ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 3, Issue 2, February 2018

Entity-Centric Multimodal Aspect-Opinion Mining in Social Media Using Named Entity Recognition

[1] Nasrin Shah, [2] S. N. Gite
MSS College Of Engineering, Jalna

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 non-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 scepticism, and so on. The 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.**

I. 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: Sudwestrund funk 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.

II. RELATED WORK

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 [22] 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

IFERP

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 3, Issue 2, February 2018

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 [18]. Several evaluations have shown the utility of contextual information [26] and have identified context words with a high impact on the polarity of ambiguous terms [8].

Aspect extraction from opinions was first studied by Hu and Liu [4] . They introduced the distinction between explicit and im-plicit aspects. However, the authors only dealt with explicit aspects and used a set of rules based on statistical observations. Hu and Liu's method was later improved by Popescu and Etzioni [10] and by Blair-Goldensohn et al. [11] . Popescu and Etzioni [10] assumed the product class is known in advance. Their algorithm detects whether a noun or noun phrase is a product feature by comput-ing the point-wise mutual information between the noun phrase and the product class. Scaffidi et al. [12] presented a method that uses language model to identify product features. They assumed that product features are more frequent in product reviews than in a general natural language text. However, their method seems to have low preci-sion since retrieved aspects are affected by noise. Some meth-ods treated the aspect term extraction as sequence labeling and used CRF for that. Such methods have performed very well on the datasets even in cross-domain experiments [6, 7]. Topic modeling has been widely used as a basis to perform ex-traction and grouping of aspects [13, 14] . Two models were con-sidered: pLSA [15] and LDA [16]. Both models introduce a latent variable "topic" between the observable variables "document" and "word" to analyze the semantic topic distribution of documents. In topic models, each document is represented as a random mix-ture over latent topics, where each topic is characterized by a dis-tribution over words. Such methods have been gaining popularity in social media analysis like emerging political topic detection in Twitter [17]. The LDA model defines a Dirichlet probabilistic gen-erative process for document-topic distribution; in each document, a latent aspect is chosen according to a multinomial distribution, controlled by a Dirichlet prior α. Then, given an aspect, a word is extracted according to another multinomial distribution, con-trolled by another Dirichlet prior β. Among existing works em-ploying these models are the extraction of global aspects (such as the brand of a product) and local aspects (such as the property of a product [18]), the extraction of key phrases [19] , the rating of multi-aspects [20] , and the summarization of aspects and senti-ments [21] . [22] Employed the maximum entropy method to train a switch variable based on POS tags of words and used it to sepa-rate aspect and sentiment words.

Mcauliffe and Blei [23] added user feedback to LDA as a response-variable related to each document Lu and Zhai [24] pro-posed a semi-supervised model. DF-LDA [25] also represents a semi-supervised model, which allows the user to set must-link and cannot-link constraints. A must-link constraint means that two terms must be in the same topic, while a cannot-link constraint means that two terms cannot be in the same topic. Poria et al. [26] integrated common-sense computing [27] in the calculation of word distributions in the LDA algorithm, thus enabling the shift from syntax to semantics in aspect-based sentiment analysis. Wang et al. [28] proposed two semi-supervised models for product aspect extraction based on the use of seeding aspects. In the category of supervised methods, [29] employed seed words to guide topic models to learn topics of specific interest to a user, while [20] and [30] employed seeding words to extract related product aspects from product reviews. On the other hand, recent approaches using deep CLASSIFIERs [9, 31] showed significant performance improvement over the state-of-the-art methods on a range of natural language processing (NLP) tasks. Collobert et al. [9] fed word embedding's into a CLASSIFIER to solve standard NLP problems such as named entity recognition (NER), part-of-speech (POS) tagging and semantic role labeling.

III. 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 ex-pressed 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.

