



AUTOMATIC DETECTION OF OPINION POLARITY AND THEIR STRENGTHS IN NEWSPAPER EDITORIALS

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ABSTRACT

In this paper, we discuss the development of our methods in performing analysis on the newspaper editorial. We discover that analyzing editorial texts for opinion polarity and strength is a daunting task. It poses several challenges – implicitness of opinions, unpredictable situation with opinion polarity and strength, variance in the language expressions and so on. We evaluate the resource based approach in detecting opinion polarity and strength thereby measuring the effectiveness of the different lexicons and rules provide current results before the last line. The results show that the current accuracy are quite low and this approach requires further efforts to achieve better scores.

INTRODUCTION

An important part of information-gathering behavior has always been to find out what other people think [3]. The rise of the the online media has triggered at outburst of digital content and accessibility. And the field of the opinion mining has never been so important than at the moment. Most opinion mining algorithms attempt to identify the polarity of sentiment in text: positive, negative or neutral [5] focused over the product reviewers, comments and micro blogging. There has been the several works done on twitter tweets, comments data like product reviews, poll prediction [2]. Currently, there are numerous tools commercially and freely available in the market. The news media and publishing firms report survey asserting public attitude toward a wide range of topics. And in this information age they too have gone online. It is hence of general interest to know the opinion and viewpoints of the online news media on a particular topic. This paper describes our work of automatically detecting opinion polarities and their strength in newspaper editorials.

MATERIALS AND METHODS

For automatic detection, we resort to the different available linguistic resources as well as our own. We also conduct a comparative evaluation of the resources in terms of their contribution in the correct detection of opinion polarity and strengths in newspaper editorials.



Corpus

Editorials from 2007 to 2012 were collected from different sources, which resulted corpus of around 10,000 articles in English language (Nepali is currently not included in the given research).

