

Big Data and Automated Content Analysis

Week 4 – Monday

»Sentiment Analysis«

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Today

① Different types of analysis

What can we do?

Systematizing analytical approaches

② Data analysis 1: Sentiment analysis

What is it?

Bag-of-words approaches

Advanced approaches

A sentiment analysis tailored to your needs!

Packages for sentiment analysis

A recipe

Machine Learning as alternative

③ Take-home message, next meetings, & exam

What we already can do

with regard to data collection:

- query a (JSON-based) API (GoogleBooks, Twitter)
- handle CSV files
- handle JSON files

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with regard to data collection:

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with regard to analysis:

Not much. We counted some frequencies and calculated some averages.

What else can we do?

For example

- sentiment analysis
- automated coding with regular expressions
- natural language processing
- supervised and unsupervised machine learning
- network analysis

Or ideally...

... a combination of these techniques.

Overview

Systematizing analytical approaches

Systematizing analytical approaches

Taking the example of Twitter:

Analyzing the *structure*

- Number of Tweets over time
- singleton/retweet ratio
- Distribution of number of Tweets per user
- Interaction networks

Bruns, A., & Stieglitz, S. (2013). Toward more systematic Twitter analysis: metrics for tweeting activities. *International Journal of Social Research Methodology*. doi:10.1080/13645579.2012.756095

Systematizing analytical approaches

Taking the example of Twitter:

Analyzing the *structure*

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⇒ **Focus on the amount of content and on the question who interacts with whom, not on what is said**

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Systematizing analytical approaches

Taking the example of Twitter:

Analyzing the *content*

- Sentiment analysis
- Word frequencies, searchstrings
- Co-word analysis (\Rightarrow frames)

Systematizing analytical approaches

⇒ **It depends on your reserach question which approach is more interesting!**

Automated Content Analysis

	Methodological approach		
	<i>Counting and Dictionary</i>	<i>Supervised Machine Learning</i>	<i>Unsupervised Machine Learning</i>
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
<div> <div>deductive</div> <div></div> <div>inductive</div> </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.

Data analysis 1:

Sentiment analysis

What is sentiment analysis?

Extracting subjective information from texts

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- the author's attitude towards the topic of the text

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What is sentiment analysis?

Extracting subjective information from texts

- the author's attitude towards the topic of the text
- *polarity*: negative—positive
- *subjectivity*: neutral—subjective *
- advanced approaches: different emotions

* Less sophisticated approaches do not see this as a sperate dimension but simply calculate $objectivity = 1 - (negativity + positivity)$

Applications

Who uses it?

- Companies
- especially for Web Analytics
- Social Scientists
- applications in data journalism, politics, ...

Many references to examples in Mostafa (2013).

⇒ Cases in which you have a huge amount of data or real-time data and you want to get an idea of the tone.

Mostafa, M. M. (2013). More than words: Social networks' text mining for consumer brand sentiments. *Expert Systems with Applications*, 40(10), 4241– 4251. doi:10.1016/j.eswa.2013.01.019

Example

```
1 >>> sentiment("Great service by @NSHighspeed")
2 (0.8, 0.75)
3 >>> sentiment("Bad service by @NSHighspeed")
4 (-0.6166666666666667, 0.6666666666666666)
```

(polarity, subjectivity) with

$$-1 \leq \textit{polarity} \leq +1$$

$$0 \leq \textit{subjectivity} \leq +1$$

This is the module `pattern.nl`, available for Python 2 via `pip`. The development branch on github supports Python 3.

De Smedt, T., & Daelemans W. (2012). Pattern for Python. *Journal of Machine Learning Research*, 13, 2063-2067.

Data analysis 1: Sentiment analysis

Bag-of-words approaches

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How does it work?

- We take each word of a text and look if it's positive or negative.

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Bag-of-words approaches

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 - More advanced: look up a subjectivity score from a table

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 - More advanced: look up a subjectivity score from a table
- e.g., add up the scores and average them.

How to do this

If you were to run an analysis like the one by Mostafa (2013), how could you do this?

