UMD DATA605 - Big Data Systems

Course Intro
Big Data
Data Models

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UMD DATA605 - Big Data Systems

Course Intro

Big Data

Data Models

Learning Outcomes

- Model and reason about data
- Process and manipulate data in different ways
  - E.g., Python, Pandas
- Introduce a variety of data models
  - E.g., relational, NoSQL, graph
  - Decide which data model is appropriate for different applications
- Use a variety of data management systems
  - E.g., PostgreSQL, MongoDB, HBase
  - Decide which system is appropriate for a data management scenario
- Build data processing pipelines
  - E.g., Docker, Airflow
- Build a big-data system end-to-end
- Contribute to an open-source project
- Project: build a (little) system with Big Data technology

Tools We Will Learn To Use

- **Programming languages**:
  - Python
- **Development tools**
  - Bash/Linux OS
  - Git (understand data model, branching)
  - GitHub (PRs, work with issues)
  - Jupyter notebooks
  - Docker
- **Big data tools**
  - ETL pipelines
  - Relational DBs (PostgreSQL)
  - NoSQL DBs (HBase, MongoDB, Couchbase, Redis)
  - Graph DBs (Neo4j, OrientDB, AllegroGraph, GraphX, Giraph)
  - Computing framework (Hadoop, Spark, Dask, Storm, Spark Streaming)
  - Workflow manager (Airflow)
  - Cloud services (AWS)
- **Tutorials** for all the tools we use for the class project

Todos

- [DATA605 - ELMS/Canvas site]
  - Make sure to enable notifications
  - How to get in touch with me/TA
- [DATA605 - Schedule]
- Clone [DATA605 - GitHub repo]
- Setup your computing environment
  - Install Linux/VMware
  - Install Docker on your laptop
  - Instructions are in the class repo
- Bring your laptop to class
  - Quizzes at the beginning of class
- Lessons are recorded
  - Still come to class!

Why I Am Interested in Big Data

- https://www.linkedin.com/in/gpsaggese/
  - Feel free to connect on LinkedIn to stay in touch
- Companies I've started
  - ZeroSoft
  - June Capital
  - Kaizen Technologies
- Open-source project I've started
  - Sorrentum
  - GitHub

Soft Skills to Succeed in the Workplace

- Work in a team
- Design software architecture (e.g., OOP, Agile, Design Patterns)
- Comment your own code
- Write external documentation (e.g., tutorials, manuals, how-tos)
- Write code that other people can understand (including future-you)
- Read other people's code
- Follow code conventions (e.g., PEP8, Google Code)
- Be clear in communications (e.g., in emails, Slack)
- File a bug report
- Reproduce (aka repro) a bug
- Have a sense of CS constants
- Have a sense of how an OS works (e.g., virtual memory, processes)
- **Goal**: model the class project to prepare you for the workplace

Class Project

- DATA605 - Class project - 2024
  - Each student implements 2 projects (one for midterm and one for finals)
  - Learn a cutting-edge modern big data technology
  - Write a (small) example of a system using it
  - Graded individually (each 30% of final grade)
  - Quizzes account for rest 40%
  - In class labs
  - Review 2 examples of complete projects
  - In-class presentation of projects
  - Will re-evaluate based on how projects go
- Check out an example of Big Data System
  - Sorrentum Git repo

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Big Data

Data Models

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
  - Scientific experiments and simulations produce enormous volumes of data
  - 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** = 2^{10} \approx 10^{6} bytes
  - Typical English book
- **Gigabyte** = 10^{9} 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/year on AWS S3
- **Exabyte** = 1M TB
  - Global yearly Internet traffic in 2004
- **Zetabyte** = 1B TB = 10^{21} bytes
  - Global yearly Internet traffic in 2016
- **Yottabytes** = 10^{24} bytes
  - Yottabyte costs $100T
- **Brontobytes** = 10^{27} bytes

Scale of Data Size

TERABYTE — Will fit 200,000 photos or mp3 songs on a single 1 terabyte hard drive.

PETABYTE — Will fit on 16 Backblaze storage pods racked in two datacenter cabinets.

EXABYTE — Will fit in 2,000 cabinets and fill a 4 story datacenter that takes up a city block.

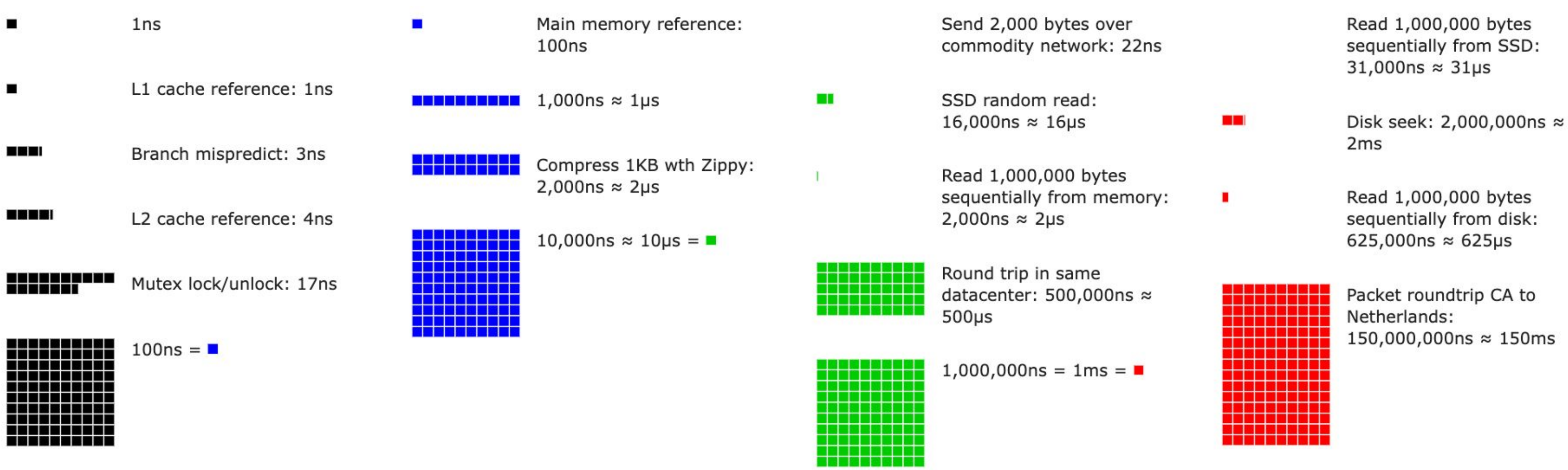
ZETTABYTE — Will fill 1,000 datacenters or about 20% of Manhattan, New York.

