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SENTIMENT MINING MODEL FOR OPINIONATED AMHARIC TEXTS

By: Selama Gebremeskel

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BY: Selama Gebremeskel

ADVISOR:

Solomon Atnafu (PhD.)

APPROVED BY:

EXAMINING BOARD:

1. Dr. Solomon Atnafu, Advisor _____
2. _____ _____
3. _____ _____

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Dedication

Dedicated to my country ***ETHIOPIA***

ሁሉም ነገር ኢትዮጵያ እንዳለችው ይሁን!!!

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List of Acronyms

ASCII	American Standard Code for Information Interchange
CTRW	Choose the Right Word
DAL	Dictionary of Affect Languages
GI	General Inquirer
IMDB	Internet Movie Database
IR	Information Retrieval
MCC	Media and communication Center
ME	Maximum Entropy
NB	Naïve Bayes
NLP	Natural Language Processing
SentiWN	Senti Word Net
SVM	Support Vector Machine
POS	Part of Speech
UN	Unclassified

Abstract

Opinions are so important that whenever we need to make a decision, we want to hear other's opinions. This is not only true for individuals but also for organizations. Due to the rapid growth of opinionated documents, reviews and posts on the Web, the need for finding relevant sources, extract related sentences with opinions, summarize them and organize them to useful form is becoming very high. Sentiment mining can play an important role in satisfying these needs. 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. In this research work, a sentiment mining model is proposed for determining the sentiments expressed in an opinionated Amharic texts or reviews. The polarity classification or semantic orientation of the opinionated texts can be positive, negative or neutral. The system designed based on the proposed model detects positive and negative sentiment terms including contextual valence shifters such as negations and assigns an initial polarity weight to all detected sentiment terms in order to determine the polarity classification of the opinionated text. The lexica of Amharic sentiment terms are used to identify and assign initial polarity value to the sentiment terms detected. A prototype system is developed to validate the proposed model and the algorithms designed. Tests on the prototype are done using movie and newspaper reviews where the result obtained with these test data is very much encouraging.

Keywords: opinions, sentiments, sentiment mining from opinionated Amharic texts, polarity classification from opinionated Amharic texts, sentiment lexicon, opinionated Amharic text

CHAPTER ONE

1. INTRODUCTION

1.1. Overview

An important part of our information-gathering behavior has always been to find out what other people think about an issue. With the growing availability and popularity of opinion-rich resources such as online review sites and personal blogs, new opportunities and challenges arise as people now can, and do, actively use information technologies to seek and understand the opinion of others [1]. The ability to automatically extract and classify opinions from texts would be enormously helpful to individuals, business intelligence, government intelligence and others in decision making. Extracted opinion also can be used effectively by recommendation and collaboration systems. A collaboration system helps users to explore recommendations from various viewpoints. Given ratings and reviewers from reviews, this system provides virtual reviewers that represent particular view points and recommendations [2, 3].

Opinion mining, which is also known as sentiment analysis, emotion mining, attitude mining or subjectivity mining [2], is a hot research discipline which is concerned with the computational study of opinions, sentiments and emotions expressed in an opinionated text. Why is opinion mining important now? It is mainly because of the web, which is full of huge volume of opinionated text.

Sentiment mining can be done at sentence level, document level or feature level. In sentence level opinion mining, there are two tasks: the subjectivity classification and sentiment classification. The first is concerned with subjectivity and objectivity classification. Sentences are classified into pre-defined binary classification subjective sentence (e.g. it is such a nice phone) or objective sentence (e.g. I bought an iPhone a few days ago). The sentiment classification is concerned with polarity classification. The sentences are classified as positive (e.g. it is just a nice phone), negative (e.g. the phone broke in two days) or neutral classification. The document level sentiment classification is concerned with classifying the document based on the overall opinion expressed by the opinion holder as positive, negative and neutral. At the feature level sentiment mining, commented features are identified, extracted and the sentiment towards these features is determined [4]. In this research our focus is on document level sentiment classification of Amharic texts such as movie reviews.

1.2. Statement of the Problem

One of the main reasons for the lack of study on opinions is the fact that there were little opinionated texts available before the World Wide Web. Before the Web, when an individual needed to make a decision, he/she typically asked for opinions from friends and families. When an organization wanted to find the opinions of sentiments of the general public about its products and services, it conducted opinion polls, surveys, and focus groups. However, with the Web, especially with the explosive growth of the user generated content on the Web in the past few years, the world has transformed [5].

We can have different opinion search queries for different purposes such as to:

1. Find opinion of a person or organization on a particular object or feature of the object (e.g. what is Obama's opinion on abortion).
2. Find positive, negative or neutral opinion on a particular object (e.g. customers' opinion on a digital camera, public opinion on political topic) and
3. Determine how object A compares with object B (e.g. gmail versus hotmail).

As online business is becoming more and more popular, the quantity of reviews toward products given by customers is growing rapidly as well. Hence it is difficult for a customer, seller or the producer to read all of the reviews and make a reasonable decision when she/he is facing the problem whether to purchase a certain product / use certain service or not [4]. Due to the availability of opinion rich documents on review sites, forums, discussion groups, blogs etc, there are too many opinions and reviews to be read which is very difficult and hence traditional techniques are inadequate. So there is a need for good sampling and classification techniques for these reviews and opinions. For this reason many researches on sentiment analysis have been done and are being under taken for English and other languages such as French [6]. But to the extent of my knowledge, sentiment classification of Amharic documents has never been studied even though the amount of opinionated Amharic documents on the web is increasing [7]. Therefore, this study investigates and aims to develop a sentiment classification model for opinionated Amharic texts.

1.3. Motivation

For specific opinion search queries that are of the same nature with finding positive, negative or neutral opinion on a particular object, we can have Amharic opinion queries such as "የሚኒባስ ባለንብረቶች ስለ አዲሱ በቀጠና መስራት ምን አስተያየት ላላቸዉ ?" where the collected review could be positive such as ("በ አዲስ አበባ ያለዉን የትራንስፖርት ችግር ስለሚፈታ በጣም ጥሩ ነው ብየ አምናለሁ።።", negative opinions such as "ይሄ አሰራር ዘላቂ መፍትሄ ላይሆንም ።" or neutral (that contains both negative and positive opinions with the same strength or weight). So we can analyze these opinions for the purpose of decision making. "የፊልም አፍቃርያን ስለ 'የዎንዶች ጉዳይ ቁ.2' ፊልም ምን አስተያየት አላቸዉ" the collected opinions may be positive such as "ድርሰቱም ሆነ ቅንብሩ በጣም ደስ ይላል። ስለ ሆነም በጣም ተመችቶኛል።", negative opinions such as "በአጠቃላይ ፊልሙ ለኔ አልተመቸኝም። or neutral (that contains both positive and negative opinions with the same strength or weight). Therefore in this research we are going to investigate the possibilities of developing an Amharic Sentiment Mining model that will be able to automatically analyze the sentiment of huge amount of collected reviews prior to making decisions.

1.4. Objectives

The general and specific objectives of this study are given below:

General Objective: the general objective of this research work is to design and develop a sentiment mining model for opinionated Amharic documents.

Specific Objectives: the specific objectives of this research work are:

- Analysis of the general structure of Amharic statements related to opinions and sentiments such as identifying negative, positive and neutral statements.
- Analyze the relationship between opinions and Amharic words and their intensity or strength.
- Design a model for sentiment mining from Amharic opinionated texts.
- Building of both domain specific and general purpose lexicon of Amharic language opinion terms where these terms are tagged as positive (+), negative (-), overstatement (>) understatement (<) or negation (Negate).
- Develop necessary algorithms to realize the proposed model in developing an Amharic sentiment mining model.
- Develop a prototype to demonstrate that the model designed is valid.
- Evaluate the model designed using movies reviews.

1.5. Scope and Limitations

Opinion mining is a complex and recent research discipline that requires the effective analysis and processing of documents. Since there are no publicly available Natural Language Processing (NLP) tools and other resources for Amharic language that can be integrated with our model, the scope of our research work is:

- Limited to sentiment (polarity) mining (only positive, negative or neutral) classification. i.e. it doesn't cover subjective or objective classification.
- We use domain specific review texts that are grammatically checked and organized.
- The opinion holder identification and reasons for positive and negative classifications are not covered in this research work.
- Attention is given to most common Amharic words used to express opinions "ጥሩ፣ ደስ ይላል፣ በጣም ጥሩ፣ መልካም ወዘተ" for positive opinions and "መጥፎ ፣ አይመቸም ፣ ደስ አይልም ወዘተ" for negative opinions. Because of their complicated nature, Amharic expressions such as "ቅኔያዊ አነጋገር" are out of the scope of this research work.
- Opinion spam detection, the process of detecting fake reviews, is not covered in this research work as it is a very complicated problem. Fake reviews are reviews that contain false positive or malicious negative opinions [4, 8].

1.6. Methodology

Literature review

Opinion mining related literatures from different sources such as published papers, journal articles and other materials are reviewed in detail to get better understanding of the area and to have detail knowledge on the various techniques of sentiment mining.

Analysis of existing opinion based texts in Amharic

Since this research work is mainly concerned with opinionated Amharic texts, it was compulsory to analyze the nature of Amharic documents that contain opinions. Therefore rules and methods were proposed to identify or categorize Amharic opinion terms.

Lexicon of Opinion terms

The proposed model is fully dependent on the lexicon of Amharic opinion terms. This lexicon contains Amharic opinion terms tagged as positive (+), negative (-), negations (negate), overstatement (>) or understatement (<). Negations and intensifiers (overstatements and understatement) are collectively known as contextual valence shifters. Those terms change the

initial value of a sentiment term. Negations are terms that can change the semantic orientation of a term. Basically these terms switch a positive term to negative term and vice versa as in *ጥሩ (good)* is positive while *ጥሩ አይደለም (not good)* is negative due to the contextual valence shifter term *አይደለም (not)*. Intensifiers are terms that change the degree of the expressed sentiment. For example, in the sentence '*ፊልሙ በጣም ጥሩ ነዉ*' (the film is very good), the terms በጣም ጥሩ (very good) are more positive than just 'ጥሩ' (good) alone [9].

We have built two lexica of opinion terms. These are: Domain specific lexicon and General purpose lexicon. The domain specific lexicon contains opinion terms restricted to a specific domain (e.g. movie reviews domain). The general purpose lexicon contains opinion terms of Amharic language terms which are not restricted to a specific domain (this lexicon is to be used by any domain such as products reviews, movie reviews, hotel reviews etc). The procedures and guidelines of building the lexica are given in chapter four.

Data Source

Most of the datasets (reviews) used for conducting the experiment are manually collected from Cinemas in Addis Ababa and previously collected reviews by undergraduate students of the department of Theatrical arts at Addis Ababa University. The rest of the dataset is collected from www.habeshafilms.com [10].

Prototyping

In order to test the proposed model, we have developed a prototype. We built a lexicon of opinion terms according to the procedures and guidelines for implementing the prototype. This lexicon of terms is then integrated for manipulation and prototyping.

1.7. Procedures

Different components and development stages (phases) are employed in developing the Amharic sentiment mining model. Three main tasks are involved throughout this research work. These tasks are: linguistic related (Amharic) studies, building Amharic opinion terms lexicon and programming language (implementation) related tasks. The linguistic related study includes studying the structure of Amharic statements related to opinion expressions while the lexicon construction is concerned with building a dictionary of opinion terms and assigning prior polarity value. The last one refers to choosing suitable working environment and implementing the prototype.

1.8. Application of Results

In the current business and political situations, knowing what other people think is a determinant factor in decision making. Hence, the Amharic Sentiment Mining model can be used for different purposes. Some of them are:

- Business and organizations (product review mining and service analysis, market intelligence) can use the system to reduce the money spent to find consumer's sentiment and opinions.
- Individuals (who are interested in other's opinion, can use it when purchasing a product such as in the case of www.epinions.com [11], using a service or finding opinions on political topics).
- Government intelligence can use the system for mining opinions of people on a particular issue.
- The system can be used to classify movie reviews as positive, negative or neutral.
- The system can be used to answer opinion questions. For instance, what is the international reaction to the 4th Ethiopian national election conducted on May 23, 2010?

1.9. Thesis organization

The remainder of this thesis report is organized as follows. Chapter two introduces an overview of opinion mining (sentiment mining) and the different techniques used in sentiment mining researches. Moreover, the general steps in sentiment mining are also discussed in this chapter. Chapter three presents reviews of related researches conducted on opinion mining/sentiment mining. In this chapter, in depth reviews of researches done on sentiment mining using different techniques for different languages is presented. Chapter four describes the general architecture of the proposed model for the Amharic sentiment mining model and the construction of Amharic sentiment terms lexicon. In addition, implementation related issues such as pre-processing, dictionary/lexicon integration and classification are also explained in the same chapter. Chapter five presents the experimental results of the proposed model in general and the different algorithms in particular. Finally, future works, recommendations and conclusions are given in the last chapter.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Introduction

The two main types of textual information available in any texts are: facts and opinions. Facts are objective statements about entities and events in the world but opinions are subjective statements that reflect people's sentiments or perceptions about the entities and events. Automatic sentiment analysis in texts, also called opinion mining, has attracted considerable attention in recent years, primarily because of its potential use in marketing study. It aims to answer questions such as 'is the customer who sent a mail to an after-sale service particularly dissatisfied?',' are the opinions about product posted in blogs positive or negative?', what is the image of political party or leader in the press?'. All these questions, which are related to the way something is presented or evaluated in a text, are particularly difficult for traditional information extraction techniques [12], which are interested with factual information. The sudden eruption of activity in the area of opinion mining and sentiment analysis, which deals with the computational treatment of opinion, sentiment and subjectivity in the text, has occurred at least in a part as a direct response to the surge of interest in new systems that deal directly with opinions as a first class object [1]. In this chapter a clear description of the area, the methodology, languages and related issues is given.

Opinions or sentiments

Opinion is a private state that is not open to objective observation or verification. It is defined as a person's idea and thought towards something and it is an assessment, judgment or evaluation of something [13]. The web contains a wealth of opinions about products, politicians, and more, which are expressed in newsgroup posts, review sites, and elsewhere. These opinions are so important that whenever we need to make a decision, we always need to hear other's opinions. As a result the problem of opinion mining has seen increasing attention [14].

Opinion words

Opinion words such as positive (e.g. beautiful, wonderful…), or negative (e.g. bad, poor, terrible...) are instrumental for sentiment mining. Some opinion words are context independent (e.g. good) while some are context dependent (e.g. increase, it is positive for the employees

when it refers to increase in salary and negative for taxpayers if it refers to increase in tax) [15].

Types of opinion words

According to [16], there are three types of opinion words. These are personal emotion (e.g. happy, delighted, proud, sad, angry, horrified, etc), appreciation (flexible, stable, efficient, reduced, ideal, backward, poor, highest etc) and judgment (e.g. active, decisive, caring, dedicated, intelligent, negligent, evil, etc). *Bing Liu* [5] divided opinion words into two types, the base types and comparative types. Base types of opinion words are used to express desired or undesired states (e.g. wonderful, poor, etc) where as comparative types of opinion words are used to express comparative or superlative opinions (e.g. better, worse, best, etc).

Context valence shifters

Context valence shifters are terms that cause the valence of a sentiment term to shift from one pole to the other or, less forcefully, to modify the valence towards a more neutral. Negations are the most obvious valence shifters. "Not" flips the valence of a term. In addition to "not", negations can belong to various classes. Simple negations include **never, none, nobody, nowhere, nothing, neither** …" As in:

*John **is clever** versus john **is not clever***

*John **is successful** at tennis versus john is **never successful** at tennis*

Of course for a shift in attitude to take place there has to be an attitude expressed in the first place. A simple sentence such as "john is home" might express a simple fact without betraying an attitude (i.e. the attitude score is 0). When negated, as in "john is not home", there is no shift in attitude (i.e. the negation of 0 is 0). Combining positive words with a negation such as "not" flips the positive valence to a negative valence [9].

Components of an opinion

The basic components of an opinion are: opinion holder, object and the actual opinion. Opinion holder refers to the person or the organization that holds a specific opinion on a particular object. The object refers to which an opinion is expressed while the opinion is the view, attitude or appraisal on an object from the opinion holder. Example: John said that the scanner is slow. Here john is the opinion holder, scanner is the object and slow is the actual opinion or sentiment towards the scanner [13].

