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]

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

[1] both 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 / emotion AI:

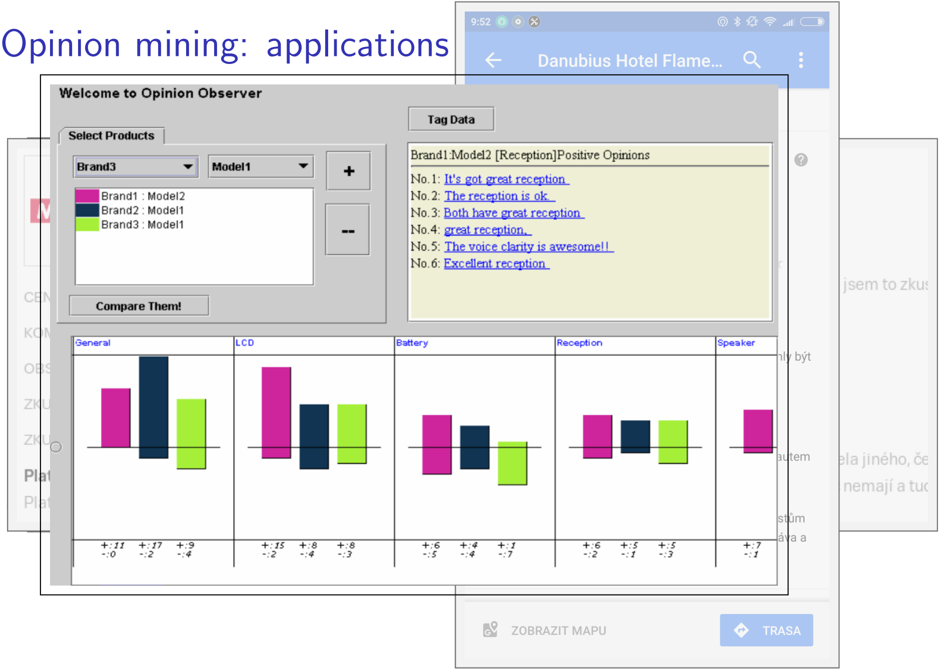
> *Given a set of subjective texts that express opinions about a certain object, the purpose is to extract those attributes (features) of the object that have been commented on in the given texts and to determine whether these texts are positive, negative or neutral. [Dinu and Iuga, 2012]*

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: 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.*

> *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, 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.
  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.*

Classification task:

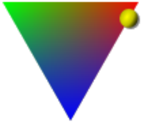
- 2-classes: positive/negative
- 3-classes: positive/negative/neutral
- 5-classes: polarity + intensity ...

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

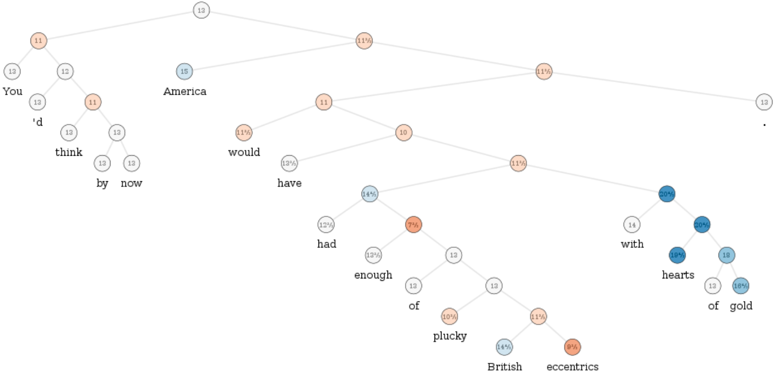
evaluative words: nice, cool, shit, bad...
SentiWordNet [Baccianella et al., 2010]



Positive: 0 Objective: 0.125 Negative: 0.875
blue = filled with melancholy and despondency

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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