YOTTABYTE — Will fill the states of Delaware and Rhode Island with a million datacenters.

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, $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)

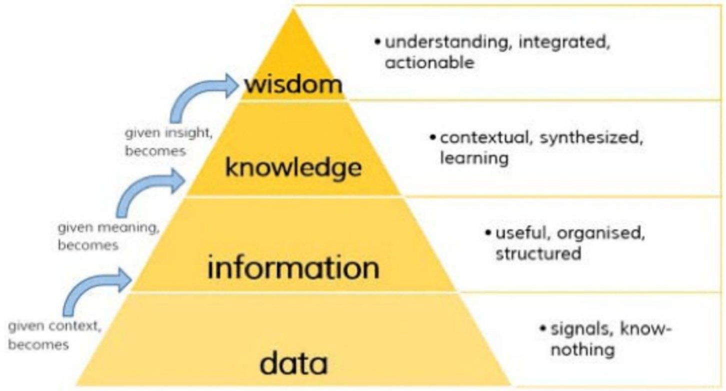
Big Data Applications

- **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

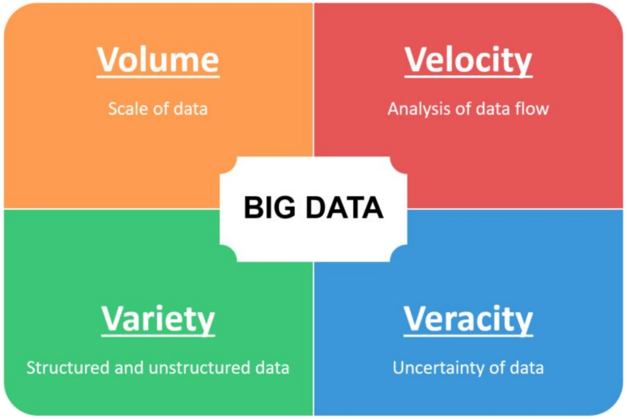
- **Goal**: from data to wisdom
  - Data (raw bytes)
  - Information (organized, structured)
  - Knowledge (learning)
  - Wisdom (understanding)
- Insights enable decisions and actions

- 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: 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)