How to do this

(given a *string* `tekst` that you want to analyze and two *lists* of strings with negative and positive words, `lijstpos=["great","fantastic",...,"perfect"]` and `lijstneg`)

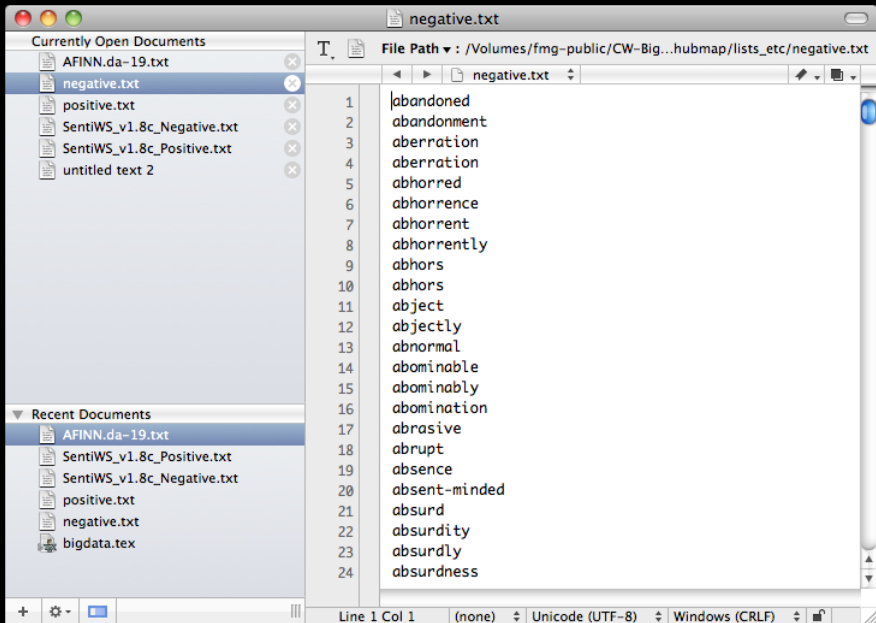
```
1 sentiment=0
2 for woord in tekst.split():
3     if woord in lijstpos:
4         sentiment=sentiment+1 #same as sentiment+=1
5     elif woord in lijstneg:
6         sentiment=sentiment-1 #same as sentiment-=1
7 print (sentiment)
```

Do we need to have the lists in our program itself?

No.

You could have them in a separate text file, one per row, and then read that file directly to a list.

```
1 poslijst=open("filewithonepositivewordperline.txt").read().splitlines()
2 neglijst=open("filewithonenegativewordperline.txt").read().splitlines()
```

More advanced versions

- CSV files or similar tables with weights
- Or some kind of dict?

AFINN.da-19.txt

Currently Open Documents

- AFINN.da-19.txt
- negative.txt
- positive.txt
- SentiWS_v1.8c_Negative.txt
- SentiWS_v1.8c_Positive.txt
- untitled text 2

Recent Documents

- AFINN.da-19.txt
- SentiWS_v1.8c_Positive.txt
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- positive.txt
- negative.txt
- bigdata.tex

File Path: /Volumes/fmg-public/CW-Big...ap/lists_etc/AFINN.da-19.txt

AFINN.da-19.txt

1	absorberet	1
2	acceptere	1
3	accepterede	1
4	accepterer	1
5	accepteres	1
6	accepteret	1
7	advare	-2
8	advarede	-2
9	advarer	-2
10	advaret	-2
11	advarsel	-3
12	advarsler	-3
13	advarslerne	-3
14	afbrudt	-2
15	afbryde	-2
16	afbrydelse	-2
17	afbrydelser	-2
18	afbrydelserne	-2
19	afbryder	-2
20	affald	-1
21	afgift	-1
22	afgifter	-1
23	afhængig	-1
24	afhængige	-1

Line 1 Col 1 (none) Unicode (UTF-8, with BOM) Wind...CRLF

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File Path: /Volumes/fmg-public/CW-Big...tc/SentiWS_v1.8c_Negative.txt

