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Sentiment Mining Model for Opinionated Afaan Oromo Texts

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ABSTRACT

Opinions are personal judgment on entity. This is not only true for individuals but also true for organizations. Opinion mining is a type of natural language processing for tracking the mood of the public about a particular product. The process of sentiment mining involves categorizing an opinionated document into predefined categories such as positive, negative or neutral based on the sentiment terms that appear within the opinionated document. For this study text document corpus is prepared by the researcher encompassing different movies 'reviews and Various techniques of text pre-processing including tokenization, normalization, stop word removal and stemming are used for this system(sentiment mining model for opinionated afaan Oromo texts). The experiment shows that the performance is on the average 0.849(84.9%) precision and 0.887(88.7%) recall. The challenging tasks in the study are handling synonymy and inability of the stemmer algorithm to all word variants, and ambiguity of words in the language. The performance the system can be increased if stemming algorithm is improved, standard test corpus is used, and thesaurus is used to handle polysemy and synonymy words in the language.

Keywords : Sentiment Dictionaries, Opinions, Sentiments, Sentiment Mining From Opinionated Afan Oromo Texts, Polarity Classification.

I. INTRODUCTION

Natural Language Processing (NLP) is an interdisciplinary research area at the border between linguistics and artificial intelligence aiming at developing computer programs capable of humanlike activities related to understanding or producing texts or speech in a natural language (Eugene, 1984). It is an area of research and application that explores how computers can be used to understand and manipulate natural language text or speech to do useful things. NLP researchers aim to gather knowledge on how human beings understand and use language so that appropriate tools and techniques can be developed to make computer systems understand and manipulate natural languages to perform the desired tasks Karen (Jones, 2001). Applications of NLP include a number of fields of studies, such as machine translation, morphology, syntax, named entity recognition, natural language text processing and summarization, multilingual and cross language information retrieval (CLIR), speech recognition, information retrieval and text clustering, and so on(Jones, 2001). Among these applications, Sentiment analysis(SA) refers to the field of study that analyses people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes(J. Tatemura,2000). There are different types of approaches in sentiment analysis like machine learning, lexicon-based, statistical and rule-based approaches. (Bing Liu, 2012).The machine learning method uses several learning algorithms to determine the sentiment by training on a known dataset. The lexicon-based approach involves calculating sentiment polarity for a review using the semantic orientation of words or sentences in the review. The "semantic orientation" is a measure of subjectivity and opinion in text. The rule-based approach looks for opinion words in a text and then classifies it based on the number of positive and negative words. It considers different rules for classification such as dictionary polarity, negation word etc.Sentiment mining can be done at sentence level, document level or feature level. Sentence level: The task at this level goes to the sentences and determines whether each sentence expressed a positive, negative, or neutral opinion. Neutral usually means no opinion. Document level: The task at this level is to classify whether a whole opinion document expresses a positive or negative sentiment.. This level of analysis assumes that each document expresses opinions on a single entity (e.g., a single product). Thus, it is not applicable to documents which evaluate or compare multiple entities.

II. DESIGN AND IMPLEMENTATION

The proposed model has the following components: pre-processing (tokenization, case folding, stemming, stop word removal, removing symbols, and punctuation), sentiment word detection, polarity and contextual valence shifter words counter, polarity classification (into positive, negative and natural) based on the polarity values the reviews Pre-processing is responsible for normalization of reviews and words segmentation to get normalized list words. In the sentiment words detection component, all possible sentiment words and contextual valence shifter terms (negation terms and intensifier terms) are checked for existence in the sentiment lexicon. The polarity words and contextual valence shifter word counter, count words which are found in both review and dictionaries. After the polarity and contextual valence shifter word counter is completed, the next step is the polarity classification of the reviews. The sentiment word detection and the polarity and contextual valence shifter word counter activities are fully dependent on the lexicon of Afaan Oromo opinion terms that contains opinion terms.

