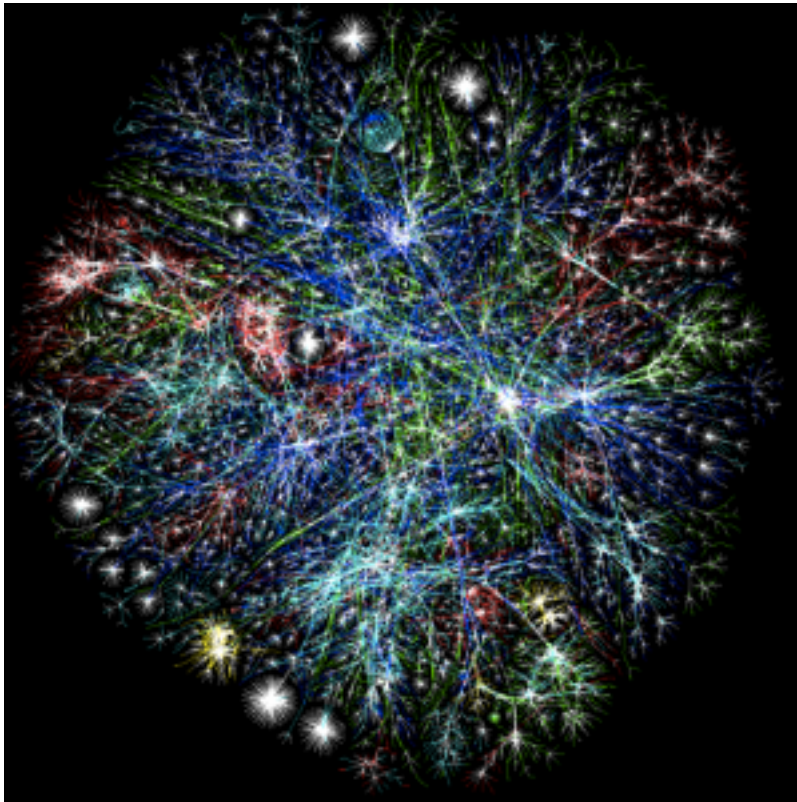


# What is Big Data? And How has it Changed?



Fred S. Roberts  
Director of  
CCICADA  
Rutgers University

Credit: commons.wikipedia.org

# What is Big Data? And How has it Changed?



Everyone is talking about *Big Data*

But what exactly is Big Data?

Why is it considered so important?

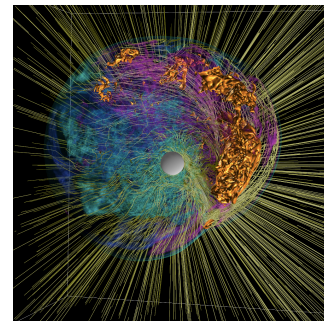
What about data has changed in the last 5 to 10 years?

What challenges do we face in the next 10 years?

<http://www.stat.columbia.edu/~cook/movabletype/archives/data.jpg>

# What is Big Data? And How has it Changed?

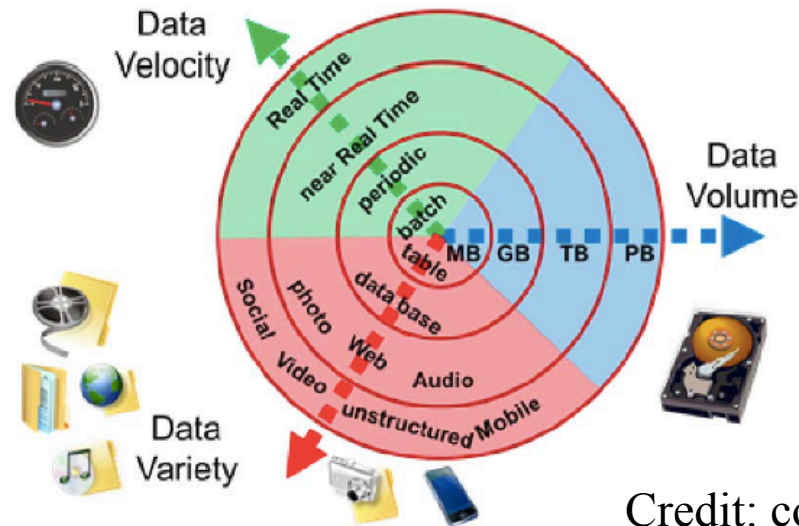
- *Massive Data* has a precise definition
  - Data not fitting into computer memory, thus requiring out of memory algorithms for solving complex problems.
- Big Data has no such definition.
- *Operational definition*: data so large that what to save is at question
  - In some cases, decisions on what to save need to be made instantaneously
  - E.g., astrophysical data



