Big Data and Automated Content Analysis

Week 1 – Monday

»Introduction«

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Afdeling Communicatiewetenschap
Universiteit van Amsterdam

5 February 2018

Today

1. Introducing...
   - ...the people
2. What is Big Data?
   - Definitions
   - Are we doing Big Data research?
3. Methods
   - Which techniques?
   - Which tools?
4. What have others done?
   - Online news sharing
   - Partisan asymmetries
5. What can we do?
   - Considerations regarding feasibility
   - Examples from last year
6. The schedule
   - Next meetings

Introducing. . .

. . . the people

Introducing. . .
Damian

dr. Damian Trilling
Assistant Professor Political Communication & Journalism

- studied Communication Science in Münster and at the VU 2003–2009
- PhD candidate @ ASCoR 2009–2012
- interested in political communication and journalism in a changing media environment and in innovative (digital, large-scale, computational) research methods

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Introducing...
Joanna

Joanna Strycharz, MSc.
PhD candidate in persuasive communication

- Researching what consumers know and think about personalized marketing
- interested in innovative research methods.

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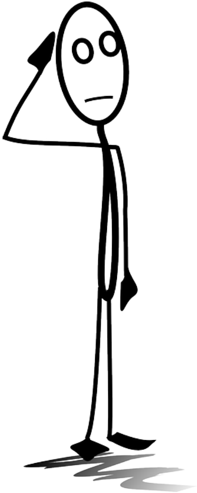
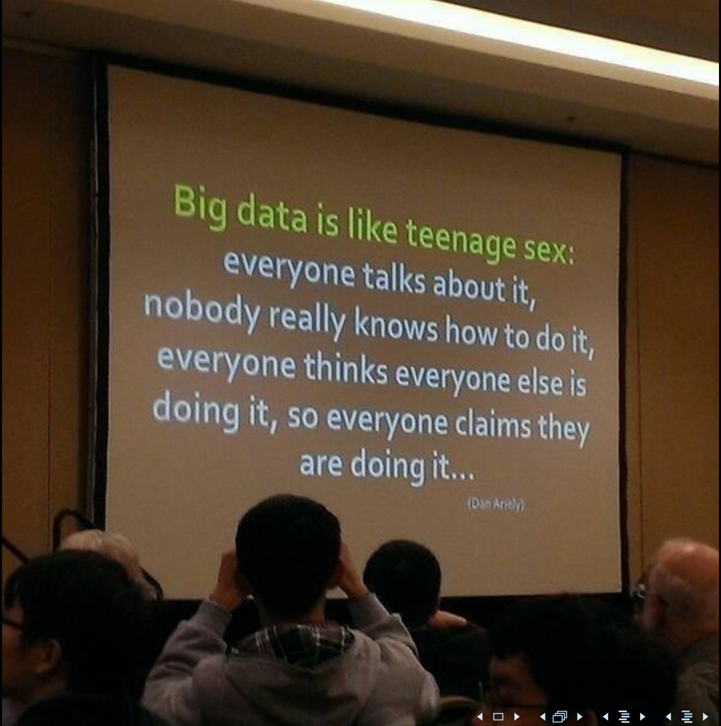
Introducing...

You



Your name?
Your background?
Your reason to follow this course?

What is Big Data?


Big data is like teenage sex:
everyone talks about it,
nobody really knows how to do it,
everyone thinks everyone else is
doing it, so everyone claims they
are doing it...
(Dan Ariely)

What is Big Data?

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A simple technical definition could be:

Everything that needs so much computational power and/or storage that you cannot do it on a regular computer.

What is Big Data?

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Vis, 2013

- “commercial” definition (Gartner): “’Big data’ is high-volume, -velocity and -variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making”

What is Big Data?

Vis, 2013

- boyd & Crawford definition:
  1. Technology: maximizing computation power and algorithmic accuracy to gather, analyze, link, and compare large data sets.
  2. Analysis: drawing on large data sets to identify patterns in order to make economic, social, technical, and legal claims.
  3. Mythology: the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy.