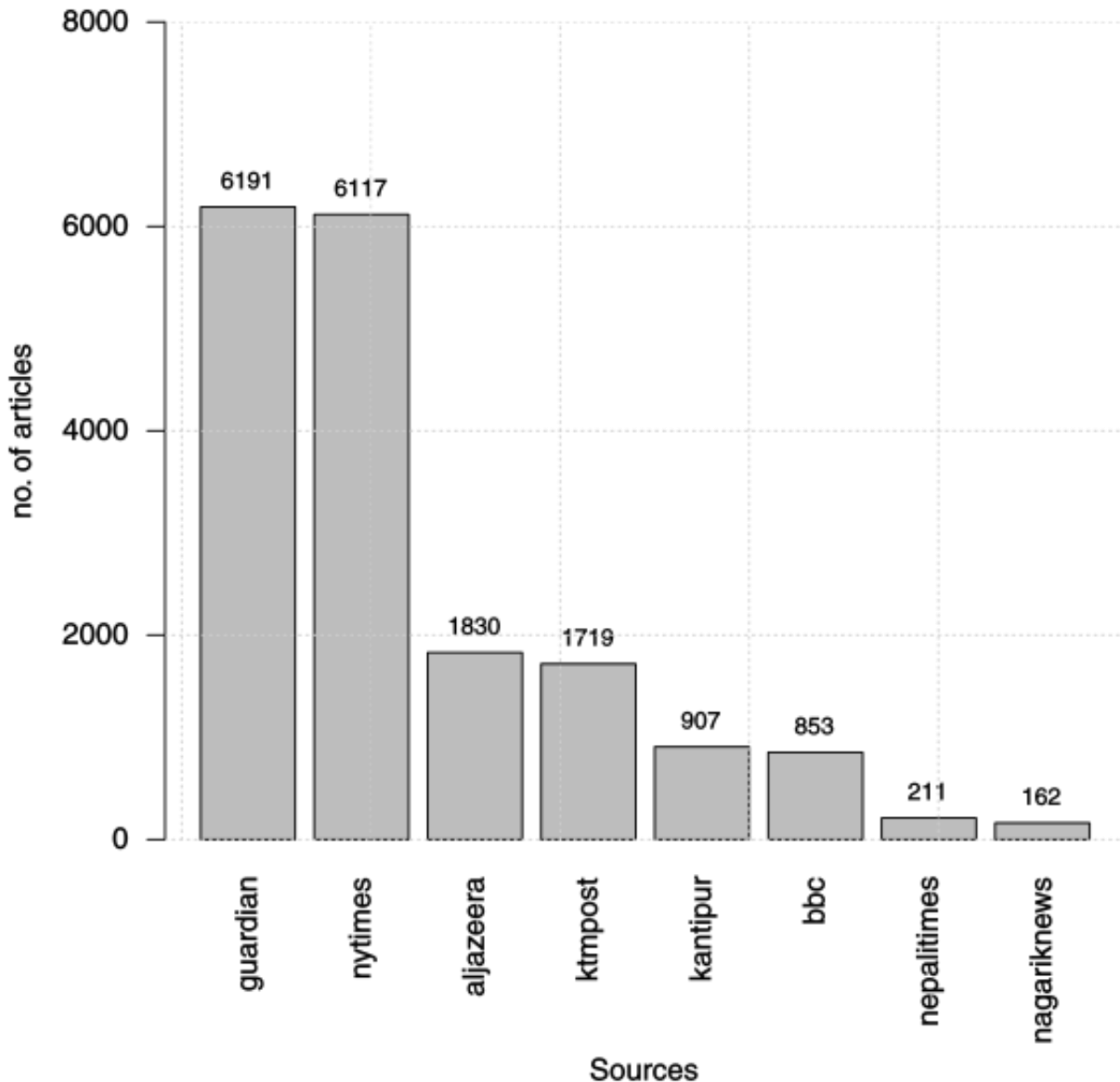


Figure 1: Statistics of corpus collected

Manual Annotation

We manually analyzed and tagged around 100 editorials for opinions as well as strength. This manually annotation is used as benchmark for comparing the automatic detection.



Lexicon

We used the following three lexicons for automatically detecting the polarity of the texts in the sentence level. We discuss each of the lexicons below:

Opinion lexicon (L1) A list of positive and negative opinion words or sentiment words for English (around 6,787 words). This list was compiled by Hu and Liu over many years starting from their first paper [1].

Subjective clues (L2) The subjective clues are collected from number of sources, some were culled from manually developed resources. Other were identified automatically using both annotated and un-annotated data. A majority of the clues were collected as part of the work presorted in [4]. There are around 6,893 words in this list. Subjectivity clues lexicon has 5167 words matches with the *Opinion Lexicon(L1)* and 1726 unique entries.

Corpus based lexicon (L3) We collected a list of opinionated words, largely collected during manual annotation of the editorials from the corpus. This list consists of entries entries specifically from corpus. It consists of around 1035 words, of which 723 negative and are 312 positive.

Modifiers

Besides detecting the polarity of opinions as *Positive*, *Negative* or *Neutral*, it is equally important to determine the strength of the opinions as expressed in text. The strength of opinions is basically attributed to modifiers or intensifiers which come mostly in front of adverbs and adjectives. The modifiers are classified into 3 categories positive intensifier, negative intensifier and flipper (inverting polarity).

Enforcing the Convention, which criminalizes bribery and outlines specific laws to curb corruption, would be a **strong** first step to creating a *more equal* world.

In the example above taken from an excerpt¹ from one of the editorials, the word “more” has a greater positive influence over the opinion word “equal”. Note that the underlined words are opinions and italic words are modifiers.

New and old leaders alike must **stop** the violence and tackle the fundamental problems that created the conditions for inequality, poverty, corruption and repression.

The second example above illustrates the role of the “flipper” or “polarity inverter”. Here, the word “stop” flips the polarity of the word “violence” to positive, which, otherwise would have been negative.

¹ <http://www.aljazeera.com/indepth/opinion/2011/12/2011122583047286468.html>



System Overview

The overall system consists of the three modules, crawler, tagging tool, and GUI-toolkit. The overall system overview is presented in Figure 2 below.

