HA NOI UNIVERSITY OF SCIENCE AND TECHNOLOGY
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Introduction to Data Science (IT4142E)

Contents

- **Lecture 1: Overview of Data Science**
- Lecture 2: Data crawling and preprocessing
- Lecture 3: Data cleaning and integration
- Lecture 4: Exploratory data analysis
- Lecture 5: Data visualization
- Lecture 6: Multivariate data visualization
- Lecture 7: Machine learning
- Lecture 8: Big data analysis
- Lecture 9: Capstone Project guidance
- Lecture 10+11: Text, image, graph analysis
- Lecture 12: Evaluation of analysis results

Introduction

Goals of data science

Some questions

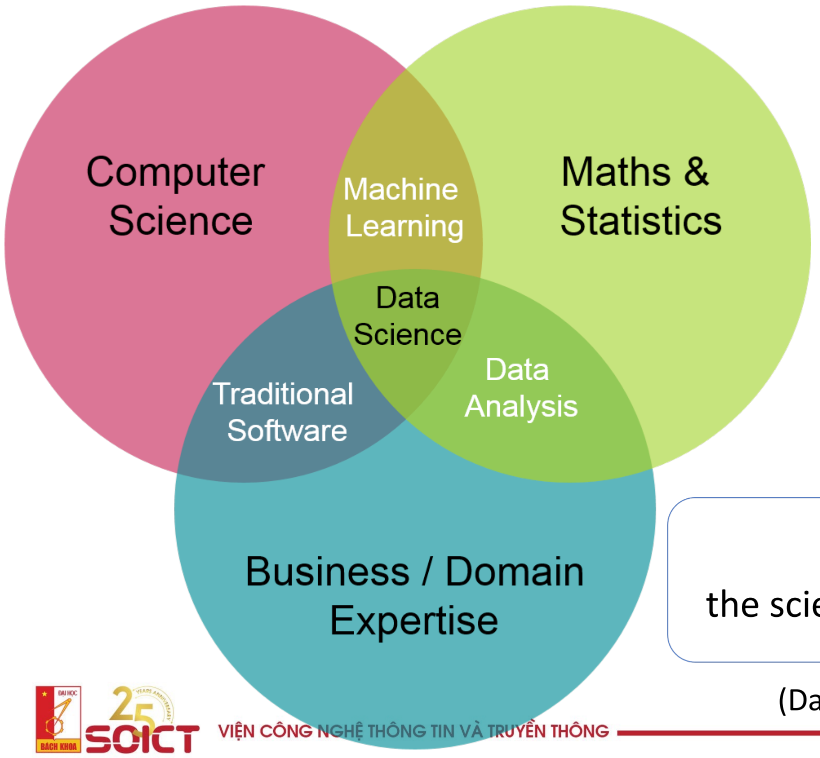
- Some questions a decision-maker might wonder:
  - What is the evolution of my stores' turnover, by month and by store?
  - Based on what client X is buying, which age range does he/she most likely
  - What mmend them,
  - What his info into accou
  - If I ac reimburse me (at

Let the data speak

- These questions are:
  - Specific
  - Sometimes, embedded in one another
  - Unpredictable

→**A simple planned report is not enough!**

What is Data Science?



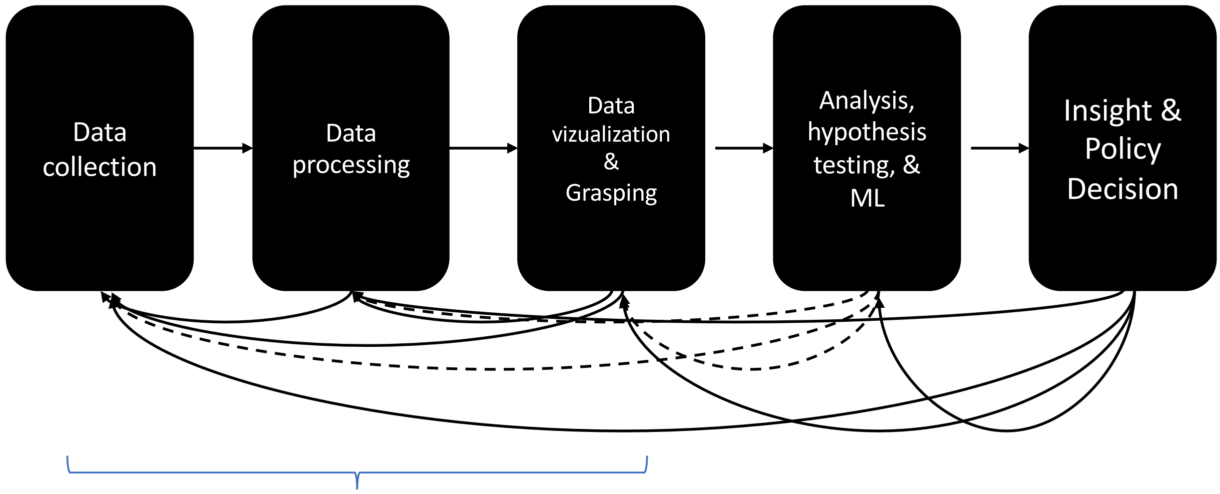
Data science is
the science of *learning from data*.

(David Donoho, Stanford University)

Goals of Data Science

- The final goals of data science might be classified into
  - Description
  - Prediction
- In order to achieve these goals, several tasks are required:
  - Data scraping
  - Data pre-processing: cleaning, transforming, and integration
  - Machine learning
  - Visualization
- Data science may apply to any kind of data
  - Raw data (numbers)
  - Text analysis
  - Image and video analysis
  - Graph analysis

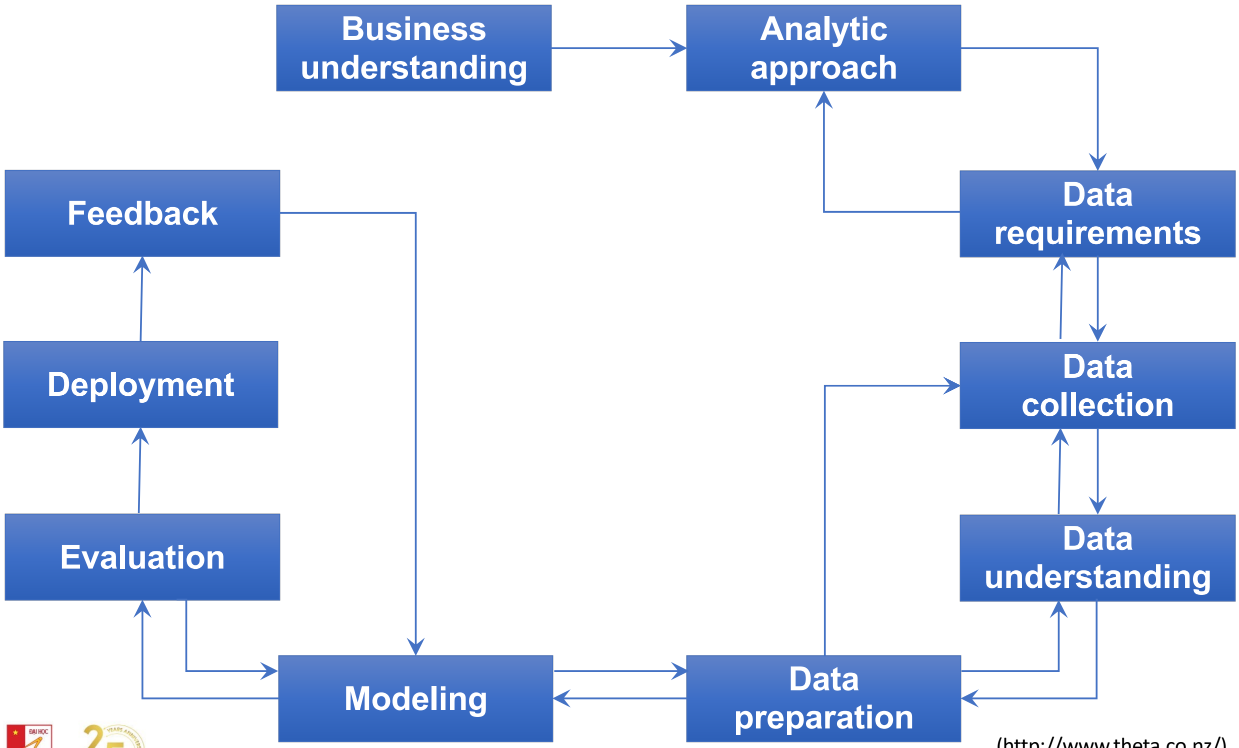
Methodology: insight-driven


Data collection
Data processing
Data vizualization & Grasping
Analysis, hypothesis testing, & ML
Insight & Policy Decision

