DATA605: Big Data Systems

Introduction

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

References:

- ***Class Intro***
- Big Data
- Data Models

Invariants of a Class Lecture

- **Invariants**
  - Focus on intuition over math
  - Emphasize realistic assumptions, numerical methods
    - Analytical solutions are outdated
  - Interactive Jupyter notebook tutorials
    - Tutorials done at home
    - Videos added over time
- **Class flow**
  - Alternate between slides, whiteboard, tutorials
- **Labs**
  - Review complete class project examples
  - Collaborate on class project

Books of the Class

- Slides
  - Are extracted from books, technical articles, Internet
  - Should be self-sufficient

Learning Outcomes

- Model and reason about data
- Process and manipulate data
  - E.g., Python, Pandas
- Introduce a variety of data models
  - E.g., relational, NoSQL, graph DBs
  - Decide appropriate data model for different applications
- Use data management systems
  - E.g., PostgreSQL, MongoDB, HBase
  - Decide appropriate system for scenarios
- Build data processing pipelines
  - E.g., Docker, Airflow
- Build a big-data system end-to-end
  - Class project
  - Contribute to an open-source project

Tools We Will Learn To Use

- **Programming languages**
  - Python
- **Development tools**
  - Bash/Linux OS
  - Git: data model, branching
  - GitHub: Pull Requests (PR), issues
  - Jupyter notebooks
  - Docker
- **Big data tools**
  - Extract-Transform-Load (ETL) pipelines
  - Relational DBs (PostgreSQL)
  - NoSQL DBs (HBase, MongoDB, Couchbase, Redis)
  - Graph DBs (Neo4j, GraphX, Giraph)
  - Computing framework (Hadoop, Spark, Dask)
  - Workflow manager (Airflow)
  - Cloud services (AWS)
- **Tutorials** for tools used in the class projects

Todos

- Study slides and materials
- DATA605 - ELMS/Canvas site
  - Enable notifications
  - Contact info for me/TAs
- DATA605 - Schedule
- DATA605 - GitHub repo
- Setup computing environment
  - Install Linux/VMware
  - Install Docker on laptop
  - Instructions in class repo
- Bring laptop to class
  - Quizzes at class start
- Lessons recorded
  - Attend class!

Grading

- **Quizzes**
  - 40% of grade
  - Multi-choice on previous 2 lessons
  - 20 questions in 20 minutes
  - 4-5 quizzes to encourage study during semester
- **Final Project**
  - 60% of grade
  - Comprehensive application of course concepts
  - Big data project in Python from a list of topics
  - Individual or group

Class Projects

- The project is *"Build X with Y"*, where X is a "use case" and Y is a "technology"
  - Study and describe technology Y
  - Implement use case X using technology Y
  - Create Jupyter notebooks to demo your project
  - Commit code to GitHub, contribute to open-source repo
  - Write a blog entry
  - Present your project in a video
- Choose from list of X and Y, e.g.,
  - Big data
  - Large language models
  - ...
- Each project:
  - Individual or group ($n < 4$)
  - Varying difficulty levels

Soft Skills to Succeed in the Workplace

- **Goal**: model class project for workplace preparation
  - Work in a team
  - Design software architecture (OOP, Agile, Design Patterns)
  - Comment your code
  - Write external documentation (tutorials, manuals, how-tos)
  - Write understandable code (including for future-you)
  - Read others' code
  - Follow code conventions (PEP8, Google Code)
  - Communicate clearly (emails, Slack)
  - File a bug report
  - Reproduce a bug
  - Intuition of CS constants
  - Basic understanding of OS (virtual memory, processes)

Links

- ELMS
- Syllabus
  - Schedule
  - GitHub project
  - Class FAQs
- Project specs

Yours Truly

- **GP Saggese**
  - 2001-2006, PhD / Postdoc at the University of Illinois at Urbana-Champaign
  - LinkedIn
  - gsaggese@umd.edu
- **University of Maryland**:
  - 2023-, Lecturer for UMD DATA605: Big Data Systems
  - 2025-, Lecturer for UMD MSML610: Advanced Machine Learning
- **In the real-world**
  - Research scientist at NVIDIA, Synopys, Teza, Engineers' Gate
  - 3x AI and fin-tech startup founder (ZeroSoft, June, Causify AI)
  - 20+ academic papers, 2 US patents

- Class Intro
- ***Big Data***
- Data Models

Data Science

- **Promises of data science**
  - 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 data science 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., cloud computing (AWS, Google Cloud), GPUs

Motivation: Data Overload

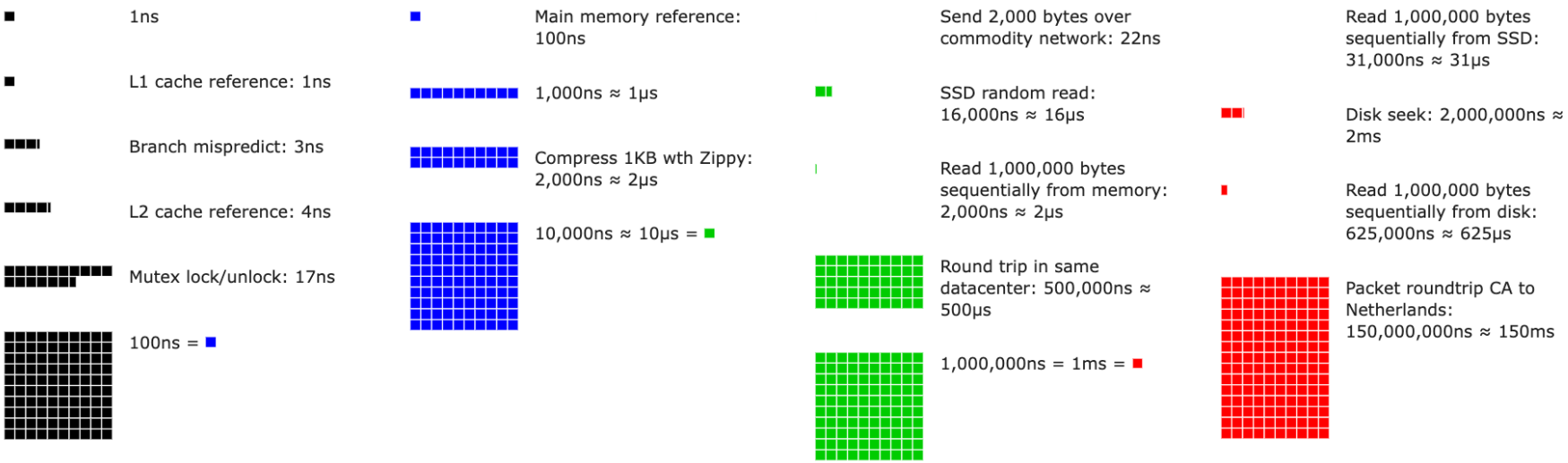
- *"Data science is the number one catalyst for economic growth"* (McKinsey, 2013)
- **Explosion of data in every domain**
  - Sensing devices/networks monitor processes 24/7
    - E.g., temperature of your room, your vital signs, pollution in the air
  - Sophisticated smart-phones
    - 80% of the world population has a smart-phone
  - 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 turns 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** = $2^{20} \approx 10^6$ bytes
  - Typical English book
- **Gigabyte** = 10^9 bytes = 1,000 MB
  - 1/2 hour of video
  - Wikipedia (compressed, no media) is 22GB
- **Terabyte** = 1 million MB
  - Human genome: ~1 TB
  - 100,000 photos
  - $50 for 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
  - Fill 20% of Manhattan, New York with data centers
- **Yottabytes** = 10^{24} bytes
  - Yottabyte costs $100T
  - Fill Delaware and Rhode Island with a million data centers
- **Brontobytes** = 10^{27} bytes

