

01 – Opinion mining, sentiment analysis

IA161 Advanced Techniques of Natural Language Processing

Z. Nevěřilová

NLP Centre, FI MU, Brno

October 08, 2020

Opinion mining, sentiment analysis

Example 1:

So boring. I enjoyed the first book but this one really didn't work for me. The story, characters, and relationships all fell flat.

Example 2:

Lair of Dreams like everything else Miss Bray writes is mind-boggling. It's big. It's insanely atmospheric and it's creepstastic.¹

¹both examples from [goodreads.com](https://www.goodreads.com)

Opinion mining, sentiment analysis

Example 1:

So *boring*. I *enjoyed the first book* but *this one* really *didn't work* for me. The *story, characters, and relationships* all fell *flat*.

Example 2:

Lair of Dreams like everything else Miss Bray writes is *mind-boggling*. It's *big*. It's *insanely atmospheric* and it's *creeptastic*.¹

this book: boring
first book: enjoyed
this book: did not work
story: flat
characters: flat
relationships: flat

Lair of Dreams: mind-boggling
LoD: big
LoD: insanely atmospheric
LoD: creepstastic

¹both examples from goodreads.com

1 Opinion mining, sentiment analysis

2 Applications of opinion mining

3 Problem definition

4 Methods

Opinion mining, sentiment analysis

Opinion mining / sentiment analysis:

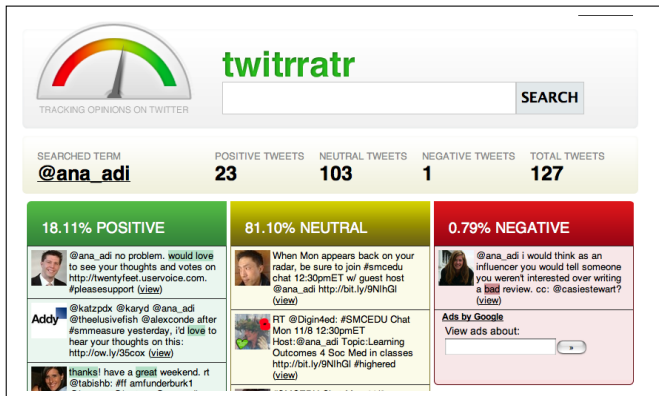
*Given a set of **subjective** texts that express opinions about a certain **object**, the purpose is to extract those **attributes** (features) of the object that have been commented on in the given texts and to **determine** whether these texts are positive, negative or neutral.
[Dinu and Iuga, 2012]*

Automatic opinion mining: why?

- many subjective texts exist
- mostly because of social media
 - ▶ people express their opinions in texts
 - ▶ one's opinions influence others' opinions
 - ▶ aggregation of opinions
- also, there are review sites that influence customer behavior
- emotions make part of a decision process (see [Minsky, 2007])

“Opinions” are key influencers of our behaviors. [Liu, 2012]

Opinion mining: applications




Opinion mining: applications

The screenshot displays the SEMANTRIA application interface within an Excel window. The ribbon includes FILE, HOME, INSERT, PAGE LAYOUT, FORMULAS, DATA, REVIEW, VIEW, and SEMANTRIA. The SEMANTRIA ribbon contains sections for 'Manage Analyses and Reports', 'Configurations', 'Text and Sentiment Analysis configuration', and 'Reporting Options'. The main workspace shows a tweet: 'thanks! have a great weekend. rt @tabishb: #ff amfunderburk1'. Two pie charts are generated: 'Entity Sentiment' and 'Categories Breakdown'. The 'Entity Sentiment' chart shows a distribution of negative (red), positive (green), and neutral (grey) sentiment. The 'Categories Breakdown' chart shows a distribution of categories: Hotels (blue), Video Games (red), Marriage (green), Automotive (purple), Beverages (orange), and Advertising (yellow). A 'Semantria for Excel' task pane is open on the right, showing a configuration dropdown set to 'English (English)' and a table of processed documents.

