Big Data and Automated Content Analysis

Cursusdossier

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Chapter 1

Short description of the course

"Big data" is a relatively new phenomenon, and refers to data that are more voluminous, but often also more unstructured and dynamic, than traditionally the case. In Communication Science and the Social Sciences more broadly, this in particular concerns research that draws on Internet-based data sources such as social media, large digital archives, and public comments to news and products This emerging field of studies is also called *Computational Social Science* (Lazer et al., 2009) or even *Comutational Communication Science* (Shah, Cappella, & Neuman, 2015).

The course will provide insights in the basic concepts, challenges and opportunities associated with data so large that traditional research methods (like manual coding) cannot be applied any more and traditional inferential statistics start to loose their meaning. Participants are introduced to strategies and techniques for capturing and analyzing digital data in communication contexts, through concrete examples and templates than can be shared and modified for the students' own research projects. We will focus on (a) data harvesting, storage, and preprocessing and (b) computer-aided content analysis, including natural language processing (NLP) and computational social science approaches.

To participate in this course, students are expected to be interested in learning how to write own programs where off-the-shelf software is not available. Some basic understanding of programming languages is helpful, but not necessary to enter the course. Students without such knowledge are encouraged to follow the (free) online course at `https://www.codecademy.com/learn/python` to prepare.

Chapter 2

Exit qualifications

The course contributes to the following three exit qualifications of the Research Master in Communication Science:

Expertise in empirical research

3. Knowledge and Understanding: Have in-depth knowledge and a thorough understanding of advanced research designs and methods.

4. Skills and abilities: Are able, independently and on their own, to set up, conduct, report and interpret advanced academic research.

Academic abilities and attitudes

6. Attitude: Accept that scientific knowledge is always 'work in progress' and that arguments must be considered and conclusions drawn on the basis of empirical results and valid criticism.

The exit qualifications are elaborated in the following 11 specifications: 3. Knowledge and Understanding: Have in-depth knowledge and a thorough understanding of advanced research designs and methods.

3.1. Have in-depth knowledge and a thorough understanding of advanced research designs and methods, including their value and limitations.

3.2. Have in-depth knowledge and a thorough understanding of advanced techniques for data analysis.

4. Skills and abilities: Are able, independently and on their own, to set up, conduct, report and interpret advanced academic research.

4.1 Are able to formulate research questions and hypotheses for advanced empirical studies

4.2 Are able to develop a research plan, choose appropriate and suitable research designs and methods for advanced empirical studies, and justify the underlying choices.

4.3 Are able to assess the validity and reliability of advanced empirical research, and to judge the scientific and professional value of findings from advanced empirical research.

4.4 Are able to apply advanced empirical research methods.

6. Academic attitudes

6.1 Regularly asses their own assumptions, strengths and weaknesses critically.

6.2 Accept that scientific knowledge is always 'work in progress' and that something regarded as 'true' may be proven to be false, and vice-versa.

6.3 Are keen to acquire new knowledge, skills and abilities.

6.4 Are willing to share and discuss arguments, results and conclusions, including submitting one's own work to peer review.

6.5 Are convinced that academic debates should not be conducted on the basis of rhetorical qualities but that arguments must be considered and conclusions drawn on the basis of empirical results and valid criticism.

Chapter 3

Testable objectives

3. Knowledge and Understanding: Have in-depth knowledge and a thorough understanding of advanced research designs and methods.

3.1. Have in-depth knowledge and a thorough understanding of advanced research designs and methods, including their value and limitations.

3.2. Have in-depth knowledge and a thorough understanding of advanced techniques for data analysis.

A Students can explain the research designs and methods employed in existing research articles on Big Data and automated content analysis.

B Students can on their own and in own words critically discuss the pros and cons of research designs and methods employed in existing research articles on Big Data and automated content analysis; they can, based on this, give a critical evaluation of the methods and, where relevant, give advice to improve the study in question.

C Students can identify research methods from computer science and computer linguistics which can be used for research in the domain of communication science; they can explain the principles of these methods and describe the value of these methods for communication science research.4. Skills and abilities: Are able, independently and on their own, to set up, conduct, report and interpret advanced academic research.

4.1 Are able to formulate research questions and hypotheses for advanced empirical studies

4.2 Are able to develop a research plan, choose appropriate and suitable research designs and methods for advanced empirical studies, and justify the underlying choices.

4.3 Are able to assess the validity and reliability of advanced empirical research, and to judge the scientific and professional value of findings from advanced empirical research.