Constants Everybody Should Know

- CPU at 3GHz: 0.3 ns per instruction
- L1 cache reference/register: 1 ns
- L2 cache reference: 4 ns
- Main memory reference: 100 ns
- Read 1MB from memory: 20-100 us
- SSD random read: 16 us
- Send 1KB over network: 1 ms
- Disk seek: 2 ms
- Packet round-trip CA to Netherlands: 150 ms



SCIENCE ACADEMY

Big Data Applications

- **Personalized marketing**
- Target each consumer individually
  - E.g., Amazon personalizes suggestions using:
    - Shopping history
    - Search, click, browse activity
    - Other consumers and trends
    - Reviews (NLP and sentiment analysis)
- Brands understand customer-product relationships
  - Use sentiment analysis from:
    - Social media, online reviews, blogs, surveys
  - Positive, negative, neutral sentiment
- E.g.,
  - In 2022, $600B spent on digital marketing

Big Data Applications

- **Mobile advertisement**
- Mobile phones are ubiquitous
  - 80% of world population has one
  - 6.5 billion smartphones
- Integrate online and offline 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"*

Big Data Applications

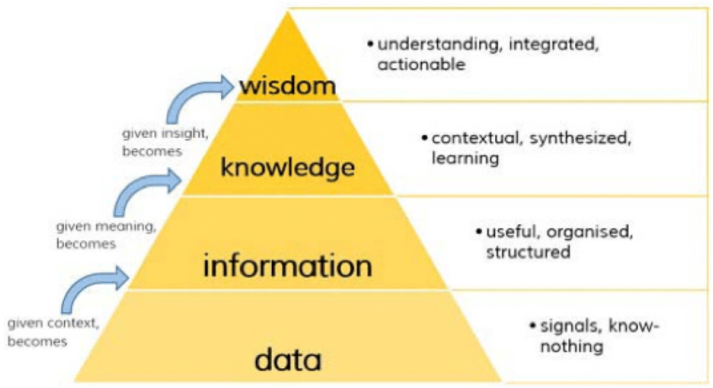
- **Biomedical data**
- Personalized medicine
  - Patients receive treatment tailored to them for efficacy
  - Genetics
  - Daily activities
  - Environment
  - Habits
- Genome sequencing
- Health tech
  - Personal health trackers (e.g., smart rings, phones)

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

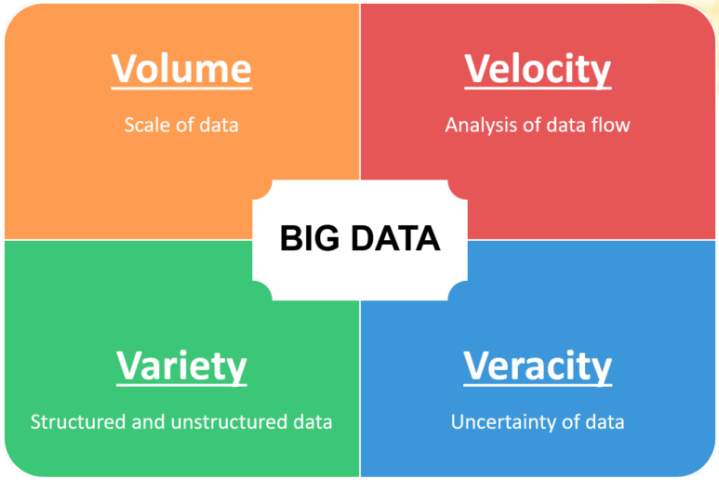
Goal of Data Science

- **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



The Six V'S of Big Data

- **Volume**
  - Vast amount of data is generated
- **Variety**
  - Different forms
- **Velocity**
  - Speed of data generation
- **Veracity**
  - Biases, noise, abnormality in data
  - Uncertainty, trustworthiness
- **Valence**
  - Connectedness of data in the form of graphs
- **Value**
  - Data must be valuable
  - Benefit an organization



The Six V's of Big Data

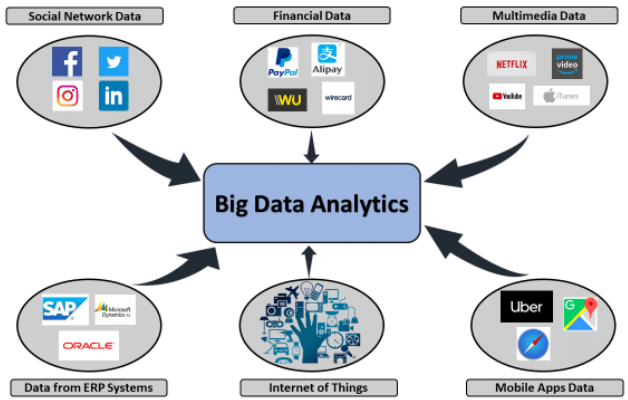
- **Volume**
  - Exponentially increasing data
  - 2.5 exabytes (1m TB) generated daily
    - 90% of data generated in last 2 years
    - Data doubles every 1.2 years
  - Twitter/X: 500M tweets/day (2022)
  - Google: 8.5B queries/day (2022)
  - Meta: 4PB data/day (2022)
  - Walmart: 2.5PB unstructured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

The Six V's of Big Data

- **Velocity**
  - Speed of data generation
    - E.g., sensors generate data streams
  - Process data off-line or in real-time
  - Real-time analytics: consume data as fast as 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

- Distinguish Big Data by 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**
  - Difficult to move, computed in-place or centralized
  - Streaming, not batch