70-90% of the whole process

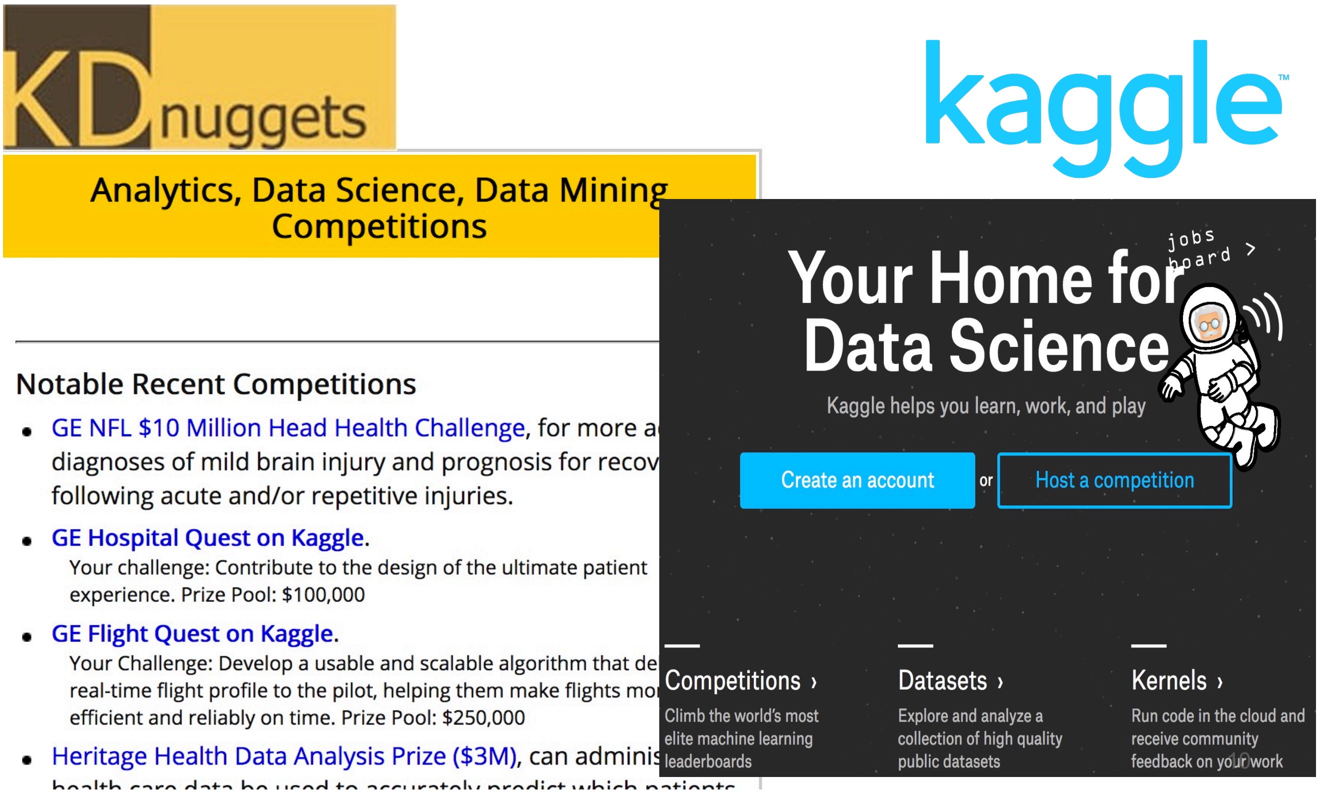
(John Dickerson, University of Maryland)

Methodology: product-driven



(http://www.theta.co.nz/)

Some online platforms for DS competitions



KDnuggets

Analytics, Data Science, Data Mining Competitions

Notable Recent Competitions

- GE NFL $10 Million Head Health Challenge, for more a diagnoses of mild brain injury and prognosis for recov following acute and/or repetitive injuries.
- GE Hospital Quest on Kaggle.
  Your challenge: Contribute to the design of the ultimate patient experience. Prize Pool: $100,000
- GE Flight Quest on Kaggle.
  Your Challenge: Develop a usable and scalable algorithm that de real-time flight profile to the pilot, helping them make flights mo efficient and reliably on time. Prize Pool: $250,000
- Heritage Health Data Analysis Prize ($3M), can adminis health care data be used to accurately predict which patients

kaggle

Your Home for Data Science

Kaggle helps you learn, work, and play

Competitions ›
Climb the world's most elite machine learning leaderboards

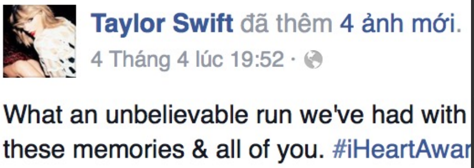
Datasets ›
Explore and analyze a collection of high quality public datasets

Kernels ›
Run code in the cloud and receive community feedback on your work

Introduction

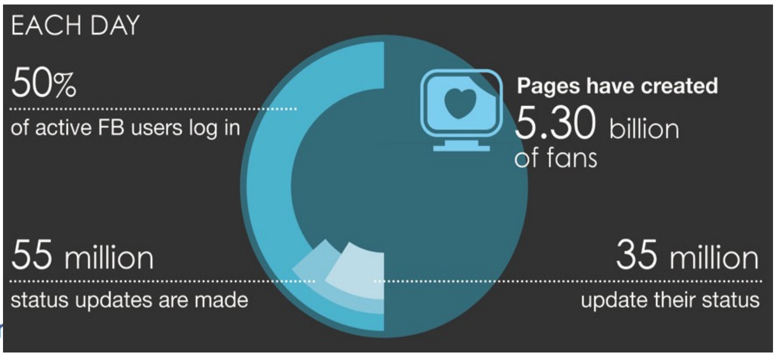
Where is the data?

Where is the data? Social networks



Taylor Swift đã thêm 4 ảnh mới.
4 Tháng 4 lúc 19:52 ·

What an unbelievable run we've had with these memories & all of you. #iHeartAwar



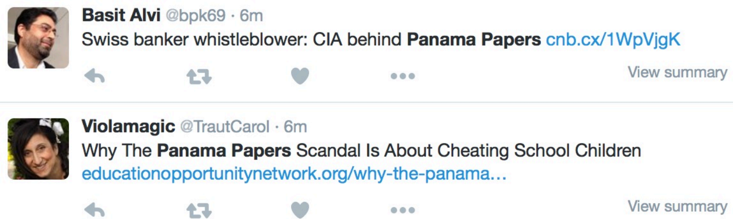
EACH DAY

50% of active FB users log in

Pages have created 5.30 billion of fans

55 million status updates are made

35 million update their status



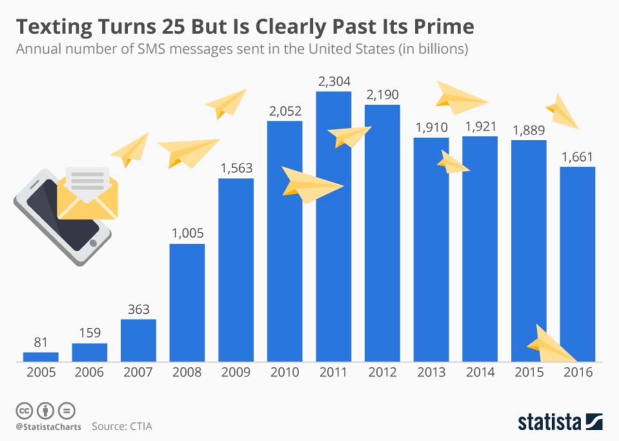
Basit Alvi @bpk69 · 6m
Swiss banker whistleblower: CIA behind **Panama Papers** cnb.cx/1WpVjgK
View summary

Violamagic @TrautCarol · 6m
Why The **Panama Papers** Scandal Is About Cheating School Children educationopportunitynetwork.org/why-the-panama…
View summary