Sentiment mining

Sentiment mining is an area of text mining that has recently received a lot of attention due to the amount of opinion information that resides in web documents. It is concerned with the identification of opinions in a text and their classification as positive, negative and neutral. Sentiment mining refers to a broad area of natural language processing, computational linguistics and text mining that aims to determine the attitude of a speaker or writer with respect to some topic [17]. *Feiyu XU & Xiwen Cheng* [13] Defined sentiment mining as a recent disciple at the cross roads of information retrieval, text mining and computational linguistics which tries to detect the opinions expressed in the natural language texts. Sentiment mining is a complex field as it involves the processing and interpretation of natural language. Hence it must deal with natural languages' inherently ambiguous natures, the importance of context, and other complications that do not lend themselves to automation. The following example demonstrates how important and difficult to get the idea expressed in a given statement. "*Just go read the book*", if this is mentioned regarding a book, this could be considered a recommendation. But if it is in reference to a film adaption of a book, it would seem to suggest the film is not worth watching [18].

Main sentiment mining activities

The main activities needed for building a sentiment mining system are: development of linguistic resources (e.g. build a lexicon of subjective terms), classification of text (entire documents, sentences) based on their content (e.g. classifying a news article either as positive or negative in relation to the subject), extraction of opinion expression from text, including relations with the rest of content (e.g. recognizing an opinion, who is expressing it, who/what is the target of the opinion), mining tools and visualization tools to extract meaningful information from the mined articles based on the sentiment tags [16].

Levels of sentiment mining

The sentiment mining process could be conducted on three different levels: document level, sentence level, or feature level. In the sequel, each of them is discussed [13].

Sentiment mining on document level*:* here, document is classified into positive, negative or neutral based on the overall sentiment expressed by the opinion holder with the assumption that each document focuses on a single object and contains opinion from a single opinion holder (*e.g. "I bought an iPhone a few days ago. It was such a nice phone. The touch screen was*

really cool. The voice quality was clear too. Although the battery life was not long, that is ok for me. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive, and wanted me to return it to the shop. …") [4].

Sentiment mining on sentence level: contains two basic tasks: the subjectivity classification and sentiment classification. The subjective classification is concerned with classifying sentences as objective (e.g. *"I bought an iPhone a few days ago"*) or subjective (e.g. "*it is such a nice iPhone*"). The sentiment classification is concerned with the subjective sentence to classify as positive (e.g. "*it is such a nice iPhone*") or negative (e.g. "*the battery life of the phone was not long*") or neutral.

Sentiment mining at feature level*:* in this level, commented features are identified and extracted and the sentiment towards these features is determined. Sentiment classification at both document level and sentence level are not enough to tell what people like and/or dislike, because a positive opinion on an object does not mean that the opinion holder likes everything (e.g. "*the touch screen was really c*ool" where the 'touch screen' is the feature of an iPhone). Similarly a negative opinion on an object does not mean that the opinion holder dislikes everything (e.g. "*the phone was too expensive*" where 'price' is a feature of an iPhone). However, some people are not very interested about features; they just want to know the general information about an object [19].

General Sentiment mining tasks

In general the tasks of sentiment mining are: determining document subjectivity, determining document polarity and determining strength of document orientation [20].

Determining document subjectivity: deciding whether a given text has a factual nature or expresses an opinion on its subject matter. This amounts to performing binary text categorization under categories of objective and subjective.

Determining document polarity: decides if a given subjective text expresses positive, negative or neutral opinion on its subject matter.

Determining strength of document orientation: decides whether the positive opinion expressed by a text on its subject matter is weakly positive, mildly positive or strongly positive. Similarly decides whether the negative opinion expressed by a text on its subject matter is weakly negative, mildly negative or strongly negative.

Components of sentiment mining

Subjectivity mining*:* is the linguistic expression of somebody's opinion, sentiments, emotions, evaluations and beliefs. The subjectivity analysis classifies content into objective or subjective. Polarity mining: attempts to identify the opinion or sentiment that a person may hold towards an object and classifies it as positive, negative or neutral [21].

Opinion spam

Reviews are used by potential customers to find opinions of existing users before deciding to purchase a product or use a service. They are also used by product manufacturers to identify problems of their products and to find competitive intelligence information about their competitors. But unfortunately, this importance of reviews also gives good incentives for spam, which contains false positive (giving undeserving positive opinions to some target products in order to promote them) and malicious negative opinions (giving unjust negative reviews to some other products in order to damage their reputation) [8].

2.2. Sentiment mining techniques

There are a number of different approaches that have been used in an attempt to solve the problem of sentiment classification. One of the most widely used methods involves classifying a single word or phrase with sentiment, and then calculating an overall sentiment rating for a target document using some weighting [18]. The most commonly applied techniques for sentiment mining are described as follows.

2.2.1. Machine learning techniques

Machine learning treats sentiment classification simply as a special case of topic based categorization (with the two topics being positive sentiment and negative sentiment). The traditional topic based categorization attempts to sort documents according to their subject matter (e.g. sports vs. politics). The three standard machine learning algorithms commonly used for sentiment classification are Naïve Bayes (NB) classification, maximum entropy (ME) classification and support vector machine (SVM) classification [22]. According to the work of *B. Pang et al*. [22], the experimental results produced via machine learning techniques are quite good. In terms of relative performance, NB tends to work the worst and SVM tends to work the best although the differences are not very large. While machine learning techniques have been found to produce good results, there are associated disadvantages. Machine learning

classification is dependent on the training data so that there is little indication of how the classification would perform in more general cases. The gathering of such a training set is tough, as it involves the gathering and human classification of huge number of different documents. In addition, with machine learning algorithm, it could be difficult to incorporate contextual valence shifters [23].

2.2.2. Natural language processing techniques

There are a number of different language analysis techniques that fall under the umbrella of natural language processing, of which the most common are: part of speech (POS) tagging, co-reference resolution and full syntactic parse tree. POS tagging is the process of labeling word occurrences with its world class. For example, whether a word is occurring as an adjective, noun, or verb. Effective tagging requires knowledge of not just the word but also its context, such as position within the sentences and surrounding word. Hidden markov model is a common technique which is used in POS tagging. To avoid constantly referring a subject by name, natural language usually contains alternative words that can be used when referring to a previously mentioned subject. Corefernce resolution is used for automating the process of connecting such references. Creating parse tree for natural languages is another central area of study in NLP. Parsing is related to POS tagging as determining sentences structure requires knowledge of which sense words are being used. 'Chunking', a simplified form of parsing that doesn't analyze sentences in as much depth, can be used in place of parsing for some applications [18].

2.2. 3.Linguistic techniques

Others have approached the sentiment mining problem in different angle, believing that the complexity of natural language make the existence of a general solution to sentiment problems unlikely. These instead focus on specific sentence or test, such as use of linguistics in attempt to classify for conditional sentences in combination with machine learning techniques. For a topic so intrinsically linked with natural language, the use of linguistics in sentiment classification is surprisingly limited, though there are some cases where it has been applied successfully [24]. It should be noted though that even when linguistic methods are used, it is often in combination with machine learning techniques [18].

2.2.4. Ontology based techniques

Ontology defines the common words and concepts (the meaning) used to describe and represent an area of knowledge. This definition has two parts: describing and representing an area of knowledge, defining the common words and concepts of the description [25]. Ontology appears specially promising for sentiment mining. The use of ontology has the potential to refine and improve the process of sentiment mining by identifying specific properties of a domain as well as relationships between different concepts from that domain [26]. Ontology itself is an explicitly defined reference model of application domain with the purpose of improving information consistency and knowledge sharing. It describes the semantics of a domain both in human-understandable and computer processable way. In general, opinion mining is quite context sensitive, and at a coarser granularity, quite domain dependent. As a result a fine grain approach for opinion mining is needed [19].

2.2.5. lexicon-based techniques

This technique uses sentiment and subjective lexicon of terms. The basic idea behind this system is to classify reviews based on how many positive and negative terms are present in the document. This is based on a rule-based classifier where if there are more positive than negative terms then it is considered to be positive. If there are more negative than positive terms then it is considered to be negative. If there is equal number of positive and negative terms then it is neutral. When using this technique, it is relatively easy to incorporate contextual valence shifters [23]. The performance of this technique depends on the effectiveness of the lexicon of opinion terms. The main resource used for identifying positive and negative terms in English is the General Inquirer (GI) [27]. GI is a system which lists terms as well as different senses for the terms. For each sense it provides a short definition as well as other information about the term. This includes tags that label the term as being positive, negative, a negation term, an overstatement, or an understatement. Some researchers as in [23] add extra terms from other resources such as the Choose the Right Word (CTRW) [28]. CTRW is a dictionary of synonyms. Adding extra opinion terms from different sources strengthens the efficiency of the lexicon. The capabilities of this technique are employed in this research work.

2.3. General steps in lexicon-based sentiment mining

In this subsection, the general steps in the lexicon based sentiment mining technique are discussed in short. This is because our research employs lexicon based approach.

Text collection

Sentiment mining starts with collecting raw texts. This can be done manually or automatically from the internet.

Text pre-processing

Noises that do not express contents are cleaned in this process. It includes word segmentation and POS tagging [19]. In this research work, tokenization and normalization are the activities done during the review pre-processing step.

Polarity words detection

This step relies on a lexicon of tagged positive and negative sentiment terms which are used to quantify positive/ negative sentiments. This tagged lexicon provides a readily interpretable positive and negative polarity values for a set of 'affective/sentiment' terms. In this step every word content is checked whether it is a polarity word defined is in the sentiment lexicon and get the corresponding sentiment polarity if found [20].

Weight assignment and propagation

In this step, every polarity word and modifier get the initial weight defined in the sentiment lexicon. If the word is linked to a modifier, the polarity value is multiplied by a coefficient [20] or some value is added to the initial value [23].

Classification

In this step, the text document or review is classified as positive, negative or neutral based on the numerical results obtained from the previous steps.

2.4. Opinion lexicon generation

Opinion words are employed in many sentiment classification tasks. Opinion words are also known as polar words, opinion-bearing words and sentiment words. To compile or collect the opinion words list, three main approaches have been investigated: manual approach, dictionary based approach and corpus-based approach [5].

2.4.1. Manual Approach

This approach is just a process of hand picking sentiment words from different sources with the goal of populating a lexicon with polar words. This manual approach is very time consuming and it is usually combined with automated approaches as the final check because automated methods make mistakes. The opinion words lexicon used in [29] are manually hand-picked based on a reading of several thousand messages. In the work of *J. Yi et al*. [30], they collected a sentiment lexicon of 3000 English sentiment terms manually from different sources. The General Inquirer (GI), dictionary of affect of language (DAL) [31] and Wordnet were the main sources and 2500 of the total terms are adjectives.

2.4.2. Dictionary based approaches

One of the techniques in this approach is based on bootstrapping using a small set of seed opinion words and online dictionary, e.g. WordNet [32]. The strategy is to first collect a small set of opinion words manually with known orientations, and then to grow this set by searching in the online dictionary for their synonyms and antonyms. The newly found words are added to the seed list. The next iteration starts. The iteration stops when no more new words are found. After the process completes, manual inspection can be carried out to remove and/or correct errors. The dictionary based approach and opinion words collected has major shortcomings. The approach is unable to find opinion words with domain specific orientations, which is quiet common. For example, for a speakerphone, if it is quiet, it is usually negative. However, for a car, if it is quiet, it is positive.

2.4.3. Corpus based approach

Corpus based approach rely on syntactic or co-occurrence patterns and also a seed list of opinion words to find other opinion words in a large corpus. The technique starts with a list of seed opinion adjectives words, and uses a set of linguistic constraints of conventions on connectives to identify additional adjective opinion words and their orientations. One of the constraints is about conjunction (AND), which says that conjoined adjectives usually have the same orientation. For example, in the sentence “this car is beautiful and spacious,” if “beautiful” is known to be positive, it can be inferred that “spacious” is also positive. This is so because people usually express the same opinion on both sides of a conjunction. The following sentence is rather unnatural, “this car is beautiful and difficult to derive”, if it is changed to “this car is beautiful but difficult to derive”, it becomes acceptable. Rules or constraints can also be designed for other connectives; OR, BUT, EITHER-OR, and NEITHER-NOR. This idea is called sentiment consistency.

2.5. Basic rules of opinions

A rule of opinion is an implication with an expression on the left and an implied opinion on the right. The expression is a conceptual one as it represents a concept, which can be expressed in many ways in actual sentence. The application of opinion words/phrases can also be represented as such rules. Let Neg be negative opinion word/phrase and Pos be positive opinion word/phrase. The rules for applying opinion words/phrases in a sentence are given as follows.

1: Neg→ Negative

2: Pos→ Positive

These rules say that Neg implies a negative opinion (denoted by *Negative*) and Pos implies a positive opinion (denoted by *Positive*) in a sentence. The effect of negations can be represented as well:

3: Negation Neg→Positive

4: Negation Pos→ Negative

These rules state that negated opinion words/phrases take their opposite orientation in a sentence. Other related rules are also outlined as follows.

Deviation from the norm or some desired value change: in some domains, an object feature may have an expected or desired value rang or norm. If it is above and or below the normal range, it is negative, e.g. "this drug causes low (or high) blood pressure". We then have the following rules.

5: Desired value range→Positive

6: Below or above desired value range→Negative

Decreased and increased quantities of opinionated items: This set rule is to the negation rules above. Decreasing or increasing the quantities associated with some opinionated items may change the orientation of the opinions. For example, "this drug reduced may pain rapidly significantly." Here pain is a negative opinion word, and the reduction of "pain" indicated a desired effect of the drug. Hence the decreased pain implies a positive opinion on the drug. The concept of decreasing also extends to "removal" or "disappearance". e.g." my pain has disappeared after taking the drug".

7: Decreased Neg→Positive

8: Decreased Pos→Negative

9: Increased Neg→Negative

10: Increased Pos→Positive

The last rules may not be as such very important as there is no change of orientation.

Producing and consuming resources and wastes: If an object produces resources, it is positive. If it consumes resources, especially a large quantity of them, it is negative. For example, "money" is a resource. The sentence, "Company-x charges a lot of money" gives a negative opinion on "Company x". Likewise, if an object produces wastes, it is negative. If it consumes wastes, it is positive. These give us the following rules:

11. Consume resource → Negative
12. Produce resource → Positive
13. Consume waste → Positive
14. Produce waste → Negative

These basic rules can also be combined to produce compound rules, e.g., "Consume decreased waste →Negative" which is a combination of rules 7 and 13. To build a practical system, all these rules and their combinations need to be considered. As noted above, these are conceptual rules. They can be expressed in many ways using different words and phrases in an actual text, and in different domains they may also manifest differently. However, by no means, it is claimed these are the only basic rules that govern expressions of positive and negative opinions. With further research, additional new rules may be discovered and the current rules may be refined or revised. Neither it is claimed that any manifestation of such rules imply opinions in a sentence. Like opinion words and phrases, just because a rule is satisfied in a sentence does not mean that it actually is expressing an opinion, which makes sentiment analysis a very challenging task [5].

2.6. Summary

In this chapter, the two different types of textual information, opinions, opinion words, and components of opinions are explained. Opinion mining, levels of sentiment mining, sentiment mining main tasks and components of sentiment mining are also described in the same chapter. In addition, the different techniques of sentiment mining that includes machine learning, natural language processing, linguistic techniques, ontology based and lexicon based are discussed. The general steps in lexicon based sentiment mining are highlighted where the high level steps are: text collection, pre-processing, polarity words detection, weight assign and propagation, and classification. The different approaches for building a sentiment lexicon that includes manual approach, dictionary based and corpus based approach are also described in this chapter. Finally, the basic rules of opinions are also described in detail.

CHAPTER THREE

3. RELATED WORKS

In this chapter, sentiment mining related researches done for different language opinionated documents such as English [33] [23] [34], Chinese [20] and French [6] using different techniques and approaches are reviewed. Different authors used different techniques such as machine learning [33], ontology based approaches [34], lexicon-based approaches [23] [20] and others [35]. In addition to the techniques, the employed approaches, goals, motivation, domain, target language, dataset source, procedures, experimental results, performance, and challenges are the main points given focus when going through the different works.

