BAN432
Applied Textual Data Analysis for Business and Finance

Introduction to Sentiment Analysis

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Packages for today's lecture:

- `rtweet`
- `sentimentr`
- `dplyr`
- `lexicon`
- `stringr`
- `reshape2`
- `ggplot2`

Data file:

`data_for_lecture_11_2022.Rdata`

Plan for today's lecture

(1) Short introduction to sentiment analysis
(2) Relationship between sentiment and stock prices: Example with TSLA and AAPL
(3) Relationship between tweet frequency and sentiment: Examples from airline tweets
(4) Analysis of Snapchat tweets: Sentiment as a long term indicator

Sentiment analysis – introduction

- text data is generated by humans and thus subjective
- difference between text data and other data is that text data contains opinions
  - "This laptop has a battery" (objective)
  - "This laptop has the best battery of all" (subjective)
- opinion-rich text sources such as blogs, customer reviews and social media can be exploited to capture a trend
- companies monitor and analyze these text sources and respond e.g. by modifying:
  - investor sentiment (trading decisions based on sentiment)
  - marketing messages
  - brand positioning
  - product development

Sentiment analysis – introduction (cont.)

- sentiment analysis is the automatic analysis of evaluative text
- it classifies the polarity of a text (or part of it), typically as positive, neutral or negative
- sentiment analysis tools are often based on "bag-of-word" models:
  - words are looked up in a dictionary
  - positive words get a positive sentiment score
  - negative words get a negative sentiment score
  - the overall sentiment of a text is the sum of the individual sentiment scores
  - often the score is weighted (e.g. nr. of words in the text or presence of intensifiers)

(1) This is a *good* restaurant. (score 1 = positive)

(2) This restaurant is neither *good* nor *bad*. (score 0 = neutral)

Sentiment analysis – introduction (cont.)

- the dictionary approach to sentiment can be error prone
  - depending on the dictionary, the results may vary a lot
  - the language input can create problems (e.g. slang, misspellings)
- better results are archived by using supervised machine learning approaches

Dictionary based sentiment analysis of tweets in R

(1) The Twitter API
(2) Package **`rtweet`**
(3) Package **`sentimentr`**

(1) The Twitter API

The Twitter-API:

- allows queries of recent or popular tweets
- behaves similarly to, but not exactly like the search on Twitter webpage
- searches against a sampling of recent tweets published in the past 7 days
- does not return a complete list of tweets that match the query
- the search API is free, but comes with limitations
- Twitter offers solutions without limitations, but they are not free
- user authentication required (you need a Twitter account)

(2) The package **rtweet**

- **`rtweet`** offers many functions to retrieve data from the Twitter API, see the documentation
- e.g.:
  - the function **`get_timelines()`**: returns up to 3,200 statuses posted to the timelines of each of one or more specified Twitter users
  - the function **`lists_members()`**: gets Twitter list members (users on a given list)

The package **sentimentr**

- there are several packages for *R* that compute sentiment scores for textual data
- we use the package `sentimentr` (feel free to use others)
- `sentimentr`:
  - can be used with many sentiment dictionaries, e.g. those included in the package **lexicon**
  - "bag-of-words" approach
  - tokens in the input are looked up in the wordlist(s)
- structure of a sentiment dictionary:

```
# The "jockers_rinker" dictionary is the standard lexicon in sentimentr
dict <- lexicon::hash_sentiment_jockers_rinker
dict[1:5,]
```

```
##               x     y
## 1:       a plus  1.00
## 2:      abandon -0.75
## 3:    abandoned -0.50
## 4:    abandoner -0.25
## 5: abandonment -0.25
```

(3) The package **sentimentr** (cont.)