SentiWS_v1.8c_Negative.txt

1	Abbau INN	-0.058	Abbaus,Abbaues,Abbauen,Abbaue
2	Abbruch INN	-0.0048	
...			
3	Abbruches,Abbrüche,Abbruchs,Abbrüchen		
4	Abdankung INN	-0.0048	Abdankungen
5	Abdämpfung INN	-0.0048	Abdämpfungen
6	Abfall INN	-0.0048	
...			
7	Abfalles,Abfälle,Abfalls,Abfällen		
8	Abfuhr INN	-0.3367	Abfahren
9	Abgrund INN	-0.3465	
10	Abhängigkeit INN	-0.3653	Abhängigkeiten
11	Ablehnung INN	-0.5118	Ablehnungen
12	Ablenkung INN	-0.0435	Ablenkungen
13	Abnahme INN	-0.0048	Abnahmen
14	Abneigung INN	-0.0048	Abneigungen
15	Abnutzung INN	-0.0048	
16	Abriss INN	-0.0048	
...			
17	Abrisse,Abrissen,Abrisses,Abriss		
18	Abrutsch INN	-0.0048	
...			
19	Abrutschen,Abrutsche,Abrutsches,Abrutschs		
20	Abschaffung INN	-0.058	Abschaffungen
21	Abschreckung INN	-0.0048	Abschreckungen
22	Abschreibung INN	-0.3345	Abschreibungen
23	Abschuß INN	-0.0048	
24	Abschwächung INN	-0.1935	Abschwächungen

Line 1 Col 1 (none) Unicode (UTF-8) Unix (LF) 216...

Mustafa 2013: Interpreting the output

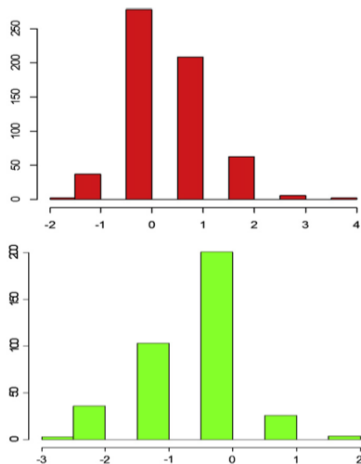


Fig. 5. Sentiment scores for Nokia (top) and Pfizer (bottom). X-axis represents score distributions, Y-axis represents count/frequencies.

Mustafa 2013: Interpreting the output

Your thoughts?

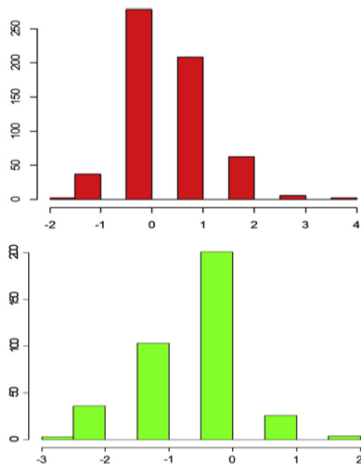


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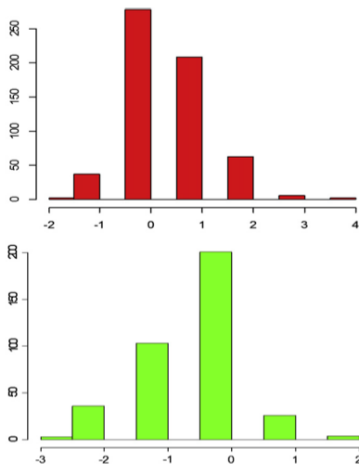


Fig. 5. Sentiment scores for Nokia (top) and Pfizer (bottom). X-axis represents score distributions, Y-axis represents count/frequencies.

Your thoughts?

- each word counts equally (1)
- many tweets contain no words from the list. What does this mean?
- Ways to improve BOW approaches?

Bag-of-words approaches

e.g., Schut, L. (2013). Verenigde Staten vs. Verenigd Koninkrijk: Een automatische inhoudsanalyse naar verklarende factoren voor het gebruik van positive campaigning en negative campaigning door vooraanstaande politici en politieke partijen op Twitter. *Bachelor Thesis*, Universiteit van Amsterdam.

Bag-of-words approaches

pro

- easy to implement
- easy to modify:
 - add or remove words
 - make new lists for other languages, other categories (than positive/negative), ...
- easy to understand (transparency, reproducibility)

e.g., Schut, L. (2013). Verenigde Staten vs. Verenigd Koninkrijk: Een automatische inhoudsanalyse naar verklarende factoren voor het gebruik van positieve campaigning en negatieve campaigning door vooraanstaande politici en politieke partijen op Twitter. *Bachelor Thesis*, Universiteit van Amsterdam.

Bag-of-words approaches

con

- simplistic assumptions
- e.g., intensifiers cannot be interpreted ("really" in "really good" or "really bad")
- or, even more important, negations.