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Implications & criticism

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boyd & Crawford, 2012

1. Big Data changes the definition of knowledge
2. Claims to objectivity and accuracy are misleading
3. Bigger data are not always better data
4. Taken out of context, Big Data loses its meaning
5. Just because it is accessible does not make it ethical
6. Limited access to Big Data creates new digital divides

APIs, researchers and tools *make* Big Data

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Vis, 2013

Inevitable influences of:

- APIs
- filtering, search strings, . . .
- changing services over time
- organizations that provide the data

Epistemologies and paradigm shifts

Kitchin, 2014

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Epistemologies and paradigm shifts

Kitchin, 2014

- (Reborn) empiricism: purely inductive, correlation is enough
- Data-driven science: knowledge discovery guided by theory
- Computational social science and digital humanities: employ Big Data research within existing epistemologies
  - DH: descriptive statistics, visualizations
  - CSS: prediction and simulation

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Depends on the definition

- Not if we take a definition that *only* focuses on computing power and the amount of data
- **But:** We are using the same techniques. And they *scale* well.
- Oh, and about that high-performance computing in the cloud: We actually *do* have access to that, so if someone has a really great idea...

Methods

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APIs, scrapers and crawlers, feeds, databases, . . .
Storage in different file formats

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2. How to analyze data

Sentiment analysis, automated content analysis, regular expressions, natural language processing, cluster analysis, machine learning, network analysis

The ACA toolbox

	Methodological approach		
	Counting and Dictionary	*Supervised Machine Learning*	*Unsupervised Machine Learning*
Typical research interests and content features	visibility analysis sentiment analysis subjectivity analysis	frames topics gender bias	frames topics
Common statistical procedures	string comparisons counting	support vector machines naive Bayes	principal component analysis cluster analysis latent dirichlet allocation semantic network analysis

deductive → **inductive**

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

The methods

The tools we use for this

The programming language Python (and the huge amount of Python modules others already wrote).

A language, not a program:
Python

Python

What?

- A language, not a specific program
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- One of *the* languages for data analysis. (The other one is R.)

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What?

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- One of *the* languages for data analysis. (The other one is R.)
  But Python is more flexible—the original version of Dropbox was written in Python. Some people say: R for numbers, Python for text and messy stuff.

Python

What?

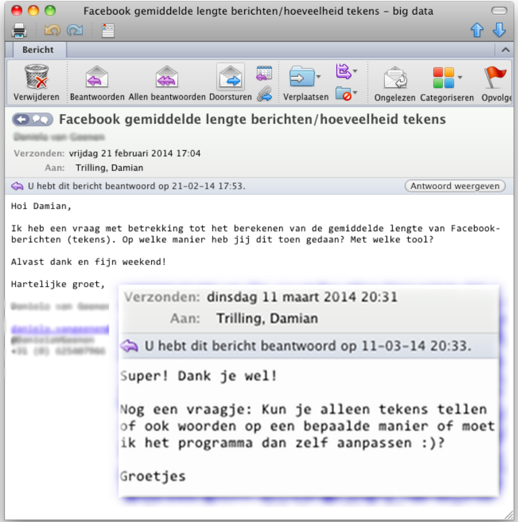
- A language, not a specific program
- Huge advantage: flexibility, portability
- One of *the* languages for data analysis. (The other one is R.)

Which version?

We use Python 3.

`http://www.google.com` or `http://www.stackexchange.com` still offer a lot of Python2-code, but that can easily be adapted. Most notable difference: In Python 2, you write `print "Hi"`, this has changed to `print ("Hi")`

Why program your own tool?



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Luckily, the problem is easily solved

The task was done with a self-written Python program. We change the line

```
lengte_list.append(len(row[textcolumn]))
```

to

```
lengte_list.append(len(row[textcolumn].split()))
```

Why program your own tool?

> Moreover, the tools we use can limit the range of questions that might be imagined, simply because they do not fit the affordances of the tool. Not many researchers themselves have the ability or access to other researchers who can build the required tools in line with any preferred enquiry. This then introduces serious limitations in terms of the scope of research that can be done. Vis, 2013