- sentiment is calculated by the functions **sentiment()**, or **sentiment_by()**

```
require(sentimentr)
text <- "I really liked the food. It was delicious."
sentiment(text)
```

```
##    element_id sentence_id word_count sentiment
## 1:          1           1          5 0.7244860
## 2:          1           2          3 0.2886751
```

```
sentiment_by(text)
```

```
##    element_id word_count        sd ave_sentiment
## 1:          1          8 0.3081648     0.5065806
```

- each word i looked up in the dictionary and a score is assigned
- each word in the surrounding of a match is looked up in a "valance shifter dictionary"; here the word *"really"* is an intensifier to *"liked"* and *"food"* $\rightarrow$ those word are weighted up.
- the functions split the text into sentences, convert **tolower()** and remove punctuation

Stock prices and sentiment

Bloomberg News and Social Sentiment Data

- Based on supervised machine learning (not word lists)
- Human annotators compile a dataset; for each tweet or news story they assign values -1, 0, 1 based on the question:

"If an investor having a long position in the security mentioned were to read this news or tweet, is he/she bullish, bearish or neutral on his/her holdings?"

- The data is fed into machine learning algorithms and the resulting model is used to classify new tweets/news storys

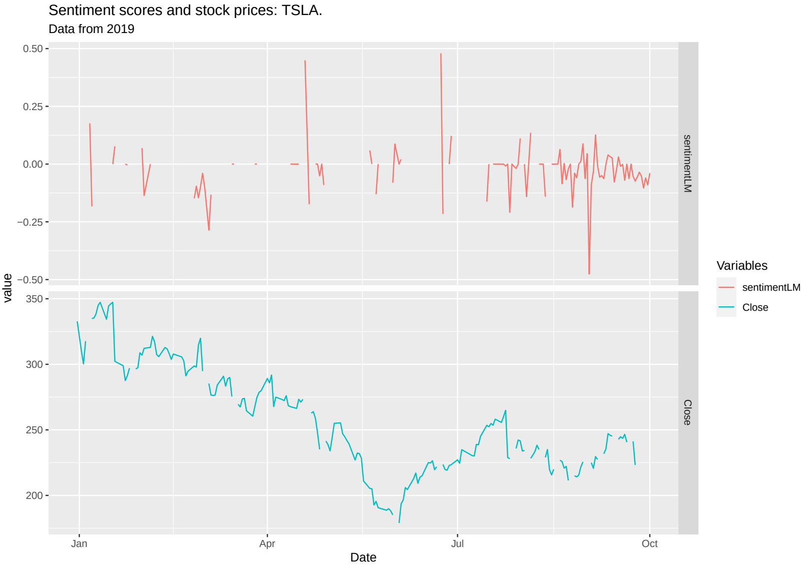
Bloomberg News and Social Sentiment Data (cont.)

Bloomberg calculates two scores:

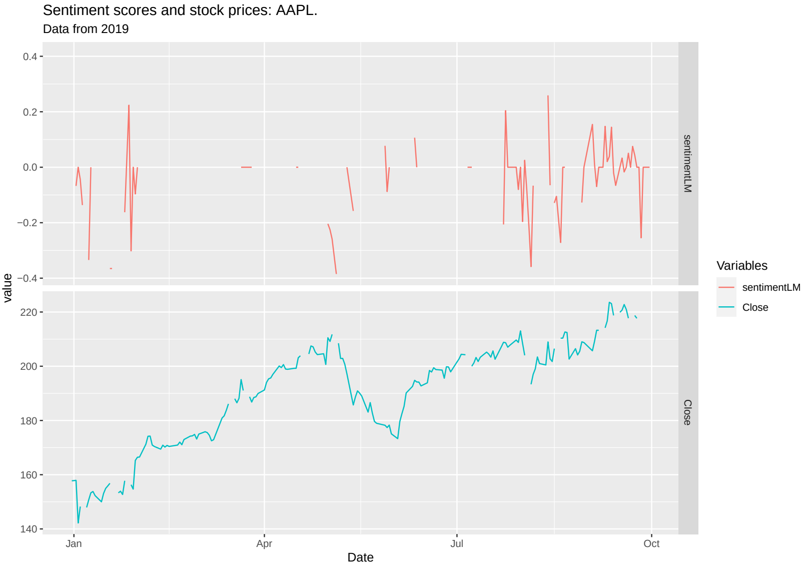
- Story-level sentiment:
  - real-time, when a story or tweet arrives
  - a categorial score (-1, 0, 1) and a confidence value (0 to 100)
- Company-level sentiment:
  - confidence weighted average of story level sentiment
  - a score ranging from -1 to 1
- Every morning, 10 minutes before the market opens, the company-level daily sentiment scores are published
  - average of the past 24h company-level sentiment scores