III. METHODS AND MATERIAL

3.1 Mining Model

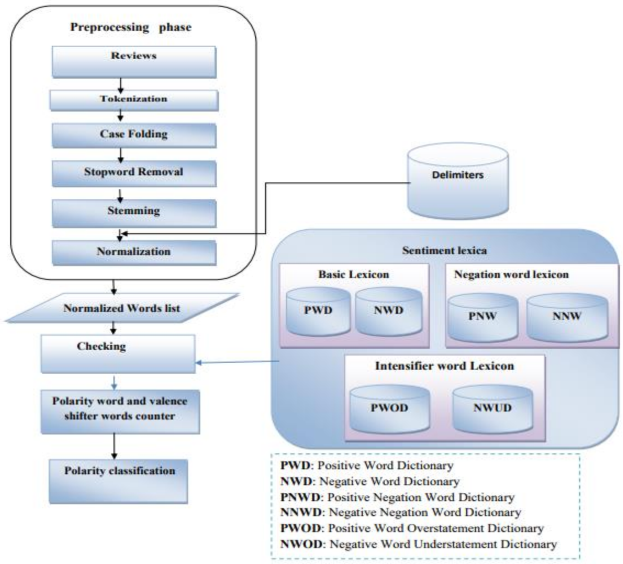

Figure 3.1 : The sentiment mining model for opinionated Afaan Oromo texts

3.2. General system architecture

The general architecture of the proposed model (sentiment mining model for opinionated Afaan Oromo texts) is shown in figure 3.1. As shown in the Figure, the system contains different components based on the processes required. These components are: pre-processing, sentiment words detection, polarity word counter, and polarity classification. The sentiment lexicon is also part of the general systems architecture

3.2.1. Pre-processing

It is very important step before further processing; it filters the reviews so that it improves accuracy and also removes unnecessary disturbances. Preprocessing has activity like Removing symbols, numbers and punctuations, Tokenization, Case folding, Stemming and Stop word removal.

3.2.2. Detecting basic polarity terms and contextual valence shifter terms.

After the review is preprocessed, every valid term in the review is checked whether it is sentiment word or not. This is done by a simple detection mechanism where the whole lexicon (dictionary) is scanned for every term (word).

These lexicons are Positive word dictionary, Negative word dictionary, Positive negation word dictionary, Negative Negation word dictionary, Positive word overstatement dictionary, Negative word understatement dictionary. On these dictionaries we have applied different tasks like, tokenization, case folding, stemming, to get normalized dictionaries.

$Rp=\sum T\ pi$………………………………. equation 1

3.2.3. Polarity classification

In this component as shown in figure 3.2, the criteria for classifying a review into predefined categories: positive, negative or neutral are described in detail. The total polarity weight of a review is calculated by adding the polarity weight of the individual sentiment terms in the review by the formula given in equation (Kennedy and Inkpen, 2006)

$Rp=\sum T\ pi$……………………………….equation 1.2

Where, Rp is review polarity value, Tp is sentiment term polarity value in all given dictionaries (positive and negative dictionaries (negations and intensifiers dictionaries,), n is number of sentiment terms within the given review and i is term instance. According to the result of the equation, if the value of Rp is greater than zero then the review is categorized into a predefined category positive. Similarly if the value of Rp is less than zero then the review is categorized in to a predefined category negative. Finally if the total average weight of all the individual terms is equal to zero, the review is categorized in to the category neutral

Algorithm for polarity classification
Rp= PC+NN+PI+NC+PN+NI
If RP>0
    Review category=positive
Else If RP<0
    Review Category=Negative
Else
    Neutral