Sources of Big Data: People

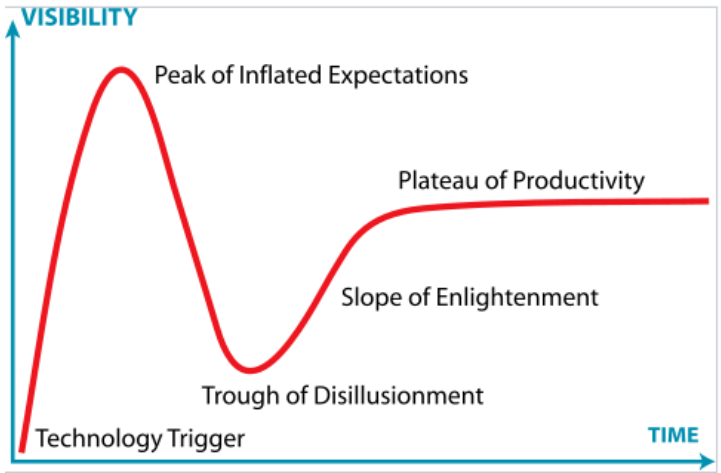
- **People** and their activities generate data
  - Social media (Instagram, Twitter, LinkedIn)
  - Video sharing (YouTube, TikTok)
  - Blogging, website comments
  - Internet searches
  - Text messages (SMS, Whatsapp, Signal, Telegram)
  - Personal documents (Google Docs, emails)
- **Pros**
  - Enable personalization
  - Valuable for business intelligence
- **Cons**
  - Semi-structured or unstructured data
    - Text, images, movies
  - Requires investment to extract 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
  - Website clicks
- **Pros**
  - Highly structured
- **Cons**
  - Store every event to predict future
    - Miss opportunities
  - Stored in "data silos" with different models
    - Each department has own system
    - Additional complexity
    - Data outdated/not visible
    - Cloud computing helps (e.g., data lakes, data warehouses)

Is Data Science Just Hype?

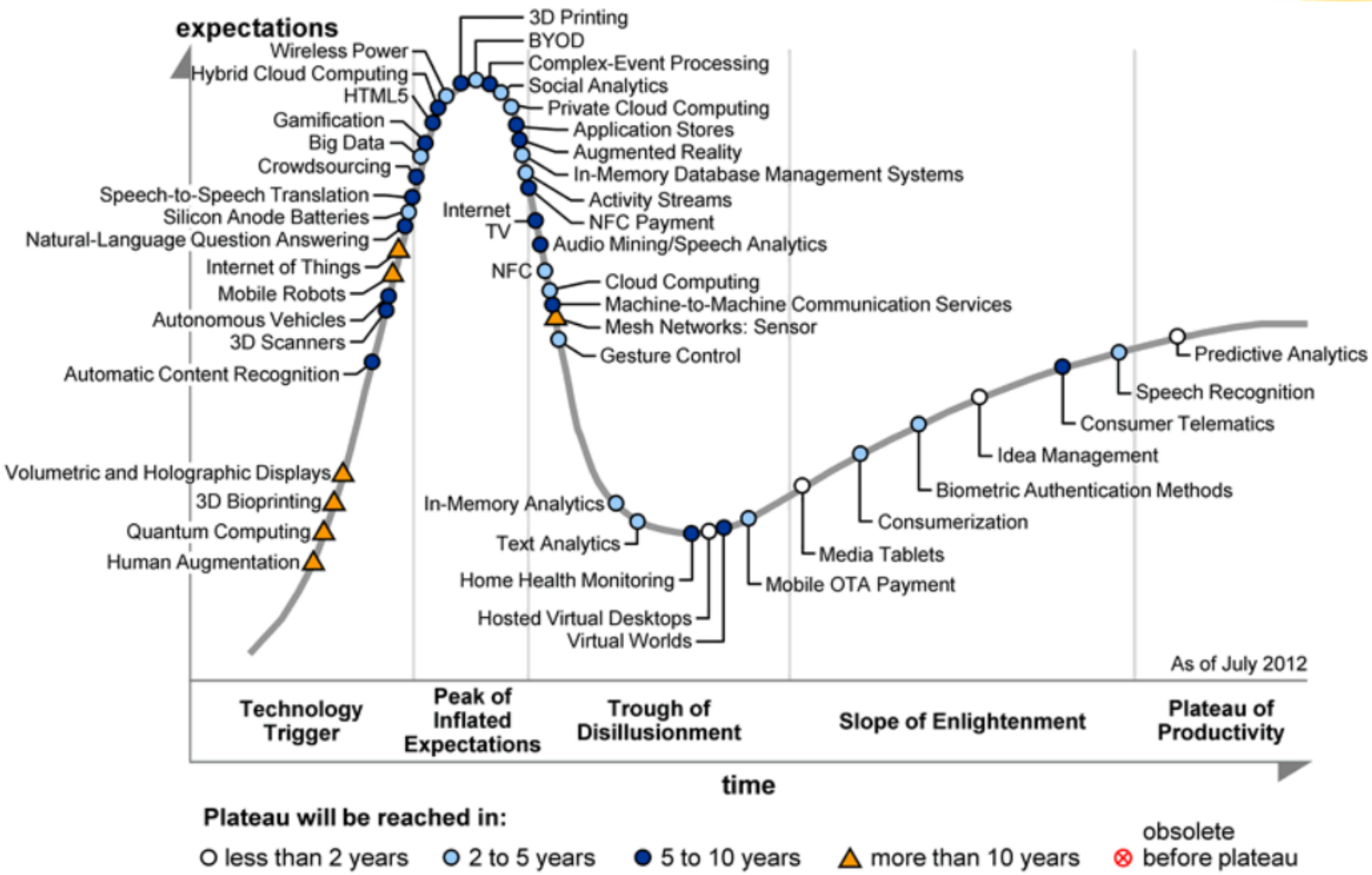
- Big data (or data science)
  - "Any process where interesting information is inferred from data"
- Data scientist called the "sexiest job" of the 21st century
  - The term has becoming very muddled at this point
- **Is it all hype?**



Is Data Science Just Hype?