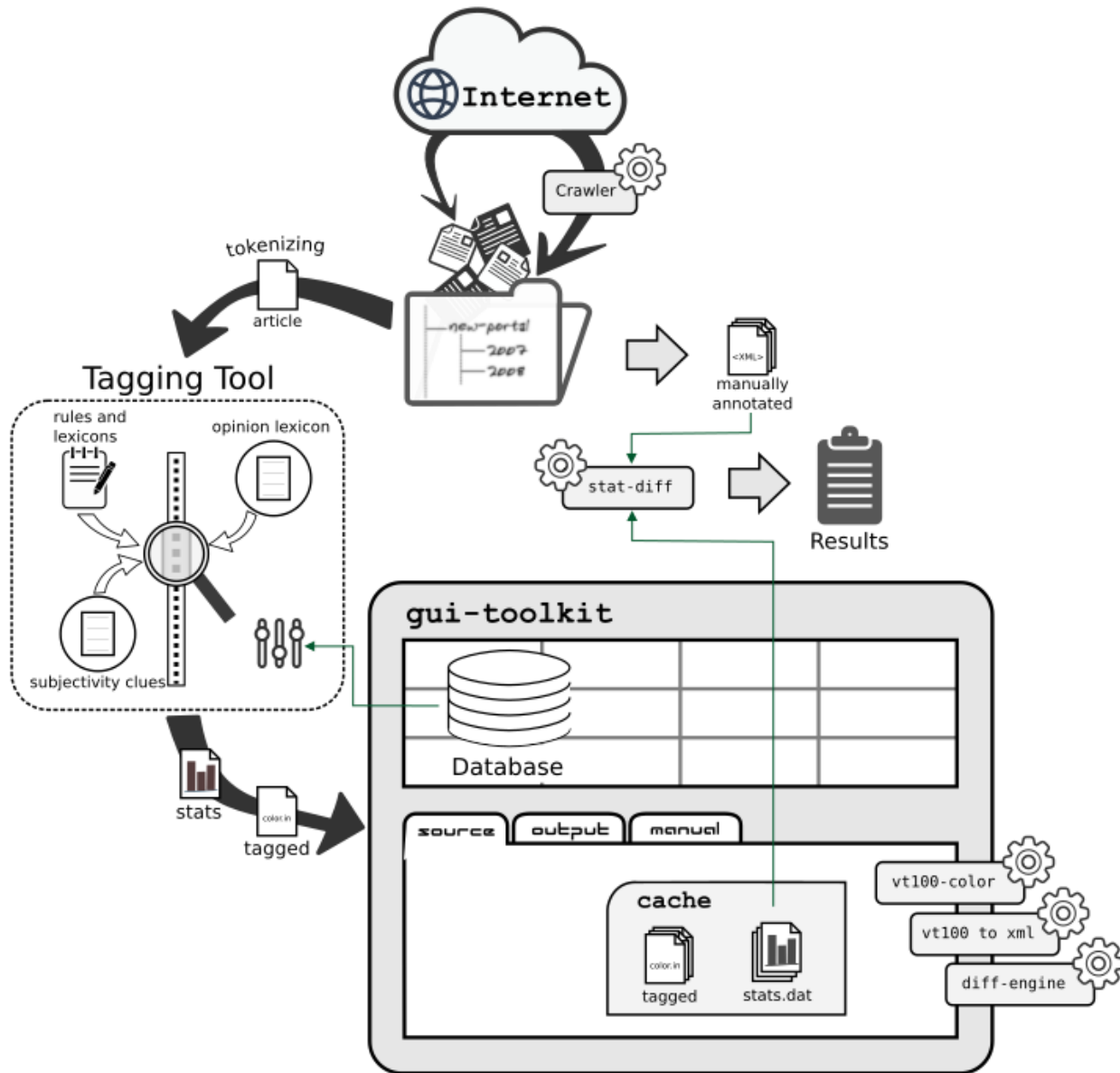


Figure 2: Overall System Overview

Crawler is responsible for downloading, cleaning and organizing the editorials from online news portals. This module must ensure that the format of text is correct and unnecessary details are stripped out.



GUI-toolkit is a front-end of the system. It maintains editorial database for annotation, searching and results. The application supports different viewing modes of annotated text color-highlighting and XML display. It does all the back-end work of file management and modules encapsulation.

Tagging Tool is responsible for segmentation, scanning and annotating the texts consulting the lexicons and rules. It annotates the texts in color modes using different color conventions to highlight the different aspects of opinions in texts, green denoting positive opinion(s), red denoting negative opinion(s), blue denoting discourse markers etc. The tool also calculates sentence level analysis from opinionated terms with the strength or degree of polarity.