3.1. Sentiment mining from opinionated English texts

Sandeep Balijepalli [33] used machine learning technique to categorize opinionated English documents taken from political blogs based on their sentiments and determine the polarity strength of the sentiments. Contents collected from the political domain are made to pass through pattern matching (Nave Bayes filter, bag of words and part of speech tagging) for obtaining the sentiment oriented sentences which are later to be indexed. The index helps to avoid the delays in fetching the data.

The framework proposed by Sandeep gets contents from the database of blogs, pass the sentences to the sentence chunker for stripping unrelated data, then the sentence is passed through filters for filtering out objective sentences and classifying subjective sentences, index opinionated sentences, divide results by bloggers party and finally sort them by their polarity strength. In the above approach, filter analysis is done by making sentences to pass through the pattern recognizer first for checking the sentences if they follow the custom developed subjective pattern. If the sentence matches the pattern, it is indexed otherwise it is passed through Nave Bayes (unigram, bigram) for further analysis where this filter depends on the training dataset. If the sentence is not indexed at this filter, it again passes through the part of speech tagging and if the sentence is found to be subjective, it is indexed otherwise it is considered as objective sentence and it is skipped. Then, other sentence undergoes the entire procedure. The experimental result shows that the system performs well with unigram approach.

Alistair Kennedy and Diana Inkpen [23] proposed a method that counts positive and negative terms but also takes contextual valence shifters such as negations and intensifiers into account.

Two approaches are compared in their work. The first approach simply counts positive and negative terms where the review is positive if the review contains more positive than negative terms. Review is negative if it contains more negative than positive terms. A review is neutral if it contains equal number of positive and negative terms. The term counting method can be easily modified to use valence shifters. The second method counts positive and negative terms, but takes contextual valence shifters into account. Their approaches are classified as basic (uses the first approach) and improved one (uses the second approach).

The main lexicon used in this work was the General Inquirer (GI) though they added extra terms from other sources. As the authors stated, their motivation to use this approach was to see the effect of incorporating contextual valence shifters to the basic method of sentiment classification. The data sets they for experimental purpose are taken from two sources. The first data set is taken from www.epinions.com [11]. Epinions.com is a general consumer review site. The data set taken contains 70 positive and 70 negative reviews. The reviews were collected from a variety of different products, including air conditioners, sewing machine, vacuums cleaners, TVs, cookware, beer and wine. The second data set is a movie reviews that contains 2000 reviews, 1000 positive and 1000 negative taken from other movie review sources.

The experimental result indicated that the proposed approaches perform well as indicated in the following. The basic approach using GI lexicon gives an accuracy of 0.679 for product reviews and 0.595 for movie reviews. The improved method using GI lexicon gives an accuracy of 0.686 for product reviews and 0.627 for movie reviews. The experimental results of adding extra terms from other resources to GI are also given in their work and some improvements are shown. In most cases the method of classification performs better when classifying product reviews than movie reviews. This is because movie reviews are known to be more difficult to classify than other reviews such as product reviews [36].

Lili Zhao and Chunping Li [34] used ontology based opinion mining for movie reviews with the goal of improving feature level opinion mining by employing ontology. The use of this approach was motivated by the role of ontology in conceptualizing domain specific information. The main components of the proposed approach are: text collection (movie reviews), preprocessing, feature identification, polarity identification and sentiment analysis with the support of ontology development. Like others the polarity identification fully relies on a lexicon of tagged positive and negative sentiment terms which are used to quantify

positive/negative sentiment. For this purpose SntiWN [37] was used as it provides a readily interpretable positive and negative polarity values for a set of 'affective' terms.

The target of the ontology development is to define common terminologies in the area, and give the definition of the relationship among the terminologies. Iterative approach is used for developing the ontology following two steps. The first step is selecting the relevant sentences including concepts and the second step is extracting the concepts from those sentences. Criteria used for selecting the sentences are: the sentences that contain conjunction word and sentences that contain at least one concept seed. At the initial state, manually labeled feature are used as seeds. Randomly selected 1400 movie reviews from internet movie database (IMDB) [38] were used as dataset where half of them are positive and the other half are negative. The experimental results indicate that the accuracy is satisfying, and proves that it is reasonable to compute the polarity score by the proposed method where the main factor is found to be the ontology structure. Even though this work is ontology based, it depends on the lexicon of opinion terms for assigning weights to the sentiment terms. Ontology is basically needed for feature extraction.

3.2. Sentiment mining from opinionated non- English texts

Xiaoying Xu et al. [20] on their work titled "categorizing term's subjectivity and polarity manually for opinion mining", proposed principles and guidelines to create a large-scale Chinese sentiment lexicon for opinion mining manually. Two experiments are conducted in their work: the first experiment is conducted to investigate the reliability of manual subjectivity labeling of the terms. The second experiment is conducted to see the effectiveness of the lexicon in judging the polarity of subjective sentences.

In this paper, it is indicated that for establishing the first and large scale human tagging Chinese sentiment lexicon, the agreement of different annotators and the reliability in sentence polarity judging system are key issues. As a result annotation principles and guidelines are needed to be established. The principles in tagging the terms subjectivity and polarity established by the authors are: the terms should be opinion mining oriented, the lexicon built will be used only in the subjective sentence in opinion mining and the word will indicate polarity in the subjective sentence. A clear guideline in annotating the sentiment word and qualified annotators are needed for realizing the principles of building the lexicon. During the tagging campaign and lexicon building, the main resource used was HowNet [39]. HowNet is an on-line common-sense knowledge base unveiling inter-conceptual relations and inter-

attribute relations of concepts as connoting in lexicons of the Chinese and their English equivalent. According to their analysis the answer they gave to the question "*what kind of word can be selected in the lexicon?*" is 'if a term has subjective meaning either in concept meaning or in emotion meaning overtone, and it can indicate the polarity in subjective sentence, it must be selected in our lexicon.

The experimental results for the first experiment show that the polarity of word sense can be reliability annotated in despite of the polarity ambiguous in words is common Chinese, and also because of its large-scale it could be very useful fundamental resource in opinion mining and other related fields. To evaluate the lexicon in real applications (the second experiment), they built simple sentence sentiment recognition system that contains text pre-processing, polarity words detection and weight assign, link construction and polarity propagation. The text pre-processing is used to segment words and tag POSs. In the polarity words detection, every polarity word is checked whether it is polarity word defined in the sentiment lexicon and get the corresponding sentiment polarity if found. Every polarity word and modifier word get the initial weight defined in the sentiment lexicon. If the polarity word is linked to a modifier word, the polarity value should be multiplied by a coefficient in the polarity propagation step. The results of the second experiment show that using the sentiment lexicon it can achieve an accuracy of more than 70%.

Sigrid Maurel et al. [6] used a combined approach (combination of symbolic and statistical) for the classification of opinionated texts in the French language. The symbolic approach includes systems for extracting information adapted to the corpora based on the rules of syntactic and semantic analyzer. This approach analyzes texts sentence by sentence and extracts relationships that convey feelings. Statistical method is based on machine learning techniques. It process text in a single step and assigns a global opinion at the whole text at the end. The hybrid approach is used in their work to increase the quality of the results. As they indicated the experimental results show that combination of statistical and symbolic (hybrid) approaches gives more accurate results than either method used separately.

3.3. Review's spam detection

Evaluative texts on the Web have become a valuable source of opinions. Existing research has been focused on classification and summarization of opinions. An important issue that has been

neglected so far is opinion spam or trustworthiness of online opinions [35]. Nitin Jindal and Bing Liu [8] attempted to study review's spam and spam detections. Spam review contains false positive or malicious negative opinions. They proposed duplicate finding and classification techniques to detect spam reviews. The duplicate approach is based on duplicate reviews using the shingle method [54] with similarity score of >0.9. The classification approach is based on 2-class classifications: spam and non-spam. As they indicated, the experiment on the manufactured products review domain showed promising results.

3.4. Summary

This chapter reviewed different research attempts to solve the problem of sentiment mining for different languages. The review showed that machine learning, ontology based and lexicon-based are the commonly used approaches to deal with sentiment mining. The works reviewed indicated that the approaches except the machine learning rely on tagged list of positive or negative sentiment terms to identify the polarity of terms. The machine learning technique is based on the concept of training the machine to learn to classify opinionated texts into predefined categories of positive, negative or neutral. Ontology is employed particularly to extract feature of an object for the purpose of refining feature level sentiment analysis. The lexicon based approaches are based on the concept of counting the sentiment terms available in the opinionated texts.

CHAPTER FOUR

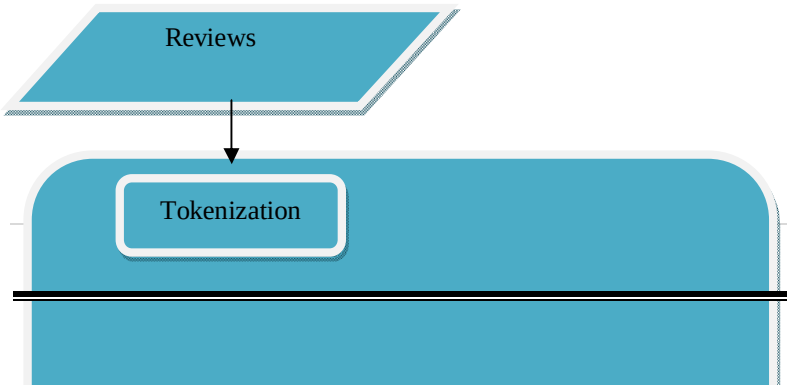
4. DESIGN AND IMPLEMENTATION

4.1. Introduction

In this chapter, the design and implementation of the proposed sentiment mining model for opinionated Amharic texts is described in detail. The proposed model has the following components: pre-processing, sentiment word detection, weight manipulation, polarity classification and polarity strength (post-polarity classification analysis). Each component is composed of sub components which are the building blocks of the system. Pre-processing is responsible for normalization of reviews and words segmentation. In the sentiment words detection component, all possible sentiment words and contextual valence shifter terms are checked for existence in the sentiment lexicon. The weight manipulation component contains sub systems: weight assignment and polarity propagation. After the weight manipulation is completed, the next step is the polarity classification of the reviews. The strength of the polarity (whether it is positive or negative) is rated in the post-classification analysis step. The sentiment word detection and weight manipulation activities are fully dependent on the lexicon of Amharic opinion terms that contains opinion terms tagged with a readily interpretable values. The procedures of building the sentiment lexica, the types of lexicon, the guidelines and principles followed during the sentiment lexicon building process are also described in this chapter. In addition, tools used for implementing the prototype and the proposed algorithms are also presented.

3.2. General system architecture

The general architecture of the proposed model (sentiment mining model for opinionated Amharic texts) is shown in figure 4.1. As shown in the Figure, the system contains different components based on the processes required. These components are: pre-processing, sentiment words detection, weight manipulation, polarity classification and post-classification analysis (reviews polarity strength). The sentiment lexicon is also part of the general systems architecture.



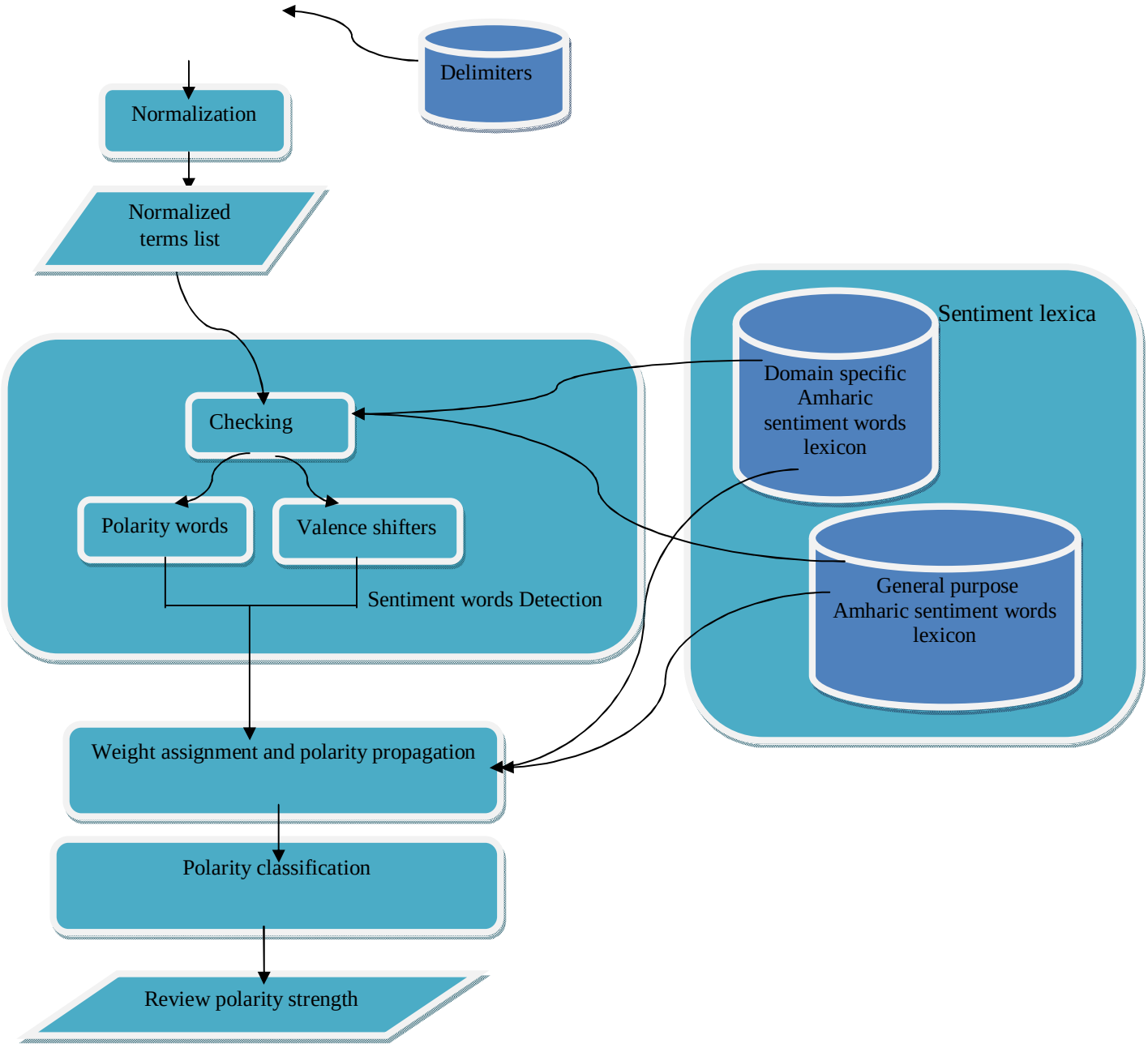


Figure 4.1: The sentiment mining model for opinionated Amharic texts

4.2.1. Pre-processing

The first phase of the sentiment mining model for opinionated Amharic texts is the pre-processing component. This component is responsible to accept the input review and produce a set of terms after performing lexical analysis (tokenization) and normalization. For our work, the pre-processing components needed are adopted from the work of [40]. The adopted components are described below.

Tokenization

Tokenization is the first step in pre-processing of the input review. Tessema [40] used a string tokenizer to construct words from a sequence of characters. The input for this activity is the actual review which is going to be categorized. This activity reads a sequence of characters as a string and tokenizes them using predefined list of delimiters such as new lines and space.

Normalization

After tokenization, it is normalization of homophones that is followed. Amharic writing system has homophone characters, characters with same pronunciation but different symbols; for example, it is common that the character ስ and ሥ are used interchangeably as ስራ and ሥራ to mean work. Such types of inconsistencies in writing words are handled by replacing characters of the same sound by a common symbol. The normalization handles:

- The replacement of Amharic alphabets that have the same pronunciation and use, but different representation with common alphabet.

- Short forms of characters that are usually written using forward slash "/") and period ("."), for example, ጠቅላይ ሚንስተር can be written as ጠ/ሚኒስተር አዲስ አበባ as አ.አ and ዶክተር as ዶ/ር.