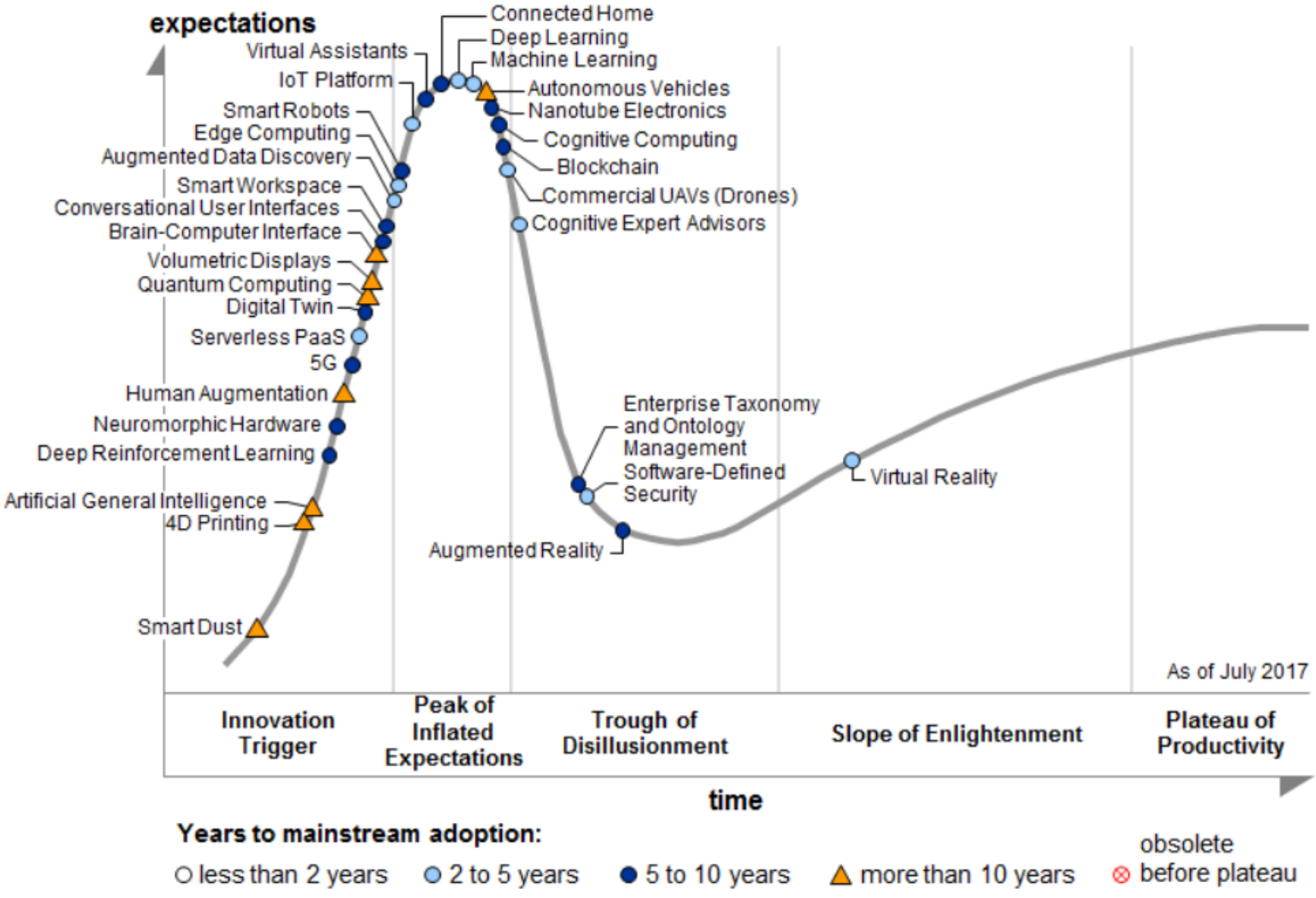
- **No**
  - Extract insights and knowledge from data
  - Big data techniques revolutionize many domains
    - E.g., education, food supply, disease epidemics
- **But**
  - Similar to what statisticians have done for years
- **What is different?**
  - More data is digitally available
  - Easy-to-use programming frameworks (e.g., Hadoop) simplify analysis
  - Cloud computing (e.g., AWS) reduces costs
  - Large-scale data + simple algorithms often outperform small data + complex algorithms

What Was Cool in 2012?



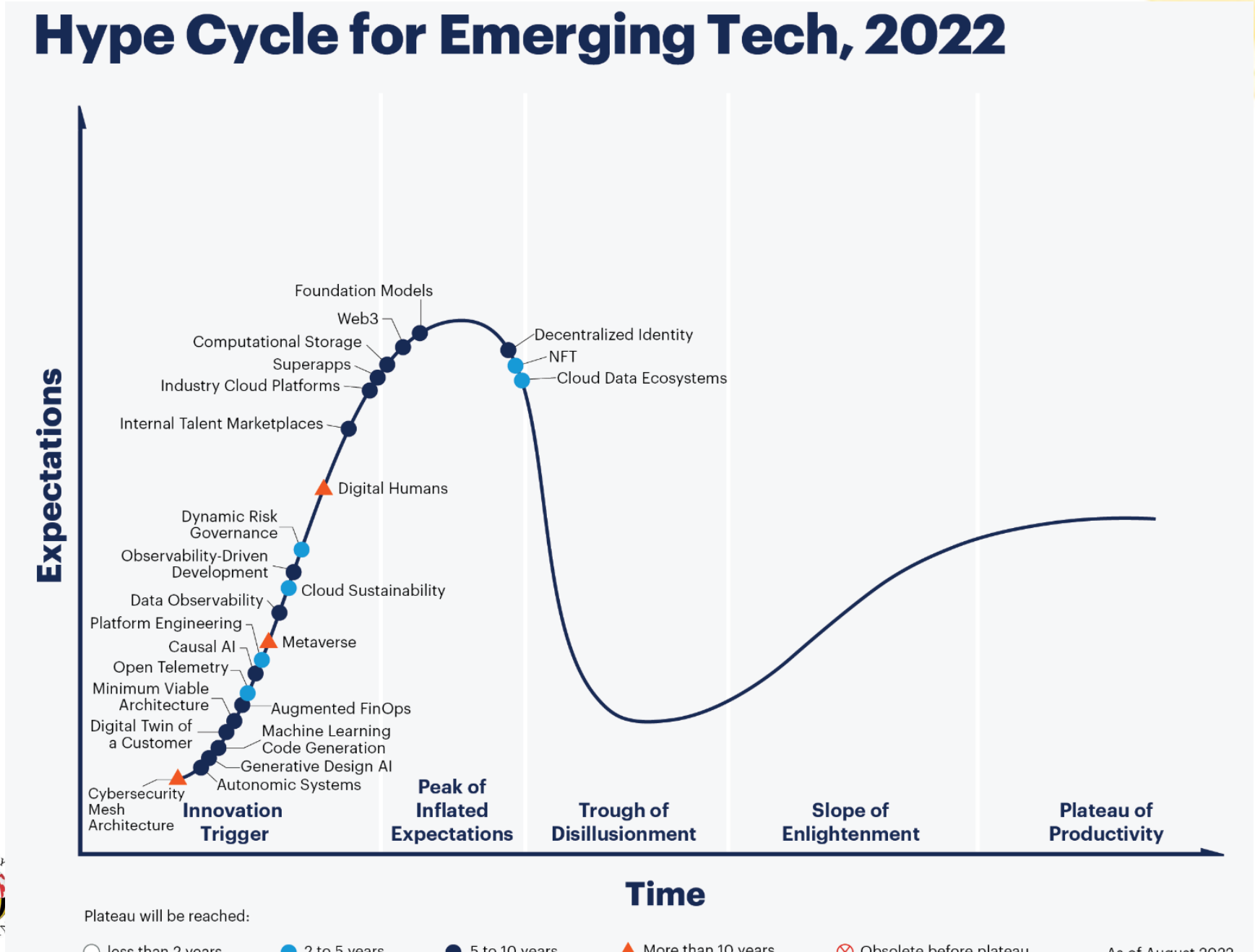
SCIENCE ACADEMY

What Was Cool in 2017?

