Introduction to Data Science

FIT5145

Monash University

About this Unit

Resources

1. Moodle contains
   - Unit Orientation, Assessments and Discussion Forums
   - as well as Lecture Notes, which contain active links to recommended videos & readings
2. review of *Alexandria*
   - LOTS of additional resources and exercises
   - use as an online textbook format, plus epub
3. additional textbook:
   - no "perfect" *Introduction to Data Science* textbook available
   - but a good introductory text available for purchase is: *The Art of Data Science* by Peng & Matsui
4. be aware also of the:
   - library services available
   - special consideration policies
   - disability support available

Getting Started

1. No tute this week (1^{st} week)
2. Check activities in Moodle
   - see Module 1: Data Science and Data in Society in Alexandria
3. How these classes are run
   - watch videos & read background material between classes
   - bring a device to lectures to participate
   - prepare for tutes
4. Want to learn more yourself?
   - see Module 7 in ePub for Data Science Resources

Contacts

Need help?

Unit Email Address: **fit5145.allcampuses-x@monash.edu**

1. ask questions during tutorials and lectures
   - *please* interrupt me with questions!
2. check for relevant Discussions Forum on Moodle
   - note in particular the "Assessments" discussion threads
   - but do NOT post your solutions to assignments ;-)
3. attend the consultation hour of the tutors or the lecturer
   - consultation hours in Moodle
4. send email to tutor or lecturer

Motivation for the Unit

Data Science is in its growth phase:

- every academic & industry community wants to claim credit
- huge community of (self proclaimed) “leading international experts,” “highly sought-after consultants,” and “thought leaders” to confuse you with advice, blogs, guidelines, ...
- huge growth in software and services

We try and cover the full extent of what makes Data Science:

- background and context
- leading review articles, lectures, introductions
- academic surveys and national programmes

Prerequisites

You will need:

- high school level of mathematics and statistics
- basic programming and database skills
- a “critical mindset”:
  - you will read/view a variety of material
  - different levels of quality and standards
  - some sales, some educational, some journalistic
- basic exposure to information technology and internet businesses:
  - software, science or business computing
  - Amazon, Google, Twitter, ...

Warning

Alexandria links to a LOT of content:

- videos, blogs, articles, ...
- there is way too much for you to read it all in detail!
- **not** all of Alexandria examinable, links tagged with:
  - — handy for aspiring data scientists
  - — important for learning outcomes

Strategy:

- limit your time per week
- get the big picture from articles/videos
- find out what is out there
- focus in on the details you need for assessment or your own development

Unit Schedule: Modules

Module	Week	Content
1.	1	overview and look at projects
	2	(job) roles, and the impact
2.	3	data business models
	4	application areas and case studies
3.	5	characterising data and "big" data
	6	data sources and case studies
4.	7	resources and standards
	8	resources case studies
5.	9	data analysis theory
	10	data analysis process
6.	11	issues in data management
	12	GUEST SPEAKER & EXAM INFO

Unit Schedule: continued!

In addition to the modules we will have practical introductions to various Data Science tools along the way:

- Brief Introduction to Python for Data Science
- Brief Introduction to R for Data Science
- Brief Introduction to the Shell for Data Science

Assessment

	Week due	Content	Percent
Assign. 1	6	Python coding	15%
Assign. 2,4,5	8,11,12	project proposal	5+15+5%
Assign. 3	9	R, bash coding	10%
Exam	TBD	MCQ and SAQ	50%

- coding tasks based on limited Python/R/bash subsets covered in tutorials
- exam based on material covered in lectures

Instructions to participate in the poll (using FLUX)

- Visit https://flux.qa on your phone, tablet or laptop
- Enter your email address
- Log in using your Monash account details
- Touch the + symbol in the top right hand corner
- Enter the code for this class (Feed code: `F3EXU8`)
- Answer questions when they pop up
- That's it ☺
- Download a copy of instructions

FLUX Question: Your Background

1. What programming language are you most experienced in?

2. What kinds of data are you familiar with?

FIT5145 Introduction to Data Science

Module 1

Data Science and Data in Society

2019 Lecture 1

Monash University

Unit Schedule: Modules

Module	Week	Content
1.	1	**overview and look at projects**
	2	**(job) roles, and the impact**
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Learning Outcomes (Week 1)

