DOI: 10.21917/ijsc.2021.0340

NOVEL MULTI-LEVEL ASPECT BASED SENTIMENT ANALYSIS FOR IMPROVED ROOT-CAUSE ANALYSIS

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Abstract

Aspect extraction and sentiment identification are the two important tasks to provide effective root cause analysis. This work presents a Multi-Level Aspect based Sentiment Analysis (MLASA) model that integrates the aspect extraction and sentiment identification modules to provide effective root cause analysis. The aspect extraction module performs token filtration, followed by rule based aspect identification. The heterogeneous multi-level sentiment identification phase performs aspect based sentiment identification. First level performs magnitude along and polarity identification of text, while the second level performs polarity identification using multiple machine learning models. The results are aggregated and ranked based on aspect significance and sentiment magnitude. Experiments and comparisons show effective performance of the MLASA model.

Keywords:

Root Cause Analysis, Sentiment Identification, Aspect Extraction, Machine Learning, Heterogeneous Modelling

1. INTRODUCTION

Today's digitized world presents many opportunities for customers and businesses alike. Social media and freedom of speech has enabled people to voice their opinions at-ease [1]. The social media platforms has enabled users to provide their unbiased views. Increase in e-commerce transactions has witnessed large number of users moving towards online shopping. The convenience of shopping from home has been a huge benefit, however, it becomes difficult for users to select a product due to the information overload [2]. Views/ reviews of users can be mined to provide opinions about the product a user is interested in. Explosion of networking technologies has resulted in a huge number of such reviews. An aggregated view of the opinions can provide the user with a better view of the product. Root-Cause Analysis (RCA) is the process that can be used for this accumulation of information [3].

Root-Cause Analysis is the process of analyzing multiple documents dealing with related products or services to provide an aggregated and opinionated view for the user. RCA is composed of two sub-components; aspect extraction and sentiment identification [4]. Aspect extraction is the process of analyzing a text and identifying its major component(s). The major component is called the aspect or aspect term. A single document might even contain several aspects. Aspects represent a feature or attribute of a product or service, or sometimes the entire product [5].

Sentiment analysis is a core task of Natural Language Processing (NLP) [6] [7]. Sentiment represents the polarity or orientation that the user has expressed in the text being analyzed. Input for this process can be a single sentence or an entire document. Sentence level polarity identifies the polarity levels of the sentence, while document level sentiment describes the overall sentiment associated with the document. Document based sentiment analysis should be approached carefully. If a review contains both positive and negative sentiments, they tend to get neutralized. Hence, aspect based sentiment identification [8] has gained prominence. This model identifies the aspects and determines the corresponding sentiment associated with the aspect. Hence, if a document contains multiple aspects, each with its own sentiment, aspect based sentiment identification model can provide fine-grained view of all the aspects individually. This process hence aids in informed decision making. This work presents a heterogeneous model that aids in aspect based sentiment analysis. The aspect extraction phase is enhanced by using a filtering mechanism to reduce the computational complexity levels. The sentiment identification phase is interlaced with the aspect extraction model to enable aspect based sentiment identification.

2. RELATED WORKS

Root-cause analysis/identification has gained prominence since the onset of e-commerce based transactions. Recent and significant works in this domain are discussed in this section.

Aspect extraction and sentiment identification are the major phases of root-cause identification system. A multi-task based model that performs aspect term extraction and aspect based sentiment analysis was proposed by Akhtar et al. [9]. This work uses a convolution neural network architecture to perform sentiment identification. Aspect extraction is performed using LSTM network. An opinion mining model developed using a probabilistic approach was proposed by Kim and Hovy [10]. This model is based on identifying both the opinion and the opinion holder. It uses WordNet repository and uses rules to identify aspects. A sentiment identification model was proposed by Ganu et al. [11]. This model specializes in identifying category specific extraction of sentiments.

A product feature and opinion extraction model was proposed by Popescu and Etzioni [12]. This work proposes an unsupervised information extraction model called OPINE. The model constructs a repository of significant features and identifies the opinion levels of these features.