Algorithm 3.7 : Polarity Classification

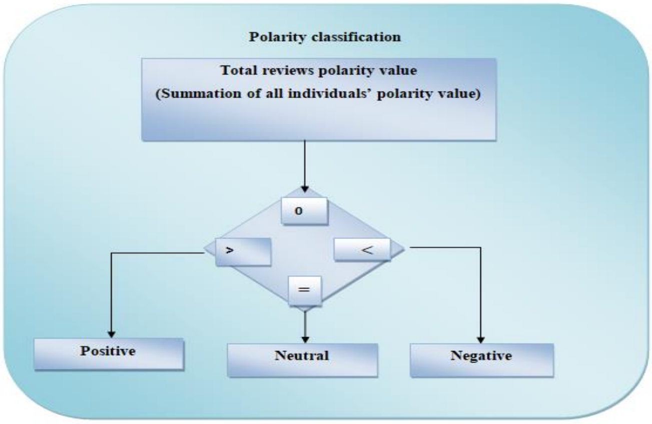

Figure 3.2 : Review Polarity Classification

For example in the sentence 'Filmiichi gaariidha. Rabbirraan filmiicha keessaa waan jiruuf bayee bareeda dha ', the sentiment terms are 'gaarii' with an initial value of +2, 'bareeda' with an initial value of +2 but since it is preceded by an 'overstatement its value is +3.Therefore the average weight is done as shown in Table 3.1.

Table 3.1 : sentiment terms' polarity propagation example

Sentiment terms	Initial weight	Overstatement	Adjusted weight
Gaarii	2		2
Bareeda	2	Baayee	3
		Total Score	5
		Category	Positive

3.3. Implementation

In this sub section, the Afaan Oromo sentiment lexicon building issues, the tools used for implementing the prototype, the procedures to integrate the different components, the proposed algorithm, the input review, output result and other related issues are described.

3.3.1. Tools

In order to achieve our objective, we used different environments and tools. Python programming language is used to develop the prototype. Python is interpreted language, Python has a design philosophy that emphasizes code readability (notably using whitespace indentation to delimit code blocks rather than curly brackets or keywords), and a syntax that allows programmers to express concepts in fewer lines of code than might be used in languages such as C++.

3.3.2. The Proposed Algorithms

From these opinion terms, the value positive opinion terms, negative negation opinion terms, positive overstatement opinion terms are positive value and its negative value in other three remaining cases (i.e. negative opinion terms, positive negation opinion terms and negative understatement opinion terms).Here is general algorithm of the system proposed (sentiment mining model for opinionate Afaan Oromo texts)

Algorithm 3.8 : general algorithm of the system

Input: Reviews
positive_counter(PC)=0
negative_counter(NC)=-0
positive_negation(PN)=0
negative_negation(NN)=0
posetive_Overstatement (PO) =0
negative_Understament (NU) =0
For every pre-processed reviews R
For every word W in the review R
If a term W exists in the Positive_Words _Dictionary (PWD)
PC++
If a term W exists in the Negative_Words _Dictionary (NWC)
NC++
If a term W exists in the Positive_Negation_Words _Dictionary (PNWD)
PN++
If a term W exists in the Negative_Negation_Words _Dictionary (NNWD)
NN++
If a term W exists in the Posetive_Overstatement_Words _Dictionary (POWD)
PO++
If a term W exists in the Negative_Understatememt_Words _Dictionary (NUWD)
NU++
Total_Posative(TP)=PC+NN+PO
Total_Negative(TN)=NC+PN+NU
Review_polarity_value(RPV)=TP+TN
If RPV>0
Positive
Else If RPV<0
Negative
Else
Neutral

IV. RESULTS AND DISCUSSION

4.1. EVALUATION AND DISCUSSION

Every system is developed to meet some functionality. These functionalities are evaluated to make sure that the systems are performing effectively. Effectiveness refers to the extent a system fulfils its objective. In the case of our prototype system, the exactness of determining polarity of opinion words polarity classification was evaluated. The experimental setups/procedures, the evaluation parameters, results and discussions of are all sub topics that will be discussed in the subsequent sections.