By the end of this week you should be able to:

- Explain what is data science
- Comprehend the usefulness of machine learning
- Explain different components of a data science process
- Differentiate data science from other related disciplines
- Learn how to install and start coding in Python with Jupyter Notebook

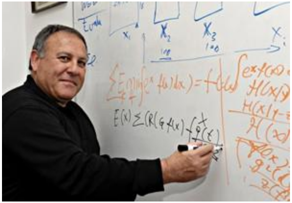
Overview of Data Science
(ePub section 1.1+1.3)

a quick overview of the context

FLUX Question : Who are the Data Scientists?

person A

person B



person C

person D

Defining Data Science

What is Data Science?

‘‘name contains the word ‘science’, so it can’t be one”

- *Note: this is an old joke ...*

“data science is what a data scientist does”

- *a circular definition!*

“data science is the technology of handling and extracting value from data”

- *less circular and a bit more useful*

“machine learning on big data”

- *useful, but too narrow!*

Defining Machine Learning

Unlike Data Science, the definition for Machine Learning is better understood and more agreed upon:
Machine Learning is concerned with the development of algorithms and techniques that allow computers to *learn*.

- concerned with building computational artifacts, i.e., computer programs that can learn, oftentimes with computational output
- but the underlying theory is statistics

see *A Gentle Guide to Machine Learning*

Why use Machine Learning?

Machine learning is useful when:

- Human expertise is not available
  e.g. Martian exploration

- Humans cannot explain their expertise (as a set of rules), or their explanation is incomplete and needs tuning
  e.g. speech recognition

- Many solutions need to be adapted automatically
  e.g. user personalisation

image src: theconversation.com, meduim.com, blog.prioridata.com

Why use Machine Learning?

Machine learning is useful when:

- Situation changes over time
  e.g. junk email

- There are large amounts of data
  e.g. discover astronomical objects

- Humans are expensive to use for the work
  e.g. handwritten zipcode recognition

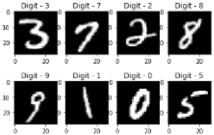


image src: lifewire.com, clrealyexplained.com, meduim.com

Why use Machine Learning?

- because you do not want to be this poor guy!
- sifting through all the data by hand

Why use Machine Learning?

Other reasons for needing Machine Learning:

- the information society
- information warfare
- information overload
- information access

Exercise: Google these to find out about them!

Data Science Examples

Some famous data science projects and investigations:

1. Google's spell checker and *translation engine*
   - we'll learn about these in Module 5
2. Amazon.com's *recommendation engine*
3. Public health: *"saturated fat is not bad for you after all"*
   - many more of this type of investigation will be coming ...
4. Microsoft's *predictive analytics for traffic*

Example of Data Science: Melbourne Datathon 2016

- (see description in Alexandria, Section 1.2)
- *Seek.com* is an online jobs website. They provided the data and the tasks.
- They had put forward the tasks:
  - job category prediction: predict if a job is in the 'Hotel and Tourism' category
  - data exploration: what useful information can be discovered from the data that Seek can use?
- See their own description of *the business context and dataset*.

Datathon Questions

- how did Seek come up with their prediction task?
- why is it important to them?
- did a data scientist come up with the task?
- all Datathon participants had to destroy their copies of the data at the end of the Datathon: why?
- how would you present results of exploratory analysis to Seek.com management? see *one such presentation by the 4Quarters team*

Datathon Questions, cont.

- how much data is there?
- what software/systems could you use to do the prediction task?
- could you introduce/find auxiliary data to do the prediction better? is that “cheating”?
- how would you estimate how well your predictions are going?
- how would Seek.com “fairly” evaluate participants in the datathon?

Historical Context

Links to resources providing historical background to data science:

- *Wolfram Alpha: computable knowledge history*
- *Cloud Infographic: Evolution Of Big Data*
- *The Web Technology timeline*
- *A brief history of Data Science*

FLUX Question

Which of the following is real world applications of Machine Learning?

