UMD DATA605: Big Data Systems

Lesson 1.2: Introduction to Big Data

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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 ($\sim$1970-80s)
  - Decision support, business intelligence ($\sim$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

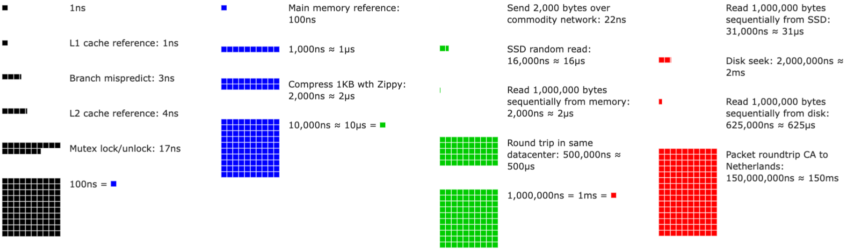
- *"Data science is the number one catalyst for economic growth"* (McKinsey, 2013)
- **Explosion of data in every domain**
  - Sensing devices/networks monitor processes 24/7
    - E.g., temperature of your room, your vital signs, pollution in the air
  - Sophisticated smart-phones
    - 80% of the world 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



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

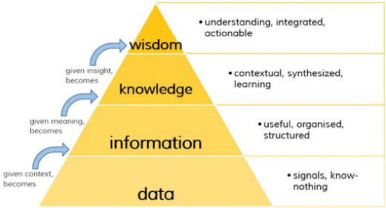
- **Personalized medicine**
  - Patients receive treatment tailored to them for efficacy
  - Genetics
  - Daily activities
  - Environment
  - Habits
- **Biomedical data**
- **Genome sequencing**
- **Health tech**
  - Personal health trackers (e.g., smart rings, phones)

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

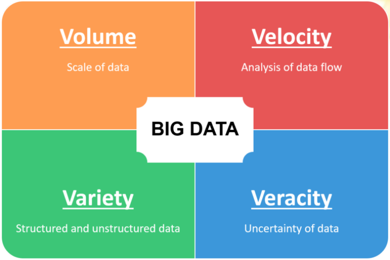
Goal of Data Science

- **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

- What makes "Big Data" big?
- **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



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The Six V's of Big Data

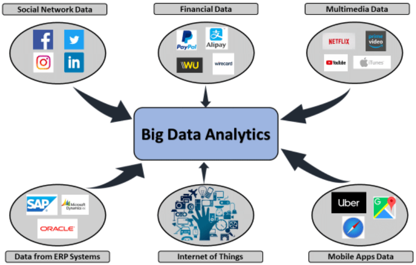
- **Volume**
  - Exponentially increasing data
  - 2.5 exabytes (1m TB) generated daily
    - 90% of data generated in last 2 years
    - Data doubles every 1.2 years
  - Twitter/X: 500M tweets/day (2022)
  - Google: 8.5B queries/day (2022)
  - Meta: 4PB data/day (2022)
  - Walmart: 2.5PB unstructured 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

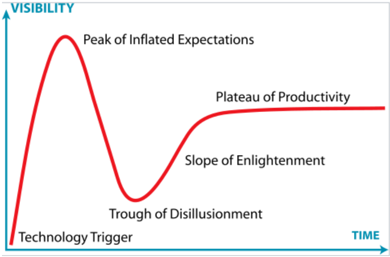
- **People and their activities generate data**
  - Social media (Instagram, Twitter, LinkedIn)
  - Video sharing (YouTube, TikTok)
  - Blogging, website comments
  - Internet searches
  - Text messages (SMS, Whatsapp, Signal, Telegram)
  - Personal documents (Google Docs, emails)
- **Pros**
  - Enable 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: Organizations

- **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) is everywhere**
  - *"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?**

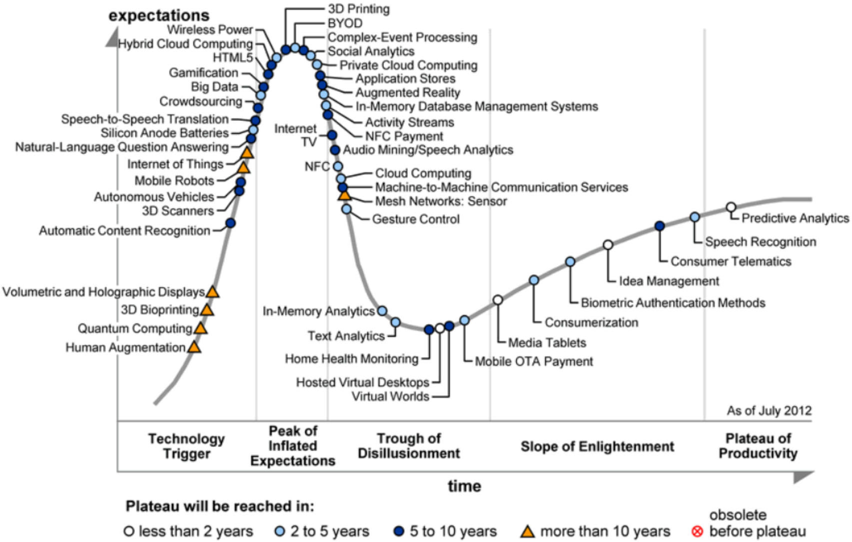


Is Data Science Just Hype?