A Linear Discriminant Analysis (LDA) based similarity identification model was proposed by Poria et al. [13]. This work proposes sentic-LDA that includes the semantic level of reviews to identify opinions. A two-fold model for aspect extraction was proposed by Rana et al. [14]. Other similar aspect identification models include an interactive technique by Hu et al. [15] and Big Data based model by Chen et al. [16].

A hybridized model for aspect and opinion extraction was proposed by Wu et al. [17]. This model combines aspect extraction and opinion extraction by combining rule based operations and machine learning models. The initial level extracts candidate aspects, followed by extraction of opinions and their corresponding targets. A dependency relation based model for sentiment and aspect extraction was proposed by Hu and Liu [18]. They are based on extracting both frequent and infrequent aspects. Rule based extraction models are utilized for this purpose. Other similar works are double propagation based models by Qiu et al. [19], and Blair et al. [20], and feature engineering system for Hidden Markov Model (HMM) by Toh and Wang [21].

Knowledge based model to perform aspect extraction, Extraction of Prominent Review Aspects (ExtRA) was proposed by Luo et al. [22]. Probase and WordNet are used as the major knowledge bases for this model. This is a graph driven and cluster based approach. An unsupervised hierarchical model for aspect term extraction was proposed by Venugopalan et al. [23]. This work contains a pre-processing module, followed by the aspect extraction phase. Aspect pruning limits the results to valid aspect terms to provide the final result. An unsupervised model for aspect extraction was presented by Chauhan et al. [24]. The model combines rule based extraction mechanisms with deep learning models to provide improved aspect extraction. Other aspect extraction models include works by Pontiki et al. [25], Rana and Cheah [26], and Shams et al. [27].

3. ROOT-CAUSE ANALYSIS USING MULTI-LEVEL ASPECT BASED SENTIMENT ANALYSIS (MLASA)

Root-Cause Analysis (RCA) requires identification of two major elements in the text; aspects and sentiments related to the aspect. Aspects correspond to the major element around which the text is formulated. Sentiment defines the user's view towards the aspect, and can be positive, negative or neutral.

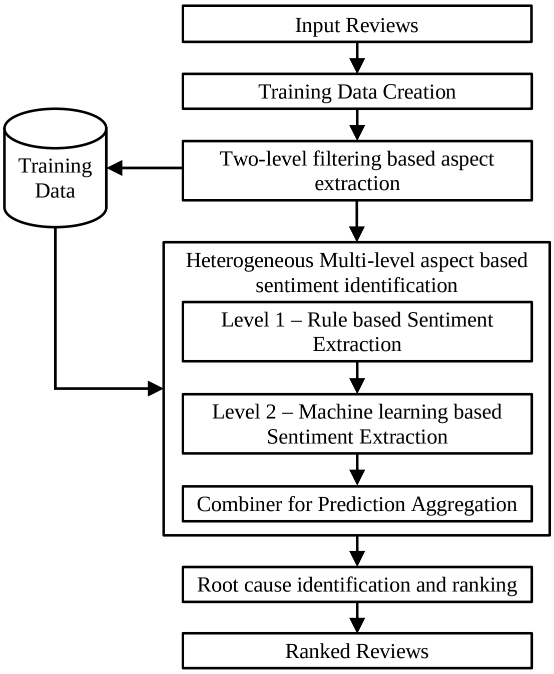

Fig.1. MLASA Architecture

This work proposes a Multi-Level Aspect based Sentiment Analysis (MLASA) model for effective Root-Cause Analysis (Fig.1). The proposed model is organized in four phases; training data creation, aspect extraction, aspect based sentiment analysis and root cause identification.