RESULTS AND DISCUSSION

Detecting Opinion & Strength

Each opinions were given the score of -1, 0, 1 for negative, neutral and positive. It was kept in mind that modifiers only effective when there is the opinion near by. To tackle this problem, the range of influence for modifiers was given up to three words to also include case of multiple modifiers like “*not so good*” where “*not*” is the flipper and “*so*” is the negative intensifier acting over the opinionated word “*good*”.

This technique, although has limited impact refrains one from the need of finding out the structure of the sentence and building the relationship map of the sentence and at the same time also skip the POS tagging process which is itself is very resource hungry.

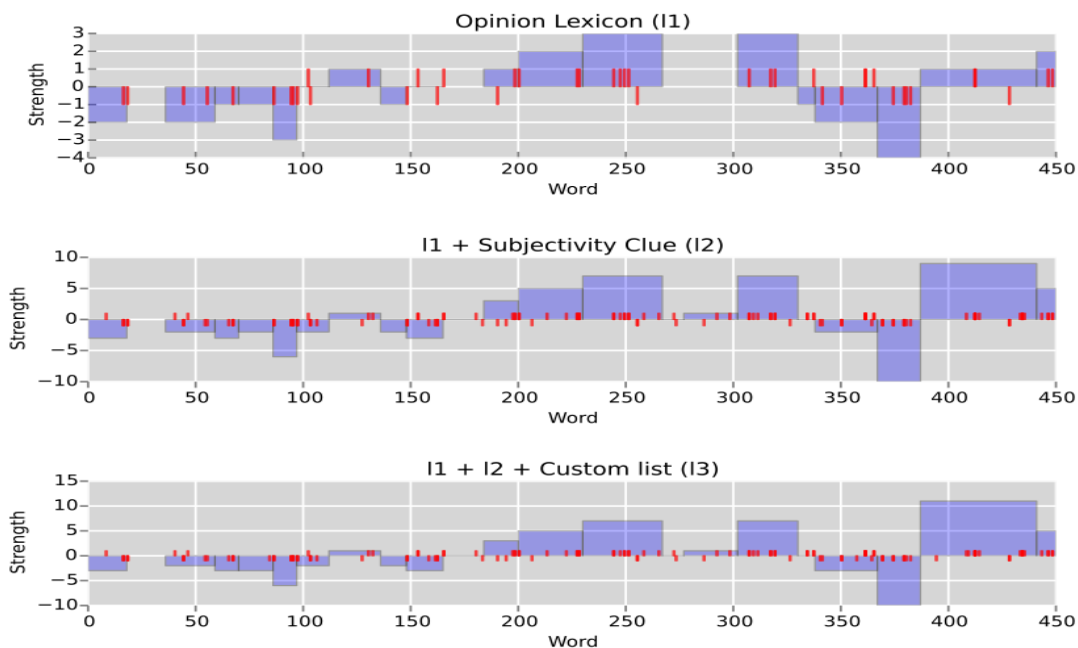


Figure 3: Polarity and Intensity in a document

Opinion strength was calculated by summing up the total no of opinions found in the sentence with the modifiers influence adjusted, which is shown in the Figure 3. The sentence-level polarity is derived from the word-level as it is shown in the Figure 4. One can consider document-level polarity classification to be just a special (more difficult) case of text categorization with sentiment. However, as noted above, we may be able to improve polarity classification by ignoring objective sentences (such as plot summaries).

A set of editorials were manually annotated for opinion polarity and strength. These manual annotations were then compared with the automatic annotations achieved by using the different lexicons and rules. The precision and recall for the corresponding tests have been presented in Table 1.