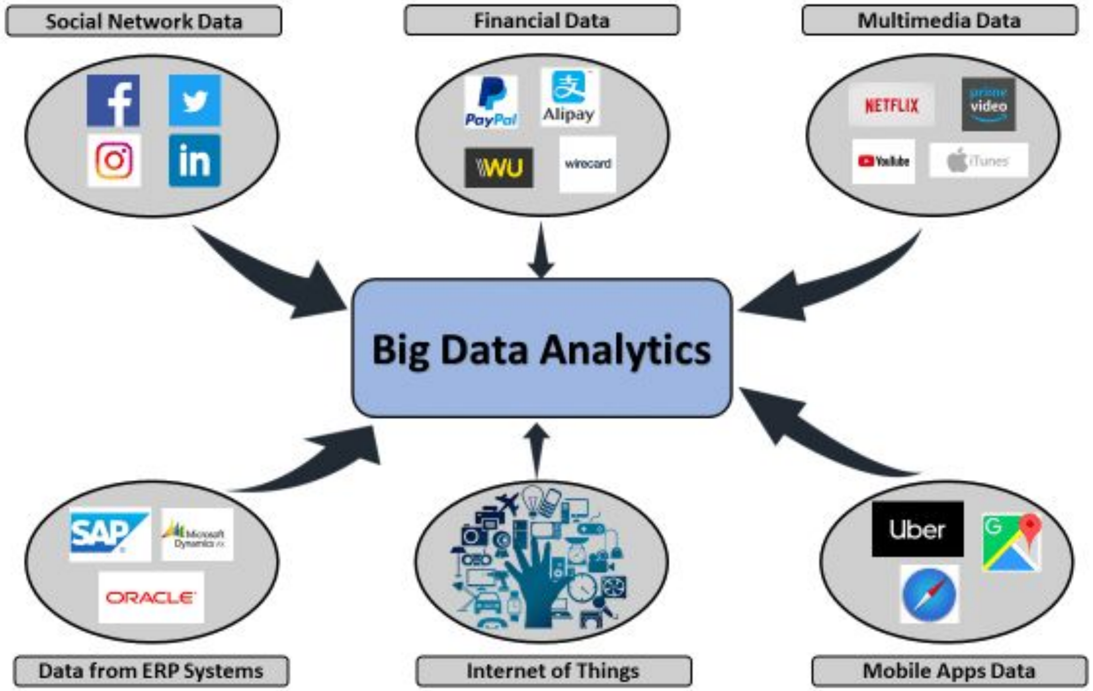
Four V’s of Big Data

- **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

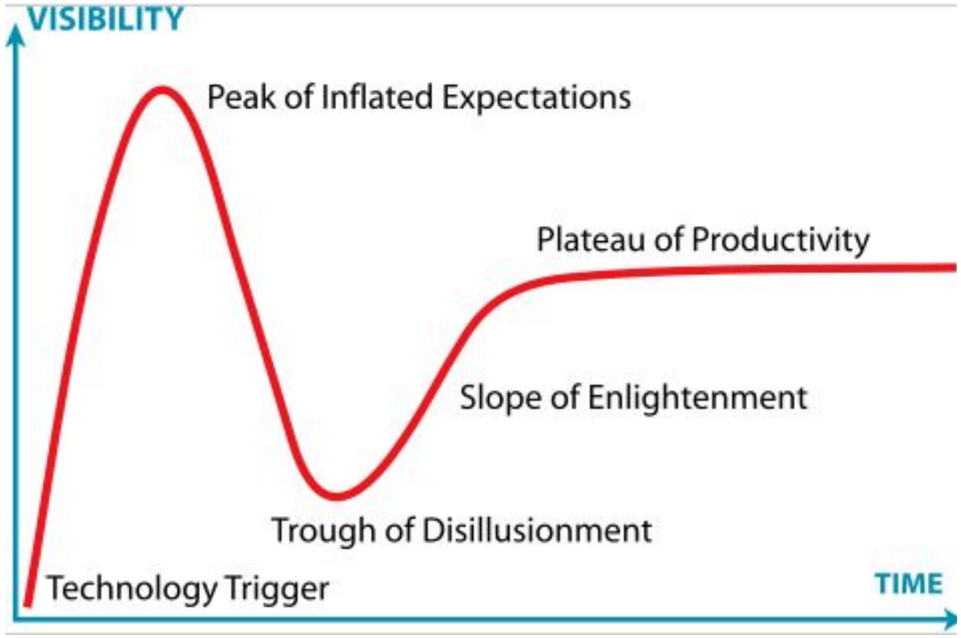
- People and their activities generate data
  - Social media (e.g., Instagram, Twitter, LinkedIn)
  - Video sharing (e.g., YouTube, TikTok)
  - Blogging and commenting on a website
  - Internet searches
  - Text messages (e.g., SMS, Whatsapp, Signal, Telegram)
  - Personal documents (e.g., Google Docs, emails)
- **Pros**
  - Allow personalization
  - Highly valuable for business intelligence
- **Cons**
  - Typically semi-structured or unstructured data
    - Text, 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?

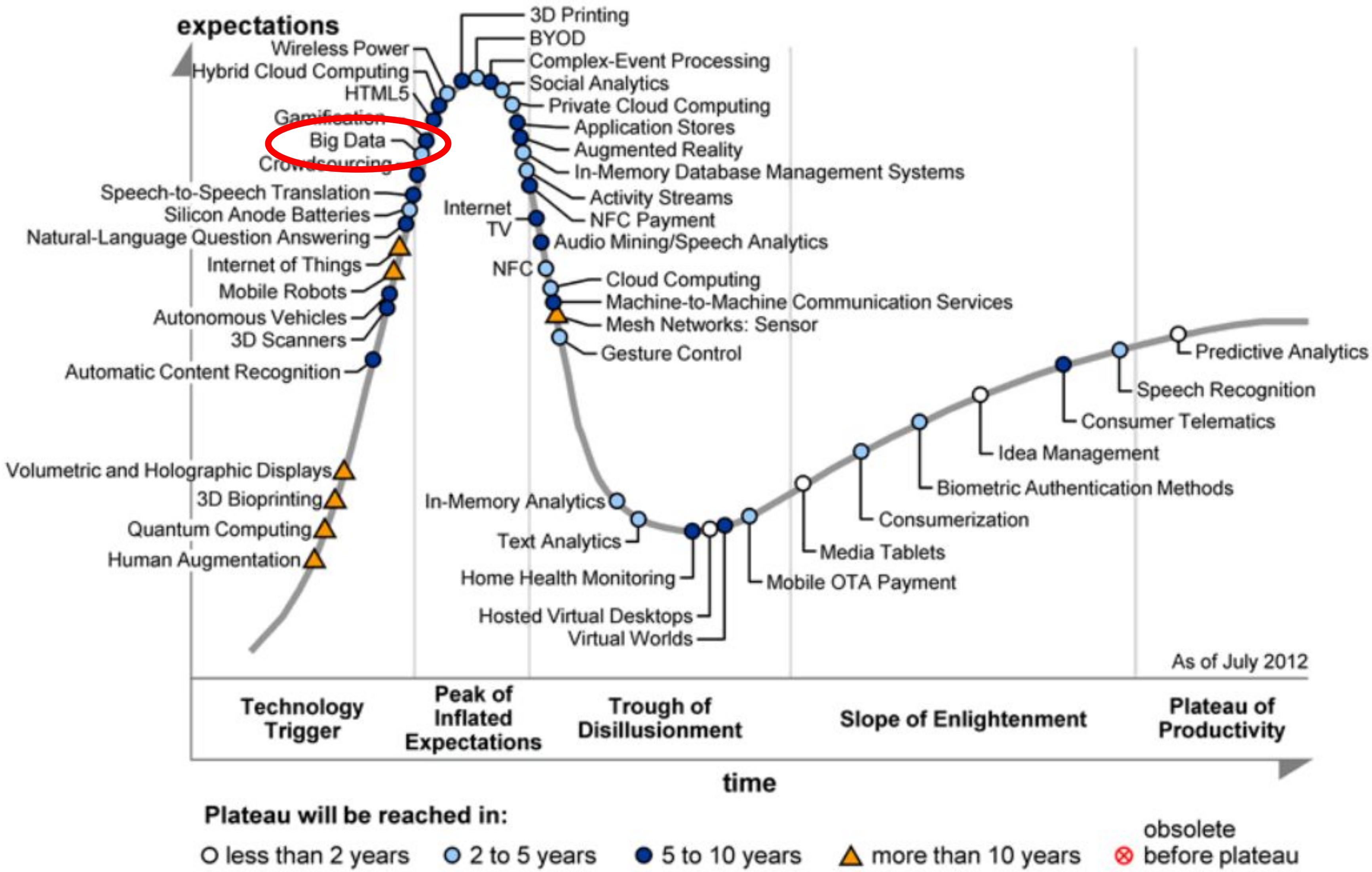
- Big data (or data science)
  - "Any process where interesting information is inferred from data"
- Data scientist called the "sexiest job" of the 21st century
  - The term has becoming very muddled at this point
- **Is it all hype?**



