Literature Survey on Multi-tasked Readability and Sentiment Analysis

1. Abstract

Sentiment Analysis deals with the automatic detection of opinion orientation in text.However, reading a sentence evokes some emotion in our mind. Sentiment Analysis is a very old field of Natural Language Processing. A lot of work has been done in the field of sentiment analysis for the textual data by considering deep learning models, statistical models etc. This chapter gives an overview of work done in the field of sentiment analysis.

2. Deep Learning for sentiment Analysis

Deep learning, which refers to deep neural networks (DNNs), is a branch of machine learning algorithms that has been widely applied to traditional artificial intelligence fields such as computer vision, speech recognition, and natural language processing. Deep learning is capable of achieving state-of-the-art performance on sentiment analysis, one of the most active topics in NLP, because it allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. [Yin et al., 2017] presented a systematic comparison of the CNN, LSTM (long short-term memory) and GRU (gated recurrent unit) on some typical NLP tasks. However, these models focuses on improving the computation power of the model instead of focusing on data.

3. The impact of Review Quality

[Korfiatis et al., 2012] proposed two content-specific features of the review text (i.e., the review length and the readability) to evaluate its content quality and helpfulness, guided by a theoretical model based on three principles (i.e., conformity, understandability and expressiveness). They examined the interplay between the helpfulness ratio of a review and the two proposed stylistic characteristics of the review text. The review readability was jointly measure by four popular formulas (i.e., the Gunning Fog Index [Gunning et al., 1952], Flesch-Kincaid Reading Ease index [Kincaid et al., 1975], Automated Readability Index [Shedlosky-Shoemaker et al., 2009], and Coleman–Liau Index [Coleman and Liau, 1975]).

They found that the word count was significant but had no influence as a coefficient on the helpfulness, and more readable texts contributed to highly helpful reviews in terms of the readability characteristic. Furthermore, the coefficients of all four readability metrics were higher than that of the word count, which indicates that the review readability had a greater effect on the helpfulness than its length. Their findings verified that the evaluation of the review length and readability provides an indication of how a review was regarded as a high-quality review.

4. Impact of textual quality on sentiment analysis

[Choi and Lee, 2017] applied four techniques—Naive Bayes, SVM, Decision Tree and SOA (sentiment orientation approaches) to four datasets—IMDB, Twitter, Hotel review, and Amazon review, to detect how different data indices, such as the training size, word count and subjectivity, affect the performances of those algorithms. By conducting comparative experiments, they found that SOA performs better for shorter texts in which the length is less than 200, and all MLA algorithms can achieve satisfactory performance for all training datasets with a 50–150 wordcount level. They also showed that documents with higher average subjectivity and a 100–150 word count can be best for the training dataset.

5. Summary

We have seen that the majority of work done in the field of sentiment analysis focuses on using the power of algorithms and computation to improve the accuracy of classification. However, very less attention is given to figure out the impact of readability on sentiment analysis.