Sentiment analysis

Prof. Luca Cagliero
Dipartimento di Automatica e Informatica
Politecnico di Torino



Outline

- Problem statement
- Levels and applications
- Subtasks
- The Sentiment Analysis pipeline
- State-of-the-art models

Sentiment analysis

- Extract writer's feeling, opinion, emotions, likes/dislikes
 Also known as opinion mining
- Identify the opinion/human behavior of a person from plain text
- It can rely either on traditional NLP rules or on Machine Learning

"I am happy with this water bottle."

"This is a bad investment."

"I am going to walk today."

Sentiment analysis

- Use cases
 - Hotel review analysis
 - News trading
 - Hate speech detection
 - Advertisement placing

0 ...

"I am happy with this water bottle."



"This is a bad investment,"



"I am going to walk today."



Example of sentiment analyzer: VADER

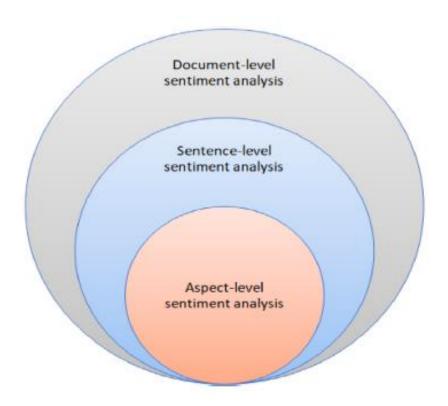
- Input sentiment_analyzer_scores("The phone is super cool.")
- Output
 The phone is super cool --- {'neg': 0.0, 'neu':0.326, 'pos': 0.674, 'compound': 0.7351}

https://github.com/cjhutto/vaderSentiment

Sentiment analysis: a special case of text categorization

- Assign a predefined label to a document or a text snippet
 - Also known as text classification
- Supervised process
 - given a set of labeled documents/snippets, learn how to automatically label new, unlabeled ones
- If multiple labels are allowed
 - multi-label text classification
- It can rely either on traditional NLP rules or on Machine Learning

Levels and applications of sentiment analysis



A comprehensive survey on sentiment analysis: Approaches, challenges and trends. Marouane Birjali, Mohammed Kasri, Abderrahim Beni-Hssane. Knowledge-Based Systems. 2021

Document-level sentiment analysis

- Classify whether the whole document expresses a negative or positive sentiment or opinion
- Works best when the document is written by one person
- Unsuitable for documents that evaluate/compare multiple entities
- Common approaches
 - Estimate the document sentiment polarity as a combination of the sentence-level scores
 - Embed document-level content into vector representations and measure the distance from labeled documents

Sentence-level sentiment analysis

- Classify a sentence that expresses
 - A factual information
 - A subjective expressing view
 - An opinion
- Can be based on entity recognition
- It does not find precisely what people like or dislike

Levels and applications of sentiment analysis

- Aspect-level
 - Fine-grained analysis
 - Find sentiments with respect to specific implicit aspects or entities
- Example

The camera of iPhone X is awesome but the battery does not last long



Entity Camera -> Positive sentiment Entity Battery -> Negative sentiment

Aspect-level sentiment analysis: example of application

- Hotel review analysis
 - Aspects
 - Location
 - Food
 - **■** WiFi
 - Service
 - Room
 - **...**



Image taken from https://www.trustyou.com/wp-content/uploads/2015/08/trivago.pnggo.png

Sentiment analysis: applications

- Business Intelligence
 - Make product/service improvements
 - Study the customers' feedback
 - Plan new marketing strategies
 - Forecast market movements
- Recommender systems
 - Suggest relevant items to users
 - E.g., movies, music, products to buy
- Government intelligence
 - Identify opinions on government policies
 - Monitor publics' mood in real time
- Healthcare
 - Shape healthcare services
 - Allow healthcare actors to obtain information about diseases, epidemics, treatments, patients' mood, etc.

Data sources for Sentiment Analysis

Social media

- Analysis of User-Generated Content
- Individual and collective life and behavior
- Web- and mobile-based Internet Applications

Review websites

- Where people can post opinions or reviews about a particular entity
- Often integrated into e-commerce platforms