4.2.2. Detection of sentiment words

This activity is responsible for detecting 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 is scanned for every term. If the term exists in the dictionary, then the term is a polarity word (positive or negative) or a contextual valence shifter (negation or intensifier). Polarity words are terms that can express opinions towards an object such as 'ጥሩ' (good) that expresses positive opinion and 'መጥፎ' (bad) that expresses negative opinion towards an object. These terms are properly tagged in the lexicon with computer interpretable values as '+' for positive opinion terms and '-' for negative opinion terms. Then, if a term is found in the lexicon and if its corresponding value is '+', then this opinion term is positive. Similarly, if a term is found in the lexicon and if its corresponding value is '-', then this opinion term is negative. As shown in figure 4.1, there are two lexica of opinion terms: the domain specific lexicon and the general purpose lexicon. This division is similar to the key sentiment words and general sentiment words indicated as a future work in the work of [20].

The key sentiment word corresponds to domain specific lexicon and the general sentiment word corresponds to general purpose lexicon. The terms in the domain specific lexicon can be selected according to the characteristics of different domains such as product reviews, film reviews, political opinions etc. In this work, we have a single domain specific lexicon of movie reviews. This lexicon contains Amharic opinions terms that are used in movie reviews domain such as 'አዝናኝ' (cheerful), 'ምርጥ' (best), 'የሚያስጠላ' (morbid), 'የሚያስቅ' (funny) etc [41].

The general purpose lexicon, as its name indicates, is used for opinion mining system in any domain. This is because the opinion terms in this lexicon are not restricted to specific domain rather it contains any opinion terms in the Amharic language. As a result the valid terms in the review are first checked in the domain specific lexicon with the assumption that both the review and specific lexicon are from the same domain (e.g. movie reviews domain). Then if at least a single term is found in the domain specific lexicon, the process continues to the next step (weight assignment and polarity propagation) otherwise the general lexicon is scanned for further search. If the term taken from the review is not found in both lexica, this term is considered as non-sentiment word and it is discarded as such terms are not important in the sentiment classification problem.

Incorporating contextual valence shifters

There are two different aspects of valence shifting that are used to improve the basic system (a system without considering contextual valence shifters). These are negations and intensifiers. Negations are terms that reverse the sentiment polarity of a certain term [9]. For example consider the following sentence '**ፊልሙ ጥሩ ነዉ**' (the film is **good**) versus '**ፊልሙ ጥሩ አይደለም**' (the film is not good). In the first one '**ጥሩ**' (good) is a positive term so this sentence is positive. When '**አይደለም**' (not) is applied to the clause, '**ጥሩ**' (good) is being used in negative context and so the sentence is negative.

Intensifiers are terms that change the degree of the expressed sentiment. For example, in the sentence '**ፊልሙ በጣም ጥሩ ነዉ**' (the film is very good), the terms **በጣም ጥሩ** (very good) are more positive than just '**ጥሩ**' (good) alone. On the other side, in the sentence '**ፊልሙ ጥሩ ቢሆንም**' , the term **ቢሆንም** (even though), makes this statement less positive. These are examples of overstatements and understatements. Overstatements are terms that increase the intensity of a positive/negative term, while the understatements decrease the intensity of that term. Terms that overstate or understate are also listed in our lexicon.

To identify overstatements and understatements, all positive sentiment terms in our model are given a value of +2. If they are preceded by an overstatement in the same clause, then they are given a value of +3. If they are followed by an understatement in the same clause, then they are given a value of +1. Negative terms are given a value of -2 by default. If they are preceded by an overstatement in the same clause, they are given a value of -3. If they are followed by an understatement in the same clause, they are given a value of -1.

4.2.3. Weight assignment and polarity propagation

In this phase the main activities are: weight assignment and polarity propagation. All possible sentiment terms are tagged in the lexica by '+' and given a default value of +2 at run time. All the negative sentiment terms are tagged by '-' and given a default value of -2. Before the final average polarity weight is calculated, the polarity propagation is done which is used to modify the initial value of the sentiment terms. This modification of the initial value or weight is done only if the sentiment word is linked to a modifier term (negations or intensifiers). The polarity propagation is done according to the following rules.

Rule 1: if any polarity term is followed by a negation term, the initial polarity value or weight of the term will be reversed.

For example in the sentence ‘ፊልሙ ጥሩ አይደለም’ (the film is not good), the sentiment term ‘ጥሩ’ (good) is given an initial value of 2. But due to the negation term ‘አይደለም’ (not), the polarity value of the term is reversed to -2. Similarly, in the sentence ‘‘ፊልሙ መጥፎ አይደለም’ (the film is not bad), the sentiment term ‘መጥፎ’ (bad) is given an initial value of -2. But due to the negation terms ‘አይደለም’ (not), the polarity value of that sentiment is reversed to +2.

Rule 2: if a positive sentiment terms is preceded by an overstatement term, then the initial value of that terms is propagated from +2 to +3.

For example in the sentence ‘ፊልሙ በጣም ጥሩ ነዉ’ (it is very good), due to the overstatement term ‘በጣም’ (very), the initial polarity value of the sentiment term ‘ጥሩ’(good) is increased by +1 from +2 to +3.

Rule 3: if a positive sentiment term is followed by an understatement term, the initial value of that term is decreased from +2 to +1.

For example in the sentence ‘ፊልሙ ጥሩ ቢሆንም’ (even though), the polarity weight of the sentiment term ‘ጥሩ’ (good) is decreased from the initial value +2 to +1 due to the understatement term ቢሆንም’ (even though).

Rule 4: if a negative sentiment term is preceded by an overstatement term, then the initial value of the term is decreased by -1 from -2 to -3.

For example in the sentence ‘ፊልሙ በጣም መጥፎ ነዉ’(it is very bad), due to the overstatement ‘በጣም’ (very), the initial weight of the sentiment word ‘መጥፎ’(bad) is decreased from -2 to -3.

Rule 5: if a negative sentiment term is followed by an undrstatement term, the initial weight of that term is increased by +1.

For example in the sentence ‘ፊልሙ መጥፎ ቢሆንም (even though), the initial weight of the sentiment term is increased from -2 to -1 due to the understatement term.

Rule 6: if a sentiment term is not linked to any contextual valence shifting term, the initially assigned weight is considered for further process.

Rule 7: The contextual valence shifting terms are applied only to the nearest single sentiment term.

4.2.4. Polarity classification

In this component as shown in figure 4.2, 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 1 [23].

$$Rp = \sum_{i=0}^{n} T\,pi \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{equation 1}$$

Where, Rp is review polarity value, Tp is sentiment term polarity value, 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.

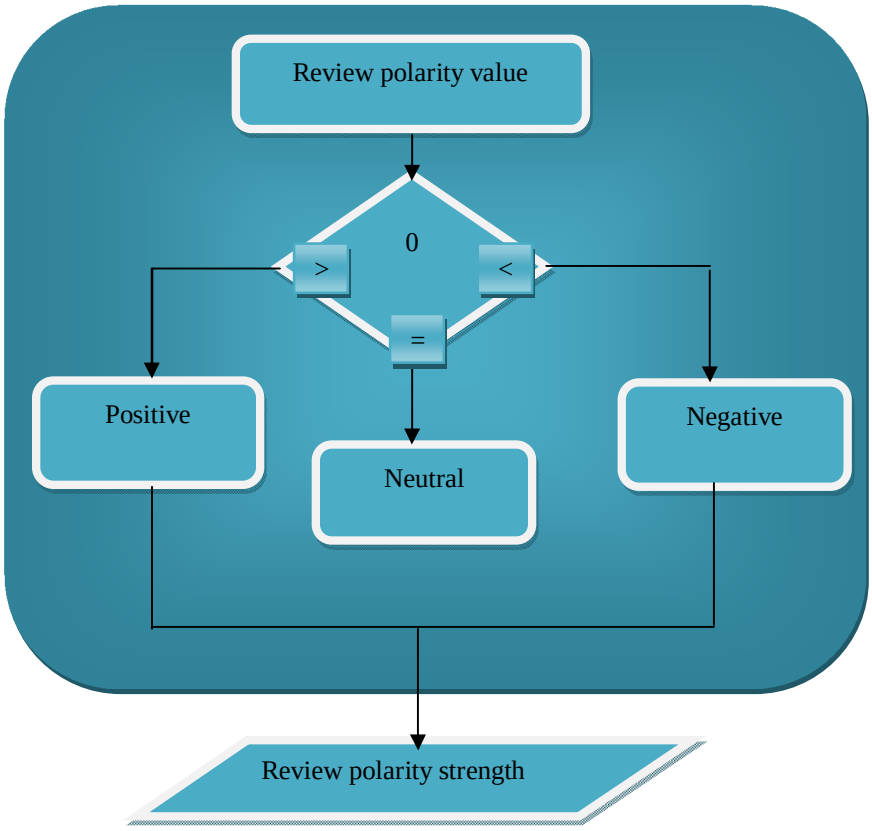


Figure 4.2: review polarity classification

For example in the sentence ‘ሳራ ጥሩ የፈጠራ ወጣት ፊልም ነ ዉ፤ ወጣቶች የ ተካ ተቱበ ት ስለ ሆነ በ ጣም የ ሚ ረ ታታ ፊልም ነ ዉ’, the sentiment terms are ‘ጥሩ’ with an initial value of +2, ‘የ ሚ ረ ታታ’ 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 4.1.

Table 4.1 sentiment terms' polarity propagation example

Sentiment terms	Initial weight	Overstatement	Adjusted weight
ጥሩ	+2		+2
የ ማ ረ ታ ታ	+2	በ ጣም	+3
		Total score	+5
		Category	Positive

4.2.5. Review's Polarity strength

Sentiment polarity strength determines how strongly a word is positive and also how strongly a word is negative [42]. This is different from rating, which is concerned with generalizing sentiment classification to fine-grained scales. Rating attempts to determine sentiment classification using ratings such as "three star", or "four stars" rather than simply determining whether a review is "positive" or negative [43].

Wilson et al. [44] used different clues and mechanisms to determine the polarity strength of individual opinion terms and phrases. But in our work, we devised a technique to determine the polarity strength of the whole review instead of the individual sentiment terms. As a result, we used a method that computes the absolute value of the total polarity weight of all the sentiment terms within a given review to determine the polarity strength of the review. The computed result corresponds to a five star scale. One star (*) indicates to weak polarity strength where as five star (*****) indicates strong polarity strength. This figurative information helps an individual to easily understand how strong positive or negative is a given review or how weak positive or negative a given review is. No scale is used to indicate the strength of neutral reviews. The polarity strength of every review is computed as follows. If the absolute value of the computed total polarity weight equals to one, it corresponds to a one star scale and it indicates that the review is weakly positive or weakly negative. If the computed absolute value of the total polarity weight equals to two, it corresponds to two star scales so that this indicates that the review's polarity is medium. If the computed absolute of the total polarity weight is equals to three, it corresponds to a three star scale and indicates the review's strong positivity or strong negativity. And finally, if the absolute value of the computed total polarity weight of

all the sentiment terms in the given review equals or greater than four, it corresponds to four or five star scale and indicates that the review is very strong positive or very strong negative. Both four and five star denotes very strong polarity with different degrees.

4.3. Implementation

In this sub section, the Amharic 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.

4.3.1. Building sentiment lexicon

The quality of lexicon-based sentiment classification systems depend on the effectiveness of the sentiment lexicon [45]. As a result we have followed some principles and guidelines when building the sentiment lexicon. In addition to the principles and guidelines, different sources and mechanisms are used to build the sentiment lexicon as there are no publicly available resources in Amharic language that can be used and integrated with our model.

The main resource we used is the subjectivity lexicon of OpinionFinder [46], which contains a list of English subjectivity terms compiled from several sources [47]. The terms in the lexicon are tagged as strong subjective or weak subjective. A clue which is subjective in most context is considered strongly subjective, and those that may only have certain subjective usages are considered weakly subjective. Moreover, the words length, part of speech (POS), and the prior polarity value (positive, negative or neutral) are also given accordingly. The sample of this lexicon is given in Appendix A. This subjectivity lexicon was used in the work of *Theresa Wilson et al*. [47] for recognizing contextual polarity in phrase-level sentiment analysis. Then, we took these subjectivity terms which are above 8000 words and we translated to their corresponding Amharic meaning using the SelamSoft electronic Amharic-English dictionary software [41]. This is a web based dictionary that works properly in both directions (English to Amharic and Amharic to English] as shown in figure 4.3. The objective of translating the English terms to Amharic is to find the corresponding possible subjective or sentiment terms in Amharic. Before going to the dictionary, we devised criteria for selecting terms from the subjectivity lexicon we used as a source. The two main criteria we used are: the strong subjectivity and POS value. Terms which indicate strong subjectivity and have POS value of adjective are given high priority for selection. The selection of terms using the criteria helps us

reduce the size of the subjectivity lexicon so that only the selected terms are translated. As a result more than 3000 words are selected using the criteria.

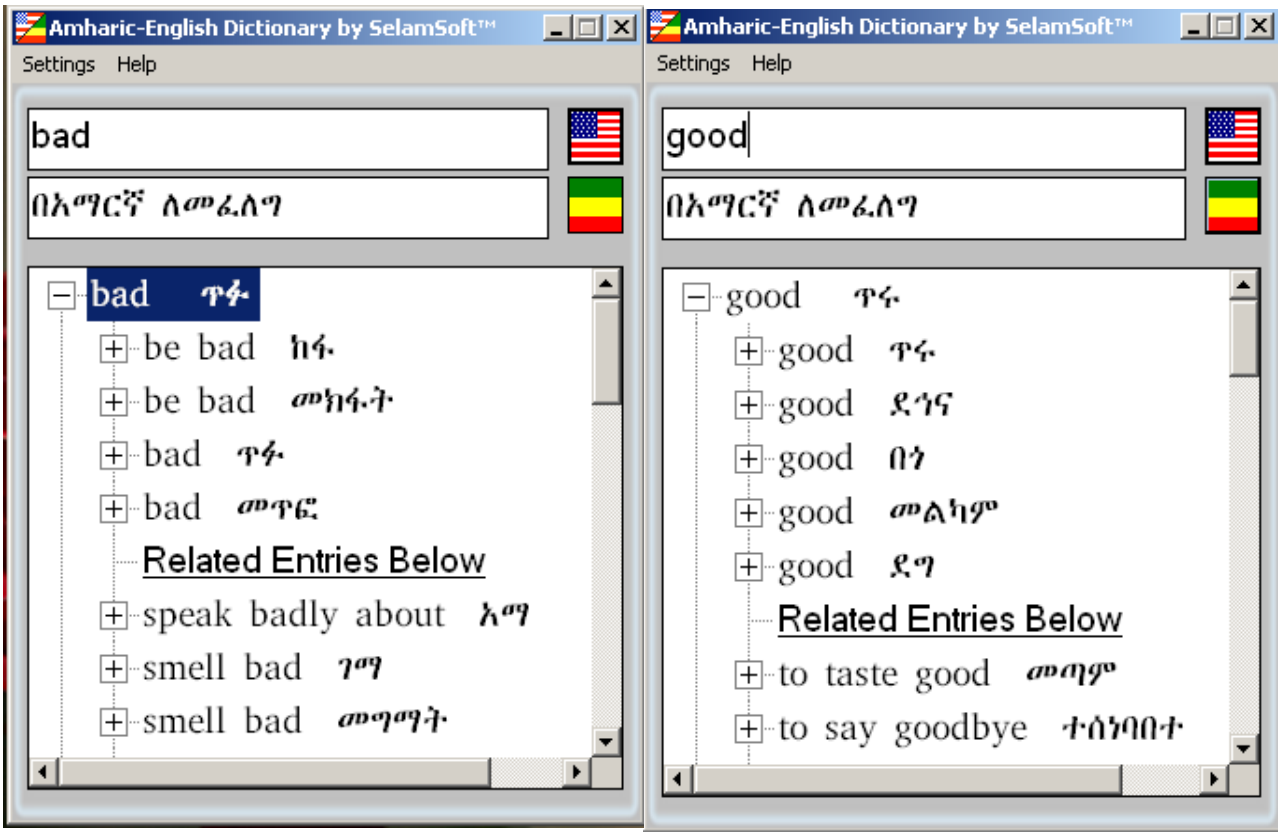


Figure 4.3 SelamSoft electronic English-Amharic dictionary used for sentiment translations

Furthermore, hard copy Amharic dictionary "አማርኛ መዝገበ ቃላት" published by Addis Ababa University [48] was used to collect additional Amharic sentiment terms. This process was done by two post-graduate students at Addis Ababa University in the department of languages and literatures. They used the dictionary to collect the opinion terms based on the following guidelines.

