Big Data and Automated Content Analysis I+II

Week 4 – Wednesday
Sentiment Analysis

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Today

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.

Data analysis: Overview
What can we do?

Data analysis: Overview
What can we do?

What do you think? What are interesting methods to analyze large data sets (like, e.g., social media data? What questions can they answer?)

What else can we do?

For example

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

What else can we do?

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*

- Number of Tweets over time
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- Distribution of number of Tweets per user
- Interaction networks

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

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 *content*

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

Systematizing analytical approaches

Taking the example of Twitter:

Analyzing the *content*

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

⇒ **Focus on what is said**

Systematizing analytical approaches

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

Automated Content Analysis

	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.

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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- advanced approaches: different emotions

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 $\textit{objectivity} = 1 - (\textit{negativity} + \textit{positivity})$

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

```
>>> sentiment("Great service by @NSHighspeed")
(0.8, 0.75)
>>> sentiment("Bad service by @NSHighspeed")
(-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
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

Bag-of-words approaches

How does it work?

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

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  - Most simple way: compare it with a list of negative words and with a list of positive words (That's what Mostafa (2013) did)

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 analyis like the one by Mostafa (2013), how could you do this?

How to do this

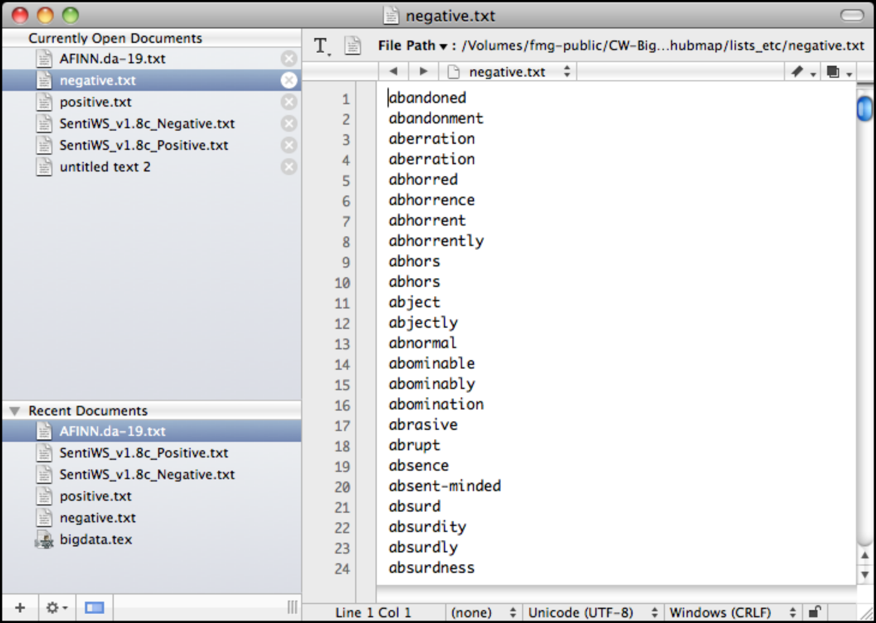
(given a *string* `tekst` that you want to analyze and two *lists* of strings with negative and positive words, `lijstpos=["great","fantastic",...,"perfect"]` and `lijstneg`)

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

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

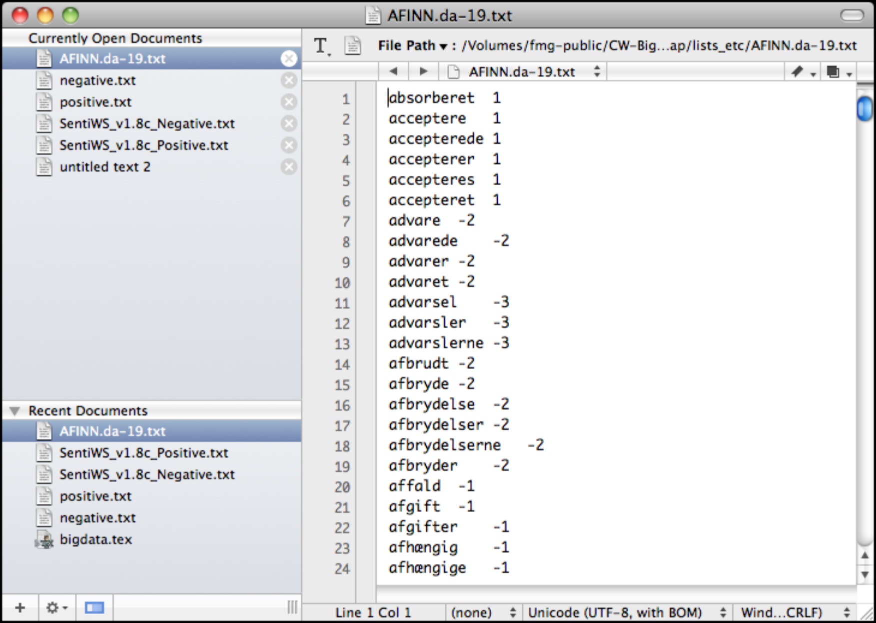
No.
You could have them in a separate text file, one per row, and then read that file directly to a list.

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


negative.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
SentiWS_v1.8c_Negative.txt
positive.txt
negative.txt
bigdata.tex
File Path ▾ : /Volumes/fmg-public/CW-Big...hubmap/lists_etc/negative.txt
negative.txt
abandoned
abandonment
aberration
aberration
abhorred
abhorrence
abhorrent
abhorrently
abhors
abhors
abject
abjectly
abnormal
abominable
abominably
abomination
abrasive
abrupt
absence
absent-minded
absurd
absurdity
absurdly
absurdness
Line 1 Col 1
(none)
Unicode (UTF-8)
Windows (CRLF)

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
SentiWS_v1.8c_Negative.txt
positive.txt
negative.txt
bigdata.tex
File Path ▾ : /Volumes/fmg-public/CW-Big...ap/lists_etc/AFINN.da-19.txt
AFINN.da-19.txt
absorberet 1
acceptere 1
accepterede 1
accepterer 1
accepteres 1
accepteret 1
advare -2
advarede -2
advarer -2
advaret -2
advarsel -3
advarsler -3
advarslerne -3
afbrudt -2
afbryde -2
afbrydelse -2
afbrydelser -2
afbrydelserne -2
afbryder -2
affald -1
afgift -1
afgifter -1
afhængig -1
afhængige -1
Line 1 Col 1
(none)
Unicode (UTF-8, with BOM)
Wind...CRLF)

SentiWS_v1.8c_Negative.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
- SentiWS_v1.8c_Negative.txt
- positive.txt
- negative.txt
- bigdata.tex

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

SentiWS_v1.8c_Negative.txt