Name	Configuration	Documents	Created
Clients feed...	English	(101/101)	2014-05-13 15:31
Clients feed...	English	(101/101)	2014-05-13 13:29
Clients feed...	English	(101/101)	2014-05-10 14:02

Opinion mining: applications

**MALL.CZ**
★★★★★ 91%
4295 hodnocení

CENA A TERMÍN DODÁNÍ	★★★★★ (4237)
KOMUNIKACE ESHOPU	★★★★★ (4163)
OBSAH ZÁSILKY	★★★★★ (4113)
ZKUŠENOST S VRÁCENÍM ZBOŽÍ	★★★★★ (579)
ZKUŠENOST S REKLAMACÍ	★★★★★ (518)

Platba: On-line platby (PaySec, Raiffeisen banka),
Platba kartou (Euro Card, Maestro, Master Card, VISA,

Hodnocení

[Přidat hodnocení](#)

jirichott ★★★★★
Kritika: Nakupovat na MALLcz už nikdy! Jednou jsem to zkusil a byla to katastrofa.NEDOPORUČUJI!!!!

Lucie.P ★★★★★ (ověřený zákazník)
Chvála: velice spokojená

Jerry ★★★★★ (ověřený zákazník)
Kritika: Místo objednaného zboží došlo něco zcela jiného, což jsem zjistil až po několika týdnech, že zboží vůbec nemají a tudíž... :-)



Přidat fotky

Přehled recenzí



Pokoje · 2,2 ★★★★★

Někteří hosté uvedli, že koupelny jsou malé a že by mohly být čistější. · Z pokojů byl pěkný výhled.

Lokalita · 4,2 ★★★★★

Blízko zastávky veřejné dopravy. · Poblíž jsou obchody, pamětihodnosti, restaurace a bary. · Snadno dostupné autem

Služby a vybavení · 4,2 ★★★★★

Hostům se líbil přátelský a profesionální personál. · Hostům se líbila sauna a fitness centrum. · Hostům se líbila správa a recepce, ale někteří uvedli, že úklid by mohl být lepší.

MALL.CZ

MAL

★★★★★
4295

CENA A TERMÍN DODÁNÍ

KOMUNIKACE ESHOPU

OBSAH ZÁSILKY

ZKUŠENOST S VRÁCENÍM

ZKUŠENOST S REKLAMACÍ

Platba: On-line platby (

Platba kartou (Euro Ca



na MALLCz už nikdy! Jednou jsem to zkusil a teď už se nikdy nevrátím. DRUČUJI!!!!

★ (ověřený zákazník)

olená

★ (ověřený zákazník)

naného zboží došlo něco zcela jiného, čemuž jsem zjistil, že zboží vůbec nemají a tudíž

Opinion mining: related applications

- document sentiment classification:
This document contains a lot of negative statements.
- sentence subjectivity classification:
This sentence is objective.
- aspect-based opinion summarization/aggregation:
Most customers of your company think that the communication is not good.
- mining comparative opinions:
Many people think that iPhone is better than SG.
- utility or helpfulness of reviews:
This review is useless.
- cross-lingual opinion mining

Problem definition

What is an opinion?

- an evaluating proposition: *Linux is great.*
- a comparative proposition: *Linux is better than Windows.*

Problem definition

What is an opinion?

- an evaluating proposition: *Linux is great.*
- a comparative proposition: *Linux is better than Windows.*

*An opinion is simply a **positive or negative** sentiment, view, attitude, emotion, or appraisal about an **entity** or an **aspect of the entity** from an **opinion holder**. [Liu, 2012]*

Problem definition

What is an opinion?

- an evaluating proposition: *Linux is great.*
- a comparative proposition: *Linux is better than Windows.*

*An opinion is simply a **positive or negative** sentiment, view, attitude, emotion, or appraisal about an **entity** or an **aspect of the entity** from an **opinion holder**. [Liu, 2012]*

entity *e* is a product, person, event, organization, or topic: iPhone, Madonna, Microsoft ...

aspect *a* (feature) is a component of *e* or attribute of *e*: battery, price, appearance, communication skills ...