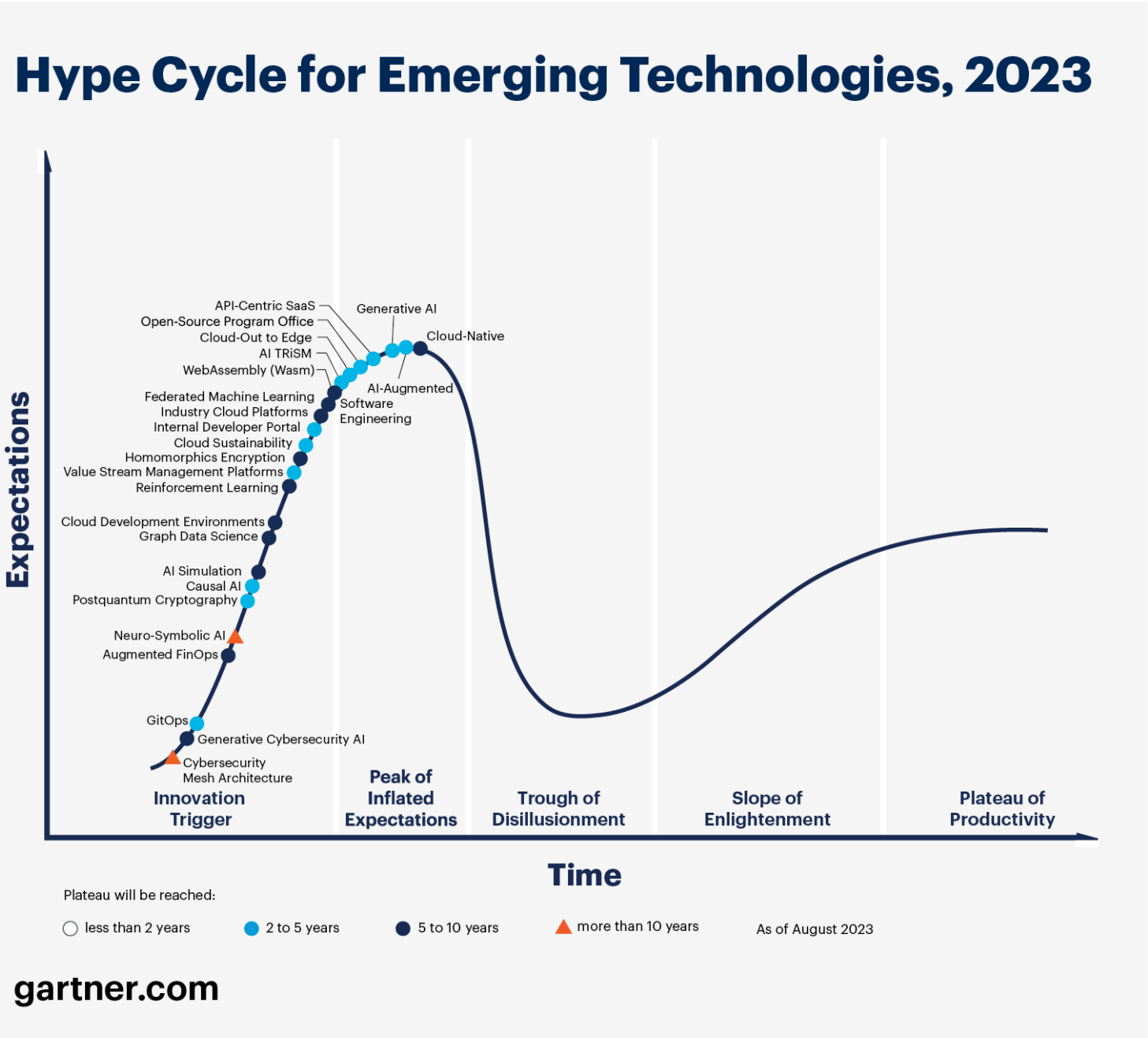


ACADEMY

What Was Cool in 2022?



What Was 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 data volumes
    - Feed into algorithms
    - Strong signal overcomes noise
- **Causation → Correlation**
  - Goal: determine cause and effect
  - Causation hard to determine → focus on correlation
    - Correlation is often sufficient
    - E.g., diapers and beer bought together
- **"Data-fication"**
  - = converting abstract concepts into data
  - E.g., "sitting posture" data-fied by sensors in your seat
  - Preferences data-fied into likes
- From: Rise of Big Data, 2013

Examples: Election Prediction

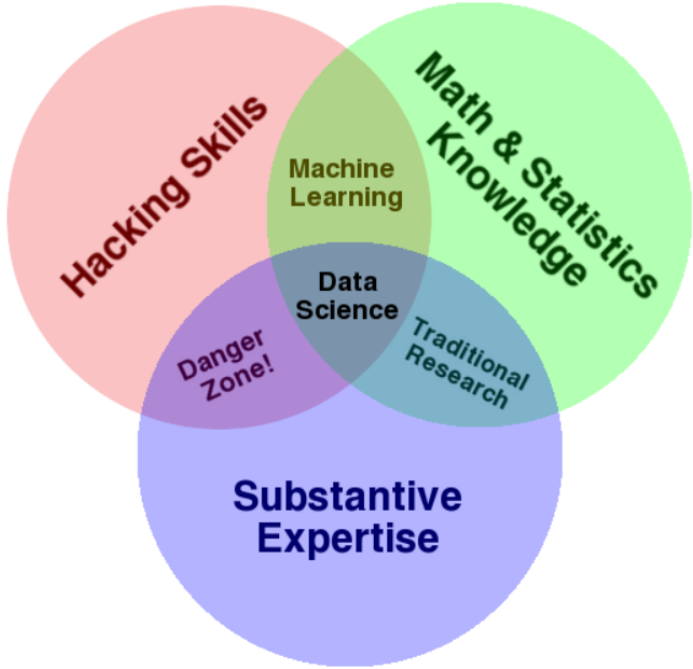
- Nate Silver and the 2012 Elections
  - Predicted 49/50 states in 2008 US elections
  - Predicted 50/50 states in 2012 US elections
- Reasons for accuracy
  - Multiple data sources
  - Historical accuracy incorporation
  - Statistical models
  - Understanding correlations
  - Monte-Carlo simulations for electoral probabilities
  - Focus on probabilities
  - Effective communication

Examples: Google Flu Trends

- 5% to 20% of US population contracts flu yearly; 40k deaths
- Early warnings enable prevention and control
- Google Flu Trends
  - Early flu outbreak warnings via search query analysis
    - 45 search terms analyzed
    - IP used to determine location
  - Predict regional flu outbreaks 1-2 weeks before CDC
  - Active from 2008 to 2015
- Caveat: accuracy declined
  - Claimed 97% accuracy
  - Out of sample accuracy lower (overshot CDC data by 30%)
  - People search about flu without knowing diagnosis
    - E.g., searching for "fever" and "cough"
  - Google Flu Trends: The Limits of Big Data

