



UNIVERSITY OF GOTHENBURG

INTRODUCTION TO DATA SCIENCE AND AI

DAT405, 2019-2020, READING PERIOD 1

Course organisation

- Part I: Introduction to data science (3 weeks)
 - Graham Kemp (kemp@chalmers.se), Computer Science and Engineering
- Part II: Statistical methods in data science and AI (2 weeks)
 - Marina Axelson-Fisk (marinaa@chalmers.se), Mathematical Sciences
- Part III: Introduction to AI (3 weeks)
 - Ashkan Panahi (ashkanp@chalmers.se), Computer Science and Engineering

Teaching assistant:

• Emilio Jorge (<u>emilio.jorge@chalmers.se</u>), Computer Science and Engineering

Examination form

- The examination is through **weekly assignments**, executed in student pairs.
- All assignments need to be passed in order to pass the course.
- Some exercises will only have a pass/fail grade, while others will be graded 3, 4, 5 (or fail).
- The final course grade will be an aggregate of the combined efforts.
- Deadline for each week's assignment will be on **Monday at noon** (12:00) the week after.

Student representatives

- Abdullah Awad
- Marcus Forsberg
- Emma Petersson Svensson
- Mattias Westerberg





UNIVERSITY OF GOTHENBURG

MODULE 1: INTRODUCTION TO DATA SCIENCE AND PYTHON

DAT405, 2019-2020, READING PERIOD 1

Introducing Data Science

Data Science is concerned with extracting meaning from (big) data.

Central topics within Data Science include:

- data mining
- machine learning
- databases
- the application of data science methods in natural sciences, life sciences, humanities and social sciences, as well as in industry and society.

The Data Science Venn Diagram



http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram

Data Science Venn Diagram v2.0



Applied Data Science

- Translating between problem and method domain for stakeholders
- Understanding data collection process and implications on results
- Understanding consequences of method choices
- Communication is a central aspect
- Expertise in Application Domain necessary
 - interpreting results
 - avoiding wrong conclusions

TEXTS IN COMPUTER SCIENCE

THE Data Science Design MANUAL





Steven S. Skiena



Application success stories

Case Study:

Influences in English Literature

Large-scale literature analysis

- 4357 novels
- 150 Years (average of 29 books per year)
- British (73%), Irish (5%), and American (22%)
- Male (55%), Female (36%), and Anonymous (9%)
- 1875 unique authors (2.32 books per author)

Author	Titl	ie	Distance			
Dickens, Charles	AI	Tale of Two Cities	0.00000	—		
Kirkland, Caroline Matilda	Th	e Fountain and the Bottle	1.361071			
Milman, Edward Augustus	Art Tro	hur Conway; or, Scenes in the pics	1.385395			
Liddell Charles Francis	Hic	Author	Title		Distance	
Dickens, Charles	Th	Austen, Jane	Pride and Prejudice 0.		0.000000	
Armstrong, Francis Claudius	Th	Austen, Jane	Emma		1.260236	
Spofford, Harriet Elizabeth Prescott	Sir	Austen, Jane	Sense and Sensibility		1.268725	
Fay, Theodore Sedgwick	No	Austen, Jane	Mansfield Park 1.421373		1.421373	
Shillaber Benjamin Penhallow	Kn	Austen, Jane	Northanger Abbey 1.600394		1.600394	
Dickens Charles	Ba	Austen, Jane	Persuasion 1.67307		1.673071	
Doulding James Kirke	Ch	Gaskell, Elizabeth	Ruth		1.716687	
Pauloing, James Kirke		Craik, Dinah Maria	Olive		1.745832	
	Church A. B. Mrs.		Greymore a Story of Cou Life	more a Story of Country		
		Grant, Louisa	Charles Stanley		1.765758	
		Tainsh, Edward Campbell	One Maiden Only		1.767951	

http://www.matthewjockers.net/slides-etc/

Matthew Jockers

Q: what to do with it?

Q: identify influental writers?

Author	Titl	'e	Distance			
Dickens, Charles	AT	Tale of Two Cities	0.000000			
Kirkland, Caroline Matilda	Th	e Fountain and the Bottle	1.361071			
Milman, Edward Augustus	Art Tro	hur Conway; or, Scenes in the pics	1.385395			
Liddell Charles Francis	Hic	Author	Title		Distance	
Dickens, Charles	Th	Austen, Jane	Pride and Prejudice		0.000000	1813
Armstrong, Francis Claudius	Th	Austen, Jane	Emma		1.260236	
Spofford, Harriet Elizabeth Prescott	Sir	Austen, Jane	Sense and Sensibility		1.268725	
Fay, Theodore Sedgwick	No	Austen, Jane	Mansfield Park		1.421373	
Shillaher Benjamin Penhallow	Kn	Austen, Jane	Northanger Abbey		1.600394	
	Tex	Austen, Jane	Persuasion		1.673071	
	Da	Gaskell, Elizabeth	Ruth		1.716687	1853
Paulding, James Kirke	Ch	Craik, Dinah Maria	Olive		1.745832	1850
		Church A. B. Mrs.	Greymore a Story of Cou Life	untry	1.747513	1860
		Grant, Louisa	Charles Stanley		1.765758	1854
		Tainsh, Edward Campbell	One Maiden Only		1.767951	1870

http://www.matthewjockers.net/slides-etc/

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Manuscript analysis – over 3000 data points



http://www.archerjockers.com/home/

Case Study:

Society and policy



UNITED NATIONS GLOBAL PULSE

Search S

SEARCH

Harnessing big data for development and humanitarian action



Projects

Welcome to the repository of Global Pulse's projects. Find out more about collaborative research, prototypes and experiments analyzing digital data to support global development and humanitarian action.



PRIVACY

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Exploring The Effects Of Extremist Violence On Online Hate Speech

Using Call Detail Records To Understand Refugee Integration In Turkey

Qatalog - An Analysis Tool For Insights Into The SDGs



Understanding Perceptions Of Migrants And Refugees With Social Media

BROWSE BY LAB

Jakarta Kampala New York

BROWSE BY PROGRAMME



Measuring poverty with roof counting



https://www.unglobalpulse.org/projects/measuring-poverty-machine-roof-counting

Rescue patterns in the Mediterranean

- Automatic Information System (AIS) - vessels regularly broadcast information, including their identifier, vessel type, latitude and longitude, speed, course and destination.
- speed and course appear to be good predictors of whether a vessel is conducting a rescue operation



https://www.unglobalpulse.org/projects/using-big-data-study-rescue-patterns-mediterranean

Case Study:

Ecology



eBird

- Quantified Bird Watching
- Bird watcher as "sensors"
- Citizen Science

eBird Science

eBird data are a powerful resource for a wide range of scientific questions. eBird Status and Trends highlights Cornell Lab analyses of continental bird abundances, range boundaries, habitats, and trends.

Explore eBird Status and Trends



Viens. Macaulay Library

eBird Status and Trends

Explore bird status and trends with maps, habitat charts, weekly migration animations, and more-all generated from modeled eBird data.

A Enter species name

AI Status and Trends species

Image: Constraint of the species

Image: Constraint of

eBird visualisation



Species Maps

Explore interactive range maps by species or subspecies — zoom in for details



Explore Hotspots

Discover the best places for birding nearby or around the world.



Search Photos and Sounds

Explore media through the Macaulay Library



Bar Charts

Find out what birds to expect throughout the year in a region or location

https://ebird.org/explore

Case Study:

Diagnosing rare genetic diseases from photographs

Overview

- (A) Overview of computational approach
- (B) Average faces

Ferry et al.. eLife (2014)



Facial feature points

 Accuracy of automatic image annotation, relative to manually annotated ground truth

Ferry et al.. eLife (2014)



Distortion graphs

- Represent the characteristic deformation of syndrome faces relative to the average control face.
- Shorter (blue), extended (red) and similar (white) distances.

Ferry et al.. eLife (2014)













Down



Treacher Collins



Fragile X



Williams-Beuren



Progeria

Clinical face phenotype space

- X fold better clustering than random expectation
- Links to the 10 nearest neighbours of each photo



Ferry et al.. eLife (2014)

Arrange these tasks into groups:

- A. Predict whether a manuscript will be a bestseller novel
- B. Find texts in a corpus that probably have the same author
- C. Predict what will be a company's share price tomorrow
- D. Predict which companies' shares will go up tomorrow
- E. Find evolutionary relationships among a set of species
- F. Determine whether a news article is fake
- G. Find "communities" of users of a music service who have similar tastes
- H. Predict the population of Gothenburg in 2030
- I. Identify sets of genes that are "switched on" in similar conditions
- J. Predict a patient's blood pressure one hour from now
- K. Diagnose a genetic disorder based on facial shape
- L. Identify whether a picture is of a cat or a dog
- M. Predict how long your journey home will take today
- N. Arrange a set of data science tasks into groups

US spending on science, space, and technology correlates with Suicides by hanging, strangulation and suffocation



Divorce rate in Maine correlates with **Per capita consumption of margarine**



tylervigen.com



https://ourworldindata.org/

Case Study:

Human Longevity

Human Longevity

- Questions:
 - What lead to increases in human longevity?
 - How should we spend resources to increase longevity?
 - Which metric should we use?

Life expectancy

Sweden



Shown is period life expectancy at birth. This corresponds to an estimate of the average number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life



Source: Clio Infra (life expectancy, both genders)

OurWorldInData.org/life-expectancy/ • CC BY-SA



Data source: The data on life expectancy by country and population by country are taken from Gapminder.org. The interactive data visualisation is available at OurWorldinData.org. There you find the raw data and more visualisations on this topic

Licensed under CC-BY-SA by the author Max Roser.

Average age at death

- Why did it increase?
 - Did the average person just live longer?
 - Other factors?
- What policies would be appropriate if the first hypothesis is true?



