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Introduction to Sentiment Analysis

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Setup

1. Git clone:

```
https://github.com/apmoore1/SentiLexTutorial.git
```

2. Within that directory run the following command:

```
pip3 install -r requirements.txt
```

3. Followed by this command:

```
python3 -m nltk.downloader stopwords
```

Sentiment Analysis Literature

What is Sentiment analysis?

is the field of study that analyzes people's opinions, sentiments, appraisals, attitudes, and emotions towards entities and their attributes expressed within text

[9]

Different levels of sentiment

1. Document

Coarse

2. Sentence

3. Aspect

Fine



Document sentiment analysis

Objective

To find the sentiment of a document.

Assumption

That the document is only discussing one entity

Datasets

1. Movie Reviews [21, 19, 12], hotel reviews [29], Amazon reviews [1, 6] and restaurant reviews (Yelp)¹.
2. Lots of labelled data out there '*in the wild*' and many more datasets that I have missed.

¹https://www.yelp.co.uk/dataset_challenge

User Reviews

★★★★★★★★★ **please made your own decision**

8 June 2017 | by

(egypt) – [See all my reviews](#)

stephen sommers two mummy movies are classic to me they are from best action adventure movies ever saw when this reboot announce i get so excited and worried in same time because the challenge was big but thank god the movie is great the story is unique the acting from all cast is great and sofia boutella performance was brilliant best mummy ever to me tom cruise very good like every time he do action movie the best thing in this movie is horror their are some good horror scenes this movie get bad review from critics like jack reacher movie that movie was good to me and entertainment please made your own decision and don't listening to any one including me don't let any body play in your head you are not a kid

37 of 67 people found this review helpful. Was this review helpful to you?

Yes

No

2

²This came from IDMB website <http://www.imdb.com/>

1. Original paper for document and sentiment analysis in general [21]
2. Unsupervised method [28]
3. Great evaluation across multiple datasets [18]
4. New Neural Network (NN) approach [31]

Sentence sentiment analysis

Objective

1. To find the sentiment of the sentence.

Datasets

1. Movie review sentences [20]

Papers

1. One of the original papers [14], used a joint model of sentence and document.
2. Comparisons of different sentence level sentiment classifiers over different datasets [22]
3. Recursive Neural Network approach RNN [25]

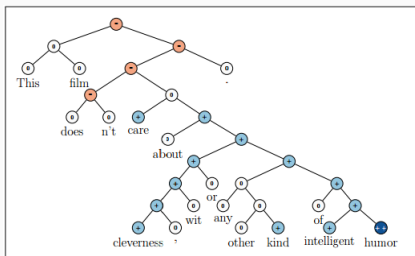
Sentence Examples



It's mildly entertaining, though its numerous famous screenwriters won't be bragging at parties about its originality.

June 19, 2017 | Rating: 2/5 | [Full Review...](#)

3



[25]

³This came from rotten tomatoes website <https://www.rottentomatoes.com>

Subjectivity within sentences

Objective

1. To determine if the sentence is subjective or objective.

Examples

1. At several different levels, it's a fascinating tale. Subjective sentence.
2. Bell Industries Inc. increased its quarterly to 10 cents from seven cents a share. Objective sentence. ⁴

Datasets

1. MPQA corpus [2]
2. Rotten tomatoes dataset [19]

⁴Both of these sentences are taken from [11]

1. Original papers [11] and [23]
2. Uses subjectivity to show that it is a good summary for document level sentiment analysis [19]

Objective

Given a Tweet predict the sentiment within it.

Datasets

1. SemEval Twitter Dataset [15]

Metric evaluation

$$F_{\text{pos}} = \frac{2(p_{\text{pos}} + r_{\text{pos}})}{p_{\text{pos}} * r_{\text{pos}}} \quad (1)$$

$$F = \frac{(F_{\text{pos}} + F_{\text{neg}})}{2} \quad (2)$$

1. Original paper [17] automatically created a training set of Pos, Neg and Objective.
2. Ensemble approach to Twitter sentiment analysis [4]
3. Word embedding approach [26]

Objective

To create a list of words/phrases that are representative/associated with a sentiment class.

Approaches

1. Manual - create a sentiment lexicon from scratch by using annotators [10].
2. Thesaurus - expand a known set of sentiment words using relations within a thesaurus e.g. synonym relations [7]
3. Corpus - created by exploiting co-occurrences within a corpus [8]

Other papers

Hamilton et al. [5] used a word embedding approach to find sentiment words that are domain dependent.

Example of corpus lexicon creation

Pros:

- The sound is natural.
- Music is easy to find.
- Can enjoy creating my favorite play-lists.

Cons:

- The remote controller does not have an LCD display.
- The body gets scratched and fingerprinted easily.
- The battery drains quickly when using the back-light.

[8]

Aspect sentiment has 7 different properties [3, 9]:

1. Aspect identification.
2. Sentiment of aspect.
3. Aspect groupings.
4. Opinion holder.
5. Time extraction.
6. Sentiment reasoning.
7. Sentiment qualifier.

Objective

Given text identify the sentiment of a specific aspect.

Approaches

1. Co-occurrences/window frame/pattern/dependencies [16]
2. Machine learning [24, 30]

Papers

1. Original paper [16]
2. Deep learning [24]
3. Deep learning with attention [30]

Within our area there is a lack of sharing of code. At the moment we are very good at:

1. Sharing papers
2. Sharing datasets

Unfortunately we are not doing the same with code and this has been noticed [13]

Sentiment Workshops

1. SemEval ⁵
2. WASSA ⁶
3. ESA ⁷
4. PEOPLES ⁸

⁵<http://alt.qcri.org/semeval2017/>

⁶<http://optima.jrc.it/wassa2017/>

⁷<http://gsi.dit.upm.es/esa2016/>

⁸<https://peoples2016.github.io/>

Questions?

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Tasks

Task 1: Online sentiment demos

Aim (spend 20 minutes on this, then we'll compare notes)

Try out existing web demos to see how they rate your test sentences and how their scores vary. Test them with a variety of capitalisation, repeated letters and exclamation marks for emphasis, plus emoticons. [27]

Systems

1. Potts Stanford (7-9 different sentiment lexicons):
`http://sentiment.christopherpotts.net/textscores/`
2. SentiStrength: `http://sentistrength.wlv.ac.uk/`
3. NLTK 2.0.4: `http://text-processing.com/demo/sentiment/`
4. TheySay: `http://apidemo.theysay.io/`
5. Daniel Soper:
`http://www.danielsoper.com/sentimentanalysis/`
6. LIWC: `http://liwc.wpengine.com/`

Task 2: Creating your own sentiment lexicon

We are going to create a sentiment lexicon using word embeddings and a few seed words [5].

Go to the Git repository that we cloned at the start in the command line and run the following command:

```
ipython3 notebook
```

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