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

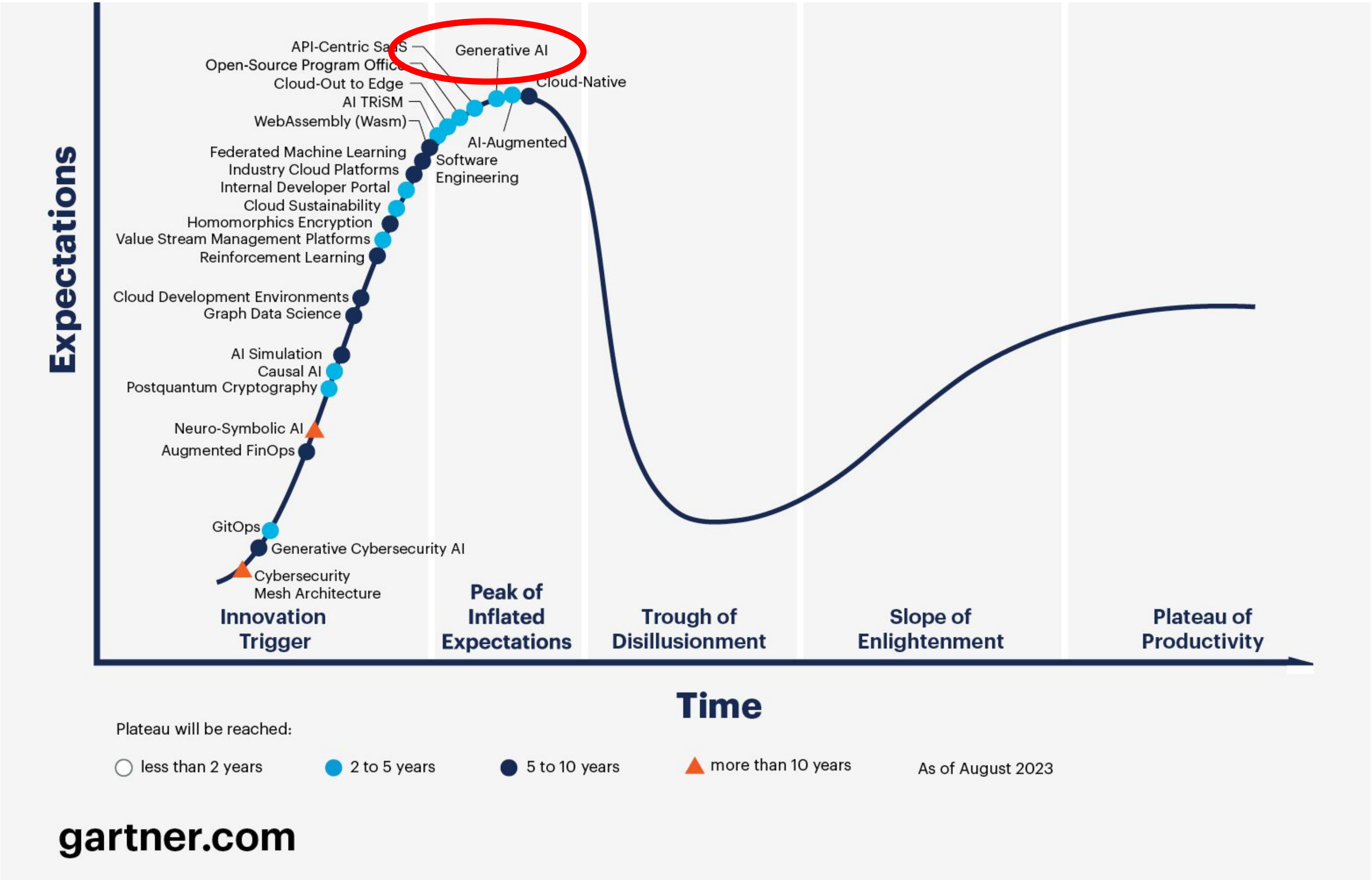
What was Cool in 2012?



What was Cool in 2017?

What was Cool in 2022?

What is Cool in 2023?



