

01 – Opinion mining, sentiment analysis

IA161 Natural Language Processing in Practice

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Opinion mining, sentiment analysis, emotion AI

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

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

Opinion mining, sentiment analysis, emotion AI

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: creeptastic

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

*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
- review sites influence customer behavior (decision making)
- framing in news (“freedom fighters” vs. “terrorists”)
- emotions make part of a decision process (see [Minsky, 2007])
- brand sentiment analysis is vital for companies, services, and celebrities

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

Opinion mining: applications



Opinion mining: applications

The screenshot shows the SEMANTRIA ribbon in Microsoft Excel, which is used for text and sentiment analysis. The ribbon includes sections for 'Manage Analyses and Reports', 'Configurations', 'Text and Sentiment Analysis configuration', and 'Reporting Options'. The 'Text and Sentiment Analysis configuration' section contains buttons for Summary, Sentiment, Entities, Themes, Phrases, Relevance, Categories, Queries, Facets, Auto Categories, Language Detection, Charts, and Output Settings. The 'Reporting Options' section includes Application Settings and About Semantria for Excel.

The task pane, titled 'Semantria for Excel', shows the current configuration set to 'English (English)'. It includes a table of analysis results:


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

Two charts are displayed in the task pane:

- Entity Sentiment:** A pie chart showing the distribution of sentiment for entities. The legend indicates: negative (red), positive (green), and neutral (grey).
- Categories Breakdown:** A pie chart showing the distribution of categories. The legend includes: Hotels (blue), Video Games (red), Marriage (green), Automotive (purple), Beverages (orange), and Advertising (yellow). A callout shows a zoomed-in view of the 'Hotels' category.

The main Excel window shows a text entry 'T32' in cell A1. A small text snippet is visible in the bottom left corner: 'thanks! have a great weekend. rt @tabishb: #ff amfunderburk1'.

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. Po několika týdnech jsem zjistil, že zboží vůbec nemají a tudíž... :-)

Opinion mining: applications



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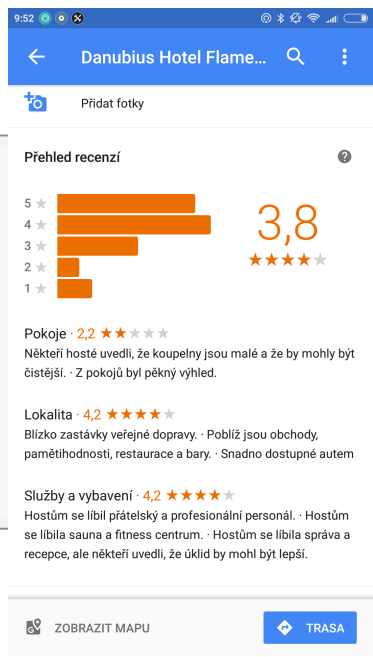
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9:52

Danubius Hotel Flame...

Přidat fotky

Přehled recenzí

5 ★ ██████████

4 ★ ██████████

3 ★ ██████████

2 ★ ██████████

1 ★ ██████████

3,8
★★★★★

Pokoje · 2,2 ★★★★★

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

Lokalita · 4,2 ★★★★★

Bližko 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.

ZOBRAZIT MAPU

TRASA

Opinion mining: applications

The screenshot displays the 'Opinion Observer' application interface. At the top, a browser window shows the URL 'Danubius Hotel Flame...'. The application window has a title 'Welcome to Opinion Observer' and a 'Tag Data' section. Below this is a 'Select Products' section with dropdown menus for 'Brand3' and 'Model1', and a list of selected products: 'Brand1 : Model2' (pink), 'Brand2 : Model1' (dark blue), and 'Brand3 : Model1' (light green). A 'Compare Them!' button is located below the list. The 'Tag Data' section shows a list of positive opinions for 'Brand1:Model2 [Reception]':

- No. 1: [It's got great reception.](#)
- No. 2: [The reception is ok.](#)
- No. 3: [Both have great reception.](#)
- No. 4: [great reception.](#)
- No. 5: [The voice clarity is awesome!!](#)
- No. 6: [Excellent reception.](#)