3.1 ASPECT BASED TRAINING DATA CREATION

Input data is textual in nature. It is composed of reviews provided by the users. Each review is annotated with the aspects and their corresponding polarities. Major challenge with such a model is that each review will be composed of multiple aspects. Each aspect will be associated with a sentiments. Identifying review polarity results in aggregation of all the polarities, which in-turn results in neutralization if polarities. Hence for effective analysis, it is necessary to split the reviews based on aspects to create text blocks. The input training data is split based on the aspects. Sentiment analysis is performed based on the text block and not the entire review. Further, sentiment pertaining to the aspect is also added as another feature. The features of training data are shown in Fig.2.

Review	Text Block	Aspect	Sentiment

Fig.2. Features of Training Data

The training data facilitates identification of aspect based sentiment analysis, rather than entire review based sentiment analysis.

3.2 TWO-LEVEL FILTERING BASED ASPECT EXTRACTION

Aspect extraction is the first phase of the root cause identification process. The input text is analyzed to identify the aspects. Aspect extraction is usually rule-based. The entire text is analyzed, resulting in increased computational complexity. Hence this work breaks the process down to two phases; TF-IDF based token filtering, which reduces the content levels and Part-Of-Speech (POS) based aspect extraction. The initial filtering process reduces tokens to a large extent leading to reduced computations.

3.2.1 TF-IDF based Token Filtering:

Overload reduction for the next phase is done by identifying significant terms in the document or review under analysis. Significance of terms represents its importance in the document. Reviews contain multiple aspects. Root causes correspond to only the most significant aspects, as most of the available aspects would exhibit low priorities. Significance of the aspects is identified using TF-IDF. Tokenization is performed, and stop word elimination is incorporated into the process to reduce insignificant tokens.

TF-IDF refers to Term Frequency - Inverted Document Frequency (TF-IDF), a combination of which provides the significance of tokens. The significance level is identified based on a base corpus, which corresponds to the review set. TF-IDF is determined by

$$Tfidf(t,d,D) = tf(t,d)\times idf(t,D) \quad (1)$$

Term Frequency (TF) refers to the frequency of tokens in the document, and is given by.

$$tf(t,d) = f(t,d)/count(w,d) \quad (2)$$

where $f(t,d)$ is the frequency of the token t in document d and $count(w,d)$ is the number of words contained in d.

$$idf(t,D) = \log(N/|d\in D:t\in d|) \tag{3}$$

where, N is the count of reviews, and $|d\in D:t\in d|$ is the number of reviews with token t.

3.2.2 POS Rule based Aspect Identification:

Tokens containing high document frequency are considered as common words and eliminated in the previous phase. IDF value is calculated for all other tokens. This value represents the significance level of the token in the document. However, not all of these tokens correspond to aspects. They only represent significant components. The IDF value aids to further prune the token set for POS rule based analysis. Text blocks containing the significant tokens are used for this phase. POS corresponding to the text blocks is identified. Rule based aspect identification is performed based on the POS vectors. The major rule includes selecting nouns and adjectives as aspects. Multi-gram aspects are also included by adding additional rules with continuous noun patterns. These are identified to be the major aspects or major causes. The sentiment related to these causes is identified in the next phase using the heterogeneous multi-level sentiment identification model.

3.3 HETEROGENEOUS MULTI-LEVEL ASPECT BASED SENTIMENT IDENTIFICATION

Text blocks corresponding to aspects identified in the previous phase are used for the analysis. A single review is composed of multiple text blocks, each representing an aspect. Hence sentiment analysis is performed based on the text blocks rather than the entire review. Every text block is analyzed in two levels to identify the sentiment. First level uses the rule based sentiment analyzer, and the second level uses machine learning based heterogeneous models.

3.3.1 Level 1-Rule based Sentiment Extraction:

Sentiment of a text block corresponds to aggregated polarity levels of each token contained in the text block. Hence token polarities are identified individually and they are aggregated to identify the final sentiment. Level 1 phase performs rule based identification of sentiment based on Valence Aware Dictionary for Sentiment Reasoning (VADER). Polarities are identified by using an opinion dictionary. Token based polarity levels are identified and aggregated to identify the sentiment of the text block. Since aspect based division is performed to derive the text blocks, polarity aggregation does not neutralize the text block.