Key Shifts Before/After Big-Data

1) **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
2) **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
3) **"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

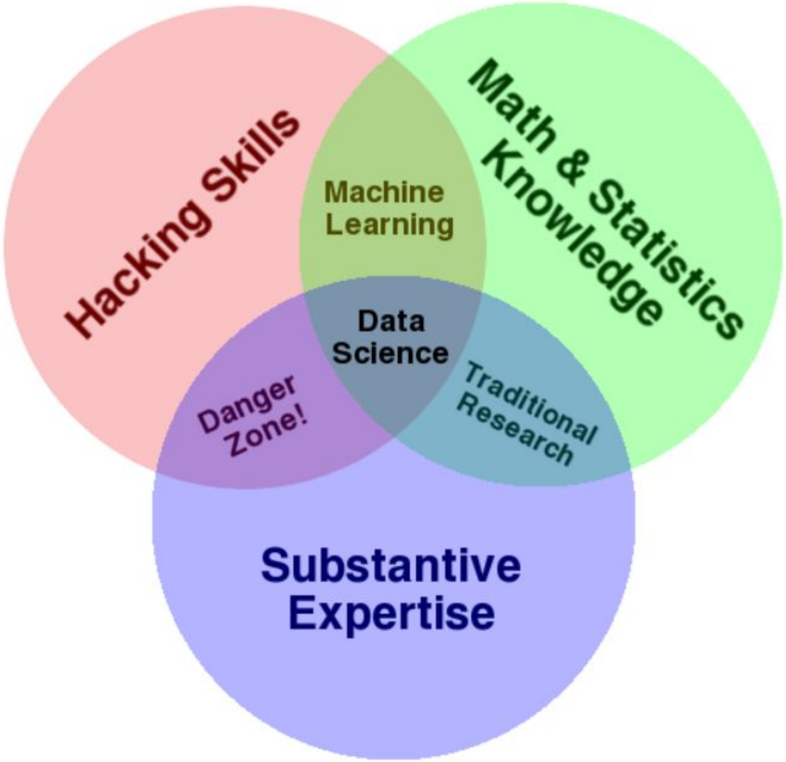
- [Nate Silver and the 2012 Elections]
  - 49 out of 50 in calling each state in 2008 US elections
  - 50 out of 50 in 2012 US elections
  - Didn’t work that well in 2016, did it?
- [Some reasons why he got things right]
  - Many sources of data, irrespective of quality
  - Incorporation of historical 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