A. Video Games
B. Self-driving cars
C. Spam filtering
D. Predictions
E. All of the options

The Rise of Big Data

in *Foreign Affairs*, by Cukier and Mayer-Schoenberger

Data Science interest is related to the arrival of "Big Data"

- data collection has changed:
  - lots of data, but more messy
  - don't look for perfect models – settle for finding patterns
  - examples: Google's *language translation* and *flu trends*
- datafication:
  - taking all aspects of life and turning them into data
  - e.g. NYC using big data to improve public services and lower costs
- the information society has come of age
  - and data brokers have started amassing huge data about individuals: *big data could become Big Brother*

Homework

From Section 1.1:

- watch *Cukier's TED talk on "Big Data"*
- watch the CERN video, *"Big Data" from Tim Smith*
- read *"What is Data Science?"* by Mike Loukides of O'Reilly

The Data Science Process
(ePub section 1.2)

what happens in a Data Science project?

- illustrating the process
  - a quick walkthrough illustrating the steps
- the standard value chain
  - our model of the process

The Data Science Process: Illustrating the Process

a quick walkthrough illustrating the steps

The Data Science Process

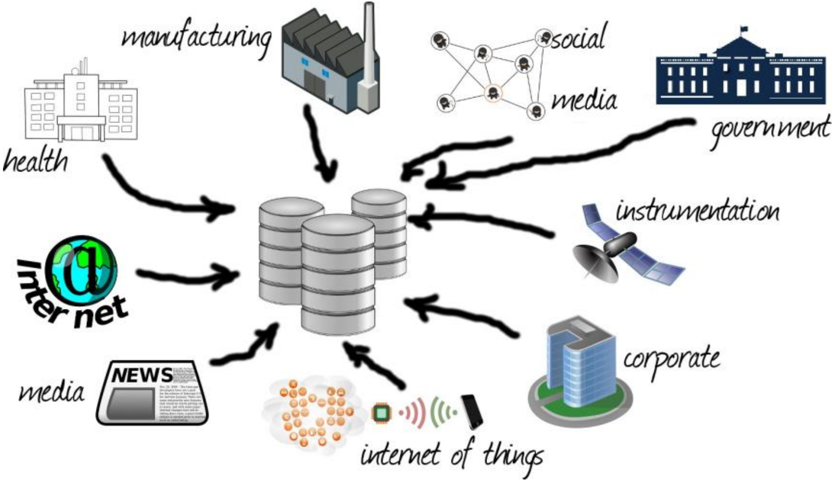
- Many different tasks come together to complete a Data Science project
  - a data scientist should be familiar with most, but doesn't need to be an expert in all
- Not all are labelled as Data Science
  - some from other field such as computer engineering, business, ...

1. Pitching ideas for data science projects to investors/managers.

2. Collecting data: researchers preparing to x-ray a patient.

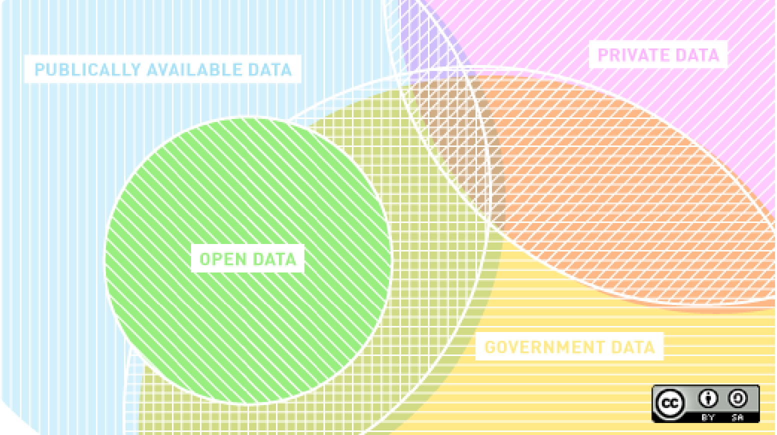
by Stephen Ausmus acquired from USDA ARS, public domain.