3.3.2 Level 2-Machine Learning based Sentiment Extraction:

Level 2 sentiment identification is performed based on machine learning models. Unlike Level 1, Level 2 machine learning models cannot operate directly on text. They require numerical vectors to perform analysis. The training data derived in the first module is used for this process. The model is constructed as a supervised learning method. Hence polarity is used as the class attribute and text blocks identified for aspects is used as the data attribute. Numerical vectors are derived from the text blocks and integrated with the polarity to generate the training data.

Count vectorization is used to derive the numerical vectors. The entire review set is used as the base document. The document is tokenized and token counts are determined and added to the dictionary. The token count dictionary is used to provide numerical labels to data. The text blocks are passed to this model, and numerical vectors are generated based on the derived dictionary. These vectors are appended with the corresponding polarity data to obtain the training data.

Heterogeneous models are used for the machine learning process. This work is based on Decision Tree and Naïve Bayes models for sentiment identification. Decision Tree is a rule based model that constructs a decision tree to derive the final prediction, while Naïve Bayes uses probability to derive the predictions. Varied operational nature of the models uncovers the hidden intricacies in the language to provide better predictions.

3.3.3 Combiner for Prediction Aggregation

Level 1 rule based model identifies the intensity of the sentiment, along with the polarity of the text. Level 2 model provides the sentiment polarity of the text blocks. This work has been constructed with two levels to handle sarcasm, which is a major challenge in processing text. Level 1 is a rule based model, and was found to be effective in identifying the polarity and also the intensity of the polarity. However, they cannot handle sarcasm in the data. Level 2 models are supervised learning models. Hence they can be trained to identify sarcasm. The predictions are to be combined to identify the final sentiment levels. The rule based combiner is used for this purpose. Intensity values from Level 1 are considered directly. Sentiment polarity is identified by voting from the level 1 model and the two level 2 models. The resultant polarity and the intensity levels are combined to form the final prediction.

3.4 ROOT-CAUSE IDENTIFICATION AND RANKING

Root Cause Analysis deals with identifying aspects with highest significance and analyzing it in terms of its overall sentiment. The major components of a root cause identification model are identifying aspects, identifying the sentiment corresponding to the aspect and identifying the significance of the aspect. Aspect is identified by the rule based aspect identification model and the sentiment is identified using the heterogeneous multi-level models. Significance of the aspect is derived using the IDF component. Integration of these components to provide the final result is performed in this phase.

3.4.1 Sentiment based Result Segregation and Aggregation

Text blocks are segregated based on the identified sentiment. Groups, one representing positive sentiment and the other representing negative sentiment are formed. Neutral reviews are eliminated. The text blocks are annotated with their corresponding aspects to signify their representations. Several reviews represents same aspects. Such reviews are aggregated to form a single component. This aggregation aids in the reduction of data size, without loss of context.

3.4.2 Ranking

Aspects identified in the reviews correspond to products by organizations. Significance and sentiment represents how well the product is receive by the consumers and how the product is perceived by the consumer. Not all aspects exhibit equal significance. Hence ranking of aspects is mandatory to avoid information overload. Significance of an aspect is identified based on its overall significance, given by its IDF value, and the magnitude of the text block (*M*), given by the Level 1 rule based sentiment identification module.

$$Significance_a = IDF_a * M_a \tag{4}$$

Aspects are ranked in descending order of their significance and provided to the user for analysis.

4. RESULTS AND DISCUSSION

Implementation of the proposed MLASA model has been done in Python. Analysis of the MLASA model has been performed using the customer review dataset [28]. The dataset is composed of reviews for five varied products; Canon and Nikon Digital Cameras, Nokia Phone, Creative MP3 player and Apex DVD player. Details about the dataset are shown in Table.1.