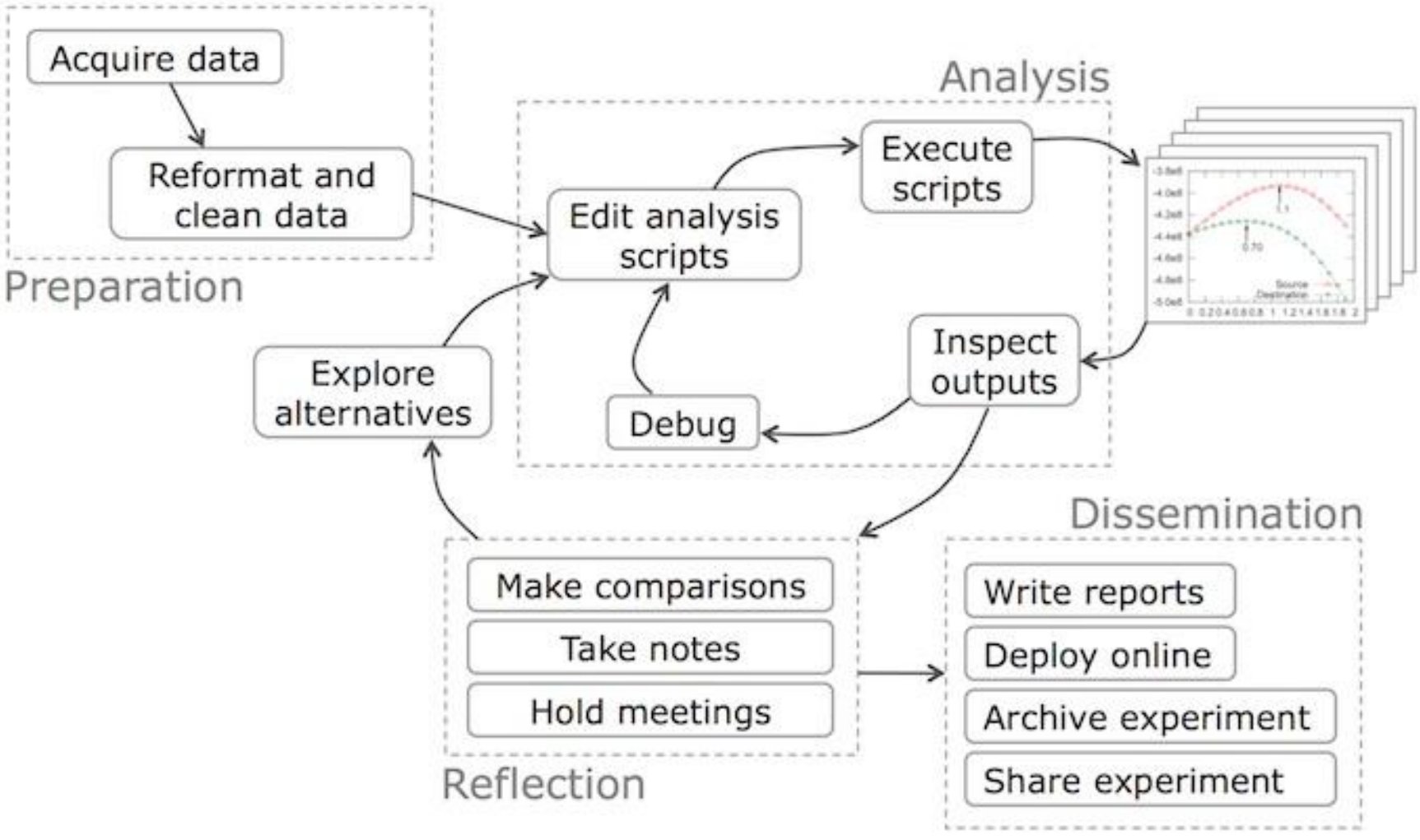
Data Scientist

- Ambiguous, ill-defined term
- From Drew Conway's Venn Diagram



Typical Data Scientist Workflow

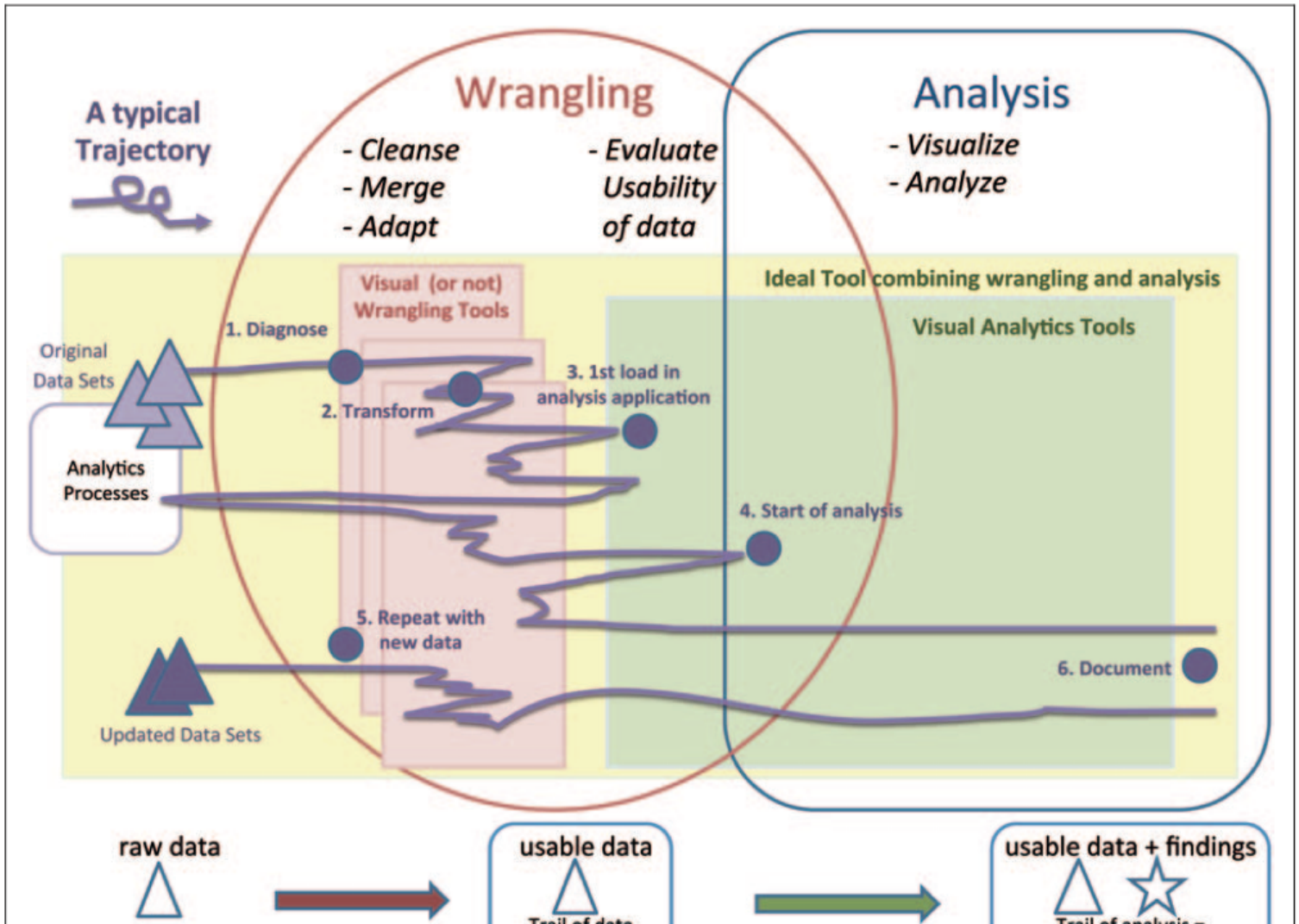
- From Data Science Workflow



[height=70%]