Problem definition

opinion = $(e_j, a_{jk}, so_{ijkl}, h_i, t_l)$, where

- e_j is a target entity.
- a_{jk} is an aspect/feature of the entity e_j .
- so_{ijkl} is the sentiment value of the opinion from the opinion holder h_i on feature a_{jk} of entity e_j at time t_l .
- h_i is an opinion holder.
- t_l is the time when the opinion is expressed.

Problem definition

opinion = $(e_j, a_{jk}, so_{ijkl}, h_i, t_l)$, where

- e_j is a target entity.
- a_{jk} is an aspect/feature of the entity e_j .
- so_{ijkl} is the sentiment value of the opinion from the opinion holder h_i on feature a_{jk} of entity e_j at time t_l .
- h_i is an opinion holder.
- t_l is the time when the opinion is expressed.

not just **one** problem

Problem definition

opinion = $(e_j, a_{jk}, so_{ijkl}, h_i, t_l)$, where

- e_j is a target entity.
named entity recognition
- a_{jk} is an aspect/feature of the entity e_j .
information extraction
- so_{ijkl} is the sentiment value of the opinion from the opinion holder h_i on feature a_{jk} of entity e_j at time t_l .
sentiment identification
- h_i is an opinion holder.
information extraction
- t_l is the time when the opinion is expressed.
information extraction

not just **one** problem

anaphora resolution + synonym matching

Problem granularity

Generally, find structure in **unstructured** data (text)

- document level opinion mining: *The document is negative.*
- sentence level: *The sentence is negative.*
- object/entity and feature/aspect level: *iPhone is expensive.*

Problem granularity

Generally, find structure in **unstructured** data (text)

- document level opinion mining: *The document is negative.*
- sentence level: *The sentence is negative.*
- object/entity and feature/aspect level: *iPhone is expensive.*

Classification task:

- 2-classes: positive/negative
- 3-classes: positive/negative/neutral
- 5-classes ...

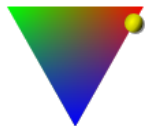
A hard problem (sometimes)

- opinion mining in tweets is relatively easy (short texts, hashtags) usually 3-classes classification for each tweet
- opinion mining in reviews is harder but still the form contains aspects and the reviewer has to mark the review positive/negative usually 2-classes classification for each aspect (e.g. high price)
- opinion mining in discussions, comments, blogs is very hard

sentiment lexicon

evaluative words: nice, cool, shit, bad...

SentiWordNet [Baccianella et al., 2010]



Positive: 0 Objective: 0.125 Negative: 0.875

blue = filled with melancholy and despondency

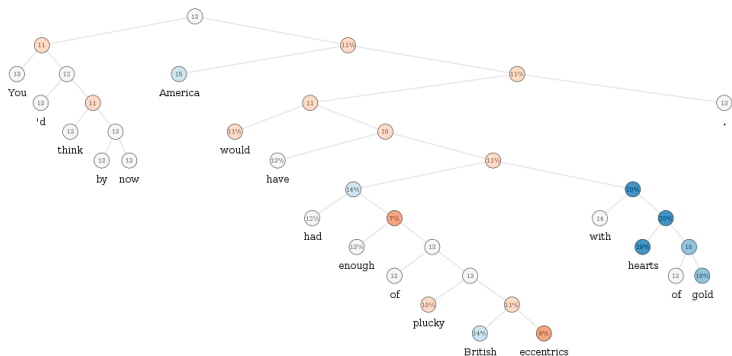
A hard problem (sometimes)

- opinion mining in tweets is relatively easy (short texts, hashtags) usually 3-classes classification for each tweet
- opinion mining in reviews is harder but still the form contains aspects and the reviewer has to mark the review positive/negative usually 2-classes classification for each aspect (e.g. high price)
- opinion mining in discussions, comments, blogs is very hard

evaluative word	aspect	sentiment
thin	phone	good
thin	steak	bad
high	value	good
high	price	bad
flat	story	bad
flat	phone	good

