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Customer Feedback Analysis in Afan Oromo Texts

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Abstract: When trying to make a good decision, we must weigh the positivity and negativity of human feedback and consider all the alternatives. As a result, human feedback is the primary part of decision making and the thought process of selecting a logical choice from the available persuasion.During decision making processes most of us get help from others and it is a natural fact that good decision can be taken on the basis of opinions of others.Accordingly, before the development of today's technologies, all the above mentioned facts have been practiced by asking families, neighbors, elders, friends and experts manually for decision making. Nowadays, opinions are found on the Internet everywhere and anytime.Despite its availability, it is unstructured and making information access challenging. To overcome this challenges, in our work we have proposed a feedback analysis model for AfanOromo texts. Feedback analysis is the process of computationally analyzing and categorizing human feedback or opinions expressed in a piece of texts especially to determine whether the writer's or Customer's attitude towards a particular topic, product, service and etc. is positive, strongly positive, weakly positive, negative, strongly negative, weakly negative or neutral. Consequently, this study proposes feedback analysis model for AfanOromo texts by using manually constructed rules and subjectivity lexicon of the language. The proposed model comprises of Nine main key components. These are: text preprocessing, morphological analysis, grammar checking, sentiment terms detection, ambiguity detection, polarity propagation, feedback's polarity weight calculation, feedback's polarity classification and the developed subjectivity lexicon of AfanOromo language. The developed prototype detects subjectivity words of a feedback from the developed lexicon and assigns an initial polarity weight for each sensed sentiment terms in order to determine the polarity classification of the feedback in AfanOromo texts. The developed lexicon of AfanOromo sentiment terms is used for recognizing and assigning initial polarity values for each of sentiment terms detected from entered feedback. The prototype has been developed for verifying the proposed model and the algorithms designed. As a result, experiments have been done on three different data sets and the achieved result with these test data is very encouraging.

Keywords: Subjectivity, Analysis, Lexicon, Feedback, Sentiment, Intensifier, Overstatement, Understatement

1. Introduction

Language is a medium of communication that enables human beings to exchange their ideas and information towards services, political policies, product, events, people, organization and a particular situation for decision making either in the form of text, speech or sign format [1]. As aresult, we can exchange knowledge, opinions, beliefs, wishes, threats, commands, thanks, promises, declarations and feelings using language. Nowadays, social media is the best tool to know about people's opinion, advice, comment, complement and their perception about any product, government policies and services [3]. One can use social media to gauge and measure customer's response, in the form of what they like or don't like, along with associated details [6]. This can support many aspects of a business including product development, customer service or marketing. During decision making processes, most of us need and get help from others [1]. It is a natural phenomenon or fact that good decision can be taken on the basis of opinions of others. Automatic detection and recognition of emotions in texts is becoming increasingly important from an applicative point of view [3]. A common usage for this technology is to determine how people feel about a particular thing and service. It intends to determine the opinion of a writer or opinion holder with respect to certain topic or target. The attitude could reflect someone's judgment, opinion or evaluation towards a particular target. Sentiment analysis is the use of natural language processing and computational linguistics to identify opinion information in source materials [7, 8, 11]. It is the study of how to analyze such expressions that may include, but not limited to, detection, extraction and classification which may be further processed to produce useful understandings into the target entities.

AfanOromo is a widely spoken language in the horn of Africa particularly in Ethiopia [14]. It is one of the major languages that is extensively spoken and used in Ethiopia. Currently, it is an official language of Oromia state. It is used by Oromo people, who are the largest ethnic group in Ethiopia, which amounts to 34.5% of the total population according to the 2008 census [15]. With regard to the writing system, since 1991 Qubee

(Latin-based alphabet) has been adopted and become the official script of AfanOromo language [16, 17]. With the fact that the language is used in media, industries and offices, there is a huge of electronic data available that informs people about the negativity and positivity of some products and services that enables people to make decision. Filtering people's feelings out of large amount of potentially relevant opinions is becoming a challenge for individuals. However, given the time constraint to processthe available information and make the best out of it, it is very wise to think of computer assisted automatic sentiment analysis as a solution for the language. Nowadays, several websites encourage users to express and exchange their views, suggestions and opinions related to product, services, polices and etc. publically [1, 18]. The increased popularity of these sites resulted in huge collection of people's opinions on the web in unstructured manner [2]. Extracting useful contents from these opinion sources becomes a challenging task and created a new field of research called sentiment analysis (SA) [6].A number of sentiment analysis (SA) systems have been developed in a variety of languages using different approaches such as English [19, 20, 21], Chinese [22], French [23], Amharic [24], and etc. But, as far as the knowledge of the researcher is concerned, no SA system was developed for AfanOromo language.

