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 receipe
   - Machine Learning as alternative
3. NLP-preview: Stopword removal
   - Natural language processing
   - A simple algorithm
4. 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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- handle JSON files

with regard to analysis:

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

Data analysis: Overview
What can we do?

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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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⇒ **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

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

Systematizing analytical approaches

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Analyzing the *content*

- Sentiment analysis
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- Co-word analysis ($\Rightarrow$frames)

$\Rightarrow$ **Focus on what is said**

Systematizing analytical approaches

$\Rightarrow$ **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

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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- *subjectivity*: neutral—subjective *

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- advanced approaches: different emotions

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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).

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

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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`)

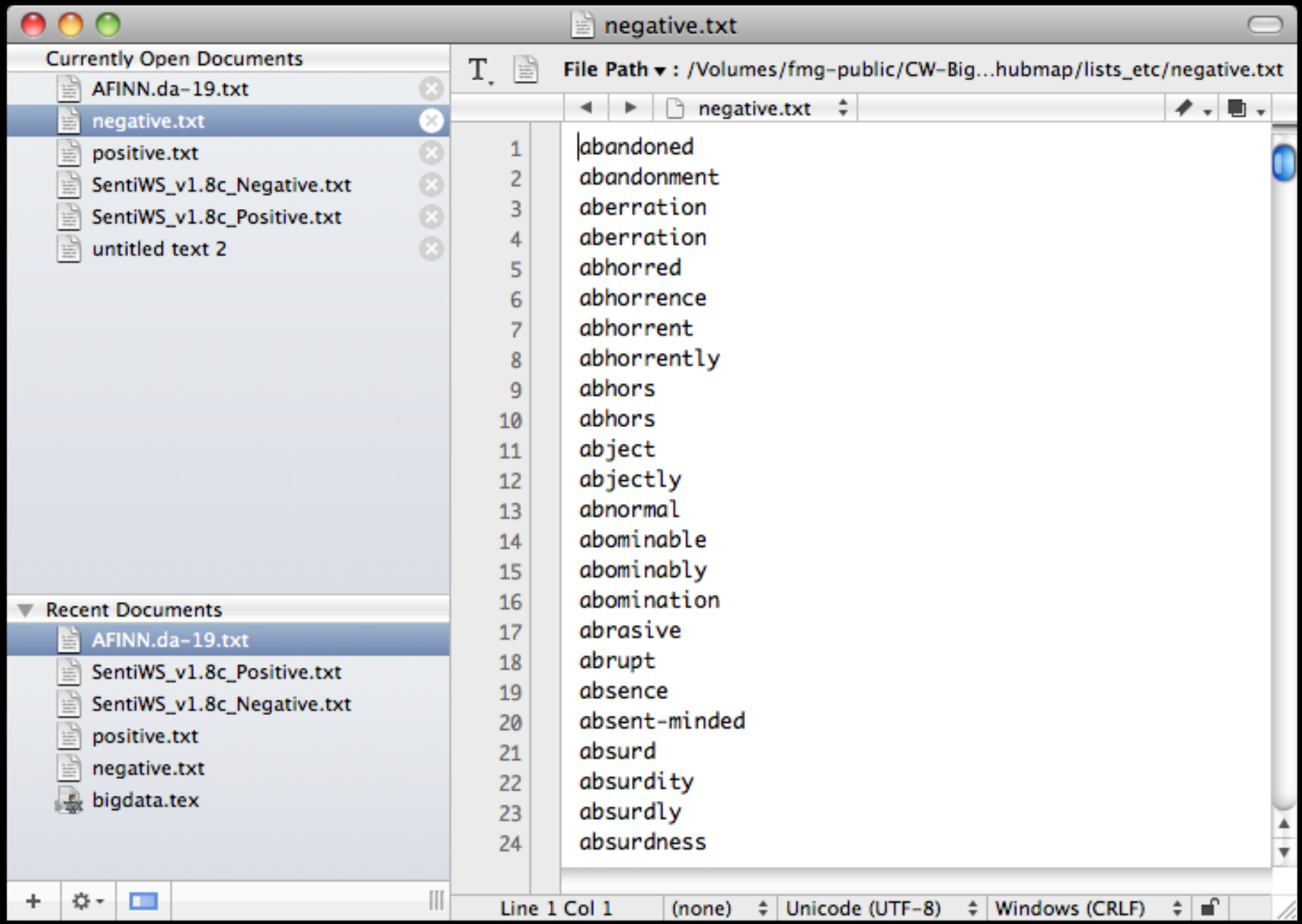
```
sentiment=0
for woord in tekst.split():
    if woord in lijstpos:
        sentiment=sentiment+1  #same as sentiment+=1
    elif woord in lijstneg:
        sentiment=sentiment-1  #same as sentiment-=1
print (sentiment)
```