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**
  - Move and manipulate data with programming
  - Scripting languages (e.g., Python)
  - Data storage tools: relational databases, key-value stores
  - Programming frameworks: SQL, Hadoop, Spark
- **Data visualization experience**
  - Draw informative data visuals
  - Tools: `D3.js`, plotting libraries
  - Know what to draw
- **Knowledge of statistics**
  - Error-bars, confidence intervals
  - Python libraries, Matlab, R
- **Experience with forecasting and prediction**
  - Basic machine learning techniques
- **Communication skills**
  - Tell the story, communicate findings

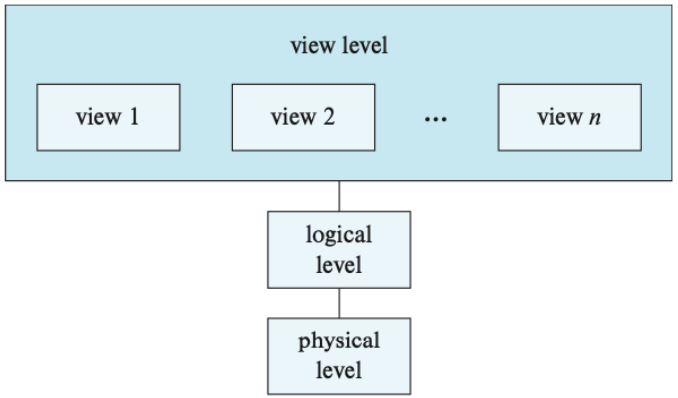
- Class Intro
- Big Data
- ***Data Models***

Data Models

- **Data modeling**
  - Represents and captures structure and properties of real-world entities
  - Abstraction: real-world $\rightarrow$ **representation**
- **Data model**
  - Describes how data is *represented* (e.g., relational, key-value) and *accessed* (e.g., insert operations, query)
  - Schema in a DB describes a specific data collection using a data model
- **Why need data model?**
  - Know data structure to write general-purpose code
  - Share data across programs, organizations, systems
  - Integrate information from multiple sources
  - Preprocess data for efficient access (e.g., building an index)

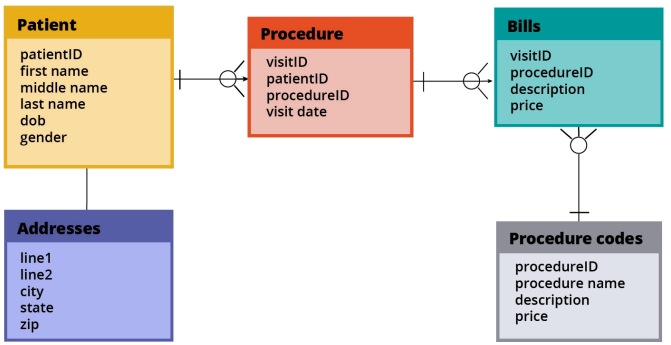
Multiple Layers of Data Modeling

- **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**
  - Concepts to represent data structure
  - E.g.,
    - Entity types
    - Entity attributes
    - Relationships between entities
    - Relationships between attributes
- **Integrity constraints**
  - Ensure data integrity
    - Avoid errors and inconsistencies
    - E.g., field can't be empty, must be 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 as data models
  - CSV
  - Parquet
  - JSON
  - Protocol Buffer
  - Avro/Thrift
  - Python Pickle

Good Data Models

- Data model should be:
  - Expressive
    - Capture real-world data
  - Easy to use
  - Perform well
- Tension between characteristics
  - Powerful models
    - Represent more datasets
    - Harder to use/query
    - Less efficient (e.g., more memory, time)
- Evolution of data modeling tools captures data structure
  - Structured data $\rightarrow$ Relational DBs
  - Semi-structured web data $\rightarrow$ XML, JSON
  - Unstructured data $\rightarrow$ NoSQL DBs

Data Independence

- **Logical data independence**
  - Change data representation without altering programs
  - E.g., API abstracting backend
- **Physical data independence**
  - Change data layout on disk without altering programs
    - Index data
    - Partition/distribute/replicate data
    - Compress data
    - Sort data

Databases: A Brief History

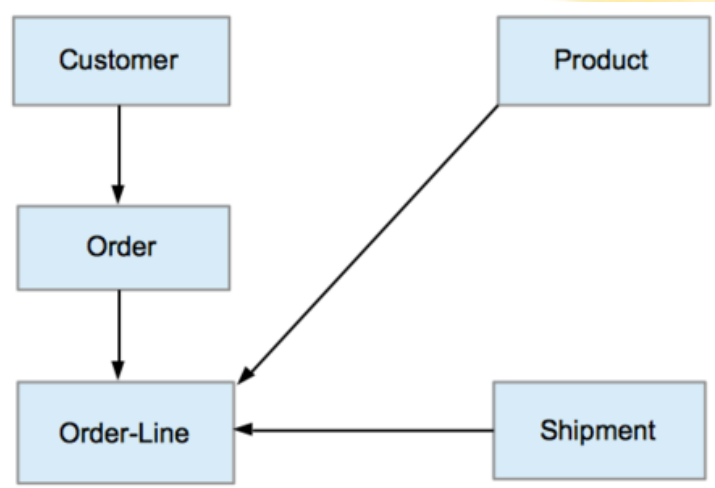
- **1960s: Early beginning**
  - Computers become attractive technology
  - Enterprises adopt computers
  - Applications use own data stores
    - Each application has its own format
    - Data unavailable to other programs
  - **Database**: term for "shared data banks" by multiple applications
    - Define data format
    - Store as "data dictionary" (schema)
    - Implement "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

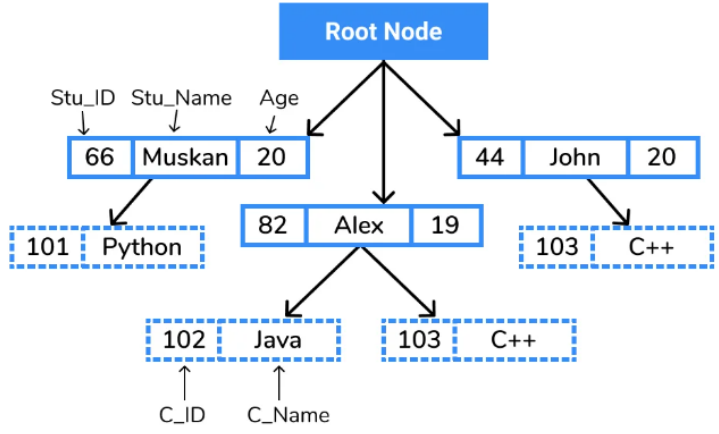
- **1960s, Hierarchical and Network Model**
  - Connect records of different types
  - Example: connect accounts with customers
  - Network model aimed for generality and flexibility
- IBM's IMS Hierarchical Database (1966)
  - Designed for Apollo space program
  - Predates hard disks
  - Used by over 95% of top Fortune 1000 companies
  - Processes 50 billion transactions daily, manages 15 million gigabytes of data
- Cons:
  - Exposed too much internal data (structures/pointers)
  - Leaky abstraction

Relational, Hierarchical, Network Model

- **Relational model**
  - Data as tuples in relations
  - SQL
- **Hierarchical model**
  - Tree-like structure
    - One parent, many children
    - Connected through links
  - XML DBs resurgence in 1990s
- **Network model**
  - Graph organization
    - Multiple parents and children
  - Graph DBs resurgence in 2010s



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	...