The increasing interest in sentiment analysis is mostly related to its practical applications in various settings. The proposed SA system analyses and categorizes opinionated AfanOromo texts to their correct predefined categories. The SA system can be applicable in analyzing people's opinions towards services, political policies, products, events, people, organizations and etc. for AfanOromo texts from a collection of documents or user's input texts.

1.1 AfanOromo Writing System

Writing system is a conservative method of visually representing verbal communication [14, 65]. Qubee, in AfanOromo, which is a Latin alphabet has been accepted and became the official scripting system of AfanOromo language since 1991 [14, 16]. The Qubee writing system of AfanOromo has a total of 33 letters that consists of all the 26 English letters (a…z) and the 7 combined consonant letters (ch, dh, sh, ny, ph, ts, zh) [14]. All the vowels in English (a, e, i, o and u) are also vowels in Qubee AfanOromo [63]. They have two natures in the writing system of AfanOromo language and results in different meanings. A vowel is said to be short, if it is one in number and long vowel if it is two which is the maximum. Example: Bona (summer), laga (river), are short vowels, whereas laagaa (throat), Boonaa (pride), are long vowels. The rest of Qubee AfanOromo is consonants. The combined consonant letters are known as "qubee dacha". Doubling of a consonant is a phonemic in AfanOromo. Example: Callaa (product), Damma (honey), Ganna (winter), and etc.

1.2 AfanOromo Morphology

Morphology is a branch of linguistics that studies patterns of word formation across languages and the study of internal structure of words [64, 66]. For instance, English and AfanOromo speakers aware of words sing, singer and singers (sirba, sirbaa, sirbituu and sirbitoota) respectively that they are thoroughly related. AfanOromo has a very rich in morphology [64]. This makes AfanOromo very challenging to create grammar checker, spelling checker and other natural language processing tasks. Morpheme is the minimum or smallest unit of morphology [66, 67]. There are two morphemes in AfanOromo: free morphemes (dhaam-jecha walabaa or ofdanda'aa) and bound morphemes (dhaam-jecha hirkataa). Free morphemes are morphemes that can stand alone and bear meaning. But, bound morphemes need collocation to other morphemes to convey meaning. Example, in the word "qulqullummaatti" (in righteousness), the word "qulqullummaa" is a free morpheme whereas the suffix "-tti" is a bound morpheme.

Based on their content, there are two bound morphemes in AfanOromo [64, 67]. These are: bound root (hundee hirkataa) and affix (fufii). Bound roots are morphemes that provide the most concrete or real role to the words meaning. Example, in words: marartoo, mararfachuu, mararsiifachuu, mararsiifatte, mararsiifate, and etc. have a bound root marar- and most of root words in AfanOromo are bound roots. Based on their location, AfanOromo affixes are classified into: prefix (fufii duree), infix (fufii giddee or gidduu), and suffix (fufii duubee) [64]. Based on grammatical functionality and the type of word class they change, affixes are categorized into: derivational affixes (fufii yaasaa) and inflectional affixes (fufiihortee). Derivational affixes or morphemes derive new words through collocation to root morphemes. Derivational affixes change the meaning and the category of the word class. In AfanOromo, they may be suffixes or prefixes. Some of the derivational affixes in AfanOromo are: hin-, -eenya,-ummaa, and etc. Example, collocating –ummaa suffix to an adjective "gaarii" will derive a new noun called "gaarummaa". But, inflectional morphemes indicate grammatical formation such as: numbers (plural), tenses (xumurtoota), persons (ramaddii) and possessions (abbummee). They never change the meaning and category of the word and/or morphemes they collocated. Some of inflectional affixes in AfanOromo are: -oota, -dhaan, -lee, -wwan, -dhaaf, -fi, -tuu, -te, -e, -an, -f and etc. Example, collocating a suffix –tuu to a noun daraaraa will create an inflected noun daraartuu.