Data analysis 1: Sentiment analysis

Advanced approaches

Improving the BOW approach

Example: The Sentistrength algorithm

- $-5 \dots -1$ and $+1 \dots +5$
- spelling correction
- "booster word list" for strengthening/weakening the effect of the following word
- interpreting repeated letters ("baaaaaad"), CAPITALS and !!!
- idioms
- negation
- Idots

Thelwall, M., Buckley, K., & Paltoglou, G. (2012). Sentiment strength detection for the social Web. *Journal of the American Society for Information Science and Technology*, 63(1), 163-173.

Advanced approaches

Take the structure of a text into account

- Try to apply linguistics concepts to identify sentence structure
- can identify negations
- can interpret intensifiers

Example

```
1 from pattern.nl import sentiment
2 >>> sentiment("Great service by @NSHighspeed")
3 (0.8, 0.75)
4 >>> sentiment("Really")
5 (0.0, 1.0)
6 >>> sentiment("Really Great service by @NSHighspeed")
7 (1.0, 1.0)
```

(polarity, subjectivity) with

$-1 \leq \text{polarity} \leq +1$

$0 \leq \text{subjectivity} \leq +1$)

Unlike in pure bag-of-words approaches, here, the overall sentiment is not just the sum or the average of its parts!

De Smedt, T., & Daelemans W. (2012). Pattern for Python. *Journal of Machine Learning Research*, 13, 2063-2067.

Advanced approaches

Advanced approaches

pro

- understand intensifiers or negation
- thus: higher accuracy

Advanced approaches

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- understand intensifiers or negation
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con

- Black box? Or do we understand the algorithm?
- Difficult to adapt to own needs
- *really* much better results?

Data analysis 1: Sentiment analysis

A sentiment analysis tailored to your needs!

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Identifying suicidal texts

- Bag-of-words-approach with very specific dictionary
- added negation
- added regular expression search for key phrases
- Very specific design requirements: False positives are OK, false negatives not!

Huang, Y.-P., Goh, T., & Liew, C.L. (2007). Hunting suicide notes in web 2.0 – preliminary findings. *Ninth IEEE International Symposium on Multimedia*. Retrieved from <http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=4476021>

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group suicide notes by these characteristics:

- swear
- family
- friend
- positive emotion
- negative emotion
- anxiety
- anger
- sad
- cognitive process
- biology
- sexual
- ingestion
- religion
- death

Pestian, J.P.; Matykiewicz, P., Linn-Gust, M., South, B., Uzuner, O., Wiebe, J., Cohen, K.B., Hurdle, J., & Brew, C. (2012). Sentiment analysis of suicide notes: A shared task. *Biomedical Informatics Insights*, 5(1), p. 3-16. Retrieved from <http://europepmc.org/article/PMC3290408?pdf-render>

Packages for sentiment analysis

Which packages are easy to use?

vader pro: in NLTK module, con: English only

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**BUT: Keep in mind that the results of *any*
off-the-shelf-package might be biased and/or noisy in *your*
domain!**

A possible recipe for doing your sentiment analysis

- ❶ Construct a list `data` of strings with your input data
- ❷ Create an empty list `sent` for storing the results
- ❸ For each text `t` in `data`, estimate the sentiment of `t` and append the result to `sent`¹
- ❹ Confirm that `len(data) == len(sent)`
- ❺ use `zip()` and a `csv.writer` to write input and output next to each other to a csv file.

¹use multiple lists instead if you estimate for instance subjectivity *and* polarity

Supervised ML (\Rightarrow week7)

An alternative state-of-the-art approach:

Use supervised machine learning

- Instead of defining rules, hand-code (“annotate”) the sentiment of some tweets manually and let the computer find out which words or characters (“features”) predict sentiment
- Then use this model to predict sentiment for other tweets
- Essentially the same like what you know since the second year of your Bachelor: regression analysis (but now with DV sentiment and IV’s word occurrences)

Gonzalez-Bailon, S., & Paltoglou, G. (2015). Signals of public opinion in online communication: A comparison of methods and data sources. *The ANNALS of the American Academy of Political and Social Science*, 659(1), 95–107.

Take-home message
Mid-term take-home exam
Next meetings

Take-home messages

What you should be familiar with:

- You should have *completely* understood last week's exercise. Re-read it if necessary.
- Approaches to the analysis (e.g., structure vs. content)
- Types of sentiment analysis, application areas, pros and cons

Next meeting

Thursday: lab session sentiment analysis

As you are working on your take-home exam, I do not expect you to prepare questions in this week (even though you can ask them if you want). Instead, I will prepare answers to frequently asked questions.

Mid-term take home exam

Have a look now on Canvas!