# What is Big Data? And How has it Changed?

- *Big Data* is sometimes described in terms of the three V's

- *Volume*
- *Variety*
- *Velocity*



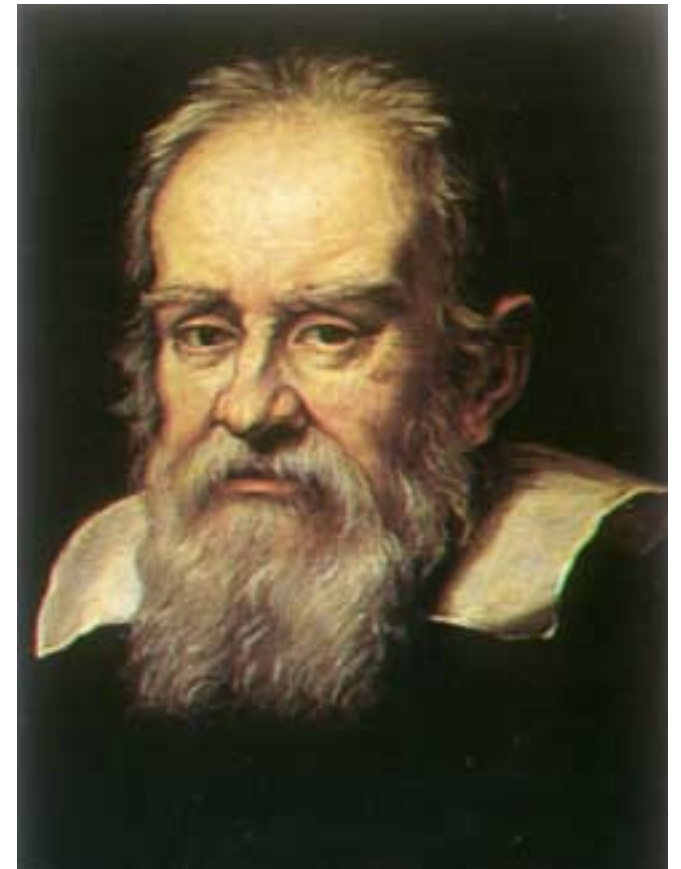
- It's not just the increase in any one of these factors that has created a challenge, but the concomitant increase in all three.

# What is Big Data? And How has it Changed?

- It is not just the three V's that define Big Data
- It is something more difficult to define and capture: *complexity*
  - Data today is very large, heterogeneous, interrelated, and complex
  - Data can be “dirty” (noisy)
  - Data can be “wide” (more variables than cases)
  - Data can be “fuzzy” (involving uncertainty)

# What is Big Data? And How has it Changed?

- Let us remember: Data science is an old field
- Galileo Galilei was a data scientist – and not the first
- So what has changed?



Credit: en.wikipedia.org

# What Leads to Big Data?

- Ever-increasing volumes of sensor data
- Ability to transmit data over ever-higher capacity networks
- Storage devices that can store and retrieve massive amounts of data
- Growing computing power
- The demand for faster solutions to complex problems
- Commercial and government applications

# Wide Variety of Sources of Data

- News
- Text
- Audio
- Images
- Video
- LiDAR
- Geophysical analyses
- Sensors of all types
- GPS systems
- Smartphones and tablets



Credit: en.wikipedia.org

*The remarkable variety of data sources present new challenges for data science*



# Resulting Challenges

- **Fusion Challenge:** Fusing information from multiple media or sources
  - Example: Flash flood prediction
    - Rain gauge networks
    - Radar
    - Satellite algorithms
    - Computer models of atmospheric processes
    - Hydrological models

Credit: en.wikipedia.org



# Resulting Challenges

- **Fusion Challenge:** Fusing information from multiple media or sources
  - Example: Earthquake prediction (still speculative) – fusing information from:
    - Changes in  $V_p/V_s$  (velocity of primary wave over velocity of secondary wave)
    - Spikes in concentration of gases such as radon
    - Seismic electric signals (geoelectric voltages)
    - Accelerating cumulative # of foreshocks
    - Anomalous animal behavior

Haiti; credit: commons.wikipedia.org



# Resulting Challenges

- **Fusion Challenge:** Fusing information from multiple media or sources
  - Example: How to combine “hard” numerical readings of sensors monitoring emergency vehicle movements with “soft” natural language utterances of the driver and “tweets” of the public?