```
Abbau|NN	-0.058	Abbaus,Abbaues,Abbauen,Abbaue
Abbruch|NN	-0.0048	Abbruches,Abbrüche,Abbruchs,Abbrüchen
Abdankung|NN	-0.0048	Abdankungen
Abdämpfung|NN	-0.0048	Abdämpfungen
Abfall|NN	-0.0048	Abfalles,Abfälle,Abfalls,Abfällen
Abfuhr|NN	-0.3367	Abfuhren
Abgrund|NN	-0.3465
Abhängigkeit|NN	-0.3653	Abhängigkeiten
Ablehnung|NN	-0.5118	Ablehnungen
Ablenkung|NN	-0.0435	Ablenkungen
Abnahme|NN	-0.0048	Abnahmen
Abneigung|NN	-0.0048	Abneigungen
Abnutzung|NN	-0.0048
Abriss|NN	-0.0048	Abrisse,Abrissen,Abrisses,Abrisss
Abrutsch|NN	-0.0048	Abrutschen,Abrutsche,Abrutsches,Abrutschs
Abschaffung|NN	-0.058	Abschaffungen
Abschreckung|NN	-0.0048	Abschreckungen
Abschreibung|NN	-0.3345	Abschreibungen
Abschuß|NN	-0.0048
Abschwächung|NN	-0.1935	Abschwächungen
```

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

Mustafa 2013: Interpreting the output

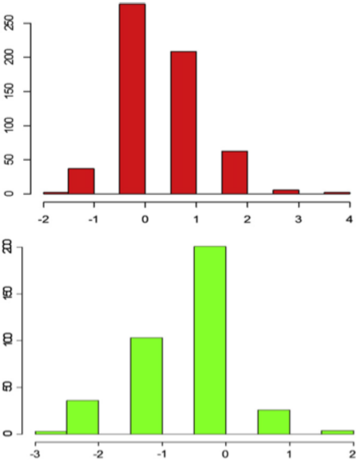


Fig. 5. Sentiment scores for Nokia (top) and Pfizer (bottom). *X*-axis represents score distributions, *Y*-axis represents count/frequencies.

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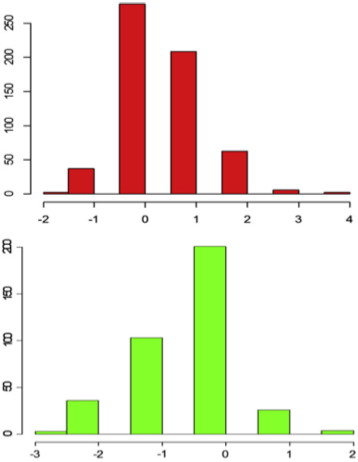

Fig. 5. Sentiment scores for Nokia (top) and Pfizer (bottom). *X*-axis represents score distributions, *Y*-axis represents count/frequencies.

Your thoughts?

Mustafa 2013: Interpreting the output

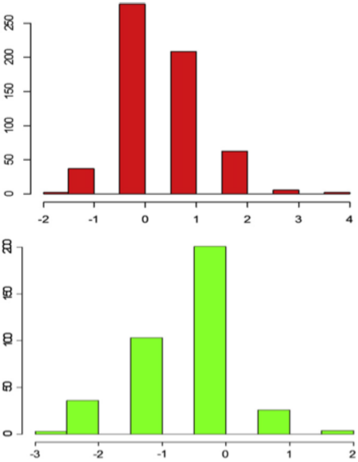

Fig. 5. Sentiment scores for Nokia (top) and Pfizer (bottom). *X*-axis represents score distributions, *Y*-axis represents count/frequencies.

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 Koningrijk: 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, reproducability)

e.g., Schut, L. (2013). Verenigde Staten vs. Verenigd Koningrijk: 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

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 Sentistrenght algorithm

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

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