Insight

- Life expectancy is impacted by
 - dying of "old age"
 - dying before reaching adulthood
- Difference in life expectancy between 1720-1920 largely dependent on reduction of child mortality.
- Two groups of individuals and their proportions changed

Modes of distributions

- A mode of a distribution is a significant peak. A distribution with
 - one peak is called unimodal
 - two peaks is called *bimodal*
 - and two or more peaks is called *multi-modal*



Averages & Modes

- Averages are appropriate for *unimodal* distributions
- For *bimodal* and *multimodal* distributions the average might be where there are no observations

 \Rightarrow Plot distributions



Child mortality

Number of children per 1,000 live births who die before reaching the age of 5.



Source: Our World in Data based on Human Mortality Database and UN Child Mortality Estimates

OurWorldInData.org/child-mortality/ • CC BY-SA

Our World in Data

Possible policy

Childhood deaths from the five most lethal infectious diseases worldwide

Our World in Data



Source: IHME Global Burden of Disease (child deaths by disease)

OurWorldInData.org/child-mortality/ • CC BY-SA



Data source: The data on life expectancy by country and population by country are taken from Gapminder.org. The interactive data visualisation is available at OurWorldinData.org. There you find the raw data and more visualisations on this topic

Licensed under CC-BY-SA by the author Max Roser.

Is this all?

• Which data should we inspect to get an insight whether reducing child mortality is all that matters?







Data source: Life expectancy at birth Clio-Infra. Data on life expectany at age 1 and older from the Human Mortality Database (www.mortality.org). The interactive data visualization is available at OurWorldinData.org. There you find the raw data and more visualizations on this topic.

Licensed under CC-BY-SA by the author Max Roser.



Stratification

- Divide data into homogeneous subpopulations before analysis
- Possible variables: gender, age, socio-economic status, ...
- Can result in further insights

Race and sex vs. life expectancy



Life expectancy at birth by race and sex, United States CDC/NCHS, National Vital Statistics System

Figure 1. U.S. Poverty Rates by Race and Hispanic or Latino Origin: 2007–2011

(For information on confidentiality protection, sampling error, nonsampling error, and definitions, see *www.census.gov/acs/www/*)



Note: Persons who report only one race among the six defined categories are referred to as the race-alone population, while persons who report more than one race category are referred to as the Two or More Races population. This figure shows data using the race-alone approach. Use of the single-race population does not imply that it is the preferred method of presenting or analyzing data. The Census Bureau uses a variety of approaches. Because Hispanics may be of any race, data in this figure for Hispanics overlap with data for race groups.

Source: U.S. Census Bureau, 2007-2011 American Community Survey.

Uninsured Population by Household Income, Percent

State of Iowa

21.5%	Less than \$15,000
22.2%	\$15,000-\$24,999
14.2%	\$25,000-\$34,999
8.8%	\$35,000-\$49,999
3.1%	\$35,000-\$49,999
1.7%	\$75,000+

Uninsured Population by Education, Percent

State of Iowa

25.3%	Less than high school graduate
11.4%	High school or G.E.D.
9.7%	Some post-high school
3.6%	College graduate

Source: Health in Iowa Annual Report from the Behavioral Risk Factor Surveillance System, Iowa 2013

Disease Prevalence by Household Income State of Iowa 11.9% 10.1% Heart Disease 9.0% Less than \$15,000 6.9% \$15,000-24,999 5.9% \$25,000-34,999 3.0% 7.3% 4.0% 3.4% 2.9% 1.5% 1.0% \$35,000-49,999 \$50,000-74,000 Stroke \$75,000+ 15.4% 12.5% 3% Cardiovascular 11.3% Disease 8.6% 6.7% 3.8% 37.9% 37.6% 38.2% High Blood Pressure 31.3% 26.0% 25.1% 54.3% 41.9% **Blood Cholesterol** 41.9 % High 38.1% 34.6% 31.5% 36.0% Overweight 36.6% 35.8% 37.9% 37.6% 37.1% 33.0% 32.1% Obesity 33.1% 29.4%

Source: Health in Iowa Annual Report from the Behavioral Risk Factor Surveillance System, Iowa 2013

U.S. gun deaths by race and gender, 2011-2013





single-year fluctuations. Source: CDC Injury Prevention & Control database.

BROOKINGS

FIGURE 1

Rate of violent victimization, by household poverty level, 2008–2012

Rate per 1,000 persons age 12 or older



Note: Poor refers to households at 0% to 100% of the Federal Poverty Level (FPL). Low income refers to households at 101% to 200% of the FPL. Mid-income refers to households at 201% to 400% of the FPL. High income refers to households at 401% or higher than the FPL. See table 1 for estimates and appendix table 1 for standard errors.

Source: Bureau of Justice Statistics, National Crime Victimization Survey, 2008–2012.

Reading

- 1.2 "Asking Interesting Questions from Data"
- 6.1 "Exploratory Data Analysis"
- 6.2 "Developing a Visual Aesthetic"

