

# Big Data and Automated Content Analysis (Part I ) Week 1 – Monday »Introduction«

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# 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. . .

## Anne



dr. Anne Kroon

Assistant Professor Corporate Communication

- Studied Journalism and Communication in Utrecht and at the UvA, 2006 - 2013
- PhD candidate corporate communication at ASCoR, 2014 - 2017
- Research focus on bias and stereotypes about minorities in media environments, and effects on (implicit) stereotypical beliefs
- Interested in using automated approaches

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# Introducing. . . Damian

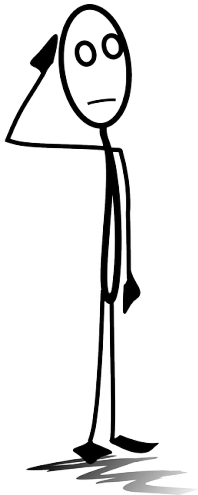


dr. Damian Trilling  
Assistant Professor Political Communication &  
Journalism

- 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. . . 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.

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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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# Are we doing Big Data research in this course?

## 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

# What we will learn the next weeks

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APIs, scrapers and crawlers, feeds, databases, . . .

Storage in different file formats

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Storage in different file formats

## 2. How to analyze data

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

# The ACA toolbox

	Methodological approach		
	<i>Counting and Dictionary</i>	<i>Supervised Machine Learning</i>	<i>Unsupervised Machine Learning</i>
<b>Typical research interests and content features</b>	visibility analysis sentiment analysis subjectivity analysis	frames topics gender bias	frames topics
<b>Common statistical procedures</b>	string comparisons counting	support vector machines naïve Bayes	principal component analysis cluster analysis latent dirichlet allocation semantic network analysis
	<div>deductive</div> <div>inductive</div>		

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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# Python

## What?

- A language, not a specific program
- Huge advantage: flexibility, portability
- 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?

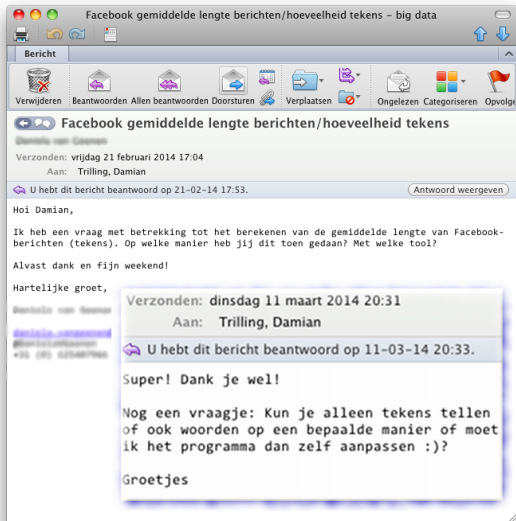
- A language, not a specific program
- Huge advantage: flexibility, portability
- One of *the* languages for data analysis. (The other one is R.)

## 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")`

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Luckily, the problem is easily solved

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

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

to

```
lengthe_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



## Why program your own tool?



Applying for research access to business (analytics) services has very mixed results. Just got basic access to a wonderful company database, yay! Yesterday I got offered a 70% discount on a 10.000 dollar package for web scraping. Just how rich do they think our university is? LOL



# Some considerations regarding the use of software in science

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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

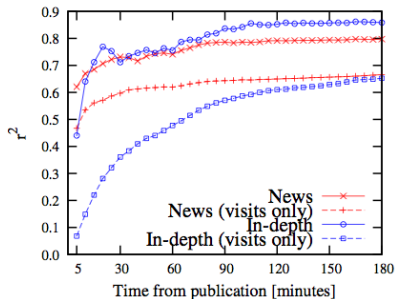


Figure 7. Proportion of explained variance ( $r^2$ ) for the prediction of total volume of visits, for News and In-depth articles.

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.stepAIC` in R. Table 4 shows the reliability of the

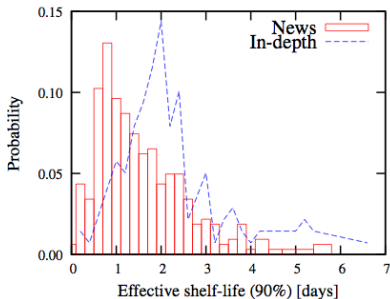


Figure 8. Distribution of effective shelf-life.

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

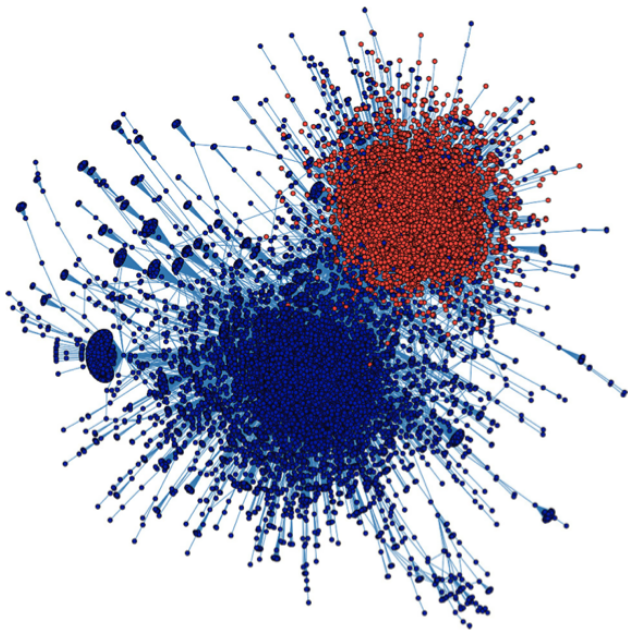
# Partisan asymmetries

## The method

Starting with two hashtags (one used by progressives, one used by conservatives), 55 co-occurring 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 (extremely) 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)  
⇒ 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 ( $\Rightarrow$  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.

# 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.

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

# The schedule

## Each week

In general: A lecture (Monday) and a lab session (Thursday).  
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

Thursday, 4–4

Getting started **chapters 2 and 3, testing everything in the VM**