3. Monitoring: Scientists watch over data collected by the gravimeter & magnetometer instruments.



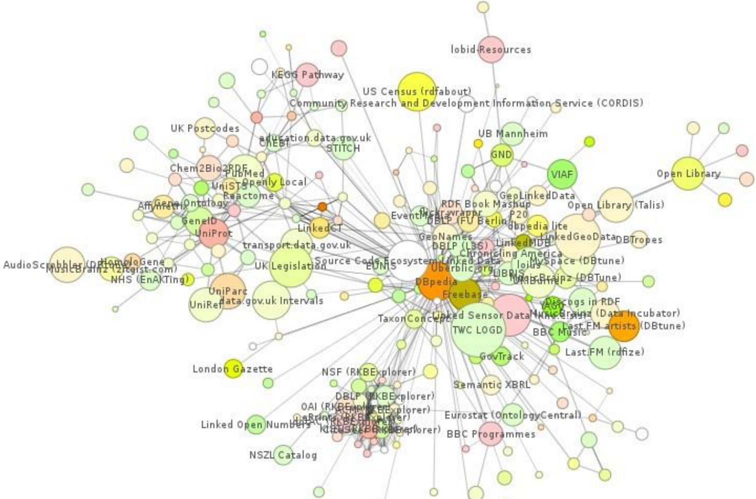
4. Integration: Data can come from many different sources.

icons from by Openclipart.org, public domain

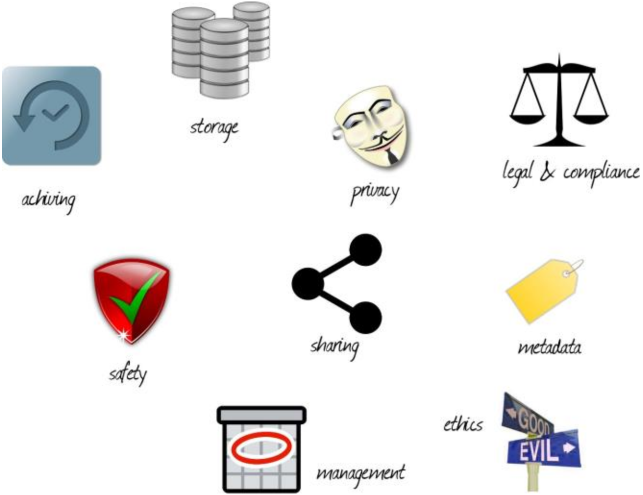


Note that some of the best data is Open (publicly available and machine readable) Data.

by Libby Levi for opensource.com, CC-BY-SA 2.0

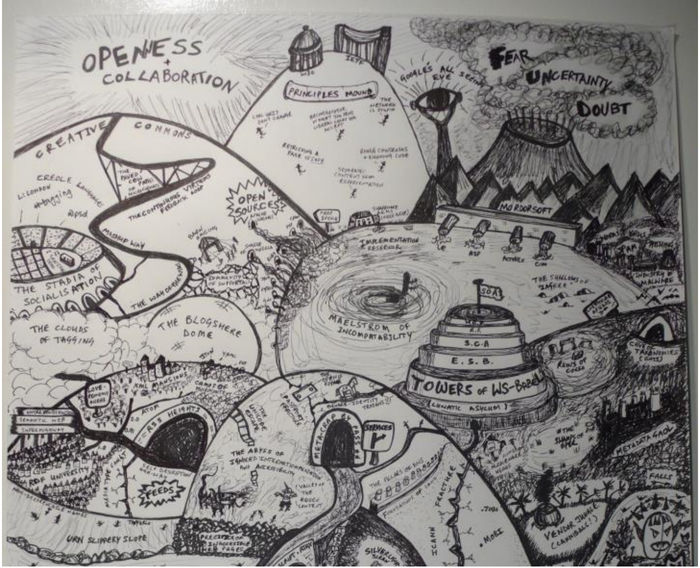


5. Interpretation: e.g. the Linked Open Data (LOD) graph can sometimes be used to ascribe meaning (semantics) to data.



6. Governance: caring for the data and its subjects.

icons from by Openclipart.org, public domain;
Good and Evil by AJC ajcann.wordpress.com, CC-BY-SA 2.0