# Resulting Challenges

- **Decision Support Challenge**
  - Today's decision makers have available to them remarkable new technologies, huge amounts of information, ability to share information at unprecedented speeds and quantities.
- **Decision Support Challenge:** These tools and resources will enable better decisions if we can surmount some of the major challenges
  - Data often incomplete or unreliable or distributed, and involves great uncertainty
  - Many sources of data need to be fused into a good decision, often in a remarkably short time



# Resulting Challenges

- **Decision Support Challenge:** These tools and resources will enable better decisions if we can surmount some of the major challenges
  - Interoperating/distributed decision makers and decision-making devices need to be coordinated
  - Decisions must be made in dynamic environments based on partial information
  - There is heightened risk due to extreme consequences of poor decisions
  - Decision makers must understand complex, multidisciplinary problems

# Resulting Challenges

- **Decision Support Challenge**
  - Allow comparison of array of alternative solutions
  - Using data to make decisions is not new
  - Big data has led to using many different techniques to make better decisions
- Resulting new field: Algorithmic Decision Theory

Second International Conference on  
**Algorithmic Decision Theory**

DIMACS, Rutgers University  
New Brunswick, New Jersey, USA

October 26-28, 2011

**An interdisciplinary forum on:**  
Algorithmic Challenges to Modern Decision Support and Automation  
Uncertainty and Robustness in Decision Making  
Preferences in Reasoning and Decision Making  
Decision Theoretic Artificial Intelligence  
Learning and Knowledge Extraction for Decision Support

Website: <http://adt2011.org/>

**Meeting Co-Chairs:**  
Ronen Brafman (Ben-Gurion University)  
Fred Roberts (Rutgers University)  
Alexis Tsoukias (University of Paris-Dauphine)

Sponsors:

The poster also features a map of the New Brunswick area with labels for 'HYATT REGENCY NEW BRUNSWICK', 'RUTGERS UNIVERSITY', 'NEW YORK CITY', 'NEWARK INT'L AIRPORT', 'ALBURNIPKE EXIT 9', 'PENNSYLVANIA TURNPIKE', 'NEW JERSEY TURNPIKE', 'PHILADELPHIA', and 'NEW JERSEY'.



# Resulting Challenges

- **Combinatorial Explosion Challenge**
  - Big data allows comparison of array of alternative solutions
  - However, the number of alternatives is often so large that we cannot take all into account in a timely way
  - We may not even be able to express all possible preferences among alternatives – too many alternatives
    - Example: “composite” auctions lead to “NP-complete” allocation problems; determining the “winner” can be computationally intractable

# Resulting Challenges

- **Combinatorial Explosion Challenge**

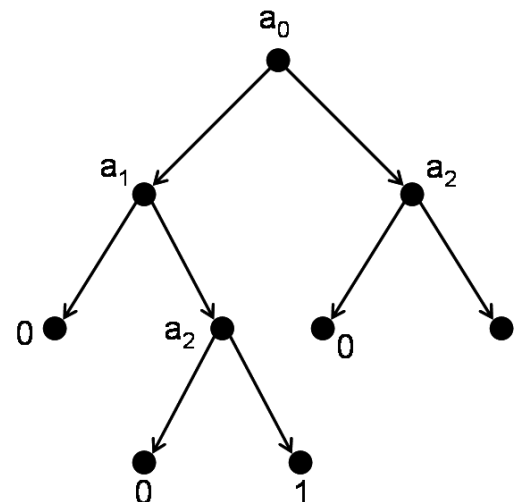
- Example: container inspection at ports

- Sequential diagnosis: tests one at a time; next test chosen based on outcome of previous test

- Represent possible tests as binary decision trees

- Find “optimal” BDT

- With 5 possible tests there are 263,515,920 possible BDTs





# Resulting Challenges

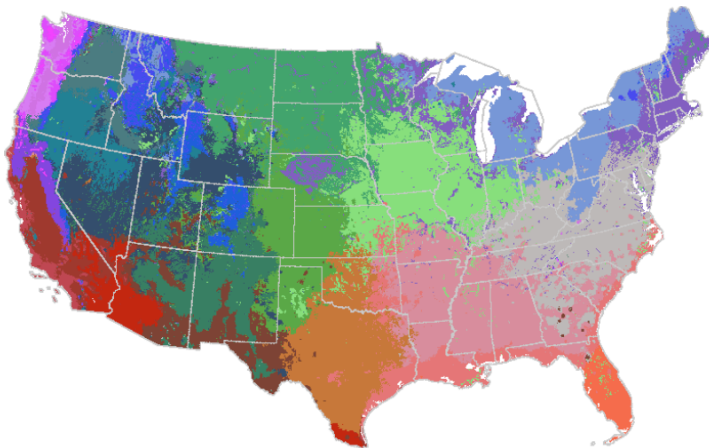
- **Combinatorial Explosion Challenge**
  - Example: Comparing performance of nuclear detection algorithms
  - Many relevant factors:
    - Type of Special Nuclear Material
    - Shielding
    - Masking
    - Altitude
    - Humidity
    - Temperature
    - Vehicle speed
  - Each has several values
  - Too many combinations to test all



Credit: en.wikipedia.org

# Resulting Challenges

- **Combinatorial Explosion Challenge**
  - Example: Environmental Monitoring
  - National Ecological Observatory Network (NEON) collecting data at 20 sites across the U.S.
    - Goal: get a continent-wide picture of the impacts of climate change, land use change and invasive species on natural resources, and biodiversity



*Credit: William Hargrove, U.S. Forest Service.*

# Resulting Challenges

- **Combinatorial Explosion Challenge**

- Example: Environmental Monitoring

- How choosing 20 sites?

