

Multimodal Aspect-Opinion Mining using NER

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Abstract: This article describes the guidelines we use to analyze our opinions, including comments on text and multimedia (images) and the perception of entities and events. Identification is a subset of confidence analysis, which consists of specifying a comment in a comment, such as a specific review of a product or service, a reviewer, a compliment, or a complaint. We use POS tagging to tag individual words in verbal or non-verbal terms. We also developed a set of linguistic forms for the same purposes and integrated them into the classifier. The traditional approach we take is a rule-based approach, which we consider subset, taking into account problems that exist in the social colony, such as noisy syntax or misspellings, oaths, or patterns. Other words of skepticism, and so on. Multimedia content analysis makes this work perfect for solving ambiguity issues and providing other contextual information. The main task for this: First, the combination of new tools to extract information from text and multimedia; Secondly, the adaptation of the NLP tool for exploring specific information to solve the problem. The classifier combination with the embedded word model for confidence analysis helps our approach to better accuracy than modern methods.

Keywords: POS, LPS, MAOM

1. Introduction

Social Web analysis concerns all users who are actively engaged and generate content. This content is dynamic, reflecting the societal and sentimental fluctuations of the authors as well as the ever-changing use of language. Reviews are pools of a wide range of articulation methods, from simple "Like" buttons to complete articles, their content representing the diversity of public opinion. User activities on social networking sites are often triggered by specific events and related entities (eg sports events, celebrations, crises, news articles) and topics (eg global warming, the financial crisis, Swine flu). With the volume of rapidly growing resources on the Web, archiving this hardware becomes an important challenge. The notion of community memory extends traditional web archives with related data from a variety of sources. To include this information, a semantic and social-based preservation model is a natural way: Web 2.0 exploitation and the wisdom of crowds can make web archiving a more selective and meaning-based process. Social media analysis can help archivists choose material for inclusion, while social media can enrich the archive by promoting structured preservation around semantic categories. In this article, we focus on the challenges in developing opinion extraction tools from textual and multimedia content. We focus on two very different areas:

socially conscious federated social archiving (realized by the national parliaments of Greece and Austria) and web archiving of the socially contextualized broadcaster (produced by two large multimedia broadcasting organizations based in Germany : Sudwestrundfunk and Deutsche Welle). The objective is to help journalists and archivists answer questions such as opinions on critical social events, their distribution, evolution, opinion leaders and their impact and influence. Parallel to natural language, a large number of interactions between participants in the social network include other media, especially images. Determining whether a specific non-textual multimedia element functions as an opinion-forming device in some interaction becomes an important challenge, even more so when the textual content of an interaction is weak or has no strong feelings. Trying to determine a feeling value for an image clearly presents great challenges, and this area of research is still in its infancy. We describe here a work we have undertaken, first of all to try to provide a value of feeling from an image outside of any specific context and, on the other hand, to use the multimodal nature of the social Facilitate the analysis of the feeling of multimedia or text.

While much work has recently focused on analyzing social media to get an idea of what people think about current topics of interest, there are still many challenges ahead. Current mining approaches of opinion, which focus on product reviews and so on, are not necessarily adapted to our task, partly because they tend to operate in a single narrow area and partly because, The objective of the opinion is either known in advance or at least to a limited subset (eg film titles, product names, companies, political parties, etc.). In general, sensing techniques can be roughly divided into lexicon based methods [12] and machine learning methods, [1]. Methods based on the Lexicon are based on a lexicon of feeling, a collection of known and pre-compiled feeling terms. Machine learning approaches use syntactic and / or linguistic characteristics, and hybrid approaches are very common, with feel lexicons playing a key role in most methods. For example, [17] establishes the polarity of the examinations by identifying the polarity of the adjectives that appear in them, with a reported accuracy of about 10% greater than pure machine learning techniques. However, such relatively successful techniques often fail when they are moved to new domains or types of text, as they are inflexible with respect to the ambiguity of the terms of feeling. The context in which a term is used can change its meaning, especially for adjectives in the lexicons of feeling [8]. Several evaluations

have shown the utility of contextual information [6] and have identified context words with a high impact on the polarity of ambiguous terms [18].

2. Proposed system and methodology

Opinions can be expressed about anything such as a product, a service, or a person by any person or organization. We use the term entity to denote the target object that has been evaluated. An entity can have a set of components (or parts) and a set of attributes. Each component may have its own sub-components and its set of attributes, and so on. Thus, an entity can be hierarchically decomposed based on the part-of relation (Liu, 2006). Definition (entity): An entity e is a product, service, person, event, organization, or topic. It is associated with a pair, $e: (T, W)$, where T is a hierarchy of components (or parts), sub-components, and so on, and W is a set of attributes of e . Each component or sub-component also has its own set of attributes. *Example:* A particular brand of cellular phone is an entity, e.g., iPhone. It has a set of components, e.g., battery and screen, and also a set of attributes, e.g., voice quality, size, and weight. The battery component also has its own set of attributes, e.g., battery life, and battery size. Based on this definition, an entity can be represented as a tree or hierarchy. The root of the tree is the name of the entity. Each non-root node is a component or sub-component of the entity. Each link is a part -of relation. Each node is associated with a set of attributes. An opinion can be expressed on any node and any attribute of the node.