2. Research Method

The proposed system is dependent on the lexicon of AfanOromo opinion terms. This lexicon contains AfanOromo opinion terms tagged as positive, negative, intensifiers and negations. Such a lexicon will be built to achieve the desired goal. The manual, corpus and dictionary based techniques are used for collecting the subjectivity terms of the language. As far as this research work is concerned with opinionated AfanOromo texts, it is compulsory to analyze and deal with the nature of AfanOromo texts that contain opinions of people towards service reviews, house rental reviews, product reviews and etc. For this reason, rules and regulations will be proposed to categorize AfanOromo opinionated texts to their corresponding predefined categories with linguists. Datasets (reviews) used for carrying out the experiment will be collected from people living in Addis Ababa city on house rental reviews, Addis Ababa Anbesa bus reviews and from a variety of social media on products or services.

2.1 Conjugation of AfanOromo Verbs

Most AfanOromo dictionaries list verbs in their infinitives and all infinitives end in –uu [68, 69].Example, hatuu (to steal). The root of hatuu is, therefore, hat- and the verb is conjugated by adding affixes to this root. Example, hata (He steals), hatti (She steals), hatu (they steal), and etc. A verb conjugation can communicate a lot of detail about a verb such as: person, number, tenses, gender, and etc. Accordingly, AfanOromo verbs fall into one of four groups (regular verbs, double consonant ending stems, verbs ending with -chuu and irregular verbs) based on their stem endings [68, 70]. Most verbs of AfanOromo are regular, that is they attach the regular person and number based suffixes to their stem without any changes to the stem or suffixes [68, 69]. These are verbs with stems or roots that do not end in a double consonant, ch, a vowel, y, or w. For example, the present future conjugations for hatuu, deemuu and beekuu are shown with suffixes in bold.

Table 1: Sample Conjugations of regular verbs

Conjugating Verbs	Personal Pronouns						
	Ani (I)	Inni(He)	Isheen/ishiin (She)	Isaan (They)	Nuyi/nuti (We)	Ati(You) singular	Isin(You)
Deemuu	Deem**a**	Deem**a**	Deem**ti**	Deem**u**	Deem**na**	Deemta	Deem**tu**
Hatuu	Hat**a**	Hat**a**	Hat**ti**	Hat**u**	Hat**na**	Hat**ta**	Hat**tu**
Beekuu	Beek**a**	Beek**a**	Beek**ti**	Beek**u**	Beek**na**	Beek**ta**	Beek**tu**

If any verb's stem ends in a double consonant, a slight modification of the regular verb conjugation must be made, because, AfanOromo does not allow three consecutive consonants to occur in a single word [16, 68]. In this conjugation techniques, for the pronouns (nuti/nuyi, ati, isin, and isheen), an "i" is added to the regular suffixes. Example, the present future conjugations for darbuu, arguu, gadduu, gorsuu and gaabbuu are shown with suffixes in bold.

Table 2: Sample Conjugations of AfanOromo Double Consonant ending Stem

Conjugating Verbs	Personal Pronouns						
	Ani	Inni	Isheen	Isaan	Nuyi/nuti	Ati	Isin
Darbuu	Darb**a**	Darb**a**	Darb**iti**	Darb**u**	Darb**ina**	darb**ita**	Darb**itu**
Arguu	Arg**a**	Arg**a**	Arg**iti**	Arg**u**	Arg**ina**	Arg**ita**	Arg**itu**
Gaabbuu	Gaabb**a**	Gaabb**a**	Gaabb**iti**	gaabb**u**	Gaabb**ina**	gaabb**ita**	Gaabb**itu**
Gadduu	Gadd**a**	Gadd**a**	Gadd**iti**	gadd**u**	Gadd**ina**	gadd**ita**	Gadd**itu**
Gorsuu	Gors**a**	Gors**a**	Gors**iti**	Gors**u**	Gors**ina**	gors**ita**	Gors**itu**

Many infinitive verbs end with -chuu. For these verbs, the ch changes to dh in the ani form and t for all other forms and the t changes to n for the nuti form [68]. Then, the standard suffixes are applied. Example, the present future conjugations for jiraachuu, argachuu, barachuuand gubachuu are shown with suffixes in bold.