- A term that can express subjectivity (positive or negative) independent of any other term is selected into the sentiment lexicon.
- Terms that have a POS value of Adjective or noun are given priority.
- Only the most commonly used contextual valence shifter terms are selected

Accordingly, 895 Amharic terms are collected from the first process (through translation) where 392 of them are positive (+) and the rest 503 are negative (-). From the second process,

393 Amharic opinion terms are collected where 159 of them are positive (+) and the rest 234 are negative (-).

From a total of 1,288 Amharic opinion terms collected from the two processes, duplicated terms are removed and 955 terms remained as a list of final lexicon where 411 of them are positive(+) and the rest 544 are negative (-). Finally, these Amharic opinion terms are validated by a professional from the Linguistics Department at Addis Ababa University. Some of the list of the collected Amharic opinion terms and the approval letter are presented in Appendix E.

As opinion mining systems are quiet domain dependent [1], a small sized additional movie reviews specific lexicon is also built that contains 97 terms. The purpose of this domain specific lexicon is to improve the effectiveness of the proposed model in the domain selected for evaluation. This is because some opinion words indicate different polarities in different domains. For example, the word "ገዳይ" as in "በሳቅ ገዳይ" is positive in movie reviews domain where as in other domains such as Law it is negative as in "ኑበስ ገዳይ".

4.3.2. Lexicon building guidelines

When building the lexicon of Amharic opinion terms, we established principles and guidelines as follows:

- Every sentiment term is selected considering the opinion mining orientation.
- The lexicon will be used only in Amharic sentiment classification systems.
- The word should indicate polarity in any subjective sentences.

It was found in many researches that adjectives are important indicators of subjectivities and opinions [5]. As a result:

- Terms with POS value of adjective are given high priority when selecting them to the Amharic sentiment lexicon in both the above processes.

As far as my knowledge, at this time there is no publicly available literature that clearly describes the opinion expressing Amharic terms and their properties. As a result:

- In the first process, only terms found in the dictionary are selected to our lexicon. Similarly, in the second process the terms considered as sentiment terms by the students' level of knowledge are selected to our lexicon.
- Commonly used and unambiguous contextual valence shifter terms are considered.

From the collected Amharic sentiment terms, sentiment terms that are ambiguous to annotate their prior polarity are removed before approval. Some of the ambiguous Amharic sentiment terms removed are: 'ቀላል', 'አይንአፋር', 'ተጠያቂ', 'ስርየት', 'ብልጥ', 'ከባድ'... etc. The removal of these terms from our sentiment lexicon doesn't mean that these sentiment terms are no more important. But, through further analysis of different domain and discussion with professionals of the language, the ambiguity of the sentiment terms can be solved.

4.3.3. Tools

In order to achieve our objective, we used different environments and tools. Python programming language is used to develop the prototype. Python is an interpreted, object oriented, high level programming language with a dynamic semantics. It's high-level built in data structures, combined with dynamic typing and dynamic binding; make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together [49]. The python programming language is a dynamically typed, object oriented, interpreted language and it is great for natural language processing (NLP) because it is simple, easy to debug (exceptions and interpreted language), easy to structure (modules and object oriented) and powerful for string manipulation.

We used python 3.0.1 version because it is possible to use encodings different than ASCII in python source files. As a result, Amharic language characters are directly interpreted by python 3.0.1 and above versions without the need to go for transliteration or feeding the Unicode representation of the characters. All the source codes and rules of the prototype are written in python 3.0.1 compatible format because this version doesn't support backward compatibility.

The SelamSoft electronic Amharic English dictionary software is used as main resource for building the Amharic sentiment lexicon.

Dictionary representation

Dictionary is a useful built in data type into python. Regular python dictionaries iterate over a key: value pairs in an arbitrary order. Dictionaries are sometimes found in other languages as "associative memories" or "associative arrays". Unlike sequences, which are indexed by a range of numbers, dictionaries are indexed by keys, which can be any immutable type; strings and numbers can always be keys. Tuples can be used as keys if they contain only strings,

numbers, or tuples. If tuple contains any mutable object directly or indirectly, it cannot be used as keys. Dictionaries in python are an unordered set of keys: values pairs, with the requirement that the keys are unique (with one dictionary). A pair of braces creates an empty dictionary: {}. Placing a comma separated list of key: value pairs within the braces adds initial key: value pairs to the dictionary. The main operations on a dictionary are storing a value with some key and extracting the value given by the keys [51].

The sentiment terms in our lexicon are written in a text file according to the dictionary syntax of python 3.0.1 where the syntax is: {"key":" value", . . .}. The "key" attribute represents the sentiment terms where as the "value" represents the corresponding initial polarity value of the sentiment term. For example the list of Amharic sentiment terms: 'ጥሩ +, በጎ +, መጥፎ -, ጥንቡ-'can be formulated into a python 3.0.1 dictionary as follows: {"ጥሩ ":"+", "በጎ": "+", "መጥፎ":" –", "ጥንቡ" :"-",} but in older versions of python this dictionary is formulated as : {'ጥሩ ':'+', 'በጎ': '+', 'መጥፎ':' –', 'ጥንቡ' :'-',}. Sample of the dictionary representation of the Amharic sentiment terms used in this research work is given in Appendix B.

The lexicon of sentiment terms (dictionary) can be put within the source code or can be imported as a text file at run time. Therefore for each key its corresponding value is returned for further process. As a result for each Amharic sentiment terms in the input review (key), the whole dictionary is scanned for its corresponding value. Sample of the input review data is given in figure 4.4.

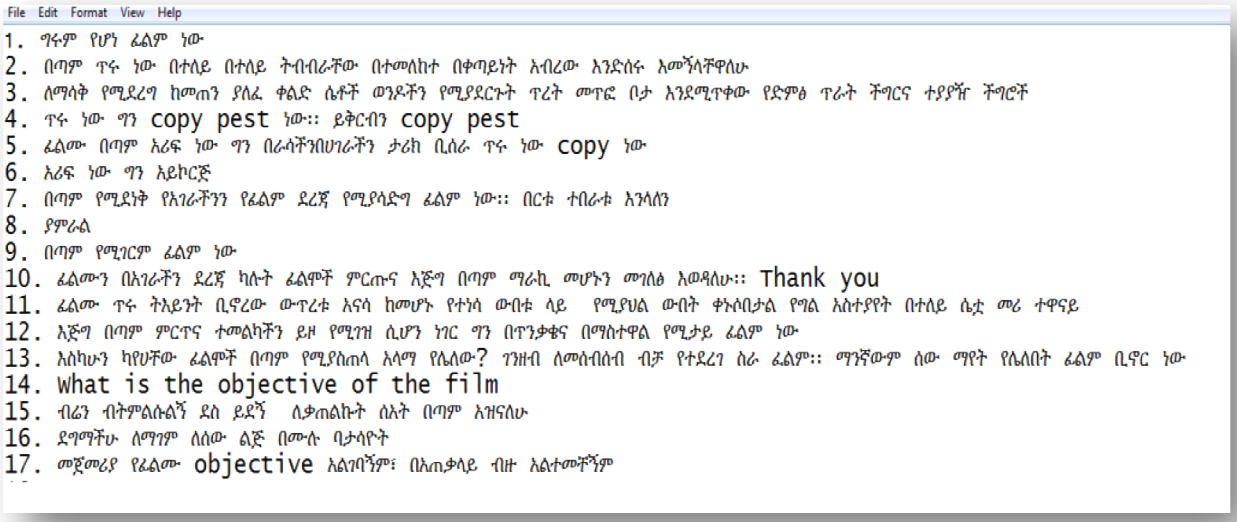


Figure 4.4 sample movie reviews input

The corresponding output of the movie review sample input given above is given in figure 4.5 as follows

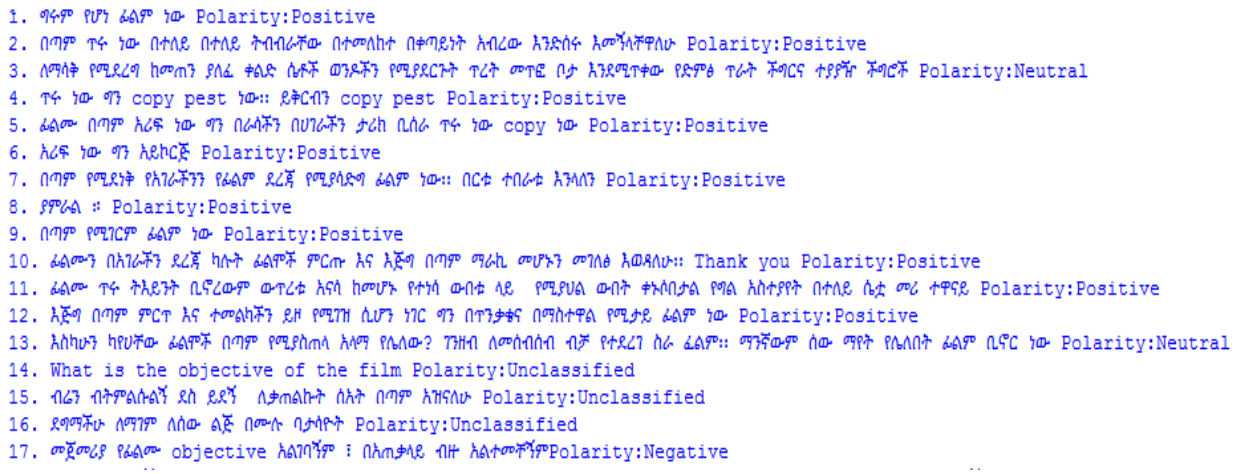


Figure 4.5 sample of polarity classified movie reviews

Sample of review polarity classification with its polarity strength is given in figure 4.6.

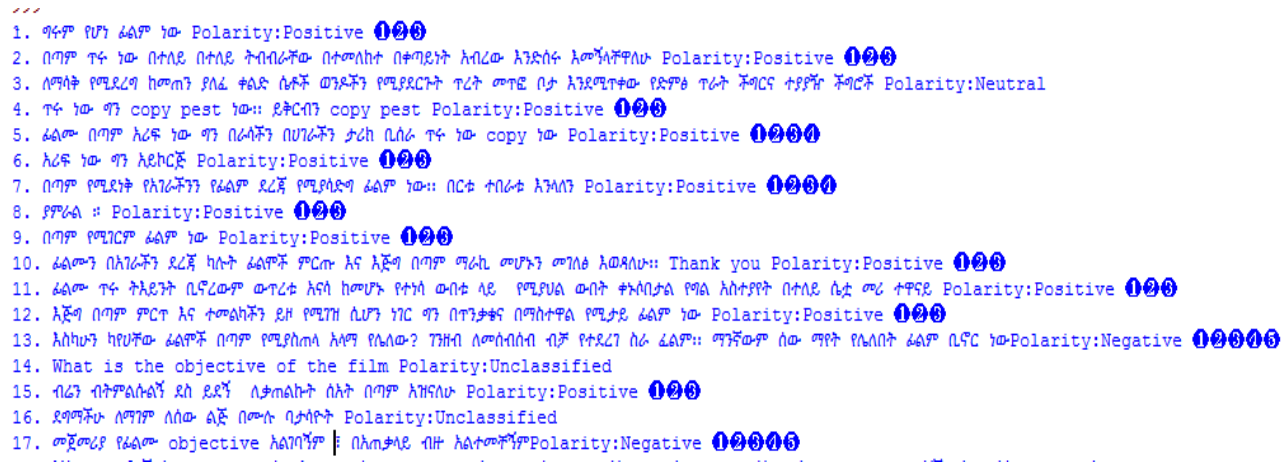


Figure 4.6 sample classified reviews with polarity strength

Sample of the prototype that shows accepting opinionated Amharic text inputs from the user through the data input widget and returning the polarity classification of the input opinionated Amharic text is given in figure 4.7. This demo indicates that the user or reviewer can write his/her comments or opinions in Amharic towards a target of object in the input text widget through their terminal or computer and submit so that the opinion can be pre-processed, classified and can be used for further analysis.

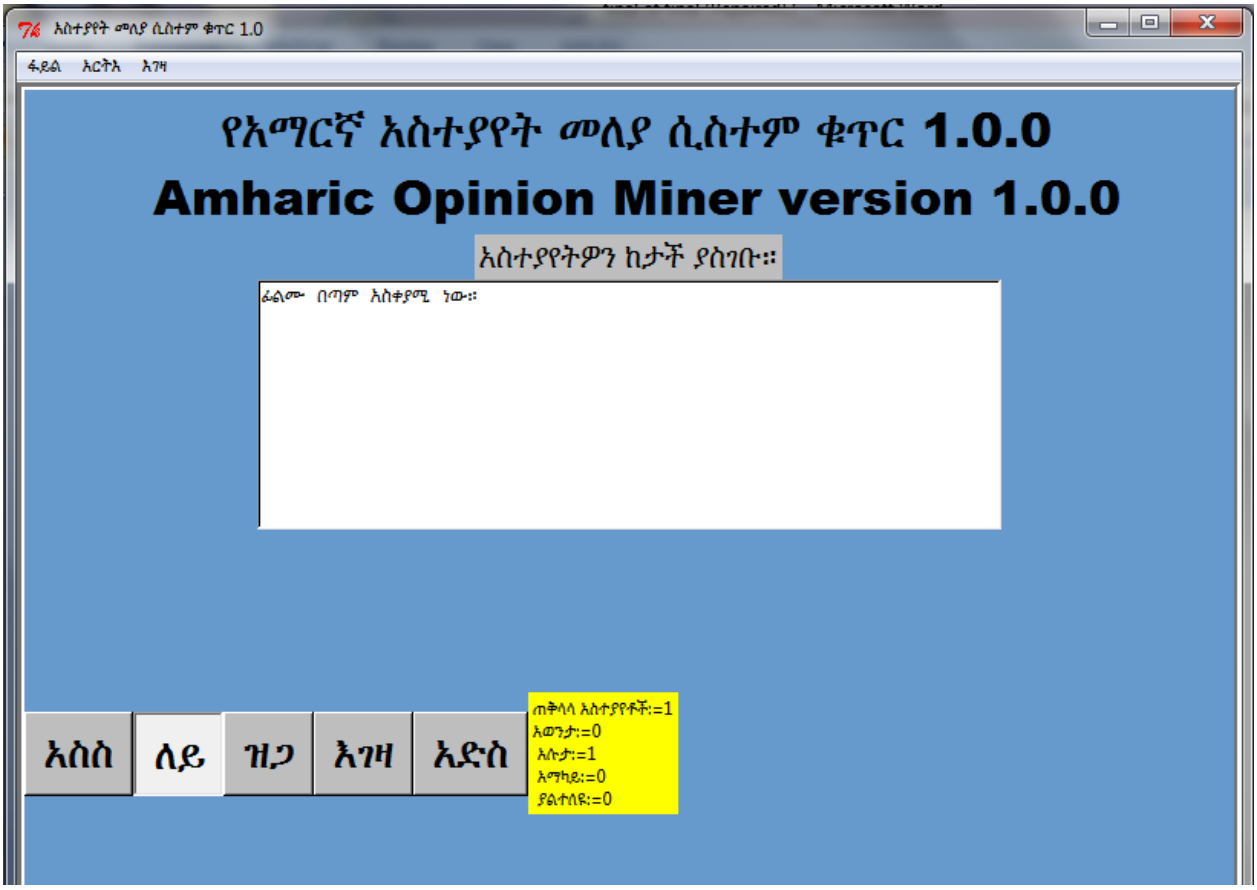


Figure 4.7 sample of accepting review from user and its polarity classification

Similarly, sample of the prototype that shows browsing Amharic opinionated texts from file and their polarity classifications are presented in figure 4.8. Large number of reviews or opinionated texts can be collected manually or automatically and stored in file. This large number of opinionated texts can be processed and classified at once. In this case, each opinionated text is processed and labeled with its polarity category as positive, negative or neutral and final statistical data that shows the number of positive opinionated texts, negative opinionated text and neutral opinionated texts of the total is generated so that this data can be used for further analysis and decision making. This is what the simple prototype in figure 4.8 tries to show.