- **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?

- Big data, Predictive analytics



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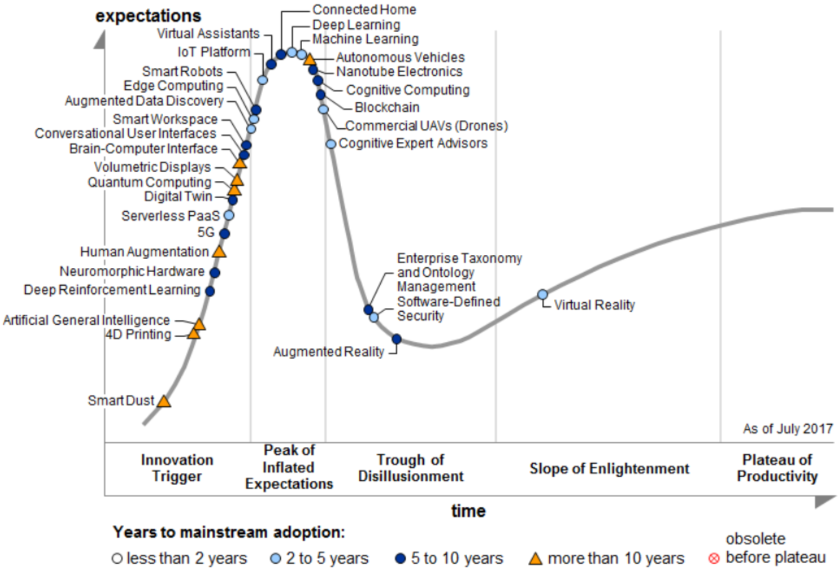
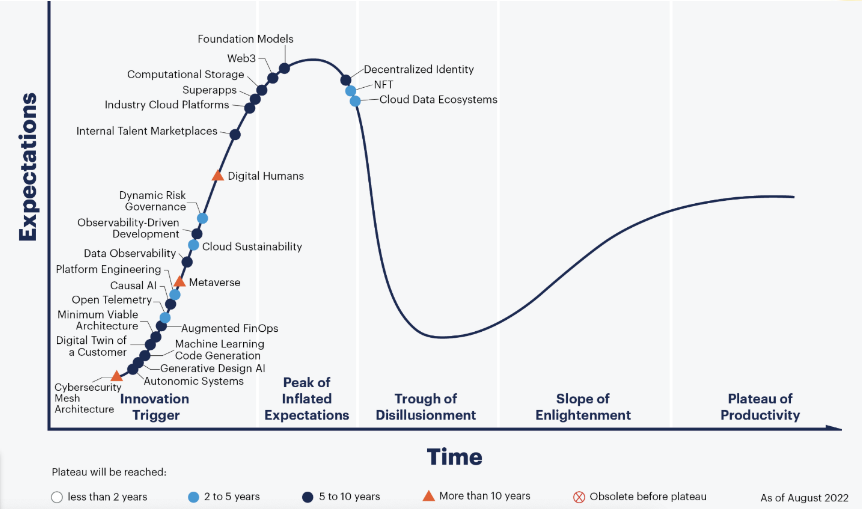
What Was Cool in 2017?

- Deep learning, Machine learning



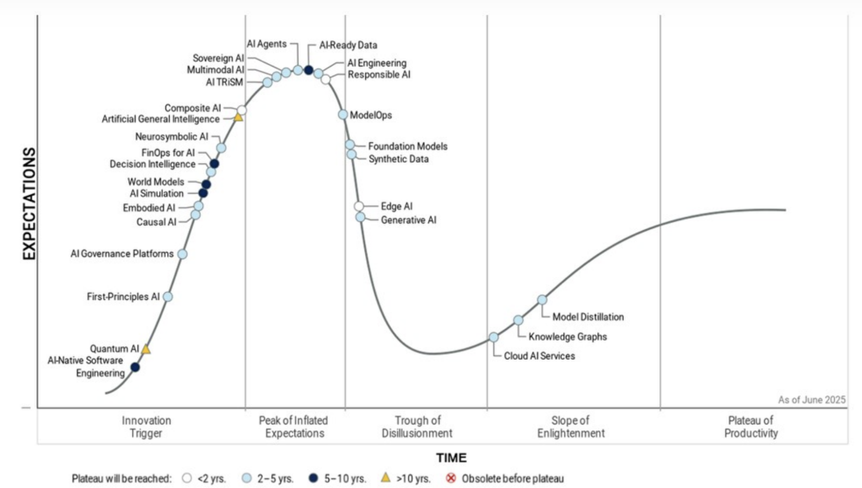
What Was Cool in 2022?