4.4 Are able to apply advanced empirical research methods.

D Students can on their own formulate a research question and hypotheses for own empirical research in the domain of Big Data.

E Students can on their own chose, execute and report on advanced research methods in the domain of Big Data and automatic content analysis.

F Students know how to collect data with scrapers, crawlers and APIs; they know how to analyze these data and to this end, they have basic knowledge of the programming language Python and know how to use Python-modules for communication science research.

6. Academic attitudes

6.1 Regularly asses their own assumptions, strengths and weaknesses critically.

6.2 Accept that scientific knowledge is always 'work in progress' and that something regarded as 'true' may be proven to be false, and vice-versa.

6.3 Are keen to acquire new knowledge, skills and abilities.

6.4 Are willing to share and discuss arguments, results and conclusions, including submitting one's own work to peer review.

6.5 Are convinced that academic debates should not be conducted on the basis of rhetorical qualities but that arguments must be considered and conclusions drawn on the basis of empirical results and valid criticism.

G Students can critically discuss strong and weak points of their own research and suggest improvements.

H Students participate actively: reading the literature carefully and on time, completing assignments carefully and on time, active participation in discussions, and giving feedback on the work of fellow students give evidence of this.

Chapter 4

Planning of testing and teaching

The seminar consists of sixteen meetings, two per week. Each week, in the first meeting, the instructor will give short lectures on the key aspects of the week, followed by seminar-style discussions. Theoretical considerations regarding Big Data and Automated Content Analysis are discussed, and techniques for analyzing Big Data are presented. We also discuss examples from the literature, in which these techniques are applied.

The second meetings each week are practicum-meetings, in which the students will apply what the techniques they have learned to own data sets. Here, they can also deepen their understanding of software tools, prepare their projects and get hands-on help. While there are in-class assignments as well as occasional assignments for at home (e.g., completing an online-tutorial to prepare for class), these are not graded.

To complete the course, next to active participation, the students have to successfully complete two summative graded assignments: a mid-term take-home exam and an individual project, in which they derive an empirical question from a theoretical starting point, and then do an Automated Content Analysis to answer the question. See Chapter 7 for details.

Chapter 5

Literature

The obligatory literature is listed in the column "Students' tasks" in the course schedule below (Chapter 6). In addition, the students have to carefully read the tutorial by Trilling (2018), which was written specificially for this course and which provides them with the computer skills necessary to use the tools we use for data retrieval and analysis.

The following books provide the interested student with more and deeper information. They are intended for the advanced reader and might be useful for final individual projects, but are by no means required literature:

- Russel, 2013. Gives a lot of examples about how to analyze a variety of online data, including Facebook and Twitter, but going much beyond that.
- Bird, Loper, & Klein, 2009. This is the official documentation of the NLTK package that we are using. A newer version of the book can be read for free at `http://nltk.org`
- McKinney, 2012: Another book with a lot of examples. A PDF of the book can be downloaded for free on `http://it-ebooks.info/book/1041/`.

Chapter 6

Specific course timetable

Week 1: Introduction

Monday, 5–2. Lecture.

We discuss what Big Data means, how the concept can be understood, what challenges and opportunities arise, and what the implications are for communication science.

Mandatory readings (in advance): boyd & Crawford, 2012, Vis, 2013, Kitchin, 2014.

Additional literature, not obligatory: Mahrt & Scharkow, 2013.

The articles mentioned above discuss the implications of Big Data methods in a very broad way. You should also have a look at some applied articles in the field to get an idea of the type of research that is currently conducted in the field. Good readings are Castillo, El-Haddad, Pfeffer, & Stempeck, 2014; Conover, Gonçalves, Flammini, & Menczer, 2012; Ellison, Gray, Vitak, Lampe, & Fiore, 2013. You do not have to read all of them in detail, but should get a general understanding of the types of methods that are used in these studies.

Wednesday, 7–2. Lab session.

✔ Chapter 2: The Linux command line
✔ Chapter 3: A language, not a program

We will get familiar with the Virtual Machine and the software we will work with. Make sure you installed everything in advance and that you can start up your machine.

Week 2: Getting started with Python

Monday, 12–2. Lecture.

✔ Chapter 4: The very, very basics of programming in Python
You will get a very gentle introduction to computer programming. During the lecture, you are encouraged to follow the examples on your own laptop.

Wednesday, 14–2. Lab session.

✔ Appendix A: Exercise 1
We will do our first real steps in Python and do some exercises to get the feeling.