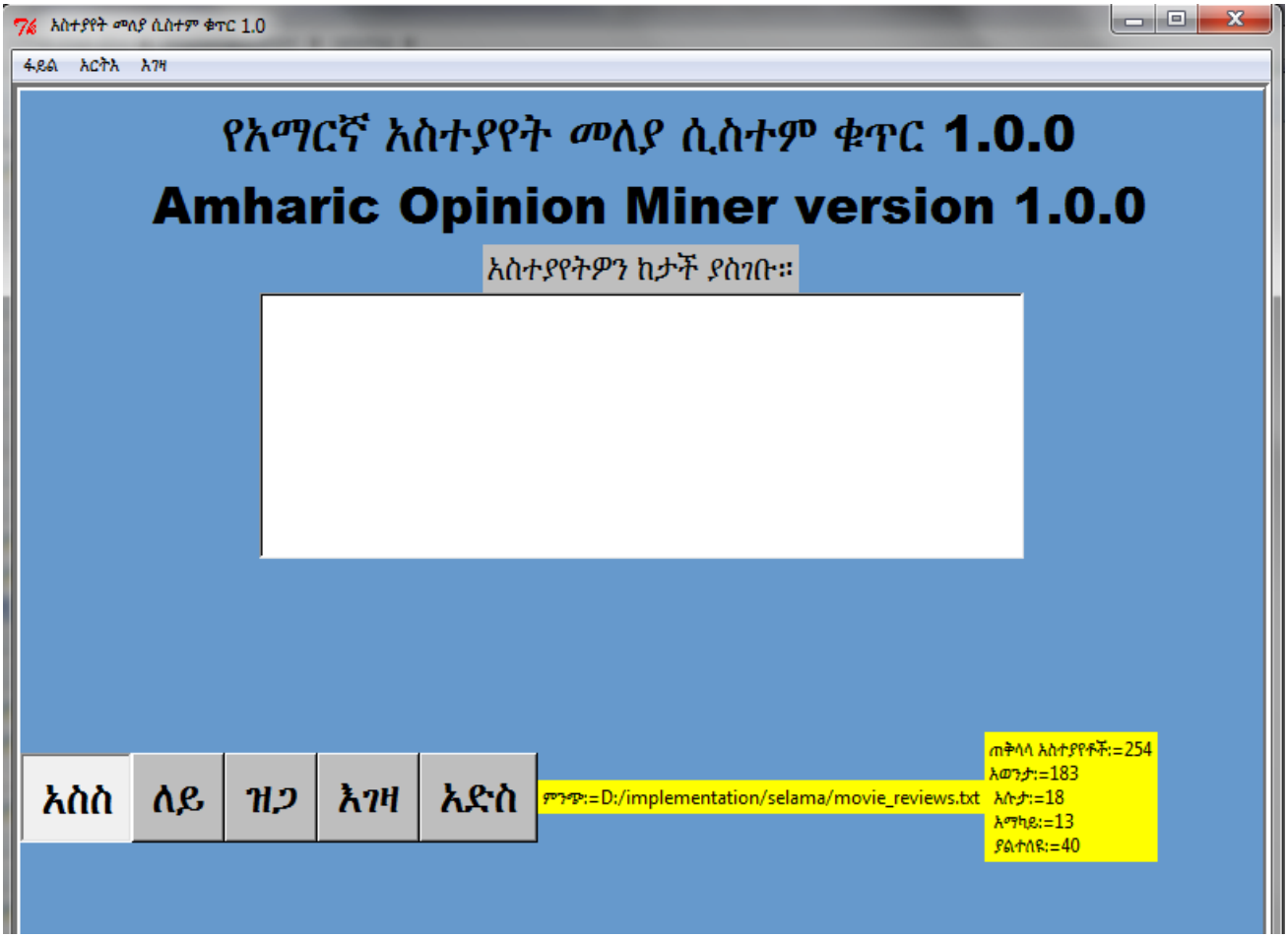


Figure 4.8 sample of browsing Amharic opinionated texts and their classification results

4.3.4. The Proposed Algorithms

Given a pre-processed review, the proposed sentiment mining model operates in three steps. First it takes tokenized and normalized review terms and checks them if they bear sentiment. This is done by checking the existence of the terms in the dictionary of sentiment terms. Next the sentiment terms are assigned initial polarity weight and polarity propagation is done if the sentiment terms are linked to contextual valence shifter terms. Finally, the review assigned into a predefined categories: positive (+), negative (-) or neutral based on the total weight obtained from the previous step. The high level view of the proposed algorithms that show how the sentiment terms are detected, classified and how the sentiment polarity value is propagated is given as follows.

Algorithm 4.1: review's sentiment detection and polarity classification

1. *For every pre-processed reviews R*
2. *For every term T in the review R, checks its existence in the lexicon of sentiments D*
3. *If a term T exists in the dictionary D*
   - *3.1. Its corresponding initial polarity weight Tpi is given*
   - *3.2. If it is linked to a contextual valence shifter term C*
     - *3.2.1. The initial polarity value Tpi of the term is propagated*
   - *3.3. Add all the polarity weights of the individual terms to get review polarity value Rp*
   - *3.4. If the total polarity weight Rp is greater than 0, then the review is categorized into predefined category positive (+)*
   - *3.5. If the total polarity weight Rp is less than zero, then the review is assigned into a predefined category negative (-)*
   - *3.6. Else the review is assigned into a predefined category of neutral.*
4. *Else the review is assigned into a unclassified class because there are no sentiment terms Ts in the given review*

Sentiment polarity propagation

The process of polarity propagation is done only if the sentiment terms T is linked to a contextual valence shifter terms C. accordingly, the procedures during the polarity propagation is given as follows.

Algorithm 4.2: Sentiment polarity propagation

1. *For every sentiment term T in review R*
2. *If a sentiment term T is linked to contextual valence term C*
   - *1.1. If a sentiment term T is linked to a negative contextual valence term C, then the prior polarity value of the term T is reversed from Tpi to –Tpi.*
   - *1.2. If the sentiment term T is linked to overstatement contextual valence shifter term C, then the prior polarity value of the term T is modified from Tpi to Tpi +1 (for positive sentiment terms) and from Tpi to Tpi-1(for negative sentiment terms)*
   - *1.3. If the sentiment term T is linked to understatement contextual valence shifter C, then the prior polarity value of the term is modified from Tpi to Tpi-1(for positive sentiment terms) and from Tpi to Tpi+1 (for negative sentiment terms)*

3. *Else the initial polarity value of the term Tpi is maintained*

.

4.4. Summary

In this chapter, we presented our proposal for the sentiment mining model of opinionated Amharic texts. The architecture of the proposed model contains components: preprocessing, sentiment words detection, weight assignment and propagation, polarity classification, polarity strength representation and sentiment lexica. After the reviews are preprocessed, each term is checked for existence in the sentiment lexica at the sentiment words detection component. The detected sentiment terms are assigned weight and the values of sentiment terms that are linked to contextual valence shifters are propagated in the weight assign and polarity propagation component. Based on the weights of the sentiment values, the reviews are classified into predefined categories: positive, negative or neutral. Finally, the polarity strength of the reviews is rated.

In addition, the implementation related issues such as Amharic sentiment lexica construction, guidelines for building the lexicon, the tools used for developing the prototype, the dictionary representation of the sentiment terms and the proposed algorithms are presented in this chapter. The sentiment lexica are built manually from different sources based on the principles and guidelines. Python programming language and python 3.0.1 interpreter are used to develop the prototype. The algorithm for sentiment polarity classification and the algorithm for sentiment polarity value propagation are the proposed algorithms.

CHAPTER FIVE

5. EXPERIMENTAL RESULTS

This chapter presents the experimental results of the developed prototype system. The experimental setups/procedures, the evaluation parameters, results and discussions of are presented in this chapter. The lack of readymade available resources such as lexicon of opinion terms, data sources and well defined tools made conducting the experiment challenging.

5.1. Procedures and Experimental Setups

To evaluate the developed sentiment mining model for opinionated Amharic texts, we used procedures and setups that include data collection, methods and manual classifications. These are described in the subsequent sections.

5.1.1. 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 Amharic language. As a result it is relatively more easy and manageable to collect movie reviews manually than any other domains. This is because it is possible to distribute questionnaires to movie funs from the different cinemas in Addis Ababa. In addition, movie viewers can write comments freely as compared to other domains such as politics. Hence most of the movie reviews we used for conducting the experiments are collected manually. This is done by preparing questionnaires and distributing them to the movie funs in the different cinemas in the city of Addis Ababa. The questioners used and sample responses to the questioner are given in Appendix C. The rest few movie reviews are collected from additional two sources. The first source is habeshafilms.com, a recently published website for promoting the Ethiopian film industry and allowing funs to leave their comments for a film they selected. The second source is from a set of movie reviews collected by an undergraduate student of Department of Theatrical Arts at Ababa University. The movies to be reviewed were randomly selected and randomly distributed by the author. As a result a total of 254 movie reviews are collected from all the sources described above.

In addition to the movie domain reviews, additional 49 reviews were taken from another domain (newspaper reviews domain). These reviews collected from reporter [52], a local Amharic bi-weekly news paper. The reviews were given by readers when the newspaper was

celebrating its 1000th edition. The purpose of using these additional reviews is to see the performance of the system prototype developed in the different domains.

Movie reviews

Movie reviews are known to be more difficult with sentiment mining. This is because movie reviews often contain many sentences with objective information about characters, directors or actors of the movie. Although these sentences are not used to express the author's opinion, they may contain many positive and negative terms. In addition, movie reviews contain more literary description than product reviews, which brings more implicit comments and results in low performance [53].

According to [36], the unique characteristics of movie reviews is: when a person writes a movie review, he/she probably comments not only movie elements (e.g. screen play, vision effects, music) but also movie related people (e.g. director, script writer, actor) while in product reviews, few people will care the issues like who has designed or manufactured the a product. Therefore, commented features in a movie review are much richer than those product reviews. As a result movie review mining is more challenging than other domains such as product review mining.

5.2.2. Manual classification

This activity is concerned with labeling the reviews for experimental purpose. All the 301 reviews (both the movie domain and newspaper domain reviews) are manually categorized by an independent individual from the domains into predefined categories: positive (+), negative (-), neutral (N) or unclassified (UN). If the given review is not related with the topic in target, it is assigned into the unclassified (UN) category. As a result, 170 of the total movie reviews are labeled as positive (+), 28 of them are labeled as negative (-), while the 29 reviews are labeled as neutral (N) and finally, the rest 27 are unclassified reviews. Similarly, 32, 14, 2 and 1 are of the total newspaper reviews that are labeled as positive, negative, neutral and unclassified respectively. The manually classified reviews helped us in crosschecking with the results obtained from our prototype system: sentiment mining model for opinionated Amharic texts.

5.3. Evaluation

This activity is responsible for describing the evaluation parameters of the designed model and its results. Evaluation of the prototype system is made with the evaluation parameter that compares the number of reviews which are categorized correctly and incorrectly. Typically, the

comparison is done between the reviews categorized by the proposed prototype system and that of the manually labeled (categorized) reviews.

Precision and recall, which are the evaluation parameters of information retrieval (IR), are used in text classifications. Precision measures the exactness of a classifier. Precision is the ratio of the number of reviews classified correctly to the total number of reviews in a given category. A high precision means less false positive, while a lower precision means more false positives.

$$P = \frac{TC}{TC + FC} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{equation 2}$$

Where, TC denotes the number of reviews which are classified correctly and FC denotes the number of reviews which are classified incorrectly.

Recall measures the completeness or sensitivity of a classifier. It is the ratio of TC and the whole reviews belonging to the category. A high recall means less false negative, while lower recall means more false negatives.

$$R = \frac{TC}{TC + MC} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{equation 3}$$

Where, MC denotes the number of reviews which are missed by the classifier, i.e. neither classified correctly or incorrectly (unclassified category).

There is trade-off between precision and recall. Greater precision decreases recall and greater recall leads to decreased precision. The F-measure is the harmonic mean of P and R and takes account of both the measures. As a result, F-measure is defined as follows:

$$F = \frac{2PR}{P + R} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{equation 4}$$

5.4. Results

In this section, we present the experimental results of the three different experiments. The first experiment (basic system) is done using a single general purpose dictionary without considering the contextual valence shifter terms. The second experiment is conducted using two sentiment lexica: the general purpose lexicon and the domain specific lexicon. And finally, the result of the experiment conducted using the two lexica and considering the contextual valence shifter terms. Comparison of all the different experimental results is also presented in this section.

All the 254 movie reviews and 49 newspaper reviews are used for conducting all the 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 labeled classifications. As a result, the results obtained for each experiment are given as follows.

5.4.1. Experiment one: Basic system

This experiment used the standard lexicon of sentiment terms i.e. the general purpose Amharic sentiment terms. The experiment is conducted for both movie and newspaper reviews domain. The results measured by accuracy, precision, recall and F-measure for each domain and classes is presented in table 5.1 as follows.

Table 5.1: Results of experiment one

System	Reviews	Class	Precision	Recall	F-measure
Basic system	Movie	Positive	0.929	0.823	0.867
		Negative	0.6	0.573	0.589
	Newspaper	Positive	0.93	0.9	0.914
		Negative	0.5	0.75	0.6

5.4.2. Experiment two: using general purpose and domain specific lexica

This experiment is conducted mainly to see the effect of using domain specific lexicon. As indicated in chapter four, domain specific lexicon refers to the list of opinion terms specific to a given domain such as movie, politics, economics, products etc. As a result, in this experiment we used both the general purpose lexicon and movie reviews domain lexicon. Only the 254 movie reviews are used for the experimental purpose. This is because we didn't build a lexicon of opinion terms specific to newspaper reviews domain. As presented in table 5.2 with similar measurements to that of experiment one, the results of this experiment show improvements when compared with the results of experiment one on movie reviews. This improvement is mainly due to the use of the domain specific lexicon in addition to the general purpose lexicon of terms.

Table 5.2: results of experiment two

System	Reviews	Class	Precision	Recall	F-measure
Basic + domain lexicon	Movie	Positive	0.937	0.943	0.939
		Negative	0.62	0.78	0.69

5.4.3. Experiment three: using both lexica and contextual valence shifter terms

This is the last experiment conducted considering the contextual valence shifter terms into account. As explained in the precious chapters, contextual valence shifter terms are terms that change the initial polarity value of a term or modify the initial value polarity value of a term. As a result, this experiment is done by using domain specific lexicon, general purpose lexicon and the contextual valence shifter terms for the movie review. Only the general purpose lexicon and the contextual valence shifter are used for the newspaper reviews. Therefore, the results of this experiment are presented in table 5.3 as follows using the measurements similar to the above experiments.

Table 5.3 results of experiment three

System	Reviews	class	precision	Recall	F-measure
complete	Movie	Positive	0.943	0.949	0.945
		Negative	0.666	0.842	0.743
General lexicon + valence shifters	Newspaper	Positive	0.93	0.900	0.914
		Negative	0.500	0.750	0.600

The experiments shown us that the results are promising despite the research work is in its infant stage. One reason for this good promising result is the convergence of the sentiment terms used by movie reviewers and the collected Amharic sentiment terms from different sources. This is because almost all of the reviews used in the experiments are very short as shown in Appendix D when compared to the reviews used by other researchers where most of the reviews are composed many paragraphs. As a result, reviewers used a very commonly used Amharic opinion words to express their opinion within those short reviews. Similarly, when we collect Amharic sentiment terms to our lexicon, the main criteria we used was the commonality of the sentiment terms. This was done by selecting sentiment terms that are commonly used by

the level of our knowledge and terms that represent opinion polarity without ambiguity. Therefore, when the length and complexity of reviews written in Amharic increases, the size and quality of the Amharic sentiment lexicon should also increased to keep and improve the system's performance.

In addition, the third experiment it re-conducted by using additional reviews given towards a newspaper. Those reviews are taken from Reporter, local bi-weekly Amharic newspaper printed on October 8, 2010 by media and communication center (MCC) [55]. The reviews are written by readers of the newspaper towards that newspaper when it was celebrating its 15th year crystal anniversary. The experimental results using these dataset are given in table 5.4. As usual, the reviews are first classified manually. As a result, 21 of the 35 reviews are assigned into positive category while the rest 10 and 4 are assigned into negative and neutral category respectively.