7,174 Tweets sent in 1 second

862,696 Tweets since opening this page
0:02:00 seconds ago

Where is the data? Mobile messages



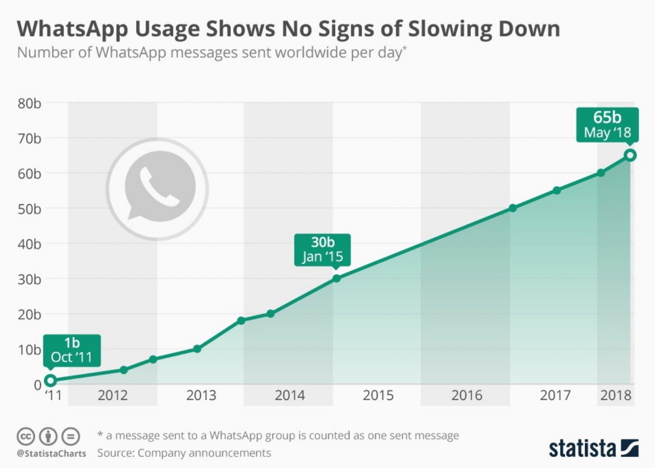
Texting Turns 25 But Is Clearly Past Its Prime

Annual number of SMS messages sent in the United States (in billions)

Source: CTIA

Rise and fall of SMS

Rise of messaging apps



WhatsApp Usage Shows No Signs of Slowing Down

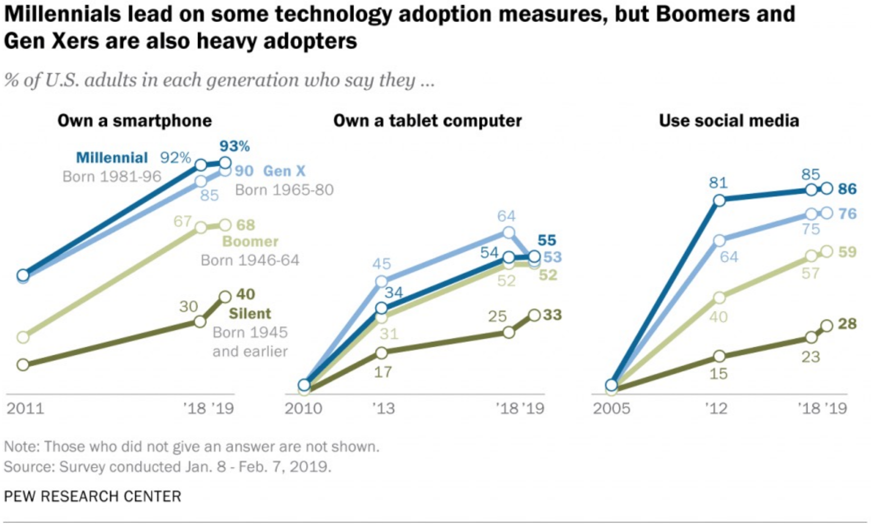
Number of WhatsApp messages sent worldwide per day*

* a message sent to a WhatsApp group is counted as one sent message

Source: Company announcements

Where is the data? Internet

- In the US:



Millennials lead on some technology adoption measures, but Boomers and Gen Xers are also heavy adopters

% of U.S. adults in each generation who say they ...

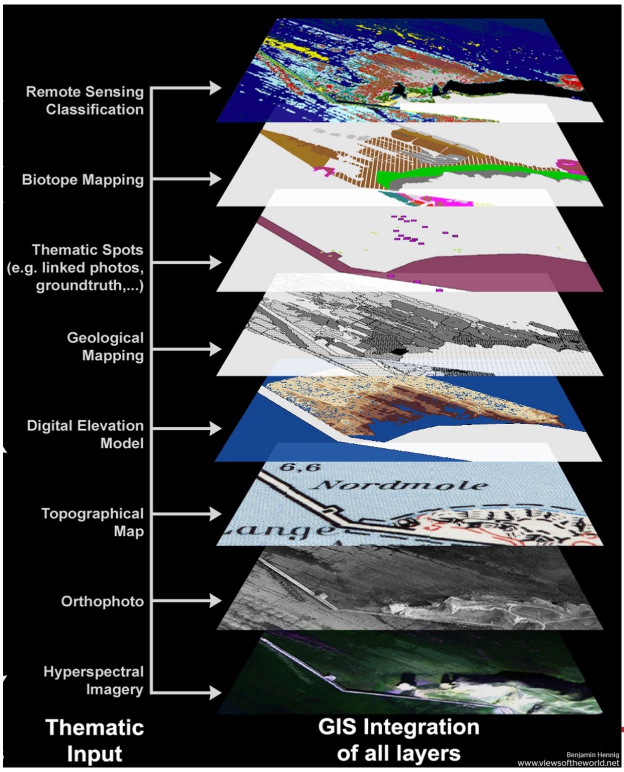
Note: Those who did not give an answer are not shown.

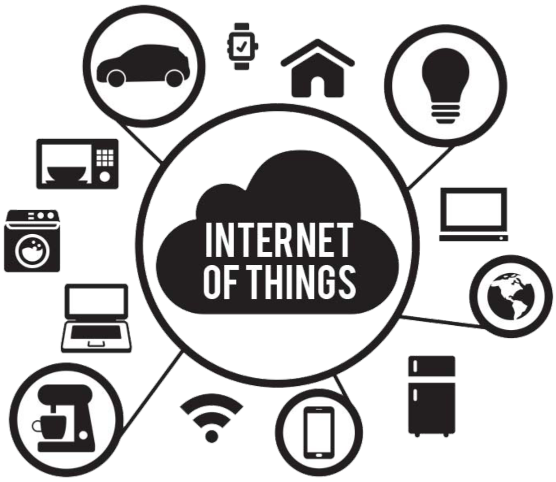
Source: Survey conducted Jan. 8 - Feb. 7, 2019.

PEW RESEARCH CENTER

- https://www.internetlivestats.com

Where is the data? And more

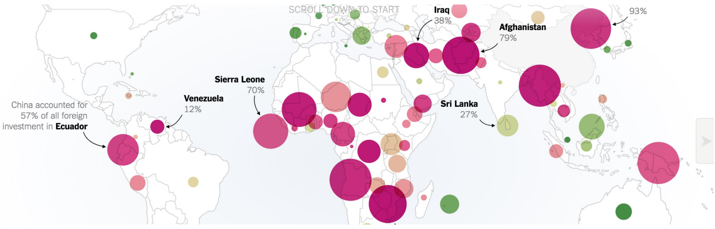


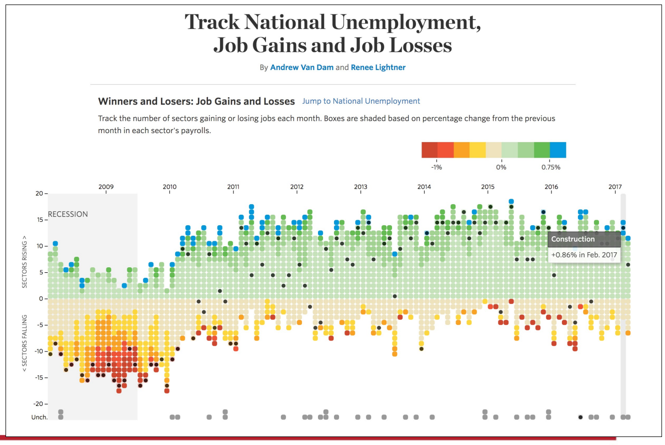


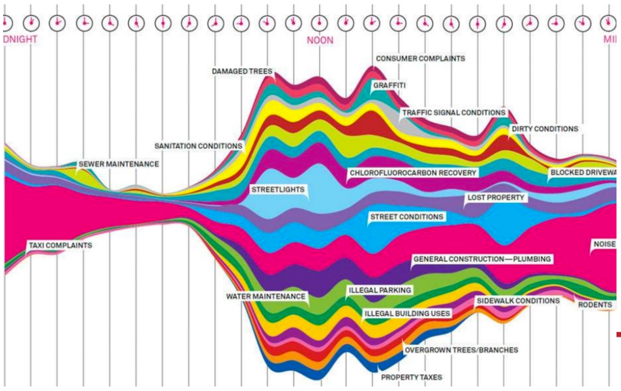
Introduction

What can we do with the data?