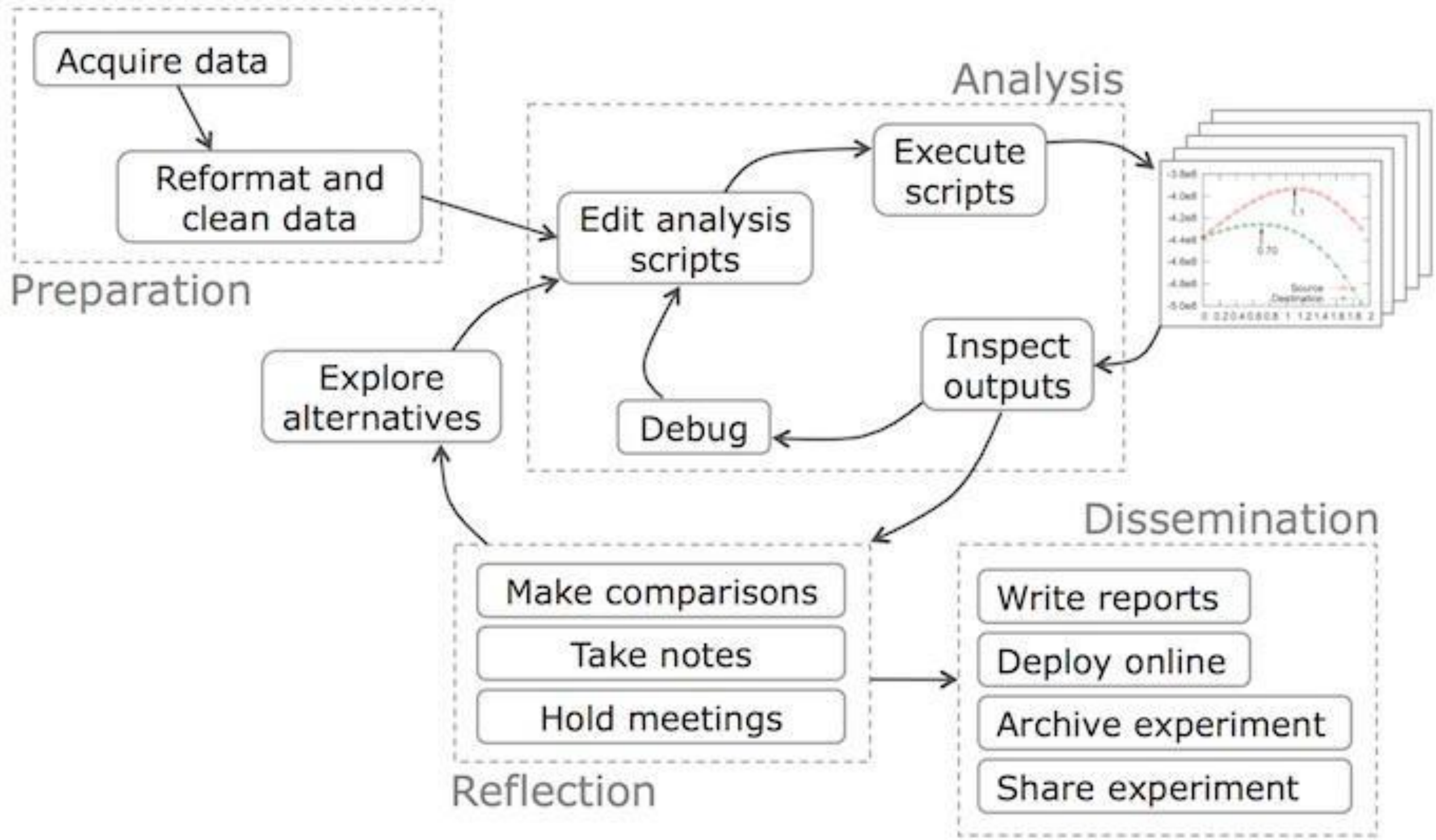
Data Scientist

- Very ambiguous and ill-defined term



- From [Drew Conway's Venn Diagram]

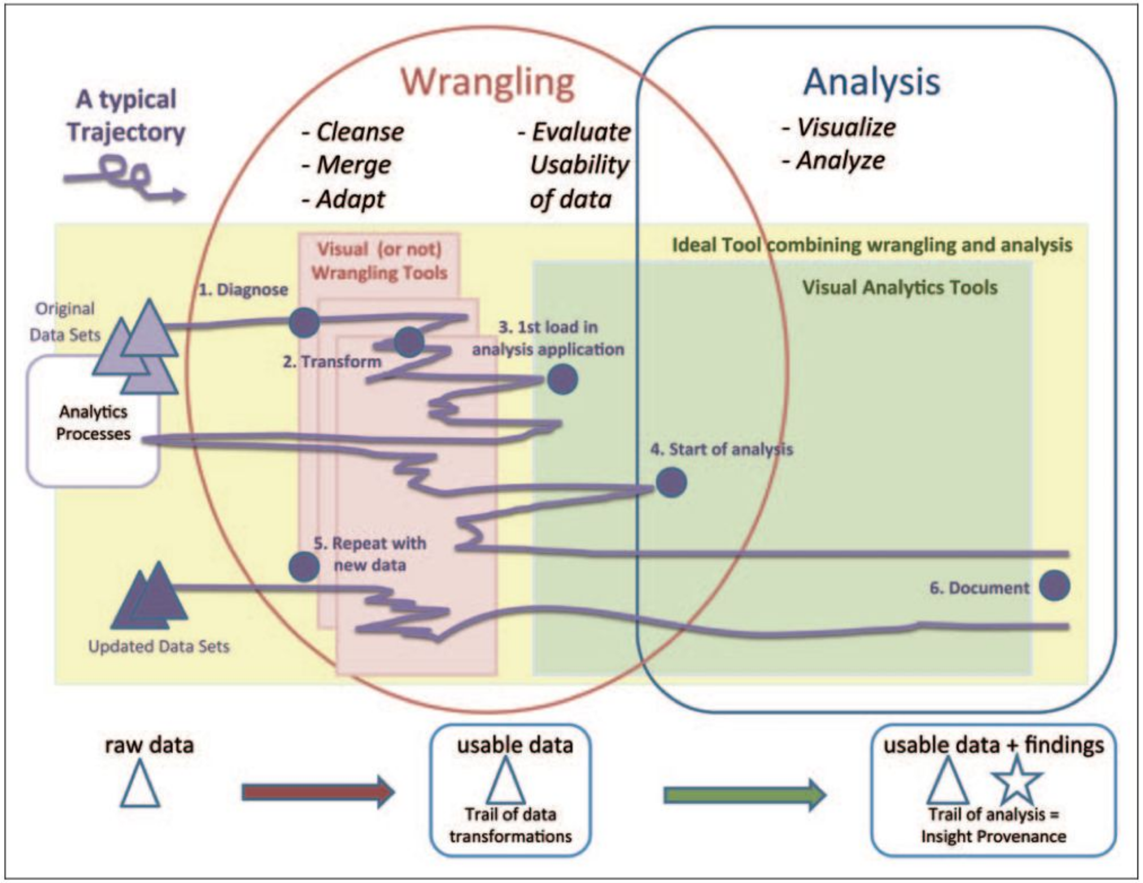
Typical Data Scientist Workflow



- From [Data Science Workflow]

Where Data Scientist Spends Most Time

- 80-90% of the work is data cleaning and wrangling
- ['Janitor Work' in Data Science]
- [Research Directions in Data Wrangling]



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

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Big data

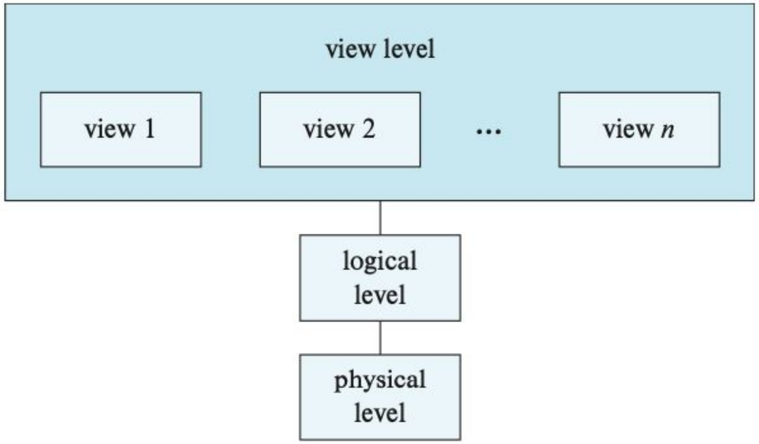
Data Models

Data Models

- **Data modeling**
  - = process of representing and capturing the structure and properties of real-world entities
  - Process of abstraction: real-world → 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)