Table 3: Sample Conjugations of AfanOromo Verbs ending with -chuu

Conjugating Verbs	Personal Pronouns						
	ani	Inni	Isheen	Isaan	Nuyi/nuti	Ati	Isin
Jiraachuu	Jiraa**dha**	Jiraa**ta**	Jiraa**tti**	Jiraa**tu**	Jiraa**nna**	Jiraa**tta**	Jiraa**ttu**
Argachuu	arga**dha**	Arga**ta**	Arga**tti**	Arga**tu**	Arga**nna**	Arga**tta**	Arga**ttu**
Barachuu	bara**dha**	Bara**ta**	Bara**tti**	Bara**tu**	Bara**nna**	Bara**tta**	Bara**ttu**
Gubachuu	Guba**dha**	Guba**ta**	Guba**tti**	Guba**tu**	Guba**nna**	Guba**tta**	Guba**ttu**

Infinitives that end with -a'uu , -o'uu, -u'uu, -e'uu, and -i'uu act as regular verbs for ani, inni, and isaanforms. However, for the other forms, the stem and/or suffixes will deviate from regular conjugations [68, 69, 70]. Example, the present future conjugations for du’uu, haasa’uu, boo’uu and danda’uu are presented.

Table 4: Sample Conjugations of AfanOromo Irregular Verbs

Conjugating verbs	Personal pronouns						
	Ani	Inni	Isheen	Isaan	Nuyi/nuti	Ati	Isin
du’uu	du’a	du’a	Duuti	du’u	Duuna	Duuta	duutu
haasa’uu	haasa’a	haasa’a	Haasofti	haasa’u	Haasofna	Haasofta	haasoftu
danda’uu	danda’a	danda’a	Dandeessi	danda’u	Dandeenya	dandeessa	dandeessu
boo’uu	boo’a	boo’a	Boossi	boo’u	Boonya	Boossa	boossu

To express actions completed in the past, verbs are conjugated in the simple past tenses. Final vowels in the present affirmatives of (a, i, u) are changed to (u, u, an) and (i, i, an(i)) in present negatives and past affirmatives respectively [68]. For the first person singular ani form, the suffix -n or -an to the consonant must be added to the word preceding the verb or the preverb nan must be used to express the verb in the affirmative [68, 70]. Example, baradheen dhufe, beekuufan baradhe, nan jiraadha, and etc. For other forms, an optional preverb ni may be used. Usually, if there is no object in the sentence, the ni is mandatory. Example, inni nibareeda, isheen nibareeddi, and etc.To express not, don't, doesn't, in AfanOromo, the prefix hin is added before the verb as an attached prefix and the last vowel in the verb conjugated in the affirmative changes as follows: for ani/inni/ati/nuyi/nuti, a → u, for isheen/ishiin, i → u and for isaan/isin, u → an/an(i) [68]. Example, ani/inni hinhatu, ati hinhattu. The exception to this is the negative form of dha, whichis miti meaning, am not, are not, and is not.

Table 5: Sample Conjugation of AfanOromo simple past affirmatives

Personal pronouns	***Jaallachuu (to love), the –chuu verb***			
	Present		**Past**	
	Affirmative	Negative	Affirmative	Negative
Ani	jaalladha/nan jaalladha	hinjaalladhu	jaalladhe/nan jaalladhe	Hinjaallanne
nuti/nuyi	jaallanna/nijaallanna	Hinjaallannu	jaallanne/nijaallanne	Hinjaallanne
Ati	jaallatta/nijaallatta	Hinjaallattu	jaallatte/nijaallatte	Hinjaallanne
Isin	jaallattu/nijaallattu	Hinjaallattan	jaallattani/nijaallattani	Hinjaallanne
Inni	jaallata/nijaallata	Hinjaallatu	jaallate/nijaallate	Hinjaallanne
Isheen	jaallatti/nijaallatti	Hinjaallattu	jaallatte/nijaallatte	Hinjaallanne
Isaan	jaallatu/nijaallatu	Hinjaallatan	jaallatani/nijaallatani	Hinjaallanne

Certain root word consonants will changed when placed before or after other specific consonants [68]. These morphological changes are foreseeable the most common changes are: an initial **t** in a suffix will changed to **d** if the stem ends in **b**, **g** and **d**, and an initial **n** in a suffix will changed to an **r** or **l** if the stem ends in **r** or **l** respectively, and **t** ending in a stem will be changed to **n** in the nuyi/nuti form if the initial of a suffix is **n**.