Table.1. Dataset Description

Data	Reviews (R)	Aspects (A)	Aspect Level (A/R)	Represent-ation
Canon Digital Camera	597	237	0.39	D1
Nikon Digital Camera	346	174	0.50	D2
Nokia Phone	546	302	0.55	D3
Creative Mp3 Player	1716	674	0.39	D4
Apex DVD Player	740	296	0.4	D5

The analysis of precision values of all the datasets is shown in Fig.3. Precision for a model is given by the ratio of total number of positives correctly identified vs. total number of records identified as positives in the data.

$$Precision = TP/(TP+FP) \tag{5}$$

Precision values range between 0 and 1, with 0 representing lowest and 1 representing the highest precision. It could be observed that the precision of all the datasets exhibits values >0.9. This exhibits effective predictions by MLASA model.

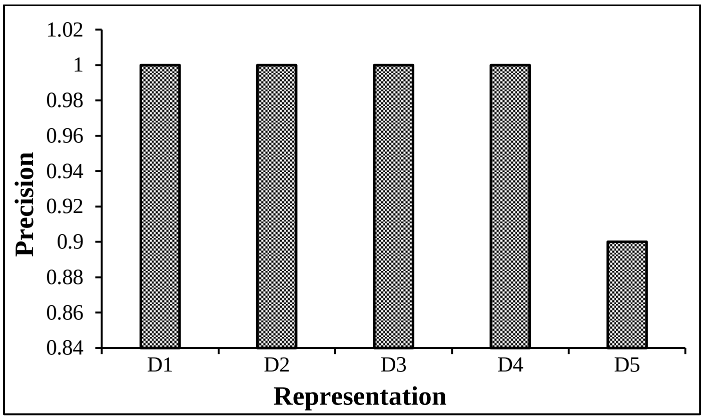

Fig.3. Precision Analysis

An analysis of the recall values is shown in Fig.4. Recall represents the total number of positives correctly identified vs. total number of actual positives contained in the data.

$$Recall = TP/(TP+FN) \tag{6}$$

It could be observed that except for the Nokia Mobile (D3) data, all other datasets exhibits significantly high recall values >0.8. The reduction in performance in the D3 data is attributed to the high aspect level of 55%. This results in the creation of too many text blocks. Presence of large number of text blocks for a single review results in insufficient information in the training data. This issue is reflected in the performance.

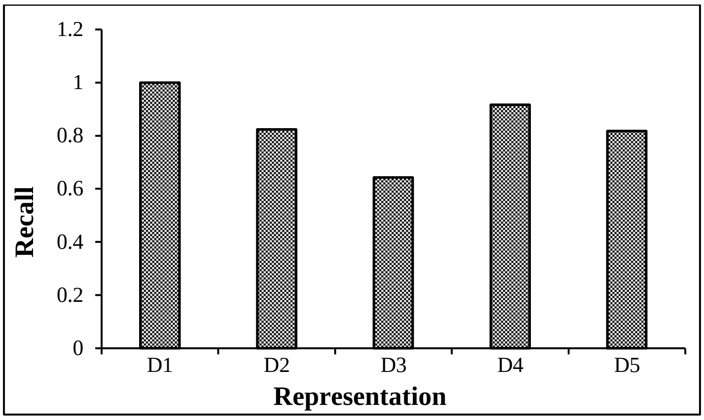

Fig.4. Recall Analysis

F-Measure or F1-Score is an aggregated metric that is based on precision and recall. F-Measure is given by,

$$\text{F-measure} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \tag{7}$$

Analysis of the F-Measure metric is shown in Fig.5. The Nokia Phone (D3) data shows a slight reduction, while all the other datasets exhibit effective F-Measure levels.