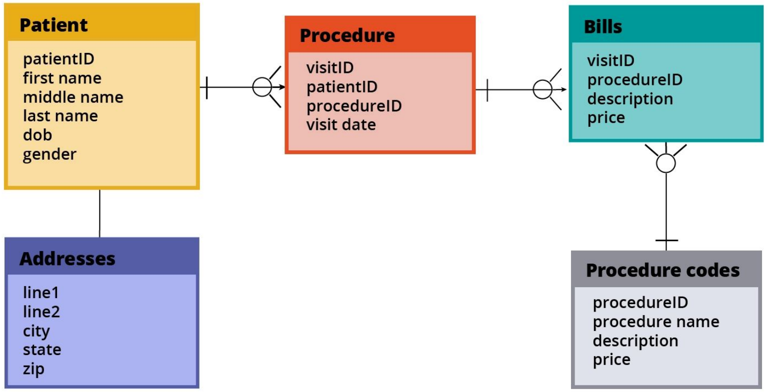
Multiple Layers of Data Modeling

- **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 → Relational DBs
  - Semi-structured web data → XML, JSON
  - Unstructured data → 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

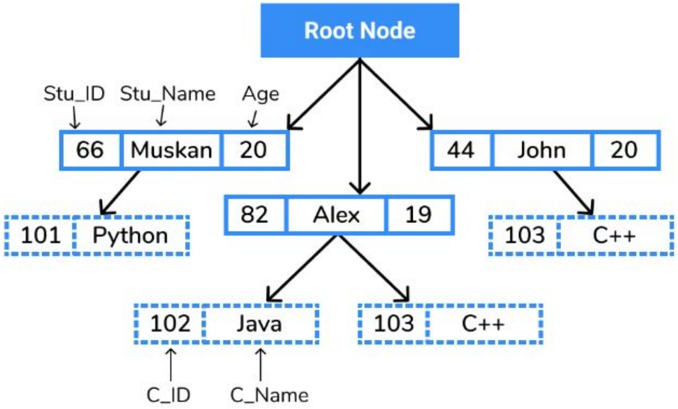
- **1960s, Hierarchical and network model (before relational model)**
  - Both allowed connecting records of different types
  - E.g., connect accounts with customers
  - Network model attempted to be very general and flexible
- IBM designed IMS hierarchical database in 1966 for the Apollo space program
  - 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

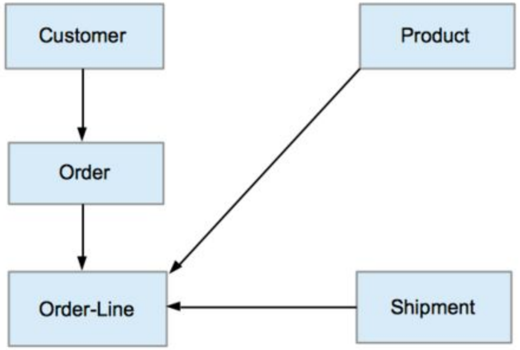
- **Relational model**
  - Data is represented as tuples grouped in relations
  - Omnipresent SQL

Customer ID	Tax ID	Name	Address	[More fields...]
1234567890	555-5512222	Ramesh	323 Southern Avenue	...
2223344556	555-5523232	Adam	1200 Main Street	...
3334445563	555-5533323	Shweta	871 Rani Jhansi Road	...
4232342432	555-5325523	Sarfaraz	123 Maulana Azad Sarani	...