- ❖ Divide the country into 8 million patches

- ❖ For each patch, collect 9 pieces of information about its ecology and climate

- ❖ Cluster the patches

- ❖ Choose representative patch for each cluster

- ❖ Better would be to use 100 pieces of information

- ❖ But: combinatorially impossible

# Resulting Challenges

- **Real-time Analytics Challenge**

- How to make decisions based on data arriving so fast humans cannot absorb it?

- Example: Power grid

- ❖ Status upgrades used to be every 2-4 seconds, now 10 times a second

- ❖ Rate too rapid for human alone to absorb anomaly in time to act

- ❖ Need software agents to act on behalf of humans



Credit: commons.wikipedia.org

# Resulting Challenges

- **Real-time Analytics Challenge**

- How to make decisions based on data arriving so fast humans cannot absorb it?
  - Example: Dutch flower auctions
  - Flowers very perishable; need quick decisions
  - Typical transaction takes ~ 4 seconds
  - Information technology allows complex auctions with many bidders
  - Even determining the winner can be computationally intractable (NP-hard)

Credit: en.wikipedia.org



# Resulting Challenges

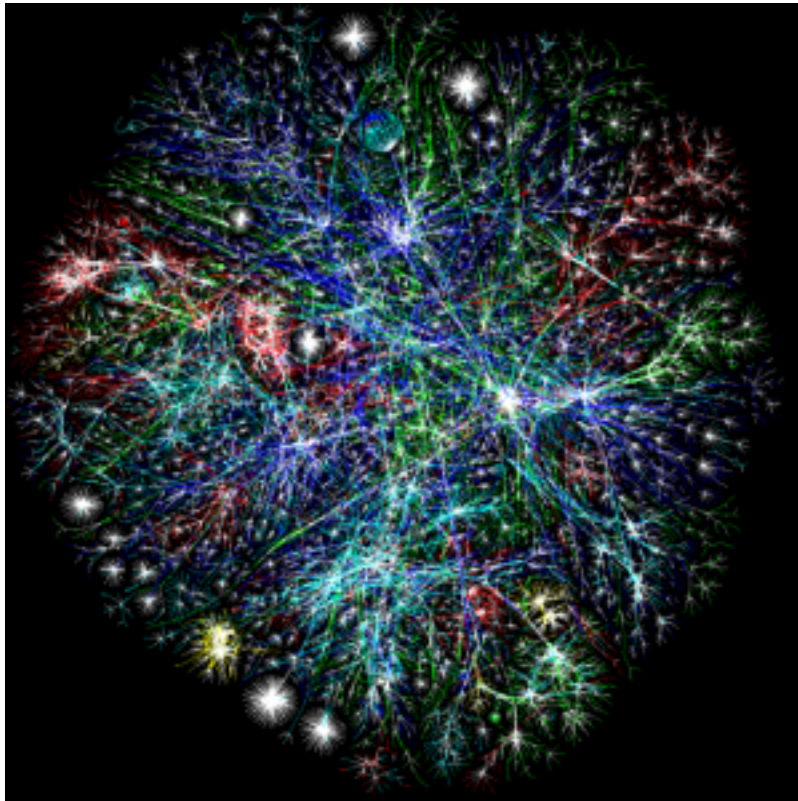
- **Streaming Data Challenge for Graphs & Networks**
  - Data such as IP traffic level, access logs, command logs arise from rapidly evolving graphs & networks
  - Situational awareness requires us to translate the data into large, interpretable, & manageable graphs
    - Graphs that can be monitored to detect local changes that may not have a visible effect on global metrics



Credit: en.wikipedia.org

# Resulting Challenges

- **Streaming Data Challenge:** New algorithms needed to deal with large and possibly massive graphs streaming in real time



Credit: commons.wikipedia.org

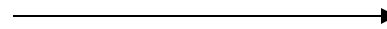
# Resulting Challenges

- **Data Summarization**

**Challenge:** How to summarize data without being able to store individual items, in a way that allows one to uncover patterns from the summaries?

- Data is gone, only summaries remain
- Identifying patterns might not have been in areas of interest at time summaries are produced:
- Can we use the summaries to get at causality, to aid in post-event mitigation or prevention of future events?