For details: download Bloomberg's whitepaper (you have to register)

Do stock prices and sentiment scores correlate?



Do stock prices and sentiment scores correlate?



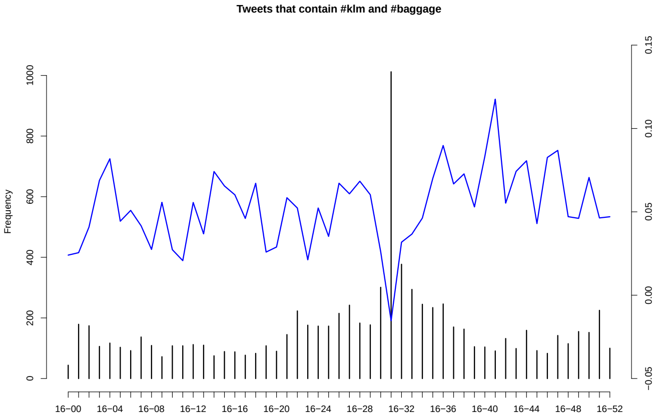
Preliminary conclusion:

- The averaged sentiment of the past 24h might predict opening prices next day (whitepaper by Bloomberg). Bloomberg uses supervised machine learning with a manually annotated training data set
- In our set up we were not able to show that time series plots of sentiment scores and stock prices are related.

Relationship between tweet frequency and sentiment

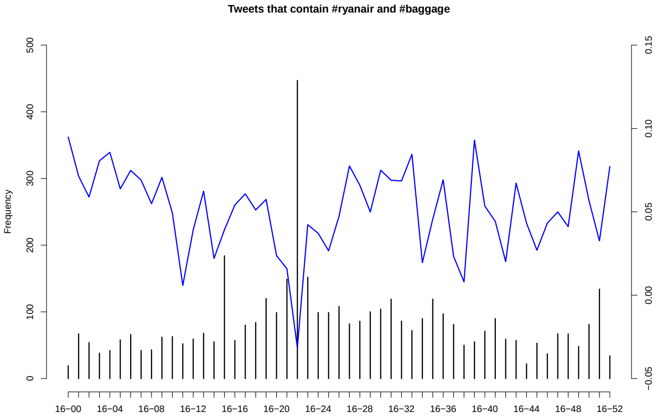
Examples from airline tweets

KLM – week 31 (cont.)



- increase in number of tweets posted per week correlates with falling sentiment in week 31
- what was the reason?

Ryanair – week 22

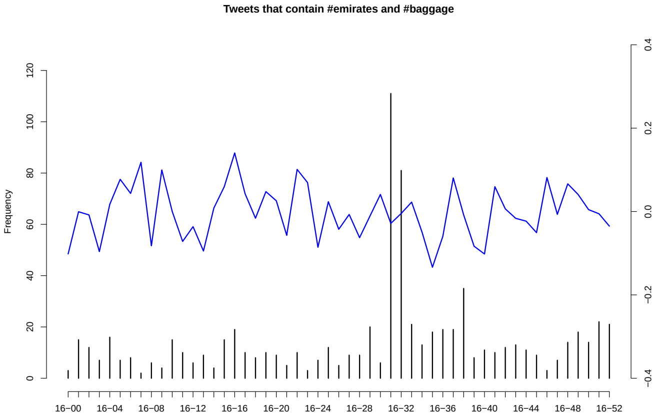


- increase in number of tweets posted per week correlates with falling sentiment in week 22
- what was the reason?