Figure System Flow Diagram

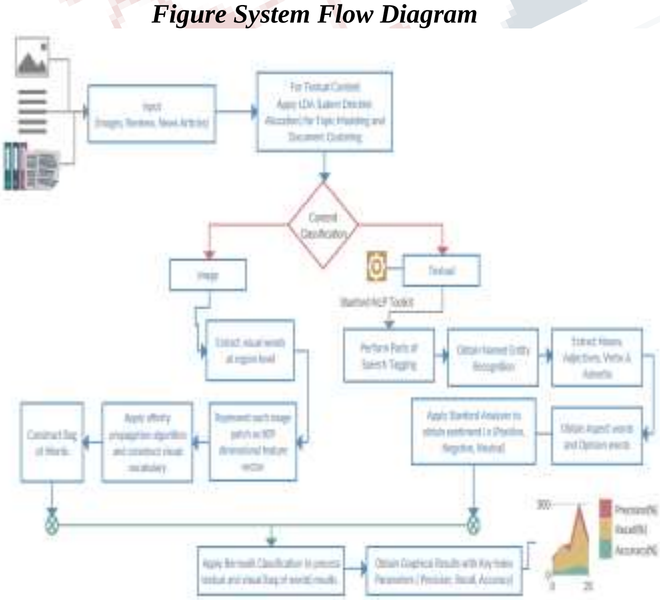


Figure System Architecture

Features and rules used

Here we present the features, the representation of the text, and linguistic rules used in our experiments.

Features

We used the following the features:

• Words embedding 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 be- low.

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 ad- verb 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 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", cam- era 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 an- other 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 off, the, a, etc., even if they were marked as aspect terms by the CLASSIFIER or the other rules.

Psuedocode:

Check each input document

Apply LDA for topic modeling and Document Clustering in case of a random collection of reviews dataset.

For each document d, check each word w and calculate:

P (subject to | document d): proportion of words in document d assigned to topic t

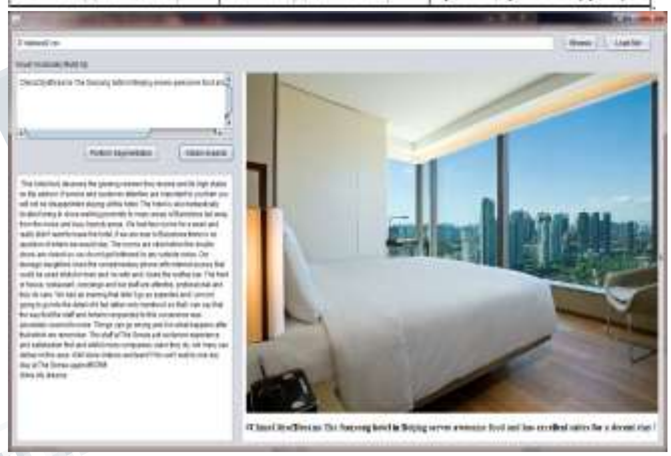
P (word w | topic t): proportion of assignments to topic t, in all documents d, coming from the word w
Reassign the word w to a new topic t ', where we choose the topic t' with probability
P (theme t '| document d) * p (word w | theme t')
This generative model predicts the probability that the topic 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 Regonition
Extract Nouns, Adjectives, Verbs & Adverbs
Obtain Aspect Words and Opinion Words
Classify using Stanford NLP and Bernoulli Classifier
Table 1 shows that our approach outperforms the state-of-the-art methods by Popescu and Etzioni [10] and Dependency Based Propagation [37] by 5%–10%, respectively. The paired t -tests show that all our improvements were statistically significant at the confidence level of 95%. Table 4 shows the accuracy of our aspect term extraction frame- work in laptop and restaurant domains. The framework gave better accuracy on restaurant domain reviews, because of the lower variety of aspect available terms than in laptop domain. However, in both cases recall was lower than precision. Table 4 shows improvement in terms of both precision and recall when the POS feature is used. Pre-trained word embeddings performed better than randomized features (each word's vector initialized randomly); see Table 3. Amazon embeddings performed better than Google word2vec embeddings. This supports our claim that the former contains opinion-specific information, which helped it to outperform the ac- curacy of Google embeddings trained on more formal texts—the Google news corpus. Because of this, in the sequel we only show the performance using Amazon embeddings, which we denote simply as WE (word embeddings).