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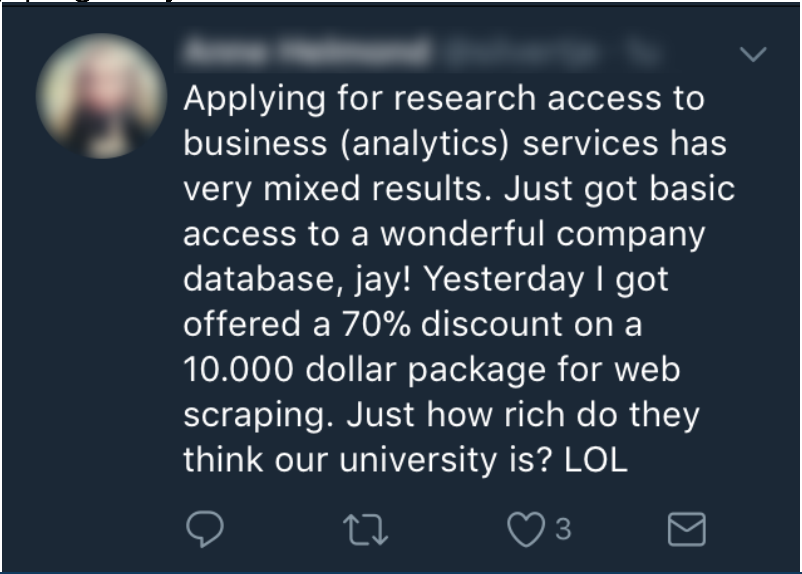

Some considerations regarding the use of software in science

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use tools that are

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This ensures it can our research (a) can be reproduced by anyone, and that there is (b) no black box that no one can look inside. ⇒ ongoing open-science debate!

Why program your own tool?

`[...] these [commercial] tools are often unsuitable for academic purposes because of their cost, along with the problematic 'black box' nature of many of these tools.` Vis, 2013

`[...] we should resist the temptation to let the opportunities and constraints of an application or platform determine the research question [...]` Mahrt & Scharkow, 2013, p. 30

What have others done?

Online news sharing

Castillo, El-Haddad, Pfeffer, & Stempeck, 2013

Online news sharing

The question

"We describe the interplay between website visitation patterns and social media reactions to news content. [...] We also show that social media reactions can help predict future visitation patterns early and accurately." (p.1)

Castillo, El-Haddad, Pfeffer, & Stempeck, 2013

Online news sharing

The method

- data set 1: log files provided by Al Jazeera
- data set 2: Facebook and Twitter API
- analysis: link 1 and 2 and estimate the relationships

Castillo, El-Haddad, Pfeffer, & Stempeck, 2013

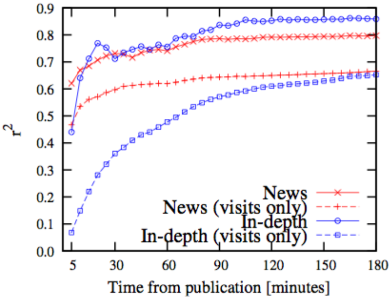

Figure 7. Proportion of explained variance (r^2) for the prediction of total volume of visits, for News and In-depth articles.

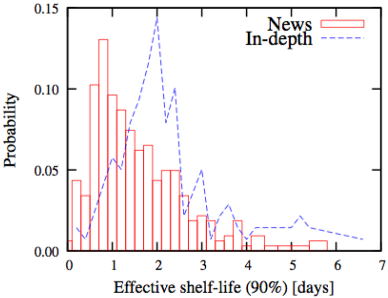

Figure 8. Distribution of effective shelf-life.

It takes about 3 hours to be able to explain > 0.6 of the variance for In-Depth articles, and the additional variables are profitable from the first minutes. After 10-20 minutes we observe the largest difference in our regression models (+0.5 in terms of r^2).

We take a closer look at the model variables after 20 minutes to identify the sources of this improvement. For this purpose we stepwise fit the model variables by AIC (Akaike information criterion) as implemented in stats.step in R. Table 4 shows the reliability of the

Table 5. Modeling effective shelf-life: Significance levels for regression models after 20 minutes.

Variable	In-depth		News	
Visits R^2	0.0005		0.0921	
Social media R^2	0.4457		0.2193	
Social media R^2 adjusted	0.2274		0.1505	
Twitter tweets	0.0138	*	0.0061	**
Twitter entropy	0.0027	**	0.0024	**
Twitter avg. followers			0.0001	***
Volume of unique tweets	0.0026	**		
Unique tweets %	0.0190	*	0.0445	*
Corporate retweets	0.0001	***		
Traffic from e-mail/IM	0.0482	*		

Online news sharing

The issues

- You need that guy at Al Jazeera
- You need the infrastructure to cope with the data
- Very much tailored to one outlet

Castillo, El-Haddad, Pfeffer, & Stempeck, 2013

Partisan asymmetries

Conover, Gonçalves, Flammini, & Menczer, 2012

Partisan asymmetries

The question

How does the Twitter behavior differ between right-wing and left-wing users?