Distributed,  
data streams



Carefully  
materialize  
**summary**



Probabilistic,  
approximate  
ad hoc queries &  
historic analyses





# Resulting Challenges

- **Vulnerabilities Challenge**
- Modern society is critically dependent on Big Data
  - Manufacturing and production
  - Power and water systems
  - Financial systems



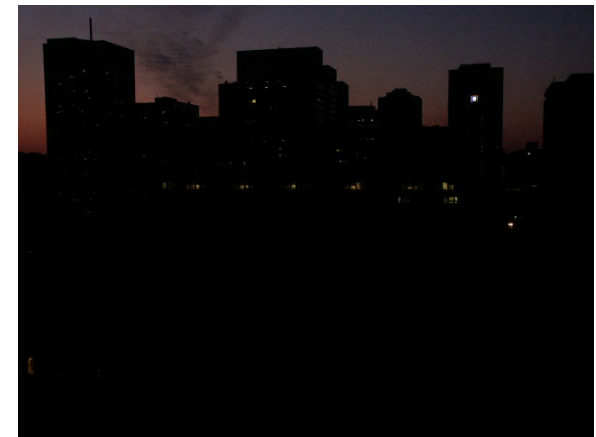
25 Credit: en.wikipedia.org



Credit: commons.wikipedia.org

# Resulting Challenges

- **Vulnerabilities Challenge**
- Modern society is critically dependent on Big Data
- Vulnerabilities are ever present
  - Cyber attacks
  - Cascading failures
  - Rapid spread of anomalies



NYC Blackout 2003

Credit: en.wikipedia.org



Credit: www.flickr.com



# Resulting Challenges

- The very ability to utilize and benefit from large amounts of data creates vulnerabilities
  - Electronic medical records lead to hospitals being subject to “ransomware”

## Surgeries in Hospitals Postponed Because of Ransomware

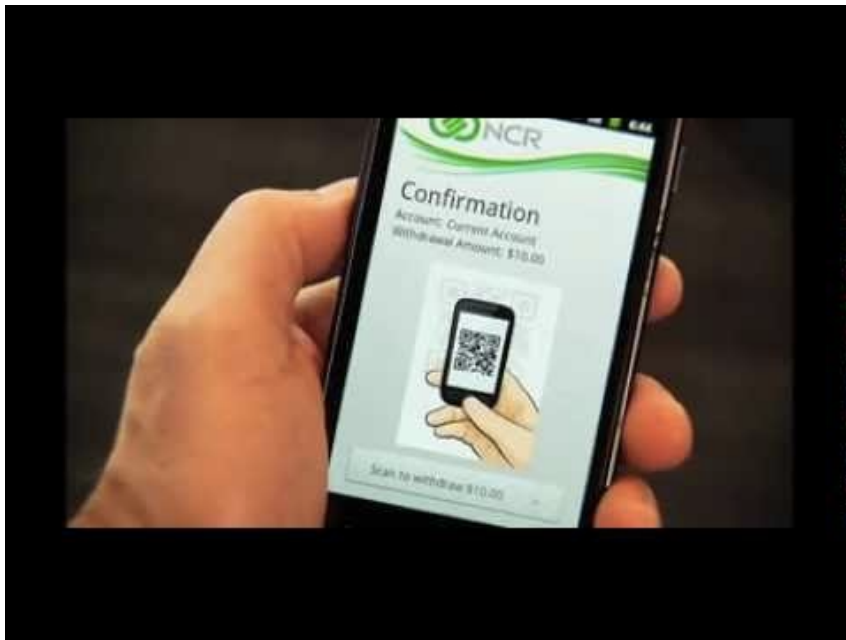


Credit: [Community.spiceworks.com](https://community.spiceworks.com)



# Resulting Challenges

- The very ability to utilize and benefit from large amounts of data creates vulnerabilities
  - Ability to do banking from anywhere we travel leads to identity theft



Credit: [www.youtube.com](http://www.youtube.com)

# Resulting Challenges

- The very ability to utilize and benefit from large amounts of data creates vulnerabilities
  - Example: Cyber-physical systems are vulnerable
  - Our cars are now computers on wheels, yet we can already hack into them and “take” control
  - Hacking into a Prius:



Credit: npr.org

# Resulting Challenges

- The very ability to utilize and benefit from large amounts of data creates vulnerabilities
  - Example: Big data allows self-driving cars.
  - But those cars can get into accidents



Recent crash of Tesla: Credit: en.wikipedia.org

# Resulting Challenges

- The very ability to utilize and benefit from large amounts of data creates vulnerabilities
  - Example: Oil drilling rigs can operate effectively thanks to dynamic positioning systems
  - However, hackers have tilted an oil rig, putting it out of business for days



Credit: [www.peakoil.net](http://www.peakoil.net)

# Resulting Challenges

- **Vulnerabilities Challenge:** How do we identify vulnerabilities caused by usage of data? How do we develop tools for monitoring and minimizing such vulnerabilities?