- **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

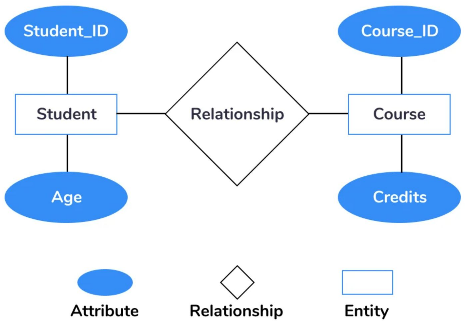


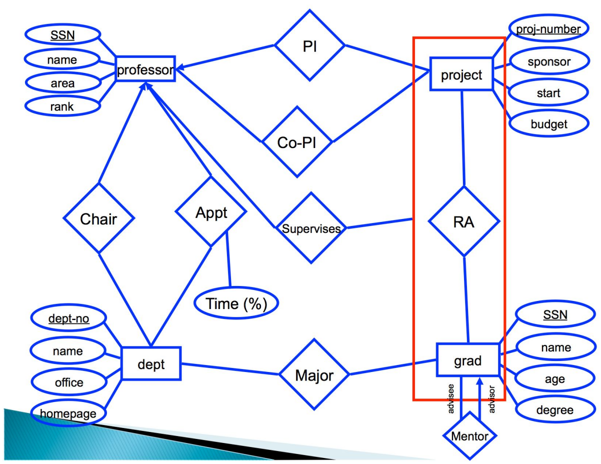
Databases: A Brief History

- **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

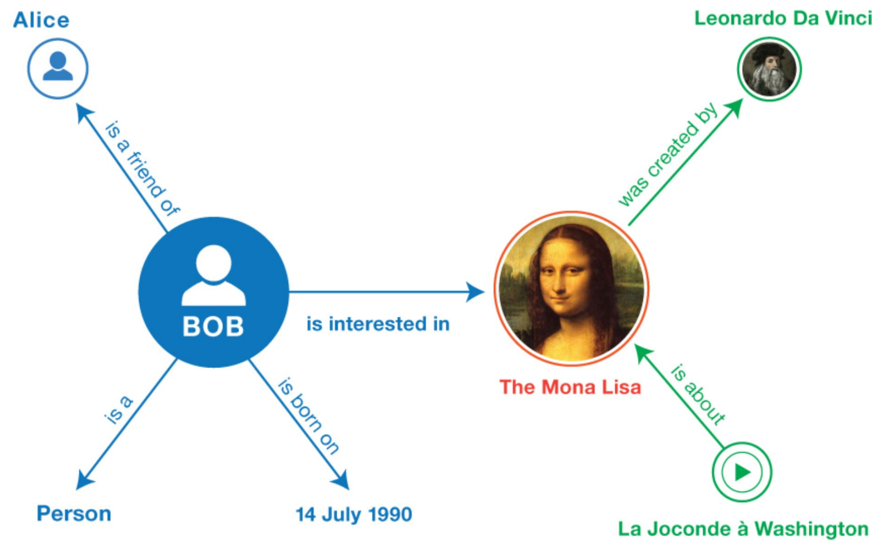
Databases: A Brief History

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

```xml
<?xml version="1.0" encoding="UTF-8"?>
<!-- Edited by XMLSpy -->
 <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>
      <COMPANY>CBS Records</COMPANY>
      <PRICE>9.90</PRICE>
      <YEAR>1988</YEAR>
     </CD>
     ...
```

Resource Description Framework

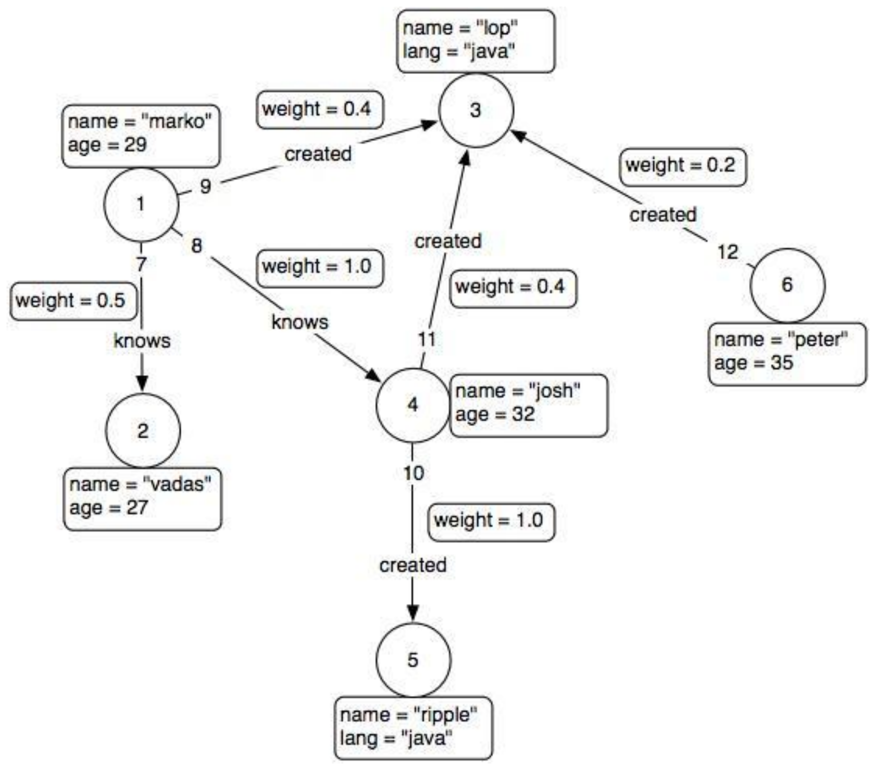
- Aka RDF
- Key construct: a "subject-predicate-object" triple, e.g.
  - subject=sky
  - predicate=has-the-color
  - object=blue
- Can be mapped to a labeled, directed multi-graph
  - More general than a tree
- Typically stored in:
  - Relational DBs
  - Dedicated "triple-stores" DBs




```
01    <http://example.org/bob#me>
<http://www.w3.org/1999/02/22-rdf-syntax-ns#type>
<http://xmlns.com/foaf/0.1/Person> .
02    <http://example.org/bob#me> <http://xmlns.com/foaf/0.1/knows>
<http://example.org/alice#me> .
03    <http://example.org/bob#me> <http://schema.org/birthDate>
"1990-07-04"^^<http://www.w3.org/2001/XMLSchema#date> .
04    <http://example.org/bob#me>
<http://xmlns.com/foaf/0.1/topic_interest>
<http://www.wikidata.org/entity/Q12418> .
05    <http://www.wikidata.org/entity/Q12418>
<http://purl.org/dc/terms/title> "Mona Lisa" .
06    <http://www.wikidata.org/entity/Q12418>
<http://purl.org/dc/terms/creator>
<http://dbpedia.org/resource/Leonardo_da_Vinci> .
07
<http://data.europeana.eu/item/04802/243FA8618938F4117025F17A8B81
3C5F9AA4D619> <http://purl.org/dc/terms/subject>
<http://www.wikidata.org/entity/Q12418> .
```

Property Graph Model

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



Class Project: TODOs

- Clone Class GitHub repo
- Look DATA605 - Class project
- Look at Sorrentum GitHub repo
- Next:
  - Dr Saggese + TA come up with list of projects