4.1.1. Opinionated Data Collection

As indicated in the previous chapters, we have considered the movie reviews domain as a major reviews domain for conducting the experiments. The main reason why we used the movie reviews domain is due to the lack of readily available reviews written in Afaan Oromo. As a result it is relatively more easy and manageable to collect movie reviews manually than any other domains. This is because of movie viewers can write comments freely as compared to other domains such as politics. Most the movie reviews we used for conducting the experiments are collected from afaan Oromo movies' YouTube particularly from Eelaa, Way fedhii koo,Agaartuu Baarraqa and Handaarii movies. The rest few movie reviews are collected manually. Generally, a total of 341 movie reviews are collected from all the sources described above

4.1.2. Manual classification

This activity is concerned with labelling the reviews for experimental purpose. All the 341reviews (collected from different sources) are manually categorized by an independent individual from the domains into predefined categories: positive (+), negative (-), neutral (N) or unclassified (UN. As a result, 231(including overstatement positive words and negative negation words) of the total movie reviews are labelled as positive (+), 87(including under statement negative words and positive negation words) of them are labelled as negative (-) and finally, the rest 23 are as neutral (N) i.e. neither positive nor negative. The manually classified reviews helped us in crosschecking with the results obtained from our prototype system (sentiment mining model for opinionated Afaan Oromo texts).

4.3. Results

In this section, we present the experimental results of the two different experiments. The first experiment is conducted by using basic system dictionary. I.e. by using only positive and negative word dictionary without considering the contextual valence shifter terms. The second experiment is conducted by using basic system dictionary and contextual valance shifter (negation and intensifier). Comparison of these two different experimental results is also presented in this section. All the 341 movie reviews sources are used for conducting these two experiments. Each review was classified by the system prototype according to the procedures described earlier and all the results were recorded. Then the results were compared with the manually labelled classifications. As a result, the results obtained for each experiment are given as follows.

4.3.1. First experiment: Basic system dictionary

Table 4.1: Results of experiment one

System	Movies	Category	Precision	Recall	F-Measure
Basic system dictionaries(only positive and negative sentiment dictionary)	Eelaa	Positive	0.931	0.627	0.749
		Negative	0.928	0.371	0.530
	Agaartuu Baarraqa	Positive	0.940	0.661	0.776
		Negative	0.941	0.695	0.800
	Handaarii	Positive	0.956	0.656	0.778
		Negative	0.933	0.371	0.531
	Way Fedhii Too	Positive	0.972	0.580	0.726
		Negative	0.800	0.108	0.190
	Manually collected	Positive	0.967	0.671	0.792
		Negative	0.939	0.837	0.885
Average			0.931	0.558	0.676

This experiment used the basic lexicon of sentiment terms which include positive and negative afaan Oromo sentiment terms. The experiment is conducted for all movie reviews stated above. The results measured by accuracy, precision, recall and F-measure for each movies and classes is presented in table 4.1 as follows.

4.3.2. Second experiment: Basic system with contextual valence shifter

This experiment is conducted mainly to see the effect of using contextual valence shifter in this experiment. we have used both the basic system lexicons (positive and negative sentiment term lexicons) and contextual valence shifter lexicons (positive negation, negative negation, and positive overstatement, negative understatement sentiment terms lexicons). As shown in table 5.2 below the results of this experiment show improvements when compared with the results of experiment one on basic system lexicons. This improvement is mainly due to the use of the contextual valence shifters lexicon in addition to the basic system lexicon of terms. i.e. by using positive negation to express negative sentiment terns(like gaarii mitti(not good=gadhee(bad)) ,using negative negation to express positive sentiment terms(like gadhee mitti(not bad)=gaarii(good)) and also there are terms which are added into basic sentiment terms as prefix and suffix to increase and decrease the degree of positive sentiment terms and negative sentiment terms respectively.