Table 6: Sample AfanOromo root word consonants change

End of Roots	Initial of suffixes	Suffixes	Example	After Morphed
b-	-t	-ta	Qa**b**+**t**a	Qab**d**a
d-	-t	-te	Saga**d**+**t**e	Sagad**d**e
g-	-t	-te	Bajig+te	Bajig**d**e
x-	-t	-te	Fi**x**+**t**e	Fix**x**e
q-	-t	-te	Baq+te	Baq**x**e
t-, x-, d-, dh-	-n	-na	Jiraadh+na	Jiraa**n**na
dh-	-t	-te	Jiraadh+te	Jiraa**t**te
s-	-t	-te	Basaas+tu	Basaa**f**te
s-	-n	-ne	Basaas+ne	Basaa**f**ne
r-	-n	-ne	Har+ne	Hare
l-	-n	-ne	Eegal+ne	Eegal**l**e

2.2 AfanOromo Syntax

A sentence is a word or set of words that is complete in itself and naturally containing a subject and predicate [63, 69, 70]. There are a lot of rules towards word ordering during sentence construction in Afan Oromao texts. However, for this study, we want to focus on main clause word ordering. The normal order of words during sentence construction in main clause follows the SOV (Subject-Object-Verb) format [63].A structured text increases the competency of NLP applications. The syntactic level of linguistic analysis concerns how words are put together to form correct sentences and determines what structural role each word plays in the sentence.Syntactic analysis requires both a grammar and a parser, the output of which is presentation of the sentence that reveals the structural dependency relationships between the words. This structural dependency can be represented using trees. Parsing assists to understand how words are put together to form the correct phrases or sentences along with the structural roles of the words and it plays a significant role in many NLP applications as it helps to reducethe overall structural complexity of sentences [69].

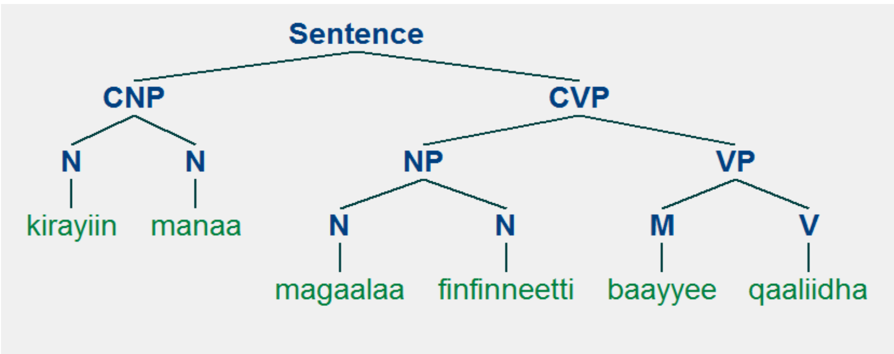

Figure 1: Sample AfanOromo Parse Tree

2.3 System Architecture

The proposed system architecture for opinionated AfanOromo sentiment analysis consists of text pre-processing, morphological analysis, grammar checking, sentiment terms detection, ambiguity detection and polarity computation components. The polarity computation itself comprises sub-components such as polarity propagation, review's polarity weight calculation and review's polarity classification sub-components. Figure 2 shows the system architecture.