Forums

Posting text messages to share thoughts and ideas

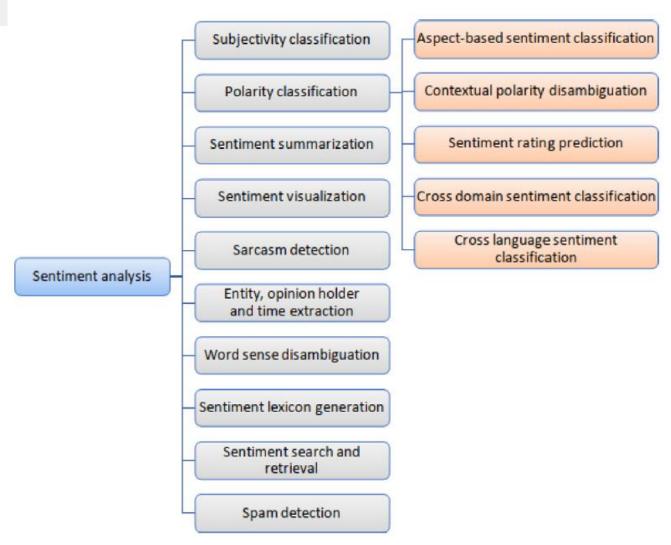
Interviews

- Transcripted record of completed oral interviews
- Either in real time or from audio or video recordings

Data connectors for Sentiment Analysis

- Application Programming Interfaces
 - Provide access to textual content using HTTP-based protocols
 - Based on search query
 - Keyword-based, location-based, etc.
- Open datasets
 - Data collected by academic institutions
 - Useful for Deep Learning model training
- Web scraping
 - Automatic process of extracting data from websites that hold valuable data
 - Main challenges: quality, noise, privacy
- Crowdsourcing
 - Outsource data creation or annotation
 - Useful for creating large data volumes in short time
 - E.g., Amazon Mechanical Turk (https://www.mturk.com/)

Sentiment analysis subtasks



A comprehensive survey on sentiment analysis: Approaches, challenges and trends. Marouane Birjali, Mohammed Kasri, Abderrahim Beni-Hssane. Knowledge-Based Systems. 2021

Data preprocessing for Sentiment Analysis

- Tokenization
 - Necessary for sentence- and aspect-level sentiment analysis
- Stopword removal
 - Unnecessary when embedding models are applied
- Text cleaning
 - Abbreviations/repetitions/punctuation can be relevant to sentiment detection
 - E.g., Oookkkkkkkkk!!!!!!

Feature extraction for Sentiment Analysis

- N-gram presence and frequency
 - Commonly used in Information Retrieval
 - Based on weighting scheme
 - E.g., Tf-idf, BM25
- POS tagging
 - Adjectives and adverbs are very important indicators of opinions

Feature extraction for Sentiment Analysis

Opinion words/phrases

- Expressions that are commonly associated with positive or negative sentiment
 - E.g., Worderful, awful
- They can be domain-dependent
 - E.g., *capital increase* in a financial news

Negations

- Also called opinion shifters or valence shifters
- Words that may shift/change the opinion orientation and reverse the sentiment polarity
 - E.g., not, never, nobody, nowhere, neither
- o <u>Important notice</u>
 - These words could be accidentally removed by stopword elimination

Feature selection for Sentiment Analysis

- Distinguish between
 - Relevant features
 - Irrelevant features (to be removed)
 - Redundant features (to be removed)
- Methods
 - Lexicon-based
 - Human-generated features
 - Collect term with a strong sentiment
 - Find synonyms etc.
 - Accurate but expensive!
 - E.g., WordNet
 - Statistical
 - Automatic feature analysis
 - Efficient but prone to errors

Statistical feature selection for Sentiment Analysis

- Filter approach
 - Based on statistical tests/measures applied to the training data
 - Chi Square test, Mutual Information, Information Gain
 - No Machine Learning
- Wrapper approach
 - Evaluate a subset of features based on the resulting performance of the applied ML algorithm
 - E.g., SVM classification
 - Computationally intensive

Statistical feature selection for Sentiment Analysis

- Embedded approach
 - Incorporate feature selection into the ML algorithm execution
 - Model dependent
 - E.g., decision trees
- Hybrid approach
 - A mix of the above

Supervised

- Require labeled data
 - Linear, probabilistic, rule-based, decision trees, etc.

