redundancies
- Influential projects:
  - INGRES (UC Berkeley), System R (IBM)
  - Didn't care about IMS compatibility (as IBM had to)
- Many debates between Relational Model vs Network Model proponents

Entity-Relationship Model

- 1976: Peter Chen proposed "Entity-Relationship Model"
- Data model describing knowledge in terms of entities and relationships
- **Entities** are physical or logical objects that can be uniquely identified
  - "Nouns"
- **Relationships** between entities
  - "Verbs"
- An ER model can be mapped onto a relational DB
  - Entities, relationships → tables



Databases: A Brief History

- **1980s: Widespread acceptance of relational model**
  - SQL emerged as a standard, in large part because of IBM's backing
  - Enriching the expressive power of relational model
    - Set-valued attributes, aggregation, etc.
- Late 80's
  - Object-oriented DBs
    - Store objects instead of tables
    - Get around *impedance mismatch* between programming languages and databases
  - Object-relational DBs
    - Allow user-defined types
    - Get many benefits of object-oriented while keeping the essence of relational model
  - No expressive difference from pure relational model

Object-Oriented

- OOP is a data model
  - Object behavior is described through data (stored as fields) and code (in the form of methods)
- **Composition**
  - Aka `has-a` relationships
  - E.g., an Employee class has an Address class
- **Inheritance**
  - Aka `is-a` relationships
  - E.g., an Employee class derives from a Person class
- **Polymorphism**
  - Code executed depends on the class of the object
  - One interface, many implementations
  - E.g., draw() method on a Circle vs Square object, both descending from Shape class
- **Encapsulation**
  - E.g., private vs public fields/members
  - Prevents external code from being concerned with inner workings of an object

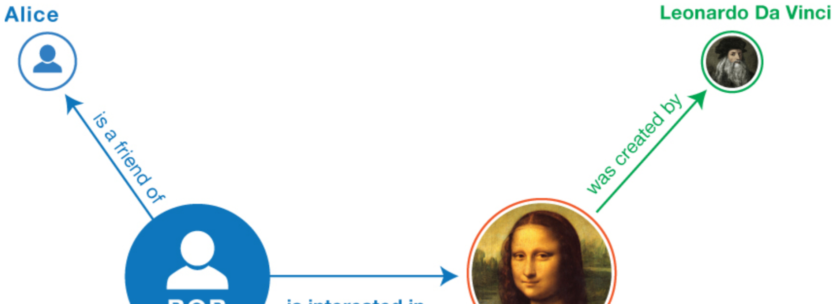
Databases: A Brief History

- **Late 90's-today**
- Web/Internet emerges
- XML: eXtensible Markup Language
  - Intended for *semi-structured* data
  - Tree-like structure
  - Flexible schema

```
<?xml version="1.0" encoding="UTF-8"?>
 <CATALOG>
     <CD>
    <TITLE>Empire Burlesque</TITLE>
      <ARTIST>Bob Dylan</ARTIST>
    <COUNTRY>USA</COUNTRY>
      <COMPANY>Columbia</COMPANY>
      <PRICE>10.90</PRICE>
    <YEAR>1985</YEAR>
    </CD>
    <CD>
    <TITLE>Hide your heart</TITLE>
    <ARTIST>Bonnie Tyler</ARTIST>
    <COUNTRY>UK</COUNTRY>
```

Resource Description Framework

- Aka RDF
- Key construct: a "subject-predicate-object" triple, e.g.
  - subject=sky
  - predicate=has-the-color
  - object=blue
- Can be mapped to a labeled, directed multi-graph
  - More general than a tree
- Typically stored in:
  - Relational DBs
  - Dedicated "triple-stores" DBs



Property Graph Model

- Graph:
  - with vertices and edges
  - with properties associated with each edge and vertex
- Typically stored in:
  - Relational DBs
  - Graph DBs