IV. EXPERIMENTAL RESULTS

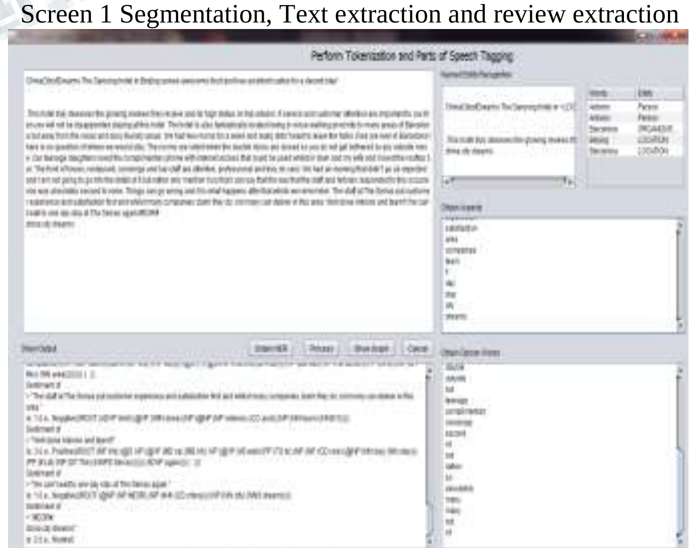
We have used Amazon dataset that contains product reviews and metadata from Amazon, including 142.8 million reviews spanning May 1996 - July 2014. This dataset includes reviews (ratings, text, helpfulness votes), product metadata (descriptions, category information, price, brand, and image features), and links (also viewed/also bought graphs).

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.
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.
The most important category measurements for binary categories are:
Precision Recall F Measure

Precision	Recall	F Measure
$P = TP/(TP+FP)$	$R = TP/(TP+FN)$	$tp+tn/tp+tn+fp+fn$



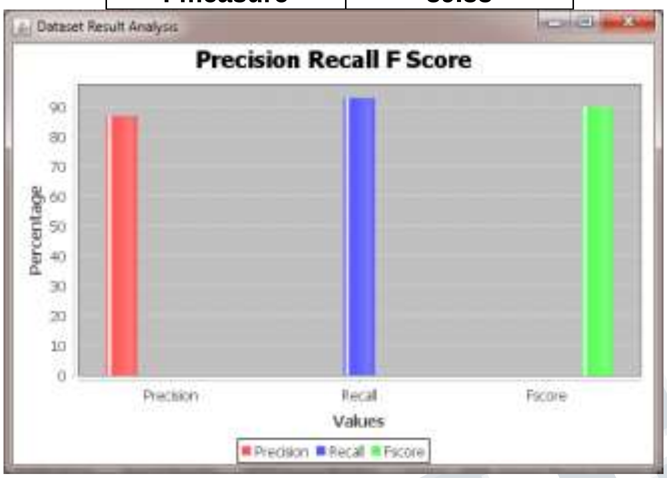
Screen 1 Segmentation, Text extraction and review extraction



Screen 2 Parts of Speech Tagging, Named Entity Recognition and Aspect Extraction using Linguistic Patterns and Rules.

Table: Confusion Matrix

True Positive	**40.0**
False Positive	**6.0**
True Negative	**3.0**
False Negative	**3.0**
Precision	**86.95**
Recall	**93.02**
Fmeasure	**89.88**



Screen 3 Precision, Recall and F Score Calculation

V. CONCLUSION

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.