Unsupervised

- Applied in the absence of labeled data
 - E.g., partition-based clustering, hierarchical clustering

Semi-supervised

- A small set of initial labeled data is used to guide the feature learning procedure
- Commonly associated with self-training
 - Step 1: the classifier is trained using a small amount of labeled data
 - Step 2: the trained classifier is used to classify the unlabeled data and transform them in the newly labeled data
 - Step 3: repeat Step 1 using all the labeled data (both new and old)

Generative

- It assumes that data in different polarity classes follow different distributions
- Estimate the distribution parameters
 - Requires at least one labeled data per class

Co-training

- It assumes that data can be represented by two independent views
 - Each view has information about each data
- Two separate classifiers are trained to teach each other based on the shared information between them
- The process stops when all unlabeled data have been used or a specific number of iterations has been reached

- Self-training
 - It assumes that data in different polarity classes follow different distributions
 - Estimate the distribution parameters
 - Requires at least one labeled data per class
- Graph-based
 - Model data as a graph
 - Vertices are instances
 - E.g., sentences
 - Edges indicate similarities between instances
- Multi-view learning
 - Treat the problem by considering multiple viewpoints
 - Train a classifier per view
 - o The overall result is an agreement between multiple views
 - As in ensemble methods

- Reinforcement learning
 - Based on a trial-and-error approach
 - An agent is rewarded in the next time step based on the evaluation at the previous stage
 - Foster interactions between the agent and the environment
 - Learn repetitive action-effect combinations
 - Similar to human beings

- Transfer learning
 - Also called cross-domain sentiment analysis
 - Apply the knowledge already learnt to address one task to another task
 - E.g., from movie reviews to book reviews
- Multimodal learning
 - Include modalities other than text
 - E.g., audio, video, images
 - Require information fusion
 - E.g., in a unified embedding space

- Deep Learning
 - Learn latent feature representation in both supervised and unsupervised manner
 - Require ad hoc computational resources

Deep Learning solutions

- Deep Learning
 - Learn latent feature representation in both supervised and unsupervised manner
 - Require ad hoc computational resources

Attention-based approaches to aspect-based sentiment analysis

- Adopt attention-based Neural Networks to implicitly aspects with opinion words
- Key idea
 - Opinion words usually do not appear too far from the aspect

Attention-based approaches to aspect-based sentiment analysis

- Explainable approach
 - Identify the aspects
 - E.g., using Named Entity Recognition
 - Analyze the attention score map to detect the words that mainly influence that aspect

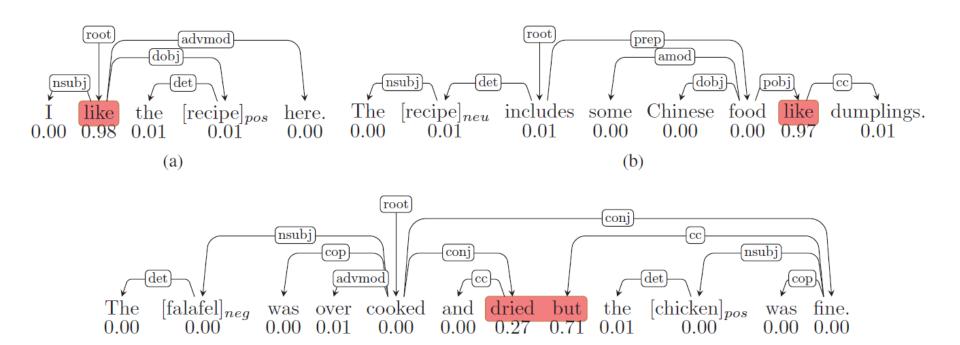
```
      Legend: ■ Negative □ Neutral ■ Positive

      True Label
      Predicted Label
      Attribution Label Attribution Score
      Word Importance

      1
      POSITIVE (1.00)
      POSITIVE 1.96
      [CLS] i like you , i love you [SEP]
```

Relational Graph Attention Network for Aspect-based Sentiment Analysis. Kai Wang, Weizhou Shen, Yunyi Yang, Xiaojun Quan, Rui Wang. ACL 2020: 3229-3238

Combine dependency parsing and attentionbased neural network learning



Relational Graph Attention Network for Aspect-based Sentiment Analysis. Kai Wang, Weizhou Shen, Yunyi Yang, Xiaojun Quan, Rui Wang. ACL 2020: 3229-3238

Additional reading on R-GAT



- Relational Graph Attention Network for Aspect-based Sentiment Analysis.
 Kai Wang, Weizhou Shen, Yunyi Yang, Xiaojun Quan, Rui Wang. ACL 2020: 3229-3238
- Download and read the paper: https://aclanthology.org/2020.acl-main.295/

Additional reading on Hate Speech Detection



- Hate speech detection using static BERT embeddings. Gaurav Rajput and Narinder Singh punn and Sanjay Kumar Sonbhadra and Sonali Agarwal. 2021
- Download and read the paper: https://arxiv.org/pdf/2106.15537.pdf

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Affiliation

- The author and his staff are currently members of the Database and Data Mining Group at Dipartimento di Automatica e Informatica (Politecnico di Torino) and of the SmartData interdepartmental centre
 - https://dbdmg.polito.it
 - https://smartdata.polito.it

Thank you!