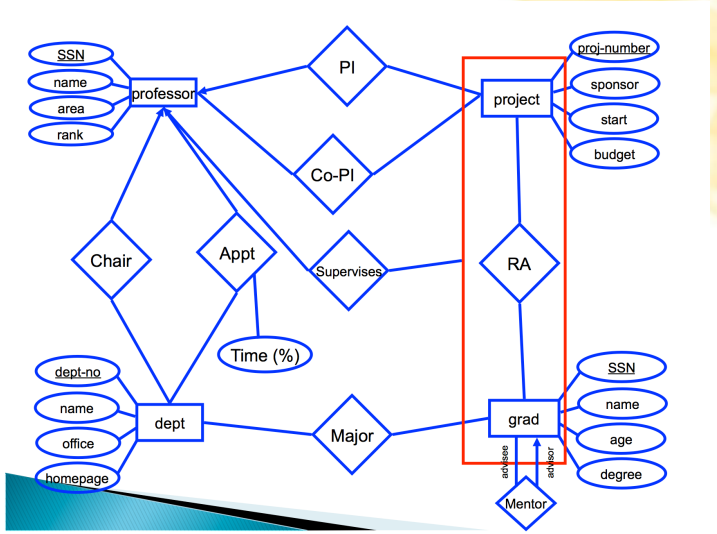
SCIENCE ACADEMY

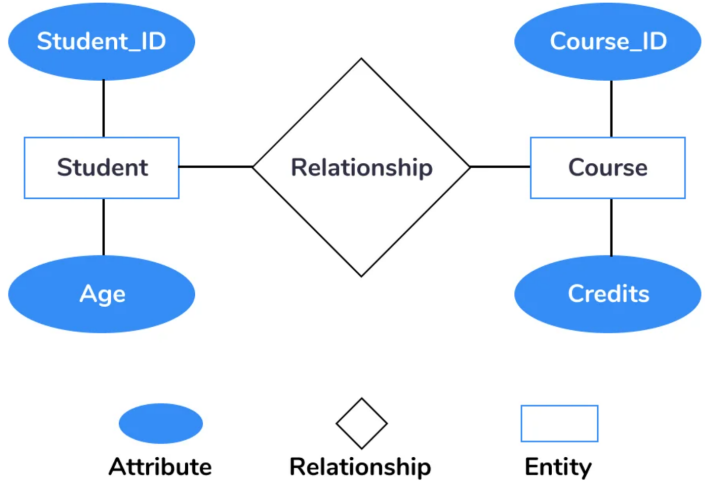
Databases: A Brief History

- **1970s: Relational model**
  - Set theory, first-order predicate logic
    - Ted Codd developed the Relational Model
  - Elegant, formal model
    - Provided data independence
    - Users didn't worry about data storage, processing
  - High-level query language
    - SQL based on relational algebra
  - Notion of normal forms
    - Reason about data and relations
    - Remove redundancies
- Influential projects:
  - INGRES (UC Berkeley), System R (IBM)
  - Ignored IMS compatibility
- Debates: Relational Model vs Network Model proponents

Entity-Relationship Model

- 1976: Peter Chen proposed "Entity-Relationship Model"
- Describes knowledge as entities and relationships
- **Entities**: Physical or logical objects, "Nouns"
- **Relationships**: Connections between entities, "Verbs"
- Map ER model to relational DB: Entities, relationships $\rightarrow$ tables





SCIENCE ACADEMY

Databases: A Brief History

- **1980s: Relational model acceptance**
  - SQL standard due to IBM's backing
  - Enhanced relational model
    - Set-valued attributes, aggregation
- Late 80's
  - Object-oriented DBs
    - Store objects, not tables
    - Overcome *impedance mismatch* between languages and databases
  - Object-relational DBs
    - User-defined types
    - Combine object-oriented benefits with relational model
  - No expressive difference from pure relational model

Object-Oriented

- OOP is a data model
  - Object behavior described through data (fields) and code (methods)
- **Composition**
  - Aka `has-a` relationships
  - E.g., `Employee` class has an `Address` class
- **Inheritance**
  - Aka `is-a` relationships
  - E.g., `Employee` class derives from `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 accessing inner workings of an object

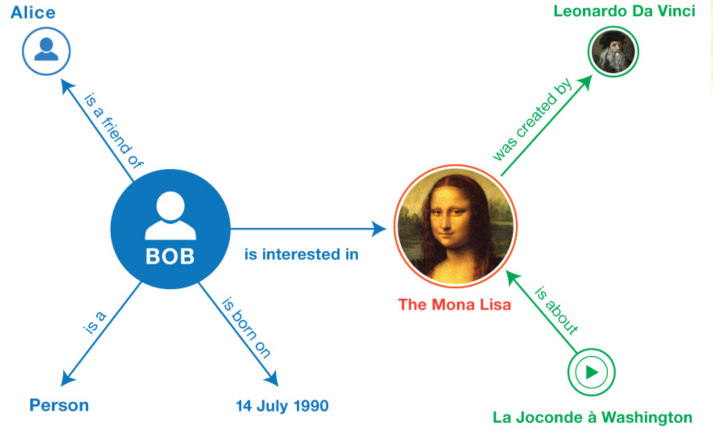
Databases: A Brief History

- **Late 90's-today**
- Web/Internet emerges
- XML: eXtensible Markup Language
  - 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:
  "subject-predicate-object" triple
  - Subject=sky
  - Predicate=has-the-color
  - Object=blue
- Maps to a labeled, directed multi-graph
  - More general than a tree
- Stored in:
  - Relational DBs
  - Dedicated "triple-stores" DBs




```
01    <http://example.org/bol
02    <http://example.org/bol
03    <http://example.org/bol
04    <http://example.org/bol
05    <http://www.wikidata.o
06    <http://www.wikidata.o
07    <http://data.europeana
```

Property Graph Model

- Graph:
  - Vertices and edges
  - Properties for each edge and vertex
- Stored in:
  - Relational DBs
  - Graph DBs