Credit: [www.flickr.com](http://www.flickr.com)



# Resulting Challenges: Information from Data

- A key challenge is to aggregate data from multiple sources with potentially questionable quality and credibility and obtain useful “information” as a result.
- Turning to challenges related to getting “information” from data.

Credit: [www.flickr.com](http://www.flickr.com)



# Information from Data

- **Information Access Challenge:** How to develop high-accuracy information search and access capabilities
  - Google already does this
  - But what are the next new ideas?
  - One approach: develop special “extraction” technology combined with machine learning to learn the “story” being told across multiple dimensions of time and space.

The Google logo is displayed in its characteristic multi-colored font: blue 'G', red 'o', yellow 'o', blue 'g', green 'l', and red 'e'.

# Information from Data

- **Information Distillation Challenge:** How to make inferences and draw hypotheses from large amounts of data, when data seldom exists in the form most suited for analysis?
  - Application: how to define “normal” in order to detect departure from normal?
  - Example: what is “normal” seismic activity?

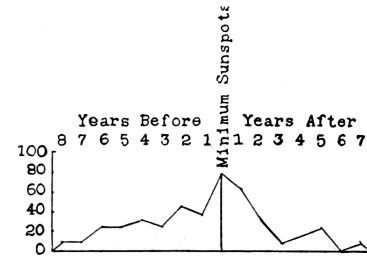


Figure 2. Simple Frequency - Sayles.

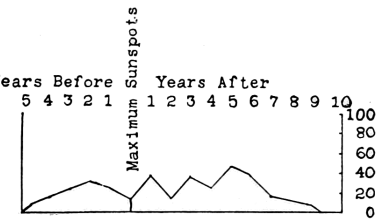


Figure 6. Simple Frequency - Sayles.

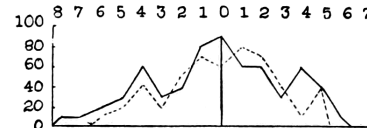


Figure 3. Simple Frequency - Jensen.

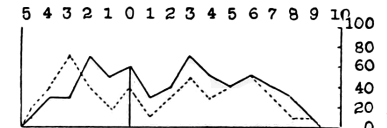


Figure 7. Simple Frequency - Jensen.

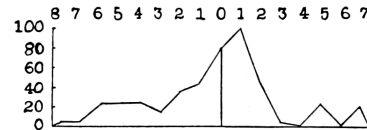


Figure 4. Intensity - Sayles.

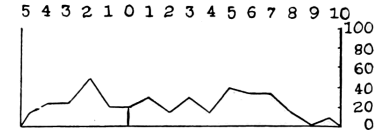


Figure 8. Intensity - Sayles.

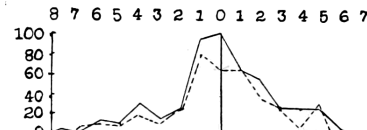


Figure 5. Intensity - Jensen.

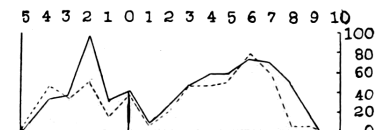


Figure 9. Intensity - Jensen.



# Information from Data

- **Information Storage & Management**

**Challenge:** How to create very large-volume databases that support data homogenization across various sources?

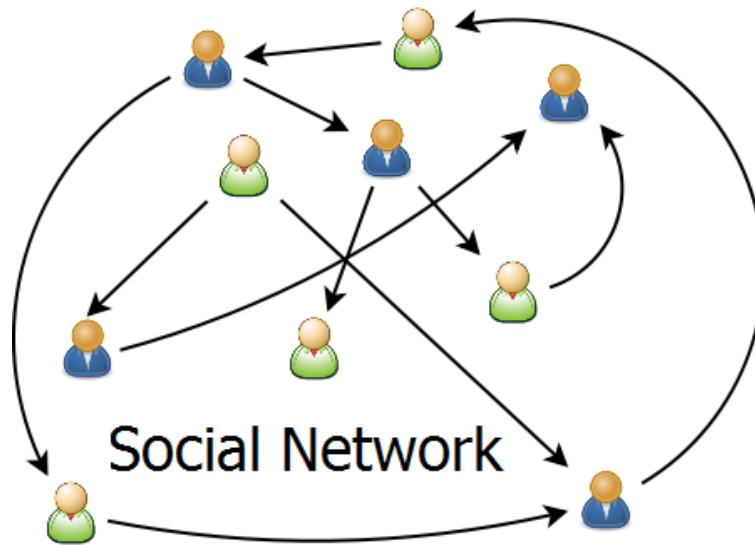
- Application: Data evolves, reflecting changing points of view, opinions, environmental conditions
- How do you follow the development dynamics of adversarial views on a topic, an interest in a technology, or an opinion?