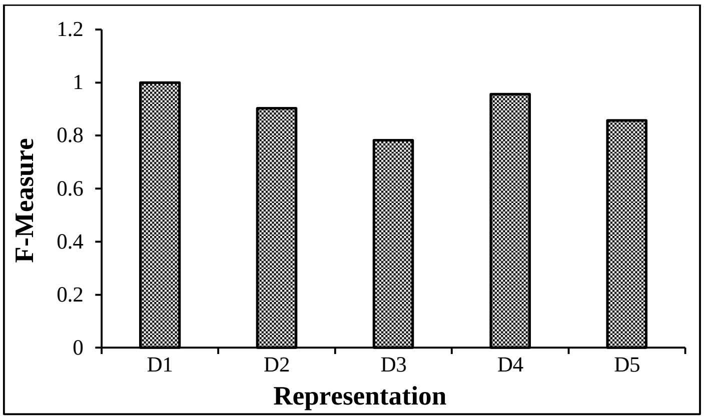

Fig.5. F-Measure Analysis

5. COMPARATIVE STUDY

The proposed MLASA model is compared with models proposed by Popescu [12], CNN+LP proposed by Poria et al. [13] and TF-RBM proposed by Rana et al. [14]. Precision, Recall and F-Measure are used as the metrics for comparison.

Average performance levels of the models on all the five datasets are calculated and used for the comparison. The comparison chart is shown in Fig.6. The MLASA model exhibits a slight reduction in the average recall values compared to the other models, best F-Measure and precision levels. F-Measure levels of MLAS are in-par with the TF-RBM model, while precision levels exhibited by the MLASA model is the best at 0.98.

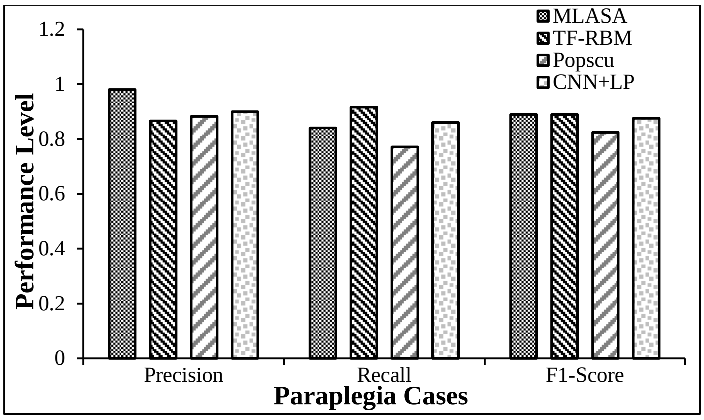

Fig.6. Performance Comparison with Existing Models

A tabulated view of the compared performances is shown in Table.2. Average performances of the models on all the five datasets are presented in the table. Best performances are shown in bold. It could be observed that the proposed MLASA model exhibits equivalent F1-Score of 0.89, which is also the best. Recall levels show a slight reduction of 7% from the best performer. This is attributed to the D3 data, which exhibits high aspect levels. However, precision score of the MLASA model is the best and shows an improvement of 10% from the best model. High precision indicates that the model is able to identify positives effectively. This proves the fact that the model identifies sarcasm effectively.

Table.2. Performance Comparison

Methods	Precision	Recall	F1-Score
CNN+LP	0.9	0.86	0.876
Popscu	0.882	0.772	0.824
TF-RBM	0.866	**0.916**	**0.89**
MLASA	**0.98**	0.84	**0.897**

6. CONCLUSION

Root cause identification plays a huge role in effective marketing and also in maintaining customer loyalty. This is enabled by the identification of customer's requirements and concentrating to improve their relationship with the products. Huge data and intrinsic complexities in data like, multiple aspects, presence of implicit aspects and sarcasm complicates the process. This work presents a Multi-Level Aspect based Sentiment Analysis (MLASA) model for root cause analysis. The major advantage of this model is that it has been designed to identify multiple aspects and focusses on aspect based sentiment analysis. Experiments and comparisons indicate effective prediction levels clearly indicating high performances.

The model has been developed to effectively handle sarcasm, which is exhibited by the high precision levels. However, aspect based text division has resulted in low recall levels in data with high aspect levels. Transfer learning models could be used to handle this issue and provide better recall levels. The model is generic and can be used for analysis of reviews in any domain. The model is based on identifying explicit aspects. Handling implicit aspects could be integrated in future to provide higher prediction levels. Another major issue in the domain is the presence of old reviews. Old products will have many reviews leading to those products always ranking higher. This issue needs to be eliminated.

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