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

No.

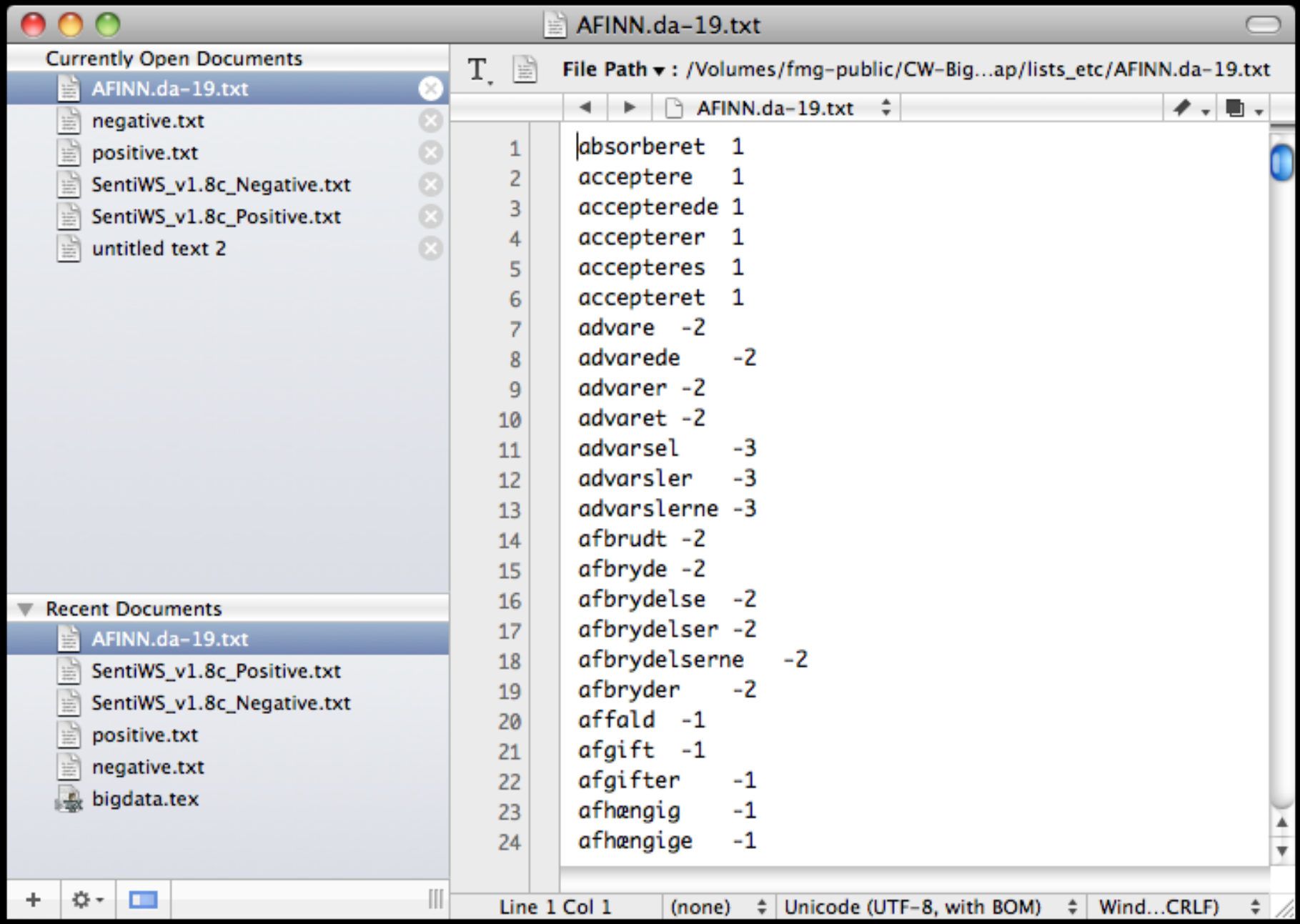
You could have them in a separate text file, one per row, and then read that file directly to a list.

```
1 poslijst=open("filewithonepositivewordperline.txt").read().splitlines()
2 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
1 abandoned
2 abandonment
3 aberration
4 aberration
5 abhorred
6 abhorrence
7 abhorrent
8 abhorrently
9 abhors
10 abhors
11 abject
12 abjectly
13 abnormal
14 abominable
15 abominably
16 abomination
17 abrasive
18 abrupt
19 absence
20 absent-minded
21 absurd
22 absurdity
23 absurdly
24 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
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negative.txt
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SentiWS_v1.8c_Negative.txt
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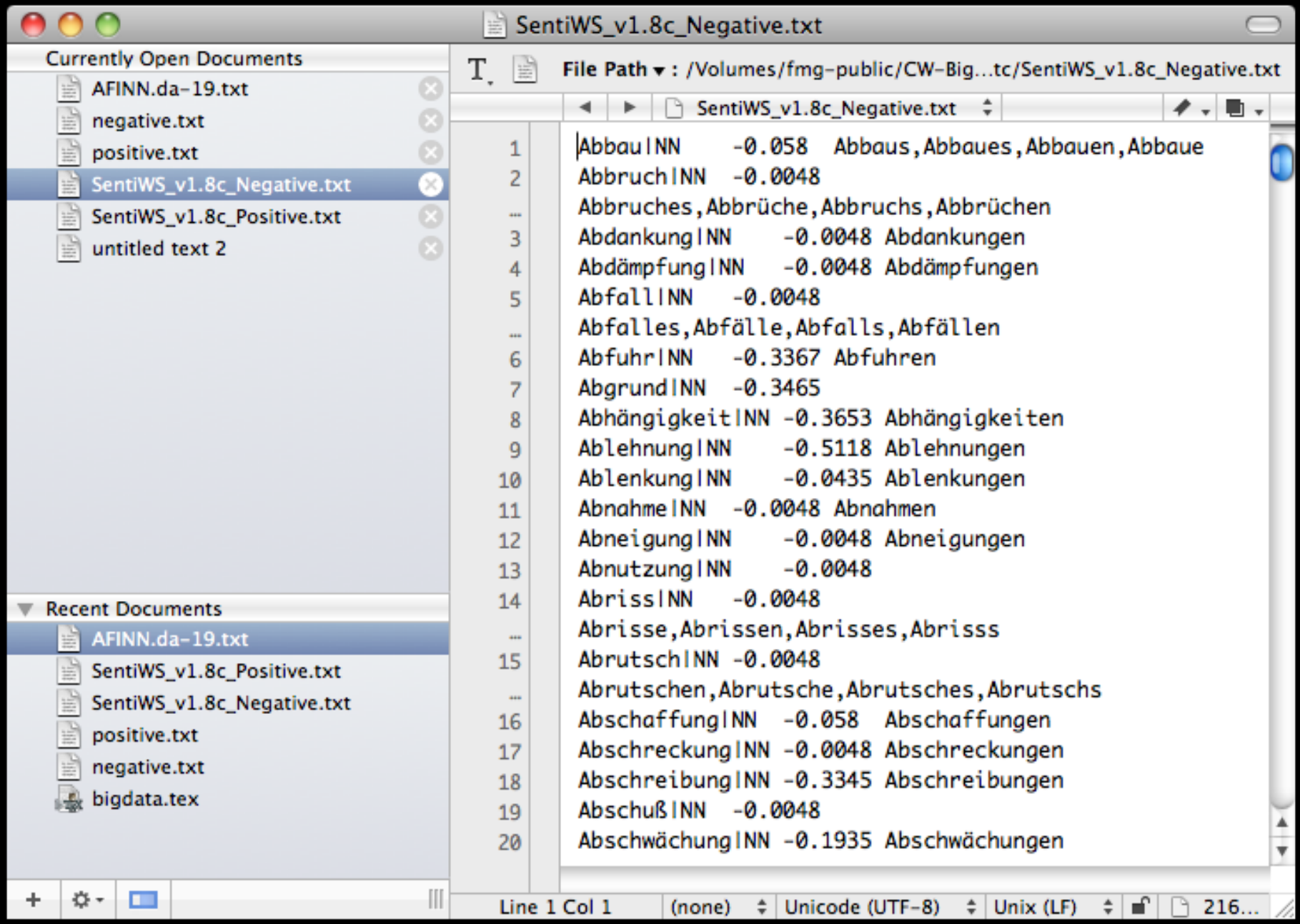
AFINN.da-19.txt
SentiWS_v1.8c_Positive.txt
SentiWS_v1.8c_Negative.txt
positive.txt
negative.txt
bigdata.tex
File Path : /Volumes/fmg-public/CW-Big...ap/lists_etc/AFINN.da-19.txt
AFINN.da-19.txt