Table 5.4 Results of experiment three with additional reviews

System	Reviews	Class	Precision	Recall	F-measure
General lexicon + valence shifters	Newspaper	Positive	0.857	0.94	0.896
		Negative	0.555	0.8	0.655

5.6. Discussion of the results

As shown above, the three different experiments are done with different experimental setups and have shown us very good and promising results. These different experimental setups are the reasons to the variations of experimental results. The variations of results, reasons for the variations of results and important examples are discussed in this section.

The first results of the first experiment show that the system prototype performs relatively well with newspaper reviews than with movie reviews. This is mainly due to the complex nature of movie reviews. As explained above, movie reviews are known to be difficult in sentiment classification systems as compared to other domains. Similarly, in both domains, the system prototype performs well with positive reviews than with negative reviews. This can be caused

by different reasons related to the nature of natural language. In this research work, we have learnt some reasons for the slanted results. The first reason is that when writing reviews in Amharic, many reviewers use positive opinion terms to express negative opinions. For example: in the review "ከራሳችን ጭንቅላት ፊልቆ የወጣ ቢሆን ጥሩ ነው። ከውጭ ሀገረ ፊልሞች ባንሰርቅ ይመረጣል*Polarity: Positive*", the expressed opinion is negative but the system prototype labeled it as positive. This is because the reviewer used the positive opinion terms 'ጥሩ' (good) in his/her complex sentence to express his/her negative opinion towards the film. The second reason we have learnt is that most of the reviews collected and used for experimental purpose are reviews that contain positive opinions. For example, from 254 movie reviews only 28 reviews are negative as learnt from the manual labeling. As a result, this less number of negative reviews may have some influence on the precision of the negative class. In addition, many reviewers do not use explicit Amharic sentiment terms to express negative opinions. For example," ፊልሙ በቤቱ ውስጥ ብቻ አለቀ Polarity:Unclassified". This is negative opinion expressed without using explicit Amharic sentiment terms and this may affect the precision of the negative class.These kinds of complexities of natural languages make sentiment mining systems more challenging. As a result, detailed analysis is needed on the Amharic languages constraints to solve such kinds of problems.

In the second experiment, the results show that the system prototype performs 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 domain specific lexicon of opinion terms: in this case movie reviews domain. Experimental results using newspaper a review is not given in this experiment. This is because we did not built media specific lexicon of opinion terms. Similar justifications from experiment one can be considered to the good

performance of the system in the second experiment with positive reviews as compared with negative reviews.

Finally in the last experiment, the results show relative improvements. As indicated earlier, this experiment is conducted considering the contextual valence shifter term such as negations. In this experiment, we can see two different improvements: subjective and objective. The negation terms are the causes for the objective improvements while the intensifiers are the causes for the subjective improvements. The objective improvement can be measured in numbers as given in table 5.3. The subjective improvement is observed in the polarity strength representation. This is because the intensifiers don not change the polarity orientation of an opinion terms rather these terms change or modify the polarity strength of an opinion term. For example in the movie review "እሸ በጣም ቆንጆ አይደለም ብዙ የተሰራበት ነገር ከመምረጡም በላይ አንድ ቤተሰብ ላይ ብቻ ገንዘብ አፍቃሪ መሆናቸውን አገነነው ለነገሩ ፊልሞቻችን አንደ አካልን ላይ ማተኮር ይወዳሉ…. *Polarity: Positive*", in the first and second experiment this review is labeled as "positive" by the system even though this review is "negative". But in the third experiment, the system prototype labeled this review as negative:" እሸ በጣም ቆንጆ አይደለም ብዙ የተሰራበት ነገር ከመምረጡም በላይ አንድ ቤተሰብ ላይ ብቻ ገንዘብ አፍቃሪ መሆናቸውን አገነነው ለነገሩ ፊልሞቻችን አንደ አካልን ላይ ማተኮር ይወዳሉ….*Polarity:Negative*". This is because the negation terms " አይደለም (not)" reverses the polarity orientation of the sentiment term "ቆንጆ (cute)" from positive to negative.

In addition, in the movie review *"በጣም ቀሸት ነው Polarity:Positive"*, the polarity strength of this movie review was represented by two stars as in "በጣም ቀሸት ነው *Polarity:Positive* ❶❷" in the first and second experimental results. But in the third experiment, the incorporation of intensifier terms modifies the polarity strength of the review. The polarity strength of the review is modified from two stars to three stars representation as in "በጣም ቀሸት ነው *Polarity:Positive* ❶❷❸". This is because the intensifier term "በጣም (very)" modifies the

polarity strength of the opinion terms “ቀሽት (cute)” by adding a value of +1 to the original polarity value of +2.

As represented in table 5.3, there is no change in the objective experimental results using the media (newspaper) reviews when compared with the results of experiment two though there is improvement in the polarity strength representation of the results using stars. This is the reviews used from this domain are very few in number (only 49 reviews) so that the probability of the occurrence of negation terms is minimum.

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. Having this we have observed opinion statements written in Amharic that express strong positivity or negativity without using explicit opinion terms. Such kinds of statements pose challenges to sentiment mining systems. For example in the review “ላለፉት ብዙ አመታት ሪፖርተር ጋዜጣ ከሌሎች ከማነባቸው እንደ ዋሽንግተን ፖስት እና ኒውዮርክ ታይምስ ከሚባሉ ጋዜጦች ያልተለየኝ ነው።።” expressed a positive opinion towards the news paper but the system does not recognize this review neither in positive nor in negative categories. This is because the reviewer did not use any explicit Amharic opinion terms in expressing his/her opinion. This kind of reviews can be managed by comparative sentiment mining system, which is concerned with addressing and mining comparative opinion expressed in documents or reviews.

CHAPTER SIX

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

The web has dramatically changed the way that people express their views and opinions. They can now post reviews of products at merchant sites and express their view on almost everything in Internet forums, discussion groups and blogs. This online word-of-mouth behavior represents new and measurable sources of information with many practical applications. Now if one wants to buy a product, he/she is no longer limited to asking his/her friends and families because there are many product reviews on the web which gives opinions of existing users of the product. For a company, it may no longer be necessary to conduct surveys, organize forum groups or employ external consultant to find consumer opinions.

However, it is difficult for a human reader to find relevant sources, extract related sentences with opinions, read them summarize them and organize them into useful forms. As a result, automated opinion discovery and summarization systems are needed. Sentiment analysis, a text mining problem, grows out of this need. Due to its tremendous value for practical applications, there has been an explosive growth of both research in academics and applications in the industry.

This research work has tried to go through the techniques of sentiment mining for opinionated Amharic texts. To classify a given opinionated document or text into predefined classes, the opinionated document passes through pre-processing, detection of sentiment words, weight assignment and polarity classification processes. Pre-processing involves normalization and tokenization. The detection of sentiment words is a process of detecting polarity words and contextual valence shifters based on the sentiment lexicon. Weight assignment and polarity propagation is responsible for assigning an initial weight for detected sentiment terms and propagating polarity value of sentiment terms that are linked to contextual valence shifters. Polarity classification is concerned with categorizing a given opinionated document into predefined categories based on the weights obtained from the weight assign and polarity propagation process.

In order to detect the sentiment terms from a given opinionated document, assign initial value to the sentiment terms and propagate the initial polarity values, lexica of properly tagged Amharic sentiment terms are used.

The high-level tasks that are undertaken to accomplish the objective and the results obtained are: identifying the techniques of building Amharic sentiment lexicon, building the sentiment lexicon where two lexica of general purpose and domain specific are built, designing the general architecture of the proposed sentiment mining model, an initial prototype for the sentiment mining model for opinionated Amharic texts is developed, and testing the developed prototype for sentiment mining model for opinionated Amharic texts with movie review as a main experimental dataset.

The results of the lexicon-based sentiment mining model for opinionated Amharic texts using the processes explained above are encouraging. However, further work can be done to improve the proposed model's results.

6.2. Contributions of the study

Some of the main contributions of this research work are given below.

- A model is proposed for sentiment mining of opinionated Amharic texts.
- We collected above 950 Amharic sentiment terms
- Different techniques are employed to build the sentiment mining lexicon that can also be advantageous to those who need to collect additional Amharic sentiment terms.
- Algorithms are developed to realize the proposed model
- We created a general understanding of the subject matter; sentiment analysis for opinionated Amharic texts.
- This research can be used as a base work for sentiment mining related research works for opinionated Amharic documents.
- A prototype system that is based on the model is developed.
- The prototype is evaluated for effectiveness and encouraging results are obtained.

6.3. Recommendations

Even though many things are done in this work to develop a sentiment mining model for opinionated Amharic texts or documents, developing a full-fledged, fully functional and a more efficient sentiment mining system needs coordinated team efforts that comprises linguistic professional, computer science professional and other people such as those who have the experiences of collecting large number of comments from the public. Therefore, good coordination of those different professionals can result a sentiment mining system with full functionality and a better performance.

6.4. Future Works

There are many possible directions for future works. In this research work, we used only subjective Amharic sentences (opinionated Amharic sentences), but a future work can broaden the scope to subjectivity classification which is concerned with classifying random documents into subjective (opinionated document) or objective (non-opinionated documents). This may help reduce the manual efforts that are needed to be applied in identifying opinionated and non-opinionated documents.

Another strategy that can be considered in the future is to improve the performance of the sentiment mining model and to enrich the available Amharic sentiment lexicon. This can be done by increasing the size of the lexicon, by considering phrase-level Amharic sentiment terms and by improving the quality of the lexicon considering more different domains. In addition, more precise analysis will be applied to the Amharic sentiment terms' polarity strength because some positive and negative sentiment terms may not be equally positive or negative. So that positive and negative terms can be given explicit weights to show how positive or how negative they are. All overstatement and understatements also may not be equally weighted.

Feature level sentiment mining can also be another future research work direction which is concerned with identification and extraction of commented features and determining the sentiments towards these features. For example, movie features such as director, actor, lighting … etc can be identified and their corresponding opinions can be determined. This is a more detailed area of study in the sentiment mining research works.

Handling reviews or opinionated documents with idiomatic expressions and longer reviews or opinionated documents from different domains can also be another focus of future research works.

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Annexes

Appendix A: sample subjectivity lexicon of OpinionFinder

type=weaksubj len=1 word1=good pos1=anypos stemmed1=n priorpolarity=positive
type=weaksubj len=1 word1=goodly pos1=adverb stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=goodness pos1=noun stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=goodwill pos1=adj stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=goodwill pos1=noun stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=goof pos1=noun stemmed1=n priorpolarity=negative
type=strongsubj len=1 word1=goof pos1=verb stemmed1=y priorpolarity=negative
type=strongsubj len=1 word1=gorgeous pos1=adj stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=gorgeously pos1=anypos stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=gossip pos1=adj stemmed1=n priorpolarity=negative
type=strongsubj len=1 word1=gossip pos1=noun stemmed1=n priorpolarity=negative
type=strongsubj len=1 word1=gossip pos1=verb stemmed1=y priorpolarity=negative
type=strongsubj len=1 word1=grace pos1=noun stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=graceful pos1=adj stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=gracefully pos1=adverb stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=graceless pos1=adj stemmed1=n priorpolarity=negative
type=strongsubj len=1 word1=gracelessly pos1=adverb stemmed1=n priorpolarity=negative
type=strongsubj len=1 word1=gracious pos1=adj stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=graciously pos1=adverb stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=graciousness pos1=noun stemmed1=n priorpolarity=positive
type=weaksubj len=1 word1=graft pos1=noun stemmed1=n priorpolarity=negative
type=weaksubj len=1 word1=grail pos1=adj stemmed1=n priorpolarity=positive
type=weaksubj len=1 word1=grail pos1=noun stemmed1=n priorpolarity=positive
type=weaksubj len=1 word1=grand pos1=adj stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=grandeur pos1=noun stemmed1=n priorpolarity=positive
type=strongsubj len=1 word1=grandiose pos1=adj stemmed1=n priorpolarity=negative

Appendix B: Sample representation of sentiment terms in our dictionary

Gen_ictionary={"ሰላም":"+","ምላሽ":"-","ተአምረኛ":"+","ጉዳት":"-","የሚያወላውል":"-","ዱብዳ":"-
","ባለፀጋ":"+","ትምክህተኛ":"-","ቁጥብ":"+","ጎሽ":"+","እድል":"+","ተመፃዳቂ":"-","አርበኛ":"+","ልክ":"+","ፍጭት":"-
","ጠቢብ":"+","ያልሰመረ":"-","አቤቱታ":"-","ፍቃድ":"+","ውሸት":"-","ግርማ":"+","ዘለቄታ":"+","አውደልዳይ":"-
","ርህራሄ":"+","አሜን":"+","ተብታባ":"-","ድካም":"-","ቅፅበታዊ":"-","አዝናኝ":"+","አስቸጋሪ":"-","ተመፃዳቂ":"-
","ትንግርት":"+","ከሀድ":"-","እርካሽ":"-","ርካሽ":"-","ቂላቂል":"-","ቅናታም":"-","ሸባ":"-","ፅዱ":"+","እብድ":"-","ቀማኛ":"-
","ቁጣ":"-","ጥገኛ":"-","አስጨናቂ":"-","ተሀድሶ":"+","ቁርጠት":"-","ማሸንከት":"-","ኋላቀርነት":"-","የማይለወጥ":"-
","ጠቃሚ":"+","ሀሰት":"-","ደህና":"+","ፈጣጣ":"-
","ቸር":"+","ምስጋና":"+","ሰብአዊ":"+","ማአረግ":"+","ስምምነት":"+","መደብደብያ":"-","ሽጋ":"+","ልቅ":"-","በቀል":"-
","ሀዘን":"-","ፍቅር":"+","የተሳሳተ":"-","በደል":"-","ወዳጅ":"+","አስተዋይ":"+","ከባድ":"-","ድንግልና":"+","ፈሪ":"-
","ድንግል":"+","ቋጣሪ":"-","ረብሻ":"-","ሞኝነት":"-","ይሉኝታ":"-","ፍቃደኛ":"+","የሞተ":"-","በደለኛ":"-
","ምሁር":"+","እርቃን":"-","ከይሲ":"-","ቸርነት":"+","አህዛብ":"+","መተዛዘኛ":"+","ተስፋ":"+","ምክር":"+","እንከን":"-
","ነጋሲ":"+","ኮስታራ":"-","ምሳሌ":"+","ተጨባጭ":"+","አስደናቂ":"+","እድፍ":"-","አበሳ":"-","የተወደደ":"+","የሚያመነታ":"-
","መረዳዳት":"+","ያልተረጋገጠ":"-","ራእይ":"+","ዝምተኛ":"+","ግልፅ":"+","ፅንፈኛ":"-","አፈንጋጭ":"-","ኩራተኛ":"-
","ደብዛዛ":"-","እክል":"-","መቅጫ":"-","መረጋጋት":"+","ጥዱ":"+","ጥል":"-","አላስፈላጊ":"-","ቀናተኛ":"-","ፈሳም":"-","ቦዘኔ":"-
","ሸባ":"-","ጭቁን":"-","አረንቋ":"-","የተስተካከለ":"+","ጀግንነት":"+","ቆራጥ":"+","አዳሚ":"-","መጮህ":"-","ወረርሽኝ":"-
","ትችት":"-","ውድ":"+","ተፈላጊ":"+","ማጭበርበር":"-","ገነት":"+","ከፍተኛ":"+","ከዳተኛ":"-","ንደት":"-","ሸባ":"-","ጋጋታ":"-
","አፀያፊ":"-","አመርቂ":"+","መቃብር":"-","አድናቆት":"+","ወልጋዳ":"-","አእምሮ":"+","ሞልጣፋ":"-","ግጭት":"-","ጥለኛ":"-
","ቃል":"+","ዘመናዊ":"+","ሰላማዊ":"+","አሰልቺ":"-","ውስብስብ":"-","ታማኝ":"+","የማይበገር":"+","ዝሙት":"-","ምቅኝነት":"-
","ደነዝ":"-","ደማቅ":"+","ምቀኛ":"-","ጭንቀት":"-","እርቅ":"+","እድገት":"+","ጩኸት":"-","ሰይጣን":"-
","አስተማማኝ":"+","ዘልዛላ":"-","ጥቅም":"+","ባርነት":"-","ውሸታም":"-","አክራሪ":"-","ፈታኝ":"+","ንፁህ":"+","አጭበርባሪ":"-
","መርዘኛ":"-","አማፂ":"-","ምኞት":"+","ልዩ":"+","ችሎታ":"+","ቁርጠኝነት":"+","መግረፍያ":"-","የሚያሳዝን":"-","ምፀት":"-
","የሚቃረን":"-","ወርቃማ":"+","ተፅእኖ":"-","ዘገምተኛ":"-","አመል":"-","ደፋር":"+","አፋኝ":"-","አስደማሚ":"+","ሀሰት":"-
","ወሬ":"-","ተአምራዊ":"+","ወሬኛ":"-","ዋጋ":"+","ጥንብ":"-","ግርማዊ":"+","ዝና":"+","አወንታ":"+","ያለመሳካት":"-
","ሸክም":"-","ጋኔን":"-","ምሁራዊ":"+","ህብረት":"+","እምቢተኛ":"-","ልምላሜ":"+","የተረጋጋ":"+","ብልሀት":"+","ከፋፋይ":"-
","ትንሽ":"-","ክህደት":"-","ነፃነት":"-","አሉታዊ":"-","አሸባሪ":"-","ጣፋጭ":"+","ሽረኛ":"-","መላምታዊ":"-","ፌዝ":"-
","ያልተጠበቀ":"-","ንቃት":"+","በን":"+","መርዝ":"-","ችኩል":"-","አድመኛ":"-","ተቃዋሚ":"-","ሌሊት":"-","ሹጣም":"-
","ትጋት":"+","ያልነቃ":"-","ጥበብ":"+","ከንቱ":"-","ወላዋይ":"-","ታታሪ":"+","እውነት":"+","የላቀ":"+","ቃጠሎ":"-","መካን":"-
","አሉባልታ":"-","ሽብርተኛ":"-","ጠሳ":"-","ወዘና":"+","ተጠቂ":"-","ሀላፊነት":"+","ዋልጌ":"-","ሚና":"-
","አብነት":"+","ባልንጀራ":"+","ድርቅ":"-","ስልጡን":"+","ገውጋዋ":"-","ምሩቅ":"+","ምሩቅ":"+","ብድር":"-","እብለት":"-
","ንፍግ":"-","ቀኝ":"+","ሌባ":"-","ሙደኛ":"+","ቀጥታ":"+","ፈታኝ":"-","ርካሽ":"-","ሙሰኛ":"-","ኩራት":"+","እጦት":"-
","ሀዋሪያ":"+","ሀርነት":"+","ተጠቃሚ":"+","አመል":"-","ጥላሸት":"-","ጥጋብ":"+","ቡካን":"-","ሰይጣን":"-
","ትብብር":"+","ትግል":"+","ጉስቁል":"-","ለፍላፊ":"-","ተንኮል":"-","አርአያ":"+","የማይረሳ":"+","ክብር":"+","ኢፍትሀዊነት":"-
","ጥፋት":"-","ብኩን":"-","ቀልጣፋ":"+","ነሁላላ":"-","ስድ":"-","ጩሀት":"-","አለመተማመን":"-
","ፅናት":"+","ቅዱስ":"+","የማይታመን":"-","ፀፅታ":"+","ድልዝ":"-","ዘላቂ":"+","ወሸኔ":"+","ደባሪ":"-","ነስቃላ":"-
","ሀቅ":"+","ሀብት":"+","ሀይለኛ":"+","ደስተኛ":"+","ነውጠኛ":"-","ነፍናፋ":"-","ፍትሀዊ":"+","ህሊና":"+","ሸርሙጣ":"-
","ዘረኝነት":"-","ስርቅታ":"-","እሺ":"+","ተድላ":"+","ደህንነት":"+","ቅናት":"-","ምስኪን":"-","አምባገነን":"-",}