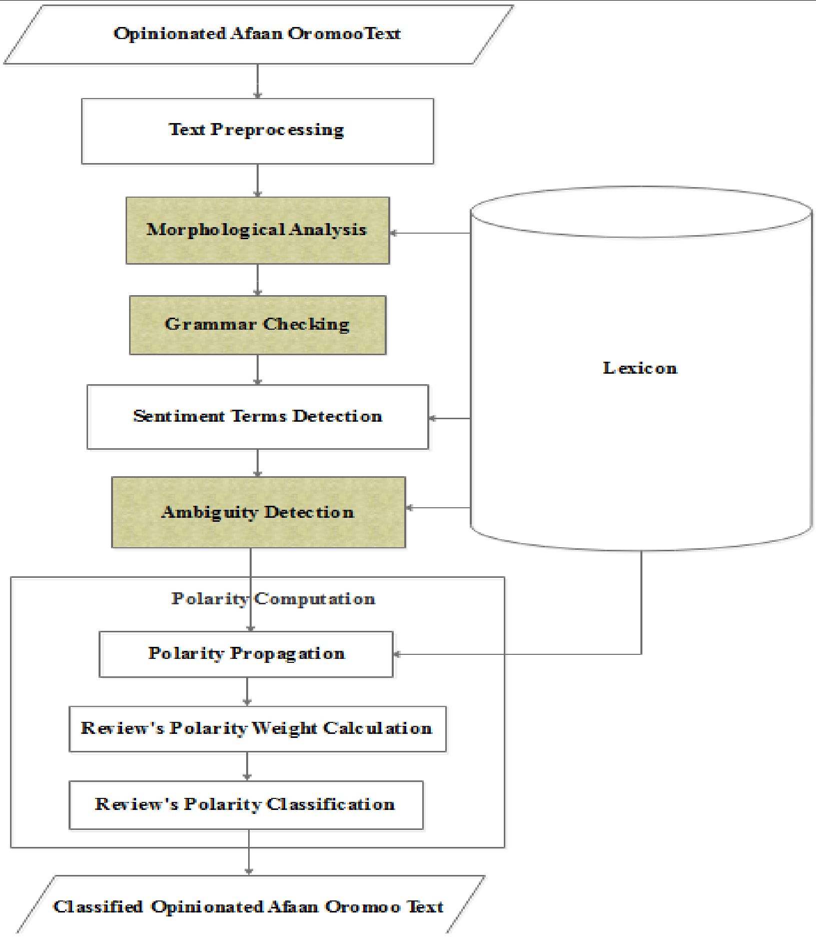

Figure 2: System Architecture for Opinionated AfanOromo Sentiment Analysis

2.4 Sentiment Terms Collection

Recognizing polarity requires a lexicon of polar words and phrases. Since, the eminence of lexicon-based sentiment analysis system is pretentious by the effectiveness of the built subjectivity lexicon we have developed a subjectivity lexicon for AfanOromo. As a result, different sources and techniques are used to build the subjectivity lexicon as there are no easily available resources in AfanOromo language that can be integrated with our work. During selection of sentiment terms from the resources we used, we considered subjectivity terms from the list. We took these subjectivity terms and translated them to their equivalent AfanOromo sentiment terms using English to AfanOromo and Amharic to AfanOromo online and offline dictionaries. Other hard copy dictionaries are also used for the translation.

2.5 Subjectivity Lexicon

While expressing a subjective view over an entity, we generally use words that convey certain senses that describe our feelings towards an entity [55]. We can categorize these words as having positive or negative polarities. A term or word is marked as positive, in the sense that it gives a positive evaluation over an entity and negative for a negative evaluation. The words ‘good’, ‘wonderful’, ‘fantastic’, and etc. can be marked as having positive polarity, while the words ‘bad’, ‘awful’, and the like can be marked as having negative polarity. It is then both reasonable and profitable to possess a list that contains these words together with their polarities. We built subjectivity lexicon as a dictionary that contains these words together with their positive and negative polarity information. Subjectivitydictionary is composed of subjective words that express desirable or undesirable states.

3. Results and Discussion

The prototype is developed to meet the proposed functionality of sentiment analysis for opinionated AfanOromo texts. In this work, the exactness of determining polarities of opinion holders’ opinionated texts to their correct predefined categories by scanning the whole Subjectivity lexicon for each word of the opinion holders' opinionated texts are evaluated. Reviewers can write their opinions in AfanOromo texts towards any target they want to review in the input box. The system displays the polarity of the opinion together with the polarity weight.

Figure 3: Customer Feedback Analysis texts entry interface

3.1 Manual Classification

This activity is concerned with labeling the reviews for experimental purpose. All the reviews (the house rental reviews, online dictionary reviews and Anbesa bus service reviews) are manually categorized by an expert of the language at Addis Ababa University into the predefined categories: positive and further classified as: (strongly positive or weakly positive), negative and further classified as: (strongly negative or weakly negative) or neutral and finally classied by the developed system.