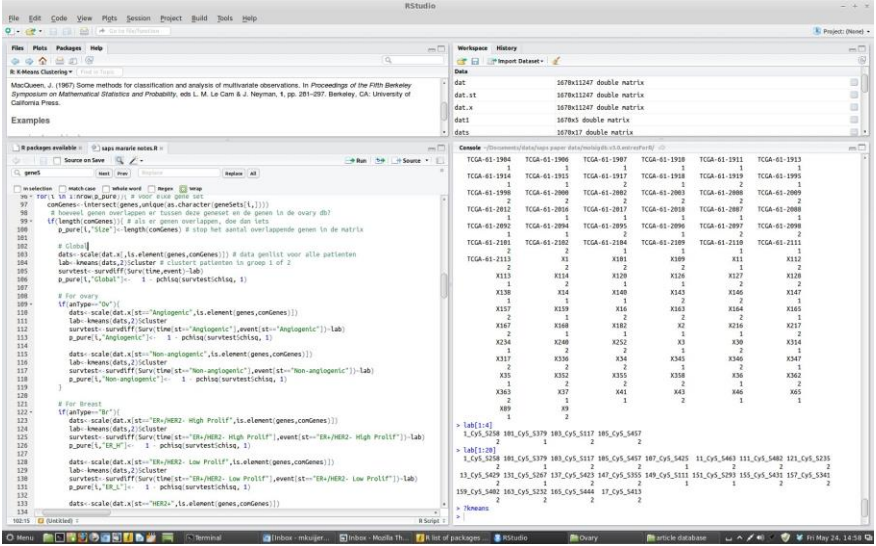


6. Governance: managing data standards and formats

"The Web is Agreement" cropped, by Paul Downey, CC-BY 2.0

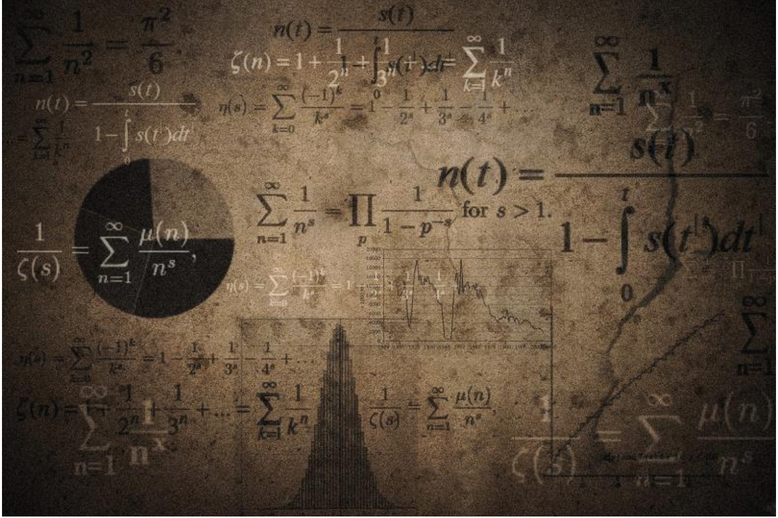
7. Engineering: Data engineers make the back-end work