A hard problem (sometimes)

- opinion mining in tweets is relatively easy (short texts, hashtags) usually 3-classes classification for each tweet
- opinion mining in reviews is harder but still the form contains aspects and the reviewer has to mark the review positive/negative usually 2-classes classification for each aspect (e.g. high price)
- opinion mining in discussions, comments, blogs is very hard



Sentiment analysis methods: supervised machine learning

- 1 get example data with labels
- 2 extract features from the data, i.e. convert the documents to feature vectors
- 3 train the parameters (choose an algorithm: SVM, Naive Bayes, Neural Networks ...)
- 4 test the model

Sentiment analysis methods: supervised machine learning

- 1 get example data with labels
- 2 extract features from the data, i.e. convert the documents to feature vectors
- 3 train the parameters (choose an algorithm: SVM, Naive Bayes, Neural Networks ...)
- 4 test the model

Sentiment analysis methods: supervised machine learning

[Dinu and Iuga, 2012] report best results on Naive-Bayes with tokens as features and bigrams as features

[Liu, 2012] reports best results with SVM on balanced (English) data

currently (after 2014), neural networks are the most used technique

Note: use of word embeddings is questionable, since context vectors do not distinguish polarity (e.g. *good* and *bad* occur in similar contexts and thus have similar vectors).

Sentiment analysis methods: state-of-the-art results

- on political tweets, [Maynard and Funk, 2012]: **78% precision** and **47% recall**
- on document level (movie reviews)[Richa Sharma and Jain, 2014]: **63% accuracy** and **70% recall**
- sentiment embeddings [Tang et al., 2016]: outperform word2vec by about 6 percentage points,
F1 of Twitter Sentiment Classification on SemEval Datasets:
pos/neg class: **86.6%**
pos/neg/neu class: **67.5%**
hybrid ranking model (neural net catching context and sentiment) + text features (word n-grams, character n-grams, ...)
- a survey on using deep learning for sentiment analysis: [Zhang et al., 2018]

References I



Baccianella, S., Esuli, A., and Sebastiani, F. (2010).

Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining.

In Chair), N. C. C., Choukri, K., Maegaard, B., Mariani, J., Odijk, J., Piperidis, S., Rosner, M., and Tapias, D., editors, *Proceedings of the Seventh International Conference on Language Resources and Evaluation (LREC'10)*, Valletta, Malta. European Language Resources Association (ELRA).



Dinu, L. P. and Iuga, I. (2012).

The Naive Bayes classifier in opinion mining: In search of the best feature set.

In Gelbukh, A., editor, *Computational Linguistics and Intelligent Text Processing*, volume 7181 of *Lecture Notes in Computer Science*, pages 556–567. Springer Berlin Heidelberg.

References II



Liu, B. (2012).

Sentiment analysis and opinion mining.

Synthesis Lectures on Human Language Technologies, 5(1):1–167.



Maynard, D. and Funk, A. (2012).

Automatic detection of political opinions in tweets.

In García-Castro, R., Fensel, D., and Antoniou, G., editors, *The Semantic Web: ESWC 2011 Workshops*, volume 7117 of *Lecture Notes in Computer Science*, pages 88–99. Springer Berlin Heidelberg.






Minsky, M. (2007).

The Emotion Machine: Commonsense Thinking, Artificial Intelligence, and the Future of the Human Mind.

SIMON & SCHUSTER.

References III

-  Richa Sharma, S. N. and Jain, R. (2014).
Opinion mining of movie reviews at document level.
International Journal of Information Theory, 3(3):13–21.
-  Tang, D., Wei, F., Qin, B., Yang, N., Liu, T., and Zhou, M. (2016).
Sentiment embeddings with applications to sentiment analysis.
IEEE Transactions on Knowledge and Data Engineering,
28(2):496–509.
-  Zhang, L. J., Wang, S., and Liu, B. (2018).
Deep learning for sentiment analysis: A survey.
Wiley Interdiscip. Rev. Data Min. Knowl. Discov., 8.