Conover, Gonçalves, Flammini, & Menczer, 2012

Partisan asymmetries

The method

Starting with two hashtags (one used by progressives, one used by conservatives), 55 co-occuring hashtags were identified.
Identification of follower networks, retweet networks, mention networks within tweets with these hashtags.

Conover, Gonçalves, Flammini, & Menczer, 2012

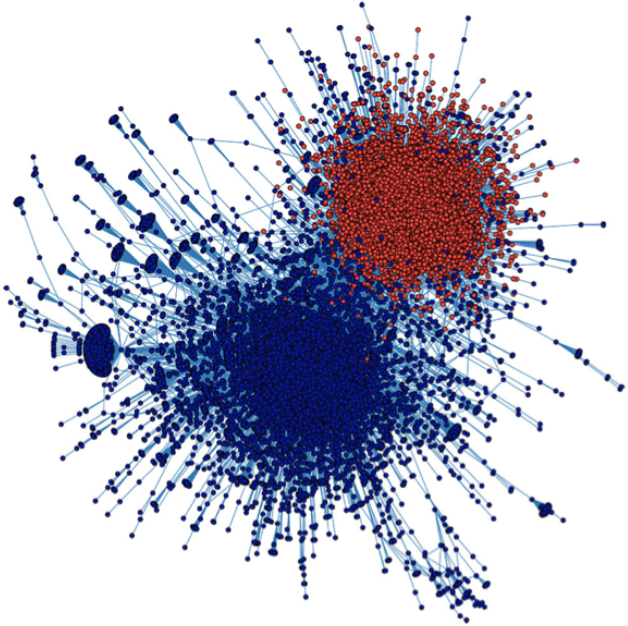

Figure 3 The network of political retweets, laid out using a force-directed algorithm. Node colors reflect cluster assignments, which correspond to politically homogeneous communities of left- and right-leaning users with 87% accuracy. (See Section 3.3.)

Partisan asymmetries

The issues

- The two seeds #tcot and #p2 oversample (extremly) partisan content, inevitably leading to the structure in Figure 3.
- But maybe no problem, as the rest of the paper aims to *compare* these groups.
- Not an empirical problem, but still: What do we learn *exactly* from this study apart from the – interesting – case?

Conover, Gonçalves, Flammini, & Menczer, 2012

To which extent could *we* conduct such studies?

What can we do?

Cool research, sure, but what can *we* do?

- Dependency from third parties:
  scraping $<$ API $<$ server-side implementation
- Restrictions (e.g., Twitter: sprinkler, garden hose, fire hose)
  $\Rightarrow$ Vis, 2013: Data are made!
- We can't just trust the numbers. Some tasks require human coders – or a qualitative approach, at least as a pre-study.

What can we do?

pros, cons, and feasibility

- APIs (Twitter, Facebook, ...)
- server-side implementations (⇒ Al Jazeera-example)
- scraping
- client-side log files
- "traditional" methods (surveys etc.)

What can we do?

What helps us answer *our* questions?

1. Draft a RQ.
2. Think of *different* ways to approach it
3. Think of *different* data sources.
4. Think of *different* analyses.

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And then:

1. Check what the technical possibilities are. (e.g., is there an API? How can we get the data?)
2. Re-evaluate all steps.

Some final projects from previous courses

Questions

- How can house prices on funda.nl be predicted?
- Where are those who edit Wikipedia-entries about companies geographically located, related to the company's HQ?
- Can we predict ratings on Hostelworld?
- What do people write in their Tinder profiles – and how do men and women differ?
- How international is the ICA, given all presentations given at all conferences in the last decade?

The schedule

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Each week

In general: A lecture (Monday) and a lab session (Wednesday).
Each week one method.

Examinations

A mid-term take-home exam in week 5 and an individual research project on which you work during the whole course.

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Self-study

Play around! You really have to *do* it to learn programming. See it as your weekly assignment ;-)

Next meetings

Week 1: Introduction

Wednesday, 7–2

Lab session.

Preparation: Read chapters 2 and 3!

Make sure in advance that your VM works!