by Intel Free Press, CC-BY 2.0

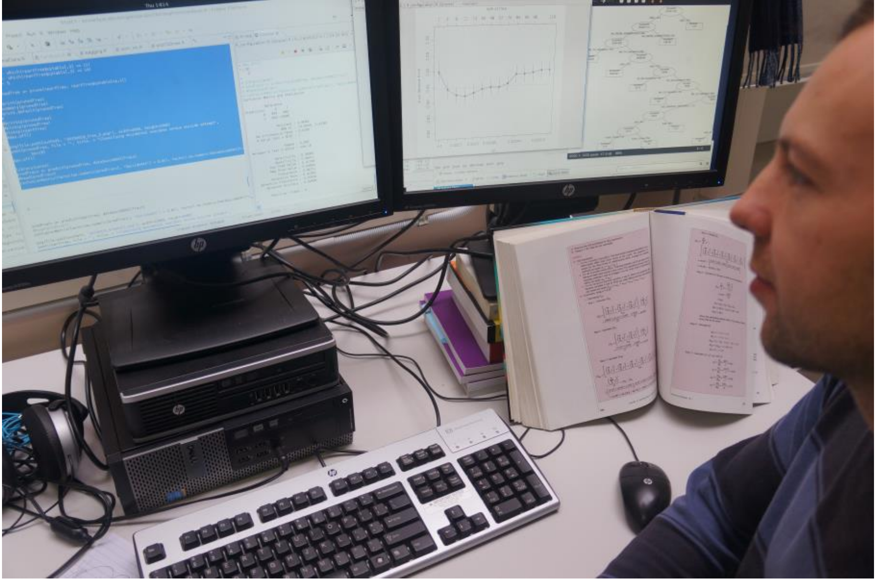


8. Wrangling: Inspecting and cleaning the data.

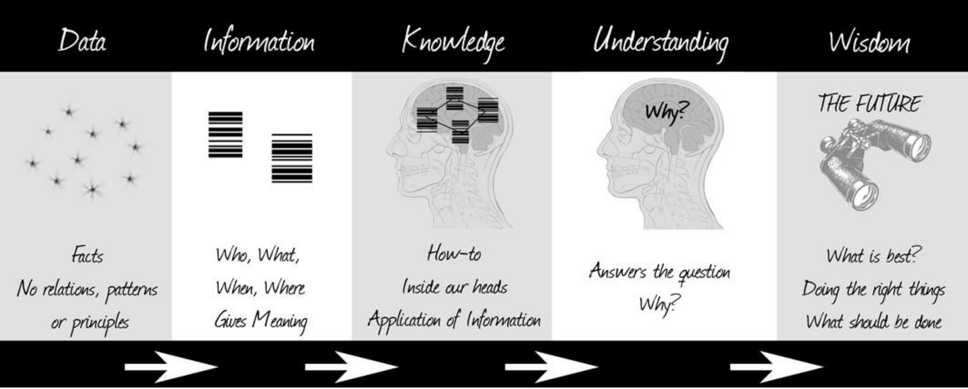
“rstudio” by mararie, CC-BY-SA 2.0



9. Modelling: Proposing a conceptual / mathematical / functional model.



9. Modelling: Analyst building models with his favourite tool.



9. Modelling: Analysis, statistics and/or machine learning works on the data.

10. Visualisation: Visualising data to interpret it and present results.

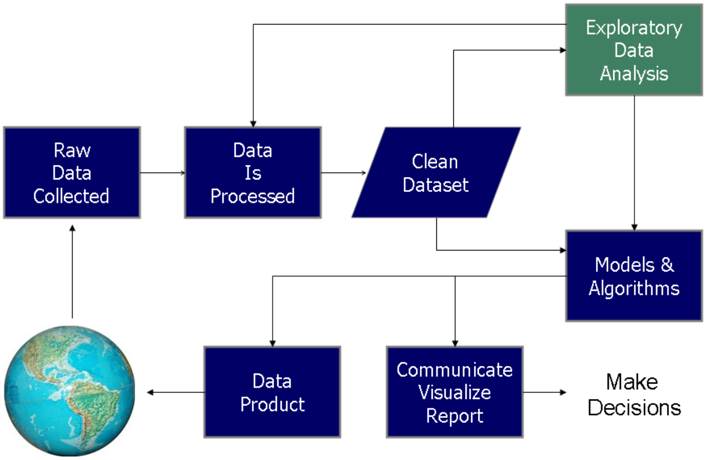
by Stephen Ausmus acquired from USDA ARS, public domain.

10. Visualisation: Choosing appropriate visualizations for the data. Many different options exist!

"Visualization Matrix" cropped, by Lauren Manning, CC-BY 2.0

11. Operationalization: putting the results to work.

Data Science Process



Putting it all together: Designing a data science process flowchart.

by Farcaster, CC-BY-SA 3.0

FLUX Question

Using a short phrase or word, which activity in data science process is the most interesting to you.