absorberet 1
acceptere 1
accepterede 1
accepterer 1
accepteres 1
accepteret 1
advare -2
advarede -2
advarer -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)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File Path : /Volumes/fmg-public/CW-Big...tc/SentiWS_v1.8c_Negative.txt
SentiWS_v1.8c_Negative.txt
1 Abbau|NN -0.058 Abbaus,Abbaues,Abbauen,Abbaue
2 Abbruch|NN -0.0048
... Abbruches,Abbrüche,Abbruchs,Abbrüchen
3 Abdankung|NN -0.0048 Abdankungen
4 Abdämpfung|NN -0.0048 Abdämpfungen
5 Abfall|NN -0.0048
... Abfalles,Abfälle,Abfalls,Abfällen
6 Abfuhr|NN -0.3367 Abfuhren
7 Abgrund|NN -0.3465
8 Abhängigkeit|NN -0.3653 Abhängigkeiten
9 Ablehnung|NN -0.5118 Ablehnungen
10 Ablenkung|NN -0.0435 Ablenkungen
11 Abnahme|NN -0.0048 Abnahmen
12 Abneigung|NN -0.0048 Abneigungen
13 Abnutzung|NN -0.0048
14 Abriss|NN -0.0048
... Abrisse,Abrissen,Abrisses,Abrisss
15 Abrutsch|NN -0.0048
... Abrutschen,Abrutsche,Abrutsches,Abrutschs
16 Abschaffung|NN -0.058 Abschaffungen
17 Abschreckung|NN -0.0048 Abschreckungen
18 Abschreibung|NN -0.3345 Abschreibungen
19 Abschuß|NN -0.0048
20 Abschwächung|NN -0.1935 Abschwächungen