What can we do with the data?
Data description through visualization



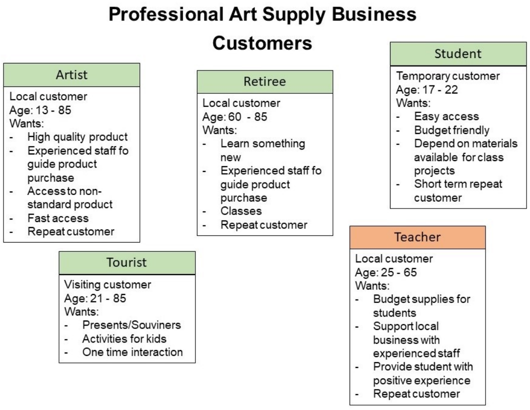




Data description

- Data description consists of summarizing the data in an “understable” way, either:
  - Through **exploratory data analysis**
    - Mostly descriptive statistics such as average, standard deviation, median, mode,…
  - Through **data visualization**

What can we do with the data?
Customer segmentation



Professional Art Supply Business

Customers

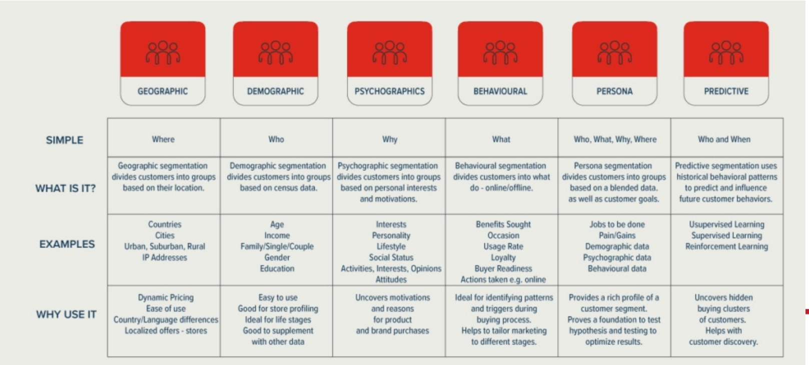
Artist
Local customer
Age: 13 - 85
Wants:
- High quality product
- Experienced staff fo guide product purchase
- Accessto non-standard product
- Fast access
- Repeat customer

Retiree
Local customer
Age: 60 - 85
Wants:
- Learn something new
- Experienced staff fo guide product purchase
- Classes
- Repeat customer

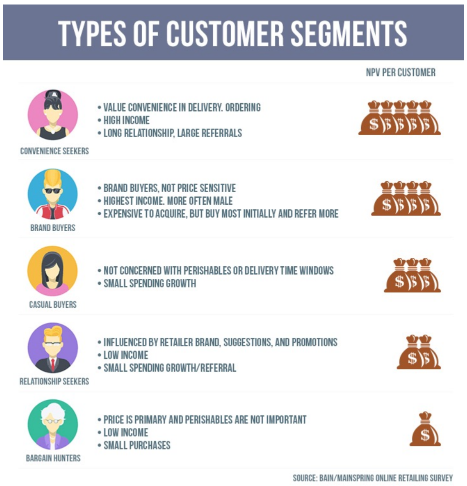
Student
Temporary customer
Age: 17 - 22
Wants:
- Easy access
- Budget friendly
- Depend on materials available for class projects
- Short term repeat customer

Tourist
Visiting customer
Age: 21 - 85
Wants:
- Presents/Souviners
- Activities for kids
- One time interaction

Teacher
Local customer
Age: 25 - 65
Wants:
- Budget supplies for students
- Support local business with experienced staff
- Provide student with positive experience
- Repeat customer



	GEOGRAPHIC	DEMOGRAPHIC	PSYCHOGRAPHICS	BEHAVIOURAL	PERSONA	PREDICTIVE
SIMPLE	Where	Who	Why	What	Who, What, Why, Where	Who and When
WHAT IS IT?	Geographic segmentation divides customers into groups based on their location.	Demographic segmentation divides customers into groups based on census data.	Psychographic segmentation divides customers into groups based on personal interests and motivations.	Behavioural segmentation divides customers into what do - online/offline.	Persona segmentation divides customers into groups based on a blended data. as well as customer goals.	Predictive segmentation uses historical behavioral patterns to predict and influence future customer behaviors.
EXAMPLES	Countries Cities Urban, Suburban, Rural IP Addresses	Age Income Family/Single/Couple Gender Education	Interests Personality Lifestyle Social Status Activities, Interests, Opinions Attitudes	Benefits Sought Occasion Usage Rate Loyalty Buyer Readiness Actions taken e.g. online	Jobs to be done Pain/Gains Demographic data Psychographic data Behavioural data	Usupervised Learning Supervised Learning Reinforcement Learning
WHY USE IT	Dynamic Pricing Ease of use Country/Language differences Localized offers - stores	Easy to use Good for store profiling Ideal for life stages Good to supplement with other data	Uncovers motivations and reasons for product and brand purchases	Ideal for identifying patterns and triggers during buying process. Helps to tailor marketing to different stages.	Provides a rich profile of a customer segment. Proves a foundation to test hypothesis and testing to optimize results.	Uncovers hidden buying clusters of customers. Helps with customer discovery.



TYPES OF CUSTOMER SEGMENTS

NPV PER CUSTOMER

CONVENIENCE SEEKERS
- VALUE CONVENIENCE IN DELIVERY. ORDERING
- HIGH INCOME
- LONG RELATIONSHIP, LARGE REFERRALS

BRAND BUYERS
- BRAND BUYERS, NOT PRICE SENSITIVE
- HIGHEST INCOME. MORE OFTEN MALE
- EXPENSIVE TO ACQUIRE, BUT BUY MOST INITIALLY AND REFER MORE

CASUAL BUYERS
- NOT CONCERNED WITH PERISHABLES OR DELIVERY TIME WINDOWS
- SMALL SPENDING GROWTH

RELATIONSHIP SEEKERS
- INFLUENCED BY RETAILER BRAND, SUGGESTIONS, AND PROMOTIONS
- LOW INCOME
- SMALL SPENDING GROWTH/REFERRAL

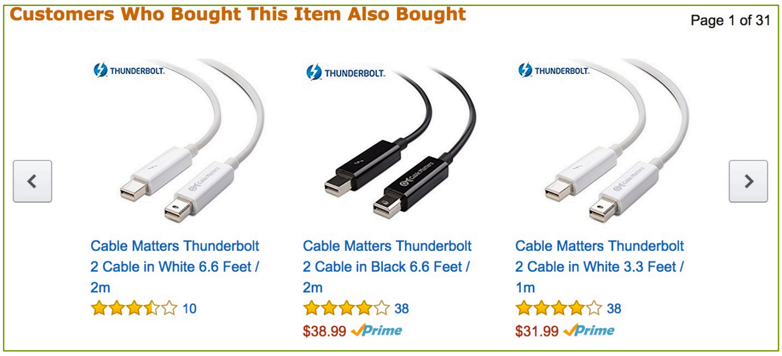
BARGAIN HUNTERS
- PRICE IS PRIMARY AND PERISHABLES ARE NOT IMPORTANT
- LOW INCOME
- SMALL PURCHASES

SOURCE: BAIN/MAINSPRING ONLINE RETAILING SURVEY

Data segmentation

- Data segmentation consists in grouping the similar records into homogeneous groups (called **clusters**)
  - Records in a group have similar attribute values
  - Technically, the goal is to lean a “new” attribute (group#) from the record’s attributes
  - **Unsupervised learning** methods can be used: see Chapter 7

What can we do with the data?
Amazon’s recommendation (association)

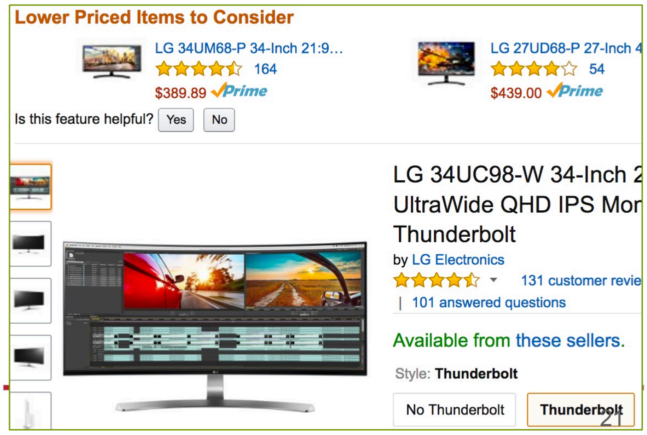


Customers Who Bought This Item Also Bought

Page 1 of 31

- Cable Matters Thunderbolt 2 Cable in White 6.6 Feet / 2m — 10
- Cable Matters Thunderbolt 2 Cable in Black 6.6 Feet / 2m — 38 — $38.99 ✓Prime
- Cable Matters Thunderbolt 2 Cable in White 3.3 Feet / 1m — 38 — $31.99 ✓Prime

“The company reported a **29% sales increase** to $12.83 billion during its second fiscal quarter, up from $9.9 billion during the same time last year.”
– Fortune, July 30, 2012



Lower Priced Items to Consider

- LG 34UM68-P 34-Inch 21:9… — 164 — $389.89 ✓Prime
- LG 27UD68-P 27-Inch 4 — 54 — $439.00 ✓Prime

Is this feature helpful? Yes No

LG 34UC98-W 34-Inch 2
UltraWide QHD IPS Mon
Thunderbolt
by LG Electronics
131 customer revie
| 101 answered questions

Available from these sellers.