REFERENCES

[1] Quan Fang, Changsheng Xu, Fellow, IEEE, Jitao Sang, M. Shamim Hossain, Senior Member, IEEE, and Ghulam Muhammad, Member, IEEE Word-of-Mouth Understanding: Entity-Centric Multimodal Aspect-Opinion Mining in Social Media

[2] B. Liu and L. Zhang, “A survey of opinion mining and sentiment analysis,” in Mining Text Data. New York, NY, USA: Springer, 2012, pp. 415–463.

[3] K. L. Keller, “Conceptualizing, measuring, and managing customer based brand equity,” J. Marketing, vol. 1, no. 1, pp. 1–22, 1993.

[4] D. Carmel, N. Zwerdling, I. Guy, S. Ofek-Koifman, N. Har’El, I. Ronen, E. Uziel, S. Yogev, and S. Chernov, “Personalized social search based on the user’s social network,” in Proc.CIKM, 2009, pp. 1227–1236.

[5] M. Hu and B. Liu, “Mining and summarizing customer reviews,” in Proc. KDD, 2004, pp. 168–177.

[6] S. Moghaddam and M. Ester, “On the design of lda models for aspectbased opinion mining,” in Proc. CIKM, 2012, pp. 803–812.

[7] Y. Fang, L. Si, N. Somasundaram, and Z. Yu, “Mining contrastive opinions on political texts using cross-perspective topic model,” in Proc.WSDM, 2012, pp. 63–72.

[8] X. Meng, F. Wei, X. Liu, M. Zhou, S. Li, and H. Wang, “Entity centric topic-oriented opinion summarization in Twitter,” in Proc. KDD, 2012, pp. 379–387.

[9] J. Dodge, A. Goyal, X. Han, A. Mensch, M. Mitchell, K. Stratos, K. Yamaguchi, Y. Choi, H. D. , III, A. C. Berg, and T. L. Berg, “Detecting visual text,” in Proc. HLT-NAACL, 2012, pp. 762–772.

[10] A. Sun and S. S. Bhowmick, “Quantifying visual-representativeness of social image tags using image tag clarity,” in Proc. Social Media Modeling Comput., 2011, pp. 3–23.

[11] J. Bian, Y. Yang, and T.-S. Chua, “Multimedia summarization for trending topics in microblogs,” in Proc. CIKM, 2013, pp. 1807–1812.

[12] Q. Hao, R. Cai, C. Wang, R. Xiao, J.-M. Yang, Y. Pang, and L. Zhang, “Equip tourists with knowledge mined from travelogues,” in Proc. WWW, 2010, pp. 401–410.

[13] A.-J. Cheng, Y.-Y. Chen, Y.-T. Huang, W. H. Hsu, and H.-Y. M. Liao, “Personalized travel recommendation by

mining people attributes from community-contributed photos," in Proc. ACM Multimedia, 2011, pp. 83–92.

[14] Q. Fang, J. Sang, and C. Xu, "Giant: Geo-informative attributes for location recognition and exploration," in Proc. ACMMultimedia, 2013, pp. 13–22.

[15] Q. Li, J. Wu, and Z. Tu, "Harvesting mid-level visual concepts from large-scale internet images," in Proc. IEEE Conf. Comput. Vis. Pattern Recog., Jun. 2013, pp. 851–858.

[16] L. Xie, A. Natsev, J. R. Kender, M. L. Hill, and J. R. Smith, "Visual memes in social media: Tracking real-world news in youtube videos," in Proc. ACM Multimedia, 2011, pp. 53–62.

[17] G. Kim and E. P. Xing, "Visualizing brand associations from web community photos," in Proc. WSDM, 2014, pp. 623–632.

[18] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," J. Mach. Learning Res., vol. 3, pp. 993–1022, 2003.

[19] D. M. Blei and M. I. Jordan, "Modeling annotated data," in Proc. SIGIR, 2003, pp. 127–134.

[20] K. Barnard, P. Duygulu, D. A. Forsyth, N. de Freitas, D. M. Blei, and M. I. Jordan, "Matching words and pictures," J. Mach. Learning Res., vol. 3, pp. 1107–1135, 2003.