Wordcloud – Ryanair tweets week 22

- frequent words:
  - “fee”, “check”, “reduc”, “cut”
- what happened?

Emirates – week 31



- sentiment score seems unaffected of increased tweet activity
- what happend?

Summary airline tweets

- tweets seem to be a problematic text type for sentiment analysis tools
  - large variation when comparing the scores for single tweets
  - but: when grouped into bigger units (weeks or a year), the results seem more uniform
- problems with tweets:
  - misspellings,
  - non textual content (pictures),
  - colloquial language (“RU kidding?”)
- in our examples tweet frequency was related to events in the real world
- but the sentiment score was not necessarily linked to tweet frequency

Summary airline tweets (cont.)

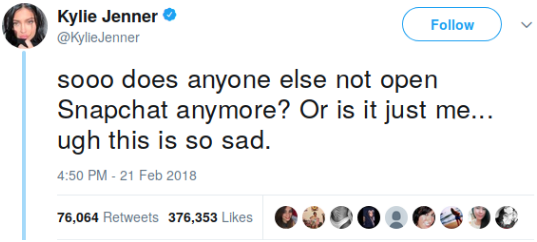
- re-tweets:
  - the same tweet might be counted several times
- tweets from the airline staff:
  - irrelevant for the customers view
- not all dictionaries cover “Twitter language”
  - `the woman at baggage Memphis just called me to tell me not to call customer service and then hung up on me.  RU KIDDING?`
- short texts:
  - unable to use context to determine sentiment
  - in longer texts, sentiment develops over a longer span of the text
- best results with english texts

Analysis of Snapchat tweets

Sentiment as a long term indicator

Snapchat – Introduction

- In early 2018 Snapchat implemented an update to their software.
- On February 21, 2018 the American reality star Kylie Jenner posted a tweet where she expressed her dissatisfaction with the latest Snapchat update.



Snapchat – Introduction

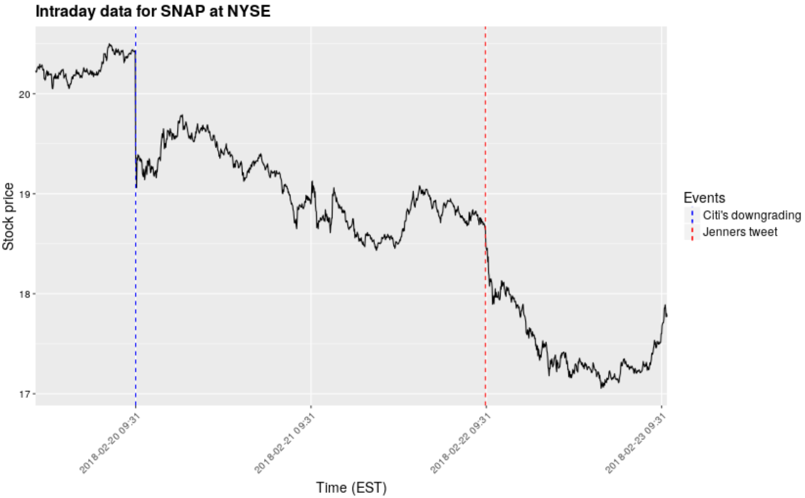
- Media reported that the Snapchat stock lost $1.3 billion after the tweet was posted.
- Jenner is considered to be a social-media influencer with 25.4 million followers on Twitter (April 2018) and her opinions and preferences presumably have an impact on her followers.