Below the tag data, there are five bar charts representing sentiment scores for different categories: General, LCD, Battery, Reception, and Speaker. Each chart compares the three selected products. The sentiment scores are as follows:

Category	Brand1 (Pink)	Brand2 (Dark Blue)	Brand3 (Light Green)
General	+11	+17	+9
LCD	+15	+8	+8
Battery	+6	+4	+1
Reception	+6	+5	+5
Speaker	+7	-	-

At the bottom of the application, there are buttons for 'ZOBRAZIT MAPU' (Show Map) and 'TRASA' (Route).

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.
- sarcasm detection:
I truly love to spend a night in this hotel.
- toxic speech detection:
No skills. Shut it down.
- cross-lingual opinion mining

Problem definition

What is an opinion?

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

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*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]*

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

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

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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 [+ machine translation]

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.*

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Classification task:

- 2-classes: positive/negative
- 3-classes: positive/negative/neutral
- 5-classes: polarity + intensity . . .

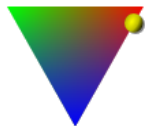
A hard problem (sometimes)

- 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

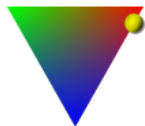
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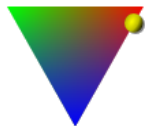
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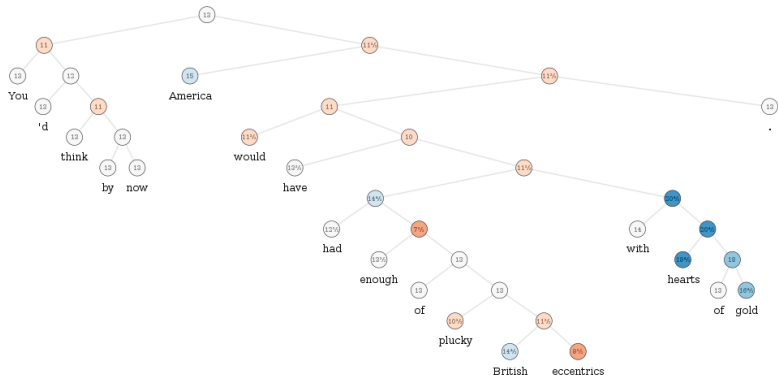


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A hard problem (sometimes) II

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



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
From approx. 2016, non-English SA performed using automatic translation.

Sentiment analysis methods: deep learning

Simple 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).

[Ma et al., 2018] LSTM with two-level attention (target-level + sentence-level)

SA is sometimes solved using multi-task oriented methods: Autoencoders (BERT), Autoregressive models, or combination (XLNet, [Yang et al., 2020])

Datasets for training

Lexicons (Word lists)

- SentiWordNet
`https://github.com/aesuli/SentiWordNet`
- afinn
`https://github.com/fnielsen/afinn`
- Subjectivity Lexicon
`http://mpqa.cs.pitt.edu/lexicons/`
- Bing Liu's Lexicon
`https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html`

Datasets for evaluation

Benchmarks for document sentiment classification

- IMDB Movie Reviews
`https://www.kaggle.com/lakshmi25npathi/sentiment-analysis-of-imdb-movie-reviews`
- Movie Review Data (Polarity dataset)
`https://www.cs.cornell.edu/people/pabo/movie-review-data/`
- Sentiment140
`http://help.sentiment140.com/for-students`
- OpinRank Review Dataset
`https://archive.ics.uci.edu/ml/datasets/opinrank+review+dataset`
- Toxic Comment Classification Challenge
`https://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge/data`

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

- on political tweets, [Maynard and Funk, 2012]: **78% precision** and **47% recall**
- on movie reviews (mixed), [Richa Sharma and Jain, 2014]: **63% accuracy** and **70% recall**
- on IMDB movie reviews, [Tang et al., 2009]: **88% accuracy**
- 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]
- XLNet [Yang et al., 2020] solves SA together with other tasks (multi-task): **97% accuracy** on SST-2 (binary classification).

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