- Causal AI



What Was Cool in 2025?

- Causal AI, Decision intelligence



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Key Shifts Before/After Big-Data

- **Datasets: small, curated, clean $\rightarrow$ 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 $\rightarrow$ Correlation**
  - Goal: determine cause and effect
  - Causation hard to determine $\rightarrow$ focus on correlation
    - Correlation is sometimes 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

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

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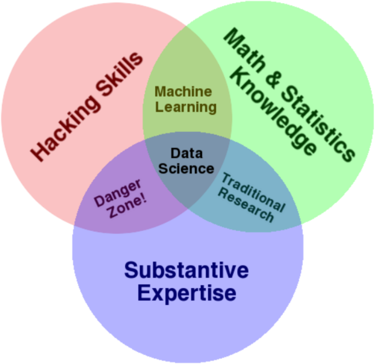
Examples: Google Flu Trends

- 5% to 20% of the US population gets the flu annually; **40k deaths**
  - Early warnings help in prevention and control
- **Google Flu Trends**
  - Provided early flu outbreak alerts via search query analysis
    - Analyzed 45 search terms
    - Used IP to determine location
  - Predicted regional flu outbreaks 1-2 weeks before CDC
  - Operated from 2008 to 2015
- **Caveat: accuracy issues**
  - Claimed 97% accuracy
  - Lower out-of-sample accuracy (overshot CDC data by 30%)
  - People search about flu without confirmed diagnosis
    - E.g., searching “fever” and “cough”

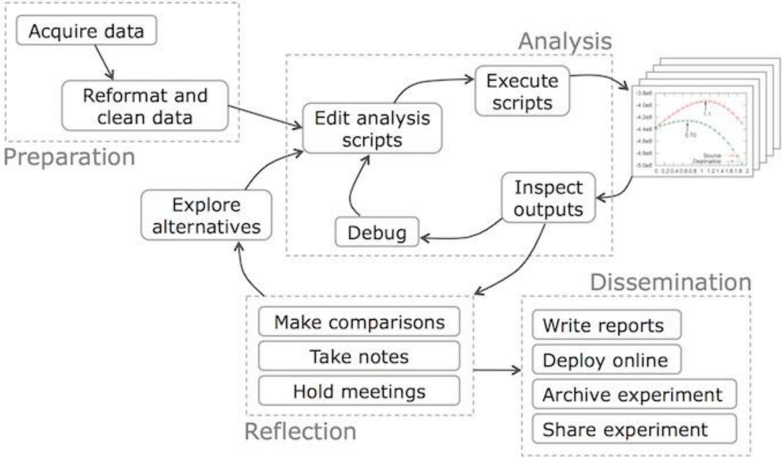
Data Scientist

- Ambiguous, 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

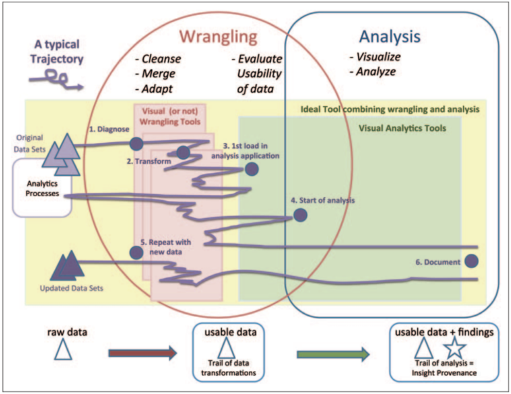


Figure 1. The iterative process of wrangling and analysis. One or more initial data sets may be used and new versions may come later. The wrangling and analysis phases overlap. While wrangling tools tend to be separated from the visual analysis tools, the ideal system would provide integrated tools (light 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 visualization and analysis tools, which typically immediately reveals new problems with the data. Wrangling might take place at all the stages of analysis as users sort out interesting insights from dirty data, or new data become available or needed. At the bottom we illustrate how the data evolves from raw data to usable data that leads to new insights.

What a Data Scientist Should Know

- **Data grappling skills** $\leftarrow$ *DATA*605
  - 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** $\leftarrow$ *DATA*605
  - Tell the story, communicate findings