Line 1 Col 1
(none)
Unicode (UTF-8)
Unix (LF)
216...

Mustafa 2013: Interpreting the output

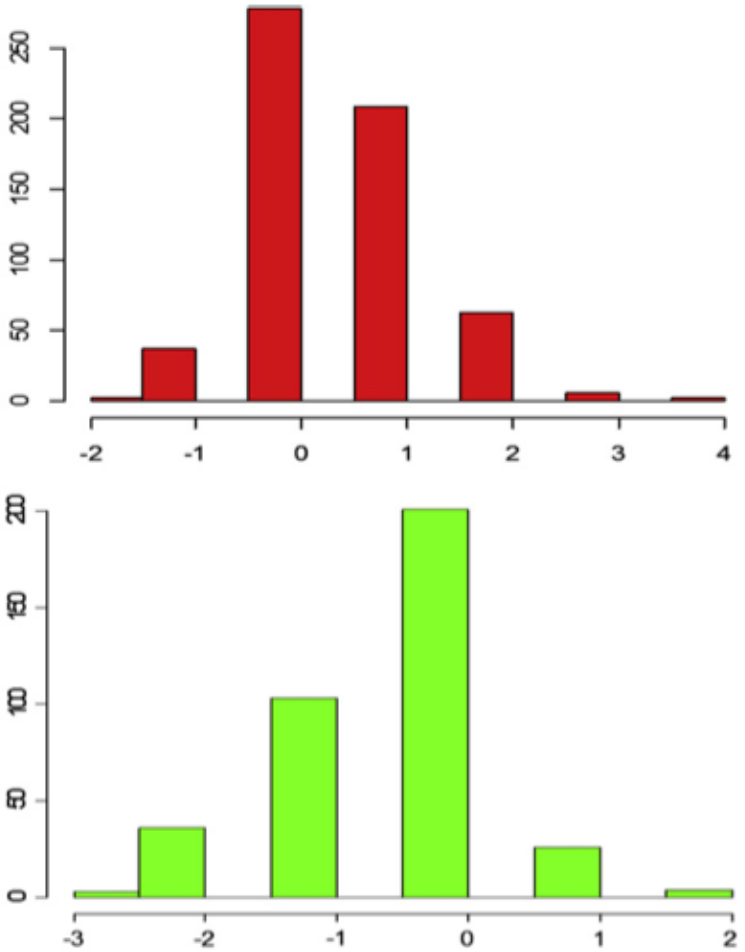

Fig. 5. Sentiment scores for Nokia (top) and Pfizer (bottom). *X*-axis represents score distributions, *Y*-axis represents count/frequencies.

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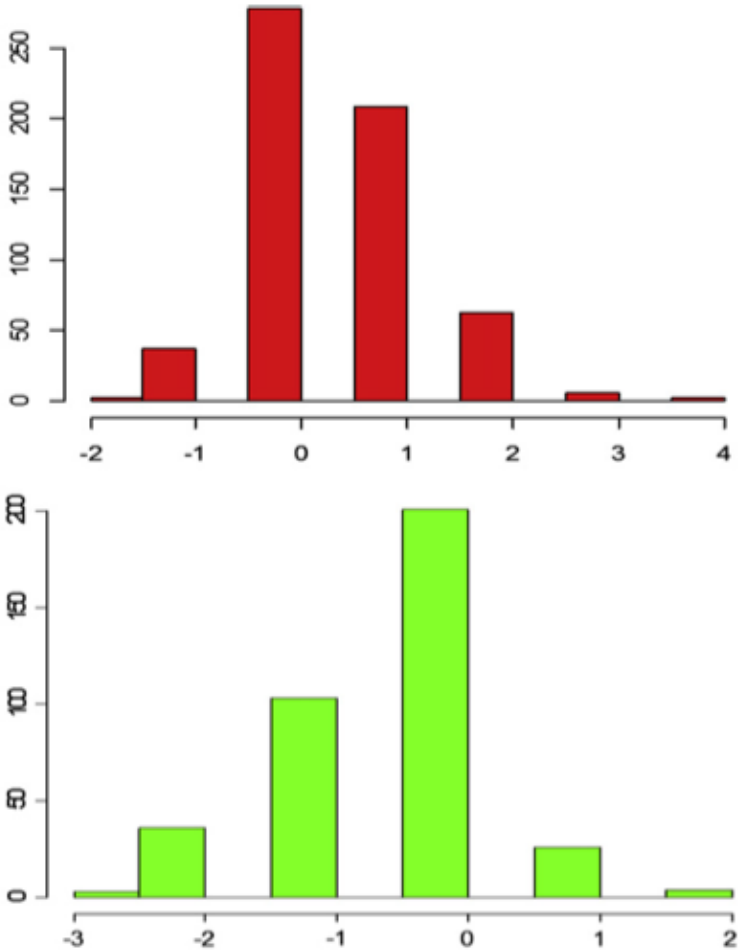

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Your thoughts?

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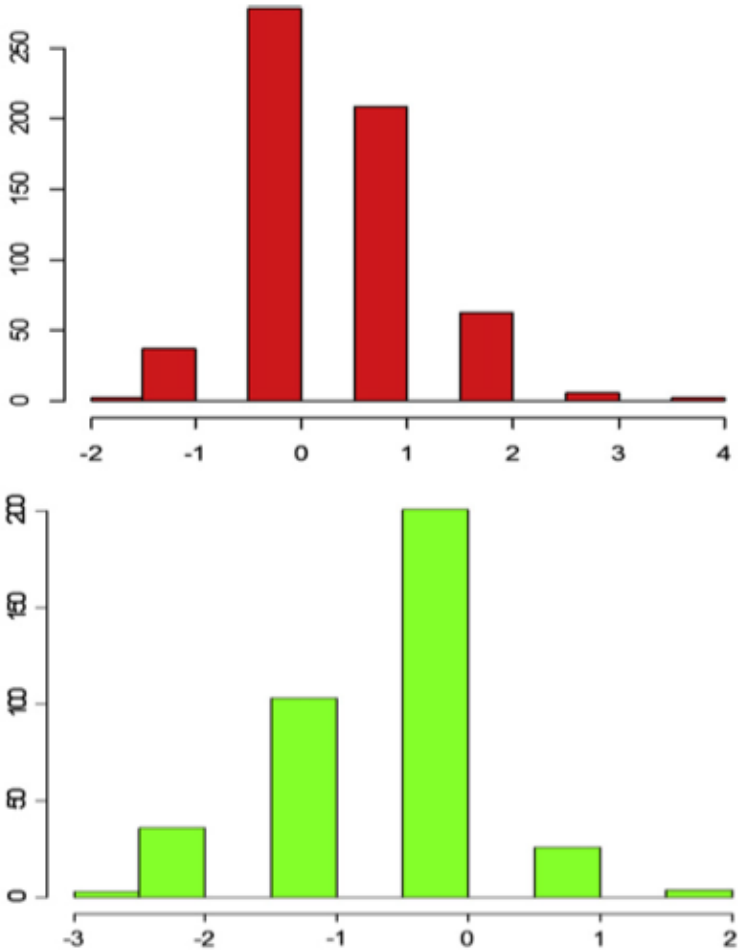

Fig. 5. Sentiment scores for Nokia (top) and Pfizer (bottom). *X*-axis represents score distributions, *Y*-axis represents count/frequencies.

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 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

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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/PMC3299408?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	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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BUT: Keep in mind that the results of *any* off-the-shelf-package might be biased and/or noisy in *your* domain!