```
from pattern.nl import sentiment
>>> sentiment("Great service by @NSHighspeed")
(0.8, 0.75)
>>> sentiment("Really")
(0.0, 1.0)
>>> sentiment("Really Great service by @NSHighspeed")
(1.0, 1.0)
```

(polarity, subjectivity) with
$-1 \leq \textit{polarity} \leq +1$
$0 \leq \textit{subjectivity} \leq +1$)

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

pro

- understand intensifiers or negation
- thus: higher accuracy

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!

A sentiment analysis tailored to your needs!

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

Already this still relatively simple approach seems to work satisfactory, but if 106 scientists from 24 competing teams (!) work on it, they can

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/articles/PMC3299408?pdf=render

Already this still relatively simple approach seems to work satisfactory, but if 106 scientists from 24 competing teams (!) work on it, they can

group suidide 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/articles/PMC3294408?pdf=render

Packages for sentiment analysis

Which packages are easy to use?

vader pro: in NLTK module, con: English only

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vader: Chapter 6.3; pattern: Chapter 6.5; sentistrength: Chapter 6.4

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vader pro: in NLTK module, con: English only

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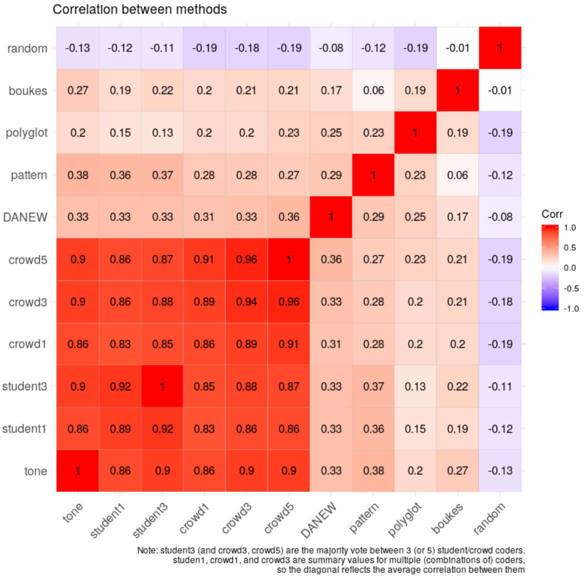
sentistrength pro: multiple languages, widely used, con: needs Python wrapper, license

vader: Chapter 6.3; pattern: Chapter 6.5; sentistrength: Chapter 6.4

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



Boukes, M., van der Velde, R.N., & Vliegenthart, R. (2018). The good and bad in economic news: Comparing (automatic) measurements of sentiment in Dutch economic news. *International Communication Association*

Packages for sentiment analysis

Category	Technique	Accuracy	Precision	Recall
Satisfaction ($N = 854$)				
Sentiment analysis	LIWC	0.05	0.06	0.04
	P	0.04	0.04	0.04
	SN	0.07	0.07	0.08
Dictionary-based	D	0.15	0.30	0.10
Machine learning	BNB	0.38	0.44	0.34
	MNB	0.32	0.67	0.21
	LR	0.51	0.38	0.76
	SGD	0.49	0.38	0.69
	SVM	0.52	0.41	0.63
	PA	0.50	0.40	0.68
Neutral ($N = 760$)				
Sentiment analysis	LIWC	0.13	0.16	0.10
	P	0.13	0.13	0.14
	SN	0.19	0.16	0.22
Dictionary-based	D	0.14	0.35	0.09
Machine learning	BNB	0.28	0.25	0.32
	MNB	0.15	0.34	0.10
	LR	0.37	0.25	0.74
	SGD	0.33	0.23	0.60
	SVM	0.36	0.24	0.69
	PA	0.34	0.24	0.60
Dissatisfaction ($N = 267$)				
Sentiment analysis	LIWC	0.20	0.15	0.29
	P	0.19	0.12	0.40
	SN	0.22	0.14	0.54
Dictionary-based	D	0.09	0.41	0.05
Machine learning	BNB	0.26	0.20	0.40
	MNB	0.25	0.48	0.16
	LR	0.35	0.23	0.77
	SGD	0.39	0.32	0.48
	SVM	0.04	0.02	1.00
	PA	0.35	0.23	0.71

Note. LIWC *Linguistic Inquiry and Word Count*; P *Pattern*; SN *Sentiment Net*; D *Dictionary-based*; BN *Bernoulli Naïve Bayes*; MNB *Multinomial Naïve Bayes*; LR *Logistic Regression*; SGD *Stochastic Gradient Descent*; SVM *Support Vector Machine*; and PA *Passive Aggressive*. Performance scores ≥0.60 have been highlighted. Results merely derived from the test set.

Vermeer, S. A. M., Araujo, T., Bernritter, S. F., & van Noort, G. (2019). Seeing the wood for the trees: How machine learning can help firms in identifying relevant electronic word-of-mouth in social media. International

A possible receipe for doing your sentiment analysis

1. Construct a list `data` of strings with your input data
2. Create an empty list `sent` for storing the results
3. For each text `t` in `data`, estimate the sentiment of `t` and append the result to `sent`[1]
4. Confirm that `len(data) == len(sent)`
5. use `zip()` and a `csv.writer` to write input and output next to each other to a csv file.

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

Superivsed ML (⇒ week 9)

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 neccessary.
- Approaches to the analysis (e.g., structure vs. content)
- Types of sentiment analysis, application areas, pros and cons

Mid-term take home exam

Week 5: Friday, 6 March, to Tuesday, 10 March

- You get the exam on Friday at the end of the meeting
- Answers have to be handed in no later than Tuesday evening, 23.59
- 20% of final grade
- 3 questions:
    1. Literature question: E.g., different methods ("Explain how... is done") and/or epistemological or theoretical implications ("What does this mean for social-scientific research?")
    2. Empirical question (conceptual)
    3. Empirical question (actual programming task)

If you *fully* understood all exercises until now, it shouldn't be difficult and won't take too long. But give yourself *a lot* of buffer time!!!

Next meetings

Friday, 28–2

Task for during the meeting: Conduct an own sentiment analysis! You can bring your own data (you will probably learn more!), but then already think about how to write some script to read the data (as we did last week and as described in Chapter 5).