Style: Thunderbolt

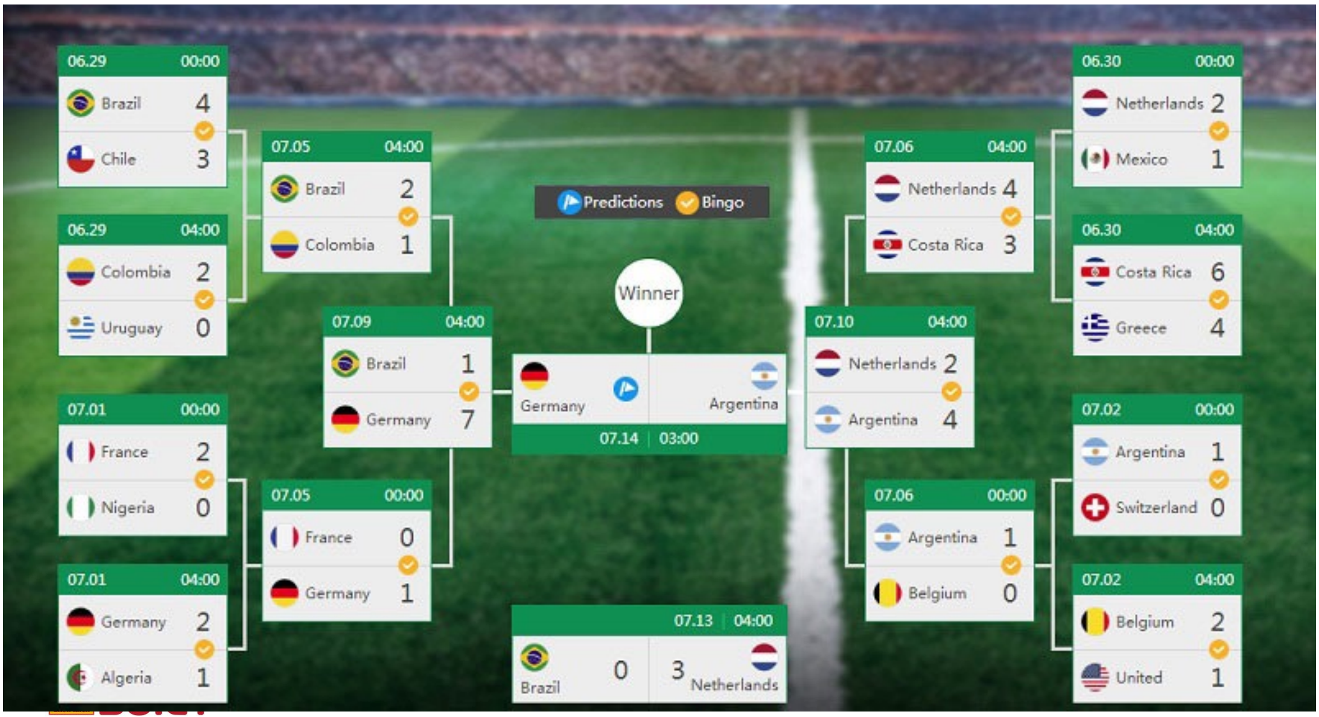
No Thunderbolt | Thunderbolt

Association rules

- Association mining: discovering association rules between records, according to pre-defined criteria
  - *E.g.* the items that are often bought during one single transaction
  - Technically, the goal is to lean a “new” information (association rules) from the record’s attributes
  - **Unsupervised** learning methods can be used: see Chapter 7

What can we do with the data?

FIFA predictions (2014)



Accuracy ~93%.

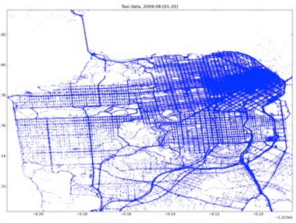
(http://yourstory.com/2014/07/germany-argentina-fifa-world-cup-2014/)

Prediction

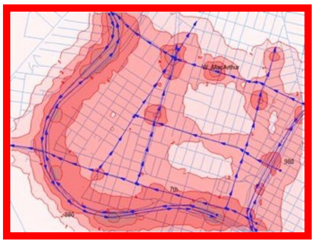
- Prediction consists in either:
  - predicting or estimating the values of an attribute for a set or records
    - This attribute is known for other records
    - This knowledge is used to predict this attribute’s values on our set of records
    - **Supervised** learning methods can be used

What can we do with the data?

Much more!!!



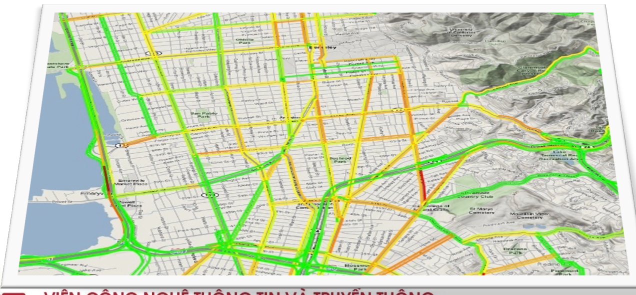
Eureka
Petrolia
km
0
50



Crowdsourcing + physical modeling + sensing + data assimilation

to produce:

Earthquake
Strong Shaking
in 5 seconds
Get under desk



(Alex Bayen, UC Berkeley)

Big data

What is it?

Big data – in 2008

http://www.wired.com/wired/issue/16-07

September 2008

The End of Science

The quest for knowledge used to begin with grand theories. Now it begins with massive amounts of data. Welcome to the Petabyte Age.

Big data – in 2014

THE AVERAGE PERSON TODAY PROCESSES MORE DATA IN A SINGLE DAY THAN A PERSON IN THE 1500'S DID IN AN ENTIRE LIFETIME

LOOK TO THE LEFT, and you see Times Square at dusk. Look to the right, and you see the same location at midmorning. Internationally acclaimed photographer Stephen Wilkes's time-altering image of New York's Times Square is part of his body of work titled *Day to Night*.

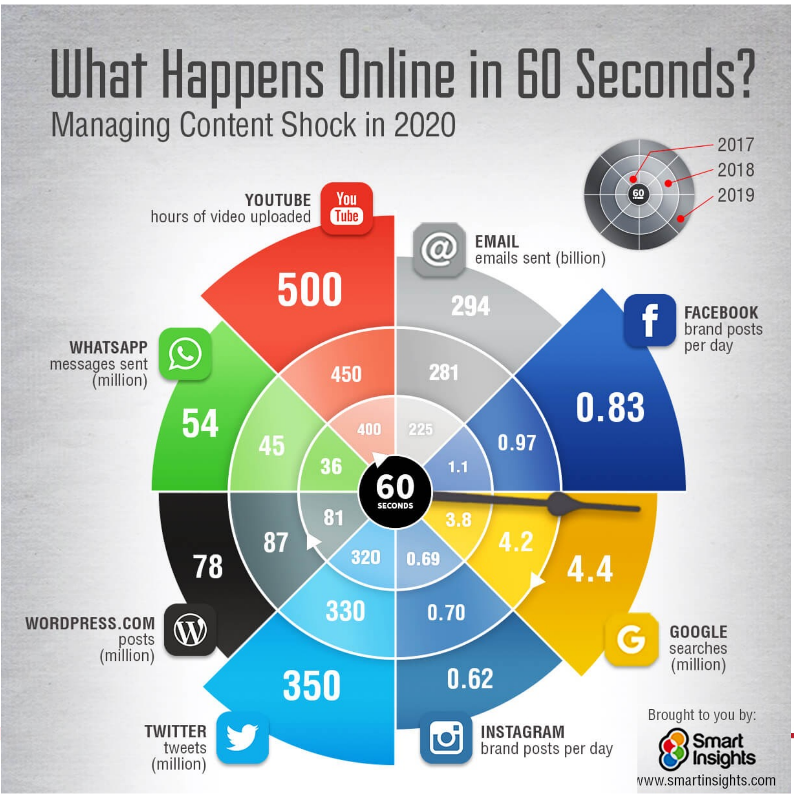
The image was created by blending more than 1,400 separate photos taken over the course of 15 hours—a meticulous process that took him nearly three months.