Week 3: Data harvesting and storage

This week is about data sources and their (dis)advantages.

Monday, 19–2. Lecture.

A conceptual overview of APIs, scrapers, crawlers, RSS-feeds, databases, and different file formats.

Read the article by Morstatter, Pfeffer, Liu, and Carley (2013) in advance. It discusses the quality of data provided by the Twitter API. As a practical example for how "dirty" input data (i.e., data that for whatever reason does not come in form of a clean, structured data set like a table) can be parsed and preprocessed, have a look at the method section of the article by (Lewis, Zamith, & Hermida, 2013).

Wednesday, 21–2. Lab session.

✔ Chapter 5: Retrieving and storing data
We will write a script to collect some data.

Week 4: Sentiment analysis

Up till now, we have mainly talked about available data and how to acquire them. From now on, we will focus on analyzing them and cover one technique per week. By now, you should also have gotten some idea about your final project.

Monday, 26–2. Lecture.

We start with an overview of different analytical approaches which we will cover in the next weeks, After that, we will focus on the first of these techniques, sentiment analysis.

Read the following two articles in advance. The first one gives an overview of how to analyze social media data, in this case, Twitter (Bruns & Stieglitz, 2013). The other one is an example of a sentiment analysis (Mostafa, 2013).

Some additional examples of sentiment analysis (not obligatory): Huang, Goh, and Liew (2007); Pestian et al. (2012). If you want to have a look under the hood of a popular sentiment analysis algorithm, you can read Thelwall, Buckley, and Paltoglou (2012) and Hutto and Gilbert (2014).

Wednesday, 28–2. Lab session.

✔ Chapter 6: Sentiment analysis
You will write a tool to read data and conduct a sentiment analysis.

Week 5: Automated content analysis with NLP and regular expressions; pandas and notebooks

Text as written by humans usually is pretty messy. You will learn how to process text to make it suitable for further analysis by using techniques of Natural Language Processing (NLP), and how to extract meaningful information (discarding the rest) using regular expressions.

Monday, 5–3. Lecture with exercises

✔ Chapter 7: Automated content analysis
This lecture will introduce you to techniques and concepts like stemming, stopword removal, n-grams, word counts and word co-occurrances, and regular expressions. We will do some exercises during the lecture.

Preparation: Mandatory reading: Boumans & Trilling, 2016. Also read the paper by Madnani (n.d.). It uses the same package (NLTK) which we use in class, If you don't get all practical details yet, that's OK. Pay special attention to the (linguistic) concepts applied.

Wednesday, 7–3. Short lecture plus lab session.

✔ Section 3.5: Jupyter Notebook
✔ Chapter 12: Statistics with Python

You have worked hard so far, so we'll do something fun and relaxing (of course, fun might be a relative concept in this course...). You are going to learn how to create visualizations, do conventional statistical tests, manage datasets with Python, save the results together with your code and your own explanations – and all of this within your browser.

Take-home exam

In week 5, the midterm take-home exam is distributed. The answer sheets and all files have to be handed in no later than end of the week (i.e., Sunday, 11–3, 23.59).

Week 6: Web scraping and parsing

Monday, 12–3. Lecture.

We will explore techniques to download data from web pages and to extract meaningful information like the text (or a photo, or a headline, or the author) from an article on `http://nu.nl`, a review (or a price, or a link) from `http://kieskeurig.nl`, or similar.

Wednesday, 14–3. Lab session

✔ Chapter 8: Web scraping
We will exercise with web scraping and parsing.

Week 7: Machine learning

Monday, 19–3. Lecture.

This lecture will introduce you to one of the most fascinating topics in automated content analysis: machine learning. I will walk you trough the ideas behind unsupervised and supervised machine learning. The nice thing is that you actually have already done it during your studies: Principal component analysis is a form of unsupervised ML and regression analysis a form of supervised ML – you just never called it like this. And you probably never thought

about using these techniques to analyze texts (or images). And that's what we are going to do.

Wednesday, 21–3. Lab session.

✔ Chapter 10: Supervised machine learning
✔ Chapter 11: Unsupervised machine learning
We will exercise with different forms of machine learning.

Week 9: Finish!

We finish working on our projects and discuss last open questions.

Monday, 26–3. Lecture.

We will look back and systematize what we have learned. Also, this lecture will leave room for possible additional topics that you became interested in during this course and that haven't been covered extensively enough. For example, we might dig a bit deeper into some specific form of ML; or we might look more in detail into the possibilities of pandas. Or we might have a look at Chapter 9, which we will otherwise skip.