Table 4.2 : Results of experiment two

System	Movies	Class	Precision	Recall	F-Measure
Basic system dictionaries with Contextual valence shifter(negation and intensifier) sentiment lexicons	Eelaa	Positive	0.909	0.930	0.919
		Negative	0.917	0.628	0.745
	Agaartuu Barraqa	Positive	0.872	0.957	0.912
		Negative	0.838	0.962	0.896
	Handaarii	Positive	0.936	0.881	0.908
		Negative	0.916	0.956	0.936
	Way Fadhii Too	Positive	0.892	0.806	0.847
		Negative	0.666	0.857	0.750
	Manually collected	Positive	0.821	0.931	0.873
		Negative	0.728	0.962	0.829
Average			**0.849**	**0.887**	**0.861**

4.4. CONCLUSION AND FUTURE WORK

The result from the first experiment show that the system precision is high when compared with that of second experiment above .This is mainly due to sentiment terms in processed movies' reviews highly matched with sentiment terms in lexicons so the probability of losing relevant terms from the retrieved terms is very low. Again from this experiment (experiment one) recall is low. As we have tried explain above, recall is comparing relevant items which retrieved by the system with relevant data from text which are checked manually by the researchers. During this cross checking there are items which missed by the system even though they are relevant. This is because of we have used only basic system lexicon which contain only the basic positive and negative sentiment terms. Many people uses negative sentiment terms to there is positive feeling and vise verse. For example to gadhee(bad) on amovies they may use gaarii miitti(not good),to say gaarii(good) they may use gadheemitti(not bad) and also to express their positive and negative feeling with high degree they use term like hedduu(very),baay'ee(very),guddaa(more),xiqqoo(less) with basic sentiment terms like gaarii(good),gadhee(bad), bareeda(beautiful) fokkisa(ugly) hawwataa(alluring), Salphina (abasement), aarii (angy), jibba (animosity),this compound words(terms) was not taken into account because of we have used basic system lexicons in this first experiment indirect loss of these compound terms in our lexicon(dictionary) make recall to be low, due to the number of relevant terms retrieved by the system and relevant items which are checked manually from the given the movies reviews. In the second experiment, the results show that the system prototype performs improvements when compared to the system prototype in the first experiment on movie reviews. The improvement of performance in the second experiment is due to the incorporation of contextual valence shifter lexicons (positive negation lexicon, Negative negation lexicon, positive overstatement lexicon, negative understatement lexicon).In this experiment (experiment two) as the result in second table shows precession decreased and recall is in increased when compared with the result in first experiment(first table).This result variation is due to the following reasons. The reason why precision is decreased in second experiment is that, the number of relevant item and retrieved items are varied. That means elements of contextual valence shifter are formed from basic system dictionaries elements by concatenating negation and intensifier word to them. And also the terms in processed reviews must be concatenated to make normalization with their lexicons. Due to this concatenation in reviews and the lexicon there is a chance in which unnecessary terms (not sentiment terms) are termed as sentiment terms. If these unnecessary terms (not sentiment term) in the reviews and in the lexicons are matched the system account as the terms as sentiment terms but, they are not predefined sentiment terms. So these were retrieved but they were not relevant. This is indirect decrease precision because of precision is the fraction of the documents retrieved that are relevant to the user's information need (total retrieved document by the system).In this second experiment the result of recall is increased due to negations and intensifier was taken into account .i.e. positive negation is accounted as negative and negative negation accounted as positive similarly, positive over statement is increase the polarity value of positive and negative understatement increase polarity value of negative. These positive negations, negative negation, positive over statement and negative understatement are increases the number of relevant item retrieved by the system. This is indirect increase recall because of recall is the number of relevant documents retrieved divided by the total number of existing relevant documents that should have been retrieved. Another parameter in these experiments (experiment one and experiment two) is F-measure, which gives equal importance to recall and precision. F-measure from these experiment are varies like precision and recall for mentioned above. These variations of F-measure are due to the variation of precision and recall in the experiments. In general, for conducting the above experiment, every component of the experimental setups is constructed from scratch and the experimental results obtained are encouraging and promising. Better performance will be achieved if stemmer algorithm is improved, and there is mechanism to handle synonymy.

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