PHOTO: STEPHEN WILKES

Big data – today

The amount of information generated during the first day of a baby's life today is equivalent to 70 times the information contained in the Library of Congress

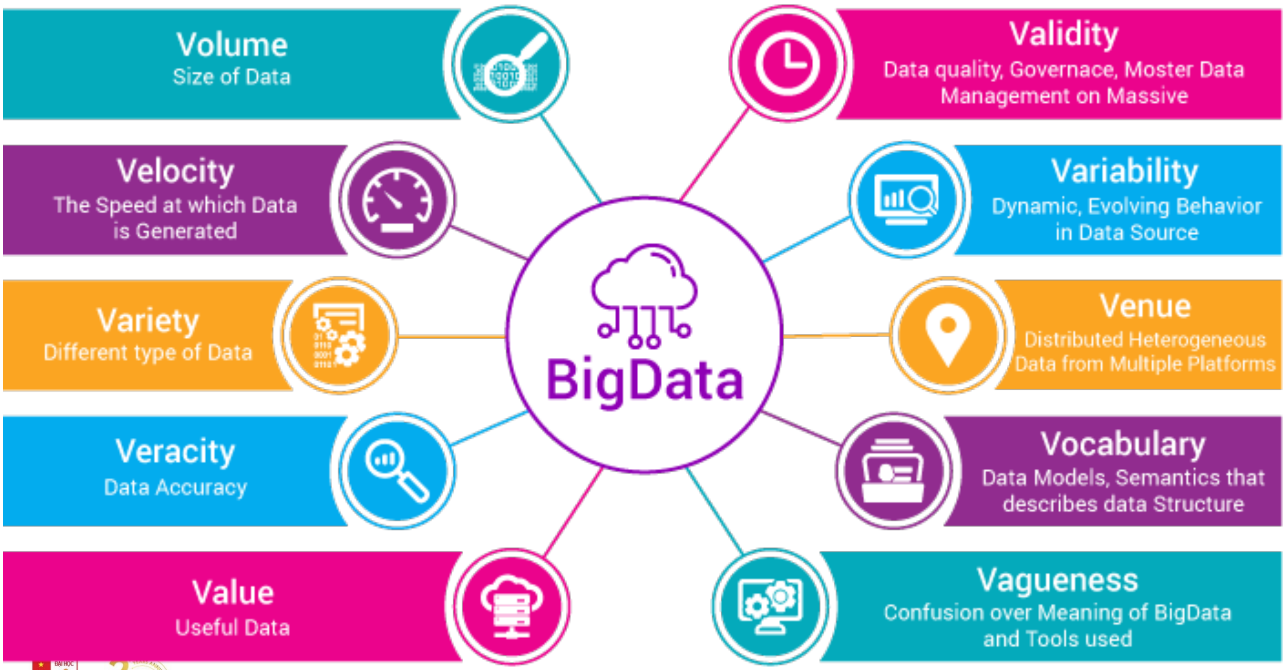
Big data – today: some numbers



Big data

Challenges

The 10 Vs of Big data


Volume
Size of Data
Velocity
The Speed at which Data is Generated
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Data Accuracy
Value
Useful Data
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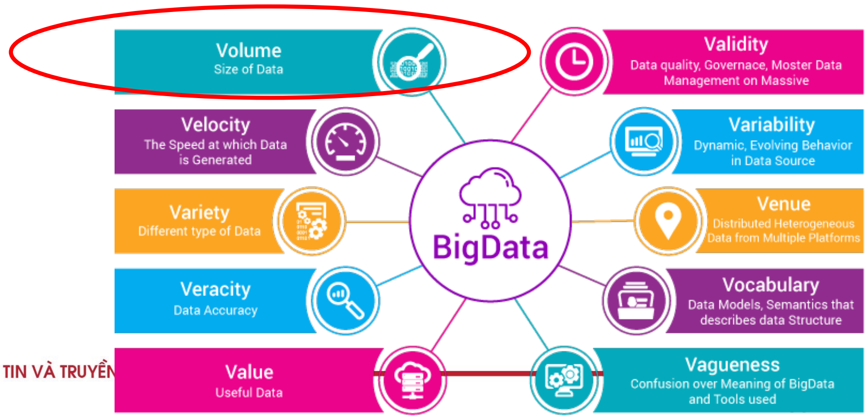
Variability
Dynamic, Evolving Behavior in Data Source
Venue
Distributed Heterogeneous Data from Multiple Platforms
Vocabulary
Data Models, Semantics that describes data Structure
Vagueness
Confusion over Meaning of BigData and Tools used

[Source: houseofbots.com]

The 10 Vs of Big data: Volume

- Volume is probably the best known characteristic of big data
- More than 90% of all today's data was created in the past 2 years
- Poses challenges in terms of:
  - Exploratory Data Analysis (see Chapter 4)
  - Data visualization (see Chapter 5)
  - and analysis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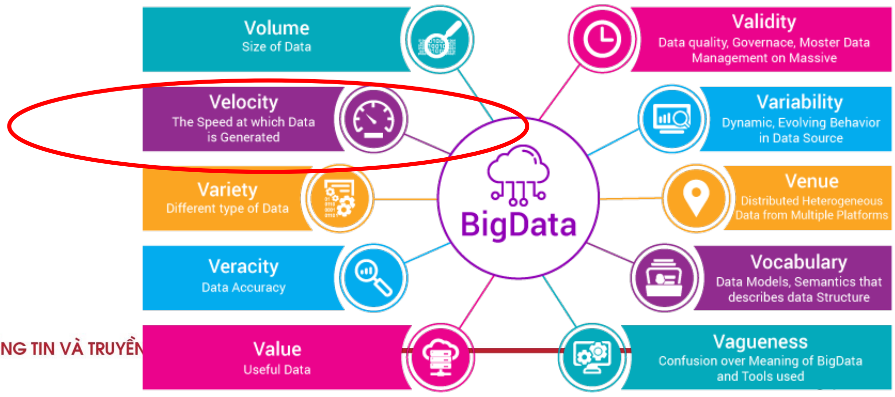
The 10 Vs of Big data: Velocity

- Velocity refers to the speed at which data is being generated, produced, created, or refreshed
  - It is ever-increasing, contributing to exponentional growth in the data volume!
  - It poses several challenges in terms of data integration (see Chapter 3) and analysis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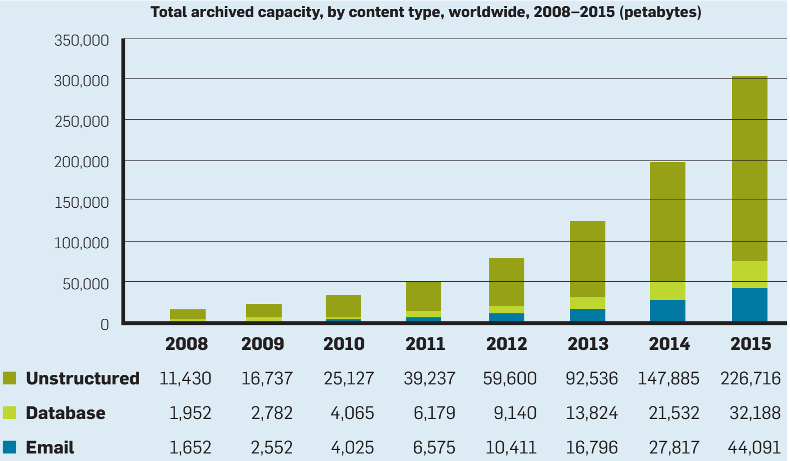
The 10 Vs of Big data: Variety

- Variety refers to the different kinds of data one has to handle:
  - **Structured** data: from OLTP datasets of Excel files for instance
  - **Unstructured** data increases extremely fast: texts, images, tags, links, likes, emotions, …

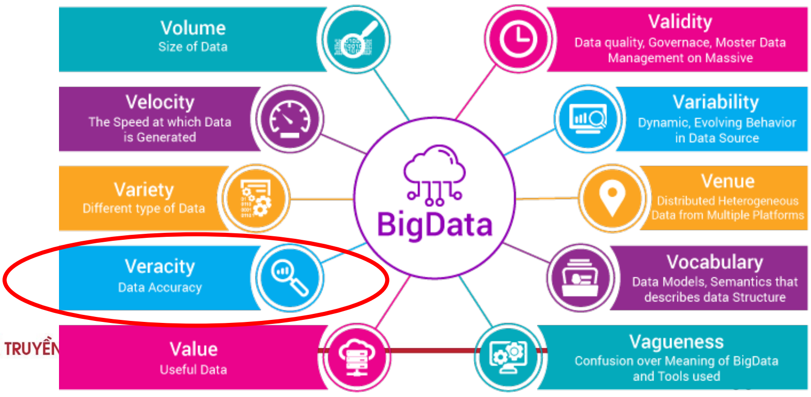

Total archived capacity, by content type, worldwide, 2008–2015 (petabytes)