The Data Science Process: Our Standard Value Chain

our model of the process

Parts of a Data Science Project

Collection: getting the data

Engineering: storage and computational resources across full lifecycle

Governance: overall management of data across full lifecycle

Wrangling: data preprocessing, cleaning

Analysis: discovery (learning, visualisation, *etc.*)

Presentation: arguing the case that the results are significant and useful

Operationalisation: putting the results to work, so as to gain benefits or value

We call this the Standard Value Chain.

Interpreting Roles in a Project

Following *Jeff Hammerbacher's* UC Berkeley 2012 course notes, we will interpret these four entities: we will interpret these

- business analyst
- programmer
- enterprise
- web company

Interpretations: the Business Analyst

Collection: copy and paste into Excel
Engineering: use Excel to store and retrieve
Wrangling: use Excel functions, VBA
Analysis: charts

Interpretations: the Programmer

Collection: web APIs, scraping, database queries

Engineering: flat files

Wrangling: Python and Perl, *etc.*

Analysis: Matplotlib in Python, R

Interpretations: the Enterprise

Collection: application databases, intranet files, server logs

Engineering: Teradata, Oracle, MS SQL Server

Wrangling: Talend, Informatica

Analysis: Cognos, Business Objects, SAS, SPSS

Interpretations: the Web Company

Collection: application databases, server logs, crawl data
Engineering: Hadoop/Hive, Flume, HBase
Wrangling: Pig, Oozie
Analysis: dashboards, R

What is Data Science?
(ePub section 1.3)

how can we define or circumscribe data science?

Definitions: from Wikipedia

Data Science is the extraction of knowledge from data, which is a continuation of the field data mining and predictive analytics.

Big data is a broad term for data sets so large or complex that traditional data processing applications are inadequate.

Definitions: from Pivotal

Data Science: The use of statistical and machine learning techniques on big multi-structured data in a distributed computing environment to identify correlations and causal relationships, classify and predict events, identify patterns and anomalies and infer probabilities, interest and sentiment.

Definitions: from NIST Big Data Working Group

Data Science is the empirical synthesis of actionable knowledge from raw data through the complete data lifecycle process.

A data scientist is a practitioner who has sufficient knowledge in the overlapping regimes of business needs, domain knowledge, analytical skills, and software and systems engineering to manage the end-to-end data processes through each stage in the data lifecycle.

Definitions: *Journal of Data Science*

Data Science is almost everything that has something to do with data: collecting, analyzing, modeling. . . . . . yet the most important part is its applications — all sorts of applications.

Definitions: Summary

narrow: machine learning on big data

broad: extraction of knowledge/value from data through the complete data lifecycle process

- broad concern with the different stages
- focus on the learning/knowledge discovery

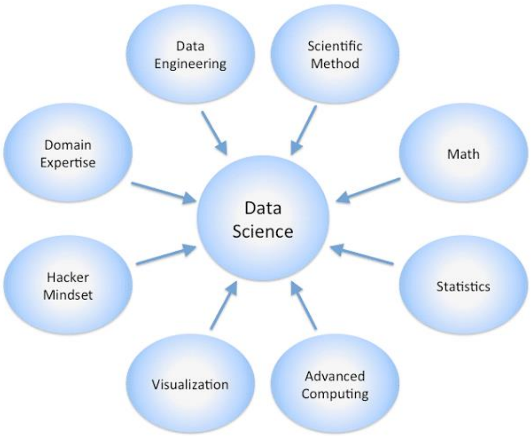
FLUX Question

Which of the following data science definition you like most?

Data Science is

A. machine learning on big data
B. extraction of knowledge/value from data through the complete data lifecycle process
C. almost everything that has something to do with data: collecting, analyzing, modeling, etc, yet the most important part is its applications — all sorts of applications

Relationship of Data Science to Other Disciplines



Related: Data Analysis

performing analysis and understanding results

- *e.g.* R, Tableau, Weka, Microsoft Azure Machine Learning, ...
- machine learning, computational statistics, visualisation, ...
- huge, continuous improvement ....

Related: Data Engineering

building scalable systems for storage, processing data

- *e.g.* Amazon Web Services, Teradata, Hadoop, ...
- databases, distributed processing, datalakes, cloud computing, GPUs, wrangling, ...
- huge, continuous improvement ....