The contributions of this work are summarized as follows. We address the multimodal aspect-opinion mining problem for entities by leveraging cross-collection social media sources. An improvised multimodal aspect-opinion model is proposed for IMAOM, which simultaneously models aspects and opinions, and enables extraction of the semantic-sensitive correlations between textual and visual modalities as well as the interdependency relationships between aspects and opinions. We investigate two practical applications of entity association visualization and multimodal aspect opinion retrieval by seamlessly incorporating the aspects and corresponding opinions derived from IMMAOM.

For the extraction of entities, supervised learning has also been the dominant approach. However, semi-supervised methods have come to the forefront lately. As in opinion mining, users often want to find competing entities for opinion analysis, they can provide some knowledge (eg entity instances) as seeds for semi-supervised learning. In this chapter, we have introduced the learning of PU and Bayesian Sets based on semi-supervised extraction methods. For evaluation, measures commonly used for extracting information, such as accuracy, recall and F-1 scores, are also frequently used in the extraction of aspects and entities. The results of the current F-1 score range from 0.60 to 0.85 depending on domains and data sets. Therefore, the problems, especially the extraction of aspects, remain very difficult. We expect future work to significantly improve accuracy. We also believe that semi-supervised and

unsupervised methods will play a greater role in these tasks. In information retrieval with binary classification, precision (also called positive predictive value) is the fraction of retrieved instances that are relevant, while recall (also called sensitivity) is the fraction of the relevant instances that are retrieved. Precision and recall are therefore based on understanding and measuring relevance.

We used the following features:

- **Word embeddings:** We used the word embeddings described as features for the network. This way, each word was encoded as 300-dimensional vector, which was fed to the network.
- **Part of speech tags** Most of the aspect terms are either nouns or noun chunk. This justifies the importance of POS features. We used the POS tag of the word as its additional feature. We used 6 basic parts of speech (noun, verb, adjective, adverb, preposition, conjunction) encoded as a 6-dimensional binary vector. We used Stanford Tagger as a POS tagger.

In our experiments, we used a set of linguistic patterns (LPs) that leverage with extensions a concept-level knowledge base for sentiment analysis. The five LPs used are listed below.

- **Rule 1** Let a noun h be a subject of a word t , which has an adverbial or adjective modifier present in a large sentiment lexicon, Stanford NLP. Then mark h as an aspect.
- **Rule 2** Except when the sentence has an auxiliary verb, such as is, was, would, should, could, etc.
- **Rule 2.1** If the verb t is modified by an adjective or adverb or is in adverbial clause modifier relation with another token, then mark h as an aspect. E.g., in "The battery lasts little", battery is the subject of lasts, which is modified by an adjective modifier little, so battery is marked as an aspect.
- **Rule 2.2** If t has a direct object, a noun n , not found in Stanford NLP, then mark n as an aspect, as, e.g., in "I like the lens of this camera".
- **Rule 3** If a noun h is a complement of a copular verb, then mark h as an explicit aspect. E.g., in "The camera is nice", camera is marked as an aspect.
- **Rule 4** If a term marked as an aspect by the CLASSIFIER or the other rules is in a noun-noun compound relationship with another word, then instead form one aspect term composed of both of them. E.g., if in "battery life", "battery" or "life" is marked as an aspect, then the whole expression is marked as an aspect.
- **Rule 5** The above rules 1–4 improve recall by discovering more aspect terms. However, to improve precision, we apply some heuristics: e.g., we remove stop-words such as of, the, a, etc., even if they were marked as aspect terms by the classifier or the other rules.

Check each input document

For each document d , check each word w and calculate:
 $P(\text{subject } t \mid \text{document } d)$: proportion of words in document d assigned to topic t
 $P(\text{word } w \mid \text{topic } t)$: proportion of assignments to topic t , in all documents d , coming from the word w
 Reassign the word w to a new topic t' , where we choose the topic t' with probability
 $P(\text{theme } t' \mid \text{document } d) * p(\text{word } w \mid \text{theme } t')$
 This generative model predicts the probability that the topic t generates the word w

Repeating the last step a large number of times, we arrive at a stable state where the assignments of subjects are quite good. These assignments are used to determine the thematic mixes of each document.

- If input file is image
- Apply OCR to obtain visual words at region level.
- Construct BOW (Bags of Words)
- Perform Parts of Speech Tagging using Stanford NLP
- Obtain Named Entity Recognition
- Extract Nouns, Adjectives, Verbs & Adverbs
- Obtain Aspect Words and Opinion Words
- Classify using Stanford NLP and Bernoulli Classifier

In simple terms, high accuracy means that an algorithm returns significantly more relevant than irrelevant results, while a high recall means that an algorithm has yielded the most relevant results.



Fig. 1. System flow diagram



Fig. 2. Segmentation and review extraction



Fig. 3. Parts of speech tagging, named entity recognition and aspect extraction

3. Conclusion

This paper presented multimodal aspect-opinion mining using NER.

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