	2008	2009	2010	2011	2012	2013	2014	2015
🟩 **Unstructured**	11,430	16,737	25,127	39,237	59,600	92,536	147,885	226,716
🟩 **Database**	1,952	2,782	4,065	6,179	9,140	13,824	21,532	32,188
🟦 **Email**	1,652	2,552	4,025	6,575	10,411	16,796	27,817	44,091

(Vasant Dhar, CACM, 2013)

The 10 Vs of Big data: Veracity

- Veracity: does the data reflect the reality? how accurate or truthful is it?
  - **Not everything that is written on the internet is TRUE!!!**
  - Hence, the need to check the data sources' quality (see Chapter 2)
    - Almost an ethical issue
  - Noises, missing values, mistakes, biases,…
  - →Challenging for analysis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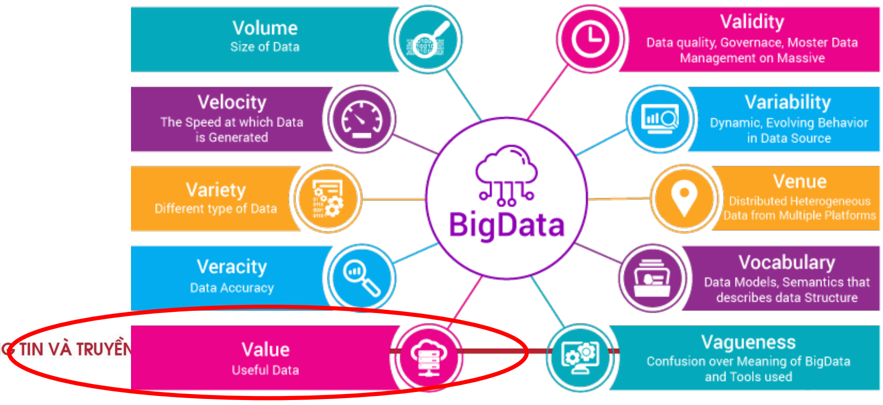
The 10 Vs of Big data: Value

- When there is so much data, it obviously poses the question of data value
  - And hence, one has to select / pre-process / integrate only the relevant data (see Chapter 2)



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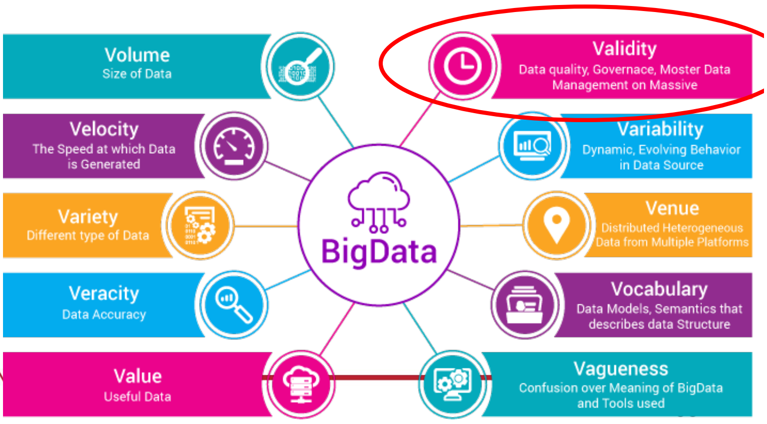
The 10 Vs of Big data: Validity

- When there is so much data, it of course poses the question of data validity
  - And hence, one has to check the quality of the data
    - Check its coherence with other sources of data
    - Remove outliers
  - This is pre-processing, led before integrating it for data analysis



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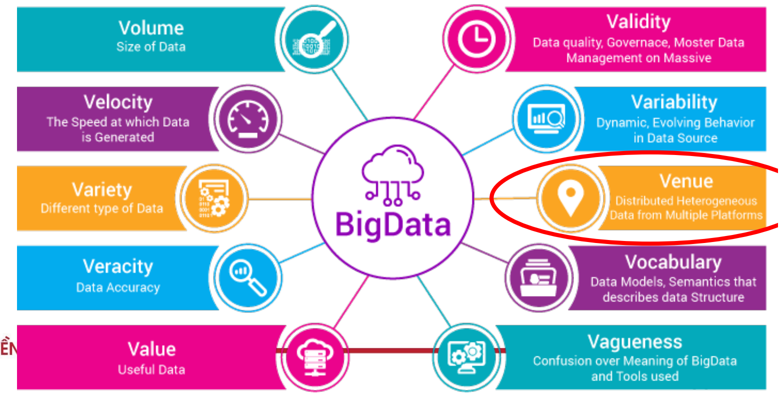
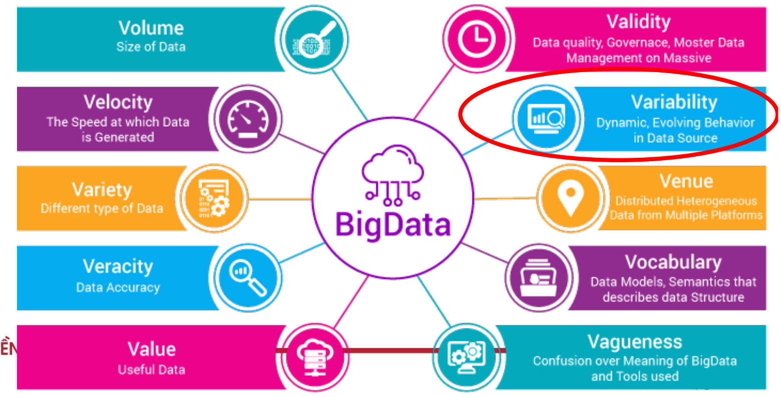
The 10 Vs of Big data: Venue

- Venue in big data refers to the multiplicity of data sources (*e.g.* Excel files, OLTP databases, …)
  - Hence the need for data integration (see Chapter 3)


Volume
Size of Data
Velocity
The Speed at which Data is Generated
Variety
Different type of Data
Veracity
Data Accuracy
Value
Useful Data
BigData
Validity
Data quality, Governace, Moster Data Management on Massive
Variability
Dynamic, Evolving Behavior in Data Source
Venue
Distributed Heterogeneous Data from Multiple Platforms
Vocabulary
Data Models, Semantics that describes data Structure
Vagueness
Confusion over Meaning of BigData and Tools used

The 10 Vs of Big data: Variability

- Variability in big data refers to two things
  - The possible evolutions in the structure of the data sources
  - The different velocities at which these data sources are refreshed
  - Poses serious issues for data integration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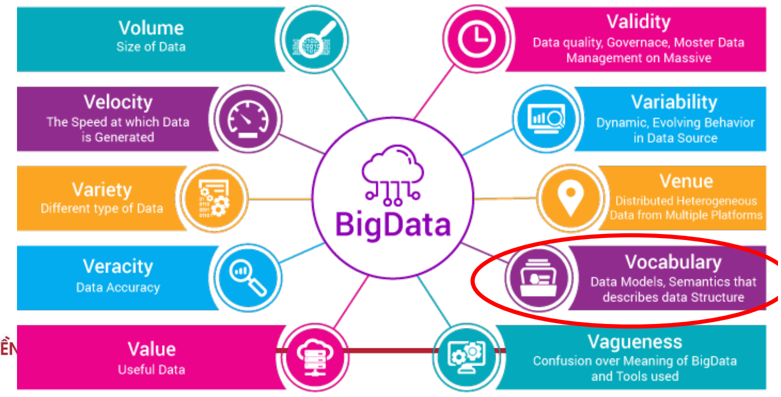
The 10 Vs of Big data: Vocabulary

- Vocabulary refers to bringing data models / semantics (knowledge, e.g. ontologies) into the data to structure / explain it
  - See the course on AI