Related: Data Management

managing data through its lifecycle

- *e.g.* ANDS, Talend, Master Data Management, ...
- ethics, privacy, providence, curation, backup, governance, ...
- huge, continuous improvement ....

Evolution of Data Science as a Discipline

Data Science has developed in fits and starts, from many precursors:

- Data Analysis (John Tukey) in 1962
- Expert Systems in the 1980's
- Machine Learning in the 1980's
- Data Mining in the 1990's
- see *Business Week's "Database Marketing" (behind firewall)* cover story September 1994

Evolution of Data Science, ...

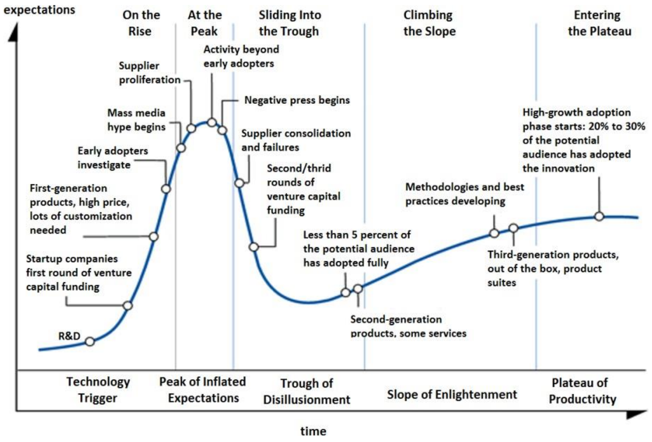
Data Science emerges around 2000

- data analysis came of age 1990's
- William Cleveland publishes in 2001 *"Data Science: An Action Plan for ... the field of Statistics"*
- data engineering came of age 2000's (Dot.Com boom)
- (digital) data management came of age 2000's (Dot.Com boom)
- the data/information society
- business pressure on decision making
- "data" as a valuable asset
- Dot.Com companies show the way

see also David Donoho's *"50 years of Data Science"* (PDF paper)

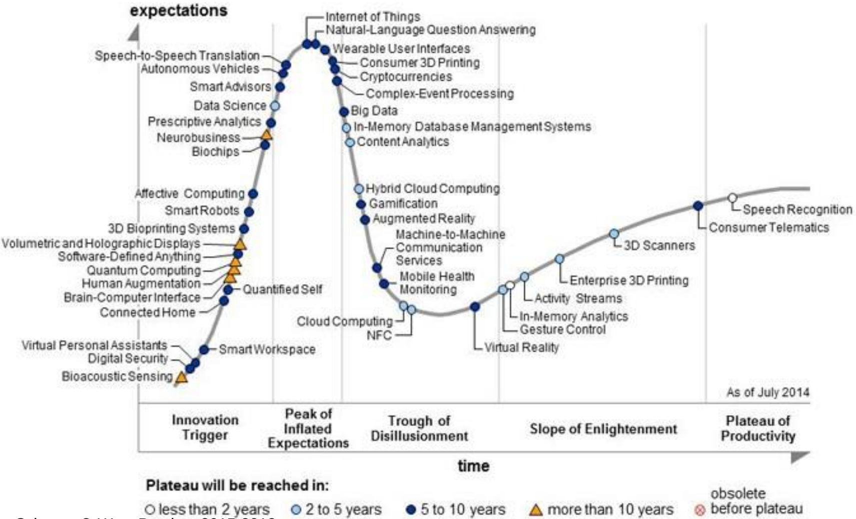
The Hype Cycle

- Gartner's Hype Cycle© attempts to quantify the level of maturity of various technologies:



Hype Cycle 2014

- Can you spot Data Science?



Data Science Research

Data Science is seeing major growth at universities internationally

Many research programs exist, including:

- US National Institute of Standards' Big Data Working Group (2013-2015)
- US National Academy of Sciences' Committee on the Analysis of Massive Data (2013)
- Alan Turing Institute for Data Science at London's new Knowledge Quarter (near National Library, 2016-)

End of Week 1