Document-level polarity

As with document-level polarity classification, we performed subjectivity detection on individual sentences by applying a standard classification algorithm on each sentence in isolation. However, modeling proximity relationships between sentences is a daunting task for the corpus of this size, so we tried to limit out work to isolated sentences.

| Lexicon | Precision | Recall |
|---------------------------|-----------|---------|
| Opinion lexicon (L1 + L2) | 50.93 % | 47.45 % |
| L1 + L2 + Corpus based | 51.80 % | 49.56 % |
| L1 + L2 + L3 + modifier | 53.90 % | 51.67 % |

Table 1: Document-level Analysis

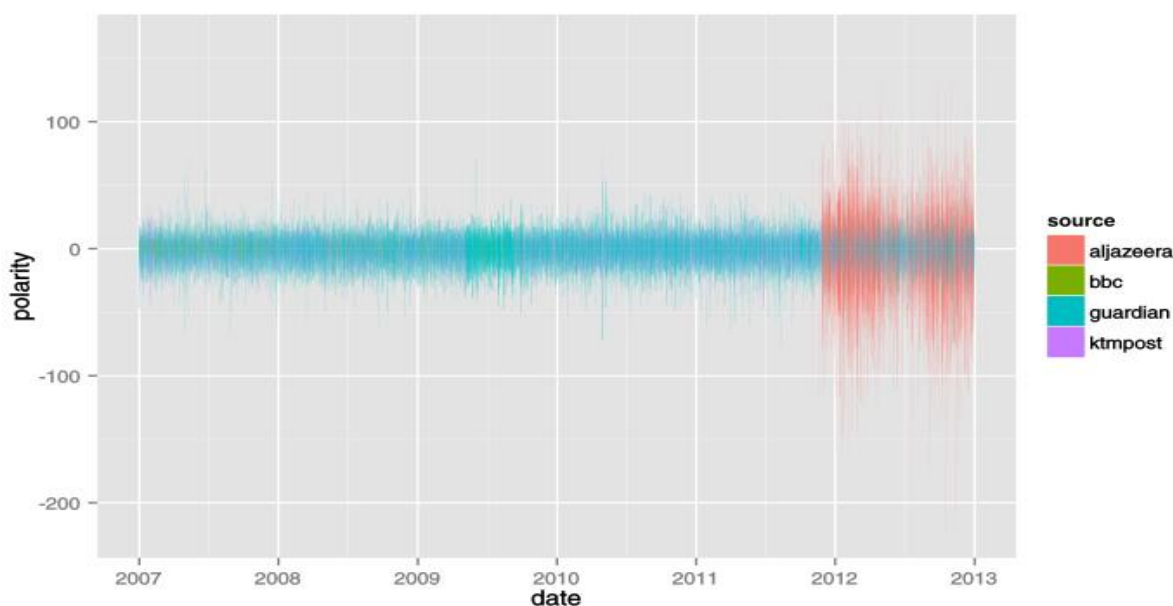


Figure 4: Polarity & Intensity map of a corpus section



The results show that there are only slight improvements in the Precision scores over different resources. We also noted that determining the strength of opinions is far more challenging than determining the polarity. The low precision and recall attributes to the implicitness of opinions being expressed in the texts and also at the same time the inadequate coverage of the current lexicons and rules.

Perspective

We are currently considering geo-tagging and pos-tagging as a measure to improve our accuracy. Machine Learning techniques are also in the plan of incorporation in the near future.

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REFERENCES

- [1] Minqing Hu and Bing Liu. Mining and Summarizing Customer Reviews. In *KDD '04: Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 168–177, New York, NY, USA, 2004. ACM.
- [2] Brendan O'Connor, Ramnath Balasubramanyan, Bryan R. Routledge, and Noah A. Smith. From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. In *Proceedings of the International AAAI Conference on Weblogs and Social Media*, May 2010.
- [3] Bo Pang and Lillian Lee. Opinion Mining and Sentiment Analysis. *Foundations and Trends in Information Retrieval*, 2:1–135, 2008.
- [4] Ellen Michele Riloff and Janyce M. Wiebe. Learning Extraction Patterns for Subjective Expressions. In Michael Collins and Mark Steedman, editors, *Proceedings of the 2003 conference on Empirical methods in natural language processing*, EMNLP '03, pages 105–112, Stroudsburg, PA, USA, 2003. Association for Computational Linguistics.
- [5] Mike Thelwall, Kevan Buckley, Georgios Paltoglou, Di Cai, and Arvid Kappas. Sentiment Strength Detection in Short Informal Text. *Journal of the American Society for Information Science and Technology*, 12:2544–2558, 2010.