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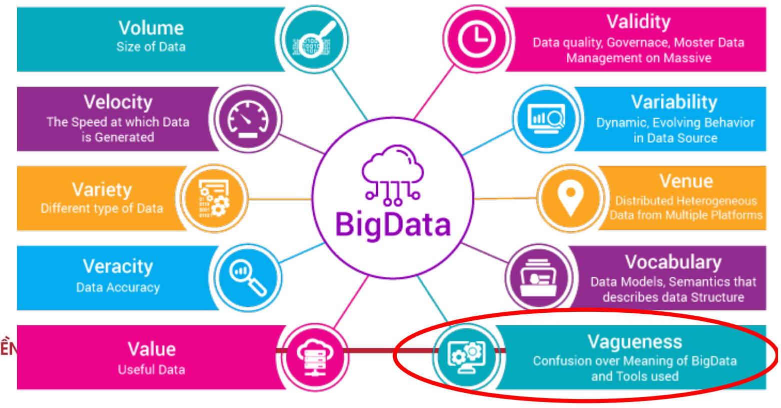
The 10 Vs of Big data: Vagueness

- Vagueness might refer to:
  - Communication issue between provider and customer
  - Difficulty for a non-specialist to interpret the analysis output
    - *E.g.* difference between correlation and causality



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More additional challenges

- The interactions or **correlations** hidden in data might be really huge
- Real problems often have extremely **high dimensions** (large number of variables)
  - Bicycle runs: 2 dimensions (a road)
  - We live in 4 dimensions
  - But an image 1024x1024: ~1 million dimensions
  - Text collections: million dimensions
  - Recommenders' system: billion dimensions (items/products)

→ The curse of dimensionality

Dữ liệu dù thu thập được lớn đến đâu thì cũng là **quá nhỏ** so với không gian của chúng

Ethical issues

- Privacy
  - Breach of privacy, collection of data without informed consent
- Security
  - The ease of stealing, including identity theft, the stealing of national security information
- Commercial exploitation
  - Commercial mining of information; targeting for commercial gain

- Issue of Power and politics
  - The use of data to perpetuate particular views, ideologies, propaganda
- Issue of Truth
  - Rumors, hoaxes, fake news
  - Bias introduced by social networks' recommender systems
- Issue of social justice
  - Information is overwhelmingly skewed towards certain groups and leaves others out of the 'digital revolution'

(Dinh Phung, Monash University)

What is a data scientist?

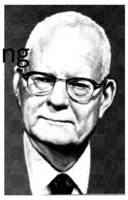
Data Science - early days

1935: "The Design of Experiments"

R.A. Fisher

1939: "Quality Control"

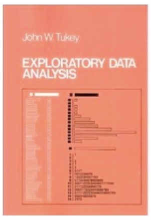
W.E. Demming



1958: "A Business Intelligence System"

Peter Luhn

1977: "Exploratory Data Analysis"

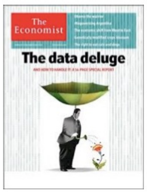


1989: "Business Intelligence"

Howard Dresner

1997: "Machine Learning"

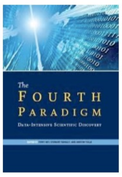
2010:"The Data Deluge"



2009:"The Unreasonable Effectiveness of Data"

1996: Google

2007:"The Fourth Paradigm"



(John Canny, UC Berkeley)

The rise of Data Science - 2009

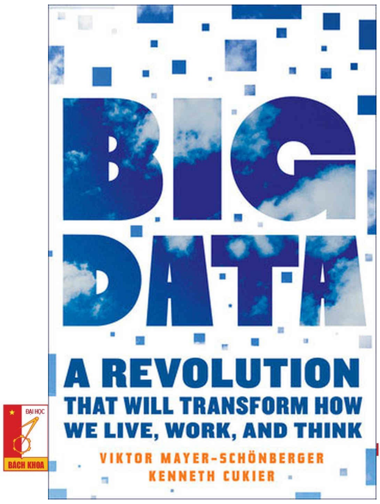
> *I keep saying the sexy job in the next ten years will be statisticians. People think I'm joking, but who would've guessed that computer engineers would've been the sexy job of the 1990s?*
>
> - Hal Varian, Google's Chief Economist, 2009

"The ability to take **data** – to be able to **understand** it, to **process** it, to **extract value** from it, to **visualize** it, to **communicate** it's going to be a hugely important skill in the next decades, not only at the professional level but even at the educational level for elementary school kids, for high school kids, for college kids. **Because now we really do have essentially free and ubiquitous data.**"
- Hal Varian, Google's Chief Economist, 2009

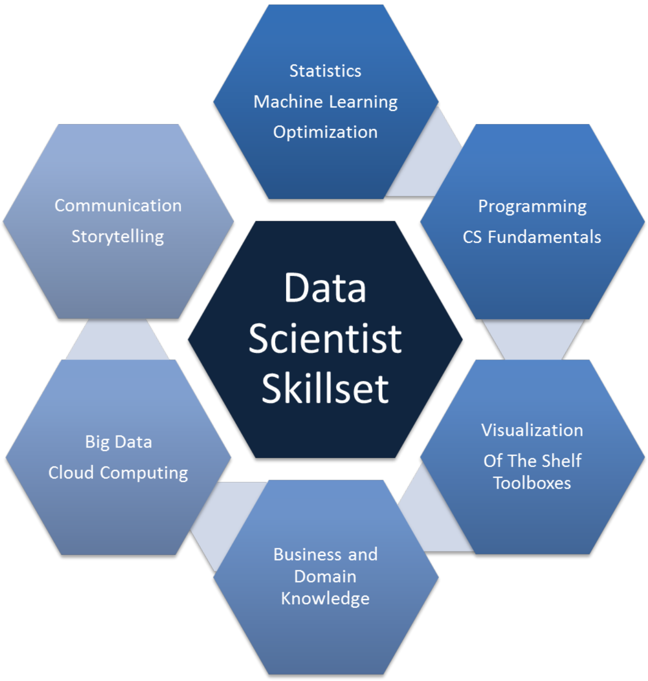
Data scientist - nowadays

Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil

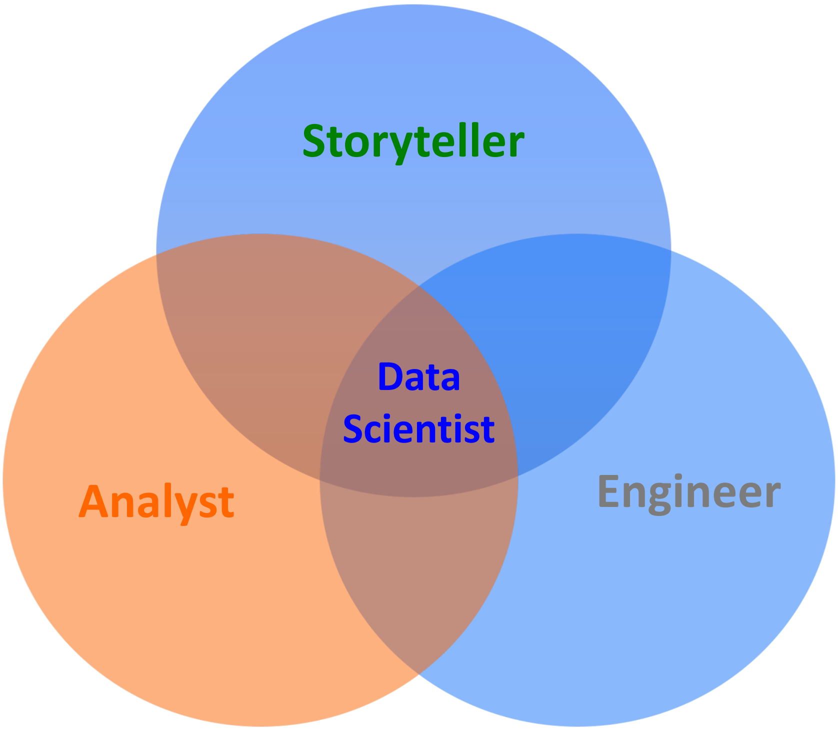


Skillset



(source: http://datasciencedojo.com/)

Roles / talents of a data scientist



Further reading

- "Job Comparison – Data Scientist vs Data Engineer vs Statistician" https://www.analyticsvidhya.com/blog/2015/10/job-comparison-data-scientist-data-engineer-statistician/
- Big Data Landscape 3.0 http://mattturck.com/big-data-landscape-2016-v18-final/
- Ten Lessons Learned from Building (real-life impactful) Machine Learning Systems http://technocalifornia.blogspot.com/2014/12/ten-lessons-learned-from-building-real.html

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VIỆN CÔNG NGHỆ THÔNG TIN VÀ TRUYỀN THÔNG

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Thank you for your attentions!

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