# Information from Data

- **Information Storage & Management**

**Challenge:** How to create very large-volume databases that support data homogenization across various sources?

- Example: Can you predict evolving connections in social networks?



Credit: commons.wikipedia.org

# Information from Data

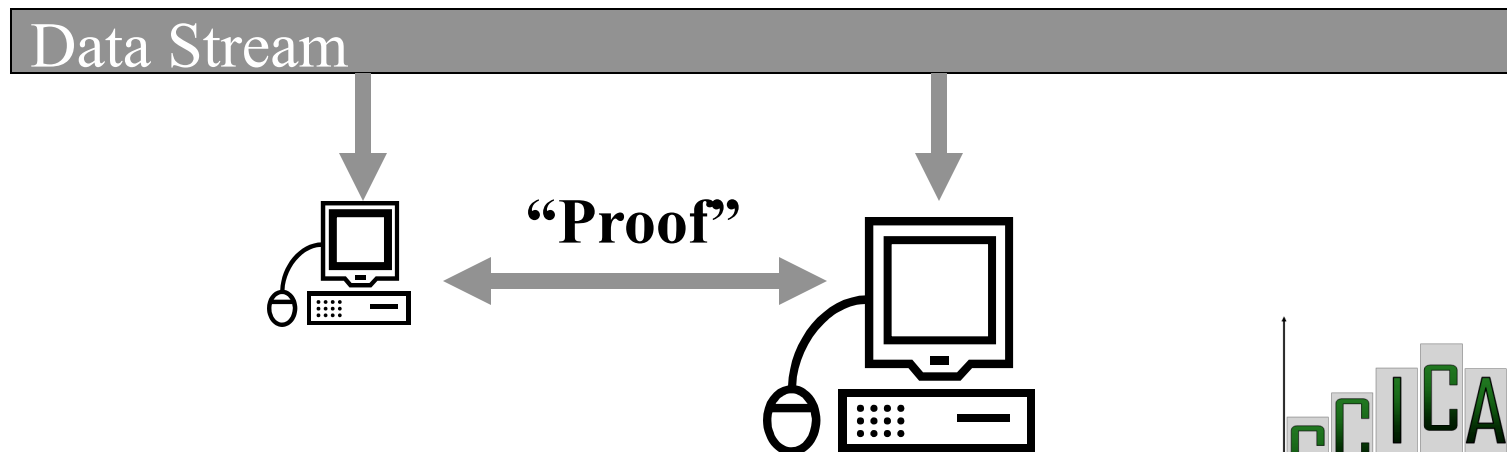
- **New Architectures Challenge:** As much data has grown too large to reside in one location, need new architectures.
- Big change in this direction: increasing emphasis on use of “the Cloud” to do computations, store data



Credit: commons.wikipedia.org

# Information from Data

- As more computation is outsourced to a potentially untrusted third party party (“the cloud”), it is now necessary to seek assurances that computations are performed correctly as claimed.
- “*Proof systems*” can give the necessary assurance, but prior work on them is not sufficiently scalable or practical.