Table 3. 1: Classification by the system

lexicon used	**Review domain**	**Polarity category**		**Precisin**	**Recall**	**F-measure**
AOSL	AO to English online dictionary reviews	Positive	Positive	0.906	0.967	0.936
			Strongly positive	0.981	0.912	0.945
			Weakly positive	0.75	0.6	0.667
		Negative	Negative	0.895	0.944	0.919
			Strongly negative	0.875	0.875	0.875
			Weakly negative	0.833	0.714	0.769
		Neutral		0.286	1.00	0.444
	A.A House Rental Reviews	Positive	Positive	0.5	0.666	0.571
			Strongly positive	0.6	0.75	0.666
			Weakly positive	0.5	0.5	0.5
		Negative	Negative	0.905	0.864	0.883
			Strongly negative	0.948	0.849	0.896
			Weakly negative	0.571	0.833	0.678

		Neutral		0.000	0.000	0.000
	A.A. Anbesa Bus Reviews	Positive	Positive	0.571	0.5	0.533
			Strongly positive	0.9	0.818	0.857
			Weakly positive	0.6	0.75	0.667
		Negative	Negative	0.813	0.65	0.722
			Strongly negative	0.875	0.7	0.778
			Weakly negative	0.714	0.833	0.769
		Neutral		0.000	0.000	0.000

The prototype performs relatively well with online dictionary reviews than the other two reviews. Similarly, the prototype performs well with positive, strongly positive and negative categories than weakly positive, strongly negative and weakly negative categories for English to AO online dictionary reviews. The result shows that most of the reviewers are satisfied. For house rental reviews, the prototype also performs well with negative and strongly negative categories than the other categories. From this result we studied that almost all of the reviewers are not satisfied with the target they reviewed. Lastly, for A.A Anbesa bus reviews, the prototype also performs well with strongly positive, strongly negative and weakly negative categories than the other categories. The result reveals that users of A.A Anbesa bus are not satisfied by the service they obtain. For the three reviewed targets, there is a deviation on the performance of some of the polarity categories. This can be caused by different reasons related to the nature of natural language complexities. In this research work, we have learnt some reasons for the slanted results of the experimental results. The first reason is that when writing reviews in AfanOromo, some of the reviewers express their negative opinions without the use of subjectivity terms. For example, in the review “yeroo ammaa kana magaalaa Finfinnee keessatti, miindaa argannuu olitti kiraa manaaf gaafatamaa jirra” (Nowadays, we are asked more than the salary we earned for house rent in Addis Ababa city). The developed prototype categorized the sentence as “Neutral”. But the expressed opinion is “negative”.

4. Conclusion

In this work, we proposed and developed a sentiment analysis model for opinionated AfanOromo text. Before going to develop the proposed model, the sentiment analysis approaches developed for different languages, and the nature, structure and pattern of AfanOromo language have been studied. A lexicon based sentiment analysis approach has been employed as a development method. AfanOromo subjectivity lexicon and algorithms to implement components of the model have been developed. Accordingly, the opinionated review text passes through components of the model such as: text pre-processing, morphological analysis, grammar checking, sentiment terms detection, ambiguity detection, polarity propagation, review’s polarity weight calculation and review’s polarity classification components for polarity analysis. The common usage for this technology is to determine how people feel about a particular thing and/or service for decision making purpose.

The pre-processing component is responsible for accepting the input review and produces a set of normalized and tokenized terms. The morphological analysis component accepts tokenized terms of a review from text preprocessing component and decomposes them to their root words and morphemes. The sentiment terms detection component detects sentiment terms within the developed lexicon. The ambiguity detection component redetects the sentiment terms of a review for ambiguity. The polarity propagation component looks for the nearby contextual valence shifter terms of the detected sentiment term within the developed lexicon for polarity propagation. The polarity weight calculator computes the total polarity weight of the given review. The polarity classifier component classifies a review into its predefined categories based on the total polarity weight obtained from the polarity calculation component.

In order to evaluate the developed prototype 127, 187 and 61 reviews with a total of 375 are collected from English to AO online dictionary reviews, Addis Ababa house rental reviews and A.A Anbesa bus reviews respectively. Accordingly, the three different collected reviews are manually categorized by an expert of the language at Addis Ababa University to their predefined categories. Finally, the three reviews are evaluated to the developed prototype, and as a result, for English to AO online dictionary reviews a precision, recall and F-Measure of 0.678, 0.890 and 0.716 respectively are achieved. For house rental reviews a precision, recall and F-Measure of 0.670, 0.744 and 0.699 respectively are achieved. For A.A Anbesa bus reviews a precision, recall and F-Measure of 0.745, 0.709 and 0.718 respectively are achieved. The results show that this study is promising.

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