Appendix C: questionnaire and sample responses

አዲስ አበባ ዩኒቨርሲቲ
ኢንፎርማቲክስ ፋኩልቲ
የኮምፒዩተር ሳይንስ ትምህርት ክፍል
<u>በፊልም ተመልካቾች የሚሞላ መጠይቅ</u>

<u>**የመጠይቁ አላማ:**</u>
በአዲስ አበባ ዩኒቨርሲቲ በኮምፒዩተር ሳይንስ ትምህርት ክፍል ለማስተርስ ዲግሪ ምርምር ማሟያ የሚሆን በአማርኛ ቋንቋ ላይ መሰረት ያደረገ ኮምፒዩተራይዝድ የፊልም ተመልካቾች አስተያየት መለያ ሲስተም ለመስራት ግብዓት የሚሆኑ አስተያየቶችን ለመሰብሰብ ነዉ::

በቅድሚያ ለሚያደርጉልን ትብብር ከልብ እናመሰግናለን::

<u>**ጥያቄ:**</u>____________________ የተሰኘዉን ፊልም አይተዉታል? እንግዲያዉስ ያሉዎትን ማንኛዉም አስተያየት አጠር ባለ መልኩ ይግለፁልን::
<u>**መልስ:**</u>____::

<u>**የመጠይቁ አዘጋጅ:**</u> ሰላማ ገ.መስቀል፣ በኮምፒዩተር ሳይንስ ትምህርት ክፍል የማስተርስ ዲግሪ ተማሪ::

አዲስ አበባ ዩኒቨርሲቲ
ኢንፎርማቲክስ ፋኩልቲ
የኮምፒተር ሳይንስ ትምህርት ክፍል
<u>በፊልም ተመልካቾች የሚሞላ መጠይቅ</u>

+1

<u>**የመጠይቁ አላማ:**</u>
በአዲስ አበባ ዩኒቨርሲቲ በኮምፒተር ሳይንስ ትምህርት ክፍል ለማስተርስ ዲግሪ ምርምር ማሟያ የሚሆን በአማርኛ ቋንቋ ላይ መሰረት ያደረገ ኮምፒተራይዝድ የፊልም ተመልካቾች አስተያየት መለያ ሲስተም ለመስራት ግብዓት የሚሆኑ አስተያየቶችን ለመሰብሰብ ነዉ::

በቅድሚያ ለሚያደርጉልን ትብብር ከልብ እናመሰግናለን::

<u>**ጥያቄ:**</u> [illegible] የተሰኘዉን ፊልም አይተዉታል? እንግዲያዉስ ያሉዎትን ማንኛዉም አስተያየት አጠር ባለ መልኩ ይግለፁልን::
<u>**መልስ:**</u> [illegible]::

<u>**የመጠይቁ አዘጋጅ:**</u> ሰላማ ገመስቀል፣ በኮምፒተር ሳይንስ ትምህርት ክፍል የማስተርስ ዲግሪ ተማሪ::

Appendix D: sample of movie reviews

1. ግሩም የሆነ ፊልም ነው

2. በጣም ጥሩ ነው በተለይ በተለይ ትብብራቸው በተመለከተ በቀጣይነት አብረው እንድሰሩ እመኝላቸዋለሁ

3. ለማሳቅ የሚደረግ ከመጠን ያለፈ ቀልድ ሴቶች ወንዶችን የሚያደርጉት ጥረት መጥፎ ቦታ እንደሚጥቀው የድምፅ ጥራት ችግርና ተያያዥ ችግሮች

4. ጥሩ ነው ግን copy pest ነው፡፡ ይቅርብን copy pest

5. ፊልሙ በጣም አሪፍ ነው ግን በራሳችን በሀገራችን ታሪክ ቢሰራ ጥሩ ነው copy ነው

6. አሪፍ ነው ግን አይኮርጅ

7. በጣም የሚደነቅ የአገራችንን የፊልም ደረጃ የሚያሳድግ ፊልም ነው፡፡ በርቱ ተበራቱ እንላለን

8. ያምራል

9. በጣም የሚገርም ፊልም ነው

10. ፊልሙን በአገራችን ደረጃ ካሉት ፊልሞች ምርጡ እና እጅግ በጣም ማራኪ መሆኑን መገለፅ እወዳለሁ፡፡ Thank you

11. ፊልሙ ጥሩ ትእይንት ቢኖረውም ውጥረቱ አናሳ ከመሆኑ የተነሳ ውበቱ ላይ የሚያህል ውበት ቀኑሶበታል የግል አስተያየት በተለይ ሴቷ መሪ ተዋናይ

12. እጅግ በጣም ምርጥ እና ተመልካችን ይዞ የሚገዝ ሲሆን ነገር ግን በጥንቃቄና በማስተዋል የሚታይ ፊልም ነው

13. እስካሁን ካየሀቸው ፊልሞች በጣም የሚያስጠላ አላማ የሌለው? ገንዘብ ለመሰብሰብ ብቻ የተደረገ ስራ ፊልም፡፡ ማንኛውም ሰው ማየት የሌለበት ፊልም ቢኖር ነው

14. What is the objective of the film

15. ብሬን ብትምልሱልኝ ደስ ይደኝ ለቃጠልኩት ሰአት በጣም አዝናለሁ

16. ደግማችሁ ለማገም ለሰው ልጅ በሙሉ ባታሳዮት

17. መጀመሪያ የፊልሙ objective አልገባኝም፣ በአጠቃላይ ብዙ አልተመቸኝም

18. እሽ በጣም ቆንጆ አይደለም ብዙ የተሰራበት ነገር ከመምረጡም በላይ አንድ ቤተሰብ ላይ ብቻ ገንዘብ አፍቃሪ መሆናቸውን አገነነው ለነገሩ ፊልሞቻችን አንደ አካልን ላይ ማተኮር ይወዳሉ….

19. በጣም የሚያስጠላ ፊልም ነው ደደብ ደራሲና ኘሮድውሰር የስራውና ያየሁት ቢቻል ከአሁን በሀላ ለህዝቡ አታሳዩ አንዳንደ ከገንዘብ ውጭ ማማሰብ ጀምሮ ለፊልሙ ለተሳተፉ

20. ከስርየት ቀጥሎ mid ውስጥ የቀረ……

21. ፊልሙ በጣም ወድጅዋለሁ በይበልጥ የፊልሙ ታሪክና ትወናው ግን የተወሰነ sod truck እና የፊልሙ ቀረፃ የተሻለ ቢሆን ፊልሙ በጣም ቆንጆ ነው

22. ብዙም እንደጠበኩት አላገኘሁትም ነገር ግን የተረደሁት ነገር ቢኖር “ ለበጐ ነገር የሚደረጉ መልካም ነገሮች ሁሉ ዋጋ አይከፈልባቸውም”

23. በጣም ጥሩ ነው

Appendix E: List of validated Amharic sentiment terms and approval letter

አዲስ አበባ ዩኒቨርሲቲ

ኢንፎርማቲክስ ፋኩልቲ

የኮምፒዩተር ሳይንስ ትምህርት ክፍል

አላማ

በአዲስ አበባ ዩኒቨርሲቲ በኮምፒዩተር ሳይንስ ትምህርት ክፍል ለማስተርስ ድግሪ ምርምር ማሟያ የሚሆን በአማርኛ ቋንቋ ላይ መሰረት ያደረገ ኮምፒዩተራይዝድ የሰዎች አስተያየት መለያ ሲስተም ለመስራት ግብአት የሚሆኑ የአማርኛ ቃላት ለመሰብሰብ ነዉ፡፡በዚሁ መሰረት አዎንታ ወይም አሉታን የሚገልፁ ከ 900 በላይ ቃላት ተሰብስበዋል፡፡ከእነዚህ ቃላት ዉስጥ አዎንታ የሆኑት በ "+" ምልክት አሉታ የሆኑት በ "-" አፍራሽ የሆኑት ደግሞ በ "negate" በሚል የኢንግሊዘኛ ቃል ተወክለዋል፡፡

ስለዚህ የእነዚህን ቃላት ትክክለኛነት እንዲያረጋግጡልን በትህትና እንጠይቃለን፡፡

ያዘጋጁት

1. ሰላማ ገ.መድህን (በኮምፒዩተር ሳይንስ ሁለተኛ ዓመት የድህረ-ምረቃ ተማሪ)

2. ገብረ እግዚአብሔር ተስፋዬ (በተግባራዊ ልሳነ-ልሳን አማርኛ ማስተማር የድህረ-ምረቃ ተማሪ)

3. ግንት መልካም ለማስ (" " " " ")

ያረጋገጠዉ

1. ፀጋዬ ኪሮስ [signature] የሊቃ- ቋንቋዎች ና ሊንጉስቲክስ

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ኋላቀርነት/- ትርምስ/- ነቃ/+ መራራ/- አመኔታ/+

አዛኸር/- ጨላማ/- እርቃን/- እዳ/- አሪፍ/+

ጎበዝ/+ ሀሴት/+ ተጫዋች/+ ትእግስት/+ የሚቃወም/-

ጌጃ/- አስመሳይ/- በሽተኛ/- ስብእና/+ ተናደደ/-

ፈዛዛ/- አዱኛ/+ አሳመረ/+ ፀጋ/+ ህገወጥ/-

ፈገግታ/+ በፍፁም/+ ማንባት/- ምርጥ/+ ዝርክርክ/-

እርግጠኛ/+ ሀሰተኛ/- አስገራሚ/+ ሂስ/- ጉድለት/-

አስፈሪ/- ቅፅበት/- መልካም/+ እከካም/- ፈተና/+

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የተወናበደ/- የተጋነነ/- ዘራፊ/- እልቂት/- መልቲ/-

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ቀውስ/- ሽታ/+ ህግ/+ በጎፍቃድ/+ አድማ/-

አስመሳይ/- ስልጣኔ/+ ባእድ/- መልከመልካም/ ቀጣፊ/-

ስርዝ/- ኪሳራ/- የሚያስቅ/+ + ጥርጣሬ/-

ቅን/+ ዝንጉ/- ደንብ/+ የማይካድ/+ ዘመናዊነት/+

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ሀቀኛ/+ ግብ/+ የማይታገስ/- ሻገተ/- ቅጥፈት/-

ቅሬታ/- እስከነአካቴው/- ባለሙያ/+ ማአረግ/+ የማይጎዳ/+

ወሸኔ/+ የሚበረታታ/+ ስጦታ/+ ወረኛ/- አሸናፊ/+

ድባቅ/- ሽንፈት/- ቸልተኛ/- ጭንቅንቅ/- አዋራጅ/-

መንፈሳዊ/+ ሀራም/- ትጋተኛ/+ ለጋሽ/+ ሰላምተኛ/+

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ቻይ/+ ነገረኛ/- የባሰ/- መጫር/- ከውካዋ/-

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ዋነኛ/+ የሚያሳፍር/- ሙየያዊ/+ አንገብጋቢ/- ታጋች/+

አለቃ/+ ፍጥጫ/- ፍሬ/+ ሀይማኖተኛ/+ ታጋሽ/+

ሹም/+ ፋና/+ ዘላቂነት/+ ስልት/+ ብልጣብልጥ/-

የሚያስጠላ/- የሚያጎድል/- ፀዳል/+ ተቃራኒ/- ድንክ/-

ሳያመነታ/+ ጎርባጣ/- ንዝንዝ/- ልእልና/+ እምቅ/+

ስሜታዊ/- ነጭናጫ/- ተአምር/+ ቀለጤ/- አማፅያን/-

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ማለፍያ/+ አደናጋሪ/- ያማረ/+ እርኩስ/- ከሀዲ/-

የማይስማማ/- አግባብ/+ ዘረኛ/- እንቆቅልሻዊ/- ወረተኛ/-

እልሀኛ/- ቅንጣት/- መንድስ/- ጉርምርምታ/- መንዛዛት/-

ብልሹ/- ንዋይ/+ ውጤት/+ ድክመት/- ቅንጦት/+

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Declaration

I, the undersigned, declare that this thesis is my original work and has not been presented for a degree in any other university, and all sources of materials for the thesis have been acknowledged.

_____

SELAMA GEBREMESKEL

This thesis has been submitted for examination with my approval as an advisor.

_____

SOLOMON ATNAFU (Ph. D.)

Addis Ababa, Ethiopia
October, 2010

Authorization

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