Wednesday, 28–3. Open Lab.

Possibility to ask last questions regarding the final project.

Final project

Deadline for handing in: Sunday, 31–3, 23.59.

Chapter 7

Testing

An overview of the testing is given in Table 7.1.

Grading

The final grade of this course will be composed of the grade of one mid-term take home exam (30%) and one individual project (70%).

Mid-term take-home exam (30%)

In a mid-term take-home exam, students will show their understanding of the literature and prove they have gained new insights during the lecture/seminar meetings. They will be asked to critically assess various approaches to Big Data analysis and make own suggestions for research.

Final individual project (70%)

The final individual project typically consists of the following elements:

- introduction including references to relevant (course) literature, an overarching research question plus subquestions and/or hypotheses (1–2 pages);
- an overview of the analytic strategy, referring to relevant methods learned in this course;
- carefully collected and relevant dataset of non-trivial size;
- a set of scripts for collecting, preprocessing, and analyzing the data. The scripts should be well-documented and tailored to the specific needs of the own project;

Table 7.1: Test matrix

	In-class assignments, reviewing work of fellow students, active participation (precondition)	Mid-term take home exam (30% of final grade)	Final individual project (70% of final grade)
A. Students can explain the research designs and methods employed in existing research articles on Big Data and automated content analysis.	X	X	
B. Students can on their own and in own words critically discuss the pros and cons of research designs and methods employed in existing research articles on Big Data and automated content analysis; they can, based on this, give a critical evaluation of the methods and, where relevant, give advice to improve the study in question.	X	X	
C. Students can identify research methods from computer science and computer linguistics which can be used for research in the domain of communication science; they can explain the principles of these methods and describe the value of these methods for communication science research.4. Skills and abilities: Are able, independently and on their own, to set up, conduct, report and interpret advanced academic research.	X	X	X
D. Students can on their own formulate a research question and hypotheses for own empirical research in the domain of Big Data.			X
E. Students can on their own chose, execute and report on advanced research methods in the domain of Big Data and automatic content analysis.			X
F. Students know how to collect data with scrapers, crawlers and APIs; they know how to analyze these data and to this end, they have basic knowledge of the programming language Python and know how to use Python-modules for communication science research.	X	X	X
G. Students can critically discuss strong and weak points of their own research and suggest improvements.			X
H. Students participate actively: reading the literature carefully and on time, completing assignments carefully and on time, active participation in discussions, and giving feedback on the work of fellow students give evidence of this.	X		

- output files;
- a well-substantiated conclusion with an answer to the RQ and directions for future research.

Grading and 2nd try

Students have to get a pass (5.5 or higher) for both the mid-term take-home exam and the individual project. If the grade of one of these is lower, an improved version can be handed in within one week after the grade is communicated to the student. If the improved version still is graded lower than 5.5, the course cannot be completed. Improved versions of the final individual project cannot be graded higher than 6.0.

Chapter 8

Lecturers' team, including division of responsibilities

dr. Damian Trilling (responsible)
dr. Theo Araujo assists during practicum sessions (30 extra hours, not included in calculation below; necessary because it is unfeasible to help > 15 students individually during practicum sessions)

Chapter 9

Calculation of students' study load (in hours)

- Elective total: 6 ECTS =168 hours
- Reading:
  - 13 articles, average 20 pages: 260 pages. 6 pages per hour, thus 43 hours for the literature
  - Reading and doing tutorials: 14 hours for reading tutorials to acquire skills.
  - Reading total: 57 hours.
- Presence:
  16*1,75 hours: 28 hours.
- Mid-term take-home exam, including preparation: 14 hours
- Final individual project, including data collection, analysis, write up: 70 hours

Total: 169 hours

Chapter 10

Calculation of lecturers' teaching load (in hours)

- Presence: 32 hours (= 16 * 2 hours)
- Preparation of course: 60 hours
- Preparation of weekly lectures, 8 * 4 hours: 32 hours
- Feedback and grading take-home exams: 25x15 minutes: 6 hours
- Feedback and grading final projects, including feedback on proposal and individual counseling: 25* 60 min: 25 hours
- Administration, e-mails, individual appointments: 9 hours

Total: 164 hours

Literature

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Boumans, J. W., & Trilling, D. (2016). Taking stock of the toolkit: An overview of relevant autmated content analysis approaches and techniques for digital journalism scholars. *Digital Journalism*, *4*(1), 8–23. doi: 10.1080/21670811.2015.1096598

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