Snapchat – Introduction

- Soon after medias first reports that linked Jenners tweet to the stock loss, other reports turned up that mentioned Citi's sell recommendation as a reason for the massive losses.
- On Februray 20, the day before Jenners tweet, Citi issued a sell recommendation for Snapchat.
- Reasons: a flood of negative reviews of the app redesign and an online petition to bring back the old design that was signed by 1.2 million people.
- Kylie Jenner seems to be just one of a million Snapchat users that were unhappy with the new app design.

Snapchat – Introduction

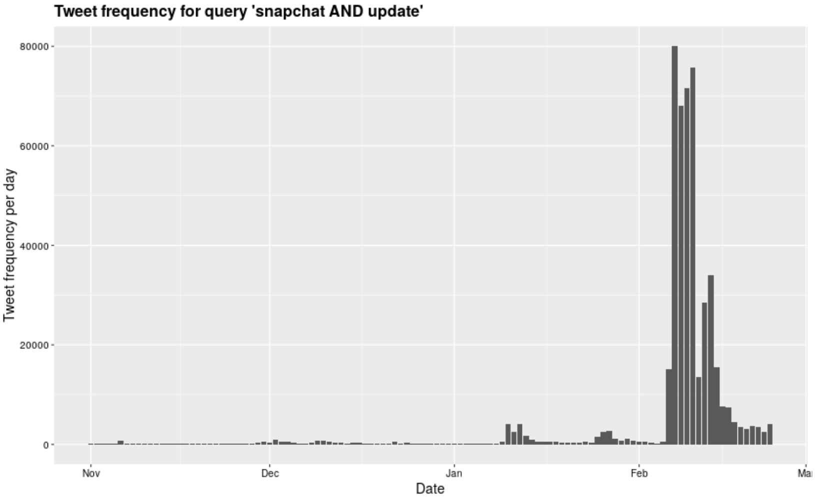
- There are two consecutive events that potentially had an influence on the development of the stock price.



Snapchat – Analyzing tweets

(1) tweet frequency
(2) tone in the tweets

Snapchat – Analyzing tweets: (1) frequency



Snapchat – Analyzing tweets: (1) frequency

- something must have happened around 6/7 February 2018 that made the number of tweets explode from a few hundred a day to almost 80,000
- that was actually the date when Snapchat rolled out their latest update!
- it was first announced on 29 November, 2017.
- at that point, the tweet frequency went up from an average of about 100 tweets per day to a top of about 900 tweets on 2 December, 2017

Snapchat – Analyzing tweets: (2) tone in tweets

- we use the afinn dictionary to calculate daily sentiment scores
- the afinn dictionary was designed for language on microblogs
- workflow:
  - as with the airline tweets
    - calculate sentiment score for each tweet
    - aggregate the tweets by the variable date and calculate the daily mean
  - make a `facet` plot
  - add a trend line to the sentiment plot

Snapchat – Analyzing tweets: (2) tone in tweets

Snapchat – Analyzing tweets: (2) tone in tweets

There are two interesting observations in the plot:

(1) Every time the tweet frequency increases the sentiment scores go down. This can be seen in the beginning of December, in the beginning and the end of January and in the beginning of February.

(2) The plot of the mean sentiment score was negative almost the entire time after the major update was announced in late November 2017.

Snapchat – Analyzing tweets: Conclusion

- The findings show negative sentiment scores for the time after the release of the update in the beginning of February 2018.
- Actually the negative tone was present in the tweets ever since the update was first announced in November 2017
- The negative tone in the tweets is in line with the low user ratings that Citi based their sell recommendation on

Summary

- dictionary based sentiment analysis of tweets is sometimes difficult because of the linguistic characteristics:
  - abbreviations
  - emotioncons convey meaning
  - misspellings
  - sarcasm
- a change in tone in tweets is often related to events in the real word
- the airline and #baggage example showed that this is not always the case
- tweet frequency can be a good indicator as well
- right dictionary is important!
- a big data set tends to compensate to a certain degree for these drawbacks