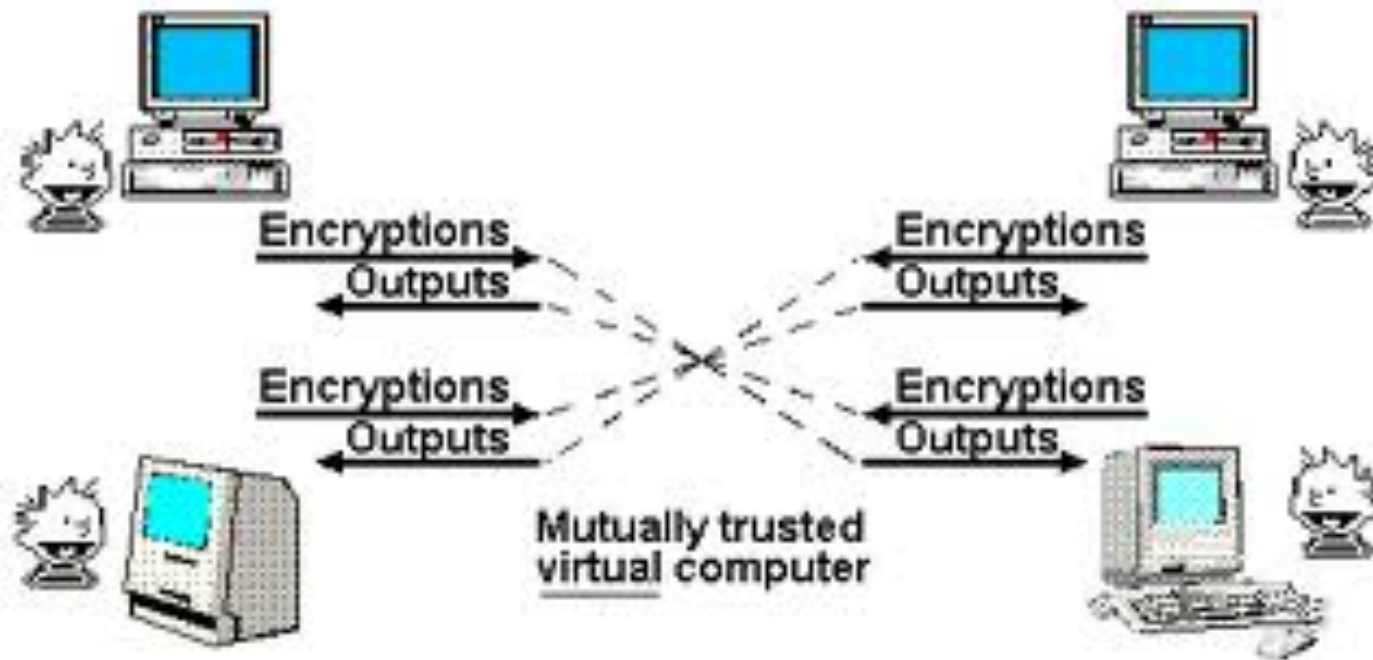
# Information from Data

- **Information Sharing Challenge:** Information sharing requires appropriately safeguarding both systems and information; selecting the most trusted information sources; and maintaining secure systems even in hostile settings
  - Example: “Secure Multiparty Computation” is a theoretical area aiming at allowing parties to jointly compute something over their inputs while keeping those inputs private.



# Information from Data

- Secure multiparty computation is a “model” for secure information sharing.



# Information from Data

- **Trustworthiness Challenge:** To utilize the vast amounts of information available to us, we have to understand what sources we can trust
  - Example: Emergency situation; lots of data as to damage, physical needs, information needs, etc. What to trust?
  - Need precise definitions of factors contributing to trustworthiness: accuracy, completeness, bias



Japanese Earthquake & Tsunami; credits: commons.wikipedia.org  
and www.flickr.com

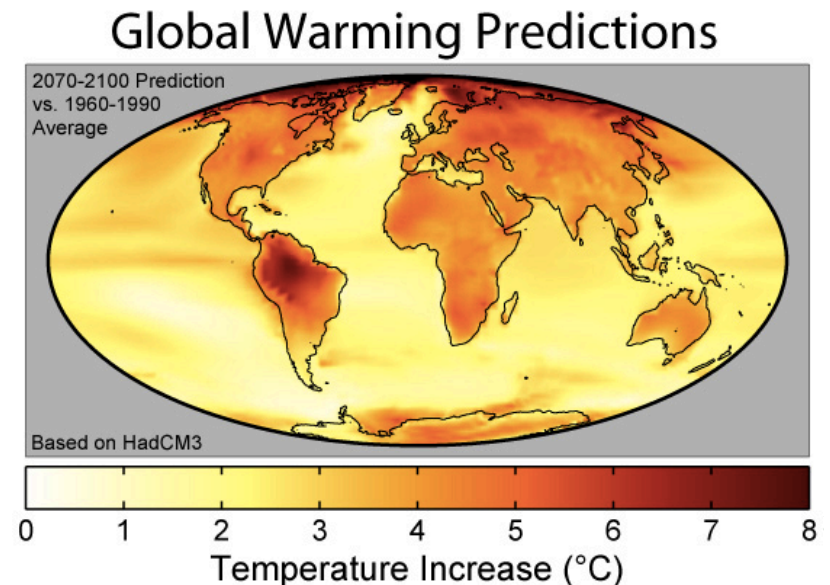
# Information into Knowledge

- In building decision-supporting models, uncertainty arises from parameter values, model relationships, recorded observations, conflicting sources
- **Uncertainty Quantification Challenge:** How best present levels of uncertainty and best resolve conflicting predictions?

# Information into Knowledge

- **Uncertainty Quantification Challenge:** How best present levels of uncertainty and best resolve conflicting predictions?
  - How to develop consensus when different models lead to at least seemingly different conclusions?
  - Example: Climate models

Credit: commons.wikipedia.com



# Closing Comment

- It doesn't matter how big or small a dataset is.
- What matters is what we can do with the data.



Credit: [www.flickr.com](http://www.flickr.com)