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

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.

Since the 6 ECTS course lasts only 7 weeks of teaching, SML is no part of the required curriculum. But SML is explained in detail in the book and you may use it for your final project if you want (the same holds true for UML).

Natural Language Processing preview:
Stopword removal

Natural Language Processing preview:
Stopword removal

Why now? — Because the logic of the algorithm is very much related to the one of our first simple sentiment analysis

Stopword removal: What and why?

Why remove stopwords?

- If we want to identify key terms (e.g., by means of a word count), we are not interested in them
- If we want to calculate document similarity, it might be inflated
- If we want to make a word co-occurance graph, irrelevant information will dominate the picture

Stopword removal: How

```
testo='He gives her a beer and a cigarette.'
testonuovo=""
stopwords=['and','the','a','or','he','she','him','her']
for verbo in testo.split():
   if verbo not in stopwords:
      testonuovo=testonuovo+verbo+" "
```

What do we get if we do:

```
print (testonuovo)
```

Can you explain the algorithm?

We get:

```
1 >>> print (testonuovo)
2 'He gives beer cigarette. '
```

Why is "He" still in there?

How can we fix this?

Stopword removal

```
1  testo='He gives her a beer and a cigarette.'
2  testonuovo=""
3  stopwords=['and','the','a','or','he','she','him','her']
4  for verbo in testo.split():
5     if verbo.lower() not in stopwords:
6        testonuovo=testonuovo+verbo+" "
```

Take-home message
Final project
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

Final project

Formal criteria

See course manual

Finding a topic

- Think of some data that you can collect and that interest you (via an API or maybe some scraping).
- Think of interesting analyses.
- Simple data collection: invest more in analysis. Very complex data collection: simpler analysis.

E-mail me if you have ideas you want to discuss!

Next meeting

Thursday: lab sesson 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!